

THE EFFECT OF THE INTEGRATION OF SENTIMENT ANALYSIS
ON DONALD J. TRUMP'S SOCIAL MEDIA POSTS
ON STOCK MARKET MOVEMENT

by

Eric Wu
A Capstone Project Proposal
Submitted to the
Graduate Faculty
of
George Mason University
In Partial fulfillment of
The Requirements for the Degree
of
Bachelor of Science
Computational and Data Science

Committee:

Director Dr. Kent Miller, Capstone Project Proposal

Dr. First Last, Committee Member

Dr. First Last, Committee Member

Dr. First Last, Department Head

Date: _____ Spring Semester 2025
George Mason University
Fairfax, VA

The Complete Title is to be Repeated Here without any Line Breaks for the Second Page
and for the Abstract Page

A capstone project proposal submitted in partial fulfillment of the requirements for the
degree of
Bachelor of Science at George Mason University

By

Eric Wu
Bachelor of Science
My Other Former School, Year of first degree

Director: Dr. Kent Miller, Professor
Department of Computational and Data Science Department

Spring Semester 2025
George Mason University
Fairfax, VA

Copyright © 2025 by Eric Wu
All Rights Reserved

Dedication

I dedicate this dissertation to ...

Acknowledgments

I would like to thank the following people who made this possible ...

Table of Contents

| | Page |
|---|------|
| List of Tables | vi |
| List of Figures | vii |
| Abstract | viii |
| 1 Topic | 1 |
| 2 Significance | 2 |
| 3 Prior Research | 3 |
| 3.1 Machine Learning or Lexicon Based Sentiment Analysis Techniques on Social Media Posts by David L. John and Bela Stantic (2022) | 3 |
| 3.2 Predicting the Effects of News Sentiments on the Stock Market by Dev Shah, Haruna Isah, and Farhana Zulkernine (2018) | 5 |
| 3.3 Sentiment Analysis on Social Media for Stock Movement Prediction by Thien H. Nguyen, Kyoaki Shirai, and Julien Velcin (2015) | 6 |
| 3.4 Effect of Public Sentiment on Stock Market Movement Prediction During the COVID-19 Outbreak by Das, Sahukhan, Chatterjee, and Charkrabarti (2022) | 10 |
| 3.5 Using Twitter to Predict the Stock Market: Where is the mood effect? (2015) | 12 |
| 3.6 Investor Sentiment in the Stock Market by Malcom Baker and Jeffery Wurgler (2007) | 15 |
| 4 Deliverables | 17 |
| 5 Data | 18 |
| 6 Theory | 23 |
| 7 Results | 25 |
| 8 Conclusion | 34 |
| 9 Software | 35 |
| 10 Capstone | 36 |
| Bibliography | 37 |

List of Tables

| Table | Page |
|---------------------------------------|------|
| 7.1 Top Terms per Topic | 30 |
| 7.2 Post-Hoc Tukey LDA | 32 |
| 7.3 Seeded Topic Dictionary | 32 |
| 7.4 Post-Hoc Tukey SLDA | 33 |

List of Figures

| Figure | Page |
|---|------|
| 5.1 Box plots of S&P500 Numerical Features | 19 |
| 5.2 Box plots of NASDAQ Composite Numerical Features | 19 |
| 5.3 S&P 500 vs. NASDAQ Normalized Performance (Closing Price) | 21 |
| 5.4 Counts of Various Data Quality Issues In Trump Truth Social Archive | 22 |
| 7.1 Sentiment Distribution of Social Media Posts | 25 |
| 7.2 Index Closing Prices by Sentiment Class | 26 |
| 7.3 Index Daily Change in Price by Sentiment Class | 26 |
| 7.4 Top 30 Most Frequent Terms Found in Donald Trump's Truth Social Posts | 29 |
| 7.5 Spread of Daily Volatility in the S&P500 by Topic | 30 |

Abstract

THE COMPLETE TITLE IS TO BE REPEATED HERE WITHOUT ANY LINE BREAKS
FOR THE SECOND PAGE AND FOR THE ABSTRACT PAGE

Eric Wu, BS

George Mason University, 2025

Capstone Project Proposal Director: Dr. Kent Miller

Enter abstract text.

Chapter 1: Topic

How powerful can a man's words be?

During his second term, the 47th president of the United States, Donald Trump, has inflicted chaos and pandemonium on the markets via his enlightened posts on social media. This unease has caused retail and institutional investors to second-guess their risk tolerance, long-term holdings, and confidence in the continued financial growth of the United States.

Do Donald Trump's colorful social media posts actually effect market performance in a measurable and meaningful manner the short and long-term?

Chapter 2: Significance

The stock market affects all of us indirectly and directly for those with exposure in said markets. Some of us depend on continued growth in the stock market for our savings or retirement, obtaining stable employment from publicly traded companies who raise capital from healthy stock markets, or rely on the growing stock market as an economic signal that the economy is thriving, bolstering consumer confidence, which in turn boosts consumer spending.

Chapter 3: Prior Research

3.1 Machine Learning or Lexicon Based Sentiment Analysis Techniques on Social Media Posts by David L. John and Bela Stantic (2022)

This text is a chapter from the textbook, “Intelligent Information and Database Systems”. This chapter explains how social media platforms provide an accessible and plentiful source of data because individuals post their thoughts and opinions across a vast sea of domains. The chapter states, “social media posts are a plentiful data source that offers a great opportunity for analysis for decision-making purposes”. [1]

Sentiment analysis is also known as opinion mining. Sentiment analysis is a natural language processing technique that aims to quantify qualitative textual data. This means, the goal of sentiment analysis is to analyze individual’s sentiments, opinions, attitudes, emotions, and appraisals. [1]

Classifying the sentiment of text relies largely on a predetermined lexicon. This pre-existing lexicon typically takes the form of a dictionary of pre-labeled words that have a known sentiment or opinion. An example would be “bad”, which typically has a negative sentiment. For example, an individual who says “I had a bad day” would usually feel and have a negative emotion, opinion and sentiment. The converse is also true. An individual saying, “I had a good day”, would generally be associated with a positive sentiment.

However, a distinction of opinion and comparative-type words in sentiment analysis needs to be made. Opinion-type words express an absolute opinion, for example “good” and “bad”. Comparative-type words, like “better”, “best”, and “worse”, cannot be used in sentiment analysis as they do not express an absolute sentiment; rather these words simply

compare A and B. Even though it is theoretically possible to assign a positive sentiment to the word “better”, a comparison does not express an absolute opinion, instead it only compares a relationship like already established.

John and Stantic (2022) [1] state, as of the date of the textbook’s publishing, the majority of sentiment analysis had been on written text. This may limit the applicability of predicting sentiment as where the text’s sentiment does not follow the norm of an opinion word’s sentiment.

The cases where sentiment analysis on written text struggles are orientation and context, sentiment-less opinion words, sarcasm or irony, and statements lacking opinion words. [1]

Orientation and context in the context of sentiment analysis refers to positive or negative opinion words having their actual sentiment reversed in a sentence because of context or domain. Opinion words may lack sentiment when observed in sentences involving questions or conditionals. Sarcasm and irony are an obvious case where sentiment can be hard to analyze as the word’s individual sentiment maybe positive, but the intended sentient of the writer was negative. Again, in this edge-case, the word’s typical sentiments did not match the individual’s expressed intent. Statements lacking opinion words may have an actual sentiment, however sentiment analysis may not be able to identify the actual sentiment due to lacking opinion words.

