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TRA 301/COS 401: Machine Translation

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Trump's Tweets, Sentiment Analysis, and the Stock Market

1. Motivations

Trump's presidential terms have been unprecedented in many ways – his administrations have openly flouted governmental norms; implemented policies that have shocked other countries, allies and enemies alike; and pushed for blatant falsehoods to become accepted as general truths. Additionally, more often than not, Trump uses Twitter (now X) to provide commentary on or even announce these unprecedented political decisions. Trump's prolific use of Twitter to declare new policies, lambast his critics, and even fire members of his own administration demonstrate Trump's own understanding of the power of his social media use and his ability to influence reality for his millions of followers. On a more fundamental level, it is also completely possible that Trump cannot help but tweet; attempts by his aides to curb his Twitter use have been completely useless. Trump insists on using Twitter as an official communications channel between himself and the world, even while his administrations' relationship with established news media has often been rather fraught (Shear et al.).

However, economists have noted that the "one authority" (Klebnikov) that will rein Trump in is the performance of the stock market. This is likely because the stock market serves as an immediate litmus test for how Trump perceives the economy will respond to his policies. Despite this, during both terms, Trump has insisted on pursuing trade wars with other countries – primarily China – which have "pushed stock volatility up to its highest level in years" (Laidley).

Therefore, given that Trump's Twitter has essentially become the most accurate representation of Trump's state of mind (and, therefore, his administration's political leanings) at any given time, it would make sense that investors would look to Trump's tweets as a sort of preview – or even warning sign – of the later-implemented policies. As a result, if it is widely believed that Trump's tweets foreshadow the official announcement of significant political decisions, investors would probably react to Trump's tweets accordingly.

By using natural language processing, we can conduct sentiment analysis on Trump's tweets to test this hypothesis. For example, if Trump's tweets have an overall positive sentiment, with no major news of Cabinet members being fired or angry condemnations of other world leaders, the markets are probably more likely to remain stable, and the opposite would also be true.

2. Literature review

In the past, researchers have attempted to conduct sentiment analysis or at least topic analysis on Trump's tweets and studied the influence the changes in sentiment have on societal or economic trends. A 2023 paper written by Jennifer Zheng from the University of Washington, Seattle, and Joseph Zompetti from the Illinois State University notes that after Trump used the #ChineseVirus hashtag on Twitter, the use of the hashtag exploded by more than 8000%. Critically, the hashtag was often used in tweets that explicitly advocated for anti-Asian hate – for example, users suggested bombing Asian cities or killing Asian people (Zompetti and Zheng). Overall, anti-Asian hate crimes increased by 77% in 2020 ("2020 FBI Hate Crimes Statistics."). While it would be unreasonable to argue that anti-Asian hate crimes were solely spurred by the use of a single hashtag by Trump, it is probably more likely that Trump's directly linking the

COVID-19 pandemic to all things "Chinese" legitimized the view of Chinese and Asian people as an outside threat, which contributed to the rise in hate crimes.

While this paper did explore the influence of Trump's tweets on public perception (which in turn influences the decisions of individual citizens), it mostly focused on applying rhetorical analysis to Trump tweets that blamed Asian people for the pandemic; the scope of this study was quite narrow. Moreover, while the link between problematic discourse from a political leader to problematic discourse from the leader's supporters is quite intuitive, the link between the "sentiment" of informal, highly frequent communication from a political leader to concrete economic decisions from investors is less so. In order to find existing research that specifically examined this correlation, I turned to a paper by researchers from the IESEG School of Management that contributed to existing oil prediction models by including Trump's tweets as a factor. The researchers ultimately concluded that by using a BERT model – a "bidirectional encoder representations from transformers" model – along with a deep neural network Long Short-Term Memory (LSTM) architecture – the oil price for a given day was predicted using the previous five days of data – the oil prediction models were significantly improved. In this paper, the BERT model was first used to remove oil-related keywords from the tweets, and then was used to completely remove tweets containing oil-related keywords before using the LSTM model in order to test the effect the tweets had on the prediction models (Creemers et al.).

