Deciphering the Public Opinion on Apple

Conducting a Twitter sentiment analysis for the SXSW Conference

INTRODUCTION, PROBLEM STATEMENT, and BUSINESS UNDERSTANDING

As digital brand advisors, we have been hired by Apple with the goal of conducting an analysis that assesses public opinion about the company based on a Twitter sentiment analysis in the South by Southwest (SXSW) conference, which celebrates the convergence of tech and other critical societal factors like education and culture..

One medium that companies can leverage to identify public opinion about their products and activities in social media platforms like Twitter. People from all walks of life share their varied opinions surrounding businesses, making Twitter a perfect source of data to obtain public sentiment.

For this project, Apple requires us to conduct a sentiment analysis of tweets presented during the SXSW Conference. Below are the objectives of our analysis:

OBJECTIVES

1. Determine how Apple is perceived as a company based on the tweets presented during the SXSW Conference, in comparison to Google which is one of their main competitors.
2. Determine consumers' reactions to Apple's SXSW announcement (how are their new products perceived, and how do people react to new announcements?)
3. Seek out insights that the tweets can give into the challenges that Apple faces during these product announcements. Are there specific challenges that should be addressed?
4. Create a model that when given a tweet or series of tweets can determine the user's sentiment (positive, negative, or neutral). Apple can use these models to assess public opinion and stay ahead of its competition.

DATA UNDERSTANDING

We will be using a dataset from data.world provided by CrowdFlower which has tweets about Google and Apple from a conference. The tweet labels were crowdsources and reflect the emotion they convey and what product/service/company the emotion is directed at based on the content.

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 emotion was expressed they were also asked to say which brand or product was the target of that emotion.

Data Limitations

Twitter is full of spelling errors, shortened words, hashtags, acronyms, tags, and very specific nouns and words. These are difficult for a model to learn.

Emotions are also complicated and a tweet can have a mix of emotions or ambuguity.

Emotions are also relative. For example, the phrase "IPhones are better than Android phones" could be negative or positive depending on the perception.

A model also learns as well as its labels and our data was labelled by humans.

These considerations make the problem tricky but the model was successful in classifying the tweets.

Our dataset has highly imbalanced target values(emotions), which means that we will have to address this during the modeling stage

```
import pandas as pd
```

DATA LOADING

```
file_path = 'data/judge-1377884607_tweet_product_company.csv'

df = pd.read_csv(file_path, encoding='latin-1')
df.head()
```

```
tweet_text  \
0               .@wesley83 I have a 3G iPhone. After 3 hrs tweeting at
#RISE_Austin, it was dead!  I need to upgrade. Plugin stations at
#SXSW.
1  @jessedee Know about @fludapp ? Awesome iPad/iPhone app that you'll
likely appreciate for its design. Also, they're giving free Ts at
#SXSW
2
@swonderlin Can not wait for #iPad 2 also. They should sale them down
at #SXSW.
3                                                            @sxsw I
hope this year's festival isn't as crashy as this year's iPhone app.
#sxsw
4           @sxtxstate great stuff on Fri #SXSW: Marissa Mayer
(Google), Tim O'Reilly (tech books/conferences) &amp; Matt Mullenweg
(Wordpress)

  emotion_in_tweet_is_directed_at  \
```

```
0                          iPhone
1            iPad or iPhone App
2                            iPad
3            iPad or iPhone App
4                          Google

  is_there_an_emotion_directed_at_a_brand_or_product
0                                   Negative emotion
1                                   Positive emotion
2                                   Positive emotion
3                                   Negative emotion
4                                   Positive emotion
```

Since the column names are too long and difficult to read, we can rename them to ease readability and interpretability.

```
df.columns = ['Tweet', 'Product/Brand', 'Emotion']
df.head()


Tweet  \
0               .@wesley83 I have a 3G iPhone. After 3 hrs tweeting at
#RISE_Austin, it was dead!  I need to upgrade. Plugin stations at
#SXSW.
1  @jessedee Know about @fludapp ? Awesome iPad/iPhone app that you'll
likely appreciate for its design. Also, they're giving free Ts at
#SXSW
2
@swonderlin Can not wait for #iPad 2 also. They should sale them down
at #SXSW.
3                                                             @sxsw I
hope this year's festival isn't as crashy as this year's iPhone app.
#sxsw
4           @sxtxstate great stuff on Fri #SXSW: Marissa Mayer
(Google), Tim O'Reilly (tech books/conferences) &amp; Matt Mullenweg
(Wordpress)

        Product/Brand           Emotion
0              iPhone  Negative emotion
1  iPad or iPhone App  Positive emotion
2                iPad  Positive emotion
3  iPad or iPhone App  Negative emotion
4              Google  Positive emotion
```

We can take a look at the unique values in the Brand/Product and Emotion columns to see what we have

```
df['Emotion'].unique()
```

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

```
df['Product/Brand'].unique()
```

```
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)
```

We can see that there is a lot of information on different products and services (mainly Apple products and services, Google, Android, Androis Apps, and NaN) and an 'I can't tell emotion'.

DATA CLEANING

Addressing Missing Values

```
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   Product/Brand  3291 non-null   object
 2   Emotion        9093 non-null   object
dtypes: object(3)
memory usage: 213.2+ KB
```

We are missing the body of text for 1 tweet and 5802 tags for the product/company that the tweet was about. Let's start by looking at the missing tweet.

```
df[df['Tweet'].isna()]
```

```
  Tweet Product/Brand                             Emotion
6   NaN           NaN  No emotion toward brand or product
```

All the information from this row is missing, including the tweet itself, so we can drop it.

```
df = df.drop([6])
df[df['Tweet'].isna()]
```

```
Empty DataFrame
Columns: [Tweet, Product/Brand, Emotion]
Index: []
```

```
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   Product/Brand  3291 non-null   object
 2   Emotion        9092 non-null   object
dtypes: object(3)
memory usage: 284.1+ KB
```

Now let's look at the missing values in the product/company column

```
df[df['Product/Brand'].isna()].head(10)
```

```
Tweet  \
5   @teachntech00 New iPad Apps For #SpeechTherapy And Communication
Are Showcased At The #SXSW Conference http://ht.ly/49n4M #iear #edchat
#asd
16                                                   Holler Gram for
iPad on the iTunes App Store -  http://t.co/kfN3f5Q (via @marc_is_ken)
#sxsw
32                                            Attn: All  #SXSW frineds,
@mention Register for #GDGTLive  and see Cobra iRadar for Android.
{link}
33
Anyone at  #sxsw want to sell their old iPad?
34
Anyone at  #SXSW who bought the new iPad want to sell their older iPad
to me?
35                                  At #sxsw.  Oooh. RT @mention
Google to Launch Major New Social Network Called Circles, Possibly
Today {link}
37                         SPIN Play - a new concept in music
discovery for your iPad from @mention &amp; spin.com {link} #iTunes
#sxsw @mention
39
VatorNews - Google And Apple Force Print Media to Evolve? {link} #sxsw

41              HootSuite - HootSuite Mobile for #SXSW ~ Updates for
iPhone, BlackBerry &amp; Android: Whether youÛªre getting friend...
{link}
42             Hey #SXSW - How long do you think it takes us to make
an iPhone case? answer @mention using #zazzlesxsw and weÛªll make you
one!

   Product/Brand                             Emotion
```

```
5             NaN  No emotion toward brand or product
16            NaN  No emotion toward brand or product
32            NaN  No emotion toward brand or product
33            NaN  No emotion toward brand or product
34            NaN  No emotion toward brand or product
35            NaN  No emotion toward brand or product
37            NaN  No emotion toward brand or product
39            NaN  No emotion toward brand or product
41            NaN  No emotion toward brand or product
42            NaN  No emotion toward brand or product
```

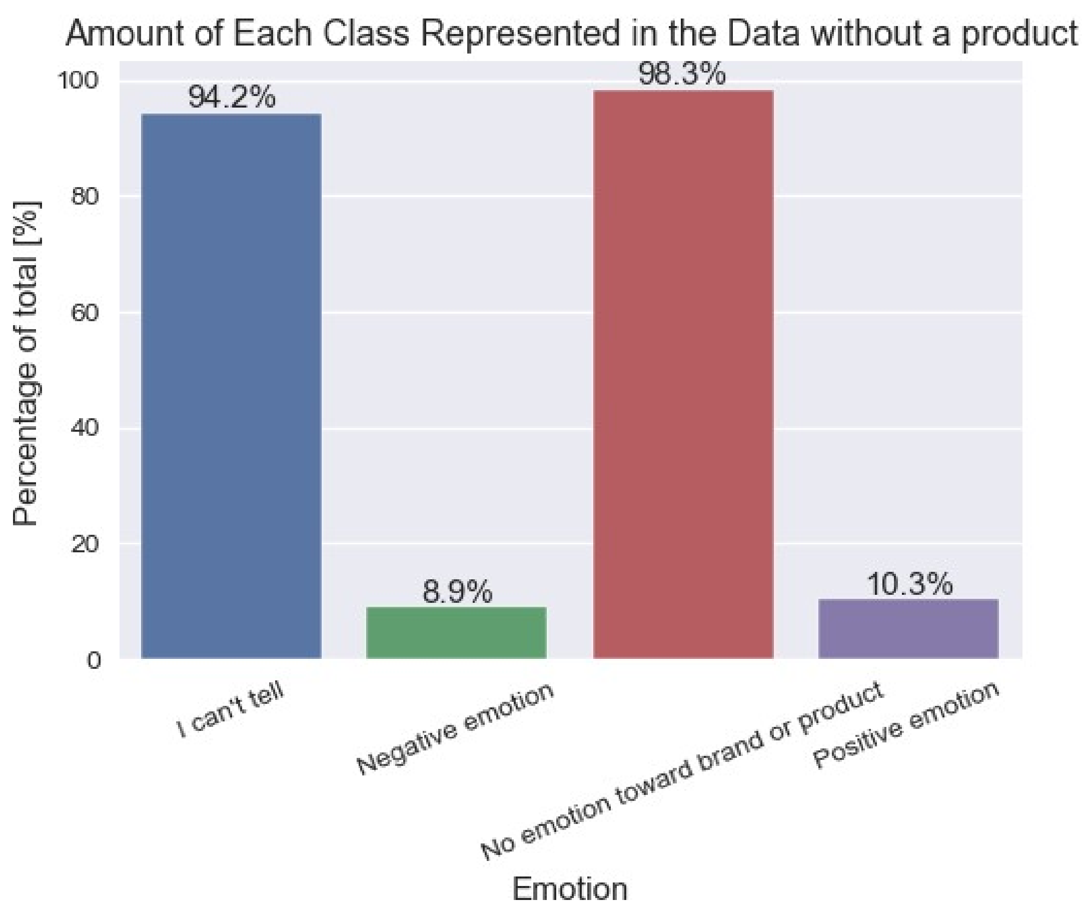
The tweets are not directed towards a specific product or brand or a generally talking about the SXSW event or something related to the event with no specific feeling.

```
print("Value Counts of emotion of entire dataset \n")
display(df['Emotion'].value_counts())
print("\n\n Value Counts of emotion of dataset with no product
attached")
display(df[df['Product/Brand'].isna()]['Emotion'].value_counts())
```

```
Value Counts of emotion of entire dataset


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



 Value Counts of emotion of dataset with no product attached

No emotion toward brand or product    5297
Positive emotion                       306
I can't tell                           147
Negative emotion                        51
Name: Emotion, dtype: int64
```

```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

full_counts = df['Emotion'].value_counts()
subbed_counts = df[df['Product/Brand'].isna()]
['Emotion'].value_counts()

#Displaying percentage of values for each class that come from subbed
set
percentage_counts = subbed_counts/full_counts
```

```
plt.figure(figsize=(6,4))
sns.set_style('darkgrid')
bp = sns.barplot(x=list(percentage_counts.keys()), y=
percentage_counts*100)

bp.set_ylabel('Percentage of total [%]', fontsize=12)
bp.set_xlabel('Emotion', fontsize=12)
bp.set_xticklabels(labels=list(percentage_counts.keys()),
rotation=22.5)
bp.set_title("Amount of Each Class Represented in the Data without a
product", fontsize=13)

for patch in bp.patches:
    x = patch.get_bbox().get_points()[:,0]
    y = patch.get_bbox().get_points()[1,1]
    bp.annotate("{:.1f}%".format(y), (x.mean(), y),\
            ha= 'center', va= 'bottom', fontsize= 'large')

plt.show()
```



This shows that when no product is discerned, it is more likely that there is no emotion directed towards a product or one cannot tell what the emotion is. We can fill the null values with

"Unknown" as a placeholder for the time being. The data missing in product/brand name has some value and information in the fact that it is missing. Most of the tweets that have no emotion are in this category and they will be left as unknown.

```
df['Product/Brand'].fillna('Unknown', inplace = True)

# Verifying that the null values have been handled
df.isna().sum()
```

```
Tweet            0
Product/Brand    0
Emotion          0
dtype: int64
```

Cleaning the Emotion Column

```
df['Emotion'].value_counts()
```

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

Similar to the initial column names, the values in the emotion column can be cleaned up for interpretability and to reduce the time required to type the code

```
emotion_dict = {'Positive emotion': 'Positive', 'Negative emotion':
'Negative', 'No emotion toward brand or product': 'Neutral', "I can't
tell": 'Unknown'}
df['Emotion'] = df['Emotion'].map(emotion_dict)
df.head()
```

```
Tweet  \
0               .@wesley83 I have a 3G iPhone. After 3 hrs tweeting at
#RISE_Austin, it was dead!  I need to upgrade. Plugin stations at
#SXSW.
1  @jessedee Know about @fludapp ? Awesome iPad/iPhone app that you'll
likely appreciate for its design. Also, they're giving free Ts at
#SXSW
2
@swonderlin Can not wait for #iPad 2 also. They should sale them down
at #SXSW.
3                                                           @sxsw I
hope this year's festival isn't as crashy as this year's iPhone app.
#sxsw
4          @sxtxstate great stuff on Fri #SXSW: Marissa Mayer
(Google), Tim O'Reilly (tech books/conferences) &amp; Matt Mullenweg
(Wordpress)
```

```
       Product/Brand   Emotion
0             iPhone  Negative
1  iPad or iPhone App  Positive
2               iPad  Positive
3  iPad or iPhone App  Negative
4             Google  Positive
```

```
df['Emotion'].value_counts()
```

```
Neutral     5388
Positive    2978
Negative     570
Unknown      156
Name: Emotion, dtype: int64
```

