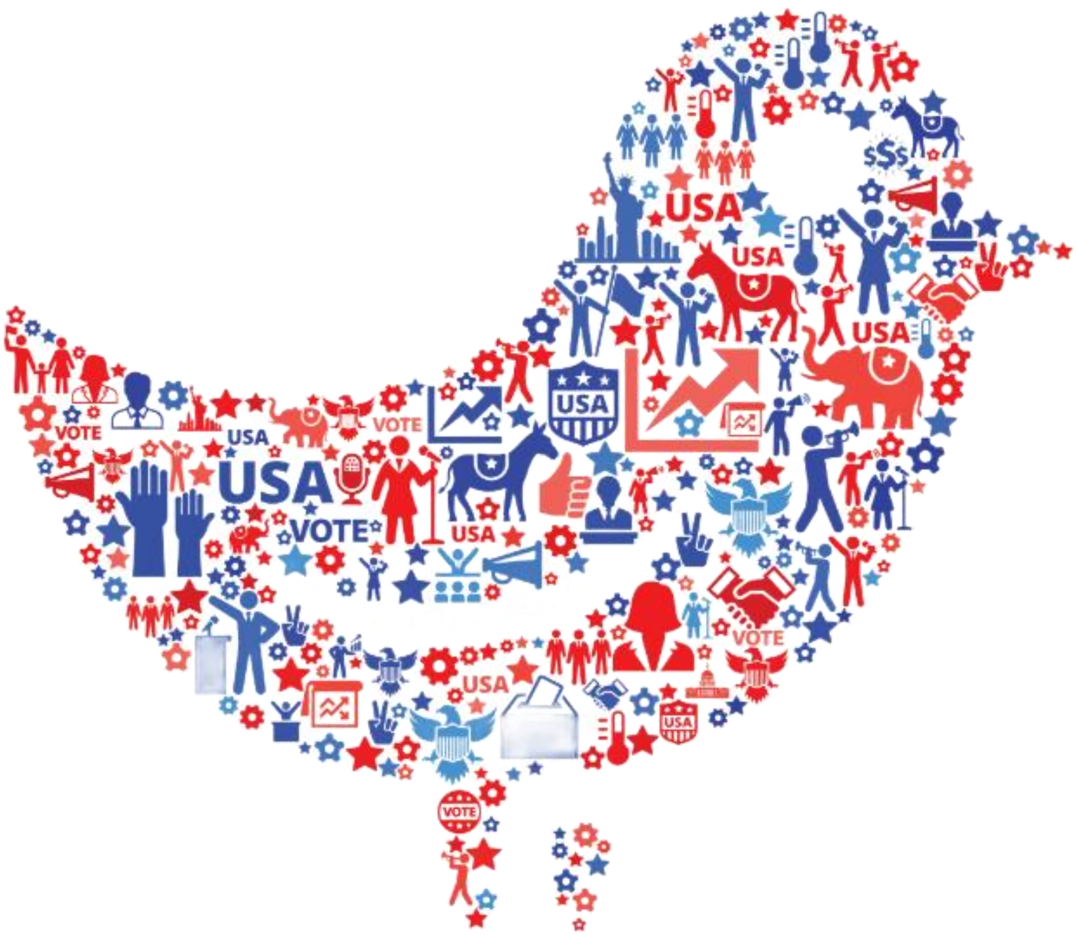

Election Sentiment In Social Media

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Abstract

American Politics has been a thoroughly discussed topic in many aspects of the casual American citizen's life. Even in the past few years, Americans have endured the politics surrounding the COVID-19 Vaccine, the rise and fallout of the January 6th Insurrection, and countless weeks of debate over the validity of the vote count for our most recent presidential election. Throughout all of this, there has been one source of information that has been vital to uncovering some of what is happening throughout the United States - *twitter.com*. And yes, there are other platforms that American citizens use to communicate with each other on social media but when thinking about former President Donald Trump, what social media site comes to mind when thinking of him? When talking about different political decisions, how does the rhetoric of Twitter exactly influence American politics? Our work focuses on the general sentiment analysis of Twitter users to then see if it tends to influence or not influence real-life politics throughout America.

