Residual Network and Embedding Usage: New Tricks of Node Classification with Graph Convolutional Networks

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Abstract. Graph Convolutional Networks (GCNs) and subsequent variants have been proposed to solve tasks on graphs, especially node classification tasks. In the literature, however, most tricks or techniques are either briefly mentioned as implementation details or only visible in source code. In this paper, we first summarize some existing effective tricks used in GCNs mini-batch training. Based on this, two novel tricks named GCN_res Framework and Embedding Usage are proposed by leveraging residual network and pre-trained embedding to improve baseline’s test accuracy in different datasets. Experiments on Open Graph Benchmark (OGB) show that, by combining these techniques, the test accuracy of various GCNs increases by 1.21%~2.84%. We open source our implementation at https://github.com/ytchx1999/PyG-OGB-Tricks.

Keywords: Graph Convolutional Networks · Node Classification · Residual Network · Embedding Usage.

1 Introduction

More recently, Graph Convolutional Networks (GCNs) and their variants have successfully extended convolution and pooling operation to graphs and achieved good performance in many fields such as computer vision, recommendation systems and natural language processing [1]. Currently, spatial-based GCNs, such as GCN [2], GraphSAGE [3] and GraphSAINT [4], have gradually replaced spectral-based GCNs in practice due to their efficiency and flexibility. In order to solve the scalability problem of GCNs, researchers have proposed two kinds of mini-batch training algorithms: sampling-based [3,4,5] and clustering-based [6], to extend GCNs to large-scale graphs. Tasks in graph representation learning can be divided into three categories: node classification, link prediction, and graph classification. The node classification task has become one of the most popular benchmarks in GCNs due to its intuitiveness and simplicity.

Much of the work has aimed at the practice of GCNs, e.g., Open Graph Benchmark (OGB) [7], which has greatly promoted the development of GCNs.
Before the release of OGB datasets and its leaderboard, GCNs have not had a unified and universally-followed experimental protocol. Different studies have used different dataset splitters and evaluators, which have a negative impact on the fairness of different experiments [8,9]. Moreover, small graph datasets used in the early days, such as Cora, Citeseer and Pubmed, are far away from the real-world graphs, making it difficult to transfer some tricks to large-scale and real-world graphs. The above factors have led to the tricks of GCNs not receiving enough attention in the early research. Some tricks are either simply mentioned in the literature or only visible in the source code. Fortunately, since the release of OGB datasets and its leaderboard, the importance of tricks has gradually emerged under relatively fair evaluation standards and real-world graphs. Besides, the gains brought by tricks have sometimes exceeded the gains brought by model architecture improvement. However, no one has summarized the tricks of GCNs, which are also not complete so far. The inner relationships between these tricks are not clear, which bring difficulties to the application and further development.

**Present work.** Firstly, we review the mini-batch training process and the existing effective tricks of GCNs which can often make training faster and better for node classification tasks. Based on this, we propose two novel tricks for node classification tasks: GCN\_res Framework and Embedding Usage. By applying (i) adaptive residual connections and initial residual connections, and (ii) softmax layer-aggregation, GCN\_res Framework can relieve the over-smoothing problem. For example, on ogbn-arxiv, the test accuracy of our model is improved by 1.39% compared to GCN. We also compare our model with other baselines such as DeeperGCN [10], GCNII [11] to show the huge gains. Furthermore, the effectiveness of Embedding Usage is verified through experiments on ogbn-mag, ogbn-products and ogbn-proteins. For example, on ogbn-mag, it increases GraphSAINT’s test accuracy by 2.15%. Finally, we also find that different combinations of tricks can often improve various GCNs. By combining different strategies, GraphSAGE’s test accuracy increases from 78.70% to 81.54% on ogbn-products, achieving the best performance of the model based on SAGEConv and its variants.

The main contributions of this research are as follows:

1) We summarize the mini-batch training process and existing effective tricks of GCNs for node classification tasks.

2) We propose two novel tricks of GCNs for node classification tasks: GCN\_res Framework and Embedding Usage, which can improve various GCNs significantly on OGB datasets. Besides, our work is also open sourced in OGB leaderboard.

3) Related work about tricks of GCNs is analyzed and discussed, and a new direction is proposed for the future work.

