FASG: FEATURE AGGREGATION SELF-TRAINING GCN FOR SEMI-SUPERVISED NODE CLASSIFICATION

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ABSTRACT

Recently, *graph convolutioal networks* (GCNs) have achieved significant success in many graph-based learning tasks, especially for node classification, due to its excellent ability in representation learning. Nevertheless, it remains challenging for GCN models to obtain satisfying predictions on graphs where few nodes are with known labels. In this paper, we propose a novel self-training algorithm based on GCN to boost semi-supervised node classification on graphs with little supervised information. Inspired by self-supervision strategy, the proposed method introduces an ingenious checking part to add new nodes as supervision after each training epoch to enhance node prediction. In particular, the embedded checking part is designed based on aggregated features, which is more accurate than previous methods and boosts node classification significantly. The proposed algorithm is validated on three public benchmarks in comparison with several state-of-the-art baseline algorithms, and the results illustrate its excellent performance.

1 INTRODUCTION

Graph convolutional network (GCN) can be seen as the migration of *convolutional neural network* (CNN) on non-Euclidean structure data. Due to its its excellent ability in representation learning, GCN has achieved significant success in many graph-based learning tasks, including node clustering, graph classification and link prediction (Dwivedi et al., 2020). Kipf & Welling (2016) proposed a GCN mode from the perspective of spectrogram theory and validated its effectiveness on semi-supervised node classification task. Subsequent models such as GraphSAGE (Hamilton et al., 2017), GAT (Veličković et al., 2017), SGCN (Wu et al., 2019) and APPNP (Klicpera et al., 2018) designed more sophisticated neighborhood aggregation functions from spatial or spectral views. These methods obtain much more effective results on semi-supervised node classification than traditional methods such as MLP, DeepWalk (Perozzi et al., 2014), etc. However, the prediction accuracy of such GCN models depends largely on the quantity and quality of supervised information, and it will decrease significantly when the quantity of labeled nodes is quite small (Li et al., 2018). The main reason lies that scarce supervised information is difficult to be spread far away in the graph so that unlabeled nodes are hardly to make full use of supervised information for prediction.

Addressing the above issue, many studies have been devoted to improving the representation ability by designing multi-layer GCN model (Li et al., 2019). However, the representation ability of GCN, as illustrated in Kipf & Welling (2016), can hardly be improved by simply stacking layers just like MLP. Moreover, stacking too many layers tends to cause over-smoothing (Xu et al., 2018) that makes all node embeddings indistinguishable. Alternatively, Li et al. (2018) proposed to improve the reasoning ability of GCN models by applying self-training techniques on the training. Rather than trying to enhance the expressive ability of the model, the self-training strategy prefers to expand the supervised information by adding unlabeled nodes with high confidences to the training set at each round. Following this line, Sun et al. (2019) proposed a *multi-stage self-training strategy* (M3S) to enrich the training set, which uses deep cluster (Caron et al., 2018) and an aligning mechanism to generate pseudo-labels of nodes for updating of the training set. Later, Zhou et al. (2019) proposed a dynamic self-training framework to continuously refresh the training set by directly using the output of GCN without a checking part. In general these self-training algorithms generate pseudo-labels using relatively simple checking mechanism, which may introduce false labels as supervision information and prevent the improvement of prediction accuracy.

In this paper, we propose a novel *feature aggregation self-training GCN* (FASG) algorithm for semi-supervised node classification. We firstly propose a lightweight classifier that applies linear SVM on aggregated node features, and validate that it achieves comparable performance to popular GCN approaches. Furthermore, this classifier is served as a checking part in the multi-round training process to generate pseudo-labels, which are used to filter unreliable nodes when expanding the supervised information. By fully considering the structural information of graph nodes, the newly developed checking part is able to improve the accuracy of the generated pseudo-labels and finally boost the node classification. Finally, we illustrate that the proposed self-training strategy can be integrated with various existing GCN models to improve the prediction performance.

The proposed algorithms is validated in comparison with several state-of-the-art baseline algorithms in three public benchmarks, and the experimental results illustrate that the proposed algorithm outperforms all compared algorithms in general on all benchmarks. We will release the source code upon publication of this paper.

