Sentiment Analysis

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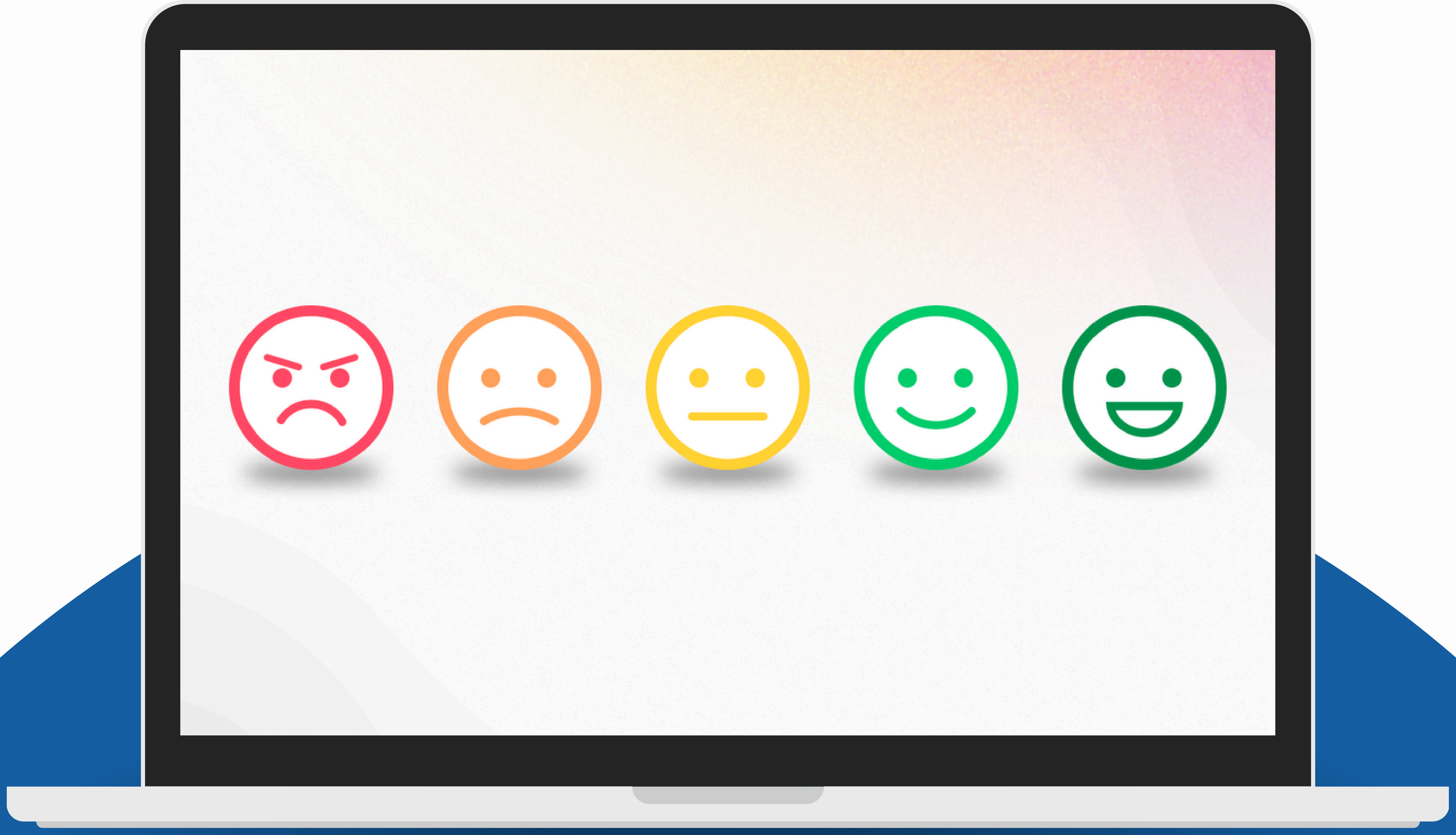
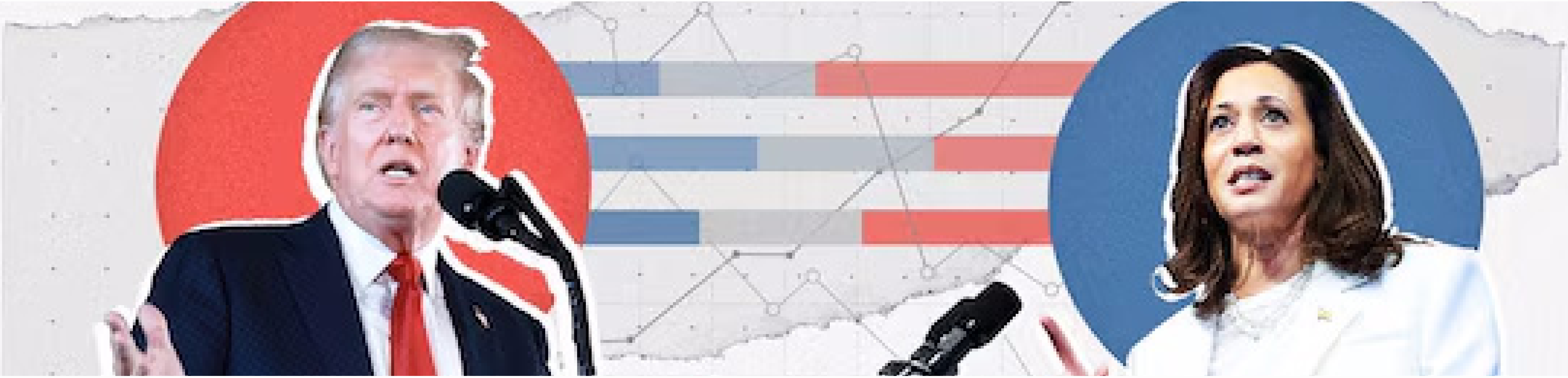




Trump Vs Harris

We conducted a sentiment analysis (analyzing written text to determine its emotional tone) using Tweets that mentioned Donald Trump and Kamala Harris

In this presentation we cover:

- Libraries we used are RoBERTa, TextBlob, Vader and Afinn
- How we processed data
- Pros and cons of each of the libraries
- Results we got from each of the libraries
- Comparing libraries
- Our favorite library

