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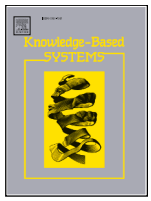

Structure adversarial augmented graph anomaly detection via multi-view contrastive learning

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ABSTRACT

Graph anomaly detection is essential for many security-related fields but faces significant challenges in handling complex real-world graph data. Due to the complex and imbalanced graph structure, it is difficult to find abnormal points among many nodes. Current contrastive learning methods often overlook structural imperfections in real-world graphs, such as redundant edges and low-degree sparse nodes. Redundant connections may introduce noise during message passing, while sparse nodes receive insufficient structural information to accurately learn representation, which can degrade detection performance. To overcome above challenges, we propose SAA-GCL, an innovative framework that integrates adaptive structure adversarial augmentation with multi-view contrastive learning. Specifically, by edge weight learning and LMSE loss calculation, our approach adaptively optimizes the structure of the augmented graph, discards redundant edges as much as possible, and retains more discriminating features. For low-degree sparse nodes, we mix their self-networks with the self-networks of auxiliary nodes to improve the representation quality. In order to fully mine abnormal information, we use the multi-view contrastive loss function to distinguish positive and negative sample pairs within the view and maintain cross-view consistency. The framework adaptively refines the graph topology to suppress noisy edges and enhance representations for structurally weak nodes, so it can improve anomaly detection performance in the imbalanced structure attribute graph. Comprehensive experiments on six real-world graph datasets show that SAA-GCL is superior to existing methods in detection accuracy. Our code is open source at https://github.com/HZAI-ZJNU/SAAGCL.

1. Introduction

From user interactions on social networks, the flow of funds in financial transactions [1,2], to protein interactions on biomedicine, attributed networks have become the main carriers [3,4] for multivariate relationship data. In this type of network, abnormal behaviors typically occur in node characteristics or graph structures, such as sudden dense connection behavior in social networks, which are structural anomalies, and the characteristics of capital flow that deviate from the normal pattern in transaction networks are characteristic anomalies. By identifying nodes or subgraphs in graph data that significantly deviate from the conventional pattern, Graph Anomaly Detection (GAD) technology has demonstrated an important value in the fields of financial anti-fraud and network security protection [2,5,6]. However, graph data are naturally characterized by heterogeneity, scale, and scarcity of annotations [7,8], which pose many challenges for anomaly detection.

Based on the unique properties of the graph data, researchers have proposed various technical routes. Early work relied mainly on feature engineering and shallow models, such as the method based on the Neighborhood Outlier Factor (LOF) to identify abnormal nodes through local density comparison [9], but its adaptability to high-dimensional features was limited. With the development of deep learning, the autoencoder architecture [10] based on Graph Neural Networks (GNNs) has become the mainstream solution [11]. However, there are two inherent drawbacks in this kind of method: on the one hand, the information transmission process [12] of GNNs smooths the local characteristics of abnormal nodes, resulting in abnormal signal attenuation; on the other hand, the reconstruction preference of autoencoder for normal samples is difficult to deal with the anomalous patterns of complex multi-modality [13].

Attributed to the rapid development of contrastive learning methods, this self-supervised learning paradigm [14,15] is now more commonly utilized in graph-based anomaly detection. GCSL-ASD [16] applies

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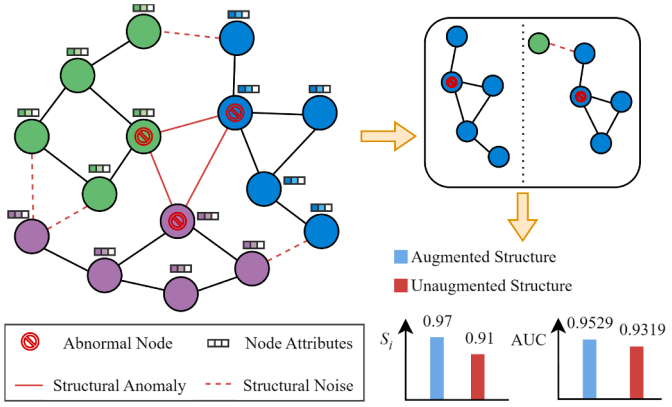


Fig. 1. Structural noise usually refers to redundant connections in a graph, for example, some objects create connections with other distant objects to disguise themselves as neighbors. When it is brought into the anomaly scoring space, the detection performance of the model will decline.

contrastive self-supervised learning to traffic trajectory anomaly detection, providing a fine-grained anomaly detection tool for traffic management. CLADHS [17] generates positive and negative subgraphs for each target node, capturing multi-scale relationships through a three-layer structure. By constructing positive and negative sample pairs, graph contrastive learning enables the model to distinguish the differences in node features and structures well. Compared to the traditional graph autoencoder, it can effectively avoid information loss during reconstruction [18] and capture both local and global anomalous features.

However, recent graph contrastive learning methods often rely on static graph enhancement strategies to improve anomaly detection performance, which typically preserve noisy connections. This allows redundant edge features to propagate through the GNN layer, contaminating the abnormal scoring space. Furthermore, due to the sparse structure of low-degree nodes, the model is prone to generating biased contrastive samples [19]. Current research focuses on optimizing overall detection performance through graph reconstruction, but largely neglects the internal issues of the graph: structural information redundancy and low-degree node feature imbalance, which degrade algorithmic robustness [20,21] in real-world graphs. Most solutions ignore the adversarial relationship [22] between view augmentation and feature learning, or the influence of the low-degree node structure on anomaly detection. SGAT [23] research shows that the adaptively constructed enhanced view by the adversarial mechanism can retain more discriminative features. In addition, when redundant information is removed, if the anomaly detection model does not extend the feature domain of low-degree nodes, its performance will obviously decline [24]. Inspired by this, we design a contrastive learning model that combines structural adversarial optimization and introduces LMSE loss to build a more discriminating embedding space, effectively addressing redundancy and imbalance in graphs. Fig. 1 shows the influence of structural noise on anomaly scoring and anomaly detection performance.

To address the above limitations, we propose SAA-GCL, a structure adversarial augmented graph anomaly detection framework based on multi-view contrastive learning, consisting of a Structure Augmented Subnetwork, Tail Auxiliary Mix Completion module, and Multi-View Contrastive Learning Network. We use edge weight learning and LMSE loss calculation to discard redundant edges as much as possible and retain more discriminative features, adaptively enhancing the graph structure through an adversarial mechanism. For low-degree nodes, we mix their self-networks with auxiliary node networks sampled based on feature similarity to expand their neighborhood scope, thus enhancing contrastive sample diversity and improving representation quality. Finally, we extract positive and negative sample pairs from both the augmented and original views to compute within-view and cross-view contrastive losses, generating final anomaly scores via multi-round sampling predictions. Extensive experiments on six benchmark datasets demonstrate the effectiveness of the model.

The main contributions of this paper can be summarized as follows.

- Propose a structural adversarial optimization method that adaptively trims redundant edges while retaining key connections. For low-degree sparse nodes, we develop a feature-aware neighborhood expansion technique to mitigate structural imbalance.
- Introduce a new multi-view contrastive learning framework, which integrates both within-view and cross-view contrast learning losses to realize joint anomaly detection inside and between the views.
- The experimental results prove that the multi-view contrastive learning strategy based on structural adversarial optimization is effective for graph anomaly detection, and SAA-GCL outperforms existing baseline methods.

The remainder of this paper is organized as follows. In Section 2, we summarize the current related research. In Section 3, we define the notation used in the work. In Section 4, we discuss the proposed method. The experimental results are given in Section 5. Finally, the conclusion is offered in Section 6.

2. Related work

2.1. Graph contrastive learning

Graph contrastive learning is a self-supervised method that learns discriminative representations by comparing positive and negative sample pairs. Unlike supervised methods, GCL does not rely on manual labels; instead, it uses the inherent structure of graph data to generate supervision signals. Pioneering work such as Deep Graph Infomax (DGI) [25] introduced contrastive learning to graph representation by maximizing mutual information between node embeddings and graph-level summaries. Graph Contrastive Coding (GCC) [26] extended this idea by sampling subgraphs as contrasting instances, while iGCL [27] eliminated the need for negative samples by learning invariant representations. LLNCL [28] dynamically updated the graph structure and features through multi-view contrastive learning to enhance the node embeddings. These methods demonstrate that GCL can effectively capture both local and global graph patterns without requiring labeled data.

