
Graphormer

Release 1.0

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Aug 12, 2022

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Graphormer is a deep learning package extended from [fairseq](#) that allows researchers and developers to train custom models for molecule modeling tasks. It aims to accelerate the research and application in AI for molecule science, such as material discovery, drug discovery, etc.

INSTALLATION GUIDE

This is a guide to install Graphormer. Currently Graphormer supports intallation on Linux only.

1.1 Linux

On Linux, Graphormer can be easily installed with the install.sh script with prepared python environments.

1. Please use Python3.9 for Graphormer. It is recommended to create a virtual environment with [conda](#) or [virtualenv](#). For example, to create and activate a conda environment with Python3.9

```
conda create -n graphormer python=3.9
conda activate graphormer
```

2. Run the following commands:

```
git clone --recursive https://github.com/microsoft/Graphormer.git
cd Graphormer
bash install.sh
```


START WITH EXAMPLE

Graphormer provides example scripts to train your own models on several datasets. For example, to train a Graphormer-slim on ZINC-500K on a single GPU card:

```
> cd examples/property_prediction/  
> bash zinc.sh
```

The content of `zinc.sh` is simply a `fairseq-train` command:

```
CUDA_VISIBLE_DEVICES=0 fairseq-train \  
  --user-dir ../../graphormer \  
  --num-workers 16 \  
  --ddp-backend=legacy_ddp \  
  --dataset-name zinc \  
  --dataset-source pyg \  
  --task graph_prediction \  
  --criterion l1_loss \  
  --arch graphormer_slim \  
  --num-classes 1 \  
  --attention-dropout 0.1 --act-dropout 0.1 --dropout 0.0 \  
  --optimizer adam --adam-betas '(0.9, 0.999)' --adam-eps 1e-8 --clip-norm 5.0 --  
↪weight-decay 0.01 \  
  --lr-scheduler polynomial_decay --power 1 --warmup-updates 60000 --total-num-update_  
↪400000 \  
  --lr 2e-4 --end-learning-rate 1e-9 \  
  --batch-size 64 \  
  --fp16 \  
  --data-buffer-size 20 \  
  --encoder-layers 12 \  
  --encoder-embed-dim 80 \  
  --encoder-ffn-embed-dim 80 \  
  --encoder-attention-heads 8 \  
  --max-epoch 10000 \  
  --save-dir ./ckpts
```

`CUDA_VISIBLE_DEVICES` specifies the GPUs to use. With multiple GPUs, the GPU IDs should be separated by commas. A `fairseq-train` with Graphormer model is used to launch training. [Command-line Tools](#) gives detailed explanations to the parameters.

Similarly, to train a Graphormer-base on PCQM4M dataset on multiple GPU cards:

```
> cd examples/property_prediction/  
> bash pcqm1.sh
```

By running the instructions in the scripts, Graphormer will automatically download the needed datasets and pre-process them.

EVALUATE PRE-TRAINED MODELS

Graphormer provides pretrained models so that users can easily evaluate, and finetune. To evaluate a pre-trained model, use the script `graphormer/evaluate/evaluate.py`.

```
python evaluate.py \
  --user-dir ../../graphormer \
  --num-workers 16 \
  --ddp-backend=legacy_ddp \
  --dataset-name pcqm4m \
  --dataset-source ogb \
  --task graph_prediction \
  --criterion l1_loss \
  --arch graphormer_base \
  --num-classes 1 \
  --batch-size 64 \
  --pretrained-model-name pcqm4mv1_graphormer_base \
  --load-pretrained-model-output-layer \
  --split valid \
  --seed 1
```

`--pretrained-model-name` specifies the pre-trained model to be evaluated. The pre-trained model will be automatically downloaded. And `--load-pretrained-model-output-layer` is set so that weights of the final fully connected layer in the pre-trained model is loaded. And `--split` specifies the split of the dataset to be evaluated, can be `train` or `valid`.