Data Processing

LOADING DATA AND INSTALLING LIBRARIES

DATA CLEANING

- Removing @usermentions (Don’t contribute to sentiment)
- Removing URLs (Not useful for sentiment analysis)
- Removing special characters & punctuations (Keeping only meaningful words)
- Converting to lowercase (Standardizing text)
- Removing stopwords (Words like "the," "is," "and," that don’t carry sentiment)
- Lemmatization (e.g., "running" → "run")
- Removing numbers (Numbers don’t contribute to sentiment)
- Remove extra spaces (Ensures uniformity)
- Dropping missing values
- Converting emoji to text (eg: 😡 → "angry face" (negative sentiment)
- Removing hashtags
- Removing duplicates
- Text tokenization (To split text into subword tokens)
- Using Retweets to amplify the weightage of tweets

LOAD MODEL

RUN MODEL

- Classify tweets into positive, negative, or neutral
- Convert outputs to sentiment labels

VISUALIZE RESULTS

- Generate tables and charts to visualise sentiments

BERT (DistilBERT, RoBERTa)

BERT is a deep learning model developed by Google AI that reads words in context from both left and right, allowing for better comprehension of meaning. While highly accurate, BERT is **computationally expensive** and **slow**, leading to the development of lighter, optimized versions like **RoBERTa** and **DistilBERT** for improved efficiency.

01

We initially used **BERT** but faced severe performance issues. It took **too long to load and compute** due to its large model size. Our system couldn't handle BERT's **high memory demand**, causing frequent failures **despite using smaller sample** sized. Due to these limitations, we needed a faster alternative, leading us to DistilBERT.

