
ThinkMatch Documentation

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USER GUIDE

1	Backends	3
2	Features	5
3	Benchmarks	7
4	Developers and Maintainers	9
4.1	What is Graph Matching	9
4.2	Get Started	12
4.3	Graph Matching Benchmark	13
4.4	pygmtools.benchmark	15
4.5	pygmtools.dataset	17
4.6	pygmtools.classic_solvers	19
4.7	pygmtools.utils	33
	Python Module Index	41
	Index	43

pygmtools provides graph matching solvers in Python and is easily accessible via the following command:

```
pip install pygmtools
```


BACKENDS

By default the solvers are executed on the `numpy` backend, and the required packages will be automatically downloaded.

For advanced and professional users, the `pytorch` backend is also available if you have installed and configured a `pytorch` runtime. The `pytorch` backend exploits the underlying GPU-acceleration feature, and also supports integrating graph matching modules into your deep learning pipeline.

FEATURES

To highlight, **pygmttools** has the following features:

- *Support various backends*, including **numpy** which is universally accessible, and the state-of-the-art deep learning architecture **pytorch** with GPU-support. The support of the following backends are also planned: **tensorflow**, **mindspore**, **paddle**, **jittor**;
- *Support various solvers*, including traditional combinatorial solvers and novel deep learning-based solvers;
- *Deep learning friendly*, the operations are designed to best preserve the gradient during computation and batched operations support for the best performance.

BENCHMARKS

pygmtools is also featured with standard data interface of several graph matching benchmarks. We also maintain a repository containing non-trivial implementation of deep graph matching models, please check out [ThinkMatch](#) if you are interested!

DEVELOPERS AND MAINTAINERS

pygmtools is currently developed and maintained by members from [ThinkLab](#) at Shanghai Jiao Tong University.

4.1 What is Graph Matching

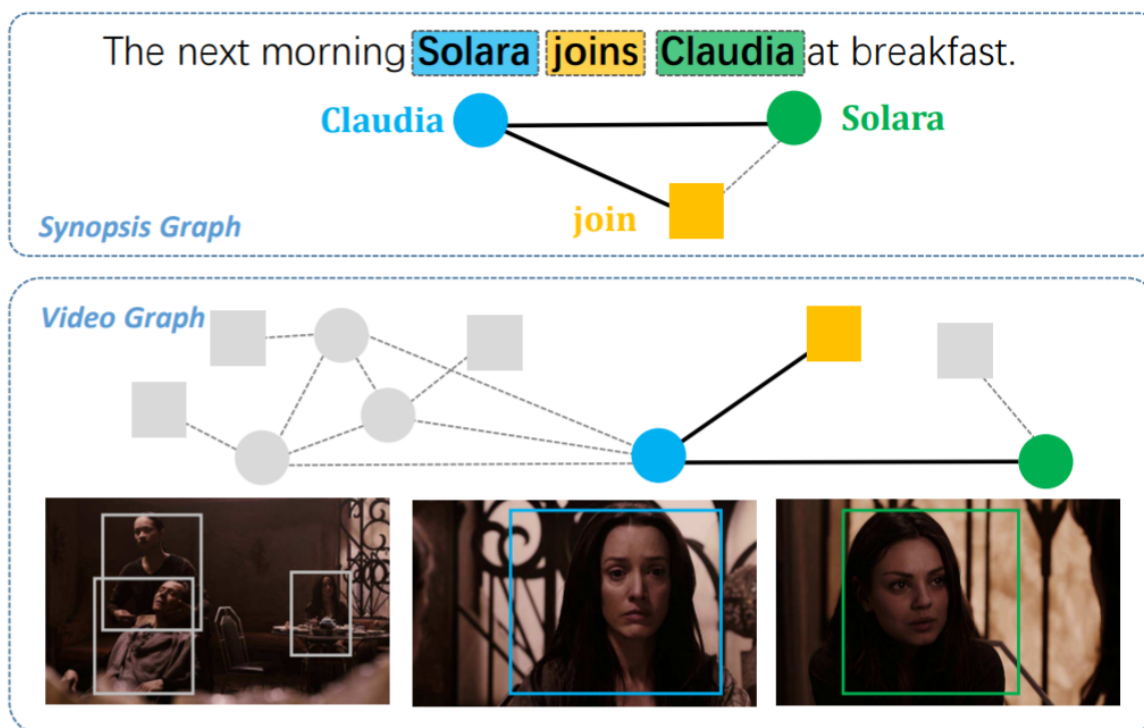
This page provides some background information for graph matching.

4.1.1 Introduction

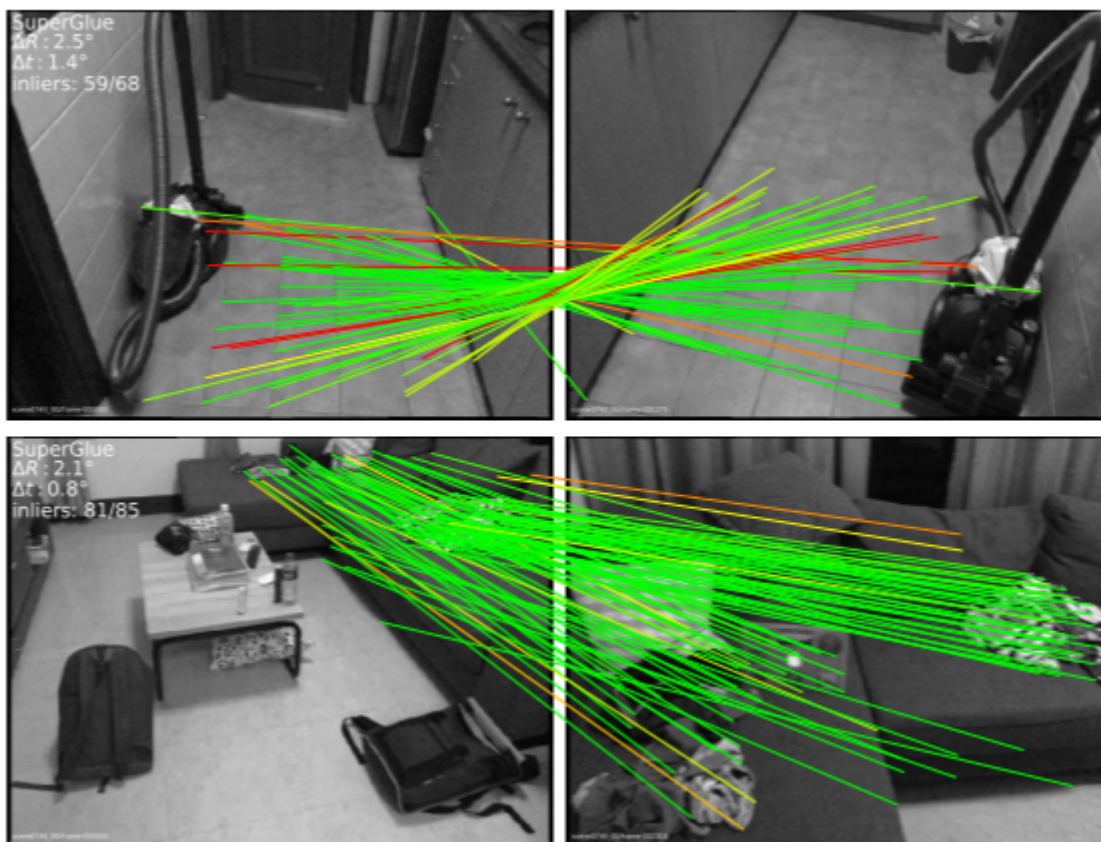
Graph Matching (GM) is a fundamental yet challenging problem in pattern recognition, data mining, and others. GM aims to find node-to-node correspondence among multiple graphs, by solving an NP-hard combinatorial problem. Recently, there is growing interest in developing deep learning based graph matching methods.

Graph matching techniques have been applied to the following applications:

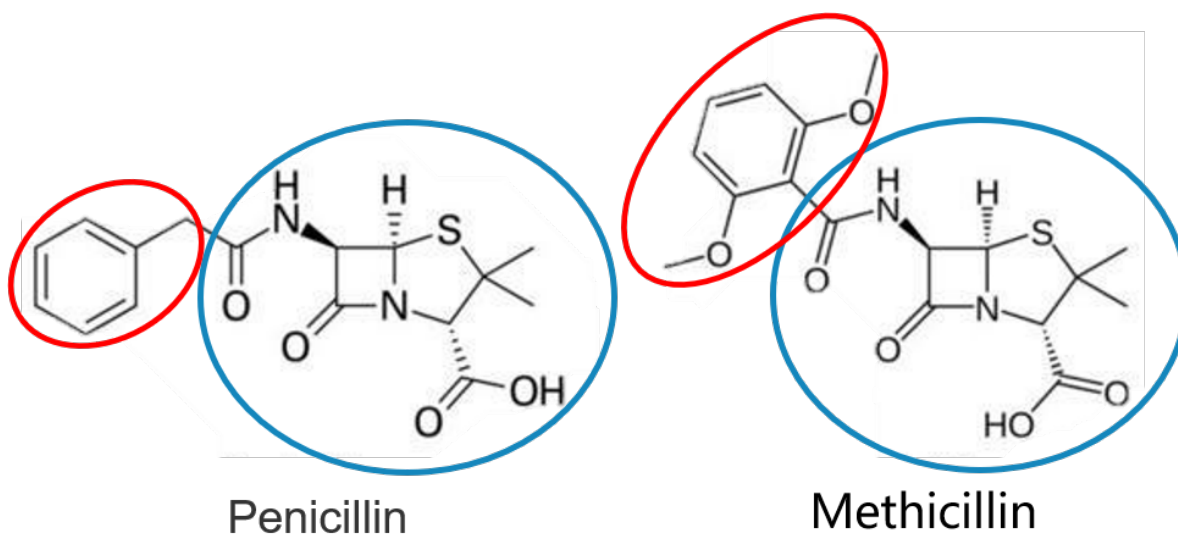
- [Bridging movie and synopses](#)



- Image correspondence



- Molecules matching



- and more...

