

Design of Fabless Supply Chain Knowledge Management Algorithm and Alarm Mechanism Combining Knowledge Association and Risk Perception

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Abstract: In the context of increasing global uncertainty and risk, Fabless supply chain is facing challenges such as inefficient design, outsourcing, packaging and testing collaboration, and lagging risk identification. Traditional statistical models are unable to meet demand due to limitations such as insufficient data integration and delayed response. This study constructs a multi-source heterogeneous supply chain knowledge graph that integrates design data, OEM information, logistics nodes, and risk events (data structuring is achieved through entity ID generation and relationship extraction), proposes a feature extraction method based on heterogeneous graph attention (defining meta paths such as "design agent test" to connect complex relationships between nodes, and combining node attention and semantic attention to generate entity embeddings), and develops an anomaly analysis model based on relationship graph neural network (risk probability prediction is achieved through relationship type driven inductive subgraph sampling and multi-layer convolutional encoder). The experimental results showed that the heterogeneous graph attention feature extraction method improved accuracy by 3.67% and AUC by 5.02% compared to the baseline method, and the relationship graph neural network anomaly analysis model improved accuracy by 5.23% and AUC by 3.53%, verifying the effectiveness of the two-stage method of "knowledge association risk perception" and accurately predicting risks such as supply chain delays and quality anomalies. Research has found that knowledge graphs can mine hidden associations by semantically integrating multi-source data. The collaboration between heterogeneous graph attention and relationship graph neural networks can enhance feature representation and risk perception capabilities, effectively solving the problems of insufficient data integration and lagging recognition in traditional methods. The Fabless supply chain knowledge management algorithm and alarm mechanism proposed in this study provide interpretable and scalable intelligent decision support for enterprises by mining implicit associations through knowledge association and dynamically evaluating abnormal probabilities through risk perception. In the future, it can further integrate unstructured data to expand graph coverage and explore cross domain application promotion.

1. Introduction

With the rapid development of the Internet and digital advertising market, the scale of the global advertising market continues to expand - in 2023, the size of the Internet advertising market will reach 573.2 billion yuan (a year-on-year increase of 12.66%), and the global mobile advertising spending will exceed 362 billion dollars. The user behavior model has undergone fundamental changes due to the popularity of mobile equipment, which puts forward higher requirements on the real-time, personalized and effect tracking of advertising. However, traditional advertising delivery systems face core challenges such as real-time data processing delays, inaccurate capture of user interests, and reliance on outdated information for delivery strategies, leading to decision-making errors and resource waste by advertisers. To overcome the above bottlenecks, this article focuses on the performance optimization and implementation path of the advertising delivery system from a full stack development perspective. The specific work includes clarifying the functional and nonfunctional boundaries of the system through requirement analysis, and using a layered architecture design to divide the four major modules of advertising promotion management, advertising push, advertising log management, and real-time data warehouse; Use class diagrams, flowcharts, and sequence diagrams in detailed design to complete module modeling and code development; Aiming at the optimization problem of advertising ranking model, a DISM model integrating DSSM dual tower model and FM factorization machine is proposed to effectively solve the shortcomings of DIN model in user behavior sequence and candidate advertisement deep level interest mining, low-level feature interaction learning, and significantly improve CTR and RPM indicators compared to traditional models; Finally, the reliability of the system is verified through functional and nonfunctional testing, forming a complete closed loop of "requirements design implementation optimization testing". In terms of structure, the introduction elaborates on the background significance, and the main body focuses on system design and model optimization. Finally, the contribution is verified through testing, providing a performance optimization path from a full stack development perspective for the efficient and intelligent implementation of advertising delivery systems.

2. Correlation theory

2.1. Financial Knowledge Graph

Financial knowledge graph[1], as a specific application of knowledge graph in the financial field, represents the relationships and attribute connections between entities through a directed graph structure[2]. Entities encompass specific objects (such as enterprises and individuals) and abstract concepts[3], while relationships and attributes describe the relationships and characteristic values between entities[4]. The construction of a knowledge graph requires four stages: data collection, knowledge extraction, modeling, and inference[5]. The data collection adopts distributed crawler technology, which automatically obtains multi-source heterogeneous data by simulating browser operations. For example[6], the Selenium framework is used to simulate user behavior, avoid anti crawling mechanisms, and ensure data accuracy[7]. Knowledge extraction extracts entities, relationships, and attributes from structured and unstructured data; Knowledge modeling defines entity types, relationship specifications[8], and attribute constraints to ensure knowledge consistency; Knowledge reasoning supplements implicit information and enriches graph content through algorithms[9]. In terms of storage, relational databases (such as MySQL) and graph databases (such as Neo4j) have their own advantages. Relational databases store data in a two-dimensional table format, which is suitable for handling strong consistency scenarios; Graph databases are based on graph theory models and stored in a node edge attribute structure[10]. They

