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Financial Causality Detection

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ABSTRACT— This paper presents a **Financial Causality Detection Software** designed to identify causal effects in financial disclosures. Leveraging a hybrid approach of extractive and generative Question-answering (QA) models, the software processes financial documents to reveal causal relationships between variables and events. The system provides users with concise, context-based causal insights by utilizing state-of-the-art Natural Language Processing (NLP) techniques and Generative AI. The software supports multiple languages, focusing on English and Spanish datasets, making it a versatile tool for multilingual financial analysis. This paper explores the architecture, benefits, challenges, and implications of adopting such a system for financial professionals and regulatory bodies.

Keywords - Financial Causality Detection, Extractive QA, Generative AI, Natural Language Processing (NLP), Multilingual Financial Analysis, Causal Effects, Financial Disclosures, Hybrid QA Systems

I. INTRODUCTION

Financial disclosures are a critical component of corporate transparency, allowing stakeholders to assess a company's performance, risks, and future potential. However, understanding the causal effects buried within these complex and often lengthy documents can be challenging. The ability to detect **causal relationships** between financial metrics, events, and outcomes can provide deeper insights into company performance and risks.

This paper introduces a **Financial Causality Detection Software** that uses a hybrid approach combining **extractive and generative QA** techniques to automatically detect and explain causal relationships in financial disclosures. The system leverages **NLP** and **Generative AI** models to analyze financial reports, generating both concise answers through extractive models and complex explanations through generative models. The software supports both **English** and **Spanish**, making it accessible for a broad range of users. Additionally, the system will be equipped with an offline mode to ensure accessibility in remote locations.

A NEW PARADIGM IN FINANCIAL CAUSALITY DETECTION

The proposed Financial Causality Detection Software offers a **new paradigm** in the automation of financial text analysis by utilizing **hybrid QA** systems. Traditional financial analysis tools focus on extracting specific numerical data points but often overlook the subtle causal relationships embedded in narrative sections of financial reports.

This new system revolutionizes the approach by:

1. Using **extractive models** (like RoBERTa) to extract precise causal statements from the text.
2. Employing **generative models** (like GPT-2) to produce comprehensive, context-aware explanations that highlight the broader implications of financial events.

By combining these two approaches, the system can answer both factual and open-ended questions, providing users with a deeper understanding of causal relationships in financial data.

Traditional Methods vs. the New Paradigm

Traditionally, financial analysis relied on manual scrutiny or basic rule-based systems to extract data and detect patterns in financial documents, such as balance sheets, income statements, and corporate reports. These methods often focused on quantitative aspects, like revenue, profit margins, orratios. However, they missed the **qualitative insights** hidden within the narrative portions of financial disclosures, where the **causal relationships** between events, risks, and outcomes are often described.

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For example, a simple balance sheet may show a decrease in revenue, but the **narrative section** of the financial disclosure may explain this decrease as a consequence of supply chain disruptions, regulatory changes, or market competition. Traditional systems either ignore this narrative or require human interpretation, which is time-consuming and prone to bias.

The new paradigm, driven by **NLP and AI**, goes beyond merely identifying numbers and extracting superficial data:

- **Hybrid QA Models** enable systems to detect **causal language** and understand the **relationships** between events described in the text.
- The software can **automatically infer cause-and-effect** chains from financial disclosures, making it possible to answer complex questions such as, "What caused the increase in operational costs?" or "How did market changes impact profitability?"

