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Python Module Index

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jumpdiff is a python library with non-parametric Nadaraya—Watson estimators to extract the parameters of jump-diffusion processes. With jumpdiff one can extract the parameters of a jump-diffusion process from one-dimensional timeseries, employing both a kernel-density estimation method combined with a set on second-order corrections for a precise retrieval of the parameters for short timeseries.
To install `jumpdiff` simply use

```
pip install jumpdiff
```

Then on your favourite editor just use

```
import jumpdiff as jd
```

The library depends on `numpy`, `scipy`, and `sympy`. 
Jump-diffusion processes

We will show here how to: (1) generate trajectories of jump-diffusion processes; (2) retrieve the parameters from a single trajectory of a jump-diffusion process. Naturally, if we already had some data – maybe from a real-world recording of a stochastic process – we would simply look at estimating the parameters for this process.

2.1 The theory

Jump-diffusion processes\(^1\), as the name suggest, are a mixed type of stochastic processes with a diffusive and a jump term. One form of these processes which is mathematically traceable is given by the Stochastic Differential Equation

\[
dX(t) = a(x, t) \, dt + b(x, t) \, dW(t) + \xi \, dJ(t),
\]

which has four main elements: a drift term \(a(x, t)\), a diffusion term \(b(x, t)\), linked with a Wiener process \(W(t)\), a jump amplitude term \(\xi(x, t)\), which is given by a Gaussian distribution \(\mathcal{N}(0, \sigma^2_\xi)\) coupled with a jump rate \(\lambda\), which is the rate of the Poissonian jumps \(J(t)\). You can find a good review on this topic in Ref. 2.

2.2 Integrating a jump-diffusion process

Let us use the functions in \texttt{jumpdiff} to generate a jump-diffusion process, and subsequently retrieve the parameters. This is a good way to understand the usage of the integrator and the non-parametric retrieval of the parameters.

First we need to load our library. We will call it \texttt{jd}

```python
import jumpdiff as jd
```

Let us thus define a jump-diffusion process and use \texttt{jd_process} to integrate it. Do notice here that we need the drift \(a(x, t)\) and diffusion \(b(x, t)\) as functions.
2.3 Using jumpdiff to retrieve the parameters

2.3.1 Moments and Kramers–Moyal coefficients

Take the timeseries $X$ and use the function moments to retrieve the conditional moments of the process. For now let us focus on the shortest time lag, so we can best approximate the Kramers—Moyal coefficients. For this case we can simply employ

```python
edges, moments = jd.moments(timeseries = X)
```

In the array edges are the limits of our space, and in our array moments are recorded all 6 powers/order of our conditional moments. Let us take a look at these before we proceed, to get acquainted with them.

We can plot the first moment with any conventional plotter, so lets use here plotly from matplotlib. To visualise the first moment, simply use
The first moment here (i.e., the first Kramers—Moyal coefficient) is given solely by the drift term that we have selected $-0.5\times x$. In the plot we have also included the theoretical curve, which we know from having selected the value of $a(x)$ in line 8.

Similarly, we can extract the second moment (i.e., the second Kramers—Moyal coefficient) is a mixture of both the contributions of the diffusive term $b(x)$ and the jump terms $\xi$ and $\lambda$.

You have this stored in `moments[2]`.

### 2.3.2 Retrieving the jump-related terms

Naturally one of the most pertinent questions when addressing jump-diffusion processes is the possibility of recovering these same parameters from data. For the given jump-diffusion process we can use the `jump_amplitude` and `jump_rate` functions to non-parametrically estimate the jump amplitude $\xi$ and $\lambda$ terms.

After having the `moments` in hand, all we need is
# first estimate the jump amplitude
xi_est = jd.jump_amplitude(moments = moments)

# and now estimated the jump rate
lamb_est = jd.jump_rate(moments = moments)

which resulted in our case in \((xi\_est) \xi = 2.43 \pm 0.17\) and \((lamb\_est) \lambda = 1.744 \times \delta t\) (don’t forget to divide lamb_est by delta_t)! We can compare these with our chose values in lines 15-16.

## 2.4 Distinguishing pure diffusions from jump-diffusions

One important question when we have some time series – possibly from real-world data – is to be able to discern if this timeseries is a pure diffusion process (a continuous stochastic process) or a jump-diffusion process (a discontinuous stochastic process). For this, jumpdiff has an easy to use function, called q_ratio. The idea behind distinguishing continuous and discontinuous processes is simple: diffusion processes diffuse over time, thus they take time to occupy space; jump-diffusion processes can jump, and thus statistically, they occupy all space very fast.

