Sentiment Analysis & Topic Modeling of the 2020 Presidential Election

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Abstract

This study analyzes public sentiment during the 2020 U.S. presidential election by examining over 1.7 million tweets. The dataset, collected from Twitter between October 15 and November 8, 2020, includes tweets with the hashtags DonaldTrump and JoeBiden. Sentiment was analyzed using the vaderSentiment library, which calculates polarity scores ranging from -1 (negative) to +1 (positive). The research aimed to explore several questions, including the overall sentiment toward each candidate and sentiment variations across U.S. states and countries. While sentiment toward both candidates was generally neutral or slightly positive, with Biden receiving a marginally higher sentiment score overall, regional sentiment varied across U.S. states. For example, traditionally red states like Indiana showed higher sentiment for Trump, while states like New Mexico exhibited higher sentiment for Biden. However, other states showed unexpected or inconsistent results, indicating the complexity of political discourse on social media. On the international front, sentiment variations by country also presented challenges. Tweets from non-English-speaking countries, including Mexico, Germany, and Italy, yielded inaccurate or neutral sentiment results due to the limitations of the sentiment analysis model, which was not designed to handle non-English text effectively. Additionally, topic modeling provided insights into the topics that were frequently mentioned at the time, and these topics closely align with many of the most politically contentious issues from this election cycle. In applying these methods, it can be observed how natural language processing may be used for future social analysis and prediction surrounding public opinions. This being said, this study also illuminates the limitations of these methods, which serve as strong reasons for them to be used with caution and understanding.

1 Introduction

With the 2024 United States presidential election fast approaching, public discourse surrounding presidential candidates has been rampant across social media platforms, especially X (formerly Twitter), one of the most prominent apps for American political discussion. Twitter's immense popularity, coupled with the concise, information-rich nature of tweets, provides an invaluable opportunity for capturing and analyzing public sentiment on a large scale. Furthermore, Twitter's API enables the harvesting of large datasets, which are publicly accessible and open for analysis. One such dataset, consisting of 1.72 million tweets related to the 2020 U.S. presidential election, serves as the focus of this study. We aim to analyze these tweets to understand public sentiment during the 2020 election cycle.

The dataset, sourced from Kaggle, includes tweets collected between October 15, 2020, and November 8, 2020, using the Twitter API. It contains two CSV files: `hashtag_donaldtrump.csv` and `hashtag_joebiden.csv`, which were generated using the hashtags #DonaldTrump and #Trump for the former, and #JoeBiden and #Biden for the latter. Each file includes 21 columns, containing various tweet attributes such as text, interactions, user data, and location. However, not all data is useful for sentiment analysis, as highlighted by Barde and Bainwad 2017. Consequently, we filtered out several attributes and retained only the most relevant, such as country and continent, to focus on geographical sentiment variations.

Research Questions:

- What is the overall sentiment expressed toward each presidential candidate in public tweets?
- What are the key topics driving polarized sentiment and political discussion in election-related tweets?
- How does public sentiment about election issues and candidates differ across different states or regions in the United States?
- How does sentiment differ across countries?
- How does the volume of election-related tweets vary by location (state or country), and what does this tell us about political engagement?

2 Background

Sentiment analysis refers to "the computational treatment of opinions, sentiments, and subjectivity of text" Medhat et al. 2014. While sentiment analysis techniques are not without their limitations, they allow for efficient quantification of sentiment within large datasets, making it an invaluable tool for analyzing corpuses too large for human analysis. Over the past decade, sentiment analysis has seen increasing use, particularly in industries like tourism. According to Alaei et al. 2017, sentiment analysis is becoming an integral part of the "big data" approach used by modern businesses. Sun et al. 2016 also argue that sentiment analysis has garnered significant attention from major industries due to its potential to yield valuable insights from large-scale social media datasets.

One of the key advantages of sentiment analysis over traditional polling methods, such as surveys, is its ability to analyze vast quantities of real-time public opinion data from platforms like Twitter Dahal et al. 2019. According to Sailunaz and Alhajj 2019, social media posts provide a rich source of data for emotion and sentiment analysis due to the sheer volume of posts and participants on platforms like Twitter.

As sentiment analysis has evolved, several studies have applied it to political contexts. For example, Yaqub et al. 2017 analyzed Twitter discourse surrounding the 2016 U.S. presidential election. Similarly, Joyce and Deng 2017 achieved a 94% correlation between Twitter sentiment and polling data for the 2016 election. These studies demonstrate the potential of sentiment analysis as an effective tool for analyzing political sentiment.

3 Related Work

Previous studies have applied sentiment analysis to Twitter data surrounding presidential elections. Yaqub et al. 2017 analyzed discourse during the 2016 U.S. presidential election, collecting over 3.1 million tweets to assess sentiment toward candidates Donald Trump and Hillary Clinton. This study, like ours, categorized sentiment into positive, negative, and neutral groups, and tracked sentiment trends over time. A similar sentiment analysis was conducted by Joyce and Deng 2017, who utilized a Naive Bayes algorithm to analyze public opinion and found a 94% correlation between Twitter sentiment and polling data.

Another significant contribution to this area is the work by Boon-Itt and Skunkan 2020, who studied public perception of the COVID-19 pandemic using sentiment analysis and topic modeling. This research is particularly useful to our study, as it presents a clear framework for dividing a large dataset into multiple facets, which helped clarify the complex data.

Additionally, Alvarez-Melis and Saveski 2021 proposed aggregating tweets and replies into ”documents” to follow conversations more effectively, which improved the application of Latent Dirichlet Allocation (LDA) models. While we may not directly apply this method, the conceptual approach of aggregating related tweets is valuable in thinking about how we can explore our dataset.

Other studies, such as Wang et al. 2012, have demonstrated the utility of sentiment analysis in political contexts, such as analyzing the 2012 U.S. presidential election. Similar methodologies have been used internationally, including in the 2018 Mexican Presidential Election Bernábe Loranca et al. 2020, where sentiment analysis was combined with topic modeling to understand political discourse.

One challenge of using Twitter data is the short length of individual tweets. This is a double-edged sword: although it allows for the analysis of large datasets, it can reduce the accuracy of sentiment interpretation. Hong and Davison 2010 addressed this issue in their work on topic modeling, which could offer insights into improving sentiment analysis accuracy.

4 Methods

4.1 Data Cleaning

4.1.1 Subsetting the Data for Required Columns:

The dataset contains various columns, including the tweet's text, creation date, and engagement metrics such as likes and retweets. It also contains the user's username and the location given on their profile. Additionally, metadata such as the date the tweet was collected and the tool used to post it is also included. To conduct our public sentiment analysis and examine sentiment variations across different locations, we selected a subset of the available data. Specifically, we focused on the following columns:

- Tweet text
- Country
- State code
- Likes
- Retweets
- User follower count

By applying a subsetting method, we extracted only the necessary columns. This reduces the size of the dataset and improves the efficiency of our analysis, enabling faster data processing.