Now let's look at the tweets with 'Unknown' emotion values to see if we notice any patterns or can easily tell whether the tweet has a negative, positive, or neutral emotion.

```
pd.set_option("display.max_colwidth", 300)
df[df['Emotion']=='Unknown']
```

```
Tweet  \
90                                     Thanks to @mention for
publishing the news of @mention new medical Apps at the #sxswi conf.
blog {link} #sxsw #sxswh
102                          ÛÏ@mention &quot;Apple has opened a pop-
up store in Austin so the nerds in town for #SXSW can get their new
iPads. {link} #wow
237                               Just what America needs. RT @mention
Google to Launch Major New Social Network Called Circles, Possibly
Today {link} #sxsw
341
The queue at the Apple Store in Austin is FOUR blocks long. Crazy
stuff! #sxsw
368                                        Hope it's better than wave
RT @mention Buzz is: Google's previewing a social networking platform
at #SXSW: {link}
...
...
9020              It's funny watching a room full of people hold their
iPad in the air to take a photo. Like a room full of tablets staring
you down. #SXSW
9032
@mention yeah, we have @mention , Google has nothing on us :) #SXSW
9037
@mention Yes, the Google presentation was not exactly what I was
expecting. #sxsw
9058  &quot;Do you know what Apple is really good at? Making you feel
```

```
bad about your Xmas present!&quot; - Seth Meyers on iPad2 #sxsw
#doyoureallyneedthat?
9066                    How much you want to bet Apple is
disproportionately stocking the #SXSW pop-up store with iPad 2? The
influencer/hipsters thank you

     Product/Brand  Emotion
90         Unknown  Unknown
102        Unknown  Unknown
237        Unknown  Unknown
341        Unknown  Unknown
368        Unknown  Unknown
...            ...      ...
9020       Unknown  Unknown
9032       Unknown  Unknown
9037       Unknown  Unknown
9058       Unknown  Unknown
9066         Apple  Unknown

[156 rows x 3 columns]
```

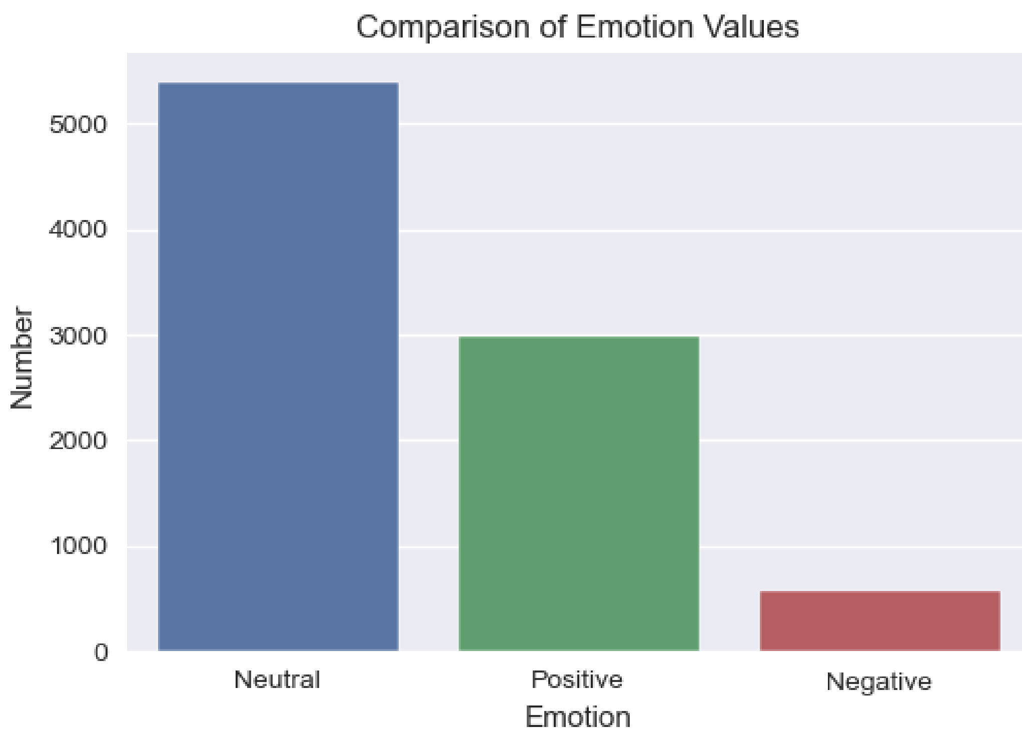
These tweets are difficult to classify without more context. Some of them could be taken as genuine or sarcastic depending on the context.

Since we need labels for our models, the tweets will not be usefulfor model development. Luckily, they make up a small percentage of our data so we can drop these rows.

```
df = df[df['Emotion']!='Unknown']
df['Emotion'].value_counts()

Neutral     5388
Positive    2978
Negative     570
Name: Emotion, dtype: int64
```

Also, the emotion column is highly imbalanced, which will have to be dealt with in the modelling stage

```
plt.figure(figsize=(6,4))
import seaborn as sns

comp = sns.countplot(data=df, x = 'Emotion', order =
df['Emotion'].value_counts().index)
comp.set_title("Comparison of Emotion Values")
comp.set_ylabel("Number")
comp.set_xlabel('Emotion')
plt.show()
```



Dealing with Duplicates

```
len(df[df.duplicated()])

22
```

There are 22 tweets in the dataset that are duplicated. Let's take a closer look at them

```
df[df.duplicated()]


Tweet  \
468
Before It Even Begins, Apple Wins #SXSW {link}
776
Google to Launch Major New Social Network Called Circles, Possibly
Today {link} #sxsw
2232                                                Marissa Mayer:
Google Will Connect the Digital &amp; Physical Worlds Through Mobile -
{link} #sxsw
2559                                                          Counting
down the days to #sxsw plus strong Canadian dollar means stock up on
Apple gear
3950  Really enjoying the changes in Gowalla 3.0 for Android! Looking
forward to seeing what else they &amp; Foursquare have up their
sleeves at #SXSW
3962        #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
4897                    Oh. My. God. The #SXSW app for iPad is pure,
unadulterated awesome. It's easier to browse events on iPad than on
the website!!!
5338                                          RT @mention ❱÷¼ GO
BEYOND BORDERS! ❱÷_ {link} ❱ã_ #edchat #musedchat #sxsw #sxswi
#classical #newTwitter
5341                      RT @mention ❱÷¼ Happy Woman's Day! Make love,
not fuss! ❱÷_ {link} ❱ã_ #edchat #musedchat #sxsw #sxswi #classical
#newTwitter
5881                                                     RT @mention
Google to Launch Major New Social Network Called Circles, Possibly
Today {link} #sxsw
5882                                                     RT @mention
Google to Launch Major New Social Network Called Circles, Possibly
Today {link} #SXSW
5883                                                     RT @mention
Google to Launch Major New Social Network Called Circles, Possibly
Today {link} #sxsw
5884                                                     RT @mention
Google to Launch Major New Social Network Called Circles, Possibly
Today {link} #SXSW
5885                                                     RT @mention
Google to Launch Major New Social Network Called Circles, Possibly
Today {link} #sxsw
6296                                    RT @mention Marissa Mayer:
Google Will Connect the Digital &amp; Physical Worlds Through Mobile -
{link} #sxsw
6297                                    RT @mention Marissa Mayer:
Google Will Connect the Digital &amp; Physical Worlds Through Mobile -
{link} #SXSW
6298                                    RT @mention Marissa Mayer:
Google Will Connect the Digital &amp; Physical Worlds Through Mobile -
{link} #sxsw
6299                                    RT @mention Marissa Mayer:
Google Will Connect the Digital &amp; Physical Worlds Through Mobile -
{link} #SXSW
6300                                    RT @mention Marissa Mayer:
Google Will Connect the Digital &amp; Physical Worlds Through Mobile -
{link} #sxsw
6546                                     RT @mention RT @mention
Google to Launch Major New Social Network Called Circles, Possibly
Today {link} #sxsw
8483                  I just noticed DST is coming this weekend. How
many iPhone users will be an hour late at SXSW come Sunday morning?
#SXSW #iPhone
8747                                        Need to buy an iPad2 while
I'm in Austin at #sxsw. Not sure if I'll need to Q up at an Austin
```

```
Apple store?

           Product/Brand   Emotion
468                Apple  Positive
776              Unknown   Neutral
2232             Unknown   Neutral
2559               Apple  Positive
3950         Android App  Positive
3962             Android  Positive
4897  iPad or iPhone App  Positive
5338             Unknown   Neutral
5341             Unknown   Neutral
5881             Unknown   Neutral
5882             Unknown   Neutral
5883             Unknown   Neutral
5884             Unknown   Neutral
5885             Unknown   Neutral
6296              Google  Positive
6297             Unknown   Neutral
6298              Google  Positive
6299             Unknown   Neutral
6300             Unknown   Neutral
6546             Unknown   Neutral
8483              iPhone  Negative
8747                iPad  Positive
```

```
df.drop_duplicates(keep='first', inplace = True)
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   Product/Brand  8914 non-null   object
 2   Emotion        8914 non-null   object
dtypes: object(3)
memory usage: 278.6+ KB
```

We can now perform EDA on the data

EDA

With the objectives in mind, we need to isolate and analyze positive and negative tweets as a whole and on a company and product basis. We will start with positive tweets.

Tweets with Positive Sentiment

```
# creating a new df for the positive tweets
df_positive = df[df['Emotion']=='Positive']
# Verifying that the negative and neutral tweets have been removed
df_positive['Emotion'].value_counts()
```

```
Positive    2970
Name: Emotion, dtype: int64
```

```
# Parsing the tweets into a list
corpus_pos = df_positive['Tweet'].to_list()
corpus_pos[0:5]
```

```
["@jessedee Know about @fludapp ? Awesome iPad/iPhone app that you'll
likely appreciate for its design. Also, they're giving free Ts at
#SXSW",
 '@swonderlin Can not wait for #iPad 2 also. They should sale them
down at #SXSW.',
 "@sxtxstate 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 @madebymany @thenextweb wrote
about our #hollergram iPad app for #sxsw! http://bit.ly/ieaVOB']
```

Tokenizing

We will use TweetTokenizer throughout this project since it has a built-in functionality like processing hashtags and handles correctly unlike other tokenizers. We will drop all handles from the tweets since we are focused on the content of the tweet.

```
from nltk import TweetTokenizer
import string

# function for the tokenization of the tweets
def tokenize_tweets(corpus, preserve_case = False, strip_handles =
True):
    """Function returns tokens based on a corpus passed in. The corpus
will be broken
    doen into tokens based on TweetTokenizer from the nltk package.
    -----------------------
    Arguments:
    corpus: the collection of words to be tokenized in a corpus
format.
    preserve_case: whether to keep the upper case letters in the words
as upper case.
    strip_handles: whether to remove Twitter handles"""
```

```
    tokenizer = TweetTokenizer(preserve_case= preserve_case,
                               strip_handles= strip_handles)
    tokens = tokenizer.tokenize(','.join(corpus))
    return tokens

# Tokenize positive tweets
tokens_pos = tokenize_tweets(corpus_pos)

# Displaying the 10 most frequent tokens
from nltk import FreqDist
freq_pos = FreqDist(tokens_pos)
freq_pos.most_common(10)
```

```
[(',', 4050),
 ('#sxsw', 2983),
 ('.', 2230),
 ('the', 1590),
 ('!', 1241),
 ('link', 1214),
 ('{', 1210),
 ('}', 1210),
 ('to', 1154),
 ('at', 1019)]
```

The tokens contain a lot of punctuation and stop words like "at" and "the" because we have not removed these yet. Before removing them, we will be lemmatizing the tokens to ensure that we are capturing any stop words that could be generated using this process.

Lemmatization

```
import nltk
from nltk.stem.wordnet import WordNetLemmatizer
nltk.download('wordnet')

# function for the lemmatization of tokens
def lemmatize_tokens(tokens_list):
    """Function lemmatizes tokens list that is passed in using
WordNetLemmatizer
    and returns lemmatized tokens.
    --------------------
    Arguments:
    tokens_list: a tokens list"""
    lemmatizer = WordNetLemmatizer()
    tokens_lemm = [lemmatizer.lemmatize(word) for word in tokens_list]
    return tokens_lemm
```

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

```
# Lemmatizing positive tweets tokens
tokens_pos_lemm = lemmatize_tokens(tokens_pos)

# displaying the 10 most common tokens
freq_pos_lemmatized = FreqDist(tokens_pos_lemm)
freq_pos_lemmatized.most_common(10)
```

```
[(',', 4050),
 ('#sxsw', 2983),
 ('.', 2230),
 ('the', 1590),
 ('!', 1241),
 ('link', 1218),
 ('{', 1210),
 ('}', 1210),
 ('to', 1154),
 ('at', 1019)]
```

We still have punctuation and stop words in our list as we have not removed them yet. We can now remove them after lemmatizing our tokens since they do not reveal anything about the sentiment of the tweets. We will see more relevant information and allow for bettwe performance of our models.

