Exploring the Virality of Trump Tweets

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Abstract

A Trump Tweet that is insulting and negative has the best chance of receiving the most favorites. This discovery reveals that, in terms of user engagement with digital political media, emotional content maximizes interaction. In our research, we aim to uncover the factors that contribute to the popularity of a Trump tweet. To analyze our dataset of 26,312 tweets we will utilize feature generation methods to create variables based on the text data and we will apply machine learning techniques like Random Forest and Gradient Boosting to explore the relationship between different factors of a tweet and its success.

1 Introduction

The main purpose of our research is to find what factors make a Trump tweet popular. Donald Trump first joined Twitter in 2009 where he remained active throughout his presidency until he was banned from the platform in 2021. During that time, Trump made 46,919 original tweets and received 1,659,180,779 favorites in total. Far from simply a personal profile, Trump made twitter a valuable tool in his political career. His tweets often communicated major news, platformed his opinions, and sparked heated political debate. Understanding the factors behind the popularity of his tweets can provide valuable insight into the relationship between politics and social media.

In order to explore this topic, we will be analyzing a text dataset of 56,571 of Trump tweets. For the purpose of this study, we will only be analyzing Trump tweets dating from 2015-2021, the time period from when Trump first announced his 2016 presidential run until he was banned from Twitter in 2021, as this is when his account receives the most interaction. Additionally, we are disregarding retweets as we are only interested in analyzing tweets written by Trump himself. After filtering out the data by year and retweets, we were left with a text dataset containing 26,312 Trump tweets. In the following sections we will employ feature generation and machine learning techniques such as Random Forest and Gradient Boosting to analyze the data.

2 Variables

2.1 Dataset Variables

The given dataset has 56,571 observations over a span of almost 12 years (5/4/09 – 1/8/21). The dataset measures 9 variables: id, text, isRetweet, isDeleted, device, favorites, retweets, date, and isFlagged.

- **id**: This variable represents the integer primary key for the dataset, where each tweet has a unique individual id associated with it.
- **text**: This variable simply contained the actual string content of each Trump tweet; this is the column where we conducted the majority of our analysis, and is our primary focus.
- **isRetweet**: This is a boolean representing whether the tweet was an original Trump tweet or simply a retweet of someone else's.
- **isDeleted**: This variable describes whether the tweet has been deleted yet or not.

- **Device**: This is a string column describing the platform from which the tweet was sent, whether that be a computer, Trump's iPhone, or even through a third-party platform like Vine.
- **favorites**: This variable measures the integer amount of likes the tweet received.
- **retweets**: This variable measures the amount of retweets.
- **date**: This shows the specific datetime that the tweet was posted, within the given date range from before (ending January 8, 2021). For our dataset, we decided to only look at data after 2015, the year Trump announced his first presidential campaign.
- **isFlagged**: This variable demonstrates which Trump tweets have been flagged by Twitter.

When looking to choose a response variable, we were easily able to narrow it down to 2 options: favorites or retweets. Here, we are looking for the best metric to gauge the popularity of a tweet. The following graph displays a time series analysis of average monthly favorites versus retweets from 2015.

