Locan Documentation

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Locan Developers

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GETTING STARTED

Locan is a python-based library with code for analyzing single-molecule localization data. Such data is typically generated in fluorescence-based super-resolution microscopy methods. Single-molecule localization microscopy (SMLM) techniques rely on finding the position of single-molecule emitters in time and space and reconstructing a super-resolved image or movie. The generated localizations are analyzed point-by-point for statistical and structural insight.

CHAPTER

ONE

INSTALLATION

1.1 Dependencies

- python 3
- standard scipy and other open source libraries

A list with all hard and optional dependencies is given in *pyproject.toml*, *environment.yml* and *requirements.txt*.

1.2 Install from pypi

Install locan directly from the Python Package Index:

```
pip install locan
```

Extra dependencies can be included:

```
pip install locan[all]
```

1.3 Install from conda-forge

Install locan with the conda package manager:

```
conda install -c conda-forge locan
```

1.4 Install from distribution or sources

In order to get the latest changes install from the GitHub repository main branch:

```
pip install git+https://github.com/super-resolution/Locan.git@main
```

or download distribution or wheel archive and install with pip:

```
pip install <distribution_file>
```

Install from local sources:

```
pip install <locan_directory>
```

1.5 Run tests

Use pytest to run the tests from the source directory:

```
pytest
```

Or run a locan script from any directory:

```
locan test
```

1.6 Using conda to set up a dedicated environment:

1) Install miniconda or anaconda (platform-independent)
2) Setup a new environment from the environment.yml file:

   ```
   conda env create --file "./environment.yml"
   ```

   or with specific python version:

   ```
   conda create --name locan python=3.10
   conda env update --name locan --file "./environment.yml"
   ```

3) Activate the environment and install locan.

We recommend using mamba to speed up dependency resolution:

```
mamba create --name locan python=3.10
mamba env update --name locan --file "./environment.yml"
mamba install --name locan -c conda-forge locan
conda activate locan
```

1.7 Jupyter

To work with jupyter notebooks install jupyter lab:

```
pip install jupyterlab
```

or inside a conda environment:

```
conda install -c conda-forge jupyterlab
```

Make sure to add the appropriate lab extensions:

```
jupyter labextension install @jupyter-widgets/jupyterlab-manager \
                             @pyviz/jupyterlab_pyviz \
                             jupyter-matplotlib
```

You may need to install node.js for rebuilding jupyter lab:

```
conda install -c conda-forge nodejs
```

1.8 Various installation issues

1) Numba requires specific numpy version:

   Numba might not be compatible with the latest numpy version.

   Solution: Install numba first.

2) Building a wheel for hdbscan raises error:

   Building a wheel for hdbscan during installation might cause the following error:

   "ValueError: numpy.ndarray size changed, may indicate binary incompatibility. "

   This error arises from version incompatibility between the numpy version installed in the current environment and the one used for building the wheel.

   Solution: Install wheel, cython, and numpy (or numba) with oldest-supported-numpy first, then build hdbscan using the installed versions (and not in isolation as done by default), and finally install locan:

   ```
   pip install wheel cython numba oldest-supported-numpy
   pip install hdbscan --no-build-isolation
   pip install locan[all]
   ```

3) Running "locan napari" in conda environment raises error:

   Starting napari in a conda environment with python>=3.8 and pyside2 causes the following error:

   "RuntimeError: PySide2 rcc binary not found in…"

   Seems like napari>0.4.5 does not work with pyside2<5.14 due to the replacement of pyside2-uic/pyside2-rcc.

   Solution: Set up an environment with python 3.7. Or set up an environment with only pyqt5 instead of pyside2. Or, if both pyqt5 and pyside2 are installed, set the environment variable "QT_API":

   ```
   import os
   os.environ["QT_API"] = "pyqt5"
   ```

CHAPTER

TWO

TUTORIALS

Tutorials give selected application examples to get familiar with typical use cases.

Tutorials are provided as Jupyter notebooks.

2.1 Tutorial about the LocData class

```
import numpy as np
import pandas as pd

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.1.1 Sample data

A localization has certain properties such as 'position_x'. A list of localizations can be assembled into a dataframe:

```
df = pd.DataFrame(
    {
        'position_x': np.arange(0,10),
        'position_y': np.random.random(10),
        'frame': np.arange(0,10),
    })
```

2.1.2 Instantiate LocData from a dataframe

A LocData object carries localization data together with metadata and aggregated properties for the whole set of localizations.

We first instantiate a LocData object from the dataframe:

```
locdata = lc.LocData.from_dataframe(dataframe=df)
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

```
attributes = [x for x in dir(locdata) if not x.startswith('_')]
attributes
```

```
['alpha_shape',
 'bounding_box',
 'centroid',
 'concat',
 'convex_hull',
 'coordinate_keys',
 'coordinates',
 'count',
 'data',
 'dataframe',
 'dimension',
 'from_chunks',
 'from_collection',
 'from_coordinates',
 'from_dataframe',
 'from_selection',
 'indices',
 'inertia_moments',
 'meta',
 'oriented_bounding_box',
 'print_meta',
 'print_summary',
 'projection',
 'properties',
 'reduce',
 'references',
 'region',
 'reset',
 'uncertainty_keys',
 'update',
 'update_alpha_shape',
 'update_alpha_shape_in_references',
 'update_convex_hulls_in_references',
 'update_inertia_moments_in_references',
```

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```
 'update_oriented_bounding_box_in_references',
 'update_properties_in_references']
```

2.1.3 LocData attributes

The class attribute Locdata.count represents the number of all current LocData instantiations.

```
print('LocData count: ', lc.LocData.count)
```

```
LocData count:  1
```

The localization dataset is provided by the data attribute:

```
print(locdata.data.head())
```

```
   position_x  position_y  frame
0           0    0.764394      0
1           1    0.597709      1
2           2    0.710542      2
3           3    0.217267      3
4           4    0.825669      4
```

Aggregated properties are provided by the attribute properties. E.g. the property `position_x` represents the mean of the `position_x` for all localizations. We keep the name, since the aggregated dataset can be treated as just a single locdata event with `position_x`. This is used when dealing with data clusters.

```
locdata.properties
```

```
{'localization_count': 10,
 'position_x': 4.5,
 'uncertainty_x': 0.9574271077563381,
 'position_y': 0.4432652879982591,
 'uncertainty_y': 0.09553020726045479,
 'frame': 0,
 'region_measure_bb': 6.939483882419593,
 'localization_density_bb': 1.4410293574330337,
 'subregion_measure_bb': 19.542107529426577}
```

Since spatial coordinates are quite important one can check on *coordinate_keys* and dimension:

```
locdata.coordinate_keys
```

```
['position_x', 'position_y']
```

```
locdata.dimension
```

```
2
```

A numpy array of spatial coordinates is returned by:

```
locdata.coordinates
```

```
array([[0.        , 0.76439418],
       [1.        , 0.59770864],
       [2.        , 0.71054167],
       [3.        , 0.2172672 ],
       [4.        , 0.82566903],
       [5.        , 0.25001971],
       [6.        , 0.69906893],
       [7.        , 0.05461526],
       [8.        , 0.21806483],
       [9.        , 0.09530343]])
```

2.1.4 Metadata

For detailed information see the `Tutorial about metadata`.

Metadata is provided by the attribute meta and can be printed as

```
locdata.print_meta()
```

```
identifier: "1"
source: DESIGN
state: RAW
history {
  name: "LocData.from_dataframe"
}
element_count: 10
frame_count: 10
creation_time {
  2024-03-14T11:51:37.225141Z
}
```

A summary of the most important metadata fields is printed as:

```
locdata.print_summary()
```

```
identifier: "1"
comment: ""
source: DESIGN
state: RAW
element_count: 10
frame_count: 10
creation_time {
  2024-03-14T11:51:37.225141Z
}
```

Metadata fields can be printed and changed individually:

```
print(locdata.meta.comment)
locdata.meta.comment = 'user comment'
print(locdata.meta.comment)
```

```
user comment
```

LocData.meta.map represents a dictionary structure that can be filled by the user. Both key and value have to be strings, if not a TypeError is thrown.

```
print(locdata.meta.map)
locdata.meta.map['user field'] = 'more information'
print(locdata.meta.map)
```

```
{}
{'user field': 'more information'}
```

Metadata can also be added at Instantiation:

```
locdata_2 = lc.LocData.from_dataframe(dataframe=df, meta={'identifier': 'myID_
↪1',
                                                          'comment': 'my own user␣
↪comment'})
locdata_2.print_summary()
```

```
identifier: "myID_1"
comment: "my own user comment"
source: DESIGN
state: RAW
element_count: 10
frame_count: 10
creation_time {
  2024-03-14T11:51:37.335529Z
}
```

2.1.5 Instantiate locdata from selection

A LocData object can also be instantiated from a selection of localizations. In this case the LocData object keeps a reference to the original locdata together with a list of indices (or a slice object)). The new dataset is assembled on request of the data attribute.

Typically a selection is derived using a selection method such that using LocData.from_selection() is not often necessary.

```
locdata_2 = lc.LocData.from_selection(locdata, indices=[1,2,3,4])
locdata_3 = lc.LocData.from_selection(locdata, indices=[5,6,7,8])

print('count: ', lc.LocData.count)
print('')
print(locdata_2.data)
```

```
count:  3

   position_x  position_y  frame
1           1    0.597709      1
2           2    0.710542      2
3           3    0.217267      3
4           4    0.825669      4
```

```
locdata_2.print_summary()
```

```
identifier: "3"
comment: "user comment"
source: DESIGN
state: MODIFIED
element_count: 4
frame_count: 4
creation_time {
  2024-03-14T11:51:37.225141Z
}
modification_time {
  2024-03-14T11:51:37.344812Z
}
```

The reference is kept in a private attribute as are the indices.

```
print(locdata_2.references)
print(locdata_2.indices)
```

```
<locan.data.locdata.LocData object at 0x7fe968721b10>
[1, 2, 3, 4]
```

The reference is the same for both selections.

```
print(locdata_2.references is locdata_3.references)
```

```
True
```

2.1.6 Instantiate locdata from collection

A LocDat object can further be instantiated from a collection of other LocData objects.

```
del(locdata_2, locdata_3)

locdata_1 = lc.LocData.from_selection(locdata, indices=[0,1,2])
locdata_2 = lc.LocData.from_selection(locdata, indices=[3,4,5])
locdata_3 = lc.LocData.from_selection(locdata, indices=[6,7,8])
locdata_c = lc.LocData.from_collection(locdatas=[locdata_1, locdata_2,␣
↪locdata_3], meta={'identifier': 'my_collection'})
```

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```
print('count: ', lc.LocData.count, '\n')
print(locdata_c.data, '\n')
print(locdata_c.properties, '\n')
locdata_c.print_summary()
```

```
count:  5

   localization_count  position_x  uncertainty_x  position_y  uncertainty_y  \
0                   3         1.0        0.57735    0.690881       0.049112
1                   3         4.0        0.57735    0.430985       0.197568
2                   3         7.0        0.57735    0.323916       0.193420

   frame  region_measure_bb  localization_density_bb  subregion_measure_bb
0      0           0.333371                 8.998981              4.333371
1      3           1.216804                 2.465476              5.216804
2      6           1.288907                 2.327553              5.288907

{'localization_count': 3, 'position_x': 4.0, 'uncertainty_x': 1.
↪7320508075688772, 'position_y': 0.6556156831335508, 'uncertainty_y': 0.
↪047321463252748025, 'frame': 0, 'region_measure_bb': 2.2017909548646597,
↪'localization_density_bb': 1.3625271706070774, 'subregion_measure_bb': 12.
↪73393031828822}

identifier: "my_collection"
comment: ""
source: DESIGN
state: RAW
element_count: 3
frame_count: 3
creation_time {
  2024-03-14T11:51:37.529283Z
}
```

In this case the reference are also kept in case the original localizations from the collected LocData object are requested.

```
print(locdata_c.references)
```

```
[<locan.data.locdata.LocData object at 0x7fe94c2ffcd0>, <locan.data.locdata.
↪LocData object at 0x7fe968721c60>, <locan.data.locdata.LocData object at␣
↪0x7fe9955d32e0>]
```

In case the collected LocData objects are not needed anymore and should be free for garbage collection the references can be deleted by a dedicated Locdata method

```
locdata_c.reduce()
print(locdata_c.references)
```

```
None
```

2.1.7 Concatenating LocData objects

Lets have a second dataset with localization data:

```
del(locdata_2)

df_2 = pd.DataFrame(
    {
        'position_x': np.arange(0,10),
        'position_y': np.random.random(10),
        'frame': np.arange(0,10),
    })

locdata_2 = lc.LocData.from_dataframe(dataframe=df_2)

print('First locdata:')
print(locdata.data.head())
print('')
print('Second locdata:')
print(locdata_2.data.head())
```

```
First locdata:
   position_x  position_y  frame
0           0    0.764394      0
1           1    0.597709      1
2           2    0.710542      2
3           3    0.217267      3
4           4    0.825669      4

Second locdata:
   position_x  position_y  frame
0           0    0.057302      0
1           1    0.946862      1
2           2    0.110801      2
3           3    0.931244      3
4           4    0.817191      4
```

In order to combine two sets of localization data from two LocData objects into a single LocData object use the class method *LocData.concat*:

```
locdata_new = lc.LocData.concat([locdata, locdata_2])
print('Number of localizations in locdata_new: ', len(locdata_new))
locdata_new.data.head()
```

```
Number of localizations in locdata_new:  20
```

```
   position_x  position_y  frame
0           0    0.764394      0
1           1    0.597709      1
2           2    0.710542      2
```

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```
3            3    0.217267      3
4            4    0.825669      4
```

2.1.8 Modifying data in place

In case localization data has been modified in place, i.e. the dataset attribute is changed, all properties and hulls must be recomputed. This is best done by re-instantiating the LocData object using `LocData.from_dataframe()`; but it can also be done using the `LocData.reset()` function.

```
del(df, locdata)

df = pd.DataFrame(
    {
        'position_x': np.arange(0,10),
        'position_y': np.random.random(10),
        'frame': np.arange(0,10),
    })

locdata = lc.LocData.from_dataframe(dataframe=df)

print(locdata.data.head())
```

```
   position_x  position_y  frame
0           0    0.084824      0
1           1    0.685775      1
2           2    0.130687      2
3           3    0.921479      3
4           4    0.764340      4
```

```
locdata.centroid
```

```
array([4.5       , 0.52797812])
```

Now if localization data is changed in place (which you should not do unless you have a good reason), properties and bounding box are not automatically adjusted.

```
locdata.dataframe = pd.DataFrame(
    {
        'position_x': np.arange(0,8),
        'position_y': np.random.random(8),
        'frame': np.arange(0,8),
    })

print(locdata.data.head())
```

```
   position_x  position_y  frame
0           0    0.746007      0
1           1    0.095743      1
```

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```
2           2    0.026744      2
3           3    0.904659      3
4           4    0.663385      4
```

```
locdata.centroid  # so this returns incorrect values here
```

```
array([4.5       , 0.52797812])
```

Update them by re-instantiating a new LocData object:

```
locdata_new = lc.LocData.from_dataframe(dataframe=locdata.data)
```

```
locdata_new.centroid
```

```
array([3.5       , 0.57268293])
```

```
locdata_new.meta
```

```
identifier: "12"
source: DESIGN
state: RAW
history {
  name: "LocData.from_dataframe"
}
element_count: 8
frame_count: 8
creation_time {
  seconds: 1710417097
  nanos: 632895000
}
```

Alternatively you can use `reset()`. In this case, however, metadata is not updated and will provide wrong information.

```
locdata.reset()
```

```
<locan.data.locdata.LocData at 0x7fe94c372200>
```

```
locdata.centroid
```

```
array([3.5       , 0.57268293])
```

```
locdata.meta
```

```
identifier: "11"
source: DESIGN
state: RAW
```

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```
history {
  name: "LocData.from_dataframe"
}
element_count: 10
frame_count: 10
creation_time {
  seconds: 1710417097
  nanos: 591943000
}
```

2.1.9 Copy LocData

Shallow and deep copies can be made from LocData instances. In either case the class variable count and the metadata is not just copied but adjusted accordingly.

```
print('count: ', lc.LocData.count)
print('')
print(locdata_2.meta)
```

```
count:  7

identifier: "9"
source: DESIGN
state: RAW
history {
  name: "LocData.from_dataframe"
}
element_count: 10
frame_count: 10
creation_time {
  seconds: 1710417097
  nanos: 562338000
}
```

```
from copy import copy, deepcopy

print('count before: ', lc.LocData.count)
locdata_copy = copy(locdata_2)
locdata_deepcopy = deepcopy(locdata_2)
print('count after: ', lc.LocData.count)
```

```
count before:  7
count after:  9
```

```
print(locdata_copy.meta)
```

```
identifier: "13"
source: DESIGN
state: MODIFIED
history {
  name: "LocData.from_dataframe"
}
history {
  name: "LocData.copy"
  parameter: "None"
}
ancestor_identifiers: "9"
element_count: 10
frame_count: 10
creation_time {
  seconds: 1710417097
  nanos: 562338000
}
modification_time {
  seconds: 1710417097
  nanos: 695318000
}
```

```
print(locdata_deepcopy.meta)
```

```
identifier: "14"
source: DESIGN
state: MODIFIED
history {
  name: "LocData.from_dataframe"
}
history {
  name: "LocData.deepcopy"
  parameter: "None"
}
ancestor_identifiers: "9"
element_count: 10
frame_count: 10
creation_time {
  seconds: 1710417097
  nanos: 562338000
}
modification_time {
  seconds: 1710417097
  nanos: 697172000
}
```

2.1.10 Adding a property

Any property that is created for a set of localizations (and represented as a python dictionary) can be added to the Locdata object. As an example, we compute the maximum distance between any two localizations and add that `max_distance` as new property to `locdata`.

```
max_distance = lc.max_distance(locdata)
max_distance
```

```
{'max_distance': 7.000054038569519}
```

```
locdata.properties.update(max_distance)
locdata.properties
```

```
{'localization_count': 8,
 'position_x': 3.5,
 'uncertainty_x': 0.8660254037844386,
 'position_y': 0.5726829316741663,
 'uncertainty_y': 0.12230954417441992,
 'frame': 0,
 'region_measure_bb': 6.161151923077077,
 'localization_density_bb': 1.2984584863157445,
 'subregion_measure_bb': 15.760329120879165,
 'region_measure_ch': 3.576550357052744,
 'localization_density_ch': 2.236792216338986,
 'subregion_measure_ch': 14.263760059605291,
 'max_distance': 7.000054038569519}
```

2.1.11 Adding a property to each localization in LocData.data

In case you have processed your data and come up with a new property for each localization in the LocData object, this property can be added to data. As an example, we compute the nearest neighbor distance for each localization and add `nn_distance` as new property.

```
locdata.data
```

	position_x	position_y	frame
0	0	0.746007	0
1	1	0.095743	1
2	2	0.026744	2
3	3	0.904659	3
4	4	0.663385	4
5	5	0.464506	5
6	6	0.906909	6
7	7	0.773512	7

```
nn = lc.NearestNeighborDistances().compute(locdata)
nn.results
```

```
   nn_distance  nn_index
0     1.192830         1
1     1.002378         2
2     1.002378         1
3     1.028695         4
4     1.019585         5
5     1.019585         4
6     1.008858         7
7     1.008858         6
```

To add `nn_distance` as new property to each localization in LocData object, use the `pandas.assign` function on the `locdata.dataframe`.

```
locdata.dataframe = locdata.dataframe.assign(nn_distance=nn.results['nn_
↪distance'])
locdata.data
```

```
   position_x  position_y  frame  nn_distance
0           0    0.746007      0     1.192830
1           1    0.095743      1     1.002378
2           2    0.026744      2     1.002378
3           3    0.904659      3     1.028695
4           4    0.663385      4     1.019585
5           5    0.464506      5     1.019585
6           6    0.906909      6     1.008858
7           7    0.773512      7     1.008858
```

Adding nn_distance as new property to each localization in LocData object with dataframe=None

In case the LocData object was created with LocData.from_selection() the LocData.dataframe attribute is None and LocData.data is generated from the referenced locdata and the index list.

In this case LocData.dataframe can still be filled with additional data that is merged upon returning LocData.data.

```
locdata_selection = lc.LocData.from_selection(locdata, indices=[1, 3, 4, 5])
locdata_selection.data
```

```
   position_x  position_y  frame  nn_distance
1           1    0.095743      1     1.002378
3           3    0.904659      3     1.028695
4           4    0.663385      4     1.019585
5           5    0.464506      5     1.019585
```

```
locdata_selection.dataframe
```

```
Empty DataFrame
Columns: []
Index: []
```

```
nn_selection = lc.NearestNeighborDistances().compute(locdata_selection)
nn_selection.results
```

```
   nn_distance  nn_index
0     2.157393         1
1     1.028695         2
2     1.019585         3
3     1.019585         2
```

Make sure the indices in nn.results match those in dat_selection.data:

```
locdata_selection.data.index
```

```
Index([1, 3, 4, 5], dtype='int64')
```

```
nn_selection.results.index = locdata_selection.data.index
nn_selection.results
```

```
   nn_distance  nn_index
1     2.157393         1
3     1.028695         2
4     1.019585         3
5     1.019585         2
```

Then assign the corresponding result to dataframe:

```
locdata_selection.dataframe = locdata_selection.dataframe.assign(nn_distance=␣
↪nn_selection.results['nn_distance'])
locdata_selection.dataframe
```

```
   nn_distance
1     2.157393
3     1.028695
4     1.019585
5     1.019585
```

Calling `data` will return the complete dataset.

```
locdata_selection.data
```

```
   position_x  position_y  frame  nn_distance_x  nn_distance_y
1           1    0.095743      1       1.002378       2.157393
3           3    0.904659      3       1.028695       1.028695
4           4    0.663385      4       1.019585       1.019585
5           5    0.464506      5       1.019585       1.019585
```

2.2 Tutorial about loading localization data from file

```
from pathlib import Path

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

Localization data is typically provided as text or binary file with different formats depending on the fitting software. Locan provides functions for loading various localization files.

All available functions can be looked up in the API documentation.

In locan there are functions availabel to deal with file types according to the constant enum `FileType`:

```
list(lc.FileType._member_names_)
```

```
['UNKNOWN_FILE_TYPE',
 'CUSTOM',
 'RAPIDSTORM',
 'ELYRA',
 'THUNDERSTORM',
 'ASDF',
 'NANOIMAGER',
 'RAPIDSTORMTRACK',
 'SMLM',
 'DECODE',
 'SMAP']
```

Currently the following io functions are available:

```
[name for name in dir(lc.locan_io) if not name.startswith("__")]
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

```
['Files',
 'annotations',
 'convert_property_names',
 'convert_property_types',
 'files',
 'find_file_upstream',
 'load_Elyra_file',
```

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```
 'load_Elyra_header',
 'load_Nanoimager_file',
 'load_Nanoimager_header',
 'load_SMAP_file',
 'load_SMAP_header',
 'load_SMLM_file',
 'load_SMLM_header',
 'load_SMLM_manifest',
 'load_asdf_file',
 'load_decode_file',
 'load_decode_header',
 'load_locdata',
 'load_rapidSTORM_file',
 'load_rapidSTORM_header',
 'load_rapidSTORM_track_file',
 'load_rapidSTORM_track_header',
 'load_thunderstorm_file',
 'load_thunderstorm_header',
 'load_txt_file',
 'locdata',
 'manifest_file_info_from_locdata',
 'manifest_format_from_locdata',
 'manifest_from_locdata',
 'save_SMAP_csv',
 'save_SMLM',
 'save_asdf',
 'save_thunderstorm_csv',
 'utilities']
```

Throughout this manual it might be helpful to use pathlib to provide path information. In all cases a string path is also usable.

2.2.1 Load rapidSTORM data file

Here we identify some data in the test_data directory and provide a path using pathlib (a pathlib object is returned by `lc.ROOT_DIR`):

```
path = lc.ROOT_DIR / 'tests/test_data/rapidSTORM_dstorm_data.txt'
print(path, '\n')
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.txt
```

The data is then loaded from a rapidSTORM localization file. The file header is read to provide correct property names. The number of localisations to be read can be limited by *nrows*

```
dat = lc.load_rapidSTORM_file(path=path, nrows=1000)
```

Print information about the data:

```
print('Data head:')
print(dat.data.head(), '\n')
print('Summary:')
dat.print_summary()
print('Properties:')
print(dat.properties)
```

```
Data head:
   position_x  position_y  frame  intensity  chi_square  local_background
0     9657.40     24533.5      0   33290.10   1192250.0        767.732971
1    16754.90     18770.0      0   21275.40   2106810.0        875.460999
2    14457.60     18582.6      0   20748.70    526031.0        703.369995
3     6820.58     16662.8      0    8531.77   3179190.0        852.789001
4    19183.20     22907.2      0   14139.60    448631.0        662.770020

Summary:
identifier: "1"
comment: ""
source: EXPERIMENT
state: RAW
element_count: 999
frame_count: 48
file {
  type: RAPIDSTORM
  path: "/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/
↪lib/python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.
↪txt"
}
creation_time {
  2024-03-14T11:51:32.809222Z
}

Properties:
{'localization_count': 999, 'position_x': 16066.234912912912, 'uncertainty_x
↪': 250.05278033739012, 'position_y': 17550.369092792796, 'uncertainty_y':␣
↪223.5338926935945, 'intensity': 9471560.21, 'local_background': 645.07007,
↪'frame': 0, 'region_measure_bb': 1064111469.8204715, 'localization_density_
↪bb': 9.388114199807877e-07, 'subregion_measure_bb': 130483.2086}
```

Column names are exchanged with standard locan property names according to the following mapping. If no mapping is defined a warning is issued and the original column name is kept.

```
lc.RAPIDSTORM_KEYS
```

```
{'Position-0-0': 'position_x',
 'Position-1-0': 'position_y',
 'Position-2-0': 'position_z',
 'ImageNumber-0-0': 'frame',
 'Amplitude-0-0': 'intensity',
 'FitResidues-0-0': 'chi_square',
```

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```
 'LocalBackground-0-0': 'local_background',
 'TwoKernelImprovement-0-0': 'two_kernel_improvement',
 'Position-0-0-uncertainty': 'uncertainty_x',
 'Position-1-0-uncertainty': 'uncertainty_y',
 'Position-2-0-uncertainty': 'uncertainty_z'}
```

2.2.2 Load Zeiss Elyra data file

The Elyra super-resolution microscopy system from Zeiss uses as slightly different file format. Elyra column names are exchanged with locan property names upon loading the data.

```
path_Elyra = lc.ROOT_DIR / 'tests/test_data/Elyra_dstorm_data.txt'
print(path_Elyra, '\n')
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/tests/test_data/Elyra_dstorm_data.txt
```

```
dat_Elyra = lc.load_Elyra_file(path=path_Elyra, nrows=1000)
```

```
print('Data head:')
print(dat_Elyra.data.head(), '\n')
print('Summary:')
dat_Elyra.print_summary()
print('Properties:')
print(dat_Elyra.properties)
```

```
Data head:
   original_index  frame  frames_number  frames_missing  position_x  \
0               1      1              1               0     15850.6
1               2      1              1               0     25617.3
2               3      1              1               0     20155.8
3               4      1              1               0     10776.9
4               5      1              1               0     28966.9

   position_y  uncertainty  intensity  local_background_sigma  chi_square  \
0     23502.1          8.6      472.0                    5.33        0.28
1     24310.2          9.5      529.0                    4.38        0.31
2     24039.1         13.0      306.0                    3.06        0.23
3     10047.4         13.4      369.0                    3.98        0.25
4      8731.6         18.1      428.0                   14.73        0.41

   psf_half_width  channel  slice_z
0      110.000000        1      1.0
1      129.800003        1      1.0
2      131.100006        1      1.0
3      143.000000        1      1.0
4      150.100006        1      1.0
```

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```
Summary:
identifier: "2"
comment: ""
source: EXPERIMENT
state: RAW
element_count: 999
frame_count: 53
file {
  type: ELYRA
  path: "/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/
↪lib/python3.10/site-packages/locan/tests/test_data/Elyra_dstorm_data.txt"
}
creation_time {
  2024-03-14T11:51:32.859880Z
}

Properties:
{'localization_count': 999, 'position_x': 19122.652093695295, 'uncertainty_x
↪': 303.29709733725053, 'position_y': 14931.696849579646, 'uncertainty_y':␣
↪317.7629231493217, 'intensity': 264951.0, 'frame': 1, 'region_measure_bb':␣
↪775271493.12, 'localization_density_bb': 1.2885808505348594e-06, 'subregion_
↪measure_bb': 111666.4}
```

2.2.3 Localization data from a custom text file

Other custom text files can be read with a function that wraps the pandas.read_table() method.

```
path_csv = lc.ROOT_DIR / 'tests/test_data/five_blobs.txt'
print(path_csv, '\n')
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/tests/test_data/five_blobs.txt
```

Here data is loaded from a comma-separated-value file. Column names are read from the first line and a warning is given if the naming does not comply with locan conventions. Column names can also be provided as *column*. The separater, e.g. a tab '\t' can be provided as *sep*.

```
dat_csv = lc.load_txt_file(path=path_csv, sep=',', columns=None, nrows=100)
```

```
print('Data head:')
print(dat_csv.data.head(), '\n')
print('Summary:')
dat_csv.print_summary()
print('Properties:')
print(dat_csv.properties)
```

```
Data head:
   index  position_x  position_y  cluster_label  frame
0      0       624.0       919.0              3      0
1      1       611.0       873.0              3      0
2      2       388.0      1015.0              0      0
3      3       209.0       465.0              2      0
4      4      1001.0       851.0              4      0

Summary:
identifier: "3"
comment: ""
source: EXPERIMENT
state: RAW
element_count: 50
frame_count: 2
file {
  type: CUSTOM
  path: "/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/
↪lib/python3.10/site-packages/locan/tests/test_data/five_blobs.txt"
}
creation_time {
  2024-03-14T11:51:32.896468Z
}

Properties:
{'localization_count': 50, 'position_x': 608.68, 'uncertainty_x': 42.
↪72002293051437, 'position_y': 777.34, 'uncertainty_y': 25.60871359996238,
↪'frame': 0, 'region_measure_bb': 493145.0, 'localization_density_bb': 0.
↪00010139005769094282, 'subregion_measure_bb': 2892.0}
```

2.2.4 Load localization data file

A general function for loading localization data is provided. Targeting specific localization file formats is done through the `file_format` parameter.

```
path = lc.ROOT_DIR / 'tests/test_data/rapidSTORM_dstorm_data.txt'
print(path, '\n')
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.txt
```

```
dat = lc.load_locdata(path=path, file_type=lc.FileType.RAPIDSTORM, nrows=1000)
```

```
dat.print_summary()
```

```
identifier: "4"
comment: ""
source: EXPERIMENT
```

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```
state: RAW
element_count: 999
frame_count: 48
file {
  type: RAPIDSTORM
  path: "/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/
↪lib/python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.
↪txt"
}
creation_time {
  2024-03-14T11:51:32.932917Z
}
```

The file type can be specified by using the enum class `FileType` and use tab control to make a choice.

```
lc.FileType.__members__
```

```
mappingproxy({'UNKNOWN_FILE_TYPE': <FileType.UNKNOWN_FILE_TYPE: 0>,
              'CUSTOM': <FileType.CUSTOM: 1>,
              'RAPIDSTORM': <FileType.RAPIDSTORM: 2>,
              'ELYRA': <FileType.ELYRA: 3>,
              'THUNDERSTORM': <FileType.THUNDERSTORM: 4>,
              'ASDF': <FileType.ASDF: 5>,
              'NANOIMAGER': <FileType.NANOIMAGER: 6>,
              'RAPIDSTORMTRACK': <FileType.RAPIDSTORMTRACK: 7>,
              'SMLM': <FileType.SMLM: 8>,
              'DECODE': <FileType.DECODE: 9>,
              'SMAP': <FileType.SMAP: 10>})
```

```
lc.FileType.RAPIDSTORM
```

```
<FileType.RAPIDSTORM: 2>
```

2.2.5 Adjust data types

The data types of localization proparties are adjusted in all load functions by default to the following standdard types:

```
lc.PROPERTY_KEYS
```

```
{'index': 'integer',
 'original_index': 'integer',
 'position_x': 'float',
 'position_y': 'float',
 'position_z': 'float',
 'frame': 'integer',
 'frames_number': 'integer',
 'frames_missing': 'integer',
```

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```
 'time': 'float',
 'intensity': 'float',
 'local_background': 'float',
 'local_background_sigma': 'float',
 'signal_noise_ratio': 'float',
 'signal_background_ratio': 'float',
 'chi_square': 'float',
 'two_kernel_improvement': 'float',
 'psf_amplitude': 'float',
 'psf_width': 'float',
 'psf_width_x': 'float',
 'psf_width_y': 'float',
 'psf_width_z': 'float',
 'psf_half_width': 'float',
 'psf_half_width_x': 'float',
 'psf_half_width_y': 'float',
 'psf_half_width_z': 'float',
 'psf_sigma': 'float',
 'psf_sigma_x': 'float',
 'psf_sigma_y': 'float',
 'psf_sigma_z': 'float',
 'uncertainty': 'float',
 'uncertainty_x': 'float',
 'uncertainty_y': 'float',
 'uncertainty_z': 'float',
 'channel': 'integer',
 'slice_z': 'float',
 'plane': 'integer',
 'cluster_label': 'integer'}
```

If this is not what you want, add `convert = False`.

```
path = lc.ROOT_DIR / 'tests/test_data/rapidSTORM_dstorm_data.txt'
print(path, '\n')
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.txt
```

```
locdata = lc.load_locdata(path=path, file_type=lc.FileType.RAPIDSTORM,␣
↪nrows=1000, convert=False)
locdata.data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 999 entries, 0 to 998
Data columns (total 6 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   position_x        999 non-null    float64
 1   position_y        999 non-null    float64
```

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```
 2   frame             999 non-null    int64
 3   intensity         999 non-null    float64
 4   chi_square        999 non-null    float64
 5   local_background  999 non-null    float64
dtypes: float64(5), int64(1)
memory usage: 47.0 KB
```

Maybe adjust types for selected localization properties.

```
other_types = {"frame": float}
df = lc.convert_property_types(locdata.data, types=other_types)
locdata.update(dataframe=df)
locdata.data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 999 entries, 0 to 998
Data columns (total 6 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   position_x        999 non-null    float64
 1   position_y        999 non-null    float64
 2   frame             999 non-null    float64
 3   intensity         999 non-null    float64
 4   chi_square        999 non-null    float64
 5   local_background  999 non-null    float64
dtypes: float64(6)
memory usage: 47.0 KB
```

2.3 Tutorial about computing hulls for localization data

For each set of localizations with 2D or 3D spatial coordinates various hull can be computed. A hull can be the minimal bounding box, the oriented minimal bounding box, the convex hull, or an alpha shape.

You can trigger computation of specific hull objects using a specific hull class or from the corresponding LocData attribute.

```
from pathlib import Path

%matplotlib inline

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import locan as lc
from locan.data.hulls import BoundingBox, ConvexHull, OrientedBoundingBox
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.3.1 Synthetic data

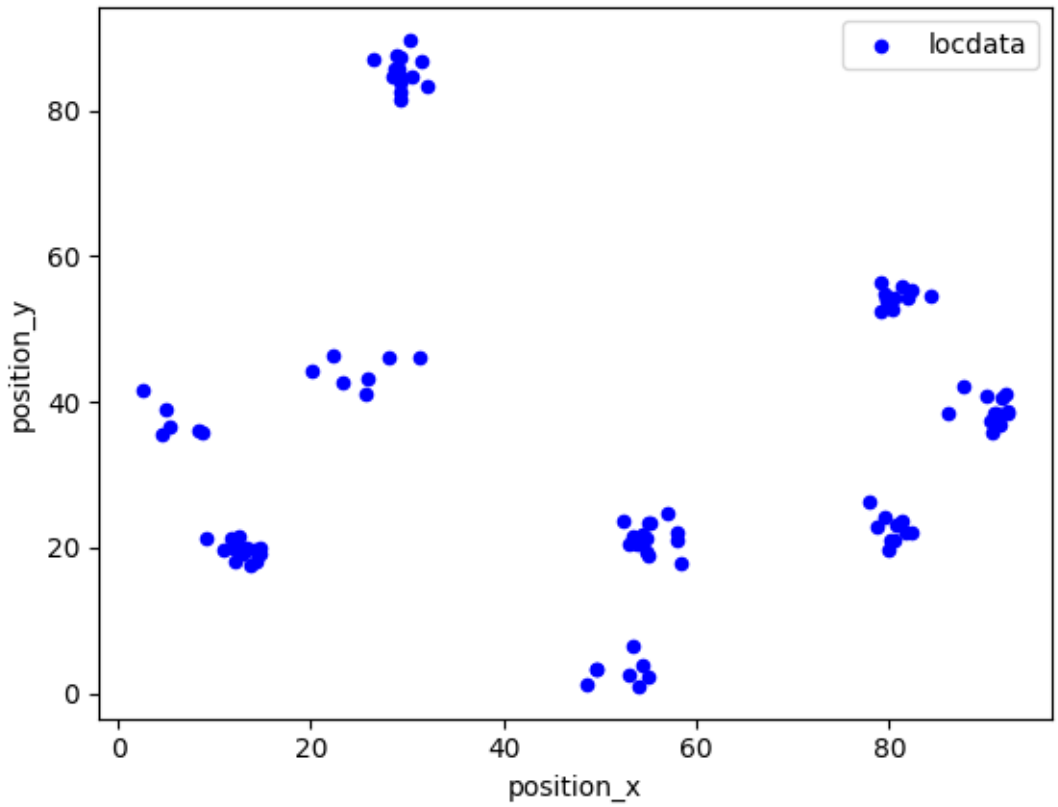
```
rng = np.random.default_rng(seed=1)
```

```
locdata = lc.simulate_Thomas(parent_intensity=1e-3, region=((0, 100), (0,␣
↪100)), cluster_mu=10, cluster_std=2, seed=rng)

locdata.print_summary()
```

```
identifier: "1"
comment: ""
source: SIMULATION
state: RAW
element_count: 100
frame_count: 0
creation_time {
  2024-03-14T11:51:42.929514Z
}
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



2.3.2 Minimal bounding box for spatial coordinates

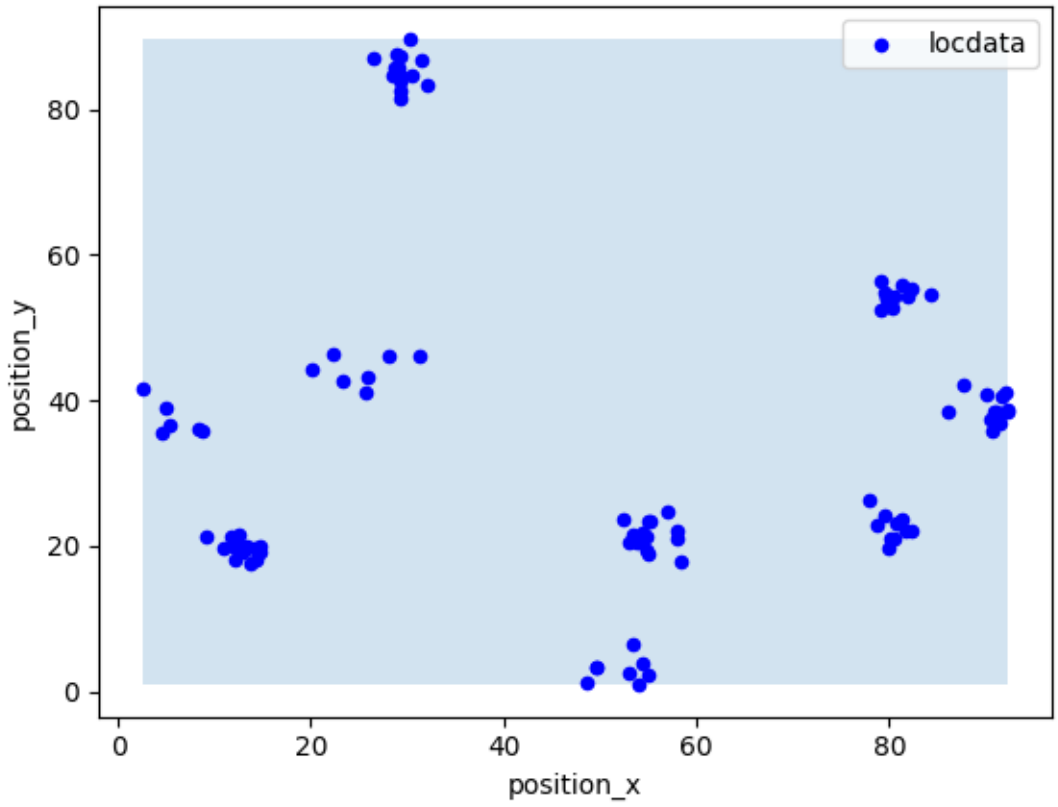
```
# H = BoundingBox(locdata.coordinates)

H = locdata.bounding_box

print('dimension: ', H.dimension)
print('hull: ', H.hull)
print('width: ', H.width)
print('vertices: ', H.vertices)
print('region_measure: ', H.region_measure)
print('subregion_measure: ', H.subregion_measure)
print('region: ', H.region)
```

```
dimension:  2
hull:  [[ 2.490921    1.02997497]
 [92.36001123 89.71010693]]
width:  [89.86909023 88.68013196]
vertices:  [[ 2.490921   92.36001123]
 [ 1.02997497 89.71010693]]
region_measure:  7969.602780428899
subregion_measure:  357.0984443733635
region:  Rectangle((2.490921001041831, 1.0299749716244107), 89.86909022532446,
↪ 88.6801319613573, 0)
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
ax.add_patch(locdata.bounding_box.region.as_artist(alpha=0.2))
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



2.3.3 Oriented minimal bounding box for spatial coordinates

```
# H = OrientedBoundingBox(locdata.coordinates)

H = locdata.oriented_bounding_box

print('dimension: ', H.dimension)
print('hull: ', H.hull)
print('vertices: ', H.vertices)
print('width: ', H.width)
print('region_measure: ', H.region_measure)
print('subregion_measure: ', H.subregion_measure)
print('region: ', H.region)
```

```
dimension:  2
hull:  POLYGON ((-9.220392369565374 31.865082145844063, 59.69001056824682 -12.
↪797641894321849, 97.75586149761332 45.9344032750304, 28.845458559801138 90.
↪5971273151963, -9.220392369565374 31.865082145844063))
vertices:  [[ -9.22039237  31.86508215]
```

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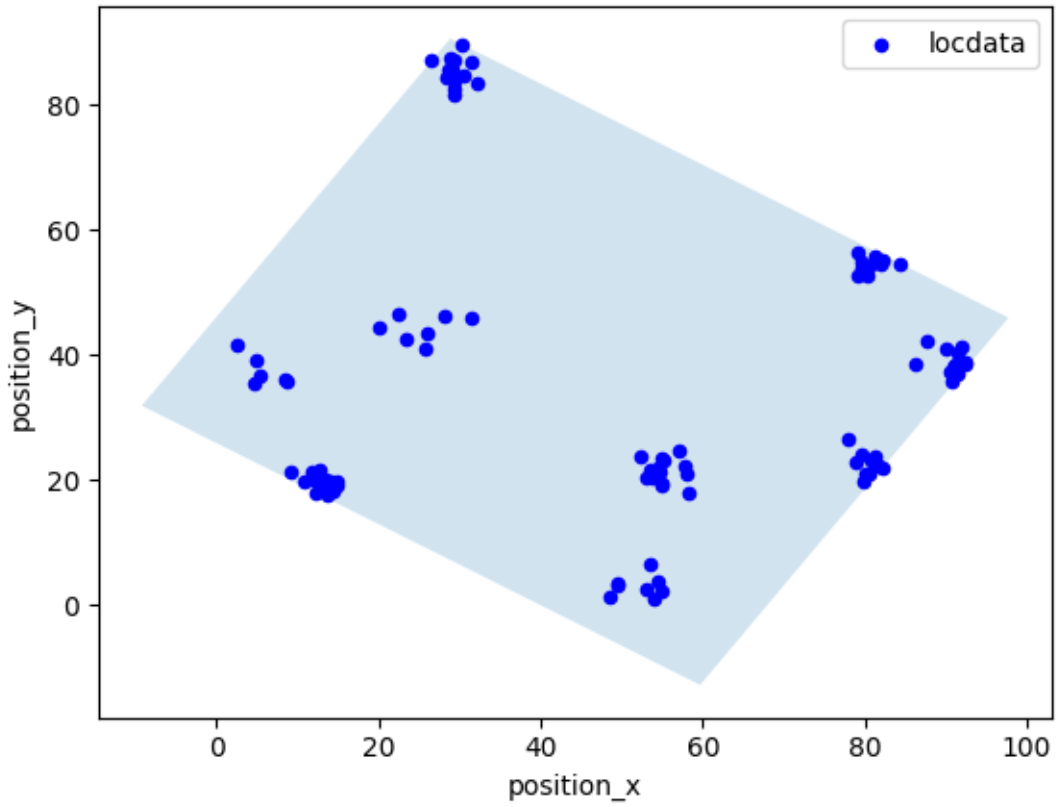
```
 [ 59.69001057 -12.79764189]
 [ 97.7558615   45.93440328]
 [ 28.84545856  90.59712732]
 [ -9.22039237  31.86508215]]
width:  [82.11822302 69.9890144 ]
region_measure:  5747.37349339424
subregion_measure:  304.21447483826086
region:  Rectangle((-9.220392369565374, 31.865082145844063), 82.
↪11822301864336, 69.98901440048706, -32.948380191618504)
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
ax.add_patch(locdata.oriented_bounding_box.region.as_artist(alpha=0.2))
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



2.3.4 Convex hull

Convex hull for spatial coordinates (scipy)

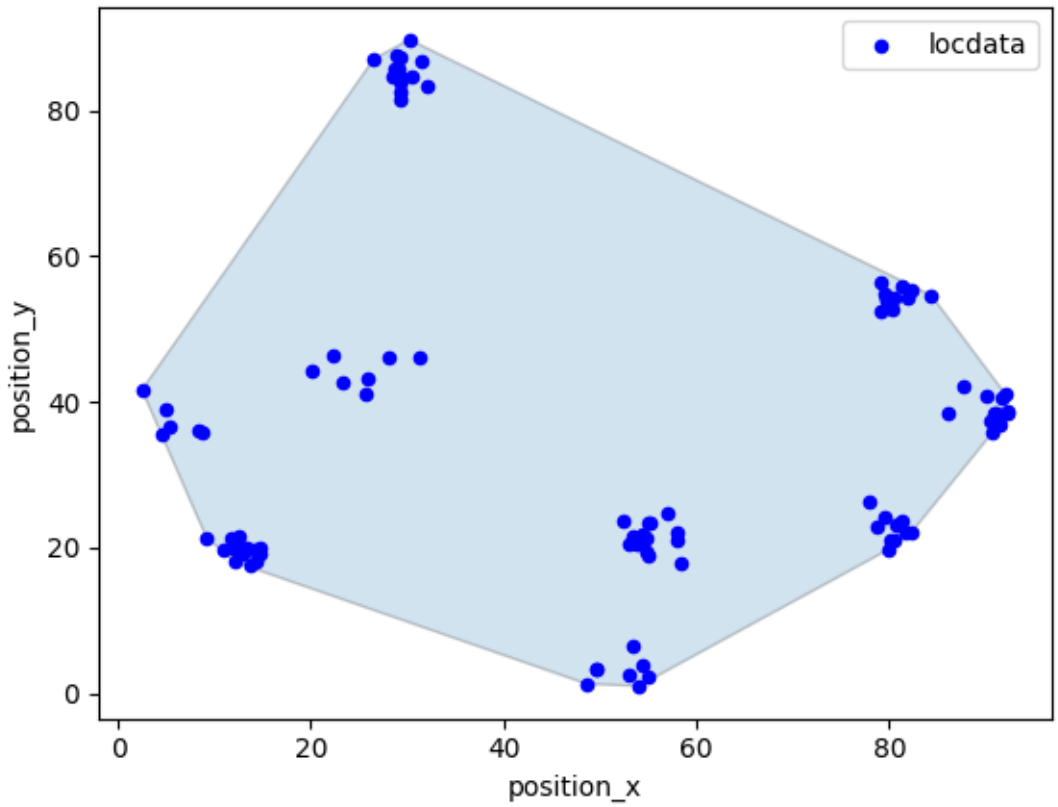
```
# H = ConvexHull(locdata.coordinates, method='scipy')

H = locdata.convex_hull

print('dimension: ', H.dimension)
print('hull: ', H.hull)
# print('vertex_indices: ', H.vertex_indices)
# print('vertices: ', H.vertices)
print('region_measure: ', H.region_measure)
print('subregion_measure: ', H.subregion_measure)
print('points on boundary: ', H.points_on_boundary)
print('points on boundary relative to all points: ', H.points_on_boundary_rel)
print('region: ', H.region)
```

```
dimension:  2
hull:  <scipy.spatial._qhull.ConvexHull object at 0x7f9472745c30>
region_measure:  4908.170783871255
subregion_measure:  264.4870519254037
points on boundary:  13
points on boundary relative to all points:  0.13
region:  Polygon(<self.points>, <self.holes>)
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
ax.add_patch(locdata.convex_hull.region.as_artist(alpha=0.2))
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



Convex hull for spatial coordinates (shapely)

Some hulls can be computed from different algorithms. If implemented, use the `methods` parameter to specify the algorithm.

```
H = ConvexHull(locdata.coordinates, method='shapely')

print('dimension: ', H.dimension)
print('hull: ', H.hull)
# print('vertices: ', H.vertices)
print('region_measure: ', H.region_measure)
print('subregion_measure: ', H.subregion_measure)
print('points on boundary: ', H.points_on_boundary)
print('points on boundary relative to all points: ', H.points_on_boundary_rel)
print('region: ', H.region)
```

```
dimension:  2
hull:  POLYGON ((54.029321929694525 1.0299749716244107, 48.634206414428576 1.
↪294631346507537, 12.175420163612081 17.997868633149913, 9.18991822286495 21.
↪36788078938049, 2.490921001041831 41.64287079543503, 26.54041545299338 87.
↪040661544405, 30.214047987922243 89.71010693298172, 84.34954910628653 54.
↪62340239857981, 91.9734281153137 41.17838012011845, 92.33940616216016 38.
↪808549274650204, 92.36001122636628 38.48950874170735, 82.28290378326082 22.
↪061077730066597, 79.83990217703906 19.69136737327613, 54.029321929694525 1.
↪0299749716244107))
region_measure:  4908.170783871255
```

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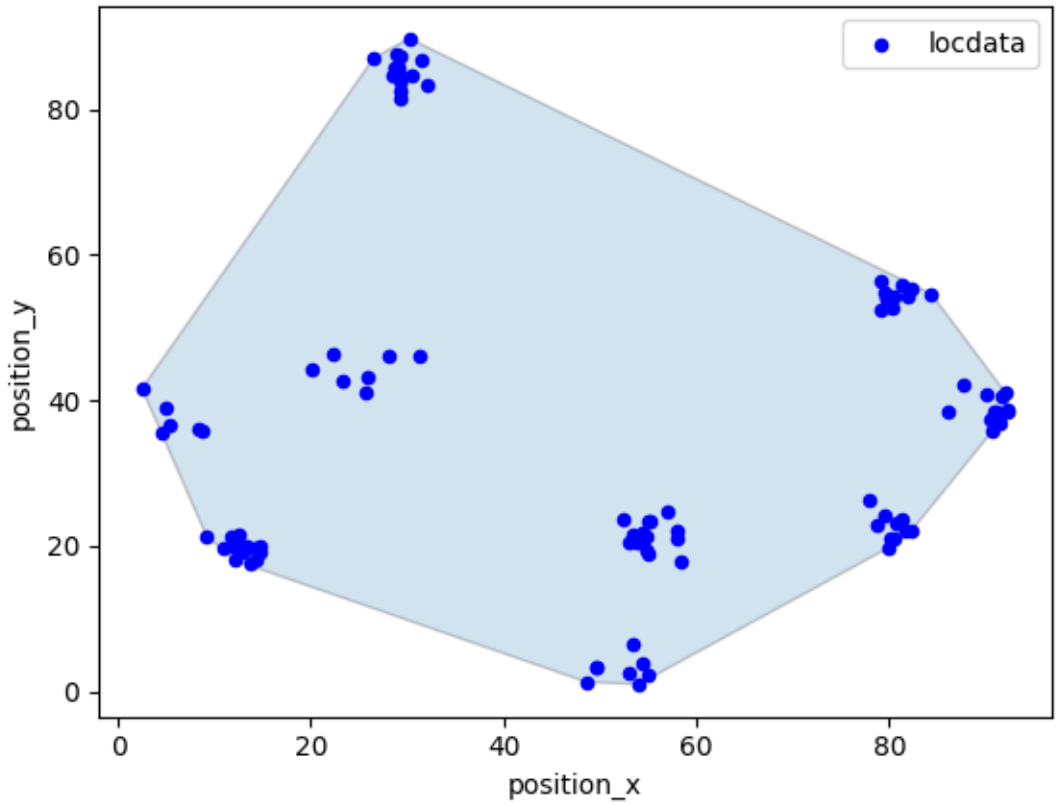
```
subregion_measure:  264.4870519254038
points on boundary:  13
points on boundary relative to all points:  0.13
region:  Polygon(<self.points>, <self.holes>)
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
ax.add_patch(H.region.as_artist(alpha=0.2))
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



2.3.5 Alpha shape for spatial coordinates

The alpha shape depends on a single parameter `alpha` (not to confuse with the alpha to specify opacity in figures). The alpha complex is an alpha-independent representation of all alpha shapes.

You can get all apha values for which the corresponding alpha shape changes.

```
lc.AlphaComplex(locdata.coordinates).alphas()
```

```
array([4.79010715e-02, 6.26886019e-02, 9.00848038e-02, 1.26327560e-01,
       1.27719280e-01, 1.35082505e-01, 1.48065929e-01, 1.59852612e-01,
       1.80345970e-01, 2.29967352e-01, 2.38528055e-01, 2.40927392e-01,
       2.41691338e-01, 2.66695006e-01, 2.77822554e-01, 2.94376165e-01,
       3.06743479e-01, 3.25282310e-01, 3.38425410e-01, 3.43041012e-01,
```

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```
       3.43184730e-01, 3.52204265e-01, 3.57124009e-01, 3.58975685e-01,
       3.62059409e-01, 3.74195019e-01, 3.78291044e-01, 3.97084183e-01,
       4.00186670e-01, 4.02716245e-01, 4.02739384e-01, 4.02815627e-01,
       4.09114331e-01, 4.18957692e-01, 4.19645900e-01, 4.33534796e-01,
       4.47358936e-01, 4.47427686e-01, 4.50668384e-01, 4.56424309e-01,
       4.67180830e-01, 4.71727787e-01, 4.75216918e-01, 4.81397069e-01,
       4.81997429e-01, 4.82183979e-01, 4.97024836e-01, 4.99990289e-01,
       5.06241764e-01, 5.08056086e-01, 5.13489111e-01, 5.25320369e-01,
       5.31023418e-01, 5.34700206e-01, 5.39200680e-01, 5.49237405e-01,
       5.53496939e-01, 5.58987615e-01, 5.59448067e-01, 5.59500547e-01,
       5.61663190e-01, 5.67027377e-01, 5.67749948e-01, 5.71279300e-01,
       5.79365256e-01, 5.81500820e-01, 5.92288917e-01, 5.97516286e-01,
       6.00674458e-01, 6.01810488e-01, 6.03314803e-01, 6.06574504e-01,
       6.06739584e-01, 6.09413711e-01, 6.10483544e-01, 6.12523184e-01,
       6.18571992e-01, 6.19312766e-01, 6.20713067e-01, 6.24167482e-01,
       6.40082879e-01, 6.43777056e-01, 6.51568398e-01, 6.62458725e-01,
       6.64871359e-01, 6.82998920e-01, 6.89013581e-01, 6.89811876e-01,
       6.95662528e-01, 6.97159840e-01, 6.97171260e-01, 7.00419524e-01,
       7.00672239e-01, 7.09851240e-01, 7.11029883e-01, 7.12728093e-01,
       7.15296258e-01, 7.19308431e-01, 7.21811422e-01, 7.28223700e-01,
       7.34206960e-01, 7.37019513e-01, 7.38740770e-01, 7.39835123e-01,
       7.40429317e-01, 7.41294381e-01, 7.46229214e-01, 7.49077113e-01,
       7.50780227e-01, 7.51443768e-01, 7.58053002e-01, 7.59431180e-01,
       7.60230149e-01, 7.61763351e-01, 7.62155416e-01, 7.63885515e-01,
       7.69292534e-01, 7.70264128e-01, 7.71759040e-01, 7.73355937e-01,
       7.84442099e-01, 7.90069055e-01, 7.91274054e-01, 7.93463861e-01,
       7.94356991e-01, 7.99868788e-01, 8.03569058e-01, 8.11065191e-01,
       8.22856563e-01, 8.25466835e-01, 8.26052181e-01, 8.33933862e-01,
       8.39957725e-01, 8.44739640e-01, 8.45350979e-01, 8.46103046e-01,
       8.49224572e-01, 8.49880234e-01, 8.51344679e-01, 8.52808232e-01,
       8.53931434e-01, 8.56196465e-01, 8.61652127e-01, 8.69376152e-01,
       8.70334553e-01, 8.79922419e-01, 8.83510627e-01, 8.87756937e-01,
       8.87768808e-01, 8.89103801e-01, 8.90296830e-01, 9.03293099e-01,
       9.03545920e-01, 9.04654590e-01, 9.13895586e-01, 9.14988676e-01,
       9.19769930e-01, 9.21694582e-01, 9.25606663e-01, 9.42225183e-01,
       9.53726892e-01, 9.60716235e-01, 9.66079966e-01, 9.79994236e-01,
       9.82754216e-01, 9.85767096e-01, 9.88304664e-01, 9.93925311e-01,
       9.98617093e-01, 1.01493196e+00, 1.01705667e+00, 1.01784033e+00,
       1.02895805e+00, 1.03002195e+00, 1.03079742e+00, 1.03230173e+00,
       1.03437394e+00, 1.03953428e+00, 1.04708194e+00, 1.04779857e+00,
       1.05264932e+00, 1.06179970e+00, 1.06613206e+00, 1.06634542e+00,
       1.08018457e+00, 1.08501873e+00, 1.09518923e+00, 1.09869778e+00,
       1.10539327e+00, 1.11120765e+00, 1.11301014e+00, 1.11444086e+00,
       1.11952155e+00, 1.13356306e+00, 1.13477392e+00, 1.13733855e+00,
       1.15128479e+00, 1.15750823e+00, 1.16736695e+00, 1.16926401e+00,
       1.17387209e+00, 1.18535636e+00, 1.18551348e+00, 1.19292617e+00,
       1.19896186e+00, 1.20048927e+00, 1.20720985e+00, 1.23595162e+00,
       1.23873969e+00, 1.25573200e+00, 1.25617021e+00, 1.26070725e+00,
       1.26125038e+00, 1.26240010e+00, 1.26532192e+00, 1.27488250e+00,
```

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```
        1.27724424e+00, 1.28234004e+00, 1.28497224e+00, 1.29840781e+00,
        1.30029954e+00, 1.31068196e+00, 1.31351678e+00, 1.31691837e+00,
        1.31734890e+00, 1.33458446e+00, 1.33515579e+00, 1.34370910e+00,
        1.34568550e+00, 1.34663685e+00, 1.34907880e+00, 1.35972579e+00,
        1.36367900e+00, 1.36709957e+00, 1.36739479e+00, 1.41309146e+00,
        1.42226765e+00, 1.42571135e+00, 1.43547786e+00, 1.43628331e+00,
        1.45069543e+00, 1.46565390e+00, 1.48152517e+00, 1.48366972e+00,
        1.48804400e+00, 1.49016566e+00, 1.52334060e+00, 1.52574832e+00,
        1.52870001e+00, 1.53542071e+00, 1.53864429e+00, 1.54408771e+00,
        1.54595694e+00, 1.55976987e+00, 1.57562096e+00, 1.58411018e+00,
        1.61295349e+00, 1.61741832e+00, 1.62776308e+00, 1.63307779e+00,
        1.63940332e+00, 1.64733370e+00, 1.65626521e+00, 1.65788434e+00,
        1.66678718e+00, 1.69711226e+00, 1.70174793e+00, 1.71050339e+00,
        1.71714404e+00, 1.72508327e+00, 1.73141334e+00, 1.73774244e+00,
        1.74668941e+00, 1.74747826e+00, 1.75133241e+00, 1.75463569e+00,
        1.77157747e+00, 1.77362769e+00, 1.77744793e+00, 1.78223117e+00,
        1.78501180e+00, 1.79207963e+00, 1.79918946e+00, 1.80015981e+00,
        1.82414077e+00, 1.82536675e+00, 1.87379584e+00, 1.89357272e+00,
        1.91381607e+00, 1.92656279e+00, 1.94884908e+00, 2.00577717e+00,
        2.01728998e+00, 2.03034431e+00, 2.04408104e+00, 2.05038818e+00,
        2.05349095e+00, 2.07285481e+00, 2.16816869e+00, 2.20910083e+00,
        2.22509947e+00, 2.24795084e+00, 2.25112215e+00, 2.27054590e+00,
        2.27811322e+00, 2.27983143e+00, 2.31343855e+00, 2.32264410e+00,
        2.32880977e+00, 2.34437210e+00, 2.37718224e+00, 2.37723128e+00,
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        2.45645949e+00, 2.45891276e+00, 2.52246605e+00, 2.54215315e+00,
        2.62136822e+00, 2.65112497e+00, 2.65972828e+00, 2.70080147e+00,
        2.79515289e+00, 2.84755996e+00, 2.85697323e+00, 2.90416046e+00,
        3.01656649e+00, 3.07917748e+00, 3.13521975e+00, 3.17783655e+00,
        3.26467278e+00, 3.38255925e+00, 3.56990862e+00, 3.57574974e+00,
        3.59260960e+00, 3.60194779e+00, 3.63036096e+00, 3.69906825e+00,
        3.95779301e+00, 4.26390245e+00, 4.29842013e+00, 4.90182079e+00,
        4.97166259e+00, 6.07922626e+00, 6.24118004e+00, 6.24890464e+00,
        6.35586273e+00, 6.39866293e+00, 6.48277005e+00, 6.65001925e+00,
        6.94378885e+00, 7.14344811e+00, 7.21201452e+00, 7.24911348e+00,
        7.26452608e+00, 7.32337306e+00, 7.41191471e+00, 7.42595448e+00,
        7.43392888e+00, 7.43433203e+00, 7.72806825e+00, 7.74336647e+00,
        7.76087118e+00, 7.78944873e+00, 7.80165047e+00, 7.82652969e+00,
        7.85021562e+00, 7.87716234e+00, 7.88724780e+00, 7.96646223e+00,
        8.04566727e+00, 8.08224562e+00, 8.09483397e+00, 8.26562220e+00,
        8.31591730e+00, 8.51342985e+00, 8.71703225e+00, 8.74628027e+00,
        8.79373820e+00, 8.94187403e+00, 8.95071004e+00, 9.00003635e+00,
        9.01595702e+00, 9.63640804e+00, 9.86227445e+00, 1.01897890e+01,
        1.02221135e+01, 1.02751450e+01, 1.03599403e+01, 1.03913311e+01,
        1.04465878e+01, 1.04471172e+01, 1.04597259e+01, 1.05636147e+01,
        1.05639307e+01, 1.05738881e+01, 1.06432177e+01, 1.06765138e+01,
        1.08061930e+01, 1.08267337e+01, 1.10126155e+01, 1.11019300e+01,
        1.17944937e+01, 1.17991373e+01, 1.19695055e+01, 1.20037920e+01,
        1.21184799e+01, 1.22848303e+01, 1.30919383e+01, 1.50017504e+01,
```

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```
       1.51307502e+01, 1.53817915e+01, 1.58322884e+01, 1.59250873e+01,
       1.59542235e+01, 1.59653821e+01, 1.66977766e+01, 1.75114153e+01,
       1.76752204e+01, 1.77796252e+01, 1.77821903e+01, 1.78396689e+01,
       1.78495038e+01, 1.78527366e+01, 1.80088206e+01, 1.87142131e+01,
       1.89454045e+01, 1.89693286e+01, 1.89963288e+01, 1.90443274e+01,
       1.91047288e+01, 1.91360626e+01, 1.91361642e+01, 1.91392739e+01,
       1.91597195e+01, 1.91653265e+01, 1.91703660e+01, 1.91811000e+01,
       1.92761620e+01, 1.94600972e+01, 1.96390949e+01, 2.00514415e+01,
       2.02227234e+01, 2.15705094e+01, 2.39869621e+01, 2.41473984e+01,
       2.41540455e+01, 2.44485075e+01, 2.46186883e+01, 2.56872419e+01,
       2.63949037e+01, 2.70955193e+01, 2.78666861e+01, 2.82256845e+01,
       2.95858969e+01, 2.98130814e+01, 3.06827051e+01, 3.22557333e+01,
       3.70800737e+01, 5.09825269e+01, 5.34146215e+01, 7.99051776e+01,
       9.91221385e+01, 1.42276409e+02, 4.34636400e+02, 4.71113175e+02,
       1.32363587e+03,            inf])
```

You can determine an optimal `alpha`, i.e. the smallest `alpha` for which all points are still part of the alpha shape.

```
opt_alpha = lc.AlphaComplex(locdata.coordinates).optimal_alpha()
opt_alpha
```

```
32.25573327495765
```

```
# H = lc.AlphaShape(opt_alpha, locdata.coordinates)

locdata.update_alpha_shape(alpha=opt_alpha)
H = locdata.alpha_shape

print('dimension: ', H.dimension)
# print('vertex_indices: ', H.vertex_indices)
# print('vertices: ', H.vertices)
print('region_measure: ', H.region_measure)
print('subregion_measure: ', H.subregion_measure)
print('points in alpha shape: ', H.n_points_alpha_shape)
print('points in alpha shape relative to all points: ', H.n_points_alpha_
↪shape_rel)
print('points on boundary: ', H.n_points_on_boundary)
print('points on boundary relative to all points: ', H.n_points_on_boundary_
↪rel)
print('region: ', H.region)
```

```
dimension:  2
region_measure:  4908.1707838712555
subregion_measure:  264.4870519254038
points in alpha shape:  100
points in alpha shape relative to all points:  1.0
points on boundary:  22
points on boundary relative to all points:  0.22
```

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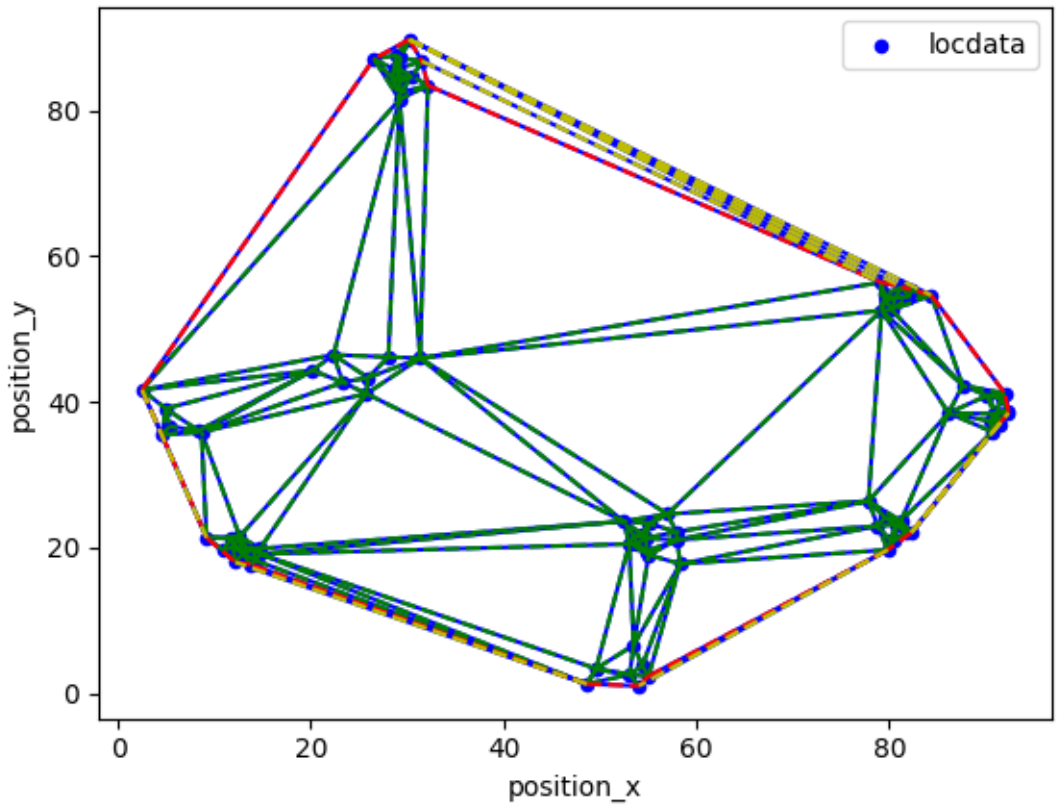
```
region:  Polygon(<self.points>, <self.holes>)
```

The alpha shape is made of different vertex types that can be differentiated as *exterior*, *interior*, *regular* or *singular*.

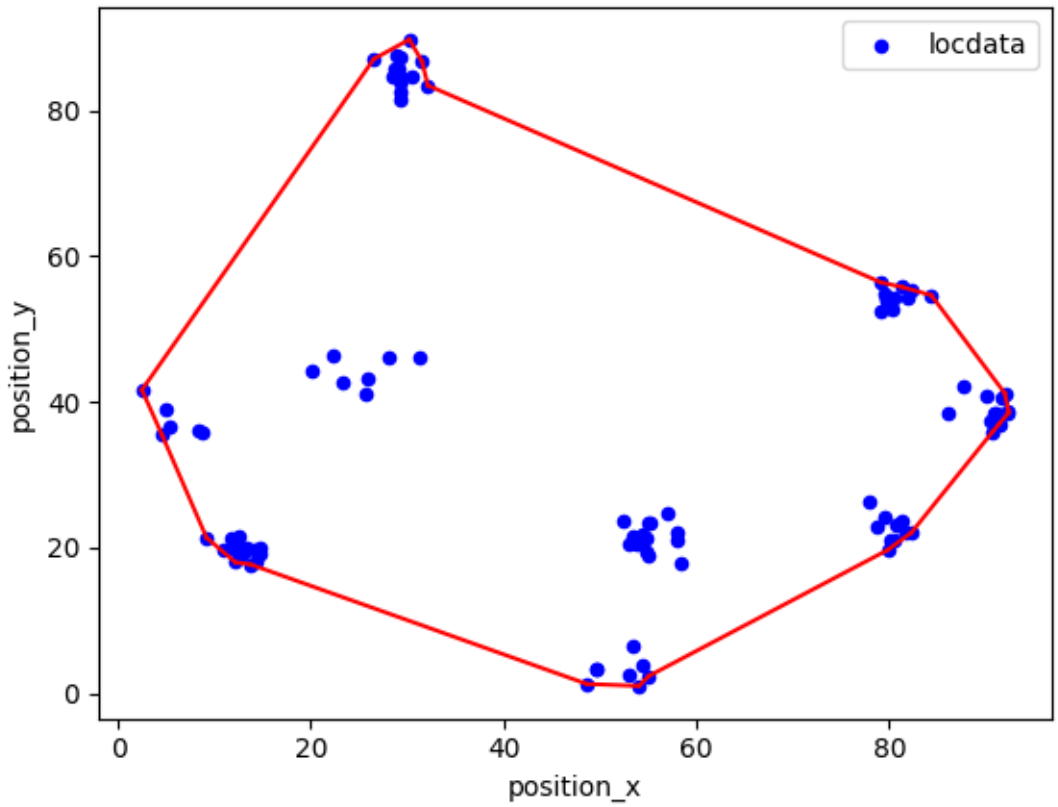
```
ac_simplices_all = H.alpha_complex.get_alpha_complex_lines(H.alpha, type='all
↪')
ac_simplices_exterior = H.alpha_complex.get_alpha_complex_lines(H.alpha, type=
↪'exterior')
ac_simplices_interior = H.alpha_complex.get_alpha_complex_lines(H.alpha, type=
↪'interior')
ac_simplices_regular = H.alpha_complex.get_alpha_complex_lines(H.alpha, type=
↪'regular')
ac_simplices_singular = H.alpha_complex.get_alpha_complex_lines(H.alpha, type=
↪'singular')
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)

for simp in ac_simplices_all:
    ax.plot(locdata.coordinates[simp, 0], locdata.coordinates[simp, 1], '-b')
for simp in ac_simplices_interior:
    ax.plot(locdata.coordinates[simp, 0], locdata.coordinates[simp, 1], '--g')
for simp in ac_simplices_regular:
    ax.plot(locdata.coordinates[simp, 0], locdata.coordinates[simp, 1], '--r')
for simp in ac_simplices_singular:
    ax.plot(locdata.coordinates[simp, 0], locdata.coordinates[simp, 1], '--y')

locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



Often the *regular* representation is good enough.

```
fig, ax = plt.subplots(nrows=1, ncols=1)
for simp in ac_simplices_regular:
    ax.plot(locdata.coordinates[simp, 0], locdata.coordinates[simp, 1], '-r')
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



You can get the connected components as list of `Region`.

```
H.connected_components
```

```
[Polygon([[26.54041545299338, 87.040661544405], [30.214047987922243, 89.
↪71010693298172], [84.34954910628653, 54.62340239857981], [91.9734281153137,␣
↪41.17838012011845], [92.33940616216016, 38.808549274650204], [92.
↪36001122636628, 38.48950874170735], [82.28290378326082, 22.061077730066597],
↪ [79.83990217703906, 19.69136737327613], [54.029321929694525, 1.
↪0299749716244107], [48.634206414428576, 1.294631346507537], [12.
↪175420163612081, 17.997868633149913], [9.18991822286495, 21.36788078938049],
↪ [2.490921001041831, 41.64287079543503], [26.54041545299338, 87.
↪040661544405]], [])]
```

```
connected_component_0 = H.connected_components[0]

print('dimension: ', connected_component_0.dimension)
print('region_measure: ', connected_component_0.region_measure)
print('subregion_measure: ', connected_component_0.subregion_measure)
```

```
dimension:  2
region_measure:  4908.1707838712555
subregion_measure:  264.4870519254038
```

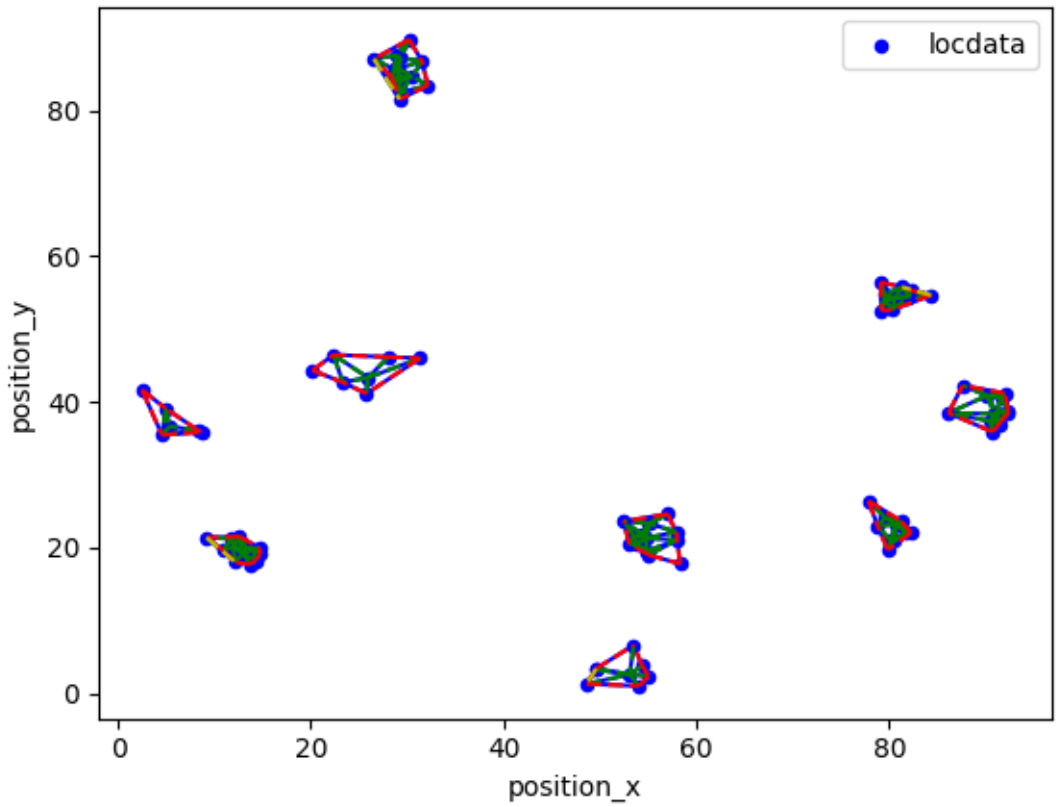
The alpha shape for a smaller alpha can have multiple connected components.

```
H = lc.AlphaShape(5, locdata.coordinates)

print('dimension: ', H.dimension)
# print('vertex_indices: ', H.vertex_indices)
# print('vertices: ', H.vertices)
print('region_measure: ', H.region_measure)
print('subregion_measure: ', H.subregion_measure)
print('points in alpha shape: ', H.n_points_alpha_shape)
print('points in alpha shape relative to all points: ', H.n_points_alpha_
↪shape_rel)
print('points on boundary: ', H.n_points_on_boundary)
print('points on boundary relative to all points: ', H.n_points_on_boundary_
↪rel)
```

```
dimension:  2
region_measure:  178.41254317639843
subregion_measure:  171.67742405936463
points in alpha shape:  100
points in alpha shape relative to all points:  1.0
points on boundary:  57
points on boundary relative to all points:  0.57
```

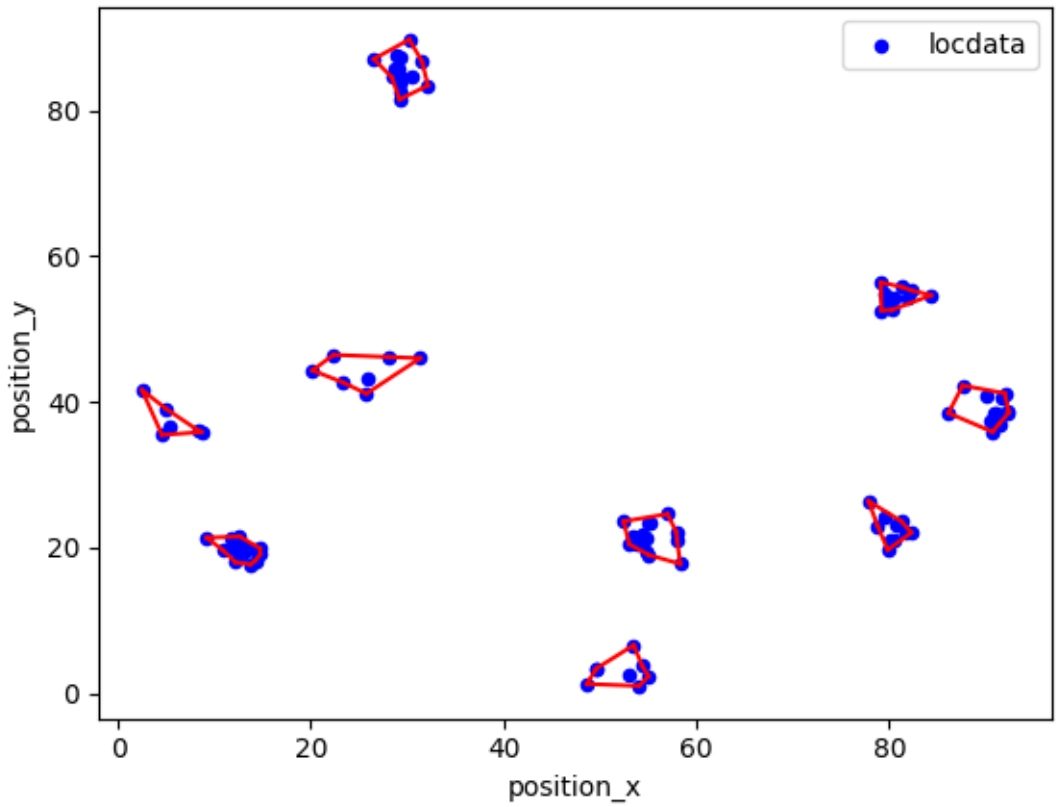
```
ac_simplices_all = H.alpha_complex.get_alpha_complex_lines(H.alpha, type='all
↪')
ac_simplices_exterior = H.alpha_complex.get_alpha_complex_lines(H.alpha, type=
↪'exterior')
ac_simplices_interior = H.alpha_complex.get_alpha_complex_lines(H.alpha, type=
↪'interior')
ac_simplices_regular = H.alpha_complex.get_alpha_complex_lines(H.alpha, type=
↪'regular')
ac_simplices_singular = H.alpha_complex.get_alpha_complex_lines(H.alpha, type=
↪'singular')
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)

for simp in ac_simplices_all:
    ax.plot(locdata.coordinates[simp, 0], locdata.coordinates[simp, 1], '-b')
for simp in ac_simplices_interior:
    ax.plot(locdata.coordinates[simp, 0], locdata.coordinates[simp, 1], '--g')
for simp in ac_simplices_regular:
    ax.plot(locdata.coordinates[simp, 0], locdata.coordinates[simp, 1], '--r')
for simp in ac_simplices_singular:
    ax.plot(locdata.coordinates[simp, 0], locdata.coordinates[simp, 1], '--y')

locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



The *regular* representation:

```
fig, ax = plt.subplots(nrows=1, ncols=1)
for simp in ac_simplices_regular:
    ax.plot(locdata.coordinates[simp, 0], locdata.coordinates[simp, 1], '-r')
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



The connected components:

```
H.connected_components
```

```
[Polygon([[4.574030584926964, 35.4547363609949], [2.490921001041831, 41.
↪64287079543503], [4.957382196904078, 39.08282122381802], [8.355461487809666,
↪ 36.04765129727869], [8.66131719294932, 35.8564682341916], [4.
↪574030584926964, 35.4547363609949]], []),
 Polygon([[25.770117329307787, 41.124276031608815], [23.31756949147803, 42.
↪6744624631213], [20.173587957294433, 44.31714346765541], [22.
↪361223833116604, 46.453014294097834], [28.048700032796415, 46.
↪15804762285728], [31.339293507790977, 45.9942555369238], [25.
↪770117329307787, 41.124276031608815]], []),
 Polygon([[9.18991822286495, 21.36788078938049], [12.636282213847565, 21.
↪529820077010385], [14.734872660721315, 19.880462363217678], [14.
↪769094009431546, 19.124654613922488], [14.266019685598483, 18.
↪241818179484355], [13.747576761626673, 17.702091783845788], [12.
↪175420163612081, 17.997868633149913], [9.18991822286495, 21.
↪36788078938049]], []),
 Polygon([[26.54041545299338, 87.040661544405], [30.214047987922243, 89.
↪71010693298172], [31.521384860659595, 86.75121552412102], [32.
↪14133335513356, 83.41408741528058], [29.20688463095611, 81.48951050894098],␣
↪[26.54041545299338, 87.040661544405]], []),
 Polygon([[79.18789302054475, 52.543982100600005], [79.11703202181116, 56.
↪39645603252982], [81.32782142473194, 55.75284367902573], [84.34954910628653,
↪ 54.62340239857981], [80.25475558909794, 52.61761293856212], [79.
↪18789302054475, 52.543982100600005]], []),
```

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```
 Polygon([[87.6064843703255, 42.247461144808746], [91.9734281153137, 41.
↪17838012011845], [92.33940616216016, 38.808549274650204], [92.
↪36001122636628, 38.48950874170735], [91.40098079916173, 36.989250622930314],
↪ [90.7011218417029, 35.889994988035625], [86.13341308357771, 38.
↪463382259593324], [87.6064843703255, 42.247461144808746]], []),
 Polygon([[54.029321929694525, 1.0299749716244107], [48.634206414428576, 1.
↪294631346507537], [49.59358344008751, 3.4015003371361145], [53.
↪482683026695234, 6.614947738231005], [54.37183424361821, 3.788452129115082],
↪ [55.03000267597442, 2.3642990669580453], [54.029321929694525, 1.
↪0299749716244107]], []),
 Polygon([[53.02310815665912, 20.494919113980316], [52.4417533406316, 23.
↪609344720491215], [56.99055629523848, 24.610250050117035], [57.
↪896406888972834, 22.172515398810596], [57.98560316805971, 21.
↪06912087658576], [58.31284235106916, 17.772793788937257], [55.
↪04194051962414, 18.999536120747145], [53.02310815665912, 20.
↪494919113980316]], []),
 Polygon([[78.79284317381992, 22.962147412197464], [77.83372328947765, 26.
↪395146222813697], [81.19928424977152, 23.660768547251035], [82.
↪28290378326082, 22.061077730066597], [79.83990217703906, 19.69136737327613],
↪ [78.79284317381992, 22.962147412197464]], [])]
```

```
connected_component_0 = H.connected_components[0]

print('dimension: ', connected_component_0.dimension)
print('region_measure: ', connected_component_0.region_measure)
print('subregion_measure: ', connected_component_0.subregion_measure)
```

```
dimension:  2
region_measure:  12.16313947011497
subregion_measure:  19.10814169604162
```

2.4 Tutorial about metadata

```
import numpy as np
import pandas as pd
from google.protobuf import json_format, text_format

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.4.1 Metadata definition

We have define a canonical set of metadata to accompany localization data.

Metadata is described by protobuf messages. Googles protobuf format is advantageous to enforce metdata definitions that can be easily attached to various file formats, exchanged with other programmes and implemented in different programming languages.

Metadata is instantiated through messages defined in the `locan.data.metadata_pb2` module.

```
list(lc.data.metadata_pb2.DESCRIPTOR.message_types_by_name.keys())
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

```
['Operation',
 'File',
 'Address',
 'Affiliation',
 'Person',
 'ExperimentalSample',
 'ExperimentalSetup',
 'OpticalUnit',
 'Illumination',
 'Detection',
 'Camera',
 'Acquisition',
 'Lightsheet',
 'Experiment',
 'Localizer',
 'Relation',
 'Property',
 'Metadata']
```

Each class contains a logical set of information that is integrated in the main class `Metadata`.

`Metadata` contains the following keys:

```
metadata = lc.data.metadata_pb2.Metadata()
list(metadata.DESCRIPTOR.fields_by_name.keys())
```

```
['identifier',
 'comment',
 'source',
 'state',
 'history',
 'ancestor_identifiers',
 'properties',
 'localization_properties',
 'element_count',
 'frame_count',
```

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```
 'file',
 'relations',
 'experiment',
 'localizer',
 'map',
 'creation_time',
 'modification_time',
 'production_time']
```

Each field has a predefined type and can be set to appropriate values:

```
metadata.comment = "This is a comment"
```

```
try:
    metadata.comment = 1
except Exception as e:
    print(e)
```

```
bad argument type for built-in operation
```

```
metadata
```

```
comment: "This is a comment"
```

Metadata values including the default values can be shown in JSON format or as dictionary:

```
json_format.MessageToDict(metadata)
```

```
{'comment': 'This is a comment'}
```

```
# except empty fields with repeated message classes
json_format.MessageToDict(metadata, including_default_value_fields=True,␣
↪preserving_proto_field_name=True)
```

```
{'comment': 'This is a comment',
 'identifier': '',
 'source': 'UNKNOWN_SOURCE',
 'state': 'UNKNOWN_STATE',
 'history': [],
 'ancestor_identifiers': [],
 'properties': [],
 'localization_properties': [],
 'element_count': '0',
 'frame_count': '0',
 'relations': [],
 'map': {}}
```

```
json_format.MessageToJson(metadata, including_default_value_fields=True,␣
↪preserving_proto_field_name=True)
```

```
'{\n  "comment": "This is a comment",\n  "identifier": "",\n  "source":
↪"UNKNOWN_SOURCE",\n  "state": "UNKNOWN_STATE",\n  "history": [],\n
↪"ancestor_identifiers": [],\n  "properties": [],\n  "localization_properties
↪": [],\n  "element_count": "0",\n  "frame_count": "0",\n  "relations": [],\
↪n  "map": {}\n}'
```

To print metadata with timestamp and duration in a well formatted string use:

```
lc.metadata_to_formatted_string(metadata)
```

```
'comment: "This is a comment"\n'
```

2.4.2 Set metadata fields

Repeated fields

To set selected fields instantiate the appropriate messages. For list fields use `message.add()`.

```
metadata = lc.data.metadata_pb2.Metadata()

ou = metadata.experiment.setups.add().optical_units.add()
ou.detection.camera.electrons_per_count = 13.26

metadata
```

```
experiment {
  setups {
    optical_units {
      detection {
        camera {
          electrons_per_count: 13.26
        }
      }
    }
  }
}
```

Timestamp fields

Timestamp fields contain information on date and time zone and are of type `google.protobuf.Timestamp`.

```
import time
metadata = lc.data.metadata_pb2.Metadata()
metadata.creation_time.GetCurrentTime()
metadata.creation_time
```

```
seconds: 1710417122
nanos: 325685000
```

```
metadata.creation_time.FromJsonString('2022-05-14T06:58:00.514893Z')
metadata.creation_time.ToJsonString()
```

```
'2022-05-14T06:58:00.514893Z'
```

Time duration fields contain information on time intervals and are of type `google.protobuf.Duration`.

```
metadata.experiment.setups.add().optical_units.add().detection.camera.
↪integration_time.FromMilliseconds(20)
metadata.experiment.setups[0].optical_units[0].detection.camera.integration_
↪time.ToMilliseconds()
# metadata.experiment.setups[0].optical_units[0].detection.camera.integration_
↪time.ToJsonString()
```

```
20
```

To print metadata with timestamp and duration in a well formatted string use:

```
lc.metadata_to_formatted_string(metadata)
```

```
'experiment {\n  setups {\n    optical_units {\n      detection {\n        ␣
↪camera {\n          integration_time {\n            0.020s\n          }\n  ␣
↪      }\n      }\n    }\n  }\n}\ncreation_time {\n  2022-05-14T06:58:00.
↪514893Z\n}\n'
```

2.4.3 Metadata scheme

The overall scheme can be instantiated and visualized:

```
metadata = lc.data.metadata_pb2.Metadata()
scheme = lc.message_scheme(metadata)
scheme
```

```
{'identifier': '',
 'comment': '',
```

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```
'source': 'UNKNOWN_SOURCE',
'state': 'UNKNOWN_STATE',
'history': {'name': '', 'parameter': ''},
'ancestor_identifiers': [],
'properties': {'identifier': '',
 'comment': '',
 'name': '',
 'unit': '',
 'type': '',
 'map': {}},
'localization_properties': {'identifier': '',
 'comment': '',
 'name': '',
 'unit': '',
 'type': '',
 'map': {}},
'element_count': '0',
'frame_count': '0',
'relations': {'identifier': '',
 'comment': '',
 'map': {},
 'file': {'identifier': '',
  'comment': '',
  'type': 'UNKNOWN_FILE_TYPE',
  'path': '',
  'groups': []}},
'map': {},
'file': {'identifier': '',
 'comment': '',
 'type': 'UNKNOWN_FILE_TYPE',
 'path': '',
 'groups': []},
'experiment': {'identifier': '',
 'comment': '',
 'experimenters': {'identifier': '',
  'comment': '',
  'first_name': '',
  'last_name': '',
  'title': '',
  'affiliations': {'institute': '',
   'department': '',
   'address': {'address_lines': [],
    'city': '',
    'city_code': '',
    'country': ''}},
  'emails': [],
  'roles': [],
  'address': {'address_lines': [],
   'city': '',
```

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```
   'city_code': '',
   'country': ''}},
 'samples': {'identifier': '',
  'comment': '',
  'targets': [],
  'fluorophores': [],
  'buffers': [],
  'map': {}},
 'setups': {'identifier': '',
  'comment': '',
  'optical_units': {'identifier': '',
   'comment': '',
   'illumination': {'identifier': '',
    'comment': '',
    'lightsource': '',
    'power': 0.0,
    'area': 0.0,
    'power_density': 0.0,
    'wavelength': 0.0,
    'map': {}},
   'detection': {'identifier': '',
    'comment': '',
    'map': {},
    'camera': {'identifier': '',
     'comment': '',
     'name': '',
     'model': '',
     'gain': 0.0,
     'electrons_per_count': 0.0,
     'pixel_count_x': 0,
     'pixel_count_y': 0,
     'pixel_size_x': 0.0,
     'pixel_size_y': 0.0,
     'flipped': False,
     'map': {},
     'offset': 0.0,
     'serial_number': '',
     'integration_time': '0s'}},
   'acquisition': {'identifier': '',
    'comment': '',
    'frame_count': 0,
    'frame_of_interest_first': 0,
    'frame_of_interest_last': 0,
    'stack_count': 0,
    'stack_step_count': 0,
    'stack_step_size': 0.0,
    'map': {},
    'time_start': '1970-01-01T00:00:00Z',
    'time_end': '1970-01-01T00:00:00Z'},
```

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```
    'lightsheet': {'identifier': '',
     'comment': '',
     'angle_x': 0.0,
     'angle_y': 0.0,
     'angle_z': 0.0,
     'map': {}}},
   'map': {}},
  'map': {}},
 'localizer': {'identifier': '',
  'comment': '',
  'software': '',
  'intensity_threshold': 0.0,
  'psf_fixed': False,
  'psf_size': 0.0,
  'map': {}},
 'creation_time': '1970-01-01T00:00:00Z',
 'modification_time': '1970-01-01T00:00:00Z',
 'production_time': '1970-01-01T00:00:00Z'}
```

Metadata from toml file

You can provide metadata in a toml file.

```
metadata_toml = \
"""
# Define the class (message) instances.

[[messages]]
name = "metadata"
module = "locan.data.metadata_pb2"
class_name = "Metadata"


# Fill metadata attributes
# Headings must be a message name or valid attribute.
# Use [[]] to add repeated elements.
# Use string '2022-05-14T06:58:00Z' for Timestamp elements.
# Use int in nanoseconds for Duration elements.

[metadata]
identifier = "123"
comment = "my comment"
ancestor_identifiers = ["1", "2"]
production_time = '2022-05-14T06:58:00Z'

[[metadata.experiment.experimenters]]
first_name = "First name"
last_name = "Last name"
```

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```
[[metadata.experiment.experimenters.affiliations]]
institute = "Institute"
department = "Department"

[[metadata.experiment.setups]]
identifier = "1"

[[metadata.experiment.setups.optical_units]]
identifier = "1"

[metadata.experiment.setups.optical_units.detection.camera]
identifier = "1"
name = "camera name"
model = "camera model"
electrons_per_count = 3.1
integration_time = 10_000_000

[metadata.localizer]
software = "rapidSTORM"

[[metadata.relations]]
identifier = "1"
"""
```

```
toml_out = lc.metadata_from_toml_string(metadata_toml)
for k, v in toml_out.items():
    print(k, ":\n\n", v)
```

```
metadata :

 identifier: "123"
comment: "my comment"
ancestor_identifiers: "1"
ancestor_identifiers: "2"
relations {
  identifier: "1"
}
experiment {
  experimenters {
    first_name: "First name"
    last_name: "Last name"
    affiliations {
      institute: "Institute"
      department: "Department"
    }
  }
  setups {
    identifier: "1"
```

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```
    optical_units {
      identifier: "1"
      detection {
        camera {
          identifier: "1"
          name: "camera name"
          model: "camera model"
          electrons_per_count: 3.1
          integration_time {
            nanos: 10000000
          }
        }
      }
    }
  }
}
localizer {
  software: "rapidSTORM"
}
production_time {
  seconds: 1652511480
}
```

To load from file:

2.4.4 Metadata for LocData

Metadata is instantiated for each LocData object and accessible through the `LocData.meta` attribute.

Sample data

```
df = pd.DataFrame(
    {
        'position_x': np.arange(0,10),
        'position_y': np.random.random(10),
        'frame': np.arange(0,10),
    })
locdata = lc.LocData.from_dataframe(dataframe=df)

locdata.meta
```

```
identifier: "1"
source: DESIGN
state: RAW
history {
  name: "LocData.from_dataframe"
}
```

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```
element_count: 10
frame_count: 10
creation_time {
  seconds: 1710417122
  nanos: 401028000
}
```

Fields can also be printed as well formatted string (using `lc.metadata_to_formatted_string`):

```
locdata.print_meta()
```

```
identifier: "1"
source: DESIGN
state: RAW
history {
  name: "LocData.from_dataframe"
}
element_count: 10
frame_count: 10
creation_time {
  2024-03-14T11:52:02.401028Z
}
```

A summary of the most important metadata is printed as:

```
locdata.print_summary()
```

```
identifier: "1"
comment: ""
source: DESIGN
state: RAW
element_count: 10
frame_count: 10
creation_time {
  2024-03-14T11:52:02.401028Z
}
```

Metadata fields can be printed and changed individually:

```
print(locdata.meta.comment)
locdata.meta.comment = 'user comment'
print(locdata.meta.comment)
```

```
user comment
```

Metadata can also be added at instantiation:

```
locdata_2 = lc.LocData.from_dataframe(dataframe=df, meta={'identifier': 'myID_
↪1',
                                                          'comment': 'my own user␣
↪comment'})
```

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```
locdata_2.print_summary()
```

```
identifier: "myID_1"
comment: "my own user comment"
source: DESIGN
state: RAW
element_count: 10
frame_count: 10
creation_time {
  2024-03-14T11:52:02.437128Z
}
```

2.5 Tutorial about regions

Regions define a support for localization data or specify a hull that captures a set of localizations. Locan provides various region classes with a standard set of attributes and methods.

```
%matplotlib inline

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.5.1 Region definitions

The standard set of attributes and methods is defined by the abstract base class `Region` that all region classes inherit.

```
lc.Region?
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

```
print("Methods:")
[method for method in dir(lc.Region) if not method.startswith('_')]
```

```
Methods:
```

```
['bounding_box',
 'bounds',
 'buffer',
 'centroid',
 'contains',
 'dimension',
 'extent',
 'from_intervals',
 'intersection',
 'max_distance',
 'points',
 'region_measure',
 'subregion_measure',
 'symmetric_difference',
 'union']
```

Further definitions can be found in the abstract classes `Region1D`, `Region2D` and `Region3D` and all specific region classes.

```
import inspect
inspect.getmembers(lc.data.region, inspect.isabstract)
```

```
[('Region', locan.data.region.Region),
 ('Region1D', locan.data.region.Region1D),
 ('Region2D', locan.data.region.Region2D),
 ('Region3D', locan.data.region.Region3D),
 ('RegionND', locan.data.region.RegionND)]
```

2.5.2 Use Region classes

Use one of the following classes to define a region in 1, 2 or 3 dimensions:

```
print("Empty Region:\n", [lc.EmptyRegion.__name__], "\n")
print("Regions in 1D:\n", [cls.__name__ for cls in lc.Region1D.__subclasses__
↪()], "\n")
print("Regions in 2D:\n", [cls.__name__ for cls in lc.Region2D.__subclasses__
↪()], "\n")
print("Regions in 3D:\n", [cls.__name__ for cls in lc.Region3D.__subclasses__
↪()], "\n")
print("Regions in nD:\n", [cls.__name__ for cls in lc.RegionND.__subclasses__
↪()], "\n")
```

```
Empty Region:
 ['EmptyRegion']

Regions in 1D:
```

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```
 ['Interval']

Regions in 2D:
 ['Rectangle', 'Ellipse', 'Polygon', 'MultiPolygon']

Regions in 3D:
 ['AxisOrientedCuboid', 'Cuboid']

Regions in nD:
 ['AxisOrientedHypercuboid']
```

The region constructors take different parameters.

REMEMBER: Angles are taken in degrees.

```
region = lc.Rectangle(corner=(0, 0), width=1, height=2, angle=45)
region
```

```
Rectangle((0, 0), 1, 2, 45)
```

```
points = ((0, 0), (0, 1), (1, 1), (1, 0.5), (0, 0))
holes = [((0.2, 0.2), (0.2, 0.4), (0.4, 0.4), (0.3, 0.25)), ((0.5, 0.5), (0.5,
↪ 0.8), (0.8, 0.8), (0.7, 0.45))]
region = lc.Polygon(points, holes)
print(region)
region
```

```
Polygon(<self.points>, <self.holes>)
```

```
Polygon([[0.0, 0.0], [0.0, 1.0], [1.0, 1.0], [1.0, 0.5], [0.0, 0.0]], [[[0.2,␣
↪0.2], [0.2, 0.4], [0.4, 0.4], [0.3, 0.25]], [[0.5, 0.5], [0.5, 0.8], [0.8,␣
↪0.8], [0.7, 0.45]]])
```

Several attributes are available, e.g. about the area or circumference.

```
dict(dimension=region.dimension, bounds=region.bounds, extent=region.extent,␣
↪bounding_box=region.bounding_box, centroid=region.centroid, max_
↪distance=region.max_distance,
     region_measure= region.region_measure, subregion_measure=region.
↪subregion_measure)
```

```
{'dimension': 2,
 'bounds': array([0., 0., 1., 1.]),
 'extent': array([1., 1.]),
 'bounding_box': Rectangle((0.0, 0.0), 1.0, 1.0, 0),
 'centroid': array([0.42723735, 0.61770428]),
 'max_distance': 1.4142135623730951,
 'region_measure': 0.6425,
 'subregion_measure': 5.480275727142994}
```

A list of points defining a polygon that resembles the region is available.

```
print("Points:\n", region.points, "\n")
print("Holes:\n", region.holes)
```

```
Points:
 [[0.  0. ]
 [0.  1. ]
 [1.  1. ]
 [1.  0.5]
 [0.  0. ]]

Holes:
 [array([[0.2 , 0.2 ],
       [0.2 , 0.4 ],
       [0.4 , 0.4 ],
       [0.3 , 0.25]]), array([[0.5 , 0.5 ],
       [0.5 , 0.8 ],
       [0.8 , 0.8 ],
       [0.7 , 0.45]])]
```

Region can be constructed from interval tuples indicating feature ranges.

```
region_1d = lc.Region.from_intervals((0, 1))
region_2d = lc.Region.from_intervals(((0, 1), (0, 1)))
region_3d = lc.Region.from_intervals([(0, 1)] * 3)
region_4d = lc.Region.from_intervals([(0, 1)] * 4)
```

```
for region in (region_1d, region_2d, region_3d, region_4d):
    print(region)
```

```
Interval(0, 1)
Rectangle((0, 0), 1, 1, 0)
AxisOrientedCuboid((0, 0, 0), 1, 1, 1)
AxisOrientedHypercuboid((0, 0, 0, 0), (1, 1, 1, 1))
```

2.5.3 Plot regions

Regions can be plotted as patch in mathplotlib figures.

```
points = ((0, 0), (0, 1), (1, 1), (1, 0.5), (0, 0))
holes = [((0.2, 0.2), (0.2, 0.4), (0.4, 0.4), (0.3, 0.25)), ((0.5, 0.5), (0.5,
↪ 0.8), (0.8, 0.8), (0.7, 0.45))]
region = lc.Polygon(points, holes)
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
ax.add_patch(region.as_artist(fill=False, color='Blue'))
ax.add_patch(region.bounding_box.as_artist(fill=False, color='Grey'))
ax.plot(*region.centroid, '*', color='Red')
```

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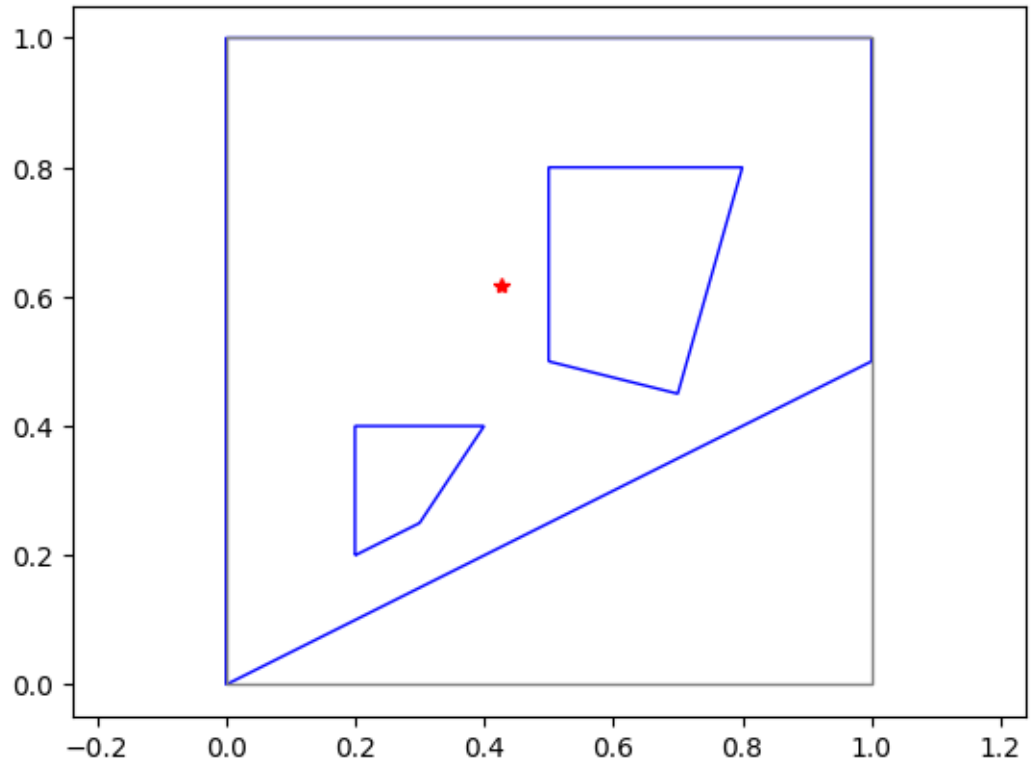
```
ax.axis('equal')
plt.show()
```



2.5.4 Intersection, union, difference of regions

Methods are provided to check for intersection, difference, union and membership.

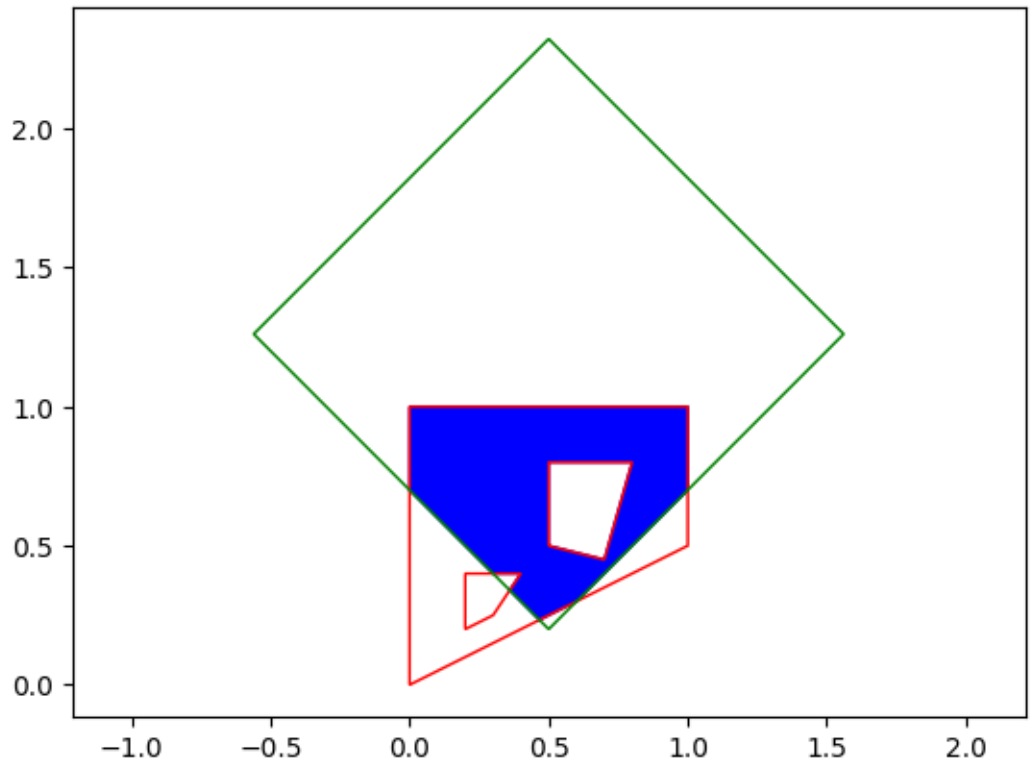
```
other_region = lc.Rectangle(corner=(0.5, 0.2), width=1.5, height=1.5,␣
↪angle=45)
other_region.shapely_object
```

```
<shapely.geometry.polygon.Polygon at 0x7f241323ec80>
```

```
result = region.intersection(other_region)
print(result)
```

```
Polygon(<self.points>, <self.holes>)
```

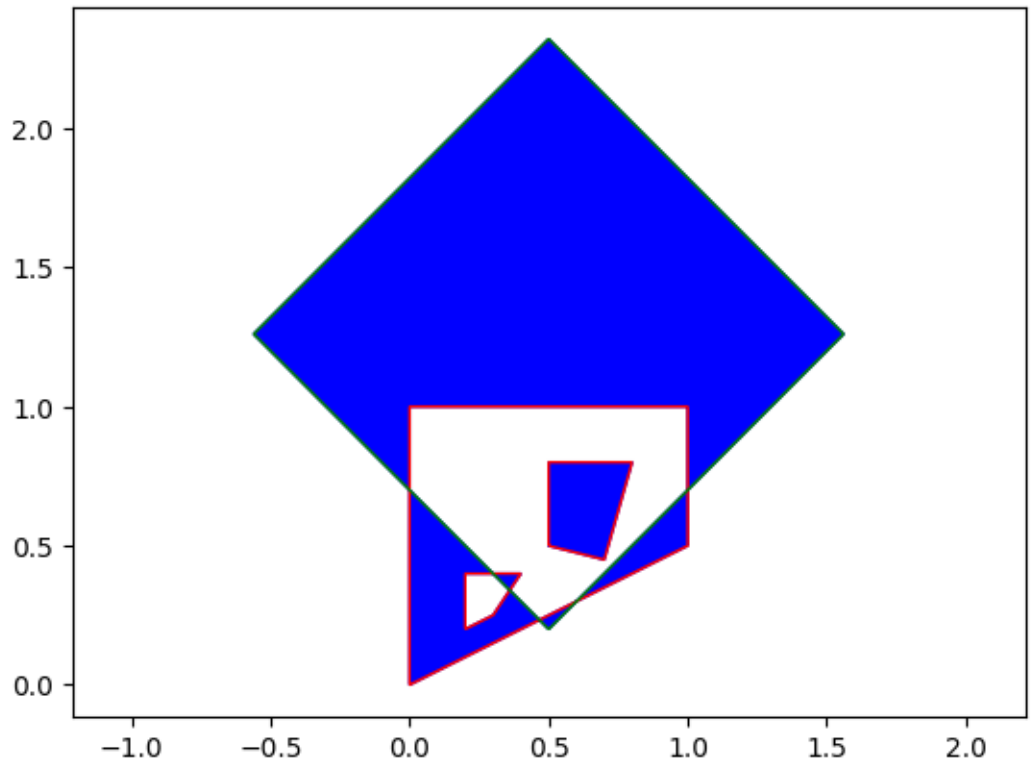
```
fig, ax = plt.subplots(nrows=1, ncols=1)
ax.add_patch(result.as_artist(fill=True, color='Blue'))
ax.add_patch(region.as_artist(fill=False, color='Red'))
ax.add_patch(other_region.as_artist(fill=False, color='Green'))
ax.axis('equal')
plt.show()
```




```
result = region.symmetric_difference(other_region)
print(result)
```

```
MultiPolygon(<self.polygons>)
```

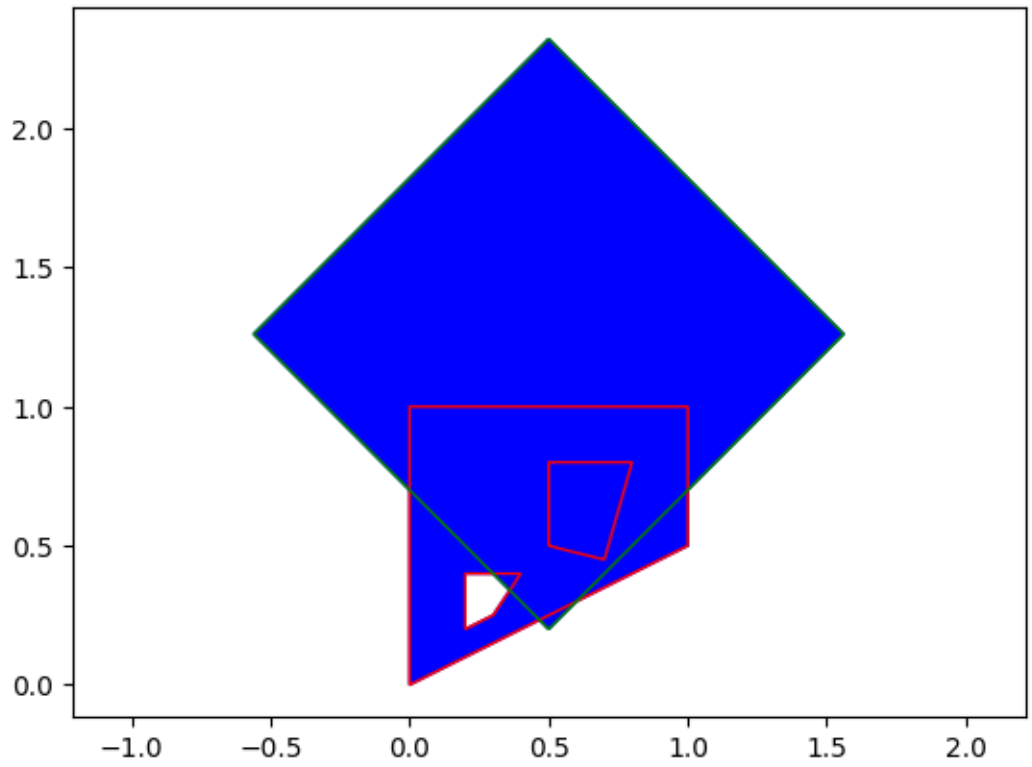
```
fig, ax = plt.subplots(nrows=1, ncols=1)
ax.add_patch(result.as_artist(fill=True, color='Blue'))
ax.add_patch(region.as_artist(fill=False, color='Red'))
ax.add_patch(other_region.as_artist(fill=False, color='Green'))
ax.axis('equal')
plt.show()
```




```
result = region.union(other_region)
print(result)
```

```
Polygon(<self.points>, <self.holes>)
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
ax.add_patch(result.as_artist(fill=True, color='Blue'))
ax.add_patch(region.as_artist(fill=False, color='Red'))
ax.add_patch(other_region.as_artist(fill=False, color='Green'))
ax.axis('equal')
plt.show()
```

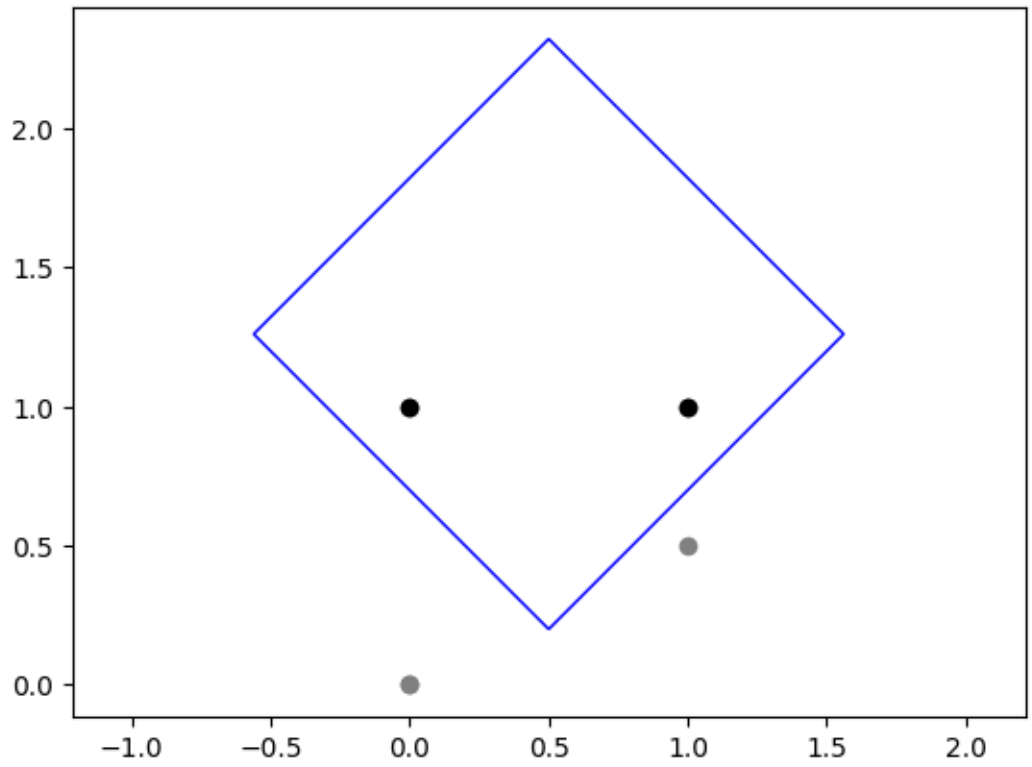


2.5.5 Check if point is in region

`Region` has a `contains` method to select points that are within the region.

```
inside_indices = other_region.contains(region.points)
contained_points = region.points[inside_indices]
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
ax.scatter(*region.points.T, color='Grey')
ax.scatter(*contained_points.T, color='Black')
ax.add_patch(other_region.as_artist(fill=False, color='Blue'))
ax.axis('equal')
plt.show()
```



2.5.6 LocData and regions

LocData bring various hulls that define regions. Also LocData typically has a unique region defined as support. This can e.g. result from the definition of a region of interest using the ROI function or as specified in a corresponding yaml file.

Create data in region:

A random dataset is created within a specified region (for other methods see simulation tutorial).

```
region = lc.Rectangle(corner=(0, 0), width=1, height=1, angle=45)
locdata = lc.simulate_uniform(n_samples=1000, region=region, seed=1)
locdata.print_summary()
```

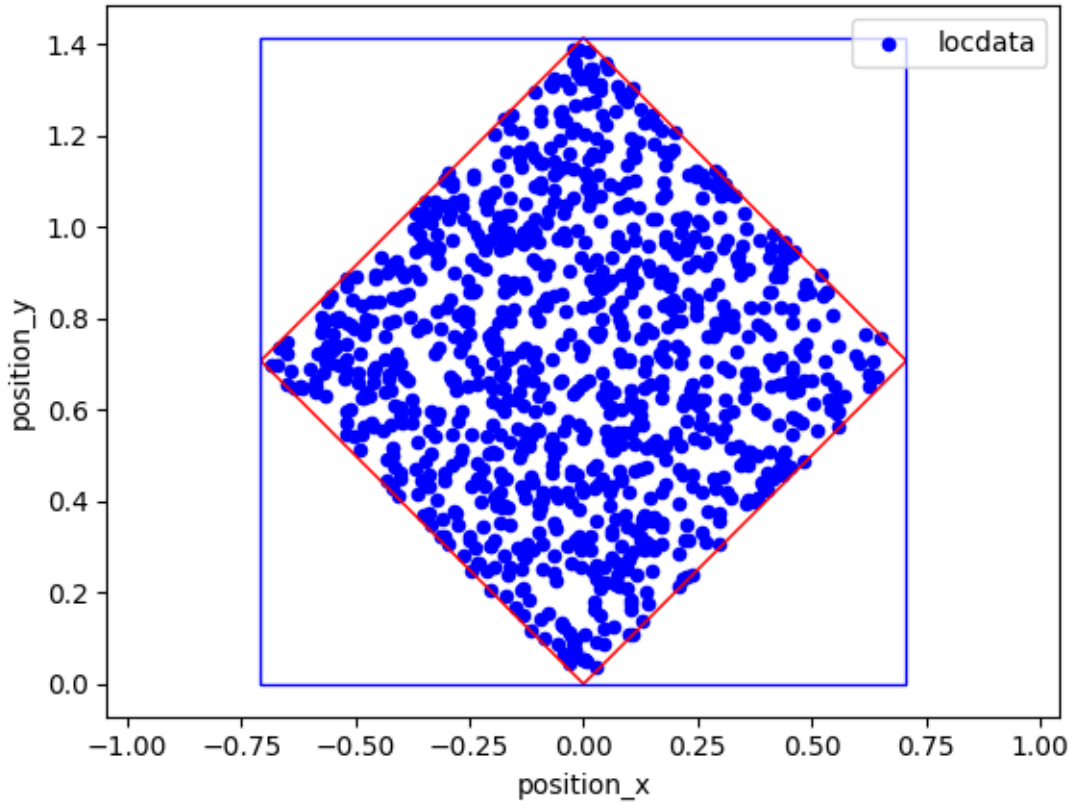
```
identifier: "1"
comment: ""
source: SIMULATION
state: RAW
element_count: 1000
frame_count: 0
creation_time {
  2024-03-14T11:52:28.981430Z
}
```

```
region
```

```
Rectangle((0, 0), 1, 1, 45)
```

Show scatter plots together with regions

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
ax.add_patch(locdata.region.as_artist(fill=False, color='Red'))
ax.add_patch(locdata.region.bounding_box.as_artist(fill=False, color='Blue'))
ax.axis('equal')
plt.show()
```



2.5.7 Select localizations within regions

LocData can be selected for localizations being inside the region.

```
region = lc.Ellipse(center=(0, 0.5), width=1, height=0.5, angle=45)
locdata_in_region = lc.select_by_region(locdata, region)
locdata_in_region.region
```

```
Ellipse((0.0, 0.5), 1, 0.5, 45)
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata', alpha=0.1)
```

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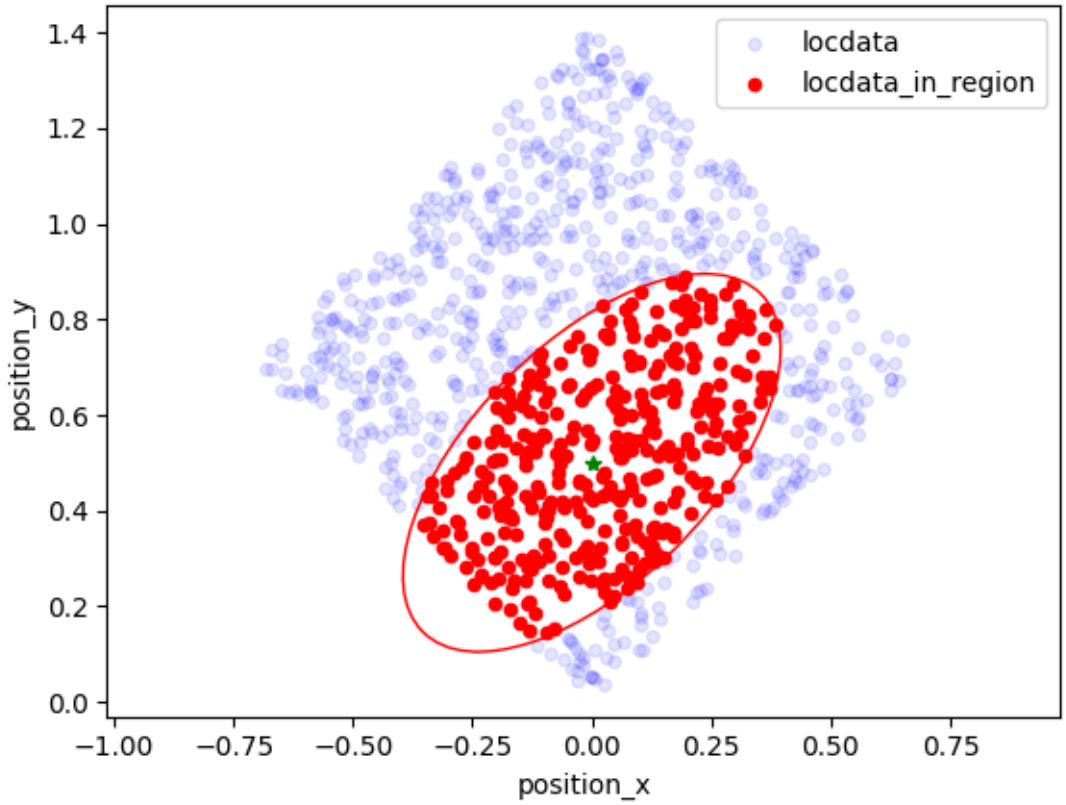
```
ax.add_patch(region.as_artist(fill=False, color='Red'))
locdata_in_region.data.plot.scatter(x='position_x', y='position_y', ax=ax,␣
↪color='Red', label='locdata_in_region')
ax.plot(*region.centroid, '*', color='Green')
ax.axis('equal')
plt.show()
```



2.5.8 Regions of interest

The Roi class is an object that defines a region of interest for a specific localization dataset. It is mostly used to save and reload regions of interest after having selected them interactively, e.g. in napari. It is therefore related to region specifications and a unique LocData object.

Define a region of interest (roi):

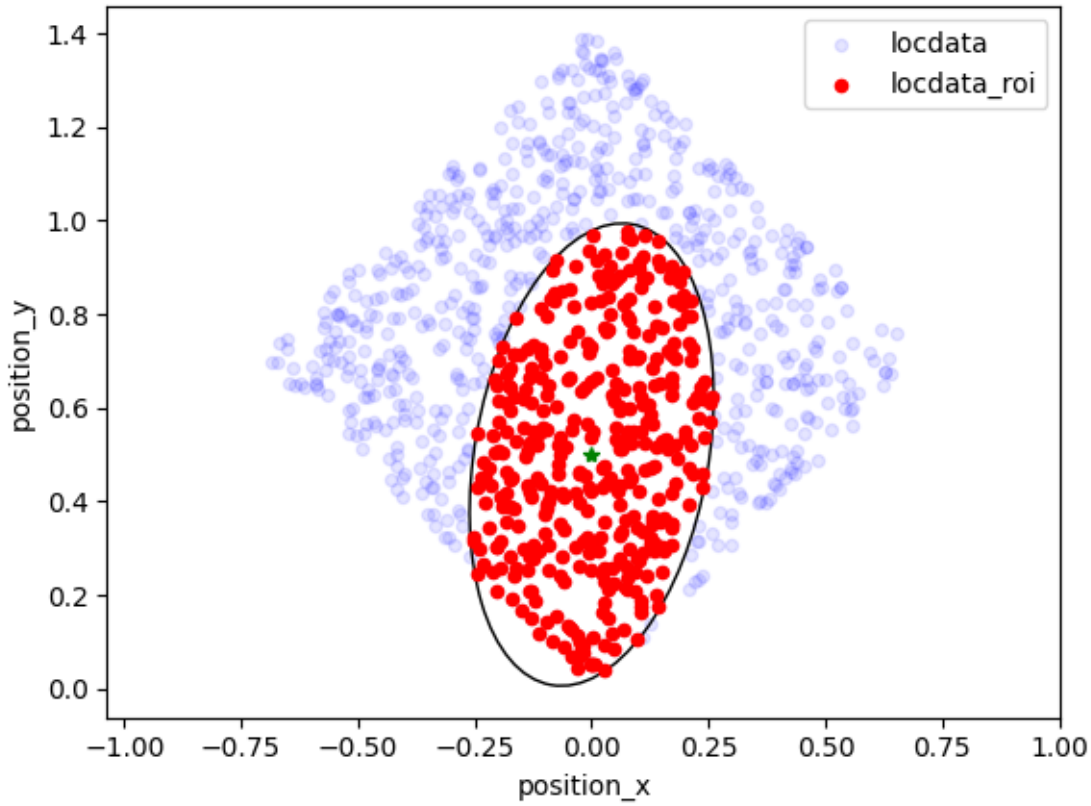
```
roi = lc.Roi(reference=locdata, region=lc.Ellipse(center=(0, 0.5), width=1,␣
↪height=0.5, angle=80))
roi
```

```
Roi(reference=<locan.data.locdata.LocData object at 0x7f2410ffef50>,␣
↪region=Ellipse((0.0, 0.5), 1, 0.5, 80),  loc_properties=())
```

Create new LocData instance by selecting localizations within a roi.

