Final Project Report

Group 12: Apollo Global Management

Eddie Fu, Pinrui Su, Qilong Yu, Xinyang Gao

Problem Statement

Introduction and Context

The global asset management sector operates in an increasingly complex environment shaped by geopolitical instability, regulatory scrutiny, and macroeconomic volatility. Apollo Global Management (NYSE: APO), a leading alternative investment firm, articulates its strategic priorities, risk exposures, and growth targets in its annual 10-K filings. These documents serve as critical resources for investors, regulators, and analysts to assess the firm's operational resilience. However, manual analysis of these lengthy, unstructured disclosures is labor-intensive and risks subjective interpretation.

Natural Language Processing (NLP) has revolutionized financial text analysis by enabling systematic, scalable extraction of qualitative insights. Seminal work by Loughran and McDonald (2011) demonstrated that NLP techniques—particularly those tailored to financial lexicons—can decode sentiment and risk narratives in 10-K filings more effectively than traditional quantitative methods. Building on this foundation, this project applies advanced NLP tools to Apollo's 2023 and 2024 10-K reports, analyzing shifts in risk perception, strategic investment themes, and alignment with market benchmarks.

Research Gap

Prior research on 10-K filings has largely focused on lexical analysis, and static sentiment scoring using general-purpose dictionaries (Tetlock et al., 2008). However, these methods often miss contextual nuances, and there is limited exploration of temporal shifts in risk sentiment, which is essential for understanding how firms adapt to evolving challenges. While some studies examine intrinsic or extrinsic risks in isolation, few analyze their interplay or collective impact on operations. Furthermore, the strategic alignment of growth targets with external benchmarks, such as S&P 500 inclusion criteria, and their connection to historical performance or industry trends remains underexplored. This project addresses these gaps by providing a holistic and dynamic analysis of Apollo's risk landscape and strategic priorities.

Research Objectives

This study addresses the above gaps by answering five key questions:

1. **Automated financial report analysis**: Automatically identify and extract the content of different chapters in the 10-K report (such as "Item 1A. Risk Factors", "Item 1. Business", "Item 7. Management's Discussion and Analysis") to solve the tedious problem of manually searching and organizing the report directory.

2. **Text preprocessing and cleaning**: Standardize the extracted text, such as word segmentation, stop word removal, word form restoration, etc., to ensure that subsequent analysis can be carried out on the basis of clean and consistent data.
3. **Keyword and context extraction**: Extract the context of keywords (such as "risk", "income", "AUM"), count the frequency of related words, and reveal the company's description, focus and emphasis in specific areas.
4. **Sentiment analysis and quantitative evaluation**: Use sentiment analysis tools (such as VADER) to score the extracted keywords and their context positively and negatively, and obtain the overall sentiment index through weighted calculation, so as to quantify the company's tone and attitude in risk disclosure, profit description, etc.
5. **Cross-year comparative analysis**: Compare reports from different years (e.g. 2023 and 2024) to capture changes in management's descriptions of risk, profitability, asset management, etc., helping users identify trends and strategic adjustment signals

Significance

In Theory: This project advances NLP methodologies in finance by integrating dependency parsing (via spaCy) to map modifier-noun relationships, such as identifying market and liquidity risks. Additionally, it employs sentiment analysis (VADER) to quantify shifts in tone around key terms like "risk" and "investment" between 2023 and 2024. For example, a decline in positive sentiment for 'credit' from 2023 to 2024 might signal heightened financial instability. This approach builds on Loughran and McDonald's (2011) lexicon-based methods while adding contextual depth through syntactic analysis.

Practical Relevance: This project offers practical value to multiple stakeholders. For investors, it provides a replicable framework to assess Apollo's risk resilience and strategic alignment by quantifying sentiment around key risks and tracking year-over-year shifts. For regulators, it highlights potential gaps in risk disclosure practices, offering insights to refine transparency and consistency in corporate filings. Last but not least, it also demonstrates the value of hybrid NLP tools—combining syntactic parsing and sentiment analysis—for advancing financial text mining methodologies.

