SGCL: Contrastive Representation Learning for Signed Graphs

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ABSTRACT

Graph contrastive representation learning aims to learn discriminative node representations by contrasting positive and negative samples. It helps models learn more generalized representations to achieve better performances on downstream tasks, which has aroused increasing research interest in recent years. Simultaneously, signed graphs consisting of both positive and negative links have become ubiquitous with the growing popularity of social media. However, existing works on graph contrastive representation learning are only proposed for unsigned graphs (containing only positive links) and it remains unexplored how they could be applied to signed graphs due to the distinct semantics and complex relations between positive and negative links. Therefore we propose a novel **S**igned **G**raph **C**ontrastive **L**earning model (**SGCL**) to bridge this gap, which to the best of our knowledge is the first research to employ graph contrastive representation learning on signed graphs. Concretely, we design two types of graph augmentations specific to signed graphs based on a significant signed social theory, i.e., balance theory. Besides, inter-view and intra-view contrastive learning are proposed to learn discriminative node representations from perspectives of graph augmentations and signed structures respectively. Experimental results demonstrate the superiority of the proposed model over state-of-the-art methods on both real-world social datasets and online game datasets.

CCS CONCEPTS

• **Computing methodologies** → **Learning latent representations**; • **Mathematics of computing** → *Graph algorithms.*

KEYWORDS

contrastive learning; signed graph; network representation; graph neural networks

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1 INTRODUCTION

With the increasing popularity of social media, various interactions between people are generated and recorded in social graphs [2, 20, 36]. While most social interactions suggest positive relationships such as like, trust and friend, there also exist negative interactions reflecting hate, distrust, etc. In general, graphs that have both positive and negative interactions/links are referred to as signed graphs [5, 27, 35]. As an illustration, Fig. 1 depicts a signed graph in the scenario of online games, where the interactions of *Like* and *Gift* indicate positive links and the interactions of *Report* imply negative links between users. In recent years, some researchers investigate network representation on signed graphs [17, 28, 42], which aims at learning low-dimensional representations of nodes and further serving for downstream network analysis tasks [26, 45]. However, there always exists interaction noise in real-world signed graphs, yet methods for signed network representation leverage the noisy interactions to optimize models, resulting in the overfitting problem on the training data as well as the performance degradation on downstream tasks.

Fortunately, graph contrastive representation learning [14, 22, 25] can help solve this problem, which defines a contrastive objective on the graph to assist learning more robust and generalized representations for downstream tasks and has aroused a growing interest in recent years. However, existing works of graph contrastive learning are only proposed for unsigned graphs (consisting of only positive links) and it remains unexplored how they could be applied to signed graphs due to the distinct semantics and complex relations between positive and negative links.

To solve the above problems, we exploit contrastive learning with graph augmentations [47, 52] for signed graphs to help the model learn more robust and generalized representations. Notably, network representation methods designed for signed graphs constrain each node closer to its "friends" (or neighbors connected with positive links) and farther from its "enemies" (or neighbors connected with negative links), which is the same as the core idea

Joint work with UX Center, Netease Games.

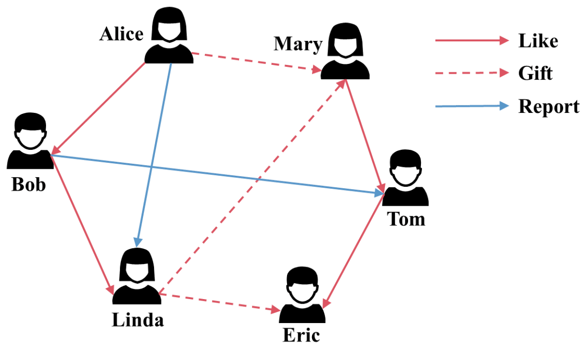


Figure 1: An illustrative example of signed graph in the scenario of online games, where the red lines represent positive interactions/links and the blue lines represent negative interactions/links.

of contrastive learning that aims at grouping positive pairs close and pushing negative pairs away.

Specifically, there exist the following challenges when designing signed graph contrastive learning:

- Existing graph contrastive learning methods perform graph augmentations by node dropping, attribute masking, etc, which are mainly designed for unsigned graphs while ignoring the diverse semantics between positive and negative links in signed graphs. Therefore, the first challenge is how to redesign graph augmentations specifically for signed graphs, which take the complex relations between positive and negative links into consideration.
- Most graph contrastive learning methods employ graph augmentations to generate different graph views and contrast augmented graphs to retain the information consistency between them, which make augmented representations of the same node to be close while pushing away representations of different nodes. However, signed graph contrastive learning also requires another contrast on signed structures to make nodes close to neighbors connected with positive links and far from those with negative links. Hence, the second challenge is how to combine the two forms of contrasts into a single coherent contrastive learning model.

To address the aforementioned challenges, we propose a novel **S**igned **G**raph **C**ontrastive **L**earning model (**SGCL**) to explore contrastive representation learning on signed graphs. Specifically, SGCL designs and performs two types of graph augmentations to help capture the invariant representations based on a significant signed social theory, i.e. balance theory [1, 9]. Then, two graph neural networks [44, 50] with attention mechanism [37] are adopted on the augmented graphs to learn representations from "friends" and "enemies" for each node respectively, followed by the inter-view and intra-view contrastive learning to combine the contrasts of augmented graphs and signed structures. Ultimately, supervised labels and the combined contrastive objective are integrated to train SGCL jointly.

To sum up, the major contributions of this paper are as follows:

- We design two types of graph augmentations specifically for signed graphs, which help capture the invariant node representations based on the balance theory.
- We propose a signed graph contrastive learning model SGCL, which combines the contrasts of augmented graphs and signed structures coherently. To the best of our knowledge, this is the first research on signed graph contrastive representation learning.
- We conduct extensive experiments on the real-world social datasets and online game datasets to comprehensively demonstrate the effectiveness of the proposed SGCL model.

The rest of the paper is organized as follows. In Section 2, we briefly review related works of graph contrastive learning and signed network representation. In Section 3, we formulate the problem of signed network representation and introduce a significant signed social theory, i.e., balance theory. Then, our proposed SGCL model is presented detailedly in Section 4, followed by extensive experiments to evaluate the effectiveness of SGCL compared with state-of-the-art methods in Section 5. Finally, we conclude the paper in Section 6.

