GCN-Based Linkage Prediction for Face Clustering on Imbalanced Datasets: An Empirical Study

Huafeng Yang, Xingjian Chen, Fangyi Zhang*, Guanyue Hei, Yunjie Wang and Rong Du
Alibaba Group
fduspectre@gmail.com, {philo.cxj, zhiyuan.zfy}@alibaba-inc.com

Abstract

In recent years, benefiting from the expressive power of Graph Convolutional Networks (GCNs), significant breakthroughs have been made in face clustering. However, rare attention has been paid to GCN-based clustering on imbalanced data. Although imbalance problem has been extensively studied, the impact of imbalanced data on GCN-based linkage prediction task is quite different, which would cause problems in two aspects: imbalanced linkage labels and biased graph representations. The problem of imbalanced linkage labels is similar to that in image classification task, but the latter is a particular problem in GCN-based clustering via linkage prediction. Significantly biased graph representations in training can cause catastrophic overfitting of a GCN model. To tackle these problems, we evaluate the feasibility of those existing methods for imbalanced image classification problem on graphs with extensive experiments, and present a new method to alleviate the imbalanced labels and also augment graph representations using a Reverse-Imbalance Weighted Sampling (RIWS) strategy, followed with insightful analyses and discussions. The code and a series of imbalanced benchmark datasets synthesized from MS-Celeb-1M and DeepFashion are available on https://github.com/espectre/GCNs_on_imbalanced_datasets.

1 Introduction

Face clustering is widely used in many applications such as face retrieval, face annotation and album classification. It aims to group together face images from a certain person in an unsupervised manner. Traditional clustering methods normally assume oversimplified data distribution [Wang et al., 2019b] that differ a lot from the distribution of large scale face images in the real world, therefore can hardly obtain satisfying performance.

In recent years, benefiting from the expressive power of Graph Convolutional Networks (GCNs), better performance has been obtained in large scale face clustering benchmarks like MS-Celeb-1M [Guo et al., 2016] by GCN-based solutions where GCNs are used for graph, node or edge recognition tasks and also feature embedding. L-GCN [Wang et al., 2019b] uses a GCN to predict whether a link exists between a “pivot” node and its 1-hop neighbors. Two GCNs are used in [Yang et al., 2019] to detect and segment cluster proposals. [Yang et al., 2020] also uses two GCNs to complete face clustering: one to estimate the confidence of vertices, and the other to measure the connectivity across vertices. DA-Net [Guo et al., 2020] leverages both local and non-local information to obtain better feature embedding.

Although the aforementioned methods have made significant progress, their performance is often greatly compromised when facing imbalanced data in real scenes (i.e., numbers of face samples for different persons vary in a large scale with an imbalanced distribution). To help reduce this kind of performance compromise, this paper particularly studies imbalance problems in GCN-based linkage prediction task (taking the L-GCN method as an exemplary baseline), where rare
attention has been paid.

In the past years, imbalance problems in image classification, whose nature lies in imbalanced numbers of positive and negative samples (i.e., imbalance in labels), have been extensively studied [Cui et al., 2019; Kang et al., 2019; Zhou et al., 2020]. In L-GCN, the same nature exists in the form of imbalanced positive and negative links. However, apart from the imbalance problem in labels, imbalanced data can also cause biased graph representations in L-GCN, which is particularly related to GCNs. Specifically, graphs generated from an imbalanced training set are prone to having imbalanced structures (with imbalanced numbers of same-class and different-class nodes and also edges), which is not good for model generalization (i.e., obtaining models that can handle any graph structure).

Therefore, we study the imbalance problems in GCN-based linkage prediction task from two aspects: imbalanced labels and biased graph representations. Some typical approaches to the imbalance problem for image classification are firstly adopted to address the imbalance problem in labels, with some of which show their effectiveness. To address the problems of both imbalanced labels and biased graph representations, a Reverse-Imbalance Weighted Sampling (RIWS) strategy is proposed in this paper to augment graph representations by providing more diverse structures yet maintaining a balanced overall distribution on training samples.