FINE-TUNING PRE-TRAINED MODELS

To fine-tune pre-trained models, use `--pretrained-model-name` to set the model name. For example, the script `examples/property_prediction/hiv_pre.sh` fine-tunes our model `pcqm4mv1_graphormer_base` on the `ogbg-molhiv` dataset. The command for fine-tune is

```
fairseq-train \
  --user-dir ../../graphormer \
  --num-workers 16 \
  --ddp-backend=legacy_ddp \
  --dataset-name ogbg-molhiv \
  --dataset-source ogb \
  --task graph_prediction_with_flag \
  --criterion binary_logloss_with_flag \
  --arch graphormer_base \
  --num-classes 1 \
  --attention-dropout 0.1 --act-dropout 0.1 --dropout 0.0 \
  --optimizer adam --adam-betas '(0.9, 0.999)' --adam-eps 1e-8 --weight-decay 0.0 \
  --lr-scheduler polynomial_decay --power 1 --warmup-updates $warmup_updates --total-
  num-update $tot_updates \
  --lr 2e-4 --end-learning-rate 1e-9 \
  --batch-size $batch_size \
  --fp16 \
  --data-buffer-size 20 \
  --encoder-layers 12 \
  --encoder-embed-dim 768 \
  --encoder-ffn-embed-dim 768 \
  --encoder-attention-heads 32 \
  --max-epoch $max_epoch \
  --save-dir ./ckpts \
  --pretrained-model-name pcqm4mv1_graphormer_base \
  --flag-m 3 \
  --flag-step-size 0.01 \
  --flag-mag 0 \
  --seed 1 \
  --pre-layernorm
```

After fine-tuning, use `graphormer/evaluate/evaluate.py` to evaluate the performance of all checkpoints:

```
python evaluate.py \
  --user-dir ../../graphormer \
  --num-workers 16 \
  --ddp-backend=legacy_ddp \
```

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```
--dataset-name ogbg-molhiv \  
--dataset-source ogb \  
--task graph_prediction \  
--arch graphormer_base \  
--num-classes 1 \  
--batch-size 64 \  
--save-dir ../../examples/property_prediction/ckpts/ \  
--split test \  
--metric auc \  
--seed 1 \  
--pre-layernorm
```

TRAINING A NEW MODEL

We take OC20 as an example to show how to train a new model on your own datasets.

First, download IS2RE train, validation, and test data in LMDB format by:

```
> cd examples/oc20/ && mkdir data && cd data/
> wget -c https://dl.fbaipublicfiles.com/opencatalystproject/data/is2res_train_val_test_
↳lmdbs.tar.gz && tar -xzf is2res_train_val_test_lmdbs.tar.gz
```

Create ckpt folder to save checkpoints during the training:

```
> cd ../ && mkdir ckpt/
```

Now we train a 48-layer graphormer-3D architecture, which has 4 blocks and each block contains 12 Graphormer layers. The parameters are sharing across blocks. The total training steps are 1 million, and we warmup the learning rate by 10 thousand steps.

