FinXABSA:
Explainable Finance through Aspect-Based Sentiment Analysis

Keane Ong¹, Wihan van der Heever², Ranjan Satapathy³, Gianmarco Mengaldo⁴ and Erik Cambria²

Abstract—This paper presents a novel approach for explainability in financial analysis by utilising the Pearson correlation coefficient to establish a relationship between aspect-based sentiment analysis and stock prices. The proposed methodology involves constructing an aspect list from financial news articles and analysing sentiment intensity scores for each aspect. These scores are then compared to the stock prices for the relevant companies using the Pearson coefficient to determine any significant correlations. The results indicate that the proposed approach provides a more detailed and accurate understanding of the relationship between sentiment analysis and stock prices, which can be useful for investors and financial analysts in making informed decisions. Additionally, this methodology offers a transparent and interpretable way to explain the sentiment analysis results and their impact on stock prices. Overall, the findings of this paper demonstrate the importance of explainability in financial analysis and highlight the potential benefits of utilising the Pearson coefficient for analysing aspect-based sentiment analysis and stock prices. The proposed approach offers a valuable tool for understanding the complex relationships between financial news sentiment and stock prices, providing a new perspective on the financial market and aiding in making informed investment decisions.

I. INTRODUCTION

In light of the increasing complexity of financial systems, as well as the increased use of artificial intelligence methods within the financial world, explainability in financial modelling [1] has grown increasingly important. This is because explainable finance provides greater transparency, trust, and accountability for financial-decision making, especially when these models are intrinsically interpretable. Explainable models enable easier identification of errors and biases within the decision-making process, providing more confidence to investors and credibility to artificial intelligence financial predictions [2].

This paper aims to validate an explainable finance method that involves aspect-based sentiment analysis (ABSA). This is done through the demonstration of statistical results between aspect-based sentiment labels, with an approach presented by [3], and selected stocks. This method will help identify important aspects, their sentiment labels, and the correlation of ABSA to the stock price movement. We have used Pearson correlation to determine the linear relationship between aspect-based sentiment and stock prices.

The structure of the paper is as follows. Section II investigates existing and current research in financial sentiment analysis. Section III focuses on the process of collecting data. Section IV briefly delineates the Sentic Graph Convolutional Network (GCN) model. Section V describes the statistical evaluation method. Section VI highlights the main results. Section VII outlines main discussion points and possible future research directions.

II. RELATED WORK

The field of Financial Sentiment Analysis (FSA) has been extensively researched, as demonstrated in [4], where the authors explore various techniques for deriving sentiment from financial text data, including lexicon-based strategies, Recurrent Neural Network (RNN), Long-Short Term Memory (LSTM), and Convolutional Neural Network (CNN) models. Researchers have also delved into aspect-based sentiment analysis (ABSA), as evidenced in [5], [6], [7], and [8]. These studies utilise transfer learning, CNNs, and Linear Support Vector Regressors (LSVR) to analyse sentiment intensity after aspects have been extracted. Despite the substantial progress made in FSA and ABSA, the field of explainable sentiment analysis in finance (XFSA) remains underexplored but holds significant potential for future research. Particularly, FSA has already demonstrated substantial use for investment, [9] & [10] utilised FSA for market and stock trend prediction, while [11] showed the importance of FSA in portfolio management. Thus, incorporating explainability can further augment FSA’s use in financial decisions by strengthening trust, accountability and transparency. In a recent study, [12] demonstrated that incorporating sentiment analysis into conventional technical analysis for predicting stock prices based on financial news articles could create a model that provides explainable predictions based on news headlines. [13] introduced a neural net framework that is interpretable for FSA, following a hierarchical approach paired with a query-driven attention mechanism to analyse the sentiment of news texts in the financial domain. Furthermore, [14] has illustrated that the level of interpretability is significantly increased (in addition to improved prediction results) with the use of ABSA in an application on Bitcoin directional forecasting from online text.

¹ National University of Singapore
² School of Computer Science and Engineering, Nanyang Technological University, Singapore
³ Institute of High Performance Computing (IHPC), Agency for Science, Technology and Research (A*STAR)
⁴ National University of Singapore & Honorary Research Fellow, Imperial College London
III. DATA COLLECTION

A. Gathering Keywords via ‘Keyword Hopping’

In order to select the keywords for Twitter API use, a framework of ‘keyword hopping’ is employed. First the keywords ‘nasdaq stock market’ were utilised to collect tweets from the last quarter of 2022. These keywords were used to gather NASDAQ stock market specific tweets, given NASDAQ’s status as a prominent exchange with more than 3,300 company listings.

