



Data handling in PyG

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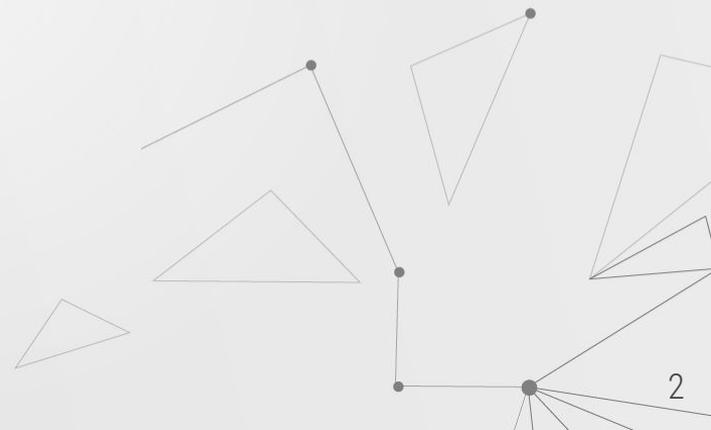
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01 Prediction Tasks on Graphs

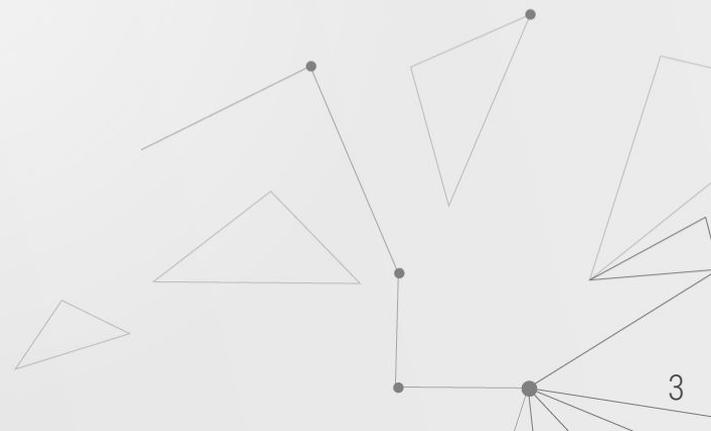
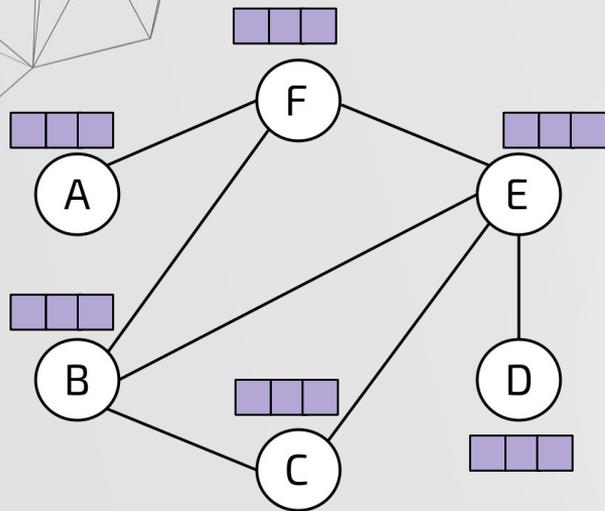
In our tutorials we mainly covered 4 tasks on graphs:

- Node prediction
- Graph prediction
- Edge prediction (property)
- Edge prediction (link between two nodes)



