Journal of Computer Technology and Software

ISSN:2998-2383

Vol. 3, No. 7, 2025

Graph-Based Discovery of Implicit Corporate Relationships Using Heterogeneous Network Learning

Zhengyi Liu[1], Zili Zhang[2]
[1]Trine University, Phoenix, USA
[2]Fordham University, New York, USA
*Corresponding Author: Zhengyi Liu; cindyliu1810@gmail.com

Abstract: This paper proposes a method based on deep heterogeneous graph neural networks and contrastive learning mechanisms to identify related transactions and hidden associations in enterprise networks. First, a heterogeneous economic network is constructed by integrating ownership relationships, supply chain transactions, and management overlaps. Multi-source data are transformed into a unified graph structure for modeling. Next, a heterogeneous graph neural network framework is designed. It combines node features, edge features, and attention aggregation. Through multi-layer feature learning, the model captures complex association patterns. To enhance the model's ability to distinguish hidden associations, a graph contrastive learning strategy is introduced. This further optimizes the discriminative power of node representations. In multiple experiments, systematic comparisons with existing heterogeneous graph learning methods validate the superior performance and robustness of the proposed method under different noise perturbations, enterprise size variations, and negative sampling strategies. The results show that this method outperforms traditional approaches in terms of Precision, Recall, and AUC. It effectively improves the accuracy of hidden related transaction detection and provides technical support for intelligent auditing and risk identification in complex enterprise network environments.

Keywords: Deep graph neural network, contrastive learning, related transaction identification, intelligent auditing

1. Introduction

As the modern economic system becomes increasingly complex, transaction structures among enterprises are becoming more diverse. Related-party transactions have played a crucial role in business operations[1]. Proper related-party transactions can improve the efficiency of resource allocation. However, a large body of research and practical cases show that such transactions are easily abused. They often become tools for benefit transfer, profit manipulation, and infringement of minority shareholders' rights. Especially against the backdrop of an increasingly active capital market and a constantly changing regulatory environment, implicit related-party transactions have become more concealed and complex. Traditional audit procedures and risk control mechanisms often fail to fully identify potential risks. Therefore, how to effectively and systematically detect related-party transactions, particularly implicit ones, has become an urgent issue in financial auditing, financial regulation, and corporate governance[2].

Traditional methods for identifying related-party transactions mainly rely on rule-based settings, financial ratio analysis, and auditors' professional judgment. This approach is not only inefficient but also limited in detecting abnormal patterns. Faced with large and complex enterprise network structures, static and linear methods struggle to capture multi-layered and multi-dimensional interactions and hidden relationships. With the development of big data technologies and artificial intelligence methods, new tools have emerged to enhance the identification of related-party transactions. Graph neural networks, as a deep learning method capable of modeling complex relationships and structured data, show great application potential. By incorporating node features, edge features, and high-order neighbor information, graph neural networks can preserve the integrity of enterprise transactions, personnel relationships, and equity investments. They can also automatically learn deep patterns hidden in data, providing technical support for identifying implicit relationships[3].

In recent years, data sources in enterprise operations have become more diverse. These include not only structured financial statements but also unstructured or semi-structured data such as supply chain information, investment chains, and management appointments. The nature of this data is graph-structured. Enterprises are represented as nodes, and transactions, investments, and management connections are represented as edges, forming complex economic networks. This feature highlights the inherent limitations of traditional machine learning methods in feature extraction and relationship modeling[4]. Deep graph neural networks can directly model and reason over the entire graph structure. They offer unique advantages in uncovering hidden association paths and abnormal transaction patterns among enterprises. Furthermore, with the development of emerging techniques such as attention mechanisms and heterogeneous graph neural networks, models are now capable of handling different types of nodes and edges in a more fine-grained manner. This enhances their ability to capture complex economic behaviors[5].

Given the growing demands of audit practices and financial supervision, enhancing the intelligence and automation of related-party transaction identification is of great practical significance. By applying deep graph neural networks, it is possible to build dynamically updating enterprise relationship maps. This allows for real-time monitoring and risk warning across large-scale enterprise data, greatly improving the coverage and precision of audit work. At the same time, intelligent systems for identifying implicit relationships can play a vital role in preventing systemic financial risks, protecting the interests of small investors, and improving capital market transparency. Especially under the current trends of economic globalization and cross-border operations, enterprise networks are showing stronger cross-national characteristics. Traditional strategies based on single markets or single industries urgently need to be upgraded. The introduction of deep learning methods fits well with this transformation.