To analyse this let us design a simple example – with some numerically generated data – that shows the use of q_ratio and how to read it.

Let us generate two trajectories, using jd_process, denoted d_timeseries and j_timeseries, for diffusion timeseries and jumpy timeseries. Naturally the first must not include a jump term. To keep it simple, we will use the same parameters for both, expect for the jumps:

```python
import jumpdiff as jd

# integration time and time sampling
t_final = 10000
delta_t = 0.01

# Drift function
def a(x):
    return -0.5 \times x

# Diffusion function
def b(x):
    return 0.75

# generate 2 trajectories
d_timeseries = jd.jd_process(t_final, delta_t, a=a, b=b, xi=0, lamb=0)
j_timeseries = jd.jd_process(t_final, delta_t, a=a, b=b, xi=2.5, lamb=1.75)
```

Note how xi and lamb are different for each process. To now examine the rate of diffusion of the processes, we need to generate a time arrow, which we denote lag. This needs to be an integer list >0.

```python
import numpy as np
lag = np.logspace(0, 3, 25, dtype=int)
```

Lastly we just need to call the q_ratio for our two timeseries

```python
d_lag, d_Q = jd.q_ratio(lag, d_timeseries)
j_lag, j_Q = jd.q_ratio(lag, j_timeseries)
```

And with the help of matplotlib's plotly, we can visualise the results in a double logarithmic scale.
As we can see, the diffusion process grows with our time arrow lag, where the jump-diffusion is constant (does not depend on lag). Jump processes will show a constant relation with code:lag, where diffusion processes a linear relation.
3.1 Installation

To install jumpdiff simply use

```bash
pip install jumpdiff
```

Then on your favourite editor just use

```python
import jumpdiff as jd
```

The library depends on numpy, scipy, and sympy.

3.2 Jump-diffusion processes

We will show here how to: (1) generate trajectories of jump-diffusion processes; (2) retrieve the parameters from a single trajectory of a jump-diffusion process. Naturally, if we already had some data – maybe from a real-world recording of a stochastic process – we would simply look at estimating the parameters for this process.

3.2.1 The theory

Jump-diffusion processes\(^1\), as the name suggest, are a mixed type of stochastic processes with a diffusive and a jump term. One form of these processes which is mathematically traceable is given by the Stochastic Differential Equation

\[
\mathrm{d}X(t) = a(x, t) \, \mathrm{d}t + b(x, t) \, \mathrm{d}W(t) + \xi \, \mathrm{d}J(t),
\]

which has four main elements: a drift term \(a(x, t)\), a diffusion term \(b(x, t)\), linked with a Wiener process \(W(t)\), a jump amplitude term \(\xi(x, t)\), which is given by a Gaussian distribution \(\mathcal{N}(0, \sigma^2)\) coupled with a jump rate \(\lambda\), which is the rate of the Poissonian jumps \(J(t)\). You can find a good review on this topic in Ref. 2.
3.2.2 Integrating a jump-diffusion process

Let us use the functions in jumpdiff to generate a jump-diffusion process, and subsequently retrieve the parameters. This is a good way to understand the usage of the integrator and the non-parametric retrieval of the parameters.

First we need to load our library. We will call it `jd`

```python
import jumpdiff as jd
```

Let us thus define a jump-diffusion process and use `jd_process` to integrate it. Do notice here that we need the drift $a(x,t)$ and diffusion $b(x,t)$ as functions.

```python
# integration time and time sampling
t_final = 10000
delta_t = 0.001

# A drift function
def a(x):
    return -0.5*x

# and a (constant) diffusion term
def b(x):
    return 0.75

# Now define a jump amplitude and rate
xi = 2.5
lamb = 1.75

# and simply call the integration function
X = jd.jd_process(t_final, delta_t, a=a, b=b, xi=xi, lamb=lamb)
```

This will generate a jump diffusion process $X$ of length $\text{int}(10000/0.001)$ with the given parameters.

![Graph of the generated jump diffusion process](image)

3.2.3 Using jumpdiff to retrieve the parameters

Moments and Kramers–Moyal coefficients

Take the timeseries $X$ and use the function `moments` to retrieve the conditional moments of the process. For now let us focus on the shortest time lag, so we can best approximate the Kramers—Moyal coefficients. For this case we can...
In the array `edges` are the limits of our space, and in our array `moments` are recorded all 6 powers/order of our conditional moments. Let us take a look at these before we proceed, to get acquainted with them.