```
locdata_roi = roi.locdata()
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata', alpha=0.1)
ax.add_patch(roi.region.as_artist(fill=False))
locdata_roi.data.plot.scatter(x='position_x', y='position_y', ax=ax, color=
↪'Red', label='locdata_roi')
ax.plot(*roi.region.centroid, '*', color='Green')
ax.axis('equal')
plt.show()
```



ROI input/output

If you have prepared rois and saved them as roi.yaml file you can read that data back in:

```
import tempfile
from pathlib import Path

with tempfile.TemporaryDirectory() as tmp_directory:
    file_path = Path(tmp_directory) / 'roi.yaml'

    roi.to_yaml(path=file_path)

    roi_new = lc.Roi.from_yaml(path = file_path)
    roi_new.reference = roi.reference
```

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```
new_locdata = roi_new.locdata()
new_locdata.meta
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/rois/roi.py:301: UserWarning: The␣
↪localization data has to be saved and the file path provided, or the␣
↪reference is lost.
  warnings.warn(
```

```
identifier: "4"
source: SIMULATION
state: MODIFIED
history {
  name: "make_uniform"
  parameter: "{\'n_samples\': 1000, \'region\': Rectangle((0, 0), 1, 1, 45), \
↪'seed\': 1}"
}
history {
  name: "locdata"
  parameter: "{\'self\': Roi(reference=<locan.data.locdata.LocData object at␣
↪0x7f2410ffef50>, region=Ellipse((0.0, 0.5), 1, 0.5, 80),  loc_
↪properties=[]), \'reduce\': True}"
}
ancestor_identifiers: "1"
element_count: 388
frame_count: 0
creation_time {
  seconds: 1710417148
  nanos: 981430000
}
modification_time {
  seconds: 1710417148
  nanos: 981430000
}
```

```
roi_new
```

```
Roi(reference=<locan.data.locdata.LocData object at 0x7f2410ffef50>,␣
↪region=Ellipse((0.0, 0.5), 1, 0.5, 80),  loc_properties=[])
```

2.6 Tutorial about filtering LocData objects

```
%matplotlib inline

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.6.1 Synthetic data

A random dataset is created.

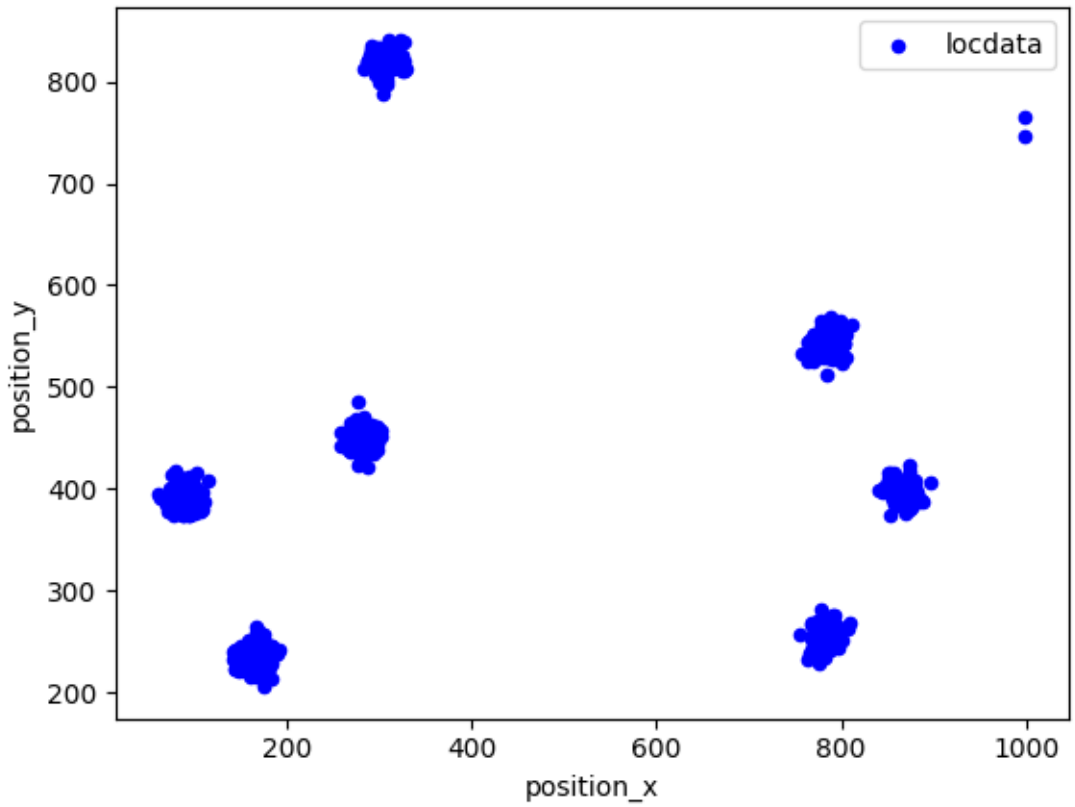
```
rng = np.random.default_rng(seed=1)
```

```
locdata = lc.simulate_Thomas(parent_intensity=1e-5, region=((0, 1000), (0,␣
↪1000)), cluster_mu=100, cluster_std=10, seed=rng)

locdata.print_summary()
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
identifier: "1"
comment: ""
source: SIMULATION
state: RAW
element_count: 705
frame_count: 0
creation_time {
  2024-03-14T11:51:26.077809Z
}
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



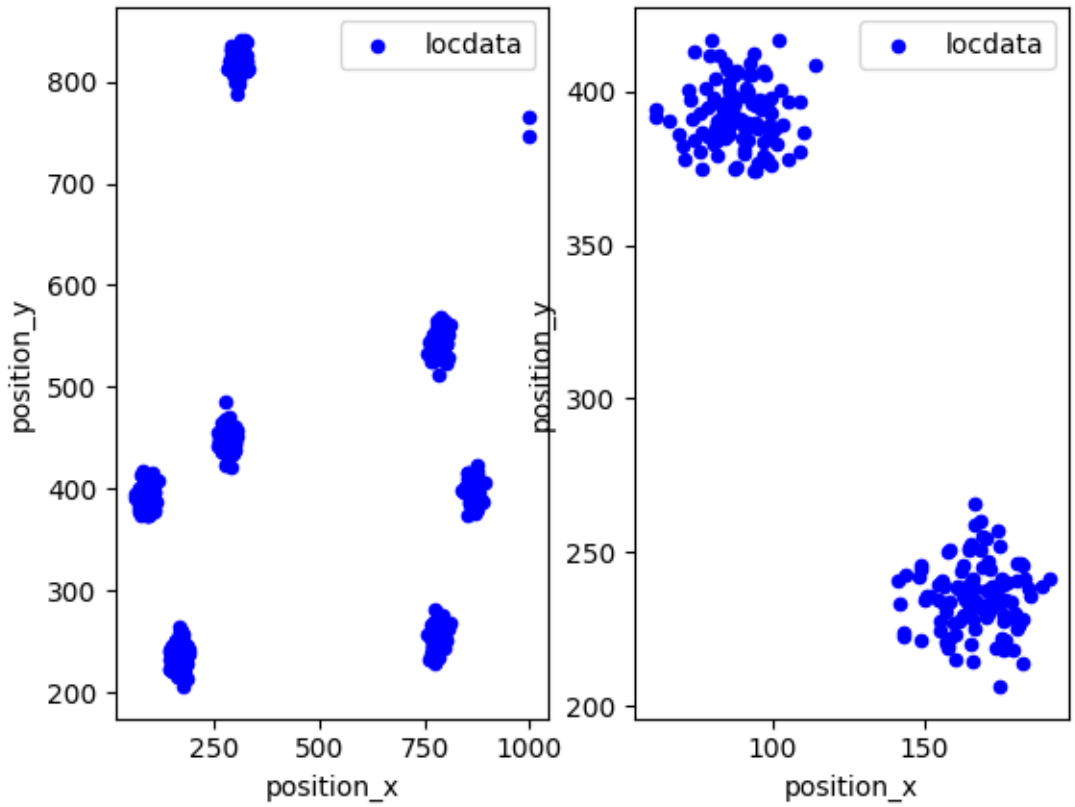
2.6.2 Select localizations according to property conditions

A LocData object carries localization data with certain properties for each localization.

We can select localisations according to property conditions.

```
locdata_select = lc.select_by_condition(locdata, condition='position_x<200')
```

```
fig, ax = plt.subplots(nrows=1, ncols=2)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax[0], color=
↪'Blue', label='locdata')
locdata_select.data.plot.scatter(x='position_x', y='position_y', ax=ax[1],␣
↪color='Blue', label='locdata')
plt.tight_layout
plt.show()
```



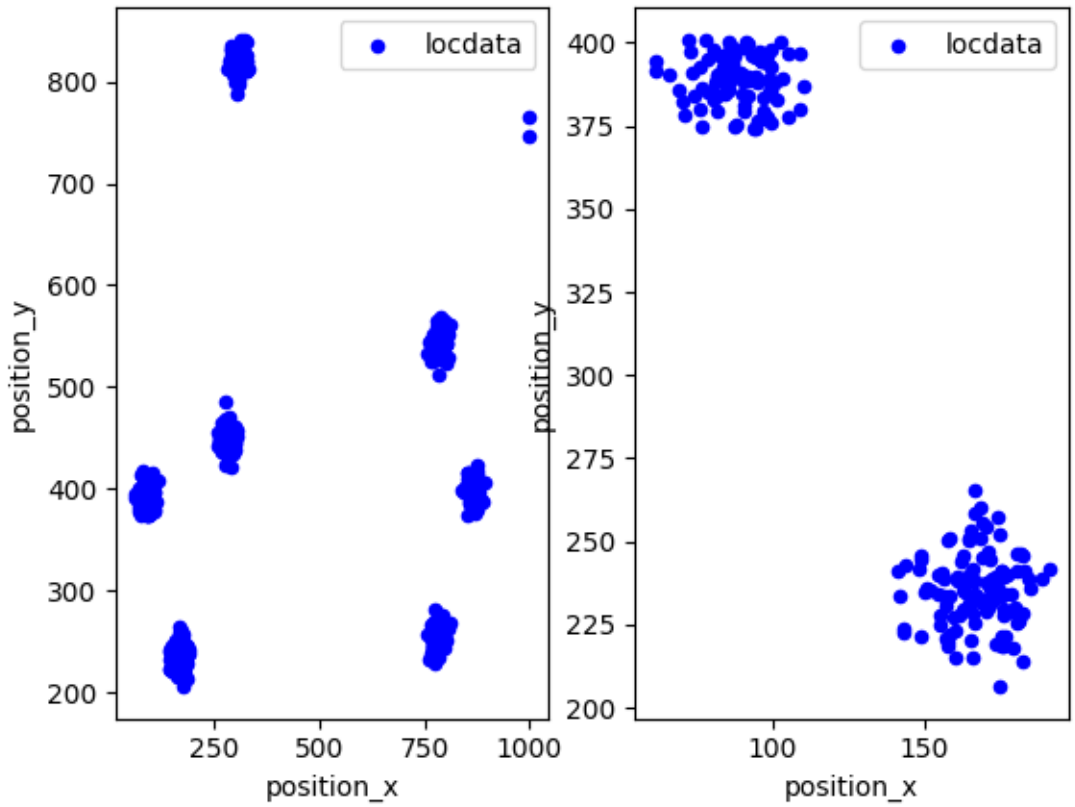
2.6.3 Select localizations in regions

Regions can be defined using the classes defined in the locan.data.region module. Please see the tutorial on Regions.

We can select localizations that within a given region.

```
region = region=lc.Rectangle((1, 1), 400, 400, 0)
locdata_roi = lc.select_by_region(locdata, region=region)
```

```
fig, ax = plt.subplots(nrows=1, ncols=2)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax[0], color=
↪'Blue', label='locdata')
locdata_roi.data.plot.scatter(x='position_x', y='position_y', ax=ax[1], color=
↪'Blue', label='locdata')
plt.tight_layout
plt.show()
```



2.6.4 Select localizations from a region of interest (ROI)

Typically a region of interest is defined for a single dataset. The `Roi` class combines a region definition with a specific data reference and provides convenience methods like input/output.

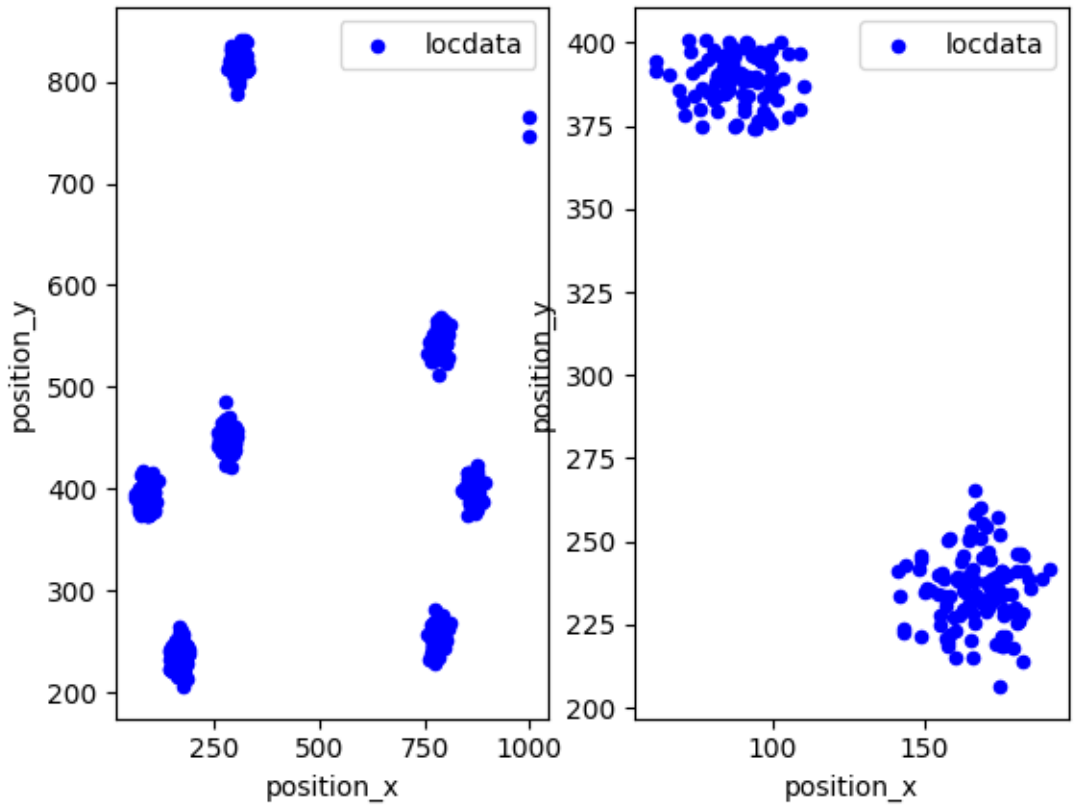
Define a region of interest (roi):

```
roi = lc.Roi(region=lc.Rectangle((1, 1), 400, 400, 0), reference=locdata)
```

Create new LocData instance by selecting localizations within a roi.

```
locdata_roi = roi.locdata()
```

```
fig, ax = plt.subplots(nrows=1, ncols=2)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax[0], color=
↪'Blue', label='locdata')
locdata_roi.data.plot.scatter(x='position_x', y='position_y', ax=ax[1], color=
↪'Blue', label='locdata')
plt.tight_layout
plt.show()
```



Save roi definitions (including region and reference) as yaml file:

```
roi
```

```
Roi(reference=<locan.data.locdata.LocData object at 0x7fc133a0e5c0>,␣
↪region=Rectangle((1, 1), 400, 400, 0),  loc_properties=())
```

```
import tempfile
from pathlib import Path

with tempfile.TemporaryDirectory() as tmp_directory:
    file_path = Path(tmp_directory) / 'roi.yaml'

    roi.to_yaml(path=file_path)

    roi_new = lc.Roi.from_yaml(path = file_path)
    roi_new.reference = roi.reference

locdata_new = roi_new.locdata()
locdata_new.meta
```

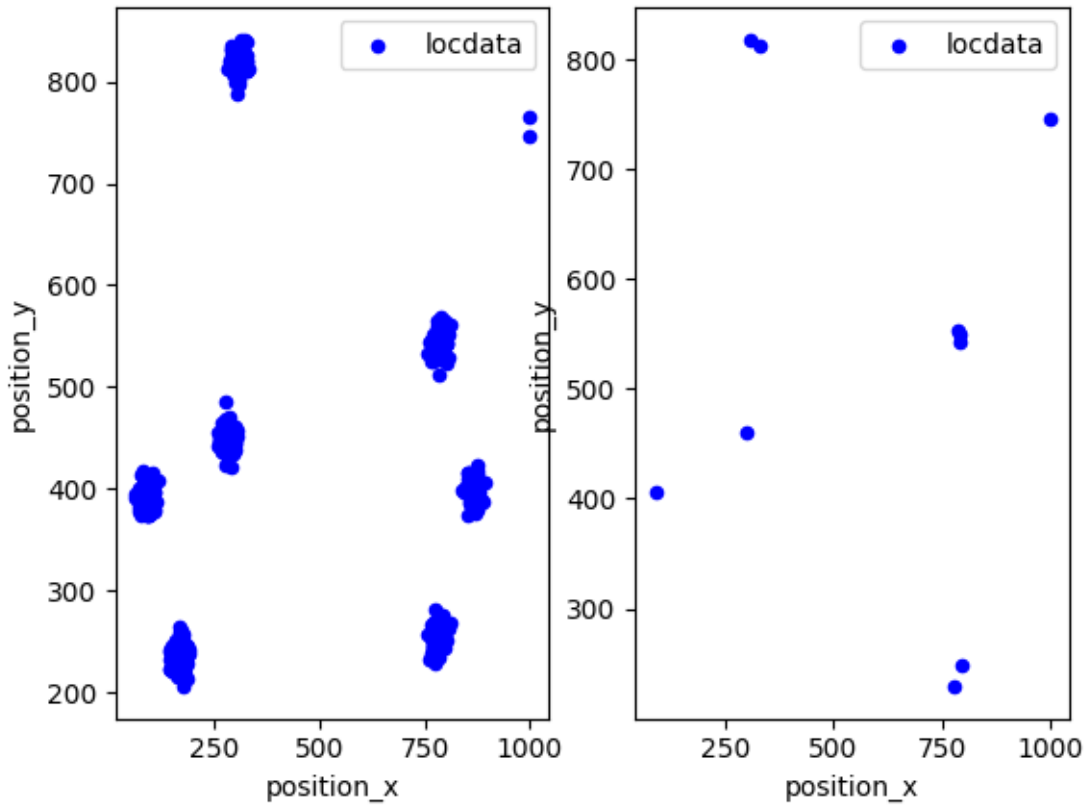
```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/rois/roi.py:301: UserWarning: The␣
↪localization data has to be saved and the file path provided, or the␣
↪reference is lost.
  warnings.warn(
```

```
identifier: "5"
source: SIMULATION
state: MODIFIED
history {
  name: "make_Thomas"
  parameter: "{\'parent_intensity\': 1e-05, \'region\': ((0, 1000), (0,␣
↪1000)), \'expansion_factor\': 6, \'cluster_mu\': 100, \'cluster_std\': 10, \
↪'clip\': True, \'shuffle\': True, \'seed\': Generator(PCG64) at␣
↪0x7FC14EA37CA0}"
}
history {
  name: "locdata"
  parameter: "{\'self\': Roi(reference=<locan.data.locdata.LocData object at␣
↪0x7fc133a0e5c0>, region=Rectangle((1, 1), 400, 400, 0),  loc_properties=[]),
↪ \'reduce\': True}"
}
ancestor_identifiers: "1"
element_count: 206
frame_count: 0
creation_time {
  seconds: 1710417086
  nanos: 77809000
}
modification_time {
  seconds: 1710417086
  nanos: 77809000
}
```

2.6.5 Select a random subset of localizations

```
locdata_random = lc.random_subset(locdata, n_points=10, seed=rng)
```

```
fig, ax = plt.subplots(nrows=1, ncols=2)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax[0], color=
↪'Blue', label='locdata')
locdata_random.data.plot.scatter(x='position_x', y='position_y', ax=ax[1],␣
↪color='Blue', label='locdata')
plt.tight_layout
plt.show()
```



2.7 Tutorial about clustering localizations data

Locan provides methods for clustering localizations in LocData objects. The methods all return a new LocDat object that represents the collected selections for each cluster.

```
from pathlib import Path

%matplotlib inline

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.7.1 Synthetic data

We simulate localization data that follows a Neyman-Scott distribution in 2D:

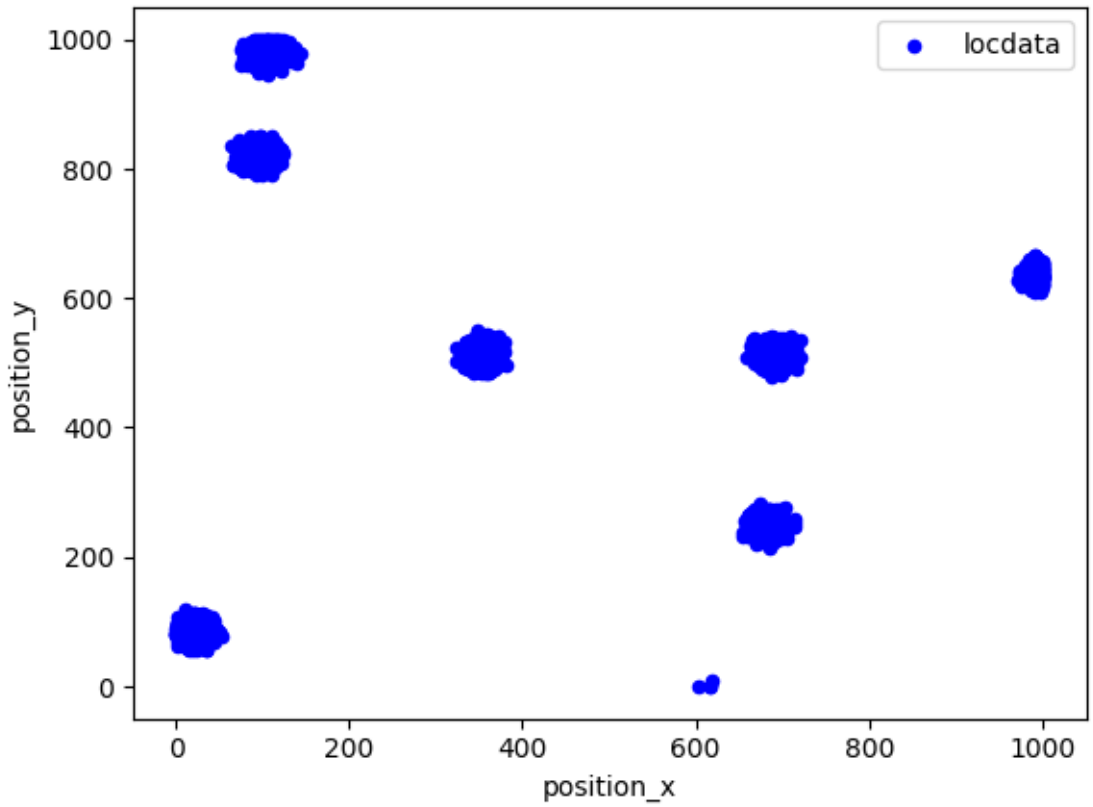
```
rng = np.random.default_rng(seed=11)
```

```
locdata = lc.simulate_Thomas(parent_intensity=1e-5, region=((0, 1000), (0,␣
↪1000)), cluster_mu=1000, cluster_std=10, seed=rng)

locdata.print_summary()
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
identifier: "1"
comment: ""
source: SIMULATION
state: RAW
element_count: 6409
frame_count: 0
creation_time {
  2024-03-14T11:51:05.645Z
}
```

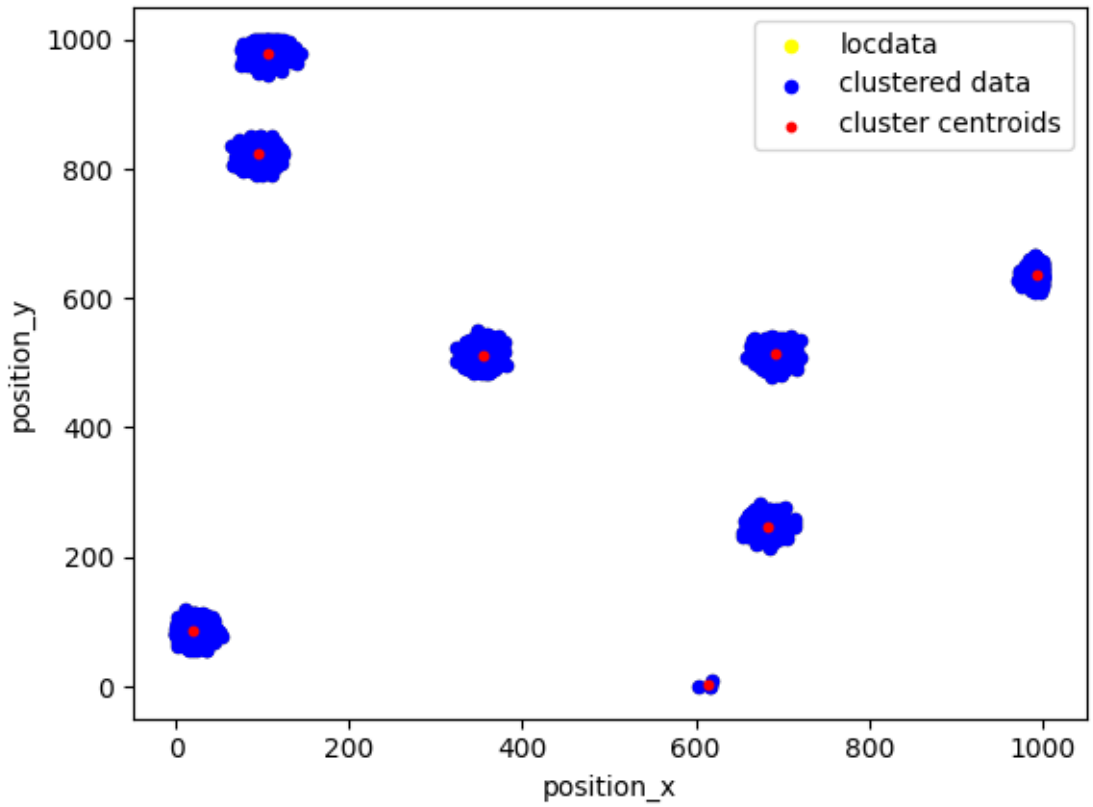
```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



2.7.2 Cluster localizations by dbscan

```
noise, clust = lc.cluster_dbscan(locdata, eps=20, min_samples=3)
assert noise.data.empty
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Yellow
↪', label='locdata')
lc.LocData.concat(clust.references).data.plot.scatter(x='position_x', y=
↪'position_y', ax=ax, color='Blue', label='clustered data')
clust.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Red',␣
↪s=10, label='cluster centroids')
plt.show()
```




```
clust.data.head()
```

```
   localization_count  position_x  uncertainty_x  position_y  uncertainty_y  \
0                1016   20.379759       0.300643   85.374381       0.314089
1                1050  681.909709       0.305784  248.276785       0.310572
2                 986  353.614004       0.302981  512.621728       0.320747
3                 996  690.951712       0.315008  513.619337       0.313548
4                 368  992.523811       0.288485  636.239028       0.548494

   region_measure_bb  localization_density_bb  subregion_measure_bb  \
0        3262.794976                 0.311389            229.091796
1        4122.205751                 0.254718            257.346576
2        3814.439353                 0.258491            248.125971
3        3935.485208                 0.253082            250.933843
4        1650.773324                 0.222926            170.375014

   region_measure  localization_density  subregion_measure
0         1000000              0.001016               4000
1         1000000              0.001050               4000
2         1000000              0.000986               4000
3         1000000              0.000996               4000
4         1000000              0.000368               4000
```

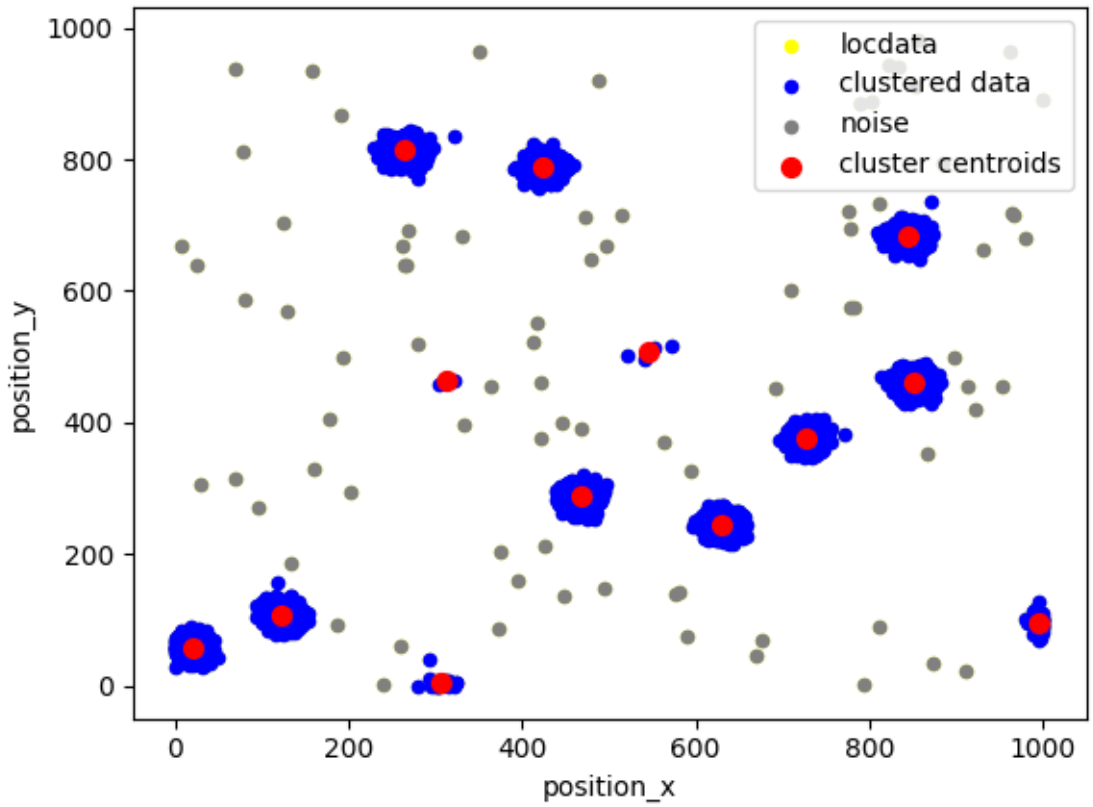
2.7.3 Cluster localizations in the presence of noise

Often homogeneously distributed localizations are present that cannot be clustered (so-called noise). In this case *noise* should be set True such that two LocData objects are returned that hold noise and the cluster collection. If *noise* is False it will be part of the returned cluster collection.

```
locdata_cluster = lc.simulate_Thomas(parent_intensity=1e-5, region=((0, 1000),
↪ (0, 1000)), cluster_mu=1000, cluster_std=10, seed=rng)
locdata_noise = lc.simulate_Poisson(intensity=1e-4, region=((0, 1000), (0,␣
↪1000)), seed=rng)
locdata = lc.LocData.concat([locdata_cluster, locdata_noise])
```

```
noise, clust = lc.cluster_dbscan(locdata, eps=30, min_samples=3)
```

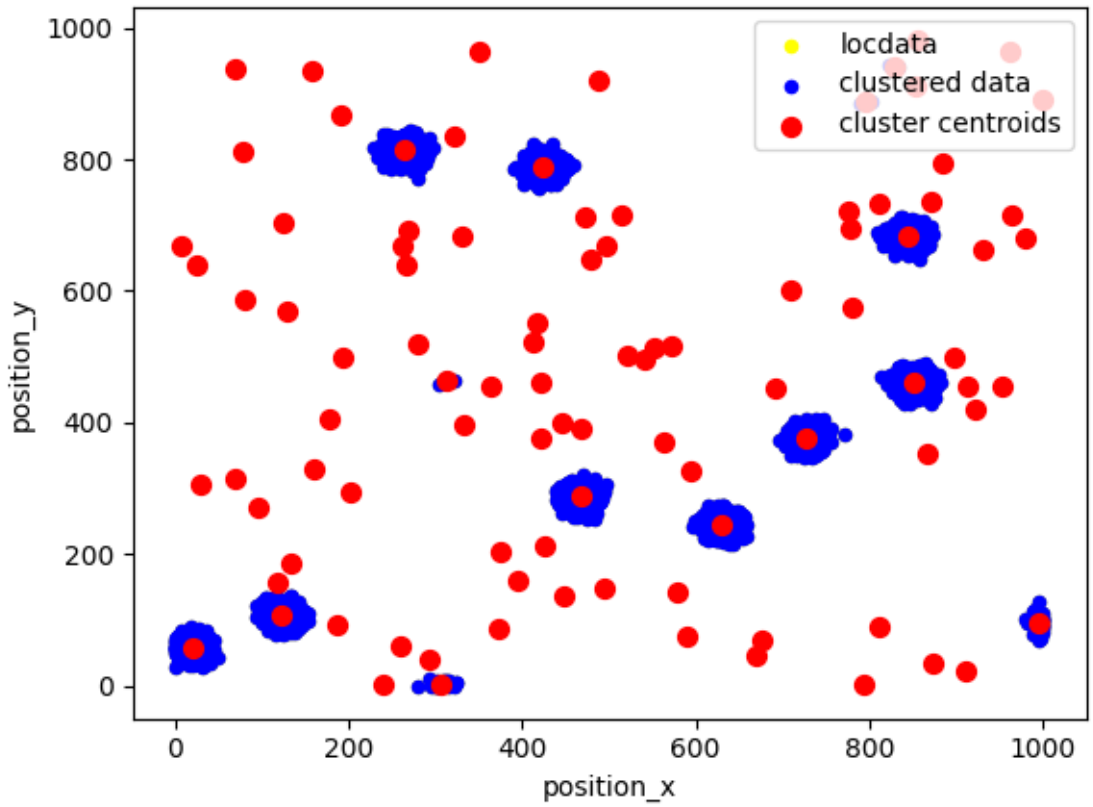
```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Yellow
↪', label='locdata')
lc.LocData.concat(clust.references).data.plot.scatter(x='position_x', y=
↪'position_y', ax=ax, color='Blue', label='clustered data')
noise.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Gray',␣
↪label='noise')
clust.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Red',␣
↪s=50, label='cluster centroids')
plt.show()
```



If single localizations should be inlcuded as individual clusters, we need to reduce `min_samples` to 1. In that case `noise` will always be None.

```
noise, clust = lc.cluster_dbscan(locdata, eps=20, min_samples=1)
assert noise.data.empty
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Yellow
↪', label='locdata')
lc.LocData.concat(clust.references).data.plot.scatter(x='position_x', y=
↪'position_y', ax=ax, color='Blue', label='clustered data')
# noise.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Gray',␣
↪label='noise')
clust.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Red',␣
↪s=50, label='cluster centroids')
plt.show()
```



Other cluster functions are available in the `locan.data.cluster`module.

2.8 Tutorial about rendering LocData

```
from pathlib import Path

%matplotlib inline
# %matplotlib widget

import numpy as np
import pandas as pd
```

(continues on next page)

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```
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.8.1 Synthetic data

Localizations are simulated that are distributed according to a Neyman-Scott distribution (blobs).

```
rng = np.random.default_rng(seed=1)
```

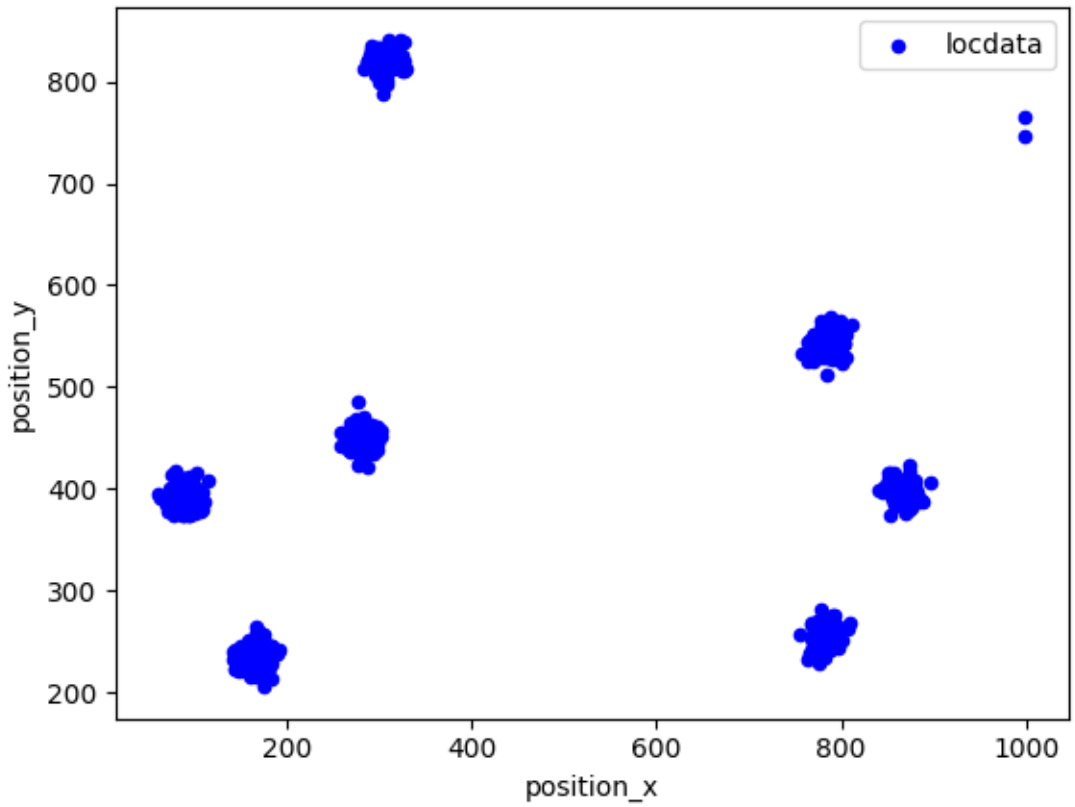
```
locdata = lc.simulate_Thomas(parent_intensity=1e-5, region=((0, 1000), (0,␣
↪1000)), cluster_mu=100, cluster_std=10, seed=rng)

locdata.print_summary()
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
identifier: "1"
comment: ""
source: SIMULATION
state: RAW
element_count: 705
frame_count: 0
creation_time {
  2024-03-14T11:52:34.465660Z
}
```

Since localization data is kept as a pandas dataframe standard plotting routines from pandas or matplotlip can be used.

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



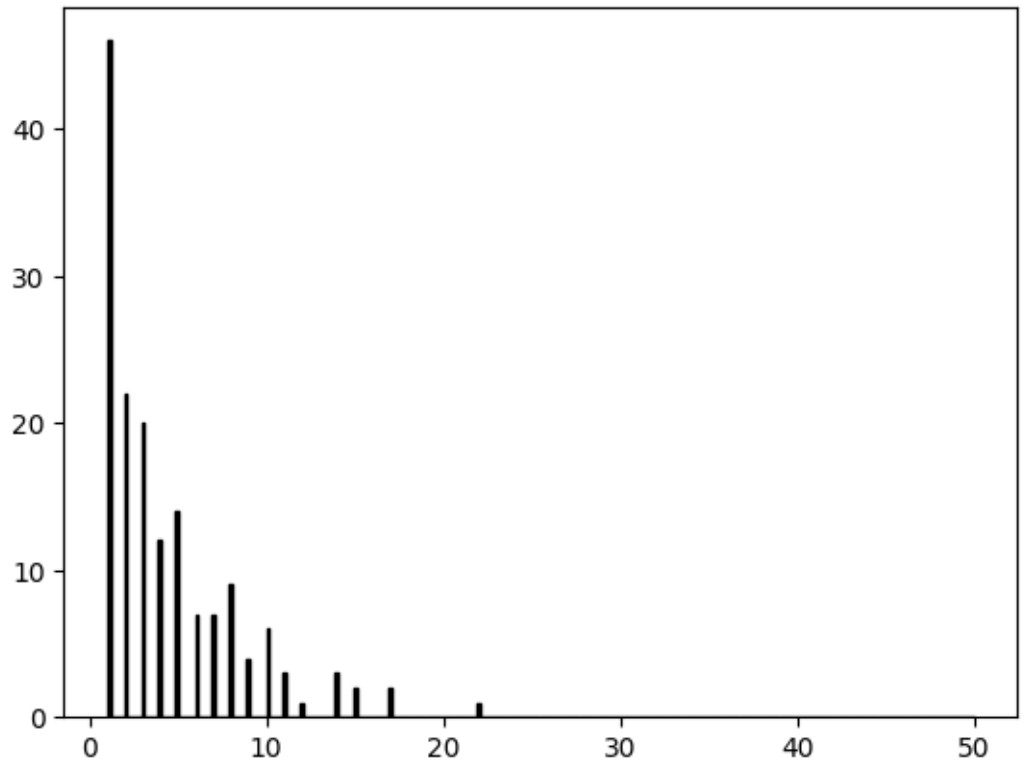
2.8.2 Render by simple 2D binning

A method for simply binning localization data in 2D pixels is provided.

```
img, bins, label = lc.histogram(locdata, bin_size=10)
```

The intensity values of the binned locdata are distributed as:

```
plt.hist(img.ravel(), bins=256, range=(1, 50), fc='k', ec='k');
```

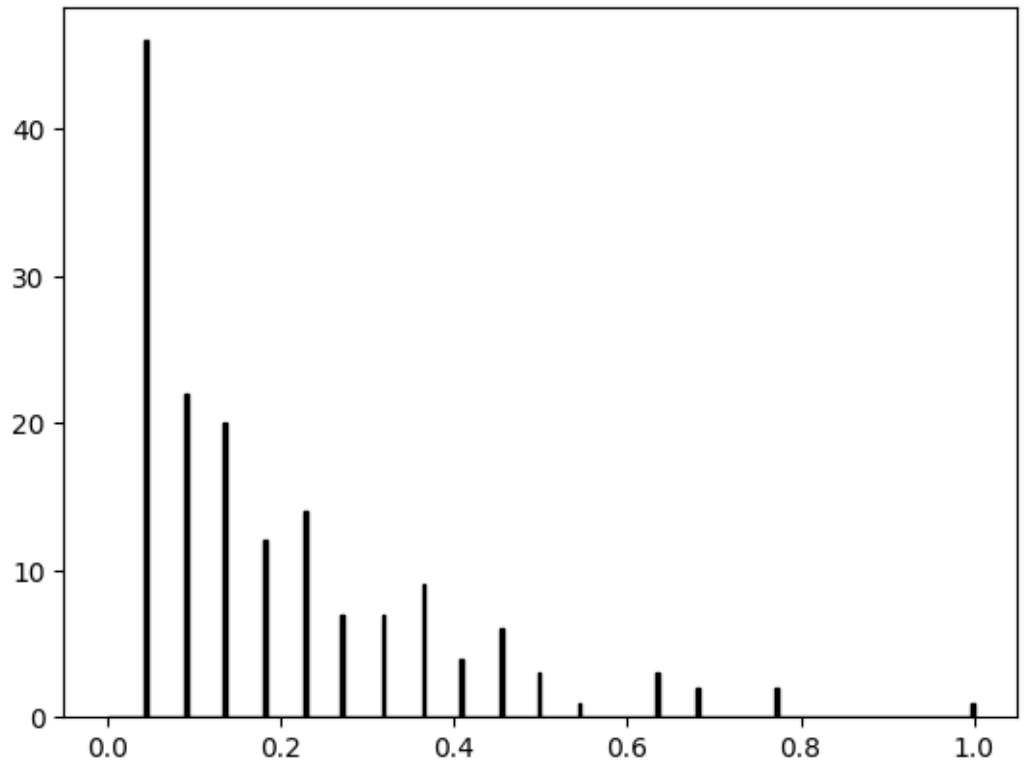


The intensity values can be rescaled in many ways. There are normalization classes and a convenience function in the locan.render.transformation module with predefined transformations as listed in locan.Trafo:

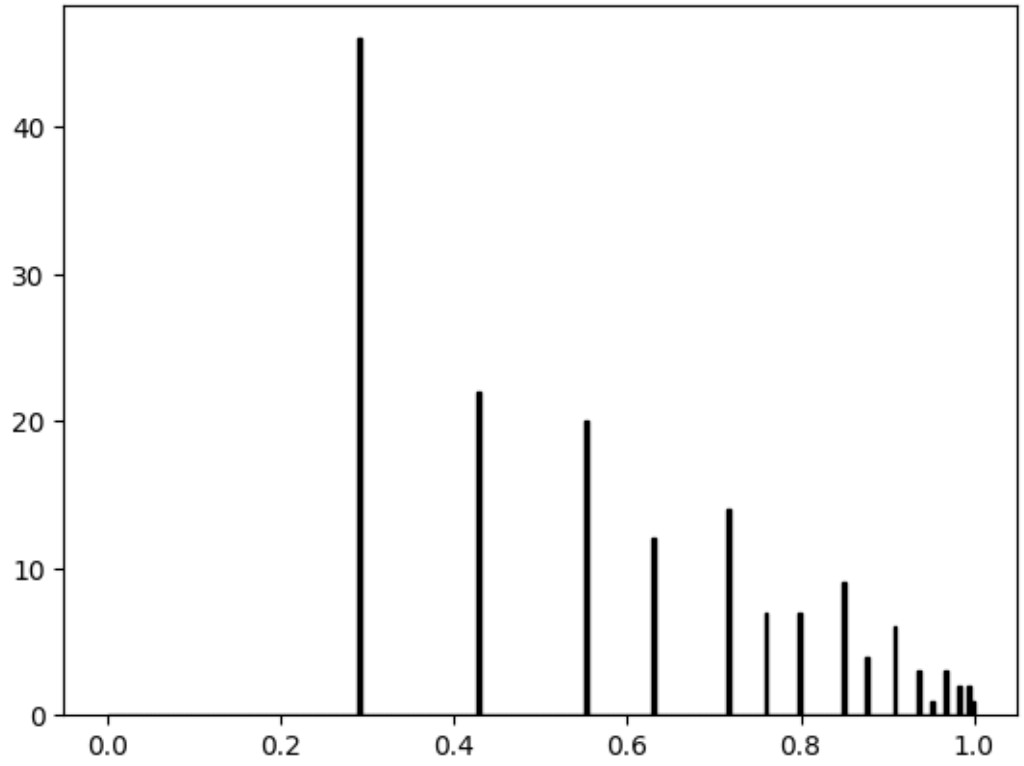
```
list(lc.Trafo)
```

```
[<Trafo.NONE: 0>,
 <Trafo.STANDARDIZE: 1>,
 <Trafo.STANDARDIZE_UINT8: 2>,
 <Trafo.ZERO: 3>,
 <Trafo.ZERO_UINT8: 4>,
 <Trafo.EQUALIZE: 5>,
 <Trafo.EQUALIZE_UINT8: 6>,
 <Trafo.EQUALIZE_ALL: 7>,
 <Trafo.EQUALIZE_ALL_UINT8: 8>,
 <Trafo.EQUALIZE_0P3: 9>,
 <Trafo.EQUALIZE_0P3_UINT8: 10>,
 <Trafo.EQUALIZE_0P3_ALL: 11>,
 <Trafo.EQUALIZE_0P3_ALL_UINT8: 12>]
```

```
img_new = lc.adjust_contrast(img, rescale=lc.Trafo.STANDARDIZE)
epsilon = np.finfo(float).resolution
plt.hist(img_new.ravel(), bins=256, range=(epsilon, 1), fc='k', ec='k');
```

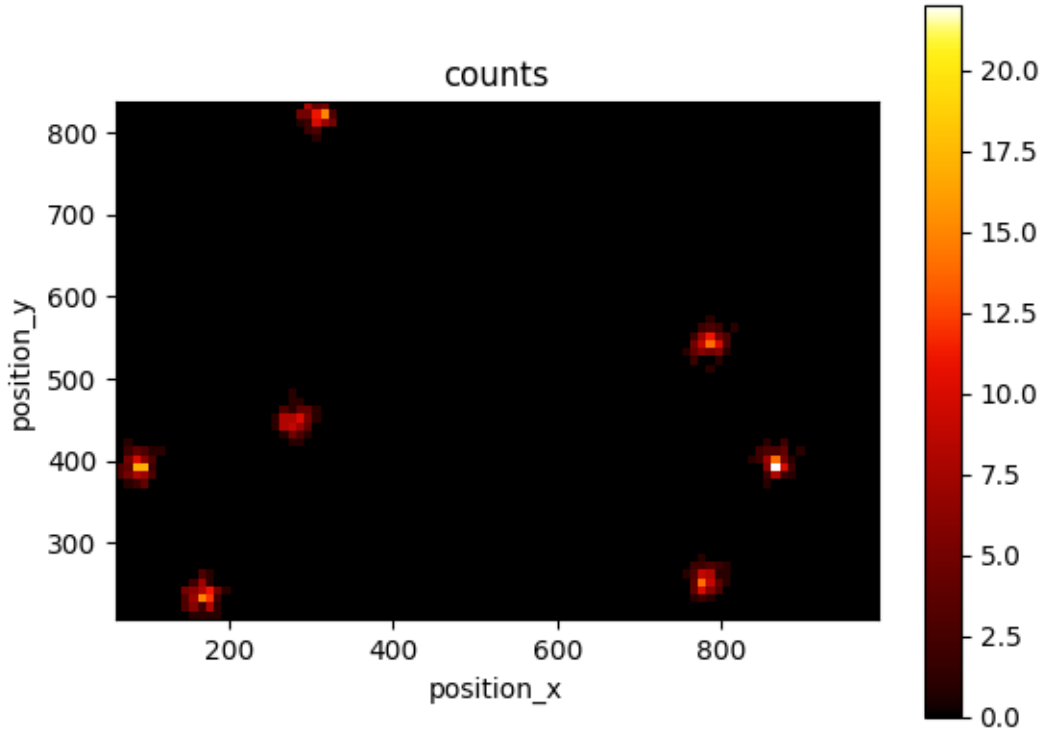



```
norm = lc.HistogramEqualization(power=1, mask=img>0)
img_new = norm(img)
plt.hist(img_new.ravel(), bins=256, range=(epsilon, 1), fc='k', ec='k');
```



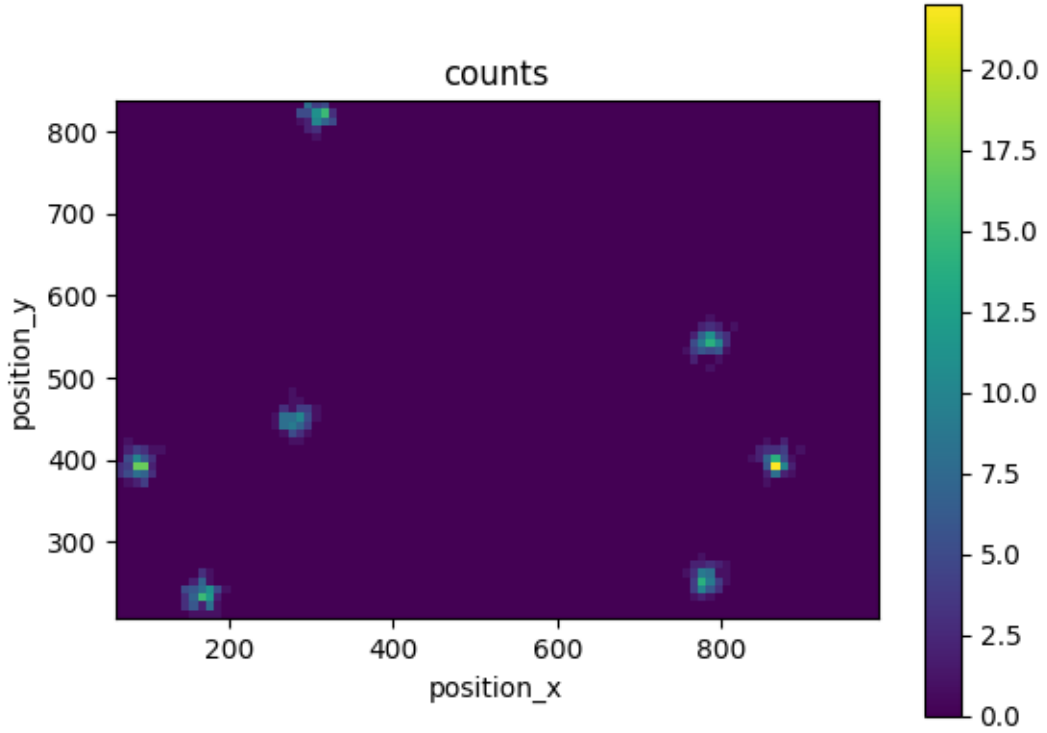
The `render_2d` method can directly provide a new figure as output.

```
lc.render_2d(locdata, bin_size=10);
```



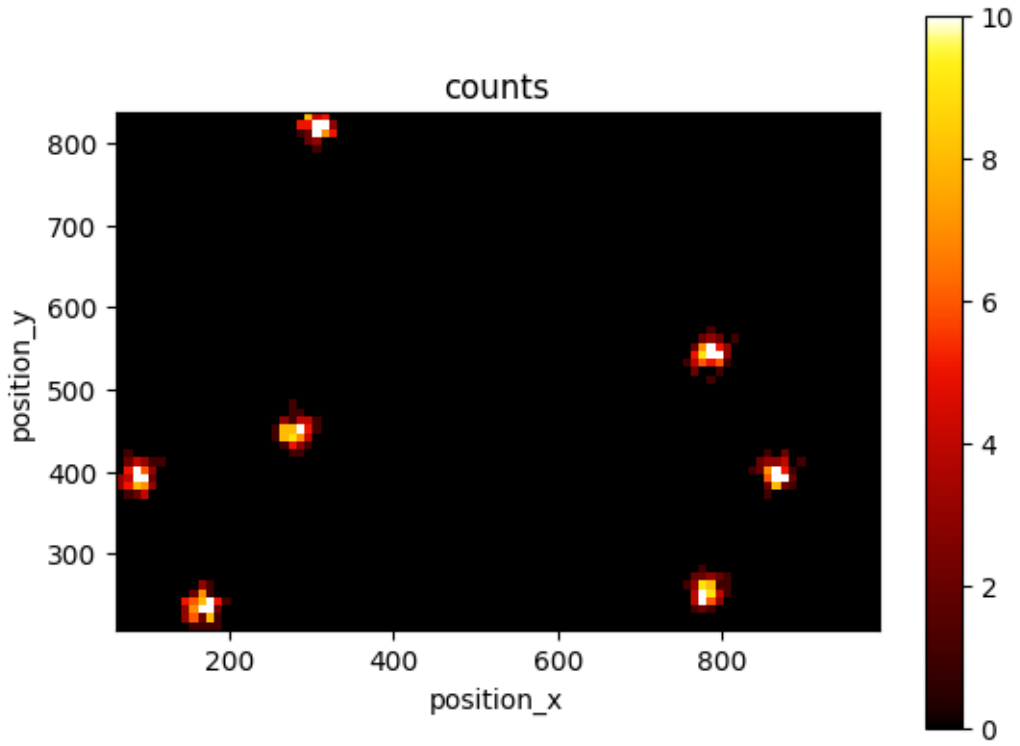
Or it can be used within the matplotlib environment.

```
fig, ax = plt.subplots(nrows=1, ncols=1)
lc.render_2d(locdata, ax = ax, bin_size=10, cmap='viridis')
plt.show()
```



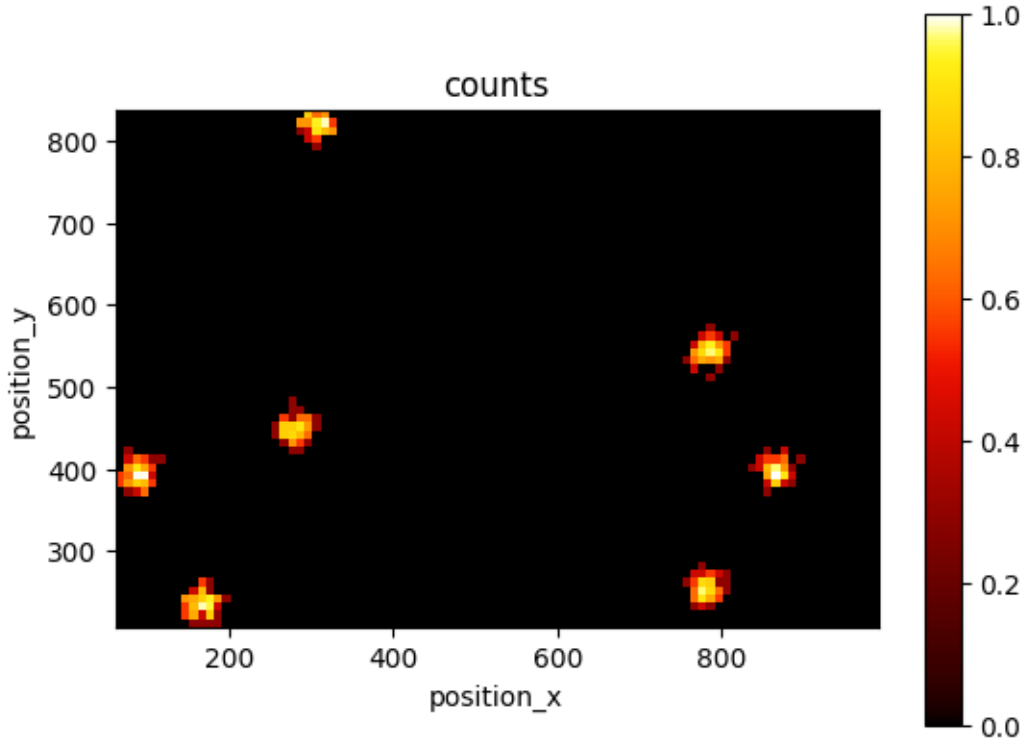
Intensity is per default scaled to the min and max intensity values but can be rescaled by applying any norm function as described for matplotlib.imshow:

```
norm = plt.Normalize(vmax=10)
lc.render_2d(locdata, bin_size=10, norm=norm);
```



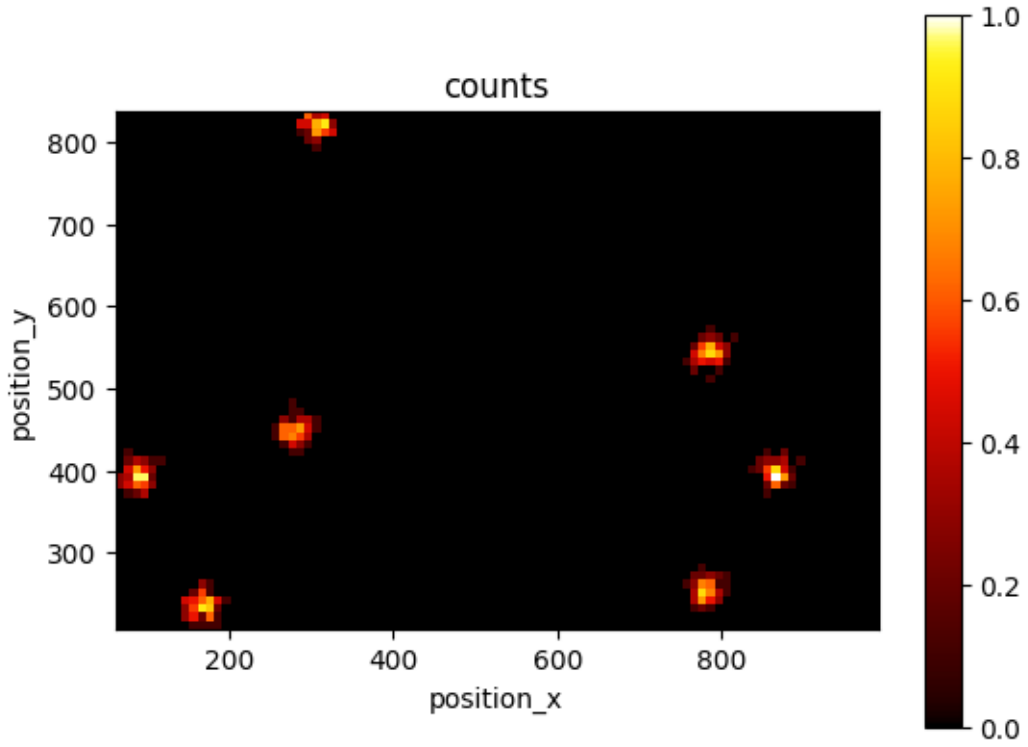
Intensity can also be rescaled by normalization functions as defined in locan.Trafo. Histogram equlization yields this image:

```
lc.render_2d(locdata, bin_size=10, rescale=lc.Trafo.EQUALIZE);
```



Histogram equlization with a power-intensification of p=0.3 yields this image:

```
lc.render_2d(locdata, bin_size=10, rescale=lc.Trafo.EQUALIZE_0P3);
```



Any callable normalization object can be passed into the rescale kwarg:

```
norm = lc.HistogramEqualization(power=0.3)
```

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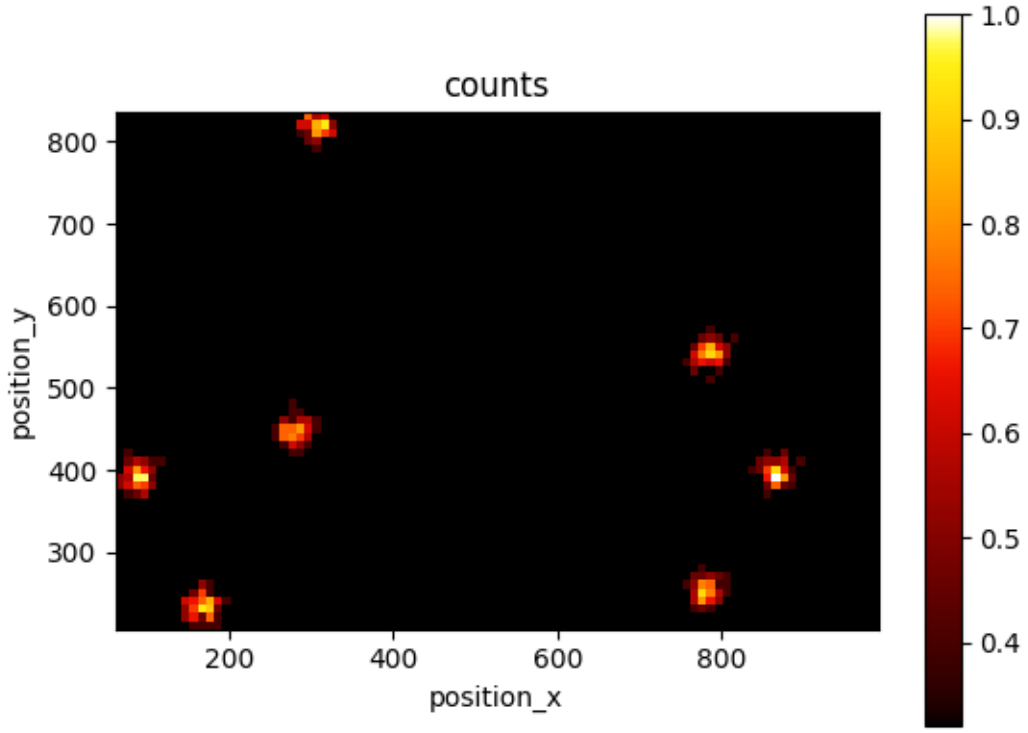
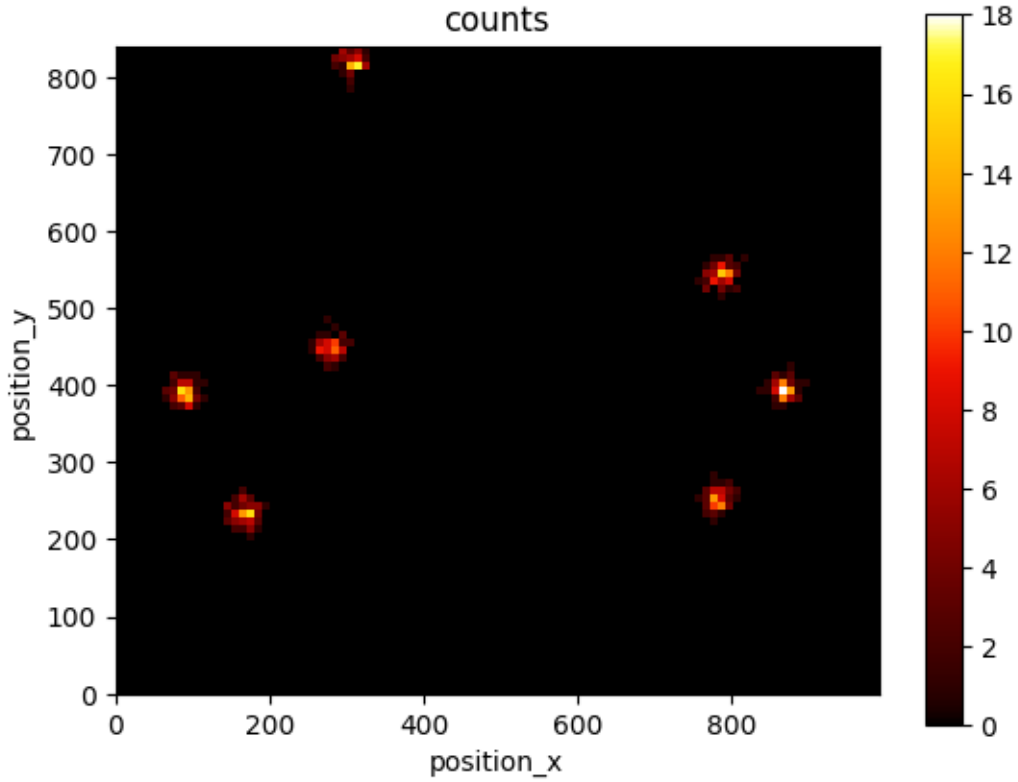
```
lc.render_2d(locdata, bin_size=10, rescale=norm);
```

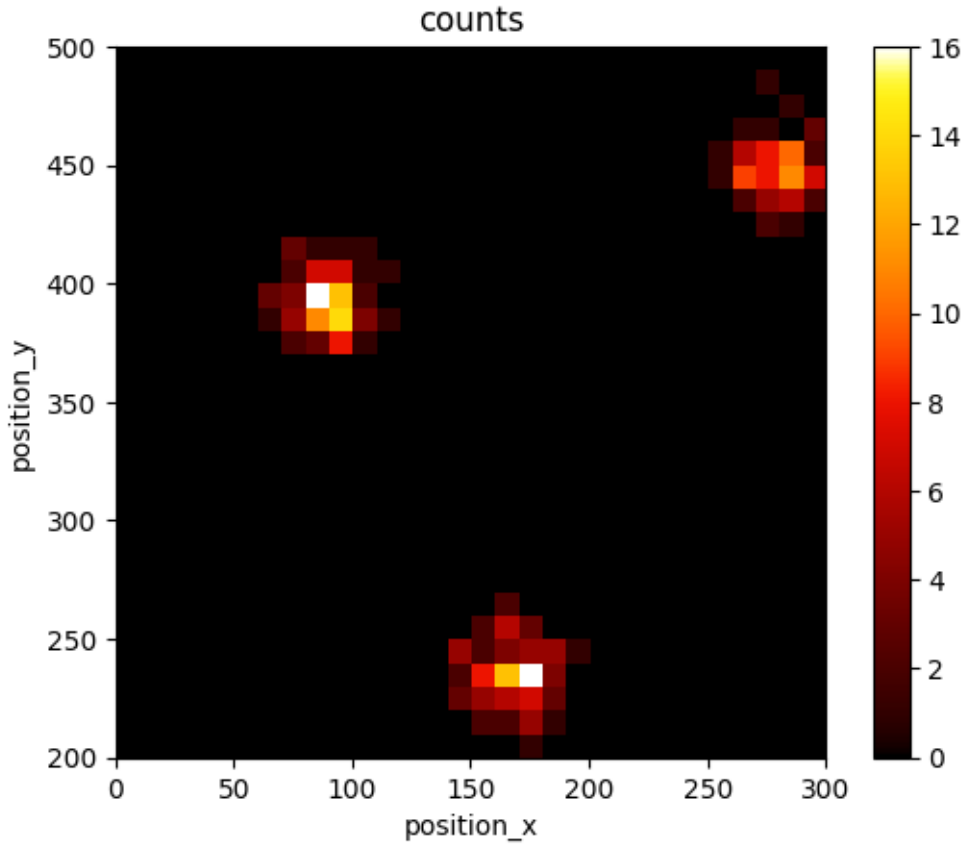


The image size is set automatically to the min and max coordinates but can be set to (0, max) or an arbitrary range.

```
lc.render_2d(locdata, bin_size=10, bin_range='zero');
```




```
lc.render_2d(locdata, bin_size=10, bin_range=((0, 300),(200, 500)));
```



2.8.3 Use different libraries for rendering

Rendering can also be carried out with a different render engine. Choose one of the following (MPL is the standard matplotlib):

```
list(lc.RenderEngine)
```

```
[<RenderEngine.MPL: 0>,
 <RenderEngine.MPL_SCATTER_DENSITY: 1>,
 <RenderEngine.NAPARI: 2>]
```

napari

As external viewer you can use **napari**.

For napari the qt gui interface has to be activated. Make sure to run the following command manually in a single cell and give enough time for this procedure to complete in the background.

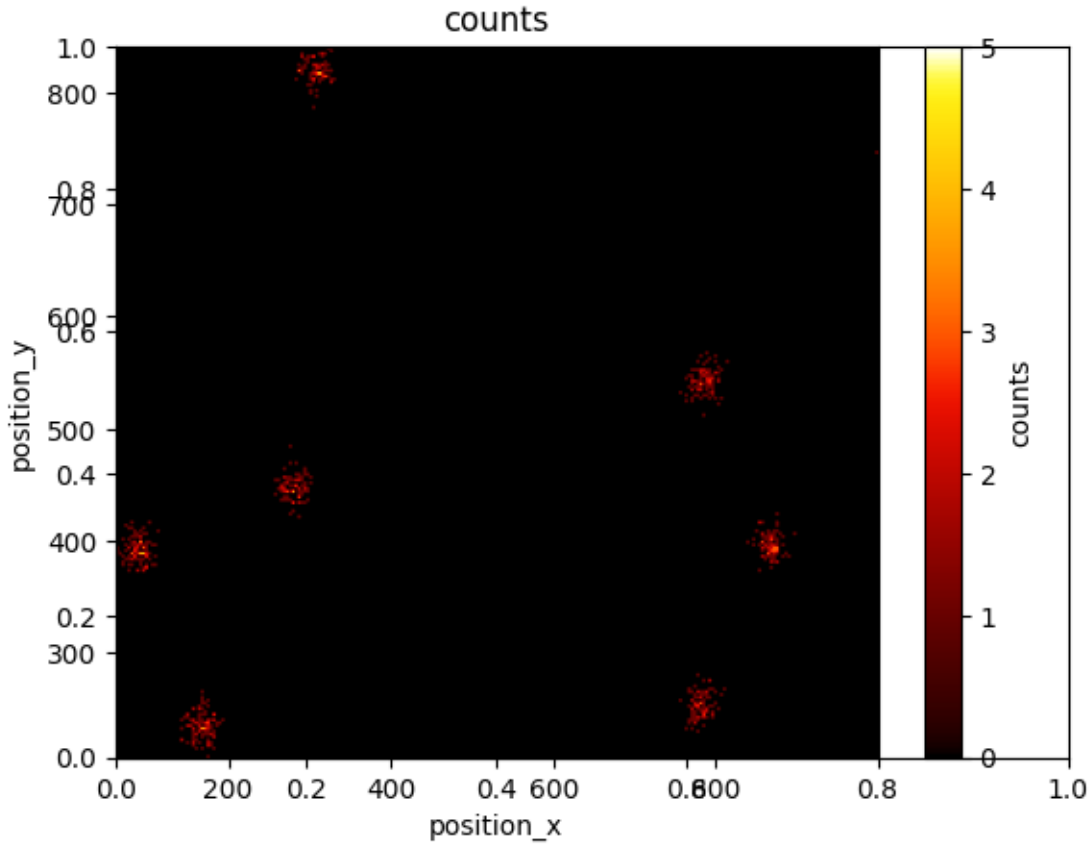
or alternatively:

mpl-scatter-density

For interactive viewing with variable binning, **mpl-scatter-density** is helpful. To run this the notebook has to be run with a new kernel applying the magic command `%matplotlib widget` before matplotib is imported.

```
lc.render_2d(locdata, render_engine=lc.RenderEngine.MPL_SCATTER_DENSITY);
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/mpl_scatter_density/generic_density_artist.py:77:␣
↪RuntimeWarning: All-NaN slice encountered
  vmin = self._density_vmin(array)
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/mpl_scatter_density/generic_density_artist.py:82:␣
↪RuntimeWarning: All-NaN slice encountered
  vmax = self._density_vmax(array)
```



2.8.4 Choose colormaps

Colormaps can be chosen in matplotlib, napari and other visualization tools.

Colormaps are identified through specific class instances or by a name.

locan.Colormap serves as adapter class for the various visualization tools.

A Colormap instance can be created with the `get_colormap` function:

```
colormap = lc.get_colormap("viridis")
colormap.name
```

```
'viridis'
```

```
colormap.matplotlib
```

A mapping of names on Colormap instances is provided and can be extended by users. If a colormap name is provided to any rendering function, first the colormap_registry is searched, then the maplotlib registry and finally napari colormap names.

```
lc.colormap_registry
```

```
{'viridis': <locan.visualize.colormap.Colormap at 0x7f7756e0af20>,
 'viridis_r': <locan.visualize.colormap.Colormap at 0x7f7756e0afb0>,
 'gray': <locan.visualize.colormap.Colormap at 0x7f7756e0b040>,
 'gray_r': <locan.visualize.colormap.Colormap at 0x7f7756e0b0d0>,
 'turbo': <locan.visualize.colormap.Colormap at 0x7f7756e0b550>,
 'coolwarm': <locan.visualize.colormap.Colormap at 0x7f7756e0b1f0>,
 'tab20': <locan.visualize.colormap.Colormap at 0x7f7756e0b280>,
 'cet_fire': <locan.visualize.colormap.Colormap at 0x7f7756e0b310>,
 'cet_fire_r': <locan.visualize.colormap.Colormap at 0x7f7756e0b3a0>,
 'cet_gray': <locan.visualize.colormap.Colormap at 0x7f7756e0b430>,
 'cet_gray_r': <locan.visualize.colormap.Colormap at 0x7f7756e0b4c0>,
 'cet_coolwarm': <locan.visualize.colormap.Colormap at 0x7f7756e0b5e0>,
 'cet_glasbey_dark': <locan.visualize.colormap.Colormap at 0x7f7756e0b670>}
```

Default colormaps are defined for use with locan and can be accessed through a mapping or an enum:

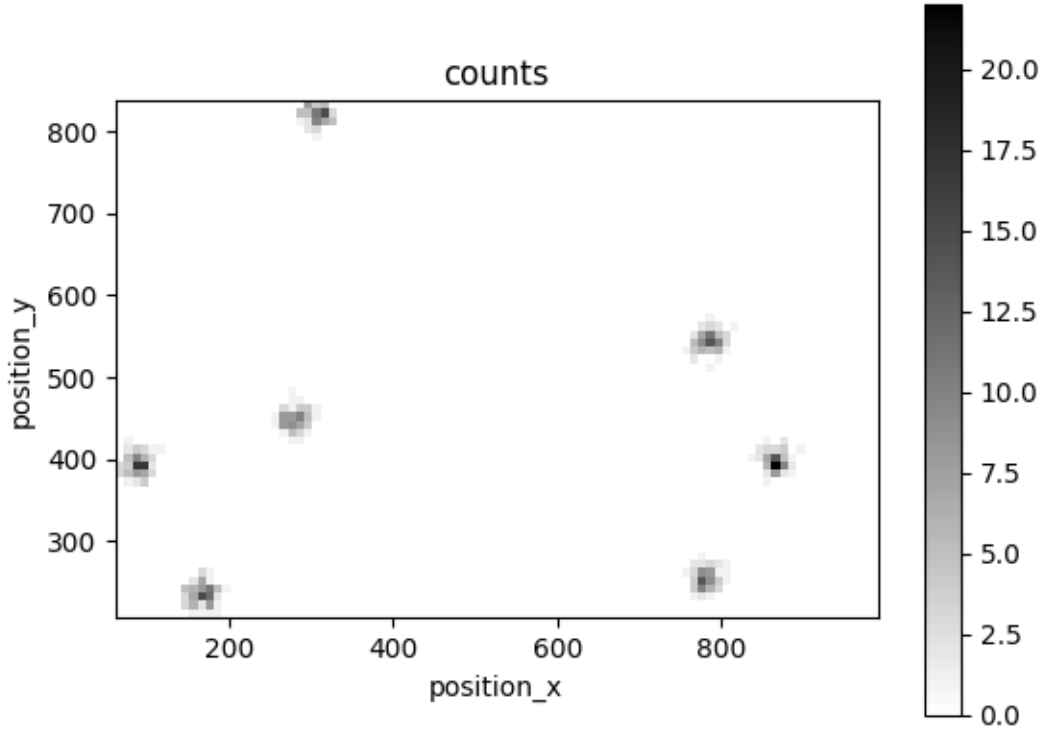
```
lc.COLORMAP_DEFAULTS
```

```
{'CONTINUOUS': 'cet_fire',
 'CONTINUOUS_REVERSE': 'cet_fire_r',
 'CONTINUOUS_GRAY': 'cet_gray',
 'CONTINUOUS_GRAY_REVERSE': 'cet_gray_r',
 'DIVERGING': 'cet_coolwarm',
 'CATEGORICAL': 'cet_glasbey_dark',
 'TURBO': 'turbo'}
```

```
list(lc.Colormaps)
```

```
[<Colormaps.CONTINUOUS: 'cet_fire'>,
 <Colormaps.CONTINUOUS_REVERSE: 'cet_fire_r'>,
 <Colormaps.CONTINUOUS_GRAY: 'cet_gray'>,
 <Colormaps.CONTINUOUS_GRAY_REVERSE: 'cet_gray_r'>,
 <Colormaps.DIVERGING: 'cet_coolwarm'>,
 <Colormaps.CATEGORICAL: 'cet_glasbey_dark'>,
 <Colormaps.TURBO: 'turbo'>]
```

```
lc.render_2d(locdata, bin_size=10, cmap=lc.Colormaps.CONTINUOUS_GRAY_REVERSE);
```



2.9 Tutorial about simulating localization data

Locan provides methods for simulating basic localization data sets as LocData objects.

```
from pathlib import Path
import numpy as np
import pandas as pd

%matplotlib inline

import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

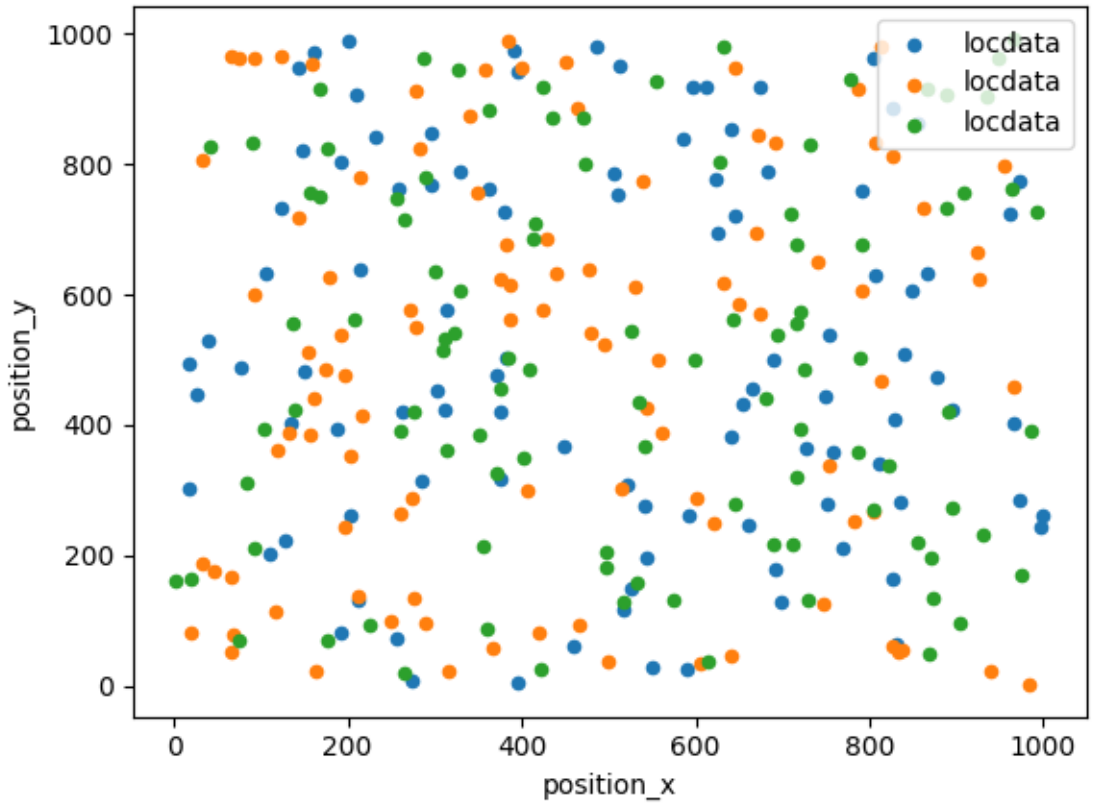
2.9.1 Use random number generator

In all simulations we make use of numpy routines for random number generation by instantiating `numpy.random.default_rng` and taking a seed parameter. Therefore, we recommend to set up a random number generator in every script and pass that generator instance to all simulation functions through the seed parameter.

```
rng = np.random.default_rng(seed=1)
locdatas = [lc.simulate_uniform(n_samples=100, region=((0, 1000), (0, 1000)),␣
↪seed=rng) for i in range(3)]
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
for i, locdata in enumerate(locdatas):
    locdata.data.plot.scatter(x='position_x', y='position_y', color=plt.cm.
↪tab10(i), ax=ax, label='locdata')
plt.show()
```



Make sure to follow the correct procedure for parallel computation as described in the numpy tutorials (https://numpy.org/doc/stable/reference/random/parallel.html).

2.9.2 Simulate localization data

Point coordinates are distributed on region as specified by `Region` instances or interval tuples.

Simulate localization data that follows a uniform distribution

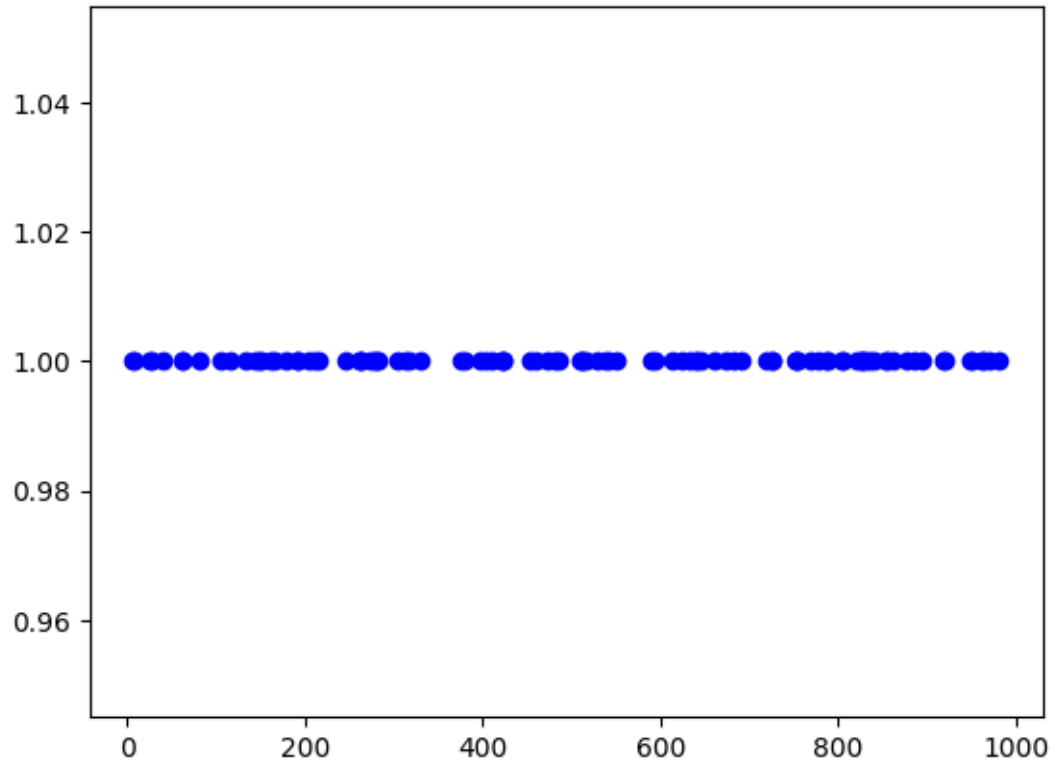
in 1d

```
locdata = lc.simulate_uniform(n_samples=100, region=lc.data.region.Interval(0,
↪ 1000), seed=1)

locdata.print_summary()
```

```
identifier: "4"
comment: ""
source: SIMULATION
state: RAW
element_count: 100
frame_count: 0
creation_time {
  2024-03-14T11:52:45.950746Z
}
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
ax.plot(locdata.data.position_x, [1] * len(locdata), 'o', color='Blue', label=
↪'locdata')
plt.show()
```



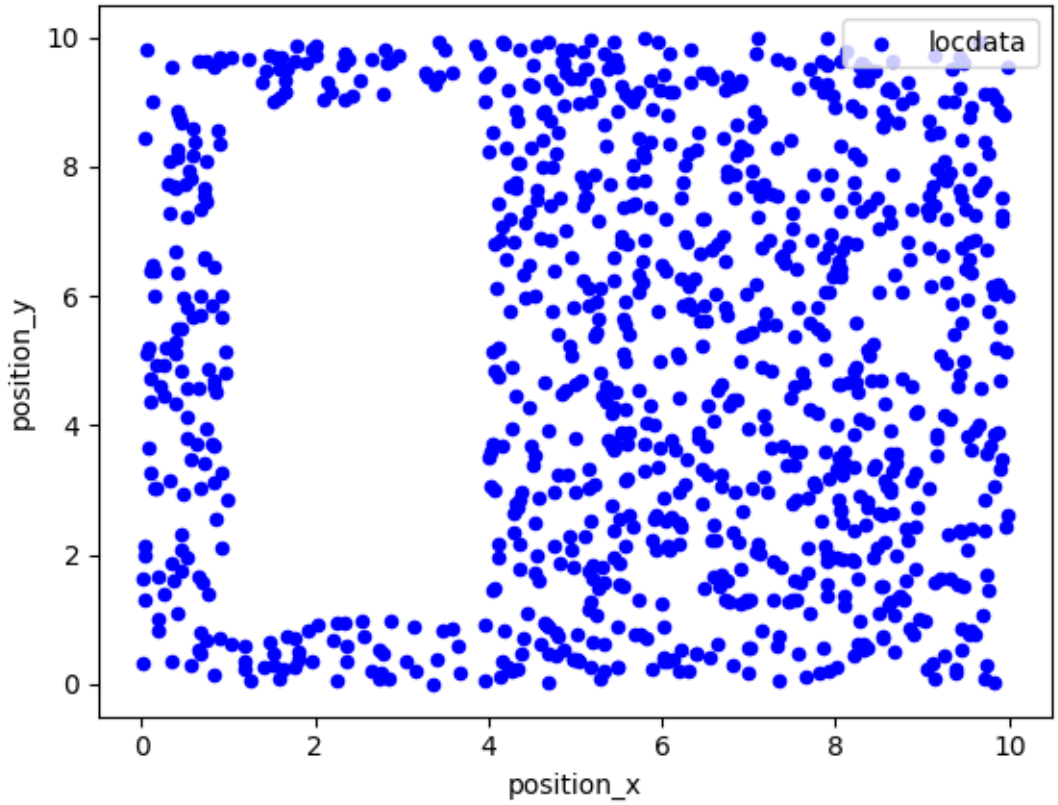
in 2d

```
points = ((0, 0), (0, 10), (10, 10), (10, 0))
holes = [((1, 1), (1, 9), (4, 9), (4, 1))]
region = lc.data.region.Polygon(points, holes)
locdata = lc.simulate_uniform(n_samples=1000, region=region, seed=1)

locdata.print_summary()
```

```
identifier: "5"
comment: ""
source: SIMULATION
state: RAW
element_count: 1000
frame_count: 0
creation_time {
  2024-03-14T11:52:46.217652Z
}
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



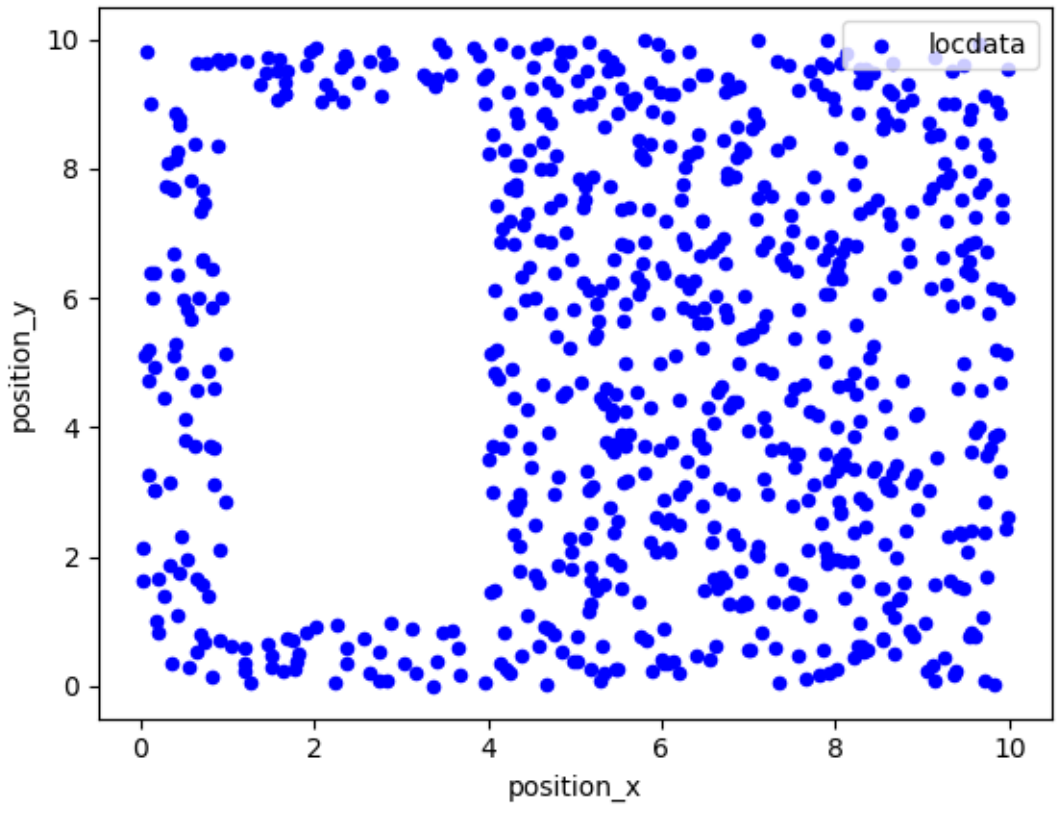
Simulate localization data that follows a homogeneous (Poisson) distribution in 2d

```
points = ((0, 0), (0, 10), (10, 10), (10, 0))
holes = [((1, 1), (1, 9), (4, 9), (4, 1))]
region = lc.data.region.Polygon(points, holes)
locdata = lc.simulate_Poisson(intensity=10, region=region, seed=1)

locdata.print_summary()
```

```
identifier: "6"
comment: ""
source: SIMULATION
state: RAW
element_count: 761
frame_count: 0
creation_time {
  2024-03-14T11:52:46.573574Z
}
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='locdata')
plt.show()
```



in 3d

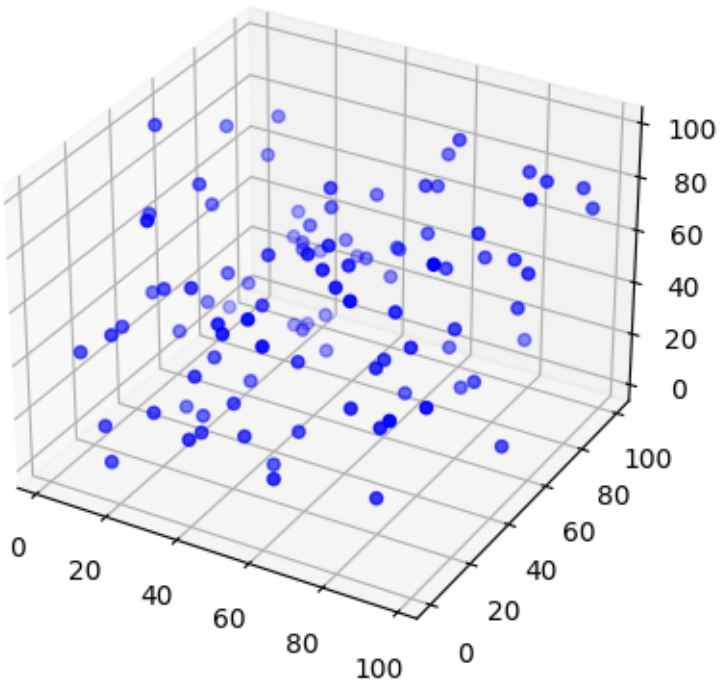
```
locdata = lc.simulate_Poisson(intensity=1e-4, region=((0, 100), (0, 100), (0,␣
↪100)), seed=1)

locdata.print_summary()
```

```
identifier: "7"
comment: ""
source: SIMULATION
state: RAW
element_count: 100
frame_count: 0
creation_time {
  2024-03-14T11:52:46.876029Z
}
```

```
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

x,y,z = locdata.coordinates.T
ax.scatter(x, y, z, color='Blue', label='locdata')
plt.show()
```



Neyman-Scott distribution

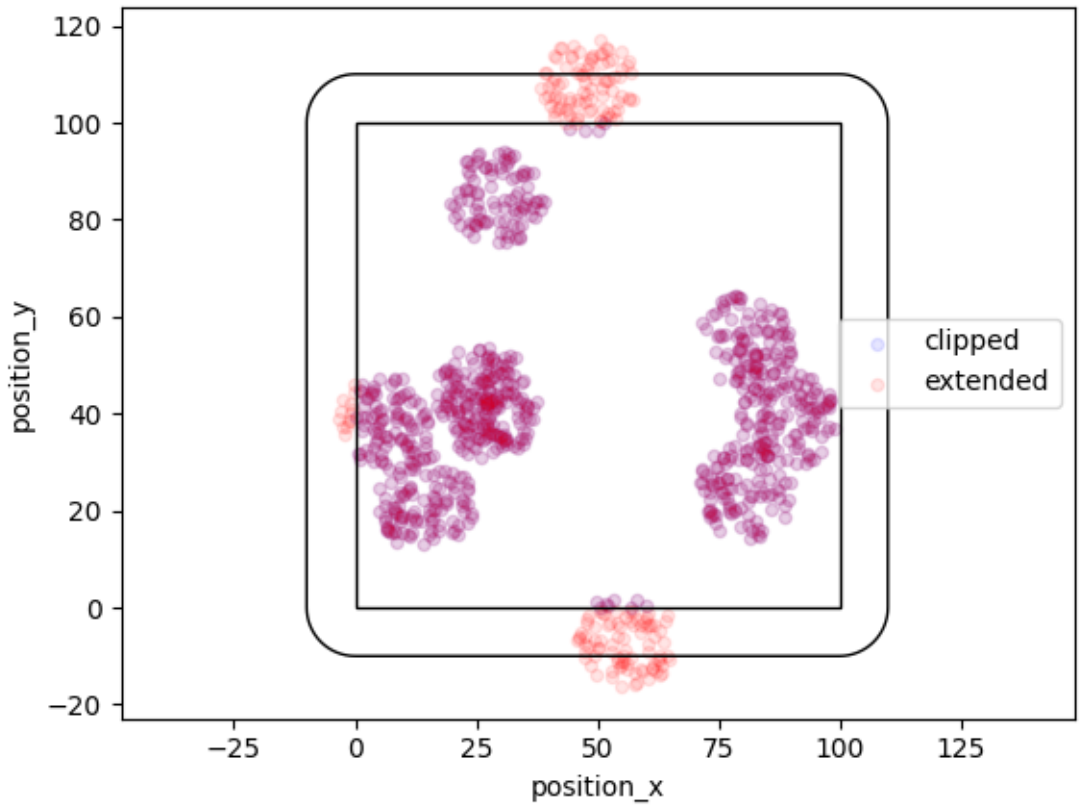
In a Neyman-Scott distribution parent events are homogeneously distributed with a certain region and each parent event brings about a number of offspring events distributed around the parent event. For a typical Neyman-Scott process, both the number of parent events and the number of offspring events for each cluster are Poisson distributed. It is important to note that parent events can be outside the support region. For correct simulation, the support region is expanded to distribute parent events and then clipped after offspring substitution.

Matern distribution

In a Matern process offspring localizations are distributed homogeneously in circles of a given radius around the parent event.

```
locdata = lc.simulate_Matern(parent_intensity=1e-3, region=((0, 100), (0,␣
↪100)), cluster_mu=100, radius=10, clip=True, seed=1)
locdata_expanded = lc.simulate_Matern(parent_intensity=1e-3, region=((0, 100),
↪ (0, 100)), cluster_mu=100, radius=10, clip=False, seed=1)
```

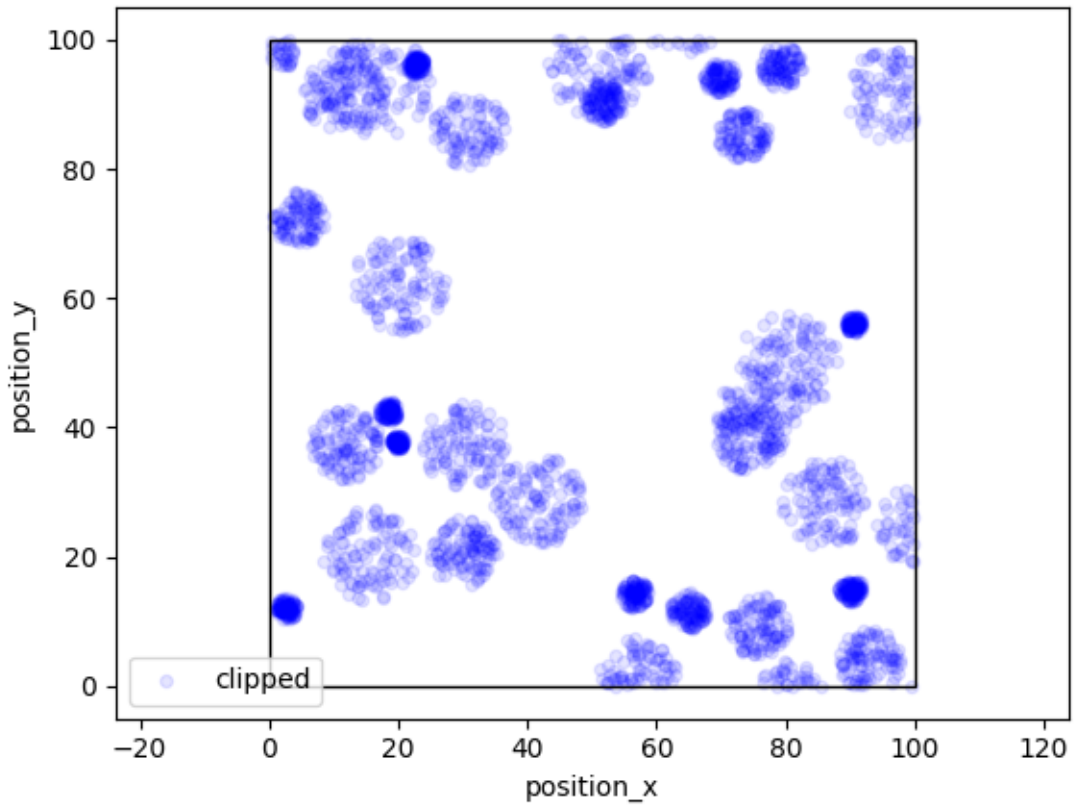
```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='clipped', alpha=0.1)
locdata_expanded.data.plot.scatter(x='position_x', y='position_y', ax=ax,␣
↪color='Red', label='extended', alpha=0.1)
ax.add_patch(locdata.region.as_artist(fill=False))
ax.add_patch(locdata_expanded.region.as_artist(fill=False))
ax.axis('equal')
plt.show()
```



More variability can be achieved by specifying arrays for radius.

```
locdata = lc.simulate_Matern(parent_intensity=3e-3, region=((0, 100), (0,␣
↪100)), cluster_mu=100, radius=np.linspace(1, 30, 300), clip=True, seed=1)
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='clipped', alpha=0.1)
ax.add_patch(locdata.region.as_artist(fill=False))
ax.axis('equal')
plt.show()
```

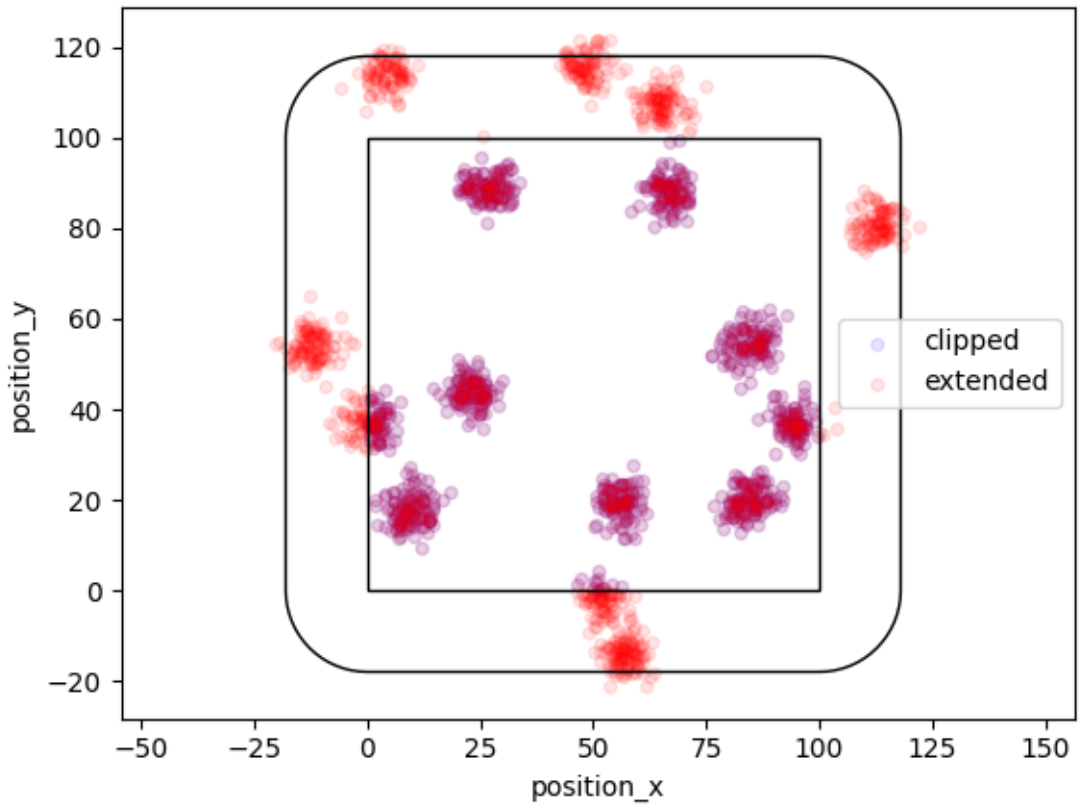


Thomas distribution

In a Thomas process offspring localizations follow a normal distribution with center being the parent event and a given standard deviation. Here the region is expanded by a distance that equals cluster_std * expansion_factor.

```
locdata = lc.simulate_Thomas(parent_intensity=1e-3, region=((0, 100), (0,␣
↪100)), cluster_mu=100, cluster_std=3, clip=True, seed=1)
locdata_expanded = lc.simulate_Thomas(parent_intensity=1e-3, region=((0, 100),
↪ (0, 100)), cluster_mu=100, cluster_std=3, clip=False, seed=1)
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='clipped', alpha=0.1)
locdata_expanded.data.plot.scatter(x='position_x', y='position_y', ax=ax,␣
↪color='Red', label='extended', alpha=0.1)
ax.add_patch(locdata.region.as_artist(fill=False))
ax.add_patch(locdata_expanded.region.as_artist(fill=False))
ax.axis('equal')
plt.show()
```



More variability can be achieved by specifying arrays of cluster_mu or cluster_std.

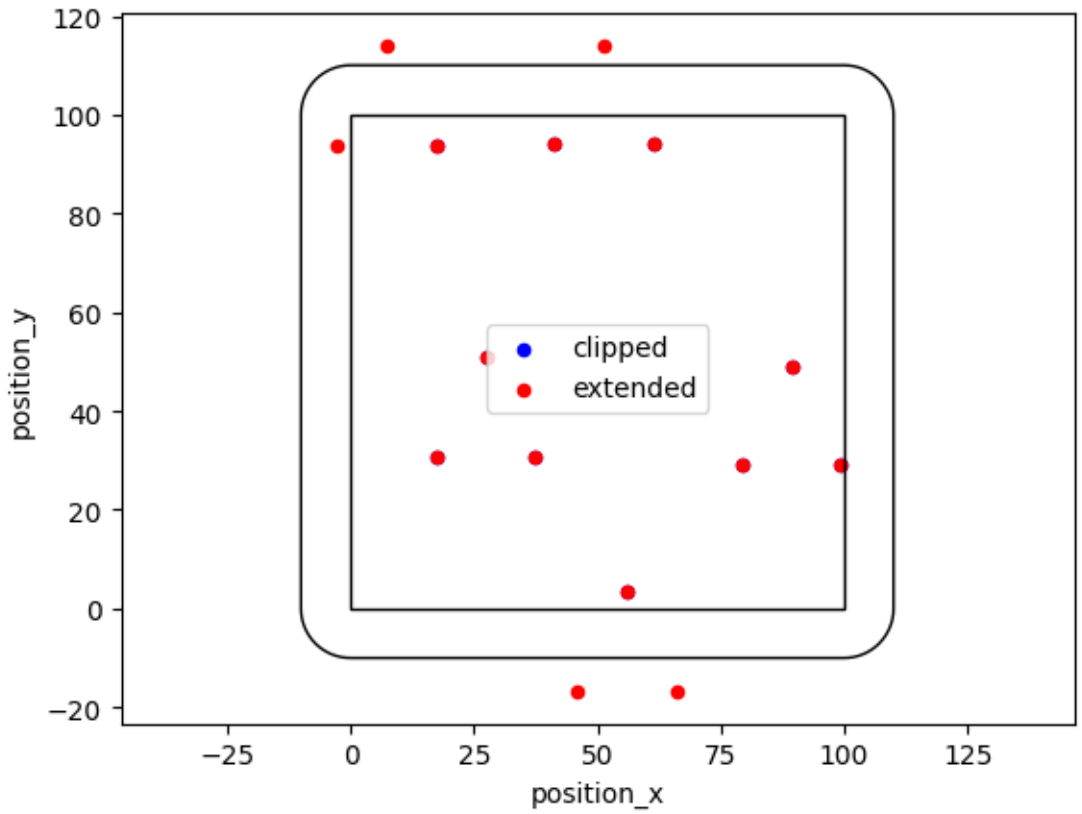
Cluster distribution

If you need a fixed number of samples, use simulate_cluster and specify arbitrary offspring distributions.

```
offspring_points = [(-10, -10), (0, 10), (10, -10))] * 5

locdata = lc.simulate_cluster(centers=5, region=((0, 100), (0, 100)),␣
↪expansion_distance=10, offspring=offspring_points, clip=True, seed=1)
locdata_expanded = lc.simulate_cluster(centers=5, region=((0, 100), (0, 100)),
↪ expansion_distance=10, offspring=offspring_points, clip=False, seed=1)
```

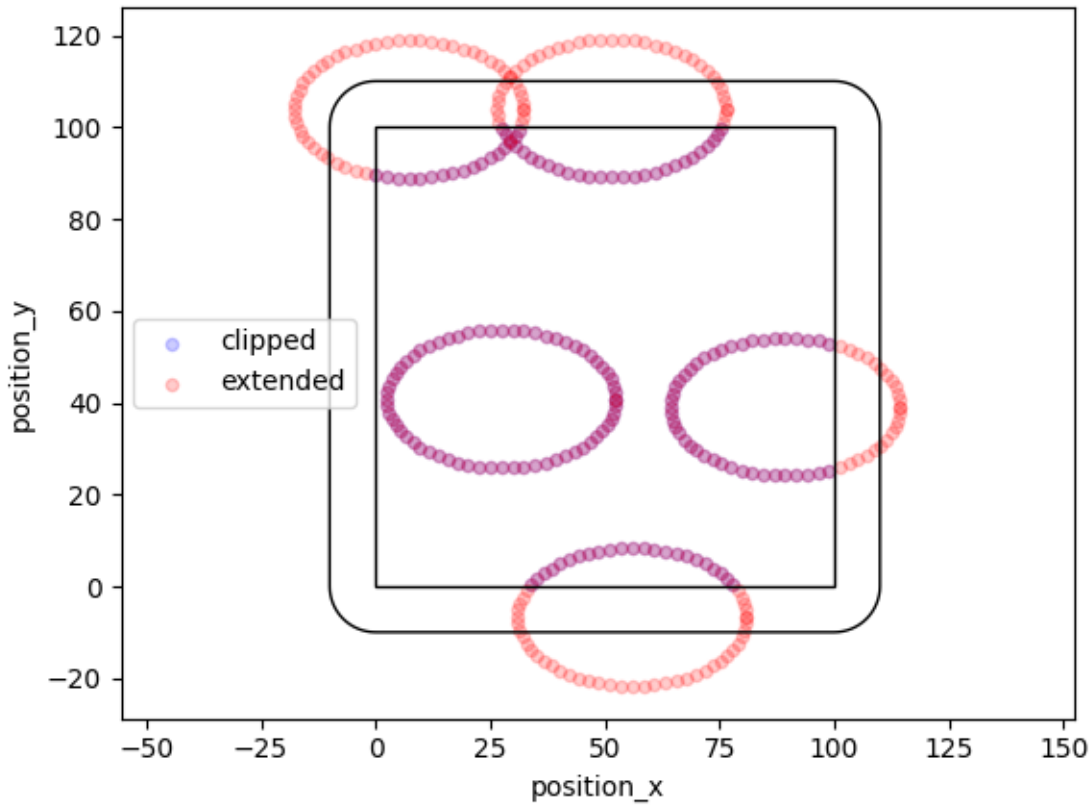
```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='clipped')
locdata_expanded.data.plot.scatter(x='position_x', y='position_y', ax=ax,␣
↪color='Red', label='extended')
ax.add_patch(locdata.region.as_artist(fill=False))
ax.add_patch(locdata_expanded.region.as_artist(fill=False))
ax.axis('equal')
plt.show()
```




```
def offspring_points(parent):
    angles = np.linspace(0, 360, 36)
    for angle in angles:
        circle = lc.data.region.Ellipse(parent, 50, 30, angle)
    return circle.points

locdata = lc.simulate_cluster(centers=5, region=((0, 100), (0, 100)),␣
↪expansion_distance=10, offspring=offspring_points, clip=True, seed=1)
locdata_expanded = lc.simulate_cluster(centers=5, region=((0, 100), (0, 100)),
↪ expansion_distance=10, offspring=offspring_points, clip=False, seed=1)
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='clipped', alpha=0.2)
locdata_expanded.data.plot.scatter(x='position_x', y='position_y', ax=ax,␣
↪color='Red', label='extended', alpha=0.2)
ax.add_patch(locdata.region.as_artist(fill=False))
ax.add_patch(locdata_expanded.region.as_artist(fill=False))
ax.axis('equal')
plt.show()
```



2.9.3 Resample data

The resample function provides additional localizations for each given localizations that are Gauss distributed around the original localizations with a standard deviation given by the `uncertainty_x` property.

```
nrg = np.random.default_rng(seed=1)
n_samples = 10
dat = lc.simulate_uniform(n_samples=n_samples, region=((0, 1000), (0, 1000)),␣
↪seed=rng)
dat.dataframe = dat.dataframe.assign(uncertainty_x= 20*rng.random(n_samples))
dat.dataframe = dat.dataframe.assign(uncertainty_y= 20*rng.random(n_samples))
```

```
dat_resampled = lc.resample(dat, n_samples=1000, seed=rng)
dat_resampled.data.tail()
```

	original_index	position_x	position_y	uncertainty_x	uncertainty_y
9995	9	85.522771	535.121307	16.728111	10.264751
9996	9	117.665446	532.110220	16.728111	10.264751
9997	9	78.991916	518.541451	16.728111	10.264751
9998	9	103.053219	543.823520	16.728111	10.264751
9999	9	96.072240	510.063092	16.728111	10.264751

```
fig, ax = plt.subplots(nrows=1, ncols=1)
dat_resampled.data.plot.scatter(x='position_x', y='position_y', ax=ax, color=
↪'Red', label='locdata resampled', alpha=0.01)
```

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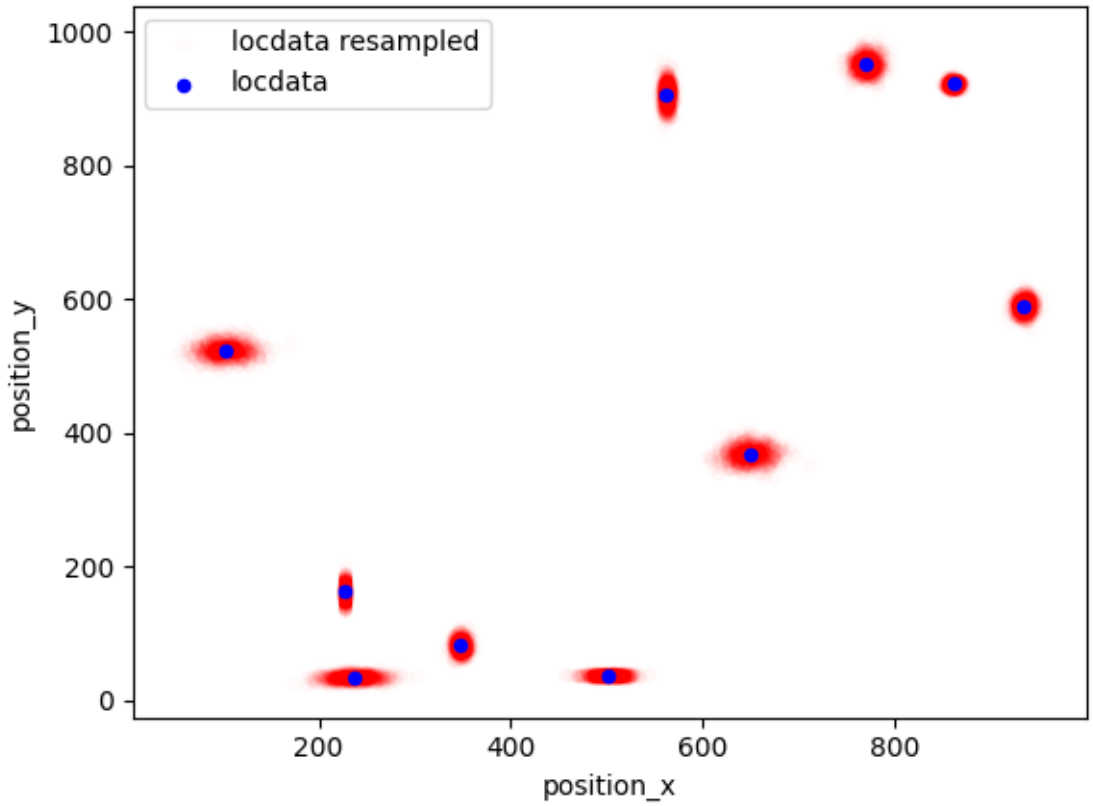
```
dat.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',␣
↪label='locdata')
plt.show()
```



2.10 Tutorial about tracking LocData objects

Tracking refers to link localizations that are close in space over multiple frames and collect those localizations in individual tracks. We here make use of the trackpy package through wrapper functions to deal with LocData objects.

```
%matplotlib inline

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

```

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```
Python:
   version: 3.10.13
```

2.10.1 Synthetic data

A random dataset is created.

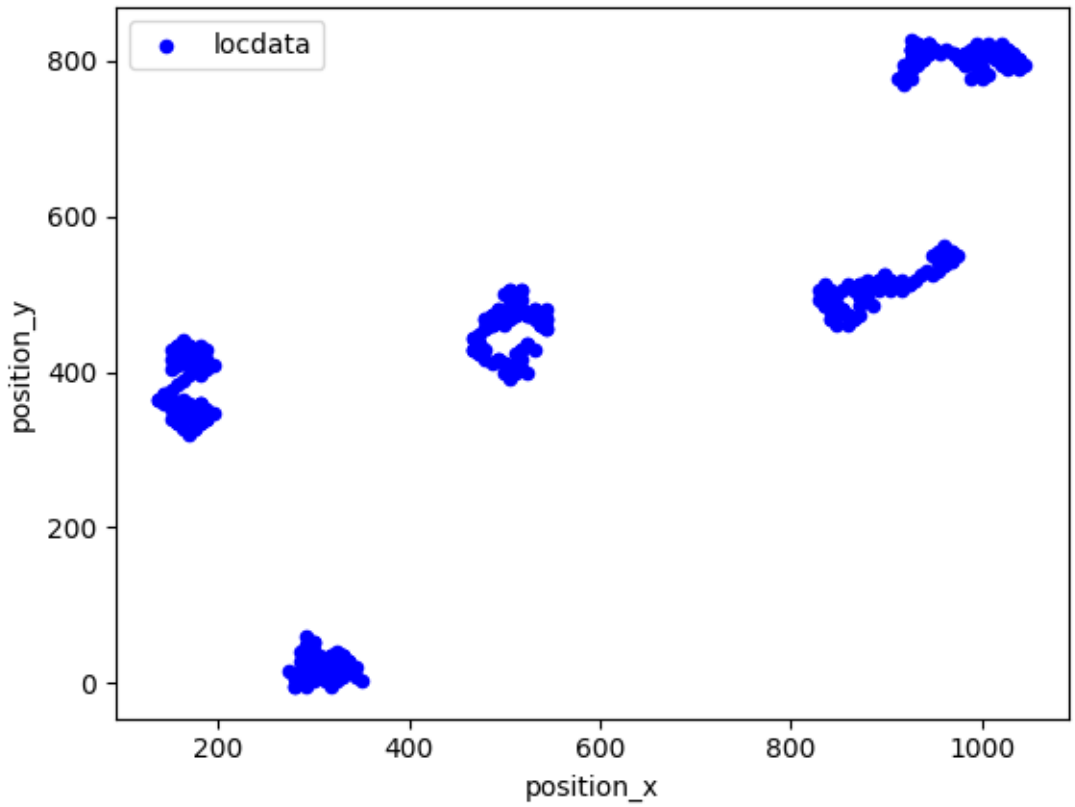
```
dat = lc.simulate_tracks(n_walks=5, n_steps=100, ranges=((0,1000),(0,1000)),
                         diffusion_constant=1, seed=1)

dat.print_meta()
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
identifier: "1"
source: SIMULATION
state: RAW
history {
  name: "simulate_tracks"
  parameter: "{\'n_steps\': 100, \'ranges\': ((0, 1000), (0, 1000)), \
↪'diffusion_constant\': 1, \'time_step\': 10, \'seed\': 1, \'n_walks\': 5}"
}
element_count: 500
frame_count: 100
creation_time {
  2024-03-14T11:52:53.614909Z
}
```

```
dat.data.head()
```

```
   position_x  position_y  frame
0  518.146180  429.651004      0
1  524.470735  435.975560      1
2  530.795291  429.651004      2
3  524.470735  435.975560      3
4  518.146180  429.651004      4
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
dat.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',␣
↪label='locdata')
plt.show()
```



2.10.2 Track locdata

The track function collects tracks in a new locdata object.

