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Conceptual Modeling and Semantic Relations in the Construction of Financial Knowledge Graphs

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Abstract: Financial Knowledge Graphs (FKGs) are increasingly recognized as essential tools for managing and leveraging financial data. This review paper explores the conceptual modeling approaches and semantic relations crucial for their construction. We begin by providing a historical overview of knowledge representation in finance, tracing the evolution from early expert systems to contemporary FKGs. The core of the paper delves into two critical themes: (A) conceptual modeling techniques, including ontologies, entity-relationship diagrams, and semantic networks, and their application to financial data; and (B) the types and roles of semantic relations (e.g., is-a, part-of, influences) in connecting financial entities and concepts. We then present a comparative analysis of these modeling techniques, highlighting their strengths, weaknesses, and challenges in capturing the complexities of financial information. Furthermore, we address the unique challenges of constructing FKGs, such as data heterogeneity, ambiguity, and the dynamic nature of financial markets. The review concludes by discussing promising future research directions, including the integration of machine learning techniques for automated knowledge graph construction and the development of novel semantic relation discovery methods. This paper serves as a comprehensive guide for researchers and practitioners interested in the design and implementation of effective FKGs for various financial applications.

Keywords: financial knowledge graph; conceptual modeling; semantic relations; ontology; financial data; knowledge representation

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1. Introduction

1.1. Motivation and Background

Financial knowledge graphs (FKGs) are increasingly vital in modern finance. Their ability to represent complex relationships between financial entities, events, and concepts offers significant advantages [1]. The motivation for leveraging FKGs stems from the need for improved decision-making, enhanced risk management, and streamlined regulatory compliance. By providing a structured and interconnected view of financial data, FKGs enable more informed analysis and prediction, ultimately contributing to a more stable and efficient financial ecosystem. The graph structure allows for representing complex relationships, such as $\text{risk} = f(\text{asset,market})$, that are difficult to capture with traditional methods.

1.2. Scope and Contribution

This paper reviews the application of conceptual modeling and semantic relations in constructing financial knowledge graphs (FKGs). The scope encompasses methodologies for representing financial concepts and their interconnections. Our contribution lies in synthesizing existing approaches, providing a structured overview of semantic relation types relevant to finance, such as $is-a$, $part-of$, and $influences$, and highlighting challenges in FKG construction, particularly concerning data heterogeneity and semantic ambiguity. We further explore the role of ontologies in addressing these challenges.

2. Historical Overview of Knowledge Representation in Finance

2.1. Early Expert Systems in Finance

Early expert systems in finance, emerging in the 1980s, aimed to codify expert knowledge into rule-based systems [2]. These systems, often using IF-THEN rules, tackled tasks like credit scoring and investment advising. However, they struggled with the inherent complexity and dynamism of financial markets. The rigidity of rule-based approaches made it difficult to adapt to new market conditions or incorporate unforeseen factors [3]. Furthermore, representing uncertainty and dealing with incomplete data, common in finance, proved challenging. The lack of learning capabilities also limited their long-term effectiveness (Table 1).

Table 1. Comparison of Early Financial Expert Systems.

Feature	Description	Limitation
Knowledge Representation	Primarily rule-based, utilizing IF-THEN structures to codify expert knowledge.	Rigidity; Difficulty adapting to new market conditions and unforeseen factors.
Application Areas	Credit scoring, investment advising.	Limited scope compared to the breadth of modern financial applications.
Handling Uncertainty	Weak; struggled to represent and manage uncertainty inherent in financial markets and incomplete data.	Inability to accurately model risk and incorporate probabilities.
Adaptability	Low; lacked learning capabilities and were difficult to update.	Static nature limited long-term effectiveness in dynamic markets.
Complexity Management	Struggled with the inherent complexity of financial markets.	Inability to effectively model complex relationships and dependencies.

2.2. Evolution Towards Knowledge Graphs

Expert systems initially dominated financial knowledge representation, relying on rigid rule-based systems [4]. A move towards semantic networks and ontologies offered greater expressiveness. The advent of the Semantic Web influenced the development of more flexible and scalable approaches. Resource Description Framework (RDF) and Web Ontology Language (OWL) enabled richer semantic descriptions. This facilitated the transition to modern knowledge graphs, where financial entities and relationships are explicitly represented, allowing for more sophisticated reasoning and analysis. The shift addresses limitations in handling complex financial data and n-ary relations.

