Apple and Google NLP Twitter Sentiment Analysis

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Business Overview

Introduction

In today's digital age, social media platforms like Twitter serve as an invaluable source of public sentiment and opinion. Understanding the sentiments of users on these platforms can provide valuable insights for businesses. In this project, the aim is to harness the power of Natural Language Processing (NLP) to analyze Twitter sentiment about products from two tech giants, Apple and Google.

Business Understanding

Apple and Google are two of the most prominent companies in the tech industry, producing a wide range of products that have a significant impact on people's lives. Monitoring the sentiment expressed by Twitter users towards these companies and their products can help businesses make informed decisions. This sentiment analysis can inform product development, marketing strategies, and customer relations.

Business Problem

The primary business problem that will be addressed is the need for a systematic and automated way to gauge the sentiment of tweets related to Apple and Google products. Twitter is a platform where millions of users express their opinions and experiences daily. Manual analysis of these tweets is not feasible due to the sheer volume of data. Therefore, there's need for a reliable NLP model that can classify tweets into positive, negative, or neutral sentiment categories.

Research Question

- How do consumers perceive one company relative to the other?

Main Objective

The main objective of this project is to build a proof-of-concept NLP model that can accurately rate the sentiment of tweets about Apple and Google products. This model will enable businesses to gain real-time insights into how their products are perceived by the Twitter community.

Specific Objectives

- **Data Collection:** A dataset of tweets related to Apple and Google products will be gathered. This dataset should include tweets that express both positive and negative sentiments.
- **Data Preprocessing:** Cleaning and preprocessing the collected data to prepare it for NLP analysis. This includes tasks like text normalization, tokenization, and handling of missing or irrelevant data.
- **Model Development:** Developing a baseline NLP model for binary sentiment classification, categorizing tweets as either positive or negative. This model will serve as a starting point for further improvements.
- **Model Evaluation:** Evaluating the binary sentiment classifier using appropriate metrics like accuracy, precision, recall, and F1-score. This will help assess the model's performance and identify areas for improvement.
- **Multiclass Classification:** Extending the binary classifier to a multiclass classifier by incorporating a neutral sentiment category. This will provide a more nuanced understanding of sentiment.
- **Business Insights:** Interpret the results and provide actionable insights to businesses.

In conclusion, this project aims to create a valuable tool for businesses in the tech industry by leveraging NLP to understand and react to public sentiment on Twitter. By achieving the specific objectives outlined, the project will provide a scalable solution for sentiment analysis that can be adapted to other products and industries, ultimately enhancing decision-making processes and customer satisfaction.

Metrics of Success

After modeling, the success metrics for the sentiment analysis on this project includes:

- **Accuracy:** Measure the accuracy of the sentiment classification model in correctly categorizing tweets into positive, negative, or neutral sentiments. This metric indicates the model's ability to make accurate predictions.
- **Precision, Recall, and F1 Score:** Calculate precision, recall, and F1 score to assess the model's performance in correctly identifying positive, negative, and neutral sentiments. These metrics provide insights into the model's ability to balance precision (correctly identifying positive/negative sentiments) and recall (identifying all positive/negative sentiments).

Experimental Design

- Data Collection.
- Read and check the data.
- Cleaning the data.
- Exploratory Data Analysis.
- Modelling.
- Findings
- Conclusions, Recommendations, and Next Steps.

Data Understanding

The data was sourced from [here (https://data.world/crowdflower/brands-and-product-emotions)](https://data.world/crowdflower/brands-and-product-emotions). Contributors evaluated tweets about multiple brands and products. The crowd was asked if the tweet expressed positive, negative, or no emotion towards a brand and/or product. If some

In [1]:
```
# importing necessary packages
import matplotlib.pyplot as plt
import nltk
import numpy as np
import pandas as pd
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")

from nltk.corpus import stopwords
from nltk.probability import FreqDist
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.tokenize import RegexpTokenizer
from wordcloud import WordCloud

from imblearn.over_sampling import RandomOverSampler
import imblearn.pipeline
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_extraction.text import CountVectorizer,\
      TfidfTransformer, TfidfVectorizer
from sklearn.linear_model import LogisticRegressionCV
from matplotlib import cm
from sklearn.metrics import confusion_matrix, classification_report,\
      precision_score, roc_curve, roc_auc_score
from sklearn import metrics
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import Pipeline

nltk.download("omw-1.4")
nltk.download("stopwords")
nltk.download("vader_lexicon")
nltk.download("wordnet")
```

```
[nltk_data] Downloading package omw-1.4 to
[nltk_data]     C:\Users\USER\AppData\Roaming\nltk_data...
[nltk_data]   Package omw-1.4 is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\USER\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\USER\AppData\Roaming\nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\USER\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Out[1]: True

In [2]:
```
# Reading the Dataset
# Use 'latin-1' encoding to handle special characters
review_df = pd.read_csv("judge-1377884607_tweet_product_company.csv",
                        encoding="latin-1")
review_df.head()
```

Out[2]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_prod
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emo
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive emo
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emo
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emo
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emo

The column names are overly lengthy and challenging to read. To improve readability, we can rename the columns.

In [3]:
```
# Confirming the changes
review_df.columns = ["tweet", "products", "emotion"]
review_df.head()
```

Out[3]:

	tweet	products	emotion
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

Checking at unique values of products and emotion to have a better understanding of what we are working with

In [4]:
```
# Displaying unique entries in "products"
review_df.products.unique()
```

Out[4]:
```
array(['iPhone', 'iPad or iPhone App', 'iPad', 'Google', nan, 'Android',
       'Apple', 'Android App', 'Other Google product or service',
       'Other Apple product or service'], dtype=object)
```

In [5]:
```
# Displaying unique entries in "emotion"
review_df.emotion.unique()
```

Out[5]:
```
array(['Negative emotion', 'Positive emotion',
       'No emotion toward brand or product', "I can't tell"], dtype=object)
```

Based on the unique values observed in the **"products"** and **"emotion"** columns, we can make several observations:

The **"products"** column contains a variety of product-related values, including specific Apple and Google products like 'iPhone,' 'iPad,' 'Google,' 'Android,' as well as more general categories like 'iPad or iPhone App,' 'Android App,' 'Other Google product or service,' and 'Other Apple product or service.' Additionally, there are some missing values (NaN).

The **"emotion"** column represents the sentiment or emotion associated with the tweets. It includes categories such as 'Negative emotion,' 'Positive emotion,' 'No emotion toward brand or product,' and "I can't tell."

Changing the names of the values in the emotion column for easy interpretability

In [6]:
```
# Replacing 'No emotion toward brand or product' with 'Neutral emotion'
#and 'I can't tell' with 'Unknown'
review_df['emotion'].replace(
    {'No emotion toward brand or product': 'Neutral emotion',
    "I can't tell": 'Unknown'}, inplace=True)
```

In [7]:
```
# Confirming the changes while
review_df.emotion.value_counts()
```

Out[7]:
```
Neutral emotion     5389
Positive emotion    2978
Negative emotion     570
Unknown              156
Name: emotion, dtype: int64
```

In [8]:
```
# Checking structure of the dataset
review_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     9092 non-null   object
 1   products  3291 non-null   object
 2   emotion   9093 non-null   object
dtypes: object(3)
memory usage: 213.2+ KB
```

From the above we can observe that we have a missing text for tweet and also were are missing some products of which the corresponding tweet was about.

Dealing with missing values

In [9]:
```
# Inspecting the row with the missing tweet
review_df[pd.isna(review_df["tweet"])]
```

Out[9]:

	tweet	products	emotion
6	NaN	NaN	Neutral emotion

We can see that both tweet and product information are missing in this row, so it would be appropriate to drop it.

In [10]:
```
# Droping the row
review_df.dropna(subset=["tweet"], inplace=True)
```

In [11]:
```
# Inspecting the rows where product column has missing value
review_df[pd.isna(review_df['products'])].head(10)
```

Out[11]:

	tweet	products	emotion
5	@teachntech00 New iPad Apps For #SpeechTherapy...	NaN	Neutral emotion
16	Holler Gram for iPad on the iTunes App Store -...	NaN	Neutral emotion
32	Attn: All #SXSW frineds, @mention Register fo...	NaN	Neutral emotion
33	Anyone at #sxsw want to sell their old iPad?	NaN	Neutral emotion
34	Anyone at #SXSW who bought the new iPad want ...	NaN	Neutral emotion
35	At #sxsw. Oooh. RT @mention Google to Launch ...	NaN	Neutral emotion
37	SPIN Play - a new concept in music discovery f...	NaN	Neutral emotion
39	VatorNews - Google And Apple Force Print Media...	NaN	Neutral emotion
41	HootSuite - HootSuite Mobile for #SXSW ~ Updat...	NaN	Neutral emotion
42	Hey #SXSW - How long do you think it takes us ...	NaN	Neutral emotion

In [12]:
```
#  Checking the percentage of the null values
missing_products_percentage = (review_df['products'].isna().sum() / len(review_
print(round(missing_products_percentage, 2))
```

```
63.8
```

These tweets are not really directed towards a specific product or brand so we can go ahead and fill the null values with "Unknown" as a placeholder value. Also, given that approximately 63.80% of the "products" column contains missing values, filling them with "Unknown" is a reasonable approach to ensure that we retain as much useful information as possible while preparing the data for analysis.

In [13]:
```
# Filling the null values with "Unknown"
review_df["products"].fillna("Unknown", inplace=True)
```

In [14]:
```
# Verifying that the missing values have been dealt with
review_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9092 entries, 0 to 9092
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   tweet     9092 non-null   object
 1   products  9092 non-null   object
 2   emotion   9092 non-null   object
dtypes: object(3)
memory usage: 284.1+ KB
```

Dropping some rows

Calculating the percentage of each emotion category

In [15]:
```
# Calculating the percentage of each emotion category
emotion_percentage = (review_df['emotion'].value_counts() / len(review_df)) * 

# Display the percentage of each emotion
print(emotion_percentage)
```

```
Neutral emotion     59.260889
Positive emotion    32.754070
Negative emotion     6.269248
Unknown              1.715794
Name: emotion, dtype: float64
```

For this project, our focus is solely on emotions categorized as positive, neutral, or negative. Therefore, we will proceed to remove rows with the "Unknown" emotion category. It's worth noting that these rows account for only up to 1.7% of our dataset, making their removal a justifiable step.

In [16]:
```
# Dropping rows with "Unknown" emotion category
review_df = review_df[review_df.emotion != "Unknown" ]

# Checking the changes
review_df.emotion.value_counts()
```

Out[16]:
```
Neutral emotion     5388
Positive emotion    2978
Negative emotion     570
Name: emotion, dtype: int64
```

Checking and Dealing with Duplicates

In [17]:
```
# Calculating the number of duplicate rows
len(review_df[review_df.duplicated()])
```

Out[17]:
```
22
```

In [18]:
```python
# Checking for duplicate rows in the DataFrame
review_df[review_df.duplicated()].head(10)
```

Out[18]:

	tweet	products	emotion
468	Before It Even Begins, Apple Wins #SXSW {link}	Apple	Positive emotion
776	Google to Launch Major New Social Network Call...	Unknown	Neutral emotion
2232	Marissa Mayer: Google Will Connect the Digital...	Unknown	Neutral emotion
2559	Counting down the days to #sxsw plus strong Ca...	Apple	Positive emotion
3950	Really enjoying the changes in Gowalla 3.0 for...	Android App	Positive emotion
3962	#SXSW is just starting, #CTIA is around the co...	Android	Positive emotion
4897	Oh. My. God. The #SXSW app for iPad is pure, u...	iPad or iPhone App	Positive emotion
5338	RT @mention □÷¼ GO BEYOND BORDERS! □÷_ {link} ...	Unknown	Neutral emotion
5341	RT @mention □÷¼ Happy Woman's Day! Make love, ...	Unknown	Neutral emotion
5881	RT @mention Google to Launch Major New Social ...	Unknown	Neutral emotion

It appears that there are 22 duplicate rows. These duplicates will be removed, retaining only the first occurrence of each row.

In [19]:
```python
# Remove duplicate rows and keep the first occurrence
review_df.drop_duplicates(inplace=True)
```

In [20]:
```python
# Display information about the DataFrame
review_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8914 entries, 0 to 9092
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   tweet     8914 non-null   object
 1   products  8914 non-null   object
 2   emotion   8914 non-null   object
dtypes: object(3)
memory usage: 278.6+ KB
```

Now we're going to clean the tweets from user mentions. This preprocessing step helps in removing user-specific information from the tweets while retaining the content.

In [21]:
```
# Creating a function that will be used to remove name tags

def remove_nametags(sentence):
    """A simple function to remove name tags"""
    clean_words = []
    for word in sentence.split():
        if "@" not in word:
            clean_words.append(word)
    return " ".join(clean_words)

review_df["tweet"] = review_df["tweet"].apply(remove_nametags)

review_df.head()
```

Out[21]:

	tweet	products	emotion
0	I have a 3G iPhone. After 3 hrs tweeting at #R...	iPhone	Negative emotion
1	Know about ? Awesome iPad/iPhone app that you'...	iPad or iPhone App	Positive emotion
2	Can not wait for #iPad 2 also. They should sal...	iPad	Positive emotion
3	I hope this year's festival isn't as crashy as...	iPad or iPhone App	Negative emotion
4	great stuff on Fri #SXSW: Marissa Mayer (Googl...	Google	Positive emotion

Exploratory Data Analysis

Exploratory data analysis is a critical step in the data analysis process that involves examining and visualizing dataset to gain insights and understand its characteristics. EDA helps in uncovering patterns, relationships, and potential issues in your data before diving into more advanced analyses.

Tweets with positve emotions

We will start our exploration with tweets with positve emotions.

In [22]:
```
# Parsing positive tweets into new df
positive_df = review_df[review_df["emotion"]=="Positive emotion"]

positive_df
```

Out[22]:

	tweet	products	emotion
1	Know about ? Awesome iPad/iPhone app that you'...	iPad or iPhone App	Positive emotion
2	Can not wait for #iPad 2 also. They should sal...	iPad	Positive emotion
4	great stuff on Fri #SXSW: Marissa Mayer (Googl...	Google	Positive emotion
7	#SXSW is just starting, #CTIA is around the co...	Android	Positive emotion
8	Beautifully smart and simple idea RT wrote abo...	iPad or iPhone App	Positive emotion
...	...	...	...
9072	your iPhone 4 cases are Rad and Ready! Stop by...	iPhone	Positive emotion
9077	your PR guy just convinced me to switch back t...	iPhone	Positive emotion
9079	"papyrus...sort of like the ipad" - ...	iPad	Positive emotion
9085	I've always used Camera+ for my iPhone b/c it ...	iPad or iPhone App	Positive emotion
9088	Ipad everywhere. #SXSW {link}	iPad	Positive emotion

2970 rows × 3 columns

In [23]:
```
# Convert the "tweet" column into a list
positive_tweet = positive_df['tweet'].tolist()

# Display the first few elements of the list
positive_tweet[:5]
```

Out[23]:
```
["Know about ? Awesome iPad/iPhone app that you'll likely appreciate for its design. Also, they're giving free Ts at #SXSW",
 'Can not wait for #iPad 2 also. They should sale them down at #SXSW.',
 "great stuff on Fri #SXSW: Marissa Mayer (Google), Tim O'Reilly (tech books/conferences) &amp; Matt Mullenweg (Wordpress)",
 '#SXSW is just starting, #CTIA is around the corner and #googleio is only a hop skip and a jump from there, good time to be an #android fan',
 'Beautifully smart and simple idea RT wrote about our #hollergram iPad app for #sxsw! http://bit.ly/ieaVOB'] (http://bit.ly/ieaVOB'])
```

Tokenization

Splitting the tweets into units of observation.

In [24]:
```
def tokenize_tweets(tweets, preserve_case=False):
    """
    Tokenizes a list of tweets using the RegexpTokenizer.