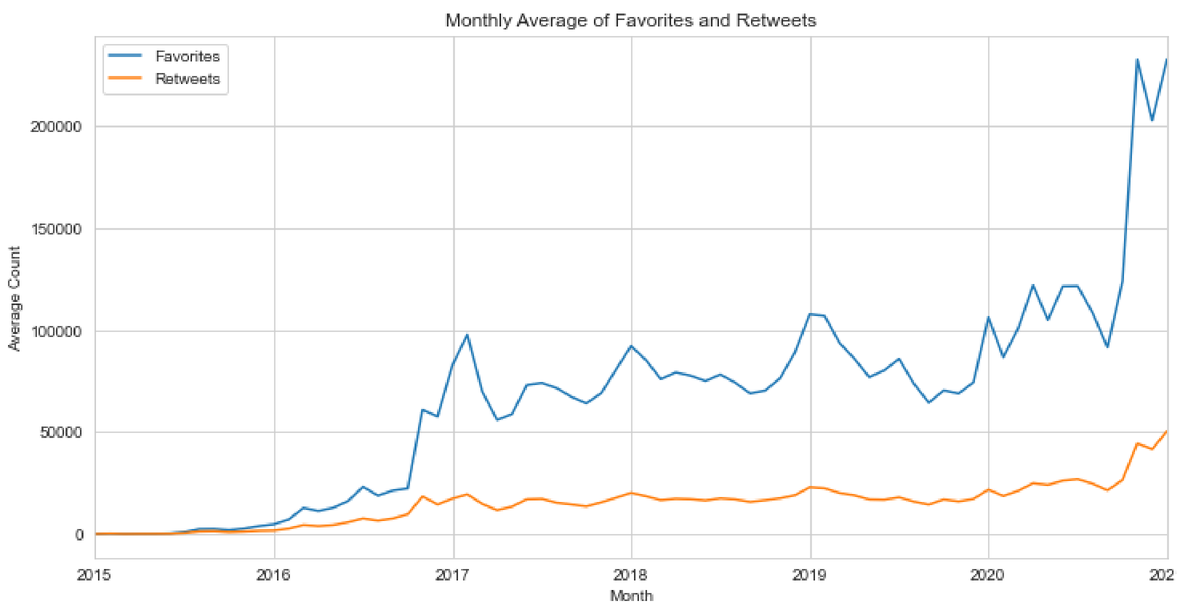

Figure 1: Time Series Analysis of Favorites vs. Retweets Over Time

Looking at the graph, we can see that retweets stay fairly steady over time. However, the amount of favorites experiences multiple highs and lows as the years progress, and specific years show significant spikes. For example, looking at the end of 2016 and 2020, we see spikes right around the presidential election, which we can expect to have seen a very public-facing, socially active (specifically on Twitter) Trump. Seeing these spikes at the end of election years led us to believe that favorites is in fact the best predictor for popularity, as the favorites is demonstrative of when Trump was most talked about in news circles and on social media. Specifically, his own tweets must have been receiving attention right around the time of the election (and when he was choosing to insult his opponents). In contrast, since the number of retweets stays pretty consistent over the years, we decided that favorites were most representative of the metric we are looking to predict.

2.2 Feature Generation

For our model, we generated 6 additional features that we thought were specifically relevant to our model. These features were ones that we thought could have a significant impact on the popularity of a Trump tweet and thus were ones we were interested in measuring. Before looking at the content of the tweets, we first categorized each tweet 1 of 4 times of day – either Morning, Afternoon, Evening, or Midnight. Here, we wanted to see if there was any specific time of day that was most popular for when Trump posted a tweet. Next, we also generated a numerical feature that simply measures the length of each tweet – looking to see if the number of words in each tweet played a role in how popular it became. We also created a boolean feature to specify if each tweet was written in all CAPS or not – if the text was in all caps, then we marked this column as True.

Looking at the actual text of the tweets, we created some of our own buckets to see if a tweet was more 'political' or 'insulting' would contribute to more likes. Firstly, we created a list of 180+ 'political' words that Trump would use periodically – i.e. 'election', 'vote', 'presidency', etc. This feature then (after removing stop-words) measured the proportion of words in each tweet that also fell within our 'political' library. We also created a smaller list of 'insulting' words – like 'crooked', 'sleepy', 'fat' – to create a feature that measured the proportion of words in each tweet that were insults. Both of these lists, political and insulting, were created by us, and we believe these features are specifically relevant to the research question at hand and seeing what makes a Trump tweet popular. After leveraging Python libraries for sentiment analysis, we also created a sentiment scoring feature through the Textblob library that measured whether each tweet had positive or negative sentiment. This numerical score was calculated after conducting sentiment analysis on the content of each tweet, and deciding whether Trump's verbiage was positive or negative.

3 Exploratory Data Analysis

3.1 EDA of Variables

- **All Caps**:

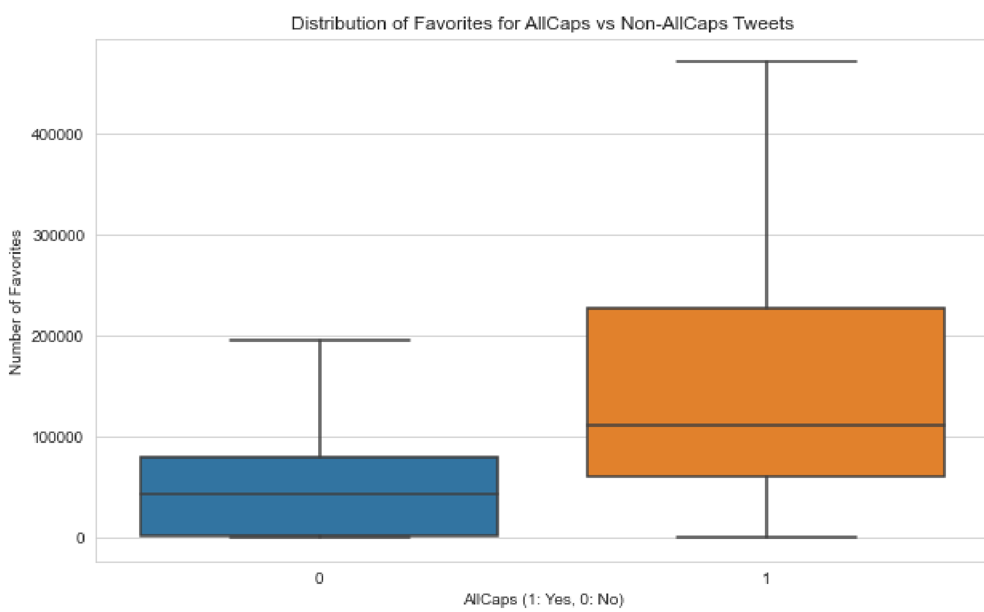

Figure 2: Distribution of Favorites for All Caps vs. Non-All Caps Tweets

The side-by-side boxplot shows that tweets written in all caps have a much higher lower quartile, median, and upper quartile in the number of favorites compared to tweets not written in all caps. Such observation makes sense because tweets written in all caps tend to convey messages with more importance and stronger emotions, which helps those tweets gain more attention and support from Trump's followers. Based on the plot, whether the tweet is written in all caps is likely to have an effect on its number of favorites.

- **Tweet Length**:

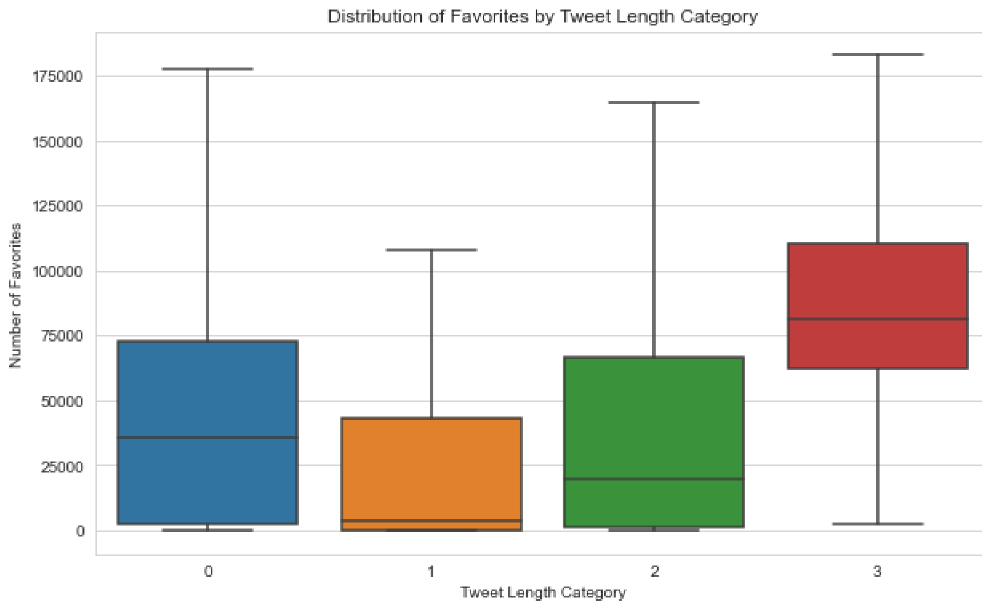

Figure 3: Distribution of Favorites by Tweet Length Category

In the side-by-side boxplot above, the category "0" represents the tweets with the shortest length, while the category "3" represents the tweets with the longest length. The plot shows that tweets with the longest length have a much higher lower quartile, median, and upper quartile in the number of favorites compared to the other tweets. It is interesting to note that tweets with the shortest length have a higher median number of favorites compared to tweets with medium length. Based on the plot, tweets that have an extreme length (either very short or very long) tend to receive more favorites.

- **Sentiment**:

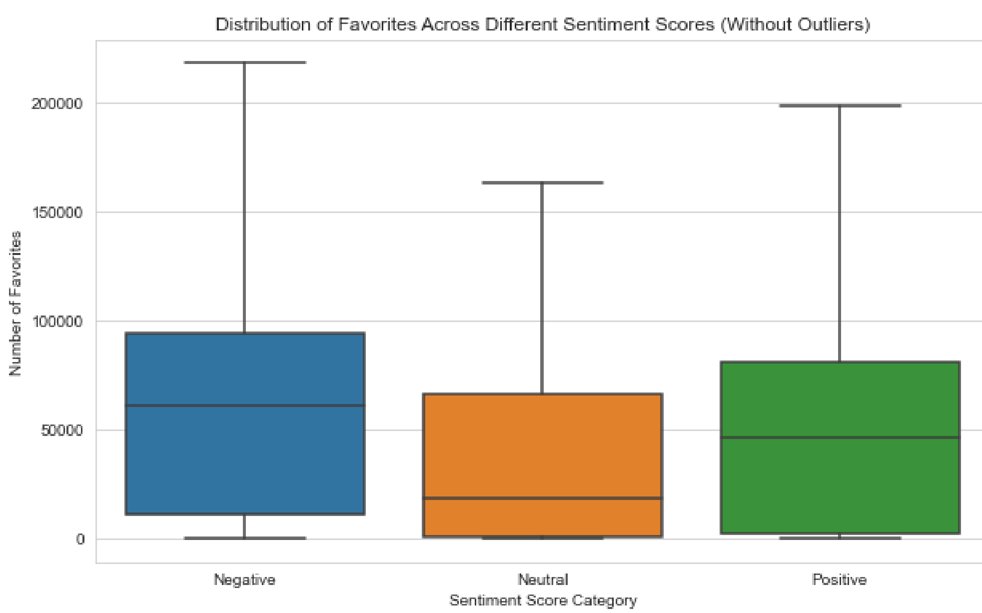

Figure 4: Distribution of Favorites Across Different Sentiments

The side-by-side boxplot shows that tweets expressing negative sentiments have a higher lower quartile, median, and upper quartile in the number of favorites compared to the other tweets. We observe that tweets expressing either negative or positive sentiments have a higher median number of favorites compared to tweets that are neutral. Such observation is reasonable because tweets expressing negative or positive sentiments often contain more emotions, thus causing Trump's followers to react strongly and favor the tweet more.

- **Time of Day**:

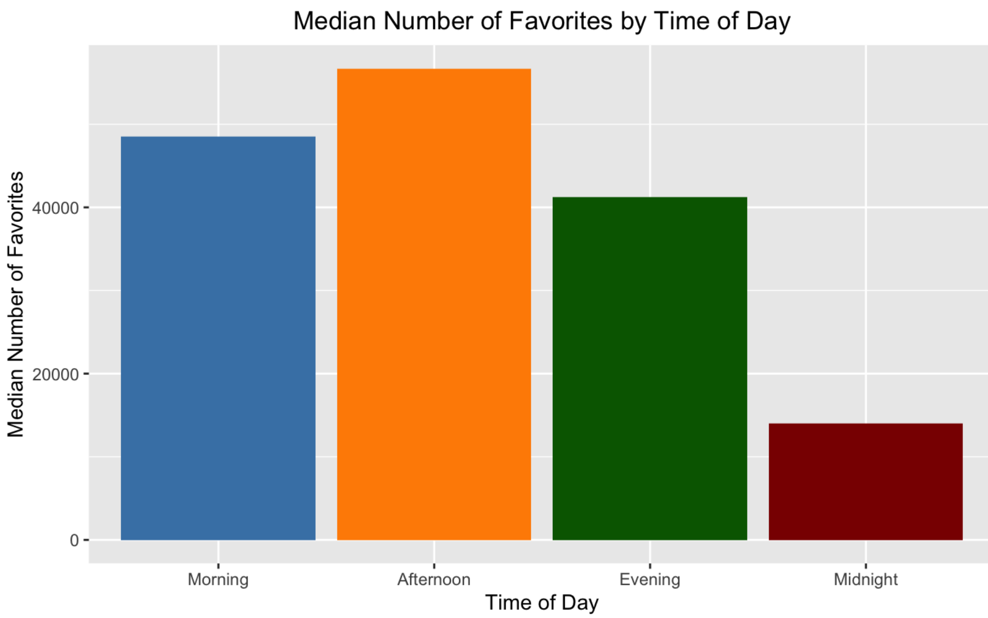

Figure 5: Median Number of Favorites by Time of Day

The side-by-side barplot shows that tweets posted in the afternoon have the highest median number of favorites compared to tweets posted during other times of the day. While the median number of favorites for tweets posted in the morning or evening are not too different from that of tweets posted in the afternoon, the median number of favorites for tweets posted in midnight is significantly lower than the median number of favorites for tweets posted at other times of the day, which makes sense because tweets posted in midnight are easier to get overlooked due to the fact that not too many users are active on Twitter during midnight.

- **Political Words**:

The side-by-side barplot below shows that tweets with a higher proportion of political words tend to have a higher median number of favorites (Figure 6). More specifically, tweets that scored in the fourth quartile of the proportion of political words (0.25 - 1) have the highest median number of favorites. Additionally, because the first quartile contains the proportion of zero, it also appears that if a tweet contains any political words that it has a much higher median number of favorites. This could be explained by the fact that Trump is a political figure. We would expect the majority of his tweets from the time period of 2015-2021 to be political in nature and for these tweets to garner the most interaction for him.