In this paper, the researchers note that oil prediction is a highly complex task with multiple possible factors, and they admit themselves that research on the influence that comments from political leaders have on the economy is a very new topic. However, given that the researchers found such a confident link between Trump's tweets and oil price movement, I wanted to know if other researchers had used different NLP techniques to filter and analyze tweets to study their impact on the economy.

Daniel Ortiz from the University of Erlangen-Nuremberg found that by using a clustering algorithm to group Trump tweets by topic, he found that tweets that fell under the topics of foreign policy and trade, monetary policy, and immigration policy had the greatest effect on market volatility, but that these effects were mostly temporary (Ortiz). Furthermore, Yusaku Nishimura from the University of International Business and Economics in Beijing also used sentiment analysis to analyze Trump's tweets, and discovered that the "stronger" the sentiment was, the more volatile the stock market was (Nishimura). Notably, Nishimura uses keywords from the Volfefe Index, which was developed by JP Morgan to track the influence of Trump's tweets on the US interest rates market; these keywords were identified by JP Morgan analysts to have the greatest impact on US interest rates (Ahmed). Additionally, Nishimura also adds some other keywords relating to economics and trade (Nishimura).

3. Methodology

Both of Trump's presidential terms have seen economically tumultuous times; I chose to focus on Trump's first presidency for a few reasons. First, Trump's second presidency has only just begun, which would have only given me a limited amount of data to experiment on. Second, his current administration made imposing tariffs on other countries an immediate priority, throwing the economy into chaos almost instantaneously; this also would have given me fewer opportunities to contrast periods of relative economic stability with more volatile periods (Minsberg). Third, a distinctive feature of Trump's second term has been his frequent use of executive orders to quickly implement policies. In this case, it would be difficult to distinguish between the effect his tweets had on the stock market and the impact his executive orders had on the stock market, particularly because Trump signs more than one executive order per day on average ("The 141 executive orders").

For Trump's tweets, I used the Trump Twitter Archive, which has stored every tweet from President Trump from 2009 to 2024. Although the website is built by a single programmer, this site is considered to be accurately faithful to its source material, and has been cited by reputable news sources such as *The New York Times* (Syckle). Before downloading the data, I filtered out all retweets, as these would not have been written in Trump's own words. For stock market data, I used MarketWatch to download S&P 500 index information. Since the S&P 500 includes information on 500 US companies by definition, this would be a fairly accurate representation of overall stock market performance as opposed to selecting a single company's stock prices, which would be more dependent on company-specific news.

Before analyzing any of the data, I preprocessed the tweets by removing all tags, links, and duplicate tweets. Since some tweets simply contained a single link, once the all links were removed, I also removed all empty tweets. Then, I grouped tweets by post date and sorted within the list of tweets each day by the number of likes each tweet received. As for the S&P 500 stock market data, I decided to select only by the closing index, as the closing index would most likely represent the position that investors would be most confident in holding when markets close for the night or over the weekend (Hayes).

I decided to use a tool developed by CardiffNLP[1], a research group from the University of Cardiff in Wales. This tool was a RoBERTa base model trained specifically on approximately 124 million tweets in order to perform sentiment analysis on tweets. (This RoBERTa model is a variant of the BERT model, which was found to be the most helpful by the IESEG researchers.) I

[1] https://huggingface.co/cardiffnlp/twitter-roberta-base-sentiment-latest

used the tool to classify every tweet into three categories – positive, negative, and neutral – with associated scores for each category label. Then, I used the softmax function to convert every score into a probability – as a result, the higher the score of a certain sentiment, the higher the probability that the tweet would be categorized as that sentiment. I decided to only select for positive sentiment scores, because I thought that the change in positive sentiment would be most closely correlated with changes in the S&P 500.

