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Article

A Data-Centric Approach to Understanding the 2020 U.S. Presidential Election

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Abstract: The application of analytics on Twitter feeds is a very popular field for research. A tweet with a 280-character limitation can reveal a wealth of information on how individuals express their sentiments and emotions within their network or community. Upon collecting, cleaning, and mining tweets from different individuals on a particular topic, we can capture not only the sentiments and emotions of an individual but also the sentiments and emotions expressed by a larger group. Using the well-known Lexicon-based NRC classifier, we classified nearly seven million tweets across seven battleground states in the U.S. to understand the emotions and sentiments expressed by U.S. citizens toward the 2020 presidential candidates. We used the emotions and sentiments expressed within these tweets as proxies for their votes and predicted the swing directions of each battleground state. When compared to the outcome of the 2020 presidential candidates, we were able to accurately predict the swing directions of four battleground states (Arizona, Michigan, Texas, and North Carolina), thus revealing the potential of this approach in predicting future election outcomes. The week-by-week analysis of the tweets using the NRC classifier corroborated well with the various political events that took place before the election, making it possible to understand the dynamics of the emotions and sentiments of the supporters in each camp. These research strategies and evidence-based insights may be translated into real-world settings and practical interventions to improve election outcomes.

Keywords: NRC classifier; lexicon-based classifier; emotion classification; US presidential election; social media

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1. Introduction

Social media and blogging sites have gained popularity, enabling individuals to express their opinions and thoughts. Over a decade now, these sites have revolutionized the digital landscape. It has empowered every individual and community to freely express their opinions, feelings, and thoughts on a variety of topics. Users of these sites are generally allowed to post short and limited-character texts. Even though these texts are limited in size, they hold a wealth of information. They clearly convey thoughts, emotions, and feelings on a particular topic within their social network. Upon mining these texts, it is possible to determine the emotions and feelings expressed by an individual on a particular topic. An individual can express any emotions or feelings, including anger, disgust, fear, joy, love, sadness, surprise, etc. These texts can be examined at different ecological levels. Sometimes, more than one emotion can also be expressed via the same text. Given the inherent lack of structure and variability in the size of these texts, understanding these emotions, whether from an individual or larger group's perspective (also known as emotion classification), can pose challenges. Further, despite significant breakthroughs in sentiment analysis within the field of Data Mining and Machine Learning, the wide range of emotions associated with human behavior has yet to be addressed. Knowing the exact emotion underlying a topic of investigation rather than a generic sentiment is critical. Since more than one emotion can be expressed via text, it becomes necessary to analyze each sentence one by one to get a better grasp of the overall emotion associated with it. Additionally, the popularity of social media is encouraging users to submit short messages, thus replacing the use of traditional electronic documents and article styles for expressing views and opinions.

Twitter tweets are short messages, unlike conventional texts. They are very peculiar in terms of size and structure. As indicated earlier, they are restricted to 280 characters. Because of this limitation, users have to use very restrictive language to express their feelings and emotions. The language used in tweets is very different from the language used in other digitized documents such as blogs, articles, and news [1]. A large variety of features (i.e., words) are used in these texts, which poses a very significant challenge. Upon representing these texts as a vector of features, each text results in exponentially increasing the size of the available features. This is because the corpus would contain a million features for a given topic [2]. A major significant challenge persists in manually classifying the text within the tweets into different emotion classes. Manually classifying the tweets into different emotion classes has been tried previously. However, manually annotating the tweets into different emotion classes is not free from ambiguity and does not also guarantee 100% accuracy [2]. It is also the inherent complexity of the various emotional states that poses a significant challenge. Differentiating the emotional classes from one another is also a complication. According to the Circumplex model [3], human beings have 28 different types of affect emotions. To explain this, Russell proposed a two-dimensional circular space model in which it was demonstrated that the 28 different emotion types differ from each other by a slight angle. Russell clearly showed that several emotion types are clustered so closely together that it becomes difficult to differentiate between them. Thus, it becomes very difficult for humans to label those texts accurately. When humans try to label these texts, there is a notable risk of mislabeling the emotions that are subtly different or close to each other. This is a serious issue because it eventually inhibits the classifier from learning the critical features that can be used to identify emotions hidden in the texts.

In this article, we focus on analyzing the tweets collected during the 2020 presidential elections. Using the lexicon-based NRC classifier, we analyzed the emotions and sentiments expressed by people toward the two presidential candidates, Donald Trump and Joe Biden, on various topics. Based on these emotions and sentiments, we predicted the swing direction of the 2020 presidential election in a subset of states deemed battleground and key to the election. To begin with, we have provided a short review of the emotion classification work performed in the past. Following that, we discussed the materials and methods employed in this study, presented the results and discussions from this study, and concluded our research with discussions on the scope for future work.

Literature Review

Studies related to sentiment and emotional classification have recently garnered considerable empirical attention. This popularity is due to the increase in the amount of unstructured opinion-rich text resources from social media, blogs, and textual corpus. These texts have given researchers and companies access to the opinions of a larger group of individuals around the globe. Meanwhile, the advances in ML and natural language processing (NLP) have also sparked increased interest in sentiment and emotion classification. For example, Hasan, Rundensteiner, and Agu (2014) have proposed the use of EMOTEX, which can detect emotions in text messages. EMOTEX uses supervised classifiers for emotion classification. Using Naïve Bayes (N.B.), Support Vector Machine (SVM), Decision trees, and the KNN (*k*-nearest neighbor), they have demonstrated 90% precision for a four-class emotion classification on the Twitter dataset [2]. Other studies, including the work by Pak et al. (2010) and Barbosa et al. (2010), have considered using ML techniques on Twitter datasets. They both have demonstrated accuracies ranging between 60% and 80% for distinguishing between positive and negative classes [4,5]. Go et al. (2009) have also performed sentiment analysis on the Twitter dataset using Western-style emoticons. They have used the N.B., SVM, and Maximum Entropy and have reported an accuracy of 80% [6].

Furthermore, Brynielsson et al. (2014) have demonstrated close to 60% accuracy on a four-class emotion (positive, fear, anger, and others) classification on the tweets related to the Sandy hurricane using the SVM classifier [7]. Last but not least, Roberts et al. (2012)

have proposed Empa Tweet that can be used to annotate and detect emotions on Twitter posts. In their work, they have discussed developing a synthetic corpus containing tweets for seven different emotion types (anger, disgust, fear, joy, love, sadness, and surprise). On their constructed synthetic dataset, they used seven different binary SVM classifiers and classified the tweets. Using their ensemble classification technique, they have classified each tweet to determine if a particular emotion was present. In addition, they have reported that their corpus contained tweets with multiple emotion labels [8].

Emotion and sentiment classification has been widely researched using various machine learning and deep learning techniques.