        Returns:
    - list: A list of tokenized tweets where each tweet is represented as a lis
    """
    # Initialize the tokenizer
    tokenizer = RegexpTokenizer(r'[a-zA-Z0-9]+')

    # Initialize an empty list to store tokenized tweets
    tokenized_tweets = []

    # Tokenize each tweet in the list
    for tweet in tweets:
        if preserve_case:
            tokenized_tweet = tokenizer.tokenize(tweet)
        else:
            tokenized_tweet = tokenizer.tokenize(tweet.lower())
        tokenized_tweets.extend(tokenized_tweet)

    return tokenized_tweets
```

In [25]:
```
# Tokenize positive tweets
positive_tokens = tokenize_tweets(positive_tweet)
```

In [26]:
```
# Displaying 50 most common token
freq = FreqDist(positive_tokens)
freq.most_common(50)
```

Out[26]:
```
[('sxsw', 3136),
 ('the', 1591),
 ('link', 1214),
 ('to', 1156),
 ('ipad', 1025),
 ('at', 1021),
 ('apple', 932),
 ('rt', 922),
 ('for', 907),
 ('a', 796),
 ('google', 734),
 ('is', 643),
 ('in', 639),
 ('of', 639),
 ('i', 630),
 ('and', 582),
 ('store', 549),
 ('iphone', 548),
 ('s', 510),
 ('2', 504),
 ('it', 475),
 ('quot', 460),
 ('up', 458),
 ('on', 439),
 ('app', 400),
 ('new', 360),
 ('you', 336),
 ('an', 327),
 ('my', 305),
 ('with', 296),
 ('austin', 295),
 ('just', 241),
 ('this', 226),
 ('pop', 214),
 ('ipad2', 210),
 ('amp', 208),
 ('android', 208),
 ('be', 204),
 ('that', 196),
 ('out', 192),
 ('by', 175),
 ('from', 174),
 ('t', 173),
 ('have', 172),
 ('launch', 160),
 ('get', 158),
 ('are', 157),
 ('they', 150),
 ('one', 148),
 ('your', 147)]
```

Upon analyzing the 50 most common tokens in positive tweets related to Apple and Google products during the SXSW Conference, we have observed recurring terms and patterns.

It is evident that the token "sxsw" prominently appears in these tweets. Given our knowledge that these tweets are related to the SXSW Conference, we may consider excluding it by adding it to the list of stopwords. Furthermore, words related to companies and products such as 'ipad,' 'apple,' 'iphone,' 'android,' and 'ipad2' should be removed. Additionally, words like 'link' and 'rt,' which likely refer to external links and retweets, should be excluded from our analysis. Moreover, common English words, often referred to as stopwords, including "the," "to," "at," and "for," have been observed frequently and should be filtered out as they do not provide substantial insights for our analysis.

Lemmatization

Before removing stopwords, we are going to reduce words to their base or dictionary form.

In [27]:
```
# A simple function to be used for creating lemmas

def lemmatize_tokens(tokens):
    """
    Lemmatizes a list of tokens using the WordNetLemmatizer from NLTK.

    Args:
    - tokens (list): A list of tokens to be lemmatized.

    Returns:
    - list: A list of lemmatized tokens.
    """
    # Initialize the WordNetLemmatizer
    lemmatizer = WordNetLemmatizer()

    # Lemmatize each token and store the result in a new list
    lemmatized_tokens = [lemmatizer.lemmatize(token) for token in tokens]

    return lemmatized_tokens
```

In [28]:
```
# Lemmatizing positive tweet tokens
positive_tokens_lemm = lemmatize_tokens(positive_tokens)

# Displaying most common 50 tokens
freq = FreqDist(positive_tokens_lemm)
freq.most_common(50)
```

Out[28]:
```
[('sxsw', 3136),
 ('the', 1591),
 ('link', 1218),
 ('to', 1156),
 ('ipad', 1025),
 ('at', 1021),
 ('apple', 933),
 ('rt', 922),
 ('for', 907),
 ('a', 870),
 ('google', 734),
 ('is', 643),
 ('in', 641),
 ('of', 639),
 ('i', 630),
 ('and', 582),
 ('store', 561),
 ('iphone', 548),
 ('2', 517),
 ('it', 511),
 ('s', 510),
 ('quot', 460),
 ('up', 458),
 ('on', 439),
 ('app', 400),
 ('new', 360),
 ('you', 336),
 ('an', 327),
 ('my', 305),
 ('with', 296),
 ('austin', 295),
 ('just', 241),
 ('this', 226),
 ('pop', 214),
 ('ipad2', 210),
 ('amp', 208),
 ('android', 208),
 ('be', 204),
 ('that', 196),
 ('out', 193),
 ('get', 181),
 ('t', 175),
 ('by', 175),
 ('from', 174),
 ('launch', 174),
 ('have', 172),
 ('are', 157),
 ('party', 152),
 ('one', 151),
 ('they', 150)]
```

Removing Stopwords

In [29]:
```
# A simple function to be used in removing stopwords

# Additional custom stop words
custom_stop_words = ["sxsw", "link", "ipad",
                     "apple", "google", "rt",
                     "iphone", "android", "ipad2"]

def remove_stopwords(tokens):
    """
    Removes stop words from a list of tokens.

    Args:
    - tokens (list): A list of tokens to be filtered for stop words.

    Returns:
    - list: A list of tokens with stop words removed.
    """
    # Get the set of English stop words
    stop_words = set(stopwords.words("english") + custom_stop_words)

    # Filter out stop words from the list of tokens
    filtered_tokens = [token for token in tokens if token.lower() not in stop_

    return filtered_tokens
```

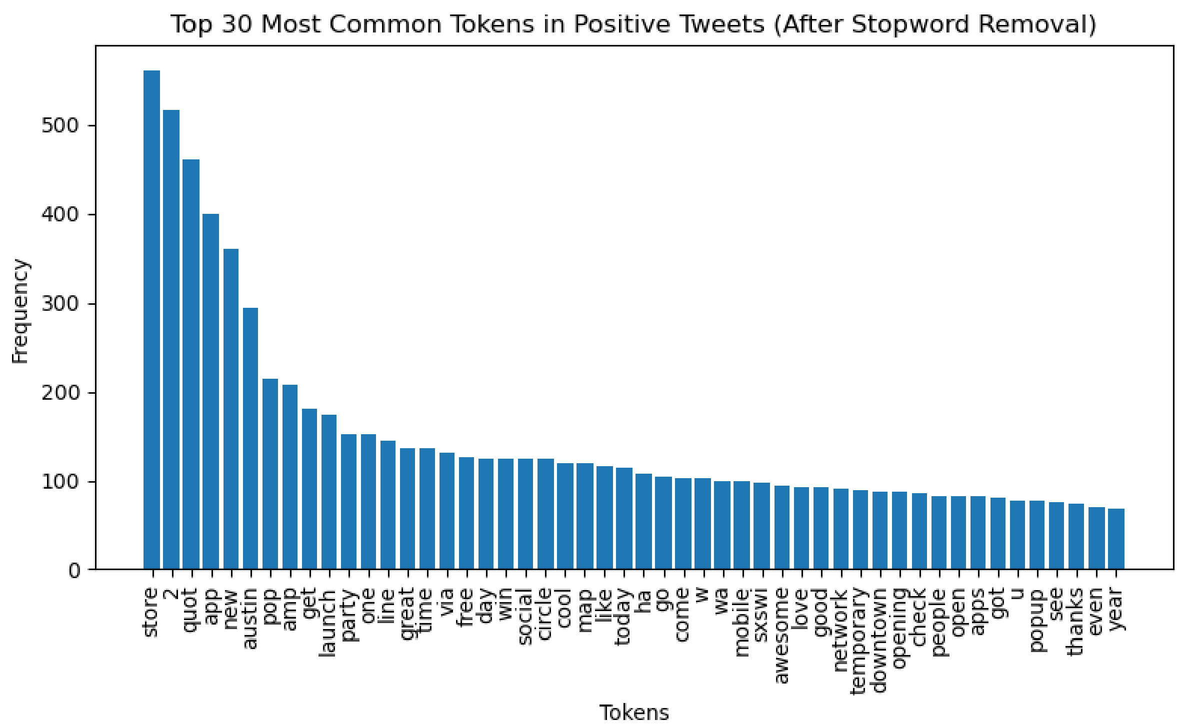
In [30]:
```
# Positive filtered tokens
positive_filtered_tokens = remove_stopwords(positive_tokens_lemm)
```

In [31]:
```
# Displaying most common 50 tokens
freq = FreqDist(positive_filtered_tokens)
freq.most_common(50)
```

Out[31]:
```
[('store', 561),
 ('2', 517),
 ('quot', 460),
 ('app', 400),
 ('new', 360),
 ('austin', 295),
 ('pop', 214),
 ('amp', 208),
 ('get', 181),
 ('launch', 174),
 ('party', 152),
 ('one', 151),
 ('line', 145),
 ('great', 137),
 ('time', 136),
 ('via', 131),
 ('free', 126),
 ('day', 125),
 ('win', 124),
 ('social', 124),
 ('circle', 124),
 ('cool', 120),
 ('map', 119),
 ('like', 116),
 ('today', 114),
 ('ha', 108),
 ('go', 105),
 ('come', 103),
 ('w', 103),
 ('wa', 100),
 ('mobile', 100),
 ('sxswi', 97),
 ('awesome', 94),
 ('love', 93),
 ('good', 92),
 ('network', 91),
 ('temporary', 89),
 ('downtown', 88),
 ('opening', 88),
 ('check', 85),
 ('people', 83),
 ('open', 83),
 ('apps', 83),
 ('got', 81),
 ('u', 77),
 ('popup', 77),
 ('see', 76),
 ('thanks', 73),
 ('even', 70),
 ('year', 69)]
```

In [32]:
```
# Creating a funtion that will be used to visualize the top 30 most common toke
def plot_token_frequency(tokens, top_n=30, title="Token Frequency Distribution
    """
    Plot the frequency distribution of tokens.

    Args:
    - tokens (list): A list of tokens to analyze.
    - top_n (int): The number of top tokens to display in the plot.
    - title (str): The title of the plot.

    """
    # Calculate the frequency distribution
    freq = FreqDist(tokens)

    # Get the top N most common tokens and their frequencies
    common_tokens = freq.most_common(top_n)

    # Separate tokens and frequencies
    tokens, frequencies = zip(*common_tokens)

    # Create a bar plot for the most common tokens
    plt.figure(figsize=(8, 5))
    plt.bar(tokens, frequencies)
    plt.xlabel("Tokens")
    plt.ylabel("Frequency")
    plt.title(title)
    plt.xticks(rotation=90)
    plt.tight_layout();
```

In [33]:
```
# Visualizing the top 30 most common tokens
plot_token_frequency(positive_filtered_tokens, top_n=50,
                     title="Top 30 Most Common Tokens in Positive Tweets (After
```



Overall, we can observe that these common positive tokens indicate a highly positive sentiment among attendees regarding Apple and its products, as well as the general tech-centric and communal atmosphere at the event.

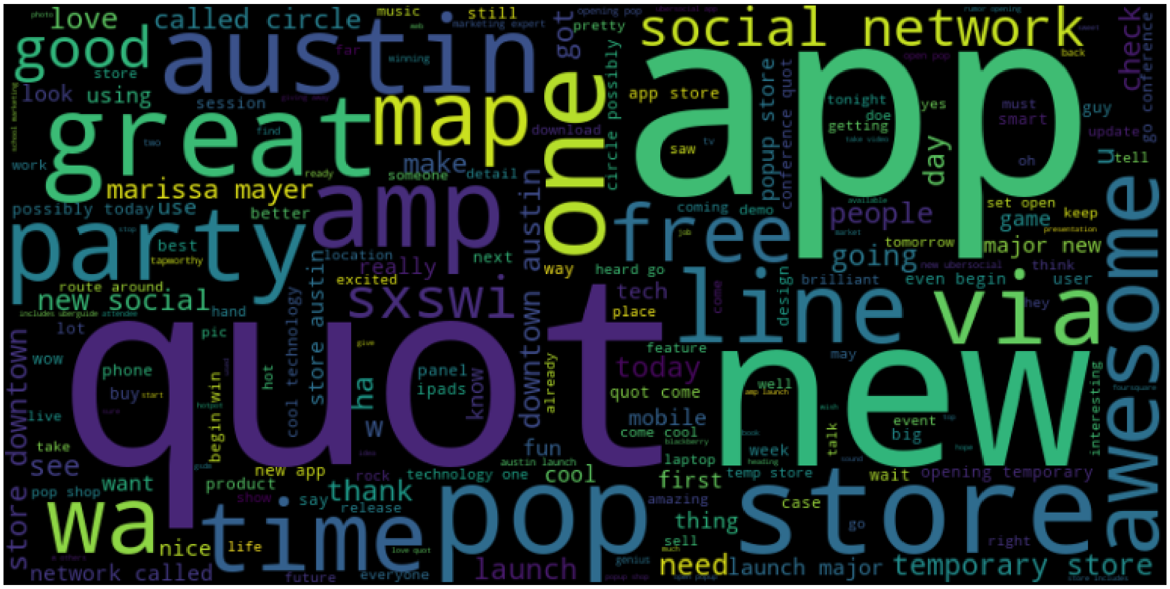
WordCloud for Positive Tweets

WordCloud is a data visualization technique used to represent text data in a visually engaging and intuitive way.

In [34]:
```
# A function to be used to generate worldcould

def generate_wordcloud(tokens, title="WordCloud"):
    """
    Generate and display a WordCloud from a list of tokens.

    Parameters:
    - tokens (list): List of tokens for generating the WordCloud.
    - title (str): Title for the WordCloud plot (optional).