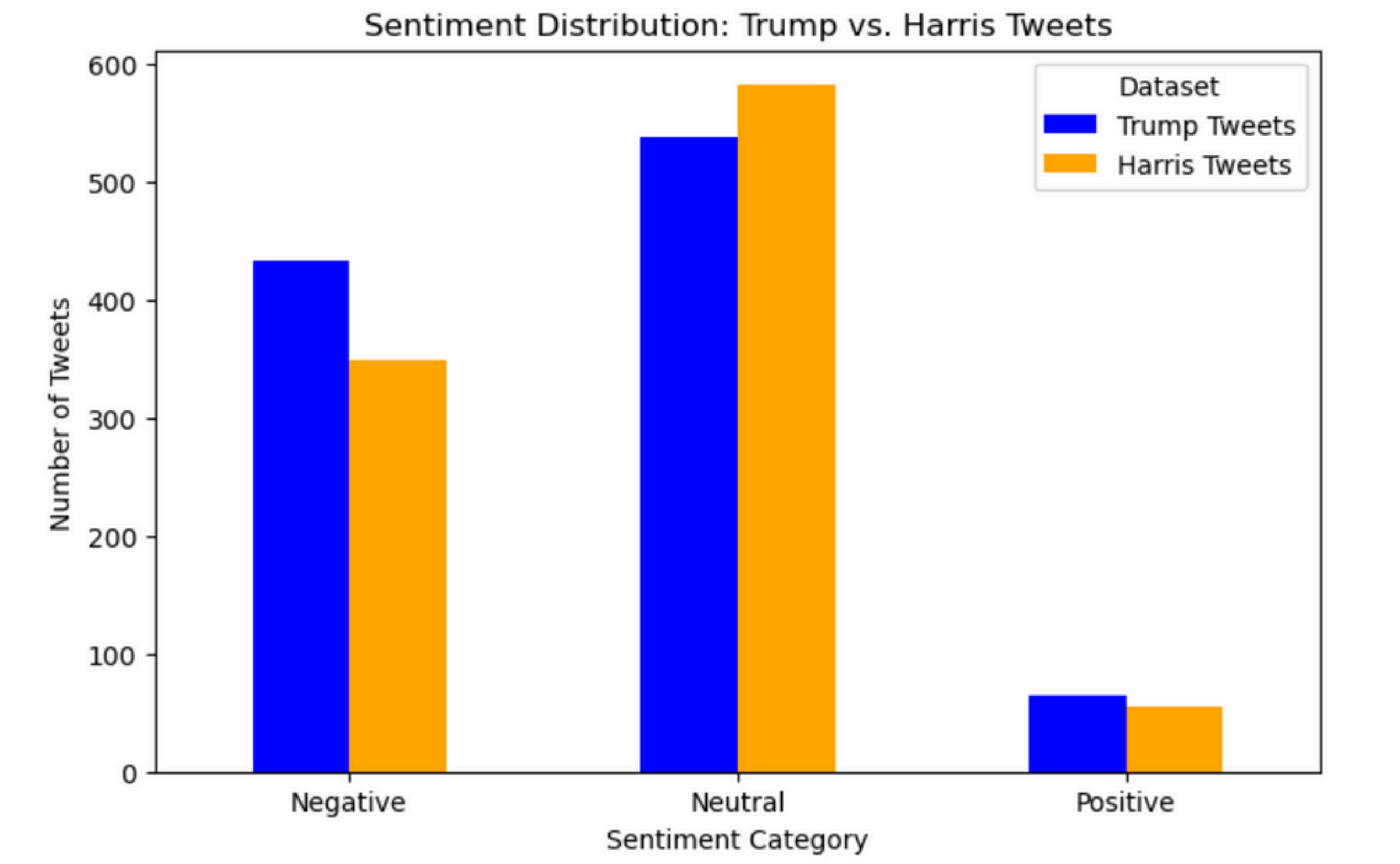
02

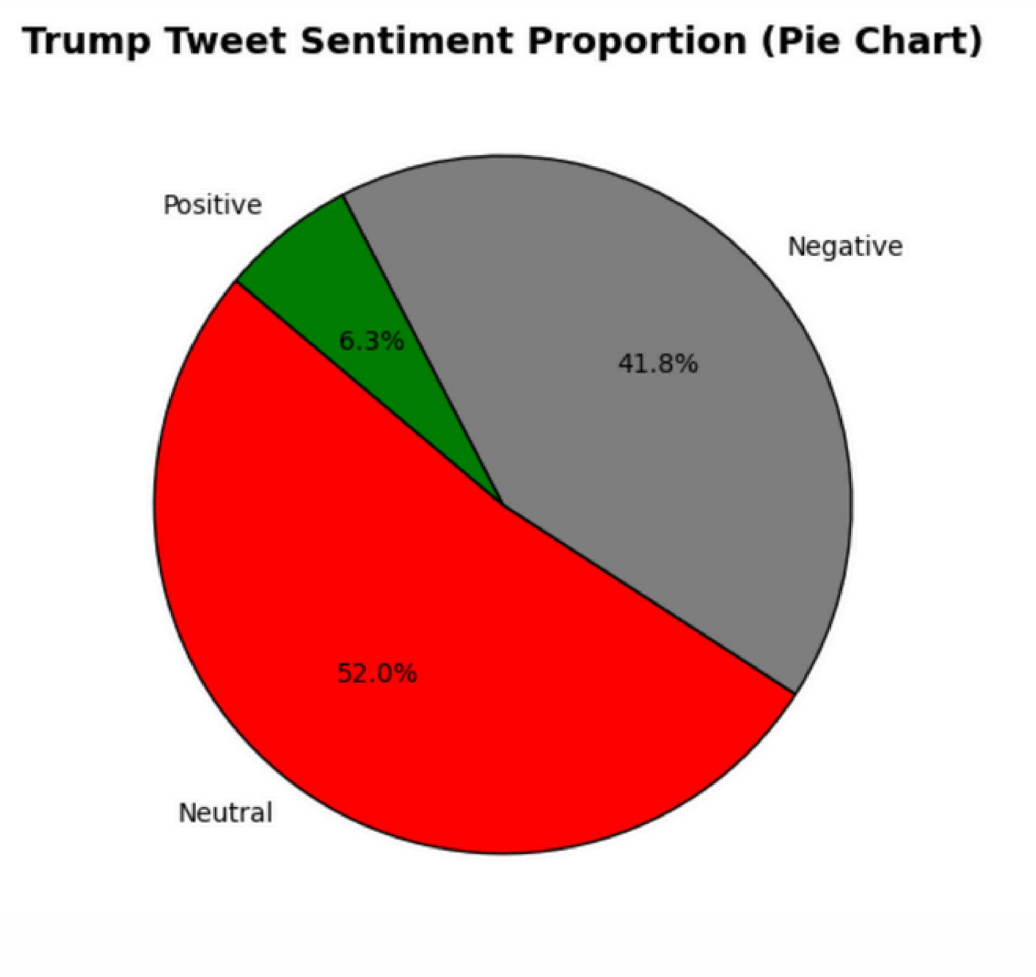
DistilBERT is a **lighter and faster** version of BERT. It significantly improved processing speed and solved kernel crash issues. However, DistilBERT only provided binary sentiment classification while we needed a Neutral category. This led us to RoBERTa.

03

RoBERTa is an **improved version** of BERT, the **Twitter RoBERTa** model (cardiffnlp/twitter-roberta-base-sentiment) is fine-tuned for analyzing tweets, making it ideal for our study. Unlike DistilBERT, RoBERTa supports three sentiment classes: Negative, Neutral, and Positive, which was essential for our analysis.

Model	Developer	Size	Speed	Accuracy	Pretraining Data	Sentiment Support	Best Use Case
BERT	Google AI	Large (110M+ parameters)	Slow (Computationally Heavy)	High	BooksCorpus & Wikipedia	Binary (Positive/Negative)	General NLP tasks
RoBERTa	Facebook AI	Large (125M+ parameters)	Moderate	Higher than BERT (More robust pretraining)	More diverse dataset (Common Crawl, News, Web)	3-class (Negative, Neutral, Positive)	Fine-tuned for sentiment analysis & NLP
DistilBERT	Hugging Face	Smaller (66M parameters)	Fast (60% of BERT's size)	Slightly lower than BERT	Same as BERT but compressed	Binary (Positive/Negative)	Optimized for efficiency and speed



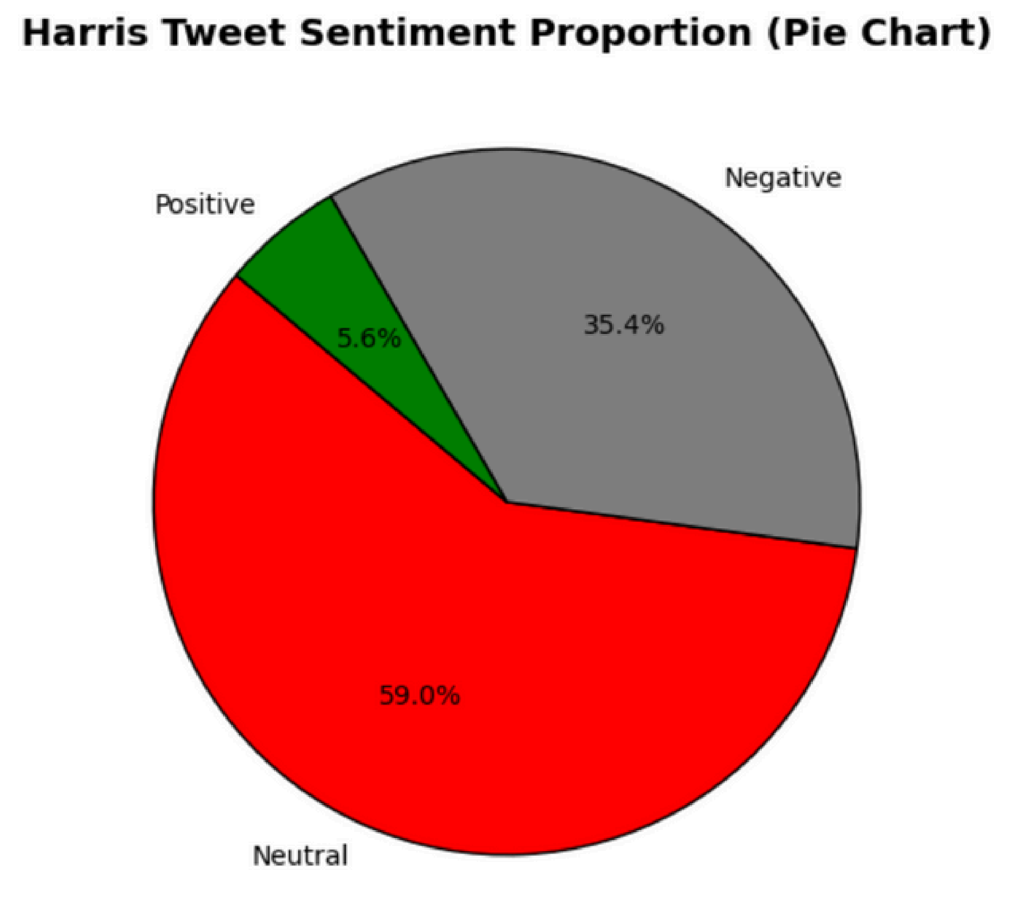


Sentiment Distribution Comparison (Bar Chart)

