NLP ANALYSIS ON TWITTER FEEDBACK ON APPLE AND GOOGLE PRODUCTS

Benson Kamau

Nancy Chelangat

Sally Kinyanjui

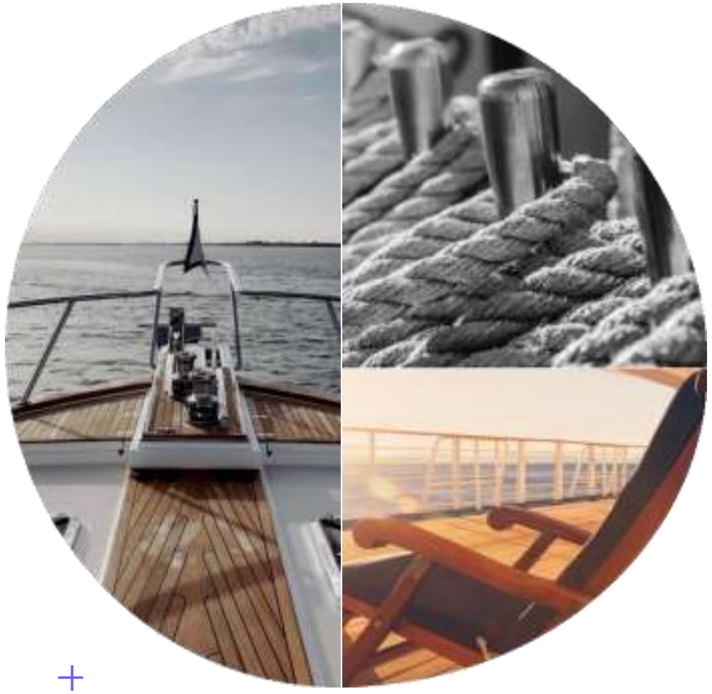
Breden Mugambi

Kevin Muchori

Business Understanding

Apple and Google continually innovate, leading to a surge in customer feedback that needs to be analyzed to understand user sentiments. Twitter provides a unique platform for collecting this feedback, essential for understanding consumer behavior and making data-driven decisions.

Problem Statement



Classifying the sentiments expressed in tweets about topics or brands into positive, negative, or neutral classes is challenging. The informal nature of Twitter data, with its slang and abbreviations, makes it complex to develop a reliable sentiment analysis model. Accurately interpreting these tweets provides valuable insights into consumer interactions with products and brands.

Objectives

Goal: Build a model to classify the sentiment of tweets based on their content.

Metrics: Achieve over 70% accuracy on testing data.

Data Understanding

Dataset: 9,093 tweets with columns for tweet text, emotion expressed, and target product/brand.

Source: CrowdFlower via data.world, focused on tweets about Apple and Google products post-2011 SXSW Conference.

Data Preparation and Cleaning

Renamed columns.

Handled null values, duplicates, and missing values.

Lemmatized tweets, removed stop words, and performed tokenization.