4.1.2 Graph Matching Pipeline

Solving a real world graph matching problem may involve the following steps:

1. Extract node/edge features from the graphs you want to match.
2. Build affinity matrix from node/edge features.
3. Solve the graph matching problem by GM solvers.

And Step 1 maybe done by methods depending on your application, Step 2&3 can be handled by **pygmtools**.

4.1.3 The Math Form

Let's involve a little bit math to better understand the graph matching pipeline. In general, graph matching is of the following form, known as **Quadratic Assignment Problem (QAP)**:

$$\begin{aligned} \max_{\mathbf{X}} \quad & \text{vec}(\mathbf{X})^\top \mathbf{K} \text{vec}(\mathbf{X}) \\ \text{s.t.} \quad & \mathbf{X} \in \{0, 1\}^{n_1 \times n_2}, \mathbf{X}\mathbf{1} = \mathbf{1}, \mathbf{X}^\top \mathbf{1} \leq \mathbf{1} \end{aligned}$$

The notations are explained as follows:

- \mathbf{X} is known as the **permutation matrix** which encodes the matching result. It is also the decision variable in graph matching problem. $\mathbf{X}_{i,a} = 1$ means node i in graph 1 is matched to node a in graph 2, and $\mathbf{X}_{i,a} = 0$ means non-matched. Without loss of generality, it is assumed that $n_1 \leq n_2$. \mathbf{X} has the following constraints:
 - The sum of each row must be equal to 1: $\mathbf{X}\mathbf{1} = \mathbf{1}$;
 - The sum of each column must be equal to, or smaller than 1: $\mathbf{X}^\top \mathbf{1} \leq \mathbf{1}$.
- $\text{vec}(\mathbf{X})$ means the column-wise vectorization form of \mathbf{X} .
- $\mathbf{1}$ means a column vector whose elements are all 1s.
- \mathbf{K} is known as the **affinity matrix** which encodes the information of the input graphs. Both node-wise and edge-wise affinities are encoded in \mathbf{K} :
 - The diagonal element $\mathbf{K}_{i+a \times n_1, i+a \times n_1}$ means the node-wise affinity of node i in graph 1 and node a in graph 2;
 - The off-diagonal element $\mathbf{K}_{i+a \times n_1, j+b \times n_1}$ means the edge-wise affinity of edge ij in graph 1 and edge ab in graph 2.

4.1.4 Other Materials

Readers are referred to the following surveys for more technical details about graph matching:

- Junchi Yan, Shuang Yang, Edwin Hancock. "Learning Graph Matching and Related Combinatorial Optimization Problems." *IJCAI 2020*.
- Junchi Yan, Xu-Cheng Yin, Weiyao Lin, Cheng Deng, Hongyuan Zha, Xiaokang Yang. "A Short Survey of Recent Advances in Graph Matching." *ICMR 2016*.

4.2 Get Started

4.2.1 Basic Install

pygmtools can be installed by the `pip install` command:

```
pip install pygmtools
```

Now the `pygmtools` is available with the `numpy` backend. You may jump to [Example: Matching Isomorphism Graphs](#) if you do not need other backends.

The following packages are required, and shall be automatically downloaded by `pip install`:

- Python ≥ 3.5
- requests $\geq 2.25.1$
- scipy $\geq 1.4.1$
- Pillow $\geq 7.2.0$
- numpy $\geq 1.18.5$
- easydict ≥ 1.7

4.2.2 Install Other Backends

Currently, we also support the state-of-the-art architecture `pytorch` which is GPU-friendly and deep learning-friendly. The support of the following backends are also planned: `tensorflow`, `mindspore`, `paddle`, `jittor`.

Please follow the install instructions on your backend.

Set the backend globally by the following command:

```
>>> import pygmtools as pygm
>>> pygm.BACKEND = 'pytorch' # you may replace 'pytorch' by other backend names
```

4.2.3 Example: Matching Isomorphism Graphs

Here we provide a basic example of matching two isomorphism graphs (i.e. two graphs that are the same, but the node permutations are unknown).

Step 0: Import packages and set backend

```
>>> import numpy as np
>>> import pygmtools as pygm
>>> pygm.BACKEND = 'numpy'
>>> np.random.seed(1)
```

Step 1: Generate a batch of isomorphic graphs

```
>>> batch_size = 3
>>> X_gt = np.zeros((batch_size, 4, 4))
>>> X_gt[:, np.arange(0, 4, dtype=np.int64), np.random.permutation(4)] = 1
>>> A1 = np.random.rand(batch_size, 4, 4)
```

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```
>>> A2 = np.matmul(np.matmul(X_gt.transpose((0, 2, 1)), A1), X_gt)
>>> n1 = n2 = np.repeat([4], batch_size)
```

Step 2: Build affinity matrix and select an affinity function

```
>>> conn1, edge1, ne1 = pygm.utils.dense_to_sparse(A1)
>>> conn2, edge2, ne2 = pygm.utils.dense_to_sparse(A2)
>>> import functools
>>> gaussian_aff = functools.partial(pygm.utils.gaussian_aff_fn, sigma=1.) # set
↳affinity function
>>> K = pygm.utils.build_aff_mat(None, edge1, conn1, None, edge2, conn2, n1, ne1, n2,
↳ne2, edge_aff_fn=gaussian_aff)
```

Step 3: Solve graph matching by RRWM

```
>>> X = pygm.rrwm(K, n1, n2, beta=100)
>>> X = pygm.hungarian(X)
>>> X # X is the permutation matrix
[[[0. 0. 0. 1.]
  [0. 0. 1. 0.]
  [1. 0. 0. 0.]
  [0. 1. 0. 0.]]

 [[0. 0. 0. 1.]
  [0. 0. 1. 0.]
  [1. 0. 0. 0.]
  [0. 1. 0. 0.]]

 [[0. 0. 0. 1.]
  [0. 0. 1. 0.]
  [1. 0. 0. 0.]
  [0. 1. 0. 0.]]]
```

Final Step: Evaluate the accuracy

```
>>> (X * X_gt).sum() / X_gt.sum()
1.0
```

4.3 Graph Matching Benchmark

pygmtools also provides a protocol to fairly compare existing deep graph matching algorithms under different datasets & experiment settings. The **Benchmark** module provides a unified data interface and an evaluating platform for different datasets. Currently, **pygmtools** supports 5 datasets:

- PascalVOC
- Willow-Object
- SPair-71k
- CUB2011
- IMC-PT-SparseGM

4.3.1 Files

- `dataset.py`: The file includes 5 dataset classes, used to automatically download dataset and process the dataset into a json file, and also save train set and test set.
- `benchmark.py`: The file includes Benchmark class that can be used to fetch data from json file and evaluate prediction result.
- `dataset_config.py`: Fixed dataset settings, mostly dataset path and classes.

4.3.2 Notes

- Our evaluation metrics include **matching_precision (p)**, **matching_recall (r)** and **f1_score (f1)**. Also, to measure the reliability of the evaluation result, we define coverage (cvg) for each class in the dataset as *the number of evaluated pairs in the class / number of all possible pairs in the class*. Therefore, larger coverage refers to higher reliability.
- Dataset can be automatically downloaded and unzipped, but you can also download the dataset yourself, and make sure it in the right path. The expected dataset paths are listed as follows.

```
# Pascal VOC 2011 dataset with keypoint annotations
PascalVOC.ROOT_DIR = 'data/PascalVOC/TrainVal/VOCdevkit/VOC2011/'
PascalVOC.KPT_ANNO_DIR = 'data/PascalVOC/annotations/'

# Willow-Object Class dataset
WillowObject.ROOT_DIR = 'data/WillowObject/WILLOW-ObjectClass'

# CUB2011 dataset
CUB2011.ROOT_PATH = 'data/CUB_200_2011/CUB_200_2011'

# SWPair-71 Dataset
SPair.ROOT_DIR = "data/SPair-71k"

# IMC_PT-SparseGM dataset
IMC_PT_SparseGM.ROOT_DIR_NPZ = 'data/IMC-PT-SparseGM/annotations'
IMC_PT_SparseGM.ROOT_DIR_IMG = 'data/IMC-PT-SparseGM/images'
```

Specifically, for PascalVOC, you should download the train/test split yourself, and make sure it looks like `data/PascalVOC/voc2011_pairs.npz`

4.3.3 Example

```
from pygmtools.benchmark import Benchmark

# Define Benchmark on PascalVOC.
bm = Benchmark(name='PascalVOC', sets='train',
               obj_resize=(256, 256), problem='2GM',
               filter='intersection')

# Random fetch data and ground truth.
data_list, gt_dict, _ = bm.rand_get_data(cls=None, num=2)
```

4.4 pygmtools.benchmark

Classes

Benchmark

The *Benchmark* module provides a unified data interface and an evaluating platform for different datasets.

4.4.1 Benchmark

```
class pygmtools.benchmark.Benchmark(name, sets, obj_resize=(256, 256), problem='2GM',
                                     filter='intersection', **args)
```

The *Benchmark* module provides a unified data interface and an evaluating platform for different datasets.

Parameters

- **name** – str, dataset name, currently support ‘PascalVOC’, ‘WillowObject’, ‘IMC_PT_SparseGM’, ‘CUB2011’, ‘SPair71k’
- **sets** – str, problem set, ‘train’ for training set and ‘test’ for test set
- **obj_resize** – tuple, resized object size
- **problem** – str, problem type, ‘2GM’ for 2-graph matching and ‘MGM’ for multi-graph matching
- **filter** – str, filter of nodes, ‘intersection’ refers to retaining only common nodes; ‘inclusion’ is only for 2GM and refers to filtering only one graph to make its nodes a subset of the other graph, and ‘unfiltered’ refers to retaining all nodes in all graphs
- **args** – specific settings for dataset