    """
    # Join the list of tokens into a single string
    text = ' '.join(tokens)

    # Create a WordCloud object
    wordcloud = WordCloud(width=800, height=400).generate(text)

    # Display the WordCloud plot
    plt.figure(figsize=(10, 5))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(title, fontsize=16)
    plt.axis("off");
```

In [35]:
```python
# Generating word cloud
cloud_positive_tweet = generate_wordcloud(positive_filtered_tokens,
                                          title="Most Common Words in Positive Tweets")
```

Most Common Words in Positive Tweets



This above analysis highlights the prominent themes and keywords in positive tweets, shedding light on the topics that resonate most with participants at SXSW.

Tweets with negative emotions

In [36]:
```
#parsing positive tweets into new df
negative_df = review_df[review_df["emotion"]=="Negative emotion"]

negative_df
```

Out[36]:

	tweet	products	emotion
0	I have a 3G iPhone. After 3 hrs tweeting at #R...	iPhone	Negative emotion
3	I hope this year's festival isn't as crashy as...	iPad or iPhone App	Negative emotion
17	I just noticed DST is coming this weekend. How...	iPhone	Negative emotion
38	- False Alarm: Google Circles Not Coming Now□Û...	Google	Negative emotion
64	Again? RT Line at the Apple store is insane.. ...	Unknown	Negative emotion
...	...	...	...
8973	Google guy at #sxsw talk is explaining how he ...	Unknown	Negative emotion
8981	I think my effing hubby is in line for an #iPa...	iPad	Negative emotion
9008	I'm pretty sure the panelist that thinks &quot...	Apple	Negative emotion
9043	Hey is anyone doing #sxsw signing up for the g...	Unknown	Negative emotion
9080	Diller says Google TV "might be run over ...	Other Google product or service	Negative emotion

569 rows × 3 columns

In [37]:
```
# Convert the "tweet" column into a list
negative_tweet = negative_df['tweet'].tolist()

# Display the first few elements of the list
negative_tweet[:5]
```

Out[37]:
```
['I have a 3G iPhone. After 3 hrs tweeting at #RISE_Austin, it was dead! I ne
ed to upgrade. Plugin stations at #SXSW.',
 "I hope this year's festival isn't as crashy as this year's iPhone app. #sxs
w",
 'I just noticed DST is coming this weekend. How many iPhone users will be an
hour late at SXSW come Sunday morning? #SXSW #iPhone',
 '- False Alarm: Google Circles Not Coming Now\x89ÛÒand Probably Not Ever? -
{link} #Google #Circles #Social #SXSW',
 'Again? RT Line at the Apple store is insane.. #sxsw']
```

Tokenization

In [38]:
```
# Tokenize negative tweets
negative_tokens = tokenize_tweets(negative_tweet)

# Displaying 10 most common token
freq = FreqDist(negative_tokens)
freq.most_common(10)
```

Out[38]:
```
[('sxsw', 585),
 ('the', 314),
 ('to', 257),
 ('ipad', 195),
 ('i', 178),
 ('quot', 172),
 ('iphone', 162),
 ('is', 159),
 ('a', 155),
 ('google', 151)]
```

Lemmatization

In [39]:
```
# Lemmatizing negative tweet tokens
negative_tokens_lemm = lemmatize_tokens(negative_tokens)

# Displaying most common 10 tokens
freq = FreqDist(negative_tokens_lemm)
freq.most_common(10)
```

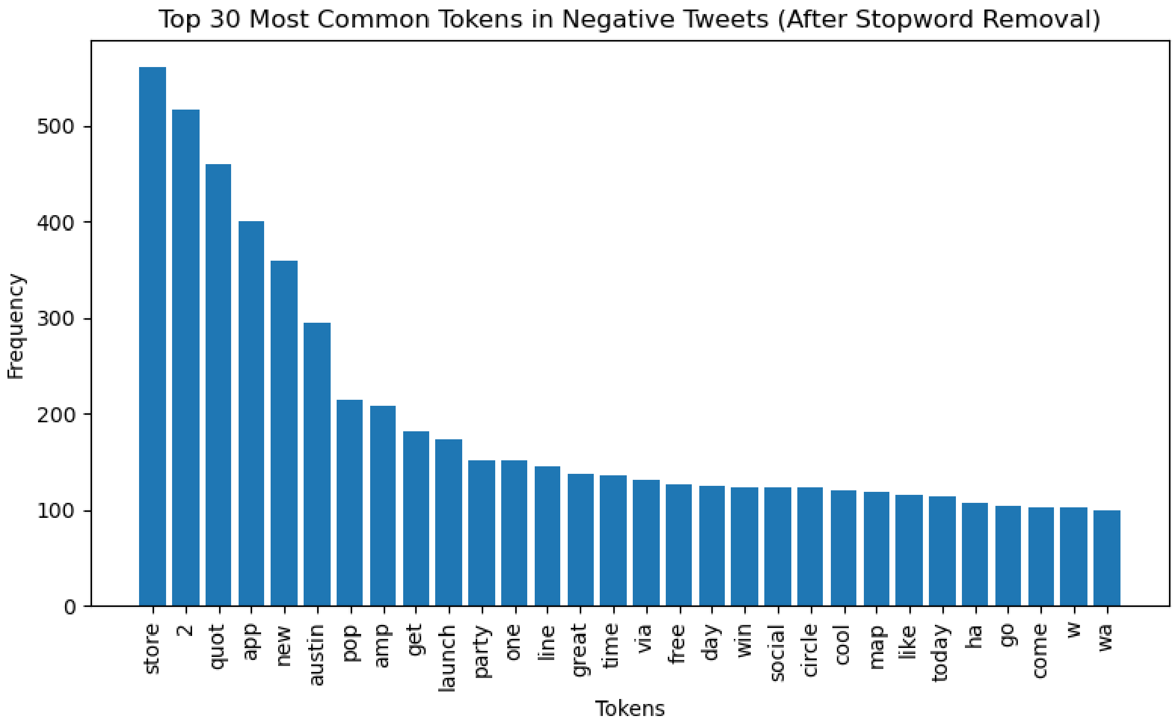
Out[39]:
```
[('sxsw', 585),
 ('the', 314),
 ('to', 257),
 ('ipad', 195),
 ('a', 194),
 ('i', 178),
 ('quot', 172),
 ('iphone', 162),
 ('is', 159),
 ('google', 151)]
```

Removing Stopwords

In [40]:
```
# Negative filtered tokens
negative_filtered_tokens = remove_stopwords(negative_tokens_lemm)

# Displaying most common 50 tokens
freq = FreqDist(negative_filtered_tokens)
freq.most_common(50)
```

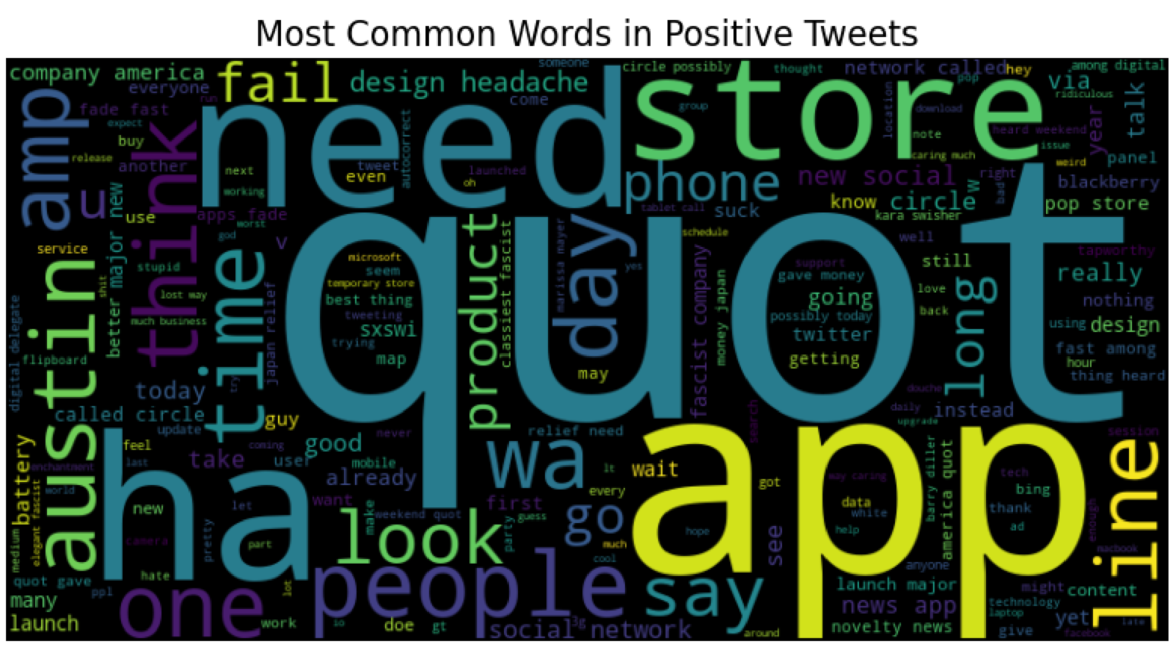
```
Out[40]: [('quot', 172),
 ('2', 72),
 ('app', 60),
 ('store', 47),
 ('new', 43),
 ('like', 43),
 ('circle', 37),
 ('need', 35),
 ('social', 31),
 ('ha', 31),
 ('apps', 30),
 ('design', 29),
 ('people', 29),
 ('austin', 28),
 ('get', 25),
 ('wa', 24),
 ('one', 23),
 ('think', 23),
 ('time', 23),
 ('line', 22),
 ('amp', 22),
 ('launch', 22),
 ('day', 22),
 ('today', 21),
 ('look', 21),
 ('say', 20),
 ('would', 19),
 ('news', 18),
 ('network', 18),
 ('phone', 18),
 ('fail', 18),
 ('year', 17),
 ('headache', 17),
 ('1', 17),
 ('go', 17),
 ('battery', 17),
 ('pop', 17),
 ('long', 17),
 ('product', 17),
 ('user', 15),
 ('thing', 15),
 ('good', 15),
 ('see', 15),
 ('much', 15),
 ('company', 15),
 ('america', 15),
 ('back', 14),
 ('money', 14),
 ('u', 14),
 ('major', 14)]
```

In [41]:
```
# Visualizing the top 30 most common tokens
plot_token_frequency(positive_filtered_tokens, top_n=30,
                     title="Top 30 Most Common Tokens in Negative Tweets (Afte
```



WordCloud for Negative Tweets

In [42]:
```
# Generating word cloud
cloud_negative_tweet = generate_wordcloud(negative_filtered_tokens,
                                         title="Most Common Words in Positive Tweets")
```



While analyzing the most common tokens in positive and negative tweets, it's evident that certain words like "store", "2", "quot" and "app" dominate both sentiment categories. However, merely focusing on sentiment alone might not provide a comprehensive understanding of the underlying trends and insights. Feature engineering will be done to consider specific companies and products.

Analyzing tweets based on specific companies(Apple and Google) will allow for a deeper dive into consumer opinions about each entity.

Feature Engeneering

In [43]:
```
# Displaying unique entries in "products"
review_df.products.unique()
```

Out[43]:
```
array(['iPhone', 'iPad or iPhone App', 'iPad', 'Google', 'Unknown',
       'Android', 'Apple', 'Android App',
       'Other Google product or service',
       'Other Apple product or service'], dtype=object)
```

In [44]:
```
# Feature engineering to have three categories: "Google," "Apple," and "Unknown
review_df['brand'] = review_df['products'].replace({
    'iPhone': 'Apple',
    'iPad or iPhone App': 'Apple',
    'iPad': 'Apple',
    'Google': 'Google',
    'Unknown': 'Unknown',
    'Android': 'Google',
    'Apple': 'Apple',
    'Android App': 'Google',
    'Other Google product or service': 'Google',
    'Other Apple product or service': 'Apple'
})

# Drop the original "products" column
review_df.drop(columns=['products'], inplace=True)

# Display unique entries in the "brand" column
review_df['brand'].unique()
```

Out[44]:
```
array(['Apple', 'Google', 'Unknown'], dtype=object)
```

Sentiment Analysis of Apple-Related Tweets

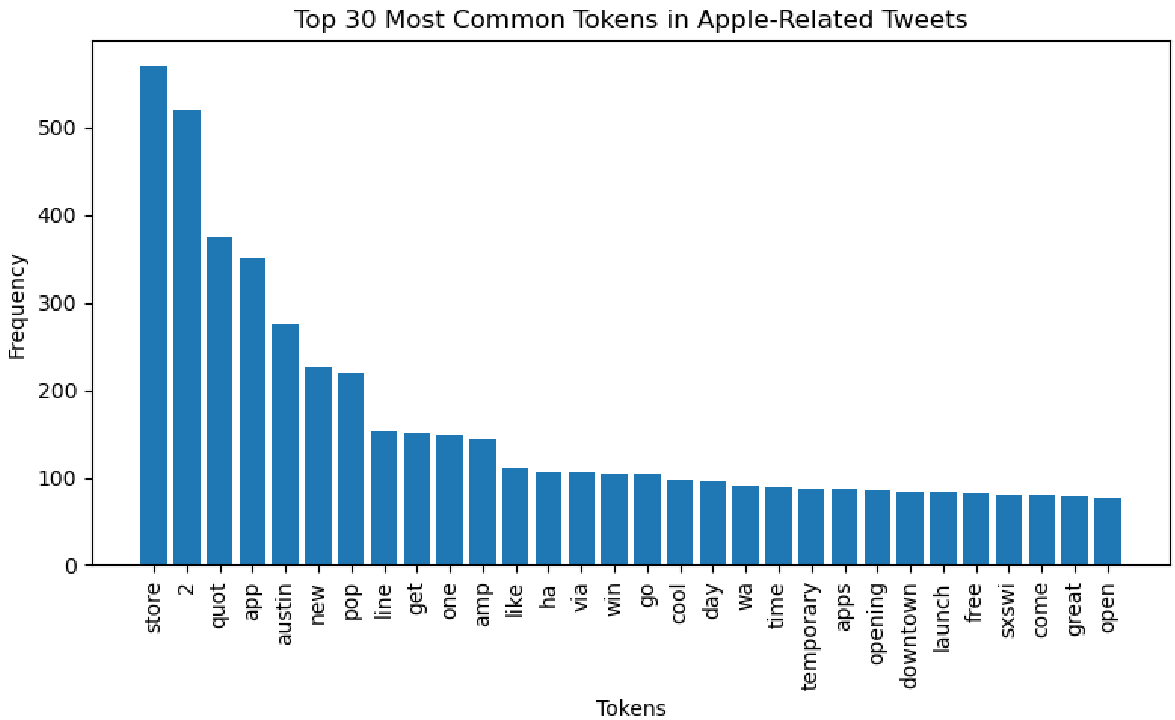
In [45]:
```
# Filtering the DataFrame to select tweets associated with Apple
apple_tweets_df = review_df[review_df['brand'] == 'Apple']

# Converting the selected tweets to a list
apple_tweets_list = apple_tweets_df['tweet'].tolist()

# Display the first few elements of the list
apple_tweets_list[:5]
```

Out[45]:
```
['I have a 3G iPhone. After 3 hrs tweeting at #RISE_Austin, it was dead! I ne
ed to upgrade. Plugin stations at #SXSW.',
 "Know about ? Awesome iPad/iPhone app that you'll likely appreciate for its
design. Also, they're giving free Ts at #SXSW",
 'Can not wait for #iPad 2 also. They should sale them down at #SXSW.',
 "I hope this year's festival isn't as crashy as this year's iPhone app. #sxs
w",
 'Beautifully smart and simple idea RT wrote about our #hollergram iPad app f
or #sxsw! http://bit.ly/ieaVOB'] (http://bit.ly/ieaVOB'])
```

In [46]:
```
#tokenize tweets
tokens_apple = tokenize_tweets(apple_tweets_list)
#lemmatize tweets
tokens_apple_lemm = lemmatize_tokens(tokens_apple)
#remove stop words using the same stop words list
tokens_apple_filtered = remove_stopwords(tokens_apple_lemm)