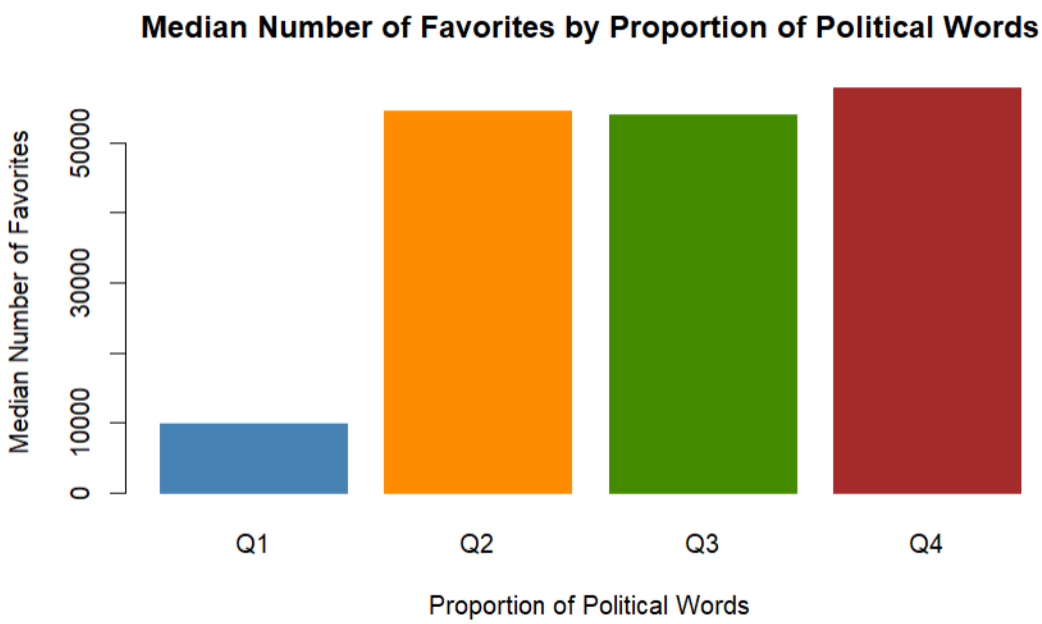

Figure 6: Median Number of Favorites by Proportion of Political Words

- **Insulting Words**:

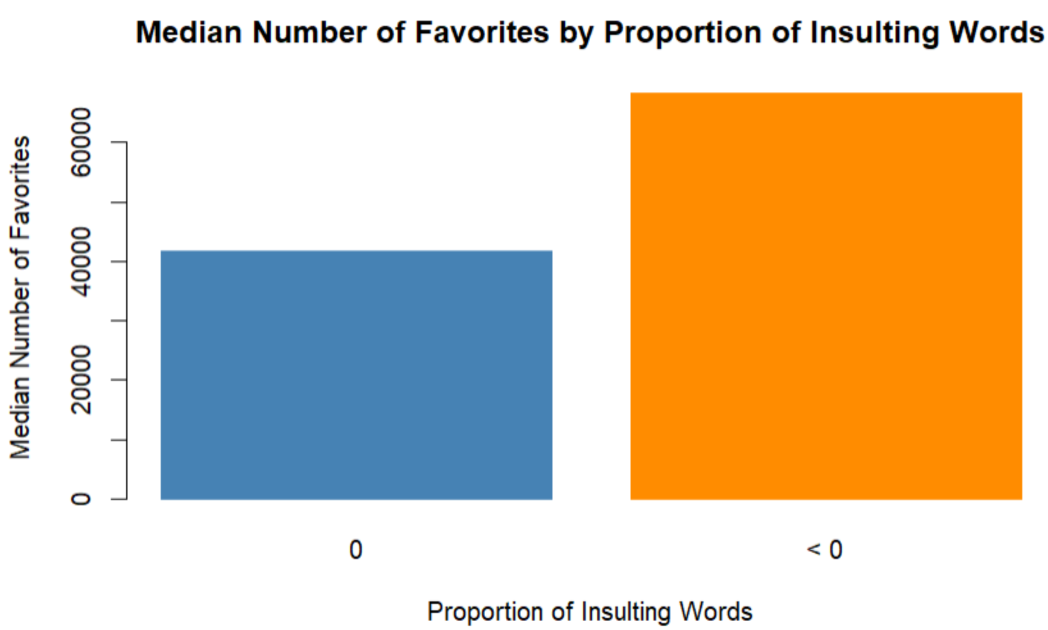

Figure 7: Median Number of Favorites by Proportion of Insulting Words

The side-by-side barplot shows that tweets that contain insulting words tend to have a higher median number of favorites. This observation can be explained by the fact that, similar to tweets that are in all caps, tweets that contain insulting words would be more emotional and provocative. Such messages are more likely to gain attention. Based on the plot, whether the tweet uses insulting words is likely to have an effect on its number of favorites.