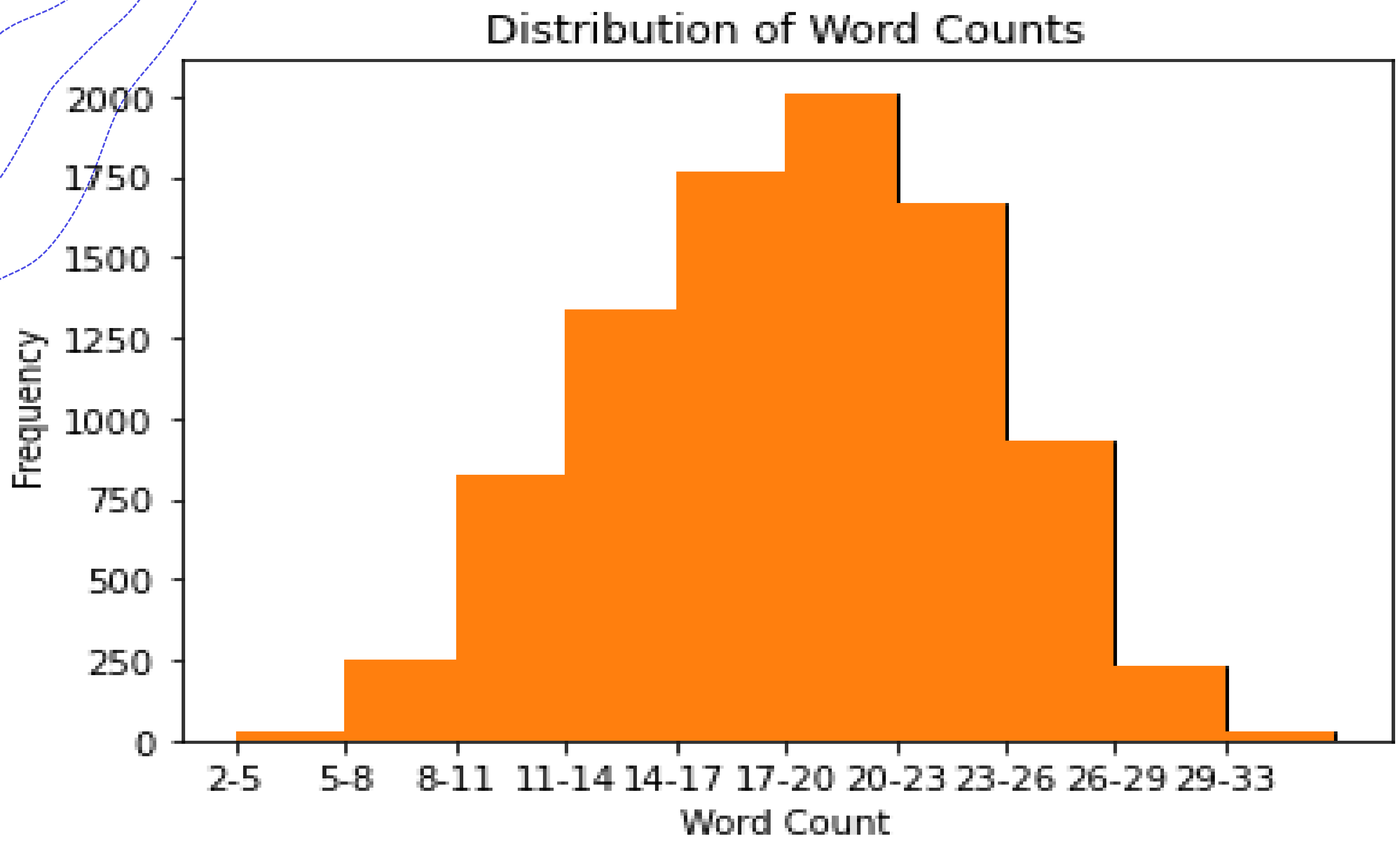
DATA ANALYSIS

Word Count Analysis: Most tweets contain 20-23 words.