# Displaying most common 20 tokens
freq = FreqDist(tokens_apple_filtered)
freq.most_common(20)
```

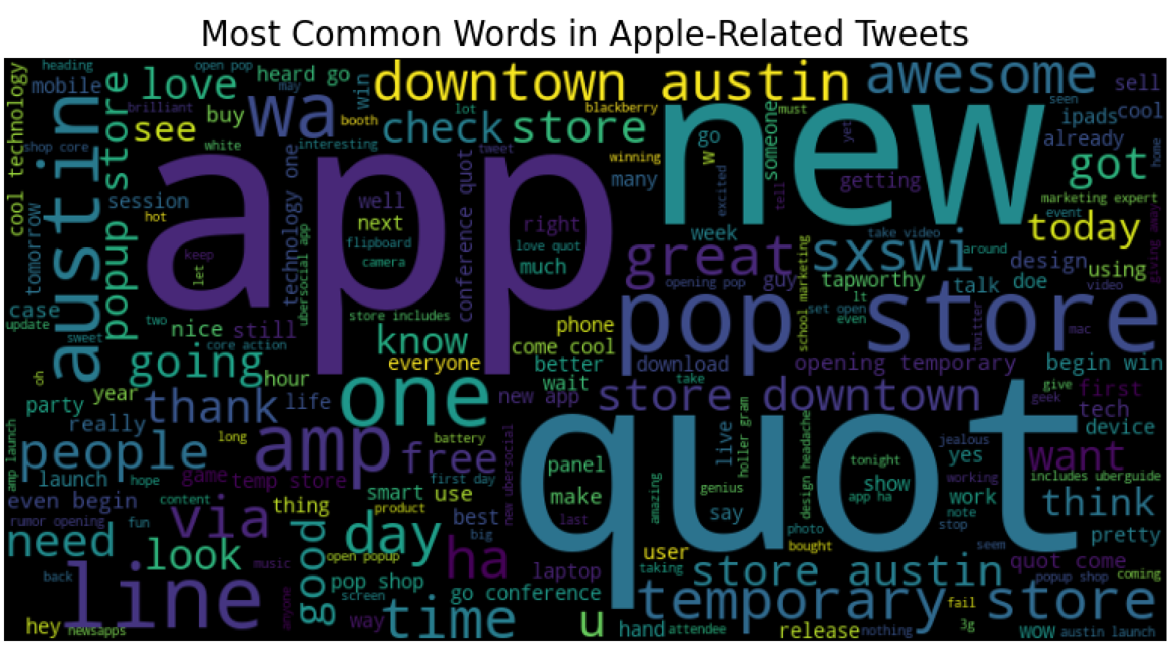
Out[46]:
```
[('store', 571),
 ('2', 520),
 ('quot', 376),
 ('app', 351),
 ('austin', 275),
 ('new', 227),
 ('pop', 221),
 ('line', 153),
 ('get', 151),
 ('one', 150),
 ('amp', 145),
 ('like', 112),
 ('ha', 107),
 ('via', 106),
 ('win', 104),
 ('go', 104),
 ('cool', 97),
 ('day', 96),
 ('wa', 91),
 ('time', 89)]
```

In [47]:
```
# Visualizing the top 30 most common tokens in Apple tweets
plot_token_frequency(tokens_apple_filtered, top_n=30,
                     title="Top 30 Most Common Tokens in Apple-Related Tweets")
```



WordCloud for Apple-related tweets

In [48]:
```
# Generating word cloud
cloud_apple_tweet = generate_wordcloud(tokens_apple_filtered,
                                       title="Most Common Words in Apple-Related Twee
```

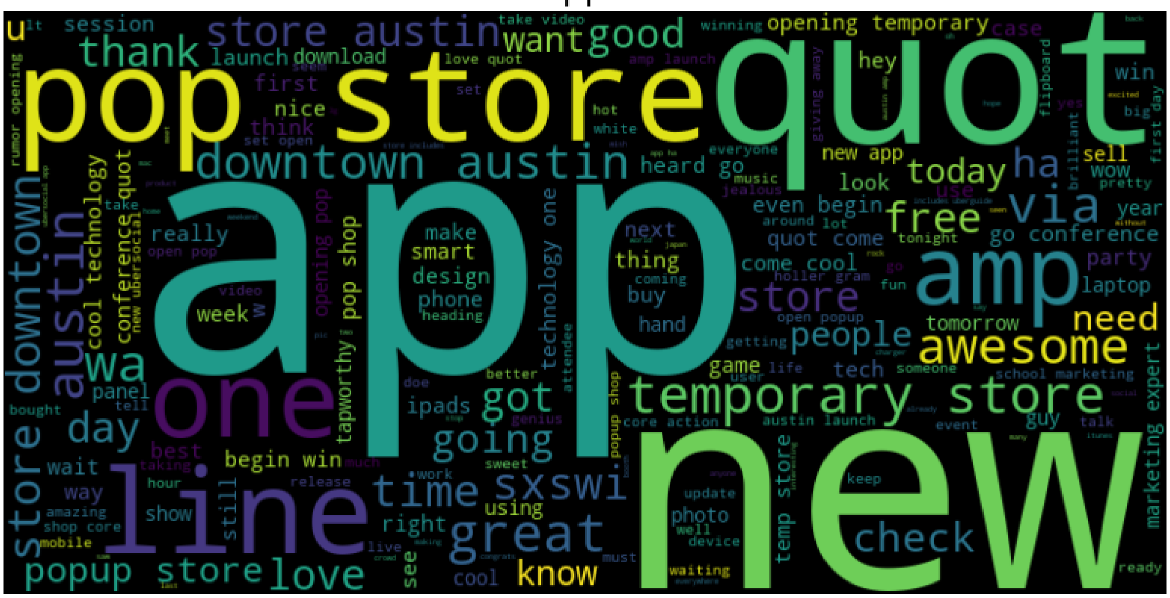


The words in Apple-related tweets that are classified as having positive sentiment.

In [49]:
```
# Filtering the DataFrame to select positive tweets associated with Apple
positive_apple_tweets_df = apple_tweets_df[apple_tweets_df['emotion'] == 'Posi

# Convert the selected positive tweets to a list
positive_apple_tweets_list = positive_apple_tweets_df['tweet'].tolist()

# Tokenize, lemmatize, and remove stopwords from positive tweets
tokens_positive_apple = tokenize_tweets(positive_apple_tweets_list)
tokens_positive_apple_lemm = lemmatize_tokens(tokens_positive_apple)
tokens_positive_apple_filtered = remove_stopwords(tokens_positive_apple_lemm)
```

In [50]:
```
# Generating word cloud
cloud_apple_tweet = generate_wordcloud(tokens_positive_apple_filtered,
                                       title="Most Common Words in Apple-Related Posi
```

Most Common Words in Apple-Related Positive Tweets



The observation from the most common words in positive tweets associated with Apple reveals some key insights:

- **Apple Store Dominance:** The term "store" stands out as the most frequent word, indicating a significant focus on Apple stores, possibly referring to new store openings or special events. This underscores the positive sentiment surrounding Apple's retail presence.
- **Product Buzz:** Words like "2" and "app" suggest excitement and discussions around Apple's latest products and applications, highlighting the strong positive sentiment related to Apple's tech offerings.
- **Event Engagement:** The presence of words like "austin," "pop," and "line" reflects active engagement in events at SXSW, including pop-up stores and long lines, contributing positively to the overall sentiment.
- **Community and Sharing:** Terms like "amp," "win," and "via" suggest a sense of community, sharing, and possibly giveaways or contests during the event, enhancing the positive atmosphere.

- **Innovation and Exploration:** Words like "cool," "go," and "launch" signify a positive outlook on innovative experiences and product launches associated with Apple.

In summary, these common words in positive Apple-related tweets demonstrate a robust positive sentiment encompassing Apple's products, events, and community engagement at

The words in Apple-related tweets that are classified as having negative sentiment.

In [51]:
```
# Filtering the DataFrame to select negative tweets associated with Apple
negative_apple_tweets_df = apple_tweets_df[apple_tweets_df['emotion'] == 'Nega

# Convert the selected positive tweets to a list
negative_apple_tweets_list = negative_apple_tweets_df['tweet'].tolist()

# Tokenize, lemmatize, and remove stopwords from positive tweets
tokens_negative_apple = tokenize_tweets(negative_apple_tweets_list)
tokens_negative_apple_lemm = lemmatize_tokens(tokens_negative_apple)
tokens_negative_apple_filtered = remove_stopwords(tokens_negative_apple_lemm)
```

In [52]:
```
# Generating word cloud
cloud_apple_tweet = generate_wordcloud(tokens_negative_apple_filtered,
                                       title="Most Common Words in Apple-Related nega
```

Most Common Words in Apple-Related negative Tweets

The observation from the most common words in negative tweets associated with Apple suggests several notable points:

- **"App" Troubles:** The term "app" stands out, indicating that a significant portion of negative sentiment may revolve around issues or frustrations related to Apple's applications.
- **Battery Concerns:** The presence of "battery" as a common word suggests that battery-related problems or concerns may be a source of dissatisfaction among users.
- **Product Design:** The term "design" appearing frequently indicates that design-related criticisms or feedback could contribute to the negative sentiment.

- **Autocorrect Issues:** The term "autocorrect" shows that issues related to autocorrect can be inferred from the negative sentiment. Users often experience frustration with autocorrect features in smartphones, and this could be reflected in the negative tweets.
- **Blackberry Mention:** The presence of "Blackberry" suggests that comparisons or references to Blackberry devices may be influencing the negative sentiment in some way.

Overall, these common words highlight some key pain points and concerns expressed in negative tweets related to Apple. Issues with applications, battery performance, design, and autocorrect functionality appear to be contributing factors to the negative sentiment. Additionally, references to other brands like Blackberry may indicate dissatisfaction or comparisons being

Percentage of Positive, Neutral and Negative Sentiments of Apple-related tweets

In [53]:
```
# A funtion that will return a DataFrame with sentiment percentages.
def calculate_sentiment_percentages(df, emotion_column):
    """
    Calculate sentiment percentages from a DataFrame containing emotions.

    Args:
    - df (pd.DataFrame): The DataFrame containing the emotion data.
    - emotion_column (str): The name of the column containing emotion labels.

    Returns:
    - pd.DataFrame: A DataFrame with sentiment percentages sorted in descending
    """
    # Calculate sentiment percentages
    sentiment_counts = df[emotion_column].value_counts(normalize=True) * 100

    # Create a DataFrame to display the sentiment percentages
    df_sentiment = pd.DataFrame(sentiment_counts).reset_index()
    df_sentiment.columns = ['emotion', 'percentage']

    # Sort the DataFrame by percentage in descending order
    df_sentiment.sort_values('percentage', ascending=False, inplace=True)

    return df_sentiment
```

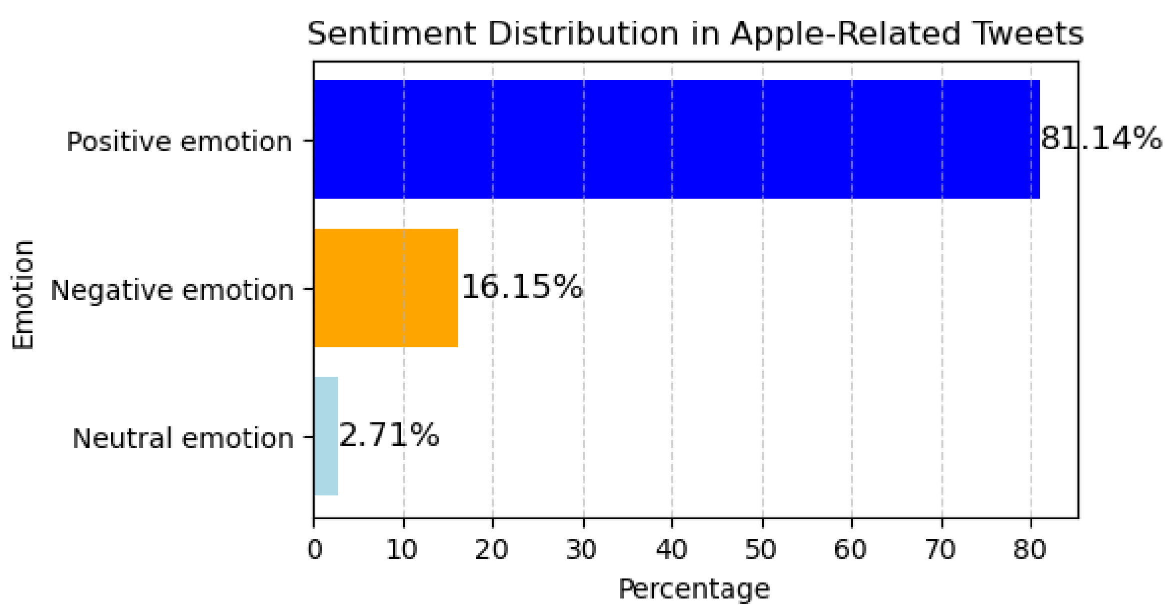
In [54]:
```
# Displying the emotions and corresponding percentages for Apple-related tweets
df_apple_sentiment = calculate_sentiment_percentages(apple_tweets_df, 'emotion
df_apple_sentiment
```

Out[54]:

	emotion	percentage
0	Positive emotion	81.143096
1	Negative emotion	16.145181
2	Neutral emotion	2.711723

In [55]:
```
# A function that will be used to visualize the percentages in a graph
def plot_sentiment_distribution(df, x_column,
                                y_column,
                                colors=None,
                                title=None,
                                xlabel=None,
                                ylabel=None,
                                invert_yaxis=True
                                ):
    """
    Create a bar plot to visualize sentiment distribution.

    """
    plt.figure(figsize=(5, 3))
    plt.barh(df[x_column], df[y_column], color=colors)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.title(title)

    if invert_yaxis:
        plt.gca().invert_yaxis()

    plt.grid(axis='x', linestyle='--', alpha=0.6)

    # Annotate the bars with percentage values
    for index, row in df.iterrows():
        plt.text(row[y_column], index,
                 f'{row[y_column]:.2f}%',
                   va='center', fontsize=12, color='black');
```

In [56]:
```
# Creating bar plot to visaulize Apple-related sentiment distribution
plot_sentiment_distribution(df_apple_sentiment, 'emotion', 'percentage',
                             colors=['blue', 'orange', 'lightblue'],
                            title='Sentiment Distribution in Apple-Related Twe
                              xlabel='Percentage', ylabel='Emotion')
```



The sentiment analysis of Apple-related tweets reveals a significant dominance of **positive emotions**, constituting approximately **81.14%** of the sentiment distribution. In contrast, **negative emotions** account for a considerably smaller proportion, standing at **16.15%**. **Neutral emotions** are relatively less prevalent, representing only **2.71%** of the analyzed tweets.

This observation underscores the overwhelmingly positive sentiment surrounding Apple products in the Twitter discussions, indicating a strong and favorable perception among users. However, the presence of some negative and neutral sentiments suggests that Apple's products and services do not elude occasional criticism or indifference within the social media landscape.

Sentiment Analysis of Google-Related Tweets

In [57]:

```
# Filtering the DataFrame to select tweets associated with Google
google_tweets_df = review_df[review_df['brand'] == 'Google']

# Converting the selected tweets to a list
google_tweets_list = google_tweets_df['tweet'].tolist()

# Display the first few elements of the list
google_tweets_list[:5]
```

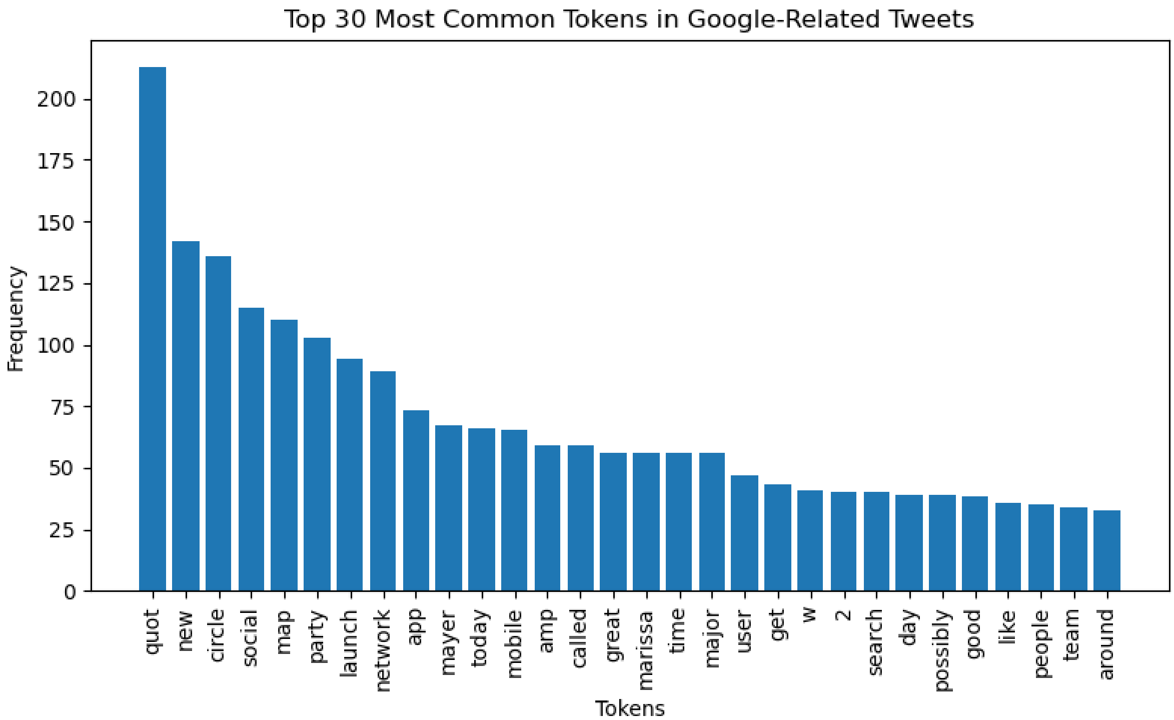
Out[57]:

```
["great stuff on Fri #SXSW: Marissa Mayer (Google), Tim O'Reilly (tech books/
conferences) &amp; Matt Mullenweg (Wordpress)",
 '#SXSW is just starting, #CTIA is around the corner and #googleio is only a
hop skip and a jump from there, good time to be an #android fan',
 'Excited to meet the at #sxsw so I can show them my Sprint Galaxy S still ru
nning Android 2.1. #fail',
 "Find &amp; Start Impromptu Parties at #SXSW With http://bit.ly/gVLrIn (htt
p://bit.ly/gVLrIn) I can't wait til the Android app comes out.",
 'Foursquare ups the game, just in time for #SXSW http://j.mp/grN7pK) (htt
p://j.mp/grN7pK)) - Still prefer by far, best looking Android app to date.']
```

In [58]:
```
#tokenize tweets
tokens_google = tokenize_tweets(google_tweets_list)
#lemmatize tweets
tokens_google_lemm = lemmatize_tokens(tokens_google)
#remove stop words using the same stop words list
tokens_google_filtered = remove_stopwords(tokens_google_lemm)

# Displaying most common 20 tokens
freq = FreqDist(tokens_google_filtered)
freq.most_common(20)
```

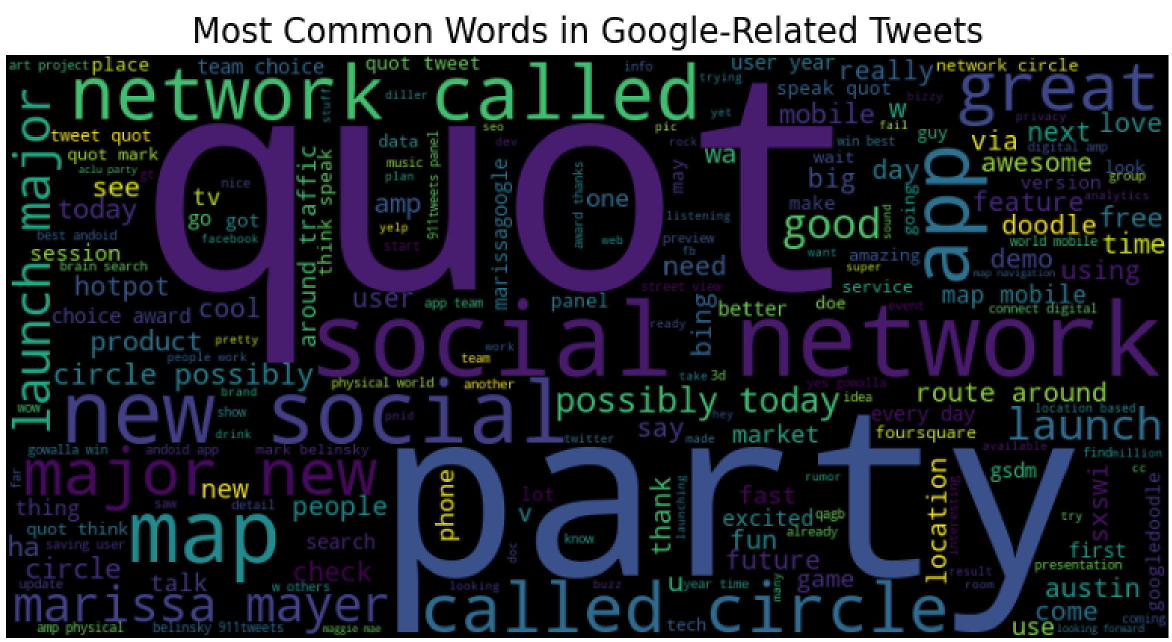
Out[58]:
```
[('quot', 213),
 ('new', 142),
 ('circle', 136),
 ('social', 115),
 ('map', 110),
 ('party', 103),
 ('launch', 94),
 ('network', 89),
 ('app', 73),
 ('mayer', 67),
 ('today', 66),
 ('mobile', 65),
 ('amp', 59),
 ('called', 59),
 ('great', 56),
 ('marissa', 56),
 ('time', 56),
 ('major', 56),
 ('user', 47),
 ('get', 43)]
```

In [59]:
```
# Visualizing the top 30 most common tokens in Google tweets
plot_token_frequency(tokens_google_filtered, top_n=30,
                     title="Top 30 Most Common Tokens in Google-Related Tweets
```



WordCloud for Google-related tweets

In [60]:
```
# Generating word cloud
cloud_google_tweet = generate_wordcloud(tokens_google_filtered,
                                        title="Most Common Words in Google-Related Twee
```

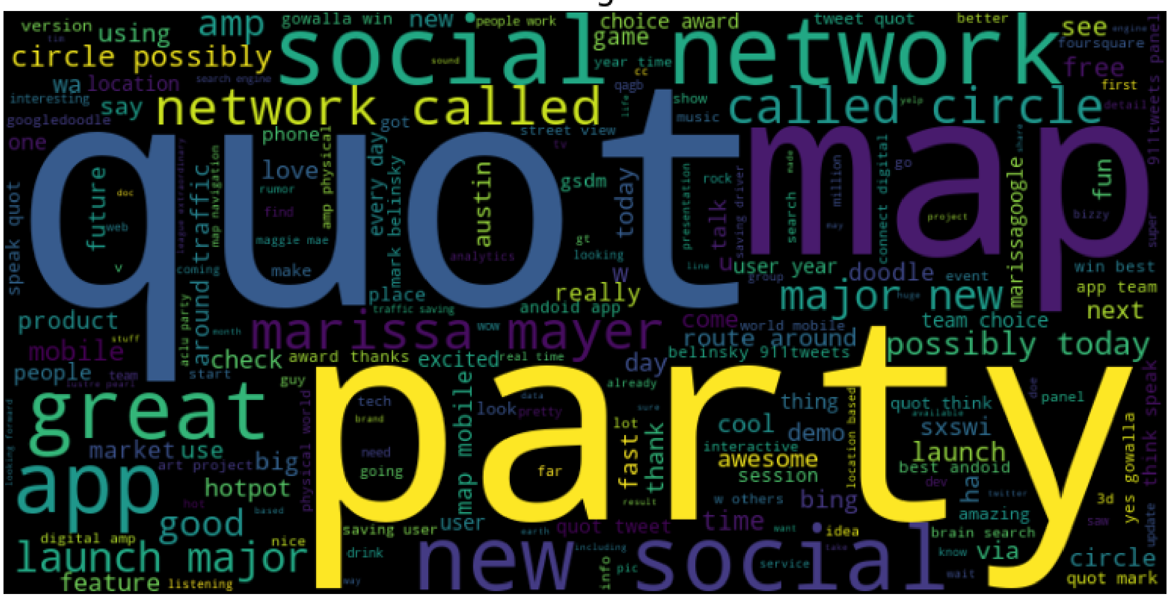


The words in Google-related tweets that are classified as having positive sentiment.

In [61]:
```
# Filtering the DataFrame to select positive tweets associated with google
positive_google_tweets_df = google_tweets_df[google_tweets_df['emotion'] == 'P

# Convert the selected positive tweets to a list
positive_google_tweets_list = positive_google_tweets_df['tweet'].tolist()

# Tokenize, lemmatize, and remove stopwords from positive tweets
tokens_positive_google = tokenize_tweets(positive_google_tweets_list)
tokens_positive_google_lemm = lemmatize_tokens(tokens_positive_google)
tokens_positive_google_filtered = remove_stopwords(tokens_positive_google_lemm
```

In [62]:
```
# Generating word cloud
cloud_google_tweet = generate_wordcloud(tokens_positive_google_filtered,
                                        title="Most Common Words in Google-Related Pos
```

Most Common Words in Google-Related Positive Tweets



The most common words in positive tweets associated with Google reveal several insights:

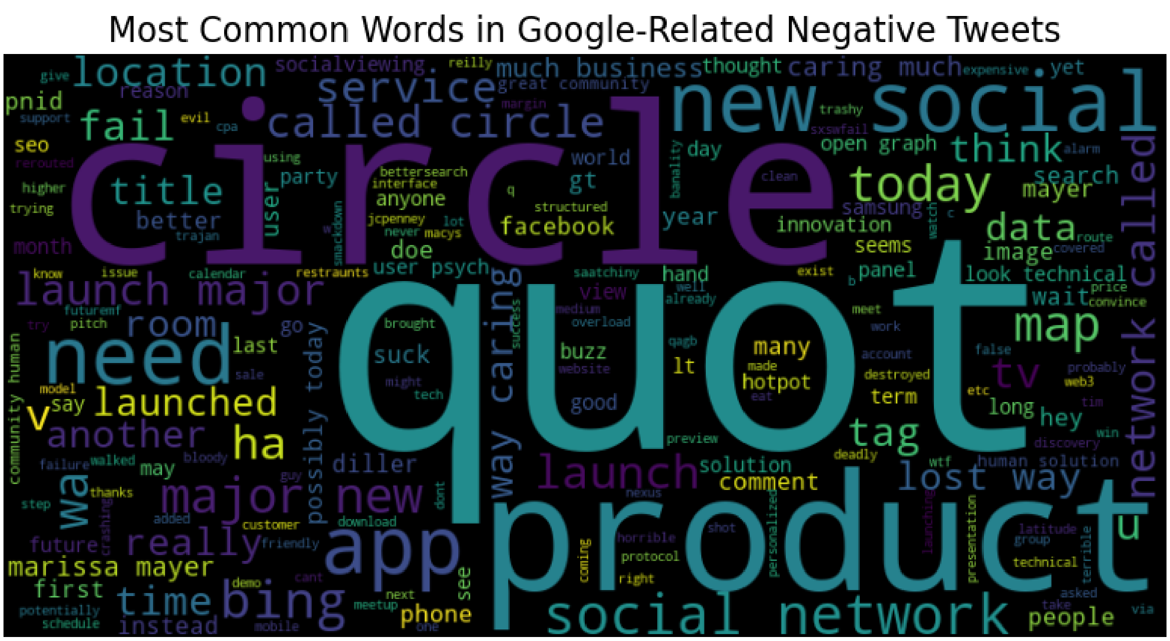
- **"Circle" and "Map":** The words "circle" and "map" are highly prevalent, suggesting that discussions about Google's social network, Google+, and its mapping services are generating positive sentiment among users.
- **"Party" and "Launch":** Terms like "party" and "launch" indicate excitement and positive discussions related to Google events, product launches, or parties.
- **"Social" and "Network":** The presence of "social" and "network" reflects discussions about Google's social networking platforms or social-related features, which seem to be received positively.
- **"Mobile" and "App":** Words like "mobile" and "app" highlight enthusiasm for Google's mobile applications and technology, indicating a tech-savvy and positive atmosphere.

Overall, these common positive words reflect a positive outlook on Google, its products, and its various offerings, including social networking, mapping services, mobile apps, and innovation in the tech industry. Users appear to be excited and engaged in discussions about these aspects, contributing to a positive sentiment surrounding Google-related tweets.

The words in Google-related tweets that are classified as having negative sentiment.

In [63]:
```
# Filtering the DataFrame to select negative tweets associated with google
negative_google_tweets_df = google_tweets_df[google_tweets_df['emotion'] == 'N

# Convert the selected positive tweets to a list
negative_google_tweets_list = negative_google_tweets_df['tweet'].tolist()

# Tokenize, lemmatize, and remove stopwords from positive tweets
tokens_negative_google = tokenize_tweets(negative_google_tweets_list)
tokens_negative_google_lemm = lemmatize_tokens(tokens_negative_google)
tokens_negative_google_filtered = remove_stopwords(tokens_negative_google_lemm
```

In [64]:
```
# Generating word cloud
cloud_google_tweet = generate_wordcloud(tokens_negative_google_filtered,
                                        title="Most Common Words in Google-Related Nega
```



In the most common words found in negative tweets associated with Google, several patterns emerge:

- **"Bing" and "Map":** Mentions of "Bing" and "map" might suggest comparisons or criticisms related to Google Maps or Google's mapping services.
- **"Location" and "Business":** The terms "location" and "business" could be associated with negative sentiments regarding Google's location-based services or business-related aspects.
- **"Circle" and "Social":** The words "circle" and "social" continue to appear, suggesting that discussions related to Google's social networking platform, Google+, may elicit negative sentiments from users.
- **"Launch" and "New":** Terms like "launch" and "new" also appear, indicating that some users express negativity about Google's product launches or new features.

Overall, while negative sentiments are expressed in these tweets, it's important to note that the frequency of negative terms is relatively lower compared to positive terms in positive tweets

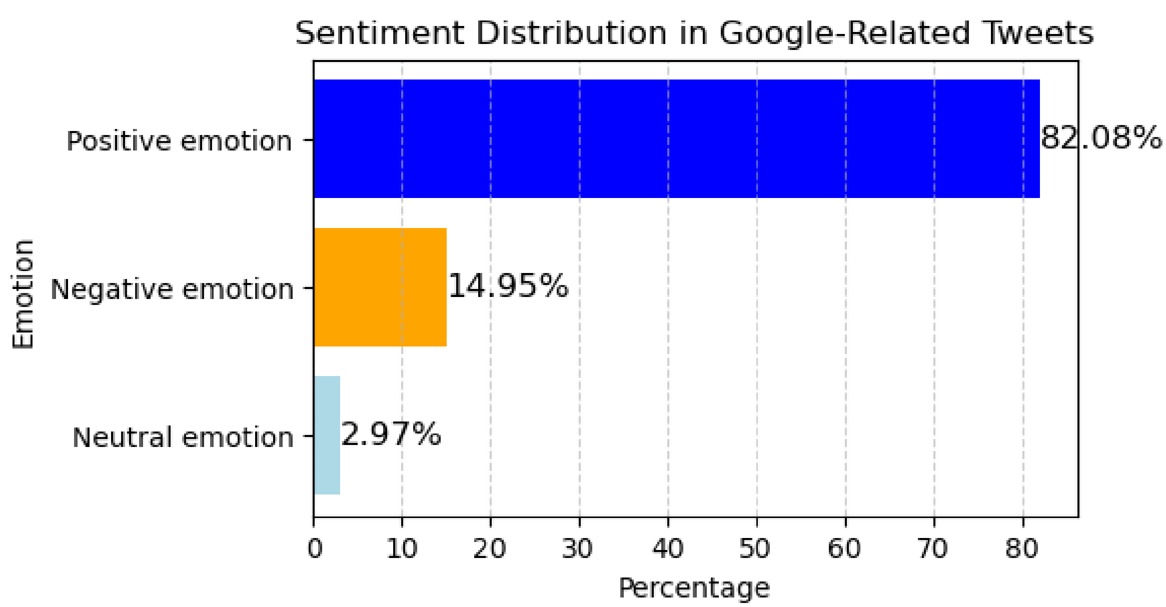
Percentage of Positive, Neutral and Negative Sentiments of Google-related tweets

In [65]:
```
# Displying the emotions and corresponding percentages for Google-related tweet
df_google_sentiment = calculate_sentiment_percentages(google_tweets_df, 'emoti
df_google_sentiment
```

Out[65]:

	emotion	percentage
0	Positive emotion	82.077626
1	Negative emotion	14.954338
2	Neutral emotion	2.968037

In [66]:
```
# Creating bar plot to visaulize Google-related sentiment distribution
plot_sentiment_distribution(df_google_sentiment, 'emotion', 'percentage',
                             colors=['blue', 'orange', 'lightblue'],
                            title='Sentiment Distribution in Google-Related Twe
                              xlabel='Percentage', ylabel='Emotion')
```



The sentiment analysis of Google-related tweets demonstrates a notably dominant **positive sentiment**, accounting for approximately **82.08%** of the overall sentiment distribution, with **negative emotions** representing a considerably smaller proportion at **14.95%**, and **neutral emotions** making up **2.97%** of the discussions, highlighting a predominantly positive sentiment surrounding Google on Twitter.

Modelling

The initial step will involve binary classification, where the model's objective is to accurately predict whether a tweet falls under the "Positive" or "Negative" category. Following this will be multiclass classification, where the "Neutral" category will be introduced, expanding the classification task into a three-way categorization.

Three models will be used and tune the best fitting model to get optimal parameters.

- Logistic Regression
- Gaussian Naive Bayes
- Random Forest Classifier

1) Binary classification

Data Preprocessing

In [67]:
```
# Getting the unique entities in "emotio" from our DataFrame
review_df['emotion'].unique()
```

Out[67]:
```
array(['Negative emotion', 'Positive emotion', 'Neutral emotion'],
      dtype=object)
```

Since we are initially focusing on binary classification, we will remove the "Neutral emotion" category from our DataFrame.

In [68]:
```
# Creating a binary DataFrame with no "Neutral emotion" category
binary_df = review_df[review_df['emotion'] != 'Neutral emotion']