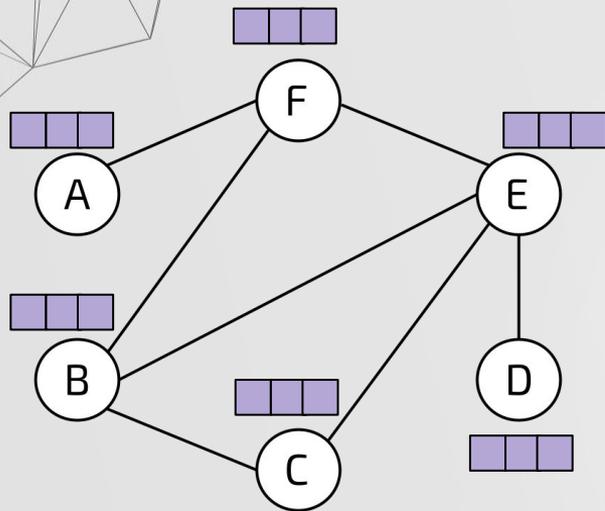
01 Prediction Tasks on Graphs

Node prediction

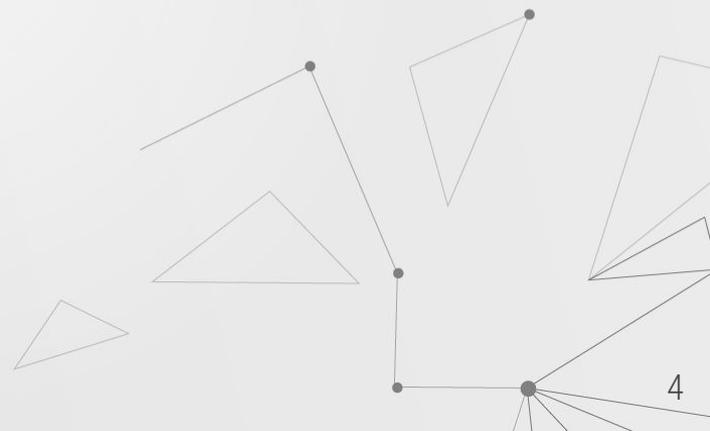


01 Prediction Tasks on Graphs

Node prediction

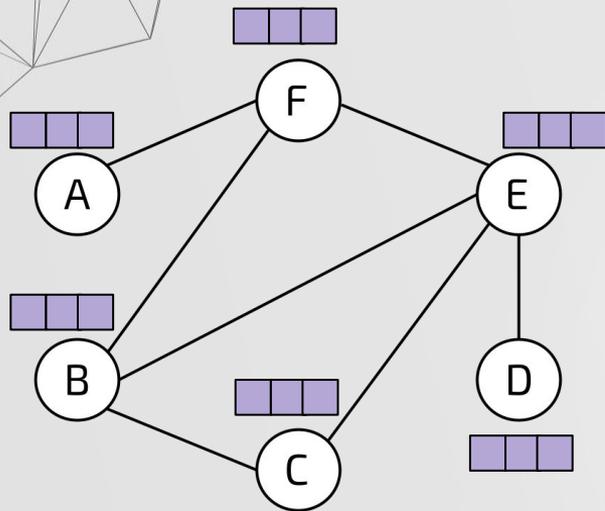


$$\mathbf{X}^{t+1} = \text{GNN}(\mathbf{W}^t, \mathbf{X}^t, \mathbf{A}) \quad t = 1, \dots, k$$

