STAT4073 Data Mining (1002)

Sentiment Analysis on the 2020 American Presidential Election

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This report was compile on December 16, 2024

Abstract

The 2020 U.S. presidential election provides a compelling case study to investigate the role of public sentiment in shaping voter behavior and election outcomes. This study aims to explore the dynamics of voter sentiment and its influence on electoral campaigns by leveraging sentiment analysis, machine learning, and predictive modeling. Utilizing a comprehensive dataset of tweets, the research applies Transformer-based models (XLNet) and traditional natural language processing methods (TextBlob) to classify sentiments and analyze their trends over time. Key findings reveal a stark contrast in sentiment polarity between the two major candidates, with Biden exhibiting a more balanced sentiment distribution compared to Trump's highly polarized sentiment trends. The research further demonstrates the superiority of advanced Transformer-based models in capturing nuanced public opinions over traditional methods. These insights highlight the critical role of social media in political discourse and offer actionable recommendations for improving campaign strategies. The study concludes with a discussion of limitations, such as irony and subtle text detection and imbalanced datasets, and outlines directions for future research, including real-time sentiment monitoring and multimodal analysis.

Keywords: *sentiment analysis, machine learning, Transformer-based models, U.S. election, political orientation*

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1. Background and Objectives

1.1. Significance of Social Media in Political Campaigns

Social media platforms like Twitter and Facebook have revolutionized political campaigns, allowing candidates to directly engage with voters at an unprecedented scale. However, the emotionally charged nature of social media interactions often drives polarization and amplifies certain narratives. This dual role makes it critical to study how social media influences public sentiment and election outcomes.

1.2. Objectives

The study addresses the following objectives:

- Analyze the relationship between social media sentiment and election outcomes.
- Evaluate changes in candidate image over time.
- Identify key voter concerns and trending issues during the 2020 U.S. election.
- Build predictive models to forecast election outcomes based on sentiment data.

2. Our Workflow

The Figure 1 below illustrates our workflow.

3. Data Preprocessing

3.1. Data Collection

The dataset comprises tweets containing hashtags such as #DonaldTrump and #JoeBiden, collected during the U.S. presidential election period. These datasets capture public sentiment, user interactions, and engagement metrics, providing a comprehensive view of election-related discussions on social media. Each dataset contains 21 attributes, including tweet text, likes, retweet counts, and user geographical information.

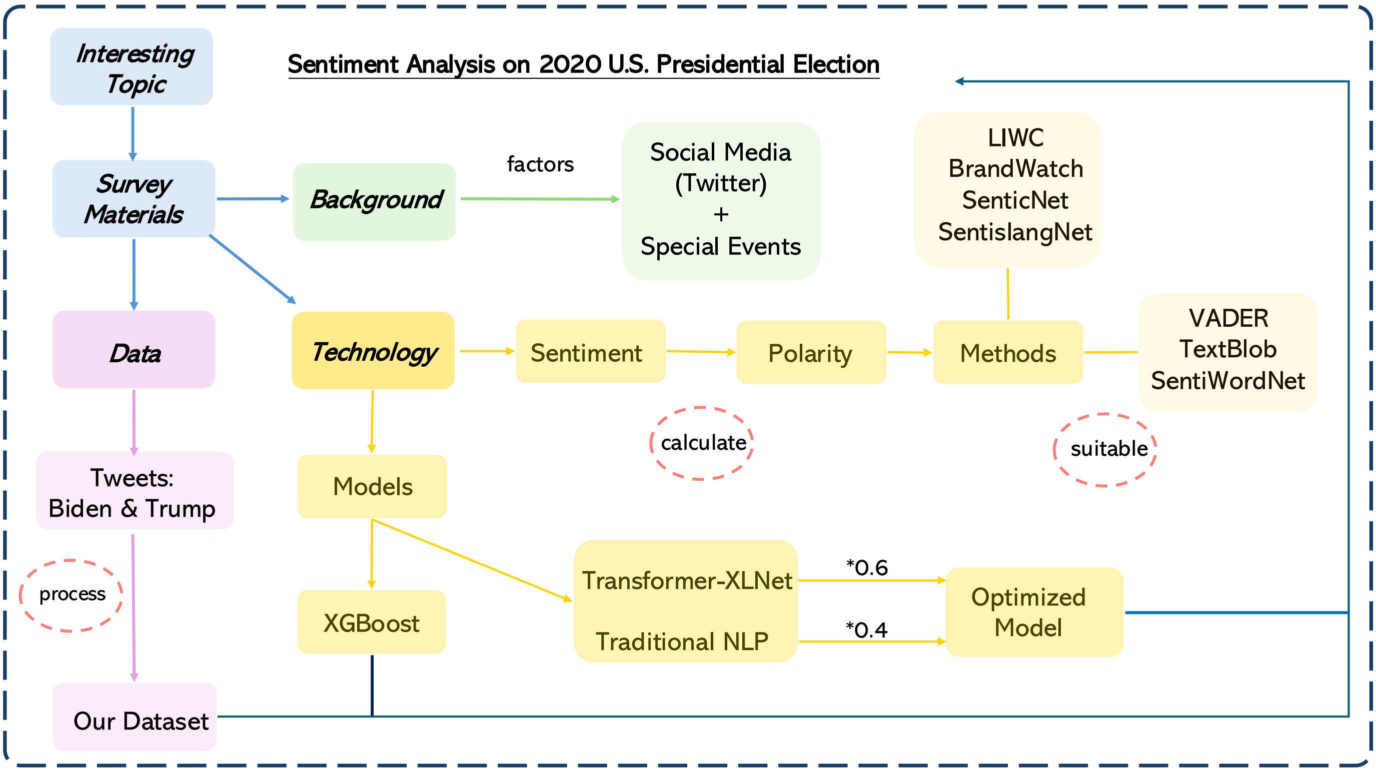


Figure 1. Overview of the workflow.

Two datasets were utilized:

- **Trump Dataset:** Contains 970,919 tweets.
- **Biden Dataset:** Contains 776,886 tweets.

3.2. Data Cleaning

To ensure data consistency and accuracy, the following preprocessing steps were conducted to clean the datasets and prepare them for analysis:

1. **Missing Data Handling:**
    - Non-null counts were inspected for all attributes. Key attributes such as `tweet_id`, `created_at`, `tweet`, and `user_id` were fully populated and retained.
    - Geographical attributes (`lat`, `long`, `city`, etc.) showed significant missing values, as illustrated in Figure 2. Attributes with over 60% missing values were removed unless deemed essential. For example, `user_location` was flagged for further inspection due to its potential importance in geographical analysis.
2. **Date Parsing:** The `created_at` field was converted into a standardized datetime format, enabling seamless temporal analyses such as trends over time and date-based filtering.
3. **Text Cleaning:**
    - URLs, special characters, emojis, and numbers were removed to focus on the semantic content of tweets.
    - All tweets were converted to lowercase for consistency in analysis.
    - Common stopwords and redundant spaces were eliminated to reduce noise and highlight significant textual patterns.
4. **Deduplication:** Duplicate tweets were identified and removed to prevent over-representation of certain tweets. Additionally, irrelevant records, such as tweets with fewer than three words, were filtered out.
5. **Geographical Data Cleaning:**
    - Raw country names in `user_location` were standardized by mapping variations (e.g., “United States,” “USA,” “US”) to a common format, as demonstrated in Figure 3.
    - Rows with inconsistent or invalid geographical data were reviewed and corrected or excluded.

