Algorithmic Detection of President Trump's Tweets Likely to Move the Market

Lena Yemelyanov

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Abstract

This study is focused on creating a classification algorithm that will flag new tweets from the @realDonaldTrump twitter account as potentially upsetting the market and increasing its volatility. The data set of flagged tweets is created by analyzing jumps in SPY.P stock and identifying tweets corresponding to jumps in the stock market returns. This data set is compared with a control data set of the other tweets that were not linked to any market movements. Using these two data sets, I create a specialized lexicon to classify future tweets as either innocuous or potentially causing market movement. This lexicon is enhanced by accounting for potential concept drift and synonym casting. The results are evaluated using the algorithm's accuracy and detection rates.

1 Introduction

Donald Trump's twitter activity and its broader impact has captured the attention of the economic and financial researchers since he announced his presidential candidacy in mid 2015. As the President of the United States, Mr. Trump has been known to announce policy and staff changes via social media. For example, on July 26, 2017, Donald Trump tweeted his decision to ban transgender individuals from serving in the US military. No such announcement was made before this tweet. Following this tweet, significant volatility was recorded in the stock market once trading opened for that day. Another similarly unexpected announcement happened when Mr. Trump fired former secretary of State, Rex Tillerson, via a single tweet. Given that @realDonaldTrump often releases unscheduled news of national importance via Twitter and that Efficient Market theory states that any publicly available news is immediately incorporated into the stock price, this work creates an algorithm that aims to predict jumps in the stock market, measured here using SPY.P indicator, by analyzing the text of each incoming tweet. This work can potentially be applicable to the social media usage of other influential individuals, whose thoughts and ideas might be construed by the market as news affecting the market sector where the individual's decisions carry importance.

2 Literature Review

The relationship between President Trump's twitter activity and its effects on the stock market has been explored in a variety of works, though prior to creation of the Volfefe index (Stewart 2019), no work has attempted to create an algorithmic predictor of the impact. The Volfefe index relies on a proprietary software created by JPMorgan Chase to quantify the volatility created by the President's tweets. Unfortunately, the explanation of the practices used to create the Volfefe Index is not publically available and therefore not included in this work. Besides Volfefe, there exists a large body of work attempting to establish a link between the behavior of the financial markets and the President's social media habits.

One of the first such attempts, described in (Simpson 2018), conducted a manual analysis of the sentiment in @realDonaldTrump tweets to establish a correlation between market returns and negative sentiments expressed by the President. This study was done using a small sample of tweets (34 total), and a strong relationship was established between the President's negative tweets and volume increase in the first two minutes following a tweet, studying both SPY and VXX minutely data.

A similar study (Fendel, Burggraf, and Huynh 2019) describes how political tweets that mention the terms "China," "trade," "trade war," and "tariffs" generally impact financial markets. The study identified and examined a very limited number of tweets (77 in total), however it was able to apply the Granger causality test to confirm the effects of Trump's tweets that use those specific terms on SP500, with stronger effects registering in the subsectors that rely heavily on international trade, especially trade with China.

In (Bianchi, Kung, and Kind 2019), the authors presented market-based evidence that the President's twitter activity influences the expectation about monetary policy. The work used the fed funds futures as a vehicle to measure this response. Bianchi et al. confirm that Trump's tweets criticizing the Federal Reserve affect the fed funds futures, leading to persistent decline in expected target rates. The payoff of these futures depends on the average fed funds rate calculated within the final month before contract expiry. Comparing this calculation to the expected fed funds rate implied by future price shows decline in the expected interest rate following a tweet. The President advocates for looser monetary policy and often threatens the independence of the agency. For the contracts that are set to expire after one or more FOMC meeting, the tweets have a negative and statistically significant impact on the expected fed funds target.

Given the probable connection between Trump's twitter activity and the financial markets explored by other researchers, in order to build a detection algorithm, this project defines a criteria of what constitutes a tweet that influences the market. Using the technique defined by (Lee and Mykland 2007), it is possible to identify abnormal returns in the SP500 without relying on Capital Asset Pricing Model (CAPM), which uses SP500 return as a point of reference. The non-parametric approach for jump detection described in (Lee and Mykland 2007) defines a threshold parameter for each of the observations in a time series. Any observation where that parameter is exceeded is considered to have a jump in return.

Another method was borrowed from (Baker, Bloom, and Davis 2016) focused on identifying particular words that help identify increase in Economic Policy Uncertainty (EPU) Index. This index was created by analyzing news articles by searching for specific terms. The index is calculated as the ratio of articles that contain the uncertainty terms to articles that do not contain said terms. Their results show clear spikes in the ratio around periods of economic uncertainty ex Gulf War, 9/11 attacks, 2008 economic stimulus and TARM legislation, etc. A similar study was then successfully repeated using other terms for specific policies - for example, the Affordable Care Act.

All previous readings suggested that the best approach for evaluating Trump twitter activity would involve building a specialized lexicon. In (Watt, Carvill, House, Livingston, and Williams 2017) Trumps tweets were characterized into three genres of rhetoric originally introduced by Aristotle: deliberative, epideictic and forensic, indicating that some types of rhetoric (for example, deliberative) are likely to carry greater meaning and impact. Extrapolating from that study, a combination or repeated use of certain parts of speech is likely to be associated with one type of tweet rather than another. Therefore, this project explores how weighing parts of speech differently may improve detection and accuracy. The more technical aspects of this are discussed further by (Kolchyna, Souza, Treleaven, and Aste 2015), which provides recipes and recommendations on working with parts of speech, stemming and lemmatization, and building a lexicon using twitter data.

I followed the step-by–step procedure for basic twitter data cleaning and analysis provided by (Bagheri and Islam 2017). Building on that, I tailored the recommendations specified by (Silge and Robinson 2017) to construct a custom dictionary using tidy data. Next, I incorporated Christopher Potts' method to calculate relative probabilities for the terms within a data set (Potts 2019). I used Potts' technique in this project to calculate tweet polarity scores. These methods are discussed at length in the following Section 3.

3 Methodology

To download the code referenced in this project and its associated documentation, use the following link: https://github.com/lenay12/algoTweetDetect

3.1 Data

In order to investigate the impact of the Presidents twitter activity on the financial markets, a minutely SPY.P dataset was used as a gauge. The SPY.P stock provides a very close approximation for the SP500 movements. The dataset comprises 668 individual files in *csv* format, each containing minutely time series data for the stock market. This allowed for the real time changes in returns to be observed and corresponded with "news" published in @realDonaldTrump twitter feed. The variables used in this project are trading date, trading time, close price and trading volume. I use an algorithm written in R to load and concatenate this data into a single data frame. The data set was subset between January 20, 2017 and September 19, 2019 to capture the beginning of Trump presidency through the start of this project.

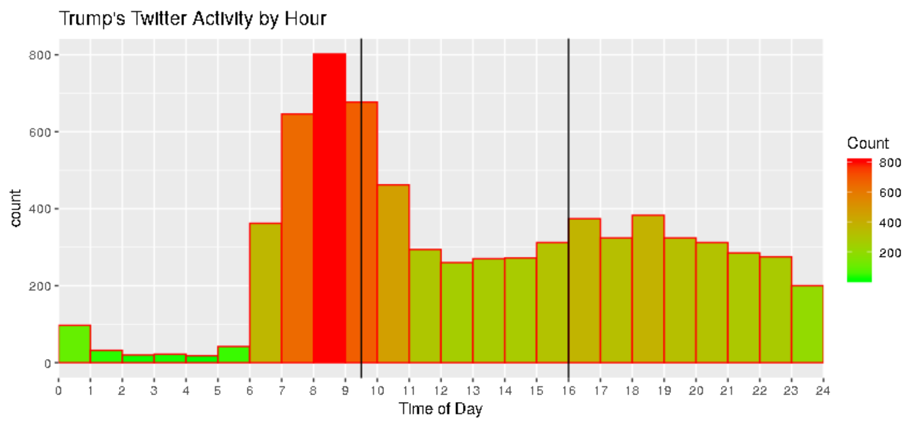
The actual twitter text data was collected from two different sources. The bulk of the data was retrieved in *json* format from (Baumgartner 2019), which spans January 20, 2017, through July 11, 2019. The data from July 12, 2019, through September 19, 2019, were obtained from (Vicinitas 2019) as a series of multiple *csv* files.