Based on this, applying deep graph neural networks to related-party and implicit relationship identification is not only an important supplement to existing audit technologies but also a key approach to promoting the intelligence of auditing, the technological advancement of supervision, and the scientific development of corporate governance. Through this study, best practices for graph data modeling in audit scenarios can be explored, driving technological innovation in the auditing industry. It also provides theoretical foundations and practical experience for building intelligent financial analysis and automated risk identification systems in the future. This exploration has profound academic significance and broad application prospects. It will help accelerate the intelligent transformation of auditing and supervision and improve the overall quality and efficiency of market operations.

2. Related work

2.1 Graph Neural Networks

Graph neural networks, as a type of deep learning model specialized for graph-structured data, have attracted widespread attention and developed rapidly in recent years. Early methods mainly focused on spectral-based or spatial-based approaches. They achieved information propagation and feature learning by aggregating local neighbor features of nodes[6]. As technology evolved, various improved models were proposed, such as GraphSAGE[7], GAT[8], and GIN[9]. These models optimized node sampling, attention mechanisms, and representational power. They greatly enhanced the efficiency and accuracy of graph neural networks in handling large-scale graph data. These foundational models have provided critical support for modeling complex relationships and capturing high-order structural features in practical applications.

To address the heterogeneity and dynamics of graph structures in real-world applications, researchers proposed methods such as Heterogeneous Graph Neural Networks and Dynamic Graph Neural Networks. Heterogeneous graph models can handle complex graph data with multiple types of nodes and edges[10]. By introducing type-aware neighbor aggregation strategies, they model interactions between different entities in a more refined manner. Dynamic graph neural networks focus on the evolution of nodes and edges over time. They adapt to data changes in enterprise networks and financial transaction networks. The development of these methods has expanded the application scope of graph neural networks from static social networks to dynamic and multi-modal domains. This has greatly enhanced their practicality and flexibility[11].

In the fields of financial auditing, risk management, and anomaly detection, graph neural networks have also shown unique advantages. By constructing graphs of transactions, equity relations, and management connections among enterprises, and by using node representation learning and edge prediction capabilities, it is possible to effectively identify abnormal patterns and potential risk behaviors hidden in complex networks. Some studies have also explored new methods such as self-supervised learning and graph contrastive learning. These approaches help mitigate the problem of scarce labeled data in auditing and improve model performance under small-sample conditions. These efforts have provided a solid theoretical foundation and methodological reference for applying graph neural networks to related-party transaction identification and implicit relationship inference. They form the starting point for further exploration in this study.

2.2 Current status of audit research based on neural network

The application of artificial intelligence technology in the field of auditing has received widespread attention in recent years. Especially with the continuous expansion of data scale and the rising complexity of audits, AI offers new solutions to improve audit efficiency and quality[12]. Early studies mainly focused on the application of machine learning methods in anomaly detection and financial fraud identification. Models such as decision trees, support vector machines, and random forests were used to classify or predict financial indicators. These methods improved data analysis capabilities in the audit process to a certain extent. However, due to heavy reliance on feature engineering and limitations in capturing complex and nonlinear data relationships, their performance in handling high-dimensional and heterogeneous audit data was restricted. They could not meet the need for deep audit risk identification[13].

With the rise of deep learning technology, especially the development of models such as convolutional neural networks (CNN), recurrent neural networks (RNN), and the Transformer with self-attention mechanisms, the audit field began to explore more complex information extraction and pattern recognition methods. Researchers attempted to apply deep learning to scenarios such as text review, automated contract analysis, and receipt and invoice recognition[14]. These efforts significantly improved the ability to process unstructured data. At the same time, natural language processing (NLP) technologies were introduced into tasks such as audit report generation and anomaly description extraction. By using automatic document understanding and generation models, audit personnel were assisted in collecting and analyzing evidence more quickly. These advances pushed audit work from a traditional rule-driven approach towards a data-driven and intelligent-assisted new stage.