Stop Word and Punctuation Removal

```
# Getting stop words from NLTK
from nltk.corpus import stopwords
stop_list = stopwords.words('english')
stop_list += list(string.punctuation)

# Adding additional characters and empty strings to stop words
additional_punctuation = ['“','”','...',"''",'’','``','']
stop_list += additional_punctuation

# Function for the removal of stop words
def remove_stop_words(tokens, stop_list = stop_list):
    """Function removes stop words from a given tokens list
    based on a stop word list
    ----------------------
    Arguments:
    tokens: a tokens list
    stop_list: a list containing stop words to be removed from
tokens"""

    # encoding or decoding tojens to remove unrecognized symbols and
    # eliminate external links
    tokens_stopped = [word.encode('ascii', 'ignore').decode()
                      for word in tokens
                      if (word not in stop_list) &
```

```python
                         (word.startswith('http')== False)]
    return tokens_stopped

# Removing stop words from lemmatized tokens
tokens_pos_list = remove_stop_words(tokens_pos_lemm)

# 50 most common tokens
freq_stop_words_removed = FreqDist(tokens_pos_list)
freq_stop_words_removed.most_common(50)
```

```
[('#sxsw', 2983),
 ('link', 1218),
 ('ipad', 1010),
 ('rt', 931),
 ('apple', 711),
 ('google', 602),
 ('2', 595),
 ('store', 554),
 ('iphone', 466),
 ('', 443),
 ('app', 387),
 ('new', 358),
 ('austin', 250),
 ('get', 181),
 ('#apple', 174),
 ('launch', 173),
 ('android', 161),
 ('party', 151),
 ('pop-up', 151),
 ('sxsw', 144),
 ('line', 143),
 ('time', 136),
 ('great', 135),
 ('via', 132),
 ('#ipad2', 129),
 ('day', 124),
 ('social', 122),
 ('free', 120),
 ('cool', 119),
 ("i'm", 115),
 ('like', 115),
 ('map', 115),
 ('one', 114),
 ('win', 112),
 ('today', 111),
 ('ha', 108),
 ('circle', 107),
 ('w', 104),
 ('go', 104),
 ('come', 103),
```

```
('wa', 100),
 ('#sxswi', 96),
 ('awesome', 93),
 ('#ipad', 93),
 ('love', 93),
 ('good', 92),
 ('network', 91),
 ('mobile', 90),
 ('temporary', 89),
 ('downtown', 88)]
```

It is clear that we still have some words that do not have valuable information surrounding the sentiment of the tweets. We know that SXSW refers to the conference and can remove all words surrounding this. Also, words like link and rt could be referring to retweets and external lunks. However, since link could have its literal meaning, we will build a function that takes a random sample of the tweets to see whether rt and link appear there and assess their usage.

```
# Adding sxsw to the stop word list
stop_list += ['#sxsw', '#sxswi', 'sxsw']

# defining a function that will provide context for given words

import numpy as np
def context_finder(word, corpus, n_samples =5, n_count = 5):
    """This function takes n_samples with each sample having n_count
tweets
    from the given corpus, and displays the tweets that have the
specified
    word in them. The goal of the function us to get some context
about a word.
    --------------------------
    Arguments:
    word: a word that the function will be providing context for
    corpus: a document that the word is contained in
    n_samples: how many samples will be collected
    n_count: how many tweets each sample will contain """

    i = 0
    for _ in list(range(0,n_samples)):
        sample = np.random.choice(corpus, n_count)
        for tweet in sample:
            if word in tweet:
                print(tweet)
                i+=1
    print('------------------------')
    print(f'Out of {n_count*n_samples} tweets analyzed, \
         {i} tweets had the word "{word}" in them.')
```

```python
#verifying that 'link' is used in reference to external web links
context_finder('link', corpus_pos)
```

```
Google to Launch Major New Social Network Called Circles  {link} #sxsw
(via @mention
The iPad 2 Takes Over #SXSW [VIDEO] {link}
Big night: Come party down with @mention and Google tonight at #sxsw:
{link} Bands, food, art, interactive maps! cc: @mention
Pic of my iPad-winning performance: {link} #sxsw #accordion
#toodamnlucky
Updated NPR Music iPhone app has song info for All Songs 24/7 &amp;
live video streaming just in time for #SXSW {link}
RT @mention Apple set to open popup shop in core of SXSW action {link}
via @mention #SXSW
RT @mention Genius move by Apple to open a temp. store in downtown
Austin for #SXSW: {link} /via @mention #ipad2
Love it . RT @mention From #Apple to Naomi Campbell: pop-up stores are
all the rage: {link} #sxsw
#IPad2 's ❱Û÷#SmartCover❱Ûª Opens to Instant Access - I should have
waited to get one! - {link} #apple #SXSW
Blogger is about due for an update... Google finally takes action and
will showcase the new design at #SXSW {link}
Report: 5th Avenue Apple Store sold 7,200 iPad 2s on launch {link}
#entry #friends #house #sxsw
------------------------
Out of 25 tweets analyzed,           11 tweets had the word "link" in
them.
```

It is clear that the word link mainly refers to web links that were removed when the data was being input int the dataset. This does not give valuable insight into what the tweet is about, and we will add the word to our stop words list

```python
stop_list += ["link"]
```

let's look at RT

```python
context_finder('RT', corpus_pos)
```

```
Here he comes ladies! @mention  @mention  RT @mention I'll be at
Austin Convention Center w/  @mention showing my  iPhone game. #SXSW
Fab! RT @mention RT @mention So @mention just spilled the beans: next
platform 4 #Flipboard is the iPhone.workin on it. #sxflip #SXSW #SXSWi
RT @mention More #SXSW Awesomeness! Apple is opening up a temporary
store in downtown Austin for #SXSW and the iPad 2 launch {link}
@mention -&gt; RT @mention New #UberSocial for #iPhone now in the App
Store includes UberGuide to #SXSW (cont) {link}
Fear not! Now extended through Wed! --&gt; RT @mention RT @mention
Last day for Apple popup is Sunday 3/13 #SXSW #AppleATXdt
RT @mention Better get in line now. RT @mention Apple is opening up a
```

```
temp store in downtown Austin for #SXSW &amp; iPad 2 launch {link}
RT @mention Announcing SXSW Quotables, a crowd-curated feed of the
hottest quotes from #SXSW. Sign up to win an iPad 2! - {link} #ipad2
RT @mention This is why social technology is amazing: Google has set
up a Person Finder in both English and Japanese: {link} #SXSW
RT @mention Google is showing skiers' geolocation overlaid on 3d
mountain model. Would love this for finding empty runs. #sxsw
------------------------
Out of 25 tweets analyzed,           9 tweets had the word "RT" in
them.
```

This also needs to be added to our tokenizer list since it denotes a retweet.

```
stop_list += ['rt']

# Let's now update our tokens list
tokens_pos_list = remove_stop_words(tokens_pos_list,
stop_list=stop_list)
```

The 50 Most Frequent Words in Positive Tweets

```
final_50_most_freq_pos = FreqDist(tokens_pos_list)
final_50_most_freq_pos.most_common(50)

[('ipad', 1010),
 ('apple', 711),
 ('google', 602),
 ('2', 595),
 ('store', 554),
 ('iphone', 466),
 ('app', 387),
 ('new', 358),
 ('austin', 250),
 ('get', 181),
 ('#apple', 174),
 ('launch', 173),
 ('android', 161),
 ('party', 151),
 ('pop-up', 151),
 ('line', 143),
 ('time', 136),
 ('great', 135),
 ('via', 132),
 ('#ipad2', 129),
 ('day', 124),
 ('social', 122),
 ('free', 120),
 ('cool', 119),
 ("i'm", 115),
```

```
 ('like', 115),
 ('map', 115),
 ('one', 114),
 ('win', 112),
 ('today', 111),
 ('ha', 108),
 ('circle', 107),
 ('w', 104),
 ('go', 104),
 ('come', 103),
 ('wa', 100),
 ('awesome', 93),
 ('#ipad', 93),
 ('love', 93),
 ('good', 92),
 ('network', 91),
 ('mobile', 90),
 ('temporary', 89),
 ('downtown', 88),
 ('opening', 88),
 ('people', 82),
 ('open', 82),
 ('#iphone', 82),
 ('got', 81),
 ('apps', 78)]
```

We can see that the most common words include "apple" and "google", but there are other words like "launch", "store", and "pop-up" show more about what the people were excited about. However, we can use a word cloud to show all these words.

Wordcloud with Product/Brand Information for Positive Tweets

```
pip install wordcloud
```

```
Requirement already satisfied: wordcloud in c:\users\rosew\anaconda3\
envs\learn-env\lib\site-packages (1.9.3)
Requirement already satisfied: numpy>=1.6.1 in c:\users\rosew\
anaconda3\envs\learn-env\lib\site-packages (from wordcloud) (1.24.4)
Requirement already satisfied: pillow in c:\users\rosew\anaconda3\
envs\learn-env\lib\site-packages (from wordcloud) (10.4.0)
Requirement already satisfied: matplotlib in c:\users\rosew\anaconda3\
envs\learn-env\lib\site-packages (from wordcloud) (3.3.1)
Requirement already satisfied: certifi>=2020.06.20 in c:\users\rosew\
anaconda3\envs\learn-env\lib\site-packages (from matplotlib-
>wordcloud) (2024.2.2)
Requirement already satisfied: cycler>=0.10 in c:\users\rosew\
anaconda3\envs\learn-env\lib\site-packages (from matplotlib-
>wordcloud) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\rosew\
anaconda3\envs\learn-env\lib\site-packages (from matplotlib-
```

```
>wordcloud) (1.2.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!
=2.1.6,>=2.0.3 in c:\users\rosew\anaconda3\envs\learn-env\lib\site-
packages (from matplotlib->wordcloud) (2.4.7)
Requirement already satisfied: python-dateutil>=2.1 in c:\users\rosew\
anaconda3\envs\learn-env\lib\site-packages (from matplotlib-
>wordcloud) (2.9.0)
Requirement already satisfied: six in c:\users\rosew\anaconda3\envs\
learn-env\lib\site-packages (from cycler>=0.10->matplotlib->wordcloud)
(1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

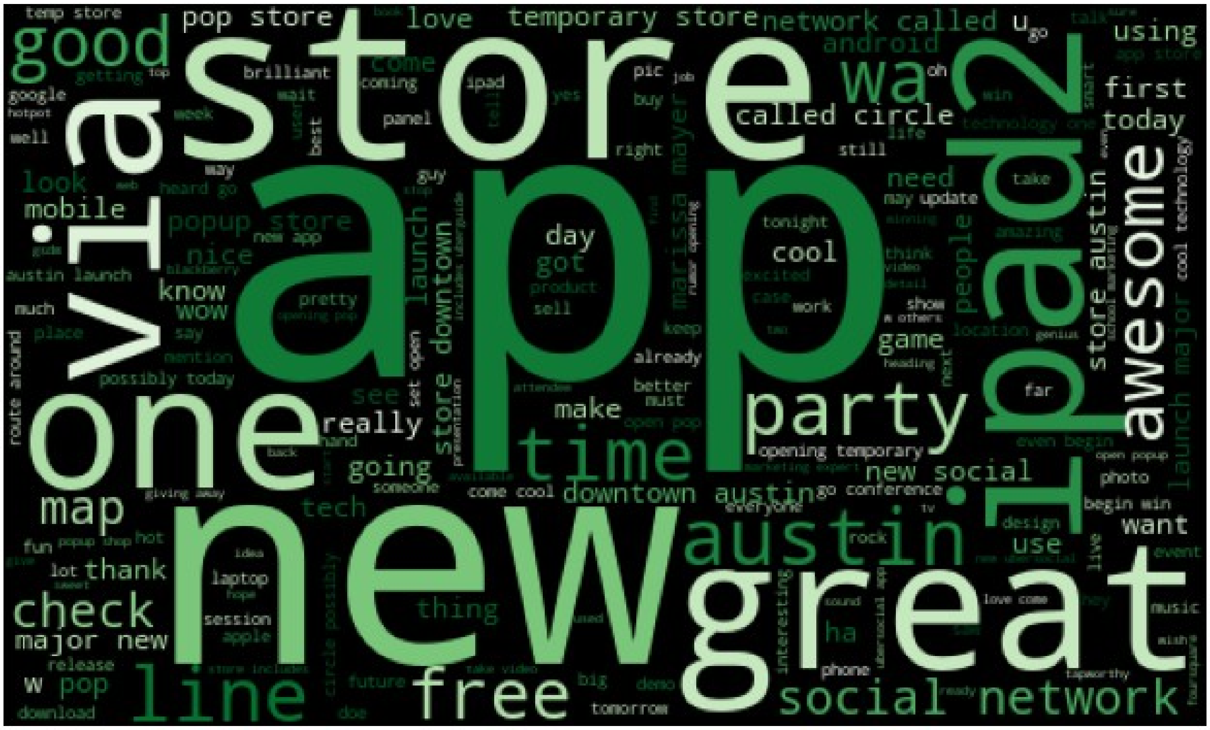
```
from wordcloud import WordCloud
import matplotlib.pyplot as plt

#defining a function for wordcloud generation
def generate_wordcloud(tokens, collocations=False,
background_color='black',
                       colormap='Greens', display=True):

    """Function generates and returns a wordcloud based on a tokens
list passed in.
    -------------------------------
    Arguments:
    tokens: a tokens list
    collocations: Whether to include collocations (bigrams) of two
words
    background_color: background color of the resulting word cloud
    colormap: the color map for the words that will be in the word
cloud
    display: Whether to show the resulting wordcloud"""

    ## Initalize a WordCloud
    wordcloud = WordCloud(collocations=collocations,
                          background_color=background_color,
                          colormap=colormap,
                          width=500, height=300)

    ## Generate wordcloud from tokens
    wordcloud.generate(','.join(tokens))

    ## Plot with matplotlib
    if display:
        plt.figure(figsize = (8, 6), facecolor = None)
        plt.imshow(wordcloud)
        plt.axis('off');
    return wordcloud
```

We will start by generating a word cloud for the tokens we were looking at above

```
# Generating the word cloud
cloud_positive_all = generate_wordcloud(tokens_pos_list,
collocations=True)
```

This shows us what the public was tweeting about in a positive way. We see that a lot of people are excited about the iPad, iPhone, and iPad 2 launch. It is also clear that people are tweeting about Apple and Google. To find additional common words through the word cloud that are not related to Apple , Google, iPhone, iPad 2, android, and others, we can remove them and visualize.

