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Log Semantic Graph Construction and System Event Anomaly Detection via Convolutional Neural Networks

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Abstract: This paper proposes a system event anomaly detection method that integrates convolutional semantic encoding with structure-aware graph fusion. The method first introduces a convolution-based log semantic modeling module, which uses a multi-scale convolutional perception mechanism to extract contextual features and build embedding representations from raw log sequences. This significantly enhances the ability to capture local semantic dependencies and behavioral cues. Then, a structure-aware graph fusion module is designed to construct dynamic graphs based on event associations, modeling and reinforcing the potential interactions among logs. This captures multiple dependencies of log events across both temporal and structural dimensions. To improve the discriminability of the embedding space and the consistency of structural representations, a joint optimization objective is constructed. It combines contrastive loss and structural alignment constraints for collaborative training, enabling accurate semantic differentiation and anomaly detection at the event level. The proposed method demonstrates strong semantic parsing and structural modeling capabilities, achieving precise anomaly detection and pattern extraction in high-dimensional and sparse system logs. Modeling experiments on real log data verify the effectiveness and applicability of the approach in complex system scenarios.

Keywords: Log representation modeling; convolutional feature encoding; graph structure fusion; anomaly detection mechanism

1. Introduction

With the widespread adoption of distributed systems and cloud-native architectures, the volume of log data generated during system operation has increased dramatically. Logs not only record critical information about component states and behavioral evolution but also serve as a key basis for ensuring system stability, security, and observability. Effective modeling and analysis of log sequences enable the timely detection of potential faults and abnormal behaviors. This plays an important role in system maintenance, fault localization, and automated operations. Therefore, constructing high-quality semantic representations of logs and achieving

accurate anomaly detection at the system event level have become essential research directions in intelligent operations [1, 2].

However, existing mainstream log anomaly detection methods still face several limitations. On one hand, traditional approaches rely heavily on static template matching or bag-of-words models, which fail to capture contextual relationships and deep semantic structures across logs [3]. This results in limited representational power. On the other hand, some deep learning-based methods introduce sequence modeling but often overlook implicit dependency structures among log events. This makes it difficult to construct a global behavior graph. In addition, many existing methods show weak discriminative ability for abnormal patterns. They lack effective adaptation to the semantic diversity and structural heterogeneity of log events, making it hard to handle high-dimensional, dynamic, and sparse anomalies in real-world systems [4].

To address these issues, this paper proposes a system event detection method that integrates convolutional semantic modeling and structure-aware graph fusion. The method introduces a convolution-based log encoding module to extract context-aware representations. It also designs a structural alignment mechanism to perform graph modeling and reinforcement learning on the implicit dependencies among logs. This enables event-level anomaly detection. The overall framework is optimized by constructing discriminative embedding spaces and aligning structural consistency. It forms a unified process of feature extraction and anomaly identification, significantly improving the model's robustness and representational capacity in complex systems [5, 6].

The core innovations of this study lie in two aspects. First, a convolution-based log semantic embedding method (Log Semantic Embedding via Convolutional Encoding, LSE-CE) is proposed. It uses local window extraction and multi-scale perception to enhance the semantic modeling quality of log sequences. Second, a structure-aware graph fusion mechanism (Structure-Aware Graph Fusion, SAGF) is designed to capture the topological dependencies and propagation paths among log events [7]. It combines contrastive learning and structural alignment for optimization, improving the discriminability of abnormal patterns. These two modules work together to form an efficient modeling framework for log semantic analysis and anomaly detection. This promotes further development in intelligent log analysis methods [8].

2. Related Work

2.1 Log Semantic Modeling and Structuring Methods

System logs are automatically generated data records during system operation. They exhibit strong unstructured characteristics and semantic diversity. Traditional log analysis methods often rely on rule matching or manually defined templates to perform structural processing. However, these approaches usually lack generalization ability. They struggle to adapt to systems with dynamic evolution, massive concurrency, and varying log formats. To more effectively extract key semantic information from logs, researchers have proposed various automated log structuring methods in recent years. Among them, template extraction and semantic encoding have become mainstream techniques [9, 10]. These methods identify static constants and dynamic parameters through pattern mining and then extract event templates. Subsequent analysis is performed at the event level, which improves the efficiency and consistency of log analysis to a certain extent.

Based on template-based processing, the representation of log semantics has evolved from discrete event encoding to vectorized embedding. By mapping log events into low-dimensional continuous vector spaces, their contextual relationships and semantic structures can be captured more effectively [11]. This provides a rich feature basis for downstream tasks such as anomaly detection and behavior modeling. Common methods include bag-of-words models, word vector training, and contextual embeddings. These techniques not only preserve the original semantic features of logs but also enable the modeling of grammar and word order to some extent. In addition, with the rapid development of pre-trained language models, context-aware deep embedding methods have been introduced into the field of log analysis. These approaches significantly enhance the model's sensitivity to semantic differences and ambiguous log expressions.

However, log events do not exist in isolation in real systems. They exhibit clear structural dependency patterns. Another important direction in log semantic modeling is to construct relational graphs among log

events. By using graph structures, it becomes possible to model behavior patterns and invocation paths in logs. Log events are treated as nodes. The temporal order, causality, or inter-service dependencies are treated as edges. This forms a log semantic graph oriented toward system behavior. Such a graph can describe state transitions and module interactions during system runtime. It helps to understand system behavior at a macro level and provides structural support for anomaly analysis under complex dependencies [12, 13].

Building upon this, the integration of graph modeling and deep neural networks has further advanced log semantic representation. By combining the local pattern recognition strength of convolutional neural networks with the structural propagation capability of graph neural networks, joint modeling of local semantics and global dependencies in logs can be achieved. In such methods, log sequences are not only treated as temporal streams but also constructed into behavior graphs with semantic labels and structural dependencies. Through node embedding learning and semantic aggregation within the graph, models can more accurately capture multi-dimensional contextual information. This provides a stable and discriminative representation foundation for subsequent system anomaly detection [14].