Further research has focused on the deep integration of AI with audit processes. Areas such as intelligent risk assessment, dynamic audit planning generation, and full-process monitoring and early warning systems have been explored. Advanced AI methods, including multimodal learning, graph neural networks, and generative adversarial networks, have been introduced to address challenges[15]. These challenges include the coexistence of structured and unstructured data, complex inter-enterprise relationships, and highly concealed fraudulent behaviors during audits. Particularly when dealing with large-scale audit targets, multinational business groups, and complex supply chain networks, AI technology has demonstrated superior processing capabilities and deeper reasoning compared to traditional audit techniques. These developments provide critical support for building intelligent auditing systems and lay a solid foundation for achieving higher levels of audit automation and intelligence in the future.

3. Method

Based on the deep graph neural network (GNN) method, this study designed a modeling framework for related transactions and implicit association identification. First, economic entities such as enterprises, shareholders, and managers are abstracted as nodes, and different types of transactions, equity, and management relationships are abstracted as edges to construct a heterogeneous economic network. The model architecture is shown in Figure 1.

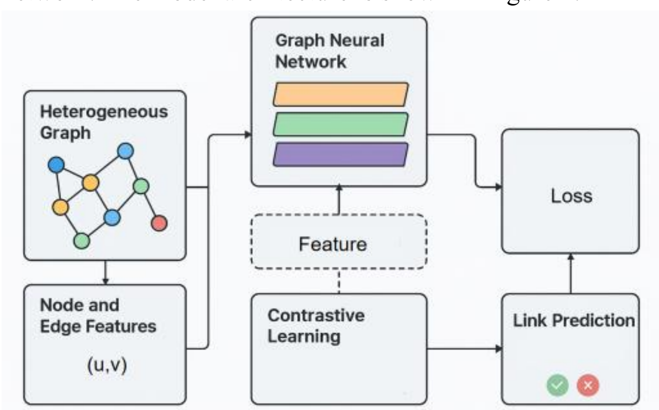

Figure 1. Overall model architecture diagram

Figure 1 illustrates the overall model architecture proposed in this paper. It aims to identify related transactions and hidden associations based on a heterogeneous graph structure. First, entities of different types, such as enterprises, equity, and management, along with their relationships, are abstracted into a heterogeneous graph. The initial features of nodes and edges are normalized and then fed into a graph neural network module for deep representation learning. Next, the model is assisted by a contrastive learning module to enhance the discriminative power of node embeddings in recognizing hidden associations. Finally, edge prediction is performed based on node representations. The model outputs the probability of potential related transactions and optimizes performance through a joint loss function. The entire process effectively combines heterogeneous structure awareness, feature learning, and contrastive enhancement mechanisms. It accurately captures abnormal association patterns in complex enterprise networks.

Assume that the graph is represented as $G=(V,E,X)$, where V is the node set, E is the edge set, $X \in R^{|V|\times d}$ is the node feature matrix, and d is the dimension of the node feature. To address the heterogeneity of node features and edge features, the original features are first normalized and embedded, using the following node initial representation:

$$h_v^{(0)} = W_0 x_v$$

Where W_0 is the trainable weight matrix and x_v is the original feature vector of node v.

In the neighbor information aggregation stage, a heterogeneous graph neural network based on the attention mechanism is used to fully model the heterogeneity of the relationships between different types of nodes and edges. For each edge $(u,v)\in E$, the attention weight between nodes is first calculated:

$$a_{uv} = \frac{\exp(LeakyRELU(a^T[Wh_u \| Wh_v]))}{\sum_{k\in N(v)} \exp(LeakyRELU(a^T[Wh_k \| Wh_v]))}$$

Where $\|$ represents the vector connection operation, a is the learnable parameter vector, and $N(v)$ is the set of neighbor nodes of node v.

After obtaining the attention weights, the node representation is updated by weighted aggregation of neighbor information. The representation update rule for node v in layer l is as follows:

$$h_v^{(l+1)} = \sigma(\sum_{u\in N(v)} a_{uv} W h_u^{(l)})$$

Where $\sigma(\cdot)$ is a nonlinear activation function (such as ReLU), and W is a transformation matrix shared by the same layer. In order to capture high-order implicit associations, this study stacked multiple layers of graph convolution operations and introduced skip connections to alleviate the over-smoothing problem, allowing nodes to effectively aggregate information from distant nodes.

