



# Political Tweet Tracker

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# Formulating Question/Problem

**Project Name:** Political Tweet Tracker

**Objective:** Analyze how political leaders' language and word choice change during election periods.

**Goal:** Uncover shifts in tone, sentiment, and messaging strategies as elections approach.

**Big Idea:** Investigate how political leaders adapt their language during election times.

**Importance:** Political messaging significantly influences voters and public opinion.

**Focus:** Analyze tweets of key political party leaders to understand changes in:

- Sentiment
- Word frequency
- Rhetoric

**Hypothesis:** Leaders may become more positive/negative, use emotionally charged language, and/or alter rhetoric to appeal to specific voter demographics during election campaigns.

# Acquiring and Cleaning Data

**Data Source:** Twitter accounts of political leaders.

**Dataset Content:**

- Tweet text
- Timestamps
- Retweets

**Tools:**

- ScrapingDog API

**Collection Process:**

- Scrape tweets from political leaders during periods leading up to, during, and after election campaigns.

**Volume of Data:** Large amount of tweets, depending on individual tweet frequency.





# Exploratory Data Analysis

## Relevant Data:

- Includes tweets
- Timestamps
- user info
- Hashtags
- Retweets

## Bias and Issues:

- Tweets may reflect partisan viewpoints
- Tweet volumes and sentiment could spike during specific events or controversies, skewing sentiment analysis.
- Some tweets may contain mixed or sarcastic tones that are challenging to classify accurately.

## Data Transformations:

- Remove irrelevant metadata (e.g., emojis) to focus on content.
- Clean text by removing stopwords, correcting spelling, and handling emojis/special characters.
- Break text into tokens (words or phrases) to analyze sentiment at the granular level.
- Apply sentiment classifiers from positive, negative, neutral word files to assess the tone in each tweet.



# Drawing Conclusions From Predictions and Inference

## Key Insights

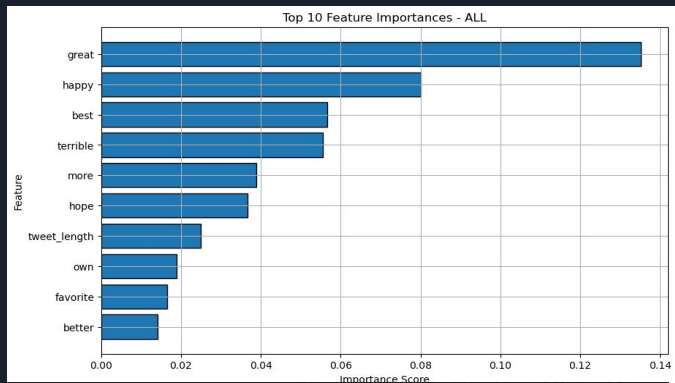
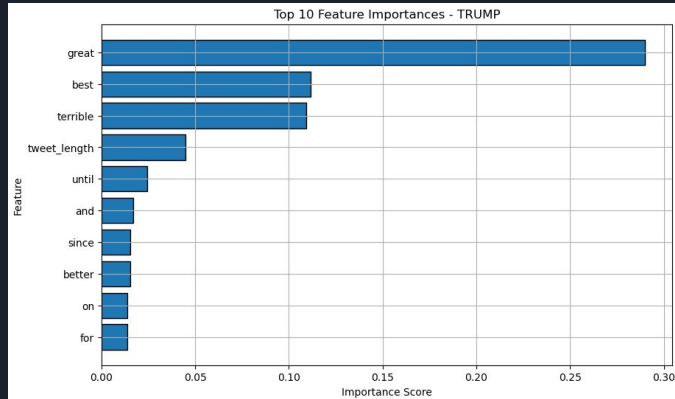
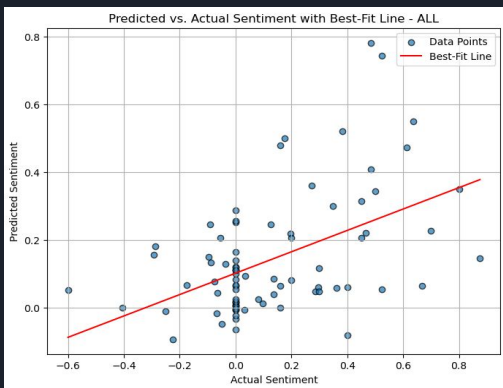
- **Political Sentiment Trends:** Analyze the overall sentiment for Trump, Clinton, and Obama over time, identifying patterns during key political events (e.g., debates, elections, controversies).
- **Sentiment Shifts:** Observe how sentiment fluctuates with political events, revealing shifts in public opinion toward each figure.
- **Differential Sentiment:** Compare the sentiment dynamics between the three figures to identify which politician garners the most positive or negative reactions at various points in time.
- **Polarization Trends:** Look for evidence of increasing polarization or divisiveness based on sentiment, potentially showing how each politician's public perception has evolved over time.