```
tracks, track_numbers = lc.track(dat, search_range=500)
```

```
Frame 99: 5 trajectories present.
```

```
tracks.print_summary()
```

```
identifier: "7"
comment: ""
source: DESIGN
state: RAW
element_count: 5
frame_count: 1
creation_time {
  2024-03-14T11:52:54.285716Z
}
```

```
tracks.data
```

```
   localization_count  position_x  uncertainty_x  position_y  uncertainty_y  \
0                 100  882.368107       4.321878  504.562854       2.382224
1                 100  169.710816       1.293090  381.371093       3.679042
```

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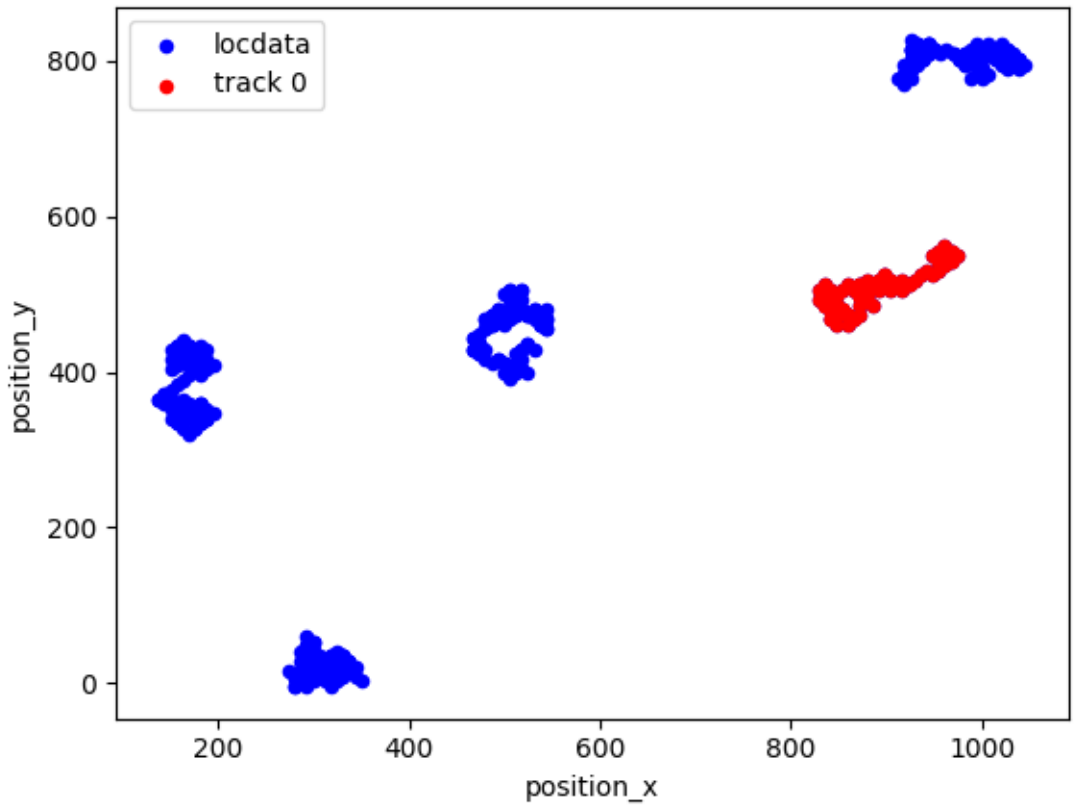
```
2                 100  505.497069       2.098581  456.720101       3.047211
3                 100  307.151281       1.787996   19.463682       1.378273
4                 100  972.599640       3.900272  805.187177       1.217117

   frame  region_measure_bb  localization_density_bb  subregion_measure_bb
0      0            14720.0                 0.006793            493.315315
1      0             6840.0                 0.014620            354.175098
2      0             8640.0                 0.011574            379.473319
3      0             4800.0                 0.020833            278.280434
4      0             7560.0                 0.013228            379.473319
```

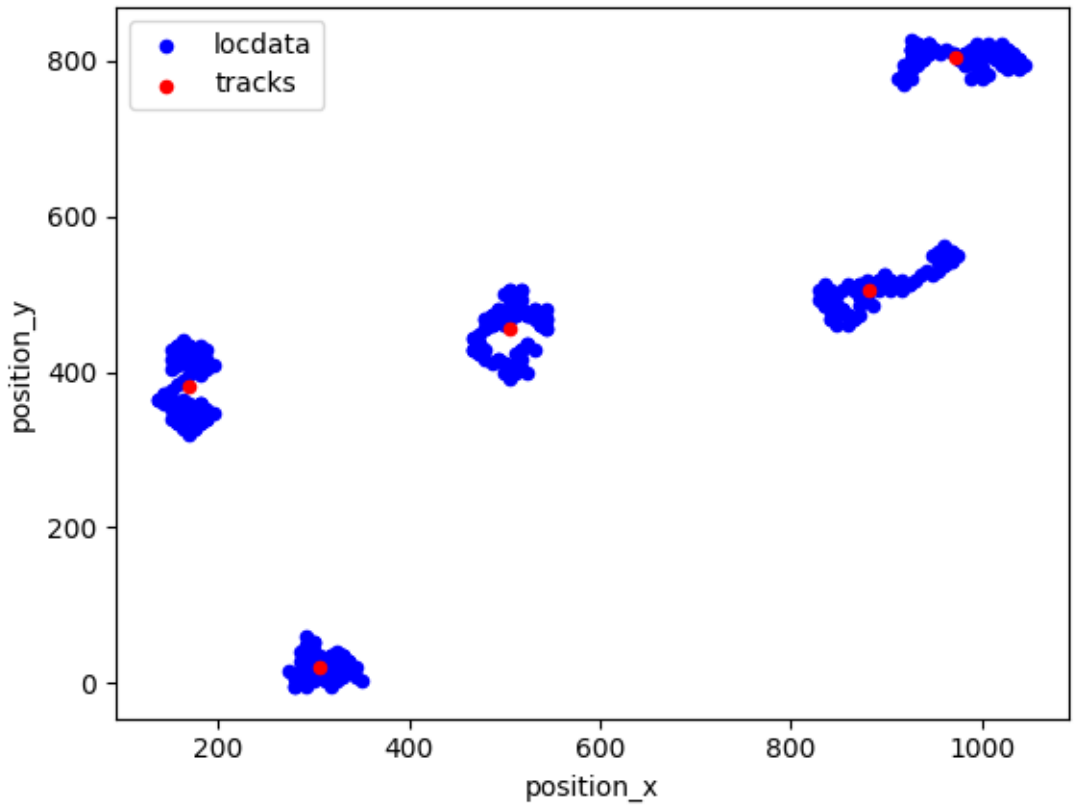
```
tracks.references[0].data.head()
```

```
     position_x  position_y  frame
300  954.974002  543.269132      0
301  961.298558  549.593688      1
302  967.623113  555.918243      2
303  961.298558  549.593688      3
304  967.623113  543.269132      4
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
dat.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',␣
↪label='locdata')
tracks.references[0].data.plot.scatter(x='position_x', y='position_y', ax=ax,␣
↪color='Red', label='track 0')
plt.show()
```




```
fig, ax = plt.subplots(nrows=1, ncols=1)
dat.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',␣
↪label='locdata')
tracks.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Red',␣
↪label='tracks')
plt.show()
```



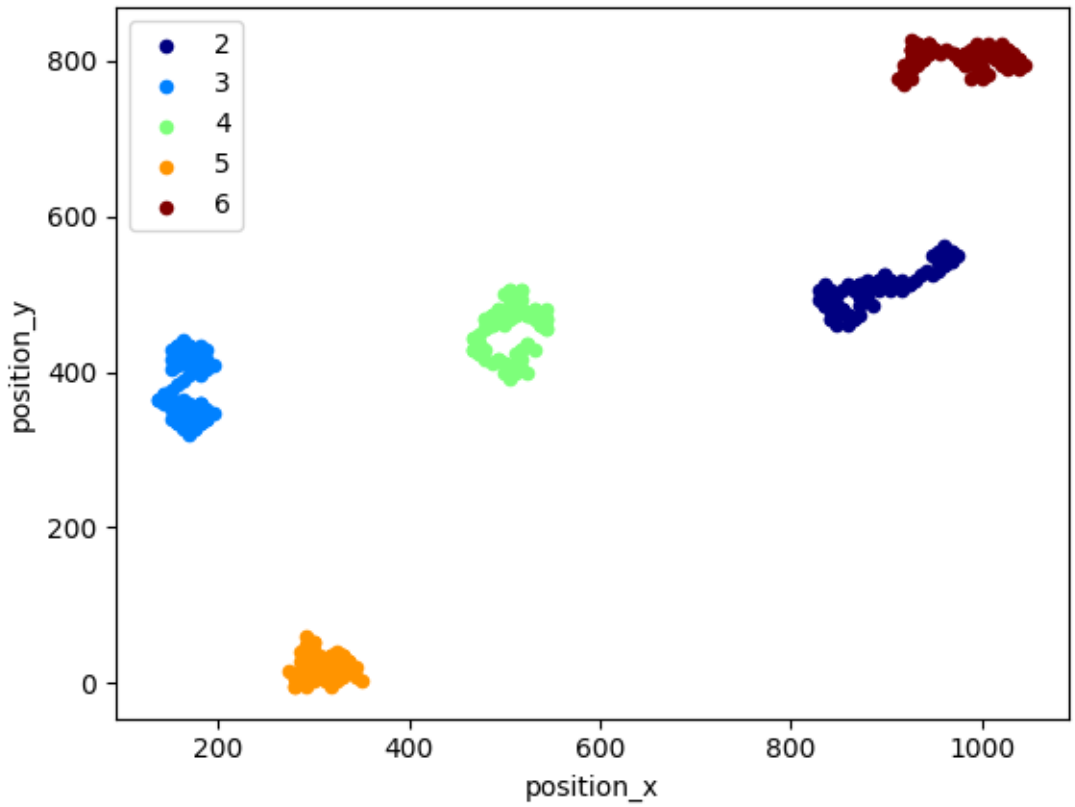
To show individual tracks make use of the reference attribute.

```
fig, ax = plt.subplots(nrows=1, ncols=1)

jet= plt.get_cmap('jet')
colors = iter(jet(np.linspace(0, 1, len(tracks))))

for ref in tracks.references:
    c=next(colors)
    ref.data.plot.scatter(x='position_x', y='position_y', ax=ax, color=(c,),␣
↪label=ref.meta.identifier)

plt.show()
```



Alternatively to a new locdata object, a pandas DataFrame can be generated using the link_locdata method.

```
links = lc.link_locdata(dat, search_range=10)
```

```
Frame 99: 5 trajectories present.
```

```
links.head()
```

```
300    0
200    1
0      2
400    3
100    4
Name: track, dtype: int64
```

Use the following to add particle column to original locdata dataset.

```
dat.data.loc[links.index,'track']=links
```

```
dat.data.head()
```

```
   position_x  position_y  frame  track
0  518.146180  429.651004      0    2.0
1  524.470735  435.975560      1    2.0
2  530.795291  429.651004      2    2.0
```

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```
3  524.470735  435.975560      3    2.0
4  518.146180  429.651004      4    2.0
```

2.10.3 Track using trackpy with locdata.data as input

For a detailed tracking analysis you might want to use trackpy functions with the pandas DataFrame carrying localization data as input. The following examples will igve a short illustration of using trackpy functions.

```
import trackpy as tp
```

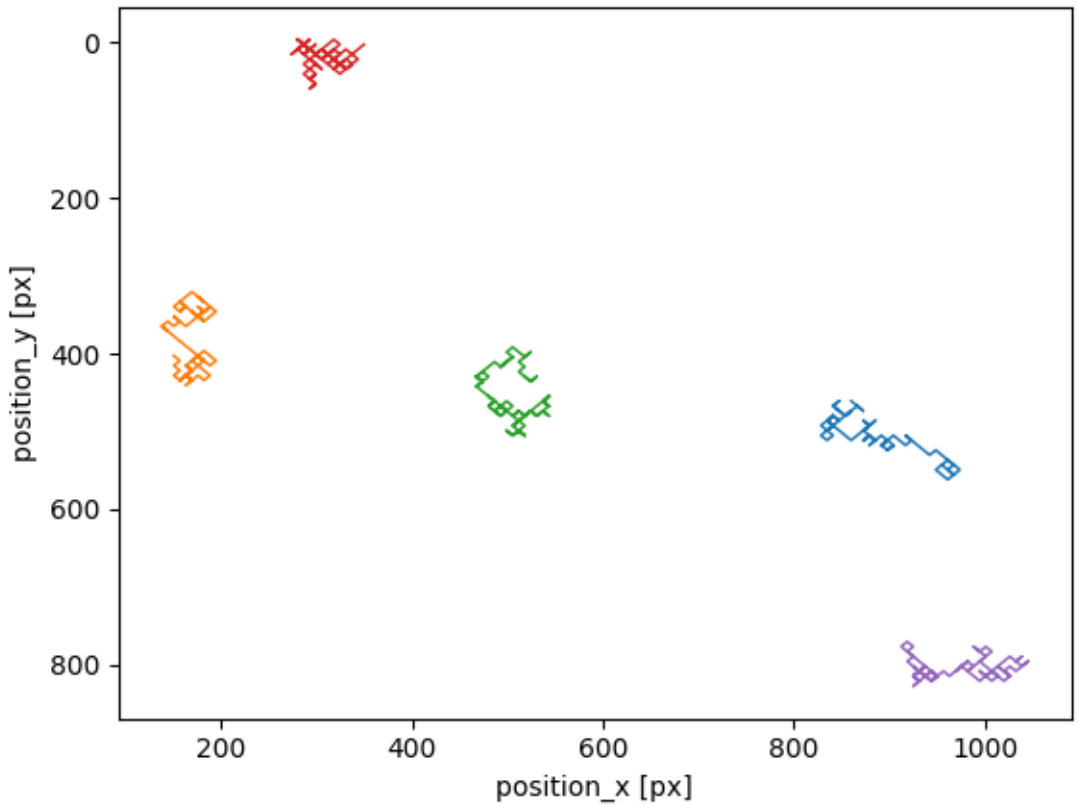
```
t = tp.link_df(dat.data, search_range=100, memory=1, pos_columns=['position_x
↪', 'position_y'], t_column='frame')

t.head(10)
```

```
Frame 99: 5 trajectories present.
```

	position_x	position_y	frame	track	particle
300	954.974002	543.269132	0	0.0	0
200	150.484168	402.874581	0	1.0	1
0	518.146180	429.651004	0	2.0	2
400	318.156007	33.883669	0	3.0	3
100	944.139141	821.378039	0	4.0	4
1	524.470735	435.975560	1	2.0	2
201	156.808723	409.199136	1	1.0	1
301	961.298558	549.593688	1	0.0	0
401	324.480563	27.559113	1	3.0	3
101	937.814586	815.053483	1	4.0	4

```
plt.figure()
tp.plot_traj(t, pos_columns=['position_x', 'position_y'], t_column='frame');
```



2.10.4 filter

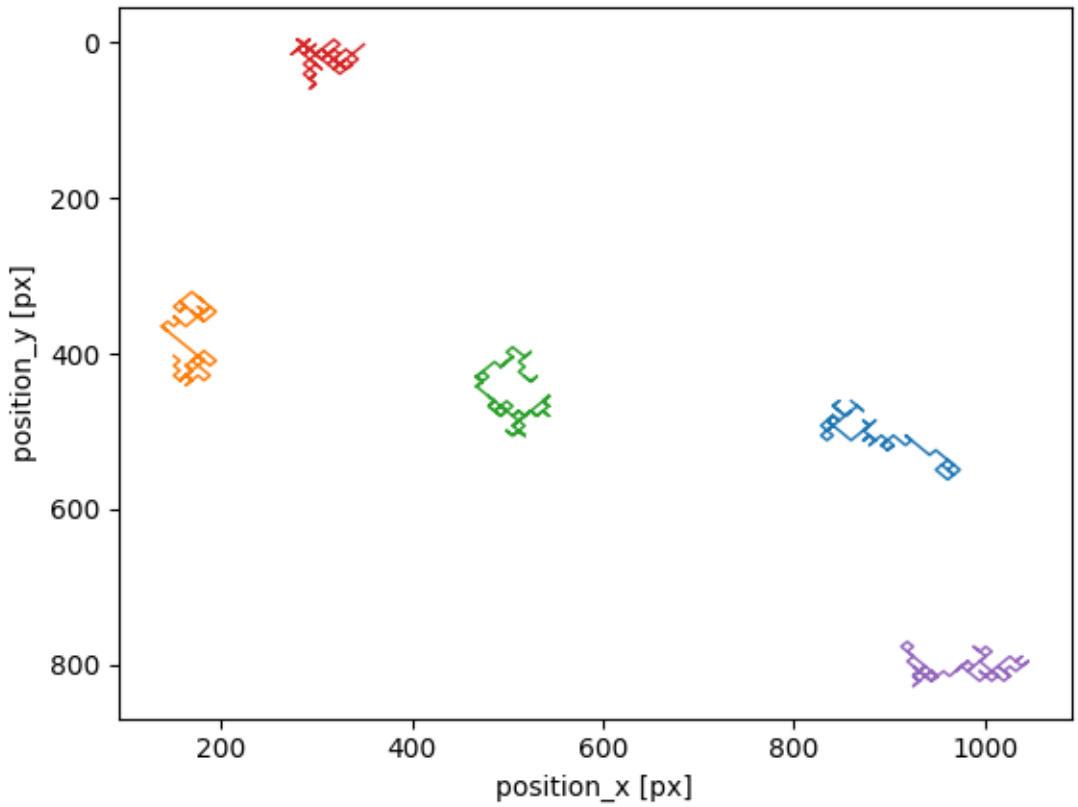
```
t.head()
```

	position_x	position_y	frame	track	particle
300	954.974002	543.269132	0	0.0	0
200	150.484168	402.874581	0	1.0	1
0	518.146180	429.651004	0	2.0	2
400	318.156007	33.883669	0	3.0	3
100	944.139141	821.378039	0	4.0	4

```
t1 = tp.filter_stubs(t, 10).reset_index(drop=True)
len(t1)
```

```
500
```

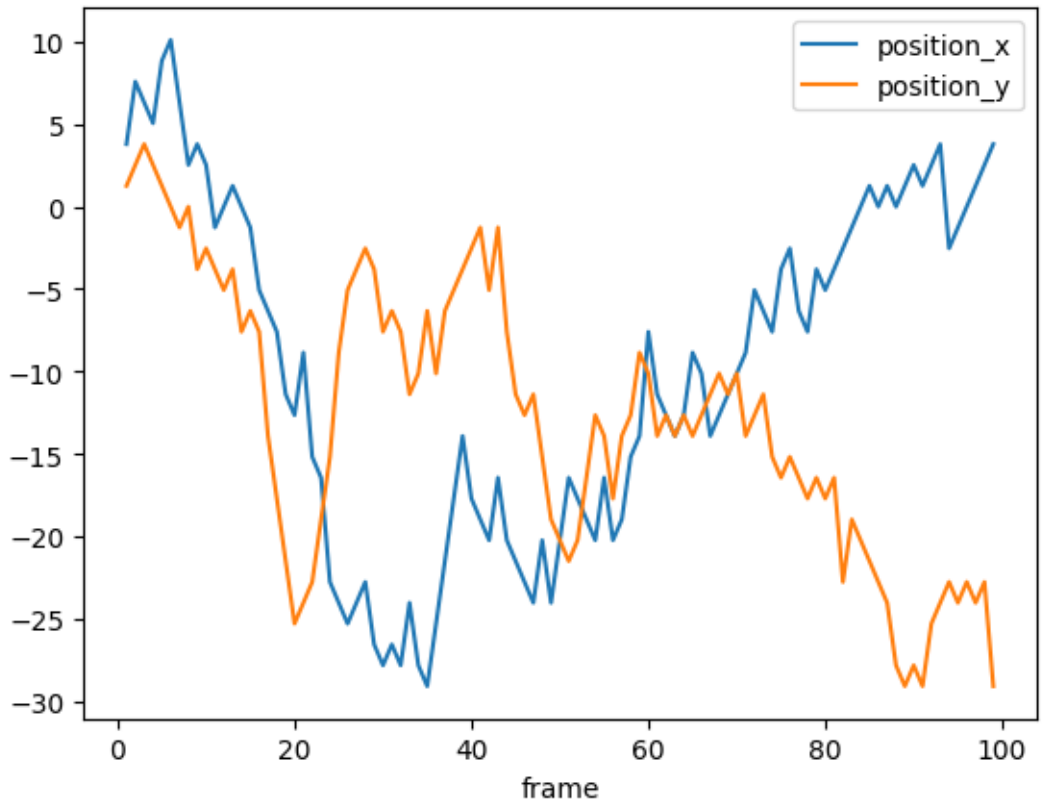
```
plt.figure()
tp.plot_traj(t1, pos_columns=['position_x', 'position_y']);
```



2.10.5 drift

```
d = tp.compute_drift(t1, pos_columns=['position_x', 'position_y'])
```

```
d.plot()
plt.show()
```



2.10.6 Mean square displacement (msd)

```
em = tp.emsd(t1,0.1, 100, pos_columns=['position_x', 'position_y']) # microns␣
↪per pixel = 100/285., frames per second = 24
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[25], line 1
----> 1 em = tp.emsd(t1,0.1, 100, pos_columns=['position_x', 'position_y']) #␣
↪microns per pixel = 100/285., frames per second = 24

File ~/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/python3.10/
↪site-packages/trackpy/motion.py:235, in emsd(traj, mpp, fps, max_lagtime,␣
↪detail, pos_columns)
    233     ids.append(pid)
    234 msds = pandas_concat(msds, keys=ids, names=['particle', 'frame'])
--> 235 results = msds.mul(msds['N'], axis=0).mean(level=1)  # weighted␣
↪average
    236 results = results.div(msds['N'].mean(level=1), axis=0)  # weights␣
↪normalized
    237 # Above, lagt is lumped in with the rest for simplicity and speed.
    238 # Here, rebuild it from the frame index.

File ~/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/python3.10/
↪site-packages/pandas/core/frame.py:11338, in DataFrame.mean(self, axis,␣
↪skipna, numeric_only, **kwargs)
```

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```
  11330 @doc(make_doc("mean", ndim=2))
  11331 def mean(
  11332     self,
   (...)
  11336     **kwargs,
  11337 ):
> 11338     result = super().mean(axis, skipna, numeric_only, **kwargs)
  11339     if isinstance(result, Series):
  11340         result = result.__finalize__(self, method="mean")

File ~/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/python3.10/
↪site-packages/pandas/core/generic.py:11969, in NDFrame.mean(self, axis,␣
↪skipna, numeric_only, **kwargs)
  11962 def mean(
  11963     self,
  11964     axis: Axis | None = 0,
   (...)
  11967     **kwargs,
  11968 ) -> Series | float:
> 11969     return self._stat_function(
  11970         "mean", nanops.nanmean, axis, skipna, numeric_only, **kwargs
  11971     )

File ~/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/python3.10/
↪site-packages/pandas/core/generic.py:11922, in NDFrame._stat_function(self,␣
↪name, func, axis, skipna, numeric_only, **kwargs)
  11911 @final
  11912 def _stat_function(
  11913     self,
   (...)
  11919     **kwargs,
  11920 ):
  11921     assert name in ["median", "mean", "min", "max", "kurt", "skew"],␣
↪name
> 11922     nv.validate_func(name, (), kwargs)
  11924     validate_bool_kwarg(skipna, "skipna", none_allowed=False)
  11926     return self._reduce(
  11927         func, name=name, axis=axis, skipna=skipna, numeric_
↪only=numeric_only
  11928     )

File ~/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/python3.10/
↪site-packages/pandas/compat/numpy/function.py:416, in validate_func(fname,␣
↪args, kwargs)
    413     return validate_stat_func(args, kwargs, fname=fname)
    415 validation_func = _validation_funcs[fname]
--> 416 return validation_func(args, kwargs)

File ~/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/python3.10/
↪site-packages/pandas/compat/numpy/function.py:88, in CompatValidator.__call__
↪(self, args, kwargs, fname, max_fname_arg_count, method)
```

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```
     86     validate_kwargs(fname, kwargs, self.defaults)
     87 elif method == "both":
---> 88     validate_args_and_kwargs(
     89         fname, args, kwargs, max_fname_arg_count, self.defaults
     90     )
     91 else:
     92     raise ValueError(f"invalid validation method '{method}'")

File ~/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/python3.10/
↪site-packages/pandas/util/_validators.py:223, in validate_args_and_
↪kwargs(fname, args, kwargs, max_fname_arg_count, compat_args)
    218         raise TypeError(
    219             f"{fname}() got multiple values for keyword argument '
↪{key}'"
    220         )
    222 kwargs.update(args_dict)
--> 223 validate_kwargs(fname, kwargs, compat_args)

File ~/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/python3.10/
↪site-packages/pandas/util/_validators.py:164, in validate_kwargs(fname,␣
↪kwargs, compat_args)
    142 """
    143 Checks whether parameters passed to the **kwargs argument in a
    144 function `fname` are valid parameters as specified in `*compat_args`
   (...)
    161 map to the default values specified in `compat_args`
    162 """
    163 kwds = kwargs.copy()
--> 164 _check_for_invalid_keys(fname, kwargs, compat_args)
    165 _check_for_default_values(fname, kwds, compat_args)

File ~/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/python3.10/
↪site-packages/pandas/util/_validators.py:138, in _check_for_invalid_
↪keys(fname, kwargs, compat_args)
    136 if diff:
    137     bad_arg = next(iter(diff))
--> 138     raise TypeError(f"{fname}() got an unexpected keyword argument '
↪{bad_arg}'")

TypeError: mean() got an unexpected keyword argument 'level'
```

```
fig, ax = plt.subplots()
ax.plot(em.index, em, 'o')
#ax.set_xscale('log')
#ax.set_yscale('log')
ax.set(ylabel=r'$\langle \Delta r^2 \rangle$ [$\mu$m$^2$]',
       xlabel='lag time $t$')
#ax.set(ylim=(1e-2, 10));
```

2.11 Tutorial about transforming LocData

Locan provides methods for transforming localization data sets into new LocData objects.

```
from pathlib import Path

%matplotlib inline

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.11.1 Spatially randomize a structured set of localizations

Assume that localizations are somehow structured throughout a region. Often it is helpful to compare analysis results to a similar dataset in which localizations are homogeneously Poisson distributed. A LocData object with this kind of data can be provided by the randomize function.

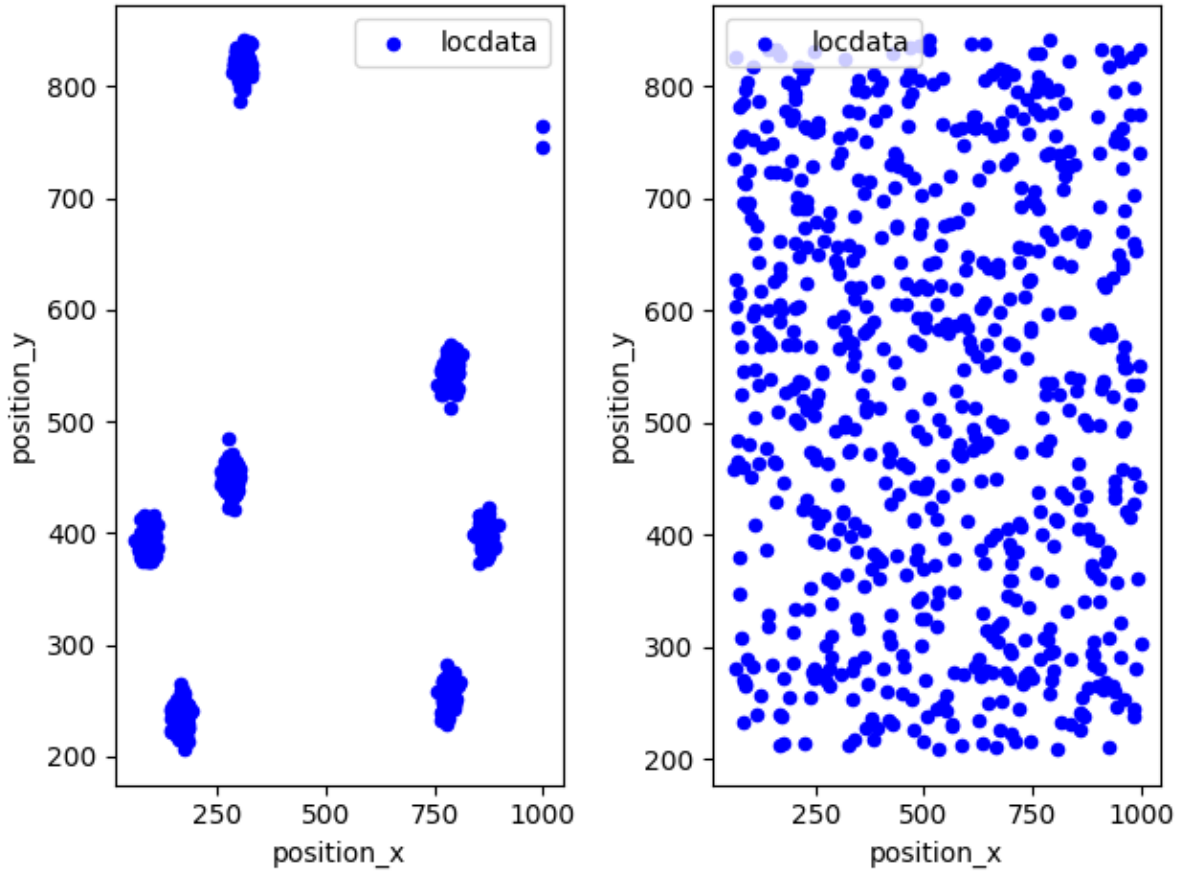
```
rng = np.random.default_rng(seed=1)
```

```
locdata = lc.simulate_Thomas(parent_intensity=1e-5, region=((0, 1000), (0,␣
↪1000)), cluster_mu=100, cluster_std=10, seed=rng)
locdata.print_summary()
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
identifier: "1"
comment: ""
source: SIMULATION
state: RAW
element_count: 705
frame_count: 0
creation_time {
  2024-03-14T11:53:02.635662Z
}
```

```
locdata_random = lc.randomize(locdata, hull_region='bb', seed=rng)
```

```
fig, ax = plt.subplots(nrows=1, ncols=2)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax[0], color=
↪'Blue', label='locdata')
locdata_random.data.plot.scatter(x='position_x', y='position_y', ax=ax[1],␣
↪color='Blue', label='locdata')
plt.tight_layout()
plt.show()
```




```
print('Area of bounding box for structured data: {:.0f}'.format(locdata.
↪properties['region_measure_bb']))
print('Area of bounding box for randomized data: {:.0f}'.format(locdata_
↪random.properties['region_measure_bb']))
print('Ratio: {:.4f}'.format(locdata_random.properties['region_measure_bb'] /␣
↪locdata.properties['region_measure_bb']))
```

```
Area of bounding box for structured data: 595088
Area of bounding box for randomized data: 592451
Ratio: 0.9956
```

Regions other from bounding box can be specified as RoiRegion instance.

```
region = lc.ConvexHull(locdata.coordinates).region
```

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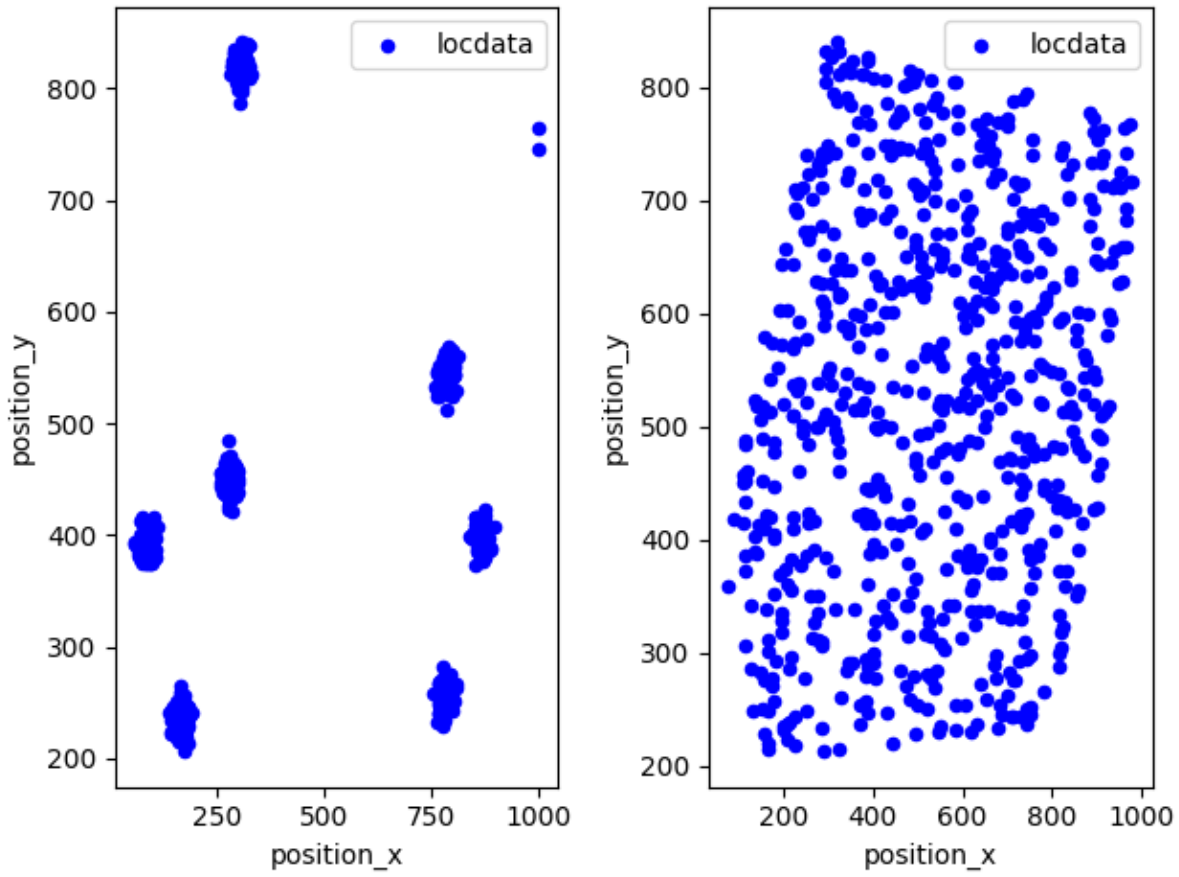
```
locdata_random = lc.randomize(locdata, hull_region=region)
```

```
fig, ax = plt.subplots(nrows=1, ncols=2)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax[0], color=
↪'Blue', label='locdata')
locdata_random.data.plot.scatter(x='position_x', y='position_y', ax=ax[1],␣
↪color='Blue', label='locdata')
plt.tight_layout()
plt.show()
```




```
print('Area of bounding box for structured data: {:.0f}'.format(locdata.
↪properties['region_measure_bb']))
print('Area of bounding box for randomized data: {:.0f}'.format(locdata_
↪random.properties['region_measure_bb']))
print('Ratio: {:.4f}'.format(locdata_random.properties['region_measure_bb'] /␣
↪locdata.properties['region_measure_bb']))
```

```
Area of bounding box for structured data: 595088
Area of bounding box for randomized data: 562580
Ratio: 0.9454
```

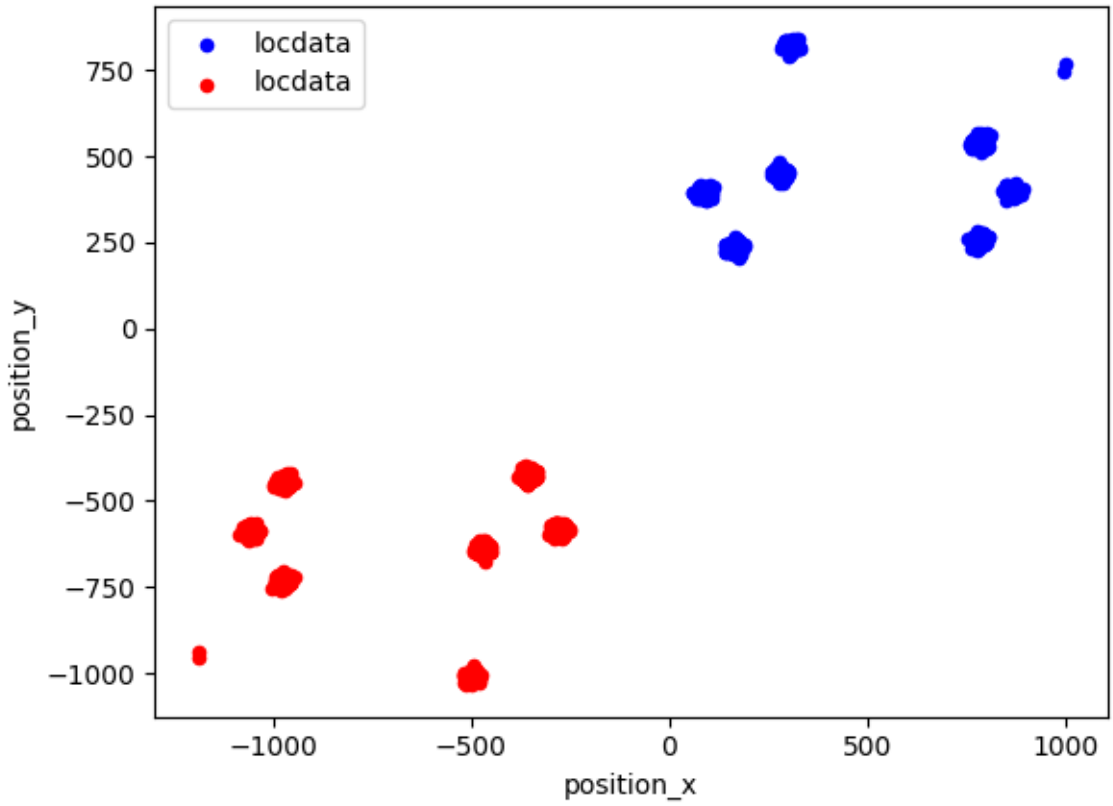
2.11.2 Apply an affine transformation to localization coordinates

A wrapper function provides affine transformations based on either numpy or open3d methods.

```
matrix = ((-1, 0), (0, -1))
offset = (10, 10)
pre_translation = (100, 100)

locdata_transformed = lc.transform_affine(locdata, matrix, offset, pre_
↪translation, method='numpy')
```

```
fig, ax = plt.subplots()
locdata.data.plot.scatter(x='position_x', y='position_y',color='Blue', label=
↪'locdata', ax=ax)
locdata_transformed.data.plot.scatter(x='position_x', y='position_y', color=
↪'Red', label='locdata', ax=ax);
```



2.11.3 Apply a BunwarpJ transformation to localization coordinates

Often a transformation matrix was computed using ImageJ. The `bunwarp` function allows applying a transformation from the raw matrix of the ImageJ/Fiji plugin BunwarpJ. Here we show a very small region with a single fluorescent bead that is recorded on a red and a green dSTORM channel.

```
matrix_path = lc.ROOT_DIR / 'tests/test_data/transform/BunwarpJ_
↪transformation_raw_green.txt'
locdata_green = lc.load_asdf_file(path=lc.ROOT_DIR /
```

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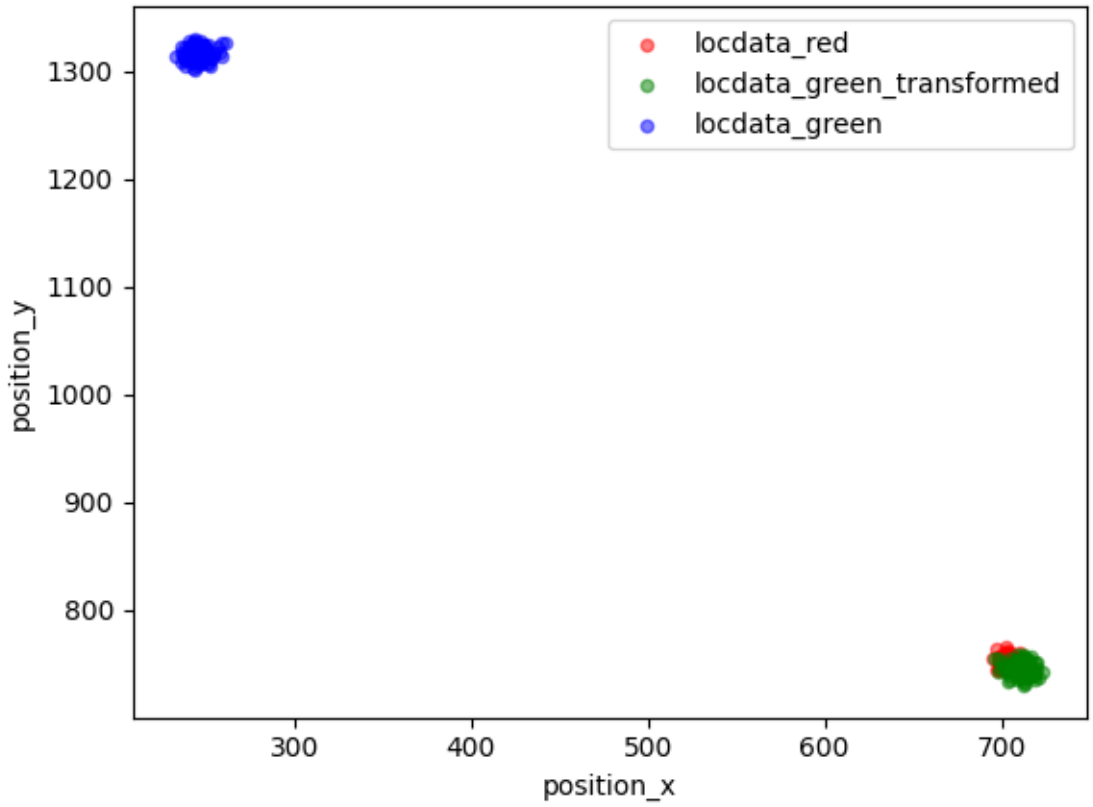
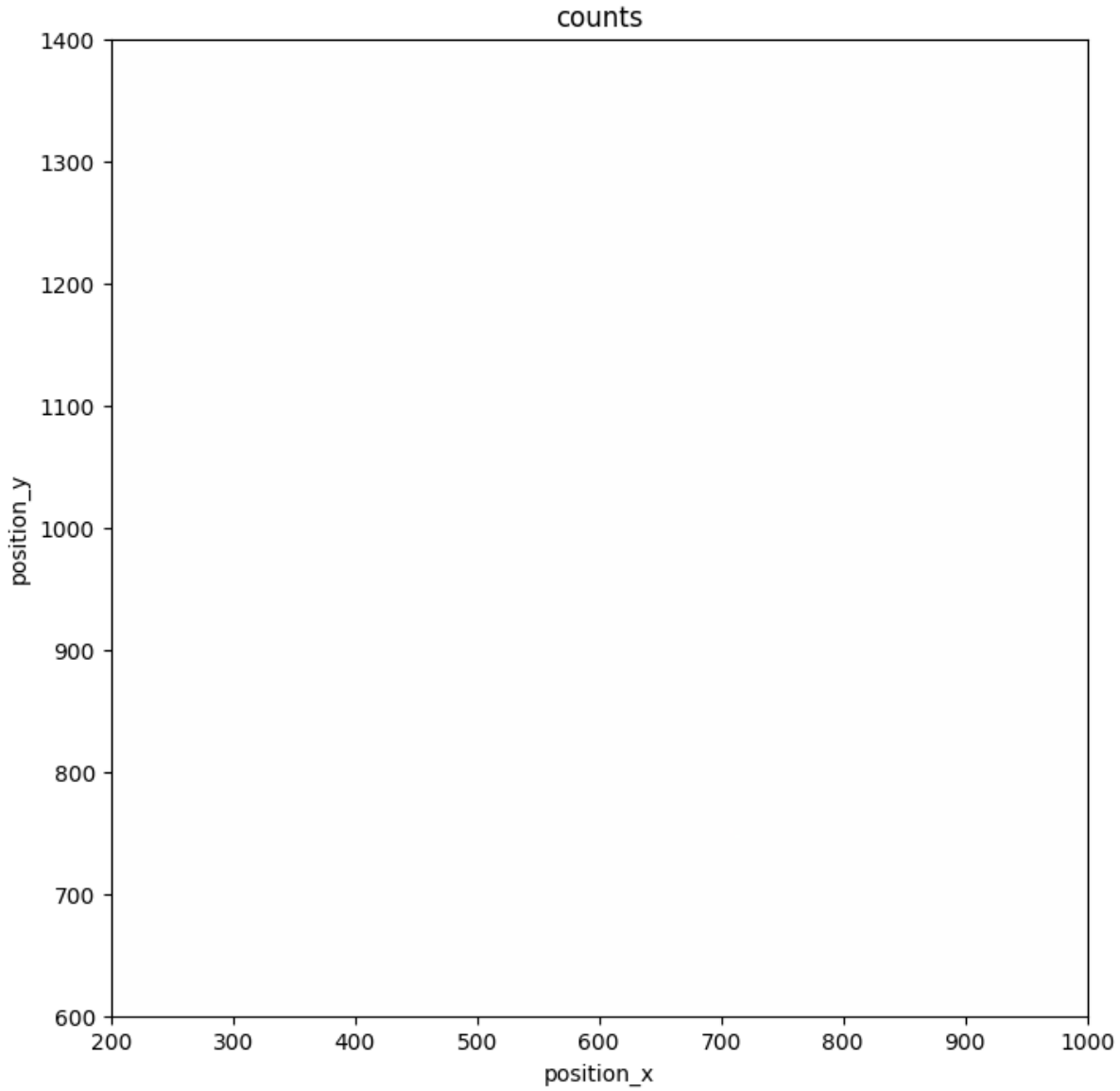
```
                                'tests/test_data/transform/rapidSTORM_beads_
↪green.asdf')
locdata_red = lc.load_asdf_file(path=lc.ROOT_DIR /
                                'tests/test_data/transform/rapidSTORM_beads_
↪red.asdf')

locdata_green_transformed = lc.bunwarp(locdata=locdata_green, matrix_
↪path=matrix_path, pixel_size=(10, 10), flip=True)
```

```
fig, ax = plt.subplots()
locdata_red.data.plot.scatter(x='position_x', y='position_y',color='Red',␣
↪label='locdata_red', alpha=0.5, ax=ax)
locdata_green_transformed.data.plot.scatter(x='position_x', y='position_y',␣
↪color='Green', label='locdata_green_transformed', alpha=0.5, ax=ax)
locdata_green.data.plot.scatter(x='position_x', y='position_y',color='Blue',␣
↪label='locdata_green', alpha=0.5, ax=ax);
```




```
fig, ax = plt.subplots(figsize=(10, 8))
lc. render_2d_rgb_mpl([locdata_red, locdata_green_transformed, locdata_green],
↪ bin_size=5, bin_range=((200, 1000), (600, 1400)), rescale='equal', ax=ax);
```



2.12 Tutorial about localizations per frame

```
from pathlib import Path

%matplotlib inline

import matplotlib.pyplot as plt

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

```

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```
Python:
   version: 3.10.13
```

2.12.1 Load rapidSTORM data file

Identify some data in the test_data directory and provide a path using pathlib.Path

```
path = lc.ROOT_DIR / 'tests/test_data/rapidSTORM_dstorm_data.txt'
print(path, '\n')

dat = lc.load_rapidSTORM_file(path=path, nrows=1000)
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.txt
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

Print information about the data:

```
print(dat.data.head(), '\n')
print('Summary:')
dat.print_summary()
print('Properties:')
print(dat.properties)
```

```
   position_x  position_y  frame  intensity  chi_square  local_background
0     9657.40     24533.5      0   33290.10   1192250.0        767.732971
1    16754.90     18770.0      0   21275.40   2106810.0        875.460999
2    14457.60     18582.6      0   20748.70    526031.0        703.369995
3     6820.58     16662.8      0    8531.77   3179190.0        852.789001
4    19183.20     22907.2      0   14139.60    448631.0        662.770020

Summary:
identifier: "1"
comment: ""
source: EXPERIMENT
state: RAW
element_count: 999
frame_count: 48
file {
  type: RAPIDSTORM
  path: "/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/
↪lib/python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.
↪txt"
}
creation_time {
```

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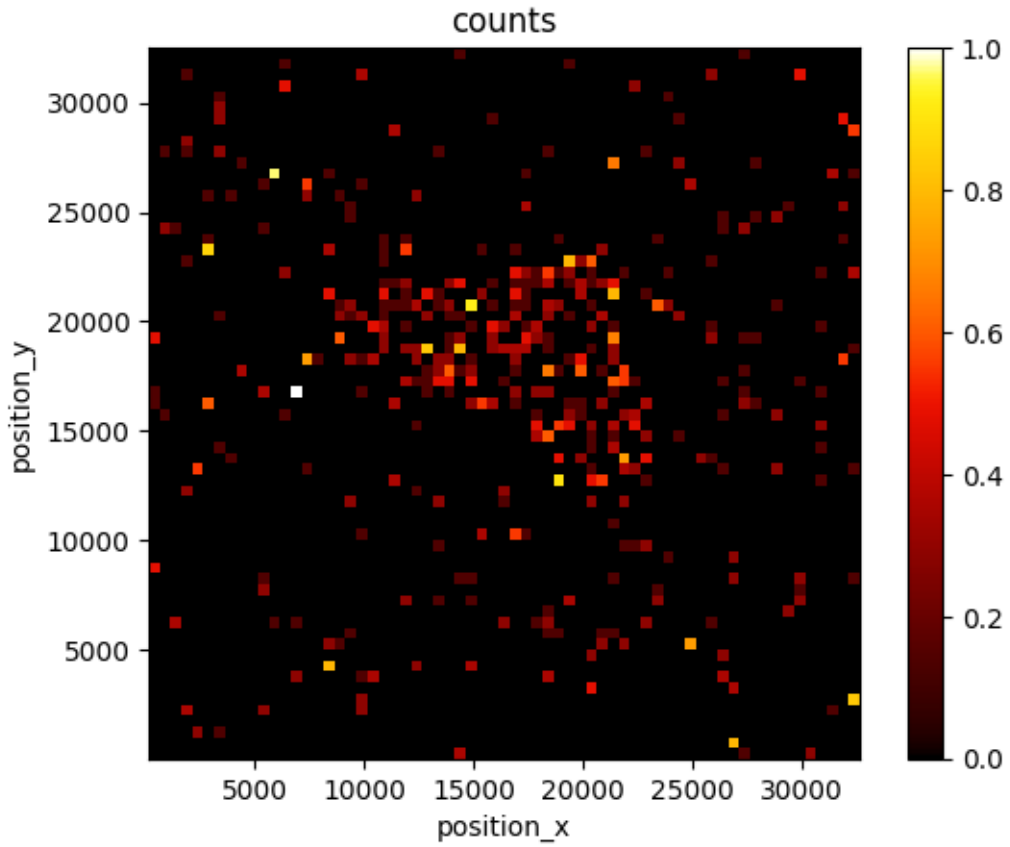
```
  2024-03-14T11:50:40.508668Z
}

Properties:
{'localization_count': 999, 'position_x': 16066.234912912912, 'uncertainty_x
↪': 250.05278033739012, 'position_y': 17550.369092792796, 'uncertainty_y':␣
↪223.5338926935945, 'intensity': 9471560.21, 'local_background': 645.07007,
↪'frame': 0, 'region_measure_bb': 1064111469.8204715, 'localization_density_
↪bb': 9.388114199807877e-07, 'subregion_measure_bb': 130483.2086}
```

2.12.2 Visualization

```
lc.render_2d(dat, bin_size=500, rescale=lc.Trafo.EQUALIZE_0P3);
```



Analyze localizations per frame

We have a look at the number of localizations that were detected in each frame.

The analysis class Localizations_per_frame provides numerical results, a plot of results versus frame, and a density graph (histogram).

```
lpf = lc.LocalizationsPerFrame()
lpf.compute(dat)
```

```
LocalizationsPerFrame(norm=None, time_delta=integration_time, resample=None)
```

```
lpf.results
```

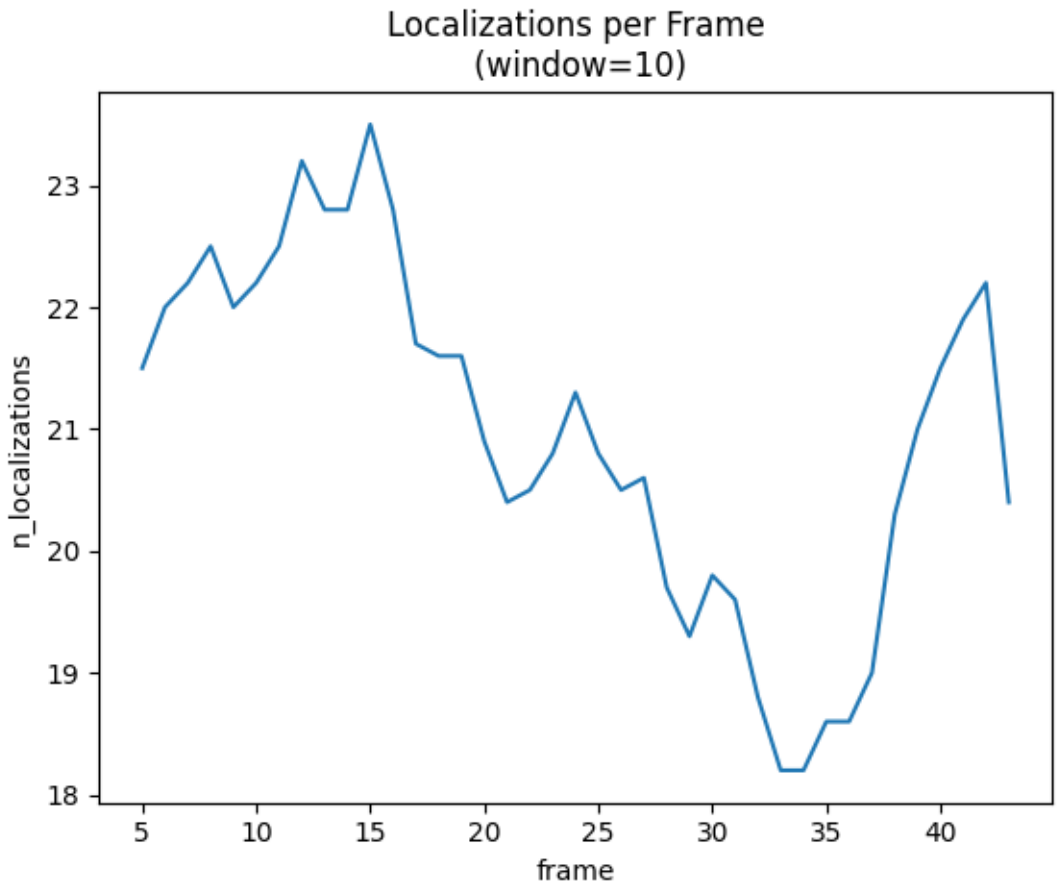
```
<locan.analysis.localizations_per_frame._Results at 0x7fae5291beb0>
```

```
print(lpf.results.time_series.head())
```

```
frame
0    22.0
1    25.0
2    21.0
3    24.0
4    21.0
Name: n_localizations, dtype: float64
```

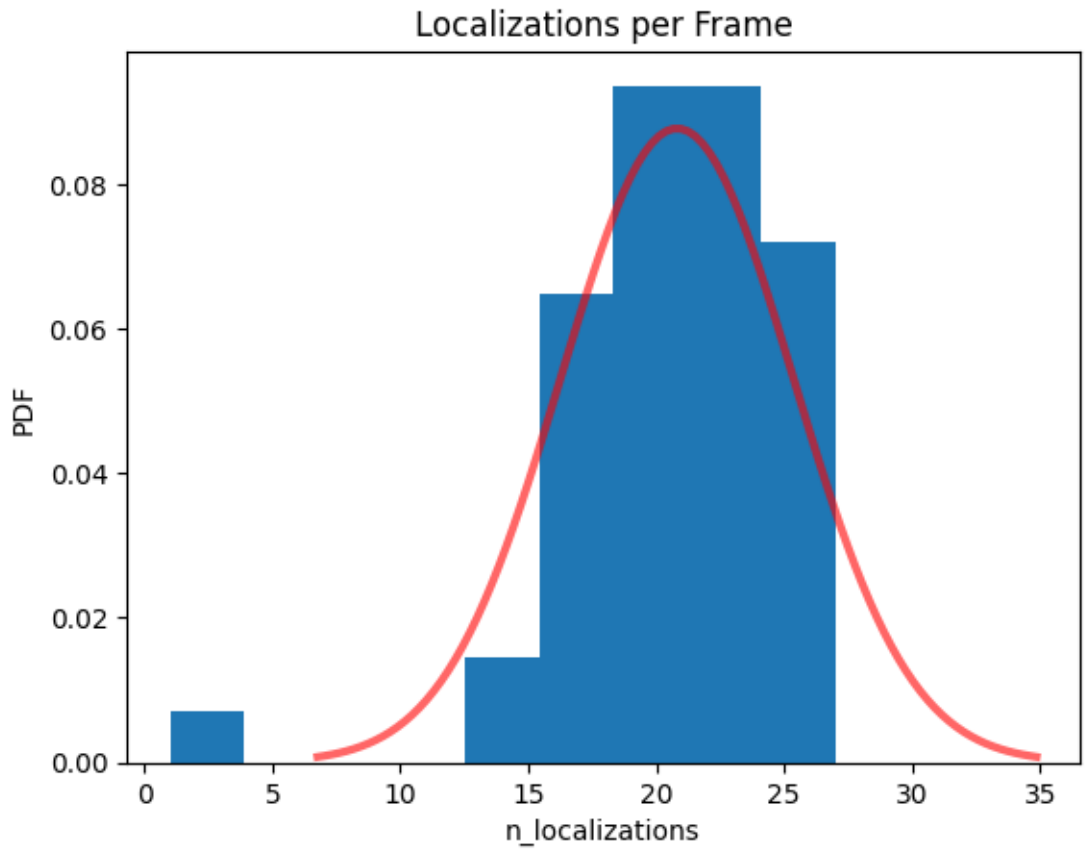
The plot shows results smoothed by a running average according to the specified window.

```
lpf.plot(window=10);
```



The histogram per default provides automatic bins, is normalized to show a probability density function and estimates a normal distribution.

```
lpf.hist();
```



The accumulation time is the time at which `fraction` of the cumulative intensity is reached.

```
lpf.results.accumulation_time()
```

```
22
```

2.12.3 Plot normalized values

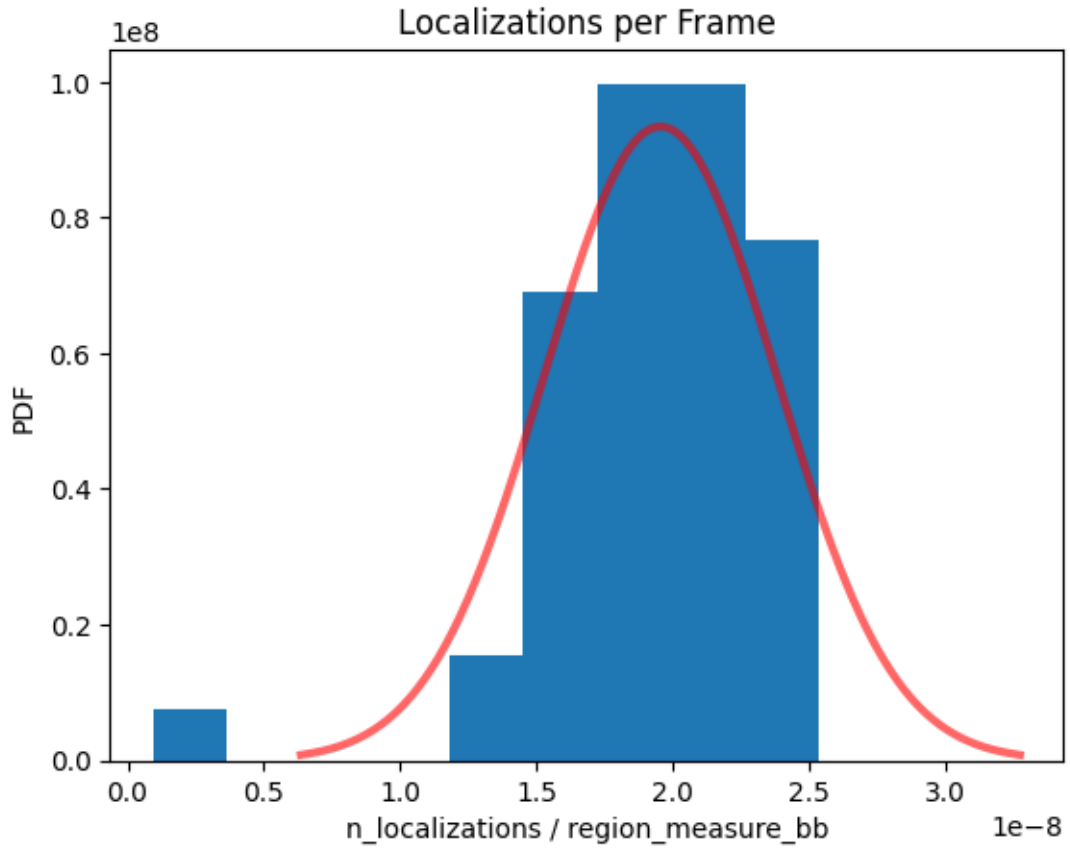
We can normalize the number of localizations to any other LocData property.

```
dat.properties
```

```
{'localization_count': 999,
 'position_x': 16066.234912912912,
 'uncertainty_x': 250.05278033739012,
 'position_y': 17550.369092792796,
 'uncertainty_y': 223.5338926935945,
 'intensity': 9471560.21,
 'local_background': 645.07007,
 'frame': 0,
 'region_measure_bb': 1064111469.8204715,
 'localization_density_bb': 9.388114199807877e-07,
 'subregion_measure_bb': 130483.2086}
```

```
lpf = lc.LocalizationsPerFrame(norm='region_measure_bb').compute(dat)
```

```
lpf.hist();
```



2.13 Tutorial about localization precision

Localization precision is determined from consecutive localizations that are identified within a certain search radius. The results include the distances between localization pairs, the position deltas for each coordinate and the corresponding frame of the first localizations.

```
from pathlib import Path

%matplotlib inline

import matplotlib.pyplot as plt

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

```

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```
Python:
   version: 3.10.13
```

2.13.1 Load rapidSTORM data file

Identify some data in the test_data directory and provide a path using `pathlib.Path` (returned by `lc.ROOT_DIR`)

```
path = lc.ROOT_DIR / 'tests/test_data/rapidSTORM_dstorm_data.txt'
print(path, '\n')

dat = lc.load_rapidSTORM_file(path=path, nrows=1000)
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.txt
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

Print information about the data:

```
print(dat.data.head(), '\n')
print('Summary:')
dat.print_summary()
print('Properties:')
print(dat.properties)
```

```
   position_x  position_y  frame  intensity  chi_square  local_background
0     9657.40     24533.5      0   33290.10   1192250.0        767.732971
1    16754.90     18770.0      0   21275.40   2106810.0        875.460999
2    14457.60     18582.6      0   20748.70    526031.0        703.369995
3     6820.58     16662.8      0    8531.77   3179190.0        852.789001
4    19183.20     22907.2      0   14139.60    448631.0        662.770020

Summary:
identifier: "1"
comment: ""
source: EXPERIMENT
state: RAW
element_count: 999
frame_count: 48
file {
  type: RAPIDSTORM
  path: "/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/
↪lib/python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.
↪txt"
}
```

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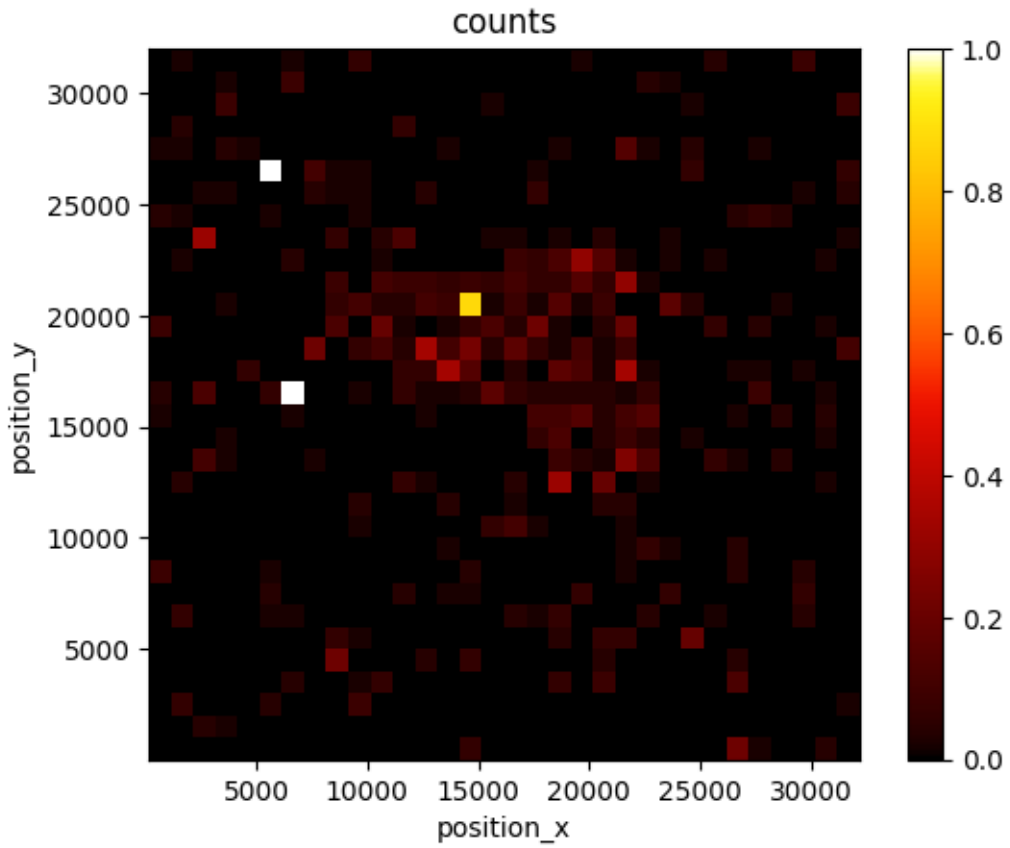
```
creation_time {
  2024-03-14T11:50:13.831476Z
}

Properties:
{'localization_count': 999, 'position_x': 16066.234912912912, 'uncertainty_x
↪': 250.05278033739012, 'position_y': 17550.369092792796, 'uncertainty_y':␣
↪223.5338926935945, 'intensity': 9471560.21, 'local_background': 645.07007,
↪'frame': 0, 'region_measure_bb': 1064111469.8204715, 'localization_density_
↪bb': 9.388114199807877e-07, 'subregion_measure_bb': 130483.2086}
```

2.13.2 Visualization

```
lc.render_2d(dat, bin_size=1000, rescale=(0,100));
```



2.13.3 Analyze localization precision

```
lp = lc.LocalizationPrecision(radius=50)
```

```
lp.compute(dat)
lp.results.head()
```

```
Processed frames::   0%|          | 0/46 [00:00<?, ?it/s]
```

```
Processed frames::  11%|         | 5/46 [00:00<00:00, 43.38it/s]
```

```
Processed frames::  22%|        | 10/46 [00:00<00:00, 46.83it/s]
```

```
Processed frames::  33%|       | 15/46 [00:00<00:00, 41.86it/s]
```

```
Processed frames::  43%|     | 20/46 [00:00<00:00, 43.02it/s]
```

```
Processed frames::  57%|    | 26/46 [00:00<00:00, 47.35it/s]
```

```
Processed frames::  70%|   | 32/46 [00:00<00:00, 49.25it/s]
```

```
Processed frames::  83%| | 38/46 [00:00<00:00, 49.82it/s]
```

```
Processed frames::  96%|| 44/46 [00:00<00:00, 47.35it/s]
```

```
Processed frames:: 100%|| 46/46 [00:00<00:00, 46.51it/s]
```

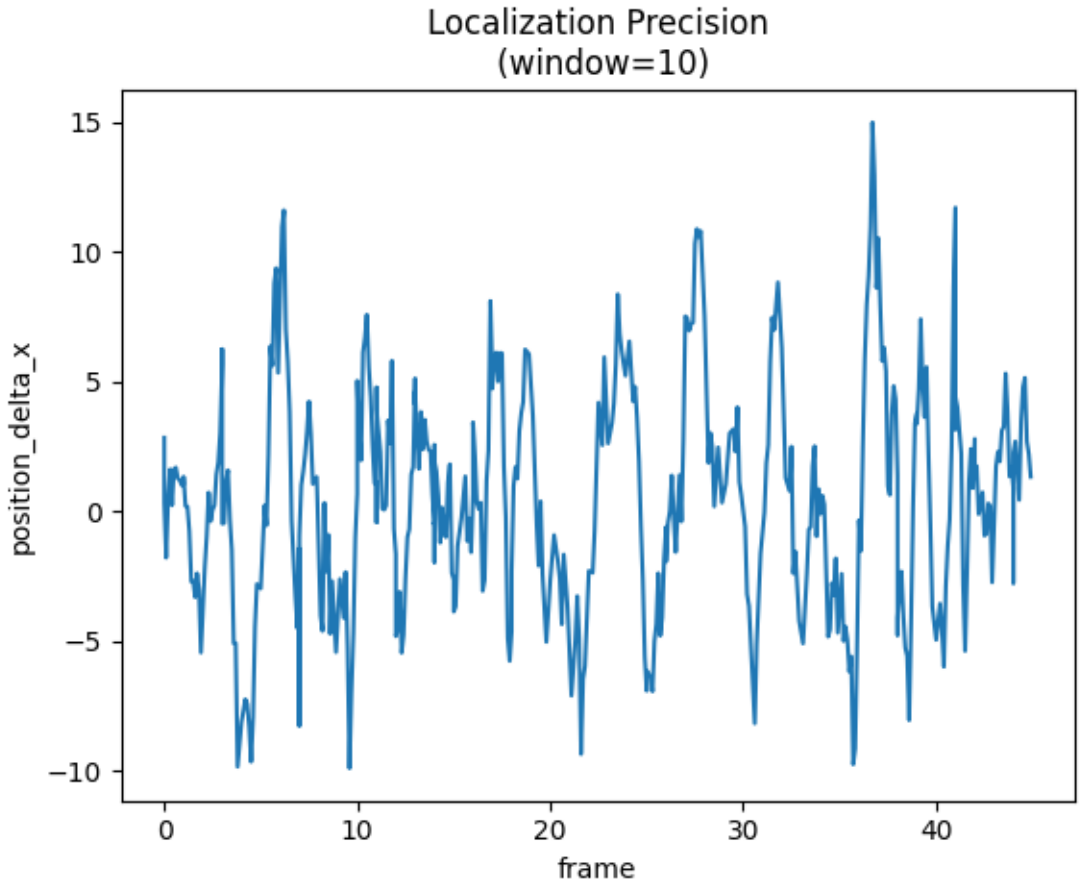
```

```

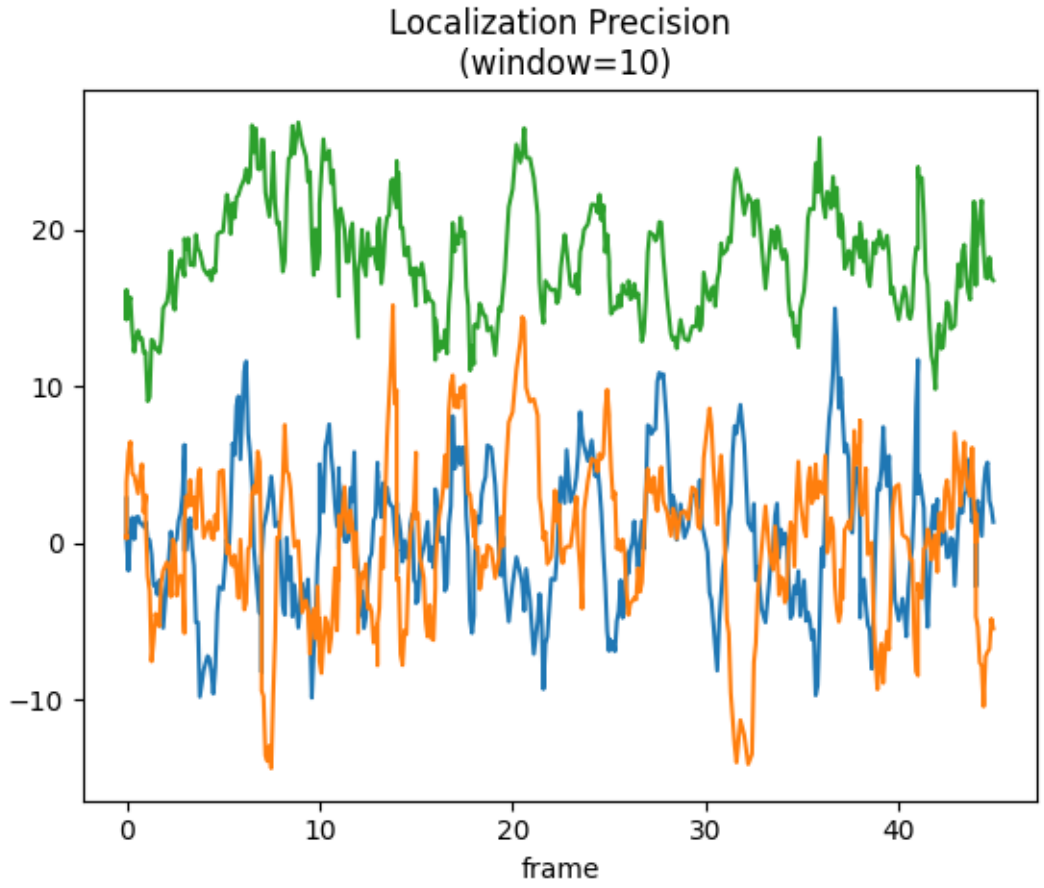
	position_delta_x	position_delta_y	position_distance	frame
0	4.6	-2.8	5.385165	0
1	-1.0	-3.4	3.544009	0
2	17.0	-17.5	24.397746	0
3	5.1	-8.1	9.571834	0
4	-14.1	22.6	26.637755	0

The plot

```
lp.plot(loc_property='position_delta_x', window=10);
```

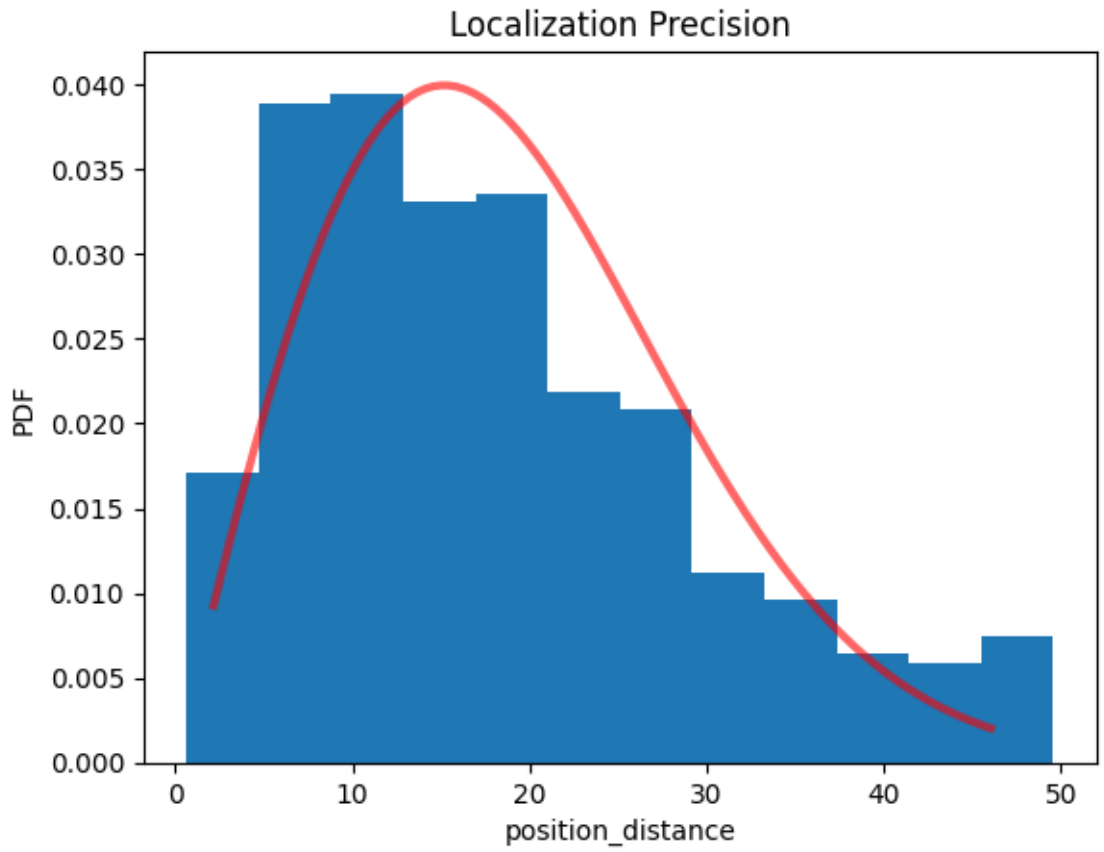



```
lp.plot(window=10);
```



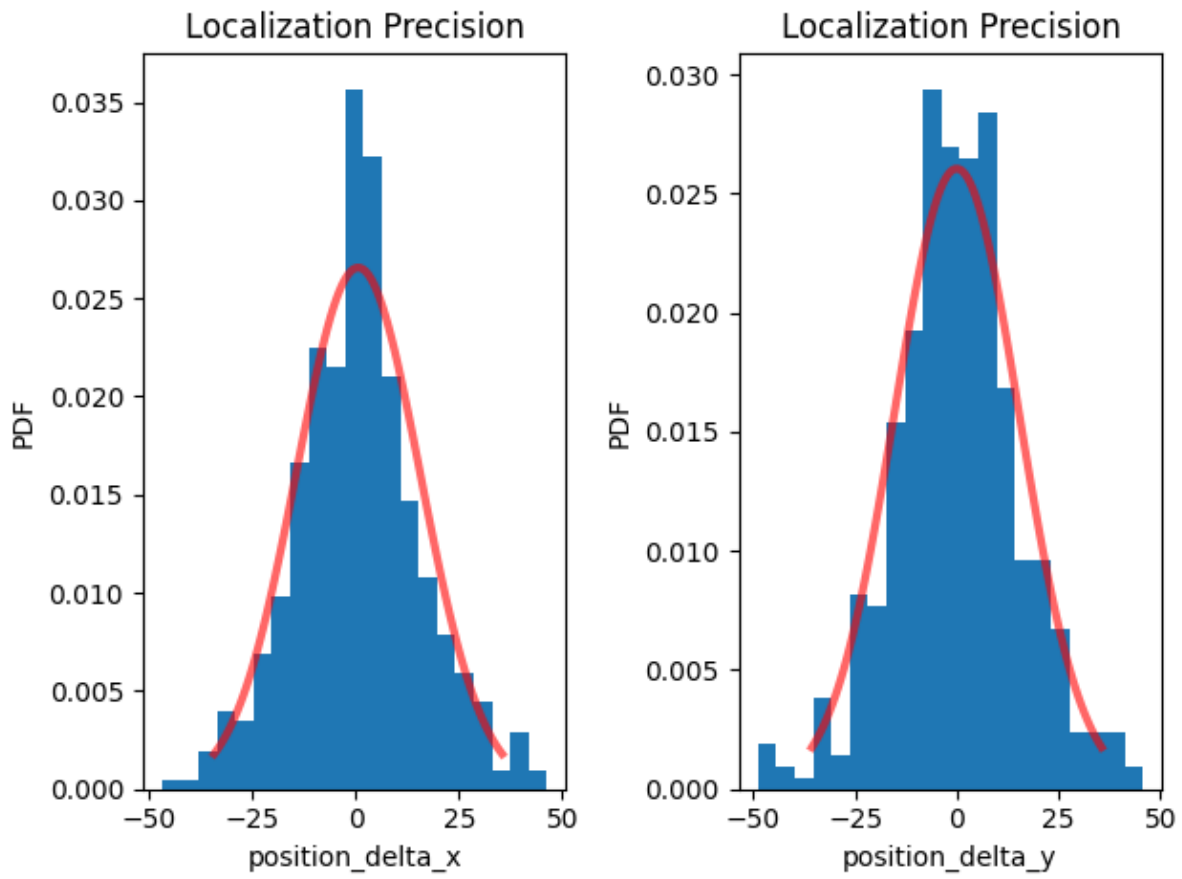
The histogram for the distances per default includes a fit to a distribution expected for normal distributed localizations. Sigma / sqrt(2) is the localization precision.

```
lp.hist();
```



Alternatively the position deltas can be histogrammed.

```
fig, ax = plt.subplots(nrows=1, ncols=2)
lp.hist(ax=ax[0], loc_property='position_delta_x')
lp.hist(ax=ax[1], loc_property='position_delta_y')
plt.tight_layout()
plt.show()
```



2.13.4 Fit distributions and show parameters

Appropriate distribution functions are fitted to the data either by calling the hist function or by running:

```
lp.fit_distributions()
```

The estimated fit parameters are provided under the `distribution_statistics` attribute

```
lp.distribution_statistics.parameter_dict()
```

```
{'position_delta_x_loc': 0.5793456521739601,
 'position_delta_x_scale': 15.01664582880988,
 'position_delta_y_loc': -0.028067391304342455,
 'position_delta_y_scale': 15.310244879968039,
 'position_distance_sigma': 15.169726562500031,
 'position_distance_loc': 0,
 'position_distance_scale': 1}
```

Remember: localization precision is typically defined as the standard deviation for the distances between localizations and their center position (the true dye position). Therefore, the estimated sigmas have to be divided by sqrt(2) to yield localization precision.

2.14 Tutorial about analyzing localization properties

```
from pathlib import Path

%matplotlib inline

import numpy as np
import matplotlib.pyplot as plt

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.14.1 Load rapidSTORM data file

Identify some data in the test_data directory and provide a path using `pathlib.Path` (returned by `lc.ROOT_DIR`)

```
path = lc.ROOT_DIR / 'tests/test_data/rapidSTORM_dstorm_data.txt'
print(path, '\n')

dat = lc.load_rapidSTORM_file(path=path, nrows=1000)
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.txt
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

Print information about the data:

```
print(dat.data.head(), '\n')
print('Summary:')
dat.print_summary()
print('Properties:')
print(dat.properties)
```

```
   position_x  position_y  frame  intensity  chi_square  local_background
0     9657.40     24533.5      0   33290.10   1192250.0        767.732971
1    16754.90     18770.0      0   21275.40   2106810.0        875.460999
2    14457.60     18582.6      0   20748.70    526031.0        703.369995
```

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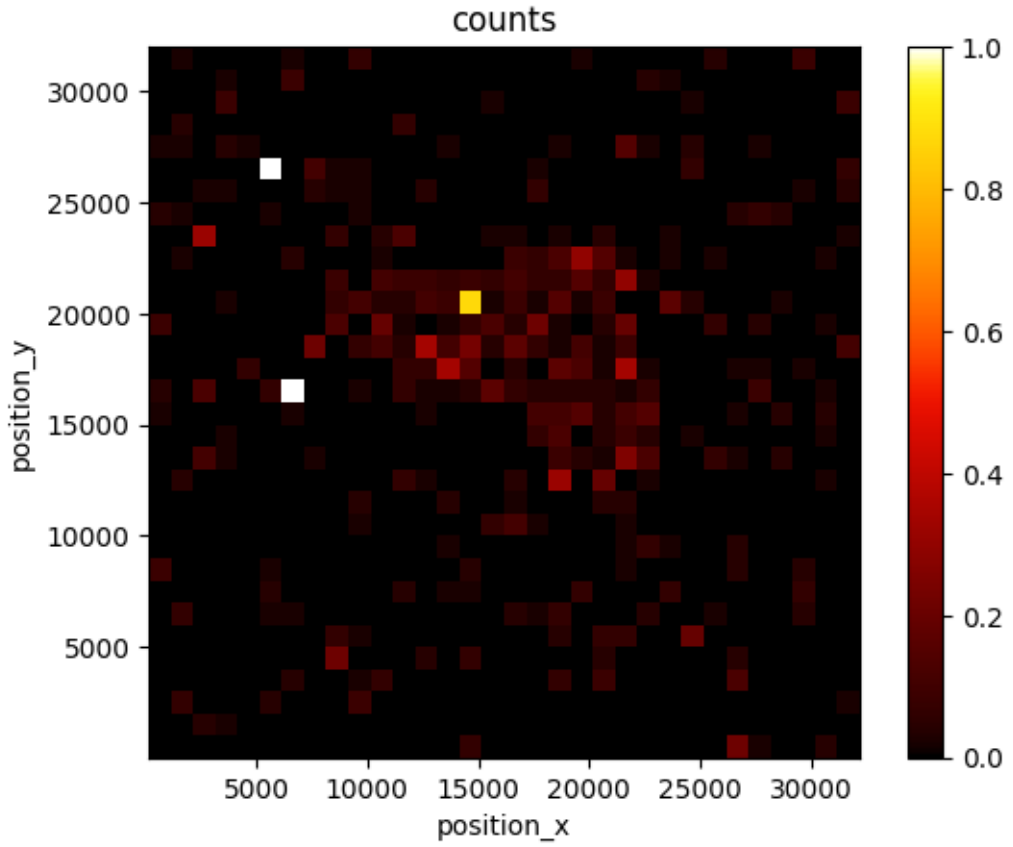
```
3     6820.58     16662.8      0    8531.77   3179190.0         852.789001
4    19183.20     22907.2      0   14139.60    448631.0         662.770020

Summary:
identifier: "1"
comment: ""
source: EXPERIMENT
state: RAW
element_count: 999
frame_count: 48
file {
  type: RAPIDSTORM
  path: "/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/
↪lib/python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.
↪txt"
}
creation_time {
  2024-03-14T11:50:30.957758Z
}

Properties:
{'localization_count': 999, 'position_x': 16066.234912912912, 'uncertainty_x
↪': 250.05278033739012, 'position_y': 17550.369092792796, 'uncertainty_y':␣
↪223.5338926935945, 'intensity': 9471560.21, 'local_background': 645.07007,
↪'frame': 0, 'region_measure_bb': 1064111469.8204715, 'localization_density_
↪bb': 9.388114199807877e-07, 'subregion_measure_bb': 130483.2086}
```

2.14.2 Visualization

```
lc.render_2d(dat, bin_size=1000, rescale=(0,100));
```



Analyze a localization property

We have a look at a certain localization property in locdata.

The analysis class `LocalizationProperty` provides a dataframe with the property as function of another property (index), and a plot or histogram of this property.

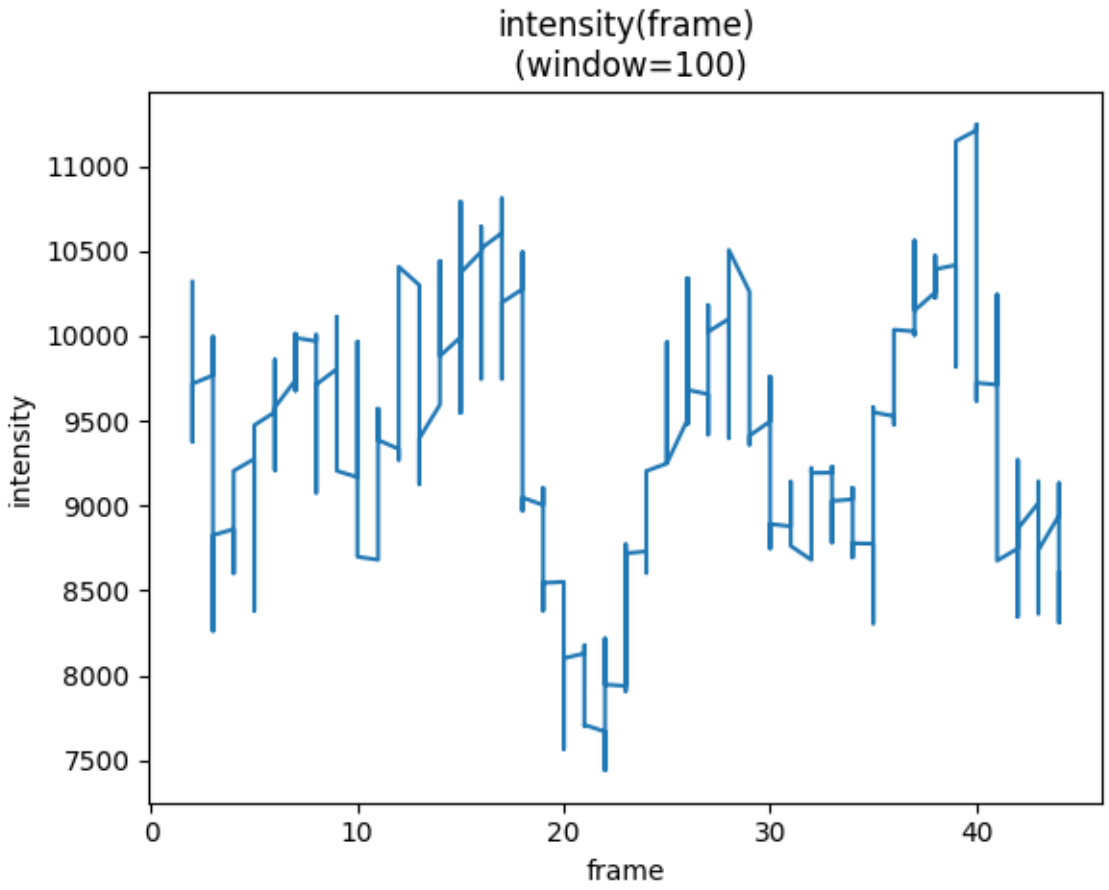
```
lprop = lc.LocalizationProperty(loc_property='intensity', index='frame')
```

```
lprop.compute(dat)
print(lprop.results.head())
```

```
       intensity
frame
0       33290.10
0       21275.40
0       20748.70
0        8531.77
0       14139.60
```

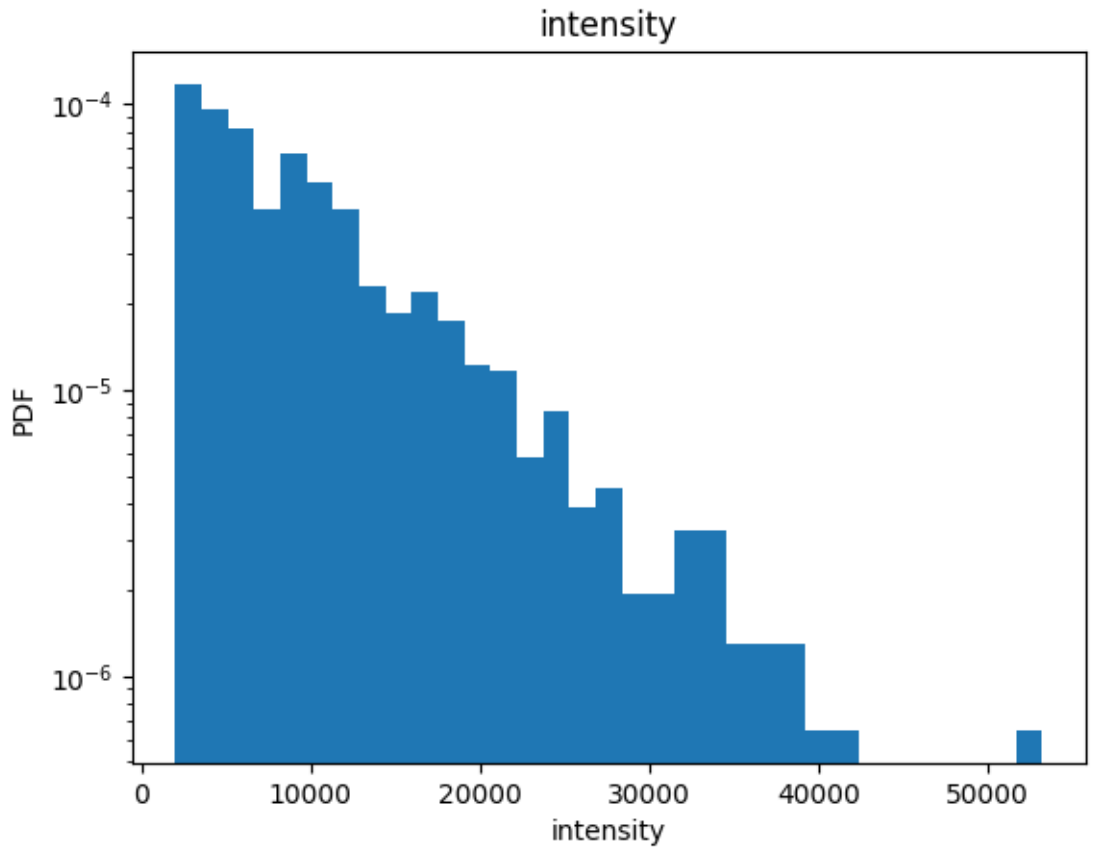
The plot shows results smoothed by a running average according to the specified window.

```
lprop.plot(window=100);
```



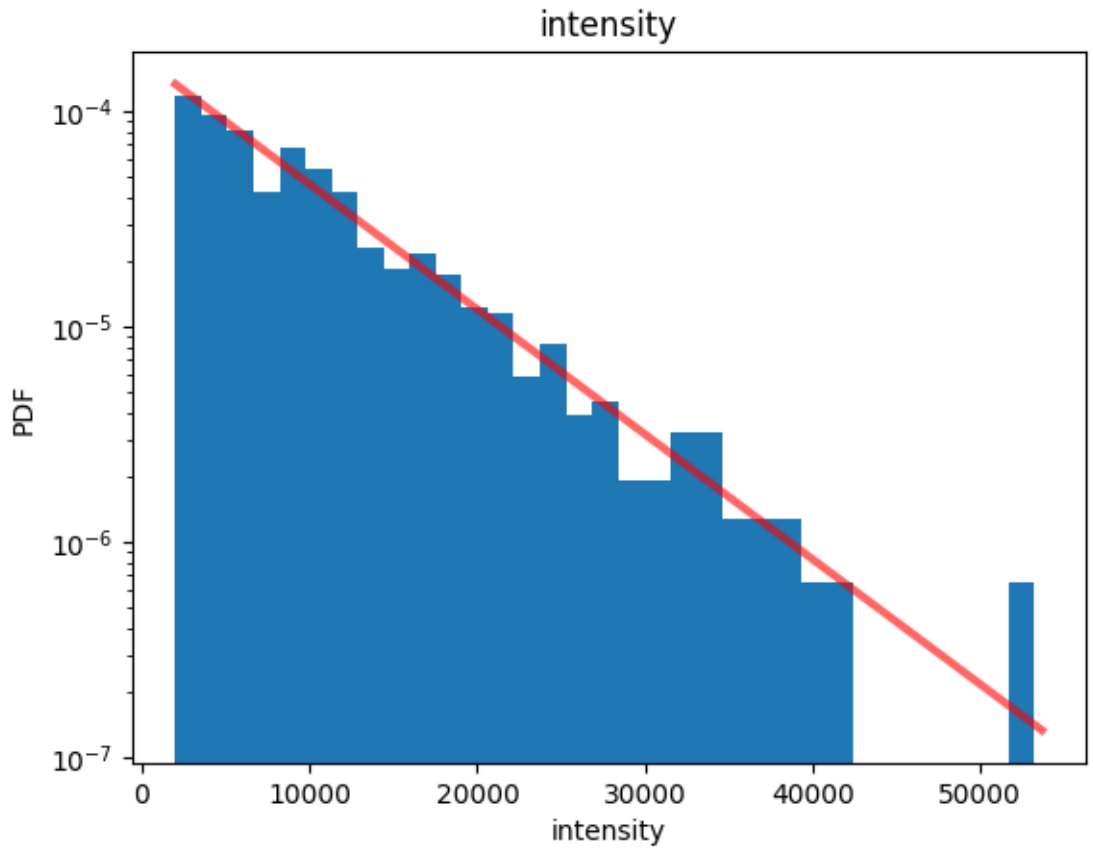
The histogram shows the probability density function of results.

```
lprop.hist(fit=False);
```



Per default the distribution is fitted to an exponential decay.

```
lprop.hist();
```



Fit results (as derived using the lmfit library) are provided in the distribution_statistics attribute.

```
lprop.distribution_statistics.parameter_dict()
```

```
{'intensity_loc': 2000.38, 'intensity_scale': 7480.661251251252}
```

```
lprop.results.min()
```

```
intensity    2000.38
dtype: float64
```

2.14.3 Fitting different distribution models

Per default the 'with_constraints' flag is True to apply standard fit constraints. This can be set to false and other parameters can be passed to the fit function.

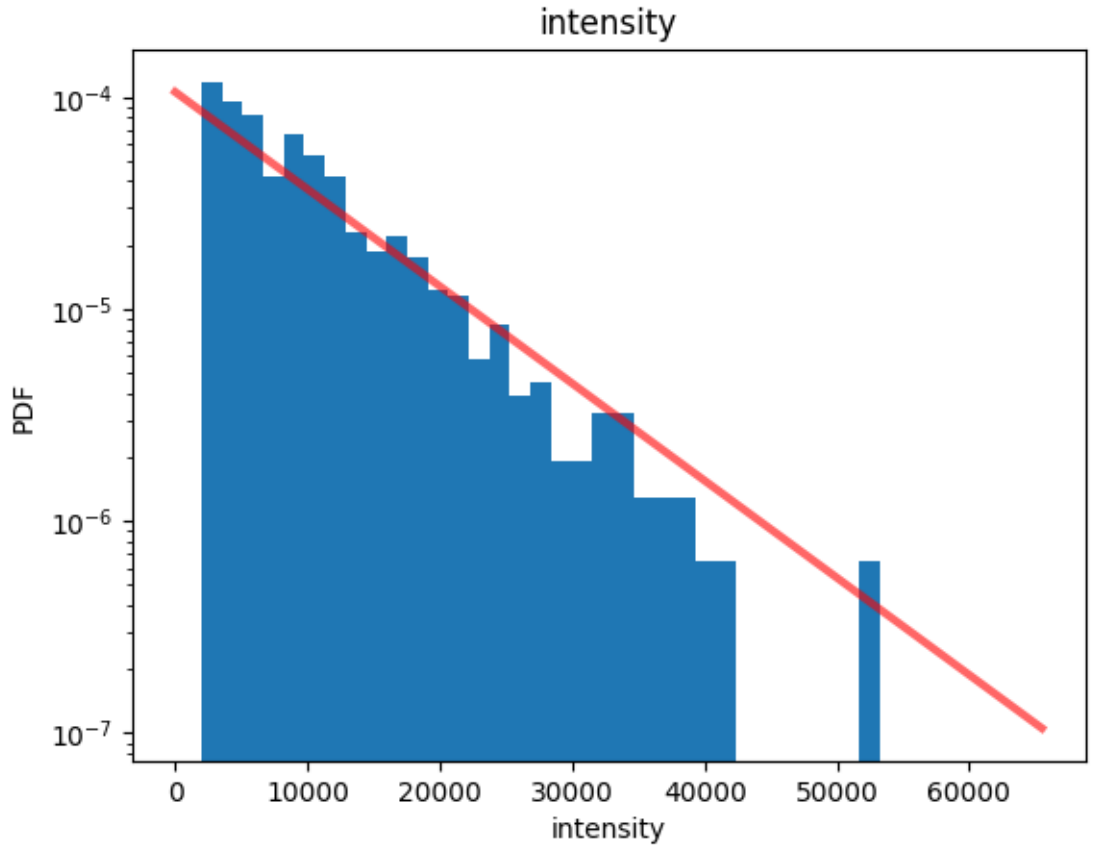
```
lprop.fit_distributions(with_constraints=False, floc=0)
```

```
lprop.distribution_statistics.parameter_dict()
```

```
{'intensity_loc': 0.0, 'intensity_scale': 9481.041251251252}
```

```
lprop.hist(fit=True)
print(lprop.distribution_statistics.parameter_dict())
```

```
{'intensity_loc': 0.0, 'intensity_scale': 9481.041251251252}
```

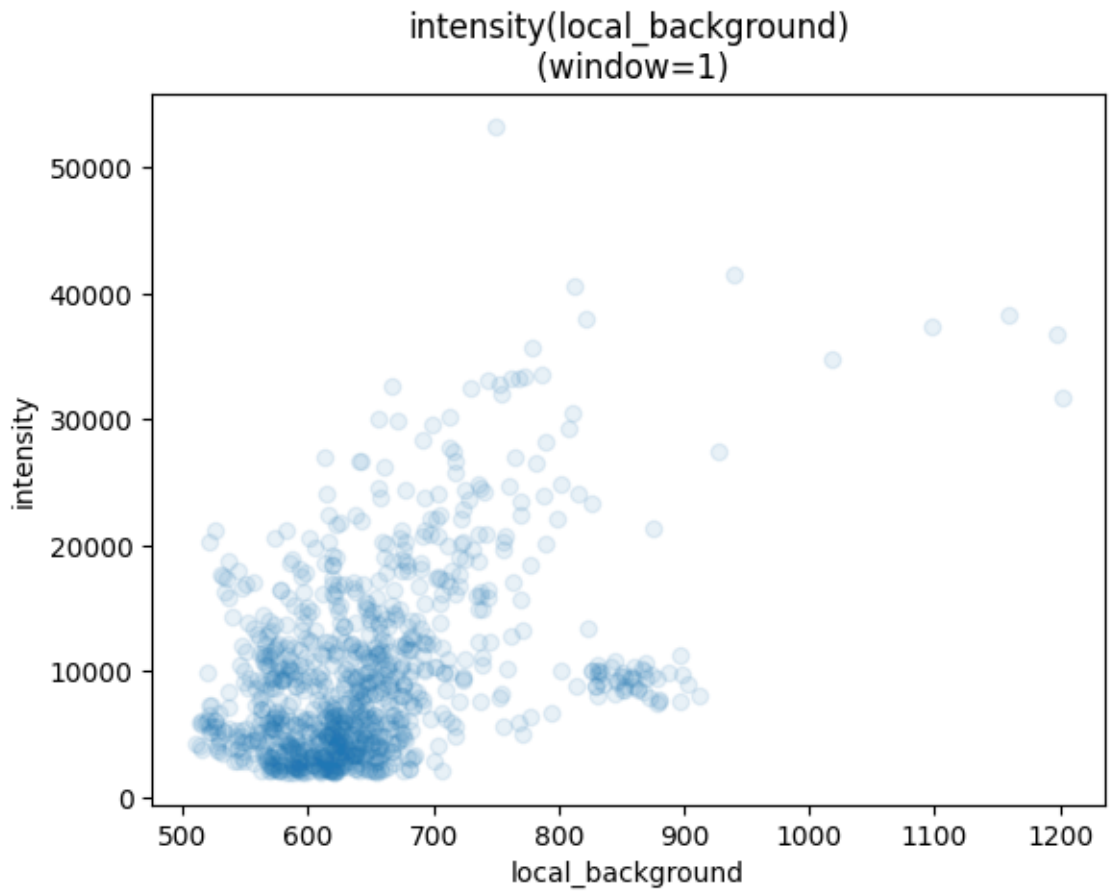


2.14.4 Showing correlations between two properties

By setting the index to another localization property correlations can be shown.

```
lprop = lc.LocalizationProperty(loc_property='intensity', index='local_
↪background').compute(dat)
```

```
lprop.plot(marker='o', linestyle="", alpha=0.1);
```

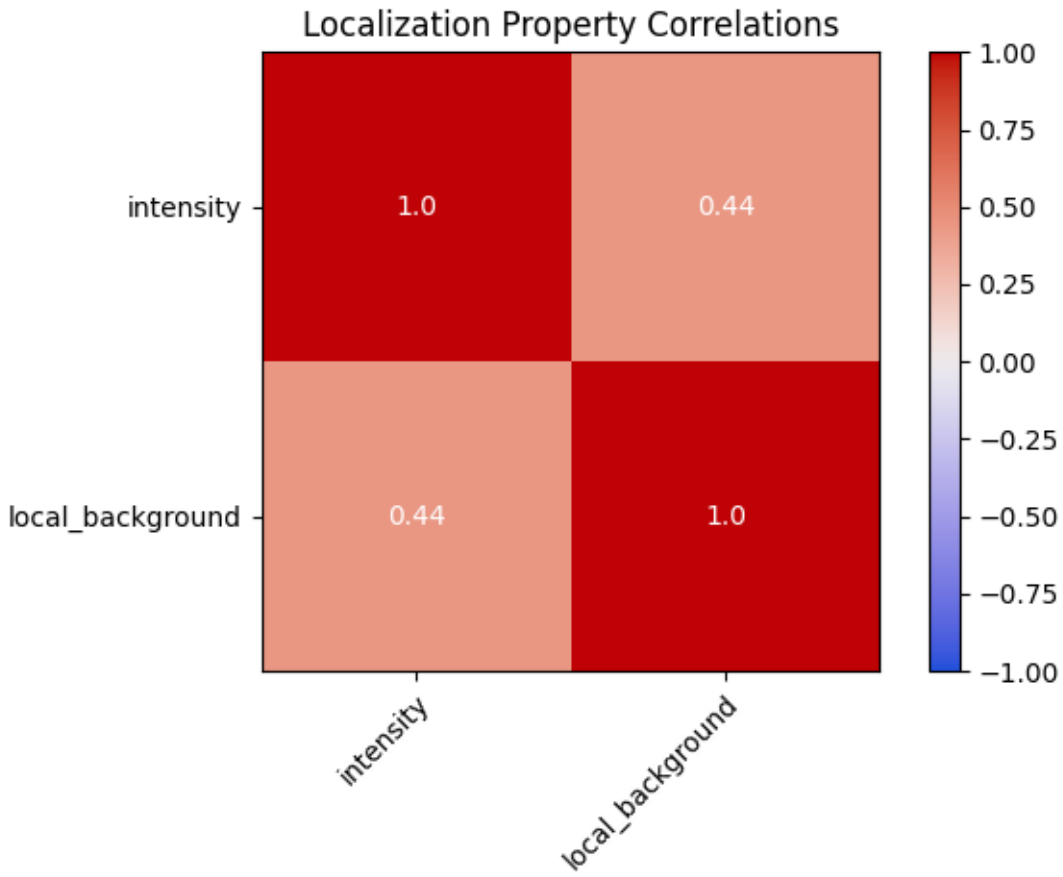


Correlation coefficients can be investigated in more detail using the LocalizationPropertyCorrelation class that is just a visualization of `pandas.DataFrame.corr()`.

```
lpcorr = lc.LocalizationPropertyCorrelations(loc_properties=['intensity',
↪'local_background']).compute(dat)
lpcorr
```

```
LocalizationPropertyCorrelations(loc_properties=['intensity', 'local_
↪background'])
```

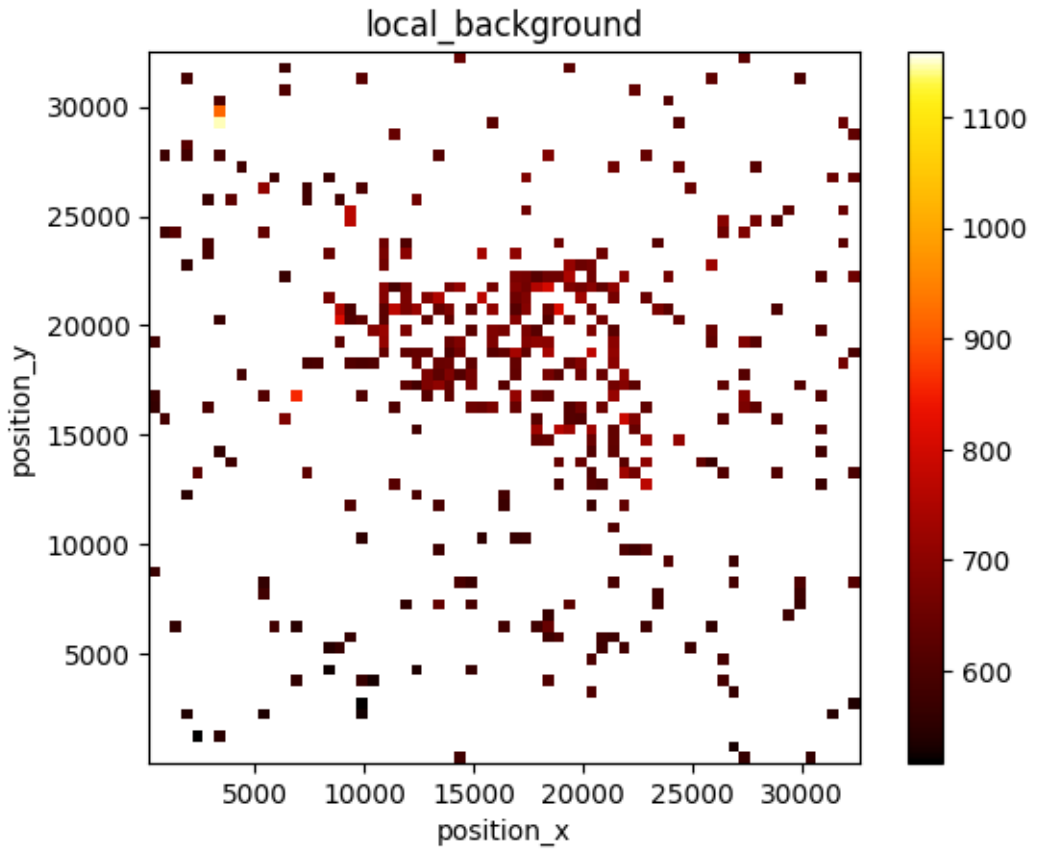
```
lpcorr.plot();
```



2.14.5 2-dimensional distribution of localization properties

In order to investigate a certain localization property in 2D you can just print the image with a color code representing the mean value of the chosen localization property in each bin.

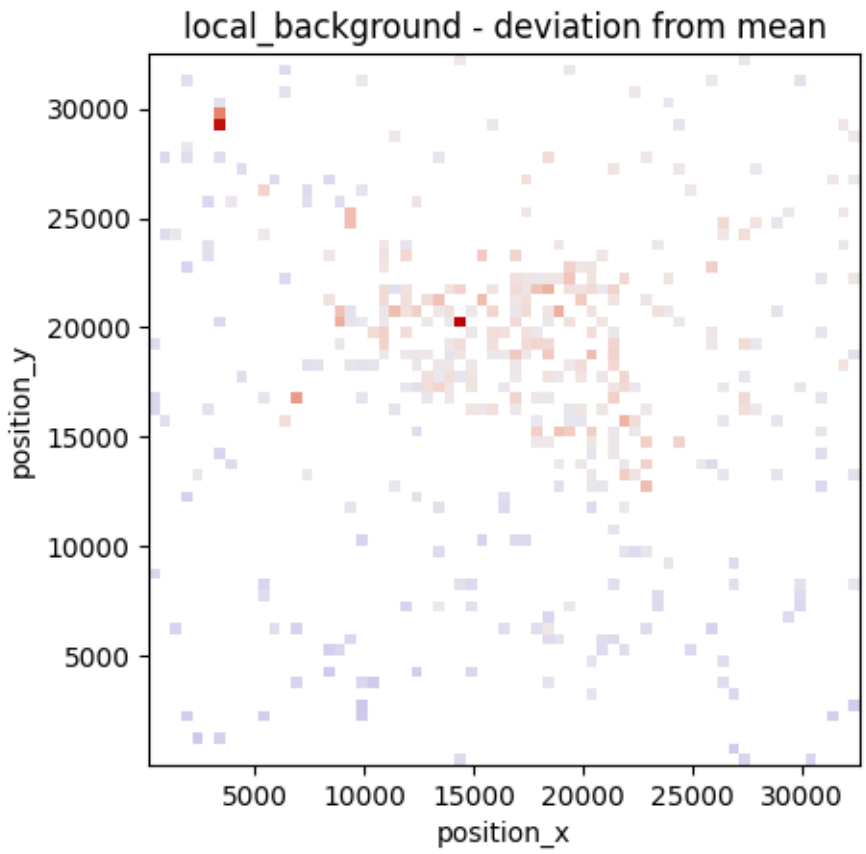
```
lc.render_2d_mpl(dat, other_property='local_background', bin_size=500);
```



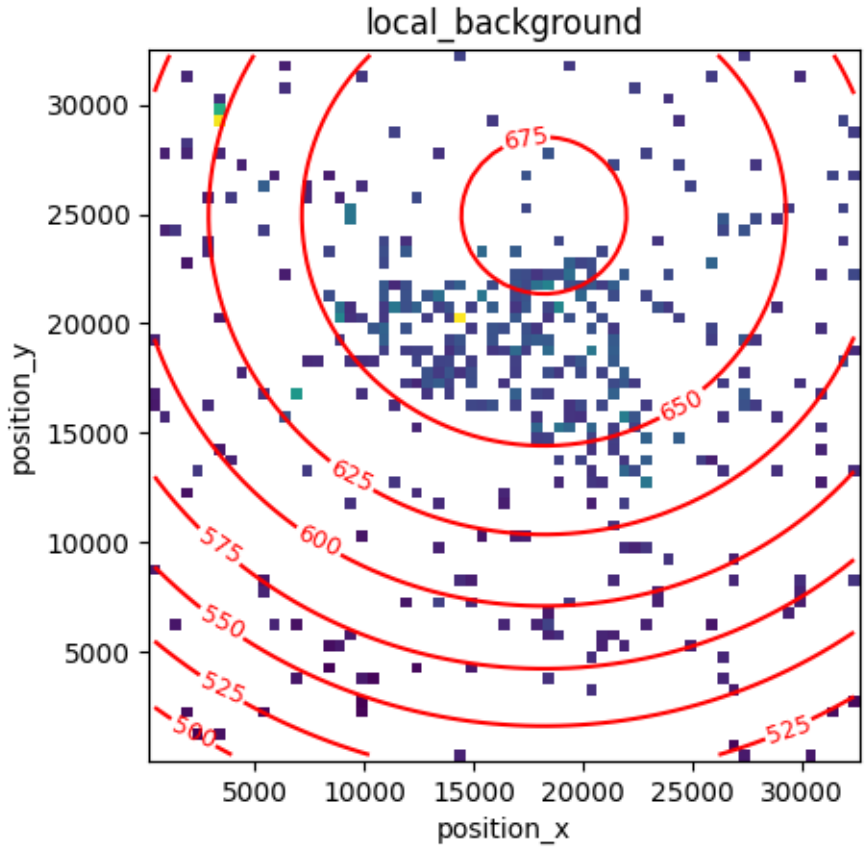
Otherwise use a specific class to analyse localization properties in 2d. Per default a bimodal normal distribution is fitted. This can e.g. help to check on even illumination during the recording.

```
lprop2d = lc.LocalizationProperty2d(loc_properties=None, other_property=
↪'local_background', bin_size=500).compute(dat)
```

```
lprop2d.plot_deviation_from_mean();
```




```
lprop2d.plot(colors="r");
```



```
lprop2d.report()
```

```
Fit results for:

[[Model]]
    Model(model_function)
[[Fit Statistics]]
    # fitting method   = leastsq
    # function evals   = 43
    # data points      = 376
    # variables        = 5
    chi-square         = 1243442.76
    reduced chi-square = 3351.59773
    Akaike info crit   = 3057.03082
    Bayesian info crit = 3076.67876
    R-squared          = 0.30136551
[[Variables]]
    amplitude:  678.367987 +/- 5.74065583 (0.85%) (init = 1159.15)
    center_x:   18232.4395 +/- 938.924230 (5.15%) (init = 16418.24)
    center_y:   24933.9120 +/- 2004.06733 (8.04%) (init = 16269.95)
    sigma_x:    37901.8750 +/- 3745.29060 (9.88%) (init = 8125)
    sigma_y:    36047.4467 +/- 3789.16551 (10.51%) (init = 8125)
[[Correlations]] (unreported correlations are < 0.250)
    C(center_y, sigma_y)   = +0.8897
    C(amplitude, center_y) = +0.6041
    C(amplitude, sigma_x)  = -0.5461
    C(amplitude, sigma_y)  = +0.3668
    C(center_x, sigma_x)   = +0.3125
    C(sigma_x, sigma_y)    = -0.2785
    C(center_y, sigma_x)   = -0.2735
Maximum fit value in image: 678.182
Minimum fit value in image: 501.283
Fit value variation over image range: 0.26
```

2.15 Tutorial about analyzing blink statistics

SMLM depends critically on the fluorescence intermittency or, in other words, the blinking of fluorescence dyes. To characterize blinking properties you can compute on- and off-periods from clustered localizations assuming that they originate from the same fluorophore.

```
from pathlib import Path

%matplotlib inline

import numpy as np
import matplotlib.pyplot as plt
import scipy.stats as stats
```

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```
import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.15.1 Synthetic data

We use synthetic data that represents localizations from a single fluorophore being normal distributed in space and emitting at a constant intensity. We assume that the on- and off-times in units of frames are distributed like a geometric distribution with a mean on_period `mean_on` and a mean off_period `mean_off`. Typically a geometric distribution is parameterized by a variable `p` with `p = 1 / mean`.

```
rng = np.random.default_rng(seed=1)
```

```
n_samples = 10_000
mean_on = 5
mean_off = 20

on_periods = stats.geom.rvs(p=1/mean_on, size=n_samples, random_state=rng)
off_periods = stats.geom.rvs(p=1/mean_off, size=n_samples, random_state=rng)
```

On- and off-times are converted in a series of frame numbers at which a localization was detected.

```
def periods_to_frames(on_periods, off_periods):
    """
    Convert on- and off-periods into a series of increasing frame values.
    """
    on_frames = np.arange(np.sum(on_periods))
    cumsums = np.r_[0, np.cumsum(off_periods)[:-1]]
    add_on = np.repeat(cumsums, on_periods)
    frames = on_frames + add_on
    return frames[:len(on_periods)]

frames = periods_to_frames(on_periods, off_periods)
```

```
offspring = [rng.normal(loc=0, scale=10, size=(n_samples, 2))]
locdata = lc.simulate_cluster(centers=[(50, 50)], region=[(0, 100), (0, 100)],
↪ offspring=offspring, clip=False, shuffle=False, seed=rng)
locdata.dataframe['intensity'] = 1
locdata.dataframe['frame'] = frames

locdata = lc.LocData.from_dataframe(dataframe=locdata.data)
```

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```
print('Data head:')
print(locdata.data.head(), '\n')
print('Summary:')
locdata.print_summary()
print('Properties:')
print(locdata.properties)
```

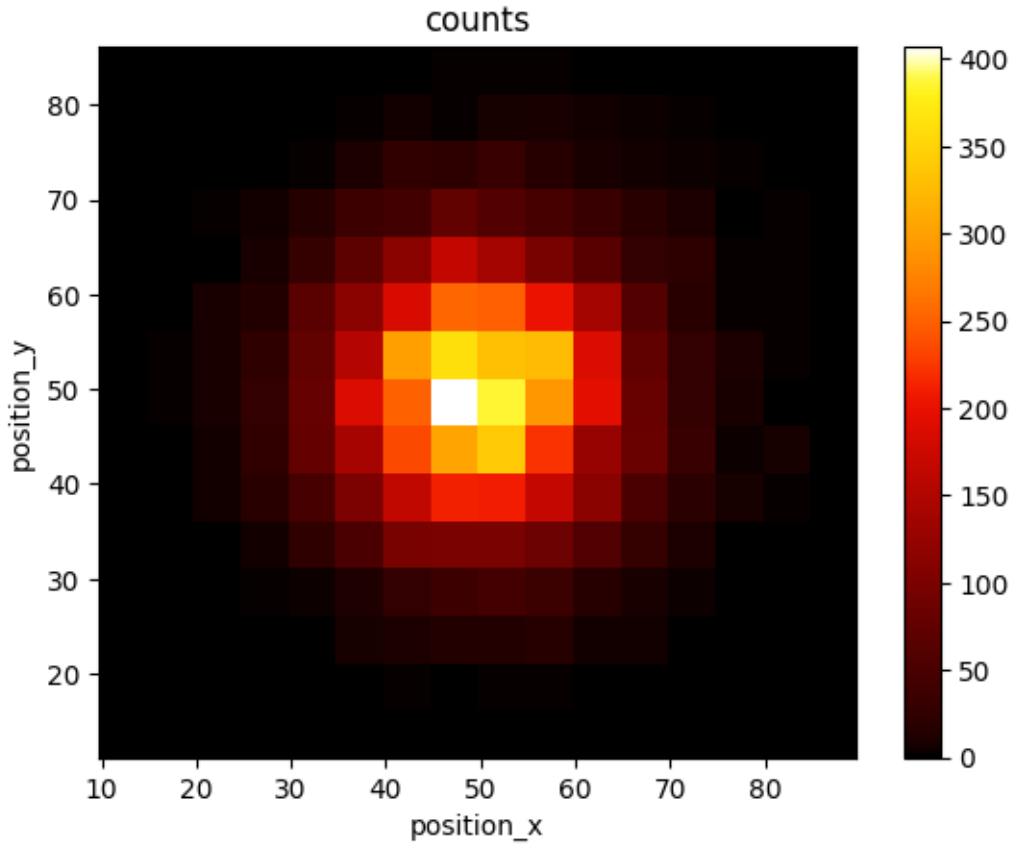
```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

```
Data head:
   position_x  position_y  cluster_label  intensity  frame
0   50.507149   36.698297              0          1      0
1   44.539062   27.969248              0          1      1
2   56.876954   42.152826              0          1      2
3   38.878363   43.999842              0          1      3
4   61.001644   54.231150              0          1      4

Summary:
identifier: "2"
comment: ""
source: DESIGN
state: RAW
element_count: 10000
frame_count: 10000
creation_time {
  2024-03-14T11:47:02.477887Z
}

Properties:
{'localization_count': 10000, 'position_x': 49.986893963647944, 'uncertainty_x
↪': 0.09881426457266232, 'position_y': 49.84659129517861, 'uncertainty_y': 0.
↪10007238629130723, 'intensity': 10000, 'frame': 0, 'region_measure_bb':␣
↪6466.041774468444, 'localization_density_bb': 1.5465411992056104,
↪'subregion_measure_bb': 322.0177777257221}
```

```
lc.render_2d(locdata, bin_size=5);
```



2.15.2 Blinking statistics

To determine on- and off-times for the observed blink events use the analysis class `BlinkStatistics`.

```
bs = lc.BlinkStatistics(memory=0, remove_heading_off_periods=False).
↪compute(locdata)
bs
```

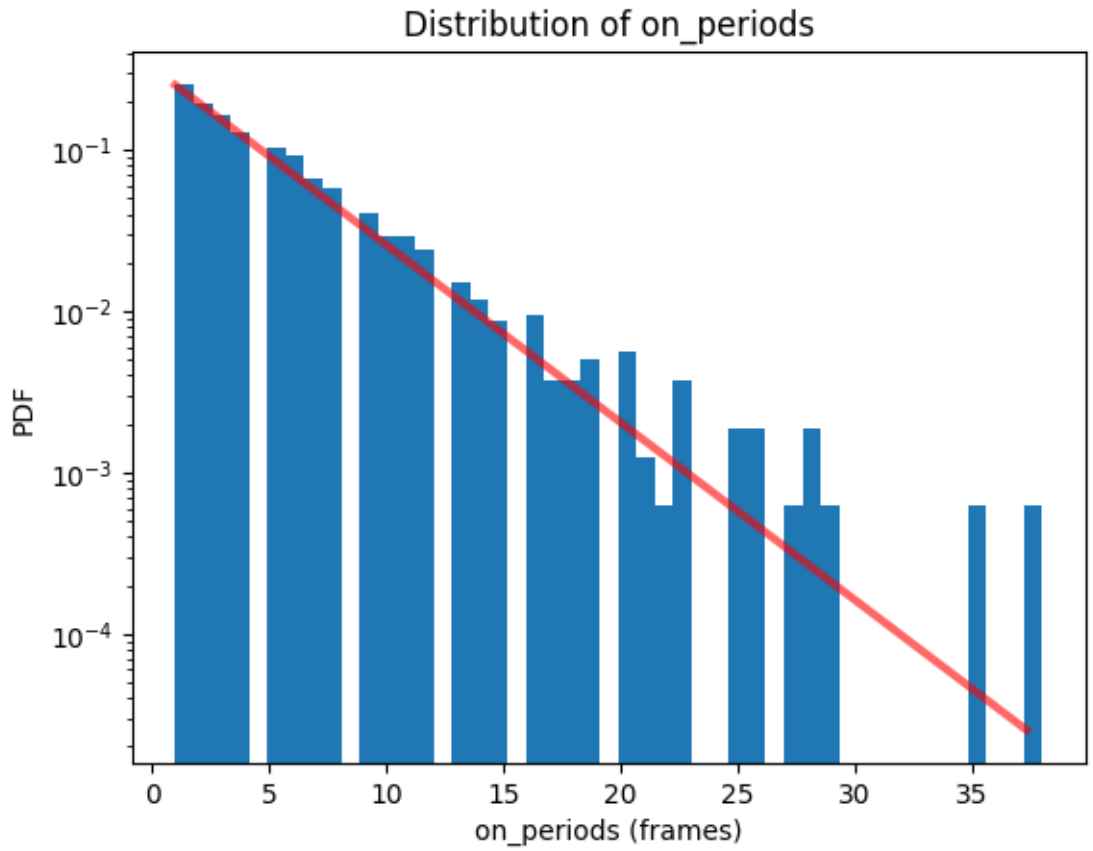
```
BlinkStatistics(memory=0, remove_heading_off_periods=False)
```

```
bs.results.keys()
```

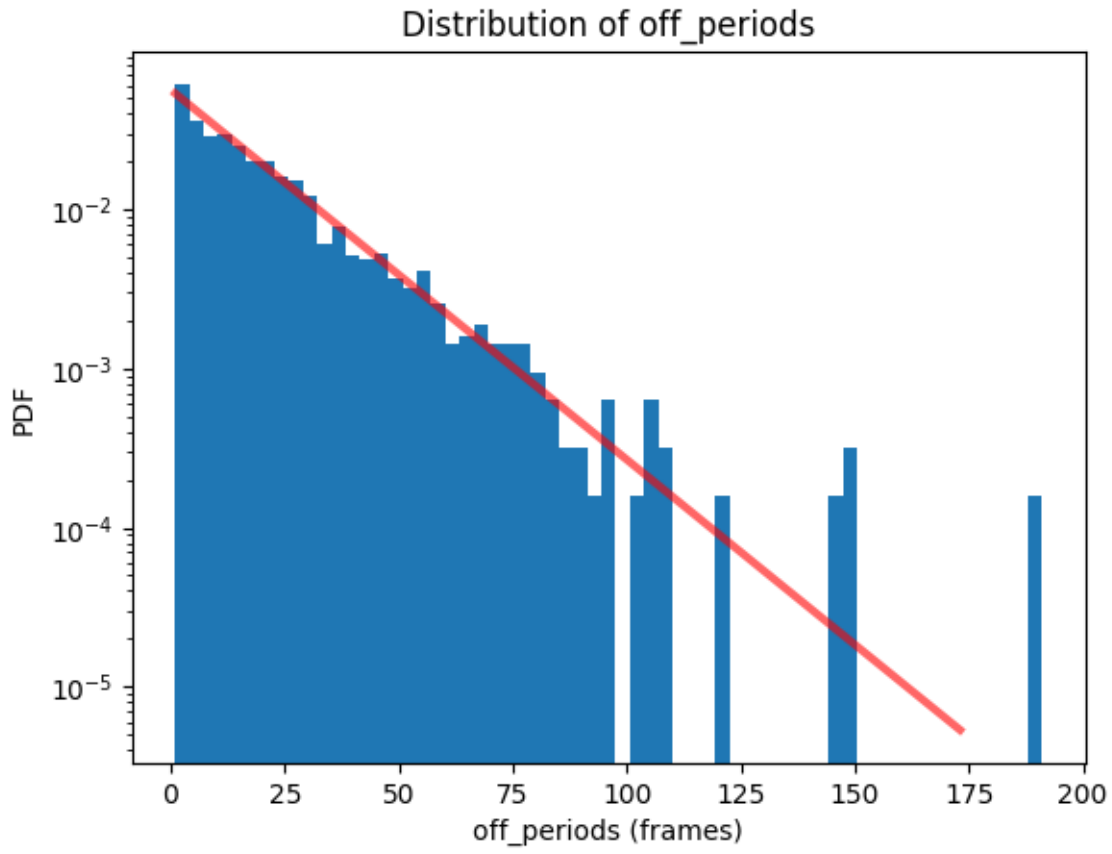
```
dict_keys(['on_periods', 'on_periods_frame', 'off_periods', 'off_periods_frame
↪', 'on_periods_indices'])
```

When plotting the histogram an exponential distribution is fitted by default.