In the entire graph-level modeling process, in order to improve the model's sensitivity to implicit association patterns, a graph contrastive learning mechanism is introduced. Specifically, for positive samples v^+ (e.g., generated by subgraph perturbations) and negative samples v^- (e.g., randomly sampling other nodes) of the same node v, the contrast loss function is defined as follows:

$$L_c = -\log \frac{\exp(A/\tau)}{\exp(A/\tau) + \sum_{v-} \exp(B/\tau)}$$

Where A represents the positive sample pair, and B represents the negative sample pair. By minimizing the loss, the model can learn more robust node representations, thereby enhancing the ability to distinguish implicit transaction relationships.

Finally, in the identification phase, for each pair of nodes (u,v), an edge prediction score function s_{uv} is defined to determine whether there is an implicit associated transaction relationship between the two nodes. The score function is calculated based on the node embedding representation as follows:

$$s_{uv} = \sigma(h_u^T M h_v)$$

Where M is a trainable bilinear weight matrix and $\sigma(\cdot)$ is a Sigmoid function. The overall loss function combines the supervised associated transaction edge prediction loss with the unsupervised contrastive learning loss and is defined as:

$$L_{total} = L_{link} + \lambda L_c$$

Where λ is a weight hyperparameter that balances the two loss terms. Through joint optimization, the model can improve the ability to identify abnormal and hidden transaction patterns while maintaining structural perception, thereby achieving more accurate audit risk warning and analysis support.

4. Experimental Results

4.1 Dataset

This study uses corporate relationships and financial data from the Orbis database as the source for modeling and experiments. Orbis, maintained by Bureau van Dijk, covers detailed information on over 400 million companies worldwide. It includes company profiles, ownership structures, management information, financial statements, and historical transaction records. To align with the research goal of identifying related transactions and hidden associations, this study selects data from listed companies and their key subsidiaries in specific regions, such as North America and Europe. It focuses on records covering ownership penetration, supply chain transactions, and management overlap to build a heterogeneous economic network graph. The data span the past five years to ensure the dynamics and completeness of nodes and edges, while meeting the temporal continuity required for graph modeling.

During data preprocessing, direct shareholding relationships, upstream and downstream transactions, and key personnel cross-appointments are extracted based on shareholder and supply chain transaction tables provided by Orbis. Different types of edges are defined accordingly. Node features include basic financial indicators, such as total assets, debt ratio, and net profit growth rate, as well as industry classification information. Edge features include transaction amounts, shareholding ratios, and management role similarities. To address missing and abnormal values, mean imputation and boundary clipping methods are applied. These steps ensure the rationality and stability of input features. In addition, only companies with complete public financial information and related transaction disclosures are retained to ensure the representativeness and authenticity of the sample.

To train and evaluate the proposed deep graph neural network model, this study constructs a corporate relationship graph based on Orbis data. The dataset is randomly divided into training, validation, and test sets, ensuring consistent sample distribution across stages. In labeling hidden related transactions, actual disclosures from company annual reports are referenced, combined with abnormal patterns observed in supply chain data. Given the sparsity and concealment of hidden related transactions, precision, recall, and AUC are introduced as evaluation metrics. These metrics comprehensively assess the model's performance across different risk identification scenarios. Modeling and experiments based on real large-scale enterprise network data validate the practical potential of the proposed method for audit and risk warning tasks.

4.2 Experimental Results

1) Experiments comparing this algorithm with other algorithms

In this section, this paper first gives the comparative experimental results of the proposed algorithm and other algorithms, as shown in Table 1.

Table 1: Comparative experimental results

Method	Precision	Recall	Auc
GNN[16]	0.782	0.745	0.821
GTN[17]	0.791	0.752	0.828
UniMP[18]	0.807	0.766	0.840
HeterFormer[19]	0.815	0.773	0.848
Ours	0.832	0.790	0.861

As shown in Table 1, different methods achieve good performance on Precision, Recall, and AUC metrics, but there are clear differences overall. Traditional GNN methods perform relatively lower on all metrics, with a Precision of 0.782, Recall of 0.745, and AUC of 0.821. This result indicates that traditional GNNs have limitations in handling heterogeneous and complex relationships. They struggle to fully capture deep and implicit transaction patterns between nodes.