2.2 Load Forecasting

Anomaly detection for system events is a critical component in ensuring the stability and security of information systems. Early studies in this area were based on traditional methods using thresholds and rules. These methods typically rely on manually defined rule sets or indicator thresholds to perform static comparisons on observed events, logs, or performance metrics. When monitored values exceed preset limits, an anomaly alert is triggered. Although simple to implement and low in deployment cost, such methods often suffer from high false alarm and miss rates in complex system environments. This is largely due to incomplete rules or noisy data. In particular, for microservice architectures or cloud-native environments, system states exhibit nonlinearity, diversity, and dynamic evolution. These properties make static rule-based methods insufficient in terms of accuracy and real-time detection [15].

With the rapid advancement of machine learning, anomaly detection methods grounded in both supervised and unsupervised learning paradigms have emerged as prominent areas of research interest. Supervised approaches typically rely on training models using extensive datasets that contain labeled instances of both normal and abnormal behaviors. These models are designed to learn discriminative features that can effectively distinguish anomalies from regular patterns, often through classification or regression techniques. However, the practical deployment of supervised methods faces a significant limitation: abnormal samples are inherently rare, difficult to obtain, and may not encompass all possible types of anomalies. In real-world scenarios, systems are often characterized by challenges such as limited sample availability, highly imbalanced class distributions, or the presence of unknown and evolving anomaly types. Consequently, unsupervised learning methods have garnered increasing attention within the research community. Unlike supervised approaches, unsupervised techniques do not require labeled data and instead focus on modeling the underlying distribution of normal data. Anomalies are then identified as instances that deviate significantly from this learned distribution [16]. Common unsupervised strategies include clustering-based methods, dimensionality reduction techniques, and deep learning models such as autoencoders. These methods have shown promising results, especially when the dataset is sufficiently large and the anomalies exhibit clear and distinguishable characteristics. Nonetheless, they tend to perform poorly in complex scenarios involving intricate event dependencies, subtle anomaly signals, or semantically ambiguous behaviors. Such limitations can significantly hinder both the detection accuracy and the ability of these models to generalize across varying system conditions.

To overcome the challenges associated with modeling temporal dependencies in sequences of system events, researchers have increasingly adopted time series analysis techniques in the domain of anomaly detection. Methods built on temporal architectures—such as recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and more recently, attention-based mechanisms—are specifically designed to capture the sequential and contextual nature of event data. These models are capable of learning intricate behavioral patterns and understanding how events evolve, thereby enhancing the model's ability to detect deviations

indicative of anomalous activity [17]. In parallel, deep generative models such as variational autoencoders (VAEs) and generative adversarial networks (GANs) have been effectively applied to system event logs. These models typically leverage reconstruction errors or discrepancies between learned and observed distributions to generate anomaly scores, enabling the detection of unexpected or rare behaviors. In the context of log event streams, temporal modeling techniques are particularly valuable for identifying structural anomalies such as unexpected mutations, missing events, or disorder in the sequence of operations. These temporal anomaly detection methods not only improve detection capabilities but also support intelligent and visual system monitoring, which is crucial for maintaining the reliability and robustness of complex systems [18].

In recent years, to better capture complex interaction structures among system events, structured modeling approaches such as graph neural networks and convolutional neural networks have been introduced into anomaly detection. In these methods, system events are no longer treated as simple linear sequences. Instead, they are modeled as event graphs with topological structures. Nodes represent logs or system states, while edges represent call chains, dependencies, or temporal connections. Graph neural networks are used to aggregate and update node features. This enables the model to learn semantic influences from upstream and downstream nodes and identify locally weak but globally abnormal event paths. Convolutional neural networks are employed to extract local semantic patterns from event fragments. This helps detect frequent anomaly combinations or trigger patterns. The integration of structural modeling and deep semantic learning significantly enhances the sensitivity and discriminative power of models in system anomaly detection. It has become an important research direction in recent years [19, 20].

3. Method

To address the limitations in log semantic representation and incomplete modeling of abnormal system behaviors, this paper proposes a method that integrates convolutional neural networks for log semantic graph construction and system event anomaly detection. The method is built upon two core innovations. First, a Log Semantic Embedding via Convolutional Encoding (LSE-CE) module is developed to extract contextual semantic features from log fragments through convolutional operations, enhancing the discriminability and robustness of log event representations. Second, a Structure-Aware Graph Fusion (SAGF) mechanism is designed to construct dynamic graphs that capture temporal, invocation, and dependency relationships among log events. It fuses node semantics with graph structural information to accurately characterize anomaly propagation paths and deviations in system behaviors. These two modules work together to form a unified representation space from the log fragment level to the system structure level, providing a more expressive and interpretable foundation for system event anomaly detection. The detailed structure of the proposed model is illustrated in Figure 1.