# Confirming the changes
binary_df['emotion'].unique()
```

Out[68]:
```
array(['Negative emotion', 'Positive emotion'], dtype=object)
```

Label encoding each unique emotion category to allow categorical data to be used in machine learning algorithms. "Positive emotion" will be mapped to 1, and "Negative emotion" to 0.

In [69]:
```
# Creating a mapping dictionary
binary_emotion_mapping = {'Positive emotion': 1, 'Negative emotion': 0}

# Mapping the 'emotion' column to numerical values using the dictionary
binary_df['emotion'] = binary_df['emotion'].map(binary_emotion_mapping)

# Confirming the changes
binary_df['emotion'].unique()
```

Out[69]:
```
array([0, 1], dtype=int64)
```

In [70]:
```
# Checking if we have class imbalance
binary_df['emotion'].value_counts(normalize=True) * 100
```

Out[70]:
```
1    83.922012
0    16.077988
Name: emotion, dtype: float64
```

The class distribution analysis of the binary dataset reveals an imbalance, with approximately 83.92% of the samples belonging to "Positive emotion" class and 16.08% to "Negative emotion". This indicates a potential class imbalance issue that should be considered during the modeling process. It is essential to be mindful of class imbalance to ensure that the machine learning model's performance is not biased towards the majority class.

Train, test split

In [71]:
```
# Splitting the features into indipendent and target variable
X = binary_df['tweet']
y = binary_df['emotion']

# Split the data into training and testing sets (e.g., 80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
```

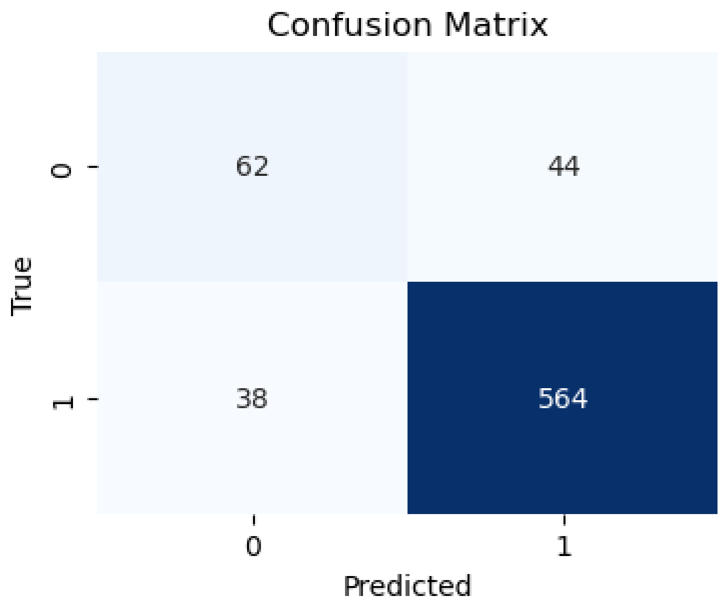
Logistic Regression

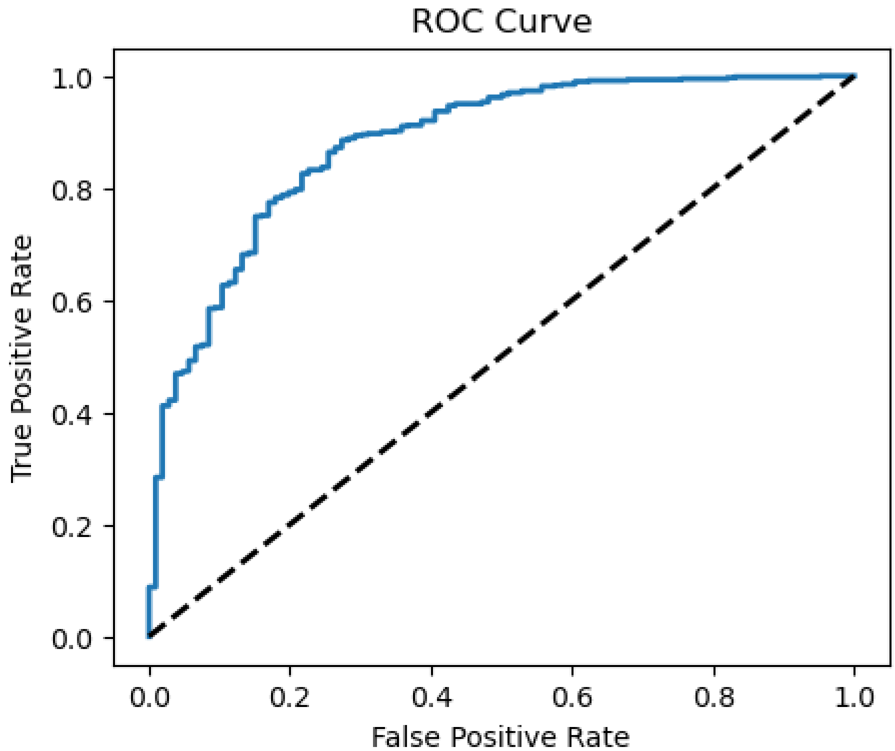
In [72]:
```
# Defining the tokenizer function
def tokenize_text(text):
    tokenizer = RegexpTokenizer(r'[a-zA-Z0-9]+')
    return tokenizer.tokenize(text.lower())

# Selecting stopword
# Additional custom stop words
custom_stop_words = ["sxsw", "link", "rt"]

stop_words = list(stopwords.words("english")) + custom_stop_words
```

In [73]:
```
# Creating a pipeline
clf_pipe = imblearn.pipeline.Pipeline([
    ('vectorizer', TfidfVectorizer(tokenizer=tokenize_text,
                                   stop_words=None,
                                   norm='l2')),
    ('os', RandomOverSampler(random_state=42)),
    ('clf', LogisticRegressionCV(class_weight='balanced', random_state=42, cv=
])

# Fit the pipeline
clf_pipe.fit(X_train, y_train)

# Make predictions
y_pred = clf_pipe.predict(X_test)
```

In [74]:
```python
# A funtion that will be used for classification evaluation
def evaluate_classification(y_true, y_pred, clf_pipe):
    # Calculating model's precision
    print(f"The model's precision is \
          {precision_score(y_test, y_pred, average='weighted'):.2%}")

    # Calculating and printing the training score
    training_score = clf_pipe.score(X_train, y_train)
    print(f"Training Score: {training_score:.2f}")

    # Calculating and printing test score
    test_score = clf_pipe.score(X_test, y_test)
    print(f"Test Score: {test_score:.2f}\n")

    # Classification Report
    report = classification_report(y_true, y_pred)
    print("Classification Report:\n", report)


    # Confusion Matrix
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(4, 3))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", cbar=False)
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.title('Confusion Matrix')
    plt.show()


    # ROC Curve
    y_prob = clf_pipe.predict_proba(X_test)
    fpr, tpr, thresholds = roc_curve(y_test, y_prob[:, 1])
    plt.figure(figsize=(5, 4))
    plt.plot(fpr, tpr, linewidth=2)
    plt.plot([0, 1], [0, 1], 'k--', linewidth=2)
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.show()

# Perform classification evaluation
evaluate_classification(y_test, y_pred, clf_pipe)
```

```
The model's precision is          88.16%
Training Score: 1.00
Test Score: 0.88

Classification Report:
              precision    recall  f1-score   support

           0       0.62      0.58      0.60       106
           1       0.93      0.94      0.93       602

    accuracy                           0.88       708
   macro avg       0.77      0.76      0.77       708
weighted avg       0.88      0.88      0.88       708
```





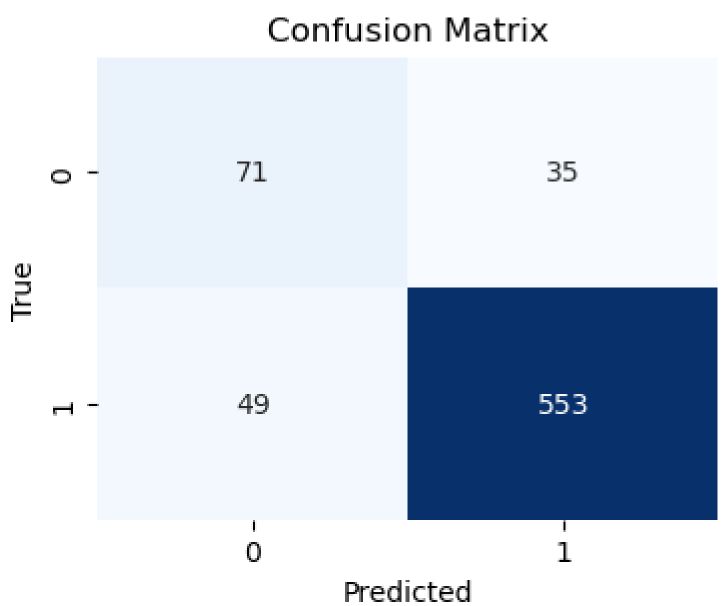
The baseline model has shown promising results in classifying sentiment in tweets as either positive (1) or negative (0). The model achieved a high training score of 1.00, indicating a perfect fit on the training data. When tested on unseen data, it achieved a respectable test score of 0.88, indicating that it generalizes well to new data. The classification report reveals that the model performs particularly well in identifying positive sentiment with a high precision, recall, and F1-score. However, there is room for improvement in recognizing negative sentiment, as indicated by slightly lower precision and recall. The confusion matrix shows that the model correctly identified the majority of positive sentiment tweets but had some difficulty in accurately classifying negative sentiment tweets. This baseline model provides a solid starting point for further refinement and optimization to enhance its performance, especially in identifying negative sentiment tweets.

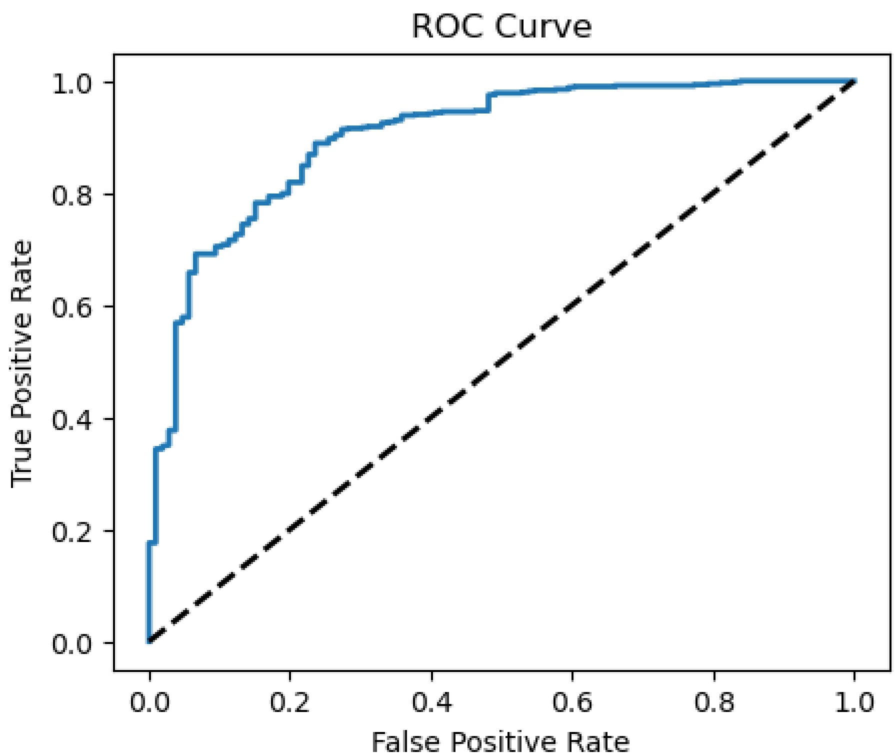
Gaussian Naive Bayes

In [75]:
```
# Creating a pipeline
clf_pipe = imblearn.pipeline.Pipeline([
    ('vectorizer', TfidfVectorizer(tokenizer=tokenize_text,
                                   stop_words=None)),
    ('os', RandomOverSampler(random_state=42)),
    ('clf', MultinomialNB(alpha=0.1))
])

# Fitting the pipeline on the training data
clf_pipe.fit(X_train, y_train)

# Making predictions on the test data
y_pred = clf_pipe.predict(X_test)
```

In [76]:
```
# Perform classification evaluation
evaluate_classification(y_test, y_pred, clf_pipe)
```

```
The model's precision is           88.83%
Training Score: 0.98
Test Score: 0.88

