Tweet Sentiment Analysis of the 2020 U.S. Presidential Election

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ABSTRACT

In this paper, we conducted a tweet sentiment analysis of the 2020 U.S. Presidential Election between Donald Trump and Joe Biden. Specially, we identified the Multi-Layer Perceptron classifier as the methodology with the best performance on the Sanders Twitter benchmark dataset. We collected a sample of over 260,000 tweets related to the 2020 U.S. Presidential Election from the Twitter website via Twitter API, processed feature extraction, and applied Multi-Layer Perceptron to classify these tweets with a positive or negative sentiment. From the results, we concluded that (1) contrary to popular poll results, the candidates had a very close negative to positive sentiment ratio, (2) negative sentiment is more common and prominent than positive sentiment within the social media domain, (3) some key events can be detected by the trends of sentiment on social media, and (4) sentiment analysis can be used as a low-cost and easy alternative to gather political opinion.

CCS CONCEPTS

• **Information systems → Social tagging systems**; *Data mining*.

KEYWORDS

Tweet; Sentiment Analysis; 2020 U.S. Presidential Election

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1 INTRODUCTION

In the last decade, the number of active social media users has increased rapidly [14, 38]. A tremendous amount of data representing people's opinions, also known as user-generated content, is now broadly available for research. Sentiment analysis is one of the domains of user-generated content analysis, which measures the opinions of collected data on a positive or negative spectrum. Natural text processing and machine learning are combined to process abstract and subjective data into classifiable emotions. It is generally used by large companies or associations to develop a better understanding of the concerns of their consumers in order to generate customer loyalty [27]. Corporations also run sentiment analysis models to measure satisfaction for specific products or brand reputation as a whole. Furthermore, it provides feedback on the potential ways to adapt and improve the company's reputation, as well as planning for future marketing and brand awareness. Less frequently, individuals use sentiment analysis models to draw conclusions that large companies with complex social networks can access more easily. Generally, they tap into easy access consumer reactions, primarily through social media, where opinions and information is abundant.

Areas of interest to either companies or individuals can include a range of topics in the fields of economics, social behavior, politics, and other domains. One of these popular topics is the stock price forecast. Stock market analysis plays an important role in better decision making in investment [3, 11, 12, 28–31]. For example, [5] investigated whether measurements of collective mood states derived from large-scale Twitter feeds are correlated to the value of the Dow Jones Industrial Average over time by analyzing the text content of daily Twitter feeds. [4] proposed a data mining algorithm to demonstrate that the price of a selection of 30 companies listed in NASDAQ and the New York Stock Exchange can actually be predicted by collected textual tweets. Another significant goal of sentiment analysis is to analyze product reviews [9, 15, 20, 22, 24, 26, 35, 44]. For customers, it is convenient to compare the products by having a summary of past users' opinions. For producers, they can obtain ideas of market demand and improve their products by analyzing reviews. [26] extracted nouns and noun phrases from each customer product review sentence, and used a Naïve Bayesian algorithm to identify whether each of the sentences is positive or negative. [44] employed prevalent ratings as weak supervision signals and proposed a deep network for product review sentiment classification.

There are some studies focusing on other topics. [10, 17, 41] predicted the time and location in which a specific type of crime will occur based on Twitter data. [1, 21, 37, 42] used social media data for disaster response management, including enhancing situation awareness, promoting emergency information flow, and predicting disasters and coordinating rescue efforts. Our work focuses on election prediction, a widely-studied topic [2, 13, 19, 23, 34, 40]. In these studies, social media platform data are used as tools to monitor users' political preferences and inclination. [18] developed a simple rule-based model for general sentiment analysis. [39] developed a general sentiment classification system, which used labeled data in a different domain. [25] presented a sentiment analysis method using Hadoop to quickly process vast amounts of data.

