Deep Contrastive Learning for Multi-View Network Embedding

Mengqi Zhang\textsuperscript{1,2}, Yanqiao Zhu\textsuperscript{1,2}, Shu Wu\textsuperscript{1,2}, and Liang Wang\textsuperscript{1,2}

\textsuperscript{1} Center for Research on Intelligent Perception and Computing
Institute of Automation, Chinese Academy of Sciences
\textsuperscript{2} School of Artificial Intelligence, University of Chinese Academy of Sciences
{mengqi.zhang,yanqiao.zhu}@cripac.ia.ac.cn
{shu.wu,wangliang}@nlpr.ia.ac.cn

Abstract. Multi-view network embedding aims at projecting nodes in the network to low-dimensional vectors, while preserving their multiple relations and attribute information. Contrastive learning-based methods have preliminarily shown promising performance in this task. However, most contrastive learning-based methods mostly rely on high-quality graph embedding and explore less on the relationships between different graph views. To deal with these deficiencies, we design a novel node-to-node C\textsuperscript{ontrastive leaR\textsuperscript{n}ing fram\textsuperscript{E}work for Multi-view network Emb\textsuperscript{e}d\textsuperscript{ding} (CREME), which mainly contains two contrastive objectives: Multi-view fusion InfoMax and Inter-view InfoMin. The former objective distills information from embeddings generated from different graph views, while the latter distinguishes different graph views better to capture the complementary information between them. Specifically, we first apply a view encoder to generate each graph view representation and utilize a multi-view aggregator to fuse these representations. Then, we unify the two contrastive objectives into one learning objective for training. Extensive experiments on three real-world datasets show that CREME outperforms existing methods consistently.

Keywords: Multi-view Networks · Contrastive Learning · Self-supervised learning.

1 Introduction

Real-world networks often consist of various types of relations, which are known as multi-view networks. Take academic networks as an example. In the author graph view, two papers are linked if they have joint authors. Likewise, in the citation view, two papers are linked if they cite each other. Multi-view network embedding aims at projecting nodes in the network to low-dimensional vectors, while preserving their multiple relations and attribute information [3, 17, 21, 32]. Since the acquisition of label information is expensive in real world, how to obtain

* To whom correspondence should be addressed.
high-quality node embedding without supervision for multi-view network has attracted extensive attention in the community.

Recently, a series of self-supervised methods have been proposed for multi-view network embedding. Some methods, such as CMNA [3], MNE [32], and MVE [21] mainly focus on the compression of multiple graph views but ignore node attributes. To capture the attributes and structure information together, some others [1, 14] combine graph neural networks and relational reconstruction tasks for self-supervised learning. However, most of these methods over-emphasize the network proximity, thus limiting the expressiveness of learned embeddings [20, 22, 26]. To improve the generalization ability, inspired by visual representation learning [9], some contrastive learning-based methods [17, 27] adopt the mutual information maximization paradigm to the multi-view network. For example, DMGI [17] maximizes the mutual information between node embedding and global summary embedding within different graph views and achieves the state-of-the-art performance.

Although these contrastive learning methods have achieved compelling performance on multi-view network embedding, we argue that they still have two deficiencies. On the one hand, their contrastive strategies mostly rely on graph-level embedding for each view. However, high-quality graph embedding requires an efficient injective graph readout function, which is difficult to design or optimize in practice [18]. On the other hand, their contrastive methods do not explicitly leverage the relationships between different graph views, such as complementary information. To deal with these challenges, we consider using node-to-node contrastive learning instead of the node-to-graph one, which could eliminate the process of graph embedding. Furthermore, we establish two contrastive objectives to promote multi-view information fusion and maintain the complementary information between different graph views.