2 RELATED WORK

2.1 Graph Contrastive Learning

Contrastive learning, whose main idea is to learn discriminative representations by contrasting positive and negative samples, has gained increasing popularity in visual representation learning [14, 22]. Inspired by the promising success of contrastive learning in images, researchers manage to extend contrastive learning to graph-structured data [31, 34, 46] in recent years, namely graph contrastive representation learning, which can help models learn more invariant and generalized node representations. For instance, DGI [39] incorporates graph neural networks and contrastive learning, and generates node representations by maximizing mutual information between global graph representations and local node representations. GraphCL [47] develops a graph contrastive learning framework that leverages various types of graph augmentations to capture the invariant node representations. GRACE [51] generates graph views by two proposed graph augmentations and maximizes the agreement of node representations in different views. MVGRL [8] introduces a self-supervised approach by maximizing mutual information between node representations from two structural graph views including first-order neighbors and a graph diffusion. Nevertheless, existing researches on graph contrastive learning are only designed for unsigned graphs, which can not distinguish the diverse properties of positive and negative links and fail to take advantage of additional information from negative links, thus not applicable for signed graphs.

2.2 Signed Network Representation

Due to the popularity of social media, signed graphs have become ubiquitous and network representation on signed graphs has attracted increasing attention in data mining and machine learning [3, 4, 40]. As the first research on signed network representation, SNE [48] utilizes the log-bilinear model and representations of all nodes along a given path to capture the edge sign information. Later, SiNE [43] is proposed, which designs an objective function

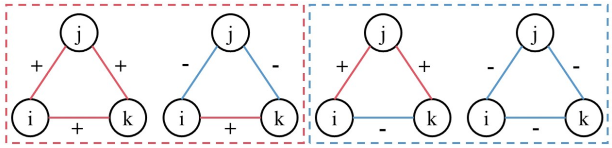


Figure 2: Illustrations of balanced and unbalanced cycles. The two cycles on the left are balanced cycles since there exist an even number of negative links. The two cycles on the right are unbalanced cycles since the number of negative links is odd.

based on the balance theory and employs deep learning to optimize the objective function. In recent years, with the popularity and success of graph neural networks, researchers begin to exploit graph neural networks for signed network representation. For example, SGCN [6] and SNEA [24] incorporate the balance theory into the aggregation processes of graph convolutional networks and graph attention networks respectively to integrate positive and negative links. SDGNN [12] proposes a framework guided by two fundamental sociological theories, i.e. balance theory and status theory, which utilizes graph attention networks to encode signed graphs and reconstructs link signs, link directions and signed directed triangles to learn node representations. However, there exists a large number of interactions between users in the real-world signed graphs, where some interactions may be noisy and spurious. The aforementioned methods are optimized by the noisy interactions in the original graphs, which are vulnerable to the attacks of noisy links and thus cause over-fitting on the training data as well as the performance degradation on downstream tasks. Therefore, more robust node representations are expected for signed graphs, and we adopt contrastive learning to generate more invariant and generalized representations in this paper.

3 PRELIMINARY

For the convenience of presentation, we first introduce some definitions and main notations used in this paper. Calligraphic math font (e.g., $\mathcal{V}$) denotes set, boldface uppercase letters (e.g., $\mathbf{A}$) denote matrices and boldface lowercase letters (e.g., $\boldsymbol{w}$) denote vectors.

Signed Graph. A signed graph is denoted as $\mathcal{G} = (\mathcal{V}, \mathcal{E}^+, \mathcal{E}^-)$, where $\mathcal{V} = \{v_1, v_2, ..., v_n\}$ represents the set of n nodes while $\mathcal{E}^+$ and $\mathcal{E}^-$ represent the set of positive and negative links respectively.

Signed Network Representation. Given a signed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}^+, \mathcal{E}^-)$, the aim of signed network representation is to learn d-dimensional representations $\mathbf{Z} \in \mathbb{R}^{n \times d}$ for the n nodes in $\mathcal{G}$.

Balance theory. Balance theory is a fundamental and indispensable signed social theory that originated and developed in social psychology. In general, cycles consisting of an even number of negative links are balanced cycles while those with an odd number of negative links are unbalanced cycles. For example, the first two cycles in Fig. 2 are balanced while the others are unbalanced. Balance theory implies that *the friend of my friend is my friend* and *the enemy of my enemy is my friend*, which has been found to be widely existing in signed graphs and thus has a vast range of applications in signed network representation [6, 11–13]. In this paper, we turn our attention to balanced cycles since they are more plausible and prevalent than unbalanced ones [1, 9] in real-world signed graphs.

4 PROPOSED METHODOLOGY

In this section, we propose a novel graph contrastive representation learning model - SGCL for signed graphs, which is illustrated in Fig. 3.

4.1 Graph Augmentation

In order to reduce the harm of interaction noise to models, we employ graph augmentations [49] to enhance the robustness and generalization ability of the proposed model. Since balance theory plays a significant role in analyzing the complex relations between positive and negative links, it is indispensable to capture the invariant structures of balanced cycles when designing graph augmentations specific to signed graphs. Concretely, through perturbing the structures of balanced cycles, some spurious balanced cycles/relationships are eliminated while some potential balanced cycles/relationships are discovered and exploited, which helps to improve the generalization performance of the proposed model. As a consequence, two approaches of graph augmentations are proposed in the following, which perturb the existing balanced cycles from different perspectives.

Connectivity Perturbation. Given the signed graph $\mathcal{G}$, we perturb the connectivity of $\mathcal{G}$ by randomly dropping and adding links. Specifically, we firstly drop some links of $\mathcal{G}$, where each link is discarded with a probability r. Supposing that p positive links and q negative links are removed from $\mathcal{G}$, we then generate $p + q$ non-existing links randomly and add them into $\mathcal{G}$, where p links are added as positive links and q links are added as negative ones. This approach supposes that the semantics of $\mathcal{G}$ has certain robustness to the variances of balanced cycles affected by link connectivity.

Sign Perturbation. Different from the graph augmentation that perturbs link connectivity, sign perturbation changes the sign of links in $\mathcal{G}$ randomly. Particularly, a positive link is transformed into a negative one with a probability r while a negative link is transformed into a positive one with the same probability similarly. This approach assumes that perturbing balanced cycles by changing link signs does not affect model predictions much.

To sum up, the two types of graph augmentations both leverage the augmentation ratio r to perturb existing balanced cycles and the number of links remains unchanged after graph augmentations. In our SGCL model, in each iteration, we apply either the connectivity perturbation or sign perturbation to transform the original graph into two different graph views, denoted as $\widetilde{\mathcal{G}_1} = (\mathcal{V}, \widetilde{\mathcal{E}}_1^+, \widetilde{\mathcal{E}}_1^-)$ and $\widetilde{\mathcal{G}_2} = (\mathcal{V}, \widetilde{\mathcal{E}}_2^+, \widetilde{\mathcal{E}}_2^-)$.