Classification Report:
               precision    recall  f1-score   support

           0       0.59      0.67      0.63       106
           1       0.94      0.92      0.93       602

    accuracy                           0.88       708
   macro avg       0.77      0.79      0.78       708
weighted avg       0.89      0.88      0.88       708
```





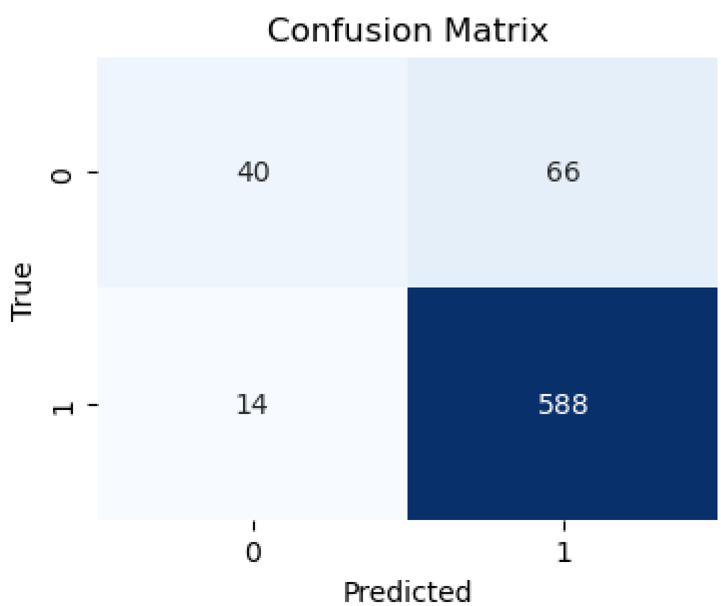
The second model, built using a Multinomial Naive Bayes classifier demonstrates a commendable performance in sentiment classification for tweets. It achieved a high training score of 0.98, indicating a strong fit to the training data, and maintained an impressive test score of 0.88 when evaluated on unseen data. The classification report shows that the model exhibits balanced precision, recall, and F1-score for both positive and negative sentiment categories. While the model excels at identifying positive sentiment tweets, it also displays notable improvements in identifying negative sentiment tweets compared to the baseline model. The confusion matrix illustrates that the model is effective at correctly classifying the majority of both positive and negative sentiment tweets. This second model serves as a substantial enhancement to the baseline and provides a robust foundation for sentiment analysis on Twitter data, with the potential for further fine-tuning and optimization.

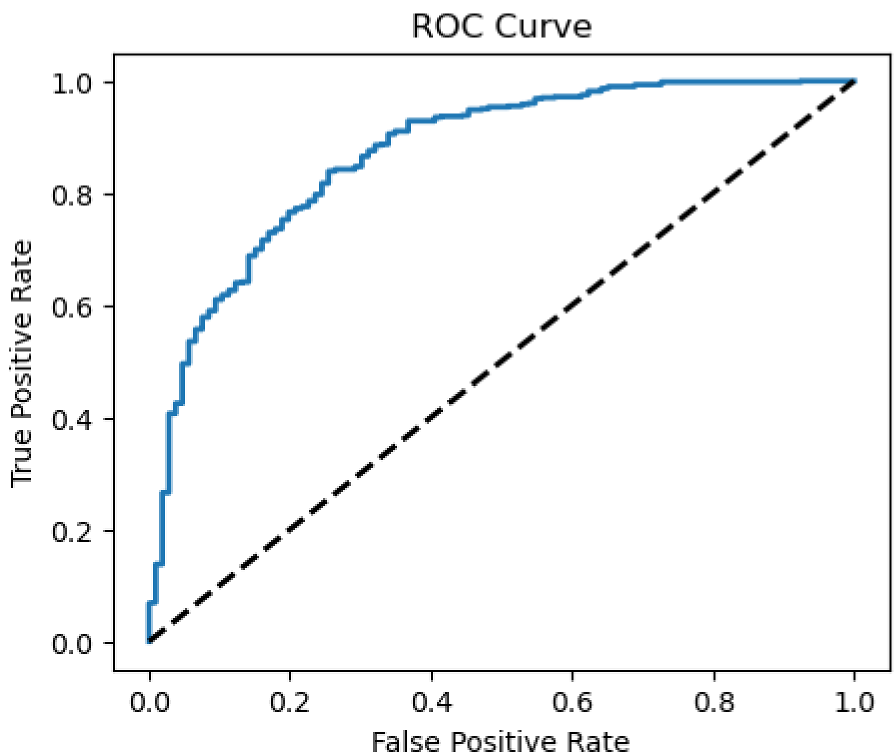
Random Forest

In [77]:
```
# Creating a pipeline
clf_pipe = imblearn.pipeline.Pipeline([
    ('vectorizer', TfidfVectorizer(tokenizer=tokenize_text,
                                   stop_words=None)),
    ('os', RandomOverSampler(random_state=42)),
    ('clf', RandomForestClassifier(class_weight='balanced', random_state=42,
                                   criterion='entropy', max_depth=None,
                                   min_samples_leaf=2))])
# Fitting the pipeline on the training data
clf_pipe.fit(X_train, y_train)

# Making predictions on the test data
y_pred = clf_pipe.predict(X_test)
```

In [78]:
```
# Perform classification evaluation
evaluate_classification(y_test, y_pred, clf_pipe)
```

```
The model's precision is          87.54%
Training Score: 0.99
Test Score: 0.89

Classification Report:
               precision    recall  f1-score   support

           0       0.74      0.38      0.50       106
           1       0.90      0.98      0.94       602

    accuracy                           0.89       708
   macro avg       0.82      0.68      0.72       708
weighted avg       0.88      0.89      0.87       708
```





The third model, utilizing a Random Forest Classifier continues to demonstrate a high level of performance in sentiment classification for tweets. It achieved an outstanding training score of 0.99, indicating an excellent fit to the training data, and maintained a robust test score of 0.89 when evaluated on unseen data. The classification report reveals strong precision, recall, and F1-score for both positive and negative sentiment categories. The model excels at identifying positive sentiment tweets and exhibits a notable improvement in precision for negative sentiment tweets compared to the previous models. The confusion matrix indicates that the model effectively classifies the majority of positive and negative sentiment tweets.

The second model, employing the Multinomial Naive Bayes classifier, stands out as the most effective among the three models, considering all our success metrics. It consistently maintains a high test score of 0.88, coupled with impressive precision and recall values for both sentiment categories. This model achieves an F1-score of 0.93 for positive sentiment and 0.63 for negative sentiment. Consequently, we intend to fine-tune its hyperparameters to further optimize its performance.

In [79]:
```
# Creating a pipeline
clf_pipe = imblearn.pipeline.Pipeline([
    ('vectorizer', TfidfVectorizer(tokenizer=tokenize_text,
                                   stop_words=None)),
    ('os', RandomOverSampler(random_state=42)),
    ('clf', MultinomialNB(alpha=0.1))
])

# Define the parameter grid for hyperparameter tuning
param_grid = {
    'clf__alpha': [0.001, 0.01, 0.1, 1]
}

# Create the GridSearchCV object
grid_search = GridSearchCV(estimator=clf_pipe, param_grid=param_grid,
                           cv=3, n_jobs=-1, scoring='f1_macro', verbose=2)

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best hyperparameters
best_params = grid_search.best_params_
print("Best Hyperparameters:", best_params)
```

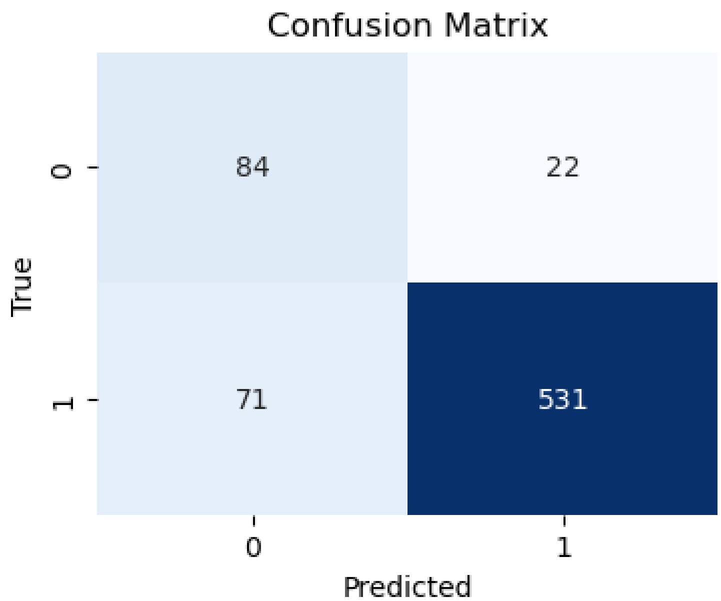
```
Fitting 3 folds for each of 4 candidates, totalling 12 fits
Best Hyperparameters: {'clf__alpha': 1}
```

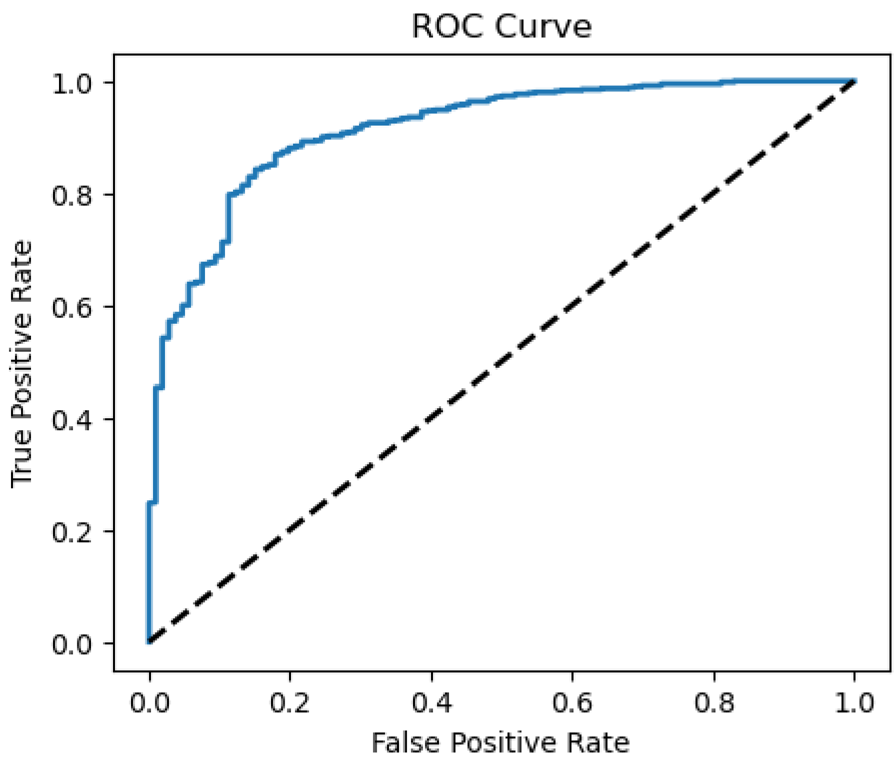
Tuned Gaussian Naive Bayes

In [80]:
```
# Creating a pipeline
clf_tuned_pipe = imblearn.pipeline.Pipeline([
    ('vectorizer', TfidfVectorizer(tokenizer=tokenize_text,
                                   stop_words=None)),
    ('os', RandomOverSampler(random_state=42)),
    ('clf', MultinomialNB(alpha=1))
])


# Fitting the pipeline on the training data
clf_tuned_pipe.fit(X_train, y_train)

# Making predictions on the test data
y_pred = clf_tuned_pipe.predict(X_test)
```

In [81]:
```
# Perform classification evaluation
evaluate_classification(y_test, y_pred, clf_tuned_pipe)
```

```
The model's precision is          89.76%
Training Score: 0.95
Test Score: 0.87

Classification Report:
               precision    recall  f1-score   support

           0       0.54      0.79      0.64       106
           1       0.96      0.88      0.92       602

    accuracy                           0.87       708
   macro avg       0.75      0.84      0.78       708
weighted avg       0.90      0.87      0.88       708
```





The last model, which was fine-tuned after hyperparameter optimization, demonstrates noticeable improvements in comparison to the previous models. The precision has increased to 89.76%, signifying that a higher percentage of predicted positive sentiments are now correctly classified as positive. Additionally, the recall for class 0 (negative sentiment) has risen to 79%, indicating that the model is more effective at accurately identifying negative sentiments. The model maintains a relatively high F1-score of 0.64 for class 0(negative sentiment) and an impressive F1-score of 0.92 for class 1 (positive sentiment). Overall, the model exhibits enhanced precision and a well-balanced performance, making it a strong choice for sentiment analysis tasks.

2) Multiclass classification

Data preprocessing

In [82]:
```
# Getting the unique entities in "emotio" from our DataFrame
review_df['emotion'].unique()
```

Out[82]:
```
array(['Negative emotion', 'Positive emotion', 'Neutral emotion'],
      dtype=object)
```

In [83]:
```
# Creating a mapping dictionary
multi_emotion_mapping = {'Positive emotion': 1, 'Negative emotion': 0, 'Neutra

# Mapping the 'emotion' column to numerical values using the dictionary
review_df['emotion'] = review_df['emotion'].map(multi_emotion_mapping)

# Confirming the changes
review_df['emotion'].unique()
```

Out[83]:
```
array([0, 1, 2], dtype=int64)
```

In [84]:
```
# Checking for class imbalance
review_df['emotion'].value_counts(normalize=True) * 100
```

Out[84]:
```
2    60.298407
1    33.318376
0     6.383217
Name: emotion, dtype: float64
```

As observed, class imbalance remains a concern that needs to be addressed during modeling. We will utilize RandomOverSampler to mitigate this issue and ensure a more balanced representation of the classes in our dataset.

Train, test split

In [85]:
```
# Splitting the features into indipendent and target variable
X = review_df['tweet']
y = review_df['emotion']

# Split the data into training and testing sets (e.g., 80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
```

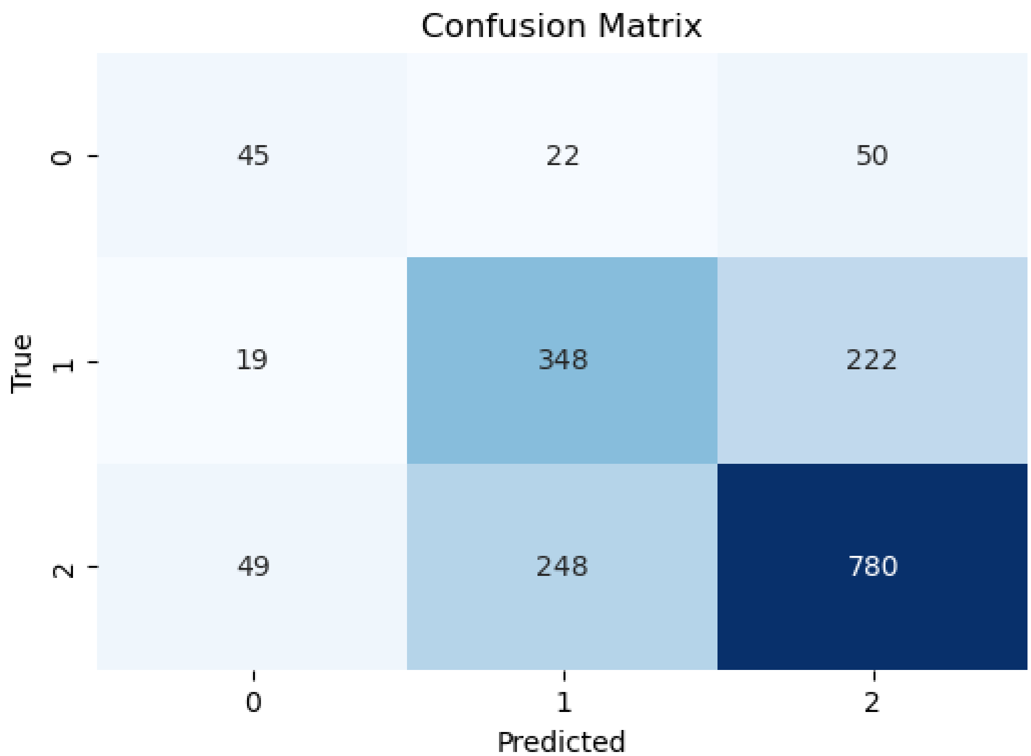
Logistic Regression

In [86]:
```
# Creating a pipeline
clf_pipe = imblearn.pipeline.Pipeline([
    ('vectorizer', TfidfVectorizer(tokenizer=tokenize_text,
                                   stop_words=None,
                                   norm='l2')),
    ('os', RandomOverSampler(random_state=42)),
    ('clf', LogisticRegressionCV(class_weight='balanced', random_state=42, cv=
])

# Fit the pipeline
clf_pipe.fit(X_train, y_train)

# Make predictions
y_pred = clf_pipe.predict(X_test)
```

In [87]:
```
# A function that will be used for classification evaluation
def multiclass_classification(y_true, y_pred, clf_pipe):
    # Calculating model's precision
    print(f"The model's precision is \
          {precision_score(y_true, y_pred, average='weighted'):.2%}")

    # Calculating and printing the training score
    training_score = clf_pipe.score(X_train, y_train)
    print(f"Training Score: {training_score:.2f}")

    # Calculating and printing test score
    test_score = clf_pipe.score(X_test, y_test)
    print(f"Test Score: {test_score:.2f}\n")

    # Classification Report
    report = classification_report(y_true, y_pred)
    print("Classification Report:\n", report)

    # Confusion Matrix
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", cbar=False)
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.title('Confusion Matrix');
```

In [88]:
```
# Perform classification evaluation
multiclass_classification(y_test, y_pred, clf_pipe)
```

```
The model's precision is          66.00%
Training Score: 0.95
Test Score: 0.66

