Trump’s Tweets and his Approval Rating

Lev Rosenberg

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Abstract

This study examines the effect of Donald Trump’s tweets on his approval rating. Using datasets of Trump’s tweets and corresponding approval ratings, a classifier was trained to predict the approval rating change that might correspond to novel Trump tweets. Additionally, sentiment analysis was performed to investigate the relationship between tweet sentiment and rating fluctuations. The classification results showed moderate success in predicting no change in approval rating but were not accurate for positive and negative changes due to training data bias. Sentiment analysis revealed that tweet sentiment, had no effect on approval rating tendency to increase, decrease, or remain the same. Further research should expand on these results to explore additional factors that might influence approval ratings and gain a deeper understanding of the dynamics between social media and public opinion.

1 Introduction

As social media becomes an increasingly popular mode of communication for political leaders, it is vital to explore the impact of social media use and its effect on public opinion. Although social media use does not cause changes in public opinion itself, analysis into it’s correlation can help us comprehend how these platforms could impact voter behavior, candidate image, and overall democratic processes. Understanding the effects of social media on public opinion might also be crucial for helping policymakers and regulatory bodies navigate the challenges and ethical considerations associated with social media use by political leaders.

I intend to study the effect of former president Donald Trump’s tweets on his approval rating. I intend to train a classification model that can distinguish between tweets that might result in an increase or decrease in approval. I also intent to explore how the sentiment of Trump’s tweets correlate with an increase or decrease in approval.

I used datasets found on Kaggle.com of Trump’s approval rating by day and all of Trump’s tweets from 2017 to 2021. First, I cleaned the tweet data, then I attached labels to each tweet corresponding to changes in approval rating before and after the tweet was posted. I then trained the spaCy text categorization classification model to distinguish between tweets that increased, decreased, or had no effect on approval rating.

I also used the pre-trained nltk sentiment analyzer to anywise the sentiment of each tweet, categorizing tweet sentiments as either positive, negative, or neutral. My code then counts the co-occurrences of each sentiment and rating combination, and calculates the percentage of each rating category within a given sentiment category. Based on the analysis, I observed that tweet sentiment had little to no correlation with approval rating changes.

2 Data

Kaggle provides the datasets used in this study at

> https://www.kaggle.com/datasets/codebreaker619/donald-trump-tweets-dataset https://www.kaggle.com/datasets/rishidamarla/trumps-approval-ratings-from-20162020

3 Methods

In this ACL paper, the following methods were employed to investigate the relationship between Trump's tweets and approval rating changes.

1. Dataset Collection

The datasets utilized in this study were obtained from Kaggle. These datasets consisted of Trump's daily approval ratings and all of his tweets from 2017 to 2021.

2. Data Cleaning

The tweet data was subjected to a data cleaning process to ensure the removal of irrelevant information, using the re regular expression python module, URLs, special characters, and @mentions were removed from each document in order to prepare the tweet data for classification.

3. Data Labeling:

Each tweet in the dataset was labeled based on changes in the approval rating that occurred before and after the tweet was posted. If the rating increased by more than 0.5%, the corresponding tweet was labeled ”increase”. If the rating decreased by more than 0.5%, the corresponding tweet was labeled ”decrease”. Rating fluctuations less than 0.5% were labeled ”no change”.

4. Text Categorization Model Training:

A text categorization model using the spaCy library was trained to differentiate between tweets that resulted in an increase, decrease, or had no effect on the approval rating. This model aimed to classify tweets based on their potential impact on the approval rating.

5. Sentiment Analysis:

The pre-trained sentiment analyzer from the nltk library was utilized to analyze the sentiment of each tweet. This analysis categorized tweet sentiments as positive, negative, or neutral.

6. Sentiment and change in approval co-occurrence:

My code implemented a process to count the co-occurrences of each sentiment and rating combination. I then code calculated the percentage of each rating category within a given sentiment category, to providing insights into the proportional effect of sentiment on different rating change categories.