In recent years, the contrastive learning paradigm has been introduced into the field of GAD due to its advantages in unsupervised representation learning. The graph contrastive learning model CoLA [29] learns the semantic consistency of normal nodes and their local contexts by constructing a node-subgraph comparison task, thus identifying abnormal nodes which deviate from this consistency. ANEMONE [30] further extends the multi-scale comparison strategy to consider relationships between node-node and node-subgraph, and use InfoNCE loss [31] to maximize mutual information between positive sample pairs. For the first time, Zhang et al. proposed Sub-CR [32] to combine multi-view contrastive learning with attribute reconstruction. This method constructs multi-view contrastive learning via local and global views and leverages neighbor nodes to reconstruct target node attributes. In contrast, Duan et al. innovatively proposed GRADATE [33], the first graph anomaly detection framework to introduce subgraph-subgraph comparison, which improves the robustness of subgraph embedding through multi-view and multi-scale contrastive learning networks.

2.2. Imbalanced structural learning on graph

The challenge of structural imbalance in graph learning has gained increasing attention, particularly in scenarios where real-world graphs exhibit skewed degree distributions with abundant low-degree nodes and few high-degree nodes. Although traditional approaches primarily address class imbalance in supervised tasks [34,35], recent studies

have shifted the focus to structural bias in graph representation learning [36,37]. Early efforts introduced degree-specific graph convolution techniques [38,39] to mitigate the representation gap between the head and tail nodes. Subsequent work, such as Tail-GNN [40], proposed neighborhood translation mechanisms to transfer structural knowledge from head to tail nodes. BalancerGNN [41] used balanced neighbor sampling to construct the graph, improving the fraud detection ability of unbalanced datasets.

In the context of graph contrastive learning (GCL), GRADE [42] demonstrated the potential of contrastive frameworks to handle structural imbalances and further improve structural fairness. Later, GRACE [43] employed structural augmented strategies to enhance the representations of the tail nodes. However, these methods predominantly focus on semi-supervised node classification. In particular, existing GAD methods often fail to adequately address the unique challenges posed by tail anomalies, and their sparse connectivity limits the diversity of contrastive pairs, leading to biased detection performance. This oversight becomes particularly critical in security-sensitive applications [44], where the tail nodes frequently harbor malicious activities.

2.3. Graph anomaly detection on attributed network

Graph anomaly detection on attributed network has attracted significant attention due to its applications in fraud detection [2,45], cybersecurity, and social network analysis [46,47]. Early approaches relied heavily on domain-specific knowledge and shallow models [48,49], but their limited capacity to capture nonlinear patterns in high-dimensional graphs restricted their performance. With the advancement of GNNs, recent methods have utilized deep learning to improve detection accuracy. CARE-GNN [50] introduced adaptive neighbor filtering to improve aggregation for fraud detection, while AnomalyDAE [51] employed dual autoencoders to jointly reconstruct node attributes and graph structure for anomaly scoring. Xu et al. first studied how to model and integrate human prior knowledge to improve detection performance, the proposed CONAD [52] transforms abstract abnormal-type knowledge into a computable form and flexibly integrates prior knowledge with incomplete labeling. Contrastive learning frameworks such as SL-GAD [53] improved unsupervised detection by contrasting node-subgraph pairs to highlight deviations. NLGAD [54] further considers node-node pairs to supplement node-level abnormal information. GADAM [55] decouples local inconsistency mining from message transmission and introduces anomaly mining from a global perspective to achieve efficient and robust graph anomaly detection.

Despite these advances, existing methods often ignore structural imperfections, such as redundant edges and low-degree nodes, which impair detection performance. These issues introduce noise and hinder representation learning. Our method introduces a structural adversarial optimization strategy that dynamically refines graph topology to suppress noisy edges while enhancing representations for sparse nodes, thus boosting detection accuracy.

3. Problem definition

In this section, we define the problem related to anomaly detection in attribute networks and the notation used. We define an attributed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathbf{X})$, where $\mathcal{V}$ denotes the set of nodes, $\mathcal{E}$ denotes the set of edges, and $\mathbf{X}$ denotes the attribute matrix. $\mathcal{V}$ and $\mathcal{E}$ can be synthetically represented by the adjacency matrix $\mathbf{A}$. For a given original graph $\mathcal{G} = (\mathbf{A}, \mathbf{X})$, we construct an augmented graph $\mathcal{G}' = (\widetilde{\mathbf{A}}, \mathbf{X})$ to improve the detection performance. Through our proposed framework, we learn the node embeddings $\mathbf{Z}^1$ and $\mathbf{Z}^2$ from both graph views, and aim to compute the anomaly scores S_i for each node v_i. The higher S_i, the greater the possibility that the node is abnormal. Table 1 summarizes the key notation used throughout our method.

Table 1
Notations summary. The specialized explanations for notations in the formulas of Section 4.

Notations	*Definitions*
$\mathcal{G}$	Original graph
$\mathcal{G}'$	Structure augmented graph
$\mathbf{X} \in \mathbb{R}^{N\times d}$	Attribute matrix
$\mathbf{A} \in \mathbb{R}^{N\times N}$	Original adjacent matrix
$\bar{\mathbf{A}} \in \mathbb{R}^{N\times N}$	Normalized adjacent matrix
$\widetilde{\mathbf{A}} \in \mathbb{R}^{N\times N}$	Augmented adjacent matrix
$\mathbf{Z}^1 \in \mathbb{R}^{N\times d'}$	Node embedding of original graph
$\mathbf{Z}^2 \in \mathbb{R}^{N\times d'}$	Node embedding of augmented graph
$\mathbf{H}^{(l)} \in \mathbb{R}^{d^{(l-1)}\times d^{(l)}}$	Weight matrix of the lth GNN layer
$\mathbf{I} \in \mathbb{R}^{N\times N}$	Identity matrix
$\mathbf{D} \in \mathbb{R}^{N\times N}$	Degree matrix
$\mathbf{E} \in \mathbb{R}^{M\times 2d'}$	Edge embedding of original graph
$\mathbf{W} \in \mathbb{R}^{M\times 1}$	Edge-oriented weight vector
$\mathbf{W}' \in \mathbb{R}^{N\times N}$	Edge-oriented weight matrix
$\boldsymbol{z}_i \in \mathbb{R}^d$	Embedding vector of node i
$\boldsymbol{z}_{\mathcal{N}_i} \in \mathbb{R}^d$	Neighbor representation of node i
$\mathbf{W}^{(d)} \in \mathbb{R}^{d\times d}$	Weight matrix of discriminator
s_i	Predicted score of the discriminator
$s_{i,p}$	Discriminator score of positive pair
$s_{i,n}$	Discriminator score of negative pair
$\mathbf{S}^1$	Discriminator score in original view
$\mathbf{S}^2$	Discriminator score in augmented view
S_i	Anomaly score of node i
R	Number of sampling rounds

4. Method

As shown in Fig. 2, the proposed SAA-GCL framework consists mainly of three key components: the Structure Augmented Subnetwork, the Tail Auxiliary Mix Completion, and the Multi-View Contrastive Learning Network. We will introduce each step according to the workflow, which is divided into the following three main steps.

- Generating a redundant edge dropout probability matrix through edge weight learning and introducing the LMSE loss to make the cross-view mapping matrix approach an identity matrix. Feature redundancy is adaptively reduced by an adversarial mechanism, ultimately yielding an augmented adjacency matrix. This is described in Section 4.2.
- For low-degree nodes, expanding their neighborhood scope by mixing their self-networks with auxiliary node self-networks sampled based on feature similarity. This enhances the diversity of contrastive samples and alleviates structural imbalance issues. Details are provided in Section 4.3.
- Combining anomaly scores and node features, within-view and cross-view contrastive losses are used to strengthen the extraction of anomalous patterns, as described in Section 4.4.