Classification Report:
               precision    recall  f1-score   support

           0       0.40      0.38      0.39       117
           1       0.56      0.59      0.58       589
           2       0.74      0.72      0.73      1077

    accuracy                           0.66      1783
   macro avg       0.57      0.57      0.57      1783
weighted avg       0.66      0.66      0.66      1783
```



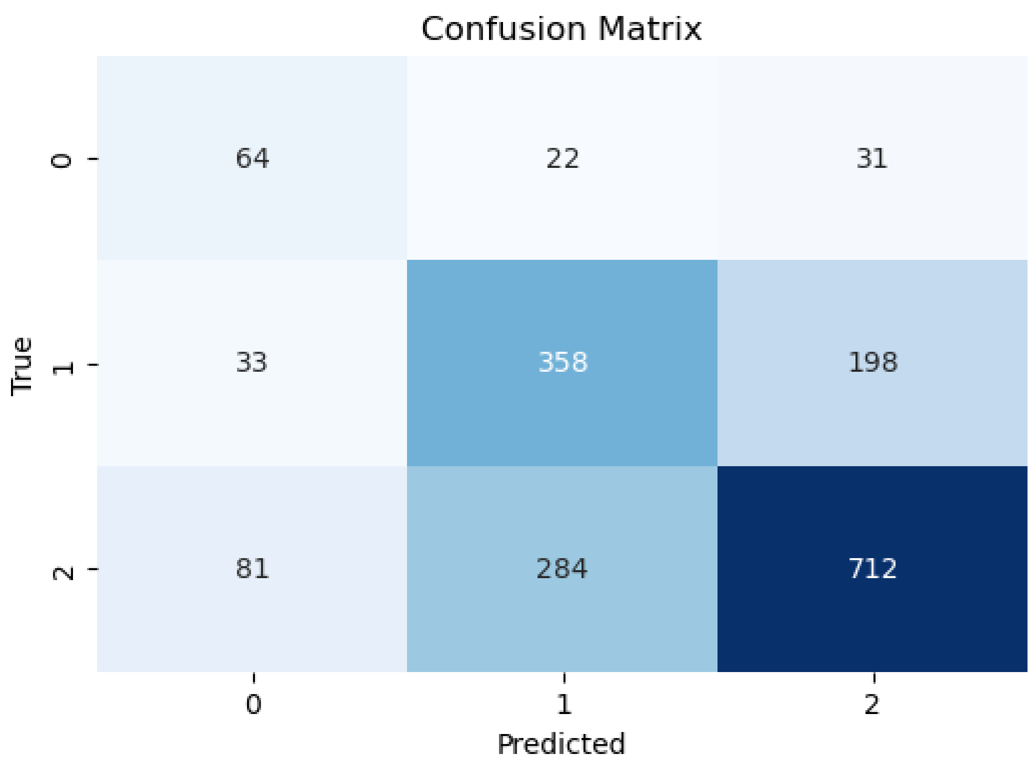
The baseline multiclass classification model exhibits a moderate level of precision at 66.00%, indicating that it correctly classifies sentiments to some extent. However, there is room for improvement, as precision varies across different sentiment classes. The model's training score is 0.95, indicating good performance on the training data, but its test score is 0.66, suggesting some degree of overfitting. The confusion matrix provides insights into the model's ability to distinguish between different emotions, highlighting areas where it can be further fine-tuned for better performance.

Gaussian Naive Bayes

In [89]:
```
# Creating a pipeline
clf_pipe = imblearn.pipeline.Pipeline([
    ('vectorizer', TfidfVectorizer(tokenizer=tokenize_text,
                                   stop_words=None)),
    ('os', RandomOverSampler(random_state=42)),
    ('clf', MultinomialNB(alpha=0.1))
])

# Fitting the pipeline on the training data
clf_pipe.fit(X_train, y_train)

# Making predictions on the test data
y_pred = clf_pipe.predict(X_test)
```

In [90]:
```
# Perform classification evaluation
multiclass_classification(y_test, y_pred, clf_pipe)
```

```
The model's precision is          65.87%
Training Score: 0.85
Test Score: 0.64

Classification Report:
               precision    recall  f1-score   support

           0       0.36      0.55      0.43       117
           1       0.54      0.61      0.57       589
           2       0.76      0.66      0.71      1077

    accuracy                           0.64      1783
   macro avg       0.55      0.61      0.57      1783
weighted avg       0.66      0.64      0.64      1783
```



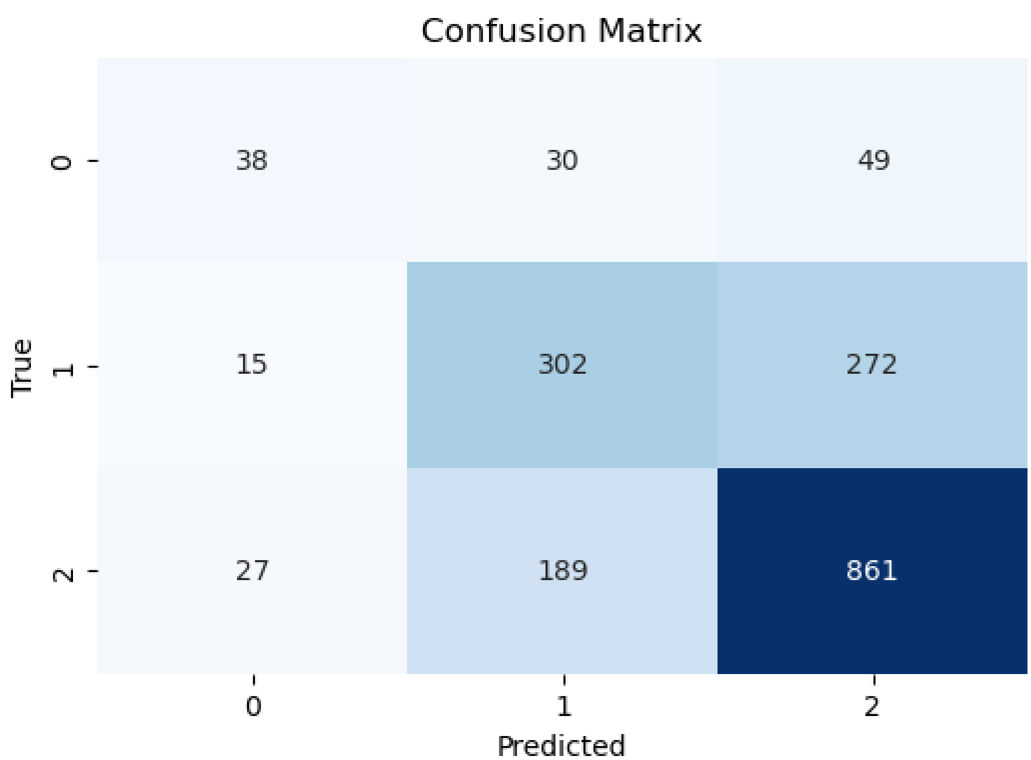
The second multiclass classification model, which employs the Multinomial Naive Bayes classifier, exhibits a precision rate of 65.87%, indicating a moderate level of accuracy in sentiment classification. However, there is room for improvement, as precision varies across different sentiment classes. While the model performs relatively well in distinguishing positive and neutral emotions, it struggles with negative emotions. The training score is 0.85, suggesting decent performance on the training data, but the test score is 0.64, indicating potential overfitting.

Random Forest

In [91]:
```
# Creating a pipeline
clf_pipe = imblearn.pipeline.Pipeline([
    ('vectorizer', TfidfVectorizer(tokenizer=tokenize_text,
                                   stop_words=None)),
    ('os', RandomOverSampler(random_state=42)),
    ('clf', RandomForestClassifier(class_weight='balanced', random_state=42,
                                   criterion='entropy', max_depth=None,
                                   min_samples_leaf=2))])
# Fitting the pipeline on the training data
clf_pipe.fit(X_train, y_train)

# Making predictions on the test data
y_pred = clf_pipe.predict(X_test)
```

In [92]:
```
# Perform classification evaluation
multiclass_classification(y_test, y_pred, clf_pipe)
```

```
The model's precision is          66.27%
Training Score: 0.92
Test Score: 0.67

Classification Report:
              precision    recall  f1-score   support

           0       0.47      0.32      0.39       117
           1       0.58      0.51      0.54       589
           2       0.73      0.80      0.76      1077

    accuracy                           0.67      1783
   macro avg       0.59      0.55      0.56      1783
weighted avg       0.66      0.67      0.67      1783
```



The third multiclass classification model, employing the Random Forest classifier, demonstrates the highest precision among the three models, with an overall precision rate of 66.27%. This indicates a good level of accuracy in sentiment classification, especially when distinguishing between positive and neutral emotions. Although there is room for improvement, this model exhibits promising results. Further hyperparameter tuning is recommended to explore the model's full potential and enhance its capabilities in sentiment analysis tasks.

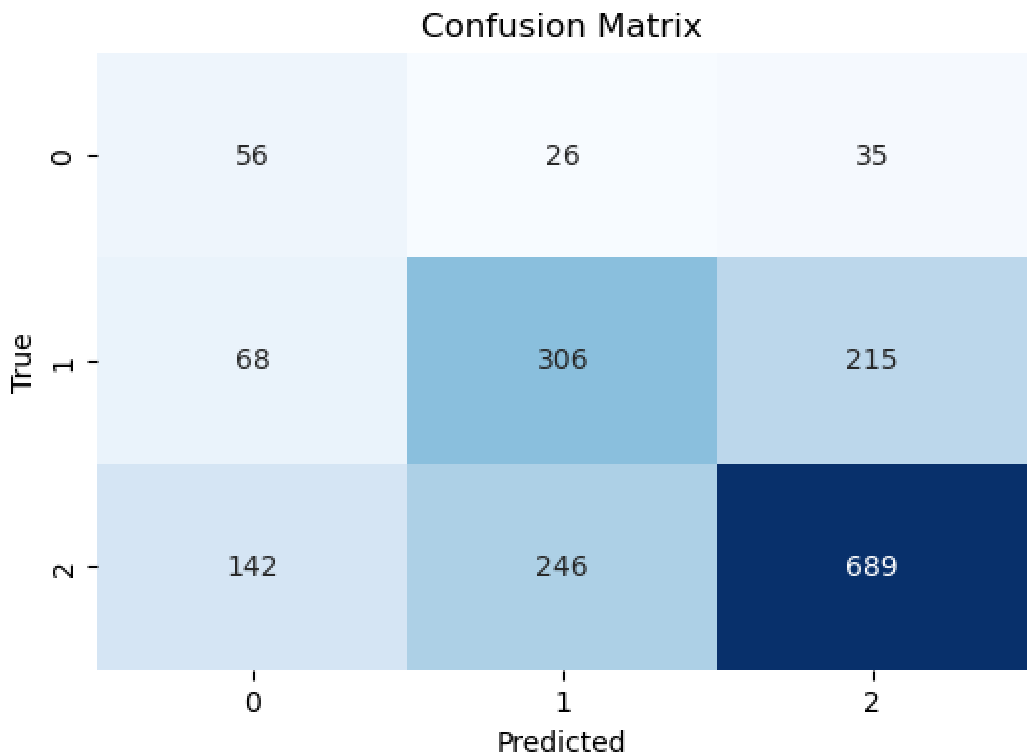
In [93]:
```
# Define the parameter grid for hyperparameter tuning
param_grid = {'clf__criterion': ['gini', 'entropy'],
            'clf__max_depth': [10, 20, None],
            'clf__min_samples_leaf': [1, 2, 3],
            'vectorizer__norm': ['l1', 'l2']}

# Create the GridSearchCV object
grid_search = GridSearchCV(estimator=clf_pipe,
                           param_grid = param_grid,
                           scoring='recall_macro',
                           n_jobs=2)

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best hyperparameters
best_params = grid_search.best_params_
print("Best Hyperparameters:", best_params)
```

```
Best Hyperparameters: {'clf__criterion': 'entropy', 'clf__max_depth': 20, 'cl
f__min_samples_leaf': 1, 'vectorizer__norm': 'l2'}
```

In [96]:
```
# Creating a pipeline
clf_tuned_pipe = imblearn.pipeline.Pipeline([
    ('vectorizer', TfidfVectorizer(tokenizer=tokenize_text,
                                   stop_words=None,
                                   norm='l2')),
    ('os', RandomOverSampler(random_state=42)),
    ('clf', RandomForestClassifier(class_weight='balanced',
                                   random_state=42,
                                   criterion='entropy',
                                   max_depth=20,
                                   min_samples_leaf=1,
                                   ))])
# Fitting the pipeline on the training data
clf_tuned_pipe.fit(X_train, y_train)

# Making predictions on the test data
y_pred = clf_tuned_pipe.predict(X_test)
```

In [97]:
```
# Perform classification evaluation
multiclass_classification(y_test, y_pred, clf_tuned_pipe)
```

```
The model's precision is          63.19%
Training Score: 0.82
Test Score: 0.59

Classification Report:
               precision    recall  f1-score   support

           0       0.21      0.48      0.29       117
           1       0.53      0.52      0.52       589
           2       0.73      0.64      0.68      1077

    accuracy                           0.59      1783
   macro avg       0.49      0.55      0.50      1783
weighted avg       0.63      0.59      0.61      1783
```



The tuned model achieved an accuracy of 59% on the test data. The models still struggles to effectively classify all three sentiment categories. Therefore, for multiclass classification, the best-performing model among the three appears to be the untuned random forest classifier, and I recommend using it for multiclass sentiment analysis.

Results Summary

In this sentiment analysis project, we aimed to gain insights into how Twitter users perceive Apple and Google products and to provide valuable sentiment classification models. We analyzed a vast collection of tweets related to these tech giants and derived several significant findings:

1) Apple Sentiment Analysis:

- **Overwhelmingly Positive Sentiment:** Approximately **81.14%** of Apple-related tweets expressed **positive sentiments**, indicating a strong and favorable perception among users.
- **Common Positive Themes:** Positive tweets often revolved around Apple stores, product excitement, community engagement at events like SXSW, and innovation.*
- **Negative Sentiment Insights:** Negative tweets **(16.15%)** highlighted issues with Apple applications, battery concerns, design criticisms, autocorrect problems, and occasional references to other brands like Blackberry.

2) Google Sentiment Analysis:

- **Strong Positive Sentiment:** Around **82.08%** of Google-related tweets conveyed **positive sentiments**, emphasizing the positive outlook toward Google and its offerings.
- **Common Positive Themes:** Positive discussions centered on Google's social networking platform, mapping services, mobile apps, product launches, and tech innovation.
- **Negative Sentiment Insights:** Negative tweets **(14.95%)** featured mentions of Bing, map comparisons, location-related concerns, and occasional criticisms related to Google+.

3) Modeling and Classification:

- **Binary Classification:** A hyperparameter-tuned Multinomial Naive Bayes classifier exhibited enhanced precision (89.76%) and recall (79%) for negative sentiments, achieving a well-balanced performance for sentiment analysis.
- **Multiclass Classification:** The untuned Random Forest classifier displayed the highest precision (66.27%) and exhibited promising results, particularly in distinguishing positive and neutral emotions.

Conclusions

- Both Apple and Google enjoy predominantly positive sentiments on Twitter, indicating strong brand perception.
- Key positive topics for Apple include retail stores, product launches, and community engagement. Negative sentiments often relate to app and autocorrect issues.
- For Google, positive discussions center around Google+, mapping services, and mobile apps. Negative sentiments occasionally touch upon Google Maps and location-based services.

Recommendations

Based on the findings, here are some actionable recommendations for businesses:

- Capitalize on the overwhelmingly positive sentiment around your brand and products. Highlight successful product launches, engage with the community, and promote events.
- Pay close attention to common pain points mentioned in negative tweets. Continuously improve app functionality, battery performance, iPad's design, and autocorrect features for Apple. For Google, address concerns related to mapping services and location-based features.
- Emphasize innovation in your product offerings, as this generates positive discussions. Encourage excitement around new features and updates.

- For both companies, maintain a strong presence on social platforms like Google+ and actively engage with users to foster positive sentiment.

Next Steps:

- Collect more data to address class imbalance issues and improve model performance.
- Explore advanced machine learning models and natural language processing techniques to further enhance sentiment analysis accuracy.