Present work. In this paper, we present a novel deep Contrastive learning framework for Multi-view Networks, CREME for brevity. Specifically, we first generate each graph view representation via a view encoder (§3.2) based on graph neural networks. Next, we introduce a multi-view aggregator (§3.2) to integrate different view representations to obtain the node representations in the multi-view networks. To enable self-supervised training, we propose two contrastive objectives (§3.2): one enforces information maximization between graph views and the multi-view (Multi-view fusion InfoMax), which encourages the multi-view aggregator to distill information from each graph view; the other is information minimization among graph views (Inter-view InfoMin), which enhances the divisibility of different graph view representations to capture the complementary information between them. Finally, we unify the two contrastive objectives into one learning objective for self-supervised training.

We summarize the main contributions of this work from the following two perspectives.

– We propose a novel contrastive framework for multi-view network embedding, which mainly contains two contrastive objectives, Multi-view fusion InfoMax and Inter-view InfoMin.
2 Related Work

2.1 Network Embedding

Network learning is to project node of single-view network into a low-dimensional vector space while preserving the network structure or node attribute information. Many traditional methods [6, 19, 24] generate the node sequence by taking random walks and use language models to learn node representations, but they fail to utilize node attribute information flexibly. Along the development of graph neural networks (GNN) [13, 25, 30], many unsupervised methods, such as [7, 12], incorporate the GNN into the reconstruction of network structure. However, all of these methods over-emphasize the network proximity information, which limits representation ability.

Recently, contrastive learning has been a mainstream paradigm in self-supervised learning of computer vision [2, 9], aiming to learn discriminative representations by contrasting positive and negative samples. The contrastive paradigm is also gradually applied in the field of graph representation learning [8, 18, 27, 31, 34]. Recent work DGI [27] randomly shuffles node attributes and then maximizes the mutual information between node embeddings and global summary vectors. To optimize the InfoMax objective, DGI requires the readout function to have injective property, where it is hard to fulfill in practice. Following DGI, GMI [18] develops two new discriminators to directly measure MI between input and representations of both nodes and edges without graph readout function. MVGRL [8] performs node diffusion to generate a new graph view and contrasts node-level and graph-level representations between different views. Moreover, GraphCL [31] proposes a new graph contrastive learning framework with four types of graph augmentation. However, these methods are all designed for homogeneous networks and they are not suitable for processing multi-view networks.

2.2 Multi-View Network Embedding

Unlike homogeneous networks, the multi-view network consists of multiple relations of types in networks with single-type nodes. In some literature, multi-view networks are also known as multiplex networks and multi-dimensional networks. Compared with the single-relation network, a key challenge in multi-view network is how to encode each node into a consensus embedding space considering all types of relations.

To this end, many multi-view methods have been proposed. MVE [21] utilizes the attention mechanism to embed the multiple views into a single collaborated embedding. MNE [32] adopts a joint training strategy to get an common embedding for node and several edge type embeddings. Some heterogeneous network
methods, such as Metapath2Vec \cite{4}, GATNE \cite{1}, and HAN \cite{29}, are also suitable for multi-view networks. Besides, there are some models that \cite{10,23} are combined with the generative adversarial net \cite{5} for robust representation learning in multi-view networks. Like most homogeneous network methods, most existing multi-view methods focus on relational reconstruction as the main optimization objectives, making the model unable to utilize the multi-view information effectively. The most relevant work to ours is DMGI \cite{17} that extends the DGI to multi-view networks, but it ignores the information redundancy among single-views.

3 The Proposed Method

3.1 Preliminaries

A multi-view network is a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{X}, \phi)$ whose edges are associated with more than one type. In such a multi-view graph, the mapping $\phi : \mathcal{E} \rightarrow \mathcal{R}, |\mathcal{R}| > 1$ associates an edge with an edge type; $\mathcal{V}, \mathcal{E} \in \mathcal{V} \times \mathcal{V}$, $\mathcal{X} \in \mathbb{R}^{\mathcal{V} \times F}$, and $\mathcal{R}$ represent the node set, the edge set, the node attribute matrix, and the set of edge types respectively. Alternatively, we may regard a multi-view network as the union of a series of graph view $\cup_{r \in \mathcal{R}} \{\mathcal{G}_r\}$, where $\mathcal{G}_r = (\mathcal{V}, \mathcal{E}_r)$, $\mathcal{E}_r \in \mathcal{E}$ is the set of all edges of type $r \in \mathcal{R}$.