4.1.2 Removing Special Characters, Emojis, and URLs:

To prepare the tweet text for sentiment analysis, we cleaned the data by removing unnecessary characters and emojis using regular expressions (regex). We applied the following regex patterns to eliminate specific elements:

- `http\` or `www.` removed any URLs present in the tweets.
- `@\w+` removed Twitter mentions (i.e., handles like `@username`).
- `#\w+` removed hashtags (i.e., #hashtag).
- `\d+` removed numeric characters.
- `[\U00010000-\U0010ffff]` removed emojis and special Unicode characters.

Additionally, missing values were removed to avoid errors during subsequent analysis and to ensure the dataset's integrity.

4.2 Sentiment Score Analysis

For sentiment analysis, we used the `vaderSentiment` library, which provides an easy-to-use API for various natural language processing tasks, including sentiment analysis. While we also considered and initially used the `TextBlob` library, another common and easy-to-use API, we decided upon the `vaderSentiment` library mainly because it is tuned for social media sentiment analysis, making it better suited to our needs. When comparing the results of both libraries, this was confirmed, as there was more variance across the sentiment scores assigned by `vaderSentiment`, which, when analyzing a random sample of Tweets, still seemed reasonable. Consequently, we found `vaderSentiment` to be more insightful without any loss of accuracy.

More specifically, we calculated the sentiment polarity score for each tweet using `vaderSentiment.vader`
For each tweet, a sentiment score ranging from -1 to 1 was assigned:

- -1 indicates a fully negative sentiment.
- 0 indicates a neutral sentiment.
- 1 indicates a fully positive sentiment.

The sentiment score for each tweet was computed based on the text content, capturing the emotional tone conveyed. Most sentiment scores in the dataset fell between -1 and 1, with a majority of tweets showing a neutral or slightly negative sentiment. These polarity scores were then used to categorize the tweets as positive, neutral, or negative, which served as the foundation for further analysis of public sentiment toward the political candidates.

This is what our data table looks like after preprocessing a few randomly selected tweets:

Tweet	Country	State	Sentiment	Likes	Retweet_count	user_followers_count
! En : dice que solo se preocupa por él mis...	United States of America	Florida	0.000000	0.0	0.0	1860.0
: As a student I used to hear for years, for t...	United States of America	Oregon	0.333333	2.0	1.0	1185.0
You get a tie! And you get a tie! 'S rally	United States of America	District of Columbia	0.000000	4.0	3.0	5393.0
Her minutes were over long time ago. Omarosa...	United States of America	California	-0.155208	2.0	0.0	2363.0
There won't be many of them. Unless you al...	United States of America	Ohio	0.178571	0.0	0.0	766.0

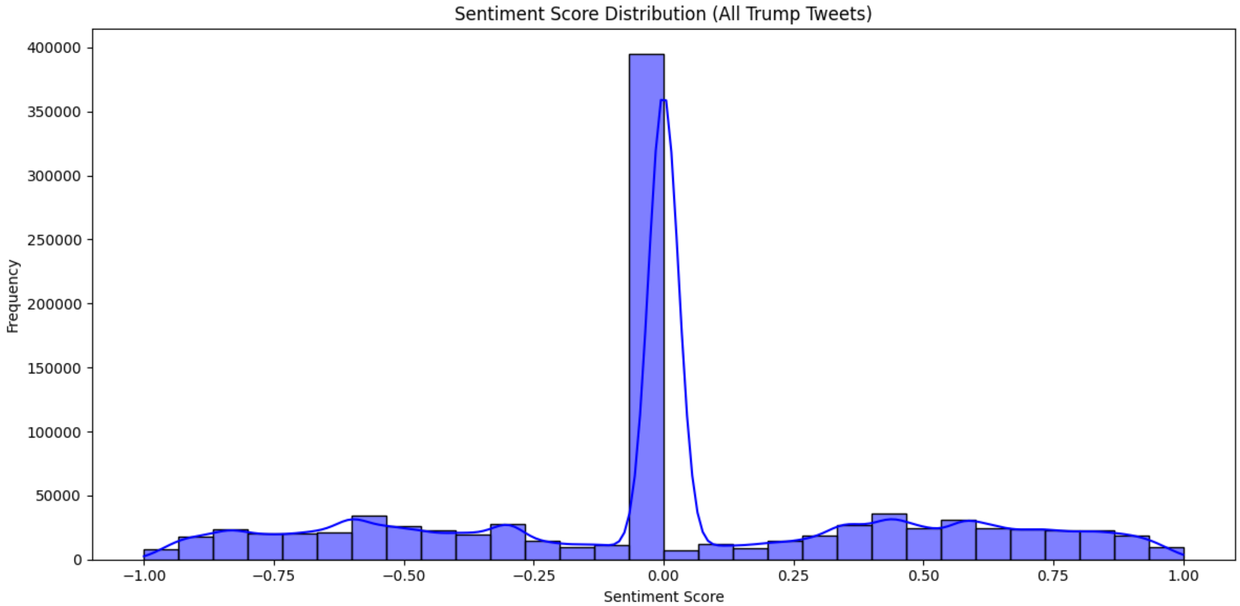
Table 1: Twitter Data Table

4.3 LDA Topic Modeling

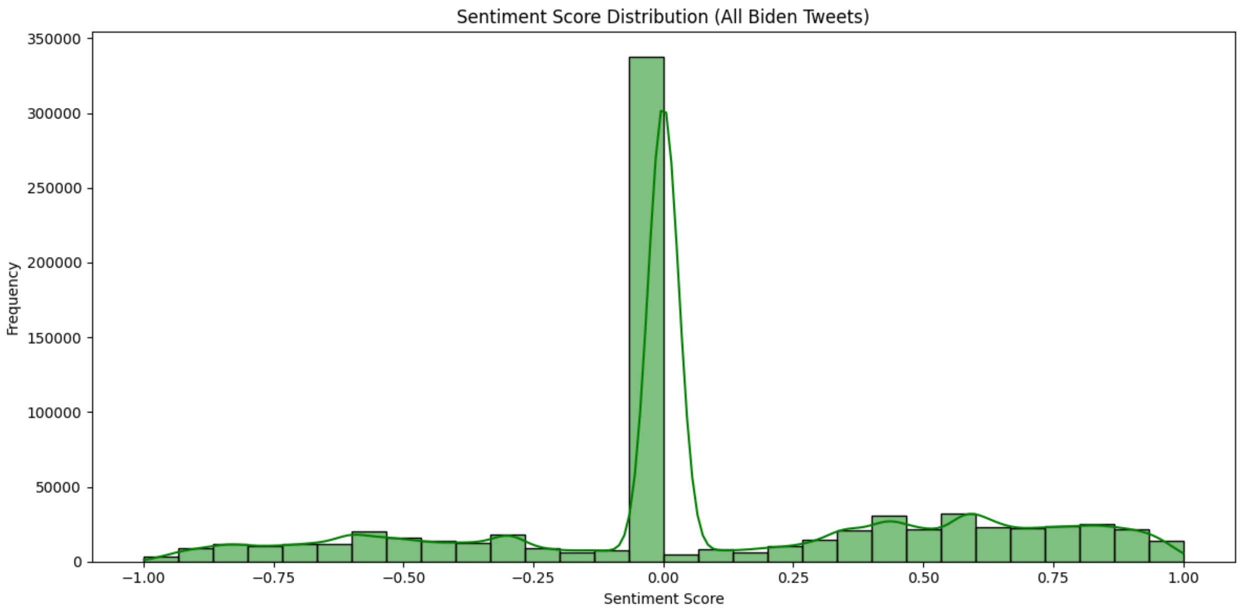
Since LDA topic modeling is an unsupervised learning algorithm that does not require labeled data, we decided it would suit our needs quite well. Consequently, this method can help determine key topics in a flexible manner. For topic modeling, we used `pyLDAvis`, specifically, `pyLDAvis.lda_model`. We found this library to be both straightforward and effective for performing LDA topic modeling.