Introduction

The nuanced nature of American Politics has been of high interest to many businesses due to the potential to serve different political parties, voters, and candidates alike. Investigating the public sentiment of the most recent midterm elections helps us determine not just the view of voters around the country; it can shape many business goals, strategies, and efforts. This issue is of high significance due to the effect recent political events have had on the business world. The January 6th Insurrection, the rioting and looting due to politically motivated protests, and controversial political campaigns have all affected the latest business and political landscapes significantly. Considering the effect of political events on the business landscape from the perspectives of both candidates and voters will enable us to strengthen business practices.

Here at 414 Consulting, our main business goal is to enable client success by considering many political, social, and economic variables. Essentially, we are a data analytics firm dedicated to political campaigns, candidates, and promotion. We will use these variables from a statistical and analytical perspective to help political candidates achieve the most success possible. Examples of work done in the political consulting business include campaign management, political research, strategic reviews, and data analysis and interpretation (Aristotle, 2022). The use of data analytics, through a political lens, is unequivocally the most optimal way for candidates to understand the right methods, strategies, and efforts needed to succeed. We will optimize our work with analytics through countless strategic analyses and reviews for political candidates of interest.

The main problem we are approaching in our work is to determine the sentiment of public opinion regarding the recent midterm elections of 2022. We will focus our efforts on an analysis of the Pennsylvania Election. We want to include Pennsylvania in our work due to the nature of its election. Out of all the states included in the 2022 midterm elections, Pennsylvania was the only state to flip parties, as Democrat John Fetterman defeated Republican Dr. Mehmet Oz. The seat was originally held by Republican Pat Toomey, but his retirement after two senate terms created the need for this election. Pennsylvania voters then flipped the seat from Republican to Democrat, which is the main reason why we wanted to put our time into this specific election.

As a consulting firm focused on candidate performance, the use of business analytics in this situation is amazingly important. We can shape our situation by analyzing the sentiment of the public on the elections into the effect social media sentiment has on the voting results. In other words, internalizing election outcomes compared to Twitter opinions will help us in our consulting with candidates on their best political strategies. In fact, analyzing this relationship could be the key difference between winning and losing an election. We can split this new idea into many smaller goals to enable more success from a business view. One way to view this idea is to determine the sentiment of tweets regarding the election. These sentiment scores (collected using Twitter APIs and related Python code) will show us the general opinions on candidates and political parties nationwide. In addition, getting baseline election result data will be another key viewpoint to our problem. This information enables us to compare Twitter's sentiment with midterm election results. Having this relationship understood, with our business goals in mind, will strengthen our consulting with candidates significantly.

To further comprehend these analytical viewpoints, we feel using the VADER model to conduct sentiment analysis is the best path to success. VADER (Valence Aware Dictionary for Sentiment Reasoning) is a model built to analyze unstructured textual data by determining its sentiment (Beri, 2020). The model takes into account positive and negative words and is intelligent enough to understand most of the context behind the text. For example, VADER can realize that the statement "did not love" is a negative statement due to the context of the text. In addition, the model also takes into account things like punctuation and capitalization. These factors significantly affect the model's calculations of certain sentiments. Thus, the VADER model is very capable of predicting the sentiment of any type of textual data, which is a key component of our research goals.

Considering our proposed data collection methods and business analytics problem, the VADER model will offer the most success since it is specifically designed for web-based communication. The methods behind the model will help us analyze Twitter data to its full capacity with many kinds of factors. We will utilize its powers in calculating sentiment scores by collecting Twitter data to understand the sentiment of both John Fetterman and Dr. Mehmet Oz.

To give a brief overview of our results, the VADER model helped us get an idea on the sentiment behind each candidate in the election. We collected over a thousand tweets on the candidates, with each tweet having a specific sentiment score. There were some cases throughout the VADER analysis where some tweets did not get a sentiment score, even considering the context of the tweet itself. In addition, retweets of the same text were found throughout our data collection, which created the same sentiment score for many duplicates. While this does indicate the popularity of the candidate along with its sentiment, having the same sentiment score for two different people tweeting might not truly represent the full spectrum of the public's opinion. Thus, the VADER model's strong capabilities in sentiment analysis is hindered by the inconsistencies of our analysis. This creates an unideal situation where we cannot get a full analytical picture of our research.