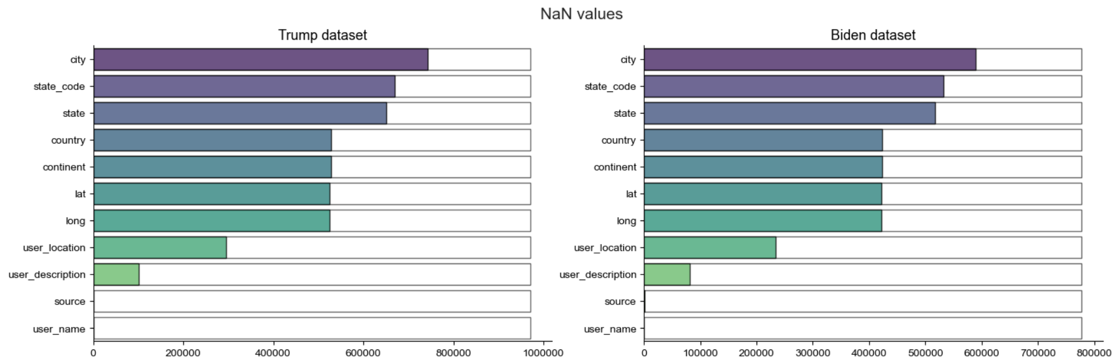
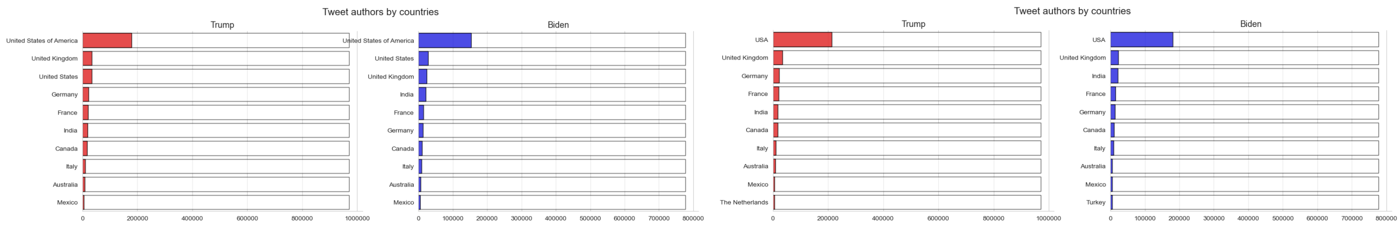


Figure 2. Visualization of missing values for the Trump and Biden datasets. Geographical attributes like `city`, `state`, and `lat` contain significant gaps.



(a) Geographical distribution (raw country names).

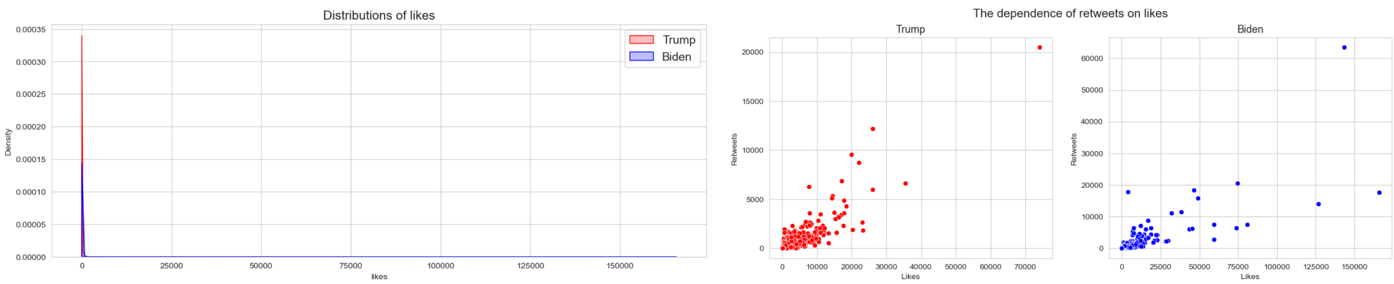
(b) Geographical distribution (cleaned country names).

Figure 3. Comparison of geographical distribution of tweet authors before and after cleaning country names. The cleaned data reveals more accurate insights into country-level tweet distributions.

3.3. Exploratory Data Analysis (EDA)

3.3.1. Tweet Engagement Analysis

The analysis of tweet engagement metrics, such as likes and retweets, provided insights into the popularity and reach of tweets in the Trump and Biden datasets.



(a) Distribution of likes.

(b) Likes vs. retweets.

Figure 4. Engagement metrics in Trump and Biden datasets. The left panel shows the distribution of likes, where Biden-related tweets received more likes on average. The right panel visualizes the positive correlation between likes and retweets for both candidates.

Temporal trends in tweet counts are depicted in Figure 5, revealing significant spikes during pivotal moments in the election campaign, such as debates and election day. These trends underline the temporal engagement patterns and the influence of key events on social media activity.

3.3.2. Correlation Analysis

Figure 6 illustrates the dependency of total likes on tweet counts, demonstrating that tweets with higher counts tend to accumulate more likes.

3.3.3. User Analysis

Top users by tweet counts and likes are shown in Figures 7a and 7b, respectively. These figures highlight the influence of specific users in driving engagement.

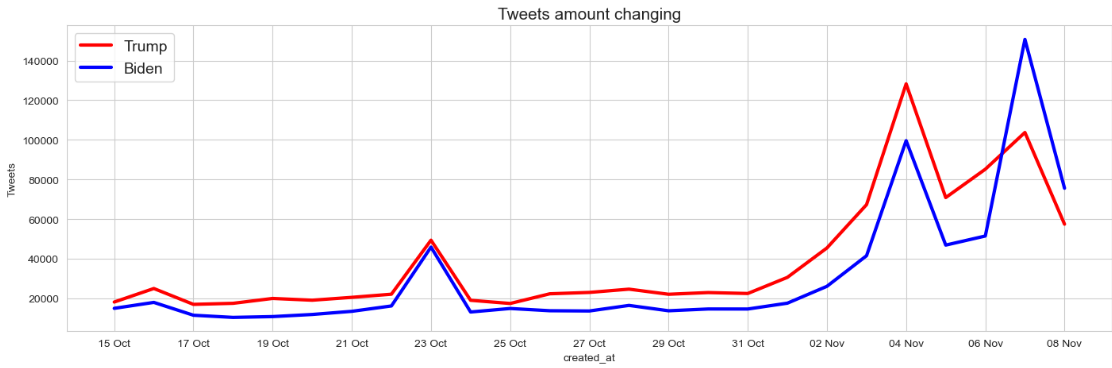
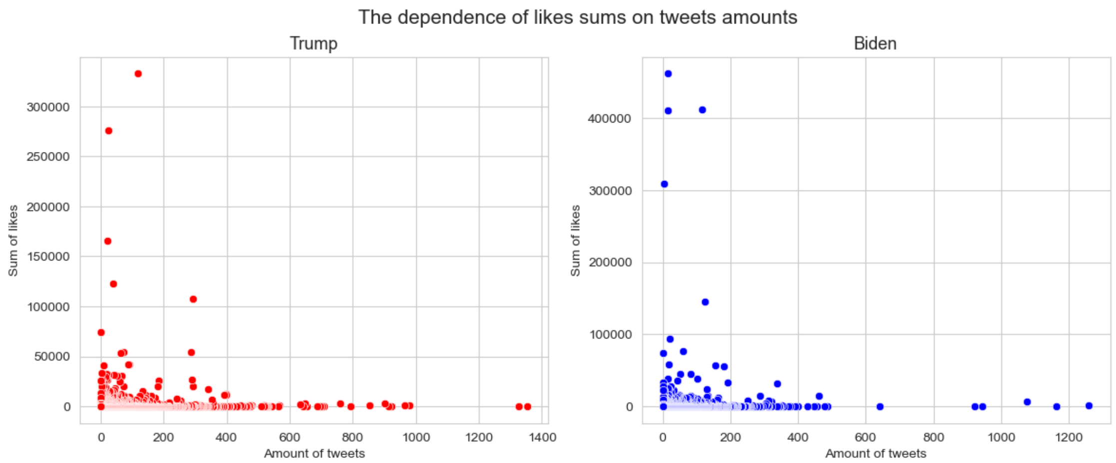
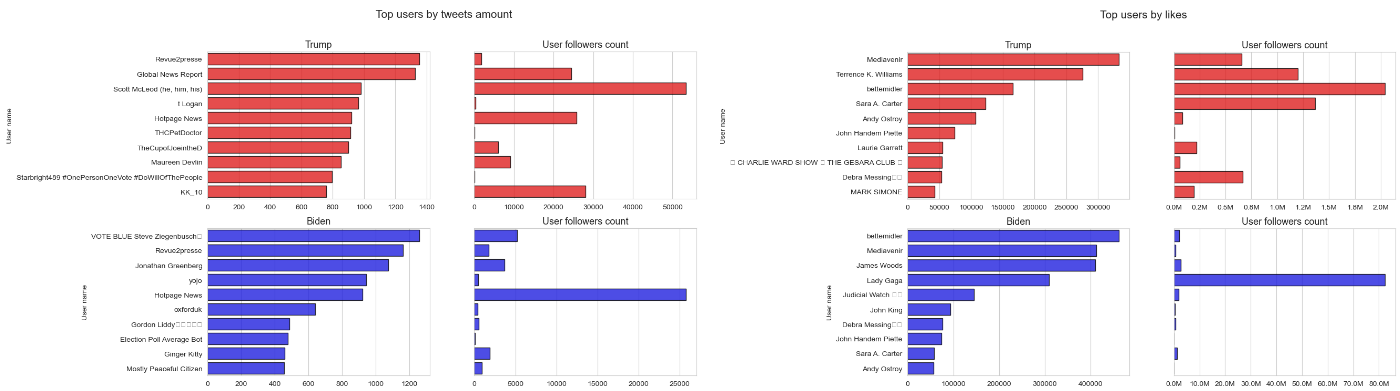


Figure 5. Temporal trends in tweet counts for Trump and Biden datasets.