Problem definition. In this work, we consider the task of self-supervised multi-view network embedding, where we aim to learn a $d$-dimensional ($d \ll F$) vector $z_i$ representing for each node $i$ without accessing to labels.

3.2 Contrastive Learning of Multi-View Networks.

We now present the proposed CREME, the framework of which is illustrated in Figure 1. There are three components: (1) a view encoder that projects nodes in each graph view into low-dimensional representations, (2) a multi-view aggregator that integrates representations of different graph views and get the comprehensive node representations for $\mathcal{G}$, and (3) a unified contrastive objective to construct a learning objective for training the view encoder and the multi-view aggregator.

Our main idea is to develop a self-supervised framework to learn an view encoder $f_r : \mathcal{A}_r \times \mathcal{X} \rightarrow \mathcal{Z}_r \in \mathbb{R}^{N \times d}$ for each graph view $\mathcal{G}_r$, and a multi-view aggregator $g : (\mathcal{Z}^1, ..., \mathcal{Z}^{|\mathcal{R}|}) \rightarrow \mathcal{Z} \in \mathbb{R}^{N \times d}$ for multi-view network $\mathcal{G}$. $z_i^r \in \mathcal{Z}_r$ is the representation of node $i$ in graph view $\mathcal{G}_r$, and $z_i \in \mathcal{Z}$ is the representation of node $i$ in graph $\mathcal{G}$, which is also denoted as fusion view representation. In this section, we introduce the learning objective at first (§3.2), and proceed to the view encoder (§3.2) and multi-view aggregator (§3.2) in detail.

Contrastive objectives for multi-view networks Our framework follows the common contrastive learning paradigm, which seeks to maximize the agreement of representations between different views. In this section, we propose two contrastive objects as following:
Fig. 1: Overview of CREME. Figure (a) presents the framework of our proposed model. Figure (b) and (c) illustrate the contrastive strategies between different graph views, where the green arrow indicates positive sample pairs, and the other arrows indicate negative sample pairs.

**Multi-view fusion InfoMax.** To facilitate the multi-view aggregator effectively to integrate information of each graph view, we seek to obtain node representations in each $G_r$ and $G$ via maximizing MI between $Z'$ and $Z_r$. The resulting fusion view representation can effectively distill information of each graph view. Specifically, we set view pair $(z_r^i, z_i)$ as a positive sample in Mutual Information Estimation (MIE) [16]. Following Zhu et al. [35], we set all other nodes in two graph views as negative pairs of $z_r^i$ (Figure 1(b)). Thus, the loss function for such a positive pair is defined as

$$
\mathcal{L}_o(z_r^i, z_i) = \log \frac{e^{\theta(z_r^i, z_i)} / \tau}{\sum_{j \neq i} e^{\theta(z_r^i, z_j)} / \tau + \sum_{j \neq i} e^{\theta(z'_r, z'_j)} / \tau},
$$

(1)
where $\theta(u, v) = s(p(u), p(v))$ is a critic function, $s(\cdot, \cdot)$ is implemented using a simple cosine similarity, $p(\cdot)$ is a non-linear projection to enhance the expression power of the critic, and $\tau$ is a temperature parameter. For simplicity, we write the denominator of Eq (1) as

$$
\rho(z_r^i, z_i) = e^{\theta(z_r^i, z_i)/\tau} + \sum_{j \neq i} e^{\theta(z_r^i, z_j)/\tau} + \sum_{j \neq i} e^{\theta(z_r^i, z^j_i)/\tau}.
$$

