Sentiment Analysis of Donald Trump Tweets Forecasting Midterm Approval Ratings

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***Abstract*—Twitter has become a hub of political debate, especially in the case of what seems to be Americas most controversial presidential nominee, presidential candidate, and later President Elect in modern history, President Donald Trump. Reporters, researchers, and analysts regularly use Twitter as a gauge of the Presidents performance in terms of public sentiment. This sentiment is collected from regular posting or reactions (e.g liking, retweeting, quoting) of individual users reference to the President himself, his policies, and actions. In addition, it is collected from the reactions of tweets posted by President Trump himself. The motive of this research was to compare the sentiment of tweets from two integral time periods: election night (November 8, 2016) and September 2018. By using this data, we determined whether sentiment regarding the President was positive, negative, or neutral, and whether these sentiments have generally improved, worsened, or remained the same in light of the midterm elections and newer approval ratings posts. We will then use machine learning techniques and logistic regression to classify tweets from the data sets as favorable or unfavorable in each of these time periods.**

***Keywords*—Twitter, Donald Trump, sentiment, approval ratings, machine learning, logistic regression**

I. Introduction

The motivation behind this research was to draw a conclusion on whether online Twitter sentiments of President Elect Donald Trump has worsened, improved, or remained stable over time, and whether Twitter sentiment corroborates with current approval ratings. In order to meet these objectives, the raw text of the tweets and well as aggregate approval ratings were gathered. Initially, the tweets were requested for and scraped from Twitter to form a database of text from the date of the election and at different periods in September 2018. A simple sentiment analysis was then conducted on the data in Python using various functions within the TextBlob and Scikit-Learn libraries. The approval ratings themselves were acquired from CNN Politics, which collected data from multiple pollsters.

The remainder of this paper contains a literature review in which works related to Twitter analyses and political affiliations are discussed. Then, the methods section details how the model and code were constructed. Afterwards, an analysis of the results is conducted. In conclusion, the final section provides closing remarks.

II. Literary Review

While researching political affiliations in tweets leading up to and after the election, it was discovered that there were many variations in research methods for different experiments which resulted in varying results. These variations are worthy of being noted and implemented into future work.

In a Twitter sentiment analysis of the 2016 Presidential Election, Ebrahimi et al. of the Department of Computer and Information Science at the University of Oregon, took an in-depth approach to creating the database of tweets. The hashtags used covered a wide range of political ideals grouped into a Favor category composed of right-leaning vocabulary such as #makeamericagreatagain, #illegalimmigration, #standwithtrump, #leftists, and an Against composed of more left-leaning vocabulary such as #gopclowncar, #racist, #hateisnotpresidential. After removing stopwords that do not help to determine the classification of a tweet, weights were applied to the other words. The use of a larger pool of tags mapped out to favorable versus unfavorable tweets, coupled with the analysis of the raw text of each individual tweet, provided more precise measures of current sentiment of Trump at that point in time.

Another approach to classifying political leanings through social media sentiment analysis was taken by Li et al. Instead of solely assigning weights to each word in the text, they also added in another factor: emojis and emoticons. Emojis are miniature pictures that depict a number of emotions. These researchers created their database from tweets both containing not containing emojis as they believed tweets with emojis would demonstrate stronger emotions and be better classified. A small subset of commonly used emojis were ranked and mapped to negative, neutral, and positive categories. Emojis deemed as sad or angry were negative, those deemed as happy were positive, and the others that did not elicit any sort of emotion were neutral. After running this experiment, it was determined that about 51.10% of the tweets were neutral, 23.5% were negative, and the remaining 25.4% were positive.

This research and the different methods used to gain insight on political opinion, although quite different from the methods in this particular study, are necessary in that they shed light on newer avenues of thought that can create a space for future studies to expand upon sentiment analysis and opinion mining on multiple social networks.

III. Sentiment Analysis

A. Dataset

For our research, we considered a preexisting dataset containing tweets from election day (November 8, 2016) and a dataset containing tweets from September 29, 2018 that we created to test against the election day dataset. To create our September 29, current, database, we utilized the Twitter API to scape English-written tweets from that day using the query trump. It was our intention to scrape tweets from the arbitrary dates August 1, 2018 to September 29, 2018 to create

TABLE I
ELECTION DAY DATABASE COMPOSITION

Number of Tweets	397,629
Fields	text created_at geo lang place coordinates user.favourites_count user.statuses_count user.description user.location user.id user.created_at user.verified user.following user.url user.listed_count user.followers_count user.default_profile_image user.utc_offset user.friends_count user.default_profile user.name user.lang user.screen_name user.geo_enabled user.profile_background_color user.profile_image_url user.time_zone id favorite_count retweeted source favorited retweet_count
Query	hilary trump #yourefired election #election2016 #electionday #uselections2016 #gop democrat #ivoted vote voted #senate #uselection #house congress #madampresident

