Chapter 11
Analysing Tweets Sentiments for Investment Decisions in the Stock Market

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Abstract The increasing practice of using social media as the basis for decision-making has made social media an important alternative information source. This is, in particular, true for investors in the stock market due to their needs to gain dynamic, real-time information and strategic persons' views. It is therefore very interesting to investigate the relationships between the sentiments of the text as published on social media and how they may influence investors' minds. In this paper, we selected several influential Twitter accounts, inc. Bloomberg, Forbes, Reuters, WSJ and Donald Trump, for sentiment analysis using SentiStrength. We found a fair amount of agreement between the sentiments as generated by the tool and those assigned from investors' point of view, esp. when plenty of positive words have been used in Tweets. However, we also discovered that not all Tweets with many positive words may generate positive sentiments in investors' minds. Furthermore, we identified interesting differentiated sentiments expressed in different Tweeter accounts that may indicate the stance of their holders, e.g. using an upbeat tone thus to promote economic growth; or being conservative, thus maintaining one's authority. Overall, we found many Tweets scored a neutral sentiment, as many of them contain references that their views cannot be determined without examining additional sources.

11.1 Introduction

Financial-market-based information is increasingly attracting attention in recent years. Traditionally, investors heavily rely on information reported in financial news articles to decide whether to buy, sell or hold stocks in the stock market. These days, social media provides much speedier, near-real-time market information and from

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G. Jezic et al. (eds.), *Agents and Multi-Agent Systems: Technologies and Applications 2021*, Smart Innovation, Systems and Technologies 241,
https://doi.org/10.1007/978-981-16-2994-5_11

a variety of rich sources, inc. independent investment advisers, personality's self-publishing, or government's financial announcements. One such example outlet is Twitter. Twitter users produce millions of Tweets simultaneously which can be used to gauge stock market sentiments and investors' trading intentions. However, it is difficult to predict the financial market accurately using Twitter information. Tweets can be cryptic that they include investment jargons or information that requires financial background to interpret; they may also include unrelated, conflicted or ambiguous information, such as sarcasm; they are also available in large volume that cannot all be manually processed in a timely manner. Carefully designed Sentiment Analysis (SA) tools are therefore often used to help understand the sentiments of Tweets. Such example SA tools are SentiStrength [1], Weka [2], NLTK [3] and Mozdeh [4].

In fact, over the years, microblogging platforms, such as Twitter, Facebook and Instagram, have become popular sources of information for analytics purposes. For example, companies are increasingly seeking automated methods to exploit social media for information about what people think about their products and services. Twitter has a large user base globally and is a great narrative of the public mood. It therefore also offers great potential for exploration in the stock market.

Twitter indeed provides a huge amount of information that can be automatically extracted to provide features to analyze and explore more hidden information. To gauge the public mood, the traditional way of a survey by questionnaires can be very expensive and time-consuming to investigate sufficiently large samples [5]. Automated text mining and sentiment analysis techniques have therefore been used to analyse moods in short text, such as Tweets [6].

However, the ambiguous or context-specific topics in Tweets can pose a challenge for automated methods. In addition, performing sentiment analysis on Tweet messages is difficult also due to the wide use of informal languages and expressions, inc. slang, abbreviations, icons and misspells. The sentiment analysis techniques can be divided into two groups [7]. The first group uses a lexicon of positive and negative words and phrases to determine the sentiments of encountered texts [1]. The second group uses machine learning techniques such as Support Vector Machine and Linear regression to classify texts based on their sentiments using results of previously learned texts [8, 9]. Zhang [10] reported the different types of Neural Network techniques applied to assess the sentiments at the document-, sentence- and aspect-levels.

Investors and researchers use SA tools for analysing the price discovery process and to make smart investment decisions. Sentiment analysis can judge the opinions of Tweets as positive, negative, or neutral, and of varying degrees—called sentiment polarity (SP) [1]. For example, SentiStrength reports two sentiment polarity values (positive and negative), which are -1 (not negative) to -5 (extremely negative) and 1 (not positive) to 5 (extremely positive). The main aim of the sentiment analysis is to infer people's points of view—by assigning contextual polarity to the text that they have expressed opinion within.

