Improving Node Classification by Co-training Node Pair Classification: A Novel Training Framework for General Graph Neural Networks

Deli Chen,1 Xiaoqian Liu,1 Yankai Lin,2 Peng Li,2 Jie Zhou,2 Qi Su,1 Xu Sun1

1MOE Key Lab of Computational Linguistics, School of EECS, Peking University
2Pattern Recognition Center, WeChat AI, Tencent Inc, China
{chendeli,liuxiaoqian,sukia,xusun}@pku.edu.cn,
{yankailin,patrickpli,withtomzhou}@tencent.com

Abstract

Semi-supervised learning is a widely used training framework for graph node classification. However, there are two problems existing in this learning method: (1) the original graph topology may not be perfectly aligned with the node classification task; (2) the supervision information in the training set has not been fully used. To tackle these two problems, we design a new task: node pair classification, to assist in training GNN models for the target node classification task. We further propose a novel training framework named Adaptive Co-training, which jointly trains the node classification and the node pair classification after the optimization of graph topology. Extensive experimental results on four representative GNN models have demonstrated that our proposed training framework significantly outperforms baseline methods across three benchmark graph datasets.

1 Introduction

Various social computing problems can be viewed as node classification on graph networks, such as post classification on Reddit (Hamilton et al., 2017), research area prediction based on co-author graphs1, and paper field prediction based on citation graph networks (Sen et al., 2008). As Graph Neural Networks (GNNs) are effective for extracting features from graphs, various GNN models have been proposed for the node classification task and achieve promising results, e.g., GCN (Kipf and Welling, 2016), GAT (Veličković et al., 2018), GraphSAGE (Hamilton et al., 2017), etc. Since annotating the entire graph is infeasible, especially for large graphs, semi-supervised learning settings are widely used in training GNNs, which utilize limited node labels in the training set to predict the category of each node in the entire graph by a transductive or inductive learning method (Yang et al., 2016).

1https://kddcup2016.azurewebsites.net

Although the semi-supervised training framework is widely used, two problems are still existing: (1) First, the original graph topology may not be perfectly aligned with the node classification task. Chen et al. (2019) find that edges linking nodes of the same class are conducive to the node classification, while edges linking nodes of different classes may cause information noises to the node classification. Thus, adjusting graph topology by adding intra-class edges and/or removing inter-class edges can benefit the training of GNN models. However, the method proposed in (Chen et al., 2019) adjusts graph topology directly based on the predicted node classification results from previous iterations. Thus, there can be inaccurate predictions of node classes and further lead to incorrect adjustments of graph edges. (2) Second, the existing semi-supervised training framework for GNN models cannot fully utilize the supervision information of the training set, because only the node label is used as training information. While the relations of node pairs, which are also helpful for training the node classifier, are ignored totally.

To tackle these two problems, we introduce a novel training framework named Adaptive Co-training for GNN models on the node classification task: node classification and node pair classification co-training with dynamic graph topology adaptation. Firstly, we propose a new task: node pair classification, which aims to predict whether two nodes are of the same class. The proposed framework shown in Figure 1 consists of three modules: (1) Assist task training module, which performs the node classification or the node pair classification to predict class labels for each node or whether two nodes are of the same class, so as to access the prediction of node pair relations. (2) Graph topology optimization module, which updates the original adjacency matrix by adding intra-class edges or/and removing inter-class edges based on the prediction result in the first module. (3) Co-training...
module, which co-trains the node pair classification and the node classification based on the updated graph topology. The co-training module enables to fully utilize the supervision information of the training set, and can act as a regularizer to make the hidden representations of nodes in the same class closer to each other and vice versa.

Experimental results on three benchmark graph datasets and four representative GNN models show that our Adaptive Co-training framework achieves consistent and significant improvement as compared to all baseline methods with limited extra computation cost. The main contributions of this paper are summarized as follows:

- We propose a novel training framework named as Adaptive Co-training for general GNN models on the node classification task, which takes the advantages of both optimized graph topology and full supervision information.

