RESEARCH PAPER

Analyzing State-Level Twitter Sentiment and Topics Preceding the U.S. 2020 Presidential Elections

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ABSTRACT
Intense political debate and public participation characterized the highly polarized and stressful 2020 US presidential election. During this period, social media platforms, especially Twitter, played a crucial role in influencing public opinion and spreading political narratives In this study, we analyze state-wise public sentiment and political discussions on Twitter leading up to the election. Using VADER for sentiment analysis, Dell-Research-Harvard's topic-politics model for topic classification, and Facebook BART for summarization, we provide a comprehensive overview of public emotions and discussion themes across 49 U.S. states. Our sentiment analysis showed a classification accuracy of 95.6%, while our topic classification was accurate to 92.7%. Outcomes from this study reveal that for 37 out of 49 U.S. states, the pre-election period yielded predominantly negative conversations, highlighting a general sense of public dissatisfaction during this critical time. The most prominent themes driving these discussions could be categorized into 4 groups, ranging from tragic events and economic struggles to optimism around progressive leadership and policy proposals. Our findings highlight variations in sentiment and dominant political topics at the state level, offering insights into the regional dynamics of public opinion. By summarizing political tweets, we distill the essence of state-wise discussions, helping to uncover key themes driving discussions in each state. This work underscores the importance of leveraging Natural Language Processing (NLP) techniques for understanding large-scale social media data in sociopolitical contexts. It contributes to the growing body of research on social media's influence in elections..

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INTRODUCTION

One of the most [1] divisive and tense presidential elections in American history was the one in 2020. Besides customary political conflicts, this election presented unprecedented challenges , such as the [2] COVID-19 pandemic, national social justice movements, and [3] extensive disinformation campaigns. These topics not only influenced public opinion, but also widened voter rifts. Subsequently, social media became a potent tool for civic engagement and political expression during these unrest-plagued times. More than [5] 233 million U.S. users were active on social media platforms, with [6] Twitter (Now X) playing an influential role in shaping public opinion, providing real-time discussion and sentiment sharing. Voter turnout among those under 30 years of age almost [5] doubled compared to the 2016 elections, owing to social media influence. Candidates, reporters, and citizens all used Twitter during the election cycle to disseminate political narratives, mobilize supporters, and vent their concerns. For instance, Donald Trump's campaign heavily utilized social media to excite his base and push divisive narratives, whereas Joe Biden's team effectively deployed digital platforms to target swing states and spread messages of unity.

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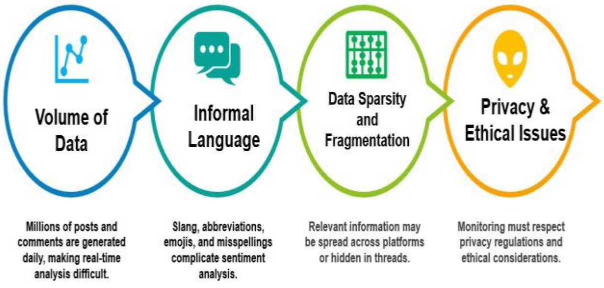

FIGURE 1. The challenges of analyzing social media data

Therefore, to assess political polarization, and analyze popular opinion, it is crucial to examine social media sentiments and discussions during significant events, such as the 2020 U.S. presidential election. Social media platforms like [4] Twitter act as a barometer for gauging public sentiment, offering researchers and politicians priceless information. However, there are many challenges in the task, as depited in Figure 1. The sheer amount of social media data poses serious difficulties for researchers looking to examine public opinion and discourse. With millions of tweets produced daily, manual analysis is impractical. Additionally, sentiment analysis is made more difficult by the intricacies of human language, [7] including slang, irony, and sarcasm. Moreover, relevant information is often spread across multiple platforms or buried within long threads and conversations. Lastly, social media data analysis must comply with privacy regulations (like GDPR) and ethical considerations. Models must be designed to respect user privacy and ensure data is used responsibly without violating confidentiality. Nevertheless using automated tools and [8] Natural Language Processing (NLP) techniques effectively can yield useful insights into patterns in public opinion.

