The impact of Elon Musk's tweets on Tesla Stock Price

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Abstract

A study was performed on Elon Musk's tweets and Tesla stock price using various statistical methods. The dataset used was a merged dataset containing the tweets, sentiment and stock price of Tesla. New variables were introduced like if the tweet was professional or not, if the stock price went up or no, and a general delta stating the net change in closing price of Tesla stock. The tweets were pre-processed by various techniques using NLTK and Regular Expressions and were then passed into the RoBERTa base model to get the sentiments for each tweet. Then, an average daily sentiment was used for a daily analysis on stock price. Chi-sq test of independence was performed on sentiments and increase in stock price variable and no relation between the sentiments and stock price was found. H-Test also yielded that there is no difference in the impact of different sentiment groups on the stock price. Whereas, with the Chi-Sq test it was found out that there is a relation between professional/non-professional tweet variable and increase in stock price variable. With the help of U-Test, it was also found out that there is statistical difference in the impact of a professinal tweet and a non-professional tweet.

1 Introduction

With 400 million monthly active users and consistent growth over the years, Twitter has become one of the most prominent social networks of this generation. The statement-based platform allows people to share thoughts with their followers, resulting in a fast spread of information over the network. The influential status of some users, combined with the capacity to propagate their opinions, makes Twitter a powerful tool to impact public perception on various areas, one of them being the stock market.

Even though is commonly accepted that the stock market operates in a generally random pattern, there is evidence of correlation between the general mood of the public and the closing prices (Teti et al., 2019). Moreover, Twitter data has been shown to produce accurate sentiment driven models in multiple studies, particularly in the stock market context (Nisar and Yeung, 2018).

In the most popular users group, with over 100 million followers, we can find Elon Musk. His contributions to the platform include professional tweets about his companies, as well as casual thoughts and jokes. On January 2021, after changing his bio to "#bitcoin", the cryptocurrency experienced a $8000 rise to the stock price in a matter of hours, resulting in a $111 billion increase in the asset's market capitalization (Ante, 2021). Similar situations happened to Tesla's stock, a company he presides, after some of Musk's tweets. However, depending on the different tweets the prices went up or down. For this reason, it is interesting to analyse the effect of the different categories of tweets (i.e. Personal or Professional) on the stock prices of the company.

The goal of this paper is to evaluate the correlation between Elon Musk's tweets and Tesla stock price, depending on the genre of the tweets. The proposed research questions are:

RQ1: Do Elon Musk's tweets impact Tesla stock price significantly?
RQ2: Does the impact of a professional tweet differ from the impact of a personal tweet?

We hypothesize that negative professional or personal tweets drive the Tesla stock price down. Regarding the second research question, the hypothesis is that professional tweets have higher impact on Tesla's stock price than personal ones.

2 Previous work

There is extensive research on tweet-based sentiment analysis as a predictor for the stock markets. For example, it was shown that trading strategies that adjust the bet's aggressiveness based on Twitter sentiment can significantly outperform passive buy and hold investment strategies (Azar Lo, 2016). Moreover, it was found that influential accounts such as The New York Times, CNN News and Investing.com, presented a high correlation between sentiments on Twitter and stock market behaviour during the events of the pandemic (Valle-Cruz et al., 2021). Although the results are yet to be determined statistically significant, there is evidence of causation between public sentiment and the market movements (Nisar and Yeung, 2018). Finally, it has been shown that Twitter sentiment has predictive power over certain cryptocurrencies, namely Bitcoin, Bitcoin Cash and Litecoin (Kraaijeveld and De Smedt, 2020).

One of the suggested underlying reasons behind this phenomenon is Twitter's capacity to effectively pool a big sample of the population. The availability of decentralised information combined with the convenient pooling resources, allows for a wide variety of sources and a fast sentiment assessment. Moreover, studies showed correlations between highly covered companies in social media and their stock price (Teti et al., 2019).