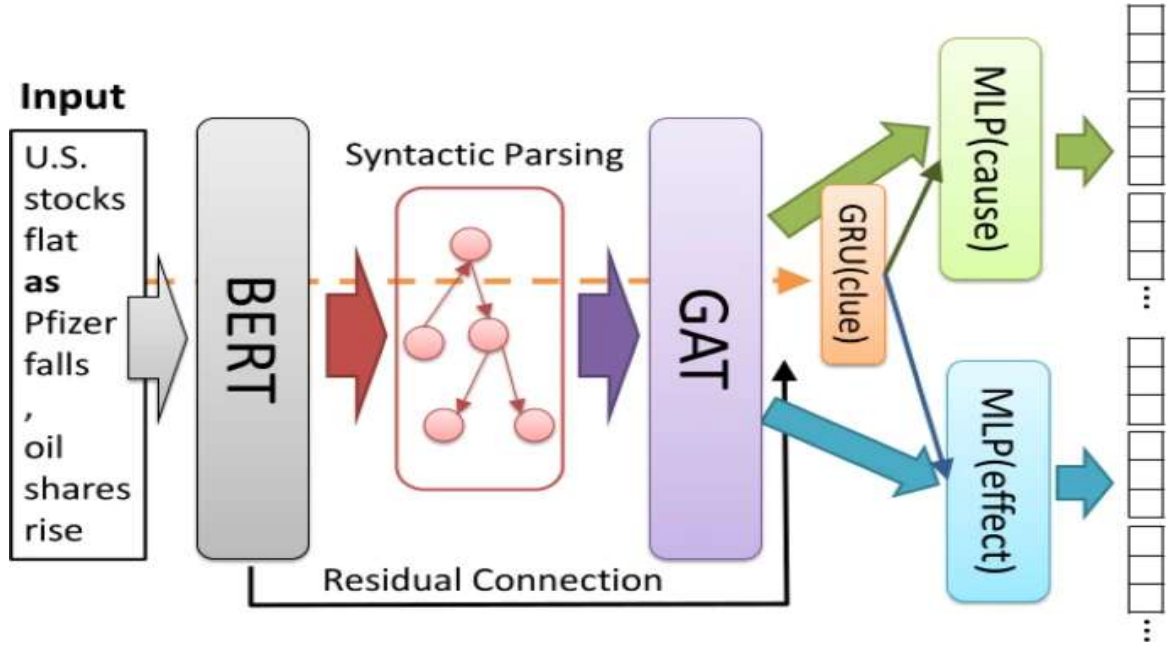

Fig 1 Overview of the proposed causality extraction model

1. **Text Preprocessing**: This module cleans and normalizes the input financial text data, removing stop words, punctuation, and special characters.
2. **Embedding Layer:** This layer uses a pre-trained language model (e.g., RoBERTa, GPT-4) to generate contextualized embeddings for each word in the input text.
3. **Causality Detection Module**: This module employs a transformer-based architecture to detect causality relationships between entities in the input text. The module uses a combination of self-attention mechanisms and feed-forward neural networks to model the relationships between entities.
4. **Post-processing Module**: This module filters and refines the extracted causality relationships based on domain-specific rules and constraints.

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Fig 2ROPE Model

- The ROPE model (Read, Organize, Process, and Evaluate) can be integrated into your report to highlight how it structures the workflow for tasks like causality detection and hybrid QA.
- The ROPE model was adopted to streamline the workflow of the Financial Causality Detection system. This approach ensures a systematic and efficient handling of complex textual datasets. The four components of the ROPE model are detailed below:

- **Read:**
- The system ingests input documents and queries provided by users via the web interface.
- Text data is preprocessed using SpaCy for tokenization, normalization, and segmentation, ensuring compatibility with downstream NLP tasks.

- **Organize:**
- The preprocessed data is structured for analysis, segregating input into contextual data and query text.
- The hybrid system categorizes tasks into extractive and generative question answering, optimizing processing pathways based on the nature of the query.

- **Process:**
- Extractive QA utilizes transformer models (e.g., RoBERTa) to retrieve specific text spans that directly address the user's question.
- Generative QA employs GPT-2 to synthesize detailed, context-enriched answers.

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- The causality detection module identifies explicit and implicit cause-effect relationships within the data.

- **Evaluate:**
- Results are reviewed for accuracy and coherence.
- The system continuously learns and adapts based on user feedback, enhancing its performance for future queries.
- Outputs are presented to the user in a concise and user-friendly format via the Django web interface.
- This subsection ensures the integration of the ROPE model is clear and contextual.