However, the opinion of Tweets may also be expressed when no obvious subjective or sentimental clues are given. In this paper, it is therefore very interesting to examine how a generic purposed SA tool, such as SentiStrength, may perform when used in a specialised domain, the stock market sentiments, and to compare the results with how the investors' may interpreter them.

11.2 Research Methodology

Figure 11.1 shows the research methodology framework. The first step is to identify promising or highly influential financial Twitter accounts by using suitable measurements. For this, we favour Twitter accounts that are operated by traditional news agents that are related to finance and have a wide readership, and influential individuals that are known to have strong impact on the stock market. In the second step, we identified an interesting period for observation. We preferred a duration where significant events have occurred, because Tweets published during this period are more likely to exhibit interesting or stronger sentiments. This is then followed by using a suitable automated tool, e.g. Twint, to collect sample Tweets within the chosen time period and Twitter accounts in the third step. The fourth step carries out the pre-processing of collected Tweets. All noises and special characters that are not processable by the SA tool will be removed.

The fifth and sixth steps are to produce the ground truth and to use a SA tool (e.g. SentiStrength) to generate sentiment scores for each Tweet. As we wish to simulate the mentality of investors when reading these Tweets, the ground truth has been created independent of stock market prices, but based on general financial and stock market knowledge to determine the impact of each Tweet that may have on the stock market. The goal here is to evaluate the SA abilities of the tool to determine

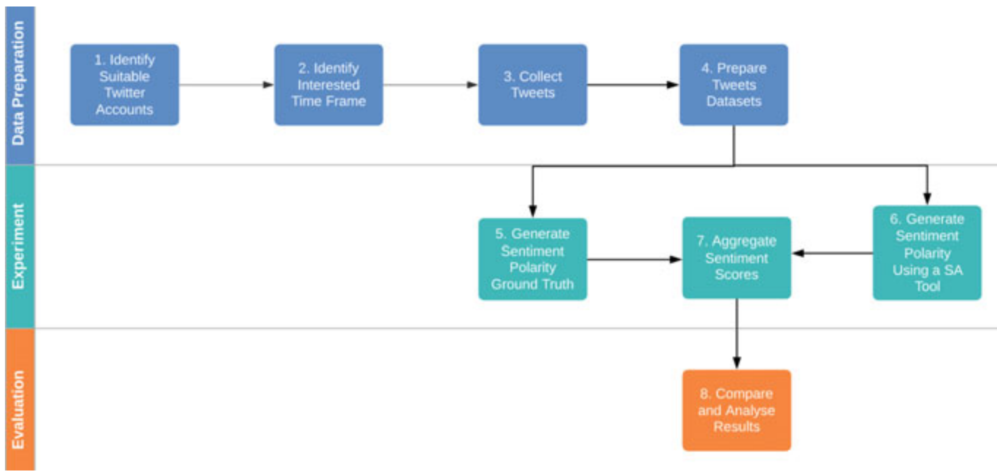


Fig. 11.1 The research methodology

a Tweet's effect on an investor in the stock market; but not in its ability to predict stock market price movements. The stock market price movements are an aggregated result of many factors other than just the particular examined Tweet. The authors, therefore, wish to separate these factors and focus on the effect of the individual Tweet in concern when evaluating the performance of the SA tool. In the seventh step, we combine the pair of sentiment polarity (SP) scores of each Tweet to generate a composite sentiment score to provide a single value sentiment measurement. We also aggregate SP scores for each Tweeter account. Finally, the SP scores are compared between the different Tweeter accounts, and between the machine-generated values and the ground truth. The distributions of sentiment values are also being analysed to derive insights.

11.3 Experiments Design

11.3.1 Data Selection and Preparation

There are many traditional, long-standing financial news outlets that have substantial readerships and are influential to the stock market. Moving into the Era of the Digital Economy, they run very active Twitter accounts that are very well followed. Examples of these are Yahoo Finance (1 million followers), Bloomberg (7 M), Forbes (16.6 M), Wall Street Journal (18.6 M) and Reuters (23.1 M). In addition, distinct personalities, such as the former US President Donald Trump who, while in the office, had a great influence on the stock market over his tweets. He also enjoyed great many followers (88 M) during our sampling period.

