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Knowledge Graph Construction for the U.S. Stock Market: A Statistical Learning and Risk Management Approach

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Abstract: This paper explores the integration of dynamic knowledge graphs (DKGs) and advanced AI techniques, such as large language models (LLMs) and graph neural networks (GNNs), for enhancing financial market analysis and risk management. By developing the Integrated Context Knowledge Graph Generator (ICKG) and the Financial Dynamic Knowledge Graph (FinDKG), the study demonstrates how these models can predict market trends, optimize investment strategies, and improve risk mitigation. The results highlight the superior performance of the KGTransformer model in link prediction tasks, showcasing its potential for more accurate and insightful financial decision-making.

Keywords: Dynamic Knowledge Graphs (DKGs), Large Language Models (LLMs), Financial Market Analysis, Risk Management.

Disciplines: Artificial Intelligence. **Subjects:** Statistical Analysis.

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1 INTRODUCTION

The knowledge graph is a technique for structuring semantic information, which represents knowledge by constructing graphical models among entities, attributes, and relationships. Organizing data into a network of entities and relationships makes it possible to reveal the hidden relationships and patterns behind the data. In recent years, with the rapid development of artificial intelligence and big data technology, knowledge graphs have been applied more and more widely in various industries. [1] Knowledge graphs can help financial institutions better manage risk in the financial industry. The complexity of financial markets makes risk management an important task for financial institutions. [2-4]By constructing the financial knowledge graph, various entities, attributes, and relationships in the financial field can be associated, helping financial institutions have a more comprehensive understanding of the market and products' risk situation and take appropriate measures for risk control. [5]The financial industry is facing increasingly complex money laundering and fraud activities, and improving its anti-money laundering and anti-fraud systems with knowledge graph technology can effectively address these risks.

Huang et al. (2024) presented a groundbreaking study titled Research on Multi-agency Collaboration Medical Images Analysis and Classification System based on Federated Learning at the 2024 International Conference on Biomedicine and Intelligent Technology [6]. This work highlights the effectiveness of federated learning in enabling secure, decentralized data sharing and collaborative analysis across multiple agencies. [7]Their approach ensures data privacy while achieving high accuracy in medical image classification, offering insights that align with modern advancements in distributed systems and privacy-preserving machine learning techniques. Similar principles of federated learning could inspire robust and secure data collaboration frameworks in financial risk management and stock market analysis, as explored in this study.

However, in traditional financial services, customers often need to spend a lot of time and energy to find financial products and services that are suitable for them. By building a knowledge graph, financial institutions can match customers' needs and preferences with financial products and services to provide personalized and efficient financial services [98-11]. By building a customer knowledge graph, financial institutions can quickly understand their customers' needs and preferences, provide them with more accurate and comprehensive financial advice, and improve customer satisfaction and loyalty. Knowledge graph can also be applied to financial public opinion analysis, credit scoring, intelligent customer service and other scenarios. With the continuous development of technology, knowledge graph will play an increasingly important role in the financial industry.

In addition, statistical learning and risk management play a crucial role in stock market analysis. They help investors extract valuable information from complex market data, develop effective investment strategies, and manage potential risks. The following is its relevant information:

The importance of statistical learning in stock market analysis: Data analysis and forecasting: Statistical learning helps investors understand market trends and predict stock price movements through data analysis and model building, Chen et al. (2024), in their preprint Advancing Prompt Recovery in NLP[12]: A Deep Dive into the Integration of Gemma-2b-it and Phi2 Models (arXiv:2407.05233), explore the integration of advanced natural language processing (NLP) models to enhance prompt recovery and response generation. By leveraging the capabilities of Gemma-2b-it and Phi2, the authors achieve significant improvements in model adaptability and precision. [13]Their findings demonstrate the power of combining multiple models for optimized performance, a principle that resonates with the use of statistical learning and multi-model approaches in constructing knowledge graphs for financial systems. Such insights further underscore the potential of deep learning in handling complex, dynamic data environments like the U.S. stock market. For example, by building a cross-sectional forecasting model to select the best-performing Chinese stocks.