2 Related work

In the past decade CNN has achieved great success in many areas of machine learning (Krizhevsky et al., 2012; LeCun et al., 1998; Sermanet et al., 2012), but its applications are mainly restricted in dealing with Euclidean structure data (Bruna et al., 2013). Consequently, in recent years more and more studies are devoted to learning the representation on non-Euclidean structure data such as graph.

Graph neural network (GNN) plays an important role in the field of graph representation learning, which can learn the representation of nodes or the whole graph. There are many famous GNN architectures including GCN (Kipf & Welling, 2016), graph recurrent neural network (Hajiramezanali et al., 2019) and graph autoencoder (Pan et al., 2018). As one of the most important architecture of GNN, GCN can be roughly categorized into spectral and spatial approaches. The spectral approaches (Bruna et al., 2013) define convolution operation by Laplacian feature decomposition of the graph, thereby filtering the graph structure in the spectral domain. On the basis of the Chebyshev polynomial (Defferrard et al., 2016) of the graph Laplacian matrix, Kipf & Welling (2016) proposed a much simper GCN framework that limits the filter to the first-order neighbor around each node. On the other hand, spatial approaches implement convolution in spatial domain by defining aggregation functions and transform functions. Notable work includes GraphSAGE (Hamilton et al., 2017) that transformed representation learning into a formal pattern called aggregation and combination and proposed several effective aggregation strategies such as mean-aggregator and max-aggregator, and GAT (Veličković et al., 2017) that focuses on the diversity in connected nodes and leverages self-attention mechanism to learn the important information in neighborhoods. Although these models have achieved far better performance on node classification than traditional methods, they still suffer from scarce supervised information due to the limitation on GCN layers making it hard to transform the supervised information to the entire graph.

Self-training is an ancient and classic topic in the NLP field before deep learning era (Hearst, 1991; Riloff et al., 1999; Rosenberg et al., 2005; Van Asch & Daelemans, 2016), and has recently been introduced into semi-supervised node classification. For making full use of supervised information to improve the prediction accuracy, Li et al. (2018) proposed to improve GCN model by self-training mechanism, which trains and applies a base model in rounds, and adds nodes with high confidences as supervision after each round. The newly added nodes are expect to be beneficial to predict rest nodes so as to enhance the final performance of the model. Following this line, the M3S training algorithm Sun et al. (2019) pretrains a model over the labeled data, and then assigns pseudo-labels to highly confident unlabeled samples that are considered as labeled data for the next round of the training. Later, Zhou et al. (2019) proposed a dynamic self-training GCN that generalizes and simplifies previous by directly using the output of GCN without a checking part to continuously refresh the training set. Similarly, Yang et al. (2020) proposed *self-enhanced GNN* (SEG) to improve the quality of the input data using the outputs of existing GNN models. These self-training methods expand the labeled node set with relatively simple checking mechanism or even directly using the output of GCN, as a result they may introduce noise as supervision and thus hurt the final prediction performance.

3 PRELIMINARIES

An attributed relational graph of n nodes can be represented by $G = (V, E, X)$, where $V = \{v_1, v_2, ..., v_n\}$ denotes the set of n nodes, and $E = \{e_{ij}\}$ is the edge set. $X = \{x_1, x_2, ...x_n\} \in R^{n\times d}$ is the set of attributes of all nodes, where x_i is the d-dimensional attribute vector associated with node v_i. Adjacency matrix $A = \{a_{ij}\} \in R^{n\times n}$ denotes the topological structure of graph G, where $a_{ij} > 0$ if there is an edge e_{ij} between node v_i and v_j and $a_{ij} = 0$ otherwise.

For semi-supervised node classification, the node set V can be split into a labeled node set $V_L \in V$ with attributes $X_L \in X$ and an unlabeled one $V_U = V \backslash V_L$ with attributes $X_U = X \backslash X_L$. We assume each node belongs to exactly one class, and denote $Y_L = \{y_i\}$ the ground-truth labels of node set V_L where y_i is the class label of node $v_i \in V_L$.

The aim of semi-supervised node classification is to learn a classifier from the graph and known node labels Y_L, and use it to predict labels for unlabeled nodes V_U. Define a classifier $f_\theta : (\tilde{Y}_L, \tilde{Y}_U) \leftarrow f_\theta(X, A, Y_L)$, where θ denotes the parameters of model, $\tilde{Y}_L$ and $\tilde{Y}_U$ are the predicted labels of nodes V_L and V_U respectively. In general, we want the predict labels $\tilde{Y}_L$ is close to the ground-truth labels Y_L as possible in favor of

$$\theta^* = \arg\min_\theta d(\tilde{Y}_L, Y_L) = \arg\min_\theta d(f_\theta(X, A, Y_L), Y_L), \tag{1}$$

where $d(\cdot, \cdot)$ is a distance measure between two label sets.

