Team: Cecily Munoz-Pastrana and Cole Whittington (equal contributions)

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Professor Gold

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Sentiment Analysis of Donald Trump's Tweets During Key Political Events: Comparing RoBERTa and LSTM Models

Introduction

Social media plays a key role in shaping public narratives, particularly when used by political leaders to communicate during key events. President-elect Donald Trump was particularly unique because he was the first president to use Twitter as a major form of communication with the American public. This project aims to analyze the sentiment of tweets authored by Trump, focusing on how his messaging shifted throughout his presidency and how the sentiment behind his tweets changed engagement from Twitter users. By comparing the performance of RoBERTa, a transformer-based Natural Language Processing model, with an LSTM neural network, we investigate which approach better captures sentiment shifts and emotional tones in his messaging.

Context

Donald Trump's tweets provide a unique case study, reflecting his use of social media as a direct communication tool, a method he uses in a robust manner. As a high-profile individual for many years, Trump has long used his influence to express his opinion about politics and his career. Analyzing these tweets helps uncover temporal patterns in sentiment and emotion, showing how his language evolved in response to events or initiated them. At the very end of his presidency, on January 6, 2021, his Twitter influence was even further put on display after he was impeached by the House of Representatives for inciting an insurrection. Soon after, on January 8, Twitter banned Trump's account, which was reinstated by then-new CEO Elon Musk nearly two years later, in November 2022.

Differences in Project Proposal and Presentation

It should be noted that this project is different than our proposed project, which would've tracked political sentiment from Twitter users about Kamala Harris before, during, and after her 2024 presidential campaign. However, due to the extensive cost of the Twitter API, the collection of these tweets was impractical. In addition, some of the results and analyses in our presentation were incorrect due to coding errors.

Data Sources

This analysis consisted of two main datasets. The Donald Trump Tweets Archive, where we gathered tweets in accordance to three distinct political phases: Before Office (May 4, 2009, to December 5, 2016), In Office (January 20, 2017, to January 8, 2021), and Post Office (up until November 14, 2024). After cleaning, the dataset included a total of 55,615 tweets with various attributes, including the date and time it was posted and the number of engagements, favorites, and retweets. However, the dataset was unlabeled and didn't contain any sentiment values. The primary purpose of this dataset was to analyze sentiment trends in Trump's tweets across different political phases. The second dataset, Sentiment140, is a pre-labeled dataset containing 1.6 million tweets classified as positive or negative. This dataset, sourced from Kaggle, served as a labeled dataset to effectively train the LSTM model without having to label thousands of Trump's tweets manually. Essentially, this dataset was used as a stand-in for the lack of labeled tweets since we needed a robust training set.

Methodology

To ensure a fair comparison between models, we created a test set of 500 Trump tweets. Since the dataset was unlabeled, we manually categorized each tweet as either positive or negative sentiment. While we considered more advanced approaches—such as adding a neutral category, using a polarity score from -1 to 1, or classifying tweets into emotions like "sadness," "anger," or "joy"—these options were not practical for several reasons.

First, our training dataset, Sentiment140, only included positive and negative categories. Expanding this to include neutral or emotional categories would have required manually labeling thousands of Trump's tweets for both training and evaluation. Second, using polarity scores or emotional classifications would require subjective decisions about Trump's rhetoric, which could lead to more inconsistency than a simple binary classification.

A binary positive/negative classification, though simple, provides an effective way to capture the sentiment of Trump's tweets. This approach fits well with our training data and offers a clear framework for comparing model performance without introducing unnecessary complexity.

To make use of a pre-trained model for our analysis due to time constraints, we utilized a RoBERTa-base model available on HuggingFace, which had been trained on a dataset of 124 million tweets spanning January 2018 to December 2021 (HuggingFace). The reason why we chose this model is that RoBERTa improves upon the BERT model– still retaining key foundational similarities with BERT– by refining several training techniques, such as removing the next sentence prediction task, increasing the training dataset size, utilizing longer input sequences, and implementing dynamic masking (Rahman 2024). With the availability of these new enhancements, we are able to look into boosting precision and adaptability for our sentiment analysis task.

To build the architecture of our LSTM, we loosely followed Francois Chollet's steps by first building a high capacity for the model and then using regularization to reduce overfitting (Gold, Lecture 12). In our experiments, as seen in Figure 1, we varied the batch size and learning rate parameters to observe how these different parameters interacted with each other and performed on our test set. As expected, without regularization, our models severely overfitted our training data and performed poorly on our testing set, although much better than our naive rule of 0.54.

Therefore, we turned to regularization techniques, such as adding a dropout layer and implementing early stopping. We used these techniques to bridge the gap between the training and validation accuracy of our model in an effort to build a model that would generalize to our Trump test set more effectively.