5 Results

We started off by analyzing the overall sentiment expressed toward each presidential candidate for all tweets.



Total number of Trump tweets: 970919
Mean Sentiment Score for all Trump tweets: 0.010



Total number of Biden tweets: 776886
Mean Sentiment Score for all Biden tweets: 0.099

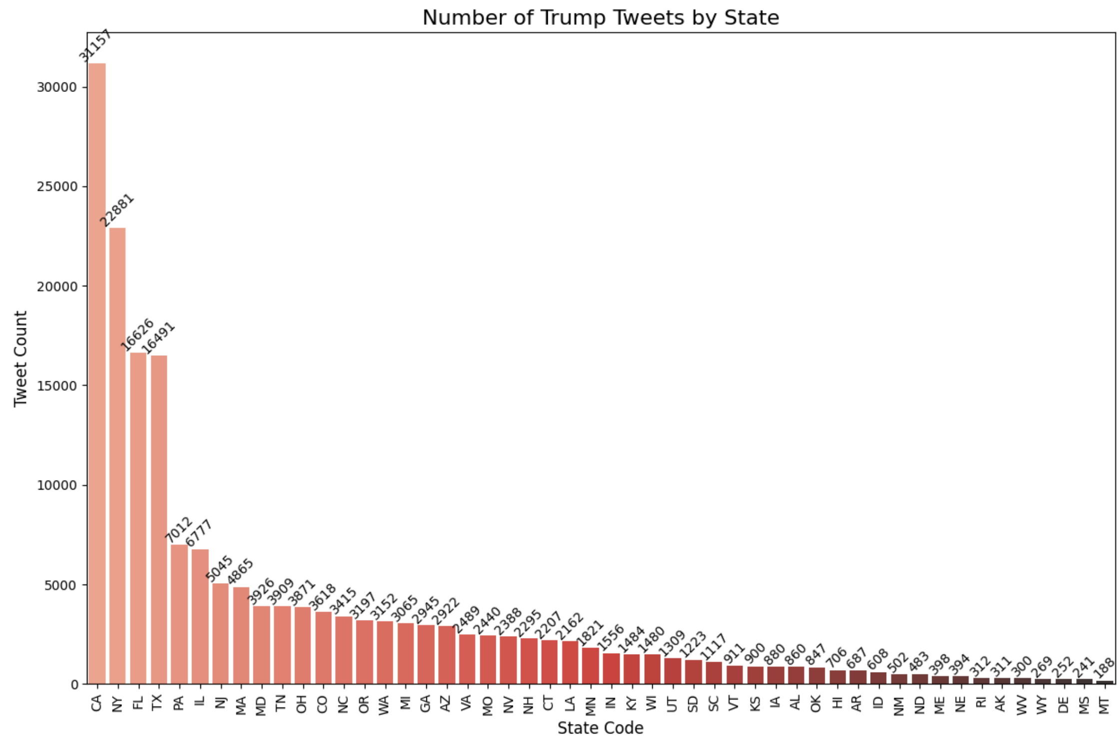
When looking at all tweets, the average sentiment for both candidates is noticeably different, with Biden's average sentiment score being significantly higher. After performing a t-test on the two datasets, we achieve a p-value of less than 0.001, suggesting that the difference in mean tweet sentiments is statistically significant. In other words, while a huge percentage of the tweets in both datasets are rated neutral, with a sentiment score of 0, the average sentiment of tweets in the Biden dataset is clearly higher and extremely unlikely to have been a result of chance.

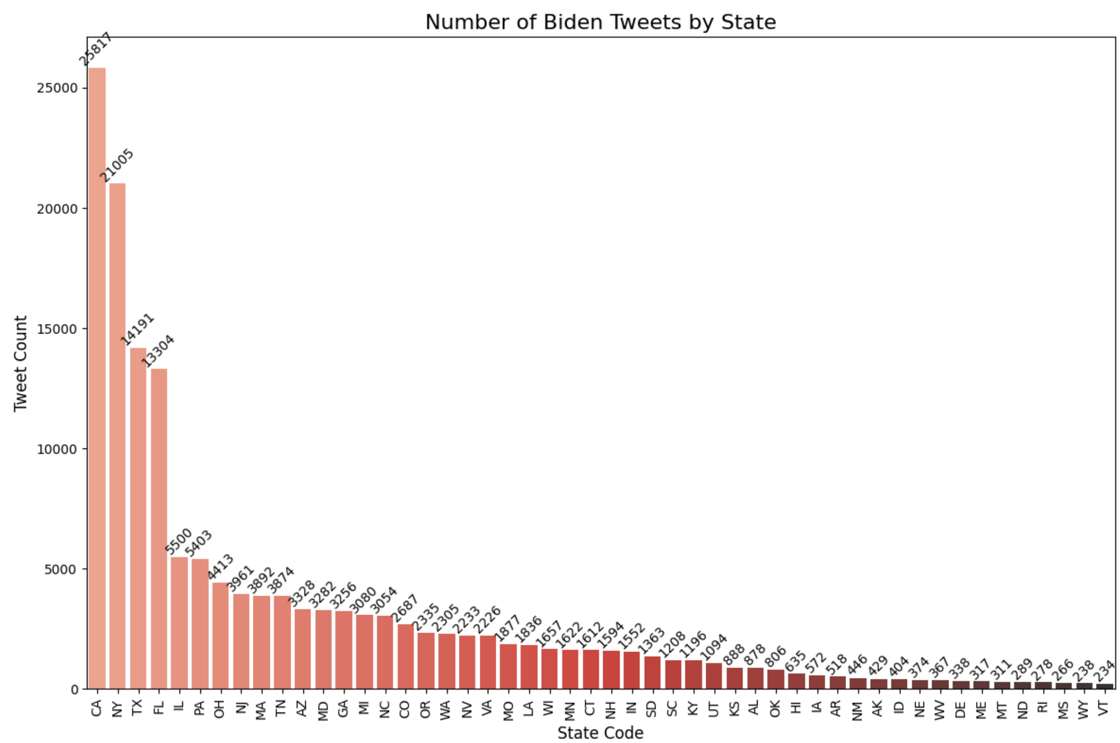
We then looked at what states had the highest and lowest sentiments for both candidates. But before doing that, we figured it was important to see how many tweets came from each state.

Selecting the 'state_code' column lead to a lot of data being dropped due to null values. In other words, many tweets are not associated with a state.

