Exploring PyTorch Geometric: a geometric deep learning library built on top of PyTorch

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Motivation

- Graphs provide a rich framework for many types of problems.
- What happens when graphs and deep learning are combined?
 - The AlphaFold and AlphaFold2 developed by DeepMind solved protein structure prediction for structural biology
 - drug discovery, social networks, and fake news detection, ...
- Open-source libraries for graph neural networks.
 - PyG: PyTorch Geometric (PyTorch)
 - DGL: Deep Graph Library (PyTorch, TensorFlow)
 - TF-GNNs: TensorFlow Graph Neural Networks (TensorFlow)
 - Spektral (Keras, TensorFlow)

The goal of the work

- Explore the functionality and connections between the various modules of PyTorch Geometric and delve into some of the important principles or modules such as MEMORY-EFFICIENT AGGREGATIONS.
- Use PyTorch Geometric to complete basic steps, such as building datasets, customising GNN networks, training GNN models, etc.
- Use PyTorch Geometric for two advanced applications.
 - Recommender Systems with GNNs in PyG.
 - Experiment with PyTorch Geometric in the area of model optimization and compression, e.g. Compressing Deep Graph Neural Networks via Adversarial Knowledge Distillation. [1]

- Deep and complicated GNNs significantly outperform shallow models on largescale graphs, implying the great expressive power of over-parameterized GNNs. (Figure 1)
- The overstacked architecture of deep graph models makes it difficult to deploy and rapidly test on mobile or embedded systems.
- Knowledge distillation via a teacher-student architecture turns out to be an effective technique.



Figure 1: Node classification accuracy v.s. graph size. Each bubble's area is proportional to the number of parameters of a model. Model name with * means the variant. The statistics are collected from OGB leaderboards.

• Existing work

- Existing work force the student network to mimic the teacher network with **hand-crafted distance functions**, of which the **optimal formulation** is hard to determine [2]. Even worse, the performance of the student trained this way is always suboptimal because it is difficult to learn the exact distribution from the teacher [3, 4].
- The predefined and fixed distance is unfit to measure the distribution discrepancy of teacher and student representations in different feature spaces.

- GraphAKD is the first to introduce adversarial training to knowledge distillation in graph domains [1].
- By adversarially training a discriminator and a generator, GraphAKD is able to transfer both inter-node and inter-class correlations from a complicated teacher GNN to a compact student GNN [1].



Figure 2: Illustration of the proposed adversarial knowledge distillation framework GraphAKD.

source: [1]

- Experiments:
 - Datasets: Performing node classification on some of the widely-used datasets.
 - Five research questions:
 - RQ1: How does GraphAKD perform on node-level classification?
 - RQ2: How does GraphAKD perform on graph-level classification?
 - RQ3: How efficient are the student GNNs trained by GraphAKD?
 - RQ4: How do different components affect the performance of GraphAKD?
 - RQ5: Do student GNNs learn better node representations when equipped with GraphAKD?

Table 2: Statistics of the eight node classification benchmarks.

Datasets	#Nodes	#Edges	#Feat.	Data Split
Cora [3, 34]	2,708	5,429	1,433	140/500/1K
CiteSeer [40]	3,327	4,732	3,703	120/500/1K
PubMed [35]	19,717	44,338	500	60/500/1K
Flickr [33, 58]	89,250	899,756	500	44K/22K/22K
Arxiv [23]	169,343	1,166,243	128	90K/29K/48K
Reddit [19, 58]	232,965	23,213,838	602	153K/23K/55K
Yelp [58]	716,847	13,954,819	300	537K/107K/71K
Products [23]	2,449,029	61,859,140	100	196K/39K/2M

Current work progress

- Reading the source code of PyTorch Geometric.
- Using PyTorch Geometric to build datasets and create GNN layers.

Work plan for the next stage

- Complete basic steps including building datasets, customising GNN networks, training GNN models, etc.
- Use PyTorch Geometric for 2 more advanced applications.
- Writing the final report.

References

[1] He H, Wang J, Zhang Z, et al. Compressing Deep Graph Neural Networks via Adversarial Knowledge Distillation[J]. arXiv preprint arXiv:2205.11678, 2022.

[2] Yunhe Wang, Chang Xu, Chao Xu, and Dacheng Tao. 2018. Adversarial Learning of Portable Student Networks. In Proc. of AAAI.

[3] Xiaojie Wang, Rui Zhang, Yu Sun, and Jianzhong Qi. 2018. KDGAN: Knowledge Distillation with Generative Adversarial Networks. In Proc. of NeurIPS.

[4] Xiaojie Wang, Rui Zhang, Yu Sun, and Jianzhong Qi. 2021. Adversarial Distillation for Learning with Privileged Provisions. IEEE Trans. Pattern Anal. Mach. Intell. (2021)