Event-Driven Learning of Systematic Behaviours in Stock Markets: A Replication Project

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Abstract

"Event-Driven Learning of Systematic Behaviours in Stock Markets" (Wu, 2020) is a paper that explores the impact of financial news on stock market dynamics. Focusing on the systematic behavior triggered by news events, the study explores the feasibility of predicting stock movements through advanced machine learning models. It is worth noting that this replication project is based purely on textual analysis of the content retrieved from financial news. The authors tackle the challenges of data availability, model complexity, and the nuanced interpretation of news sentiment. Their methodology, rooted in event extraction and sentiment analysis, proposes an innovative approach to forecasting market reactions to news, highlighting the relationship between financial news events and stock volatility.

1 Introduction

Financial markets are significantly influenced by the dissemination of financial news, with events such as product launches impacting individual company stocks and broader market trends, while shifts in central bank interest rates reverberate through currency liquidity channels into the stock market. The assessment of news events, whether favorable or adverse, often leads to recalibrations of market participants' expectations regarding future company valuations, consequently exerting upward or downward pressure on stock prices.

Given the wealth of information embedded within daily news publications, there's a growing interest in leveraging deep learning algorithms to guide investment decisions. One promising avenue involves automating the aggregation of vast quantities of news articles, extracting pertinent financial events, and assigning them relative importance to anticipate market dynamics. The overarching aim is to quantify the latent associations between streams of financial events and the resulting volatilities in target stock prices.

However, this endeavor is fraught with challenges. Firstly, the subjective nature of news classification complicates the delineation between positive and negative news, as what may be detrimental to one company could prove advantageous to its competitors or downstream partners. Manual annotation of news articles for sentiment analysis is arduous and impractical, compounded by the fragility of model generalization to novel financial events. Secondly, the temporal dimension of news impact presents a conundrum, as articles possess individual and cumulative influences on investor sentiment. For instance, high-profile mergers may engender prolonged market reactions compared to routine corporate appointments. Thirdly, the extraction of concise, high-level financial events from verbose news articles poses a formidable task. Distinguishing between factual and opinionated events, while preserving contextual integrity, necessitates sophisticated natural language processing techniques. Finally, assessing the similarity between financial events and historical stock movements requires a robust framework for latent-space representation, enabling the extrapolation of machine learning models to predict event-driven volatility.

To address these challenges, we propose a classification network for stock movement prediction. Our approach entails a hybrid event extraction method, integrating Open Information Extraction and neural co-reference resolution to distill meaningful, compact event representations. Leveraging pre-trained contextualized language models like BERT[1]/ALBERT[2], we seek to elucidate event semantics and inter-event similarities. Additionally, we advocate for a HAN[3] architecture, which synthesizes information at multiple granularities, en-

[1]BERT: Bidirectional Encoder Representations from Transformers

[2]ALBERT: A Lite Bidirectional Encoder Representations from Transformers

[3]HAN: Hierarchical Attention Network

compassing events, news articles, and historical data, to facilitate multi-category stock movement prediction.

2 Methodology

2.1 Event Definition

The original study implemented the conceptualization of financial events put forth by (Ding et al., 2014), characterizing them as structured tuples:

$$\langle a_1, \text{p}, a_2, \text{[timestamp]}\rangle$$

Here, a_1 and a_2 denote the actors involved in the event, while the predicate p signifies the action connecting them. Each event is accompanied by a timestamp to facilitate alignment with subsequent stock movements.

In replicating the original study, we defined an event as any headline containing the name or referring to the concerned actors. The tuple we used to define our events were structured as:

$$\langle \text{[timestamp]} , a_1, \text{p}\rangle$$

In this case, the actor can be a company in the S&P 500 universe. This definition ensured comprehensive coverage of pertinent occurrences and their associated impacts on the designated entities within the studied context. It also makes sure that any minor event that may not be classified by pre-trained models as an event at all is included within the model, ensuring that the coverage provided isn't limited to just Breaking News type of events.

