TrendyPy

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CHAPTER

ONE

TRENDYPY

TrendyPy is a small Python package for sequence clustering. It is initially developed to create time series clusters by calculating trend similarity distance with Dynamic Time Warping.

1.1 Installation

You can install TrendyPy with pip.

```
pip install trendypy
```

TrendyPy depends on Pandas, Numpy and fastdtw and works in Python 3.6+.

1.2 Quickstart

Trendy has scikit-learn like api to allow easy integration to existing programs. Below is a quick example to show how it clusters increasing and decreasing trends.

```
>>> from trendypy.trendy import Trendy
>>> a = [1, 2, 3, 4, 5] # increasing trend
>>> b = [1, 2.1, 2.9, 4.4, 5.1] # increasing trend
>>> c = [6.2, 5, 4, 3, 2] # decreasing trend
>>> d = [7, 6, 5, 4, 3, 2, 1] # decreasing trend
>>> trendy = Trendy(n_clusters=2)
>>> trendy.fit([a, b, c, d])
>>> print(trendy.labels_)
[0, 0, 1, 1]
>>> trendy.predict([[0.9, 2, 3.1, 4]]) # another increasing trend
[0]
```

It can also be utilized to cluster strings by using string similarity metrics.

```
>>> from trendypy.trendy import Trendy
>>> from trendypy.algos import levenshtein_distance
>>> company_names = [
...         'apple inc',
...         'Apple Inc.',
...         'Microsoft Corporation',
...         'Microsft Corp.']
>>> trendy = Trendy(n_clusters=2, algorithm=levenshtein_distance)
```

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```
>>> trendy.fit(company_names)
>>> print(trendy.labels_)
[0, 0, 1, 1]
>>> trendy.predict(['Apple'])
[0]
```

Refer to extensive demo to see it in clustering stock trends, images or to see how to define your own metric or just check API Reference for details.

1.3 Post

The idea is originated from the post Trend Clustering.

CHAPTER

TWO

SEE IN ACTION

Let's see how TrendyPy works with a few use cases.

2.1 Stock Data

In this demo, I'd like to show you how to use TrendyPy in some `stock data` between 2018-01-01 and 2020-06-28. You can download the data from `here` to reproduce the demo.

Let's say we have some stock data from a combination of tech and banking. And, we want to identify an unknown trend if it's a tech stock or banking. For this purpose, we'll use FB (i.e. Facebook), GOOGL (i.e. Google), AMZN (i.e Amazon), BAC (i.e. Bank of America) and WFC (i.e. Wells Fargo) for training data then AAPL (i.e. Apple) and c (i.e. Citigroup) for prediction data.

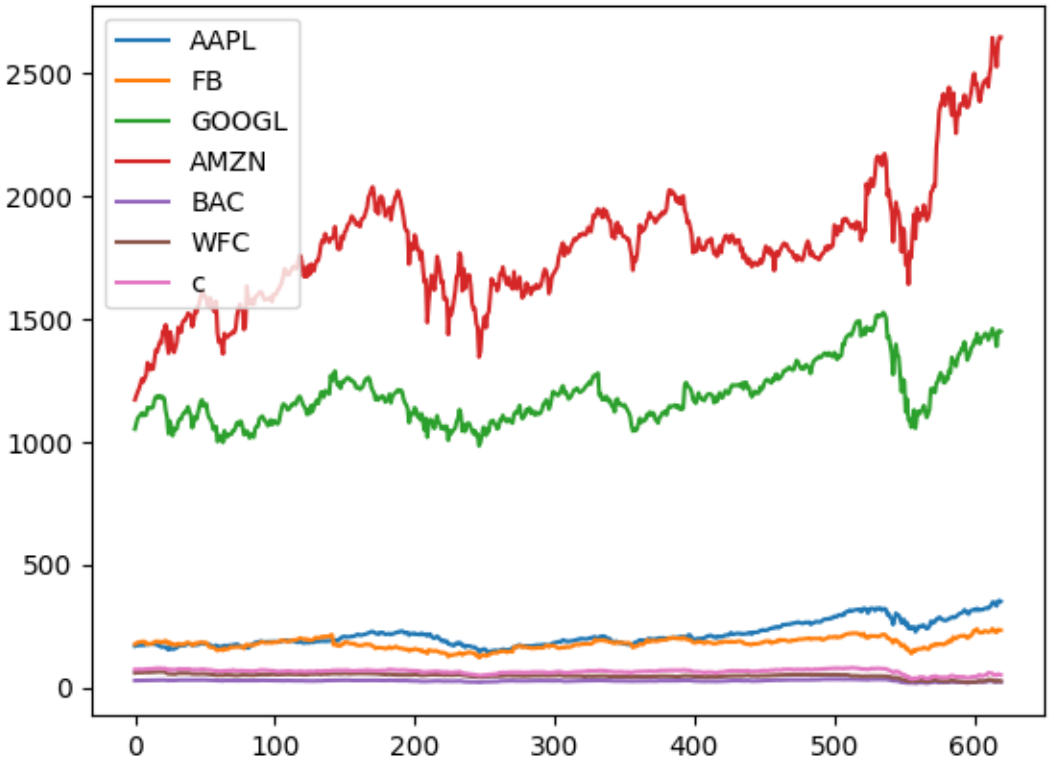
But first, here is how the data looks.