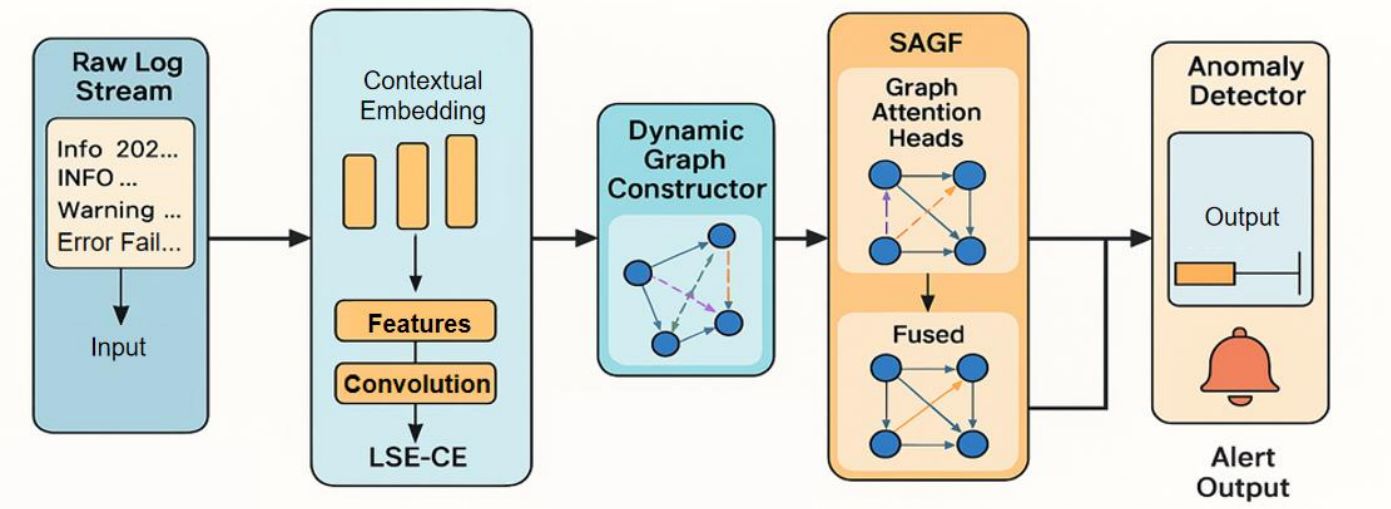


Figure 1. Overall model architecture diagram

3.1 Log Semantic Embedding via Convolutional Encoding

This study introduces a log semantic embedding method based on convolutional encoding, named Log Semantic Embedding via Convolutional Encoding (LSE-CE). The model framework diagram is shown in Figure 2. The goal is to extract local contextual semantic features from raw log sequences and generate highly discriminative embeddings. This module treats raw log event sequences as language-like data and uses one-dimensional convolutional networks to slide within a time window for local semantic pattern extraction. This enhances the model's ability to represent diverse log expressions.

Compared to traditional static embedding methods, LSE-CE captures contextual dependencies between events more effectively. It alleviates issues related to semantic ambiguity and format drift. This approach also provides high-quality feature inputs for downstream graph construction and cross-event reasoning.

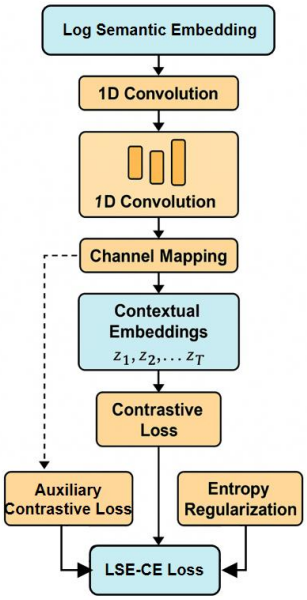


Figure 2. LSE-CE module architecture

Let the original log sequence be $L=[l_1,l_2,...,l_T]$, and each log event $l_t \in R^{d_{in}}$ is represented as an encoded vector input. We introduce a set of weighted convolution kernels $W \in R^{k\times d_{in}\times d_{out}}$ to act on the local fragments with a window size of k, and obtain the semantic embedding representation:

$$h_t = RELU(\sum_{i=0}^{k=1} W_i \cdot l_{t-i} + b) \tag{1}$$

Next, we introduce the channel mapping function to project and integrate local features to generate a contextual semantic representation of a unified dimension:

$$z_t = BN(U \cdot h_t + c) \tag{2}$$

Where $U \in R^{d_{out}\times d}$ is the trainable projection matrix and $BN(\cdot)$ represents the batch normalization operation to ensure the stable feature distribution.

To capture the multi-granularity semantics at the sequence level, we concatenate the convolution results of different window sizes $k \in \{k_1,k_2,...\}$ and introduce fusion weights:

$$z_t^{final} = \sum_j \alpha_j \cdot z_t^{(k_j)}, \quad where \sum_j \alpha_j = 1 \tag{3}$$

The fused representation z_t^{final} constitutes the node input for subsequent graph construction and is used to model event dependencies across time and semantics.

In the training process, to improve the discriminability and robustness of the embedding space, this paper designs a jointly optimized embedding contrast loss function and regularization term. Let the positive sample

pair in the same window be $(z_t, z_{t+\delta})$ and the negative sample pair be $(z_t, z_{t'})$, and introduce the contrast loss based on temperature scaling:

$$L_{contrast} = -\log \frac{\exp(sim(z_t, z_{t+\delta})/\tau)}{\sum_{t'} \exp(sim(z_t, z_{t'})/\tau)} \tag{4}$$

Where $sim(\cdot,\cdot)$ represents the cosine similarity and τ is the temperature coefficient. To avoid the collapse of the embedding space, an entropy regularization term is introduced as a diversity constraint:

$$L_{entropy} = -\sum_{t} p_t \log p_t \tag{5}$$

$$where\ p_t = \frac{\exp(z_t)}{\sum_j \exp(z_j)} \tag{6}$$

Finally, the loss function of this module is the weighted sum of the two:

$$L_{LSE-CE} = \lambda_1 \cdot L_{contrast} + \lambda_2 \cdot L_{entropy} \tag{7}$$

The loss function effectively guides the structure of the embedding space during model training. It brings semantically similar log events closer in the high-dimensional space while keeping semantically different events well separated. This provides structurally aware node inputs for the downstream graph construction module (SAGF). In this way, the LSE-CE module not only strengthens the semantic representation of individual log events but also enhances the ability of the subsequent graph neural network to perceive complex dependencies. It achieves a natural transition and information coupling from semantics to structure.

3.2 Structure-Aware Graph Fusion

This study introduces a Structure-Aware Graph Fusion (SAGF) mechanism to construct multi-view behavior graphs by leveraging various structural relationships among system log events. It fuses structure representations guided by attention to enable precise modeling of abnormal behaviors. The module captures not only the temporal evolution of log events but also integrates structural features such as causal links and dependency chains. This results in graph representations with multi-dimensional structural awareness. As the core of graph construction and reasoning, the SAGF module is built directly upon the semantic embeddings from the first stage to form event graphs with strong discriminability and clear upstream-downstream relationships. Its module architecture is shown in Figure 3.