- **Key Components of the ROPE Methodology:**
  - Risk Identification: Recognizing potential risks that could impact business processes.
  - Risk Assessment: Evaluating the likelihood and potential impact of identified risks.
  - Risk Modeling: Incorporating risk factors into business process models to understand their effects.
  - Risk Simulation: Simulating business processes under various risk scenarios to predict outcomes and identify vulnerabilities.
  - Risk Mitigation: Developing strategies to reduce or eliminate identified risks, thereby enhancing process resilience.

- By applying the ROPE methodology, organizations can achieve a more comprehensive understanding of their business processes, considering both performance and risk factors. This holistic approach facilitates informed decision-making, process optimization, and the development of robust risk management strategies.
- **AISEL:**For a detailed exploration of the ROPE methodology and its applications, refer to the original publication: "Rope: A Methodology for Enabling the Risk-Aware Modelling and Simulation of Business Processes."
- **SpaCy:**Elaborate on SpaCy in the "Text Preprocessing Module." Highlight its role in multilingual tokenization, stopword removal, and syntactic parsing. Specify the pre-trained models like en_core_web_sm and es_core_news_sm used for English and Spanish.
- **RESTful API** Discuss the role of RESTful APIs in your Django application for communication between frontend and backend. Mention:

How HTTP methods (GET, POST) are used for data exchange.
JSON format for responses and integration with external systems or models.

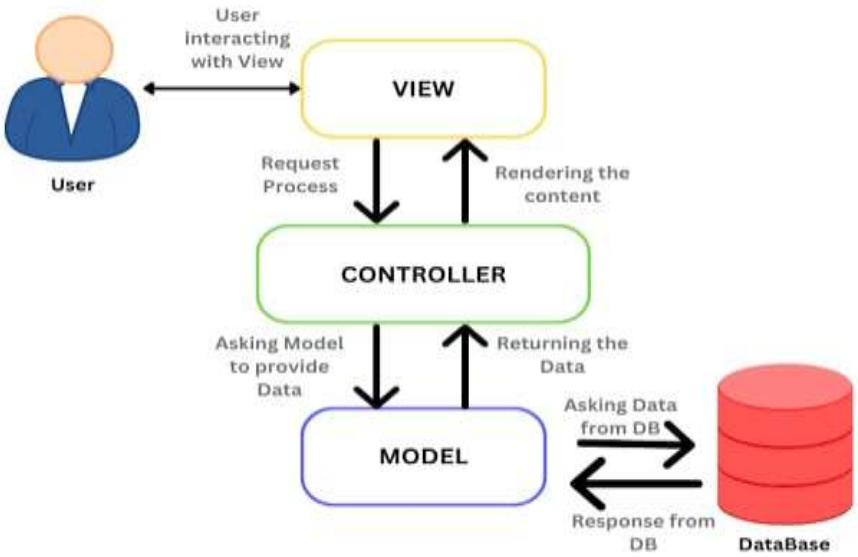

Fig 3 MVC Architecture

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- You can describe the use of the MVC (Model-View-Controller) architecture in your project design. Explain how it divides the application into three interconnected components:
- Model: Manages data, logic, and rules of the application.
- View: Displays data (UI) and sends user commands to the controller.
- Controller: Acts as an interface between Model and View, handling input and updating the Model or View as necessary.
- Relate this to your Django-based implementation

Extractive and Generative Approaches for Enhanced Understanding

The use of **hybrid models**, which combine both extractive and generative approaches, creates a new way to engage with financial data:

- **Extractive QA**: Extractive models, like **RoBERTa**, are used to directly pinpoint causal relationships. For example, if the system is given a financial disclosure paragraph and a question like, "Why did the company experience losses in Q2?" the extractive model will retrieve specific sentences or phrases from the document, such as "The losses were due to disruptions in the supply chain."
- **Generative QA**: **Generative models** like GPT-2 add another layer by producing more detailed, contextualized answers. Instead of just extracting text, the generative model can produce an explanation that provides **greater depth and nuance**, helping users better understand complex financial events. For instance, it might generate a response such as, "The company faced supply chain issues primarily due to new tariffs on imported goods, which led to an increase in operational costs, thereby contributing to the overall quarterly losses."