In our work, we focused on Twitter sentiment analysis of the 2020 U.S. Presidential Election between Donald Trump and Joe Biden. We used a sample of data from a Sanders corpus to train the model and identified the Multi-Layer Perceptron model as the classifier with the highest performance. We then fitted the model with tweet data on the 2020 U.S. Presidential Election collected from 10/19/2020 to 11/02/2020. Several interesting phenomena were found as follows:

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Table 1: Characteristics of Sanders Twitter Dataset

Class	Count	Examples
neg	529	I would be a lot happier if #Microsoft Word didn't freeze every 5 minutes.
		I just need to exchange a cord at the apple store why do I have to wait for a genius? @apple
		facial recognition failed #IceCreamSandwich jajajaja-jajaj #FacialUnlock #samsumg #Google
pos	483	I have been blown away by technological innovations.... #microsoft should do more #marketing!!
		Play on ma man. Loving the camera in the #iphone4s. Well done @apple #fb http://t.co/tmdFqRe1
		Google ICS looks awesome, can't wait til it gets ported over to my evo, face unlock?! ... #android #google

- Both candidates received similar results in positive and negative opinions with a less than 1% difference in sentiment rating, predicting a very close race between two candidates, contradicting commonly watched poll numbers; these polls turned out to overestimate Biden's chances.
- Social networks are more likely to broadcast negative opinions, as reflected by the higher percentage of negative sentiment tweets for both candidates.
- Sentiment analysis can help predict the impact of potential political events, such as presidential debates, during and right after which a large spike of tweets were observed.

2 APPROACH

In this section, we first introduce a benchmark dataset for sentiment analysis and illustrate the three steps of preprocessing the dataset. With the extracted features, we test different machine learning classifiers and select the best one for tweet sentiment analysis. Finally, we report the performance of Support Vector Machine, Decision Tree Classifier, Gaussian Naïve Bayes, AdaBoost Classifier, and Multi-Layer Perceptron Classifier on the benchmark.

2.1 Benchmark Dataset

Sanders Twitter Dataset [36] is composed of 5,513 tweets that target four companies: Apple, Google, Microsoft, and Twitter. Tweets were annotated with one of 4 categories: positive, negative, neutral, or irrelevant. In our experiments, we only considered positive and negative categories. Table 5 shows several tweet examples from the positive and negative categories. This dataset was used to select the best sentiment classifier for our application on tweet sentiment analysis of the 2020 U.S. Presidential Election.

2.2 Preprocessing

Much of Twitter content is ingrained with internet slang, which is an issue for text preprocessing; therefore, it is necessary to remove words, phrases, and characters irrelevant to the core sentiment and message of the tweet. Without such filtering, data might be prone to cause decreased model accuracy and lower time efficiency. We follow the work of Sentiment-Analysis-Twitter[1] for data preprocessing. Three steps were taken to process the raw data into input features for the model: replacing, stemming, and feature extraction.

[1]https://github.com/ayushoriginal/Sentiment-Analysis-Twitter

Table 2: Predefined strings

Strings	Examples
__HNDL	@Trump
__URL	https://twitter.com/
__EMOT_SMILEY	:-), :), (:, (-:
__EMOT_LAUGH	:-D, :D, X-D, XD, xD
__EMOT_LOVE	<3, :*
__EMOT_WINK	;-), ;), ;-D, ;D, (;, (-;
__EMOT_FROWN	:-(, :(, (:, (-:
__EMOT_CRY	:,(, :'(, :"(, :((
__PUNC_EXCL	!, ¡
__PUNC_QUES	?, ¿
__PUNC_ELLP	..., . . .

Replacing. Multiple special characters are common to Twitter, but they are not important for the purpose of sentiment classification. For example, a particular Uniform Resource Locator (URL) is not informative because it does not reflect any positive or negative opinion. To handle this problem and reduce feature space dimension, we replaced handles, URLs, emoticons, and punctuation with predefined strings. All the predefined strings, including handles, URLS, emojis, and punctuation marks, are shown in Table 2.

The hashtag is a special Twitter character, important in denoting the subject of the tweet to others. A hashtag is created by putting a hash symbol in front of a word. We processed hashtags by adding a predefined prefix "__HASH_" to identify trending topics. Another common Twitter phenomenon is repeating characters, which is widely used for emotional expression. For example, users might write "gooood" instead of "good" to show their exciting feelings. We handle repeating characters by replacing them with two characters.

Stemming. English words of a particular meaning may have different spellings due to tense, part of speech, and so on. We employed [33] to remove the common morphological and inflectional endings from words, which could further reduce the feature space dimension. It is based on the idea that suffixes in the English language are made up of a combination of smaller and simpler suffixes. Figure 2 shows an example of replacing and stemming.