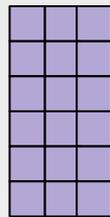


01 Prediction Tasks on Graphs

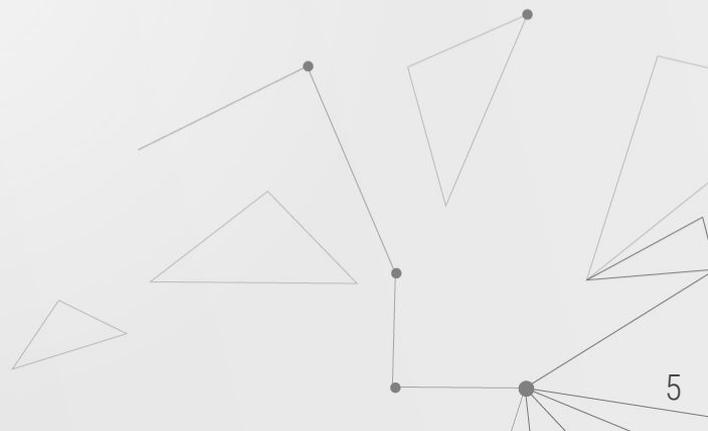
Node prediction



\mathbf{X}^k

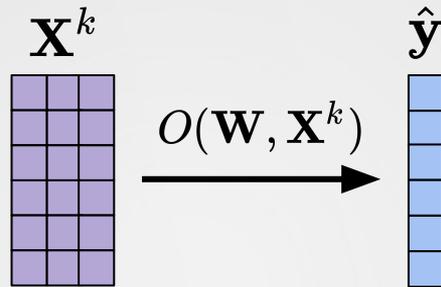
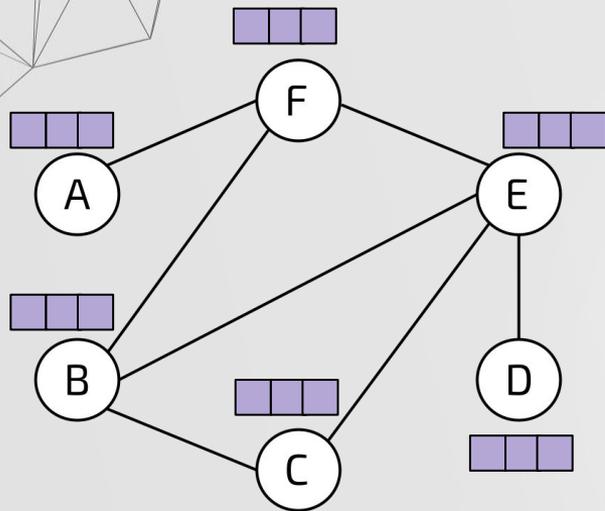


$$\mathbf{X}^{t+1} = \text{GNN}(\mathbf{W}^t, \mathbf{X}^t, \mathbf{A}) \quad t = 1, \dots, k$$



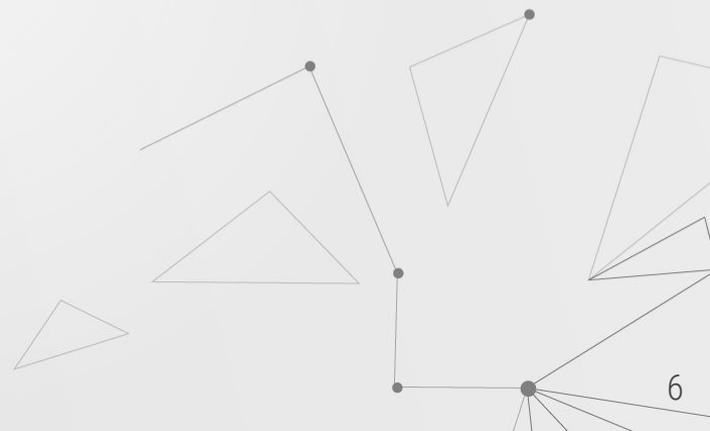
01 Prediction Tasks on Graphs

Node prediction



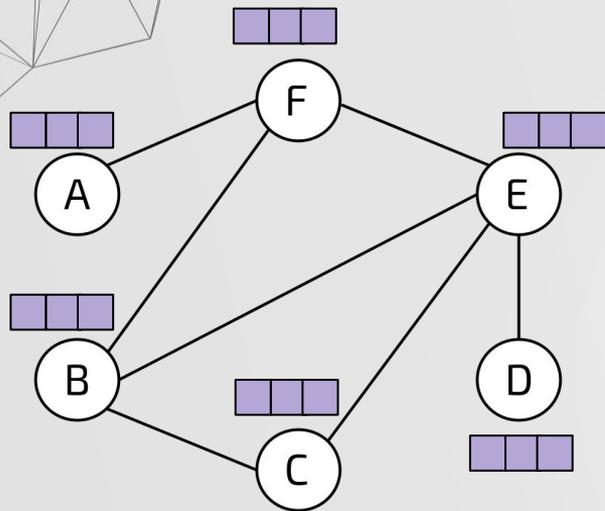
$$\mathbf{X}^{t+1} = \text{GNN}(\mathbf{W}^t, \mathbf{X}^t, \mathbf{A}) \quad t = 1, \dots, k$$