- We design a new task: node pair classification, to assist in training GNN models by two methods: (1) predicting the relation between two nodes; (2) co-training with the node classification.

- Extensive experimental results on multiple GNN models have demonstrated that our proposed training framework significantly outperforms baseline methods across three benchmark datasets. Besides, we also show that additional computation cost is very limited.

2 Method

In this section, we will introduce the new task: node pair classification, as compared to the node classification task first, and then provide details of the proposed training framework Adaptive Co-training for GNN models on the semi-supervised node classification task.

2.1 Node Pair Classification

For an undirected graph given the node feature matrix $X \in \mathbb{R}^{n \times h}$ and the node adjacency matrix $A \in \mathbb{R}^{n \times n}$ ($n$ denotes the node size of the graph and $h$ denotes the dimension size of the initial node embedding), the node classification task aims to train a classifier $f_n$ (usually a GNN model) to distinguish nodes of different classes:

$$\hat{l} = f_n(X, A)$$ (1)

where $\hat{l} \in \mathbb{R}^{n}$ is the predicted class label for all nodes. Different from the node classification task, we design a new task named as the node pair classification to assist in training GNN models. The node pair classification aims to train a different classifier $f_p$ to predict whether two nodes are of the same class:

$$\hat{r} = f_p(X, A)$$ (2)

where $\hat{r} \in \mathbb{R}^{n \times n}$ and $\hat{r}_{i,j} \in \{0, 1\}$ (0 denotes inter-class and 1 denotes intra-class).

2.2 Adaptive Co-training

As shown in Figure 1, the proposed Adaptive Co-training framework consists of three modules: (1) Assisting task training module, in which the assisting task (the node classification or the node pair classification) aims to predict class labels for each node or whether two nodes are of the same class; (2) Graph topology optimization module, which optimizes the graph topology by adding and/or removing edges between two nodes based on the prediction results of the first module; (3) Co-training Module, which co-trains the node classification and the node pair classification to predict class labels for each node of the graph. We provide details of the three modules as follows.

2.2.1 Assisting Task Training

This module is designed to access the prediction matrix of node pair relation (whether two nodes are of the same class) $R, R \in \mathbb{R}^{n \times n}$ and $R_{i,j} \in \{0, 1\}$ for the graph optimization operation in the next module. The assisting task of this module can be the node classification task or the node pair classification task. Chen et al. (2019) shows that the original graph topology may not be perfect for downstream tasks and optimizing the graph topology by adding intra-class edges and/or removing inter-class edges can improve the performance of downstream tasks, such as the node classification task. Inspired by this conclusion, the assisting task aims to predict class labels for each node or whether two nodes are of the same class for graph topology optimization. In Chen et al. (2019), the assisting task is to train GNN models on the node classification task:

$$y = \text{GNN}_\alpha(X, A)$$ (3)

$$\hat{l} = \text{softmax}(y)$$ (4)

where $\hat{l}$ is the predicted node labels and the GNN$_\alpha$ can be any graph neural network. The node classi-
Node Embedding

Raw Adjacency Matrix

GNN Model $\beta$

Node / Node Pair Classification

Updated Adjacency Matrix

Adjacency Matrix Adaption

Node / Node Pair Classification

GNN Model $\alpha$

Figure 1: The overview of the proposed Adaptive Co-training framework. There are three modules in this framework (separated by blue dotted lines): (1) Assisting task training; (2) Graph topology optimization; (3) Co-training.

Classification loss is then calculated as:

$$L_n = \sum_{i=1}^{n} -l_i \log p(\hat{l}_i)$$  \hspace{1cm} (5)

where $l$ is the gold labels. Then $R$ is accessed by comparing the labels of two nodes:

$$R_{i,j} = \begin{cases} 
1, & \hat{l}_i = \hat{l}_j \\
0, & \hat{l}_i \neq \hat{l}_j 
\end{cases}$$  \hspace{1cm} (6)

$I_i, I_j$ is the predicted label for the $i$-th and $j$-th node, respectively.

