Aspect-Based Sentiment Analysis of Tweets Directed at Brands and Products using Natural Language Processing.

1 Business Understanding

1.1 Business Overview

Social media platforms like Twitter are where people openly share their thoughts, complaints, and praise about products and brands. These conversations show how customers truly feel and what matters to them. For big companies like Apple and Google, understanding this feedback is key to improving products and maintaining a strong brand image.

According to Aga Khan University (2022),https://ecommons.aku.edu/cgi/viewcontent.cgi?article=1069&context=etd_ke_gsmc_ma-digjour, analyzing social media discussions gives organizations valuable insights into consumer attitudes and market trends that support smarter business decisions. Listening to what people say online helps companies respond faster, build trust, and stay connected to their customers.

1.2 Problem Statement

Apple and Google continuously monitor customer satisfaction to stay ahead in the technology market. However, given the massive volume and speed of data generated on Twitter, manual tracking of sentiment is impractical. Without automated systems, valuable insights into customer satisfaction, emerging issues, and product perception may be overlooked.

This project aims to address this challenge by developing a machine learning model capable of classifying tweets related to Apple and Google as positive, negative, or neutral. The outcome will support organizations in understanding real-time consumer opinions, measuring brand perception, and identifying areas for improvement based on public feedback.

1.3 Business Objective

1.3.1 Main objective:

To develop an NLP-based sentiment analysis model that automatically classifies tweets about Apple and Google into positive, negative, or neutral categories.

1.3.2 Specific objectives:

1. To explore and clean the tweet dataset, handling missing values, duplicates, and irrelevant characters.
2. To preprocess textual data through tokenization, stopword removal, and lemmatization.
3. To convert cleaned text into numerical features using appropriate vectorization techniques such as TF-IDF or Word2Vec.
4. To train and evaluate multiple classification algorithms (Logistic Regression, Naive Bayes, SVM) to identify the best-performing model.
5. To interpret and visualize model predictions, identifying which features most influence positive and negative sentiment.
6. To provide actionable insights that can guide Apple and Google in improving customer experience and brand perception.

1.4 Research Questions

1. How can the dataset be explored and cleaned to ensure data quality and reliability for sentiment analysis?
2. What preprocessing techniques are most effective for preparing Twitter text data for modeling?
3. Which text vectorization method (e.g., TF-IDF) produces better numerical representations for tweet classification?
4. Which classification algorithms yield the highest accuracy and robustness in predicting tweet sentiment?
5. Which textual features (words, phrases, or hashtags) most strongly influence model predictions of sentiment?
6. How can the resulting sentiment insights be applied by Apple and Google to improve customer satisfaction and brand reputation?

1.5 Success Criteria

Model Performance: Achieve at least 85% classification accuracy and a macro F1-score ≥ 0.80 across all sentiment classes (positive, negative, neutral).

Model Interpretability: Clearly explain which features (words, hashtags, expressions) most affect sentiment predictions.

Business Value: Provide insights that help Apple and Google understand customer sentiment, identify common issues, and track brand reputation effectively.

2. Data Understanding

2.1 Data overview

The dataset contains 9,093 tweets collected from crowdFlower, with the goal of identifying whether the emotion in a tweet is directed at a brand or product, and if so, what sentiment it carries. It includes 3 columns,

- tweet_text: The raw text of the tweet, expressing user opinions or emotions.
- emotion_in_tweet_is_directed_at: The specific brand or product the emotion is directed at.
- is_there_an_emotion_directed_at_a_brand_or_product: Indicates whether the tweet expresses emotion toward a brand/product

data characteristics

- Number of rows: 9,093
- Number of columns: 3
- Data types: All columns are of type object.
- Target variable: is_there_an_emotion_directed_at_a_brand_or_product.
- Feature variable: tweet_text.
- Filtering scope: Tweets directed at Apple or Google will be selected for analysis.

our target variable includes various sentiment labels such as Positive emotion, Negative emotion, and No emotion toward brand or product.

In [83]:
```
#Importing libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
import re
warnings.filterwarnings('ignore')
```

In [84]:
```
df = pd.read_csv("judge-1377884607_tweet_product_company.csv", encoding="latin1")
df
```

Out[84]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_pr
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative en
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive en
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive en
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative en
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive en
...	...	...	
9088	Ipad everywhere. #SXSW {link}	iPad	Positive en
9089	Wave, buzz... RT @mention We interrupt your re...	NaN	No emotion toward brand or pr
9090	Google's Zeiger, a physician never reported po...	NaN	No emotion toward brand or pr
9091	Some Verizon iPhone customers complained their...	NaN	No emotion toward brand or pr
9092	ÛÏ¡ÛÏàÛü_ÛÛÊÛÛÎÛÛÒÛÛ£ÛÛÁÛâàÛÛ_ÛÛ£ÛÛÛÛâ_ÛÛâRT @...	NaN	No emotion toward brand or pr

9093 rows × 3 columns

In [85]:
```
#list all columns
df.columns
```

Out[85]:
```
Index(['tweet_text', 'emotion_in_tweet_is_directed_at',
       'is_there_an_emotion_directed_at_a_brand_or_product'],
      dtype='object')
```

In [86]:
```
#df.shape
df.shape
```

Out[86]:
```
(9093, 3)
```

In [87]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9093 entries, 0 to 9092
Data columns (total 3 columns):
 #   Column                                              Non-Null Count  Dtype 
---  ------                                              --------------  ----- 
 0   tweet_text                                          9092 non-null   object
 1   emotion_in_tweet_is_directed_at                     3291 non-null   object
 2   is_there_an_emotion_directed_at_a_brand_or_product  9093 non-null   object
dtypes: object(3)
memory usage: 213.2+ KB
```

All columns are object type,the tweet_text has i missing row,the emotion directed at column has alot of missing values with only 3291 non-null.

In [88]:
```
#finding missing values
df.isnull().sum()
```

Out[88]:
```
tweet_text                                               1
emotion_in_tweet_is_directed_at                       5802
is_there_an_emotion_directed_at_a_brand_or_product       0
dtype: int64
```

In [89]:
```
#finding the percentage of missing values
df.isnull().sum()/df.shape[0] * 100
```

Out[89]:
```
tweet_text                                             0.010997
emotion_in_tweet_is_directed_at                       63.807324
is_there_an_emotion_directed_at_a_brand_or_product     0.000000
dtype: float64
```

In [90]:
```
#finding duplicates
df.duplicated().sum()
```

Out[90]: 22

In [91]:
```
# removing duplicates
df.drop_duplicates(inplace=True)
#rechecking duplicates
df.duplicated().sum()
```

Out[91]: 0

In [92]:
```
# df.describe
df.describe()
```

Out[92]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
count	9070	3282	9071
unique	9065	9	4
top	RT @mention RT @mention It's not a rumor: Appl...	iPad	No emotion toward brand or product
freq	2	945	5376

In [93]:
```
#descriprtive statistics
df.describe(include='object')
```

Out[93]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
count	9070	3282	9071
unique	9065	9	4
top	RT @mention RT @mention It's not a rumor: Appl...	iPad	No emotion toward brand or product
freq	2	945	5376

In [94]:
```
df['is_there_an_emotion_directed_at_a_brand_or_product'].unique().tolist()
```

Out[94]:
```
['Negative emotion',
 'Positive emotion',
 'No emotion toward brand or product',
 "I can't tell"]
```

The target variable contains 4 sentiment classes.The Negative emotion,Positive emotion,No emotion toward brand or product and the i can't tell.

In [95]:
```
df['emotion_in_tweet_is_directed_at'].unique().tolist()
```

Out[95]:
```
['iPhone',
 'iPad or iPhone App',
 'iPad',
 'Google',
 nan,
 'Android',
 'Apple',
 'Android App',
 'Other Google product or service',
 'Other Apple product or service']
```

Handling missing values

After identifying the missing values based on their percentages and importance of the column we will drop the single missing row.

In [96]:
```
# handling missing values
# Dropping the single missing row in tweet_text
df = df.dropna(subset=['tweet_text'])
df.isnull().sum()
```

Out[96]:
```
tweet_text                                              0
emotion_in_tweet_is_directed_at                      5788
is_there_an_emotion_directed_at_a_brand_or_product      0
dtype: int64
```

In [97]:
```
# Filtering the "emotion is directed at" to Keep Apple and Google tweets only.
df = df[df['emotion_in_tweet_is_directed_at'].isin(['Apple', 'Google'])]
df
```

Out[97]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion
9	Counting down the days to #sxsw plus strong Ca...	Apple	Positive emotion
38	@mention - False Alarm: Google Circles Not Co...	Google	Negative emotion
40	@mention - Great weather to greet you for #sx...	Apple	Positive emotion
47	HOORAY RT ÛÏ@mention Apple Is Opening A Pop-U...	Apple	Positive emotion
...	...	...	...
9029	[TOP STORY] At #SXSW, Apple schools the market...	Apple	Positive emotion
9033	@mention yep! I can't believe they set up a po...	Apple	Positive emotion
9048	@mention You bet man! Kindle and Apple for sur...	Apple	Positive emotion
9064	@mention you should see the line here at #SXSW...	Apple	Positive emotion
9066	How much you want to bet Apple is disproportio...	Apple	I can't tell

1087 rows × 3 columns

In [98]:

```
# rechecking the missing values
df.isnull().sum()
```

Out[98]:
```
tweet_text                                            0
emotion_in_tweet_is_directed_at                       0
is_there_an_emotion_directed_at_a_brand_or_product    0
dtype: int64
```

In [99]:
```
# Tweet length analysis(number of characters in tweet)
df['tweet_length'] = df['tweet_text'].str.len()
df
```

Out[99]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	tweet_length
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion	131
9	Counting down the days to #sxsw plus strong Ca...	Apple	Positive emotion	88
38	@mention - False Alarm: Google Circles Not Co...	Google	Negative emotion	119
40	@mention - Great weather to greet you for #sx...	Apple	Positive emotion	144
47	HOORAY RT ÛÏ@mention Apple Is Opening A Pop-U...	Apple	Positive emotion	91
...	...	...	...	...
9029	[TOP STORY] At #SXSW, Apple schools the market...	Apple	Positive emotion	125
9033	@mention yep! I can't believe they set up a po...	Apple	Positive emotion	92
9048	@mention You bet man! Kindle and Apple for sur...	Apple	Positive emotion	91
9064	@mention you should see the line here at #SXSW...	Apple	Positive emotion	125
9066	How much you want to bet Apple is disproportio...	Apple	I can't tell	131

1087 rows × 4 columns

In [100…

```
# adding the number of words in tweet column
df['word_count'] = df['tweet_text'].apply(lambda x: len(str(x).split()))
df
```

Out[100…

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	tweet_length	word_count
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion	131	17
9	Counting down the days to #sxsw plus strong Ca...	Apple	Positive emotion	88	16
38	@mention - False Alarm: Google Circles Not Co...	Google	Negative emotion	119	18
40	@mention - Great weather to greet you for #sx...	Apple	Positive emotion	144	23
47	HOORAY RT ÛÏ@mention Apple Is Opening A Pop-U...	Apple	Positive emotion	91	16
...	...	...	...	...	...
9029	[TOP STORY] At #SXSW, Apple schools the market...	Apple	Positive emotion	125	19
9033	@mention yep! I can't believe they set up a po...	Apple	Positive emotion	92	20

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	tweet_length	word_count
9048	@mention You bet man! Kindle and Apple for sur...	Apple	Positive emotion	91	17
9064	@mention you should see the line here at #SXSW...	Apple	Positive emotion	125	24
9066	How much you want to bet Apple is disproportio...	Apple	I can't tell	131	21

1087 rows × 5 columns

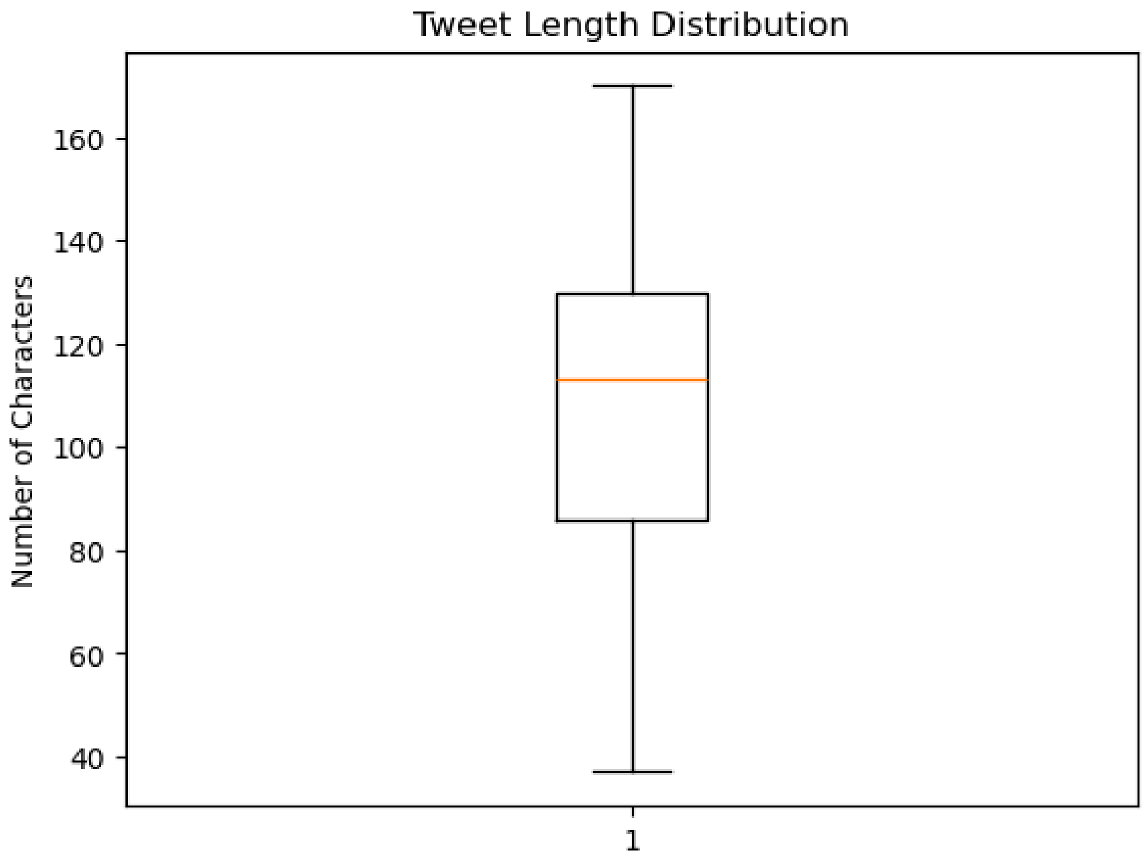
In [101…