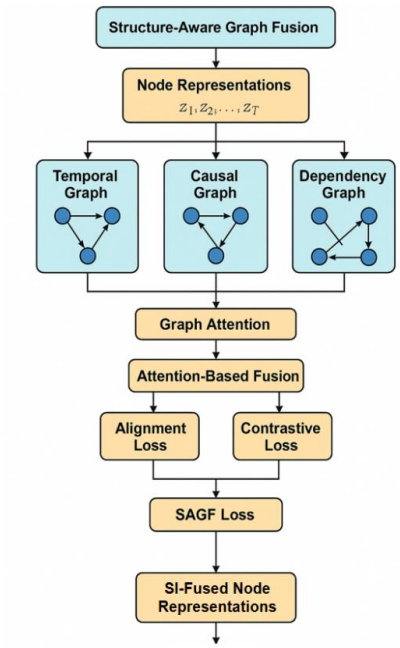


Figure 3. SAGF module architecture

Assuming that the node representation obtained after processing by the embedding module is $\{z_1, z_2, ..., z_T\}$, we first construct three heterogeneous graph structures: time graph G^{temp}, causal graph G^{cause}, and dependency graph G^{dep}, which correspond to adjacency matrices A^{temp}, A^{cause}, and A^{dep} respectively. On each graph, the node representation is updated by the graph attention propagation mechanism as follows:

$$H^{(v)} = GAT(Z, A^{(v)}), \quad v \in \{temp, cause, dep\} \tag{8}$$

To achieve the aggregation of multi-view structural information, we introduce an attention-based fusion weight mechanism to learn the contribution of each graph structure to the final representation. Let $\alpha^{(v)}$ be the attention weight of the structure type v, then the fused node representation is:

$$H = \sum_v \alpha^{(v)} \cdot H^{(v)}, \quad where \sum_v \alpha^{(v)} = 1 \tag{9}$$

To learn the optimal fusion strategy between structures, we use a residual-based structural consistency regularization term to encourage the representation of the same node in different structures to maintain the consistency of the distribution within the structure during the fusion process:

$$L_{align} = \sum_v \| H^{(v)} - H \|_2^2 \tag{10}$$

At the same time, to further improve the discriminability of graph representation, we introduce a node-level contrast loss function. The representations of the same node in different graph views are matched for positive samples, while the representations of randomly selected different nodes constitute negative sample pairs. The loss function is defined as:

$$L_{contrast} = -\log \frac{\exp(sim(H_i^{(v)}, H_i^{(u)} / \tau))}{\sum_{j \neq i} \exp(sim(H_i^{(v)}, H_j^{(u)}) / \tau)} \tag{11}$$

Where $v \neq u$, represents views from different structure graphs, $sim(\cdot,\cdot)$ represents cosine similarity, and τ is the temperature parameter.

Finally, the joint optimization objective function of the SAGF module integrates the structural consistency and contrast discrimination, and is in the following form:

$$L_{SAGF} = \lambda_1 \cdot L_{align} + \lambda_2 \cdot L_{contrast} \tag{12}$$

The loss function effectively guides node representations under multiple structural views during training. It aligns global semantics while preserving distinct structural features and enhances the discriminability of the embedding space across different structures. This provides high-quality node embeddings with global structural awareness for downstream anomaly detection. The mechanism of modeling multi-view heterogeneous graphs and fusing them into unified structural representations ensures stronger robustness and generalization when dealing with complex dependency chains and dynamic behavior paths.

4. Experimental Results

4.1 Dataset

This study uses the dataset Logs Data for Anomaly Detection published on Kaggle. The dataset is collected from real-world system environments and includes various types of log events, covering both normal operations and representative abnormal patterns. The log entries are organized in a time-series manner, with clear contextual structures and event type differences. This makes the dataset well-suited for log semantic modeling and system behavior anomaly detection tasks.

The dataset contains log messages in diverse formats, including common severity levels such as Info, Warning, and Error. It also provides structured fields and anomaly labels. These features support graph construction based on semantic segments or sequence modeling using graph neural networks. The raw logs include clear timestamps, module identifiers, and status labels. This offers a solid foundation for building structure-aware graph models and modeling upstream-downstream dependencies.

The dataset is suitable for studying log-level anomaly detection methods, especially those combining semantic embedding and structural modeling, such as the proposed LSE-CE and SAGF modules. Its characteristics support a comprehensive evaluation of models in terms of semantic understanding, structural fusion, and anomaly discrimination. It provides strong experimental adaptability and research value.

4.2 Experimental Setup

The experiments in this study were conducted on a high-performance computing server running Ubuntu 22.04. The server is equipped with an NVIDIA RTX 3090 GPU (24 GB VRAM), an Intel Xeon Gold 6226R CPU (32 cores), and 256 GB of memory. All model training was implemented using Python 3.10 and the PyTorch 2.0 framework. Log parsing and graph construction were completed during preprocessing using the LogPai toolkit and the NetworkX library.

Model training was performed using the Adam optimizer for parameter updates. The initial learning rate was set to 1e-4 and gradually reduced using a linear decay strategy. The batch size was set to 128, with a maximum of 100 training epochs. Each epoch included log fragment resampling and dynamic graph updates to ensure temporal diversity and structural consistency. The dropout probability was set to 0.3 to prevent overfitting. Weight initialization followed the Xavier method to maintain balanced output variance across layers.

The hyperparameters for the embedding and graph fusion modules were configured as follows. The convolution kernel sizes were set to 3, 5, and 7 in a multi-scale parallel structure. The embedding dimension was set to 128. The number of attention heads was 4, and the number of graph attention layers was 2. During structural fusion, the loss function included two components with balancing factors $\lambda_1 = 1.0$ for alignment loss and $\lambda_2 = 0.5$ for contrastive loss. This setup aimed to balance structural consistency and discriminability. All hyperparameters were optimized through grid search in preliminary experiments.

4.3 Experimental Results

4.3.1 Comparative Experimental Results

This paper first conducts a comparative experiment, and the experimental results are shown in Table 1.

