Twitter Sentiments Analysis

Summary

This project aims to analyze the sentiment of tweets related to Apple and Google products using Natural Language Processing (NLP) techniques. The dataset used contains over 9,000 tweets rated by human raters as either positive, negative, or neutral. The goal is to build a model capable of determining the sentiment of a tweet based on its content, which can be used for analyzing public perception of these tech companies.

The project involved the following steps:

- Data Preparation: Cleaned the data, removed irrelevant content, and vectorized the text using TF-IDF.
- Model Building: A baseline Logistic Regression model and a DecisionTreeClassifier were first built for binary classification (positive vs. negative). We then extended them to multiclass classification to include neutral tweets.
- Advanced Models: We applied XGBoost on both binary and multiclass classification.
- Model Evaluation: The models were evaluated and compared using metrics such as accuracy. The best-performing model was the XGBoost for binary classification and DecisionTreeClassifier for the multiclass classification, which showed high accuracy and balanced precision and recall across all classes. These models provide practical solutions for real-time analysis of tweet sentiments related to Apple and Google products.
- In conclusion, this project highlights the effectiveness of different machine learning models in sentiment analysis tasks, with XGBoost for binary classification and DecisionTreeClassifier for the multiclass classification proving to be the most suitable for our dataset.

Business Understanding

1. Objective:

The goal is to build an NLP model that rates the sentiment of a Tweet as positive, negative, or neutral, based on its content. This is useful for companies to understand customer opinions, make decisions, and improve products.

2. Target Audience:

The sentiment analysis could help marketers, product managers, and customer service teams understand how users feel about products.

3. Success Criteria:

Success is measured by the accuracy and other classification metrics (Precision, Recall and F1-score) of the model. An acceptable model should classify sentiments effectively

Data Understanding

- The dataset, sourced from `CrowdFlower` via data.world, contains over 9,000 tweets rated by human annotators as positive, negative, or neutral.
- The dataset comprises tweets collected from Twitter, containing:

1. Tweet Text: The content of the tweets where users express their opinions.
2. Emotion Directed At: The specific product or brand the sentiment is directed towards (e.g., Apple, Google).
3. Type of Emotion: The sentiment type classified into categories such as positive, negative, and neutral

Importing Relevant Libraries

In [71]:

```
#Import the neccessary libraries
#Libraries for Loading the dataset and EDA
import pandas as pd
from collections import Counter
import itertools
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
#Libraries for NLP
import nltk
from nltk.tokenize import RegexpTokenizer
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from wordcloud import WordCloud
import re
#Libraries for modeling
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix, roc_
curve, auc, roc_auc_score

import warnings
warnings.filterwarnings('ignore')
```

Data Preprocessing

In [72]:

```
#Load the datatset
tweets = pd.read_csv('judge-1377884607_tweet_product_company.csv', encoding='ISO-8859-1')
tweets.head(15)
```

Out[72]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emotion
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive emotion
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emotion
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion
5	@teachntech00 New iPad Apps For #SpeechTherapy...	NaN	No emotion toward brand or product
6	NaN	NaN	No emotion toward brand or product
7	#SXSW is just starting, #CTIA is around the co...	Android	Positive emotion
8	Beautifully smart and simple idea RT @madebyma...	iPad or iPhone App	Positive emotion
9	Counting down the days to #sxsw plus strong Ca...	Apple	Positive emotion
10	Excited to meet the @samsungmobileus at #sxsw ...	Android	Positive emotion
11	Find & Start Impromptu Parties at #SXSW Wi...	Android App	Positive emotion

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
12	Foursquare ups the game, just in time for #SXS...	Android App	Positive emotion
13	Gotta love this #SXSW Google Calendar featurin...	Other Google product or service	Positive emotion
14	Great #sxsw ipad app from @madebymany: http://...	iPad or iPhone App	Positive emotion

In [73]:

```
tweets.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
```

In [74]:

```
tweets.describe()
```

Out[74]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
count	9092	3291	9093
unique	9065	9	4
top	RT @mention Marissa Mayer: Google Will Connect...	iPad	No emotion toward brand or product
freq	5	946	5389

In [75]:

```
tweets.isnull().sum()
```

Out[75]:

```
tweet_text                                               1
emotion_in_tweet_is_directed_at                       5802
is_there_an_emotion_directed_at_a_brand_or_product       0
dtype: int64
```

In [76]:

```
#drop missing data in tweet_text
tweets.dropna(subset =['tweet_text'], inplace = True)
```

In [77]:

```
#handle the missing data
tweets['emotion_in_tweet_is_directed_at'].fillna('Unknown', inplace = True)
```

In [78]:

```
#check if values are filled
tweets.isnull().sum()
```

Out[78]:

```
tweet_text                                            0
emotion_in_tweet_is_directed_at                       0
is_there_an_emotion_directed_at_a_brand_or_product    0
dtype: int64
```

In [79]:

```
#Check the groupings of the dataset for is_there_an_emotion_directed_at_a_brand_or_produc
t
tweets.is_there_an_emotion_directed_at_a_brand_or_product.value_counts()
```

Out[79]:

```
is_there_an_emotion_directed_at_a_brand_or_product
No emotion toward brand or product    5388
Positive emotion                      2978
Negative emotion                       570
I can't tell                           156
Name: count, dtype: int64
```

In [80]:

```
#reduce the options for is_there_an_emotion_directed_at_a_brand_or_product
tweets['is_there_an_emotion_directed_at_a_brand_or_product'] = tweets['is_there_an_emotio
n_directed_at_a_brand_or_product'].replace(["No emotion toward brand or product","I can't
tell"], 'Neutral')
tweets.is_there_an_emotion_directed_at_a_brand_or_product.value_counts()
```

Out[80]:

```
is_there_an_emotion_directed_at_a_brand_or_product
Neutral             5544
Positive emotion    2978
Negative emotion     570
Name: count, dtype: int64
```

In [81]:

```
#Verify they have been reduced
tweets.head(35)
```

Out[81]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emotion
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive emotion
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emotion
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion
5	@teachntech00 New iPad Apps For #SpeechTherapy...	Unknown	Neutral
7	#SXSW is just starting, #CTIA is around the co...	Android	Positive emotion
8	Beautifully smart and simple idea RT @madebyma...	iPad or iPhone App	Positive emotion
9	Counting down the days to #sxsw plus strong Ca...	Apple	Positive emotion
10	Excited to meet the @samsungmobileus at #sxsw ...	Android	Positive emotion
11	Find & Start Impromptu Parties at #SXSW Wi...	Android App	Positive emotion
12	Foursquare ups the game, just in time for #SXS...	Android App	Positive emotion
13	Gotta love this #SXSW Google	Other Google product or service	Positive emotion

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
	Calendar featurin...		
14	Great #sxsw ipad app from @madebymany: http://...	iPad or iPhone App	Positive emotion
15	haha, awesomely rad iPad app by @madebymany ht...	iPad or iPhone App	Positive emotion
16	Holler Gram for iPad on the iTunes App Store -...	Unknown	Neutral
17	I just noticed DST is coming this weekend. How...	iPhone	Negative emotion
18	Just added my #SXSW flights to @planely. Match...	iPad or iPhone App	Positive emotion
19	Must have #SXSW app! RT @malbonster: Lovely re...	iPad or iPhone App	Positive emotion
20	Need to buy an iPad2 while I'm in Austin at #s...	iPad	Positive emotion
21	Oh. My. God. The #SXSW app for iPad is pure, u...	iPad or iPhone App	Positive emotion
22	Okay, this is really it: yay new @Foursquare f...	Android App	Positive emotion
23	Photo: Just installed the #SXSW iPhone app, wh...	iPad or iPhone App	Positive emotion
24	Really enjoying the changes in Gowalla 3.0 for...	Android App	Positive emotion
25	RT @LaurieShook: I'm looking forward to the #S...	iPad	Positive emotion
26	RT haha, awesomely rad iPad app by @madebymany...	iPad or iPhone App	Positive emotion
27	someone started an #austin @PartnerHub group i...	Other Google product or service	Positive emotion
28	The new #4sq3 looks like it is going to rock. ...	iPad or iPhone App	Positive emotion
29	They were right, the @gowalla 3 app on #androi...	Android App	Positive emotion
30	Very smart from @madebymany #hollergram iPad a...	iPad or iPhone App	Positive emotion
31	You must have this app for your iPad if you ar...	iPad or iPhone App	Positive emotion
32	Attn: All #SXSW frineds, @mention Register fo...	Unknown	Neutral
33	Anyone at #sxsw want to sell their old iPad?	Unknown	Neutral
34	Anyone at #SXSW who bought the new iPad want ...	Unknown	Neutral
35	At #sxsw. Oooh. RT @mention Google to Launch ...	Unknown	Neutral

In [82]:

```
#Let's look at the value_counts for the emotion_is_directed_at column
tweets.emotion_in_tweet_is_directed_at.value_counts()
```

Out[82]:

```
emotion_in_tweet_is_directed_at
Unknown                            5801
iPad                                946
Apple                               661
iPad or iPhone App                  470
Google                              430
iPhone                              297
Other Google product or service     293
```

```
Android App                         81
Android                             78
Other Apple product or service      35
Name: count, dtype: int64
```

In [83]:

```
#Remove the columns where the emotion_in_tweet_is_directed_at is 'Unknown'
tweets = tweets[tweets['emotion_in_tweet_is_directed_at']!= 'Unknown']
```

In [84]:

```
#Verify the 'unknown'values have been removed
tweets.head(25)
```

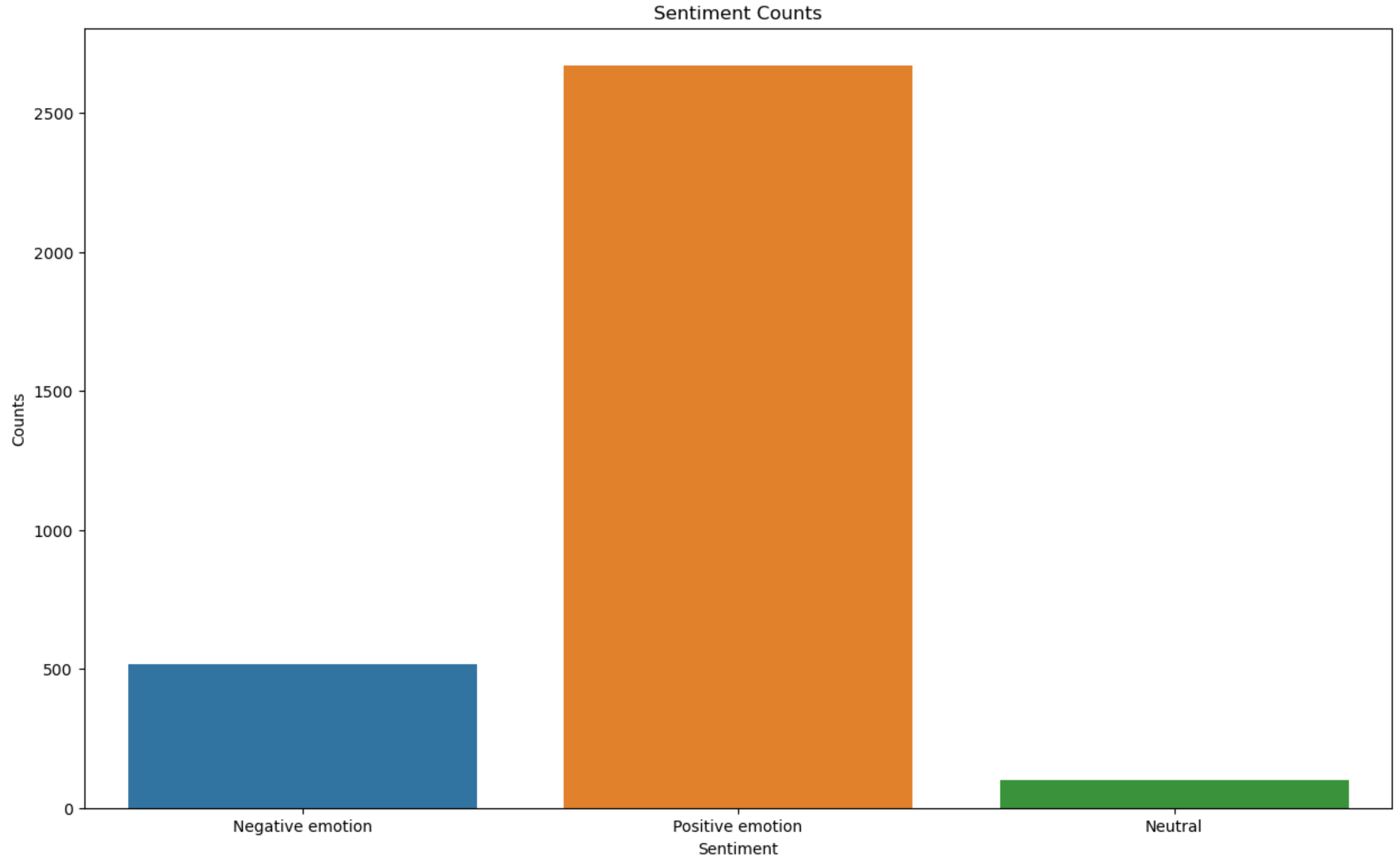
Out[84]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emotion
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive emotion
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emotion
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion
7	#SXSW is just starting, #CTIA is around the co...	Android	Positive emotion
8	Beautifully smart and simple idea RT @madebyma...	iPad or iPhone App	Positive emotion
9	Counting down the days to #sxsw plus strong Ca...	Apple	Positive emotion
10	Excited to meet the @samsungmobileus at #sxsw ...	Android	Positive emotion
11	Find & Start Impromptu Parties at #SXSW Wi...	Android App	Positive emotion
12	Foursquare ups the game, just in time for #SXS...	Android App	Positive emotion
13	Gotta love this #SXSW Google Calendar featurin...	Other Google product or service	Positive emotion
14	Great #sxsw ipad app from @madebymany: http://...	iPad or iPhone App	Positive emotion
15	haha, awesomely rad iPad app by @madebymany ht...	iPad or iPhone App	Positive emotion
17	I just noticed DST is coming this weekend. How...	iPhone	Negative emotion
18	Just added my #SXSW flights to @planely. Match...	iPad or iPhone App	Positive emotion
19	Must have #SXSW app! RT @malbonster: Lovely re...	iPad or iPhone App	Positive emotion
20	Need to buy an iPad2 while I'm in Austin at #s...	iPad	Positive emotion
21	Oh. My. God. The #SXSW app for iPad is pure, u...	iPad or iPhone App	Positive emotion
22	Okay, this is really it: yay new @Foursquare f...	Android App	Positive emotion
23	Photo: Just installed the #SXSW iPhone app, wh...	iPad or iPhone App	Positive emotion