In comparison, GTN and UniMP outperform basic GNNs on all metrics. UniMP, in particular, achieves a Precision of 0.807 and a Recall of 0.766. This shows that meta-path learning and unified message passing mechanisms can better adapt to complex graph structures and improve the detection of related transactions. However, GTN and UniMP still show limitations in identifying more hidden associations. Their AUC scores do not exceed 0.85, reflecting limited capability in modeling higher-order hidden patterns.

HeterFormer, a heterogeneous graph neural network integrating the Transformer mechanism, performs better in this experiment. It achieves a Precision of 0.815, a Recall of 0.773, and an AUC of 0.848. Its strong performance verifies the potential of introducing a global attention mechanism. This addition improves the model's ability to capture long-range dependencies and extract complex structural features. It effectively enhances the detection of potential risk transactions in heterogeneous enterprise networks.

The method proposed in this study outperforms all other compared methods across all metrics. It achieves a Precision of 0.832, a Recall of 0.790, and an AUC of 0.861, demonstrating comprehensive advantages. These results show that the designed joint modeling framework, based on deep heterogeneous graph neural networks and contrastive learning, can more effectively capture complex and multi-dimensional enterprise relationship features. It also improves the accuracy and robustness in identifying hidden related transactions, offering high practical value and potential for broader application.

2) Model robustness test under graph structure perturbations

Furthermore, this paper gives the experimental results of the model robustness test under graph structure perturbations, as shown in Figure 2.

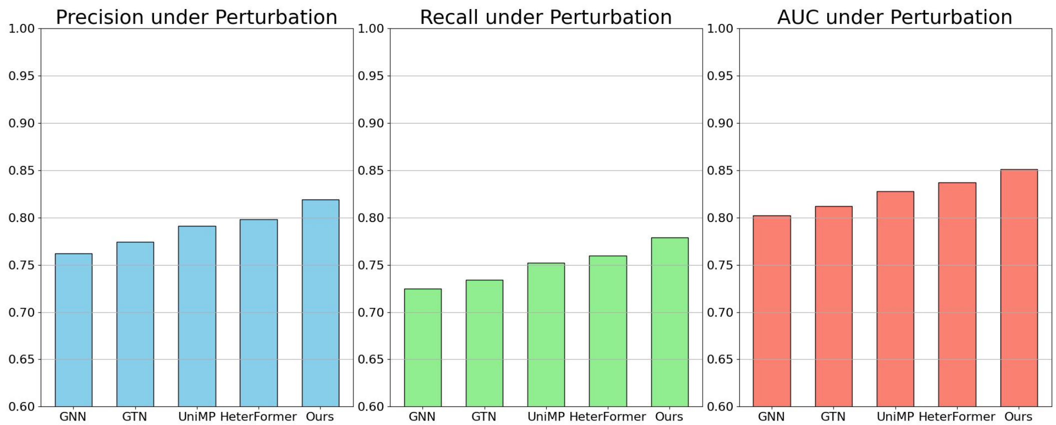

Figure 2. Model robustness test under graph structure perturbations

As shown in Figure 2, under graph structure perturbations, all models experience a certain degree of decline in Precision, Recall, and AUC. However, the overall ranking trend remains stable. Traditional GNN models show large performance fluctuations across all three metrics. Their Precision and Recall are at the lowest levels, indicating weak adaptability to changes in graph structures. They struggle to maintain stable recognition performance in complex and dynamic enterprise relationship networks.

In contrast, methods such as GTN, UniMP, and HeterFormer show clear improvements in both Precision and Recall. HeterFormer, in particular, benefits from its global attention mechanism, providing stronger robustness in capturing higher-order dependencies. UniMP also demonstrates good resistance to perturbations in overall performance. Its AUC shows a significant improvement compared to basic GNNs, verifying the advantage of a unified message passing framework in modeling different types of relationships consistently.

The method proposed in this study achieves the best results under all perturbation conditions. Its Precision, Recall, and AUC are all significantly higher than those of other methods. This indicates that the proposed heterogeneous graph neural network, combined with contrastive learning, effectively enhances the model's robustness and generalization ability in complex environments. It further verifies the reliability and practical value of the method when facing data noise and structural instability in real-world applications.