This allows us to obtain roughly 11k tweets that we will use to obtain a greater list of keywords according to their frequency of appearance [15]. This frequency describes the number of tweets that a keyword appears in. That is, if the same word appears in a tweet, it is only counted once. We sort and extract keywords with the highest frequencies (above 100). Thereafter, we remove keywords which are too specific (i.e., tesla, google, apple) and those without significant financial meaning (i.e., cnbc). We also add keywords we deem as financially and contextually important such as sharemarket, stocks to buy, pandemic. The full keyword list is indicated in the next section and will be used for the next round of tweet collection. We argue that ‘keyword hopping’ allows us to obtain a corpus of tweets with richer information as it increases the diversity of tweets collected.

B. Twitter API

Tweets were collected via the Twitter API v2 with academic access from the last quarter of 2022 (1 October to 31 December). Due to the sheer number of tweets from the Twitter full archive search, we collected the tweets from only the turn of the hour for every hour each day. We utilised the following keywords: stock market, Nasdaq, inflation, investors, friday sharemarket, monday sharemarket, china stock, china market, china economy, recession, Tuesday sharemarket, stock fall, thursday sharemarket, stock market, market rally, wednesday sharemarket, finance, economy, market closes, stock closes, financial market, sharemarket, stocks to buy, sharemarket drops, pandemic stock. Within our keyword list, the comma separator denotes ‘OR’ while the space in between words denotes ‘AND’ for building a twitter API query. For congruence, we excluded retweets and set the tweet language to English. In total, roughly 120k tweets were collected, which we will use for sentiment analysis.

C. Stock Prices

The financial performance of various companies can be evaluated by monitoring their stock prices, which are a reflection of their overall market value. Data has been collected for the closing stock prices of six companies. We chose to analyse stocks from the sustainable energy sector given the increasing prominence of sustainable finance and decided to contrast this with an analysis of traditional energy stocks. Additionally, we also selected stocks with a significant market share in their respective fields. Traditional energy stocks include British Petroleum, Exxon, Shell while sustainable energy stocks include NextEra, Clearway, and Brookfield Renewables. The time frame of analysis is the last quarter of 2022 and data is collected from Yahoo finance.

The stock prices of these companies are crucial indicators of their financial health and are closely monitored by investors, analysts, and financial experts. The collected data can be analysed to understand the market trends, as well as the performance of individual companies, during the period in question.

By examining the fluctuations in stock prices, one can gain insights into the companies’ financial stability, growth potential, and overall market positioning. This information can be useful for investors who are considering investing in these companies, as well as for financial experts who are analysing broader market trends. Overall, the collected data on the closing stock prices of these companies provides a valuable resource for understanding the current state of the market and the financial performance of these key players within it.

D. Collecting financial aspects for Sentic Graph Convolutional Networks

As will be explained later on, a list of aspects (attributes or components of a sentence) is necessary for our task of ABSA. When working in the context of FSA, these aspects comprise lists of words used daily in the financial world, for example, "share", "profit" or "risk". An extensive list of aspects yields a greater compilation of text data, therefore we exploit previous research in the FSA domain and draw upon the groundwork of [5], [16] and [17]. The justification for making use of these existing aspect lists is that of trusted statistical methods to generate these words, such as Non-negative Matrix Factorisation (NMF), Latent Dirichlet Allocation (LDA), and Principal Component Analysis (PCA), and annotations by experts in the field, even though only [5] share a similar goal to this paper. Thus a list of 109 aspects was assembled to aid our analysis. However, we focus on the 20 aspects that occurred most frequently in the text data. These, along with the relevant aspect categorisation can be found in Table I.

<table>
<thead>
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<th>Economic</th>
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<th>Financial Institution</th>
<th>Corporate</th>
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TABLE I: List of top 20 aspects, topically categorised.

IV. SENTIC GRAPH CONVOLUTIONAL NETWORK

The SenticNet-based Graph Convolutional Network (GCN), proposed by [3], consists of two components, namely learning contextual representations and leveraging graph information. The first component is accomplished through
LSTM layers, which derives latent contextual representations from the embedding matrix of each input sentence, while the second component entails utilising GCN layers. These layers can express the potential sentiment dependencies of the contextual words by taking as input the hidden contextual representations, together with the matching affective enhanced graph.

Thereafter, the model merges the representations of these two elements in order to deduce, with respect to a particular aspect, the most substantial dependencies. Previously, the majority of graph-based models only considered the syntactical information contained within a sentence. The Sentic GCN, or SGCN, model prioritises words with strong aspect-related sentiment by capitalising on the contextual sentiment dependencies concerning the specific aspect. This is done since the feature of aspect-related sentiment is crucial in ABSA tasks and as such the model refines the sentence’s graph structure in an explicable manner. The entire process of the SGCN model is illustrated visually in Figure 2 where the final representation is the polarity of the different aspects of an input sentence.