```
# View summary statistics
print(df['tweet_length'].describe())
```

```
count    1087.000000
mean      107.690892
std        28.154731
min        37.000000
25%        86.000000
50%       113.000000
75%       130.000000
max       170.000000
Name: tweet_length, dtype: float64
```

In [102…

```
# tweet length distribution plot
plt.boxplot(df['tweet_length'])
plt.title('Tweet Length Distribution')
plt.ylabel('Number of Characters')
plt.show()
```



In [103…

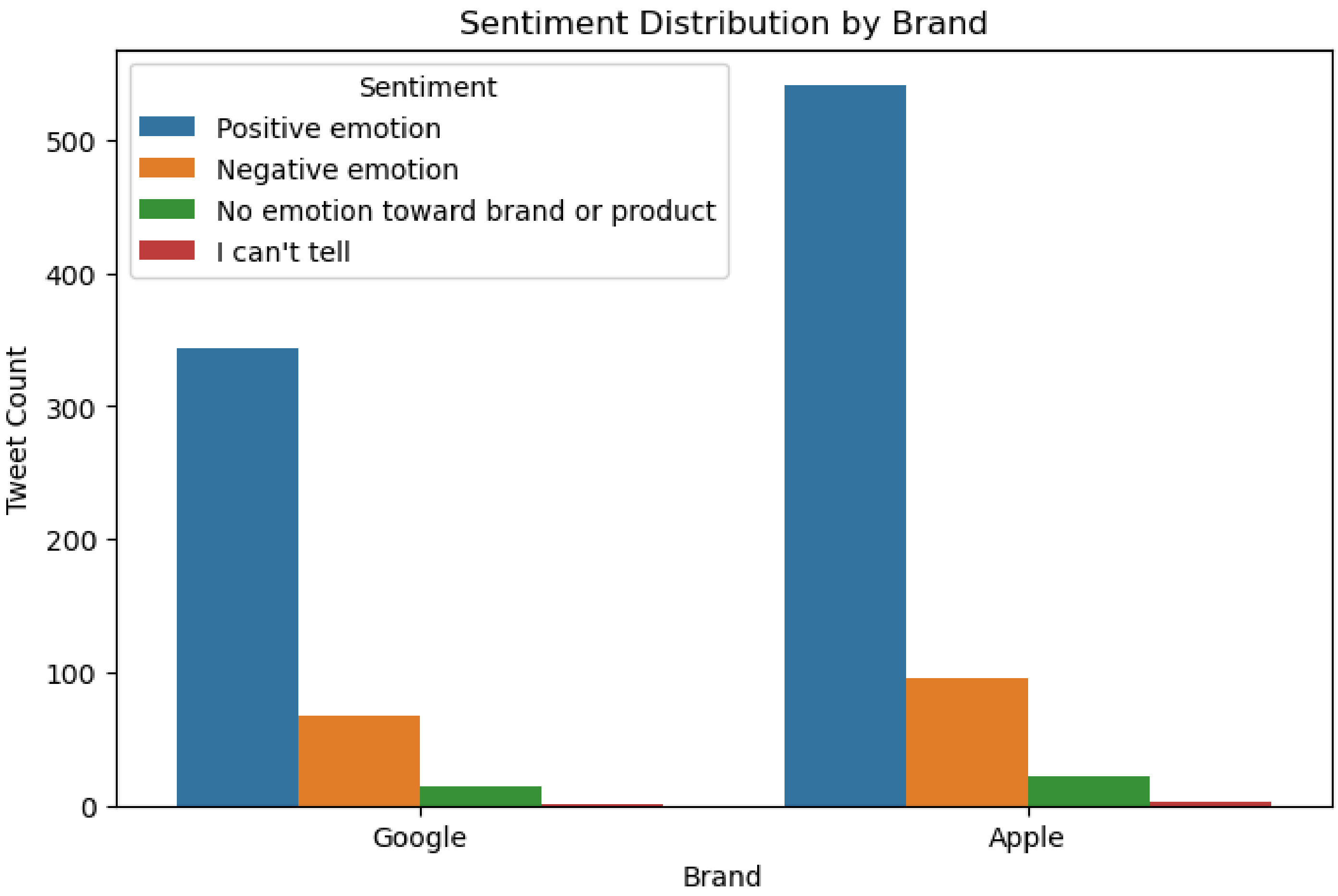
```
print(df['word_count'].describe())
```

```
count    1087.000000
mean       18.049678
std         4.894214
min         5.000000
25%        14.000000
50%        19.000000
75%        22.000000
max        33.000000
Name: word_count, dtype: float64
```

In [104…

```
# plotting for sentiment distribution by brand
plt.figure(figsize=(8,5))
```

```
sns.countplot(x='emotion_in_tweet_is_directed_at', hue='is_there_an_emotion_directed_at_a_brand_or_product', data=df)
plt.title('Sentiment Distribution by Brand')
plt.xlabel('Brand')
plt.ylabel('Tweet Count')
plt.legend(title='Sentiment')
plt.show()
```



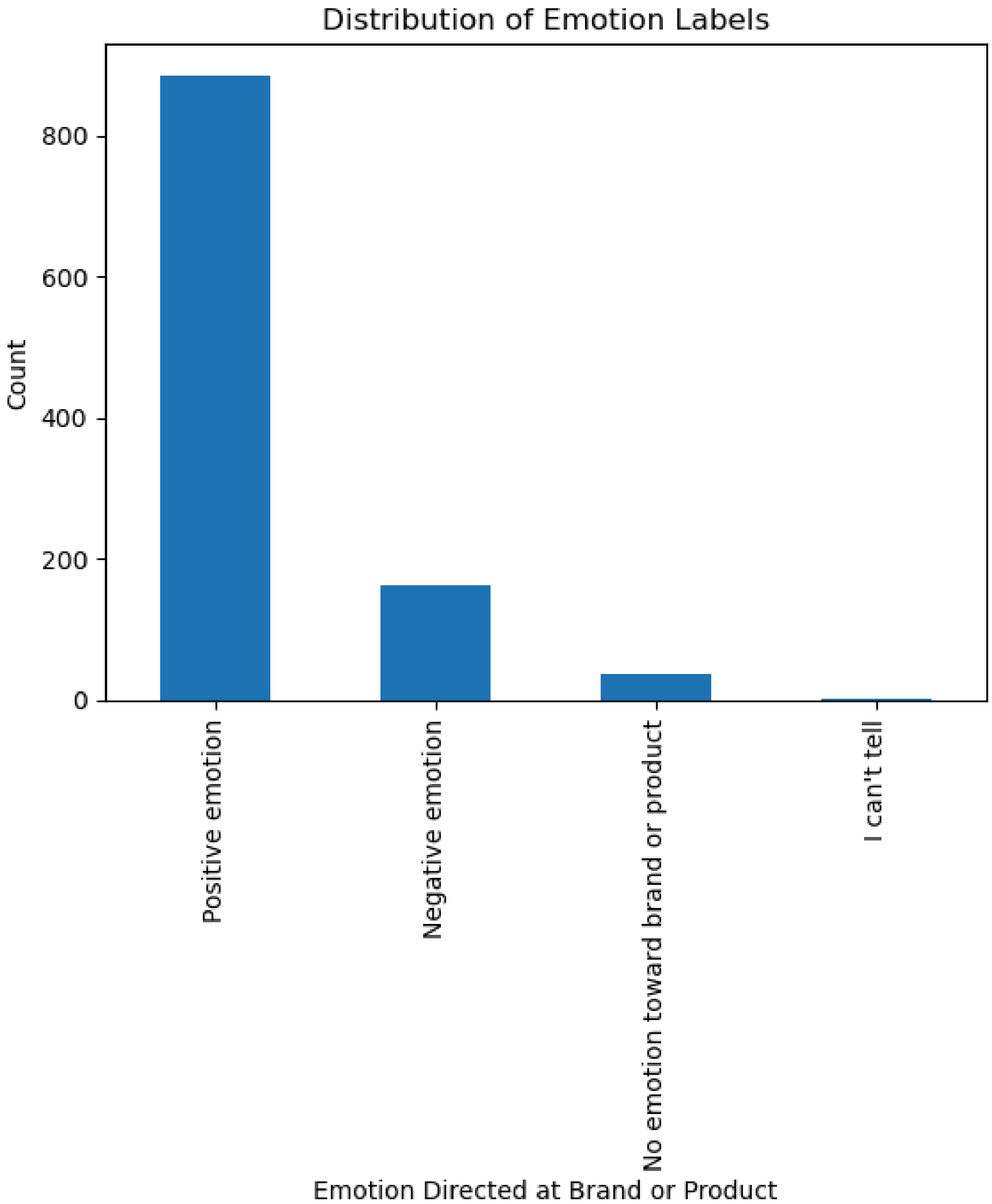
From the distribution of sentiments both brands get a mix of sentiments with the I cant tell being the least ,the positive sentiments dominates in both brands but the Apple brand recieves more positive sentiments compared to the Google brand.

In [105…
```
# checking for class imbalance
df['is_there_an_emotion_directed_at_a_brand_or_product'].value_counts(normalize=True)
```

Out[105…
```
is_there_an_emotion_directed_at_a_brand_or_product
Positive emotion                      0.814167
Negative emotion                      0.149954
No emotion toward brand or product    0.033119
I can't tell                          0.002760
Name: proportion, dtype: float64
```

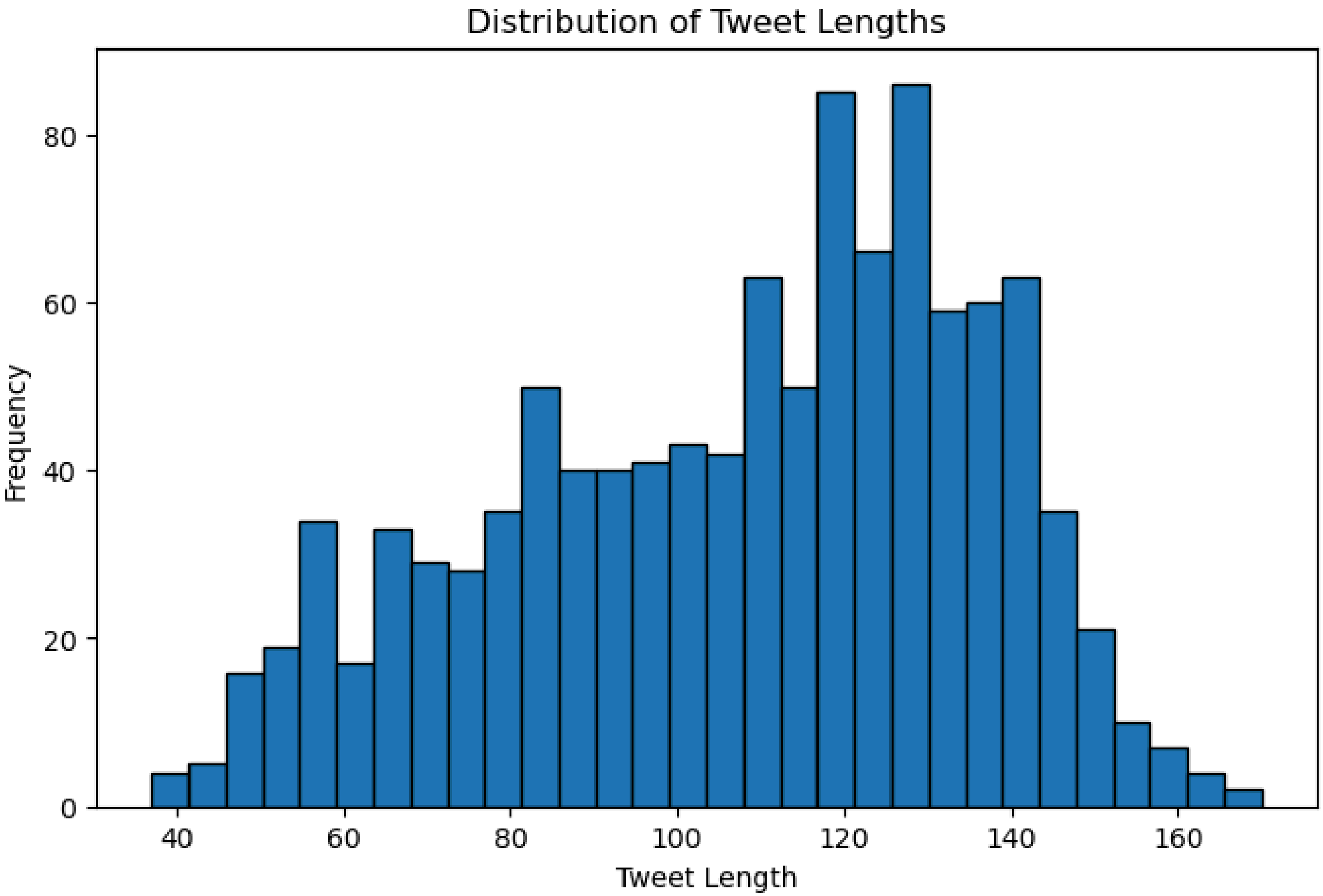
From the output our classes are imbalanced with the I can't tell having extremely low count.

In [106…
```
# Visualizing the distribution of emotion labels helps identify class imbalance.
# This guides modeling decisions such as resampling or weighting during training.