```
compute_img_num(classes)
```

Compute number of images in specified classes.

Parameters **classes** – list of dataset classes

Returns list of numbers of images in each class

```
compute_length(cls=None, num=2)
```

Compute the length of image combinations in specified class.

Parameters

- **cls** – int or str, class of expected data. None for all classes
- **num** – int, number of images in each image ID list; for example, 2 for 2GM

Returns length of combinations

```
eval(prediction, classes, verbose=False)
```

Evaluate test results and compute matching accuracy and coverage.

Parameters

- **prediction** – list, prediction result, like [{'ids': (id1, id2), 'cls': cls, 'permmat': np.array or scipy.sparse},...]
- **classes** – list of evaluated classes
- **verbose** – bool, whether to print the result

Returns evaluation result in each class and their averages, including p, r, f1 and their standard deviation and coverage

eval_cls(*prediction, cls, verbose=False*)

Evaluate test results and compute matching accuracy and coverage on one specified class.

Parameters

- **prediction** – list, prediction result on one class, like `[{'ids': (id1, id2), 'cls': cls, 'perm_mat': np.array or scipy.sparse}, ...]`
- **cls** – str, evaluated class
- **verbose** – bool, whether to print the result

Returns evaluation result on the specified class, including p, r, f1 and their standard deviation and coverage

get_data(*ids, test=False, shuffle=True*)

Fetch a data pair or pairs of data by image ID for training or test.

Parameters

- **ids** – list of image ID, usually in ‘train.json’ or ‘test.json’
- **test** – bool, whether the fetched data is used for test; if true, this function will not return ground truth
- **shuffle** – bool, whether to shuffle the order of keypoints

Returns

data_list: list of data, like `[{'img': np.array, 'kpts': coordinates of kpts}, ...]`

perm_mat_dict: ground truth, like `{(0,1):scipy.sparse, (0,2):scipy.sparse, ...}`, `(0,1)` refers to data pair `(ids[0],ids[1])`

ids: list of image ID

get_id_combination(*cls=None, num=2*)

Get the combination of images and length of combinations in specified class.

Parameters

- **cls** – int or str, class of expected data. None for all classes
- **num** – int, number of images in each image ID list; for example, 2 for 2GM

Returns

id_combination_list: list of combinations of image ids

length: length of combinations

rand_get_data(*cls=None, num=2, test=False, shuffle=True*)

Randomly fetch data for training or test. Implemented by calling `get_data` function.

Parameters

- **cls** – int or str, class of expected data. None for random class
- **num** – int, number of images; for example, 2 for 2GM
- **test** – bool, whether the fetched data is used for test; if true, this function will not return ground truth
- **shuffle** – bool, whether to shuffle the order of keypoints

Returns

`data_list`: list of data, like `[{'img': np.array, 'kpts': coordinates of kpts}, ...]`

`perm_mat_dict`: ground truth, like `{(0,1):scipy.sparse, (0,2):scipy.sparse, ...}`, `(0,1)` refers to data pair `(ids[0],ids[1])`

`ids`: list of image ID

`rm_gt_cache(last_epoch=False)`

Remove ground truth cache.

Parameters `last_epoch` – Boolean variable, whether this epoch is last epoch; if true, the directory of cache will also be removed.

4.5 pygmtools.dataset

Classes

<i>CUB2011</i>	This class is defined to download and preprocess CUB2011 dataset.
<i>IMC_PT_SparseGM</i>	This class is defined to download and preprocess IMC_PT_SparseGM dataset.
<i>PascalVOC</i>	This class is defined to download and preprocess PascalVOC dataset.
<i>SPair71k</i>	This class is defined to download and preprocess SPair71k dataset.
<i>WillowObject</i>	This class is defined to download and preprocess WillowObject dataset.

4.5.1 CUB2011

`class pygmtools.dataset.CUB2011(sets, obj_resize, ds_dict=None, **args)`

This class is defined to download and preprocess CUB2011 dataset.

Parameters

- **`sets`** – str, problem set, ‘train’ for training set and ‘test’ for test set
- **`obj_resize`** – tuple, resized image size
- **`ds_dict`** – settings of dataset, containing at most 1 param(key) for CUB2011:
CLS_SPLIT: str, ‘ori’ (original split), ‘sup’ (super class) or ‘all’ (all birds as one class)

`download(url=None)`

Automatically download CUB2011 dataset.

Parameters `url` – str, web url of CUB2011

`process()`

Process the dataset and generate ‘data.json’ for preprocessed dataset, ‘train.json’ for training set, and ‘test.json’ for test set.

4.5.2 IMC_PT_SparseGM

class pygmtools.dataset.**IMC_PT_SparseGM**(sets, obj_resize, ds_dict=None, **args)

This class is defined to download and preprocess IMC_PT_SparseGM dataset.

Parameters

- **sets** – str, problem set, ‘train’ for training set and ‘test’ for test set
- **obj_resize** – tuple, resized image size
- **ds_dict** – settings of dataset, containing at most 1 param(key) for IMC_PT_SparseGM:
TOTAL_KPT_NUM: int, maximum kpt_num in an image

download(url=None)

Automatically download IMC_PT_SparseGM dataset.

Parameters **url** – str, web url of IMC_PT_SparseGM

process()

Process the dataset and generate ‘data.json’ for preprocessed dataset, ‘train.json’ for training set, and ‘test.json’ for test set.

4.5.3 PascalVOC

class pygmtools.dataset.**PascalVOC**(sets, obj_resize, **args)

This class is defined to download and preprocess PascalVOC dataset.

Parameters

- **sets** – str, problem set, ‘train’ for training set and ‘test’ for test set
- **obj_resize** – tuple, resized image size

download(url=None, name=None)

Automatically download PascalVOC dataset.

Parameters

- **url** – str, web url of PascalVOC and PascalVOC annotation
- **name** – str, “PascalVOC” to download PascalVOC and “PascalVOC_anno” to download PascalVOC annotation

process()

Process the dataset and generate ‘data.json’ for preprocessed dataset, ‘train.json’ for training set, and ‘test.json’ for test set.

4.5.4 SPair71k

class pygmtools.dataset.**SPair71k**(sets, obj_resize, problem='2GM', ds_dict=None, **args)

This class is defined to download and preprocess SPair71k dataset.

Parameters

- **sets** – str, problem set, ‘train’ for training set and ‘test’ for test set
- **obj_resize** – tuple, resized image size
- **problem** – str, problem type, only ‘2GM’ in SPair71k

- **ds_dict** – settings of dataset, containing at most 4 params(keys) for SPair71k:

TRAIN_DIFF_PARAMS: list of images that should be dumped in train set

EVAL_DIFF_PARAMS: list of images that should be dumped in test set

COMB_CLS: bool, whether to combine images in different classes

SIZE: str, 'large' for SPair71k-large and 'small' for SPair71k-small

download(url=None)

Automatically download SPair71k dataset.

Parameters **url** – str, web url of SPair71k

process()

Process the dataset and generate 'data.json' for preprocessed dataset, 'train.json' for training set, and 'test.json' for test set.

4.5.5 WillowObject

class `pygmtools.dataset.WillowObject(sets, obj_resize, ds_dict=None, **args)`

This class is defined to download and preprocess WillowObject dataset.

Parameters

- **sets** – str, problem set, 'train' for training set and 'test' for test set
- **obj_resize** – tuple, resized image size
- **ds_dict** – settings of dataset, containing at most 4 params(keys) for WillowObject:
 TRAIN_NUM: int, number of images for train in each class
 SPLIT_OFFSET: int, offset when split train and test set
 TRAIN_SAME_AS_TEST: bool, whether to use same images for training and test
 RAND_OUTLIER: int, number of added outliers in one image

download(url=None)

Automatically download WillowObject dataset.

Parameters **url** – str, web url of WillowObject

process()

Process the dataset and generate 'data.json' for preprocessed dataset, 'train.json' for training set, and 'test.json' for test set.

4.6 pygmtools.classic_solvers

Functions

<i>hungarian</i>	Solve optimal LAP permutation by hungarian algorithm.
<i>ipfp</i>	Integer Projected Fixed Point (IPFP) method for graph matching (QAP).
<i>rrwm</i>	Reweighted Random Walk Matching (RRWM) solver for graph matching (QAP).

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Table 3 – continued from previous page

<i>sinkhorn</i>	Sinkhorn algorithm turns the input matrix into a doubly-stochastic matrix.
<i>sm</i>	Spectral Graph Matching solver for graph matching (QAP).

4.6.1 pygmtools.classic_solvers.hungarian

`pygmtools.classic_solvers.hungarian(s, n1=None, n2=None, nproc: int = 1, backend=None)`

Solve optimal LAP permutation by hungarian algorithm. The time cost is $O(n^3)$.

Parameters

- **s** – ($b \times n_1 \times n_2$) input 3d tensor. *b*: batch size. Non-batched input is also supported if *s* is of size ($n_1 \times n_2$)
- **n1** – (*b*) (optional) number of objects in dim1
- **n2** – (*b*) (optional) number of objects in dim2
- **nproc** – (default: 1, i.e. no parallel) number of parallel processes
- **backend** – (default: `pygmtools.BACKEND` variable) the backend for computation.

Returns ($b \times n_1 \times n_2$) optimal permutation matrix

Note: The parallelization is based on multi-processing workers that run on multiple CPU cores.

Note: For all backends, `scipy.optimize.linear_sum_assignment` is called to solve the LAP, therefore the computation is based on `numpy` and `scipy`. The backend argument of this function only affects the input-output data type.

Note: We support batched instances with different number of nodes, therefore *n1* and *n2* are required to specify the exact number of objects of each dimension in the batch. If not specified, we assume the batched matrices are not padded.

Example for `numpy` backend:

```
>>> import numpy as np
>>> import pygmtools as pygm
>>> pygm.BACKEND = 'numpy'
>>> np.random.seed(0)

# 2-dimensional (non-batched) input
>>> s_2d = np.random.rand(5, 5)
>>> s_2d
array([[0.5488135 , 0.71518937, 0.60276338, 0.54488318, 0.4236548 ],
       [0.64589411, 0.43758721, 0.891773 , 0.96366276, 0.38344152],
       [0.79172504, 0.52889492, 0.56804456, 0.92559664, 0.07103606],
       [0.0871293 , 0.0202184 , 0.83261985, 0.77815675, 0.87001215],
       [0.97861834, 0.79915856, 0.46147936, 0.78052918, 0.11827443]])
```

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```

>>> x = pygm.hungarian(s_2d)
>>> x
array([[0., 1., 0., 0., 0.],
       [0., 0., 1., 0., 0.],
       [0., 0., 0., 1., 0.],
       [0., 0., 0., 0., 1.],
       [1., 0., 0., 0., 0.]])

# 3-dimensional (batched) input
>>> s_3d = np.random.rand(3, 5, 5)
>>> n1 = n2 = np.array([3, 4, 5])
>>> x = pygm.hungarian(s_3d, n1, n2)
>>> x
array([[[0., 0., 1., 0., 0.],
        [0., 1., 0., 0., 0.],
        [1., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0.]],

       [[1., 0., 0., 0., 0.],
        [0., 1., 0., 0., 0.],
        [0., 0., 1., 0., 0.],
        [0., 0., 0., 1., 0.],
        [0., 0., 0., 0., 0.]],

       [[0., 0., 1., 0., 0.],
        [1., 0., 0., 0., 0.],
        [0., 0., 0., 0., 1.],
        [0., 1., 0., 0., 0.],
        [0., 0., 0., 1., 0.]]])

```

Example for Pytorch backend:

```

>>> import torch
>>> import pygtools as pygm
>>> pygm.BACKEND = 'pytorch'

# 2-dimensional (non-batched) input
>>> s_2d = torch.from_numpy(s_2d)
>>> s_2d
tensor([[0.5488, 0.7152, 0.6028, 0.5449, 0.4237],
        [0.6459, 0.4376, 0.8918, 0.9637, 0.3834],
        [0.7917, 0.5289, 0.5680, 0.9256, 0.0710],
        [0.0871, 0.0202, 0.8326, 0.7782, 0.8700],
        [0.9786, 0.7992, 0.4615, 0.7805, 0.1183]], dtype=torch.float64)
>>> x = pygm.hungarian(s_2d)
>>> x
tensor([[0., 1., 0., 0., 0.],
        [0., 0., 1., 0., 0.],
        [0., 0., 0., 1., 0.],
        [0., 0., 0., 0., 1.],
        [1., 0., 0., 0., 0.]], dtype=torch.float64)

```

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```
# 3-dimensional (batched) input
>>> s_3d = torch.from_numpy(s_3d)
>>> n1 = n2 = torch.tensor([3, 4, 5])
>>> x = pygm.hungarian(s_3d, n1, n2)
>>> x
tensor([[[0., 0., 1., 0., 0.],
         [0., 1., 0., 0., 0.],
         [1., 0., 0., 0., 0.],
         [0., 0., 0., 0., 0.],
         [0., 0., 0., 0., 0.]],
        [[1., 0., 0., 0., 0.],
         [0., 1., 0., 0., 0.],
         [0., 0., 1., 0., 0.],
         [0., 0., 0., 1., 0.],
         [0., 0., 0., 0., 0.]],
        [[0., 0., 1., 0., 0.],
         [1., 0., 0., 0., 0.],
         [0., 0., 0., 0., 1.],
         [0., 1., 0., 0., 0.],
         [0., 0., 0., 1., 0.]]], dtype=torch.float64)
```

Note: If you find this graph matching solver useful for your research, please cite:

```
@article{hungarian,
  title={Algorithms for the assignment and transportation problems},
  author={Munkres, James},
  journal={Journal of the society for industrial and applied mathematics},
  volume={5},
  number={1},
  pages={32--38},
  year={1957},
  publisher={SIAM}
}
```

4.6.2 pygmtools.classic_solvers.ipfp

`pygmtools.classic_solvers.ipfp(K, n1=None, n2=None, n1max=None, n2max=None, x0=None, max_iter: int = 50, backend=None)`

Integer Projected Fixed Point (IPFP) method for graph matching (QAP).

Parameters

- **K** – ($b \times n_1 n_2 \times n_1 n_2$) the input affinity matrix, b : batch size.
- **n1** – (b) number of nodes in graph1 (optional if $n1max$ is given, and all $n1=n1max$).
- **n2** – (b) number of nodes in graph2 (optional if $n2max$ is given, and all $n2=n2max$).
- **n1max** – (b) max number of nodes in graph1 (optional if $n1$ is given, and $n1max=\max(n1)$).

- **n2max** – (b) max number of nodes in graph2 (optional if n_2 is given, and $n2max=\max(n_2)$).
- **x0** – ($b \times n_1 \times n_2$) an initial matching solution for warm-start. If not given, x_0 will be filled with $\frac{1}{n_1 n_2}$.
- **max_iter** – (default: 50) max number of iterations in IPFP. More iterations will lead to more accurate result, at the cost of increased inference time.
- **backend** – (default: `pygmtools.BACKEND` variable) the backend for computation.

Returns ($b \times n_1 \times n_2$) the solved matching matrix

Note: We support batched instances with different number of nodes, therefore n_1 and n_2 are required to specify the exact number of objects of each dimension in the batch. If not specified, we assume the batched matrices are not padded.

Note: This solver is non-differentiable. The output is a discrete matching matrix (i.e. permutation matrix).

Example for numpy backend:

```
>>> import numpy as np
>>> import pygmtools as pygm
>>> pygm.BACKEND = 'numpy'
>>> np.random.seed(1)

# Generate a batch of isomorphic graphs
>>> batch_size = 10
>>> X_gt = np.zeros((batch_size, 4, 4))
>>> X_gt[:, np.arange(0, 4, dtype=np.int64), np.random.permutation(4)] = 1
>>> A1 = np.random.rand(batch_size, 4, 4)
>>> A2 = np.matmul(np.matmul(X_gt.transpose((0, 2, 1)), A1), X_gt)
>>> n1 = n2 = np.repeat([4], batch_size)

# Build affinity matrix
>>> conn1, edge1, ne1 = pygm.utils.dense_to_sparse(A1)
>>> conn2, edge2, ne2 = pygm.utils.dense_to_sparse(A2)
>>> import functools
>>> gaussian_aff = functools.partial(pygm.utils.gaussian_aff_fn, sigma=1.) # set
↳affinity function
>>> K = pygm.utils.build_aff_mat(None, edge1, conn1, None, edge2, conn2, n1, None,
↳n2, None, edge_aff_fn=gaussian_aff)

# Solve by IPFP
>>> X = pygm.ipfp(K, n1, n2)
>>> X[0]
array([[0., 0., 0., 1.],
       [0., 0., 1., 0.],
       [1., 0., 0., 0.],
       [0., 1., 0., 0.]])

# Accuracy
>>> (pygm.hungarian(X) * X_gt).sum() / X_gt.sum()
1.0
```

Example for Pytorch backend:

```
>>> import torch
>>> import pygtools as pygm
>>> pygm.BACKEND = 'pytorch'
>>> _ = torch.manual_seed(1)

# Generate a batch of isomorphic graphs
>>> batch_size = 10
>>> X_gt = torch.zeros(batch_size, 4, 4)
>>> X_gt[:, torch.arange(0, 4, dtype=torch.int64), torch.randperm(4)] = 1
>>> A1 = torch.rand(batch_size, 4, 4)
>>> A2 = torch.bmm(torch.bmm(X_gt.transpose(1, 2), A1), X_gt)
>>> n1 = torch.tensor([4] * batch_size)
>>> n2 = torch.tensor([4] * batch_size)

# Build affinity matrix
>>> conn1, edge1, ne1 = pygm.utils.dense_to_sparse(A1)
>>> conn2, edge2, ne2 = pygm.utils.dense_to_sparse(A2)
>>> import functools
>>> gaussian_aff = functools.partial(pygm.utils.gaussian_aff_fn, sigma=1.) # set_
↪affinity function
>>> K = pygm.utils.build_aff_mat(None, edge1, conn1, None, edge2, conn2, n1, None,
↪n2, None, edge_aff_fn=gaussian_aff)

# Solve by IPFP
>>> X = pygm.ipfp(K, n1, n2)
>>> X[0]
tensor([[0., 1., 0., 0.],
        [0., 0., 0., 1.],
        [0., 0., 1., 0.],
        [1., 0., 0., 0.]])

