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Master’s Programme in Data Science

Automating Information Extraction from Non-Standard Financial Reports Using Large Language Models

Enhancing Efficiency through Format-Aware Extraction with Large Language Models

Gabriel Gomes Ziegler

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Abstract

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Sammandrag

Sammandraget är en kort beskrivning av arbetets centrala innehåll: vad undersöktes, hur undersöktes det och vilka var de viktigaste resultaten?

I lärdomsprov som skrivs på svenska skrivs sammandraget på svenska och engelska, på motsvarande sätt skrivs sammandraget på finska och engelska i lärdomsprov på finska. Finsk- eller svenskspråkiga studerande som skriver sitt lärdomsprov på engelska ska skriva sammandraget på engelska och på sitt skolutbildningsspråk. Studerande vars skolutbildningsspråk inte är svenska eller finska skriver sammandraget endast på engelska. Den studerande kan om hen så önskar lägga till ett andra eller tredje sammandrag på sitt eget modersmål. Sammandraget fungerar då ofta som mognadsprov och bör i så fall vara minst 300 ord långt. Information om mognadsprov på svenska finns på MyCourses:
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Nyckelord Nyckelord på svenska, temperatur

Preface

Thanks notes

Otaniemi, 31 August 2024

Eddie E. Engineer

Contents

1 Introduction

1.1 Structure of the thesis

The thesis is composed by a comprehensive comparison of methods for extracting information from financial reports, with a focus on non-standard reports. The thesis is structured as follows:

1. Introduction (Context, Problem Definition, Objectives)
2. Literature review (Concepts, State of the Art)
3. Methodology (Dataset, Detail how experiments were conducted)
4. Results (Present the results of the experiments)
5. Conclusion (Interpretation of results, implications, limitations)
6. References

1.2 Background of the Field of Study

The field of data extraction from financial reports has evolved significantly with advancements in text processing and machine learning technologies. Historically, this task involved manual data entry or rule-based systems that were labor-intensive and prone to errors. The emergence of LLMs, such as GPT and Bidirectional Encoder Representations from Transformers (BERT), has revolutionized this domain. These models have the ability to understand and extract complex financial information from unstructured data, thereby increasing accuracy and efficiency. Recent studies have demonstrated the potential of LLMs in automating financial data extraction, highlighting improvements in processing time and data accuracy over traditional methods.

1.3 General Objective

This study aims to extend the current capabilities of data extraction systems by incorporating advanced LLMs and exploring novel methodologies in the field. The primary goals include: ellaborating a comprehensive comparison of methods for extracting information from financial reports, with a focus on non-standard reports,

enhancing the precision and efficiency of data extraction from financial reports, developing a scalable system capable of processing large volumes of data, and comparing the effectiveness of various LLMs and extraction techniques. By achieving these goals, the study seeks to contribute to the broader understanding of automated data extraction and its application in financial analysis.

1.4 Research Question and Sub-Problems

The primary research question of this study focuses on: "What are the best strategies for using LLMs for more accurate and efficient extraction of financial data from unstructured reports?". Sub-problems in this line of inquiry include: identifying the most effective LLM architectures for financial data recognition, developing methodologies for context-aware data extraction, enhancing the system' ability to handle diverse report formats, and evaluating the impact of training data quality and volume on model performance. These sub-problems are essential for understanding the intricacies of applying LLMs to financial data extraction and for developing a comprehensive solution.

1.5 Scope and Constraints

The scope of this study is limited to the extraction of financial data from English-language reports, focusing on publicly available annual and quarterly financial statements. Key constraints include the variability in report formats, the complexity of financial terminology, and the inherent limitations of current LLM technologies in understanding domain-specific contexts. The study primarily revolves around the use of GPT and BERT models, considering their widespread adoption and state-of-the-art performance in text processing tasks. Main concepts involved include Natural Language Processing (NLP), machine learning, data extraction, and financial analysis, with a particular emphasis on the adaptation and optimization of LLMs for specialized data extraction tasks.