```
In [1]: import pandas as pd

In [2]: import matplotlib.pyplot as plt

In [3]: df = pd.read_csv('stock_data.csv')

In [4]: df.plot()
Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x7fadbde074a8>
```

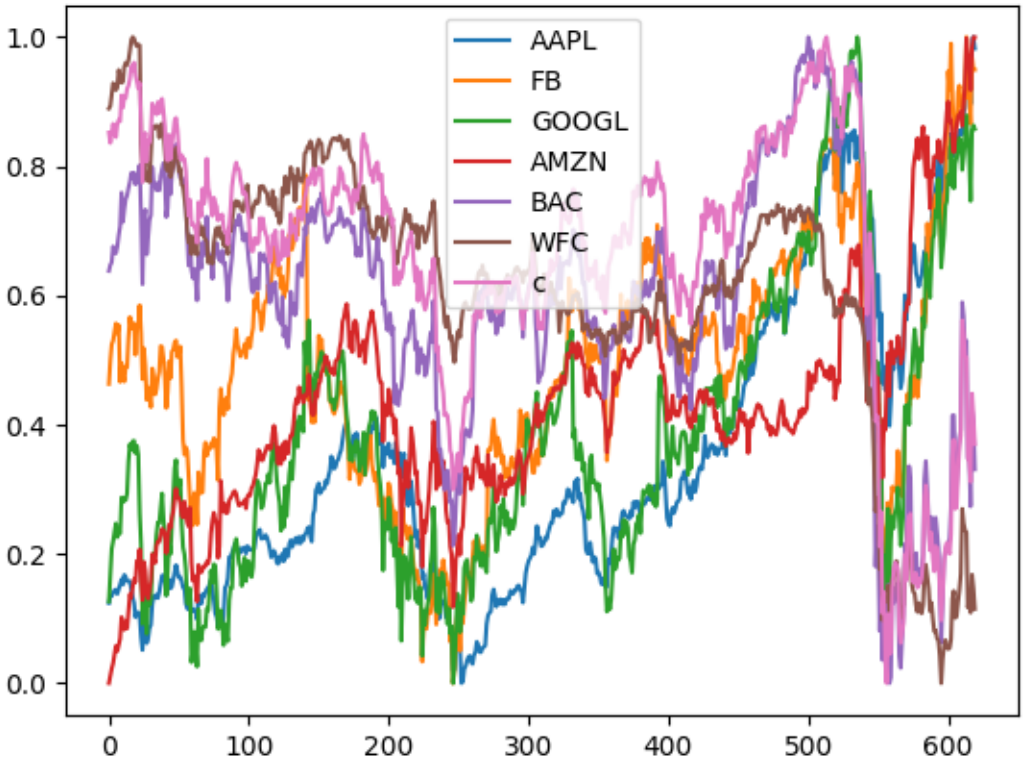


If we cluster like this, the expensive stocks like GOOGL and AMZN will alone constitute one cluster which it's clearly not intended. So, let's scale first.