3) Experiment on the relationship between enterprise size and difficulty of detecting implicit associations

This paper also presents an experiment that investigates the relationship between enterprise size and the difficulty of detecting implicit associations. The purpose of this experiment is to explore whether the scale of an enterprise influences the model’ s ability to identify hidden patterns and relationships. The experimental results, which provide insights into this relationship, are illustrated in Figure 3.

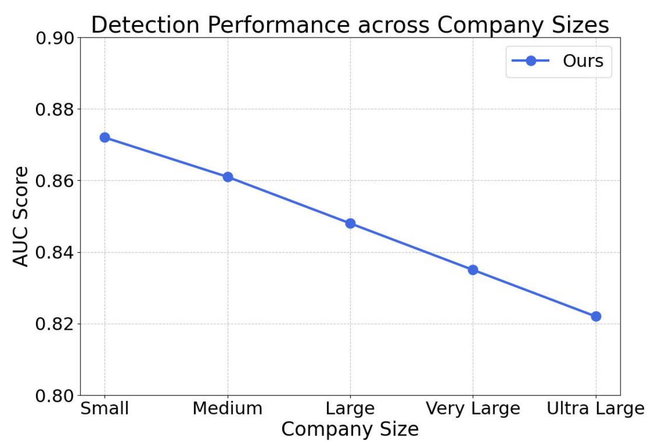

Figure 3. Experiment on the relationship between enterprise size and difficulty of detecting implicit associations

As shown in Figure 3, as enterprise size increases from Small to Ultra Large, the AUC scores of the models in hidden association detection tasks show a continuous downward trend. This phenomenon indicates that larger enterprises have more complex related transaction structures and more hidden paths. As a result, the models face greater challenges in uncovering potential associations, and the detection difficulty increases accordingly.

In small and medium-sized enterprises, the ownership structures and transaction networks are relatively simple. Hidden association features are more evident. The models can easily learn effective patterns and maintain high detection performance. However, as enterprise size grows, the number of subsidiaries rises sharply. Cross-industry and cross-regional transactions become more frequent. Management overlaps and ownership penetration also become more complex. The concealment of hidden associations increases significantly, and traditional graph structure features become less effective in capturing these relationships.

Nevertheless, the method proposed in this study maintains a high AUC level across enterprises of different sizes. It still achieves an AUC of 0.822 in ultra-large enterprises. This result shows that the designed deep heterogeneous graph neural network combined with contrastive learning can partially mitigate performance degradation caused by data complexity. It provides strong technical support for detecting hidden associations in large-scale enterprises.

4) The impact of different negative sampling strategies on experimental results

This paper also gives the impact of different negative sampling strategies on the experimental results, and the experimental results are shown in Figure 4.

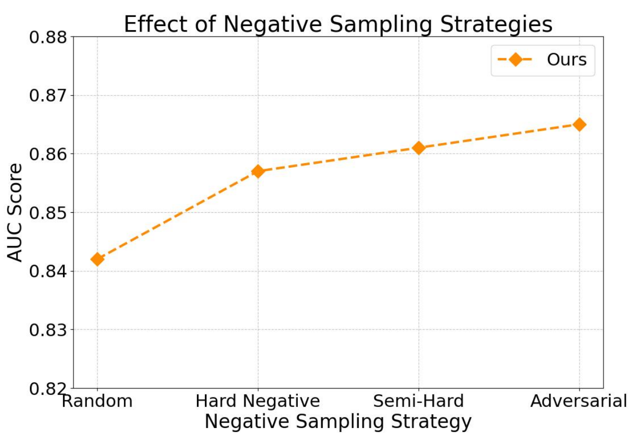

Figure 4. The impact of different negative sampling strategies on experimental results

As shown in Figure 4, different negative sampling strategies have a significant impact on the model's performance. It can be observed that as the difficulty level of the negative samples increases, the AUC score gradually rises. When employing the Random negative sampling strategy, the model primarily obtains relatively simple and easily distinguishable negative samples. This simplicity leads to the learning of a rough and less accurate decision boundary, which results in a lower AUC score. In contrast, when the Hard Negative and Semi-Hard sampling strategies are adopted, the model encounters more challenging negative samples during the training process. Exposure to these harder examples improves the model's ability to identify and distinguish hidden and subtle relationships between data points.