2 Concepts and State of the Art

Ever since Portable Document Format (PDF)s were created by Adobe in 1993, they have been used to store and share information. These document standard quickly became a way of companies reporting their financial information for the public as well as Key Performance Indicator (KPI)s and other important information internally. This has led to a large amount of information being stored in PDFs, which has led to a need to extract information from these files. A series of professions have arised from this need, such as data entry, data extraction, and data analysis. The extraction of information from PDFs has been a manual process for most of the tasks until recent years, when Optical Character Recognition (OCR) and NLP technologies have been developed to automate processes involving processing PDFs.

The procedure of extracting information from a document — recently referred to as “Document AI” [1] — is a complex problem due to the diverse nature of data that PDFs allow to store. Such problem often involves cross-modal interactions where information is represented in both text and visual form. This is particularly true for financial reports, where information is presented in text, tables, charts, and infographics. The problem is further complicated by the fact that financial reports are often not standardized, and the information is presented in diverse range of formats.

2.1 LLMs

Large Language Models (LLMs) are a class of artificial intelligence models that have been designed to understand, generate, and interact with human language at a large scale. These models are trained on vast amounts of text data, allowing them to learn language patterns, grammar, context, and even domain-specific knowledge. As a result, LLMs can perform a wide range of language-related tasks, such as translation, summarization, question answering, and more, with remarkable proficiency. The development and evolution of LLMs have been instrumental in advancing the field of natural language processing (NLP), enabling more natural and effective human-computer interactions. The capabilities of LLMs have found applications in various sectors, including but not limited to customer service, content creation, and, notably, in extracting and analyzing information from documents in the field known as Document AI [?].

2.2 GPT

2.3 GPT-4

GPT-4 — the fourth GPT release by OpenAI, brought a significant leap in the capabilities of LLMs when compared to its predecessor GPT-3. This model builds upon the architecture and training methodologies of its predecessors, incorporating lessons learned and innovations to achieve unprecedented performance across a broad spectrum of language tasks. GPT-4 is characterized by its deep learning architecture, which allows it to generate human-like text, comprehend complex instructions, and provide accurate information and analysis based on the context provided to it. Its training involved feeding the model with diverse and extensive datasets, enabling it to grasp nuances across different languages, cultures, and domains. GPT-4's versatility and adaptability have made it a valuable tool in numerous applications, from creative writing assistance to sophisticated data analysis and interpretation in academic research [2].

2.4 GPT-4V

GPT-4 Vision represents an extension of the capabilities of traditional LLMs into the realm of visual understanding and analysis. By integrating vision-based artificial intelligence technologies with the language processing prowess of GPT-4, this model can interpret and analyze images, diagrams, and visual data in conjunction with textual information. This multimodal approach enables GPT-4 Vision to perform tasks that require an understanding of both visual and textual content, such as extracting data from charts and graphs in financial reports, identifying key information in documents with complex layouts, and answering questions that depend on visual cues. The development of GPT-4 Vision is a testament to the ongoing advancements in AI, highlighting the move towards more integrated and comprehensive models that can navigate the complexities of human communication and information processing [3].

2.5 LLMs for Document AI

LLMs have become a popular strategy in the field of Document AI, transforming how information is extracted, processed, and analyzed from documents. In the context of Document AI, LLMs are utilized to understand the content within documents, ranging from simple text to complex structures like tables and charts, and the relationships between different pieces of information. These models leverage their extensive training on diverse datasets to adapt to the specific challenges posed by document analysis, such as varying formats, layouts, and the integration of multimodal data. Through techniques such as transfer learning and fine-tuning, LLMs can be specialized to perform tasks including but not limited to information extraction, document summarization, and semantic search within documents. Their ability to process and analyze documents at scale significantly reduces the time and effort required for data entry, extraction, and analysis, enabling more efficient and accurate handling of document-based information [**?**].