```
In [5]: from trendypy import utils

In [6]: df = df.apply(utils.scale_01)

In [7]: df.plot()
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x7fadbd8d5e80>
```



It's a bit apparent that BAC, WFC and c are different than the others. Let's put sectors side by side to see the difference better.

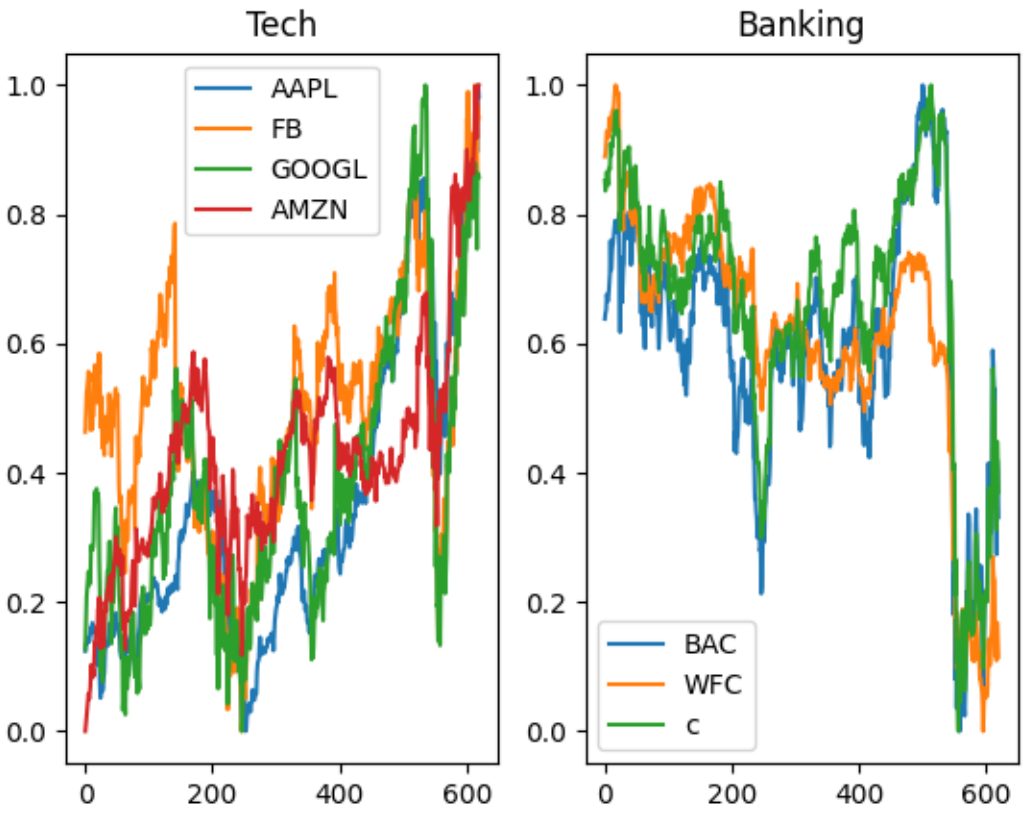
```
In [8]: fig, axes_ = plt.subplots(nrows=1, ncols=2)

In [9]: axes_[0].set_title('Tech')
Out[9]: Text(0.5, 1.0, 'Tech')

In [10]: axes_[1].set_title('Banking')
Out[10]: Text(0.5, 1.0, 'Banking')

In [11]: df[['AAPL', 'FB', 'GOOGL', 'AMZN']].plot(ax=axes_[0])
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7fadbd7e5a20>

In [12]: df[['BAC', 'WFC', 'c']].plot(ax=axes_[1])
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7fadbd815630>
```



Now, we can use the training data to fit. Remember, we're setting AAPL and c aside to predict later and only fit by using the rest.

```
In [13]: from trendypy.trendy import Trendy

In [14]: trendy = Trendy(n_clusters=2) # 2 for tech and banking

In [15]: trendy.fit([df.FB, df.GOOGL, df.AMZN, df.BAC, df.WFC])

In [16]: trendy.labels_
Out[16]: [0, 0, 0, 1, 1]
```

You can also use fit_predict method for this purpose, it's essentially the same.

```
In [17]: trendy.fit_predict([df.FB, df.GOOGL, df.AMZN, df.BAC, df.WFC])
Out[17]: [0, 0, 0, 1, 1]
```

As expected, it successfully assigns FB, GOOGL and AMZN into the first cluster (i.e. `0`) and BAC and WFC into the second (i.e. `1`). So, we can name `0` as tech and `1` as banking.

Now, let's make predictions on the prediction data that we set aside earlier (i.e. AAPL, c).