However, the predicted node classification results may be inaccurate, and the predicted errors can be accumulated in Eq 6, which further causes incorrect adjustments on graph edges. In addition, for graph topology optimization, all we need is the relation of two nodes (intra-class or inter-class) instead of the specific node class label. Therefore, we propose to train the node pair classification, which is a binary classification task, and is much easier than the multi-class node classification task, to provide more accurate predicted results for adjusting the graph topology. For the node pair classification, we first use Eq 3 to get the hidden representations $y$ of the nodes. Then we predict whether a pair of nodes is of the same class as:

$$\hat{r} = \text{sigmoid}(y \cdot y^\top)$$  \hspace{1cm} (7)

where $\hat{r} \in \mathbb{R}^{n \times n}$ is the node pair prediction matrix. $\hat{r}_{i,j}$ denotes the relation between the $i$-th node and the $j$-th node: intra-class or inter-class. The node pair classification loss is calculated by the binary cross entropy loss:

$$L_p = - \sum_{i=1}^{n} \sum_{j=1}^{n} \{r_{i,j} \cdot \log(\hat{r}_{i,j}) + (1 - r_{i,j}) \cdot \log(1 - \hat{r}_{i,j})\}$$  \hspace{1cm} (8)

where $r$ is the gold label for each node pair from the raw adjacency matrix $A$. Then the prediction matrix $R$ is calculated with a threshold $t \in [0, 1]$:

$$R_{i,j} = \begin{cases} 
1, & \hat{r}_{i,j} \geq t \\
0, & \hat{r}_{i,j} < t 
\end{cases}$$  \hspace{1cm} (9)

2.2.2 Graph Topology Optimization

In the second module, we optimize the adjacency matrix based on the predicted results of node labels or node relations $R$ from either Eq 6 or Eq 9. For the adaption of the graph topology, there are two options: adding edges between two nodes of the same class or removing edges between two nodes of different classes:

$$A' = \begin{cases} 
A + R, & \text{add-edge} \\
A - (O - R), & \text{remove-edge} 
\end{cases}$$  \hspace{1cm} (10)

where $A'$ is the updated adjacency matrix and $O$ is a matrix in the same size with $A$ and filled with value 1. Then we correct each value $A_{i,j}$ in $A'$ to conform to the format of the adjacency matrix:

$$A_{i,j} = \min(\max(A_{i,j}, 0), 1)$$  \hspace{1cm} (11)

In practice, we update the adjacency matrix on a sub-matrix of $A$ for two purposes: (1) control the number of adding/removing edges because excessive adjustments of graph edges results in performance degradation; (2) add/remove edges in a dense way due to the worse performance of sparse adjusting. The optimization of graph topology is based on the predicted results of either the node classification or the node pair classification in the first module (Eq 6 or Eq 9) depending on the effect of the two assisting tasks.
2.2.3 Co-training

After graph topology optimization, we further design a co-training module to train the node pair classification jointly and the node classification for two purposes: (1) making full use of the supervision information of the training set by utilizing the relations of node pairs, which are ignored in the standard node classifier training, are also helpful for the node classification task; (2) acting as a regularizer to make the hidden representations of intra-class nodes closer to each other and vice versa, which makes it more easier to classify nodes.

