Twitter Sentiment Analysis

Analysis and Modeling of Twitter Data for Sentiment and Emotion Detection

GROUP 4 : MONICA, FESTUS, ISAAC, MICHAEL, KABARE

Introduction

Objective

Develop a Natural Language Processing (NLP) model to accurately classify the sentiment of Tweets about Apple and Google products into three categories: positive, negative, and neutral.

The data, sourced from CrowdFlower, contains over 9,000 Tweets labeled by human raters. By analyzing this data, the model will help Apple and Google better understand customer perceptions of their products, allowing them to make informed decisions for marketing, customer service, and product development.

Business Problem & Stakeholder

Business Problem

Public perception of tech products can heavily influence a company's sales, customer satisfaction, and brand loyalty. For companies like Apple and Google, understanding how customers feel about their products can provide valuable insights into areas for improvement, marketing strategies, and product development.

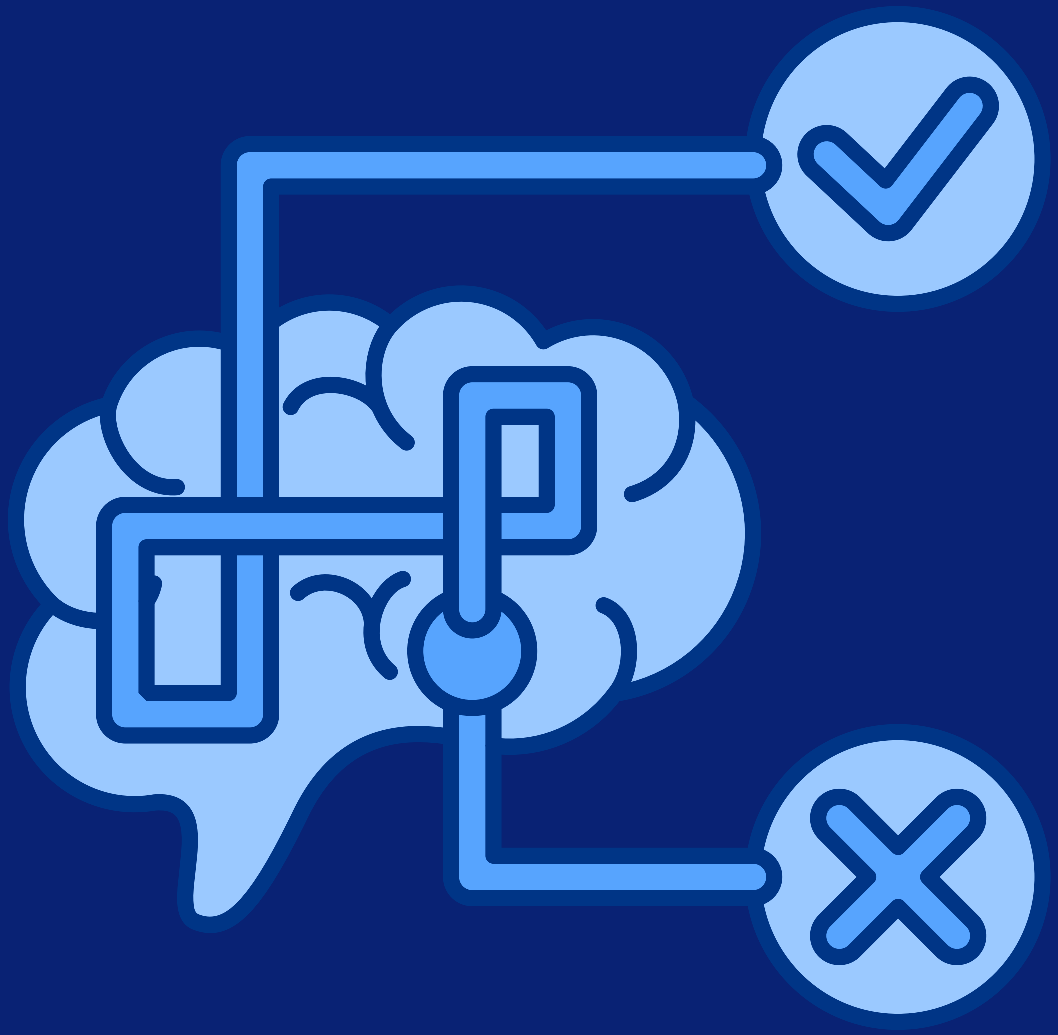
In this project, we aim to develop a model that automatically classifies the sentiment of Tweets regarding Apple and Google products as positive, negative, or neutral. This can help companies quickly gauge public sentiment at scale, providing actionable insights for decision-making.

