AdaGCN: Adaptive Boosting Algorithm for Graph Convolutional Networks on Imbalanced Node Classification

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Abstract The Graph Neural Network (GNN) has achieved remarkable success in graph data representation. However, the previous work only considered the ideal balanced dataset, and the practical imbalanced dataset was rarely considered, which, on the contrary, is of more significance for the application of GNN. Traditional methods such as resampling, reweighting and synthetic samples that deal with imbalanced datasets are no longer applicable in GNN. Ensemble models can handle imbalanced datasets better compared with single estimator. Besides, ensemble learning can achieve higher estimation accuracy and has better reliability compared with the single estimator. In this paper, we propose an ensemble model called AdaGCN, which uses a Graph Convolutional Network (GCN) as the base estimator during adaptive boosting. In AdaGCN, a higher weight will be set for the training samples that are not properly classified by the previous classifier, and transfer learning is used to reduce computational cost and increase fitting capability. Experiments show that the AdaGCN model we proposed achieves better performance than GCN, GraphSAGE, GAT, N-GCN.
and the most of advanced reweighting and resampling methods on synthetic imbalanced datasets, with an average improvement of 4.3%. Our model also improves state-of-the-art baselines on all of the challenging node classification tasks we consider: Cora, Citeseer, Pubmed, and NELL.

**Keywords** Graph Neural Network · Imbalanced datasets · Ensemble learning · Node classification

1 Introduction

GCN (Kipf and Welling, 2016) has achieved remarkable success in multiple graph data-related tasks, including recommendation system (Yu and Qin, 2020; Chen et al., 2020), molecular recognition (Zitnik and Leskovec, 2017), traffic forecast (Bai et al., 2020), point cloud segmentation (Li et al., 2019). GCNs are based on the neighborhood aggregation scheme, which generates node embedding by combining information from neighborhoods.

Node classification is a fundamental problem in graph data analysis, and the goal is to predict unknown nodes through a marked graph (Kipf and Welling, 2016; Rong et al., 2019). GCNs achieve promising performance in solving node classification problems compared with conventional methods, but it is adversely affected by dataset imbalance. However, previous studies on GCNs have been all aimed at balanced datasets, and they did not consider the problem of imbalanced datasets.

In the field of machine learning, the processing of imbalanced data sets has always been a difficulty (Taherkhani et al., 2020; Carlson et al., 2010). Imbalanced dataset distribution will make the model’s fitting ability insufficient because it’s difficult for the model to learn useful information in unevenly distributed datasets (Japkowicz and Stephen, 2002). A balanced dataset consists of almost the same number of training samples in each class. In reality, it is difficult to get the same number of training samples of different classes because the data of different classes generally will not be ideally uniform distribution (Japkowicz and Stephen, 2002; Han et al., 2005). There are many possible reasons for the imbalance of training dataset categories, such as deviation sampling and measurement errors. Samples may be collected from narrow geographical areas or from a specific time period, and samples may be collected in different areas and at different times, with a completely different sample type distribution. A large number of datasets used in deep learning research, *e.g.*, ImageNet ILSVRC 2012 (Russakovsky et al., 2015), MS COCO (Lin et al., 2014) and Places Database (Zhou et al., 2018), etc., are balanced datasets, in which the amount of data in different categories is basically the same. In recent years, more and more imbalanced datasets reflecting real-world challenges have been built and released, *e.g.*, iNaturalist (Cui et al., 2018), LVIS (Gupta et al., 2019) and RPC (Wei et al., 2019). Traditional pattern recognition methods are challenging to achieve good results on imbalanced datasets, so methods that can deal with imbalanced datasets are needed.

For imbalanced datasets, additional processing is carried out to reduce the adverse effects brought by the imbalance (Japkowicz and Stephen, 2002). The previous machine learning methods mainly consists of resampling, data synthesis and reweighting. 1) Resampling is based on the original data to samples, including undersampling and oversampling. Undersampling is removing part of most class data so that majority class data can be matched with the minority class data. Oversampling is copying the minority class data. 2) Data synthesis, *i.e.*, SMOTE (Chawla et al., 2002) and its improved algorithm (Ramentol et al., 2011; Douzas and Baçao, 2019; Han et al., 2005) or other minority class synthesis method (He et al., 2008), makes the new sample artificially by analyzing the minority class samples. 3) Reweighting assigns different weights to different samples in the loss function to improve the performance of the model on imbalanced datasets.
In the GNN, the previous processing method of imbalanced datasets in machine learning is not applicable. 1) The data distribution problem of imbalanced datasets can’t be overcome by resampling. Using oversampling, the model may introduce a large number of repeated samples, which reduces the training speed and leads to overfitting easily. In the case of undersampling, valuable samples that are important to feature learning may be discarded, making it difficult for the model to learn the actual data distribution. 2) Using the method of data synthesis or oversampling, the connection relationship between the newly generated samples and the previous samples in the GNN is missing, which will affect the aggregation process of nodes. 3) Reweighting, as Focal Loss (Lin et al., 2017), CB Focal Loss (Cui et al., 2019) and etc, can solve the task of GCN on imbalanced dataset to some extent, but it fails to consider the connection relationship between training samples to achieve a good effect in dealing with imbalanced datasets.