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
24	Really enjoying the changes in Gowalla 3.0 for...	Android App	Positive emotion
25	RT @LaurieShook: I'm looking forward to the #S...	iPad	Positive emotion
26	RT haha, awesomely rad iPad app by @madebymany...	iPad or iPhone App	Positive emotion
27	someone started an #austin @PartnerHub group i...	Other Google product or service	Positive emotion

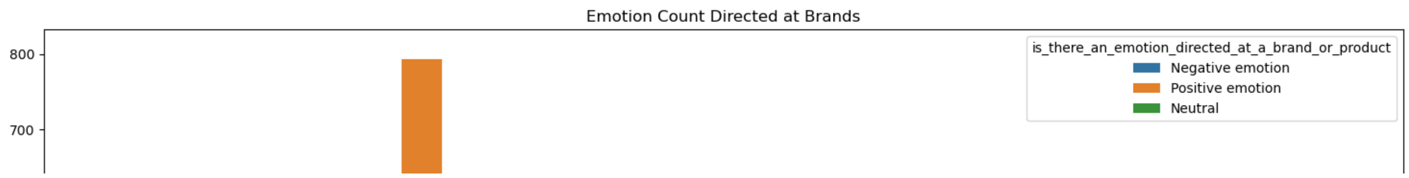
In [85]:

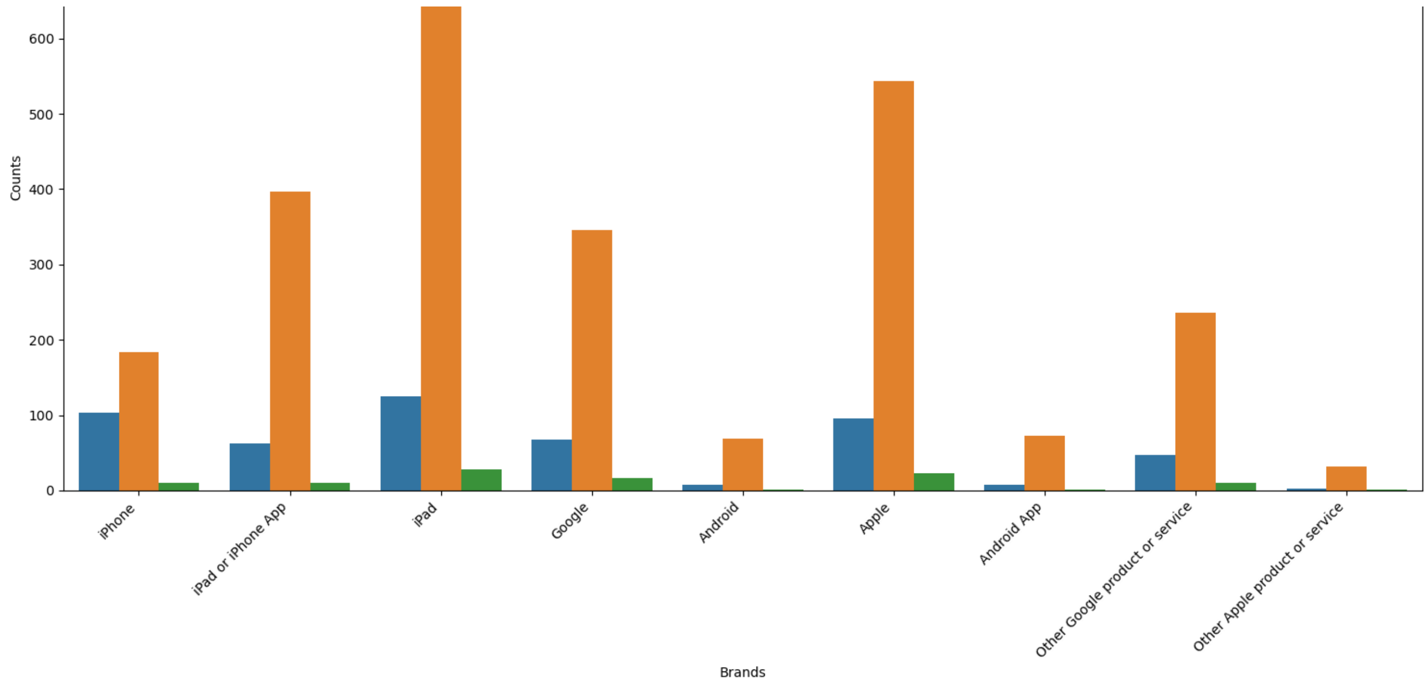
```
#plot the distribution of the count for is_there_an_emotion_directed_at_a_brand_or_produc
t
plt.figure(figsize=(15,9))
sns.countplot(x='is_there_an_emotion_directed_at_a_brand_or_product', data = tweets)
plt.title('Sentiment Counts')
plt.xlabel('Sentiment')
plt.ylabel('Counts')
plt.show()
```



In [86]:

```
#plot the distribution of the count for is_there_an_emotion_directed_at_a_brand_or_produc
t
plt.figure(figsize=(15,9))
sns.countplot(x='emotion_in_tweet_is_directed_at', hue = 'is_there_an_emotion_directed_at
_a_brand_or_product',data = tweets)
plt.title('Emotion Count Directed at Brands')
plt.xlabel('Brands')
plt.ylabel('Counts')
plt.xticks(rotation = 45, ha = 'right')
plt.tight_layout()
plt.show()
```





In [87]:

```
#Preprocess the text
tokenizer = RegexpTokenizer(r'\b\w{3,}\b')
stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()

def clean_tweet_text(text):
    text = text.lower()
    # Remove mentions, hashtags, and URLs
    text = re.sub(r'@\w+|#\w+|http\S+|www\S+|https\S+', '', text)
    # Remove punctuation and numbers
    text = re.sub(r'[^a-zA-Z\s]', '', text)
    # Tokenize text using `tokenizer`
    tokens = tokenizer.tokenize(text)
     # Remove stopwords using `stopwords_list`
    clean_text = [word for word in tokens if word not in stop_words]
    #Perform stemming
    clean_text = [lemmatizer.lemmatize(word) for word in clean_text]
    return clean_text
```

In [88]:

```
#clean the tweet_text column
tweets['clean_tweet_text'] = tweets['tweet_text'].apply(lambda x: clean_tweet_text(x))
```

In [89]:

```
tweets.head(15)
```

Out[89]:

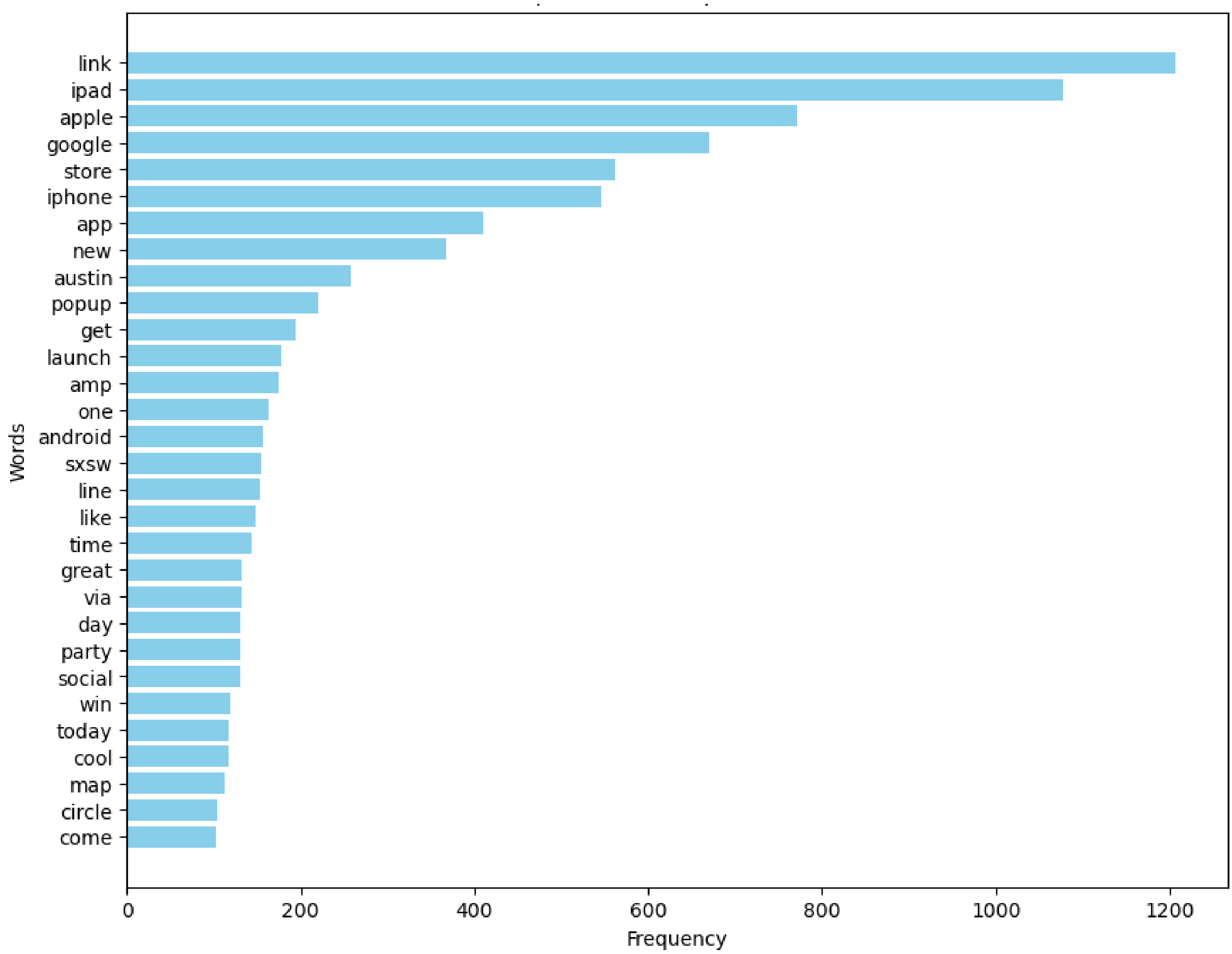
	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	clean_tweet_text
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emotion	[iphone, hr, tweeting, dead, need, upgrade, pl...
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive emotion	[know, awesome, ipadiphone, app, youll, likely...
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion	[wait, also, sale]
3	@sxsw I hope this year's festival isn't	iPad or iPhone App	Negative emotion	[hope, year, festival, isnt,

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	clean_tweet_text
3	year's festival isn't	iPad or iPhone App	Negative emotion	crashy, year, iph...
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion	[great, stuff, fri, marissa, mayer, google, ti...
7	#SXSW is just starting, #CTIA is around the co...	Android	Positive emotion	[starting, around, corner, hop, skip, jump, go...
8	Beautifully smart and simple idea RT @madebyma...	iPad or iPhone App	Positive emotion	[beautifully, smart, simple, idea, wrote, ipad...
9	Counting down the days to #sxsw plus strong Ca...	Apple	Positive emotion	[counting, day, plus, strong, canadian, dollar...
10	Excited to meet the @samsungmobileus at #sxsw ...	Android	Positive emotion	[excited, meet, show, sprint, galaxy, still, r...
11	Find & Start Impromptu Parties at #SXSW Wi...	Android App	Positive emotion	[find, amp, start, impromptu, party, cant, wai...
12	Foursquare ups the game, just in time for #SXS...	Android App	Positive emotion	[foursquare, ups, game, time, still, prefer, f...
13	Gotta love this #SXSW Google Calendar featurin...	Other Google product or service	Positive emotion	[gotta, love, google, calendar, featuring, top...
14	Great #sxsw ipad app from @madebymany: http://...	iPad or iPhone App	Positive emotion	[great, ipad, app]
15	haha, awesomely rad iPad app by @madebymany ht...	iPad or iPhone App	Positive emotion	[haha, awesomely, rad, ipad, app]
17	I just noticed DST is coming this weekend. How...	iPhone	Negative emotion	[noticed, dst, coming, weekend, many, iphone, ...

