Sentiment Analysis of 2016 Presidential Tweets: To What Extent Did Tweets from Hillary Clinton and Donald Trump Reflect or Amplify Partisan Divides in Sentiment During the 2016 Campaign?

1.0 Introduction

During the 2016 election, social media giants like Twitter (now known as X) and Facebook (now known as Meta) faced widespread criticism because of their inability to crack down on misleading information about the outcome of the election shared by former US President Donald Trump about the outcome of the election, (Conger, K., Isaac, M., & Wakabayashi, D). In this paper we will look at the extent to which tweets from Hillary Clinton and Donald Trump reflect or amplify partisan divides in sentiment during the 2016 US presidential election campaign. To do this we will perform a sentiment analysis by comparing tweets from both candidates to the poll data at the corresponding dates and times to see if the sentiment of tweets are reflected in voter/audience poll data. The sentiment analysis will be performed using TextBlob, which assigns a polarity score to each tweet, ranging from -1 (highly negative) to 1 (highly positive). The sentiment analysis graph will then be overlaid with a graph of poll data of sentiment towards the candidates at different points leading up to the exit poll data and the actual vote count. In this initial study, we found that people tend to react more to negative sentiment tweets, thus fueling Donald Trump's anti-democratic and anti-Clinton propaganda. He demonstrated a large range of sentiments across his tweets from the start of 2016 till October 2016, compared to Hillary Clinton's smaller ranged mostly positive tweets. It goes on to show that alongwith the party principles, the presidential candidate's personality plays a decisive role in gaining public support. Donald Trump's negative sentiment tweets resonated more with the masses as they gained maximum engagement. Our research on how social media engagement affected the outcome of the 2016 US presidential election led us to the following research questions: "How did the sentiment range of Tweets by Donald Trump and Hillary Clinton during the 2016 presidential campaign differ? Did the sentiment of Tweets by the two presidential candidates have any direct correlation or impact with the result of the 2016 election or events during the campaign?"

1.1 Background and Related Work

In the lead-up to the 2016 U.S. presidential election, concerns emerged regarding the quality, credibility, and broader influence of political information circulating on social media—particularly on Twitter. Although only a small fraction of users were responsible for the bulk of questionable or partisan content, this raised awareness of the importance of maintaining a well-informed electorate. After all, a healthy democracy relies on voters having access to accurate and substantive political information.

Within this environment, Twitter and other social media platforms played a critical role in shaping political discourse and public opinion. Research shows that candidates' messaging, along with user-generated political content, can influence online engagement patterns and may correlate with electoral outcomes (Tumasjan, Sprenger, Sandner, & Welpe, 2010; Bode & Dalrymple, 2016). Understanding not only the volume and direction of this discourse, but also its emotional tenor, is thus crucial.

Against this backdrop, sentiment analysis has emerged as a valuable tool for interpreting the tone, polarization, and strategic framing employed by political actors on social media (Conover et al., 2011; Barberá, Jost, Nagler, Tucker, & Bonneau, 2015). By examining existing literature on sentiment patterns, we identify key points where our approach diverges from previous work. This enables us to contribute new insights into how emotional cues in candidate communications may resonate with or diverge from evolving voter sentiment trends.

In another paper, Sentiment Analysis of Before and After Elections: Twitter Data of U.S. Election 2020, the authors used a Naive Bayes Algorithm to analyze the 2020 elections and found that the result of the election polls generally aligned with the sentiment expressed on social media, (Chaudhry., Javed., Kulsoom, Mehmood, Khan,, Shoaib, & Janjua). Unlike some other papers on here, they did access location data where possible (a little over 40% of tweets). They also performed pre- and post-election analysis and found that in many states, the result of the election influenced Twitter sentiments, even when they differed from the election outcomes. (For example, in Arizona and Wisconsin, positive sentiment increased for Biden and decreased for Trump). They wrote: "Sentiment analysis is defined as a process that automates the mining of attitudes, opinions, views, and emotions from text, speech, tweets, and database sources through Natural Language Processing (NLP)."

The paper most similar to ours was "Sentiment Analysis of Tweets for the 2016 US Presidential Election." This paper uses a binary approach to analyzing tweets to label them as either positive or negative for Hillary Clinton and Donald Trump, (Joyce & Deng.). Analysis of hashtags on Twitter recorded sentiment drops for Trump and Hillary upon the releases of the "locker room" conversation and the Clinton investigation's e-mails, respectively, (Joyce & Deng.). The authors found that their method of deploying automatic algorithms accurately correlated with polling data, (Joyce & Deng).. Unlike our paper, they do no further comparison to outside data to develop or delve deeper into the meaning of this sentiment analysis.

Some current trends in the sentiment analysis on twitter include real time analysis, emotion detection, multimodal analysis, and network analysis. Tools that provide instantaneous insights are gaining popularity due to an increasing focus on real-time sentiment analysis to gauge public opinion during live events, such as debates or elections. Beyond basic sentiment (positive, negative, neutral), researchers are exploring finer-grained emotion detection (e.g., anger, joy, sadness) to capture more nuanced public feelings. Integrating data from various sources (e.g., images, videos) along with text is becoming common, as sentiments are often expressed through multiple channels. Researchers are increasingly examining the social network structures of Twitter, looking at how information spreads and how sentiments influence each other within political discourse. A network analysis in our work has the potential to deepen the meaning of our work and broaden our understanding of how the sentiment affected voters.