```
In [18]: trendy.predict([df.AAPL]) # expecting `0` since AAPL is a part of tech
Out[18]: [0]

In [19]: trendy.predict([df.c]) # expecting `1` since c is a part of banking
```

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```
Out[19]: [1]
```

As seen above, it correctly predicts trends.

You can easily pickle the model object to be used later with to_pickle method.

```
In [20]: trendy.to_pickle('my_first_trendy.pkl')
```

And, that's all.

2.2 Image Clustering

If you have the proper distance metric function for the right data, you can use TrendyPy to even cluster images. In this demo, I'll use black & white images from MPEG7 CE Shape-1 Part B database. The goal is to correctly cluster the images and assign new ones to the appropriate clusters. Here are some simple images that'll be used to create the clusters. Each image is slightly different than the others in the same group. You can `download the images` if you want to reproduce the demo.

Fig. 1: car-01.gif	Fig. 2: car-02.gif	Fig. 3: car-03.gif
Fig. 4: carriage-02.gif	Fig. 5: carriage-03.gif	Fig. 6: carriage-04.gif
Fig. 7: chopper-01.gif	Fig. 8: chopper-02.gif	Fig. 9: chopper-03.gif

Define a function to read the image and convert to a numpy array.

```
In [21]: from PIL import Image

In [22]: import numpy as np

In [23]: def load_image(file):
   ....:     img = Image.open(file)
   ....:     img.load()
   ....:     return np.asarray(img, dtype="int32")
   ....:
```

Read images and assign them into lists.

```
In [24]: cars = [
   ....:     load_image('image_data/car-01.gif'),
   ....:     load_image('image_data/car-02.gif'),
   ....:     load_image('image_data/car-03.gif')]
   ....:

In [25]: carriages = [
   ....:     load_image('image_data/carriage-02.gif'),
   ....:     load_image('image_data/carriage-03.gif'),
   ....:     load_image('image_data/carriage-04.gif')]
   ....:

In [26]: choppers = [
   ....:     load_image('image_data/chopper-01.gif'),
   ....:     load_image('image_data/chopper-02.gif'),
```

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```
   ....:     load_image('image_data/chopper-03.gif')]
   ....:
```

Euclidean Distance can be used to calculate the similarity between images. So, let's import euclidean_distance from utils module, then assign it as *algorithm* argument during the initialization.

```
In [27]: from trendypy.trendy import Trendy

In [28]: from trendypy.utils import euclidean_distance

In [29]: trendy = Trendy(n_clusters=3, algorithm=euclidean_distance)

In [30]: trendy.fit(cars + carriages + choppers)

In [31]: trendy.labels_
Out[31]: [0, 0, 0, 1, 1, 1, 2, 2, 2]
```

As expected, it correctly clusters these simple images. Let's see if it predicts new data correctly.

Fig. 10: car-20.gif	Fig. 11: carriage-20.gif	Fig. 12: chopper-08.gif

```
In [32]: new_car = load_image('image_data/car-20.gif')

In [33]: new_carriage = load_image('image_data/carriage-20.gif')

In [34]: new_chopper = load_image('image_data/chopper-08.gif')

In [35]: trendy.predict([new_car, new_carriage, new_chopper])
Out[35]: [0, 1, 2]
```

Looks like it correctly predicts new data as well.

Note: Because of the limitation of the selected metric function (i.e. Euclidean Distance), I had to cherry pick images with exact same sizes (i.e. 352×288). Depending on the function you choose, you may or may not do the same.

2.3 Custom Metric

TrendyPy is flexible enough to be able to utilize user defined metrics. In this example, I'll show how to create your own metric and use it during the clustering.

Let's say we want to cluster DNA sequences and need a metric to do that. Needleman–Wunsch algorithm is an algorithm used in bioinformatics to align protein or nucleotide sequences. It's not a metric but it inspires us to create our own metric. The metric basically compares two sequences with same length and it penalizes each mismatch by increasing the distance by p then divides it to total length.

```
In [36]: def my_metric(x, y, p=1):
   ....:     assert len(x) == len(y)
   ....:     dist = 0
   ....:     for i in range(len(x)):
   ....:         if x[i] != y[i]:
```

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```
   ....:             dist += p
   ....:     return dist/len(x)
   ....:
```

As you can see, you just need to consider inputs and output of your custom function. Specifically,

1. Input must have *x* and *y* for two data points to compare. You may have other default arguments (e.g. *p*).
2. Output must be a float. 0 indicates same and greater is farther.