Sentiment Analysis

Sentiment analyzers are computational tools that use NLP, machine learning, and lexicon-based approaches to determine the emotional tone or sentiment behind text data. These systems categorize text into positive, negative, neutral, or more complex emotional states (such as joy, rage, or grief) by examining the linguistic features like word choice, syntax, and semantic context. In literature, sentiment analyzers are often used on social media data to interpret public's emotional health.

compares the performance of BERT-based models (BERT-CNN, BERT-RNN, and BERT-BiLSTM) with

traditional NLP approaches to identify sentiments in tweets based on the context of the writer. They proposed a BERT model which identified sentiment in tweets based on the context of the writer, achieving an accuracy of 93% and F-measure of 95%.

analyzed public sentiment on Twitter during the COVID-19 pandemic,to understand public emotions and responses to the crisis. They utilized VADER, a lexicon- based sentiment analyzer to classify tweets into positive, negative, and neutral sentiments. The results indicated a predominance of negative sentiment during the early phases of the pandemic, largely driven by misinformation, rising case counts, and uncertainty. The study demonstrated the efficacy of VADER in identifying large-scale sentiment trends and provided insights into how sentiment evolved with major pandemic milestones.

Lastly, [11] also used VADER in their study to analyze public sentiment during the 2020 U.S elections. For tweets addressing important political figures like Joe Biden and Donald Trump, the authors calculate daily polarity scores. The study also classified tweets into entity-specific sentiments using keyword matching. The results showed that the two candidates' sentiments were clearly polarized, with notable sentiment spikes occurring at important campaign events. This method demonstrated how useful it is to combine VADER with keyword-driven entity recognition for in-depth political discourse analysis.

Topic Classifiers

Topic classification assigns predefined categories to a text based on its content. Using machine learning and NLP techniques, topic classification helps to automatically organize and interpret large volumes of textual data by identifying their themes or subjects. Often, its been used on social media to group posts or tweets according to their underlying topic. For example, [12] use Random Forest classifier and [13]Naive Bayes algorithm to rapidly classify the relevance of Twitter data during disasters and emergencies. They present a system that incorporates active, incremental, and online learning approaches to improve the classification of relevant tweets in such scenarios. The data is classified into categories such as: Relevant (tweets contributing to useful information for decision-making or situational awareness during emergencies), and Not Relevant (tweets with no actionable or significant information).

perform topic classification on Weibo, a popular Chinese social media platform, to analyze COVID-19- related posts in Wuhan city. Using BERT (Bidirectional Encoder Representations from Transformers) and LDA (Latent Dirichlet Allocation), they classified their posts into five main categories: family care, home life, epidemic report, response status, and appreciation and praying, depending on their topic. Thus by combining temporal and spatial information with their classification results, [14] demonstrate the feasibility of their method in practical cases.

analyze tweets collected over two years, focusing on trending topics for diverse content. Using transformer-based models like BERT, tweet embeddings are created to capture

their semantic context. Then, tweets are manually annotated into a taxonomy of 23 topics including social events, natural phenomena, public health, technology, cultural and global issues. Thus using transformer embeddings ensured a deeper understanding of tweet content, even with informal and short texts, while the taxonomy captured a broad range of trends, making the model applicable to diverse real-world scenarios.

Text Summarizers

Text summarization of Twitter data is essential to stay updated with trending discussion topics without information overload. It helps filter out noisy content and bring forth only noteworthy and relevant insights from the vast ocean of tweets generated every day. [16] conducts a study to understand societal perception of the mask-wearing protocol during the outbreak of corona virus. They first collected a COVID'19-related dataset from Twitter, performed sentiment analysis to assign polarity scores to each tweet in the dataset, and then clustered it into 15 high-level themes, each with 15 sub-topics. Next, to interpret the underlying themes in each topic, DistilBART, trained for extreme summarization, was used. A document of 20 tweets, closest to the centroid of each cluster, were given to DistilBART to produce summaries for each cluster. Output of their model proved DistilBART's capability to produce accurate and concise summaries.