$$O(\mathbf{W}, \mathbf{X}^k) \longrightarrow \text{node readout function}$$

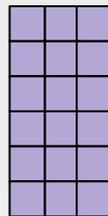


01 Prediction Tasks on Graphs

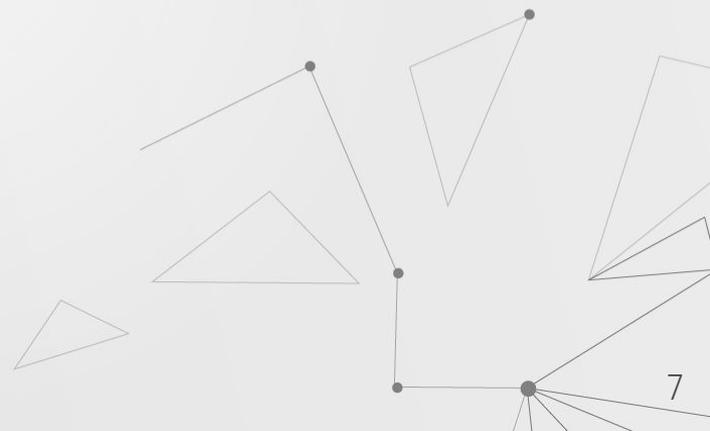
Graph prediction



\mathbf{X}^k

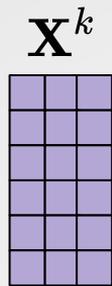
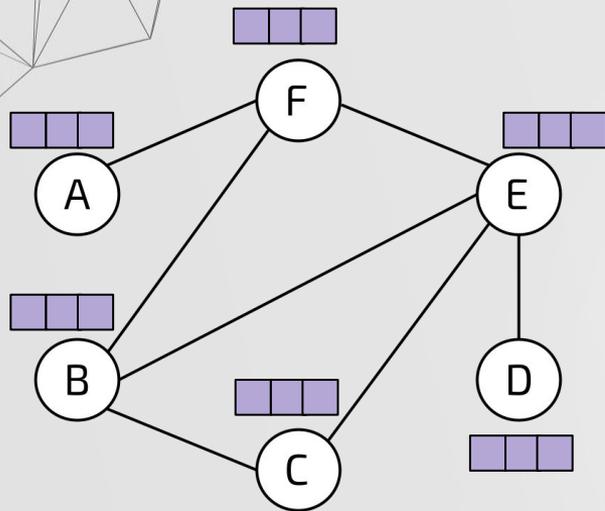


$$\mathbf{X}^{t+1} = \text{GNN}(\mathbf{W}^t, \mathbf{X}^t, \mathbf{A}) \quad t = 1, \dots, k$$



01 Prediction Tasks on Graphs

Graph prediction



$GPool(\mathbf{X}^k)$



max
mean
sum
... or others

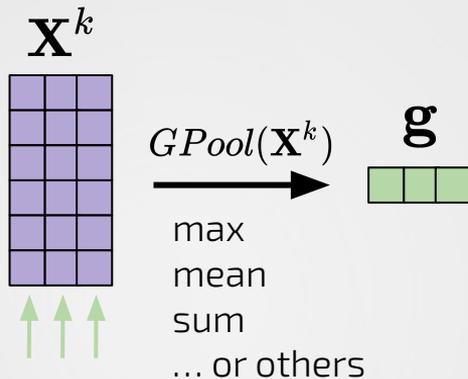
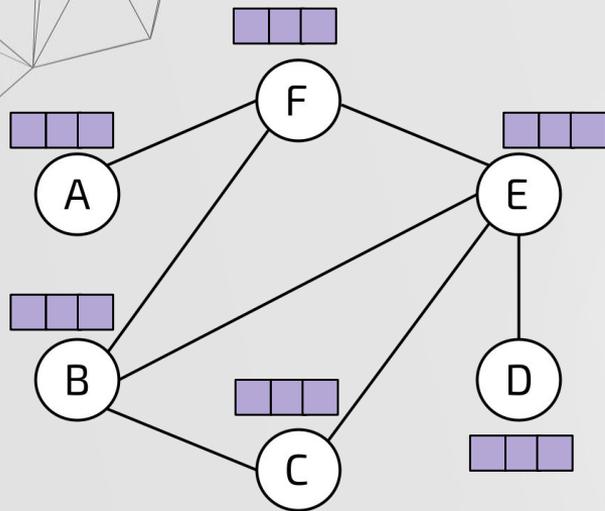
$$\mathbf{X}^{t+1} = \text{GNN}(\mathbf{W}^t, \mathbf{X}^t, \mathbf{A}) \quad t = 1, \dots, k$$