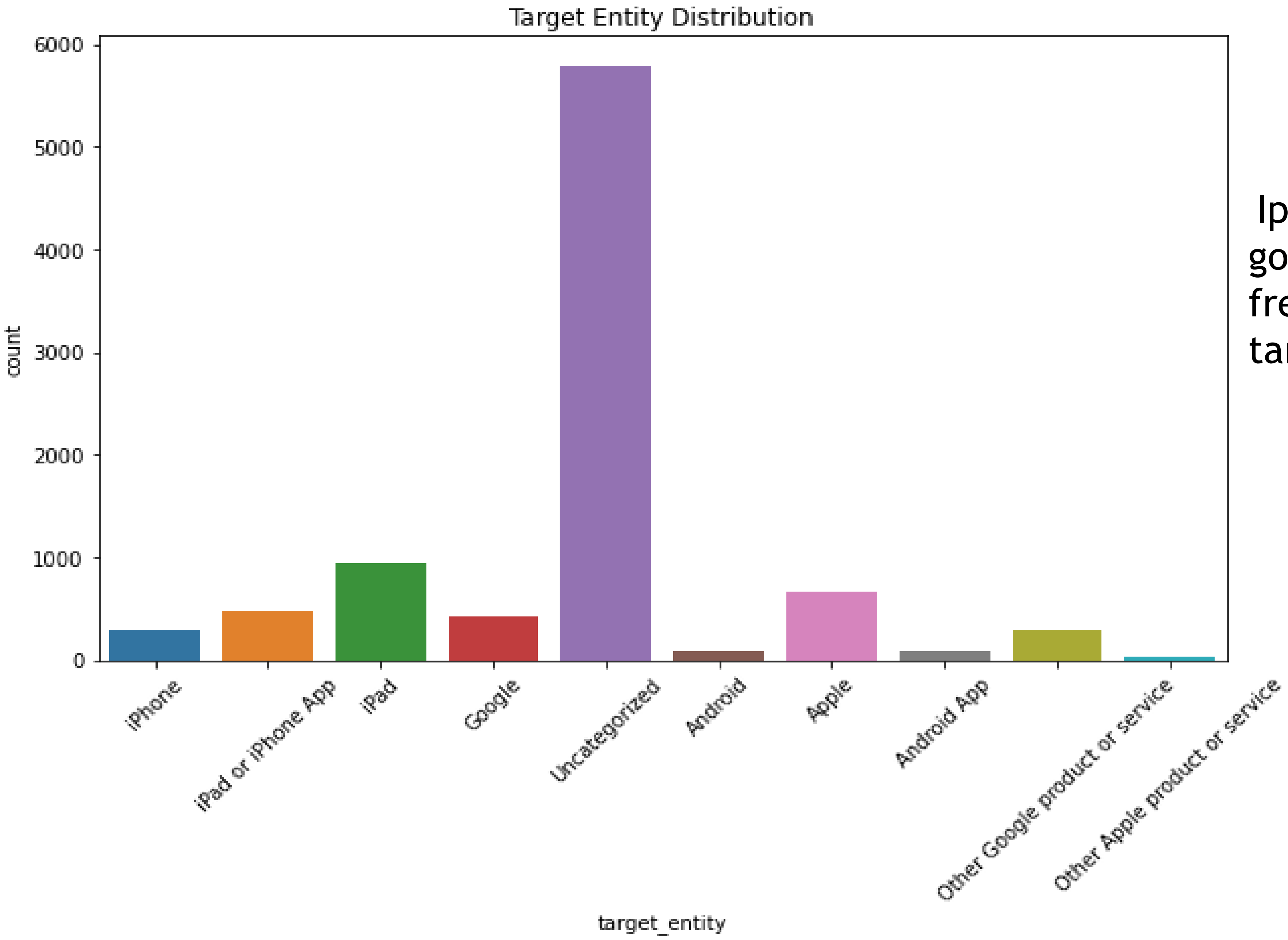
Frequent Entries: "iPad," "Apple," and "Google" are the most frequent target entries.

Word Cloud: Visual representation of the most common terms.