- Most tweets were neutral for both Trump (52%) and Harris (59%), showing that Twitter discussions were largely non-opinionated.
- Trump had more negative tweets (41.8%) compared to Harris (35.4%), suggesting higher criticism directed towards him.
- Positive sentiment was very low for both figures (Trump: 6.3%, Harris: 5.6%), indicating a lack of strong public support on Twitter.

Sentiment Breakdown (Pie Charts)

- Harris-related tweets leaned more neutral, while Trump-related tweets had a sharper divide between negative and neutral opinions.
- The lack of positivity for both figures suggests that political discussions on Twitter are more critical than supportive.



TEXTBLOB

TextBlob is a Python library for **natural language processing** (NLP) that simplifies text analysis. It provides easy-to-use functions for tasks like **sentiment analysis, part-of-speech tagging, noun phrase extraction, and text translation.**

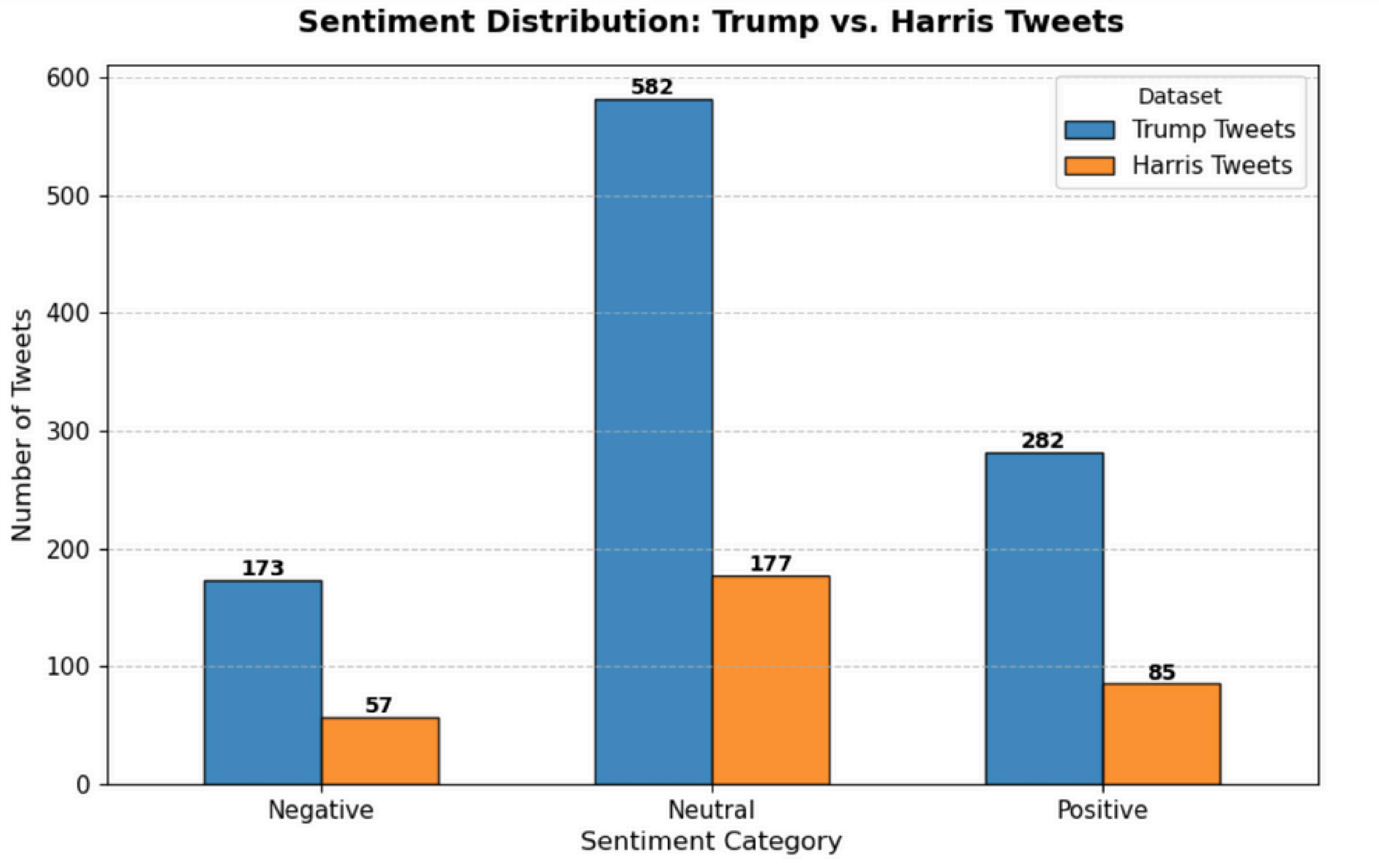
01

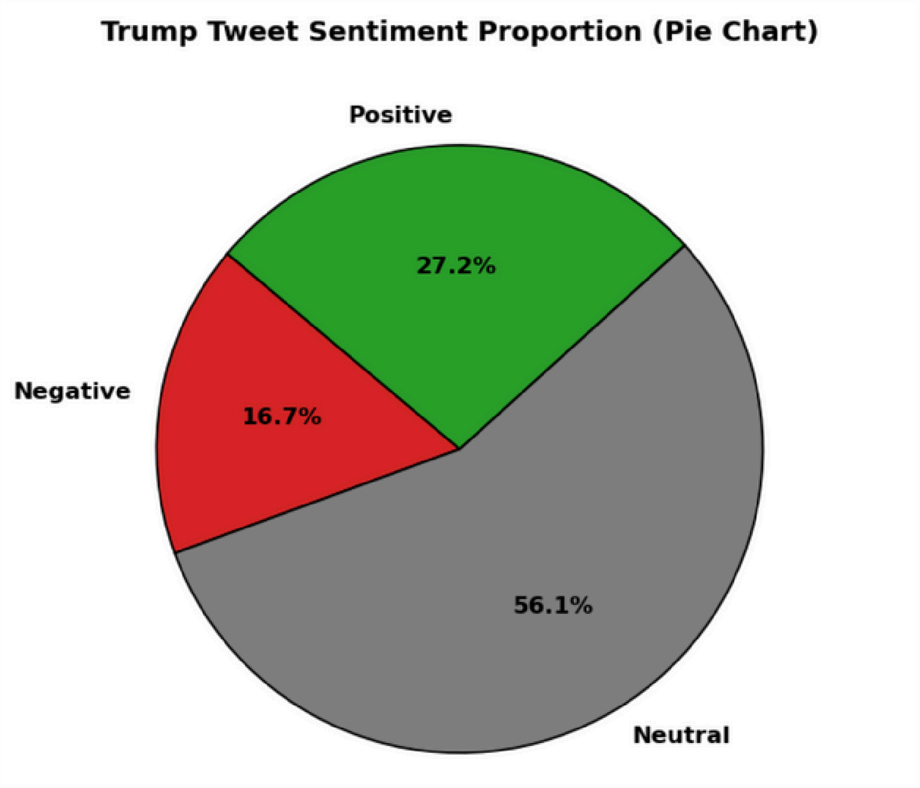
One of **TextBlob's key strengths** is its ease of use, making it ideal for **quick sentiment classification of tweets, reviews, and news articles**. It also supports tokenization, breaking text into words or sentences, and noun phrase extraction to identify key topics. Additionally, it can detect language and perform translation, adding flexibility for multilingual sentiment analysis.