[17] develops a Fake News Detection (FND) system to filter out misleading content from Twitter by summarizing texts before classifying them as fake or genuine. They perform a comparative analysis between Luhn's Model, LSA, and BERTSUM to investigate which of these models produce the most accurate and concise extractive summaries. Luhn's model assumes that word significance comes from normal distribution and removes k% words from both ends before reassigning significance scores to sentences and developing an extractive summary which contains the top m sentences. LSA creates a word count matrix for each document in the dataset, performs Singular Value Decomposition (SVD) to reduce the number of sentences, and finally, using cosine similarity, compares every sentence with each other to choose the dissimilar sentences for the summary. BERTSUM works by assigning [CLS] tokens to each sentence in a document and then selecting the k maximum scoring sentences for the summary. BERTSUM outperformed its competitors by producing the most precise summaries that were classified by DistilBERT with an accuracy of 85%. Nevertheless text summarization of tweets appears to be a developing research arena. Most papers opt for extractive summarization over abstractive summarization, where [18] variations of BERT come across as a popular choice

Existing Approaches in Social Media Monitoring

Several studies have leveraged advanced NLP models on Twitter data from before, after, and during the U.S. 2020 elections. [19] analyzed state-wise Twitter sentiment during the 2020 U.S. presidential election to identify its correlation

with the election results. Using Naive Bayes classifier for

sentiment analysis, the study found that the state-wise election outcomes coincided with the sentiment expressed on social media in most cases. Their sentiment classification was accurate to 94.58%. While [19] provided a state-wise analysis of sentiment from before, after, and during the elections, their research lacks exploration of the key themes driving these discussions thus failing to uncover the factors shaping public discourse.

Then, [20] analyze Twitter users and their tweets mentioning "QAnon" in the context of the 2020 US Presidential Elections, to understand their profiles and opinions using sentiment analysis and topic modeling. The study used VADER for sentiment analysis to evaluate the position of Twitter users towards Trump and Biden. Additionally, [20] created performed topic modeling using BERT on user profile descriptions to create word clouds. Their findings revealed that most tweets and users mentioning "QAnon" were Trump supporters. However, the study lacked a state- wise analysis and provided limited depth in the thematic exploration of topics. Thus a comprehensive study is needed to address these gaps in prior studies

Contribution

The purpose of this research is to examine state-wise political discourse and public opinion on Twitter during the U.S. 2020 presidential election. We present a comprehensive analysis of public sentiment and conversation topics in 49 U.S. states using advanced NLP models on a subset of publicly available Twitter dataset. Specifically our goals are two-fold: (1) use sentiment analysis to evaluate public opinion across states and (2) compile political tweets to identify the main themes influencing state-level discourse.

The dataset for this study is obtained from a publicly available tweets dataset from the 2020 U.S. pre- and post-election period. Using the Dell-Research-Harvard topic classifier, we first separated political tweets from non-political achieving an 92.7% accuracy. Then using VADER, we evaluated tweet sentiment with a classification accuracy of 95.6%, and finally, Facebook BART was used to generate concise summaries of political tweets, enabling us to distill complex discussions into actionable insights. This study makes the following contributions:

Conducts a state-wise sentiment analysis of all political tweets in the dataset, offering a granular understanding of public opinion across different regions.

Highlights regional variations in sentiment and dis- course, providing valuable insights into the sociopolit- ical landscape during the election period.

Provides comprehensive summaries of political discussions in several U.S. states thus helping understand the emotional and contextual drivers of public conversation during the elections.

Demonstrates the efficacy of combining sentiment analysis, topic classification, and summarization for analyz- ing large-scale social media data.

The remainder of the paper is divided into the following sections: Section 2 details about the proposed framework, Section 3 discusses its findings and results, and finally Section 4 is the Conclusion.

FRAMEWORK FOR STATE-WISE SENTIMENT AND TRENDS ANALYSIS

This study aims to analyze political discourse on Twitter, focusing on the sentiment and topical trends across different

U.S. states during their 2020 presidential elections. The proposed framework, as shown in Figure 2, provides a systematic pipeline for extracting valuable insights from the tweets datatset. The pipeline consists of the following steps: data preprocessing, topic classification, sentiment analysis, text summarization, and model evaluation, discussed further in the upcoming sections.