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3 [https://ogb.stanford.edu/docs/nodeprop/](https://ogb.stanford.edu/docs/nodeprop/)

4 [https://ogb.stanford.edu/docs/leader_nodeprop/](https://ogb.stanford.edu/docs/leader_nodeprop/)
Residual Network and Embedding Usage

In Section 2, we will introduce the training process of GCNs and the existing tricks. In Section 3, we will present and discuss two novel tricks: GCN_res Framework and Embedding Usage. In Section 4, we will conduct our experiments and ablation studies on OGB datasets. In Section 5, we will summarize this research.

2 Preliminaries

2.1 The Training Procedures of GCNs

The template of training GCNs with mini-batch stochastic gradient descent is shown in Algorithm 1. Before initializing the model, we need to sample the whole graph to generate subgraphs required for mini-batch training first. In each iteration, we randomly select a subgraph to compute the gradients and then update the network parameters. It stops after N passes through the dataset. Finally, we can get the final node representation $Z$ through a post-processing step of the base prediction. All functions and hyper-parameters in Algorithm 1 can be implemented in many different ways.

Algorithm 1: Train GCNs with mini-batch gradient descent.

| Input: | Graph $G$; input feature matrix $X$ |
|--------|-----------------------------------|
| Output:| Final node representation $Z$ |
| 1:     | train_loader ← Sampling($G$, $X$); |
| 2:     | initialize(model); |
| 3: for epoch = 1, . . . ,N do |
| 4: for Sub_Graph in train_loader do |
| 5:     | out ← forward(model, $X$, Sub_Graph); |
| 6:     | loss ← criterion(out, y); |
| 7:     | grad ← backward(loss); |
| 8:     | update(model, grad); |
| 9: end for |
| 10: end for |
| 11: $Z$ ← Post-processing($G$, out); |

2.2 Existing Efficient Tricks

A. Mini-batch Training and Sampling. In large-scale graphs, it is quite difficult to train the whole graph at a time in full-batch algorithms. Therefore, some researchers have proposed sampling-based mini-batch algorithms to control the scale of graphs in the training process. The first row and the fourth row in Algorithm 1 are the steps for subgraph sampling and subgraph loading.

There are some commonly used samplers such as random sampler, neighbor sampler [3] and GraphSAINT sampler [4]. In each batch, we only need to train the subgraphs generated by sampling which not only saves the GPU memory,
but also facilitates parallel computing across multiple GPUs. Sampling can even be regarded as a kind of regularization method that randomly drops edges for nodes, so that the accuracy of GCNs can be slightly improved.

B. Normalization and Dropout. Normalization and dropout [12] are widely used in CV, NLP and other fields. Although they may be essential for training, they are rarely mentioned in papers of GCNs.

How to normalize node features is a very important issue while training. Many models will employ BatchNorm (BN) [13] or LayerNorm (LN) [14] during training. However, normalization will also lead to a loss of node degree information and obscure various graph structure features. Generally, Hamilton et al. [15] point out that normalization is most helpful in tasks where node feature information is much more useful than structure information, or where there is a very wide range of node degrees. Both BN and LN can be written as

\[ x_i' = \frac{x - \text{E}[x]}{\sqrt{\text{Var}[x]} + \epsilon} \odot \gamma + \theta \]  

(1)

where E[x] and Var[x] stand for the mean and standard deviation respectively.

The BN/LN is very effective in GCNs, which can generally stabilize the value, especially for deep GCNs. If there is no BN/LN, then a numeric overflow may occur during training. Therefore, more and more GCNs begin to use normalization. Recently, several new normalization methods, such as PairNorm [16] and NodeNorm [17], are proposed to alleviate the over-smoothing problem in small graphs. Besides, normalization can also be used with dropout to prevent the overfitting problem.

C. Adversarial Training (FLAG). Standard adversarial training was first proposed to solve the min-max problem. Recently, many researchers are trying to adopt adversarial training in GCNs for security purposes [18,19]. However, it remains unclear whether adversarial training can improve the accuracy of GCNs.

The FLAG [20] is a large-scale adversarial augmentation on graphs, which can tackle the overfitting problem by adding gradient-based adversarial perturbations to the input node features. Kong et al. [20] also point out that combining FLAG with normalization and dropout can further improve the performance of GCNs.

D. Label Propagation and Usage. Some recent research attempts to connect label propagation with GCNs in order to utilize label information. Inspired by label propagation (LP) [21], Huang et al. [22] have proposed Correct and Smooth (C&S) method, which corrects and smooths the base prediction through two LPs. The C&S method is often applied during the post-processing step in Algorithm 1.