In [90]:

```
# Split each cleaned tweet into words and combine them into a single list
all_words = list(itertools.chain.from_iterable(tweets['clean_tweet_text']))
# Count the frequency of each word
word_counts = Counter(all_words)

# Get the 30 most common words
most_common_words = word_counts.most_common(30)

# Plot the 30 most common words using a bar chart
words, counts = zip(*most_common_words)  # Unpack the word-count pairs

# Create a horizontal bar chart
plt.figure(figsize=(10, 8))
plt.barh(words, counts, color='skyblue')  # Horizontal bar chart
plt.xlabel('Frequency')
plt.ylabel('Words')
plt.title('Top 30 Most Frequent Words')
plt.gca().invert_yaxis()  # Invert y-axis to have the highest count on top
plt.show()
```

Top 30 Most Frequent Words

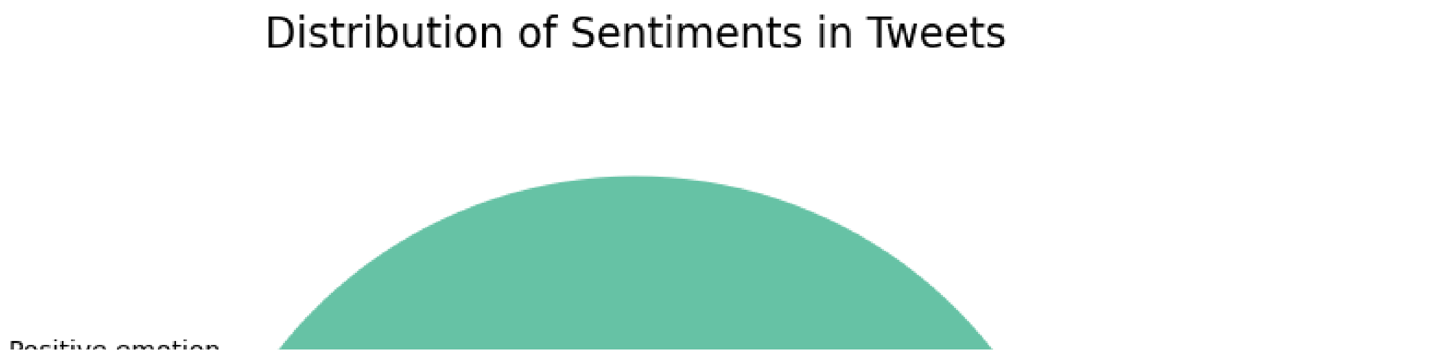


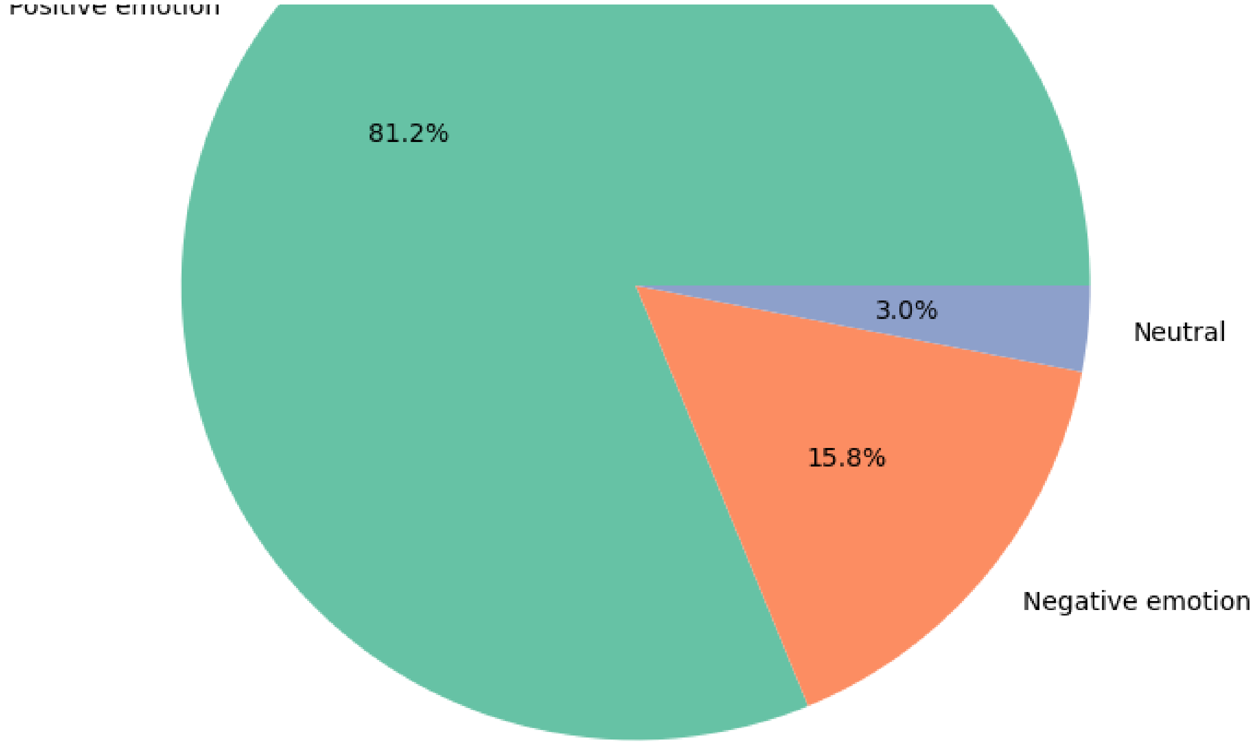
Distribution of Sentiments in Tweets

- **Let's count the number of occurrences for each sentiment and plot a pie chart showing the Distribution of Sentiments in Tweets**

In [91]:

```
# Count the number of occurrences for each sentiment
sentiment_counts = tweets['is_there_an_emotion_directed_at_a_brand_or_product'].value_cou
nts()

# Plot the distribution using a pie chart
plt.figure(figsize=(8, 8))
plt.pie(sentiment_counts.values, labels=sentiment_counts.index, autopct='%1.1f%%', color
s=sns.color_palette("Set2"))

# Customize the plot
plt.title('Distribution of Sentiments in Tweets', fontsize=16)

# Show the plot
plt.show()
```

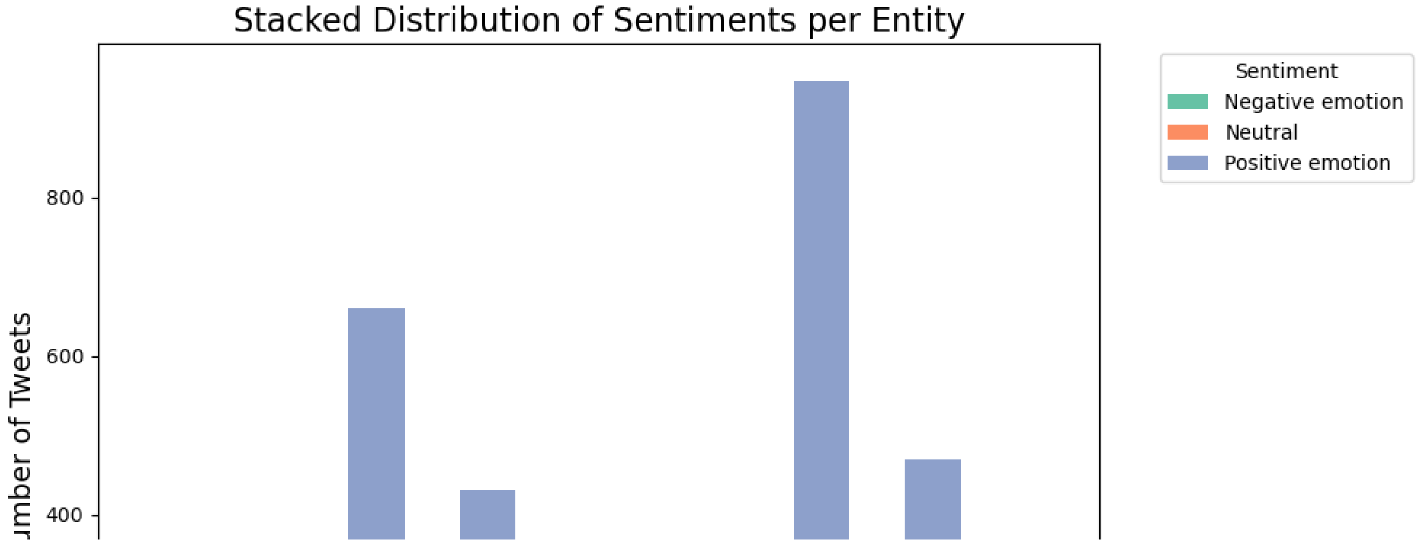


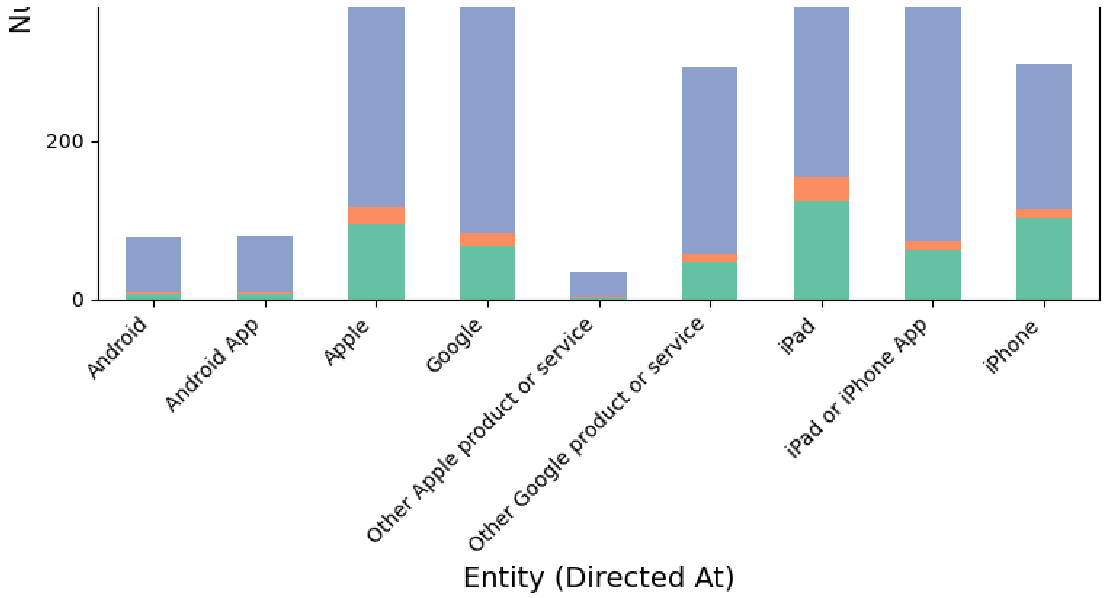


A Stacked Distribution of Sentiments per Entity

In [92]:

```
sentiment_per_entity = tweets.groupby(['emotion_in_tweet_is_directed_at', 'is_there_an_em
otion_directed_at_a_brand_or_product']).size().reset_index(name='count')
pivot_data = sentiment_per_entity.pivot(index='emotion_in_tweet_is_directed_at', columns=
'is_there_an_emotion_directed_at_a_brand_or_product', values='count')

# Plot the stacked bar chart
pivot_data.plot(kind='bar', stacked=True, figsize=(10, 8), color=sns.color_palette("Set2
"))

# Customize the plot
plt.title('Stacked Distribution of Sentiments per Entity', fontsize=16)
plt.xlabel('Entity (Directed At)', fontsize=14)
plt.ylabel('Number of Tweets', fontsize=14)
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for readability
plt.legend(title='Sentiment', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()

# Show the plot
plt.show()
```





Word Cloud Sentiment Distribution

In [93]:

```
tweets['sentiment'] = tweets['is_there_an_emotion_directed_at_a_brand_or_product'].map({
     "Positive emotion": 1,
     "Negative emotion": -1,
     "Neutral": 0
     })
tweets['sentiment'].value_counts()
```

Out[93]:

```
sentiment
 1    2672
-1     519
 0     100
Name: count, dtype: int64
```

In [94]:

```
tweets['clean_tweets_text'] = [' '.join(tweet) if isinstance(tweet, list) else tweet for
tweet in tweets['clean_tweet_text']]
positive_text = " ".join(tweet for tweet in tweets[tweets['sentiment'] == 1.0]['clean_tw
eets_text'])
negative_text = " ".join(tweet for tweet in tweets[tweets['sentiment'] == -1.0]['clean_t
weets_text'])
neutral_text = " ".join(tweet for tweet in tweets[tweets['sentiment'] == 0.0]['clean_twe
ets_text'])
```