Furthermore, as the IESEG researchers and Nishimura found, filtering tweets by topic often returned the most interesting results. For this, I used Facebook's bart-large-mnli model[2] as a classifier to find the probability that a given tweet would fall under the "economy" and "no economy" label. The model developers also noted that this particular model would work the best when paired with RoBERTa as well.

4. Findings

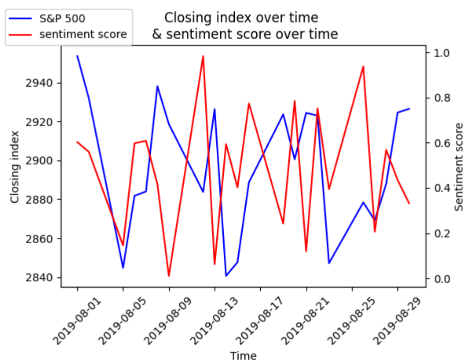
For every test iteration below, I took tweet data and stock market data in batches of one month at a time. However, because there is obviously only one closing index per day, I had to decide how to calculate a single representative sentiment score per day out of all of Trump's tweets per day. When I was analyzing the tweet data, I provided several options: calculating the maximum, mean, or median positive sentiment score; changing *n*, or the number of most-liked tweets included in the calculation; including or removing the economy topic filter; and finally, when the economy topic filter is included, changing the probability threshold at which a tweet is included under the economy topic or not.

[2] https://huggingface.co/facebook/bart-large-mnli

Initially, for these trial runs, I decided to use the month of August 2019. During this month, in the midst of Trump's first trade war with China, economic tensions and tariffs escalated. On August 23, China retaliated against Trump's tariffs (Bown).

First, I experimented with calculating the maximum, mean, or median. I filtered the tweets to only include tweets relating to the economy, with a filter threshold of 0.5, and considered only the top five most liked tweets per day in my calculations.

Using the mean:

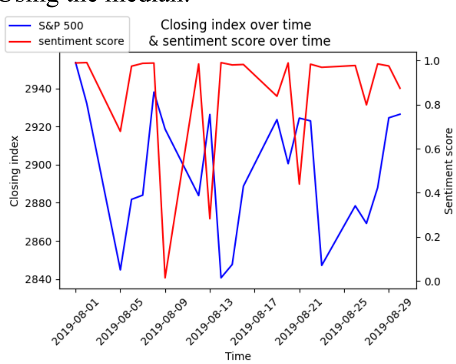


Correlation coefficient: -0.1232

Using the maximum:

Correlation coefficient: -0.2109

Using the median:

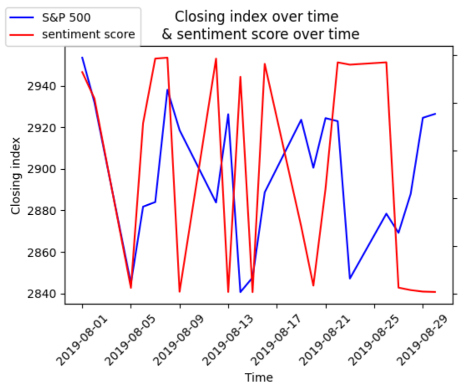


Correlation coefficient: 0.0080

Although the correlation is very small, taking the median still provides the strongest correlation. This is relatively unsurprising; the median would exclude outliers by definition, and would hypothetically be more representative of Trump's overall mood throughout the day without considering more erratic bursts of extremely positive or extremely negative sentiment.

