Paper Title

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Abstract

Graph Neural Networks (GNN) is an emerging field for learning on non-Euclidean data. Recently, there has been great interest in designing GNN that scales to large graphs. Most existing techniques use "graph sampling" or "layer-wise sampling" technique to reduce training time.

解决了什么问题？论文主要工作？效果如何？

1 Introduction

Recently, the field of Graph Neural Network has drawn increasing attention due to its wide range of applications such as social analysis, biology, recommendation system, and computer vision. Graph Neural Network (GCN) adopts a message-passing approach and gathers information from the neighbors of each node from the previous layer to form new representation. The vanilla GCN uses a full-batch training process and stores each node's representation in the GPU memory, which leads to limited scalability. On the other hand, training GCN with mini-batches is difficult, as the neighborhood size could grow exponentially with the number of layers.

论文所处的背景

当前的现状？

本文所做的主要工作和贡献

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Our contribution. In this paper, we first carefully analyze the theoretical complexity of existing scalable GNNs and explain why they cannot scale to graphs with billions of edges. Then, we present GBP (Graph neural network via Bidirectional Propagation), a scalable Graph Neural Network with sub-linear time complexity in theory and superior performance in practice.

2 Related work

2.1 Work1

2.2 Work2

2.3 Work3

3 Proposed Method

这里是论文最重要的部分，描述自己的方法。

3.1 Analysis

4 Experiments

Datasets We use seven open graph datasets with different size: three citation networks Cora, Citeser and Pubmed [**?**], a Protein-Protein interaction network PPI [**?**], a customer ineraction network Yelp [**?**], a co-purchasing networks Amazonz [**?**] and a large social network Friendster [**?**]. Table 2 summarizes the statistics of the datasets. We first evaluate GBP's performance for transductive semi-supervised learning on the three popular citation networks (Cora, Citeseer, and Pubmed). Then, we compare GBP with scalable GNN methods three medium to large graphs PPI, Yelp, Amazon in terms of inductive learning ability. Finally, we present the first empirical study of transductive semi-supervised on billion-scale network Friendster.

表 1: Dataset statistics.

Dataset	Task	Nodes	Edges	Features	Classes	Label rate
Cora	multi-class	2,708	5,429	1,433	7	0.052
Citeseer	multi-class	3,327	4,732	3,703	6	0.036
Pubmed	multi-class	19,717	44,338	500	3	0.003
PPI	multi-label	56,944	818,716	50	121	0.79
Yelp	multi-label	716,847	6,977,410	300	100	0.75
Amazon	multi-class	2,449,029	61,859,140	100	47	0.70
Friendster	multi-class	65,608,366	1,806,067,135	100 (random)	500	0.001

Baselines and detailed setup

表 2: Results on Cora, Citeseer and Pubmed.

Method	Cora	Citeseer	Pubmed
GCN	81.5 ± 0.6	71.3 ± 0.4	79.1 ± 0.4
GAT	83.3 ± 0.8	71.9 ± 0.7	78.0 ± 0.4
GDC	83.3 ± 0.2	72.2 ± 0.3	78.6 ± 0.4
APPNP	83.3 ± 0.3	71.4 ± 0.6	80.1 ± 0.2
SGC	81.0 ± 0.1	71.8 ± 0.1	79.0 ± 0.1
LADIES	79.6 ± 0.5	68.6 ± 0.3	77.0 ± 0.5
PPRGo	82.4 ± 0.2	71.3 ± 0.3	80.0 ± 0.4
GraphSAINT	81.3 ± 0.4	70.5 ± 0.4	78.2 ± 0.8
GBP	$\mathbf{83.9} \pm \mathbf{0.7}$	$\mathbf{72.9} \pm \mathbf{0.5}$	$\mathbf{80.6} \pm \mathbf{0.4}$

Inductive learning on medium to large graphs

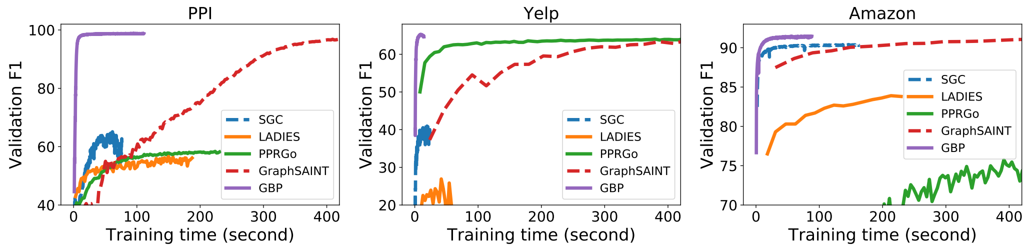

图 1: Convergence curves of 4-layer models.

Transductive semi-supervised learning on billion-scale graph Friendster.

5 Conclusion

Acknowledgments