Words	['__hndl', 'have', 'not', 'vote', 'yet']
1-gram	[(__hndl), (have), (not), (vote), (yet)]
2-gram	[(__hndl, have), (have, not), (not, vote), (vote, yet)]
3-gram	[(__hndl, have, not), (have, not, vote), (not, vote, yet)]
Neg_l	[0.0, 0.0, 1.0, 0.9, 0.8]
Neg_r	[0.8, 0.9, 1.0, 0.0, 0.0]

Figure 1: An example of n-gram and negativity.

Feature Extraction. We used word n-grams together with negation for feature extraction. An n-gram is a contiguous sequence of n words from a given text. Specifically, both unigrams, bigrams, and trigrams (that is, $n = 1$, $n = 2$, and $n = 3$) were used in our experiments. Negation features were included to handle the situation in which the meaning of a word is actually the opposite when it is near a negation word like "no", "nothing", or "never". The negation features consisted of left and right negativity, which denoted the possibility of words to have the opposite meanings. Figure 1 shows an example of n-gram, left negativity and right negativity.

Table 3: Dimensions of extracted features

Feature	1-gram	2-gram	3-gram	Negation
Dimension	2590	9426	10644	5180

The dimensions of each type of feature are listed in Table 3. 2-gram and 3-gram features have higher dimensions than 1-gram because they are combinations of words. The dimension of negation features is twice that of 1-gram, as negation features include both left and right negativity.

Origin	#Election Just voted at https://www.vote.org/ :D
Replacing	__HASH_election Just voted at __URL __EMOT_LAUGH
Stemming	__hash_elect just vote __url __emot_laugh

Figure 2: An example of replacing and stemming.

2.3 Classification Performance

With the above preprocessing and feature extraction, we have 27, 840 dimensions to present a tweet for classification. We selected five classifiers provided by scikit-learn [32]: Support Vector Machine [8], Decision Tree Classifier [6], Gaussian Naïve Bayes [43], AdaBoost Classifier [16], and Multi-layer Perceptron (MLP) Classifier. 10-fold cross-validation [7] was performed on Sanders Twitter Dataset to evaluate the model performance. Table 4 shows the cross-validation performance of five classifiers in terms of accuracy. Among them, MLP performs the best and has a significant advantage against the other four methods. This is because MLP has multiple layers and perceptrons that can distinguish non-linear data. This makes it a more expressive method than others.

Table 4: Cross-validation performance

Classifier	SVM	DecisionTree	NaïveBayes	AdaBoost	MLP
Accuracy	0.5234	0.7217	0.7713	0.7492	**0.8153**

3 APPLICATION ON 2020 U.S. PRESIDENTIAL ELECTION

In this section, we conduct an analysis of tweet sentiment on the 2020 U.S. Presidential Election. First, we collect 2020 U.S. Presidential Election related tweets from 10/19/2020 to 11/02/2020. We then apply the best performing classifier MLP in Section 2 for sentiment analysis. Finally, we analyze the sentiment analysis results.

3.1 Experimental Setup

Collected Twitter Data. The 2020 U.S. presidential election was held between the incumbent Republican candidate Donald Trump and his Democrat opponent Joe Biden. We collected this dataset from Twitter[2] by the Twitter API[3]. Keywords such as "Biden", "Trump", "president", and "election" were used to filter data. The author, date of the tweet, and retweet status were stored alongside the tweet for further handling. The collected data ranges from 10/19/2020 to 11/02/2020, containing a total of 600,000 tweets; of these, 260,498 were relevant and applied to either Trump or Biden.

[2]https://twitter.com
[3]https://developer.twitter.com/en/docs/twitter-api

Table 5: Examples of our collected dataset

Class	Keyword	Example
neg	Biden	Joe Biden wants to keep kids trapped in failing schools. That alone is reason for him to lose this election!
pos	Biden	Former President Barack Obama will join Joe Biden in Michigan on Saturday for their first joint in-person campaign event of the election.
neg	Trump	If President Trump wins, it will be one of the biggest rejections of the establishment we have ever seen.
pos	Trump	@kathynajimy Allan Lichtman's predictions are worth paying attention to because he has accurately forecast every election since 1984, including President Donald Trump's stunning victory in 2016 over Democratic rival Hillary Clinton.