To prepare twitter data, two separate R algorithms were created to ingest the data. The variables that contain the time created, tweet text, and tweet type were employed for further analysis. Next, the text data was stripped of all non-UTF8 characters, links, and hashtags. Furthermore, careful investigation and adjustment of time zone had to be made to the "time created" variable to ensure that each tweet timestamp could be accurately matched to the market data. Since each of the tweets has a secondly time value, this temporal value is converted to minutely frequency by rounding each minute down to zero seconds. This design decision allows me to check the current minute and the following minute for changes in return and reduces some of the guesswork.

In order to make sure that the empirical analysis could be conducted in a robust way, only the data captured during the market's operating hours (business days between 9:30am and 4:00pm EST) was used. This decision was made because of trading volume dropping significantly before and after the market hours and therefore making it more difficult to identify abnormal returns.

Unfortunately, using twitter data generated during the open market hours significantly limited the size of the twitter data set. There was a total of 9,911 tweets in the initial twitter data set, however, once this data was updated to include only the tweets generated during the open market times, only 1,523 tweets remained. This outcome is not that surprising considering the President's typical twitter activity by hour of the day (see Figure 1). While the President tweets throughout most of the day, taking a break between midnight and 6 a.m., his heaviest twitter usage occurs between 7 a.m. and 10 a.m.; a majority of that window occurs before the markets open.

Figure 1: Likelihood of Tweets by Time of Day



3.2 Stock Market Jumps in Return and Volume

In order to identify which of the tweets will be treated by the market as unscheduled news announcements, I use a non-parametric test to detect jumps and identify abnormal returns in the stock market. This methodology is discussed at length by (Lee and Mykland 2007). (Lee and Mykland 2007) define a jump as significant discontinuity in returns generated by financial markets. The theory for the jump detection assumes that continuously compounded return can be written as $dlogS(t)$ for $t >= 0$ where $S(t)$ is the asset price at time t. In the absence of jumps $S(t)$ takes on the following form:

$$dlogS(t) = \mu(t)dt + \sigma(t)dW(t)$$

where a standard Brownian motion $W(t)$, drift $\mu(t)$ and volatility $\sigma(t)$ are measurable functions.

However, when jumps are present, the stock return behavior can be modeled by the equation above with an added term $Y(t)dJ(t)$:

$$dlogS(t) = \mu(t)dt + \sigma(t)dW(t) + Y(t)dJ(t)$$

where $J(t)$ is a counting process independent of $W(t)$; $Y(t)$ is the jump size, where jumps at times t are independent of one another and identically distributed.

In order to detect these jumps $Y(t)$, (Lee and Mykland 2007) define jump statistic $\mathcal{L}$ as a ratio of realized return to the estimated instantaneous volatility $\widehat{\sigma(t_i)}$ Examining the relationship between the size of the returns and the instantaneous volatility, allows the distinction between the return increases due to high volatility and actual jumps.

$$\mathcal{L} \equiv \frac{logS(t_i)/S(t_{i-1})}{\widehat{\sigma(t_i)}} \tag{1}$$

where

$$\widehat{\sigma(t_i)}^2 \equiv \frac{1}{K-2} \sum_{j=i-K+2}^{i-1} |logS(t_j)/S(T_{j-1})||logS(t_{j-1})/S(t_{j-2})| \tag{2}$$

The instantaneous volatility can be estimated as the sum of squared returns and the calculated using sliding window K. The optimal size of sliding window is defined as:

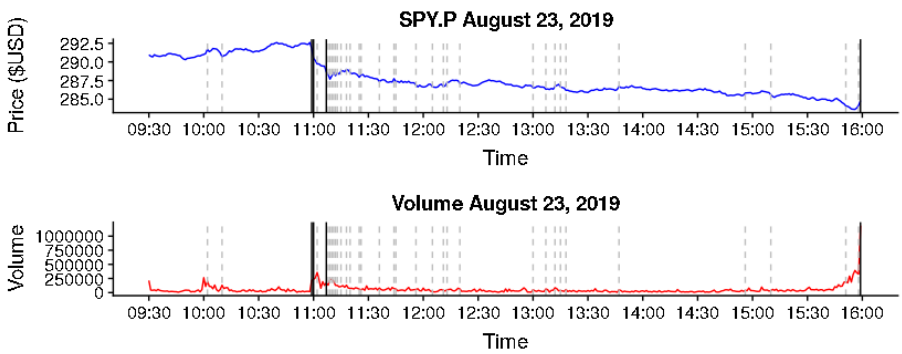
$$K = \sqrt{252 * nobs}$$

The number 252 is used to represent the total days the market is open during the year and $nobs = hourperday * minutesperhour$. Therefore, the selected window $K = \sqrt{252 * 24 * 60} = 603$

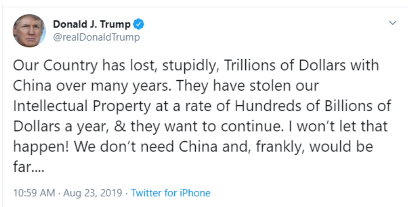
In absence of jumps $\mathcal{L}(i)$ will behave as a standard normal variable. For the purposes of this work, the rejection region for the null hypothesis is selected to be 2 standard deviations away from the mean, rather than a larger statistic defined in (Lee and Mykland 2007). This decision allows this project to capture market fluctuations that are outside of the 95th percentile of the probability distribution. This design choice allows me to capture greater amount of relevant data. This paper defines a "jump" when the statistic is greater than $\mu + 2\sigma$, where $\mu = 0$ and $\sigma = \sqrt{\frac{\pi}{2}}$ therefore a jump i will occur when $\mathcal{L} > 2.51$

Once the jumps in the SPY.P data set are identified, the market data set is joined to the tweet data set on the time axis as described above. Figure 2a illustrates a particularly turbulent stock market day. The larger jump perfectly aligns with the tweets shown below in Figure 2b and Figure 2c.

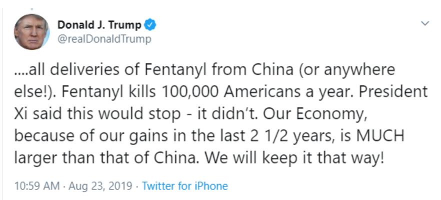
Figure 2: Donald Trump tweet corresponding to the market jump



(a) Stock Market Jumps, August 23, 2019



(b) Part 1



(c) Part 2

3.3 Tweet Clustering

In order to further conduct textual analysis, the data is clustered into two categories: tweets of interest and tweets with no impact, referenced from here on as Impact and NoImpact data sets, respectively. The jumps defined in Section 3.2 are used as the decision variable to identify the category where each tweet will be placed. Impact data contains a total of 270 tweets, while the remaining 1253 tweets are categorized as NoImpact. Given the small number of observations in the two data sets, further examination is done using customized term frequency analysis rather than out of the box machine learning models.

3.4 Custom Dictionary

To analyze and compare the two project data sets, the most frequently occurring terms were identified in each of the data frames. The underlying goal was to build two distinct lexicons that could be applied to a posted tweet to classify whether it would be more likely to belong in the Impact data set rather than NoImpact. To that end, terms that appeared in both data sets within some range of equal probability were removed from both lexicons, since they did not add additional information. For example, the term "great" is equally likely to appear in tweets that impact the market as it is in tweets that do not impact the market. However, in recent months, any reference to presidential candidate Biden was far more likely to appear in the tweets that impacted the market than in the tweets that had no effect on the market. Conversely, "thank" or "thank you" were almost never in the high impact data set and can typically be considered a signal that tweets with these words will have no market impact. In the following sections, each of these concepts will be discussed individually and in greater detail.

3.4.1 Frequently Used Terms in Each Cluster

Before beginning term frequency analysis, text data was subset using the preselected time window in order to reduce the concept drift; this ensures that only currently trending terms in each data set are considered. For further discussion on this, consult Section 3.4.4. Next, each term in a sentence is tagged with its part of speech (see Section 3.4.2).