(a) Top users by likes for Trump and Biden datasets.

(b) Distribution of word counts in tweets.

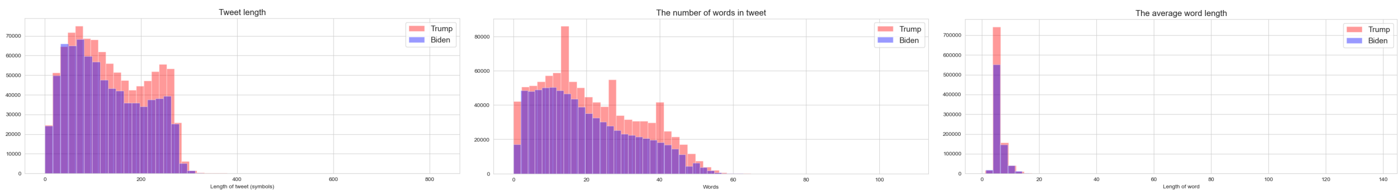
Figure 7. Comparison of user engagement and tweet word counts for Trump and Biden datasets.

Figure 6. Top users by tweet counts for Trump and Biden datasets.

3.3.4. Tweet Length and Word Frequency

The analysis of tweet length and word frequency provides insight into the communication styles in the Trump and Biden datasets. These features highlight differences in the structure and content of their tweets.

As shown in Figure 8, the distribution of tweet lengths (Figure 8a) indicates that Trump's tweets are generally shorter, while Biden's tweets tend to have a wider range of lengths. The word count distribution (Figure 8b) reflects that Biden's tweets contain slightly more words on average, indicating more detailed messaging. The average word length (Figure 8c) suggests a similarity in lexical complexity, with no significant difference between the two datasets.

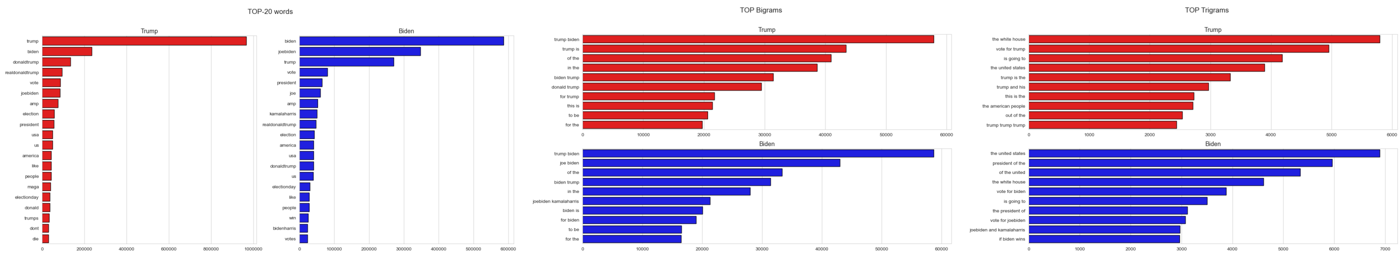


(a) Tweet length distribution. **(b)** Word count distribution. **(c)** Average word length.

Figure 8. Comparison of tweet length, word count, and average word length in Trump and Biden datasets.

3.3.5. N-gram Analysis

To uncover patterns in tweet composition, an N-gram analysis was conducted to identify the most frequent unigrams, bigrams, and trigrams within the Trump and Biden datasets.



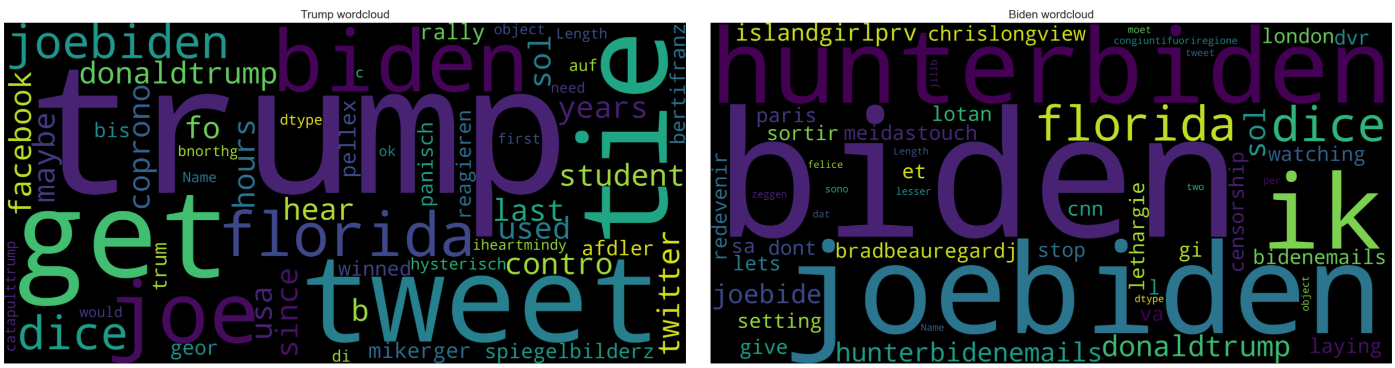
(a) Top 20 unigrams. **(b)** Top 20 bigrams. **(c)** Top 20 trigrams.

Figure 9. Comparison of the most frequent unigrams, bigrams, and trigrams in Trump and Biden datasets.

Figure 9 illustrates the most common unigrams, bigrams, and trigrams in the datasets. Unigrams like "Trump" and "Biden" dominate both datasets, reflecting their central focus. Bigrams such as "Trump Biden" and "vote for" frequently appear, indicating campaign-related messaging. The trigrams, including "the white house" and "vote for Trump," emphasize key themes and repetitive phrases used for reinforcing campaign strategies. This analysis highlights the distinct focus and recurring topics in the communication styles of the two datasets.

3.3.6. Word Cloud Analysis

Word clouds were generated to visually represent the most frequently used words in the Trump and Biden datasets. These visualizations provide insights into the key terms dominating the respective datasets, reflecting their campaign narratives and public focus.



(a) Trump word cloud. **(b)** Biden word cloud.

Figure 10. Word clouds highlighting dominant terms in Trump and Biden datasets.

The Trump word cloud (Figure 10a) prominently features terms like "Trump," "Biden," and "Florida," highlighting the candidate's focus on opponents and specific states. Similarly, the Biden word cloud (Figure 10b) emphasizes terms such as "Biden," "Trump," and "vote," aligning with themes of mobilizing voters and addressing campaign issues. These word clouds underline the contrasting strategies and topics of interest between the two campaigns.

4. Sentiment Analysis

4.1. Subjectivity Analysis

Subjectivity analysis distinguishes between factual (objective) and opinion-based (subjective) content. Subjective text often includes adjectives, adverbs, or specific verbs that convey emotions or biases.

Message	**Subjectivity Indicators**
@realDonaldTrump: So nice—great Americans outside Trump Tower right now. Thank you!	nice, great

Table 1. Example of Subjectivity Indicators in Social Media Posts.

Using the **TextBlob** library, subjectivity scores are assigned on a scale of 0 (objective) to 1 (subjective). Subjective text is further analyzed for polarity, which measures sentiment intensity and direction.

Measure	**Definition**	**Range**
Subjectivity	Classifies text as fact (objective) or opinion (subjective). Higher scores indicate stronger opinions.	[0, 1]
Polarity	Measures sentiment direction (positive, negative, neutral). Positive values indicate positive sentiment.	[-1, 1]

Table 2. Subjectivity and Polarity Metrics.

Subjectivity analysis provides insights into public discourse, identifying opinion trends and distinguishing emotional content from factual reporting. This method is essential for media monitoring and political analysis.

4.2. Polarity Analysis

The following table compares the three sentiment analysis tools: VADER, SentiWordNet, and TextBlob. These tools differ in their definitions, strengths, applications, and weaknesses.

Tool	**Definition, Strengths, Applications, and Weaknesses**
VADER	*Definition:* Lexicon-based tool designed for social media sentiment analysis. *Strengths:* Handles social media language effectively, including informal text and emojis. *Applications:* Social media sentiment analysis. *Weaknesses:* Limited in detecting sarcasm and contextually complex language.
SentiWordNet	*Definition:* Semantic-based sentiment scoring tool relying on word meanings. *Strengths:* Provides fine-grained sentiment scores suitable for nuanced analysis. *Applications:* Sentiment analysis requiring deeper semantic understanding. *Weaknesses:* Context-dependent performance, struggles with informal or ambiguous text.
TextBlob	*Definition:* Python-based library for sentiment analysis and text processing. *Strengths:* Simple and efficient, supports multiple languages, quick for basic tasks. *Applications:* Quick sentiment analysis for general purposes. *Weaknesses:* Lacks depth in semantic understanding, struggles with complex or informal text.