Fig. 1 shows some of the typical subgraph structures (mainly 1-hop nodes with their edges ignored for easier reading) constructed by RIWS, where both balanced and imbalanced structures are covered. In comparison, subgraphs constructed by the original L-GCN tend to be extremely imbalanced (Fig. 1 (a)), while subgraphs generated via normal re-sampling approaches are all prone to having absolutely balanced structures (Fig. 1 (b)), both of which are biased, towards either imbalanced or balanced. The effectiveness of the RIWS strategy is demonstrated in both face clustering (MS-Celeb-1M) and clothes clustering (DeepFashion), where steady performance gains are obtained.

In summary, this paper has three major contributions as below:

- imbalance problems in GCN-based linkage prediction tasks are studied for the first time, and a benchmark with imbalanced datasets is designed;
- typical re-sampling and re-weighting approaches for the imbalance problem in image classification are transferred to tackle the label imbalance problem in GCN-based linkage prediction task, with evaluations on their effectiveness and insightful analyses;
- a novel strategy named RIWS is proposed to tackle the problems of both imbalanced labels and biased graph representations by increasing the diversity of graph structures yet maintaining a balanced overall distribution on training samples.

2 Related Work

GCN-based face clustering. Face clustering is essential for exploiting unlabeled face data, and has been widely used in many scenarios. Traditional methods, such as K-Means [Lloyd, 1982], DBSCAN [Ester et al., 1996] and HAC [Sibson, 1973], are first applied in face clustering task. However, due to some naive assumptions (e.g., same density or convex shape for all clusters), these methods can not handle large scale face data in real world [Wang et al., 2019b]. In recent years, Graph Convolution Networks (GCNs) is becoming an increasingly powerful technique for clustering, and has achieved significant performance improvement. The graph nature of GCN makes it superior to solve non-Euclidean data related tasks. Recently, considerable research effort has been devoted to solving face clustering with GCNs, since it can capture the complex relationship between different faces.

L-GCN [Wang et al., 2019b] formulates face clustering as a linkage prediction problem. If two faces are predicted to be linked, they are clustered together. In [Yang et al., 2019], two GCN modules, namely GCN-D (detection) and GCN-S (segmentation), are exploited to cluster faces. It is a two-stage procedure, where GCN-D is utilized to select high-quality cluster proposals, and GCN-S is used to remove noises in the proposals. Similar to [Yang et al., 2019], [Yang et al., 2020] is also a two-stage solution. In the first stage, GCN-V (vertex) estimates the confidence of all vertices, and only vertices with higher confidence are selected to construct subgraph for the next stage. GCN-E (edge) serves as a connectivity estimator, similar to Linkage [Wang et al., 2019b], it outputs a score for each node in the subgraph, which indicates how likely it shares the same identity with the pivot node.

In most GCN-based face clustering methods, GCN mainly utilizes local information to enhance face features, without taking the global information into account. DA-Net [Guo et al., 2020] exploits local and non-local information through clique and chain to obtain better feature embedding.

Class imbalanced learning. Most public datasets (e.g., ImageNet [Deng et al., 2009], CIFAR [Krizhevsky et al., 2009] and MS-Celeb-1M [Guo et al., 2016]) are generally artificially balanced, which means the number of instances in every category have no much difference. However, in the real world, the data are more likely to be imbalanced distribution, which leads to great challenge. Since most of instances belong to some head classes, thus the head classes dominate the training phase, while the performance for the classes with less samples is significantly worse.