Since the labels can provide more information, Wang et al. [23] have proposed Label Usage, which uses a masking technology to merge node features and labels.
as input. The motivation is similar to Embedding Usage that we are proposed later, but in comparison, Embedding Usage is more powerful.

3 Proposed Methods

3.1 GCN_res Framework and Residual Network

Residual connection, also called skip-connection, was first proposed in ResNet [24] to solve the overfitting issue of deep CNNs. Inspired by ResNet, recent research has attempted to apply various residual connections to GCNs to alleviate the over-smoothing problem, including CLN [25], Highway GCN [26] and JKNet [27]. However, the effectiveness of these methods is not satisfactory in large-scale graphs. In spite of this, several research still shows that residual connections are essential for deep GCNs, which can not only make GCNs have a more stable gradient, but also partly alleviate the over-smoothing problem [10,11].

![Overview of GCN_res Framework](image)

**Fig. 1.** Overview of GCN_res Framework with a 4-layer toy example. The GCNs-Block consists of four parts: GCNsConv layer, Norm layer, activation function, and Dropout unit. Data stream of residual connections is indicated by arrows.

In this paper, inspired by residual network, we propose GCN_res Framework by two main strategies in the forward propagation: (i) adaptive residual connections and initial residual connections; and (ii) softmax layer-aggregation. As an example, we show a 4-layer model which uses GCN_res Framework in Fig. 1. We also show the pseudo code of its forward propagation algorithm (Algorithm 2). In order to avoid the expensive cost caused by high-dimension input feature matrix $X$, we first reduce its dimension as $X^{(0)}$ in the initialization phase by a Linear layer. Next, in each layer, $X^{(k)}$ passes through GCNsConv layer, Norm layer, ReLu function and Dropout unit in turn. Then, we make $X^{(k)}$ weighted summation with $X^{(0)}$ and $X^{(k-1)}$ according to the scale coefficients $\alpha$ and $\beta$ respectively. In our experiments, we fix $\alpha$ and $\beta$ as hyper-parameters,
Algorithm 2: GCN res Framework (i.e., forward propagation)

Input: Graph $G$; input feature matrix $X$; depth $K$; weight matrices $W^{(k)}, \forall k \in \{1, \ldots, K\}$; scale coefficients $\alpha, \beta$

Output: Node representation $Z$

1: $X^{(0)} \leftarrow \text{Linear}(X)$
2: for $k = 1, \ldots, K$ do
3:   $X^{(k)} \leftarrow \text{GCNsConv}(X^{(k-1)}, G)$
4:   $X^{(k)} \leftarrow \text{Norm}(X^{(k)})$
5:   $X^{(k)} \leftarrow \text{Relu}(X^{(k)})$
6:   $X^{(k)} \leftarrow \text{Dropout}(X^{(k)})$
7:   $X^{(k)} \leftarrow X^{(k)} + \alpha \cdot X^{(0)} + \beta \cdot X^{(k-1)}$
8: end for
9: $W^{(1)}, \ldots, W^{(K)} \leftarrow \text{Softmax}(W^{(k)}, \forall k \in \{1, \ldots, K\})$
10: for $k = 1, \ldots, K$ do
11:  $X^{(k)} \leftarrow W^{(k)} \odot X^{(k)}$
12: end for
13: $Z \leftarrow \text{Sum}(X^{(1)}, \ldots, X^{(K)})$
14: $Z \leftarrow \text{Linear}(Z)$
15: $Z \leftarrow \text{LogSoftmax}(Z)$

which can also be obtained through learning. Finally, the node representations $\{X^{(1)}, \ldots, X^{(K)}\}$ of each layer are aggregated by softmax layer-aggregation to obtain the final node representation $Z$.

Adaptive Residual Connections. Inspired by DeeperGCN [10], APPNP [28] and GCNII [11], as shown in Algorithm 2, we apply adaptive residual connections and initial residual connections to each layer in the forward propagation to accelerate the convergence of GCNs and alleviate the over-smoothing problem. By applying the above strategies to GCNs, the graph convolutional operator of our model can be rewritten as

$$X^{(k)} = \sigma \left( \text{Norm} \left( \text{GCNsConv} \left( X^{(k-1)}, G \right) \right) \right) + \alpha \cdot X^{(0)} + \beta \cdot X^{(k-1)}, \quad (2)$$

where $\sigma(\cdot)$ is an activation function, $\text{Norm}(\cdot)$ stands for the normalization functions, $\text{GCNsConv}(\cdot)$ stands for a convolutional layer, $\alpha$ and $\beta$ are two hyperparameters.

