



Sentiment Analysis of Apple & Google Products on Twitter

Leveraging NLP to Understand Customer Perceptions.

Introduction

Objective

This project targets the utilization of Natural Language Processing methodologies to analyze customers' sentiment towards products offered by Apple and Google on Twitter. The insight generated will inform marketing and product development strategies.





Business Problem & Stakeholder

Business Problem

Understanding public sentiment is important to Apple and Google for improving customer satisfaction, optimizing product development, and adapting marketing communications.

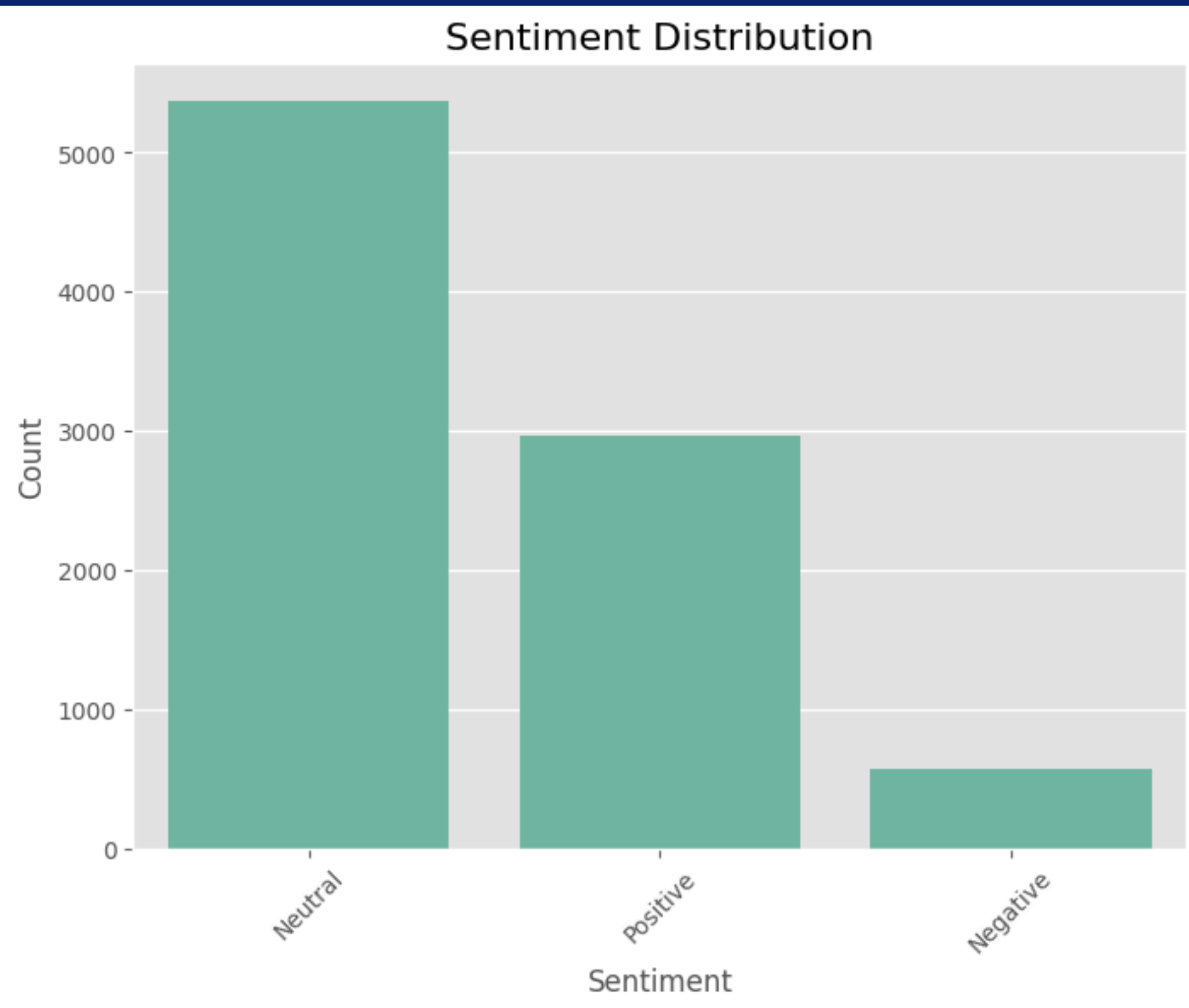


Stakeholders

- **Apple and Google Product Teams:** Use sentiment data to improve products and address customer pain points.
- **Marketing Departments:** Tailor campaigns to target sentiment-driven messaging.
- **Customer Support Teams:** Identify negative feedback more quickly to address concerns.
- **Executives/Decision Makers:** Gain a high-level view of public opinion, enabling better strategic planning.