Sentiment analysis can be performed using Bayesian network classifiers, support vector machines (SVMs) and random forests. John and Stantic (2022) [1] compared several of the most common sentiment analysis techniques, including the ANEW, LIWC, SentiWordNet, and machine learning derived techniques like Naive Bayes classifiers, SVMs and decision tree-based classifiers. They found the open-sourced VADER lexicon, was the most accurate sentiment analysis tool in accurately predicting the sentiment of tweets. An advantage of the VADER lexicon is in its pre-complied nature; this fact enables the lexicon to be more computationally efficient. They discovered neural network-based methods may be less sensitive to changes in sentiment as the standard deviation between the maximum and minimum sentiment values for their dataset. [1]

These findings are particularly relevant to the stated goal of this capstone project. The finding that VADER was particularly efficient and effective at assessing the sentiment of short text strings scraped from twitter should mean using VADER to assign sentiment scores to Donald Trump's truth social posts as Truth Social is essentially an alternative analogue to twitter posts.

3.2 Predicting the Effects of News Sentiments on the Stock Market by Dev Shah, Haruna Isah, and Farhana Zulkernine (2018)

This article states the large amount online text data has an observable influence on the stock market by way of influence through public sentiment. The paper focused public sentiment derived from the public domain via Wikipedia, social media posts, and news outlets. In particular, they derived sentiment from news outlets to achieve a 70.59% accuracy in predicting the direction of stock pricing from stocks in the pharmaceutical industry. [2]

Public sentiment can be measured or proxied through individuals expressing sentiments like moods and emotions through social media posts. However, an air of skepticism must be acknowledged. Social media in its nature of acting as a public forum, enables malicious users, bots, and unintentional misinformation to propagate, causing users to value or devalue products, values, and ideologies. Quality measures and controls need to be created and assessed to mitigate the influence of these users.

Public sentiment through societal mood can contribute to an equities' perceived value or lack thereof value. They also state other research has shown the value in incorporating public sentiment measures can improve the predictive accuracy of analytical stock models.

[2]

This paper used a dictionary-based approach to compute public sentiment. They also note lexicon-based approaches have an inherent advantage versus other rule-based approaches because they generally have good cross domain performance due to being trained and designed on a variety of data sources. [2]

The authors extracted news articles and preprocessed and transformed them using traditional NLP techniques. Then they assigned the news articles sentiment scores from a pre-compiled dictionary. After, they cross-validated the buy and hold positions based on the assigned sentiment values to understand the effects of sentiment on the decision-making process of stock traders.

The pre-compiled dictionary was manually labeled with text that pertained to pharmaceutical companies. They stated a word weight measure may enhance the accuracy of their model as some words are likely to be more significant in the pricing of stock. [2] In addition to that statement, the introduction of a hybrid model may also enhance model performance.

The findings regarding a manually created lexicon on a specific use-case may mean an altered version of the VADER lexicon could be needed for my capstone project. Donald Trump does have a particular way of speaking and posting on social media. He uses rather short sentences with an emphasis on talking about nouns or people, in particular.

3.3 Sentiment Analysis on Social Media for Stock Movement Prediction by Thien H. Nguyen, Kiyoaki Shirai, and Julien Velcin (2015)

In this article, the authors extracted mood information from social media data using sentiment analysis. Then, they integrated this mined data to predict stock movement. They note, social media posts often contain slang, shorthand, misspellings, and uncommon grammar constructions.[3] This diversity in language can make sentiment analysis difficult.

This article proposes a “topic-sentiment” feature to improve a stock movement model’s predictive ability; this feature is a derivation of the extracted topics from the texts in tandem with the associated sentiments. The paper uses two such topic models to test their theory. They use a latent model called the joint sentiment/topic model (JST), which is an existing model where the extracted topics and sentiments are latent, meaning they are hidden. Whereas their second model is of their own design and topic and sentiment are not hidden.

Predictive stock movement models ought to operate under the efficient market hypothesis (EMH). The efficient market hypothesis states that the stock market should reflect all of the publicly available information. This should mean as publicly available information iterates, in this case from the news, the stock market should reflect the changes in information in real time. When considering the news cycle, as it updates, the stock market should reflect the changes from the news cycle.

Because the news operates in an unknowable and random pattern, it can be modeled with a random walk; a random walk should only be about 50% predictable. Therefore, stock movements should similarly follow a random walk. This would mean the accuracy of a stock movement model would be no more than 50%.

However, there have been researchers who have disproven or disregarded this line of reasoning. The researchers who state that stock market prices do not follow a random walk, and are somewhat predictable, use the evidence of a 56% directional accuracy of predictive models; this ought to negate the first assertion that the stock market’s pricing operates under a random walk. [3]

Other than the efficient market hypothesis and the random walk theories, the trading philosophies of investors need to be considered. There are two distinct schools of trading philosophies: fundamental analysis and technical analysis. [3]

Fundamental analysis refers to the use of the company’s fundamentals to predict a stock price. [3] Fundamental analysis would consider the company’s financial conditions, operations, and macroeconomic indicators.

The other philosophy, technical analysis, focuses on using historic information and time-series data to predict a stock's price.[3] Technical analysis operates under the belief prices follow historical trends. Since history tends to repeat itself, some researchers have tried to use historical prices to predict a stock's future performance. To discover these historical patterns, researchers have used Bayesian networks, auto-regressive models, moving average models, auto-regressive average models, etc.

While all of these models are valid approaches to predicting stock movement, they mostly fail to account for the psychology of investors in pricing the stock market. [3] As sentiment has been long known to be a measure of an individual's mood, opinion, and emotion, it may improve these models' predictive ability. A simple example of which would be the usage of a linear regression model for modeling historical pricing data in combination with sentiment scores derived from news articles.

The joint sentiment/topic model previously mentioned to asses text content's combined topic and sentiment was created with the intent of extracting topic and sentiment from movie reviews. Because the model simultaneously extracts topic and sentiment, it is an applicable analog to compare with the proposed topic-sentiment model by the author.

The authors, Nguyen, Shirai, and Velcin, extracted historical stock quotes from Yahoo finance for 18 large cap stocks. The data contained the following features: date, open, high, low, close, and adjusted close to account for splits and dividends. Since adjusted close prices are more representative in the long term, most researchers chose the adjusted close as the predicted feature.

The textual features were extracted from the Yahoo Finance Message Board, an online forum where investors post about company news, investing opinions, and comments. The extracted messages span a period of one year from July 23, 2012, to July 19, 2013. A feature of these comments was the annotations of buy, sell, or hold that 15 percent of messages had been annotated by forum users.

The text extracted from these forum messages contained errors similar to those in the previous study. [3] The text often contained uncommon grammar constitutions, misspellings, and was rather short. The text also faces an issue of validity, which is similar to the findings of the use of Twitter as a source for sentiment analysis to predict stock movement.

The authors used a support vector machine for classification of the stock's predicted movement. SVMs are known to efficiently handle high dimensional data and perform well at classification tasks. Therefore, the authors selected a linear kernelled SVM model to predict stock movement.

They used $price_{t-1}$, $price_{t-2}$, $Hsent_{i,t}$, $Hsent_{i,t-1}$ as the features for training the SVM. The $Hsent_{i,t}$ and $Hsent_{i,t-1}$ are the percentages of the messages extracted from the forums at time, t, that belong to the sentiment classes of strong buy, buy, hold, sell, and strong sell. As only about 15% of messages were user annotated, the researchers first trained a model to train a topic model to extract classes from the remaining 84.4% of messages. [3]

To extract those classes, they removed stopwords, then lemmatized the messages, and weighed the features using a TF-IDF, and finally chose a SVM with a linear kernel to classify the remaining message's sentiment classes.