Furthermore, with the introduction of Adversarial negative sampling, the model achieves its highest AUC score. This demonstrates that dynamically generating negative samples with high deceptive potential can significantly enhance both the discriminative power and the robustness of the model. The improved ability to handle more complex and confusing examples allows the model to establish a more precise decision boundary. These experimental findings clearly confirm the critical importance of carefully designing an effective negative sampling mechanism in tasks that aim to recognize hidden relationships within complex datasets.

5) Loss function changes with epoch

Finally, this paper presents a graph illustrating the changes in the loss function over the course of training epochs, as shown in Figure 5. This graph provides a visual representation of the model's convergence process and helps to further validate the stability and effectiveness of the proposed training method.

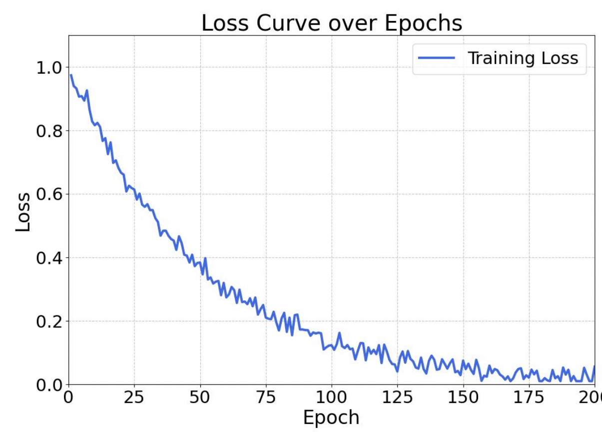

Figure 5. Loss function changes with epoch

As observed in Figure 5, the loss function shows a clear downward trend as the number of training epochs increases. The decline is fastest within the first 50 epochs. This indicates that the model quickly captures the main feature patterns in the early stage. It can effectively learn and represent basic patterns, demonstrating a fast convergence speed during training.

In the middle and later stages of training, especially after around 100 epochs, the decline in the loss function becomes more gradual. The fluctuations decrease, indicating that the model enters a fine-tuning phase. At this stage, the model mainly optimizes complex relationships and fine-grained features. The overall training process remains stable, without significant oscillations or signs of overfitting. This shows that the designed training mechanism has strong robustness.

At the end of 200 epochs, the loss value stabilizes at a low level. This verifies that the proposed method has good convergence and training efficiency. Combined with the previous experimental performance results, it can be inferred that the model maintains a stable optimization process during training and demonstrates good generalization ability and detection performance in practical applications. This further confirms the rationality of the method design.

5. Conclusion

This paper proposes a modeling framework based on deep graph neural networks and contrastive learning mechanisms to address the problem of identifying related transactions and hidden associations. By constructing a heterogeneous economic network of enterprises and integrating multi-dimensional features of nodes and edges, a model system with both structure-aware and relation-aware capabilities is designed. Experiments show that the proposed method achieves excellent performance across multiple comparative experiments. It maintains strong robustness and stability under conditions of graph structure perturbations, enterprise size variations, and different negative sampling strategies, effectively demonstrating its potential for application in complex audit scenarios.

Through systematic experimental design and analysis, this study reveals how the structural characteristics of enterprise networks affect the difficulty of detecting hidden related transactions. It also verifies the important role of contrastive learning strategies in enhancing the discriminative ability of node representations. This method not only improves the accuracy of related transaction identification but also provides a new technological path for practical applications such as intelligent auditing, risk monitoring, and financial regulation. Especially when dealing with large-scale and dynamically changing enterprise networks, the proposed framework shows good scalability and adaptability, laying a solid technical foundation for the intelligent transformation of related fields.

Despite the positive progress achieved, several issues remain for further exploration. Future work could incorporate more temporal dynamic features to model the evolution of hidden associations over time. It could also integrate natural language processing technologies, such as large language models, to further extract hidden transaction intents and potential risks from textual data. Moreover, efficient modeling and inference for ultra-large-scale graphs represent another important direction for broadening and deepening the applications of the method.