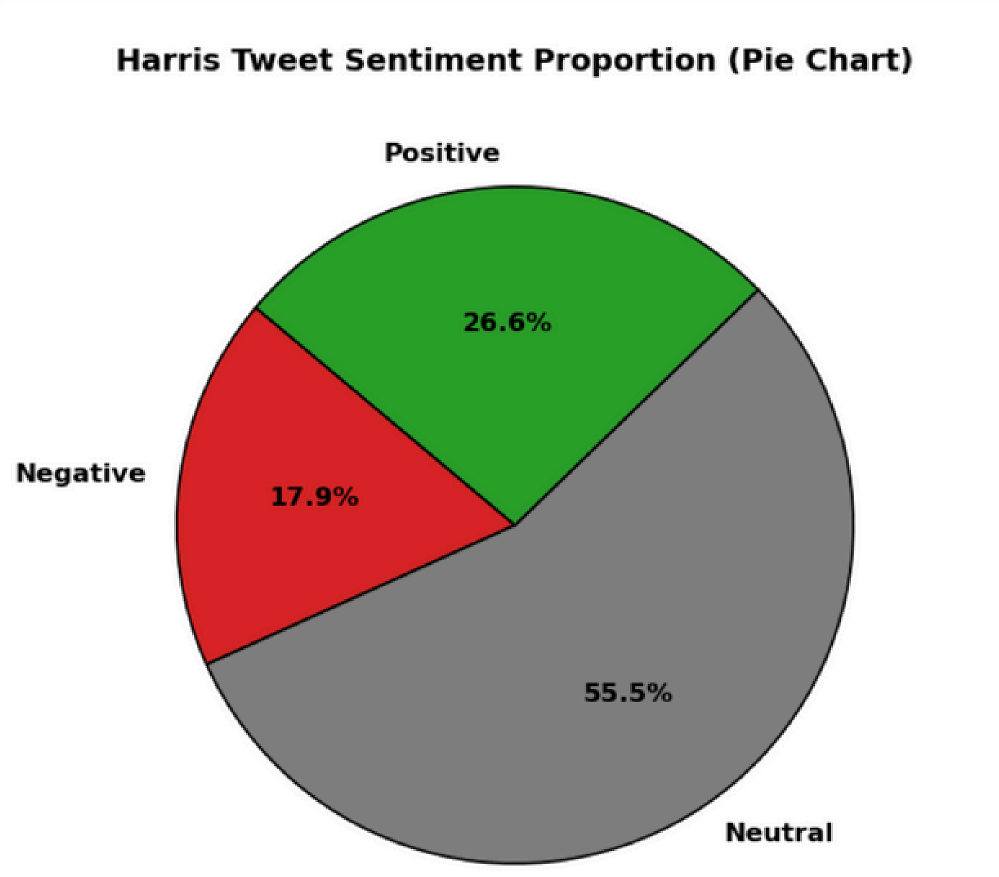
02

Despite its advantages, TextBlob relies on pre-built lexicons and is less context-aware than advanced deep learning models like BERT or GPT. It is best suited for lightweight sentiment analysis tasks but **may struggle with sarcasm, irony, or complex sentence structures.** For more accurate sentiment analysis, it can be combined with machine learning techniques or lexicon-based **tools like VADER.**

TEXTBLOB







Key Insights for Presentation:

Sentiment Distribution (Bar Chart)

Neutral sentiment dominates: **582 (Trump), 583 (Harris) tweets.**
Negative sentiment is higher for **Trump (433 tweets) vs. Harris (350 tweets).**
Positive sentiment is lowest: **Trump (65 tweets), Harris (55 tweets).**

Sentiment Breakdown (Pie Charts)

Neutral sentiment is the most common: **56.1% (Trump), 55.5% (Harris).**
Trump-related tweets show slightly higher negative sentiment **(16.7%) than Harris (17.9%).**
Positive sentiment is low: **27.2% (Trump), 26.6% (Harris**) → Discussions are **more neutral** or critical.

Final Takeaways

Discussions are **mostly neutral or negative** for both figures.
Trump tweets have a **sharper neutral vs. negative divide,** while Harris tweets lean more neutral.
Low positive sentiment suggests Twitter discussions are **critical or disengaged**.
Future analysis: Explore what drives **negative sentiment** and how discourse changes over time.