Ensemble learning methods are more effective in enhancing the classification performance of imbalanced data than data sampling techniques (Khoshgoftaar et al., 2015). It is difficult for a single model to accurately predict rare and few points on an imbalanced dataset, and overall performance is limited. Ensemble learning is a learning process of aggregating multiple base classifiers to improve the generalization ability of classifiers. The ensemble approach shows significant improvement in the accuracy of classical machine learning methods. Briefly, ensemble learning uses multiple weak classifiers to predict the dataset. Inspired by ensemble learning, we propose an ensemble GCN classifier that can deal with the imbalanced dataset. The AdaBoost algorithm is combined with GCN, which trains GCN classifiers by serialization and reweights the samples according to the calculation results, thereby improving the classification performance of GCN on the imbalanced dataset. The main contributions of this paper are as follows:

- We were the first to study the GCN imbalanced dataset problem. We propose an AdaGCN model to take care of imbalanced datasets in semi-supervised nodes classification. Also, a transfer learning strategy is applied for our AdaGCN model’s training to reduce the training times.
- We constructed four imbalanced datasets based on the four benchmark datasets our model evaluated on, and our proposed model achieves superior performance over previous competing approaches.
- We discuss the effect of ensemble learning on the robustness of GCN and further discover that ensemble learning can significantly promote the robustness of GCN.

The rest of this paper is organized as follows. Sect. 2 introduces the related work of dealing with imbalanced data sets and the application of integrated learning in deep learning. In Sect. 3, we discuss the proposed principle of AdaGCN. Then, the experimental results are discussed in Sect. 4. The experimental Section describes four data sets and a proposed method for evaluating the performance of the experiment. Finally, we conclude with our contributions in Sect. 5.

2 Related works

Due to the prevalence of imbalanced data in practical applications, imbalanced data sets have attracted more and more attention. Recent researches mainly have the following three directions:

2.1 Resampling

Resampling can be specifically divided into two types: 1) Oversampling by copying data in minority classes (Byrd and Lipton, 2019; Buda et al., 2018). Because some samples will be repeated in
the dataset after oversampling, the model could not learn more robust, and the generalization performance will be worse on imbalanced data. 2) Undersampling by selecting data in the majority class (Byrd and Lipton, 2019; Buda et al., 2018). Undersampling may cause major class information loss. The model only learns a part of the overall pattern, which may lead to underfitting (Shen and Lin, 2016). K-means and stratified random sampling to undersample (KSS) (Zhou et al., 2020) performs undersampling after K-means clustering for most classes, and good results have been obtained.

2.2 Synthetic samples

The method of data synthesis is to use the existing samples to generate more samples similar to a few samples. Among this method, the classic is SMOTE (Chawla et al., 2002). The specific method is as follows: for each sample in a small sample set, a random sample is selected from its K-nearest neighbor, and then a random point on the line between the sample and the selected sample is selected as a new sample. However, the overlapping degree will be increased by synthesizing the same number of new samples for each minority sample. The Borderline-SMOTE (Han et al., 2005) synthesizes the new sample to minority classes of samples that are on the classification boundary. SMOTE-RSB* (Ramentol et al., 2011) using the synthetic minority oversampling technique together with the editing technique based on the rough set theory. G-SMOTE (Douzas and Baçao, 2019) generates a synthetic sample around each of the selected few instances in a geometric region of the input space. ADASYN (He et al., 2008) algorithm synthesizes different number of new samples for different minority samples.

2.3 Reweighting

Reweighting typically assigns different weights to different samples in the loss function. In general, reweighting assigns large weights to minority classes of training samples (Wang et al., 2017). In addition, finer control of loss can be achieved at the sample level. For example, Focal Loss (Lin et al., 2017) designed a weight adjustment scheme to improve the imbalanced dataset classification performance. CB Focal Loss (Cui et al., 2019) introduced a weight factor inversely proportional to the effective sample number, used the effective sample number of each class to rebalance the loss, and reached the most advanced level in the imbalanced dataset.