2.6 Question answering with RAG

RAG represents a novel approach in leveraging LLMs for the task of question answering. RAG combines the generative capabilities of models like GPT with retrieval-based methods, which search a large corpus of documents to find relevant information that can aid in generating accurate and informative answers. This technique involves two main components: a retriever, which identifies relevant documents or passages given a query, and a generator, which synthesizes the retrieved information into a coherent response. By integrating these two processes, RAG is able to produce answers that are not only contextually relevant but also enriched with details and insights drawn from a wide range of sources. This method has shown significant promise in improving the accuracy and depth of responses provided by AI systems in question answering applications, particularly in domains where detailed and specific knowledge is required, such as academic research and technical support [**?**].

2.7 Issues with LLMs for Document AI

2.7.1 Hallucinations

Despite their many advantages, LLMs have known limitations when applied to Document AI tasks. One issue that is introduced with the generative nature of these models is the potential for generating incorrect or misleading information, especially when the input data is ambiguous or incomplete. These mistakes — oftentimes referred to as hallucinations — occur when the generative model create plausible and convincing responses that are incorrect. Although, it is possible to identify and mitigate these so-called hallucinations, studies have shown via learning theory that these mistakes are inherent to the generative nature of LLMs and cannot be completely extinguished [4]. The fact that these mistakes are realistic increases the difficulty of detecting them and bring uncertainty about the reliability of the information provided by the model in a productive environment. Comprehensive studies have been conducted to understand the causes of hallucinations and found that these come from a variety of reasons including noisy data, poor parametric choices, incorrect attention mechanism, improper training procedure, among others. There are two distinct categories of hallucinations identified in the literature: intrinsic hallucination and extrinsic hallucination and they require different strategies to be mitigated [5]. Consider that we have the following source data used as input to an LLM model:

> *The company reported revenues of $1 million in Q1 2022, and $2 million in Q2 2022.*

- **Intrinsic hallucination**: This type of hallucination occurs when the model generates information that contradicts the input data. A case of intrinsic hallucination would be if the model generated the following output:

  > *The company reported revenues of $1 million in Q1 2022, and $3 million in Q2 2022.*

  Here, the model has generated information that is inconsistent with the input data since the revenue reported in Q2 2022 is incorrect according to the source data. This type of hallucination can be particularly problematic in document analysis and is the one that this study dives the most into.

- **Extrinsic hallucination**: Extrinsic hallucination occurs when the model generates incorrect information that is not present in the input data but is plausible given the context. For example, if the model generated the following output:

The company is projected to report revenues of $3 million in Q3 2022.

This information is not present in the input data and cannot be inferred from the given context, therefore it is classified as an extrinsic hallucination.

There are several techniques that aim in mitigating these issues, such as using retrieval-based methods [6], fine-tuning a model on a specific domain [7] or by retrying the generation process multiple times while validating the output against a defined model such as the tools *LangChain* [8] and *instructor* [9] propose. In this study, we show applications of how using defined models with *pydantic* [10] and *instructor* can help in mitigating hallucinations in the context of document data extraction.

2.7.2 Interpretability and Explainability

Ever since Deep Learning (DL) models gained popularity in productive environments, many concerns have been raised regarding the interpretability and explainability of these models, particularly in high-stakes applications such as healthcare, finance, and law where accountability and transparency are crucial. As already demonstrated in several studies, DL models are often treated as black boxes, because of the complex and non-linear nature of their architectures, making it difficult to understand how they arrive at their decisions and generate their outputs [11, 12]. LLMs are no exception to this issue, as their complex attention mechasnisms and deep learning architectures make it challenging to interpret the reasoning behind their predictions and the information they generate.

The lack of interpretability and explainability can be a significant barrier to the adoption of LLMs in critical applications, as it not only raises concerns about the reliability, trustworthiness, and ethical implications of the decisions made by these models, but also increases complexity when debugging and improving the models. The uncertainty involving LLMs outputs poses a challenge for users who need to understand what kinds of inputs lead to incorrect outputs. This is particularly important in the context of this study as the information extracted from financial reports is used to make critical business decisions, and the reliability and accuracy of the extracted data are paramount. For these reasons, we investigate nuances on the documents that lead to errouneous predictions so that they can be avoided in the future.

3 Financial Reports Dataset

Dataset used to benchmark different methods.