# Check the distribution of the target variable
df['is_there_an_emotion_directed_at_a_brand_or_product'].value_counts().plot(kind='bar', color='#1f77b4')
plt.title('Distribution of Emotion Labels')
plt.xlabel('Emotion Directed at Brand or Product')
plt.ylabel('Count')
plt.show()
```


Distribution of Emotion Labels
Count
0
200
400
600
800
Positive emotion
Negative emotion
No emotion toward brand or product
I can't tell
Emotion Directed at Brand or Product

In [107…

```
# visualizing the distribution of tweet lengths
plt.figure(figsize=(8,5))
plt.hist(df['tweet_length'], bins=30, edgecolor='black')
plt.title('Distribution of Tweet Lengths')
plt.xlabel('Tweet Length')
plt.ylabel('Frequency')
plt.show()
```



In [108…

```
df['tweet_length'].describe()
```

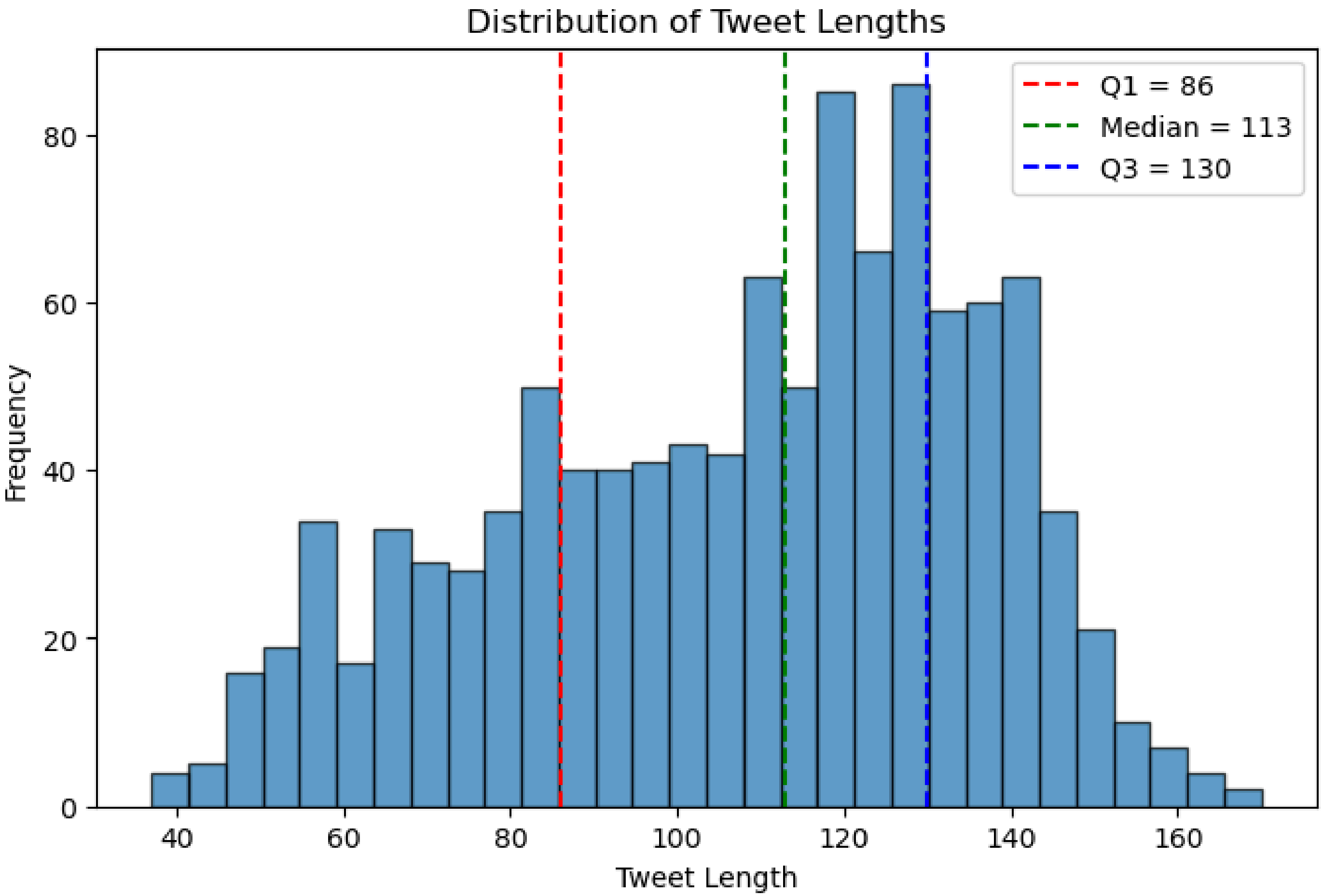
Out[108…

```
count    1087.000000
mean      107.690892
std        28.154731
min        37.000000
25%        86.000000
50%       113.000000
75%       130.000000
max       170.000000
Name: tweet_length, dtype: float64
```

The distribution of tweet lengths , most tweets ranging between 80 and 130 characters.

In [109…

```
# plotting a more visual histogram plot for range analysis.
# Basic histogram
plt.figure(figsize=(8,5))
plt.hist(df['tweet_length'], bins=30, edgecolor='black', alpha=0.7)
plt.title('Distribution of Tweet Lengths')
plt.xlabel('Tweet Length')
plt.ylabel('Frequency')

# Calculating percentiles
q1 = df['tweet_length'].quantile(0.25)
median = df['tweet_length'].median()
q3 = df['tweet_length'].quantile(0.75)

# Adding vertical lines for Q1, Median, Q3 for clear data interpretation.
plt.axvline(q1, color='red', linestyle='--', label=f'Q1 = {q1:.0f}')
plt.axvline(median, color='green', linestyle='--', label=f'Median = {median:.0f}')
plt.axvline(q3, color='blue', linestyle='--', label=f'Q3 = {q3:.0f}')

plt.legend()
plt.show()
```



The distribution of tweet lengths is fairly concentrated, with most tweets ranging between approximately 80 and 130 characters. This range corresponds to the interquartile range (Q1–Q3), indicating that the majority of tweets are of moderate length.

TEXT PREPROCESSING

In [110…

```
import seaborn as sns
import emoji
from nltk.corpus import stopwords
from sklearn.model_selection import train_test_split
```

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (
    classification_report,
    confusion_matrix,
    accuracy_score,
    f1_score
)
from sklearn.pipeline import Pipeline
import joblib
import warnings
from sklearn.feature_extraction.text import CountVectorizer
import nltk
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
from wordcloud import WordCloud
from nltk.stem.porter import PorterStemmer #reduce the word to its root form
from nltk.corpus import stopwords, wordnet
warnings.filterwarnings("ignore")


# Ensure required NLTK resources are downloaded
nltk.download('punkt', quiet=True)
nltk.download('wordnet', quiet=True)
nltk.download('omw-1.4', quiet=True)

# Download stopwords
nltk.download('stopwords', quiet=True)
```

Out[110… True

In [111…

```
# Initialize tools
STOP_WORDS = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()

def preprocess_tweet(text, keep_emojis=False):
    """
    Clean, tokenize, remove stopwords, and lemmatize a tweet.
    Returns a cleaned string ready for modeling.
```

```
    """
    if not isinstance(text, str):
        return ""

    # 1. Convert to lowercase
    text = text.lower()

    # 2convert emojis to text form
    if keep_emojis:
        text = emoji.demojize(text)

    # 3.Remove URLs, mentions, and hashtags
    text = re.sub(r"http\S+|www\S+|https\S+", '', text)
    text = re.sub(r"@\w+", '', text)
    text = re.sub(r'#', '', text)  # removing only the '#' symbol and keeps the hashtag word

    # 4.Removing non-alphabetic characters
    text = re.sub(r"[^a-z\s]", ' ', text)

    # 5.Tokenization
    tokens = word_tokenize(text)

    # 6.Removing stopwords and short tokens
    tokens = [word for word in tokens if word not in STOP_WORDS and len(word) > 1]

    # 7.Lemmatization
    tokens = [lemmatizer.lemmatize(word) for word in tokens]

    # 8.Joinning back to a single string
    clean_text = " ".join(tokens)

    return clean_text.strip()  # Removes any leading/trailing spaces
```

In [112…

```
# Applying the preprocessing function to each tweet in 'tweet_text'
# stores the cleaned output in a new column 'cleaned_tweet'
df['cleaned_tweet'] = df['tweet_text'].apply(lambda x: preprocess_tweet(x, keep_emojis=True))
```

In [113…

```
# Remove rows where the cleaned tweet is empty or contains only whitespace.
df = df[df['cleaned_tweet'].str.strip() != ""]
```

In [114...

```
# Preview of the original vs cleaned tweets
df[['tweet_text', 'cleaned_tweet']].sample(5, random_state=42)
```

Out[114...

	tweet_text	cleaned_tweet
6037	RT @mention How Cool is this! #Apple opening a...	rt cool apple opening temporary store ipad lau...
352	.@mention Bad Apple: shows up late, Qs the pro...	bad apple show late q process poo poos idea le...
5410	RT @mention Apparently, if you Google "ad...	rt apparently google quot ad preference quot s...
7410	At the Apple Store downtown. Apple should real...	apple store downtown apple really keep store o...
5661	RT @mention DELICIOUSLY IRONIC GOOGLE PRIVACY ...	rt deliciously ironic google privacy party mad...

In [115...

```
df
```

Out[115…

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	tweet_length	word_count	
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion	131	17	gre
9	Counting down the days to #sxsw plus strong Ca...	Apple	Positive emotion	88	16	cou ca
38	@mention - False Alarm: Google Circles Not Co...	Google	Negative emotion	119	18	cc
40	@mention - Great weather to greet you for #sx...	Apple	Positive emotion	144	23	ne
47	HOORAY RT ÛÏ@mention Apple Is Opening A Pop-U...	Apple	Positive emotion	91	16	st
...	...	...	...	...	...	
9029	[TOP STORY] At #SXSW, Apple schools the market...	Apple	Positive emotion	125	19	m
9033	@mention yep! I can't believe they set up a po...	Apple	Positive emotion	92	20	po

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	tweet_length	word_count	
9048	@mention You bet man! Kindle and Apple for sur...	Apple	Positive emotion	91	17	
9064	@mention you should see the line here at #SXSW...	Apple	Positive emotion	125	24	see
9066	How much you want to bet Apple is disproportio...	Apple	I can't tell	131	21	disp

1087 rows × 6 columns

Bag of words

In [116...

```
tweets = df['cleaned_tweet']

# Initialize CountVectorizer
vectorizer = CountVectorizer(stop_words='english')  # removs common words like 'the', 'and'
X = vectorizer.fit_transform(tweets)

# Convert to DataFrame for easy viewing
word_counts = pd.DataFrame({
    'word': vectorizer.get_feature_names_out(),
    'count': X.toarray().sum(axis=0)  # sum each column to get total occurrences
})

# Sort by frequency
word_counts = word_counts.sort_values(by='count', ascending=False)
```

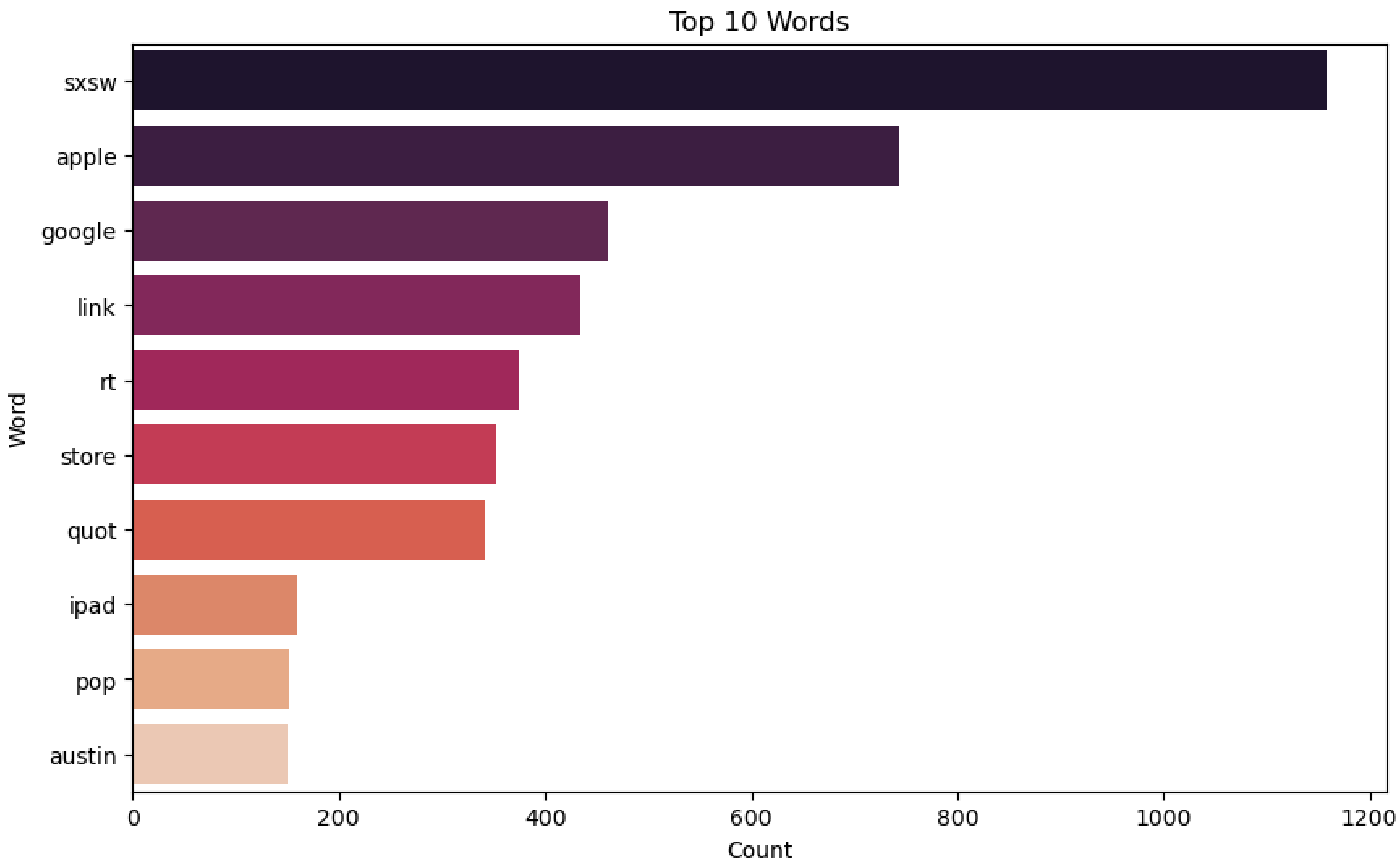
```
word_counts.head(10)
```

Out[116…

	word	count
1916	sxsw	1159
83	apple	743
841	google	461
1145	link	435
1660	rt	374
1858	store	352
1560	quot	342
1029	ipad	160
1467	pop	151
120	austin	150