We can plot the first moment with any conventional plotter, so let's use here `plotly` from `matplotlib`. To visualise the first moment, simply use

```python
import matplotlib.pyplot as plt
plt.plot(edges, moments[1]/delta_t)
```

The first moment here (i.e., the first Kramers–Moyal coefficient) is given solely by the drift term that we have selected $-0.5*x$. In the plot we have also included the theoretical curve, which we know from having selected the value of $a(x)$ in line 8.

Similarly, we can extract the second moment (i.e., the second Kramers–Moyal coefficient) is a mixture of both the contributions of the diffusive term $b(x)$ and the jump terms $\xi$ and $\lambda$.

You have this stored in `moments[2]`.

3.2. Jump-diffusion processes
Retrieving the jump-related terms

Naturally one of the most pertinent questions when addressing jump-diffusion processes is the possibility of recovering these same parameters from data. For the given jump-diffusion process we can use the jump_amplitude and jump_rate functions to non-parametrically estimate the jump amplitude $\xi$ and $\lambda$ terms.

After having the moments in hand, all we need is

```python
# first estimate the jump amplitude
xi_est = jd.jump_amplitude(moments = moments)

# and now estimated the jump rate
lamb_est = jd.jump_rate(moments = moments)
```

which resulted in our case in $(\xi_{\text{est}}) = 2.43 \pm 0.17$ and $(\lambda_{\text{est}}) = 1.744 \times \text{delta}_t$ (don’t forget to divide lamb_est by delta_t)! We can compare these with our chose values in lines 15-16.

3.3 Distinguishing pure diffusions from jump-diffusions

One important question when we have some time series – possibly from real-world data – is to be able to discern if this timeseries is a pure diffusion process (a continuous stochastic process) or a jump-diffusion process (a discontinuous stochastic process). For this, jumpdiff has an easy to use function, called q_ratio. The idea behind distinguishing continuous and discontinuous processes is simple: diffusion processes diffuse over time, thus they take time to occupy space; jump-diffusion processes can jump, and thus statistically, they occupy all space very fast.

To analyse this let us design a simple example – with some numerically generated data – that shows the use of q_ratio and how to read it.

Let us generate two trajectories, using jd_process, denoted d_timeseries and j_timeseries, for diffusion timeseries and jumpy timeseries. Naturally the first must not include a jump term. To keep it simple, we will use the same parameters for both, except for the jumps:

```python
import jumpdiff as jd

# integration time and time sampling
t_final = 10000
delta_t = 0.01

# Drift function
def a(x):
    return -0.5*x

# Diffusion function
def b(x):
    return 0.75

# generate 2 trajectories
d_timeseries = jd.jd_process(t_final, delta_t, a=a, b=b, xi=0, lamb=0)
j_timeseries = jd.jd_process(t_final, delta_t, a=a, b=b, xi=2.5, lamb=1.75)
```

Note how $\xi$ and $\lambda$ are different for each process. To now examine the rate of diffusion of the processes, we need to generate a time arrow, which we denote $\text{lag}$. This needs to be a integer list $>0$.

```python
import numpy as np
lag = np.logspace(0, 3, 25, dtype=int)
```
Lastly we just need to can the \texttt{q\_ratio} for our two timeseries:

```python
20 d_lag, d_Q = jd.q_ratio(lag, d_timeseries)
21 j_lag, j_Q = jd.q_ratio(lag, j_timeseries)
```

And with the help of \texttt{matplotlib\_pyplot}, we can visualise the results in a double logarithmic scale:

```python
import matplotlib.plotly as plt
22 plt.loglog(d_lag, d_Q, '-', label='diffusion')
23 plt.loglog(j_lag, j_Q, 'o-', label='jump-diffusion')
```

As we can see, the diffusion process grows with our time arrow \texttt{lag}, where the jump-diffusion is constant (does not depend on \texttt{lag}). Jump processes will show a constant relation with code \texttt{lag}, where diffusion processes a linear relation.

### 3.4 Functions

Documentation for all the functions in \texttt{jumpdiff}.