Total number of Trump tweets from the 50 states: 178894

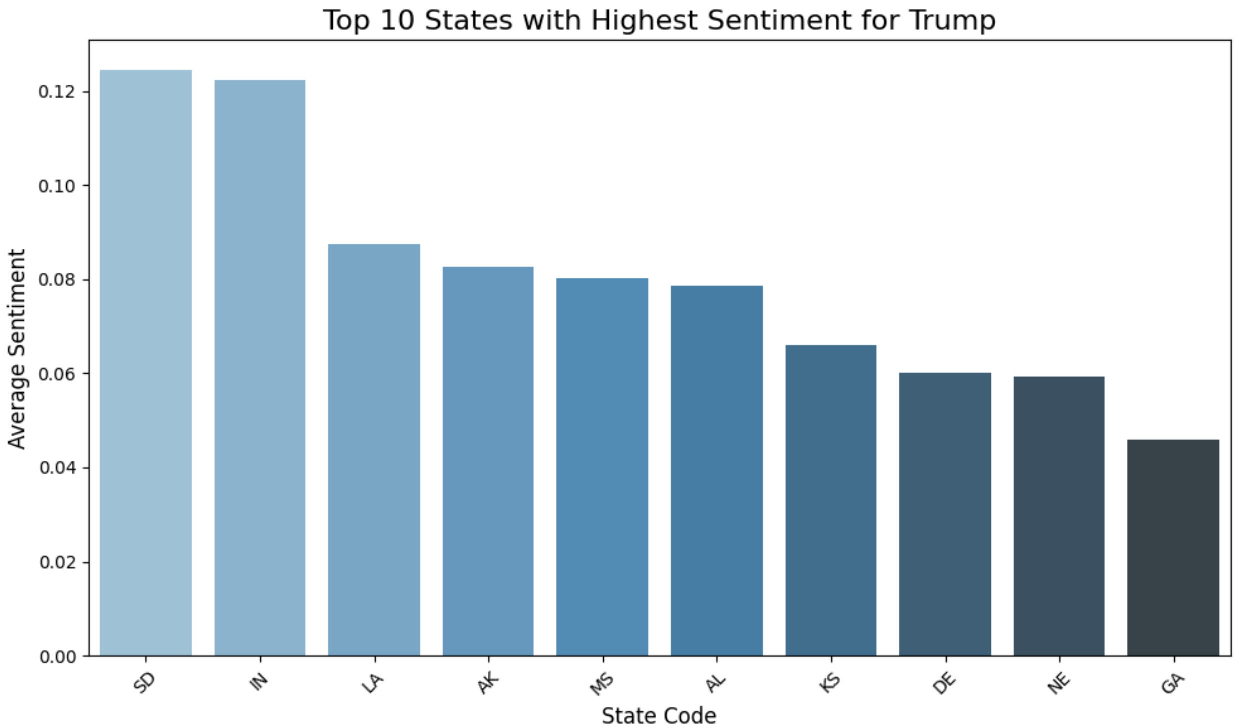
Total number of Biden tweets from the 50 states: 154345

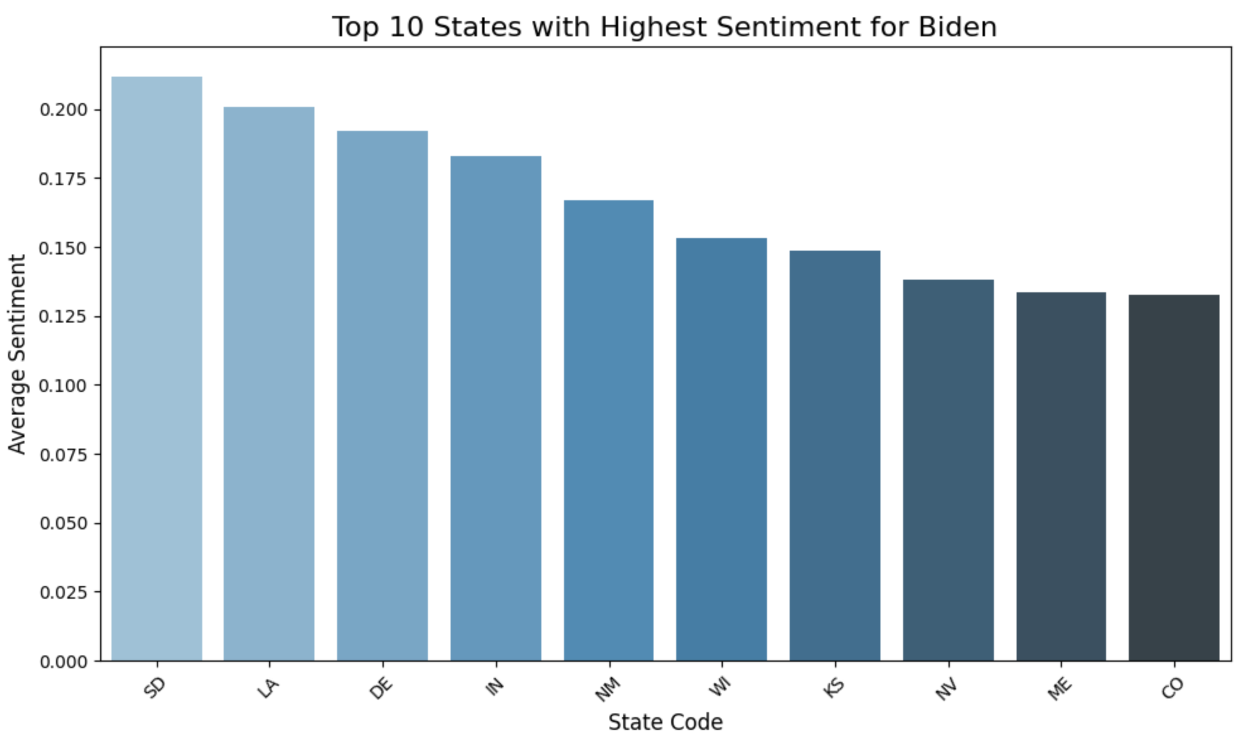




It should come as no surprise that the states with the largest populations, California, New York, Texas, and Florida, all had the most tweets.

Here are the plots for the states with the *highest* sentiment for both Trump and Biden, respectively.