After the models where trained, the aspect-based sentiment model, they proposed was the most performant, achieving an average accuracy of 54.41%. [3] This average was calculated from the average of the performance of the model on each individual stock. They found that the model was more performant for some stocks like 71.05% for Amazon and 64.47% for Dell. [3]

The aspect-based sentiment model outperformed the sentiment classification model by 2.54%, the LDA-based method by 2.14%, and the JST-based model by 2.87%. [3] They do state there are several limitations associated with their approach. For some of the individual stocks, the price-based time series model more accurately predicted the stock's prices. Another potential explanation to low performance could be due to the sentiments

of the individual's on the Yahoo Finance Messaging board not being clean enough or the individual's assessments of the market overall being faulty.

To build upon their research, the authors adding features to the model and fine-tuning the model. They presented a novel approach for capturing topics and sentiments together from investor's messages an investment related forum. This approach is similar to the approach I am going to use in my capstone project. I plan on following in their research by combining a sentiment metric with a topic class to improve the predictive accuracy of a stock pricing model. However, my approach diverges from this research article by focusing on an individual's social media posts instead of a mass of individual's messages to gauge public sentiment. Instead of being reactionary, my approach assumes the importance and gravity of the subject's opinions, emotions, and ideology.

3.4 Effect of Public Sentiment on Stock Market Movement Prediction During the COVID-19 Outbreak by Das, Sahukhan, Chatterjee, and Charkrabarti (2022)

Das, Sahukhan, Chatterjee, and Charkrabarti (2022) present a stock movement prediction model that aggregates sentiment data from four different online sources and integrates to sentiment data with historical stock data to predict a stock's future movement. The online text sources to gauge public sentiment are stock related news articles, user posts from twitter, financial news from the “Economic Times”, and comments from Facebook. They then extracted sentiment using a process similar to a consensus model to ascertain an average sentiment score from seven tools. The tools are as follows: VADER, logistic regression, Loughran-McDonald, Henry, TextBlob, Linear SVC, and Stanford.

The authors reason that given the existing mass of literature on the applicability and efficacy of sentiment analysis tools, in this case opinion mining to identify the polarity of text sources' messaging relating to individual's opinions of the stock market.

Opinion mining was used by the authors to identify the polarity of the sentiments associated with the text sources regarding stocks. They used lexicon-based and machine learning-based tools to discern the public sentiment associated with the stock market.

The previous works researched in the prior research section seem to support the authors' assertions that the text sources of the media types of social media and news outlets are valid data sources for opinion mining regarding the public sentiment of the stock market. [2] [3] The authors' selection of dictionary and lexicon-based and ML-based sentiment analysis tools is also supported by the previous articles in the prior research section of this paper. [2] [3]

Regarding the sentiment analysis tools used in this model, compared to the researchers, the authors used lexicon-based and ML-based tools, rather than simply using pre-compiled and pre-computed lexicon-based tools. The dictionary-based tools were: Loughran-McDonald and Henry, The Lexicon-based tool was textblob. The ml-based tools used in their model were support vector machines (SVMs), Stanford, a large classifier neural network sentiment analysis tool, VADER, a rule-based classifier, probabilistic classifiers, and logistic regression.

Their model sourced online textual data from the before mentioned sources and applied the standard natural language processing pre-processing pipeline to clean the data. This included extracting the data from the web and applying the appropriate preprocessing steps per model, for example, lemmatizing the text to then apply VADER's .polarity_scores() ¹ function. Then, the model applied each of the seven sentiment analysis tools to each entry and obtained an average sentiment score across the seven sentiment analysis tools. Finally, the average sentiment score in addition to the relevant stock market data were fed into a long short-term memory (LSTM) model to assess the performance and impact of public sentiment on stock movement.

¹nltk.sentiment.vader.SentiText.polatity_scores() is a python function that returns the sentiment score of an input.

An LSTM model is applicable because stock data is inherently time-series data. [4] LTSMs are and are an advanced branch of the RNNs, that are efficient at processing time-series data. The model's performance was then measured using regression and classification metrics including r-squared, MSE, MAE, accuracy, recall, and F1.

The combination of features that resulted in the most performant model used sentiment scores applied to Facebook comments regarding stock information in addition to stock data. The linear SVC, VADER, and Loghran-McDonald sentiment analysis tools were found to be the most performant. They found that the linear SVC sentiment scores had a significant influence on the model's stock movement prediction accuracy. [4] The linear SVC achieved a 98.32% accuracy score in predicting stock market movement prediction. The highest prediction accuracy was achieved using average sentiment scores from Facebook comments from a linear SVC paired with stock data with an accuracy of 98.11%. [4]

Overall, it appears the combination of the sentiment mining of news headlines and historical stock quotes had a meaningful improvement to stock forecasting accuracy.

3.5 Using Twitter to Predict the Stock Market: Where is the mood effect? (2015)

The author notes, “the stock market can be driven by emotions of stock market participants”. [5] This behavioral finance notion builds upon the notion that individual's sentiments, being their emotions, ideologies, and attitudes cause a meaningful effect on the stock market's prices and performance. This chapter analyzes the effect of mood states, mood contagion, and mood states scrapped from twitter and their effects on the German stock market in a behavioral finance perspective.

They used twitter as a proxy for approximating mood states. They point to evidence supporting the notion that “lead-users” exert influence on their followers, which in turn causes a reaction impacting their followers mood states, known as mood contagion. [5]

In behavioral finance, investors are humans who may be driven to make errors due to emotions. [5] The author points to evidence in market abnormalities that at least contradict how the market ought to behave under the efficient market hypothesis. For example, a prediction of stock market prices should not be possible, if each piece of information is continuously priced into the market.

Examples of abnormalities that may contradict the efficient market hypothesis include: calendar abnormalities and technical abnormalities. [5] Calendar abnormalities are time-based, like seasonal, trends that move stock prices. The authors point to the January effect as one such example. The January effect is a trend that states the average return in the month of January tends to be higher than other months of the year, however, a hypothesis that may explain this phenomenon may be tax-loss harvesting for the previous tax year. Technical abnormalities involve the use of historical trends to predict or explain future performance. An example cited is the momentum effect, where previous winners will continue to win, with the converse being true. This phenomenon directly counters the EMH as it would cause an inefficiency in the market.

Now, integrating investor's psychology into an explanation for stock market movements requires understanding two groups. The two groups are defined by the authors as rational arbitragers and noise traders. Rational arbitragers are investors who are well informed and are not prone to sentiment related trading errors.[5] Noise traders are the investors who seemingly irrationally give weight to non-fundamental related information; these traders are prone to rely on sentiment to make trades.[5]

Under the EMH, price increases are driven by the selling and buying of stocks between the rational arbitragers and the noise traders. An exogenous shock would drive noise traders to buy or sell and then rational arbitragers will then drive the prices back up to fundamental value.[5] The author points to an example where rational arbitragers may predict the noise, instead of following the fundamentals, which in turn contradicts the EMH. [5] The author believes, using the behavioral financial lens, better explains this phenomenon.

The author proposes a framework that explains the attribution of mood, its effect on risk attitude, and the effect of risk attitude on investment behavior. They argue a fluctuation in mood can cause an increase in risk attitude, which in turn increases an individual's willingness to invest in a riskier asset.