There are already numerous research focusing on imbalance problem, and we divide them into three families: re-sampling methods, re-weighting methods, and transfer learning based methods. The re-sampling strategies [Zhou et al., 2020; Wang et al., 2019a; Kang et al., 2019] mainly by over-sampling the minority samples and under-sampling the majority samples to construct balanced data distribution. According to the proportion of the samples, re-weighting methods [Chou et al., 2020; Cao et al., 2019; Cui et al., 2019; Jamal et al., 2020] assign appropriate weights by designing re-weighted loss to balance the data distribution, whose core idea lies on the intuition that tail categories should have larger loss weights. Inspired by transferring learning, some literature [Xiang et al., 2020; Liu et al., 2019; Liu et al., 2020] tries to transfer knowledge from head-classes to tail-classes to get improve the diversity of the tail classes.
In this work, we mainly focus on the imbalance problems in GCN-based linkage prediction task. To the best of our knowledge, it’s the first work related to imbalance problems in GCN-based linkage prediction task. The imbalance problems of GCN-based tasks lies on two sides, in addition to the number of nodes for each class, the diversity of subgraph structures are also imbalanced. As illustrated in Fig.1 (a), if a node is surrounded by too many nodes with the same identity, subgraph constructed based on the k-nearest neighbors (KNN) is extremely imbalanced. Although traditional re-sampling methods can reduce the imbalanced labels problem, it is invalid to the biased graph representations problem. Fortunately, the RIWS strategy proposed in this paper could alleviate the problems by constructing diverse subgraphs with balanced distribution.

3 Problem Formulation

In the GCN-based linkage prediction task, the imbalanced datasets could cause two critical problems: imbalanced linkage labels and biased graph representations. The former is similar to the imbalance problem for image classification, that is, the imbalance between positive and negative samples. The latter is a unique problem in GCN-based tasks. The subgraphs constructed directly as L-GCN tend to be biased towards the distribution of the training set, which is prone to overfitting.

In this work, we aim to solve the imbalance problems of GCN-based linkage prediction task. In order to facilitate explanation, let’s use $G = \{V, E\}$ to denote the feature graph, where $V = \{v_1, v_2, \ldots, v_N\}$ is a set of nodes in the feature space $R^d$. Assuming each face’s identity is represented by $Y_i$, and $N$ face images can be divided into $C$ identities $\{Y_1, Y_2, \ldots, Y_C\}$. In the real scenes, the ratio between positive and negative samples is extremely imbalanced, and it poses great challenge to the face clustering problems. We formulate this task as

$$
\hat{Y} = f(X', g(X', A'), \theta),
$$

where $\hat{Y}$ is the predicted result. $X'$ and $A'$ denote the subgraph’s features and adjacency matrix of sampling neighbors. $g(\cdot)$ is the mean aggregation operation, and $\theta$ is the learned weights.

4 Methods

This paper mainly studies the imbalance problems in GCN-based linkage prediction task. There are already numerous researchers focusing on the imbalance problem between positive and negative samples. We select some representative methods and evaluate their effectiveness in GCN-based linkage prediction task. However, existing methods only deal with imbalanced labels problem, without taking the biased graph representations problem into account. Therefore, we propose a Reverse-Imbalance Weighted Sampling (RIWS) strategy, which can effectively alleviate these problems.

4.1 Methods for Imbalanced Linkage Labels

The current mainstream methods mainly include re-weighting methods and re-sampling methods. Class balance loss and focal loss are selected to evaluate the influence of re-weighting methods, while the over-sampling and under-sampling methods are used to assess the performance of re-sampling methods.

**Class balance loss.** In the edge classification stage for face clustering, we need to predict whether the linkage exists between the pivot and its 1-hop neighbors, which is a binary classification problem. If the model is trained on an imbalanced dataset, the pivots’ KNN may be dominated by the majority positive or negative samples. Taking Fig. 1 (a) as an example, the pivot’s KNN is dominated by positive samples, which leads to an imbalanced subgraph, and then seriously affect the learning of the model.

