Semantic Causality Knowledge Graph with Ontology Integration for Financial Analysis

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Abstract. In recent years, knowledge graphs have become vital for financial decision support by allowing structured representation and reasoning through complex textual data. However, traditional methods such as Financial Causality Knowledge Graph (FinCaKG) fail in inconsistent or semantically weak settings due to their dependance on raw text strings without ontology alignment. Hence, a Financial Causality Knowledge Graph with Ontology Integration (FinCaKG-Onto) framework was proposed to confirm accurate causality extraction and semantically consistent financial knowledge representation. Initially, financial reports (10-K filings) from FinCausal benchmark dataset were gathered. After that, a Bidirectional Encoder Representations from Transformers (BERT)-based causality detection module studies to recognize cause effect spans in financial reports by state observations from labeled datasets. Furthermore, the extracted spans were dynamically mapped to standardized financial concepts through entity linking with Financial Industry Business Ontology (FIBO). Then, causality bonding mechanism creates explicit cause–effect relations among normalized entities, whereas ontology integration preserves semantic consistency and hierarchical structure. Subsequently, a schema-based organization was applied to allow lightweight reasoning across financial concepts, in which nodes were aligned to their ontology classes and subclasses. Finally, the experimental results showed the proposed FinCaKG-Onto outperformed FinCaKG by attaining an ontology consistency of 95.6% across large-scale financial reports.

1 Introduction

In recent years Financial Decision Support System (FDSS) is used in several real-life applications like in complex financial decision making, risk management, fraud detection and real estate investment. FDSS is a computer-based system designed to support in financial decision making by analyzing data and assessing possible outcomes [1]. It uses various technologies like Machine Learning (ML), Deep Learning (DL) and Natural Language Processing (NLP). Moreover, this FDSS benefits organizations and companies by reducing their time through analyzing data for good decision making to improve market and business [2]. Furthermore, it facilitates better communication among different teams in the organization by providing a common platform for data analysis [3]. However, traditional FDSS were not so accurate in terms of accurate predictions which leads to wrong business decisions. Moreover, these normal techniques lack in terms of adaptability to the new data that company or organization produces [4]. Additionally, this traditional FDSS was time consuming because of its manual process. these challenges lead to risk management, violates the market, fraud detection and many financial tasks [5]. To overcome these challenges, FDSS is integrated with Convolutional Neural Network (CNN) and Bidirectional Encoder Representation Transformer (BERT) to analyze visual data and understand the context of text data to visualizing Knowledge Graph for financial prediction performance [6]. Therefore, this approach helps in working of FDSS to identify the relationships among financial aspects of an organization. Additionally, this FDSS along with BERT and CNN will be able to identify financial concepts of the company like net share, loss, market share, cashflow, net income and total value [7]. The state of art methods includes Relational Graph Convolutional Network (RGCN) model where it is passed through RGCN at different time intervals for Financial Knowledge Graph. which helps to handle graph unstructured data [8]. Moreover, this model has the potential to visualize a knowledge graph according to their subject-predicate and object relationship [9]. However, this RGCN struggles to visualize real world complex problems which contains diverse node types and relationships [10]. Simultaneously BERT mechanism to understand the context and order of text data and it converts all the text data into numerical data for the machine to understand. Additionally, this financial knowledge

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graph failed to visualize in human understandable structure and to represent the financial knowledge graph in structured manner additionally it didn't fully capture the complete information [11]. However, this model failed to generalize the relationships among nodes when organization information varies [12].

The main contribution of this research includes:

- A Financial Causality Knowledge Graph with Ontology Integration (FinCaKG-Onto) is presented as a structured and semantically reliable framework for representing financial cause–effect relations.
- The collected reports are processed by a Bidirectional Encoder Representation Transformer (BERT)-based causality detection module that classifies causal sentences and extracts precise cause-effect spans.
- The identified spans are normalized by linking them to standardized financial concepts by entity linking techniques maintained by FIBO ontology and WikiData identifiers that confirms consistency across various data sources
- Additionally, schema-based organization is applied to discriminate among concept-level (T-Box) and instance-level (A-Box) knowledge by allowing lightweight reasoning across financial concepts.

The organization of this research is structured as: Section 2 specifies literature review, Section 3 demonstrates proposed methodology, Section 4 explains experimental results with corresponding discussion, Section 5 signifies conclusion.