For this study, we therefore selected five top influential newsagent Twitter accounts for analysis, namely Bloomberg@business, @Reuters, @Forbes, @WSJ and @realdonaldtrump. These accounts are interested in the stock market and have great influence on investors' opinions [11, 12]. The selection of news providers are also based on their neutral position on stock market investments (i.e. not supporting or biased towards a particular company), the frequency of posting (so that they are active and current), and the usefulness and relevance of their Tweets to the stock market (i.e. less advertisements or social-related postings) [13]. In addition, as our sampling period overlaps with his presidency, we included the Tweeter account of the former US President Donald Trump. As his Tweets, when holding such an influential role, have been observed to have significant impacts on the movements of the stock market's prices [14]. This includes Tweets of policy announcements ahead of their implementations. These five accounts are financially related, and their followers have similar interests, reflecting a strong likelihood that their followers belong to the active investment community.

There are several relevant Tweets datasets, such as Trump's Twitter Archive [13], which includes 50,049 Tweets from the former US President Donald Trump. Also, there are useful Python tools that scrape Tweets, such as Twint. However, most datasets are not free to use and have time restrictions. Twitter's official API also has the restriction of time that users cannot acquire Tweets for more than a week old. In addition, Twitter limits each IP address to 2,000 requests per hour via their API. In this paper, the Python tool Twint was used to scrape Tweets data from several users. It mimics a user's search using the Twitter search bar to overcome the aforementioned limitations.

The data set was collected from Twitter from "29 February 2020" to "3 April 2020". This was an interesting period because there is a major and sudden global stock market crash between 20 February 2020 and 7 April due to Coronavirus. The safety measure of "trading curb" was triggered four times during this period. On 9 March 2020, stock market prices fell all around the world dramatically, such as S&P 500 in the US fell 7.6%, FTES 100 in the UK fell 7.7%, the TSX Composite Index in Canada fell more than 10% and the STOXX Europe 600 fell more than 20% [15].

We randomly collected 1,000 Tweets from each of the above-selected Tweeter user accounts to a total of 5,000 Tweets. Each Tweet download includes a unique id, permalink (link to access the Tweet), username, text, publication date, the number of reTweets, number of favourites, number of mentions and hashtags. The texts of each Tweet were extracted and prepared for sentiment analysis where noises and non-text symbols have been removed.

11.3.2 Sentiment Analysis and Sentiment Polarity

The lexicon-based sentiment analysis method is to make use of sentiment lexicons which include labelled positive and negative words and that each word can be weighted with a degree of sentimental. The input texts are matched with these sentiment lexicons and assessed to generate their sentiment values. This represents the sentiment polarity (SP) of the text.

In this paper, the SentiStrength, a lexicon-based classifier, has been used to detect the sentiments of Tweets [1]. The sentiment polarity is indicated by two integers: the positive sentiment is denoted between 1 and 5; and the negative sentiment between -1 and -5. Two scales are used because every text may include both positive and negative sentiments. It is important to detect them separately before an overall sentiment is proposed. 1 represents no sentiment and 5 strong positive sentiment. The result of 3, -5 means moderate positive sentiment and strong negative sentiment. 1 and -1 indicate neutral sentiments.

There are several useful features in SentiStrength. It provides a sentiment lexicon assigned with polarity and strength judgements. SentiStrength also contains booster word lists, idiom lists and negating word lists. It can identify the sentiment of common phrases and overrides individual sentiment word strengths. For example, "is like" has a score 1 (means neutral text). "like" is a comparator after "is" rather than a positive term (positive 2). The algorithm of SentiStrength detects each word to check whether there is an increase or decrease of 1. The algorithm repeats until all words are checked.

Weka is an open-source machine learning software that can be used by terminal applications, Java API and graphical user interfaces. It includes a lot of built-in tools and useful packages. SentiStrength is wrapped in the AffactiveTweets Weka package, and it can be accessed through the WekaPackage manager. The collections of Tweets are saved as CSV files and loaded through the Weka SentiStrength Package. Next, the newly generated CSV files with sentiment scores will be analysed.