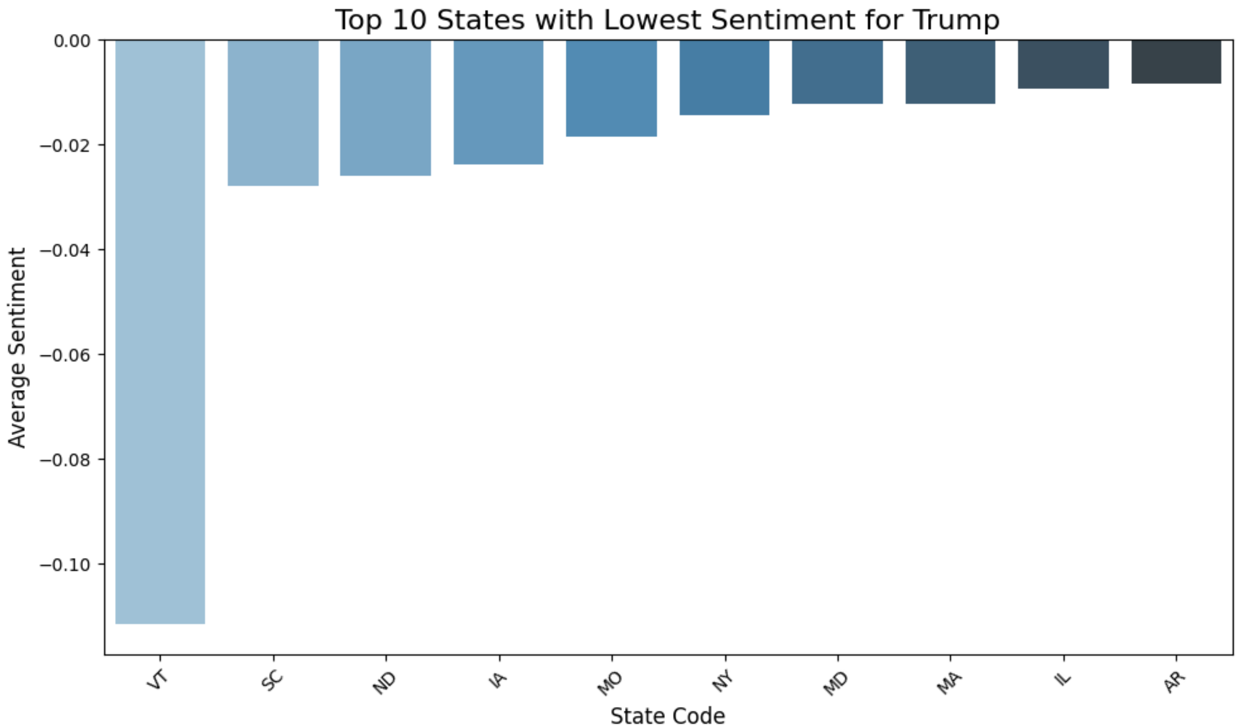


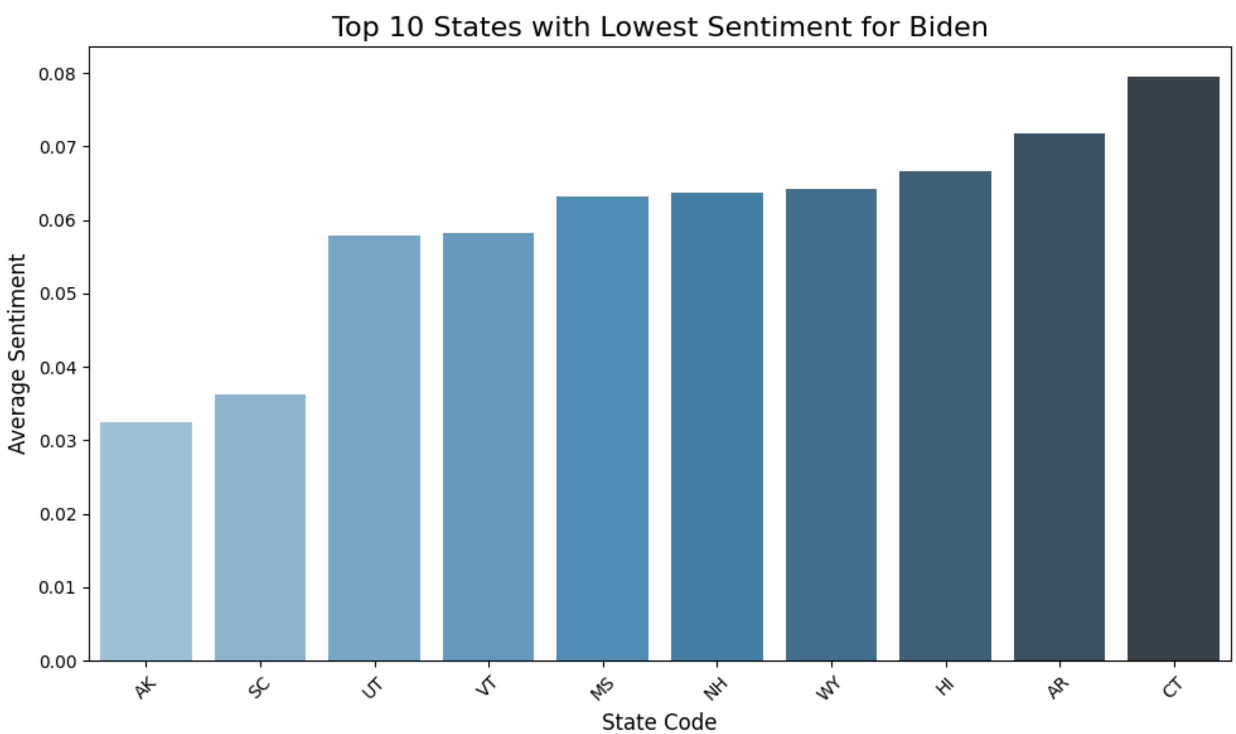


As expected, states with the highest sentiment for Trump included historically red states like South Dakota, Indiana, Louisiana, Arkansas, and Missouri, all states Trump won in 2020. Interestingly enough, Delaware and Georgia are among Trump's top 10, both states that Biden won in 2020. The appearance of Georgia is less surprising, as Georgia is historically a swing state and a political 'battleground'. On the other hand, the appearance of Delaware is somewhat confounding, though, the small population of the state may be a contributing factor to why its average sentiment for Trump was so high, since a smaller number of people, which correlates to a smaller number of tweets, gives each tweet more weight. This being said, it should also be noted that the highest sentiment score, South Dakota, came in at only slightly above 0.12. Additionally, the average sentiment for Trump among his top 10 states was 0.081, which is well below Biden's average global sentiment score. When performing a difference of means t-test comparing Biden's global average sentiment score to Trump's top 10 states average, we once again get a p-value below 0.001, suggesting that this difference is statistically significant.

The Biden plot results were a little more unexpected, sharing several of the states on the Trump plot: South Dakota, Louisiana, Delaware, and Indiana. The inclusion of Delaware, Biden's home state, makes far more sense here than in the Trump dataset, since Delaware overwhelmingly voted for Biden in 2020. However, the other three states all overwhelmingly voted for Trump in 2020, yet they still managed to make the ranking. But again, it should be noted that the state with the highest sentiment score, South Dakota, only scored a 0.21, which is closer to neutral than it is to positive. This being said, the fact that for South Dakota, a state which overwhelmingly voted for Trump in 2020, Biden has a higher sentiment score. Once again, when performing a t-test, we get a p-value below 0.001, suggesting that this difference is statistically significant. If anything, this may suggest that Democrat Twitter presence was stronger than Republican Twitter presence in 2020, even in Republican strongholds such as South Dakota. Surprisingly, California and New York, which both had over 20,000 tweets and are often touted as 'democratic strongholds', did not even make the list. The average sentiment score for Biden in his top ten states was 0.166, over double that of Trump. Just as before, a t-test finds this difference to be statistically significant, with a p-value below 0.001.