Bhowmick et al. (2010) performed an experiment where they observed that humans and machine learning models exhibited a very similar level of performance for emotion and sentiment classification on multiple data sets. Therefore, they concluded that the machine learning (deep learning) models can be trusted for this task [9]. Chatterjee et al. (2019) also confirmed through their study that methods employing Deep neural networks outperform other off-the-shelf models for emotion classification in textual data [10]. Kim (2014) performed several experiments on emotion classification using CNN on multiple benchmark datasets, including the fine-grained Stanford Sentiment Treebank. A simple CNN with slight hyperparameter tuning demonstrated excellent results for binary classifications of different emotions [11]. In a work by Kalchbrenner et al., 2014 Dynamic Convolutional Neural Network (DCNN) has been explored for sentiment classification on the Twitter dataset. According to them, DCNN is capable of handling varying lengths of input texts in any language. They have reasoned that the use of Dynamic k-Max Pooling makes DCNN a potential method for sentiment analysis of Twitter data [12]. Acharya et al. (2018) have explored emotion detection in EEG signals. In their study, they have explored and demonstrated the potential of using the complex 13-layer CNN architecture [13]. In one of the studies, Hamdi et al. (2020) utilized the CNN streams and the pre-trained word embeddings (Word2Vec) to achieve a staggering 84.9% accuracy on the Stanford Twitter Sentiment dataset [14]. On the contrary, Zhang et al. (2016) have proposed the Dependency Sensitive Convolutional Neural Networks (DSCNN) that outperforms traditional CNNs. They have reported 81.5% accuracy in the sentiment analysis of Movie Review Data (MR) [15]. Zhou et al. (2015) have proposed C-LSTM, which utilizes both the CNN and LSTM for a 5-class classification task. However, they have only reported an accuracy of 49.2% [16].

Since emotion and sentiment classification is a sequence problem, several studies have focused on exploring recurrent neural networks or RNNs. Lai et al. (2015) have explored RNNs and have determined that RNNs have the capability to capture the key features and phases in texts that can help boost performance for emotion and sentiment classification [17]. Abdul-Mageed and Ungar (2017) have explored Gated RNN or GRNN for emotion and sentiment classification in several dimensions and have demonstrated significantly high accuracies [18]. Kratzwald et al. (2018) have explored six benchmark datasets for emotion classification using the combination of both the RNN and sent2affect. They have reported exceptional performance of this combination when compared against any traditional machine learning algorithm [19].

Using the Recursive Neural Tensor Network (RNTN) for the famous Stanford Sentiment Treebank dataset (SST), Socher et al. (2013) have reported 85.4% accuracy for sentiment classification [20]. Zhou et al. (2016) used the BLSTM-2DCNN architecture for Stanford Sentiment Treebank binary and fine-grained classification tasks, archiving a mere 52.4% accuracy. In their study, they observed that the BLSTM-2DCNN architecture was very efficient in capturing long-term sentence dependencies [21]. Czarnek et al. (2022) used the Linguistic Inquiry and Word Count (LIWC) and NRC Word-Emotion Association Lexicon (NRC) to investigate whether older people have more positive expressions through their language use. They examined nearly five million tweets created by 3573 people between 18 and 78 years old and found that both methods show an increase in positive affect until age 50. They also concluded that according to NRC, the growth of positive affect increases steadily until age 65 and then levels off [22]. Barnes, J. (2023) has presented a systematic comparison of sentiment and emotion classification methods.

In this study, different methods for sentiment and emotion classification have been compared, ranging from rule- and dictionary-based methods to recently proposed few-shot and prompting methods with large language models. In this study, it has been reported that in different settings—including the in-domain, out-of-domain, and cross-lingual—the rule- and dictionary-based methods outperformed the few-shot and prompting methods in low-resource settings [23].

There are three types of classifiers for emotion and sentiment classification: supervised, unsupervised, and lexicon-based classifiers. Supervised classifiers are more commonly used to address the emotion and sentiment classification problem [2,4–6,8,24–32]. However, a training dataset is required to employ a supervised classifier for the classification problem. More specifically, a domain-specific training dataset is required. Obtaining a domain-specific training dataset for a task in hand is hard as it might not always be available. Therefore, it is wise to explore unsupervised or lexicon-based classifiers.

Unsupervised classifiers are utilized to model the underlying structure or the distribution of the data. Therefore, these algorithms are left on their own to discover and present interesting patterns. Upon using unsupervised learning, users are left to look at those patterns and assign the class labels. In the Lexicon-based approach, the aim is to identify certain patterns that occur together with a seed list of sentiment/emotion-related words. More specifically, similar sentiment/emotion-related words are identified from a large corpus with the same feature-specific orientations. For this study, the unavailability of the domain-specific corpus is a major challenge [33]. Therefore, we have opted for a lexicon-based classifier, NRC [34,35], to determine the emotions and sentiments expressed within the collected tweets. In previous works related to US presidential elections [36–41], it has been clearly demonstrated that the NRC classifiers are best suited for emotion and sentiment classification of tweets compared to several different supervised learning techniques.

2. Methods and Materials

2.1. Methodology

Collecting and mining Twitter feeds related to political events provides insight into the opinion expressed by an individual or an entire community. In this particular context, the Twitter feeds have the potential to serve as a proxy for the voter's vote. These tweets also have the potential to predict and understand all the major events related to the presidential elections, ultimately leading to determining the outcomes. Srinivasan et al. (2019) clearly demonstrated that the collected Twitter feeds relating to the 2016 presidential election had the potential to predict the major events that led to the final outcome of the election [36]. In this study, we have chosen to collect data from a secondary source (social media sites). To address the research queries in this study, we have identified collecting tweets from Twitter. Here, we will first introduce the lexicon-based NRC classifier that will be used to classify the tweets. Secondly, we will discuss the data collection process in detail.

2.1.1. NRC Classifier

The tweets collected for this study were classified using the NRC classifier. We implemented the NRC classifier in R (version 3.6.0) using the *Syuzhet* package. The *Syuzhet* package implements the NRC classifier using the function *get_nrc_sentiment ()*. This function classifies tweets across eight emotions and two sentiments.

The NRC is a lexicon-based classifier with annotations for about 14,182 words. Using these words, the NRC classifier can classify texts into eight different emotions—anger, anticipation, disgust, fear, joy, sadness, surprise, and trust—as well as sentiments: negative and positive. This lexicon corpus (words) of the NRC classifier was constructed based on two measures, namely the Strength of Association (SOA) and Pointwise Mutual Information (PMI). The use of the two measures mentioned above ensures that the lexicon corpus has the potential to determine a particular emotion class in a sentence [34,35]. A significant drawback of the NRC classifier is that it cannot classify those sentences that do not contain the words that belong to the lexicon corpus.

Across each state, we determined each candidate's average net sentiment score, which is the difference between the fraction of the positive sentiment tweet to the total number of tweets and the fraction of the negative sentiment tweet to the total number of tweets. We predicted that a state would swing in favor of a candidate if a candidate received the highest number of net positive tweets. Similarly, we determined the average score for each of the eight emotions as a fraction of the total number of tweets.

2.1.2. Data Collection

To retrieve the tweets from Twitter, we developed an automated script. This script was designed to retrieve tweets using both the Search API, which is part of the Twitter REST API, and the built-in Twitter API package within the R Studio. To successfully execute the automated script, we established a developer account on Twitter that provided us with access to various Tokens and API keys. The automated script identified and used appropriate handles for both candidates, Donald Trump and Joe Biden, to selectively retrieve the tweets. Tweets were collected over eight months in 2020.