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.

Modeling Approach

- 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.

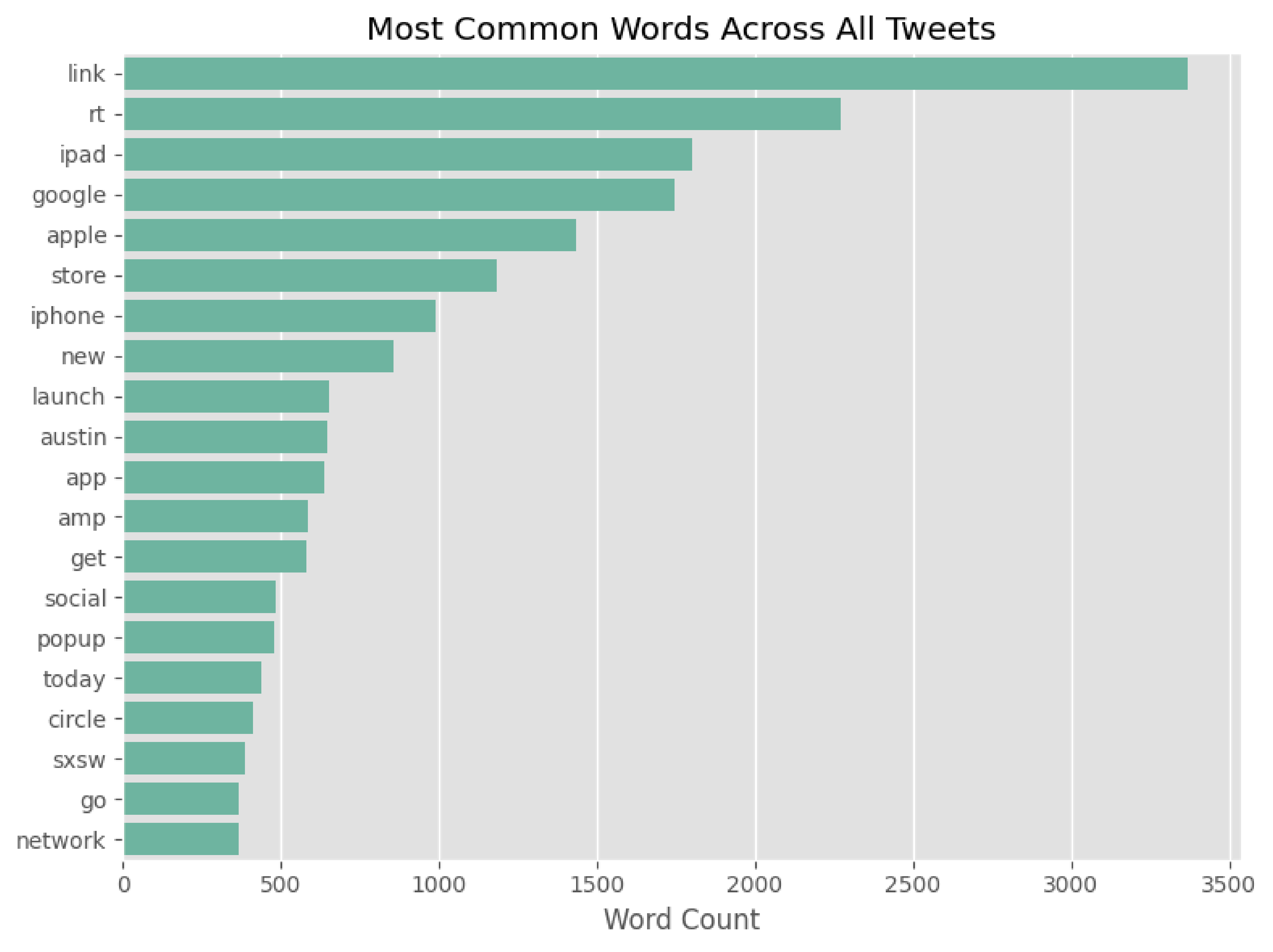
Naive Bayes is quite efficient for high-dimensional and sparse text data and very fast and scalable. Applying both models will give us an opportunity to compare the performance of these two models and choose the best one for our sentiment analysis.