In recent years GCN has become a popular model for semi-supervised node classification, which aggregates a structural feature for each node and use the formed features, rather than the initial attributes X, for label prediction.

4 THE PROPOSED METHOD

In this section, we will elaborate our proposed framework, namely *feature aggregation self-training GCN* (FASG), for semi-supervised node classification. Firstly, we do analysis of pseudo-labels to explain the importance of checking part in self-training framework. Secondly, we illustrate the design of checking part in our framework and show the superiority of our checking part in graph networks. Then we elaborate every part of the framework and display the FASG training algorithm. Finally we integrate our framework with various GNN models.

4.1 ANALYSIS OF PSEUDO-LABELS

It is common for existing self-training GCN models to assign pseudo-labels to highly confident nodes and expand them as supervised information. Therefore, the quality of the generated pseudo-labels is crucial for node classification and the wrongly introduced supervision information may hurt the final prediction performance. Table 1 summarizes the prediction accuracy of the GCN model (Kipf & Welling, 2016) on Cora when it is trained given different ratios of falsely labeled nodes. It is shown that the accuracy decreases significantly with the ratio of bad training nodes increasing.

Table 1: Performance of GCN model trained with different ratio of bad training nodes.

Ratio	**0%**	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**
Acc	81.9%	77.9%	71.5%	69.1%	65.4%	57.9%	56.3%

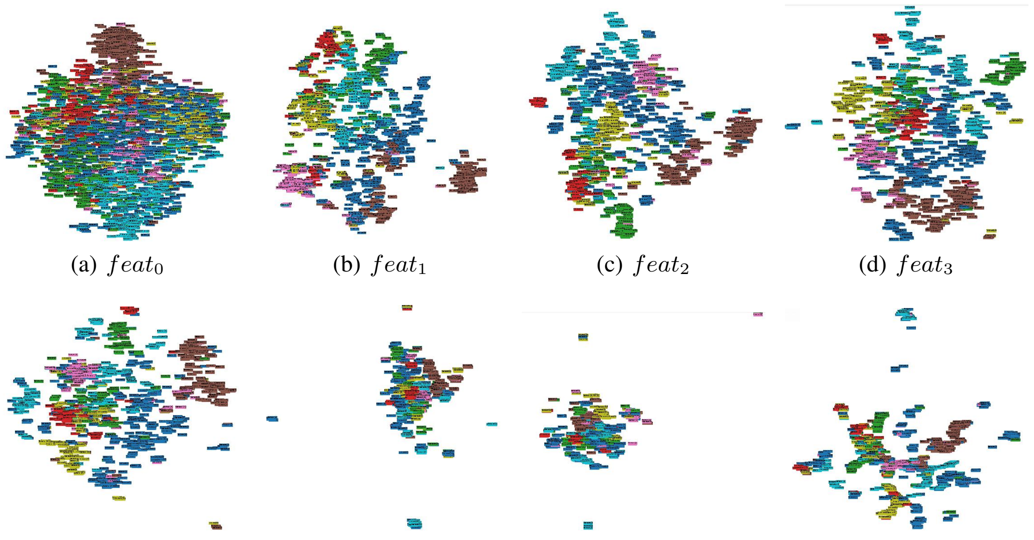
4.2 CHECKING PART WITH FEATURE AGGREGATION

To guarantee the quality of the generated pseudo-labels, we develop a delicate checking part in the assistance of feature aggregation. The implementation of feature aggregation can be described as $X^{aggre} = \tilde{D}^{-1}\tilde{A}X$, where D is digree matrix of the graph, $\tilde{D} = D + I$, $\tilde{A} = A + I$. We use deep graph library DGL (Wang et al., 2019) to implement feature aggregation.