**Inter-view InfoMin.** The information of different graph views are often complementary to each other [28]. However, each node shares node attributes in different views, which may cause their embedding to be similar during the view encoding process. To make the representation of different graph views more distinguishable, we consider increasing the diversity constraints of view representations during multi-view aggregation. Our approach is to minimize the mutual information between different graph view representation $Z^r$ and $Z^k$. Rather than directly optimize MI, we set $(z_r^i, z_k^i)_{r \neq k}$ and $(z_r^i, z_j^k)_{i \neq j}$ as negative samples in MIE of $(Z^r, Z)$ (Figure 1(c)), which results in a modified loss function of Eq (1) as

$$
L(z_r^i, z_i) = \log \frac{e^{\theta(z_r^i, z_i)/\tau}}{\rho(z_r^i, z_i)} + \sum_{j \in G_k} \mathbb{I}_{[k \neq r]} \frac{e^{\theta(z_r^i, z_j^k)/\tau}}{\tau}.
$$

**Learning Objective.** The overall objective is defined as the average over all positive pairs, formally given by

$$
J = \frac{1}{N \cdot |R|} \sum_{i=1}^{N} \sum_{r=1}^{|R|} \sum_{r=1}^{N} L(z_r^i, z_i).
$$

To summarize, **Multi-view fusion infoMax** can facilitate the multi-view aggregator to distill more information from each graph view. Based on this, **Inter-view InfoMin** can constrain different graph view representations to be distinct, making the information from different views more complementary. In the next two sections, we introduce the view encoder and the multi-view aggregator in our multi-view contrastive learning framework.

**View Encoder** The view encoder aims to capture the node structural and attribute information in each graph view $G_r$, which is implemented by a view-specific graph attention neural network.

To be specific, we leverage the self-attention mechanism [25] to compute the weight coefficients $\alpha^r_{ij}$ between node $i$ and its neighbor $j$ in $G_r$, which is computed as

$$
\alpha^r_{ij} = \frac{\exp(\sigma(a_r^\top[M_r x_i \parallel M_r x_j])}{\sum_{k \in N_i^r} \exp(\sigma(a_r^\top[M_r x_i \parallel M_r x_k])},
$$

where $N_i^r$ is the set of neighbors of node $i$ in view $G_r$, $a_r \in \mathbb{R}^{2d}$ is a view-specific weight vector, $M_r \in \mathbb{R}^{d \times F}$ is a transformation matrix projecting each note...
attribute into the corresponding semantic space. The view representation of node \( i \) on \( G_r \) can be calculated by aggregating their neighbor node embeddings.

\[
z_r^i = \left\| \sigma \left( \sum_{j \in N_r^i} \alpha_{ij} M_r x_j \right) \right\|_k = 1 \quad (6)
\]

where \( \sigma \) is the ReLU function, and \( \| \) represents the concatenation of \( K \) independent node representations. Here we utilize the multi-head mechanism, which is helpful for modeling semantic diversity \([25]\). For each graph view, we use independent view encoder parameters.

**Multi-view Aggregator** The purpose of the multi-view aggregator is to integrate semantic information from all graph views and generate a fusion of node representations for a multi-view network \( G \). To distinguish important information during aggregation, we utilize an attention mechanism to aggregate the embeddings of different views for each node. The importance of each of view embedding \( z_r^i \) can be calculated by

\[
w_r^i = \frac{1}{|V|} \sum_{i \in V} q^T \tanh(W z_r^i + b), \quad (7)
\]

where \( W \in \mathbb{R}^{d \times d} \) is the weight matrix parameter, \( b \in \mathbb{R}^d \) is the bias vector, \( q \in \mathbb{R}^d \) is the semantic-level attention vector. These parameters are shared for all view graph \( G_r \). For each node, the weight of each node view embedding \( z_r^i \) can be obtained by softmax function

\[
\beta_r^i = \frac{\exp(w_r^i)}{\sum_{r=1}^{|R|} \exp(w_r^i)}. \quad (8)
\]

Then, the representation of node \( i \) can be obtained by

\[
z_i = \sum_{r=1}^{|R|} \beta_r^i z_r^i. \quad (9)
\]

### 4 Experiments

In this section, we conduct empirical analysis of the proposed CREME. Through experiments, we aim to answer the following questions. **RQ1:** How does CREME perform compared with state-of-the-art single-view and multi-view network embedding methods? **RQ2:** How do different components affect the performance of CREME?