Table 3. Comparison of Sentiment Analysis Tools: Definitions, Strengths, Applications, and Weaknesses.

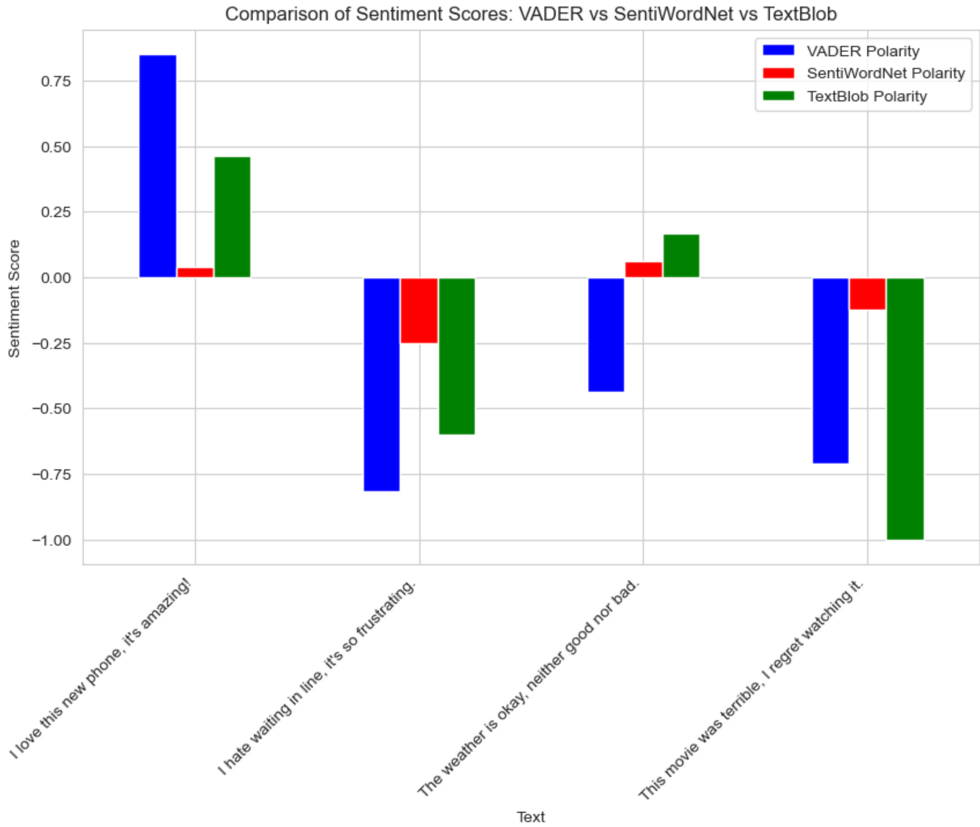
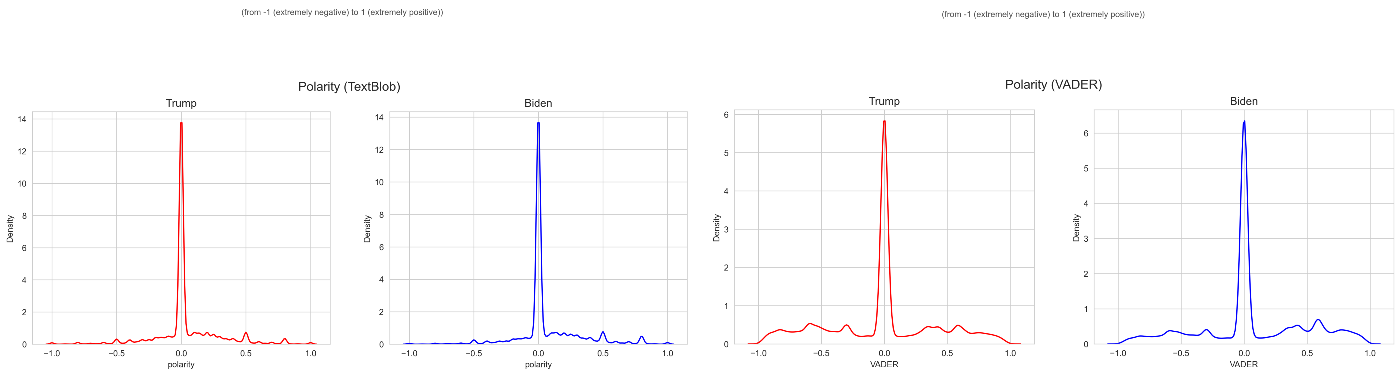


Figure 11. Comparison of Sentiment Scores: VADER vs. SentiWordNet vs. TextBlob.

4.3. Results and Analysis

Daily sentiment polarity trends for Trump and Biden were analyzed using three tools: VADER, SentiWordNet, and TextBlob. Figure 12 highlights the polarity distributions derived from TextBlob and VADER, showing the differences in sentiment evaluation for both candidates.



(a) Polarity Analysis with TextBlob.

(b) Polarity Analysis with VADER.

Figure 12. Comparison of Polarity Analysis Tools for Trump and Biden.

4.4. Sentiment Analysis Visualizations

To explore sentiment polarity in more detail, the following visualizations depict trends for Trump, Biden, and sentiment polarity by country.

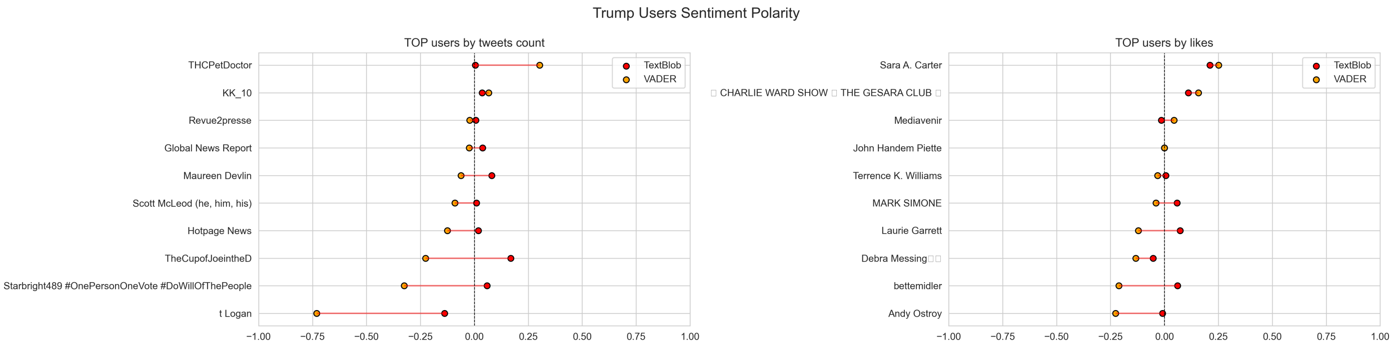


Figure 13. Trump Sentiment Polarity Trends.

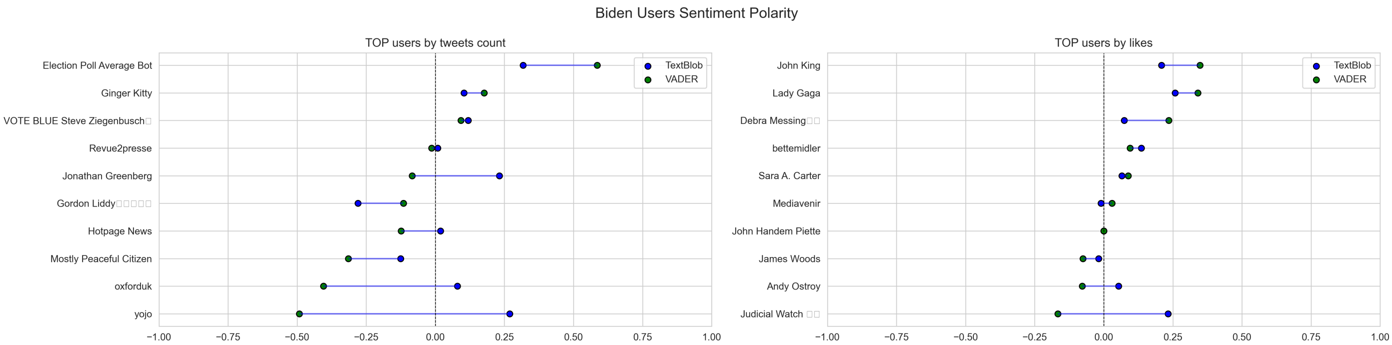


Figure 14. Biden Sentiment Polarity Trends.