Current challenges with sentiment analysis include sarcasm and irony, data noise, contextual understanding, and bias in data. Detecting sarcasm or ironic statements poses significant challenges, as traditional sentiment analysis models often misinterpret these nuances. The vast volume of data on Twitter includes a lot of noise (spam, irrelevant content), making it difficult to extract meaningful insights without sophisticated filtering techniques. Political sentiment can be heavily context-dependent. Understanding the political landscape, historical events, or specific issues is crucial for accurate analysis but can be difficult for models. Furthermore, Twitter user demographics can skew sentiment analysis results. The platform is not representative of the general population, leading to potential biases in findings.

1.2 Dataset

The dataset used for this study captures a wide range of metadata for each tweet, making it useful for sentiment analysis and deeper explorations of user interactions, retweet behavior, and geographical information.

Here's a summary of the columns and the type of data they contain:

1. **id**: A unique identifier for each tweet.
2. **handle**: The Twitter handle (username) of the account that posted the tweet.
3. **text**: The content of the tweet.
4. **is_retweet**: A boolean value indicating whether the tweet is a retweet (True or False).
5. **original_author**: If it is a retweet, this shows the original author of the tweet.
6. **time**: Timestamp indicating when the tweet was posted (in ISO 8601 format).
7. **in_reply_to_screen_name**: The screen name of the user to whom the tweet is replying (if applicable).
8. **in_reply_to_status_id**: The ID of the tweet being replied to (if applicable).
9. **in_reply_to_user_id**: The user ID being replied to (if applicable).
10. **is_quote_status**: Indicates if the tweet is quoting another tweet.
11. **place_type**, **place_country_code**, **place_country**, **place_contained_within**: Geographical metadata associated with the tweet (if available).
12. **place_attributes**, **place_bounding_box**: Additional geographical attributes and bounding box information for location-based tweets.
13. **source_url**: The URL identifying the platform or application used to post the tweet.
14. **truncated**: Boolean flag indicating if the tweet is truncated.
15. **entities**: JSON-like structure containing metadata such as hashtags, media, URLs, and user mentions embedded in the tweet.
16. **extended_entities**: More detailed entities information, including media content associated with the tweet

1.3 Initial Inferences

The dataset contains Twitter data starting from January 2016 for Trump and from April 2016 for Clinton. and continues until the end of September 2016. Trump's average sentiment trends slightly negative overall, while Clinton's is neutral; however, both tended to tweet more positive sentiments than negative, on average. Interestingly, Trump's tweets expressed more extreme sentiments on both ends; Trump was responsible for the most negatively analyzed tweet (in March 2016) and the most positively analyzed tweet (in May 2016).

One possible reading of the sentiment analysis is that Trump's originally positively-oriented tweets became slightly more negative as a result of the polls solidifying against him during the campaign. (See the FiveThirtyEight graph below.) Trump may have been showing the negativity he and/or his campaign team were feeling leading up to Election Day in 2016 with time running out to sway public opinion in his favor. For example, here is a typical negative Trump tweet from September 2016:

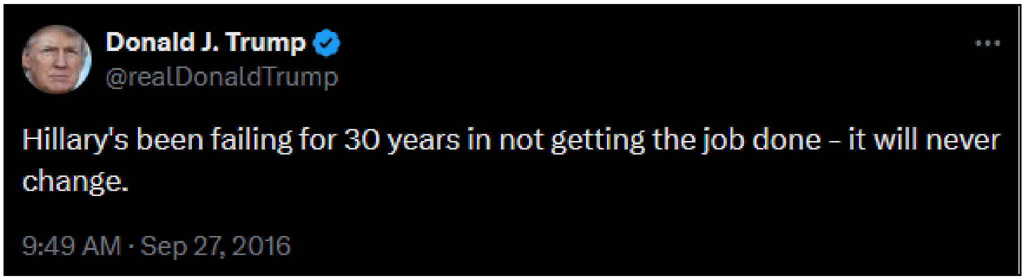

Fig. 1(a) A negative Donald Trump tweet from Sept 27, 2016.

2.0 Exploratory Data Analysis

Sentiment analysis was conducted on the text of each tweet using the **TextBlob library**, which applies a lexicon-based approach to determine the emotional tone of textual data. Here's how a lexicon-based approach works for sentiment analysis:

1. *Create a sentiment lexicon:* A manually created list of words labeled as positive or negative.
2. *Compare words in the text to the lexicon:* Assign each word in the text a positive or negative sentiment value.
3. *Calculate the overall sentiment:* Use a combining function, like sum or average, to calculate the overall sentiment of the text.
4. *Classify the text:* The text is classified as positive, negative, or neutral based on the overall sentiment score.

This approach is usually faster and simpler to implement than other methods, but it may not capture nuances as well. Each tweet's content was analyzed to compute a **sentiment polarity score**, a numerical value ranging from -1 to 1 that reflects the overall sentiment:

- **Negative sentiment**: Scores closer to -1 indicate a highly negative emotional tone.
- **Neutral sentiment**: Scores near 0 suggest the absence of strong emotional language or a balanced tone.
- **Positive sentiment**: Scores closer to 1 represent highly positive emotional expressions.