```
#removing product/company names
stop_lst_no_comp = stop_list + ['iphone', 'ipad', 'iphone app',
'google', 'android', 'apple',
                              '#apple', '#google', '#ipad',
'#iphone']

tokens_pos_list = remove_stop_words(tokens_pos_list,
stop_list=stop_lst_no_comp)

cloud_positive_without_company = generate_wordcloud(tokens_pos_list,
collocations=True)
```



N-grams of Positive Reviews

Positive Bigrams and Trigrams

```
from nltk.collocations import *
bigrams_measures = nltk.collocations.BigramAssocMeasures()
trigrams_measures = nltk.collocations.TrigramAssocMeasures()

# initializing finders
finder_bi_pos = BigramCollocationFinder.from_words(tokens_pos_list)
finder_tri_pos = TrigramCollocationFinder.from_words(tokens_pos_list)

# Getting frequency information from finder
bigrams = finder_bi_pos.score_ngrams(bigrams_measures.raw_freq)
trigrams = finder_tri_pos.score_ngrams(trigrams_measures.raw_freq)

bigrams[:30]
```

```
[(('pop-up', 'store'), 0.004340211680499505),
 (('social', 'network'), 0.003274194776517107),
 (('temporary', 'store'), 0.00304576258280667),
 (('new', 'social'), 0.00293154648595142),
 (('store', 'downtown'), 0.0026650422599558366),
 (('downtown', 'austin'), 0.002626970227670753),
 (('2', 'launch'), 0.002208177872534836),
 (('called', 'circle'), 0.0021701058402497525),
 (('network', 'called'), 0.0021701058402497525),
 (('marissa', 'mayer'), 0.0021320338079646693),
```

```
 (('launch', 'major'), 0.002055889743394502),
 (('major', 'new'), 0.002055889743394502),
 (('popup', 'store'), 0.002055889743394502),
 (('store', 'austin'), 0.001903601614254168 8),
 (('pop', 'store'), 0.0017513134851138354),
 (('austin', '2'), 0.0016370973882585853),
 (('opening', 'temporary'), 0.0016370973882585853),
 (('possibly', 'today'), 0.0015609533236884184),
 (('circle', 'possibly'), 0.0015228812914033 35),
 (('even', 'begin'), 0.0015228812914033 35),
 (('cool', 'technology'), 0.0012944490976928348),
 (('ever', 'heard'), 0.0012944490976928348),
 (("one's", 'ever'), 0.0012944490976928348),
 (('app', 'store'), 0.0012563770654077514),
 (('begin', 'win'), 0.0012183050331226 68),
 (('go', 'conference'), 0.0012183050331226 68),
 (('technology', "one's"), 0.0012183050331226 68),
 (('come', 'cool'), 0.0011802330008375847),
 (('heard', 'go'), 0.0011802330008375847),
 (('temp', 'store'), 0.0011421609685525014)]
```

```
trigrams[:30]
```

```
[(('new', 'social', 'network'), 0.00281733038909617),
 (('store', 'downtown', 'austin'), 0.002398538033960253),
 (('social', 'network', 'called'), 0.002170105840249 7525),
 (('network', 'called', 'circle'), 0.0021320338079646693),
 (('launch', 'major', 'new'), 0.002055889743394502),
 (('major', 'new', 'social'), 0.002055889743394502),
 (('opening', 'temporary', 'store'), 0.0015609533236884184),
 (('circle', 'possibly', 'today'), 0.0015228812914033 35),
 (('called', 'circle', 'possibly'), 0.0014848092591182517),
 (('temporary', 'store', 'downtown'), 0.0014467372268331684),
 (('austin', '2', 'launch'), 0.0013325211299779183),
 (("one's", 'ever', 'heard'), 0.0012944490976928348),
 (('downtown', 'austin', '2'), 0.0012563770654077514),
 (('cool', 'technology', "one's"), 0.0012183050331226 68),
 (('even', 'begin', 'win'), 0.0012183050331226 68),
 (('technology', "one's", 'ever'), 0.0012183050331226 68),
 (('ever', 'heard', 'go'), 0.0011802330008375847),
 (('come', 'cool', 'technology'), 0.001104088936267418),
 (('heard', 'go', 'conference'), 0.0010660169039823347),
 (('pop-up', 'store', 'austin'), 0.0007995126779867509),
 (('school', 'marketing', 'expert'), 0.0007995126779867509),
 (('app', 'store', 'includes'), 0.0007614406457016675),
 (('store', 'includes', 'uberguide'), 0.0007614406457016675),
 (('#ubersocial', 'app', 'store'), 0.0007233686134165842),
 (('new', '#ubersocial', 'app'), 0.0007233686134165842),
 (("google's", 'marissa', 'mayer'), 0.0006852965811315008),
 (('rumor', 'opening', 'temporary'), 0.0006852965811315008),
```

```
 (('shop', 'core', 'action'), 0.0006852965811315008),
 (('popup', 'shop', 'core'), 0.0006472245488464174),
 (('2', 'take', 'video'), 0.000609152516561334)]
```

We can see that a lot of people are excited about a new temporary popup store downtown in Austin, the iPad 2's launch, the new social network called Circle, and Google's Marissa Mayer. We now have an initial understanding of positive tweets and can look at the negative ones.

Tweets with Negative Sentiment

```
# Creating a new dataframe for negative Tweets
df_negative = df[df['Emotion']=='Negative']
df_negative['Emotion'].value_counts()
```

```
Negative    569
Name: Emotion, dtype: int64
```

```
# Creating a list for them
corpus_neg = df_negative['Tweet']. to_list()
corpus_neg[0:5]
```

```
['.@wesley83 I have a 3G iPhone. After 3 hrs tweeting at #RISE_Austin,
it was dead!  I need to upgrade. Plugin stations at #SXSW.',
 "@sxsw I hope this year's festival isn't as crashy as this year's
iPhone app. #sxsw",
 'I just noticed DST is coming this weekend. How many iPhone users
will be an hour late at SXSW come Sunday morning? #SXSW #iPhone',
 '@mention  - False Alarm: Google Circles Not Coming Now\x89ÛÒand
Probably Not Ever? - {link} #Google #Circles #Social #SXSW',
 'Again? RT @mention Line at the Apple store is insane.. #sxsw']
```

Tokenization, Lemmatization, and Removing Stop Words

```
# tokenize tweets
tokens_negative = tokenize_tweets(corpus_neg)
# Lemmatize tweets
tokens_neg_lem = lemmatize_tokens(tokens_negative)
# Remove stop words and punctuation
tokens_neg_list = remove_stop_words(tokens_neg_lem, stop_list=
stop_list)
```

50 Most Frequent Words in the Negative Tweets

```
final_50_most_freq_neg = FreqDist(tokens_neg_list)
final_50_most_freq_neg.most_common(50)
```

```
[('ipad', 179),
 ('iphone', 145),
 ('google', 136),
 ('apple', 100),
```

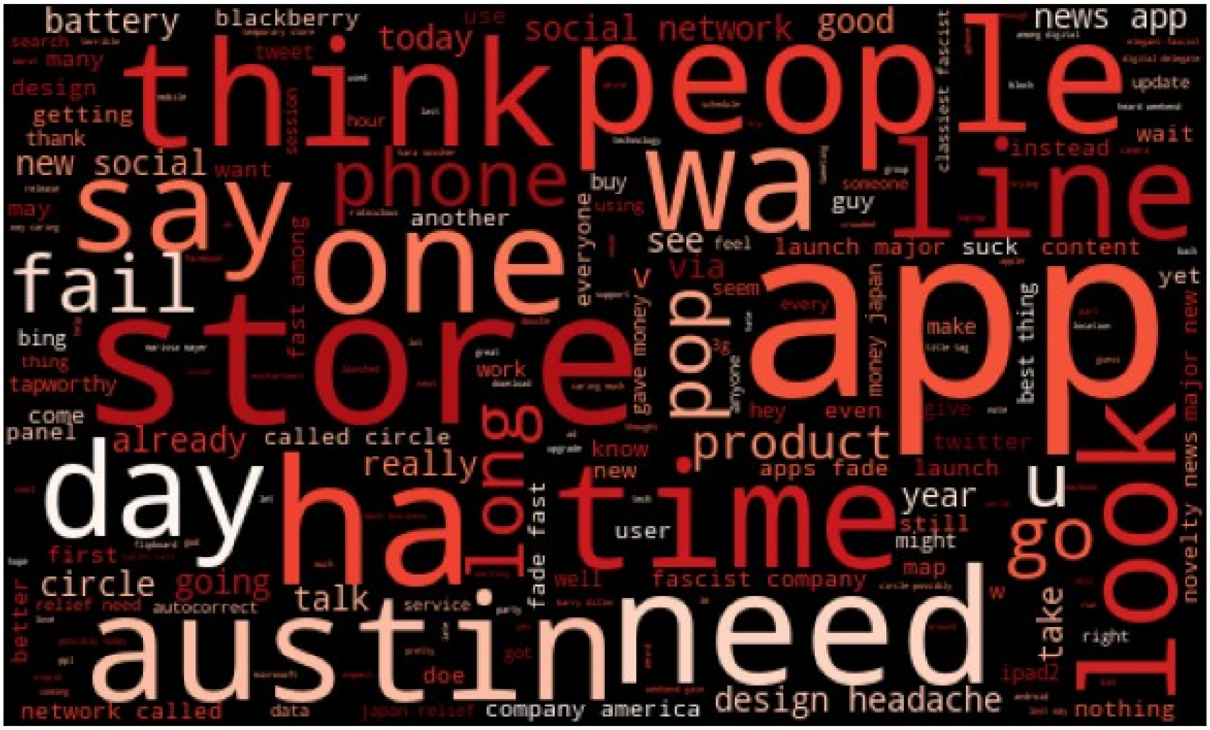
```
 ('2', 81),
 ('', 69),
 ('app', 60),
 ('store', 47),
 ('new', 43),
 ('like', 43),
 ('need', 35),
 ('ha', 31),
 ('circle', 29),
 ('design', 29),
 ('people', 29),
 ('social', 28),
 ('apps', 26),
 ('get', 25),
 ('wa', 24),
 ('austin', 23),
 ('think', 23),
 ('time', 23),
 ('launch', 22),
 ('one', 22),
 ('day', 21),
 ('today', 21),
 ('look', 21),
 ('line', 20),
 ('say', 20),
 ('android', 19),
 ('#ipad', 19),
 ('would', 19),
 ('network', 18),
 ('phone', 18),
 ('headache', 17),
 ('news', 17),
 ('go', 17),
 ('long', 17),
 ('product', 17),
 ("i've", 16),
 ("i'm", 16),
 ('battery', 16),
 ('user', 15),
 ('thing', 15),
 ('#apple', 15),
 ('good', 15),
 ('see', 15),
 ('much', 15),
 ('company', 15),
 ('america', 15)]
```

Apple, Google, iphone, ipad are common among the negative tweets. We can visualize this with a word cloud

```python
#generating word cloud for negative tweets
cloud_neg_with_company = generate_wordcloud(tokens_neg_list,
colormap='Reds',
                                            collocations=True)
```

Once again, we will remove the company names to get additional information

```python
# Removing company/product information from the tokens
tokens_neg_list = remove_stop_words(tokens_neg_list, stop_list=
stop_lst_no_comp)
# Generating the word cloud
cloud_neg_without_company = generate_wordcloud(tokens_neg_list,
colormap='Reds', collocations=True)
```



Most negative tweets were talking about stores, apps, austin, think, fail, and pop.

N-grams of Negative Reviews

Negative Bigrams and Trigrams

```
from nltk.collocations import *
bigrams_measures = nltk.collocations.BigramAssocMeasures()
trigrams_measures = nltk.collocations.TrigramAssocMeasures()

# initializing finders
finder_bi_neg = BigramCollocationFinder.from_words(tokens_neg_list)
finder_tri_neg = TrigramCollocationFinder.from_words(tokens_neg_list)

# Getting frequency information from finder
bigrams_neg_all =
finder_bi_neg.score_ngrams(bigrams_measures.raw_freq)
trigrams_neg_all =
finder_tri_neg.score_ngrams(trigrams_measures.raw_freq)

bigrams_neg_all[:30]
```

```
[(('design', 'headache'), 0.003249235474006116),
 (('new', 'social'), 0.0030581039755351682),
 (('social', 'network'), 0.0028669724770642203),
 (('company', 'america'), 0.0024847094801223),
 (('fascist', 'company'), 0.0022935779816513763),
 (('major', 'new'), 0.0022935779816513763),
```

```
 (('network', 'called'), 0.0021024464831804281),
 (('called', 'circle'), 0.0019113149847094801),
 (('launch', 'major'), 0.0019113149847094801),
 (('fade', 'fast'), 0.0017201834862385322),
 (('fast', 'among'), 0.0017201834862385322),
 (('news', 'apps'), 0.0017201834862385322),
 (('novelty', 'news'), 0.0017201834862385322),
 (('#japan', 'relief'), 0.0015290519877675841),
 (('2', 'money'), 0.0015290519877675841),
 (('best', 'thing'), 0.0015290519877675841),
 (('classiest', 'fascist'), 0.0015290519877675841),
 (('gave', '2'), 0.0015290519877675841),
 (("i've", 'heard'), 0.0015290519877675841),
 (('need', '2'), 0.0015290519877675841),
 (('relief', 'need'), 0.0015290519877675841),
 (('thing', "i've"), 0.0015290519877675841),
 (('among', 'digital'), 0.0013379204892966361),
 (('digital', 'delegate'), 0.0013379204892966361),
 (('kara', 'swisher'), 0.0013379204892966361),
 (('money', '#japan'), 0.0013379204892966361),
 (('pop-up', 'store'), 0.0013379204892966361),
 (('possibly', 'today'), 0.0013379204892966361),
 (('app', 'store'), 0.0011467889908256881),
 (('apps', 'fade'), 0.0011467889908256881)]
```

```
trigrams_neg_all[:30]
```

```
[(('new', 'social', 'network'), 0.0024847094801223241),
 (('major', 'new', 'social'), 0.0022935779816513763),
 (('fascist', 'company', 'america'), 0.0021024464831804281),
 (('social', 'network', 'called'), 0.0021024464831804281),
 (('launch', 'major', 'new'), 0.0019113149847094801),
 (('network', 'called', 'circle'), 0.0019113149847094801),
 (('fade', 'fast', 'among'), 0.0017201834862385322),
 (('#japan', 'relief', 'need'), 0.0015290519877675841),
 (('best', 'thing', "i've"), 0.0015290519877675841),
 (('classiest', 'fascist', 'company'), 0.0015290519877675841),
 (('gave', '2', 'money'), 0.0015290519877675841),
 (('relief', 'need', '2'), 0.0015290519877675841),
 (('thing', "i've", 'heard'), 0.0015290519877675841),
 (('2', 'money', '#japan'), 0.0013379204892966361),
 (('among', 'digital', 'delegate'), 0.0013379204892966361),
 (('fast', 'among', 'digital'), 0.0013379204892966361),
 (('money', '#japan', 'relief'), 0.0013379204892966361),
 (('apps', 'fade', 'fast'), 0.0011467889908256881),
 (('called', 'circle', 'possibly'), 0.0011467889908256881),
 (('circle', 'possibly', 'today'), 0.0011467889908256881),
 (('heard', 'weekend', 'gave'), 0.0011467889908256881),
 (("i've", 'heard', 'weekend'), 0.0011467889908256881),
 (('news', 'apps', 'fade'), 0.0011467889908256881),
```

```
 (('novelty', 'news', 'apps'), 0.0011467889908256881),
 (('weekend', 'gave', '2'), 0.0011467889908256881),
 (('caring', 'much', 'business'), 0.00095565749235474),
 (('lost', 'way', 'caring'), 0.00095565749235474),
 (('way', 'caring', 'much'), 0.00095565749235474),
 (('2011', 'novelty', 'news'), 0.0007645259938837921),
 (('alarm', 'circle', 'coming'), 0.0007645259938837921)]
```

The new social network circle is mentioned a lot in the negative Tweets, with other comments surrounding a company being referred to a "fascist", probably Google or Apple.

Tweets Related to Products/Brands

To analyze tweets related specifically to Google and Apple, we will engineer the company column by mapping the different values to either Google, Apple, or other brand.