For illustration of the effectiveness of feature aggregation, we apply t-SNE (Maaten & Hinton, 2008) to visualize the aggregated features of each node on the Cora dataset in Fig 1, where $feat_i$ denotes the features aggregated from the original features for i times. As shown in Fig. 1(a), the original node features are mixed together and are difficult to distinguish. As the fusion of node features going deeper from $feat_1$ to $feat_4$, nodes with the same label tend to aggregate into clusters in 2-D space. However, the cluster boundaries become blur again after the aggregation goes up to a certain level, e.g.. $feat_{15}$ and $feat_{20}$.

Furthermore, we apply linear svm (Cortes & Vapnik, 1995) on aggregated features $feat_5$ to form a classifier, and report its performance in Table 2 in comparison with several GCN models on three citation networks, Cora, CiteSeer and PubMed. Clearly, this relatively simple classifier is able to achieve comparable performance with popular GCN models due to the representation ability of aggregated features.

As for the self-training mechanism, we employ the above classifier that combines feature aggregation with line svm to serve as check part for generation of pseudo-labels of nodes. In Fig. 2, we compare the quality of pseudo-labels generated by different checking mechanisms including plain self-training method (Li et al., 2018), deep cluster Sun et al. (2019) and the proposed checking part with feature aggregation. It is shown that our method introduces less bad training nodes than the compared methods in different label rates on both Cora and CiteSeer, which accounts for the better performance on node classification shown in Sec. 5.


(a) $feat_0$ (b) $feat_1$ (c) $feat_2$ (d) $feat_3$

(e) $feat_4$ (f) $feat_{15}$ (g) $feat_{20}$ (h) $feat_{100}$

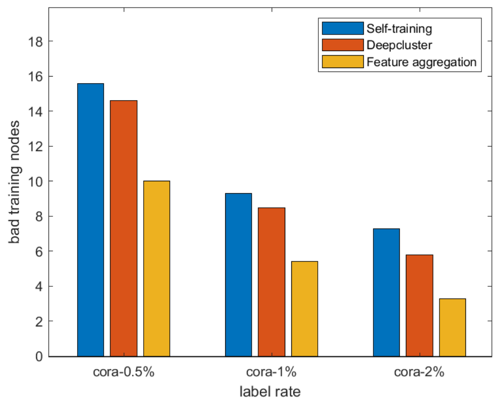
Figure 1: T-SNE visualization of aggregated features in the Cora dataset.

Table 2: Performance of aggregation and classic methods

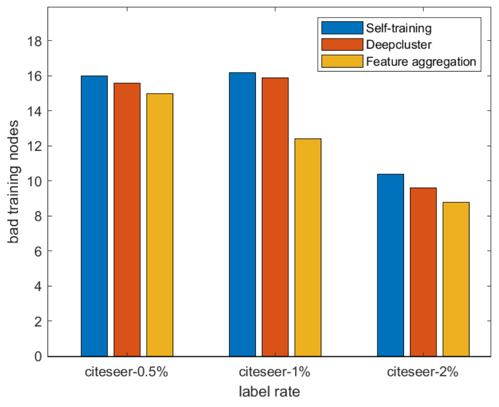
Dataset	**MLP**	**ChebyNet**	**GCN**	**GAT**	**feat5+svm**
Cora	55.1%	81.2%	81.5%	83.0%	83.2%
CiteSeer	46.5%	69.8%	70.3%	72.5%	72.3%
PubMed	71.4%	74.4%	79.0%	79.0%	78.8%

4.3 Multi-stage self-training framework

The overall framework of the proposed *feature aggregation self-training GCN* (FASG) algorithm is illustrated in Fig. 3. Instead of using deep cluster and aligning mechanism, we firstly apply feature aggregation and linear SVM classifier to build a checking part. After each training round we use



(a) falsely labeled nodes on Cora



(b) falsely labeled nodes on CiteSeer

Figure 2: Comparison of the number of falsely labeled nodes introduced by different checking mechanism.

both the output GCN confidence and the checking part to choose reliable nodes as supervised ones at the next round. The training iterates K rounds and then output the final predictions of unlabeled nodes.