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.

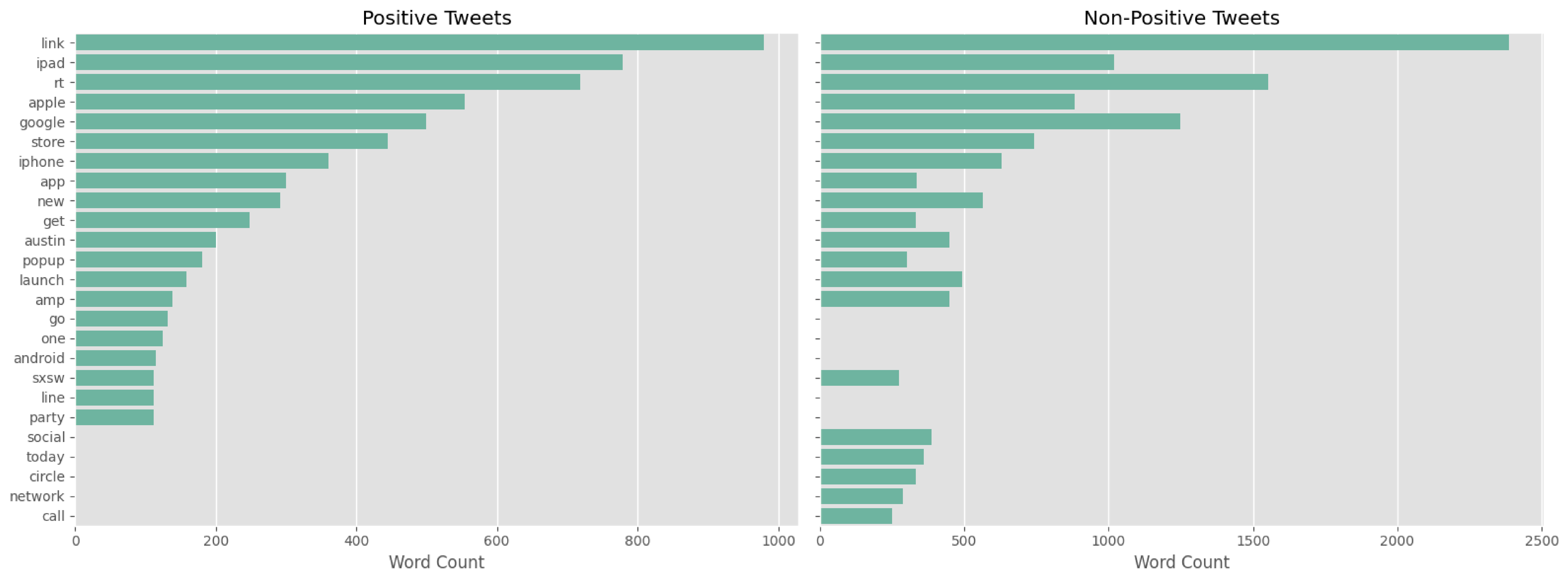
02 **Event Relevance:** Words like "launch", "austin", "sxsw" show that there is also a focus on the events held within the tech industry, so perhaps these may be the kind of events which create the biggest consumer involvement and discussion.

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.