3.2 Text Mining

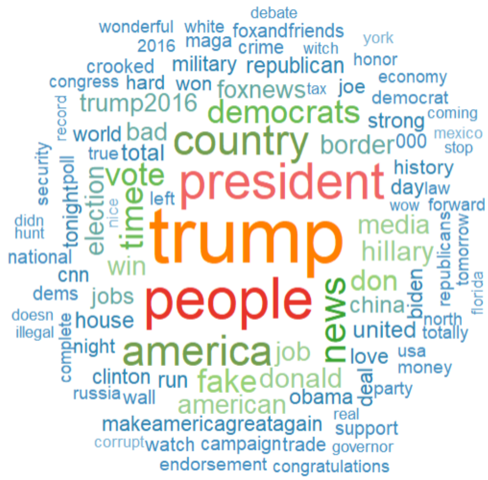

Figure 8: Frequency of Top 100 Words in Tweets

This word cloud shows the top one hundred most frequent words to appear in Trump tweets. The most commonly used words seem to either be referencing politicians (i.e. "trump", "hillary", "obama") or surrounding the topic of politics itself (i.e. "president", "vote", "democrats").

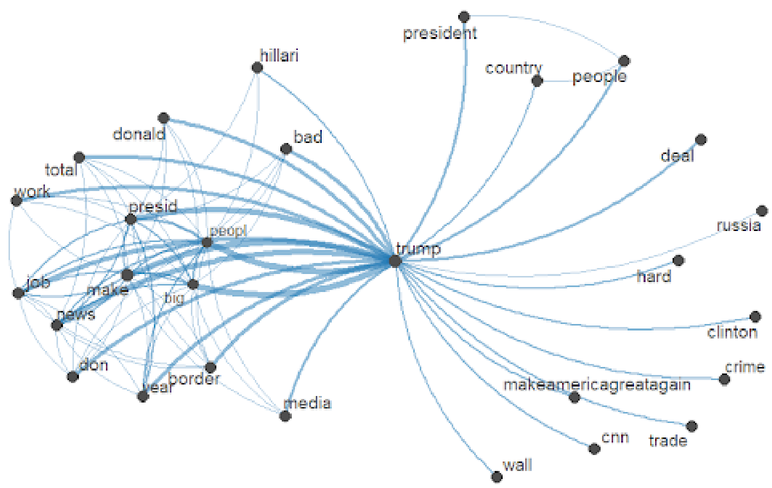

Figure 9: Text Network of Word Association in Tweets

The text network displays connections between words, offering insights into how words generally relate to each other within tweets. Thicker connecting lines represent a stronger connection in how two words are used together. Additionally, words placed in the center of the network are most critical in connecting ideas. We can see that the strongest word association occurs between the word "trump" to words like "president", "people", and "big". We can also observe how the words on the left appear to be more interconnected with each other than the words on the right.

4 Statistical Analysis of Research Question

The primary objective was to systematically identify key factors contributing to the popularity of Trump's tweets, as defined by the number of favorites received. The analysis employed a multifaceted approach that integrated both Natural Language Processing (NLP) and predictive modeling techniques. Our methodology was designed to both uncover patterns within the textual data and also model these insights against engagement.

To predict tweet popularity, we utilized several machine learning model,

- **Random Forest Regressor**: With its robustness and ability to model non-linear relationships effectively, Random Forest was a great initial model that was adept at handling overfitting with a relatively low MSE and high R-squared.
- **Gradient Boosting**: This was a prime candidate, as correcting errors of weak learners and being adaptable to complex datasets such as our textual one was a major plus.
- **Linear Regression**: A good baseline model, we valued its simplicity and interpretability for initial insights.
- **Decision Tree**: Offers clear interpretability, which helps in understanding the decision-making process for the model.

The model performance was evaluated using Mean-Squared Error (MSE) and R-squared metrics under a cross-validation framework to ensure both robustness and generalizability. The results followed,

Model	MSE	R-squared
Random Forest Regressor	0.3465	0.7283
Gradient Boosting Machine	0.2846	0.7768
Linear Regression	0.4074	0.6805
Decision Tree Regressor	0.5219	0.5907

Table 1: Model Performance Metrics

Gradient Boosting demonstrated the highest effectiveness in predicting tweet popularity, indicated by the lowest MSE and the highest R-squared value. Consequently, our focus shifted towards refining and optimizing the GBM model to enhance its predictive power.