Softmax Layer-aggregation. Inspired by CLN [25] and JKNet [27], we also propose softmax layer-aggregation. The difference between our method and jumping knowledge is that we use learnable weights which obey the softmax distribution in weighted summation for each layer instead of simply sum or max. The softmax layer-aggregation can be written as
softmax \left( W^{(1)}, ..., W^{(K)} \right), \quad (3)

Z = \sum_{k=1}^{K} W^{(k)} \odot X^{(k)}, \quad (4)

where $W^{(k)}$ is a learnable weight matrix for weighted summation. The softmax layer-aggregation can effectively use the node representation information of each layer to further alleviate the over-smoothing problem.

In addition, Li et al. [10] propose a pre-activated variant of residual connections for deep GCNs. In order to adjust GCN res Framework to the pre-activated version, we can put normalization and activation functions in front of GCNConv layer. By integrating the above strategies together, GCN res Framework can be flexibly applied to various baselines rather than limit to GCN, and it also provides a new possibility for the future work of deep GCNs.

### 3.2 Embedding Usage

At present, models such as DeepWalk [29] and Node2vec [30] can generate embeddings for nodes in graphs through random walk. It has been confirmed that these embeddings contain rich graph structural information, however, the final accuracy of using these embeddings alone for node classification is generally low. This motivates the more general questions: Are these embeddings really useful? Can GCNs use these embeddings?

![Fig. 2. Embedding Usage for GCNs. We merge input features with embedding to generate new features for GCNs.](image)

In this work, we take an initial step towards answering the questions above by proposing Embedding Usage to enhance node features. As shown in Fig. 2, we merge the input feature matrix $X$ with embedding obtained by pre-training, and then take the new feature matrix as input for GCNs. The merge process can be written as

$$X = \text{Merge}(X, \text{Embeddings})$$
where *Embeddings* in Eq. (5) can be Node2vec embedding in homogeneous graphs or MetaPath2vec [31] embedding in heterogeneous graphs. The *Merge* function can be *sum*, *concat* (in our experiments) or other functions.

Theoretically, we can use any model to pre-train the embeddings. For example, in heterogeneous graphs, we can also use TransE [32] or DistMult [33] embedding. Considering the cost and other factors, the model that uses to generate embeddings is generally simpler than GCNs. These embeddings contain a lot of graph structural information either in homogeneous or heterogeneous graphs, which can greatly improve the performance of GCNs. Particularly, embeddings can play a pivotal role in the training process for heterogeneous graphs, where GCNs are severely under-fitting.

Besides, we can also use domain knowledge to handcraft more features. For example, in molecular graph datasets, we can use chemical information and knowledge to handcraft more features for molecular representation learning, which is an interdisciplinary research direction.

4 Experiments

4.1 Dataset

| Dataset          | Nodes     | Edges        | Classes | Metric   |
|------------------|-----------|--------------|---------|----------|
| ogbn-arxiv       | 169,343   | 1,166,243    | 40      | Accuracy |
| ogbn-mag         | 1,939,743 | 21,111,007   | 349     | Accuracy |
| ogbn-products    | 2,449,029 | 66,859,140   | 47      | Accuracy |
| ogbn-proteins    | 132,534   | 39,561,252   | 2       | ROC-AUC  |

We conduct our experiments to evaluate the performance gain from two proposed tricks on four node classification datasets of OGB [7], including *ogbn-arxiv*, *ogbn-mag*, *ogbn-products* and *ogbn-proteins*. The statistics of each dataset is shown in Table 1. Moreover, *ogbn-arxiv*, *ogbn-mag* and *ogbn-products* all contain node features, and their evaluation metrics are Accuracy; *ogbn-proteins* only contains edge features, and its evaluation metric is ROC-AUC.

4.2 Results and Discussions

In our experiments, we evaluate these tricks through ablation studies. In order to ensure the fairness of the experiments, the hyper-parameters in the same dataset are kept consistent. For GCN_res, we set $\alpha=0.2$, $\beta=0.7$ in Eq. (2). In order to follow the rules of OGB leaderboard, the average and unbiased standard
deviation of test accuracy are taken over 10 different random seeds. Except for special instructions, the best model for each dataset in our experiments can be found in OGB leaderboard. The bold in the tables represents that the model is improved by our proposed tricks.