are adept at handling complex relationships and dynamic queries. For example, Neo4j achieves efficient storage through node labels, relationship types, and attribute values, and supports Cypher query language for relationship retrieval and pattern matching. The financial knowledge graph integrates enterprise relationships, transaction patterns, and asset liability information to achieve anomaly analysis, risk assessment, and decision support. Its dynamic updating and cross domain integration capabilities provide an intelligent knowledge management framework for the financial sector, helping enterprises build a scientific anomaly management system, improve decision-making accuracy, and reduce investment risks.

2.2. Collaborative methodology for financial knowledge graph representation and classification

The financial knowledge graph achieves entity relationship modeling and abnormal node recognition through low dimensional vector mapping and graph neural networks. At the representation level, TransE (Translation Embedding) is an operational logic that uses the head entity vector plus the relationship vector to equal the tail entity vector. It efficiently embeds multiple relationship graphs and is suitable for analyzing the correlation between macroeconomic indicators and industry trends, constructing inferential risk prediction models; Heterogeneous Graph Attention Network (HAN) improves the feature representation accuracy of enterprise anomaly analysis by allocating attention weights at both node and semantic levels, integrating complex associations between heterogeneous nodes. At the classification level, Graph Convolutional Networks (GCNs) use graph topology to update node features and enhance robustness in data loss scenarios, making them suitable for financial anomaly detection and fraud recognition; The Relationship Graph Convolutional Network (RGCN) introduces edge relationship types to distinguish entity associations, deepen multi type edge semantic mining, and optimize credit risk assessment and investment plans. Collaboration between TransE and HAN enhances the ability to extract dynamic features from graphs, while GCN and RGCN support precise classification of topological structures and relationship features, jointly constructing an intelligent anomaly management and risk control framework to assist financial institutions in achieving efficient decision-making and risk management.

3 Research method

3.1. Dynamic modeling of multi-source data in financial knowledge graph

The construction of a financial knowledge graph dataset requires the integration of heterogeneous financial data from multiple sources to support enterprise anomaly analysis. Its core lies in the collection, processing, and correlation modeling of multidimensional data. The data sources include director information, industry classification, concept classification, and risk warning information. Automated tools simulate browser operations to access financial websites, and path parsing technology is used to extract structured data such as director names, positions, genders, ages, and other attributes; The industry classification covers 48 categories such as biopharmaceuticals, finance, and non-ferrous metals, while the conceptual classification involves 150 topics such as sewage treatment, energy conservation, and automotive electronics, all of which are obtained and stored as structured files through open source financial data interfaces. Risk warning information identifies entities that require special supervision by labeling ST (financial/operational abnormalities) and * ST (delisting risk) enterprises. During the data collection process, distributed web crawling technology is used to process dynamic web pages, extract key fields through element localization, and handle missing or incomplete data to ensure information

quality and credibility. The final constructed financial knowledge graph dataset integrates multi-source data through the entity association network framework, forming a dynamic and scalable data foundation, providing data support for subsequent anomaly analysis algorithms such as node classification, relationship inference, and risk prediction tasks.