2.0.1 Steps in Calculating Sentiment Polarity

1. **Tokenization**:
   - Each tweet was split into individual words or tokens, enabling the model to evaluate sentiment at a granular level.
   - TextBlob's tokenizer handled standard text preprocessing, including case normalization and removal of special characters.
2. **Word Sentiment Scoring**:
   - TextBlob utilizes an internal lexicon that assigns predefined sentiment scores to words and phrases based on their emotional connotations (e.g., "great" has a positive score, while "terrible" has a negative score).

    - Words were evaluated within the context of the tweet to account for modifiers (e.g., "not great" results in a reduced positive score).
3. **Aggregation**:
    - The sentiment polarity score for the entire tweet was calculated as a weighted average of the scores of individual tokens, adjusted for factors like negation and punctuation emphasis.
    - For instance, tweets with repeated exclamation points ("!!!") were more strongly weighted in their sentiment evaluation.

2.0.2 Categorization of Emotional Tone

To categorize emotional tone, tweets were grouped based on their polarity scores into three sentiment types:

- **Negative**: Tweets with polarity scores ranging from -1.0 to -0.1.
- **Neutral**: Tweets with polarity scores between -0.1 and 0.1.
- **Positive**: Tweets with polarity scores between 0.1 and 1.0.

This categorization allowed for straightforward aggregation and comparison of sentiment trends between the candidates. Additionally, these categories were used to analyze engagement metrics, such as retweets, by sentiment type.

2.0.3 Example Tweets with Sentiment Polarity Scores

- **Negative:** *"Crooked Hillary Clinton is a disaster!"* (Polarity Score: -1.0)
- **Neutral:** *"Looking forward to the debate tonight."* (Polarity Score: 0.0)
- **Positive:** *"Together, we can build a stronger America!"* (Polarity Score: +1.0)

By incorporating the above systematic approach, the sentiment analysis provides both numerical and categorical insights into the emotional tone of tweets, enabling a deeper exploration of engagement patterns and trends over time. Following are the steps on how to:

1. *Twitter API Authentication:* Replace the placeholder strings with your Twitter API credentials.
2. *Fetch Tweets:* The `get_tweets` function retrieves tweets containing the specified query.
3. *Sentiment Analysis:* The `analyze_sentiment` function uses TextBlob to analyze the sentiment of each tweet.
4. *Output:* It prints the tweet text along with its sentiment polarity.

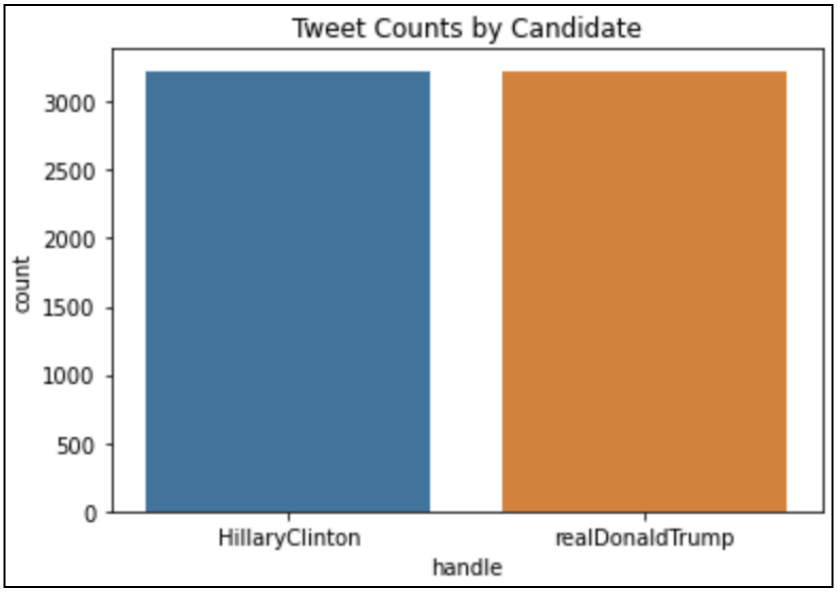

Fig. 2(a) Number of tweets per candidate in the year 2016 during the election campaign.

The bar chart titled "Tweet Counts by Candidate" displays the total number of tweets posted by each candidate, Hillary Clinton and Donald Trump. Both candidates have a nearly equal number of tweets, as represented by the similar heights of the bars, indicating a well-balanced dataset in terms of tweet counts between the two. This balance ensures that subsequent analyses, such as sentiment comparison or engagement metrics, are not biased due to a disparity in the volume of tweets from either candidate.

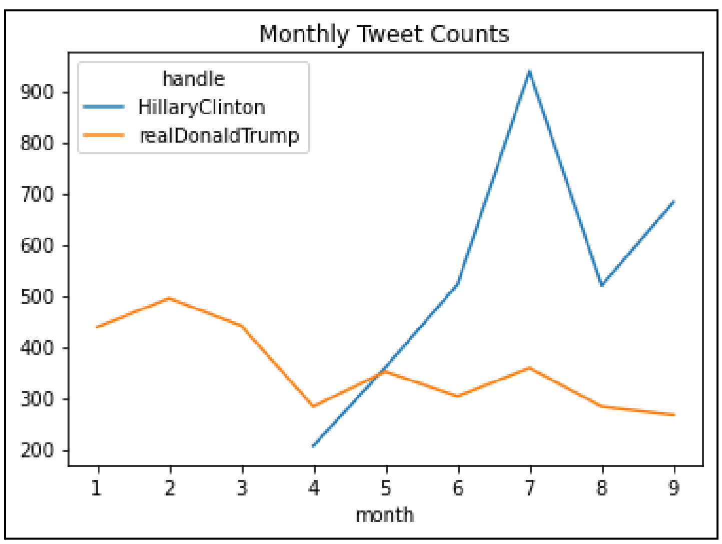

Fig. 2(b) Number of monthly tweets per candidate in the year 2016 during the election campaign.

