Interpolation-based Correlation Reduction Network for Semi-Supervised Graph Learning

Xihong Yang, Yue Liu, Sihang Zhou, Xinwang Liu, En Zhu

ABSTRACT
Graph Neural Networks (GNNs) have achieved promising performance in semi-supervised node classification in recent years. However, the problem of insufficient supervision, together with representation collapse, largely limits the performance of the GNNs in this field. To alleviate the collapse of node representations in semi-supervised scenario, we propose a novel graph contrastive learning method, termed Interpolation-based Correlation Reduction Network (ICRN). In our method, we improve the discriminative capability of the latent feature by enlarging the margin of decision boundaries and improving the cross-view consistency of the latent representation. Specifically, we first adopt an interpolation-based strategy to conduct data augmentation in the latent space and then force the prediction model to change linearly between samples. Second, we enable the learned network to tell apart samples across two interpolation-perturbed views through forcing the correlation matrix across views to approximate an identity matrix. By combining the two settings, we extract rich supervision information from both the abundant unlabeled nodes and the rare yet valuable labeled nodes for discriminative representation learning. Extensive experimental results on six datasets demonstrate the effectiveness and the generality of ICRN compared to the existing state-of-the-art methods.

CCS CONCEPTS
• Computing methodologies → Semi-supervised learning settings.

1 INTRODUCTION
In recent years, with the strong representation learning capacity, graph learning methods have become a hot research spot in many fields of multimedia, including the recommendation system [22], 3D estimation [11, 14], multi-modal dialog system [47], and so on. Semi-supervised node classification, which aims to classify nodes in the graph with limited labels, is a crucial yet challenging graph learning task. Thanks to the powerful feature extraction capability, Graph Convolutional Network (GCN) [17] has recently achieved promising performance in this scenario. As a result, it has attracted considerable attention in this field, and many methods [4, 18, 34, 42] have been proposed.

Although preferable performances have been achieved by the existing algorithms, in the semi-supervised node classification task, insufficient supervision has largely aggravated the problem of representation collapse in graph learning, leading to indiscriminate representation across classes. To solve the problem, a commonly used strategy is to path the supervision information from the labeled data to the unlabeled data according to the linkages within the adjacent matrix as guidance for network training [9, 17, 34, 42]. Moreover, in MixupForGraph [38], a graph mixup operation is designed to enhance the robustness and discriminative capability of the aggregated sample embedding over the labeled samples. Since the embedding of the labeled samples has integrated information of both the labeled sample and its unlabeled neighbors while pushing the predictions to their corresponding ground truth, the information of the unlabeled samples are also integrated for network training in a form of implicit regularization. Though valuable information is introduced, the performance of these methods could be significantly influenced by the inaccurate connections within the data. Recently, to alleviate the adverse influence of the inaccurate connections, MVGRL[10] introduces contrastive learning as an auxiliary task for discriminative information exploitation. In this method, the authors design an InfoMax loss to maximize the cross-view mutual information between the node and the global summary of the graph. Although large improvement has been made, the current data augmentation and loss function setting of MVGRL fails to exploit abundant intuitive information within the unlabeled data thus limiting its classification performance. This phenomenon can be witnessed in the cosine similarity matrix of latent representation illustration in Fig. 1. As we can see, although the categorical information is revealed by the learned representations to different extent, more discriminative information is needed for further performance enhancement.

To solve this issue, we propose a novel graph contrastive semi-supervised learning method termed Interpolation-based Correlation

Figure 1: Visualization of cosine similarity matrices in the latent space of GCN [17], MixupForGraph [38], MVGRL[10] and our proposed method on the ACM dataset. The sample order is rearranged to make samples from the same cluster beside each other.
Reduction Network (ICRN), which improves the discriminative capability of node embedding by enlarging the margin of decision boundaries and improving the cross-view consistency of the latent representation among samples. To be specific, we first adopt an interpolation-based strategy to conduct data augmentation in the latent space and then force the prediction model to change linearly between samples as done in the field of image recognition [36]. After that, by forcing the correlation matrix across two interpolation-perturbed views to approximate an identical matrix, we guide our network to be able to recognize whether two perturbed samples are the same samples or not. In this manner, the sample representations would be more discriminative, thus alleviating the collapsed representations. This could be clearly seen in Fig. 1 (d) that the similarity matrix generated by our method can obviously reveal the hidden distribution structure better than the compared methods. The key contributions of this paper are listed as follows:

- We proposed a novel graph contrastive learning method to solve the representation collapse issue in the field of semi-supervised node classification.
- An interpolation-based strategy is adopted to force the prediction model to change linearly between samples to enlarge the decision boundaries margin.
- To further improve discriminative capability of representations, we design a correlation reduction mechanism to enable our network to tell apart the same sample against different samples across two interpolation-perturbed views.
- Extensive experimental results on six datasets demonstrate the superiority of our method against the compared state-of-the-art method. The ablation study and module transferring experiments demonstrate the effectiveness and the generality of our proposed modules.

2 RELATED WORK

2.1 Semi-supervised Node Classification

Semi-supervised node classification [41, 48, 49] aims to classify nodes in the graph with few human annotations. Recently, Graph Neural Networks (GNNs) have achieved promising performance for their strong representation capability of graph-structured data. The pioneer GCN-Cheby [5] generalizes CNN [19] to graphs in the spectral domain by proposing the Chebyshev polynomials graph filter. Following GCN-Cheby, GCN [17] reveals the underlying graph structure by feature transformation and aggregation operations in the spatial domain. After that, GraphSage [9] generates embeddings by sampling and aggregating features from the node neighborhoods. GAT[34] proposed graph attention networks on graph-structured data to improve the performance. JK-Net[42] flexibly leverages different neighborhood ranges to enable better structure-aware representation. In addition, SGC[39] simplifies GCN by removing feature transformation between consecutive layers. Furthermore, Geom-GCN[27] proposes a geometric aggregation scheme to overcome the issue of neighborhood node structural information loss. Different from them, PPNP/APPNP [18] separates the feature transformation from aggregation operation and enhances the aggregation operation with PageRank [26]. More recently, following PPNP/APPNP, GPRGNN[4] jointly optimizes sample feature and topological information by learning the aggregation weights adaptively.

In our proposed method, we adopt GPRGNN [4] as our backbone and further improve its discriminative capability by enlarging the margin of decision boundaries and improving the cross-view consistency of the latent representation.

2.2 Representation Collapse

Contrastive learning methods [3, 6, 13, 23, 45] have achieved promising performance on images in recent years. Motivated by their success, contrastive learning strategies have been increasingly adopted to the graph data [1, 10, 31, 35, 44, 50].

The pioneer DGI [35] is proposed to learn node embedding by maximizing the mutual information between the local and global fields of the graph. GMI[28] and HDMI[15] improve DGI by regarding edges and node attributes, respectively, to alleviate collapse representation. Besides, MVG[10] and InfoGraph [30] demonstrate the effectiveness of maximizing the mutual information to learn graph-level representations in the graph classification task. Subsequently, GraphCL [44] and GRACE [50] first generate two augmented views and then learn node embeddings by pulling together the same node in two augmented views while pushing away different nodes. However, representation collapse is a common problem that, without the adequate guidance of human annotations, the model tends to embed all samples to the same representation [20].

In order to alleviate representation collapse, BGRL [31] is proposed to learn node embeddings by two separate GCN encoders. Specifically, the online encoder is trained to pull together the same node from two views while the target encoder is updated by an exponential moving average of online encoder. More recently, G-BT [1] is proposed to avoid representation collapse by reducing the redundancy of features. ICRN implicitly achieves the redundancy-reduction principle through an interpolation-based correlation reduction mechanism in the sample level, described in section 3.3 to solve the representation collapse issue in the semi-supervised node classification task.