Exploratory Data Analysis

Sentiment Class Breakdown



Mainly, the Neutral Sentiment Dominates: The majority of these tweets, numbering over 5,000, are dominated by neutral sentiment, whereby a majority of users do not hold strongly positive or negative opinions with regard to the discussed topics.

01

Positive sentiment stands second; there are more than 3,000 tweets classified as positive. This depicts favorable opinions and excitement within the discussions.

02

Low Negative Sentiment: Negative sentiment is the least expressed in less than 1,000 tweets, meaning that less often do the users share critical or unfavorable content regarding the analyzed subjects.

03



Most Common Words

01

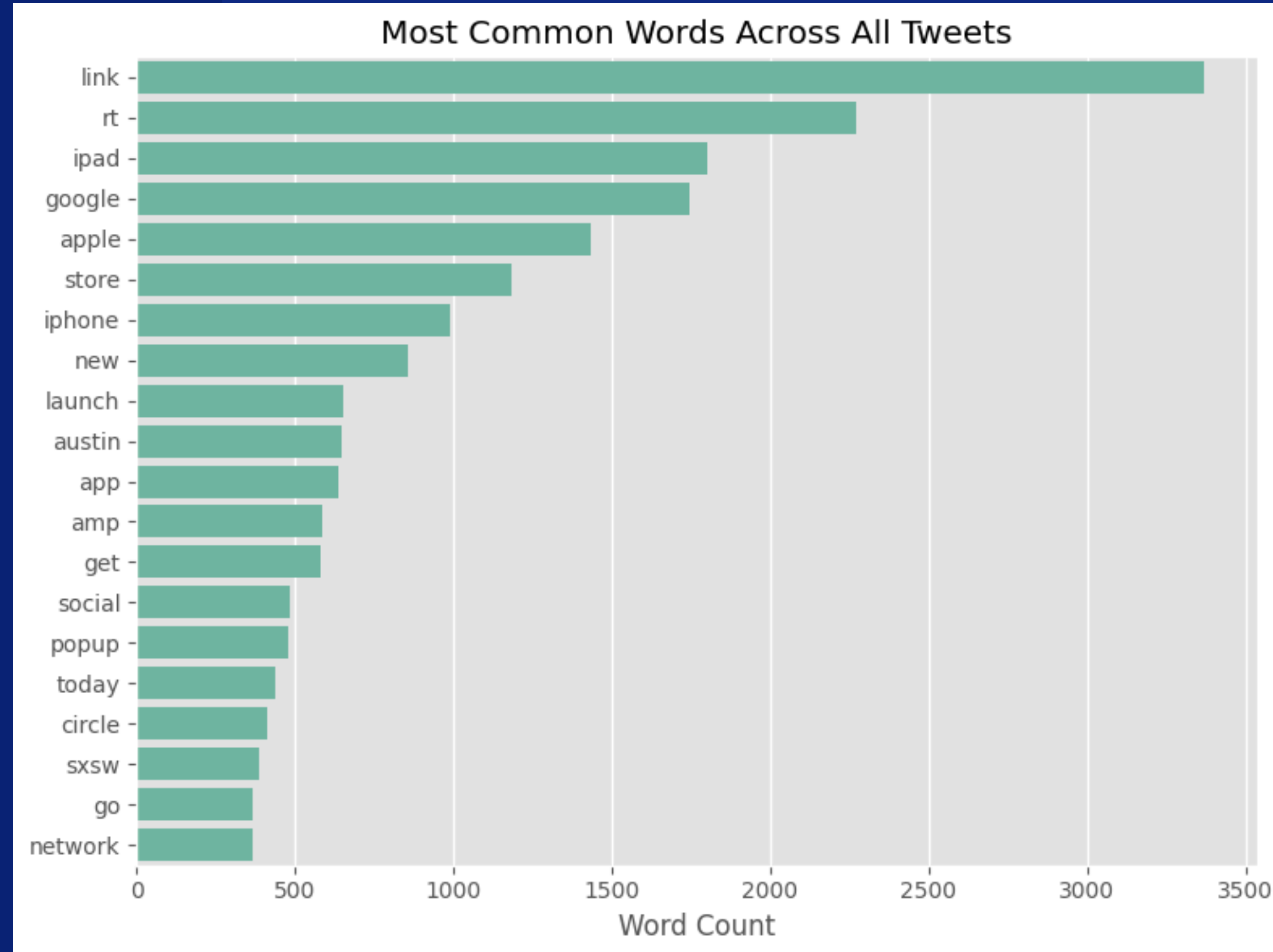
Tech Product Focus: The iterated use of product terminology, such as "ipad", "google", "apple", "iphone", makes frequent references to product launches and consumer preferences.