#### 3.4.1 Jump-diffusion timeseries generator

\texttt{jumpdiff.jd\_process.\texttt{jd\_process} (time: float, delta\_t: float, a: callable, b: callable, xi: float, lamb: float, init: float = None, solver: str = 'Euler', b\_prime: callable = None) → numpy.ndarray}

Integrates a jump-diffusion process with drift \( a(x) \), diffusion \( b(x) \), jump amplitude \( \xi \), and jump rate \( \lambda \).

\[
dX(t) = a(x, t) \, dt + b(x, t) \, dW(t) + \xi \, dJ(t),
\]

with \( J \) Poisson with jump rate \( \lambda \). This integrator has both an Euler–Maruyama and a Milstein method of integration. For Milstein one has to introduce the derivative of the diffusion term \( b \), denoted \texttt{b\_prime}.

**Parameters**

- \texttt{time (float > 0)} – Total integration time. Positive float or int.
- \texttt{delta\_t (float > 0)} – Time sampling, the smaller the better.
• **a** (*callable*) – The drift function. Can be a function of a lambda. For an Ornstein–Uhlenbeck process with drift \(-2x\), a takes the form

\[
a = \lambda x: -2x.
\]

• **b** (*callable*) – The diffusion function. Can be a function of a lambda. For an Ornstein–Uhlenbeck process with diffusion 1, a takes the form

\[
b = \lambda x: 1.
\]

• **xi** (*float > 0*) – Variance of the jump amplitude, which will be turned into a normal distribution like \(\mathcal{N}(0, \xi)\).

• **lamb** (*float > 0*) – Jump rate of the Poissonian jumps. This is implemented as the numpy function `np.random.poisson(lam = lamb * delta_t)`.

• **init** (*float (default None)*) – Initial conditions. If None given, generates a random value from a normal distribution \(\mathcal{N}(0, \delta_t)\).

• **solver** (*'Euler' or 'Milstein' (default 'Euler')*) – The regular Euler–Maruyama solver ‘Euler’ is the default, with an order of \(\delta_t\). To employ a state-dependent diffusion, i.e., \(b(x)\) as a function of \(x\), the Milstein scheme has an order of \(\delta_t\). You must introduce as well the derivative of \(b(x)\), i.e., \(b'(x)\), as the argument \(b_prime\).

Returns **X** – Timeseries of size \(\text{int}(\text{time}/\delta_t)\)

Return type **np.array**

### 3.4.2 Moments


Estimates the moments of the Kramers–Moyal expansion from a timeseries using a Nadaraya–Watson kernel estimator method. These later can be turned into the drift and diffusion coefficients after normalisation.

Parameters

• **timeseries** (*np.ndarray*) – A 1-dimensional timeseries.

• **bw** (*float*) – Desired bandwidth of the kernel. A value of 1 occupies the full space of the bin space. Recommended are values \(0.005 < \text{bw} < 0.4\).

• **bins** (*np.ndarray (default None)*) – The number of bins for each dimension, defaults to \(\text{np.array([5000])}\). This is the underlying space for the Kramers–Moyal conditional moments.

• **power** (*int (default 6)*) – Upper limit of the the Kramers–Moyal conditional moments to calculate. It will generate all Kramers–Moyal conditional moments up to power.

• **lag** (*list (default 1)*) – Calculates the Kramers–Moyal conditional moments at each indicated lag, i.e., for `timeseries[::lag]`. Defaults to 1, the shortest timestep in the data.

• **corrections** (*bool (default True)*) – Implements the second-order corrections of the Kramers–Moyal conditional moments directly

• **norm** (*bool (default False)*) – Sets the normalisation. False returns the Kramers–Moyal conditional moments, and True returns the Kramers–Moyal coefficients.
- **kernel** (callable (default None)) – Kernel used to convolute with the Kramers–Moyal conditional moments. To select example an Epanechnikov kernel use
  
  ```python
  kernel = kernels.epanechnikov
  ```

  If None the Epanechnikov kernel will be used.

- **tol** (float (default 1e-10)) – Round to zero absolute values smaller than tol, after convolutions.

- **conv_method** (str (default auto)) – A string indicating which method to use to calculate the convolution. docs.scipy.org/doc/scipy/reference/generated/scipy.signal.convolve.

- **verbose** (bool (default False)) – If True will report on the bandwidth used.

Returns

- **edges** (np.ndarray) – The bin edges with shape (D,bins.shape) of the calculated moments.