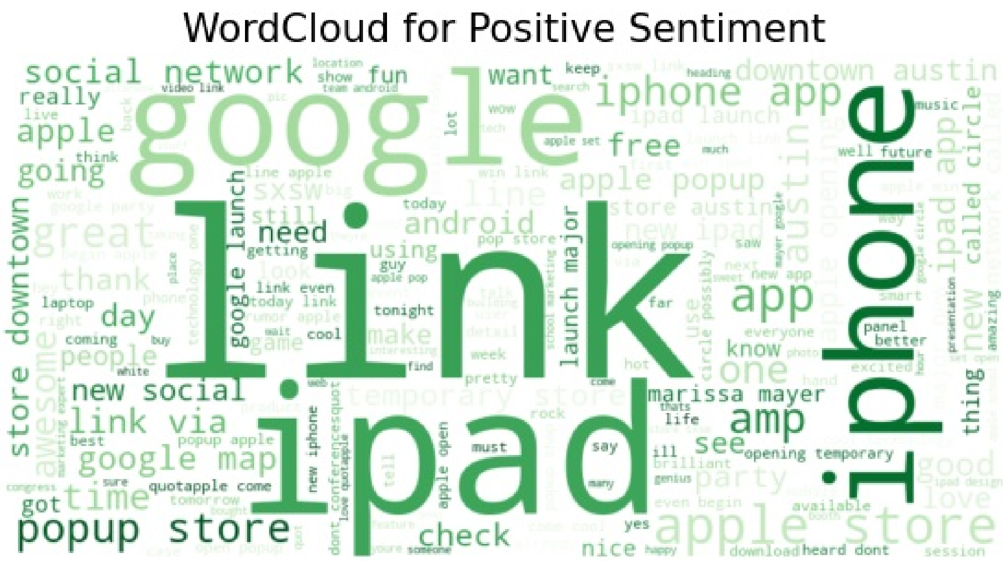
In [95]:

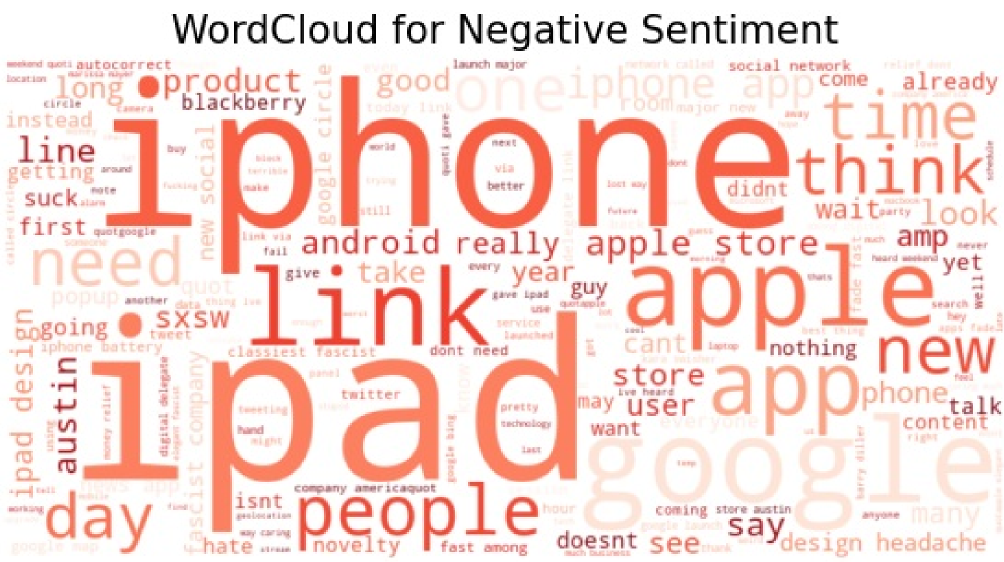
```
# Positive Sentiment WordCloud
wordcloud_positive = WordCloud(width=800, height=400, background_color='white', colormap=
'Greens').generate(positive_text)

# Negative Sentiment WordCloud
wordcloud_negative = WordCloud(width=800, height=400, background_color='white', colormap=
'Reds').generate(negative_text)

 # Neutral Sentiment WordCloud
wordcloud_neutral = WordCloud(width=800, height=400, background_color='white', colormap=
'Blues').generate(neutral_text)
```

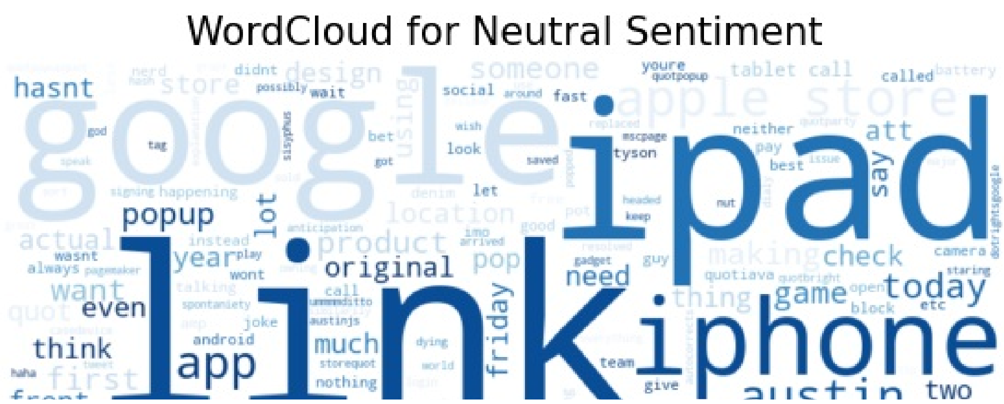
In [96]:

```
# Plot Positive Sentiment
plt.figure(figsize=(16, 12))
plt.subplot(3, 1, 1)
plt.imshow(wordcloud_positive, interpolation='bilinear')
```

```
plt.axis('off')
plt.title('WordCloud for Positive Sentiment', fontsize=15)
plt.show()

# Plot Negative Sentiment
plt.figure(figsize=(16, 12))
plt.subplot(3, 1, 2)
plt.imshow(wordcloud_negative, interpolation='bilinear')
plt.axis('off')
plt.title('WordCloud for Negative Sentiment', fontsize=15)
plt.show()

# Plot Neutral Sentiment
plt.figure(figsize=(16, 12))
plt.subplot(3, 1, 3)
plt.imshow(wordcloud_neutral, interpolation='bilinear')
plt.axis('off')
plt.title('WordCloud for Neutral Sentiment', fontsize=15)
plt.show()
```







- **Positive Sentiment: The word cloud for positive sentiment will show the most frequently occurring words in positive tweets.**
- **Negative Sentiment: The word cloud for negative sentiment will highlight terms most frequently occurring in negative tweets.**
- **Neutral Sentiment: A word cloud here shows words that are used frequently in neutral tweets.**

In [97]:

```
#View the new dataset
tweets.head()
```

Out[97]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	clean_tweet_text	sentim
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emotion	[iphone, hr, tweeting, dead, need, upgrade, pl...	
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive emotion	[know, awesome, ipadiphone, app, youll, likely...	
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion	[wait, also, sale]	
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emotion	[hope, year, festival, isnt, crashy, year, iph...	
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion	[great, stuff, fri, marissa, mayer, google, ti...	

In [98]:

```
tweets.emotion_in_tweet_is_directed_at.value_counts()
```

Out[98]:

```
emotion_in_tweet_is_directed_at
iPad                               946
Apple                              661
iPad or iPhone App                 470
Google                             430
iPhone                             297
Other Google product or service    293
Android App                         81
Android                             78
Other Apple product or service      35
Name: count, dtype: int64
```

MODELING

For this part we want to create models in two ways:

1. `Binay Models` **: This will have only two classes in the target value i.e.** `Positive` **and** `Negative`
2. `Multiclass Models` **: These will have more than two classes in the target variable i.e.** `Postive` **,** `Neutral` **and** `Negative`

BINARY MODELS

In [99]:

```
#create a simple dataframe to perform a binary classification with target only positive a
nd negative
bc_tweets = tweets.copy()
```

In [100]:

```
#Look at the available classes
bc_tweets.is_there_an_emotion_directed_at_a_brand_or_product.value_counts()
```

Out[100]:

```
is_there_an_emotion_directed_at_a_brand_or_product
Positive emotion    2672
Negative emotion     519
Neutral              100
Name: count, dtype: int64
```

In [101]:

```
#Remove the columns where 'is_there_an_emotion_directed_at_a_brand_or_product'  is 'Neutr
al'
bc_tweets = bc_tweets[bc_tweets['is_there_an_emotion_directed_at_a_brand_or_product']!= '
Neutral']
```

In [102]:

```
#make the token lists into strings
bc_tweets['joined_clean_text'] = bc_tweets['clean_tweet_text'].str.join(' ')
```

In [103]:

```
bc_tweets.head(25)
```

Out[103]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	clean_tweet_text
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emotion	[iphone, hr, tweeting, dead, need, upgrade, pl...
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive emotion	[know, awesome, ipadiphone, app, youll, likely...
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion	[wait, also, sale]
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emotion	[hope, year, festival, isnt, crashy, year, iph...
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion	[great, stuff, fri, marissa, mayer, google, ti...
	#SXSW is just			[starting,

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	clean_tweet_text
7	#SXSW is just starting, #CTIA is around the co...	Android	Positive emotion	around, corner, hop, skip, jump, go...
8	Beautifully smart and simple idea RT @madebyma...	iPad or iPhone App	Positive emotion	[beautifully, smart, simple, idea, wrote, ipad...
9	Counting down the days to #sxsw plus strong Ca...	Apple	Positive emotion	[counting, day, plus, strong, canadian, dollar...
10	Excited to meet the @samsungmobileus at #sxsw ...	Android	Positive emotion	[excited, meet, show, sprint, galaxy, still, r...
11	Find & Start Impromptu Parties at #SXSW Wi...	Android App	Positive emotion	[find, amp, start, impromptu, party, cant, wai...
12	Foursquare ups the game, just in time for #SXS...	Android App	Positive emotion	[foursquare, ups, game, time, still, prefer, f...
13	Gotta love this #SXSW Google Calendar featurin...	Other Google product or service	Positive emotion	[gotta, love, google, calendar, featuring, top...
14	Great #sxsw ipad app from @madebymany: http://...	iPad or iPhone App	Positive emotion	[great, ipad, app]
15	haha, awesomely rad iPad app by @madebymany ht...	iPad or iPhone App	Positive emotion	[haha, awesomely, rad, ipad, app]
17	I just noticed DST is coming this weekend. How...	iPhone	Negative emotion	[noticed, dst, coming, weekend, many, iphone, ...
18	Just added my #SXSW flights to @planely. Match...	iPad or iPhone App	Positive emotion	[added, flight, matching, people, planesairpor...
19	Must have #SXSW app! RT @malbonster: Lovely re...	iPad or iPhone App	Positive emotion	[must, app, lovely, review, forbes, sxsw, ipad...
20	Need to buy an iPad2 while I'm in Austin at #s...	iPad	Positive emotion	[need, buy, ipad, austin, sure, ill, need, aus...
21	Oh. My. God. The #SXSW app for iPad is pure, u...	iPad or iPhone App	Positive emotion	[god, app, ipad, pure, unadulterated, awesome,...
22	Okay, this is really it: yay new @Foursquare f...	Android App	Positive emotion	[okay, really, yay, new, app, kthxbai]
23	Photo: Just installed the #SXSW iPhone app, wh...	iPad or iPhone App	Positive emotion	[photo, installed, iphone, app, really, nice]
24	Really enjoying the changes in Gowalla 3.0 for...	Android App	Positive emotion	[really, enjoying, change, gowalla, android, l...

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	clean_tweet_text
25	RT @LaurieShook: I'm looking forward to the #S...	iPad	Positive emotion	[looking, forward, pre, party, wed, hoping, il...
26	RT haha, awesomely rad iPad app by @madebymany...	iPad or iPhone App	Positive emotion	[haha, awesomely, rad, ipad, app, via]
27	someone started an #austin @PartnerHub group i...	Other Google product or service	Positive emotion	[someone, started, group, google, group, pre, ...

Prepare the data for the models by encoding the target and vectorizing the required features then use `train_test_split` to create train and test sets

In [104]:

```
#create the train and test split

#define the target and the features
X = bc_tweets['clean_tweets_text']
y = bc_tweets['is_there_an_emotion_directed_at_a_brand_or_product']

#perform Label encoding on the target
#Initialize the encoder
le = LabelEncoder()
#fit the encoder on the target
y_encoded = le.fit_transform(y)

tfidf = TfidfVectorizer()
X_vec = tfidf.fit_transform(X)

#create the train and test split
X_train, X_test, y_train, y_test = train_test_split(X_vec,y_encoded, test_size=0.2, rand
om_state=42)
```

Logistic regression Model

Start by looking at the Vanilla Model

In [105]:

```
#Create a Logistic regression
logreg = LogisticRegression()
#Fit the regressor on the train set
logreg.fit(X_train, y_train)
```

Out[105]:

▾ LogisticRegression i ?