Dataset

For this study, we utilized a subset of a publicly available tweets dataset about the U.S. 2020 presidential elections. To ensure a focused and manageable analysis, we selected 1,000 tweets containing the hashtag #DonaldTrump and 1,000 tweets containing the hashtag #JoeBiden, all posted on October 16, 2020. These tweets provide a representative snapshot of public sentiment and political discourse across the United States during the critical weeks leading up to the 2020 U.S. presidential election.

Data Cleaning and Preprocessing

Adequate preprocessing is essential to ensure reliable and accurate textual data analysis. As covered in Figure 2, the preprocessing stage covered the following steps:

Translation of emojis: Emojis in tweets were translate to their corresponding meaning using python's ”emoji” library. This is important because emojis convey emo- tions that may otherwise be missed in textual data.

Removal of URLs and special characters: To elimi- nate noise and reduce the feature space, special charac- ters, and URLs were removed from the tweets, leaving behind a significantly refined dataset.

Text Normalization: Lastly, data was normalized by converting all uppercase letters to lower case to ensure uniformity and enhance the performance of LLMs in subsequent steps

Topic Classification

Processed tweets were then fed to NLP models to extract meaningful insights for the pre-election online environment. First, to separate political and non-political tweets, the Dell- Research-Harvard Topic Politics Classifier was used. This model was created especially to recognize and categorize tweets pertaining to political conversation. The classifier employs a supervised machine learning approach based on a refined Transformer-based model (similar to BERT-like architectures) to understand contextual relationships in short text formats, like tweets. In order to ensure strong performance in identifying political information across a variety of textual sources, the model was trained on a sizable, annotated political dataset that includes tweets, news headlines, and parliamentary speeches.

Sentiment Analysis

Pretrained sentiment analysis tool, VADER (Valence Aware Dictionary and sEntiment Reasoner) was used to assign polarity scores and positive/negative labels to each tweet. A polarity score of 0 and above (maximum:1) was marked as having positive sentiment, and a score below 0 (minimum:-1) was marked as negative. VADER is particularly well-suited for analyzing tweets because it is specifically designed to handle the informal and slang language of social media platforms. It excels at capturing the intricate details of sentiment in short, concise texts like tweets, and provides accurate sentiment scores without requiring large amounts of pre-labeled training data.

Summarization

Finally, to generate concise summaries of political tweets classified as positive and negative in each state, Facebook BART (Bidirectional and Auto-Regressive Transformers) was used. BART is a sequence-to-sequence Transformer model by Facebook AI, specifically designed for text summarization, and translation.

BART combines the strengths of bidirectional encoders (like BERT) and auto-regressive decoders (like GPT), enabling it to understand the context of input text while generating fluent, coherent summaries. The model was pre-trained on large-scale datasets such as CNN/DailyMail, which consist of news articles and their human-written summaries. In our study, the preprocessed political tweets were grouped by sentiment (positive or negative) for each state, and BART was applied to generate state-wise summaries. These summaries distilled the dominant themes and narratives driving public discussions, providing a clear and comprehensive overview of the key talking points within the politically charged online discourse

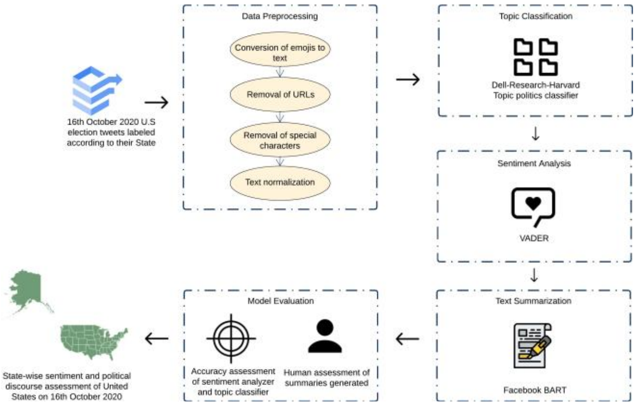

FIGURE 2. High-level view of the proposed framework

Model Evaluation

To assess the performance and reliability of the proposed framework, we employed a multi-faceted evaluation ap- proach across sentiment analysis, topic classification, and text summarization tasks. The dataset was manually anno- tated to serve as the ground truth for two key aspects:

Sentiment Class: Each tweet was labeled as either positive or negative based on its tone and content.
Topic Class: Tweets were categorized as political or non-political to validate the performance of the topic classification model.