4.1. Preliminaries

4.1.1. Graph encoder

In this paper, we use GCN-Encoder to learn a graph embedding representation. It employs a three-layer structure built on graph convolutional network (GCN) [56] to learn node embeddings by combining information from the immediate neighbors of each node. The encoder implements neighborhood aggregation through the following layer-wise propagation:

$$\mathbf{Z}^{(l)} = \sigma(\mathbf{D}^{-\frac{1}{2}}(\mathbf{A}+\mathbf{I})\mathbf{D}^{-\frac{1}{2}}\mathbf{Z}^{(l-1)}\mathbf{H}^{(l)}), \tag{1}$$

where $\mathbf{Z}^{(l)} \in \mathbb{R}^{N\times d^{(l)}}$ represents the lth layer node embeddings with dimensionality $d^{(l)}$, and $\mathbf{H}^{(l)} \in \mathbb{R}^{d^{(l-1)}\times d^{(l)}}$ contains trainable parameters. $\mathbf{D}^{-\frac{1}{2}}(\mathbf{A}+\mathbf{I})\mathbf{D}^{-\frac{1}{2}} = \bar{\mathbf{A}} \in \mathbb{R}^{N\times N}$ represents the normalized adjacency matrix, and $\mathbf{A} \in \mathbb{R}^{N\times N}$ denotes the original adjacent matrix. $\mathbf{I} \in \mathbb{R}^{N\times N}$ is an identity matrix and $\mathbf{D} = \mathrm{diag}(d_1, d_2, \ldots, d_N) \in \mathbb{R}^{N\times N}$ denotes a degree

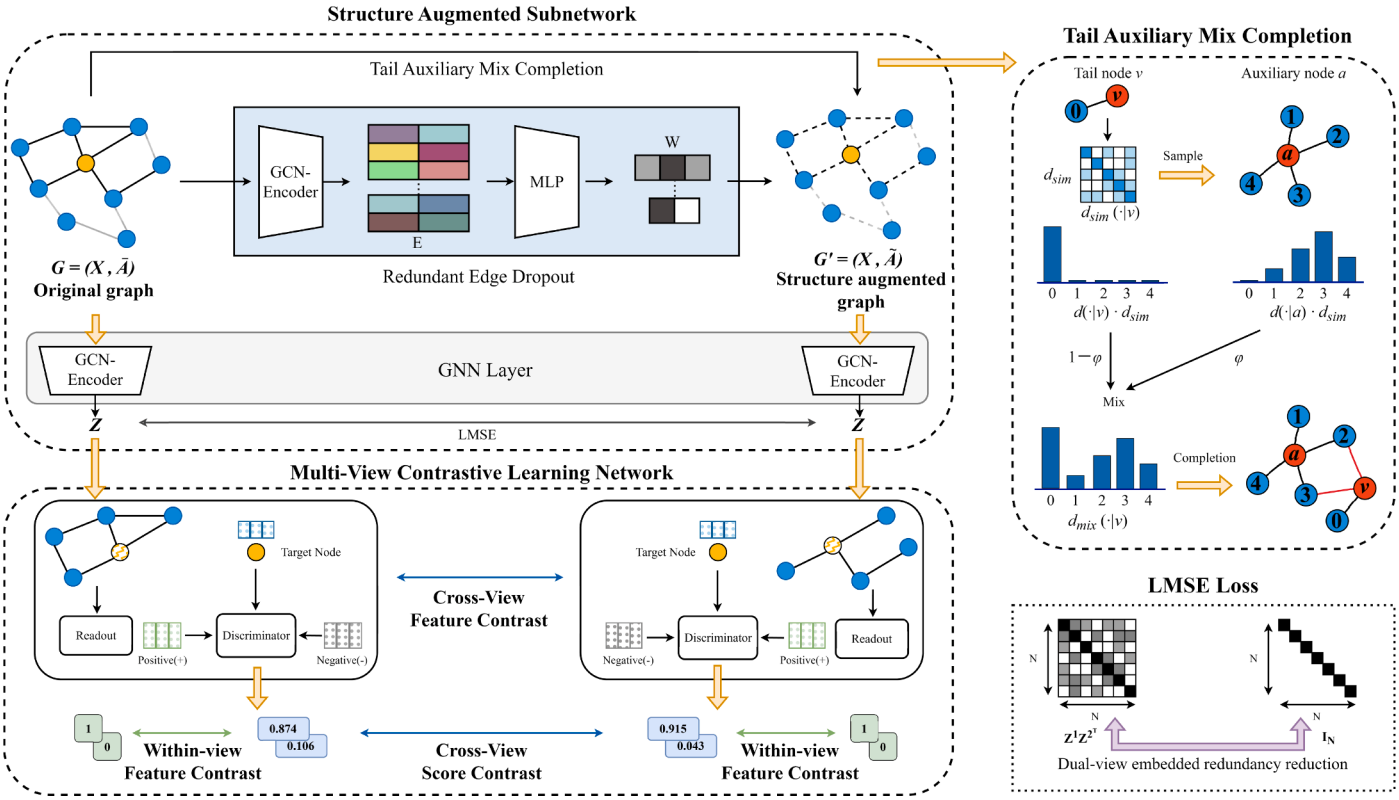


Fig. 2. The proposed SAA-GCL framework comprises three components: (1) the Structure Augmented Subnetwork that generates an augmented adjacency matrix through edge weight learning and LMSE loss optimization, reducing feature redundancy via adversarial training; (2) the Tail Auxiliary Mix Completion module that expands neighborhood representations for low-degree nodes by integrating their self-networks with feature-sampled auxiliary node networks; and (3) the Multi-View Contrastive Learning Network that computes both within-view and cross-view contrastive losses, ultimately generating anomaly scores through multiple rounds of positive and negative sampling.

matrix where $d_n = \sum_{j=1}^{N} \mathbf{A}_{nj}$. We employ tanh as the nonlinear activation function $\sigma(\cdot)$.

4.1.2. Mutual information maximization

In order to learn effective graph embedding, graph contrastive learning (GCL) maximizes the consistency between positive sample pairs and minimizes the similarity between negative sample pairs to improve the representation quality. For this purpose, we employ mutual information maximization (Info-Max) [57] to calculate the consistency between sample pairs, with the primary learning goal expressed as:

$$I(\mathbf{Z}^1, \mathbf{Z}^2) = \frac{1}{N} \sum_{i=1}^{N} \log \frac{\exp(\mathrm{sim}(z_i^1, z_i^2))}{\sum_{i'=1, i' \neq i}^{N} \exp(\mathrm{sim}(z_i^1, z_{i'}^2))}, \tag{2}$$

where $I(\cdot,\cdot)$ denotes mutual information between two views and $\mathrm{sim}(\cdot,\cdot)$ calculates the similarity. $\mathbf{Z}^1 \in \mathbb{R}^{N \times d'}$ and $\mathbf{Z}^2 \in \mathbb{R}^{N \times d'}$ are node embeddings learned from the original graph and the augmented graph, respectively. z_i^1 and z_i^2 respectively represent the specific rows in two graph embeddings.

4.2. Structure augmented subnetwork

In existing graph contrastive learning (GCL) methods, edge perturbation and node feature perturbation are two widely adopted data augmentation strategies. These augmented graphs are typically generated statically before training and serve as fixed supervisory signals to guide the learning of node representation, rather than being dynamically adjusted during training. Because the augmented graph is transformed from the original graph, it may retain incorrect connections or redundant edges. If such noisy structures persist unaddressed during network training, the subsequent anomaly scoring space will inherit them. To mitigate this issue, we design a Structure Augmented Subnetwork that learns a structure-aware augmented graph. This subnetwork employs edge weight learning to prune redundant edges and enforces the cross-view mapping matrix to approach an identity matrix. Through an adversarial mechanism, it adaptively generates adjacency matrices to minimize redundant information in the embeddings while retaining more robust and discriminative features.