In order to avoid the positive or negative samples dominate the subgraph, we introduce class balance loss to balance the weights of positive and negative samples in each subgraph. Specifically, we firstly calculate the average loss values for positive and negative samples respectively, and then take the average of the two loss values as the final loss value.

$$
\mathcal{L}_{CB}(\mathbf{z}) = -\alpha_P y \log \left( \frac{\exp(z_P)}{\exp(z_P) + \exp(z_N)} \right) - \alpha_N (1 - y) \log \left( \frac{\exp(z_P)}{\exp(z_N) + \exp(z_N)} \right),
$$

where $z_P$ and $z_N$ are logits for positive sample and negative sample respectively. $\alpha_P$ and $\alpha_N$ are weights computed according to the frequency of occurrence, and they satisfy $\alpha_P = \frac{N_p}{N_p + N_N}$, $\alpha_N = \frac{N_N}{N_p + N_N}$ ($N_p$ and $N_N$ are the number of positive and negative samples respectively)

**Focal loss.** Focal loss was first proposed in [Lin et al., 2017] for object detection, and it is specially designed to handle difficult training samples. In our methods, we want to determine if there is an edge between pivot and its 1-hop nodes. If we define the output probability for a 1-hop node as $P = [p_P, p_N]$, where $p_P$ indicates the probability of existing an edge. Then the focal loss for linkage prediction can be formulated as

$$
\mathcal{L}_{\text{Focal}}(\mathbf{z}) = -y \alpha_P (1 - p_P)^\gamma \log(p_P) - (1 - y) \alpha_N (1 - p_N)^\gamma \log(p_N).
$$

where $y$ is the ground truth label, and $y = 1$ if there exists an edge. Hyper-parameter $\alpha (\alpha_P + \alpha_N = 1)$ is utilized to balance the impact of positive and negative samples, and $\gamma$ is used for mining hard examples.

**Re-sampling.** Random over-sampling or under-sampling are the most straightforward and representative methods. Random over-sampling replicates random samples in minority classes, while random under-sampling randomly removes samples in majority classes. Despite simplicity, these methods can achieve good performance.

4.2 Method for Both Imbalanced Labels and Biased Graph Representations

**RIWS.** Current methods for imbalance problem mainly pay attention to the ratio of positive and negative samples, such
Figure 2: GCN-based linkage prediction pipeline. Baseline pipeline: (1) generate subgraphs through their KNN, (2) perform GCN aggregation, (3) linkage merging. Our pipeline: (1) obtain eKNN before generating subgraphs, (2) sample nodes according to specific strategies to obtain different subgraphs, (3) performs GCN aggregation and classifiers classification, (4) linkage merging. In this figure, we just show the selection process of the 1-hop nodes, while the selection of the 2-hop nodes and the edge connection process of the subgraph are consistent with L-GCN.

As re-weighting the weights, over-sampling the minority and under-sampling the majority. However, in the GCN-based linkage prediction task, if all the subgraphs are forced to construct a balanced structure like the conventional re-sampling method, it is prone to overfitting. In the inference stage, the model often performs poorly while facing subgraph structures of different ratios. This problem caused by learning from graph structures of insufficient diversity is defined as biased graph representations.

The biased graph representation problem in the GCN-based linkage prediction task was not considered in previous works. In this paper, based on the basic re-sampling method, RIWS is proposed to construct the subgraphs. Similar to L-GCN [Wang et al., 2019b], we take each instance in the dataset as a center (called “pivot”) and a subgraph is constructed based on the pivot’s KNN. After that, the GCN model aggregates the subgraph’s features, and then the classifier predicts whether a linkage exists between the pivot and its each 1-hop neighbor.

Compared with the initial subgraph construction method, we add an expansion coefficient $\gamma$. With this coefficient, the selection interval of 1-hop nodes is increased from $k$ to $k^*\gamma$, which is defined as expanded $k$ nearest neighbors (eKNN) and then $k$ nodes in eKNN are selected as 1-hop neighbors, which is used to control the positive and negative samples’ distribution to a certain extent.

Fig.1 demonstrates the selected 1-hop nodes of some subgraph examples by different methods. Assuming $k=10$ and $\gamma=1.5$, in each sub-picture, the node surrounded by a green solid circle is the pivot sample, and the 1-hop candidate nodes are composed of the pivot’s 15-NN in the feature space. Fig.1 (a) indicates the selected $k$ neighbors with L-GCN, where 10 nodes closest to the pivot in feature space are selected, without considering the imbalance problem of samples. When conventional re-sampling strategy is adopted, the selected 1-hop neighbors is illustrated in Fig.1 (b), where 5 positive samples (blue dots) are randomly selected (under-sampling), and 5 negative samples are selected. If the number of negative samples is insufficient, over-sampling needs to be carried out by duplication.