2 Literature review

Ziwei Xu and Ryutaro Ichise [13] demonstrated Financial Expertise Depiction via Casualty knowledge graph and domain anthology. Initially data was collected from United Stated (US) Securities Exchange Commission Website (SEC) website and Wikipedia which contains financial reports of 3000 companies from different years which was a labeled data. First the data was processed through causality detection module by using span identification model to detect the casual spans in a sentence. Then the entity linking module with Financial Causality Knowledge Graph (FinCaKG) was applied for mapping the financial vocabulary in the reports. Moreover, this model has the potential to present financial reports with interconnected from transactions to the investments. However, this financial knowledge graph failed to visualize in human understandable structure.

Brindha Priyadarshini Jeyaraman et al. [14] developed temporal relational graph through convolutional network approach for financial performance prediction. Initially data was sourced publicly available data which contains tweets about companies like amazon, apple, Microsoft and google from the year 2015 to 2020 consists of tweet ID, number of comments and retweets. First the data was preprocessed by removing stop words from all the text regarding tweets. Then the processed data was fed into Bidirectional Encoder Representation Transformer (BERT) and Named Entity Recognition (NER) model for extracting the entities. Therefore, BERT extracts relationships in the form of subject object information from the text data. Moreover, this model has the capability to identify various financial concepts of the company like net share, loss, market share, cashflow, net income and total value. However, this model failed to represent the financial knowledge graph in structured manner additionally it failed to capture the complete information.

Oriyomi Badmus et al. [15] demonstrated Artificial Intelligence (AI) powered knowledge graph and Natural Language Processing (NLP) summarization for financial reporting. Initially data was collected from multilingual languages like English, German and Japanese filings. Then the data was preprocessed through Optical Character Recognition (OCR) to convert the text into numerical values and normalized all the values using normalization. After that the preprocessed data was fed into NLP layers for Entity extraction using Named Entity Recognition (NER), section classification and summary generation. After that the extracted data was visualized and created dashboards and reports. Moreover, this AI based approach benefits global financial reporting by reducing time beneath fast evolving regularity regimes.

Pablo Camarillo-Ramirez [16] demonstrated semantic based summarization approach for mapping the knowledge graphs. Initially data was collected from publicly available platform Data Base (DB) pedia (Wikipedia) namely Science fiction movies.Net, fantasy novel.net contains novels and movies. First data was processed through Partitioning Around Medoids (PAM) for capturing the semantic distance between nodes in the knowledge graph. After that the processed data was fed into Machine Learning (ML) clustering algorithms to visualize the relationships between nodes. Moreover, this model has the ability to establish the relationship among nodes in the knowledge graph. However, this model failed to extract meaning information to summarize the text based on certain criteria.

Yixin Song et al. [17] demonstrated semantic analysis model for construction of event-based knowledge graph. Initially data was collected from government websites, news websites and industry websites consist of financial operation difficulties and credit events. First the data was preprocessed using semantic analysis technique for separating words and de duplicating the words. Then the preprocessed data was fed into semantic based event extraction and rule-based causality extraction pipeline for further event and relationship matching. Moreover, this model has the potential to visualize a knowledge graph according to their subject-predicate and object relationship. However, this model failed to manage the credit card management completely especially in policy restrictions.

Existing researchers have explored financial knowledge graphs over causality detection, temporal graph networks, semantic summarization, and AI-driven reporting. While these works established entity extraction, relationship modeling, and partial

visualization, like the models faced the limitations like lack of structured ontology alignment, incomplete information capture, incomplete interpretability, and incapability to represent causal dependencies in a human-understandable manner. Finally, the proposed Financial Causality Knowledge Graph with Ontology Integration (FinCaKG–Onto) model overcomes these challenges by incorporating financial causality extraction with ontology-driven alignment by FIBO by allowing the structured, semantically enriched, and interpretable financial knowledge graphs that increase the prediction, reasoning, and decision support.