2.3 Interpolation-based Augmentation

Mixup[37, 46] is an effective data augmentation strategy for image classification [7, 8, 12, 24, 43]. It generates synthetic samples by linearly interpolating random image pairs and their labels as follows:

\[
\begin{align*}
\lambda & \sim \text{Beta}(\alpha, \beta), \\
\lambda' &= \max(\lambda, 1 - \lambda), \\
x' &= \lambda' x_1 + (1 - \lambda') x_2, \\
y' &= \lambda' y_1 + (1 - \lambda') y_2,
\end{align*}
\]

where \(\alpha\) and \(\beta\) are the hyper-parameters of Beta distribution. Besides, \(\lambda \in [0, 1]\) denotes the interpolation rate. Actually, Mixup incorporates the prior knowledge that interpolations of input samples should lead to interpolations of the associated targets [46]. In this manner, it extends the training distribution by constructing virtual training samples across all classes, thus improving the image classification performance [36, 37].
However, it is challenging to extend Mixup methods to the graph data, which contains many irregular connections. To solve this problem, GraphMixup [40] designs feature and edge Mixup mechanisms to improve the performance of class-imbalanced node classification. Besides, MixupForGraph [38] proposed the two-branch graph convolution to mix the receptive field sub-graphs for the paired nodes. Different from the previous methods, we propose a simple interpolation fashion. Specially, we interpolate the embeddings and associated labels directly.

### 3 METHODOLOGY

In this section, we proposed a novel graph contrastive learning method, termed Interpolation-based Correlation Reduction Network (ICRN), to improve the latent feature’s discriminative capability and alleviate the collapsed representation. As shown in Fig 2, our proposed method mainly contains two modules, i.e., the graph interpolation module and correlation reduction module. In the following subsections, we first define the main notations and the problem. Then we detail the two main modules and loss function of ICRN.

#### 3.1 Notations and Problem Definition

To an undirected graph $\{V, E\}$ with $K$ classes of nodes, the node set and the edge set are denoted as $V = \{v_1, v_2, \ldots, v_N\}$ and $E$, respectively. The graph contains an attribute matrix $X \in \mathbb{R}^{N \times D}$ and an adjacency matrix $A = (a_{ij})_{N \times N}$, where $a_{ij} = 1$ if $(v_i, v_j) \in E$, otherwise $a_{ij} = 0$. The degree matrix is denoted as $D = \text{diag}(d_1, \ldots, d_N) \in \mathbb{R}^{N \times N}$ and $d_i = \sum_{(v_i, v_j) \in E} a_{ij}$. The normalized adjacency matrix $\widetilde{A} \in \mathbb{R}^{N \times N}$ could be calculated through calculating $D^{-\frac{1}{2}}(A + I)D^{-\frac{1}{2}}$, where $I \in \mathbb{R}^{N \times N}$ is an identity matrix. Besides, $\| \cdot \|_2$ denotes the $\ell^2$-norm. In this paper, our target is to embed the nodes into the latent space and classify them in a semi-supervised manner. The notations are summarized in Table 1.

#### 3.2 Graph Interpolation Module

Recent works [36, 46] demonstrate that Mixup is an effective data augmentation of images to improve the discriminative capability of samples by achieving larger margin-decision boundaries. Different from images, the nodes in the graph are irregularly connected. Thus, the interpolation for the graph data is still an open question [38, 40].

To overcome this issue, we propose a simple yet effective interpolation method on graph data as shown in the orange box in Fig.2. Specifically, we first encode the nodes into the latent space through Eq. (2).

$$H = F(X, A). \quad (2)$$

Here, $F(\cdot)$ denotes the encoder of our feature extraction framework.

In our paper, we take the encoder of GPRGNN [4], which learns node embeddings from node features and topological information for sample embedding.

Subsequently, we adopt a simple linear interpolation function $G_k(\cdot)$ to mix the node embeddings as formulated:

$$H^{(k)} = G_k(H) = \lambda H + (1 - \lambda)S_k(H), \quad (3)$$

where $H^{(k)}$ denotes the $k$-th view of the node embedding and $\lambda = 0.9$ is the interpolation rate. $S_k(\cdot)$ is the shuffle function that randomly permutes the input of the function and output the same samples with a new order. As $\lambda = 0.9$, the interpolation function could be regarded as an operation that introduces perturbation to the principal embedding $H$. Similar to Eq. (3), the interpolated labels can be formulated as:

$$Y^{(k)} = G_k(Y) = \lambda Y + (1 - \lambda)S_k(Y). \quad (4)$$

In this manner, we construct two perturbations $(H^{(q)}, Y^{(q)})$ as two different views of the principle sample batch in the latent space by mixing the node embeddings and the corresponding labels. Subsequently, we enhance the discriminative capability of the network by forcing the prediction model to change linearly between samples through the classification loss:

$$\mathcal{L}_c = CE(Y^{(q)}_2, \hat{Y}^{(q)}_2), \quad (5)$$

where $CE(\cdot)$ denotes the Cross-Entropy loss [25] and $\hat{Y}^{(q)}_2$ is the prediction of training data. According to [36, 46], in image classification applications, the decision boundaries are pushed far away from the class boundaries by enabling the network to recognize the interpolation operation. Through minimizing $\mathcal{L}_c$ in our paper, we can also acquire the larger-margin decision boundaries shown in Fig.5, thus alleviating the representation collapse problem.

#### 3.3 Correlation Reduction Module

To further improve the discriminative capability of samples, we improve the cross-view consistency of the latent representation. Following this idea, as shown in the red box in Fig. 2, we propose a correlation reduction module, which pulls together the same samples while pushing away different samples from two interpolation-perturbed views. In this way, our network is encouraged to learn more discriminative embeddings, thus avoiding the representation collapse problem.

Concretely, the process of correlation reduction is divided into three steps. First, we utilize the proposed graph interpolation module to construct two interpolation-perturbed views of node embeddings, i.e., $H^{(q)}$ and $H^{(q)}_2$ in Fig. 2.

Second, the correlation matrix $Z \in \mathbb{R}^{N \times N}$ across two interpolation-perturbed views is calculated as:

$$Z_{ij} = \frac{(H^{(q)}_i^T) (H^{(q)}_j^T)^T}{\|H^{(q)}_i\|_2 \|H^{(q)}_j\|_2}. \quad (6)$$

Table 1: Notation summary.

| Notations | Meaning |
|-----------|---------|
| $X \in \mathbb{R}^{N \times D}$ | The Attribute Matrix |
| $A \in \mathbb{R}^{N \times N}$ | The Adjacency Matrix |
| $D \in \mathbb{R}^{N \times N}$ | The Degree Matrix |
| $I \in \mathbb{R}^{N \times N}$ | The Identity Matrix |
| $H \in \mathbb{R}^{N \times D}$ | The Node Embeddings |
| $Z \in \mathbb{R}^{N \times N}$ | The Cross-view Sample Correlation Matrix |
| $Y \in \mathbb{R}^{N \times C}$ | The Prediction Distribution |
| $Y \in \mathbb{R}^{N \times C}$ | The Label Distribution |
where $Z_{ij}$ is the cosine similarity between $i$-th node embedding of the first view $H^{v1}$ and $j$-th node embedding of the second view $H^{v2}$.

Furthermore, we force the correlation matrix $Z$ to be equal to an identity matrix $I \in \mathbb{R}^{N \times N}$ by minimizing the information correlation reduction loss, which can be presented as:

$$
\mathcal{L}_R = \frac{1}{N^2} \sum_{i=1}^{N} (Z_{ii} - 1)^2 \\
= \frac{1}{N} \sum_{i=1}^{N} (Z_{ii} - 1)^2 + \frac{1}{N^2 - N} \sum_{i=1}^{N} \sum_{j \neq i} (Z_{ij})^2.
$$

In detail, the first term in Eq. (7) forces the diagonal elements of $Z$ to 1, which indicates that the embeddings of each node are forced to agree with each other in two views. Besides, the second term in Eq. (7) makes the off-diagonal elements of $Z$ to approach 0 so as to push away different nodes across two views.

By this decorrelation operation, we enlarge the distance between different samples in the latent space while preserving the view-invariance latent feature of each sample, thus keeping cross-view consistent of latent representation. Consequently, our network is guided to learn more discriminative features about input samples and further avoid the collapsed representation.