```
> fairseq-train --user-dir ../../graphormer \
  ./data/is2res_train_val_test_lmdbs/data/is2re/all --valid-subset val_id,val_ood_ads,
↳val_ood_cat,val_ood_both --best-checkpoint-metric loss \
  --num-workers 0 --ddp-backend=c10d \
  --task is2re --criterion mae_deltapos --arch graphormer3d_base \
  --optimizer adam --adam-betas '(0.9, 0.98)' --adam-eps 1e-6 --clip-norm $clip_norm \
  --lr-scheduler polynomial_decay --lr 3e-4 --warmup-updates --total-num-update_
↳1000000 --batch-size 4 \
  --dropout 0.0 --attention-dropout 0.1 --weight-decay 0.001 --update-freq 1 --seed 1 \
  --fp16 --fp16-init-scale 4 --fp16-scale-window 256 --tensorboard-logdir ./tsbs \
  --embed-dim 768 --ffn-embed-dim 768 --attention-heads 48 \
  --max-update 1000000 --log-interval 100 --log-format simple \
  --save-interval-updates 5000 --validate-interval-updates 2500 --keep-interval-updates_
↳30 --no-epoch-checkpoints \
  --save-dir ./ckpt --layers 12 --blocks 4 --required-batch-size-multiple 1 --node-
↳loss-weight 15
```

Please note that `--batch-size 4` requires at least 32GB of GPU memory. If out of GPU memory occurs, one may try to reduce the batchsize then train with more GPU cards, or increase the `--update-freq` to accumulate the gradients.

COMMAND-LINE TOOLS

Graphormer reuses the `fairseq-train` command-line tools of `fairseq` for training, and here we mainly document the additional parameters in Graphormer and parameters of `fairseq-train` used by Graphormer.

6.1 Model

- `--arch`, type=enum, options: `graphormer_base`, `graphormer_slim`, `graphormer_large`
 - Predefined graphormer architectures
- `--encoder-ffn-embed-dim`, type = float
 - encoder embedding dimension for FFN
- `--encoder-layers`, type = int
 - number of graphormer encoder layers
- `--encoder-embed-dim`, type = int
 - encoder embedding dimension
- `--share-encoder-input-output-embed`, type = bool
 - if set, share encoder input and output embeddings
- `--share-encoder-input-output-embed`, type = bool
 - if set, share encoder input and output embeddings
- `--encoder-learned-pos`, type = bool
 - if set, use learned positional embeddings in the encoder
- `--no-token-positional-embeddings`, type = bool
 - if set, disables positional embeddings” ” (outside self attention)
- `--max-positions`, type = int
 - number of positional embeddings to learn
- `--activation-fn`, type = enum, options: `gelu`, `relu`
 - activation function to use
- `--encoder-normalize-before`
 - if set, apply layernorm before each encoder block

6.2 Training

- `--task`, type = enum, options: `graph_prediction`, `is2re`
 - the task for training
 - * `graph_prediction`: ordinary graph-level prediction task, predict a single target for a graph
 - * `is2re`: for IS2RE task of [Open Catalyst Challenge](#)
- `--criterion`, type = enum, options: `l1_loss`, `binary_logloss`, `multiclass_cross_entropy`, `mae_deltapos`, `l1_loss_with_flag`, `binary_logloss_with_flag`, `multiclass_cross_entropy_with_flag`
 - the criterion, or objective function for training.
 - * `l1_loss`: mean absolute error (MAE) for regression tasks
 - * `binary_logloss`: binary cross entropy for binary classification
 - * `multiclass_cross_entropy`: multi-class cross entropy for multi-class classification
 - * `mae_deltapos`: criterion for IS2RE task of [Open Catalyst Challenge](#)
 - * `l1_loss_with_flag`: `l1_loss` with [FLAG](#)
 - * `binary_logloss_with_flag`: `binary_logloss` with [FLAG](#)
 - * `multiclass_cross_entropy_with_flag`: `multiclass_cross_entropy` with [FLAG](#)
- `--apply-graphormer-init`, type = bool
 - if set, use custom param initialization for Graphormer
- `--dropout`, type = float
 - dropout probability
- `--attention-dropout`, type = float
 - dropout probability for attention weights
- `--act-dropout`, type = float
 - dropout probability after activation in FFN
- `--seed`, type = int
 - random seed
- `--pretrained-model-name`, type = enum, default= `none`, options: `pcqm4mv1_graphormer_base`, `pcqm4mv2_graphormer_base`
 - name of used pretrained model
 - * `pcqm4mv1_graphormer_base`: Pretrained Graphormer base model with [PCQM4M v1](#) dataset.
 - * `pcqm4mv2_graphormer_base`: Pretrained Graphormer base model with [PCQM4M v2](#) dataset.
- `--load-pretrained-model-output-layer`, type = bool