Overall, this study provides new ideas and methods for fields such as auditing, financial risk control, and corporate governance in addressing complex related transaction problems. By introducing advanced deep learning technologies, it overcomes the limitations of traditional manual rules and static modeling. It promotes the evolution of intelligent auditing and risk identification technologies and strongly supports the construction of a more transparent, efficient, and intelligent enterprise supervision system.

References

[1] Ahmadi, N., Sand, H., & Papotti, P. (2022). Building A Knowledge Graph for Audit Information. In EDBT/ICDT Workshops.

[2] Ding, Rui. "Enterprise intelligent audit model by using deep learning approach." Computational Economics 59.4 (2022): 1335-1354.

[3] Wang, J., Wang, X., Ma, C., & Kou, L. (2021). A survey on the development status and application prospects of knowledge graph in smart grids. IET Generation, Transmission & Distribution, 15(3), 383-407.

[4] Wang J, Wang X, Ma C, Kou L.A survey on the development status and application prospects of knowledge graph in smart grids. arXiv preprint arXiv:2211.00901, Nov 2022.

[5] Wang, J., Wang, X., Ma, C., & Kou, L. (2021). A survey on the development status and application prospects of knowledge graph in smart grids. IET Generation, Transmission & Distribution, 15(3), 383-407.

[6] Chen, Q., Li, Q., Wu, J., Mao, C., Peng, G., & Wang, D. (2022). Application of knowledge graph in power system fault diagnosis and disposal: A critical review and perspectives. Frontiers in Energy Research, 10, 988280.

[7] Liu, Jielun, Ghim Ping Ong, and Xiqun Chen. "GraphSAGE-based traffic speed forecasting for segment network with sparse data." IEEE Transactions on Intelligent Transportation Systems 23.3 (2020): 1755-1766.

[8] Heger, Andreas, et al. "GAT: a simulation framework for testing the association of genomic intervals." Bioinformatics 29.16 (2013): 2046-2048.

[9] Guo, P., & Yin, Q. (2020). Synergetic learning systems: concept, architecture, and algorithms. arXiv preprint arXiv:2006.06367.

[10] Dou, Y., Liu, Z., Sun, L., Deng, Y., Peng, H., & Yu, P. S. (2020, October). Enhancing graph neural network-based fraud detectors against camouflaged fraudsters. In Proceedings of the 29th ACM international conference on information & knowledge management (pp. 315-324).

[11] Wang, Xiangyu, Xueming Yan, and Yaochu Jin. "A graph neural network with negative message passing and uniformity maximization for graph coloring." Complex & Intelligent Systems 10.3 (2024): 4445-4455.

[12] Rawashdeh, A. (2024). A deep learning-based SEM-ANN analysis of the impact of AI-based audit services on client trust. Journal of Applied Accounting Research, 25(3), 594-622.

[13] Srinivasagopalan, L. N. (2022). AI-enhanced fraud detection in healthcare insurance: A novel approach to combatting financial losses through advanced machine learning models. European Journal of Advances in Engineering and Technology, 9(8), 82-91.

[14] Wagner, Patrick, et al. "Explaining deep learning for ECG analysis: building blocks for auditing and knowledge discovery." Computers in biology and medicine 176 (2024): 108525.

[15] Don't Walk, Oliver J. Bear, et al. "Auditing Learned Associations in Deep Learning Approaches to Extract Race and Ethnicity from Clinical Text." AMIA Annual Symposium Proceedings. Vol. 2023. 2024.

[16] Kipf, Thomas N., and Max Welling. "Semi-Supervised Classification with Graph Convolutional Networks." International Conference on Learning Representations (ICLR), 2017.

[17] Kim, Hyunwoo. "Graph Transformer Networks." Advances in Neural Information Processing Systems (NeurIPS). Neural Information Processing Systems (NeurIPS), 2019.

[18] Shi, Yunsheng, et al. "Masked label prediction: Unified message passing model for semi-supervised classification." arXiv preprint arXiv:2009.03509 (2020).

[19] Jin, Bowen, et al. "Heterformer: Transformer-based deep node representation learning on heterogeneous text-rich networks." Proceedings of the 29th ACM SIGKDD conference on knowledge discovery and data mining. 2023.