02

Event Relevance: Words like "launch", "austin", "sxsw" show that there is also a focus on the events held within the tech industry, so perhaps these may be the kind of events which create the biggest consumer involvement and discussion.

03

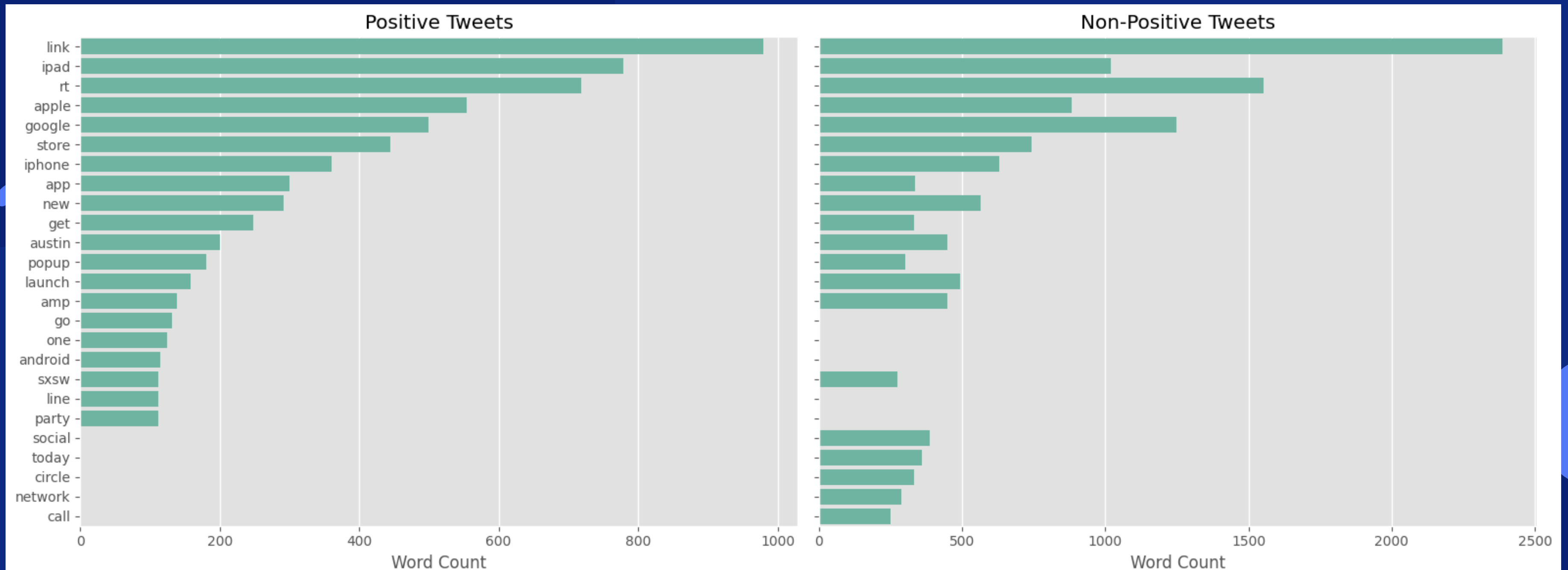
E-commerce Discussions: This includes the use of the terms "store," "app," and "popup," indicating it's a discussion related to online purchasing, the use of apps, and strategies by retailers.





Positive vs. Non-Positive Tweets

Tech products like "ipad", "apple", "iphone" dominate both the positive and non-positive tweets, while event-related terms drive engagement: "austin", "launch", and "sxsw". Besides, positive tweets were about product features and launches, whereas nonpositive tweets talked about frustrations with aspects like "network" and "call".