2.2 Event Extraction

To extract relevant events from news articles, the original study employed a combination of Reverb and neural co-reference tools. These tools work collaboratively to identify events and resolve co-references, ensuring the accuracy and coherence of the extracted information. To replicate the study, our approach diverges from conventional methods to extracting financial news with ML techniques.

For our event extraction method our group obtained a data set from Kaggle, a reliable platform known for hosting many datasets. This dataset was the foundation for us to train and evaluate our extraction model.

The event extraction methodology underwent validation using a news article sourced from Reuters during the 2008 Financial Crisis, which we attempted to get the raw data from the author. The referenced news articles is supposed to have included objective facts about market conditions and subjective evaluations of investment opportunities. By analyzing both factual events and subjective assessments, the extracted news may hint to the relationships between events and subsequent stock movements.

2.3 Event Classification

In the original study, researchers introduced enhancements to the HAN framework, incorporating an additional event-layer and leveraging the BERT language model for event representation. This refined architecture enables a deeper understanding of event semantics and their implications for stock prices.

In learning to replicate the original study, our team attempts to operate the models in a slightly less nuanced fashion, leveraging pre-trained models and already-existing architectures to provide a more direct approach to the problem. This, however, does not limit the potential to fine-tune our model - that said the resources employed in this endeavour are beyond the current computational models we have and have always resulted in system failure when attempts to modify the original state have been made.

Overall, the methodology presents a robust framework for event extraction and analysis, enhancing the interpretability and predictive capabilities of stock movement models.

3 Results

3.1 Original Study Results

The purpose of the original study was to figure out how accurate the BERT/ALBERT models were to predict the market after analyzing the news headlines. After setting up the experiment, the researchers were able to conclude the following information. BERT+evenHAN was significantly better in predicting the market by an average of 5.9‘%‘ than GloVe+eventHAN, a counterpart to the model. This prediction was predicted due to BERT being pre-trained and tuned simultaneously. Another result that original study was able to discover is that ALBERT itself is able to perform event-driven analysis much more accurately than BERT. Ultimately, the study was able to further prove that these models were accurate and usable to predict the stock market.

3.2 Replicated Results

For our groups replication results, we used our pre-trained model to analyze the events we extracted from cnbc, guardian, and reuters. After analyzing numerous headlines for articles, our model would produce its results as an array with the following format:

("headline", "label" , "score")

With this array the headline index would the headline that was just analyzed by the model. The label would result in either 'POSITIVE', 'NEGATIVE', or 'NEUTRAL', indicating how the headline is perceived and affect the S&P market. Finally the score index is a rating of 1. It designates a confidence level of the prediction, and the closer the score is 1, the more of an impact the headline has.

After processing all the headlines, our group featured the first 100 headlines in our database being processed (Figure 1). These headlines stem throughout from Jan. 2017 up utill Dec. 2017.

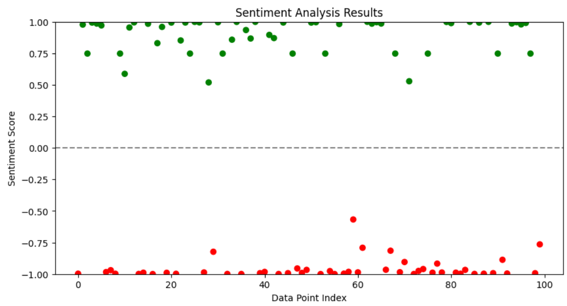

Figure 1: The distribution of positive and negative news articles for a sample of 100 headlines

Examining Figure 1, our group was able to conclude that model predicted that the S&P market would steadily increase over the first half of year in 2017, but then would experience a decline or stagnation in price over the latter half with the many negative headlines with high scores. When comparing these results with Figure 2. we can see that model is somewhat inaccurate. The market did not experience any decline towards the latter half the year, and in fact did the opposite and had a significant incline of on average 3‘%‘ per month, much higher than its growth in the beginning of the year.