## Conclusions

- **Influence of Media and Events:** Strong correlations between major media coverage, events, and sentiment spikes in tweets suggest the influence of external factors on public opinion.
- **Differing Public Perceptions:** By examining how sentiment toward each politician varies, we can conclude that public opinion is highly divided based on party lines, with each figure experiencing spikes in both positive and negative sentiment.
- **Trends in Public Engagement:** Higher engagement during election cycles or political scandals suggests increased public interest and sentiment volatility.

# ML models

- Using regression techniques and sentiment prediction, we were able to analyze the language used by all the candidates to see how it impacted engagement (Top right/center right).
- We successfully displayed sentiment analysis with a features line of best fit (bottom left).
- Using the classifier, we were able to classify individual tweets after training a model to differentiate between sentiments (bottom right).

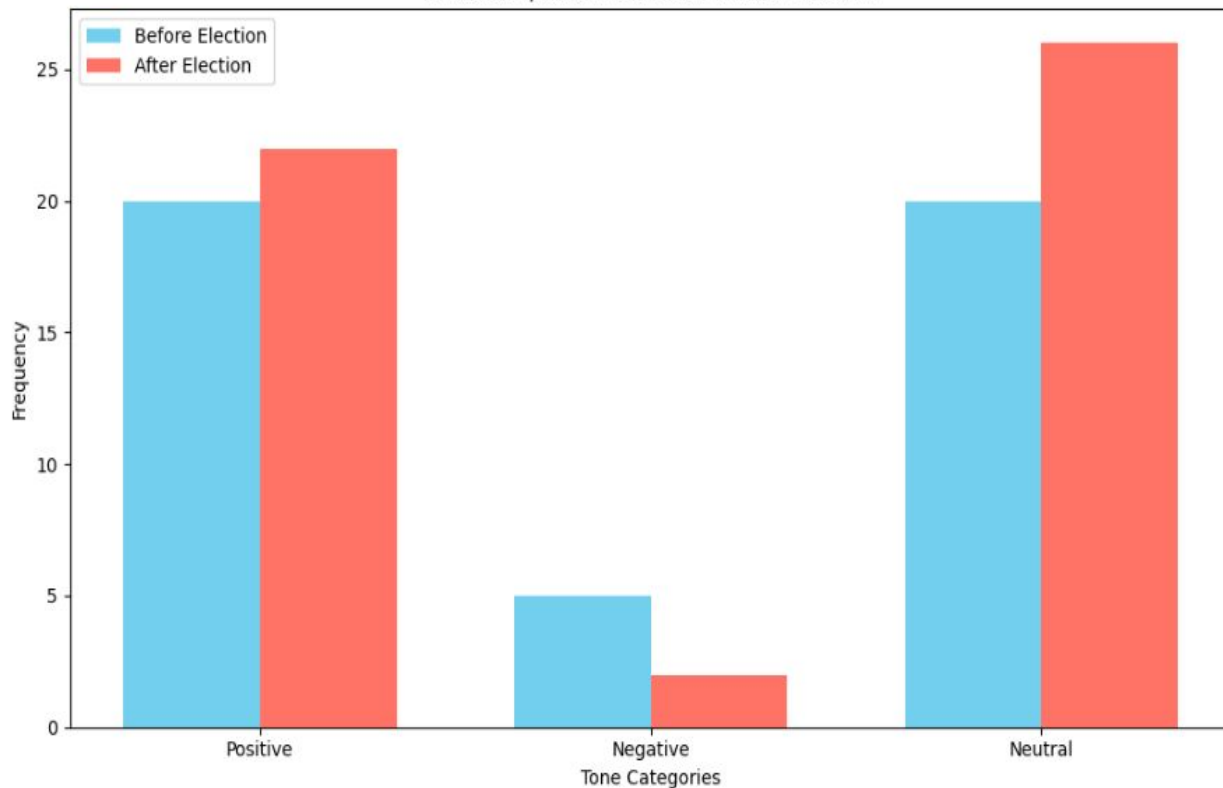


```
0 The Manufacturing Index rose to 59%, the highe...
1 Senator Luther Strange has gone up a lot in th...
2 Great interview on @foxandfriends with the par...
3 Since Congress can't get its act together on H...
4 Stock Market has increased by 5.2 Trillion dol...
```

```
tweet predicted_label
0 Positive
1 Positive
2 Positive
3 Negative
4 Negative
```