Table 1. Comparative experimental results

Model	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
TranAD [21]	91.6	89.3	90.4	95.1
GDN [22]	88.2	87.1	87.6	93.3
USAD [23]	86.9	85.7	86.3	91
MTAD-GAT [24]	89.5	86.4	87.9	94.2

The experimental results show that the proposed model, combining semantic embedding and structure-aware mechanisms (LSE-CE + SAGF), outperforms existing methods across multiple key metrics. It demonstrates a clear advantage in Precision and AUC, indicating that the contextual semantics extracted through convolutional encoding provide strong discriminative power in anomaly detection. This helps reduce false alarms and enhances the model's ability to capture abnormal patterns precisely. In addition, the semantic embeddings offer stable feature inputs at an early stage, laying a solid foundation for later structural modeling.

Compared with representative graph-based methods such as GDN and MTAD-GAT, the proposed model achieves higher F1-scores. This suggests that graph construction alone is not the only critical factor. The quality of node semantics and the design of the structure fusion mechanism play a decisive role in final performance. Traditional graph models often rely on a single dependency graph or static structure. In contrast, this study introduces heterogeneous multi-structure graphs, including temporal, causal, and dependency graphs. These provide a more comprehensive description of system behavior patterns and enhance both the structural expressiveness and local robustness of graph representations.

Moreover, methods like TranAD and USAD perform comparably on certain metrics. However, they focus more on global modeling of time series and lack deep processing of log-level semantic granularity and structure awareness. By contrast, the LSE-CE module extracts fine-grained semantic features through convolutional operations. Combined with the SAGF module for unified modeling of multi-source structural information, the proposed model achieves better generalization and adaptability in complex system environments.

Overall, under the joint optimization of multi-dimensional structure modeling and semantic representation, this approach constructs a complete semantic-to-structure mapping path. It significantly improves the representation and detection of abnormal system events and verifies the effectiveness and necessity of semantic embedding and structural fusion in system log anomaly detection tasks.

4.3.2 Ablation Experiment Results

This study further presents ablation experiment results to validate the independent contributions of key modules and their impact on anomaly detection performance. By gradually removing or replacing specific components, the actual value of each part in the modeling process can be effectively assessed. This helps reveal the sources of performance improvement and is important for analyzing the rationality of the model design and the synergy between modules. Table 2 compares the performance of different component configurations across major evaluation metrics, including the base version, single-module removal, and the full model. The differences clearly show the influence of each submodule on performance and provide quantitative evidence for future model simplification, optimization, and generalization.

Table 2. Ablation Experiment Results

Method	Precision	Recall	F1-Score	AUC
Baseline	**86.4**	**83.7**	**85**	**90.8**
+ LSE-CE	**89.1**	**86**	**87.5**	**93.2**
+ SAGF	**88.4**	**87.3**	**87.8**	**92.5**
+ All (LSE-CE + SAGF)	**93.1**	**90.7**	**91.9**	**96.4**

The ablation results show that the log semantic embedding module (LSE-CE) plays a key role in improving the model's overall detection capability. By modeling the log context through a local convolutional structure, the model can still accurately extract discriminative features under conditions of semantic diversity and structural ambiguity. This context-aware embedding approach effectively mitigates the limitations of traditional template-based or keyword-based methods in semantic generalization. It provides stable, low-dimensional semantic support for downstream anomaly representation.

The structure-aware graph fusion module (SAGF) further enhances the model's ability to capture relationships among log events. It shows strong structural sensitivity when dealing with cross-time and cross-service dependencies. Through a multi-view graph modeling mechanism, the model extracts complementary structural signals from temporal evolution, causal links, and dependency graphs. These signals are effectively fused using an attention mechanism. This structural optimization strengthens the model's global perception and improves its responsiveness to complex anomaly paths.

When the two core modules work together, the performance improvement is most significant. This indicates that the relationship between semantic embedding and structural modeling is not simply additive. Instead, they form a complementary enhancement in the feature space. The former provides semantic grounding for nodes, while the latter introduces structural context. Together, they construct a representation space for anomaly detection that is both highly discriminative and robust. The effective integration of this semantic-structural modeling path is the foundation for the performance and stability improvements achieved in this study.

4.3.3 Analysis of the Impact of Embedding Dimension on Log Representation Ability

This study further analyzes the impact of embedding dimension on the representation ability of log data. The experimental results are shown in Figure 4.