In the co-training module, we train a different GNN model $GNN_\beta$ on the updated adjacency matrix $A'$ from scratch following Eq 4,7 with two outputs: the predicted node class label $\hat{l}$ and the predicted relation of two nodes $\hat{r}$ (intra-class or inter-class).

$$\hat{l} = GNN_\beta(X, A')$$  \hspace{1cm} (12)

$$\hat{r} = GNN_\beta(X, A')$$  \hspace{1cm} (13)

We then calculate the node classification loss $L_n$, and the node pair classification loss $L_p$ following Eq 5,8. The final training objective of the co-training module is an addition of the two losses in:

$$\mathcal{L} = \mathcal{L}_n + \lambda \cdot \mathcal{L}_p$$  \hspace{1cm} (14)

where $\lambda$ is the parameter to control the influence of the node pair classification task. Moreover, experimental results show worse performances of GNN models when there is a shared GNN architecture and layer numbers between the target model $GNN_\beta$ and the $GNN_\alpha$ trained in the first module. Thus, we tune the $GNN_\alpha$ in the first module to achieve a better updated graph topology, and then select the target model $GNN_\beta$ in the co-training module, which can improve the performances of multiple GNN models on the same graph dataset.

3 Experiments

3.1 Datasets and Models

We evaluate our proposed training framework Adaptive Co-training on three benchmark graph datasets: Cora, CiteSeer, and Pubmed (Sen et al., 2008). These datasets are citation graph networks, which have been widely used to evaluate GNN models (Maehara, 2019; Li et al., 2018; Bianchi et al., 2019; Fey, 2019). Besides, to verify the generalizability of Adaptive Co-training, we select four representative GNN architectures as the experimental models:

- **GCN** (Graph Convolutional Network) (Kipf and Welling, 2016) which uses the spectral method to conduct convolution operation.

- **GAT** (Graph Attention Network) (Veličković et al., 2018) which adopts the attention mechanism to aggregate neighborhood node information differently.

- **SAGE** (GraphSAGE) (Hamilton et al., 2017) which uses the sampling method to propagate information along edges in large graphs.

- **Hyper** (HyperGraph) (Bai et al., 2019) which utilizes the high-order information of graphs.

3.2 Experiment Settings

Following (Shchur et al., 2018; Sun et al., 2019), we run 5 random dataset splitting methods by 20/30/rest splitting (each class has 20 samples for training and 30 for validation; the rest nodes are used for testing) and 3 random initial seeds for each splitting method in each experiment to relieve the random error caused by dataset splitting and initial seeds. To achieve a highly reliable confidence of graph topology optimization, we set the class threshold of the node pair classification to a rather high value (0.9), which aims to achieve a high-precision and low-recall classifier for two nodes of the same class (there is no need to add all the intra-class edges, but the precision of added edges need to be guaranteed).

The implementation of the baseline methods is based on Pytorch (Paszke et al., 2017) and Pytorch-geometric (Fey and Lenssen, 2019), without changing the implementation of the convolutional layer in Pytorch-geometric. Hyperparameters of each GNN model are tuned on each graph dataset. We mainly tune the dropout rate, the learning rate, the activation function, and the hidden size. All the hyperparameters (including the splitting seeds and the initial seeds) are fixed in each experiment group (experiments about the same model and graph) for comparison. Since the negative samples are far more than the positive samples of in the node pair classification, we increase the weight of positive samples.
Table 1: Experimental results compared with the baselines. The mean accuracy and the standard deviation of each experiment are calculated after 15 running times. Experiments of the same column set the same hyperparameters for comparison. The first two rows (BaseGNN and +AdaGraph) show baseline results; the 3-4 rows (+Pipeline and +Co-training) are experimental results of two ablation versions of our proposed training framework; the last row (+Adaptive Co-training) shows the results of our proposed method.

## 4 Results and Analysis

### 4.1 Baselines

We set four baseline methods for comparison to evaluate the effect of our proposed training framework.

- **BaseGNN**: The GNN models trained on the original graph topology with standard semi-supervised framework (Yang et al., 2016).