3. Core Theme A: Conceptual Modeling Techniques

3.1. Ontologies for Financial Knowledge Representation

Ontologies provide a structured framework for defining financial concepts, their relationships, and associated axioms, enabling machine-readable knowledge representation. Ontology languages like OWL (Web Ontology Language) and RDF (Resource Description Framework) are commonly employed. OWL, with its richer expressivity, allows for defining complex relationships and logical constraints, suitable for capturing intricate financial instruments and regulations [5]. RDF, being simpler, is often used for representing metadata and basic relationships. Existing financial ontologies, such as the Financial Industry Business Ontology (FIBO), offer standardized vocabularies for describing financial instruments, market data, and organizational structures. The choice of ontology language depends on the complexity of the financial domain being modeled and the desired level of reasoning capabilities. The use of x and y can represent financial variables within the ontology [6].

3.2. Entity-Relationship (ER) Diagrams and Extensions

ER diagrams offer a foundational approach for modeling financial entities like Customer, Account, and Transaction, and their relationships such as "owns" or "transfers". However, classical ER models often fall short in capturing the nuances of financial data. Extensions like inheritance allow us to represent specialized account types (e.g., SavingsAccount inheriting from Account). Aggregation can model complex entities, such as a Portfolio composed of multiple Asset instances [7].

To improve upon classical ER diagrams, we propose incorporating semantic annotations directly within the model. This involves attaching metadata to entities and relationships, specifying data types, units of measure (e.g., currency for Amount), and validation rules [8]. Furthermore, incorporating temporal aspects, such as transaction timestamps and the validity periods of relationships, is crucial for financial modeling. These enhancements enable a more expressive and semantically rich representation of financial knowledge [9].

3.3. Semantic Networks

Semantic networks offer a conceptual modeling approach particularly suited for representing relationships within financial data. Nodes represent financial concepts (e.g., assets, liabilities, equity), while edges denote semantic relations (e.g., "is-a," "part-of," "affects"). This facilitates reasoning about financial instruments and market dynamics.

A key advantage is their intuitive graphical representation, aiding understanding by domain experts. However, semantic networks struggle with scalability. As the number of nodes and relations increases, the network becomes complex and difficult to manage. Reasoning becomes computationally expensive, especially when inferring indirect relationships. Furthermore, defining consistent and unambiguous semantic relations across diverse financial data sources presents a significant challenge. The lack of standardized semantics can lead to inconsistencies and hinder effective knowledge integration. The complexity grows exponentially with the number of concepts, making maintenance and querying difficult when n() and r () are large (Table 2).

Table 2. Comparison of Conceptual Modeling Techniques.

Feature	Semantic Networks
Representation	Nodes represent financial concepts, edges represent semantic relations
Suitability	Representing relationships within financial data and reasoning about financial instruments
Advantages	Intuitive graphical representation, aids understanding
Scalability	Struggles with scalability, complexity increases with n(number of nodes) and r (number of relations)
Reasoning Complexity	Computationally expensive, especially for indirect relationships
Semantic Consistency	Defining consistent and unambiguous semantics across diverse data sources is a challenge
Knowledge Integration	Lack of standardized semantics hinders effective knowledge integration

Maintenance & Querying	Difficult when n and r are large

4. Core Theme B: Semantic Relations in Financial Knowledge Graphs

4.1. Types of Semantic Relations

Semantic relations form the backbone of Financial Knowledge Graphs (FKGs), defining the connections between entities [10]. These relations can be broadly categorized. The 'is-a' relation represents hierarchical classification; for example, a Bond is-a Security. The 'part-of' relation indicates composition, such as a BalanceSheet part-of a FinancialReport. 'Influences' captures causal or correlational relationships; for instance, InterestRate influences HousingMarket. 'Competes-with' denotes rivalry, like Visa competes-with Mastercard. Finally, 'regulates' signifies regulatory oversight, where SEC regulates PublicCompanies. Understanding these relation types is crucial for effective knowledge representation and reasoning within FKGs (Table 3).

Table 3. Types of Semantic Relations in FKGs.

Relation Type	Description	Example
is-a	Represents hierarchical classification.	Bond is-a Security
part-of	Indicates composition.	BalanceSheet part-of a FinancialReport
influences	Captures causal or correlational relationships.	InterestRate influences HousingMarket
competes-with	Denotes rivalry.	Visa competes-with Mastercard
regulates	Signifies regulatory oversight.	SEC regulates PublicCompanies

4.2. Representing Complex Financial Relationships

Representing complex financial relationships necessitates going beyond simple subject-predicate-object triples. Causality, for instance, can be represented using relations like CAUSES, where an event ACAUSES event B. Correlation, indicating a statistical association, can be modeled with a CORRELATES_WITH relation, potentially quantified with a correlation coefficient r. Dependency, crucial in risk assessment, can be expressed using relations like DEPENDS_ON, signifying that the value of asset XDEPENDS_ON the performance of market factor Y. Relation properties, such as strength or direction, can further enrich these relations. Qualifiers, like temporal constraints (e.g., DURING, BEFORE), add contextual meaning, specifying when the relationship holds true. This nuanced approach enables a more comprehensive and accurate representation of financial knowledge.