11.4 Results

11.4.1 Tweets Statistics and Their Interpretations

The outputs of SentiStrength include a positive (from 1 to 5) and a negative (from −1 to −5) polarity scores. These two scores are summated to represent the sentiment composite value. Figure 11.2 shows the distributions of the composite and ground truth scores. Most Tweets produce a 0 (neutral) result, and that reflects the fact that most Tweets are informative and do not express sentiments directly in their texts. Ground truth values are generated based on judgements of their influence on the stock market from an investor's view. When a 0 value is produced, it indicates that the Tweet, based on its text and without reading into additional information such as attached links/URLs, does not have an obvious influence on stock market price movements.

To do this, for each Tweet, the two pairs of negative and positive sentiment values as produced by the tool and the ground truth are each summated to produce two composite scores. As a result, the Reuters produced the most neutral scored (0) sentiment Tweets as assessed by the tool (728), as seen in Fig. 11.2 (left) and Table 11.1. However, it was judged to have an overall slightly negative sentiment (−1) from its ground truth scores. Figure 11.2 (right) shows a skewed line peaked at −1. This indicates that although Reuters use a lot of neutral words/phrases in their Tweets, they are perceived to have a slightly negative influence on the stock market.

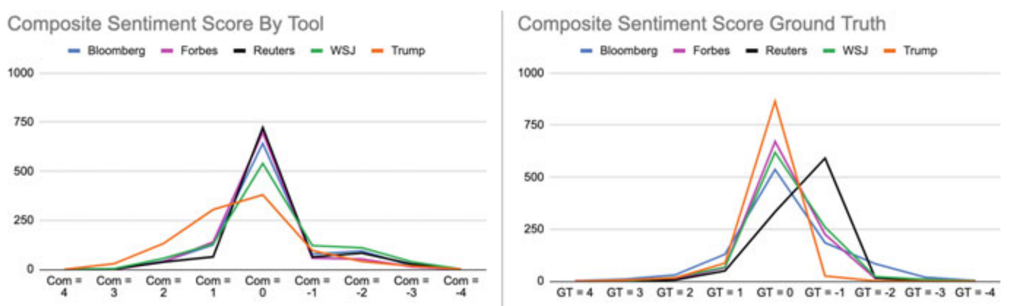


Fig. 11.2 Distributions of composite sentiment scores as generated by SentiStrength (left) and ground truth (right)

Table 11.1 Sentiment polarity scores by tool

	Positive	Neutral	Negative
Bloomberg	167	642	191
Forbes	178	698	124
Reuters	104	**723**	173
WSJ	189	540	**271**
Donald Trump	**466**	380	154

On the contrary, Donald Trump uses a great number of positive words and phrases and that the positive composite sentiment scores generated by the tool are much higher than other users. This is evident by the skewed curve that is leaning to the positive spectrum as seen in Fig. 11.2 (left). However, when comparing them with the ground truth, their potential influence on the stock market is only moderately more positive—the orange peak is only slightly leaning to the left, as seen in Fig. 11.2 (right).

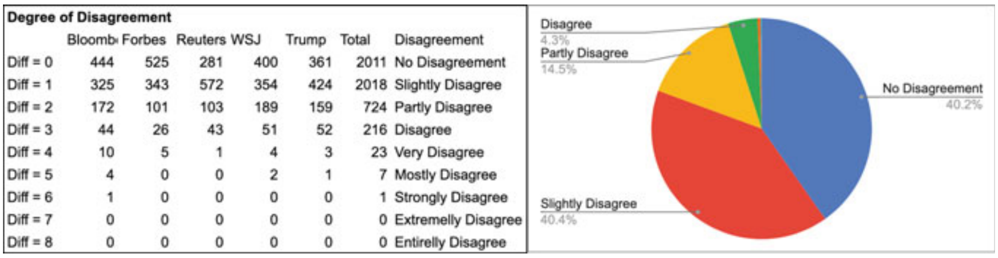
Overall, the distributions of the sentiment scores generated by the tool among all users are relatively similar, except for Donald Trump's. As the president of the time, it is understandable that he would wish to project positivity into the stock market—esp. at a time when stock market crash was observed. Overall, the results are within the normal distribution, and many Tweets obtained the scores as 0. Most of them exhibit similar distributions between the machine-generated and ground truth scores.