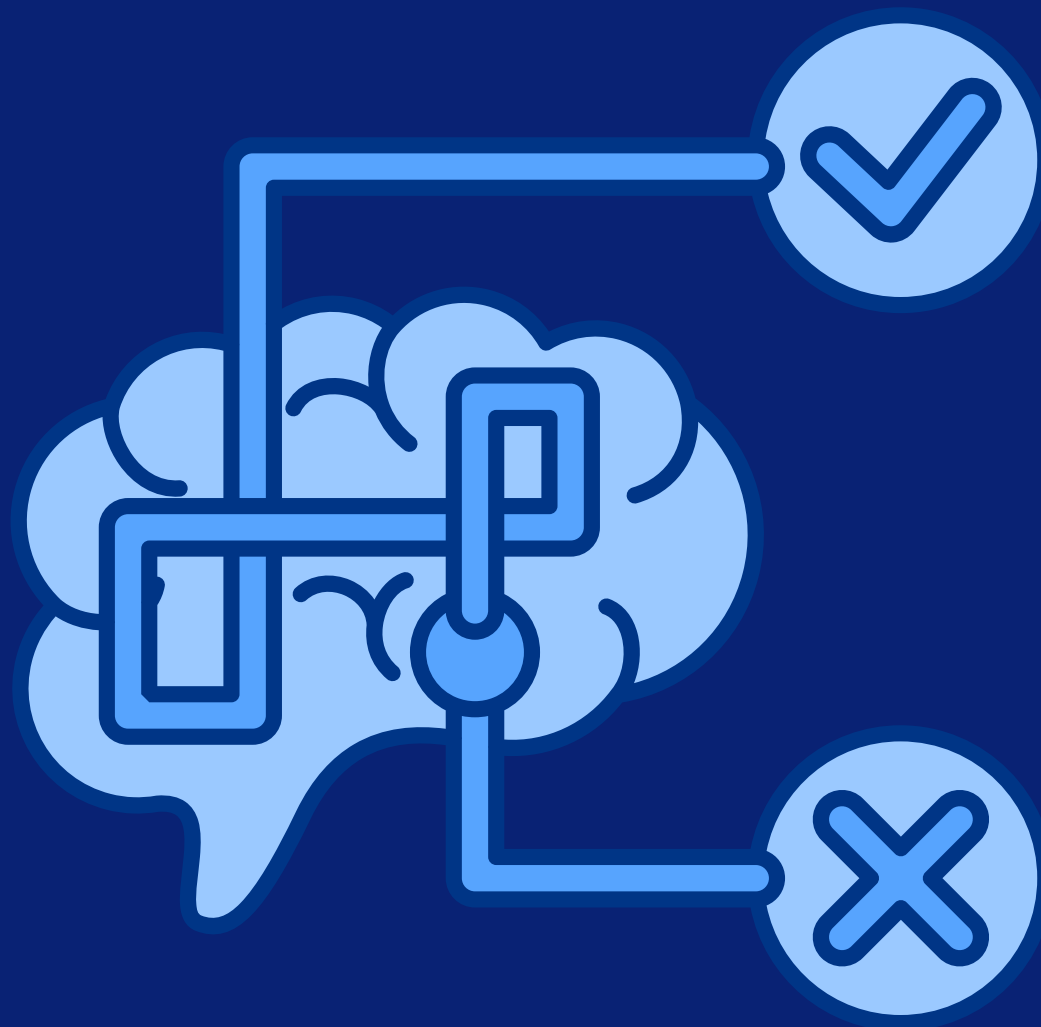




Modeling Approach

Binary Classification

- ✓ Logistic Regression
- ✓ Naive Bayes



Logistic Regression was chosen because of its simplicity, interpretability, and excellent performance for binary classification, especially when combined with TF-IDF features.

Naive Bayes is quite efficient for high-dimensional and sparse text data and very fast and scalable. Applying both models will give us an opportunity to compare the performance of these two models and choose the best one for our sentiment analysis.



Model Performance Overview

Logistic Regression

The Logistic Regression Model could achieve 87% accuracy in either predicting the sentiments of the tweets.

Accuracy

87%

In the classification of positive sentiment, it was 85%, which means 85% of the tweets that the model classified as positive were indeed positive.

Precision

85%

The model was able to recall 80%, meaning the model correctly found 80% of the actual positive sentiments.