Once this pre-processing is complete, each data set is handled independently in order to identify the unique frequency of the term in two separate classes of tweets. The method of identifying term frequency is described in detail in (Kolchyna, Souza, Treleaven, and Aste 2015) with additional emphasis on using R, as in (Silge and Robinson 2017). In this technique, with the help of *tm* package in R, each of the subsets is converted to corpus, then cleaned of punctuation and special characters and converted to lower case. The stop words, defined as the most common words in the English language that contribute little to the content, are removed from corpus. Once the initial pre-processing is complete, the tweet corpus is transformed to a matrix using *DocumentTermMatrix* where each row represents a tweet and each column represents a word in that tweet.

Following the method described in (Potts 2019), this matrix can be used to identify and collate the most common terms used in the tweet corpus to create a data set that ranks each term by how frequently it is used. The Impact and NoImpact classes in the full tweet set are imbalanced, since one of the classes has many more observations than the other. This becomes problematic when comparing two ranked term data frames of Impact and NoImpact data sets. In order to make sure that both of the datasets are weighted appropriately, the larger number of sparse terms is dropped in NoImpact data set.

This calculation is done using the following intuition: the minimum number of times a word must appear in the Impact data set is chosen to be 4. Using 4 as our defined minimum term frequency for the Impact data set, NoImpact term frequency is calculated as follows:

$$min(TF_{noimpact}) = min(TF_{impact}) * size(noimpact)/size(impact)$$

I keep only the minimum number of terms required by the above guidelines, defined uniquely for each of the datasets. Once all of the infrequently appearing terms are eliminated the total term dataset size is now defined as $\hat{n}$ rather than n. Next, a ratio for each of the remaining terms in the data set can be calculated:

$$Ratio_k = \frac{\Sigma k}{\hat{n}}$$

These calculations are done for each of the data sets individually. For each term k, this ratio is compared in both data sets If the ratio of term in Impact is within 20% of the ratio for that same term within NoImpact, then I remove the terms from both of the dictionaries. Otherwise, I calculate the difference of the two ratios and assign this number a plus (+) for the terms in the Impact data set and a minus (-) for the terms in the NoImpact data set. Once these manipulations are completed, the two data sets are concatenated into a single dictionary that contains both positive and negative terms. The terms are defined as positive or negative for the sake of identifying the final score as Impact or NoImpact, with zero being the decision boundary.

3.4.2 Parts of Speech

Based on the information presented in (Watt, Carvill, House, Livingston, and Williams 2017), it stands to reason that some types of tweets are less likely to be market news than other types. For example, epideictic (ceremonial) tweets are far less likely to have a market impact than deliberative (political) tweets. Therefore, the grammatical structures - or, more simply, parts of speech - within the tweets should be accounted for when creating a lexical model. In order to incorporate these notions, the model uses part of speech tagging within the dictionary and then assigns different weights to the different parts of speech by using an optimization.

The methodology for part of speech tagging is described in detail in (Janosi 2017). The tweet is split into sentences and each sentence is tokenized individually using *tokenizers* R package. Each term in the tokenzied sentence is tagged with one of abbreviations for parts of speech defined in the *RDRPOSTagger* R package.

Each of the abbreviations can then be assigned a weight that will be used in calculating the final tweet score. These weights will be optimized to ensure best Area under the ROC Curve (AUC) results. See Section 3.4.6.

3.4.3 Synonym Casting

Due to the limited amount of data, with only 1523 applicable tweets, it was imperative to standardize the language used within the tweets to mask each of these irregular fields with a uniform substitution. This standardization would allow for a more robust clustering of the terms that may have a significant effect on the market. For example, the President uses a variety of nicknames to reference Joe Biden, including "1 Percent Biden," "Crazy Joe," "Quid Pro Joe," and "Sleepy Joe." Without normalizing all of these references, the frequently used terms would likely split between "Joe" and "Biden" indicating a lower frequency of reference and therefore lowering detection rate.

In order to address these variations in the text data, three sets of additional reference tables were created. After consulting the text data, the following sets were selected "List of nicknames used by Trump" (Wikipedia contributors 2019c), "Heads of foreign states" (Wikipedia contributors 2019b), and "Independent agencies of the United States government" (Wikipedia contributors 2019a), which was cross-referenced with each of the agencies' heads. These data sets are interesting due to potential domestic and foreign policy implications. These Wikipedia data sets were transformed into reference tables using PERL regular expressions. The following additional logic was added in the main application:

1. The full tweet data set was searched for any occurrence of nicknames used by Trump, and the nicknames were replaced with the last name of the person being referenced. See A.1

2. The next step in the process was to search for the last name of world leaders and the name of the countries mentioned and replace each with the corresponding country name with spaces removed. See A.2. Note that, if a foreign leader in question was referenced via a nickname, that would have been resolved in the previous step.

3. Finally, the text data was searched for any reference to the independent government agencies or their heads. Each incident is replaced with the abbreviation of the agency. See A.3.

See Table 1 for an example of these substitutions, the initial text contains terms in blue and the substitutions are marked in red.

Table 1: Sample of Normalized Tweets

tweet.createdAt	cleanTweet	normalizedTweet
2019-08-28 10:36:41	Our **Federal Reserve** cannot mentally keep up with the c ompetition other countries At the G7 in France all of the other Leaders were giddy about how low their Interest Co sts have gone Germany is actually getting paid to borrow money ZERO INTEREST PLUS No Clue **Fed**	Our **FRB** cannot mentally keep up with the competitio n other countries At the G7 in France all of the other L eaders were giddy about how low their Interest Costs have gone Germany is actually getting paid to borrow money ZERO INTEREST PLUS No Clue **FRB**
2019-08-28 09:36:43	Would be very hard for Jeremy Corbyn the leader of Brita ins Labour Party to seek a noconfidence vote against Ne w Prime Minister **Boris Johnson** especially in light of the fact that Boris is exactly what the UK has been looking fo r and will prove to be a great one Love UK	Would be very hard for Jeremy Corbyn the leader of B ritains Labour Party to seek a noconfidence vote again st New Prime Minister **UnitedKingdom** especially in l ight of the fact that Boris is exactly what the UK has be en looking for and will prove to be a great one Love U K
2019-08-27 18:04:01	They do stories so big on **Elizabeth Pocahontas** Warren s crowd sizes adding many more people than are actually there and yet my crowds which are far bigger get no cov erage at all Fake News	They do stories so big on **Warren** Warrens crowd size s adding many more people than are actually there an d yet my crowds which are far bigger get no coverage at all Fake News

3.4.4 Concept Drift

The twitter text data set is a time series, with the subject matter being discussed continuously changing because of changes in current events and political environment. The concept drift might occur when a term in the dictionary becomes outdated and no longer indicates an impactful tweet. For example, references to Keystone Pipeline were much more likely to excite the market during the Spring of 2017 before the policy was finalized, while references to the former Vice President Biden are much more relevant now as he is Trump's democratic contender. Therefore, the terms selected must be important within the current frame of reference. The dictionary is calculated for each individual tweet by subsetting the data set during the time interval starting some number of months m before the tweet was created and ending one day prior to the date of the tweet. Essentially, I use a rolling window calculated for each tweet rather than a static dictionary. Ending the window one day prior to the tweet ensures that no future information is mixed into the evaluation, while starting the window at some predetermined time minimizes the risk of selecting "stale" terms in the dictionary. The exact size of the window is determined during the optimization; Section 3.4.6.

3.4.5 Tweet Score

In order to determine the tweet score for a new tweet, an individual dictionary is calculated based on the window size m discussed in 3.4.4 and then converted to R tidy format. The tweet is first transformed to a vector of words and then to the data frame format. The tweet data frame is then joined to the dictionary data frame using inner join, using the method discussed by (Silge and Robinson 2017). This will select only the terms in the tweet that are also present in the dictionary. The score for each term is a product of the Part of Speech (POS) weight and the probability rank discussed in 3.4.2 and 3.4.1 respectively. The terms that are likely to appear in the Impact cluster are given a positive score, while the terms that are more likely to appear in NoImpact cluster are given a negative score. Once all of the terms scores are added up, the tweet is classified as likely to have an impact if the score is positive and likely to not have an impact otherwise.