The sentiment analysis results, obtained using the VADER model, and the topic classification outputs, generated through the Dell-Research-Harvard Topic Politics classifier, were evaluated for accuracy against these manually annotated labels. For the text summarization step, the summaries produced by Facebook BART were individually reviewed and validated to ensure that the generated summaries were reliable and accurate in capturing the context of the tweets.

RESULTS AND DISCUSSION

The dataset used in this case study consisted of 2000 tweets from 49 U.S. states (all states are included except South Dakota, for which no data was obtained from the U.S. elections 2020 dataset). 1000 tweets were taken from the #donaldtrump dataset, and 1000 were taken from #joebiden dataset.

Figure 3 presents a bar graph showing the distribution of tweets across different states. New York has the highest number of tweets, exceeding 350, followed by California and Florida with more than 300 and 200 tweets, respectively. Texas, Pennsylvania, and Illinois fall into the mid-tier range, contributing between 60 and 200 tweets. Finally, there is a long tail of low contributing states (¡ 20 tweets) which include Mississippi, Delaware, and Hawaii. The states with large metropolitan areas, such as New York, California, and Texas, dominate the tweet counts indicating the high digital engagement expected from urban centers. The distribution also aligns with state populations, as [21-23] larger states (California, Floride, Texas, New York) contribute more tweets, while States like Montana, Wyoming, and Vermont have very low tweet contributions owing to their [21] smaller populations and possibly less social media activity. Generally,Northeastern and Southern states seem to have

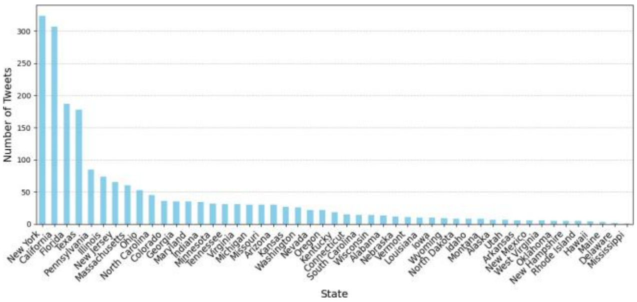

FIGURE 3. Tweet density across different U.S. states.

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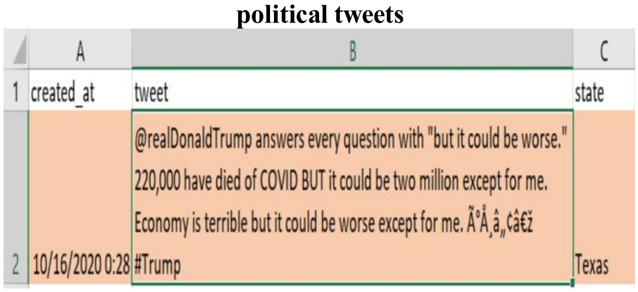
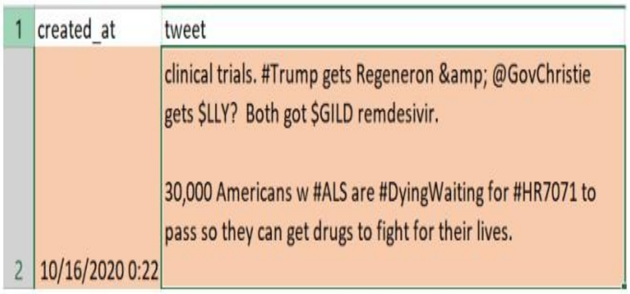
FIGURE 4. Percentage share of political and non-political tweets



	A	B	C
1	created_at	tweet	state
2	10/16/2020 0:28	@realDonaldTrump answers every question with "but it could be worse." 220,000 have died of COVID BUT it could be two million except for me. Economy is terrible but it could be worse except for me. Ã°Å¸â„¢â€ž #Trump	Texas

FIGURE 5. Tweet 1



1	created_at	tweet
2	10/16/2020 0:22	clinical trials. #Trump gets Regeneron & @GovChristie gets $LLY? Both got $GILD remdesivir. 30,000 Americans w #ALS are #DyingWaiting for #HR7071 to pass so they can get drugs to fight for their lives.