Here are the plots for the states with the *lowest* sentiment for both Trump and Biden, respectively.

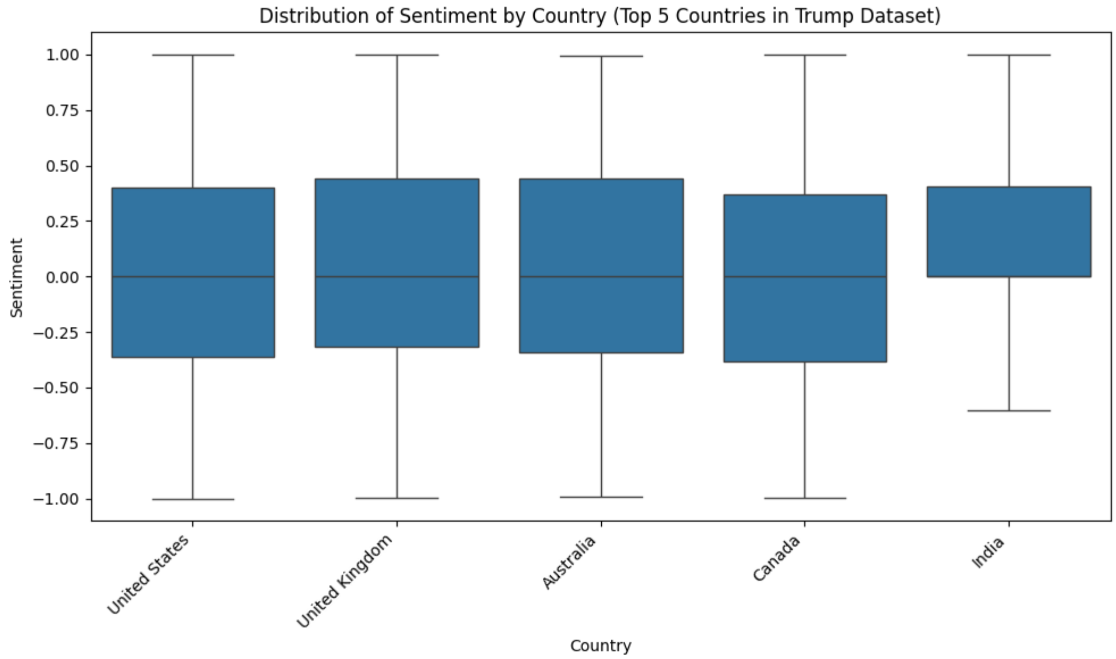




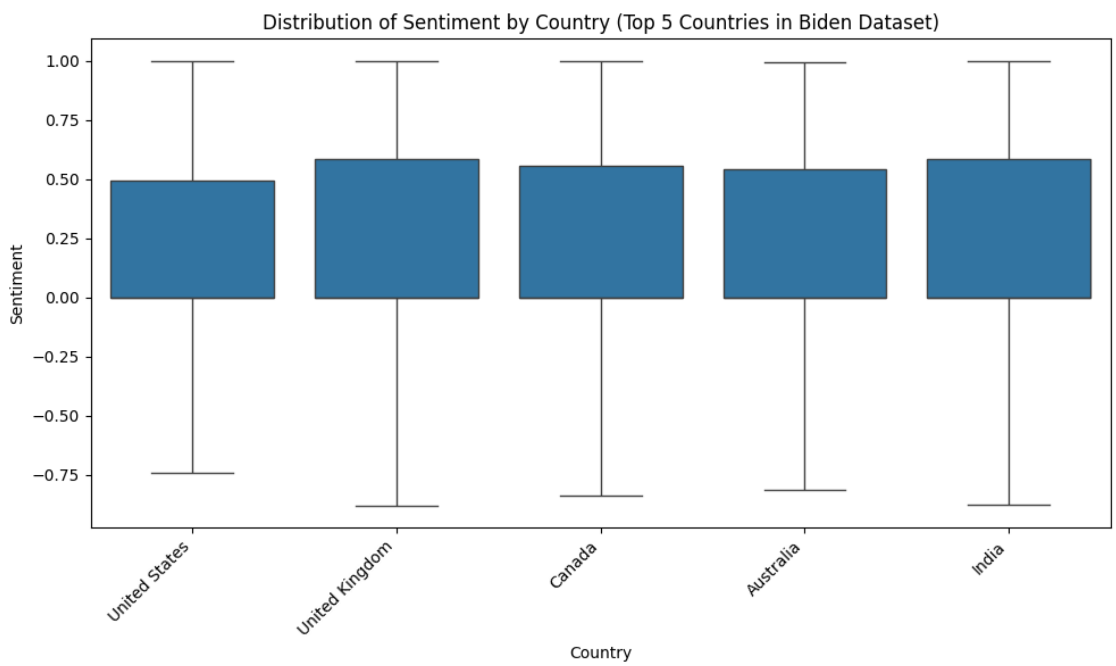
Leading the Trump plot is Vermont, with a sentiment score of -0.11, far below that of any other state in either dataset. This is consistent with the election results, as Vermont was an overwhelming victory for Biden. However, this plot does not seem very indicative of how the election turned out as it is riddled with a mix of both red and blue states. This can perhaps be attributed to the demographic of people, likely younger people, who are actually online tweeting about the election. The average sentiment score for Trump in his bottom ten states was -0.026.

As for the Biden plot, the results were also quite inconsistent with our expectations based on the election results, with Vermont, Massachusetts, New Hampshire, Hawaii, and Connecticut, all states which Biden overwhelmingly won, making appearances. Once again, this raises the question of how the demographics of Twitter vary from the average American voter. At the very least, our findings thus far suggest that the sentiments of American Twitter users, when analyzed across states, may differ from those of voters. The average sentiment score for Biden in his bottom ten states was 0.059.

The last thing we examined was the distribution of sentiment scores for different countries. We took the top ten countries, ranked by the number of tweets, for both candidates and plotted their distributions. Five of these countries—Mexico, Germany, Italy, France, and The Netherlands—had an overall sentiment score of zero, which led us to believe that the tweets were likely in their native languages, and the sentiment analysis might not have been accurate for these languages. As a result, we decided to remove these countries from our analysis. Here are the plot for both candidates.



Mean sentiment score for Trump's top 5 countries: 0.018



Mean sentiment score for Biden's top 5 countries: 0.126

When performing t-tests comparing the average sentiments of each of these 5 countries, we found that the difference in means was significant in all 5 cases, all with p-values below 0.001. Given the vast size of these datasets and the number of tweets coming from each country (over 5000 per country for each dataset), this is not surprising. While unsurprising, this confirms that there is a statistically significant difference in international sentiment towards Trump and Biden on Twitter, with Biden being favored in the 5 countries above.

To further investigate how tweets are related to each other, we used LDA topic modeling to cluster any similar tweets that are from the US.