Algorithm 1 ICRN

**Input**: An undirected graph $G = (X, A)$; Iteration number $t$; Hyper-parameters $\alpha, \lambda$.

**Output**: Class prediction $\hat{Y}$ and the trained network $\mathcal{F}(-)$.

1. for $i = 1$ to $t$ do
2. Encode the nodes with the feature extraction network $\mathcal{F}(-)$ to obtain the node embeddings $H$;
3. Utilize the graph interpolation module to construct two interpolation-perturbed embeddings $H^{v1}$ and $H^{v2}$;
4. Construct the interpolated labels $Y^{v2}$ with Eq. (4);
5. Calculate the classification loss $\mathcal{L}_C$ with Eq. (5);
6. Calculate the correlation matrix $Z$ with Eq. (6);
7. Force $Z$ to approximate an identity matrix and calculate information correlation reduction loss $\mathcal{L}_R$ with Eq. (7);
8. Update the whole network by minimizing $\mathcal{L}$ in Eq. (8);
9. end for
10. Output the predicted classification result $\hat{Y}$.
11. return $\hat{Y}$ and $\mathcal{F}(-)$.

3.4 Loss Function

The proposed method ICRN jointly optimizes two losses: the classification loss $\mathcal{L}_C$ and the information correlation reduction loss $\mathcal{L}_R$. 
In summary, the objective of ICRN is formulated as:
\[
\mathcal{L} = \mathcal{L}_C + \alpha \mathcal{L}_R, \tag{8}
\]
where \(\alpha\) is a trade-off hyper-parameter. The detailed learning procedure of ICRN is illustrated in Algorithm 1.

4 EXPERIMENT

4.1 Datasets & Metric

To verify the effectiveness of our proposed method, extensive experiments have been conducted on six benchmark datasets, including DBLP, ACM, AMAP, AMAC, CITESEER, and CORA [21, 29]. Detailed dataset statistics are summarized in Table 2. The detail descriptions are summarized as follows:

- **DBLP** [2]: This author network contains authors from four areas including information retrieval, machine learning, data mining, and database. The edge is constructed between two authors if they are the co-author relationship. The features of the authors are the bag-of-words of keywords.

- **ACM** [2]: It is a network of papers. An edge will be constructed between two papers if they are written by the same author. The features of the papers are the bag-of-words of the keywords. The papers published in MobiCOMM, SIGCOMM, SIGMOD, KDD are selected and divided into three classes, including data mining, wireless communication, and database.

- **AMAP** [32]: This is a co-purchase graph from Amazon. The nodes in the graph denote the products, and the features are the reviews encoded by the bag-of-words. The edges indicate whether two products are frequently co-purchased or not. The nodes are divided into eight classes.

- **AMAC** [32]: AMAC is extracted from Amazon co-purchase graph, where nodes represent products, edges represent whether two products are frequently co-purchased or not, features represent product reviews encoded by bag-of-words, and labels are predefined product categories.

- **CITESEER** [32]: It consists of 3327 scientific publications classified into one of six classes. The citation network consists of 4732 links. Each publication in the dataset is described by a 0/1-valued word vector indicating the absence or presence of the corresponding word from the dictionary. The dictionary consists of 3703 unique words.

- **CORA** [32]: The Cora dataset consists of 2708 scientific publications classified into one of seven classes. The citation network consists of 5429 links. Each publication in the dataset is described by a 0/1-valued word vector indicating the absence/presence of the corresponding word from the dictionary. The dictionary consists of 1433 unique words.

For fairness, we follow GPRGNN [4] and adopt the sparse splitting (2.5% / 2.5% / 95% for train / validation / test) in the origin literature for all datasets. The classification performance is evaluated by the widely-used accuracy metric.

4.2 Experiment Setup

All experiments are implemented with one NVIDIA 1080Ti GPU on PyTorch platform. To alleviate the influence of randomness, we run each method for 10 times and report the mean values with standard deviations. Besides, to all methods, we train them for 1000 epochs until convergence. For ACM and DBLP datasets, we adopt the code of compared methods and reproduce the results. For the performance of baselines on other datasets, we reported the corresponding values from GPRGNN [4] directly. In our proposed method, we adopt GPRGNN as our feature extraction backbone network, and our network is trained with the Adam optimizer [16]. Besides, the learning rate is set to 1e-3 for CITESEER, 5e-2 for DBLP, 2e-2 for CORA and AMAC, 1e-2 for ACM and AMAP, respectively. The interpolation rate \(\lambda\) and the trade-off hyper-parameter \(\alpha\) are set to 0.9 and 0.5, respectively.