As shown in Fig.2, the RIWS procedure is as follows. Firstly, for each pivot, the nodes in its eKNN are used as candidate nodes of its subgraph, and the weight of each candidate sample is calculated according to the number of positive and negative samples by

$$w^i_j = \begin{cases} \frac{1}{2} \sum_{v_j \in N_i} \frac{1}{\|y_j = y_i\}} & \text{if } y_i = y_j \\ \frac{1}{2} \sum_{v_j \in N_i} \frac{1}{\|y_j \neq y_i\}} & \text{if } y_i \neq y_j \end{cases}$$

where $w^i_j$ is the weight of the $j$-th neighbour node in the $i$-th sample’s eKNN (i.e., the probability of $j$-th neighbour node to be selected as a node in the subgraph pivoted by the $i$-th sample node). Then, $k$ nodes are selected from each eKNN based on these weights to construct its subgraph. In this way, the balance and diversity of subgraphs can both be guaranteed. On one hand, this balancing weight can ensure that the overall distribution of positive and negative samples in the 1-hop neighbors is balanced; on the other hand, the weighted random sampling process provides diverse structures (including all those shown in Fig.1 (a, b, c, d)). These two properties together help address the problems of both imbalanced labels and biased graph representations.

5 Experiments

In this section, we construct imbalanced datasets and conduct extensive experiments to evaluate whether the methods for conventional imbalanced classification problem are still effective when extended to GCN-based linkage prediction task, as well as verifying the performance of our proposed RIWS method.
5.1 Settings

Imbalanced datasets construction. In order to evaluate the performance of each method on imbalanced datasets, referring to [Liu et al., 2020], we construct a series of imbalanced datasets based on two public datasets: MS-Celeb-1M [Guo et al., 2016] and DeepFashion [Liu et al., 2016]. Taking MS-Celeb-1M as an example, the construction procedure of the imbalanced datasets is as follows.

Based on part0 of the cleaned MS-Celeb-1M [Yang et al., 2020], we synthesized 8 imbalanced training sets according to two hyper-parameters: majority_identity_count \( m \) and minority_identity_size \( n \). Specifically, the identities are sorted by their number of samples, and top \( m \) identities are selected as the majority classes. For the remaining part, \( n \) samples are taken randomly from each identity. If the identity size is lower than \( n \), all samples would be taken. We adopt 200, 500, 1000, 2000 for \( m \), and 3, 5 for \( n \). In this way, 8 imbalanced datasets can be constructed, denoted as (H200, S3), (H200, S5), and so on. We train models on 8 imbalanced datasets, and then test them on part1 of the cleaned MS-Celeb-1M, respectively.

Similar to MS-Celeb-1M, we also constructed 2 imbalanced training set based on DeepFashion.

Evaluation metrics. We decouple the edge classification module and the linkage merging stage of clustering to eliminate the influence of linkage merging stage. In the stage of edge classification, AP (Average Precision) is selected as the evaluation metric, and for clustering stage, Bcubed F score is selected.

5.2 Experiments on Face Clustering

Comparison for each method and combinations. In order to eliminate the influence of hyper-parameters of the merging stage, we select edge classification AP as the basic metric to demonstrate the performance of each method and their combinations.