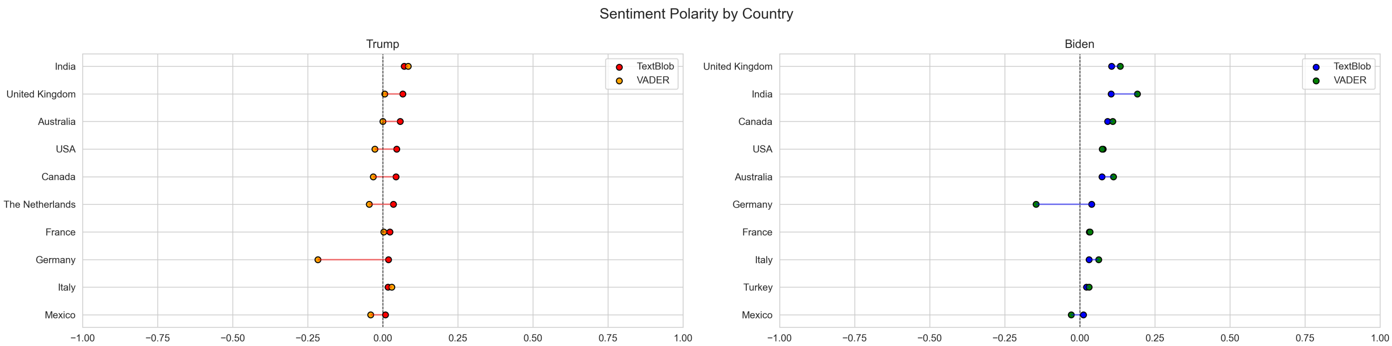


Figure 15. Sentiment Polarity by Country.

4.4.1. Polarity Distribution for Trump and Biden

The polarity distributions for Trump and Biden, segmented into positive and negative sentiments, provide a closer look at the nature of public reactions. Table 4 presents examples of tweets reflecting both positive and negative sentiments.

4.4.2. Key Observations

- **Trump's Sentiment:** His tweets elicited a wider range of polarizing reactions, with extreme sentiments being more prevalent in both positive and negative categories.
- **Biden's Sentiment:** Biden's tweets leaned towards balanced sentiment trends, showing a slightly higher proportion of positive expressions compared to negative ones.
- **Geographical Insights:** As seen in Figure 15, sentiment polarity varied significantly by region, reflecting localized voter concerns and cultural differences.

4.5. Sentiment Trends Across Regions

Geographical sentiment heatmaps were created to analyze regional trends in public opinion for Donald Trump and Joe Biden, using average sentiment polarity scores derived from Twitter data. These heatmaps were compared with the actual 2020 U.S. election results.

Candidate	Positive Tweets (Examples)	Negative Tweets (Examples)
Trump	*Amazing crowd outside Trump Tower.* *Trump's best speech yet.*	*Trump is the worst president ever.* *Debate was a disaster.*
Biden	*Biden shines in the debate.* *Great leadership from Biden.*	*Biden seemed unprepared for this.* *Biden is a weak candidate.*

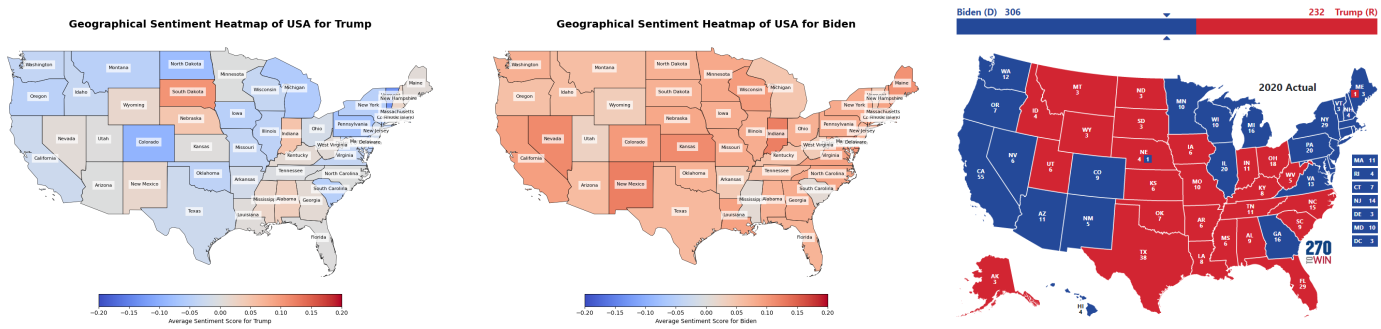
Table 4. Examples of Positive and Negative Tweets for Trump and Biden.

Interpretation of Heatmaps:

- **Red Shades:** Positive sentiment (higher polarity scores).
- **Blue Shades:** Negative sentiment (lower polarity scores).
- **Gray:** Neutral sentiment or insufficient data.

Key Observations:

1. **Trump:** Positive sentiment dominated in states like South Dakota and Alabama, while Vermont and Colorado showed negative trends.
2. **Biden:** Higher positive sentiment was observed in states like Delaware and Nevada, with negative sentiment in regions such as Mississippi.
3. **Alignment:** Sentiment trends closely matched election outcomes in key swing states like Michigan and Pennsylvania.



(a) Trump Sentiment.

(b) Biden Sentiment.

(c) Election Results.

Figure 16. Regional Sentiment Heatmaps for Trump and Biden Compared to 2020 Election Results.

Insights:

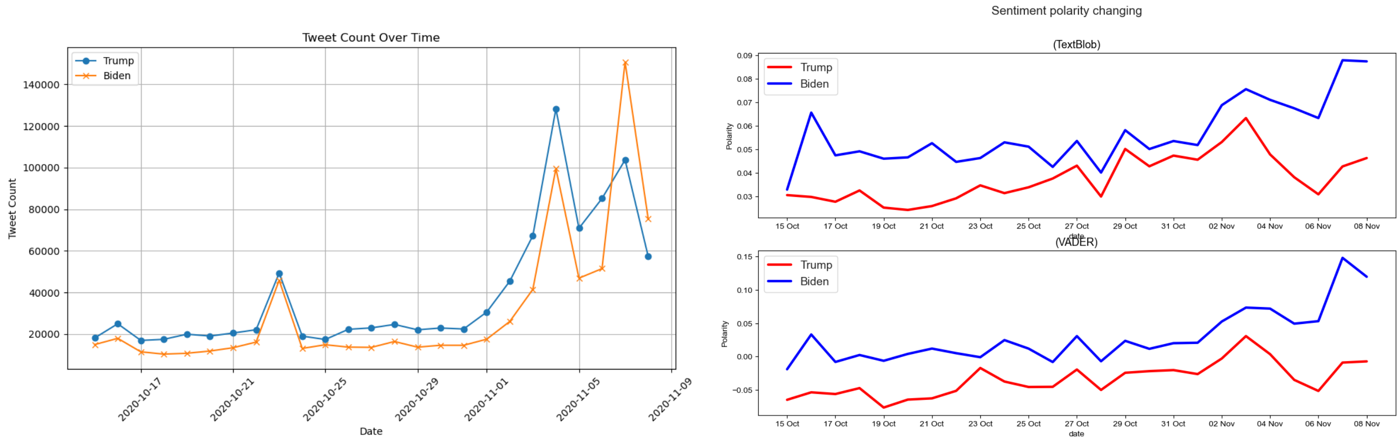
- Sentiment polarity provides insights into regional public opinion, correlating with electoral outcomes in several states.
- Regional sentiment is influenced by demographics and local issues.
- Further analysis could explore connections between sentiment trends and key events or voter demographics.

4.6. Time Series Emotion Tracking

To track the evolution of public sentiment for Donald Trump and Joe Biden over time, we conducted a time-series analysis of sentiment polarity scores from October 15 to November 8, 2020. Using tools like TextBlob and VADER, polarity trends for both positive and negative sentiments were extracted. This analysis aims to observe how sentiment patterns change dynamically during key events in the election campaign period.

As shown in Figure 17a, the number of tweets mentioning each candidate increased significantly during critical moments such as debates, Election Day, and the announcement of results. This rise in activity indicates heightened public engagement during these events.

Figure 17b illustrates the sentiment polarity trends for Trump and Biden over time. Biden's positive sentiment steadily increases as Election Day approaches, peaking during the announcement of results, whereas Trump's polarity reflects a mixed sentiment.