4.2 Graph Encoder

After generating two graph views by graph augmentations, we further utilize graph neural networks (GNNs) to learn node representations on all views. In signed graphs, positive and negative links have distinct semantic properties, where positive links reflect closeness to friends and negative links imply hatred to enemies, motivating us to design two separate GNNs to aggregate positive and negative links respectively, which also serves for the contrastive objective introduced in the next subsection. More specifically, we split

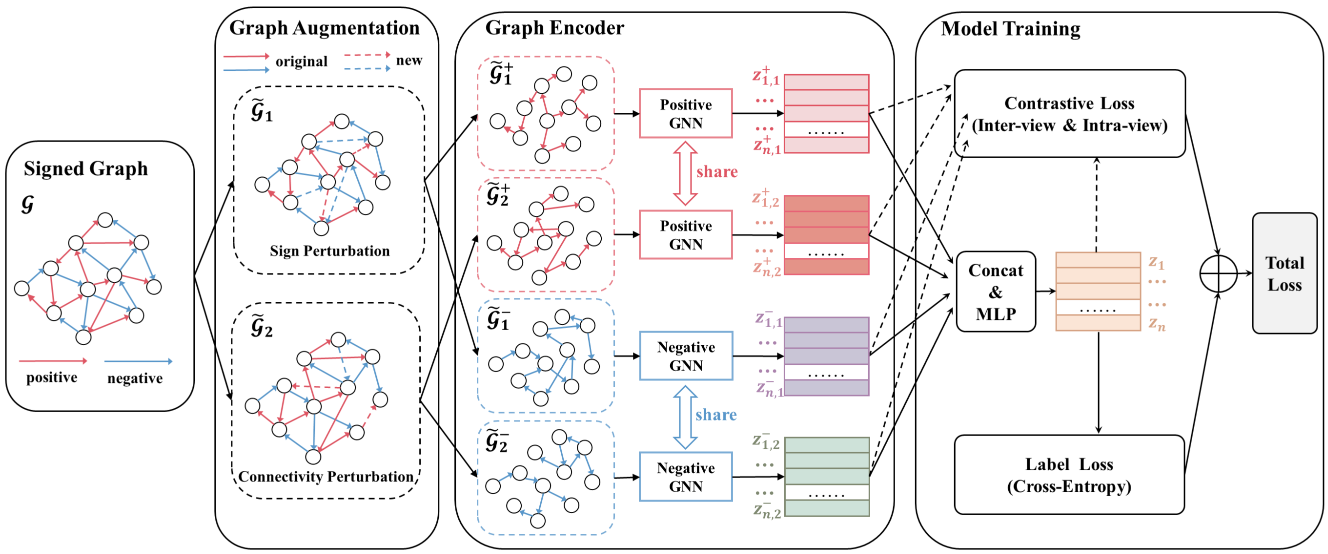


Figure 3: The overall architecture of SGCL, which consists of three major components: (a) Graph Augmentation, (b) Graph Encoder, (c) Model Training.

each graph view $\widetilde{\mathcal{G}}_i = (\mathcal{V}, \widetilde{\mathcal{E}}_i^+, \widetilde{\mathcal{E}}_i^-)$ into two graphs containing only positive links and only negative links, referred to as **positive graph** $\widetilde{\mathcal{G}}_i^+ = (\mathcal{V}, \widetilde{\mathcal{E}}_i^+)$ and **negative graph** $\widetilde{\mathcal{G}}_i^- = (\mathcal{V}, \widetilde{\mathcal{E}}_i^-)$ respectively. Then a **positive GNN** is leveraged to learn node representations from the positive graphs while a **negative GNN** is employed to learn representations from the negative graphs, which are shared across the positive and negative graphs of all views, respectively. The learned representations from positive graphs are denoted as **consistent representations** while the ones from negative graphs are denoted as **inconsistent representations**.

In the following, we introduce the aggregation layer used in positive and negative GNNs in detail. Since the contributions of neighbors are different for each node, we utilize the attention mechanism to learn neighbors' importance for each node during the aggregation process. Concretely, for a given node v_i and its neighbor v_j in the positive/negative graph, we leverage the attentional mechanism parametrized by a weight vector $\boldsymbol{a}^+ \in \mathbb{R}^{1\times 2d_{out}}$ for the positive GNN (or $\boldsymbol{a}^- \in \mathbb{R}^{1\times 2d_{out}}$ for the negative GNN) and apply the LeakyReLU nonlinearity (with negative input slope $\alpha = 0.2$) to compute the attention coefficient α_{ij} of node v_j to node v_i, which can be formulated as follows:

$$\alpha_{ij}^+ = \frac{\exp(\text{LeakyReLU}(\boldsymbol{a}^+[\boldsymbol{h}_i^+\mathbf{W}_a^+ || \boldsymbol{h}_j^+\mathbf{W}_a^+]^T))}{\sum_{t\in\mathcal{N}_i^+}\exp(\text{LeakyReLU}(\boldsymbol{a}^+[\boldsymbol{h}_i^+\mathbf{W}_a^+ || \boldsymbol{h}_t^+\mathbf{W}_a^+]^T))}, \tag{1}$$

$$\alpha_{ij}^- = \frac{\exp(\text{LeakyReLU}(\boldsymbol{a}^-[\boldsymbol{h}_i^-\mathbf{W}_a^- || \boldsymbol{h}_j^-\mathbf{W}_a^-]^T))}{\sum_{t\in\mathcal{N}_i^-}\exp(\text{LeakyReLU}(\boldsymbol{a}^-[\boldsymbol{h}_i^-\mathbf{W}_a^- || \boldsymbol{h}_t^-\mathbf{W}_a^-]^T))}, \tag{2}$$

where N_i^+ and N_i^- denote neighbors of node v_i in the positive graph and negative graph respectively, $\boldsymbol{h}_i^+, \boldsymbol{h}_i^- \in \mathbb{R}^{d_{in}}$ represent the input consistent and inconsistent representation of node v_i, $\mathbf{W}_a^+, \mathbf{W}_a^- \in \mathbb{R}^{d_{in}\times d_{out}}$ are the weight matrices in the positive and negative GNNs respectively, d_{in} and d_{out} denote the input and output representation dimensions of the aggregation layer and we set d_{out} to be equal to d in each aggregation layer. In addition, $\cdot^T$ denotes transposition and $||$ represents concatenation. Obviously, the attention coefficient is normalized across all choices of node v_j.