4.2.1. Edge weight learning

As shown in Fig. 2, in the redundant edge dropout process, there exists a GCN-Encoder that has an identical architecture as the one in the GNN layer. The GCN handles the normalized adjacency matrix $\bar{\mathbf{A}}$ and the attribute matrix $\mathbf{X}$, producing embeddings $\mathbf{Z} \in \mathbb{R}^{N \times d'}$. These embeddings generate edge representations $\mathbf{E}_m = C(z_i, z_j) \in \mathbb{R}^{M \times 2d'}$ by concatenating adjacent node pairs (v_i, v_j), where z_i and z_j are the embeddings of node v_i and v_j, respectively. Subsequently, using a sigmoid-activated multilayer perceptron to process the acquired edge embedding $\mathbf{E} = \{\mathbf{E}_1, \mathbf{E}_2, \ldots, \mathbf{E}_M\} \in \mathbb{R}^{M \times 2d'}$, we can get the edge-oriented weight vector:

$$\mathbf{W} = \mathrm{sigmoid}\big(\mathrm{MLP}(\mathbf{E})\big), \tag{3}$$

where $\mathbf{W} = [w_1, w_2, \ldots, w_M]^{\mathbf{T}} \in \mathbb{R}^{M \times 1}$, w_i represents the probability that the corresponding edge e_i will be retained. The weight vector is then reorganized into an edge-oriented weight matrix $\mathbf{W}' \in \mathbb{R}^{N \times N}$ by filling in $\mathbf{W}'_{ij}$, where $\mathbf{W}'_{ij} = w_k$ when the edge e_k connects the node pair (v_i, v_j), otherwise its value is 0. The adjacent matrix of the augmented graph derives from:

$$\tilde{\mathbf{A}} = \mathbf{W}' \odot \bar{\mathbf{A}}, \tag{4}$$

where $\odot$ denotes the Hadamard product, it represents the multiplication of elements at the corresponding position, i.e., $\tilde{\mathbf{A}}_{ij} = \mathbf{W}'_{ij} \times \bar{\mathbf{A}}_{ij}$. Finally, the augmented graph $\mathcal{G}'$ can be expressed as $\mathcal{G}' = (\tilde{\mathbf{A}}, \mathbf{X})$.

To control the degree of structural information discard and adequately filter redundant information, we append a regularization term $\frac{1}{M}\sum_{i=1}^{M} w_i$ to Eq. (2) to control the trade-off between preservation and reduction of structural information, where w_i represents the preservation probability of the ith edge.

In conclusion, the final objective function of redundant edge dropout can be formulated as follows:

$$\min\left(I(\mathbf{Z}^1, \mathbf{Z}^2) + \frac{1}{M}\sum_{i=1}^{M} w_i\right), \tag{5}$$

where $I(\mathbf{Z}^1, \mathbf{Z}^2)$ measures the mutual information between the original graph and the augmented graph, $\frac{1}{M}\sum_{i=1}^{M} w_i$ indicates the proportion of reserved edges. The formula forces the model to learn to remove redundant edges and controls the retention of edges while minimizing mutual information to generate an augmented graph that is sufficiently different from the original graph.

4.2.2. Structure adversarial optimization

Although the Info-Max principle improves the effectiveness of GCL-based methods, it can lead to the encoding of redundant features during agreement estimation. To cope with this problem, we constrain the cross-view mapping matrix to approach an identity matrix:

$$\mathcal{L}_{MSE} = \frac{1}{N}\left\|\mathbf{Z}^1\mathbf{Z}^{2^\top} - \mathbf{I}_N\right\|_F^2, \tag{6}$$

where $\mathbf{I}_N$ represents the identity matrix and $\|\cdot\|$ represents the Frobenius norm, the element (i, j) of the cross-view mapping matrix $\mathbf{Z}^1\mathbf{Z}^{2^\top}$ indicates the embedding similarity between the node i of the original view and the node j of the augmented view. The LMSE loss restricts the embeddings of different nodes to be orthogonal, reducing redundancy between the dual-view embeddings.

Finally, the objective function of structure adversarial optimization can be formulated as follows:

$$\max\left(I(\mathbf{Z}^1, \mathbf{Z}^2) - \mathcal{L}_{MSE}\right), \tag{7}$$

it requires the model to maximize mutual information while minimizing the redundancy of latent space through LMSE loss.

By minimizing Eq. (5) and maximizing Eq. (7), the former tries to generate an augmented graph that is difficult to learn according to the Info-Min principle, while the latter needs to overcome this interference based on the Info-Max principle. This confrontation process forces the former to keep the most critical edges, while the latter learns more robust features. Therefore, the structure adversarial optimization method minimizes redundancy in the latent space while preserving more discriminative features.

4.3. Tail auxiliary mix completion

Due to the structural sparsity of low-degree nodes, generating diverse contrastive sample pairs is challenging, leading the discriminator to overfit their limited neighborhoods and misclassify anomalous nodes as normal. Traditional approaches to improve the detection accuracy for low-degree nodes typically focus on augmenting their neighborhoods by adding inferred connections [45]. However, such graph completion methods can introduce bias due to the non-independent and identical distributed characteristics [24] of the graph data, potentially worsening rather than improving results. To resolve these issues, we propose a tail-assisted completion strategy. First, we sample auxiliary nodes similar to the target tail nodes based on feature similarity distributions. Then, we expand the neighborhood of low-degree nodes by blending their self-networks with those of the auxiliary nodes. This unsupervised method extends the neighborhood of low-degree nodes, effectively improving their anomaly detection performance.

For a node $v \in \mathcal{V}$, $\mathcal{N}_v$ denotes its neighborhood and $|\mathcal{N}_v|$ represents its degree. Following prior work [40,58], we define K as a predefined degree threshold: if $|\mathcal{N}_v| \le K$, node v is classified as a tail node.

We define the neighbor distribution as follows:

$$d(u|v) = \begin{cases} \frac{1}{|\mathcal{N}_v|}, & \text{if } u \in \mathcal{N}_v \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

and the similarity distribution is defined as:

$$d_{sim}(u|v) = \begin{cases} \mathrm{sim}(x_u, x_v), & \text{if } u \neq v \\ 0, & \text{if } u = v \end{cases} \tag{9}$$

where $x_\cdot$ is the ℓ_2-normalized feature and $\mathrm{sim}(\cdot,\cdot)$ denotes the cosine similarity $\mathrm{sim}(u, v) = u^\top v/(\|u\|\|v\|)$.

For each tail node v, an auxiliary node a is sampled from the feature similarity distribution $d_{sim}(\cdot|v)$. Subsequently, we construct the augmented neighborhood distribution by combining the self-networks of v and a. Formally, the mixed neighborhood distribution of v is expressed as:

$$d_{mix}(\cdot|v) = (1-\varphi)\big(d(\cdot|v)\cdot d_{sim}(\cdot|v)\big) + \varphi\big(d(\cdot|a)\cdot d_{sim}(\cdot|a)\big), \tag{10}$$

where the mixing coefficient φ for the auxiliary node a is positively correlated with its similarity to the tail node v and $\varphi \le 0.5$. Afterwards, we sample the neighbors of v from $d_{\mathrm{mix}}(\cdot|v)$. Last but not least, neighbor number sampling is performed according to the original degree distribution to maintain unified degree statistics.

4.4. Multi-view contrastive learning network

In the multi-view contrastive learning network, we regard the target nodes and their neighbors as within-view positive pairs, and the neighbors of other nodes as within-view negative pairs. Moreover, we consider the original graph and the structure augmented graph as contrastive views. In the early phase of training, we use redundant edge pruning to generate the augmented graph. During the later training phase, we utilize the tail auxiliary mix completion strategy to generate the augmented graph. Through cross-view contrastive learning, the quality of node embedding is further improved.

In detail, we consider the graphs $\mathcal{G} = (\bar{\mathbf{A}}, \mathbf{X})$ and $\mathcal{G}' = (\widetilde{\mathbf{A}}, \mathbf{X})$ to the original graph and the augmented graph. Node representations are generated through a GCN-based encoder $g(\cdot)$:

$$\mathbf{Z}^1 = g(\bar{\mathbf{A}}, \mathbf{X}), \tag{11}$$

$$\mathbf{Z}^2 = g(\widetilde{\mathbf{A}}, \mathbf{X}), \tag{12}$$

where $\mathbf{Z}^1 \in \mathbb{R}^{N\times d'}$ and $\mathbf{Z}^2 \in \mathbb{R}^{N\times d'}$ are the node embeddings of the original graph and the augmented graph, respectively.

Subsequently, we compute the neighbor representation of the node by employing the Readout function, a well-established approach in existing work [59]. The function is defined as follows:

$$\boldsymbol{z}_{\mathcal{N}_i} = \mathrm{Readout}\left(\left\{\boldsymbol{z}_j, \forall j \in \hat{\mathcal{N}}_i\right\}\right), \tag{13}$$

where $\boldsymbol{z}_{\mathcal{N}_i} \in \mathbb{R}^d$ denotes the neighbor representation of node i. $\hat{\mathcal{N}}_i$ is obtained by applying the random walk with restart [60] on $\mathcal{G}^{view}$. We employ a practical parameter-free average pooling as our readout function.