Consider Figure 3 where Figure 3a shows the text of Donald Trump's tweet from September 3rd, 2019, with the Impact terms from the associated dictionary outlined in red and NoImpact terms - in blue. The Figure 3b shows a corresponding joined data frame of the custom dictionary and the tweet vector. The score calculation is as follows:

$$TweetScore = 1.0 * 0.0367 + 1.0 * 0.0367 + 0.2 * 0.152 - 0.2 * 0.187 = 0.0055$$

This tweet would be correctly classified as likely to have market moving impact, given that the total tweet score exceeds the value of zero. It is important to note that while the term "China" had been characterized as Impact, meaning more likely to appear in the Impact data set, the term has also appeared in NoImpact data set with some frequency, therefore the term rank is relatively low. On the other hand, the verbs "go" and "get" had been far more common in the NoImpact dataset, and therefore boasted a stronger rank score. It should be evident in this example that the verbs are far less important to predicting the overall tweet score than are the proper nouns.

Figure 3: Sample Tweet Score Calculation

(a) Tweet, September 3, 2019

term	score	rank
china	1	0.03663
china	1	0.03663
get	-0.2	0.152015
go	-0.2	0.186813

(b) Joined dicitonary and tweet dataframe

3.4.6 Optimization

As discussed in the previous sections, a number of parameters used in the model were selected using intuition alone. In order to maximize model performance, a grid search optimization is primarily used to identify the POS weights. The optimization also selects the size of the rolling dictionary window, and the threshold for the probability difference necessary for sorting the term into the Impact or NoImpact dictionary and disposing of terms that are similarly likely to appear in either data set.

I use grid search to optimize this problem, where I determine weights (ranging from 0 to 1) for proper nouns, nouns, verbs, adjectives and adverbs with all other parts of speech being set to 0. The rolling window is calculated between 4 and 12 months, and the minimum threshold for the probability difference is assumed to be between (1.1 and 1.8). The final optimization results suggest that proper nouns should be weighed highest at 1.0, adjectives second highest at 0.7, with verbs at 0.2, nouns at 0.1, and the remaining parts of speech at 0. The optimal window size is 6 months, and the rank threshold should be set to 1.2 - that is, the term should be at least 20% more likely to appear in one data set over another in order to be included in the classification dictionary.

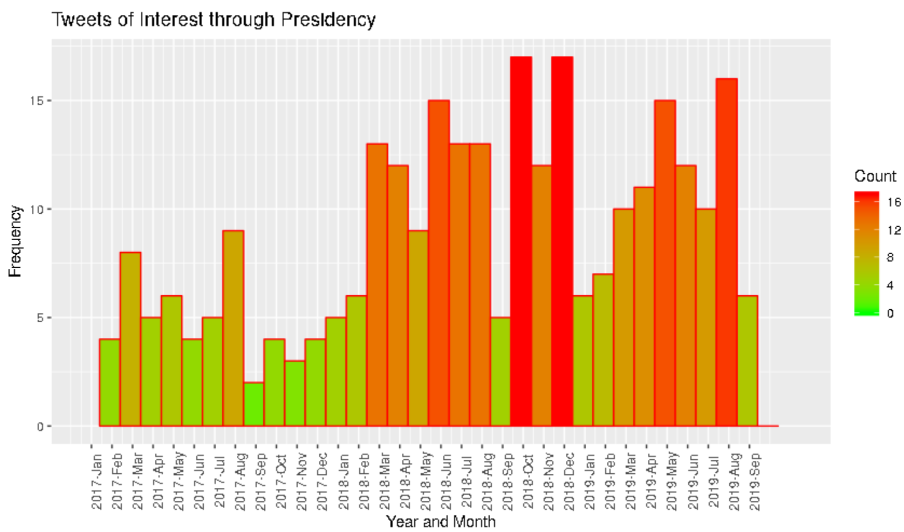
This optimization was done using *NMOF* R package, with the objective function set to maximize AUC (using *cvAUC* R package). The concept of Area under the ROC Curve (AUC) was discussed in (Burkov 2019). The classifier is considered to be better than random if AUC is higher than 0.5. The final optimization rendered an AUC score of 0.51. Although this ROC score appears to only be negligibly larger than 0.5, the discussion in Section 4 will demonstrate why the algorithm might be behaving better than this AUC number would indicate.

4 Results

4.1 General Discussion

The clustering of tweets based on market impact renders an imbalanced data set, with the Impact class being significantly smaller (270 observations) and the NoImpact class containing the remaining 1253 observations. The bar chart in Figure 3 shows that, during certain months, the effects of Trump's twitter activity are more significant than during other months. One can also note that Trump's effect on the stock market was significantly smaller during the first year of his presidency but registered very high during the fall of 2018 followed by another spike in the summer of 2019.

Figure 4: Impact Tweets Count by Month



As demonstrated in Figure 5, the months that saw a high correlation between market volatility and the President's tweets also had the highest number of impact terms in the dictionary. Table 2 shows a list of calculated impact dictionaries throughout the month of August 2019. The most commonly occurring proper nouns are shown in the table in bold font, which displays a definite trend in which specific terms are correlated to market reaction. The most popular high impact references were Hillary Clinton, Joe Biden, with an honorable mention going to the Federal Reserve.

4.2 Model Limitations

It is important to note that both data sets appear to be less than perfect. Based on the tweet text alone, certain tweets classified as high impact should not have

Figure 5: High Frequency Terms in Impact Dataset

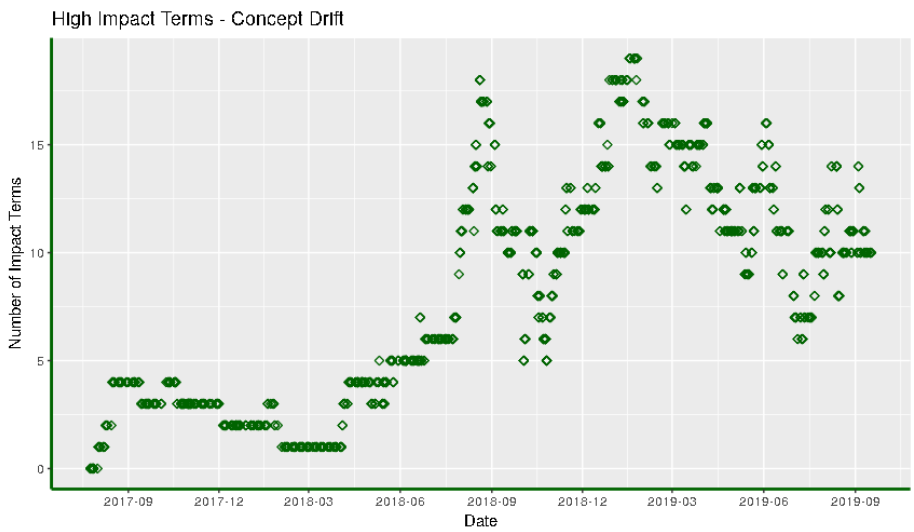
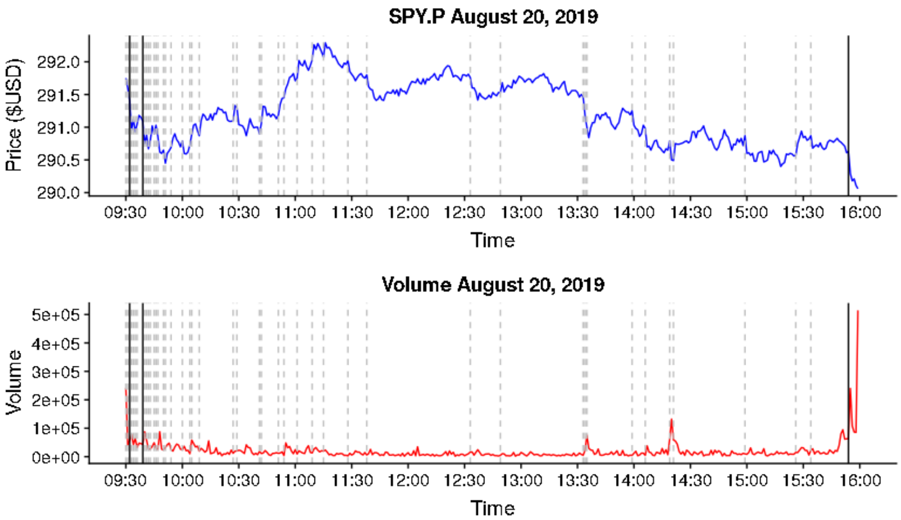