4.3. Semantic Relation Discovery Techniques

Semantic relation discovery is crucial for constructing comprehensive financial knowledge graphs. Techniques range from rule-based approaches, leveraging predefined patterns and domain expertise, to statistical methods that identify correlations and associations between entities. Machine learning algorithms, particularly those based on natural language processing (NLP), are increasingly employed to extract implicit relations from textual data, such as news articles and financial reports. These algorithms can identify relationships like "" or "" by analyzing sentence structure and semantic context. Furthermore, methods exist for discovering relations from structured data, such as financial statements, by analyzing numerical patterns and relationships between different financial variables like $revenue$ and $profit$. The choice of technique depends on the nature of the data and the desired level of accuracy and automation.

5. Comparison of Techniques and Challenges

5.1. Comparative Analysis of Modeling Approaches

Conceptual modeling techniques for financial knowledge graphs, as explored in Chapter 3, offer distinct advantages and disadvantages. Ontology-based approaches, leveraging languages like OWL, provide high expressiveness, enabling complex relationship definitions and reasoning capabilities. However, this comes at the cost of increased complexity and potentially limited scalability when dealing with massive datasets [11]. Property graph models, conversely, prioritize simplicity and scalability, facilitating efficient storage and retrieval of interconnected data. Their expressiveness, though, is generally lower than that of ontologies, potentially hindering the representation of intricate financial concepts [12]. Semantic networks offer a middle ground, balancing expressiveness and scalability, but may lack the formal rigor of ontologies. The choice of technique depends on the specific requirements of the financial knowledge graph, considering the trade-off between expressiveness (E), scalability (S), and ease of use (U) (Table 4).

Table 4. Pro/Cons Analysis of Modeling Approaches for FKGs.

Modeling Approach	Advantages	Disadvantages	Trade-off
Ontology-based (e.g., OWL)	High expressiveness (E): enables complex relationship definitions and reasoning.	Increased complexity and potentially limited scalability (S) with massive datasets.	High E, Low S, Low U
Property Graph Models	Simplicity and high scalability (S): facilitates efficient storage and retrieval.	Lower expressiveness (E): may hinder representation of intricate financial concepts.	Low E, High S, High U
Semantic Networks	Balances expressiveness (E) and scalability (S).	May lack the formal rigor of ontologies.	Medium E, Medium S, Medium U

5.2. Challenges in Constructing Financial Knowledge Graphs

Constructing Financial Knowledge Graphs (FKGs) presents unique challenges. Data heterogeneity, stemming from diverse sources like news articles, financial reports, and market data, requires sophisticated integration techniques. Ambiguity in financial terminology and inconsistent reporting practices further complicate knowledge extraction. The dynamic nature of financial markets, with constantly evolving regulations and market conditions, necessitates continuous updating of the FKG. These challenges impact the quality of FKGs by introducing noise and inaccuracies. Usability is affected as incomplete or outdated information can lead to flawed analyses and decision-making. Addressing these issues is crucial for building robust and reliable FKGs that can effectively support financial applications. The velocity v of data change is a key factor.

6. Future Perspectives

6.1. Integration of Machine Learning

The integration of machine learning (ML) presents significant opportunities for automating the construction and maintenance of financial knowledge graphs (KGs). ML techniques can streamline entity recognition, identifying key financial entities like companies, instruments, and regulatory bodies from unstructured text. Relation extraction, crucial for defining connections between entities, can be enhanced through supervised and unsupervised ML models, learning patterns from financial news, reports, and regulatory filings. Furthermore, knowledge graph completion, addressing the inherent incompleteness of KGs, benefits from techniques like link prediction, utilizing graph embeddings and neural networks to infer missing relationships. These ML-driven approaches can significantly reduce manual effort, improve KG accuracy, and enable dynamic updates as new financial data becomes available, leading to more robust and insightful financial knowledge representation. The use of x and y variables can be used to represent the nodes in the graph and r to represent the relation between them.