```
bs.hist(data_identifier='on_periods');
```




```
bs.hist(data_identifier='off_periods');
```



```
bs.distribution_statistics
```

```
{'on_periods': _DistributionFits(analysis_class=BlinkStatistics,␣
↪distribution=expon_gen, data_identifier=on_periods),
 'off_periods': _DistributionFits(analysis_class=BlinkStatistics,␣
↪distribution=expon_gen, data_identifier=off_periods)}
```

The fit results provide `loc` and `scale` parameter (see `scipy.stats` documentation). For `loc = 0`, `scale` describes the mean of the distribution..

```
bs.distribution_statistics['on_periods'].parameter_dict()
```

```
{'on_periods_loc': 1.0, 'on_periods_scale': 3.9455984174085064}
```

```
bs.distribution_statistics['off_periods'].parameter_dict()
```

```
{'off_periods_loc': 1.0, 'off_periods_scale': 18.682830282038594}
```

Due to the default setting for the scaling parameter `loc` the mean on_period is `on_periods_scale + on_periods_loc` in agreement with our input value.

2.15.3 Geometric distribution

We can compare this with a geometric distribution that is estimated from the observed mean on_period `on_periods_mean`.

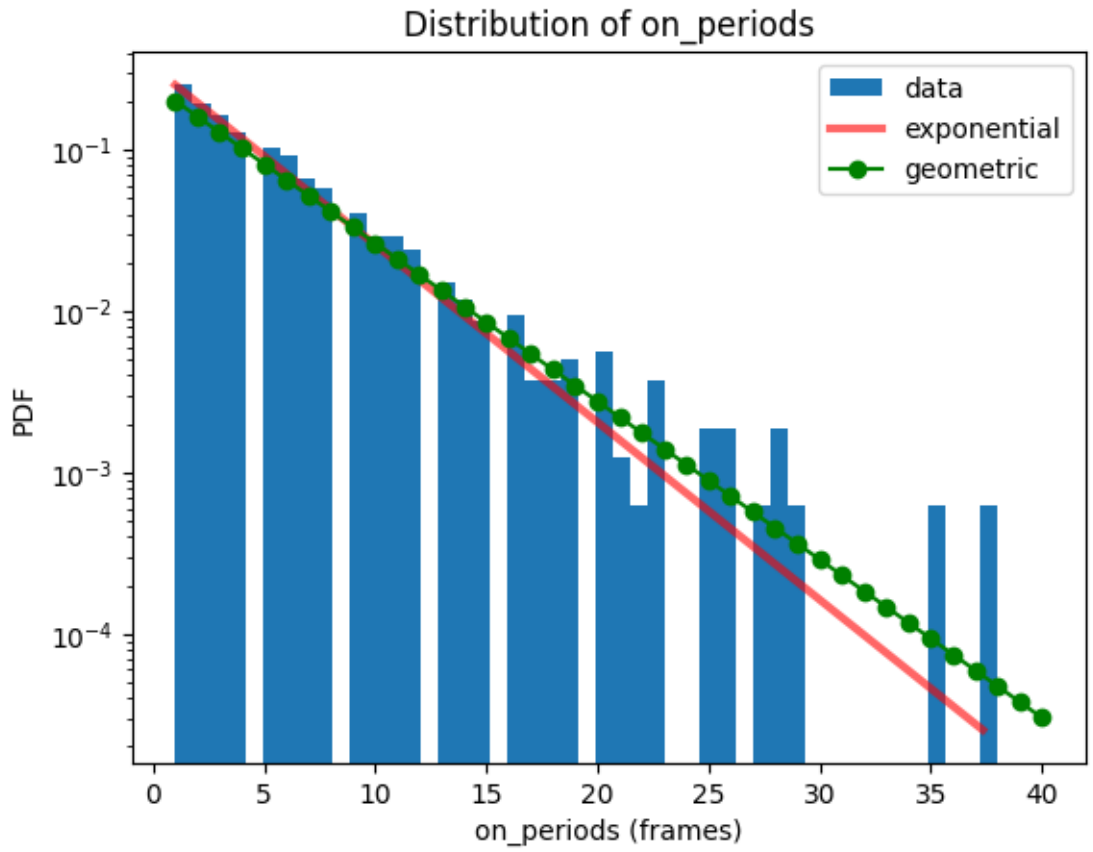
```
on_periods_mean = bs.results['on_periods'].mean()
on_periods_mean.round(2)
```

```
4.95
```

```
off_periods_mean = bs.results['off_periods'].mean()
off_periods_mean.round(2)
```

```
19.68
```

```
# test result
x = np.arange(stats.geom.ppf(0.01, 1/on_periods_mean), stats.geom.ppf(0.9999,␣
↪1/on_periods_mean))
y = stats.geom.pmf(x, 1/on_periods_mean)
fig, ax = plt.subplots()
bs.hist(data_identifier='on_periods', fit=False, label='data')
bs.distribution_statistics['on_periods'].plot(label='exponential')
ax.plot(x, y, '-go', label='geometric')
ax.set_yscale('log')
ax.legend(loc='best')
plt.show()
```



2.16 Tutorial about coordinate-based colocalization

Coordinate-based colocalization of two selections is computed as introduced by Malkusch et al. (1). A local density of locdata A is compared with the local density of locdata B within a varying radius for each localization in selection A. Local densities at various radii are compared by Spearman-rank-correlation and weighted by an exponential factor including the Euclidean distance to the nearest neighbor for each localization. The colocalization coefficient can take a value between -1 and 1 with -1 indicating anti-correlation (i.e. nearby localizations of selection B), 0 no colocalization, 1 strong colocalization.

The colocalization coefficient is provided as property for each localization within the corresponding dataset. The property key refers to colocalizing locdata A with locdata B.

```
from pathlib import Path

%matplotlib inline

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.colors as colors

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.16.1 Synthetic data

Provide synthetic data made of clustered localizations that are normal distributed around their center positions.

```
rng = np.random.default_rng(seed=1)
```

```
def set_centers(n_centers_1d=3, feature_range = (0, 1000)):
    dist = (feature_range[1] - feature_range[0])/(n_centers_1d + 1)
    centers = np.mgrid[feature_range[0] + dist : feature_range[1] : dist,␣
↪feature_range[0] + dist : feature_range[1] : dist].reshape(2, -1).T
    return centers
```

```
n_centers_1d = 3
feature_range = (0, 1000)
centers = set_centers(n_centers_1d, feature_range)
```

```
offspring = rng.normal(loc=0, scale=20, size=(len(centers), 100, 2))
locdata = lc.simulate_cluster(centers=centers, region=[feature_range] * 2,␣
↪offspring=offspring, clip=True, shuffle=True, seed=rng)

locdata.print_summary()
```

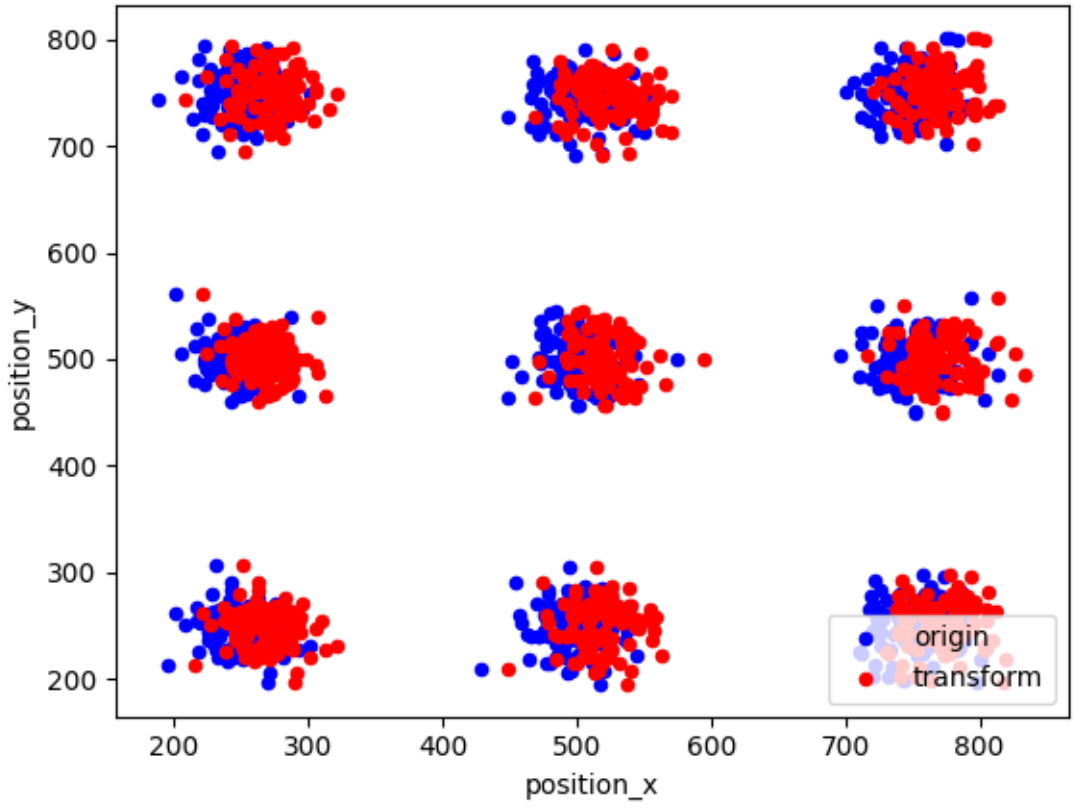
```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
identifier: "1"
comment: ""
source: SIMULATION
state: RAW
element_count: 900
frame_count: 0
creation_time {
  2024-03-14T11:47:43.997957Z
}
```

A second dataset is provided by shifting the first dataset by an offset.

```
locdata_trans = lc.transform_affine(locdata, offset=(20,0))
locdata_trans.print_summary()
```

```
identifier: "2"
comment: ""
source: SIMULATION
state: MODIFIED
element_count: 900
frame_count: 0
creation_time {
  2024-03-14T11:47:43.997957Z
}
modification_time {
  2024-03-14T11:47:44.013679Z
}
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
locdata.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Blue',
↪ label='origin')
locdata_trans.data.plot.scatter(x='position_x', y='position_y', ax=ax, color=
↪'Red', label='transform')
plt.show()
```



2.16.2 CBC computation

```
cbc = lc.CoordinateBasedColocalization(radius=100, n_steps=10).
↪compute(locdata=locdata, other_locdata=locdata_trans)
```

```
cbc.results.head()
```

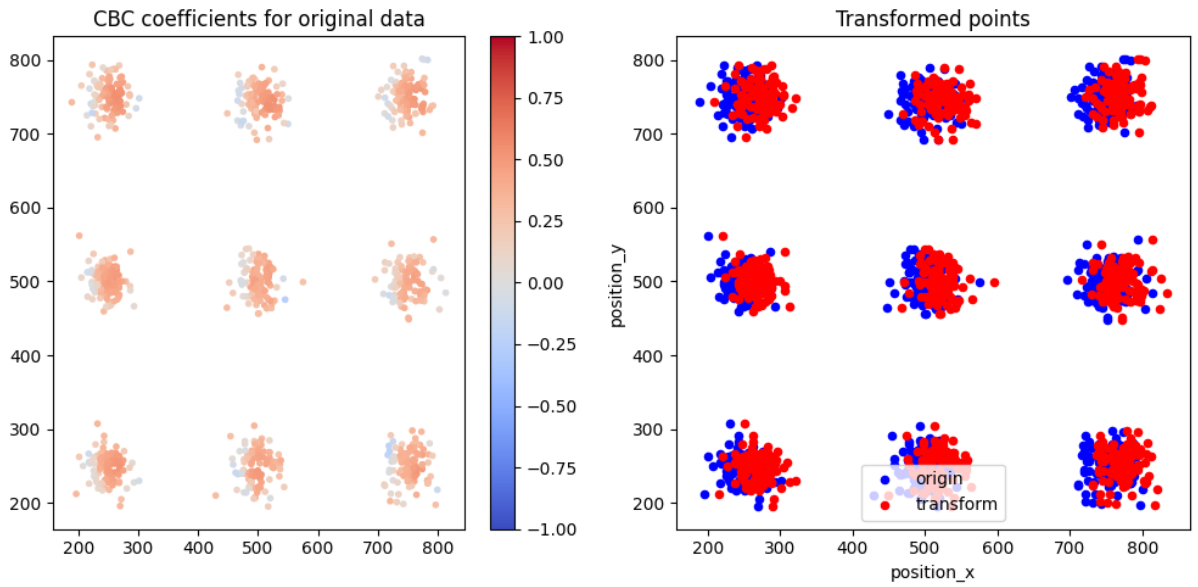
```
   colocalization_cbc_2
0              0.382530
1              0.280571
2              0.036730
3              0.152874
4              0.385790
```

2.16.3 Results

```
points = locdata.coordinates
color = cbc.results['colocalization_cbc_2'].values

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(10, 5))
cax = axes[0].scatter(x=points[:,0], y=points[:,1], marker='.', c=color, cmap=
↪'coolwarm', norm= colors.Normalize(-1., 1.), label='points')
axes[0].set_title('CBC coefficients for original data')

# axes[1].scatter(x=points[:,0], y=points[:,1], marker='.', color='Blue', label=
↪'points')
# axes[1].scatter(x=points_trans[:,0], y=points_trans[:,1], marker='o', color=
↪'Red', label='transformed points')
locdata.data.plot.scatter(x='position_x', y='position_y', ax=axes[1], color=
↪'Blue', label='origin')
locdata_trans.data.plot.scatter(x='position_x', y='position_y', ax=axes[1],␣
↪color='Red', label='transform')
axes[1].set_title('Transformed points')
plt.colorbar(cax, ax=axes[0])
plt.tight_layout()
plt.show()
```



2.16.4 CBC for various shifts

```
n_centers_1d = 3
feature_range = (0, 2000)
centers = set_centers(n_centers_1d, feature_range)
```

```
offspring = rng.normal(loc=0, scale=20, size=(len(centers), 100, 2))
locdata = lc.simulate_cluster(centers=centers, region=[feature_range] * 2,␣
↪offspring=offspring, clip=True, shuffle=True, seed=rng)

locdata.print_summary()
```

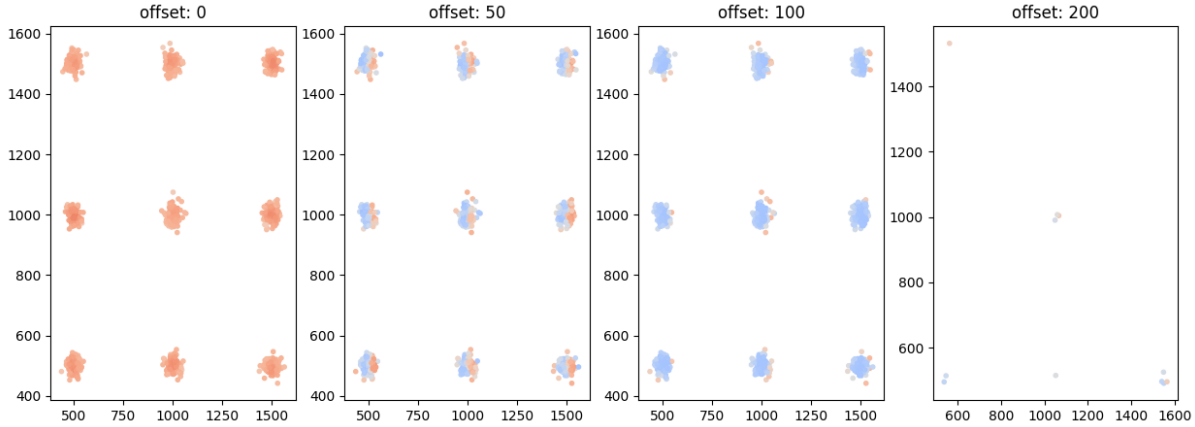
```
identifier: "3"
comment: ""
source: SIMULATION
state: RAW
element_count: 900
frame_count: 0
creation_time {
  2024-03-14T11:47:46.473832Z
}
```

```
offsets = [0, 50, 100, 200]
locdata_trans_list = [lc.transform_affine(locdata, offset=(offset, 0)) for␣
↪offset in offsets]
```

```
cbc_list = [lc.CoordinateBasedColocalization(radius=100, n_steps=10).
↪compute(locdata=locdata, other_locdata=other_locdata) for other_locdata in␣
↪locdata_trans_list]
```

```
points = locdata.coordinates
n_rows = 1
n_cols = 4

fig = plt.figure(figsize=(15, 5))
for n, (cbc, offset) in enumerate(zip(cbc_list, offsets)):
    ax = fig.add_subplot(n_rows, n_cols, n+1)
    color = cbc.results.iloc[:, 0].values
    ax.scatter(x=points[:,0], y=points[:,1], marker='.', c=color, cmap=
↪'coolwarm', norm=colors.Normalize(-1., 1.))
    ax.set_title(f'offset: {offset}')
plt.show()
```



2.16.5 CBC on various length scales (for small cluster)

```
n_centers_1d = 3
feature_range = (0, 2000)
centers = set_centers(n_centers_1d, feature_range)
```

```
offspring = rng.normal(loc=0, scale=20, size=(len(centers), 100, 2))
locdata = lc.simulate_cluster(centers=centers, region=[feature_range] * 2,␣
↪offspring=offspring, clip=True, shuffle=True, seed=rng)
```

```
offsets = [0, 50, 100, 200]
locdata_trans_list = [lc.transform_affine(locdata, offset=(offset,0)) for␣
↪offset in offsets]
```

```
radii = [50, 100, 150, 200, 250, 300, 350, 400]
cbc_list = [lc.CoordinateBasedColocalization(radius=radius, n_steps=10).
↪compute(locdata=locdata, other_locdata=other_locdata) for radius in radii
            for other_locdata in locdata_trans_list
           ]
```

```
points = locdata.coordinates
params = [(radius, offset) for radius in radii for offset in offsets]
```

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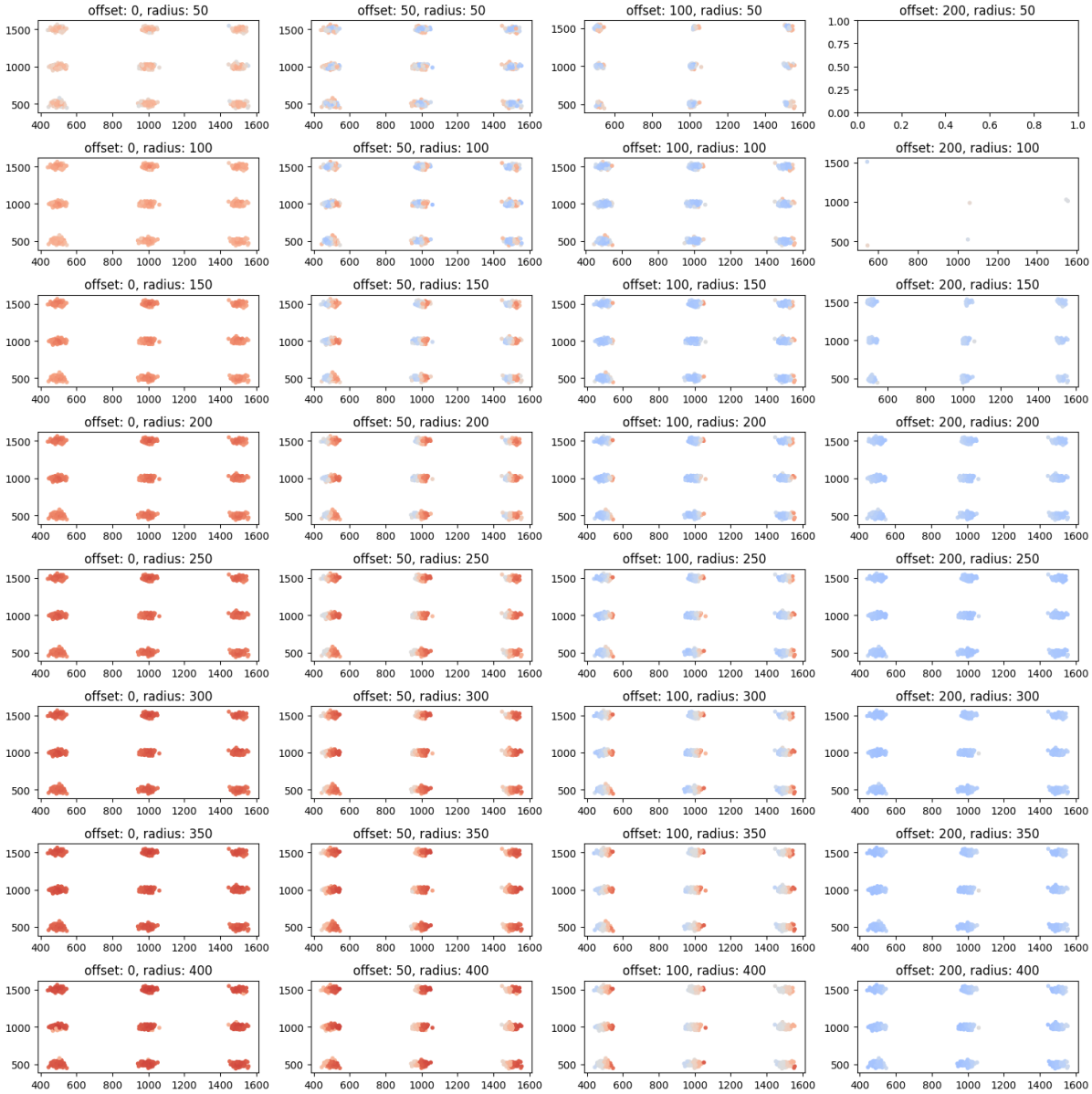
```
n_rows = len(radii)
n_cols = len(offsets)

fig = plt.figure(figsize=(15, 15))
for n, (cbc, (radius, offset)) in enumerate(zip(cbc_list, params)):
    ax = fig.add_subplot(n_rows, n_cols, n+1)
    color = cbc.results.iloc[:, 0].values
    if not all(np.isnan(color)):
        ax.scatter(x=points[:,0], y=points[:,1], marker='.', c=color, cmap=
↪'coolwarm', norm=colors.Normalize(-1., 1.))
    ax.set_title(f'offset: {offset}, radius: {radius}')
plt.tight_layout()
plt.show()
```



2.16.6 CBC on various length scales (for larger cluster)

```
n_centers_1d = 3
feature_range = (0, 10_000)
centers = set_centers(n_centers_1d, feature_range)
```

```
offspring = rng.normal(loc=0, scale=100, size=(len(centers), 100, 2))
locdata = lc.simulate_cluster(centers=centers, region=[feature_range] * 2,␣
↪offspring=offspring, clip=True, shuffle=True, seed=rng)
```

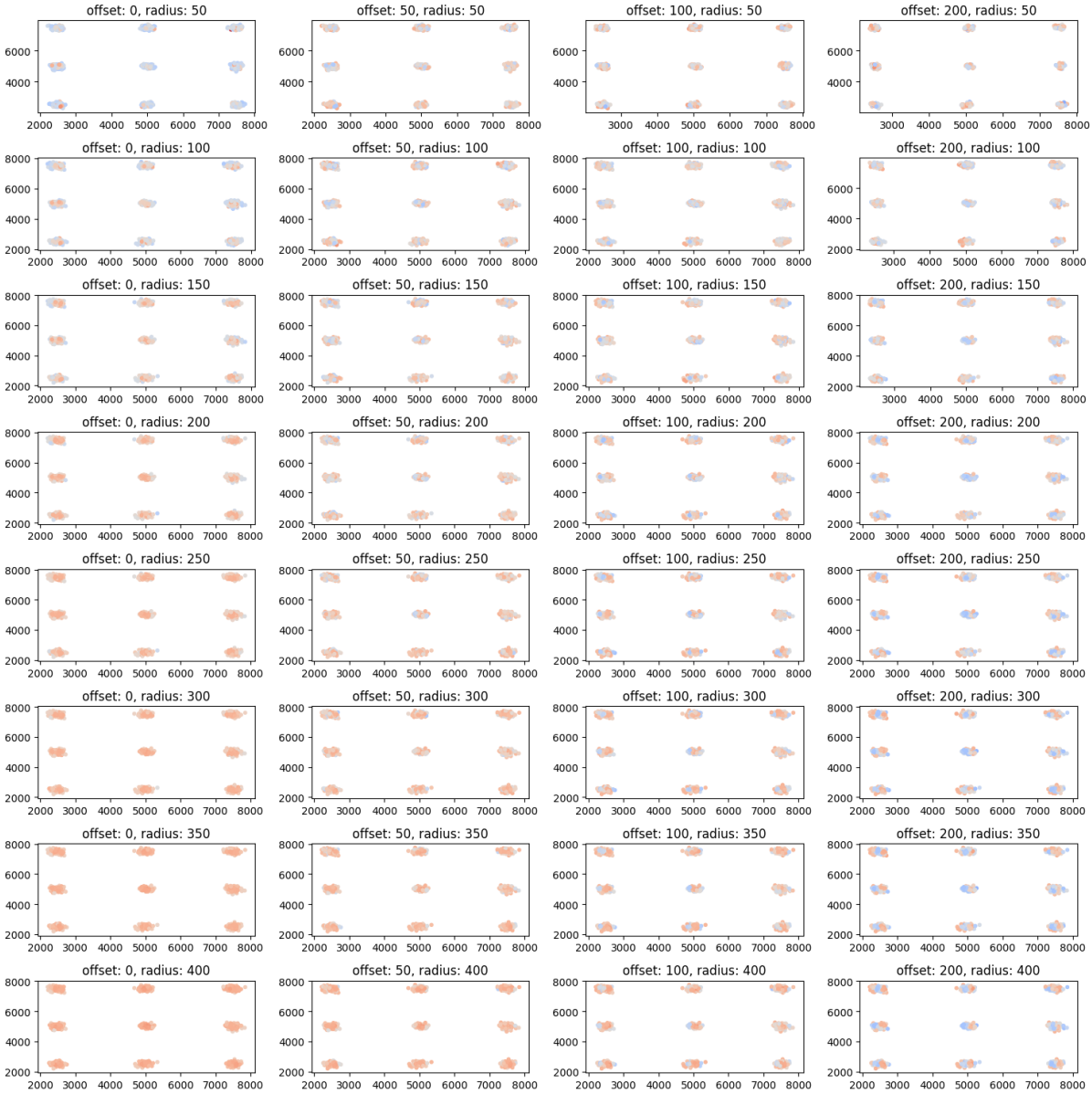
```
offsets = [0, 50, 100, 200]
locdata_trans_list = [lc.transform_affine(locdata, offset=(offset,0)) for␣
↪offset in offsets]
```

```
radii = [50, 100, 150, 200, 250, 300, 350, 400]
cbc_list = [lc.CoordinateBasedColocalization(radius=radius, n_steps=10).
↪compute(locdata=locdata, other_locdata=other_locdata) for radius in radii
            for other_locdata in locdata_trans_list
           ]
```

```
points = locdata.coordinates
params = [(radius, offset) for radius in radii for offset in offsets]

n_rows = len(radii)
n_cols = len(offsets)

fig = plt.figure(figsize=(15, 15))
for n, (cbc, (radius, offset)) in enumerate(zip(cbc_list, params)):
    ax = fig.add_subplot(n_rows, n_cols, n+1)
    color = cbc.results.iloc[:, 0].values
    ax.scatter(x=points[:,0], y=points[:,1], marker='.', c=color, cmap=
↪'coolwarm', norm=colors.Normalize(-1., 1.))
    ax.set_title(f'offset: {offset}, radius: {radius}')
plt.tight_layout()
plt.show()
```



2.17 Tutorial about drift analysis and correction

Lateral drift correction is useful in most SMLM experiments. To determine the amount of drift a method based on image cross-correlation or an iterative closest point algorithm can be applied.

We demonstrate drift analysis and correction on simulated data.

```
from pathlib import Path

%matplotlib inline

import numpy as np
import matplotlib.pyplot as plt
import scipy.stats as stats

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.17.1 Synthetic data

We use synthetic data that follows a Neyman-Scott spatial distribution (blobs). The intensity values are exponentially distributed and the number of localizations per frame follows a Poisson distribution:

```
rng = np.random.default_rng(seed=1)
```

```
intensity_mean = 1000
localizations_per_frame_mean = 3
```

```
dat_blob = lc.simulate_Thomas(parent_intensity=1e-4, region=((0, 1000), (0,␣
↪1000)), cluster_mu=1000, cluster_std=10, seed=rng)
dat_blob.dataframe['intensity'] = stats.expon.rvs(scale=intensity_mean,␣
↪size=len(dat_blob), loc=500)
dat_blob.dataframe['frame'] = lc.simulate_frame_numbers(n_samples=len(dat_
↪blob), lam=localizations_per_frame_mean, seed=rng)

dat_blob = lc.LocData.from_dataframe(dataframe=dat_blob.data)

print('Data head:')
print(dat_blob.data.head(), '\n')
print('Summary:')
dat_blob.print_summary()
print('Properties:')
print(dat_blob.properties)
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

```
Data head:
   position_x  position_y  cluster_label    intensity  frame
0  915.763326  465.421770             28  5095.090347      0
1  729.786200   81.672520             56  1028.556965      1
2  869.708004    9.266125             41  1180.104826      1
3  521.743493   54.508814             14  3338.589490      2
4  430.972011  375.461311             61  1291.304555      3

Summary:
identifier: "2"
```

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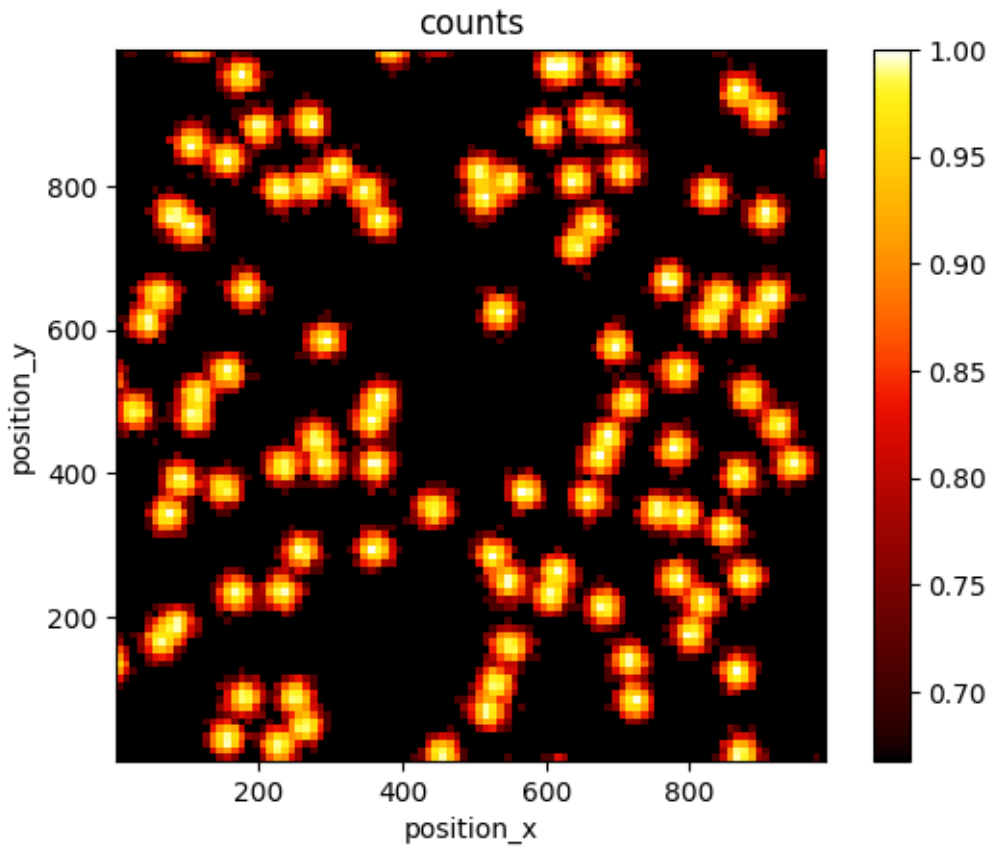
```
comment: ""
source: DESIGN
state: RAW
element_count: 98201
frame_count: 31016
creation_time {
  2024-03-14T11:47:11.068185Z
}

Properties:
{'localization_count': 98201, 'position_x': 495.13588743804684, 'uncertainty_x
↪': 0.8971814298938875, 'position_y': 507.65355920347866, 'uncertainty_y': 0.
↪8964573205917536, 'intensity': 147436243.22855878, 'frame': 0, 'region_
↪measure_bb': 999959.2361869529, 'localization_density_bb': 0.
↪09820500321039116, 'subregion_measure_bb': 3999.918472062067}
```

```
lc.render_2d(dat_blob, bin_size=10, rescale='equal');
```

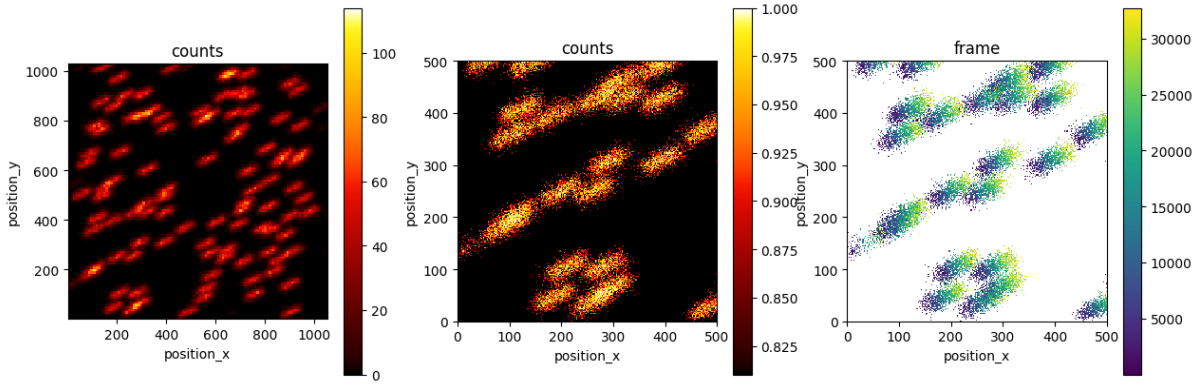


2.17.2 Add linear drift

We add linear drift with a velocity given in length units per frame.

```
dat_blob_with_drift = lc.add_drift(dat_blob, velocity=(0.002, 0.001),␣
↪seed=rng)
```

```
fig, axes = plt.subplots(1, 3, figsize=(15, 5))
lc.render_2d(dat_blob_with_drift, ax=axes[0], bin_size=10);
lc.render_2d(dat_blob_with_drift, ax=axes[1], bin_size=2, rescale='equal',␣
↪bin_range=((0, 500),(0, 500)));
lc.render_2d_mpl(dat_blob_with_drift, ax=axes[2], other_property='frame', bin_
↪size=2, bin_range=((0, 500),(0, 500)), cmap='viridis');
```



2.17.3 Estimate RMS errors

Knowing the ground truth, you can define a root mean squared error between the original localization coordinates and those after drift and later after correction.

```
def rmse(locdata, other_locdata):
    return np.sqrt(np.mean(np.square(np.subtract(locdata.coordinates, other_
↪locdata.coordinates)), axis=0))
```

```
rmse(dat_blob, dat_blob_with_drift).round(2)
```

```
array([37.76, 18.88])
```

2.17.4 Estimate drift

Drift can be estimated by comparing different chunks of successive localizations using either an “iterative closest point” algorithm or a “cross-correlation” algorithm. Per default, the icp algorithm is applied.

```
%%time
drift = lc.Drift(chunk_size=10_000, target='first', method='icp').compute(dat_
↪blob_with_drift)
```

```
CPU times: user 7.99 s, sys: 21.8 ms, total: 8.01 s
Wall time: 4.46 s
```

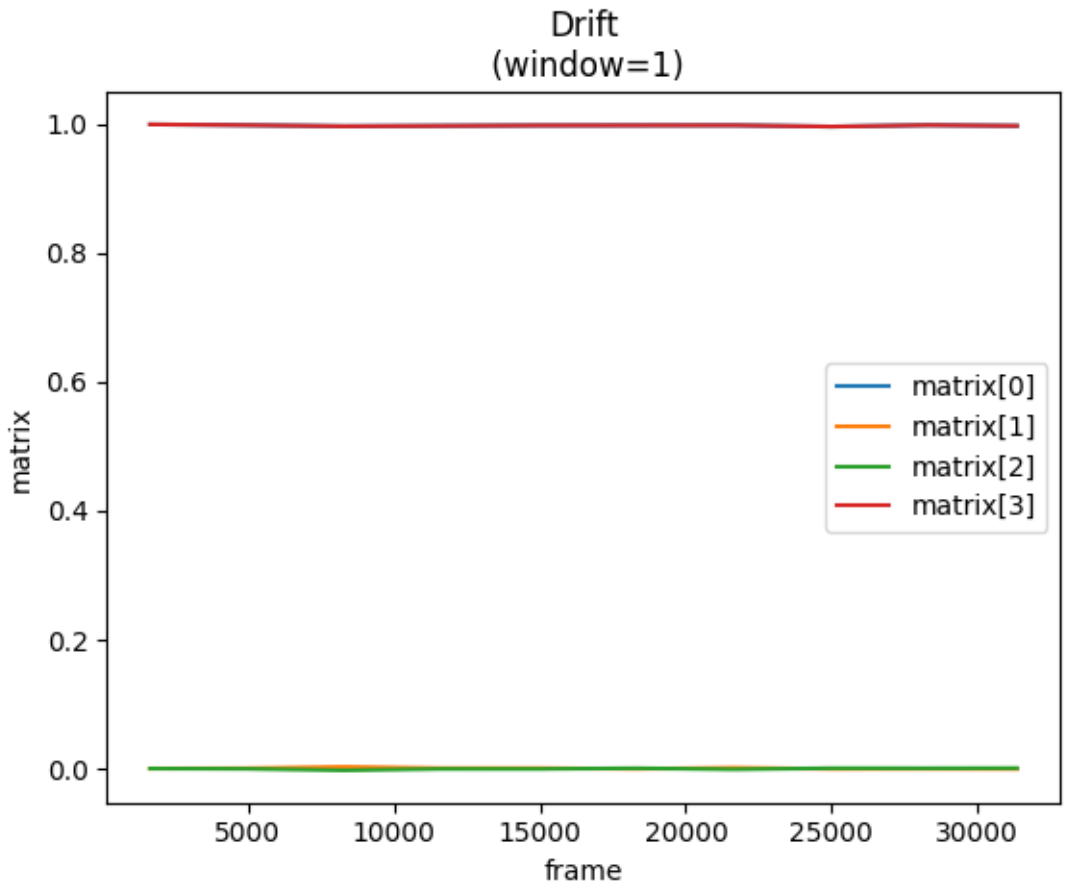
Transformations to register the different data chunks are represented by a transformation matrix and a transformation offset that together specifiy an affine transformation. The tansformation parameters are kept under the `transformations` attribute.

```
drift.transformations
```

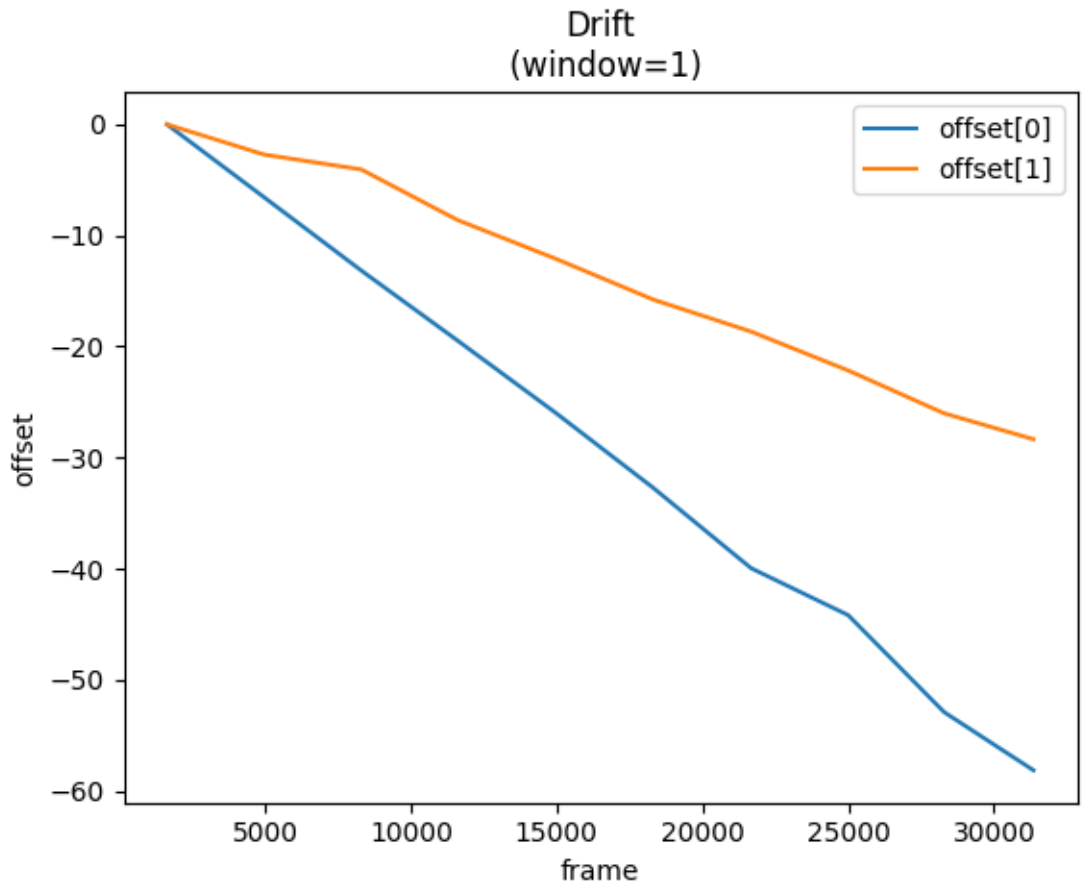
```
[Transformation(matrix=array([[1., 0.],
        [0., 1.]]), offset=array([0., 0.])),
 Transformation(matrix=array([[ 9.98792443e-01,  4.43801557e-04],
        [-4.43801557e-04,  9.98792443e-01]]), offset=array([-6.56553239, -2.
↪7171172 ])),
 Transformation(matrix=array([[ 0.99716405,  0.00268322],
        [-0.00268322,  0.99716405]]), offset=array([-13.15345296,  -4.
↪05470652])),
 Transformation(matrix=array([[ 9.97764214e-01,  5.81845172e-04],
        [-5.81845172e-04,  9.97764214e-01]]), offset=array([-19.46087507,  -8.
↪60939708])),
 Transformation(matrix=array([[ 9.98398817e-01,  6.25680278e-04],
        [-6.25680278e-04,  9.98398817e-01]]), offset=array([-25.94756073, -12.
↪08151622])),
 Transformation(matrix=array([[ 9.98495460e-01, -4.65982241e-04],
        [ 4.65982241e-04,  9.98495460e-01]]), offset=array([-32.71859007, -15.
↪76861207])),
 Transformation(matrix=array([[ 0.99857889,  0.00120287],
        [-0.00120287,  0.99857889]]), offset=array([-39.95058187, -18.
↪65026698])),
 Transformation(matrix=array([[ 9.96629116e-01, -5.37378964e-04],
        [ 5.37378964e-04,  9.96629116e-01]]), offset=array([-44.18251022, -22.
↪15203275])),
 Transformation(matrix=array([[ 9.98851114e-01, -4.33292180e-04],
        [ 4.33292180e-04,  9.98851114e-01]]), offset=array([-52.9063275 , -26.
↪00989829])),
 Transformation(matrix=array([[ 9.97771654e-01, -6.47144209e-04],
        [ 6.47144209e-04,  9.97771654e-01]]), offset=array([-58.14458854, -28.
↪33975215]))]
```

The parameters can be visualized using the plot function. The matrix in this case is close to the unit matrix.

```
drift.plot(transformation_component='matrix', element=None);
plt.legend();
```




```
drift.plot(transformation_component='offset', element=None)
plt.legend();
```

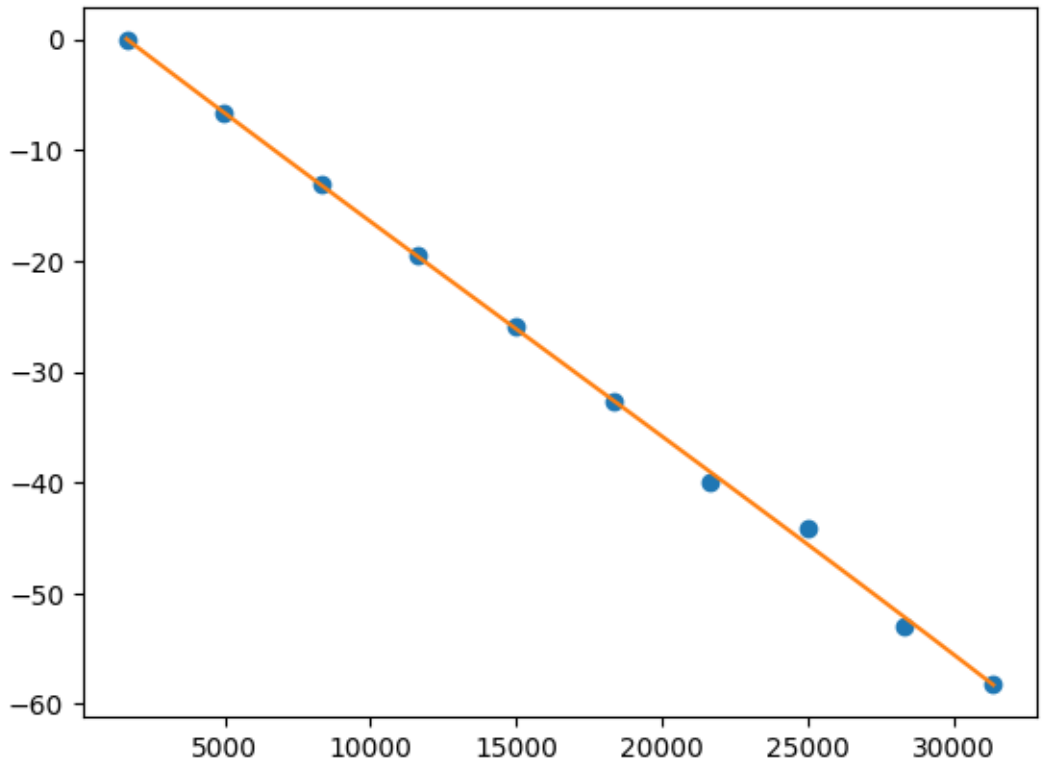


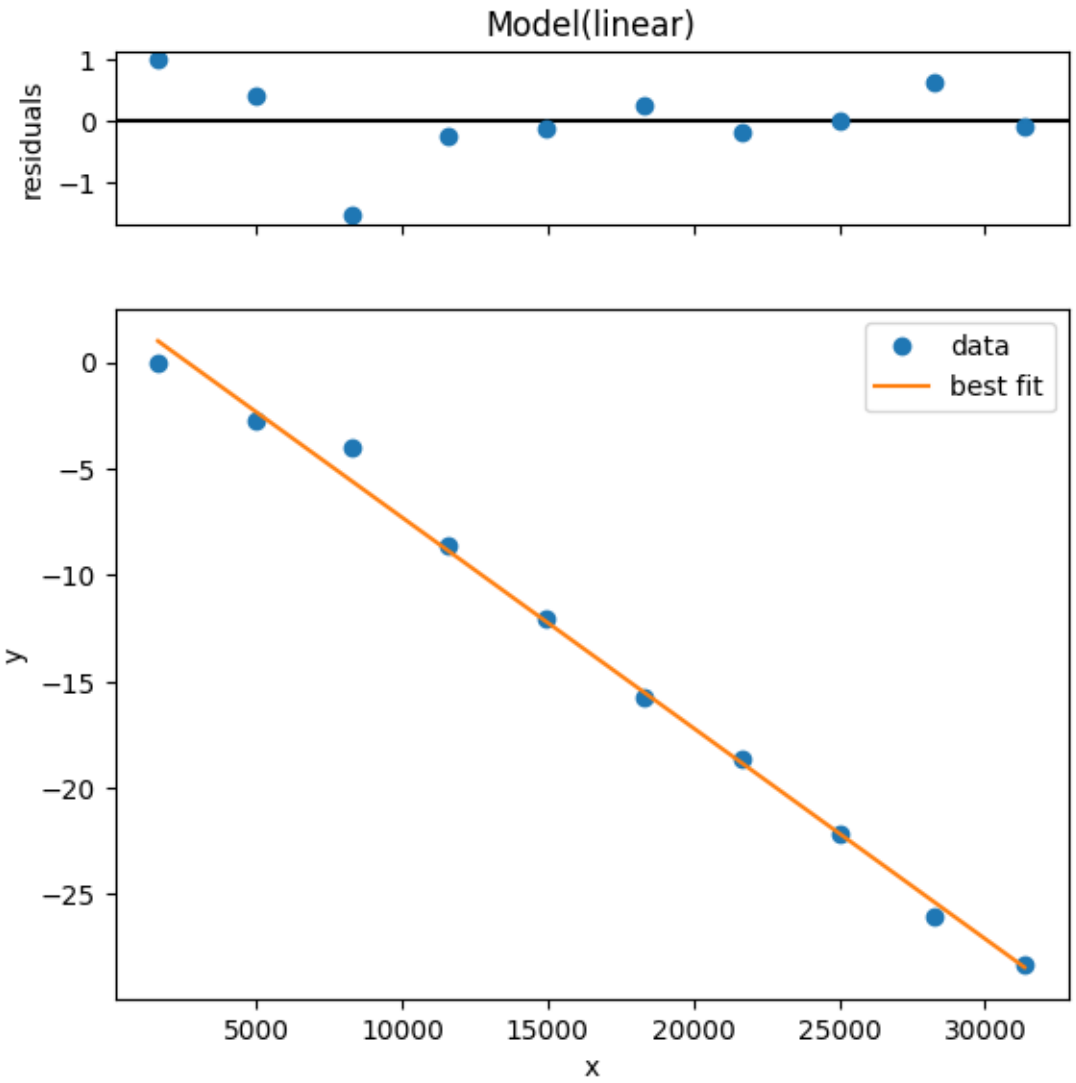
2.17.5 Model drift

A continuous transformation model as function of frame number is estimated by fitting the individual transformation components with the specified fit models. Fit models can be provided as `DriftComponent` or by a string representing standard model functions.

```
from lmfit.models import ConstantModel, LinearModel, PolynomialModel

drift.fit_transformations(slice_data=slice(None), offset_models=(lc.
↪DriftComponent('spline', s=100), 'linear'), verbose=True);
```


0
−10
−20
−30
−40
−50
−60
5000
10000
15000
20000
25000
30000



The fit models are represented as `DriftComponent` and can be accessed through the transformation_models attribute.

```
drift.transformation_models
```

```
{'matrix': None,
 'offset': [<locan.analysis.drift.DriftComponent at 0x7ff97cd4eaa0>,
  <locan.analysis.drift.DriftComponent at 0x7ff97cdbca30>]}
```

```
drift.transformation_models['offset'][0].type
```

```
'spline'
```

```
drift.transformation_models['offset'][0].eval(0)
```

```
array(3.33056629)
```

Each `DriftModel` carries detailed information about the fit under the model_result attribute. In most cases, except splines, this will be a `lmfit.ModelResult` object.

```
drift.transformation_models['offset'][0].model_result
```

```
(array([ 1639.0867    ,  1639.0867    ,  1639.0867    ,  1639.0867    ,
        31356.39897573, 31356.39897573, 31356.39897573, 31356.39897573]),
 array([ 3.39564863e-02, -1.98083279e+01, -3.82432449e+01, -5.82808309e+01,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00,  0.00000000e+00]),
 3)
```

```
drift.transformation_models['offset'][1].type
```

```
'linear'
```

```
drift.transformation_models['offset'][1].model_result
```

```
<lmfit.model.ModelResult at 0x7ff97cdbdfc0>
```

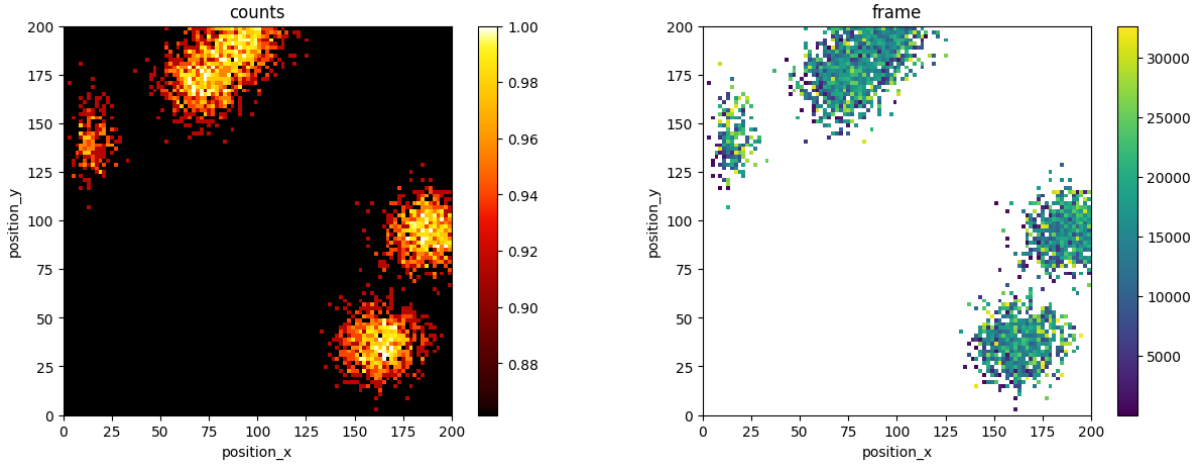
2.17.6 Drift correction

The estimated drift is corrected by applying a transformation on the localization chunks (from_model=False).

```
%%time
drift.apply_correction(from_model=False);
```

```
CPU times: user 390 ms, sys: 8.14 ms, total: 398 ms
Wall time: 397 ms
```

```
fig, axes = plt.subplots(1, 2, figsize=(15, 5))
lc.render_2d(drift.locdata_corrected, ax=axes[0], bin_size=2, rescale='equal',
↪ bin_range=((0, 200),(0, 200)));
lc.render_2d_mpl(drift.locdata_corrected, ax=axes[1], other_property='frame',␣
↪bin_size=2, bin_range=((0, 200),(0, 200)), cmap='viridis');
```



```
rmse(dat_blob, drift.locdata_corrected).round(2)
```

```
array([9.55, 4.82])
```

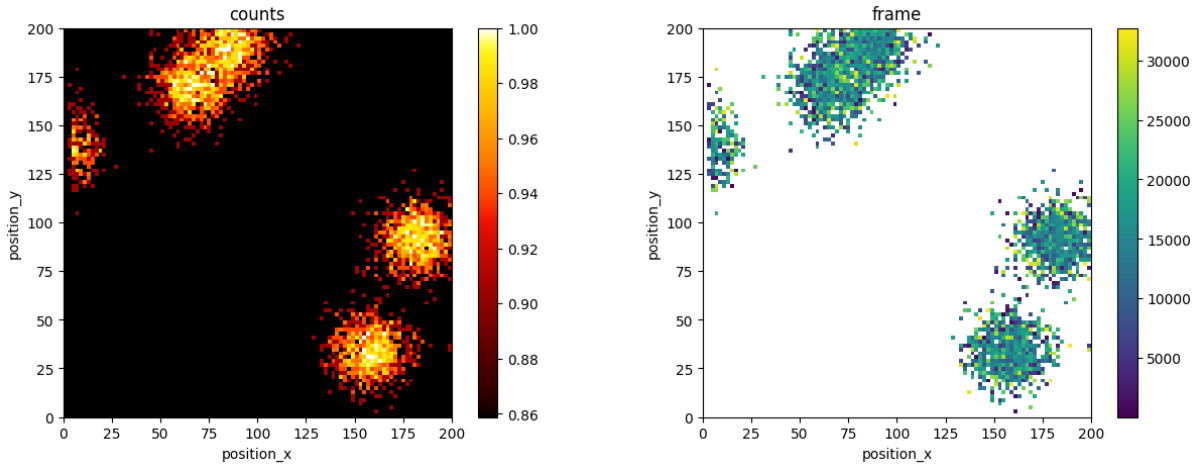
Or the estimated drift is corrected by applying a transformation on each individual localization using the drift models (from_model=True).

```
%%time
drift.apply_correction(from_model=True)
```

```
CPU times: user 68.7 ms, sys: 8.03 ms, total: 76.7 ms
Wall time: 76.1 ms
```

```
Drift(chunks=None, chunk_size=10000, n_chunks=None, target=first, method=icp,␣
↪kwargs_chunk=None, kwargs_register=None)
```

```
fig, axes = plt.subplots(1, 2, figsize=(15, 5))
lc.render_2d(drift.locdata_corrected, ax=axes[0], bin_size=2, rescale='equal',
↪ bin_range=((0, 200),(0, 200)));
lc.render_2d_mpl(drift.locdata_corrected, ax=axes[1], other_property='frame',␣
↪bin_size=2, bin_range=((0, 200),(0, 200)), cmap='viridis');
```




```
rmse(dat_blob, drift.locdata_corrected).round(2)
```

```
array([3.93, 2.77])
```

```
drift.locdata_corrected.meta
```

```
identifier: "26"
source: DESIGN
state: MODIFIED
history {
  name: "LocData.from_dataframe"
}
history {
```

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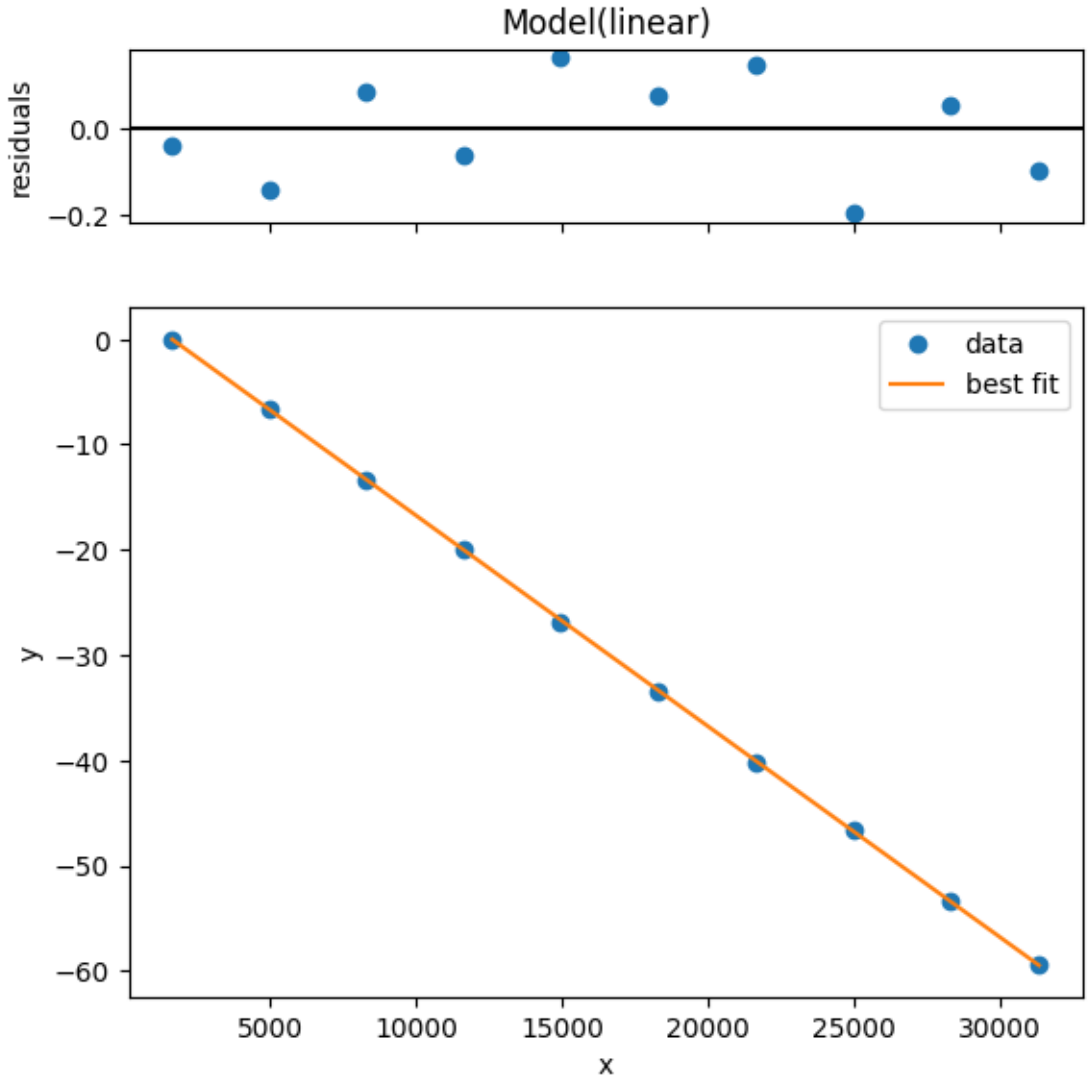
```
  name: "add_drift"
  parameter: "{\'locdata\': <locan.data.locdata.LocData object at␣
↪0x7ff99ba29cf0>, \'diffusion_constant\': None, \'velocity\': (0.002, 0.001),
↪ \'seed\': Generator(PCG64) at 0x7FF99B992B20}"
}
history {
  name: "apply_correction"
  parameter: "{\'self\': Drift(chunks=None, chunk_size=10000, n_chunks=None,␣
↪target=first, method=icp, kwargs_chunk=None, kwargs_register=None), \
↪'locdata\': None, \'from_model\': True}"
}
ancestor_identifiers: "2"
ancestor_identifiers: "3"
element_count: 98201
frame_count: 31016
creation_time {
  seconds: 1710416831
  nanos: 68185000
}
modification_time {
  seconds: 1710416840
  nanos: 437788000
}
```

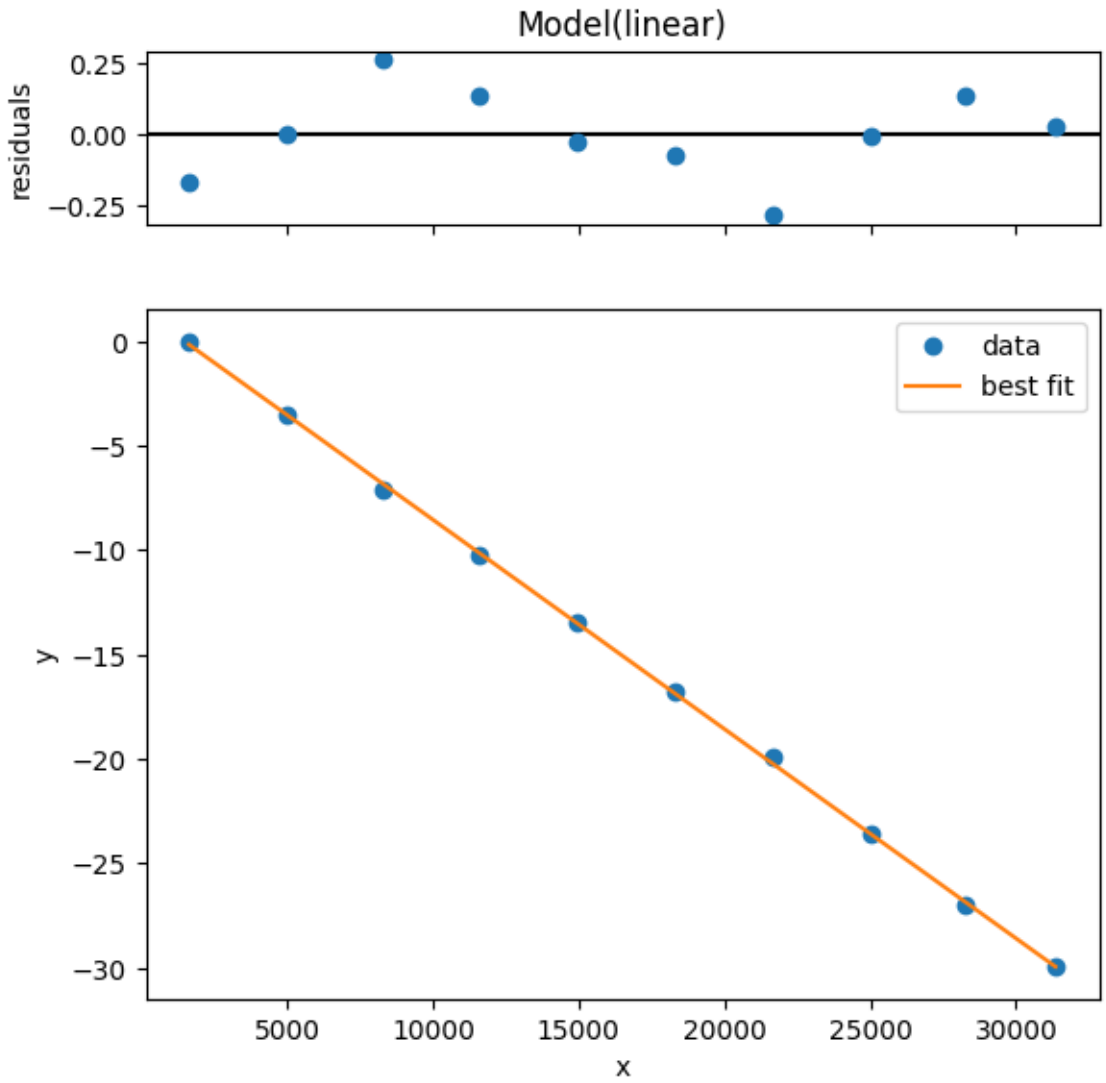
2.17.7 Drift analysis by a cross-correlation algorithm

The same kind of drift estimation and correction can be applied using the image cross-correlation algorithm.

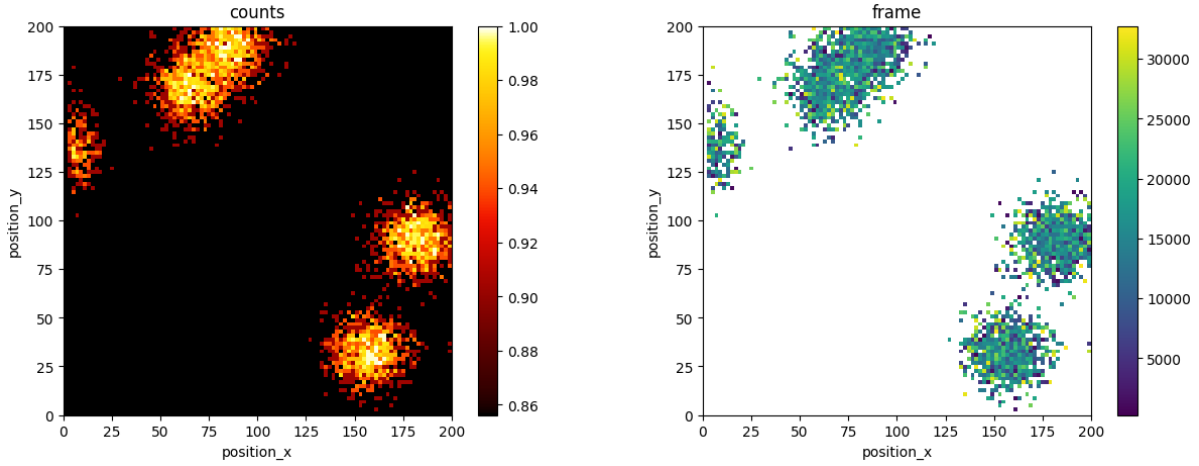
```
%%time
drift = lc.Drift(chunk_size=10_000, target='first', method='cc').\
        compute(dat_blob_with_drift).\
        fit_transformations(slice_data=slice(None), offset_
↪models=(LinearModel(), LinearModel()), verbose=True).\
        apply_correction(from_model=True);
```

```
CPU times: user 1.28 s, sys: 140 ms, total: 1.42 s
Wall time: 1.21 s
```


Model(linear)
residuals
0.0
−0.2
data
best fit
y
x
0
−10
−20
−30
−40
−50
−60
5000
10000
15000
20000
25000
30000




```
fig, axes = plt.subplots(1, 2, figsize=(15, 5))
lc.render_2d(drift.locdata_corrected, ax=axes[0], bin_size=2, rescale='equal',
↪ bin_range=((0, 200),(0, 200)));
lc.render_2d_mpl(drift.locdata_corrected, ax=axes[1], other_property='frame',␣
↪bin_size=2, bin_range=((0, 200),(0, 200)), cmap='viridis');
```



```
rmse(dat_blob, drift.locdata_corrected)
```

```
array([3.24348153, 1.44281642])
```

2.18 Tutorial about nearest neighbor distances

```
from pathlib import Path

%matplotlib inline

import matplotlib.pyplot as plt

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.18.1 Load rapidSTORM data file

Identify some data in the test_data directory and provide a path using pathlib.Path

```
path = lc.ROOT_DIR / 'tests/test_data/rapidSTORM_dstorm_data.txt'
print(path, '\n')

dat = lc.load_rapidSTORM_file(path=path, nrows=1000)
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.txt
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

Print information about the data:

```
print(dat.data.head(), '\n')
print('Summary:')
dat.print_summary()
print('Properties:')
print(dat.properties)
```

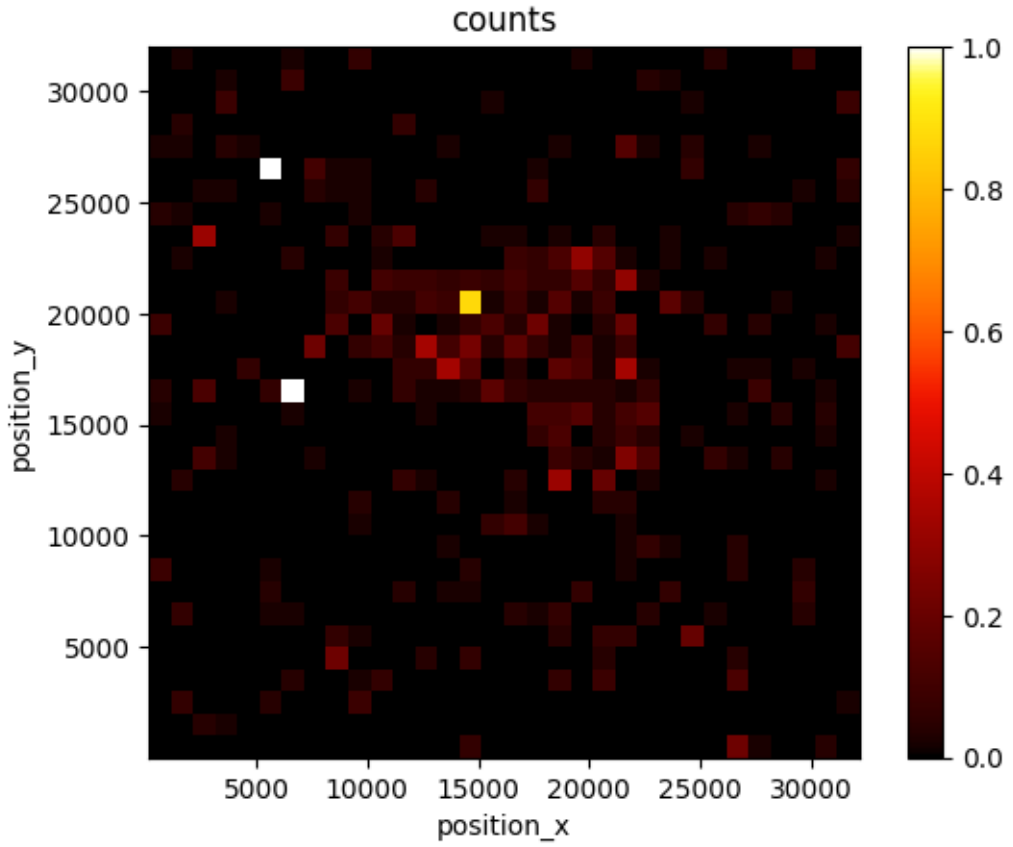
```
   position_x  position_y  frame  intensity  chi_square  local_background
0     9657.40     24533.5      0   33290.10   1192250.0        767.732971
1    16754.90     18770.0      0   21275.40   2106810.0        875.460999
2    14457.60     18582.6      0   20748.70    526031.0        703.369995
3     6820.58     16662.8      0    8531.77   3179190.0        852.789001
4    19183.20     22907.2      0   14139.60    448631.0        662.770020

Summary:
identifier: "1"
comment: ""
source: EXPERIMENT
state: RAW
element_count: 999
frame_count: 48
file {
  type: RAPIDSTORM
  path: "/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/
↪lib/python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.
↪txt"
}
creation_time {
  2024-03-14T11:50:46.806773Z
}

Properties:
{'localization_count': 999, 'position_x': 16066.234912912912, 'uncertainty_x
↪': 250.05278033739012, 'position_y': 17550.369092792796, 'uncertainty_y':␣
↪223.5338926935945, 'intensity': 9471560.21, 'local_background': 645.07007,
↪'frame': 0, 'region_measure_bb': 1064111469.8204715, 'localization_density_
↪bb': 9.388114199807877e-07, 'subregion_measure_bb': 130483.2086}
```

2.18.2 Visualization

```
lc.render_2d(dat, bin_size=1000, rescale=(0,100));
```



2.18.3 Analyze nearest neighbor distances

The k-nearest neighbor distances can be analyzed for all localizations or a random subset.

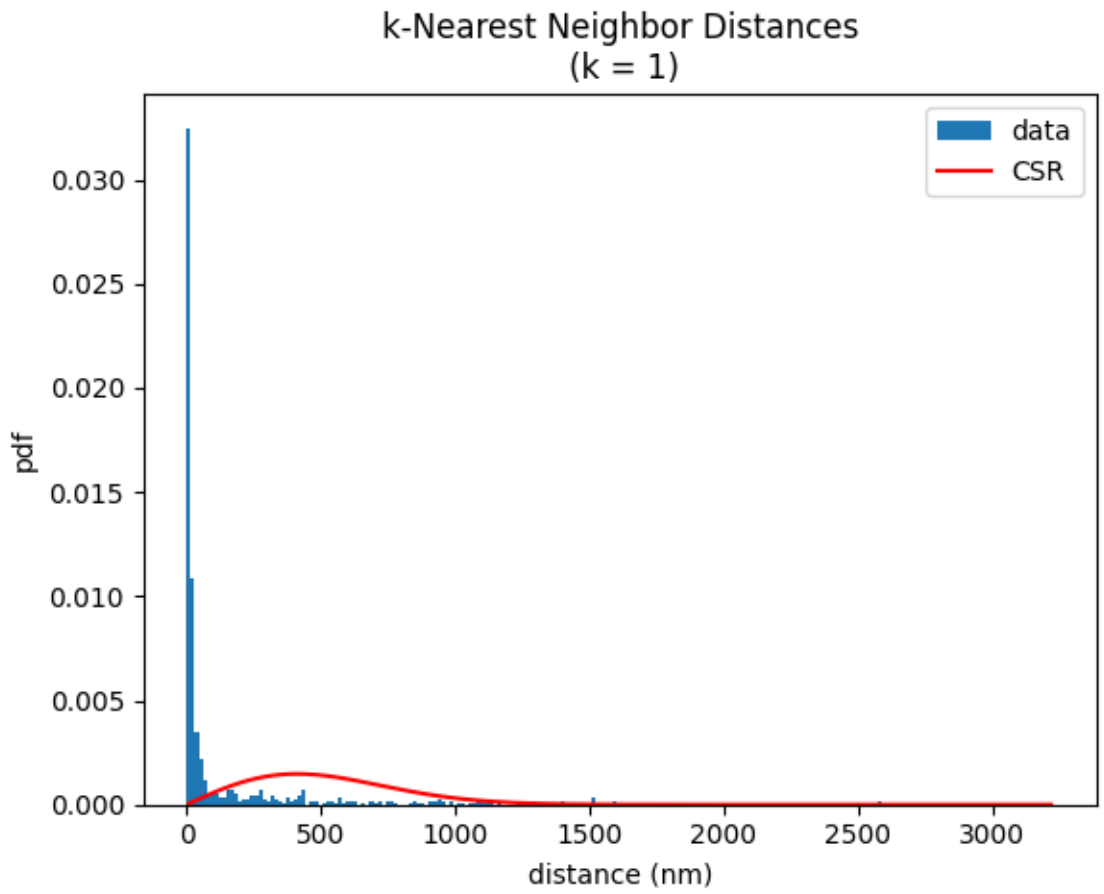
```
nn = lc.NearestNeighborDistances()
```

```
nn.compute(dat)
nn.results.head()
```

```
   nn_distance  nn_index
0   909.435242       276
1    54.429771        38
2     5.385165        30
3     5.047187       706
4     3.544009        27
```

The histogram shows the experimental distribution and for comparision the expectation for a spatial distribution of complete spatial randomness given the experimental localization density (per default relative to the minimum bounding box region).

```
nn.hist();
```



The localization_density relative to the minimum bounding box region is retweated by the localization_density attribute.

```
nn.localization_density
```

```
9.388114199807877e-07
```

2.18.4 Meta data for the analysis procedure

```
nn.meta
```

```
identifier: "1"
method {
  name: "NearestNeighborDistances"
  parameter: "{\'k\': 1}"
}
creation_time {
  seconds: 1710417047
  nanos: 823138000
}
```

2.19 Tutorial about Ripley's k function

```
from pathlib import Path

%matplotlib inline

import numpy as np
import matplotlib.pyplot as plt

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.19.1 Synthetic data

We simulate localization data that is homogeneously Poisson distributed (also described as complete spatial randomness, csr).

```
rng = np.random.default_rng(seed=1)
```

```
locdata_csr = lc.simulate_Poisson(intensity=1e-3, region=((0,1000), (0,1000)),
↪ seed=rng)

print('Data head:')
print(locdata_csr.data.head(), '\n')
print('Summary:')
locdata_csr.print_summary()
print('Properties:')
print(locdata_csr.properties)
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
Data head:
   position_x  position_y
0  144.159613  948.649447
1  311.831452  423.326449
2  827.702594  409.199136
3  549.593688   27.559113
4  753.513109  538.143313

Summary:
```

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```
identifier: "1"
comment: ""
source: SIMULATION
state: RAW
element_count: 1001
frame_count: 0
creation_time {
  2024-03-14T11:47:28.335905Z
}

Properties:
{'localization_count': 1001, 'position_x': 497.1480704304259, 'uncertainty_x
↪': 8.846806436903796, 'position_y': 503.49401443075675, 'uncertainty_y': 9.
↪309630174812341, 'region_measure_bb': 997049.9168748705, 'localization_
↪density_bb': 0.001003961770677952, 'subregion_measure_bb': 3994.
↪0982202393607, 'region_measure': 1000000, 'localization_density': 0.001001,
↪'subregion_measure': 4000}
```

We also simulate data that follows a Neyman-Scott distribution (blobs):

```
locdata_blob = lc.simulate_Thomas(parent_intensity=1e-4, region=((0, 1000),␣
↪(0, 1000)), cluster_mu=100, cluster_std=5, seed=rng)

print('Data head:')
print(locdata_blob.data.head(), '\n')
print('Summary:')
locdata_blob.print_summary()
print('Properties:')
print(locdata_blob.properties)
```

```
Data head:
   position_x  position_y  cluster_label
0  639.830857  587.034592             13
1  499.121280    3.258363             15
2  347.348453  532.577203             62
3  563.963921  711.136973             61
4  258.865522   24.737190             47

Summary:
identifier: "2"
comment: ""
source: SIMULATION
state: RAW
element_count: 9860
frame_count: 0
creation_time {
  2024-03-14T11:47:28.389251Z
}
```

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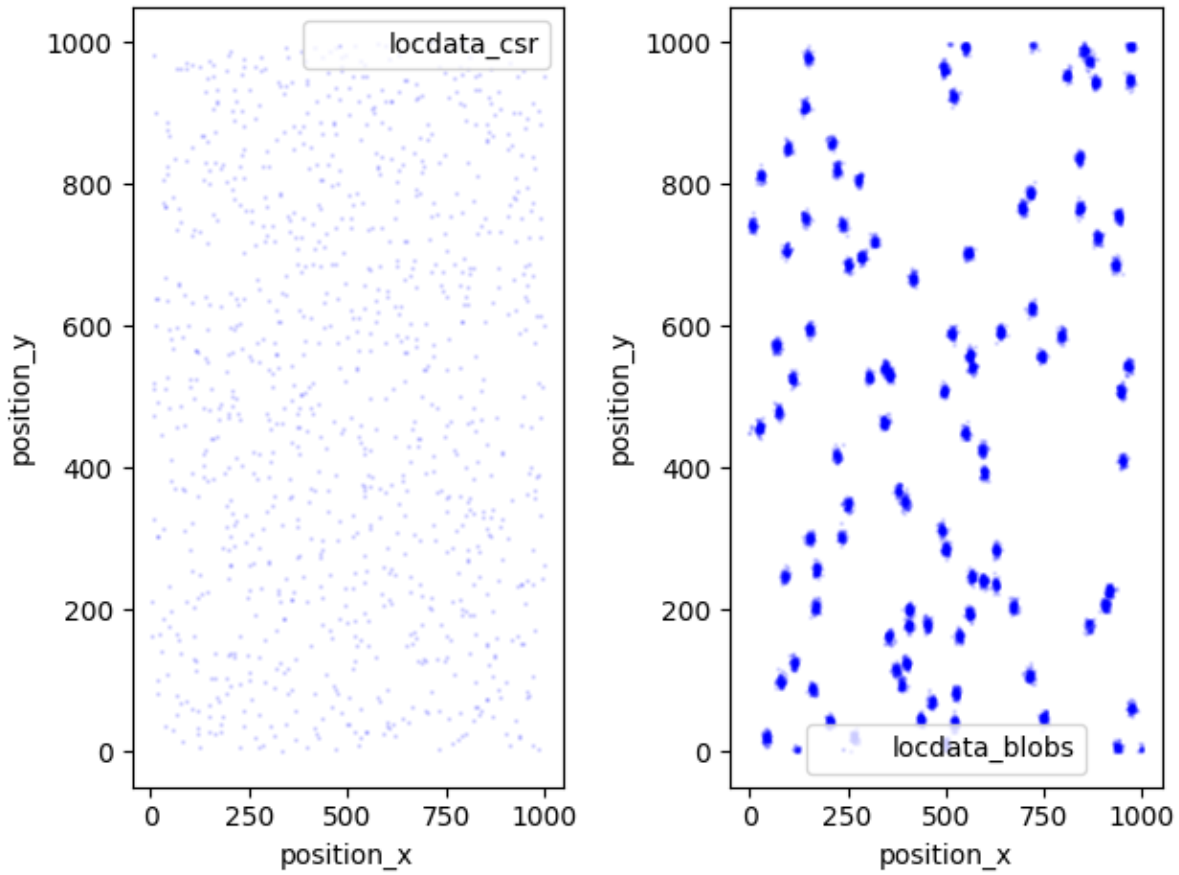
```
Properties:
{'localization_count': 9860, 'position_x': 486.6445632771076, 'uncertainty_x
↪': 2.851385115124155, 'position_y': 467.1399336108736, 'uncertainty_y': 3.
↪0359994421575136, 'region_measure_bb': 999385.4817400454, 'localization_
↪density_bb': 0.009866062875791034, 'subregion_measure_bb': 3998.
↪7709412537642, 'region_measure': 1000000, 'localization_density': 0.00986,
↪'subregion_measure': 4000}
```

Scatter plot

```
fig, ax = plt.subplots(nrows=1, ncols=2)
locdata_csr.data.plot.scatter(x='position_x', y='position_y', ax=ax[0], color=
↪'Blue', s=1, alpha=0.1, label='locdata_csr')
locdata_blob.data.plot.scatter(x='position_x', y='position_y', ax=ax[1],␣
↪color='Blue', s=1, alpha=0.1, label='locdata_blobs')
plt.tight_layout()
plt.show()
```



2.19.2 Analyze Ripley's h function

We have a look at the Ripley's h function from all localizations in locdata.

The analysis class Ripley_h_function provides numerical results, and a plot of results versus radii.

```
rhf_csr = lc.RipleysHFunction(radii=np.linspace(0, 200, 50))
rhf_csr.compute(locdata_csr)
rhf_csr.results.head()
```

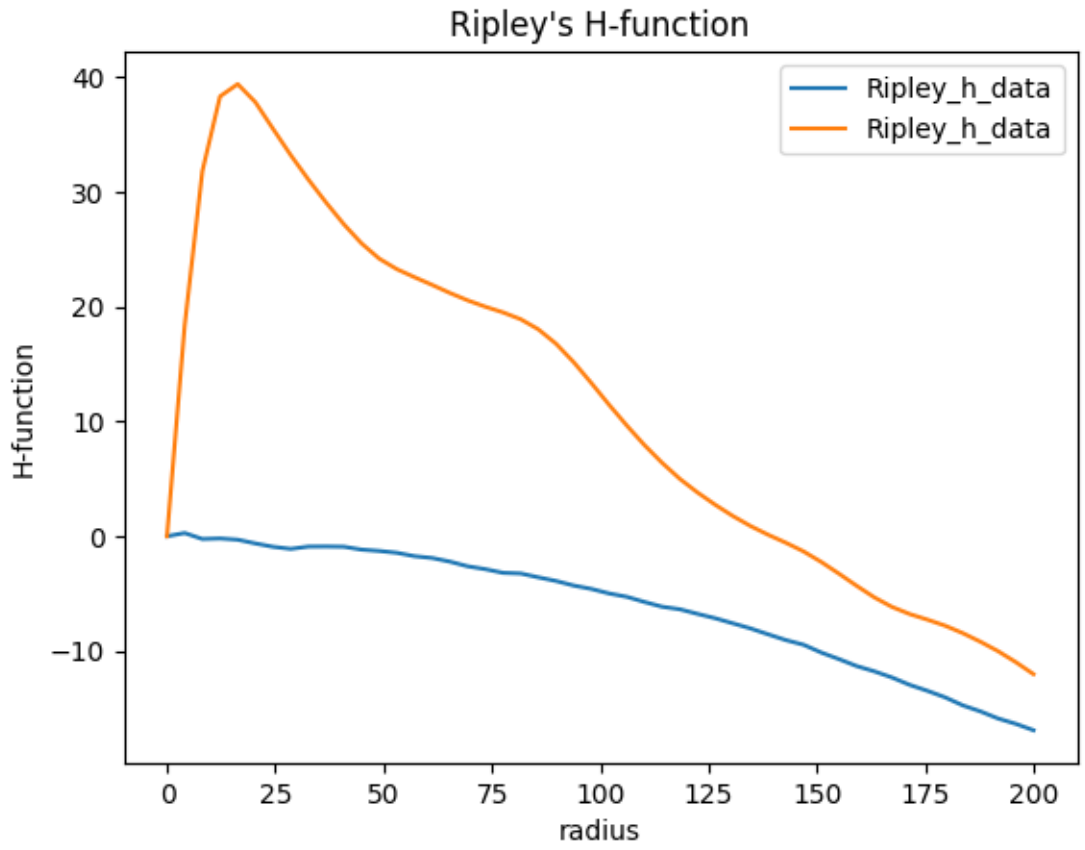
```
           Ripley_h_data
radius
0.000000        0.000000
4.081633        0.279930
8.163265       -0.240094
12.244898      -0.194560
16.326531      -0.301127
```

```
rhf_blob = lc.RipleysHFunction(radii=np.linspace(0, 200, 50))
rhf_blob.compute(locdata_blob)
rhf_blob.results.head()
```

```
           Ripley_h_data
radius
0.000000        0.000000
4.081633       18.353371
8.163265       31.787540
12.244898      38.295378
16.326531      39.369222
```

The plot reflects the amount of clustering. For homogeneous distributed data it decreases towards negative values since edge effects are not taken into account.

```
rhf_csr.plot()
rhf_blob.plot();
```



The maximum of the computed H-function is provided by the attribute.

```
rhf_blob.Ripley_h_maximum
```

```
                radius  Ripley_h_maximum
Ripley_h_data  16.326531         39.369222
```

2.19.3 Estimate Ripley's h function

We can speed up the computation of an estimated Ripley's k function by providing a subset of the original localizations as test points.

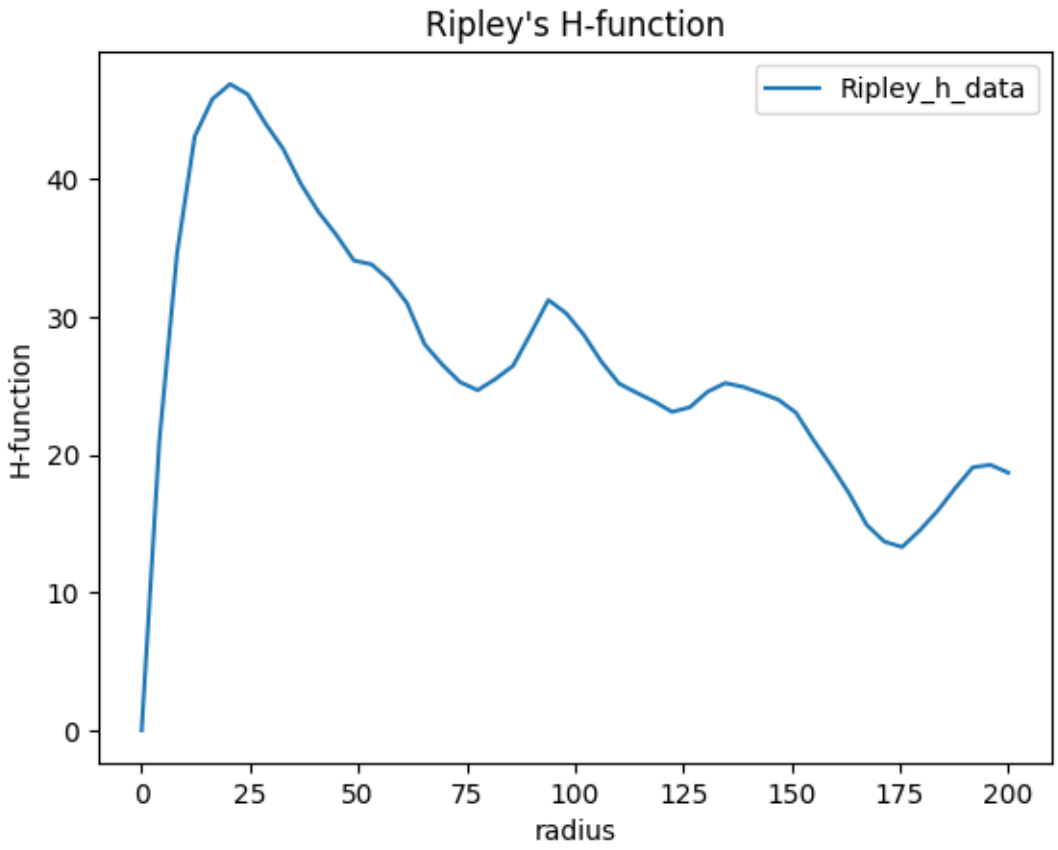
We first take a random subset of the original localizations as test data. Here we provide 10 shuffeled data sets.

```
from locan.data.filter import random_subset
subsets = [lc.random_subset(locdata_blob, n_points=5, seed=rng) for i in␣
↪range(10)]
```

We then compute the estimated Ripley's h function'

```
rhf_estimate = lc.RipleysHFunction(radii=np.linspace(0, 200, 50)).
↪compute(locdata_blob, other_locdata=subsets[0])
```

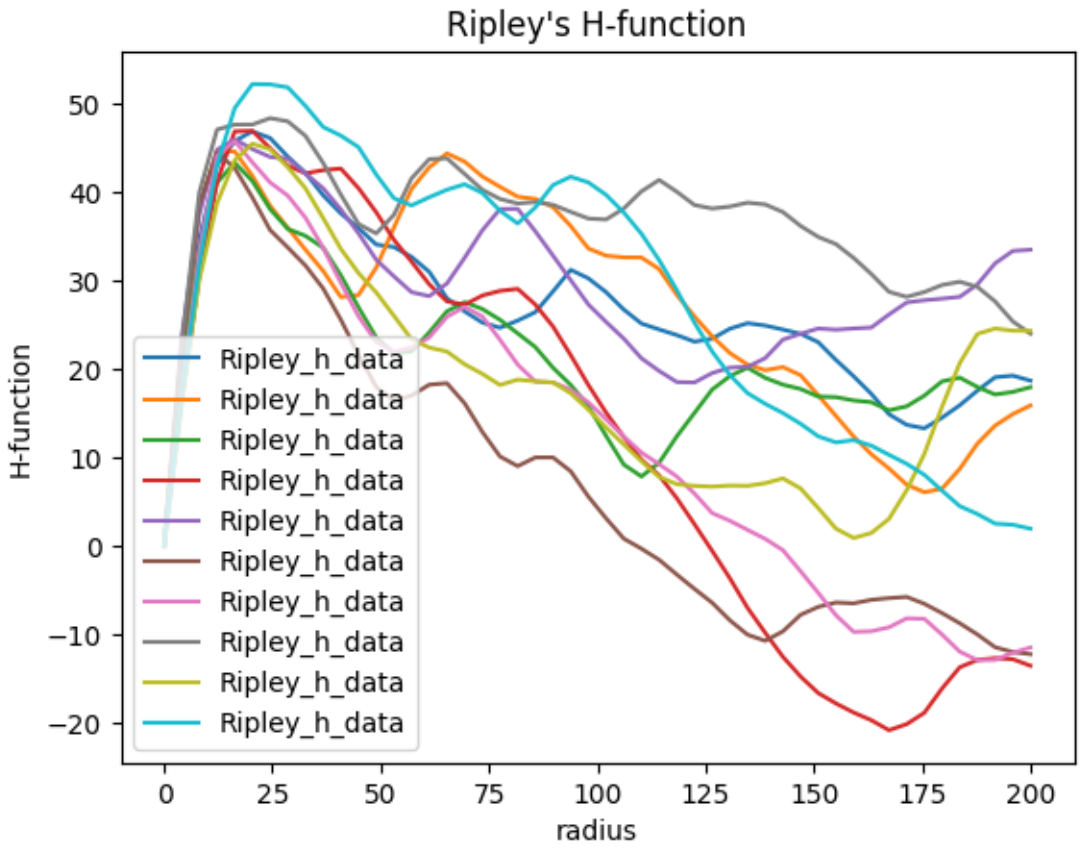
```
rhf_estimate.plot();
```



We can do the same for all subsets

```
rhf_estimates = [lc.RipleysHFunction(radii=np.linspace(0, 200, 50)).
↪compute(locdata_blob, other_locdata=subset) for subset in subsets]
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
for estimate in rhf_estimates:
    estimate.plot(ax=ax)
plt.show()
```

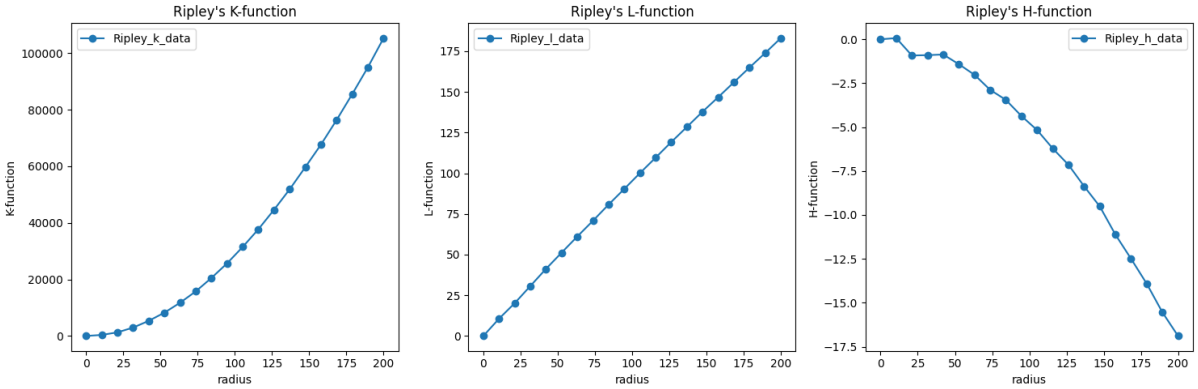


2.19.4 Compute Ripley's k, l and h function

We can compute Ripley's k, l and h function

```
rkf_csr = lc.RipleysKFunction(radii=np.linspace(0, 200, 20)).compute(locdata_
↪csr)
rlf_csr = lc.RipleysLFunction(radii=np.linspace(0, 200, 20)).compute(locdata_
↪csr)
rhf_csr = lc.RipleysHFunction(radii=np.linspace(0, 200, 20)).compute(locdata_
↪csr)
```

```
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(15, 5))
for estimate, ax in zip([rkf_csr, rlf_csr, rhf_csr], axes.ravel()):
    estimate.plot(marker='o', ax=ax)
plt.tight_layout()
plt.show()
```



2.19.5 Estimate Ripley's h function for 3D data

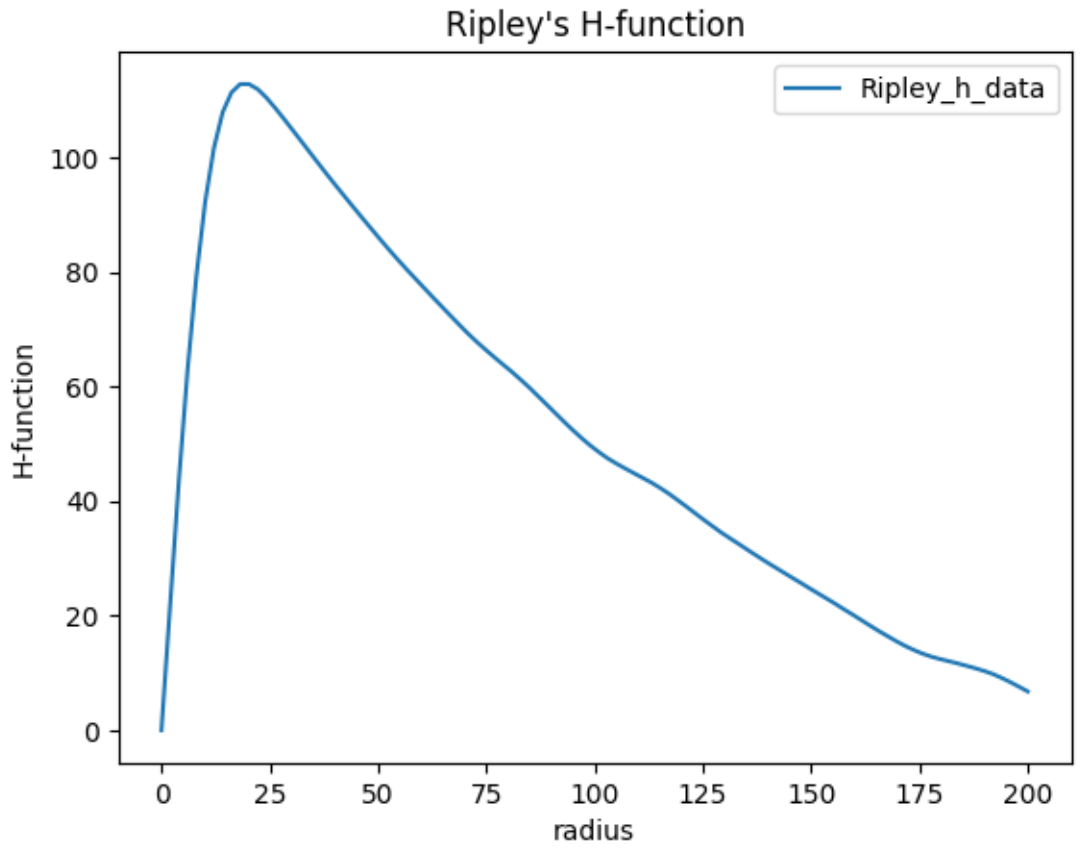
```
dat_blob_3D = lc.simulate_Thomas(parent_intensity=1e-7, region=((0, 1000), (0,
↪ 1000), (0, 1000)), cluster_mu=100, cluster_std=5, seed=rng)
dat_blob_3D.print_summary()
```

```
identifier: "23"
comment: ""
source: SIMULATION
state: RAW
element_count: 9394
frame_count: 0
creation_time {
  2024-03-14T11:47:38.232131Z
}
```

```
sub = lc.random_subset(dat_blob_3D, n_points=1000, seed=rng)
```

```
rhf_3D = lc.RipleysHFunction(radii=np.linspace(0, 200, 100)).compute(dat_blob_
↪3D, other_locdata=sub)
```

```
rhf_3D.plot();
```



2.20 Tutorial about analyzing grouped cluster properties

Localization properties vary within clusters. Analyzing such variations can help to characterize cluster populations. Here, we show examples for variations in convex hull properties or coordinate variances.

```
from pathlib import Path

%matplotlib inline

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from colorcet import m_fire, m_gray, m_dimgray

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.20.1 Synthetic data

We simulate localization data that follows a Neyman-Scott distribution in 2D:

```
rng = np.random.default_rng(seed=1)
```

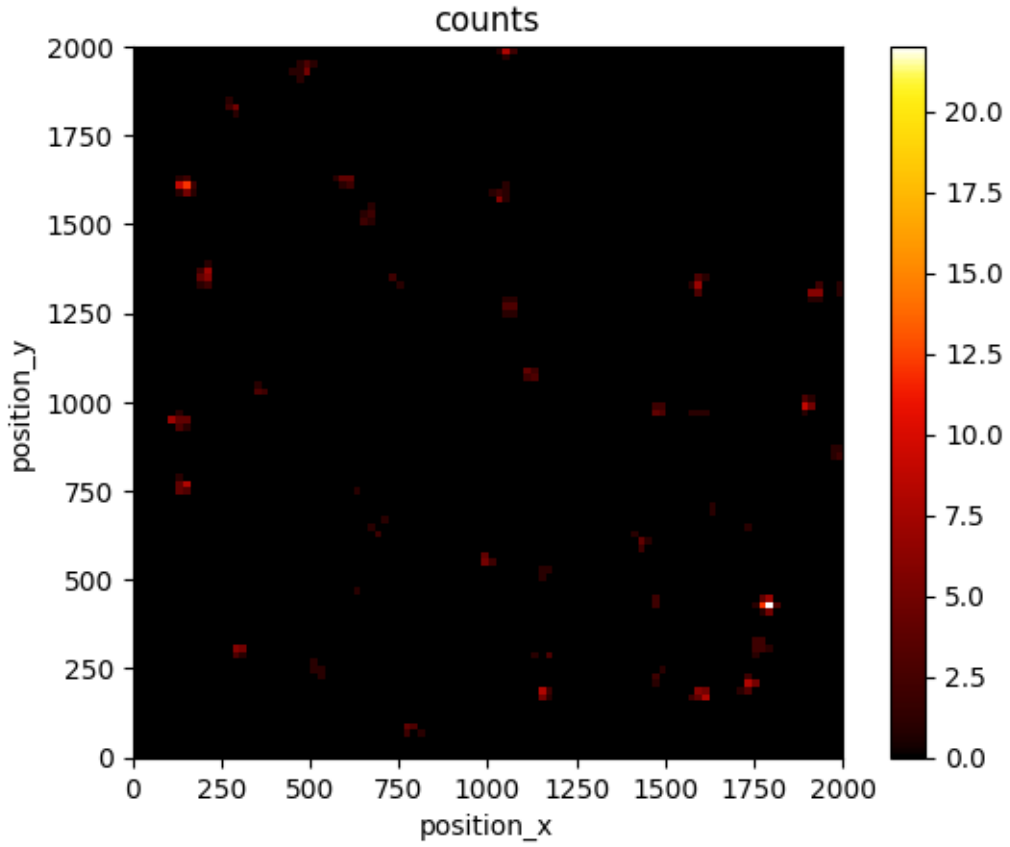
```
locdata = lc.simulate_dstorm(parent_intensity=1e-5, region=((0, 10_000), (0,␣
↪10_000)), cluster_mu=10, cluster_std=10, seed=rng)

locdata.print_summary()
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
identifier: "1"
comment: ""
source: SIMULATION
state: RAW
element_count: 10380
frame_count: 0
creation_time {
  2024-03-14T11:48:39.401538Z
}
```

```
bin_range=((0, 2_000), (0, 2_000))
```

```
lc.render_2d_mpl(locdata, bin_size=20, bin_range=bin_range)
```

```
<Axes: title={'center': 'counts'}, xlabel='position_x', ylabel='position_y'>
```



2.20.2 True clusters

First we look at ground truth clusters.

```
grouped = locdata.data.groupby("cluster_label")
clust = lc.LocData.from_collection([lc.LocData.from_selection(locdata,␣
↪indices=group.index) for name, group in grouped])
```

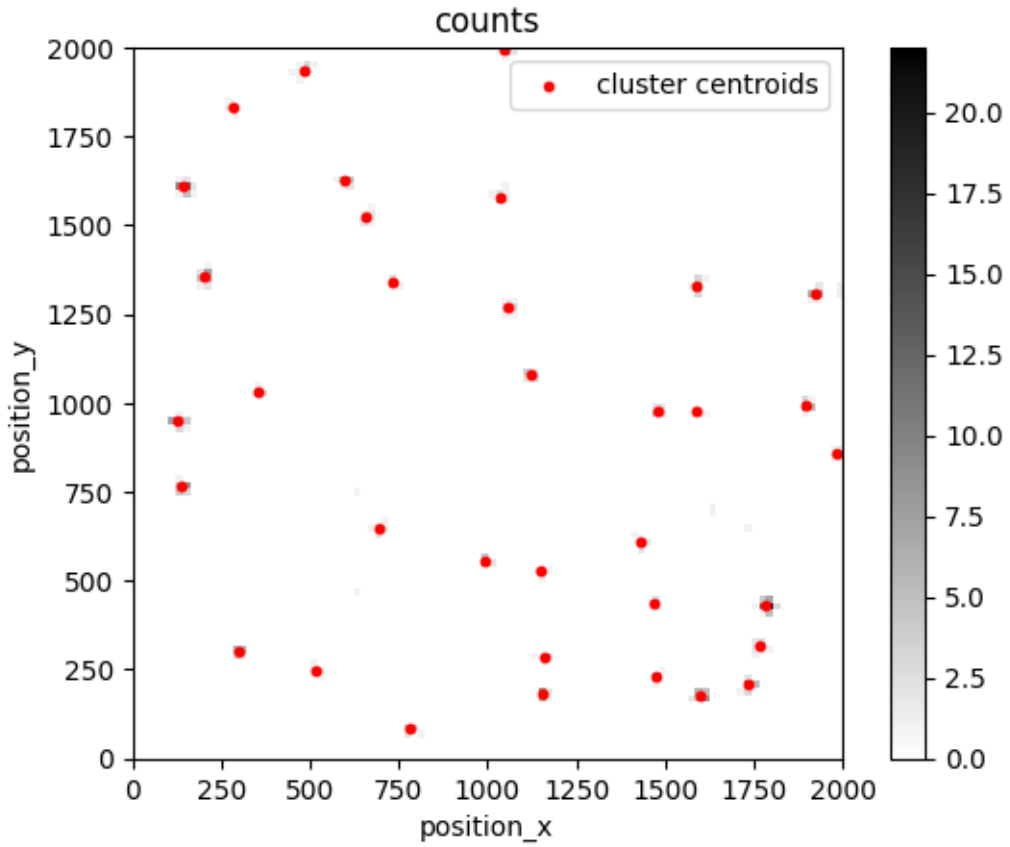
Filter out clusters with less than 3 localizations since on convex hull can be computed for such clusters.

```
clust_selection = lc.select_by_condition(clust, condition="2 < localization_
↪count")
references_ = [clust.references[i] for i in clust_selection.indices]
clust_selection.reduce()
clust_selection.references = references_
clust = clust_selection
```

```
n_clustered_loc = np.sum([ref.properties['localization_count'] for ref in␣
↪clust.references])
print(f"Number of clusters: {clust.properties['localization_count']}")
print(f"Number of clustered localizations: {n_clustered_loc}")
print(f"Ratio cluster to noise localizations: {n_clustered_loc /␣
↪len(locdata):.3}")
```

```
Number of clusters: 771
Number of clustered localizations: 10172
Ratio cluster to noise localizations: 0.98
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
lc.render_2d_mpl(locdata, bin_size=20, bin_range=bin_range, cmap=m_gray.
↪reversed())
clust.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Red',␣
↪s=10, label='cluster centroids', xlim=bin_range[0], ylim=bin_range[1])
plt.show()
```




```
clust.data.head()
```

```
   localization_count   position_x  uncertainty_x   position_y  uncertainty_y␣
↪ \
0                  24  1399.549521       1.877356  9539.052779       1.853978
2                   3  8303.079096      10.889812  4081.419445       3.852366
3                   7  5507.141828       2.444467   224.387484       2.132102
4                   4  7561.723474       3.515554  5385.880528       5.842642
5                   7  3279.865197       5.284643  7918.206789       2.848332

   region_measure_bb  localization_density_bb  subregion_measure_bb  \
0        1025.930045                 0.023393            128.121678
2         456.241155                 0.006575             96.259339
```

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```
3          336.278485                0.020816             73.989892
4          443.103490                0.009027             87.512555
5          774.964110                0.009033            117.649012

   region_measure  localization_density  subregion_measure
0       100000000          2.400000e-07              40000
2       100000000          3.000000e-08              40000
3       100000000          7.000000e-08              40000
4       100000000          4.000000e-08              40000
5       100000000          7.000000e-08              40000
```

```
clust.properties
```

```
{'localization_count': 771,
 'position_x': 5078.461816893804,
 'uncertainty_x': 138.598117645907,
 'position_y': 5571.31780554545,
 'uncertainty_y': 421.90449657593706,
 'region_measure_bb': 99518129.6386362,
 'localization_density_bb': 7.7473320971727e-06,
 'subregion_measure_bb': 39903.55763820844}
```

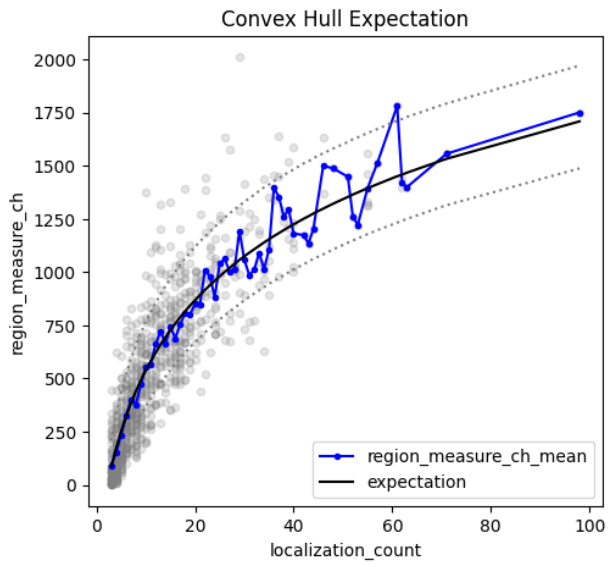
2.20.3 Investigate the convex hull areas

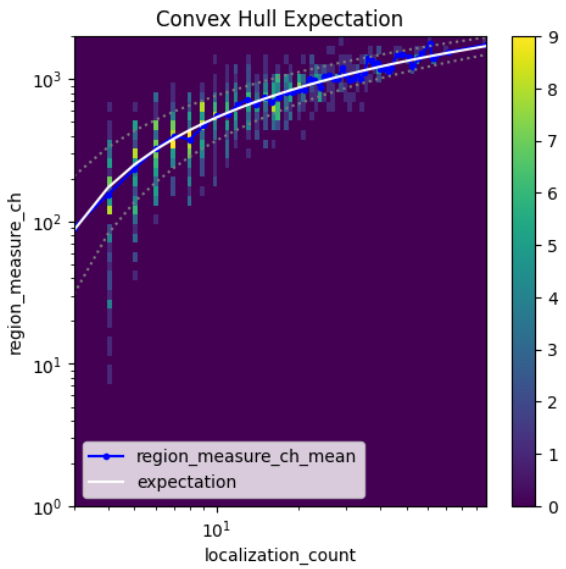
Localization clusters can be analyzed with respect to their convex hull region properties as function of localization_count as outlined in Ebert et al. (https://doi:10.1093/bioinformatics/btac700).

```
che = lc.ConvexHullExpectation(convex_hull_property='region_measure_ch',␣
↪expected_variance=10**2).compute(locdata=clust)
che.results
```

```
<locan.analysis.convex_hull_expectation.ConvexHullExpectationResults at␣
↪0x7efc1364cb20>
```

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))
che.plot(ax=axes[0])
che.hist(ax=axes[1]);
```





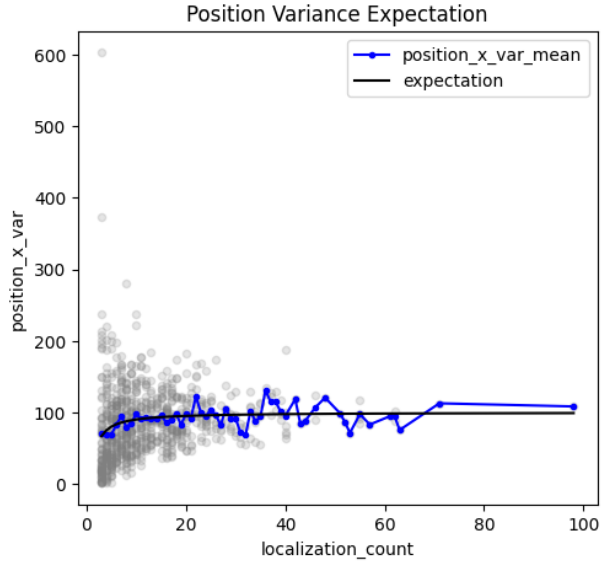
2.20.4 Investigate the position variances

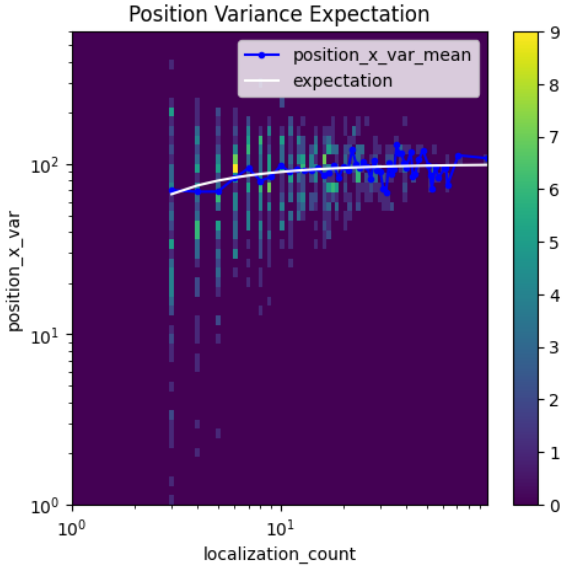
Localization coordinates in localization clusters come with a certain variance. The variance is related to the localization precision or other localization properties but also varies with localization_count if determined as biased sample variance (i.e. without Bessel's correction).