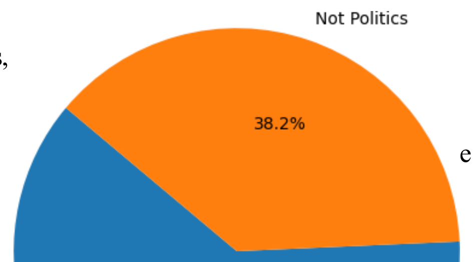
FIGURE 6. Tweet 2

FIGURE 7. Examples of tragedy and politics mixed tweets

relatively more engagement compared to Midwestern or rural states.

Topic Classifier Insights

As Figure 4 shows, topic classification of tweets revealed that XYZ% of the tweets were political, and the remaining non-political tweets were excluded from further analysis. Dell-research-harvard topic politics classifier was accurate to 92.7% compared against the manually annotated tweets. While majority tweets were solely related to politics, a significant portion also focused on local tragedies mixed with politics. Such tweets often discussed incidents of
murder, or theft tied to political figures, like Biden or Trump, framing these local tragedies in the context of their leadership.



For instance, Figure 5 references Donald Trump, and criticizes his responses handling of the COVID-19 pandemic and the economy. It mentions political themes such as leadership and economic performance, using the hashtag ”#Trump”. However,the tweet references the loss of 220,000 lives due to COVID-19, which is a direct element of tragedy. Similarly, Figure 6 references Donald Trump and Governor Chris Christie, both prominent political figures, and discusses their access to experimental treatments for COVID-19. It also refers to HR7071, a

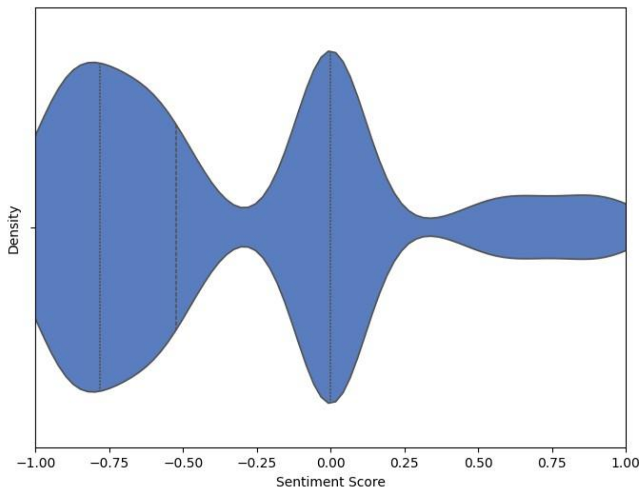


FIGURE 8. Polarity score distribution across the dataset. The width at various sentiment score (from -1 to 1) indicates how many tweets have that score.

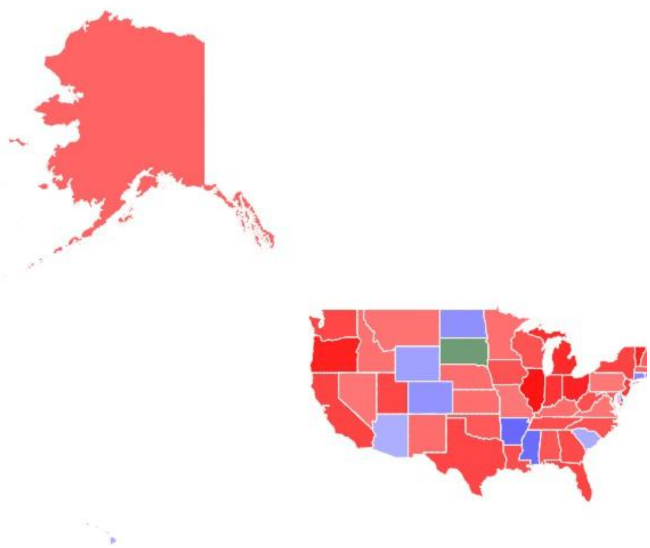


FIGURE 9. Polarity map of the United States during the 2020 Presidential Elections. The red indicates negative sentiment and blue indicates positive.