Regarding Elon Musk's Twitter presence, previous research suggests a highly significant increase in cryptocurrencies trading volume and prices after certain tweets. Furthermore, the effect of the posts is surprisingly fast, showing changes ranging between 3% and 12% in Dodgecoin trading in as little as two minutes. Similar effects have been observed in other cryptocurrencies (Ante, 2022).

Finally, after classifying Musk's tweets into positive, negative and neutral, a correlation between the positive ones and the stock price has been observed. Moreover, there is a strong correlation between Elon's engagement on this social network and the closing prices. An important outcome to take into account is that these correlations only become apparent when analyzed over months or years rather than short-term (Pyeong Kang Kim et al., 2021).

3 Data

The research included two sets of data. One is the corpus of Elon Musk's Tweets and the other is the daily closing price of TSLA (Tesla ticker in the stock market).

Elon Musk's Tweets were obtained from Olteanu's public dataset on Kaggle (Olteanu, 2021) containing the raw information for all the Tweets. The final dataset consisted of every tweet in Elon Musk's account from 2010 to 2020 which amounted to 12562 Tweets. The historical data of TSLA was gathered using the Yahoo Finance API and the YF library in Python.

3.1 Twitter dataset

Twitter is a social network that enables users to communicate via short messages called tweets. These tweets might include text, links, photos or even videos. Outlined below are some general concepts for the platform:

- Retweet: re-posting of a tweet, this means sharing someone else's tweet with all your followers.
- Tweet reply: response to someone else's tweet.
- Tweet like: represented by a small heart, used to show appreciation to someone else's tweet.

Figure 1 shows the variables extracted from the Twitter dataset, as well as their operational definition and data type. And shown in Figure 2 is the unprocessed initial dataset for Twitter.

Variable	Operational definition	Data Type
Date	date when the tweet was posted	DateTime
Time	time of day when the tweet was posted	DateTime
Username	Twitter user that posted the tweet	String
Tweet	Content of the tweet	String
Mentions	List of Twitter users mentioned in the tweet	List of strings
Urls	List of urls included on the tweet	List of strings
Photos	List of links of photos in the tweet	List of strings
Replies count	Number of responses to the tweet	Int
Retweets count	Number of retweets for the tweet.	Int
Likes count	Number of likes for the tweet.	Int
Hashtags	List of hashtags appearing in the tweet.	List of strings
Link	Tweet's link	String
Year	Year in which the tweet was posted.	Int

Figure 1: Variables for Twitter dataset.

date	username	tweet	replies_count	retweets_count	likes_count
2021-11-04	elonmusk	@vincent13031925 For now. Costs are decreasing...	640	444	15281
2021-11-04	elonmusk	Love this beautiful shot	2464	1517	71161
2021-11-04	elonmusk	@agnostoxxx @CathieDWood @ARKInvest Trust the ...	115	48	1380
2021-11-04	elonmusk	The art In Cyberpunk is incredible	8437	10329	228144
2021-11-04	elonmusk	@itsALLrisky 🤣🤣	446	542	7489
2021-11-04	elonmusk	@seinfeldguru @WholeMarsBlog Nope haha	234	65	2536
2021-11-04	elonmusk	@WholeMarsBlog If you don't say anything &...	222	201	2625
2021-11-04	elonmusk	@DeltavPhotos @PortCanaveral That rocket is a ...	214	296	11956
2021-11-04	elonmusk	Blimps rock https://t.co/e8cu5FkNOI	8811	6661	165302
2021-10-04	elonmusk	@engineers_feed Due to lower gravity, you can ...	1595	1936	48034

Figure 2: Initial columns in Twitter dataset

3.2 Tesla Stock dataset

Shown in Figure 3 are the variables utilized for the Tesla stock information. The dataset shows each of these values on a daily basis starting from 04/06/2010 to 12/31/2020, and the starting dates and ending dates match the tweets database.