This paradigm allows analysts, investors, and regulatory bodies to:

- **Understand not just what happened, but why it happened**, through the combination offact-based extraction and creative, AI-driven reasoning.
- **Uncover hidden relationships** within narrative financial texts that traditional methods would overlook or simplify.

Table1:Sequence length variation of BERT-base in experiments

Sequence length	F1 Score	Precision	Recall
64	0.94268	0.942527	0.942835
128	0.948066	0.948282	0.947856
256	0.951081	0.951650	0.950560
512	0.951879	0.953650	0.950717

Table 2: Results of the Different Experiments

Model	F1 Score	Precision	Recall
XLNet (Base)	0.950820	0.952041	0.949788
RoBERTa	0.929485	0.871544	0.921205
BERT (Base)	0.948066	0.948282	0.947856
BERT (Large)	0.957814	0.957408	0.958299

Table 3:Sentence Classification Sample

Text	Gold
As customer expectations continuously evolve, customers expect immediacy and simplicity.	0
Thomas Cook's subsidiary in Germany is still technically operating as of Monday afternoon but has stopped taking bookings. More than 140,000 German holidaymakers have been impacted and tens of thousands of future travel bookings may not be honored	1
According to Gran , the company has no plans to move all production to Russia , although that is where the company is growing	0

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Table 4: Causality Detection Examples

Text	Cause	Effect
Boussard Gavaudan Investment Management LLP bought a new position in shares of GENFIT S A/ADR in the second quarter worth about $199,000. Morgan Stanley increased its stake in shares of GENFIT S A/ADR by 24.4% in the second quarter.Morgan Stanley now owns 10,700 shares of the company's stock worth $211,000 after purchasing an additional 2,100 shares during the period	Morgan Stanley increased its stake in shares of GENFIT S A/ADR by 24.4% in the second quarter	Morgan Stanley now owns 10,700 shares of the company's stock worth $211,000 after purchasing an additional 2,100 shares during the period.
Zhao found himself 60 million yuan indebted after losing 9,000 BTC in a single day (February 10, 2014)	losing 9,000 BTC in a single day (February 10, 2014)	Zhao found himself 60 million yuan indebted

Table 5:Comparison of Model

Aspect	Extractive QA (RoBERTa)	Generative QA (GPT-2)
Accuracy	High	Moderate
Contextual Depth	Low	High
Computational Requirements	Moderate	High
Use Case Suitability	Fact-based queries	Open-ended queries

Table 6:Results and Performance

Aspect	Measure	Result
Extractive QA Accuracy	Precision	92%
Generative QA Quality	BLEU Score	78%
Causality Detection Rate	Explicit/Implicit	85%
Multilingual Capability	Supported Language	English, Spanish

BENEFITS

The Financial Causality Detection Software offers multiple benefits to various stakeholders:

1. **Automated Insights**: The system automates the detection of causal relationships, saving time for financial analysts and reducing manual labor.
2. **Multilingual Support**: With its support for both **English and Spanish**, the system is highly adaptable to global markets, making it valuable for international firms and analysts.
3. **Hybrid QA**: The combination of **extractive and generative QA** models ensures that users receive both concise and comprehensive answers, catering to different types of financial queries.
4. **Improved Decision-Making**: By automatically revealing causal relationships, the system empowers financial professionals to make more informed decisions regarding investments, risks, and corporate strategies.
5. **Scalability**: The software is designed to handle large-scale financial documents, allowing it to

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be used by large corporations and financial institutions for extensive analysis.