Execution of Sentiment Analysis

- **Lexicon-Based Scoring**

VADER has a dictionary of words, each assigned a sentiment score between -1 (negative) and +1 (positive). Example: "great" → 0.8 (positive) "bad" → -0.6 (negative) "awesome" → 0.9 (positive)

- **Intensity Modification Using Punctuation & Capitalization**

Emphasizers like exclamation marks, question marks, and ALL CAPS increase or decrease sentiment intensity. Example: "This is great!" gets a higher score than "This is great." Negation Handling
Words like "not" and "never" flip the polarity of nearby words. Example: "Not good" → Less positive than "good."

- **Conjunction Handling (e.g., "but")**

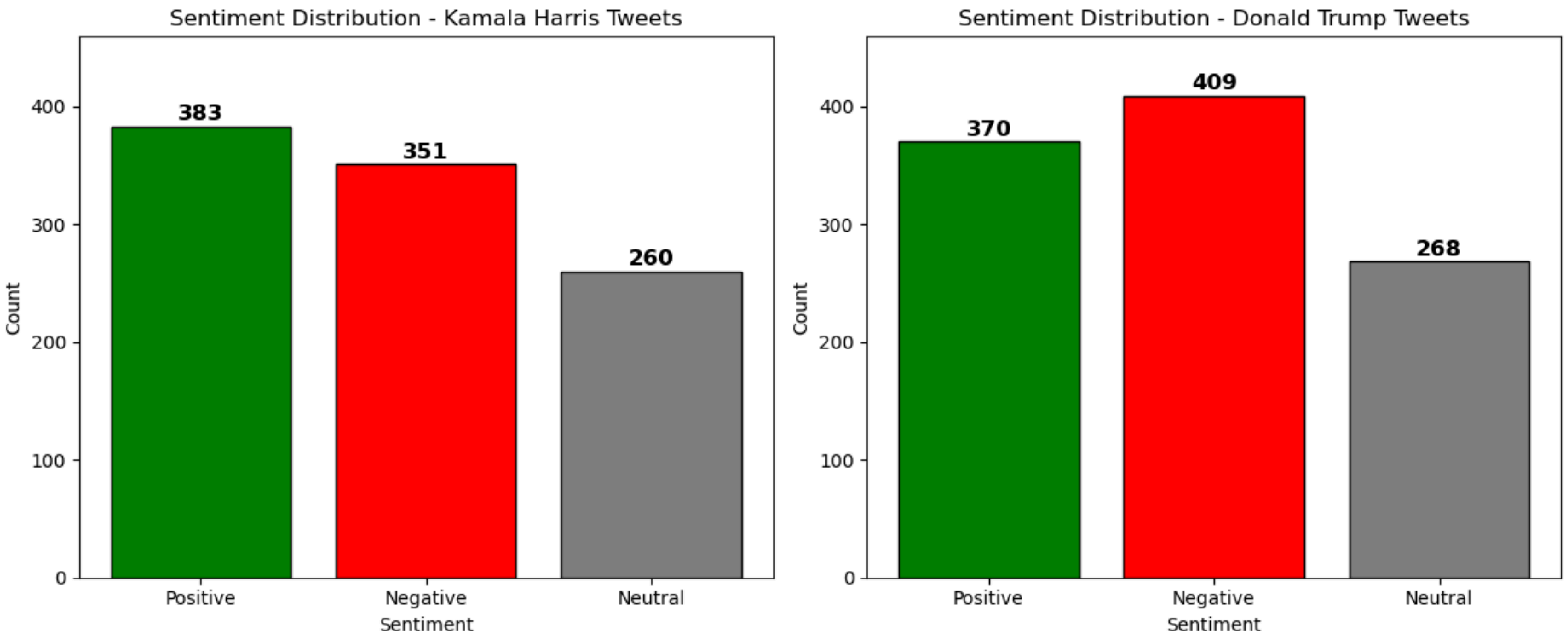
VADER gives more weight to words after contrastive conjunctions (e.g., "but," "however"). Example: "The movie was great, but the ending was terrible." Here, "terrible" has a stronger effect.

- **Compound Score Calculation**

VADER provides four sentiment scores: Positive: Proportion of positive words Negative: Proportion of negative words Neutral: Proportion of neutral words Compound: A single normalized score between -1 (most negative) and +1 (most positive) The compound score is the most useful for overall sentiment interpretation.

VADER

(Valence Aware Dictionary and sEntiment Reasoner)



Comparison Analysis of Sentiment Distribution in Tweets: Kamala Harris vs. Donald Trump:

The sentiment analysis of tweets from Kamala Harris and Donald Trump provides insights into public perception and sentiment polarity.

Key Takeaways

- More Criticism for Trump: Trump received a higher number of negative sentiment tweets (409) compared to Harris (354), suggesting that his tweets may have been more polarizing.
- Slightly Higher Positive Engagement for Harris: Harris had a slightly higher number of positive sentiment tweets than Trump, though the difference is minimal (381 vs. 371).
- Neutral Sentiment is Balanced: The neutral sentiment distribution is almost equal, indicating that a similar proportion of tweets for both figures are neutral or indifferent in tone.

AFINN Sentiment Analysis

AFINN Sentiment Analysis: A Simple yet Effective Approach
What is AFINN?

- AFINN is a precompiled sentiment lexicon developed by Finn Årup Nielsen that contains words associated with pre-assigned sentiment scores. It is widely used for rule-based sentiment analysis due to its simplicity and effectiveness.

How AFINN Works

Word-Level Sentiment Scoring

- Each word in the AFINN lexicon has a sentiment score ranging from -5 (very negative) to +5 (very positive).

Example:

"happy" → +3

"sad" → -2

"terrible" → -3

"fantastic" → +4

Sentence/Document-Level Sentiment Computation

- Tokenize the text into words.
- Look up each word in the AFINN lexicon.
- Sum up the individual word scores to calculate the overall sentiment score for a sentence or document.
- If no words from the AFINN list are present, the score is 0 (neutral).

Affin Analysis Findings

Sentiment Distribution

- Negative and Neutral sentiments dominate for both Harris and Trump.
- Trump has slightly more Negative tweets than Harris.
- Neutral tweets are the most common, indicating a balanced mix of opinions.