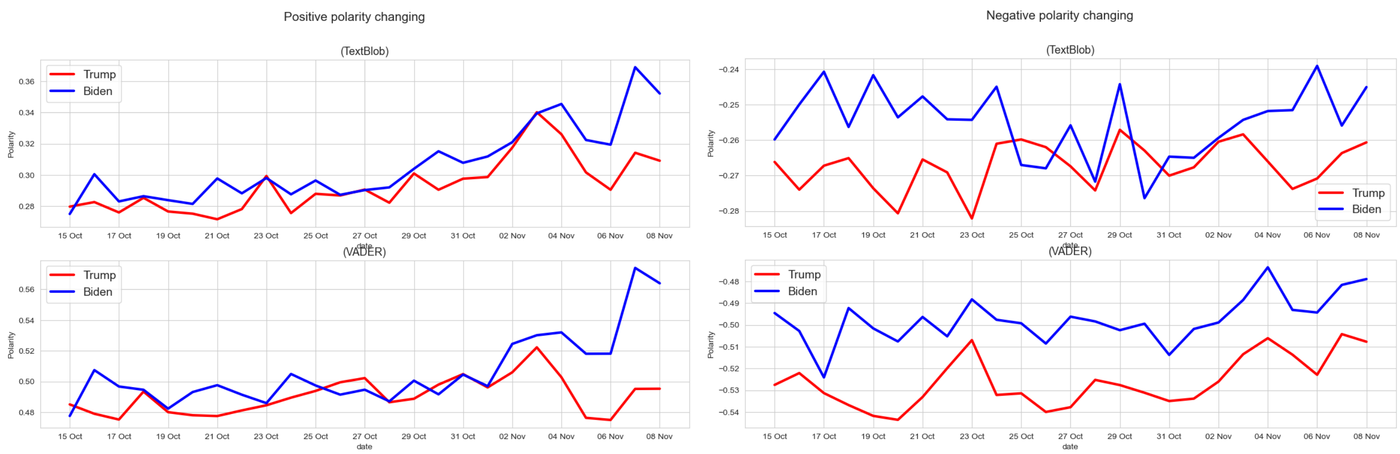
(a) Tweet Count Over Time for Trump and Biden. **(b)** Sentiment Polarity Changing Over Time (TextBlob and VADER).

Figure 17. Time Series Analysis: Tweet Counts and Sentiment Polarity Trends for Trump and Biden.

4.7. The Sentiment Impact of Major Events

The time series analysis of sentiment polarity scores reveals how major political events shaped public opinion. Key events from October 15 to November 8, 2020, included:

- **October 26:** The confirmation of Amy Coney Barrett to the Supreme Court. This event elicited polarized reactions, boosting positive sentiments among Trump supporters while raising concerns among Biden supporters.
- **November 3:** Election Day. Sentiments fluctuated sharply as the voting process unfolded, reflecting the uncertainty and tension surrounding the event.
- **November 7:** The media's declaration of Joe Biden as the winner. Biden's positive sentiment peaked sharply, while Trump faced a rise in negative sentiment due to his response.
- **November 8:** Trump's refusal to concede the election. His statements on voter fraud led to further polarization of sentiments, as reflected in a significant drop in his positive polarity scores.



(a) Positive Polarity Changing. **(b)** Negative Polarity Changing.

Figure 18. Polarity Changes Over Time for Trump and Biden.

Figures 18a and 18b show how positive and negative sentiment polarity scores evolved during the critical election period. Biden's positive polarity surged after November 7, reflecting public approval of his victory, while Trump's negative polarity increased, indicating dissatisfaction with his refusal to concede.

5. XLNet Model

5.1. Introduction

- XLNet is a novel autoregressive pre-training method used for language comprehension tasks.
- It combines the advantages of autoregressive (AR) language models and autoencoder (AE) models, enabling bidirectional context learning.
- XLNet leverages permutation-based training objectives, enhancing its ability to handle a wide range of NLP tasks.

5.2. Theory

5.2.1. Bidirectional Contextual Learning

Permutation Language Modeling forms the theoretical backbone of XLNet. It maximizes the expected log-likelihood over all possible permutations of a sequence:

$$\max_{\theta} \mathbb{E}_{z \sim Z_T} \left[\sum_{t=1}^{T} \log p_\theta(x_{z_t} | x_{z_{<t}}) \right]$$

Here:

- $p_\theta(x_{z_t} | x_{z_{<t}})$: Conditional probability distribution at position z_t, given the context up to $z_{<t}$.
- Z_T: Set of all possible permutations for a sequence of length T.

This formulation enables XLNet to effectively capture bidirectional context.

5.2.2. Two-Stream Self-Attention

XLNet employs a two-stream self-attention mechanism to distinguish content from context:

- **Content Stream:** Handles both the content and context:

$$h(m)_{z_t} \leftarrow \text{Attention}(Q = h(m-1)_{z_t}, KV = h(m-1)_{z_{\leq t}}; \theta)$$

- **Query Stream:** Focuses solely on context:

$$g(m)_{z_t} \leftarrow \text{Attention}(Q = g(m-1)_{z_t}, KV = h(m-1)_{z_{<t}}; \theta)$$

5.2.3. Target-Aware Prediction Distribution

XLNet employs a target-aware prediction mechanism, utilizing the query stream representation from the final layer to compute the conditional probability of a target token x based on the prior context $x_{z_{<t}}$. The prediction formula is given as:

$$p_\theta(X_{z_t} = x | x_{z_{<t}}) = \frac{\exp\left(e(x)^T g_{z_t}^{(M)}\right)}{\sum_{x'} \exp\left(e(x')^T g_{z_t}^{(M)}\right)}$$

Key Components:

- $g_{z_t}^{(M)}$: The query stream representation at the final layer, encoding contextual information specific to position z_t.
- $e(x)$: The embedding of token x, representing its semantic and syntactic properties.

Key Concept: This formulation allows XLNet to compute the likelihood of a target token x while effectively leveraging bidirectional context. By capturing dependencies through the query stream, XLNet ensures robust contextual understanding without introducing data leakage, a challenge common in conventional autoregressive models.

Objective: The goal of this target-aware prediction mechanism is to maximize the likelihood of the correct token x, enhancing XLNet's performance in downstream tasks such as sentiment analysis, text classification, and machine translation. The embeddings $e(x)$ and the query stream representation $g_{z_t}^{(M)}$ are designed to align the model's predictions with semantic relationships, leading to improved accuracy and generalization.

5.3. Fine-Tuning with TextAttack

The XLNet model was fine-tuned using TextAttack, a comprehensive NLP framework providing:

- **Adversarial Attacks:** Enhances model robustness.
- **Data Augmentation:** Increases dataset diversity for better generalization.
- **Ease of Training:** Simplifies model optimization via intuitive APIs.

Fine-tuning details:

- Trained for 5 epochs with a batch size of 32.
- Used a learning rate of 2×10^{-5} and sequence length of 512.
- Achieved 0.95352 accuracy on the evaluation set after 2 epochs.

5.4. Modeling and Results

5.4.1. Sentiment Analysis Models

Two sentiment analysis models were used:

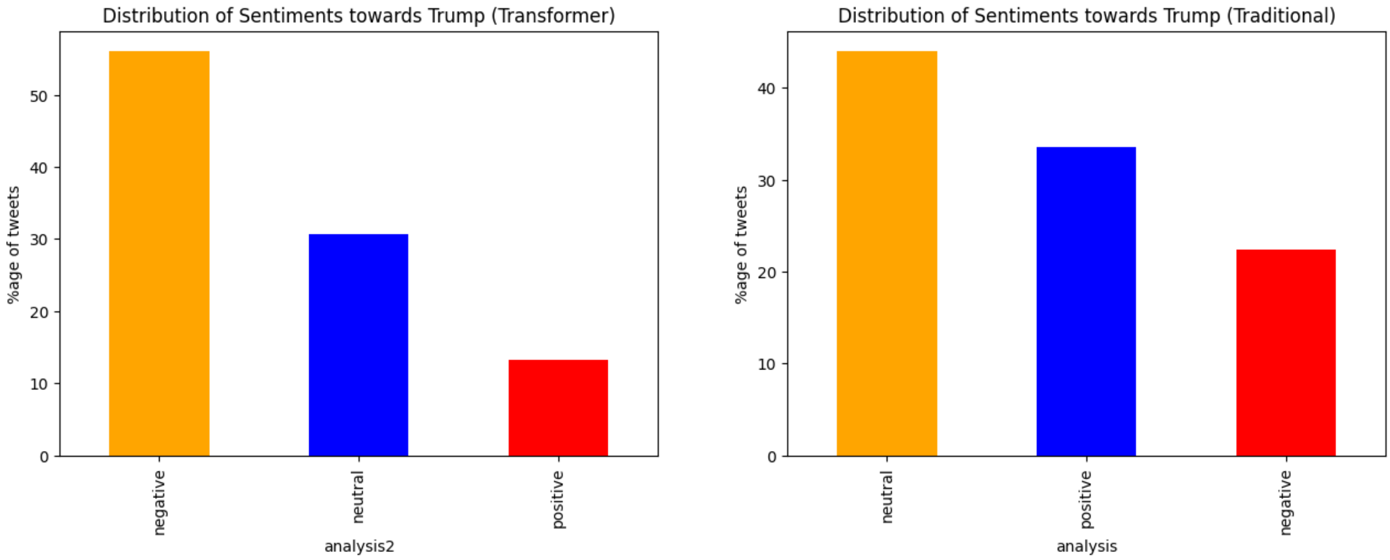
- **Transformer-XLNet Model:** A Transformer-based model fine-tuned with TextAttack, using the following thresholds:
$$\text{Neutral: Score} \leq 0.585, \quad \text{Positive/Negative: Score} > 0.585$$
- **Traditional NLP Model (TextBlob):** A baseline model for sentiment classification comparison.