The next step is to understand the predictive value of social media. The author points to a study where overall sentiment measured from twitter had predictive value over the Dows Jones Industrial Average (DIJA). [5]

Emotional/mood contagion are contagious; even in environments where direct social interaction is absent, like social media interactions, emotional contagion may still occur. [5] The crux of this phenomenon can be observed in an example illustrated by the author where individuals on Facebook produced fewer positive status updates as they were subjected to an increasingly large volume of negatively charged posts on social media feeds. [5] They hypothesize a relationship between increased user mood states from social media and greater stock market returns.

They derived a weighted social mood index from:

$$WMSI = \frac{\text{positive mood} * \text{followers}}{(\text{positive mood} * \text{followers}) + (\text{negative mood} * \text{followers})} \quad (3.1)$$

They found an increased WMSI compared to the previous day, tended to cause an increase in stock price and a decreased WMSI compared to the previous day tended to cause a decrease in stock price. This was confirmed as their trading strategy was to buy the DAX index on days where the WMSI increased and shorted the DAX on days where the WMSI decreased, which led to their portfolio outperforming the average weighted return over 6 months by at least 6%. [5] They conclude that the network structure of twitter should be considered when analyzing the relationship between mood levels and share returns.

3.6 Investor Sentiment in the Stock Market by Malcom Baker and Jeffery Wurgler (2007)

Baker and Wurdler (2007) build upon a theoretical framework that combines the notions that investors as individuals that are affected by sentiment and the macroeconomic investor sentiment approach proposed by them.

The investor sentiment approach they proposed is a top-down model, unlike the bottom-up approach used by previous researchers used by previous researchers to explain the effects of sentiment related mood states of individual investor's under-reaction or overreactions of past returns or fundamentals. [6] The top-down approach they presented is distinctly macroeconomic. They reason in behavioral finance, the bottom-up approach developed by other researchers, is unable to fully capture the psychology of individual investors. [6] For example, this approach fails to account for the variance of selected biases and trading frictions of individuals. Instead, the top-down approach aims to capture the aggregate sentiment of investors and traces the aggregate sentiment of investors as a whole to explain the overall market and individual stocks.

The top-down model is compatible with the irrefutable assumptions of behavioral finance; those assumptions being sentiment and the limits of arbitrage to explain why specific stocks are more affected by sentiment instead of a blanket notion that the overall market is affected by sentiment. [6]

There are two key ideas that come with this approach. The first is the possibility demand shocks may vary across firms due to sentiment, i.e. when sentiment increases, the speculative stocks are likely to have higher than average returns. The second is the stocks that are most difficult to price are the ones that are the most difficult to arbitrage, i.e. stocks that are most prone to sentiment-based demand shocks.

They propose a sentiment beta. This measure relates to the effect sentiment plays on the valuation of a stock. [6] For example, a stock with a sentiment beta greater than 1 will

indicate that a stock has a relatively higher market risk, with the converse being true. This means market returns are negatively related to changes in sentiment.

At the time of this paper's writing, sentiment analysis and opinion mining from textual sources to gauge public sentiment to ascertain a sentiment score were not as developed. Therefore, this paper makes do with sentiment proxies that derive a sentiment measure from data sources including momentum, retail investor trades, investor surveys, exogenous mood-related factors, and fundamental data. [6] The fundamental data included: dividend premiums to measure market confidence, closed-end fund discounts, IPO first day returns, short-term IPO volume, and the volume of equity issued over time.

The effect of this approach was measured as sentiment betas increase, stocks become more difficult for arbitrage. The found a significant correlation of 0.43 between the market indexes' returns and changes in their sentiment index. [6] Therefore, they assert the cause of investor sentiment is exogenous and has a quantifiable effect on the market.

Chapter 4: Deliverables

- Capstone project paper documenting my methodology, research, and findings
- Science paper documenting my findings
- Slide presentation for presenting my research and findings

Chapter 5: Data

In this project, 3 datasets were used. Two datasets come from Yahoo Finance, a leading media company that provides finance related news, including stock quotes. These two data sets contain stock movement data for the following index funds, the SP500, Standards and Poors 500, and IXIC, the NASDAQ 500. Yahoo finance partners with trading exchanges and providers of financial market data to collect and provide historical stock quote data [7, 8].

The index funds' data sets contain the following features:

| <i>Column</i> | <i>Comment</i> |
|---------------|---|
| Date | Date |
| Open | Opening price of the equity |
| High | Maximum price of the equity for the given day |
| Low | Minimum price of the equity for the given day |
| Close | The closing price of the equity |

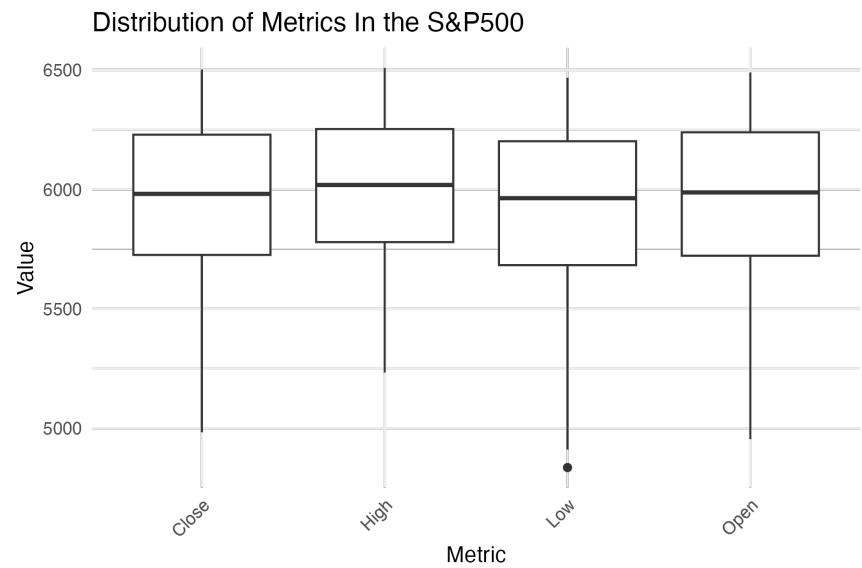


Figure 5.1: Box plots of S&P500 Numerical Features

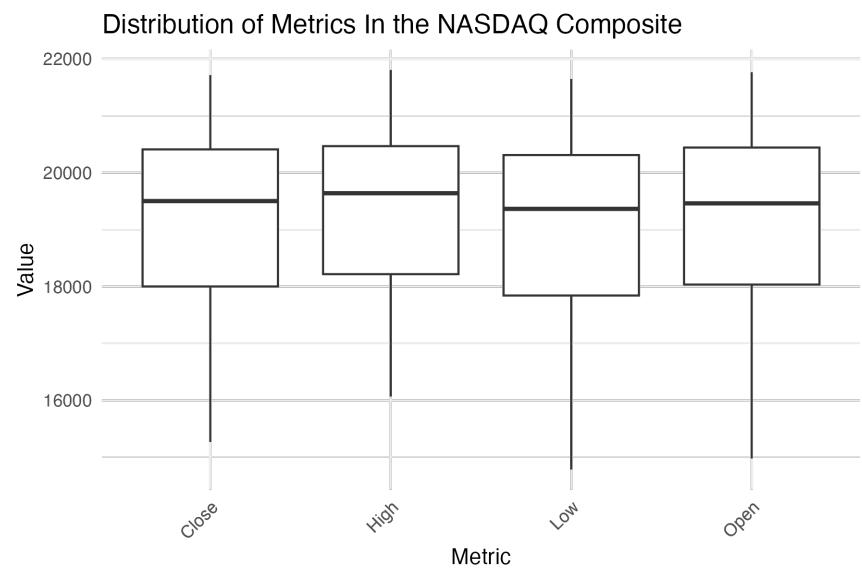


Figure 5.2: Box plots of NASDAQ Composite Numerical Features

The third data set used for this project is a web scrape of all of Donald J. Trump's posts on his social media platform, Truth social. This data includes his direct posts, re-posts, and his interactions with various truth social users. The web scrape was provided using open sourced tool from the github user stiles user who provides a scraped mirror of Donald Trump's posts for research purposes [9]. This dataset contains the following features:

| <i>Column</i> | <i>Comment</i> |
|------------------|---|
| id | The unique identifier for the post |
| created at | Timestamp when the post was made |
| content | The text content of the post |
| url | Direct link to the post on Truth Social |
| media | An array of image and video URLs if the post contains media |
| replies count | Number of replies to Trump post |
| reblogs count | Number of re-posts, or re-truths, to Trump post |
| favourites count | Number of favorites to Trump post |