The top part of table 1 shows the edge classification AP of L-GCN and other methods on the constructed 8 datasets based on MS-Celeb-1M. Among these methods, CB stands for class balance loss, FL means focal loss, RS denotes conventional re-sampling method.

| Method      | (200,3)  | (200,5)  | (500,3)  | (500,5)  | (1000,3) | (1000,5) | (2000,3) | (2000,5) | Avg     |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|---------|
| L-GCN       | 0.9588   | 0.9686   | 0.9606   | 0.9683   | 0.9672   | 0.9716   | 0.9772   | 0.9778   | 0.9688  |
| CB          | 0.9660   | 0.9731   | 0.9683   | 0.9733   | 0.9746   | 0.9769   | 0.9817   | 0.9823   | 0.9745  |
| FL          | 0.9694   | 0.9731   | 0.9720   | 0.9745   | 0.9760   | 0.9763   | 0.9816   | 0.9805   | 0.9754  |
| RS          | 0.9625   | 0.9679   | 0.9698   | 0.9754   | 0.9758   | 0.9770   | 0.9819   | 0.9809   | 0.9739  |
| RIWS        | 0.9658   | 0.9729   | 0.9739   | 0.9772   | 0.9813   | 0.9825   | 0.9860   | 0.9867   | 0.9783  |
| CB+RS       | 0.9681   | 0.9697   | 0.9736   | 0.9763   | 0.9762   | 0.9782   | 0.9833   | 0.9839   | 0.9762  |
| FL+RS       | 0.9740   | 0.9761   | 0.9777   | 0.9788   | 0.9795   | 0.9804   | 0.9804   | 0.9815   | 0.9786  |
| CB+RIWS     | 0.9699   | 0.9754   | 0.9774   | 0.9786   | 0.9822   | 0.9826   | **0.9868**| **0.9875**| 0.9800  |
| FL+RIWS     | 0.9736   | **0.9764**| **0.9791**| **0.9800**| **0.9828**| **0.9830**| 0.9858   | 0.9858   | **0.9808**|

Table 1: Edge classification AP on MS-Celeb-1M imbalanced sub-datasets for each method and their combinations.

Except for individual case, the performance of each method for imbalance problems is significantly better than that of the baseline method. In the sub-datasets with a smaller majority identity count, such as sub-dataset (H200, S3), focal loss achieves better result of 0.9694. Maybe the imbalanced ratio between positive and negative samples is more serious in this configuration, so focal loss could alleviate the imbalance problem by its ability of learning on hard examples and down-weight the numerous easy negatives, while the sampling-based methods perform poorly due to lack of sufficient samples to be sampled. In the sub-dataset with a larger majority identity count, the effect of the biased graph representations is gradually manifested. The RIWS method proposed in this paper achieves better results than other methods, which has reached a high AP of 0.9867 in sub-dataset (H2000,S5).

The four methods can be divided into two categories: re-sampling methods and re-weighting methods. The former methods are mainly used in the subgraph construction stage, while the latter are applied for the training of the classifier.

In order to further demonstrate the performance of each method, we combine the two categories of methods, and the experimental results are shown in the bottom part of table 1. All results are significantly higher than the experimental results of the baseline. Class balance loss combined with RIWS is significantly higher than the class balance loss with regular re-sampling method, and except for (H200, S3) sub-dataset, focal loss with RIWS far exceeds focal loss combined with re-sampling method, indicating that the method proposed in this paper can not only show better results than the re-sampling method when used alone, but also has better results when combined with the re-weighting method.

Comparison for hyper-parameter sensitivity. In this paper, we introduce a new parameter \( \gamma \), which controls the ratio of candidate nodes and selected neighbors of each subgraph. When \( \gamma = 1 \), our subgraph construction method is equivalent to the L-GCN baseline. The performance with different \( \gamma \) values of regular re-sampling and RIWS methods are shown in Fig.3. The dot-and-dash line, the dashed line and the solid line denote respectively baseline, re-sampling and RIWS method. And each method alleviates the imbalance problems based on the baseline.
Figure 3: Hyper-parameter sensitivity comparison between re-sampling and RIWS Methods.

| Method         | Training set     | Samples | AP  | F score |
|----------------|------------------|---------|-----|---------|
| L-GCN          | MS-Celeb-1M      | 576k    | 0.9839 | 0.8437*|
| L-GCN          | (H2000, S3)      | 250k    | 0.9772 | 0.7924  |
| FL+RIWS        | (H2000, S3)      | 250k    | 0.9858 | 0.8397  |
| L-GCN          | DeepFashion      | 26k     | 0.8076 | 0.6013*|
| L-GCN          | (H500,S3)        | 19k     | 0.7981 | 0.5918  |
| CB+RIWS        | (H500,S3)        | 19k     | 0.8066 | 0.6001  |

Table 3: Comparison with baseline trained on full dataset.