 - if set, the weights of the final fully connected layer in the pre-trained model is loaded
- `--optimizer`, type = enum
 - optimizers from [fairseq](#)
- `--lr`, type = float
 - learning rate

- `--lr-scheduler`, type=enum
 - learning rate scheduler from [fairseq](#)
- `--fp16`, type=bool
 - if set, use mixed precision training
- `--data-buffer-size`, type=int, default=10
 - number of batches to preload
- `--batch-size`, type=int
 - number of examples in a batch
- `--max-epoch`, type=int, default=0
 - force stop training at specified epoch
- `--save-dir`, type=str, default=`checkpoints`
 - path to save checkpoints

6.3 Dataset

- `--dataset-name`, type = str, default= `pcqm4m`
 - name of the dataset
- `--dataset-source`, type = str, default= `ogb`
 - source of graph dataset, can be: `pyg`, `dgl`, `ogb`
- `--num-classes`, type = int, default=-1
 - number of classes or regression targets
- `--num-atoms`, type = int, default=512 * 9
 - number of atom types in the graph
- `--num-edges`, type = int, default=512 * 3
 - number of edge types in the graph
- `--num-in-degree`, type = int, default=512
 - number of in degree types in the graph
- `--num-out-degree`, type = int, default=512
 - number of out degree types in the graph
- `--num-spatial`, type = int, default=512
 - number of spatial types in the graph
- `--num-edge-dis`, type = int, default=128
 - number of edge dis types in the graph
- `--multi-hop-max-dist`, type = int, default=5
 - max number of edges considered in the edge encoding
- `--spatial-pos-max`, type = int, default=1024

- max distance of attention in graph
- `--edge-type`, type = str, default="multi_hop"
 - edge type in the graph
- `--edge-type`, type = str, default="multi_hop"
 - edge type in the graph
- `--user-data-dir`, type = str, default=""
 - path to the module of user-defined dataset

DATASETS

Graphormer supports training with both existing datasets in graph libraries and customized datasets.

7.1 Existing Datasets

Graphormer supports training with datasets in existing libraries. Users can easily exploit datasets in these libraries by specifying the `--dataset-source` and `--dataset-name` parameters.

`--dataset-source` specifies the source for the dataset, can be:

1. `dgl` for [DGL](#)
2. `pyg` for [Pytorch Geometric](#)
3. `ogb` for [OGB](#)

`--dataset-name` specifies the dataset in the source. For example, by specifying `--dataset-source pyg` and `--dataset-name zinc`, Graphormer will load the [ZINC](#) dataset from Pytorch Geometric. When a dataset requires additional parameters to construct, the parameters are specified as `<dataset_name>:<param_1>=<value_1>, <param_2>=<value_2>, ..., <param_n>=<value_n>`. When the type of a parameter value is a list, the value is represented as a string with the list elements concatenated by `+`. For example, if we want to specify multiple `label_keys` with `mu`, `alpha`, and `homo` for [QM9](#) dataset, `--dataset-name` should be `qm9:label_keys=mu+alpha+homo`.

When dataset split (`train`, `valid` and `test` subsets) is not configured in the original dataset source, we randomly partition the full set into `train`, `valid` and `test` with ratios `0.7`, `0.2` and `0.1`, respectively. If you want customized split of a dataset, you may implement a 'customized dataset'. Currently, only integer features of nodes and edges in the datasets are used.

A full list of supported datasets of each data source:

Dataset Source	Dataset Name	Link	#Label/#Class
dgl	qm7b	QM7B dataset	14
	qm9	QM9 dataset	Depending on label_keys
	qm9edge	QM9Edge dataset	Depending on label_keys
	minigc	MiniGC dataset	8
	gin	Graph Isomorphism Network dataset	1
	fakenews	FakeNewsDataset dataset	1
pyg	moleculenet	MoleculeNet dataset	1
	zinc	ZINC dataset	1
ogb	ogbg-molhiv	ogbg-molhiv dataset	1
	ogbg-molpcba	ogbg-molpcba dataset	128
	pcqm4m	PCQM4M dataset	1
	pcqm4mv2	PCQM4Mv2 dataset	1

7.2 Customized Datasets

Users may create their own datasets. To use customized dataset:

1. Create a folder (for example, with name *customized_dataset*), and a python script with arbitrary name in the folder.
2. In the created python script, define a function which returns the created dataset. And register the function with `register_dataset`. Here is a sample python script. We define a QM9 dataset from dgl with customized split.