Table 2: Sample Impact Terms throughout August 2019

# Impact Terms	Date	Impact Terms
9	8/30/2019 13:44	c(**"biden"**, **"clinton"**, "deal", "dollar", **"frb"**, "meet", "mexico", "think", "time")
9	8/30/2019 10:10	c(**"biden"**, **"clinton"**, "deal", "dollar", **"frb"**, "meet", "mexico", "think", "time")
10	8/27/2019 12:37	c(**"biden"**, **"clinton"**, "deal", "dollar", "ever", **"frb"**, "know", "meet", "mexico", "think")
8	8/23/2019 10:59	c("president", **"biden"**, **"clinton"**, "deal", "ever", **"frb"**, "meet", "think")
8	8/21/2019 9:38	c("deal", "president", **"biden"**, **"clinton"**, "ever", **"frb"**, "meet", "think")
8	8/20/2019 16:00	c("deal", "president", **"biden"**, **"clinton"**, "ever", **"frb"**, "meet", "think")
8	8/20/2019 9:54	c("deal", "president", **"biden"**, **"clinton"**, "ever", **"frb"**, "meet", "think")
8	8/20/2019 9:51	c("deal", "president", **"biden"**, **"clinton"**, "ever", **"frb"**, "meet", "think")
8	8/20/2019 9:47	c("deal", "president", **"biden"**, **"clinton"**, "ever", **"frb"**, "meet", "think")
8	8/20/2019 9:43	c("deal", "president", **"biden"**, **"clinton"**, "ever", **"frb"**, "meet", "think")
8	8/20/2019 9:41	c("deal", "president", **"biden"**, **"clinton"**, "ever", **"frb"**, "meet", "think")
10	8/14/2019 11:39	c("president", **"biden"**, **"clinton"**, "deal", "ever", "know", "meet", "think", "time", "win")
10	8/14/2019 11:34	c("president", **"biden"**, **"clinton"**, "deal", "ever", "know", "meet", "think", "time", "win")
10	8/13/2019 9:38	c("president", **"biden"**, **"clinton"**, "deal", "ever", "know", "meet", "think", "time", "win")
13	8/5/2019 14:12	c("fake", "president", "time", **"biden"**, **"clinton"**, "deal", "ever", "first", "know", "meet", "muellerreport", "page", "think")
10	8/1/2019 13:26	c("fake", "president", "time", **"biden"**, **"clinton"**, "ever", "know", "meet", "muellerreport", "page")

caused market movement. However, some tweets classified as NoImpact had clearly influencial content that should have had an effect on the market. More than likely, this effect could not be captured as an instantaneous jump that happened within 2 minutes of the tweet. The algorithm explored in this paper has no way of examining content that is not featured in the tweet text, such as images, attached video announcements, or linked tweets by other authors. Thus, while certain tweets might appear innocuous based on text alone, they could have a significant message in a linked video. Table B.2 shows a sample of tweets identified as Impact; tweets highlighted in blue show little context for market reaction based on the text. For example, tweets 10 through 14 appear to be thought fragments that don't specifically reference anything. One explanation for their classification is that they occurred on August 20, 2019, the day that had registered significant volatility in the market, see Figure 6. The volatility could be attributed to a barrage of economically themed @realDonaldTrump tweets that occured before the stock market opened, which potentially caused the market to respond each time a new tweet was posted. As another example, tweet 17 that reads "Thank you Steve" actually makes a reference to a highly controversial Unite the Right rally in Charlottesville, VA based on the included link to a different tweet. The text of the referenced tweet was not captured in the @realDonaldTrump tweet.

Figure 6: August 20, 2019



Recorded jumps in grey

Table B.1 shows a sample of NoImpact, where tweets very similar to those highlighted in red were typically a part of the Impact data set with the subjects focusing on illegal immigration, China, and polling. All in all, these discrepancies in the content of the data set make the detection of high impact tweets less reliable, but the trends in the two data sets are still distinct and detectable to a human eye.

4.3 Model Performance

As mentioned in Section 3.4.6, the optimized AUC was still extremely close to the 0.5 value. However, this evaluation criterion does not tell the full story. Two additional performance metrics are detection rate (or recall) and model accuracy. The detection rate can be calculated using equation 3; it is the ratio of all the detected high impact tweets to the total number of high impact tweets in the data set. Detected high impact tweets are referred to as true positives (TP) listed in Table B.3. High impact tweets that were not classified by the algorithm as such are called false negatives (FN). A sample of August and July FN is shown in Table B.4. Given that only 22 out of 270 high impact tweets were identified, the detection rate is only 8.14%.

$$DetectionRate = \frac{TruePositive}{TruePositive + FalseNegative} \tag{3}$$

When examining false negatives more closely, it becomes apparent that about one-third of the tweets in that category show no obvious indication as to why they might affect the market (highlighted in blue in the table). More than likely, either the tweets occurred simultaneously with the jump, but the two events were unrelated or the tweet contained addition non-textual information. This is potentially related to the discussion above in Section 4.1.

For comparison, a second detection rate can be calculated where we consider the false negative results based on their content and reclassify results by hand accordingly. The original sample was categorized using stock market jumps as the only signal and did not assess the content of the tweet as a part of this classification. Manual processing of 82 false positive results show as many as 50 were political or economic tweets: the type of tweets that primarily made up the tweets of interest dataset. Approximately 88 out of 248 false negative results can be manually classified as having no context to influence the market. Using these numbers, the detection rate can be recalculated as follows, giving the adjusted detection rate of 31.03%:

$$DetectionRate_{manual} = \frac{22 + 50}{22 + 50 + (248 - 88)} = 0.3103$$

The next metric considered is the overall accuracy see Equation 4. Using my sample the calculated value is 1193 correct guesses out of 1523 total sample size which is 78.3% accuracy.

$$Accuracy = \frac{TruePositive + TrueNegative}{SampleSize} \tag{4}$$

Similar to the argument made above, this quantity can be recalculated by revisiting false negative and false positive values to see if the content would in reality suggest a different classification. With the adjusted numbers, the manual accuracy calculation would be as follows, with the new number being 87.39%:

$$Accuracy_{manual} = \frac{22 + 50 + 1171 + 88}{1523} = 0.8739$$

To illustrate this further compare the two confusion matrices in Figure 7.

4.4 Further Investigation

The recalculated numbers are based in intuition and therefore require further research to see where these detected tweets would reflect in the market. The model would perform better in identifying similar tweets if the initial sample

Figure 7: Confusion Matrices of Results

	Impact (Predicted)	No Impact (Predicted)
Impact (Actual)	22	248
No Impact (Actual)	82	1171

(a) Confusion Matrix of Results – Fully Automated

	Impact (Predicted)	No Impact (Predicted)
Impact (Actual)	72	160
No Impact (Actual)	32	1259

(b) Confusion Matrix of Results – Manually Reclassified

classification was done manually, however this would defeat the purpose of creating an automated model. This experiment should be considered as a proof of concept and would need to have better tuned initial selection criteria in order to be effective as a trading tool. One way to enhance this tool would be to download and examine meta data associated with linked content - images, videos and referenced tweet to see if more useful information about pithy "thank you" or "MAGA" tweets can be obtained. This method could also be applied to a specific market sector where the fluctuations are more apparent or alternatively a more robust way of determining SP500 market reaction should be investigated. Additionally, it is important to determine the window of tweet influence, this particular aspect of the problem had not been investigated in this project. However, in order to make this model profitable, identifying an effective method is imperative.