After obtaining the normalized attention coefficients, we compute the linear combinations of input node representations corresponding to the coefficients and apply a nonlinearity to generate the output representations for each node. Furthermore, the multi-head attention mechanism [37] which learns K independent attention aggregations are leveraged to make the learning process more stable, i.e.,

$$\boldsymbol{h}_i^{+\prime} = \Big\Vert_{k=1}^{K} \sigma\Big(\sum_{j\in N_i^+} \alpha_{ij}^{k,+}\, \boldsymbol{h}_j^+\, \mathbf{W}_b^{k,+}\Big), \tag{3}$$

$$\boldsymbol{h}_i^{-\prime} = \Big\Vert_{k=1}^{K} \sigma\Big(\sum_{j\in N_i^-} \alpha_{ij}^{k,-}\, \boldsymbol{h}_j^-\, \mathbf{W}_b^{k,-}\Big), \tag{4}$$

where $\boldsymbol{h}_i^{+\prime}, \boldsymbol{h}_i^{-\prime} \in \mathbb{R}^{d_{out}}$ represent the output consistent and inconsistent representations respectively, $\alpha_{ij}^{k,+}, \alpha_{ij}^{k,-}$ and $\mathbf{W}_b^{k,+}, \mathbf{W}_b^{k,-}$ are the normalized attention coefficients and the transformation matrices for positive and negative GNNs in the k-th head, σ denotes the nonlinear activation function such as ReLU.

Ultimately, the positive and negative GNNs are built by stacking multiple aggregation layers proposed in Eq. 3- 4, which are shared across all graph views, as shown in Fig. 3. Since representations in different layers emphasize the connectivity of different order, we concatenate representations of all layers to constitute the final node representations:

$$z_i^+ = [\boldsymbol{h}_i^{(0)+} \| \boldsymbol{h}_i^{(1)+} \| \cdots \| \boldsymbol{h}_i^{(L)+}]\mathbf{W}_c^+, \tag{5}$$

$$z_i^- = [\boldsymbol{h}_i^{(0)-} \| \boldsymbol{h}_i^{(1)-} \| \cdots \| \boldsymbol{h}_i^{(L)-}]\mathbf{W}_c^-, \tag{6}$$

where L denotes the layers of GNNs, $\boldsymbol{h}_i^{(l)+}$ and $\boldsymbol{h}_i^{(l)-}$ denotes the consistent and inconsistent representation of node v_i in the l-th layer, $\mathbf{W}_c^+, \mathbf{W}_c^- \in \mathbb{R}^{(Ld+d)\times d}$ denote the transformation matrices, $z_i^+, z_i^- \in \mathbb{R}^d$ denote the final consistent and inconsistent representation of v_i respectively. Note that $\boldsymbol{h}_i^{(0)+}, \boldsymbol{h}_i^{(0)-}$ are obtained by a linear transformation of node attribute. As a consequence, the proposed graph encoder finally generates two representations on each graph view for node v_i, denoted as $z_{i,m}^+$ and $z_{i,m}^-$, where m represents the m-th view of augmented graphs. As a consequence, $z_{i,m}^+$ and $z_{i,m}^-$ convey the information of v_i's friends (or neighbors connected with positive links) and enemies (or neighbors connected with negative links) in the m-th graph view respectively.

4.3 Contrastive Objective

In this section, we form the contrastive objective by the inter-view and intra-view contrastive learning, which distinguish positive samples from negative samples based on augmented graphs and signed structures respectively. Fig. 4 illustrates an example of inter-view and intra-view contrastive learning.

4.3.1 Inter-view Contrastive Learning. In order to retain the information consistency between different augmented graphs, SGCL maximizes the agreements of representations between the same node in different graph views while minimizes the representation similarities between different nodes, which is a contrastive learning process between different nodes and thus is called **inter-view contrastive learning**. Since SGCL splits each graph view into a positive graph and a negative graph, we maximize the mutual information between the learned consistent representations as well as between the learned inconsistent representations across all views.

In the following, we firstly introduce the inter-view contrastive objective for consistent representations. Concretely, given a minibatch $\mathcal{B}$ containing I nodes, for a query consistent representation $z_{i,m}^+$, its inter-view positive samples are the consistent representations generated from the same node in other graph views, and its inter-view negative samples are the ones generated from different nodes in other graph views. Inspired by the InfoNCE loss [7, 29, 32], the inter-view consistent contrastive loss is defined as follows:

$$\mathcal{L}_{inter_{pos}} = -\frac{1}{I}\sum_{i=1}^{I} \log \frac{\exp(\mathrm{sim}(z_{i,m}^+, z_{i,m'}^+)/\tau)}{\sum_{j=1, j\neq i}^{I} \exp(\mathrm{sim}(z_{i,m}^+, z_{j,m'}^+)/\tau)} \tag{7}$$

where $z_{i,m}^+$ represents the consistent representation of node v_i in the m-th augmented positive graph view, $\mathrm{sim}(z_{i,m}^+, z_{i,m'}^+)$ represents the cosine similarity function between the two representations and τ denotes the preset temperature parameter.

Similarly, for a query inconsistent representation $z_{i,m}^-$, its inter-view positive samples are the inconsistent representations generated from the same node in other graph views while its inter-view negative samples are the ones generated from different nodes in other graph views. As a consequence, the inter-view inconsistent contrastive loss is defined as:

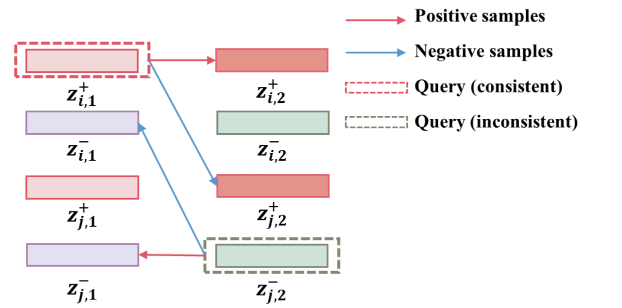
$$\mathcal{L}_{inter_{neg}} = -\frac{1}{I}\sum_{i=1}^{I} \log \frac{\exp(\mathrm{sim}(z_{i,m}^-, z_{i,m'}^-)/\tau)}{\sum_{j=1, j\neq i}^{I} \exp(\mathrm{sim}(z_{i,m}^-, z_{j,m'}^-)/\tau)} \tag{8}$$