In addition, there are transfer learning, domain adaptation and other methods to cope with imbalanced datasets. The method based on transfer learning solves the problem of imbalanced training data by transferring the characteristics learned from most classes to minority classes (Yin et al., 2019). Domain adaptive method processes different types of data and can learn how to reweight adaptively (Zou et al., 2018). These methods are beyond the scope of this article.

2.4 Ensemble classifiers

Ensemble classifiers are more effective than sampling methods to deal with the imbalance problem (Khoshgoftaar et al., 2015). Some approaches adopted resampling approaches to balance the data before training it with the base classifiers. The combination of data level techniques with ensemble algorithms resulted in better performance. The used ensemble method could be divided
into boosting-based ensembles and bagging-based ensembles. SMOTEBoost (Chawla et al., 2003) combine SMOTE with AdaBoost.M2 (Schapire and Singer, 1998), and shows improvement in prediction performance on the minority class. After training a classifier, the weights of the original dataset samples are updated. In each round, the weights for minority class examples are increased. RUSBoost (Seiffert et al., 2010) combines data sampling and boosting, and further improves the performance of SMOTEBoost. EUSBoost (Galar et al., 2013) combines random undersampling with boosting algorithm based on RUSBoost, enhancing the base classifiers’ performance by using the evolutionary undersampling approach. There are also plenty of bagging-based ensembles to handle the class imbalance problem. Neighbourhood Balanced Bagging (Blaszczyński and Stefanowski, 2015), in which sampling probabilities of examples are modified according to their neighborhood’s class distribution. UnderOverBagging (Nanni et al., 2015) is a combination of UnderBagging and OverBagging, in which the small classes are oversampled and large classes are undersampled. The resampling scale is determined by the ratio of the minimum class size and the maximum class size.

There are also methods to ensemble model directly. (Hai-xiang et al., 2016) proposes using KNN as the basic classifier to generate a boosting classifier, which improves the accuracy of multi-class imbalanced data classification problems. In AdaBoost-CNN (Taherkhani et al., 2020), AdaBoost is integrated with a CNN to improved accuracy on imbalanced data.

Although few studies on ensemble models in the GNN, many GNN models have already adopted the ensemble ideas. N-GCN (Abu-El-Haija et al., 2019a) obtains the feature representation of nodes by convolving in the neighborhood of nodes of different scales and then fusing all the convolution results. MixHop (Abu-El-Haija et al., 2019b) learns node characteristics by repeatedly mixing the characteristic representations of neighbors at different distances. These methods can be regarded as an ensemble model.

3 The Proposed Method
3.1 GCN model

Given the input undirected graph $G = \{V, E\}$, where $V$ and $E$ separately denote the set of $N$ nodes and the set of $e$ edges. The corresponding adjacency matrix $A \in \mathbb{R}^{N \times N}$ is an $N \times N$ sparse matrix describing its edge with $(i, j)$ entry equaling to 1 if there is an edge between $i$ and $j$, and 0 otherwise. The degree matrix $D$ is a diagonal matrix where each entry on the diagonal is equal to the degree of vertex, can be computed as $d_i = \sum_j a_{ij}$. Each node is associated with an $F$-dimensional feature vector and $X \in \mathbb{R}^{N \times F}$ denotes the feature matrix for all nodes. GCN model of semi-supervised classification with two layers (Kipf and Welling, 2016), in which every layer computes the transformation:

$$H^{(l+1)} = \sigma(Z^{(l+1)}), Z^{(l+1)} = \hat{A}H^{(l)}W^{(l)}$$

(1)

Where $\hat{A}$ is normalized adjacency obtained by $\hat{A} = D^{-\frac{1}{2}}AD^{-\frac{1}{2}}$. $W^{(l)}$ is the layer’s trainable weights. $\sigma(\cdot)$ denotes an activation function (usually ReLU), $H^{(l)} \in \mathbb{R}^{N \times d_l}$ is the input activation matrix to the $l$th hidden layer, where each row represents a $d_l$-dimensional node representation vector. The initial node representations are just the original input features:

$$H^{(0)} = X$$

(2)

Two-layer GCN model can be defined in terms of vertex features $X$ and $\hat{A}$ as:
$\text{GCN}_{2\text{-layer}}(\hat{A}, X; \theta) = \text{softmax}(\hat{A} \cdot \sigma(\hat{A}XW(0))W(1))$  

(3)

The GCN is trained by the back propagation learning algorithm. The last layer uses the softmax function for classification, we evaluate the cross-entropy loss over all labeled examples:

$$L = -\sum_{|Y_L| \in \mathcal{Y}_L} \sum \text{loss}(y_i, z^L_i)$$  

(4)

Formally, given a dataset with $n$ entities $(X, Y) = \{(x_i, y_i)\}_{i=1}^N$ where $x_i$ represents the word embedding for entity $i$ and $y_i \in \{1, \cdots, C\}$ represents its label. Multiple weak classifiers are combined with AdaBoost techniques to make a single strong classifier.