3.2. Entity and Relationship Model Design and Data Preprocessing

The construction of financial knowledge graph focuses on the structured expression of entities and relationships in the financial field, covering three core aspects: entity type definition, relationship model construction, and data preprocessing. Entity types include four categories: person, company, concept, and industry: person entity represents corporate executives, with attributes including name, gender, and age; The company entity corresponds to the enterprise entity, and its attributes include stock name and stock code (used for ST risk labeling); Conceptual entity describes financial concepts, with the attribute being the concept name; The industry entity represents the industry category, with the attribute being the industry name. The relationship model defines three types of core associations: the "employ_of" relationship between individuals and companies (including job attributes such as "chairman" and "executive director"), the "concept_of" relationship between companies and concepts (identifying the category of the concept), and the "industry_of" relationship between companies and industries (identifying the category of the industry). The data preprocessing stage improves data quality through standardized operations: entity ID generation adopts a differentiation strategy - executive ID is encoded based on name and attribute hash, stock ID is directly encoded with stock code, and industry and concept ID are generated through hash encoding to ensure uniqueness and stability; Relationship extraction extracts structured associations from multiple sources of data, forming three types of relationship tables: "executive company", "company concept", and "company industry". The preprocessed data is stored in CSV format, including executive, company, concept, industry entity tables, and relationship tables (such as executive_stock、stock_industry、stock_concept) , And through the Neo4j import tool, batch import the Neo4j graph database to achieve visual storage of nodes (entities) and edges (relationships). Data statistics show that the distribution of entities presents a characteristic of "high proportion of people, low proportion of enterprises/concepts/industries" - there are 20872 person entities (85%), 3188 company entities (13%), 163 concept entities (1.5%), and 49 industry entities (0.5%); In the relational data, there are 24775 "employ_of" relationships (the highest proportion), 9442 "concept_of" relationships, and 2908 "industrialist_of" relationships; There are 104 abnormal enterprises marked and 3084 normal enterprises, with a ratio of approximately 29:1. The advantage of this dataset lies in the fusion of multi-source heterogeneous data, rich entity types, high relationship complexity, and the assurance of data accuracy and completeness through preprocessing. Especially, the annotation of abnormal enterprises provides direct support for risk analysis, laying a solid data foundation for financial entity association mining and enterprise anomaly analysis as a whole.

3.3. Financial feature extraction method based on heterogeneous graph attention and experimental verification

This study proposes a financial feature extraction method based on heterogeneous graph attention, which generates financial entity node embeddings through three parts: financial knowledge graph meta path, financial entity node attention, and financial entity semantic attention. The meta path of financial knowledge graph is defined as a path pattern composed of entity nodes and edges

$$(\phi = v_1 r_1 v_2 r_2 \cdots v_{k-1} r_{k-1} v_k) \quad (1)$$

, used to describe semantic associations between different types of entities (such as the "Company Concept Company" path reflecting the similarity of enterprise concepts, and the "Company Person Company" path inferring the association of independent director appointments). At the level of node attention, through the node type transformation matrix ($h'_i = M_{\phi_i} \cdot h_i$) map heterogeneous nodes to a unified feature space and adopt asymmetric attention mechanism $e_{ij}^{\phi} = \text{att}_{\text{node}}(h'_i, h'_j, \phi)$ learning the importance weights of neighboring nodes to the target node under the meta path ($\alpha_{ij}^{\phi} = \text{Softmax}_j(e_{ij}^{\phi})$), ultimately generating meta path specific node embeddings through weighted aggregation

$$(z_i^{\phi} = \sigma(\sum_{j \in N_i^{\phi}} \alpha_{ij}^{\phi} \cdot h'_j)) \quad (2)$$

and combined with multi head attention ($z_i^{\phi} = \parallel_{k=1}^K \sigma(\sum_{j \in N_i^{\phi}} \alpha_{ij}^{\phi} \cdot h'_j)$) enhance feature expression ability. Semantic attention is achieved through deep neural networks ($\beta_{\phi_1}, \dots, \beta_{\phi_p}$) = $\text{att}_{\text{scm}}(Z_{\phi_1}, \dots, Z_{\phi_p})$ automatically learn the weights of different meta paths, and perform nonlinear transformation and similarity calculation $W_{\phi_1} = \frac{1}{|V|} \sum_{i \in V} q^T \cdot \text{Tanh}(W \cdot z_i^{\phi} + b)$ and Softmax normalization ($\beta_{\phi_i} = \frac{\exp(\beta_{\phi_i})}{\sum_{i=1}^P \exp(\beta_{\phi_i})}$) Finally, multiple semantic embeddings are fused to generate a comprehensive node representation. The method fully describes the process, including steps such as meta path traversal, feature transformation, attention calculation, and embedding fusion, to effectively capture and learn feature representations of complex relationships between financial entities.