In [117…

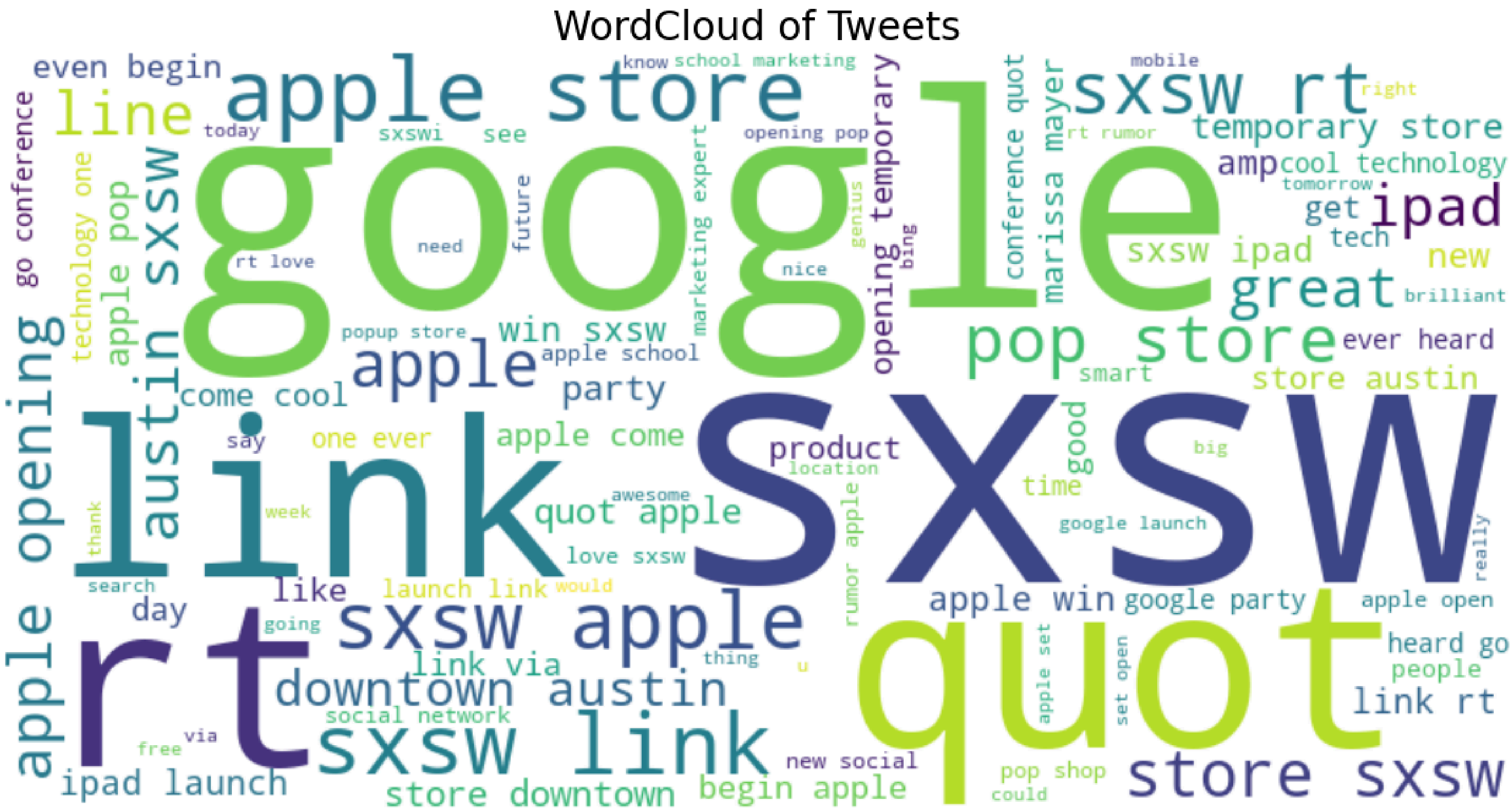
```
top_words = word_counts.head(10)
plt.figure(figsize=(10,6))
sns.barplot(x='count', y='word', data=top_words, palette='rocket')
plt.title("Top 10 Words")
plt.xlabel("Count")
plt.ylabel("Word")
plt.show()
```



In [118…

```
# Combining all cleaned tweets into a single string
text = " ".join(df['cleaned_tweet'])

# Creating a WordCloud to display top 100 words
wordcloud = WordCloud(
    width=800,
    height=400,
```

```
    background_color='white',
    stopwords=STOP_WORDS,
    max_words=100
).generate(text)

# Plot
plt.figure(figsize=(15,7))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title("WordCloud of Tweets", fontsize=20)
plt.show()
```



words like google and SXSW ,link and apple seem to have the most appearances .

Target Variable Mapping

In [119…

```python
# Target Variable Mapping
def map_manual_sentiment(label):
    if label == 'Positive emotion':
        return 'Positive'
    elif label == 'Negative emotion':
```

```
        return 'Negative'
    else:
        return 'Neutral'

df['manual_sentiment'] = df['is_there_an_emotion_directed_at_a_brand_or_product'].apply(map_manual_sentiment)
```

BASELINE SENTIMENT ANALYSIS (VADER)

In [120…

```
from nltk.sentiment.vader import SentimentIntensityAnalyzer
import nltk

# Download VADER lexicon (run once)
nltk.download('vader_lexicon', quiet=True)

# Initialize analyzer
analyzer = SentimentIntensityAnalyzer()

# Computing polarity scores
df['vader_polarity'] = df['cleaned_tweet'].apply(
    lambda text: analyzer.polarity_scores(str(text))['compound']
)

# Defining 3-class sentiment using thresholds
def classify_vader_sentiment(score):
    if score >= 0.05:
        return 'Positive'
    elif score <= -0.05:
        return 'Negative'
    else:
        return 'Neutral'

df['vader_sentiment'] = df['vader_polarity'].apply(classify_vader_sentiment)

# View results
df[['cleaned_tweet', 'vader_polarity', 'vader_sentiment']].head(20)
```

Out[120…

	cleaned_tweet	vader_polarity	vader_sentiment
4	great stuff fri sxsw marissa mayer google tim ...	0.6249	Positive
9	counting day sxsw plus strong canadian dollar ...	0.5106	Positive
38	false alarm google circle coming probably ever...	-0.3400	Negative
40	great weather greet sxsw still need sweater ni...	0.7506	Positive
47	hooray rt apple opening pop store austin sxsw ...	0.5106	Positive
49	wooooo apple store downtown austin open til mi...	0.0000	Neutral
55	talking link google effort allow user open sys...	0.2263	Positive
62	omfg rt heard apple pop store downtown austin ...	0.0000	Neutral
63	smile rt think apple quot pop store quot austi...	0.6369	Positive
72	rt come party google tonight sxsw link band fo...	0.6597	Positive
75	holla rt google party best ever get butt sxsw	0.7845	Positive
83	nice rt hey apple fan get peek space slated po...	0.6249	Positive
84	one thing great get great earth face google co...	0.9246	Positive
98	fast fun amp future google presenting sxsw sea...	0.5106	Positive
104	quot google launched checkins month ago quot c...	0.4019	Positive
106	quot google tweet quot new quot think speak qu...	0.0000	Neutral
109	kawasaki quot lewis level reasoning apple cont...	0.2732	Positive
111	kawasaki quot pagemaker saved apple quot oh da...	0.4215	Positive
116	sxsw apple school marketing expert link	0.0000	Neutral
118	temporary apple store def tent powerhouse gym ...	0.0000	Neutral

In [121…

```python
# perform sentiment analysis using Vader
from nltk.sentiment.vader import SentimentIntensityAnalyzer
nltk.download('vader_lexicon')

analyzer = SentimentIntensityAnalyzer()

df['vader_polarity'] = df['cleaned_tweet'].map(
    lambda text: analyzer.polarity_scores(text)['compound']
)

def classify_vader_sentiment(score):
    if score >= 0.05:
        return 'Positive'
    elif score <= -0.05:
        return 'Negative'
    else:
        return 'Neutral'

df['vader_sentiment'] = df['vader_polarity'].apply(classify_vader_sentiment)
df.head(20)
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\Celine\AppData\Roaming\nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

Out[121…

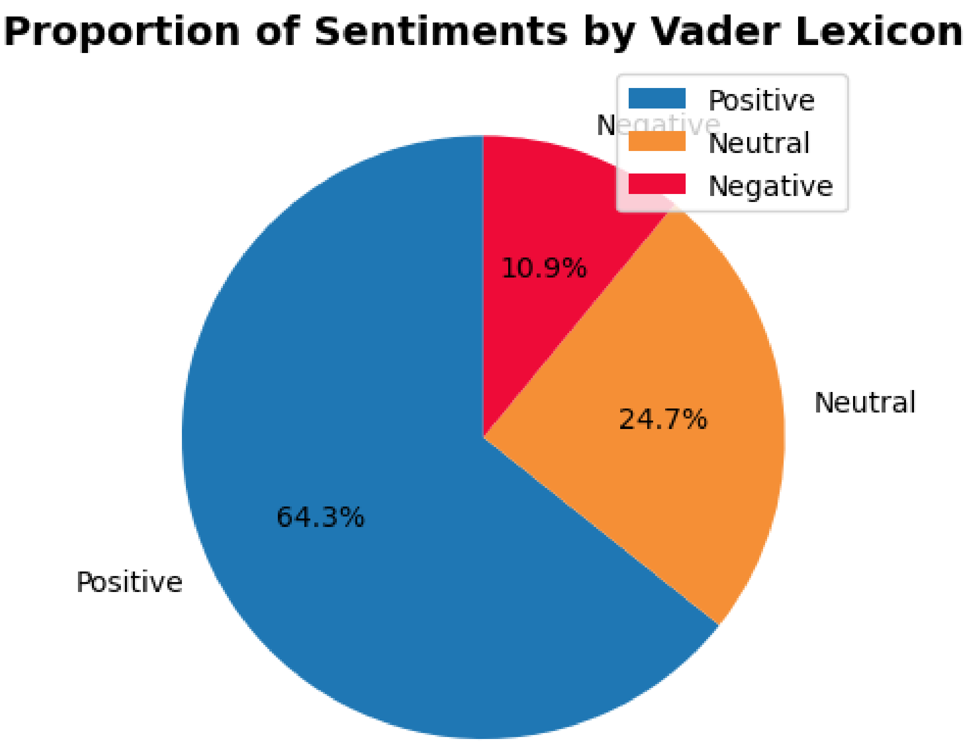
	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	tweet_length	word_count
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion	131	17
9	Counting down the days to #sxsw plus strong Ca...	Apple	Positive emotion	88	16
38	@mention - False Alarm: Google Circles Not Co...	Google	Negative emotion	119	18
40	@mention - Great weather to greet you for #sx...	Apple	Positive emotion	144	23
47	HOORAY RT □ÛÏ@mention Apple Is Opening A Pop-U...	Apple	Positive emotion	91	16
49	wooooo!!! □ÛÏ@mention Apple store downtown Aus...	Apple	Positive emotion	77	10
55	□ÛÏ@mention @mention talking about {link} - Go...	Google	Positive emotion	117	17

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	tweet_length	word_count
62	#OMFG! RT @mention Heard about Apple's pop-up ...	Apple	Positive emotion	120	19
63	#Smile RT @mention I think Apple's "pop-u...	Apple	No emotion toward brand or product	145	24
72	Do it. RT @mention Come party w/ Google tonigh...	Google	Positive emotion	119	21
75	Holla! RT @mention At google party. Best ever!...	Google	Positive emotion	77	14
83	Nice!! RT @mention Hey, Apple fans! Get a peek...	Apple	Positive emotion	123	23
84	one thing @mention is doing so great is get a ...	Google	Positive emotion	131	28
98	Fast, Fun & Future: @mention of Google pre...	Google	Positive emotion	90	15
104	.@mention "Google	Google	Positive emotion	121	19

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	tweet_length	word_count
	launched checkins a mon...				
106	□ÛÏ@mention "Google before you tweet&quot...	Google	Positive emotion	141	19
109	Kawasaki: "Not C.S. Lewis level reasoning...	Apple	Positive emotion	137	19
111	Kawasaki: "pagemaker saved Apple." O...	Apple	Positive emotion	109	14
116	At #SXSW, #Apple schools the marketing experts...	Apple	Positive emotion	55	9
118	Temporary #apple store is def not a tent, it's...	Apple	Positive emotion	77	14

In [122...