The above plot (Fig. 2b) displays the total number of tweets posted by each candidate, separated by month. It highlights the frequency of Twitter activity as the campaign progresses, allowing for easy identification of any spikes in activity that may correspond with key campaign events or debates.

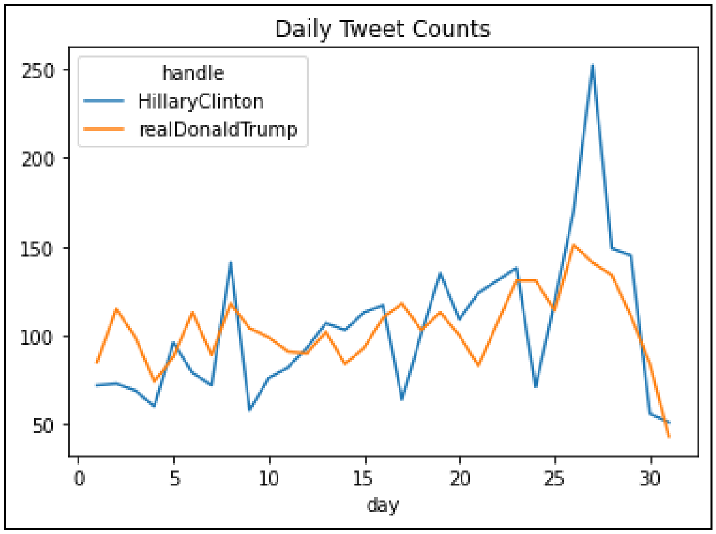

Fig. 2(c) Number of daily tweets per candidate in the year 2016 during the election campaign.

The above plot (Fig. 2c) illustrates the number of tweets by each candidate on a day-to-day basis, showcasing both candidates' engagement patterns. This granularity can reveal specific dates with increased tweeting, possibly linked to particular news cycles or political events.

2.1 Methodology & Visualization

The following steps were followed to perform the sentiment analysis and generate the plots:

1. **Refining the Dataset:**
   The dataset was carefully filtered to keep only the tweets written by Hillary Clinton and Donald Trump. This was done by looking at the handle column and selecting tweets that matched "HillaryClinton" and "realDonaldTrump," without worrying about whether the letters were uppercase or lowercase. This method ensured that only the relevant tweets from these two political figures were included for further analysis. To enable effective time-based analysis, the 'time' column containing the precise timestamps for each tweet was transformed into a standardized datetime format. This conversion was crucial, as it allowed for the accurate representation of dates and times, ensuring that all timestamps were consistent and easily interpretable. By converting the timestamps, we could then group and aggregate tweets based on their dates, facilitating a clearer understanding of trends and patterns over time. This capability is essential for analyzing how tweet activity varies by day, allowing for insights into specific events or periods of heightened engagement.

2. **Performing Sentiment Analysis:**
   Sentiment analysis was conducted on the text of each tweet using the TextBlob library, a powerful tool for processing textual data. This analysis involved calculating the sentiment polarity score for every tweet, a metric that quantifies the emotional tone of the text on a scale from -1 to 1. A score of -1 indicates a very negative sentiment, while a score of 1 reflects a very positive sentiment. This nuanced approach allows us to gauge the overall mood conveyed in each tweet. To organize

this information, the calculated sentiment polarity scores were stored in a new column labeled 'sentiment' within both the datasets for Hillary Clinton and Donald Trump. This addition not only enhances the datasets by providing a clear indicator of the emotional context of each tweet but also sets the stage for deeper analysis of how sentiment varies between the two political figures over time or in response to specific events. By tracking sentiment in this way, we can better understand public perception and the impact of their messages.

3. **Grouping and Averaging Sentiments:**
   Sentiment scores were systematically grouped by date, allowing us to analyze how the emotional tone of tweets varied over time. For each day, the average sentiment score was calculated, providing a clear snapshot of the overall sentiment expressed in the tweets from both political figures. This process culminated in the creation of two distinct time series: one representing Hillary Clinton's average daily sentiment, referred to as "clinton_sentiment_daily", and the other representing Donald Trump's average daily sentiment, labeled "trump_sentiment_daily". These time series offer valuable insights into trends and shifts in public sentiment towards each candidate over specific periods. By examining these averages, we can identify patterns that may correlate with significant political events, media coverage, or changes in public opinion, thereby enhancing our understanding of the emotional landscape surrounding their respective campaigns.

4. **Engagement Analysis:**
   Retweet counts, a measure of engagement, were analyzed based on the sentiment of the tweets. The average retweet count for each sentiment type (Positive, Neutral, Negative) was calculated for both candidates. This metric provides insights into which types of sentiment received the highest engagement from followers.