Each model's performance was assessed with MSE and R-squared metrics with cross-validation techniques applied to evaluate robustness and generalization ability. Based on the performance metrics, gradient boosting demonstrated highest effectiveness in predicting tweet popularity.

5 Summary of Results

5.1 Feature Importance

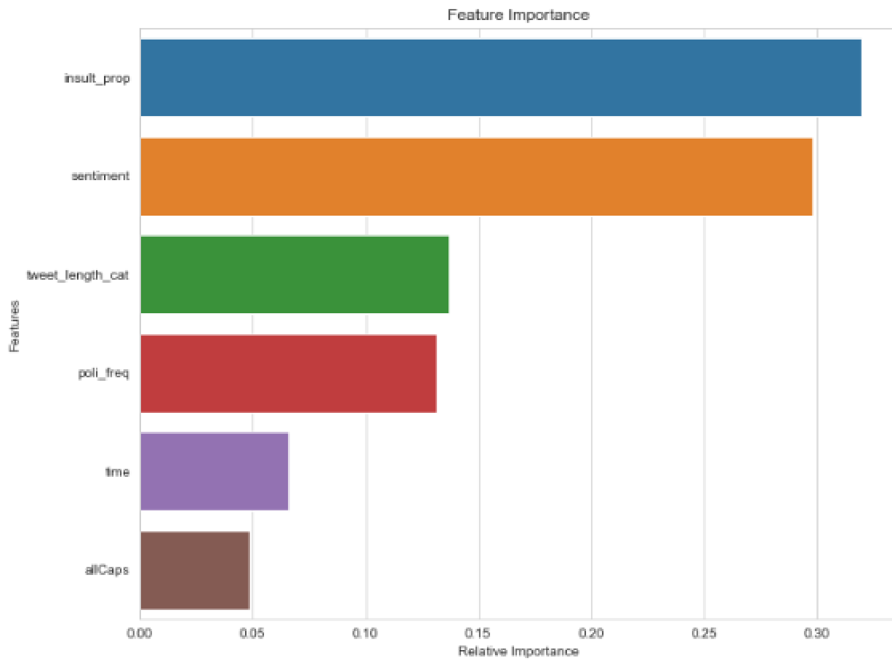

Figure 10: Feature Importance in Gradient Boosting Model

We chose Gradient Boosting as our final model since it greatly outperforms Random Forest, Decision Tree, or Linear Regression. The descending order of feature importance in this model is as follows: the proportion of insulting words, sentiment, tweet length, proportion of political words, time of day, and whether a tweet is in all caps.

5.2 R-Squared

The table presents the R-Squared values for different variables in a Gradient Boosting Model. The R-Squared values represent the proportion of the variance in the dependent variable that is explained by the independent variables. Higher R-Squared values suggest a stronger explanatory power of the variable in predicting the dependent variable.

Variable	R-Squared
Poli_freq	0.249
Insult_prop	0.244
Tweet length	0.119
Sentiment	0.082
AllCaps	0.060
Time	0.014

Table 2: R-Squared Decomposition of Gradient Boosting Model

The total R-squared is 0.7768 which means that this model explains 77.68% of the variation in the number of favorites of Trump tweets. The variables poli_freq (proportion of political words) and insult_prop (proportion of insulting words in a tweet) exhibit the highest explanatory power, with R-squared values of 0.249 and 0.244 respectively. Tweet length and sentiment in total account for about 20% of the variation. In contrast, the time of day explains only 1.4% of the variance while whether or not a tweet is in all caps explains 6%.

6 Interpretation of Results

We can observe that the top 4 variables are proportion of insulting words, frequency of political words, sentiment, and tweet length. In other words, a Twitter post from Trump that involves extreme emotions, employs offensive language, and delves into political themes is likely to gain increased traction and popularity on the platform.

However, there are some notable disparities regarding the variables' ordered rankings with respect to feature importance and R-squared value. This is because R-squared measures the overall goodness of fit while feature importance assesses the individual contribution of each predictor variable to the model's predictive performance. Insulting words' proportion and sentiment rank higher in feature importance but have relatively lower R-squared values because their effect is partially offset by other variables. Similarly, a variable with lower importance, like the frequency of political words, may still contribute meaningfully to explaining the variance when combined with other features, leading to a high R-squared value.

7 Conclusions

The output of our model shows that a Trump's tweet that is more emotional, offensive, and political tends to be more viral. Given Trump's reputation as a controversial political figure, this aligns with our expectations. The combination of heightened emotional expression, provocative language, and a strong political stance creates a recipe for increased attention and interaction. These elements not only reflect Trump's distinctive communication style but also resonate with the nature of contemporary online discourse. As a consequence, the combination of these factors plays a pivotal role in the considerable engagement observed across every one of Trump's tweets. The inherent controversy and political resonance within his messages appear to fuel the amplified response and widespread dissemination of his content on the platform.