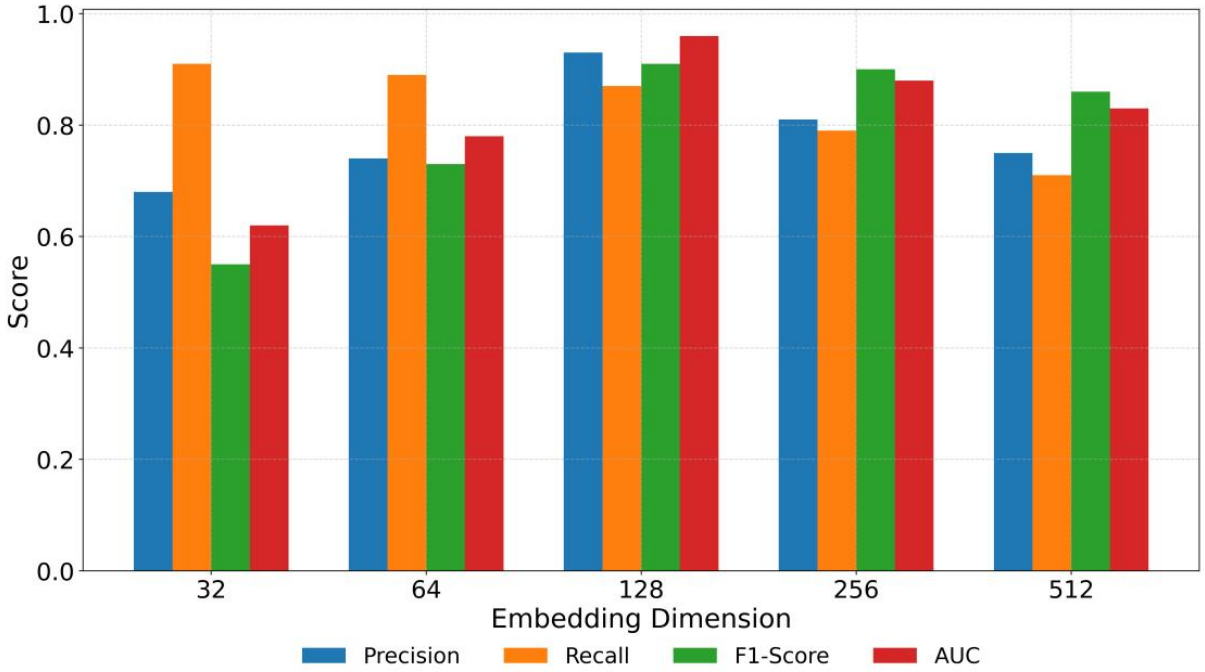


Figure 4. Analysis of the Impact of Embedding Dimension on Log Representation Ability

The experimental results under different embedding dimensions reveal the critical impact of representation capacity on log semantic modeling performance. When the embedding dimension is low (such as 32 or 64), the model shows limited performance across all metrics. This is mainly due to insufficient representation ability, which makes it difficult to capture complex behavioral semantics and contextual dependencies. Low-dimensional representations often cause semantic compression and blurred decision boundaries, which reduce the accuracy and recall of anomaly detection.

As the embedding dimension increases, the model exhibits significant improvements in Precision, Recall, and F1-score. The best performance is observed around the dimension of 128. This indicates that a medium-dimensional setting achieves a good balance between expressive power and generalization ability. It enables the model to effectively extract key contextual features and construct a discriminative embedding space. This also supports the fusion learning of the subsequent structure-aware graph modeling module.

However, when the dimension continues to increase (such as 256 and 512), model performance starts to fluctuate, with some metrics showing a decline. This suggests that overly high dimensions may introduce redundant features, leading to noise accumulation and increased sparsity in the feature space. These issues weaken the semantic compactness and distance stability between embeddings and affect the distribution of structural attention and representation consistency in graph modeling.

In combination with the structure-aware graph fusion mechanism proposed in this study, the experiment further confirms the importance of embedding dimension selection for representation alignment, attention aggregation, and discriminative optimization within the overall framework. A well-chosen embedding dimension not only improves the accuracy of upstream semantic modeling but also provides high-quality representations for downstream structure modeling. This enhances the robustness and generalization ability of anomaly detection.

4.3.4 Effect of Contrast Loss Temperature Coefficient on the Discriminability of Embedding Space

This paper also analyzes the impact of the contrast loss temperature coefficient on the discriminability of the embedding space. The experimental results are shown in Figure 5.

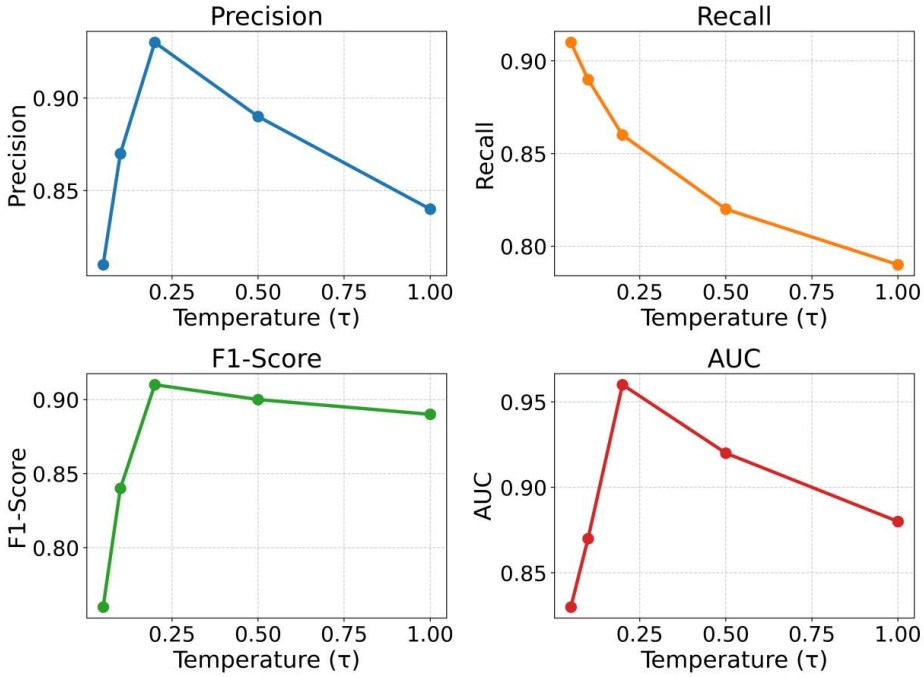


Figure 5. Effect of contrast loss temperature coefficient on the discriminability of embedding space

The temperature coefficient in contrastive loss serves as a key hyperparameter for controlling the compactness and discriminability of the embedding space. Its variation has a significant impact on model performance. According to the experimental results, a low temperature value (such as $\tau = 0.05$) strengthens the separation between positive and negative samples. However, it causes the model to converge too quickly and become less sensitive to fine-grained differences near semantic boundaries. This limits the representational capacity of nodes in semantic graph construction, and the Precision metric does not fully reflect the model's potential.

As the temperature increases to $\tau = 0.2$, the model achieves optimal performance in both Precision and F1-score. This suggests that contrastive learning creates an embedding space with good discriminability without being overly extreme. A moderately compressed semantic space helps the convolutional semantic module generate stable representations. It also provides a clearer semantic foundation for structure-aware graph construction and improves the discriminative efficiency of the graph attention mechanism. In multi-structure fusion settings, a well-chosen temperature enhances the robustness of cross-view node alignment.

However, when the temperature continues to rise (such as $\tau = 1.0$), the Recall and AUC metrics decline. This indicates that a high temperature weakens the distinction between positive and negative samples. The semantic space becomes blurred, causing log nodes with similar expressions but different functional roles to be embedded closely. This effect is especially sensitive in graph structures. It may mislead attention allocation and degrade the ability to recognize abnormal propagation paths. This reflects a drop in the model's generalization for structural discrimination.