Preprocessing Techniques

To prepare the datasets for analysis, we applied a series of preprocessing steps. These included the removal of special characters, URLs, hashtags, and stopwords from the text to ensure clean inputs for the models. Tweets were also normalized by converting them to lowercase to maintain consistency and by standardizing dateTime formats across the dataset for temporal analysis. Tokenization was performed to break down text into individual units, and sequences were padded to ensure uniform input lengths for the LSTM model. Additionally, user mentions were replaced with placeholders, and duplicate tweets were removed to avoid redundancy in the training data. These preprocessing steps were essential for preparing the data for sentiment analysis using both RoBERTa and LSTM models.

Evaluation Metrics

To evaluate the performance of our sentiment analysis models, we used two metrics: accuracy and confusion matrices. Accuracy provided a straightforward measure of overall correctness, and since our dataset was balanced, using other accuracy metrics such as recall or precision wasn't required. Additionally, the confusion matrix offered a detailed breakdown of model predictions, highlighting misclassifications by category.

Model Performance

Figure 1: LSTM Model Results

	LSTM Units	Batch Size	Learning Rate	Train Accuracy	Validation Accuracy	Test Accuracy	Epochs	Regularization^
Model 1	128	32	0.001	99.02%	83.32%	71.20%	20	
Model 1r	128	32	0.001	90.92%	82.85%	69.80%	20*	Dropout, ES
Model 2	128	64	0.001	98.95%	83.42%	68.40%	20	
Model 2r	128	64	0.001	90.04%	82.38	72.79%	20*	Dropout, ES
Model 3	128	128	0.001	98.38%	83.42%	69.40%	20	
Model 3r	128	128	0.001	87.81%	82.51%	71.79%	20*	Dropout, ES
Model 4	128	32	0.005	88.38%	81.52%	71.39%	20	
Model 4r	128	32	0.005	89.11%	82.73%	70.00%	20*	Dropout, ES
Model 4+**	128	32	0.005	92.34%	83.11%	72.20%	20*	Dropout, ES

* Early_stopping led to a reduced number of epochs
** Added a Dense layer with 64 neurons
^ Dropout = 0.5, ES = Early Stopping after three epochs without a decrease in validation loss

When running the pre-trained RoBERTa model on the testing set, the model achieved an accuracy of 91%. This is significantly better than our best LSTM model, with an accuracy of 72%. The results from the nine LSTM models we trained can be seen in Figure 1. RoBERTa outperformed our LSTM model because of its ability to capture the context and complexity of Trump's tweets. Unlike the LSTM, which processes text sequentially, RoBERTa uses attention mechanisms to analyze word relationships across entire inputs, which helps with the rhetorical "complexity" present in Donald Trump's tweets. Its pre-training on a large set of tweets also added to its ability to generalize to social media-specific language, which makes it a better model for this analysis.

Analysis

We then generalized this model to the entire Trump Tweets dataset, assuming it would maintain its 91% accuracy. From these sentiment scores, we were able to conduct our analysis.

Figure 2: How Sentiment Effects Activity Metrics

Activity Metric	Overall	Positive Sentiment Tweets	Negative Sentiment Tweets
Engagement	37,512	31,381	44,743
Favorites	30,410	25,765	35,888
Retweets	7,102	5,615	8,855

The sentiment analysis of Donald Trump's tweets reveals fascinating insights into the role of sentiment in shaping user activity, directly supporting the goals of our project to understand how sentiment shifts influenced his communication strategy and audience reactions. Figure 2 shows a clear connection between negative sentiment in Donald Trump's tweets and heightened user engagement. Tweets classified as negative consistently outperformed positive tweets in terms of overall engagement (44,743 vs. 31,381), favorites (35,888 vs. 25,765), and retweets (8,855 vs. 5,615). This demonstrates that emotionally charged or controversial messaging was more effective at driving interaction, a key insight into Trump's communication strategy.

Figure 3: Sentiment and Activity Metrics Across Time Periods

	Percentage of Negative Tweets	Average Engagement	Average Retweets	Average Favorites
Before Presidency (2009-2017)	40.42%	4,497	1,269	3,227
During Presidency (2017-2021)	48.18%	94,553	16,990	77,563
After Presidency (2021-present)	55.76%	23,840	5,020	18,819

When looking at sentiment and activity metrics across different periods, it's evident that Trump's tweets have become increasingly negative. To the surprise of no one, Trump's activity metrics were significantly higher during his presidential term than before or after due to his occupation of a very high-profile role. However, even with an increased percentage of negative tweets, activity metrics have all dropped off since Trump left office. This could be true for multiple reasons, including the fact that many of Trump's followers left Twitter for Trump's own social media platform, TruthSocial, leading to a decrease in engagement on his Tweets following his reinstatement at the end of 2022 (Politico). Moreover, for the first 22 months after the end of his term, Trump was banned from Twitter, which likely led to a smaller audience once he was reinstated.