```
pve_biased = lc.PositionVarianceExpectation(loc_property="position_x",␣
↪expectation=10**2, biased=True).compute(locdata=clust)
pve_biased.results
```

```
<locan.analysis.position_variance_expectation.
↪PositionVarianceExpectationResults at 0x7efc12c5b4f0>
```

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))
pve_biased.plot(ax=axes[0])
pve_biased.hist(ax=axes[1]);
```



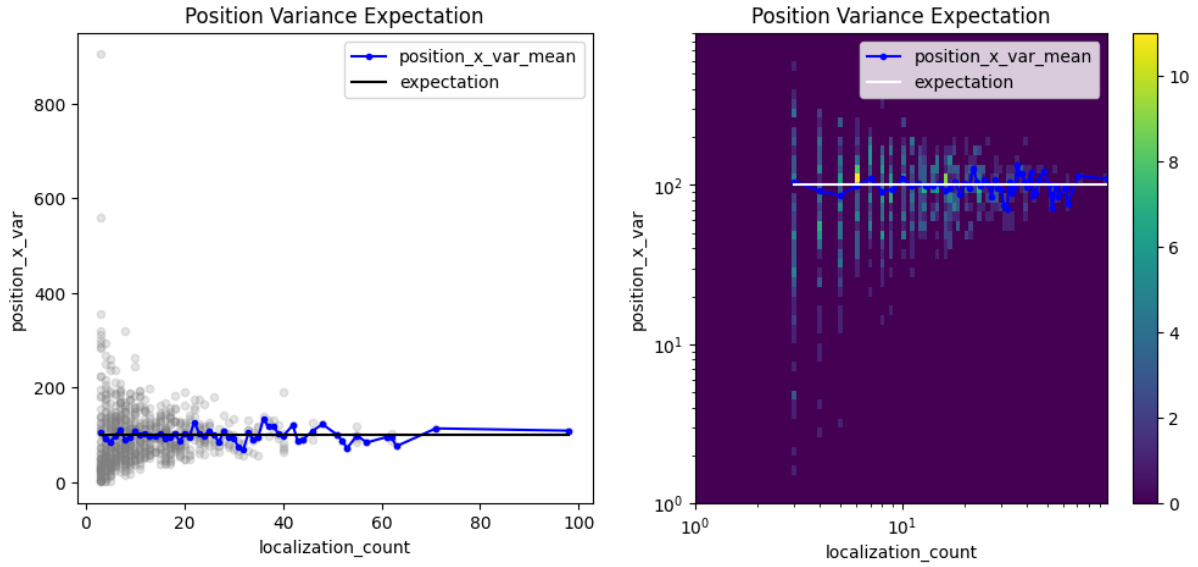


A similar analysis can be performed with unbiased variances in which Bessel's correction is applied.

```
pve = lc.PositionVarianceExpectation(loc_property="position_x",␣
↪expectation=10**2, biased=False).compute(locdata=clust)
pve.results
```

```
<locan.analysis.position_variance_expectation.
↪PositionVarianceExpectationResults at 0x7efc12924e80>
```

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))
pve.plot(ax=axes[0])
pve.hist(ax=axes[1], log=True);
```



2.20.5 Investigate any grouped property

A similar analysis can be carried out with any LocData property. For instance, let's check the coordinate uncertainties of cluster centroids. The uncertainty in one dimension should follow the square root of the biased position variance for clusters with variable number of localizations.

It is important to consider the differences between variance and standard deviation. Position uncertainties are usually given as standard deviation with units equal to position units. Converting the ground truth for the coordinate standard deviation in each cluster (std as used in the simulations above) requires a Bessel correction on the squared std being the variance). In addition the coordinate uncertainties of cluster centroids should scale with the inverse square root of the number of localizations per cluster.

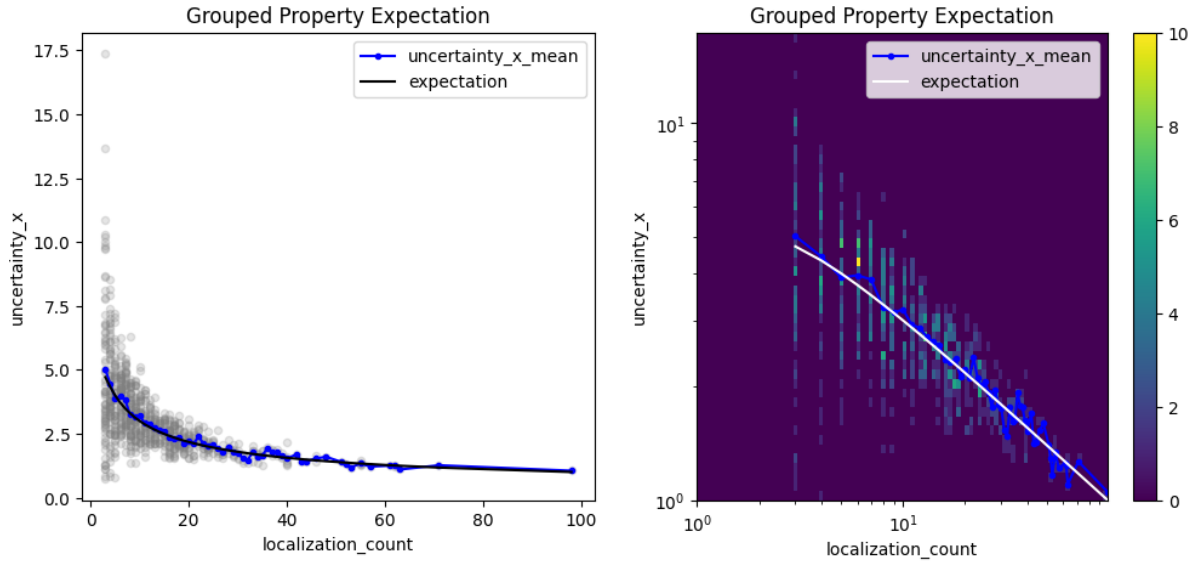
```
n_locs = np.arange(1, 1000)
ground_truth_std = 10
ground_truth_variance = ground_truth_std**2
biased_variance = ground_truth_variance * (1 - 1 / n_locs)
biased_uncertainty = np.sqrt(biased_variance)
expected_uncertainty = biased_uncertainty / np.sqrt(n_locs)
expectation = pd.Series(data=expected_uncertainty, index=n_locs)
expectation;
```

```
loc_property = "uncertainty_x"
other_loc_property = "localization_count"
```

```
gpe = lc.GroupedPropertyExpectation(loc_property=loc_property, other_loc_
↪property=other_loc_property, expectation=expectation).compute(locdata=clust)
gpe.results
```

```
<locan.analysis.grouped_property_expectation.
↪GroupedPropertyExpectationResults at 0x7efc10f4a8f0>
```

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))
gpe.plot(ax=axes[0])
gpe.hist(ax=axes[1]);
```



2.20.6 Cluster localizations by dbscan

When clustering data by dbscan slight deviations appear between expectation and computed properties.

```
noise, clust = lc.cluster_dbscan(locdata, eps=20, min_samples=3)
```

```
n_clustered_loc = np.sum([ref.properties['localization_count'] for ref in␣
↪clust.references])
print(f"Number of clusters: {clust.properties['localization_count']}")
print(f"Number of noise localizations: {noise.properties['localization_count
↪']}")
print(f"Number of clustered localizations: {n_clustered_loc}")
print(f"Ratio cluster to noise localizations: {n_clustered_loc / (n_clustered_
↪loc + noise.properties['localization_count']):.3}")
```

```
Number of clusters: 725
Number of noise localizations: 415
```

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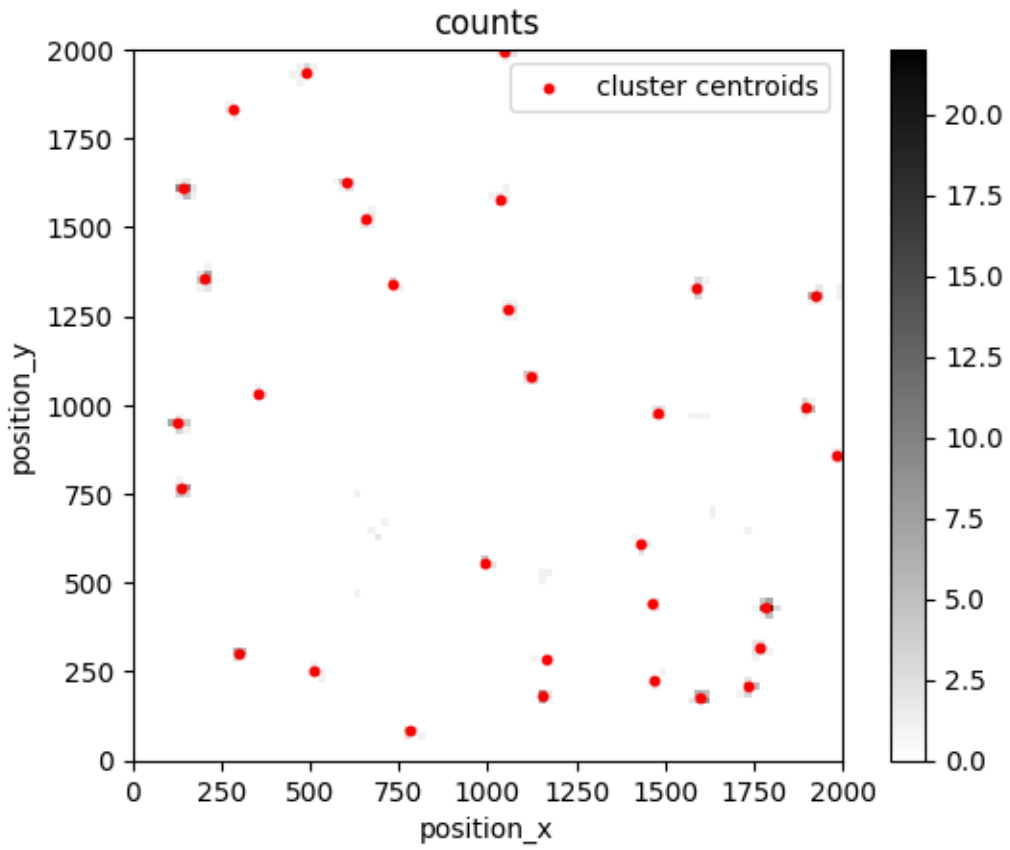
```
Number of clustered localizations: 9965
Ratio cluster to noise localizations: 0.96
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
lc.render_2d_mpl(locdata, bin_size=20, bin_range=bin_range, cmap=m_gray.
↪reversed())
clust.data.plot.scatter(x='position_x', y='position_y', ax=ax, color='Red',␣
↪s=10, label='cluster centroids', xlim=bin_range[0], ylim=bin_range[1])
plt.show()
```

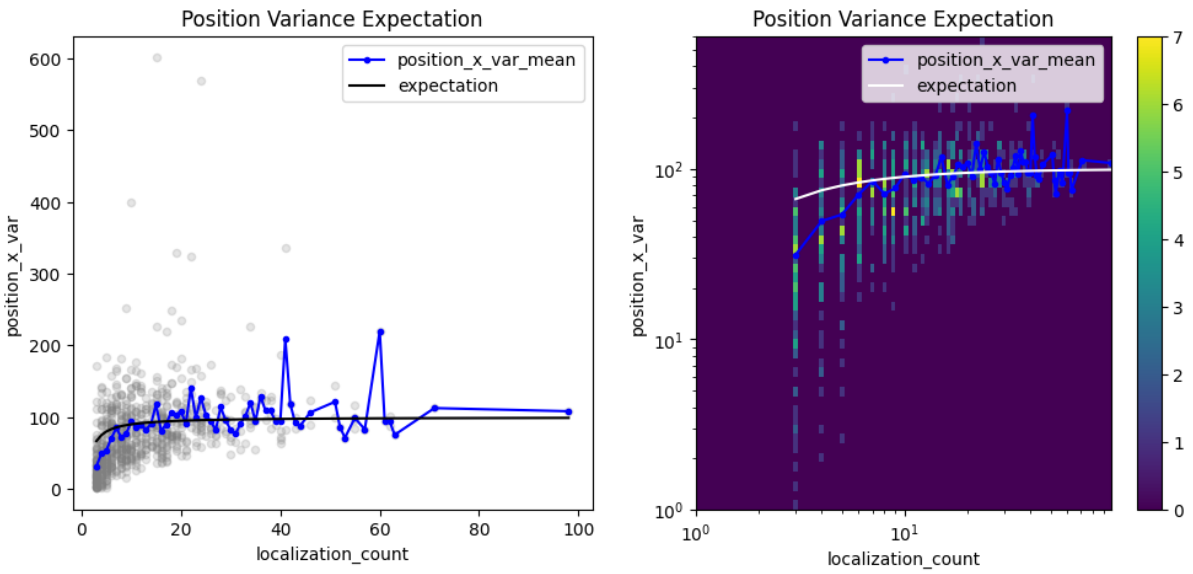


2.20.7 Investigate the position variances

```
pve_biased = lc.PositionVarianceExpectation(loc_property="position_x",␣
↪expectation=10**2, biased=True).compute(locdata=clust)
pve_biased.results
```

```
<locan.analysis.position_variance_expectation.
↪PositionVarianceExpectationResults at 0x7efc12cca500>
```

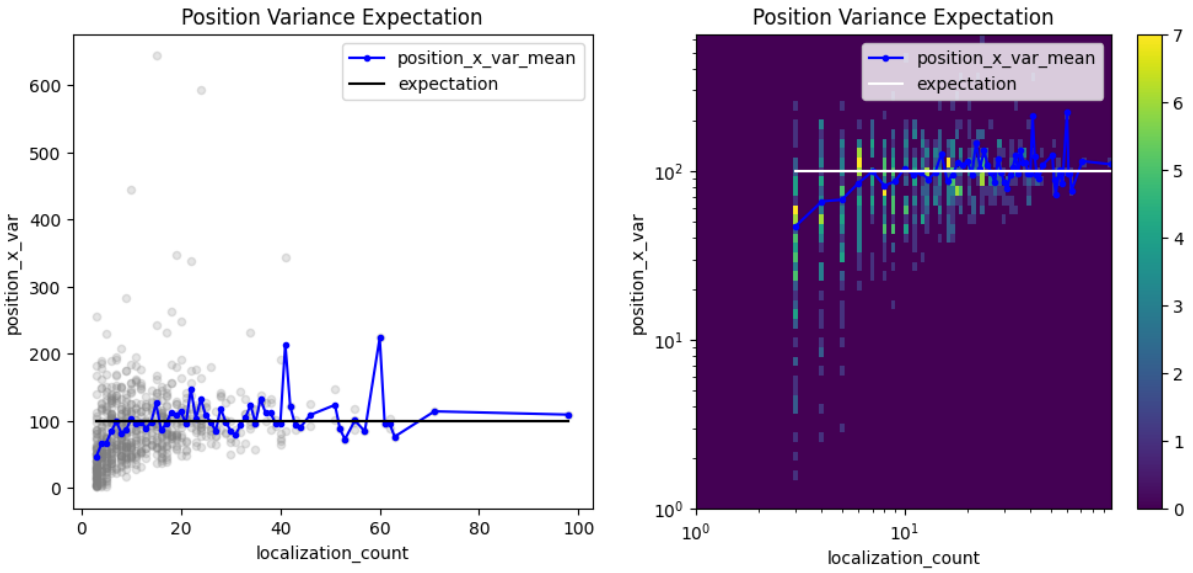
```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))
pve_biased.plot(ax=axes[0])
pve_biased.hist(ax=axes[1]);
```




```
pve = lc.PositionVarianceExpectation(loc_property="position_x",␣
↪expectation=10**2, biased=False).compute(locdata=clust)
pve.results
```

```
<locan.analysis.position_variance_expectation.
↪PositionVarianceExpectationResults at 0x7efc110bbcd0>
```

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))
pve.plot(ax=axes[0])
pve.hist(ax=axes[1], log=True);
```

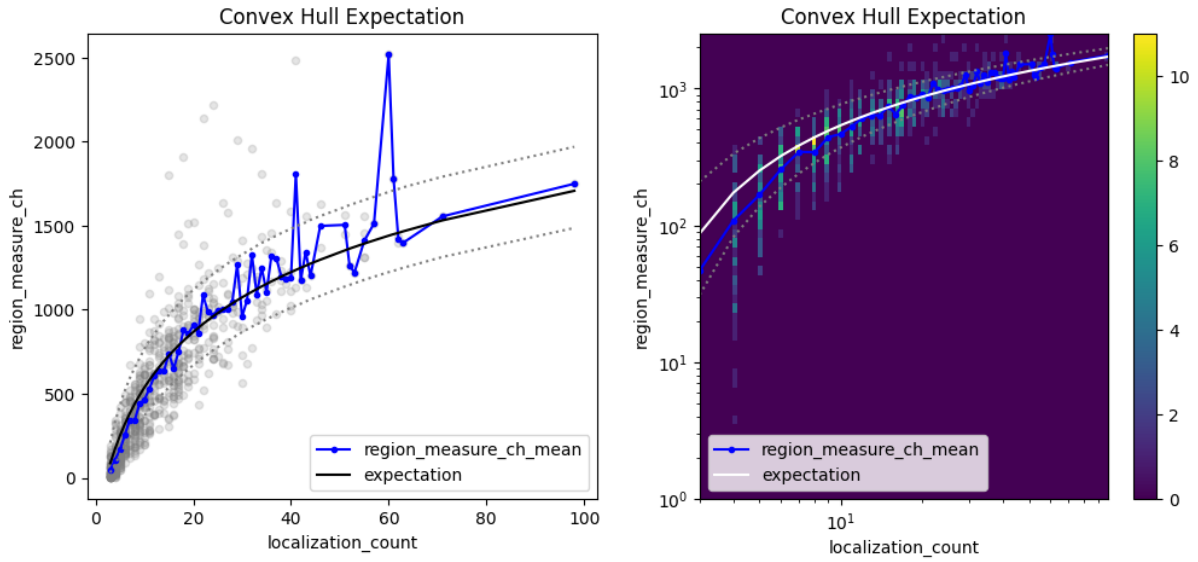


2.20.8 Investigate the convex hull areas

```
che = lc.ConvexHullExpectation(convex_hull_property='region_measure_ch',␣
↪expected_variance=10**2).compute(locdata=clust)
che.results
```

```
<locan.analysis.convex_hull_expectation.ConvexHullExpectationResults at␣
↪0x7efc10c1bcd0>
```

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))
che.plot(ax=axes[0])
che.hist(ax=axes[1]);
```



2.20.9 Investigate the uncertainties for cluster centroids

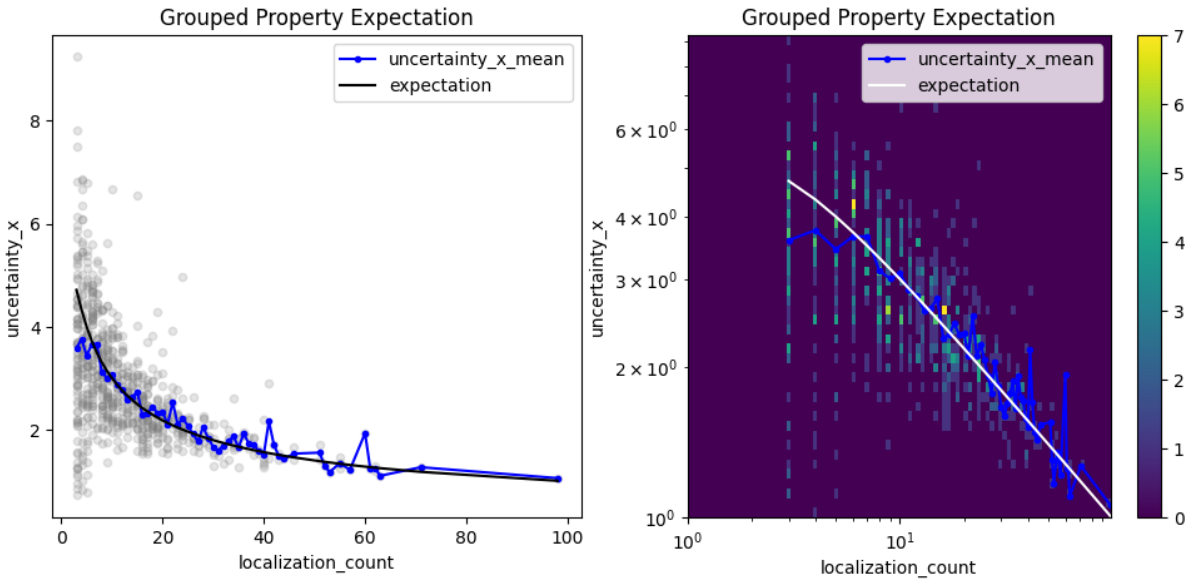
```
n_locs = np.arange(1, 1000)
ground_truth_std = 10
ground_truth_variance = ground_truth_std**2
biased_variance = ground_truth_variance * (1 - 1 / n_locs)
biased_uncertainty = np.sqrt(biased_variance)
expected_uncertainty = biased_uncertainty / np.sqrt(n_locs)
expectation = pd.Series(data=expected_uncertainty, index=n_locs)
expectation;
```

```
loc_property = "uncertainty_x"
other_loc_property = "localization_count"
```

```
gpe = lc.GroupedPropertyExpectation(loc_property=loc_property, other_loc_
↪property=other_loc_property, expectation=expectation).compute(locdata=clust)
gpe.results
```

```
<locan.analysis.grouped_property_expectation.
↪GroupedPropertyExpectationResults at 0x7efc1732a7a0>
```

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))
gpe.plot(ax=axes[0])
gpe.hist(ax=axes[1]);
```



2.21 Tutorial about how to use a standard Analysis class

```
from pathlib import Path

%matplotlib inline

import matplotlib.pyplot as plt

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.21.1 Load rapidSTORM data file

Identify some data in the test_data directory and provide a path using pathlib.Path

```
path = lc.ROOT_DIR / 'tests/test_data/rapidSTORM_dstorm_data.txt'
print(path, '\n')
dat = lc.load_rapidSTORM_file(path=path, nrows=1000)
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.txt
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

```
print(dat.data.head(), '\n')
print('Summary:')
dat.print_summary()
print('Properties:')
print(dat.properties)
```

```
   position_x  position_y  frame  intensity  chi_square  local_background
0     9657.40     24533.5      0   33290.10   1192250.0        767.732971
1    16754.90     18770.0      0   21275.40   2106810.0        875.460999
2    14457.60     18582.6      0   20748.70    526031.0        703.369995
3     6820.58     16662.8      0    8531.77   3179190.0        852.789001
4    19183.20     22907.2      0   14139.60    448631.0        662.770020

Summary:
identifier: "1"
comment: ""
source: EXPERIMENT
state: RAW
element_count: 999
frame_count: 48
file {
  type: RAPIDSTORM
  path: "/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/
↪lib/python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.
↪txt"
}
creation_time {
  2024-03-14T11:49:59.929443Z
}

Properties:
{'localization_count': 999, 'position_x': 16066.234912912912, 'uncertainty_x
↪': 250.05278033739012, 'position_y': 17550.369092792796, 'uncertainty_y':␣
↪223.5338926935945, 'intensity': 9471560.21, 'local_background': 645.07007,
↪'frame': 0, 'region_measure_bb': 1064111469.8204715, 'localization_density_
↪bb': 9.388114199807877e-07, 'subregion_measure_bb': 130483.2086}
```

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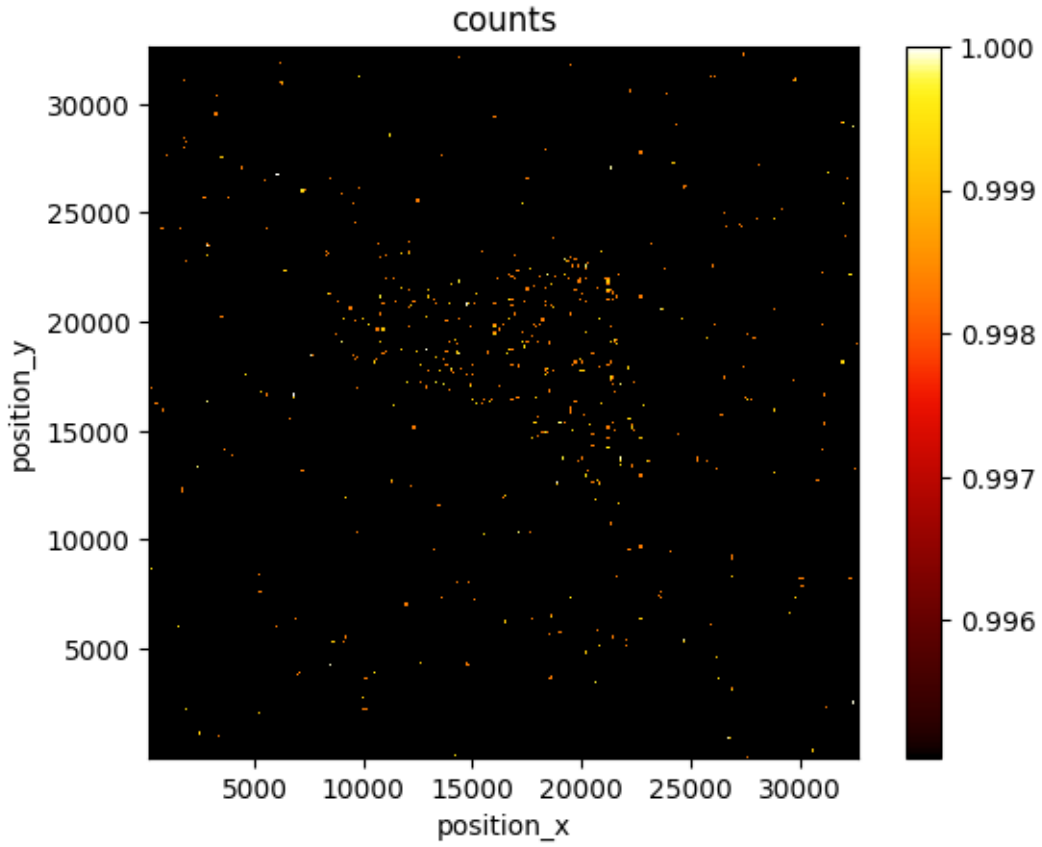
2.21.2 Visualization

For visualizing the data use one of the rendering methods.

```
lc.render_2d_mpl(dat, bin_size=100, rescale='equal');
```



2.21.3 A simple analysis procedure: localization precision

Instantiation

Create an instance of the analysis class. By doing this you set all parameters in the parameter attribute. To start the actual computation you have to call instance.compute().

```
lp = lc.LocalizationPrecision(radius=50)
```

Each analysis class provides some attributes and methods for the most common interactions with the computed results.

```
attributes = [x for x in dir(lp) if not x.startswith('_')]
attributes
```

```
['compute',
 'count',
 'distribution_statistics',
 'fit_distributions',
 'hist',
 'meta',
 'parameter',
 'plot',
 'report',
 'results']
```

The results attribute

A standard analysis class has an attribute *results* to hold the most fundamental results as number, numpy array or pandas series or dataframe.

```
lp.compute(dat)
print('type of lpf.results: ', type(lp.results), '\n')
print(lp.results.head())
```

```
Processed frames::   0%|          | 0/46 [00:00<?, ?it/s]
```

```
Processed frames::  11%|         | 5/46 [00:00<00:00, 44.00it/s]
```

```
Processed frames::  24%|       | 11/46 [00:00<00:00, 46.71it/s]
```

```
Processed frames::  35%|      | 16/46 [00:00<00:00, 42.59it/s]
```

```
Processed frames::  46%|     | 21/46 [00:00<00:00, 44.85it/s]
```

```
Processed frames::  59%|    | 27/46 [00:00<00:00, 47.38it/s]
```

```
Processed frames::  72%|  | 33/46 [00:00<00:00, 50.50it/s]
```

```
Processed frames::  85%| | 39/46 [00:00<00:00, 49.23it/s]
```

```
Processed frames::  96%|| 44/46 [00:00<00:00, 47.52it/s]
```

```
Processed frames:: 100%|| 46/46 [00:00<00:00, 46.84it/s]
```

```
type of lpf.results:  <class 'pandas.core.frame.DataFrame'>

   position_delta_x  position_delta_y  position_distance  frame
0               4.6              -2.8           5.385165      0
1              -1.0              -3.4           3.544009      0
2              17.0             -17.5          24.397746      0
```

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```
3                5.1              -8.1            9.571834      0
4              -14.1              22.6           26.637755      0
```

Results can be saved by specifying a path

```
from pathlib import Path
temp_directory = Path('.') / 'temp'
temp_directory.mkdir(parents=True, exist_ok=True)

path = temp_directory / 'results.txt'
path
```

```
PosixPath('temp/results.txt')
```

and saving the data using numpy or pandas routines

```
lp.results.to_csv(path, sep='\t')
```

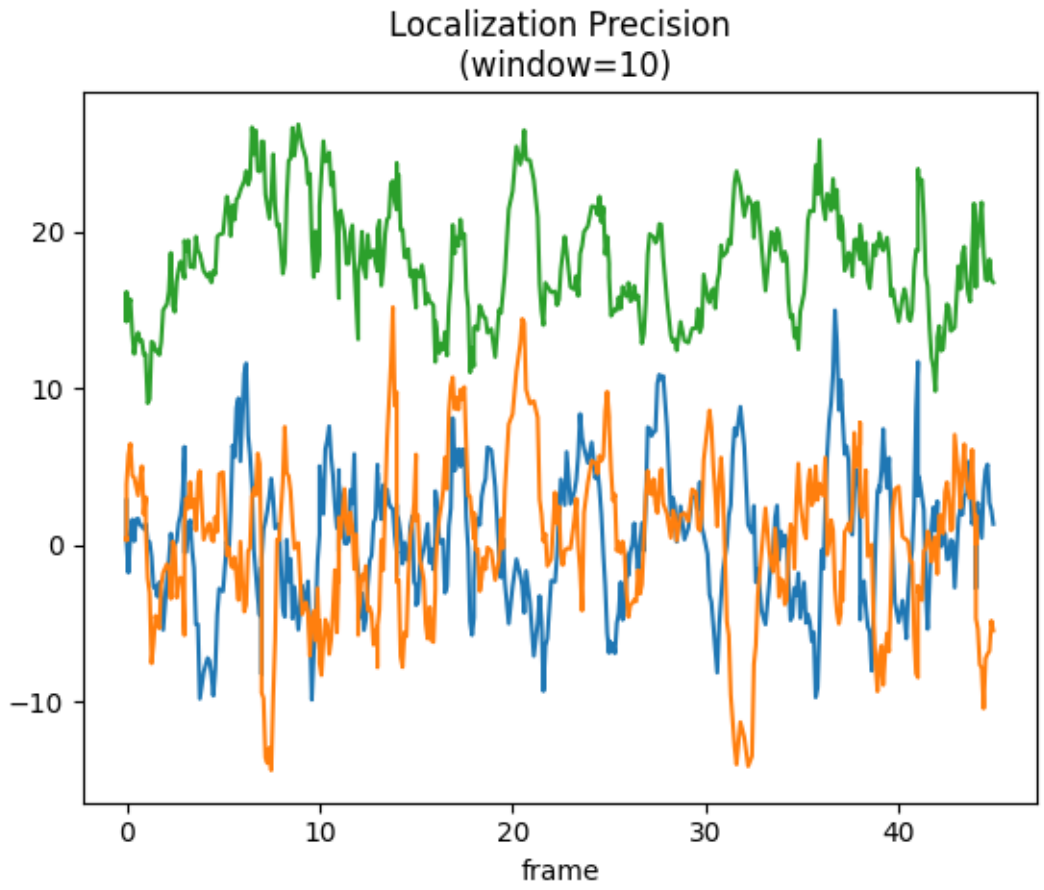
Delete the file and empty directory

```
path.unlink()
temp_directory.rmdir()
```

A simple standardized plot

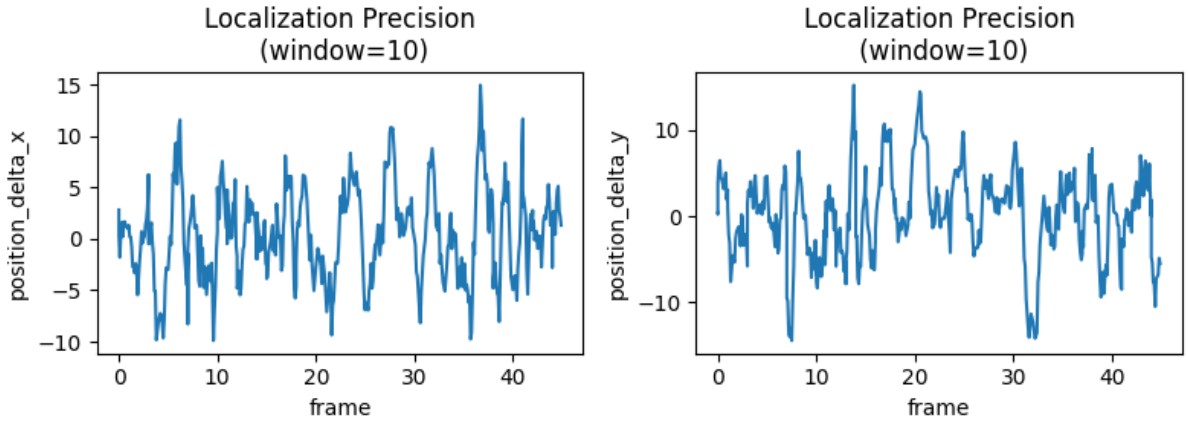
Most likely the results should be inspected by looking at a typical plot. In this case the plot shows results smoothed by a running average according to the specified window.

```
lp.plot(window=10);
```



For more advanced plotting schemes use the matplotlip framework.

```
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(8,3))
lp.plot(ax=ax[0], window=10, loc_property='position_delta_x')
lp.plot(ax=ax[1], window=10, loc_property='position_delta_y')
plt.tight_layout()
plt.show()
```

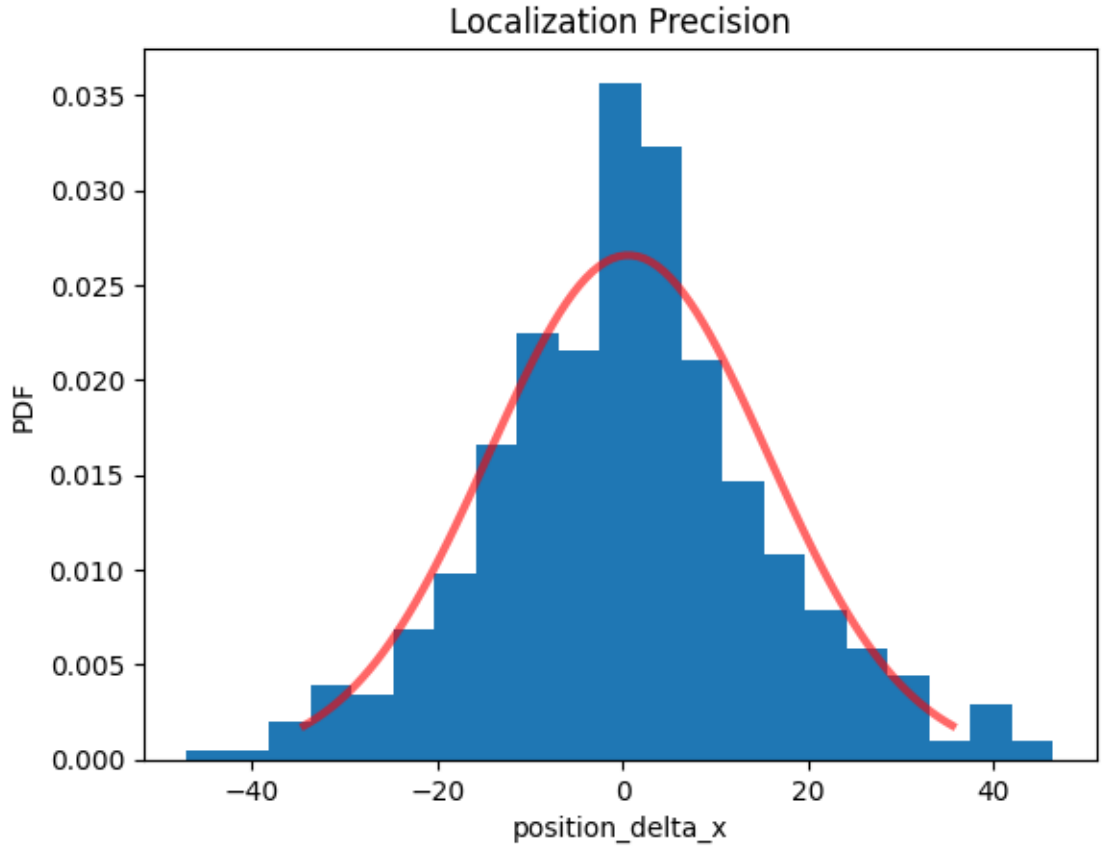


A simple standardized histogram

Quite often the results are best presented as a histogram. The histogram for the distances per default includes a fit to a distribution expected for normal distributed localizations. Sigma is the localization precision.

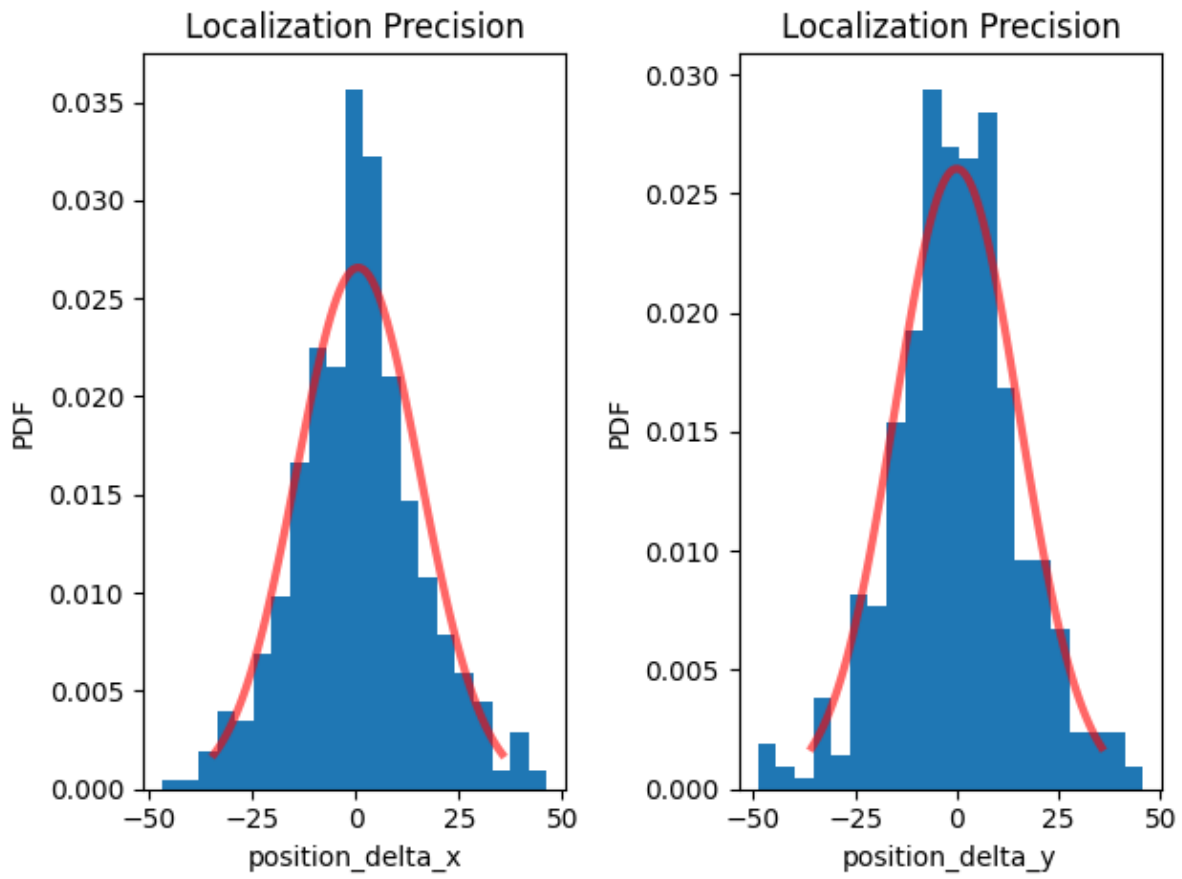
The histogram per default provides automatic bins and is normalized to show a probability density function.

```
lp.hist(loc_property='position_delta_x');
```



Alternatively the position deltas can be histogrammed.

```
fig, ax = plt.subplots(nrows=1, ncols=2)
lp.hist(ax=ax[0], loc_property='position_delta_x')
lp.hist(ax=ax[1], loc_property='position_delta_y')
plt.tight_layout()
plt.show()
```



Secondary results

Secondary results are e.g. fit parameter derived from analyzing the distribution of *results* values. Secondary results are different for each analysis routine. They are included as additional attributes.

Localization precision can e.g. be derived from fitting the position distances to an appropriate distribution and estimating the sigma parameter.

```
lp.distribution_statistics.parameter_dict()
```

```
{'position_delta_x_loc': 0.5793456521739601,
 'position_delta_x_scale': 15.01664582880988,
 'position_delta_y_loc': -0.028067391304342455,
 'position_delta_y_scale': 15.310244879968039,
 'position_distance_sigma': 15.169726562500031,
 'position_distance_loc': 0,
 'position_distance_scale': 1}
```

```
print('position_distance_sigma: ', lp.distribution_statistics.parameter_
↪dict()['position_distance_sigma'])
```

```
position_distance_sigma:  15.169726562500031
```

Metadata

Each analysis class is supplied with meta data. The main purpose is to (i) capture methods and parameters that were supplied in each instantiation and (ii) provide information on the dataset on which the particular analysis was carried out. Metadata is structured using protocol buffers.

```
lp.meta
```

```
identifier: "1"
method {
  name: "LocalizationPrecision"
  parameter: "{\'radius\': 50}"
}
creation_time {
  seconds: 1710417000
  nanos: 955077000
}
```

You can add some user-defined key-value pairs:

```
lp.meta.map['some key'] = 'some value'
lp.meta.map
```

```
{'some key': 'some value'}
```

2.21.4 Metadata can be used to rerun the analysis with the same parameter.

```
lp.meta.method.name
```

```
'LocalizationPrecision'
```

```
lp.meta.method.parameter
```

```
"{'radius': 50}"
```

```
import ast
import locan.analysis
params = ast.literal_eval(lp.meta.method.parameter)
print(params)
lp_2 = getattr(locan.analysis, lp.meta.method.name)(**params)
lp_2.compute(dat)
lp_2.results.head()
```

```
{'radius': 50}
```

```
Processed frames::   0%|          | 0/46 [00:00<?, ?it/s]
```

```
Processed frames::  11%|          | 5/46 [00:00<00:00, 44.18it/s]
```

```
Processed frames::  24%|        | 11/46 [00:00<00:00, 46.86it/s]
```

```
Processed frames::  35%|       | 16/46 [00:00<00:00, 42.53it/s]
```

```
Processed frames::  46%|      | 21/46 [00:00<00:00, 44.95it/s]
```

```
Processed frames::  59%|     | 27/46 [00:00<00:00, 47.15it/s]
```

```
Processed frames::  72%|   | 33/46 [00:00<00:00, 50.41it/s]
```

```
Processed frames::  85%| | 39/46 [00:00<00:00, 49.62it/s]
```

```
Processed frames::  96%|| 44/46 [00:00<00:00, 47.87it/s]
```

```
Processed frames:: 100%|| 46/46 [00:00<00:00, 46.86it/s]
```

```

```

	position_delta_x	position_delta_y	position_distance	frame
0	4.6	-2.8	5.385165	0
1	-1.0	-3.4	3.544009	0
2	17.0	-17.5	24.397746	0
3	5.1	-8.1	9.571834	0
4	-14.1	22.6	26.637755	0

2.22 Tutorial about setting up an analysis pipeline and batch processing

Quite often you experiment with various analysis routines and appropriate parameters and come up with an analysis pipeline. A pipeline procedure then is a script defining analysis steps for a single locdata object (or a single group of corresponding locdatas as for instance used in 2-color measurements).

The `Pipeline` class can be used to combine the pipeline code, metadata and analysis results in a single pickleable object (meaning it can be serialized by the python pickle module).

This pipeline might then be applied to a number of similar datasets. A batch process is such a procedure for running a pipeline over multiple locdata objects and collecting and combing results.

```
from pathlib import Path

%matplotlib inline

import matplotlib.pyplot as plt

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.22.1 Apply a pipeline of different analysis routines

Load rapidSTORM data file

```
path = lc.ROOT_DIR / 'tests/test_data/rapidSTORM_dstorm_data.txt'
print(path)
dat = lc.load_rapidSTORM_file(path=path, nrows=1000)
dat.print_summary()
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.txt
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
identifier: "1"
comment: ""
source: EXPERIMENT
state: RAW
element_count: 999
frame_count: 48
file {
  type: RAPIDSTORM
  path: "/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/
↪lib/python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.
↪txt"
}
creation_time {
  2024-03-14T11:50:52.930353Z
}
```

```
dat.properties
```

```
{'localization_count': 999,
 'position_x': 16066.234912912912,
 'uncertainty_x': 250.05278033739012,
 'position_y': 17550.369092792796,
 'uncertainty_y': 223.5338926935945,
 'intensity': 9471560.21,
```

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```
 'local_background': 645.07007,
 'frame': 0,
 'region_measure_bb': 1064111469.8204715,
 'localization_density_bb': 9.388114199807877e-07,
 'subregion_measure_bb': 130483.2086}
```

Set up an analysis procedure

First define the analysis procedure (pipeline) in form of a computation function. Make sure the first parameter is the `self` refering to the Pipeline object. Add arbitrary keyword arguments thereafter. When finishing with `return self` the compute method can easily be called with instantiation.

```
def computation(self, locdata, n_localizations_min=4):

    # import required modules
    from locan.analysis import LocalizationPrecision

    # prologue
    self.file_indicator = locdata.meta.file.path
    self.locdata = locdata

    # check requirements
    if len(locdata)<=n_localizations_min:
        return None

    # compute localization precision
    self.lp = LocalizationPrecision().compute(self.locdata)

    return self
```

Run the analysis procedure

Instantiate a Pipeline object and run compute():

```
pipe = lc.Pipeline(computation=computation, locdata=dat, n_localizations_
↪min=4).compute()
pipe.meta
```

```
Processed frames::   0%|          | 0/46 [00:00<?, ?it/s]
```

```
Processed frames::  11%|         | 5/46 [00:00<00:00, 43.69it/s]
```

```
Processed frames::  22%|       | 10/46 [00:00<00:00, 44.55it/s]
```

```
Processed frames::  33%|      | 15/46 [00:00<00:00, 39.90it/s]
```

```
Processed frames::  43%|     | 20/46 [00:00<00:00, 41.39it/s]
```

```
Processed frames::  57%|    | 26/46 [00:00<00:00, 45.92it/s]
```

```
Processed frames::  70%|   | 32/46 [00:00<00:00, 47.89it/s]
```

```
Processed frames::  83%| | 38/46 [00:00<00:00, 49.06it/s]
```

```
Processed frames::  93%|| 43/46 [00:00<00:00, 45.69it/s]
```

```
Processed frames:: 100%|| 46/46 [00:01<00:00, 45.18it/s]
```

```

```

```
identifier: "1"
method {
  name: "Pipeline"
  parameter: "{\'computation\': <function computation at 0x7f3890ad6a70>, \
↪'locdata\': <locan.data.locdata.LocData object at 0x7f38ae548250>, \'n_
↪localizations_min\': 4}"
}
creation_time {
  seconds: 1710417053
  nanos: 530357000
}
```

Results are available from Pipeline object in form of attributes defined in the compute function:

```
[attr for attr in dir(pipe) if not attr.startswith('__') and not attr.
↪endswith('__')]
```

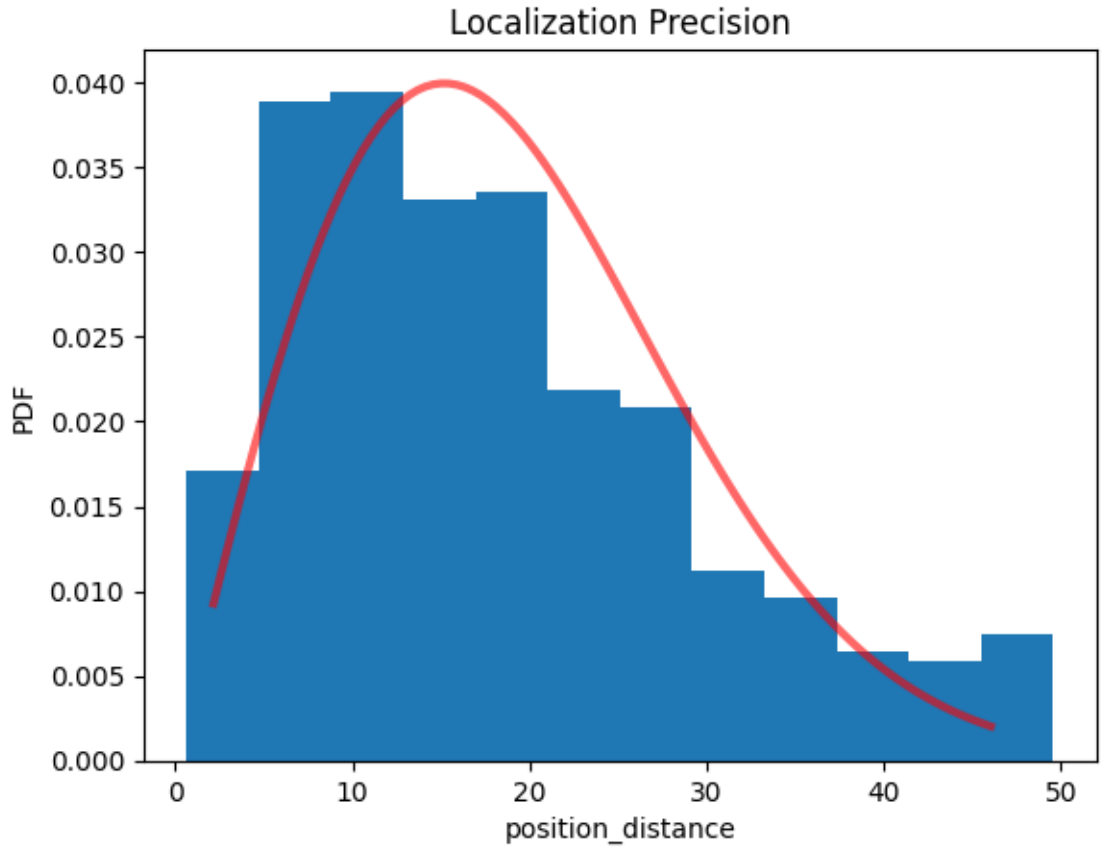
```
['_get_parameters',
 '_init_meta',
 '_update_meta',
 'computation',
 'computation_as_string',
 'compute',
 'count',
 'file_indicator',
 'kwargs',
 'locdata',
 'lp',
 'meta',
 'parameter',
 'report',
 'results',
 'save_computation']
```

```
pipe.lp.results.head()
```

	position_delta_x	position_delta_y	position_distance	frame
0	4.6	-2.8	5.385165	0
1	-1.0	-3.4	3.544009	0
2	17.0	-17.5	24.397746	0
3	5.1	-8.1	9.571834	0
4	-14.1	22.6	26.637755	0

```
pipe.lp.hist();
print(pipe.lp.distribution_statistics.parameter_dict())
```

```
{'position_delta_x_loc': 0.5793456521739601, 'position_delta_x_scale': 15.
↪01664582880988, 'position_delta_y_loc': -0.028067391304342455, 'position_
↪delta_y_scale': 15.310244879968039, 'position_distance_sigma': 15.
↪169726562500031, 'position_distance_loc': 0, 'position_distance_scale': 1}
```



You can recover the computation procedure:

```
pipe.computation_as_string()
```

```
'def computation(self, locdata, n_localizations_min=4):\n    \n    # import␣
↪required modules\n    from locan.analysis import LocalizationPrecision\n    ␣
↪\n    # prologue\n    self.file_indicator = locdata.meta.file.path\n    ␣
↪self.locdata = locdata\n    \n    # check requirements\n    if len(locdata)
↪<=n_localizations_min:\n        return None\n    \n    # compute␣
↪localization precision\n    self.lp = LocalizationPrecision().compute(self.
↪locdata)\n    \n    return self\n'
```

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or save it as text protocol:

The Pipeline object is pickleable and can thus be saved for revisits.

2.22.2 Apply the pipeline on multiple datasets - a batch process

Let's create multiple datasets:

```
path = lc.ROOT_DIR / 'tests/test_data/rapidSTORM_dstorm_data.txt'
print(path)
dat = lc.load_rapidSTORM_file(path=path)

locdatas = [lc.select_by_condition(dat, f'{min}<index<{max}') for min, max in␣
↪((0,300), (301,600), (601,900))]
locdatas
```

```
/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/
↪python3.10/site-packages/locan/tests/test_data/rapidSTORM_dstorm_data.txt
```

```
[<locan.data.locdata.LocData at 0x7f388e72d300>,
 <locan.data.locdata.LocData at 0x7f388eef79a0>,
 <locan.data.locdata.LocData at 0x7f388c74b2e0>]
```

Run the analysis pipeline as batch process

```
pipes = [lc.Pipeline(computation=computation, locdata=dat).compute() for dat␣
↪in locdatas]
```

```
Processed frames::   0%|          | 0/12 [00:00<?, ?it/s]
```

```
Processed frames::  33%|      | 4/12 [00:00<00:00, 32.17it/s]
```

```
Processed frames::  67%|   | 8/12 [00:00<00:00, 34.22it/s]
```

```
Processed frames:: 100%|| 12/12 [00:00<00:00, 34.51it/s]
```

```
Processed frames:: 100%|| 12/12 [00:00<00:00, 34.12it/s]
```

```

```

```
Processed frames::   0%|          | 0/13 [00:00<?, ?it/s]
```

```
Processed frames::  31%|       | 4/13 [00:00<00:00, 33.99it/s]
```

```
Processed frames::  62%|   | 8/13 [00:00<00:00, 36.22it/s]
```

```
Processed frames:: 100%|| 13/13 [00:00<00:00, 37.80it/s]
```

```
Processed frames:: 100%|| 13/13 [00:00<00:00, 37.06it/s]
```

```

```

```
Processed frames::   0%|          | 0/14 [00:00<?, ?it/s]
```

```
Processed frames::  36%|      | 5/14 [00:00<00:00, 43.95it/s]
```

```
Processed frames::  71%|  | 10/14 [00:00<00:00, 40.48it/s]
```

```
Processed frames:: 100%|| 14/14 [00:00<00:00, 38.56it/s]
```

```

```

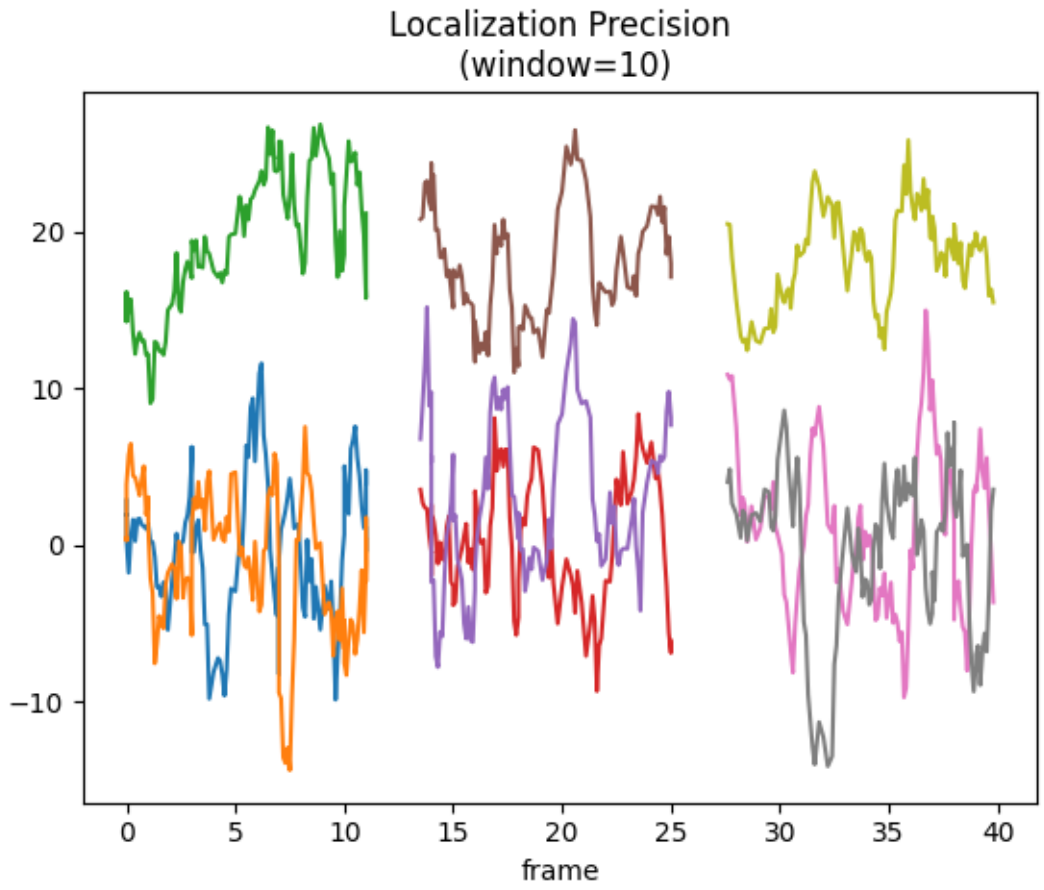
As long as the batch procedure runs in a single computer process, the identifier increases with every instantiation.

```
[pipe.meta.identifier for pipe in pipes]
```

```
['2', '3', '4']
```

Visualize the combined results

```
fig, ax = plt.subplots(nrows=1, ncols=1)
for pipe in pipes:
    pipe.lp.plot(ax=ax, window=10)
plt.show()
```



2.23 Tutorial about managing files in batch processing

When analysing a set of experiments you want to collect, match and group files according to information content and experimental conditions.

The Files class will help you.

```
from pathlib import Path
import tempfile

%matplotlib inline

import matplotlib.pyplot as plt

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

2.23.1 Some file structure to be analysed

```
directory = Path(tempfile.mkdtemp())
subdirectory = directory.joinpath("sub_directory")
subdirectory.mkdir()
```

```
files = [
    directory / "sub_directory" / "file_group_a_0.data",
    directory / "sub_directory" / "file_group_a_1.data",
    directory / "sub_directory" / "file_group_b_2.data",
    directory / "sub_directory" / "corresponding_file_0.data",
    directory / "metadata.meta",
]
for file_ in files:
    file_.touch()
```

```
list(directory.glob("**/*.*"))
```

```
[PosixPath('/tmp/tmpcgz5_v20/metadata.meta'),
 PosixPath('/tmp/tmpcgz5_v20/sub_directory/file_group_b_2.data'),
 PosixPath('/tmp/tmpcgz5_v20/sub_directory/file_group_a_1.data'),
 PosixPath('/tmp/tmpcgz5_v20/sub_directory/file_group_a_0.data'),
 PosixPath('/tmp/tmpcgz5_v20/sub_directory/corresponding_file_0.data')]
```

2.23.2 The Files class

```
lc.Files?
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

2.23.3 Identify files

```
files = lc.Files.from_glob(
    directory=directory,
    pattern="**/*.*"
)
files.df
```

```
                                           file_path
0                       /tmp/tmpcgz5_v20/metadata.meta
1  /tmp/tmpcgz5_v20/sub_directory/file_group_b_2....
2  /tmp/tmpcgz5_v20/sub_directory/file_group_a_1....
3  /tmp/tmpcgz5_v20/sub_directory/file_group_a_0....
4  /tmp/tmpcgz5_v20/sub_directory/corresponding_f...
```

For each file a Path object is stored:

```
files.df.applymap(lambda x: x.name)
```

```
/tmp/ipykernel_1346/1019267881.py:1: FutureWarning: DataFrame.applymap has␣
↪been deprecated. Use DataFrame.map instead.
  files.df.applymap(lambda x: x.name)
```

```
                   file_path
0              metadata.meta
1        file_group_b_2.data
2        file_group_a_1.data
3        file_group_a_0.data
4  corresponding_file_0.data
```

```
files.print_summary()
```

```
Number of files: 5
Base directory: /tmp/tmpcgz5_v20
Columns: Index(['file_path'], dtype='object')
       file_path
count          5
unique         5
```

2.23.4 Exclude files

```
files = lc.Files.from_glob(
    directory=directory,
    pattern="**/*.*"
)

files.df.applymap(lambda x: x.name)
```

```
/tmp/ipykernel_1346/641744908.py:6: FutureWarning: DataFrame.applymap has␣
↪been deprecated. Use DataFrame.map instead.
  files.df.applymap(lambda x: x.name)
```

```
                   file_path
0              metadata.meta
1        file_group_b_2.data
2        file_group_a_1.data
3        file_group_a_0.data
4  corresponding_file_0.data
```

```
stoplist = lc.Files.concatenate([
    lc.Files.from_glob(directory=files.directory, pattern="**/*.meta"),
    lc.Files.from_glob(directory=files.directory, pattern="**/*group_b*.*")
```

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```
])
stoplist.df.applymap(lambda x: x.name)
```

```
/tmp/ipykernel_1346/823210556.py:5: FutureWarning: DataFrame.applymap has␣
↪been deprecated. Use DataFrame.map instead.
  stoplist.df.applymap(lambda x: x.name)
```

```
              file_path
0        metadata.meta
1  file_group_b_2.data
```

```
files.exclude(stoplist=stoplist)
files.df.applymap(lambda x: x.name)
```

```
/tmp/ipykernel_1346/3083961993.py:2: FutureWarning: DataFrame.applymap has␣
↪been deprecated. Use DataFrame.map instead.
  files.df.applymap(lambda x: x.name)
```

```
                   file_path
2        file_group_a_1.data
3        file_group_a_0.data
4  corresponding_file_0.data
```

2.23.5 Match corresponding files

```
files = lc.Files.from_glob(
    directory=directory,
    pattern="**/*.*",
    regex="group_a_0"
)
files.df.applymap(lambda x: x.name)
```

```
/tmp/ipykernel_1346/3682074927.py:6: FutureWarning: DataFrame.applymap has␣
↪been deprecated. Use DataFrame.map instead.
  files.df.applymap(lambda x: x.name)
```

```
              file_path
0  file_group_a_0.data
```

```
corresponding_files = lc.Files.from_glob(
    directory=directory,
    pattern="**/*.*",
    regex="corresponding"
)
corresponding_files.df.applymap(lambda x: x.name)
```

```
/tmp/ipykernel_1346/257078577.py:6: FutureWarning: DataFrame.applymap has␣
↪been deprecated. Use DataFrame.map instead.
  corresponding_files.df.applymap(lambda x: x.name)
```

```
                    file_path
0  corresponding_file_0.data
```

```
files.match_files(files=corresponding_files.df)
files.df.applymap(lambda x: x.name)
```

```
/tmp/ipykernel_1346/1564609699.py:2: FutureWarning: DataFrame.applymap has␣
↪been deprecated. Use DataFrame.map instead.
  files.df.applymap(lambda x: x.name)
```

```
              file_path            other_file_path
0  file_group_a_0.data  corresponding_file_0.data
```

2.23.6 Match metadata files

```
files = lc.Files.from_glob(
    directory=directory,
    pattern="**/*.*",
    regex="group_a_0"
)
files.df.applymap(lambda x: x.name)
```

```
/tmp/ipykernel_1346/3682074927.py:6: FutureWarning: DataFrame.applymap has␣
↪been deprecated. Use DataFrame.map instead.
  files.df.applymap(lambda x: x.name)
```

```
              file_path
0  file_group_a_0.data
```

```
files.match_file_upstream(pattern="*.meta")
files.df.applymap(lambda x: x.name)
```

```
/tmp/ipykernel_1346/745566580.py:2: FutureWarning: DataFrame.applymap has␣
↪been deprecated. Use DataFrame.map instead.
  files.df.applymap(lambda x: x.name)
```

```
              file_path       metadata
0  file_group_a_0.data  metadata.meta
```

2.23.7 Group files

```
files = lc.Files.from_glob(
    directory=directory,
    pattern="**/file*.data"
)
files.df.applymap(lambda x: x.name)
```

```
/tmp/ipykernel_1346/1768514306.py:5: FutureWarning: DataFrame.applymap has␣
↪been deprecated. Use DataFrame.map instead.
  files.df.applymap(lambda x: x.name)
```

	file_path
0	file_group_b_2.data
1	file_group_a_1.data
2	file_group_a_0.data

```
files.set_group_identifier(name="A", pattern="group_a")
files.df
```

	file_path	group
0	/tmp/tmpcgz5_v20/sub_directory/file_group_b_2....	NaN
1	/tmp/tmpcgz5_v20/sub_directory/file_group_a_1....	A
2	/tmp/tmpcgz5_v20/sub_directory/file_group_a_0....	A

```
files.set_group_identifier(name="B", pattern="group_b")
files.df
```

	file_path	group
0	/tmp/tmpcgz5_v20/sub_directory/file_group_b_2....	B
1	/tmp/tmpcgz5_v20/sub_directory/file_group_a_1....	A
2	/tmp/tmpcgz5_v20/sub_directory/file_group_a_0....	A

```
files.group_identifiers()
```

```
Index(['A', 'B'], dtype='object')
```

```
grouped = files.grouped()
grouped.groups
```

```
{'A': [1, 2], 'B': [0]}
```

2.23.8 Indexing and iterating over files

```
files = lc.Files.from_glob(
    directory=directory,
    pattern="**/file*.data"
)
files.df.applymap(lambda x: x.name)
```

```
/tmp/ipykernel_1346/1768514306.py:5: FutureWarning: DataFrame.applymap has␣
↪been deprecated. Use DataFrame.map instead.
  files.df.applymap(lambda x: x.name)
```

	file_path
0	file_group_b_2.data
1	file_group_a_1.data
2	file_group_a_0.data

Slicing Files yield a new Files instance:

```
files[0:3]
```

```
<locan.locan_io.files.Files at 0x7f2f5bc44940>
```

Indexing Files yields a Series with the selected row:

```
files[0]
```

```
file_path    /tmp/tmpcgz5_v20/sub_directory/file_group_b_2....
Name: 0, dtype: object
```

Iterating over Files yields a namedtuple for each row:

```
for file in files:
    print(file)
    print(file.file_path)
```

```
Files(Index=0, file_path=PosixPath('/tmp/tmpcgz5_v20/sub_directory/file_group_
↪b_2.data'))
/tmp/tmpcgz5_v20/sub_directory/file_group_b_2.data
Files(Index=1, file_path=PosixPath('/tmp/tmpcgz5_v20/sub_directory/file_group_
↪a_1.data'))
/tmp/tmpcgz5_v20/sub_directory/file_group_a_1.data
Files(Index=2, file_path=PosixPath('/tmp/tmpcgz5_v20/sub_directory/file_group_
↪a_0.data'))
/tmp/tmpcgz5_v20/sub_directory/file_group_a_0.data
```

2.24 Tutorial about mutiprocessing using ray

We will describe how to set up an analysis pipeline to process multiple datasets in parallel using the framework ray.

```
import sys
import logging

%matplotlib inline

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import ray

import locan as lc
```

```
lc.show_versions(dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13

System:
python-bits: 64
    system: Linux
   release: 5.19.0-1028-aws
   version: #29~22.04.1-Ubuntu SMP Tue Jun 20 19:12:11 UTC 2023
   machine: x86_64
 processor: x86_64
 byteorder: little
    LC_ALL: None
      LANG: C.UTF-8
    LOCALE: {'language-code': 'en_US', 'encoding': 'UTF-8'}
```

2.24.1 Activate logging

```
logging.basicConfig(stream=sys.stdout, level=logging.INFO, format='
↪%(asctime)s - %(name)s - %(levelname)s - %(message)s')
logger = logging.getLogger()
```

For changing the configuration logging has to be reloaded or the kernel be restarted.

2.24.2 Synthetic data

Simulate 3 datasets of localization data that is homogeneously Poisson distributed and treat them as files.

```
rng = np.random.default_rng(seed=1)
```

```
locdatas = [lc.simulate_Poisson(intensity=1e-3, region=((0,1000), (0,1000)),␣
↪seed=rng) for _ in range(3)]
files = locdatas

print("Element_counts:", [locdata.meta.element_count for locdata in locdatas])
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
Element_counts: [1001, 994, 978]
```

2.24.3 Analysis pipeline

Define an analysis pipeline. Typically a pipeline processes a single file, which in this example will be a an element of locdatas.

Within the analysis procedure there will be more random number generation involved. Therefore a correctly generated seed has to be passed.

```
def computation(self, file, seed):
    logging.basicConfig(level=logging.INFO)
    logger.info(f'computation started for file: {file}')

    rng = np.random.default_rng(seed=seed)

    other_locdata = lc.simulate_Poisson(intensity=1e-3, region=((0,1000), (0,
↪1000)), seed=rng)
    self.nn = lc.NearestNeighborDistances().compute(locdata=file, other_
↪locdata=other_locdata)

    return self
```

2.24.4 Run analysis in parallel

```
ray.init()
# ray.init(num_cpus = 4)
```

```
2024-03-14 11:52:09,528        WARNING services.py:1832 -- WARNING: The␣
↪object store is using /tmp instead of /dev/shm because /dev/shm has only␣
↪67108864 bytes available. This will harm performance! You may be able to␣
↪free up space by deleting files in /dev/shm. If you are inside a Docker␣
↪container, you can increase /dev/shm size by passing '--shm-size=1.77gb' to
↪'docker run' (or add it to the run_options list in a Ray cluster config).␣
↪Make sure to set this to more than 30% of available RAM.
```

```
2024-03-14 11:52:09,590        INFO worker.py:1621 -- Started a local Ray␣
↪instance.
```

```
RayContext(dashboard_url='', python_version='3.10.13', ray_version='2.6.3',␣
↪ray_commit='8a434b4ee7cd48e60fa1531315d39901fac5d79e', protocol_
↪version=None)
```

```
%%time
@ray.remote
def worker(file, seed):
    pipe = lc.Pipeline(computation=computation, file=file, seed=seed).
↪compute()
    return pipe

n_processes = len(files)
ss = np.random.SeedSequence()
child_seeds = ss.spawn(n_processes)

futures = [worker.remote(file=file, seed=seed) for file, seed in zip(locdatas,
↪ child_seeds)]
pipes = ray.get(futures)
```

```
(worker pid=1715) INFO:root:computation started for file: <locan.data.locdata.
↪LocData object at 0x7efdccd291e0>
(worker pid=1715) INFO:root:computation started for file: <locan.data.locdata.
↪LocData object at 0x7efe6c20d720>
```

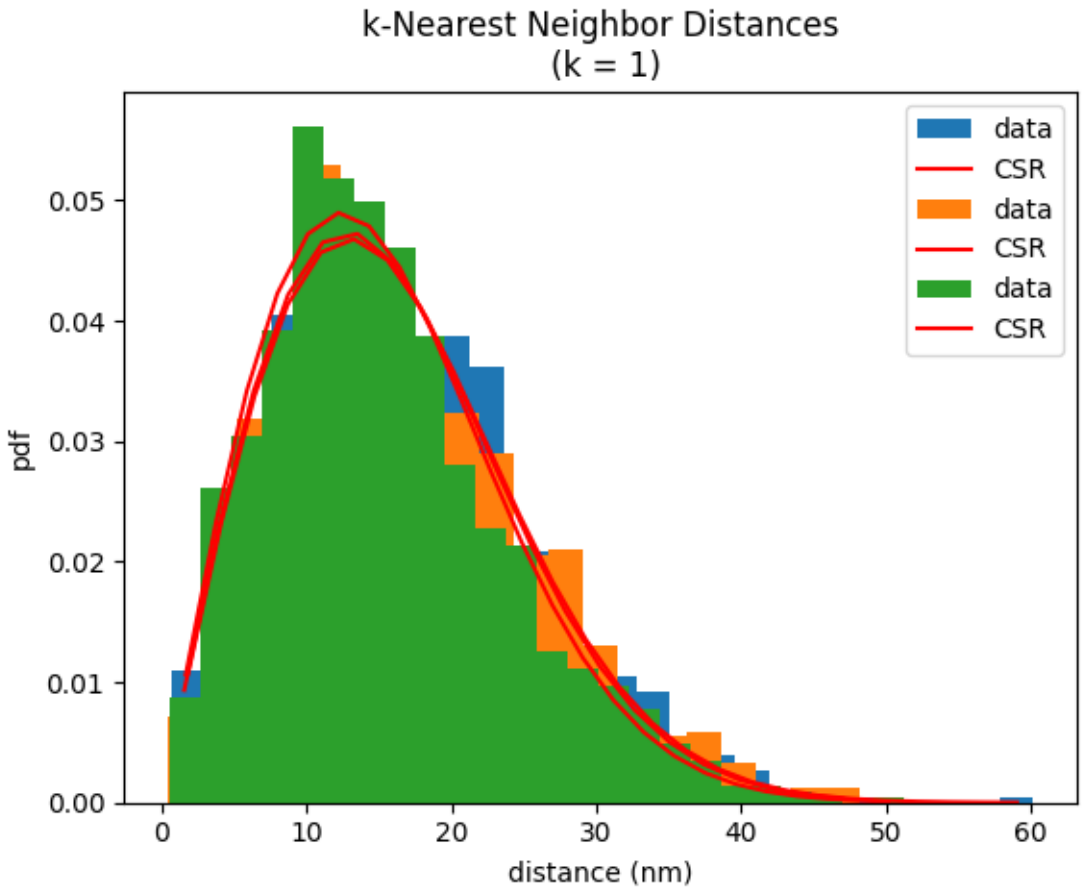
```
CPU times: user 721 ms, sys: 95.7 ms, total: 817 ms
Wall time: 6.52 s
```

2.24.5 Visualize the combined results

```
[pipe.meta for pipe in pipes]
```

```
[identifier: "1"
 method {
   name: "Pipeline"
   parameter: "{\'computation\': <function computation at 0x7efe6c21a680>, \
↪'file\': <locan.data.locdata.LocData object at 0x7efdccd291e0>, \'seed\':␣
↪SeedSequence(\n    entropy=127780349092226534857580436219185235194,\n   ␣
↪spawn_key=(0,),\n)}"
 }
 creation_time {
   seconds: 1710417137
   nanos: 852773000
 },
 identifier: "1"
 method {
   name: "Pipeline"
   parameter: "{\'computation\': <function computation at 0x7fa37699a680>, \
↪'file\': <locan.data.locdata.LocData object at 0x7fa2c5ef7610>, \'seed\':␣
↪SeedSequence(\n    entropy=127780349092226534857580436219185235194,\n   ␣
↪spawn_key=(1,),\n)}"
 }
 creation_time {
   seconds: 1710417137
   nanos: 957157000
 },
 identifier: "1"
 method {
   name: "Pipeline"
   parameter: "{\'computation\': <function computation at 0x7efe6c21a680>, \
↪'file\': <locan.data.locdata.LocData object at 0x7efe6c20d720>, \'seed\':␣
↪SeedSequence(\n    entropy=127780349092226534857580436219185235194,\n   ␣
↪spawn_key=(2,),\n)}"
 }
 creation_time {
   seconds: 1710417137
   nanos: 884582000
 }]
```

```
fig, ax = plt.subplots(nrows=1, ncols=1)
for pipe in pipes:
    pipe.nn.hist(ax=ax)
plt.show()
```



2.25 Tutorial about example datasets

```
import sys
from pathlib import Path
import shutil
import logging

import requests

import locan as lc
```

```
lc.show_versions(system=False, dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13
```

```
logging.basicConfig(stream=sys.stdout, level=logging.INFO, format='
↪%(asctime)s - %(name)s - %(levelname)s - %(message)s')
logger = logging.getLogger()
```

2.25.1 Load SMLM data from ShareLoc.XYZ

SMLM data can e.g. be found on ShareLoc.XYZ, an open platform for sharing single-molecule localization microscopy data.

Copy a specific download link for downloading a smlm-file.

```
url = "https://zenodo.org/api/files/48a8996a-e9ef-49d8-be2b-25026c3c5dbd/
↪UniWue_Tubulin_AF647_3/data.smlm"
url
```

```
'https://zenodo.org/api/files/48a8996a-e9ef-49d8-be2b-25026c3c5dbd/UniWue_
↪Tubulin_AF647_3/data.smlm'
```

```
response = requests.get(url)
print("Response is ok: ", response.status_code == requests.codes.ok)
```

```
Response is ok:  False
```

```
file_path = Path.home() / Path(url).name

with open(file_path, 'wb') as file:
    for chunk in response.iter_content(chunk_size=128):
        file.write(chunk)

file_path
```

```
PosixPath('/home/docs/data.smlm')
```

Load data and visualize

```
locdata = lc.load_SMLM_file(file_path)
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
```

```
---------------------------------------------------------------------------
BadZipFile                                Traceback (most recent call last)
Cell In[7], line 1
----> 1 locdata = lc.load_SMLM_file(file_path)

File ~/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/python3.10/
↪site-packages/locan/locan_io/locdata/smlm_io.py:363, in load_SMLM_file(path,
↪ nrows, convert)
    338 def load_SMLM_file(
    339     path: str | os.PathLike[Any] | IO[Any],
    340     nrows: int | None = None,
```

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```
    341     convert: bool = True,
    342 ) -> LocData | list[LocData]:
    343     """
    344     Load data from a SMLM single-molecule localization file.
    345
   (...)
    361         LocData if multiple tables are found.
    362     """
--> 363     zf = zipfile.ZipFile(path, "r")
    364     file_names = zf.namelist()
    365     if "manifest.json" not in file_names:

File ~/.asdf/installs/python/3.10.13/lib/python3.10/zipfile.py:1269, in␣
↪ZipFile.__init__(self, file, mode, compression, allowZip64, compresslevel,␣
↪strict_timestamps)
   1267 try:
   1268     if mode == 'r':
-> 1269         self._RealGetContents()
   1270     elif mode in ('w', 'x'):
   1271         # set the modified flag so central directory gets written
   1272         # even if no files are added to the archive
   1273         self._didModify = True

File ~/.asdf/installs/python/3.10.13/lib/python3.10/zipfile.py:1336, in␣
↪ZipFile._RealGetContents(self)
   1334     raise BadZipFile("File is not a zip file")
   1335 if not endrec:
-> 1336     raise BadZipFile("File is not a zip file")
   1337 if self.debug > 1:
   1338     print(endrec)

BadZipFile: File is not a zip file
```

Print information about the data:

```
print('Data head:')
print(locdata.data.head(), '\n')
print('Summary:')
locdata.print_summary()
print('Properties:')
print(locdata.properties)
```

```
Data head:
   original_index    position_x  local_background  chi_square     intensity  \
0               1   1653.339966        733.021973   6224440.0  13324.799805
1               2   5672.879883        798.614990   2066740.0  10348.000000
2               3   7117.830078        909.901978   1787550.0   6864.439941
3               4   3707.459961        804.187012   2542450.0   9038.549805
4               5  14038.200195        815.343994   1842030.0   8774.750000
```

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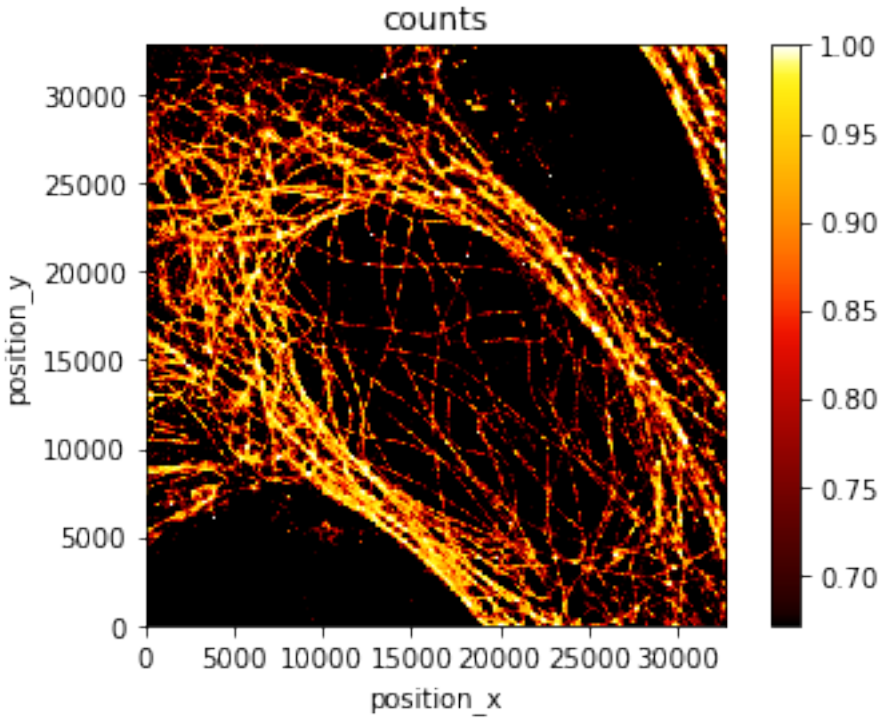
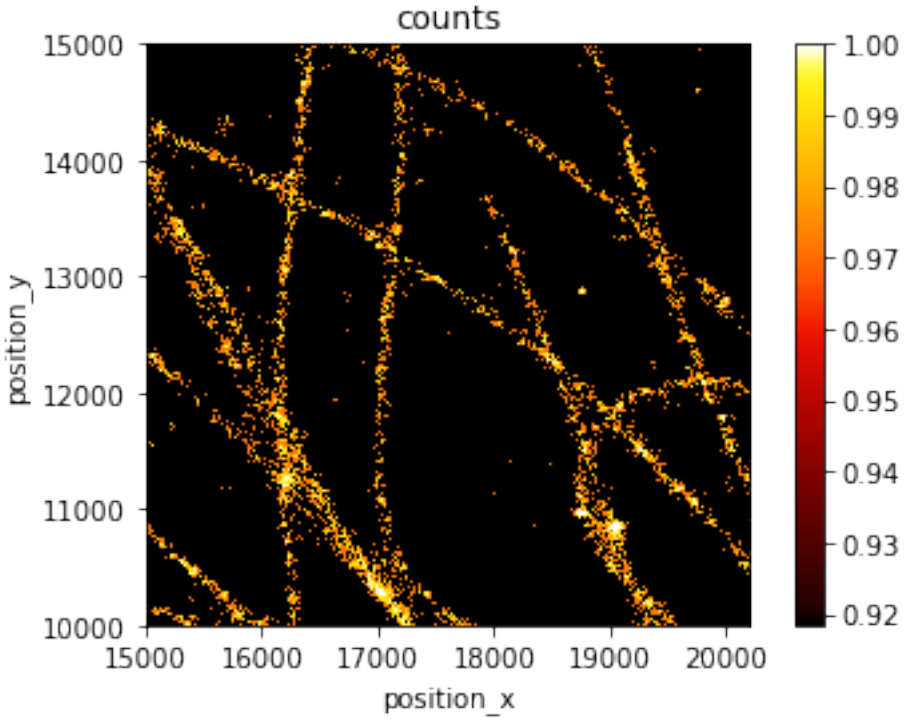
```
   frame    position_y
0      0   8879.339844
1      0   9851.900391
2      0  11888.099609
3      0  15224.799805
4      0   5597.879883

Summary:
identifier: "1"
comment: ""
creation_date: "2022-02-09 11:12:03 +0100"
modification_date: ""
source: EXPERIMENT
state: RAW
element_count: 4582761
frame_count: 45000
file_type: SMLM
file_path: "C:\\Users\\sod28mb\\data.smlm"

Properties:
{'localization_count': 4582761, 'position_x': 15788.7705, 'position_y': 16751.
↪121, 'region_measure_bb': 1078728300.0, 'localization_density_bb': 0.
↪004248299516230371, 'subregion_measure_bb': 131376.0}
```

```
lc.render_2d(locdata, bin_size=100, rescale='equal');
```



```
lc.render_2d(locdata, bin_size=10, rescale='equal',
             bin_range=((15_000, 20_200), (10_000, 15_000)));
```



2.25.2 Load SMLM data from LocanDatasets

Selected example datasets are provided in a separate directory (repository) called `LocanDatasets`.

These datasets can be loaded by ready-to-go utility functions.

Set up a datasets directory

```
lc.DATASETS_DIR = Path.home() / 'LocanDatasets'
lc.DATASETS_DIR.mkdir(exist_ok=True)
```

Load dSTORM data of nuclear pore complexes

This is a rather large 2D dataset with > 2 mio localizations.

```
url = "https://raw.github.com/super-resolution/LocanDatasets/main/smlm_data/
↪npc_gp210.asdf"
```

```
response = requests.get(url)
print("Response is ok: ", response.status_code == requests.codes.ok)
```

```
Response is ok:  True
```

```
file_path = lc.DATASETS_DIR / 'npc_gp210.asdf'

with open(file_path, 'wb') as file:
    for chunk in response.iter_content(chunk_size=128):
        file.write(chunk)

file_path
```

```
WindowsPath('C:/Users/sod28mb/LocanDatasets/npc_gp210.asdf')
```

```
dat = lc.load_npc()
```

Print information about the data:

```
print('Data head:')
print(dat.data.head(), '\n')
print('Summary:')
dat.print_summary()
print('Properties:')
print(dat.properties)
```

```
Data head:
     position_x    position_y  frame     intensity  two_kernel_improvement  \
0   5768.129883  20242.400391    0.0  83745.398438                     0.0
1  21402.800781  18154.599609    0.0  67648.296875                     0.0
2  11410.700195   3155.639893    0.0  73358.398438                     0.0
3  15570.599609  15854.599609    0.0  65827.898438                     0.0
4  22235.500000  12840.900391    0.0  56347.398438                     0.0

   chi_square  local_background
0   4355630.0       1511.459961
1   8383720.0       1637.000000
2   2420450.0       1480.380005
3   2539930.0       1540.670044
4  16152800.0       1572.040039

Summary:
identifier: "13"
comment: ""
creation_date: "2021-11-30 15:40:00 +0100"
modification_date: ""
source: EXPERIMENT
state: RAW
element_count: 2285189
frame_count: 24999
file_type: RAPIDSTORM
file_path: "c:\\users\\sod28mb\\mydata\\programming\\python\\projects\\
↪LocanDatasets\\smlm_data\\npc_gp210.txt"
```

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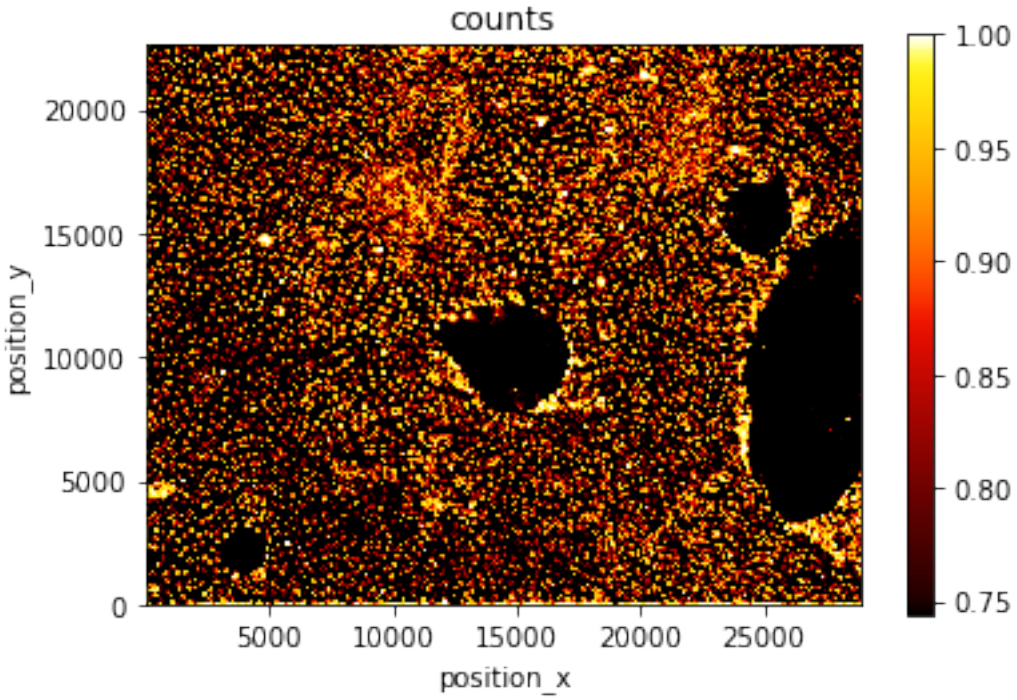
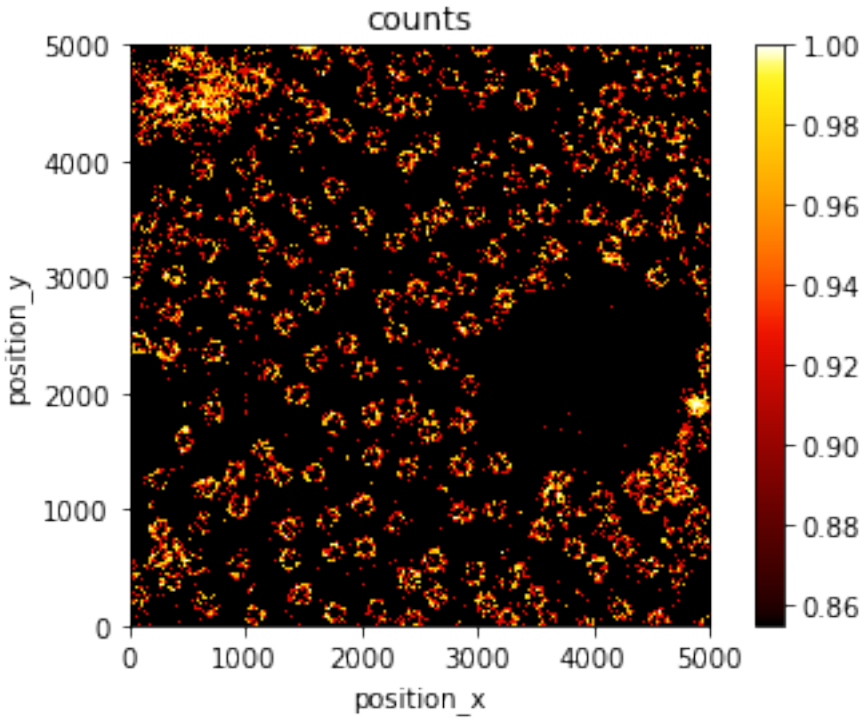
```
Properties:
{'localization_count': 2285189, 'position_x': 14570.823, 'position_y': 12028.
↪225, 'region_measure_bb': 655392800.0, 'localization_density_bb': 0.
↪0034867473545268047, 'subregion_measure_bb': 103168.0}
```

```
lc.render_2d(dat, bin_size=100, rescale='equal');
```




```
lc.render_2d(dat, bin_size=10, rescale='equal',
             bin_range=((0, 5000), (0, 5000)));
```



Load dSTORM data of microtubules

This is a rather large 2D dataset with about 1.5 mio localizations.

```
url = "https://raw.github.com/super-resolution/LocanDatasets/main/smlm_data/
↪tubulin_cos7.asdf"
```

```
response = requests.get(url)
print("Response is ok: ", response.status_code == requests.codes.ok)
```

```
Response is ok:  True
```

```
file_path = lc.DATASETS_DIR / 'tubulin_cos7.asdf'

with open(file_path, 'wb') as file:
    for chunk in response.iter_content(chunk_size=128):
        file.write(chunk)

file_path
```

```
WindowsPath('C:/Users/sod28mb/LocanDatasets/tubulin_cos7.asdf')
```

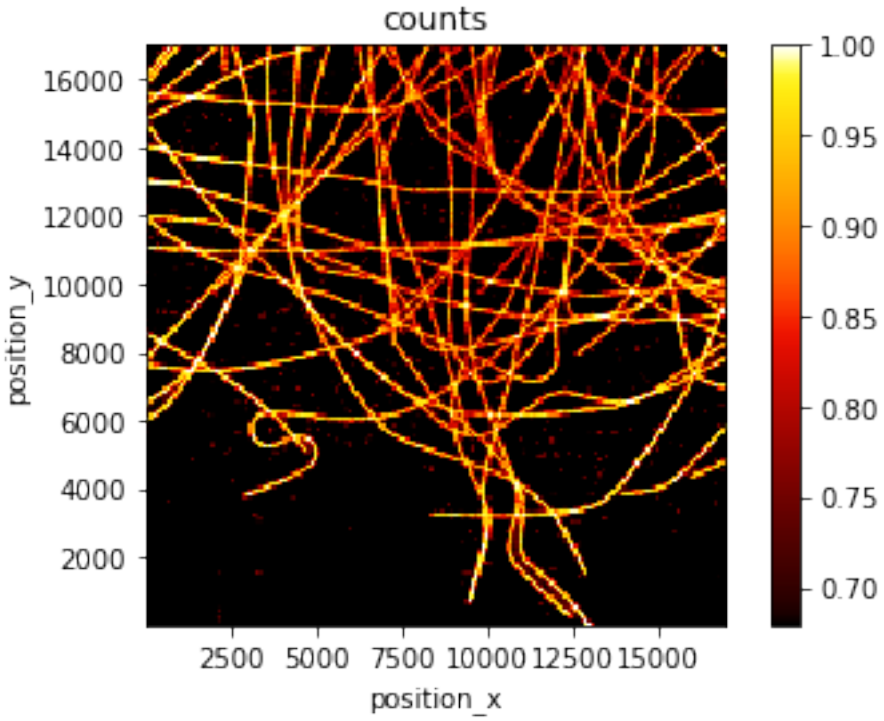
```
dat = lc.load_tubulin()
```

Print information about the data:

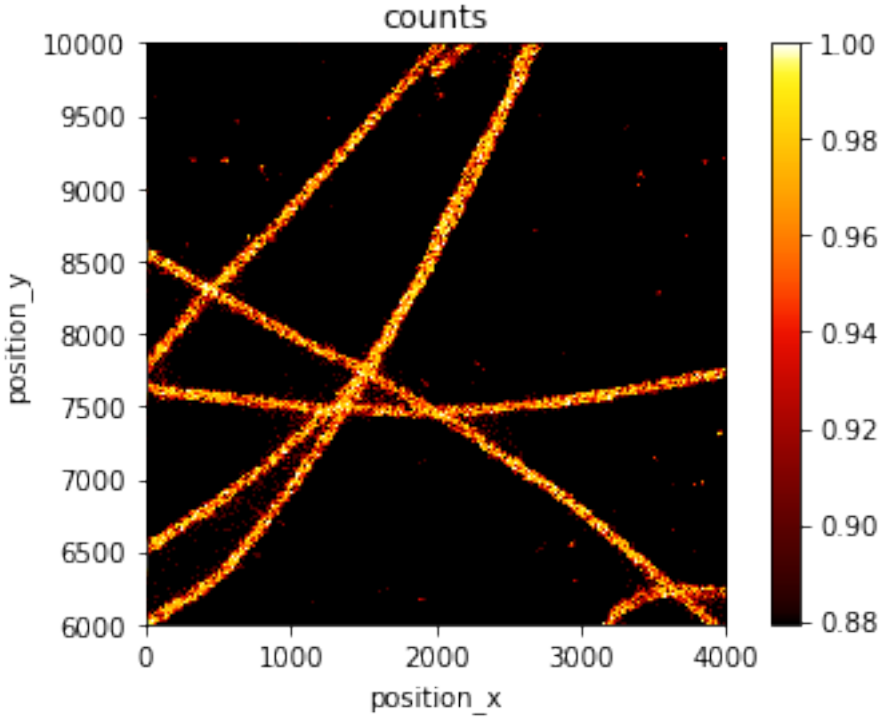
```
print('Data head:')
print(dat.data.head(), '\n')
print('Summary:')
dat.print_summary()
print('Properties:')
print(dat.properties)
```

```
Data head:
     position_x    position_y  frame     intensity  chi_square  \
0   9937.400391  16751.300781    0.0  40501.601562   3744920.0
1   9998.709961  12022.799805    0.0  36280.300781  14295400.0
2   9566.769531   8078.229980    0.0  29984.000000  12302200.0
3  15492.500000  10120.400391    0.0  38488.300781   3219820.0
4   6381.459961  16057.700195    0.0  37093.300781   1620450.0

   local_background
0         709.413025
1         800.455017
2         890.807007
3         495.067993
4         476.035004

Summary:
identifier: "7"
comment: ""
creation_date: "2021-11-30 14:52:17 +0100"
modification_date: ""
source: EXPERIMENT
state: RAW
element_count: 1506568
frame_count: 74969
file_type: RAPIDSTORM
file_path: "c:\\users\\sod28mb\\mydata\\programming\\python\\projects\\
↪LocanDatasets\\smlm_data\\tubulin_cos7.txt"

Properties:
{'localization_count': 1506568, 'position_x': 8833.605738466662, 'position_y
↪': 10446.826432598386, 'region_measure_bb': 289612323.4905808,
↪'localization_density_bb': 0.0052020162051184225, 'subregion_measure_bb':␣
↪68071.99994013172}
```

```
lc.render_2d(dat, bin_size=100, rescale='equal');
```




```
lc.render_2d(dat, bin_size=10, rescale='equal',
             bin_range=((0, 4000), (6000, 10_000)));
```



2.26 Tutorial about logging

Logging as supplied by the python standard library can be used.

We make use of the standard logging levels DEBUG, INFO, WARNING, ERROR, CRITICAL.

```
import logging
import sys
from pathlib import Path

import numpy as np
import pandas as pd

import locan as lc
```

```
lc.show_versions(dependencies=False, verbose=False)
```

```
Locan:
   version: 0.19.1

Python:
   version: 3.10.13

System:
python-bits: 64
    system: Linux
   release: 5.19.0-1028-aws
   version: #29~22.04.1-Ubuntu SMP Tue Jun 20 19:12:11 UTC 2023
   machine: x86_64
 processor: x86_64
 byteorder: little
    LC_ALL: None
      LANG: C.UTF-8
    LOCALE: {'language-code': 'en_US', 'encoding': 'UTF-8'}
```

2.26.1 Activate logging

In any script or notebook logging has to be enabled e.g. for streaming to stdout.

For changing the configuration logging has to be reloaded or the kernel be restarted.

```
logging.basicConfig(stream=sys.stdout, level=logging.INFO, format='
↪%(asctime)s - %(name)s - %(levelname)s - %(message)s')
```

A top-level logger has to be instantiated to process any log messages from the library.

```
logger = logging.getLogger()
logger
```

```
<RootLogger root (INFO)>
```

Further log messages can be added:

```
logger.info("test")
```

```
2024-03-14 11:51:49,813 - root - INFO - test
```

Handling locan.logger

To change the filter level of locan log records, use an instance of the locan logger identified by its module name.

```
locan_logger = logging.getLogger('locan')
locan_logger.setLevel(logging.INFO)
locan_logger
```

```
<Logger locan (INFO)>
```

2.26.2 Logging in locan

Many functions provide warnings if some unusual behavior occurs:

```
locdata = lc.LocData.from_coordinates([(0, 0), (1, 2), (2, 1), (5, 5)])
locdata.region = lc.Rectangle((0, 0), 2, 2, 0)
```

```
Jupyter environment detected. Enabling Open3D WebVisualizer.
[Open3D INFO] WebRTC GUI backend enabled.
[Open3D INFO] WebRTCWindowSystem: HTTP handshake server disabled.
2024-03-14 11:51:52,056 - locan.data.locdata - WARNING - Not all coordinates␣
↪are within region.
```

Changing the level of the locan logger to `logging.WARNING` or higher, will switch off most locan log records.

```
locan_logger.setLevel(logging.ERROR)

locdata = lc.LocData.from_coordinates([(0, 0), (1, 2), (2, 1), (5, 5)])
locdata.region = lc.Rectangle((0, 0), 2, 2, 0)
```

```
locan_logger.setLevel(logging.INFO)

locdata = lc.LocData.from_coordinates([(0, 0), (1, 2), (2, 1), (5, 5)])
locdata.region = lc.Rectangle((0, 0), 2, 2, 0)
```

```
2024-03-14 11:51:52,080 - locan.data.locdata - WARNING - Not all coordinates␣
↪are within region.
```

Levels can be set for selected loggers by specifying the module or function name:

```
logger_locan_data = logging.getLogger('locan.data')
logger_locan_data.setLevel(logging.ERROR)

locdata = lc.LocData.from_coordinates([(0, 0), (1, 2), (2, 1), (5, 5)])
locdata.region = lc.Rectangle((0, 0), 2, 2, 0)
```

```
logger_locan_data.setLevel(logging.INFO)

locdata = lc.LocData.from_coordinates([(0, 0), (1, 2), (2, 1), (5, 5)])
locdata.region = lc.Rectangle((0, 0), 2, 2, 0)
```

```
2024-03-14 11:51:52,103 - locan.data.locdata - WARNING - Not all coordinates␣
↪are within region.
```

Logging in a pipeline

```
def computation(self, file):
    logger.info(f'computation started for file: {file}')
    return self
```

```
pipes = [lc.Pipeline(computation=computation, file=file).compute() for file␣
↪in range(3)]
```

```
2024-03-14 11:51:52,817 - root - INFO - computation started for file: 0
```

```
2024-03-14 11:51:52,818 - root - INFO - computation started for file: 1
```

```
2024-03-14 11:51:52,819 - root - INFO - computation started for file: 2
```

Another example how to use logging in analysis pipelines is given by the `computation_test` function.

```
pipes = [lc.Pipeline(computation=lc.analysis.pipeline.computation_test,␣
↪locdata=file).compute() for file in range(3)]
```

```
2024-03-14 11:51:52,827 - locan.analysis.pipeline - INFO - computation␣
↪finished for locdata: 0
```

```
2024-03-14 11:51:52,828 - locan.analysis.pipeline - WARNING - An exception␣
↪occurred for locdata: 0
```

```
2024-03-14 11:51:52,830 - locan.analysis.pipeline - INFO - computation␣
↪finished for locdata: 1
```

```
2024-03-14 11:51:52,831 - locan.analysis.pipeline - WARNING - An exception␣
↪occurred for locdata: 1
```

```
2024-03-14 11:51:52,832 - locan.analysis.pipeline - INFO - computation␣
↪finished for locdata: 2
```

```
2024-03-14 11:51:52,833 - locan.analysis.pipeline - WARNING - An exception␣
↪occurred for locdata: 2
```

```
print(pipes[0].computation_as_string())
```

```
def computation_test(
    self: T_Pipeline,
    locdata: LocData | None = None,
    parameter: str = "test",
) -> T_Pipeline:
    """A pipeline definition for testing."""
    self.locdata = locdata  # type: ignore
    something = "changed_value"
    logger.debug(f"something has a : {something}")
    self.test = parameter  # type: ignore
    logger.info(f"computation finished for locdata: {locdata}")

    try:
        raise NotImplementedError
    except NotImplementedError:
        logger.warning(f"An exception occurred for locdata: {locdata}")

    return self
```

Logging in multiprocessing with ray

To enable logging in multiprocessing using ray you need to include a default configuration in the computation function: `logging.basicConfig(level=logging.INFO)`.

```
if False:
    def computation(self, file):
        logging.basicConfig(level=logging.INFO)
        logger.info(f'computation started for file: {file}')
        return self
```

```
if False:
    import ray

    ray.init()
    # ray.init(num_cpus = 4)
```

```
%%time
if False:
    @ray.remote
    def worker(file):
```

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```
        pipe = lc.Pipeline(computation=computation, file=file).compute()
        return pipe

    futures = [worker.remote(file) for file in range(3)]
    pipes = ray.get(futures)
    len(pipes)
```

```
CPU times: user 2 µs, sys: 0 ns, total: 2 µs
Wall time: 6.44 µs
```

2.26.3 Logging in locan - third party libraries

Some third-party libraries provide their own logging system. Typically the individual loggers can be imported and modified.

```
import trackpy as tr
```

```
tr.logger
```

```
<Logger trackpy (INFO)>
```

alternatively

```
trackpy_logger = logging.getLogger('trackpy')
trackpy_logger
```

```
<Logger trackpy (INFO)>
```

Depending on the library various methods can be used to change the logging level. All of the following can be used.

`trackpy_logger.setLevel(logging.WARN)`

`tr.logger.setLevel(logging.WARN)`

`tr.quiet()`

`tr.ignore_logging()` # this switches off the trackpy logging system and forwards all logs up the logger hirarchy.

```
dat = lc.simulate_tracks(n_walks=1, n_steps=100, ranges=((0,1000),(0,1000)),
                         diffusion_constant=1, seed=1)

dat.print_meta()
```

```
identifier: "6"
source: SIMULATION
state: RAW
history {
```

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(continued from previous page)

```
  name: "simulate_tracks"
  parameter: "{\'n_steps\': 100, \'ranges\': ((0, 1000), (0, 1000)), \
↪'diffusion_constant\': 1, \'time_step\': 10, \'seed\': 1, \'n_walks\': 1}"
}
element_count: 100
frame_count: 100
creation_time {
  2024-03-14T11:51:52.898362Z
}
```

```
locdata_new, track_series = lc.track(dat, search_range=5)
```

```
Frame 99: 1 trajectories present.
```

```
2024-03-14 11:51:55,511 - locan.data.locdata_utils - WARNING - Zero␣
↪uncertainties occurred resulting in nan for weighted_mean and weighted_
↪variance.
```

```
2024-03-14 11:51:55,513 - locan.data.locdata_utils - WARNING - Zero␣
↪uncertainties occurred resulting in nan for weighted_mean and weighted_
↪variance.
```

```
trackpy_logger.setLevel(logging.WARN)
locdata_new, track_series = lc.track(dat, search_range=5)
```

```
2024-03-14 11:51:57,879 - locan.data.locdata_utils - WARNING - Zero␣
↪uncertainties occurred resulting in nan for weighted_mean and weighted_
↪variance.
```

```
2024-03-14 11:51:57,881 - locan.data.locdata_utils - WARNING - Zero␣
↪uncertainties occurred resulting in nan for weighted_mean and weighted_
↪variance.
```

2.27 Notebook execution table

Document	Modified	Method	Run Time (s)	Status
tutorials/notebooks/Analysis_Blinking	2024-03-14 11:47	force	8.44	
tutorials/notebooks/Analysis_Drift	2024-03-14 11:47	force	17.62	
tutorials/notebooks/Analysis_Ripley	2024-03-14 11:47	force	15.6	
tutorials/notebooks/Analysis_coordinate_based_colocalization	2024-03-14 11:48	force	55.15	
tutorials/notebooks/Analysis_grouped_cluster_properties	2024-03-14 11:49	force	80.66	
tutorials/notebooks/Analysis_how_to_use_an_analysis_class	2024-03-14 11:50	force	13.75	
tutorials/notebooks/Analysis_localization_precision	2024-03-14 11:50	force	17.34	
tutorials/notebooks/Analysis_localization_property	2024-03-14 11:50	force	9.48	
tutorials/notebooks/Analysis_localizations_per_frame	2024-03-14 11:50	force	6.26	
tutorials/notebooks/Analysis_nearest_neighbor_distances	2024-03-14 11:50	force	6.12	
tutorials/notebooks/Analysis_pipeline	2024-03-14 11:51	force	12.58	
tutorials/notebooks/Cluster_LocData	2024-03-14 11:51	force	10.04	
tutorials/notebooks/Example Datasets	2024-03-14 11:51	force	5.72	(CellExecutionError)
tutorials/notebooks/File_management	2024-03-14 11:51	force	4.72	
tutorials/notebooks/Filter_LocData	2024-03-14 11:51	force	6.39	
tutorials/notebooks/Load_LocData	2024-03-14 11:51	force	4.68	
tutorials/notebooks/LocData	2024-03-14 11:51	force	5.53	
tutorials/notebooks/LocData_hulls	2024-03-14 11:51	force	9.17	
tutorials/notebooks/Logging	2024-03-14 11:51	force	10.02	
tutorials/notebooks/Metadata	2024-03-14 11:52	force	4.52	
tutorials/notebooks/Multiprocessing_with_ray	2024-03-14 11:52	force	21.13	
tutorials/notebooks/Regions	2024-03-14 11:52	force	6.7	
tutorials/notebooks/Render_LocData	2024-03-14 11:52	force	10.95	
tutorials/notebooks/Simulate_LocData	2024-03-14 11:52	force	8.02	
tutorials/notebooks/Track_LocData	2024-03-14 11:52	force	9.03	
tutorials/notebooks/Transform_LocData	2024-03-14	force	7.56	

CHAPTER

THREE

DOCKER

You can use the provided Dockerfiles to set up a docker image and run the project within a container.

3.1 Prepare for using Docker

1) Install docker (Docker Desktop)
2) Switch to Linux containers
3) Make shared drives on your host system accessible to mount local directories:

   Docker –> Settings –> Shared Drives

3.2 Dockerfiles

We provide dockerfiles for testing and deployment.

1) Run tests in a Python 3 environment based on miniconda or a virtual environment (venv) on Debian Linux.
2) Run the project in a Python 3 miniconda environment with Jupyter lab for interactive work (Debian Linux).

3.3 Build a docker image

Download the source code in a project directory. Make sure the .dockerignore file is present.

Enter the project directory and run the following command to build the docker image from one of the Dockerfiles:

```
docker build -t <ImageName> -f <docker/choose directory/Dockerfile> .
```

3.4 Start a container from the image

3.4.1 Run project tests:

Run a container to just run the project tests and close afterwards:

```
docker run --rm <ImageName>
```

3.4.2 Run project in an interactive environment:

Open a bash shell for interactive work within a container:

```
docker run -it <ImageName> bash
```

Open the shell with a host directory mounted as volume:

```
docker run -it -v <host directory>:/home/asterix/shared <ImageName> bash
```

To make sure a gui output (e.g. from napari) is directed to an X server (that must be installed on your host) add the DISPLAY environment variable:

```
docker run -it -v <host directory>:/home/asterix/shared -e DISPLAY=<IP-
↪address>:0.0 <ImageName> bash
```

3.4.3 Use Jupyter notebooks:

Start a container providing browser access to jupyter lab with a host directory mounted as volume:

```
docker run -p 8888:8888 -e JUPYTER_ENABLE_LAB=yes -v <host directory>:/home/
↪asterix/shared <ImageName>
```

For gui (e.g. napari) interaction add the DISPLAY environment variable.

3.5 Clean up

After closing a jupyter lab you might have to delete the container before running the image again (e.g. if the option –rm was omitted):

```
docker rm -f <container>
```

or close all containers:

```
docker rm -f $(docker ps -q)
```

To clean up your system:

```
docker system prune
```

CHAPTER

FOUR

PACKAGE DESIGN

4.1 Data structures

Locan provides `LocData` as the one data class to deal with the following data structures:

1) localization data
2) selections of localization data
3) collections of selections

4.1.1 Comments on LocData:

1) **Properties:** Localization data consists of a list of individual localizations with spatial coordinates and several other properties (detailed list in *Properties*) like

   - coordinates
   - intensity
   - frame
   - ...

   There is no fundamental difference between 2D and 3D localization data.

   Multiple sets of localization data like two-color localizations will be represented by independent `LocData` objects.

   The unit for length throughout the project is given by the input unit for localization coordinates, unless specified in the metadata. In most cases the unit will be nanometre.

2) **Dataset:** A `LocData` object is typically instantiated from an experimental or simulated localization dataset. The list of localizations is represented in a `pandas.DataFrame` under the attribute `LocData.data`. In addition `LocData` has some single-number-properties describing the dataset as a whole. Such properties could be (detailed list in *Properties*):

   - total number of localizations
   - centroid
   - total emission strength
   - area/volume (for all possible hulls)
   - ...

3) **Selection:** A `LocData` object can also be instantiated from a selection of localizations. Selections carry a reference to another `LocData` object and a list of selected indices to not copy the original dataset with all localization properties for each selection. This way a large set of selections can be created with minimal memory requirements.

4) **Collection:** A `LocData` object can also represent a list of selections as e.g. generated by clustering the localization data. The `LocData.data` of a collection consists of the list of all properties from the collected `LocData` (e.g. selections).

5) **Hulls:** For the spatial coordinates in each `LocData` object there are various hulls that might be of interest:

   1. minimal bounding box
   2. convex hull
   3. alpha complex or alpha shape
   4. minimal oriented bounding box

   These hulls are provided from stand-alone methods or through `LocData` attributes. Hull objects expose attributes such as `LocData.region_measure` (among others) that are also added as `LocData` properties.

6) **Additional properties:** Other `LocData` properties might be provided by independent methods.

4.2 Metadata

Each instance of the LocData class carries metadata that give details about the data history and allows the addition of further comments.

Each instance of an analysis class carries metadata that includes input parameters for reprocessing and allows the addition of further comments.

Metadata is saved together with data or analysis results in order to provide serialized human- and machine-readable information and serve information exchange between methods.

All metadata is structured as (nested) key:value pairs and implemented through Google's protobuf format.

4.2.1 Structure of metadata for LocData

A standard set of metadata elements is implemented into the metadata classes that are accessible by the *meta* attribute. The current structure for metadata of the LocData class is defined in `locan/data/metadata.proto` and can be accessed through `locan/data/metadata_pb2`. It includes the following keys:

- **identifier: `str`** Some short name.
- **comment: `str`** A user comment.
- **production_date: `str` (ISO standard)** Date and time when the data was initially generated by experiment or simulation.
- **creation_date: `str` (ISO standard)** Date and time when the current dataset was created from original data.
- **modification_date: `str` (ISO standard)** Date and time when the data was last modified.

- **source: `enum`** Describes where the data is from. Must be one of the following:

  [unknown_source, design, experiment, simulation, import (from some other program)]

- **state: `enum`** Indicator if data is original (as recorded) or has been modified.

  [unknown_state, raw, modified]

- **history: `Operation`** Operation that was applied to the original data containing a function name and parameter for the applied method.
- **ancestor_identifiers: `str`** Identifier of locdata from which this locdata object is derived.
- **units: `Unit`** Units for localization properties containing *property* and *unit* keys.
- **element_count: `int`** Number of elements in locdata.
- **frame_count: `int`** Number of frames in locdata.
- **file_type: `enum`** Name of the file or program that produced the data (a fitter or simulation program).

  [unknown_file_Type, custom, rapidstorm, elyra, thunderstorm, asdf, nanoimager]

- **file_path: `str`** Path and name of data file.
- **experimental_setup: `map(str, str)`** Information about the setup on which the data was generated in form of variable key-value pairs.
- **experimental_sample: `map(str, str)`** Information about the sample that was imaged in form of variable key-value pairs.
- **map: `map(str, str)`** Miscellaneous information in form of variable key-value pairs.

4.2.2 Structure of metadata for analysis classes

The current structure for metadata of Analysis classes is defined in *locan/analysis/metadata_analysis.proto* and can be accessed through `locan/analysis/metadata_analysis_pb2`. It includes the following keys:

- **identifier: `str`** Some short name.
- **comment: `str`** A user comment.
- **creation_date: `str` (ISO standard)** Date and time when the results were created.
- **modification_date: `str` (ISO standard)** Date and time when the results were last recreated.
- **method: `Analysis_routine`** A dictionary with 'name' and 'parameter' describing the applied analysis procedure. This data can be used to programmatically rerun the procedure.
- **map: `map(str, str)`** Miscellaneous information in form of variable key-value pairs.

4.3 Properties

`LocData`, the data class for localization data, carries certain properties that describe individual (localization properties) or averaged features of the underlying localizations or groups thereof (LocData properties). In the following we provide names (or keys) for those properties.

The datatype for all keys is *string*. We stick to the following conventions:

- be explicit
- start with lower case letters
- use underscore
- do not use CamelCase or blanks
- use reverse notation in the sense that coordinate identifiers or identifiers of statistical functions are added in the end (`position_x_mean_mean`)

A list of well defined property keys used throughout locan is given by the constant: `locan/constants/PropertyKey`. An up-to-date description can be inspected by *locan/constants/PropertyKey.index.value.description*.

4.3.1 Localization properties:

Each localization has properties that can usually be identified in the various input (file) formats. We will use the following keys (where *c* stands for the coordinate *x*, *y* or *z*):

- ***index*** localization index
- ***position_c*** coordinate for the c-position
- ***frame*** frame number in which the localization occurs
- ***intensity*** intensity or emission strength as estimated by the fitter
- ***local_background*** background in the neighborhood of localization as estimated by the fitter
- ***local_background_sigma*** variation of local background in terms of standard deviation
- ***signal_noise_ratio*** ratio between mean intensity (i.e. intensity for a single localization) and the standard deviation of local_background (i.e. local_background_sigma for a single localization)
- ***signal_background_ratio*** ratio between mean intensity (i.e. *intensity* for a single localization) and the local_background
- ***chi_square*** chi-square value of the fitting procedure as estimated by the fitter
- ***psf_sigma_c*** sigma of the fitted Gauss-function in c-dimension as estimated by the fitter
- ***psf_sigma*** sigma of the fitted Gauss-function - being isotropic or representing the root-mean-square of psf_sigma_c for all dimensions
- ***psf_width_c*** full-width-half-max of the fitted Gauss-function in c-dimension as estimated by the fitter
- ***psf_width*** full-width-half-max of the fitted Gauss-function - being isotropic or representing the root-mean-square of psf_width_c for all dimensions

- ***uncertainty_c*** localization error in c-dimension estimated by a fitter or representing a value proportional to psf_sigma_c / sqrt(intensity)
- ***uncertainty*** localization error for all dimensions or representing a value proportional to psf_sigma / sqrt(intensity) or representing the root-mean-square of uncertainty_c for all dimensions.
- ***channel*** identifier for various channels
- ***two_kernel_improvement*** a rapidSTORM parameter describing the improvement from two kernel fitting
- ***frames_number*** number of frames that contribute to a merged localization
- ***frames_missing*** number of frames that occurred between two successive localizations

Additional localization properties are computed by various analysis procedures including (among others):

- ***cluster_label*** identifier for a localization cluster
- ***nn_distance*** nearest-neighbor distance
- ***nn_distance_k*** k-nearest-neighbor distance (k can be any integer)
- ***colocalization_cbc*** coordinate-based colocalization value

4.3.2 LocData properties:

A group of localizations makes up a LocData entity for which further properties are defined.

The coordinates for a localization group are defined by their centroids.

In general, we will use the following keys for statistics of localization properties:

- ***property_stats*** where property is the localization property key and stats is one of the following:
  - count (number of elements)
  - min (minimum of all elements)
  - max (maximum of all elements)
  - sum (sum of all elements)
  - mean (the mean of all elements)
  - std (standard deviation of all elements)
  - sem (standard error of the mean of all elements)

For example:

- ***intensity_sum*** total intensity of all localizations in the group

Some properties are derived from a hull of all element positions. We provide four hulls:

1. bounding box
2. convex hull
3. alpha shape
4. oriented bounding box

From each hull a region measure (e.g. the area in 2D) and a subregion measure (e.g. the circumference in 2D) is computed.

We will use the following keys for additional properties (where *c* stands for the coordinate *x*, *y* or *z* and *h* stands for the corresponding hull *bb*, *ch*, *as*, *obb*):

- **centroid** tuple with mean of all localization coordinates
- ***localization_count*** number of localizations within a group
- ***region_measure_h*** area/volume (for all possible hulls)
- ***subregion_measure_h*** circumference/surface (for all possible hulls)
- ***localization_density_h*** density of localizations (for all possible hulls)
- ***boundary_localizations_h*** absolute number of localizations on boundary (for all possible hulls)
- ***boundary_localizations_ratio_h*** ratio between number of localizations on hull boundary and within hull (for all possible hulls)
- ***max_distance*** maximum distance between any two localizations
- ***inertia_moments*** inertia moments of all localizations
- ***orientation_obb*** angle between the x-axis and the long axis of the oriented bounding box
- ***orientation_im*** angle between inertia moment principal component vectors
- ***circularity_obb*** elongation estimated from oriented bounding box
- ***circularity_im*** excentricity estimated from inertia moments

4.4 Methods for data analysis

Locan will provide methods to work on `LocData` objects and carry out standard analysis procedures. Some of these functions are merely wrapper functions for well established analysis routines in third-party packages.

The methods in this context can either be stand-alone functions with a well-defined input and output and absolutely no side-effects.

In general however, results consist of numeric data, statistical properties (e.g. a histogram of numeric results) and/or fit parameter from comparing the numeric results with theoretical expectations, and annotated plots. In this case the method will be part of a more complex analysis class.

Locan therefore provides specific analysis classes that follow a common structure. Any `Analysis` object is instantiated with a set of parameters that define the precise analysis procedure. The computation is then performed by calling `Analysis.compute()` with a parameter specifying one or more `LocData` objects on which to perform the analysis. The main result is typically provided under the attribute `Analysis.results` and accompanied by a flexible set of further attributes. Common methods often include plot, hist, and report functions. Metadata is provided under the `Analysis.meta` attribute.

4.5 Aim

We aim at providing a python package with data structures and methods for analyzing single-molecule localization data. Locan is a Python package providing functionality to load, manipulate and analyze localization data.

The package provides:

- a class structure for localization data with appropriate meta data
- rendering functions to visualize localization data
- methods for carrying out established analysis routines
- an interface to save analysis results and run batch processes.

Locan provides standard routines and interfaces for setting up reproducible analysis pipelines and batch processes. At the same time it allows flexibility on all programmatic levels either in Python scripts, Jupyter notebooks or dashboard apps. We provide original algorithms and include existing solutions by providing appropriate wrapper functions.

4.6 Outline

Locan provides a standardized class structure to hold and deal with *data structures* such as localization data and analysis results.

Metadata will be part of each data class and is either added by user input or generated during manipulation of data classes.

`LocData`, the data class for localization data, carries certain properties that describe individual or averaged features of the underlying localizations or groups thereof. We suggest a canonical set of *Properties*.

Methods will either create or manipulate these data structures or perform some analysis routine and provide the results in an appropriate form.

CHAPTER

FIVE

COMMAND-LINE INTERFACE

Locan is designed as a Python library. Full functionality of the package is accessible through Python scripts or Jupyter notebooks.

A command-line interface is provided for selected routines. It is accessible from any terminal by the base command `locan` and provides a number of compound commands. For a complete description of available commands see documentation of the *locan.scripts* module or look up command-line help using `locan -h`.

CHAPTER

SIX

COLORMAPS

For visual inspection and presentation SMLM data is typically rendered in 2D or 3D images. Various binning algorithms are used to create a representation of localisation densities. Intensity values are represented by color according to a selected colormap. Various colormaps can be chosen that accentuate certain data structures.

For SMLM images we aim at using colormaps that SMLM users are used to but that perform well with respect to human perception. Therefore, we recommend using colormaps that are optimized for accurate perception as for instance provided by the colorcet library.

We recommend default use for various types of colormaps: All 2D one-channel plot functions use the fire colormap as default if *colorcet* is installed. Otherwise we use the matplotlib colormap viridis as default.

For categorical data we use glasbey_dark from *colorcet* as default colormap or alternatively *tab20* from *matplotlib*. For diverging data we use coolwarm from *colorcet* as default colormap or alternatively *coolwarm* from *matplotlib*. For rainbow/jet-like data we use turbo as default colormap.

For details on how to use colormaps see API documentation for `locan.visualize.colormap`.

CHAPTER

SEVEN

USER INTERFACE

Locan is mostly designed to work without a graphical user interface (gui). However, a few methods make use of a gui or interact with third-party libraries that provide a gui.

Locan and various other libraries make use of *qt* as a gui backend if it is installed together with appropriate python bindings. Different python bindings exist to interact with *qt* including *pyside2* and *pyqt5*.

Locan makes use of *pyqt* to choose a binding. To force locan and other libraries to use a specific binding you can set the python environment variable *QT_API* before importing any QT-dependent package:

```
import os
os.environ["QT_API"] = "pyside2"
```

For more details see also the documentation on the *locan.gui* module.

CHAPTER

EIGHT

API REFERENCE

Locan consists of the following modules:

analysis	Standard analysis procedures.
constants	Constants used throughout the project.
configuration	Configuration variables used throughout the project.
data	Localization data.
datasets	Utility functions to deal with exemplary datasets.
dependencies	Module to deal with required and optional dependencies.
gui	User interfaces.
locan_io	File input/output functions.
rois	Region of interest.
scripts	Command-line utility scripts
simulation	Synthetic data
tests	Test the locan package.
utils	Utility functions.
visualize	Visualize localization data.

8.1 locan.analysis

Standard analysis procedures.

This module contains classes and functions for carrying out standardized analysis procedures on localization data. All functions typically take LocData objects as input and provide an analysis class with derived analysis results and standard functions for presentation.

8.1.1 Submodules:

accumulation_analysis	Localization-density variation analysis to characterize localization cluster.
blinking	Compute on- and off-periods from localization frames.
cbc	Coordinate-based colocalization.
convex_hull_expectation	Analyze geometrical properties of the convex hull of localization coordinates.
drift	Drift analysis for localization coordinates.
grouped_property_expectation	Analyze grouped property expectations.
localization_precision	Compute localization precision from successive nearby localizations.
localization_property	Analyze localization property.
localization_property_2d	Analyze the distribution of a localization property in 2D.
localization_property_correlations	Analyze cross dependencies between localization properties.
localizations_per_frame	Compute localizations per frame.
nearest_neighbor	Nearest-neighbor distance distribution analysis
pipeline	Building an analysis pipeline.
position_variance_expectation	Analyze variance of localization coordinates.
ripley	Compute Ripley's k function.
subpixel_bias	Compute subpixel bias in localization data.
uncertainty	Compute localization uncertainty.

locan.analysis.accumulation_analysis

Localization-density variation analysis to characterize localization cluster.

The existence of clusters is tested by analyzing variations in cluster area and localization density within clusters. The analysis routine follows the ideas in[1] and[2].

Note: The analysis procedure is in an exploratory state and has not been fully developed and tested.

[1] Baumgart F., Arnold AM., Leskovar K., Staszek K., Fölser M., Weghuber J., Stockinger H., Schütz GJ., Varying label density allows artifact-free analysis of membrane-protein nanoclusters. Nat Methods. 2016 Aug;13(8):661-4. doi: 10.1038/nmeth.3897

[2] Spahn C., Herrmannsdörfer F., Kuner T., Heilemann M. Temporal accumulation analysis provides simplified artifact-free analysis of membrane-protein nanoclusters. Nat Methods. 2016 Nov 29;13(12):963-964. doi: 10.1038/nmeth.406

References

Classes

AccumulationClusterCheck([meta, ...])	Check for the presence of clusters in localization data by analyzing variations in cluster area and localization density within clusters.

locan.analysis.accumulation_analysis.AccumulationClusterCheck

class locan.analysis.accumulation_analysis.**AccumulationClusterCheck**(*meta=None*, *region_measure='bb'*, *algorithm=<function cluster_hdbscan>*, *algo_parameter=None*, *hull='bb'*, *n_loc=10*, *divide='random'*, *n_extrapolate=5*)

Bases: locan.analysis.analysis_base._Analysis

Check for the presence of clusters in localization data by analyzing variations in cluster area and localization density within clusters.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata | None*) – Metadata about the current analysis routine.
- **region_measure** (*float | Literal["bb", "ch"]*) –

  Region measure (area or volume) for the support of locdata. String can be any of standard hull identifier.
- **algorithm** (*Callable[..., tuple[LocData, LocData]]*) – Clustering algorithm.
- **algo_parameter** (*dict*) – Dictionary with kwargs for *algorithm*.
- **hull** (*Literal["bb", "ch"]*) – Hull computation that is used to compute cluster region measures (area or volume). The identifier string can be one of the defined hulls.
- **n_loc** (*int | Sequence[int]*) – If n_loc is an int, it defines the number of localization subsets into which the total number of localizations are distributed. If n_loc is a sequence, it defines the number of localizations used for each localization subset.
- **divide** (*Literal["random", "sequential"]*) – Identifier to choose how to partition the localization data. For *random* localizations are selected ran-

domly. For *sequential* localizations are selected as chuncks of increasing size always starting from the first element.

- **n_extrapolate** (*int*) – The number of rho values taken to extrapolate rho_zero.

Variables

- **count** (*int*) – A counter for counting instantiations.
- **parameter** (*dict[str, Any]*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (*pandas.DataFrame*) – Data frame with localization density, relative area coverage by the clusters (eta), average density of localizations within apparent clusters (rho), and rho normalized to the extrapolated value of rho for localization_density=0 (rho_zero). If the extrapolation of rho yields a negative value rho_zero is set to 1.

Methods

`__init__`([meta, region_measure, algorithm, ...])	
compute(locdata)	Run the computation.
plot([ax])	Provide plot of results as `matplotlib.axes.Axes` object.
`report`(*args, **kwargs)	Show a report about analysis results.

Attributes

count	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*)

Run the computation.

Parameters **locdata** (*LocData*) – Localization data that might be clustered.

Return type Self

count: int = 0

A counter for counting Analysis class instantiations (class attribute).

plot(*ax=None*, ***kwargs*)

Provide plot of results as `matplotlib.axes.Axes` object.

Parameters

- **ax** (`Optional[Axes]`) – The axes on which to show the image
- **kwargs** (`Any`) – Other parameters passed to `matplotlib.pyplot.plot()`.

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

locan.analysis.blinking

Compute on- and off-periods from localization frames.

Assuming that the provided localizations are acquired from the same label, we analyze the times of recording as provided by the *frame* property.

Classes

BlinkStatistics([meta, memory, ...])	Estimate on and off times from the frame values provided.

locan.analysis.blinking.BlinkStatistics

class locan.analysis.blinking.**BlinkStatistics**(*meta=None*, *memory=0*, *remove_heading_off_periods=True*)

Bases: locan.analysis.analysis_base._Analysis

Estimate on and off times from the frame values provided.

On and off-periods and the first frame of each period are determined from the sorted frame values. A series of frame values that constantly increase by one is considered an on-period. Each series of missing frame values between two given frame values is considered an off-period.

A log warning is provided if a frame number occurs multiple times.

Missing localizations within an on-period can be taken into account by increasing the *memory* parameter. There is no way to correct for false positive localizations.

Parameters

- **memory** (*int*) – The maximum number of intermittent frames without any localization that are still considered to belong to the same on-period.
- **remove_heading_off_periods** (*bool*) – Flag to indicate if off-periods at the beginning of the series are excluded.
- **meta** (*metadata_analysis_pb2.AMetadata | None*) – Metadata about the current analysis routine.

Variables

- **count** (*int*) – A counter for counting instantiations.
- **parameter** (*dict[str, Any]*) – A dictionary with all settings for the current computation.
- **meta** (*metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.

- **results** (dict[str, npt.NDArray[np.int_ | np.float_] | list[int | float]] | None) – 'on_periods' and 'off_periods' in units of frame numbers. 'on_periods_frame' and 'off_periods_frame' with the first frame in each on/off-period. 'on_periods_indices' are groups of indices to the input frames or more

  precise np.unique(frames)

- **distribution_statistics** (*dict[str, Any]*) – Distribution parameters derived from MLE fitting of results.

Methods

`__init__`([meta, memory, ...])	

compute(locdata)	Run the computation.
fit_distributions([distribution, ...])	Fit probability density functions to the distributions of on- and off-periods in the results using MLE (scipy.stats).
hist([data_identifier, ax, bins, log, fit])	Provide histogram as `matplotlib.axes.Axes` object showing hist(results).
`report`(*args, **kwargs)	Show a report about analysis results.

Attributes

count	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*)

Run the computation.

Parameters **locdata** (Union[*LocData*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Localization data or just the frame values of given localizations.

Return type Self

count: int = 0

A counter for counting Analysis class instantiations (class attribute).

fit_distributions(*distribution=<scipy.stats._continuous_distns.expon_gen object>*, *data_identifier=('on_periods', 'off_periods')*, *with_constraints=True*, ***kwargs*)

Fit probability density functions to the distributions of on- and off-periods in the results using MLE (scipy.stats).

If with_constraints is true we put the following constraints on the fit procedure: If distribution is expon then floc=np.min(self.analysis_class.results[self.loc_property].values).

Parameters

- **distribution** (str | rv_continuous) – Distribution model to fit.
- **data_identifier** (str | Iterable[str]) – String to identify the data in *results* for which to fit an appropriate distribution, here 'on_periods' or 'off_periods'. For True all are fitted.
- **with_constraints** (bool) – Flag to use predefined constraints on fit parameters.
- **kwargs** (Any) – Other parameters are passed to the *scipy.stat.distribution.fit()* function.

Return type None

hist(*data_identifier='on_periods'*, *ax=None*, *bins='auto'*, *log=True*, *fit=True*, ***kwargs*)

Provide histogram as matplotlib.axes.Axes object showing hist(results).

Parameters

- **data_identifier** (str) – 'on_periods' or 'off_periods'.
- **ax** (Optional[Axes]) – The axes on which to show the image
- **bins** (int | Sequence[int | float] | str) – Bin specifications (passed to matplotlib.hist()).
- **log** (bool) – Flag for plotting on a log scale.
- **fit** (Optional[bool]) – Flag indicating if distribution fit is shown. The fit will only be computed if *distribution_statistics* is None.
- **kwargs** (Any) – Other parameters passed to matplotlib.pyplot.hist().

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

locan.analysis.cbc

Coordinate-based colocalization.

Colocalization is estimated by computing a colocalization index for each localization using the so-called coordinate-based colocalization algorithm[1].

References

Classes

CoordinateBasedColocalization([meta, ...])	Compute a colocalization index for each localization by coordinate-based colocalization (CBC).

[1] Malkusch S, Endesfelder U, Mondry J, Gelléri M, Verveer PJ, Heilemann M., Coordinate-based colocalization analysis of single-molecule localization microscopy data. Histochem Cell Biol. 2012, 137(1):1-10. doi: 10.1007/s00418-011-0880-5

locan.analysis.cbc.CoordinateBasedColocalization

class locan.analysis.cbc.**CoordinateBasedColocalization**(*meta=None*, *radius=100*, *n_steps=10*)

Bases: locan.analysis.analysis_base._Analysis

Compute a colocalization index for each localization by coordinate-based colocalization (CBC).

The colocalization index is calculated for each localization in *locdata* by finding nearest neighbors in *locdata* or *other_locdata* within *radius*. A normalized number of nearest neighbors at a certain radius is computed for *n_steps* equally-sized steps of increasing radii ranging from 0 to *radius*. The Spearman rank correlation coefficent is computed for these values and weighted by Exp[-nearestNeighborDistance/distanceMax].

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **radius** (*int | float*) – The maximum radius up to which nearest neighbors are determined
- **n_steps** (*int*) – The number of bins from which Spearman correlation is computed.

Variables

- **count** (*int*) – A counter for counting instantiations.
- **parameter** (*dict*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (*pandas.DataFrame*) – Coordinate-based colocalization coefficients for each input point.

Methods

__init__([meta, radius, n_steps])	

compute(locdata[, other_locdata])	Run the computation.
hist([ax, bins, density])	Provide histogram as matplotlib.axes.Axes object showing hist(results).
report(*args, **kwargs)	Show a report about analysis results.

Attributes

count	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*, *other_locdata=None*)

Run the computation.

Parameters

- **locdata** (*LocData*) – Localization data for which CBC values are computed.
- **other_locdata** (Optional[*LocData*]) – Localization data to be colocalized. If None other_locdata is set to locdata.

Return type Self

count: int = 0

A counter for counting Analysis class instantiations (class attribute).

hist(*ax=None*, *bins=(- 1, - 0.3333, 0.3333, 1)*, *density=True*, ***kwargs*)

Provide histogram as `matplotlib.axes.Axes` object showing hist(results).

Parameters

- **ax** (Optional[Axes]) – The axes on which to show the image
- **bins** (Union[int, Sequence[int | float], Literal['auto']]) – Bin specification as used in `matplotlib.hist()`.
- **density** (bool) – Flag for normalization as used in `matplotlib.hist()`. True returns probability density function; None returns counts.
- **kwargs** (Any) – Other parameters passed to `matplotlib.hist()`.

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

locan.analysis.convex_hull_expectation

Analyze geometrical properties of the convex hull of localization coordinates.

Localization coordinates in localization clusters come with a certain variance. In resolution-limited clusters the variance is determined by the localization precision. Accordingly, the geometrical properties of convex hulls also vary and can be analyzed as function of localization counts to help characterize localization clusters[1].

[1] Ebert V, Eiring P, Helmerich DA, Seifert R, Sauer M, Doose S. Convex hull as diagnostic tool in single-molecule localization microscopy. Bioinformatics 38(24), 2022, 5421-5429, doi: 10.1093/bioinformatics/btac700.

References

Classes

ConvexHullExpectation([meta, ...])	Analyze geometrical properties of the convex hull of localization coordinates in relation to expected values.
ConvexHullExpectationBatch([meta, ...])	Analyze geometrical properties of the convex hull of localization coordinates in relation to expected values.
ConvexHullExpectationResults([values, grouped])	
ConvexHullExpectationValues(n_points, ...)	
ConvexHullProperty(value)	An enumeration.

locan.analysis.convex_hull_expectation.ConvexHullExpectation

class locan.analysis.convex_hull_expectation.**ConvexHullExpectation**(*meta=None*, *convex_hull_property='region_mea*, *expected_variance=None*)

Bases: locan.analysis.analysis_base._Analysis

Analyze geometrical properties of the convex hull of localization coordinates in relation to expected values.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata | None*) – Metadata about the current analysis routine.
- **convex_hull_property** (*Literal["region_measure_ch", "subregion_measure_ch"]*) – One of 'region_measure_ch' (i.e. area or volume) or 'subregion_measure_ch' (i.e. circumference or surface.)
- **expected_variance** (*float | Iterable[float] | None*) – The expected variance for all or each localization property. The expected variance equals the squared localization precision for localization position coordinates.

Variables

- **count** (*int*) – A counter for counting instantiations (class attribute).
- **parameter** (*dict[str, Any]*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (ConvexHullExpectationResults | *None*) – Computed results.

- **distribution_statistics** (*dict[str, Any] | None*) – Distribution parameters derived from MLE fitting of results.

Methods

`__init__`([meta, convex_hull_property, ...])	

compute(locdata)	Run the computation.
hist([ax, bins, n_bins, bin_size, ...])	Provide plot as `matplotlib.axes.Axes` object showing the 2-dimensional histogram of convex_hull_property and localization counts.
plot([ax])	Provide plot as `matplotlib.axes.Axes` object showing the convex_hull_property as function of localization counts.
`report`(*args, **kwargs)	Show a report about analysis results.

Attributes

`count`	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*)

Run the computation.

Parameters **locdata** (LocData) – Localization data.

Return type Self

hist(*ax=None*, *bins=None*, *n_bins=None*, *bin_size=None*, *bin_edges=None*, *bin_range=None*, *log=True*, *fit=False*, ***kwargs*)

Provide plot as `matplotlib.axes.Axes` object showing the 2-dimensional histogram of convex_hull_property and localization counts.

Parameters

- **ax** (Optional[Axes]) – The axes on which to show the image
- **bins** (Union[*Bins*, Axis, AxesTuple, None]) – The bin specification as defined in Bins
- **bin_edges** (Union[Sequence[float], Sequence[Sequence[float]], None]) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], None]) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2).
- **n_bins** (Union[int, Sequence[int], None]) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.

- **bin_size** (Union[float, Sequence[float], Sequence[Sequence[float]], None]) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.
- **log** (bool) – Flag for plotting on a log scale.
- **fit** (bool) – Flag indicating if distribution fit is shown. The fit will only be computed if *distribution_statistics*

  is None.
- **kwargs** (Any) – Other parameters passed to matplotlib.pyplot.pcolormesh().

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

plot(*ax=None*, ***kwargs*)

Provide plot as matplotlib.axes.Axes object showing the convex_hull_property as function of localization counts.

Parameters

- **ax** (Optional[Axes]) – The axes on which to show the image
- **kwargs** (Any) – Other parameters passed to matplotlib.pyplot.plot().

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

locan.analysis.convex_hull_expectation.ConvexHullExpectationBatch

class locan.analysis.convex_hull_expectation.**ConvexHullExpectationBatch**(*meta=None*, *convex_hull_property='regio*
expected_variance=None)

Bases: locan.analysis.analysis_base._Analysis

Analyze geometrical properties of the convex hull of localization coordinates in relation to expected values.

See also:

ConvexHullExpectation

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.

- **convex_hull_property** (*Literal['region_measure_ch', 'subregion_measure_ch']*) – One of 'region_measure_ch' (i.e. area or volume) or 'subregion_measure_ch' (i.e. circumference or surface.)
- **expected_variance** (*float | Iterable[float] | None*) – The expected variance for all or each localization property. The expected variance equals the squared localization precision for localization position coordinates.

Variables

- **count** (*int*) – A counter for counting instantiations (class attribute).
- **parameter** (*dict*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (ConvexHullExpectationResults) – Computed results.
- **distribution_statistics** (*Distribution_stats, None*) – Distribution parameters derived from MLE fitting of results.

Methods

`__init__`([meta, convex_hull_property, ...])	
compute(locdatas)	Run the computation.
from_batch(batch[, dimension])	**rtype** Self
hist([ax, bins, n_bins, bin_size, ...])	**rtype** Axes
plot([ax])	**rtype** Axes
report(*args, **kwargs)	Show a report about analysis results.

Attributes

count	A counter for counting Analysis class instantiations (class attribute).

compute(*locdatas*)

Run the computation.

Parameters **locdatas** (*Iterable[LocData]*) – Localization data.

Return type Self

from_batch(*batch*, *dimension=None*)

Return type Self

hist(*ax=None*, *bins=None*, *n_bins=None*, *bin_size=None*, *bin_edges=None*, *bin_range=None*, *log=True*, *fit=False*, ***kwargs*)

Return type Axes

plot(*ax=None*, ***kwargs*)

Return type Axes

locan.analysis.convex_hull_expectation.ConvexHullExpectationResults

class locan.analysis.convex_hull_expectation.**ConvexHullExpectationResults**(*values=<factory>*, *grouped=<factory>*)

Bases: object

Methods

__init__([values, grouped])

Attributes

values
grouped

grouped: **pandas.core.frame.DataFrame**

values: **pandas.core.frame.DataFrame**

locan.analysis.convex_hull_expectation.ConvexHullExpectationValues

class locan.analysis.convex_hull_expectation.**ConvexHullExpectationValues**(*n_points*, *expectation*, *std_pos*, *std_neg*)

Bases: NamedTuple

Methods

`__init__`()

`count`(value, /)	Return number of occurrences of value.
`index`(value[, start, stop])	Return first index of value.

Attributes

expectation	Alias for field number 1
n_points	Alias for field number 0
std_neg	Alias for field number 3
std_pos	Alias for field number 2

expectation: numpy.ndarray[Any, numpy.dtype[numpy.int64 | numpy.float64]]

Alias for field number 1

n_points: list[int] | numpy.ndarray[Any, numpy.dtype[numpy.int64]]

Alias for field number 0

std_neg: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Alias for field number 3

std_pos: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Alias for field number 2

locan.analysis.convex_hull_expectation.ConvexHullProperty

class locan.analysis.convex_hull_expectation.**ConvexHullProperty**(*value*)

Bases: enum.Enum

An enumeration.

Attributes

REGION_MEASURE_2D
SUBREGION_MEASURE_2D
REGION_MEASURE_3D
SUBREGION_MEASURE_3D

REGION_MEASURE_2D = 1

REGION_MEASURE_3D = 3

SUBREGION_MEASURE_2D = 2

SUBREGION_MEASURE_3D = 4

Functions

compute_convex_hull_region_measure_2d(n_points)	Compute the expected convex hull area for *n_points* data points that are normal distributed in 2-dimensional space with standard deviation *sigma*.

locan.analysis.convex_hull_expectation.compute_convex_hull_region_measure_2d

locan.analysis.convex_hull_expectation.**compute_convex_hull_region_measure_2d**(*n_points*, *sigma=1*)

Compute the expected convex hull area for *n_points* data points that are normal distributed in 2-dimensional space with standard deviation *sigma*.

Parameters

- **n_points** (int) – Number of points of convex hull
- **sigma** (float) – Standard deviation of normal-distributed point coordinates

Returns Expectation value for convex hull area

Return type float

locan.analysis.drift

Drift analysis for localization coordinates.

This module provides functions for estimating spatial drift in localization data.

Software based drift correction using image correlation has been described in several publications . Methods employed for drift estimation comprise single molecule localization analysis (an iterative closest point (icp) algorithm as implemented in the open3d library[1],[2]) or image cross-correlation analysis[3],[4],[5].

[1] Qian-Yi Zhou, Jaesik Park, Vladlen Koltun, Open3D: A Modern Library for 3D Data Processing, arXiv 2018, 1801.09847

[2] Rusinkiewicz and M. Levoy, Efficient variants of the ICP algorithm, In 3-D Digital Imaging and Modeling, 2001.

[3] C. Geisler, Drift estimation for single marker switching based imaging schemes, Optics Express. 2012, 20(7):7274-89.

[4] Yina Wang et al., Localization events-based sample drift correction for localization microscopy with redundant cross-correlation algorithm, Optics Express 2014, 22(13):15982-91.

[5] Michael J. Mlodzianoski et al., Sample drift correction in 3D fluorescence photoactivation localization microscopy, Opt Express. 2011 Aug 1;19(16):15009-19.

Examples

Please use the following procedure to estimate and correct for spatial drift:

```
from lmfit import LinearModel
drift = Drift(chunk_size=1000, target='first').\
        compute(locdata).\
        fit_transformations(slice_data=slice(0, -1),
                            matrix_models=None,
                            offset_models=(LinearModel(), LinearModel())).\
        apply_correction()
locdata_corrected = drift.locdata_corrected
```

References

Classes

Drift([meta, chunks, chunk_size, n_chunks, ...])	Estimate drift from localization coordinates by registering points in successive time-chunks of localization data using an iterative closest point algorithm (icp) or image cross-correlation algorithm (cc).
DriftComponent([type])	Class carrying model functions to describe drift over time (in unit of frames).
DriftModel(*args, **kwargs)	

locan.analysis.drift.Drift

class locan.analysis.drift.**Drift**(*meta=None*, *chunks=None*, *chunk_size=None*, *n_chunks=None*, *target='first'*, *method='icp'*, *kwargs_chunk=None*, *kwargs_register=None*)

Bases: `locan.analysis.analysis_base._Analysis`

Estimate drift from localization coordinates by registering points in successive time-chunks of localization data using an iterative closest point algorithm (icp) or image cross-correlation algorithm (cc).

Parameters

- **locdata** (*LocData*) – Localization data representing the source on which to perform the manipulation.
- **chunks** (*Sequence[tuple[int, ...]] | None*) – Localization chunks as defined by a list of index-tuples. One of *chunks*, *chunk_size* or *n_chunks* must be different from None.
- **chunk_size** (*int | None*) – Number of consecutive localizations to form a single chunk of data. One of *chunks*, *chunk_size* or *n_chunks* must be different from None.

- **n_chunks** (*int | None*) – Number of chunks. One of *chunks*, *chunk_size* or *n_chunks* must be different from None.
- **target** (*Literal["first", "previous"]*) – The chunk on which all other chunks are aligned. One of 'first', 'previous'.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **method** (*Literal["cc", "icp"]*) – The method used for computation. One of iterative closest point algorithm 'icp' or image cross-correlation algorithm 'cc'.
- **bin_size** (*tuple*) – Only for method='cc': Size per image pixel
- **kwargs_chunk** (*dict[str, Any] | None*) – Other parameter passed to `LocData.from_chunks()`.
- **kwargs_icp** (*dict[str, Any] | None*) – Other parameter passed to `_register_icp_open3d()`.
- **kwargs_cc** (*dict[str, Any] | None*) – Other parameter passed to `register_cc()`.

Variables

- **count** (*int*) – A counter for counting instantiations.
- **parameter** (*dict*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **locdata** (LocData | *None*) – Localization data representing the source on which to perform the manipulation.
- **collection** (LocData | *None*) – Collection of locdata chunks
- **transformations** (*list[Transformation] | None*) – Transformations for locdata chunks
- **transformation_models** (*dict[str, list[DriftModel | DriftComponent] | None]*) – The fitted model objects.
- **locdata_corrected** (LocData | *None*) – Localization data with drift-corrected coordinates.

Methods

`__init__`([meta, chunks, chunk_size, ...])	

apply_correction([locdata, from_model])	Correct drift by applying the estimated transformations to locdata.
compute(locdata)	Run the computation.
fit_transformation([slice_data, ...])	Fit drift model to selected component of the estimated transformations.
fit_transformations([slice_data, ...])	Fit model parameter to all estimated transformation components.
plot([ax, transformation_component, ...])	Plot the transformation components as function of average frame for each locdata chunk.
report(*args, **kwargs)	Show a report about analysis results.

Attributes

count	A counter for counting Analysis class instantiations (class attribute).

apply_correction(*locdata=None*, *from_model=True*)

Correct drift by applying the estimated transformations to locdata.

Parameters

- **locdata** (Optional[*LocData*]) – Localization data to apply correction on. If None correction is applied to self.locdata.
- **from_model** (bool) – If *True* compute transformation matrix from fitted transformation models and apply interpolated transformations. If False use the estimated transformation matrix for each data chunk.

Return type Self

compute(*locdata*)

Run the computation.

Parameters **locdata** (*LocData*) – Localization data representing the source on which to perform the manipulation.

Return type Self

count: int = 0

A counter for counting Analysis class instantiations (class attribute).

fit_transformation(*slice_data=None*, *transformation_component='matrix'*, *element=0*, *drift_model='linear'*, *verbose=False*)

Fit drift model to selected component of the estimated transformations.

Parameters

- **slice_data** (Optional[slice]) – Reduce data to a selection on the localization chunks.

- **transformation_component** (Literal['matrix', 'offset']) – One of 'matrix' or 'offset'
- **element** (int) – The element of flattened transformation matrix or offset
- **drift_model** (UnionType[*DriftComponent*, str, None]) – A drift model as defined by a *DriftComponent* instance or the parameter *type* as defined in *DriftComponent*. For None no change will occur. To reset transformation_models set the transformation_component to None: e.g. self.transformation_components = None or self.transformation_components['matrix'] = None.
- **verbose** (bool) – Print the fitted model curves using lmfit.

Return type Self

fit_transformations(*slice_data=None*, *matrix_models=None*, *offset_models=None*, *verbose=False*)

Fit model parameter to all estimated transformation components.

Parameters

- **slice_data** (Optional[slice]) – Reduce data to a selection on the localization chunks.
- **matrix_models** (Optional[list[*DriftComponent*]]) – Models to use for fitting each matrix component. Length of list must be equal to the square of the transformations dimension (4 or 9). If None, no matrix transformation will be carried out when calling *apply_correction()*.
- **offset_models** (Optional[list[*DriftComponent*]]) – Models to use for fitting each offset component. Length of list must be equal to the transformations dimension (2 or 3). If None, no offset transformation will be carried out when calling *apply_correction()*.
- **verbose** (bool) – Print the fitted model curves.

Return type Self

plot(*ax=None*, *transformation_component='matrix'*, *element=None*, *window=1*, ***kwargs*)

Plot the transformation components as function of average frame for each locdata chunk.

Parameters

- **ax** (Optional[Axes]) – The axes on which to show the image
- **transformation_component** (Literal['matrix', 'offset']) – One of 'matrix' or 'offset'
- **element** (Optional[int]) – The element of flattened transformation matrix or offset to be plotted; if None all plots are shown.
- **window** (int) – Window for running average that is applied before plotting. Not implemented yet.
- **kwargs** (Any) – Other parameters passed to matplotlib.pyplot.plot().

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

locan.analysis.drift.DriftComponent

class locan.analysis.drift.**DriftComponent**(*type=None*, ***kwargs*)

Bases: object

Class carrying model functions to describe drift over time (in unit of frames). DriftComponent provides a transformation to apply a drift correction.

Standard models for constant, linear or polynomial drift correction are taken from `lmfit.models`. For fitting splines we use the scipy function `scipy.interpolate.splrep()`.

Parameters **type** (*Literal["none", "zero", "one", "constant", "linear", "polynomial", "spline"] | lmfit.models.Model | None*) – Model class or indicator for setting up the corresponding model class.

Variables

- **type** – String indicator for model.
- **model** (*lmfit.models.Model | None*) – The model definition (return value of `scipy.interpolate.splrep()`)
- **model_result** (*lmfit.model.ModelResult, collection of model results.*) – The results collected from fitting the model to specified data.

Methods

`__init__`([type])	
eval(x)	Compute a transformation for time *x* from the drift model.
fit(x, y[, verbose])	Fit model to the given data and create *self.model_results*.

eval(*x*)

Compute a transformation for time *x* from the drift model.

Parameters **x** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – frame values

Return type npt.NDArray[**np.float_**].

fit(*x*, *y*, *verbose=False*, ***kwargs*)

Fit model to the given data and create *self.model_results*.

Parameters

- **x** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – x data

- **y** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – y values
- **verbose** (bool) – show plot
- **kwargs** (Any) – Other parameters passed to lmfit.model.fit() or to scipy.interpolate.splrep() Use the parameter *s* to set the amount of smoothing.

Return type Self

locan.analysis.drift.DriftModel

class locan.analysis.drift.**DriftModel**(**args*, ***kwargs*)

Bases: Protocol

Methods

__init__(*args, **kwargs)	
eval(*args, **kwargs)	**rtype** Any
fit(*args, **kwargs)	**rtype** Any
plot(*args, **kwargs)	**rtype** Any

eval(**args*, ***kwargs*)

Return type Any

fit(**args*, ***kwargs*)

Return type Any

plot(**args*, ***kwargs*)

Return type Any

locan.analysis.grouped_property_expectation

Analyze grouped property expectations.

As an example, assume a collection of locdatas representing localization clusters. Some property of locdata *loc_property (i.e. cluster property; e.g. intensity) might depend on another property `other_loc_property* (e.g. number of localizations in cluster). For inspection, all values of loc_property are grouped by other_loc_property and mean with standard deviations are displayed.

See also:

`position_variance_expectation`, `convex_hull_expectation`

Classes

GroupedPropertyExpectation([meta, ...])	Analyze variation of localization property in relation to other localization property that is grouped.
GroupedPropertyExpectationResults([values, ...])	

locan.analysis.grouped_property_expectation.GroupedPropertyExpectation

class locan.analysis.grouped_property_expectation.**GroupedPropertyExpectation**(*meta=None*, *loc_property=None*, *other_loc_property=None*, *expectation=None*)

Bases: `locan.analysis.analysis_base._Analysis`

Analyze variation of localization property in relation to other localization property that is grouped.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **loc_property** (*str | None*) – The localization property to analyze.
- **other_loc_property** (*str | None*) – The localization property to group on.
- **expectation** (*int | float | Mapping | pd.Series[Any] | None*) – The expected value for all or each other localization property.

Variables

- **count** (*int*) – A counter for counting instantiations (class attribute).
- **parameter** (*dict[str, Any]*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.

- **results** (GroupedPropertyExpectationResults) – Computed results.
- **distribution_statistics** (*Distribution_stats, None*) – Distribution parameters derived from MLE fitting of results.grouped.

Methods

`__init__`([meta, loc_property, ...])	

compute(locdata)	Run the computation.
hist([ax, bins, n_bins, bin_size, ...])	Provide plot as `matplotlib.axes.Axes` object showing the 2-dimensional histogram.
plot([ax])	Provide plot as `matplotlib.axes.Axes` object showing the variances as function of localization counts.
report(*args, **kwargs)	Show a report about analysis results.

Attributes

count	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*)

Run the computation.

Parameters **locdata** (*LocData*) – Localization data.

Return type Self

hist(*ax=None*, *bins=None*, *n_bins=None*, *bin_size=None*, *bin_edges=None*, *bin_range=None*, *log=True*, *fit=False*, ***kwargs*)

Provide plot as `matplotlib.axes.Axes` object showing the 2-dimensional histogram.

Parameters

- **ax** (Optional[Axes]) – The axes on which to show the image
- **bins** (Union[*Bins*, Axis, AxesTuple, None]) – The bin specification as defined in Bins
- **bin_edges** (Union[Sequence[float], Sequence[Sequence[float]], None]) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], None]) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2).
- **n_bins** (Union[int, Sequence[int], None]) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.

- **bin_size** (Union[float, Sequence[float], Sequence[Sequence[float]], None]) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.
- **log** (bool) – Flag for plotting on a log scale.
- **fit** (bool) – Flag indicating if distribution fit is shown.
- **kwargs** (Any) – Other parameters passed to matplotlib.pyplot.pcolormesh().

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

plot(*ax=None*, ***kwargs*)

Provide plot as matplotlib.axes.Axes object showing the variances as function of localization counts.

Parameters

- **ax** (Optional[Axes]) – The axes on which to show the image
- **kwargs** (Any) – Other parameters passed to matplotlib.pyplot.plot().

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

locan.analysis.grouped_property_expectation.GroupedPropertyExpectationResults

class locan.analysis.grouped_property_expectation.**GroupedPropertyExpectationResults**(*values=<*, *grouped=*

Bases: object

Methods

__init__([values, grouped])

Attributes

values
grouped

grouped: pandas.core.frame.DataFrame

values: pandas.core.frame.DataFrame

locan.analysis.localization_precision

Compute localization precision from successive nearby localizations.

Localization precision is estimated from spatial variations of all localizations that appear in successive frames within a specified search radius[1].

Localization pair distance distributions are fitted according to the probability density functions in[2].

The estimated sigmas describe the standard deviation for pair distances. Localization precision is often defined as the standard deviation for localization distances from the center position. With that definition, the localization precision is equal to sigma / sqrt(2).

References

[1] Endesfelder, Ulrike, et al., A simple method to estimate the average localization precision of a single-molecule localization microscopy experiment. Histochemistry and Cell Biology 141.6 (2014): 629-638.

[2] L. Stirling Churchman, Henrik Flyvbjerg, James A. Spudich, A Non-Gaussian Distribution Quantifies Distances Measured with Fluorescence Localization Techniques. Biophysical Journal 90 (2), 2006, 668-671, doi.org/10.1529/biophysj.105.065599.

Classes

LocalizationPrecision([meta, radius])	Compute the localization precision from consecutive nearby localizations.
PairwiseDistance1d([momtype, a, b, xtol, ...])	A random variable describing the distribution of pair distances for two normal distributed point clouds in 1D.
PairwiseDistance1dIdenticalSigmaZeroMu([A])	A random variable describing the distribution of pair distances for two normal distributed point clouds in 1D.
PairwiseDistance2d([momtype, a, b, xtol, ...])	A random variable describing the distribution of pair distances for two normal distributed point clouds in 2D.
PairwiseDistance2dIdenticalSigma([momtype, ...])	A random variable describing the distribution of pair distances for two normal distributed point clouds in 2D.
PairwiseDistance2dIdenticalSigmaZeroMu([A])	A random variable describing the distribution of pair distances for two normal distributed point clouds in 2D.
PairwiseDistance3d([momtype, a, b, xtol, ...])	A random variable describing the distribution of pair distances for two normal distributed point clouds in 3D.
PairwiseDistance3dIdenticalSigmaZeroMu([A])	A random variable describing the distribution of pair distances for two normal distributed point clouds in 3D.

locan.analysis.localization_precision.LocalizationPrecision

class locan.analysis.localization_precision.**LocalizationPrecision**(*meta=None*, *radius=50*)

Bases: locan.analysis.analysis_base._Analysis

Compute the localization precision from consecutive nearby localizations.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata | None*) – Metadata about the current analysis routine.
- **radius** (*int | float*) – Search radius for nearest-neighbor searches.

Variables

- **count** (*int*) – A counter for counting instantiations (class attribute).
- **parameter** (*dict*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (*pandas.DataFrame*) – Computed results.

- **distribution_statistics** (*Distribution_fits | None*) – Distribution parameters derived from MLE fitting of results.

Methods

`__init__`([meta, radius])	

compute(locdata)	Run the computation.
fit_distributions([loc_property])	Fit probability density functions to the distributions of *loc_property* values in the results using MLE (scipy.stats).
hist([ax, loc_property, bins, fit])	Provide histogram as `matplotlib.axes.Axes` object showing the distributions of results.
plot([ax, loc_property, window])	Provide plot as `matplotlib.axes.Axes` object showing the running average of results over window size.
`report`(*args, **kwargs)	Show a report about analysis results.

Attributes

`count`	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*)

Run the computation.

Parameters **locdata** (*LocData*) – Localization data.

Return type Self

fit_distributions(*loc_property=None*, ***kwargs*)

Fit probability density functions to the distributions of *loc_property* values in the results using MLE (scipy.stats).

Parameters

- **loc_property** (*str*) – The LocData property for which to fit an appropriate distribution; if None all plots are shown.
- **kwargs** (Any) – Other parameters passed to the *distribution.fit()* method.

Return type None

hist(*ax=None*, *loc_property='position_distance'*, *bins='auto'*, *fit=True*, ***kwargs*)

Provide histogram as `matplotlib.axes.Axes` object showing the distributions of results.

Parameters

- **ax** (`Optional[Axes]`) – The axes on which to show the image
- **loc_property** (`str`) – The property for which to plot localization precision.

- **bins** (int | Sequence[int | float] | str) – Bin specifications (passed to matplotlib.hist()).
- **fit** (bool) – Flag indicating if distributions fit are shown.
- **kwargs** (Any) – Other parameters passed to matplotlib.pyplot.his().

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

plot(*ax=None*, *loc_property=None*, *window=1*, ***kwargs*)

Provide plot as matplotlib.axes.Axes object showing the running average of results over window size.

Parameters

- **ax** (Optional[Axes]) – The axes on which to show the image
- **loc_property** (Union[str, list[str], None]) – The property for which to plot localization precision; if None all plots are shown.
- **window** (int) – Window for running average that is applied before plotting.
- **kwargs** (Any) – Other parameters passed to matplotlib.pyplot.plot().

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

locan.analysis.localization_precision.PairwiseDistance1d

class locan.analysis.localization_precision.**PairwiseDistance1d**(*momtype=1*, *a=None*, *b=None*, *xtol=1e-14*, *badvalue=None*, *name=None*, *longname=None*, *shapes=None*, *seed=None*)

Bases: scipy.stats._distn_infrastructure.rv_continuous

A random variable describing the distribution of pair distances for two normal distributed point clouds in 1D.

The continuous distribution class inherits from scipy.stats.rv_continuous a set of methods and is defined by overriding the _pdf method.

For theoretical background see[1].

Parameters

- **x** (*npt.ArrayLike*) – distance
- **mu** (*npt.ArrayLike*) – Distance between the point cloud center positions.
- **sigma_1** (*npt.ArrayLike*) – Standard deviation for one point cloud.

[1] L. Stirling Churchman, Henrik Flyvbjerg, James A. Spudich, A Non-Gaussian Distribution Quantifies Distances Measured with Fluorescence Localization Techniques. Biophysical Journal 90 (2), 2006, 668-671, doi.org/10.1529/biophysj.105.065599.

- **sigma_2** (*npt.ArrayLike*) – Standard deviation for the other point cloud.

References

Methods

`__init__`([momtype, a, b, xtol, badvalue, ...])	
`cdf`(x, *args, **kwds)	Cumulative distribution function of the given RV.
`entropy`(*args, **kwds)	Differential entropy of the RV.
`expect`([func, args, loc, scale, lb, ub, ...])	Calculate expected value of a function with respect to the distribution by numerical integration.
`fit`(data, *args, **kwds)	Return estimates of shape (if applicable), location, and scale parameters from data.
`fit_loc_scale`(data, *args)	Estimate loc and scale parameters from data using 1st and 2nd moments.
`freeze`(*args, **kwds)	Freeze the distribution for the given arguments.
`interval`(confidence, *args, **kwds)	Confidence interval with equal areas around the median.
`isf`(q, *args, **kwds)	Inverse survival function (inverse of *sf*) at q of the given RV.
`logcdf`(x, *args, **kwds)	Log of the cumulative distribution function at x of the given RV.
`logpdf`(x, *args, **kwds)	Log of the probability density function at x of the given RV.
`logsf`(x, *args, **kwds)	Log of the survival function of the given RV.
`mean`(*args, **kwds)	Mean of the distribution.
`median`(*args, **kwds)	Median of the distribution.
`moment`(order, *args, **kwds)	non-central moment of distribution of specified order.
`nnlf`(theta, x)	Negative loglikelihood function.
`pdf`(x, *args, **kwds)	Probability density function at x of the given RV.
`ppf`(q, *args, **kwds)	Percent point function (inverse of *cdf*) at q of the given RV.
`rvs`(*args, **kwds)	Random variates of given type.
`sf`(x, *args, **kwds)	Survival function (1 - *cdf*) at x of the given RV.
`stats`(*args, **kwds)	Some statistics of the given RV.
`std`(*args, **kwds)	Standard deviation of the distribution.
`support`(*args, **kwargs)	Support of the distribution.
`var`(*args, **kwds)	Variance of the distribution.

Attributes

random_state	Get or set the generator object for generating random variates.

locan.analysis.localization_precision.PairwiseDistance1dIdenticalSigmaZeroMu

class locan.analysis.localization_precision.**PairwiseDistance1dIdenticalSigmaZeroMu**(*momtype=1*, *a=None*, *b=None*, *xtol=1e-14*, *badvalue=None*, *name=None*, *longname=None*, *shapes=None*, *seed=None*)

Bases: scipy.stats._distn_infrastructure.rv_continuous

A random variable describing the distribution of pair distances for two normal distributed point clouds in 1D.

The continuous distribution class inherits from scipy.stats.rv_continuous a set of methods and is defined by overriding the _pdf method.

For theoretical background see[1].

Parameters

- **x** (*npt.ArrayLike*) – distance
- **sigma** (*npt.ArrayLike*) – Standard deviation for point clouds

[1] L. Stirling Churchman, Henrik Flyvbjerg, James A. Spudich, A Non-Gaussian Distribution Quantifies Distances Measured with Fluorescence Localization Techniques. Biophysical Journal 90 (2), 2006, 668-671, doi.org/10.1529/biophysj.105.065599.

References

Methods

`__init__`([momtype, a, b, xtol, badvalue, ...])	
`cdf`(x, *args, **kwds)	Cumulative distribution function of the given RV.
`entropy`(*args, **kwds)	Differential entropy of the RV.
`expect`([func, args, loc, scale, lb, ub, ...])	Calculate expected value of a function with respect to the distribution by numerical integration.
`fit`(data, *args, **kwds)	Return estimates of shape (if applicable), location, and scale parameters from data.
`fit_loc_scale`(data, *args)	Estimate loc and scale parameters from data using 1st and 2nd moments.
`freeze`(*args, **kwds)	Freeze the distribution for the given arguments.
`interval`(confidence, *args, **kwds)	Confidence interval with equal areas around the median.
`isf`(q, *args, **kwds)	Inverse survival function (inverse of *sf*) at q of the given RV.
`logcdf`(x, *args, **kwds)	Log of the cumulative distribution function at x of the given RV.
`logpdf`(x, *args, **kwds)	Log of the probability density function at x of the given RV.
`logsf`(x, *args, **kwds)	Log of the survival function of the given RV.
`mean`(*args, **kwds)	Mean of the distribution.
`median`(*args, **kwds)	Median of the distribution.
`moment`(order, *args, **kwds)	non-central moment of distribution of specified order.
`nnlf`(theta, x)	Negative loglikelihood function.
`pdf`(x, *args, **kwds)	Probability density function at x of the given RV.
`ppf`(q, *args, **kwds)	Percent point function (inverse of *cdf*) at q of the given RV.
`rvs`(*args, **kwds)	Random variates of given type.
`sf`(x, *args, **kwds)	Survival function (1 - *cdf*) at x of the given RV.
`stats`(*args, **kwds)	Some statistics of the given RV.
`std`(*args, **kwds)	Standard deviation of the distribution.
`support`(*args, **kwargs)	Support of the distribution.
`var`(*args, **kwds)	Variance of the distribution.

Attributes

random_state	Get or set the generator object for generating random variates.

locan.analysis.localization_precision.PairwiseDistance2d

class locan.analysis.localization_precision.**PairwiseDistance2d**(*momtype=1*, *a=None*, *b=None*, *xtol=1e-14*, *badvalue=None*, *name=None*, *longname=None*, *shapes=None*, *seed=None*)

Bases: scipy.stats._distn_infrastructure.rv_continuous

A random variable describing the distribution of pair distances for two normal distributed point clouds in 2D.

The continuous distribution class inherits from scipy.stats.rv_continuous a set of methods and is defined by overriding the _pdf method.

For theoretical background see[1].

Parameters

- **x** (*npt.ArrayLike*) – distance
- **mu** (*npt.ArrayLike*) – Distance between the point cloud center positions.
- **sigma_1** (*npt.ArrayLike*) – Standard deviation for one point cloud.
- **sigma_2** (*npt.ArrayLike*) – Standard deviation for the other point cloud.

[1] L. Stirling Churchman, Henrik Flyvbjerg, James A. Spudich, A Non-Gaussian Distribution Quantifies Distances Measured with Fluorescence Localization Techniques. Biophysical Journal 90 (2), 2006, 668-671, doi.org/10.1529/biophysj.105.065599.

References

Methods

`__init__`([momtype, a, b, xtol, badvalue, ...])	
`cdf`(x, *args, **kwds)	Cumulative distribution function of the given RV.
`entropy`(*args, **kwds)	Differential entropy of the RV.
`expect`([func, args, loc, scale, lb, ub, ...])	Calculate expected value of a function with respect to the distribution by numerical integration.
`fit`(data, *args, **kwds)	Return estimates of shape (if applicable), location, and scale parameters from data.
`fit_loc_scale`(data, *args)	Estimate loc and scale parameters from data using 1st and 2nd moments.
`freeze`(*args, **kwds)	Freeze the distribution for the given arguments.
`interval`(confidence, *args, **kwds)	Confidence interval with equal areas around the median.
`isf`(q, *args, **kwds)	Inverse survival function (inverse of *sf*) at q of the given RV.
`logcdf`(x, *args, **kwds)	Log of the cumulative distribution function at x of the given RV.
`logpdf`(x, *args, **kwds)	Log of the probability density function at x of the given RV.
`logsf`(x, *args, **kwds)	Log of the survival function of the given RV.
`mean`(*args, **kwds)	Mean of the distribution.
`median`(*args, **kwds)	Median of the distribution.
`moment`(order, *args, **kwds)	non-central moment of distribution of specified order.
`nnlf`(theta, x)	Negative loglikelihood function.
`pdf`(x, *args, **kwds)	Probability density function at x of the given RV.
`ppf`(q, *args, **kwds)	Percent point function (inverse of *cdf*) at q of the given RV.
`rvs`(*args, **kwds)	Random variates of given type.
`sf`(x, *args, **kwds)	Survival function (1 - *cdf*) at x of the given RV.
`stats`(*args, **kwds)	Some statistics of the given RV.
`std`(*args, **kwds)	Standard deviation of the distribution.
`support`(*args, **kwargs)	Support of the distribution.
`var`(*args, **kwds)	Variance of the distribution.

Attributes

random_state	Get or set the generator object for generating random variates.

locan.analysis.localization_precision.PairwiseDistance2dIdenticalSigma

class locan.analysis.localization_precision.**PairwiseDistance2dIdenticalSigma**(*momtype=1*, *a=None*, *b=None*, *xtol=1e-14*, *badvalue=None*, *name=None*, *longname=None*, *shapes=None*, *seed=None*)

Bases: scipy.stats._distn_infrastructure.rv_continuous

A random variable describing the distribution of pair distances for two normal distributed point clouds in 2D.

The continuous distribution class inherits from scipy.stats.rv_continuous a set of methods and is defined by overriding the _pdf method.

For theoretical background see[1].

Parameters

- **x** (*npt.ArrayLike*) – distance
- **mu** (*npt.ArrayLike*) – Distance between the point cloud center positions.
- **sigma** (*npt.ArrayLike*) – Standard deviation for both point clouds.

References

[1] L. Stirling Churchman, Henrik Flyvbjerg, James A. Spudich, A Non-Gaussian Distribution Quantifies Distances Measured with Fluorescence Localization Techniques. Biophysical Journal 90 (2), 2006, 668-671, doi.org/10.1529/biophysj.105.065599.

Methods

`__init__`([momtype, a, b, xtol, badvalue, ...])	
`cdf`(x, *args, **kwds)	Cumulative distribution function of the given RV.
`entropy`(*args, **kwds)	Differential entropy of the RV.
`expect`([func, args, loc, scale, lb, ub, ...])	Calculate expected value of a function with respect to the distribution by numerical integration.
`fit`(data, *args, **kwds)	Return estimates of shape (if applicable), location, and scale parameters from data.
`fit_loc_scale`(data, *args)	Estimate loc and scale parameters from data using 1st and 2nd moments.
`freeze`(*args, **kwds)	Freeze the distribution for the given arguments.
`interval`(confidence, *args, **kwds)	Confidence interval with equal areas around the median.
`isf`(q, *args, **kwds)	Inverse survival function (inverse of *sf*) at q of the given RV.
`logcdf`(x, *args, **kwds)	Log of the cumulative distribution function at x of the given RV.
`logpdf`(x, *args, **kwds)	Log of the probability density function at x of the given RV.
`logsf`(x, *args, **kwds)	Log of the survival function of the given RV.
`mean`(*args, **kwds)	Mean of the distribution.
`median`(*args, **kwds)	Median of the distribution.
`moment`(order, *args, **kwds)	non-central moment of distribution of specified order.
`nnlf`(theta, x)	Negative loglikelihood function.
`pdf`(x, *args, **kwds)	Probability density function at x of the given RV.
`ppf`(q, *args, **kwds)	Percent point function (inverse of *cdf*) at q of the given RV.
`rvs`(*args, **kwds)	Random variates of given type.
`sf`(x, *args, **kwds)	Survival function (1 - *cdf*) at x of the given RV.
`stats`(*args, **kwds)	Some statistics of the given RV.
`std`(*args, **kwds)	Standard deviation of the distribution.
`support`(*args, **kwargs)	Support of the distribution.
`var`(*args, **kwds)	Variance of the distribution.

Attributes

random_state	Get or set the generator object for generating random variates.

locan.analysis.localization_precision.PairwiseDistance2dIdenticalSigmaZeroMu

class locan.analysis.localization_precision.**PairwiseDistance2dIdenticalSigmaZeroMu**(*momtype=1*, *a=None*, *b=None*, *xtol=1e-14*, *badvalue=None*, *name=None*, *longname=None*, *shapes=None*, *seed=None*)

Bases: scipy.stats._distn_infrastructure.rv_continuous

A random variable describing the distribution of pair distances for two normal distributed point clouds in 2D.

The continuous distribution class inherits from scipy.stats.rv_continuous a set of methods and is defined by overriding the _pdf method.

For theoretical background see[1].

Parameters

- **x** (*npt.ArrayLike*) – distance
- **sigma** (*npt.ArrayLike*) – Standard deviation for point clouds

[1] L. Stirling Churchman, Henrik Flyvbjerg, James A. Spudich, A Non-Gaussian Distribution Quantifies Distances Measured with Fluorescence Localization Techniques. Biophysical Journal 90 (2), 2006, 668-671, doi.org/10.1529/biophysj.105.065599.

References

Methods

`__init__`([momtype, a, b, xtol, badvalue, ...])	
`cdf`(x, *args, **kwds)	Cumulative distribution function of the given RV.
`entropy`(*args, **kwds)	Differential entropy of the RV.
`expect`([func, args, loc, scale, lb, ub, ...])	Calculate expected value of a function with respect to the distribution by numerical integration.
`fit`(data, *args, **kwds)	Return estimates of shape (if applicable), location, and scale parameters from data.
`fit_loc_scale`(data, *args)	Estimate loc and scale parameters from data using 1st and 2nd moments.
`freeze`(*args, **kwds)	Freeze the distribution for the given arguments.
`interval`(confidence, *args, **kwds)	Confidence interval with equal areas around the median.
`isf`(q, *args, **kwds)	Inverse survival function (inverse of *sf*) at q of the given RV.
`logcdf`(x, *args, **kwds)	Log of the cumulative distribution function at x of the given RV.
`logpdf`(x, *args, **kwds)	Log of the probability density function at x of the given RV.
`logsf`(x, *args, **kwds)	Log of the survival function of the given RV.
`mean`(*args, **kwds)	Mean of the distribution.
`median`(*args, **kwds)	Median of the distribution.
`moment`(order, *args, **kwds)	non-central moment of distribution of specified order.
`nnlf`(theta, x)	Negative loglikelihood function.
`pdf`(x, *args, **kwds)	Probability density function at x of the given RV.
`ppf`(q, *args, **kwds)	Percent point function (inverse of *cdf*) at q of the given RV.
`rvs`(*args, **kwds)	Random variates of given type.
`sf`(x, *args, **kwds)	Survival function (1 - *cdf*) at x of the given RV.
`stats`(*args, **kwds)	Some statistics of the given RV.
`std`(*args, **kwds)	Standard deviation of the distribution.
`support`(*args, **kwargs)	Support of the distribution.
`var`(*args, **kwds)	Variance of the distribution.

Attributes

random_state	Get or set the generator object for generating random variates.

locan.analysis.localization_precision.PairwiseDistance3d

class locan.analysis.localization_precision.**PairwiseDistance3d**(*momtype=1*, *a=None*, *b=None*, *xtol=1e-14*, *badvalue=None*, *name=None*, *longname=None*, *shapes=None*, *seed=None*)

Bases: scipy.stats._distn_infrastructure.rv_continuous

A random variable describing the distribution of pair distances for two normal distributed point clouds in 3D.

The continuous distribution class inherits from scipy.stats.rv_continuous a set of methods and is defined by overriding the _pdf method.

For theoretical background see[1].

Parameters

- **x** (*npt.ArrayLike*) – distance
- **mu** (*npt.ArrayLike*) – Distance between the point cloud center positions.
- **sigma_1** (*npt.ArrayLike*) – Standard deviation for one point cloud.
- **sigma_2** (*npt.ArrayLike*) – Standard deviation for the other point cloud.

[1] L. Stirling Churchman, Henrik Flyvbjerg, James A. Spudich, A Non-Gaussian Distribution Quantifies Distances Measured with Fluorescence Localization Techniques. Biophysical Journal 90 (2), 2006, 668-671, doi.org/10.1529/biophysj.105.065599.

References

Methods

`__init__`([momtype, a, b, xtol, badvalue, ...])	
`cdf`(x, *args, **kwds)	Cumulative distribution function of the given RV.
`entropy`(*args, **kwds)	Differential entropy of the RV.
`expect`([func, args, loc, scale, lb, ub, ...])	Calculate expected value of a function with respect to the distribution by numerical integration.
`fit`(data, *args, **kwds)	Return estimates of shape (if applicable), location, and scale parameters from data.
`fit_loc_scale`(data, *args)	Estimate loc and scale parameters from data using 1st and 2nd moments.
`freeze`(*args, **kwds)	Freeze the distribution for the given arguments.
`interval`(confidence, *args, **kwds)	Confidence interval with equal areas around the median.
`isf`(q, *args, **kwds)	Inverse survival function (inverse of *sf*) at q of the given RV.
`logcdf`(x, *args, **kwds)	Log of the cumulative distribution function at x of the given RV.
`logpdf`(x, *args, **kwds)	Log of the probability density function at x of the given RV.
`logsf`(x, *args, **kwds)	Log of the survival function of the given RV.
`mean`(*args, **kwds)	Mean of the distribution.
`median`(*args, **kwds)	Median of the distribution.
`moment`(order, *args, **kwds)	non-central moment of distribution of specified order.
`nnlf`(theta, x)	Negative loglikelihood function.
`pdf`(x, *args, **kwds)	Probability density function at x of the given RV.
`ppf`(q, *args, **kwds)	Percent point function (inverse of *cdf*) at q of the given RV.
`rvs`(*args, **kwds)	Random variates of given type.
`sf`(x, *args, **kwds)	Survival function (1 - *cdf*) at x of the given RV.
`stats`(*args, **kwds)	Some statistics of the given RV.
`std`(*args, **kwds)	Standard deviation of the distribution.
`support`(*args, **kwargs)	Support of the distribution.
`var`(*args, **kwds)	Variance of the distribution.

Attributes

random_state	Get or set the generator object for generating random variates.

locan.analysis.localization_precision.PairwiseDistance3dIdenticalSigmaZeroMu

class locan.analysis.localization_precision.**PairwiseDistance3dIdenticalSigmaZeroMu**(*momtype=1*, *a=None*, *b=None*, *xtol=1e-14*, *badvalue=None*, *name=None*, *longname=None*, *shapes=None*, *seed=None*)

Bases: scipy.stats._distn_infrastructure.rv_continuous

A random variable describing the distribution of pair distances for two normal distributed point clouds in 3D.

The continuous distribution class inherits from scipy.stats.rv_continuous a set of methods and is defined by overriding the _pdf method.

For theoretical background see[1].

Parameters

- **x** (*npt.ArrayLike*) – distance
- **sigma** (*npt.ArrayLike*) – Standard deviation for point clouds

[1] L. Stirling Churchman, Henrik Flyvbjerg, James A. Spudich, A Non-Gaussian Distribution Quantifies Distances Measured with Fluorescence Localization Techniques. Biophysical Journal 90 (2), 2006, 668-671, doi.org/10.1529/biophysj.105.065599.

References

Methods

`__init__`([momtype, a, b, xtol, badvalue, ...])	
`cdf`(x, *args, **kwds)	Cumulative distribution function of the given RV.
`entropy`(*args, **kwds)	Differential entropy of the RV.
`expect`([func, args, loc, scale, lb, ub, ...])	Calculate expected value of a function with respect to the distribution by numerical integration.
`fit`(data, *args, **kwds)	Return estimates of shape (if applicable), location, and scale parameters from data.
`fit_loc_scale`(data, *args)	Estimate loc and scale parameters from data using 1st and 2nd moments.
`freeze`(*args, **kwds)	Freeze the distribution for the given arguments.
`interval`(confidence, *args, **kwds)	Confidence interval with equal areas around the median.
`isf`(q, *args, **kwds)	Inverse survival function (inverse of *sf*) at q of the given RV.
`logcdf`(x, *args, **kwds)	Log of the cumulative distribution function at x of the given RV.
`logpdf`(x, *args, **kwds)	Log of the probability density function at x of the given RV.
`logsf`(x, *args, **kwds)	Log of the survival function of the given RV.
`mean`(*args, **kwds)	Mean of the distribution.
`median`(*args, **kwds)	Median of the distribution.
`moment`(order, *args, **kwds)	non-central moment of distribution of specified order.
`nnlf`(theta, x)	Negative loglikelihood function.
`pdf`(x, *args, **kwds)	Probability density function at x of the given RV.
`ppf`(q, *args, **kwds)	Percent point function (inverse of *cdf*) at q of the given RV.
`rvs`(*args, **kwds)	Random variates of given type.
`sf`(x, *args, **kwds)	Survival function (1 - *cdf*) at x of the given RV.
`stats`(*args, **kwds)	Some statistics of the given RV.
`std`(*args, **kwds)	Standard deviation of the distribution.
`support`(*args, **kwargs)	Support of the distribution.
`var`(*args, **kwds)	Variance of the distribution.

Attributes

random_state	Get or set the generator object for generating random variates.

locan.analysis.localization_property

Analyze localization property.

Localizations come with a range of properties including position coordinates, emission strength, local background etc.. Most properties represent random variables that were drawn from an unknown probability distribution. It is often useful to analyze the properties from all localizations within a selection and estimate the corresponding probability distribution.

Classes

LocalizationProperty([meta, loc_property, index])	Analyze localization property with respect to probability density or variation over a specified index.

locan.analysis.localization_property.LocalizationProperty

class locan.analysis.localization_property.**LocalizationProperty**(*meta=None*, *loc_property='intensity'*, *index=None*)

Bases: locan.analysis.analysis_base._Analysis

Analyze localization property with respect to probability density or variation over a specified index.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **loc_property** (*str*) – The property to analyze.
- **index** (*str | None*) – The property name that should serve as index (i.e. x-axis in x-y-plot)

Variables

- **count** (*int*) – A counter for counting instantiations (class attribute).
- **parameter** (*dict[str, Any]*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (*pandas.DataFrame*) – Computed results.
- **distribution_statistics** (*Distribution_stats | None*) – Distribution parameters derived from MLE fitting of results.

Methods

`__init__`([meta, loc_property, index])	

compute(locdata)	Run the computation.
fit_distributions([distribution, ...])	Fit probability density functions to the distributions of *loc_property* values in the results using MLE (scipy.stats).
hist([ax, bins, log, fit])	Provide histogram as `matplotlib.axes.Axes` object showing hist(results).
plot([ax, window])	Provide plot as `matplotlib.axes.Axes` object showing the running average of results over window size.
`report`(*args, **kwargs)	Show a report about analysis results.

Attributes

`count`	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*)

Run the computation.

Parameters **locdata** (*LocData*) – Localization data.

Return type Self

fit_distributions(*distribution=<scipy.stats._continuous_distns.expon_gen object>*, *with_constraints=True*, ***kwargs*)

Fit probability density functions to the distributions of *loc_property* values in the results using MLE (scipy.stats).

If with_constraints is true we put the following constraints on the fit procedure: If distribution is expon then *floc=np.min(self.analysis_class.results[self.loc_property].values)*.

Parameters

- **distribution** (`str | rv_continuous`) – Distribution model to fit.
- **with_constraints** (`bool`) – Flag to use predefined constraints on fit parameters.
- **kwargs** (`Any`) – Other parameters are passed to *scipy.stat.distribution.fit()*.

Return type `None`

hist(*ax=None*, *bins='auto'*, *log=True*, *fit=True*, ***kwargs*)

Provide histogram as `matplotlib.axes.Axes` object showing hist(results). Nan entries are ignored.

Parameters

- **ax** (`Optional[Axes]`) – The axes on which to show the image

- **bins** (int | Sequence[int | float] | str) – Bin specifications (passed to matplotlib.hist()).
- **log** (bool) – Flag for plotting on a log scale.
- **fit** (Optional[bool]) – Flag indicating if distribution fit is shown. The fit will only be computed if *distribution_statistics* is None.
- **kwargs** (Any) – Other parameters passed to matplotlib.pyplot.hist().

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

plot(*ax=None*, *window=1*, ***kwargs*)

Provide plot as matplotlib.axes.Axes object showing the running average of results over window size.

Parameters

- **ax** (*matplotlib.axes.Axes*) – The axes on which to show the image
- **window** (int) – Window for running average that is applied before plotting.
- **kwargs** (Any) – Other parameters passed to matplotlib.pyplot.plot().

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

locan.analysis.localization_property_2d

Analyze the distribution of a localization property in 2D.

Analyze the distribution of a localization property as function of two other localization properties in 2D. E.g. looking at how the local background is distributed over localization coordinates helps to characterize the illumination profile in SMLM experiments.

Classes

FitImageResults(image, bins, label, model_result)	
LocalizationProperty2d([meta, ...])	Analyze 2d distribution of histogram for two localization properties.

locan.analysis.localization_property_2d.FitImageResults

class locan.analysis.localization_property_2d.**FitImageResults**(*image*, *bins*, *label*, *model_result*)

Bases: NamedTuple

Methods

`__init__`()	

`count`(value, /)	Return number of occurrences of value.
`index`(value[, start, stop])	Return first index of value.

Attributes

bins	Alias for field number 1
image	Alias for field number 0
label	Alias for field number 2
model_result	Alias for field number 3

bins: *locan.data.aggregate.Bins*

Alias for field number 1

image: **numpy.ndarray[Any, numpy.dtype[Any]]**

Alias for field number 0

label: **list[str]**

Alias for field number 2

model_result: **lmfit.model.ModelResult**

Alias for field number 3

locan.analysis.localization_property_2d.LocalizationProperty2d

class locan.analysis.localization_property_2d.**LocalizationProperty2d**(*meta=None*, *loc_properties=None*, *other_property='local_backg*
bins=None, *n_bins=None*, *bin_size=100*, *bin_edges=None*, *bin_range=None*, *rescale=None*)

Bases: `locan.analysis.analysis_base._Analysis`

Analyze 2d distribution of histogram for two localization properties.

Fit a two dimensional Gauss distribution.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **loc_properties** (*Sequence[str] | None*) – Localization properties to be grouped into bins. If None, the coordinate_values of locdata are used.

- **other_property** (*str | None*) – Localization property (columns in locdata.data) that is averaged in each pixel. If None, the localization counts are shown.
- **bins** (Bins | *boost_histogram.axis.Axis | boost_histogram.axis.AxesTuple | None*) – The bin specification as defined in Bins
- **bin_edges** (*Sequence[float] | Sequence[Sequence[float]] | None*) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (*tuple[float, float] | Sequence[float] | Sequence[Sequence[float]] | str | None*) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2). If None (min, max) ranges are determined from data and returned; if 'zero' (0, max) ranges with max determined from data are returned. if 'link' (min_all, max_all) ranges with min and max determined from all combined data are returned.
- **n_bins** (*int | Sequence[int] | None*) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (*float | Sequence[float] | Sequence[Sequence[float]] | None*) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.
- **rescale** (*int | str | locan.Trafo | Callable[..., Any] | bool | None*) – Transformation as defined in locan.Trafo or by transformation function. For None or False no rescaling occurs. Legacy behavior: For tuple with upper and lower bounds provided in percent, rescale intensity values to be within percentile of max and min intensities. For 'equal' intensity values are rescaled by histogram equalization.

Variables

- **count** (*int*) – A counter for counting instantiations (class attribute).
- **parameter** (*dict*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (*lmfit.model.ModelResult*) – Computed fit results.

Methods

`__init__`([meta, loc_properties, ...])	

compute(locdata)	Run the computation.
plot([ax])	Provide histogram as `matplotlib.axes.Axes` object showing plot(results).
plot_deviation_from_mean([ax])	Provide histogram as `matplotlib.axes.Axes` object showing plot(results).
plot_deviation_from_median([ax])	Provide histogram as `matplotlib.axes.Axes` object showing plot(results).
plot_residuals([ax])	Provide histogram as `matplotlib.axes.Axes` object showing plot(results).
report()	Show a report about analysis results.

Attributes

`count`	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*)

Run the computation.

Parameters **locdata** (*LocData*) – Localization data.

Return type Self

plot(*ax=None*, ***kwargs*)

Provide histogram as `matplotlib.axes.Axes` object showing plot(results).

Parameters

- **ax** (`Optional[Axes]`) – The axes on which to show the image
- **kwargs** (`Any`) – Other parameters passed to `matplotlib.pyplot.contour()`.

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

plot_deviation_from_mean(*ax=None*)

Provide histogram as `matplotlib.axes.Axes` object showing plot(results).

Parameters **ax** (`Optional[Axes]`) – The axes on which to show the image

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

plot_deviation_from_median(*ax=None*)

Provide histogram as `matplotlib.axes.Axes` object showing plot(results).

Parameters **ax** (`Optional[Axes]`) – The axes on which to show the image

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

`plot_residuals`(*ax=None*, ***kwargs*)

Provide histogram as `matplotlib.axes.Axes` object showing plot(results).

Parameters

- **ax** (`Optional[Axes]`) – The axes on which to show the image
- **kwargs** (`Any`) – Other parameters passed to `matplotlib.pyplot.contour()`.

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

`report`()

Show a report about analysis results.

Return type `None`

locan.analysis.localization_property_correlations

Analyze cross dependencies between localization properties.

Analyze cross dependencies as indicated by the correlation coefficients between any two localization properties.

Classes

LocalizationPropertyCorrelations([meta, ...])	Compute and analyze correlation coefficients between any two localization

locan.analysis.localization_property_correlations.LocalizationPropertyCorrelations

class locan.analysis.localization_property_correlations.**LocalizationPropertyCorrelations**(*me*
loc

Bases: `locan.analysis.analysis_base._Analysis`

Compute and analyze correlation coefficients between any two localization properties.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **loc_properties** (*list[str] | None*) – Localization properties to be analyzed. If None all are used.

Variables

- **count** (*int*) – A counter for counting instantiations (class attribute).

- **parameter** (*dict[str, Any]*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata | None*) – Metadata about the current analysis routine.
- **results** (*pandas.DataFrame | None*) – The correlation coefficients..

Methods

`__init__`([meta, loc_properties])	

compute(locdata)	Run the computation.
plot([ax, cbar, colorbar_kws])	Provide heatmap of all correlation values as `matplotlib.axes.Axes` object.
report()	Show a report about analysis results.

Attributes

`count`	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*)

Run the computation.

Parameters **locdata** (*LocData*) – Localization data.

Return type Self

plot(*ax=None*, *cbar=True*, *colorbar_kws=None*, ***kwargs*)

Provide heatmap of all correlation values as `matplotlib.axes.Axes` object.

Parameters

- **ax** (`Optional[Axes]`) – The axes on which to show the image
- **cbar** (`bool`) – If true draw a colorbar.
- **colorbar_kws** (`Optional[dict[str, Any]]`) – Keyword arguments for `matplotlib.pyplot.colorbar()`.
- **kwargs** (`Any`) – Other parameters passed to `matplotlib.pyplot.imshow()`.

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

report()

Show a report about analysis results.

Return type `None`

locan.analysis.localizations_per_frame

Compute localizations per frame.

Classes

LocalizationsPerFrame([meta, norm, ...])	Compute localizations per frame.

locan.analysis.localizations_per_frame.LocalizationsPerFrame

class locan.analysis.localizations_per_frame.**LocalizationsPerFrame**(*meta=None*, *norm=None*, *time_delta='integration_time'*, *resample=None*, ***kwargs*)

Bases: `locan.analysis.analysis_base._Analysis`

Compute localizations per frame.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **norm** (*int | float | str | None*) – Normalization factor that can be None, a number, or another property in *locdata*.
- **time_delta** (*int | float | str | pd.Timedelta | None*) – Time per frame in milliseconds. String must specify the unit like "10ms".

  For "integration_time" the time is taken from

  locdata.meta.experiment.setups[0].optical_units[0].detection.camera.integration_time
- **resample** (*DateOffset | Timedelta | str*) – Parameter for `pandas.Series.resample()`: The offset string or object representing target conversion.
- **kwargs** (Any) – Other parameters passed to `pandas.Series.resample()`.

Variables

- **count** (*int*) – A counter for counting instantiations.
- **parameter** (*dict*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (*pandas.Series*) – Computed results.
- **distribution_statistics** (*Distribution_fits object | None*) – Distribution parameters derived from MLE fitting of results.

Methods

`__init__`([meta, norm, time_delta, resample])	
compute(locdata)	Run the computation.
fit_distributions(**kwargs)	Fit probability density functions to the distributions of ` loc_property` values in the results using MLE (scipy.stats).
hist([ax, fit, bins])	Provide histogram as `matplotlib.axes.Axes` object showing hist(results).
plot([ax, window, cumulative, normalize])	Provide plot as `matplotlib.axes.Axes` object showing the running average of results over window size.
`report`(*args, **kwargs)	Show a report about analysis results.

Attributes

count	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*)

Run the computation.

Parameters **locdata** (Union[*LocData*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Points in time: either localization data that contains a column *frame* or an array with time points.

Return type Self

count: int = 0

A counter for counting Analysis class instantiations (class attribute).

fit_distributions(***kwargs*)

Fit probability density functions to the distributions of ` loc_property` values in the results using MLE (scipy.stats).

Parameters **loc_property** (*str*) – The LocData property for which to fit an appropriate distribution; if None all plots are shown.

Return type None

hist(*ax=None*, *fit=True*, *bins='auto'*, ***kwargs*)

Provide histogram as `matplotlib.axes.Axes` object showing hist(results).

Parameters

- **ax** (Optional[Axes]) – The axes on which to show the image
- **bins** (int | Sequence[int | float] | str) – Bin specifications (passed to matplotlib.hist).

- **fit** (bool) – Flag indicating if distributions fit are shown.
- **kwargs** (Any) – Other parameters passed to `matplotlib.pyplot.hist()`.

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

plot(*ax=None*, *window=1*, *cumulative=False*, *normalize=False*, ***kwargs*)

Provide plot as `matplotlib.axes.Axes` object showing the running average of results over window size.

Parameters

- **ax** (Optional[Axes]) – The axes on which to show the image
- **window** (int) – Window for running average that is applied before plotting.
- **cumulative** (bool) – Plot the cumulated results if true.
- **normalize** (bool) – Normalize cumulative plot to the last value
- **kwargs** (Any) – Other parameters passed to `matplotlib.pyplot.plot()`.

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

locan.analysis.nearest_neighbor

Nearest-neighbor distance distribution analysis

Nearest-neighbor distance distributions provide information about deviations from a spatial homogeneous Poisson process (i.e. complete spatial randomness, CSR). Point-event distances are given by the distance between a random point (not being an event) and the nearest event. The point-event distance distribution is estimated from a number of random sample points and plotted in comparison to the analytical function for equal localization density.

For a homogeneous 2D Poisson process with intensity ρ (expected number of points per unit area) the distance from a randomly chosen event to the nearest other event (nearest-neighbor distance) is distributed according to the following probability density (pdf) or cumulative density function (cdf)[1]:

$$pdf(w) = 2\rho\pi w\ exp(-\rho\pi w^2)$$
$$cdf(w) = 1 - exp(-\rho\pi w^2)$$

The same distribution holds for point-event distances if events are distributed as a homogeneous Poisson process with intensity ρ.

[1] Philip M. Dixon, Nearest Neighbor Methods, Department of Statistics, Iowa State University, 20 December 2001

References

Classes

NNDistances_csr_2d([momtype, a, b, xtol, ...])	Continuous distribution function for nearest-neighbor distances of points distributed in 2D under complete spatial randomness.
NNDistances_csr_3d([momtype, a, b, xtol, ...])	Continuous distribution function for nearest-neighbor distances of points distributed in 3D under complete spatial randomness.
NearestNeighborDistances([meta, k])	Compute the k-nearest-neighbor distances within data or between data and other_data.

locan.analysis.nearest_neighbor.NNDistances_csr_2d

class locan.analysis.nearest_neighbor.**NNDistances_csr_2d**(*momtype=1*, *a=None*, *b=None*, *xtol=1e-14*, *badvalue=None*, *name=None*, *longname=None*, *shapes=None*, *seed=None*)

Bases: scipy.stats._distn_infrastructure.rv_continuous

Continuous distribution function for nearest-neighbor distances of points distributed in 2D under complete spatial randomness.

Parameters **density** (*float*) – Shape parameter *density*, being the density of points.

Methods

`__init__`([momtype, a, b, xtol, badvalue, ...])	
`cdf`(x, *args, **kwds)	Cumulative distribution function of the given RV.
`entropy`(*args, **kwds)	Differential entropy of the RV.
`expect`([func, args, loc, scale, lb, ub, ...])	Calculate expected value of a function with respect to the distribution by numerical integration.
`fit`(data, *args, **kwds)	Return estimates of shape (if applicable), location, and scale parameters from data.
`fit_loc_scale`(data, *args)	Estimate loc and scale parameters from data using 1st and 2nd moments.
`freeze`(*args, **kwds)	Freeze the distribution for the given arguments.
`interval`(confidence, *args, **kwds)	Confidence interval with equal areas around the median.
`isf`(q, *args, **kwds)	Inverse survival function (inverse of *sf*) at q of the given RV.
`logcdf`(x, *args, **kwds)	Log of the cumulative distribution function at x of the given RV.
`logpdf`(x, *args, **kwds)	Log of the probability density function at x of the given RV.
`logsf`(x, *args, **kwds)	Log of the survival function of the given RV.
`mean`(*args, **kwds)	Mean of the distribution.
`median`(*args, **kwds)	Median of the distribution.
`moment`(order, *args, **kwds)	non-central moment of distribution of specified order.
`nnlf`(theta, x)	Negative loglikelihood function.
`pdf`(x, *args, **kwds)	Probability density function at x of the given RV.
`ppf`(q, *args, **kwds)	Percent point function (inverse of *cdf*) at q of the given RV.
`rvs`(*args, **kwds)	Random variates of given type.
`sf`(x, *args, **kwds)	Survival function (1 - *cdf*) at x of the given RV.
`stats`(*args, **kwds)	Some statistics of the given RV.
`std`(*args, **kwds)	Standard deviation of the distribution.
`support`(*args, **kwargs)	Support of the distribution.
`var`(*args, **kwds)	Variance of the distribution.

Attributes

`random_state`	Get or set the generator object for generating random variates.

locan.analysis.nearest_neighbor.NNDistances_csr_3d

class locan.analysis.nearest_neighbor.**NNDistances_csr_3d**(*momtype=1*, *a=None*, *b=None*, *xtol=1e-14*, *badvalue=None*, *name=None*, *longname=None*, *shapes=None*, *seed=None*)

Bases: `scipy.stats._distn_infrastructure.rv_continuous`

Continuous distribution function for nearest-neighbor distances of points distributed in 3D under complete spatial randomness.

Parameters

- **x** (*float*) – distance
- **density** (*float*) – Shape parameter *density*, being the density of points.

Methods

`__init__`([momtype, a, b, xtol, badvalue, ...])	
`cdf`(x, *args, **kwds)	Cumulative distribution function of the given RV.
`entropy`(*args, **kwds)	Differential entropy of the RV.
`expect`([func, args, loc, scale, lb, ub, ...])	Calculate expected value of a function with respect to the distribution by numerical integration.
`fit`(data, *args, **kwds)	Return estimates of shape (if applicable), location, and scale parameters from data.
`fit_loc_scale`(data, *args)	Estimate loc and scale parameters from data using 1st and 2nd moments.
`freeze`(*args, **kwds)	Freeze the distribution for the given arguments.
`interval`(confidence, *args, **kwds)	Confidence interval with equal areas around the median.
`isf`(q, *args, **kwds)	Inverse survival function (inverse of *sf*) at q of the given RV.
`logcdf`(x, *args, **kwds)	Log of the cumulative distribution function at x of the given RV.
`logpdf`(x, *args, **kwds)	Log of the probability density function at x of the given RV.
`logsf`(x, *args, **kwds)	Log of the survival function of the given RV.
`mean`(*args, **kwds)	Mean of the distribution.
`median`(*args, **kwds)	Median of the distribution.
`moment`(order, *args, **kwds)	non-central moment of distribution of specified order.
`nnlf`(theta, x)	Negative loglikelihood function.
`pdf`(x, *args, **kwds)	Probability density function at x of the given RV.
`ppf`(q, *args, **kwds)	Percent point function (inverse of *cdf*) at q of the given RV.
`rvs`(*args, **kwds)	Random variates of given type.
`sf`(x, *args, **kwds)	Survival function (1 - *cdf*) at x of the given RV.
`stats`(*args, **kwds)	Some statistics of the given RV.
`std`(*args, **kwds)	Standard deviation of the distribution.
`support`(*args, **kwargs)	Support of the distribution.
`var`(*args, **kwds)	Variance of the distribution.

Attributes

random_state	Get or set the generator object for generating random variates.

locan.analysis.nearest_neighbor.NearestNeighborDistances

class locan.analysis.nearest_neighbor.**NearestNeighborDistances**(*meta=None*, *k=1*)

Bases: locan.analysis.analysis_base._Analysis

Compute the k-nearest-neighbor distances within data or between data and other_data.

The algorithm relies on sklearn.neighbors.NearestNeighbors.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **k** (*int*) – Compute the kth nearest neighbor.

Variables

- **count** (*int*) – A counter for counting instantiations.
- **parameter** (*dict*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (*pandas.DataFrame*) – Computed results.
- **distribution_statistics** (*Distribution_stats | None*) – Distribution parameters derived from MLE fitting of results.

Methods

__init__([meta, k])	

compute(locdata[, other_locdata])	Run the computation.
fit_distributions([with_constraints])	Fit probability density functions to the distributions of *loc_property* values in the results using MLE (scipy.stats).
hist([ax, bins, density, fit])	Provide histogram as matplotlib.axes.Axes object showing hist(results).
report(*args, **kwargs)	Show a report about analysis results.

Attributes

count	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*, *other_locdata=None*)

Run the computation.

Parameters

- **locdata** (*LocData*) – Localization data.
- **other_locdata** (Optional[*LocData*]) – Other localization data from which nearest neighbors are taken.

Return type Self

count: int = 0

A counter for counting Analysis class instantiations (class attribute).

fit_distributions(*with_constraints=True*)

Fit probability density functions to the distributions of *loc_property* values in the results using MLE (scipy.stats).

If with_constraints is true we put the following constraints on the fit procedure: If distribution is expon then floc=np.min(self.analysis_class.results[self.loc_property].values).

Parameters **with_constraints** (bool) – Flag to use predefined constraints on fit parameters.

Return type None

hist(*ax=None*, *bins='auto'*, *density=True*, *fit=False*, ***kwargs*)

Provide histogram as matplotlib.axes.Axes object showing hist(results).

Parameters

- **ax** (Optional[Axes]) – The axes on which to show the image.
- **bins** (Union[int, list[int | float], Literal['auto']]) – Bin specification as used in matplotlib.hist()
- **density** (bool) – Flag for normalization as used in matplotlib.hist. True returns probability density function; None returns counts.
- **fit** (bool) – Flag indicating to fit pdf of nearest-neighbor distances under complete spatial randomness.
- **kwargs** (Any) – Other parameters passed to matplotlib.plot().

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

Functions

pdf_nnDistances_csr_2D(x, density)	Probability density function for nearest-neighbor distances of points distributed in 2D with complete spatial randomness.
pdf_nnDistances_csr_3D(x, density)	Probability density function for nearest-neighbor distances of points distributed in 3D with complete spatial randomness.

locan.analysis.nearest_neighbor.pdf_nnDistances_csr_2D

`locan.analysis.nearest_neighbor.`**`pdf_nnDistances_csr_2D`**(*x*, *density*)

Probability density function for nearest-neighbor distances of points distributed in 2D with complete spatial randomness.

Parameters

- **x** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – distance
- **density** (float) – density of points

Returns Probability density function pdf(x).

Return type float

locan.analysis.nearest_neighbor.pdf_nnDistances_csr_3D

`locan.analysis.nearest_neighbor.`**`pdf_nnDistances_csr_3D`**(*x*, *density*)

Probability density function for nearest-neighbor distances of points distributed in 3D with complete spatial randomness.

Parameters

- **x** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – distance
- **density** (float) – density of points

Returns Probability density function pdf(x).

Return type npt.NDArray[**np.float_**]

locan.analysis.pipeline

Building an analysis pipeline.

Pipeline refers to sequential analysis steps that are applied to a single LocData object. An analysis pipeline here includes true piped analysis, where a preliminary result serves as input to the next analysis step, but also workflows that provide different results in parallel.

A batch process is a procedure for running a pipeline over multiple LocData objects while collecting and combing results.

This module provides a class *Pipeline* to combine the analysis procedure, parameters and results in a single pickleable object.

Classes

Pipeline(computation[, meta])	The base class for a specialized analysis pipeline to be used on LocData objects.

locan.analysis.pipeline.Pipeline

class locan.analysis.pipeline.**Pipeline**(*computation*, *meta=None*, ***kwargs*)

Bases: locan.analysis.analysis_base._Analysis

The base class for a specialized analysis pipeline to be used on LocData objects.

The custom analysis routine has to be added by implementing the method *computation(self, **kwargs)*. Keyword arguments must include the locdata reference and optional parameters.

Results are provided as customized attributes. We suggest abbreviated standard names for the most common procedures

such as:

- lp - Localization Precision
- lprop - Localization Property
- lpf - Localizations per Frame
- rhf - Ripley H function
- clust - locdata with clustered elements

Parameters

- **computation** (*Callable[..., Any]*) – A function *computation(self, **kwargs)* specifying the analysis procedure.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **kwargs** (Any) – Locdata reference and optional parameters passed to *computation(self, **kwargs)*.

Variables

- **count** (*int*) – A counter for counting instantiations (class attribute).
- **parameter** (*dict*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata | None*) – Metadata about the current analysis routine.
- **computation** (*Callable[..., Any]*) – A function *computation(self, **kwargs)* specifying the analysis procedure.
- **kwargs** – All parameters including the locdata reference that are passed to *computation(self, **kwargs)*.

Note: The class variable *Pipeline.count* is only incremented in a single process. In multiprocessing *Pipeline.count* and *Pipeline.meta.identifier* (which is set using *count*) cannot be used to identify distinct Pipeline objects.

Note: For the Pipeline object to be pickleable attention has to be paid to the `computation()` method. With multiprocessing it will have to be re-injected for each Pipeline object by *pipeline.computation = computation* after computation and before pickling.

Methods

`__init__`(computation[, meta])	

computation_as_string()	Return the analysis procedure (i.e.
compute()	Run the analysis procedure.
`report`(*args, **kwargs)	Show a report about analysis results.
save_computation(path)	Save the analysis procedure (i.e.

Attributes

`count`	A counter for counting Analysis class instantiations (class attribute).

computation_as_string()

Return the analysis procedure (i.e. the computation() method) as string.

Return type `str`

compute()

Run the analysis procedure. All parameters must be given upon Pipeline instantiation.

Return type `Any`

save_computation(*path*)

Save the analysis procedure (i.e. the computation() method) as human readable text.

Parameters **path** (*str | os.PathLike[Any]*) – Path and file name for saving the text file.

Return type None

Functions

computation_test(self[, locdata, parameter])	A pipeline definition for testing.

locan.analysis.pipeline.computation_test

locan.analysis.pipeline.**computation_test**(*self*, *locdata=None*, *parameter='test'*)

A pipeline definition for testing.

Return type TypeVar(T_Pipeline, bound= Pipeline)

locan.analysis.position_variance_expectation

Analyze variance of localization coordinates.

Localization coordinates in localization clusters come with a certain variance. In resolution-limited clusters the variance is determined by the localization precision.

A close look at the variance of localization coordinates as function of localization counts helps to characterize localization clusters[1].

References

Classes

PositionVarianceExpectation([meta, ...])	Analyze variation of localization properties in relation to expected variations.
PositionVarianceExpectationResults([values, ...])	

[1] Ebert V, Eiring P, Helmerich DA, Seifert R, Sauer M, Doose S. Convex hull as diagnostic tool in single-molecule localization microscopy. Bioinformatics 38(24), 2022, 5421-5429, doi: 10.1093/bioinformatics/btac700.

locan.analysis.position_variance_expectation.PositionVarianceExpectation

class locan.analysis.position_variance_expectation.**PositionVarianceExpectation**(*meta=None*, *loc_property='p*
ex-
pec-
ta-
tion=None,
bi-
ased=True)

Bases: `locan.analysis.analysis_base._Analysis`

Analyze variation of localization properties in relation to expected variations.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **loc_property** (*str*) – The localization property to analyze.
- **expectation** (*int | float | Mapping[str, Any] | pd.Series[Any] | None*) – The expected variance for all or each localization property. The expected variance equals the squared localization precision for localization position coordinates.
- **biased** (*bool*) – Flag to use biased or unbiased (Bessel-corrected) variance

Variables

- **count** (*int*) – A counter for counting instantiations (class attribute).
- **parameter** (*dict*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (PositionVarianceExpectationResults) – Computed results.
- **distribution_statistics** (*Distribution_stats, None*) – Distribution parameters derived from MLE fitting of results.

Methods

`__init__`([meta, loc_property, expectation, ...])	
compute(locdata)	Run the computation.
hist([ax, bins, n_bins, bin_size, ...])	Provide plot as `matplotlib.axes.Axes` object showing the 2-dimensional histogram of variances and localization counts.
plot([ax])	Provide plot as `matplotlib.axes.Axes` object showing the variances as function of localization counts.
`report`(*args, **kwargs)	Show a report about analysis results.

Attributes

count	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*)

Run the computation.

Parameters **locdata** (*LocData*) – Localization data.

Return type Self

hist(*ax=None*, *bins=None*, *n_bins=None*, *bin_size=None*, *bin_edges=None*, *bin_range=None*, *log=True*, *fit=False*, ***kwargs*)

Provide plot as `matplotlib.axes.Axes` object showing the 2-dimensional histogram of variances and localization counts.

Parameters

- **ax** (`Optional[Axes]`) – The axes on which to show the image
- **bins** (`Union[Bins, Axis, AxesTuple, None]`) – The bin specification as defined in `Bins`
- **bin_edges** (`Union[Sequence[float], Sequence[Sequence[float]], None]`) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (`Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], None]`) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2).
- **n_bins** (`Union[int, Sequence[int], None]`) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (`Union[float, Sequence[float], Sequence[Sequence[float]], None]`) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.
- **log** (`bool`) – Flag for plotting on a log scale.
- **fit** (`bool`) – Flag indicating if distribution fit is shown. The fit will only be computed if *distribution_statistics*

  is None.
- **kwargs** (`Any`) – Other parameters passed to `matplotlib.pyplot.pcolormesh()`.

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

plot(*ax=None*, ***kwargs*)

Provide plot as `matplotlib.axes.Axes` object showing the variances as function of localization counts.

Parameters

- **ax** (`Optional[Axes]`) – The axes on which to show the image
- **kwargs** (`Any`) – Other parameters passed to `matplotlib.pyplot.plot()`.

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

locan.analysis.position_variance_expectation.PositionVarianceExpectationResults

class locan.analysis.position_variance_expectation.**PositionVarianceExpectationResults**(*values=*
groupe

Bases: `object`

Methods

`__init__`([values, grouped])

Attributes

values
grouped

grouped: **pandas.core.frame.DataFrame**

values: **pandas.core.frame.DataFrame**

locan.analysis.ripley

Compute Ripley's k function.

Spatial clustering of localization data is characterized by Ripley's k or related l and h functions[1].

Ripley's k function is computed for 2D and 3D data for a series of radii as described in[2] in order to provide evidence for deviations from a spatially homogeneous Poisson process (i.e. complete spatial

[1] B.D. Ripley, Modelling spatial patterns. Journal of the Royal Statistical Society, 1977, 172–212.

[2] Kiskowski, M. A., Hancock, J. F., and Kenworthy, A. K., On the use of Ripley's K-function and its derivatives to analyze domain size. Biophysical journal, 2009, 97, 1095–1103.

randomness, CSR). Ripley' s k function is estimated by summing all points or over test points being a random subset of all points:

$$k(r) = \frac{1}{\lambda(n-1)} \sum_{i=1}^{n} N_{p_i}(r)$$

here p_i is the i^{th} point of n test points, N_{p_i} is the number of points within the region of radius r around p_i, and λ is the density of all points.

We follow the definition of l and h functions in[Page 321, 2]. Ripley's l function is:

$$l(r) = \sqrt{k(r))/\pi} \qquad \text{in 2D}$$

$$l(r) = \sqrt[3]{\frac{3}{4\pi} k(r)} \qquad \text{in 3D}$$

And Ripley's h function is:

$$h(r) = l(r) - r$$

References

Classes

RipleysHFunction([meta, radii, region_measure])	Compute Ripley's H function for two- or three-dimensional data at the given radii.
RipleysKFunction([meta, radii, region_measure])	Compute Ripley's K function for two- or three-dimensional data at the given radii.
RipleysLFunction([meta, radii, region_measure])	Compute Ripley's L function for two- or three-dimensional data at the given radii.

locan.analysis.ripley.RipleysHFunction

class locan.analysis.ripley.**RipleysHFunction**(*meta=None*, *radii=None*, *region_measure='bb'*)

Bases: locan.analysis.analysis_base._Analysis

Compute Ripley's H function for two- or three-dimensional data at the given radii.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata | None*) – Metadata about the current analysis routine.
- **radii** (*npt.ArrayLike | None*) – Radii at which to compute Ripley's k function.
- **region_measure** (*float | Literal['bb']*) – Region measure (area or volume) for point region. For 'bb' the region measure of the bounding_box is used.

Variables

- **count** (*int*) – A counter for counting instantiations.

- **parameter** (*dict[str, Any]*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (*pd.DataFrame | None*) – Data frame with radii as provided and Ripley's H function.
- **Ripley_h_maximum** (*pd.DataFrame | None*) – Data frame with radius and Ripley's H value for the radius at which the H function has its maximum.

Methods

`__init__`([meta, radii, region_measure])	
compute(locdata[, other_locdata])	Run the computation.
plot([ax])	**rtype** Axes
report(*args, **kwargs)	Show a report about analysis results.

Attributes

Ripley_h_maximum	**rtype** Optional[DataFrame]
count	A counter for counting Analysis class instantiations (class attribute).

property Ripley_h_maximum: pandas.core.frame.DataFrame | None

Return type Optional[DataFrame]

compute(*locdata*, *other_locdata=None*)

Run the computation.

Parameters

- **locdata** (*LocData*) – Localization data with 2D or 3D coordinates on which to estimate Ripley's H function.
- **other_locdata** (Optional[*LocData*]) – Other localization data from which to estimate Ripley's H function (e.g. subset of points). For None other_points is set to points (default).

Return type Self

count: int = 0

A counter for counting Analysis class instantiations (class attribute).

plot(*ax=None*, ***kwargs*)

Return type Axes

locan.analysis.ripley.RipleysKFunction

class locan.analysis.ripley.**RipleysKFunction**(*meta=None*, *radii=None*, *region_measure='bb'*)

Bases: locan.analysis.analysis_base._Analysis

Compute Ripley's K function for two- or three-dimensional data at the given radii.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata | None*) – Metadata about the current analysis routine.
- **radii** (*Iterable[float] | None*) – Radii at which to compute Ripley's k function.
- **region_measure** (*float | Literal['bb']*) – Region measure (area or volume) for point region. For 'bb' the region measure of the bounding_box is used.

Variables

- **count** (*int*) – A counter for counting instantiations.
- **parameter** (*dict*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (*pandas.DataFrame*) – Data frame with radii as provided and Ripley's K function.

Methods

__init__([meta, radii, region_measure])	
compute(locdata[, other_locdata])	Run the computation.
plot([ax])	**rtype** Axes
report(*args, **kwargs)	Show a report about analysis results.

Attributes

count	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*, *other_locdata=None*)

Run the computation.

Parameters

- **locdata** (*LocData*) – Localization data with 2D or 3D coordinates on which to estimate Ripley's K function.
- **other_locdata** (Optional[*LocData*]) – Other localization data from which to estimate Ripley's K function (e.g. subset of points). For None other_points is set to points (default).

Return type Self

count: int = 0

A counter for counting Analysis class instantiations (class attribute).

plot(*ax=None*, ***kwargs*)

Return type Axes

locan.analysis.ripley.RipleysLFunction

class locan.analysis.ripley.**RipleysLFunction**(*meta=None*, *radii=None*, *region_measure='bb'*)

Bases: locan.analysis.analysis_base._Analysis

Compute Ripley's L function for two- or three-dimensional data at the given radii.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata | None*) – Metadata about the current analysis routine.
- **radii** (*npt.ArrayLike | None*) – Radii at which to compute Ripley's k function.
- **region_measure** (*float | Literal["bb"]*) – Region measure (area or volume) for point region. For 'bb' the region measure of the bounding_box is used.

Variables

- **count** (*int*) – A counter for counting instantiations.
- **parameter** (*dict*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.

- **results** (*pandas.DataFrame*) – Data frame with radii as provided and Ripley's L function.

Methods

`__init__`([meta, radii, region_measure])	
compute(locdata[, other_locdata])	Run the computation.
plot([ax])	**rtype** Axes
`report`(*args, **kwargs)	Show a report about analysis results.

Attributes

count	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*, *other_locdata=None*)

Run the computation.

Parameters

- **locdata** (*LocData*) – Localization data with 2D or 3D coordinates on which to estimate Ripley's L function.
- **other_locdata** (Optional[*LocData*]) – Other localization data from which to estimate Ripley's L function (e.g. subset of points). For None other_points is set to points (default).

Return type Self

count: int = 0

A counter for counting Analysis class instantiations (class attribute).

plot(*ax=None*, ***kwargs*)

Return type Axes

Functions

plot(self[, ax])	Provide plot of results as `matplotlib.axes.Axes` object.

locan.analysis.ripley.plot

locan.analysis.ripley.**plot**(*self*, *ax=None*, ***kwargs*)

Provide plot of results as `matplotlib.axes.Axes` object.

Parameters

- **ax** (`Optional[Axes]`) – The axes on which to show the image
- **kwargs** (`Any`) – Other parameters passed to `matplotlib.pyplot.plot()`.

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

locan.analysis.subpixel_bias

Compute subpixel bias in localization data.

Subpixel bias in localization coordinates may arise depending on the localization algorithm[1].

References

Classes

SubpixelBias([meta, pixel_size])	Check for subpixel bias by computing the modulo of localization coordinates for each localization's spatial coordinate in locdata.

locan.analysis.subpixel_bias.SubpixelBias

class locan.analysis.subpixel_bias.**SubpixelBias**(*meta=None*, *pixel_size=None*)

Bases: `locan.analysis.analysis_base._Analysis`

Check for subpixel bias by computing the modulo of localization coordinates for each localization's spatial coordinate in locdata.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata | None*) – Metadata about the current analysis routine.
- **pixel_size** (*int | float | Sequence[int | float]*) – Camera pixel size in coordinate units.

Variables

- **count** (*int*) – A counter for counting instantiations.
- **parameter** (*dict*) – A dictionary with all settings for the current computation.

[1] Gould, T. J., Verkhusha, V. V. & Hess, S. T., Imaging biological structures with fluorescence photoactivation localization microscopy. Nat. Protoc. 4 (2009), 291–308.

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (*pandas.DataFrame*) – The number of localizations per frame or the number of localizations per frame normalized to region_measure(hull).

Methods

`__init__`([meta, pixel_size])	

compute(locdata)	Run the computation.
hist([ax, bins, log])	Provide histogram as `matplotlib.axes.Axes` object showing hist(results).
`report`(*args, **kwargs)	Show a report about analysis results.

Attributes

count	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*)

Run the computation.

Parameters **locdata** (*LocData*) – Localization data.

Return type Self

count: int = 0

A counter for counting Analysis class instantiations (class attribute).

hist(*ax=None*, *bins='auto'*, *log=True*, ***kwargs*)

Provide histogram as `matplotlib.axes.Axes` object showing hist(results). Nan entries are ignored.

Parameters

- **ax** (`Optional[Axes]`) – The axes on which to show the image
- **bins** (`int | Sequence[int | float] | str`) – Bin specifications (passed to `matplotlib.hist()`).
- **log** (`bool`) – Flag for plotting on a log scale.
- **kwargs** (`Any`) – Other parameters passed to `matplotlib.pyplot.hist()`.

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

locan.analysis.uncertainty

Compute localization uncertainty.

A theoretical estimate for localization uncertainty is given by the Cramer-Rao-lower-bound for the localization precision. The localization precision depends on a number of experimental factors including camera and photophysical characteristics[1][2]. We provide functions to compute localization uncertainty from available localization properties as predicted by the Cramer-Rao-lower-bound for the localization precision.

References

Classes

LocalizationUncertainty([meta, model])	Compute the Cramer Rao lower bound for localization uncertainty for each localization's spatial coordinate in locdata.

locan.analysis.uncertainty.LocalizationUncertainty

class locan.analysis.uncertainty.**LocalizationUncertainty**(*meta=None*, *model=1*, ***kwargs*)

Bases: locan.analysis.analysis_base._Analysis

Compute the Cramer Rao lower bound for localization uncertainty for each localization's spatial coordinate in locdata.

Uncertainty is computed according to one of the following model functions:

1) 1 / sqrt(intensity)
2) psf_sigma / sqrt(intensity)
3) f(psf_sigma, intensity, pixel_size, background)

Localization properties have to be available for all or each spatial dimension (like *psf_sigma* or *psf_sigma_x*). The localization property *intensity* must have the unit *photons*. The unit of *pixel_size* must be the same as that of position coordinates.

Parameters

- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata | None*) – Metadata about the current analysis routine.
- **model** (*int*) – Model function for theoretical localization uncertainty.
- **kwargs** (Any) – kwargs for the chosen model. If none are given the localization properties are taken from locdata.

Variables

- **count** (*int*) – A counter for counting instantiations.

[1] K.I. Mortensen, L. S. Churchman, J. A. Spudich, H. Flyvbjerg, Nat. Methods 7 (2010): 377–384.

[2] Rieger B., Stallinga S., The lateral and axial localization uncertainty in super-resolution light microscopy. Chemphyschem 17;15(4), 2014:664-70. doi: 10.1002/cphc.201300711

- **parameter** (*dict*) – A dictionary with all settings for the current computation.
- **meta** (*locan.analysis.metadata_analysis_pb2.AMetadata*) – Metadata about the current analysis routine.
- **results** (*pandas.DataFrame*) – Uncertainty for each localization and in each dimension.

Methods

`__init__`([meta, model])	

compute(locdata)	Run the computation.
`report`(*args, **kwargs)	Show a report about analysis results.

Attributes

count	A counter for counting Analysis class instantiations (class attribute).

compute(*locdata*)

Run the computation.

Parameters **locdata** (*LocData*) – Localization data.

Return type Self

count: int = 0

A counter for counting Analysis class instantiations (class attribute).

Functions

localization_precision_model_1(intensity)	Localization precision as function of intensity (I) according to:
localization_precision_model_2(intensity, ...)	Localization precision as function of intensity (I), PSF width (sigma_PSF) according to:
localization_precision_model_3(intensity, ...)	Localization precision as function of intensity (I), PSF size (sigma_{PSF}), pixel size (a), background (b) according to:

locan.analysis.uncertainty.localization_precision_model_1

locan.analysis.uncertainty.**localization_precision_model_1**(*intensity*)

Localization precision as function of intensity (I) according to:

$$\sigma_{loc} = \frac{1}{\sqrt{I}}$$

Parameters **intensity** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Intensity values

Return type npt.NDArray[**np.float_**]

locan.analysis.uncertainty.localization_precision_model_2

locan.analysis.uncertainty.**localization_precision_model_2**(*intensity*, *psf_sigma*)

Localization precision as function of intensity (I), PSF width (sigma_PSF) according to:

$$\sigma_{loc} = \frac{\sigma_{PSF}}{\sqrt{I}}$$

Parameters

- **intensity** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Intensity values
- **psf_sigma** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The PSF size

Return type npt.NDArray[**np.float_**]

locan.analysis.uncertainty.localization_precision_model_3

locan.analysis.uncertainty.**localization_precision_model_3**(*intensity*, *psf_sigma*, *pixel_size*, *local_background*)

Localization precision as function of intensity (I), PSF size (sigma_{PSF}), pixel size (a), background (b) according to:

$$\sigma_a^2 = \sigma_{PSF}^2 + a^2/12$$
$$\tau = 2 * \pi * b * \sigma_a^2/(I * a^2)$$
$$\sigma_{loc}^2 = \sigma_a^2/I * (1 + 4 * \tau + \sqrt{2 * \tau/(1 + 4 * \tau)})$$

Parameters

- **intensity** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Intensity values
- **psf_sigma** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The PSF size
- **pixel_size** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Size of camera pixel
- **local_background** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The local background

Return type npt.NDArray[**np.float_**]

8.2 locan.constants

Constants used throughout the project.

ROOT_DIR	Path subclass for non-Windows systems.
PROPERTY_KEYS	Keys for the most common LocData properties.
DECODE_KEYS	Mapping column names in DECODE files to *LocData* property keys
ELYRA_KEYS	Mapping column names in Zeiss Elyra files to *LocData* property keys
NANOIMAGER_KEYS	Mapping column names in Nanoimager files to *LocData* property keys
RAPIDSTORM_KEYS	Mapping column names in RapidSTORM files to *LocData* property keys
SMAP_KEYS	Mapping column names in SMAP files to *LocData* property keys
SMLM_KEYS	Mapping column names in SMLM files to *LocData* property keys
THUNDERSTORM_KEYS	Mapping column names in Thunderstorm files to *LocData* property keys

8.2.1 locan.constants.ROOT_DIR

locan.constants.**ROOT_DIR: pathlib.Path = PosixPath('/home/docs/checkouts/readthedocs.org/user_builds/locan/envs/stable/lib/python3.10/site-packages/locan')**

Path subclass for non-Windows systems.

On a POSIX system, instantiating a Path should return this object.

8.2.2 locan.constants.PROPERTY_KEYS

locan.constants.**PROPERTY_KEYS = {'channel': 'integer', 'chi_square': 'float', 'cluster_label': 'integer', 'frame': 'integer', 'frames_missing': 'integer', 'frames_number': 'integer', 'index': 'integer', 'intensity': 'float', 'local_background': 'float', 'local_background_sigma': 'float', 'original_index': 'integer', 'plane': 'integer', 'position_x': 'float', 'position_y': 'float', 'position_z': 'float', 'psf_amplitude': 'float', 'psf_half_width': 'float', 'psf_half_width_x': 'float', 'psf_half_width_y': 'float', 'psf_half_width_z': 'float', 'psf_sigma': 'float', 'psf_sigma_x': 'float', 'psf_sigma_y': 'float', 'psf_sigma_z': 'float', 'psf_width': 'float', 'psf_width_x': 'float', 'psf_width_y': 'float', 'psf_width_z': 'float', 'signal_background_ratio': 'float', 'signal_noise_ratio': 'float', 'slice_z': 'float', 'time': 'float', 'two_kernel_improvement': 'float', 'uncertainty': 'float', 'uncertainty_x': 'float', 'uncertainty_y': 'float', 'uncertainty_z': 'float'}**

Keys for the most common LocData properties. Values suggest a type for conversion. If 'integer', 'signed', 'unsigned', 'float' `pandas.to_numeric()` can be applied. Otherwise `pandas.astype()` can be applied.

8.2.3 locan.constants.DECODE_KEYS

locan.constants.**DECODE_KEYS: Final[dict[str, str]] = {'bg': 'local_background', 'frame_ix': 'frame', 'id': 'original_index', 'phot': 'intensity', 'x': 'position_x', 'y': 'position_y', 'z': 'position_z'}**

Mapping column names in DECODE files to *LocData* property keys

8.2.4 locan.constants.ELYRA_KEYS

locan.constants.**ELYRA_KEYS: Final[dict[str, str]] = {'Background variance': 'local_background_sigma', 'Channel': 'channel', 'Chi square': 'chi_square', 'First Frame': 'frame', 'Frames Missing': 'frames_missing', 'Index': 'original_index', 'Number Frames': 'frames_number', 'Number Photons': 'intensity', 'PSF half width [nm]': 'psf_half_width', 'PSF width [nm]': 'psf_width', 'Position X [nm]': 'position_x', 'Position Y [nm]': 'position_y', 'Position Z [nm]': 'position_z', 'Precision [nm]': 'uncertainty', 'Z Slice': 'slice_z'}**

Mapping column names in Zeiss Elyra files to *LocData* property keys

8.2.5 locan.constants.NANOIMAGER_KEYS

locan.constants.**NANOIMAGER_KEYS: Final[dict[str, str]] = {'Background': 'local_background', 'Channel': 'channel', 'Frame': 'frame', 'Photons': 'intensity', 'X (nm)': 'position_x', 'Y (nm)': 'position_y', 'Z (nm)': 'position_z'}**

Mapping column names in Nanoimager files to *LocData* property keys

8.2.6 locan.constants.RAPIDSTORM_KEYS

locan.constants.**RAPIDSTORM_KEYS: Final[dict[str, str]] = {'Amplitude-0-0': 'intensity', 'FitResidues-0-0': 'chi_square', 'ImageNumber-0-0': 'frame', 'LocalBackground-0-0': 'local_background', 'Position-0-0': 'position_x', 'Position-0-0-uncertainty': 'uncertainty_x', 'Position-1-0': 'position_y', 'Position-1-0-uncertainty': 'uncertainty_y', 'Position-2-0': 'position_z', 'Position-2-0-uncertainty': 'uncertainty_z', 'TwoKernelImprovement-0-0': 'two_kernel_improvement'}**

Mapping column names in RapidSTORM files to *LocData* property keys

8.2.7 locan.constants.SMAP_KEYS

locan.constants.**SMAP_KEYS: Final[dict[str, str]] = {'bg': 'local_background', 'channel': 'channel', 'frame': 'frame', 'phot': 'intensity', 'xnm': 'position_x', 'xnmerr': 'uncertainty_x', 'ynm': 'position_y', 'ynmerr': 'uncertainty_y', 'znm': 'position_z', 'znmerr': 'uncertainty_z'}**

Mapping column names in SMAP files to *LocData* property keys

8.2.8 locan.constants.SMLM_KEYS

locan.constants.**SMLM_KEYS: Final[dict[str, str]] = {'Amplitude_0_0': 'intensity', 'FitResidues_0_0': 'chi_square', 'LocalBackground_0_0': 'local_background', 'background': 'local_background', 'frame': 'frame', 'id': 'original_index', 'intensity': 'intensity', 'uncertainty [nm]': 'uncertainty', 'uncertainty_xy [nm]': 'uncertainty_x', 'uncertainty_z [nm]': 'uncertainty_z', 'x': 'position_x', 'x_position': 'position_x', 'y': 'position_y', 'y_position': 'position_y', 'z': 'position_z', 'z_position': 'position_z'}**

Mapping column names in SMLM files to *LocData* property keys

8.2.9 locan.constants.THUNDERSTORM_KEYS

locan.constants.**THUNDERSTORM_KEYS: Final[dict[str, str]] = {'bkgstd [photon]': 'local_background_sigma', 'chi2': 'chi_square', 'detections': 'frames_number', 'frame': 'frame', 'id': 'original_index', 'intensity [photon]': 'intensity', 'offset [photon]': 'local_background', 'sigma [nm]': 'psf_sigma', 'sigma1 [nm]': 'psf_sigma_x', 'sigma2 [nm]': 'psf_sigma_y', 'uncertainty [nm]': 'uncertainty', 'uncertainty_xy [nm]': 'uncertainty_x', 'uncertainty_z [nm]': 'uncertainty_z', 'x [nm]': 'position_x', 'y [nm]': 'position_y', 'z [nm]': 'position_z'}**

Mapping column names in Thunderstorm files to *LocData* property keys

Classes

FileType(value)	File types for localization files.
HullType(value)	Hull definitions that are supported for *LocData* objects.
PropertyDescription(name, type[, unit_SI, ...])	A property of a localization or group of localizations representing column names in *LocData.data* and *LocData.properties*.
PropertyKey(value)	Property descriptions for standard properties used in *locan.LocData* and throughout locan.
RenderEngine(value)	Engine to be used for rendering and displaying localization data as 2d or 3d images.

8.2.10 locan.constants.FileType

class locan.constants.**FileType**(*value*)

Bases: enum.Enum

File types for localization files.

The listed file types are supported with input/output functions in `io.io_locdata()`. The types correspond to the metadata keys for LocData objects. That is, they are equal to the file types in the protobuf message *locan.data.metadata_pb2.Metadata*.

Attributes

UNKNOWN_FILE_TYPE
CUSTOM
RAPIDSTORM
ELYRA
THUNDERSTORM
ASDF
NANOIMAGER
RAPIDSTORMTRACK
SMLM
DECODE
SMAP

ASDF = 5

CUSTOM = 1

DECODE = 9

ELYRA = 3

NANOIMAGER = 6

RAPIDSTORM = 2

RAPIDSTORMTRACK = 7

SMAP = 10

SMLM = 8

THUNDERSTORM = 4

UNKNOWN_FILE_TYPE = 0

8.2.11 locan.constants.HullType

class locan.constants.**HullType**(*value*)

Bases: enum.Enum

Hull definitions that are supported for *LocData* objects.

Attributes

BOUNDING_BOX
CONVEX_HULL
ORIENTED_BOUNDING_BOX
ALPHA_SHAPE

ALPHA_SHAPE = 'alpha_shape'

BOUNDING_BOX = 'bounding_box'

CONVEX_HULL = 'convex_hull'

ORIENTED_BOUNDING_BOX = 'oriented_bounding_box'

8.2.12 locan.constants.PropertyDescription

class locan.constants.**PropertyDescription**(*name*, *type*, *unit_SI=None*, *unit=None*, *description=''*)

Bases: object

A property of a localization or group of localizations representing column names in *LocData.data* and *LocData.properties*.

Variables

- **name** (*str*) – property name
- **type** (*str*) – property type
- **unit_SI** (*str | None*) – SI unit that is appropriate for property
- **unit** (*str | None*) – The actual unit currently used
- **description** (*str*) – Explanation what the property represents

Methods

`__init__`(name, type[, unit_SI, unit, ...])	

Attributes

description	
unit	
unit_SI	
name	
type	

description: str = ''

name: str

type: str

unit: str | None = None

unit_SI: str | None = None

8.2.13 locan.constants.PropertyKey

class locan.constants.**PropertyKey**(*value*)

Bases: enum.Enum

Property descriptions for standard properties used in *locan.LocData* and throughout locan.

Methods

coordinate_properties()	Property descriptions for properties representing spatial coordinates
coordinate_keys()	Property keys for properties representing spatial coordinates
uncertainty_properties()	Property descriptions for properties representing spatial coordinate uncertainties
uncertainty_keys()	Property keys for properties representing spatial coordinate uncertainties.
intensity_properties()	Property descriptions for properties representing photon intensities.
intensity_keys()	Property keys for properties representing photon intensities.
summary()	A formatted string representation of PropertyKey showing all elements with attributes.

Attributes

index
original_index
position_x
position_y
position_z
frame
frames_number
frames_missing
time
intensity
local_background
local_background_sigma
signal_noise_ratio
signal_background_ratio

continues on next page

Table 1 – continued from previous page

chi_square
two_kernel_improvement
psf_amplitude
psf_width
psf_width_x
psf_width_y
psf_width_z
psf_half_width
psf_half_width_x
psf_half_width_y
psf_half_width_z
psf_sigma
psf_sigma_x
psf_sigma_y
psf_sigma_z
uncertainty
uncertainty_x
uncertainty_y
uncertainty_z
channel
slice_z
plane
cluster_label

channel = PropertyDescription(name='channel', type='integer', unit_SI=None, unit=None, description='identifier for an imaging channel')

chi_square = PropertyDescription(name='chi_square', type='float', unit_SI=None, unit=None, description='chi-square value of the fitting procedure as estimated by the fitter')

cluster_label = PropertyDescription(name='cluster_label', type='integer', unit_SI=None, unit=None, description='identifier for a localization cluster')

classmethod coordinate_keys()

Property keys for properties representing spatial coordinates

Return type list[str]

classmethod coordinate_properties()

Property descriptions for properties representing spatial coordinates

Return type list[*PropertyKey*]

frame = PropertyDescription(name='frame', type='integer', unit_SI=None, unit=None, description='frame number in which the localization occurs')

frames_missing = PropertyDescription(name='frames_missing', type='integer', unit_SI=None, unit=None, description='number of frames that occurred between two successive localizations')

frames_number = PropertyDescription(name='frames_number', type='integer', unit_SI=None, unit=None, description='number of frames that contribute to a merged localization')

index = PropertyDescription(name='index', type='integer', unit_SI=None, unit=None, description='a positive integer identifying the localization')

intensity = PropertyDescription(name='intensity', type='float', unit_SI=None, unit=None, description='intensity or emission strength as estimated by the fitter')

classmethod intensity_keys()

Property keys for properties representing photon intensities.

Return type list[str]

classmethod intensity_properties()

Property descriptions for properties representing photon intensities.

Return type list[*PropertyKey*]

local_background = PropertyDescription(name='local_background', type='float', unit_SI=None, unit=None, description='background in the neighborhood of localization as estimated by the fitter')

local_background_sigma = PropertyDescription(name='local_background_sigma', type='float', unit_SI=None, unit=None, description='variation of local background in terms of standard deviation')

```
original_index = PropertyDescription(name='original_index',
type='integer', unit_SI=None, unit=None, description='')

plane = PropertyDescription(name='plane', type='integer', unit_SI=None,
unit=None, description='identifier for an imaging plane')

position_x = PropertyDescription(name='position_x', type='float',
unit_SI='m', unit=None, description='spatial coordinate.')

position_y = PropertyDescription(name='position_y', type='float',
unit_SI='m', unit=None, description='spatial coordinate.')

position_z = PropertyDescription(name='position_z', type='float',
unit_SI='m', unit=None, description='spatial coordinate.')

psf_amplitude = PropertyDescription(name='psf_amplitude', type='float',
unit_SI=None, unit=None, description='')

psf_half_width = PropertyDescription(name='psf_half_width', type='float',
unit_SI=None, unit=None, description='')

psf_half_width_x = PropertyDescription(name='psf_half_width_x',
type='float', unit_SI=None, unit=None, description='')

psf_half_width_y = PropertyDescription(name='psf_half_width_y',
type='float', unit_SI=None, unit=None, description='')

psf_half_width_z = PropertyDescription(name='psf_half_width_z',
type='float', unit_SI=None, unit=None, description='')

psf_sigma = PropertyDescription(name='psf_sigma', type='float',
unit_SI=None, unit=None, description='sigma of the fitted Gauss-function -
being isotropic or representing the root-mean-square of psf_sigma_c for
all dimensions')

psf_sigma_x = PropertyDescription(name='psf_sigma_x', type='float',
unit_SI=None, unit=None, description='sigma of the fitted Gauss-function
in x-dimension as estimated by the fitter')

psf_sigma_y = PropertyDescription(name='psf_sigma_y', type='float',
unit_SI=None, unit=None, description='sigma of the fitted Gauss-function
in y-dimension as estimated by the fitter')

psf_sigma_z = PropertyDescription(name='psf_sigma_z', type='float',
unit_SI=None, unit=None, description='sigma of the fitted Gauss-function
in z-dimension as estimated by the fitter')