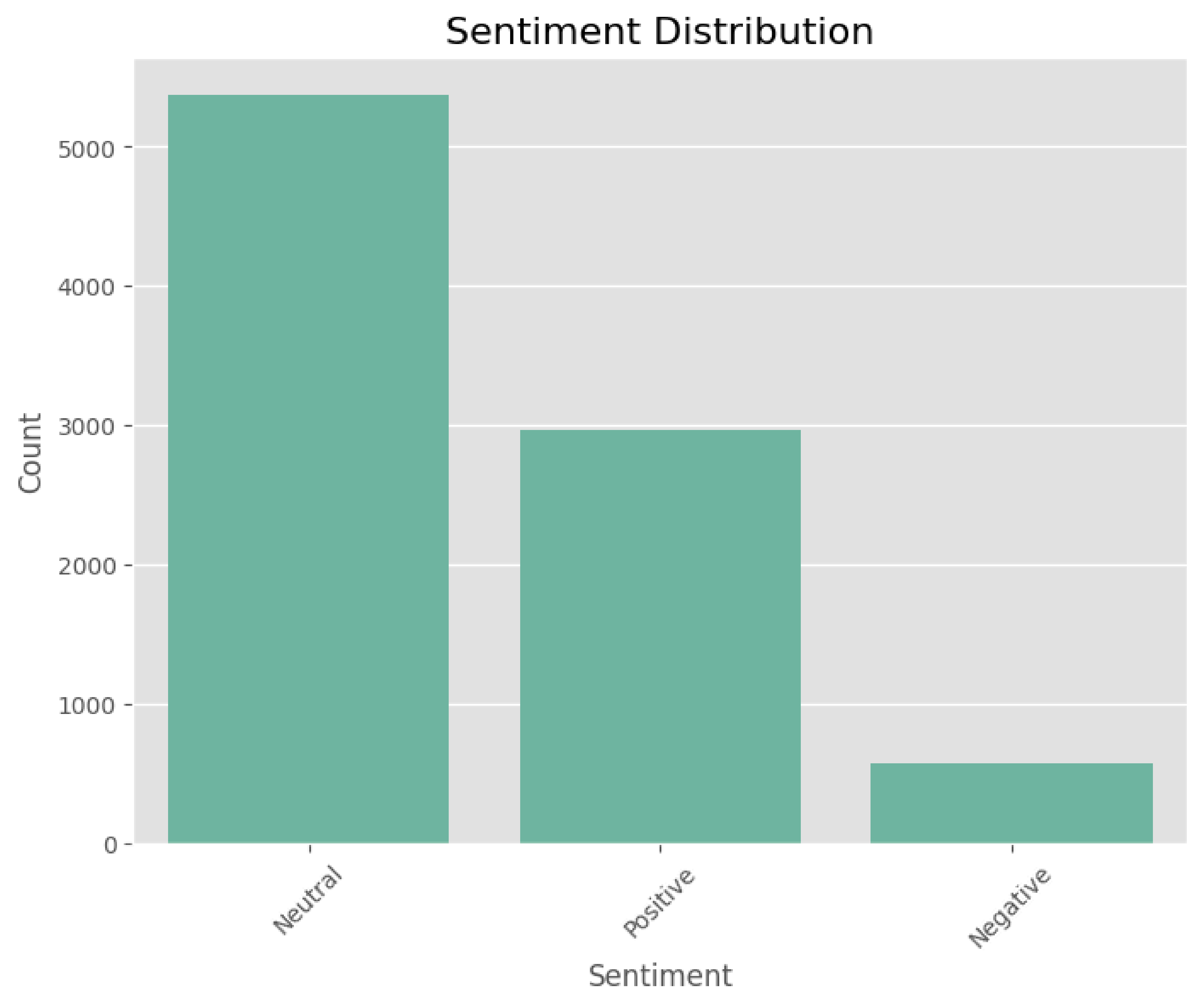


Positive vs. Non-Positive Tweets

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".