Note: Technically, any float range should work as the output of the custom function as long as greater is farther. However, it won't be named as *metric* in that case.

Anyway, let's use it.

```
In [37]: set_of_sequences = [
   ....:     'AAATTT', 'AAACTT', 'AAATCT', # group 1
   ....:     'GACTAG', 'GGCTAG', 'GACAAG' # group 2
   ....: ]
   ....:
```

```
In [38]: from trendypy.trendy import Trendy

In [39]: trendy = Trendy(
   ....:     n_clusters=2, # there are 2 groups
   ....:     algorithm=my_metric # this is where to set custom metric
   ....: )
   ....:

In [40]: trendy.fit(set_of_sequences)

In [41]: trendy.labels_
Out[41]: [0, 0, 0, 1, 1, 1]
```

It clearly clusters first and second group. Now, let's see on new data.

```
In [42]: new_seq1 = 'AAAGGT' # similar to group 1

In [43]: new_seq2 = 'GTCCAG' # similar to group 2

In [44]: trendy.predict([new_seq1, new_seq2])
Out[44]: [0, 1]
```

Very simple.

CHAPTER

THREE

API REFERENCE

3.1 trendy

class trendy.**Trendy**(*n_clusters*, *algorithm=<function fastdtw_distance>*)

Bases: object

Estimator to cluster trend-lines and assign new lines accordingly.

Notes

Scaling and missing values need to be handled externally.

Parameters

- **n_clusters** (*int*) – The number of clusters to form.
- **algorithm** (*callable*) – Algorithm to calculate the difference. Default is fast DTW with Euclidean.

Example

```
>>> a = [1, 2, 3, 4, 5] # increasing trend
>>> b = [1, 2.1, 2.9, 4.4, 5.1] # increasing trend
>>> c = [6.2, 5, 4, 3, 2] # decreasing trend
>>> d = [7, 6, 5, 4, 3, 2, 1] # decreasing trend
>>> trendy = Trendy(n_clusters=2)
>>> trendy.fit([a, b, c, d])
>>> print(trendy.labels_)
[0, 0, 1, 1]
>>> trendy.predict([[0.9, 2, 3.1, 4]]) # another increasing trend
[0]
```

labels_ = None

cluster_centers_ = None

fit(*X*)

Compute clustering based on given distance algorithm.

Parameters **X** (*array of arrays*) – Training instances to cluster.

Example

```
>>> a = [1, 2, 3, 4, 5] # increasing
>>> b = [1, 2.1, 2.9, 4.4, 5.1] # increasing
>>> c = [6.2, 5, 4, 3, 2] # decreasing
>>> d = [7, 6, 5, 4, 3, 2, 1] # decreasing
>>> trendy = Trendy(2)
>>> trendy.fit([a, b, c, d])
>>> print(trendy.labels_)
[0, 0, 1, 1]
```

predict(*X*)

Predict the closest cluster each sample in X belongs to.

Parameters **X** (*array of arrays*) – New data to predict.

Returns Index of the cluster each sample belongs to.

Return type list

Example

```
>>> a = [1, 2, 3, 4, 5] # increasing
>>> b = [1, 2.1, 2.9, 4.4, 5.1] # increasing
>>> c = [6.2, 5, 4, 3, 2] # decreasing
>>> d = [7, 6, 5, 4, 3, 2, 1] # decreasing
>>> trendy = Trendy(2)
>>> trendy.fit([a, b, c, d])
>>> trendy.predict([[0.9, 2, 3.1, 4]])
[0]
>>> trendy.predict([[0.9, 2, 3.1], [7, 6.6, 5.5, 4.4]])
[0, 1]
```

assign(*X*)

Alias of *predict()*

fit_predict(*X*)

Compute cluster centers and predict cluster index for each sample.

Parameters **X** (*array of arrays*) – Training instances to cluster.

Returns predicted labels

Return type list

Example

```
>>> a = [1, 2, 3, 4, 5] # increasing
>>> b = [1, 2.1, 2.9, 4.4, 5.1] # increasing
>>> c = [6.2, 5, 4, 3, 2] # decreasing
>>> d = [7, 6, 5, 4, 3, 2, 1] # decreasing
>>> trendy = Trendy(2)
>>> trendy.fit_predict([a, b, c, d])
[0, 0, 1, 1]
```

to_pickle(*path*)

Pickle (serialize) object to a file.