To sum up, we maximize the similarities of representations generated from the same node and minimize the similarities of representations generated from different nodes on both augmented positive and negative graphs. The inter-view contrastive loss is formed as:

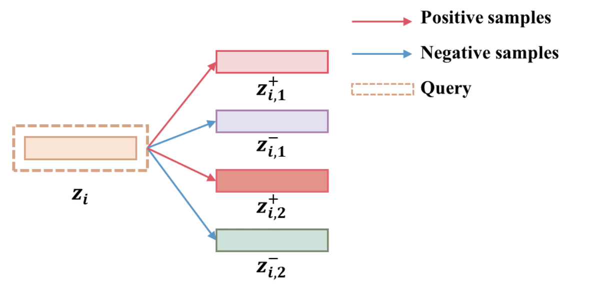
$$\mathcal{L}_{inter} = \mathcal{L}_{inter_{pos}} + \mathcal{L}_{inter_{neg}} \tag{9}$$

4.3.2 Intra-view Contrastive Learning. Because the consistent representation $z_{i,m}^+$ learned from positive graph implies the information of v_i's friends (or neighbors with positive links) while the inconsistent representation $z_{i,m}^-$ learned from negative graph conveys the information of v_i's enemies (or neighbors with negative links), SGCL performs contrastive learning on signed structures by constraining the ultimate representation of each node close to its consistent representations and far from its inconsistent representations, which is a contrastive learning process on the same node and thus is called **intra-view contrastive learning**.

Specifically, given a minibatch $\mathcal{B}$ containing I nodes, for each node v_i, we generate the representation of v_i by concatenating



(a) Inter-view Contrastive Learning



(b) Intra-view Contrastive Learning

Figure 4: Illustrations of inter-view and intra-view contrastive learning.

$z^+_{i,1}, z^+_{i,2}, z^-_{i,1}, z^-_{i,2}$ since all theses representations contain useful information of diverse aspects, which is formulated as:

$$z_i = g(z^+_{i,1} \| z^+_{i,2} \| z^-_{i,1} \| z^-_{i,2}), \tag{10}$$

where g is a 2-layer MLP and $z_i \in \mathbb{R}^d$ is the final representation of node v_i. Hence, for the query node representation z_i, we regard the consistent representations of v_i in all graph views as the intra-view positive samples and the inconsistent representations in all graph views as the intra-view negative samples. In this way, we can make nodes more similar to neighbors connected with positive links and dissimilar to those with negative links. Formally, the intra-view contrastive objective is defined in the following:

$$\mathcal{L}_{intra} = -\frac{1}{I} \sum_{i=1}^{I} \log \frac{\sum_{m=1}^{M} \exp(\mathrm{sim}(z_i, z^+_{i,m})/\tau)}{\sum_{m=1}^{M} \exp(\mathrm{sim}(z_i, z^-_{i,m})/\tau)}, \tag{11}$$

where M denotes the number of graph views, which equals to 2 in this paper.

4.3.3 Combined Contrastive Learning. For a given minibatch $\mathcal{B}$ containing I nodes, we perform both inter-view and intra-view contrastive learning, which generates the combined contrastive objective as follows:

$$\mathcal{L}_{CL} = (1-\alpha) \cdot \mathcal{L}_{inter} + \alpha \cdot \mathcal{L}_{intra}, \tag{12}$$

where α is the weight coefficient that controls the significance between the two losses.

4.4 Model Training

In this paper, we focus on the most fundamental signed network analysis task, namely link sign prediction [23, 33] that predicts whether the link is positive or negative, whose training data is the existing signed links in the graphs, which is the same as the training data of our proposed contrastive learning. Hence, we propose to train the contrastive learning task and the target link sign prediction task jointly, where contrastive learning can be viewed as the regularization of the target task.

Specifically, after generating the final representations for all nodes by Eq. 10, we utilize a 2-layer MLP f to estimate the sign scores between two nodes:

$$\hat{y}_{i,j} = f(z_i \| z_j), \tag{13}$$

where $\hat{y}_{i,j}$ indicates the predicted score of the link sign between node v_i and v_j. The loss function of the link sign prediction is formulated based on the cross entropy:

$$\begin{aligned} \mathcal{L}_{label} = &- \sum_{(i,j)\in\Omega^+} y_{i,j} \log \sigma_a(\hat{y}_{i,j}) \\ &- \sum_{(i',j')\in\Omega^-} (1 - y_{i',j'}) \log(1 - \sigma_a(\hat{y}_{i',j'})), \end{aligned} \tag{14}$$

where Ω^+ denotes the training positive node pairs and Ω^- denotes the training negative node pairs, $\sigma_a(\cdot)$ represents the sigmoid function, $y_{i,j}$ represent the sign ground truth, which equals to 1 when the sign is positive and equals to 0 when the sign is negative.

Ultimately, SGCL is trained by the joint loss of link sign prediction and the combined contrastive learning, which is formulated as:

$$\mathcal{L} = \mathcal{L}_{label} + \beta \cdot \mathcal{L}_{CL}, \tag{15}$$

Table 1: Descriptive Statistics of four datasets.

Dataset	# nodes	# pos links	# neg links	% pos ratio
Bitcoin-Alpha	3783	22,650	1,536	0.9365
Bitcoin-OTC	5881	32,029	3,563	0.8999
Knives Out	428,803	902,006	1,226,409	0.4238
Tom & Jerry	413,410	898,008	298,344	0.7506

where β is the weight parameter that balances the magnitude and controls the significance between the two tasks. Note that during testing, we feed the original graph instead of the augmented ones into the graph encoder, i.e., the augmented ratio $r = 0$. The detailed learning algorithm is summarized in Algorithm 1.