4. Results and discussion

4.1. A framework for enterprise anomaly analysis based on relationship graph neural network

This experiment is based on the constructed financial knowledge graph dataset, which includes four types of nodes (Person 20872, Company 3188, Concept 163, Industry 49, as shown in Table 1)

Table 1. Statistics of the Number of Financial Entity Nodes

Financial entity node type	Number of nodes
Person	20872
Company	3188
Concept	163
Industry	49

and three types of relationships (employing 24775, concept_of 9442, and industrialization 2908, as shown in Table 2),

Table 2. Statistics of the Number of Financial Entity Relationships

Types of financial entity relationships	Number of relationships
employ_of	24775
concept_of	9442
industry_of	2908

Preprocess and generate files such as edge.csv (including source/target node IDs, types, and edge types), node.csv (including node IDs, types, and 256 dimensional feature vectors), and label the "Company" node exception label for training. The baseline methods used include DeepWalk MLP (random walk+skip gram node embedding), TransE-MLP (triplet relationship modeling), and HAN-MLP (heterogeneous graph neural network), with evaluation metrics of Accuracy and AUC (area

under the ROC curve). Performance evaluation shows that FHAN-MLP is significantly better than DeepWalk MLP (50.59%/46.31%), TransE-MLP (90.98%/30.68%), and HAN-MLP (90.24%/87.12%) in accuracy (94.65%) and AUC (92.14%), as shown in Table 3

Table 3. Comparison of Financial Feature Extraction Experiments

Model algorithm	Accuracy	AUC
DeepWalk-MLP	0.5059	0.4631
TransE-MLP	0.9098	0.3068
HAN-MLP	0.9024	0.8712
FHAN-MLP	0.9465	0.9214

4.2. Model experiment

This paragraph proposes a framework for enterprise anomaly analysis based on relational graph neural networks to address the issues of complex entity relationships and large data scales in financial knowledge graphs, resulting in low computational efficiency and insufficient interpretability of anomaly detection. This method relies on the attention feature extraction results of heterogeneous graphs in Chapter 4 to define a financial knowledge graph $G = (V, \varepsilon, R)$ (including four types of nodes: Person, Company, Concept, and Industry, as well as three types of relationships: employ_of, concept_of, and industrialization). Anomaly analysis is achieved through two stages: "inductive subgraph sampling based on relationship types" and "neural network encoder based on relationship graphs". In the subgraph sampling stage, a random sampling strategy with put back is adopted, and neighbor nodes are sampled hop by hop according to relationship types (such as Company's employ_of, concept_of, industrialized neighbors) to construct a low computational complexity subgraph; In the encoder stage, the 256 dimensional node features are first mapped to the embedding space through a fully connected layer, and then multiple convolutional layers are used to aggregate neighbor information by edge type (formula

$$h_i^{(k+1)} = \sigma(\sum_r \in \sum_j \in N_i^r (C_{ijr}^{-1} W_r^{(k)} h_j^{(k)} + W_0^{(k)} h_i^{(k)})) \quad (3)$$

Among them, there is a relation specific weight matrix to achieve parameter sharing for edges of the same type; Finally, the enterprise anomaly probability is output by combining the Softmax activation function and cross entropy loss function through the classification layer. To alleviate the overfitting of rare relationships, cardinality decomposition is introduced to regularize the weight matrix. This method reduces computational overhead through relationship type driven subgraph sampling, and combines relationship aware graph convolution operations to capture complex associations between entities, ultimately achieving high-precision and interpretable enterprise anomaly detection.

4.3. Effect analysis

This paragraph validates the effectiveness of the enterprise anomaly analysis method based on relationship graph neural networks through three sets of comparative experiments: DeepWalk MLP and DeepWalk RGCN, TransE-MLP and TransE RGCN, and FHAN-MLP and FHAN-RGCN. The baseline method uses DeepWalk, TransE, and the proposed FHAN (Financial Feature Extraction Based on Heterogeneous Graph Attention) for node embedding, combined with MLP and RGCN for node classification. Performance evaluation experiments showed that the accuracy (96.21%) and AUC value (0.5292) of DeepWalk RGCN were significantly better than those of DeepWalk MLP (0.5059, 0.4631); The accuracy (0.9467) and AUC value (0.5718) of TransE RGCN were significantly improved compared to TransE-MLP (0.9098, 0.3068); The accuracy (97.91%) and

AUC value (0.9438) of FHAN-RGCN were improved by 2.51% and 3.53% respectively compared to FHAN-MLP (0.9465, 0.9214) (as shown in Figure 1)