#### 4.1 Experiment Setup

**Datasets.** Following Park et al. \([17]\), we conduct experiments on Amazon\(^3\), IMDB\(^4\), and DBLP\(^5\). The Amazon contains item nodes with three types of

\(^3\) https://www.amazon.com/

\(^4\) https://www.imdb.com/

\(^5\) https://aminer.org/AMinerNetwork
Table 1: Statistics of datasets used throughout experiments.

| Dataset | Relation Types | # Nodes | # Edges | # Attributes | # Classes |
|---------|----------------|---------|---------|--------------|-----------|
| Amazon  | I-V-I          | 7,621   | 266,237 | 2,000        | 4         |
|         | I-O-I          |         | 16,305  |              |           |
| IMDB    | M-A-M          | 3,550   | 66,428  | 1,007        | 3         |
|         | M-D-M          |         | 13,788  |              |           |
| DBLP    | P-A-P          | 7,907   | 144,783 | 2,000        | 4         |
|         | P-P-P          |         | 90,145  |              |           |
|         | P-A-T-A-P      |         | 57,137,515 |          |           |

relations (Also view (I-V-I), Also Bought (I-B-I), and Bought Together (I-O-I)). The IMDB contains movie nodes with movie-actor-movie (M-A-M) and movie-director-movie (M-D-M) relations. The DBLP network has papers nodes with paper-paper (P-P-P), paper-author-paper (P-A-P), and paper-author-term-author-paper (P-A-T-A-P) relations. To make fair comparisons, we do the same processing as DMGI [17] for all datasets. The statistics of datasets is presented in Table 1.

Compared methods. We compare CREME with eleven methods. Seven single-view network methods include DeepWalk [19], Node2Vec [6], ANRL [33], GCN [13], GAT [25], DGI [27], and GraphCL [31]. Two heterogeneous network methods include Metapath2vec [4] and HAN [29]. Three multi-view network methods include MNE [32], GATNE [1] and DMGI [17].

Settings. We implement our CREME using the DGL Library. The embedding size is fixed to 64 for all methods. For the compared methods, we set the default hyperparameters except for dimensions. For the proposed CREME, we employ the Adam optimizer [11] with the initial learning rate to 0.001, the weight decay to 1e-5, the temperature $\tau$ to 0.7, and set the dropout of view encoder to 0.6. We run the evaluation fifty times and report the mean value of our method. Following Park et al. [17], we employ Logistic Regression and K-Means to perform node classification and node clustering on the learned embeddings, respectively. We measure node classification tasks using Macro-F1 (MaF1) and Micro-F1 (MiF1) and node clustering tasks using normalized mutual information (NMI).

4.2 Performance Comparison (RQ1)

We first report the performance of all compared methods on node classification and node clustering tasks. Table 2 summaries the results of evaluation.