Recall

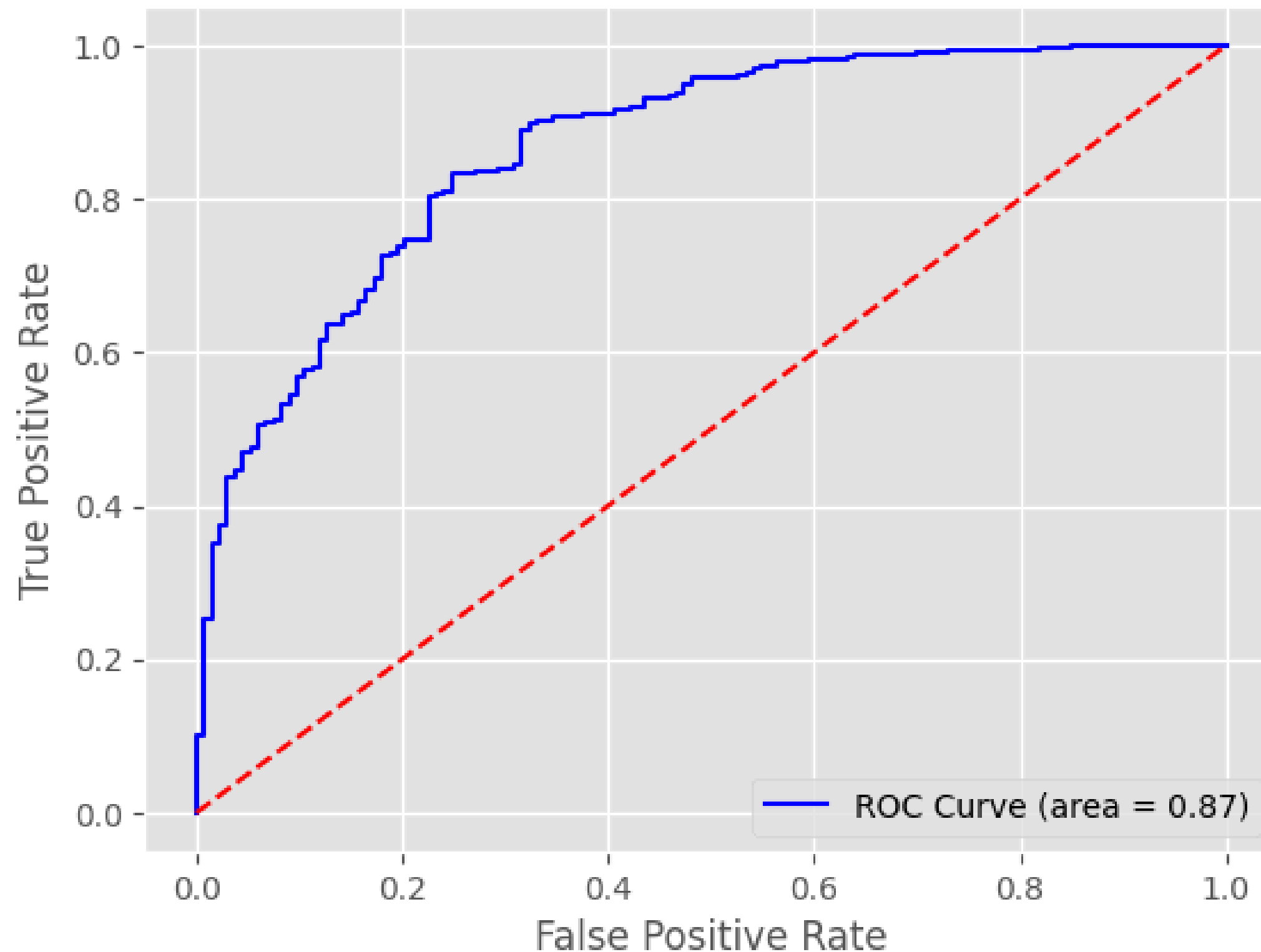
80%

The F1-score stood at 82%, representing good balance between precision and recall, ensuring the classification was relevant as well as complete.