Sentiment by Topic

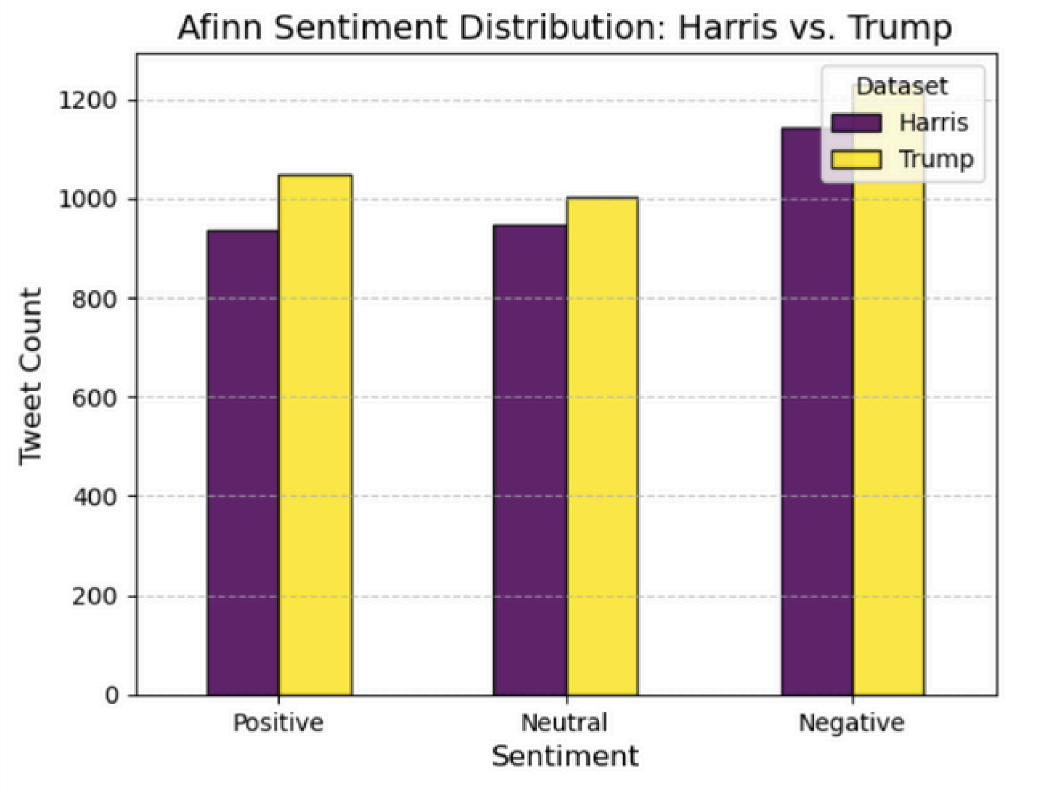
- Harris has a higher Positive sentiment on Healthcare compared to Trump.
- Trump's tweets are more Negative on Immigration than Harris'.
- Both candidates show Neutral sentiment when discussing Taxes.

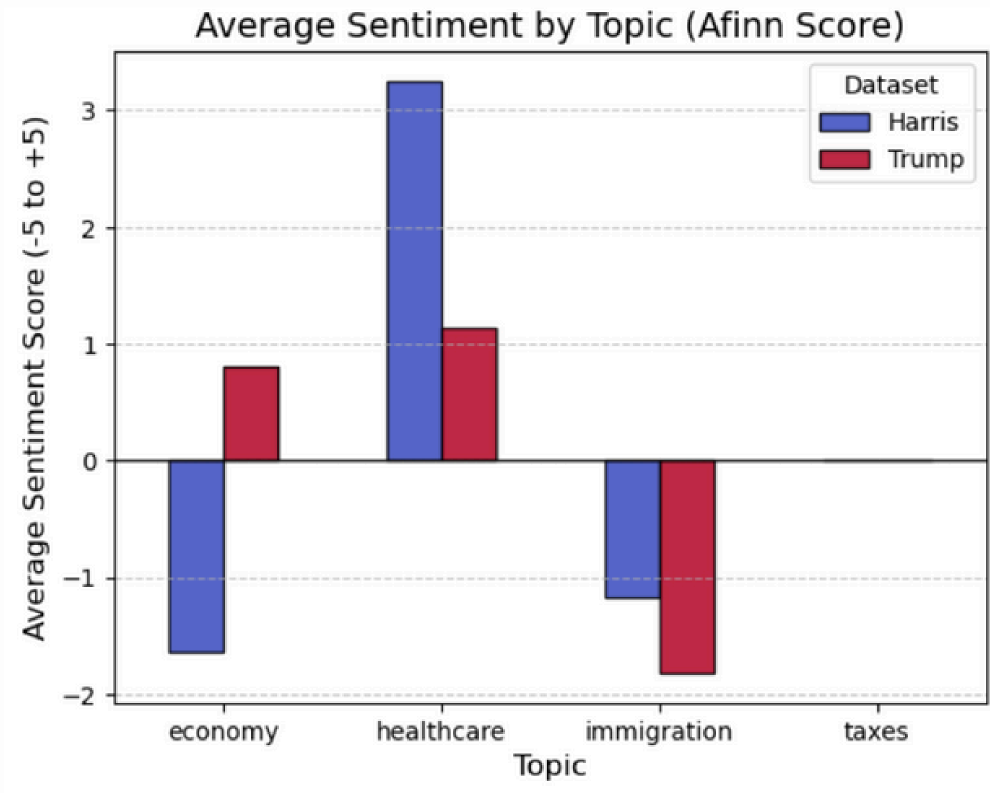
Sentiment vs. Retweets (Harris)