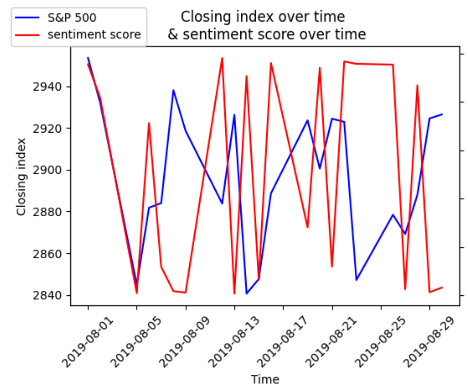
However, I also wanted to experiment with the number of most-liked tweets that would be considered when calculating the median. The results are as follows:

n = 1:



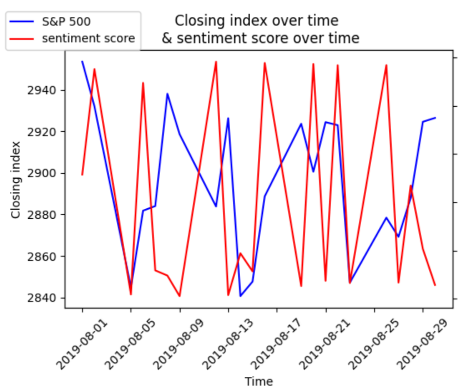
Correlation coefficient: -0.0075

n = 3:



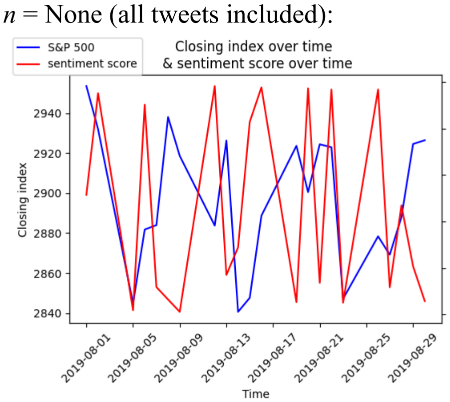
Correlation coefficient: -0.1387

n = 10:



Correlation coefficient: 0.0728

n = None (all tweets included):

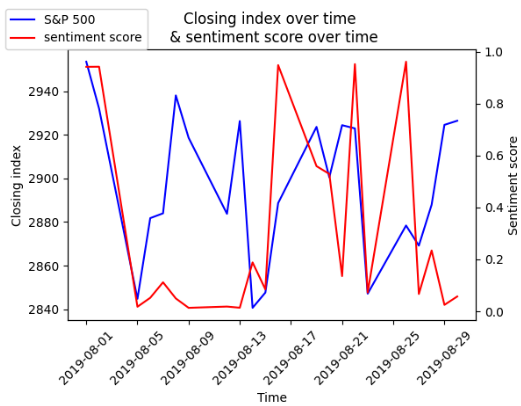


Correlation coefficient: -0.0560

Considering the top 10 tweets per day returned the highest correlation. On the days where Trump tweets less than 10 times a day, all the tweets for that day were included in the median calculations. It was not exactly clear to me why only considering the top 10 tweets per day was better than considering all the tweets per day. One possible reason was that a generally higher *n* is better in order to consider more potential representative scores, but an *n* that is too high would also capture tweets with little substance, such as photos with brief commentary. (I had originally hypothesized that selecting for the single most-liked tweet per day would actually correlate the most with the stock market, since the most-liked tweet would likely provide the most shocking or dramatic news.)

I also wanted to see what would happen when I did not filter by the economy topic at all.

filter_trade = False

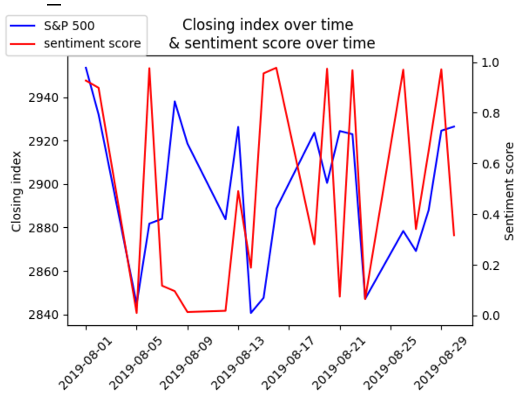


Correlation coefficient: 0.3026

This was very surprising, but perhaps reflects the reality that any kind of political action will eventually impact the economy, so all of Trump's tweets are relevant to investors.