Using 20 different hashtags, a total of 7,653,518 tweets were collected for both presidential candidates between 3 March 2020 and 30 October 2020. Of these hashtags, the most popular were *Trump*, *Trump2000*, and *Joe Biden*. The unique number of tweeters who tweeted about Donald Trump and Joe Biden was 6,258,545 and 1,394,973, respectively. Table 1 provides a monthly distribution of the collected tweets. It is evident that there were at least five times the number of tweets collected for Donald Trump than for Joe Biden (see Table 1).

Table 1. Month-wise distribution of tweets collected for the U.S. 2020 presidential candidates.

Months	**Total**	**Number of Tweets**	
		Donald Trump	**Joe Biden**
March	574,020	460,509	113,511
April	579,452	525,014	54,438
May	557,608	494,448	63,160
June	723,169	663,650	59,519
July	506,005	446,262	59,743
August	1,598,082	1,288,131	309,951
September	1,502,981	1,166,885	336,096
October	1,612,201	1,213,646	398,555
Total		6,421,511	1,232,007

Once the tweets were collected, extensive cleaning was performed. To clean the tweets, we used the *gsub* function from the *stringr* package in R. Stanton outlined the steps for cleaning the tweets [42]. The focus of data cleaning was to get rid of unnecessary spaces, get rid of the URLs, and remove the retweet header, hashtags, and references to other links. We used the R statistical package *cldr* and identified that ~10% of the tweets were posted in 38 different languages. The rest of the tweets were in English. All the non-English tweets were identified and filtered out.

Both data collection and cleaning took about ten hours per Twitter handle. The entire workload was distributed evenly across several Google Cloud Computing (GCC) engines. Two machines, each running seven different GCC virtual machines, took approximately seven hours to collect the data. Once the data was collected, the data was validated by a two-fold mechanism. A Python script was first used to compare the daily tweets collected by the "Streaming APIs" of Twitter in order to confirm the completeness of the tweets' content and attributes. Another R script using the same "Streaming APIs" was compared against the main script, but instead of comparing the daily tweets collected, it was compared on a weekly basis to confirm the completeness of the collected tweets.

All the collected tweets were classified using the NRC classifier, which was implemented in R using the Syuzhet package. This package contains an implementation of an interface (function) called *get_nrc_sentiment ()*. All the tweets were classified into one of the eight different emotions and one of the two sentiments. For each tweet, the NRC classifier gives a nominal value ranging between zero (low) and seven (high) across eight emotions and two sentiments. We assigned a unique label to each tweet by determining which emotion was prominent (high nominal value) within it. If a tweet had more than one prominent emotion, then we duplicated those tweets as a separate instance and assigned all the respective prominent emotions to it. While classifying the tweets, we also encountered situations where tweets had no emotion or sentiment label attached. This was because the NRC classifier assigned a zero (0) nominal value across eight emotions and two sentiments. Such tweets were removed from further processing and analysis. In addition to that, we also computed the average net sentiment score for each candidate. We determined each candidate's average net sentiment score, which is the difference between the fraction of the positive sentiment tweet to the total number of tweets and the fraction of the negative sentiment tweet to the total number of tweets. We predicted that a state would swing in favor of a candidate if a candidate received the highest number of net positive tweets. Similarly, we determined the average score for each of the eight emotions as a fraction of the total number of tweets.

3. Results

Using the NRC classifier, we determined the general population's emotions and sentiments expressed toward both presidential candidates in these tweets. Figure 1 shows a higher overall positive sentiment for Biden (0.917) than for Trump (0.827). Overall, the negative sentiment was similar, slightly more toward Trump (0.869) than Biden (0.859). People expressed more anger toward Biden than Trump but were more surprised, disgusted, and less trusting toward Trump.

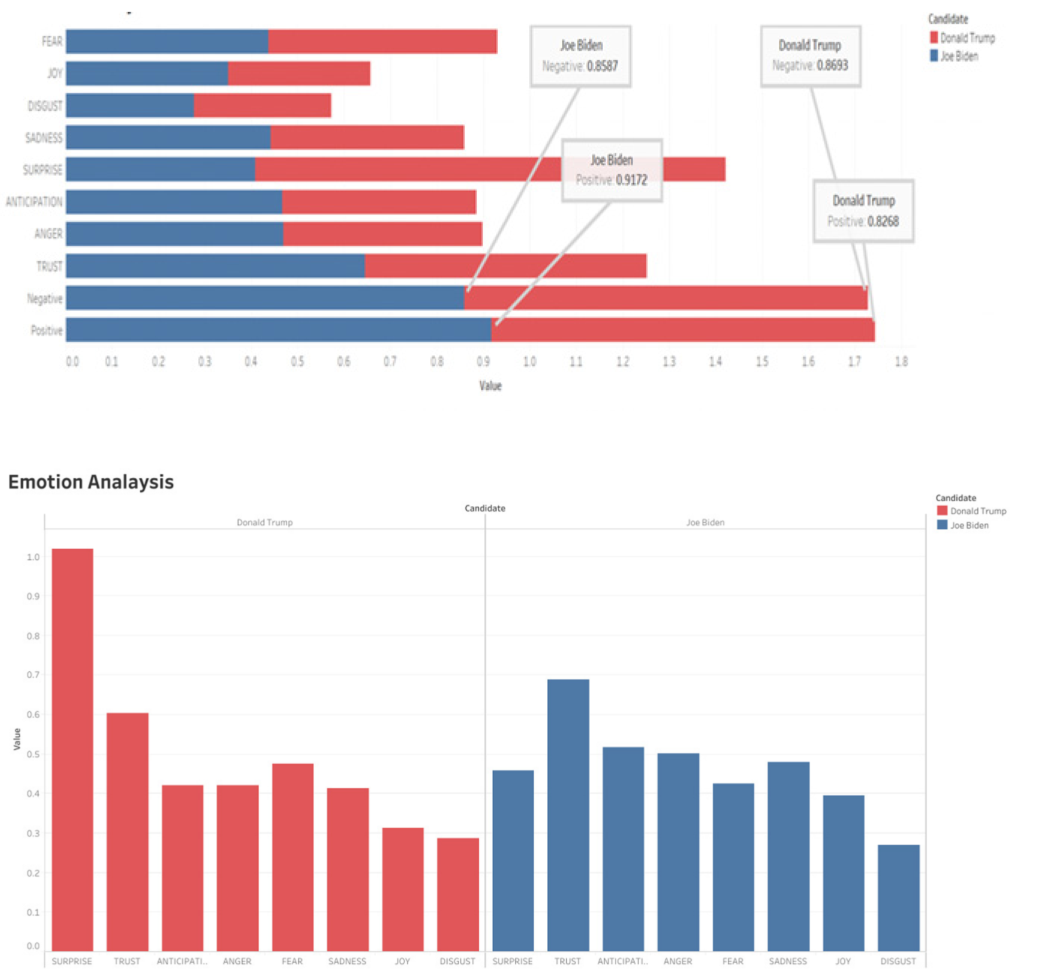

Figure 1. Sentiment and emotion analysis of people toward the 2020 U.S. presidential candidates.