Variable	Operational definition	Data Type
Date	Date for the stock information	DateTime
Opening price	Stock price at the beginning of the trading window	Float
Volume of stocks sold for the day	Number of shares traded in the stock	Int
Highest price of the day	Highest price reached by the stock during the day.	Float
Lowest price of the Day	Lowest price reached by the stock during the day.	Float
Closing price	Stock price at the end of the trading window.	Float
Adjusted closing price	Closing price amended to reflect that stock's value after accounting for any corporate actions	Float

Figure 3: Stock price dataset

Figure 4 shows the first 3 rows of the data. This data was then further saved as a .csv file for easier use.

Date	Open	High	Low	Close	Adj Close	Volume
2010-06-29	1.266667	1.666667	1.169333	1.592667	1.592667	281494500
2010-06-30	1.719333	2.028000	1.553333	1.588667	1.588667	257806500
2010-07-01	1.666667	1.728000	1.351333	1.464000	1.464000	123282000

Figure 4: Stock price dataset

3.3 Data preprocessing

For the Twitter dataset, the first step was removing irrelevant fields such as unique tweet ids (irrelevant for generalizing results), or fields which had incorrect data types and yielded null values. Then, the date was split in year, date of month and time, to perform further analysis over these variables (as we know from previous research that the time of day affects social media engagement).

Moreover, the following data cleansing techniques were performed over both datasets to ensure a sound analysis:

- Hashtags removal: hashtags were removed from the text of tweets and were moved to a separate column.
- Emoji translation: any emojis that occurred in the text were translated to text or Unicode with the emot library in Python.
- Usernames removal: usernames which start with '@' were removed from the text .
- Links removal: any sort of URLs including 'http', 'bit.ly and any other irrelevant links were removed from the text.
- Non-ASCII character removal.
- Email address removal.
- Punctuation removal: any sort of punctuation was removed from the tweet in order to make the text classification more efficient.
- Stopwords removal: with the help of NLTK library in Python, any sort of stopwords used in English language of NLTK corpus were removed from the text.
- Special characters removal.

All these methods were applied in Python using regular expression and the regex library, and the process is summarized in Figure 5.

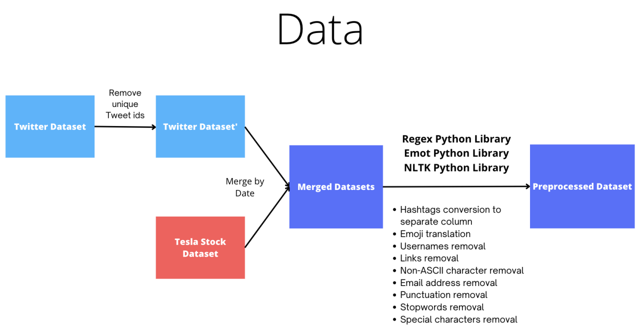

Figure 5: Final dataset construction flow

date	username	new_tweet	replies_count	retweets_count	likes_count
2021-11-04	elonmusk	now costs decreasing rapidly	640	444	15281
2021-11-04	elonmusk	love beautiful shot	2464	1517	71161
2021-11-04	elonmusk	trust shrub	115	48	1380
2021-11-04	elonmusk	art cyberpunk incredible	8437	10329	228144
2021-11-04	elonmusk		446	542	7489
2021-11-04	elonmusk	nope haha	234	65	2536
2021-11-04	elonmusk	dont say anything amp engage autopilot soon gu...	222	201	2625
2021-11-04	elonmusk	rocket hardcore veteran missions	214	296	11956
2021-11-04	elonmusk	blimps rock	8811	6661	165302
2021-10-04	elonmusk	due lower gravity travel surface mars surface ...	1595	1936	48034

Figure 6: Preprocessed tweets

4 Method

The tweets were first split into two categories: 'Personal' and 'Professional'. Because this study is evaluating the Tesla stock, a Tweet was considered 'Professional' if it included the word 'Tesla', and 'Personal' otherwise for a trivial evaluation. Further, a corpus could be made for Tesla words and non-Tesla words and a model could be trained to more efficiently classify tweets but that is beyond the scope of this project.