Algorithm 1 SGCL Training Algorithm

for $epoch = 0, 1, \cdots$ **do**
  // Graph Augmentations
  Generate two graph views $\widetilde{\mathcal{G}}_1$ and $\widetilde{\mathcal{G}}_2$ by perturbing $\mathcal{G}$
  // Graph Encoders
  Split $\widetilde{\mathcal{G}}_1$, $\widetilde{\mathcal{G}}_2$ into $\widetilde{\mathcal{G}}^+_1$, $\widetilde{\mathcal{G}}^-_1$ and $\widetilde{\mathcal{G}}^+_2$, $\widetilde{\mathcal{G}}^-_2$ respectively
  Obtain consistent representations of $\widetilde{\mathcal{G}}^+_1$, $\widetilde{\mathcal{G}}^+_2$ via Eq. (1), (3), (5)
  Obtain inconsistent representations of $\widetilde{\mathcal{G}}^-_1$, $\widetilde{\mathcal{G}}^-_2$ via Eq. (2), (4), (6)
  Obtain the ultimate representations $\mathbf{Z}$ via Eq. (10)
  // Contrastive Learning
  Compute inter-view contrastive loss $\mathcal{L}_{inter}$ via Eq. (7), (8), (9)
  Compute intra-view contrastive loss $\mathcal{L}_{intra}$ via Eq. (11)
  Compute the combined contrastive objective $\mathcal{L}_{CL}$ via Eq. (12)
  // Model Training
  Compute the loss of sign link prediction task via Eq. (14)
  Compute the whole objective function $\mathcal{L}$ via Eq. (15) and update model parameters θ by $\frac{\partial \mathcal{L}}{\partial \theta}$
end for
return node representations $\mathbf{Z}$

5 EXPERIMENTS

In this section, we conduct link sign prediction to evaluate the performance of SGCL and compare it with state-of-the-art methods in signed network representation and graph contrastive learning.

5.1 Datasets

Experiments are conducted on two real-world *social datasets* (i.e., *Bitcoin-Alpha*, *Bitcoin-OTC*) and two online *game datasets* (i.e., *Knives Out*, *Tom and Jerry: Chase*) to evaluate the effectiveness of the proposed model. The descriptive statistics of these datasets are summarized in Table 1.

5.1.1 Social Datasets. *Bitcoin-Alpha* and *Bitcoin-OTC* [21] are two public datasets collected from Bitcoin trading platforms BitcoinAlpha[1] and BitcoinOTC[2] respectively. Due to the anonymity of these trading platforms, users can label other users as trust (positive) or distrust (negative) users to prevent transactions with fraudulent and risky users. In the experiments, we randomly select 80% links as training set and the remaining 20% as testing set. Since these datasets have no attributes, we randomly generate a 64-dimensional vector for each node as the initial attribute.

[1]https://www.btc-alpha.com/
[2]https://www.bitcoin-otc.com/

5.1.2 Game Datasets. *Knives Out*[3] and *Tom and Jerry: Chase*[4] (abbreviated as *Tom & Jerry*) are two datasets collected from online games released by *NetEase Games*, a leading provider of self-developed games to world-wide users. All data has been anonymized to protect the privacy of all users, and the desensitized data is irreversible to restore the user profiles. For *Knives Out*, we extract user interactions from April 12th, 2020 to May 12th, 2020 as training set and those in the following week from May 13th, 2020 as testing set, where the positive links are interactions of *Chat* and *Gift*, and the negative links are interactions of *Report*. As for *Tom & Jerry*, user interactions from June 1st, 2020 to June 8th, 2020 are extracted as training set while those in the following day from June 9th, 2020 are collected as testing set, where interactions of *Chat* and *Friend Request* constitute the positive links and interactions of *Report* constitute the negative links. The attributes on these datasets contain user profiles, social activities and competitive performances in games, whose dimension is 47 and 73 for *Knives Out* and *Tom & Jerry*, respectively.

5.2 Baselines and Experiment Setting

To validate the effectiveness of SGCL, we compare it with several state-of-the-art methods in the fields of graph neural networks (i.e., GCN and GAT), signed network representation (i.e., SiNE, SGCN and ROSE) and graph contrastive learning (i.e., DGI, GraphCL and GRACE).

- **GCN** [19] utilizes an efficient layer-wise propagation rule based on a first-order approximation of spectral convolutions on graphs.
- **GAT** [38] introduces an attention-based architecture to process the graph-structured data, which computes the hidden representation of each node in the graph by aggregating neighbors, following a self-attention strategy.
- **SiNE** [43] is a deep learning framework for signed network representation. The design of the objective function follows the guidance of balance theory, which expects nodes to be more similar to their friends than their foes.
- **SGCN** [6] bridges the gap between unsigned GCN and signed graph analysis. It makes an effort to design a new information aggregator based on balance theory and generalizes GCN to signed graphs.
- **ROSE** [15] introduces a novel graph transformation based framework, which firstly transforms the original signed graph to an unsigned bipartite graph and then utilizes unsigned representation learning methods (e.g., graph attention networks) to obtain node representations.
- **DGI** [39] maximizes local-global mutual information between substructure representations and graph-level representations to generate node representations.
- **GraphCL** [47] proposes various types of graph augmentations for unsigned graphs and generates representations by maximizing feature consistency under different augmented graphs, where different graph augmentations help learn different invariant properties of node representations. In this paper, we adopt node dropping as the graph augmentation of GraphCL.
- **GRACE** [51] leverages a contrastive objective at the node level. Two graph views are generated by composite graph augmentations, which firstly remove edges and then mask node features randomly. Ultimately, node representations are learned by maximizing the agreement of node representations in these two views.

We use the authors' released codes for SiNE[5], DGI[6], GraphCL[7], GRACE[8] and leverage the code from GitHub for SGCN[9]. For GCN, GAT and ROSE, we reproduce their codes based on their papers. We follow the authors' suggested hyperparameter settings and set the embedding dimension to be 128 for all methods to achieve a fair comparison. For graph contrastive learning methods, we follow the papers' guidance and train their models with fine-tune strategy [10, 16]. Specifically, these methods adopt GCN as encoders and firstly train encoders with contrastive loss, after which the encoders initialized by the pre-trained parameters are trained together with the 2-layer MLP classifier on the link sign prediction task.

The proposed model SGCL is implemented by PyTorch [30] and DGL [41] with the Adam [18] optimizer, whose learning rate is set to be 0.01. We stack 2 layers for both positive and negative GNNs to generate node representations. The dimensions of hidden and output representations are both 128, with the number of attention heads K and temperature parameter τ being 8 and 0.05 on all datasets. The value of β and augmentation ratio r is set to be 0.0001, 0.1 for *Bitcoin-Alpha* and *Bitcoin-OTC* while is 0.01, 0.3 for *Knives Out* and 0.01, 0.4 for *Tom & Jerry*. As for the parameter of α, it is set to be 0.2 for *Bitcoin-OTC* and *Tom & Jerry* while is 0.8 for the other two datasets.