```
df['Product/Brand'].unique()
```

```
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)
```

These will be converted to three categories: Apple, Google, and Unknown.

```
product_replacement_dict = {'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' }
df['Brand'] = df['Product/Brand'].map(product_replacement_dict)
df.head()
```

```
Tweet  \
0              .@wesley83 I have a 3G iPhone. After 3 hrs tweeting at
#RISE_Austin, it was dead!  I need to upgrade. Plugin stations at
#SXSW.
1  @jessedee Know about @fludapp ? Awesome iPad/iPhone app that you'll
likely appreciate for its design. Also, they're giving free Ts at
#SXSW
2
@swonderlin Can not wait for #iPad 2 also. They should sale them down
at #SXSW.
3                                                             @sxsw I
hope this year's festival isn't as crashy as this year's iPhone app.
#sxsw
4          @sxtxstate great stuff on Fri #SXSW: Marissa Mayer
```

```
(Google), Tim O'Reilly (tech books/conferences) &amp; Matt Mullenweg
(Wordpress)

        Product/Brand   Emotion   Brand
0              iPhone  Negative   Apple
1  iPad or iPhone App  Positive   Apple
2                iPad  Positive   Apple
3  iPad or iPhone App  Negative   Apple
4              Google  Positive  Google
```

```python
df['Brand'].unique()
```

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

```python
for brand in df['Brand'].unique():
    print("----Value Counts for {}----".format(brand))
    display(df[df['Brand'] == brand]['Emotion'].value_counts())
    display(df[df['Brand'] == brand]
['Emotion'].value_counts(normalize=True))
    print("\n")
```

```
----Value Counts for Apple----

Positive    1945
Negative     387
Neutral       65
Name: Emotion, dtype: int64

Positive    0.811431
Negative    0.161452
Neutral     0.027117
Name: Emotion, dtype: float64



----Value Counts for Google----

Positive    719
Negative    131
Neutral      26
Name: Emotion, dtype: int64

Positive    0.820776
Negative    0.149543
Neutral     0.029680
Name: Emotion, dtype: float64



----Value Counts for Unknown----
```

```
Neutral     5284
Positive     306
Negative      51
Name: Emotion, dtype: int64

Neutral     0.936713
Positive    0.054246
Negative    0.009041
Name: Emotion, dtype: float64
```

For both brands, positive reviews are more than negative ones

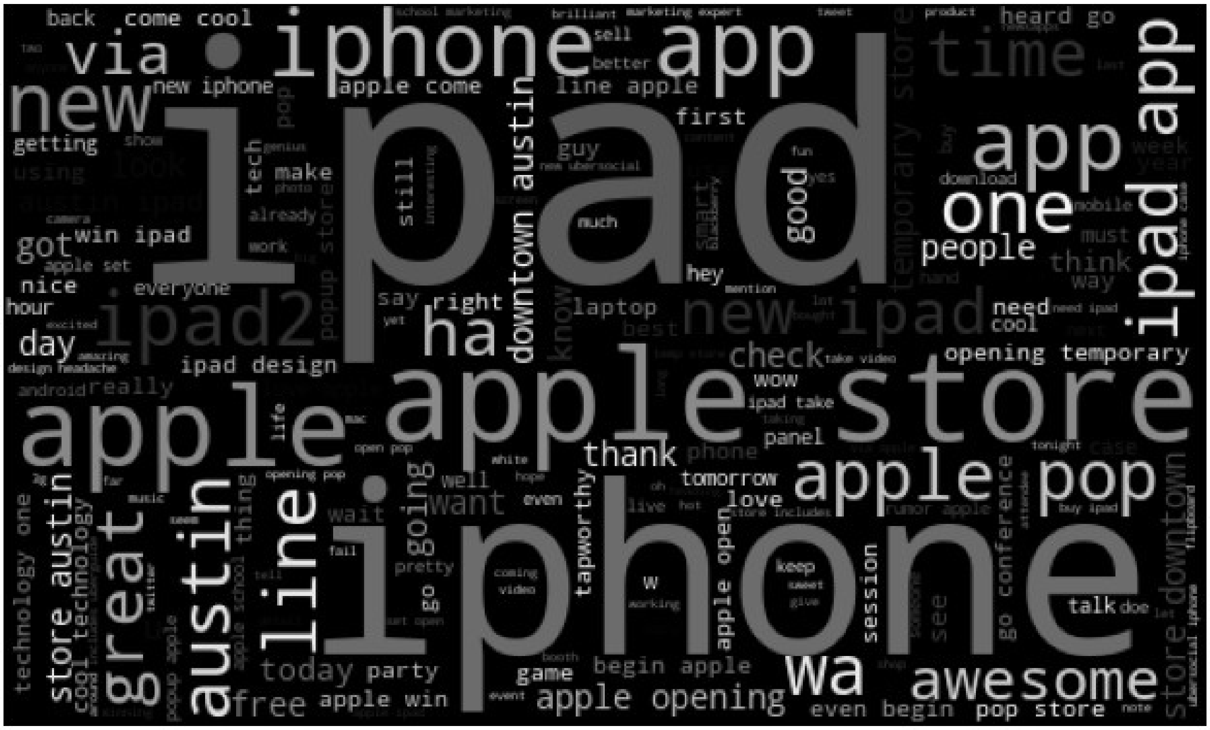
Now that we have only three categories, let's start with Apple

Tweets Related To Apple

```
df_apple = df[df["Brand"]== 'Apple']
corpus_for_apple = df_apple['Tweet'].to_list()

# tokenize tweets
tokens_apple = tokenize_tweets(corpus_for_apple)
# Lemmatize tweets
tokens_lem_apple = lemmatize_tokens(tokens_apple)
# Remove stop words and punctuation
tokens_apple_list = remove_stop_words(tokens_lem_apple, stop_list=
stop_list)
```

A WordCloud with Product Information

```
generate_wordcloud(tokens_apple_list, colormap="Greys",
collocations=True);
```



Word Cloud without Product information

We will add some other stop words to apple's list like the ipad 2 and Austin.

```python
apple_stop_words_no_comp = stop_lst_no_comp + ['ipad 2','store',
'app', 'austin','apps']
# ['iphone', 'ipad', 'iphone app', 'google', 'android', 'apple',
#                                  '#apple', '#google', '#ipad',
'#iphone']
tokens_apple_list = remove_stop_words(tokens_apple_list,
stop_list=apple_stop_words_no_comp)
generate_wordcloud(tokens_apple_list, colormap='Greys',
collocations=True);
```

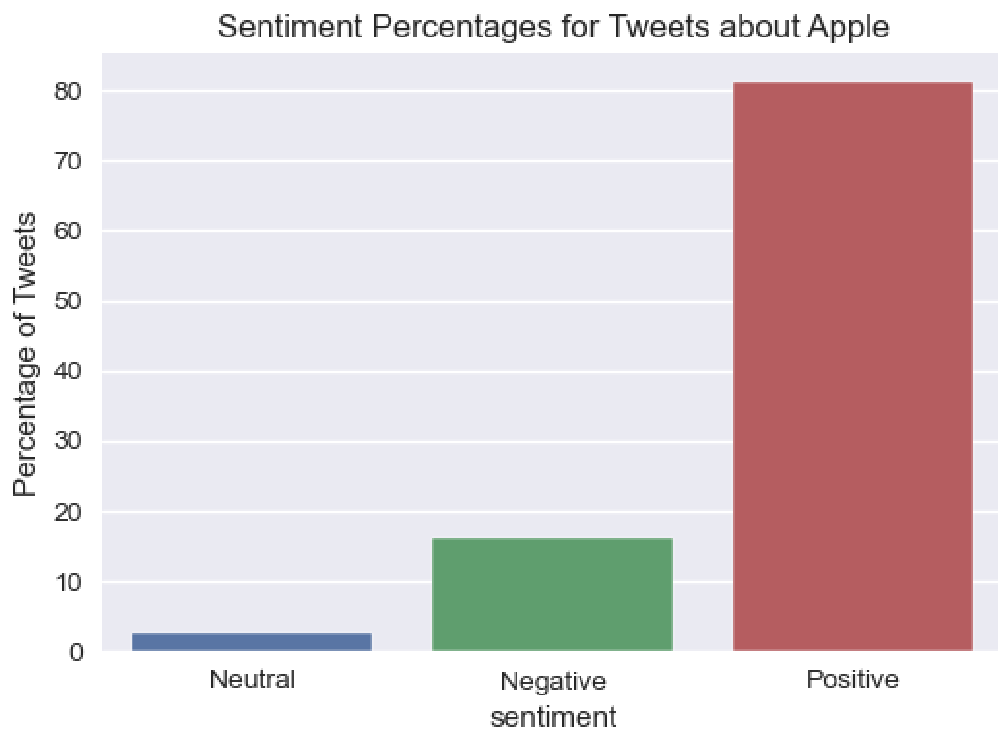
Percentage of Positive, Neutral, and Negative Sentiment

Visualizing the percentage of tweets that had positive, negative, or neutral sentiments is a good way of gauging the overall sentiment towards the company.

```
df_apple_sentiments =
pd.DataFrame(df_apple['Emotion'].value_counts(normalize=True)).reset_i
ndex()
df_apple_sentiments.columns = ['Emotion', 'Percentage']
display(df_apple_sentiments)
df_apple_sentiments.sort_values('Percentage', ascending=True,
inplace=True)
```

	Emotion	Percentage
0	Positive	0.811431
1	Negative	0.161452
2	Neutral	0.027117

```
plt.figure(figsize=(6,4))
ax = sns.barplot(x = df_apple_sentiments['Emotion'], y
=df_apple_sentiments['Percentage']*100)
ax.set_xlabel('sentiment')
ax.set_ylabel('Percentage of Tweets')
ax.set_title('Sentiment Percentages for Tweets about Apple');
```



Tweets Related To Google

```
df_google = df[df["Brand"]== 'Google']
corpus_for_google = df_google['Tweet'].to_list()

# tokenize tweets
tokens_google = tokenize_tweets(corpus_for_google)
# Lemmatize tweets
tokens_lem_google = lemmatize_tokens(tokens_google)
# Remove stop words and punctuation
tokens_google_list = remove_stop_words(tokens_lem_google, stop_list=
stop_list)
```

A WordCloud with Product Information

```
generate_wordcloud(tokens_google_list, colormap="Blues",
collocations=True);
```

Word Cloud without Product information

We will add some other stop words to Google's list.

```
google_stop_words_no_comp = stop_lst_no_comp + ['app','apps',
'google','called','android','app','apps']
tokens_google_list = remove_stop_words(tokens_google_list,
stop_list=google_stop_words_no_comp)
generate_wordcloud(tokens_google_list, colormap='Blues',
collocations=True);
```

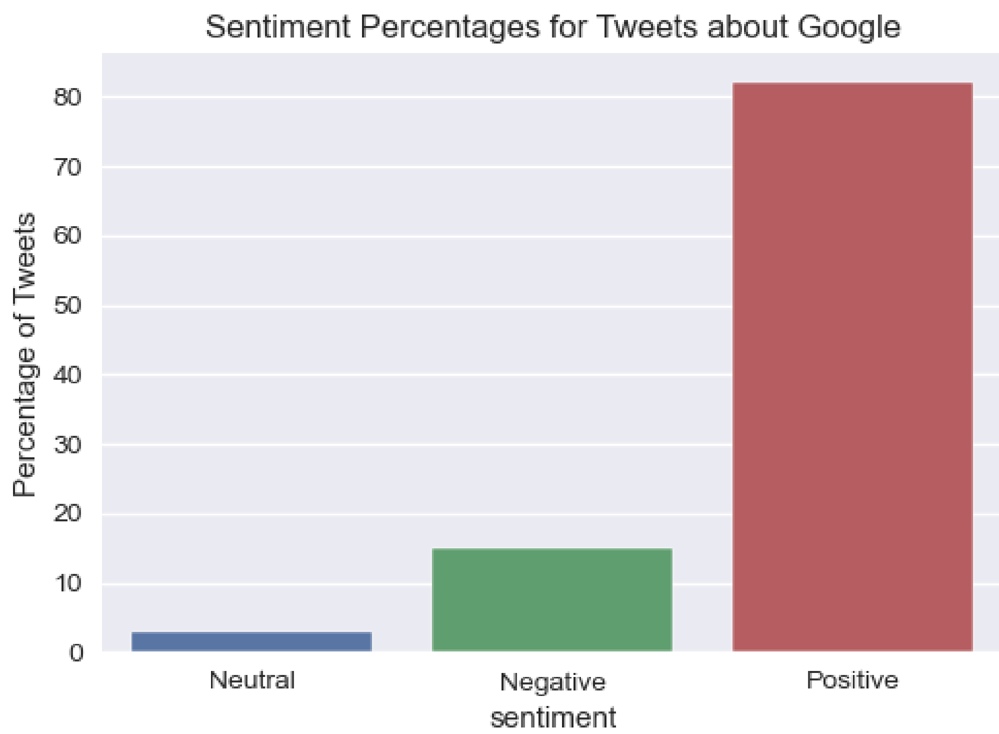
Percentage of Positive, Neutral, and Negative Sentiment

Visualizing the percentage of tweets that had positive, negative, or neutral sentiments is a good way of gauging the overall sentiment towards the company.