F1-score

82%

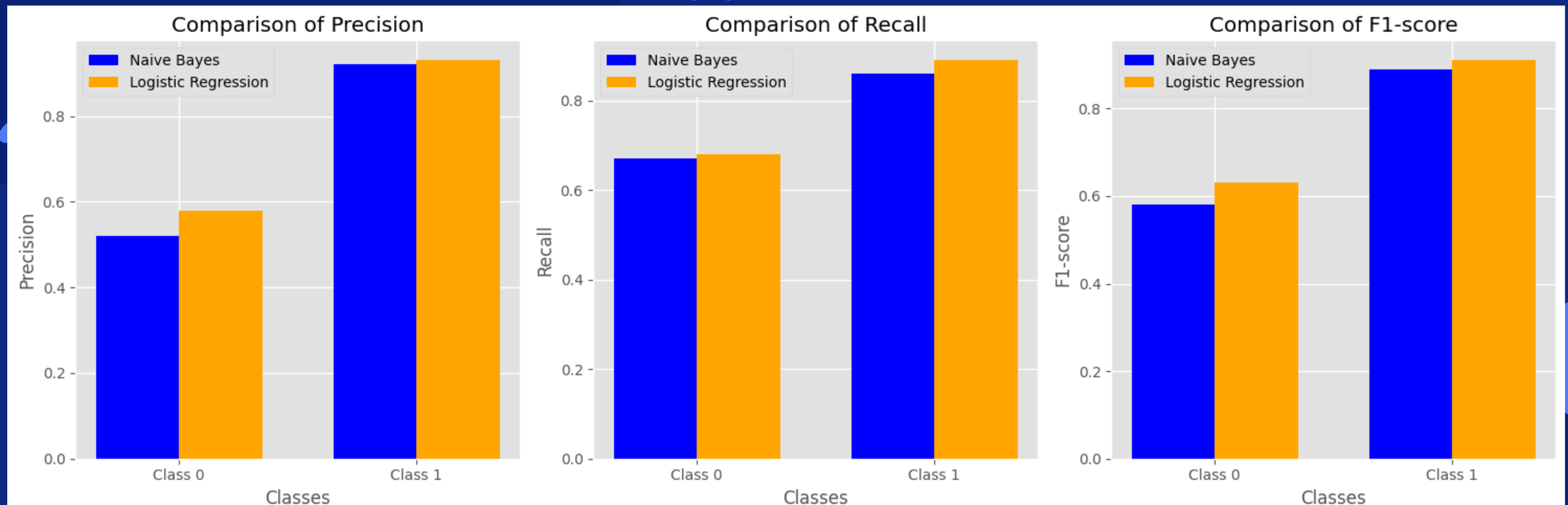
ROC Curve for Logistic Regression





Comparison Charts

Logistic Regression scores a little higher in precision and F1-score in the positive sentiment classification, which means the model performs better in classifying positive tweets correctly. On the other hand, Naive Bayes does a little better on recall, which suggests it identifies more true positive tweets out of all the positive tweets.