After the data was pre-processed, RoBERTa-base model was used for Sentiment Analysis to classify the data into three categories: Positive, Negative or Neutral. The pre-trained model (Hugging Face, 2021) was trained on 124 million tweets from January 2018 to December 2021. RoBERTa or 'a robustly optimized BERT pretraining approach' builds on BERT and does hyperparameter tuning, removes next-sentence pretraining objective and trains with much larger mini-batches and learning rates. It outputs 0 for Negative, 1 for Neutral and 2 for Positive for some input text. The twitter data was first tokenized accordingly and then this model was applied in order to classify it into sentiments.

Finally, for each date, a sentiment score was computed by averaging the sentiments for all the tweets for the given date.

For the Tesla Stock dataset, a delta score was computed by calculating the difference between the closing price for a date and the previous day. This value was then classified as 'Increase' or 'Decrease' depending if it was bigger or smaller than 0 to perform the analysis.

The process for building the predictions and corresponding scores is summarized in Figure 7:

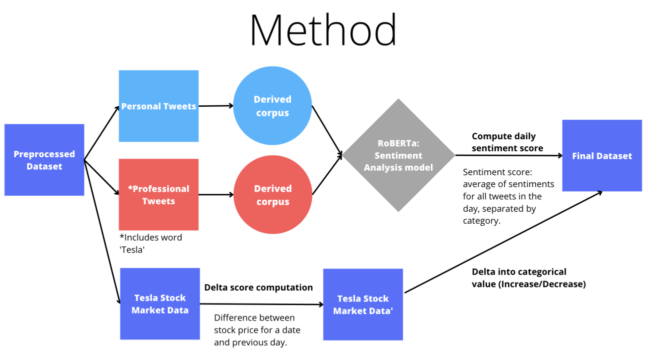

Figure 7: Method diagram

5 Results & Discussion

For the initial analysis, Elon Musk's presence in Twitter was analyzed. His presence has grown over the years, starting with 0 tweets in 2010 until reaching almost 3500 in 2020, as shown in Figure 8.

As well as the number of tweets, Elon's popularity increased over the years, as shown in Figure 9. This was analyzed by reviewing the likes, responses, and retweets over the years. The graphs show an increase of over 400% for the average likes and retweets, and an increase of over 120% for the average replies. This is consistent with the presence growth.

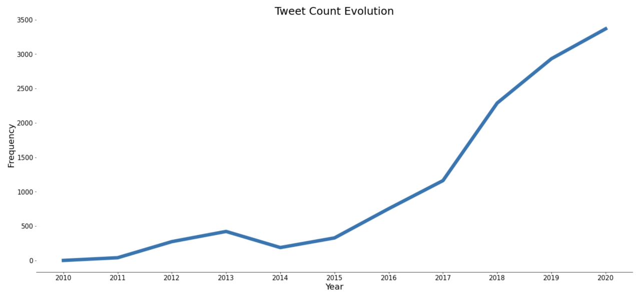

Figure 8: Tweet count evolution

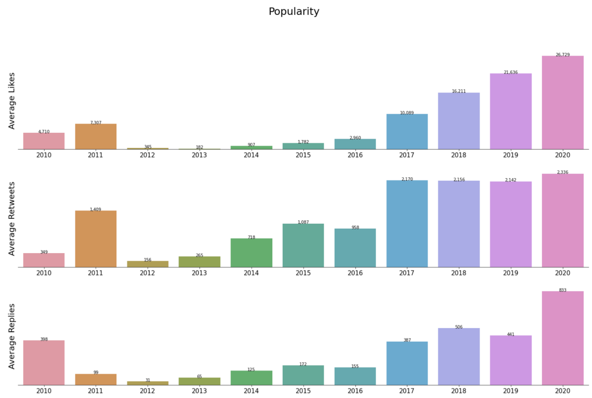

Figure 9: Elon Musk's Tweets popularity

It was found that 50% of the tweets were negative, 38% were positive and rest 12% were neutral (Fig. 10). Further, the **Chi-Square test of Independence** was used in order to check if the sentiments are likely to be related to the prices of stock going up.

$$H_0 : \text{Variables are independent}$$

$$H_a : \text{Variables are dependent}$$

Since, the Chi-Sq test is usually performed on two-categorical variables, new variable was created to indicate the increase in price. It was set to 1 to indicate if the closing price increased that day and it was 0 to indicate if the stock price didn't increase. Now, that two categorical variables were available, and they satisfied the conditions of Chi-Sq test-the variables were collected independently from each other, and no cell had an expected count of zero, the test yielded the following results.