3 Methodology

In this step, a Financial Causality Knowledge Graph with Ontology Integration (FinCaKG-Onto) is presented as a structured and semantically reliable framework for representing financial cause–effect relations. Initially, financial reports from the FinCausal benchmark dataset and 10-K filings are used as the main textual input. After, the collected reports are processed by a Bidirectional Encoder Representation Transformer (BERT)-based causality detection module that classifies causal sentences and extracts precise cause-effect spans. Then, the identified spans are normalized by linking them to standardized financial concepts by entity linking techniques maintained by FIBO ontology and WikiData identifiers that confirms consistency across various data sources. Subsequently, the causality bonding mechanism validates directed cause-effect connections among normalized entities by converting unstructured textual relations into structured graph-based pathways. Further, ontology incorporation progresses the graph by positioning all entities and relations with FIBO-defined classes and subclasses by continuing both hierarchical structure and semantic clarity. Additionally, schema-based organization is applied to discriminate among concept-level (T-Box) and instance-level (A-Box) knowledge by allowing lightweight reasoning across financial concepts. Finally, FinCaKG-Onto attains reliable, domain-specific representation of financial causality by offering a consistent, ontology-driven graph that supports reasoning, causal chain exploration, and decision-making in large-scale financial analysis. The pictorial representation of the proposed FinCaKG-Onto is detailly explained in the below Figure 1.

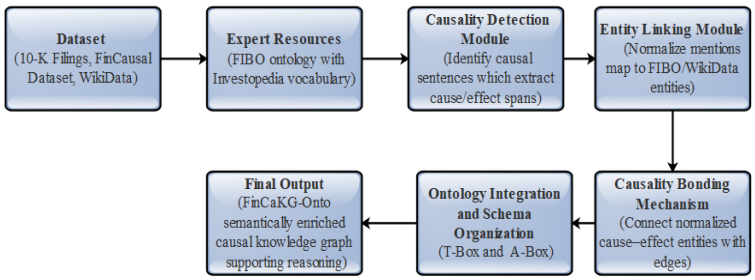

Fig. 1. Pictorial representation of the proposed FinCaKG-Onto.

3.1 Data collection

In this research, publicly available financial datasets [11] and domain-specific resources are applied to match real-world financial reporting environments. Moreover, the main dataset involves like annual 10-K filings which are gathered from the U.S. Securities and Exchange Commission (SEC), which provide complete disclosures of company performance and regulatory impacts. These reports attend as authentic textual sources that contains natural occurrences of causal reasoning in financial contexts. Initially, the FinCausal benchmark dataset is used by allowing the pre-annotated cause–effect spans that facilitate supervised training and estimation of causality detection models. To confirm semantic grounding and interoperability, WikiData entities are incorporated by allowing the cross-referencing of financial terms with globally recognized identifiers. Additionally, expert-curated vocabularies from the Financial Industry Business Ontology (FIBO) and Investopedia are integrated to regulate terminology and resolve ambiguities across various reporting formats. Therefore, each data instance is developed with hierarchical concepts, normalized entity mappings, and explicit causal annotations. Together, these resources simulate a realistic financial knowledge environment which supports the construction, training, and evaluation of FinCaKG-Onto. This curated and labeled dataset collection confirms both empirical grounding and semantic consistency for ontology-driven causal knowledge graph development.

3.2 Expert resources

The construction of FinCaKG-Onto highly depends on expert-curated resources that deliver a standardized financial vocabulary and hierarchical structure. The Financial Industry Business Ontology (FIBO) acts as the key backbone which encircled the well-defined concepts, relationships, and taxonomic hierarchies across financial instruments and processes. Moreover, the ontology stores formal semantics that guide entity alignment and confirm consistent classification of financial concepts. Alongside FIBO, supplementary terminology from Investopedia is integrated to capture extensively utilized to market terms and contextual expressions that often appear in financial reporting. These resources together minimize the ambiguity, that removes the redundancy, and provide support semantic integrity during entity mapping. By highlighting both formal ontologies and practical terminology, FinCaKG-Onto confirms that extracted entities are appropriately

contextualized and hierarchically classified. This expert knowledge base plays an important role in maintaining logical consistency and demonstrating a foundation for participating causality information in later phases.

3.3 Causality detection module

In this stage, the procedure begins with causality detection, where causal data is systematically extracted from raw financial reports which activates in two phases. Initially, sentences are classified as causal or non-causal utilizing the BERT-based classifier which is trained on FinCausal data that permits accurate identification of sentences which describe cause–effect relations. Once causal sentences are recognized, a span extraction model finds the exact cause and effect spans within each sentence. For instance, phrases which are relating about the market losses or regulatory impacts are extracted as structured spans by removing the unnecessary textual noise. By highlighting contextual embeddings, the model confirms the robustness across different reporting styles and complex sentence structures typical of financial documents. The output of this module contains structured cause–effect spans, which generate the basis for entity normalization and subsequent graph construction. This phase is vital, as accurate identification of causal structures confirms precision and reliability in the downstream modules.