Building on existing GCL-based anomaly detection work [29], we design a discriminator module that evaluates the potential edge relationships by node representations and node neighbor representations. The discriminator employs a bilinear scoring function, predicting the similarity score using the following formula:

$$s_i = \mathrm{Bilinear}\left(\boldsymbol{z}_{\mathcal{N}_j}, \boldsymbol{z}_i\right) = \phi\left(\boldsymbol{z}_{\mathcal{N}_j}\mathrm{W}\boldsymbol{z}_i^\top\right), \tag{14}$$

where $\phi(\cdot)$ is a sigmoid function and $\mathbf{W}$ is a trainable matrix. For input of graph neighbor relationships, that is, $i = j$, the discriminator outputs

the positive pair score $s_{i,p}$, while for input of negative pairs, that is, $i \neq j$, it outputs the score $s_{i,n}$.

The normal nodes that account for the majority in the graph typically exhibit similar representations to their neighbors, with the aim of $s_{i,p}$ being close to 1. In contrast, negative pairs between normal nodes and neighbors of other nodes show dissimilarity. Consequently, we utilize binary cross-entropy (BCE) loss [25] to optimize the within-view contrastive pairs of two views:

$$\mathcal{L}_{within}^{v1} = -\frac{1}{2n}\sum_{i=1}^{n}\left(\log\left(s_{i,p}^{v1}\right) + \log\left(1 - s_{i,n}^{v1}\right)\right), \tag{15}$$

$$\mathcal{L}_{within}^{v2} = -\frac{1}{2n}\sum_{i=1}^{n}\left(\log\left(s_{i,p}^{v2}\right) + \log\left(1 - s_{i,n}^{v2}\right)\right), \tag{16}$$

where $s_{i,p}^{v1}$ and $s_{i,p}^{v2}$ denote positive pair scores of the original and augmented views, while $s_{i,n}^{v1}$ and $s_{i,n}^{v2}$ are negative pair scores. The within-view contrastive loss $\mathcal{L}_{within}$ can be formulated as $\mathcal{L}_{within} = \mathcal{L}_{within}^{v1} + \mathcal{L}_{within}^{v2}$.

Then, we align two contrastive views by InfoNCE [31] to keep their cross-view agreement. We consider node features and discriminator scores as cross-view positive pairs, formulating the cross-view contrastive loss as:

$$\mathcal{L}_{cross} = \mathcal{L}_{ctr}\left(\mathbf{Z}^1, \mathbf{Z}^2\right) + \mathcal{L}_{ctr}\left(\mathbf{S}^1, \mathbf{S}^2\right), \tag{17}$$

where $\mathbf{Z}$ and $\mathbf{S}$ denote the node feature and the discriminator score, respectively. $\mathcal{L}_{ctr}(\cdot,\cdot)$ is defined as:

$$\mathcal{L}_{ctr}(\mathbf{U}, \mathbf{V}) = -\sum_{i=1}^{N}\log\frac{\exp\left(\mathrm{u}_i \cdot \mathrm{v}_i/\tau\right)}{\sum_{j=1}^{N}\exp\left(\mathrm{u}_i \cdot \mathrm{v}_j/\tau\right)}, \tag{18}$$

where τ is a temperature parameter used to control the distribution steepness of similarity scores.

After obtaining the within-view and cross-view contrastive losses, the total target loss of the model can be expressed as:

$$\mathcal{L} = \mathcal{L}_{within} + \alpha\mathcal{L}_{cross}, \tag{19}$$

where the loss coordination parameter α controls the relative weighting between both.

4.5. Anomaly score calculation

After effective training of the contrastive learning network, our model calculates anomaly scores for all nodes according to the principle of local inconsistency in the reasoning stage. We perform multiple rounds of positive and negative sampling at the target node to obtain the prediction score [29]. The final anomaly score S_i of node i is as follows:

$$S_i = \frac{1}{R}\sum_{r=1}^{R}\left(s_{i,n}^{r} - s_{i,p}^{r}\right), \tag{20}$$

where R denotes the sampling rounds. The discriminator for each round generates positive pair scores $s_{i,p}^{r}$ and negative pair scores $s_{i,p}^{r}$. Generally speaking, normal nodes typically exhibit the situation that the positive pair score $s_{i,p}$ tends to 1, but the negative pair score $s_{i,n}$ tends to 0. In contrast, there is no such rule in abnormal nodes, the difference between $s_{i,p}$ and $s_{i,n}$ is relatively small. Higher S_i values indicate stronger evidence of abnormality. In short, the general algorithm procedures of SAA-GCL are shown in Algorithm 1.

4.6. Complexity analysis

The time complexity of our proposed algorithm is mainly due to the following components. For structure augmented subnetwork, the GCN encoder for edge embedding has complexity $O(LMd + LNd^2)$, the MLP requires $O(Md^2)$ and the LMSE loss yields $O(N^2d)$, where L is the number of GCN layers, M is the number of edges, N is the number of nodes and d is the hidden dimension. The time complexity of tail auxiliary mix completion is $O(N^2d + NK\eta)$, where K is the subgraph size and η is the average degree. Discriminator costs $O(Nd^2)$ and contrastive loss cost $O(N^2d)$ in the contrastive learning module. Combining all modules and assuming T training epochs and R inference rounds, the total time complexity is $O((LMd + LNd^2 + Md^2 + N^2d + NK\eta)(T + R))$.

To better clarify the scalability of the model, we provide a theoretical scalability comparison with several representative baselines in Table 2. It reveals that the asymptotic time complexity of SAA-GCL is close to its peers in order of magnitude, demonstrating that our proposed approach does not introduce prohibitive computational overhead and has computational feasibility in large-scale data environments.

Algorithm 1 Proposed model SAA-GCL.

Input: Attributed graph $\mathcal{G} = (\mathbf{A}, \mathbf{X})$; Training epochs E; Degree threshold K.
Output: Anomaly scores S_i.

for $e = 1$ to E **do**
  // Structure Augmentation
  Generate edge weights $\mathbf{W}$ via Eq. (3) and augmented adjacency $\widetilde{\mathbf{A}}$ via Eq. (4);
  Calculate LMSE loss via Eq. (6);
  Update edge weight learner using Eqs. (5) and (7).
  // Tail Node Processing
  for each node v_i with $|\mathcal{N}_i| \leq K$ **do**
    Sample auxiliary node a from similarity distribution $d_{sim}(\cdot|v_i)$ and calculate mixed neighborhood $d_{mix}(\cdot|v_i)$ via Eq. (10);
    Expand neighborhood $\hat{\mathcal{N}}_i$ via RWR sampling.
  end for
  // Multi-View Contrastive Learning
  Generate embeddings of the original and augmented graph $\mathbf{Z}^1$, $\mathbf{Z}^2$ and calculate neighbor representations respectively via Eq. (11)–(13);
  Calculate discriminator scores of the positive and negative pairs via Eq. (14);
  Calculate within-view loss and cross-view loss via Eqs. (15)–(17);
  Update model parameters using total loss $\mathcal{L}$ via Eq. (19).
end for
// Anomaly Scoring
for each node $v_i \in \mathcal{V}$ **do**
  for $r = 1$ to R **do**
    Sample positive/negative pairs and compute $s_{i,p}^{r}$, $s_{i,n}^{r}$ via discriminator.
  end for
  Calculate final anomaly score S_i via Eq. (20).
end for

Table 2
We summarize the asymptotic time complexity of SAA-GCL and baseline methods concerning key variables: number of nodes N, edges M, and hidden dimension d.

Model	Asymptotic Time Complexity
DOMINANT	$O(N^2d + Nd^2 + Md)$
CoLA	$O(Nd^2 + Nd)$
Sub-CR	$O(N^3 + Nd^2 + Nd)$
SAA-GCL	$O(N^2d + Nd^2 + Md^2)$

5. Experiment

In this section, we validate the effectiveness of the proposed SAA-GCL model through a comparative experiment on six real-world datasets. Furthermore, to verify how each component and hyperparameter of SAA-GCL affects its performance, we conduct ablation and

Table 3
Datasets statistics. There are number of nodes, edges, attributes, and anomaly ratio in the table.

Dataset	#Nodes	#Edges	#Attributes	#Anomalies
Blogcatalog	5196	171,743	8189	5.8%
ACM	16,484	71,980	8337	3.6%
Cora	2708	5429	1433	5.5%
Citeseer	3327	4732	3703	4.5%
Pubmed	19,717	44,338	500	3.0%
Reddit	10,984	168,016	64	3.3%

parameter sensitivity experiments. Detailed results will be presented in subsequent sections.