All the tweets were preprocessed by replacing, stemming and feature extraction described in Section 2. The best-performing MLP was employed to classify our collected tweets into positive or negative sentiment. Finally, the number of positive and negative tweet ratings were added to achieve a final result.

Table 6: Tweets sentiment analysis on Trump and Biden

Class	Trump Count	Biden Count	Both Candidates
neg	93,512 (35.90%)	78,807 (30.25%)	172,319 (66.15%)
pos	48,746 (18.71%)	39,433 (15.14%)	88,179 (33.85%)
all	142,258 (54.61%)	118,240 (45.39%)	260,498 (100%)

3.2 Result Analysis

Table 6 shows the sentiment analysis results. A total of 118,240 tweets were collected on Biden, of which 78,807 were negative and 39,433 were positive. A total of 142,258 tweets were collected on Trump, of which 93,512 were negative and 48,746 were positive. Trump had a larger pool of tweets with 54.61% of the combined tweets, which is likely due to him holding the current presidency and receiving greater attention from the media. This might also result from Twitter being the main channel for Trump to communicate with the public. Both candidates have overwhelmingly negative sentiment, with only 33.85% of the total tweets being positive. Social networks, in general, are more likely to be used to broadcast negative opinions. This is a recurring pattern observed by many social media based sentiment analysis projects.

Figure 4 shows the total percentages of positive and negative tweets Biden and Trump received. Biden had a 66.65% negativity rate and a 33.35% positive rate, while Trump had a 65.73% negativity rate and a 34.27% positive rate. In general, both candidates for the election received similar results in both positive and negative opinions with a less than 1% difference in sentiment rating, predicting a very close race between two candidates. Biden officially received over 81 million popular votes and 306 electoral votes, while Trump received over 74 million popular votes and 232 electoral votes. The voting result is shown in Figure 6. The final poll results from major polling agencies on Nov 2nd is shown in Figure 5, predicting a victory for Biden by a large margin of 8%. In some swing states, such as Georgia, Arizona and, Pennsylvania, the gap between the two candidates is 0.2%, 0.3%, and 1.2%, much narrower than final state-level polls indicate. Even after Nov 3rd, the date of the main voting,

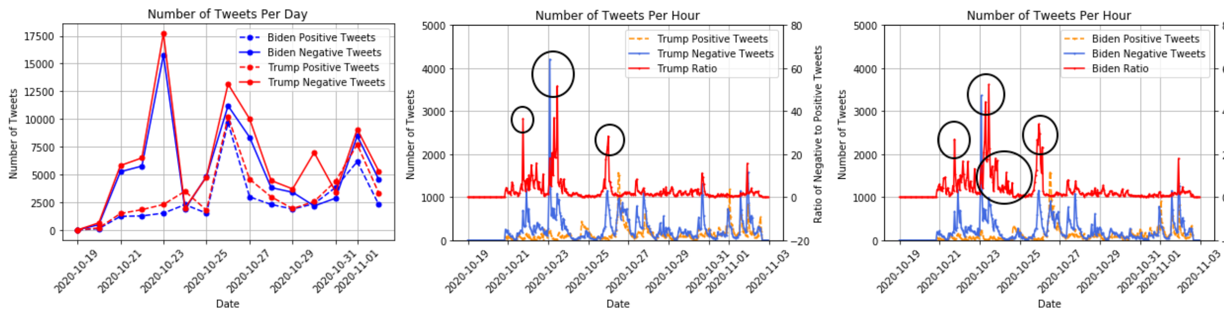

Figure 3: Sentiment trends of Trump and Biden starting from October 19th and ending on November 2nd, by day and hour.

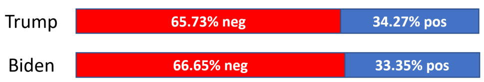

Figure 4: Positive and negative percentage of Biden and Trump from our prediction in terms of their total counts.