Data Collection and Preparation

For the collection of data, the only way to test finding a sentiment of tweets from Twitter was to use real tweets regarding a current election. Thankfully, the US Midterms just happened earlier this November so we are going to use data from there - specifically we are using tweets from November 7th to November 9th. These will help us gather the sentiment of Twitter users before Election Day (November 8th) and the sentiment of Twitter users after Election Day. Another source of data that we plan to utilize is to find the actual election results from Reuters, a neutral political reporting organization. By using all of these pieces of information, the goal is to gain a better insight into the social aspects of our rapidly changing political climate in America.

I. Twitter API

The way that we are going to collect this data would be through the use of the Twitter Developer API and the tweepy package on Python. From there, we can store all of the tweets that our code has gathered in a MongoDB database. With all of this data that we can gather from Twitter between the 7th and the 9th of November, we will be able to acquire a better insight into public sentiment towards elections. One thing to consider with the Twitter API, however, is that a Retweet, or a re-posting of another user's tweet, cannot be filtered out through a query since that feature is no longer available through tweepy. This poses a potential issue if there is one specific tweet that is either mostly positive or mostly negative that is retweeted and analyzed several times.

II. Reuters Election Data

Then we want to look at the results of the actual election itself but that was not something that could be easily found through live tweets. We instead wanted to use a different method and use Python to then Web-Scrape data off of Reuters. This website can give us the Midterm Election results percentages for each party. Information on this site included each candidate's votes received and percentage of votes, with state and county level statistics as well. To benefit our research purposes, we wanted to collect state-level data for the election. First, we went into Python to retrieve the site URL and got the source code for the web page. This helped us get our data of interest by using regular expressions. As mentioned before, we wanted the data for each candidate's votes received, percentage of the vote, and political party. Luckily for us, all that data was easily accessible through the use of one regular expression. After using this regular expression, we narrowed down our list of results to the ones we needed. All of our data was in one list, so we needed to split up each category of data. Once this was done, we entered the candidate names to finish our data collection. Through the creation of a Data Frame in Python, we then extracted this raw data to a CSV for further analysis within our research.

III. Results

We ended up gathering 1740 tweets, and from those tweets, we gathered two different kinds of queries to fit our model to the typical two-party system in America. The first query is related to tweets containing the hashtag '#JohnFetterman' (1380) and the other query, are those containing '#MehmetOz' (360). Each query contains the name of the candidate for each major political party (John Fetterman as a Democrat and Mehmet Oz as a Republican) to understand what the public is saying about each of the candidates on Twitter. When storing the data, only the tweet's unique id, its text, and the time at which it was created are kept. The ID is used to ensure the same exact tweet isn't counted more than once, the text is what sentiment analysis is applied to, and the time created is kept for use in further analysis, specifically after the Pennsylvania election was called to determine differences in pre-election sentiment from post-election sentiment. The remainder of the variables stored in the tweet objects that we obtain are not particularly important when considering election sentiment, so they will be discarded. One exception would be the media associated with the tweet, however, analyzing images as well as tweets may prove to be exceedingly complex and unlikely to hold a different message than the text, so it has been filtered. Since the API returns data that is formatted similarly to logs, the data is retrieved from Twitter, given a score based on sentiment analysis performed on the data, stored in a data frame, and finally inserted into a MongoDB database. The ID of the tweet is not stored in the MongoDB database, as the IDs are only stored locally to compare against new incoming tweets; it is not relevant to later analysis since the aggregation of scores and counts is performed in MongoDB, rather than in Python.

The VADER sentiment analysis considers any word it does not know to be neutral, and since the "RT" and original poster's tag are considered irrelevant to our analysis, all of the text can be safely stored. In addition, many items in our collected dataset will have duplicate text, and therefore duplicate sentiment scores. This decision was made because the free API would not allow filtering of retweets, which are also received when collecting tweets, and giving more weight to multiple people sharing a tweet would give more accurate results than only counting it once or manually filtering retweets. For example, if one tweet had three retweets and another had 250, the latter should be prioritized rather than normalized.