```

1  from graphormer.data import register_dataset
2  from dgl.data import QM9
3  import numpy as np
4  from sklearn.model_selection import train_test_split
5
6  @register_dataset("customized_qm9_dataset")
7  def create_customized_dataset():
8      dataset = QM9(label_keys=["mu"])
9      num_graphs = len(dataset)
10
11     # customized dataset split
12     train_valid_idx, test_idx = train_test_split(
13         np.arange(num_graphs), test_size=num_graphs // 10, random_state=0
14     )
15     train_idx, valid_idx = train_test_split(
16         train_valid_idx, test_size=num_graphs // 5, random_state=0
17     )
18     return {
19         "dataset": dataset,
20         "train_idx": train_idx,
21         "valid_idx": valid_idx,
22         "test_idx": test_idx,
23         "source": "dgl"
24     }

```

The function returns a dictionary. In the dictionary, `dataset` is the dataset object. `train_idx` is the graph indices used for training. Similarly we have `valid_idx` and `test_idx`. Finally `source` records the underlying graph library used by the dataset.

3. Specify the `--user-data-dir` as `customized_dataset` when training. And set `--dataset-name` as `customized_qm9_dataset`. Note that `--user-data-dir` should not be used together with `--dataset-source`. All datasets defined in all python scripts under the `customized_dataset` will be registered automatically.

PRETRAINED MODELS

Graphormer provides a series of pre-trained model to help users leverage the power of the model quickly and smoothly. Contributing your pre-trained model by creating a pull request.

- Quick-Start: as a exmple using pre-trained models.

Pre-trained models from specific papers:

- [Do Transformers Really Perform Badly for Graph Representation?](#)

OVERVIEW

Basically, Graphormer inherits the extending usage of fairseq, which means it could easily support user-defined [plugins](#).

For example, the Graphormer-base model could be defined through `GraphormerModel`, which inherits the `FairseqModel` class.

It's also easy to extend the Graphormer-base model, which means you could define your own [model](#) and [criterion](#), and then use them in Graphormer.

Also, development of new model is easy. We provide a tutorial of how to implement a simple MLP model on graph in [Tutorials](#).

SIMPLE MLP TUTORIAL

In this tutorial, we will extend Graphormer by adding a new GraphMLP that transforms the node features, and uses a sum pooling layer to combine the output of the MLP as graph representation.

This tutorial covers:

1. **Writing a new Model** so that the node token embeddings can be transformed by the MLP.
2. **Training the Model** using the existing command-line tools.

10.1 1. Writing a new GraphMLP Model

First, we create a new file with filename `graphormer/models/graphmlp.py`:

```
import torch
import torch.nn as nn
import torch.nn.functional as F
from fairseq.models import FairseqEncoderModel, register_model

@register_model("graphmlp")
class GraphMLP(FairseqEncoderModel):
    def __init__(self, args, encoder):
        super().__init__(encoder)
        self.args = args

    @staticmethod
    def add_args(parser):
        """Add model-specific arguments to the parser."""
        parser.add_argument(
            "--encoder-layers", type=int, metavar="N", help="num encoder layers"
        )
        parser.add_argument(
            "--max-nodes", type=int, metavar="N", help="num max nodes"
        )
        parser.add_argument(
            "--encoder-embed-dim", type=int, metavar="N", help="encoder embedding_
↪ dimension",
        )

    def max_nodes(self):
        return self.encoder.max_nodes
```

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```

@classmethod
def build_model(cls, args, task):
    """Build a new model instance."""
    # make sure all arguments are present in older models
    graphmlp_architecture(args)
    encoder = GraphMLPEncoder(args)
    return cls(args, encoder)

def forward(self, batched_data, **kwargs):
    return self.encoder(batched_data, **kwargs)