**A. OGBn-Arxiv.** ogbn-arxiv is a homogeneous graph dataset. The results are presented in Table 2. We use GCN\(_\text{res}\) to denote a 8-layer GCN with GCN\(_\text{res}\) Framework, which increases the test accuracy by 0.88% compared to GCN. We also combine GCN\(_\text{res}\) Framework with FLAG or C&S respectively to achieve further improvements. It is worth mentioning that GCN\(_\text{res}\) + C&S\(_v2\) has a 1.39% increase of the test accuracy compared to GCN. It achieves the best performance of models whose kernel are GCN and its variants, which confirms the flexibility and robustness of GCN\(_\text{res}\) Framework. Besides, GCN\(_\text{res}\) + C&S\(_v3\), which uses the validation label in C&S, is not announced in OGB leaderboard, however, its performance exceeds many GAT-based models. Compared with some baselines in OGB leaderboard, such as DeeperGCN [10], GCNII [11] and UniMP [34], our model achieves the best performance, which confirms the effectiveness of GCN\(_\text{res}\) Framework on ogbn-arxiv.

**Table 2.** The results of node classification on ogbn-arxiv in terms of Accuracy. The number in parentheses next to the model name indicates the number of layers.

| Model               | Test(%) | Valid(%) |
|---------------------|---------|----------|
| MLP                 | 55.50±0.23 | 57.65±0.12 |
| GCN (3) [2]         | 71.74±0.29 | 73.00±0.17 |
| GCN + FLAG (3)      | 72.04±0.20 | 73.30±0.10 |
| SIGN [35]           | 71.95±0.11 | 73.23±0.06 |
| DeeperGCN [10]      | 71.92±0.16 | 72.62±0.14 |
| DAGNN [36]          | 72.09±0.25 | 72.90±0.11 |
| JKNet [27]          | 72.19±0.21 | 73.35±0.07 |
| GCNII [11]          | 72.74±0.16 | —         |
| UniMP [34]          | 73.11±0.20 | 74.50±0.05 |
| GCN\(_\text{res}\) (8) | 72.62±0.37 | 73.69±0.21 |
| GCN\(_\text{res}\) + FLAG (8) | 72.76±0.24 | 73.89±0.12 |
| GCN\(_\text{res}\) + C&S\(_v2\) (8) | 73.13±0.17 | 74.45±0.11 |
| GCN\(_\text{res}\) + C&S\(_v3\) (8) | 73.91±0.14 | 73.61±0.21 |

For a more intuitive comparison, we visualize the final test node representations by t-SNE. The results are shown in Fig. 3. It is obvious that our model can achieve more separated clusters than MLP and GCN, which demonstrates that GCN\(_\text{res}\) Framework helps to learn more meaningful node embeddings.

**B. OGBn-Mag.** ogbn-mag is a heterogeneous graph dataset. As shown in Table 3, only by adding MetaPath2vec embedding for input features, the test accu-
Fig. 3. t-SNE visualization results on ogbn-arxiv.

The accuracy of GraphSAINT increases by 2.15%. On this basis, GraphSAINT + metapath2vec + FLAG even achieves the best performance of models whose kernel are R-GCN and its variants in OGB leaderboard. Interestingly, C&S, which is an effective method in homogeneous graphs, will make GCNs suffer an accuracy drop in heterogeneous graphs. The reason lies in the theoretical motivation for label propagation algorithm (LPA [21]) — adjacent nodes should have similar labels. However, there are different types of nodes in heterogeneous graphs, and even adjacent nodes will have completely different labels. Moreover, although FLAG can improve the performance of R-GCNs, the effect is not obvious.

Table 3. The results of node classification on ogbn-mag in terms of Accuracy.

| Model                                      | Test(%)  | Valid(%)  |
|--------------------------------------------|----------|-----------|
| GraphSAINT (R-GCN aggr) [4]                | 47.51 ± 0.22 | 48.37 ± 0.26 |
| GraphSAINT + metapath2vec                  | 49.66 ± 0.22 | 50.66 ± 0.17 |
| GraphSAINT + metapath2vec + C&S            | 48.43 ± 0.24 | 49.36 ± 0.24 |
| GraphSAINT + metapath2vec + FLAG           | 49.69 ± 0.22 | 50.88 ± 0.18 |

Due to the complexity of heterogeneous graphs, the test and validation accuracy of GCNs on ogbn-mag are relatively low. Many tricks used in homogeneous
graphs cannot be directly transferred to heterogeneous graphs. Nevertheless, it is clear that embedding information is crucial for heterogeneous graphs, and how to use this information rationally may become a future research direction.