As $\gamma$ increases, the performance of the re-sampling method first increases and then decreases, and reaches the maximum value at $\gamma=1.2$, while RIWS continues to increase as the growth of $\gamma$, with the growth rate beginning to slow down sharply at $\gamma=2.0$. In our experiments, we select $\gamma=1.2$ for re-sampling method, and in order not to add too much computational overhead, 2.0 is chosen for the RIWS method. In this configuration, re-sampling and RIWS methods obtain average AP values on 8 imbalanced sub-datasets of 0.9739 and 0.9783, respectively, which both far exceed the baseline of 0.9688. And our proposed RIWS method is significantly better than regular re-sampling method in each sub-dataset.

### 5.3 Experiments on Fashion Clustering

In order to validate the generalization ability of the methods for imbalance problems, we conduct experiments on two sub-datasets of DeepFashion, which is (H200, S3) and (H500,S3). As shown in table 2, all methods except focal loss exceed L-GCN baseline, and class balance loss combined with RIWS achieves the best performance.

### 5.4 Experiments on Partial/Full Datasets

Table 3 demonstrates the comparison between the best combination of imbalanced methods and the baseline. Notice that our combination is trained on imbalanced sub-dataset, while baseline is trained on the full dataset. Results marked with an asterisk are obtained from [Yang et al., 2020]. Although trained on less data with imbalanced distribution, our method obtains comparable results with baseline trained on full MS-Celeb-1M or DeepFashion datasets, which strongly validates the effectiveness of our methods.

### 6 Conclusion and Discussion

The imbalance problems in GCN-based linkage prediction tasks were studied in this paper for the first time from two aspects: imbalanced labels and biased graph representations. Extensive experiments were conducted to evaluate the effectiveness of four typical approaches to the imbalance problem in image classification on addressing the imbalanced label problem in GCN-based tasks, showing that all of them can bring some extent of performance improvement, and that some of their combinations can further extend the improvement. A Reverse-Imbalance Weighted Sampling (RIWS) strategy was proposed in this paper as a trial to tackle the problems of both imbalanced labels and biased graph representations, whose effectiveness was demonstrated in numerous experiments on MS-Celeb-1M and DeepFashion datasets.

These results provide some references on selecting and designing approaches to tackling imbalance problems in GCN-based node and edge classification tasks (not only L-GCN) where imbalanced data can cause problems in the aforementioned two aspects: imbalanced labels and biased graph representations. The RIWS strategy is a trial of designing approaches to addressing the two problems simultaneously, but not necessarily the optimal one. More studies are required and welcomed for better solutions for various scenarios. The code and benchmarking imbalanced datasets synthesized from MS-Celeb-1M and DeepFashion are available at https://github.com/espectre/GCNs_on_imbalanced_datasets.

### References

[Cao et al., 2019] Kaidi Cao, Colin Wei, Adrien Gaidon, Nikos Arechiga, and Tengyu Ma. Learning imbalanced datasets with label-distribution-aware margin loss. *arXiv preprint arXiv:1906.07413*, 2019.

[Chou et al., 2020] Hsin-Ping Chou, Shih-Chieh Chang, Jia-Yu Pan, Wei Wei, and Da-Cheng Juan. Remix: Rebalanced mixup. In *European Conference on Computer Vision*, pages 95–110. Springer, 2020.
[Cui et al., 2019] Yin Cui, Menglin Jia, Tsung-Yi Lin, Yang Song, and Serge Belongie. Class-balanced loss based on effective number of samples. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 9268–9277, 2019.

[Deng et al., 2009] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 248–255, 2009.