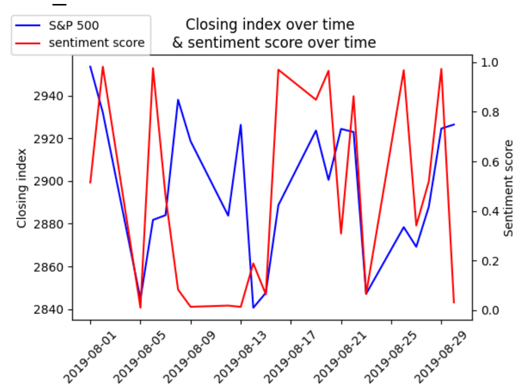
However, I wanted to make sure that the issue was not with the filter threshold. By successively raising the filter threshold, I was able to test if only selecting tweets that were more definitively related to the economy would make any difference.

filter_threshold = 0.6



Correlation coefficient: 0.1774

filter_threshold = 0.7



Correlation coefficient: 0.2379

filter_threshold = 0.8

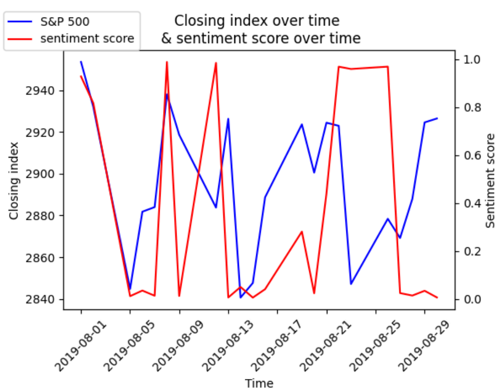
Correlation coefficient: 0.2128

filter_threshold = 0.9

Correlation coefficient: 0.2344

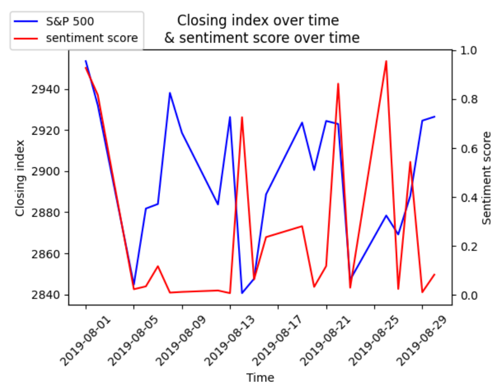
In this case, the correlation coefficient seems to peak at around 0.7, but completely removing the economy topic filter is better. Moreover, $n = 10$ without the economy topic filter is still best.

$n = 1$:



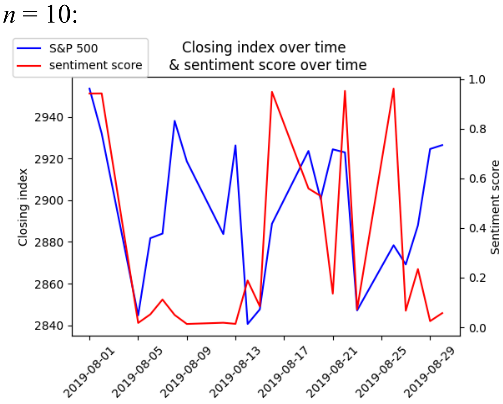
Correlation coefficient: 0.2607

$n = 5$:



Correlation coefficient: 0.1631

$n = 10$:



Correlation coefficient: 0.3026

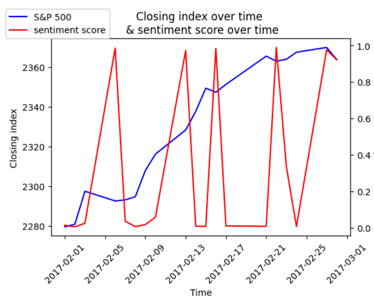
$n =$ None:

Correlation coefficient: 0.2122

5. Observations, discussions, future work

It is completely possible that the decisions I made to "adjust" to the August 2019 data would not work for other months. For example, when I used February 2017, the first month of Trump's first term, setting n = None was ultimately better.