5 Conclusion

The goal of this work was to create a classification algorithm to identify incoming tweets from the @realDonaldTrump twitter account that could potentially move the stock market. A custom lexicon was created using two clustered data sets of tweets. Impact data contains the tweets that were associated with the jumps in SPY.P, and NoImpact data contained the rest of the tweets that were issued during the stock market hours. This custom lexicon was adjusted to reduce concept drift and improve classification by synonym casting. Unfortunately, both data sets contained imperfect original classifications because of the lack of information for non-textual data, the stock market reacting to Trump's tweets that took place before or after hours, and occasionally pure coincidence. Other times, no reaction was captured to a highly political tweet within the first 2 minutes of the tweet, and the algorithm was not robust enough to identify impact in other ways. Despite its imperfection, the algorithm performs better than a random classifier. Using manual adjustments, the algorithm has a $\sim$30% detection rate, with an overall accuracy of 87%. There are a number of ways to improve on this work, such as exploring other market data (such as VIX) or using a different way to measure market reaction to including text for linked tweets and metadata for the included media.

A Appendix A

Table A.1: Example of nicknames given by President Trump

Nickname	Real Name	Replace
Dumbo	Randolph "Tex" Alles	Alles
Quid Pro Joe	Joe Biden	Biden
Sleepy Joe	Joe Biden	Biden
SleepyCreepy Joe	Joe Biden	Biden
Sleepy One	Joe Biden	Biden
Da Nang Dick	Richard Blumenthal	Blumenthal
The Dick	Richard Blumenthal	Blumenthal
Mr. Tough Guy	John R. Bolton	Bolton

Red is the replacement for blue

Table A.2: Example of heads of foreign states

Country	Leader	LeaderLast	Replace
Canada	Justin Trudeau	Trudeau	Canada
Cape Verde	Ulisses Correia e Silva	Silva	CapeVerde
Central African Republic	Firmin Ngrbada	Ngrbada	CentralAfricanRepublic
Chad	Idriss Dby	Dby	Chad
Chile	Sebastin Piera	Piera	Chile
China	Xi Jinping	Jinping	China
Colombia	Ivn Duque	Duque	Colombia
Comoros	Azali Assoumani	Assoumani	Comoros
Congo	Sylvestre Ilunga	Ilunga	Congo

Red is the replacement for blue

Table A.3: Example of heads of independent federal agencies

Agency	Acronym	Head	Lastname
Environmental Protection Agency	EPA	Henry Darwin	Darwin
Federal Communications Commission	FCC	Ajit Pai	Pai
Federal Election Commission	FEC	Ellen Weintraub	Weintraub
Federal Energy Regulatory Commission	FERC	Neil Chatterjee	Chatterjee
Federal Maritime Commission	FMC	Michael Khouri	Khouri
Federal Reserve	FRB	Jerome Powell	Powell
Federal Retirement Thrift Investment Board	FRTIB	Michael Kennedy	Kennedy
Federal Trade Commission	FTC	Joseph Simons	Simons

Red is the replacement for blue

B Appendix B

Table B.1: Sample of Tweets of no Impact

ID	Time Stamp	Tweet Text
1	9/17/2019 13:49	Such a beautiful Opening Statement by Corey Lewandowski Thank you Corey CLewandowski
2	9/17/2019 13:05	Just departed New Mexico for California where we are delivering results
3	9/16/2019 15:26	This afternoon at the WhiteHouse it was my great honor to present our nations highest civilian honor the Presidential Medal of Freedom to American baseball legend MarianoRivera Congratulations on this extraordinary achievement Mo
4	9/16/2019 15:16	Thank you working hard KAG2020
5	9/16/2019 14:57	Big crowd expected in New Mexico tonight where we will WIN Your Border Wall is getting stronger each and every day see you in a few hours
6	9/16/2019 13:59	In a short while I will be presenting the New York Yankees MarianoRivera the greatest relief pitcher Closer of all time with the Presidential Medal of Freedom in the East Room of the WhiteHouse
7	9/13/2019 10:48	The two big Congressional wins in North Carolina on Tuesday Dan Bishop and Greg Murphy have reverberated all over the World They showed a lot of people how strong the Republican Party is and how well it is doing 2020 is a big and very important Election We will WIN
8	**9/13/2019 10:41**	**Illegal Immigration costs the USA over 300 Billion Dollars a year There is no reason for this and things are being set in motion to have this number come WAY DOWN Democrats could end Loopholes and it would be a whole lot easier and faster But it will all happen anyway**
9	9/12/2019 13:22	In fact my views on Venezuela and especially Cuba were far stronger than those of John Bolton He was holding me back
10	9/12/2019 10:15	This should have been over with after the Mueller Report came out guypbenson FoxNews
11	9/12/2019 10:07	We cant beat him so lets impeach him Democrat Rep Al Green
12	9/11/2019 13:23	Today and every day we pledge to honor our history to treasure our liberty to uplift our communities to live up to our values to prove worthy of our heroes and above all to NEVER FORGET Honor911
13	9/10/2019 11:58	I informed John Bolton last night that his services are no longer needed at the White House I disagreed strongly with many of his suggestions as did others in the Administration and therefore
14	9/10/2019 11:04	Vote today for Dan Bishop Will be great for North Carolina and our Country
15	**9/10/2019 10:31**	**One of the greatest and most powerful weapons used by the Fake and Corrupt News Media is the phony Polling Information they put out Many of these polls are fixed or worked in such a way that a certain candidate will look good or bad Internal polling looks great the best ever**
16	9/10/2019 10:23	ABC/Washington Post Poll was the worst and most inaccurate poll of any taken prior to the 2016 Election When my lawyers protested they took a 12 point down and brought it to almost even by Election Day It was a Fake Poll by two very bad and dangerous media outlets Sad
17	9/9/2019 13:56	We have been serving as policemen in Afghanistan and that was not meant to be the job of our Great Soldiers the finest on earth Over the last four days we have been hitting our Enemy harder than at any time in the last ten years
18	9/9/2019 13:49	A lot of Fake News is being reported that I overruled the VP and various advisers on a potential Camp David meeting with the Taliban This Story is False I always think it is good to meet and talk but in this case I decided not to The Dishonest Media likes to create
19	9/9/2019 10:55	The Trump Administration has achieved more in the first 2 1/2 years of its existence than perhaps any administration in the history of our Country We get ZERO media credit for what we have done and are doing but the people know and thats all that is important
20	9/9/2019 9:52	I had nothing to do with the decision of our great VP Mike Pence to stay overnight at one of the Trump owned resorts in Doonbeg Ireland Mikes family has lived in Doonbeg for many years and he thought that during his very busy European visit he would stop and see his family
21	**9/9/2019 9:43**	**I know nothing about an Air Force plane landing at an airport which I do not own and have nothing to do with near Turnberry Resort which I do own in Scotland and filling up with fuel with the crew staying overnight at Turnberry they have good taste NOTHING TO DO WITH ME**
22	**9/6/2019 11:14**	**China is eating the Tariffs Billions pouring into USA Targeted Patriot Farmers getting massive Dollars from the incoming Tariffs Good Jobs Numbers No InflationFed China having worst year in decades Talks happening good for all**
23	9/6/2019 10:38	The Economy is great The only thing adding to uncertainty is the Fake News