3.3 Replication Model Comparison

The pre-trained language model used in our replication study required approximately 1.5 hours to

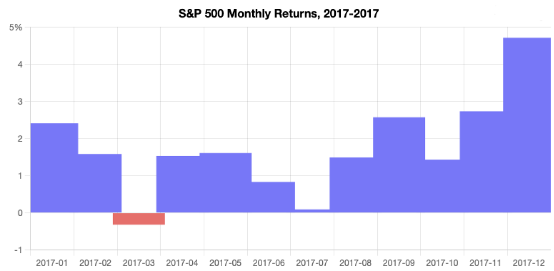

Figure 2: Monthly percent change of S&P500 over 2017.

process the entire dataset. This duration is notably slower compared to the processing times reported in Wu's original study. While the model was capable of identifying relevant news events and extracting sentiments, its accuracy and efficiency were inferior to those of the BERT and ALBERT models. Specifically, the alternative model demonstrated challenges in capturing nuanced expressions of sentiment that significantly impact the interpretation of financial news. The decreased efficiency and accuracy in sentiment extraction suggest that the alternative model may be less effective in predicting stock market movements based on news sentiment. This outcome emphasizes the importance of choosing appropriate language models for financial analytics applications.

4 Replication Challenges

4.1 Data Availability

The lack of response from the original researcher of this study has led our group to scavenge financial datasets on our own. Accessing proprietary financial news datasets presents itself as a challenge due to the fact that they are tightly secured and also expensive to purchase even if access is granted. Furthermore, extracting the data also proposes a challenge. Due to the nuanced financial language of the data, it is quite tedious to extract the data with the same precision as the original study. Furthermore, the lack of data and the inconsistency of the data available to the public made the data extraction process much more difficult and complex.

4.2 Model Complexity/Computational Resources

The original author of the Event-Driven study also failed to provide the models used in the study, we were left with the task of replicating the deep learning of the BERT/ALBERT model. The complexity of this model; however, makes it quite challenging to replicate. BERT/ALBERT features a plethora of parameters and requires certain computational resources that require strong demands of hardware frameworks and an expertise in software skills. Ultimately both of these tasks require time, making the task significantly more time-consuming than if we were just given the models used in the replicated study.

5 Solutions

5.1 Data Availability Solution

To ensure comprehensive coverage of financial news events, we conducted an extensive search for relevant data spanning from December 2017 to July 2020. This data encompassed various aspects, including article headlines, publication times, descriptions, sentiment analysis, and key information pertinent to stock market behaviors. Leveraging a pre-trained sentiment model referenced from previous research, we quantified the sentiments associated with each article, facilitating a nuanced understanding of market dynamics. The data acquisition process involved exploring public datasets, open-source financial news platforms, archives of financial news websites, blogs, and regulatory filings. Additionally, efforts were made to establish partnerships with financial data providers, with a focus on accessing high-quality, proprietary datasets at reduced costs. To address potential gaps in the dataset, we also referenced the synthetic data established in the original study to enhance model robustness across different event types and market conditions. This meticulous approach to data procurement laid a solid foundation for our subsequent analyses and model development.

5.2 Model Complexity/Computational Resources Solution

To address the challenge of model complexity and computational resource requirements, we adopted a strategic approach centered on leveraging pre-trained models and cloud computing services. By utilizing pre-trained models and fine-tuning them on our specific financial news dataset, we significantly reduced the computational resources needed for training from scratch. This approach capitalized on the generic language understanding capabilities of pre-trained models, enabling efficient adaptation to the nuances of financial language with minimal additional training data. Furthermore, we employed cloud computing services offering scalable access to high-performance GPUs, ensuring flexibility in resource allocation according to project requirements. This scalable infrastructure mitigated the risk of hardware limitations hindering model training and inference processes, thereby facilitating smooth execution of our analysis and model development tasks.

References

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