6.2. Novel Semantic Relation Discovery Methods

Novel semantic relation discovery in finance necessitates moving beyond traditional rule-based systems. We propose leveraging deep learning architectures, specifically graph neural networks (GNNs), to learn complex relationships from financial text and data. GNNs can model entities as nodes and relations as edges, allowing for the propagation of information and the discovery of hidden connections. Furthermore, we suggest exploring transformer-based models fine-tuned for financial language, enabling nuanced relation extraction from unstructured data. Incorporating attention mechanisms can highlight crucial phrases indicative of specific relationships, such as X impacting Y or A being a risk factor for B. These methods, combined with active learning strategies to minimize annotation effort, promise to significantly enhance the accuracy and completeness of financial knowledge graphs (Table 5).

Table 5. Future Research on Semantic Relation Discovery.

Area	Description	Benefits
Deep Learning Architectures for Relation Discovery	Leveraging GNNs to model entities as nodes and relations as edges, enabling information propagation and discovery of hidden connections.	Enhanced accuracy and completeness of financial knowledge graphs by capturing complex relationships.
Transformer-Based Models for Financial Language	Fine-tuning transformer models for nuanced relation extraction from unstructured financial data.	Improved relation extraction from textual data, identifying subtle relationships.
Attention Mechanisms for Relation Identification	Incorporating attention mechanisms to highlight crucial phrases indicative of specific relationships, such as X impacting Y or A being a risk factor for B.	Enables precise identification of relationships within textual data.
Active Learning Strategies	Employing active learning strategies to minimize annotation effort while maximizing model performance.	Reduces the cost and time associated with data annotation, making the process more efficient.

7. Conclusion

This review highlights the crucial role of conceptual modeling in defining the structure and content of financial knowledge graphs. We found that explicit semantic relations, such as $is\text{-}a$ and $part\text{-}of$, are essential for enabling effective knowledge representation and reasoning. The choice of conceptual modeling approach directly impacts the graph's ability to support complex financial analyses and decision-making. Furthermore, the integration of diverse data sources, guided by a well-defined conceptual model, significantly enhances the richness and utility of the resulting knowledge graph.

References

1. C. Peng, F. Xia, M. Naseriparsa, and F. Osborne, "Knowledge graphs: Opportunities and challenges," *Artif. Intell. Rev.*, vol. 56, no. 11, pp. 13071-13102, 2023.

2. A. Chis, "Applying management theories as a conceptualization lens for knowledge graphs and conceptual modeling methods," in *BIR Workshops*, 2023, pp. 257-270.
3. Z. Ge, "Knowledge graphs and its applications in finance," *The Future and Fintech: ABCDI and Beyond*, pp. 155-214, 2022.
4. A. Hur, N. Janjua, and M. Ahmed, "A survey on state-of-the-art techniques for knowledge graphs construction and challenges ahead," in *2021 IEEE Fourth International Conference on Artificial Intelligence and Knowledge Engineering (AIKE)*, 2021, pp. 99-103.
5. Z. Liu, S. Chen, and Z. Zhang, "Construction of Financial Event Knowledge Big Graph: An Event-Driven Knowledge Organization Framework," in *Knowledge Organization for Resilience in Times of Crisis: Challenges and Opportunities*, 2024, pp. 89-100.
6. S. Prakash, "Demystifying Knowledge Graphs for AI-Enhanced Financial Decision Support with Graph Neural Networks," *J. Comput. Sci. Technol. Stud.*, vol. 7, no. 6, pp. 580-590, 2025.
7. M. Schröder *et al.*, "Towards Cyber Mapping the German Financial System with Knowledge Graphs," in *European Semantic Web Conference*, 2024, pp. 270-288.
8. S. Elhammadi, *Financial knowledge graph construction*, Doctoral dissertation, University of British Columbia, 2020.
9. Z. Xu, H. Takamura, and R. Ichise, "FinCaKG: A Framework to Construct Financial Causality Knowledge Graph from Text," *Int. J. Semantic Comput.*, pp. 1-20, 2025.
10. S. B. Viswanathan and G. Singh, "Advancing financial operations: leveraging knowledge graph for innovation," *Int. J. Comput. Trends Technol*, vol. 71, no. 10, pp. 51-60, 2023.
11. Z. Xu and R. Ichise, "FinCaKG-Onto: the financial expertise depiction via causality knowledge graph and domain ontology," *Appl. Intell.*, vol. 55, no. 6, pp. 1-17, 2025.
12. S. Zehra, S. F. M. Mohsin, S. Wasi, S. I. Jami, M. S. Siddiqui, and M. K. U. R. R. Syed, "Financial knowledge graph based financial report query system," *IEEE Access*, vol. 9, pp. 69766-69782, 2021.