4 Results

The text classifier was applied to analyze Trump's tweets and their impact on his approval rating. The classifier's performance was evaluated using precision (P), recall (R), and F1 score (F) metrics. The results of the analysis are presented in Table 1.

Rating Change	**Precision**	**Recall**	**F1 Score**
increase	27.01	15.55	19.73
decrease	25.42	14.77	18.68
no change	83.08	91.33	87.01

Table 1: Text Classifier Performance on Approval Rating Changes

The precision, recall, and F1 scores for the "nochange" category are substantially higher compared to the "increase" and "decrease" categories. This disparity suggests that the classifier performs better in identifying tweets that would have no effect on the approval rating. The precision of 83.08% indicates that when the classifier predicts a tweet as "nochange," it is correct approximately 83.08% of the time. Additionally, the high recall of 91.33% indicates that the classifier can capture a significant portion of the actual "nochange" instances.

However, the precision and recall values for the "increase" and "decrease" categories are notably lower. This discrepancy could be attributed to the bias in the training data, where there is a relatively higher number of instances representing "nochange." Consequently, the classifier might struggle to accurately predict the specific direction of rating changes, leading to lower precision and recall scores. The precision of 27.01% and 25.42% for "increase" and "decrease" respectively implies that the classifier had a lower accuracy in identifying tweets that resulted in these rating changes. Similarly, the recall values of 15.55% and 14.77% suggest that the classifier missed a significant number of instances where the approval rating actually increased or decreased.

In addition to the tweet classifier, I also analyzed the co-occurrences of each sentiment and rating combination.

Sentiment Category	Increase	Decrease	No Change
Positive	39.55%	38.17%	38.58%
Negative	12.28%	13.87%	13.30%
Neutral	48.17%	47.96%	48.12%

Table 2: Sentiment Category Distribution

The results demonstrate the distribution of sentiments across different types of rating changes.

For positive, negative and neutral sentiment, the percentages for the "increase," "decrease," and "nochange" categories are all relatively evenly distributed.

Percentages for positive sentiments all fall in the 38-39% range. Percentages for negative sentiments all fall in the 12-13% range. Percentages for neutral sentiments all fall in the 47-48% range.

5 Discussion

These findings suggest that Trump's tweet sentiment alone is not a strong indicator of changes in his approval rating. This finding is significant in that it suggests political leaders can freely express their opinions on social media without being concerned about the impact of sentiment on their popularity. I also found that text categorization fails when training data is too heavily biased towards one category.

Other factors and contextual information should be considered to gain a comprehensive understanding of the dynamics between sentiment and rating changes. Further analysis and exploration of these factors could contribute to a more nuanced understanding of the relationship between tweet sentiment and approval rating changes.

In regards to the failures of the tweet classifier, it is important to consider the bias in the training data towards the 'nochange' class. All in all, 2296 were labeled as 'increase', 2062 'decrease', and 18948 'nochange'. In other words over 80% of Trump's tweets corresponded with a approval rating change less than 0.5%. Because of this imbalance, the text classifier is likely more reliable in identifying tweets that have no impact on the approval rating.

A significant flaw in the structure of this study is that approval rating changes are much more closely linked to actions rather than the language used in social media. While analyzing the impact of Trump's tweets on his approval rating can provide some insights, it is crucial to recognize that public sentiment and approval ratings are influenced by many factors beyond tweet content, such as policy decisions, speeches, and public events.

Take the example of one of the tweets analyzed in this study: "Last night, we made history and confirmed Amy Coney Barrett to the United States Supreme

Court! Justice Barrett will defend our rights, our liberties, and our God-Given FREEDOM". This tweet was associated with an "increase" label, because Trumps approval rating jumped significantly after her confirmation. However, we know that it is not Trump's tweet that caused an increase in approval, but rather the events of that day. Therefore, while analyzing tweet content and sentiment is valuable, it is important to interpret the results within the broader context of the political landscape, policy actions, and other events occurring simultaneously.