5.4.2. Transformer and Traditional Results

Trump Sentiment Analysis The sentiment distribution for Trump was analyzed using Transformer-XLNet and TextBlob models. The results are summarized in Table 5:

Table 5. Sentiment Distribution for Trump

Model	Negative (%)	Neutral (%)	Positive (%)
Transformer-XLNet	56.01	30.67	13.32
TextBlob	22.43	43.99	33.58



(a) Trump: Transformer-based.

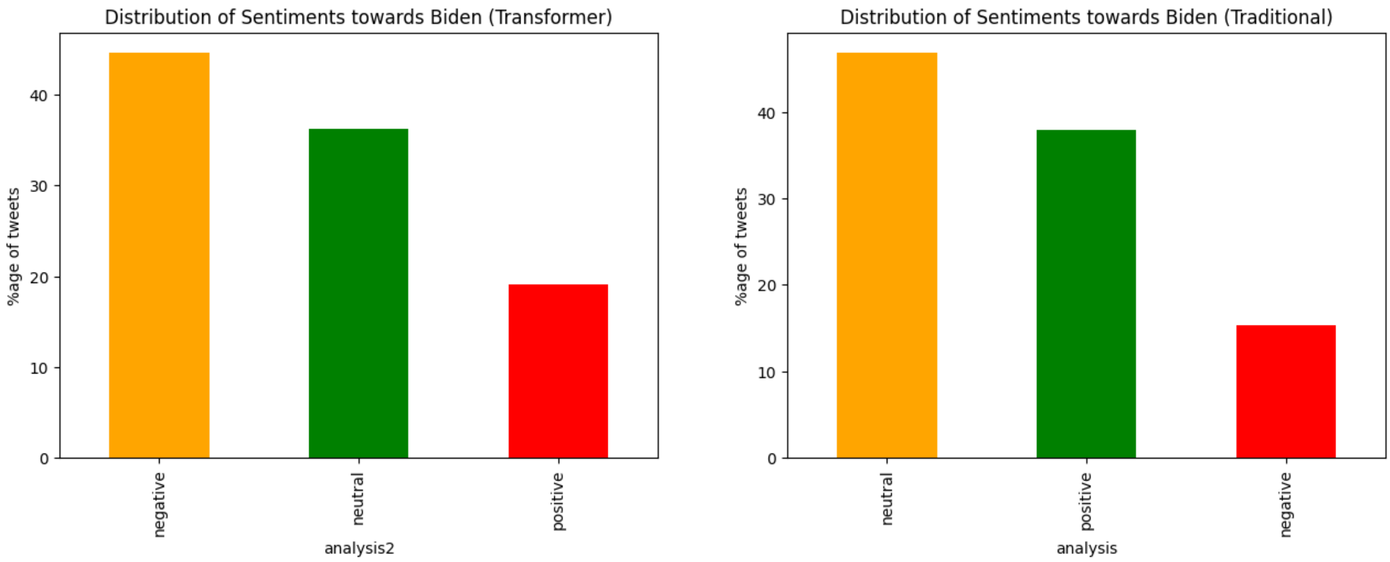
(b) Trump: Traditional-based.

Figure 19. Sentiment distribution comparison for Trump.

Biden Sentiment Analysis The sentiment distribution for Biden was analyzed using Transformer-XLNet and TextBlob models. The results are summarized in Table 6:

Table 6. Sentiment Distribution for Biden

Model	Negative (%)	Neutral (%)	Positive (%)
Transformer-XLNet	44.64	36.23	19.13
TextBlob	15.28	46.83	37.89



(a) Biden: Transformer-based.

(b) Biden: Traditional-based.

Figure 20. Sentiment distribution comparison for Biden.

5.4.3. XLNET Model (Final Score)

The **Final Score** combines results from the two models with the following formula:

$$\text{Final\_Score} = 0.4 \times \text{Transformer\_Score} + 0.6 \times \text{TextBlob\_Score}$$

Sentiment types were converted to numeric values: Positive $= +1$, Neutral $= 0$, Negative $= -1$.

5.4.4. Final Score Results

Table 7 summarizes the aggregated final scores for Trump and Biden:

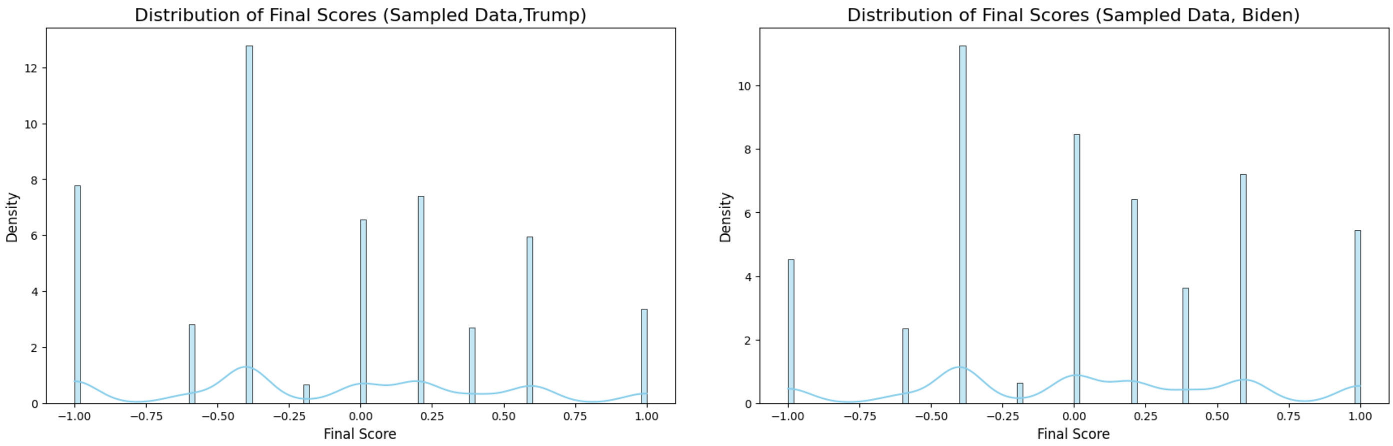
Table 7. Final Scores for Trump and Biden

Candidate	Transformer Final Score	TextBlob Final Score
Trump	-10035.199	-5889.543
Biden	2881.599	4125.891

Final Scores Result

$$\text{Trump\_Final\_Score} < \text{Biden\_Final\_Score}$$

This analysis indicates that sentiment towards Biden was overall more favorable compared to Trump during the examined period.



(a) Trump: Final Score Distribution.

(b) Biden: Final Score Distribution.

Figure 21. Final Score Distributions for Trump and Biden.

6. XGBoost Model for Election Prediction

XGBoost, an advanced machine learning algorithm based on Gradient Boosted Decision Trees (GBDT), has been employed to predict election outcomes by leveraging its capability to handle large datasets, optimize performance, and improve generalization through regularization and second-order derivative calculations.

6.1. Model Overview

- **Objective Function:** For a given sample i, with true label y_i and predicted value $\hat{y}_i$, the objective function is:

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k),$$

where l is the loss function, $\Omega(f_k)$ represents the regularization term, K is the number of trees, and f_k is the prediction function of the k-th tree.