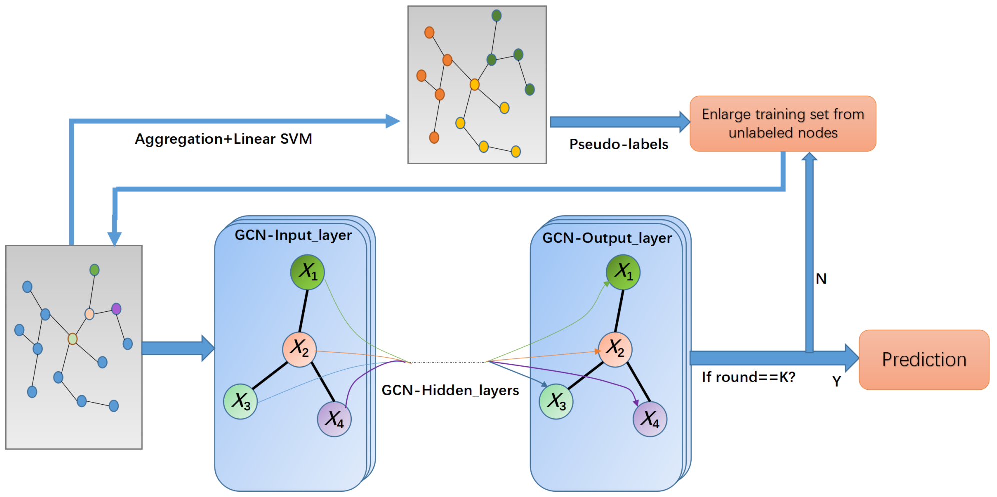


Figure 3: The overall FASG framework for semi-supervised node classification.

The proposed FASG algorithm is described in details in Algo. 1. At the beginning, we concatenate features from $feat_0$ to $feat_{10}$ and put them into a linear SVM to build the checking part. At each round if the output of a node predicted by the GCN model is consistent with its pseudo-label generated by the checking part, then we tend to expand this node with high certainty to the supervised set. To avoid expanding too much nodes at one time, only t nodes with top confidence are checked at each round. Note that the base GCN model in Algo. 1 is not specified, i.e. the proposed FASG algorithms can be integrated with various GCN models to boost node classification, of which the effectiveness is validated in Table. 6.

Algorithm 1 The FASG Algorithm

```
Input:
    $G = (V, E, X)$: the input graph.
    $A$: the adjacent matrix of graph $G$.
    $L, U$: the labeled and unlabeled node set of respectively.
    $GCNconv(\cdot)$: the base GCN model.
    $SVM(\cdot)$: the linear SVM classifier.
    $K$: the number of self-training rounds.
Output:
    predictions of all the unlabeled nodes $\tilde{Y}_U$;
 1: Conduct feature aggregation to generate $feat_1, \dots, feat_9$.
 2: Form concatenation $feat \leftarrow [feat_1, \dots, feat_9]$.
 3: Generate pseudo-labels $Y'_U = SVM(feat, L, U)$.
 4: Let $L' \leftarrow L, U' \leftarrow= U$;
 5: for $k = 1$ to $K$ do
 6:     Train GCN model and get predictions and confidence matix:
        $\tilde{Y}_U, M = GCNconv(A, X, L', U')$.
 7:     for each class j do
 8:         Select $t$ nodes $\{v_{j1}, \dots, v_{jt}\}$ in $U'$ with top confidences.
 9:         for $i = 1$ to $t$ do
10:             if $\tilde{y}_{ji}$ equals $y'_{ji}$ then
11:                 $L' \leftarrow L' \cup \{v_{ji}\}, U' \leftarrow U' \backslash \{v_{ji}\}$.
12:             end if
13:         end for
14:     end for
15: end for
16: Compute the final predictions $\tilde{Y}_U = GCNconv(A, X, L', U')$.
17: return $\tilde{Y}_U$
```

5 Experiments

5.1 Experimental settings

We conduct experiments on three open graph datasets derived from citation networks (including Cora, CiteSeer, PubMed) (Sen et al., 2008) for the semi-supervised node classification task. In these citation networks nodes denote documents whose features are formed by bag-of-words representations, and edges denote their relationships with labels indicating what field the corresponding documents belong to.

Though our framework can be integrated with various GNN models, we choose plain GCN (Kipf & Welling, 2016) as the base model in Algo. 1 in this experiment. Specifically, we set the number of GCN layers n_layers=2, learning rate lr=1e-2, training epochs=600, weight_decay=5e-4 for the GCN model, and fix $t = 10$ in Algo. 1. Similar to the M3S algorithm (Sun et al., 2019), we also regard the option of rounds K as a hyper-parameter and assign the most suitable K for each testing of different label rate. We choose K as 40,10,5,4,4 for Cora dataset, 30,25,15,10,10 for CiteSeer and 5,4,3 for PubMed. The label rate indicates the amount of labeled nodes, which are randomly chosen from the whole node set under an extra measures that is to guarantee the balance between different classes. For each trial we repeat the testing 10 times and report the mean accuracy.