```
# Visualizing the proportions of sentiments by Vader using a pie-chart
fig, ax = plt.subplots()
colors = ('#1f77b4',"#f58f36","#EE0B38")
sentiment_props = df['vader_sentiment'].value_counts()
ax.pie(sentiment_props.values, colors=colors, labels=sentiment_props.index, autopct="%1.1f%%", startangle=90)
plt.title("Proportion of Sentiments by Vader Lexicon",fontsize=14, fontweight='bold')
plt.legend(loc='upper right')
plt.show()
```



Distribution of sentiments on a pie chart showing the positive class is dominating with 64.3% ,followef by the Neutral with 24.7% and the Negative being the least with 10.9%.

In [123…

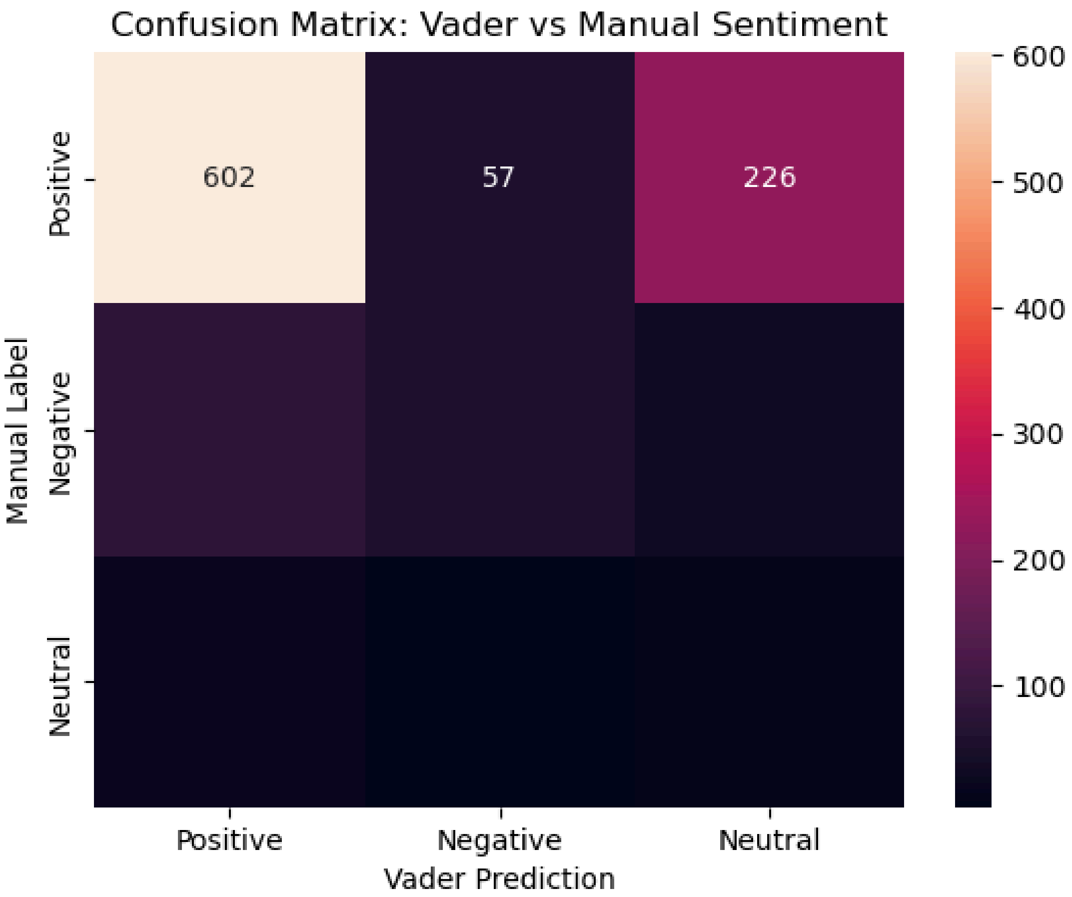
```
from sklearn.metrics import accuracy_score, f1_score, classification_report, confusion_matrix

accuracy = accuracy_score(df['manual_sentiment'], df['vader_sentiment'])
f1 = f1_score(df['manual_sentiment'], df['vader_sentiment'], average='macro')
print(f"Vader Accuracy: {accuracy:.4f}")
print(f"Vader Macro F1-score: {f1:.4f}\n")
print(classification_report(df['manual_sentiment'], df['vader_sentiment']))
```

```
Vader Accuracy: 0.6201
Vader Macro F1-score: 0.4208

              precision    recall  f1-score   support

    Negative       0.49      0.36      0.41       163
     Neutral       0.05      0.36      0.09        39
    Positive       0.86      0.68      0.76       885

    accuracy                           0.62      1087
   macro avg       0.47      0.47      0.42      1087
weighted avg       0.78      0.62      0.68      1087
```

The Vader analysis shows an accuracy of 62%. From the classes,the positive is generalizing better but the neutral and negative have a very poor perfomance,this calls for need to try other advanced machine learning models ,such as logistic regression e.t.c.

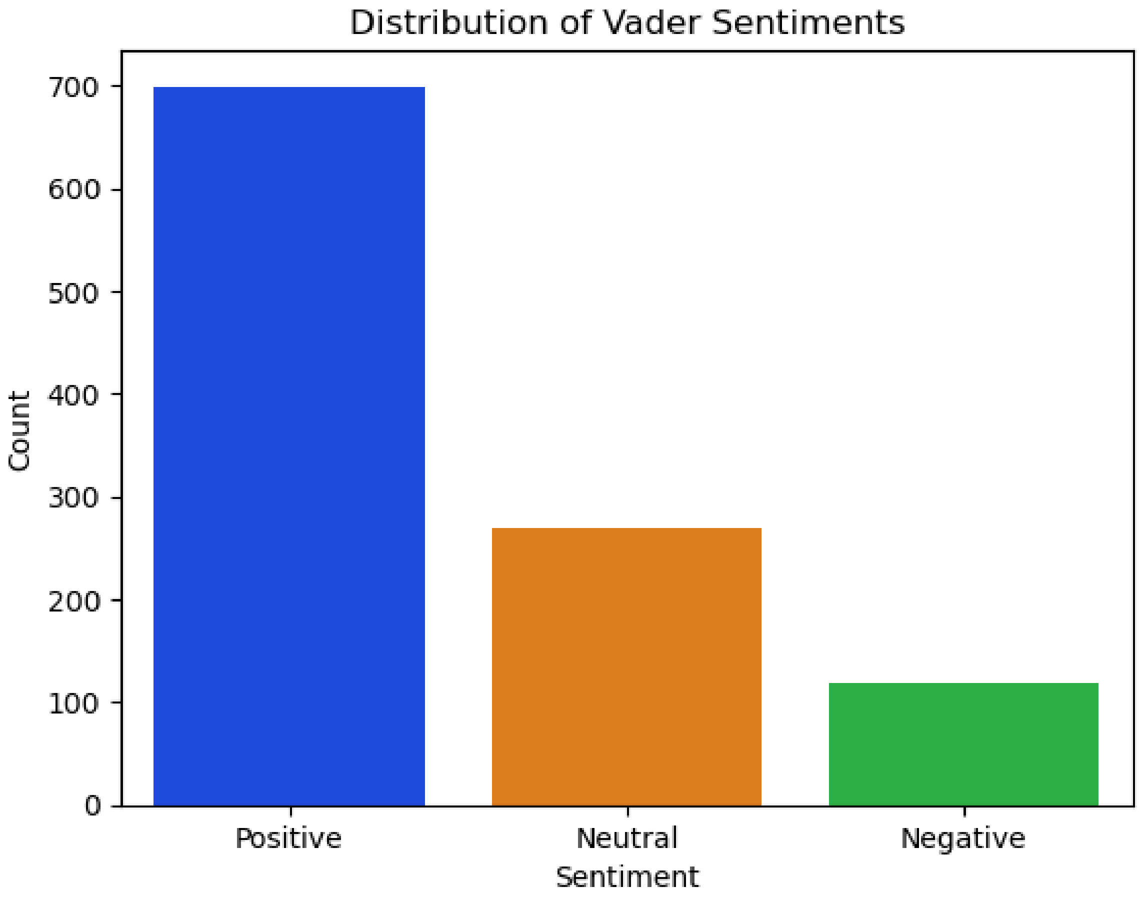
In [124…

```
#Confusion matrix visualization
cm = confusion_matrix(df['manual_sentiment'], df['vader_sentiment'], labels=['Positive', 'Negative', 'Neutral'])
sns.heatmap(cm, annot=True, fmt='d', xticklabels=['Positive','Negative','Neutral'], yticklabels=['Positive','Negative','Neu
plt.xlabel('Vader Prediction')
plt.ylabel('Manual Label')
plt.title('Confusion Matrix: Vader vs Manual Sentiment')
plt.show()
```



In [125…

```
# distribution of Vader sentiments
sentiment_props = df['vader_sentiment'].value_counts()
sns.barplot(x=sentiment_props.index, y=sentiment_props.values, palette='bright')
plt.title("Distribution of Vader Sentiments")
plt.xlabel("Sentiment")
plt.ylabel("Count")
plt.show()
```



From the distribution the Positive class is dominating with over 600 count while the Negative being the least with about 100 counts.

In [126…
```
# Check class distribution in the original dataset
class_counts_before = df['manual_sentiment'].value_counts()
class_counts_before
```

Out[126…
```
manual_sentiment
Positive    885
Negative    163
Neutral      39
Name: count, dtype: int64
```

ADVANCED MODELLING

Handling class imbalance

In [127…

```
# Checking class distribution
class_counts_before = df['manual_sentiment'].value_counts()
class_counts_before
```

Out[127…

```
manual_sentiment
Positive    885
Negative    163
Neutral      39
Name: count, dtype: int64
```

From the class distribution,the classes are imbalanced ,therefore before beginning our modelling we will first balance the classes

In [128…

```
from sklearn.utils import resample

# Using only relevant columns for modeling
df_model = df[['cleaned_tweet', 'manual_sentiment']]
df_model.head()
```

Out[128…

	cleaned_tweet	manual_sentiment
4	great stuff fri sxsw marissa mayer google tim ...	Positive
9	counting day sxsw plus strong canadian dollar ...	Positive
38	false alarm google circle coming probably ever...	Negative
40	great weather greet sxsw still need sweater ni...	Positive
47	hooray rt apple opening pop store austin sxsw ...	Positive

In [129…
```
# List of unique classes
classes = df_model['manual_sentiment'].unique()
classes
```

Out[129…
```
array(['Positive', 'Negative', 'Neutral'], dtype=object)
```

In [130…
```
# Determining the max class size
max_size = df_model['manual_sentiment'].value_counts().max()
max_size
```

Out[130…
```
885
```

In [131…
```
# Empty dataframe for balanced data
df_balanced_model = pd.DataFrame()
```

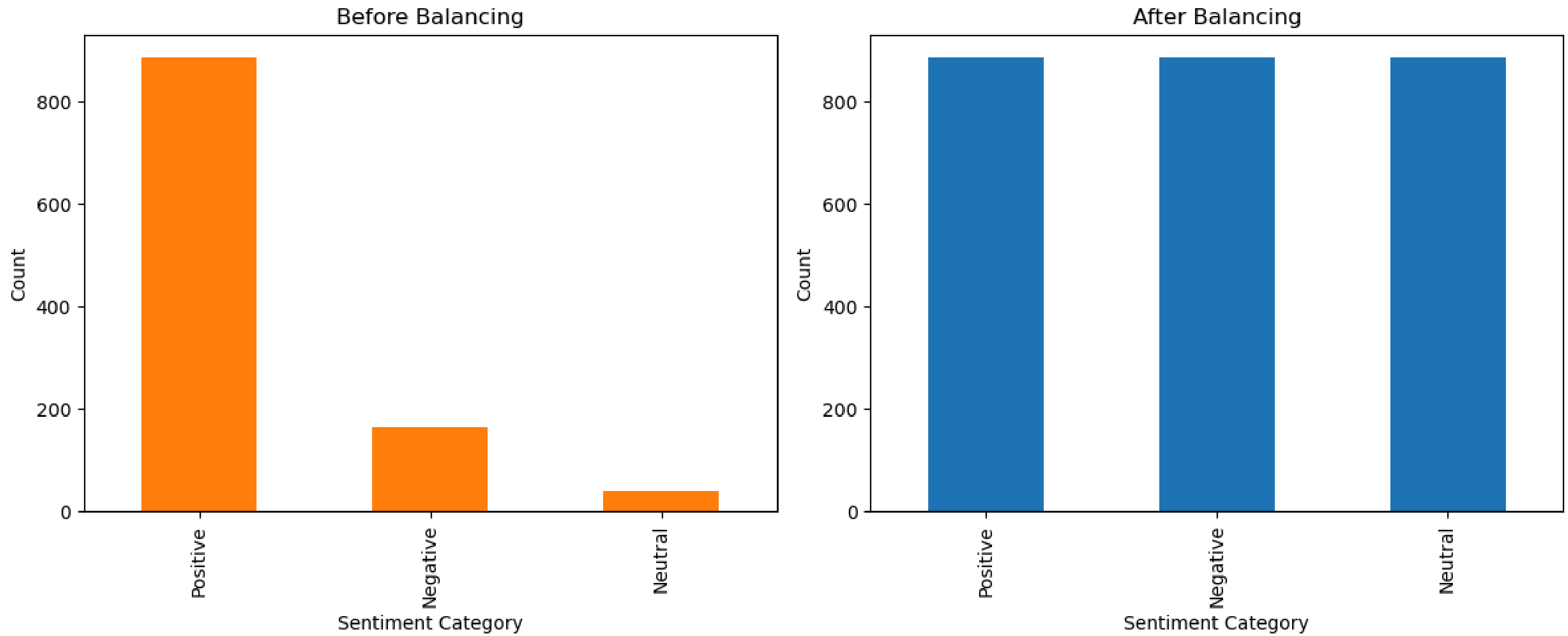
In [132…
```
# Upsample minority classes
for label in classes:
    df_class = df_model[df_model['manual_sentiment'] == label]
    df_class_upsampled = resample(
        df_class,
        replace=True,
        n_samples=max_size,
        random_state=42
    )
    df_balanced_model = pd.concat([df_balanced_model, df_class_upsampled])