Figure 2 indicates that the average positive sentiment for Trump has increased steadily since June but decreased again in October as the election approached. On the other hand, the average negative sentiment for Trump has been decreasing since mid-July, while the negative sentiment for Biden has been increasing since August.

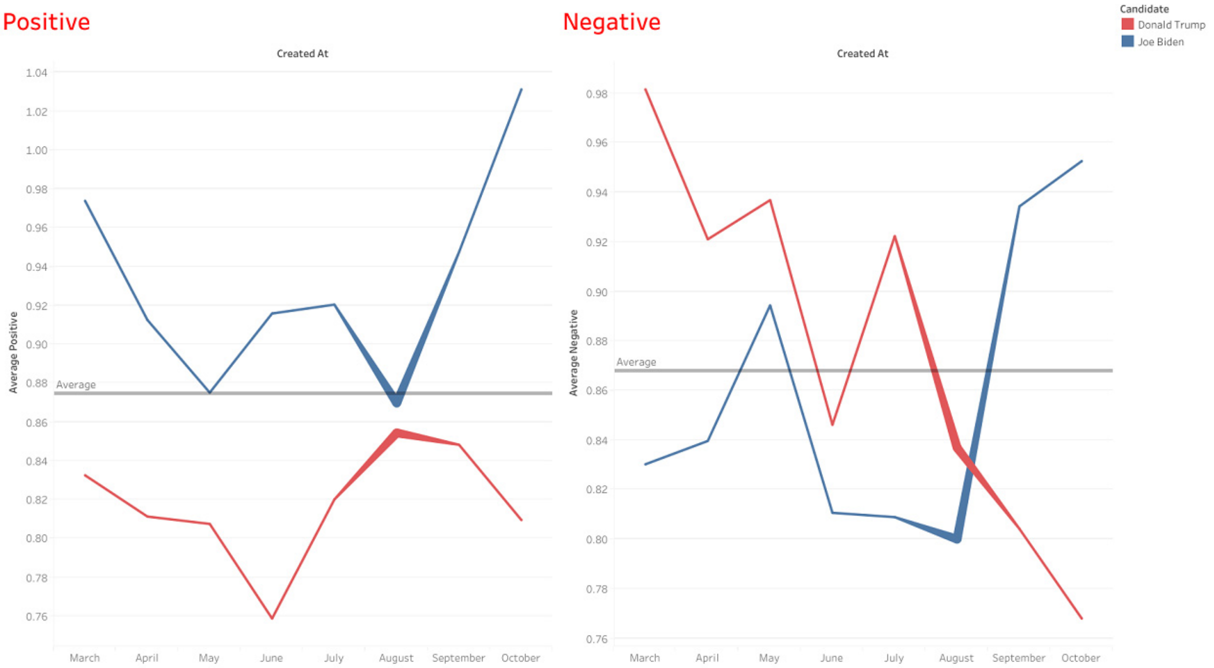

Figure 2. Month-wise analyses of positive and negative sentiments for both the 2020 U.S. presidential candidates.

Figure 3 shows the net sentiment (net sentiment = positive − negative) score for both presidential candidates, and it is clear that Trump has been gaining ground steadily since August compared to Biden and was holding a slight advantage.

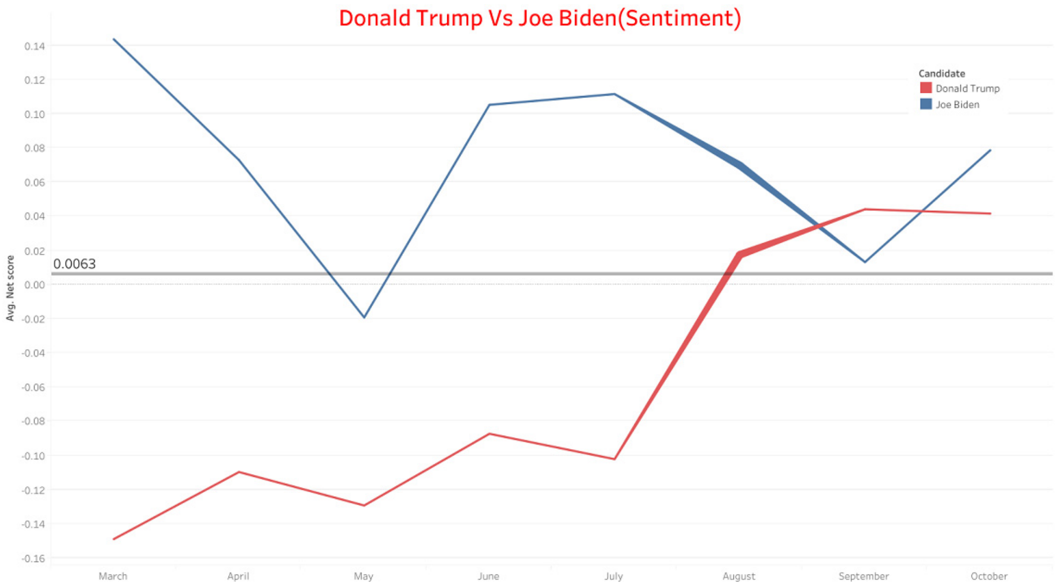

Figure 3. Month-wise analyses of the net sentiment score for both the 2020 U.S. Presidential Candidates.

We analyze both the candidates' stand related to healthcare, immigration, economy, race relations, trade and tariffs, foreign affairs, and climate change, which were essential to the electorate in the 2020 election cycle. Based on Figure 4, Biden held an advantage on most of the issues except for the matters pertaining to trade and tariffs as well as race relations.

Under Trump' presidency, the US economy shrank by 4.8%, which took a significant hit for Trump in the 2020 presidential election. In terms of the economy, foreign affairs, and immigration, Trump's average net score was low until July, but then it started picking up as the election got closer. With respect to trade and tariffs, people showed more faith in Trump than in Biden.