Table 11.1 gives the summary of the Sentiment Polarity Scores by tool. Based on our samples, Donald Trump has the most positive Tweets (466), and WSJ has the most negative Tweets (271). Reuters produces the most neutral Tweets (723) that may be an indication that it is more informative rather than judgmental. Table 11.2 shows the ground truth results of SP classification. It shows Bloomberg has the most positive scores (172) that is similar to the assessment by the tools (167). Reuters has the most negative Tweets in ground truth results, but many of these negativities were not detected by the tool (only 173 were assessed to be negative). Overall, it also shows that most Twitter users have more negative sentiments, when they are compared with machine-generated sentiments, except for Donald Trump.

Figure 11.3 shows the differences in scores between the ground truth and SentiStrength generated composite scores. There is not a big difference between them: 40.2% (difference = 0) indicates no disagreement was found and 40.4% (difference = 1) indicates slightly disagreement. These closely matching results may also

Table 11.2 Sentiment polarity scores of ground truth/in investor's eyes

	Positive	Neutral	Negative
Bloomberg	**172**	537	291
Forbes	79	671	250
Reuters	56	334	**610**
WSJ	88	619	293
Donald Trump	109	**864**	27



Degree of Disagreement	Bloomb	Forbes	Reuters	WSJ	Trump	Total	Disagreement
Diff = 0	444	525	281	400	361	2011	No Disagreement
Diff = 1	325	343	572	354	424	2018	Slightly Disagree
Diff = 2	172	101	103	189	159	724	Partly Disagree
Diff = 3	44	26	43	51	52	216	Disagree
Diff = 4	10	5	1	4	3	23	Very Disagree
Diff = 5	4	0	0	2	1	7	Mostly Disagree
Diff = 6	1	0	0	0	0	1	Strongly Disagree
Diff = 7	0	0	0	0	0	0	Extremelly Disagree
Diff = 8	0	0	0	0	0	0	Entirelly Disagree

Fig. 11.3 Degree of disagreement between ground truth and SentiStrength scores

be contributed by the fact that many Tweets are information based and do not contain obvious sentiments towards stock market movements or otherwise.

11.4.2 Accuracy and Evaluation

To measure the performance of SentiStrength, we used standard calculation methods for calculating the Accuracy as provided in Formula 11.1 and 11.2 below [16]

$$Accuracy = \frac{Numbers\ of\ results\ predicted\ correctly}{Counts\ of\ all\ possible\ results} \tag{11.1}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{11.2}$$

where True Positive (TP) and True Negative (TN) indicate where both the tool and ground truth detected the same sentiments of either neutral, positive or negative; and False Positive (FP) and False Negative (FN) indicate where the tool and the ground truth disagree. Table 11.3 presents the results of the tool performance evaluated using composite sentiment scores. Formulas 11.3, 11.4 and 11.5 provide the calculation for generating the Precision, Recall and F1 Scores.

$$Precision = \frac{TP}{TP + FP} \tag{11.3}$$

Table 11.3 SentiStrength performance based on composite scores

	Accuracy	Precision	Recall	F1 score
Bloomberg	0.690	0.746	0.852	0.796
Forbes	0.412	0.387	**0.869**	0.5355
Reuters	0.435	0.394	0.836	0.5357
WSJ	0.638	0.737	0.760	0.748
Donald Trump	**0.839**	**0.980**	0.852	**0.911**

$$Recall = \frac{TP}{TP + FN} \tag{11.4}$$

F1 score strikes a balance between the precision and recall. It is the harmonic mean of precision. When the result is difficult to decide by using precision and recall, the F1 Score is often used to validate the performance of results.

$$F1Score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{11.5}$$

Based on sampled Tweets, SentiStrength obtained the best performance on Donald Trump's dataset for Accuracy (83.9%), Precision (98%) and F1 Score (91.1%). Such high scores may be due to the fact that Donald Trump uses a lot of generally positive words, such as lovely, brilliantly, right, support and confidence that the sentiments of Tweets can be easier detected. Although comparably high on the Recall counts, other performance indicators for Forbes are at the lowest. This may be because most texts from Forbes merely state facts, but they do not include sentimental or subjective clues. For example, the below Tweets from Forbes:

> The stock market bounced back today amid reports that the Trump administration is making progress on plans for a massive fiscal stimulus package that could exceed $1 trillion in an effort to reinvigorate the U.S. economy.
>
> Facebook has announced a $100 million grant for small businesses being impacted by COVID-19.