As index funds typically aim to capture a diverse subset of the overall market, therefore increasing diversification, leading to reducing risk, while not necessarily reducing reward. While, the NASDAQ composite index fund had historically been seen and regarded as the more performant and safer fund, I found when the performance metric, in this case the normalized closing price of the index funds performed very similarly in the time-frame of Trump's second presidency.

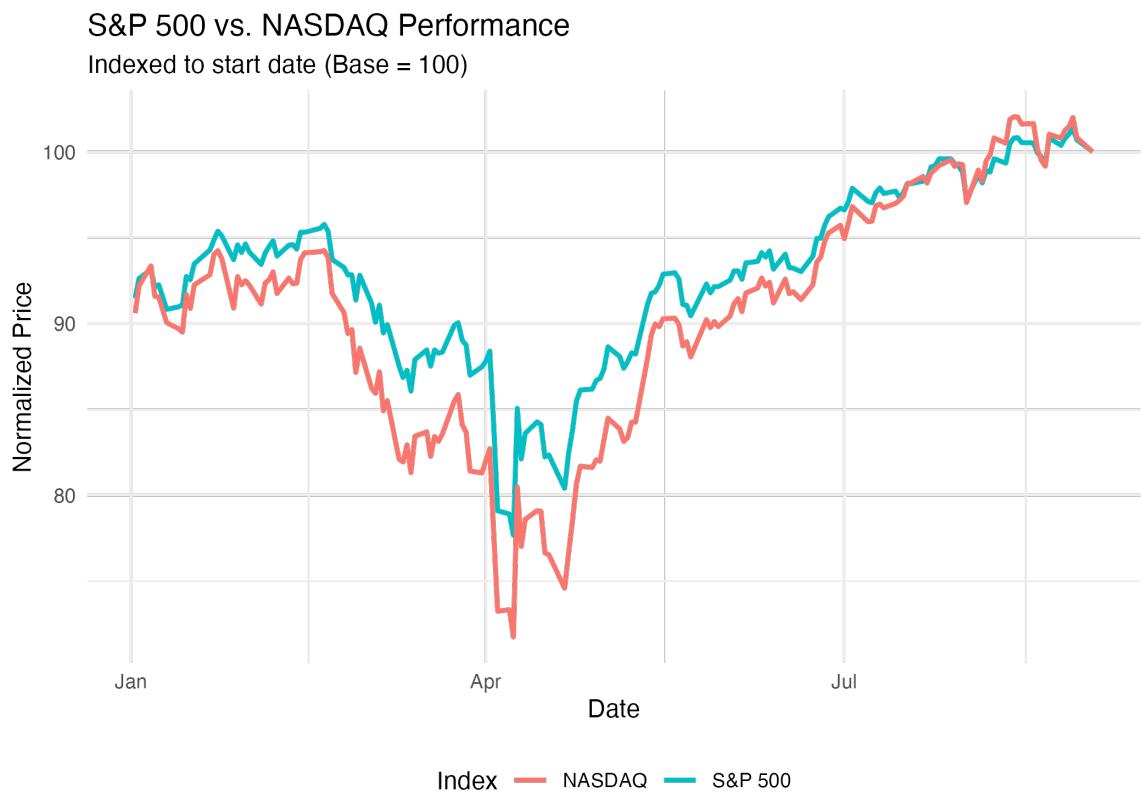


Figure 5.3: S&P 500 vs. NASDAQ Normalized Performance (Closing Price)

Another point in the similarity or the lack of meaningful differentiation in performance, between the two index funds from 01/01/2025 until 09/20/2025, that had been chosen to abstract the overall performance of the United States stock market is in the relative both indexes behaved similarly in both sets of hypothesis tests, as shown in the theory and results chapters.

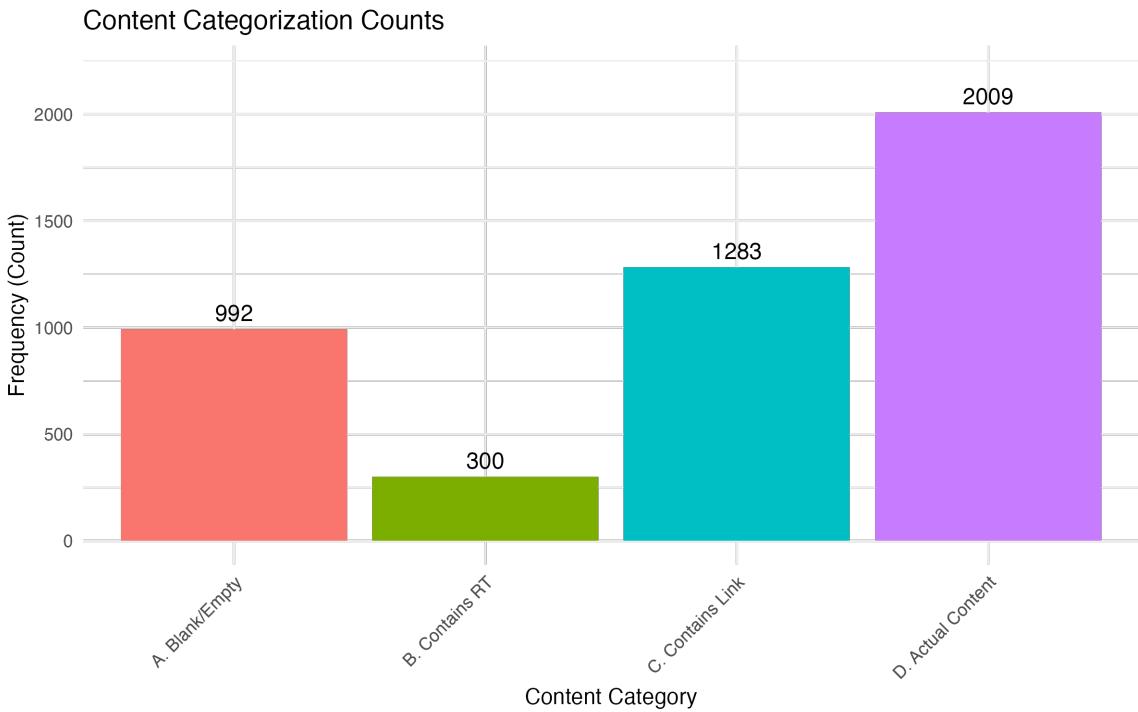


Figure 5.4: Counts of Various Data Quality Issues In Trump Truth Social Archive

While the index fund data was clean, the same is not the case for the Trump Truth Social Archive. The archive had empty rows without text content, retweets, and responses to other users in addition to Trump's direct posts during the time frame of his second presidency. This finding regarding the unprocessed nature of the Trump Truth Social Archive will require extensive cleaning, preprocessing, and filtering to yield usable and clean data for modeling.