# Checking the distribution
df_balanced_model['manual_sentiment'].value_counts(normalize=True)
```

Out[132…
```
manual_sentiment
Positive    0.333333
Negative    0.333333
Neutral     0.333333
Name: proportion, dtype: float64
```

From the output ,we can see the sentiment classes are now balanced ,this ensures our model will not be biased.

In [133…

```
#Visualiznig the before and after balancing distribution of the sentiment classes.
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
# Before balancing
df_model['manual_sentiment'].value_counts().plot(kind='bar', ax=axes[0], color='#ff7f0e')
axes[0].set_title('Before Balancing')
axes[0].set_xlabel('Sentiment Category')
axes[0].set_ylabel('Count')

# After balancing
df_balanced_model['manual_sentiment'].value_counts().plot(kind='bar', ax=axes[1], color='#1f77b4')
axes[1].set_title('After Balancing')
axes[1].set_xlabel('Sentiment Category')
axes[1].set_ylabel('Count')

plt.tight_layout()
plt.show()
```



splitting the data

In [134…

```
# splitting the data
X = df_balanced_model['cleaned_tweet']
y = df_balanced_model['manual_sentiment']
```

In [135…

```
# performing the train test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)
```

TEXT VECTORIZATION

In [136…

```
# Converting textual data into numerical data using TF-IDF
tfidf = TfidfVectorizer(max_features=5000, ngram_range=(1,2))

 #Fitting the vectorizer on training data and transform it into TF-IDF numerical features
X_train_tfidf = tfidf.fit_transform(X_train)
# Transform test data into TF-IDF numerical features
X_test_tfidf = tfidf.transform(X_test)
```

1. Baseline logistic regression

In [137…

```
# Create a Logistic Regression pipeline
lr_pipeline = Pipeline([
    ('tfidf', TfidfVectorizer(max_features=5000, ngram_range=(1, 2))),
    ('logreg', LogisticRegression(max_iter=1000))
])

# Train the pipeline
lr_pipeline.fit(X_train, y_train)
```

Out[137…

```
▸ Pipeline
  ▸ TfidfVectorizer
  ▸ LogisticRegression
```

In [138…

```
# Predict sentiment for the test set
# Predict on the test set
y_pred_lr = lr_pipeline.predict(X_test)
```

In [139…

```
# Accuracy and classification report
print("Accuracy:", accuracy_score(y_test,y_pred_lr))
print(classification_report(y_test, y_pred_lr))
```

```
Accuracy: 0.975517890772128
              precision    recall  f1-score   support

    Negative       0.98      0.95      0.97       177
     Neutral       0.99      1.00      0.99       177
    Positive       0.96      0.98      0.97       177

    accuracy                           0.98       531
   macro avg       0.98      0.98      0.98       531
weighted avg       0.98      0.98      0.98       531
```

from the report the baseline model has an overall accuracy of 98%.looking at other metrices the positive seems to be perfoming better while the other classes have a poor perfomance.

next suggested step is to handle class imbalance.

In [140…

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred_lr, labels=lr_pipeline.classes_)
```

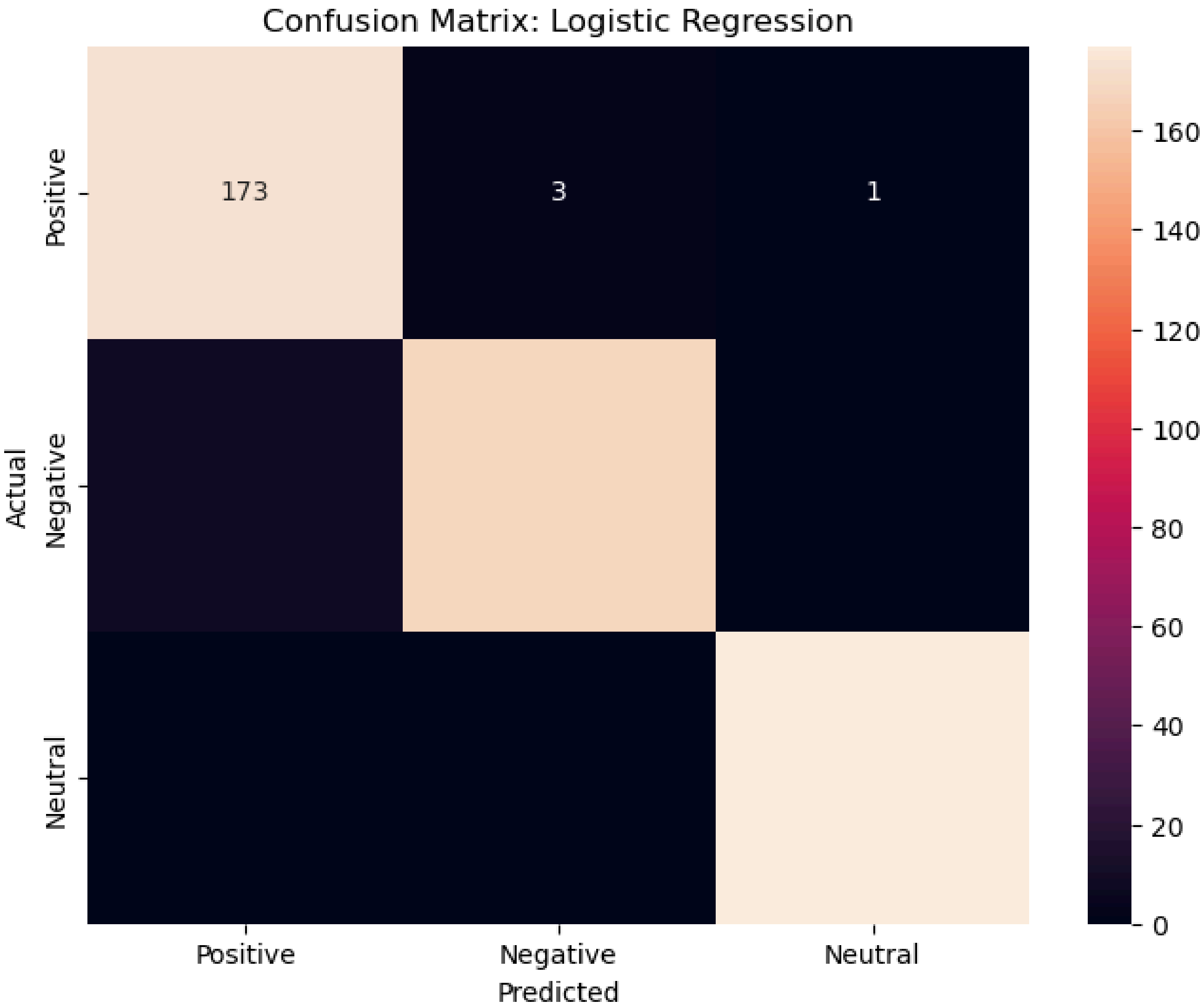
```
cm
```

Out[140…

```
array([[168,   1,   8],
       [  0, 177,   0],
       [  3,   1, 173]], dtype=int64)
```

In [141…

```
# Confusion matrix visualization
cm = confusion_matrix(y_test, y_pred_lr, labels=['Positive', 'Negative', 'Neutral'])
plt.figure(figsize=(8,6))
sns.heatmap(cm, annot=True, fmt='d', xticklabels=['Positive','Negative','Neutral'],
            yticklabels=['Positive','Negative','Neutral'], cmap='rocket')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix: Logistic Regression')
plt.show()
```



from the confusion matrix the : Negative: 168 correctly classified and a few misclassified as positive. Neutral:it correctly classifies ,with all 177 showing perfect generalization. Positive: 173 is correctly classified ,with only 4 misclassifications.

this shows our model is perfoming better on all classes.

Checking for overfitting on our logistic regression model

In [142...

```
# Predicting on the training set
y_train_pred = lr_pipeline.predict(X_train)
y_test_pred = lr_pipeline.predict(X_test)

# Computing the accuracies
train_accuracy = accuracy_score(y_train, y_train_pred)
test_accuracy = accuracy_score(y_test, y_test_pred)

print(f"Training Accuracy: {train_accuracy:.4f}")
print(f"Test Accuracy: {test_accuracy:.4f}")
```

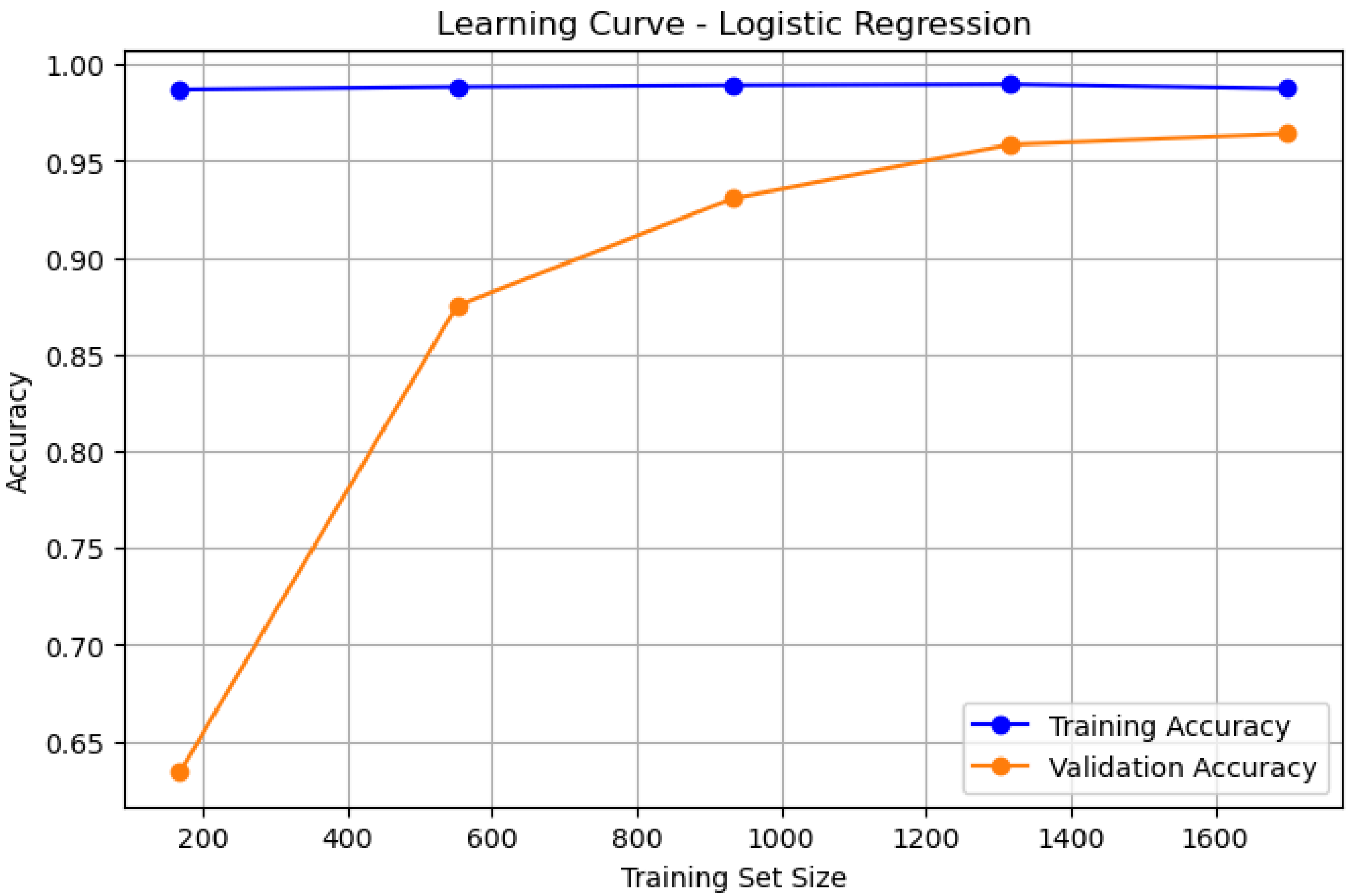
```
Training Accuracy: 0.9882
Test Accuracy: 0.9755
```

this shows the model is performing well on both the training and test data

In [143...

```
# Checking for overfitting / underfitting using the learning curve
from sklearn.model_selection import learning_curve
import numpy as np
import matplotlib.pyplot as plt

#using the pipeline
train_sizes, train_scores, test_scores = learning_curve(
    lr_pipeline,
    X_train,
    y_train,
    cv=5,
    scoring='accuracy',
    n_jobs=-1
)

# Compute mean scores across folds
train_mean = np.mean(train_scores, axis=1)
test_mean = np.mean(test_scores, axis=1)

# Plot the learning curve
plt.figure(figsize=(8,5))
```

```
plt.plot(train_sizes, train_mean, 'o-', color='blue', label='Training Accuracy')
plt.plot(train_sizes, test_mean, 'o-', color='#ff7f0e', label='Validation Accuracy')
plt.title('Learning Curve - Logistic Regression')
plt.xlabel('Training Set Size')
plt.ylabel('Accuracy')
plt.legend(loc='best')
plt.grid(True)
plt.show()
```



From the small gap at the ends of the Training and Validation shows the model is perfoming well and not overfitting.

In [144…

```
# comparing the Vader model with our Logistic regression model.
# VADER metrics
vader_accuracy = accuracy_score(df['manual_sentiment'], df['vader_sentiment'])
vader_f1 = f1_score(df['manual_sentiment'], df['vader_sentiment'], average='macro')

# Logistic Regression metrics
lr_accuracy = accuracy_score(y_test, y_pred_lr)
lr_f1 = f1_score(y_test, y_pred_lr, average='macro')

print(f"VADER Accuracy: {vader_accuracy:.4f}, Macro F1: {vader_f1:.4f}")
print(f"Logistic Regression Accuracy: {lr_accuracy:.4f}, Macro F1: {lr_f1:.4f}")
```

```
VADER Accuracy: 0.6201, Macro F1: 0.4208
Logistic Regression Accuracy: 0.9755, Macro F1: 0.9755
```

Logistic regression model outperfoms the Vader model with an accuracy of 98% and macro F1 of 98% . data ,compared to the Vader that had an accuracy of 62% and Macro F1 of 42% showing an imbalance . Vader perfoms better on positive class and struggles with the rest of the classes.