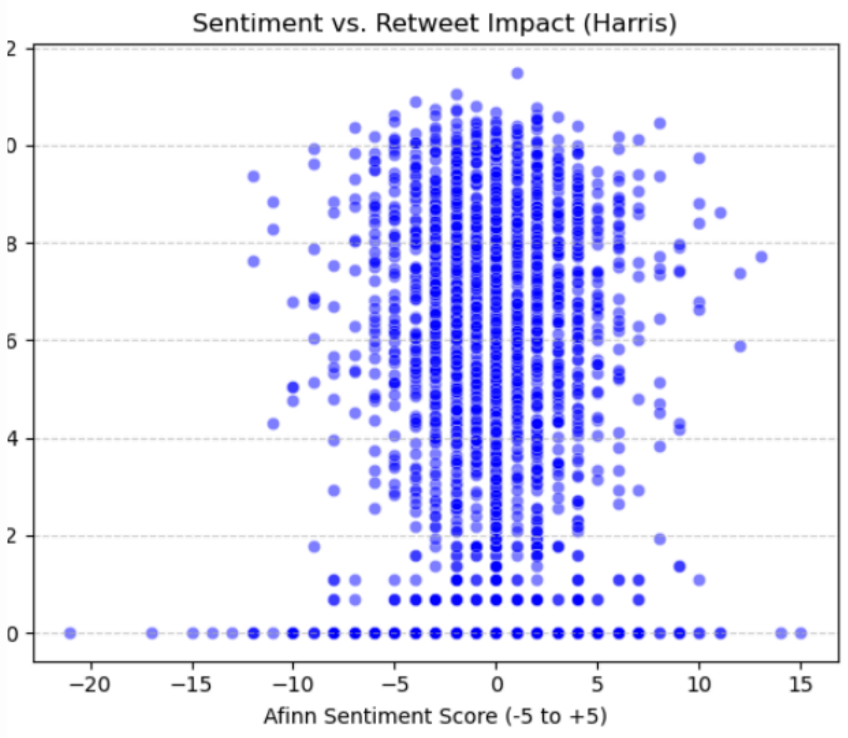
- No strong correlation between sentiment and retweets.
- Most tweets have low retweet weight, indicating limited virality.
- Both Positive and Negative tweets get shared, but no clear pattern emerges.

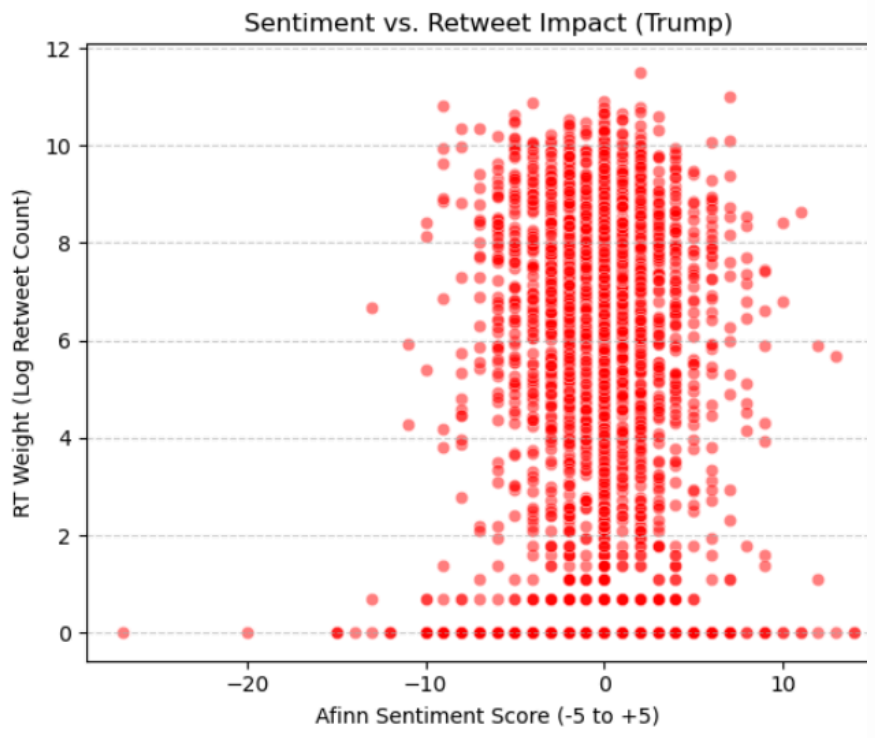
Sentiment vs. Retweets (Trump)

- Trump's tweets show a wider engagement spread compared to Harris'.
- Both Positive and Negative tweets can go viral.
- More tweets reached high retweet weight, demonstrating Trump's higher engagement potential.







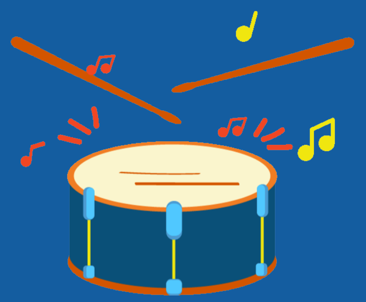


Comparing RoBERTa, Vader, TextBlob and AFINN

Feature	RoBERTa 🏆	VADER 🚀	TextBlob 📊	AFINN ⚡
Approach	Deep Learning (Transformer)	Lexicon-based rule model	Lexicon-based (Rule + Statistics)	Wordlist-based (Predefined Scores)
Best For	Long texts, complex sentiment, high accuracy	Short texts, social media, real-time analysis	Basic sentiment analysis, small datasets	Quick sentiment scoring, simple use cases
Handles Context?	✅ Yes	❌ No	❌ No	❌ No
Handles Negation?	✅ Yes	✅ Yes	❌ No	❌ No
Understands Sarcasm?	✅ Somewhat	❌ No	❌ No	❌ No
Understands Emojis, Slang?	❌ No	✅ Yes	❌ No	❌ No
Computational Cost	❌ High (Needs GPU for best results)	✅ Low (Fast, runs on CPU)	✅ Low (Fast, runs on CPU)	✅ Low (Fast, runs on CPU)
Speed	❌ Slow	✅ Extremely fast	✅ Fast	✅ Fast
Fine-tuning Possible?	✅ Yes (can be trained on specific datasets)	❌ No	❌ No	❌ No
Accuracy	✅✅ Very High	✅ Medium-High (Optimized for social media)	❌ Low-Medium	❌ Low-Medium

Cue drumroll

Conclusion: Our Favourite Library?



Use Case	Best Choice
News articles, long reviews, complex sentiment	RoBERTa
Short social media posts (tweets, comments, chats)	VADER
Real-time analysis (fast sentiment classification)	VADER
Fine-tuning on domain-specific sentiment tasks	RoBERTa
Financial, political, or business sentiment analysis	RoBERTa
Emojis, punctuation-based sentiment analysis	VADER

Vader!!

Why?

- Fast, lightweight, and real-time analysis, especially for tweets and social media

Thank You