Investment strategy development: Statistical learning methods such as logistic regression, joinpoint regression, etc., can be used to analyze the basic logic of stock trading, such as identifying changes in trends and potential buying and selling points.[14-16]Risk management: Statistical learning can also be used in risk management to predict potential market risks through models and help investors develop corresponding risk response strategies.

1. The importance of risk management in stock market analysis: Identifying and assessing risk: Risk management helps investors identify and assess market risks, such as systemic and non-systemic risks, to make more informed investment decisions.
2. Develop a response strategy: Risk management can help contain potential losses and protect investor capital by setting stop loss and profit points and diversifying investments.
3. Portfolio Optimization[17]: Risk management helps investors balance risk and return in different market environments and optimize portfolio performance through asset allocation.

Statistical learning and risk management are indispensable tools in the stock market to help investors make more informed decisions and achieve their investment goals in a complex and volatile market environment.

2 THEORETICAL BACKGROUND AND METHODOLOGICAL FRAMEWORK

2.1 KNOWLEDGE GRAPH CONSTRUCTION METHOD

This paper focuses on Dynamic Knowledge Graphs (DKGs), a novel approach that combines large language models (LLMs) and dynamic knowledge graphs (DKGs) to detect global trends in financial markets. This paper proposes a new open-source fine-tuned large-scale language model called Integrated Context Knowledge Graph Generator (ICKG) for generating dynamic knowledge graph FinDKG from financial news articles[18-21]. In addition, an attention-based graph neural network architecture, KGTransformer, is proposed for the analysis of FinDKG, and its superior performance in the link prediction task is demonstrated. KGTransformer is also able to make thematic investments on FinDKG, going beyond existing thematic exchange-traded funds (ETFs)[22].

The knowledge graph (KG) is a data structure that encodes entities and their relationships, while the dynamic Knowledge Graph (DKG) extends the static KG by adding timestamps to capture the temporal evolution of events[23-25]. In financial applications, DKG can be used for strategic thematic investments based on information from financial news articles. The paper proposes a method of using large language models (LLMs) as DKG generators and develops a fine-tuned LLM, ICKG, to systematically extract entities and relationships from text data and assemble them into event quadruples[26].

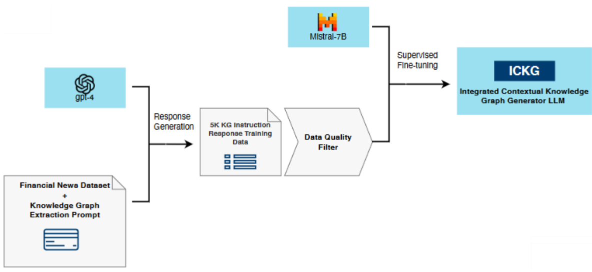

Figure 1: Flowchart of the fine-tuned ICKG LLM for knowledge graph construction, outlining the training methodology.

Learning through Graph neural networks (GNNs) are a fast-growing branch of deep learning focused on extracting low-dimensional latent spatial representations of graphs to improve performance for downstream applications. In the context of knowledge graphs, representation learning aims to derive low-dimensional vector representations of entities and relationships (called embeddings). [27-29]In finance, financial systems are often characterized by complex and dynamically evolving relationships that can be expressed as DKG for applications such as fraudulent transaction identification, stock return forecasting, and more. In addition, the application of LLMs in the financial sector is also increasing, for example, to enhance financial sentiment analysis through advanced natural language processing (NLP) capabilities.

2.2 INTEGRATED CONTEXT KNOWLEDGE GRAPH GENERATOR (ICKG)

The Integrated Context Knowledge Graph Generator (ICKG) is an open-source fine-tuned large language model (LLM) specifically optimized for the task of building knowledge graphs from textual data. ICKG's training process consists of three main steps: First, build fine-tuning datasets using about 5,000 open-source financial news articles that are processed one by one through PGT-4 with tips for knowledge graph extraction to extract triples and classify entities into predefined categories or meta-entities[31]; Secondly, a data quality filter is applied to reduce noise and randomness in GPT-4 output by retaining only article responses that strictly follow instruction prompts and return more than 5 quads; Finally, these quadruples are used to fine-tune the open source Mistral 7B model, resulting in the final ICKG[32-35]. The FinDKG dataset is a new open-source financial Dynamic Knowledge Graph dataset that was extracted using ICKG from approximately 400,000 Wall Street Journal financial news articles spanning from 1999 to 2023. [36-38]Each article contains metadata such as publication time, title, category, and full-text content. When you built FinDKG, you excluded article topics that are not closely related to economics and finance, such as entertainment, book recommendations, opinion columns, and so on. ICKG is used to extract a quintuple of entities, entity categories, and relationship types from each news article, with a timestamp corresponding to the publication date. In addition, entity disambiguation is carried out by Sentence-BERT to ensure the correctness and accuracy of the entity[39].