Data Analysis and Evaluation

Now that all of the tweets have been collected, we want to use that information as a consulting firm to explain trends and see if there is any correlation between social media sentiment analysis and elections. And while the term ‘Sentiment Analysis’ has been brought up several times, it's important to not only fully understand the phrase, but also to understand how important it is, especially to data analytics. Sentiment Analysis, otherwise known as ‘Opinion Mining’, is “a research area which aims to analyze people’s sentiments or opinions toward entities such as topics, events, individuals, issues, services, products, organizations, and their attributes” (Springer, 2019). This information can be extremely useful, especially when used in a political setting since it can be used to look at what is being said about a candidate and even can track what a candidate's general sentiment is when communicating online. And politics is not the only area that sentiment analysis can shine in, it can also be used for public security to track events before they potentially happen or even for both consumers and merchants to provide online advice for advertising (Springer, 2019).

Each of the tweets that were collected during the data collection phase is then evaluated using the VADER sentiment analysis package available in python. Many of the results returned by VADER unfortunately do not match expectations. One such example was the phrase that was retweeted multiple times, “#JohnFetterman for president #2024!”. This tweet expresses an obvious positive sentiment, however, VADER returned and gave this tweet a sentiment score of zero, completely neutral. This is because none of the words in the tweet are a part of the set of known words by VADER and thus are all given a sentiment score of zero. The results of this Pennsylvania-centered analysis are also potentially inaccurate, as the location of the tweet is not taken into account due to the limitations of the Twitter API, and their estimate of 1% of all tweets having a geolocation associated with the tweet. The result of this is that tweets from all over the world will be included in the dataset instead of only tweets that originate from Pennsylvania, which itself doesn’t restrict . This would have excluded too many tweets from Pennsylvania about the candidates too small for meaningful analysis, so the names of the candidates were used instead.

Hypothesis tests were conducted using one-sample z-tests for each of the queries that were executed on tweets that were created before the election was called to determine if Twitter is able to accurately predict based on user sentiment. The positive score would be considered the total score from all of the tweets that were collected in the query. The mean that is assumed for each of the tests is .66 * the actual percentage of votes that each candidate received, to account for the assumption that someone is twice as likely to make a positive post about their preferred candidate than they are to post negatively about the other candidate. The results of the tests can be found in the notebook used to run the code, and would generally suggest that Twitter may be a decent predictor for democratic sentiment with all of the given assumptions. Unfortunately, this would not be the case for republican candidates, as it certainly fails the test when comparing total sentiment to the percentage of the vote the candidate received, and has to have its parameters altered to even allow the test to function properly. The total score is so low potentially due other social media sources taking portions of the republican voters' attention, as well as many other possible factors that would restrict positive tweets from being represented in the dataset. In addition, if a tweet was positive toward Mehmet Oz without specifically being negative toward John Fetterman, but included #JohnFetterman in the post, it would count as a positive tweet for John instead of Mehmet, since each tweet could only be counted once over both candidates and the tweets containing #JohnFetterman were analyzed first. However, this could be a result of the low total scores caused by poor analysis from VADER as mentioned previously.

Conclusion

While the use of sentiment analysis can be used as aid in several different areas of interest (politics, public safety, etc.), the analysis that we used with this particular election was not 100% effective. With the lack of tweets, or rather an abundance of retweets, that we could gather from Twitter's API to VADER having a less-than-ideal analysis, the overall results from our model were a good effort but not as effective as we wanted them to be. That does not mean, however, that we think that the sentiment analysis that we have done (or could have done differently) was not important enough to analyze; sentiment analysis can be, and should be, used to track how people interact with not only one another but also about certain topics of interest. With more time, preparation, and access to the premium version of Twitter Developer, it would have been a better outcome. At this time however, this project is not recommended for deployment due to limitations with the free Twitter API and the limited success of sentiment analysis using VADER.A

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