5. **Visualization of Sentiment Analysis:**
   A line plot was designed to effectively visualize the daily average sentiment for both Hillary Clinton and Donald Trump across the specified time period. This graphical representation allows for a straightforward comparison between the two candidates' sentiments over time. In the plot, individual data points are marked clearly to highlight the average sentiment for each day, making it easy to identify fluctuations and specific values. Solid lines connect these points, providing a continuous view of the sentiment trends, which helps to illustrate how public perceptions of each candidate have evolved. The combination of markers and connecting lines enhances the clarity of the visualization, allowing viewers to quickly grasp significant trends, peaks, and dips in sentiment. This approach not only makes the data more accessible but also facilitates a deeper understanding of how various events or statements may have influenced public opinion over time. Overall, the line plot serves as a valuable tool for analyzing and communicating the emotional dynamics surrounding both political figures throughout the timeline of their tweets. Linear trendlines were incorporated into both sentiment series using a first-degree polynomial fit, which is essentially a straight line that best represents the data points in each series. By adding these trendlines, we gain a clearer visual indication of the overall direction and trajectory of sentiment for both Hillary Clinton and Donald Trump over time. These trendlines clearly indicate whether sentiment is generally increasing, decreasing, or remaining stable across the analyzed period. The slope of each line reflects the average change in sentiment, helping to contextualize the emotional

responses associated with various events or communications from each candidate. Moreover, these trendlines enhance the interpretability of the plot by smoothing out daily fluctuations and highlighting broader patterns that may not be immediately apparent in the individual data points. This approach allows for a more comprehensive understanding of how public sentiment has shifted in response to the candidates' actions and messaging, making it easier to identify significant trends and correlations in the data. Overall, the inclusion of linear trendlines adds depth to the analysis and supports more informed conclusions about the evolving emotional landscape surrounding both political figures. A plot was customized with a title "Sentiment Analysis of Hillary Clinton and Donald Trump Over Time with Trendlines", and the x-axis was labeled as ‘Date’ while the y-axis was labeled as ‘Average Sentiment’. A legend was added to distinguish between the lines representing Clinton and Trump. Additionally, a grid was included to enhance readability.

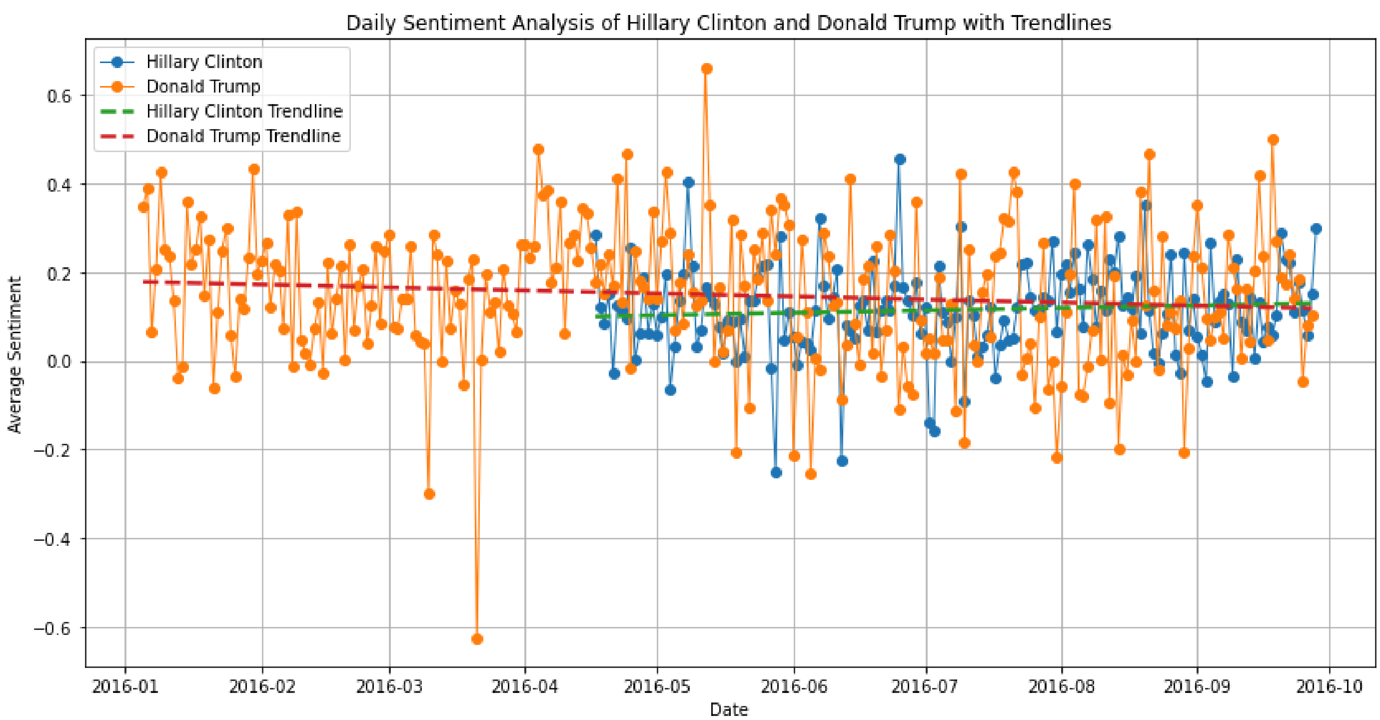

Fig. 2(d) Sentiment Scale depicting the sentiment of both candidates’ tweets

The orange spikes and drops on **Trump’s** graph were caused by positive and negative sentiments respectively in his tweets. However, the criticizing nature of his tweets often increased his popularity among citizens due to the following topics and current state of affairs.