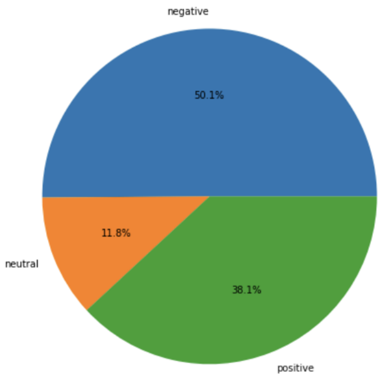

Figure 10: Sentiment analysis.

The **p-value** was found out to be **0.8679** which is more than 0.05. Here, the null hypothesis was accepted and it was observed that sentiment and increase in stock price were independent of each other. This test yields interesting results as it was observed that the sentiment does not drive the stock price according to the chi-sq test. It means according to our data set, the sentiments are independent of the increase in stock price.

Whereas, the same test was also performed on the variable which defines if the tweet is a professional tweet or not. The variable is 1 if the tweet is a professional tweet and zero otherwise. The **p-value** was found out to be **zero**. The analysis was done using the researchpy library in Python which approximates values to zero when they are too small. Here, the value was lower than 0.05 and the null-hypothesis was rejected which implies that there could be a possible relation if a tweet is professional or not and if the stock price goes up or not.

Since, the number of professional tweets that contained the word 'Tesla' was found out to be 2378, and 10184 tweets were unprofessional not containing the word 'Tesla', they were normalized and percentage of the said specific tweets was used to find out if they led to increase in stock price. Specifically, it was 51.52% of Tesla tweets and 51.65% of non-Tesla tweets which led to increase in stock price.

Next, Analysis of Variance(ANOVA) was supposed to be used to test if different sentiments had a varied impact on the closing price but since the data is not normally distributed, and does not follow any particular distribution, ANOVA could not be performed. Instead, **Kruskall Wallis H-Test** was performed which is a non-parametric alternative to ANOVA and is used when the conditions for ANOVA are not met. The **p-value** was found out to be **0.095** which led to the acceptance of null-hypothesis and it can be said that there is not statistical difference in the impact of different sentiments on the Tesla stock price.

Matt Whitney U-Test was performed on the professional(Tesla)/non-professional tweets and the Tesla closing price. The U-Test is performed when there are only two groups. The data contains 5 sentiments which is why H-Test was performed but since the tweet classification is only binary i.e. contains two groups, the U-Test was preferred over the H-Test. The **p-value** was found out to be **zero**, thus leading to a rejection in null-hypothesis which means that the impact of non-professional tweets versus the impact of professional tweets on the Tesla stock price differ.

6 Conclusion

The following observations were made after performing the various test and analysis.

- It was found out that the change in stock price is independent of the sentiment of tweets. On the other hand, the stock price does depend on whether the tweets contains the word Tesla i.e. if the tweet is professional or not.
- The impact of different emotional groups on the stock price was also checked and it was seen that there is no difference in impact of different emotions on the stock price.
- Whereas, it was found out that the impact that a professional tweet has on the stock price differs from that of a non-professional tweet.

7 Future Aspects

Further, this study can be extended and the effect of tweets grouped by more categories could be looked at for the analysis. A better model to classify the tweets into professional and non-professional/casual tweets could also be introduced. Also, it is trivial that a tweet is not the only parameter which affects the stock price of a company and hence, the study could look at major events which might have caused an inflation or deflation in the stock price and disregard the impact of tweets for those specific days or rather remove those days from the dataset and normalizing it to include just the impact of tweets. A time series machine learning model maybe introduced to see if a the prediction made by just the category of tweet follows the trend that stock price makes up.

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