LogisticRegression()

In [106]:

```
#Make prediction for the train and test
y_log_train_pred = logreg.predict(X_train)
y_log_test_pred = logreg.predict(X_test)
```

Evaluate the model

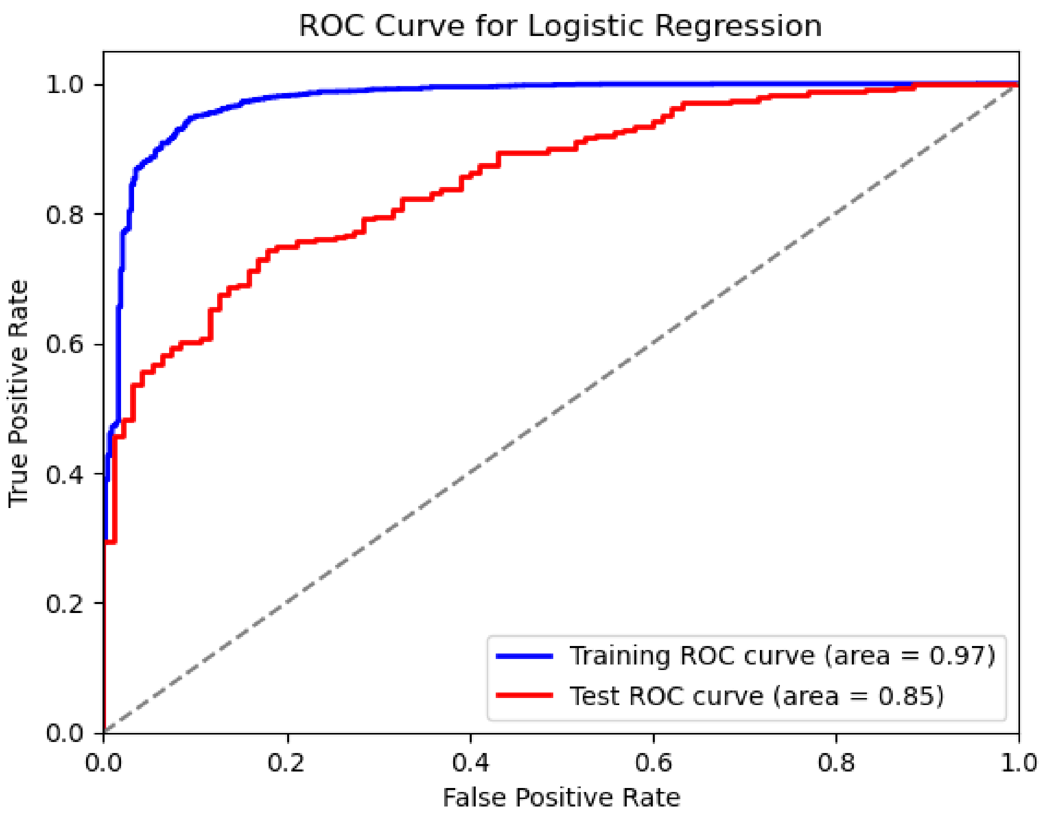
In [107]:

```
#Model Evaluation
#Creating a classification report
```

```python
train_class_report = classification_report(y_train, y_log_train_pred)
test_class_report = classification_report(y_test, y_log_test_pred)
#Display the results of the classification report
print('The outcome of the training classification report is:')
print(train_class_report)
print('\n\n')
print('The outcome of the test classification report is:')
print(test_class_report)
print('\n\n')

#Let's create a confusion matrix that can helpprovide a summary of prediction results
train_conf_mat = confusion_matrix(y_train, y_log_train_pred)
test_conf_mat = confusion_matrix(y_test, y_log_test_pred)
#Display the confusion matrix results for the train and test sets
print('The confusion matric for the train set is:')
print(train_conf_mat)
print('\n\n')
print('The confusion matric for the test set is:')
print(test_conf_mat)
print('\n\n')

#Now let's look at the accuracy score for both sets
train_acc = accuracy_score(y_train, y_log_train_pred)
test_acc = accuracy_score(y_test, y_log_test_pred)
#Display the results of the accuracy score
print('The accuracy score for the train set is:', train_acc)
print('The accuracy score for the test set is:', test_acc)

#Fianlly we should consider the ROC curve and the AUC
#start by getting probability estimates of the positive class
y_train_prob = logreg.predict_proba(X_train)[:, 1]
y_test_prob = logreg.predict_proba(X_test)[:, 1]
#ROC curve for the training data
fpr_train, tpr_train, threshold_train = roc_curve(y_train, y_train_prob)
roc_auc_train = auc(fpr_train, tpr_train)
#ROC curve for the test set
fpr_test, tpr_test, threshold_test = roc_curve(y_test, y_test_prob)
roc_auc_test = auc(fpr_test, tpr_test)
#plot the ROC curve
plt.figure()
plt.plot(fpr_train, tpr_train, color='blue', lw=2, label=f'Training ROC curve (area = {r
oc_auc_train:.2f})')
plt.plot(fpr_test, tpr_test, color='red', lw=2, label=f'Test ROC curve (area = {roc_auc_
test:.2f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Logistic Regression')
plt.legend(loc="lower right")
plt.show()
```

```
The outcome of the training classification report is:
              precision    recall  f1-score   support

           0       0.99      0.17      0.29       424
           1       0.86      1.00      0.92      2128

    accuracy                           0.86      2552
   macro avg       0.92      0.59      0.61      2552
weighted avg       0.88      0.86      0.82      2552




The outcome of the test classification report is:
              precision    recall  f1-score   support

           0       0.88      0.07      0.14        95
           1       0.86      1.00      0.92       544
```

```
    accuracy                           0.86       639
   macro avg       0.87      0.54      0.53       639
weighted avg       0.86      0.86      0.81       639


The confusion matric for the train set is:
[[  73  351]
 [   1 2127]]


The confusion matric for the test set is:
[[  7  88]
 [  1 543]]


The accuracy score for the train set is: 0.8620689655172413
The accuracy score for the test set is: 0.8607198748043818
```



For the training set: Despite a high accuracy (0.86), the recall for class 0 (which represents the "negative emotion" or minority class) is quite low at 0.17. This indicates that the model is not correctly identifying the "negative" class and is highly skewed towards predicting class 1, which has the majority of data points. The high accuracy score is misleading due to class imbalance.

For the test set: It shows similar patterns: the model is heavily biased towards class 1, with only 7 out of 95 instances of class 0 correctly predicted, leading to a recall of 0.07 for class 0. Again, the high accuracy (0.86) is misleading due to class imbalance.

Interpretation of the Graph:

`Blue line` **(Training ROC curve, AUC = 0.97): The ROC curve for the training set shows excellent performance. The curve is close to the top-left corner, and the AUC of 0.97 indicates that the model is performing very well on the training data.**

`Red line` **(Test ROC curve, AUC = 0.85): The ROC curve for the test set is not as close to the top-left corner as the training curve, but it still shows reasonably good performance. The AUC of 0.85 suggests that the model can distinguish between the classes well on unseen data, but it is not as perfect as the training performance.**

`Training vs. Test Performance` **: The model performs better on the training data (AUC = 0.97) than on the**

`Training vs. Test Performance`: The model performs better on the training data (AUC = 0.91) than on the test data (AUC = 0.85), which might indicate some overfitting. The model might have learned the training set too well, capturing noise or specific details that don't generalize well to new, unseen data.

`Good Generalization`: **Despite the drop in test performance, an AUC of 0.85 is still good. This means the model has a decent ability to generalize and make correct predictions on new data.**

Recommendations to Address the Issues: Class Imbalance: introducing SMOTE (Synthetic Minority Over-sampling Technique)might help the address the problem of the class imbalance

In [108]:

```
#address the class imbalance
#Import neccessary library
from imblearn.over_sampling import SMOTE
#initialize the
smote = SMOTE(random_state=42)
#Ffit on the train sets
smote_X_train, smote_y_train = smote.fit_resample(X_train, y_train)
smote_X_test, smote_y_test = smote.fit_resample(X_test, y_test)
```

Retrain the Logistic Regression Model after applying SMOTE

In [109]:

```
#train the model
logreg.fit(smote_X_train, smote_y_train)
```

Out[109]:

```
▼ LogisticRegression i ?

LogisticRegression()
```

In [110]:

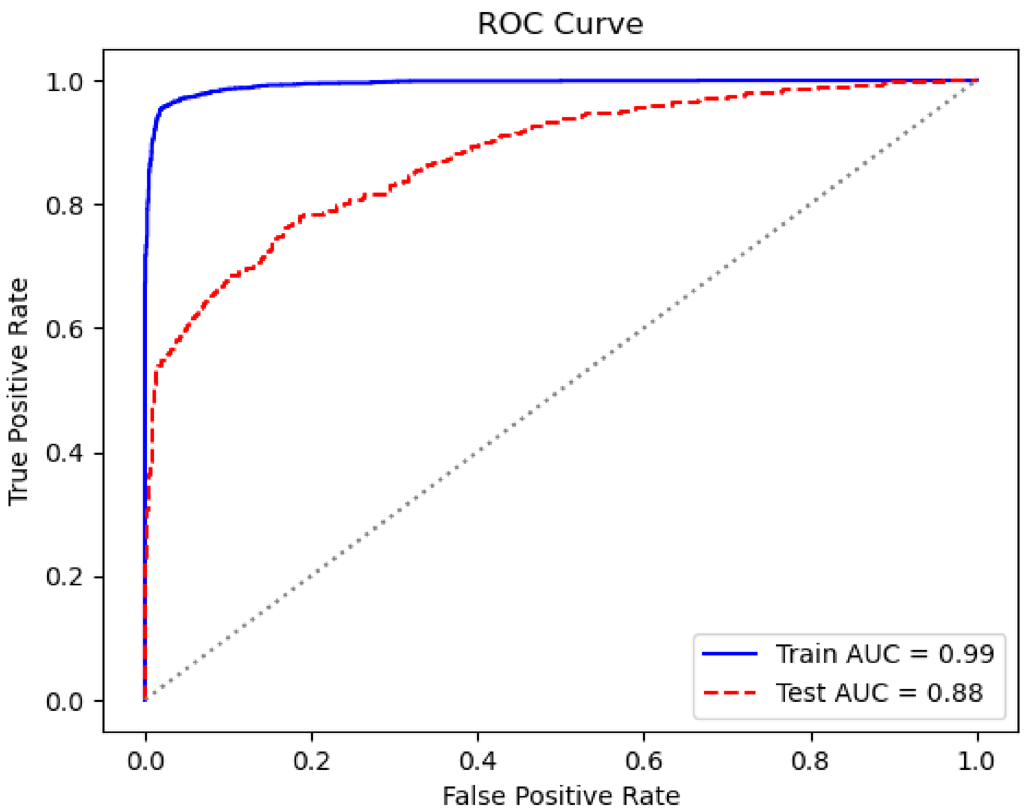
```
#make prediction on for the train and test sets
smote_log_train_pred = logreg.predict(smote_X_train)
smote_test_log_pred = logreg.predict(smote_X_test)
```

In [111]:

```
# Evaluate the model
#Look at the classification report
print('The classification report for the training set is:')
print(classification_report(smote_y_train, smote_log_train_pred))
print('\n')
print('The classification report for the test set is:')
print(classification_report(smote_y_test, smote_test_log_pred))
print('\n\n')
#Show accuracy for both sets
print('the accuracy for the training set is:',accuracy_score(smote_y_train, smote_log_tra
in_pred))
print('the accuracy for the test set is:', accuracy_score(smote_y_test, smote_test_log_pr
ed))
print('\n')


#Create the ROC curve and AUC for both sets
#start by getting the probability for each od the sets
clf_train_prob = logreg.predict_proba(smote_X_train)[:, 1]
clf_test_prob = logreg.predict_proba(smote_X_test)[:, 1]
#calculate the ROC and auc
train_fpr, train_tpr, train_threshold = roc_curve(smote_y_train, clf_train_prob)
train_auc = auc(train_fpr, train_tpr)
test_fpr, test_tpr, test_threshold = roc_curve(smote_y_test, clf_test_prob)
test_auc = auc(test_fpr, test_tpr)
#plot the ROC roc_curve
plt.figure()
```

```python
plt.plot(train_fpr, train_tpr, color='blue', label=f'Train AUC = {train_auc:.2f}')
plt.plot(test_fpr, test_tpr, color='red', linestyle='--', label=f'Test AUC = {test_auc:.2f}')
plt.plot([0, 1], [0, 1], color='grey', linestyle=':')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```

```
The classification report for the training set is:
              precision    recall  f1-score   support

           0       0.96      0.97      0.97      2128
           1       0.97      0.96      0.97      2128

    accuracy                           0.97      4256
   macro avg       0.97      0.97      0.97      4256
weighted avg       0.97      0.97      0.97      4256



The classification report for the test set is:
              precision    recall  f1-score   support