3.2 Proposed Algorithm

**Aggregation**

AdaGCN aggregates GCN through AdaBoost algorithm, which can improve the performance on imbalanced datasets. First, the overall formula of AdaGCN can be expressed as:

$$F_M(x) = \sum_{m=1}^M \alpha_m \cdot G_m(x; \theta_m)$$  

(5)

Where $F_M(x)$ is the ensemble classifier obtained after $M$ rounds of training. Train a new GCN classifier $G_m(x; \theta_m)$ in each round, $\theta_m$ is the optimal parameter learned by the base classifier. The weight of the classifier $\alpha_m$ denotes the importance of classifier and could be obtained according to the error of the classifier. According to (5), Formula (6) can be obtained:

$$F_m(x) = F_{m-1}(x) + \alpha_m \cdot G_m(x; \theta_m)$$  

(6)

$F_{m-1}(x)$ is the weighted aggregation of the previously trained base classifier. In each iteration, the new base classifier $G_m(x; \theta_m)$ and its weights $\alpha_m$ are solved. AdaGCN uses an exponential loss function:

$$L(y, F(x)) = e^{-y \cdot F(x)}$$  

(7)

The above loss function, when the classification is correct, the exponent part is a negative number; when the classification is wrong, the exponent part is a positive number, which conforms to the meaning of the loss function. When training the base classifier, suppose the training dataset is $T = \{(x_i, y_i)\}_{i=1}^N$, $x_i$ is the feature vector of the $i$th node, and $y_i$ is the category label of the $i$th node, $y_i \in \{1, ..., C\}$, Where $C$ is the total number of classes.
Reweight Samples

Assume that during the first training, the samples are evenly distributed and all weights are the same. The data weights are initialized by:

$$D_1 = \{w_1^1, w_1^2, \ldots, w_N^1\}.$$ Where $w_i^1 = 1/N, i = 1, \ldots, N$. $N$ is the number of samples. Train $M$ networks in sequence on the training set, and the expected loss $\varepsilon_m$ at the $m$th iteration is:

$$\varepsilon_m = \sum_{y_i \neq G_m(x_i; \theta_m)} w_i^m \Pi(y_i \neq G_m(x_i; \theta_m))$$ (8)

$\Pi(\cdot)$ is the indicator function. When the input is true, the function value is 1, and when the input is false, the function value is 0. $\varepsilon_m$ is the sum of the weights of all misclassified samples.

$\alpha_m$ can be treated as a hyper-parameter to be tuned manually, or as a model parameter to be optimized automatically. In our module, to keep it simply, $\alpha_m$ is assigned according to $\varepsilon_m$.

$$\alpha_m = \frac{1}{2} \ln \frac{1 - \varepsilon_m}{\varepsilon_m}$$ (9)

$\alpha_m$ decreases as $\varepsilon_m$ increases. The first GCN is trained on all the training samples with the same weight of $1/N$. The importance of all samples is the same. After training the $M$ estimators, the output of GCN can be obtained, which is a $C$-dimensional vector. The vector contains the predicted values of $C$ classes, and the predicted values respectively indicate the confidence of belonging to the corresponding category. When the $m$th GCN input sample is $x_i$, the output vector is $p_m(x_i)$, $p_k^m(x_i)$ is the $k$th element of $p_m^m(x_i)$, where $k = 1, 2, \ldots, C$.

$$w_i^{m+1} = w_i^m e^{\left( -\frac{1}{C} y_i \log(p_m^m(x_i)) \right)}$$ (10)

$w_i^m$ is the weight of the $i$th training sample of the $m$th GCN. $y_i$ is the one-hot label vector encoded according to the $i$th training sample. Formula (10) is obtained according to Adaboost’s Samme.r algorithm (Hastie et al., 2009), which is used to update the sample weight. If the output vector of the misclassified sample is not related to the output label, the exponential term will get a large value, and the misclassified sample will get a larger sample weight in the next GCN classifier. Similarly, a properly classified sample will get a smaller sample weight in the next GCN classifier. In summary, the weight vector $D$ is updated to reduce the weight of the correctly classified samples and increase the weight of the misclassified samples.