- **AdaGraph**: The AdaGraph method proposed in Chen et al. (2019) aims to optimize graph topology based on the predicted results of the node classification from previous iterations. The main differences between AdaGraph and our proposed Adaptive Co-training are: (1) our proposed training framework involves the joint training of the node classification and the node pair classification, while AdaGraph does not involve the node pair classification task; (2) our proposed training framework consists of different GNN models in different modules, while AdaGraph trains a same GNN model iteratively.

- **Pipeline**: An ablation version of the Adaptive Co-training which replaces the co-training stage with the standard node classification task. This baseline is designed to evaluate the effect of using the node pair classification as the assisting task.

- **Co-training**: Another ablation version of the Adaptive Co-training which consists of the co-training stage in section 2.2.3 only and train the GNN model on the original graph topology. This baseline is designed to evaluate the effect of the co-training.

Figure 2: Experimental results of the node classification and the node pair classification with different loss weights of the node pair classification. The node classification results are measured by the accuracy value; the node pair classification results are measured by the precision value on the intra-class relation between two nodes, which directly affects the results of graph topology optimization.

### 4.2 Overall Results

The performance of our Adaptive Co-training method and other baselines are shown in Table 1. From the results, we can observe that:

(1) **Pipeline Method** The AdaGraph method and the Pipeline method which optimize the graph topology before the node classification achieve significant improvement as compared to the baseline GNN models trained on the original graph topology. The results demonstrate that optimizing graph topology benefits the target node classification task, and the Pipeline method involving the node pair classification to assist in training GNN models is more effective than the AdaGraph method.
(2) Co-training Method  The Co-training method outperforms all the baseline GNN methods across the datasets, which validates the effect of the new task node pair classification in training GNN models on the node classification task. The reasons may be first, it can make full use of the supervision information of the training set and second, acts as a regularizer to make the hidden representations of nodes of the same class closer to each other and vice versa.

(3) Adaptive Co-training Method  Consisting of both graph topology optimization and co-training operation, the proposed Adaptive Co-training framework outperforms all the baseline methods, especially improving the performance of the baseline GNN models trained in the standard semi-supervised framework by a large margin. The results demonstrate both the effectiveness and the generalizability of our proposed Adaptive Co-training framework. Specifically, the proposed Adaptive Co-training method performs well on the GraphSAGE architecture, which is designed for large-scale graph networks. Thus, our Adaptive Co-training method shows great potential on the large graph networks.

4.3 Effect of Node Pair Classification in Co-training
To examine the effect of the node pair classification in the co-training module in section 2.2.3, we modify the node pair classification loss weight $\lambda$ in Eq 14 and observe the changes. The result-loss weight curves of the two tasks are shown in Figure 2. We can observe that with the increase of the node pair loss weight from 0.25 to 1, the results of both the node and node pair classification tasks keep rising, which validates the effect of the co-training module. When the loss weight continuously rises, the performance of the node pair classification keeps improving, while the node classification shows the opposite result due to the over-attention of the node pair classification task, which indicates that the reasonable value of the loss weight is around 1.0.

4.4 Analysis of Additional Computation Cost
Compared to the standard semi-supervised node classification, the module of graph topology optimization and the module of co-training in the proposed Adaptive Co-training framework will cause inevitable additional computation cost. However, the extra calculations are limited.

(1) Graph Optimization Cost  In experiments, we observe that a well-optimized graph topology can improve all the GNN model performance stably. Thus, the graph optimization can be conducted in a few training processes for each graph dataset and then can be used on all the GNN models.

(2) Co-training Cost  The Eq 7 is presented for a better understanding and can be optimized in practice. When training the node pair classification task, the supervision information is accessed from the training set of the node classification task, which is very small in the semi-supervised framework (20 nodes from each class as the training set; the whole training set usually has 60-200 nodes). Thus the size of training node pairs for the node pair classification task is also limited. When computing the training loss, we access the training set nodes first and then conduct matrix multiply in Eq 7, thus the computational complexity is $O(m \cdot m)$ instead of $O(n \cdot n)$ ($m$ denotes the training size and $n$ denotes the node size; usually $m \ll n$). Besides, in the co-training module, the prediction of the node pair relation requires no extra trainable parameters and causes only a small increase in GPU memory occupancy.