The result of topic modeling for #Trump is as follows:

- Topic 1: trump like amp just vote care people doesn biden say election president watch said going want plan did donald says
- Topic 2: amp vote trump election people votes just don like win supporters voting know think country president states time years biden
- Topic 3: trump amp just biden president let like time lies don god america joe family people administration did china money country
- Topic 4: la en que el lo se las por trump es para del ha al lo una van su le presidente
- Topic 5: trump biden president new white debate house qt joe blue history covid donald final york free presidential vote lost american

The first revolves around general discussions about Trump and Biden in the context of elections. Words like "vote," "doesn," "care," and "plan" suggest debates on policies, potentially healthcare. References to Trump and Biden reflect partisan divides, where individuals either strongly support or oppose their respective candidates. Terms such as "watch," "going," and "want" suggest live debates or speeches, which often spark intense emotional reactions from both supporters and critics. Supporters of Trump or Biden would praise their candidate's policies, while detractors criticize them, creating a highly polarized discourse. Topic 2 focuses more on the voting process and its outcomes. Words like "win," "supporters," and "votes" suggest discussions about election legitimacy, which became a contentious issue in 2020 election. The focus on "supporters" and "states" reflects geographic and demographic divisions, with "red states" vs. "blue states" framing much of the debate. Topic 3 captures polarize opinions about Trump and Biden. Terms like "lies," "god," and "family" reflect moral and ideological debates between the two political sides. The presence of terms like "china," and "money" indicates arguments about foreign policy and economic impacts, which often divide opinions based on ideological learnings. Topic 4 is distinct, focusing on Spanish tweets. Words like "presidente" and "para" suggest discussions related to Trump's presidency, possibly touching on his immigration policies or relation with Latin American communities/countries. Immigration has been one of the most polarizing issues, with strong opinions both for and against Trump's stance on border security. Trump's strict immigration policies generated strong emotional reactions, especially in Hispanic communities. The final topic emphasizes the historic nature of the 2020 election and its aftermath. Words like "blue," "covid," "final," and "lost" point to critical moments of the 2020 election, including Trump's handling of the pandemic and the loss to Biden. "Blue" (Democrats) and "history" reflect the ideological divide, particularly as Biden's victory marked a turning point in American politics.

The result of topic modeling for #Biden is as follows:

- Topic 1: votes trump biden amp election win pa wins lead vote joe mail victory count won state just states ballots wi
- Topic 2: president vote joe biden america amp voted trump new day elect let people states today voting country united harris need
- Topic 3: biden joe amp trump hunter debate campaign president media like family son said news china did watch just twitter story
- Topic 4: trump amp like just don people know going vote think right want say did make way country election time years
- Topic 5: la en que el los trump biden se por las es para del al presidente lo una ha watch su

Topic 1 highlights discussions surrounding election results and voting processes. Key terms like "win," "election," "mail," "victory," and "count" reflects contentious debates over vote counting and mail-in ballots. These issues were deeply polarizing, with Trump's supporters questioning the legitimacy of the process and Biden's supporters defending its integrity. The inclusion of "pa" (Pennsylvania) and "wi" (Wisconsin) points to battleground states critical to the election results, and they were flashpoints for accusations of fraud versus celebrations of victory. The second topic revolves around Biden's presidency and his broader role in the election. While words like "voted," "elect," and "new day" suggest optimism and support for Biden, these terms simultaneously highlight divisions. Supporters celebrated Biden's win as a "new day" for America, while critics viewed it as a loss for the country. The third topic delves into media narratives and controversies surrounding Biden and his campaign. Words like "hunter," "china," and "family" directly reference scandals and controversies that polarized public opinion. Supporters dismissed these narratives as smear campaigns, while critics used them to question Biden's integrity and suitability for leadership. Topic 4 reflects general public sentiment and election dynamics. The conversational tone of this topic reflects the clash of opinions about the state of the country. Words like "don," "know," "right," and "want" suggest heated debates about Biden's leadership and whether he represented the "right" direction for America. The last topic highlights how Biden and Trump's policies, especially on immigration, resonated differently within Spanish-speaking communities. Some saw Biden as a symbol of hope for more inclusive policies, while others viewed his presidency with skepticism, especially regarding economic or cultural impacts. Spanish terms like "presidente" and "para" may reflect both excitement and apprehension among Latino voters, depending on their political leanings and personal priorities.

Based on our findings in topic modeling, we can attribute polarized sentiment to partisan politics, stark disagreements over policies, debates over election legitimacy, social media based echo chambers, and even cultural identity.

6 Considerations and Future Directions

While this study certainly gives us valuable insight into the 2020 election, it has several limitations worth considering. Firstly, as mentioned previously, this data was collected using the hashtags #DonaldTrump, #Trump, #JoeBiden and #Biden, with the former two corresponding to the Trump dataset, and the latter two corresponding to the Biden dataset. There are several imperfections with this method of data collection.

Firstly, some tweets ended up in both datasets, which can be seen even by looking at the beginning of each, as the first tweet in both datasets is exactly the same, which is confirmed by the tweet_id, which matches. Tweets like these will bring the average sentiment scores of each dataset closer to the average sentiment score of both datasets combined, potentially lowering the difference and therefore adding noise to our analysis. While we would like to filter out these tweets, this is quite computationally intensive, as it requires indexing through all of one of our datasets and comparing each tweet_id to those of the other dataset, and when a match is found, the tweet must be removed from both datasets. In the future, this is something worth exploring, as it may improve the integrity of our data, however, it is hard to say whether it will drastically change our findings.

Additionally, the aforementioned collection method is not a surefire way to collect tweets that align with a certain candidate or party. A major feature of Twitter is a 'trending' hashtag, which is a hashtag that has recently gained lots of engagement. These hashtags are often shown to users as suggestions, and very easily found with additionally supporting data online. As a result, many Twitter users use hashtags to boost the popularity of their tweets, regardless of the relevance of the hashtag. This leads to hashtags often being saturated with many irrelevant tweets, which again, would be very demanding to remove. The only feasible way to do this on a large scale without manually removing every irrelevant tweet would be to employ a supervised machine learning method, which would be a time-consuming and computationally expensive endeavor. Similar to removing duplicate tweets, this would likely improve the integrity of our dataset and its alignment to our intended use-cases, though it is unclear if it would significantly alter our findings. This being said, if removing duplicate tweets would change our findings, this step in our data-cleaning process would almost certainly change our findings more, so it is absolutely worth investigating in the future.

Last, and arguably most important, while social media data is often very insightful, it does not neatly map onto the demographics it is often used to study. Not every Twitter user tweets, not every user who does, tweets about politics, and not every person who cares about American politics uses Twitter. Not every American who cares about politics votes in the general election, not every person who expresses their political opinion online does so on Twitter, and more. While many steps can be taken to mitigate these factors, such as including user data from people without tweets or combining data from multiple sites, no methods of data collection and cleaning will ever perfectly match the population being studied. During our study we could see this play out, with how certain states had sentiments far higher or lower than expected based on voting outcomes. Going forward, we can only seek to improve the integrity of our data for its intended purpose, but we must keep in mind that it will always be an imperfect fit.