It is, however, not difficult for an investor (inc. a novice one) to know that these two Tweets would have big positive effects on the stock market. But the results of SentiStrength were neutral. For SentiStrength, it will also be difficult to judge the polarity of the texts in a specialised context, because it classifies sentiments based on generic lexicon. Although it can identify some specific idioms, it does not explore the meaning of a sentence beyond the literature text. The case of Forbes therefore highlights a great challenge that is similarly presented in the case of Reuters. The performance of the tool can be summarised using the F1 score that is a composited measurement based on Precision and Recall. Overall, the performance for determining the sentiments of Donald Trump's Tweets gained the highest scores.

Figure 11.4 shows a comparison box plot diagram of the ground truth and tool-generated scores. The differences of medians are less than 1 across different Tweeter accounts. Most medians are located between 0 and -1, except for Donald Trump's that is observably higher (0.425 of grey box). It shows most texts have the neutral or slightly negative sentiment (approx. 75% of the population is below 0). It also shows that the automatically generated results from SentiStrength and ground truth exhibit similar distributions.

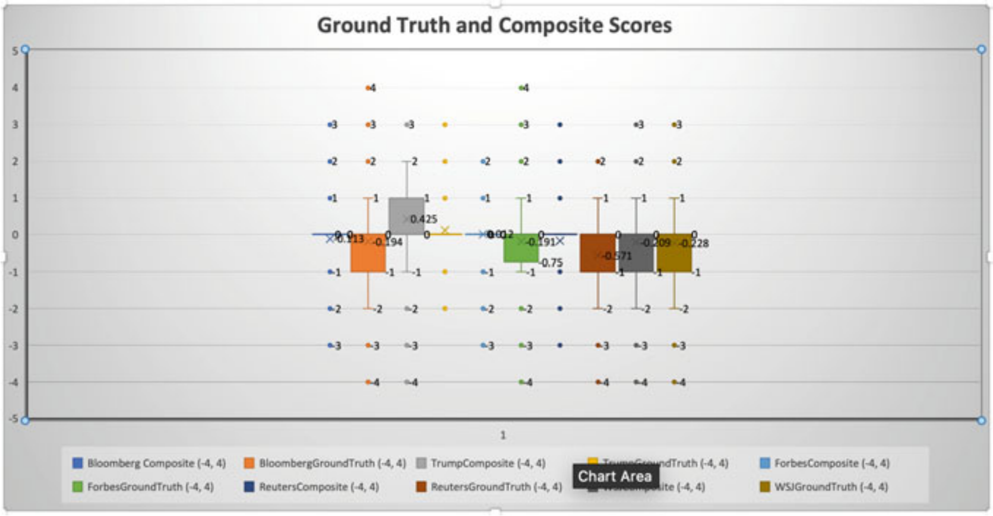


Fig. 11.4 Box plot of ground truth and SentiStrength composite scores

11.5 Related Works

Yuan [17] found Trump's Tweets have obvious impacts on Dow Jones Indexes—which is amplified when re-iterated by other newsagents. Trump's Tweets were found to be useful in predicting stock market price movements. However, their impacts tend to be short term. This finding agrees with our results that Trump publishes many encouraging Tweets, but many sentiments were judged as neutral in investor's mind, therefore many impacts of these Tweets would be short lived. Bollen [5] investigated whether generic Twitter mood could be used to predict the Dow Jones Index movements. The "calm" mood assessed by Google Profile of Mood States classifier was found to have a delayed impact on the stock market within the 2–5 days duration, whereas the OpinionFinder's mood classification did not show correlation. This research also showed that there is a close Tweeter's public mood correspondence with the presidential election and Thanksgiving holiday. Rather than comparing the sentiments of generic Tweets with stock market movements, we use financial-related Tweets and compare them with the minds of stock market investors. Interestingly, Schumaker [18] noted an "inverse" effect of sentiments in news articles, i.e. prices go up when there are negative sentiments and vice versa—indicating contrarian manners of investors. This research reached the best prediction accuracy of 59%. Hagenau [19] deploys a combined approach of using selected 1- and 2-words from news articles and a feedback mechanism for their SA analysis and found their best accuracy at 76%. In this paper, SentiStrength employs 1-, 2- and 3-words lexicon and the best accuracy generated for Donald Trump's Tweets is 83.9%, but not quite as high for other Tweeter accounts.