### Table 2: Dataset summary

| Dataset | Sample | Dimension | Edges | Classes |
|---------|--------|-----------|-------|---------|
| DBLP    | 4057   | 334       | 7056  | 4       |
| ACM     | 3025   | 1870      | 26256 | 3       |
| AMAP    | 7650   | 745       | 287326| 8       |
| AMAC    | 13752  | 767       | 491722| 10      |
| CITESEER| 3327   | 3703      | 4732  | 6       |
| CORA    | 2708   | 1433      | 5429  | 7       |

4.3 Performance Comparison

To demonstrate the superiority of our method, we conduct performance comparison experiments for our proposed ICRN and 9 baselines. Specially, classical GCN-base methods [4, 5, 9, 17, 18, 34, 39, 42] path the supervision information from the labeled data to the unlabeled data according to the linkages within the adjacency matrix as guidance for network training. Besides, the Mixup-enhanced method [38] improves the robustness and discriminative capability of the aggregated sample embedding over the labeled samples. Moreover, we report the results of the contrastive methods [10, 35, 50, 51], which design auxiliary tasks for discriminative information exploitation.

From these results in Table 3, we observe and analyze as follows. 1) It could be observed that the classical GCN-based methods are not comparable with our proposed ICRN. For example, on CORA dataset, ICRN exceeds GCN [17] by 5.68%. This is because these methods would suffer from the representation collapse problem caused by the inaccurate connections within data in the adjacency matrix. 2) Compared with the Mixup-enhance method MixupForGraph [38], ICRN achieves better classification performance. The reason is that MixupForGraph does not consider the contrastive learning method to improve the discriminative capacity in the semi-supervised node classification task. 3) Moreover, our ICRN consistently outperforms other contrastive learning methods including DGI[35], GCA[51], GRACE[50] and, MVGRL[10]. We conjecture that those methods fail to exploit abundant intuitive information within the unlabeled data, thus achieving sub-optimal performance.

Different from them, our method aims to alleviate collapsed representations by improving the discriminative capability of the latent space from two aspects. Firstly, we proposed a graph interpolation module to force the prediction model to change linearly between samples, thus enlarging the margin of decision boundaries. Besides, the proposed correlation reduction mechanism further improves
Table 3: The average semi-supervised classification performance with mean±std on six datasets. The red and blue values indicate the best and the runner-up results, respectively.

| Method           | DBLP     | ACM      | AMAP     | AMAC     | CITESEER | CORA     |
|------------------|----------|----------|----------|----------|----------|----------|
| GCN-Cheby [5]    | 60.48±0.00 | 79.98±3.07 | 90.09±0.28 | 82.41±0.28 | 65.67±0.38 | 71.39±0.51 |
| GCN [17]         | 67.64±0.38 | 84.95±0.21 | 90.54±0.21 | 82.52±0.32 | 67.30±0.35 | 75.21±0.38 |
| GraphSage [9]    | 29.49±0.03 | 37.65±0.01 | 90.51±0.25 | 83.11±0.23 | 61.52±0.44 | 70.89±0.54 |
| APPNP [18]       | 67.75±0.44 | 74.61±0.67 | 91.11±0.26 | 81.99±0.26 | 68.59±0.30 | 79.41±0.38 |
| JK-Net [42]      | 64.51±0.53 | 81.20±0.11 | 87.70±0.70 | 77.80±0.97 | 60.85±0.76 | 73.22±0.64 |
| GAT [34]         | 68.58±0.42 | 83.88±0.35 | 90.09±0.27 | 81.95±0.38 | 67.20±0.46 | 76.70±0.42 |
| SGC [39]         | 53.66±2.15 | 72.99±2.96 | 83.80±0.46 | 76.27±0.36 | 58.89±0.47 | 70.81±0.67 |
| GPRGNN [4]       | 67.84±0.30 | 80.93±2.26 | 91.93±0.26 | 82.90±0.37 | 67.63±0.38 | 79.51±0.36 |
| MixupForGraph [38] | 68.51±0.78 | 86.24±0.62 | 89.87±0.10 | 77.30±2.10 | 57.41±0.33 | 67.11±0.63 |
| DGI [35]         | 68.90±1.34 | 81.26±1.48 | 83.10±0.50 | 75.90±0.60 | 65.43±2.94 | 73.74±1.43 |
| GCA [51]         | 20.82±1.94 | 19.10±1.73 | 89.98±1.28 | 81.86±1.80 | 56.39±3.94 | 74.49±3.70 |
| GRACE [50]       | 68.88±0.04 | 85.93±0.56 | 90.60±0.03 | 72.76±0.02 | 66.54±0.01 | 78.62±0.62 |
| MVGRL [10]       | 67.89±0.34 | 83.78±0.27 | 79.37±0.03 | 70.22±0.02 | 67.98±0.05 | 78.06±0.07 |
| ICRN             | Ours     | 70.60±0.76 | 87.88±0.54 | 92.64±0.24 | 83.99±0.90 | 69.18±0.43 | 80.89±0.95 |