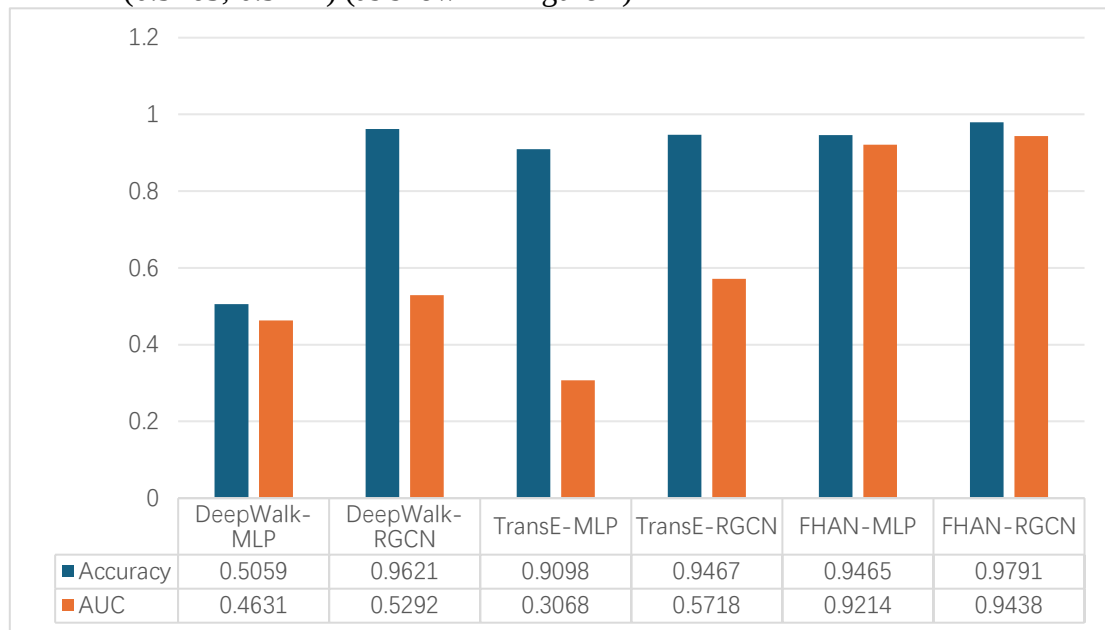


Figure 1. Performance Comparison of Enterprise Anomaly Analysis Models

The results indicate that RGCN improves the classification performance of financial entity nodes by capturing complex relationships and hierarchical structures between nodes. The efficiency evaluation experiment compared the running time under the same hardware and dataset, and FHAN-RGCN performed the best. Its efficiency comes from automatic learning of feature importance, utilization of enterprise related information, and simplification of the calculation process. Parameter sensitivity analysis shows that when the learning rate $\beta = 0.001$, the accuracy and AUC values reach their peak. This chapter also introduces the model framework, including inductive subgraph sampling based on relationship types and the construction of relationship graph neural network encoder. By aggregating node features of different edge types, the abnormal probability values of enterprise nodes are obtained. Experimental results have shown that the method of combining heterogeneous graph attention feature extraction with relational graph neural networks outperforms the baseline in both accuracy and efficiency, providing effective support for enterprise anomaly analysis.

5. Conclusion

To address the challenges of Fabless supply chain management in the context of increasing global uncertainty, this paper proposes a supply chain knowledge management algorithm and alarm mechanism that combines knowledge association and risk perception. At the level of data construction, multiple heterogeneous data sources such as design data, OEM information, logistics nodes, and supply chain risk events are integrated to construct a supply chain knowledge graph through entity ID generation and relationship extraction. This solves the problem of scattered and complex data in the semiconductor supply chain; At the level of knowledge association, a feature extraction method based on heterogeneous graph attention is adopted, defining meta paths such as design manufacturing packaging testing to connect complex relationships between supply chain nodes. Combining node attention and semantic attention, entity embeddings are generated to enhance the feature representation ability of supply chain entities. The experiment shows that the

accuracy is improved by 3.67% and the AUC is improved by 5.02% compared to the baseline method; At the level of risk perception, an anomaly analysis model based on relationship graph neural network is constructed. Through relationship type driven inductive subgraph sampling and multi-layer convolutional encoder, the probability prediction of risks such as supply chain delay and quality anomalies is achieved. The experiment shows that the accuracy is improved by 5.23% and the AUC is improved by 3.53% compared to the baseline method, verifying the effectiveness of the algorithm. The overall supply chain knowledge management is achieved through a two-stage method of "knowledge association risk perception", effectively avoiding supply chain risks. In the future, we can conduct in-depth research on the fine definition of meta paths to capture finer grained relationships, deepen the application of attention mechanisms to enhance feature learning effectiveness, and integrate unstructured data such as social media and news to expand knowledge graph coverage. At the same time, we can explore the application promotion in fields such as healthcare and logistics to form a broader knowledge management and risk warning system.

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