Figure 4: Sentiment and Engagement During Key Moments

	Start Date	**End Date**	**Percentage of Negative Tweets**	**Average Engagement**
First Year in Office	2017-01-21	2017-12-31	43.44%	86,021
Tax Cuts and Jobs Act	2017-12-22	2017-12-25	34.78%	115,690
2018 Midterm Elections	2018-11-01	2018-11-09	28.97%	81,003
2018 Government Shutdown	2018-12-21	2019-01-25	55.52%	127,010
COVID Pandemic in 2020	2020-03-01	2020-12-31	47.05%	224,105
January 6 Insurrection	2021-01-05	2021-01-08	51.72%	278,168

In addition, we looked at average sentiment around key moments during Trump's presidency. In Figure 4, it's evident that there was high engagement during polarizing periods such as the January 6 insurrection and the COVID-19 pandemic throughout 2020. Taken together, these results show high engagement through nearly all of Trump's last months in office. In the few days before and after the 2018 Midterm Elections, Trump's overall sentiment was substantially more positive, with around 71% of his tweets being positive. Ironically, this sentiment was positive despite Republicans–Trump's political party– losing control of the House of Representatives to the Democratic Party, a major legislative body (CNN). Trump's sentiment was also notably more positive compared to his overall presidential term immediately after the passing of the Tax Cuts and Jobs Act, a major legislative accomplishment for Republicans and the Trump Administration (Trump National Archives). During the 2018 Government Shutdown, the longest in American history, the overall negative sentiment of Trump's tweets was seven percentage points higher than his average throughout his presidential term (CBS News).

Limitations

One of the first limitations we encountered due to time and technology constraints was the fact that we did not perform context-aware pre-processing, which would mean retaining hashtags and mentions, which often carry sentiment-relevant information. We also had the limitation of not having a "neutral" sentiment in our datasets due to the fact that Sentiment140 only had "positive" and "negative" sentiments. In the future, it would be critical to add this third category, specifically trained against Donald Trump's own rhetoric, so that there is a better boundary between "positive" and "negative" emotions in Trump's words.

Ethical Considerations

We also considered the ethical implications associated with analyzing social media data, particularly from a high-profile individual like Donald Trump. One significant ethical concern was the potential bias introduced by the dataset itself. Sentiment140, while a widely used dataset, does not account for the unique rhetorical style and polarizing nature of Trump's tweets. This limitation raises questions about whether the sentiment labels applied to general tweets are fully representative of the sentiment, specifically his messages. Additionally, the decision to include or exclude certain tweets, such as retweets or replies, required careful deliberation to avoid skewing the analysis.

On a similar plane to the limitations we encountered, another ethical consideration was the interpretation of sentiment as "positive" or "negative" without a neutral category, which could oversimplify the complexity of Trump's language. This binary classification might inadvertently reinforce polarizing narratives or fail to capture the subtleties in his communication. Finally, we recognize the broader implications of using sentiment analysis to evaluate political figures. Such analyses can influence public opinion and reinforce biases if not conducted and presented responsibly. In the end, we remain mindful of the potential impact of our findings and strive to approach our conclusions with caution, emphasizing the limitations and context of our methodology.

Conclusion

From our analysis, we identified three major takeaways: controversy drives engagement, legislative success can reduce negativity, and crisis amplifies polarization. First, our results show that tweets with negative sentiment consistently generated higher levels of user activity compared to positive tweets based on their higher averages in retweets, likes, and overall engagement. This suggests that emotionally charged or polarizing content is more effective at capturing attention, reinforcing Donald Trump's strategic use of rhetoric during key events such as the January 6 insurrection and the COVID-19 pandemic. Second, legislative success, such as the passing of the Tax Cuts and Jobs Acts, correlated with a significant decrease in negativity in Trump's tweets. These moments demonstrate how positive sentiment, although less engaging than negative sentiment, can effectively align with accomplishments and bolster public perception during critical policy milestones. Finally, crises such as the 2018 government shutdown and the pandemic amplify polarization and negative sentiment, reflecting the challenges of managing public narratives during high-stakes periods. While these tweets saw heightened engagement, they also reveal the role of negativity in driving public discourse during divisive times.

From a methodological standpoint, the project emphasized the power of advanced models such as RoBERTa in capturing nuanced sentiment and highlighted the limitation of traditional LSTM approaches for analyzing complex political communication. Additionally, we learned the importance of carefully curating datasets and balancing simplicity with the need for accurate representation of sentiment. Future research should incorporate more context-aware pre-processing and include a more complex sentiment structure to better capture the subtleties of political rhetoric.

Ultimately, this analysis shows how Donald Trump's use of Twitter shaped public engagement and reflected the dynamic of his presidency via his rhetoric. We gained insight into the interaction between political messaging, sentiment, and public response in the digital age and how important it can be for a political figure's success. Furthermore, this analysis can also be applied to future tweets to see how the use of Twitter in Trump's second term drives engagement.

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