Tweets that are likely to have had undetected market impact in red

Table B.2: Sample of Tweets of Interest

ID	Time Stamp	Tweet Text
1	9/16/2019 9:35	Democrats would rather talk about gun control than get something done Governor John Sununu FoxNews BillHemmer The big questions are will they move the goalposts and is this just a ploy to TAKE YOUR GUNS AWAY I hope NOT on both counts but Ill be able to figure it out
2	9/6/2019 9:34	Larry Kudlow on Varneyco now
3	9/3/2019 10:28	Based on the IG Report the whole Witch Hunt against me and my administration was a giant and illegal SCAM The House of Representatives should now get back to work on drug prices healthcare infrastructure and all else The Mueller Report showed No Collusion No Obstruction
4	9/3/2019 9:33	For all of the geniuses out there many who have been in other administrations and taken to the cleaners by China that want me to get together with the EU and others to go after China Trade practices remember the EU and all treat us VERY unfairly on Trade also Will change
5	8/30/2019 13:44	The United States of America was not involved in the catastrophic accident during final launch preparations for the Safir SLV Launch at Semnan Launch Site One in Iran I wish Iran best wishes and good luck in determining what happened at Site One
6	8/30/2019 10:10	If the Fed would cut we would have one of the biggest Stock Market increases in a long time Badly run and weak companies are smartly blaming these small Tariffs instead of themselves for bad managementand who can really blame them for doing that Excuses
7	8/27/2019 12:37	The Federal Reserve loves watching our manufacturers struggle with their exports to the benefit of other parts of the world Has anyone looked at what almost all other countries are doing to take advantage of the good old USA Our Fed has been calling it wrong for too long
8	8/23/2019 10:59	Our Country has lost stupidly Trillions of Dollars with China over many years They have stolen our Intellectual Property at a rate of Hundreds of Billions of Dollars a year and they want to continue I wont let that happen We dont need China and frankly would be far
9	8/21/2019 9:38	My proposal to the politically correct Automobile Companies would lower the average price of a car to consumers by more than 3000 while at the same time making the cars substantially safer Engines would run smoother Very little impact on the environment Foolish executives
10	8/20/2019 9:54	Just another disgruntled former employee who got fired for gross incompetence
11	8/20/2019 9:51	Ratings are way down lost all credibility Beautiful to watch
12	8/20/2019 9:47	Maria despite all of their will and energy it wont work
13	8/20/2019 9:43	Thank you Mike
14	8/20/2019 9:41	Two incredible people I cant believe theyre not working few work harder
15	8/14/2019 11:39	The Fed has got to do something The Fed is the Central Bank of the United States not the Central Bank of the World Mark Grant Varneyco Correct The Federal Reserve acted far too quickly and now is very very late Too bad so much to gain on the upside
16	8/14/2019 11:34	Join me tomorrow night in Manchester New Hampshire at 700 PM Eastern KAG2020
17	8/13/2019 9:38	Thank you Steve
18	8/5/2019 14:12	We must honor the sacred memory of those we have lost by acting as ONE PEOPLE Open wounds cannot heal if we are divided We must seek real bipartisan solutions that will truly make America safer and better for all
19	8/1/2019 13:26	Our representatives have just returned from China where they had constructive talks having to do with a future Trade Deal We thought we had a deal with China three months ago but sadly China decided to renegotiate the deal prior to signing More recently China agreed to
20	7/31/2019 11:31	CNNs Don Lemon the dumbest man on television insinuated last night while asking a debate question that I was a racist when in fact I am the least racist person in the world Perhaps someone should explain to Don that he is supposed to be neutral unbiased and fair
21	7/30/2019 12:23	Great reception in Jamestown by both REPUBLICANS and DEMOCRATS Respect for our Countrys incredible Heritage Thank you
22	7/25/2019 13:04	Beautiful Welcome Ceremony at the Pentagon this morning for our new Secretary of Defense Mark EsperDoD
23	7/22/2019 10:32	Going with First Lady to pay our respects to Justice Stevens Leaving now
24	7/19/2019 9:42	Fed There is almost no inflation

Tweets where text indicates no potential for market impact in blue

Table B.3: All Detected True Positives

Time Stamp	Tweet Text
9/3/2019 9:33	For all of the geniuses out there many who have been in other administrations and taken to the cleaners by China that want me to get together with the EU and others to go after China Trade practices remember the EU and all treat us VERY unfairly on Trade also Will change
8/30/2019 10:10	If the Fed would cut we would have one of the biggest Stock Market increases in a long time Badly run and weak companies are smartly blaming these small Tariffs instead of themselves for bad managementand who can really blame them for doing that Excuses
5/30/2019 11:34	Robert Mueller came to the Oval Office along with other potential candidates seeking to be named the Director of the FBI He had already been in that position for 12 years I told him NO The next day he was named Special Counsel A total Conflict of Interest NICE
5/13/2019 9:59	Bernie Sanders The Economy is doing well and Im sure I dont have to give Trump any credit Im sure hell take all the credit that he wants Wrong Bernie the Economy is doing GREAT and would have CRASHED if my opponent and yours Crooked Hillary Clinton had ever won
1/3/2019 9:52	The United States Treasury has taken in MANY billions of dollars from the Tariffs we are charging China and other countries that have not treated us fairly In the meantime we are doing well in various Trade Negotiations currently going on At some point this had to be done
12/27/2018 14:44	The reason the DACA for Wall deal didnt get done was that a ridiculous court decision from the 9th Circuit allowed DACA to remain thereby setting up a Supreme Court case After ruling Dems dropped deal and thats where we are today Democrat obstruction of the needed Wall
11/12/2018 11:31	The California Fire Fighters FEMA and First Responders are amazing and very brave Thank you and God Bless you all
11/9/2018 10:55	BrianKempGA ran a great race in Georgia he won It is time to move on
10/3/2018 10:02	Thank you to Congressman Tom Reed of New York for your wonderful comments on our great new Trade Deal with Mexico and Canada the USMCA I have long ago given you my Full Endorsement and for good reason Keep up the Great Work Varneyco
8/9/2018 15:43	LindseyGrahamSC Why didnt the FBI tell President Trump that they had concerns about Carter Page Is there a double standard here They told Senator Diane Feinstein that she had a spy but not Trump Is that entrapment or did they just want to use Page as an excuse to SPY
7/27/2018 11:58	TroyBalderson of Ohio is running for Congress so important to the Republican Party Cast you early vote or vote on August 7th Troy is strong on crime and borders loves our Military our Vets and our Second Amendment He has my full and total Endorsement
7/24/2018 11:50	Im very concerned that Russia will be fighting very hard to have an impact on the upcoming Election Based on the fact that no President has been tougher on Russia than me they will be pushing very hard for the Democrats They definitely dont want Trump
7/19/2018 9:35	Trump recognized Russian Meddling MANY TIMES
7/10/2018 14:42	A recent Emerson College ePoll said that most Americans especially Hispanics feel that they are better off under President Trump than they were under President Obama
6/7/2018 11:10	When will people start saying thank you Mr President for firing James Comey
6/6/2018 9:37	Gold Star father Ceejay Metcalf whose great son Michael was just honored at the White House was fantastic this m
5/2/2018 9:33	NEW BOOK A MUST READ The Russia Hoax The Illicit Scheme to Clear Hillary Clinton and Frame Donald Trump by t
4/24/2018 14:41	President Trump Calls the USFrance Relationship Unbreakable History Shows Hes Right
12/22/2017 10:07	Will be signing the biggest ever Tax Cut and Reform Bill in 30 minutes in Oval Office Will also be signing a much
11/8/2017 13:17	Congratulations to all of the DEPLORABLES and the millions of people who gave us a MASSIVE 304227 Electoral Co
10/25/2017 15:56	The long anticipated release of the JFKFiles will take place tomorrow So interesting
8/23/2017 9:50	If Republican Senate doesn't get rid of the Filibuster Rule and go to a simple majority which the Dems would do they are just wasting time