```

The main component in GraphMLP is the GraphMLPEncoder. Here we implement it by adding following codes in graphormer/models/graphmlp.py:

```

from fairseq.models import FairseqEncoder
from ..modules import GraphNodeFeature

class GraphMLPEncoder(FairseqEncoder):
    def __init__(self, args):
        super().__init__(dictionary=None)
        self.max_nodes = args.max_nodes
        self.emb_dim = args.encoder_embed_dim
        self.num_layer = args.encoder_layers
        self.num_classes = args.num_classes

        self.atom_encoder = GraphNodeFeature(
            num_heads=1,
            num_atoms=512*9,
            num_in_degree=512,
            num_out_degree=512,
            hidden_dim=self.emb_dim,
            n_layers=self.num_layer,
        )

        self.linear = torch.nn.ModuleList()
        self.batch_norms = torch.nn.ModuleList()

        for layer in range(self.num_layer):
            self.linear.append(torch.nn.Linear(self.emb_dim, self.emb_dim))
            self.batch_norms.append(torch.nn.BatchNorm1d(self.emb_dim))

        self.graph_pred_linear = torch.nn.Linear(self.emb_dim, self.num_classes)

    def forward(self, batched_data, **unused):
        h=self.atom_encoder(batched_data)
        for layer in range(self.num_layer):
            h = self.linear[layer](h)
            h = h.transpose(1,2)
            h = self.batch_norms[layer](h)

```

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```

        h = h.transpose(1,2)

        if layer != self.num_layer - 1:
            h = F.relu(h)

        h = h.sum(dim=1)
        out = self.graph_pred_linear(h)

        return out.unsqueeze(1)

    def max_nodes(self):
        return self.max_nodes

```

Since we will validate our GraphMLP model on a graph representation task, we choose dataset in MoleculeNet. Therefore, we employ the GraphNodeFeature to encode the node features.

And finally, we register the model architecture by adding following codes in `graphormer/models/graphmlp.py`:

```

from fairseq.models import register_model_architecture
@register_model_architecture("graphmlp", "graphmlp")
def graphmlp_architecture(args):
    args.encoder_embed_dim = getattr(args, "encoder_embed_dim", 768)
    args.encoder_layers = getattr(args, "encoder_layers", 12)

    args.max_nodes = getattr(args, "max_nodes", 512)

```

10.2 2. Training the Model

Next, we prepare the training script for the model. We create a bash file `examples/property_prediction/graphmlp.sh`:

```

#!/bin/bash
CUDA_VISIBLE_DEVICES=0 fairseq-train \
--user-dir ../../graphormer \
--num-workers 16 \
--ddp-backend=legacy_ddp \
--dataset-name moleculenet:name=bbbp \
--dataset-source pyg \
--task graph_prediction \
--criterion binary_logloss \
--arch graphmlp \
--num-classes 1 \
--optimizer adam --adam-betas '(0.9, 0.999)' --adam-eps 1e-8 --clip-norm 5.0 --weight-
↪decay 0.0 \
--lr-scheduler polynomial_decay --power 1 --total-num-update 1000000 \
--lr 0.001 --end-learning-rate 1e-9 \
--batch-size 32 \
--fp16 \
--data-buffer-size 20 \
--encoder-layers 5 \

```

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```
--encoder-embed-dim 256 \  
--max-epoch 100 \  
--save-dir ./ckpts \  
--save-interval-updates 50000 \  
--no-epoch-checkpoints
```

By executing the script, after the dataset is downloaded and processed, the training of the GraphMLP model starts.

INDICES AND TABLES

- `genindex`
- `modindex`
- `search`