Figure 4. *Cont.*

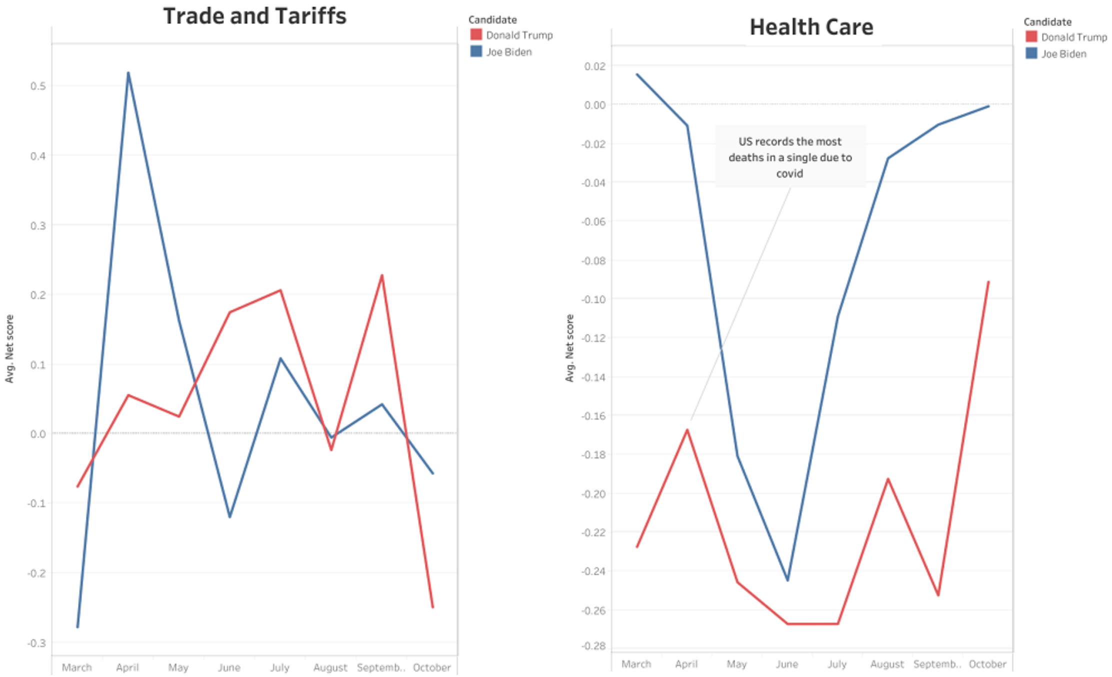

Figure 4. Candidates' stand on the issues important to the electorate in the 2020 election cycle.

Figure 5 shows the overall sentiment for Trump and Biden and important events between March and October 2020. Interestingly, the increase in unemployment had a much more dramatic effect on Biden than on Trump. Trump's attempt to block John Bolton's book and his views on delaying the 2020 presidential election impacted the overall sentiment he garnered. By contrast, Joe Biden's selection of his vice presidential running mate did not seem to have helped him. Overall, Trump held a slight edge over Biden since the first presidential debate.

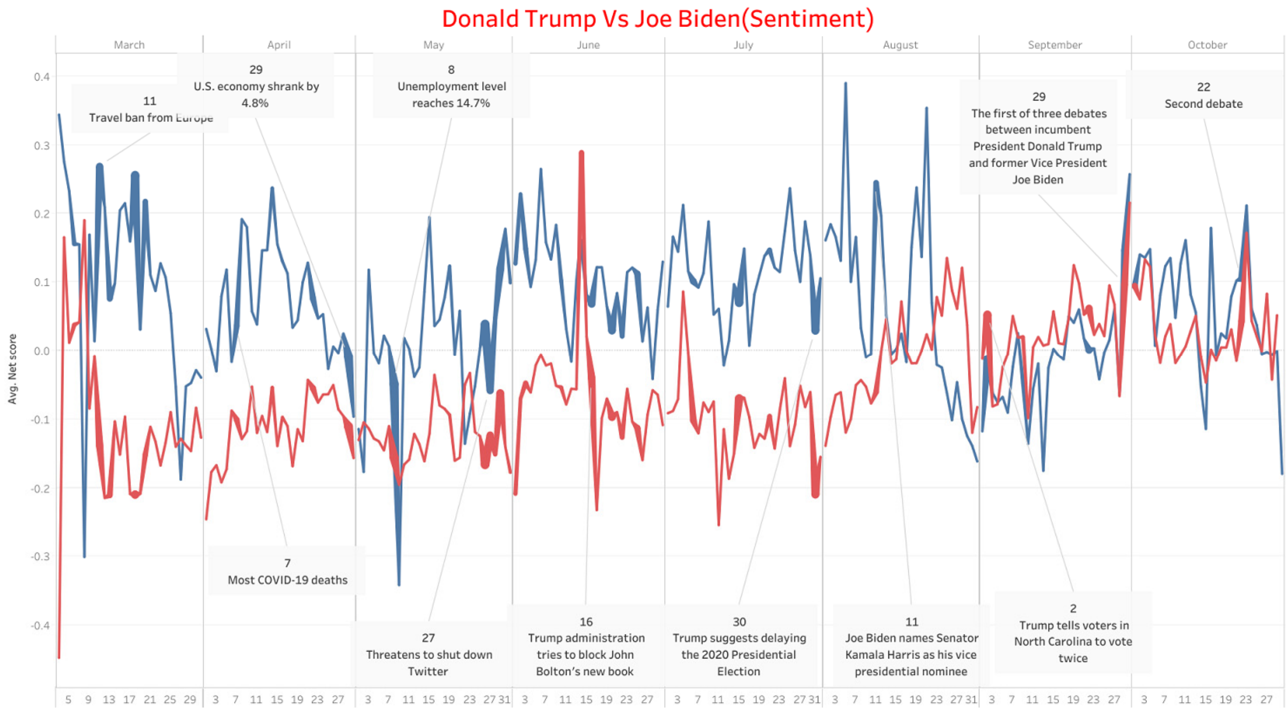

Figure 5. Month-wise analysis of the *overall average sentiment* for both the 2020 U.S. Presidential Candidates (blue for Biden, red for Trump) correlated with major events.

We also performed sentiment and emotion analyses on tweets collected from seven battleground states (Texas, Florida, Arizona, Michigan, Wisconsin, Pennsylvania, and North Carolina). A total of 1,507,525 tweets were analyzed across the seven battleground states collected since July 2020. As depicted in Figure 6, a vast majority of the tweets came from Texas and Florida, and Trump received relatively more tweets than Biden.

Figure 6. Distribution of tweets collected from the seven battleground states.

As shown in Figure 7, Biden secured a higher net sentiment score in Pennsylvania and Arizona, but Trump was in a close race in North Carolina and Wisconsin and held a lead in Florida, Michigan, and Texas.

Figure 7. Weekly distribution of the average net sentiment score for the 2020 U.S. presidential candidates across seven battleground states.

4. Analysis of the Battleground States

4.1. Arizona

In Arizona, Trump had gained a significant lead in trust over Biden. Even though the public expressed greater anger and disgust toward him (see Table 2), Trump had garnered a steady increase in positive sentiment. However, in October, as shown in Figure 8, there was a substantial increase in the positive sentiment for Biden and a significant drop in positive sentiment for Trump, suggesting that Arizona would likely swing toward Biden.

Table 2. Emotions toward both the presidential candidates in Arizona.