- **moments** (np.ndarray) – The calculated moments from the Kramers–Moyal expansion of the timeseries at each lag. To extract the selected orders of the moments, use `moments[i, :, j]`, with i the order according to powers, j the lag (if any introduced).

`jumpdiff.moments.corrections(m: numpy.ndarray, power: int)`

The moments function will by default apply the corrections. You can turn the corrections off in that function by setting `corrections = False`.

Second-order corrections of the Kramers–Moyal coefficients (conditional moments), given by

\[
F_1 = M_1,
\]

\[
F_2 = \frac{1}{2} (M_2 - M_1^2),
\]

\[
F_3 = \frac{1}{6} (M_3 - 3M_1M_2 + 3M_1^3),
\]

\[
F_4 = \frac{1}{24} (M_4 - 4M_1M_3 + 18M_1^2M_2 - 3M_2^2 - 15M_1^4),
\]

\[
F_5 = \frac{1}{120} (M_5 - 5M_1M_4 + 30M_1^2M_3 - 150M_1^3M_2 + 45M_1M_2^2 - 10M_2M_3 + 105M_1^5),
\]

\[
F_6 = \frac{1}{720} (M_6 - 6M_1M_5 + 45M_1^2M_4 - 300M_1^3M_3 + 1575M_1^4M_2 - 675M_2^2M_2^2 - 78M_1M_2M_3^2 + 180M_1M_2M_3 - 95M_2M_4 - 9M_4^3),
\]

with the prefactor the normalisation, i.e., the normalised results are the Kramers–Moyal coefficients. If norm is False, this results in the Kramers–Moyal conditional moments.

Parameters

- **(moments)** (m) – The calculated conditional moments from the Kramers–Moyal expansion of the at each lag. To extract the selected orders of the moments use `moments[i, :, j]`, with i the order according to powers, j the lag.

- **power** (int) – Upper limit of the Kramers–Moyal conditional moments to calculate. It will generate all Kramers–Moyal conditional moments up to power.

Returns **F** – The corrections of the calculated Kramers–Moyal conditional moments from the Kramers–Moyal expansion of the timeseries at each lag. To extract the selected orders of the moments, use `F[i, :, j]`, with i the order according to powers, j the lag (if any introduced).

Return type **np.ndarray**
3.4.3 Parameters

`jumpdiff.parameters.jump_amplitude` *(moments: numpy.ndarray, tol: float = 1e-10, full: bool = False, verbose: bool = False) → numpy.ndarray*

Retrieves the jump amplitude \( \xi (\xi) \) via

\[
\lambda(x, t) = \frac{M_4(x, t)}{3\sigma_\xi^4}.
\]

Take notice that the different normalisation of the `moments` leads to a different results.

**Parameters**

- `moments` *(np.ndarray)* – Moments extracted with the function `moments`. Needs moments up to order 6.
- `tol` *(float (default 1e-10))* – Toleration for the division of the moments.
- `full` *(bool (default False))* – If True returns also the (biased) weighed standard deviation of the averaging process.
- `verbose` *(bool (default True))* – Prints the result.

**Returns** `xi_est` – Estimator of the jump amplitude \( \xi (\xi) \).

**Return type** `np.ndarray`

**References**


`jumpdiff.parameters.jump_rate` *(moments: numpy.ndarray, xi_est: numpy.ndarray = None, tol: float = 1e-10, full: bool = False, verbose: bool = False) → numpy.ndarray*

Retrieves the jump rate \( \lambda (\lambda) \) via

\[
\sigma_\xi^2 = \frac{M_6(x, t)}{5M_4(x, t)}.
\]

Take notice that the different normalisation of the `moments` leads to a different results.

**Parameters**

- `tol` *(float (default 1e-10))* – Toleration for the division of the moments.
- `full` *(bool (default False))* – If True returns also the (biased) weighed standard deviation of the averaging process.
- `verbose` *(bool (default True))* – Prints the result.