5.1. Datasets

As shown in Table 3, we use six real-world graph datasets to evaluate the performance of SAA-GCL and its counterparts. Including BlogCatalog [29], Reddit [61], ACM [46], Cora [62], Citeseer [62], and Pubmed [63]. They are mainly divided into social networks and citation networks, which are described in detail as follows.

(1) Social Networks. Both Blogcatalog and Reddit are social network datasets with similar graph characteristics. The Blogcatalog dataset originates from a social blogging platform, where nodes represent users, and edges denote their social connections. In contrast, the Reddit dataset is derived from an online discussion community, with nodes representing user posts and edges indicating reply relationships or other interactions between posts.

(2) Citation Networks. ACM, Cora, Citeseer, and Pubmed are citation network datasets. The nodes represent scholars or papers, while the edges represent the cooperative relationship of the author or the citation relationship of the paper.

Reddit contains genuine anomaly labels, which can validate the generalization ability of SAA-GCL to naturally occurring anomalies. Except for Reddit, other datasets lack genuine anomaly labeling, so we adopt the strategy of artificially injecting synthetic anomalies. To ensure fairness of the experiments, all data are based on the original datasets rather than the preprocessed versions used in existing research. The synthesis method is implemented with reference to the previous research flow [29,64,65].

5.2. Experimental settings

In our experiment, the model parameters are optimized using the Adam [66] optimizer, and we set the subgraph size to 4, the dimension of the graph embedding hidden layer to 64, the batch size to 300, and the number of GNN layers to 3. We set the learning rates for six datasets as 0.003 (Citeseer), 0.004 (Blogcatalog, Pubmed, Reddit) and 0.005 (ACM, Cora). The training epoch is set to 100 (ACM, Blogcatalog, Pubmed, Reddit) and 200 (Cora, Citeseer). The number of test rounds is 256. In the configuration of experimental environment, our model is implemented in Python 3.8 using PyTorch 1.12.1 and PyG, and DGL is used for graph data preprocessing. We run all experiments on an NVIDIA RTX 2080 Ti GPU with 22GB of memory.

We select AUC-ROC as the evaluation metric of model performance. The AUC-ROC curve plots the true positive rate against the false positive rate at different thresholds. The area under the curve is the value of AUC. Higher AUC values indicate better detection capability.

5.3. Comparison experiments

For performance evaluation, we compare our SAA-GCL model with a set of representative baselines using standard metrics. The baselines consist of three autoencoder-based approaches and seven contrastive learning methods. Among them, three are implemented based on the autoencoder generative framework: they are DOMINANT [64], AnomalyDAE [51], and ADA-GAD [67]. The other seven are based on the contrastive learning neural network framework, including CoLA [29], CONAD [52], Sub-CR [32], GRADATE [33], NLGAD [54], GAD-NR [61] and CLADHS [17]. These seven state-of-the-art methods will be briefly described as follows:

Table 4
Performance comparison (AUC-ROC) between SAA-GCL and baseline methods. We **bold** the best result in each column and underline the second-best.

Model	Blogcatalog	ACM	Cora	Citeseer	Pubmed	Reddit
DOMINANT	0.7530	0.7466	0.8247	0.8383	0.8071	0.5622
AnomalyDAE	0.7642	0.8471	0.8980	0.8475	0.8914	0.5574
ADA-GAD	0.7340	0.8575	0.8413	0.9005	0.9010	0.5546
CoLA	0.7839	0.8217	0.8740	0.8954	0.9487	0.5573
CONAD	0.6733	0.8495	0.8716	0.8501	0.8561	0.5642
Sub-CR	0.7939	0.7831	0.9092	0.9260	0.9629	0.5582
GRADATE	0.7244	0.8598	0.9220	0.8820	0.9286	0.5679
NLGAD	0.7291	0.8622	0.9184	0.9442	0.9554	0.5902
GAD-NR	0.7874	0.8298	0.8849	0.9060	0.8923	0.5799
CLADHS	0.7788	0.8740	0.9026	0.9061	0.9205	0.5569
SAA-GCL	**0.8127**	**0.9049**	**0.9358**	**0.9529**	**0.9743**	**0.6258**

- **CoLA** [29]: by unsupervised contrastive learning, it captures local relationships between nodes and their adjacent subgraphs, detecting structural and attribute anomalies.
- **CONAD** [52]: abstracts abnormal knowledge into a computable form and integrates prior knowledge to improve detection performance by semi-supervised contrastive learning.
- **Sub-CR** [32]: combines multi-view contrastive learning with attribute reconstruction, implementing collaborative anomaly detection of topology-attribute.
- **GRADATE** [33]: introduces subgraph-subgraph comparison for the first time, and combines node-subgraph and node-node comparison to form a multi-view and multi-scale detection framework.
- **NLGAD** [54]: designs a hybrid strategy to screen normal nodes from unlabeled data and adopts a two-stage training to improve the distinguishing ability of abnormal nodes.
- **GAD-NR** [61]: proposes a new variant of the graph autoencoder, which takes neighborhood reconstruction as the core index of GAD for the first time.
- **CLADHS** [17]: constructs hierarchical subgraphs and combines contrastive learning, solving the problem of sparse connections and irregular feature distribution.

We evaluate our SAA-GCL model through extensive comparative experiments with ten baseline methods. The quantitative results for six real-world graph datasets are summarized in Table 4, while Fig. 3 visualizes the comparisons of the ROC curve. Based on these experimental results, we can observe the following conclusions:

- Our proposed SAA-GCL achieves state-of-the-art performance across all six benchmark datasets, outperforms the current best baseline by 1.88%, 3.56%, 3.09%, 1.38%, 0.87%, and 1.14% on Blogcatalog, Reddit, ACM, Cora, Citeseer, and Pubmed, respectively. This shows that the model performs excellently in detecting genuine anomalies. The results demonstrate the effectiveness of suppressing feature redundancy and retaining key structural information, which can improve the learning quality of graph representation to achieve better anomaly detection results.
- Fig. 4 visualizes the distribution of the anomaly scores for each dataset. From the visualization diagram, it can be seen that the proposed SAA-GCL method exhibits a highly concentrated distribution of anomaly scores, making the distribution difference between normal and abnormal nodes more obvious.
- Reconstruction-based methods DOMINANT, AnomalyDAE, and ADA-GAD show limited competitiveness, especially on social