piece of legislation concerning access to experimental drugs for people with ALS (Amyotrophic Lateral Sclerosis), highlighting a political issue related to healthcare policy and access to treatments. This makes it fitting for the political topic, but the tweet also highlights the tragic situation of 30,000 Americans with ALS and their dire circumstances as they wait for the passage of a bill (HR7071) to access drugs that could help them fight for their lives. The use of hashtags like #DyingWaiting and #MND (Motor Neurone Disease, another term for ALS) emphasizes the tragic and life-threatening nature of the issue.

Sentiment Analysis Insights

VADER classified political tweets into two sentiments: positive and negative. Its accuracy against the manually annoated dataset was 96.7%. Figure 8 shows the distribution of sentiment scores across all tweets in the dataset revealing a significant polarization of opinions. The majority of sentiment scores cluster around negative values, with peaks near -0.75 and -0.25, suggesting that a substantial portion of the tweets express negative sentiment. The distribution also shows a secondary concentration near neutral sentiment (0.0), while only a smaller proportion of tweets display positive sentiment, with values extending towards 0.75 and beyond. This predominantly negative sentiment landscape in the dataset, is likely driven by the socio-political nature of discussions during the 2020 U.S. Presidential Election.

Figure 9 shows the state-wise sentiment map provinding a granular view of sentiment trends across the United States. States shaded in red represent regions with predominantly negative sentiment, while blue regions indicate relatively positive sentiment. The darker the red of a state is the more intense is the negative sentiment, the darker the blue is for a state the more intense the postive sentiment is. For South Dakota (green state) no data was available. Table 1 shows the average polarity score for each state. From Figure 9 and Table 1 it can be observed that states such as Illinois (- 0.844), Vermont (-0.719), and Oregon (-0.740) exhibited the most negative average sentiment, reflecting strong dissatis- faction or criticism in political discussions. Conversely, states like Mississippi (0.3818), Arkansas (0.4035), and Delaware (0.3182) showed the highest positive sentiment, indicating localized optimism or supportive discourse. The variation in sentiment scores reflects regional disparities in public opin- ion. For instance, while Mississippi (0.381) and Arkansas (0.404) demonstrate positive sentiment, neighboring states such as Alabama (-0.314) and Tennessee (-0.381) exhibit relatively negative sentiment, underscoring complex local factors influencing discourse.

State-wise Public Discourse Trends

The state-level summaries from Facebook BART for positive and negative political discussions were thoroughly analyzed to ensure for accuracy and reliability. The model yielded exceptional summaries with only a few incidents of

non- cohesive text. The analysis of state-level summaries revealed that the main themes of political discussions during the 2020
U.S. Presidential Elections can be broadly categorized into four groups

States with Economic and Policy-Driven Sentiments

In Ohio, Pennsylvania, Illinois, North Carolina, and Georgia the focus was heavily on economic policies, unemployment, and tax reforms. Negative sentiment often revolved around criticisms of the Trump administration's handling of stimulus packages and economic recovery during the pandemic. For instance, in Ohio, tweets expressed anger over corporate bailouts and skepticism toward Biden's economic proposals. In Pennsylvania, there was significant discourse on Trump's tax policies and Biden's healthcare promises, reflecting a polarized economic narrative.

States Highlighting Polarized Political Discourse

For Alabama, Florida, West Virginia, and Minnesota tweets were highly polarized, reflecting entrenched support or oppo- sition for Trump and Biden. In Alabama, strong negative sen- timent targeted Biden as an "anti-American puppet," while Trump was simultaneously criticized for misinformation. In Florida, tweets often described Trump's town hall perfor- mances as divisive, yet some highlighted Biden's perceived lack of transparency, revealing deep partisan divides.