The primary goal of this project is to explain the phenomena of the April stock market crash, which seems to be universally understood or partially attributed to Donald J. Trump's social media posts on tariffs and trade wars. To explain this, this project aims to either prove or disprove an empirical link between Donald J. Trump's posts on Truth Social and stock market movement.

Chapter 6: Theory

My original theory was that the sentiment of Donald Trump's posts would effect the stock market. I used index funds to abstract the stock market, in this case the S&P500 and NASDAQ Composite.

My null hypothesis for this initial theory was:

$$H_0 : \mu_{positive} = \mu_{neutral} = \mu_{negative} \quad (6.1)$$

In the initial stages of exploratory data analysis after cleaning and preprocessing Trump's posts dataset to a usable state, I applied a sentiment model to the textual data stored in content. Using the VADER lexicon to assign each post a sentiment score, we can then derive sentiment categories of positive, neutral, and negative with a threshold of any compound sentiment of 0.05 is positive, less than minus 0.05 is negative, and those falling between the threshold are considered neutral. An interesting finding here was the distinct lack of any difference in means for either index's performance, when measuring the sentiment category versus the closing price in a faceted box plot.

The VADER lexicon for sentiment analysis was created in by Hutto and Gilbert in 2014 [10]. The equation for deriving sentiment from text corpus is as follows:

$$\text{Compound_Score}_i = \frac{x_i}{\sqrt{x_i^2 + a}} \quad (6.2)$$

¹ [10]

Following the failure to reject that null hypothesis, I pivoted to using topic modeling to extract the latent topics in the content of Donald Trump's posts.

In this new theory, I theorized that there may be a difference in the mean daily change, daily volatility, or closing price given a topic category.

My null hypothesis for this theory was that the sample means for each topic are the same:

$$H_0 : \mu_0 = \dots = \mu_{i-1} = \mu_i \quad (6.3)$$

The Latent Dirichlet Allocation topic analysis model applied to machine learning was proposed by Blei, David M., and Ng, Andrew Y (2003). [11] The LDA topic model is a three-layered hierachal Bayesian model, which is a generative probabilistic model that collects discrete terms to provide an explicit representation for each document. [11]

There is no singular equation for LDA topic modeling, instead Gibb's sampling or other algorithmic methods are used to identify latent structures. [11]

¹x = the sum of all the sentiment valence scores as calculated by the VADER lexicon's heuristic rules. a = the normalization parameter; usually 15, which should match the maximum expected x. [10]

Chapter 7: Results

The results of my first hypothesis regarding the impact of sentiment categories derived from Donald J Trump's posts from Truth Social using the Vader Lexicon sentiment analyzer model on Stock Market Movement are as follows:

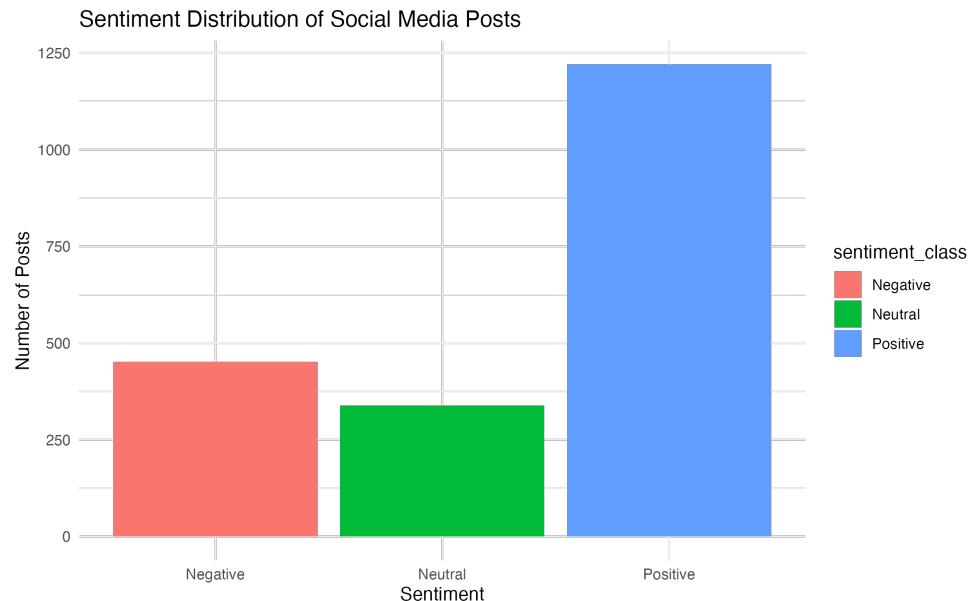


Figure 7.1: Sentiment Distribution of Social Media Posts

The distribution of sentiment by social media posts seems suspect. From manually sampling Donald Trump's posts, a majority of the posts would either be interpreted as negatively emotionally charged, meaning they seem to be written with a strong emotional or opinionated undertone, which does not seem to line up with this distribution of mostly positively labeled sentiments per post.



Figure 7.2: Index Closing Prices by Sentiment Class

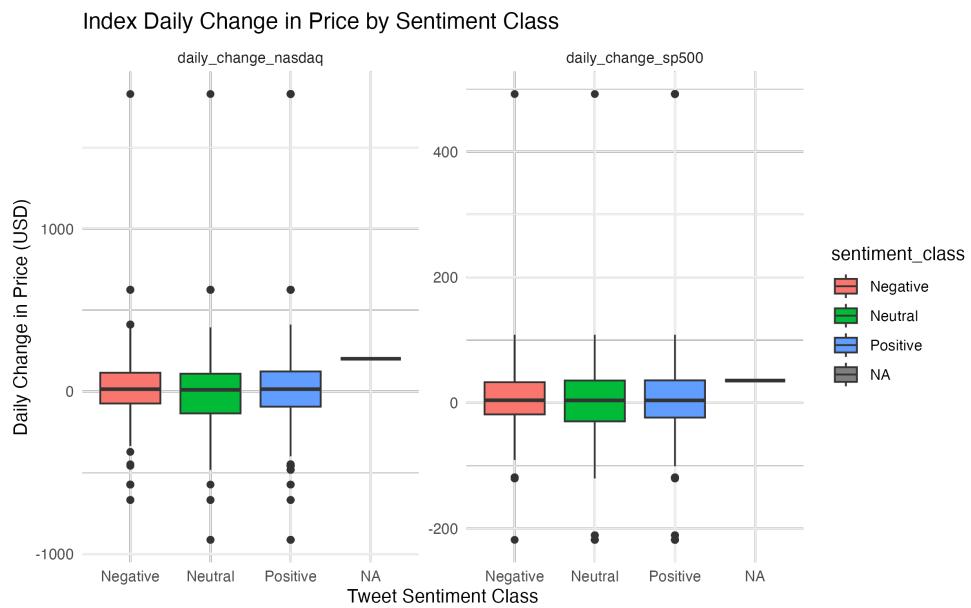


Figure 7.3: Index Daily Change in Price by Sentiment Class

Given that there was not a significant difference in means between the sentiment classes when measuring the sample means from closing_price and daily_change, we do not fit the criteria to perform an ANOVA test. The primary criteria for a single factor ANOVA test.