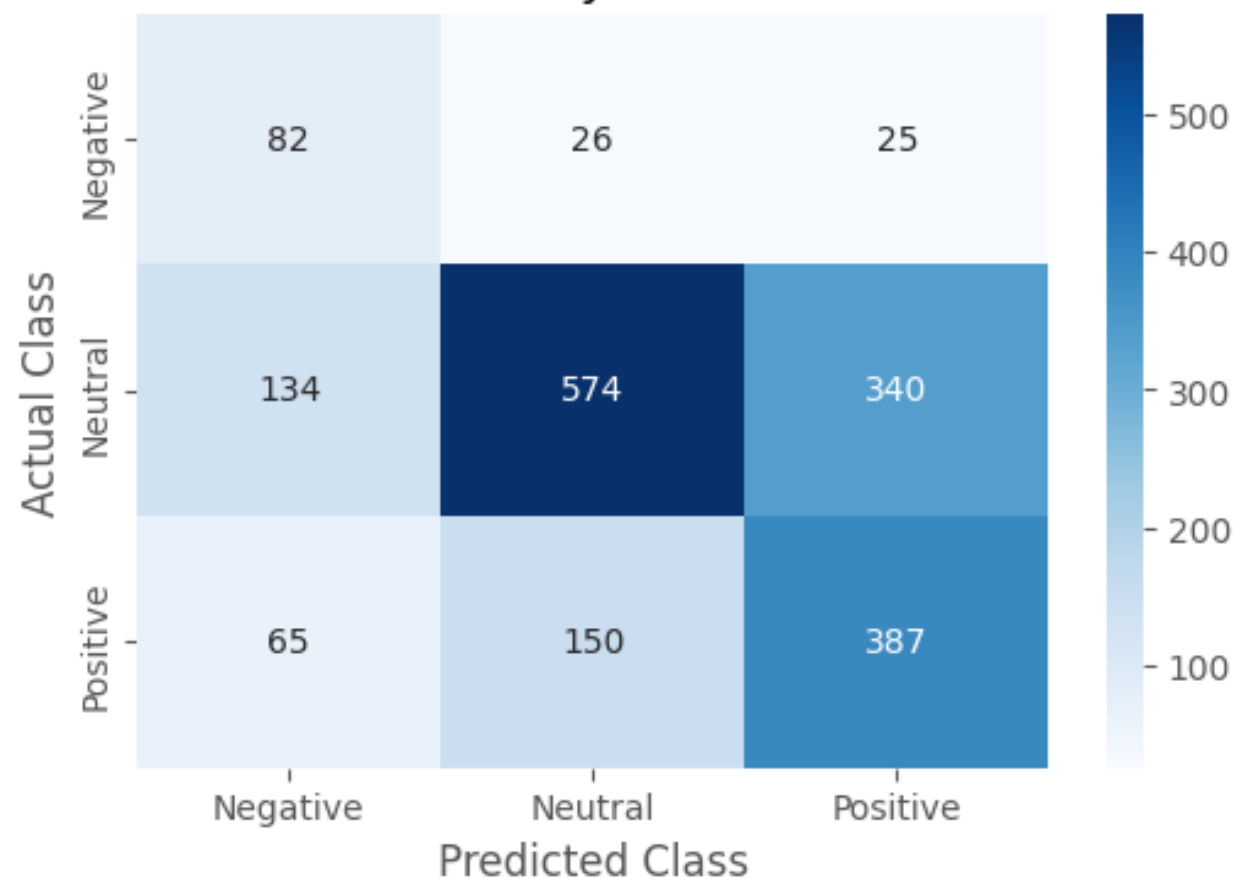




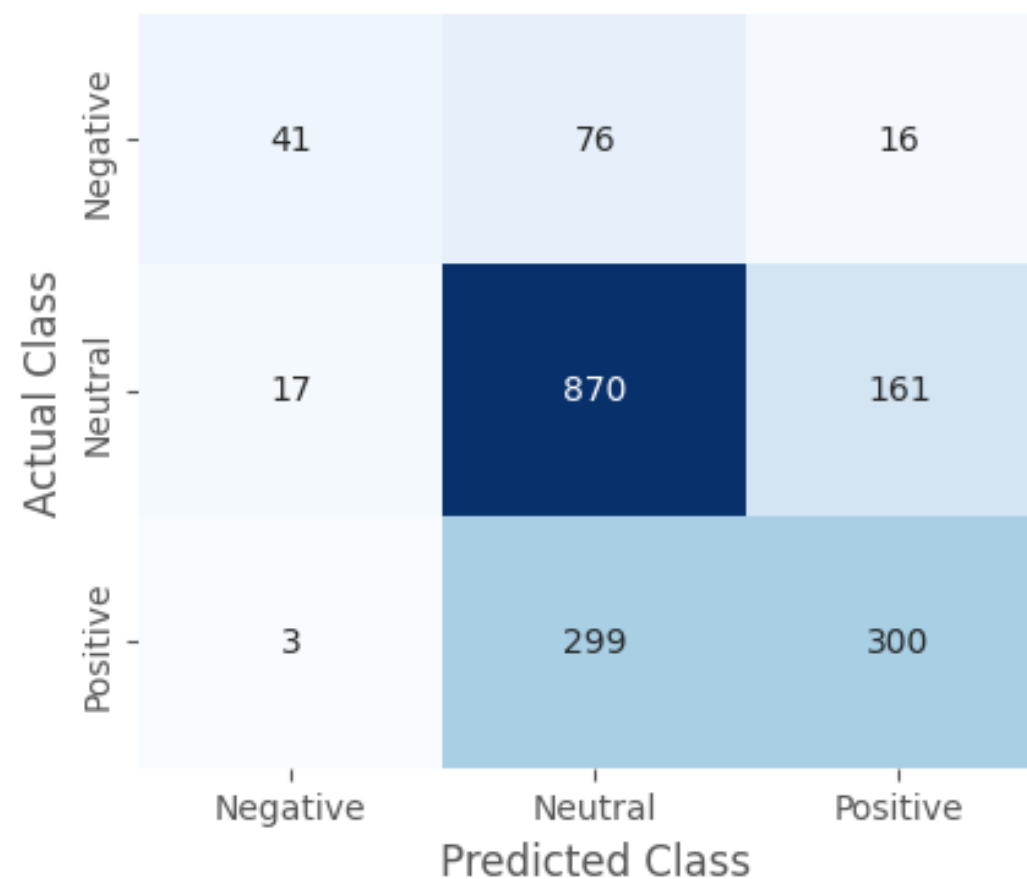
Multiclass Classification (Positive, Negative, Neutral)

- All three models performed best when identifying **Neutral** sentiments, but struggled with **Positive** and **Negative** classification.
- **Logistic Regression** showed the most balanced performance overall, while **Random Forest** excelled in recognizing **Neutral** sentiments but faced difficulties with **Positive** and **Negative** classifications.
- **Multinomial Naive Bayes** is more prone to confusion between **Neutral** and **Positive** sentiments.