1. **Trump’s Positive Sentiment Tweet Topics:**
    - Trump's iconic campaign slogan, "Make America Great Again," was a central theme in his tweets. He used it to rally his supporters, emphasizing the idea that America had declined under previous administrations and that he would restore its former greatness.

- Trump tweeted about the support he received from various public figures, such as former New York Mayor Rudy Giuliani and other political allies. He also often expressed gratitude to his supporters, rallying his base through enthusiastic posts.
- Trump emphasized his plans to bring jobs back to the U.S. by renegotiating trade deals like NAFTA and criticizing companies that outsourced jobs to other countries.

2. **Trump's Negative Sentiment Tweet Topics:**
    - Trump frequently tweeted about the need to secure U.S. borders, particularly the construction of a wall along the U.S.-Mexico border. He argued that illegal immigration posed a significant threat to national security and economic stability.
    - Trump was highly critical of mainstream media outlets like CNN, The New York Times, and The Washington Post. He often accused them of being biased against him and promoting "fake news".
    - He frequently targeted his Democratic opponent, Hillary Clinton. He criticized her emails scandal, her handling of classified information, and her role in the 2012 Benghazi attack.
    - He regularly tweeted about the threat of radical Islamic terrorism, calling for stronger measures to combat it.

The blue spikes and drops on **Clinton's** graph were caused by positive and negative sentiments respectively in her tweets. The uplifting and empowering nature of her tweets gained her popularity.

1. **Clinton's Positive Sentiment Tweet Topics:**
    - As the first woman to be nominated for president by a major political party, Clinton frequently tweeted about women's rights, gender equality, and the importance of breaking the "glass ceiling."
    - Clinton was a strong proponent of expanding and improving the Affordable Care Act (ACA), often tweeting about the need to protect and build on Obamacare. She advocated for universal coverage and reducing health care costs.
    - Clinton was vocal about issues of racial and social justice, tweeting about police reform, ending mass incarceration, and the Black Lives Matter movement.
    - She positioned herself as a leader on environmental issues, stressing the importance of global cooperation to address climate challenges.

2. **Clinton's Negative Sentiment Tweet Topics:**
    - She referred to Trump as "unfit" for the presidency and used hashtags like #TrumpIsNotFit to emphasize this point. She also criticized his handling of issues like national security and his business dealings.
    - She often criticized Trump's refusal to acknowledge the threat posed by Russia and its efforts to undermine U.S. democracy.
    - She tweeted about the need for comprehensive background checks, banning assault weapons, and closing loopholes in gun sales.