After updating the weights of all training samples for the current GCN, they are normalized by dividing the overall sum of their weights. When the classifier is $F_m(x)$, the training dataset’s weight distribution is updated for the next iteration. When training the subsequent GCN-based classifier, instead of starting the GCN training from a random initial condition, the parameters learned from the previous GCN are transferred to the $(m+1)$th GCN. GCN is fine-tuned based on the previous GCN parameters. The use of transfer learning can reduce the number of training rounds and make the model fit faster.

Moreover, due to the change of sample weight, the subsequent GCN focuses on untrained samples. The subsequent GCN performs complete training from scratch on a small number of training samples, which easily causes GCN to overfit a small dataset. For a large number of training samples, after training, the expected label output $p^m(x_i)$ by the GCN has a strong correlation with the real label $y_i$. In the subsequent GCN classifier, the trained sample’s weight has a smaller value than the sample without previous GCN training. Use transfer learning to avoid overfitting on small datasets.
Testing with AdaGCN

After training the $M$ base classification predictors, Equation (11) can be used to predict the category of the input sample. The outputs of $M$ base classifiers are summed. In the summed probability vector, the category with the highest confidence is the predicted category.

$$Q(x) = \arg\max_k \sum_{m=1}^M h^m_k(x)$$  \hspace{1cm} (11)

$h^m_k$ is the prediction probability of the $m$th basis classifier for the $k$th sample, $k = 1, 2, \ldots, C$, which can be calculated from the Equation (12).

$$h^m_k = (C - 1) \cdot \left( \log (p^m_k(x)) - \frac{1}{C} \sum_{i=1}^C \log (p^m_i(x)) \right)$$  \hspace{1cm} (12)

Where $p^m_k(x)$ is the $k$th element of the output vector of the $m$th GCN classifier when the input is $x$. Fig. 1 shows the schematic of the proposed AdaGCN. The first GCN is first trained using the initial sample weight $D_1$. Then, based on the output of the first GCN, the data weights that $D_2$ uses to update the second GCN are obtained, in addition, the parameters learned from the first GCN are transferred to the second GCN. After the $m$th base classifier was trained in order, all base classifiers were aggregated to obtain the final AdaGCN classifier.

Fig. 1: Schematic of the proposed AdaGCN

The pseudo-code for an AdaGCN is shown in Algorithm 1. In each iteration of sequential learning, the corresponding classifiers are first trained using training data and corresponding data weights. Then, according to the results of the classifier after training, the data weights are updated for the next iteration. Perform both operations until $M$ base classifiers are trained.
Algorithm 1 Framework of the AdaGCN algorithm.

**Input:** Training set \( T = \{ (x_1, y_1), \ldots, (x_N, y_N) \} \);

**Output:** Ensemble of classifiers \( F_M(x) \);

1. Initialization: \( w_i^1 = 1/N \) for all \( 1 \leq i \leq N \)
2. for \( m = 1, 2, \cdots, N \) do;
3. \hspace{1em} if \( m = 1 \) then
4. \hspace{2em} Train GCN classifier with weighted sample set \( \{ T, D_1 \} \);
5. \hspace{1em} else
6. \hspace{2em} Transfer the learning parameters of the \( m-1 \)th GCN to the \( m \)th GCN classifier;
7. \hspace{2em} Train the \( m \)th GCN classifier with weighted sample set;
8. \hspace{1em} end if
9. \hspace{1em} Calculate the output category estimate for the \( C \) classes of the \( m \)th GCN classifier \( p_k^m(x) \), where \( k = 1, 2, \cdots, C \);
10. \hspace{1em} Calculate the training error \( \varepsilon_m \) of the \( m \)th classifier;
11. \hspace{1em} Assign the weight value \( \alpha_m \) to the classifier according to \( \varepsilon_m \);
12. \hspace{1em} Update the sample weight \( D_{m+1} \) according to \( p_k^m(x) \), and normalize the sample weight \( D_{m+1} \);
13. end for

4 Experiments and Analysis

4.1 Experimental Settings

We experimented on three well-known citation network datasets: Cora, Citeseer and Pubmed (Sen et al., 2008). The citation datasets are prepared by (Kipf and Welling, 2016). We choose the aforementioned datasets because they are available online and are used by our baselines. In addition, we also conducted experiments on the Never Ending Language Learning (NELL) dataset, NELL (Carlson et al., 2010) is a bipartite graph dataset extracted from a knowledge graph. It has a larger scale than the citation datasets, with 210 node classes.