5 Related Work
The semi-supervised learning framework is widely used on the node classification task (Kipf and Welling, 2016, 2017; Hamilton et al., 2017). In this learning method, a classifier can be trained with limited node labels in the training set. Different GNN architectures (Wu et al., 2019; Defferrard et al., 2016; Verma et al., 2018; Li et al., 2016; Morris et al., 2019; Li et al., 2019) have been designed for graph-related tasks with different motivations. However, most existing works directly use the original graph topology, while Chen et al. (2019) proves that the GNN model performance can be improved by graph topology optimization and their proposed AdaGraph algorithm enables to adjust the graph topology directly based on predicted results of the node classification from previous iterations.

Some other works also refer to the dynamic graphs. Pareja et al. (2019) propose the EvolveGCN model to use the RNN model to update the GCN model. Yang et al. (2019) propose to train the GCN model and refine the topology at the same time. However, these works are model-dependent while
our Adaptive Co-training is model-independent thus can be used for any GNN model. Rong et al. (2019) propose the DropEdge method, which likes dropout, removes all edges randomly at the beginning of each epoch and acts like a data augmenter or a message passing reducer so as to build a very deep GNN model, while our graph optimization wants to find a more suitable graph for the downstream task and adjust the graph topology before the training begins.

6 Conclusion and Future Work

In this work, we introduce a novel training framework named Adaptive Co-training for GNN models on the node classification task, which consists of three modules: (1) Assisting task training module; (2) Graph topology optimization module; and (3) Co-training module. Extensive experiments on multiple graph datasets and GNN models have demonstrated that our proposed Adaptive Co-training can significantly improve the performance of GNN models on the node classification task with limited extra computational cost, which proves the validity and versatility of our training framework.

In the ablation experiments, we have verified the effect of the two modules in the Adaptive Co-training: graph topology optimization and co-training of the node classification and the node pair classification. Each module can help improve the training results independently, and the two modules can together improve the performance. Besides, our method performs well on the GraphSAGE model, which is designed for large-scale graph networks. We also prove that the additional computation cost of extra modules are limited even in the large graphs, thus our method shows great potential on the large graph networks.

In the future, we will explore the improvement of the Adaptive Co-training framework from two directions: (1) training a better assisting task, (2) designing a better co-training module. We also plan to study the mechanism of adjusting graph topology and try to find a better solution for adding or removing edges.

7 Acknowledgements

This work was supported in part by a Tencent Research Grant and National Natural Science Foundation of China (No. 61673028). Xu Sun is the corresponding author of this paper.

References

Song Bai, Feihu Zhang, and Philip HS Torr. 2019. Hypergraph Convolution and Hypergraph Attention. arXiv preprint arXiv:1901.08150.

Filippo Maria Bianchi, Daniele Grattarola, Lorenzo Livi, and Cesare Alippi. 2019. Graph Neural Networks with Convolutional Arma Filters. arXiv preprint arXiv:1901.01343.

Deli Chen, Yankai Lin, Wei Li, Peng Li, Jie Zhou, and Xu Sun. 2019. Measuring and relieving the over-smoothing problem for graph neural networks from the topological view. arXiv preprint arXiv:1909.03211.

Michaël Defferrard, Xavier Bresson, and Pierre Vandergheynst. 2016. Convolutional Neural Networks on Graphs with Fast Localized Spectral Filtering. In Advances in Neural Information Processing Systems, pages 3837–3845.

Matthias Fey. 2019. Just Jump: Dynamic Neighborhood Aggregation in Graph Neural Networks. arXiv preprint arXiv:1904.04849.

Matthias Fey and Jan E. Lenssen. 2019. Fast Graph Representation Learning with PyTorch Geometric. In ICLR Workshop on Representation Learning on Graphs and Manifolds.