4 Strategies for information extraction from financial reports

Different strategies for extracting information from financial reports have been implemented in order to compare their effectiveness across diverse report formats and content types. The study brings a strategy that is focused solely on text information, an image-analysis approach that extracts information from images contained in the reports, and a multimodal approach that combines image and text information to validate extracted data from more than one source of truth. For these different experiments, we consider that the core engine changes, but we maintain the same pre-processing steps across them to ensure that the comparison only takes into account the core feature of extracting data from a given input.

4.1 Common processing steps

For all of the experiments, the system receives a PDF as input and common pre and post-processing steps are applied to the data to ensure that the system is able to extract the information from the reports.

4.1.1 Finding pages of interest

A common pre-processing step is to find the pages of interest — those that might contain the information that we are looking for — in the PDF document.

```python
def extract_data_from_pdf(pdf_file: str):
  # Load the PDF file
  doc = fitz.open(pdf_file)

  for page in doc:
    # extract text from page
    text = page.get_text("text")

    # function that will look for matches
    # for the indicators of interest
    matches = search_for_keywords(text)

    # this page does not contain
    # any relevant information
    if matches is None:
        return

    # Then different strategies follow...
```

This pre-processing step is used to iterate over the pages in the PDF document and find the pages of interest so that the core engine is only applied to these pages. This is an important step to reduce the processing time and to avoid unnecessary processing of pages that do not contain relevant information, however it is also crucial to make sure that no false negatives are generated, as this could lead to missing pages of interest.

4.1.2 Consolidating information from different pages

In an ideal world, all the information that we are looking for would be contained in one and only one page of the PDF document and our system would be able to find the page, extract and return. However, this is not the case in practice, as different companies choose different designs to display their information and sometimes the indicators are spread across different pages, or even repeated in different sections of the report. Since our system needs to be able to resolve conflicts in the scenario of having multiple pages with the same information (potentially with different values due to different local regulations, units, and so forth), a strategy for consolidating the information is needed. After testing out different strategies like frequency bags, picking the output with most found values, and LLMs, we have decided to stick with the LLM, more especially the GPT-4 model, to consolidate the information from different pages. Here is a demonstration of how this can be done:

```python
def consolidate_data(data: list[str]) -> str:
  """
  Consolidate data from different pages

  Args:
    data: List of JSON strings containing the data
          extracted from different pages

  Returns:
    consolidated_data: Unique JSON string containing
                       the consolidated data
  """
  # Load the GPT-4 model
  consolidated_data = openai.chat.completions.create(
    model=self.model,
      response_format={"type": "json"},
      messages=[
        {
          "role": "system",
          "content": """Consolidate the following data
                        into only one JSON string..."""",
        },
        {"role": "user", "content": data},
      ]
    )
  return consolidated_data
```

This is a simple example of how the GPT-4 model can be used to consolidate information from different pages of the PDF document and can definitely be improved by adding more context and validation steps, such as checking for inconsistencies in the data, before returning the consolidated information.

4.2 Metrics and Evaluation Criteria

4.3 System Specifications

Define the system specifications and requirements used to run the experiments

4.4 LLM to make sense of text

LLM model using only text to identify key indicators reported in PDF files.

4.5 Multimodal LLMs to extract information from images

4.6 Multimodal LLMs to extract information from images and text

5 Results

Present the results of your study here and answer the research questions, asked earlier in the thesis (in the introduction, perhaps), this study strives to answer. The scientific value of your work is measured by the results you obtain along with the arguments you give to back the answers to your research questions.

Be critical of the significance of your results. You may critically scrutinise the results and your interpretation of the results here, or you may do so later in the chapter with the discussion of your work or in the conclusions part.

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5.1 Limitations of the data extraction systems

Explain what are the observed limitations

6 Summary/Conclusions

This is where you tie up any loose ends. Tell your reader briefly and clearly what you have done, what you have discovered, and the value of your discovery in the context of similar work done earlier. Draw clear conclusions regarding the research problem, sub-problems or hypotheses. You also discuss future lines of study and new questions your study might have posed.

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