The average semi-supervised classification performance with mean±std on six datasets. The red and blue values indicate the best and the runner-up results, respectively.

The discriminative capability of the features by keeping the cross-view consistency of the latent representations. Consequently, the proposed ICRN alleviates collapsed representations and achieves the top-level performance on six datasets.

4.4 Transferring Modules to Other Methods

To further investigate the effectiveness and the generality of our proposed modules, we transfer the graph interpolation module and correlation reduction module to five baselines including GCN-Cheby [5], GCN [17], APPNP [18], JK-Net [42], GAT [34]. Table 4 reports the performance of the five methods with their variants on DBLP, ACM, CITESEER, and CORA dataset. Here, we denotes the baseline and the baseline with the two proposed modules as B and B-O, respectively.

From these results, we observed that, enhanced by our proposed modules, the baselines significantly achieve better performance. Specifically, our modules improve the classification accuracy of GCN by 4.79% on DBLP, 0.82% on ACM, 1.23% on CITESEER, 2.49% on CORA, respectively. The reason is that the two proposed modules enhance the discriminative capability of samples by enlarging the margin of decision boundaries and improving the cross-view consistency of the node representations. In this manner, the baselines alleviate the collapsed representation, thus achieving better classification performance.

4.5 Ablation Studies

In this section, we first conduct ablation studies to verify the effectiveness of the proposed modules, and then we analyze the robustness of ICRN to the hyper-parameters.

4.5.1 Effectiveness of the Proposed Modules. To investigate the effectiveness of the proposed graph interpolation module and correlation reduction module, extensive ablation studies are conducted in Fig. 3. Here, we adopt GPNGNN [4] as “Baseline”. Besides, “B”, “B+I”, “B+C” and “Ours” denote the baseline, the baseline with graph interpolation module, correlation reduction module and both, respectively. From these results, we have observed as follows. 1) Compared with “Baseline”, “B+I” has about 1.81% performance improvement on average of six datasets since the proposed graph interpolation module enlarges the margin of decision boundaries by forcing the prediction model to change linearly between samples. 2) Benefited from the correlation reduction module, the classification performance is improved. Taking the result on DBLP dataset for example, “B+C” exceeds “Baseline” by 2.05%. This demonstrates that the correlation reduction module improves the discriminative
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| Dataset | GCN-Cheby | GCN | APPNP | JKNet | GAT |
|---------|-----------|-----|-------|-------|-----|
|         | B         | B-O| B     | B-O   |     |
| DBLP    | 60.48±0   | 63.52±1.46 | 67.64±0.38 | 72.43±0.62 |       |
| ACM     | 79.98±3.07 | 83.02±1.03 | 84.95±0.21 | 85.77±1.33 |     |
| CITESEER| 65.67±0.38 | 66.52±0.65 | 67.30±0.35 | 68.53±0.59 |     |
| CORA    | 71.39±0.51 | 72.95±1.06 | 75.21±0.38 | 77.70±0.44 |     |

Table 4: Transferring our proposed modules to other models on four datasets. 'B' and 'B-O' represent the baseline and the baseline with our method, respectively. Boldface letters are used to mark the best results.

Figure 3: Ablation comparisons of the proposed modules on six datasets. "B", "B+I", "B+C" and "Ours" denote the baseline, the baseline with graph interpolation module, correlation reduction module and both, respectively.