Emotion	Donald Trump	Joe Biden
Anger	0.4606	0.3950
Disgust	0.2918	0.2490
Fear	0.4458	0.3675
Joy	0.3822	0.3185
Trust	0.6545	0.5840

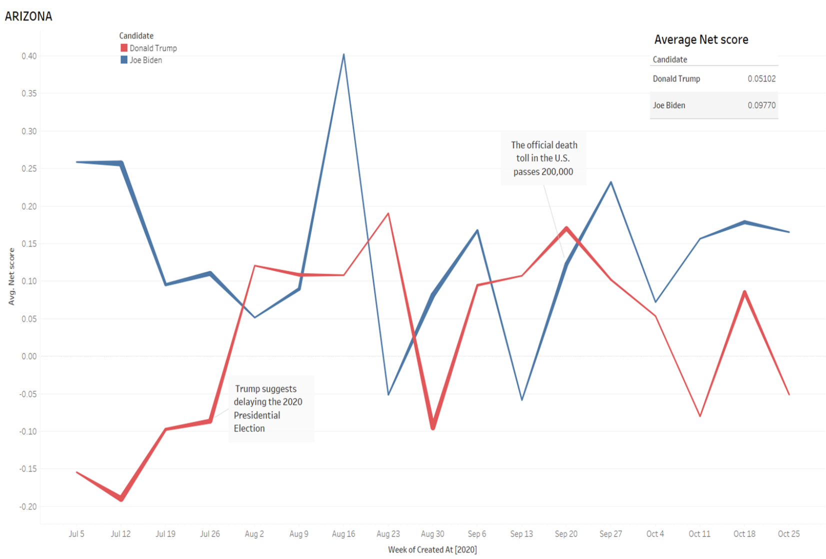

Figure 8. Monthly-wise net sentiment analysis of both the presidential candidates in Arizona.

4.2. Florida

In Florida, people showed more trust toward Trump but also expressed more anger, disgust, joy, and fear toward him than Biden (see Table 3). As shown in Figure 9, we noticed a substantial increase in the positive sentiment for Biden since October and a significant drop in positive sentiment for Trump, thus suggesting that Florida would likely swing toward Biden.

Table 3. Emotions toward presidential candidates in Florida.

Emotion	Donald Trump	Joe Biden
Anger	0.4106	0.3629
Disgust	0.2662	0.2250
Fear	0.4302	0.3484
Joy	0.3682	0.3171
Trust	0.6535	0.5882

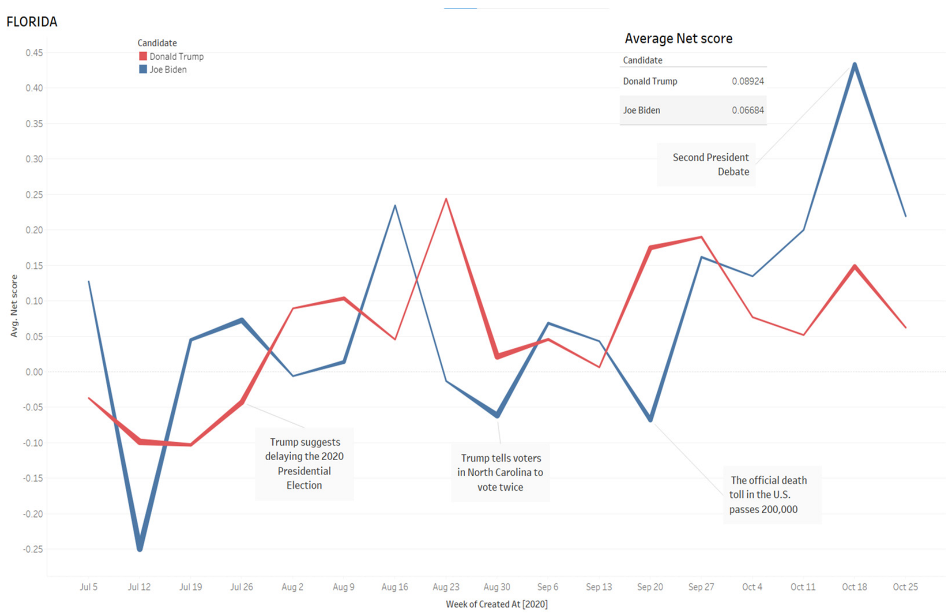

Figure 9. Monthly-wise net sentiment analysis of both presidential candidates in Florida.

4.3. Michigan

In Michigan, we noted an increase in trust in Trump. Comparatively, in Michigan, Trump experienced more disgust, fear, anger, and joy than Biden (see Table 4). As indicated in Figure 10, Trump consistently outperformed Biden in the net sentiment score. However, soon after the second presidential debate in late October, Biden gained a significant net sentiment suggesting that Michigan could swing toward him.

Table 4. Emotions toward presidential candidates in Michigan.

Emotion	Donald Trump	Joe Biden
Anger	0.3941	0.3657
Disgust	0.2576	0.2329
Fear	0.4447	0.3532
Joy	0.3768	0.2937
Trust	0.6549	0.5619

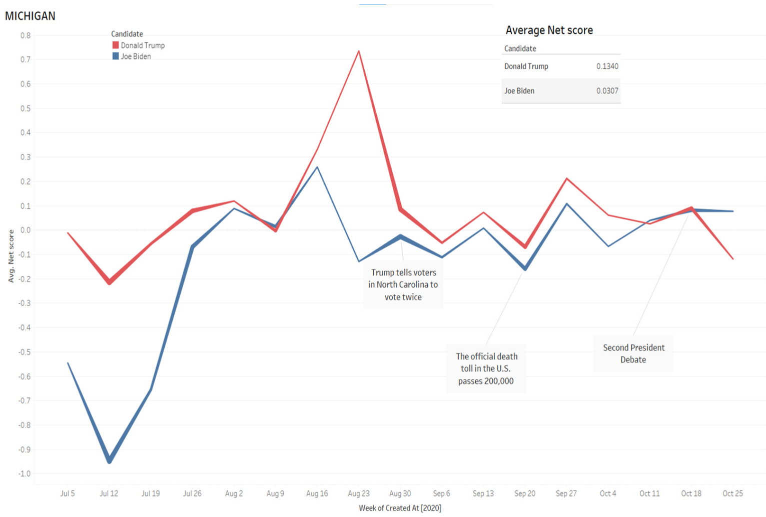

Figure 10. Monthly-wise net sentiment analysis of both the presidential candidates in Michigan.

4.4. North Carolina

In North Carolina, Trump held a significant lead over Biden in trust but also received more disgust, anger, and fear (see Table 5). We also observed a substantial increase in the net sentiment toward Trump since September, even though the official death toll due to the COVID-19 pandemic surpassed 200,000. For both candidates, the number of tweets collected from North Carolina was very close, with slightly more tweets collected for Trump (i.e., ~9k for Trump and ~6k for Biden). Although we noticed a substantial rise in the net sentiment for Biden toward the end of September and the beginning of October, there was a steep drop in positive sentiment for Biden, suggesting that North Carolina would undoubtedly swing toward Trump (see Figure 11).

Table 5. Emotions toward presidential candidates in North Carolina.