2.3 KEY ALGORITHMS OF FINANCIAL MARKET RELATIONSHIP MODELING

In the turbulent global financial market, the traditional linear financial model has shown its limitations. The complexity and uncertainty of financial markets require us to adopt more advanced and flexible modeling methods. The emergence of nonlinear financial modeling and forecasting technology is to deal with this challenge and provide a new perspective for understanding and forecasting complex financial phenomena. 1. Understand the complexity of financial markets Financial markets are a highly complex and dynamic system consisting of numerous interrelated and frequently changing elements. Market price fluctuations are influenced by a variety of factors, including economic data, political events, and market sentiment. The interaction between these factors is usually non-linear, that is, their relationship is not simply linear. As a result, traditional linear models such as regression analysis and time series analysis often fail to accurately capture this complexity. 2. The importance of nonlinear models the emergence of nonlinear financial modeling techniques has made it possible to capture this complexity of the market. These models can better reflect the true dynamics of financial markets, thus providing more accurate forecasts and insights. Nonlinear models consider the non-linear interactions between market variables, allowing financial analysts and policymakers to better understand market volatility and develop more effective strategies.

Limitations of traditional financial modeling In traditional financial modeling, analysts usually assume that there is a stable linear relationship between market variables. However, this simplified assumption often does not hold in real financial markets. For example, extreme market events such as financial crises and emergencies often lead to the failure of model predictions. The linear model is inadequate in dealing with the nonlinear characteristics of the financial market and can not effectively predict the extreme changes and fluctuations of the market. 2. Basic Principles of nonlinear financial modeling The core of nonlinear financial modeling is the use of more complex mathematical functions to describe the relationship between variables. These models no longer reduce the relationship between market variables to a straight line, but instead take a curve or more complex mathematical form. Nonlinear models can be diverse, including but not limited to neural networks, support vector machines (SVMS), and models based on chaos theory. These models can more accurately reflect the true dynamics of financial markets and provide a deeper understanding of market volatility.

2.4 METHODS OF NONLINEAR FINANCIAL MODELING

2.4.1 Neural network model

Neural network models are powerful nonlinear modeling tools that mimic the way the human brain processes, recognizing and learning complex patterns in data. In the financial field, neural networks are widely used in stock price prediction, credit scoring and market trend analysis. The advantage of this model lies in its powerful data processing power and learning ability, which can extract useful patterns and relationships from large amounts of historical data.

2.4.2 Support Vector Machine (SVM) model

Support vector machine (SVM) is an efficient nonlinear classifier that differentiates different classes of data by finding the optimal splitter (or hyperplane) in a high-dimensional space. In financial market forecasting, SVM has demonstrated a strong ability to fit complex data structures. It can efficiently handle small sample data sets and is excellent at predicting market trends and stock prices.

2.4.3 Chaos theory model Chaos theory

The application in financial modeling is based on a core idea: even in seemingly random market data, there are inherent certainties and patterns. The chaos theory model attempts to describe the dynamic behavior of the financial market through nonlinear differential equations and reveal the deep rules of market price changes. This method is particularly suitable for analyzing long-term trends and

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cyclical changes in the market. Nonlinear financial modeling not only provides financial analysts with powerful tools to understand and predict the market but also opens up a new path for the study of financial markets. By applying these advanced models, dynamic changes in the market can be more accurately captured, thus providing a solid theoretical and empirical basis for financial decisions. In the following sections, we will explore the performance of nonlinear financial forecasting in practical applications, as well as potential directions and challenges for future development.