5.3 Experiment Results

In this subsection, **SGCL-comp** represents the model whose augmented graphs are generated by connectivity perturbation and sign perturbation respectively. **SGCL-conn** denotes the model that only utilizes connectivity perturbation as graph augmentations while **SGCL-sign** denotes the one that only utilizes sign perturbation to generate graph views. In general, SGCL-comp, SGCL-conn and SGCL-sign are collectively referred to as **SGCL**. In the experiments, we adopt Area Under Curve (AUC), Micro-F1 Binary-F1, and Macro-F1 scores to evaluate the performances of all models, where higher values imply better performances. We repeat all experiments 5 times and report the average results in Table 2, where the highest values are emphasized in bold and the second ones are marked with underlines. The last column indicates the percentage of improvements gained by the best performance of our proposed model compared to the best baseline. We summarize some major observations as follows:

- SGCN and ROSE which leverage graph neural networks as graph encoders outperforms GCN and GAT, verifying the benefits of considering the complex relations and diverse semantics between positive and negative links of signed

[3] https://hy.163.com/index.html. The data is extracted from game of PC version and the users are from Chinese mainland.

[4] https://tom.163.com/index.html. The users are from Chinese mainland.

[5] https://faculty.ist.psu.edu/szw494/codes/SiNE.zip

[6] https://github.com/PetarV-/DGI

[7] https://github.com/Shen-Lab/GraphCL

[8] https://github.com/CRIPAC-DIG/GRACE

[9] https://github.com/benedekrozemberczki/SGCN

Table 2: The results of link sign prediction on real-world social datasets and online game datasets.

		GNNs		Signed Network			Contrastive Learning			Proposed Model			
Dataset	Metric	GCN	GAT	SiNE	SGCN	ROSE	DGI	GraphCL	GRACE	SGCL-comp	SGCL-conn	SGCL-sign	Impro
Bitcoin-Alpha	Micro-F1	0.7582	0.7767	0.9439	0.9204	0.9387	0.9404	0.9428	0.9436	**0.9523**	0.9501	0.9516	0.89%
	Binary-F1	0.8517	0.8664	0.9707	0.9574	0.9674	0.9687	0.9697	0.9701	**0.9748**	0.9736	0.9745	0.42%
	Macro-F1	0.5645	0.5857	0.6604	0.6622	0.7309	0.6680	0.7294	0.7398	**0.7622**	0.7577	0.7578	3.03%
	AUC	0.8217	0.8519	0.8777	0.8261	0.8845	0.8334	0.8686	0.8483	**0.9104**	0.9054	0.9090	2.93%
Bitcoin-OTC	Micro-F1	0.7781	0.8296	0.9136	0.9053	0.9225	0.9131	0.9189	0.9234	0.9399	0.9397	**0.9427**	2.09%
	Binary-F1	0.8618	0.8983	0.9535	0.9477	0.9575	0.9519	0.9547	0.9574	0.9670	0.9670	**0.9686**	1.16%
	Macro-F1	0.6415	0.6836	0.6762	0.7188	0.7583	0.7521	0.7818	0.7860	0.8139	0.8109	**0.8188**	4.17%
	AUC	0.8648	0.8708	0.8553	0.8760	0.8870	0.8713	0.8836	0.8760	0.9117	0.9053	**0.9159**	3.26%
Knives Out	Micro-F1	0.7073	0.7197	0.7295	0.7697	0.7910	0.7473	0.7537	0.6971	0.7992	0.7958	**0.8052**	1.80%
	Binary-F1	0.6541	0.6706	0.6970	0.7619	0.7677	0.6850	0.6927	0.5662	0.7941	0.7931	**0.7969**	3.80%
	Macro-F1	0.7001	0.7133	0.7264	0.7687	0.7886	0.7370	0.7436	0.6667	0.7978	0.7958	**0.8049**	2.07%
	AUC	0.7713	0.7847	0.7983	0.8442	0.8680	0.8498	0.8565	0.8116	0.8785	0.8737	**0.8811**	1.51%
Tom & Jerry	Micro-F1	0.5999	0.6238	0.7703	0.6919	0.8007	0.7591	0.7678	0.7281	0.7984	0.7927	**0.8073**	0.82%
	Binary-F1	0.6822	0.7108	0.8523	0.7579	0.8675	0.8376	0.8454	0.8169	0.8673	0.8647	**0.8728**	0.61%
	Macro-F1	0.5702	0.5861	0.6679	0.6663	0.7327	0.6844	0.6893	0.6444	0.7233	0.7099	**0.7379**	0.71%
	AUC	0.6565	0.6732	0.7300	0.7973	0.8239	0.7692	0.7755	0.7280	0.8189	0.8042	**0.8352**	1.37%

graphs. In addition, DGI, GraphCL, GRACE perform better than GCN and GAT, which demonstrates the effectiveness of graph contrastive learning. Combining these two strengths, our proposed model consistently achieves the best performances compared with state-of-the-art methods, which offers significant improvements of 1.37%-3.26% on AUC in the four datasets and especially gains 1.16%-4.17% improvements on *Bitcoin-OTC* and *Knives Out* datasets for all indicators.

- SGCL-conn and SGCL-sign show superiority over signed network representation methods, i.e., SiNE, SGCN and ROSE, strongly proving the usefulness of graph contrastive learning. To be more specific, graph contrastive learning in our model employs graph augmentations specifically designed for signed graphs and maximizes the agreement between augmented graphs, which help SGCL generate more invariant and robust representations, thus leading to better performances on downstream tasks.
- Our proposed model achieves considerable improvements compared to graph contrastive learning methods, while in particular SGCL-sign performs the best almost on all datasets. On the one hand, SGCL adopts separate encoders to aggregate positive and negative links respectively rather than mixing all types of links, which distinguishes different semantics between them. On the other hand, our proposed models employ graph augmentations based on balance theory (i.e., connectivity and sign perturbation), which are specifically designed for signed graphs and thus boost the performances.
- It can be observed that SGCL-sign consistently outperforms SGCL-conn, proving that the semantics of signed graphs are more sensitive to link connectivities than link signs, and perturbing balanced cycles by randomly dropping and adding links hurt the semantics more, thus resulting in worse performances on downstream tasks. Besides, there exists a surprising phenomenon that SGCL-comp which utilizes both connectivity and sign perturbation does not usually lead to the best performance compared with SGCL-sign and SGCL-conn. We argue that connectivity perturbation is not as effective as sign perturbation and thus SGCL-comp which composes these two augmentations performs better than SGCL-conn while performs worse than SGCL-sign in most cases.

Table 3: The AUC performances with SGCL and its variants.