Statistical Significance for the ANOVA test on Closing price of S&P500 Sentiment Category:

Analysis of Variance Table

Response: Close_sp500

| | Df | Sum Sq | Mean Sq | F value | Pr(>F) |
|-----------------|------|-----------|---------|---------|--------|
| sentiment_class | 2 | 158986 | 79493 | 0.6511 | 0.5216 |
| Residuals | 1613 | 196938196 | 122094 | | |

Statistical Significance for the ANOVA test on the daily volatility of the price of S&P500 Sentiment Category

Analysis of Variance Table

Response: daily_volatility_sp500

| | Df | Sum Sq | Mean Sq | F value | Pr(>F) |
|-----------------|------|---------|---------|---------|--------|
| sentiment_class | 2 | 7886 | 3942.8 | 0.8504 | 0.4274 |
| Residuals | 1613 | 7478507 | 4636.4 | | |

Statistical Significance for the ANOVA test on Closing price of NASDAQ Composite Sentiment Category:

Analysis of Variance Table

Response: Close_nasdaq

| | Df | Sum Sq | Mean Sq | F value | Pr(>F) |
|-----------------|------|------------|---------|---------|--------|
| sentiment_class | 2 | 3233757 | 1616878 | 0.6429 | 0.5259 |
| Residuals | 1613 | 4056464149 | 2514857 | | |

Statistical Significance for the ANOVA test on the daily volatility of the price of NASDAQ Composite Sentiment Category

Analysis of Variance Table

Response: daily_volatility_nasdaq

| | Df | Sum Sq | Mean Sq | F value | Pr(>F) |
|-----------------|------|----------|---------|---------|--------|
| sentiment_class | 2 | 105530 | 52765 | 0.8919 | 0.4101 |
| Residuals | 1613 | 95423509 | 59159 | | |

As the criteria necessary to perform a single factor ANOVA were not met, meaning a significant difference in means was not fulfilled, the p-values for any of these 4 ANOVA tests are not statistically significant. The p-value from none of these tests were less than the significance level of $\alpha = 0.05$, therefore there is not sufficient evidence to reject the null hypothesis.

The results of my second hypothesis on the impact of the topic categories derived from Donald J Trump's posts from Truth Social using the Latent Dirichlet Allocation Topic Model on Stock Market Movement are as follows:

In order to perform topic modeling using Latent Dirichlet Allocation, a document term matrix needs to be constructed from a text corpora. The most frequent terms in the Trump Truth Social Archive text corpus are:

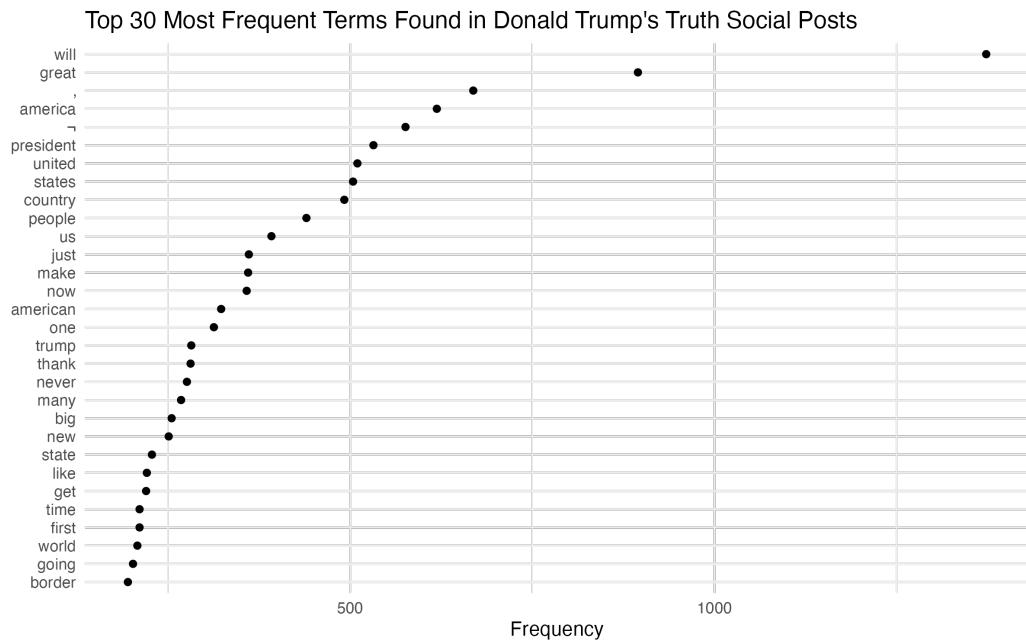


Figure 7.4: Top 30 Most Frequent Terms Found in Donald Trump's Truth Social Posts

Due to a double encoding error, there are some non ASCII characters that show up. This is likely due to the text in the Trump Truth Social Archive corpus being encoded in a non-standard uft encoding then re-encoded into uft-8. However, this is not a prevalent issue, nor will it cause issues, since these symbols are removed in a preprocessing step before applying the topic model.

The LDA topic model was applied using the following parameters $a = 15, k = 10, seed = 123$. The 10 topics found were:

| Topic 1 | Topic 2 | Topic 3 | Topic 4 | Topic 5 | Topic 6 | Topic 7 | Topic 8 | Topic 9 | Topic 10 |
|---------|---------|-----------|-------------|----------------|-----------|-----------------|-----------|-------------|-----------|
| will | fake | will | great | president | great | will | will | secure | country |
| great | new | america | will | trump | will | states | president | will | biden |
| country | news | united | america | will | one | united | war | great | will |
| crime | york | tariffs | make | administration | big | announce | russia | complete | just |
| people | great | states | republican | including | beautiful | pleased | just | total | people |
| now | people | great | big | law | america | great | ukraine | endorsement | joe |
| america | bad | country | house | pro | bill | congratulations | iran | border | democrats |
| thank | case | countries | republicans | donald | tax | secretary | peace | always | america |
| just | judge | trade | senate | bono | people | serve | united | let | states |
| states | even | china | bill | justice | ever | district | great | second | election |

Table 7.1: Top Terms per Topic

After the topics had been extracted using the unseeded LDA model, I compared the topics against the daily volatility of the S&P500. Below is the boxplot shoeing the spreads of daily volatility in the S&P500 across the discovered topics.

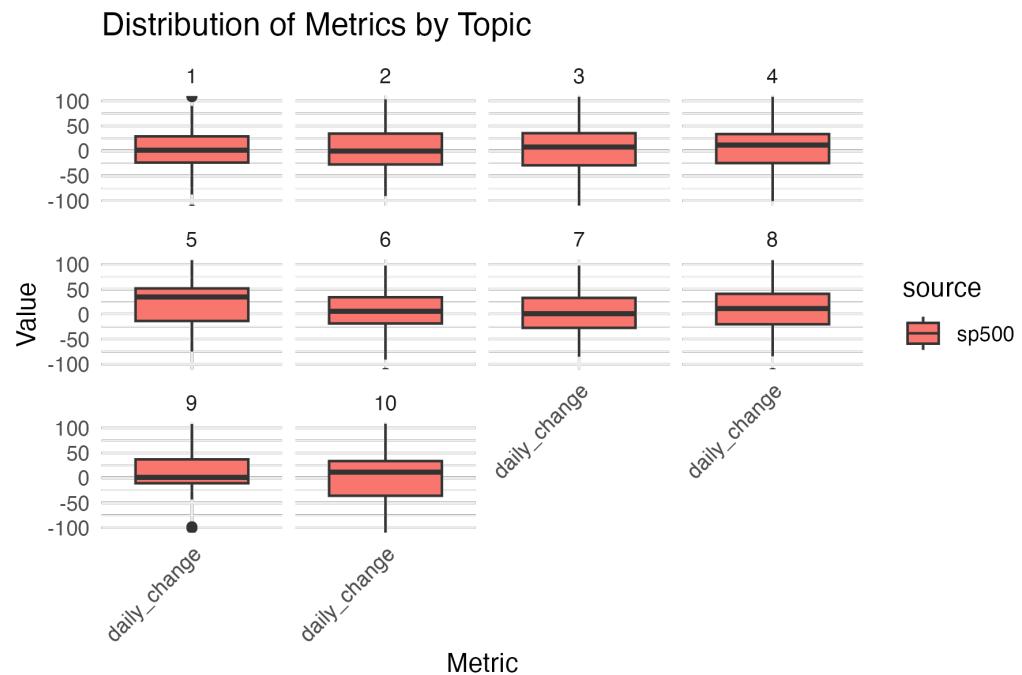


Figure 7.5: Spread of Daily Volatility in the S&P500 by Topic

Although the means did not appear to be distinct, i.e. the boxplots did not appear to have considerable differences in means, I still elected to conduct an ANOVA test. This ANOVA test is of the explanatory variable, topic, and the response variable, the daily volatility of the S&P500.