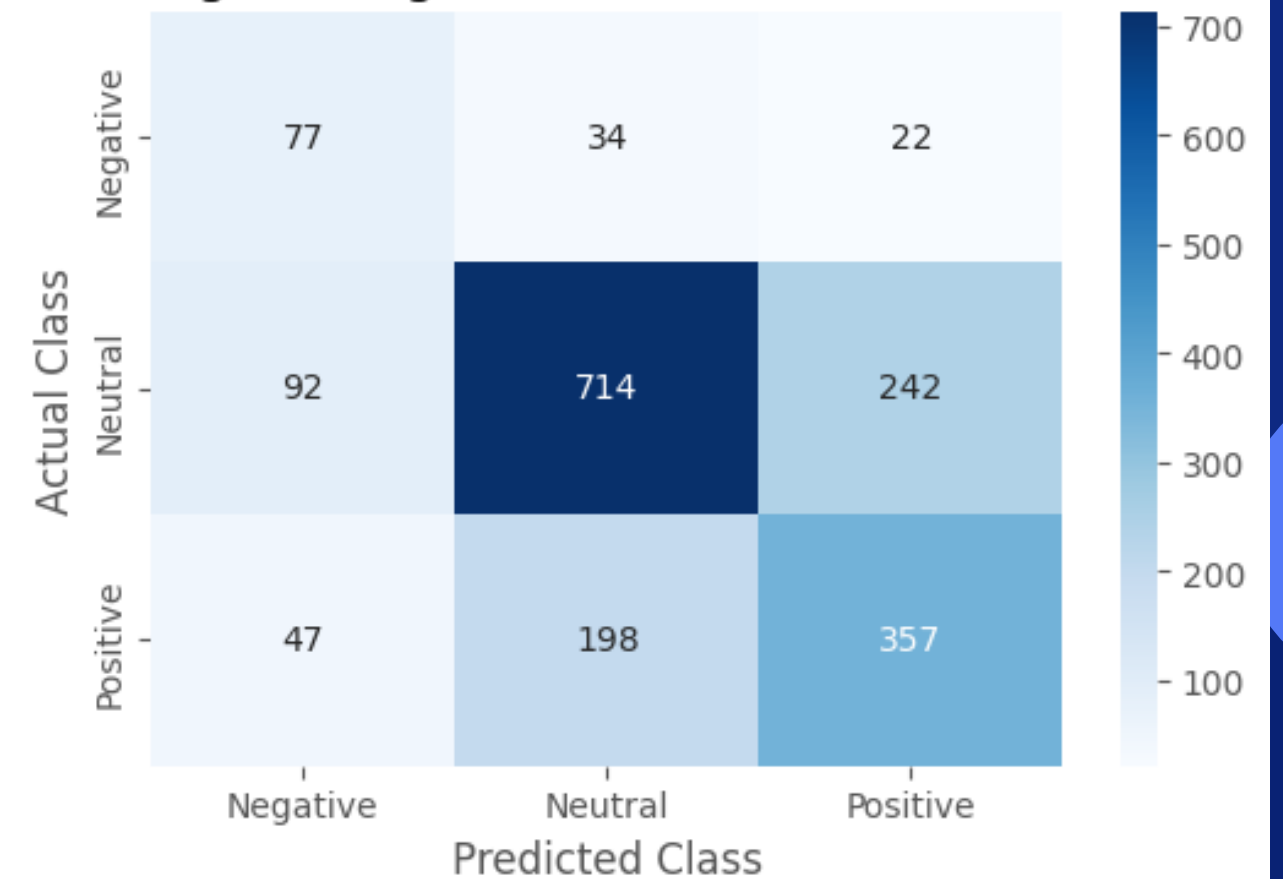
Multinomial Naive Bayes - Confusion Matrix



Random Forest - Confusion Matrix



Logistic Regression - Confusion Matrix





Final Model Selection

Logistic Regression

- **Negative Class:**

- 43 true negatives (correctly classified as Negative)
- 64 false positives (predicted as Positive but are actually Neutral)
- 26 false negatives (predicted as Negative but are actually Positive)

- **Neutral Class:**

- 813 true positives (correctly classified as Neutral)
- 31 false positives (predicted as Negative but are actually Neutral)
- 204 false negatives (predicted as Neutral but are actually Positive)

- **Positive Class:**

- 333 true positives (correctly classified as Positive)
- 11 false positives (predicted as Negative but are actually Positive)
- 258 false negatives (predicted as Positive but are actually Neutral)

Logistic Regression

Confusion Matrix

True label	Predicted label		
	Negative	Neutral	Positive
Negative	44	63	26
Neutral	31	816	201
Positive	11	262	329



Business Insights



**Customer Sentiment
Distribution**

includes a majority of Neutral sentiments, showing the number of balanced feelings among customers. At the same time, there is also negative sentiments reflecting improvements to be made.



**Key Topics of
Interest**

Words that frequently appear in positive or negative sentiments can help the companies understand which features or services are most praised or criticized. For example, the frequency of the words "advice," "ranking," and "website" in positive sentiments depicts aspects of the business with which the customers are satisfied.



**Enhancing Customer
Relations**

Prevailing sentiment will also let Apple and Google devise appropriate policies of customer service, gearing them towards dispelling negative perceptions and strengthening positive responses.

Conclusion

The sentiment analysis model categorized the tweets as positive, neutral, and negative, respectively. Such valuable information would help a brand learn about customer opinions, which may guide marketing strategy and improve customer engagement through aligning offerings to customer expectations. This will also improve customer satisfaction and loyalty by identifying trends in sentiment in a timely manner.