psf_width = PropertyDescription(name='psf_width', type='float',
unit_SI=None, unit=None, description='full-width-half-max of the fitted
Gauss-function - being isotropic or representing the root-mean-square of
psf_width_c for all dimensions')
```

psf_width_x = PropertyDescription(name='psf_width_x', type='float', unit_SI=None, unit=None, description='full-width-half-max of the fitted Gauss-function in x-dimension as estimated by the fitter')

psf_width_y = PropertyDescription(name='psf_width_y', type='float', unit_SI=None, unit=None, description='full-width-half-max of the fitted Gauss-function in y-dimension as estimated by the fitter')

psf_width_z = PropertyDescription(name='psf_width_z', type='float', unit_SI=None, unit=None, description='full-width-half-max of the fitted Gauss-function in z-dimension as estimated by the fitter')

signal_background_ratio = PropertyDescription(name='signal_background_ratio', type='float', unit_SI=None, unit=None, description='ratio between mean intensity (i.e. intensity for a single localization) and the local_background')

signal_noise_ratio = PropertyDescription(name='signal_noise_ratio', type='float', unit_SI=None, unit=None, description='ratio between mean intensity (i.e. intensity for a single localization) and the standard deviation of local_background (i.e. local_background_sigma for a single localization)')

slice_z = PropertyDescription(name='slice_z', type='float', unit_SI=None, unit=None, description='identifier for an imaging slice')

classmethod summary()

A formatted string representation of PropertyKey showing all elements with attributes.

Return type str

time = PropertyDescription(name='time', type='float', unit_SI='s', unit=None, description='')

two_kernel_improvement = PropertyDescription(name='two_kernel_improvement', type='float', unit_SI=None, unit=None, description='a rapidSTORM parameter describing the improvement from two kernel fitting')

uncertainty = PropertyDescription(name='uncertainty', type='float', unit_SI=None, unit=None, description='localization error for all dimensions or representing a value proportional to psf_sigma / sqrt(intensity) or representing the root-mean-square of uncertainty_c for all dimensions.')

classmethod uncertainty_keys()

Property keys for properties representing spatial coordinate uncertainties.

Return type list[str]

classmethod uncertainty_properties()

Property descriptions for properties representing spatial coordinate uncertainties

Return type list[*PropertyKey*]

uncertainty_x = PropertyDescription(name='uncertainty_x', type='float', unit_SI=None, unit=None, description='localization error in x-dimension estimated by a fitter or representing a value proportional to psf_sigma_x / sqrt(intensity)')

uncertainty_y = PropertyDescription(name='uncertainty_y', type='float', unit_SI=None, unit=None, description='localization error in y-dimension estimated by a fitter or representing a value proportional to psf_sigma_y / sqrt(intensity)')

uncertainty_z = PropertyDescription(name='uncertainty_z', type='float', unit_SI=None, unit=None, description='localization error in z-dimension estimated by a fitter or representing a value proportional to psf_sigma_z / sqrt(intensity)')

8.2.14 locan.constants.RenderEngine

class locan.constants.**RenderEngine**(*value*)

Bases: enum.Enum

Engine to be used for rendering and displaying localization data as 2d or 3d images.

Each engine represents a library to be used as backend for rendering and plotting.

Attributes

MPL	matplotlib
MPL_SCATTER_DENSITY	mpl-scatter-density
NAPARI	napari

MPL = 0

matplotlib

MPL_SCATTER_DENSITY = 1

mpl-scatter-density

NAPARI = 2

napari

8.3 locan.configuration

Configuration variables used throughout the project.

DATASETS_DIR	Standard directory for example datasets.
RENDER_ENGINE	Render engine.
N_JOBS	The number of cores that are used in parallel for some algorithms.
COLORMAP_DEFAULTS	Mapping a type of colormap to its default colormap that is used throughout locan.
TQDM_LEAVE	Leave tqdm progress bars after finishing the iteration.
TQDM_DISABLE	Disable tqdm progress bars.

8.3.1 locan.configuration.DATASETS_DIR

locan.configuration.**DATASETS_DIR = PosixPath('/home/docs/LocanDatasets')**

Standard directory for example datasets.

8.3.2 locan.configuration.RENDER_ENGINE

locan.configuration.**RENDER_ENGINE = RenderEngine.MPL**

Render engine.

8.3.3 locan.configuration.N_JOBS

locan.configuration.**N_JOBS: int = 1**

The number of cores that are used in parallel for some algorithms. Following the scikit convention: n_jobs is the number of parallel jobs to run. If -1, then the number of jobs is set to the number of CPU cores.

8.3.4 locan.configuration.COLORMAP_DEFAULTS

locan.configuration.**COLORMAP_DEFAULTS: collections.abc.Mapping[str, str] = {'CATEGORICAL': 'cet_glasbey_dark', 'CONTINUOUS': 'cet_fire', 'CONTINUOUS_GRAY': 'cet_gray', 'CONTINUOUS_GRAY_REVERSE': 'cet_gray_r', 'CONTINUOUS_REVERSE': 'cet_fire_r', 'DIVERGING': 'cet_coolwarm', 'TURBO': 'turbo'}**

Mapping a type of colormap to its default colormap that is used throughout locan. See details in locan documentation on colormaps.

8.3.5 locan.configuration.TQDM_LEAVE

locan.configuration.**TQDM_LEAVE: bool = True**

Leave tqdm progress bars after finishing the iteration. Flag to leave tqdm progress bars.

8.3.6 locan.configuration.TQDM_DISABLE

locan.configuration.**TQDM_DISABLE: bool = False**

Disable tqdm progress bars. Flag to disable all tqdm progress bars.

8.4 locan.data

Localization data.

This module contains classes and functions to deal with single-molecule localization data. All functions provide or modify LocData objects.

8.4.1 Submodules:

locdata	A class to carry localization data.
properties	Compute additional properties for locdata objects.
hulls	Hull objects of localization data.
region	Regions as support for localization data.
region_utils	Utility functions for working with regions.
register	Register localization data.
aggregate	Aggregate localization data.
filter	Filter localization data.
transform	Transform localization data.
cluster	This module provides functions for clustering localizations.
tracking	Track localizations.
metadata_utils	Deal with metadata in LocData objects.
validation	Validate localization data.

locan.data.locdata

A class to carry localization data.

Classes

LocData([references, dataframe, indices, meta])	This class carries localization data, aggregated properties and meta data.

locan.data.locdata.LocData

class locan.data.locdata.**LocData**(*references=None*, *dataframe=None*, *indices=None*, *meta=None*)

Bases: `object`

This class carries localization data, aggregated properties and meta data.

Data consist of individual elements being either localizations or other *LocData* objects. Both, localizations and *Locdata* objects have properties. Properties come from the original data or are added by analysis procedures.

Parameters

- **references** – A *LocData* reference or an array with references to *LocData* objects referring to the selected localizations in dataset.
- **dataframe** – Dataframe with localization data.
- **indices** – Indices for dataframe in references that makes up the data. *indices* refers to index label, not position.
- **meta** – Metadata about the current dataset and its history.

Variables

- **references** (*LocData | list[LocData] | None*) – A LocData reference or an array with references to LocData objects referring to the selected localizations in dataframe.
- **dataframe** (*pandas.DataFrame*) – Dataframe with localization data.
- **indices** (*slice | list[int] | None*) – Indices for dataframe in references that makes up the data.
- **meta** (*locan.data.metadata_pb2.Metadata*) – Metadata about the current dataset and its history.
- **properties** (*dict[str, Any]*) – List of properties generated from data.
- **coordinate_keys** (*list[str]*) – The available coordinate properties.
- **uncertainty_keys** (*list[str]*) – The available uncertainty properties.
- **dimension** (*int*) – Number of coordinates available for each localization (i.e. size of *coordinate_keys*).

Methods

`__init__`([references, dataframe, indices, meta])	
concat(locdatas[, meta])	Concatenate LocData objects.
from_chunks(locdata[, chunks, chunk_size, ...])	Divide locdata in chunks of localization elements.
from_collection(locdatas[, meta])	Create new LocData object by collecting LocData objects.
from_coordinates([coordinates, ...])	Create new LocData object from a sequence of localization coordinates.
from_dataframe([dataframe, meta])	Create new LocData object from DataFrame with localization data.
from_selection(locdata[, indices, meta])	Create new LocData object from selected elements in another *LocData*.
print_meta()	Print Locdata.metadata.
print_summary()	Print a summary containing the most common metadata keys.
projection(coordinate_labels)	Reduce dimensions by projecting all localization coordinates onto selected coordinates.
reduce([reset_index])	Clean up references.
reset([reset_index])	Reset hulls and properties.
update(dataframe[, reset_index, meta])	Update the dataframe attribute in place.
update_alpha_shape(alpha)	Compute the alpha shape for specific *alpha* and update *self.alpha_shape*.
update_alpha_shape_in_references(alpha)	Compute the alpha shape for each element in *locdata.references* and update *locdata.dataframe*.
update_convex_hulls_in_references()	Compute the convex hull for each element in locdata.references and update locdata.dataframe.
update_inertia_moments_in_references()	Compute inertia_moments for each element in locdata.references and update locdata.dataframe.
update_oriented_bounding_box_in_references()	Compute the oriented bounding box for each element in locdata.references and update locdata.dataframe.
update_properties_in_references([properties])	Add properties for each element in self.references and update self.dataframe.

Attributes

alpha_shape	Return an object representing the alpha-shape of all localizations.
bounding_box	Return an object representing the axis-aligned minimal bounding box.
centroid	Return coordinate values of the centroid (being the property values for all coordinate labels).
convex_hull	Return an object representing the convex hull of all localizations.
coordinate_keys	**rtype** list[str]
coordinates	Return all coordinate values.
count	A counter for counting LocData instantiations (class attribute).
data	Return all elements either copied from the reference or referencing the current dataframe.
inertia_moments	Inertia moments are returned as computed by locan.data.properties.inertia_moments().
oriented_bounding_box	Return an object representing the oriented minimal bounding box.
region	Return the region that supports all localizations.
uncertainty_keys	**rtype** list[str]

property alpha_shape: *locan.data.hulls.alpha_shape.AlphaShape* **| None**

Return an object representing the alpha-shape of all localizations.

Type Hull object

Return type Optional[*AlphaShape*]

property bounding_box: *locan.data.hulls.hull.BoundingBox* **| None**

Return an object representing the axis-aligned minimal bounding box.

Type Hull object

Return type Optional[*BoundingBox*]

property centroid: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Return coordinate values of the centroid (being the property values for all coordinate labels).

Type npt.NDArray[**np.float_**]

Return type ndarray[Any, dtype[float64]]

classmethod concat(*locdatas*, *meta=None*)

Concatenate LocData objects.

Parameters

- **locdatas** (Iterable[*LocData*]) – Locdata objects to concatenate.
- **meta** (Union[Metadata, dict[str, Any], str, bytes, PathLike[Any], BinaryIO, None]) – Metadata about the current dataset and its history.

Returns A new LocData instance with dataframe representing the concatenated data.

Return type *LocData*

property convex_hull: *locan.data.hulls.hull.ConvexHull* | None

Return an object representing the convex hull of all localizations.

Type Hull object

Return type Optional[*ConvexHull*]

property coordinate_keys: list[str]

Return type list[str]

property coordinates: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Return all coordinate values.

Type npt.NDArray[float]

Return type ndarray[Any, dtype[float64]]

count = 0

A counter for counting LocData instantiations (class attribute).

Type int

property data: pandas.core.frame.DataFrame

Return all elements either copied from the reference or referencing the current dataframe.

Type pandas.DataFrame

Return type DataFrame

classmethod from_chunks(*locdata*, *chunks=None*, *chunk_size=None*, *n_chunks=None*, *order='successive'*, *drop=False*, *meta=None*)

Divide locdata in chunks of localization elements.

Parameters

- **locdata** (*LocData*) – Locdata to divide.
- **chunks** (Optional[Sequence[tuple[int, ...]]]) – Localization chunks as defined by a list of index-tuples. One of *chunks*, *chunk_size* or *n_chunks* must be different from None.
- **chunk_size** (Optional[int]) – Number of consecutive localizations to form a single chunk of data. One of *chunks*, *chunk_size* or *n_chunks* must be different from None.
- **n_chunks** (Optional[int]) – Number of chunks. One of *chunks*, *chunk_size* or *n_chunks* must be different from None.

- **order** (Literal['successive', 'alternating']) – The order in which to select localizations. One of 'successive' or 'alternating'.
- **drop** (bool) – If True the last chunk will be eliminated if it has fewer localizations than the other chunks.
- **meta** (Union[Metadata, dict[str, Any], str, bytes, PathLike[Any], BinaryIO, None]) – Metadata about the current dataset and its history.

Returns A new LocData instance with references and dataframe elements representing the individual chunks.

Return type *LocData*

classmethod from_collection(*locdatas*, *meta=None*)

Create new LocData object by collecting LocData objects.

Parameters

- **locdatas** (Iterable[*LocData*]) – Locdata objects to collect.
- **meta** (Union[Metadata, dict[str, Any], str, bytes, PathLike[Any], BinaryIO, None]) – Metadata about the current dataset and its history.

Returns A new LocData instance with dataframe representing the concatenated data.

Return type *LocData*

classmethod from_coordinates(*coordinates=None*, *coordinate_labels=None*, *meta=None*)

Create new LocData object from a sequence of localization coordinates.

Parameters

- **coordinates** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], None]) – Sequence of tuples with localization coordinates with shape (n_loclizations, dimension)
- **coordinate_labels** (Optional[Sequence[str]]) – The available coordinate properties.
- **meta** (Union[Metadata, dict[str, Any], str, bytes, PathLike[Any], BinaryIO, None]) – Metadata about the current dataset and its history.

Returns A new LocData instance with dataframe representing the oncatenated data.

Return type *LocData*

classmethod from_dataframe(*dataframe=None*, *meta=None*)

Create new LocData object from DataFrame with localization data.

Parameters

- **dataframe** (Optional[DataFrame]) – Localization data.
- **meta** (Union[Metadata, dict[str, Any], str, bytes, PathLike[Any], BinaryIO, None]) – Metadata about the current dataset and its history.

Returns A new LocData instance with dataframe representing the concatenated data.

Return type *LocData*

classmethod from_selection(*locdata*, *indices=None*, *meta=None*)

Create new LocData object from selected elements in another *LocData*.

Parameters

- **locdata** – Locdata object from which to select elements.
- **indices** – Index labels for elements in locdata that make up the new data. Note that contrary to usual python slices, both the start and the stop are included (see pandas documentation). *Indices* refer to index value not position in list.
- **meta** – Metadata about the current dataset and its history.

Returns A new LocData instance with dataframe representing the selected data.

Return type *LocData*

Note: No error is raised if indices do not exist in locdata.

---

property inertia_moments: *locan.data.properties.misc.InertiaMoments* **| None**

Inertia moments are returned as computed by `locan.data.properties.inertia_moments()`.

Return type `Optional[InertiaMoments]`

property oriented_bounding_box:
locan.data.hulls.hull.OrientedBoundingBox **| None**

Return an object representing the oriented minimal bounding box.

Type Hull object

Return type `Optional[OrientedBoundingBox]`

print_meta()

Print Locdata.metadata.

See also:

locan.data.metadata_utils.metadata_to_formatted_string()

Return type `None`

print_summary()

Print a summary containing the most common metadata keys.

Return type `None`

projection(*coordinate_labels*)

Reduce dimensions by projecting all localization coordinates onto selected coordinates.

Parameters **coordinate_labels** (str | list[str]) – The coordinate labels to project onto.

Return type *LocData*

reduce(*reset_index=False*)

Clean up references.

This includes to update *Locdata.dataframe* and set *LocData.references* and *LocData.indices* to None.

Parameters **reset_index** (bool) – Flag indicating if the index is reset to integer values. If True the previous index values are discarded.

Returns The modified object

Return type Self

property region: *locan.data.region.Region* | None

Return the region that supports all localizations.

Type RoiRegion object

Return type Optional[*Region*]

reset(*reset_index=False*)

Reset hulls and properties. This is needed after the dataframe attribute has been modified in place.

Note: Should be used with care because metadata is not updated accordingly. The region property is not changed. Better to just re-instantiate with *LocData.from_dataframe()* or use *locdata.update()*.

Parameters **reset_index** (bool) – Flag indicating if the index is reset to integer values. If True the previous index values are discarded.

Returns The modified object

Return type Self

property uncertainty_keys: list[str]

Return type list[str]

update(*dataframe*, *reset_index=False*, *meta=None*)

Update the dataframe attribute in place.

Use this function rather than setting locdata.dataframe directly in order to automatically update the attributes for dimension, hulls, properties, and metadata.

Parameters

- **dataframe** (Optional[DataFrame]) – Dataframe with localization data.
- **reset_index** (bool) – Flag indicating if the index is reset to integer values. If True the previous index values are discarded.

- **meta** (*locan.data.metadata_pb2.Metadata | dict | str | bytes | os.PathLike | BinaryIO | None*) – Metadata about the current dataset and its history.

Returns The modified object

Return type Self

update_alpha_shape(*alpha*)

Compute the alpha shape for specific *alpha* and update *self.alpha_shape*.

Parameters **alpha** (float) – Alpha parameter specifying a unique alpha complex.

Returns The modified object

Return type Self

update_alpha_shape_in_references(*alpha*)

Compute the alpha shape for each element in *locdata.references* and update *locdata.dataframe*.

Parameters **alpha** (float) – Alpha parameter specifying a unique alpha complex.

Returns The modified object

Return type Self

update_convex_hulls_in_references()

Compute the convex hull for each element in locdata.references and update locdata.dataframe.

Returns The modified object

Return type Self

update_inertia_moments_in_references()

Compute inertia_moments for each element in locdata.references and update locdata.dataframe.

Returns The modified object

Return type Self

update_oriented_bounding_box_in_references()

Compute the oriented bounding box for each element in locdata.references and update locdata.dataframe.

Returns The modified object

Return type Self

update_properties_in_references(*properties=None*)

Add properties for each element in self.references and update self.dataframe.

Parameters **properties** – new property values for each reference or function to compute property for LocData object.

Return type Self

locan.data.properties

Compute additional properties for locdata objects.

These functions take locdata as input, and compute one or more new properties.

Submodules:

misc	Functions to compute locdata properties.
statistics(locdata[, statistic_keys])	Compute selected statistical parameter for localization data.

locan.data.properties.misc

Functions to compute locdata properties.

Classes

InertiaMoments(eigenvalues, eigenvectors, ...)	

locan.data.properties.misc.InertiaMoments

class locan.data.properties.misc.**InertiaMoments**(*eigenvalues*, *eigenvectors*, *variance_explained*, *orientation*, *eccentricity*)

Bases: NamedTuple

Methods

__init__()	

count(value, /)	Return number of occurrences of value.
index(value[, start, stop])	Return first index of value.

Attributes

eccentricity	Alias for field number 4
eigenvalues	Alias for field number 0
eigenvectors	Alias for field number 1
orientation	Alias for field number 3
variance_explained	Alias for field number 2

eccentricity: float

Alias for field number 4

eigenvalues: numpy.ndarray[Any, numpy.dtype[Any]]

Alias for field number 0

eigenvectors: numpy.ndarray[Any, numpy.dtype[Any]]

Alias for field number 1

orientation: float

Alias for field number 3

variance_explained: list[float]

Alias for field number 2

Functions

distance_to_region(locdata, region)	Determine the distance to the nearest point within *region* for all localizations.
distance_to_region_boundary(locdata, region)	Determine the distance to the nearest region boundary for all localizations.
inertia_moments(points)	Return inertia moments (or principal components) and related properties for the given points.
max_distance(locdata)	Return maximum of all distances between any two localizations in locdata.

locan.data.properties.misc.distance_to_region

locan.data.properties.misc.**distance_to_region**(*locdata*, *region*)

Determine the distance to the nearest point within *region* for all localizations. Returns zero if localization is within the region.

Parameters

- **locdata** (*LocData*) – Localizations for which distances are determined.
- **region** (*Region*) – Region from which the closest point is selected.

Returns Distance for each localization.

Return type npt.NDArray[np.float_]

locan.data.properties.misc.distance_to_region_boundary

locan.data.properties.misc.**distance_to_region_boundary**(*locdata*, *region*)

Determine the distance to the nearest region boundary for all localizations. Returns a positive value regardless of weather the point is within or outside the region.

Parameters

- **locdata** (*LocData*) – Localizations for which distances are determined.
- **region** (*Region*) – Region from which the closest point is selected.

Returns Distance for each localization.

Return type npt.NDArray[**np.float_**]

locan.data.properties.misc.inertia_moments

locan.data.properties.misc.**inertia_moments**(*points*)

Return inertia moments (or principal components) and related properties for the given points. Inertia moments are represented by eigenvalues (and corresponding eigenvectors) of the covariance matrix. Variance_explained represents the eigenvalues normalized to the sum of all eigenvalues. For 2-dimensional data, orientation is the angle (in degrees) between the principal axis with the largest variance and the x-axis. Also, for 2-dimensional data, eccentricity is computed as e=Sqrt(1-M_min/M_max).

Parameters **points** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Coordinates of input points with shape (npoints, ndim).

Returns A tuple with eigenvalues, eigenvectors, variance_explained, orientation, eccentricity

Return type *InertiaMoments*

Note: The data is not standardized.

---

locan.data.properties.misc.max_distance

locan.data.properties.misc.**max_distance**(*locdata*)

Return maximum of all distances between any two localizations in locdata.

Parameters **locdata** (*LocData*) – Localization data

Returns A dict with key *max_distance* and the corresponding value being the maximum distance.

Return type dict[str, float]

locan.data.properties.statistics

locan.data.properties.**statistics**(*locdata*, *statistic_keys=('count', 'min', 'max', 'mean', 'median', 'std', 'sem')*)

Compute selected statistical parameter for localization data.

Parameters

- **locdata** – Localization data
- **statistic_keys** – Pandas statistic functions. Default: ('count', 'min', 'max', 'mean', 'median', 'std', 'sem')

Returns A dict with descriptive statistics.

Return type dict[str, Any]

locan.data.hulls

Hull objects of localization data.

Submodules:

hull	Hull objects of localization data.
alpha_shape	Alpha shape

locan.data.hulls.hull

Hull objects of localization data.

This module computes specific hulls for the bounding box, convex hull and oriented bounding box and related properties for LocData objects.

Classes

BoundingBox(points)	Class with bounding box computed using numpy operations.
ConvexHull(points[, method])	Class with convex hull of localization data.
OrientedBoundingBox(points)	Class with oriented bounding box computed using the shapely minimum_rotated_rectangle method.

locan.data.hulls.hull.BoundingBox

class locan.data.hulls.hull.**BoundingBox**(*points*)

Bases: object

Class with bounding box computed using numpy operations.

Parameters **points** (*npt.ArrayLike*) – Coordinates of input points with shape (npoints, ndim).

Variables

- **hull** (npt.NDArray[**np.float_**]) – Array of point coordinates of shape (2, ndim) that represent [[min_coordinates], [max_coordinates]].
- **dimension** (*int*) – Spatial dimension of hull
- **vertices** (npt.NDArray[**np.float_**]) – Coordinates of points that make up the hull. Array of shape (ndim, 2).
- **width** (npt.NDArray[**np.float_**]) – Array with differences between max and min for each coordinate.
- **region_measure** (*float*) – Hull measure, i.e. area or volume
- **subregion_measure** (*float*) – Measure of the sub-dimensional region, i.e. circumference or surface
- **region** (RoiRegion) – Convert the hull to a RoiRegion object.

Methods

__init__(points)	

Attributes

region	**rtype** *Region*
vertices	**rtype** ndarray[Any, dtype[float64]]

property region: *locan.data.region.Region*

Return type *Region*

property vertices: **numpy.ndarray[Any, numpy.dtype[numpy.float64]]**

Return type ndarray[Any, dtype[float64]]

locan.data.hulls.hull.ConvexHull

class locan.data.hulls.hull.**ConvexHull**(*points*, *method='scipy'*)

Bases: object

Class with convex hull of localization data.

Parameters

- **points** (*npt.ArrayLike*) – Coordinates of input points. Array with shape (npoints, ndim).
- **method** (*Literal['scipy', 'shapely']*) – Specific class to compute the convex hull and attributes. One of 'scipy', 'shapely'.

Variables

- **method** (*Literal['scipy', 'shapely']*) – Specific class to compute the convex hull and attributes. One of 'scipy', 'shapely'.
- **hull** (*Hull*) – Polygon object from the .convex_hull method
- **dimension** (*int*) – Spatial dimension of hull
- **vertices** (npt.NDArray[**np.float_**]) – Coordinates of points that make up the hull. Array of shape (ndim, 2).
- **vertex_indices** (npt.NDArray[**np.int_**]) – indices identifying a polygon of all points that make up the hull
- **points_on_boundary** (*int*) – The absolute number of points on the hull
- **points_on_boundary_rel** (*int*) – The number of points on the hull relative to all input points
- **region_measure** (*float*) – hull measure, i.e. area or volume
- **subregion_measure** (*float*) – measure of the sub-dimensional region, i.e. circumference or surface
- **region** (Region) – Convert the hull to a Region object.

Methods

__init__(points[, method])	

locan.data.hulls.hull.OrientedBoundingBox

class locan.data.hulls.hull.**OrientedBoundingBox**(*points*)

Bases: object

Class with oriented bounding box computed using the shapely minimum_rotated_rectangle method.

Parameters **points** (*npt.ArrayLike*) – Coordinates of input points with shape (npoints, ndim).

Variables

- **hull** (Polygon) – Polygon object from the minimum_rotated_rectangle method
- **dimension** (*int*) – Spatial dimension of hull
- **vertices** (npt.NDArray[**np.float_**]) – Coordinates of points that make up the hull. Array of shape (ndim, 2).
- **width** (npt.NDArray[**np.float_**]) – Array with lengths of box edges.
- **region_measure** (*float*) – hull measure, i.e. area or volume
- **subregion_measure** (*float*) – measure of the sub-dimensional region, i.e. circumference or surface
- **region** (Region) – Convert the hull to a Region object.
- **angle** (*float*) – Orientation defined as angle (in degrees) between the vector from first to last point and x-axis.

Methods

__init__(points)

Attributes

region	**rtype** *Rectangle*
vertices	**rtype** ndarray[Any, dtype[float64]]

property region: *locan.data.region.Rectangle*

Return type *Rectangle*

property vertices: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Return type ndarray[Any, dtype[float64]]

locan.data.hulls.alpha_shape

Alpha shape

This module provides methods for computing the alpha complex and specific alpha shapes together with related properties for LocData objects.

Alpha shape is a hull object that defines a group of localizations bordering a concave hull (which does not have to be connected and might have holes)[1]. It depends on a single parameter *alpha* (here defined to be a distance with a unit equal to the coordinate units of the given localization data). For *alpha* approaching infinity the alpha shape is equal to the convex hull.

In this context we call an alpha-complex the subgroup of simplexes of a Delaunay triangulation that is computed according to Edelsbrunner algorithm. All localizations that lie on the boundary of the alpha-complex make up the alpha shape.

Internally we also work with an alpha-independent representation of the alpha-complex that allows efficient computation of alpha shapes for arbitrary alpha values.

Simplices are classified as exterior (not part of the alpha complex), interior (not part of the boundary), regular (part of the boundary but not singular), and singular (part of the boundary but all simplices of higher dimension they are incident to are exterior).

References

Classes

AlphaComplex(points[, delaunay])	Class for an alpha-independent representation of the alpha complex of the given points.
AlphaShape(alpha[, points, alpha_complex, ...])	Class for the alpha shape of points for a specific alpha value.

locan.data.hulls.alpha_shape.AlphaComplex

class locan.data.hulls.alpha_shape.**AlphaComplex**(*points*, *delaunay=None*)

Bases: object

Class for an alpha-independent representation of the alpha complex of the given points.

Here the alpha complex is the simplicial subcomplex of the Delaunay triangulation together with the intervals defining simplex membership for an alpha complex for a specific *alpha*.

Parameters

- **points** (*npt.ArrayLike*) – Coordinates of input points with shape (npoints, ndim).

[1] H. Edelsbrunner and E. P. Mücke, Three-dimensional alpha shapes. ACM Trans. Graph. 13(1):43-72, 1994.

- **delaunay** (*scipy.spatial.Delaunay | None*) – Object with attribute *simplices* specifying a list of indices in the array of points that define the simplexes in the Delaunay triangulation. Also, an attribute *neighbor* is required that specifies indices of neighboring simplices. If None, scipy.stat.Delaunay(points) is computed.

Variables

- **lines** (*list[tuple[tuple[int, ...], float, float, float]]*) – 1-simplices (lines) that represent a simplicial subcomplex of the Delaunay triangulation with intervals. Array with shape (n_lines, 2).
- **triangles** (*list[tuple[int, float, float, float]]*) – 2-simplices (triangles) that represent a simplicial subcomplex of the Delaunay triangulation with intervals. Array with shape (n_triangles, 3).
- **tetrahedrons** (*list[tuple]*) – 3-simplices (tetrahedrons) that represent a simplicial subcomplex of the Delaunay triangulation with intervals. Array with shape (n_tetrahedrons, 4).
- **dimension** (*int*) – Spatial dimension of the hull.
- **delaunay_triangulation** (*scipy.spatial.Delaunay*) – Object with attribute *simplices* specifying a list of indices in the array of points that define the simplexes in the Delaunay triangulation. Also, an attribute *neighbor* is required that specifies indices of neighboring simplices.

Methods

`__init__`(points[, delaunay])	
alpha_shape(alpha)	Return the unique alpha shape for *alpha*.
alphas()	Return alpha values at which the corresponding alpha shape changes.
get_alpha_complex_lines(alpha[, type])	Simplicial subcomplex (lines) of the Delaunay triangulation for the specific alpha complex for the given *alpha*.
get_alpha_complex_triangles(alpha[, type])	Simplicial subcomplex (triangles) of the Delaunay triangulation for the specific alpha complex for the given *alpha*.
graph_from_lines(alpha[, type])	Return networkx Graph object with nodes and edges from selected lines.
graph_from_triangles(alpha[, type])	Return networkx Graph object with nodes and edges from selected triangles.
optimal_alpha()	Find the minimum alpha value for which all points belong to the alpha shape, in other words, no edges of the Delaunay triangulation are exterior.

alpha_shape(*alpha*)

Return the unique alpha shape for *alpha*.

Parameters **alpha** (`float`) – Alpha parameter specifying a unique alpha complex.

Return type *AlphaShape*

`alphas()`

Return alpha values at which the corresponding alpha shape changes.

Return type npt.NDArray[**np.float_**]

`get_alpha_complex_lines(alpha, type='all')`

Simplicial subcomplex (lines) of the Delaunay triangulation for the specific alpha complex for the given *alpha*.

Parameters

- **alpha** (`float`) – Alpha parameter specifying a unique alpha complex.
- **type** (`Literal['all', 'regular', 'singular', 'interior', 'exterior']`) – Type of alpha complex edges to be included in the graph. One of 'all', 'regular', 'singular', 'interior', 'exterior'.

Returns The indices to specific points in *self.points*.

Return type list[list[int]]

`get_alpha_complex_triangles(alpha, type='all')`

Simplicial subcomplex (triangles) of the Delaunay triangulation for the specific alpha complex for the given *alpha*.

Parameters

- **alpha** (`float`) – Alpha parameter specifying a unique alpha complex.
- **type** (`Literal['all', 'regular', 'singular', 'interior', 'exterior']`) – Type of alpha complex edges to be included in the graph. One of 'all', 'regular', 'singular', 'interior', 'exterior'.

Returns The indices to specific d-simplices in *self.delaunay_triangulation.simplices*.

Return type list[int]

`graph_from_lines(alpha, type='all')`

Return networkx Graph object with nodes and edges from selected lines.

Parameters

- **alpha** (`float`) – Alpha parameter specifying a unique alpha complex.
- **type** (`Literal['all', 'regular', 'singular', 'interior', 'exterior']`) – Type of alpha complex edges to be included in the graph. One of 'all', 'regular', 'singular', 'interior', 'exterior'.

Return type networkx.Graph

`graph_from_triangles(alpha, type='all')`

Return networkx Graph object with nodes and edges from selected triangles.

Parameters

- **alpha** (`float`) – Alpha parameter specifying a unique alpha complex.

- **type** (Literal['all', 'regular', 'singular', 'interior', 'exterior']) – Type of alpha complex edges to be included in the graph. One of 'all', 'regular', 'singular', 'interior', 'exterior'.

Return type networkx.Graph

optimal_alpha()

Find the minimum alpha value for which all points belong to the alpha shape, in other words, no edges of the Delaunay triangulation are exterior.

Return type float | None

locan.data.hulls.alpha_shape.AlphaShape

class locan.data.hulls.alpha_shape.**AlphaShape**(*alpha*, *points=None*, *alpha_complex=None*, *delaunay=None*)

Bases: object

Class for the alpha shape of points for a specific alpha value.

Here the alpha complex is the simplicial subcomplex of the Delaunay triangulation for a given alpha value. The alpha shape is the union of all simplexes of the alpha complex, specified by the boundary points of the alpha complex.

In order to update an existing AlphaShape object to a different *alpha* reset AlphaShape.alpha.

Parameters

- **alpha** (*float*) – Alpha parameter specifying a unique alpha complex.
- **points** (*npt.ArrayLike | None*) – Coordinates of input points with shape (npoints, ndim). Either *points* or *alpha_complex* have to be specified but not both.
- **alpha_complex** (AlphaComplex | *None*) – The unfiltered alpha complex with computed interval values.
- **delaunay** (*scipy.spatial.Delaunay | None*) – Object with attribute *simplices* specifying a list of indices in the array of points that define the simplexes in the Delaunay triangulation. Also, an attribute *neighbor* is required that specifies indices of neighboring simplices. If None, scipy.stat.Delaunay(points) is computed.

Variables

- **alpha_complex** (AlphaComplex) – The unfiltered alpha complex with computed interval values.
- **alpha_shape** (*npt.NDArray*) – The list of k-simplices (edges) from the alpha complex that make up the alpha shape. Or: Simplicial subcomplex of the Delaunay triangulation with regular simplices from the alpha complex.
- **region** (Region) – Region object.
- **connected_components** (*list[Region]*) – Connected components, i.e. a list of the individual unconnected polygons that together make up the alpha shape.

- **dimension** (*int*) – Spatial dimension of the hull as determined from the dimension of *points*
- **vertices** (*npt.NDArray*) – Coordinates of points that make up the hull with shape (n_points, 2). (regular alpha_shape line-simplices).
- **vertex_indices** (*list[int]*) – Indices identifying a polygon of all points that make up the hull (regular alpha_shape line-simplices).
- **vertices_alpha_shape** (*npt.NDArray*) – Coordinates of points with shape (n_points, 2) that make up the interior and boundary of the hull (regular, singular and interior alpha_shape line-simplices).
- **vertex_alpha_shape_indices** (*list[int]*) – Indices to all points that make up the interior and boundary of the hull. (regular, singular and interior alpha_shape line-simplices).
- **vertices_connected_components_indices** (*list[list[int]]*) – Indices to the points for each connected component of the alpha shape.
- **n_points_on_boundary** (*float*) – The number of points on the hull (regular and singular alpha_shape simplices).
- **n_points_on_boundary_rel** (*float*) – The number of points on the hull (regular and singular alpha_shape simplices) relative to all alpha_shape points.
- **n_points_alpha_shape** (*int*) – Absolute number of points that are part of the alpha_shape (regular, singular and interior alpha_shape simplices).
- **n_points_alpha_shape_rel** (*int*) – Absolute number of points that are part of the alpha_shape relative to all input points (regular, singular and interior alpha_shape simplices).
- **region_measure** (*float*) – Hull measure, i.e. area or volume.
- **subregion_measure** (*float*) – Measure of the sub-dimensional region, i.e. circumference or surface.

Methods

`__init__`(alpha[, points, alpha_complex, ...])

Attributes

alpha	**rtype** float
alpha_shape	**rtype** list[list[int]]
connected_components	**rtype** list[*Region*]
region	**rtype** *Region*
vertex_alpha_shape_indices	**rtype** list[int]
vertex_indices	**rtype** list[int]
vertices	**rtype** ndarray[Any, dtype[float64]]
vertices_alpha_shape	**rtype** ndarray[Any, dtype[float64]]
vertices_connected_components_indices	**rtype** list[list[int]]

property alpha: float

Return type float

property alpha_shape: list[list[int]]

Return type list[list[int]]

property connected_components: list[*locan.data.region.Region*]

Return type list[*Region*]

property region: *locan.data.region.Region*

Return type *Region*

property vertex_alpha_shape_indices: list[int]

Return type list[int]

property vertex_indices: list[int]

Return type list[int]

property vertices: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Return type ndarray[Any, dtype[float64]]

property vertices_alpha_shape: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Return type ndarray[Any, dtype[float64]]

property vertices_connected_components_indices: list[list[int]]

Return type list[list[int]]

locan.data.region

Regions as support for localization data.

This module provides classes to define geometric regions for localization data. All region classes inherit from the abstract base class *Region*.

Classes

AxisOrientedCuboid([corner, length, width, ...])	Region class to define an axis-oriented cuboid.
AxisOrientedHypercuboid([corner, lengths])	Region class to define an axis-oriented n-dimensional hypercuboid.
Cuboid([corner, length, width, height, ...])	Region class to define a cuboid.
Ellipse([center, width, height, angle])	Region class to define an ellipse.
EmptyRegion()	Region class to define an empty region that has no dimension.
Interval([lower_bound, upper_bound])	Region class to define an interval.
MultiPolygon(polygons)	Region class to define a region that represents the union of multiple polygons.
Polygon([points, holes])	Region class to define a polygon.
Rectangle([corner, width, height, angle])	Region class to define a rectangle.
Region()	Abstract Region class to define the interface for Region-derived classes that specify geometric objects to represent regions of interest.
Region1D()	Abstract Region class to define the interface for 1-dimensional Region classes.
Region2D()	Abstract Region class to define the interface for 2-dimensional Region classes.
Region3D()	Abstract Region class to define the interface for 3-dimensional Region classes.
RegionND()	Abstract Region class to define the interface for n-dimensional Region classes.
RoiRegion(region_type, region_specs)	Deprecated Region object to specify regions of interest.

locan.data.region.AxisOrientedCuboid

class locan.data.region.**AxisOrientedCuboid**(*corner=(0, 0, 0)*, *length=1*, *width=1*, *height=1*)

Bases: *locan.data.region.Region3D*

Region class to define an axis-oriented cuboid.

This is a 3-dimensional convex region with rectangular faces and edges that are parallel to coordinate axes. Extension in x-, y-, z-coordinates correspond to length, width, height.

Parameters

- **corner** (*npt.ArrayLike*) – A point that defines the lower left corner with shape (3,)
- **length** (*float*) – The length of a vector describing the edge in x-direction.
- **width** (*float*) – The length of a vector describing the edge in y-direction.
- **height** (*float*) – The length of a vector describing the edge in z-direction.

Methods

`__init__`([corner, length, width, height])	

as_artist([origin])	Matplotlib patch object for this region (e.g.
buffer(distance, **kwargs)	Extend the region perpendicular by a *distance*.
contains(points)	Return list of indices for all points that are inside the region of interest.
from_intervals(intervals)	Constructor for instantiating Region from list of (min, max) bounds.
`intersection`(other)	Returns a region representing the intersection of this region with `other`.
`plot`([ax])	Provide plot of region as `matplotlib.axes.Axes` object.
`symmetric_difference`(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
`union`(other)	Returns a region representing the union of this region with `other`.

Attributes

bounding_box	A region describing the minimum axis-aligned bounding box that encloses the original region.
bounds	Region bounds min_x, min_y, ..., max_x, max_y, .
centroid	Point coordinates for region centroid.
corner	A point that defines the lower left corner.
dimension	The region dimension.
extent	The extent (max_x - min_x), (max_y - min_y), .
height	The length of a vector describing the edge in z-direction.
intervals	Provide bounds in a tuple (min, max) arrangement.
length	The length of a vector describing the edge in x-direction.
max_distance	The maximum distance between any two points within the region.
points	Point coordinates.
region_measure	Region measure, i.e. area (for 2d) or volume (for 3d).
subregion_measure	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).
width	The length of a vector describing the edge in y-direction.

as_artist(*origin=(0, 0)*, ***kwargs*)

Matplotlib patch object for this region (e.g. *matplotlib.patches.Ellipse*).

Parameters

- **origin** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The (x, y, z) pixel position of the origin of the displayed image. Default is (0, 0, 0).
- **kwargs** (Any) – Other parameters passed to the *matplotlib.patches* object.

Returns Matplotlib patch for the specified region.

Return type matplotlib.patches.Patch

property bounding_box: typing_extensions.Self

A region describing the minimum axis-aligned bounding box that encloses the original region.

Return type *Region*

property bounds: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Region bounds min_x, min_y, ..., max_x, max_y, ... for each dimension.

Returns of shape (2 * dimension,)

Return type npt.NDArray[np.float_] | None

buffer(*distance*, ***kwargs*)

Extend the region perpendicular by a *distance*.

Parameters **distance** (float) – Distance by which the region is extended.

Returns The extended region.

Return type *Region*

property centroid: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates for region centroid.

Returns of shape (dimension,)

Return type npt.NDArray[np.float_] | None

contains(*points*)

Return list of indices for all points that are inside the region of interest.

Parameters **points** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Coordinates of points that are tested for being inside the specified region.

Returns Array with indices for all points in original point array that are within the region.

Return type npt.NDArray[np.int_]

property corner: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

A point that defines the lower left corner.

Returns with shape (2,)

Return type npt.NDArray[np.float_]

property extent: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

The extent (max_x - min_x), (max_y - min_y), ... for each dimension.

Returns of shape (dimension,)

Return type npt.NDArray[np.float_] | None

classmethod from_intervals(*intervals*)

Constructor for instantiating Region from list of (min, max) bounds.

Parameters **intervals** (*npt.ArrayLike*) – The region bounds for each dimension of shape (3, 2)

Return type *AxisOrientedCuboid*

property height: float

The length of a vector describing the edge in z-direction.

Return type float

property intervals: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Provide bounds in a tuple (min, max) arrangement.

Returns ((min_x, max_x), ...) of shape(dimension, 2)

Return type tuple[tuple[float, float], ...]

property length: float

The length of a vector describing the edge in x-direction.

Return type float

property max_distance: float

The maximum distance between any two points within the region.

Return type float

property points: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates.

Returns of shape (n_points, dimension)

Return type npt.NDArray[**np.float_**] | list[npt.NDArray[**np.float_**]]

property region_measure: float

Region measure, i.e. area (for 2d) or volume (for 3d).

Return type float

property subregion_measure: float

Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

Return type float

property width: float

The length of a vector describing the edge in y-direction.

Return type float

locan.data.region.AxisOrientedHypercuboid

class locan.data.region.**AxisOrientedHypercuboid**(*corner=(0, 0, 0)*, *lengths=(1, 1, 1)*)

Bases: *locan.data.region.RegionND*

Region class to define an axis-oriented n-dimensional hypercuboid.

This is a n-dimensional convex region with rectangular faces and edges that are parallel to coordinate axes. Extension in x-, y-, z-coordinates correspond to length, width, height.

Parameters

- **corner** (*npt.ArrayLike*) – A point with shape (dimension,) that defines the lower left corner.
- **lengths** (*npt.ArrayLike*) – Array of shape(dimension,) of length values for the 1-dimensional edge vectors.

Methods

`__init__`([corner, lengths])	

buffer(distance, **kwargs)	Extend the region perpendicular by a *distance*.
contains(points)	Return list of indices for all points that are inside the region of interest.
from_intervals(intervals)	Constructor for instantiating Region from list of (min, max) bounds.
`intersection`(other)	Returns a region representing the intersection of this region with `other`.
`symmetric_difference`(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
`union`(other)	Returns a region representing the union of this region with `other`.

Attributes

bounding_box	A region describing the minimum axis-aligned bounding box that encloses the original region.
bounds	Region bounds min_x, min_y, ..., max_x, max_y, .
centroid	Point coordinates for region centroid.
corner	A point that defines the lower left corner.
dimension	The region dimension.
extent	The extent (max_x - min_x), (max_y - min_y), .
intervals	Provide bounds in a tuple (min, max) arrangement.
lengths	Array of length values for the 1-dimensional edge vectors.
max_distance	The maximum distance between any two points within the region.
points	Point coordinates.
region_measure	Region measure, i.e. area (for 2d) or volume (for 3d).
subregion_measure	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

property bounding_box: typing_extensions.Self

A region describing the minimum axis-aligned bounding box that encloses the original region.

Return type *Region*

property bounds: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Region bounds min_x, min_y, ..., max_x, max_y, ... for each dimension.

Returns of shape (2 * dimension,)

Return type npt.NDArray[np.float_] | None

buffer(*distance*, ***kwargs*)

Extend the region perpendicular by a *distance*.

Parameters **distance** (float) – Distance by which the region is extended.

Returns The extended region.

Return type *Region*

property centroid: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates for region centroid.

Returns of shape (dimension,)

Return type npt.NDArray[np.float_] | None

contains(*points*)

Return list of indices for all points that are inside the region of interest.

Parameters **points** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Coordinates of points that are tested for being inside the specified region.

Returns Array with indices for all points in original point array that are within the region.

Return type npt.NDArray[np.int_]

property corner: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

A point that defines the lower left corner.

Returns with shape (dimension,)

Return type npt.NDArray[np.float_]

property dimension: int

The region dimension.

Return type int | None

property extent: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

The extent (max_x - min_x), (max_y - min_y), ... for each dimension.

Returns of shape (dimension,)

Return type npt.NDArray[np.float_] | None

classmethod from_intervals(*intervals*)

Constructor for instantiating Region from list of (min, max) bounds.

Parameters **intervals** (*npt.ArrayLike*) – The region bounds for each dimension of shape (dimension, 2)

Return type *AxisOrientedHypercuboid*

property intervals: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Provide bounds in a tuple (min, max) arrangement.

Returns ((min_x, max_x), ...) of shape(dimension, 2).

Return type tuple[tuple[float, float], ...]

property lengths: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Array of length values for the 1-dimensional edge vectors.

Returns of shape(dimension,)

Return type npt.NDArray[**np.float_**]

property max_distance: float

The maximum distance between any two points within the region.

Return type float

property points: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates.

Returns of shape (n_points, dimension)

Return type npt.NDArray[**np.float_**] | list[npt.NDArray[**np.float_**]]

property region_measure: float

Region measure, i.e. area (for 2d) or volume (for 3d).

Return type float

property subregion_measure: float

Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

Return type float

locan.data.region.Cuboid

class locan.data.region.**Cuboid**(*corner=(0, 0, 0)*, *length=1*, *width=1*, *height=1*, *alpha=0*, *beta=0*, *gamma=0*)

Bases: *locan.data.region.Region3D*

Region class to define a cuboid.

This is a 3-dimensional convex region with rectangular faces. Extension in x-, y-, z-coordinates correspond to length, width, height. Corresponding Euler angles are defined by alpha, beta, gamma.

Parameters

- **corner** (*npt.ArrayLike*) – A point that defines the lower left corner with shape (2,).
- **length** (*float*) – The length of a vector describing the edge in x-direction.
- **width** (*float*) – The length of a vector describing the edge in y-direction.
- **alpha** (*float*) – The first Euler angle (in degrees) by which the cuboid is rotated.

- **beta** (*float*) – The second Euler angle (in degrees) by which the cuboid is rotated.
- **gamma** (*float*) – The third Euler angle (in degrees) by which the cuboid is rotated.

Methods

`__init__`([corner, length, width, height, ...])	

as_artist([origin])	Matplotlib patch object for this region (e.g.
buffer(distance, **kwargs)	Extend the region perpendicular by a *distance*.
contains(points)	Return list of indices for all points that are inside the region of interest.
`from_intervals`(intervals)	Constructor for instantiating axis-oriented, box-like Region from list of (min, max) bounds.
`intersection`(other)	Returns a region representing the intersection of this region with `other`.
`plot`([ax])	Provide plot of region as `matplotlib.axes.Axes` object.
`symmetric_difference`(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
`union`(other)	Returns a region representing the union of this region with `other`.

Attributes

alpha	The first Euler angle (in degrees) by which the cuboid is rotated.
beta	The sescond Euler angle (in degrees) by which the cuboid is rotated.
bounding_box	A region describing the minimum axis-aligned bounding box that encloses the original region.
bounds	Region bounds min_x, min_y, ..., max_x, max_y, .
centroid	Point coordinates for region centroid.
corner	A point that defines the lower left corner.
dimension	The region dimension.
extent	The extent (max_x - min_x), (max_y - min_y), .
gamma	The third Euler angle (in degrees) by which the cuboid is rotated.
height	The length of a vector describing the edge in z-direction.
length	The length of a vector describing the edge in x-direction.
max_distance	The maximum distance between any two points within the region.
points	Point coordinates.
region_measure	Region measure, i.e. area (for 2d) or volume (for 3d).
subregion_measure	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).
width	The length of a vector describing the edge in y-direction.

property alpha: float

The first Euler angle (in degrees) by which the cuboid is rotated.

Return type float

as_artist(*origin=(0, 0)*, ***kwargs*)

Matplotlib patch object for this region (e.g. *matplotlib.patches.Ellipse*).

Parameters

- **origin** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The (x, y, z) pixel position of the origin of the displayed image. Default is (0, 0, 0).
- **kwargs** (Any) – Other parameters passed to the *matplotlib.patches* object.

Returns Matplotlib patch for the specified region.

Return type matplotlib.patches.Patch

property beta: float

The sescond Euler angle (in degrees) by which the cuboid is rotated.

Return type float

property bounding_box: typing_extensions.Self

A region describing the minimum axis-aligned bounding box that encloses the original region.

Return type *Region*

property bounds: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Region bounds min_x, min_y, ..., max_x, max_y, ... for each dimension.

Returns of shape (2 * dimension,)

Return type npt.NDArray[**np.float_**] | None

buffer(*distance*, ***kwargs*)

Extend the region perpendicular by a *distance*.

Parameters **distance** (float) – Distance by which the region is extended.

Returns The extended region.

Return type *Region*

property centroid: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates for region centroid.

Returns of shape (dimension,)

Return type npt.NDArray[**np.float_**] | None

contains(*points*)

Return list of indices for all points that are inside the region of interest.

Parameters **points** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Coordinates of points that are tested for being inside the specified region.

Returns Array with indices for all points in original point array that are within the region.

Return type npt.NDArray[**np.int_**]

property corner: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

A point that defines the lower left corner.

Returns with shape (2,)

Return type npt.NDArray[**np.float_**]

property extent: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

The extent (max_x - min_x), (max_y - min_y), ... for each dimension.

Returns of shape (dimension,)

Return type npt.NDArray[**np.float_**] | None

property gamma: float

The third Euler angle (in degrees) by which the cuboid is rotated.

Return type float

property height: float

The length of a vector describing the edge in z-direction.

Return type float

property length: float

The length of a vector describing the edge in x-direction.

Return type float

property max_distance: float

The maximum distance between any two points within the region.

Return type float

property points: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates.

Returns of shape (n_points, dimension)

Return type npt.NDArray[**np.float_**] | list[npt.NDArray[**np.float_**]]

property region_measure: float

Region measure, i.e. area (for 2d) or volume (for 3d).

Return type float

property subregion_measure: float

Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

Return type float

property width: float

The length of a vector describing the edge in y-direction.

Return type float

locan.data.region.Ellipse

class locan.data.region.**Ellipse**(*center=(0, 0)*, *width=1*, *height=1*, *angle=0*)

Bases: *locan.data.region.Region2D*

Region class to define an ellipse.

Parameters

- **center** (*npt.ArrayLike*) – A point that defines the center of the ellipse with shape (2,).
- **width** (*float*) – The length of a vector describing the principal axis in x-direction (before rotation).
- **height** (*float*) – The length of a vector describing the principal axis in y-direction (before rotation).

- **angle** (*float*) – The angle (in degrees) by which the ellipse is rotated counterclockwise around the center point.

Methods

`__init__`([center, width, height, angle])	

as_artist([origin])	Matplotlib 2D patch object for this region (e.g.
buffer(distance, **kwargs)	Extend the region perpendicular by a *distance*.
contains(points)	Return list of indices for all points that are inside the region of interest.
from_intervals(intervals)	Constructor for instantiating axis-oriented, box-like Region from list of (min, max) bounds.
from_shapely(shapely_object)	Constructor for instantiating Region from *shapely* object.
intersection(other)	Returns a region representing the intersection of this region with `other`.
plot([ax])	Provide plot of region as `matplotlib.axes.Axes` object.
symmetric_difference(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
union(other)	Returns a region representing the union of this region with `other`.

Attributes

angle	The angle (in degrees) by which the ellipse is rotated counterclockwise around the center point.
bounding_box	A region describing the minimum axis-aligned bounding box that encloses the original region.
bounds	Region bounds min_x, min_y, ..., max_x, max_y, .
center	A point that defines the center of the ellipse.
centroid	Point coordinates for region centroid.
dimension	The region dimension.
extent	The extent (max_x - min_x), (max_y - min_y), .
height	The length of a vector describing the principal axis in y-direction (before rotation).
max_distance	The maximum distance between any two points within the region.
points	Point coordinates.
region_measure	Region measure, i.e. area (for 2d) or volume (for 3d).
region_specs	Legacy interface to serve legacy RoiRegion.
shapely_object	Geometric object as defined in *shapely*.
subregion_measure	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).
width	The length of a vector describing the principal axis in x-direction (before rotation).

property angle: float

The angle (in degrees) by which the ellipse is rotated counterclockwise around the center point.

Return type float

as_artist(*origin=(0, 0)*, ***kwargs*)

Matplotlib 2D patch object for this region (e.g. *matplotlib.patches.Ellipse*).

Parameters

- **origin** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The (x, y) pixel position of the origin of the displayed image. Default is (0, 0).
- **kwargs** (Any) – Other parameters passed to the *matplotlib.patches* object.

Returns Matplotlib patch for the specified region.

Return type matplotlib.patches.Patch

property center: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

A point that defines the center of the ellipse.

Returns with shape (2,)

Return type npt.NDArray[np.float_]

property centroid: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates for region centroid.

Returns of shape (dimension,)

Return type npt.NDArray[np.float_] | None

contains(*points*)

Return list of indices for all points that are inside the region of interest.

Parameters **points** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Coordinates of points that are tested for being inside the specified region.

Returns Array with indices for all points in original point array that are within the region.

Return type npt.NDArray[np.int_]

property height: float

The length of a vector describing the principal axis in y-direction (before rotation).

Return type float

property max_distance: float

The maximum distance between any two points within the region.

Return type float

property points: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates.

Returns of shape (n_points, dimension)

Return type npt.NDArray[np.float_] | list[npt.NDArray[np.float_]]

property region_measure: float

Region measure, i.e. area (for 2d) or volume (for 3d).

Return type float

property region_specs

Legacy interface to serve legacy RoiRegion.

> **Warning:** Do not use - will be deprecated.

Return type dict

property shapely_object: shapely.geometry.polygon.Polygon

Geometric object as defined in *shapely*.

Return type Shapely object

property subregion_measure: float

Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

Return type float

property width: float

The length of a vector describing the principal axis in x-direction (before rotation).

Return type float

locan.data.region.EmptyRegion

class locan.data.region.**EmptyRegion**

Bases: *locan.data.region.Region*

Region class to define an empty region that has no dimension.

Methods

__init__()	
as_artist(**kwargs) **rtype** None	
buffer(distance, **kwargs)	Extend the region perpendicular by a *distance*.
contains(points)	Return list of indices for all points that are inside the region of interest.
from_intervals(intervals)	Constructor for instantiating axis-oriented, box-like Region from list of (min, max) bounds.
from_shapely(shapely_object) **rtype** *EmptyRegion*	
intersection(other)	Returns a region representing the intersection of this region with other.
symmetric_difference(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
union(other)	Returns a region representing the union of this region with other.

Attributes

bounding_box	A region describing the minimum axis-aligned bounding box that encloses the original region.
bounds	Region bounds min_x, min_y, ..., max_x, max_y, .
centroid	Point coordinates for region centroid.
dimension	The region dimension.
extent	The extent (max_x - min_x), (max_y - min_y), .
max_distance	The maximum distance between any two points within the region.
points	Point coordinates.
region_measure	Region measure, i.e. area (for 2d) or volume (for 3d).
subregion_measure	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

as_artist(***kwargs*)

Return type None

property bounding_box: *locan.data.region.EmptyRegion*

A region describing the minimum axis-aligned bounding box that encloses the original region.

Return type *Region*

property bounds: **None**

Region bounds min_x, min_y, …, max_x, max_y, … for each dimension.

Returns of shape (2 * dimension,)

Return type npt.NDArray[**np.float_**] | None

buffer(*distance*, ***kwargs*)

Extend the region perpendicular by a *distance*.

Parameters **distance** (float) – Distance by which the region is extended.

Returns The extended region.

Return type *Region*

property centroid: **None**

Point coordinates for region centroid.

Returns of shape (dimension,)

Return type npt.NDArray[**np.float_**] | None

contains(*points*)

Return list of indices for all points that are inside the region of interest.

Parameters **points** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Coordinates of points that are tested for being inside the specified region.

Returns Array with indices for all points in original point array that are within the region.

Return type npt.NDArray[**np.int_**]

property dimension: None

The region dimension.

Return type int | None

property extent: None

The extent (max_x - min_x), (max_y - min_y), ... for each dimension.

Returns of shape (dimension,)

Return type npt.NDArray[**np.float_**] | None

classmethod from_shapely(*shapely_object*)

Return type *EmptyRegion*

intersection(*other*)

Returns a region representing the intersection of this region with `other`.

Parameters **other** (Region) – Other region

Return type *Region*

property max_distance: int

The maximum distance between any two points within the region.

Return type float

property points: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates.

Returns of shape (n_points, dimension)

Return type npt.NDArray[**np.float_**] | list[npt.NDArray[**np.float_**]]

property region_measure: int

Region measure, i.e. area (for 2d) or volume (for 3d).

Return type float

property subregion_measure: int

Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

Return type float

symmetric_difference(*other*)

Returns the union of the two regions minus any areas contained in the intersection of the two regions.

Parameters **other** (Region) – Other region

Return type *Region*

union(*other*)

Returns a region representing the union of this region with `other`.

Parameters **other** (`Region`) – Other region

Return type *Region*

locan.data.region.Interval

class locan.data.region.**Interval**(*lower_bound=0*, *upper_bound=1*)

Bases: *locan.data.region.Region1D*

Region class to define an interval.

Parameters

- **lower_bound** (`float`) – The lower bound of the interval.
- **upper_bound** (`float`) – The upper bound of the interval.

Methods

`__init__`([lower_bound, upper_bound])	

as_artist([origin])	Matplotlib 2D patch object for this region (e.g.
buffer(distance, **kwargs)	Extend the region perpendicular by a *distance*.
contains(points)	Return list of indices for all points that are inside the region of interest.
from_intervals(intervals)	Constructor for instantiating Region from list of (min, max) bounds.
intersection(other)	Returns a region representing the intersection of this region with `other`.
symmetric_difference(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
union(other)	Returns a region representing the union of this region with `other`.

Attributes

bounding_box	A region describing the minimum axis-aligned bounding box that encloses the original region.
bounds	Region bounds min_x, min_y, ..., max_x, max_y, .
centroid	Point coordinates for region centroid.
dimension	The region dimension.
extent	The extent (max_x - min_x), (max_y - min_y), .
intervals	Provide bounds in a tuple (min, max) arrangement.
lower_bound	The lower boundary.
max_distance	The maximum distance between any two points within the region.
points	Point coordinates.
region_measure	Region measure, i.e. area (for 2d) or volume (for 3d).
region_specs	Legacy interface to serve legacy RoiRegion.
subregion_measure	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).
upper_bound	The upper boundary.

as_artist(*origin=(0, 0)*, ***kwargs*)

Matplotlib 2D patch object for this region (e.g. *matplotlib.patches.Ellipse*).

Parameters

- **origin** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The (x, y) pixel position of the origin of the displayed image. Default is (0, 0).
- **kwargs** (Any) – Other parameters passed to the *matplotlib.patches* object.

Returns Matplotlib patch for the specified region.

Return type matplotlib.patches.Patch

property bounding_box: typing_extensions.Self

A region describing the minimum axis-aligned bounding box that encloses the original region.

Return type *Region*

property bounds: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Region bounds min_x, min_y, ..., max_x, max_y, ... for each dimension.

Returns of shape (2 * dimension,)

Return type npt.NDArray[**np.float_**] | None

buffer(*distance*, ***kwargs*)

Extend the region perpendicular by a *distance*.

Parameters **distance** (float) – Distance by which the region is extended.

Returns The extended region.

Return type *Region*

property centroid: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates for region centroid.

Returns of shape (dimension,)

Return type npt.NDArray[**np.float_**] | None

contains(*points*)

Return list of indices for all points that are inside the region of interest.

Parameters **points** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Coordinates of points that are tested for being inside the specified region.

Returns Array with indices for all points in original point array that are within the region.

Return type npt.NDArray[**np.int_**]

property extent: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

The extent (max_x - min_x), (max_y - min_y), ... for each dimension.

Returns of shape (dimension,)

Return type npt.NDArray[**np.float_**] | None

classmethod from_intervals(*intervals*)

Constructor for instantiating Region from list of (min, max) bounds. Takes array-like intervals instead of interval to be consistent with *Rectangle.from_intervals*.

Parameters **intervals** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region bounds for each dimension of shape (2,)

Return type *Interval*

property intervals: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Provide bounds in a tuple (min, max) arrangement.

Returns ((min_x, max_x), ...) of shape(dimension, 2).

Return type tuple[tuple[float, float], ...]

property lower_bound: float

The lower boundary.

Return type float

property max_distance: float

The maximum distance between any two points within the region.

Return type float

property points: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates.

Returns of shape (n_points, dimension)

Return type npt.NDArray[**np.float_**] | list[npt.NDArray[**np.float_**]]

property region_measure: float

Region measure, i.e. area (for 2d) or volume (for 3d).

Return type float

property region_specs: tuple[float, float]

Legacy interface to serve legacy RoiRegion.

> **Warning:** Do not use - will be deprecated.

Return type tuple[float, float]

property subregion_measure: int

Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

Return type float

property upper_bound: float

The upper boundary.

Return type float

locan.data.region.MultiPolygon

class locan.data.region.**MultiPolygon**(*polygons*)

Bases: *locan.data.region.Region2D*

Region class to define a region that represents the union of multiple polygons.

Parameters **polygons** (*list[Polygon]*) – Polygons that define the individual polygons.

Methods

`__init__`(polygons)	

as_artist([origin])	Matplotlib 2D patch object for this region (e.g.
`buffer`(distance, **kwargs)	Extend the region perpendicular by a *distance*.
contains(points)	Return list of indices for all points that are inside the region of interest.
`from_intervals`(intervals)	Constructor for instantiating axis-oriented, box-like Region from list of (min, max) bounds.
from_shapely(multipolygon)	Constructor for instantiating Region from *shapely* object.
`intersection`(other)	Returns a region representing the intersection of this region with `other`.
`plot`([ax])	Provide plot of region as `matplotlib.axes.Axes` object.
`symmetric_difference`(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
`union`(other)	Returns a region representing the union of this region with `other`.

Attributes

`bounding_box`	A region describing the minimum axis-aligned bounding box that encloses the original region.
`bounds`	Region bounds min_x, min_y, ..., max_x, max_y, .
centroid	Point coordinates for region centroid.
`dimension`	The region dimension.
`extent`	The extent (max_x - min_x), (max_y - min_y), .
holes	Points defining holes.
max_distance	The maximum distance between any two points within the region.
points	Exterior polygon points.
polygons	All polygons that make up the MultiPolygon
region_measure	Region measure, i.e. area (for 2d) or volume (for 3d).
region_specs	Legacy interface to serve legacy RoiRegion.
shapely_object	Geometric object as defined in *shapely*.
subregion_measure	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

as_artist(*origin=(0, 0)*, ***kwargs*)

Matplotlib 2D patch object for this region (e.g. *matplotlib.patches.Ellipse*).

Parameters

- **origin** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The (x, y) pixel position of the origin of the displayed image. Default is (0, 0).
- **kwargs** (Any) – Other parameters passed to the *matplotlib.patches* object.

Returns Matplotlib patch for the specified region.

Return type matplotlib.patches.Patch

property centroid: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates for region centroid.

Returns of shape (dimension,)

Return type npt.NDArray[**np.float_**] | None

contains(*points*)

Return list of indices for all points that are inside the region of interest.

Parameters **points** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Coordinates of points that are tested for being inside the specified region.

Returns Array with indices for all points in original point array that are within the region.

Return type npt.NDArray[**np.int_**]

classmethod from_shapely(*multipolygon*)

Constructor for instantiating Region from *shapely* object.

Parameters **shapely_object** – Geometric object to be converted into Region

Return type *Polygon* | *MultiPolygon* | *EmptyRegion*

property holes: list[list[numpy.ndarray[Any, numpy.dtype[numpy.float64]]] | None]

Points defining holes.

Returns list of polygon holes

Return type list[list[npt.NDArray[**np.float_**]] | None]

property max_distance: float

The maximum distance between any two points within the region.

Return type float

property points: list[numpy.ndarray[Any, numpy.dtype[numpy.float64]]]

Exterior polygon points.

Returns n_polygons of shape(n_points, dimension)

Return type list[npt.NDArray[**np.float_**]]

property polygons: list[*locan.data.region.Polygon*]

All polygons that make up the MultiPolygon

Return type list[*Polygon*]

property region_measure: float

Region measure, i.e. area (for 2d) or volume (for 3d).

Return type float

property region_specs

Legacy interface to serve legacy RoiRegion.

> **Warning:** Do not use - will be deprecated.

Return type dict

property shapely_object: shapely.geometry.multipolygon.MultiPolygon

Geometric object as defined in *shapely*.

Return type Shapely object

property subregion_measure: float

Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

Return type float

locan.data.region.Polygon

class locan.data.region.**Polygon**(*points=((0, 0), (0, 1), (1, 1), (1, 0))*, *holes=None*)

Bases: *locan.data.region.Region2D*

Region class to define a polygon.

The polygon is constructed from a list of points that can be closed (i.e. the first and last point are identical) or not (in this case the list of points will be closed implicitly).

Parameters

- **points** (*npt.ArrayLike*) – Points with shape (n_points, 2) that define the exterior boundary of a polygon.
- **holes** (*list[npt.ArrayLike] | None*) – Points with shape (n_holes, n_points, 2) that define holes within the polygon.

Methods

`__init__`([points, holes])	
as_artist([origin])	Matplotlib 2D patch object for this region (e.g.
`buffer`(distance, **kwargs)	Extend the region perpendicular by a *distance*.
contains(points)	Return list of indices for all points that are inside the region of interest.
`from_intervals`(intervals)	Constructor for instantiating axis-oriented, box-like Region from list of (min, max) bounds.
from_shapely(polygon)	Constructor for instantiating Region from *shapely* object.
`intersection`(other)	Returns a region representing the intersection of this region with `other`.
`plot`([ax])	Provide plot of region as `matplotlib.axes.Axes` object.
`symmetric_difference`(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
`union`(other)	Returns a region representing the union of this region with `other`.

Attributes

`bounding_box`	A region describing the minimum axis-aligned bounding box that encloses the original region.
`bounds`	Region bounds min_x, min_y, ..., max_x, max_y, .
centroid	Point coordinates for region centroid.
`dimension`	The region dimension.
`extent`	The extent (max_x - min_x), (max_y - min_y), .
holes	Holes where each hole is specified by polygon points.
max_distance	The maximum distance between any two points within the region.
points	Exterior polygon points.
region_measure	Region measure, i.e. area (for 2d) or volume (for 3d).
region_specs	Legacy interface to serve legacy RoiRegion.
shapely_object	Geometric object as defined in *shapely*.
subregion_measure	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

as_artist(*origin=(0, 0)*, ***kwargs*)

Matplotlib 2D patch object for this region (e.g. *matplotlib.patches.Ellipse*).

Parameters

- **origin** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The (x, y) pixel position of the origin of the displayed image. Default is (0, 0).
- **kwargs** (Any) – Other parameters passed to the *matplotlib.patches* object.

Returns Matplotlib patch for the specified region.

Return type matplotlib.patches.Patch

property centroid: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates for region centroid.

Returns of shape (dimension,)

Return type npt.NDArray[**np.float_**] | None

contains(*points*)

Return list of indices for all points that are inside the region of interest.

Parameters **points** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Coordinates of points that are tested for being inside the specified region.

Returns Array with indices for all points in original point array that are within the region.

Return type npt.NDArray[**np.int_**]

classmethod from_shapely(*polygon*)

Constructor for instantiating Region from *shapely* object.

Parameters **shapely_object** – Geometric object to be converted into Region

Return type *Polygon* | *MultiPolygon* | *EmptyRegion*

property holes: list[numpy.ndarray[Any, numpy.dtype[numpy.float64]]] | None

Holes where each hole is specified by polygon points.

Returns n_holes of shape(n_points, dimension)

Return type list[npt.NDArray[**np.float_**]] | None

property max_distance: float

The maximum distance between any two points within the region.

Return type float

property points: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Exterior polygon points.

Returns of shape(n_points, dimension)

Return type npt.NDArray[**np.float_**]

property region_measure: float

Region measure, i.e. area (for 2d) or volume (for 3d).

Return type float

property region_specs

Legacy interface to serve legacy RoiRegion.

> **Warning:** Do not use - will be deprecated.

Return type dict[str, Any]

property shapely_object: shapely.geometry.polygon.Polygon

Geometric object as defined in *shapely*.

Return type Shapely object

property subregion_measure: float

Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

Return type float

locan.data.region.Rectangle

class locan.data.region.**Rectangle**(*corner=(0, 0)*, *width=1*, *height=1*, *angle=0*)

Bases: *locan.data.region.Region2D*

Region class to define a rectangle.

Parameters

- **corner** (*npt.ArrayLike*) – A point that defines the lower left corner with shape (2,).
- **width** (*float*) – The length of a vector describing the edge in x-direction.
- **height** (*float*) – The length of a vector describing the edge in y-direction.
- **angle** (*float*) – The angle (in degrees) by which the rectangle is rotated counterclockwise around the corner point.

Methods

`__init__`([corner, width, height, angle])	

as_artist([origin])	Matplotlib 2D patch object for this region (e.g.
`buffer`(distance, **kwargs)	Extend the region perpendicular by a *distance*.
contains(points)	Return list of indices for all points that are inside the region of interest.
from_intervals(intervals)	Constructor for instantiating Region from list of (min, max) bounds.
`from_shapely`(shapely_object)	Constructor for instantiating Region from *shapely* object.
`intersection`(other)	Returns a region representing the intersection of this region with `other`.
`plot`([ax])	Provide plot of region as `matplotlib.axes.Axes` object.
`symmetric_difference`(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
`union`(other)	Returns a region representing the union of this region with `other`.

Attributes

angle	The angle (in degrees) by which the rectangle is rotated counterclockwise around the corner point.
bounding_box	A region describing the minimum axis-aligned bounding box that encloses the original region.
bounds	Region bounds min_x, min_y, ..., max_x, max_y, .
centroid	Point coordinates for region centroid.
corner	A point that defines the lower left corner.
dimension	The region dimension.
extent	The extent (max_x - min_x), (max_y - min_y), .
height	The length of a vector describing the edge in y-direction.
intervals	Provide bounds in a tuple (min, max) arrangement.
max_distance	The maximum distance between any two points within the region.
points	Point coordinates.
region_measure	Region measure, i.e. area (for 2d) or volume (for 3d).
region_specs	Legacy interface to serve legacy RoiRegion.
shapely_object	Geometric object as defined in *shapely*.
subregion_measure	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).
width	The length of a vector describing the edge in x-direction.

property angle: float

The angle (in degrees) by which the rectangle is rotated counterclockwise around the corner point.

Return type float

as_artist(*origin=(0, 0)*, ***kwargs*)

Matplotlib 2D patch object for this region (e.g. *matplotlib.patches.Ellipse*).

Parameters

- **origin** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The (x, y) pixel position of the origin of the displayed image. Default is (0, 0).
- **kwargs** (Any) – Other parameters passed to the *matplotlib.patches* object.

Returns Matplotlib patch for the specified region.

Return type matplotlib.patches.Patch

property centroid: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates for region centroid.

Returns of shape (dimension,)

Return type npt.NDArray[np.float_] | None

contains(*points*)

Return list of indices for all points that are inside the region of interest.

Parameters **points** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Coordinates of points that are tested for being inside the specified region.

Returns Array with indices for all points in original point array that are within the region.

Return type npt.NDArray[np.int_]

property corner: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

A point that defines the lower left corner.

Returns with shape (2,)

Return type npt.NDArray[np.float_]

classmethod from_intervals(*intervals*)

Constructor for instantiating Region from list of (min, max) bounds.

Parameters **intervals** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region bounds for each dimension of shape (2, 2)

Return type cls

property height: float

The length of a vector describing the edge in y-direction.

Return type float

property intervals: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Provide bounds in a tuple (min, max) arrangement.

Returns ((min_x, max_x), . . .) of shape(dimension, 2)

Return type npt.NDArray[np.float_]

property max_distance: float

The maximum distance between any two points within the region.

Return type float

property points: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Point coordinates.

Returns of shape (n_points, dimension)

Return type npt.NDArray[np.float_] | list[npt.NDArray[np.float_]]

property region_measure: float

Region measure, i.e. area (for 2d) or volume (for 3d).

Return type float

property region_specs

Legacy interface to serve legacy RoiRegion.

> **Warning:** Do not use - will be deprecated.

Return type dict

property shapely_object: shapely.geometry.polygon.Polygon

Geometric object as defined in *shapely*.

Return type Shapely object

property subregion_measure: float

Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

Return type float

property width: float

The length of a vector describing the edge in x-direction.

Return type float

locan.data.region.Region

class locan.data.region.**Region**

Bases: abc.ABC

Abstract Region class to define the interface for Region-derived classes that specify geometric objects to represent regions of interest.

Methods

`__init__`()

buffer(distance, **kwargs)	Extend the region perpendicular by a *distance*.
contains(points)	Return list of indices for all points that are inside the region of interest.
from_intervals(intervals)	Constructor for instantiating axis-oriented, box-like Region from list of (min, max) bounds.
intersection(other)	Returns a region representing the intersection of this region with `other`.
symmetric_difference(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
union(other)	Returns a region representing the union of this region with `other`.

Attributes

bounding_box	A region describing the minimum axis-aligned bounding box that encloses the original region.
bounds	Region bounds min_x, min_y, ..., max_x, max_y, .
centroid	Point coordinates for region centroid.
dimension	The region dimension.
extent	The extent (max_x - min_x), (max_y - min_y), .
max_distance	The maximum distance between any two points within the region.
points	Point coordinates.
region_measure	Region measure, i.e. area (for 2d) or volume (for 3d).
subregion_measure	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

abstract property bounding_box: *locan.data.region.Region*

A region describing the minimum axis-aligned bounding box that encloses the original region.

Return type *Region*

abstract property bounds: **numpy.ndarray[Any, numpy.dtype[numpy.float64]] | None**

Region bounds min_x, min_y, …, max_x, max_y, … for each dimension.

Returns of shape (2 * dimension,)

Return type npt.NDArray[**np.float_**] | None

abstract buffer(*distance*, ***kwargs*)

Extend the region perpendicular by a *distance*.

Parameters **distance** (float) – Distance by which the region is extended.

Returns The extended region.

Return type *Region*

abstract property centroid: numpy.ndarray[Any, numpy.dtype[numpy.float64]] | None

Point coordinates for region centroid.

Returns of shape (dimension,)

Return type npt.NDArray[**np.float_**] | None

abstract contains(*points*)

Return list of indices for all points that are inside the region of interest.

Parameters **points** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Coordinates of points that are tested for being inside the specified region.

Returns Array with indices for all points in original point array that are within the region.

Return type npt.NDArray[**np.int_**]

abstract property dimension: int | None

The region dimension.

Return type int | None

abstract property extent: numpy.ndarray[Any, numpy.dtype[numpy.float64]] | None

The extent (max_x - min_x), (max_y - min_y), ... for each dimension.

Returns of shape (dimension,)

Return type npt.NDArray[**np.float_**] | None

static from_intervals(*intervals*)

Constructor for instantiating axis-oriented, box-like Region from list of (min, max) bounds. Takes array-like intervals instead of interval to be consistent with *Rectangle.from_intervals*.

Parameters **intervals** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region bounds for each dimension of shape (dimension, 2).

Return type *Interval* | *Rectangle* | *AxisOrientedCuboid* | *AxisOrientedHypercuboid*

abstract intersection(*other*)

Returns a region representing the intersection of this region with other.

Parameters **other** (Region) – Other region

Return type *Region*

abstract property max_distance: float

The maximum distance between any two points within the region.

Return type float

abstract property points: numpy.ndarray[Any, numpy.dtype[numpy.float64]] | list[numpy.ndarray[Any, numpy.dtype[numpy.float64]]]

Point coordinates.

Returns of shape (n_points, dimension)

Return type npt.NDArray[**np.float_**] | list[npt.NDArray[**np.float_**]]

abstract property region_measure: float

Region measure, i.e. area (for 2d) or volume (for 3d).

Return type float

abstract property subregion_measure: float

Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

Return type float

abstract symmetric_difference(*other*)

Returns the union of the two regions minus any areas contained in the intersection of the two regions.

Parameters **other** (Region) – Other region

Return type *Region*

abstract union(*other*)

Returns a region representing the union of this region with `other`.

Parameters **other** (Region) – Other region

Return type *Region*

locan.data.region.Region1D

class locan.data.region.**Region1D**

Bases: *locan.data.region.Region*

Abstract Region class to define the interface for 1-dimensional Region classes.

Methods

`__init__`()	

as_artist([origin])	Matplotlib 2D patch object for this region (e.g.
`buffer`(distance, **kwargs)	Extend the region perpendicular by a *distance*.
`contains`(points)	Return list of indices for all points that are inside the region of interest.
`from_intervals`(intervals)	Constructor for instantiating axis-oriented, box-like Region from list of (min, max) bounds.
intersection(other)	Returns a region representing the intersection of this region with `other`.
symmetric_difference(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
union(other)	Returns a region representing the union of this region with `other`.

Attributes

`bounding_box`	A region describing the minimum axis-aligned bounding box that encloses the original region.
`bounds`	Region bounds min_x, min_y, ..., max_x, max_y, .
`centroid`	Point coordinates for region centroid.
dimension	The region dimension.
`extent`	The extent (max_x - min_x), (max_y - min_y), .
`max_distance`	The maximum distance between any two points within the region.
`points`	Point coordinates.
`region_measure`	Region measure, i.e. area (for 2d) or volume (for 3d).
`subregion_measure`	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

abstract as_artist(*origin=(0, 0)*, ***kwargs*)

Matplotlib 2D patch object for this region (e.g. *matplotlib.patches.Ellipse*).

Parameters

- **origin** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The (x, y) pixel position of the origin of the displayed image. Default is (0, 0).
- **kwargs** (Any) – Other parameters passed to the *matplotlib.patches* object.

Returns Matplotlib patch for the specified region.

Return type matplotlib.patches.Patch

property dimension: int

The region dimension.

Return type int | None

intersection(*other*)

Returns a region representing the intersection of this region with `other`.

Parameters **other** (`Region`) – Other region

Return type *Region*

symmetric_difference(*other*)

Returns the union of the two regions minus any areas contained in the intersection of the two regions.

Parameters **other** (`Region`) – Other region

Return type *Region*

union(*other*)

Returns a region representing the union of this region with `other`.

Parameters **other** (`Region`) – Other region

Return type *Region*

locan.data.region.Region2D

class locan.data.region.**Region2D**

Bases: *locan.data.region.Region*

Abstract Region class to define the interface for 2-dimensional Region classes.

Methods

`__init__`()	

as_artist([origin])	Matplotlib 2D patch object for this region (e.g.
buffer(distance, **kwargs)	Extend the region perpendicular by a *distance*.
`contains`(points)	Return list of indices for all points that are inside the region of interest.
`from_intervals`(intervals)	Constructor for instantiating axis-oriented, box-like Region from list of (min, max) bounds.
from_shapely(shapely_object)	Constructor for instantiating Region from *shapely* object.
intersection(other)	Returns a region representing the intersection of this region with `other`.
plot([ax])	Provide plot of region as `matplotlib.axes.Axes` object.
symmetric_difference(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
union(other)	Returns a region representing the union of this region with `other`.

Attributes

bounding_box	A region describing the minimum axis-aligned bounding box that encloses the original region.
bounds	Region bounds min_x, min_y, ..., max_x, max_y, .
`centroid`	Point coordinates for region centroid.
dimension	The region dimension.
extent	The extent (max_x - min_x), (max_y - min_y), .
`max_distance`	The maximum distance between any two points within the region.
`points`	Point coordinates.
`region_measure`	Region measure, i.e. area (for 2d) or volume (for 3d).
shapely_object	Geometric object as defined in *shapely*.
`subregion_measure`	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

abstract as_artist(*origin=(0, 0)*, ***kwargs*)

Matplotlib 2D patch object for this region (e.g. *matplotlib.patches.Ellipse*).

Parameters

- **origin** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The (x, y) pixel position of the origin of the displayed image. Default is (0, 0).
- **kwargs** (Any) – Other parameters passed to the *matplotlib.patches* object.

Returns Matplotlib patch for the specified region.

Return type matplotlib.patches.Patch

property bounding_box: *locan.data.region.Rectangle*

A region describing the minimum axis-aligned bounding box that encloses the original region.

Return type *Region*

property bounds: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Region bounds min_x, min_y, ..., max_x, max_y, ... for each dimension.

Returns of shape (2 * dimension,)

Return type npt.NDArray[np.float_] | None

buffer(*distance*, ***kwargs*)

Extend the region perpendicular by a *distance*.

Parameters

- **distance** (float) – Distance by which the region is extended.
- **kwargs** (Any) – Other parameters passed to shapely.geometry.buffer().

Returns The extended region.

Return type *Polygon* | *MultiPolygon* | *EmptyRegion*

property dimension: int

The region dimension.

Return type int | None

property extent: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

The extent (max_x - min_x), (max_y - min_y), ... for each dimension.

Returns of shape (dimension,)

Return type npt.NDArray[np.float_] | None

static from_shapely(*shapely_object*)

Constructor for instantiating Region from *shapely* object.

Parameters **shapely_object** (Polygon | MultiPolygon) – Geometric object to be converted into Region

Return type *Polygon* | *MultiPolygon* | *EmptyRegion*

intersection(*other*)

Returns a region representing the intersection of this region with `other`.

Parameters **other** (`Region`) – Other region

Return type *Region*

plot(*ax=None*, ***kwargs*)

Provide plot of region as `matplotlib.axes.Axes` object.

Parameters

- **ax** (`Optional[Axes]`) – The axes on which to show the image
- **kwargs** (`Any`) – Other parameters passed to the *matplotlib.patches* object.

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

abstract property shapely_object: Any

Geometric object as defined in *shapely*.

Return type Shapely object

symmetric_difference(*other*)

Returns the union of the two regions minus any areas contained in the intersection of the two regions.

Parameters **other** (`Region`) – Other region

Return type *Region*

union(*other*)

Returns a region representing the union of this region with `other`.

Parameters **other** (`Region`) – Other region

Return type *Region*

locan.data.region.Region3D

class locan.data.region.**Region3D**

Bases: *locan.data.region.Region*

Abstract Region class to define the interface for 3-dimensional Region classes.

Methods

`__init__`()	

as_artist([origin])	Matplotlib patch object for this region (e.g.
`buffer`(distance, **kwargs)	Extend the region perpendicular by a *distance*.
`contains`(points)	Return list of indices for all points that are inside the region of interest.
`from_intervals`(intervals)	Constructor for instantiating axis-oriented, box-like Region from list of (min, max) bounds.
intersection(other)	Returns a region representing the intersection of this region with `other`.
plot([ax])	Provide plot of region as `matplotlib.axes.Axes` object.
symmetric_difference(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
union(other)	Returns a region representing the union of this region with `other`.

Attributes

`bounding_box`	A region describing the minimum axis-aligned bounding box that encloses the original region.
`bounds`	Region bounds min_x, min_y, ..., max_x, max_y, .
`centroid`	Point coordinates for region centroid.
dimension	The region dimension.
`extent`	The extent (max_x - min_x), (max_y - min_y), .
`max_distance`	The maximum distance between any two points within the region.
`points`	Point coordinates.
`region_measure`	Region measure, i.e. area (for 2d) or volume (for 3d).
`subregion_measure`	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

abstract as_artist(*origin=(0, 0, 0)*, ***kwargs*)

Matplotlib patch object for this region (e.g. *matplotlib.patches.Ellipse*).

Parameters

- **origin** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float,

complex, str, bytes]]]) – The (x, y, z) pixel position of the origin of the displayed image. Default is (0, 0, 0).

- **kwargs** (Any) – Other parameters passed to the *matplotlib.patches* object.

Returns Matplotlib patch for the specified region.

Return type matplotlib.patches.Patch

property dimension: int

The region dimension.

Return type int | None

intersection(*other*)

Returns a region representing the intersection of this region with other.

Parameters **other** (Region) – Other region

Return type *Region*

plot(*ax=None*, ***kwargs*)

Provide plot of region as matplotlib.axes.Axes object.

Parameters

- **ax** (Optional[Axes]) – The axes on which to show the image
- **kwargs** (Any) – Other parameters passed to the *matplotlib.patches* object.

Returns Axes object with the plot.

Return type matplotlib.axes.Axes

symmetric_difference(*other*)

Returns the union of the two regions minus any areas contained in the intersection of the two regions.

Parameters **other** (Region) – Other region

Return type *Region*

union(*other*)

Returns a region representing the union of this region with other.

Parameters **other** (Region) – Other region

Return type *Region*

locan.data.region.RegionND

class locan.data.region.**RegionND**

Bases: *locan.data.region.Region*

Abstract Region class to define the interface for n-dimensional Region classes.

Methods

`__init__`()	

`buffer`(distance, **kwargs)	Extend the region perpendicular by a *distance*.
`contains`(points)	Return list of indices for all points that are inside the region of interest.
`from_intervals`(intervals)	Constructor for instantiating axis-oriented, box-like Region from list of (min, max) bounds.
intersection(other)	Returns a region representing the intersection of this region with `other`.
symmetric_difference(other)	Returns the union of the two regions minus any areas contained in the intersection of the two regions.
union(other)	Returns a region representing the union of this region with `other`.

Attributes

`bounding_box`	A region describing the minimum axis-aligned bounding box that encloses the original region.
`bounds`	Region bounds min_x, min_y, ..., max_x, max_y, .
`centroid`	Point coordinates for region centroid.
`dimension`	The region dimension.
`extent`	The extent (max_x - min_x), (max_y - min_y), .
`max_distance`	The maximum distance between any two points within the region.
`points`	Point coordinates.
`region_measure`	Region measure, i.e. area (for 2d) or volume (for 3d).
`subregion_measure`	Measure of the sub-dimensional region, i.e. circumference (for 2d) or surface (for 3d).

intersection(*other*)

Returns a region representing the intersection of this region with `other`.

Parameters **other** (Region) – Other region

Return type *Region*

symmetric_difference(*other*)

Returns the union of the two regions minus any areas contained in the intersection of the two regions.

Parameters **other** (Region) – Other region

Return type *Region*

union(*other*)

Returns a region representing the union of this region with `other`.

Parameters **other** (Region) – Other region

Return type *Region*

locan.data.region.RoiRegion

class locan.data.region.**RoiRegion**(*region_type*, *region_specs*)

Bases: `object`

Deprecated Region object to specify regions of interest.

A region that defines a region of interest with methods for getting a printable representation (that can also be saved in a yaml file), for returning a matplotlib patch that can be shown in a graph, for finding points within the region.

Warning: This class is to be deprecated and should only be used to deal with legacy _roi.yaml files. Use Region classes instead.

Parameters

- **region_type** (*str*) – A string indicating the roi shape. In 1D it can be *interval*. In 2D it can be either *rectangle*, *ellipse*, or closed *polygon*. In 2D it can also be *shapelyPolygon* or *shapelyMultiPolygon*. In 3D it can be either *cuboid* or *ellipsoid* or *polyhedron* (not implemented yet).
- **region_specs** (*tuple*) – 1D rois are defined by the following tuple: * interval: (start, stop) 2D rois are defined by the following tuples: * rectangle: ((corner_x, corner_y), width, height, angle) with angle in degree * ellipse: ((center_x, center_y), width, height, angle) with angle in degree * polygon: ((point1_x, point1_y), (point2_x, point2_y), ..., (point1_x, point1_y)) * shapelyPolygon: ((point_tuples), ((hole_tuples), ...)) * shapelyMultiPolygon: (shapelyPolygon_specs_1, shapelyPolygon_specs_2, ...) 3D rois are defined by the following tuples: * cuboid: ((corner_x, corner_y, corner_z), length, width, height, angle_1, angle_2, angle_3) * ellipsoid: ((center_x, center_y, center_z), length, width, height, angle_1, angle_2, angle_3) * polyhedron: (...)

Variables

- **region_type** (*str*) – Type of region
- **region_specs** (*tuple*) – Specifications for region
- **_region** (RoiRegion) – RoiRegion instance for the specified region type.
- **polygon** (*tuple[npt.ArrayLike, ...]*) – Array of points for a closed polygon approximating the region of interest in clockwise orientation. The first and last point must be identical.
- **dimension** (*int*) – Spatial dimension of region

- **centroid** (*tuple[float, ...]*) – Centroid coordinates
- **max_distance** (npt.NDArray[**np.float_**]) – Maximum distance between any two points in the region
- **region_measure** (*float*) – Hull measure, i.e. area or volume
- **subregion_measure** (*float*) – Measure of the sub-dimensional region, i.e. circumference or surface.

Methods

`__init__`(region_type, region_specs)	
as_artist(**kwargs)	Matplotlib patch object for this region (e.g.
contains(points)	Return list of indices for all points that are inside the region of interest.
from_shapely(region_type, shapely_obj)	
to_shapely()	Convert region to a polygon and return as shapely object.

Attributes

region

as_artist(***kwargs*)

Matplotlib patch object for this region (e.g. *matplotlib.patches.Ellipse*).

Parameters **kwargs** (Any) – Other parameters passed to the *matplotlib.patches* object.

Returns Matplotlib patch for the specified region.

Return type matplotlib.patches.Patch

contains(*points*)

Return list of indices for all points that are inside the region of interest.

Parameters **points** (*npt.ArrayLike*) – 2D or 3D coordinates of oints that are tested for being inside the specified region.

Returns Array with indices for all points in original point array that are within the region.

Return type npt.NDArray[**np.int_**]

classmethod from_shapely(*region_type*, *shapely_obj*)

property region

to_shapely()

Convert region to a polygon and return as shapely object.

Return type shapely.Polygon

locan.data.region_utils

Utility functions for working with regions.

See also:

locan.data.filter.select_by_region(), *locan.data.properties.misc.distance_to_region()*, *locan.data.properties.misc.distance_to_region_boundary()*

Functions

expand_region(region[, distance, support])	Expand a region by *distance*.
regions_union(regions)	Return the union of *regions*.
surrounding_region(region[, distance, support])	Define surrounding region by extending a region and returning the extended region excluding the input region.

locan.data.region_utils.expand_region

locan.data.region_utils.**expand_region**(*region*, *distance=100*, *support=None*, ***kwargs*)

Expand a region by *distance*. If region contains a list of regions, the unification of all expanded regions is returned.

Parameters

- **region** (*Region*) – Original region(s)
- **distance** (int | float) – Distance by which the region is expanded orthogonal to its boundary.
- **support** (Optional[*Region*]) – A region defining the maximum outer boundary.
- **kwargs** (Any) – Other parameters passed to shapely.geometry.buffer() for Region2D objects.

Return type *Region*

locan.data.region_utils.regions_union

locan.data.region_utils.**regions_union**(*regions*)

Return the union of *regions*.

Parameters **regions** (list[*Region*]) – Original region(s)

Return type *Region*

locan.data.region_utils.surrounding_region

locan.data.region_utils.**surrounding_region**(*region*, *distance=100*, *support=None*, ***kwargs*)

Define surrounding region by extending a region and returning the extended region excluding the input region. If region contains a list of regions, the unification of all extended regions is returned.

Parameters

- **region** (*Region*) – Original region(s)
- **distance** (int | float) – Distance by which the region is extended orthogonal to its boundary.
- **support** (Optional[*Region*]) – A region defining the maximum outer boundary.
- **kwargs** (Any) – Other parameters passed to shapely.geometry.buffer() for Region2D objects.

Return type *Region*

locan.data.register

Register localization data.

This module registers localization data and provides transformation parameters to put other localization data in registry.

Parts of this code is adapted from https://github.com/jungmannlab/picasso. (MIT license, Copyright (c) 2016 Jungmann Lab, MPI of Biochemistry)

Classes

Transformation(matrix, offset)

locan.data.register.Transformation

class locan.data.register.**Transformation**(*matrix*, *offset*)

Bases: NamedTuple

Methods

__init__()

count(value, /)	Return number of occurrences of value.
index(value[, start, stop])	Return first index of value.

Attributes

matrix	Alias for field number 0
offset	Alias for field number 1

matrix: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Alias for field number 0

offset: numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Alias for field number 1

Functions

register_cc(locdata, other_locdata[, ...])	Register *points* or coordinates in *locdata* by a cross-correlation algorithm.
register_icp(locdata, other_locdata[, ...])	Register *points* or coordinates in *locdata* by an "Iterative Closest Point" algorithm using open3d.

locan.data.register.register_cc

locan.data.register.**register_cc**(*locdata*, *other_locdata*, *max_offset=None*, *bins=None*, *n_bins=None*, *bin_size=None*, *bin_edges=None*, *bin_range=None*, *verbose=False*)

Register *points* or coordinates in *locdata* by a cross-correlation algorithm.

This function is based on code from picasso/imageprocess by Joerg Schnitzbauer, MPI of Biochemistry https://github.com/jungmannlab/picasso/blob/master/picasso/imageprocess.py

Parameters

- **locdata** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], *LocData*]) – Localization data representing the source on which to perform the manipulation.

- **other_locdata** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], *LocData*]) – Localization data representing the target.
- **max_offset** (Union[int, float, None]) – Maximum possible offset.
- **bins** (Union[*Bins*, Axis, AxesTuple, None]) – Specific class specifying the bins.
- **bin_edges** (Union[Sequence[float], Sequence[Sequence[float]], None]) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], Literal['zero', 'link'], None]) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2). If None (min, max) ranges are determined from data and returned; if 'zero' (0, max) ranges with max determined from data are returned. if 'link' (min_all, max_all) ranges with min and max determined from all combined data are returned.
- **n_bins** (Union[int, Sequence[int], None]) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (Union[float, Sequence[float], Sequence[Sequence[float]], None]) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.
- **verbose** (bool) – Flag indicating if transformation results are printed out.

Returns Matrix and offset representing the optimized transformation.

Return type *Transformation*

locan.data.register.register_icp

locan.data.register.**register_icp**(*locdata*, *other_locdata*, *matrix=None*, *offset=None*, *pre_translation=None*, *max_correspondence_distance=1000*, *max_iteration=10000*, *verbose=True*)

Register *points* or coordinates in *locdata* by an "Iterative Closest Point" algorithm using open3d.

Parameters

- **locdata** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float,

complex, str, bytes]], *LocData*]) – Localization data representing the source on which to perform the manipulation.

- **other_locdata** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], *LocData*]) – Localization data representing the target.
- **matrix** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], None]) – Transformation matrix with shape (d, d) used as initial value. If None the unit matrix is used.
- **offset** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], None]) – Translation vector with shape (d,) used as initial value. If None a vector of zeros is used.
- **pre_translation** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], None]) – Values for translation of coordinates before registration.
- **max_correspondence_distance** (float) – Threshold distance for the icp algorithm. Parameter is passed to open3d algorithm.
- **max_iteration** (int) – Maximum number of iterations. Parameter is passed to open3d algorithm.
- **verbose** (bool) – Flag indicating if transformation results are printed out.

Returns Matrix and offset representing the optimized transformation.

Return type *Transformation*

locan.data.aggregate

Aggregate localization data.

This module provides functions to bin LocData objects to form a histogram or image.

Specify bins through one of the parameters (*bins*, *bin_edges*, *n_bins*, *bin_size*, *bin_range*, *labels*) as further outlined in the documentation for *Bins*.

Classes

Bins([bins, n_bins, bin_size, bin_edges, ...])	Bin definitions to be used in histogram and render functions.

locan.data.aggregate.Bins

class locan.data.aggregate.**Bins**(*bins=None*, *n_bins=None*, *bin_size=None*, *bin_edges=None*, *bin_range=None*, *labels=None*, *extend_range=None*)

Bases: `object`

Bin definitions to be used in histogram and render functions. Bin edges are continuous, contiguous and monotonic. Bins can be instantiated from specifications for *bins* or *bin_edges* or for one of *n_bins* or *bin_size* in combination with *bin_range*. One and only one of (*bins*, *bin_edges*, *n_bins*, *bin_size*) must be different from None in any instantiating function. To pass bin specifications to other functions use an instance of *Bins* or *bin_edges*.

Parameters

- **bins** (*Bins | boost_histogram.axis.Axis | boost_histogram.axis.AxesTuple | None*) – Specific class specifying the bins.
- **bin_edges** (*Sequence[float] | Sequence[Sequence[float]] | None*) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (*tuple[float, float] | Sequence[float] | Sequence[Sequence[float]]*) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2).
- **n_bins** (*int | Sequence[int] | None*) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (*float | Sequence[float] | Sequence[Sequence[float]] | None*) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.
- **labels** (*list[str] | None*) – Names for each bin axis with shape (dimension,)
- **extend_range** (*bool | None*) – If for equally-sized bins the final bin_edge is different from the maximum bin_range, the last bin_edge will be smaller than the maximum bin_range but all bins are equally-sized (None); the last bin_edge will be equal to the maximum bin_range but bins are not equally-sized (False); the last bin_edge will be larger than the maximum bin_range but all bins are equally-sized (True).

If for variable-sized bins the final bin_edge is different from the maximum bin_range, the last bin_edge will be smaller than the maximum bin_range (None); the last bin_edge will be equal to the maximum bin_range (False); the last bin_edge will be larger than the maximum bin_range but taken from the input sequence (True).

Variables

- **dimension** (*int*) – The number of dimensions for which bins are provided.
- **bin_range** (*tuple[tuple[float, float], ...]*) – Minimum and maximum edge for each dimension with shape (dimension, 2).
- **bin_edges** (tuple[npt.NDArray[**np.float_**], ...]) – Array(s) with bin edges for each dimension with shape (dimension,)
- **n_bins** (*tuple[int, ...]*) – Number of bins for each dimension with shape (dimension,)
- **bin_size** (tuple[float, ...] | tuple[npt.NDArray[**np.float_**], ...]) – Size of bins for each dimension with shape (dimension,) or with shape (dimension, n_bins).
- **bin_centers** (tuple[npt.NDArray[**np.float_**], ...]) – Array(s) with bin centers for all or each dimension with shape (dimension,).
- **labels** (*list[str] | None*) – Names for each bin axis.
- **boost_histogram_axes** (*boost_histogram.axis.AxesTuple*) – Axis definitions for boost-histogram

Methods

`__init__`([bins, n_bins, bin_size, ...])	
equalize_bin_size()	Return a new instance of *Bins* with bin_size set equal to the first bin_size element in each dimension and extend_range=None.

Attributes

bin_centers	**rtype** tuple[ndarray[Any, dtype[float64]], ...]
bin_edges	**rtype** tuple[ndarray[Any, dtype[float64]], ...]
bin_range	**rtype** tuple[tuple[float, float], ...]
bin_size	**rtype** tuple[float, ...] | tuple[ndarray[Any, dtype[float64]], ...]
boost_histogram_axes	Axis definitions for boost-histogram
dimension	**rtype** int
is_equally_sized	True for each dimension if all bins are of the same size.
labels	**rtype** Optional[list[str]]
n_bins	**rtype** tuple[int, ...]

property bin_centers: tuple[numpy.ndarray[Any, numpy.dtype[numpy.float64]], ...]

Return type tuple[ndarray[Any, dtype[float64]], ...]

property bin_edges: tuple[numpy.ndarray[Any, numpy.dtype[numpy.float64]], ...]

Return type tuple[ndarray[Any, dtype[float64]], ...]

property bin_range: tuple[tuple[float, float], ...]

Return type tuple[tuple[float, float], ...]

property bin_size: tuple[float, ...] | tuple[numpy.ndarray[Any, numpy.dtype[numpy.float64]], ...]

Return type tuple[float, ...] | tuple[ndarray[Any, dtype[float64]], ...]

property boost_histogram_axes: boost_histogram.axis.AxesTuple

Axis definitions for boost-histogram

Return type AxesTuple

property dimension: int

Return type int

equalize_bin_size()

Return a new instance of *Bins* with bin_size set equal to the first bin_size element in each dimension and extend_range=None.

Return type *Bins*

property is_equally_sized: tuple[bool, ...]

True for each dimension if all bins are of the same size.

Return type tuple[bool, ...]

property labels: list[str] | None

Return type Optional[list[str]]

property n_bins: tuple[int, ...]

Return type tuple[int, ...]

Functions

histogram(locdata[, loc_properties, ...])	Make histogram of loc_properties (columns in *locdata.data*) by binning all localizations or averaging other_property within each bin.
is_array_like(anything)	Return true if *anything* can be turned into a numpy.ndarray without creating elements of type object.

locan.data.aggregate.histogram

locan.data.aggregate.**histogram**(*locdata*, *loc_properties=None*, *other_property=None*, *bins=None*, *n_bins=None*, *bin_size=None*, *bin_edges=None*, *bin_range=None*)

Make histogram of loc_properties (columns in *locdata.data*) by binning all localizations or averaging other_property within each bin.

Parameters

- **locdata** (*LocData*) – Localization data.
- **loc_properties** (Union[str, Iterable[str], None]) – Localization properties to be grouped into bins. If None The coordinate_values of locdata are used.
- **other_property** (Optional[str]) – Localization property that is averaged in each pixel. If None localization counts are shown.
- **bins** (Union[*Bins*, Axis, AxesTuple, None]) – The bin specification as defined in *Bins*

- **bin_edges** (Union[Sequence[float], Sequence[Sequence[float]], None]) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], Literal['zero', 'link'], None]) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2). If None (min, max) ranges are determined from data and returned; if 'zero' (0, max) ranges with max determined from data are returned. if 'link' (min_all, max_all) ranges with min and max determined from all combined data are returned.
- **n_bins** (Union[int, Sequence[int], None]) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (Union[float, Sequence[float], Sequence[Sequence[float]], None]) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.

Returns namedtuple('Histogram', "data bins labels")

Return type (npt.NDArray[np.int_ | np.float_], Bins, list[str])

locan.data.aggregate.is_array_like

locan.data.aggregate.**is_array_like**(*anything*)

Return true if *anything* can be turned into a numpy.ndarray without creating elements of type object.

Catches numpy.VisibleDeprecationWarning or ValueError when setting an array element with a sequence.

Parameters **anything** (Any) – Anything to be classified as being array-like or not.

Return type bool

locan.data.filter

Filter localization data.

This module provides functions for filtering LocData objects. The functions take LocData as input and compute new LocData objects.

Classes

Selector(loc_property, activate, ...)	Define selection interval for a single localization property.

locan.data.filter.Selector

class locan.data.filter.**Selector**(*loc_property*, *activate*, *lower_bound*, *upper_bound*)

Bases: object

Define selection interval for a single localization property.

Parameters

- **loc_property** (str) – Localization property
- **activate** (bool) – Indicator to apply the selection or not
- **lower_bound** (int | float) – min fo selection interval
- **upper_bound** (int | float) – max of selection interval

Variables

- **loc_property** (*str*) – Localization property
- **activate** (*bool*) – Indicator to apply the selection or not
- **lower_bound** (*int | float*) – min fo selection interval
- **upper_bound** (*int | float*) – max of selection interval
- **interval** (Interval) – Class with interval specifications
- **condition** (*str*) – specification turned into condition string

Methods

__init__(loc_property, activate, ...)	

Attributes

condition	**rtype** str
lower_bound	**rtype** int | float
upper_bound	**rtype** int | float

property condition: str

Return type str

property lower_bound: int | float

Return type int | float

property upper_bound: int | float

Return type int | float

Functions

exclude_sparse_points(locdata[, ...])	Exclude localizations by thresholding a local density.
filter_condition(selectors)	Get a condition string from selection specifications.
localizations_in_cluster_regions(locdata, ...)	Identify localizations from *locdata* within the regions of all *collection* elements.
random_subset(locdata, n_points[, replace, seed])	Take a random subset of localizations.
select_by_condition(locdata, condition)	Select by specifying conditions on data properties.
select_by_image_mask(locdata, mask)	Select by masking using a binary image(e.g.
select_by_region(locdata, region[, ...])	Select localizations from *locdata* that are within *region* and return a new LocData object.

locan.data.filter.exclude_sparse_points

locan.data.filter.**exclude_sparse_points**(*locdata*, *other_locdata=None*, *radius=50*, *min_samples=5*)

Exclude localizations by thresholding a local density.

A subset of localizations, that exhibit a small local density of localizations from locdata or alternatively from other_locdata, is identified as noise and excluded. Noise is identified by using a nearest-neighbor search (`sklearn.neighbors.NearestNeighbors`) to find all localizations within a circle (sphere) of the given *radius*. If the number of localizations is below the threshold value *min_samples*, the localization is considered to be noise.

The method identifies the same noise points as done by the clustering algorithm DBSCAN[1].

Parameters

- **locdata** (*LocData*) – Specifying the localization data from which to exclude localization data.
- **other_locdata** (Optional[*LocData*]) – Specifying the localization data on which to compute local density.

[1] Martin Ester, Hans-Peter Kriegel, Jörg Sander, Xiaowei Xu, A density-based algorithm for discovering clusters in large spatial databases with noise. In: Evangelos Simoudis, Jiawei Han, Usama M. Fayyad (Hrsg.): Proceedings of the Second International Conference on Knowledge Discovery and Data Mining (KDD-96). AAAI Press, 1996, S. 226-231, ISBN 1-57735-004-9.

- **radius** (float) – Radius of a circle or sphere in which neighbors are identified (equivalent to epsilon in DBSCAN).
- **min_samples** (int) – The minimum number of samples in the neighborhood that need to be found for each localization to not be identified as noise (equivalent to minPoints in DBSCAN).

Returns All localizations except those identified as sparse (noise) points.

Return type *LocData*

References

locan.data.filter.filter_condition

locan.data.filter.**filter_condition**(*selectors*)

Get a condition string from selection specifications.

Parameters **selectors** (Iterable[*Selector*]) – Specifications for loc_property selections

Return type str

locan.data.filter.localizations_in_cluster_regions

locan.data.filter.**localizations_in_cluster_regions**(*locdata*, *collection*, *hull_type=HullType.CONVEX_HULL*)

Identify localizations from *locdata* within the regions of all *collection* elements.

Parameters

- **locdata** (*LocData*) – Localization data that is tested for being inside the region
- **collection** (*LocData* | list[*LocData*]) – A set of Locdata objects collected in a collection or list.
- **hull_type** (*HullType* | str) – The hull type for each LocData object that is used to define the region.

Returns A collection of LocData objects with all elements of locdata contained by the region.

Return type *LocData*

locan.data.filter.random_subset

locan.data.filter.**random_subset**(*locdata*, *n_points*, *replace=True*, *seed=None*)

Take a random subset of localizations.

Parameters

- **locdata** (*LocData*) – Specifying the localization data from which to select localization data.
- **n_points** (int) – Number of localizations to randomly choose from locdata.
- **replace** (bool) – Indicate if sampling is with or without replacement
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – Random number generation seed

Returns A new instance of LocData carrying the subset of localizations.

Return type *LocData*

locan.data.filter.select_by_condition

locan.data.filter.**select_by_condition**(*locdata*, *condition*)

Select by specifying conditions on data properties.

Parameters

- **locdata** (*LocData*) – Specifying the localization data from which to select.
- **condition** (str) – Conditions as input in select method. More precise: query specifications to be used with pandas query.

Returns A new instance of LocData referring to the specified dataset.

Return type *LocData*

locan.data.filter.select_by_image_mask

locan.data.filter.**select_by_image_mask**(*locdata*, *mask*)

Select by masking using a binary image(e.g. generated by thresholding a transmitted-light microscopy image.

Parameters

- **locdata** (LocData) – specifying the localization data from which to select.
- **mask** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – binary image.

Returns a new instance of Selection referring to the specified dataset.

Return type *LocData*

locan.data.filter.select_by_region

locan.data.filter.**select_by_region**(*locdata*, *region*, *loc_properties=None*, *reduce=True*)

Select localizations from *locdata* that are within *region* and return a new LocData object. Selection is with respect to loc_properties or to localization coordinates that correspond to region dimension.

Parameters

- **locdata** (*LocData*) – Localization data that is tested for being inside the region.
- **region** (*Region*) – Tested region
- **loc_properties** (Optional[list[str]]) – Localization properties to be tested.
- **reduce** (bool) – Return the reduced LocData object or keep references alive.

Returns A new instance of LocData with all localizations within region of interest.

Return type *LocData*

Note: Points on boundary of regions are considered outside if region is a shapely object, but inside if region is a matplotlib (which is the case for RoiRegion) object.

locan.data.transform

Transform localization data.

This module provides functions that take locdata as input, transform the localization data, and return a new LocData object.

Submodules:

bunwarpj	Transform localization data with a BUnwarpJ transformation matrix.
spatial_transformation	Transform localization data.
intensity_transformation	Transform localization intensities.

locan.data.transform.bunwarpj

Transform localization data with a BUnwarpJ transformation matrix.

This module provides functions to transform coordinates in LocData objects by applying a B-spline transformation as defined with the ImageJ/Fiji plugin BunwarpJ[1],[2].

[1] I. Arganda-Carreras, C. O. S. Sorzano, R. Marabini, J.-M. Carazo, C. Ortiz-de Solorzano, and J. Kybic, "Consistent and Elastic Registration of Histological Sections using Vector-Spline Regularization", Lecture Notes in Computer Science, Springer Berlin / Heidelberg, volume 4241/2006, CVAMIA: Computer Vision Approaches to Medical Image Analysis, pages 85-95, 2006.

[2] C.Ó. Sánchez Sorzano, P. Thévenaz, M. Unser, "Elastic Registration of Biological Images Using Vector-Spline Regularization", IEEE Transactions on Biomedical Engineering, vol. 52, no. 4, pages 652-663, 2005.

References

Functions

bunwarp(locdata, matrix_path, pixel_size[, flip])	Transform coordinates by applying a B-spline transformation as represented by a raw transformation matrix from BunwarpJ.

locan.data.transform.bunwarpj.bunwarp

locan.data.transform.bunwarpj.**bunwarp**(*locdata*, *matrix_path*, *pixel_size*, *flip=False*)

Transform coordinates by applying a B-spline transformation as represented by a raw transformation matrix from BunwarpJ.

Parameters

- **locdata** (*LocData*) – specifying the localization data on which to perform the manipulation.
- **matrix_path** (str | PathLike[Any]) – Path to file with a raw matrix from BunwarpJ.
- **pixel_size** (tuple[float, float]) – Pixel sizes used to determine transition matrix in ImageJ
- **flip** (bool) – Flip locdata along x-axis before transformation

Returns New localization data with transformed coordinates.

Return type *LocData*

locan.data.transform.spatial_transformation

Transform localization data.

This module takes localization data and applies transformation procedures on coordinates or other properties.

Functions

overlay(locdatas[, centers, orientations])	Translate locdatas to their common center and rotate according to their orientation.
standardize(locdata[, loc_properties, ...])	Transform locdata properties by centering to the mean and property-wise scaling to unit standard deviation (variance).
transform_affine(locdata[, matrix, offset, ...])	Transform *points* or coordinates in *locdata* by an affine transformation.

locan.data.transform.spatial_transformation.overlay

locan.data.transform.spatial_transformation.**overlay**(*locdatas*, *centers='centroid'*, *orientations=None*)

Translate locdatas to their common center and rotate according to their orientation.

Parameters

- **locdatas** (Iterable[*LocData*]) – Localization data to overlay.
- **centers** (UnionType[Iterable[Any], str, None]) – centers to which locdatas are translated. Must have the same length as locdatas. One of *centroid*, *ch*, 'bb', 'obb', or 'region'. If None, no translation is applied.
- **orientations** (Union[Sequence[UnionType[int, float, str, None]], str, None]) – Orientation value to use in degree. Must have the same length as locdatas. If str, it must be one of *orientation_im*, *orientation_obb*. If None, no rotation is applied.

Returns Collection with transformed locdatas.

Return type *LocData*

locan.data.transform.spatial_transformation.standardize

locan.data.transform.spatial_transformation.**standardize**(*locdata*, *loc_properties=None*, *with_mean=True*, *with_std=True*)

Transform locdata properties by centering to the mean and property-wise scaling to unit standard deviation (variance).

Note: This function makes use of :func:sklearn.preprocessing.scale and thus works with a biased estimator for the standard deviation.

Parameters

- **locdata** (*LocData*) – Localization data to be standardized.
- **loc_properties** (Optional[list[str]]) – Localization properties to be standardized. If None The coordinate_values of locdata are used.
- **with_mean** (bool) – If True center to the mean.
- **with_std** (bool) – If True scale to unit standard deviation (variance).

Returns New localization data with standardized properties.

Return type *LocData*

locan.data.transform.spatial_transformation.transform_affine

locan.data.transform.spatial_transformation.**transform_affine**(*locdata*, *matrix=None*, *offset=None*, *pre_translation=None*, *method='numpy'*)

Transform *points* or coordinates in *locdata* by an affine transformation.

Parameters

- **locdata** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], *LocData*]) – Localization data on which to perform the manipulation.
- **matrix** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], None]) – Transformation matrix. If None the unit matrix is used. Array with shape (ndim, ndim). If None the unit matrix is used.
- **offset** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], None]) – Translation vector. Array with shape (ndim,). If None a vector of zeros is used.
- **pre_translation** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], None]) – Translation vector for coordinates applied before affine transformation. Array with shape (ndim,). The reverse translation is applied after the affine transformation.
- **method** (Literal['numpy', 'open3d']) – The method (i.e. library or algorithm) used for computation. One of 'numpy', 'open3d'.

Returns New localization data with transformed coordinates.

Return type npt.NDArray[**np.float_**] | LocData

locan.data.transform.intensity_transformation

Transform localization intensities.

Localization intensities can be given in counts, electrons or photons. This module provides often used transformation functions.

Functions

transform_counts_to_photons(locdata[, ...])	Convert camera analog-to-digital converter (ADC) counts into photo electrons.

locan.data.transform.intensity_transformation.transform_counts_to_photons

locan.data.transform.intensity_transformation.**transform_counts_to_photons**(*locdata*, *loc_properties=None*, *metadata=None*)

Convert camera analog-to-digital converter (ADC) counts into photo electrons. Quantum efficiency at the detected wavelength and collection efficiency of the optical system are not taken into account here.

Parameters

- **locdata** (*LocData*) – Localization data on which to perform the manipulation.
- **loc_properties** (Union[str, list[str], None]) – Localization properties to be converted. If None the *intensity* values of locdata are used.
- **metadata** (Optional[Camera]) – Camera metadata with attribute offset, gain, electrons_per_count If None, locdata.meta.experiment.setups[0].optical_units[0].detection.camera is used.

Returns Localization data with converted intensity values.

Return type *LocData*

locan.data.cluster

This module provides functions for clustering localizations.

The functions take LocData as input and compute new LocData objects representing collections of clustered localizations.

Submodules:

clustering	Methods for clustering localization data in LocData objects.
utils	Utility methods for clustering locdata.

locan.data.cluster.clustering

Methods for clustering localization data in LocData objects.

Functions

cluster_by_bin(locdata[, loc_properties, ...])	Cluster localizations in locdata by binning all localizations with regard to *loc_properties* and collecting all localizations per bin as cluster.
cluster_dbscan(locdata[, eps, min_samples, ...])	Cluster localizations in locdata using the dbscan clustering algorithm as implemented in sklearn.
cluster_hdbscan(locdata[, min_cluster_size, ...])	Cluster localizations in locdata using the hdbscan clustering algorithm.

locan.data.cluster.clustering.cluster_by_bin

locan.data.cluster.clustering.**cluster_by_bin**(*locdata*, *loc_properties=None*, *min_samples=1*, *bins=None*, *n_bins=None*, *bin_size=None*, *bin_edges=None*, *bin_range=None*, *return_counts=False*)

Cluster localizations in locdata by binning all localizations with regard to *loc_properties* and collecting all localizations per bin as cluster.

Parameters

- **locdata** (*LocData*) – Localization data.
- **loc_properties** (Optional[list[str]]) – Localization properties to be grouped into bins. If None The coordinate_values of locdata are used.
- **min_samples** (int) – The minimum number of samples per bin to be considered as cluster.
- **bins** (Union[*Bins*, Axis, AxesTuple, None]) – The bin specification as defined in Bins
- **bin_edges** (Union[Sequence[float], Sequence[Sequence[float]], None]) – Array of bin edges with shape (n_bin_edges,) or (dimension, n_bin_edges) for all or each dimension.
- **n_bins** (Union[int, Sequence[int], None]) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (Union[float, Sequence[float], Sequence[Sequence[float]], None]) – The size of bins in units of locdata coordinate units for all or each dimension. 5 would describe bin_size of 5 for all bins in all dimensions. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. To specify arbitrary sequence of *bin_sizes* use *bin_edges* instead.
- **bin_range** (*tuple[float, ...] | tuple[tuple[float, float], ...] | Literal['zero'] | None*) – The data bin_range to be taken into

consideration for all or each dimension. ((min_x, max_x), (min_y, max_y), ...) bin_range for each coordinate; for None (min, max) bin_range are determined from data; for 'zero' (0, max) bin_range with max determined from data.

- **return_counts** (bool) – If true, n_elements per bin are returned.

Returns Tuple with bins, bin_indices, collection of all generated selections (i.e. localization clusters), and counts per bin.

Return type tuple[Bins | None, npt.NDArray[np.int_], LocData, npt.NDArray[np.int_] | None]

locan.data.cluster.clustering.cluster_dbscan

locan.data.cluster.clustering.**cluster_dbscan**(*locdata*, *eps=20*, *min_samples=5*, *loc_properties=None*, ***kwargs*)

Cluster localizations in locdata using the dbscan clustering algorithm as implemented in sklearn.

Parameters

- **locdata** (*LocData*) – specifying the localization data on which to perform the manipulation.
- **eps** (float) – The maximum distance between two samples for them to be considered as in the same neighborhood.
- **min_samples** (int) – The number of samples in a neighborhood for a point to be considered as a core point. This includes the point itself.
- **loc_properties** (Optional[list[str]]) – The LocData properties to be used for clustering. If None, *locdata.coordinates* will be used.
- **kwargs** (Any) – Other parameters passed to *sklearn.cluster.DBSCAN*.

Returns A tuple with noise and cluster. The first LocData object is a selection of all localizations that are defined as noise, in other words all localizations that are not part of any cluster. The second LocData object is a LocData instance assembling all generated selections (i.e. localization cluster).

Return type tuple[*LocData*, *LocData*]

locan.data.cluster.clustering.cluster_hdbscan

locan.data.cluster.clustering.**cluster_hdbscan**(*locdata*, *min_cluster_size=5*, *loc_properties=None*, *allow_single_cluster=False*, ***kwargs*)

Cluster localizations in locdata using the hdbscan clustering algorithm.

Parameters

- **locdata** (*LocData*) – Localization data on which to perform the manipulation.
- **loc_properties** (Optional[list[str]]) – The LocData properties to be used for clustering. If None, *locdata.coordinates* will be used.

- **min_cluster_size** (int) – Minimumm cluster size in HDBSCAN algorithm (default: 5)
- **allow_single_cluster** (bool) – If True, return single cluster (default: False)
- **kwargs** (Any) – Other parameters passed to *hdbscan.HDBSCAN*.

Returns A tuple with noise and cluster. The first LocData object is a selection of all localizations that are defined as noise, in other words all localizations that are not part of any cluster. The second LocData object is a LocData instance assembling all generated selections (i.e. localization cluster).

Return type tuple[*LocData*, *LocData*]

locan.data.cluster.utils

Utility methods for clustering locdata.

Functions

serial_clustering(locdata, algorithm, ...)	Run and analyse a series of clustering processes to identify optimal parameters.

locan.data.cluster.utils.serial_clustering

locan.data.cluster.utils.**serial_clustering**(*locdata*, *algorithm*, *parameter_lists*, ***kwargs*)

Run and analyse a series of clustering processes to identify optimal parameters.

Parameters

- **locdata** (*LocData*) – Localization data.
- **algorithm** (Callable[..., Any]) – The locan clustering algorithm to use on locdata.
- **parameter_lists** (dict[str, Any]) – A dictionary with all parameter lists that are to be iterated. The keys should be identical to parameter names of the used algorithm.
- **kwargs** (Any) – Optional keyword arguments that are passed to the algorithm.

Returns The first element is a LocData object with a selection of all localizations that are defined as noise. If noise is false this element will be None. The second element is a new LocData instance assembling all generated selections (i.e. localization cluster).

Return type tuple[*LocData*, ...]

locan.data.tracking

Track localizations.

This module provides functions for tracking localizations (i.e. clustering localization data in time). The functions take LocData as input and compute new LocData objects. It makes use of the trackpy package.

Functions

link_locdata(locdata[, search_range, memory])	Track localizations, i.e. cluster localizations in time when nearby in successive frames.
track(locdata[, search_range, memory])	Cluster (in time) localizations in LocData that are nearby in successive frames.

locan.data.tracking.link_locdata

locan.data.tracking.**link_locdata**(*locdata*, *search_range=40*, *memory=0*, ***kwargs*)

Track localizations, i.e. cluster localizations in time when nearby in successive frames. This function applies the trackpy linking method to LocData objects.

Parameters

- **locdata** – Localization data on which to perform the manipulation.
- **search_range** – The maximum distance features can move between frames, optionally per dimension
- **memory** – The maximum number of frames during which a feature can vanish, then reappear nearby, and be considered the same particle.
- **kwargs** – Other parameters passed to trackpy.link_df().

Returns A series named 'Track' referring to the track number.

Return type pandas.Series[Any]

Note: In order to switch off the printout from `trackpy.link()` and increase performance use `trackpy.quiet()` to silence the logging outputs.

---

locan.data.tracking.track

locan.data.tracking.**track**(*locdata*, *search_range=40*, *memory=0*, ***kwargs*)

Cluster (in time) localizations in LocData that are nearby in successive frames. Clustered localizations are identified by the trackpy linking method.

The new locdata object carries properties with the same name as the original *locata*. They are computed as sum for *intensity*, as the first value for *frame*, and as mean for all other properties.

Parameters

- **locdata** – Localization data on which to perform the manipulation.

- **search_range** – The maximum distance features can move between frames, optionally per dimension
- **memory** – The maximum number of frames during which a feature can vanish, then reappear nearby, and be considered the same particle.
- **kwargs** – Other parameters passed to trackpy.link_df.

Returns A new LocData instance assembling all generated selections (i.e. localization cluster). A series named 'Track' referring to the track number.

Return type tuple[Locdata, pandas.Series[Any]]

Note: In order to switch off the printout from `trackpy.link()` and increase performance use `trackpy.quiet()` to silence the logging outputs.

---

locan.data.metadata_utils

Deal with metadata in LocData objects.

Functions to modify metadata in LocData objects.

Functions

load_metadata_from_toml(path_or_file_like)	Turn toml file into protobuf message instances.
merge_metadata([metadata, other_metadata])	Merge *other_metadata* into Locdata.meta.
message_scheme(message)	Provide message scheme with defaults including nested messages.
metadata_from_toml_string(toml_string)	Turn toml string into protobuf message instances.
metadata_to_formatted_string(message, **kwargs)	Get formatted string from Locdata.metadata.

locan.data.metadata_utils.load_metadata_from_toml

locan.data.metadata_utils.**load_metadata_from_toml**(*path_or_file_like*)

Turn toml file into protobuf message instances.

Note: Parses Timestamp elements from string '2022-05-14T06:58:00Z'. Parses Duration elements from int in nanoseconds.

Parameters **path_or_file_like** (UnionType[str, bytes, PathLike[Any], BinaryIO, None]) – File path or file-like for a TOML file.

Returns Message instances with name as declared in toml file.

Return type dict[str, google.protobuf.message.Message] | None

locan.data.metadata_utils.merge_metadata

locan.data.metadata_utils.**merge_metadata**(*metadata=None*, *other_metadata=None*)

Merge *other_metadata* into Locdata.meta.

Parameters

- **metadata** (Optional[Metadata]) – Original LocData metadata before modification
- **other_metadata** (Union[Metadata, dict[str, Any], str, bytes, PathLike[Any], BinaryIO, None]) – Metadata to be merged.

Returns Merged metadata

Return type locan.data.metadata_pb2.Metadata

locan.data.metadata_utils.message_scheme

locan.data.metadata_utils.**message_scheme**(*message*)

Provide message scheme with defaults including nested messages.

Parameters **message** (Message) – Protobuf message

Returns A nested dictionary with all message fields including default values.

Return type dict[str, Any]

locan.data.metadata_utils.metadata_from_toml_string

locan.data.metadata_utils.**metadata_from_toml_string**(*toml_string*)

Turn toml string into protobuf message instances.

Note: Parses Timestamp elements from string '2022-05-14T06:58:00Z'. Parses Duration elements from int in nanoseconds.

Parameters **toml_string** (Optional[str]) – TOML string with metadata.

Returns Message instances with name as declared in toml file.

Return type dict[str, google.protobuf.message.Message] | None

locan.data.metadata_utils.metadata_to_formatted_string

locan.data.metadata_utils.**metadata_to_formatted_string**(*message*, ***kwargs*)

Get formatted string from Locdata.metadata.

Parameters

- **message** (Message) – Protobuf message like locan.data.metadata_pb2.Metadata

- **kwargs** (Any) – Other kwargs that are passed to `google.protobuf.text_format.MessageToString()`.

Returns Formatted metadata string.

Return type str

locan.data.validation

Validate localization data.

This module provides functions to validate LocData properties.

Classes

Collection(*args, **kwargs)

locan.data.validation.Collection

class locan.data.validation.**Collection**(**args*, ***kwargs*)

Bases: Protocol

Methods

__init__(*args, **kwargs)

Attributes

data
references
coordinate_keys

coordinate_keys: list[str]

data: pandas.core.frame.DataFrame

references: collections.abc.Iterable[*locan.data.locdata.LocData*]

8.5 locan.datasets

Utility functions to deal with exemplary datasets.

The data is located in a separate repository *https://github.com/super-resolution/LocanDatasets*.

When calling a function the datasets are expected to reside in a directory specified by the *locan.constants.DATASETS_DIR* variable. If the directory does not exist the exemplary files are downloaded from GitHub.

Functions

load_npc(**kwargs)	Locdata representing nuclear pore complexes.
load_tubulin(**kwargs)	Locdata representing microtubules.

8.5.1 locan.datasets.load_npc

locan.datasets.**load_npc**(***kwargs*)

Locdata representing nuclear pore complexes.

The data was generated by dSTORM[1]. It shows the gp210 protein of the nuclear pore complex labeled with AlexaFluor647.

References

Parameters **kwargs** (Any) – Parameters passed to *locan.load_asdf_file()*.

Return type *LocData*

8.5.2 locan.datasets.load_tubulin

locan.datasets.**load_tubulin**(***kwargs*)

Locdata representing microtubules.

The data was generated by dSTORM[1]. It shows alpha-tubulin as part of microtubules within COS-7 cells. Tubulin was targeted by primary IgG-antibodies labeled with AlexaFluor647 (2.1 degree of labeling) and recorded over 75_000 frames.

[1] Löschberger A, van de Linde S, Dabauvalle MC, Rieger B, Heilemann M, Krohne G, Sauer M., Super-resolution imaging visualizes the eightfold symmetry of gp210 proteins around the nuclear pore complex and resolves the central channel with nanometer resolution. J Cell Sci. 2012, 125:570-5, doi: 10.1242/jcs.098822.

[1] Dominic A. Helmerich, Gerti Beliu, and Markus Sauer, Multiple-Labeled Antibodies Behave Like Single Emitters in Photoswitching Buffer ACS Nano 2020, 14, 10, 12629–12641, DOI: 10.1021/acsnano.0c06099

References

Parameters **kwargs** (Any) – Parameters passed to *locan.load_rapidSTORM_file()*.

Return type *LocData*

8.6 locan.dependencies

Module to deal with required and optional dependencies.

Optional dependencies are defined in pyproject.toml.

In any module that requires an optional dependency the import should be conditioned:

if HAS_DEPENDENCY[“package”]: import package

Any function that makes use of the optional dependency should be decorated with
@needs_package(“package”)

CONSTANTS

INSTALL_REQUIRES	List of required dependencies (PyPi package names)
EXTRAS_REQUIRE	List of optional dependencies (PyPi package names)
IMPORT_NAMES	A dictionary mapping PyPi package names to import names if they are different
HAS_DEPENDENCY	A dictionary indicating if dependency is available.

8.6.1 locan.dependencies.INSTALL_REQUIRES

locan.dependencies.**INSTALL_REQUIRES: set[str] = {'asdf', 'boost-histogram', 'cython', 'fast-histogram', 'lazy-loader', 'lmfit', 'matplotlib', 'networkx', 'numpy', 'pandas', 'protobuf', 'qtpy', 'ruamel', 'scikit-image', 'scikit-learn', 'scipy', 'shapely', 'tifffile', 'tomli', 'tqdm', 'typing-extensions'}**

List of required dependencies (PyPi package names)

8.6.2 locan.dependencies.EXTRAS_REQUIRE

locan.dependencies.**EXTRAS_REQUIRE: set[str] = {'PyQt5', 'PySide2', 'asv', 'black', 'build', 'colorcet', 'coverage', 'cupy', 'furo', 'h5py', 'hdbscan', 'ipython', 'locan', 'mpl-scatter-density', 'mypy', 'myst-nb', 'napari', 'numpy', 'open3d', 'open3d-cpu', 'pandas-stubs', 'pre-commit', 'pytest', 'pytest-qt', 'ray', 'requests', 'ruff', 'sphinx', 'sphinx-autodoc-typehints', 'sphinx-copybutton', 'sphinx-rtd-theme', 'trackpy', 'twine', 'types-protobuf', 'types-requests', 'types-tqdm'}**

List of optional dependencies (PyPi package names)

8.6.3 locan.dependencies.IMPORT_NAMES

locan.dependencies.**IMPORT_NAMES = {'boost-histogram': 'boost_histogram', 'fast-histogram': 'fast_histogram', 'mpl-scatter-density': 'mpl_scatter_density', 'protobuf': 'google.protobuf', 'pytest-qt': 'pytestqt', 'ruamel': 'ruamel.yaml', 'scikit-image': 'skimage', 'scikit-learn': 'sklearn'}**

A dictionary mapping PyPi package names to import names if they are different

8.6.4 locan.dependencies.HAS_DEPENDENCY

locan.dependencies.**HAS_DEPENDENCY = {'PyQt5': True, 'PySide2': False, 'asdf': True, 'asv': False, 'black': False, 'boost_histogram': True, 'build': True, 'colorcet': True, 'coverage': False, 'cupy': False, 'cython': True, 'fast_histogram': True, 'furo': True, 'google.protobuf': True, 'h5py': True, 'hdbscan': True, 'ipython': False, 'lazy-loader': False, 'lmfit': True, 'locan': True, 'matplotlib': True, 'mpl_scatter_density': True, 'mypy': False, 'myst-nb': False, 'napari': True, 'networkx': True, 'numpy': True, 'open3d': True, 'open3d-cpu': False, 'pandas': True, 'pandas-stubs': False, 'pre-commit': False, 'pytest': True, 'pytestqt': False, 'qt': True, 'qtpy': True, 'ray': True, 'requests': True, 'ruamel.yaml': True, 'ruff': False, 'scipy': True, 'shapely': True, 'skimage': True, 'sklearn': True, 'sphinx': True, 'sphinx-autodoc-typehints': False, 'sphinx-copybutton': False, 'sphinx-rtd-theme': False, 'tifffile': True, 'tomli': True, 'tqdm': True, 'trackpy': True, 'twine': False, 'types-protobuf': False, 'types-requests': False, 'types-tqdm': False, 'typing-extensions': False}**

A dictionary indicating if dependency is available.

Classes

QtBindings(value)	Python bindings to interact with Qt.

8.6.5 locan.dependencies.QtBindings

class locan.dependencies.**QtBindings**(*value*)

Bases: enum.Enum

Python bindings to interact with Qt.

Attributes

NONE
PYSIDE2
PYQT5
PYSIDE6
PYQT6

NONE = ''

PYQT5 = 'pyqt5'

PYQT6 = 'pyqt6'

PYSIDE2 = 'pyside2'

PYSIDE6 = 'pyside6'

Functions

needs_package(package[, import_names, ...])	Function that returns a decorator to check for optional dependency.

8.6.6 locan.dependencies.needs_package

locan.dependencies.**needs_package**(*package*, *import_names=None*, *has_dependency=None*)

Function that returns a decorator to check for optional dependency.

Parameters

- **package** (str) – Package or dependency name that needs to be imported.
- **import_names** (Optional[dict[str, str]]) – Mapping of package names onto import names.
- **has_dependency** (Optional[dict[str, bool]]) – Dictionary with bool indicator if package (import name) is available.

Returns A decorator that raises ImportError if package is not available.

Return type callable

8.7 locan.gui

User interfaces.

This module provides functions and classes for using graphical user interfaces (GUI).

Functions provide a GUI based on QT if the QT backend and appropriate python bindings are available. Supported bindings are found in the enum class *locan.QtBindings*.

The configuration variable *locan.QT_BINDING* declares which python binding to use if several are installed. If an environment variable *QT_API* is defined it takes precedence over *locan.QT_BINDING*.

If neither *locan.QT_BINDING* nor *QT_API* is defined, qtpy will choose the binding.

8.7.1 Submodules:

io	Functions for user interaction with paths and file names.

locan.gui.io

Functions for user interaction with paths and file names.

Note: These functions start a QT app and might interfere with previously started apps.

Functions

file_dialog([directory, message, filter])	Select file names in a ui dialog.
set_file_path_dialog([directory, message, ...])	Set file path (path/name.suffix) in a ui dialog.

locan.gui.io.file_dialog

locan.gui.io.**file_dialog**(*directory=None*, *message='Select a file...'*, *filter='Text files (*.txt);; All files (*)'*)

Select file names in a ui dialog.

Parameters

- **directory** (Optional[str]) – directory path to start dialog in. If None the current directory is used.
- **message** (str) – Hint what to do
- **filter** (str) – filter for file type

Returns list with file names or empty list

Return type str | list[str]

locan.gui.io.set_file_path_dialog

locan.gui.io.**set_file_path_dialog**(*directory=None*, *message='Set a file path...'*, *filter='All files (*)'*)

Set file path (path/name.suffix) in a ui dialog.

Parameters

- **directory** (Optional[str]) – directory path to start dialog in. If None the current directory is used.
- **message** (str) – Hint what to do
- **filter** (str) – filter for file type

Returns new file path

Return type str

8.8 locan.locan_io

File input/output functions.

This module provides functions for file input and output of data related to single-molecule localization microscopy.

8.8.1 Submodules:

files	File manager
locdata	File input/output for localization data.
utilities	Utility functions for file input/output.

locan.locan_io.files

File manager

Identify, match, and group files to be batch-processed. The class Files is a wrapper for a pandas.DataFrame with selected methods to identify, match, and group file paths.

Classes

Files([df, directory, exists, column])	Wrapper for a pandas.DataFrame with selected methods to identify, match, and group file paths.

locan.locan_io.files.Files

class locan.locan_io.files.**Files**(*df=None*, *directory=None*, *exists=True*, *column='file_path'*)

Bases: `object`

Wrapper for a pandas.DataFrame with selected methods to identify, match, and group file paths.

Note: Iteration and indexing is implemented in a way that integer indexing or iterating over the Files instance returns a single row (as Series or namedtuple). Slice indexing returns a new Files instance with selected rows.

Parameters

- **df** (*pd.DataFrame | dict[str, str] | None*) – file names
- **directory** (*str | os.PathLike[Any] | None*) – base directory
- **exists** (*bool*) – raise *FileExistsError* if file in *df* does not exist
- **column** (*str*) – key/column in *df* from which to take a file list

Variables

- **df** (*pd.DataFrame*) – dataframe carrying file paths
- **directory** (*Path*) – base directory

Methods

`__init__`([df, directory, exists, column])	
add_glob([pattern, regex, column])	Search for file paths using glob and/or regex pattern in base directory and provide files in new *column*.
concatenate([files, directory, exists])	Concatenate the file lists from multiple File instances and set the base directory without further action.
exclude([stoplist, column, column_stoplist])	Exclude files in *self.df.column* according to stoplist.
from_glob([directory, pattern, regex, column])	Instantiate *Files* from a search with glob and/or regex patterns.
from_path([files, directory, column])	Instantiate *Files* from a collection of file paths.
group_identifiers()	Get categories defined in self.df.group.
grouped()	Get groupby instance based on group_identifiers.
match_file_upstream([column, pattern, ...])	Find a matching file by applying `locan.find_file_upstream()` on each file in *self.df[column]*.
match_files(files[, column, other_column])	Add files in new column.
print_summary()	Print summary of Files.
set_group_identifier([name, pattern, glob, ...])	Set group_identifier *name* for files in *column* as identified by string pattern and/or glob pattern and/or regex and keep them in column "group".

add_glob(*pattern='*.txt'*, *regex=None*, *column='other_file_path'*)

Search for file paths using glob and/or regex pattern in base directory and provide files in new *column*.

A logging.warning is given if the number of found files and those in *self.df* are different.

Parameters

- **pattern** (`Optional[str]`) – glob pattern passed to `Path.glob()`
- **regex** (`Optional[str]`) – regex pattern passed to `re.search()` and applied in addition to glob pattern
- **column** (*str*) – Name of column in *Files.df* carrying these files

Return type Self

classmethod concatenate(*files=None*, *directory=None*, *exists=True*)

Concatenate the file lists from multiple File instances and set the base directory without further action.

Parameters

- **files** (`Optional[Iterable[Files]]`) – sequence with File instances
- **directory** (`Union[str, PathLike[Any], None]`) – new base directory

- **exists** (bool) – raise *FileExistsError* if file in files does not exist

Return type *Files*

exclude(*stoplist=None*, *column='file_path'*, *column_stoplist='file_path'*)

Exclude files in *self.df.column* according to stoplist.

Parameters

- **stoplist** (Union[*Files*, Iterable[bool | str | PathLike[Any]], None]) – Files to be excluded
- **column** (str) – key/column in *df* from which to exclude files
- **column_stoplist** (str) – key/column in *stoplist* from which to take files

Return type Self

classmethod from_glob(*directory=None*, *pattern='*.txt'*, *regex=None*, *column='file_path'*)

Instantiate *Files* from a search with glob and/or regex patterns.

Parameters

- **pattern** (str) – glob pattern passed to Path.glob()
- **regex** (Optional[str]) – regex pattern passed to re.search() and applied in addition to glob pattern
- **directory** (Union[str, PathLike[Any], None]) – new base directory in which to search
- **column** (str) – Name of column in *Files.df* carrying these files

Return type *Files*

classmethod from_path(*files=None*, *directory=None*, *column='file_path'*)

Instantiate *Files* from a collection of file paths.

Parameters

- **files** (Union[Sequence[str | PathLike[Any]], str, PathLike[Any], None]) – sequence with File instances
- **directory** (Union[str, PathLike[Any], None]) – new base directory
- **column** (str) – Name of column in *Files.df* carrying these files

Return type *Files*

group_identifiers()

Get categories defined in self.df.group.

Return type categories

grouped()

Get groupby instance based on group_identifiers.

Return type pandas.core.groupby.DataFrameGroupBy

match_file_upstream(*column='file_path'*, *pattern='*.toml'*, *regex=None*, *directory=None*, *other_column='metadata'*)

Find a matching file by applying locan.find_file_upstream() on each file in *self.df[column]*.

Parameters

- **column** (str) – Name of column in *Files.df* carrying files to match
- **pattern** (Optional[str]) – glob pattern passed to Path.glob()
- **regex** (Optional[str]) – regex pattern passed to re.search() and applied in addition to glob pattern
- **directory** (Union[str, PathLike[Any], None]) – top directory in which to search
- **other_column** (str) – Name of new column carrying files

Return type Self

match_files(*files*, *column='file_path'*, *other_column='other_file_path'*)

Add files in new column.

A logging.warning is given if the number of files and those in *self.df* are different.

Parameters

- **files** – New file list
- **column** – Name of column in *Files.df* carrying files to match
- **other_column** – Name of new column carrying files

Return type Self

print_summary()

Print summary of Files.

Return type None

set_group_identifier(*name=None*, *pattern=None*, *glob=None*, *regex=None*, *column='file_path'*)

Set group_identifier *name* for files in *column* as identified by string pattern and/or glob pattern and/or regex and keep them in column "group".

Parameters

- **name** (Optional[str]) – new group_identifier
- **pattern** (Optional[str]) – string pattern
- **glob** (Optional[str]) – glob pattern passed to Path.match()
- **regex** (Optional[str]) – regex pattern
- **column** (str) – Name of column in *Files.df* carrying files to match

Return type Self

locan.locan_io.locdata

File input/output for localization data.

There are functions for reading the following file structures (with an indicator string in parenthesis - see also *locan.constants.FileType*):

- custom text file (CUSTOM)
- rapidSTORM file format (RAPIDSTORM)[1]
- Elyra file format (ELYRA)
- Thunderstorm file format (THUNDERSTORM)[2]
- asdf file format (ASDF)[3]
- Nanoimager file format (NANOIMAGER)
- rapidSTORM track file format (RAPIDSTORMTRACK)[1]
- smlm file format (SMLM)[4],[5]
- decode file (DECODE)[6]
- smap file format (SMAP)[7]

[1] Wolter S, Löschberger A, Holm T, Aufmkolk S, Dabauvalle MC, van de Linde S, Sauer M., rapidSTORM: accurate, fast open-source software for localization microscopy. Nat Methods 9(11):1040-1, 2012, doi: 10.1038/nmeth.2224

[2] M. Ovesný, P. Křížek, J. Borkovec, Z. Švindrych, G. M. Hagen. ThunderSTORM: a comprehensive ImageJ plugin for PALM and STORM data analysis and super-resolution imaging. Bioinformatics 30(16):2389-2390, 2014.

[3] Greenfield, P., Droettboom, M., & Bray, E., ASDF: A new data format for astronomy. Astronomy and Computing, 12: 240-251, 2015, doi:10.1016/j.ascom.2015.06.004

[4] Ouyang et al., Deep learning massively accelerates super-resolution localization microscopy. Nat. Biotechnol. 2018, doi:10.1038/nbt.4106.

[5] https://github.com/imodpasteur/smlm-file-format

[6] Artur Speiser, Lucas-Raphael Müller, Philipp Hoess, Ulf Matti, Christopher J. Obara, Wesley R. Legant, Anna Kreshuk, Jakob H. Macke, Jonas Ries, and Srinivas C. Turaga, Deep learning enables fast and dense single-molecule localization with high accuracy. Nat Methods 18: 1082–1090, 2021, doi:10.1038/s41592-021-01236-x

[7] Ries, J., SMAP: a modular super-resolution microscopy analysis platform for SMLM data. Nat Methods 17: 870–872, 2020, doi.org/10.1038/s41592-020-0938-1

References

Submodules:

io_locdata	File input/output for localization data.
utilities	Utility functions for file input/output of localization data.
rapidstorm_io	File input/output for localization data in rapidSTORM files.
thunderstorm_io	File input/output for localization data in Thunderstorm files.
elyra_io	File input/output for localization data in Elyra files.
nanoimager_io	File input/output for localization data Nanoimager files.
asdf_io	File input/output for localization data in ASDF files
smlm_io	File input/output for localization data in SMLM files.
decode_io	File input/output for localization data in DECODE files.
smap_io	File input/output for localization data in SMAP files.

locan.locan_io.locdata.io_locdata

File input/output for localization data.

Functions

load_locdata(path[, file_type, nrows])	Load data from localization file as specified by type.
load_txt_file(path[, sep, columns, nrows, ...])	Load localization data from a txt file.

locan.locan_io.locdata.io_locdata.load_locdata

locan.locan_io.locdata.io_locdata.**load_locdata**(*path*, *file_type=1*, *nrows=None*, ***kwargs*)

Load data from localization file as specified by type.

This function is a wrapper for read functions for the various types of SMLM data.

Parameters

- **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a localization data file to load.

- **file_type** (*int | str | locan.constants.FileType | locan.data.metadata_pb2.Metadata*) – Indicator for the file type. Integer or string should be according to locan.constants.FileType.
- **nrows** (*int | None*) – The number of localizations to load from file. None means that all available rows are loaded.
- **kwargs** (*Any*) – kwargs passed to the specific load function.

Returns A new instance of LocData with all localizations.

Return type *LocData*

locan.locan_io.locdata.io_locdata.load_txt_file

locan.locan_io.locdata.io_locdata.**load_txt_file**(*path*, *sep=','*, *columns=None*, *nrows=None*, *property_mapping=None*, *convert=True*, ***kwargs*)

Load localization data from a txt file.

Locan column names are either supplied or read from the first line header.

Parameters

- **path** (*str | os.PathLike[str] | SupportsRead[Any]*) – File path for a localization file to load.
- **sep** (*str*) – separator between column values (Default: ‘,’)
- **columns** (*list[str] | None*) – Locan column names. If None the first line is interpreted as header (Default: None).
- **nrows** (*int | None*) – The number of localizations to load from file. None means that all available rows are loaded (Default: None).
- **property_mapping** (*dict[str, str] | list[dict[str, str]] | None*) – Mappings between column names and locan property names
- **convert** (*bool*) – If True convert types by applying type specifications in locan.constants.PROPERTY_KEYS.
- **kwargs** (*Any*) – Other parameters passed to *pandas.read_csv()*.

Returns A new instance of LocData with all localizations.

Return type *LocData*

locan.locan_io.locdata.utilities

Utility functions for file input/output of localization data.

Functions

convert_property_names(properties[, ...])	Convert property names to standard locan property names if a mapping is provided.
convert_property_types(dataframe, types[, ...])	Convert data types according to the column-type mapping in types.
open_path_or_file_like(path_or_file_like[, ...])	Provide open-file context from *path_or_file_like* input.

locan.locan_io.locdata.utilities.convert_property_names

locan.locan_io.locdata.utilities.**convert_property_names**(*properties*, *property_mapping=None*)

Convert property names to standard locan property names if a mapping is provided. Otherwise, leave the property name as is and throw a warning.

Parameters

- **properties** (Iterable[str]) – Properties to be converted
- **property_mapping** (Union[dict[str, str], Iterable[dict[str, str]], None]) – Mappings between other property names and locan property names

Returns Converted property names

Return type list[str]

locan.locan_io.locdata.utilities.convert_property_types

locan.locan_io.locdata.utilities.**convert_property_types**(*dataframe*, *types*, *loc_properties=None*)

Convert data types according to the column-type mapping in types. If the target type is one of 'integer', 'signed', 'unsigned', 'float' then `pandas.to_numeric()` will be applied. Otherwise, if the target type is any type object like *int*, *str*, *np.float64* or similar then `pandas.astype()` will be applied.

Parameters

- **dataframe** (DataFrame) – Data to be converted
- **types** (Mapping[str, str | type]) – Mapping of loc_properties to types
- **loc_properties** (Optional[Iterable[str]]) – The columns in dataframe to be converted. If None, all columns will be converted according to types.

Returns A copy of dataframe with converted types

Return type pandas.DataFrame

locan.locan_io.locdata.utilities.open_path_or_file_like

locan.locan_io.locdata.utilities.**open_path_or_file_like**(*path_or_file_like*, *mode='r'*, *encoding=None*)

Provide open-file context from *path_or_file_like* input.

Parameters

- **path_or_file_like** (*str | bytes | os.PathLike[Any] | int | SupportsRead[Any]*) – Identifier for file
- **mode** (*str*) – same as in *open()*
- **encoding** (*str | None*) – same as in *open()*

Return type context for file object

locan.locan_io.locdata.rapidstorm_io

File input/output for localization data in rapidSTORM files.

Functions

load_rapidSTORM_file(path[, nrows, convert])	Load data from a rapidSTORM single-molecule localization file.
load_rapidSTORM_header(path)	Load xml header from a rapidSTORM single-molecule localization file and identify column names.
load_rapidSTORM_track_file(path[, nrows, ...])	Load data from a rapidSTORM single-molecule localization file with tracked localizations.
load_rapidSTORM_track_header(path)	Load xml header from a rapidSTORM (track) single-molecule localization file and identify column names.

locan.locan_io.locdata.rapidstorm_io.load_rapidSTORM_file

locan.locan_io.locdata.rapidstorm_io.**load_rapidSTORM_file**(*path*, *nrows=None*, *convert=True*, ***kwargs*)

Load data from a rapidSTORM single-molecule localization file.

Parameters

- **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a rapidSTORM file to load.
- **nrows** (*int | None*) – The number of localizations to load from file. None means that all available rows are loaded.
- **convert** (*bool*) – If True convert types by applying type specifications in locan.constants.PROPERTY_KEYS.
- **kwargs** (*Any*) – Other parameters passed to *pandas.read_csv()*.

Returns A new instance of LocData with all localizations.

Return type *LocData*

locan.locan_io.locdata.rapidstorm_io.load_rapidSTORM_header

locan.locan_io.locdata.rapidstorm_io.**load_rapidSTORM_header**(*path*)

Load xml header from a rapidSTORM single-molecule localization file and identify column names.

Parameters **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a rapidSTORM file to load.

Returns A list of valid dataset property keys as derived from the rapidSTORM identifiers.

Return type list[str]

locan.locan_io.locdata.rapidstorm_io.load_rapidSTORM_track_file

locan.locan_io.locdata.rapidstorm_io.**load_rapidSTORM_track_file**(*path*, *nrows=None*, *convert=True*, *collection=True*, *min_localization_count=1*, ***kwargs*)

Load data from a rapidSTORM single-molecule localization file with tracked localizations.

Parameters

- **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a rapidSTORM file to load.
- **nrows** (*int | None*) – The number of localizations to load from file. None means that all available rows are loaded.
- **convert** (*bool*) – If True convert types by applying type specifications in locan.constants.PROPERTY_KEYS.
- **collection** (*bool*) – If True a collection of all tracks is returned. If False LocData with center positions is returned.
- **min_localization_count** (*int*) – If collection is True, only clusters with at least *min_localization_count* localizations are loaded.
- **kwargs** (*Any*) – Other parameters passed to *pandas.read_csv()*.

Returns A new instance of LocData with all localizations/tracks as a collection.

Return type *LocData*

locan.locan_io.locdata.rapidstorm_io.load_rapidSTORM_track_header

locan.locan_io.locdata.rapidstorm_io.**load_rapidSTORM_track_header**(*path*)

Load xml header from a rapidSTORM (track) single-molecule localization file and identify column names.

Parameters **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a rapidSTORM file to load.

Returns A list of valid dataset property keys as derived from the rapidSTORM identifiers.

Return type tuple[list[str], list[str]]

locan.locan_io.locdata.thunderstorm_io

File input/output for localization data in Thunderstorm files.

Functions

load_thunderstorm_file(path[, nrows, convert])	Load data from a Thunderstorm single-molecule localization file.
load_thunderstorm_header(path)	Load csv header from a Thunderstorm single-molecule localization file and identify column names.
save_thunderstorm_csv(locdata, path)	Save LocData attributes Thunderstorm-readable csv-file.

locan.locan_io.locdata.thunderstorm_io.load_thunderstorm_file

locan.locan_io.locdata.thunderstorm_io.**load_thunderstorm_file**(*path*, *nrows=None*, *convert=True*, ***kwargs*)

Load data from a Thunderstorm single-molecule localization file.

Parameters

- **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a Thunderstorm file to load.
- **nrows** (*int | None*) – The number of localizations to load from file. None means that all available rows are loaded.
- **convert** (*bool*) – If True convert types by applying type specifications in locan.constants.PROPERTY_KEYS.
- **kwargs** (*Any*) – Other parameters passed to *pandas.read_csv()*.

Returns A new instance of LocData with all localizations.

Return type *LocData*

locan.locan_io.locdata.thunderstorm_io.load_thunderstorm_header

locan.locan_io.locdata.thunderstorm_io.**load_thunderstorm_header**(*path*)

Load csv header from a Thunderstorm single-molecule localization file and identify column names.

Parameters **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a Thunderstorm file to load.

Returns A list of valid dataset property keys as derived from the Thunderstorm identifiers.

Return type list[str]

locan.locan_io.locdata.thunderstorm_io.save_thunderstorm_csv

locan.locan_io.locdata.thunderstorm_io.**save_thunderstorm_csv**(*locdata*, *path*)

Save LocData attributes Thunderstorm-readable csv-file.

In the Thunderstorm csv-file file format we store only localization data with Thunderstorm-readable column names.

Parameters

- **locdata** (LocData) – The LocData object to be saved.
- **path** (*str | os.PathLike[Any] | SupportsWrite[Any]*) – File path including file name to save to.

Return type None

locan.locan_io.locdata.elyra_io

File input/output for localization data in Elyra files.

Functions

load_Elyra_file(path[, nrows, convert])	Load data from a rapidSTORM single-molecule localization file.
load_Elyra_header(path)	Load xml header from a Zeiss Elyra single-molecule localization file and identify column names.

locan.locan_io.locdata.elyra_io.load_Elyra_file

locan.locan_io.locdata.elyra_io.**load_Elyra_file**(*path*, *nrows=None*, *convert=True*, ***kwargs*)

Load data from a rapidSTORM single-molecule localization file.

Parameters

- **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a rapidSTORM file to load.
- **nrows** (*int | None*) – The number of localizations to load from file. None means that all available rows are loaded.
- **convert** (*bool*) – If True convert types by applying type specifications in locan.constants.PROPERTY_KEYS.
- **kwargs** (*Any*) – Other parameters passed to *pandas.read_csv()*.

Returns A new instance of LocData with all localizations.

Return type *LocData*

Note: Data is loaded with encoding = 'latin-1' and only data before the first NUL character is returned. Additional information appended at the end of the file is thus ignored.

---

locan.locan_io.locdata.elyra_io.load_Elyra_header

locan.locan_io.locdata.elyra_io.**load_Elyra_header**(*path*)

Load xml header from a Zeiss Elyra single-molecule localization file and identify column names.

Parameters **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a rapidSTORM file to load.

Returns A list of valid dataset property keys as derived from the rapidSTORM identifiers.

Return type list[str]

locan.locan_io.locdata.nanoimager_io

File input/output for localization data Nanoimager files.

Functions

load_Nanoimager_file(path[, nrows, convert])	Load data from a Nanoimager single-molecule localization file.
load_Nanoimager_header(path)	Load csv header from a Nanoimager single-molecule localization file and identify column names.

locan.locan_io.locdata.nanoimager_io.load_Nanoimager_file

locan.locan_io.locdata.nanoimager_io.**load_Nanoimager_file**(*path*, *nrows=None*, *convert=True*, ***kwargs*)

Load data from a Nanoimager single-molecule localization file.

Parameters

- **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a Nanoimager file to load.
- **nrows** (*int | None*) – The number of localizations to load from file. None means that all available rows are loaded.
- **convert** (*bool*) – If True convert types by applying type specifications in locan.constants.PROPERTY_KEYS.
- **kwargs** (*Any*) – Other parameters passed to *pandas.read_csv()*.

Returns A new instance of LocData with all localizations.

Return type *LocData*

locan.locan_io.locdata.nanoimager_io.load_Nanoimager_header

locan.locan_io.locdata.nanoimager_io.**load_Nanoimager_header**(*path*)

Load csv header from a Nanoimager single-molecule localization file and identify column names.

Parameters **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a Nanoimager file to load.

Returns A list of valid dataset property keys as derived from the Nanoimager identifiers.

Return type list[str]

locan.locan_io.locdata.asdf_io

File input/output for localization data in ASDF files

Functions

load_asdf_file(path[, nrows, convert])	Load data from ASDF localization file.
save_asdf(locdata, path)	Save LocData attributes in an asdf file.

locan.locan_io.locdata.asdf_io.load_asdf_file

locan.locan_io.locdata.asdf_io.**load_asdf_file**(*path*, *nrows=None*, *convert=True*)

Load data from ASDF localization file.

Parameters

- **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a rapidSTORM file to load.
- **nrows** (*int | None*) – The number of localizations to load from file. None means that all available rows are loaded.
- **convert** (*bool*) – If True convert types by applying type specifications in locan.constants.PROPERTY_KEYS.

Returns A new instance of LocData with all localizations.

Return type *LocData*

locan.locan_io.locdata.asdf_io.save_asdf

locan.locan_io.locdata.asdf_io.**save_asdf**(*locdata*, *path*)

Save LocData attributes in an asdf file.

In the Advanced Scientific Data Format (ASDF) file format we store metadata, properties and column names as human-readable yaml header. The data is stored as binary numpy.ndarray.

Note: Only selected LocData attributes are saved. Currently these are: 'data', 'columns', 'properties', 'meta'.

Parameters

- **locdata** (LocData) – The LocData object to be saved.
- **path** (*str | os.PathLike[Any] | SupportsWrite[Any]*) – File path including file name to save to.

Return type None

locan.locan_io.locdata.smlm_io

File input/output for localization data in SMLM files.

File specifications are provided at https://github.com/imodpasteur/smlm-file-format/blob/master/specification.md.

Code is adapted from https://github.com/imodpasteur/smlm-file-format/blob/master/implementations/Python/smlm_file.py. (MIT license)

Functions

load_SMLM_file(path[, nrows, convert])	Load data from a SMLM single-molecule localization file.
load_SMLM_header(path)	Read header (manifest) from a SMLM single-molecule localization file and identify column names.
load_SMLM_manifest(path)	Read manifest.json (version 0.2) from a SMLM single-molecule localization (zip) file.
manifest_file_info_from_locdata(locdata)	Prepare a manifest["file_info"] protobuf from locdata.
manifest_format_from_locdata(locdata)	Prepare a manifest["format"] protobuf from locdata.
manifest_from_locdata(locdata[, ...])	Prepare a manifest protobuf from locdata.
save_SMLM(locdata, path[, manifest])	Save LocData attributes in a SMLM single-molecule localization (zip) file with manifest.json (version 0.2).

locan.locan_io.locdata.smlm_io.load_SMLM_file

locan.locan_io.locdata.smlm_io.**load_SMLM_file**(*path*, *nrows=None*, *convert=True*)

Load data from a SMLM single-molecule localization file.

Parameters

- **path** (Union[str, PathLike[Any], IO[Any]]) – File path for a SMLM file to load.
- **nrows** (Optional[int]) – The number of localizations to load from file. None means that all available rows are loaded.
- **convert** (bool) – If True convert types by applying type specifications in locan.constants.PROPERTY_KEYS.

Returns A new instance of LocData with all localizations. Returns a list of LocData if multiple tables are found.

Return type *LocData* | list[*LocData*]

locan.locan_io.locdata.smlm_io.load_SMLM_header

locan.locan_io.locdata.smlm_io.**load_SMLM_header**(*path*)

Read header (manifest) from a SMLM single-molecule localization file and identify column names.

Parameters **path** (Union[str, PathLike[str], IO[Any]]) – File path for a SMLM file to load.

Returns A list of dataset property keys as derived from the SMLM identifiers.

Return type list[str]

locan.locan_io.locdata.smlm_io.load_SMLM_manifest

locan.locan_io.locdata.smlm_io.**load_SMLM_manifest**(*path*)

Read manifest.json (version 0.2) from a SMLM single-molecule localization (zip) file.

Parameters **path** (Union[str, PathLike[str], IO[Any]]) – File path for a SMLM file to load.

Returns manifest in json format

Return type dict[str, Any]

locan.locan_io.locdata.smlm_io.manifest_file_info_from_locdata

locan.locan_io.locdata.smlm_io.**manifest_file_info_from_locdata**(*locdata*)

Prepare a manifest["file_info"] protobuf from locdata. The manifest holds metadata for smlm files.

Parameters **locdata** (LocData) – The LocData object.

Returns The manifest file information

Return type locan.locan_io.locdata.manifest_pb2.FileInfo

locan.locan_io.locdata.smlm_io.manifest_format_from_locdata

locan.locan_io.locdata.smlm_io.**manifest_format_from_locdata**(*locdata*)

Prepare a manifest["format"] protobuf from locdata. The manifest holds metadata for smlm files.

Parameters **locdata** (LocData) – The LocData object.

Returns The manifest format

Return type locan.locan_io.locdata.manifest_pb2.Format

locan.locan_io.locdata.smlm_io.manifest_from_locdata

locan.locan_io.locdata.smlm_io.**manifest_from_locdata**(*locdata*, *return_json_string=False*)

Prepare a manifest protobuf from locdata. The manifest holds metadata for smlm files.

Parameters

- **locdata** (LocData) – The LocData object.
- **return_json_string** (*bool*) – Flag for returning json string

Returns The manifest

Return type locan.locan_io.locdata.manifest_pb2.Manifest | str

locan.locan_io.locdata.smlm_io.save_SMLM

locan.locan_io.locdata.smlm_io.**save_SMLM**(*locdata*, *path*, *manifest=None*)

Save LocData attributes in a SMLM single-molecule localization (zip) file with manifest.json (version 0.2).

In the smlm file format we store metadata as a human- readable manifest. The data is stored as byte string.

Note: Only selected LocData attributes are saved. These are: 'data', 'columns', 'meta'.

Parameters

- **locdata** (*LocData*) – The LocData object to be saved.
- **path** (Union[str, PathLike[Any], IO[Any]]) – File path including file name to save to.
- **manifest** (Optional[Manifest]) – Protobuf with manifest to use instead of an autogenerated manifest.

Return type None

locan.locan_io.locdata.decode_io

File input/output for localization data in DECODE files.

Functions

load_decode_file(path[, nrows, convert])	Load data from a DECODE single-molecule localization file.
load_decode_header(path)	Load header from a DECODE single-molecule localization file and identify column names.

locan.locan_io.locdata.decode_io.load_decode_file

locan.locan_io.locdata.decode_io.**load_decode_file**(*path*, *nrows=None*, *convert=True*)

Load data from a DECODE single-molecule localization file.

Parameters

- **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path or file-like object for a Thunderstorm file to load.
- **nrows** (*int | None*) – The number of localizations to load from file. None means that all available rows are loaded.
- **convert** (*bool*) – If True convert types by applying type specifications in locan.constants.PROPERTY_KEYS.

Returns A new instance of LocData with all localizations.

Return type *LocData*

locan.locan_io.locdata.decode_io.load_decode_header

locan.locan_io.locdata.decode_io.**load_decode_header**(*path*)

Load header from a DECODE single-molecule localization file and identify column names.

The hdf5 file should contain the following keys: <KeysViewHDF5 ['data', 'decode', 'meta']>

Parameters **path** (*str | os.PathLike | SupportsRead*) – File path or file-like object for a DECODE file to load.

Returns Tuple with identifiers, meta and decode sections. Identifiers are list of valid dataset property keys as derived from the DECODE identifiers.

Return type tuple[list[str], dict[str, Any], dict[str, Any]]

locan.locan_io.locdata.smap_io

File input/output for localization data in SMAP files.

Functions

load_SMAP_file(path[, nrows, convert])	Load data from a SMAP single-molecule localization file.
load_SMAP_header(path)	Identify column names from a SMAP single-molecule localization file.
save_SMAP_csv(locdata, path)	Save LocData to SMAP-readable csv-file.

locan.locan_io.locdata.smap_io.load_SMAP_file

locan.locan_io.locdata.smap_io.**load_SMAP_file**(*path*, *nrows=None*, *convert=True*)

Load data from a SMAP single-molecule localization file.

Parameters

- **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a Thunderstorm file to load.
- **nrows** (*int | None*) – The number of localizations to load from file. None means that all available rows are loaded.
- **convert** (*bool*) – If True convert types by applying type specifications in locan.constants.PROPERTY_KEYS.

Returns A new instance of LocData with all localizations.

Return type *LocData*

locan.locan_io.locdata.smap_io.load_SMAP_header

locan.locan_io.locdata.smap_io.**load_SMAP_header**(*path*)

Identify column names from a SMAP single-molecule localization file.

Parameters **path** (*str | os.PathLike[Any] | SupportsRead[Any]*) – File path for a file to load.

Returns A list of valid dataset property keys as derived from the rapidSTORM identifiers.

Return type list[str]

locan.locan_io.locdata.smap_io.save_SMAP_csv

locan.locan_io.locdata.smap_io.**save_SMAP_csv**(*locdata*, *path*)

Save LocData to SMAP-readable csv-file.

In the csv-file file format we store only localization data with SMAP-readable column names.

Parameters

- **locdata** (LocData) – The LocData object to be saved.

- **path** (*str | os.PathLike[Any] | SupportsWrite[Any]*) – File path including file name to save to.

Return type None

locan.locan_io.utilities

Utility functions for file input/output.

Functions

find_file_upstream(sub_directory, pattern[, ...])	Search for first upstream parent of sub_directory that contains pattern.

locan.locan_io.utilities.find_file_upstream

locan.locan_io.utilities.**find_file_upstream**(*sub_directory*, *pattern*, *regex=None*, *top_directory=None*)

Search for first upstream parent of sub_directory that contains pattern. Return first pattern found. Return None if no pattern has been found when parent equals directory.

Parameters

- **sub_directory** (str | PathLike[str]) – Directory or file path to start with.
- **pattern** (Optional[str]) – glob pattern passed to Path.glob()
- **regex** (Optional[str]) – regex pattern passed to re.search() and applied in addition to glob pattern
- **top_directory** (Union[str, PathLike[str], None]) – Directory in which to stop the search.

Return type Path | None

8.9 locan.rois

Region of interest.

This module provides functions for managing regions of interest in localization data.

8.9.1 Submodules:

roi	The Roi class is an object that defines a region of interest within a localization dataset.

locan.rois.roi

The Roi class is an object that defines a region of interest within a localization dataset. It is therefore related to region specifications and a unique LocData object.

The Roi object provides methods for saving all specifications to a yaml file, for loading them, and for returning LocData with localizations selected to be within the roi region.

Classes

Roi(region[, reference, loc_properties])	Class for defining a region of interest for a referenced LocData object.
RoiLegacy_0(region_type, region_specs[, ...])	Class for a region of interest on LocData (roi).

locan.rois.roi.Roi

class locan.rois.roi.**Roi**(*region*, *reference=None*, *loc_properties=None*)

Bases: object

Class for defining a region of interest for a referenced LocData object.

Parameters

- **region** (Region) – Geometrical region of interest.
- **reference** (LocData | *dict* | *locan.data.metadata_pb2.Metadata* | *locan.data.metadata_pb2.File* | *None*) – Reference to localization data for which the region of interest is defined. It can be a LocData object, a reference to a saved SMLM file, or None for indicating no specific reference. When dict it must have keys *file_path`and `file_type*. When Metadata message it must have keys *file.path* and *file.type* for a path pointing to a localization file and an integer or string indicating the file type. Integer or string should be according to locan.constants.FileType.
- **loc_properties** (*Sequence[str]* | *None*) – Localization properties in LocData object on which the region selection will be applied (for instance the coordinate_keys).

Variables

- **region** (Region) – Geometrical region of interest.
- **reference** (LocData | *locan.data.metadata_pb2.Metadata* | *None*) – Reference to localization data for which the region of interest is defined. It can be a LocData object, a reference to a saved SMLM file, or None for indicating no specific reference. When referencing a saved SMLM

file, reference has attributes *file.path* and *file.type* for a path pointing to a localization file and an integer indicating the file type.

- **loc_properties** (*tuple[str, ...] | None*) – Localization properties in LocData object on which the region selection will be applied (for instance the coordinate_keys).

Methods

`__init__`(region[, reference, loc_properties])	
from_yaml(path)	Read Roi object from yaml format.
locdata([reduce])	Localization data according to roi specifications.
to_yaml([path])	Save Roi object in yaml format.

Attributes

region	**rtype** *Region*

classmethod from_yaml(*path*)

Read Roi object from yaml format.

Parameters **path** (`str | PathLike[Any]`) – Path for yaml file.

Return type `TypeVar(T_Roi, bound= Roi)`

locdata(*reduce=True*)

Localization data according to roi specifications.

The ROI is applied on locdata properties as specified in self.loc_properties or by taking the first applicable locdata.coordinate_keys.

Parameters **reduce** (`bool`) – Return the reduced LocData object or keep references alive.

Returns A new instance of LocData with all localizations within region of interest.

Return type *LocData*

property region: *locan.data.region.Region*

Return type *Region*

to_yaml(*path=None*)

Save Roi object in yaml format.

Parameters **path** (`Union[str, PathLike[str], None]`) – Path for yaml file. If None a roi file path is generated from the metadata.

Return type `None`

locan.rois.roi.RoiLegacy_0

class locan.rois.roi.**RoiLegacy_0**(*region_type*, *region_specs*, *reference=None*, *properties_for_roi=()*)

Bases: `object`

Class for a region of interest on LocData (roi).

Roi objects define a region of interest for a referenced LocData object.

Parameters

- **reference** (LocData, *dict*, *locan.data.metadata_pb2.Metadata*, *None*) – Reference to localization data for which the region of interests are defined. It can be a LocData object, a reference to a saved SMLM file, or None for indicating no specific reference. When referencing a saved SMLM file, reference must be a dict or locan.data.metadata_pb2.Metadata with keys *file_path* and *file_type* for a path pointing to a localization file and an integer or string indicating the file type. Integer or string should be according to locan.constants.FileType.
- **region_type** (*str*) – A string indicating the roi shape. In 1D it can be *interval*. In 2D it can be either *rectangle*, *ellipse*, or closed *polygon*. In 3D it can be either *cuboid* or *ellipsoid* or *polyhedron* (not implemented yet).
- **region_specs** (*tuple*) – 1D rois are defined by the following tuple: * interval: (start, stop) 2D rois are defined by the following tuples: * rectangle: ((corner_x, corner_y), width, height, angle) * ellipse: ((center_x, center_y), width, height, angle) * polygon: ((point1_x, point1_y), (point2_x, point2_y), …, (point1_x, point1_y)) 3D rois are defined by the following tuples: * cuboid: ((corner_x, corner_y, corner_z), length, width, height, angle_1, angle_2, angle_3) * ellipsoid: ((center_x, center_y, center_z), length, width, height, angle_1, angle_2, angle_3) * polyhedron: (…)
- **properties_for_roi** (*tuple[str, ...]*) – Localization properties in LocData object on which the region selection will be applied (for instance the coordinate_keys).

Variables

- **reference** (LocData | *locan.data.metadata_pb2.Metadata* | *None*) – Reference to localization data for which the regions of interest are defined. It can be a LocData object, a reference (locan.data.metadata_pb2.Metadata) to a saved SMLM file, or None for indicating no specific reference. When referencing a saved SMLM file, reference as attributes *file_path* and *file_type* for a path pointing to a localization file and an integer indicating the file type. The integer should be according to locan.data.metadata_pb2.Metadata.file_type.
- **_region** (RoiRegion | *list[RoiRegion]*) – Object specifying the geometrical region of interest. In case a list of RoiRegion is provided it is the union that makes up the region of interest.
- **properties_for_roi** (*tuple[str, ...]*) – Localization properties in LocData object on which the region selection will be applied (for instance the coordinate_keys).

Warning: *RoiLegacy* is deprecated and should only be used to read legacy _roi.yaml files. Use `locan.Roi` instead.

Methods

`__init__`(region_type, region_specs[, ...])	

from_yaml(path)	Read Roi object from yaml format.
locdata([reduce])	Localization data according to roi specifications.
to_yaml([path])	Save Roi object in yaml format.

Attributes

region

classmethod from_yaml(*path*)

Read Roi object from yaml format.

Parameters **path** (*str | os.PathLike*) – Path for yaml file.

locdata(*reduce=True*)

Localization data according to roi specifications.

The ROI is applied on locdata properties as specified in self.loc_properties or by taking the first applicable locdata.coordinate_keys.

Parameters **reduce** (*bool*) – Return the reduced LocData object or keep references alive.

Returns A new instance of LocData with all localizations within region of interest.

Return type *LocData*

property region

to_yaml(*path=None*)

Save Roi object in yaml format.

Parameters **path** (*str | os.PathLike | None*) – Path for yaml file. If None a roi file path is generated from the metadata.

Functions

rasterize(locdata[, support, n_regions, ...])	Provide regions of interest by dividing the locdata support in equally sized rectangles.

locan.rois.roi.rasterize

locan.rois.roi.**rasterize**(*locdata*, *support=None*, *n_regions=(2, 2, 2)*, *loc_properties=()*)

Provide regions of interest by dividing the locdata support in equally sized rectangles.

Parameters

- **locdata** (*LocData*) – The localization data from which to select localization data.
- **support** (Optional[tuple[tuple[int], ...]]) – Coordinate intervals that are divided in *n_regions* subintervals. For None intervals are taken from the bounding box.
- **n_regions** (tuple[int, ...]) – Number of regions in each dimension. E.g. *n_regions* = (2, 2) returns 4 rectangular Roi objects.
- **loc_properties** (Iterable[str]) – Localization properties in LocData object on which the region selection will be applied. (Only implemented for coordinates labels)

Returns A sequence of Roi objects

Return type tuple[*Roi*, ...]

8.10 locan.scripts

Command-line utility scripts

The locan package provides a command-line interface. It is accessible by the base command `locan` and provides a number of compound commands. See available commands using `locan -h`.

This subpackage contains implementations of command-line scripts. Scripts are installed in bin/ as simple wrappers for these modules. They can be run directly from a terminal through `locan command options` as long as the correct environment is activated.

8.10.1 Submodules:

script_check	Show original SMLM images overlaid with localization data.
script_rois	Define regions of interest with napari and save as roi files.
script_draw_roi	Define regions of interest with matplotlib and save as roi files.
script_napari	Render localization data in napari.
script_show_versions	Show system information and dependency versions.
script_test	Run project test suite with pytest.

locan.scripts.script_check

Show original SMLM images overlaid with localization data. Data is rendered in napari.

To run the script:

```
locan check <pixel size> -f <images file> -l <localization file> -t <file␣
↪type>
```

Try for instance:

```
locan check 133 -f "locan/tests/test_data/images.tif" -l "locan/tests/test_
↪data/rapidStorm_from_images.txt" -t 2
```

Functions

main([args])	**rtype** None
render_locs_per_frame_napari(images, ...[, ...])	Display original recording and overlay localization spots in napari.
sc_check(pixel_size[, file_images, ...])	Load and display original recording and load and overlay localization spots in napari.

locan.scripts.script_check.main

locan.scripts.script_check.**main**(*args=None*)

Return type None

locan.scripts.script_check.render_locs_per_frame_napari

locan.scripts.script_check.**render_locs_per_frame_napari**(*images*, *pixel_size*, *locdata*, *viewer=None*, *transpose=True*, *kwargs_image=None*, *kwargs_points=None*)

Display original recording and overlay localization spots in napari.

Parameters

- **images** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Stack of raw data as recorded by camera.
- **pixel_size** (float | tuple[float]) – Pixel size for images (in locdata units) with shape (2,).
- **transpose** (bool) – If True transpose x and y axis of *images*.
- **locdata** (*LocData*) – Localization data that corresponds to *images* raw data.
- **viewer** (Optional[Viewer]) – The viewer object on which to add the image
- **kwargs_image** (Optional[dict[str, Any]]) – Other parameters passed to napari.Viewer().add_image().
- **kwargs_points** (*dict*) – Other parameters passed to napari.Viewer().add_points().

Returns Viewer with the image.

Return type napari.Viewer

locan.scripts.script_check.sc_check

locan.scripts.script_check.**sc_check**(*pixel_size*, *file_images=None*, *file_locdata=None*, *file_type=FileType.RAPIDSTORM*, *viewer=None*, *transpose=True*, *kwargs_image=None*, *kwargs_points=None*)

Load and display original recording and load and overlay localization spots in napari.

Parameters

- **pixel_size** (float | tuple[float]) – Pixel size for images (in locdata units) with shape (2,).
- **file_images** (Union[str, PathLike[Any], None]) – File path for stack of raw data as recorded by camera.
- **file_locdata** (Union[str, PathLike[Any], None]) – File path for localization data that corresponds to *images* raw data.
- **file_type** (int | str | *FileType* | Metadata) – Indicator for the file type. Integer or string should be according to locan.constants.FileType.

- **transpose** (bool) – If True transpose x and y axis of *images*.
- **viewer** (*napari.Viewer*) – The viewer object on which to add the image
- **kwargs_image** (*dict*) – Other parameters passed to napari.Viewer.add_image().
- **kwargs_points** (*dict*) – Other parameters passed to napari.Viewer.add_points().

Return type None

locan.scripts.script_rois

Define regions of interest with napari and save as roi files.

With this script you can choose a file name, open the localization file in napari. Draw regions of interest as additional shapes in napari. Upon closing napari each shape is taken as single roi and saved as _roi.yaml file.

To run the script:

```
locan rois -f <file> -t <file type> -i <roi file indicator> --bin_size <>
--rescale <string with tuple or rescale>
```

Try for instance:

```
locan rois -f "locan/tests/test_data/five_blobs.txt" -t 1 -i "_roi" --bin_
↪size 10
```

See also:

locan.visualize.render_napari.utilities.select_by_drawing_napari

Functions

main([args])	**rtype** None
sc_draw_roi_napari([file_path, file_type, ...])	Define regions of interest by drawing a boundary.

locan.scripts.script_rois.main

locan.scripts.script_rois.**main**(*args=None*)

Return type None

locan.scripts.script_rois.sc_draw_roi_napari

locan.scripts.script_rois.**sc_draw_roi_napari**(*file_path=None*, *file_type=FileType.CUSTOM*, *roi_file_indicator='_roi'*, ***kwargs*)

Define regions of interest by drawing a boundary.

Parameters

- **file_path** (Union[str, PathLike[Any], None]) – File path to localization data.
- **file_type** (int | str | *FileType* | Metadata) – Indicator for the file type. Integer or string should be according to locan.constants.FileType.
- **roi_file_indicator** (str) – Indicator to add to the localization file name and use as roi file name (with further extension .yaml).
- **kwargs** (Any) – Other parameters passed to `render_2d_napari()`.

Returns File paths for all roi files

Return type list[Path]

locan.scripts.script_draw_roi

Define regions of interest with matplotlib and save as roi files.

With this script you can choose a file name, open the localization file and draw a rectangular region of interest. Within the matplotlib image draw a rectange, type '+' to add the roi to the list, then type 'q' to quit. The roi is then saved as _roi.yaml file.

To run the script:

```
locan draw_roi_mpl -f <file> -t <file type> -i <roi file indicator> -r
↪<region type>
```

Try for instance:

```
locan draw_roi_mpl -f "locan/tests/test_data/five_blobs.txt" -t 1 -i "_roi" -
↪r "ellipse"
```

See also:

`locan.rois.select_by_drawing_mpl`

Functions

main([args])	rtype None
sc_draw_roi_mpl([file_path, file_type, ...])	Define regions of interest by drawing a boundary.

locan.scripts.script_draw_roi.main

locan.scripts.script_draw_roi.**main**(*args=None*)

Return type None

locan.scripts.script_draw_roi.sc_draw_roi_mpl

locan.scripts.script_draw_roi.**sc_draw_roi_mpl**(*file_path=None*, *file_type=1*, *roi_file_indicator='_roi'*, *region_type='rectangle'*)

Define regions of interest by drawing a boundary.

Parameters

- **file_path** (Union[str, PathLike[Any], None]) – File path to localization data.
- **file_type** (int | str | *FileType* | Metadata) – Indicator for the file type. Integer or string should be according to locan.constants.FileType.
- **roi_file_indicator** (str) – Indicator to add to the localization file name and use as roi file name (with further extension .yaml).
- **region_type** (Literal['rectangle', 'ellipse', 'polygon']) – rectangle, ellipse, or polygon specifying the selection widget to use.

Return type None

locan.scripts.script_napari

Render localization data in napari.

With this script you can choose a file name and render the localization file in napari.

To run the script:

```
locan napari -f <file> -t <file type> -k <string with kwargs for render␣
↪function> --bin_size <>
--rescale <string with tuple or rescale>
```

Try for instance:

```
locan napari -f "locan/tests/test_data/five_blobs.txt" -t 1 --bin_size 10 --
↪rescale "0 1"
```

See also:

`locan.render.render2d.render_2d_napari`

Functions

main([args])	**rtype** None
sc_napari([file_path, file_type])	Render localization data in napari.

locan.scripts.script_napari.main

`locan.scripts.script_napari.`**main**(*args=None*)

Return type None

locan.scripts.script_napari.sc_napari

`locan.scripts.script_napari.`**sc_napari**(*file_path=None*, *file_type=FileType.CUSTOM*, ***kwargs*)

Render localization data in napari.

Parameters

- **file_path** (Union[str, PathLike[Any], None]) – File path to localization data.
- **file_type** (int | str | *FileType* | Metadata) – Indicator for the file type. Integer or string should be according to locan.constants.FileType.
- **kwargs** (Any) – Other parameters passed to `render_2d_napari()`.

Return type None

locan.scripts.script_show_versions

Show system information and dependency versions.

To run the script:

```
locan show_versions -v -e -o <module name> [<module name>...]
```

Try for instance:

```
locan show_versions -v -e
```

See also:

locan.utils.system_information.show_versions

Functions

main([args])	**rtype** None

locan.scripts.script_show_versions.main

locan.scripts.script_show_versions.**main**(*args=None*)

Return type None

locan.scripts.script_test

Run project test suite with pytest.

To run the script:

```
test
```

Try for instance:

```
test
```

See also:

locan.tests.test

Functions

main([args])	**rtype** None

locan.scripts.script_test.main

locan.scripts.script_test.**main**(*args=None*)

Return type None

8.11 locan.simulation

Synthetic data

This module provides functions to simulate localization and other data that can be used for testing and development.

8.11.1 Submodules:

simulate_locdata	Simulate localization data.
simulate_drift	Simulate drift and apply it to localization data.

locan.simulation.simulate_locdata

Simulate localization data.

This module provides functions to simulate localization data and return LocData objects. Localizations are often distributed either by a spatial process of complete-spatial randomness or following a Neyman-Scott process[1]. For a Neyman-Scott process parent events (representing single emitters) yield a random number of cluster_mu events (representing localizations due to repeated blinking). Related spatial point processes include Matérn and Thomas processes.

Functions that are named as make_* provide point data arrays. Functions that are named as simulate_* provide locdata.

Parts of this code is adapted from scikit-learn/sklearn/datasets/_samples_generator.py . (BSD 3-Clause License, Copyright (c) 2007-2020 The scikit-learn developers.)

[1] Neyman, J. & Scott, E. L., A Theory of the Spatial Distribution of Galaxies. Astrophysical Journal 1952, vol. 116, p.144.

References

Functions

make_Matern([parent_intensity, region, ...])	Generate clustered point data following a Matern cluster random point process.
make_NeymanScott([parent_intensity, region, ...])	Generate clustered point data following a Neyman-Scott random point process.
make_Poisson(intensity[, region, seed])	Provide points that are distributed by a uniform Poisson point process within the boundaries given by *region*.
make_Thomas([parent_intensity, region, ...])	Generate clustered point data following a Thomas random point process.
make_cluster([centers, region, ...])	Parent positions are taken from *centers* or are distributed according to a homogeneous Poisson process with exactly *centers* within the boundaries given by *region* expanded by the expansion_distance.
make_dstorm([parent_intensity, region, ...])	Generate clustered point data following a Thomas-like random point process.
make_uniform(n_samples[, region, seed])	Provide points that are distributed by a uniform (complete spatial randomness) point process within the boundaries given by *region*.
randomize(locdata[, hull_region, seed])	Transform locdata coordinates into randomized coordinates that follow complete spatial randomness on the same region as the input locdata.
resample(locdata[, n_samples, seed])	Resample locdata according to localization uncertainty.
simulate_Matern([parent_intensity, region, ...])	Generate clustered point data following a Matern cluster random point process.
simulate_NeymanScott([parent_intensity, ...])	Generate clustered point data following a Neyman-Scott random point process.
simulate_Poisson(intensity[, region, seed])	Provide points that are distributed by a uniform Poisson point process within the boundaries given by *region*.
simulate_Thomas([parent_intensity, region, ...])	Generate clustered point data following a Thomas random point process.
simulate_cluster([centers, region, ...])	Generate clustered point data.
simulate_dstorm([parent_intensity, region, ...])	Generate clustered point data following a Thomas-like random point process.
simulate_frame_numbers(n_samples, lam[, seed])	Simulate Poisson-distributed frame numbers for a list of localizations.
simulate_tracks([n_walks, n_steps, ranges, ...])	Provide a dataset of localizations representing random walks with starting points being spatially-distributed on a rectangular shape or cubic volume by complete spatial randomness.
simulate_uniform(n_samples[, region, seed])	Provide points that are distributed by a uniform Poisson point process within the boundaries given by *region*.

locan.simulation.simulate_locdata.make_Matern

locan.simulation.simulate_locdata.**make_Matern**(*parent_intensity=1*, *region=(0, 1.0)*, *cluster_mu=1*, *radius=1.0*, *clip=True*, *shuffle=True*, *seed=None*)

Generate clustered point data following a Matern cluster random point process. Parent positions are distributed according to a homogeneous Poisson process with *parent_intensity* within the boundaries given by *region* expanded by the maximum radius. Each parent position is then replaced by spots of size *radius* with Poisson distributed points inside. Offspring from parent events that are located outside the region are included.

Parameters

- **parent_intensity** (int | float) – The intensity (points per unit region measure) of the Poisson point process for parent events.
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for all features. If array-like it must provide upper and lower bounds for each feature.
- **cluster_mu** (int | float) – The mean number of points of the Poisson point process for cluster(cluster_mu) events.
- **radius** (float | Sequence[float]) – The radius for the spots. If tuple, the number of elements must be larger than the expected number of parents.
- **clip** (bool) – If True the result will be clipped to 'region'. If False the extended region will be kept.
- **shuffle** (bool) – If True shuffle the samples.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns The generated samples, labels, parent_samples of shape (n_samples, n_features) and region

Return type tuple[npt.NDArray[**np.float_**], npt.NDArray[**np.int_**], npt.NDArray[**np.float_**], Region]

locan.simulation.simulate_locdata.make_NeymanScott

locan.simulation.simulate_locdata.**make_NeymanScott**(*parent_intensity=100*, *region=(0, 1.0)*, *expansion_distance=0*, *offspring=None*, *clip=True*, *shuffle=True*, *seed=None*)

Generate clustered point data following a Neyman-Scott random point process. Parent positions are distributed according to a homogeneous Poisson process with *parent_intensity* within the boundaries given by *region* expanded by the expansion_distance. Each parent position is then replaced by offspring points as passed or generated by a given function. Offspring from parent events that are located outside the region are included.

Parameters

- **parent_intensity** (int | float) – The intensity (points per unit region measure) of the Poisson point process for parent events.
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for all features. If array-like it must provide upper and lower bounds for each feature.
- **expansion_distance** (float) – The distance by which region is expanded on all boundaries.
- **offspring** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], Callable[..., Any], None]) – Points or function for point process to provide offspring points. Callable must take single parent point as parameter. If array-like it must have enough elements to fit the randomly generated number of parent events.
- **clip** (bool) – If True the result will be clipped to 'region'. If False the extended region will be kept.
- **shuffle** (bool) – If True shuffle the samples.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns The generated samples, labels, parent_samples of shape (n_samples, n_features) and region

Return type tuple[npt.NDArray[**np.float_**], npt.NDArray[**np.int_**], npt.NDArray[**np.float_**], Region]

locan.simulation.simulate_locdata.make_Poisson

locan.simulation.simulate_locdata.**make_Poisson**(*intensity*, *region=(0, 1)*, *seed=None*)

Provide points that are distributed by a uniform Poisson point process within the boundaries given by *region*.

Parameters

- **intensity** (int | float) – The intensity (points per unit region measure) of the point process
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for all features. If array-like it must provide upper and lower bounds for each feature.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns The generated samples of shape (n_samples, n_features).

Return type npt.NDArray[**np.float_**]

locan.simulation.simulate_locdata.make_Thomas

locan.simulation.simulate_locdata.**make_Thomas**(*parent_intensity=1*, *region=(0, 1.0)*, *expansion_factor=6*, *cluster_mu=1*, *cluster_std=1.0*, *clip=True*, *shuffle=True*, *seed=None*)

Generate clustered point data following a Thomas random point process. Parent positions are distributed according to a homogeneous Poisson process with *parent_intensity* within the boundaries given by *region* expanded by an expansion distance that equals expansion_factor * max(cluster_std). Each parent position is then replaced by n offspring points where n is Poisson-distributed with mean number *cluster_mu* and point coordinates are normal-distributed around the parent point with standard deviation *cluster_std*. Offspring from parent events that are located outside the region are included.

Parameters

- **parent_intensity** (int | float) – The intensity (points per unit region measure) of the Poisson point process for parent events.
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for all features. If array-like it must provide upper and lower bounds for each feature.
- **expansion_factor** (int | float) – Factor by which the cluster_std is multiplied to set the region expansion distance.
- **cluster_mu** (int | float | Sequence[float]) – The mean number of points for normal-distributed offspring points.
- **cluster_std** (float | Sequence[float] | Sequence[Sequence[float]]) – The standard deviation for normal-distributed offspring points.
- **clip** (bool) – If True the result will be clipped to 'region'. If False the extended region will be kept.
- **shuffle** (bool) – If True shuffle the samples.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns The generated samples, labels, parent_samples of shape (n_samples, n_features) and region

Return type tuple[npt.NDArray[**np.float_**], npt.NDArray[**np.int_**], npt.NDArray[**np.float_**], Region]

locan.simulation.simulate_locdata.make_cluster

locan.simulation.simulate_locdata.**make_cluster**(*centers=3*, *region=(0, 1.0)*, *expansion_distance=0*, *offspring=None*, *clip=True*, *shuffle=True*, *seed=None*)

Parent positions are taken from *centers* or are distributed according to a homogeneous Poisson process with exactly *centers* within the boundaries given by *region* expanded by the expansion_distance. Each parent position is then replaced by cluster_mu offspring points as passed or generated by a given function. Offspring from parent events that are located outside the region are included.

Parameters

- **centers** (Union[int, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The number of parents or coordinates for parent events, where each parent represents a cluster center.
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for all features. If array-like it must provide upper and lower bounds for each feature.
- **expansion_distance** (float) – The distance by which region is expanded on all boundaries.
- **offspring** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], Callable[..., Any], None]) – Points or function for point process to provide cluster. Callable must take single parent point as parameter and return an iterable. If array-like it must have the same length as parent events.
- **clip** (bool) – If True the result will be clipped to 'region'. If False the extended region will be kept.
- **shuffle** (bool) – If True shuffle the samples.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns The generated samples, labels, parent_samples of shape (n_samples, n_features) and region

Return type tuple[npt.NDArray[**np.float_**], npt.NDArray[**np.int_**], npt.NDArray[**np.float_**], Region]

locan.simulation.simulate_locdata.make_dstorm

locan.simulation.simulate_locdata.**make_dstorm**(*parent_intensity=1*, *region=(0, 1.0)*, *expansion_factor=6*, *cluster_mu=1*, *min_points=0*, *cluster_std=1.0*, *clip=True*, *shuffle=True*, *seed=None*)

Generate clustered point data following a Thomas-like random point process. Parent positions are distributed according to a homogeneous Poisson process with *parent_intensity* within the boundaries given by *region* expanded by an expansion distance that equals expansion_factor * max(cluster_std). Each parent position is then replaced by n offspring points where n is geometrically-distributed with mean number *cluster_mu* and point coordinates are normal-distributed around the parent point with standard deviation *cluster_std*. Offspring from parent events that are located outside the region are included.

Parameters

- **parent_intensity** (int | float) – The intensity (points per unit region measure) of the Poisson point process for parent events.
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for all features. If array-like it must provide upper and lower bounds for each feature.
- **expansion_factor** (int | float) – Factor by which the cluster_std is multiplied to set the region expansion distance.
- **cluster_mu** (int | float | Sequence[float]) – The mean number of points for normal-distributed offspring points.
- **min_points** (int) – The minimum number of points per cluster.
- **cluster_std** (float | Sequence[float] | Sequence[Sequence[float]]) – The standard deviation for normal-distributed offspring points.
- **clip** (bool) – If True the result will be clipped to 'region'. If False the extended region will be kept.
- **shuffle** (bool) – If True shuffle the samples.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns

The generated samples, labels, parent_samples of shape (n_samples, n_features) and region

Return type tuple[npt.NDArray[**np.float_**], npt.NDArray[**np.int_**], npt.NDArray[**np.float_**], Region]

locan.simulation.simulate_locdata.make_uniform

locan.simulation.simulate_locdata.**make_uniform**(*n_samples*, *region=(0, 1)*, *seed=None*)

Provide points that are distributed by a uniform (complete spatial randomness) point process within the boundaries given by *region*.

Parameters

- **n_samples** (int) – The total number of localizations of the point process
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for all features. If array-like it must provide upper and lower bounds for each feature.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – Random number generation seed

Returns The generated samples of shape (n_samples, n_features).

Return type npt.NDArray[**np.float_**]

locan.simulation.simulate_locdata.randomize

locan.simulation.simulate_locdata.**randomize**(*locdata*, *hull_region='bb'*, *seed=None*)

Transform locdata coordinates into randomized coordinates that follow complete spatial randomness on the same region as the input locdata.

Parameters

- **locdata** (*LocData*) – Localization data to be randomized
- **hull_region** (Union[*Region*, Literal['bb', 'ch', 'as', 'obb']]) – Region of interest. String identifier can refer to the corresponding hull.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns New localization data with randomized coordinates.

Return type *LocData*

locan.simulation.simulate_locdata.resample

locan.simulation.simulate_locdata.**resample**(*locdata*, *n_samples=10*, *seed=None*)

Resample locdata according to localization uncertainty. Per localization *n_samples* new localizations are simulated normally distributed around the localization coordinates with a standard deviation set to the uncertainty in each dimension. Uncertainties are taken from "uncertainty_c" or "uncertainty". The resulting LocData object carries new localizations with the following new properties: position coordinates, 'original_index'.

Parameters

- **locdata** (*LocData*) – Localization data to be resampled

- **n_samples** (int) – The number of localizations generated for each original localization.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns New localization data with simulated coordinates.

Return type *LocData*

locan.simulation.simulate_locdata.simulate_Matern

locan.simulation.simulate_locdata.**simulate_Matern**(*parent_intensity=1*, *region=(0, 1.0)*, *cluster_mu=1*, *radius=1.0*, *clip=True*, *shuffle=True*, *seed=None*)

Generate clustered point data following a Matern cluster random point process. Parent positions are distributed according to a homogeneous Poisson process with *parent_intensity* within the boundaries given by *region* expanded by the maximum radius. Each parent position is then replaced by spots of size *radius* with Poisson distributed points inside. Offspring from parent events that are located outside the region are included.

Parameters

- **parent_intensity** (int | float) – The intensity (points per unit region measure) of the Poisson point process for parent events.
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for each feature. If array-like it must provide upper and lower bounds for each feature.
- **cluster_mu** (int | float) – The mean number of points of the Poisson point process for cluster(cluster_mu) events.
- **radius** (float | Sequence[float]) – The radius for the spots. If tuple, the number of elements must be larger than the expected number of parents.
- **clip** (bool) – If True the result will be clipped to 'region'. If False the extended region will be kept.
- **shuffle** (bool) – If True shuffle the samples.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns The generated samples.

Return type *LocData*

locan.simulation.simulate_locdata.simulate_NeymanScott

locan.simulation.simulate_locdata.**simulate_NeymanScott**(*parent_intensity=100*, *region=(0, 1.0)*, *expansion_distance=0*, *offspring=None*, *clip=True*, *shuffle=True*, *seed=None*)

Generate clustered point data following a Neyman-Scott random point process. Parent positions are distributed according to a homogeneous Poisson process with *parent_intensity* within the boundaries given by *region* expanded by the expansion_distance. Each parent position is then replaced by offspring points as passed or generated by a given function. Offspring from parent events that are located outside the region are included.

Parameters

- **parent_intensity** (int | float) – The intensity (points per unit region measure) of the Poisson point process for parent events.
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for each feature. If array-like it must provide upper and lower bounds for each feature.
- **expansion_distance** (float) – The distance by which region is expanded on all boundaries.
- **offspring** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], Callable[..., Any], None]) – Points or function for point process to provide offspring points. Callable must take single parent point as parameter. If array-like it must have enough elements to fit the randomly generated number of parent events.
- **clip** (bool) – If True the result will be clipped to 'region'. If False the extended region will be kept.
- **shuffle** (bool) – If True shuffle the samples.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns The generated samples.

Return type *LocData*

locan.simulation.simulate_locdata.simulate_Poisson

locan.simulation.simulate_locdata.**simulate_Poisson**(*intensity*, *region=(0, 1)*, *seed=None*)

Provide points that are distributed by a uniform Poisson point process within the boundaries given by *region*.

Parameters

- **intensity** (int | float) – The intensity (points per unit region measure) of the point process
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for each feature. If array-like it must provide upper and lower bounds for each feature.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns The generated samples.

Return type *LocData*

locan.simulation.simulate_locdata.simulate_Thomas

locan.simulation.simulate_locdata.**simulate_Thomas**(*parent_intensity=1*, *region=(0, 1.0)*, *expansion_factor=6*, *cluster_mu=1*, *cluster_std=1.0*, *clip=True*, *shuffle=True*, *seed=None*)

Generate clustered point data following a Thomas random point process. Parent positions are distributed according to a homogeneous Poisson process with *parent_intensity* within the boundaries given by *region* expanded by an expansion distance that equals expansion_factor * max(cluster_std). Each parent position is then replaced by n offspring points where n is Poisson-distributed with mean number *cluster_mu* and point coordinates are normal-distributed around the parent point with standard deviation *cluster_std*. Offspring from parent events that are located outside the region are included.

Parameters

- **parent_intensity** (int | float) – The intensity (points per unit region measure) of the Poisson point process for parent events.
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for each feature. If array-like it must provide upper and lower bounds for each feature.
- **expansion_factor** (int | float) – Factor by which the cluster_std is multiplied to set the region expansion distance.
- **cluster_mu** (int | float | Sequence[float]) – The mean number of points for normal-distributed offspring points.

- **cluster_std** (float | Sequence[float] | Sequence[Sequence[float]]) – The standard deviation for normal-distributed offspring points.
- **clip** (bool) – If True the result will be clipped to 'region'. If False the extended region will be kept.
- **shuffle** (bool) – If True shuffle the samples.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns The generated samples.

Return type *LocData*

locan.simulation.simulate_locdata.simulate_cluster

locan.simulation.simulate_locdata.**simulate_cluster**(*centers=3*, *region=(0, 1.0)*, *expansion_distance=0*, *offspring=None*, *clip=True*, *shuffle=True*, *seed=None*)

Generate clustered point data. Parent positions are taken from *centers* or are distributed according to a homogeneous Poisson process with exactly *centers* within the boundaries given by *region* expanded by the expansion_distance. Each parent position is then replaced by offspring points as passed or generated by a given function. Offspring from parent events that are located outside the region are included.

Parameters

- **centers** (Union[int, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The number of parents or coordinates for parent events, where each parent represents a cluster center.
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for each feature. If array-like it must provide upper and lower bounds for each feature.
- **expansion_distance** (float) – The distance by which region is expanded on all boundaries.
- **offspring** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], Callable[..., Any], None]) – Points or function for point process to provide cluster. Callable must take single parent point as parameter and return an iterable. If array-like it must have the same length as parent events.
- **clip** (bool) – If True the result will be clipped to 'region'. If False the extended region will be kept.
- **shuffle** (bool) – If True shuffle the samples.

- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns The generated samples.

Return type *LocData*

locan.simulation.simulate_locdata.simulate_dstorm

locan.simulation.simulate_locdata.**simulate_dstorm**(*parent_intensity=1*, *region=(0, 1.0)*, *expansion_factor=6*, *cluster_mu=1*, *min_points=0*, *cluster_std=1.0*, *clip=True*, *shuffle=True*, *seed=None*)

Generate clustered point data following a Thomas-like random point process. Parent positions are distributed according to a homogeneous Poisson process with *parent_intensity* within the boundaries given by *region* expanded by an expansion distance that equals expansion_factor * max(cluster_std). Each parent position is then replaced by n offspring points where n is geometrically-distributed with mean number *cluster_mu* and point coordinates are normal-distributed around the parent point with standard deviation *cluster_std*. Offspring from parent events that are located outside the region are included.

Parameters

- **parent_intensity** (int | float) – The intensity (points per unit region measure) of the Poisson point process for parent events.
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for each feature. If array-like it must provide upper and lower bounds for each feature.
- **expansion_factor** (int | float) – Factor by which the cluster_std is multiplied to set the region expansion distance.
- **cluster_mu** (int | float | Sequence[float]) – The mean number of points for normal-distributed offspring points.
- **min_points** (int) – The minimum number of points per cluster.
- **cluster_std** (float | Sequence[float] | Sequence[Sequence[float]]) – The standard deviation for normal-distributed offspring points.
- **clip** (bool) – If True the result will be clipped to 'region'. If False the extended region will be kept.
- **shuffle** (bool) – If True shuffle the samples.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns The generated samples.

Return type *LocData*

locan.simulation.simulate_locdata.simulate_frame_numbers

locan.simulation.simulate_locdata.**simulate_frame_numbers**(*n_samples*, *lam*, *seed=None*)

Simulate Poisson-distributed frame numbers for a list of localizations.

Return numpy.ndarray of sorted integers with each integer i being repeated n(i) times where n(i) is drawn from a Poisson distribution with mean *lam*.

Use the following to add frame numbers to a given LocData object:

```
frames = simulate_frame_numbers(n_samples=len(locdata), lam=5)
locdata.dataframe = locdata.dataframe.assign(frame = frames)
```

Parameters

- **n_samples** (int) – number of elements to be returned
- **lam** (float) – mean of the Poisson distribution (lambda)
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns The generated sequence of integers with shape (n_samples,)

Return type npt.NDArray[**np.int_**]

locan.simulation.simulate_locdata.simulate_tracks

locan.simulation.simulate_locdata.**simulate_tracks**(*n_walks=1*, *n_steps=10*, *ranges=((0, 10000), (0, 10000))*, *diffusion_constant=1*, *time_step=10*, *seed=None*)

Provide a dataset of localizations representing random walks with starting points being spatially-distributed on a rectangular shape or cubic volume by complete spatial randomness.

Parameters

- **n_walks** (int) – Number of walks
- **n_steps** (int) – Number of time steps (i.e. frames)
- **ranges** (tuple[tuple[int, int], tuple[int, int]]) – the range for valid x[, y, z]-coordinates
- **diffusion_constant** (int | float) – Diffusion constant with unit length per seconds^2
- **time_step** (float) – Time per frame (or simulation step) in seconds.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns A new LocData instance with localization data.

Return type *LocData*

locan.simulation.simulate_locdata.simulate_uniform

locan.simulation.simulate_locdata.**simulate_uniform**(*n_samples*, *region=(0, 1)*, *seed=None*)

Provide points that are distributed by a uniform Poisson point process within the boundaries given by *region*.

Parameters

- **n_samples** (int) – The total number of localizations of the point process
- **region** (Union[*Region*, _SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The region (or support) for each feature. If array-like it must provide upper and lower bounds for each feature.
- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns The generated samples.

Return type *LocData*

locan.simulation.simulate_drift

Simulate drift and apply it to localization data.

Drift can be linear in time or resemble a random walk.

Functions

add_drift(locdata[, diffusion_constant, ...])	Compute position deltas as function of frame number.

locan.simulation.simulate_drift.add_drift

locan.simulation.simulate_drift.**add_drift**(*locdata*, *diffusion_constant=None*, *velocity=None*, *seed=None*)

Compute position deltas as function of frame number.

Parameters

- **locdata** (*LocData*) – Original localization data
- **diffusion_constant** (Optional[tuple[float, ...]]) – Diffusion constant for each dimension specifying the drift velocity with shape (point_dimension,). The diffusion constant has the unit of square of localization coordinate unit per frame unit.
- **velocity** (Optional[tuple[float, ...]]) – Drift velocity in units of localization coordinate unit per frame unit with shape (point_dimension,)

- **seed** (Union[None, int, Sequence[int], SeedSequence, BitGenerator, Generator]) – random number generation seed

Returns A new LocData instance with localization data.

Return type *LocData*

8.12 locan.tests

Test the locan package.

This module includes unit tests for all modules within the locan package. The tests are organized following the subpackage structure of locan.

Functions

test([args])	Running tests with pytest.

8.12.1 locan.tests.test

locan.tests.**test**(*args=None*)

Running tests with pytest.

Parameters **args** (Union[str, list[str], None]) – Parameters passed to pytest.main()

Return type int | ExitCode

8.13 locan.utils

Utility functions.

8.13.1 Submodules:

miscellaneous	Miscellaneous functions without a home.
statistics	Statistics related tools.
system_information	Utility methods to print system and dependency information.

locan.utils.miscellaneous

Miscellaneous functions without a home.

Functions

iterate_2d_array([n_elements, n_cols])	Iterator for 2-dimensional array iterating first over columns then over rows.

locan.utils.miscellaneous.iterate_2d_array

locan.utils.miscellaneous.**iterate_2d_array**(*n_elements=5*, *n_cols=2*)

Iterator for 2-dimensional array iterating first over columns then over rows.

Parameters

- **n_elements** (int) – Number of elements
- **n_cols** (int) – Number of columns

Returns Indices for (row, column) in each iteration.

Return type Iterator[tuple[int, int]]

locan.utils.statistics

Statistics related tools.

Classes

WeightedMeanVariance(weighted_mean, ...)	

locan.utils.statistics.WeightedMeanVariance

class locan.utils.statistics.**WeightedMeanVariance**(*weighted_mean*, *weighted_mean_variance*)

Bases: NamedTuple

Methods

`__init__`()	

`count`(value, /)	Return number of occurrences of value.
`index`(value[, start, stop])	Return first index of value.

Attributes

weighted_mean	Alias for field number 0
weighted_mean_variance	Alias for field number 1

weighted_mean: float | numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Alias for field number 0

weighted_mean_variance: float | numpy.ndarray[Any, numpy.dtype[numpy.float64]]

Alias for field number 1

Functions

biased_variance(variance, n_samples)	The sample variance is biased if not corrected by Bessel's correction.
ratio_fwhm_to_sigma()	The numeric value of the ratio between full-width-half-max (fwhm) width and standard deviation (sigma) of a normal distribution.
weighted_mean_variance(values, weights)	Compute weighted mean (average) and the corresponding weighted mean variance [1]_.

locan.utils.statistics.biased_variance

locan.utils.statistics.**biased_variance**(*variance*, *n_samples*)

The sample variance is biased if not corrected by Bessel's correction. This function yields the biased variance by applying the inverse correction.

$$E(variance_{biased}) = variance * (1 - 1/localization_counts).$$

Parameters

- **variance** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – An unbiased variance.
- **n_samples** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float,

complex, str, bytes]]]) – Number of samples from which the biased sample variance would be computed.

Return type npt.NDArray[np.float_]

locan.utils.statistics.ratio_fwhm_to_sigma

locan.utils.statistics.**ratio_fwhm_to_sigma**()

The numeric value of the ratio between full-width-half-max (fwhm) width and standard deviation (sigma) of a normal distribution.

Return type float

locan.utils.statistics.weighted_mean_variance

locan.utils.statistics.**weighted_mean_variance**(*values*, *weights*)

Compute weighted mean (average) and the corresponding weighted mean variance[1].

Parameters

- **values** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Values from which to compute the weighted average.
- **weights** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], None]) – Weights to use for weighted average.

Returns weighted_mean, weighted_mean_variance

Return type *WeightedMeanVariance*

References

locan.utils.system_information

Utility methods to print system and dependency information.

adapted from pandas.show_versions() (*locan/licences/PANDAS.rst*) (BSD 3-Clause License, Copyright (c) 2008-2011, AQR Capital Management, LLC, Lambda Foundry, Inc. and PyData Development Team, Copyright (c) 2011-2021, Open source contributors.) and from scikit-learn.show_versions() (*locan/licences/SCIKIT-LEARN.rst*) (BSD 3-Clause License, Copyright (c) 2007-2020 The scikit-learn developers.)

[1] Donald F. Gatz, Luther Smith, The standard error of a weighted mean concentration — I. Bootstrapping vs other methods. Atmospheric Environment 29(11), 1995: 1185-1193, https://doi.org/10.1016/1352-2310(94)00210-C.

Functions

dependency_info([extra_dependencies, ...])	Overview of the installed version of main dependencies.
show_versions([locan, python, system, ...])	Print useful debugging information on system and dependency versions.
system_info([verbose])	Return system information.

locan.utils.system_information.dependency_info

locan.utils.system_information.**dependency_info**(*extra_dependencies=True*, *other_dependencies=None*)

Overview of the installed version of main dependencies.

Parameters

- **extra_dependencies** (bool) – Include extra dependencies as specified in setup.py
- **other_dependencies** (Optional[list[str]]) – Include other module names.

Returns Version information on relevant Python libraries

Return type dict

locan.utils.system_information.show_versions

locan.utils.system_information.**show_versions**(*locan=True*, *python=True*, *system=True*, *dependencies=True*, *verbose=True*, *extra_dependencies=True*, *other_dependencies=None*)

Print useful debugging information on system and dependency versions.

Parameters

- **locan** (bool) – Show locan version
- **python** (bool) – Show python version
- **system** (bool) – Show system information
- **verbose** (bool) – If True information on node and executable path are added.
- **dependencies** (bool) – Show main dependencies
- **extra_dependencies** (bool) – Include extra dependencies as specified in setup.py if True.
- **other_dependencies** (Optional[list[str]]) – Include other module names.

Return type None

locan.utils.system_information.system_info

locan.utils.system_information.**system_info**(*verbose=True*)

Return system information.

Parameters **verbose** (bool) – If True information on node and executable path are added.

Returns System information

Return type dict

8.14 locan.visualize

Visualize localization data.

This module provides functions to visualize localization data with matplotlib or napari.

8.14.1 Submodules:

colormap	Provide colormaps for visualization.
render	Render localization data.
render_mpl	Render localization data with matplotlib.
render_napari	Render localization data with napari.
transform	Transform intensity values.

locan.visualize.colormap

Provide colormaps for visualization.

This module provides convenience functions for using colormap definitions from various visualization packages.

Default colormaps in locan are set through the *locan.configuration.COLORMAP_DEFAULTS* mapping.

Named colormaps are registered through the `locan.visualization.colormap.colormap_registry` mapping.

In locan `locan.Colormap` serves as adapter class to provide an interface for various visualization functions. Instances of `locan.Colormap` can be requested through the `locan.visualization.colormap.get_colormap()` function and contain references to matplotlib and napari colormap instances.

Examples

```
>>> colormap = locan.get_colormap("viridis")
>>> assert isinstance(colormap.matplotlib, mcolors.Colormap)
>>> colormap.name
viridis
```

```
>>> colormap = locan.Colormap.from_matplotlib(colormap="viridis")
>>> assert isinstance(colormap.matplotlib, mcolors.Colormap)
>>> colormap.name
viridis
```

Variables

colormap_registry	A mapping of names onto Colormap instances.

locan.visualize.colormap.colormap_registry

locan.visualize.colormap.**colormap_registry: collections.abc.Mapping[str, *locan.visualize.colormap.Colormap*] = {'cet_coolwarm': <locan.visualize.colormap.Colormap object>, 'cet_fire': <locan.visualize.colormap.Colormap object>, 'cet_fire_r': <locan.visualize.colormap.Colormap object>, 'cet_glasbey_dark': <locan.visualize.colormap.Colormap object>, 'cet_gray': <locan.visualize.colormap.Colormap object>, 'cet_gray_r': <locan.visualize.colormap.Colormap object>, 'coolwarm': <locan.visualize.colormap.Colormap object>, 'gray': <locan.visualize.colormap.Colormap object>, 'gray_r': <locan.visualize.colormap.Colormap object>, 'tab20': <locan.visualize.colormap.Colormap object>, 'turbo': <locan.visualize.colormap.Colormap object>, 'viridis': <locan.visualize.colormap.Colormap object>, 'viridis_r': <locan.visualize.colormap.Colormap object>}**

A mapping of names onto Colormap instances.

Classes

Colormap(colormap)	Container class for colormaps.
Colormaps(value)	Preferred colormap types to be used for visualization.

locan.visualize.colormap.Colormap

class locan.visualize.colormap.**Colormap**(*colormap*)

Bases: object

Container class for colormaps.

A locan Colormap can be instantiated from other colormaps and serves as adapter class.

Methods

__init__(colormap)	
from_colorcet(cls, colormap)	**rtype** TypeVar(T_Colormap, bound= Colormap)
from_matplotlib(colormap)	**rtype** TypeVar(T_Colormap, bound= Colormap)
from_napari(cls, colormap)	**rtype** TypeVar(T_Colormap, bound= Colormap)
from_registry(colormap)	**rtype** *Colormap*

Attributes

matplotlib	**rtype** Colormap
name	**rtype** str
napari	**rtype** Colormap

__call__(**args*, ***kwargs*)

Call self as a function.

Return type float | tuple[float, float, float, float] | ndarray[Any, dtype[float64]]

classmethod from_colorcet(*cls*, *colormap*)

Return type TypeVar(T_Colormap, bound= Colormap)

classmethod from_matplotlib(*colormap*)

Return type TypeVar(T_Colormap, bound= Colormap)

classmethod from_napari(*cls*, *colormap*)

Return type TypeVar(T_Colormap, bound= Colormap)

classmethod from_registry(*colormap*)

Return type *Colormap*

property matplotlib: matplotlib.colors.Colormap

Return type Colormap

property name: str

Return type str

property napari: napari.utils.colormaps.colormap.Colormap

Return type Colormap

locan.visualize.colormap.Colormaps

class locan.visualize.colormap.**Colormaps**(*value*)

Bases: enum.Enum

Preferred colormap types to be used for visualization.

Note: This enum is automatically generated from COLORMAP_DEFAULTS and should not be modified.

Attributes

CONTINUOUS

CONTINUOUS_REVERSE

CONTINUOUS_GRAY

CONTINUOUS_GRAY_REVERSE

DIVERGING

CATEGORICAL

TURBO

CATEGORICAL = 'cet_glasbey_dark'

CONTINUOUS = 'cet_fire'

CONTINUOUS_GRAY = 'cet_gray'

CONTINUOUS_GRAY_REVERSE = 'cet_gray_r'

CONTINUOUS_REVERSE = 'cet_fire_r'

DIVERGING = 'cet_coolwarm'

TURBO = 'turbo'

Functions

get_colormap(colormap)	Get a locan.Colormap instance from colormap searching string identifier through colormap_registry, matplotlib colormaps, napari_colormaps.

locan.visualize.colormap.get_colormap

locan.visualize.colormap.**get_colormap**(*colormap*)

Get a locan.Colormap instance from colormap searching string identifier through colormap_registry, matplotlib colormaps, napari_colormaps.

Parameters **colormap** (Union[str, *Colormaps*, *Colormap*, Colormap, Colormap]) – Colormap request

Return type *Colormap*

locan.visualize.render

Render localization data.

This module provides convenience functions for rendering localization data.

Functions

render_2d(locdata[, render_engine])	Wrapper function to render localization data into a 2D image.
render_3d(locdata[, render_engine])	Wrapper function to render localization data into a 3D image.

locan.visualize.render.render_2d

locan.visualize.render.**render_2d**(*locdata*, *render_engine=RenderEngine.MPL*, ***kwargs*)

Wrapper function to render localization data into a 2D image. For complete signatures see render_2d_mpl or corresponding functions.

Return type Any

locan.visualize.render.render_3d

locan.visualize.render.**render_3d**(*locdata*, *render_engine=RenderEngine.MPL*, ***kwargs*)

Wrapper function to render localization data into a 3D image. For complete signatures see render_3d_mpl or corresponding functions.

Return type Any

locan.visualize.render_mpl

Render localization data with matplotlib.

This module provides functions to render and present localization data making use of matplotlib.

Submodules:

render2d	This module provides functions for rendering locdata objects in 2D.
render3d	This module provides functions for rendering *LocData* objects in 3D.

locan.visualize.render_mpl.render2d

This module provides functions for rendering locdata objects in 2D.

Functions

apply_window(image[, window_function])	Apply window function to image.
render_2d_mpl(locdata[, loc_properties, ...])	Render localization data into a 2D image by binning x,y-coordinates into regular bins.
render_2d_rgb_mpl(locdatas[, ...])	Render localization data into a 2D RGB image by binning x,y-coordinates into regular bins.
render_2d_scatter_density(locdata[, ...])	Render localization data into a 2D image by binning x,y-coordinates into regular bins.
scatter_2d_mpl(locdata[, ax, index, text_kwargs])	Scatter plot of locdata elements with text marker for each element.
select_by_drawing_mpl(locdata[, region_type])	Select region of interest from rendered image by drawing rois.

locan.visualize.render_mpl.render2d.apply_window

locan.visualize.render_mpl.render2d.**apply_window**(*image*, *window_function='tukey'*, ***kwargs*)

Apply window function to image.

Parameters

- **image** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Image
- **window_function** (str) – Window function to apply. One of 'tukey', 'hann' or any other in *scipy.signal.windows*.
- **kwargs** (Any) – Other parameters passed to the *scipy.signal.windows* window function.

Return type ndarray[Any, dtype[float64]]

locan.visualize.render_mpl.render2d.render_2d_mpl

locan.visualize.render_mpl.render2d.**render_2d_mpl**(*locdata*, *loc_properties=None*, *other_property=None*, *bins=None*, *n_bins=None*, *bin_size=10*, *bin_edges=None*, *bin_range=None*, *rescale=None*, *ax=None*, *cmap='cet_fire'*, *cbar=True*, *colorbar_kws=None*, *interpolation='nearest'*, ***kwargs*)

Render localization data into a 2D image by binning x,y-coordinates into regular bins.

Parameters

- **locdata** (*LocData*) – Localization data.
- **loc_properties** (Optional[list[str]]) – Localization properties to be grouped into bins. If None The coordinate_values of *locdata* are used.
- **other_property** (Optional[str]) – Localization property (columns in *locdata.data*) that is averaged in each pixel. If None, localization counts are shown.
- **bins** (Union[*Bins*, Axis, AxesTuple, None]) – The bin specification as defined in Bins
- **bin_edges** (Union[Sequence[float], Sequence[Sequence[float]], None]) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], Literal['zero', 'link'], None]) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2). If None (min, max) ranges are determined from data and

returned; if 'zero' (0, max) ranges with max determined from data are returned. if 'link' (min_all, max_all) ranges with min and max determined from all combined data are returned.

- **n_bins** (Union[int, Sequence[int], None]) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (UnionType[float, Sequence[float], Sequence[Sequence[float]], None]) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.
- **rescale** (Union[int, str, *Trafo*, Callable[..., Any], bool, None]) – Transformation as defined in locan.Trafo or by transformation function. For None or False no rescaling occurs. Legacy behavior: For tuple with upper and lower bounds provided in percent, rescale intensity values to be within percentile of max and min intensities. For 'equal' intensity values are rescaled by histogram equalization.
- **ax** (Optional[Axes]) – The axes on which to show the image
- **cmap** (Union[str, *Colormaps*, *Colormap*, Colormap, Colormap]) – The Colormap object used to map normalized data values to RGBA colors.
- **cbar** (bool) – If true draw a colorbar. The colobar axes is accessible using the cax property.
- **colorbar_kws** (Optional[dict[str, Any]]) – Keyword arguments for matplotlib.pyplot.colorbar().
- **interpolation** (str) – Keyword argument for matplotlib.axes.Axes.imshow().
- **kwargs** (Any) – Other parameters passed to matplotlib.axes.Axes.imshow().

Returns Axes object with the image.

Return type matplotlib.axes.Axes

locan.visualize.render_mpl.render2d.render_2d_rgb_mpl

locan.visualize.render_mpl.render2d.**render_2d_rgb_mpl**(*locdatas*, *loc_properties=None*, *other_property=None*, *bins=None*, *n_bins=None*, *bin_size=10*, *bin_edges=None*, *bin_range=None*, *rescale=None*, *ax=None*, *interpolation='nearest'*, ***kwargs*)

Render localization data into a 2D RGB image by binning x,y-coordinates into regular bins.

Note: For rescale=False no normalization is carried out image intensities are clipped to (0, 1) for float value or (0, 255) for integer values according to the matplotlib.imshow behavior. For rescale=None we apply a normalization to (min, max) of all intensity values. For all other rescale options the normalization is applied to each individual image.

Parameters

- **locdatas** (list[*LocData*]) – Localization data.
- **loc_properties** (Optional[list[str]]) – Localization properties to be grouped into bins. If None The coordinate_values of *locdata* are used.
- **other_property** (Optional[str]) – Localization property (columns in *locdata.data*) that is averaged in each pixel. If None, localization counts are shown.
- **bins** (Union[*Bins*, Axis, AxesTuple, None]) – The bin specification as defined in Bins
- **bin_edges** (Union[Sequence[float], Sequence[Sequence[float]], None]) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], Literal['zero', 'link'], None]) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2). If None (min, max) ranges are determined from data and returned; if 'zero' (0, max) ranges with max determined from data are returned. if 'link' (min_all, max_all) ranges with min and max determined from all combined data are returned.
- **n_bins** (Union[int, Sequence[int], None]) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (UnionType[float, Sequence[float], Sequence[Sequence[float]], None]) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.
- **rescale** (Union[int, str, *Trafo*, Callable[..., Any], bool, None]) – Transformation as defined in locan.Trafo or by transformation function. For None or False no rescaling occurs. Legacy behavior: For tuple with upper and lower bounds provided in percent, rescale intensity values to be within percentile of max and min intensities. For 'equal' intensity values are rescaled by histogram equalization.
- **ax** (Optional[Axes]) – The axes on which to show the image
- **interpolation** (str) – Keyword argument for matplotlib.axes.Axes.imshow().

- **kwargs** (Any) – Other parameters passed to matplotlib.axes.Axes.imshow().

Returns Axes object with the image.

Return type matplotlib.axes.Axes

locan.visualize.render_mpl.render2d.render_2d_scatter_density

locan.visualize.render_mpl.render2d.**render_2d_scatter_density**(*locdata*, *loc_properties=None*, *other_property=None*, *bin_range=None*, *ax=None*, *cmap='cet_fire'*, *cbar=True*, *colorbar_kws=None*, ***kwargs*)

Render localization data into a 2D image by binning x,y-coordinates into regular bins.

Prepare matplotlib.axes.Axes with image.

Note: To rescale intensity values use norm keyword.

Parameters

- **locdata** (*LocData*) – Localization data.
- **loc_properties** (Optional[list[str]]) – Localization properties to be grouped into bins. If None The coordinate_values of *locdata* are used.
- **other_property** (Optional[str]) – Localization property (columns in *locdata.data*) that is averaged in each pixel. If None, localization counts are shown.
- **bin_range** (Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], Literal['zero', 'link'], None]) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2). If None (min, max) ranges are determined from data and returned; if 'zero' (0, max) ranges with max determined from data are returned. if 'link' (min_all, max_all) ranges with min and max determined from all combined data are returned.
- **ax** (Optional[Axes]) – The axes on which to show the image
- **cmap** (Union[str, *Colormaps*, *Colormap*, Colormap, Colormap]) – The Colormap object used to map normalized data values to RGBA colors.
- **cbar** (bool) – If true draw a colorbar. The colobar axes is accessible using the cax property.
- **colorbar_kws** (Optional[dict[str, Any]]) – Keyword arguments for matplotlib.pyplot.colorbar().

- **kwargs** (Any) – Other parameters passed to `mpl_scatter_density.ScatterDensityArtist`.

Returns Axes object with the image.

Return type matplotlib.axes.Axes

locan.visualize.render_mpl.render2d.scatter_2d_mpl

locan.visualize.render_mpl.render2d.**scatter_2d_mpl**(*locdata*, *ax=None*, *index=True*, *text_kwargs=None*, ***kwargs*)

Scatter plot of locdata elements with text marker for each element.

Parameters

- **locdata** (*LocData*) – Localization data.
- **ax** (Optional[Axes]) – The axes on which to show the plot
- **index** (bool) – Flag indicating if element indices are shown.
- **text_kwargs** (Optional[dict[str, Any]]) – Keyword arguments for `matplotlib.axes.Axes.text()`.
- **kwargs** (Any) – Other parameters passed to `matplotlib.axes.Axes.scatter()`.

Returns Axes object with the image.

Return type matplotlib.axes.Axes

locan.visualize.render_mpl.render2d.select_by_drawing_mpl

locan.visualize.render_mpl.render2d.**select_by_drawing_mpl**(*locdata*, *region_type='rectangle'*, ***kwargs*)

Select region of interest from rendered image by drawing rois.

Parameters

- **locdata** (*LocData*) – The localization data from which to select localization data.
- **region_type** (str) – rectangle, or ellipse specifying the selection widget to use.
- **kwargs** (Any) – Other parameters as specified for `render_2d()`.

Return type list[*Roi*]

See also:

locan.scripts.sc_draw_roi_mpl() script for drawing rois

matplotlib.widgets selector functions

locan.visualize.render_mpl.render3d

This module provides functions for rendering *LocData* objects in 3D.

Functions

scatter_3d_mpl(locdata[, ax, index, text_kwargs])	Scatter plot of locdata elements with text marker for each element.

locan.visualize.render_mpl.render3d.scatter_3d_mpl

locan.visualize.render_mpl.render3d.**scatter_3d_mpl**(*locdata*, *ax=None*, *index=True*, *text_kwargs=None*, ***kwargs*)

Scatter plot of locdata elements with text marker for each element.

Parameters

- **locdata** (*LocData*) – Localization data.
- **ax** (Optional[Axes]) – The axes on which to show the plot
- **index** (bool) – Flag indicating if element indices are shown.
- **text_kwargs** (Optional[dict[str, Any]]) – Keyword arguments for matplotlib.axes.Axes.text().
- **kwargs** (Any) – Other parameters passed to matplotlib.axes.Axes.scatter().

Returns Axes object with the image.

Return type matplotlib.axes.Axes3D

locan.visualize.render_napari

Render localization data with napari.

This module provides functions to interact with napari.

Submodules:

render2d	This module provides functions to interact with napari for rendering locdata objects in 2D.
render3d	This module provides functions to interact with napari for rendering *LocData* objects in 3D.
utilities	Utility functions for interacting with napari.

locan.visualize.render_napari.render2d

This module provides functions to interact with napari for rendering locdata objects in 2D.

Functions

render_2d_napari(locdata[, loc_properties, ...])	Render localization data into a 2D image by binning x,y-coordinates into regular bins.
render_2d_napari_image(locdata[, ...])	Render localization data into a 2D image by binning x,y-coordinates into regular bins.
render_2d_rgb_napari(locdatas[, ...])	Render localization data into a 2D RGB image by binning x,y-coordinates into regular bins.

locan.visualize.render_napari.render2d.render_2d_napari

locan.visualize.render_napari.render2d.**render_2d_napari**(*locdata*, *loc_properties=None*, *other_property=None*, *bins=None*, *n_bins=None*, *bin_size=None*, *bin_edges=None*, *bin_range=None*, *rescale=None*, *viewer=None*, *cmap='cet_fire'*, ***kwargs*)

Render localization data into a 2D image by binning x,y-coordinates into regular bins. Render the data using napari.

Parameters

- **locdata** (*LocData*) – Localization data.
- **loc_properties** (Optional[list[str]]) – Localization properties to be grouped into bins. If None The coordinate_values of *locdata* are used.
- **other_property** (Optional[str]) – Localization property (columns in *locdata.data*) that is averaged in each pixel. If None, localization counts are shown.
- **bins** (Union[*Bins*, Axis, AxesTuple, None]) – The bin specification as defined in Bins
- **bin_edges** (Union[Sequence[float], Sequence[Sequence[float]], None]) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], Literal['zero', 'link'], None]) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2). If None (min, max) ranges are determined from data and returned; if 'zero' (0, max) ranges with max determined from data are returned. if 'link' (min_all, max_all) ranges with min and max determined from all combined data are returned.

- **n_bins** (Union[int, Sequence[int], None]) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (Union[float, Sequence[float], Sequence[Sequence[float]], None]) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.
- **rescale** (Union[int, str, *Trafo*, Callable[..., Any], bool, None]) – Transformation as defined in locan.Trafo or by transformation function. For None or False no rescaling occurs. Legacy behavior: For tuple with upper and lower bounds provided in percent, rescale intensity values to be within percentile of max and min intensities. For 'equal' intensity values are rescaled by histogram equalization.
- **viewer** (Optional[Viewer]) – The viewer object on which to add the image
- **cmap** (*str | Colormap*) – The Colormap object used to map normalized data values to RGBA colors.
- **kwargs** (Any) – Other parameters passed to napari.Viewer.add_image().

Return type napari.Viewer

locan.visualize.render_napari.render2d.render_2d_napari_image

locan.visualize.render_napari.render2d.**render_2d_napari_image**(*locdata*, *loc_properties=None*, *other_property=None*, *bins=None*, *n_bins=None*, *bin_size=None*, *bin_edges=None*, *bin_range=None*, *rescale=None*, *cmap='cet_fire'*, ***kwargs*)

Render localization data into a 2D image by binning x,y-coordinates into regular bins. Provide layer data for napari.

Parameters

- **locdata** (*LocData*) – Localization data.
- **loc_properties** (Optional[list[str]]) – Localization properties to be grouped into bins. If None The coordinate_values of *locdata* are used.
- **other_property** (Optional[str]) – Localization property (columns in *locdata.data*) that is averaged in each pixel. If None, localization counts are shown.

- **bins** (Union[*Bins*, Axis, AxesTuple, None]) – The bin specification as defined in Bins
- **bin_edges** (Union[Sequence[float], Sequence[Sequence[float]], None]) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], Literal['zero', 'link'], None]) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2). If None (min, max) ranges are determined from data and returned; if 'zero' (0, max) ranges with max determined from data are returned. if 'link' (min_all, max_all) ranges with min and max determined from all combined data are returned.
- **n_bins** (Union[int, Sequence[int], None]) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (Union[float, Sequence[float], Sequence[Sequence[float]], None]) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.
- **rescale** (Union[int, str, *Trafo*, Callable[..., Any], bool, None]) – Transformation as defined in locan.Trafo or by transformation function. For None or False no rescaling occurs. Legacy behavior: For tuple with upper and lower bounds provided in percent, rescale intensity values to be within percentile of max and min intensities. For 'equal' intensity values are rescaled by histogram equalization.
- **cmap** (Union[str, *Colormaps*, *Colormap*, Colormap, Colormap]) – The Colormap object used to map normalized data values to RGBA colors.
- **kwargs** (Any) – Other parameters passed to napari.Viewer.add_image().

Returns Tuple with data, image_kwargs, layer_type="image"

Return type napari.types.LayerData

locan.visualize.render_napari.render2d.render_2d_rgb_napari

locan.visualize.render_napari.render2d.**render_2d_rgb_napari**(*locdatas*, *loc_properties=None*, *other_property=None*, *bins=None*, *n_bins=None*, *bin_size=10*, *bin_edges=None*, *bin_range=None*, *rescale=None*, *viewer=None*, ***kwargs*)

Render localization data into a 2D RGB image by binning x,y-coordinates into regular bins.

Note: For rescale=False no normalization is carried out image intensities are clipped to (0, 1) for float value or (0, 255) for integer values according to the matplotlib.imshow behavior. For rescale=None we apply a normalization to (min, max) of all intensity values. For all other rescale options the normalization is applied to each individual image.

Parameters

- **locdatas** (Iterable[*LocData*]) – Localization data.
- **loc_properties** (Optional[list[str]]) – Localization properties to be grouped into bins. If None The coordinate_values of *locdata* are used.
- **other_property** (Optional[str]) – Localization property (columns in *locdata.data*) that is averaged in each pixel. If None, localization counts are shown.
- **bins** (Union[*Bins*, Axis, AxesTuple, None]) – The bin specification as defined in Bins
- **bin_edges** (Union[Sequence[float], Sequence[Sequence[float]], None]) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], Literal['zero', 'link'], None]) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2). If None (min, max) ranges are determined from data and returned; if 'zero' (0, max) ranges with max determined from data are returned. if 'link' (min_all, max_all) ranges with min and max determined from all combined data are returned.
- **n_bins** (Union[int, Sequence[int], None]) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (UnionType[float, Sequence[float], Sequence[Sequence[float]], None]) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins).

5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.

- **rescale** (Union[int, str, *Trafo*, Callable[..., Any], bool, None]) – Transformation as defined in `locan.Trafo` or by transformation function. For None or False no rescaling occurs. Legacy behavior: For tuple with upper and lower bounds provided in percent, rescale intensity values to be within percentile of max and min intensities. For 'equal' intensity values are rescaled by histogram equalization.
- **viewer** (Optional[Viewer]) – The viewer object on which to add the image
- **kwargs** (Any) – Other parameters passed to `napari.Viewer.add_image()`.

Return type napari.Viewer

locan.visualize.render_napari.render3d

This module provides functions to interact with napari for rendering *LocData* objects in 3D.

Functions

render_3d_napari(locdata[, loc_properties, ...])	Render localization data into a 3D image by binning x,y,z-coordinates into regular bins.
render_3d_napari_image(locdata[, ...])	Render localization data into a 3D image by binning x,y,z-coordinates into regular bins. Provide layer data for napari.
render_3d_rgb_napari(locdatas[, ...])	Render localization data into a 3D RGB image by binning x,y,z-coordinates into regular bins.

locan.visualize.render_napari.render3d.render_3d_napari

locan.visualize.render_napari.render3d.**render_3d_napari**(*locdata*, *loc_properties=None*, *other_property=None*, *bins=None*, *n_bins=None*, *bin_size=10*, *bin_edges=None*, *bin_range=None*, *rescale=None*, *viewer=None*, *cmap='cet_fire'*, ***kwargs*)

Render localization data into a 3D image by binning x,y,z-coordinates into regular bins. Render the data using napari.

Parameters

- **locdata** (*LocData*) – Localization data.

- **loc_properties** (Optional[list[str]]) – Localization properties to be grouped into bins. If None The coordinate_values of *locdata* are used.
- **other_property** (Optional[str]) – Localization property (columns in *locdata.data*) that is averaged in each pixel. If None, localization counts are shown.
- **bins** (Union[*Bins*, Axis, AxesTuple, None]) – The bin specification as defined in Bins
- **bin_edges** (Union[Sequence[float], Sequence[Sequence[float]], None]) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], Literal['zero', 'link'], None]) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2). If None (min, max) ranges are determined from data and returned; if 'zero' (0, max) ranges with max determined from data are returned. if 'link' (min_all, max_all) ranges with min and max determined from all combined data are returned.
- **n_bins** (Union[int, Sequence[int], None]) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (UnionType[float, Sequence[float], Sequence[Sequence[float]], None]) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.
- **rescale** (Union[int, str, *Trafo*, Callable[..., Any], bool, None]) – Transformation as defined in locan.Trafo or by transformation function. For None or False no rescaling occurs. Legacy behavior: For tuple with upper and lower bounds provided in percent, rescale intensity values to be within percentile of max and min intensities. For 'equal' intensity values are rescaled by histogram equalization.
- **viewer** (Optional[Viewer]) – The viewer object on which to add the image
- **cmap** (Union[str, *Colormaps*, *Colormap*, Colormap, Colormap]) – The Colormap object used to map normalized data values to RGBA colors.
- **kwargs** (Any) – Other parameters passed to napari.Viewer.add_image().

Return type napari.Viewer

locan.visualize.render_napari.render3d.render_3d_napari_image

locan.visualize.render_napari.render3d.**render_3d_napari_image**(*locdata*, *loc_properties=None*, *other_property=None*, *bins=None*, *n_bins=None*, *bin_size=10*, *bin_edges=None*, *bin_range=None*, *rescale=None*, *cmap='cet_fire'*, ***kwargs*)

Render localization data into a 3D image by binning x,y,z-coordinates into regular bins.

Provide layer data for napari.

Parameters

- **locdata** (*LocData*) – Localization data.
- **loc_properties** (Optional[list[str]]) – Localization properties to be grouped into bins. If None The coordinate_values of *locdata* are used.
- **other_property** (Optional[str]) – Localization property (columns in *locdata.data*) that is averaged in each pixel. If None, localization counts are shown.
- **bins** (Union[*Bins*, Axis, AxesTuple, None]) – The bin specification as defined in Bins
- **bin_edges** (Union[Sequence[float], Sequence[Sequence[float]], None]) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).
- **bin_range** (Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], Literal['zero', 'link'], None]) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2). If None (min, max) ranges are determined from data and returned; if 'zero' (0, max) ranges with max determined from data are returned. if 'link' (min_all, max_all) ranges with min and max determined from all combined data are returned.
- **n_bins** (Union[int, Sequence[int], None]) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (UnionType[float, Sequence[float], Sequence[Sequence[float]], None]) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.

- **rescale** (Union[int, str, *Trafo*, Callable[..., Any], bool, None]) – Transformation as defined in `locan.Trafo` or by transformation function. For None or False no rescaling occurs. Legacy behavior: For tuple with upper and lower bounds provided in percent, rescale intensity values to be within percentile of max and min intensities. For 'equal' intensity values are rescaled by histogram equalization.
- **cmap** (Union[str, *Colormaps*, *Colormap*, Colormap, Colormap]) – The Colormap object used to map normalized data values to RGBA colors.
- **kwargs** (Any) – Other parameters passed to `napari.Viewer.add_image()`.

Returns Tuple with data, image_kwargs, "image"

Return type napari.types.LayerData

locan.visualize.render_napari.render3d.render_3d_rgb_napari

locan.visualize.render_napari.render3d.**render_3d_rgb_napari**(*locdatas*, *loc_properties=None*, *other_property=None*, *bins=None*, *n_bins=None*, *bin_size=10*, *bin_edges=None*, *bin_range=None*, *rescale=None*, *viewer=None*, ***kwargs*)

Render localization data into a 3D RGB image by binning x,y,z-coordinates into regular bins.

Note: For rescale=False no normalization is carried out image intensities are clipped to (0, 1) for float value or (0, 255) for integer values according to the matplotlib.imshow behavior. For rescale=None we apply a normalization to (min, max) of all intensity values. For all other rescale options the normalization is applied to each individual image.

Parameters

- **locdatas** (Iterable[*LocData*]) – Localization data.
- **loc_properties** (Optional[list[str]]) – Localization properties to be grouped into bins. If None The coordinate_values of *locdata* are used.
- **other_property** (Optional[str]) – Localization property (columns in *locdata.data*) that is averaged in each pixel. If None, localization counts are shown.
- **bins** (Union[*Bins*, Axis, AxesTuple, None]) – The bin specification as defined in Bins
- **bin_edges** (Union[Sequence[float], Sequence[Sequence[float]], None]) – Bin edges for all or each dimension with shape (dimension, n_bin_edges).

- **bin_range** (Union[tuple[float, float], Sequence[float], Sequence[Sequence[float]], Literal['zero', 'link'], None]) – Minimum and maximum edge for all or each dimensions with shape (2,) or (dimension, 2). If None (min, max) ranges are determined from data and returned; if 'zero' (0, max) ranges with max determined from data are returned. if 'link' (min_all, max_all) ranges with min and max determined from all combined data are returned.
- **n_bins** (Union[int, Sequence[int], None]) – The number of bins for all or each dimension. 5 yields 5 bins in all dimensions. (2, 5) yields 2 bins for one dimension and 5 for the other dimension.
- **bin_size** (UnionType[float, Sequence[float], Sequence[Sequence[float]], None]) – The size of bins for all or each bin and for all or each dimension with shape (dimension,) or (dimension, n_bins). 5 would describe bin_size of 5 for all bins in all dimensions. ((2, 5),) yield bins of size (2, 5) for one dimension. (2, 5) yields bins of size 2 for one dimension and 5 for the other dimension. ((2, 5), (1, 3)) yields bins of size (2, 5) for one dimension and (1, 3) for the other dimension. To specify arbitrary sequence of *bin_size* use *bin_edges* instead.
- **rescale** (Union[int, str, *Trafo*, Callable[..., Any], bool, None]) – Transformation as defined in `locan.Trafo` or by transformation function. For None or False no rescaling occurs. Legacy behavior: For tuple with upper and lower bounds provided in percent, rescale intensity values to be within percentile of max and min intensities. For 'equal' intensity values are rescaled by histogram equalization.
- **viewer** (Optional[Viewer]) – The viewer object on which to add the image
- **kwargs** (Any) – Other parameters passed to `napari.Viewer.add_image()`.

Return type napari.Viewer

locan.visualize.render_napari.utilities

Utility functions for interacting with napari.

Functions

get_rois(shapes_layer[, reference, ...])	Create rois from shapes in napari.viewer.Shapes.
save_rois(rois[, file_path, roi_file_indicator])	Save list of Roi objects.
select_by_drawing_napari(locdata[, napari_run])	Select region of interest from rendered image by drawing rois in napari.

locan.visualize.render_napari.utilities.get_rois

locan.visualize.render_napari.utilities.**get_rois**(*shapes_layer*, *reference=None*, *loc_properties=None*)

Create rois from shapes in napari.viewer.Shapes.

Parameters

- **shapes_layer** (Shapes) – Napari shapes layer like *viewer.layers["Shapes"]*
- **reference** (Union[*LocData*, dict[str, str], Metadata, File, None]) – Reference to localization data for which the region of interest is defined. It can be a LocData object, a reference to a saved SMLM file, or None for indicating no specific reference. When dict it must have keys *file_path`and `file_type*. When Metadata message it must have keys *file.path* and *file.type* for a path pointing to a localization file and an integer or string indicating the file type. Integer or string should be according to locan.constants.FileType.
- **loc_properties** (Optional[Sequence[str]]) – Localization properties in LocData object on which the region selection will be applied (for instance the coordinate_keys).

Return type list[*Roi*]

See also:

locan.scripts.rois() script for drawing rois

locan.visualize.render_napari.utilities.save_rois

locan.visualize.render_napari.utilities.**save_rois**(*rois*, *file_path=None*, *roi_file_indicator='_roi'*)

Save list of Roi objects.

Parameters

- **rois** (Iterable[*Roi*]) – The rois to be saved.
- **file_path** (Union[str, PathLike[Any], Literal['roi_reference'], None]) – Base name for roi files or existing directory to save rois in. If "roi_reference", roi.reference.file.path is used. If None, a file dialog is opened.
- **roi_file_indicator** (str) – Indicator to add to the localization file name and use as roi file name (with further extension .yaml).

Returns New created roi file paths.

Return type list[Path]

locan.visualize.render_napari.utilities.select_by_drawing_napari

locan.visualize.render_napari.utilities.**select_by_drawing_napari**(*locdata*, *napari_run=True*, ***kwargs*)

Select region of interest from rendered image by drawing rois in napari.

Rois will be created from shapes in napari.viewer.layers['Shapes'].

Parameters

- **locdata** (*LocData*) – The localization data from which to select localization data.
- **napari_run** (bool) – If *True* napari.run is called (set to *False* for testing).
- **kwargs** (Any) – Other parameters passed to `render_2d_napari()`.

Return type list[*Roi*]

See also:

locan.scripts.rois() script for drawing rois

locan.visualize.transform

Transform intensity values.

This module provides functions and classes to rescale intensity values. In addition to the presented functions, rescaling can further be performed by third-party modules like: 1) matplotlib.colors 2) skimage.exposure 3) astropy.visualization.

Callable transformation classes that inherit from `matplotlib.colors.Normalize` and specify an inverse transformation can be passed to the *norm* parameter.

Classes

HistogramEqualization([vmin, vmax, ...])	Histogram equalization with power intensification.
Trafo(value)	Standard definitions for intensity transformation.
Transform()	Abstract base class for transformation classes.

locan.visualize.transform.HistogramEqualization

class locan.visualize.transform.**HistogramEqualization**(*vmin=None*, *vmax=None*, *reference=None*, *power=1*, *n_bins=65536*, *mask=None*)

Bases: `matplotlib.colors.Normalize`, *locan.visualize.transform.Transform*

Histogram equalization with power intensification.

The transformation function as described in[1] is $f(a, p)$ according to:

$$\frac{f(a) - f(a_min)}{f(a_max) - f(a_min)} = \frac{\int_{a_min}^{a} h^p(a')da'}{\int_{a_min}^{a_max} h^p(a')da'}$$

Here, a is an intensity value, p the power (a parameter), and $h(a)$ the histogram of intensities.

Note: The default for n_bins is 65536 (16 bit). For most SMLM datasets this should be sufficient to resolve individual localizations despite a large dynamic range. Setting n_bins to 256 (8 bit) is too course for many SMLM datasets.

References

Parameters

- **vmin** (Union[int, float, None]) – min intensity
- **vmax** (Union[int, float, None]) – max intensity
- **reference** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], None]) – The data values to define the transformation function. If None then the values in *__call__* are used.
- **power** (float) – The *power* intensification parameter.
- **n_bins** (int) – Number of bins used to compute the intensity histogram.
- **mask** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]], None]) – A bool mask with shape equal to that of values. If reference is None, reference is set to values[mask]. The transformation determined from reference is then applied to all values.

Methods

__init__([vmin, vmax, reference, power, ...])	**type vmin** Union[int, float, None]

autoscale(A)	Set *vmin*, *vmax* to min, max of *A*.
autoscale_None(A)	If vmin or vmax are not set, use the min/max of *A* to set them.
inverse(values)	A Transformation object that performs the inverse operation.
process_value(value)	Homogenize the input *value* for easy and efficient normalization.
scaled()	Return whether vmin and vmax are set.

[1] Yaroslavsky, L. (1985) Digital picture processing. Springer, Berlin.

Attributes

clip
vmax
vmin

__call__(*values*)

Histogram equalization with power intensification.

Parameters **values** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The input values.

Return type npt.NDArray

inverse(*values*)

A Transformation object that performs the inverse operation.

Return type ndarray[Any, dtype[Any]]

locan.visualize.transform.Trafo

class locan.visualize.transform.**Trafo**(*value*)

Bases: enum.Enum

Standard definitions for intensity transformation.

Attributes

NONE	no transformation
STANDARDIZE	rescale (min, max) to (0, 1)
STANDARDIZE_UINT8	rescale (min, max) to (0, 255)
ZERO	rescale (0, max) to (0, 1)
ZERO_UINT8	rescale (0, max) to (0, 255)
EQUALIZE	equalize histogram from all values > 0
EQUALIZE_UINT8	equalize histogram from all values > 0 onto (0, 255)
EQUALIZE_ALL	equalize histogram
EQUALIZE_ALL_UINT8	equalize histogram onto (0, 255)
EQUALIZE_0P3	equalize histogram with power = 0.3 from all values > 0
EQUALIZE_0P3_UINT8	equalize histogram with power = 0.3 from all values > 0 onto (0, 255)
EQUALIZE_0P3_ALL	equalize histogram with power = 0.3
EQUALIZE_0P3_ALL_UINT8	equalize histogram with power = 0.3 onto (0, 255)

EQUALIZE = 5
equalize histogram from all values > 0

EQUALIZE_0P3 = 9
equalize histogram with power = 0.3 from all values > 0

EQUALIZE_0P3_ALL = 11
equalize histogram with power = 0.3

EQUALIZE_0P3_ALL_UINT8 = 12
equalize histogram with power = 0.3 onto (0, 255)

EQUALIZE_0P3_UINT8 = 10
equalize histogram with power = 0.3 from all values > 0 onto (0, 255)

EQUALIZE_ALL = 7
equalize histogram

EQUALIZE_ALL_UINT8 = 8
equalize histogram onto (0, 255)

EQUALIZE_UINT8 = 6
equalize histogram from all values > 0 onto (0, 255)

NONE = 0
no transformation

STANDARDIZE = 1
rescale (min, max) to (0, 1)

STANDARDIZE_UINT8 = 2
rescale (min, max) to (0, 255)

ZERO = 3
rescale (0, max) to (0, 1)

ZERO_UINT8 = 4
rescale (0, max) to (0, 255)

locan.visualize.transform.Transform

class locan.visualize.transform.**Transform**

Bases: abc.ABC

Abstract base class for transformation classes.

Methods

`__init__`()	
inverse(values)	A transformation that performs the inverse operation.

abstract __call__(*values*, *clip=True*)

Transform values.

Parameters

- **values** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – The input values
- **clip** (bool) – If *True* values outside the [0:1] range are clipped to the [0:1] range.

Returns The transformed values.

Return type npt.NDArray[Any]

abstract inverse(*values*)

A transformation that performs the inverse operation.

Return type ndarray[Any, dtype[Any]]

Functions

adjust_contrast(image[, rescale])	Adjust contrast of image by a predefined transformation:

locan.visualize.transform.adjust_contrast

locan.visualize.transform.**adjust_contrast**(*image*, *rescale=True*, ***kwargs*)

Adjust contrast of image by a predefined transformation:

Parameters

- **image** (Union[_SupportsArray[dtype[Any]], _NestedSequence[_SupportsArray[dtype[Any]]], bool, int, float, complex, str, bytes, _NestedSequence[Union[bool, int, float, complex, str, bytes]]]) – Values to be adjusted
- **rescale** (UnionType[int, str, *Trafo*, Callable[..., Any], bool, None]) – Transformation as defined in `locan.constants.Trafo` or by transformation function. For None or False no rescaling occurs. Legacy behavior: For tuple with upper and lower bounds provided in percent, rescale intensity values to be within percentile of max and min intensities. For 'equal' intensity values are rescaled by histogram equalization.

- **kwargs** (Any) – Other parameters that are passed to the specific Transformation class.

Return type npt.NDArray[np.float_]

CHAPTER

NINE

CHANGELOG

9.1 0.19.1 - 2024-03-14

9.1.1 Other Changes and Additions

- constrain protobuf version to <5

9.2 0.19 - 2023-12-12

9.2.1 Other Changes and Additions

- add lazy_imports of API
- introduce src-layout in code base

9.3 0.18 - 2023-12-06

9.3.1 API Changes

- add colormaps module and change management of colormaps
- remove outdated module with analysis example

9.3.2 Bug Fixes

- fix version readout with readthedocs

9.3.3 Other Changes and Additions

- add GitHub action for deploying to PyPI and TestPyPI
- configure setuptools_scm for branching model

9.4 0.17 - 2023-10-26

9.4.1 New Features

- feat: adapt LocData.from_dataframe to take any dataframe that supports the dataframe interchange protocol.
- feat: add gui dialog to set file path

9.4.2 API Changes

- remove deprecated LocalizationUncertaintyFromIntensity

9.4.3 Bug Fixes

- fix: tests for shapely 2.0.2 with geos 3.12.0 in conda environment
- fix: bin-to-pixel relation in render in napari
- fix: readthedocs version readout

9.4.4 Other Changes and Additions

- refactor: update to python 3.12

9.5 0.16 - 2023-10-05

9.5.1 API Changes

- refactor: delete qt and needs_datasets marker for pytest

9.5.2 Bug Fixes

- fix: import of pytest for type checking

9.5.3 Other Changes and Additions

- refactor: reduce load in GitHub actions
- add locan to conda-forge

9.6 0.15 - 2023-09-28

9.6.1 New Features

- feat: Selector class to specify loc_property selections

9.6.2 API Changes

- refactor: change return type of clustering algorithms for noise from None to LocData()

9.6.3 Bug Fixes

- fix: convert_property_types and add documentation.

9.6.4 Other Changes and Additions

- Add type hints
- Add type checking with mypy in pre-commit and GitHub actions CI workflow
- Extend ruff linting
- refactor(test): include pytest-qt in standard tests.
- drop support for python 3.8

9.7 0.14 - 2023-06-30

9.7.1 New Features

- Add analysis routine for *SubpixelBias*
- Add function *merge_metadata* to merge metadata from class instance or file
- Add class *Files* for managing file selections to be used in batch processing
- Add *utilities/statistics* module with helper function to compute *WeightedMeanVariance*
- Add *locdata.utilities.statistics.ratio_fwhm_to_sigma* function
- Add *locdata.utilities.statistics.biased_variance* function
- Add analysis routine for *ConvexHullExpectation*, *GroupedPropertyExpectation* and *PositionVarianceExpectation*.
- Add function to standardize locdata.
- add *Locdata.update_properties_in_references* method
- add analysis class *locdata.analysis.ConvexHullExpectationBatch*.

9.7.2 API Changes

- Change *find_pattern_upstream* into *find_file_upstream*
- Add analysis class *LocalizationUncertainty* and deprecate *LocalizationUncertaintyFromIntensity*
- Refactor *LocData.properties* to include weighted coordinate averages and properties for frame and intensity
- Refactor *locan.simulation.simulate_locdata.resample*
- Change *LoData.coordinate_properties* to *LocData.coordinate_keys* and add *LocData.uncertainty_keys* and corresponding functions in *locan.constants.PropertyKeys*

9.7.3 Bug Fixes

- Fix use of callables in *LocalizationUncertainty*
- Adapt to to bug fixes in lmfit 1.2.0

9.7.4 Other Changes and Additions

- Use ruff for linting
- Use pyproject.toml for all specifications and deprecate use of setup.cfg
- Use import open3d-cpu instead of open3d
- docs: add tutorial for analysis of grouped cluster properties

9.8 0.13 - 2023-02-15

9.8.1 New Features

- Add CLI for –info and –version
- Add overlay function to transform locdatas
- Add function to standardize locdata.
- Add function load_metadata_from_toml to read metadata from toml file
- Add function find_pattern_upstream.
- Add function transform_counts_to_photons.

9.8.2 API Changes

- Add boost_histogram_axes property to Bins

9.8.3 Bug Fixes

- Fix intensity transform with nan
- Fix simulation on region being a rotated rectangle
- Fix Roi.from_yaml for rotated rectangular rois
- Fix Roi.from_yaml to work with Polygon regions
- Fix bug in localization_property_2d.
- Fix bug in localizations_per_frame concerning the time units
- Fix histogram with bins=Bins_instance as input
- Fix conversion of bin_edges to bin_size for float numbers
- Fix tests by excluding shapely 2.0.0 and 2.0.1
- Use np.random.default_rng for random number generation in simulate_drift.py

9.8.4 Other Changes and Additions

- Use of pre-commit
- Adapt to isort, black, flake8, bandit
- Integrate qtpy
- Add benchmark setup for Airspeed Velocity
- Modify dockerfiles to run with slim-bullseye
- Add conditional import of tomllib to replace tomli for python>=3.11
- Add CITATION.cff file
- Add some type hints

9.9 0.12 - 2022-06-02

9.9.1 API Changes

locan.configuration

- Introduced module locan.configuration to hold user-specific configuration values

locan.constants

- Introduced enum *PropertyKey* that holds *PropertyDescription* dataclasses with information on name, type, units and description

locan.data

- Provided new scheme for metadata
- Added tutorial about metadata for LocData
- Introduced use of protobuf Timestamp and Duration types in metadata messages
- Added function in *locan.data.metadata_utils* to provide scheme of default metadata
- Added function in *locan.data.metadata_utils* to read metadata from toml file

locan.io

- Refactored locan_io.locdata module structure

locan.render

- Changed default value for n_bins in HistogramEqualization to increase intensity resolution. Note: This modification changes the visual presentation of localization data with a large dynamic range.

9.9.2 Bug Fixes

locan.utils.system_information

- Fixed *show_version* to read out all dependency versions

locan.data

- Fixed bug in cluster functions such that setting the region of empty collections does not raise a TypeError anymore
- Fixed protobuf issues related to protobuf 4.21

9.9.3 Other Changes and Additions

- Dropped support for python 3.7
- Various minor changes of documentation and code
- Removed numba as dependency
- Based conda-related dockerfiles on mambaforge
- Introduced use of fixture from pytest-qt for testing QT interfaces

9.10 0.11.1 - 2022-04-08

9.10.1 Bug Fixes

locan.scripts

- Fix a bug introduced in 0.11 in napari and rois script.

9.11 0.11 - 2022-03-22

9.11.1 New Features

locan.data

- Modified Polygon.contains function to increase performance.
- Implemented randomize function for all hull types.

locan.io

- Added methods to load DECODE and SMAP files.

locan.render

- Added rendering functions for 3D
- Added rendering functions for RGB image (multi-color overlay)

9.11.2 API Changes

locan.io

- Extended load_txt_files to convert property names to locan standard property names.

locan.render

- Refactored intensity rescaling by introducing standard normalization procedures.

9.11.3 Bug Fixes

locan.data

- Fixed bunwarp transformation

locan.io

- Fixed lineterminator in load_rapidstorm_track_file

9.11.4 Other Changes and Additions

- Ensured support of locan and all optional dependencies for Python 3.9
- Ensured support of locan (without optional dependencies) for Python 3.10
- Turned hdbscan into optional dependency

9.12 0.10 - 2021-11-23

9.12.1 New Features

locan.io

- Add function to load rapidSTORM file with tracked data.
- Add function to load and save SMLM file.

9.12.2 Other Changes and Additions

- Locan went public.
- Readthedocs was set up.
- Zenodo DOI was generated.

9.13 0.9 - 2021-11-11

9.13.1 API Changes

locan.analysis

- Refactor computation of blinking_statistics

locan.data

- Restructured Region management introducing new classes in locan.data.region
- Rename function to computer inertia moments

locan.render

- Change image orientation in render_2d_napari to be consistent with points coordinates.

locan.simulation

- Refactored simulation functions to make use of numpy random number generator.
- Refactored simulation functions to generate Neyman-Scott point processes in expanded regions.
- Add function to simulate dSTORM data as localization clusters with normal-distributed coordinates and geometric-distributed number of localizations.

9.13.2 Other Changes and Additions

- Added or modified tutorials on mutiprocessing, regions and simulation.
- Introduce pytest markers for test functions that are excluded from test run per default.

9.14 0.8 - 2021-05-06

9.14.1 API Changes

locan.scripts

- Default values for verbose and extra flags in script show_versions were changed.

9.14.2 Bug Fixes

locan.analysis

- Fit procedure was fixed for NearestNeighborDistances.

9.14.3 Other Changes and Additions

- Library was renamed to LOCAN
- Documentation and tutorials were modified accordingly
- Test coverage was improved and use of coverage.py introduced
- _future module was deprecated

9.15 0.7 - 2021-03-26

9.15.1 API Changes

locan.analysis

- Added new keyword parameters in LocData.from_chunks and Drift.
- Extended class for blinking analysis.

9.15.2 Other Changes and Additions

- Turn warning into log for file io.
- Restructured documentation, added tutorials, and changed html-scheme to furo.

9.16 0.6 - 2021-03-04

9.16.1 New Features

- Introduced logging capability.
- Added script for running tests from command line interface.

locan.analysis

- Make all analysis classes pickleable.
- Refactored Pipeline class
- Enabled and tested multiprocessing based on multiprocessing or ray.
- Added more processing bars.
- Added drift analysis and correction based on imagecorrelation and iterative closest point registration.

locan.data

- Made LocData class pickleable.
- Added computation of inertia moments.
- Added orientation property based on oriented bounding box and inertia moments.
- Added elongation property based on oriented bounding box.
- Add transformation method to overlay LocData objects.

locan.io

- Added loading function for Nanoimager data.

locan.render

- Added windowing function for image data.

9.16.2 API Changes

locan.analysis

- Fixed and extended methods for Drift analysis and correction.

locan.data

- Implemented copy and deepcopy for LocData.
- Changed noise output in clustering methods. Removed noise parameter.

locan.datasets

- Added dataset for microtubules

locan.io

- Added option for file-like objects in io_locdata functions.
- Added Bins class, introduced use of boost-histogram package, and restructured binning.
- Introduced use of napari.run.
- Changed default value in render_2d_mpl to interpolation='nearest'.

locan.scripts

- Added arguments for locan napari and locan rois.

locan.simulation

- Added simulation of frame values.

9.16.3 Bug Fixes

locan.data

- Fixed treatment of empty LocData in clustering and hull functions.

locan.gui

- Use PySide2 as default QT backend depending on QT_API setting.

locan.io

- Fixed enconding issues for loading Elyra data.

9.16.4 Other Changes and Additions

- Test data is included in distribution.
- New dockerfiles for test and deployment.
- Included pyproject.toml file

9.17 0.5.1 - 2020-03-25

- Update environment and requirement files

9.18 0.5 - 2020-03-22

9.18.1 New Features

locan.utils

- Module locan.utils.system_information with methods to get debugging information is added.

locan.analysis

- LocalizationPropertyCorrelation analysis class is added.

locan.data

- LocData.from_coordinates() is added.
- LocData.update() method is added to change dataframe with correspodning updates of hull, properties and metadata.
- Methods to compute alpha shape hulls are added.
- Pickling capability for LocData is added.

locan.render

- scatter_2d_mpl() is added. to show locdata as scatter plot

locan.scripts

- show_versions()

9.18.2 API Changes

locan.analysis

- LocalizationProperty2D was modified and fixed.

locan.data

- locan.data.region_utils module is added with utility functions to analyze locdata regions.
- RoiRegions are added that support shapely Polygon and MultiPolygon objects.

9.18.3 Bug Fixes

locan.analysis

- Adapt colormap and rescaling in LocalizationProperty2D plot functions.

9.19 0.4.1 - 2020-02-16

9.19.1 Bug Fixes

locan.analysis

- Fix LocalizationProperty2d fit procedure

9.19.2 Other Changes and Additions

- Increase import performance

9.20 0.4 - 2020-02-13

9.20.1 New Features

- New function test() to run pytest on whole test suite.

locan.data

- New rasterize function to divide localization support into rectangular rois.
- New functions to perform affine transformation using open3d.
- New functions to perform registration using open3d.
- New function for drift correction using icp (from open3d).
- Increase performance of maximum distance computation of localization data.

locan.datasets

- Added functions to load example datasets. The datasets will be provided in a separate directory (repository).

locan.scripts

- Introduced command-line interface with compound commands.
- New script to render localization data in napari
- New script to define and save rois using napari
- New script to render localizations onto raw data images

9.20.2 API Changes

locan.analysis

- New analysis class for drift estimation.
- New analysis class for analysing 2d distribution of localization property.

locan.data

- Deprecate *update_convex_hull_in_collection()*. Use *LocData.update_convex_hulls_in_references()*.
- Metadata on time is changed from timestamp to formatted time expression.

locan.render

- Default colormaps are set to selected ones from colorcet or matplotlib.
- Add histogram function for rendering localization data.
- Add render functions to work with mpl, mpl-scatter-density, napari

locan.scripts

- Add selection option for ellipse roi.

locan.simulation

- Add functions for drift simulation.

9.20.3 Bug Fixes

locan.data

- Fixed update of bounding_box, convex_hull and oriented bounding box.

9.20.4 Other Changes and Additions

- Added centroid and dimension property to LocData.
- Implemented use of QT_API to set the QT bindings and work in combination with napari.
- Make shapely a required dependency.

9.21 0.3 - 2019-07-09

9.21.1 New Features

locan.analysis

- Added analysis class BlinkStatistics to compute on/off times in localization cluster.

locan.data

- Introduced global variable locdata_id that serves as standard running ID for LocData objects.
- Added function update_convex_hulls_in_collection

9.21.2 API Changes

locan.analysis

- Refactored all analysis class names to CamelCode.
- Refactored handling of LocData input in analysis classes to better resemble the scikit-learn API.

locan.simulation

- Deleted deprecated simulation functions.

9.21.3 Other Changes and Additions

- Refactored all localization property names to follow the convention to start with small letters.
- Changed import organization by adding __add__ to enable import locan as sp.
- Added dockerfiles for using and testing locan.
- various other small changes and fixes as documented in the version control log.

9.22 0.2 - 2019-03-22

9.22.1 New Features

locan.analysis

- implemented an analysis class CoordinateBasedColocalization.
- implemented an analysis class AccumulationClusterCheck.

locan.data

- implemented a function exclude_sparse_points to eliminate localizations in low local density regions.
- implemented a function to apply affine coordinate transformations.
- implemented a function to to apply a Bunwarp-transformation based on the raw transformation matrix from the ImageJ plugin BUnwarpJ

locan.simulation

- implemented functions to simulate localization data based on complete spatial randomness, Thomas, or Matern processes.
- implemented functions simulate_xxx to provided LocData objects.
- implemented functions make_xxx to provide point coordinates.

9.22.2 API Changes

locan.data

- implemented a new region of interest management. A RoiRegion class was defined as region object in Roi objects.

9.22.3 Bug Fixes

locan.data

- corrected index handling in track.track(), LocData.data and LocData.reduce().

locan.io

- changed types for column values returned from load_thunderstorm_file.

9.23 0.1 - 2018-12-09

9.23.1 New Features

locan.analysis

- localization_precision
- localization_property
- localizations_per_frame
- nearest_neighbor
- pipeline
- ripley
- uncertainty

locan.data

- cluster
- properties
- filter
- hulls
- locdata
- rois
- track
- transformation

locan.gui

- io

locan.io

- io_locdata

locan.render

- render2d

locan.scripts

- sc_draw_roi_mpl

locan.simulation

- simulate_locdata

9.23.2 Other Changes and Additions

locan.tests

- corresponding unit tests

docs

- rst files for sphinx documentation.

locan

- CHANGES.rst
- LICENSE.md
- README.md
- environment.yml
- environment_dev.yml

CHAPTER

TEN

CONTRIBUTIONS

10.1 Idea and Lead

- Sören Doose

10.2 Various Contributions

(in alphabetical order)

- Sarah Aufmkolk
- Philip Kollmansberger
- Sebastian Reinhard
- Felix Repp
- Sven Proppert
- Felix Wäldchen
- Steve Wolter

CHAPTER

ELEVEN

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CHAPTER

TWELVE

OTHER LICENSES

Locan makes use of libraries and code that are compatibly licensed as listed in the licences directory.

CHAPTER

THIRTEEN

DOCUMENTATION

Documentation is provided as restructured text, myst markdown, and as docstrings within the code. HTML pages and other documentation formats are build using Sphinx.

We follow standard recommendations for python documentation and the numpy conventions.

13.1 Update documentation

To update the documentation from sources delete `/docs/sources/generated` and run:

```
sphinx-build -b html -E YOUR_PATH\Locan\docs YOUR_PATH\Locan\docs\_build
```

13.2 Type hints

We try to make use of type checking using mypy as much as possible.

Type hints should be given as annotations to enable type checking.

Using the sphinx extension sphinx_autodoc_typehints (and napoleon), we convert type hints from function annotations automatically into the numpy-style documentation.

In case of duplicate documentation (annotation and docstring) the docstring is transferred into the sphinx-generated documentation but annotations are used for type-checking.

13.3 Example docstring

We try to follow standard docstrings as illustrated here:

```
def function(
    par: None | UserClass = None, **kwargs
) -> None:
    """
    Short title.

    Long description about parameter `par` with some literature reference [1]_.

    This paragraph might describe some ``code`` and include an equation:

```

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```
    .. math::

        \\f(x) = \\frac{a}{(b + c)}

    Parameters
    ----------
    par : None | UserClass
        Description
    kwargs : dict
        Parameters passed to some other documented function :func:`function_
↪name`

    Returns
    -------
    None

    Examples
    --------
    >>> 1 + 2
    3

    See Also
    --------
    :func:`locan.tests.test`

    Note
    ----
    Whatever there is to note.

    References
    ----------
    .. [1] <authors>, <title>. <journal> <year>, <volume>:<pages>. <doi>
    """
    return None



class SomeClass:
    """
    Short title.

    Long description.

    Parameters
    ----------
    par : None, other type
        Description
    kwargs : dict
        Parameters passed to some other documented function :func:`function_
↪name`
```

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```
    Attributes
    ----------
    arg : None, other type
        Description
    """
    return None
```

CHAPTER

FOURTEEN

DEVELOPMENT

We welcome any contributions for improving or further developing this package.

However, please excuse that we are limited in time for development and support.

Some things to keep in mind when adding code…

14.1 Install

A few extra libraries are needed for development:

```
pip install .[dev]
```

Alternatively, you may use the requirement files *requirements_dev.txt* or *environment_dev.yml*.

14.2 Import Conventions

The following import conventions are used throughout Locan source code and documentation:

- import numpy as np
- import pandas as pd
- import matplotlib as mpl
- import matplotlib.pyplot as plt
- import scipy as sp
- import open3d as o3d
- import networkx as nx
- import boost_histogram as bh

This is enforced through ruff following specifications in pyproject.toml.

14.3 Unit tests

For testing we use py.test.

A test suite is provided in locan/tests.

For unit testing we supply test data as data files located in locan/tests/test_data.

14.4 Coverage

For measuring code coverage in testing we use coverage.py.

Configurations are kept in pyproject.toml.

14.5 Versioning

We use SemVer for versioning. For all versions available, see the releases in this repository.

14.6 To remember:

- The package makes use of third party packages that are only used by a few routines.

  These optional packages are treated as extra_dependencies. Import of optional packages is tried in the *constants* module and a *_has_package* variable is defined. In each module that makes use of an optional import a conditional import is carried out

  ```
  if _has_package: import package
  ```

  In addition any user-accessible function that makes use of the optional package raises an import error if the optional package is not available.

  Test functions that require optional dependencies should be marked with:

  ```
  @pytest.mark.skipif(not _has_package,reason="requires optional package")
  ```

- The length of code and docstring lines should be kept to 88 and 75 characters, respectively.
- Use notation *n_something* for *number_of_something*.
- Provide commit messages with subject in imperative style (see Chris Beams, How to Write a Git Commit Message). If possible follow the specifications for conventional commits.

CHAPTER

FIFTEEN

INDICES AND TABLES

- genindex
- modindex
- search
- glossary

PYTHON MODULE INDEX

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