           0       0.87      0.57      0.68       544
           1       0.68      0.91      0.78       544

    accuracy                           0.74      1088
   macro avg       0.77      0.74      0.73      1088
weighted avg       0.77      0.74      0.73      1088



the accuracy for the training set is: 0.9661654135338346
the accuracy for the test set is: 0.7389705882352942
```



Interpretation of the results:

`Training set` **: The high accuracy (96.6%) and balanced precision, recall, and F1-scores indicate that SMOTE** worked well on the training set. Since SMOTE creates synthetic samples, the model was able to learn from a more balanced dataset, resulting in good performance across both classes.

`Test set`: However, despite SMOTE's application, the test set shows a significant drop in performance (accuracy: 74%) and varying metrics between class 0 and class 1.

Potential Reasons for the Performance Drop:

1. Overfitting: Even with SMOTE, the model may still be overfitting to the training set. This is suggested by the large performance gap between the training and test sets. While SMOTE balances the training data, it doesn't necessarily improve the model's ability to generalize to unseen test data, particularly for complex models like decision trees that can easily overfit.
2. Synthetic Data Limitations: The synthetic data generated by SMOTE might not represent the true distribution of the minority class well. As a result, while the model performs well on the training data (which includes synthetic samples), it may not generalize well to real-world test data, especially for class 0.
3. Class Separation: The model seems to do much better with class 1 (high recall) on the test set, potentially at the expense of correctly identifying class 0. This imbalance could indicate that the decision tree is more tuned to detecting class 1 and struggles with separating class 0 in the test set.

Interpretation for the graph:

The `blue line` represents the ROC curve for the training set, with an Area Under the Curve (AUC) of 0.99.

- This indicates almost perfect classification on the training data with the model achieving very high sensitivity and specificity.
- The curve being very close to the top-left corner shows that the model is performing well, correctly classifying both positive and negative instances on the training set.

The `red dashed line` represents the ROC curve for the test set, with an AUC of 0.88.

- While this is still a strong performance, the AUC on the test data is significantly lower than on the training data.
- The red curve is slightly less steep, indicating that the model is less accurate on unseen data, though it still performs well overall.

Insights from the graph:

- Train AUC = 0.99: The model is almost perfect on the training set, which could indicate overfitting.
- Test AUC = 0.88: The model performs well on the test set, but the drop in AUC compared to the training set suggests that the model may not generalize as well to new data

DECISION TREE CLASSIFIER

In [112]:

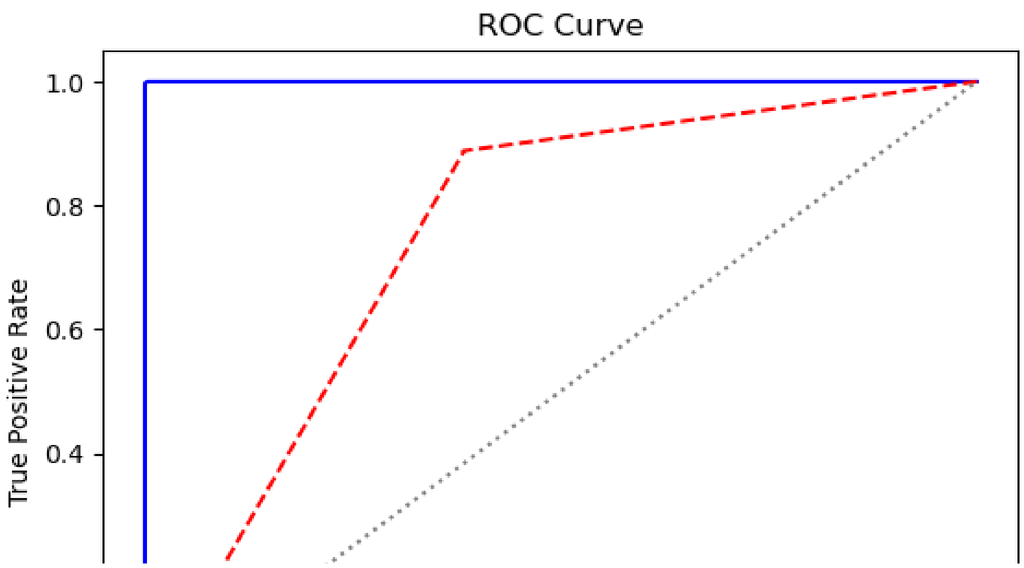
```
#Initialize the classifier

dct = DecisionTreeClassifier()

#fit the train model
dct. fit(smote_X_train, smote_y_train)
# fit the test model as well
#make predictions
smote_tree_train_pred = dct.predict(smote_X_train)
smote_tree_test_pred = dct.predict(smote_X_test)
```

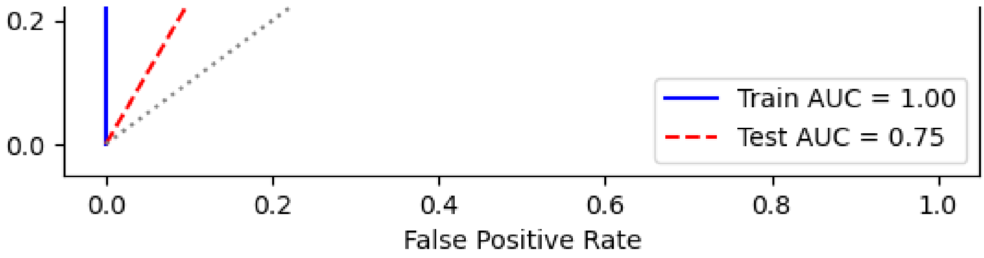
In [113]:

```
print("Classification Report for Training Set:")
print(classification_report(smote_y_train, smote_tree_train_pred))
print("Classification Report for Test Set:")
print(classification_report(smote_y_test, smote_tree_test_pred))
print('\n\n')
#Show accuracy for both sets
print('the accuracy for the training set is:',accuracy_score(smote_y_train, smote_tree_tr
```

```
ain_pred))
print('the accuracy for the test set is:', accuracy_score(smote_y_test, smote_tree_test_p
red))
print('\n')

#Create the ROC curve and AUC for both sets
#start by getting the probability for each od the sets
clf_train_prob = dct.predict_proba(smote_X_train)[:, 1]
clf_test_prob = dct.predict_proba(smote_X_test)[:, 1]
#calculate the ROC and auc
train_fpr, train_tpr, train_threshold = roc_curve(smote_y_train, clf_train_prob)
train_auc = auc(train_fpr, train_tpr)
test_fpr, test_tpr, test_threshold = roc_curve(smote_y_test, clf_test_prob)
test_auc = auc(test_fpr, test_tpr)
#plot the ROC roc_curve
plt.figure()
plt.plot(train_fpr, train_tpr, color='blue', label=f'Train AUC = {train_auc:.2f}')
plt.plot(test_fpr, test_tpr, color='red', linestyle='--', label=f'Test AUC = {test_auc:.
2f}')
plt.plot([0, 1], [0, 1], color='grey', linestyle=':')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```

```
Classification Report for Training Set:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2128
           1       1.00      1.00      1.00      2128

    accuracy                           1.00      4256
   macro avg       1.00      1.00      1.00      4256
weighted avg       1.00      1.00      1.00      4256

Classification Report for Test Set:
              precision    recall  f1-score   support

           0       0.85      0.62      0.71       544
           1       0.70      0.89      0.78       544

    accuracy                           0.75      1088
   macro avg       0.77      0.75      0.75      1088
weighted avg       0.77      0.75      0.75      1088



the accuracy for the training set is: 0.9985902255639098
the accuracy for the test set is: 0.7527573529411765
```





Interpretation of the Classsification report On the train set:

- Precision, Recall, and F1-Score for both classes (0 and 1) are all 1.00, indicating perfect performance.
- Support: The number of samples in each class is balanced (2128 for both class 0 and 1).
- Overall Accuracy: 99.86% (very close to 100%).

This model confirms the earlier observation that the model is overfitting on the training data. The model classifies both classes perfectly in the training set, which is rare for real-world data and suggests it may have memorized the training data rather than learning generalizable patterns.

On the test set:

1. Class 0:

- Precision (0.85): The model correctly identifies 85% of the samples classified as class 0.
- Recall (0.62): Only 62% of the actual class 0 instances are correctly identified. The model is missing many true negatives.
- F1-Score (0.72): This is the harmonic mean of precision and recall, reflecting the model's imbalanced performance in identifying class 0.

1. Class 1:

- Precision (0.70): The model correctly identifies 70% of the samples predicted as class 1.
- Recall (0.90): The model successfully identifies 90% of actual class 1 instances.
- F1-Score (0.79): The relatively high recall improves the overall F1-score.
- Overall Accuracy: 75.64%, significantly lower than the training accuracy. This suggests the model struggles with generalization, as performance drops notably on the test set.

Insights:

- Training Set (Accuracy = 99.86%): The near-perfect performance in the training set is a strong sign of overfitting.
- Test Set (Accuracy = 75.64%): The significant drop in performance indicates the model does not generalize well to unseen data. This could be due to overfitting caused by the Decision Tree model learning noise or specifics of the training data, rather than underlying patterns.

Interpretation of the graph: Observations:

- The blue line represents the ROC curve for the training set, with an AUC of 1.00, indicating perfect classification on the training data. This curve reaches the top-left corner immediately, implying no false positives and all true positives are perfectly classified.
- The red dashed line represents the ROC curve for the test set, with an AUC of 0.76. This curve is less steep compared to the training curve, suggesting that the model's performance on unseen data (test set) is not as strong. The AUC of 0.76 still indicates decent performance but much lower compared to the training set.

Insights:

- Train AUC = 1.00: This indicates that the model classifies the training set perfectly. However, such performance on the training data strongly suggests overfitting, as a perfectly trained model on real-world data is unusual.
- Test AUC = 0.76: While this value still indicates some predictive power, it shows a significant decline in performance on the test set, further confirming overfitting. The ROC curve's deviation from the top-left corner shows the model is missing a considerable number of true positives and generating some false positives on the test set.

- The gap between the train and test AUCs is significant, confirming that the model is likely overfitting to the training data. It is too complex and has learned patterns that don't generalize well to unseen data.

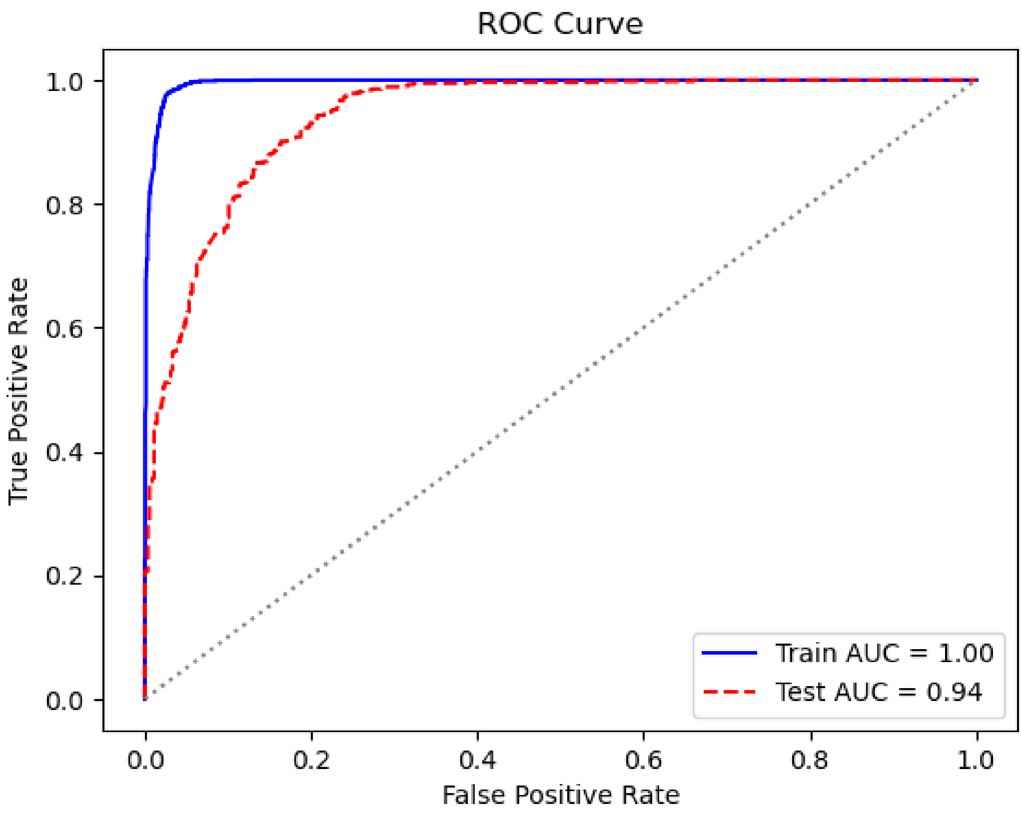
XGBOOST Classifier

In [114]:

```
# Instantiate XGBClassifier
xgb = XGBClassifier()

# Fit XGBClassifier
xgb.fit(smote_X_train, smote_y_train)

# Predict on training and test sets
training_preds = xgb.predict(smote_X_train)
test_preds = xgb.predict(smote_X_test)

## Evaluate the model
#Look at the classification report
print('The classification report for the training set is:')
print(classification_report(smote_y_train, training_preds))
print('\n')
print('The classification report for the test set is:')
print(classification_report(smote_y_test, test_preds))
print('\n\n')
#Show accuracy for both sets
print('the accuracy for the training set is:',accuracy_score(smote_y_train, training_pred
s))
print('the accuracy for the test set is:', accuracy_score(smote_y_test, test_preds))
print('\n')
#Create the ROC curve and AUC for both sets
#start by getting the probability for each od the sets
clf_train_prob = xgb.predict_proba(smote_X_train)[:, 1]
clf_test_prob = xgb.predict_proba(smote_X_test)[:, 1]
#calculate the ROC and auc
train_fpr, train_tpr, train_threshold = roc_curve(smote_y_train, clf_train_prob)
train_auc = auc(train_fpr, train_tpr)
test_fpr, test_tpr, test_threshold = roc_curve(smote_y_test, clf_test_prob)
test_auc = auc(test_fpr, test_tpr)
#plot the ROC roc_curve
plt.figure()
plt.plot(train_fpr, train_tpr, color='blue', label=f'Train AUC = {train_auc:.2f}')
plt.plot(test_fpr, test_tpr, color='red', linestyle='--', label=f'Test AUC = {test_auc:.
2f}')
plt.plot([0, 1], [0, 1], color='grey', linestyle=':')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```

```
The classification report for the training set is:
              precision    recall  f1-score   support

           0       1.00      0.94      0.97      2128
           1       0.94      1.00      0.97      2128

    accuracy                           0.97      4256
   macro avg       0.97      0.97      0.97      4256
weighted avg       0.97      0.97      0.97      4256



The classification report for the test set is:
              precision    recall  f1-score   support

           0       0.95      0.77      0.85       544
           1       0.81      0.96      0.87       544

    accuracy                           0.86      1088
   macro avg       0.88      0.86      0.86      1088
```