*Citation networks*

The nodes in the citation datasets represent articles in different fields, the labels of nodes represent the corresponding journal the articles published, the edges between two nodes represent the reference relationship between articles, and if edges connect the nodes, there is a reference relationship between articles. Each node has a one-hot vector obtained by the keywords in the corresponding article. The task of categorization is to predict the domain of unlabeled articles based on a subset of tagged nodes and references to all articles.

*NELL*

NELL is the dataset extracted from the knowledge graph (Carlson et al., 2010). We adopt the preprocessing scheme as described in (Yang et al., 2016). Each relationship is represented as a triplet \( (e_1, r, e_2) \), where \( e_1, r \), and \( e_2 \) respectively represent the head entity, the relationship, and the tail entity. We treat each entity \( E \) as a node in the graph, and each relationship \( r \) is divided into two nodes \( r_1 \) and \( r_2 \) in the graph. For each \( (e_1, r, e_2) \), we add two edges \( (e_1, r_1) \) and \( (e_2, r_2) \) to the graph. We construct a binary, symmetric adjacency matrix from this graph by setting entries \( A_{ij} = 1 \), if one or more edges are present between nodes \( i \) and \( j \) (Kipf and Welling, 2016). All entity nodes are described by sparse feature vectors with dimensions of 5414. Table 1 summarizes dataset statistics.

*Synthetic imbalanced Datasets*

We construct different imbalanced datasets based on the datasets mentioned above.
Table 1: Dataset used for experiments

| Dataset | Cora | Citeseer | Pubmed | NELL |
|---------|------|----------|--------|------|
| Vertices | 2,708 | 3,327 | 19,717 | 65,755 |
| Edges   | 5,429 | 4,732 | 44,338 | 266,144 |
| Classes | 7    | 6    | 3    | 210  |
| Features| 1,433 | 3,703 | 500   | 5,414 |

In the citation datasets, we randomly selected one of the classes as the majority category and fixed the number of training samples to 30. The remaining classes are minority classes. Change the number of samples for minority classes. For example, in the Cora dataset, there are 7 types of samples, the number of samples of one type is fixed to 30, and the number of samples of the other 6 types is changed. Each time the training is conducted, a certain number of samples are randomly selected as the training set. In the knowledge graph dataset, one category was randomly selected as the majority category, and the rest were minority classes. We used the test set divided by (Kipf and Welling, 2016) to evaluate different models’ results.

Parameter Settings

In AdaGCN, 5 GCN base classifiers are used. All networks contain two layers, and we train all models for a maximum of 100 epochs (training iterations) using Adam optimizer with learning rate 0.01. Following sets of hyperparameters are used for Citeseer, Cora and Pubmed: 5e-4 (L2 regularization) and 16 (number of hidden units); and for NELL: 1e-5 (L2 regularization) and 128 (number of hidden units). For GCN, GraphSAGE, GAT and other algorithms, a total of 500 epochs were trained. Take the highest accuracy as the result of a single experiment, mean accuracy of 10 runs with random sample split initializations. We use a different random seed for every run (i.e. removing different features per node), but the same 10 random seeds across models.

All the experiments are conducted on a machine with two NVIDIA Tesla V100 GPU (32 GB memory), 20-core Intel Xeon CPU (2.20 GHz), and 192 GB of RAM.

4.2 Baseline Methods

To evaluate the performance of the proposed method, we compare it with three groups of methods:

**GCN methods**

In experiments, we compare our AdaGCN model with the following representative baselines:

- GCN (Chawla et al., 2002) produces node embedding vectors by truncating the Chebyshev polynomial to the first-order neighborhoods.
- GAT (Velickovic et al., 2018) generates node embedding vectors for each node by introduce an attention mechanism when computing node and its neighboring nodes.
- GraphSAGE (Hamilton et al., 2017) generate the embedding vector of the target vertex by learning a function that aggregates neighbor vertices. We use the default settings of sampled sizes for each layer ($S_1 = 25$, $S_2 = 10$) in GraphSAGE.
- N-GCN (Abu-El-Haija et al., 2019a) obtains the feature representation of the node by convolving at different neighbor scales, and then fusing the convolution results of all scales.

We employ training with cross-entropy loss as our baselines in above models.
**RS method**
We use KSS (Zhou et al., 2020) method to be compared with, which is a kind of $K$-means clustering based undersampling that achieve state-of-the-art on an imbalanced medical dataset.

**RE method**
We compare AdaGCN with GCN, GraphSAGE, GAT these classic models using Focal Loss (Lin et al., 2017) and CB-Focal Loss (Cui et al., 2019) which achieve good classification accuracy on imbalanced datasets.