William L. Hamilton, Zhitao Ying, and Jure Leskovec. 2017. Inductive Representation Learning on Large Graphs. In Advances in Neural Information Processing Systems, pages 1024–1034.

Thomas N Kipf and Max Welling. 2016. Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907.

Thomas N Kipf and Max Welling. 2017. Semi-supervised Classification with Graph Convolutional Networks. In 5th International Conference on Learning Representations, ICLR 2017.

Qimai Li, Zhichao Han, and Xiao-Ming Wu. 2018. Deeper Insights into Graph Convolutional Networks for Semi-supervised Learning. In Thirty-Second AAAI Conference on Artificial Intelligence.

Wei Li, Jingjing Xu, Yancheng He, Shengli Yan, Yunfang Wu, et al. 2019. Coherent Comment Generation for Chinese Articles with a Graph-to-Sequence Model. In Proceedings of the 57th Conference of the Association for Computational Linguistics, pages 4843–4852.

Yujia Li, Daniel Tarlow, Marc Brockschmidt, and Richard S. Zemel. 2016. Gated Graph Sequence Neural Networks. In 4th International Conference on Learning Representations, ICLR 2016.

Takanori Maehara. 2019. Revisiting graph neural networks: All we have is low-pass filters. arXiv preprint arXiv:1905.09550.
Christopher Morris, Martin Ritzert, Matthias Fey, William L. Hamilton, Jan Eric Lenssen, Gaurav Rattan, and Martin Grohe. 2019. Weisfeiler and Leman go Neural: Higher-order Graph Neural Networks. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pages 4602–4609.

Aldo Pareja, Giacomo Domeniconi, Jie Chen, Tengfei Ma, Toyotaro Suzumura, Hiroki Kanezashi, Tim Kaler, and Charles E Leisersen. 2019. Evolvegcn: Evolving graph convolutional networks for dynamic graphs. arXiv preprint arXiv:1902.10191.

Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. 2017. Automatic differentiation in pytorch. In NIPS-W.

Yu Rong, Wenbing Huang, Tingyang Xu, and Junzhou Huang. 2019. The truly deep graph convolutional networks for node classification. arXiv preprint arXiv:1907.10903.

Prithviraj Sen, Galileo Namata, Mustafa Bilgic, Lise Getoor, Brian Galligher, and Tina Eliassi-Rad. 2008. Collective classification in network data. AI magazine, 29(3):93–93.

Oleksandr Shchur, Maximilian Mumme, Aleksandar Bojchevski, and Stephan Günnemann. 2018. Pitfalls of Graph Neural Network Evaluation. arXiv preprint arXiv:1811.05868.

Ke Sun, PiotrKoniusz, and JeffWang. 2019. Fisher-Bures Adversary Graph Convolutional Networks. In Proceedings of the Thirty-Fifth Conference on Uncertainty in Artificial Intelligence, page 161.

Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. 2018. Graph Attention Networks. In 6th International Conference on Learning Representations, ICLR 2018.

Nitika Verma, Edmond Boyer, and Jakob Verbeek. 2018. Feastnet: Feature-steered Graph Convolutions for 3d Shape Analysis. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2598–2606.

Jun Wu, Jingrui He, and Jiejun Xu. 2019. Net: Degree-specific graph neural networks for node and graph classification. arXiv preprint arXiv:1906.02319.

Liang Yang, Zesheng Kang, Xiaochun Cao, Di Jin, Bo Yang, and Yuanfang Guo. 2019. Topology Optimization based Graph Convolutional Network. In Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI 2019, pages 4054–4061.

Zhilin Yang, William W Cohen, and Ruslan Salakhutdinov. 2016. Revisiting Semi-supervised Learning with Graph Embeddings. In Proceedings of the 33nd International Conference on Machine Learning, ICML 2016, pages 40–48.