Models	Bitcoin Alpha	Bitcoin OTC	Knives Out	Tom & Jerry
SGCL	**0.9090**	**0.9159**	**0.8811**	**0.8352**
SGCL$_{w/o\ aug}$	0.8606	0.8746	0.8535	0.6359
SGCL$_{w/o\ GCL}$	0.8710	0.8715	0.8403	0.6037
SGCL$_{w/o\ inter}$	0.9029	0.9116	0.8760	0.8292
SGCL$_{w/o\ intra}$	0.9051	0.9083	0.8769	0.8269

5.4 Ablation Study

We conduct ablation study to investigate the effectiveness of different components in our proposed model, where we choose sign perturbation as the graph augmentation in this subsection to analyze performances. Concretely, we compare SGCL with its four variants: SGCL$_{w/o\ GCL}$, SGCL$_{w/o\ aug}$, SGCL$_{w/o\ inter}$, SGCL$_{w/o\ intra}$, which are defined as follows:

- SGCL$_{w/o\ aug}$: The graph augmentation in contrastive learning is removed. In this variant, original graphs instead of augmented graphs are exploited during training, i.e., $r = 0$.
- SGCL$_{w/o\ GCL}$: This variant generates node representations without graph contrastive learning, where the original graphs are fed into encoders and the objective function only takes link sign prediction loss into considerations, i.e., $r = 0$ and $\beta = 0$.
- SGCL$_{w/o\ inter}$: This variant ignores the inter-view contrastive loss and only performs intra-view contrastive learning, which learns discriminative representations by the contrast of signed structures, i.e., $\alpha = 1$.

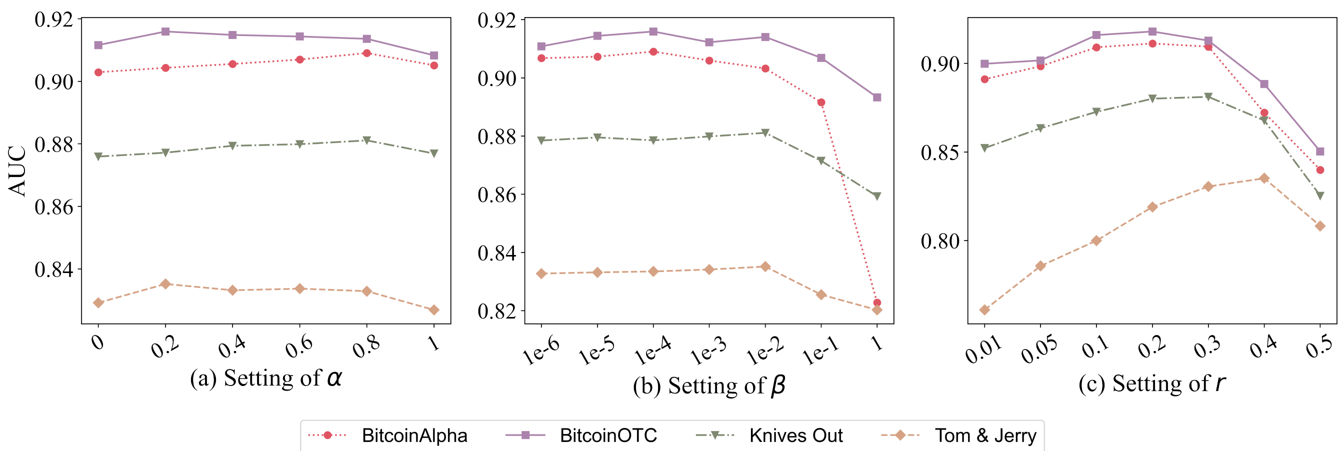


Figure 5: Parameter sensitivity of SGCL with regard to α, β, r.

- SGCL$_{w/o\ intra}$: Contrary to the previous variant, this variant ignores the intra-view contrastive loss and only performs inter-view contrastive learning to generate node representations from the contrast of augmented graphs, i.e. $\alpha = 0$.

The AUC comparisons of SGCL with the four variants are summarized in Table 3. From this table, we can conclude that:

- SGCL$_{w/o\ aug}$ and SGCL$_{w/o\ GCL}$ perform much worse than SGCL, which demonstrates the effectiveness of graph contrastive learning component in our model.
- Comparing SGCL with SGCL$_{w/o\ inter}$ and SGCL$_{w/o\ intra}$, we can see that combining inter-view and intra-view contrastive losses can boost the performance of SGCL, verifying that our proposed model gains improvements from both contrasts of augmented graphs and signed structures.

5.5 Parameters Analysis

In this section, we investigate the sensitivity of three major hyperparameters in our proposed model: α that balances inter-view and intra-view contrastive losses, β that balances the loss of graph contrastive learning and link sign prediction, and augmentation ratio r. We fix other hyperparameters when evaluating each of them and utilize sign perturbation to generate augmented graphs as the same as the previous subsection. The detailed AUC performances are illustrated in Fig. 5 and observations are summarized as follows:

- Revealed by Fig. 5(a), the model leveraging the combination of inter-view and intra-view contrastive losses achieves better performance than those using either inter-view or intra-view contrastive loss, which is consistent with the previous analysis in the ablation study.
- From Fig. 5(b), the performance rises with the value of β increases, verifying that graph contrastive learning helps learn higher-quality representations in a more invariant and robust feature-space and thus results in better performances on downstream tasks. Nevertheless, performances drop sharply when β becomes too large, especially on *Bitcoin-Alpha* dataset, which is reasonable since larger β forces the model to pay too much attention to contrastive learning rather than the sign link prediction task, thus leading to unwanted results.
- The optimal augmented ratio r falls on 0.2 for social datasets, which is smaller than those for game datasets falling on 0.3-0.4. On the one hand, we argue that online game datasets contain much more interaction noise than public social datasets, thus requiring stronger augmentations for graph contrastive learning to obtain invariant representations. On the other hand, since game datasets own attributes information while social datasets do not, game datasets may have a better ability of suffering larger graph perturbations. Last but not least, the performance decreases when the augmentation ratio becomes too large, demonstrating that over-perturbation leads to the loss of information of the original graphs.

6 CONCLUSION

In this paper, we propose a novel signed graph contrastive representation learning model - SGCL, which is the first work to employ graph contrastive learning on signed graphs to the best of our knowledge. Concretely, SGCL designs and performs two types of graph augmentations specifically for signed graphs, i.e., connectivity perturbation and sign perturbation, which help capture more invariant and robust representations based on balance theory. Moreover, we exploit inter-view and intra-view contrastive learning to combine the contrasts of augmented graphs and signed structures into a coherent model. The conducted experiments on two real-world social graphs and two online game graphs suggest that SGCL consistently outperforms state-of-the-art methods across all datasets, demonstrating the effectiveness of our proposed model.

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