3.4 Entity linking module

Entity linking converts raw cause–effect spans into normalized financial entities in this phase. Initially, the process starts with the string-level matching against domain-specific terminology which is derived from FIBO and Investopedia. Moreover, advanced retrieval models including Generative ENtity REtrieval (GENRE) and multilingual Generative ENtity REtrieval (mGENRE) are employed when particular matches are inadequate due to dissimilarities in expression. These models map provides signals to WikiData entities by integrating synonyms and contextual cues. The grouping of expert terminology and exterior identifiers confirms that the both semantic accuracy and global interoperability. Thus, each mention is converted into an exclusive, ontology-aligned entity and avoiding ambiguity across the knowledge graph. This alignment allows the consistent representation of financial instruments, irrespective of their different textual appearances. The final outcome of this phase is a reliable entity set that supports as the semantic foundation for causal relation bonding and ontology integration.

3.5 Causality bonding mechanism

After normalization, explicit cause–effect relations are formalized via an attachment mechanism. Therefore, each cause span is paired with its conforming effect span, and the mapped entities are linked by directed edges that encode financial dependencies. This process methodically converts unstructured text into a structured causality network. For example, an identified causal link like “economic downturn” leads to “decline in corporate earnings” develops a graph relation where the normalized entity “economic downturn” is connected to “corporate earnings” over a directed causal edge. The bonding mechanism confirms that the extracted knowledge is logically protected and eagerly usable for reasoning tasks. By incorporating the normalized entities into directed causal pathways, this stage allows the knowledge graph to signify complex interdependencies among the financial events, risk factors, and organizational outcomes. Finally, the outcome is an organized network of causal relations that exactly captures both language patterns and the financial reasoning which are existing in the source text.

3.6 Ontology integration and schema organization

Ontology integration explains the stage of FinCaKG-Onto by confirming that extracted causal knowledge is embedded within a semantically coherent and hierarchically structured framework. At this phase, all normalized entities and their causal links are properly allocated with the FIBO, which provides authoritative domain classes and subclasses. Therefore, by doing that financial mentions from unstructured reports are mapped into an officially defined semantic space that conserves both accuracy and interoperability. Additionally, the dual-level categorization is applied to differentiate among the concept-level knowledge (T-Box) and instance-level knowledge (A-Box). Moreover, the T-Box captures abstract groups such as Financial Instrument, while the A-Box stores existing entities like Apple Inc. common stock or Federal Reserve interest rate decision. This schema-based separation confirms clarity in representation while permitting causal relationships to flow consistently across both abstract concepts and real-world instances. Additionally, integration with commanding identifiers from Linked Open Data, mainly WikiData, improves connectivity and spreads the knowledge graph’s value beyond standalone use. The structured organization not only captures causal relations but also inserts them into a logically coherent and semantically augmented ontology, which makes the knowledge graph suitable for advanced reasoning and inference tasks across various financial datasets. Finally, the proposed FinCaKG-Onto attains semantic coherence, interoperability, and scalability. It reaches accurate alignment of entities, reliable preservation of causal relations, and improved reasoning capabilities, presenting a robust ontology-driven causal knowledge graph for financial text analysis.

4 Experimented results

In this research, financial causality knowledge graph and domain ontology FinCaKG - Onto is proposed for proposed to confirm accurate causality extraction and semantically consistent financial knowledge representation. For implementation it requires cloud

platforms like google Collab and to run in windows 10 pro, intel i3 processor system with 8 GB RAM running speed at 3.70GHz. The evaluation metrics Accuracy, Precision, sensitivity and F1 score are considered and described in Equations (1)-(3).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{TP+TN}{Total\ number\ of\ observations} \quad (1)$$

$$F1 = 2.\frac{precison\ .senstivity}{precision+senstivity} \quad (2)$$

$$Consistency\ score = 1 - \frac{I}{A} \quad (3)$$

Where, True Positive (TP) represents number of correctly classified observations i.e. "Yes," True Negative (TN) represents number correctly classified observations i.e. "No," False Positive (FP) indicates number of incorrectly classified observations False negative (FN) represents number of incorrectly classified observations.

4.1 Performance analysis

The performance analysis metrics are used to confirm accurate causality extraction and semantically consistent financial knowledge representation. The evolution metrics are accuracy, precision, sensitivity and F1 scores are compared with BERT and RCNN models. Therefore, the FinCaKG – Onto model performed better accuracy, F1 score and Ontology consistency scores than BERT and RGCNN results than both BERT and RGCNN. The performance results are given in the Figure 2.