Whether or not a tweet is in all caps demonstrates a small but non-negligible effect on its popularity. Because all caps represent an extremity of emotions, its effect may overlap with that of insulting words and sentiment. Therefore, the individual impact of this variable may be significantly reduced. The time a tweet is posted also has little influence on its popularity. This lack of impact is unsurprising given that Twitter users live in many different time zones. However, tweets posted at midnight consistently perform worse. This trend can be attributed to the fact that a majority of Trump followers reside in America, and so it is still midnight for them across various time zones in the country. Thus, while the exact time a tweet is posted may not have a significant impact, the substantial delay between posting and viewing does emerge as a critical factor in determining the tweet's popularity.

Overall, our project provides valuable insights into how Donald Trump gathered such a large number of favorites, retweets, and replies in every tweet. It is undeniable that he used Twitter as a powerful political tool whose power extended beyond traditional political propaganda. This study affords us a glimpse into the complex relationship between social media dynamics, political discourse, and the ability of emotionally charged rhetoric to permeate and resonate within online communities.

8 Challenges of the Study

8.1 Subjectivity of political and insulting words

We manually looked through the top 3000 words in Trump's tweets to filter through words deemed to be political or insulting. This requires taking into account the context in which they appear as well as being knowledgeable of the political scenes at the time of the tweet. For example, "sleepy" alone might not be particularly insulting but Trump's practice of saying "sleepy Joe" is clearly meant as an insult to Joe Biden. Similarly, many words are not inherently political; however, if they are consistently used by Trump in a political context, we still put them in the political category. This includes names of

Donald Trump's political opponents, names of countries that Trump considers to be threatening to America, and more.

While we do our best to ensure that the words have insulting and political connotations regardless of political beliefs, as this process of categorizing words is done by a human, it is impossible to completely eliminate bias. A set of insulting and political words chosen by someone else might be very different. In that case, the influence of insulting and political words on Trump's tweets' popularity could be reduced.

8.2 Subjectivity of sentiment

In order to determine the sentiment of a tweet, we used a package called TextBlob which "ranks" the negative/ positive connotation of a piece of text. While this package is considered to include the objective sentiment of a word, the subjective and context-dependent sentiment of words can oftentimes be much more important. Certain words might be particularly negative for a Trump supporter versus an anti-Trump individual and vice versa. Therefore, while our analysis shows that tweets that are more negative tend to gain more favorites, these tweets could actually be perceived as positive by his supporters.

8.3 Determining the response variable

In this project, we chose the number of favorites as our response variable, believing it to be an optimal indicator of a Trump tweet's popularity. However, it is evident that a tweet's popularity extends beyond the count of favorites alone. Metrics like the number of retweets also play a role in assessing popularity. A more comprehensive approach involves looking into the complex relationship between favorites and retweets, while considering how Twitter values each in terms of reflecting a tweet's popularity. Through obtaining a deeper understanding of their interplay, we could potentially assign appropriate weights to both favorites and retweets, combining them into a standardized popularity score, which might prove more representative compared to our current reliance on the number of favorites alone.

8.4 Correlation of Variables

It is easy to recognize that many of the variables are highly correlated with each other. We could reasonably expect that tweets that are more aggressive or emotionally charged would be in all caps. Similarly, since insulting words are often used in the context of Trump's political opponents, we would expect tweets with a high proportion of insulting words to also have a high proportion of political words. Therefore, the effect of a particular variable may not be accurately captured in this model.

9 Recommendations for the Future

While we decided to choose favorites as the dependent variable, we also acknowledge the importance of retweets. Therefore, for future research, it may be beneficial to assign weights to the number of favorites and the number of tweets respectively, and combine them to create a single response variable. Determining the exact values of the weights could be difficult and highly controversial in itself, however, this method may allow the models to capture the importance of both retweets and favorites.

The relationship between retweets and favorites could be an area desiring further research. Since there are overwhelmingly more favorites than retweets across all tweets, it could be interesting to look into what makes a tweet worth retweeting rather than just simply favorite-ing. Those who retweet might actually be those who provide the most meaningful engagement to Trump's content since the act of retweeting is often seen as synonymous with strong approval. By analyzing tweets that have comparatively fewer favorites but more retweets, we can gain insights into what makes a tweet appealing to pro-Trump supporters over the general public and vice versa.

Finally, because the variables are highly correlated with one another, future analysts should look into principal component analysis (PCA) to reduce dimensionality and ensure that the predictor variables are uncorrelated. We did not do this in the interest of interpretability, but this would reduce the effect of confounding variables and enhance the efficiency of the models.