7 Conclusion

This study explored the use of sentiment analysis to examine public sentiment during the 2020 U.S. presidential election, analyzing over 1.7 million tweets related to the candidates Donald Trump and Joe Biden. The analysis revealed that, on average, sentiment was slightly more positive toward Biden, with a mean sentiment score of 0.099 across all tweets, compared to 0.010 for Trump. When focusing solely on U.S. tweets, the difference in sentiment between the two candidates became more pronounced, with Trump's U.S. tweets having a mean sentiment score of 0.010 and Biden's U.S. tweets scoring 0.113. This suggests a somewhat more positive engagement with Biden across both datasets, particularly in U.S.-based conversations.

Regional Variations in U.S. Sentiment: The analysis revealed distinct regional patterns in sentiment. For Trump, the average sentiment score in his top 10 states was 0.081, with higher engagement in traditionally red states such as Louisiana and Kentucky. However, his bottom 10 states had a significantly lower average sentiment score of -0.026, with states like Delaware and Vermont showing more negative or neutral sentiment.

In contrast, Biden's sentiment was more evenly distributed across states. His top 10 states showed an average sentiment score of 0.166, with notable enthusiasm in states like New Mexico and Louisiana. This is especially interesting because Louisiana was a state Biden lost by a wide margin in 2020, yet the sentiment toward him there was unexpectedly higher. Biden's bottom 10 states, such as Mississippi and South Carolina, had an average sentiment score of 0.059, which was notably higher than Trump's bottom states.

International Sentiment Variations: Sentiment analysis across countries revealed that Biden had a higher mean sentiment score of 0.126 in his top 5 countries, compared to Trump's mean score of 0.018. However, sentiment analysis was less accurate for tweets in languages other than English, with countries like Mexico, Germany, and Italy showing neutral or inaccurate sentiment due to the limitations of the sentiment model.

Implications of Sentiment Analysis: While sentiment analysis provided valuable insights into the public's perception of the candidates, the results also highlighted the limitations of using social media data as a sole indicator of political sentiment. Regional factors, demographics, and the nature of Twitter discourse can all influence the sentiment expressed in these tweets. Additionally, multilingual data posed challenges in accurately capturing sentiment across different countries.

Topic Modeling: Using LDA topic modeling, it became clear that the most discussed political topics on Twitter at the time of the 2020 election cycle were a subset of the most discussed topics of this time, which makes sense. Unsurprisingly, topics like border security, mail in voting, China, and COVID-19 appeared. On the other hand, major topics like abortion and supreme court justices were uncommon based on the results of our topic modeling, which suggests that these issues may have been of lesser concern to Twitter users than other media outlets.

Final Remarks: This study underscores the potential of sentiment analysis as a tool for tracking public opinion and understanding political discourse on social media. The findings provide a foundation for future research into the role of sentiment analysis in electoral studies, particularly in the context of large-scale public engagement and digital campaigning. Furthermore, topic modeling gives a different dimension of insight into public discussions.

When the two NLP strategies are used in conjunction, they provide multiple layers of context and understanding that can be used to gain insight into public opinions, but also to understand how data from any one source may have discrepancies with the target population.

References

Alaei, A. R., S. Becken, and B. Stantic (2017). "Sentiment Analysis in Tourism: Capitalizing on big data". In: *Journal of Travel Research* 58.2, pp. 175–191. DOI: 10.1177/0047287517747753. URL: https://doi.org/10.1177/0047287517747753.

Alvarez-Melis, D. and M. Saveski (2021). "Topic modeling in Twitter: Aggregating tweets by conversations". In: *Proceedings of the International AAAI Conference on Web and Social Media*. Vol. 10. 1, pp. 519–522. DOI: 10.1609/icwsm.v10i1.14817. URL: https://doi.org/10.1609/icwsm.v10i1.14817.

Barde, B. V. and A. M. Bainwad (2017). "An overview of topic modeling methods and tools". In: *2017 International Conference on Intelligent Computing and Control Systems (ICICCS)*. Madurai, India, pp. 745–750. DOI: 10.1109/ICCONS.2017.8250563. URL: https://doi.org/10.1109/ICCONS.2017.8250563.

Bernábe Loranca, M. B. et al. (2020). "Algorithm for collecting and sorting data from Twitter through the use of dictionaries in Python". In: *Computación y sistemas* 24.2, pp. 719–724. DOI: 10.13053/cys-24-2-3405. URL: https://doi.org/10.13053/cys-24-2-3405.

Boon-Itt, S. and Y. Skunkan (2020). "Public perception of the COVID-19 pandemic on Twitter: Sentiment analysis and topic modeling study". In: *JMIR Public Health and Surveillance* 6.4, e21978. DOI: 10.2196/21978. URL: https://doi.org/10.2196/21978.

Dahal, B., S. A. P. Kumar, and Z. Li (2019). "Topic modeling and sentiment analysis of global climate change tweets". In: *Social Network Analysis and Mining* 9.1, pp. 1–15. DOI: 10.1007/s13278-019-0568-8. URL: https://doi.org/10.1007/s13278-019-0568-8.

Hong, L. and B. D. Davison (2010). "Empirical study of topic modeling in Twitter". In: *SOMA '10: Proceedings of the First Workshop on Social Media Analytics*. DOI: 10.1145/1964858.1964870. URL: https://doi.org/10.1145/1964858.1964870.

Joyce, B. and J. Deng (2017). "Sentiment analysis of tweets for the 2016 US presidential election". In: *2017 IEEE MIT Undergraduate Research Technology Conference*. DOI: 10.1109/urtc.2017.8284176. URL: https://doi.org/10.1109/urtc.2017.8284176.

Medhat, W., A. Hassan, and H. Korashy (2014). "Sentiment analysis algorithms and applications: A survey". In: *Ain Shams Engineering Journal* 5.4, pp. 1093–1113. DOI: 10.1016/j.asej.2014.04.011. URL: https://doi.org/10.1016/j.asej.2014.04.011.

Sailunaz, K. and R. Alhajj (2019). "Emotion and sentiment analysis from Twitter text". In: *Journal of Computational Science* 36, p. 101003. DOI: 10.1016/j.jocs.2019.05.009. URL: https://doi.org/10.1016/j.jocs.2019.05.009.

Sun, S., C. Luo, and J. Chen (2016). "A review of natural language processing techniques for opinion mining systems". In: *Information Fusion* 36, pp. 10–25. DOI: 10.1016/j.inffus.2016.10.004. URL: https://doi.org/10.1016/j.inffus.2016.10.004.

Wang, Hao et al. (2012). "A system for real-time Twitter sentiment analysis of 2012 US presidential election cycle". In: *Proceedings of the ACL 2012 System Demonstrations*. URL: https://aclanthology.org/P12-3020.pdf.

Yaqub, U., S. A. Chun, V. Atluri, and J. Vaidya (2017). "Analysis of political discourse on Twitter in the context of the 2016 US presidential elections". In: *Government Information Quarterly* 34.4, pp. 613–626. DOI: 10.1016/j.giq.2017.11.001. URL: https://doi.org/10.1016/j.giq.2017.11.001.