V. PEARSON CORRELATION

The Pearson correlation test is conducted to obtain the coefficient $r$, which measures the strength of linear relationship between two continuous variables $x$ and $y$. In our paper, $x$ represents sentiment score for a day while $y$ represents closing price of stock for a day. $n$ refers to the total number of $x$, $y$ pairs which is equivalent to the total days of 2022 Q4 (92 days).

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$  \hspace{1cm} (1)
of sentiment polarity frequency $x_{fp}$ or $x_{fn}$ and normalised sentiment polarity frequency $x_{nfp}$ or $x_{nfn}$. For each day within 2022 Q4, $x_{fp}$, $x_{fn}$, $x_{nfp}$, $x_{nfn}$ are each separately paired with $y$ to produce separate sets of correlation results across the entire period.

After computing $x_{fs}$ for each aspect in 2022 Q4, we can calculate the average number of sentiment labels per day for each aspect. Then, we obtain the top 20 aspects with the greatest average values.

**B. Correlation results for sustainable energy stocks**

Within the $|r| > 0.5$ range, nextera_stockprice has the greatest magnitude for negative correlation $-0.643$ with $x_{fp}$ corresponding to the inflation aspect. Likewise, nextera_stockprice has the greatest magnitude for negative correlation $(-0.662, -0.632, -0.519)$ with $x_{fn}$ corresponding to the economy, inflation, tax aspects respectively.

$r$ values for aspect normalised sentiment polarity frequency $x_{nfp}$, $x_{nfn}$ are noticeably smaller in magnitude compared to absolute sentiment polarity frequency $x_{fp}$, $x_{fn}$. However, for $0.4 < |r| \leq 0.5$, nextera_stockprice yields an $r$ value of 0.419 with $x_{nfp}$ for the stockmarket aspect.

**C. Correlation results for traditional energy stocks**

Of the 3 traditional energy stocks (bp, exxon, shell) analysed, bp and shell consistently yield the greatest magnitude for Pearson correlation values.
Within the $|r| > 0.5$ range, bp_stockprice and shell_stockprice have $r$ values of $-0.66$ and $-0.64$ with $x_{fp}$ corresponding to the inflation aspect.

For $0.4 < |r| \leq 0.5$, exxon_stockprice has an $r$ value of $-0.419$ with $x_{fp}$ corresponding to the inflation aspect. On the other hand, bp_stockprice and shell_stockprice have $r$ values of $-0.452$ and $-0.41$ with $x_{fn}$ corresponding to the "economy" aspect. bp_stockprice and shell_stockprice also have $r$ values of $-0.438$ and $-0.409$ with $x_{fn}$ corresponding to the inflation aspect. bp_stockprice, exxon_stockprice, shell_stockprice have $r$ values of $(0.45, 0.418, 0.412)$ with $x_{nfp}$ corresponding to the economy aspect, while exxon_stockprice has an $r$ value of $-0.457$ with $x_{nfp}$ corresponding to the inflation aspect.

There is a clear correlation among some of the aspects. This is notable for inflation and economy, as these aspects consistently yield $0.4 < |r| \leq 0.7$ with the different energy stocks. inflation yields similar $r$ for both $x_{fp}$ and $x_{fn}$, which indicates how they are more strongly correlated with the frequency of occurrence of the aspect as opposed to their sentiment. Conversely, $r$ values associated with the economy aspect have greater meaning. For economy, $x_{nfp}$ yields positive $r$ with stockprices while $x_{fn}$ yields negative $r$ with stockprices. Additionally, on one occasion each, the aspects tax and stockmarket yielded $0.4 < |r| \leq 0.6$. Beyond these, all handcrafted aspects are also important as they are meaningful within the financial context, notwithstanding their lower correlations.

This paper emphasises the significance of explainability.
in financial analysis and showcases the potential advantages of using the Pearson coefficient to analyse aspect-based sentiment analysis and stock prices. This proposed approach is novel in that it is the first step to finding a correlation between aspect-based sentiment analysis (gained from social media) and price movement in a stock market context. Our future work would entail extending the considered time period from 3 months to a year or more. Besides this, more elaborate methods like predicting stock price prediction, and analysing the statistical relationship can be employed such as Granger Causality and Cross-Convergent Mapping. We will also focus on incorporating microtext normalisation [19] as well as interpretability techniques and their evaluative tools [20]. These can further enhance explainability.

REFERENCES