11.6 Conclusions and Future Work

One of the goals of this research is to determine the influence of Tweets on investor's mind in the context of stock market trading, especially for Tweets generated by influential news providers and well-known Tweeter users. One way of doing this is by comparing the sentiments of their Tweets and the Ground Truth values as would be perceived by investors.

Twint was utilised to extract Tweets from Twitter. The data was collected from five accounts: Forbes, Reuters, WSJ, and Bloomberg, and the former US President Donald Trump during a very interesting time period where global stock market crashes due to Coronavirus. This duration was chosen as Tweets during this period may exhibit stronger sentiments. We used the generic purposed SentiStrength SA tool to assign sentiment polarity to each Tweet and determine whether it is suitable for the specialised domain of stock market. We found a high correlation of sentiments between machine-generated results and the ground truth when obvious positive words and phrases were used in a Tweet. It is, however, much more difficult for the machine to detect sentiments when only fact-based information is provided without any emotional clues.

Overall, we found a fair level of agreements on the distributions of machine-generated and ground truth sentiment values. It was very interesting to find sampled news outlets produced only slightly negative sentiments during a period when there is a global stock market downturn (trading curb triggered four times in the US) via what is conveyed through the text—this may reflect a conservative stance of these companies. However, understandably as someone who would promote US economic growth and ensure stability, the former president Donald Trump, published many Tweets containing positive, encouraging words and phrases. Unfortunately, not all of these Tweets generated similar positive sentiments in the investor's eyes.

The best accuracy results achieved by the SentiStrength were obtained on Tweets of Donald Trump's (83.9%) because they deliver his opinion more clearly. We also found most users have their majority of Tweets judged to be neutral, except for Donald Trump's that is leaning to the positive spectrum—with its median arrives at a positive sentiment of 0.425; where news agents' medians are between neutral 0 and slight negative sentiment of -1.

Based on sentiment scores by tool, WSJ has the most negative Tweets (27.1% of their Tweets are negative)—for ground truth, Tweets of negative sentiments increase to 29.3%. Reuters has the greatest number of neutral scores (72.3%) and 17.3% of its Tweets were determined to be negative by the tool. However, many of these neutral Tweets were perceived to be negative by investors, i.e. 61.0% of their Tweets were judged to have a negative impact on the stock market. This phenomenon indicates that Tweets that do not contain emotional words can still cause negative sentiments on the financial market.

It is challenging to judge text precisely and acquire correct sentimental polarity from words and phrases. Many Tweets may have meanings beyond the text. SentiStrength can categorise sentiments based on words, but it is difficult to explore the concealed information beyond the actual concepts of sentences. Some sentences are also complicated, and they cannot be easily understood accurately. The lexicon of sentiments might be quite general which is not specific to finance or the stock market. The domain-related sentiments may require more specific words and meanings and for specific contexts. The content of the lexicon would therefore ideally be expanded and improved.

Future work may also focus on the understanding beyond the text such as sarcasm and ambiguous words. Tweets would ideally be classified based on words in context and their weightings placed on the whole sentence and not just words, to improve the quality of polarity classification. In this paper, the generic SA tool of SentiStrength has been put to the test in a very specialised domain and had produced variable performance. More syntactic patterns can be considered to indicate subjectivity and sentiments to improve their accuracy. The lexicon sets can be enlarged to include more domain-specific words, phrases and idioms to enhance the performance. It will be important to develop finance-related lexicon to improve the accuracy of sentiment analysis. Furthermore, ontology-based methods may be utilised to enable domain-specific sentiment annotations and to help build decision support systems by combining knowledge from several related ontological sources.

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