C. OGBn-Products. ogbn-products is a homogeneous graph dataset. As shown in Table 4, using mini-batch algorithm based on neighbor sampling (NS) can improve GraphSAGE’s test accuracy slightly. The results also prove that sampling can not only make training easier, but also be regarded as regularization to improve the performance of GCNs. Through the combination of BN, C&S and Node2vec embedding, we raise GraphSAGE’s test accuracy from 78.50% to 81.54%, which achieves the best performance of models whose kernel are GraphSAGE and its variants in OGB leaderboard. It is worth mentioning that Node2vec embedding significantly improves the accuracy of GCNs, thus confirming the effectiveness and necessity of embedding information once again.

Table 4. The results of node classification on ogbn-products in terms of Accuracy.

| Model                     | Test(%) | Valid(%) |
|---------------------------|---------|----------|
| Full-batch GraphSAGE [3]  | 78.50±0.14 | 92.24±0.07 |
| GraphSAGE w/NS            | 78.70±0.36 | 91.70±0.09 |
| GraphSAGE w/NS + FLAG     | 79.36±0.57 | 92.05±0.07 |
| GraphSAGE w/NS + BN + C&S | 80.41±0.22 | 92.38±0.07 |
| GraphSAGE w/NS + BN + C&S + node2vec | 81.54±0.50 | 92.38±0.06 |

D. OGBn-Proteins. ogbn-proteins is a homogeneous dataset. It should be noted that ogbn-proteins does not have node features at first, so we use the summation edge features as initial node features in our experiments. As shown in Table 5, only using FLAG, the test accuracy of GEN [10,37] will decrease instead. By combining FLAG and Node2vec embedding, the test accuracy of GEN increases by 1.21%, which achieves the best performance of models whose kernel are GEN and its variants in OGB leaderboard. The Node2vec embedding enhances the node features, thus improving the accuracy of GCNs.

Table 5. The results of node classification on ogbn-proteins in terms of ROC-AUC.

| Model                  | Test(%) | Valid(%) |
|------------------------|---------|----------|
| GEN [10,37]            | 81.30±0.65 | 85.74±0.53 |
| GEN + FLAG             | 81.29±0.67 | 85.87±0.54 |
| GEN + FLAG + node2vec  | 82.51±0.43 | 86.56±0.37 |
E. Discussions. Since the inner relationship between tricks is not clear, there are few papers that combine tricks with different motivations in their experiments. In our experiments, we use two novel proposed tricks in combination with other existing tricks, and discuss the effects of various combination strategies in different datasets. Kong et al. [20] point out that whether or not tricks are effective depends on data distribution. Different graph structures will greatly affect the expressive abilities of tricks. Therefore, different tricks and their combinations should be used for different datasets.

Through experiments on these datasets, we find that GCN_res Framework in the citation network ogbn-arxiv successfully alleviates over-smoothing issue of GCNs, which can also easily integrate various types of tricks due to its good generality and flexibility. The Node2vec or MetaPath2vec embedding can make GCNs have an obvious improvement in most scenarios so that we strongly recommend you to use embeddings in GCNs. Besides, normalization and dropout are generally used to stabilize the gradient of GCNs and prevent the problem of overfitting. In addition, C&S has a positive effect on homogeneous graphs, but is not applicable in heterogeneous graphs. FLAG can slightly improve the performance of GCNs on most datasets, but this is not a large increase.

The combination of various tricks can achieve better performance gain than a single trick, for example, GCN_res + C&S v3, GraphSAIN T + metapath2vec + FLAG, GraphSAGE w/NS + BN + C&S + node2vec and GEN + FLAG + node2vec all achieve the best performance in our experiments. Therefore, exploring the inner relationship between different types of tricks and making rational use of them may be a future research direction.

5 Conclusion

In this paper, we first summarize the mini-batch training process and existing effective tricks of GCNs for node classification tasks from a practical perspective. In addition, we also propose two novel tricks: GCN_res Framework and Embedding Usage, which can improve various GCNs via residual network and pre-trained embedding. Experiments on OGB datasets show that the combination of these tricks can greatly improve the performance of GCNs. Due to the low cost and flexibility, tricks will play an important role in practical applications of GCNs in the future.
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