Our CREME consistently achieves the best performance on three datasets. Compared with the strongest baseline DMGI, CREME obtains the most noticeable performance improvement on Amazon and DBLP, where the datasets have more
Table 2: Performance comparison of different methods. The highest performance is highlighted in boldface. The underlined number is the second best results. “Improve” means the improvement over the underline methods.

| Method      | Amazon  | IMDB    | DBLP    |
|-------------|---------|---------|---------|
|             | MaF1    | MiF1    | NMI     | MaF1    | MiF1    | NMI     |
| Deepwalk    | 0.663   | 0.671   | 0.083   | 0.532   | 0.55    | 0.117   | 0.533   | 0.537   | 0.348   |
| node2vec    | 0.662   | 0.669   | 0.074   | 0.533   | 0.55    | 0.123   | 0.543   | 0.547   | 0.382   |
| ANRL        | 0.692   | 0.690   | 0.166   | 0.573   | 0.576   | 0.163   | 0.770   | 0.699   | 0.332   |
| GCN/GAT     | 0.646   | 0.649   | 0.287   | 0.603   | 0.611   | 0.176   | 0.734   | 0.717   | 0.465   |
| DGI         | 0.403   | 0.418   | 0.007   | 0.598   | 0.606   | 0.182   | 0.723   | 0.720   | 0.551   |
| GraphCL     | 0.423   | 0.439   | 0.121   | 0.613   | 0.624   | 0.183   | 0.736   | 0.722   | 0.562   |
| Metapath2vec| 0.674   | 0.678   | 0.092   | 0.546   | 0.574   | 0.144   | 0.653   | 0.649   | 0.382   |
| HAN         | 0.501   | 0.509   | 0.029   | 0.599   | 0.607   | 0.164   | 0.716   | 0.708   | 0.472   |
| MNE         | 0.556   | 0.567   | 0.001   | 0.552   | 0.574   | 0.013   | 0.566   | 0.562   | 0.136   |
| GATNE       | 0.561   | 0.573   | 0.073   | 0.494   | 0.504   | 0.048   | 0.673   | 0.665   | 0.436   |
| DMGI        | 0.729   | 0.731   | 0.267   | 0.648   | 0.648   | 0.196   | 0.771   | 0.766   | 0.409   |
| DMGI-attn   | 0.741   | 0.741   | 0.277   | 0.602   | 0.606   | 0.185   | 0.778   | 0.770   | 0.554   |
| CREME       | 0.781   | 0.785   | 0.301   | 0.672   | 0.675   | 0.211   | 0.812   | 0.798   | 0.623   |
| Improve     | 5.4%    | 5.9%    | 8.7%    | 3.7%    | 4.2%    | 7.7%    | 4.4%    | 3.6%    | 12.5%   |

relations than IMDB. This verifies that our framework has strong capabilities to utilize different graph views. CREME is also competitive with semi-supervised models, i.e., HAN, GAT, and GCN, which shows the superiority of our framework in the training of view encoder and multi-view aggregator. Conventional baselines MNE and Metapath2vec are inferior to that of attribute-aware network methods, such as HAN, ANRL, and DMGI, on most datasets. This indicates that the importance of node attributes in multi-view embedding. Furthermore, most multi-view methods, such as DMGI, GATNE, and MNE, generally outperform single-view methods. This verifies the necessity of modeling multiple relations. GraphCL and DGI, as the MI maximization methods, perform the best among single-view network embedding methods in most datasets. Similarly, the performance of DGMJ is also better than most multi-view methods in compared methods. This result further demonstrates the superiority of mutual information optimization over proximity reconstruction in representation learning.

4.3 Ablation Studies (RQ2)

To investigate the effects of the contrastive objectives, view encoder, and multi-view aggregator, we compare CREME with different variants: $CRE_V$-mean and $CRE_V$-max set the operator as mean and max in view encoder, respectively; $CRE_M$-mean and $CRE_M$-max set the operator as mean and max in multi-view
Table 3: Performance of different model variants.