5.2 Comparison with baseline algorithms

The compared baseline algorithms in this experiment include traditional learning method such as Node2Vec (Grover & Leskovec, 2016) ,LP (Wu et al., 2012) and classic GNN approach such as GCN (Kipf & Welling, 2016), GAT (Veličković et al., 2017) and ChebNet (Defferrard et al., 2016). We also include Co-training and Self-training proposed by Li et al. (2018) and other self-learning based approaches MultiStage (Sun et al., 2019), M3S (Sun et al., 2019) as baseline. The relevant experimental settings and results are all taken from original papers.

Table 3: Comparison of prediction accuracy on Cora dataset

Label Rate	**0.5%**	**1%**	**2%**	**3%**	**4%**
Node2Vec	32.4%	44.4%	50.2%	54.5%	57.4%
LP	57.6%	61.0%	63.5%	64.3%	65.7%
Cheby	38.0%	52.0%	62.4%	70.8%	74.1%
GCN	50.6%	58.4%	70.0%	75.7%	76.5%
GAT	49.0%	60.7%	72.8%	77.7%	79.7%
Co-training	53.9%	57.0%	69.7%	74.8%	75.6%
Self-training	56.8%	60.4%	71.7%	76.8%	77.7%
MultiStage	61.1%	63.7%	74.4%	76.1%	77.2%
M3S	61.5%	67.2%	75.6%	77.8%	78.0%
FASG	**62.8%**	**68.5%**	**76.1%**	**78.0%**	**80.3%**

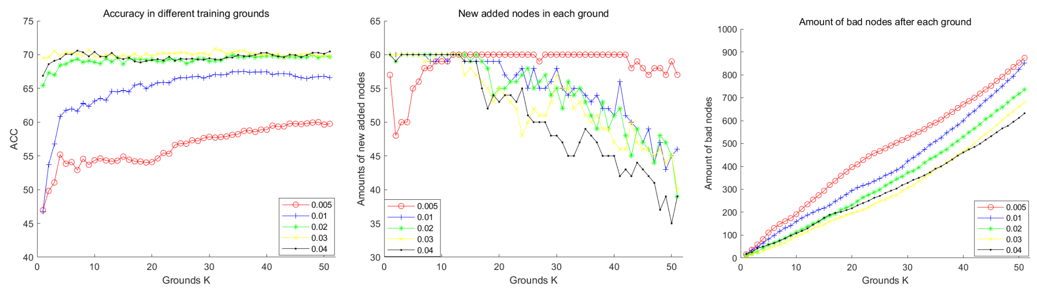
Table 4: Comparison of prediction accuracy on CiteSeer dataset

Label Rate	**0.5%**	**1%**	**2%**	**3%**	**4%**
Node2Vec	24.9%	29.1%	34.4%	35.7%	38.8%
LP	37.7%	41.6%	41.9%	44.4%	44.8%
Cheby	31.7%	42.8%	59.9%	66.2%	68.3%
GCN	44.8%	54.7%	61.2%	67.0%	69.0%
GAT	44.6%	53.7%	64.6%	66.4%	69.3%
Co-training	42.0%	50.0%	58.3%	64.7%	65.3%
Self-training	51.4%	57.1%	64.1%	67.8%	68.8%
MultiStage	53.0%	57.8%	63.8%	68.0%	69.0%
M3S	56.1%	62.1%	66.4%	70.3%	70.5%
FASG	**58.3%**	**66.4%**	**70.2%**	**70.3%**	**70.8%**

The comparison of these algorithms on the three benchmarks is summarized in Tables 3, 4 and 5 respectively. It is observed that GNN-based approaches surpass traditional learning approaches in general on all three datasets. By adopting multi-rounds training strategy and expanding the supervised information iteratively, the algorithms based on self-training mechanism achieve remarkable improvement in prediction accuracy, especially when the label rate is quite small. Furthermore, the proposed FASG algorithm outperforms all baseline algorithms in all tested scenarios. The superiority of our method derives from the delicate checking part based feature aggregation, which is able to guarantee the high quality of the expanded supervised information as illustrated in Fig. 2.