Data Analysis

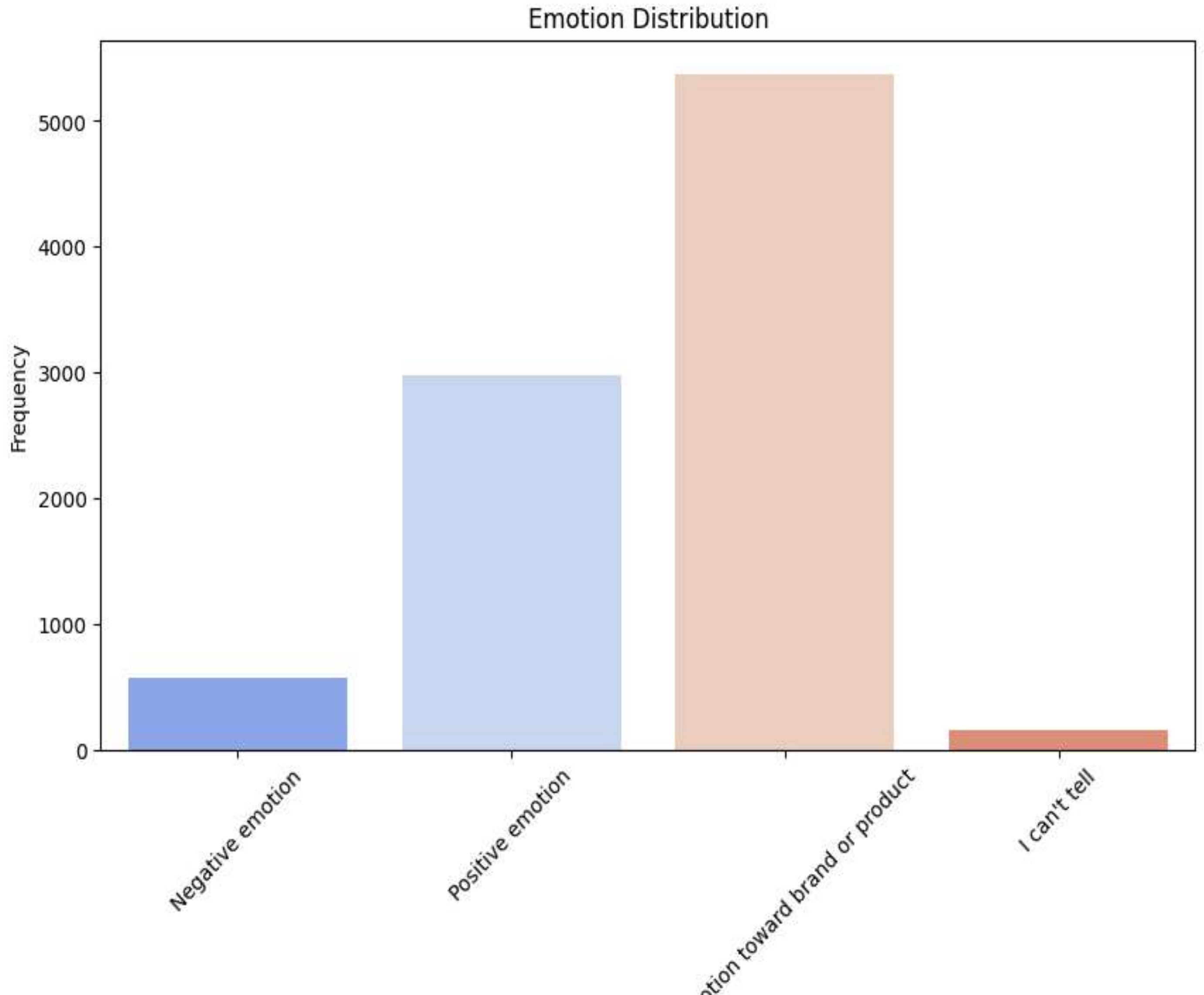


Most of the words in the document lie between 20-23 words.



Ipad, apple and google are the most frequent entered target entries.

Emotion distribution



Modeling

Explored different models to predict tweet sentiments:

Naive Bayes: This was our baseline model with a testing accuracy of 67%.

Logistic Regression: 68% accuracy.

Decision Tree: 61% accuracy.

Support Vector Machine (SVM): 71% accuracy.

Deep Learning

CNN: Highest training accuracy (91.22%) but potential overfitting. Testing accuracy was 65.43%
LSTM and GRU: Training accuracy (87.42% and 87.00%) with better generalization on unseen data. Testing accuracy was 64.66% & 64.22% respectively.

Performance: CNN outperformed LSTM and GRU in precision and recall for different classes.

CONCLUSION

The models performed well on training data but struggled with test data, likely due to dataset imbalance. SVM, with 71% accuracy, is recommended for classifying tweet sentiments.

Business Recommendations

- **Enhance Product Features Based on Feedback**: Regularly monitor and analyze sentiment trends to understand user satisfaction and areas needing improvement. Implement changes to product features based on the insights gained from sentiment analysis.

- **Improve Customer Engagement**: Utilize positive feedback to reinforce marketing strategies and address negative feedback by improving customer service and support mechanisms. Engage with users on social media to acknowledge their feedback and show responsiveness.

- **Tailor Marketing Campaigns**: Use sentiment analysis to tailor marketing campaigns. Positive sentiments can highlight strengths in advertising, while negative sentiments can guide addressing user concerns proactively.

- **Monitor Competitor Products:** Keep track of sentiments related to competitors (e.g., Apple's iPad and Google's products). Understanding how competitors are perceived can provide strategic advantages in positioning your products.

Next Steps

Model Refinement:
Incorporate slang and urban abbreviations.
Regularly assess and update the model with new data.

Real-Time Analysis:
Implement real-time sentiment monitoring.
Quickly detect and respond to shifts in public sentiment.

Expand Data Sources:
Broaden the dataset to include diverse sources for comprehensive analysis