Methodology

(1) Data Sources

- **Primary Data**: Apollo's 2023 and 2024 10-K filings, with emphasis on:

    - *Item 1A (Risk Factors)*: Extracted via regex-based page-range detection.
    - *Item 7 (Management's Discussion)*: Processed for growth-related clauses.

(2) Analytical Tools Selection
This project employs the following tools and techniques:

- **Text Extraction**: The pdfplumber library converts Apollo's 10-K PDFs into structured text, enabling further analysis.
- **Dependency Parsing**: Using spaCy's rule-based engine, the code identifies grammatical relationships between words, such as adjectives modifying nouns.
- **Sentiment Analysis**: The VADER lexicon, validated for financial contexts, scores the sentiment polarity of keywords like "credit" or "liquidity."
- **Validation**: A subset of sentences is manually reviewed to ensure the accuracy of text extraction and keyword identification.

Limitations

Scope*:* The analysis relies exclusively on Apollo's self-reported data from its 10-K filings. While these documents are comprehensive, they may reflect a management bias toward presenting the firm in a favorable light. In cooperating external sources from third-parties can provide a more comprehensive analysis

Tool Constraints: While VADER is effective for general sentiment scoring, it may underdetect nuanced tonal shifts in formal financial language. Although spaCy is a powerful tool, its accuracy depends on the complexity of sentence structures. Long, convoluted sentences common in legal and financial documents can sometimes lead to parsing errors.

Generalizability: The methodology we employed is designed for U.S. asset managers, specifically who have similar models with Apollo. Therefore, significant adaptation is required for researching into other sectors.

Detailed Coverage

Libraries Used

The procedure we undertook was to take multiple libraries that include pdfplumber, spaCy, NLTK, vadersentiment, and pandas from the python library..

Extracting the File

Using the pdfplumber, we are able to extract a complex pdf file and transform them into specific blocks to analyze. This chops the long pdf into smaller subsections and allows us to analyze the pdf easier without querying through the whole document.

Storing Each Token

Next, we use the spaCy library and load the function en_core_web_sm a pre-trained model that allows us to tokenize each word within the predefined subsection. We can then store these extracted words into a Dataframe using the library pandas. After this preprocessing and extracting step, we are then able to identify key words we want to use for our sentiment analysis. This provides a database of tuples that pairs an identified word with a token.

Identifying Sentiments

For our sentiment analysis, we used vaderSentiment, a pre-built lexicon of words that identifies whether a given word is positive, negative, or neutral. This allows us to find the sentiment of the words that identify and quantify a score of their sentiment to compare with from 2023 and 2024. By doing this step, we are able to assign a score to the word as well as the frequency that it appears in. Now our stored database of tuples has frequencies as well as a score attached to the sentiment. By adding this up we can identify any significant changes between 2023 and 2024.

Finally, we move to our examples to identify risk factors, investment strategies, value generation, and total assets change as well as a sentiment to identify any major changes.

Lessons Learned

Analysis Quality

First, we realized that data quality determines analysis quality. When we first parsed the 10-K report, we found that the PDF file format was not uniform and text parsing was easily disturbed by headers, footers, and line breaks. Therefore, data cleaning and standardization are the first steps to a successful text analysis project. In the preprocessing process, tokenization, stop word removal, stemming, and lemmatization play an important role in improving analysis accuracy.

Determining Sentiment

In addition, sentiment analysis requires industry context support. We used VADER for sentiment analysis, but found that some words in the financial context have special meanings, and general sentiment dictionaries may not be applicable. For example, "exposure" is not always a negative word in the financial field, and "leverage" may mean financial strategy rather than leverage risk. In the future, we can add custom sentiment dictionaries or introduce financial-specific NLP models (such as FinBERT) to improve analysis accuracy.