Figure 4: Testing of the effectiveness and sensitivity of hyper-parameter \( \alpha \) and \( \lambda \). The result perturbation with the variation of the two parameters on all six datasets are illustrated in the figures.

4.5.2 Hyper-parameter Analysis. Furthermore, we investigate the robustness of our proposed method to the hyper-parameters on six datasets. Specifically, to the trade-off hyper-parameter \( \alpha \), we conduct ablation studies as shown in Fig. 4 (a). From these results, we observe that the classification accuracy will not fluctuate greatly when \( \alpha \) increasing. This demonstrates that our model ICRN is insensitive to the variation of the hyper-parameter \( \alpha \). Besides, the accuracy of semi-supervised node classification with different values of the interpolation rate \( \lambda \) are illustrated in Fig. 4 (b). It’s observed that the performance of ICRN is decreased when \( \lambda \) is about less than 0.9 since \( \lambda \) controls the perturbation to the principal embedding \( H \). It is worth mentioning that \( \lambda \) is set as 0.9 in all experiments.
we randomly select two categories of all samples so as to illustrate the proposed correlation reduction module aims to keep the cross-view consistency of the embeddings. Benefited from these two modules, our network is guided to learn more discriminative representations, thus alleviating the representation collapse problem. Extensive experiments on six datasets demonstrate the superiority of our proposed methods.

REFERENCES

[1] Piotr Bielak, Tomasz Kajdanowicz, and Nitesh V Chawla. 2021. Graph Barlow Twins: A self-supervised representation learning framework for graphs. arXiv preprint arXiv:2106.02466 (2021).
[2] Deyu Bo, Xiao Wang, Chuan Shi, Meiqi Zhu, Emiao Lu, and Peng Cui. 2020. Structural deep clustering network. In Proc. of WWW.
[3] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. 2020. A simple framework for contrastive learning of visual representations. In International conference on machine learning.
[4] Eli Chien, Jianhao Peng, Pan Li, and Olgica Milenkovic. 2020. Adaptive universal generalized pagerank: graph neural network. arXiv preprint arXiv:2006.07988 (2020).
[5] Michael Defferrard, Xavier Bresson, and Pierre Vandergheynst. 2016. Convolutional neural networks on graphs with fast localized spectral filtering. Advances in neural information processing systems (2016).
[6] Jean-Bastien Grill, Florian Strub, Florent Altché, Corentin Tallec, Pierre-H Richard, Elena Buchatskaya, Carl Doerthe, Bernardo Avila Pires, Zhao-han Daniel Guo, Mohammad Ghanighaghi Azar, et al. 2020. Bootstrap your own latent: A new approach to self-supervised learning. arXiv preprint arXiv:2006.07733 (2020).
[7] Hongyu Guo. 2020. Nonlinear mixup: Out-of-manifold data augmentation for text classification. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34: 4044–4051.
[8] Hongyu Guo, Yongyi Mao, and Richong Zhang. 2019. Augmenting data with mixup for sentence classification: An empirical study. arXiv preprint arXiv:1905.08941 (2019).
[9] William I Hamilton, Rex Ying, and Jure Leskovec. 2017. Inductive representation learning on large graphs. In Proc. of ICDM.
[10] Karev Hassan and Amir Hosein Khashamadi. 2020. Contrastive multi-view representation learning on graphs. In Proc. of ICML.
[11] Qian He, Desen Zhen, Bo Wan, and Xuming He. 2021. Single Image 3D Object Estimation with Primitive Graph Networks. In Proceedings of the 29th ACM International Conference on Multimedia. 2353–2361.
[12] Dan Hendrycks, Norman Mu, Ekin D Cubuk, Barrett Zoph, Justin Gilmer, and Balaji Lakshminarayanan. 2019. Augmix: A simple data processing method to improve robustness and uncertainty. arXiv preprint arXiv:1912.02791 (2019).
[13] R Devon Hjelm, Alex Fedorov, Samuel Laviole-Marichal, Karan Grewal, Phil Bachman, Adam Trischler, and Yoshua Bengio. 2018. Learning deep representations by mutual information estimation and maximization. In International Conference on Learning Representations.