**Returns** `xi_est` – Estimator on the jump rate lamb \( \lambda (\lambda) \)

**Return type** `np.ndarray`
References


3.4.4 Q-ratio

```python
jumpdiff.q_ratio.q_ratio(lag: numpy.ndarray, timeseries: numpy.ndarray, loc: int = None, correction: bool = False) → numpy.ndarray
```

q_ratio method to distinguish pure diffusion from jump-diffusion timeseries, Given by the relation of the 4th and 6th Kramers–Moyal coefficient with increasing lag

\[ Q(x, \tau) = \frac{D_6(x, \tau)}{5D_4(x, \tau)} = \begin{cases} b(x)^2\tau, & \text{diffusive} \\ \sigma_\zeta^2(x), & \text{jumpy} \end{cases} \]

Parameters

- **lag** *(np.ndarray of ints)* – An array with the time-lag to extract the Kramers–Moyal coefficient for different lags.
- **timeseries** *(np.ndarray)* – A 1-dimensional timeseries.
- **loc** *(float (default None)) – Use a particular point in space to calculate the ratio. If None given, the maximum of the probability density function is taken.
- **corrections** *(bool (default False)) – Select whether to use corrective terms.

Returns

- **lag** *(np.ndarray of ints)* – Same as input, but only lag > 0 and as ints.
- **ratio** *(np.ndarray of len(lag)) – Ratio of the sixth-order over forth-order Kramers–Moyal coefficient.

References


3.4.5 Formulae

```python
jumpdiff.formulae.m_formula(power, tau=True)
```

Generate the formula for the conditional moments with second-order corrections based on the relation with the ordinary Bell polynomials

\[ M_n(x', \tau) \sim (n!)\tau D_n(x') + \frac{(n!)^2\tau^2}{2} \sum_{m=1}^{n-1} D_m(x')D_{n-m}(x') \]

Parameters **power** *(int)* – Desired order of the formula.

Returns **term** – Expression up to given power.
**Return type** sympy.symbols**

**jumpdiff.formulae.f_formula**(power)

Generate the formula for the conditional moments with second-order corrections based on the relation with the ordinary Bell polynomials

\[
D_n(x) = \frac{1}{\tau(n!)} \left[ \hat{B}_{n,1}(M_1(x, \tau), M_2(x, \tau), \ldots, M_n(x, \tau)) - \frac{\tau}{2} \hat{B}_{n,2}(M_1(x, \tau), M_2(x, \tau), \ldots, M_{n-1}(x, \tau)) \right].
\]

**Parameters**

- **power**(int) – Desired order of the formula.

**Returns**

- **term** – Expression up to given **power**.

**Return type** sympy.symbols**

**jumpdiff.formulae.f_formula_solver**(power)

Generate the reciprocal relation of the moments to the Kramers–Moyal coefficients by sequential iteration.

\[
D_n(x) = \frac{1}{\tau(n!)} \left[ \hat{B}_{n,1}(M_1(x, \tau), M_2(x, \tau), \ldots, M_n(x, \tau)) - \frac{\tau}{2} \hat{B}_{n,2}(M_1(x, \tau), M_2(x, \tau), \ldots, M_{n-1}(x, \tau)) \right].
\]

**Parameters**

- **power**(int) – Desired order of the formula.

**Returns**

- **term** – Expression up to given **power**.

**Return type** sympy.symbols

### 3.4.6 Helping functions

**Kernels function**

**jumpdiff.kernels.kernel**(kernel_func)

Transforms a kernel function into a scaled kernel function (for a certain bandwidth bw).

**Currently implemented kernels are:** Epanechnikov, Gaussian, Uniform, Triangular, Quartic.


**jumpdiff.kernels.volume_unit_ball**(dims: int) → float

Returns the volume of a unit ball in dimensions dims.

**jumpdiff.kernels.epanechnikov**(x: numpy.ndarray, dims: int) → numpy.ndarray

The Epanechnikov kernel in dimensions dims.

**jumpdiff.kernels.gaussian**(x: numpy.ndarray, dims: int) → numpy.ndarray

Gaussian kernel in dimensions dims.

**jumpdiff.kernels.uniform**(x: numpy.ndarray, dims: int) → numpy.ndarray

Uniform, or rectangular kernel in dimensions dims

**jumpdiff.kernels.triagular**(x: numpy.ndarray, dims: int) → numpy.ndarray

Triangular kernel in dimensions dims

**jumpdiff.kernels.quartic**(x: numpy.ndarray, dims: int) → numpy.ndarray

Quartic, or biweight kernel in dimensions dims
3.5 License

MIT License

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3.6 Contact

If you need help with something, find a bug, issue, or typo on the repository or in the code, you can contact me here: leonardo.rydin@gmail.com or open an issue on the GitHub repository.
CHAPTER 4

Literature


An extensive review on the subject can be found here.
CHAPTER 5

Funding

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