# Accuracy
>>> (pygm.hungarian(X) * X_gt).sum() / X_gt.sum()
tensor(1.)
```

Note: If you find this graph matching solver useful in your research, please cite:

```
@article{ipfp,
  title={An integer projected fixed point method for graph matching and map_
↪inference},
  author={Leordeanu, Marius and Hebert, Martial and Sukthankar, Rahul},
  journal={Advances in neural information processing systems},
  volume={22},
  year={2009}
}
```

4.6.3 pygmsolvers.classic_solvers.rrwm

`pygmsolvers.classic_solvers.rrwm(K, n1=None, n2=None, n1max=None, n2max=None, x0=None, max_iter: int = 50, sk_iter: int = 20, alpha: float = 0.2, beta: float = 30, backend=None)`

Reweighted Random Walk Matching (RRWM) solver for graph matching (QAP). This algorithm is implemented by power iteration with Sinkhorn reweighted jumps.

The official matlab implementation is available at <https://cv.snu.ac.kr/research/~RRWM/>

Parameters

- **K** – ($b \times n_1 n_2 \times n_1 n_2$) the input affinity matrix, b : batch size.
- **n1** – (b) number of nodes in graph1 (optional if $n1max$ is given, and all $n1=n1max$).
- **n2** – (b) number of nodes in graph2 (optional if $n2max$ is given, and all $n2=n2max$).
- **n1max** – (b) max number of nodes in graph1 (optional if $n1$ is given, and $n1max=\max(n1)$).
- **n2max** – (b) max number of nodes in graph2 (optional if $n2$ is given, and $n2max=\max(n2)$).
- **x0** – ($b \times n_1 \times n_2$) an initial matching solution for warm-start. If not given, $x0$ will filled with $\frac{1}{n_1 n_2}$.
- **max_iter** – (default: 50) max number of iterations (i.e. number of random walk steps) in RRWM. More iterations will be lead to more accurate result, at the cost of increased inference time.
- **sk_iter** – (default: 20) max number of Sinkhorn iterations. More iterations will be lead to more accurate result, at the cost of increased inference time.
- **alpha** – (default: 0.2) the parameter controlling the importance of the reweighted jump. α should lie between 0 and 1. If $\alpha=0$, it means no reweighted jump; if $\alpha=1$, the reweighted jump provides all information.
- **beta** – (default: 30) the temperature parameter of exponential function before the Sinkhorn operator. β should be larger than 0. A larger β means more confidence in the jump. A larger β will usually require a larger **sk_iter**.
- **backend** – (default: `pygmsolvers.BACKEND` variable) the backend for computation.

Returns ($b \times n_1 \times n_2$) the solved matching matrix

Note: We support batched instances with different number of nodes, therefore **n1** and **n2** are required to specify the exact number of objects of each dimension in the batch. If not specified, we assume the batched matrices are not padded.

Note: This solver is differentiable and supports gradient back-propagation.

Warning: The solver's output is normalized with a sum of 1, which is in line with the original implementation. If a doubly- stochastic matrix is required, please call `sinkhorn()` after this. If a discrete permutation matrix is required, please call `hungarian()`. Note that the Hungarian algorithm will truncate the gradient.

Example for numpy backend:

```

>>> import numpy as np
>>> import pygtools as pygm
>>> pygm.BACKEND = 'numpy'
>>> np.random.seed(1)

# Generate a batch of isomorphic graphs
>>> batch_size = 10
>>> X_gt = np.zeros((batch_size, 4, 4))
>>> X_gt[:, np.arange(0, 4, dtype=np.int64), np.random.permutation(4)] = 1
>>> A1 = np.random.rand(batch_size, 4, 4)
>>> A2 = np.matmul(np.matmul(X_gt.transpose((0, 2, 1)), A1), X_gt)
>>> n1 = n2 = np.repeat([4], batch_size)

# Build affinity matrix
>>> conn1, edge1, ne1 = pygm.utils.dense_to_sparse(A1)
>>> conn2, edge2, ne2 = pygm.utils.dense_to_sparse(A2)
>>> import functools
>>> gaussian_aff = functools.partial(pygm.utils.gaussian_aff_fn, sigma=1.) # set_
↳affinity function
>>> K = pygm.utils.build_aff_mat(None, edge1, conn1, None, edge2, conn2, n1, None,
↳n2, None, edge_aff_fn=gaussian_aff)

# Solve by RRWM. Note that X is normalized with a sum of 1
>>> X = pygm.rrwm(K, n1, n2, beta=100)
>>> X.sum(axis=(1, 2))
array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.])

# Accuracy
>>> (pygm.hungarian(X) * X_gt).sum() / X_gt.sum()
1.0

```

Example for Pytorch backend:

```

>>> import torch
>>> import pygtools as pygm
>>> pygm.BACKEND = 'pytorch'
>>> _ = torch.manual_seed(1)

# Generate a batch of isomorphic graphs
>>> batch_size = 10
>>> X_gt = torch.zeros(batch_size, 4, 4)
>>> X_gt[:, torch.arange(0, 4, dtype=torch.int64), torch.randperm(4)] = 1
>>> A1 = torch.rand(batch_size, 4, 4)
>>> A2 = torch.bmm(torch.bmm(X_gt.transpose(1, 2), A1), X_gt)
>>> n1 = n2 = torch.tensor([4] * batch_size)

# Build affinity matrix
>>> conn1, edge1, ne1 = pygm.utils.dense_to_sparse(A1)
>>> conn2, edge2, ne2 = pygm.utils.dense_to_sparse(A2)
>>> import functools
>>> gaussian_aff = functools.partial(pygm.utils.gaussian_aff_fn, sigma=1.) # set_
↳affinity function
>>> K = pygm.utils.build_aff_mat(None, edge1, conn1, None, edge2, conn2, n1, None,
↳n2, None, edge_aff_fn=gaussian_aff)

```

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```

# Solve by RRWM. Note that X is normalized with a sum of 1
>>> X = pygm.rrwm(K, n1, n2, beta=100)
>>> X.sum(dim=(1, 2))
tensor([1.0000, 1.0000, 1.0000, 1.0000, 1.0000, 1.0000, 1.0000, 1.0000, 1.0000,
        1.0000])

# Accuracy
>>> (pygm.hungarian(X) * X_gt).sum() / X_gt.sum()
tensor(1.)

# This solver supports gradient back-propagation
>>> K = K.requires_grad_(True)
>>> pygm.rrwm(K, n1, n2, beta=100).sum().backward()
>>> len(torch.nonzero(K.grad))
272

```

Note: If you find this graph matching solver useful in your research, please cite:

```

@inproceedings{rrwm,
  title={Reweighted random walks for graph matching},
  author={Cho, Minsu and Lee, Jungmin and Lee, Kyoung Mu},
  booktitle={European conference on Computer vision},
  pages={492--505},
  year={2010},
  organization={Springer}
}

```

4.6.4 pygmtools.classic_solvers.sinkhorn

`pygmtools.classic_solvers.sinkhorn(s, n1=None, n2=None, dummy_row: bool = False, max_iter: int = 10, tau: float = 1.0, batched_operation: bool = False, backend=None)`

Sinkhorn algorithm turns the input matrix into a doubly-stochastic matrix.

Sinkhorn algorithm firstly applies an \exp function with temperature τ :

$$S_{i,j} = \exp\left(\frac{S_{i,j}}{\tau}\right)$$

And then turns the matrix into doubly-stochastic matrix by iterative row- and column-wise normalization:

$$\begin{aligned} \mathbf{S} &= \mathbf{S} \oslash (\mathbf{1}_{n_2} \mathbf{1}_{n_2}^\top \cdot \mathbf{S}) \\ \mathbf{S} &= \mathbf{S} \oslash (\mathbf{S} \cdot \mathbf{1}_{n_2} \mathbf{1}_{n_2}^\top) \end{aligned}$$

where \oslash means element-wise division, $\mathbf{1}_n$ means a column-vector with length n whose elements are all 1s.

Parameters

- **s** – ($b \times n_1 \times n_2$) input 3d tensor. b : batch size. Non-batched input is also supported if **s** is of size ($n_1 \times n_2$)
- **n1** – (optional) (b) number of objects in dim1
- **n2** – (optional) (b) number of objects in dim2

- **dummy_row** – (default: False) whether to add dummy rows (rows whose elements are all 0) to pad the matrix to square matrix.
- **max_iter** – (default: 10) maximum iterations
- **tau** – (default: 1) the hyper parameter τ controlling the temperature
- **batched_operation** – (default: False) apply batched_operation for better efficiency (but may cause issues for back-propagation)
- **backend** – (default: `pygmtools.BACKEND` variable) the backend for computation.

Returns $(b \times n_1 \times n_2)$ the computed doubly-stochastic matrix

Note: `tau` is an important hyper parameter to be set for Sinkhorn algorithm. `tau` controls the distance between the predicted doubly-stochastic matrix, and the discrete permutation matrix computed by Hungarian algorithm (see [hungarian\(\)](#)). Given a small `tau`, Sinkhorn performs more closely to Hungarian, at the cost of slower convergence speed and reduced numerical stability.

Note: Setting `batched_operation=True` may be preferred when you are doing inference with this module and do not need the gradient. It is assumed that `row number <= column number`. If not, the input matrix will be transposed.

Note: We support batched instances with different number of nodes, therefore `n1` and `n2` are required to specify the exact number of objects of each dimension in the batch. If not specified, we assume the batched matrices are not padded.

Note: The original Sinkhorn algorithm only works for square matrices. To handle cases where the graphs to be matched have different number of nodes, it is a common practice to add dummy rows to construct a square matrix. After the row and column normalizations, the padded rows are discarded.