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

Model Performance Overview

Accuracy

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

87%

Precision

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

85%

Recall

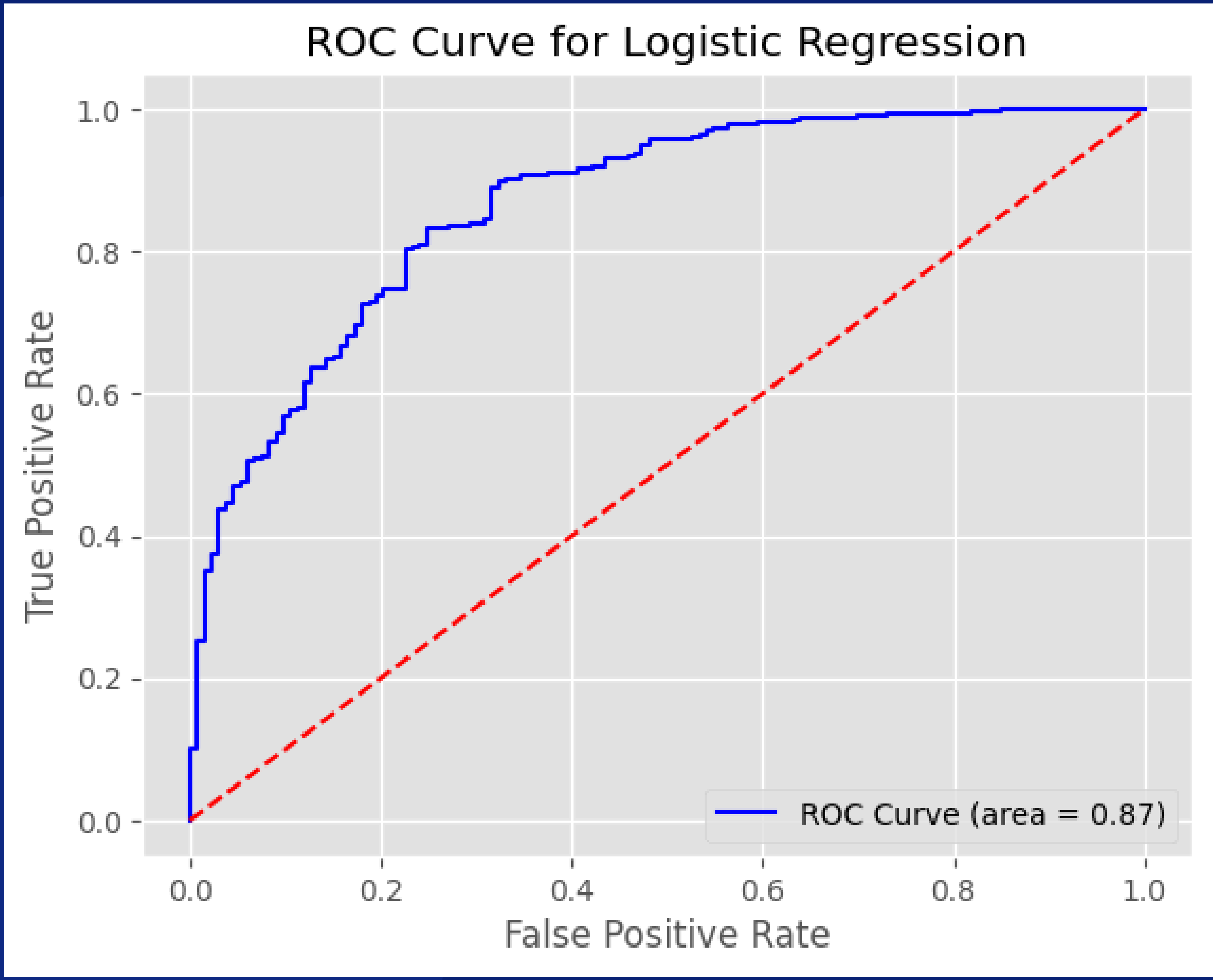
The model was able to recall 80%, meaning the model correctly found 80% of the actual positive sentiments.

80%

F1-score

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

82%



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.