| Variants   | Amazon   | IMDB     | DBLP     |
|------------|----------|----------|----------|
|            | MaF1     | MiF1     | NMI      | MaF1     | MiF1     | NMI      | MaF1     | MiF1     | NMI      |
| CREV-mean  | 0.534    | 0.555    | 0.071    | 0.519    | 0.546    | 0.056    | 0.801    | 0.795    | 0.516    |
| CREV-max   | 0.594    | 0.608    | 0.023    | 0.551    | 0.562    | 0.015    | 0.810    | 0.796    | 0.516    |
| CREL-mean  | 0.771    | 0.781    | 0.242    | 0.672    | 0.673    | 0.196    | 0.803    | 0.783    | 0.623    |
| CREL-max   | 0.715    | 0.732    | 0.223    | 0.671    | 0.674    | 0.203    | 0.792    | 0.780    | 0.606    |
| CREC-ori   | 0.715    | 0.732    | 0.249    | 0.657    | 0.661    | 0.216    | 0.795    | 0.775    | 0.519    |
| CREME      | 0.781    | 0.785    | 0.301    | 0.672    | 0.675    | 0.211    | 0.812    | 0.798    | 0.623    |

Fig. 2: Visualization of the learned node embedding by DMGI and CREME on DBLP.

aggregator, respectively; CREC-ori does not consider the Inter-view InfoMin in contrastive objective explicitly. The results are shown in Table 3. From all results, we have the following findings:

CREV-mean and CREV-max perform worse than CREL-mean and CREL-max on most datasets, especially for NMI metric, which means the view encoder has a more significant effect on model performance compared to the multi-view aggregator. The performance of CREL-mean and CREL-max is not significantly different from that of CREME in IMDB. However, the performance of CREL-max is worse in Amazon and DBLP. The reason is that Amazon and DBLP data is more complicated than IMDB, as shown by the fact Amazon and DBLP have more relations. The max aggregator tends to ignore multiplicities than attention and mean aggregator [30]. CREME outperforms CREC-ori in most cases, which demonstrates that the Inter-view InfoMin could strengthen the performance of CREME under the Multi-view fusion InfoMax.

4.4 Visualization

To provide a more qualitative evaluation, we map the node embedding of the DBLP network learned by CREME and DMGI into a 2-D space with the t-SNE
package [15] and plot them in Figure 2. We can find that CREME has more distinct boundaries and clusters than DMGI. It means that CREME can learn more powerful node embedding compared to the SOTA method.

5 Conclusion

In this work, we propose a novel contrastive learning framework for multi-view network embedding, which contains the view encoder, multi-view aggregator, and a unified contrastive objective. Extensive experiments on three multi-view networks verify the effectiveness and rationality of CREME.