6.2. Regularization Term

To prevent overfitting, XGBoost includes a regularization term:

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2,$$

where γ is the minimum loss reduction required for a split, λ is the L2 regularization parameter, T is the number of leaf nodes, and w_j is the weight of the j-th leaf.

6.3. Loss Function

For binary classification tasks, XGBoost uses the logloss function:

$$l(y_i, \hat{y}_i) = -y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i).$$

6.4. Tree Construction

The model iteratively builds trees to minimize the following objective:

$$\min_{f_k} \sum_{i=1}^{n} l(y_i, \hat{y}_{i,k}) + \Omega(f_k),$$

where $\hat{y}_{i,k} = \hat{y}_{i,k-1} + f_k(x_i)$ represents the prediction after adding the k-th tree.

6.5. Approximation Algorithm

XGBoost efficiently handles sparse data by leveraging weighted quantile sketches, accelerating tree learning while maintaining accuracy.

6.6. Feature Engineering

The dataset (`trump_cleaned`, limited to USA data) contains features critical for analysis:

- **user_join_date:** Indicates the date when a user joins the platform.
- **tweet_length:** The number of characters per tweet.
- **hashtag_count:** The number of hashtags (words beginning with #) in each tweet.
- **mention_count:** The number of mentions (words beginning with @) in each tweet.
- **influence_score:** A user's influence score, which is calculated as:

$$\text{influence\_score} = \log(1 + \text{number of followers}) \times \text{days on platform},$$

  where *days on platform* is the difference in days between the user's join date and the maximum join date in the dataset.
- **engagement_rate:** Engagement rate per tweet, calculated as:

$$\text{engagement\_rate} = \frac{\text{likes} + \text{retweets}}{\text{number of followers} + 1}.$$

- **is_swing_state:** A binary variable indicating whether the user's state is a swing state.
- **tweet_hour:** Extracts the hour portion of the time when the tweet was created.
- **tweet_day_of_week:** Retrieves the day of the week when the tweet was created.

6.7. Results

We construct a two-category classification model (XGBoost) based on the relevant characteristics of the selected tweets above, and predict the political orientation of the state from which the tweets come, in order to identify whether each state is more Democratic or Republican politically.

We assigned a political orientation label to each state as follows:

- **0:** Republican states, such as Texas.
- **1:** Democratic states, such as California.

The reason for choosing Texas and California here is that the sample size of these two states is large, which is conducive to the training and testing of the model and improves the generalization ability of the model.

Mean Cross-Validation Accuracy: 0.7553

Class	Precision	Recall	F1-Score	Support
0	0.89	0.55	0.68	16491
1	0.80	0.96	0.88	31145
Accuracy		0.82		47636
Macro Avg	0.85	0.76	0.78	47636
Weighted Avg	0.83	0.82	0.81	47636

Table 8. Classification Report for Trump Data

6.8. Feature Importance

The importance of features in predicting election outcomes is visualized below:

Key Features:

- `influence_score` and `user_followers_count` emerged as the most impactful predictors.
- Features such as `tweet_hour` and `tweet_length` also contributed significantly.

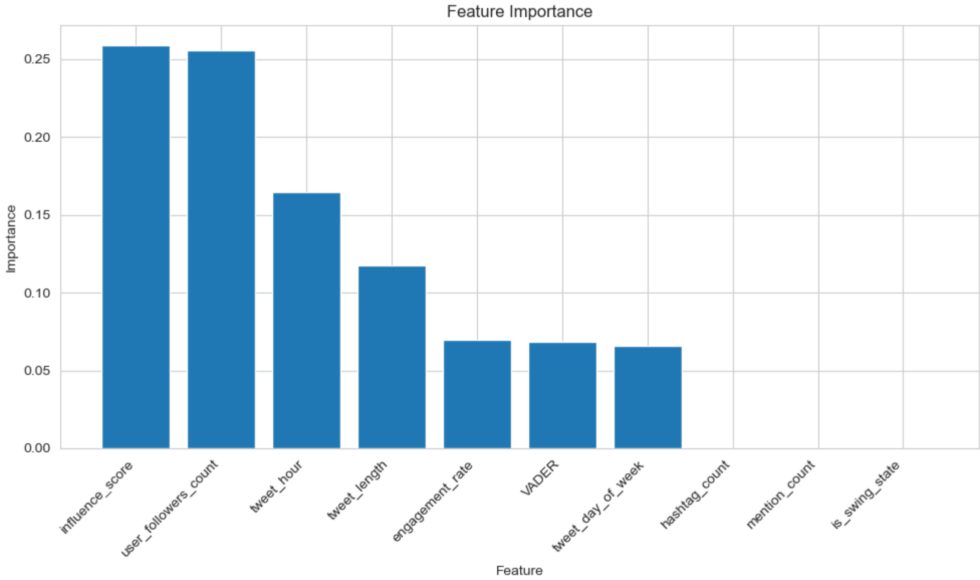


Figure 22. Feature Importance Ranking in XGBoost Model

7. Conclusion

7.1. Summary of Findings

This study employed Transformer-XLNet and traditional TextBlob models to analyze election-related sentiment. Key findings include:

- Transformer-XLNet outperformed TextBlob in sentiment detection, capturing nuanced public opinions.
- Weighted sentiment scoring revealed higher positive sentiment for Biden compared to Trump.
- Temporal and contextual visualizations provided insights into sentiment trends during the election.

7.2. Contributions

This research contributes to election sentiment analysis by:

- Developing a hybrid framework combining traditional and Transformer-based models.
- Proposing a weighted scoring mechanism to quantify overall sentiment.
- Demonstrating the value of NLP tools in supplementing traditional political analysis methods.

7.3. Limitations

Key challenges encountered include:

- Difficulty in detecting sarcasm and highly nuanced text.
- Imbalanced sentiment data affecting model precision.
- Limited contextual understanding in traditional models like TextBlob.
- Platform-specific biases inherent to social media data.

7.4. Future Directions

Future work can address these limitations by:

- Enhancing pre-trained Transformer models for political discourse.
- Collecting balanced datasets to reduce class bias.
- Integrating multimodal analysis with text, image, and video content.
- Developing real-time tools for election sentiment monitoring.
- Conducting cross-platform analyses for comprehensive sentiment insights.

Conclusion: This research highlights the utility of advanced NLP techniques in understanding election sentiment. By addressing limitations and exploring future directions, this approach can significantly enhance political analysis.

References

1. D. O. Oyewola, L. A. Oladimeji, S. O. Julius, L. B. Kachalla, and E. G. Dada, "Optimizing sentiment analysis of Nigerian 2023 presidential election using two-stage residual long short-term memory," *Heliyon*, vol. 9, p. e14836, 2023. [Online]. Available: https://doi.org/10.1016/j.heliyon.2023.e14836
2. M. Alfonso and D. B. Rarasati, "Sentiment analysis of 2024 presidential candidates election using SVM algorithm," *Jurnal Informatika dan Sains*, vol. 6, no. 2, 2023. [Online]. Available: https://www.ssrn.com/abstract=4259283
3. S. B. Clark, M. Anderson, D. Lee, M. Zhu, H. R. Boyajieff, B. Goldschmidt, S. Harn, and A. Karami, "Sentiment analysis of tweets in the 2020 U.S. presidential election," *Preprint*, 2021. [Online]. Available: https://www.researchgate.net/publication/352296067
4. D. Shah, Y. Li, and A. Hadaegh, "Twitter-based sentiment analysis of each presidential candidate using long short-term memory," *International Journal of Computer Science and Security*, vol. 15, no. 3, pp. 87–97, 2021. [Online]. Available: https://www.cscjournals.org/journals/IJCSS/description.php
5. W. Budiharto and M. Meiliana, "Prediction and analysis of Indonesia presidential election from Twitter using sentiment analysis," *Journal of Big Data*, vol. 5, p. 51, 2018. [Online]. Available: https://doi.org/10.1186/s40537-018-0164-1
6. T. Hamling and A. Agrawal, "Sentiment analysis of tweets to gain insights into the 2016 US election," *CUSJ*, 2016. [Online]. Available: https://www.researchgate.net/publication/321228303
7. U. Yaqub, S. A. Chun, V. Atluri, and J. Vaidya, "Sentiment-based analysis of tweets during the US presidential elections," in *Proc. ACM Digital Government Research*, Staten Island, NY, 2017. [Online]. Available: https://doi.org/10.1145/3085228.3085285
8. R. Pandarachalil, S. Sendhilkumar, and G. S. Mahalakshmi, "Twitter sentiment analysis for large-scale data: An unsupervised approach," *Cognitive Computation*, vol. 7, pp. 254–262, 2014. [Online]. Available: https://doi.org/10.1007/s12559-014-9310-z