# Barack Obama

Tone Comparison Before and After Election



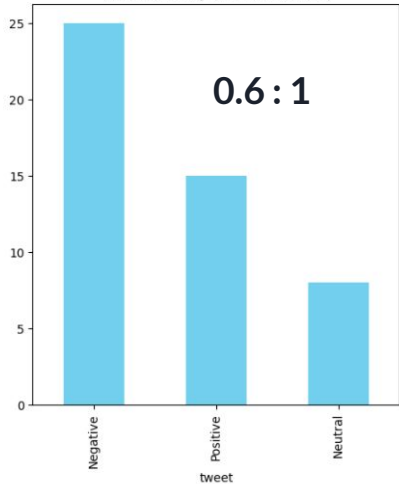
## Most Common Words After Election

- Favorite
- Happy
- Right
- Top
- Vice
- Hug
- Smile
- Winning
- Victory
- Best

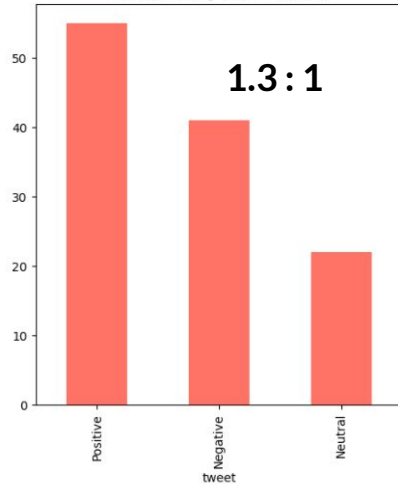
# Donald Trump

# Hillary Clinton

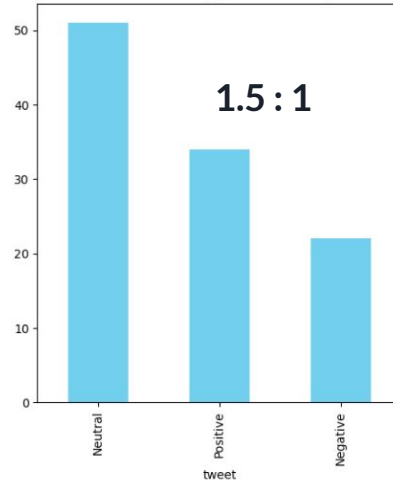
Tone Summary (Before Election)



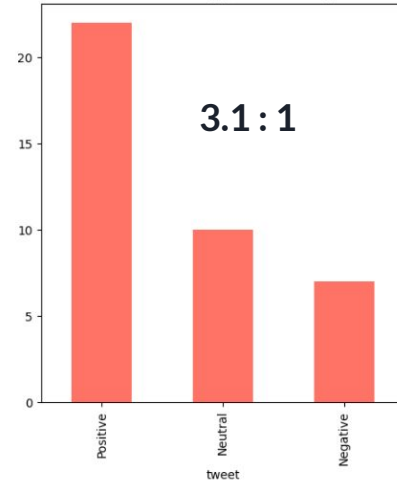
Tone Summary (After Election)



Tone Summary (Before Election)



Tone Summary (After Election)







# Conclusion and Future Work

We've concluded that candidates differed in sentiment depending on the time of their campaigns.

ML techniques showed that Trump tended to use more negative language compared to other candidates and this reason is what contributed to more engagement to users.

Future work that could better the results of this project would be the addition of data to better enhance our models