Example for numpy backend:

```
>>> import numpy as np
>>> import pygmtools as pygm
>>> pygm.BACKEND = 'numpy'
>>> np.random.seed(0)

# 2-dimensional (non-batched) input
>>> s_2d = np.random.rand(5, 5)
>>> s_2d
array([[0.5488135 , 0.71518937, 0.60276338, 0.54488318, 0.4236548 ],
       [0.64589411, 0.43758721, 0.891773  , 0.96366276, 0.38344152],
       [0.79172504, 0.52889492, 0.56804456, 0.92559664, 0.07103606],
       [0.0871293 , 0.0202184 , 0.83261985, 0.77815675, 0.87001215],
       [0.97861834, 0.79915856, 0.46147936, 0.78052918, 0.11827443]])
>>> x = pygm.sinkhorn(s_2d)
>>> x
array([[0.18880224, 0.24990915, 0.19202217, 0.16034278, 0.20892366],
       [0.18945066, 0.17240445, 0.23345011, 0.22194762, 0.18274716],
```

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```

[0.23713583, 0.204348 , 0.18271243, 0.23114583, 0.1446579 ],
[0.11731039, 0.1229692 , 0.23823909, 0.19961588, 0.32186549],
[0.26730088, 0.2503692 , 0.15357619, 0.18694789, 0.1418058 ]])

# 3-dimensional (batched) input
>>> s_3d = np.random.rand(3, 5, 5)
>>> x = pygm.sinkhorn(s_3d)
>>> print('row_sum:', x.sum(2))
row_sum: [[1. 1. 1. 1. 1. ]
 [0.99999998 1.00000002 0.99999999 1.00000003 0.99999999]
 [1. 1. 1. 1. 1. ]]
>>> print('col_sum:', x.sum(1))
col_sum: [[1. 1. 1. 1. 1.]
 [1. 1. 1. 1. 1.]
 [1. 1. 1. 1. 1.]]

# If the 3-d tensor are with different number of nodes
>>> n1 = np.array([3, 4, 5])
>>> n2 = np.array([3, 4, 5])
>>> x = pygm.sinkhorn(s_3d, n1, n2)
>>> x[0] # non-zero size: 3x3
array([[0.36665934, 0.21498158, 0.41835906, 0. , 0. ],
 [0.27603621, 0.44270207, 0.28126175, 0. , 0. ],
 [0.35730445, 0.34231636, 0.3003792 , 0. , 0. ],
 [0. , 0. , 0. , 0. , 0. ],
 [0. , 0. , 0. , 0. , 0. ]])
>>> x[1] # non-zero size: 4x4
array([[0.28847831, 0.20583051, 0.34242091, 0.16327021, 0. ],
 [0.22656752, 0.30153021, 0.19407969, 0.27782262, 0. ],
 [0.25346378, 0.19649853, 0.32565049, 0.22438715, 0. ],
 [0.23149039, 0.29614075, 0.13784891, 0.33452002, 0. ],
 [0. , 0. , 0. , 0. , 0. ]])
>>> x[2] # non-zero size: 5x5
array([[0.20147352, 0.19541986, 0.24942798, 0.17346397, 0.18021467],
 [0.21050732, 0.17620948, 0.18645469, 0.20384684, 0.22298167],
 [0.18319623, 0.18024007, 0.17619871, 0.1664133 , 0.29395169],
 [0.20754376, 0.2236443 , 0.19658101, 0.20570847, 0.16652246],
 [0.19727917, 0.22448629, 0.19133762, 0.25056742, 0.13632951]])

# non-squared input
>>> s_non_square = np.random.rand(4, 5)
>>> x = pygm.sinkhorn(s_non_square, dummy_row=True) # set dummy_row=True for non-
↪ squared cases
>>> print('row_sum:', x.sum(1), 'col_sum:', x.sum(0))
row_sum: [1. 1. 1. 1.] col_sum: [0.78239609 0.80485526 0.80165627 0.80004254 0.
↪ 81104984]

```

Example for Pytorch backend:

```

>>> import torch
>>> import pygtools as pygm
>>> pygm.BACKEND = 'pytorch'

```

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```

# 2-dimensional (non-batched) input
>>> s_2d = torch.from_numpy(s_2d)
>>> s_2d
tensor([[0.5488, 0.7152, 0.6028, 0.5449, 0.4237],
        [0.6459, 0.4376, 0.8918, 0.9637, 0.3834],
        [0.7917, 0.5289, 0.5680, 0.9256, 0.0710],
        [0.0871, 0.0202, 0.8326, 0.7782, 0.8700],
        [0.9786, 0.7992, 0.4615, 0.7805, 0.1183]], dtype=torch.float64)
>>> x = pygm.sinkhorn(s_2d)
>>> x
tensor([[0.1888, 0.2499, 0.1920, 0.1603, 0.2089],
        [0.1895, 0.1724, 0.2335, 0.2219, 0.1827],
        [0.2371, 0.2043, 0.1827, 0.2311, 0.1447],
        [0.1173, 0.1230, 0.2382, 0.1996, 0.3219],
        [0.2673, 0.2504, 0.1536, 0.1869, 0.1418]], dtype=torch.float64)
>>> print('row_sum:', x.sum(1), 'col_sum:', x.sum(0))
row_sum: tensor([1.0000, 1.0000, 1.0000, 1.0000, 1.0000], dtype=torch.float64) col_
↪sum: tensor([1.0000, 1.0000, 1.0000, 1.0000, 1.0000], dtype=torch.float64)

# 3-dimensional (batched) input
>>> s_3d = torch.from_numpy(s_3d)
>>> x = pygm.sinkhorn(s_3d)
>>> print('row_sum:', x.sum(2))
row_sum: tensor([[1.0000, 1.0000, 1.0000, 1.0000, 1.0000],
                  [1.0000, 1.0000, 1.0000, 1.0000, 1.0000],
                  [1.0000, 1.0000, 1.0000, 1.0000, 1.0000]], dtype=torch.float64)
>>> print('col_sum:', x.sum(1))
col_sum: tensor([[1.0000, 1.0000, 1.0000, 1.0000, 1.0000],
                  [1.0000, 1.0000, 1.0000, 1.0000, 1.0000],
                  [1.0000, 1.0000, 1.0000, 1.0000, 1.0000]], dtype=torch.float64)

# If the 3-d tensor are with different number of nodes
>>> n1 = torch.tensor([3, 4, 5])
>>> n2 = torch.tensor([3, 4, 5])
>>> x = pygm.sinkhorn(s_3d, n1, n2)
>>> x[0] # non-zero size: 3x3
tensor([[0.3667, 0.2150, 0.4184, 0.0000, 0.0000],
        [0.2760, 0.4427, 0.2813, 0.0000, 0.0000],
        [0.3573, 0.3423, 0.3004, 0.0000, 0.0000],
        [0.0000, 0.0000, 0.0000, 0.0000, 0.0000],
        [0.0000, 0.0000, 0.0000, 0.0000, 0.0000]], dtype=torch.float64)
>>> x[1] # non-zero size: 4x4
tensor([[0.2885, 0.2058, 0.3424, 0.1633, 0.0000],
        [0.2266, 0.3015, 0.1941, 0.2778, 0.0000],
        [0.2535, 0.1965, 0.3257, 0.2244, 0.0000],
        [0.2315, 0.2961, 0.1378, 0.3345, 0.0000],
        [0.0000, 0.0000, 0.0000, 0.0000, 0.0000]], dtype=torch.float64)
>>> x[2] # non-zero size: 5x5
tensor([[0.2015, 0.1954, 0.2494, 0.1735, 0.1802],
        [0.2105, 0.1762, 0.1865, 0.2038, 0.2230],
        [0.1832, 0.1802, 0.1762, 0.1664, 0.2940],

```

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```

[0.2075, 0.2236, 0.1966, 0.2057, 0.1665],
[0.1973, 0.2245, 0.1913, 0.2506, 0.1363]], dtype=torch.float64)

# non-squared input
>>> s_non_square = torch.from_numpy(s_non_square)
>>> x = pygm.sinkhorn(s_non_square, dummy_row=True) # set dummy_row=True for non-
→squared cases
>>> print('row_sum:', x.sum(1), 'col_sum:', x.sum(0))
row_sum: tensor([1.0000, 1.0000, 1.0000, 1.0000], dtype=torch.float64) col_sum:
→tensor([0.7824, 0.8049, 0.8017, 0.8000, 0.8110], dtype=torch.float64)

```

Note: If you find this graph matching solver useful for your research, please cite:

```

@article{sinkhorn,
  title={Concerning nonnegative matrices and doubly stochastic matrices},
  author={Sinkhorn, Richard and Knopp, Paul},
  journal={Pacific Journal of Mathematics},
  volume={21},
  number={2},
  pages={343--348},
  year={1967},
  publisher={Mathematical Sciences Publishers}
}

```

4.6.5 pygmtools.classic_solvers.sm

`pygmtools.classic_solvers.sm(K, n1=None, n2=None, n1max=None, n2max=None, x0=None, max_iter: int = 50, backend=None)`

Spectral Graph Matching solver for graph matching (QAP). This algorithm is also known as Power Iteration method, because it works by computing the leading eigenvector of the input affinity matrix by power iteration.

For each iteration,

$$\mathbf{v}_{k+1} = \mathbf{K}\mathbf{v}_k / \|\mathbf{K}\mathbf{v}_k\|_2$$

Parameters

- **K** – ($b \times n_1 n_2 \times n_1 n_2$) the input affinity matrix, b : batch size.
- **n1** – (b) number of nodes in graph1 (optional if **n1max** is given, and all $n1=n1max$).
- **n2** – (b) number of nodes in graph2 (optional if **n2max** is given, and all $n2=n2max$).
- **n1max** – (b) max number of nodes in graph1 (optional if **n1** is given, and $n1max=\max(n1)$).
- **n2max** – (b) max number of nodes in graph2 (optional if **n2** is given, and $n2max=\max(n2)$).
- **x0** – ($b \times n_1 \times n_2$) an initial matching solution for warm-start. If not given, **x0** will be randomly generated.
- **max_iter** – (default: 50) max number of iterations. More iterations will help the solver to converge better, at the cost of increased inference time.
- **backend** – (default: `pygmtools.BACKEND` variable) the backend for computation.

Returns ($b \times n_1 \times n_2$) the solved doubly-stochastic matrix

Example for numpy backend:

```
>>> import numpy as np
>>> import pygtools as pygm
>>> pygm.BACKEND = 'numpy'
>>> np.random.seed(1)

# Generate a batch of isomorphic graphs
>>> batch_size = 10
>>> X_gt = np.zeros((batch_size, 4, 4))
>>> X_gt[:, np.arange(0, 4, dtype=np.int64), np.random.permutation(4)] = 1
>>> A1 = np.random.rand(batch_size, 4, 4)
>>> A2 = np.matmul(np.matmul(X_gt.transpose((0, 2, 1)), A1), X_gt)
>>> n1 = n2 = np.repeat([4], batch_size)

# Build affinity matrix
>>> conn1, edge1, ne1 = pygm.utils.dense_to_sparse(A1)
>>> conn2, edge2, ne2 = pygm.utils.dense_to_sparse(A2)
>>> import functools
>>> gaussian_aff = functools.partial(pygm.utils.gaussian_aff_fn, sigma=1.) # set_
↪affinity function
>>> K = pygm.utils.build_aff_mat(None, edge1, conn1, None, edge2, conn2, n1, None,
↪n2, None, edge_aff_fn=gaussian_aff)

# Solve by SM. Note that X is normalized with a squared sum of 1
>>> X = pygm.sm(K, n1, n2)
>>> (X ** 2).sum(axis=(1, 2))
array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.])