```
weighted avg       0.88      0.86      0.86      1088


the accuracy for the training set is: 0.9680451127819549
the accuracy for the test set is: 0.8630514705882353
```



Insights from Classification Report:

- **Training Set (Accuracy = 96.62%): The model performs very well on the training data, but the relatively high recall for class 1 and precision for class 0 suggests the model might be somewhat biased toward the majority class, even with SMOTE applied.**
- **Test Set (Accuracy = 86%): The performance drops noticeably on the test set, particularly in identifying class 0 instances (with a recall of 0.77). This indicates that the model's ability to generalize to new data is limited.**

Performance Details for the curve: The blue line (Train ROC Curve):

- **AUC = 1.00: This indicates that the model achieves perfect classification on the training set. The line reaches the top-left corner, suggesting the model correctly identifies all positive and negative instances without error.**
- **This perfect AUC is another clear indicator of overfitting on the training data, as real-world models rarely achieve such flawless performance.**

The red dashed line (Test ROC Curve):

- **AUC = 0.94: The model performs well on the test set, with a high AUC of 0.94. This suggests that the model distinguishes between the two classes with good accuracy on unseen data.**
- **However, compared to the training set, the test ROC curve does not reach the top-left corner, meaning the model makes some false positive and false negative classifications on the test set. Nevertheless, the curve's proximity to the top-left corner reflects strong performance.**

Comparison to Previous Results:

- **The ROC curve shows a significant improvement in test performance compared to the earlier test AUC of 0.76. This suggests that recent adjustments (e.g., hyperparameter tuning or resampling strategies) have enhanced the model's ability to generalize to new data.**
- **The train AUC remains 1.00, which reinforces the idea that while the model is highly optimized for the training data, it is still prone to overfitting.**

training data, it is still prone to overfitting.

Conclusion:

- **Train AUC (1.00) indicates overfitting, where the model performs perfectly on training data, but this performance is unlikely to generalize well.**
- **Test AUC (0.94) reflects strong performance on unseen data, suggesting that despite some overfitting, the model has good predictive power.**

In [115]:

```
#tune the XGBoost Classifier

param_grid = {
    'learning_rate': [0.1, 0.2],
    'max_depth': [30],
    'min_child_weight': [1, 2],
    'subsample': [0.5, 0.7],
    'n_estimators': [100],
}

#initialize the GridSSearchCV
grid_clf = GridSearchCV(xgb, param_grid ,scoring='accuracy', n_jobs=1)
grid_clf.fit(smote_X_train, smote_y_train)

best_parameters = grid_clf.best_params_
#Show the best parameters for the
print('Grid Search found the following optimal parameters: ')
for param_name in sorted(best_parameters.keys()):
    print('%s: %r' % (param_name, best_parameters[param_name]))

training_accuracy = accuracy_score(smote_y_train, training_preds)
test_accuracy = accuracy_score(smote_y_test, test_preds)

#Show accuracy
print('')
print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Grid Search found the following optimal parameters:
learning_rate: 0.2
max_depth: 30
min_child_weight: 1
n_estimators: 100
subsample: 0.7

Training Accuracy: 96.8%
Validation accuracy: 86.31%
```

Model Performance:

- **Training Accuracy = 96.80%: This indicates that the model does not perfectly fit the training data, which is generally a good sign as it suggests the model is not overfitting.**
- **Validation Accuracy = 86.31%: The validation accuracy is higher than the training accuracy, suggesting that the model is performing well on unseen data (validation set) and that overfitting has been reduced. This is a positive sign of a well-generalized model that can predict accurately on test data.**

MULTICLASS MODELS

In [116]:

```
#create a dataframe with multiple classes for the targer
mc_tweets = tweets.copy()
mc_tweets.head(35)
```

Out[116]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	clean_tweet_text
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emotion	[iphone, hr, tweeting, dead, need, upgrade, pl...
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive emotion	[know, awesome, ipadiphone, app, youll, likely...
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion	[wait, also, sale]
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emotion	[hope, year, festival, isnt, crashy, year, iph...
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion	[great, stuff, fri, marissa, mayer, google, ti...
7	#SXSW is just starting, #CTIA is around the co...	Android	Positive emotion	[starting, around, corner, hop, skip, jump, go...
8	Beautifully smart and simple idea RT @madebyma...	iPad or iPhone App	Positive emotion	[beautifully, smart, simple, idea, wrote, ipad...
9	Counting down the days to #sxsw plus strong Ca...	Apple	Positive emotion	[counting, day, plus, strong, canadian, dollar...
10	Excited to meet the @samsungmobileus at #sxsw ...	Android	Positive emotion	[excited, meet, show, sprint, galaxy, still, r...
11	Find & Start Impromptu Parties at #SXSW Wi...	Android App	Positive emotion	[find, amp, start, impromptu, party, cant, wai...
12	Foursquare ups the game, just in time for #SXS...	Android App	Positive emotion	[foursquare, ups, game, time, still, prefer, f...
13	Gotta love this #SXSW Google Calendar featurin...	Other Google product or service	Positive emotion	[gotta, love, google, calendar, featuring, top...
14	Great #sxsw ipad app from @madebymany: http://...	iPad or iPhone App	Positive emotion	[great, ipad, app]
15	haha, awesomely rad iPad app by @madebymany ht...	iPad or iPhone App	Positive emotion	[haha, awesomely, rad, ipad, app]
17	I just noticed DST is coming this weekend. How...	iPhone	Negative emotion	[noticed, dst, coming, weekend, many, iphone, ...
18	Just added my #SXSW flights to @planely. Match...	iPad or iPhone App	Positive emotion	[added, flight, matching, people, planesairpor...
19	Must have #SXSW app! RT @malbonster: Lovely re...	iPad or iPhone App	Positive emotion	[must, app, lovely, review, forbes, sxsw, ipad...

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	clean_tweet_text
20	Need to buy an iPad2 while I'm in Austin at #s...	iPad	Positive emotion	[need, buy, ipad, austin, sure, ill, need, aus...
21	Oh. My. God. The #SXSW app for iPad is pure, u...	iPad or iPhone App	Positive emotion	[god, app, ipad, pure, unadulterated, awesome,...
22	Okay, this is really it: yay new @Foursquare f...	Android App	Positive emotion	[okay, really, yay, new, app, kthxbai]
23	Photo: Just installed the #SXSW iPhone app, wh...	iPad or iPhone App	Positive emotion	[photo, installed, iphone, app, really, nice]
24	Really enjoying the changes in Gowalla 3.0 for...	Android App	Positive emotion	[really, enjoying, change, gowalla, android, l...
25	RT @LaurieShook: I'm looking forward to the #S...	iPad	Positive emotion	[looking, forward, pre, party, wed, hoping, il...
26	RT haha, awesomely rad iPad app by @madebymany...	iPad or iPhone App	Positive emotion	[haha, awesomely, rad, ipad, app, via]
27	someone started an #austin @PartnerHub group i...	Other Google product or service	Positive emotion	[someone, started, group, google, group, pre, ...
28	The new #4sq3 looks like it is going to rock. ...	iPad or iPhone App	Positive emotion	[new, look, like, going, rock, update, iphone,...
29	They were right, the @gowalla 3 app on #androi...	Android App	Positive emotion	[right, app, sweeeeet, nice, job, team]
30	Very smart from @madebymany #hollergram iPad a...	iPad or iPhone App	Positive emotion	[smart, ipad, app, may, leave, vuvuzela, home]
31	You must have this app for your iPad if you ar...	iPad or iPhone App	Positive emotion	[must, app, ipad, going]
36	The best! RT @mention Ha! First in line for #...	iPad	Positive emotion	[best, first, line, quotpopupquot, apple, stor...
38	@mention - False Alarm: Google Circles Not Co...	Google	Negative emotion	[false, alarm, google, circle, coming, nowand,...
40	@mention - Great weather to greet you for #sx...	Apple	Positive emotion	[great, weather, greet, still, need, sweater, ...
45	#IPad2 's Û÷#SmartCoverÛª Opens to Instant A...	iPad or iPhone App	Positive emotion	[open, instant, access, waited, get, one, link]
47	HOORAY RT ÛÏ@mention Apple Is Opening A Pop-U...	Apple	Positive emotion	[hooray, apple, opening, popup, store, austin,...

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product	clean_tweet_text
49	Woooooo!!! ÛÏ@mention Apple store downtown Aus...	Apple	Positive emotion	[woooooo, apple, store, downtown, austin, open,...

In [117]:

```
mc_tweets.is_there_an_emotion_directed_at_a_brand_or_product.value_counts()
```

Out[117]:

```
is_there_an_emotion_directed_at_a_brand_or_product
Positive emotion    2672
Negative emotion     519
Neutral              100
Name: count, dtype: int64
```

In [118]:

```
#make the token lists into strings
mc_tweets['joined_clean_text'] = mc_tweets['clean_tweet_text'].str.join(' ')
```

In [119]:

```
#create the train and test split

X = mc_tweets['joined_clean_text']
y = mc_tweets['is_there_an_emotion_directed_at_a_brand_or_product']

#label the target column
y_map = y.map({'Positive emotion':1, 'Neutral':0, 'Negative emotion':-1})

#Vectorize the features
X_vect = tfidf.fit_transform(X)

#create the test and train split
mc_X_train, mc_X_test, mc_y_train, mc_y_test = train_test_split(X_vect, y_map, test_size
=0.2, random_state=42)
```

Logistic Regression for Multiclass classification

In [120]:

```
#Create a Logistic regression
mc_logreg = LogisticRegression()
#Fit the regressor on the train set
mc_logreg.fit(mc_X_train, mc_y_train)
```

Out[120]:

```
▼ LogisticRegression i ?

LogisticRegression()
```

In [121]:

```
#Make prediction for the train and test
mc_y_log_train_pred = mc_logreg.predict(mc_X_train)
mc_y_log_test_pred = mc_logreg.predict(mc_X_test)
```

In [122]:

```
#Model Evaluation
#Creating a classification report
mc_train_class_report = classification_report(mc_y_train, mc_y_log_train_pred)
mc_test_class_report = classification_report(mc_y_test, mc_y_log_test_pred)
#Display the results of the classification report
print('The outcome of the training classification report is:')
```

```
print(mc_train_class_report)
print('\n\n')
print('The outcome of the test classification report is:')
print(mc_test_class_report)
print('\n\n')
```

```
The outcome of the training classification report is:
              precision    recall  f1-score   support

          -1       0.94      0.38      0.54       414
           0       0.00      0.00      0.00        81
           1       0.87      1.00      0.93      2137

    accuracy                           0.87      2632
   macro avg       0.60      0.46      0.49      2632
weighted avg       0.85      0.87      0.84      2632




The outcome of the test classification report is:
              precision    recall  f1-score   support

          -1       0.94      0.16      0.28       105
           0       0.00      0.00      0.00        19
           1       0.83      1.00      0.91       535

    accuracy                           0.84       659
   macro avg       0.59      0.39      0.39       659
weighted avg       0.83      0.84      0.78       659
```

Training Set Results: Accuracy: 86.21%

The model correctly classified 86% of the instances in the training set. `Class -1`**:**

- **Precision = 0.94: The model correctly predicted class -1 in 94% of the cases when it made a prediction for class -1.**
- **Recall = 0.38: The model only correctly identified 38% of the actual instances of class -1. This is quite low, indicating that the model is struggling to recognize class -1.**
- **F1-score = 0.54: This is low due to the imbalance between precision and recall, reflecting poor overall performance for class -1.**

`Class 0`**:**

- **Precision, Recall, F1-score = 0.00: The model completely failed to classify instances of class 0. This is a significant issue, as it suggests that the model does not recognize class 0 at all.**

`Class 1`**:**

- **Precision = 0.87: The model predicted class 1 correctly in 87% of the cases where it made such a prediction. Recall = 1.00: The model captured all instances of class 1 (100% recall).**
- **F1-score = 0.93: Strong performance for class 1, likely dominating the overall accuracy due to the imbalance between class sizes.**

Test Set Results:

- **Accuracy: 84%**

The model's performance on the test set is consistent with the training set, showing a similar accuracy of around 86%. `Class -1`**:**

- **Precision = 0.94: When predicting class -1, the model was correct 94% of the time, but...**
- **Recall = 0.16: The model only identified 16% of the true class -1 instances, meaning it is missing most of the class -1 cases.**
- **F1-score = 0.28: This is quite low, reflecting the poor balance between precision and recall for class -1**

- F1-score = 0.28: This is quite low, reflecting the poor balance between precision and recall for class -1.

`Class 0`:

- Precision, Recall, F1-score = 0.00: Again, the model completely fails to classify class 0 in the test set, just like in the training set. `Class 1`:
- Precision = 0.83: The model correctly predicted class 1 in 83% of the cases.
- Recall = 1.00: All instances of class 1 were correctly identified.
- F1-score = 0.91: The model shows strong performance for class 1, similar to the training set.

Key Issues & Insights:

`Class Imbalance`:

The model struggles to recognize class -1 (especially in recall) and completely fails to classify class 0. This suggests there is a class imbalance, with the majority of instances likely being in class 1, leading to bias in the model's predictions.

`Poor Generalization for Minority Classes`:

The recall for class -1 is extremely low in both the training and test sets, and the model does not predict class 0 at all. This suggests the model is focusing on class 1 at the expense of the other two classes.

`Overfitting to Class 1`:

The model performs well on class 1 in both training and test sets, likely because class 1 has the majority of instances, but it overfits to this class while neglecting the other two classes, especially class 0. Recommendations:

`Address Class Imbalance`:

Apply techniques such as SMOTE (Synthetic Minority Over-sampling Technique) or class weighting to balance the training set. This will help the model better learn to distinguish the minority classes (-1 and 0) while reducing the bias toward class 1.

Addressing the Class Imbalance

In [123]:

```
#Adress the class imbalance
mc_smote = SMOTE(random_state=42)
#fit on the train and seets
mc_smote_X_train, mc_smote_y_train = mc_smote.fit_resample(mc_X_train, mc_y_train)
mc_smote_X_test, mc_smote_y_test = mc_smote.fit_resample(mc_X_test, mc_y_test)
```

Logistic Regression with SMOTE applied

In [124]:

```
#train the model
mc_logreg.fit(mc_smote_X_train, mc_smote_y_train)
```

Out[124]:

```
▼ LogisticRegression i ?