### 4.3 Node Classification Accuracy
We implement our method in Keras. For the other methods, we use all the original papers’ code from their github pages. On synthetic imbalanced datasets, when the number of training samples for majority class is 30 and the number of training samples for minority classes is 10, the classification accuracy of methods N-GCN, GCN, GraphSAGE, GAT and AdaGCN are shown in the Table 2.

| Model      | Cora    | Citeseer | Pubmed | NELL    |
|------------|---------|----------|--------|---------|
| N-GCN      | 67.3±0.6| 65.4±0.3 | 72.3±0.3| 73.3±1.2|
| GCN        | 65.6±0.8| 62.2±0.5 | 72.8±0.6| 68.5±1.4|
| GraphSAGE  | 66.3±0.8| 59.7±0.6 | 69.7±0.6| 69.6±1.3|
| GAT        | 67.4±0.7| 60.3±0.6 | 66.2±0.7| 70.3±1.6|
| GCN-FL     | 67.8±1.2| 65.1±0.8 | 72.4±0.8| 72.2±1.4|
| GraphSAGE-FL| 66.5±1.2| 59.5±0.8 | 69.7±1.3| 72.1±1.1|
| GAT-FL     | 67.4±1.3| 61.3±0.7 | 69.2±1.2| 72.6±1.0|
| GCN-CB     | 70.6±0.9| 65.1±0.6 | 75.7±0.8| 72.9±1.4|
| GraphSAGE-CB| 66.3±0.9| 59.7±0.9 | 72.7±0.9| 69.8±1.4|
| GAT-CB     | 67.6±1.0| 60.3±1.0 | 73.2±0.9| 73.4±1.5|
| GCN-RE     | 70.4±1.0| 61.8±1.1 | 70.4±1.1| 68.9±2.1|
| AdaGCN     | 73.2±0.7| 65.7±0.7 | 73.1±0.7| 74.9±1.0|

Results in Table 2 shows that AdaGCN outperforms the classic GNN models and state-of-the-arts imbalanced datasets processing methods.

Implementation details are as following: As divided in (Kipf and Welling, 2016), 500 nodes are used as the validation set and 1000 nodes as the test set. We use a two-layer GNN, and the activation function is ReLU. For a more balanced comparison, however, we use the same training procedure for all the models.

### 4.4 Effect of different levels of imbalance in the training data
We change the levels of imbalance in the training data by gradually increasing the number of samples of minority classes from 1 to 10. We compared the evaluation results with GCN, GraphSAGE, GAT, and the results were shown in Fig. 2.
Fig. 2: The classification accuracy for GCN, GraphSAGE, GAT and AdaGCN on imbalanced datasets.

Results in Fig. 2 show that models’ classification accuracy varies with the minority classes' sample number. When the number of samples of minority classes was relatively small, the degree of imbalance in the training data was large, the classification accuracy of AdaGCN was higher than that of GCN, GraphSAGE and GAT. As the numbers of minority categories' samples decrease, advantages of AdaGCN increase gradually. Experiments show that when the sample imbalance is large, aggregation can significantly reduce the sample imbalance’s adverse effects and improve the classification accuracy. The accuracy of AdaGCN exceeds GCN, GraphSAGE, and GAT by 7.5%, 6.4%, and 6.2% respectively at most on Cora dataset.
4.5 Impact of numbers of base estimators

We changed the number of base estimators, tested the classification accuracy on imbalanced datasets with different base estimators, and compared with the classification results of GCN.

The experimental results show that aggregation can lead to performance improvements. As the number of base classifiers increases, the performance improvement is more and more significant. The number of base classifiers increases from 3 to 11, and the number of base classifiers is odd. The data of Cora, Pubmed and Citeseer were verified, and the division of train set and test set was the same as that of Sect. 4.3. Ten experiments were conducted, with 100 epochs and 200 epochs trained for each base estimators. We randomly selected training samples for each experiment, and Table 3 showed the experiment’s average results.