# Accuracy
>>> (pygm.hungarian(X) * X_gt).sum() / X_gt.sum()
1.0
```

Example for Pytorch backend:

```
>>> import torch
>>> import pygtools as pygm
>>> pygm.BACKEND = 'pytorch'
>>> _ = torch.manual_seed(1)

# Generate a batch of isomorphic graphs
>>> batch_size = 10
>>> X_gt = torch.zeros(batch_size, 4, 4)
>>> X_gt[:, torch.arange(0, 4, dtype=torch.int64), torch.randperm(4)] = 1
>>> A1 = torch.rand(batch_size, 4, 4)
>>> A2 = torch.bmm(torch.bmm(X_gt.transpose(1, 2), A1), X_gt)
>>> n1 = n2 = torch.tensor([4] * batch_size)

# Build affinity matrix
>>> conn1, edge1, ne1 = pygm.utils.dense_to_sparse(A1)
>>> conn2, edge2, ne2 = pygm.utils.dense_to_sparse(A2)
>>> import functools
```

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```

>>> gaussian_aff = functools.partial(pygm.utils.gaussian_aff_fn, sigma=1.) # set_
↳affinity function
>>> K = pygm.utils.build_aff_mat(None, edge1, conn1, None, edge2, conn2, n1, None,
↳n2, None, edge_aff_fn=gaussian_aff)

# Solve by SM. Note that X is normalized with a squared sum of 1
>>> X = pygm.sm(K, n1, n2)
>>> (X ** 2).sum(dim=(1, 2))
tensor([1.0000, 1.0000, 1.0000, 1.0000, 1.0000, 1.0000, 1.0000, 1.0000, 1.0000,
        1.0000])

# Accuracy
>>> (pygm.hungarian(X) * X_gt).sum() / X_gt.sum()
tensor(1.)

# This solver supports gradient back-propagation
>>> K = K.requires_grad_(True)
>>> pygm.sm(K, n1, n2).sum().backward()
>>> len(torch.nonzero(K.grad))
2560

```

Note: If you find this graph matching solver useful for your research, please cite:

```

@inproceedings{sm,
  title={A spectral technique for correspondence problems using pairwise_
↳constraints},
  author={Leordeanu, Marius and Hebert, Martial},
  year={2005},
  pages={1482-1489},
  booktitle={International Conference on Computer Vision},
  publisher={IEEE}
}

```

4.7 pygmtools.utils

Functions

<i>build_aff_mat</i>	Build affinity matrix for graph matching from input node/edge features.
<i>build_batch</i>	Build a batched tensor from a list of tensors.
<i>dense_to_sparse</i>	Convert a dense connectivity/adjacency matrix to a sparse connectivity/adjacency matrix and an edge weight tensor.
<i>from_numpy</i>	Convert a numpy ndarray to a tensor.
<i>gaussian_aff_fn</i>	Gaussian kernel affinity function.
<i>inner_prod_aff_fn</i>	Inner product affinity function.
<i>to_numpy</i>	Convert a tensor to a numpy ndarray.

4.7.1 pygmtools.utils.build_aff_mat

`pygmtools.utils.build_aff_mat(node_feat1, edge_feat1, connectivity1, node_feat2, edge_feat2, connectivity2, n1=None, ne1=None, n2=None, ne2=None, node_aff_fn=None, edge_aff_fn=None, backend=None)`

Build affinity matrix for graph matching from input node/edge features. The affinity matrix encodes both node-wise and edge-wise affinities and formulates the Quadratic Assignment Problem (QAP), which is the mathematical form of graph matching.

Parameters

- **node_feat1** – ($b \times n_1 \times f_{node}$) the node feature of graph1
- **edge_feat1** – ($b \times ne_1 \times f_{edge}$) the edge feature of graph1
- **connectivity1** – ($b \times ne_1 \times 2$) sparse connectivity information of graph 1. `connectivity1[i, j, 0]` is the starting node index of edge j at batch i, and `connectivity1[i, j, 1]` is the ending node index of edge j at batch i
- **node_feat2** – ($b \times n_2 \times f_{node}$) the node feature of graph2
- **edge_feat2** – ($b \times ne_2 \times f_{edge}$) the edge feature of graph2
- **connectivity2** – ($b \times ne_2 \times 2$) sparse connectivity information of graph 2. `connectivity2[i, j, 0]` is the starting node index of edge j at batch i, and `connectivity2[i, j, 1]` is the ending node index of edge j at batch i
- **n1** – (b) number of nodes in graph1. If not given, it will be inferred based on the shape of `node_feat1` or the values in `connectivity1`
- **ne1** – (b) number of edges in graph1. If not given, it will be inferred based on the shape of `edge_feat1`
- **n2** – (b) number of nodes in graph2. If not given, it will be inferred based on the shape of `node_feat2` or the values in `connectivity2`
- **ne2** – (b) number of edges in graph2. If not given, it will be inferred based on the shape of `edge_feat2`
- **node_aff_fn** – (default: `inner_prod_aff_fn`) the node affinity function with the characteristic `node_aff_fn(2D Tensor, 2D Tensor) -> 2D Tensor`, which accepts two node feature tensors and outputs the node-wise affinity tensor. See [inner_prod_aff_fn\(\)](#) as an example.
- **edge_aff_fn** – (default: `inner_prod_aff_fn`) the edge affinity function with the characteristic `edge_aff_fn(2D Tensor, 2D Tensor) -> 2D Tensor`, which accepts two edge feature tensors and outputs the edge-wise affinity tensor. See [inner_prod_aff_fn\(\)](#) as an example.
- **backend** – (default: `pygmtools.BACKEND` variable) the backend for computation.

Returns ($b \times n_1 n_2 \times n_1 n_2$) the affinity matrix

Example for numpy backend:

```
>>> import numpy as np
>>> import pygmtools as pygm
>>> pygm.BACKEND = 'numpy'

# Generate a batch of graphs
>>> batch_size = 10
```

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```

>>> A1 = np.random.rand(batch_size, 4, 4)
>>> A2 = np.random.rand(batch_size, 4, 4)
>>> n1 = n2 = np.repeat([4], batch_size)

# Build affinity matrix by the default inner-product function
>>> conn1, edge1, ne1 = pygm.utils.dense_to_sparse(A1)
>>> conn2, edge2, ne2 = pygm.utils.dense_to_sparse(A2)
>>> K = pygm.utils.build_aff_mat(None, edge1, conn1, None, edge2, conn2, n1, ne1,
    ↪n2, ne2)

# Build affinity matrix by gaussian kernel
>>> import functools
>>> gaussian_aff = functools.partial(pygm.utils.gaussian_aff_fn, sigma=1.)
>>> K2 = pygm.utils.build_aff_mat(None, edge1, conn1, None, edge2, conn2, n1, ne1,
    ↪n2, ne2, edge_aff_fn=gaussian_aff)

# Build affinity matrix based on node features
>>> F1 = np.random.rand(batch_size, 4, 10)
>>> F2 = np.random.rand(batch_size, 4, 10)
>>> K3 = pygm.utils.build_aff_mat(F1, edge1, conn1, F2, edge2, conn2, n1, ne1, n2,
    ↪ne2, edge_aff_fn=gaussian_aff)

# The affinity matrices K, K2, K3 can be further processed by GM solvers

```

Example for Pytorch backend:

```

>>> import torch
>>> import pygmtools as pygm
>>> pygm.BACKEND = 'pytorch'

# Generate a batch of graphs
>>> batch_size = 10
>>> A1 = torch.rand(batch_size, 4, 4)
>>> A2 = torch.rand(batch_size, 4, 4)
>>> n1 = n2 = torch.tensor([4] * batch_size)

# Build affinity matrix by the default inner-product function
>>> conn1, edge1, ne1 = pygm.utils.dense_to_sparse(A1)
>>> conn2, edge2, ne2 = pygm.utils.dense_to_sparse(A2)
>>> K = pygm.utils.build_aff_mat(None, edge1, conn1, None, edge2, conn2, n1, ne1,
    ↪n2, ne2)

# Build affinity matrix by gaussian kernel
>>> import functools
>>> gaussian_aff = functools.partial(pygm.utils.gaussian_aff_fn, sigma=1.)
>>> K2 = pygm.utils.build_aff_mat(None, edge1, conn1, None, edge2, conn2, n1, ne1,
    ↪n2, ne2, edge_aff_fn=gaussian_aff)

# Build affinity matrix based on node features
>>> F1 = torch.rand(batch_size, 4, 10)
>>> F2 = torch.rand(batch_size, 4, 10)
>>> K3 = pygm.utils.build_aff_mat(F1, edge1, conn1, F2, edge2, conn2, n1, ne1, n2,
    ↪ne2, edge_aff_fn=gaussian_aff)

```

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```
# The affinity matrices K, K2, K3 can be further processed by GM solvers
```

4.7.2 pygmtools.utils.build_batch

`pygmtools.utils.build_batch(input, return_ori_dim=False, backend=None)`

Build a batched tensor from a list of tensors. If the list of tensors are with different sizes of dimensions, it will be padded to the largest dimension.