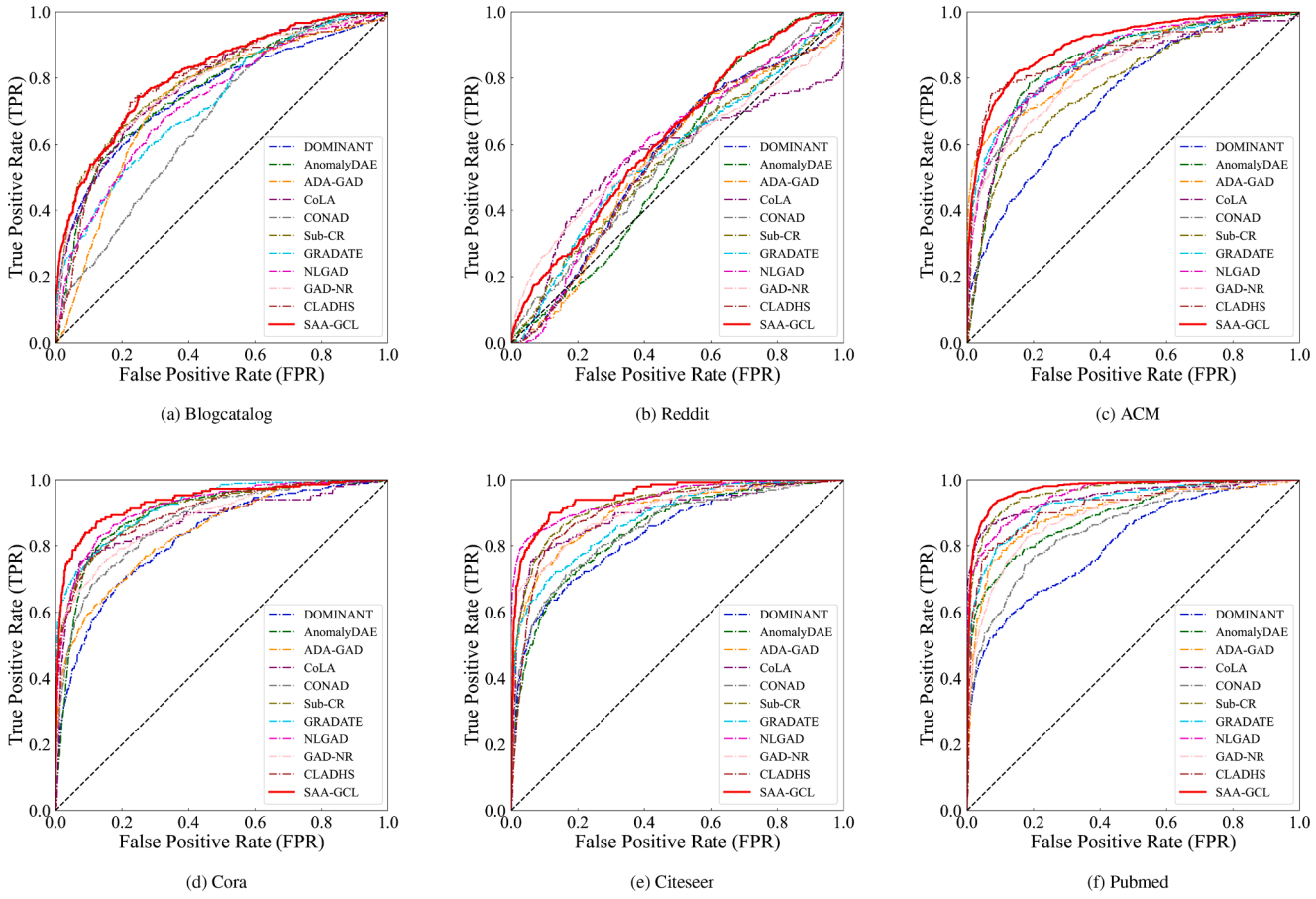


Fig. 3. AUC-ROC curves on six benchmark datasets.

Table 5
Ablation study of SAA-GCL components, w/o means to remove the corresponding component.

Component Removed	BlogCatalog	ACM	Cora	Citeseer	Pubmed	Reddit
w/o SAS	0.7755	0.8720	0.9171	0.9319	0.9399	0.6104
w/o TAMC	0.7820	0.8869	0.9222	0.9394	0.9548	0.5982
w/o Within-CL	0.5416	0.6372	0.6595	0.6673	0.7063	0.4686
w/o Cross-CL	0.7807	0.8845	0.9246	0.9367	0.9506	0.6061
All	**0.8127**	**0.9049**	**0.9358**	**0.9529**	**0.9743**	**0.6258**

networks. Unlike contrastive learning methods, which have excellent representation ability, these methods are difficult to fully capture key features in graphs with complex structures, especially when dealing with large-scale high-dimensional data. At the same time, they lack the ability to automatically distinguish between normal reconstruction errors and real anomalies.

- Among contrastive methods, CLADHS, CoLA, GRADATE, and NLGAD show strengths in local pattern recognition but exhibit limitations in capturing global dependencies. This limits their ability to detect long-range dependencies and global graph anomalies. The performance of CONAD is affected by the community structure, so it is weaker in datasets that lack clear communities. Sub-CR exploits the cooperative signal of node attributes and topological structure but ignores the influence of noise structure on contrastive learning. GAD-NR lacks adequate modeling of non-Gaussian neighbor features, leading to limitations in neighborhood reconstruction.
- We also observe that the performance improvement of the proposed model is relatively small in social network datasets, suggesting that heterogeneous node interactions may pose unique challenges for structural augmentation. These findings point to promising directions for future research, particularly in developing specialized adaptations for heterogeneous graph structures.

5.4. Ablation study

We conduct comprehensive ablation studies to evaluate the contribution of each SAA-GCL module. There are two groups in our ablation experiment, one focused on the graph structure enhancement strategy, including w/o SAS (removal of the Structure augmented subnetwork) and w/o TAMC (deletion of the Tail auxiliary mix completion). The other is aimed at the contrastive learning module, where w/o Within-CL indicates that no within-view contrastive loss was used, and w/o Cross-CL indicates that no cross-view contrastive loss was used. Table 5 presents the results of the ablation experiment. We analyze the experimental results as follows:

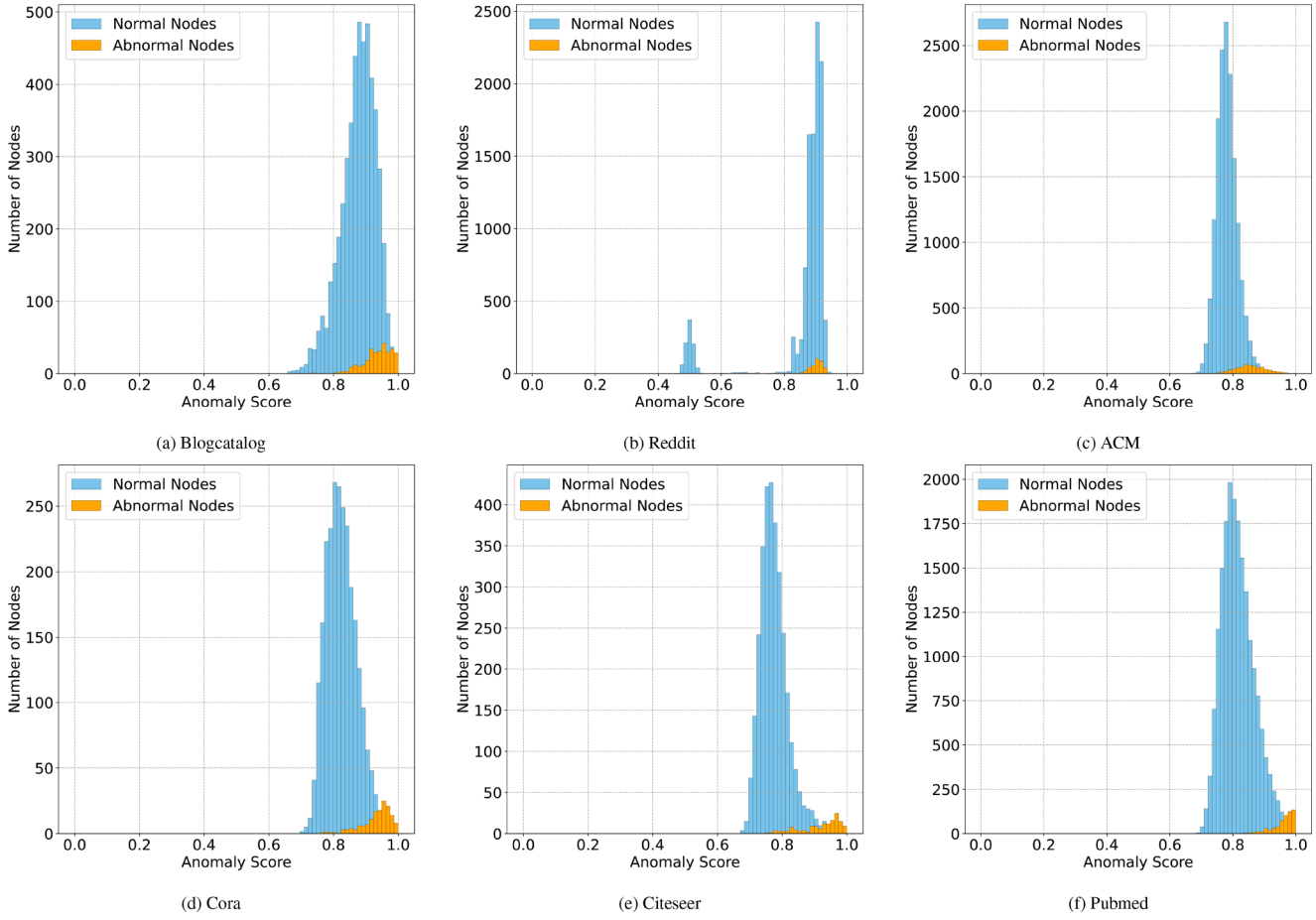


Fig. 4. Anomaly score distributions (range 0–1) visualized on six datasets.