Emotion	Donald Trump	Joe Biden
Anger	0.4248	0.3453
Disgust	0.2966	0.2124
Fear	0.4430	0.3232
Joy	0.3685	0.2959
Trust	0.6402	0.5153

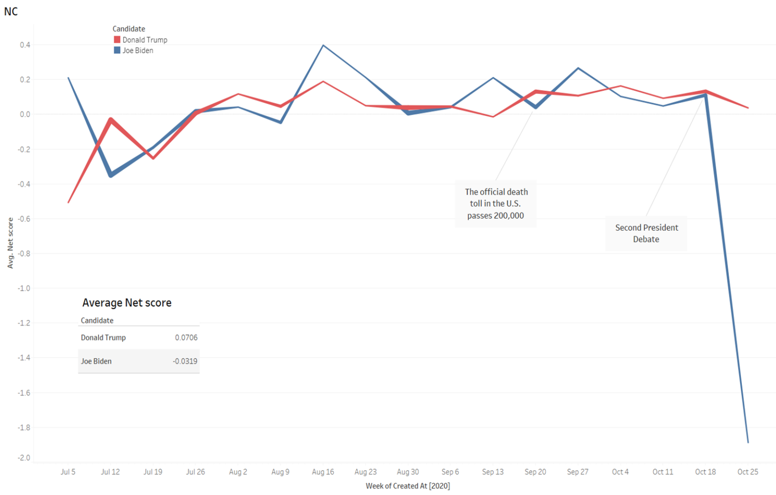

Figure 11. Monthly-wise net sentiment analysis of both the presidential candidates in North Carolina.

4.5. Pennsylvania

In Pennsylvania, both candidates experienced similar levels of trust, with Trump slightly ahead of Biden. At the same time, Trump was also experiencing more disgust, anger, and fear among people in Pennsylvania (see Table 6). In Pennsylvania, Trump encountered a lot of negative sentiment due to a variety of reasons, including suggesting that the election should be delayed, recommending voters in North Carolina to vote twice, and the official death toll for COVID-19 that surpassed 200,000, among others. However, in the final weeks of the election, Trump surpassed Biden in the net average sentiment, strongly suggesting that Pennsylvania would likely swing toward Trump (see Figure 12). Before the election's final weeks, this state appeared to be consistently swinging toward Biden.

Table 6. Emotions toward presidential candidates in Pennsylvania.

Emotion	Donald Trump	Joe Biden
Anger	0.4651	0.3666
Disgust	0.3156	0.2304
Fear	0.5068	0.3660
Joy	0.3423	0.3495
Trust	0.6551	0.6115

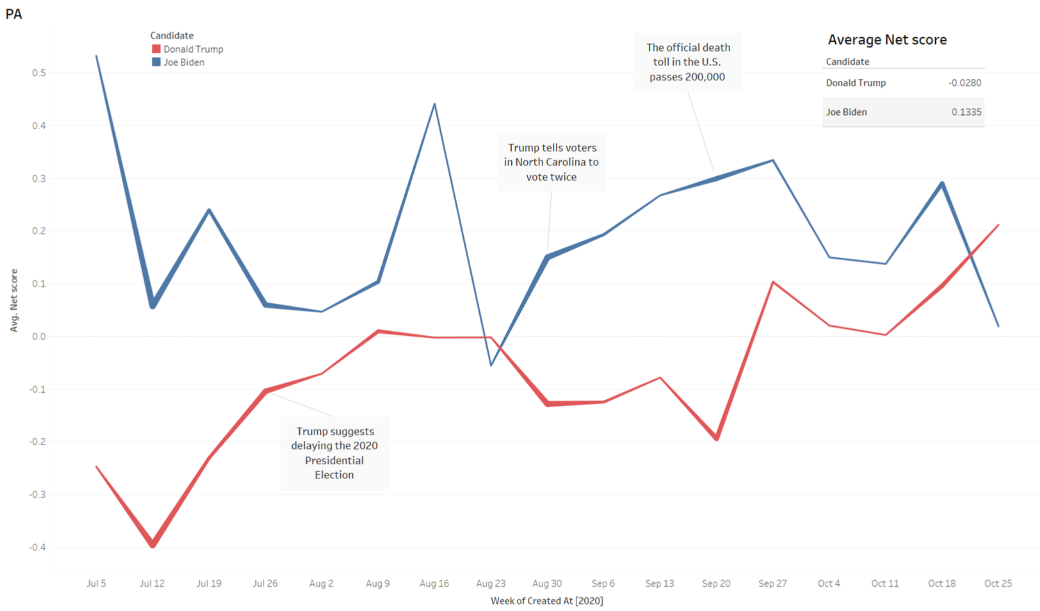

Figure 12. Monthly-wise net sentiment analysis of both the presidential candidates in Pennsylvania.

4.6. Texas

In Texas, Trump garnered notably greater trust among people over Biden. At the same time, people showed slightly more anger, disgust, fear, and joy toward him (see Table 7). In the later part of October, after the second presidential debate, Biden experienced a substantial decline in the positive sentiment, consequently ceding ground to Trump, suggesting that Texas would swing toward Trump. From Figure 13, it is evident that the pandemic had no significant impact on the candidates. Even as the U.S. death toll surpassed 200,000, both candidates were experiencing an increase in the average net sentiment score, with Biden receiving a steeper rise, surpassing Trump in the latter part of September.

Table 7. Emotions toward presidential candidates in Texas.

Emotion	Donald Trump	Joe Biden
Anger	0.3986	0.3708
Disgust	0.2595	0.2233
Fear	0.4154	0.3849
Joy	0.3644	0.2875
Trust	0.6085	0.5477

Figure 13. Monthly-wise net sentiment analysis of both the presidential candidates in Texas.

4.7. Wisconsin

In Wisconsin, Trump experienced significantly more trust than Biden but also more anger and fear. On the other hand, Biden received slightly more disgust (see Table 8). Unlike in different states, Biden encountered a steep increase in the average net sentiment soon after he nominated Senator Kamala Harris as his running mate. However, as noted in Texas, Biden experienced a decrease in the positive sentiment following the second presidential debate, bringing both Biden and Trump into a close race in late October (see Figure 14). As the election date approached, Trump surpassed Biden on the average net sentiment score, suggesting that Wisconsin would likely favor Trump.

Table 8. Emotions toward presidential candidates in Wisconsin.

Emotion	Donald Trump	Joe Biden
Anger	0.4172	0.4013
Disgust	0.2811	0.2966
Fear	0.4261	0.3718
Joy	0.3473	0.3205
Trust	0.6083	0.5799