Table 3: Results of AdaGCN with varying numbers of base estimators in terms of accuracy (in percent).

| Numbers of base estimators | epoch:100   | epoch:200   |
|----------------------------|-------------|-------------|
|                            | Cora Citeseer Pubmed Cora Citeseer Pubmed |
| 3                          | 75.7±2.4 65.5±2.5 63.9±2.4 | 75.4±2.1 65.6±1.1 72.0±0.8 |
| 5                          | 73.2±0.7 65.7±0.7 73.1±0.7 | 75.6±2.3 65.9±0.5 73.1±1.1 |
| 7                          | 73.5±1.4 64.5±0.5 73.5±1.4 | 74.1±2.7 64.7±0.4 73.5±0.8 |
| 9                          | 72.0±0.5 63.6±0.5 72.0±0.5 | 73.9±2.0 64.2±0.3 72.6±1.1 |
| 11                         | 73.0±0.7 64.5±0.6 73.0±0.7 | 74.1±2.3 65.1±0.3 71.5±0.7 |

To sum up, when the number of base classifiers is small, the classification accuracy increases with the number of base classifiers. When the number of base classifiers reaches a certain degree, the accuracy will decrease due to overfitting.

4.6 Tolerance to feature noise

We test our method under feature noise perturbations by removing node features at random as (Abu-El-Haija et al., 2019a). This is practical, for example, in the Citation networks datasets, features could be missing as article authors might forget to include relevant terms in the article abstract. By removing different features per node, the performs of GCN, GraphSAGE, and GAT are compared.

Fig. 3 shows the performance of different methods when features are removed. As we increase the removed features, the performance is always better than GCN, GraphSAGE, and GAT. The greater the proportion of features removed, the greater the advantage of AdaGCN over other models. This suggests that our approach can restore the deleted features to some extent by pulling in features directly from nearby and distant neighbors.

4.7 Why ensemble method helped?

This Section analyzes why the ensemble learning approach works on imbalanced datasets and the advantages of AdaGCN over traditional GCN. Ensemble learning can be divided into two steps:
Fig. 3: Classification accuracy for the Cora dataset, and features removed at random, averaging 10 runs. We use a different random seed for every run (i.e. removing different features per node), but the same 10 random seeds across models.

1) Generates multiple base estimators for integration. Our model could adjust the weight of samples, adopt specific strategies to reconstruct the dataset, and assign smaller sample weights to the determined samples and larger sample weights to the uncertain samples. It makes subsequent base estimators focus more on samples that are difficult to be classified. In general, the sample of minority classes in imbalanced datasets are more likely to be misclassified. By changing the sample weights, subsequent base estimators can allocate more attention to these minority classes’ samples.

2) Combining the results of the base estimators. The weight of the classifier is obtained according to the error of the classifier. The base classifier with high classification accuracy has greater weight and has a greater influence on the final combined classifier. The base classifier with low classification accuracy has less weight and impact on the final combined classifier.

We selected 5 training samples from the Cora and Citeseer datasets respectively, and Fig. 4 visualized the selected sample weights of different base classifiers in different colors. The weights of the samples were all the same when the first base classifier was trained. After the training of the first base classifier, the weights of the training samples were adjusted. The weights of easily misclassified samples increased, and the subsequent base classifier paid more attention to these samples.
On the imbalanced datasets constructed by using the citation datasets, the last class is selected as the majority class, and the other classes are selected as the minority class. To increase the imbalance, the number of samples for the majority class was 30, and the number of samples for minority classes was 5, and 10 experiments were conducted. The confusion matrix of the experimental average results is shown in Fig. 5. Compared with the confusion matrix of the products classified by the GCN directly using the same parameters, AdaGCN has a better classification effect.

![Confusion Matrix for Cora, Citeseer, and Pubmed Datasets](image)

Due to the imbalance of category samples, the classifier tends to divide the samples to be predicted into the categories of most samples, which is reflected in the fact that the last column of the confusion matrix tends to have the maximum value (with the brightest color). Compared with GCN, AdaGCN has been improved to a certain extent, especially in Cora dataset. After the Aggregation of base estimators, The values of the diagonal increase and the values of the last column decrease.

In summary, AdaGCN integrates multiple GCN classifiers to reduce the risk of overfitting in certain degree. Moreover, AdaGCN can reduce the deviation caused by a single classifier and has better robustness. AdaGCN is an improvement of traditional GCN and makes AdaBoost compatible with GCN, and can achieve higher accuracy than a single GCN on imbalanced datasets with the same number of learning epochs.
5 Conclusion

In this paper, we proposed a multi-class AdaBoost for GCN, called AdaGCN. In the proposed method, a number of GCNs are used as base estimators. The GCNs are trained sequentially, and errors of an earlier GCN are used to update the sample weights for its next GCN. After updating the sample weights, the trained GCN learning parameters are transferred to the next GCN. Transfer learning in the proposed AdaBoost method increases accuracy. The training sample weights are incorporated to the cross-entropy error function in the GCN back propagation learning algorithm. The ability of the proposed AdaGCN in the processing imbalanced data is tested.

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