TABLE II
CURRENT DATABASE COMPOSITION

Number of Tweets	6,020
Fields	Date Tweet Name ScreenName Retweets
Query	trump

an extensive dataset that represented sentiment from Twitter users reactions to the Trump Administrations policies over an extended period of time, yet we could not achieve this due to access limitations with the API. Table I and Table II show the composition for the election day dataset and current dataset respectively.

B. Process and Results

In order to gain a more accurate reading from our sentiment analysis, we preprocessed our data by making all letters lower case and removing stop words, words such as ”as”, ”the”, ”under”, and ”which”, provided by the NLTK library. We then removed all traces of webpage links (http), mentions (@), hashtags (#), and the acronym retweet (RT).

Using TextBlob’s sentiment analysis function, we fed each, individual tweet through the function and scored it as positive, negative, or neutral with values of 1, -1, and 0 respectively. These values were then counted and averaged to give the results shown in Tables III and IV.

C. Statistics

After a simple T-test was completed based off of the two means gathered from the election day and current tweet databases, the resulting T-test statistic was 2.50501172812e-14. Since this statistics is less than the normal significance

TABLE III
ELECTION DAY DATABASE SENTIMENT RESULTS

Sentiment	Value
Negative	0.12962334236184986
Neutral	0.5577208905789065
Positive	0.3126557670592437

Statistics	Value
Mean	0.33333333333333337
Size	397629
Standard Deviation	0.21479652931932655

TABLE IV
CURRENT DATABASE SENTIMENT RESULTS

Sentiment	Value
Negative	0.17109634551495018
Neutral	0.5099667774086378
Positive	0.31893687707641194

Statistics	Value
Mean	0.3333333333333333
Size	6020
Standard Deviation	0.16989330730644361

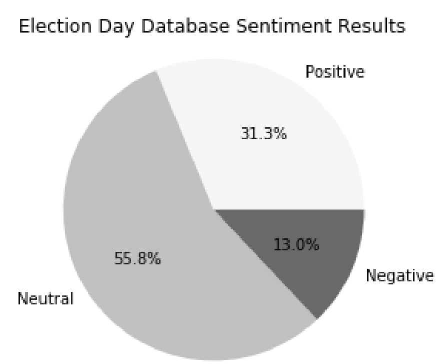

Fig. 1. Pie chart giving visualization for Election Day Database Sentiment Results

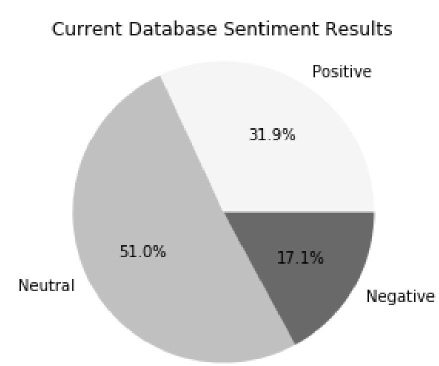

Fig. 2. Pie chart giving visualization for Current Database Sentiment Results

level considered for such tests, 0.05, it was determined that there was not a significant shift in sentiment as expected.

The less expected results of these experiments could have occurred from a number of factors that should be noted and considered. The sample sizes between the two databases varied largely, with the size of the current tweet database being significantly smaller. This may account for the lack of a larger shift in the test statistic. Also, solely 397,629 text samples were used in the election day database. Although this is a large amount of tweets to parse and analyze, this might not be representative enough as this was only a fraction of the millions of tweets made that day. Apart from these possibilities, the use of neutral data could have hurt the model to an extent as the objective behind this study was to represent the individuals that felt more strongly instead of public opinions that could be flipped in different ways.

IV. Conclusion

This study used the social network Twitter to determine public opinion of President Elect Donald Trump on election day as well as recent times with the purpose of discovering a shift in sentiment for the worse. The data collected and the results gathered proved otherwise, showing that public sentiment has proved quite stable since election day. In the future, this study can be restructured to create more conclusive results by increasing the sample sizes to have a more representative group of tweets. In addition to enlarging the samples, other research methods are to be considered. Taking into account the weight that emoji and emoticons have in describing strong emotion and hashtags that clearly define political affiliation, as other researchers have, could show stronger opinions that have more of an effect of the results.

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