In [145…

```
# Extract TF-IDF feature names and the trained Logistic Regression model
vectorizer = lr_pipeline.named_steps['tfidf']
model = lr_pipeline.named_steps['logreg']

feature_names = vectorizer.get_feature_names_out()

# For multi-class, get coefficients for each class
for i, class_label in enumerate(model.classes_):
    coefficients = model.coef_[i]
    top_positive_words = [feature_names[j] for j in np.argsort(coefficients)[-10:]]
    top_negative_words = [feature_names[j] for j in np.argsort(coefficients)[:10]]

    print(f"\nClass: {class_label}")
    print("Top words influencing positive sentiment:", top_positive_words)
    print("Top words influencing negative sentiment:", top_negative_words)
```

```
Class: Negative
Top words influencing positive sentiment: ['rt temporary', 'google circle', 'company', 'attention', 'fascist company', 'amer
ica', 'company america', 'fascist', 'fail', 'rt google']
Top words influencing negative sentiment: ['link', 'party', 'sxsw link', 'pop', 'austin', 'popup', 'wow', 'store', 'love',
'going']

Class: Neutral
Top words influencing positive sentiment: ['link', 'actual', 'link sxsw', 'apple like', 'austin', 'pop', 'wow rt', 'rt pop',
'quot party', 'launch']
Top words influencing negative sentiment: ['day', 'rt google', 'temporary', 'opening', 'quot apple', 'get', 'sxswi', 'apple
opening', 'great', 'store downtown']

Class: Positive
Top words influencing positive sentiment: ['store downtown', 'opening', 'smart', 'marketing', 'cool', 'set', 'amp', 'great',
'link', 'love']
Top words influencing negative sentiment: ['quot', 'launch', 'like', 'apple like', 'want', 'location', 'first', 'seems', 'qu
ot party', 'fail']
```

SUPPORT VECTOR MACHINE (SVM)

why SVM?

Logistic Regression gave strong baseline results, but SVM is often better at handling complex, high-dimensional text data like TF-IDF. It can pick up on subtle differences between sentiments—especially Neutral and Negative—so it’s a good choice to compare against the baseline.

In [146…

```python
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.svm import LinearSVC

# Build the SVM pipeline
svm_pipeline = Pipeline([
    ('tfidf', TfidfVectorizer(max_features=5000, ngram_range=(1, 2))),
    ('svm', LinearSVC(random_state=42))
])
```

In [147…

```
# Train on training data
svm_pipeline.fit(X_train, y_train)
```

Out[147…

```
Pipeline
  TfidfVectorizer
  LinearSVC
```

In [148…

```
# Predict on test data
y_pred_svm = svm_pipeline.predict(X_test)
```

In [149…

```
# Evaluate
print("SVM Pipeline Accuracy:", accuracy_score(y_test, y_pred_svm))
print(classification_report(y_test, y_pred_svm))
```

```
SVM Pipeline Accuracy: 0.9811676082862524
              precision    recall  f1-score   support

    Negative       0.98      0.97      0.97       177
     Neutral       0.99      1.00      1.00       177
    Positive       0.97      0.98      0.97       177

    accuracy                           0.98       531
   macro avg       0.98      0.98      0.98       531
weighted avg       0.98      0.98      0.98       531
```

The SVM model achieved an impressive 98.1% accuracy, slightly outperforming Logistic Regression. High precision, recall, and F1-scores across all classes indicate strong generalization and effective handling of subtle sentiment differences

In [150…

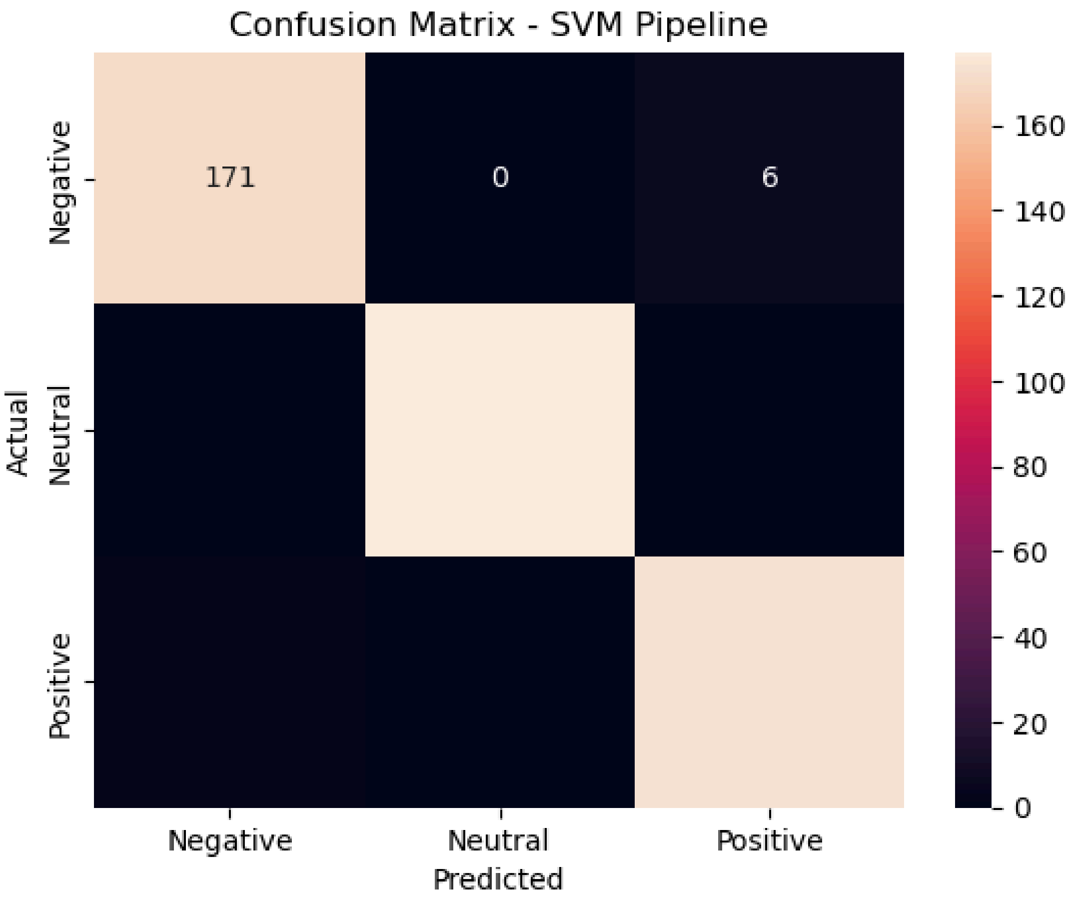
```
cm = confusion_matrix(y_test, y_pred_svm, labels=svm_pipeline.named_steps['svm'].classes_)
cm
```

Out[150…

```
array([[171,   0,   6],
       [  0, 177,   0],
       [  3,   1, 173]], dtype=int64)
```

In [151…

```
cm = confusion_matrix(y_test, y_pred_svm, labels=svm_pipeline.classes_)
sns.heatmap(cm, annot=True, fmt='d', cmap='rocket',
            xticklabels=svm_pipeline.classes_,
            yticklabels=svm_pipeline.classes_)
plt.title('Confusion Matrix - SVM Pipeline')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



The SVM confusion matrix shows very few errors — 6 Negative tweets were misclassified as Positive, and 4 Positive tweets were slightly mixed up. Overall, the model performed very well, especially for Neutral tweets, which were all correctly predicted

checking for overfitting in the SVM MODEL

In [152…

```
# Checkiiing  for overfitting in our SVM model
train_accuracy = svm_pipeline.score(X_train, y_train)
test_accuracy = svm_pipeline.score(X_test, y_test)

print(f"Training Accuracy: {train_accuracy:.4f}")
print(f"Test Accuracy: {test_accuracy:.4f}")
```

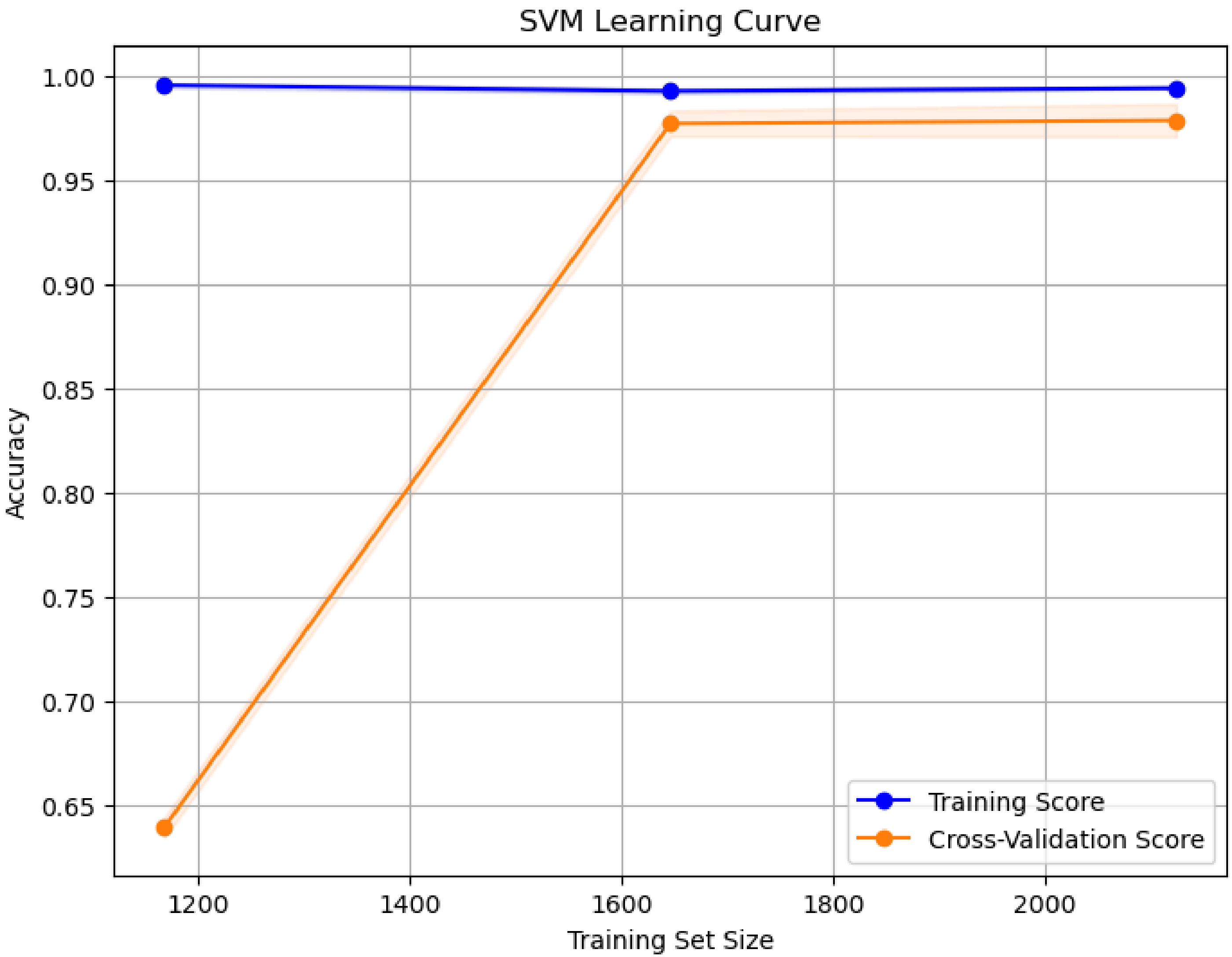
```
Training Accuracy: 0.9929
Test Accuracy: 0.9812
```

The SVM model achieved a training accuracy of 99.3% and a test accuracy of 98.1%, showing only a small difference between the two. This indicates that the model generalizes well and there is no significant overfitting.

In [153…

```
# Generate learning curve data for SVM pipeline
train_sizes, train_scores, test_scores = learning_curve(
    svm_pipeline, X, y, cv=5, scoring='accuracy', n_jobs=-1, train_sizes=np.linspace(0.1, 1.0, 5), random_state=42
)

# Compute mean and standard deviation
train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

# Plot
plt.figure(figsize=(8,6))
plt.plot(train_sizes, train_mean, 'o-', color='blue', label='Training Score')
plt.plot(train_sizes, test_mean, 'o-', color='#ff7f0e', label='Cross-Validation Score')
plt.fill_between(train_sizes, train_mean - train_std, train_mean + train_std, color='blue', alpha=0.1)
plt.fill_between(train_sizes, test_mean - test_std, test_mean + test_std, color='#ff7f0e', alpha=0.1)
plt.title("SVM Learning Curve")
plt.xlabel("Training Set Size")
plt.ylabel("Accuracy")
```

```
plt.legend(loc="best")
plt.grid(True)
plt.show()
```



- The two curves are close together, suggesting the model generalizes well and is not overfitting. As the training size increases, validation accuracy stabilizes, confirming the model's strong and reliable performance across the dataset

- Logistic Regression reached around 97.5% accuracy, while SVM slightly improved to about 98.1%. The learning curves for both models show minimal gaps between training and validation scores, indicating low overfitting. However, SVM showed a slightly stronger generalization capability, making it a more robust choice for sentiment classification in this dataset.

In [154…

```
#Top words influencing sentiments in our SVM model

# Extract TF-IDF feature names and the trained SVM model
vectorizer = svm_pipeline.named_steps['tfidf']
model = svm_pipeline.named_steps['svm']

feature_names = vectorizer.get_feature_names_out()

# For multi-class SVM, extract coefficients for each class
for i, class_label in enumerate(model.classes_):
    coefficients = model.coef_[i]
    top_positive_words = [feature_names[j] for j in np.argsort(coefficients)[-10:]]
    top_negative_words = [feature_names[j] for j in np.argsort(coefficients)[:10]]

    print(f"\nClass: {class_label}")
    print("Top words influencing positive sentiment:", top_positive_words)
    print("Top words influencing negative sentiment:", top_negative_words)
```