```
df_google_sentiments =
pd.DataFrame(df_google['Emotion'].value_counts(normalize=True)).reset_
index()
df_google_sentiments.columns = ['Emotion', 'Percentage']
display(df_google_sentiments)
df_google_sentiments.sort_values('Percentage', ascending=True,
inplace=True)
```

	Emotion	Percentage
0	Positive	0.820776
1	Negative	0.149543
2	Neutral	0.029680

```
plt.figure(figsize=(6,4))
ax = sns.barplot(x = df_google_sentiments['Emotion'], y
=df_google_sentiments['Percentage']*100)
ax.set_xlabel('sentiment')
ax.set_ylabel('Percentage of Tweets')
ax.set_title('Sentiment Percentages for Tweets about Google');
```



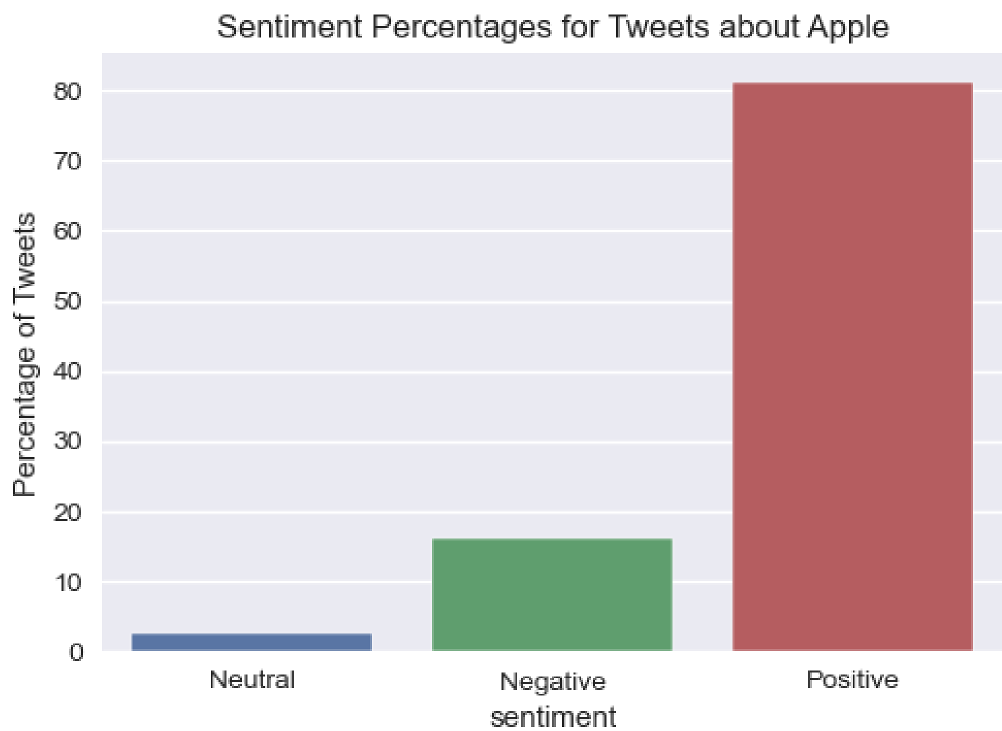
EDA CONCLUSIONS AND RECOMMENDATIONS

Conclusions

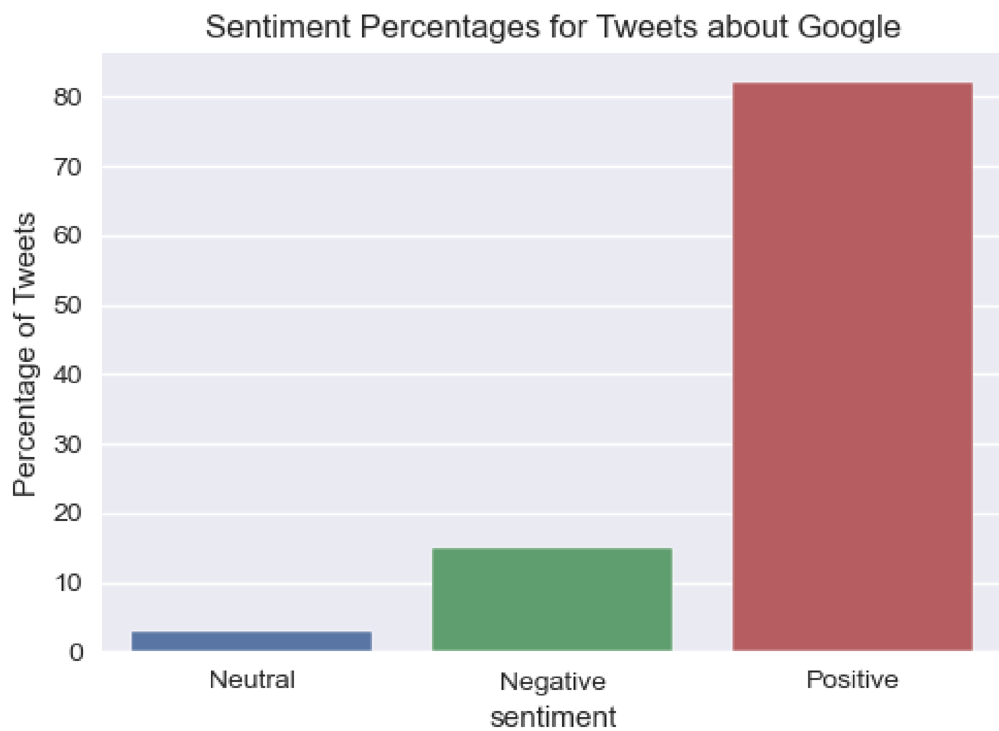
1. Determine how Apple is perceived as a company based on the tweets presented during the SXSW Conference, in comparison to Google which is one of their main competitors.

During the SXSW conference, 81.1% of all tweets related to Apple were positive compared to Google's 82%

```
plt.figure(figsize=(6,4))
ax = sns.barplot(x = df_apple_sentiments['Emotion'], y
=df_apple_sentiments['Percentage']*100)
ax.set_xlabel('sentiment')
ax.set_ylabel('Percentage of Tweets')
ax.set_title('Sentiment Percentages for Tweets about Apple');
```



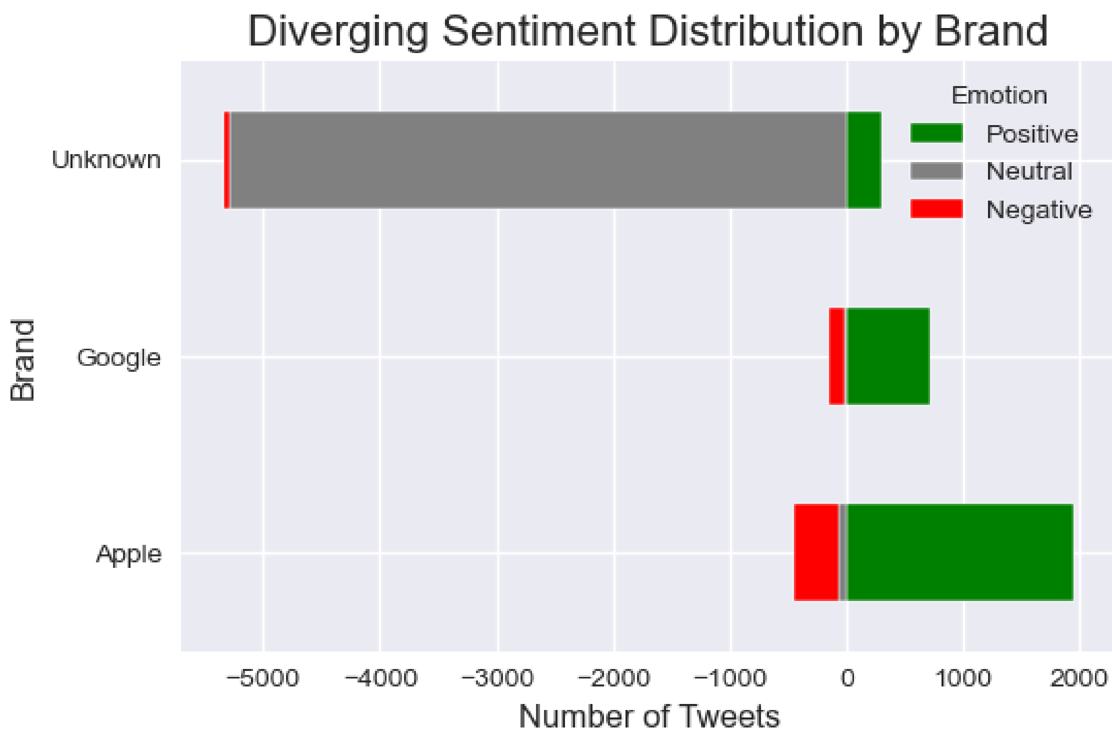

```
plt.figure(figsize=(6,4))
ax = sns.barplot(x = df_google_sentiments['Emotion'], y
=df_google_sentiments['Percentage']*100)
ax.set_xlabel('sentiment')
ax.set_ylabel('Percentage of Tweets')
ax.set_title('Sentiment Percentages for Tweets about Google');
```



This suggests that both companies and their products and services are mostly perceived positively.

Diverging Sentiment Distribution for Both Brands

```
df_grouped = df.groupby(['Brand',
'Emotion']).size().unstack(fill_value=0)

# df

# df_grouped = df_filtered.groupby(['brand_mapped',
'emotion']).size().unstack(fill_value=0)

df_grouped['Positive'] = df_grouped['Positive'] * 1
df_grouped['Neutral'] = df_grouped['Neutral'] * -1
df_grouped['Negative'] = df_grouped['Negative'] * -1

df_grouped[['Positive', 'Neutral', 'Negative']].plot(kind='barh',
stacked=True, color=['green', 'gray', 'red'], figsize=(6, 4))

plt.title('Diverging Sentiment Distribution by Brand', fontsize=16)
plt.xlabel('Number of Tweets', fontsize=12)
plt.ylabel('Brand', fontsize=12)

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



2. Determine consumers' react to Apple's SXSW announcement (how are their new products perceived, and how do people react to new announcements?)

Apple - Positives:

- Positive tweets about Apple suggest that the temporary pop-up store in downtown Austin was generally received well.
- The iPad 2 was frequently discussed positively, with people excited about its launch.

Apple - Negatives:

The iPhone's battery is frequently discussed in negative tweets.

- Design of the iPad was referred to as a "design headache."
- There are several references to Apple as a "fascist company."
- Several apps are referred to as "battery killer" and the design of the News app seems to have not been received positively.

Recommendations

Based on the insights provided above, our recommendations for Apple are:

- Users are not pleased with the iPhone's batter performance, meaning that improvements should be made.
- The iPad's design should integrate more of the public's opinion.

PREPARATION FOR MODELING

```
# Converts emotion data into numbers to use for modeling
df['Emotion'].replace({'Positive': 2, 'Negative': 1, 'Neutral': 0},
inplace = True)

df.head()
```

```
Tweet  \
0               .@wesley83 I have a 3G iPhone. After 3 hrs tweeting at
#RISE_Austin, it was dead!  I need to upgrade. Plugin stations at
#SXSW.
1  @jessedee Know about @fludapp ? Awesome iPad/iPhone app that you'll
likely appreciate for its design. Also, they're giving free Ts at
#SXSW
2
@swonderlin Can not wait for #iPad 2 also. They should sale them down
at #SXSW.
3                                                            @sxsw I
hope this year's festival isn't as crashy as this year's iPhone app.
#sxsw
4           @sxtxstate great stuff on Fri #SXSW: Marissa Mayer
(Google), Tim O'Reilly (tech books/conferences) &amp; Matt Mullenweg
(Wordpress)

        Product/Brand  Emotion   Brand
0              iPhone        1   Apple
1  iPad or iPhone App        2   Apple
2                iPad        2   Apple
3  iPad or iPhone App        1   Apple
4              Google        2  Google
```

Train Test Split

To further explore the data and avoid data leakage, let's split the data into train and test sets and hold out the latter for final evaluation.

```
from sklearn.model_selection import train_test_split

X = df['Tweet']
y = df['Emotion']

X.head()
```

```
0                .@wesley83 I have a 3G iPhone. After 3 hrs tweeting
at #RISE_Austin, it was dead!  I need to upgrade. Plugin stations at
#SXSW.
1     @jessedee Know about @fludapp ? Awesome iPad/iPhone app that
you'll likely appreciate for its design. Also, they're giving free Ts
```

```
at #SXSW
2
@swonderlin Can not wait for #iPad 2 also. They should sale them down
at #SXSW.
3                                                              @sxsw I
hope this year's festival isn't as crashy as this year's iPhone app.
#sxsw
4            @sxtxstate great stuff on Fri #SXSW: Marissa Mayer
(Google), Tim O'Reilly (tech books/conferences) &amp; Matt Mullenweg
(Wordpress)
Name: Tweet, dtype: object
```

```
import re

def preprocess(X):
    """Takes in string X and processes it to tokens"""
    # Lowercases everything
    X = X.lower()

    # Removes all mentions and all punctuations
    subpattern = f'(@[A-z0-9]*)|
[{string.punctuation[1:].replace("@","")}]*'
    replacer = re.compile(subpattern)
    X = replacer.sub('',X)

    #Tokenizes the text. wrote it this way so that it also pulls words
with numbers
    tokenpattern = '([0-9]*[a-z]+[0-9]*[a-z]*)'
    tokenizer = re.compile(tokenpattern)
    X = tokenizer.findall(X)

    #Removes stopwords
    # Remove words related to the conference that appear across all
sentiments
    # # and terms specific to the twitter platform
    stopwords_list = stopwords.words('english') + ['sxsw', 'sxswi',
'link', 'quot', 'rt', 'amp', 'mention', 'apple', 'google', 'iphone',
'ipad',
        'ipad2', 'austin', 'today', 'quotroutearoundquot',
'rtmention', 'store', 'doesnt', 'theyll']
    X = [word for word in X if word not in stopwords_list]

    #lemmatizes
    lemmatizer = WordNetLemmatizer()
    X = [lemmatizer.lemmatize(word) for word in X]
    X = ' '.join(X)

    return X
```

```
#Removing punctuation, mentions, stopwords, and lemmatizing the text
X = X.apply(lambda x: preprocess(x))

X.head()

0                                  3g hr tweeting riseaustin dead need
upgrade plugin station
1        know awesome ipadiphone app youll likely appreciate design
also theyre giving free t
2
wait also sale
3                                                      hope year
festival isnt crashy year app
4    great stuff fri marissa mayer tim oreilly tech booksconferences
matt mullenweg wordpress
Name: Tweet, dtype: object

y.head()

0    1
1    2
2    2
3    1
4    2
Name: Emotion, dtype: int64

# We are using the default test size of 0.25
X_train, X_test, y_train, y_test = train_test_split(X, y,
random_state=42)

X_train.head()

9055                                                   give away yet
4204    reallllllly need upgrade phone haha apps probably need use
1278     know u u selling weve never talked hate product check heyo
6333                               first blog post grand opening popup
5516      join u drink tonight 7pm fado irish pub 4th wed love meet
Name: Tweet, dtype: object

X_train.shape, X_test.shape

((6685,), (2229,))

y_test.shape, y_train.shape

((2229,), (6685,))

# storing for retrieval in the Grid Search Notebook
%store X_train

Stored 'X_train' (Series)
```

```
# Storing for retrieval in the Grid Search Notebook
%store X_test

Stored 'X_test' (Series)

# Storing for retrieval in the Grid Search Notebook
%store y_train

Stored 'y_train' (Series)

# Storing for retrieval in the Grid Search Notebook
%store y_test

Stored 'y_test' (Series)
```