Terms:

| | topic | Residuals |
|-----------------|--------|-----------|
| Sum of Squares | 151055 | 6063361 |
| Deg. of Freedom | 9 | 1265 |

Residual standard error: 69.23273

Estimated effects may be unbalanced

| | Df | Sum Sq | Mean Sq | F value | Pr(>F) | | | | | | |
|----------------|------|---------|---------|---------|--------------|-----|------|-----|-----|-----|---|
| topic | 9 | 151055 | 16784 | 3.502 | 0.000272 *** | | | | | | |
| Residuals | 1265 | 6063361 | 4793 | | | | | | | | |
| | --- | | | | | | | | | | |
| Signif. codes: | 0 | '***' | 0.001 | '**' | 0.01 | '*' | 0.05 | '.' | 0.1 | ' ' | 1 |
| [1] | "" | | | | | | | | | | |

The ANOVA test found a p value of 0.000272, which is very significant at a 5 percent significance level, meaning I can reject the null hypothesis of no difference in means between groups. I then conducted a post-hoc test using TukeyHSD. Below is the Tukey test:

My null hypothesis for the post-hoc test is:

$$H_0 : \mu_i = \mu_j \quad (7.1)$$

The TukeyHSD found a significant difference between topic 3 and topics 2, 7, 8, and 9. From this result, having significant p values, I can reject the null hypothesis. I believe there is evidence to support the possibility that topic 3 has a tangible effect on the daily volatility of the S&P500.

| | diff | lwr | upr | pval |
|-----|--------|--------|-------|------|
| 3-2 | 28.20 | 0.82 | 55.59 | 0.04 |
| 7-3 | -33.48 | -58.98 | -7.98 | 0.00 |
| 8-3 | -25.02 | -49.28 | -0.75 | 0.04 |
| 9-3 | -33.83 | -62.33 | -5.33 | 0.01 |

Table 7.2: Post-Hoc Tukey LDA

I then tried a seeded LDA model where I defined 5 topics, immigration, rates, trade, war, and social in a dictionary. These topics were meant to model topics that Donald Trump frequently posted about that might move the market. The topics were seeded with as follows:

| | IMIGRATION | RATES | TRADE | WAR | SOCIAL |
|----|-------------|-----------|--------------|-----------|----------|
| 1 | aliens | bill | canada | defense | elon |
| 2 | border | budget | china | hostages | musk |
| 3 | borders | capital | india | ceasefire | cost |
| 4 | enforcement | inflation | negotiations | iran | cut |
| 5 | homeland | job | steel | israel | costs |
| 6 | illegal | jobs | tariff | military | cuts |
| 7 | illegally | jerome | tariffs | putin | cutting |
| 8 | illegals | powell | trade | russia | security |
| 9 | migrant | price | war | russian | social |
| 10 | mexico | prices | commerce | ukraine | veterans |
| 11 | patrol | rate | | vladimir | |
| 12 | | rates | | zelenskyy | |
| 13 | | tax | | | |
| 14 | | treasury | | | |
| 15 | | economy | | | |
| 16 | | economic | | | |
| 17 | | taxes | | | |
| 18 | | fed | | | |

Table 7.3: Seeded Topic Dictionary

I also allowed the seededLDA to discover 3 nondefined topics, leading to a total number of 8 topics for the seedLDA.

Terms:

```

          slda_topic Residuals

Sum of Squares      80064   4291314
Deg. of Freedom       7        1087

Residual standard error: 62.83193
Estimated effects may be unbalanced

          Df  Sum Sq Mean Sq F value Pr(>F)
slda_topic     7  80064   11438    2.897 0.00528 **
Residuals     1087 4291314    3948
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
[1] ""
[1] "Post-hoc test"

```

| | diff | lwr | upr | pval |
|--------------|--------|--------|-------|------|
| TRADE-other1 | 24.99 | 4.34 | 45.64 | 0.01 |
| TRADE-other2 | 23.11 | 1.22 | 45.01 | 0.03 |
| TRADE-other3 | 21.42 | 0.09 | 42.76 | 0.05 |
| WAR-TRADE | -25.48 | -46.77 | -4.18 | 0.01 |

Table 7.4: Post-Hoc Tukey SLDA

Chapter 8: Conclusion

Chapter 9: Software

The IDE used in this project was RStudio and the programming language used was GNU R.

The following R libraries where used:

Chapter 10: Capstone

The project integrates what we learned in:

CDS-230 Modeling and Simulation I, and

CDS-301 Scientific Information and Data Visualization, and

CDS-321 Natural Language Processing, and

CDS-402 Machine Learning

With the intention of discovering the power an individual's words can have.

Bibliography

- [1] David L. John, Bela Stantic, Tien Khoa Tran, Ualsher Tukayev, Tzung-Pei Hong, Bogdan Trawiński, Edward Szczerbicki, and Ngoc Thanh Nguyen. Machine learning or lexicon based sentiment analysis techniques on social media posts. In *Intelligent Information and Database Systems*, volume 13758 of *Lecture Notes in Computer Science*, pages 3–12. Springer, Switzerland, 2022.
- [2] Dev Shah, Haruna Isah, and Farhana Zulkernine. Predicting the effects of news sentiments on the stock market, 2018.
- [3] Thien Hai Nguyen, Kiyoaki Shirai, and Julien Velcin. Sentiment analysis on social media for stock movement prediction. *Expert systems with applications*, 42(24):9603–9611, 2015.
- [4] Nabanita Das, Bikash Sadhukhan, Tanusree Chatterjee, and Satyajit Chakrabarti. Effect of public sentiment on stock market movement prediction during the covid-19 outbreak. *Social Network Analysis and Mining*, 12(1):92, 2022.
- [5] Michael. Nofer. The value of social media for predicting stock returns : Preconditions, instruments and performance analysis, 2015.
- [6] Malcolm Baker and Jeffrey Wurgler. Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2):129–152, Spring 2007.
- [7] Historical stock quote for ixic, 2025.
- [8] Historical stock quote for gspc, 2025.
- [9] Matt Stiles. Trump-truth-social-archive. <https://github.com/stiles/trump-truth-social-archive>, 2025.
- [10] C. Hutto and Eric Gilbert. Vader: A parsimonious rule-based model for sentiment analysis of social media text. *Proceedings of the International AAAI Conference on Web and Social Media*, 8(1):216–225, May 2014.
- [11] David M. Blei, Andrew Y. Ng, and Michael I. Jordan. Latent dirichlet allocation. *J. Mach. Learn. Res.*, 3(null):993–1022, March 2003.

Biography

Include your *biography* here detailing your background, education, and professional experience.