```
Class: Negative
Top words influencing positive sentiment: ['suck', 'suck link', 'sxsw suck', 'attention', 'fail', 'perfect attention', 'atte
ntion detail', 'detail rt', 'rt google', 'rt temporary']
Top words influencing negative sentiment: ['rt apple', 'link', 'rt pop', 'wow rt', 'party', 'love', 'wow', 'great', 'love sx
sw', 'quot via']

Class: Neutral
Top words influencing positive sentiment: ['wow', 'denim', 'sxsw apple', 'gadget', 'launch', 'quot party', 'link photo', 'li
nk sxsw', 'wow rt', 'rt pop']
Top words influencing negative sentiment: ['rt google', 'detail rt', 'attention detail', 'perfect attention', 'detail', 'per
fect', 'attention', 'gt', 'opening', 'apple ipad']

Class: Positive
Top words influencing positive sentiment: ['love sxsw', 'cool', 'party', 'amp', 'marketing', 'set', 'smart', 'great', 'lin
k', 'love']
Top words influencing negative sentiment: ['rt temporary', 'link sxsw', 'fail', 'link photo', 'launch', 'want', 'suck', 'suc
k link', 'sxsw suck', 'sxsw apple']
```

NAIVE-BAYES

In [155…

```
from sklearn.naive_bayes import MultinomialNB
# Build a Nive-Bayes pipeline
nb_pipeline = Pipeline([
    ('tfidf', TfidfVectorizer(max_features=5000, ngram_range=(1, 2))),
    ('nb', MultinomialNB())
])

#Training the pipeline
nb_pipeline.fit(X_train, y_train)
```

Out[155…

```
▸ Pipeline
  ▸ TfidfVectorizer
  ▸ MultinomialNB
```

In [156…

```
# Predictions
y_pred_nb = nb_pipeline.predict(X_test)
```

In [157…

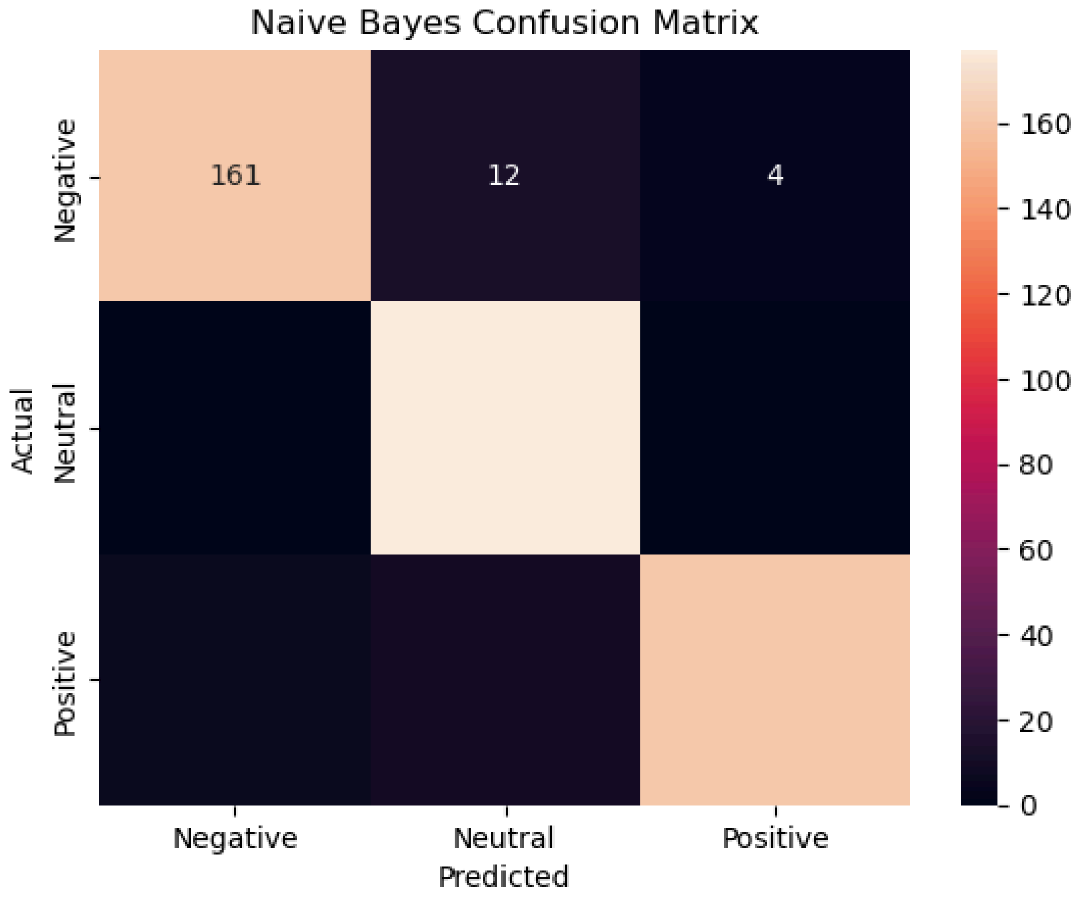
```
# Metrics
print("Naive Bayes Accuracy:", accuracy_score(y_test, y_pred_nb))
print("\nClassification Report:\n", classification_report(y_test, y_pred_nb))
```

```
Naive Bayes Accuracy: 0.9397363465160076

Classification Report:
               precision    recall  f1-score   support

    Negative       0.96      0.91      0.94       177
     Neutral       0.89      1.00      0.94       177
    Positive       0.98      0.91      0.94       177

    accuracy                           0.94       531
   macro avg       0.94      0.94      0.94       531
weighted avg       0.94      0.94      0.94       531
```

The Naive Bayes model achieved an accuracy of 93.97% with a macro F1-score of 0.94, with a strong and balanced performance across all classes. It achieved high precision for Negative 0.96 and Positive 0.98 sentiments, and perfectly recalled the Neutral class 1.00. However, it performed slightly below SVM and Logistic Regression.

In [158…

```
cm = confusion_matrix(y_test, y_pred_nb, labels=nb_pipeline.classes_)

sns.heatmap(cm, annot=True, fmt='d', cmap='rocket',
            xticklabels=nb_pipeline.classes_,
            yticklabels=nb_pipeline.classes_)
plt.title("Naive Bayes Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



MODELS EVALUATION and SELECTION

In [159…

```
# Model evaluation and selction of the best model
# Get predictions from each pipeline
y_pred_lr = lr_pipeline.predict(X_test)
y_pred_svm = svm_pipeline.predict(X_test)
y_pred_nb = nb_pipeline.predict(X_test)

#VADER
```

```
vader_accuracy = accuracy_score(df['manual_sentiment'], df['vader_sentiment'])
vader_f1 = f1_score(df['manual_sentiment'], df['vader_sentiment'], average='macro')
```

In [160…

```
# Storing the model predictions in a dictionary
models = {
    "VADER (Lexicon)": None,
    "Logistic Regression": y_pred_lr,
    "SVM": y_pred_svm,
    "Naive Bayes": y_pred_nb
}
```

In [161…

```
for name, obj in models.items():
    print(name, type(obj))
```

```
VADER (Lexicon) <class 'NoneType'>
Logistic Regression <class 'numpy.ndarray'>
SVM <class 'numpy.ndarray'>
Naive Bayes <class 'numpy.ndarray'>
```

In [162…

```
# Computing accuracy and F1-score for each model
results = {}

for name, preds in models.items():
    if name == "VADER (Lexicon)":
        results[name] = {
            "Accuracy": vader_accuracy,
            "F1-score": vader_f1
        }
    else:
        results[name] = {
            "Accuracy": accuracy_score(y_test, preds),
            "F1-score": f1_score(y_test, preds, average='macro')
        }
```

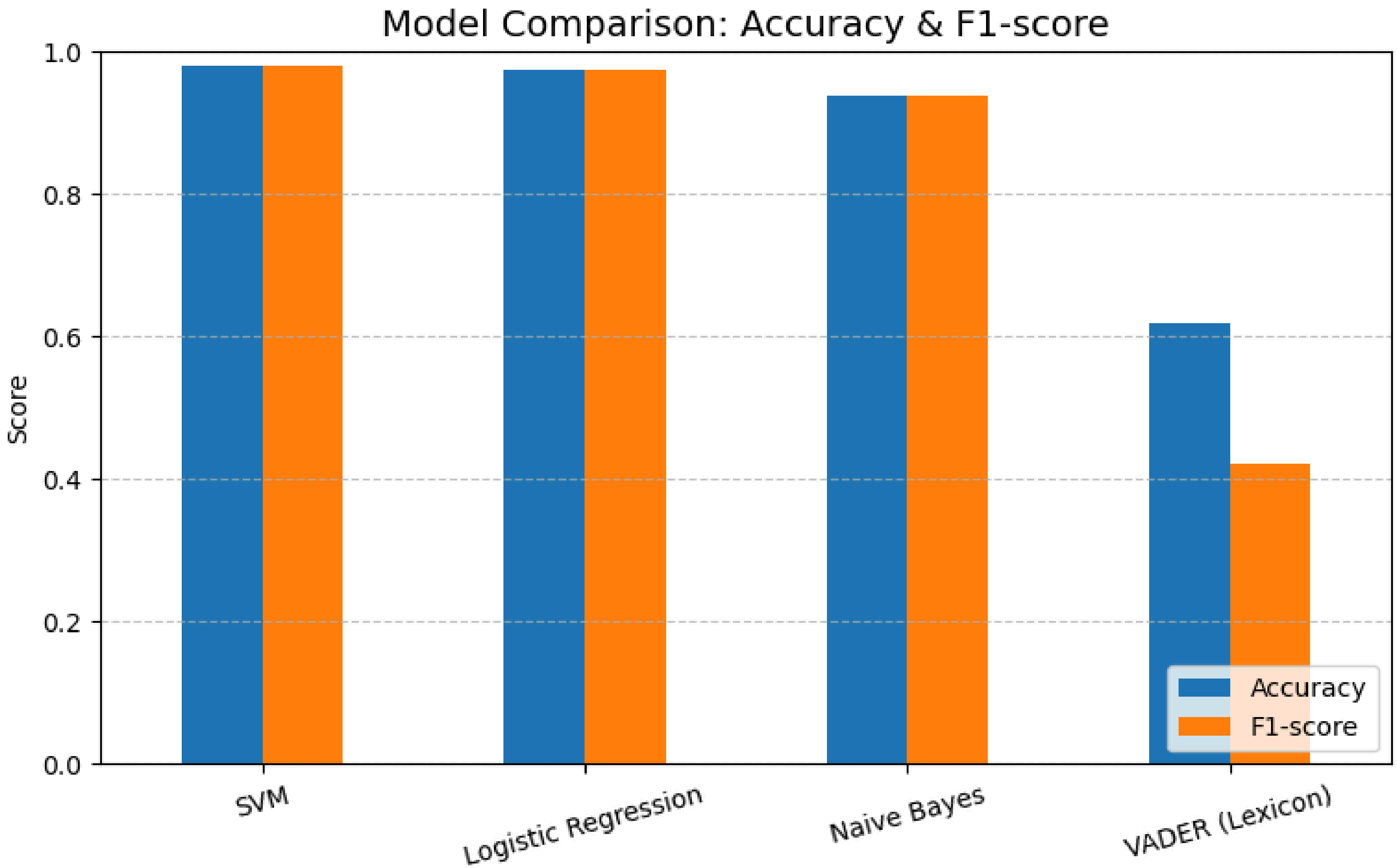
In [163…

```
#Creating a DataFrame for comparison
results_df = pd.DataFrame(results).T.sort_values(by="Accuracy", ascending=False)
display(results_df)
```

	Accuracy	F1-score
SVM	0.981168	0.981151
Logistic Regression	0.975518	0.975460
Naive Bayes	0.939736	0.939685
VADER (Lexicon)	0.620055	0.420786

In [164…

```
#Visualization on the comparison of the models perfomance
results_df.plot(kind='bar', figsize=(9,5), color=['#1f77b4', '#ff7f0e'])
plt.title('Model Comparison: Accuracy & F1-score', fontsize=14)
plt.ylabel('Score')
plt.xticks(rotation=15)
plt.ylim(0, 1.0)
plt.legend(loc='lower right')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()

best_model = results_df.index[0]
best_acc = results_df.iloc[0, 0]
print(f" Best Model: {best_model} with Accuracy = {best_acc:.4f}")
```




```
Best Model: SVM with Accuracy = 0.9812
```

From our comparison of all models tested, SVM achieved the highest accuracy of 98.12%, slightly outperforming Logistic Regression of 97.55% and Naive Bayes of 93.97%. This shows that SVM handled the high-dimensional TF-IDF features most effectively, making it the best overall model for this multiclass sentiment classification task.

Conclusion and Recomendation

Conclusion

- This project explored different models for sentiment analysis, including VADER, Naive Bayes, Logistic Regression, and SVM. The SVM model performed best, achieving an accuracy of 0.9812, showing strong ability to understand patterns in the text. Overall, machine learning models, especially those using TF-IDF features, performed much better than rule-based approaches like VADER.

Recommendations

1. Use SVM as Primary model

- SVM achieved the highest performance with an Accuracy and F1-score of 0.98, making it the most reliable for classifying tweets about Apple and Google.
- Business impact: Ideal for real-time sentiment tracking and decision-making due to its high precision and consistency.

2. Use Logistic regression when interpretability matters

- Logistic Regression performed strongly with Accuracy of 0.98 and F1 of 0.97.
- Recommendation: Use alongside SVM when transparency and stakeholder understanding are priorities.

3. Use Naïve Bayes as a supporting model

- Naive Bayes achieved moderate results Accuracy of 0.94
- Recommendation: Suitable lightweight analysis tools, but not for production sentiment monitoring.

4. Use tools like LIME for model interpratability.
5. Keep improving the model with new data to maintain accuracy.