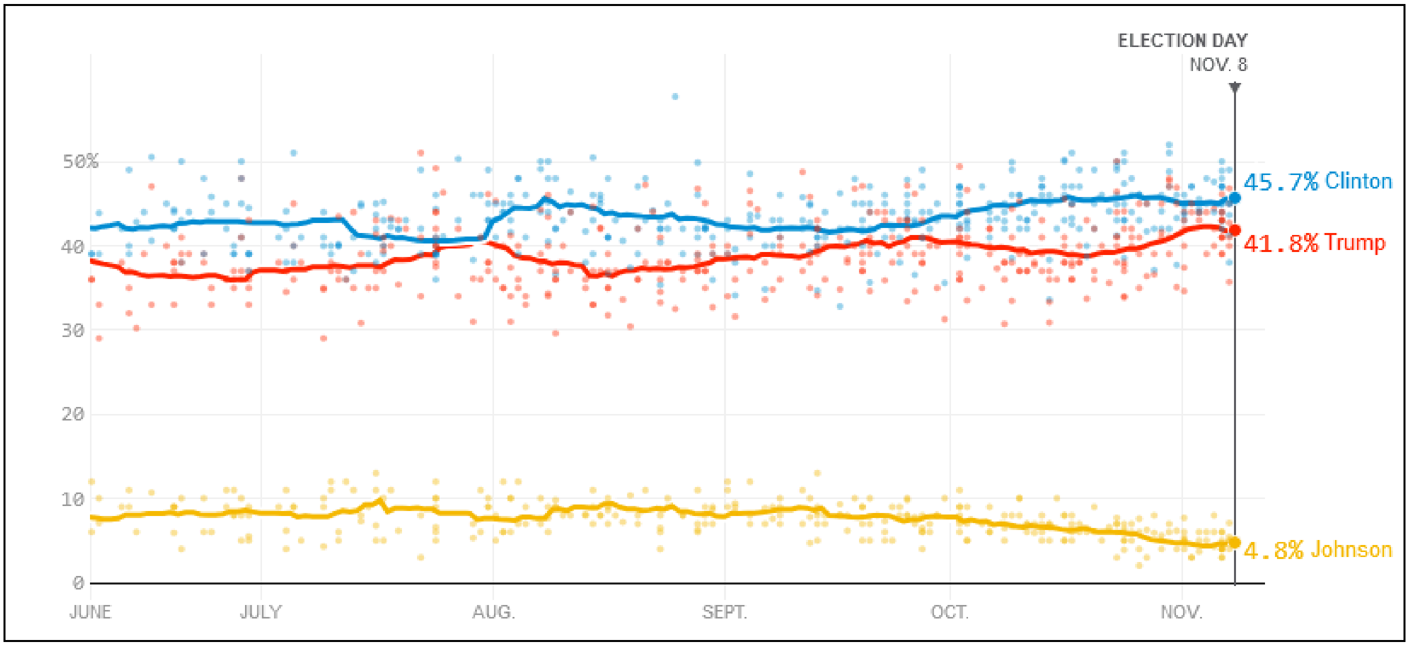

Fig. 2(e) 2016 US Presidential election forecast - 08 Nov 2016.

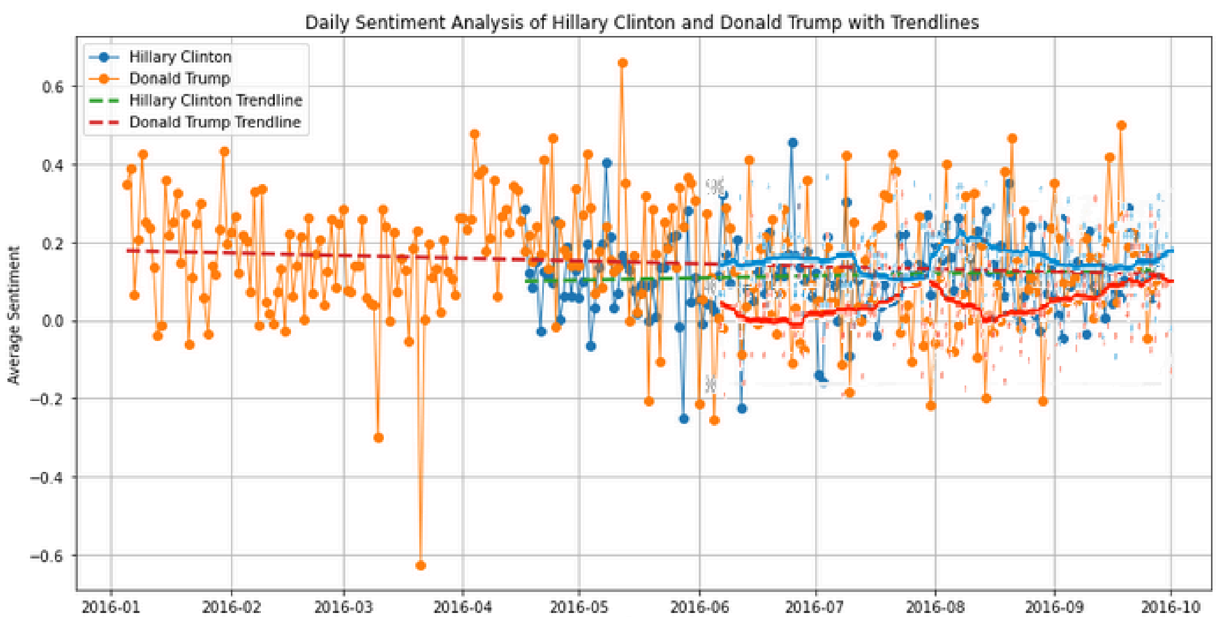

Fig. 2(f) Rough overlay of the above two graphs. Note that the timescale of the two graphs does not match up – the election forecast data only begins in June 2016.

3.0 Implications of NLP Techniques on Twitter Sentiment Analysis

While lexicon-based approaches can provide useful insights for basic text analysis tasks, they are limited by their inability to account for context, domain-specific nuances, and more complex linguistic phenomena like irony or sarcasm. They also lack the flexibility of machine learning-based approaches that can adapt and improve over time. Common constraints include:

1. Lexicons do not capture context well.
2. Limited vocabulary coverage due to relying on a finite set of words in the lexicon.
3. Lexicons need to be manually updated to include new words or meanings, which can be a time-consuming process.
4. If a lexicon grows too large, searching through it for every word in a text can lead to performance issues, especially with big datasets.