Source	Date	Sample	Biden	Trump	Other
Poll Averages*			51.1%	43.1%	-
Redfield & Wilton	11/02/2020	8,765 LV ±1%	53%	41%	6%
Economist/YouGov	11/02/2020	1,363 LV ±3%	53%	43%	4%
Quinnipiac	11/02/2020	1,516 LV ±2.5%	50%	39%	11%
Research Co.	11/02/2020	1,025 LV ±3%	50%	42%	8%
RMG Research	11/02/2020	1,200 LV ±2.8%	51%	44%	5%
Yahoo/YouGov	11/02/2020	1,360 LV	53%	43%	4%
Rasmussen Reports	11/02/2020	1,500 LV ±2.5%	48%	47%	5%
IBD/TIPP	11/02/2020	1,080 LV ±3.2%	50%	45%	5%
Morning Consult	11/02/2020	14,663 LV ±1%	52%	44%	4%
IBD/TIPP	11/01/2020	1,072 LV ±3.2%	50%	44%	6%

Figure 5: Positive and negative percentage of Biden and Trump from major polling agencies.

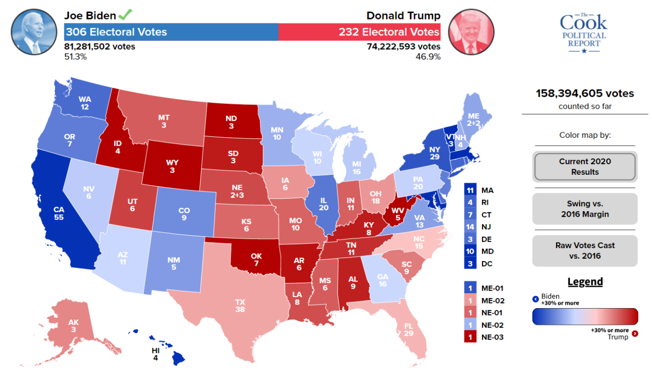

Figure 6: 2020 U.S. election result.

some states recounted their final results due to the slim margin between the two candidates. For instance, Georgia's margin was so small that three recounts took place, eventually affirming Biden's victory. Our sentiment model correctly predicted the margin of the election is very small, better than the polls.

We also divided the tweets by day and hour and studied the negative to positive tweet ratios to further observe patterns of sentiment trends, as shown in Figure 3. Small cycles of spikes and dips demonstrate the natural user activity patterns on Twitter. More drastic spikes are generated by important political activities. The largest spike for both candidates, which occurred on October 23rd, 2020, was most likely due to the last presidential debate, which took place the night before. No other major events were within the time span of the tweets. This spike was larger in number vs. the second-largest spike by a margin of around 5,000 tweets. This spike contributed materially to the eventual sentiment score of both candidates. The ratio of negative to positive tweets further demonstrates public sentiment in regards to the last presidential debate, outlined by circles within Figure 3; before the debate, Trump had a larger negative to positive ratio. During and after the debate, this ratio decreased rapidly to be less than Biden's, allowing us to surmise that the presidential debate went favorably for Trump.

Our research demonstrates that sentiment analysis using social media data can be an accurate and low-cost way to gauge general opinion towards candidates and predict election results. However, there are shortcomings that require further improvements. The model represents a popular vote decision in which all votes are equally influential. The United States, however, utilizes a more complex electoral college voting system. Votes in different states are not weighted equally, and so sometimes, a candidate with higher popular votes may lose the election. Moreover, the electoral system is based on the results from each state, hence it is necessary to gather state-based locations of users. Furthermore, social media biases are not accounted for either; we did not alter the model to detect and reduce the natural biases of the Twitter community.

4 CONCLUSION

In this paper, we focused on the tweet sentiment analysis of the 2020 U.S. Presidential Election. We compared five classifiers for sentiment analysis on the benchmark Sanders Twitter dataset. The best classifier, MLP, was used to analyze our collected tweets that are related to the 2020 U.S. election. According to the experimental results, both candidates were not favored by the general public, and the results of electoral votes would be very close, contrasting the results most polls predicted. Our prediction of a close race was later verified by the 2020 U.S. Election results. This demonstrates that social media data can be utilized as an alternative tool to predict election results. Beyond this, we also discovered some interesting phenomena, such as the important role of negative sentiment within social media and the correlation between political events and sentiment trends.

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