Table B.4: August and July 2019 False Negatives

Time Stamp	Tweet Text
8/30/2019 13:44	The United States of America was not involved in the catastrophic accident during final launch preparations for the Safir SLV Launch at Semnan Launch Site One in Iran I wish Iran best wishes and good luck in determining what happened at Site One
8/27/2019 12:37	The Federal Reserve loves watching our manufacturers struggle with their exports to the benefit of other parts of the world Has anyone looked at what almost all other countries are doing to take advantage of the good old USA Our Fed has been calling it wrong for too long
8/23/2019 10:59	Our Country has lost stupidly Trillions of Dollars with China over many years They have stolen our Intellectual Property at a rate of Hundreds of Billions of Dollars a year and they want to continue I wont let that happen We dont need China and frankly would be far
8/21/2019 9:38	My proposal to the politically correct Automobile Companies would lower the average price of a car to consumers by more than 3000 while at the same time making the cars substantially safer Engines would run smoother Very little impact on the environment Foolish executives
8/20/2019 9:54	**Just another disgruntled former employee who got fired for gross incompetence**
8/20/2019 9:51	**Ratings are way down lost all credibility Beautiful to watch**
8/20/2019 9:47	**Maria despite all of their will and energy it wont work**
8/20/2019 9:43	**Thank you Mike**
8/20/2019 9:41	**Two incredible people I cant believe theyre not working few work harder**
8/14/2019 11:39	The Fed has got to do something The Fed is the Central Bank of the United States not the Central Bank of the World Mark Grant Varneyco Correct The Federal Reserve acted far too quickly and now is very very late Too bad so much to gain on the upside
8/14/2019 11:34	**Join me tomorrow night in Manchester New Hampshire at 700 PM Eastern KAG2020**
8/13/2019 9:38	**Thank you Steve**
8/5/2019 14:12	**We must honor the sacred memory of those we have lost by acting as ONE PEOPLE Open wounds cannot heal if we are divided We must seek real bipartisan solutions that will truly make America safer and better for all**
8/1/2019 13:26	Our representatives have just returned from China where they had constructive talks having to do with a future Trade Deal We thought we had a deal with China three months ago but sadly China decided to renegotiate the deal prior to signing More recently China agreed to
7/31/2019 11:31	CNNs Don Lemon the dumbest man on television insinuated last night while asking a debate question that I was a racist when in fact I am the least racist person in the world Perhaps someone should explain to Don that he is supposed to be neutral unbiased and fair
7/30/2019 12:23	**Great reception in Jamestown by both REPUBLICANS and DEMOCRATS Respect for our Countrys incredible Heritage Thank you**
7/25/2019 13:04	**Beautiful Welcome Ceremony at the Pentagon this morning for our new Secretary of Defense Mark EsperDoD**
7/22/2019 10:32	**Going with First Lady to pay our respects to Justice Stevens Leaving now**
7/19/2019 9:42	Fed There is almost no inflation
7/16/2019 11:11	Kevin McCarthy GOPLeader The Presidents Tweets were not Racist The controversy over the tweets is ALL POLITICS I will vote against this resolution Thank you Kevin
7/15/2019 10:49	Here we go with the Fake Polls Just like what happened with the Election against Crooked Hillary Clinton ABC NBC CNN nytimes washingtonpost they all got it wrong on purpose Suppression Polls so early They will never learn
7/11/2019 10:52	Dow just hit 27000 for first time EVER
7/10/2019 9:44	Our company has grown since Trump has taken control of the White House and the Presidency in the sense that we have better opportunities now to do what weve been wanting to do for quite some time and that is to create manufacturing jobs I believe that President Trump has
7/2/2019 10:25	**Big 4th of July in DC Salute to America The Pentagon and our great Military Leaders are thrilled to be doing this and showing to the American people among other things the strongest and most advanced Military anywhere in the World Incredible Flyovers and biggest ever Fireworks**

Tweets unlikely to be considered presidential announcement in blue

Table B.5: August 2019 False Positives

Time Stamp	Tweet Text
9/12/2019 10:15	This should have been over with after the Mueller Report came out guypbenson FoxNews
9/4/2019 9:52	US Winning Trade War With China In Dollars CNBC
9/3/2019 9:45	Germany and so many other countries have negative interest rates they get paid for loaning money and our Federal Reserve fails to act Remember these are also our weak currency competitors
8/28/2019 10:36	Our Federal Reserve cannot mentally keep up with the competition other countries At the G7 in France all of the other Leaders were giddy about how low their Interest Costs have gone Germany is actually getting paid to borrow money ZERO INTEREST PLUS No Clue Fed
8/15/2019 15:29	Biden doesnt have a clue I will solve the China problem
8/15/2019 10:04	If President Xi would meet directly and personally with the protesters there would be a happy and enlightened ending to the Hong Kong problem I have no doubt
8/8/2019 10:38	As your President one would think that I would be thrilled with our very strong dollar I am not The Feds high interest rate level in comparison to other countries is keeping the dollar high making it more difficult for our great manufacturers like Caterpillar Boeing
8/7/2019 15:01	Watching Sleepy Joe Biden making a speech Sooo Boring The LameStream Media will die in the ratings and clicks with this guy It will be over for them not to mention the fact that our Country will do poorly with him It will be one big crash but at least China will be happy
8/5/2019 12:00	China is intent on continuing to receive the hundreds of Billions of Dollars they have been taking from the US with unfair trade practices and currency manipulation So onesided it should have been stopped many years ago
6/7/2019 12:36	China is subsidizing its product in order that it can continue to be sold in the USA Many firms are leaving China for other countries including the United States in order to avoid paying the Tariffs No visible increase in costs or inflation but US is taking in Billions
5/13/2019 10:09	Democrat Rep Tlaib is being slammed for her horrible and highly insensitive statement on the Holocaust She obviously has tremendous hatred of Israel and the Jewish people Can you imagine what would happen if I ever said what she said and says
4/9/2019 11:36	Whats completely unacceptable is for Congesswoman Omar to target Jews in this case Stephen Miller Jeff Ballabon B2 Strategic CEO Varneyco
3/29/2019 11:37	through their country and our Southern Border Mexico has for many years made a fortune off of the US far greater than Border Costs If Mexico doesnt immediately stop ALL illegal immigration coming into the United States throug our Southern Border I will be CLOSING
3/13/2019 10:14	Comey testified under oath that it was a unanimous decision on Crooked Hillary Lisa Page transcripts show he LIED jasoninthehouse
2/25/2019 15:12	China Trade Deal and more in advanced stages Relationship between our two Countries is very strong I have therefore agreed to delay US tariff hikes Lets see what happens
2/8/2019 15:13	Deepest sympathies to Congresswoman Debbie Dingell and the entire family of John Dingell Longest serving Congressman in Countrys history which if people understand politics means he was very smart A great reputation and highly respected man

Tweets that could be consdiered "news" or presidential announcment in red

Table B.6: August 2019 Sample of True Negatives

Date	Tweet Text
8/13/2019 13:11	Many are blaming me and the United States for the problems going on in Hong Kong I cant imagine why
8/13/2019 10:53	ALL THE NEWS THATS NOT FIT TO PRINT The New York Times is no longer the paper we grew up with It is no longer a news organization It is now an agenda driven organization out to change the Country for the worse Michael Goodwin Highly Respected New York Post Columnist
8/13/2019 10:10	As usual China said they were going to be buying big from our great American Farmers So far they have not done what they said Maybe this will be different
8/13/2019 10:04	Would Chris Cuomo be given a Red Flag for his recent rant Filthy language and a total loss of control He shouldnt be allowed to have any weapon Hes nuts
8/8/2019 10:38	As your President one would think that I would be thrilled with our very strong dollar I am not The Feds high interest rate level in comparison to other countries is keeping the dollar high making it more difficult for our great manufacturers like Caterpillar Boeing
8/7/2019 15:48	Just left Dayton Ohio where I met with the Victims and families Law Enforcement Medical Staff and First Responders It was a warm and wonderful visit Tremendous enthusiasm and even Love Then I saw failed Presidential Candidate 0 Sherrod Brown and Mayor Whaley totally
8/7/2019 10:46	Today we honor all of our Countrys Purple Heart recipients their loved ones and our Gold Star Families for their immeasurable sacrifice These American Patriots represent the unyielding and unmatched strength and determination of the US Armed Forces
8/6/2019 12:28	Thank you JimCramer CNBC
8/6/2019 12:24	Thank you Mr Wonderful I like you too kevinolearytv CNBC
8/5/2019 13:10	Today I am also directing the Department of Justice to propose legislation ensuring that those who commit hate crimes and mass murders face the DEATH PENALTY and that this capital punishment be delivered quickly decisively and without years of needless delay
8/5/2019 12:00	China is intent on continuing to receive the hundreds of Billions of Dollars they have been taking from the US with unfair trade practices and currency manipulation So onesided it should have been stopped many years ago
8/2/2019 13:41	AAP Rocky released from prison and on his way home to the United States from Sweden It was a Rocky Week get home ASAP AAP
8/1/2019 11:55	A string of court cases that have been run through the legal system that have hit DEAD ENDS BillHemmer AmericaNewsroom
8/1/2019 10:44	BIG RALLY tonight in Cincinnati Ohio See you there PS Our Country is doing GREAT
8/1/2019 10:30	Budget Deal is phenomenal for our Great Military our Vets and Jobs Jobs Jobs Two year deal gets us past the Election Go for it Republicans there is always plenty of time to CUT
8/1/2019 10:24	China Iran and other foreign countries are looking at the Democrat Candidates and drooling over the small prospect that they could be dealing with them in the not too distant future They would be able to rip off our beloved USA like never before With President Trump NO WAY

Tweets that could potentially be considered "news" are marked in red

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