4.0 Results & Conclusion

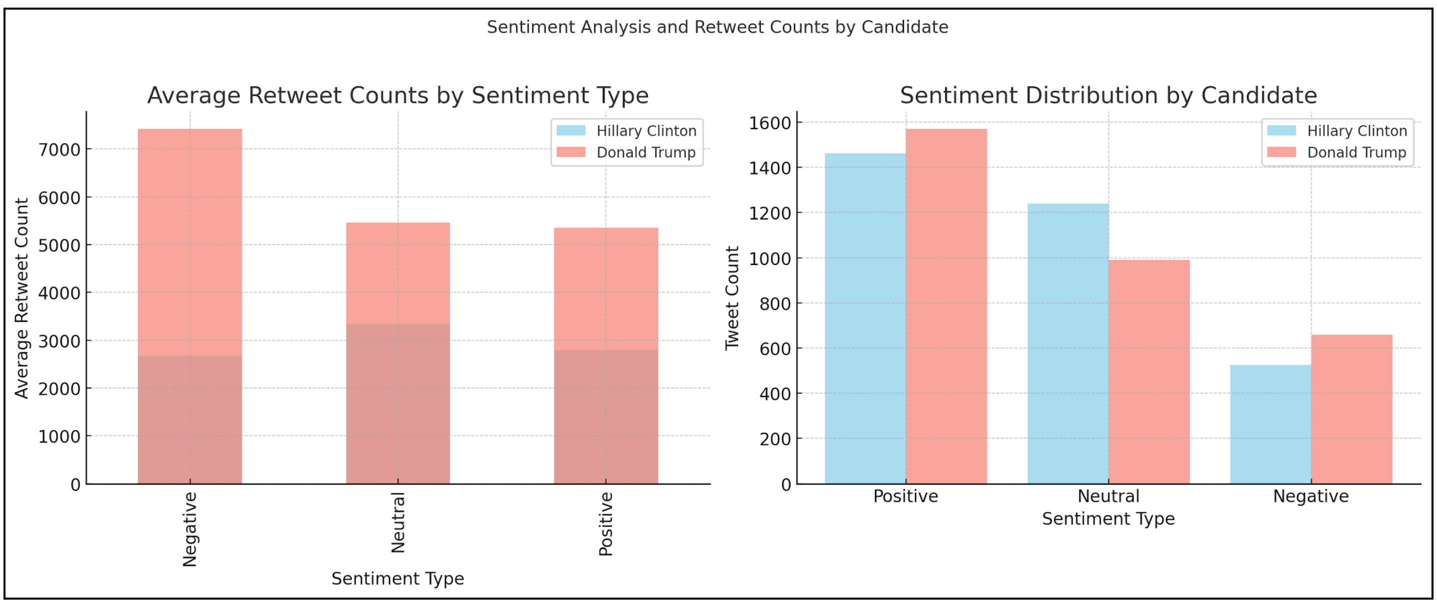

Fig. 4(a) Average Retweet Counts and Sentiment Analysis

Average Retweet Counts by Sentiment Type:

- Donald Trump's tweets generally received more retweets across all sentiment types, with his negative tweets attracting the highest engagement.
- Hillary Clinton's neutral tweets had the highest average retweets, followed by positive and negative tweets.

Sentiment Distribution by Candidate:

- Both candidates tweeted more positively than negatively.

- Donald Trump's tweet sentiment shows a slightly higher proportion of positive tweets than Hillary Clinton, aligning with his higher average sentiment score of 0.146 compared to Clinton's 0.115.

After comparing their average sentiment scores, we can say that, overall, both candidates tended to tweet more positively than negatively. Notably, Trump's tweets reflected a slightly higher average positive sentiment compared to his opponent. This trend suggests that, despite the competitive nature of the political landscape, both candidates were able to maintain a largely optimistic tone in their social media communications. However, remarkably, Trump also experienced significantly higher engagement levels for his negative tweets. Specifically, his most negative tweet, which registered a sentiment score of -0.62, occurred towards the end of March 2016. It indicates that audiences were more responsive to the negative sentiments expressed in his tweets, which may signal a strong Republican support base or a reactionary outrage among his haters. Alternatively, the increased engagement levels on negative tweets may counter the idea that Trump's overall more positive sentiment was a contributing factor to his electoral victory in 2016.

Considering the overlaid graph in figure 3(c), Trump's projected chances increased slightly as Election Day closed in, while both candidates' negative sentiments increased very slightly overall. By the time Trump's projected odds were the highest (September 2016), he was completely avoiding any tweets with a largely negative sentiment (less than -0.2).

5.0 Future Work

Due to limitations in capturing context and semantics, exploring NLP techniques like word embedding and tools like Word2Vec, GloVe, and FastText will help map words based on their surrounding context, allowing them to capture semantic relationships. While detecting sarcasm remains a challenge, embeddings can still provide contextual clues based on patterns across large datasets, helping models recognize when words are being used in an ironic way.

The sentiment analysis performed in this study raises important questions about the dynamics of political engagement on social media, particularly how negative messaging can sometimes foster greater interaction and visibility than positive messaging. It invites further exploration into how the sentiment of candidates' tweets correlates with actual polling predictions during that period. By examining these correlations, we can gain deeper insights into the strategies candidates employ in their communications and how these strategies resonate with their voter base. Ultimately, this analysis could reveal critical patterns in political communication that might influence future electoral outcomes.

In light of Trump's electoral victory in the 2024 presidential election against Kamala Harris, there is plenty of room for follow-up analyses of 2016, 2020, and 2024, given that Trump was the Republican presidential candidate in all three elections. Studying social media posts of prominent candidates or other political figures might lead to similar or different conclusions than those outlined in this paper, solidifying our understanding of how political posts online can influence an election or people's view of a candidate. However, access and analysis of Trump and his opponents is sure to differ across the years. Trump was banned from Twitter in Janurary 2021 over incitement of violence, and though his account was reinstated by X (formerly Twitter) CEO Elon Musk in November 2022, he did not return to the platform. While both Democratic and Republican candidates continued to use X as a platform, Trump would remain on his own platform, Truth Social, which has a far smaller user base than Twitter/X. A potentially interesting unexplored area is how the different audiences of each social media platform react to Trump's and/or Harris's sentiments and the political events occuring during the 2024 campaign.

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