MODELING

Baseline Model- Logistic Regression

```
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report, roc_auc_score, roc_curve, auc
from sklearn.feature_extraction.text import CountVectorizer

cv = CountVectorizer(stop_words='english')

baseline_model = LogisticRegression(max_iter= 1000, random_state= 42)

# Build a pipeline using the CountVectorizer and Logistic Regression
CV
baseline = Pipeline(steps=[('vectorizer', cv), ('baseline',
baseline_model)])
baseline.fit(X_train, y_train)

baseline_pred = baseline.predict(X_test)


train_accuracy_score =
accuracy_score(y_train,baseline.predict(X_train))
test_accuracy_score = accuracy_score(y_test, baseline_pred)

print("Train Accuracy Score:", train_accuracy_score)
print("Test Accuracy Score:", test_accuracy_score)

Train Accuracy Score: 0.9044128646222888
Test Accuracy Score: 0.6828174069089278
```

Training and Test Data Classification Report and Confusion Matrix

```
print("--Training Data--")
display(confusion_matrix(y_train, baseline.predict(X_train)))
print("\n"+ classification_report(y_train, baseline.predict(X_train)))
print("--Test--")
display(confusion_matrix(y_test, baseline.predict(X_test)))
print("\n"+ classification_report(y_test, baseline.predict(X_test)))
```

```
--Training Data--

array([[3919,    4,  117],
       [  85,  313,   16],
       [ 415,    2, 1814]], dtype=int64)


              precision    recall  f1-score   support

           0       0.89      0.97      0.93      4040
           1       0.98      0.76      0.85       414
           2       0.93      0.81      0.87      2231

    accuracy                           0.90      6685
   macro avg       0.93      0.85      0.88      6685
weighted avg       0.91      0.90      0.90      6685

--Test--

array([[1113,   19,  203],
       [  99,   33,   23],
       [ 354,    9,  376]], dtype=int64)


              precision    recall  f1-score   support

           0       0.71      0.83      0.77      1335
           1       0.54      0.21      0.31       155
           2       0.62      0.51      0.56       739

    accuracy                           0.68      2229
   macro avg       0.63      0.52      0.54      2229
weighted avg       0.67      0.68      0.67      2229
```

Term Frequency-Inverse Document Frequency measures the frequency of a word occurring in a document, down-weighted by the number of documents in which it occurs.

Change count vectorizer to the Tfidf vectorizer:

```
from sklearn.feature_extraction.text import TfidfVectorizer
tfidf = TfidfVectorizer(stop_words='english', lowercase=False,
ngram_range=(1,2))
```

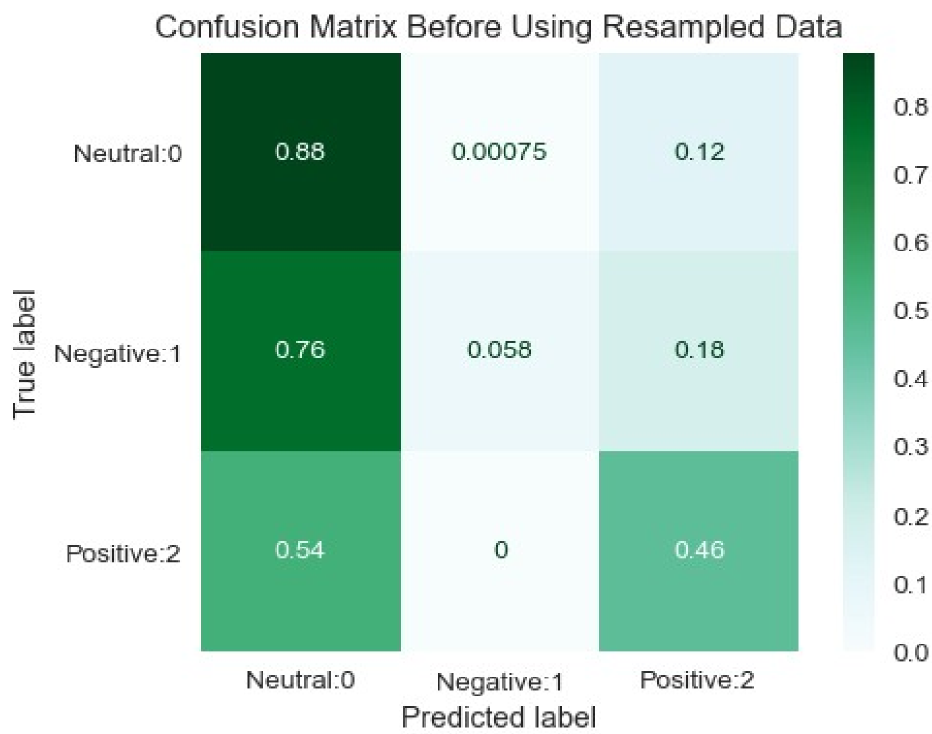
```
# Build a pipeline using the TF-IDF Vectorizer and Logistic Regression
tfidfpipe = Pipeline(steps=[('tfidf', tfidf), ('baseline',
baseline_model)])
tfidfpipe.fit(X_train, y_train)

tfidf_pred = tfidfpipe.predict(X_test)


train_accuracy_score = accuracy_score(y_train,
tfidfpipe.predict(X_train))
test_accuracy_score = accuracy_score(y_test, tfidf_pred)

print("Train Accuracy Score:", train_accuracy_score)
print("Test Accuracy Score:", test_accuracy_score)
```

```
Train Accuracy Score: 0.8604338070306656
Test Accuracy Score: 0.6819201435621355
```

Training and Test Data Classification Report and Confusion Matrix

```
from sklearn.metrics import ConfusionMatrixDisplay

print("--Training Data--")
print("\n"+ classification_report(y_train,
tfidfpipe.predict(X_train)))
print("--Test Data--")

fig, ax = plt.subplots(figsize= (6,4))
ConfusionMatrixDisplay.from_predictions(y_test,
tfidfpipe.predict(X_test), ax=ax, display_labels=['Neutral:0',
'Negative:1', 'Positive:2'], normalize='true', cmap='BuGn')
plt.title("Confusion Matrix Before Using Resampled Data")
plt.grid(False)
plt.show()
print("\n"+ classification_report(y_test, tfidfpipe.predict(X_test)));
```

```
--Training Data--

              precision    recall  f1-score   support

           0       0.83      0.99      0.90      4040
           1       0.98      0.13      0.22       414
           2       0.95      0.77      0.85      2231

    accuracy                           0.86      6685
   macro avg       0.92      0.63      0.66      6685
weighted avg       0.88      0.86      0.84      6685

--Test Data--
```




```
              precision    recall  f1-score   support

           0       0.69      0.88      0.77      1335
           1       0.90      0.06      0.11       155
           2       0.64      0.46      0.54       739

    accuracy                           0.68      2229
   macro avg       0.74      0.47      0.47      2229
weighted avg       0.69      0.68      0.65      2229
```

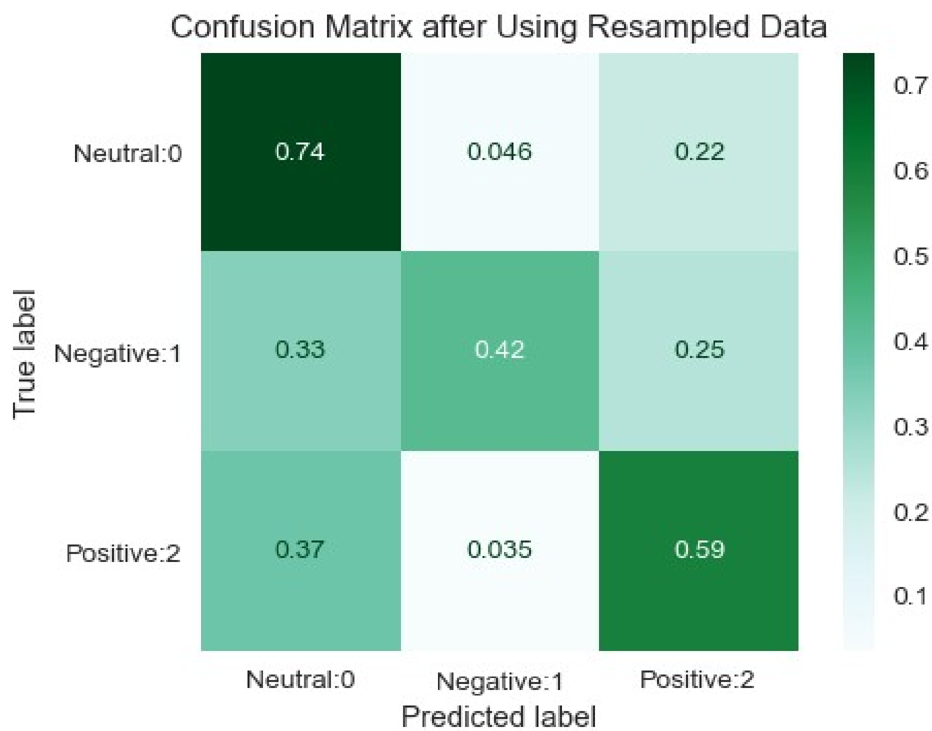
TF-IDF does better as it reduces the overfitting. We will use it moving forward

Dealing With Class Imbalance Using Random Oversampling

To balance the class distribution, random oversampling is done by randomly duplicating examples of the minority classes in the training set.

```
from imblearn.over_sampling import RandomOverSampler
oversample = RandomOverSampler(sampling_strategy='not majority',
random_state=112221)

processed = pd.DataFrame(X_train)
X_train_res, y_train_res = oversample.fit_resample(processed, y_train)

X_train_res.shape
```

```
(12120, 1)

y_train.shape

(6685,)

# Storing for retrieval in the Grid Search Notebook
%store X_train_res

Stored 'X_train_res' (DataFrame)

# Storing for retrieval in the Grid Search Notebook
%store y_train_res

Stored 'y_train_res' (Series)

X_train_res = X_train_res.squeeze()

tfidfpipe.fit(X_train_res, y_train_res)


resampled = tfidfpipe.predict(X_test)
accuracy_score(y_test, resampled)

0.6662180349932705

fig, ax = plt.subplots(figsize=(6,4))

# Plot the confusion matrix of the model using the resampled data
ConfusionMatrixDisplay.from_predictions(y_test, resampled,
display_labels=['Neutral:0', 'Negative:1', 'Positive:2'], ax=ax,
normalize='true', cmap='BuGn')
plt.title("Confusion Matrix after Using Resampled Data")
plt.grid(False)
plt.show()
```




```
from sklearn.pipeline import Pipeline
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score


# Create a function to run the classification models
def run_model(models, model_type, cmap):
    '''
    Fits the model on train set, and returns the confusion matrix and
accuracy scores.
    '''
    metric_table = pd.DataFrame(columns=['Model', 'CV Score', 'Train
Accuracy', 'Test Accuracy', 'Type'])

    count = 0
    for name, model in models.items():
        print(f'Running... {name} Model')
        pipeline = Pipeline(steps=[('tfidf', tfidf), ('classifier',
model['classifier'])])
        pipeline.fit(X_train_res, y_train_res)

        cross_val = cross_val_score(pipeline, X_train_res,
y_train_res, cv=3)
        cross_val_mean = round(np.mean(cross_val), 4)

        y_pred = pipeline.predict(X_test)
        y_train_pred = pipeline.predict(X_train)
```

```
        train_accuracy = accuracy_score(y_train, y_train_pred)
        test_accuracy = accuracy_score(y_test, y_pred)

        metric_table = metric_table.append({'Model': name,
                                            'CV Score':
cross_val_mean,
                                            'Train Accuracy':
round(train_accuracy,4),
                                            'Test Accuracy':
round(test_accuracy, 4),
                                            'Type': model_type},
ignore_index=True)



        print(f'Cross Validation Score: {metric_table.iloc[-1,1]}')
        print(f'Train Accuracy Score: {metric_table.iloc[-1,2]}')
        print(f'Test Accuracy Score: {metric_table.iloc[-1,3]}\n')

        print("Classification Report:""\n",
classification_report(y_test, y_pred))



        fig, ax = plt.subplots(ncols=2, figsize=(12, 5))

        ConfusionMatrixDisplay.from_predictions(y_test,
pipeline.predict(X_test), display_labels=['Neutral:0', 'Negative:1',
'Positive:2'],
                                                ax=ax[0],
normalize='true', cmap='BuGn')

        ax[0].grid(False)



        pred_prob = pipeline.predict_proba(X_test)
        # roc curve
        n_class = 3
        fpr={}
        tpr={}
        thresh={}
        for i in range(n_class):
            fpr[i], tpr[i], thresh[i] = roc_curve(y_test,
pred_prob[:,i], pos_label=i)

        ax[1].plot(fpr[0], tpr[0], linestyle='--',color='red',
label='Negative vs Rest')
        ax[1].plot(fpr[1], tpr[1], linestyle='--',color='blue',
label='Neutral vs Rest')
```

```
        ax[1].plot(fpr[2], tpr[2], linestyle='--',color='green',
label='Positive vs Rest')
        ax[1].set_title('Multiclass ROC curve')
        ax[1].set_xlabel('False Positive Rate')
        ax[1].set_ylabel('True Positive rate')
        ax[1].legend(loc='best')

        #Plotting the 50-50 guessing plot for reference
        ax[1].plot([0,1], [0,1], ls='--', color='orange')

        plt.show()

    count += 1

    return metric_table
```