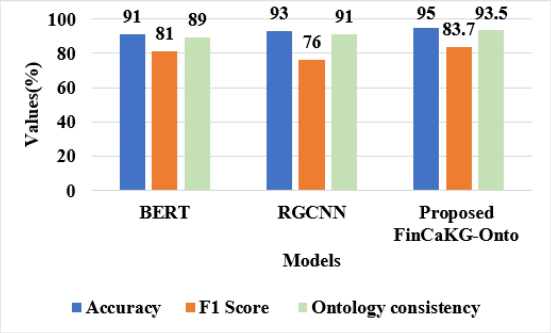

Fig. 2. Performance analysis of proposed FinCaKG-Onto.

From the above Figure 2, the performance results, FinCaKG- Onto achieved better accuracy score of 95 %, F1 score of 83.7% and ontology score of 93.5%. Therefore, proposed method outperformed all the traditional BERT and RGCNN methods respectively.

4.2 Comparative analysis

In comparative analysis, proposed FinCaKG – Onto achieved better metric results than existing Financial Causality knowledge graph (FinCaKG) [13] method. The comparative analysis of proposed FinCaKG – Onto is explained in the below Table 1.

Table 1. Comparative Analysis of proposed FinCaKG – Onto.

Comparative Models	Accuracy (%)	F1 Score (%)	Ontology consistency (%)
FinCaKG [13]	93	81	91
Proposed FinCaKG- Onto	95	83.7	93.5

From the above Table 1, the comparative analysis of FinCaKG and FinCaKG – Onto shown in the above table. where FinCaKG – Onto outperformed traditional FinCaKG [13] method in all metric scores with 95 % accuracy score, 83.7 F1 score and 93.5 anthology score. Therefore, the proposed FinCaKG-Onto helps to confirm accurate causality extraction and semantically consistent financial knowledge representation. The existing FinCaKG method achieved an accuracy of 93%, F1 score of 81% and ontology consistency score of 91% respectively.

4.3 Discussion

The primary objective of this research paper is to develop Financial Causality knowledge graph and domain ontology FinCaKG – Onto to extract cause-effect relationships from financial reports to build a standard financial ontology system. Simultaneously, this helps organizations to analyze why profit and loss happened moreover makes the organization to take better financial decisions in terms of investment and business strategies. The results show that proposed FinCaKG - Onto Model overcame the challenges of existing FinCaKG [13] model and traditional BERT and RGCNN models struggles to navigate financial knowledge in standardize way. The existing FinCaKG model was not able to find specify nuances in complex financial relationships. Thus, the proposed FinCaKG - Onto Model handles specialized textual information smoothly and be able to extract financial trustworthy insights for financial decision systems. Moreover, this model has the potential to link and identify the reasons behind financial loss or business risks and helps the organization to take precautions for avoiding financial loss. Similarly, BERT and RGCNN models are not able to fully discover the essential patterns like handling stock market price drops moreover both treats text as sequence of words which leads to not understand the deeper or semantic meaning that requires for financial systems. In this research the proposed FinCaKG -Onto Model comfortably adapts to multiple heterogeneous documents where it does not worry whether the data is structures or unstructured. Furthermore, this method has the potential to represent multi-interference and specific vocabulary that avoid misinterpretation. Finally, our proposed FinCaKG -Onto model decisively outperforms BERT and RGCNN models by developing a Semantic Knowledge Graphs for Financial Decision Support Systems.

5 Conclusion

In this research, a financial semantic knowledge graph is developed for financial decision system with the proposed FinCaKG – Onto model. The traditional BERT and RGCNN models struggle to identify complex patterns in financial relationships. These challenges were resolved by integrating financial causality knowledge graph and domain ontology to develop a standardized financial ontology system. Initially the financial reports were collected from 10k filings from FinCasual benchmark data to ensure the correct causality extraction. First the sourced data preprocessed by labeling the data to make the model understand cause and the effect spans using data labeling moreover normalized the data to correctly understand the financial sentences using normalization technique. Finally, the preprocessed data was fed into BERT model and FIBO for understanding the context of financial reports and represent those reports in a structural graph. From the results FinCaKG- Onto achieved better accuracy score of 95 %, F1 score of 83.7% and ontology score of 93.5%. In the future, the proposed model further explores the optimizing Graphical Neural Networks (GNN) for learning deeper patterns which improves prediction and reasoning.

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