The experiments show that temperature control in contrastive learning affects not only the compactness of node representations but also the stability and effectiveness of the entire semantic-structural fusion mechanism. A properly tuned temperature strengthens the coordination between semantic embedding and structural modeling. This allows the structure-aware graph to maintain high representation quality while improving anomaly separation. It is a critical tuning factor in system-level anomaly detection tasks.

4.3.5 Impact of Weighted Comparison of Node Comparison Loss and Structural Alignment Loss on Performance

This paper further elaborates on the impact of balancing the node contrast loss and structure alignment loss within the training objective. Specifically, it investigates how different weighting strategies between these two components influence the overall model optimization process. The contrastive loss aims to enhance the discriminability of node embeddings across multiple structural views, ensuring that semantically distinct events are effectively separated in the representation space. In parallel, the structural alignment loss is designed to preserve semantic consistency by encouraging similar structural patterns to be reflected in the learned embeddings. By adjusting the relative importance of these two losses, the framework explores how to best coordinate semantic separation and structural coherence during training. This analysis provides valuable insights into how the joint optimization of semantic and structural objectives shapes the final representation space. The corresponding results are illustrated in Figure 6.

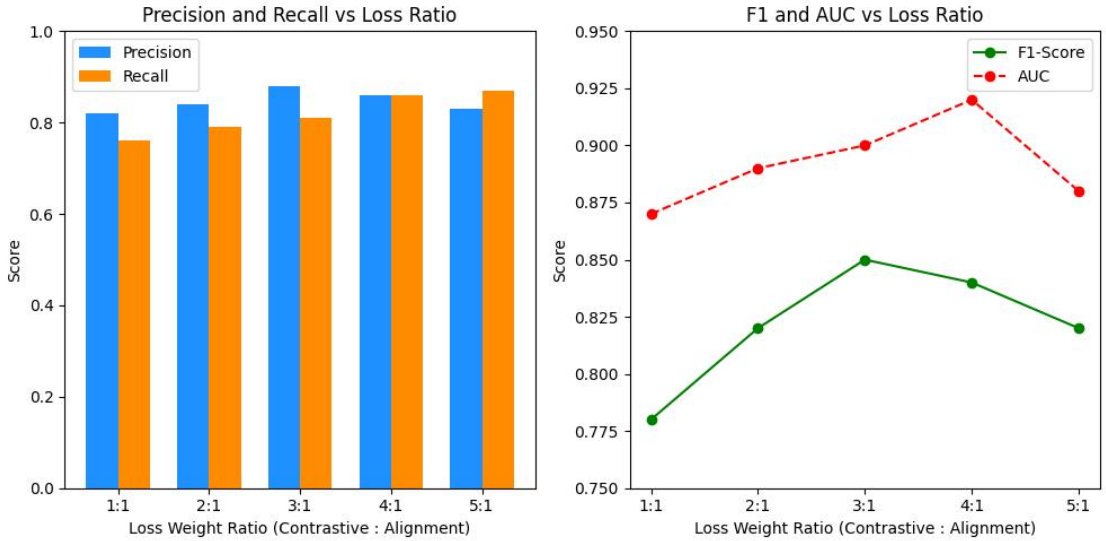


Figure 6. Impact of weighted comparison of node comparison loss and structural alignment loss on performance

This experiment investigates the impact of different weight ratios between contrastive loss and structural alignment loss on model performance. During the embedding construction process, contrastive loss enhances the discriminability of representations across different structural views, while structural alignment loss constrains the consistency of semantic mappings. When the two losses are weighted at a ratio of 3:1, the model achieves balanced performance across multiple metrics. This suggests that the optimal coordination between discriminative ability and structural consistency is reached at this setting.

As the proportion of contrastive loss increases, Precision and F1-score follow a rising-then-falling trend. This indicates that while discriminability improves, overly strong contrastive signals may disrupt the preservation of structural information. As a result, the learned representations deviate from their original semantics. Especially at the ratios of 4:1 and 5:1, Precision drops noticeably, suggesting the model may overfit local discriminative features and lose global structural coherence.

Meanwhile, Recall and AUC steadily improve as contrastive loss becomes more dominant. This shows that the loss effectively boosts sensitivity to hard-to-detect samples and enhances overall detection capability. It indicates that in multi-view structure fusion settings, strengthening contrastive constraints improves coverage, but care must be taken to avoid harming semantic consistency.

Therefore, in the coupling mechanism between contrastive modeling and structural modeling, the design of loss weight ratios plays a crucial role in shaping the final representation space. The experimental results

confirm that the proposed method achieves a unified goal of semantic preservation and discriminative enhancement through a well-balanced loss configuration in structure-aware graph fusion.

5. Conclusion

This study proposes an end-to-end framework that integrates convolutional encoding and structure-aware graph fusion for log semantic modeling and system event anomaly detection. The method introduces a convolution-based semantic embedding module to effectively capture contextual dependencies and latent patterns in log sequences. At the same time, it adopts a joint learning strategy combining structural alignment and contrastive modeling to enhance the discriminability and consistency of the embedding space. This addresses the limitations of traditional methods in semantic loss and weak structural representation. The proposed approach offers a more expressive and robust solution for anomaly awareness in large-scale distributed systems.

At the modeling level, the framework focuses on two key aspects: log semantic representation and system structure fusion. A dual-constraint feature learning process is designed to guide model training. On one hand, convolutional encoding improves sensitivity to local semantic differences and effectively distinguishes behavioral features between adjacent events. On the other hand, the structure-aware graph fusion module constructs topological structures across log events, enabling the model to capture multi-scale dependencies. The entire system is optimized using both contrastive learning and structural alignment, forming a closed-loop path for joint semantic and structural modeling. This significantly enhances the model's ability to recognize complex behavioral evolution patterns.