LogisticRegression()
```

In [125]:

```
mc_smote_log_train_pred = mc_logreg.predict(mc_smote_X_train)
mc_smote_test_log_pred = mc_logreg.predict(mc_smote_X_test)
```

In [126]:

```
# Evaluate the model
#Look at the classification report
print('The classification report for the training set is:')
```

```
print(classification_report(mc_smote_y_train, mc_smote_log_train_pred))
print('\n')
print('The classification report for the test set is:')
print(classification_report(mc_smote_y_test, mc_smote_test_log_pred))
print('\n\n')
#Show accuracy for both sets
print('the accuracy for the training set is:',accuracy_score(mc_smote_y_train, mc_smote_l
og_train_pred))
print('the accuracy for the test set is:', accuracy_score(mc_smote_y_test, mc_smote_test_
log_pred))
print('\n')
```

```
The classification report for the training set is:
              precision    recall  f1-score   support

          -1       0.97      0.98      0.97      2137
           0       0.97      1.00      0.98      2137
           1       0.99      0.96      0.98      2137

    accuracy                           0.98      6411
   macro avg       0.98      0.98      0.98      6411
weighted avg       0.98      0.98      0.98      6411



The classification report for the test set is:
              precision    recall  f1-score   support

          -1       0.74      0.56      0.64       535
           0       0.64      0.08      0.14       535
           1       0.43      0.90      0.58       535

    accuracy                           0.52      1605
   macro avg       0.60      0.52      0.45      1605
weighted avg       0.60      0.52      0.45      1605




the accuracy for the training set is: 0.9781625331461551
the accuracy for the test set is: 0.5158878504672897
```

Training Set Results: Accuracy: 97.82% The model performs exceptionally well on the training set, achieving high precision, recall, and F1-scores across all classes.

`Class Performance`:

- **Class -1: Precision = 0.97, Recall = 0.98, F1-score = 0.97**
- **Class 0: Precision = 0.97, Recall = 1.00, F1-score = 0.98**
- **Class 1: Precision = 0.99, Recall = 0.96, F1-score = 0.98**

These scores suggest the model is performing very well on all three classes in the training set.

Test Set Results: Accuracy: 51.59%

The model's accuracy on the test set drops sharply to just 51.59%, which is concerning since it indicates the model is not generalizing well to unseen data. Class Performance:

- **Class -1: Precision = 0.74, Recall = 0.56, F1-score = 0.64 The recall is particularly low, suggesting the model misses many true instances of class -1.**
- **Class 0: Precision = 0.64, Recall = 0.08, F1-score = 0.14 The model is significantly struggling with class 0, as indicated by the extremely low recall (8%) and F1-score (0.14). It fails to identify most instances of class 0 in the test set.**
- **Class 1: Precision = 0.43, Recall = 0.90, F1-score = 0.58 While the model manages to identify most of the class 1 instances (recall = 90%), its precision is low (43%). This means that many instances classified as class 1 are actually false positives.**

DECISION TREE CLASSIFIER

In [127]:

```
#Initialize the classifier

mc_dct = DecisionTreeClassifier()

#fit the model
mc_dct. fit(mc_smote_X_train, mc_smote_y_train)

#make predictions
mc_smote_tree_train_pred = mc_dct.predict(mc_smote_X_train)
mc_smote_tree_test_pred = mc_dct.predict(mc_smote_X_test)
```

In [128]:

```
print("Classification Report for Training Set:")
print(classification_report(mc_smote_y_train, mc_smote_tree_train_pred))
print("Classification Report for Test Set:")
print(classification_report(mc_smote_y_test, mc_smote_tree_test_pred))
print('\n\n')
#Show accuracy for both sets
print('the accuracy for the training set is:',accuracy_score(mc_smote_y_train, mc_smote_t
ree_train_pred))
print('th eaccuracy for the test set is:', accuracy_score(mc_smote_y_test, mc_smote_tree_
test_pred))
print('\n')
```

```
Classification Report for Training Set:
              precision    recall  f1-score   support

          -1       1.00      1.00      1.00      2137
           0       1.00      1.00      1.00      2137
           1       1.00      1.00      1.00      2137

    accuracy                           1.00      6411
   macro avg       1.00      1.00      1.00      6411
weighted avg       1.00      1.00      1.00      6411

Classification Report for Test Set:
              precision    recall  f1-score   support

          -1       0.66      0.60      0.63       535
           0       0.75      0.32      0.45       535
           1       0.54      0.89      0.67       535

    accuracy                           0.60      1605
   macro avg       0.65      0.60      0.58      1605
weighted avg       0.65      0.60      0.58      1605




the accuracy for the training set is: 0.9979722352207144
th eaccuracy for the test set is: 0.6024922118380063
```

`Training Set Results` : Accuracy: 99.80% The model demonstrates outstanding performance on the training set, achieving perfect precision, recall, and F1-scores across all classes. Class Performance:

- **Class -1: Precision = 1.00, Recall = 1.00, F1-score = 1.00**
- **Class 0: Precision = 1.00, Recall = 1.00, F1-score = 1.00**
- **Class 1: Precision = 1.00, Recall = 1.00, F1-score = 1.00**

The model is perfectly predicting all instances of each class, which is generally a sign of overfitting.

`Test Set Results` : The performance on the test set is much lower compared to the training set. Key metrics:

`Test Set Results`: The performance on the test set is much lower compared to the training set. Key metrics:

- **Precision: This indicates how often the model's positive predictions were correct: Class -1: 0.66 Class 0: 0.75 Class 1: 0.54**
- **Recall: This measures how well the model identifies actual positives in the test data: Class -1: 0.60 Class 0: 0.32 (lowest recall, meaning it misses a lot of true instances of class 0) Class 1: 0.89 (highest recall, meaning it catches most true instances of class 1)**
- **F1-Score: The harmonic mean of precision and recall, reflecting a balance: Class -1: 0.63 Class 0: 0.45 (lowest f1-score, reflecting poor performance in class 0) Class 1: 0.67**
- **Overall Accuracy: The model achieves an accuracy of 0.60 (60%) on the test set, which is a significant drop compared to the training set.**

XGBOOST CLASSIFIER

In [129]:

```
#remap the values for y to be non-negative for the XGBoost Classifier
mc_y_map_fixed = mc_smote_y_train.map({1: 1, 0: 0, -1: 2})
#do the same for the test
mc_y_test_map_fixed = mc_smote_y_test.map({1: 1, 0: 0, -1: 2})
```

In [130]:

```
# Instantiate XGBClassifier
mc_xgb = XGBClassifier()

# Fit XGBClassifier
mc_xgb.fit(mc_smote_X_train, mc_y_map_fixed)

# Predict on training and test sets
mc_xgb_training_preds = mc_xgb.predict(mc_smote_X_train)
mc_xgb_test_preds = mc_xgb.predict(mc_smote_X_test)

# Accuracy of training and test sets
mc_xgb_training_accuracy = accuracy_score(mc_smote_y_train, mc_xgb_training_preds)
mc_xgb_test_accuracy = accuracy_score(mc_y_test_map_fixed, mc_xgb_test_preds)

print('Training Accuracy: {:.4}%'.format(mc_xgb_training_accuracy * 100))
print('Test accuracy: {:.4}%'.format(mc_xgb_test_accuracy * 100))
```

```
Training Accuracy: 66.09%
Test accuracy: 68.91%
```

In [132]:

```
## Evaluate the model
#Look at the classification report
print('The classification report for the training set is:')
print(classification_report(mc_smote_y_train, mc_xgb_training_preds))
print('\n')
print('The classification report for the test set is:')
print(classification_report(mc_smote_y_test, mc_xgb_test_preds))
print('\n\n')
#Show accuracy for both sets
print('the accuracy for the training set is:',accuracy_score(mc_smote_y_train, mc_xgb_tra
ining_preds))
print('the accuracy for the test set is:', accuracy_score(mc_smote_y_test, mc_xgb_test_pr
eds))
print('\n')
```

```
The classification report for the training set is:
              precision    recall  f1-score   support

          -1       0.00      0.00      0.00      2137
           0       1.00      0.99      0.99      2137
           1       0.94      1.00      0.97      2137
           2       0.00      0.00      0.00         0

    accuracy                           0.66      6411
```

```
    accuracy                           0.66      6411
   macro avg       0.48      0.50      0.49      6411
weighted avg       0.65      0.66      0.65      6411



The classification report for the test set is:
              precision    recall  f1-score   support

          -1       0.00      0.00      0.00       535
           0       0.87      0.37      0.52       535
           1       0.71      0.96      0.81       535
           2       0.00      0.00      0.00         0

    accuracy                           0.44      1605
   macro avg       0.39      0.33      0.33      1605
weighted avg       0.52      0.44      0.44      1605




the accuracy for the training set is: 0.6608953361410076
the accuracy for the test set is: 0.4423676012461059
```

`Training Set Results`**: Accuracy: 66.09%**

The model has a relatively low accuracy of approximately 66%. This suggests that it is not performing well across the dataset. Class Performance:

- **Class -1: Precision = 0.00, Recall = 0.00, F1-score = 0.00 The model fails to identify any instances of class -1, indicating a severe issue with this class.**
- **Class 0: Precision = 1.00, Recall = 0.99, F1-score = 0.99 The model performs well in identifying class 0, achieving high precision and recall.**
- **Class 1: Precision = 0.94, Recall = 1.00, F1-score = 0.97 The model also performs well for class 1, with high precision and recall.**
- **Class 2: Precision = 0.00, Recall = 0.00, F1-score = 0.00 Similar to class -1, the model does not recognize any instances of class 2.**

`Test Set Results`**: Accuracy: 44.24%**

The accuracy drops significantly to approximately 44%, indicating that the model is struggling to generalize to new data. Class Performance:

- **Class -1: Precision = 0.00, Recall = 0.00, F1-score = 0.00 The model again fails to identify any instances of class -1 in the test set.**
- **Class 0: Precision = 0.87, Recall = 0.37, F1-score = 0.52 The model has a high precision for class 0 but fails to capture many instances (low recall), indicating a tendency to miss true positives.**
- **Class 1: Precision = 0.71, Recall = 0.96, F1-score = 0.81 Class 1 shows decent performance, with good recall but lower precision, suggesting some false positives.**
- **Class 2: Precision = 0.00, Recall = 0.00, F1-score = 0.00 Again, class 2 is completely unrecognized.**

CONCLUSIONS AND RECOMMENDATION

COCLUSIIONS

BINARY CLASSIFICATION

We used three models i.e Logistic Rgression, Decision tree and XGBoost for modeling the data for binary target.

- **Logistic Regression It had an accuracy of 86.07% on the test data**
- **Logistic Regression with SMOTE Accuracy of 73.89% on the test set**
- **Decision Tree accuracy of 75.64% on the test set**
- **XGBoost It had an accuracy of 86.31% on the test set**

- **Tuned XGBoost It had an accuracy of 87.79 on the test set From the data above it was eVident that the XGBoost Model was the best to use for the Binary Classification with the highest accuracy of 87.79%. Meaning it performed the best on unseen data.**

  #### MULTICLASS CLASSIFICATION The models used performed as follows:
- **Logistic Regression It had an accuracy of 84% on the test set**

  This showed us that we had an imbalance hence we needed to apply SMOTE to address issue of class imbalance
- **Logistic Regression with SMOTE It had an accuracy of 51.59% on the test set**
- **Decision Tree It had an accuracy of 60.24% on the test set**
- **XGBoost It had an accuracy of 44.24% on the test set After addressing the issue with the class imbalance we could clearly see that the best model would be the Decision Tree with an accuracy of 60.24%**

RECOMMENDATIONS

1) Address Negative Sentiment Through Targeted Feedback:

Although the negative sentiment is relatively low, it's still essential to address concerns promptly. Monitoring negative sentiments, especially those related to specific products like Google and iPhone, can help companies quickly resolve issues and improve customer experiences.

2) Encourage Neutral Sentiment Engagement:

A significant portion of the tweets are neutral, showing "No emotion toward brand or product." This provides an opportunity to engage neutral audiences and convert them into advocates. Encouraging user interaction through promotions, updates, and addressing questions can help turn neutral sentiments into positive ones.

3) Model Selection:

For binary classification the best model would be the XGBoost with an accuracy of 87.79%. While for a multiclass classification approach the best model would be to use the Decision Tree with an accuracy of 80.88%. Further tuning could improve the models' performances for both the binary and multiclass classification tasks.