$GPool(\mathbf{X}^k) \longrightarrow$ global pooling function



01 Prediction Tasks on Graphs

Graph prediction



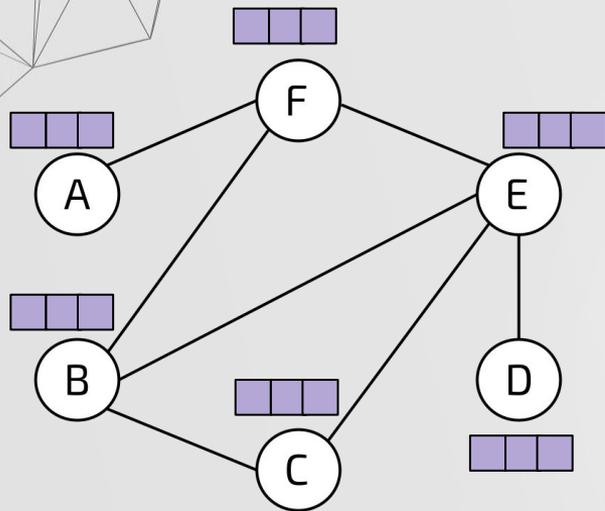
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$\text{GPool}(\mathbf{X}^k) \longrightarrow$ global pooling function

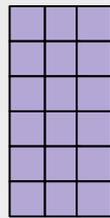


01 Prediction Tasks on Graphs

Graph prediction



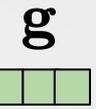
\mathbf{X}^k



$GPool(\mathbf{X}^k)$



max
mean
sum
... or others



$O(\mathbf{W}, \mathbf{g})$



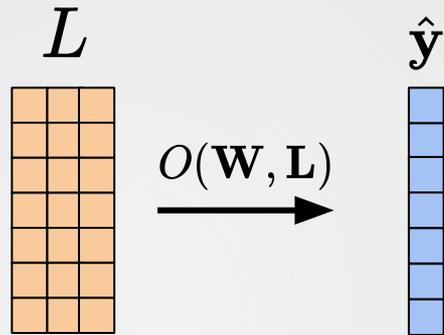
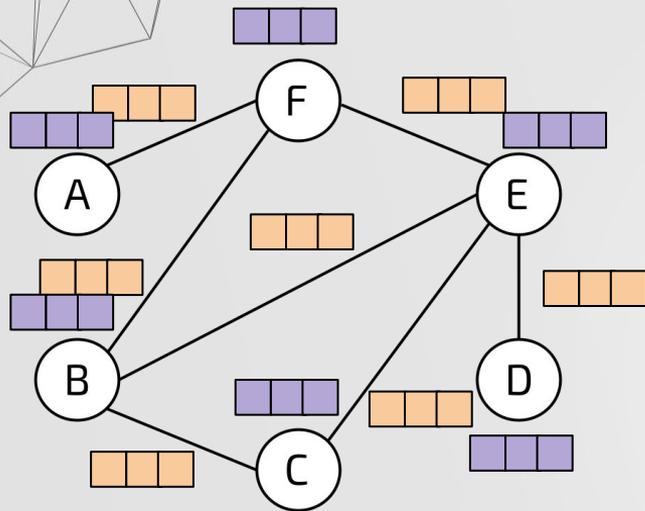
$$\mathbf{X}^{t+1} = \text{GNN}(\mathbf{W}^t, \mathbf{X}^t, \mathbf{A}) \quad t = 1, \dots, k$$