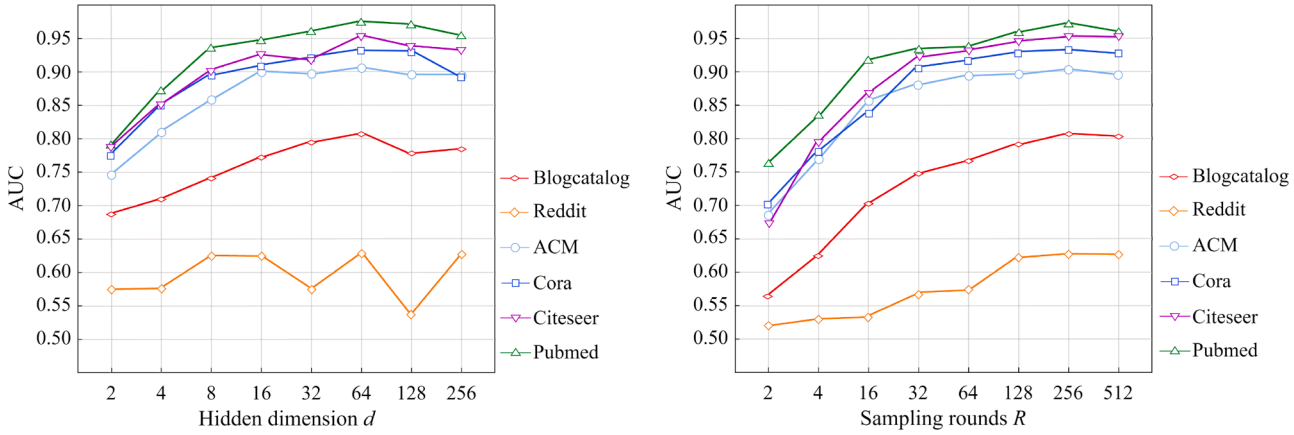
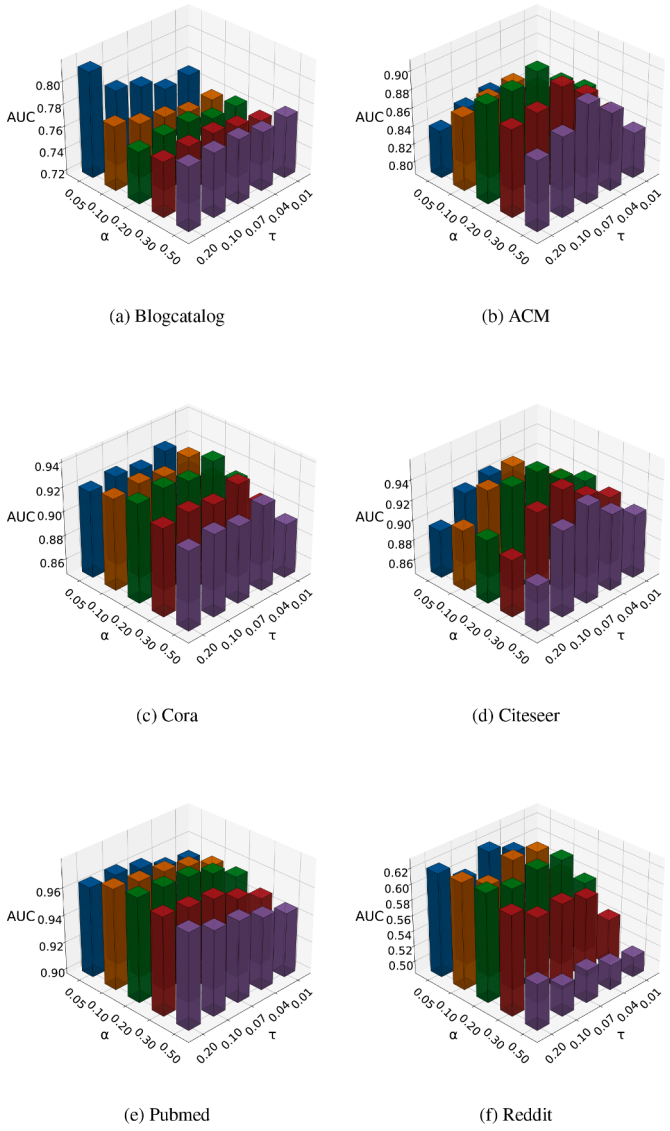


Fig. 5. Parameter sensitivity analysis: (a) Impact of hidden layer dimension d; (b) Effect of sampling rounds R.

- The complete SAA-GCL model achieves optimal performance across all datasets, demonstrating the synergistic effect of integrating structural augmentation with multi-view contrastive learning. Structure Augmented Subnetwork (SAS) enhances edge feature discrimination through adversarial weight learning, while Tail Auxiliary Mix Completion (TAMC) mitigates structural imbalance in low-degree nodes. Their combined contribution improves performance by 1.5 to 4.7% compared to partial configurations, validating the necessity of both modules.
- Removing within-view contrastive loss (w/o Within-CL) causes the most severe performance drop, highlighting its critical role in local anomaly discrimination. Cross-view contrastive loss (Cross-CL) ensures cross-view consistency, particularly vital for social networks.
- SAS removal most affects citation networks, confirming its edge weight optimization efficacy, while TAMC ablation severely degrades sparse graph performance, underscoring its tail node adaptation capability.



(a) Blogcatalog (b) ACM

(c) Cora (d) Citeseer

(e) Pubmed (f) Reddit

Fig. 6. Parameter sensitivity analysis: hyperparameter α and τ.

5.5. Parameter sensitivity

We conduct a series of parametric analysis experiments on SAA-GCL, focusing on four key hyperparameters: the hidden dimension d, the sampling rounds R, the loss coordination parameter α and the temperature parameter τ for the loss function.

The results for hidden dimensions and sampling rounds are shown in Fig. 5. It is clear from the figure that performance consistently improves across the hidden dimension range from 2 to 64. However, exceeding this threshold will lead to performance degradation, because too high a parameter value will increase the risk of overfitting, thus reducing the detection efficiency. To achieve the best results, we generally set the dimensionality of the hidden representation to 64. Then, it can be observed that the AUC increases continuously and tends to be stable with increasing sampling rounds R. The R value close to 128 can stabilize the result. This improvement can be attributed to the fact that large rounds of sampling can more accurately estimate the normality difference between the positive and negative sample pairs of nodes. However, when R reaches 256, further increase will not improve the performance, so we set the sampling rounds to 256.

In addition, we explore the influence of the loss coordination parameter α and the temperature parameter τ on the model performance. The parameter analysis experiments of α and τ are shown in Fig. 6. α plays a key role in balancing the within-view and cross-view contrastive losses. τ controls the distribution of similarity scores between positive and negative samples. The smaller τ makes the model pay more attention to difficult negative samples, while the larger τ makes the training gradient smoother. Finally, we observe that setting α to 0.05, 0.2, 0.2, 0.2, 0.2, 0.2 and τ to 0.2, 0.07, 0.04, 0.07, 0.2, 0.2 will produce the best results on Blogcatalog, ACM, Cora, Citeseer, Pubmed and Reddit.

6. Conclusion

In this paper, we propose SAA-GCL, a novel graph anomaly detection method that proposes an effective solution to the problem of structural imbalance. By structure adversarial optimization, the model dynamically and selectively removes redundant edges and retains key connections. Moreover, the TAMC strategy expands the neighborhoods of sparse nodes and increases the diversity of contrastive samples. Finally, by introducing the multi-view contrastive loss to enhance the mining of abnormal patterns, SAA-GCL effectively identifies abnormal nodes in the attributed network. Experimental results on six graph datasets demonstrate that our method outperforms existing baselines.

The main limitations concern computational efficiency for very large graphs and handling of extreme heterogeneity. Future work will consider designing a general GAD model to realize cross-domain anomaly detection by training a single graph dataset, which significantly reduces the training cost and improves scalability. For the heterogeneity of graph data, an advanced Relational GCN can be introduced to handle heterogeneous relationships. These improvements will further enhance the practical applicability of the method for real-world tasks.

CRediT authorship contribution statement

Qian Chen: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis; **Huiying Xu:** Validation, Software, Resources, Funding acquisition; **Ruidong Wang:** Writing – review & editing, Supervision, Methodology, Formal analysis; **Yue Liu:** Writing – review & editing, Data curation, Conceptualization; **Xinzhong Zhu:** Supervision, Resources, Funding acquisition.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The author is an Editorial Board Member/Editor-in-Chief/Associate Editor/Guest Editor for this journal and was not involved in the editorial review or the decision to publish this article.

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