[Ester et al., 1996] Martin Ester, Hans-Peter Kriegel, Jörg Sander, Xiaowei Xu, et al. A density-based algorithm for discovering clusters in large spatial databases with noise. In Kdd, volume 96, pages 226–231, 1996.

[Guo et al., 2016] Yandong Guo, Lei Zhang, Yuxiao Hu, Xiaodong He, and Jianfeng Gao. Ms-celeb-1m: A dataset and benchmark for large-scale face recognition. In European conference on computer vision, pages 87–102. Springer, 2016.

[Guo et al., 2020] Senhui Guo, Jing Xu, Dapeng Chen, Chao Zhang, Xiaoang Wang, and Rui Zhao. Density-aware feature embedding for face clustering. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 6698–6706, 2020.

[Jamal et al., 2020] Muhammad Abdullah Jamal, Matthew Brown, Ming-Hsuan Yang, Liqiang Wang, and Boqing Gong. Rethinking class-balanced methods for long-tailed visual recognition from a domain adaptation perspective. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 7610–7619, 2020.

[Kang et al., 2019] Bingyi Kang, Saining Xie, Marcus Rohrbach, Zhicheng Yan, Albert Gordo, Jiashi Feng, and Yannis Kalantidis. Decoupling representation and classifier for long-tailed recognition. arXiv preprint arXiv:1910.09217, 2019.

[Krizhevsky et al., 2009] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. Tech Report, 2009.

[Lin et al., 2017] Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár. Focal loss for dense object detection. In Proceedings of the IEEE international conference on computer vision, pages 2980–2988, 2017.

[Liu et al., 2016] Ziwei Liu, Ping Luo, Shi Qiu, Xiaogang Wang, and Xiaoou Tang. Deepfashion: Powering robust clothes recognition and retrieval with rich annotations. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1096–1104, 2016.

[Liu et al., 2019] Ziwei Liu, Zhongqi Miao, Xiaohang Zhan, Jiayun Wang, Boqing Gong, and Stella X Yu. Large-scale long-tailed recognition in an open world. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2537–2546, 2019.

[Liu et al., 2020] Jialun Liu, Yifan Sun, Chuchu Han, Zhaopeng Dou, and Wenhui Li. Deep representation learning on long-tailed data: A learnable embedding augmentation perspective. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2970–2979, 2020.

[Lloyd, 1982] Stuart Lloyd. Least squares quantization in pcm. IEEE Transactions on Information Theory, 28(2):129–137, 1982.

[Sibson, 1973] Robin Sibson. Slink: an optimally efficient algorithm for the single-link cluster method. The Computer Journal, 16(1):30–34, 1973.

[Wang et al., 2019a] Yiru Wang, Weihao Gan, Jie Yang, Wei Wu, and Junjie Yan. Dynamic curriculum learning for imbalanced data classification. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 5017–5026, 2019.

[Wang et al., 2019b] Zhongdao Wang, Liang Zheng, Yali Li, and Shengjin Wang. Linkage based face clustering via graph convolution network. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 1117–1125, 2019.

[Xiang et al., 2020] Liuyu Xiang, Guiguang Ding, and Jun-gong Han. Learning from multiple experts: Self-paced knowledge distillation for long-tailed classification. In European Conference on Computer Vision, pages 247–263. Springer, 2020.

[Yang et al., 2019] Lei Yang, Xiaohang Zhan, Dapeng Chen, Junjie Yan, Chen Change Loy, and Dahua Lin. Learning to cluster faces on an affinity graph. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2298–2306, 2019.

[Yang et al., 2020] Lei Yang, Dapeng Chen, Xiaohang Zhan, Rui Zhao, Chen Change Loy, and Dahua Lin. Learning to cluster faces via confidence and connectivity estimation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 13369–13378, 2020.

[Zhou et al., 2020] Boyan Zhou, Quan Cui, Xiu-Shen Wei, and Zhao-Min Chen. Bbn: Bilateral-branch network with cumulative learning for long-tailed visual recognition. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 9719–9728, 2020.