$GPool(\mathbf{X}^k) \longrightarrow$ global pooling function

$O(\mathbf{W}, \mathbf{g}) \longrightarrow$ graph readout function

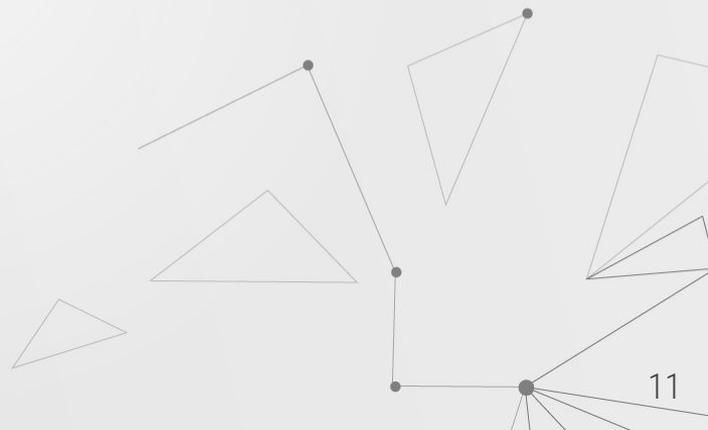
01 Prediction Tasks on Graphs

Edge prediction (property)



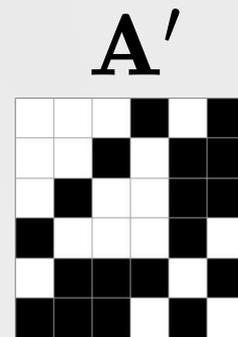
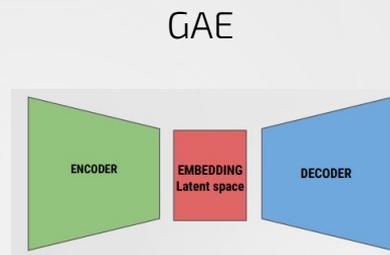
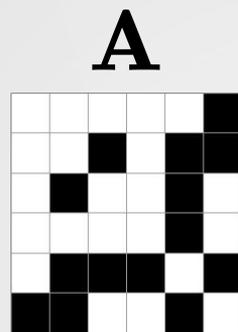
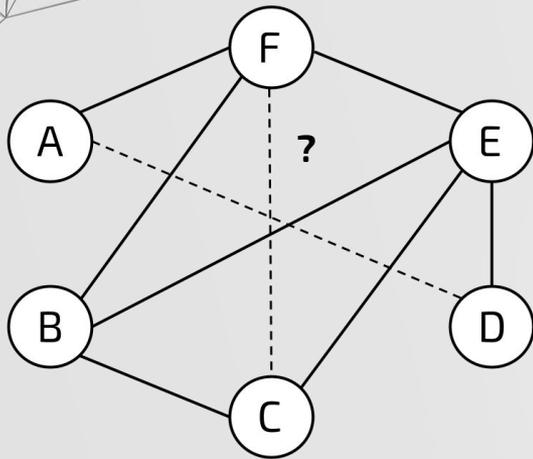
$$\mathbf{l}_{u,v} = \frac{1}{2} (\mathbf{x}_u^k, \mathbf{x}_v^k)$$

$O(\mathbf{W}, \mathbf{L}) \longrightarrow$ edge readout function



01 Prediction Tasks on Graphs

Edge prediction (link)



02 Data submodule

Two modules for data handling:

- **torch_geometric.Data** -> classes and methods for creating and managing (collection of) graphs
- **torch_geometric.Datasets** -> module with a collection of datasets

02 Data submodule

torch_geometric.data.data.Data : base class for representing a graph

```
CLASS Data ( x=None, edge_index=None, edge_attr=None, y=None, pos=None, normal=None, face=None,
**kwargs ) \[source\]
```

A plain old python object modeling a single graph with various (optional) attributes:

- PARAMETERS:**
- **x** (*Tensor, optional*) – Node feature matrix with shape `[num_nodes, num_node_features]` . (default: `None`)
 - **edge_index** (*LongTensor, optional*) – Graph connectivity in COO format with shape `[2, num_edges]` . (default: `None`)
 - **edge_attr** (*Tensor, optional*) – Edge feature matrix with shape `[num_edges, num_edge_features]` . (default: `None`)
 - **y** (*Tensor, optional*) – Graph or node targets with arbitrary shape. (default: `None`)
 - **pos** (*Tensor, optional*) – Node position matrix with shape `[num_nodes, num_dimensions]` . (default: `None`)
 - **normal** (*Tensor, optional*) – Normal vector matrix with shape `[num_nodes, num_dimensions]` . (default: `None`)
 - **face** (*LongTensor, optional*) – Face adjacency matrix with shape `[3, num_faces]` . (default: `None`)

02 Data submodule

torch_geometric.data.batch.Batch : data object that represents a collection of graphs

CLASS Batch (batch=None, ptr=None, **kwargs) [\[source\]](#)

A plain old python object modeling a batch of graphs as one big (disconnected) graph. With `torch_geometric.data.Data` being the base class, all its methods can also be used here. In addition, single graphs can be reconstructed via the assignment vector `batch`, which maps each node to its respective graph identifier.

CLASSMETHOD from_data_list (data_list, follow_batch=[], exclude_keys=[]) [\[source\]](#)

Constructs a batch object from a python list holding `torch_geometric.data.Data` objects. The assignment vector `batch` is created on the fly. Additionally, creates assignment batch vectors for each key in `follow_batch`. Will exclude any keys given in `exclude_keys`.

PROPERTY num_graphs

Returns the number of graphs in the batch.

to_data_list () → List[torch_geometric.data.data.Data] [\[source\]](#)

Reconstructs the list of `torch_geometric.data.Data` objects from the batch object. The batch object must have been created via `from_data_list()` in order to be able to reconstruct the initial objects.

02 Data submodule

torch_geometric.data.cluster.ClusterData
& **torch_geometric.data.cluster.ClusterLoader** : group nodes into smaller subgraphs and load them in batches for faster computation on large graphs

```
CLASS ClusterData ( data, num_parts: int, recursive: bool = False, save_dir: Optional[str] = None, log: bool = True ) [source]
```

Clusters/partitions a graph data object into multiple subgraphs, as motivated by the "Cluster-GCN: An Efficient Algorithm for Training Deep and Large Graph Convolutional Networks" paper.

PARAMETERS:

- **data** (*torch_geometric.data.Data*) – The graph data object.
- **num_parts** (*int*) – The number of partitions.
- **recursive** (*bool, optional*) – If set to `True`, will use multilevel recursive bisection instead of multilevel k-way partitioning. (default: `False`)
- **save_dir** (*string, optional*) – If set, will save the partitioned data to the `save_dir` directory for faster re-use. (default: `None`)
- **log** (*bool, optional*) – If set to `False`, will not log any progress. (default: `True`)

```
CLASS ClusterLoader ( cluster_data, **kwargs ) [source]
```

The data loader scheme from the "Cluster-GCN: An Efficient Algorithm for Training Deep and Large Graph Convolutional Networks" paper which merges partitioned subgraphs and their between-cluster links from a large-scale graph data object to form a mini-batch.

Note

Use `torch_geometric.data.ClusterData` and `torch_geometric.data.ClusterLoader` in conjunction to form mini-batches of clusters. For an example of using Cluster-GCN, see [examples/cluster_gcn_reddit.py](#) or [examples/cluster_gcn_ppi.py](#).

02 Data submodule

torch_geometric.data.sampler.NeighborSampler : samples a specific number of nodes in a neighborhood

```
CLASS NeighborSampler ( edge_index: Union[torch.Tensor, torch_sparse.tensor.SparseTensor], sizes: List[int], node_idx: Optional[torch.Tensor] = None, num_nodes: Optional[int] = None, return_e_id: bool = True, transform: Optional[Callable] = None, **kwargs ) [source]
```

PARAMETERS:

- **edge_index** (*Tensor or SparseTensor*) – A `torch.LongTensor` or a `torch_sparse.SparseTensor` that defines the underlying graph connectivity/message passing flow. `edge_index` holds the indices of a (sparse) symmetric adjacency matrix. If `edge_index` is of type `torch.LongTensor`, its shape must be defined as `[2, num_edges]`, where messages from nodes `edge_index[0]` are sent to nodes in `edge_index[1]` (in case `flow="source_to_target"`). If `edge_index` is of type `torch_sparse.SparseTensor`, its sparse indices `(row, col)` should relate to `row = edge_index[1]` and `col = edge_index[0]`. The major difference between both formats is that we need to input the *transposed* sparse adjacency matrix.
- **sizes** (*List*) – The number of neighbors to sample for each node in each layer. If set to `sizes[1] = -1`, all neighbors are included in layer `1`.
- **node_idx** (*LongTensor, optional*) – The nodes that should be considered for creating mini-batches. If set to `None`, all nodes will be considered.
- **num_nodes** (*int, optional*) – The number of nodes in the graph. (default: `None`)

03 Datasets submodule

torch_geometric.datasets.Dataset : base class for implementing a dataset

CLASS Dataset (`root=None`, `transform=None`, `pre_transform=None`, `pre_filter=None`) [\[source\]](#)

Dataset base class for creating graph datasets. See [here](#) for the accompanying tutorial.

PARAMETERS:

- **root** (*string, optional*) – Root directory where the dataset should be saved. (optional: `None`)
- **transform** (*callable, optional*) – A function/transform that takes in an `torch_geometric.data.Data` object and returns a transformed version. The data object will be transformed before every access. (default: `None`)
- **pre_transform** (*callable, optional*) – A function/transform that takes in an `torch_geometric.data.Data` object and returns a transformed version. The data object will be transformed before being saved to disk. (default: `None`)
- **pre_filter** (*callable, optional*) – A function that takes in an `torch_geometric.data.Data` object and returns a boolean value, indicating whether the data object should be included in the final dataset. (default: `None`)

03 Datasets submodule

Two types of datasets can be implemented, using **Dataset** class or **InMemoryDataset** class (which extends **Dataset**):

InMemoryDataset is a dataset that fits entirely in the memory (RAM), it is loaded once. Four methods need to be implemented:

- **torch_geometric.data.InMemoryDataset.raw_file_names()**: A list of files in the `raw_dir` which needs to be found in order to skip the download.
- **torch_geometric.data.InMemoryDataset.processed_file_names()**: A list of files in the `processed_dir` which needs to be found in order to skip the processing.
- **torch_geometric.data.InMemoryDataset.download()**: Downloads raw data into `raw_dir`.
- **torch_geometric.data.InMemoryDataset.process()**: Processes raw data and saves it into the `processed_dir`.

Dataset is used also for large datasets, in which data is loaded and stored to files during the computation, methods to be implemented:

- **torch_geometric.data.Dataset.len()**: Returns the number of examples in your dataset.
- **torch_geometric.data.Dataset.get()**: Implements the logic to load a single graph.

03 Datasets submodule

Torch_geometric.transforms: list of functions to perform transformation of graphs data:

'ToSparseTensor',
'ToUndirected',
'Constant',
'Distance',
'Cartesian',
'OneHotDegree',
'TargetIndegree',
'LinearTransformation',
'RandomScale',
'RandomRotate',
'RandomShear',
'NormalizeFeatures',
'AddSelfLoops',
'RemoveIsolatedNodes',

03 Datasets submodule

torch_geometric.data.DataLoader : class for composing batches of graphs in a dataset

```
CLASS DataLoader ( dataset, batch_size=1, shuffle=False, follow_batch=[], exclude_keys=[],  
**kwargs ) \[source\]
```

Data loader which merges data objects from a `torch_geometric.data.dataset` to a mini-batch.

PARAMETERS:

- **dataset** (*Dataset*) – The dataset from which to load the data.
- **batch_size** (*int, optional*) – How many samples per batch to load. (default: `1`)
- **shuffle** (*bool, optional*) – If set to `True`, the data will be reshuffled at every epoch. (default: `False`)
- **follow_batch** (*list or tuple, optional*) – Creates assignment batch vectors for each key in the list. (default: `[]`)
- **exclude_keys** (*list or tuple, optional*) – Will exclude each key in the list. (default: `[]`)
- ****kwargs** (*optional*) – Additional arguments of `torch.utils.data.DataLoader`.