3 KNOWLEDGE GRAPH CONSTRUCTION FOR THE U.S. STOCK MARKET

3.1 FINDKG: FINANCIAL DYNAMIC KNOWLEDGE GRAPH

This website provides the Financial Dynamic Knowledge Graph (FinDKG) portal, driven by graph AI model KGTransformer, from the streams of global financial news. Should you use the data or model, kindly cite the paper.

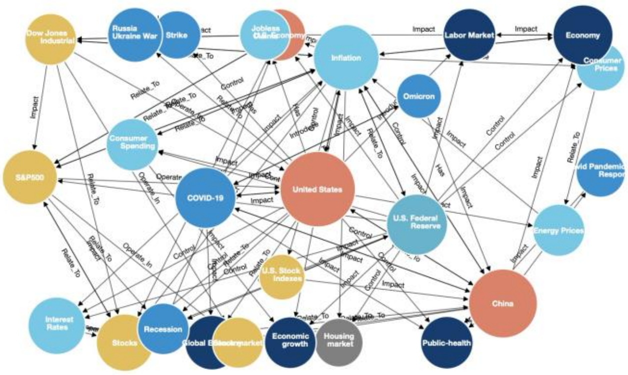
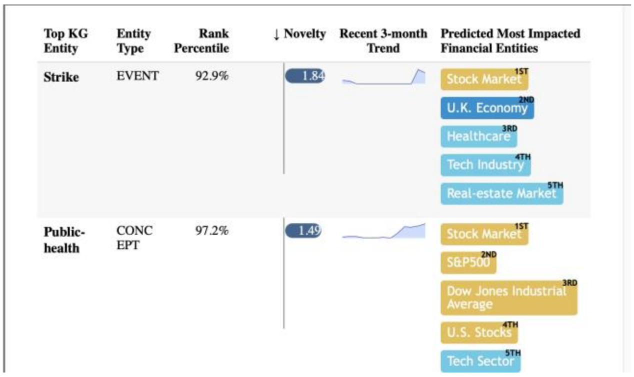


FIGURE 2. THE FINDKG ANALYTICAL TABLE PROVIDES A DETAILED PROFILE OF THESE "TOP KG ENTITIES"

The column labeled "Predicted Most Impacted Financial Entities" identifies the financial variables that are forecasted to experience the most significant changes in the week ahead. Additionally, the table ranks these entities within a vast universe of over 10,000 other entities, using the “Rank Percentile” score (0% to 100%) to signify their relative importance of the FinDKG. A separate "Novelty" z-score is included to highlight how recently the entity has appeared in the dataset. Moreover, by scrutinizing the "Recent 3-month Trend" column, users can discern the evolving influence trend of a particular entity over the past quarter.



Top KG Entity	Entity Type	Rank Percentile	↓ Novelty	Recent 3-month Trend	Predicted Most Impacted Financial Entities
Strike	EVENT	92.9%	1.84		Stock Market 1ST U.K. Economy 2ND Healthcare 3RD Tech Industry 4TH Real-estate Market 5TH
Public-health	CONCEPT	97.2%	1.49		Stock Market 1ST S&P500 2ND Dow Jones Industrial Average 3RD U.S. Stocks 4TH Tech Sector 5TH

FIGURE3. THE U.S STOCK MARKET KNOWLEDGE GRAPH REAL CASE

3.2 DYNAMIC KNOWLEDGE GRAPH LEARNING

This paper presents a probabilistic framework-based learning method for estimating DKG models from observed data. The framework incorporates KGTransformer's time-varying embeddings to learn model parameters by minimizing the composite loss function. The goal of the learning process is to estimate the best description of the observed graph G*A*. The model parameters, involve modeling the temporal dynamics and structural characteristics of entities and relationships. The performance of the model is evaluated by the link prediction task, which predicts the most likely entities for a given source entity, relationship, and future point in time. KGTransformer excels at this task, especially when it comes to data sets containing metadata information, where performance gains can be significant. This demonstrates the effectiveness of KGTransformer in handling dynamic knowledge graphs and predicting future links.

3.3 EXPERIMENT AND APPLICATION

A series of experiments demonstrate the performance of KGTransformer on the link prediction task and evaluate the potential of the FinDKG dataset generated by ICKG for financial trend analysis and thematic investing.