$n = 1$:

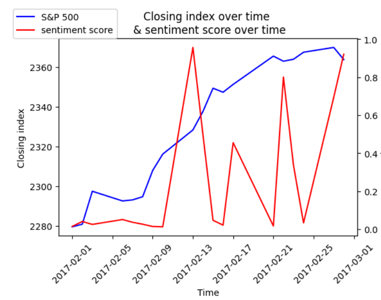


Correlation coefficient: 0.3338

$n = 10$:

Correlation coefficient: 0.5044

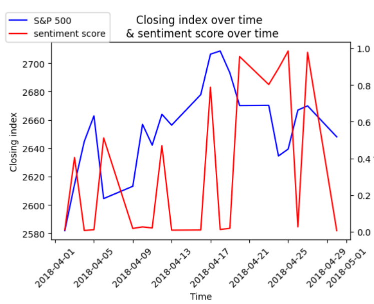
n = None:



Correlation coefficient: 0.5049

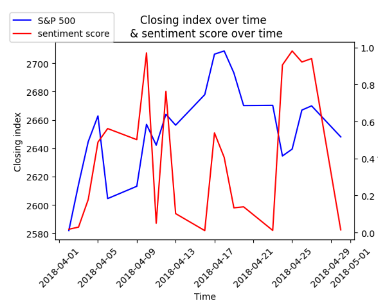
This was also true for April 2018, when China retaliated to Trump's tariffs on solar panels (Mistreanu).

$n = 1$:



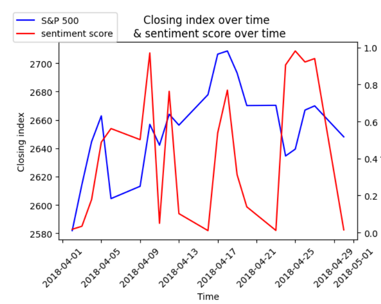
Correlation coefficient: 0.0770

$n = 10$:



Correlation coefficient: 0.0761

n = None:



Correlation coefficient: 0.1862

Clearly, small changes in the calculation process can return very different results.

Additionally, even the highest correlation coefficients were still relatively low, which reflects the complicated nature of the stock market – there are simply too many variables to narrow down on one specific source of information, given my rather simplistic method. This method also does not differentiate between correlation and causation. Since the stock market has such a strong influence on Trump, it is also likely that a drop in the S&P 500 could cause Trump to become more pessimistic, and thus tweet more negatively. For later work, I could focus more on the specific timestamps of each tweet, and track changes in the stock market during the immediate time period after Trump posts a tweet.

In addition, the topic classifier was rather flawed; since other studies filtered by keywords, perhaps using keywords would be better in addition to or in place of the classification model I used above. Alternatively, I could also make the classifier more specific by including more than just one pair of binary labels (I only used “economy” vs. “no economy”).

Finally, after Trump’s second term has ended, I could utilize the timestamp strategy as mentioned above in order to differentiate between the effect of Trump’s executive orders and Trump’s tweets. However, because Trump now posts on Truth Social in addition to Twitter, I would also scrape his Truth Social account as well for a more complete dataset.

Ultimately, though it seems rather ridiculous that social media posts from the president are correlated with stock market performance, the results show at least a partial connection. This is not ideal; America’s stock market should not be dependent on the rapidly changing sentiment of anyone’s tweets. However, as Trump’s tweets grow more and more frequent, those around him are unfortunately reluctant to dissuade him from using the app. Dramatic fluctuations in the S&P 500 index will unfortunately become increasingly prevalent.

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