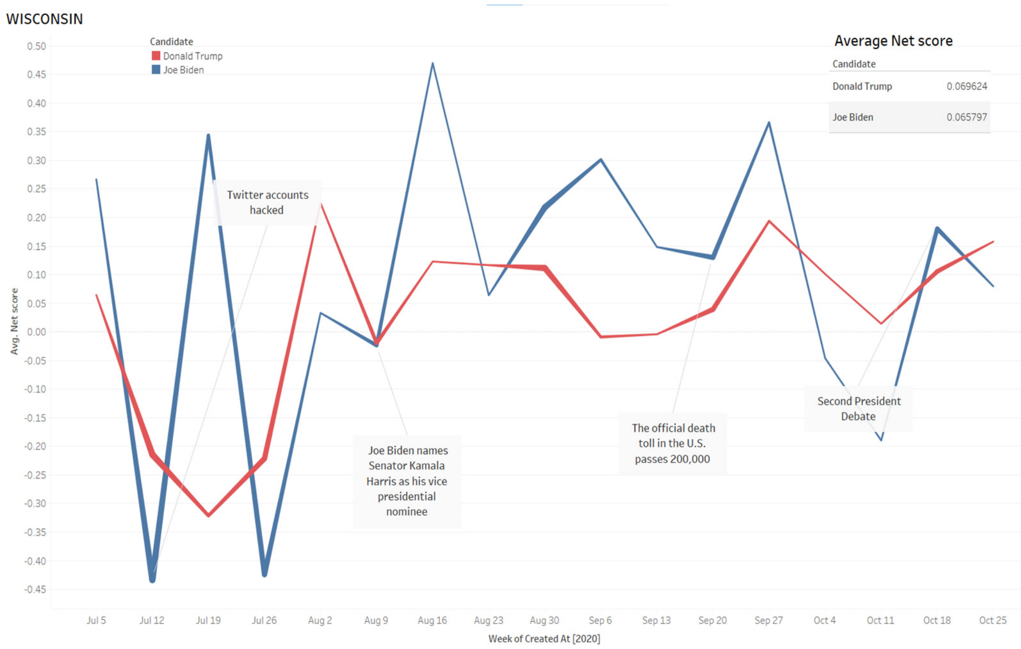

Figure 14. Monthly-wise net sentiment analysis of both the presidential candidates in Wisconsin.

Table 9 compares our study predictions with the outcome across the seven battleground states. The cells in Table 9 with bolded texts indicate the battleground states where our predictions matched the outcomes. Out of the seven battleground states we analyzed, our predictions were accurate for the four states (North Carolina, Texas, Arizona, and Michigan).

Table 9. Comparison of our study predictions with the final outcome.

Battleground State	**OUR PREDICTION**	**Actual Outcome of the 2020 U.S. Presidential Election**
Pennsylvania	Likely Trump	Biden
Florida	Likely Biden	Trump
North Carolina	**Likely Trump**	Trump
Wisconsin	Likely Trump	Biden
Texas	**Likely Trump**	Trump
Michigan	**Likely Biden**	Biden
Arizona	**Likely Biden**	Biden

Figure 15 is a convenient way to visualize multivariate data. The spider chart in Figure 15 compares the media predictions and the actual outcome of the 2020 U.S. presidential election. The projections by the media were closer to the outcomes in Georgia, Nevada, Arizona, and North Carolina. However, the differences were huge in Wisconsin, Michigan, and Florida. Figure 16 compares our predictions against the actual outcomes. Our predictions were closer to the states of North Carolina, Nevada, Wisconsin, Florida, and the U.S. However, our predictions varied mainly in Pennsylvania and Ohio.

Our predictions were better than the media predictions for North Carolina, Nevada, Wisconsin, Florida, and the U.S. However, in Michigan, Pennsylvania, Georgia, and Ohio, the media predictions outperformed ours. In Arizona and Texas, both our predictions and the predictions by the media were comparable (see Figures 15 and 16).

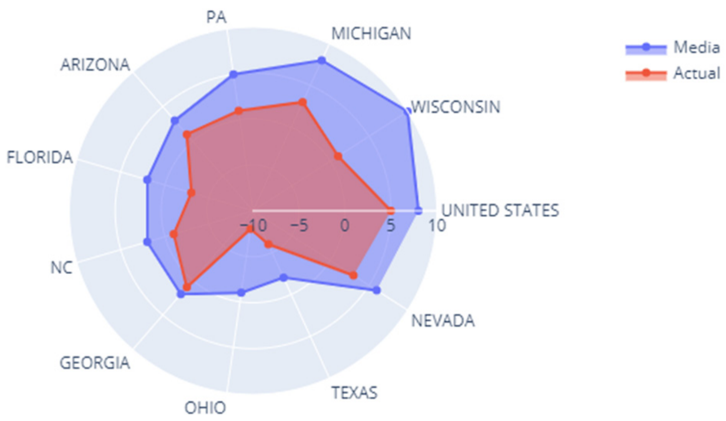

Figure 15. Spider chart comparing the media predictions to the actual outcomes of the 2020 presidential election.

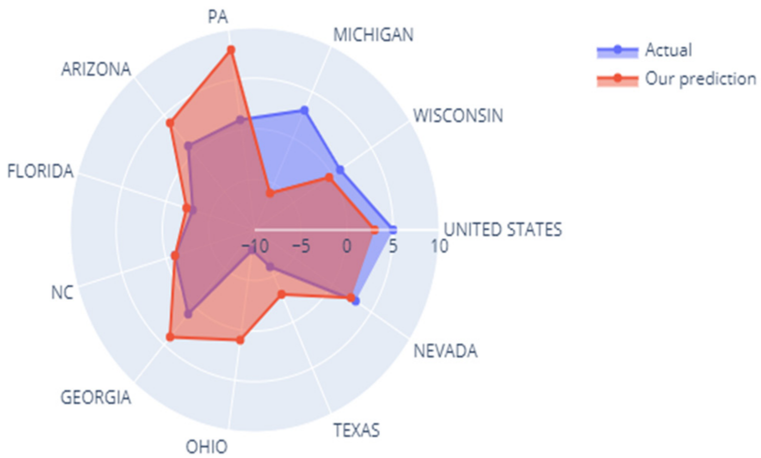

Figure 16. Spider chart comparing our predictions to the actual outcomes of the 2020 presidential election.

5. Discussion and Conclusions

In this study, we have demonstrated the potential and utility of the NRC classifier for emotion and sentiment classification. Using the NRC classifier, we have classified about seven million tweets related to the 2020 U.S. presidential election. In four battleground states (Arizona, Michigan, Texas, and North Carolina), we were able to understand the emotions and sentiments expressed by the supporters and have determined their swing directions. In North Carolina, Nevada, Wisconsin, Florida, and the U.S., our predictions were more accurate than the media predictions, suggesting that the emotions and sentiments expressed by individuals over the tweets have the potential to serve as proxies for their votes. The emotion and sentiment classification by NRC for each week before the elections corroborated well and accurately with the various political events that took place during that period, thus making it possible to understand the dynamics in the emotions and sentiments of the supporters. This study has evidently highlighted the potential of mining social media data and the wealth of information it holds. At the same time, advances in the big data infrastructure and technology have paved the way for capturing, storing, and processing large volumes of social media data from different sources. Together, they have made it possible to design and implement automated real-time predictive analytics systems. In sum, analyzing emotions and sentiments embedded on Twitter using a data-centric approach has provided valuable insights into understanding public sentiment in real time. We encourage refining these predictive models to help policymakers better understand important societal trends in order to make informed decisions and facilitate effective targeted interventions.

This study highlights the superior performance of the NRC classifier in identifying the emotions and sentiments expressed by individuals or a community toward the candidates of the 2020 U.S. presidential election. We believe this approach to mine social media data and understanding the emotions and sentiments of an individual or a community has broad applicability not just in predicting the outcomes of political events but also in studying public sentiment surrounding social policy and public policy issues. Therefore, we believe that this study could be a great case for assessing public sentiment regarding major party platforms or ballot initiatives.

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