The authors selected several real-world DKG datasets, including YAGO, WIKI, ICEWS14, and the newly created FinDKG, to test the link prediction capabilities of the KGTransformer model. The goal of the link prediction task is to predict the missing entities or relationships in the knowledge graph. The author adopted Mean Reciprocal Rank (MRR) and Hits@n (specifically Hits@3 and Hits@10) as performance evaluation indicators. Compared to existing static graph models (such as R-GCN) and dynamic graph models (such as RE-Net and EvoKG), KGTransformer shows superior performance on multiple datasets, especially on the FinDKG dataset, which contains entity type information. KGTransformer offers even more dramatic performance improvements.

3.4 Identifying trends in financial news

The authors use the FinDKG dataset to analyze and track the dynamics of global financial networks. By constructing a rolling monthly snapshot knowledge graph, the authors calculate the entity centrality index, including degree centrality, intermediate centrality, eigenvector centrality, and PageRank. Using these centrality indicators, the authors show how the attention of COVID-19 entities in financial news has changed over time, demonstrating that the FinDKG dataset can effectively capture important trends in financial news.

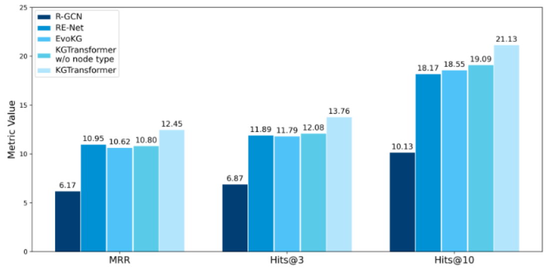


Figure 4: Performance comparison of models on FinDKG.

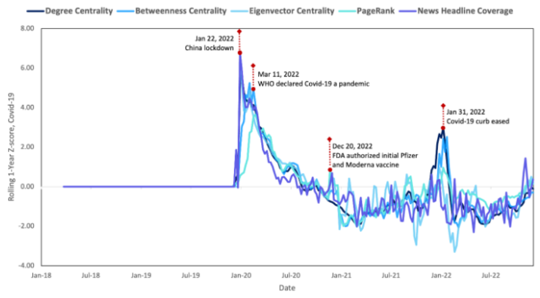


Figure 5: Evolution of the Covid-19 entity centrality measures over time between January 2018 and December 2022.

You can see the application of the FinDKG dataset in thematic investing. Thematic investing is an investment strategy against a theme or trend that is expected to affect the future industrial and economic landscape. Taking artificial intelligence (AI) as the theme, the authors use the KGTransformer model to predict the correlation of stock entities with AI themes and construct an AI-based portfolio.When compared to existing AI-themed ETFs and EvoKG model-based portfolios, the FindKG-based AI portfolio achieved the highest annualized returns and Sharpe ratio during the evaluation period, demonstrating the potential of the KGTransformer model for financial investment applications.

4 CONCLUSION

In conclusion, the integration of knowledge graphs, particularly dynamic knowledge graphs (DKGs), with advanced AI techniques such as large language models (LLMs) and graph neural networks (GNNs) provides significant improvements in financial market analysis and risk management. The development of the Integrated Context Knowledge Graph Generator (ICKG) and the dynamic financial knowledge graph (FinDKG) offers a powerful tool for detecting global trends in financial markets, predicting market changes, and making informed investment decisions. By leveraging the rich temporal and relational data extracted from financial news articles, these models not only enhance predictive accuracy but also provide a deeper understanding of market dynamics, enabling more effective risk mitigation and thematic investing strategies.

Furthermore, the application of DKGs in risk management, portfolio optimization, and fraud detection can significantly reduce the complexities and uncertainties in financial markets. The experiments demonstrate the superior performance of the KGTransformer model in link prediction tasks, showcasing its potential in identifying trends and forecasting stock prices with higher accuracy than traditional models. As the financial industry continues to evolve, incorporating dynamic knowledge graphs and AI-driven methodologies into risk management and investment strategies will be crucial in staying ahead of market fluctuations, improving decision-making, and optimizing financial performance. The future of financial analytics is undoubtedly intertwined with the continuous advancement of these innovative technologies, providing a more robust framework for navigating the complexities of modern financial markets.

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The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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AUTHOR CONTRIBUTIONS

Not applicable.

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