As with the previous point, we deeply thought about the necessity of combining domain knowledge with data analysis. Machine learning and NLP methods can efficiently process large-scale documents, but when faced with complex financial wording, manual review is still required. For example, some seemingly negative wording may actually be legally required disclosures rather than real risk signals. Therefore, automated analysis can provide quantitative indicators (such as keyword weights and sentiment distribution), but the final business decision still needs to be combined with human interpretation. Therefore, our project emphasizes the value of interdisciplinary cooperation. NLP experts are responsible for text parsing, and financial analysts are responsible for interpreting risk and investment signals. The final conclusion is more comprehensive than relying solely on data scientists or financial experts.

Comparative Analysis

Later, we also realized the importance of time series comparative analysis. Analyzing only a single year's 10-K may miss important trends. For example, after comparing the 10-K reports of 2023 and 2024, we found that the wording of risk factors (Item 1A) changed in different years, reflecting the company's different expectations for the market and regulatory environment. And because we used the comparison of keyword frequency and sentiment scores, we can help us discover the strategic adjustments of company management in market uncertainty.

Finally, we also realized the efficiency improvement brought by modular and reusable design. When building the analysis process, we adopted a modular design, splitting the entire process into sub-modules such as text extraction, preprocessing, keyword extraction, sentiment analysis, and comparative analysis. This approach brings two benefits: Easy debugging and optimization: When a certain link performs poorly, we can optimize it separately without affecting the entire process. Easy to reuse and expand: The same method can be applied to 10-K analysis of different companies, and even extended to other financial documents (such as annual reports, investor letters).

Future Work

Incorporating More

First, instead of only analyzing words related to key terms, we plan to expand our analysis to entire sentences containing those key terms. By incorporating full-sentence context, we can better understand the nuances and intent behind the use of these terms. This deeper linguistic analysis will help us extract meaningful insights into how Apollo communicates risks and opportunities, rather than relying solely on isolated words. This shift to contextual analysis will also help identify the main focus and underlying reasoning behind sentiment shifts.

Tracking Long Term Trends

We intend to conduct a more comprehensive temporal analysis across multiple years. By extending our sentiment analysis beyond just the 2023 and 2024 filings, we can track long-term trends in Apollo's risk disclosures, strategic priorities, and market positioning. This historical comparison would allow us to detect whether sentiment shifts are temporary reactions to specific market events or indicative of deeper strategic changes. We could further enhance this by introducing trend visualization tools, such as time-series graphs and sentiment heatmaps, to make these changes more accessible and interpretable.

Additional Improvements

Another potential avenue for improvement involves leveraging advanced Large Language Models (LLMs) such as the ChatGPT API. While VADER provides an effective lexicon-based sentiment scoring method, it does not always capture the complex sentiment embedded in financial language. Using more sophisticated NLP models like ChatGPT or FinBERT could improve accuracy by considering contextual dependencies and industry-specific nuances. These advanced models could also help classify sentiment into more refined categories, such as regulatory risk, operational uncertainty, and market optimism, rather than a simple positive, negative, or neutral classification.

Integrating Named Entity Recognition (NER) and topic modeling could enrich our findings by identifying and categorizing key entities (such as competitors, regulators, or market events) associated with sentiment shifts. This would provide additional granularity in understanding the factors driving changes in Apollo's risk and investment language.

Lastly, incorporating a broader dataset beyond Apollo's filings—such as earnings call transcripts, investor letters, and regulatory filings—could enhance our sentiment analysis by providing additional perspectives on company strategy and market outlook. This multi-source approach would help us validate our findings and create a more holistic view of Apollo's risk and investment narratives.

Reference

LOUGHRAN, T. and MCDONALD, B. (2011) 'When is a liability not a liability? textual analysis, dictionaries, and 10-KS', *The Journal of Finance*, 66(1), pp. 35–65. doi:10.1111/j.1540-6261.2010.01625.x.