5.3 Ablation Studies

5.3.1 The number of training rounds



(a) Accuracy (b) New added nodes (c) Bad training nodes

Figure 4: Accuracy, new added nodes and bad training nodes in each round

Table 5: Comparison of prediction accuracy on PubMed dataset

Label Rate	**0.03%**	**0.05%**	**0.1%**
Node2Vec	37.2%	38.2%	42.9%
LP	58.3%	61.3%	63.8%
Cheby	40.4%	47.3%	51.2%
GCN	51.1%	58.0%	67.5%
GAT	50.6%	59.1%	65.0%
Co-training	55.5%	61.6%	67.8%
Self-training	56.3%	63.6%	70.0%
MultiStage	57.4%	64.3%	70.2%
M3S	59.2%	64.4%	70.6%
FASC	**60.1%**	**65.2%**	**70.7%**

In order to reveal how our algorithm is affected by the number of training rounds K, we report the numbers of newly added nodes, bad training nodes and the prediction accuracy on the CiteSeer dataset for different label rates with increasing K from 0 to 50. Note that when K is 0, the framework degrades to the plain GCN model. As shown in Fig. 4(a), accuracies grow rapidly during the first few rounds for all label rates. For a small label rate (e.g. 0.005), the accuracy tends to grow continuously with K increasing. On the contrary, for a relatively large label rate (e.g. 0.04) the accuracy will reach the peak rapidly with a small K and saturate afterward.

Fig. 4(b) shows the number of newly added nodes after each training round, which is consistent with the change of the accuracy in Fig. 4(a). There are numbers of newly nodes that are expanded as supervision information at each round for a small label rate, so the accuracy is improved continuously. While, for a relatively large label rate, the number of newly added nodes drops markedly after a few training rounds, which results in the saturation of the accuracy.

Table 6: Performance of our framework integrated with different base GNN models

GNN Model	**GCN**	**GAT**	**APPNP**	**GS-M**	**GS-P**
Acc of normal GNN	44.8%	46.8%	45.7%	40.9%	34.9%
Acc in our framework	58.3%	59.8%	57.6%	59.1%	51.0%

5.3.2 Integration with different base GCN models

As described in Sec. 4.3, the proposed FASG algorithm can be integrated with various base GCN models to improve their prediction performances. For validation, we combine FASG with several popular GCN models, and report their prediction accuracy on the CiteSeer dataset with label rate 0.5% in Table 6, where GS-M and GS-P represent GraphSage with mean and maxpool aggregator respectively. It is shown that all tested base GCN models achieve similar performances, and they are all benefitted significantly in prediction accuracy by applying our FASG to expand supervised information iteratively.

6 Conclusion

In this paper, we firstly analyzed the limitations of plain GCN models in dealing with semi-supervised node classification tasks, and subsequently proposed a feature aggregation self-training GCN algorithm aiming to improve the prediction accuracy. Our algorithm iteratively expand reliable nodes into the supervised set by checking both the GCN outputs and the pseudo-labels of nodes that are generated through applying a linear SVM classifier on the aggregated features. This checking mechanism is able to provide supervised information of better quality than previous methods and boosts the final node classification significantly. In experiments, the proposed algorithm outperforms state-of-the-art baseline algorithms in general on all tested benchmarks, especially when the ratio of labeled nodes is quite small.

REFERENCES

Joan Bruna, Wojciech Zaremba, Arthur Szlam, and Yann LeCun. Spectral networks and locally connected networks on graphs. *arXiv preprint arXiv:1312.6203*, 2013.

Mathilde Caron, Piotr Bojanowski, Armand Joulin, and Matthijs Douze. Deep clustering for unsupervised learning of visual features. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pp. 132–149, 2018.

Corinna Cortes and Vladimir Vapnik. Support-vector networks. *Machine learning*, 20(3):273–297, 1995.

Michaël Defferrard, Xavier Bresson, and Pierre Vandergheynst. Convolutional neural networks on graphs with fast localized spectral filtering. In *Advances in neural information processing systems*, pp. 3844–3852, 2016.