The batched tensor and the number of original dimensions will be returned.

Parameters

- **input** – list of input tensors
- **return_ori_dim** – (default: False) return the original dimension
- **backend** – (default: `pygmtools.BACKEND` variable) the backend for computation.

Returns batched tensor, (if `return_ori_dim=True`) a list of the original dimensions

Example for numpy backend:

```
>>> import numpy as np
>>> import pygmtools as pygm
>>> pygm.BACKEND = 'numpy'

# batched adjacency matrices
>>> A1 = np.random.rand(4, 4)
>>> A2 = np.random.rand(5, 5)
>>> A3 = np.random.rand(3, 3)
>>> batched_A, ori_shape = pygm.utils.build_batch([A1, A2, A3], return_ori_dim=True)
>>> batched_A.shape
(3, 5, 5)
>>> ori_shape
([4, 5, 3], [4, 5, 3])

# batched node features (feature dimension=10)
>>> F1 = np.random.rand(4, 10)
>>> F2 = np.random.rand(5, 10)
>>> F3 = np.random.rand(3, 10)
>>> batched_F = pygm.utils.build_batch([F1, F2, F3])
>>> batched_F.shape
(3, 5, 10)
```

Example for Pytorch backend:

```
>>> import torch
>>> import pygmtools as pygm
>>> pygm.BACKEND = 'pytorch'

# batched adjacency matrices
>>> A1 = torch.rand(4, 4)
>>> A2 = torch.rand(5, 5)
```

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```

>>> A3 = torch.rand(3, 3)
>>> batched_A, ori_shape = pygm.utils.build_batch([A1, A2, A3], return_ori_dim=True)
>>> batched_A.shape
torch.Size([3, 5, 5])
>>> ori_shape
(tensor([4, 5, 3]), tensor([4, 5, 3]))

# batched node features (feature dimension=10)
>>> F1 = torch.rand(4, 10)
>>> F2 = torch.rand(5, 10)
>>> F3 = torch.rand(3, 10)
>>> batched_F = pygm.utils.build_batch([F1, F2, F3])
>>> batched_F.shape
torch.Size([3, 5, 10])

```

4.7.3 pygmtools.utils.dense_to_sparse

`pygmtools.utils.dense_to_sparse(dense_adj, backend=None)`

Convert a dense connectivity/adjacency matrix to a sparse connectivity/adjacency matrix and an edge weight tensor.

Parameters

- **dense_adj** – ($b \times n \times n$) the dense adjacency matrix. This function also supports non-batched input where the batch dimension b is ignored
- **backend** – (default: `pygmtools.BACKEND` variable) the backend for computation.

Returns ($b \times ne \times 2$) sparse connectivity matrix, ($b \times ne \times 1$) edge weight tensor, (b) number of edges

Example for numpy backend:

```

>>> import numpy as np
>>> import pygmtools as pygm
>>> pygm.BACKEND = 'numpy'
>>> np.random.seed(0)

>>> batch_size = 10
>>> A = np.random.rand(batch_size, 4, 4)
>>> A[:, np.arange(4), np.arange(4)] = 0 # remove the diagonal elements
>>> A.shape
(10, 4, 4)

>>> conn, edge, ne = pygm.utils.dense_to_sparse(A)
>>> conn.shape # connectivity: (batch x num_edge x 2)
(10, 12, 2)

>>> edge.shape # edge feature (batch x num_edge x feature_dim)
(10, 12, 1)

>>> ne
[12, 12, 12, 12, 12, 12, 12, 12, 12, 12]

```

Example for Pytorch backend:

```
>>> import torch
>>> import pygmtools as pygm
>>> pygm.BACKEND = 'pytorch'
>>> _ = torch.manual_seed(0)

>>> batch_size = 10
>>> A = torch.rand(batch_size, 4, 4)
>>> torch.diagonal(A, dim1=1, dim2=2)[:] = 0 # remove the diagonal elements
>>> A.shape
torch.Size([10, 4, 4])

>>> conn, edge, ne = pygm.utils.dense_to_sparse(A)
>>> conn.shape # connectivity: (batch x num_edge x 2)
torch.Size([10, 12, 2])

>>> edge.shape # edge feature (batch x num_edge x feature_dim)
torch.Size([10, 12, 1])

>>> ne
tensor([12, 12, 12, 12, 12, 12, 12, 12, 12, 12])
```

4.7.4 pygmtools.utils.from_numpy

`pygmtools.utils.from_numpy(input, backend=None)`

Convert a numpy ndarray to a tensor. This is the helper function to convert tensors across different backends via numpy.

Parameters

- **input** – input ndarray
- **backend** – (default: `pygmtools.BACKEND` variable) the backend for computation.

Returns tensor for the backend

4.7.5 pygmtools.utils.gaussian_aff_fn

`pygmtools.utils.gaussian_aff_fn(feat1, feat2, sigma=1.0, backend=None)`

Gaussian kernel affinity function. The affinity is defined as

$$\exp\left(-\frac{(\mathbf{f}_1 - \mathbf{f}_2)^2}{\sigma}\right)$$

Parameters

- **feat1** – $(b \times n_1 \times f)$ the feature vectors \mathbf{f}_1
- **feat2** – $(b \times n_2 \times f)$ the feature vectors \mathbf{f}_2
- **sigma** – (default: 1) the parameter σ in Gaussian kernel
- **backend** – (default: `pygmtools.BACKEND` variable) the backend for computation.

Returns $(b \times n_1 \times n_2)$ element-wise Gaussian affinity matrix

4.7.6 pygmtools.utils.inner_prod_aff_fn

`pygmtools.utils.inner_prod_aff_fn(feat1, feat2, backend=None)`

Inner product affinity function. The affinity is defined as

$$\mathbf{f}_1^\top \cdot \mathbf{f}_2$$

Parameters

- **feat1** – ($b \times n_1 \times f$) the feature vectors \mathbf{f}_1
- **feat2** – ($b \times n_2 \times f$) the feature vectors \mathbf{f}_2
- **backend** – (default: `pygmtools.BACKEND` variable) the backend for computation.

Returns ($b \times n_1 \times n_2$) element-wise inner product affinity matrix

4.7.7 pygmtools.utils.to_numpy

`pygmtools.utils.to_numpy(input, backend=None)`

Convert a tensor to a numpy ndarray. This is the helper function to convert tensors across different backends via numpy.

Parameters

- **input** – input tensor
- **backend** – (default: `pygmtools.BACKEND` variable) the backend for computation.

Returns numpy ndarray

PYTHON MODULE INDEX

p

- `pygmtools.benchmark`, [15](#)
- `pygmtools.classic_solvers`, [19](#)
- `pygmtools.dataset`, [17](#)
- `pygmtools.utils`, [33](#)

B

Benchmark (class in `pygertools.benchmark`), 15
 build_aff_mat() (in module `pygertools.utils`), 34
 build_batch() (in module `pygertools.utils`), 36

C

compute_img_num() (`pygertools.benchmark.Benchmark` method), 15
 compute_length() (`pygertools.benchmark.Benchmark` method), 15
 CUB2011 (class in `pygertools.dataset`), 17

D

dense_to_sparse() (in module `pygertools.utils`), 37
 download() (`pygertools.dataset.CUB2011` method), 17
 download() (`pygertools.dataset.IMC_PT_SparseGM` method), 18
 download() (`pygertools.dataset.PascalVOC` method), 18
 download() (`pygertools.dataset.SPair71k` method), 19
 download() (`pygertools.dataset.WillowObject` method), 19

E

eval() (`pygertools.benchmark.Benchmark` method), 15
 eval_cls() (`pygertools.benchmark.Benchmark` method), 16

F

from_numpy() (in module `pygertools.utils`), 38

G

gaussian_aff_fn() (in module `pygertools.utils`), 38
 get_data() (`pygertools.benchmark.Benchmark` method), 16
 get_id_combination() (`pygertools.benchmark.Benchmark` method), 16

H

hungarian() (in module `pygertools.classic_solvers`), 20

I

IMC_PT_SparseGM (class in `pygertools.dataset`), 18

inner_prod_aff_fn() (in module `pygertools.utils`), 39
 ipfp() (in module `pygertools.classic_solvers`), 22

M

module
 `pygertools.benchmark`, 15
 `pygertools.classic_solvers`, 19
 `pygertools.dataset`, 17
 `pygertools.utils`, 33

P

PascalVOC (class in `pygertools.dataset`), 18
 process() (`pygertools.dataset.CUB2011` method), 17
 process() (`pygertools.dataset.IMC_PT_SparseGM` method), 18
 process() (`pygertools.dataset.PascalVOC` method), 18
 process() (`pygertools.dataset.SPair71k` method), 19
 process() (`pygertools.dataset.WillowObject` method), 19
`pygertools.benchmark`
 module, 15
`pygertools.classic_solvers`
 module, 19
`pygertools.dataset`
 module, 17
`pygertools.utils`
 module, 33

R

rand_get_data() (`pygertools.benchmark.Benchmark` method), 16
 rm_gt_cache() (`pygertools.benchmark.Benchmark` method), 17
 rrwm() (in module `pygertools.classic_solvers`), 25

S

sinkhorn() (in module `pygertools.classic_solvers`), 27
 sm() (in module `pygertools.classic_solvers`), 31
 SPair71k (class in `pygertools.dataset`), 18

T

to_numpy() (in module `pygertools.utils`), 39

W

`WillowObject` (*class in `pygmtools.dataset`*), [19](#)