Parameters **path** (*str*) – file path where the pickled object will be stored

Example

To save a **.pkl* file:

```
>>> t1 = Trendy(n_clusters=2)
>>> t1.fit([[1, 2, 3], [2, 3, 3]])
>>> t1.to_pickle(path='trendy.pkl')
```

To load the same object later:

```
>>> import pickle, os
>>> pkl_file = open('trendy.pkl', 'rb')
>>> t2 = pickle.load(pkl_file)
>>> pkl_file.close()
>>> os.remove('trendy.pkl')
```

3.2 algos

Algorithms for the package.

algos.**dtw_distance**(*x*, *y*, *d=<function euclidean_distance>*, *scaled=False*)

Returns the distance of two arrays with dynamic time warping method.

Parameters

- **x** (*iter*) – input array 1
- **y** (*iter*) – input array 2
- **d** (*func*) – distance function, default is euclidean
- **scaled** (*bool*) – should arrays be scaled (i.e. 0-1) before calculation

Returns distance, 0.0 means arrays are exactly same, upper limit is positive infinity

Return type float

References

https://en.wikipedia.org/wiki/Dynamic_time_warping

Examples

```
>>> dtw_distance([1, 2, 3, 4], [1, 2, 3, 4])
0.0
>>> dtw_distance([1, 2, 3, 4], [0, 0, 0])
10.0
>>> dtw_distance([1, 2, 3, 4], [0, 2, 0, 4])
4.0
>>> dtw_distance([1, 2, 3, 4], [10, 20, 30, 40])
90.0
>>> dtw_distance([1, 2, 3, 4], [10, 20, 30, 40], scaled=True)
0.0
```

algos.**fastdtw_distance**(*x*, *y*, *d=<function euclidean_distance>*)

Dynamic Time Warping (DTW) algorithm with an O(N) time and memory complexity.

Parameters

- **x** (*iter*) – input array 1
- **y** (*iter*) – input array 2
- **d** (*func*) – distance function, default is euclidean

Returns distance, 0.0 means arrays are exactly same, upper limit is positive infinity

Return type float

References

https://pypi.org/project/fastdtw/

Examples

```
>>> fastdtw_distance([1, 2, 3, 4], [1, 2, 3, 4])
0.0
>>> fastdtw_distance([1, 2, 3, 4], [0, 0, 0])
10.0
>>> fastdtw_distance([1, 2, 3, 4], [0, 2, 0, 4])
4.0
>>> fastdtw_distance([1, 2, 3, 4], [10, 20, 30, 40])
90.0
```

algos.**levenshtein_distance**(*x*, *y*)

Levenshtein distance for string similarity.

Parameters

- **x** (*str*) – input string 1
- **y** (*str*) – input string 2

Returns distance, 0 means strings are exactly same, upper limit is positive infinity

Return type int

References

https://en.wikipedia.org/wiki/Levenshtein_distance

Examples

```
>>> levenshtein_distance('Apple', 'Apple')
0
>>> levenshtein_distance('Apple', 'apple')
1
>>> levenshtein_distance('Apple Inc.', 'apple inc')
3
```

3.3 utils

Utility functions for the package.

utils.**scale_01**(*x*)

Scales array to 0-1.

Parameters **x** (*iter*) – 1d array of float

Returns scaled 1d array

Return type np.array

Example

```
>>> scale_01([1, 2, 3, 5]).tolist()
[0.0, 0.25, 0.5, 1.0]
```

utils.**abs_distance**(*x*, *y*)

Returns absolute distance.

Parameters

- **x** (*float*) – input 1
- **y** (*float*) – input 2

Returns |x-y|

Return type float

Example

```
>>> abs_distance(5, 7)
2.0
>>> abs_distance(4, 1)
3.0
```

utils.**euclidean_distance**(*x*, *y*)

Returns Euclidean distance.

Parameters

- **x** (*float or iter*) – input 1
- **y** (*float or iter*) – input 2

Returns Euclidean distance

Return type float

References

https://numpy.org/doc/stable/reference/generated/numpy.linalg.norm.html

Examples

```
>>> x, y = 1, 2
>>> euclidean_distance(x, y)
1.0
>>> x, y = [1, 2], [4, 6]
>>> euclidean_distance(x, y)
5.0
```

CHAPTER

FOUR

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