State	Average Polarity Score	State	Average Polarity Score
Washington	-0.43	Idaho	-0.09
Montana	-0.08	Tennessee	-0.38
Minnesota	-0.11	Michigan	-0.65
Ohio	-0.73	Pennsylvania	-0.03
New York	-0.47	Vermont	-0.72
Indiana	-0.59	Maine	0.05
Arizona	0.00	California	-0.47
New Mexico	-0.13	Texas	-0.44
Alaska	-0.20	Louisiana	-0.38
Mississippi	0.38	Alabama	-0.31
Florida	-0.45	Georgia	-0.41
South Carolina	0.01	North Carolina	-0.33
Virginia	-0.07	Maryland	-0.29
Delaware	0.32	New Jersey	-0.54
Connecticut	0.23	Rhode Island	0.19
Massachusetts	-0.22	Oregon	-0.74
Hawaii	0.01	Utah	-0.44
Wyoming	0.08	Nevada	-0.07
Colorado	0.16	Nebraska	-0.12
Kansas	-0.12	Oklahoma	-0.28
Iowa	-0.34	Missouri	-0.06
Wisconsin	-0.33	Illinois	-0.84
Kentucky	-0.13	Arkansas	0.40
North Dakota	0.18	West Virginia	-0.36
New Hamp-	-0.24		

TABLE 1. Average Polarity Scores by State

1) States Focused on Tragic Events and Public Health Concerns

States like Arizona, California, Michigan, Texas, New York, Oregon, New Jersey, Florida, and Wisconsin exhibited numerous tweets centered on local tragedies and public health crises, such as COVID-19 fatalities and healthcare inequities. For example, in Arizona, discussions about the Biden crime bills and access to experimental treatments reflected both personal tragedies and policy critiques. Similarly, in California, tweets lamented the Trump administration's rejection of disaster assistance for wildfires, framing it as a political failure tied to public suffering. These discussions, while labeled as political, often stemmed from deeply personal narratives of loss and frustration, highlighting the intersection of individual experiences and governance

States with Positive Sentiment on Progressive Leadership

Delaware, Rhode Island, Massachusetts, Connecticut, and Colorado demonstrated a relatively positive sentiment toward Biden's campaign, focusing on themes like social justice, healthcare reforms, and climate policies. For instance, in Colorado, tweets praised Biden's plans for
decriminalizing marijuana and racial equity, contrasting sharply with negative sentiments about Trump's handling of racial justice.

CONCLUSION

This study examined the sentiment of each state and the main topics of political discourse on Twitter during the 2020 U.S. Presidential election using advanced Natural Language Processing (NLP) techniques. We successfully captured the dynamics of public opinion across 49 U.S. states by using dell-research-harvard topic classifier to separate non-political tweets form the political ones, VADER for sentiment analysis, and Facebook BART for text summarization. The findings showed that, in 37 states, pre-election sentiment was overwhelmingly negative and fueled by themes of political conflict, social unrest, and economic hardship. The study emphasized NLP techniques can be used afor turning massive amounts of unstructured social media data into insightful knowledge.

Although the results provide a thorough understanding of Twitter-based conversations during the election season, several limitations must be acknowledged. First off, relying solely on data from Twitter can introduce selection bias because it might not accurately reflect the views of people who do not regularly use the platform. Secondly, the dataset used for this study was based solely on English language, excluding multilingual viewpoints that could have enhanced the analysis. Moreover, the dataset was limited, which could impact the generalizability of the findings, particularly for less populous states. Finally, the generated text summaries were evaluated qualitatively rather than through quantitative metrics, limiting the speed and measurability of the analysis. Future research can overcome these constraints by combining information from several platforms like Facebook, and Reddit, and produce a more diverse picture of popular opinion. The analysis can be scaled by increasing the tweet volume and including multilingual tweets as well. Moreover, with a rising preference of visual content, future avenues of this research can incoportate multimedia data such as images, and videos for an even deeper understanding. Finally, future research can also incorporate quantitative metrics to evaluate text summarization, making the process faster and more measurable

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