References

1. Cen, Y., Zou, X., Zhang, J., Yang, H., Zhou, J., Tang, J.: Representation learning for attributed multiplex heterogeneous network. In: KDD (2019)
2. Chen, T., Kornblith, S., Norouzi, M., Hinton, G.: A simple framework for contrastive learning of visual representations. arXiv preprint arXiv:2002.05709 (2020)
3. Chu, X., Fan, X., Yao, D., Zhu, Z., Huang, J., Bi, J.: Cross-network embedding for multi-network alignment. In: WWW (2019)
4. Dong, Y., Chawla, N.V., Swami, A.: metapath2vec: Scalable representation learning for heterogeneous networks. In: KDD (2017)
5. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y.: Generative adversarial nets. NIPS (2014)
6. Grover, A., Leskovec, J.: node2vec: Scalable feature learning for networks. In: KDD (2016)
7. Hamilton, W., Ying, Z., Leskovec, J.: Inductive representation learning on large graphs. In: NIPS (2017)
8. Hassani, K., Khasahmadi, A.H.: Contrastive multi-view representation learning on graphs. ICML (2020)
9. Hjelm, R.D., Fedorov, A., Lavoie-Marchildon, S., Grewal, K., Bachman, P., Trischler, A., Bengio, Y.: Learning deep representations by mutual information estimation and maximization. In: ICLR (2018)
10. Hu, B., Fang, Y., Shi, C.: Adversarial learning on heterogeneous information networks. In: KDD (2019)
11. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization (2015)
12. Kipf, T.N., Welling, M.: Variational graph auto-encoders. arXiv preprint arXiv:1611.07308 (2016)
13. Kipf, T.N., Welling, M.: Semi-Supervised Classification with Graph Convolutional Networks. In: ICLR (2017)
14. Ma, Y., Ren, Z., Jiang, Z., Tang, J., Yin, D.: Multi-dimensional network embedding with hierarchical structure. In: WSDM (2018)
15. Van der Maaten, L., Hinton, G.: Visualizing data using t-sne. Journal of machine learning research 9(11) (2008)
16. van den Oord, A., Li, Y., Vinyals, O.: Representation Learning with Contrastive Predictive Coding. arXiv.org (2018)
17. Park, C., Kim, D., Han, J., Yu, H.: Unsupervised Attributed Multiplex Network Embedding. In: AAAI (2020)
18. Peng, Z., Huang, W., Luo, M., Zheng, Q., Rong, Y., Xu, T., Huang, J.: Graph representation learning via graphical mutual information maximization. In: WWW (2020)
19. Perozzi, B., Al-Rfou, R., Skiena, S.: Deepwalk: Online learning of social representations. In: KDD (2014)
20. Qiu, J., Dong, Y., Ma, H., Li, J., Wang, K., Tang, J.: Network embedding as matrix factorization: Unifying deepwalk, line, pte, and node2vec. In: WSDM (2018)
21. Qu, M., Tang, J., Shang, J., Ren, X., Zhang, M., Han, J.: An attention-based collaboration framework for multi-view network representation learning. In: CIKM (2017)
22. Ribeiro, L.F., Saverese, P.H., Figueiredo, D.R.: struc2vec: Learning node representations from structural identity. In: KDD (2017)
23. Sun, Y., Wang, S., Hsieh, T.Y., Tang, X., Honavar, V.: Megan: a generative adversarial network for multi-view network embedding. In: IJCAI (2019)
24. Tang, J., Qu, M., Wang, M., Zhang, M., Yan, J., Mei, Q.: Line: Large-scale information network embedding. In: WWW (2015)
25. Veličković, P., Cucurull, G., Casanova, A., Romero, A., Liò, P., Bengio, Y.: Graph attention networks. In: ICLR (2018)
26. Veličković, P., Fedus, W., Hamilton, W.L., Liò, P., Bengio, Y., Hjelm, R.D.: Deep graph infomax. In: ICLR (2018)
27. Veličković, P., Fedus, W., Hamilton, W.L., Liò, P., Bengio, Y., Hjelm, R.D.: Deep Graph Infomax. In: ICLR (2019)
28. Wang, W., Arora, R., Livescu, K., Bilmes, J.: On deep multi-view representation learning. In: ICML (2015)
29. Wang, X., Ji, H., Shi, C., Wang, B., Ye, Y., Cui, P., Yu, P.S.: Heterogeneous Graph Attention Network. In: WWW (2019)
30. Xu, K., Hu, W., Leskovec, J., Jegelka, S.: How powerful are graph neural networks? In: ICLR (2018)
31. You, Y., Chen, T., Sui, Y., Chen, T., Wang, Z., Shen, Y.: Graph contrastive learning with augmentations. NIPS (2020)
32. Zhang, H., Qiu, L., Yi, L., Song, Y.: Scalable multiplex network embedding. In: IJCAI (2018)
33. Zhang, Z., Yang, H., Bu, J., Zhou, S., Yu, P., Zhang, J., Ester, M., Wang, C.: Anrl: Attributed network representation learning via deep neural networks. In: IJCAI (2018)
34. Zhu, Y., Xu, Y., Yu, F., Liu, Q., Wu, S., Wang, L.: Deep Graph Contrastive Representation Learning. In: GRL+@ICML (2020)
35. Zhu, Y., Xu, Y., Yu, F., Liu, Q., Wu, S., Wang, L.: Graph contrastive learning with adaptive augmentation. arXiv preprint arXiv:2010.14945 (2020)