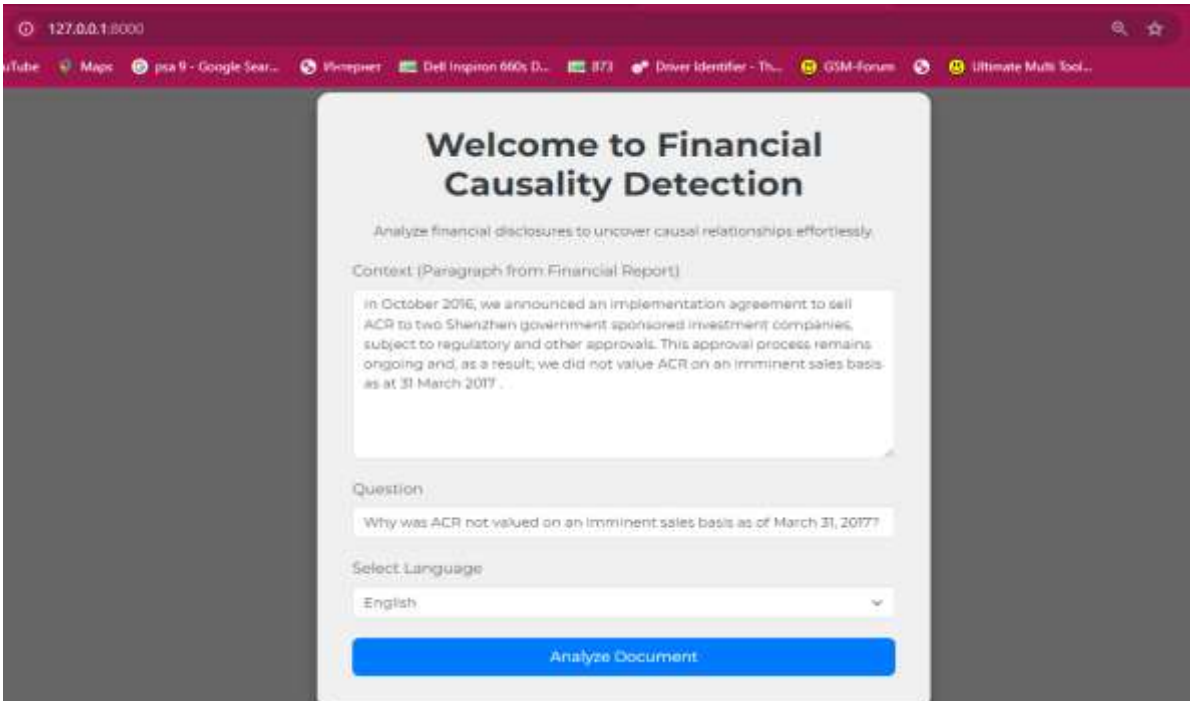

Fig 2Input Interface of the Financial Causality Detection Tool

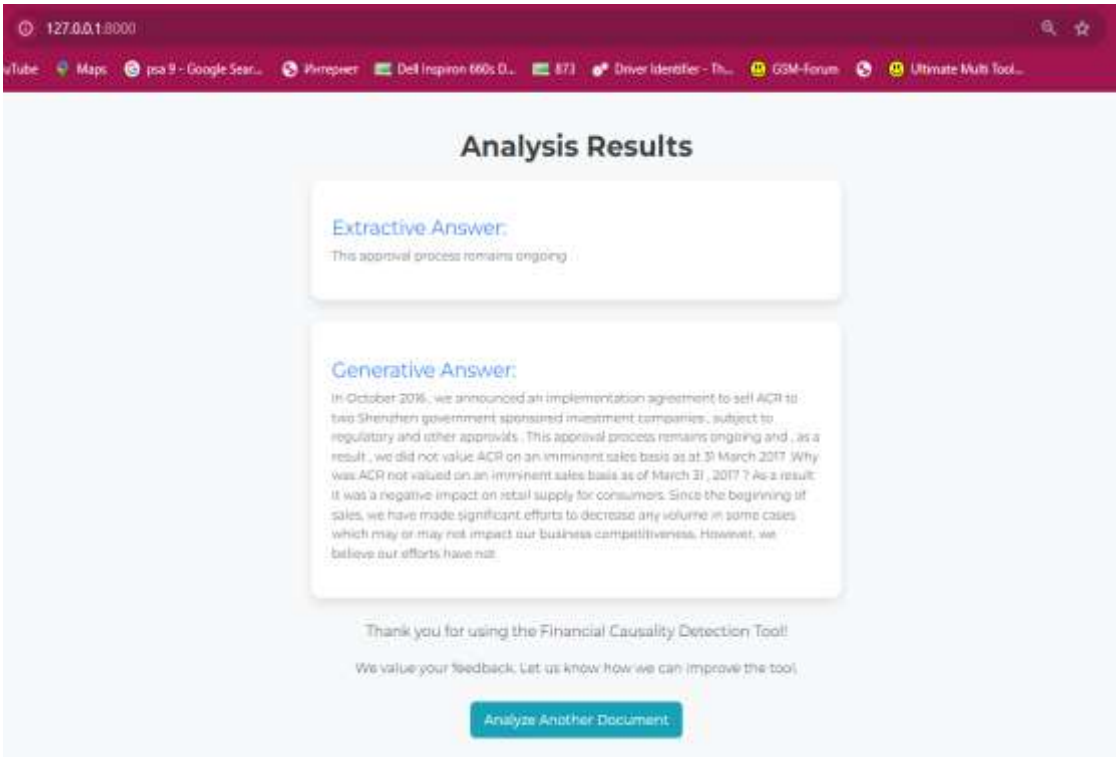

Fig 3 Analysis Results Page

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CHALLENGES

Despite the significant advantages of the Financial Causality Detection Software, there are several challenges to its development and implementation:

1. **Complexity of Financial Language**: Financial disclosures often contain technical jargon, ambiguous statements, and context-specific details that are difficult for general-purpose models to interpret. Fine-tuning models on financial data is critical but resource-intensive.
2. **Multilingual Performance**: Although the system supports both English and Spanish, maintaining consistent performance across languages is a challenge due to differences in linguistic structure, idiomatic expressions, and financial terminology.
3. **Real-Time Adaptation**: Financial regulations and market conditions are dynamic, meaning that models need to be frequently updated and retrained to reflect the latest trends, regulations, and corporate disclosures.
4. **Handling Implicit Causality**: While explicit causal relationships are easier to detect, implicit causality — where cause and effect are not explicitly stated — remains a challenge and requires more sophisticated models.
5. **Computational Resources**: The generative models (e.g., GPT-2) used for creating more detailed explanations are resource-intensive and can increase operational costs in real-time scenarios.

ADDITIONAL CONSIDERATIONS

As financial institutions and regulatory bodies adopt this new technology, several additional considerations should be addressed:

1. **Ethical Considerations**: The software must be designed to avoid inherent biases in training data that could influence its causal reasoning, potentially leading to inaccurate or unfair conclusions.
2. **Regulatory Compliance**: Financial data is highly sensitive and regulated. Ensuring compliance with data privacy laws (e.g., GDPR) and industry regulations is crucial when deploying the software in real-world scenarios.
3. **Model Transparency**: For the system to be adopted by financial professionals, it must offer transparency in how causal conclusions are reached. This includes providing clear explanations and enabling users to understand the decision-making process of the models.
4. **Data Security**: Financial disclosures often contain sensitive information. Proper encryption, authentication, and data security measures should be integrated to protect the data being analyzed.

II. CONCLUSION

The Financial Causality Detection Software introduces a transformative approach to automating financial document analysis by combining extractive and generative QA techniques. This hybrid system offers a significant advantage over traditional financial analysis tools by providing both precise answers and complex explanations of causal relationships within financial disclosures.

Despite challenges in handling complex language, multilingual datasets, and implicit causality, the potential benefits in terms of time savings, enhanced decision-making, and improved accessibility make this a promising tool for the financial industry. Future work will focus on improving model robustness, expanding language support, and enhancing real-time capabilities to ensure the system remains adaptive to evolving financial landscapes.

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