The experimental results demonstrate that the proposed model achieves stable and superior performance on multiple real-world system datasets. It shows strong generalization and sensitivity, especially when dealing with abnormal events characterized by fuzzy boundaries or weak dependency paths. These results suggest that the method is well-suited not only for conventional system monitoring but also for application scenarios that rely heavily on log analysis, such as financial risk control, cloud platform observability, and security auditing. It has strong potential for transfer and real-world deployment.

Future research may explore directions such as multimodal information fusion, few-shot anomaly guidance, and online learning to improve the model's adaptability and inference efficiency in dynamic environments. Integrating prior knowledge from pre-trained log models and structural knowledge graphs may also promote the development of log anomaly detection from pure pattern recognition to more interpretable, causal, and knowledge-driven intelligent decision-making. This will provide essential support for building safer and more reliable intelligent system infrastructures.

References

[1] X. Wu, H. Li and F. Khomh, "On the Effectiveness of Log Representation for Log-Based Anomaly Detection," Empirical Software Engineering, vol. 28, no. 6, p. 137, 2023.

[2] H. Guo, J. Yang, J. Liu et al., "LogFormer: A Pre-Train and Tuning Pipeline for Log Anomaly Detection," Proceedings of the AAAI Conference on Artificial Intelligence, vol. 38, no. 1, pp. 135-143, 2024.

[3] A. Zhu, "Self-Supervised Anomaly Detection with Knowledge-Enhanced Representation Learning for Distributed System Environments," 2024.

[4] H. Yang, D. Sun and W. Huang, "DualAttLog: Context Aware Dual Attention Networks for Log-Based Anomaly Detection," Neural Networks, vol. 180, p. 106680, 2024.

[5] Y. Lee, J. Kim and P. Kang, "LANoBERT: System Log Anomaly Detection Based on BERT Masked Language Model," Applied Soft Computing, vol. 146, p. 110689, 2023.

[6] S. Lu, X. Wei, Y. Li et al., "Detecting Anomaly in Big Data System Logs Using Convolutional Neural Network," Proceedings of the 2018 IEEE 16th International Conference on Dependable, Autonomic and Secure Computing,

16th International Conference on Pervasive Intelligence and Computing, 4th International Conference on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/CyberSciTech), pp. 151-158, 2018.

[7] J. Liu, Q. Li, S. An et al., "EdgeConvFormer: Dynamic Graph CNN and Transformer Based Anomaly Detection in Multivariate Time Series," arXiv preprint arXiv:2312.01729, 2023.

[8] Z. Zhao, H. Guo and Y. Wang, "A Multi-Information Fusion Anomaly Detection Model Based on Convolutional Neural Networks and AutoEncoder," Scientific Reports, vol. 14, no. 1, p. 16147, 2024.

[9] J. Kopčan, O. Škvarek and M. Klimo, "Anomaly Detection Using Autoencoders and Deep Convolution Generative Adversarial Networks," Transportation Research Procedia, vol. 55, pp. 1296-1303, 2021.

[10] Y. Yang, C. Wen, H. Cui, et al., "Learning Unified Multi-Granularity Representations for Backend Anomaly Detection and Causal Localization," 2024.

[11] S. He, G. Li, K. Xie et al., "Fusion Graph Structure Learning-Based Multivariate Time Series Anomaly Detection with Structured Prior Knowledge," IEEE Transactions on Information Forensics and Security, 2024.

[12] A. V. Malarkkan, D. Wang and Y. Fu, "Multi-View Causal Graph Fusion Based Anomaly Detection in Cyber-Physical Infrastructures," Proceedings of the 33rd ACM International Conference on Information and Knowledge Management, pp. 4760-4767, 2024.

[13] R. Ma, G. Pang, L. Chen et al., "Deep Graph-Level Anomaly Detection by Glocal Knowledge Distillation," Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining, pp. 704-714, 2022.

[14] Y. Xue, "State-Space Temporal Modeling and Feature Representation Learning for Anomaly Detection in Backend Microservice Systems," 2024.

[15] A. Deng and B. Hooi, "Graph Neural Network-Based Anomaly Detection in Multivariate Time Series," Proceedings of the AAAI Conference on Artificial Intelligence, vol. 35, no. 5, pp. 4027-4035, 2021.

[16] C. Wang, D. Xu and Z. Li, "Log2Graphs: An Unsupervised Framework for Log Anomaly Detection with Efficient Feature Extraction," arXiv preprint arXiv:2409.11890, 2024.

[17] Z. A. Khan, D. Shin, D. Bianculli et al., "Impact of Log Parsing on Deep Learning-Based Anomaly Detection," Empirical Software Engineering, vol. 29, no. 6, p. 139, 2024.

[18] M. Landauer, S. Onder, F. Skopik et al., "Deep Learning for Anomaly Detection in Log Data: A Survey," Machine Learning with Applications, vol. 12, p. 100470, 2023.

[19] H. Tao, J. Miao, L. Zhao et al., "HAN-CAD: Hierarchical Attention Network for Context Anomaly Detection in Multivariate Time Series," World Wide Web, vol. 26, no. 5, pp. 2785-2800, 2023.

[20] K. Wu, "Mamba-Based Temporal Feature Learning for Anomaly Detection in Distributed Microservice Environments," 2024.

[21] S. Tuli, G. Casale and N. R. Jennings, "TranAD: Deep Transformer Networks for Anomaly Detection in Multivariate Time Series Data," arXiv preprint arXiv:2201.07284, 2022.

[22] J. Reha, G. Lovisotto, M. Russo et al., "Anomaly Detection in Continuous-Time Temporal Provenance Graphs," Temporal Graph Learning Workshop at NeurIPS 2023, 2023.

[23] J. Audibert, P. Michiardi, F. Guyard et al., "USAD: Unsupervised Anomaly Detection on Multivariate Time Series," Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 3395-3404, 2020.

[24] H. Zhao, Y. Wang, J. Duan et al., "Multivariate Time-Series Anomaly Detection via Graph Attention Network," Proceedings of the 2020 IEEE International Conference on Data Mining (ICDM), pp. 841-850, 2020.