Vijay Prakash Dwivedi, Chaitanya K Joshi, Thomas Laurent, Yoshua Bengio, and Xavier Bresson. Benchmarking graph neural networks. *arXiv preprint arXiv:2003.00982*, 2020.

Aditya Grover and Jure Leskovec. node2vec: Scalable feature learning for networks. In *Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 855–864, 2016.

Ehsan Hajiramezanali, Arman Hasanzadeh, Krishna Narayanan, Nick Duffield, Mingyuan Zhou, and Xiaoning Qian. Variational graph recurrent neural networks. In *Advances in neural information processing systems*, pp. 10701–10711, 2019.

Will Hamilton, Zhitao Ying, and Jure Leskovec. Inductive representation learning on large graphs. In *Advances in neural information processing systems*, pp. 1024–1034, 2017.

Marti Hearst. Noun homograph disambiguation using local context in large text corpora. *Using Corpora*, pp. 185–188, 1991.

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

Johannes Klicpera, Aleksandar Bojchevski, and Stephan Günnemann. Predict then propagate: Graph neural networks meet personalized pagerank. *arXiv preprint arXiv:1810.05997*, 2018.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pp. 1097–1105, 2012.

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

Guohao Li, Matthias Muller, Ali Thabet, and Bernard Ghanem. Deepgcns: Can gcns go as deep as cnns? In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 9267–9276, 2019.

Qimai Li, Zhichao Han, and Xiao-Ming Wu. Deeper insights into graph convolutional networks for semi-supervised learning. *arXiv preprint arXiv:1801.07606*, 2018.

Laurens van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of machine learning research*, 9(Nov):2579–2605, 2008.

Shirui Pan, Ruiqi Hu, Guodong Long, Jing Jiang, Lina Yao, and Chengqi Zhang. Adversarially regularized graph autoencoder for graph embedding. *arXiv preprint arXiv:1802.04407*, 2018.

Bryan Perozzi, Rami Al-Rfou, and Steven Skiena. Deepwalk: Online learning of social representations. In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 701–710, 2014.

Ellen Riloff, Rosie Jones, et al. Learning dictionaries for information extraction by multi-level bootstrapping. In *AAAI/IAAI*, pp. 474–479, 1999.

Chuck Rosenberg, Martial Hebert, and Henry Schneiderman. Semi-supervised self-training of object detection models. 2005.

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

Pierre Sermanet, Soumith Chintala, and Yann LeCun. Convolutional neural networks applied to house numbers digit classification. In *Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012)*, pp. 3288–3291. IEEE, 2012.

Ke Sun, Zhanxing Zhu, and Zhouchen Lin. Multi-stage self-supervised learning for graph convolutional networks. *arXiv preprint arXiv:1902.11038*, 2019.

Vincent Van Asch and Walter Daelemans. Predicting the effectiveness of self-training: Application to sentiment classification. *arXiv preprint arXiv:1601.03288*, 2016.

Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. Graph attention networks. *arXiv preprint arXiv:1710.10903*, 2017.

Minjie Wang, Lingfan Yu, Da Zheng, Quan Gan, Yu Gai, Zihao Ye, Mufei Li, Jinjing Zhou, Qi Huang, Chao Ma, et al. Deep graph library: Towards efficient and scalable deep learning on graphs. *arXiv preprint arXiv:1909.01315*, 2019.

Felix Wu, Tianyi Zhang, Amauri Holanda de Souza Jr, Christopher Fifty, Tao Yu, and Kilian Q Weinberger. Simplifying graph convolutional networks. *arXiv preprint arXiv:1902.07153*, 2019.

Xiao-Ming Wu, Zhenguo Li, Anthony M So, John Wright, and Shih-Fu Chang. Learning with partially absorbing random walks. In *Advances in neural information processing systems*, pp. 3077–3085, 2012.

Keyulu Xu, Weihua Hu, Jure Leskovec, and Stefanie Jegelka. How powerful are graph neural networks? *arXiv preprint arXiv:1810.00826*, 2018.

Han Yang, Xiao Yan, Xinyan Dai, and James Cheng. Self-enhanced gnn: Improving graph neural networks using model outputs. *arXiv preprint arXiv:2002.07518*, 2020.

Ziang Zhou, Shenzhong Zhang, and Zengfeng Huang. Dynamic self-training framework for graph convolutional networks. *arXiv preprint arXiv:1910.02684*, 2019.