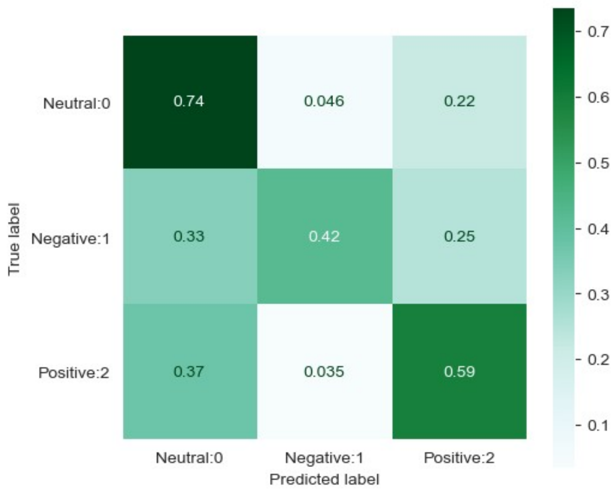
```
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,
ExtraTreesClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.linear_model import SGDClassifier

# Default parameters
default_models = {'LogisticRegression': {'classifier':
LogisticRegression(max_iter=1000, random_state=42)},
                  'MultinomialNB': {'classifier': MultinomialNB()},
                  'DecisionTree': {'classifier':
DecisionTreeClassifier(random_state= 42)},
                  'GradientBoost': {'classifier':
GradientBoostingClassifier(random_state=42)},
                  'VectorClass': {'classifier': SVC(random_state=42,
probability=True)},
                  'SGDClassifier': {'classifier':
SGDClassifier(random_state=42, loss='log_loss')}}

# Store for retrieval at grid search notebook
%store default_models
```

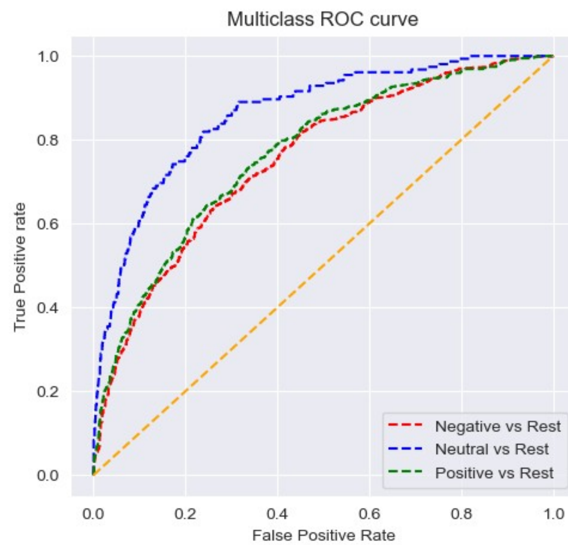
```
Stored 'default_models' (dict)
```

```
default_metrics = run_model(default_models, 'Default', 'Blues')
default_metrics
```

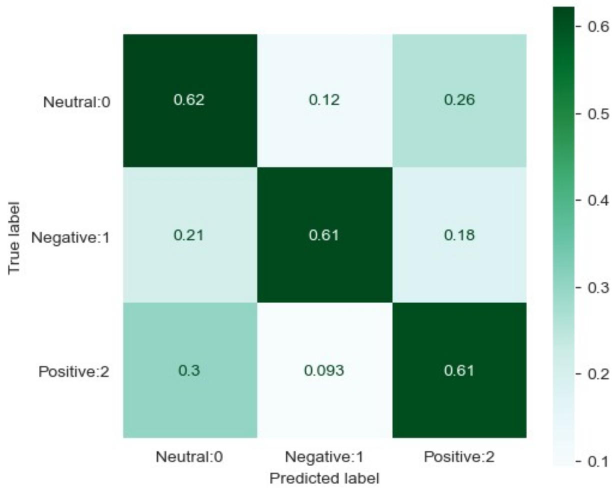
```
Running... LogisticRegression Model
Cross Validation Score: 0.832
Train Accuracy Score: 0.9282
Test Accuracy Score: 0.6662

Classification Report:
```

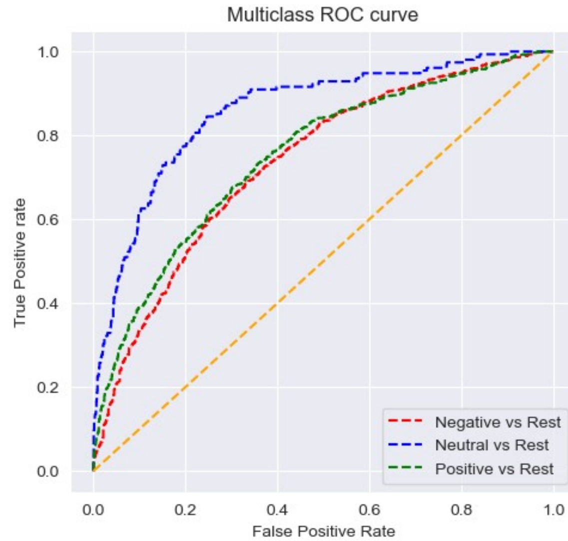
```
              precision    recall  f1-score   support

           0       0.75      0.74      0.74      1335
           1       0.42      0.42      0.42       155
           2       0.57      0.59      0.58       739

    accuracy                           0.67      2229
   macro avg       0.58      0.58      0.58      2229
weighted avg       0.67      0.67      0.67      2229
```



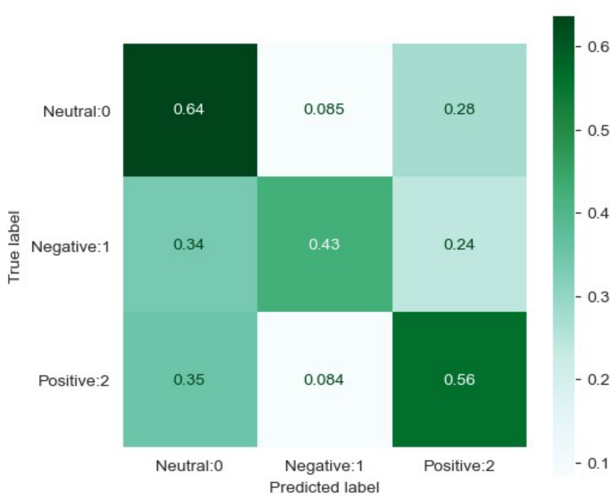


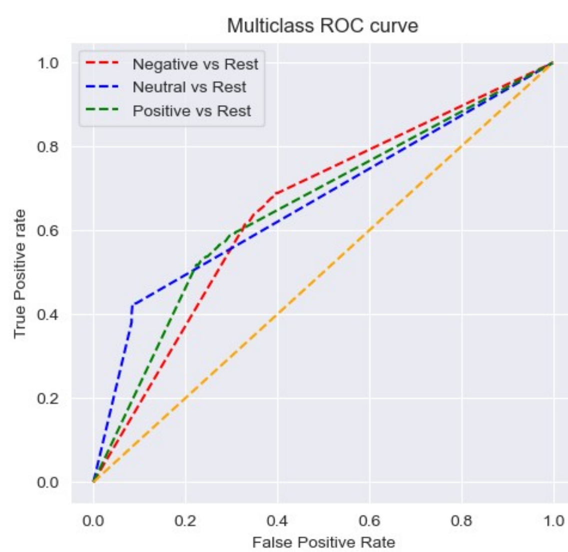

```
Running... MultinomialNB Model
Cross Validation Score: 0.7932
Train Accuracy Score: 0.9004
Test Accuracy Score: 0.6178

Classification Report:
              precision    recall  f1-score   support

           0       0.77      0.62      0.69      1335
           1       0.30      0.61      0.40       155
           2       0.55      0.61      0.58       739

    accuracy                           0.62      2229
   macro avg       0.54      0.61      0.55      2229
weighted avg       0.66      0.62      0.63      2229
```



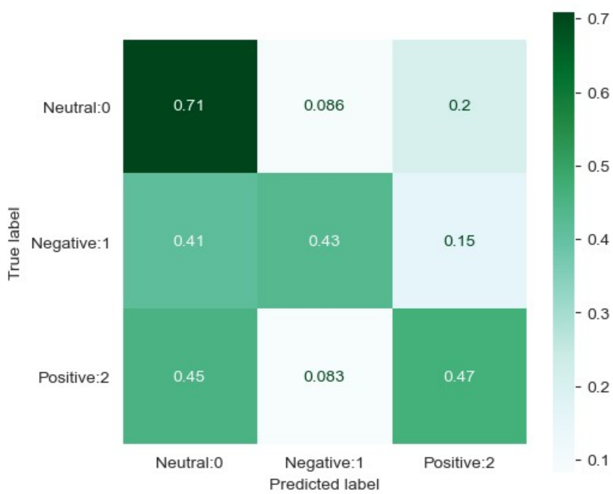


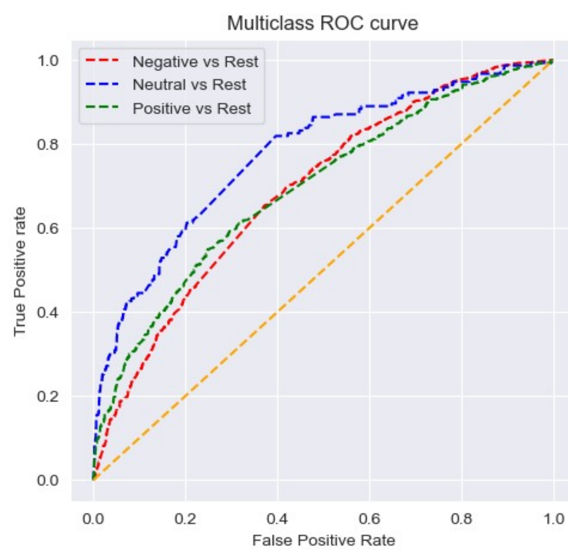

```
Running... DecisionTree Model
Cross Validation Score: 0.8083
Train Accuracy Score: 0.958
Test Accuracy Score: 0.5989

Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.64      0.68      1335
           1       0.27      0.43      0.33       155
           2       0.51      0.56      0.53       739

    accuracy                           0.60      2229
   macro avg       0.50      0.54      0.52      2229
weighted avg       0.63      0.60      0.61      2229
```





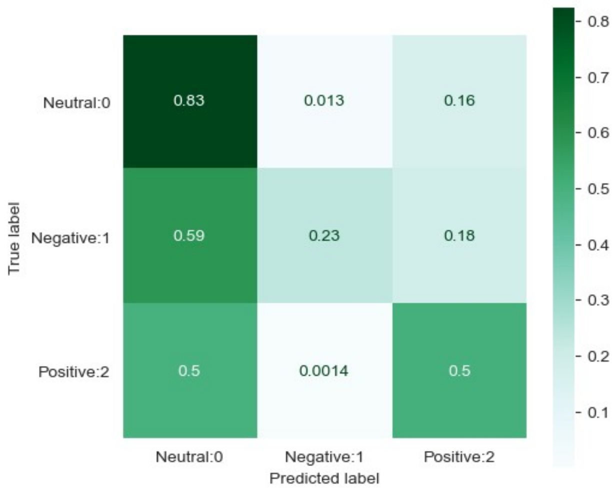
```
Running... GradientBoost Model
Cross Validation Score: 0.6453
Train Accuracy Score: 0.7225
Test Accuracy Score: 0.6101

Classification Report:
              precision    recall  f1-score   support

           0       0.70      0.71      0.71      1335
           1       0.28      0.43      0.34       155
           2       0.54      0.47      0.50       739

    accuracy                           0.61      2229
   macro avg       0.51      0.54      0.51      2229
weighted avg       0.62      0.61      0.61      2229
```

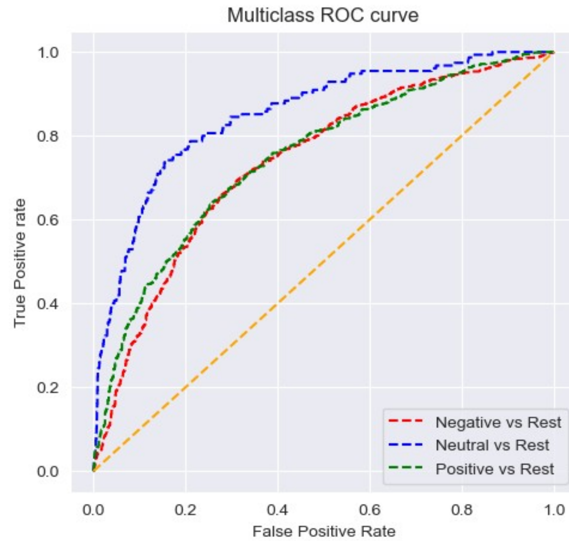




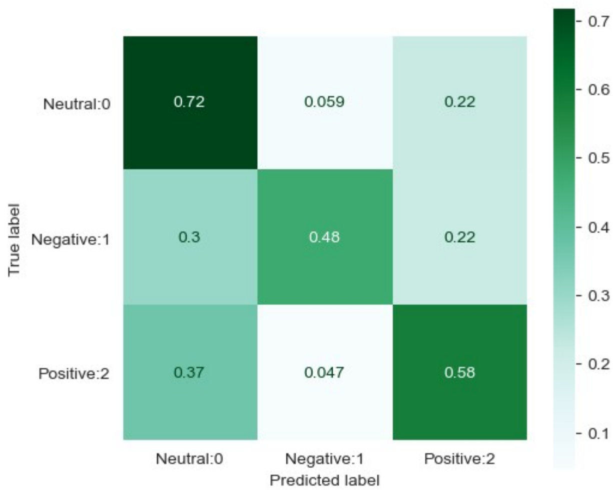

```
Running... VectorClass Model
Cross Validation Score: 0.8624
Train Accuracy Score: 0.9478
Test Accuracy Score: 0.6774

Classification Report:
              precision    recall  f1-score   support

           0       0.71      0.83      0.76      1335
           1       0.65      0.23      0.34       155
           2       0.61      0.50      0.55       739

    accuracy                           0.68      2229
   macro avg       0.66      0.52      0.55      2229
```

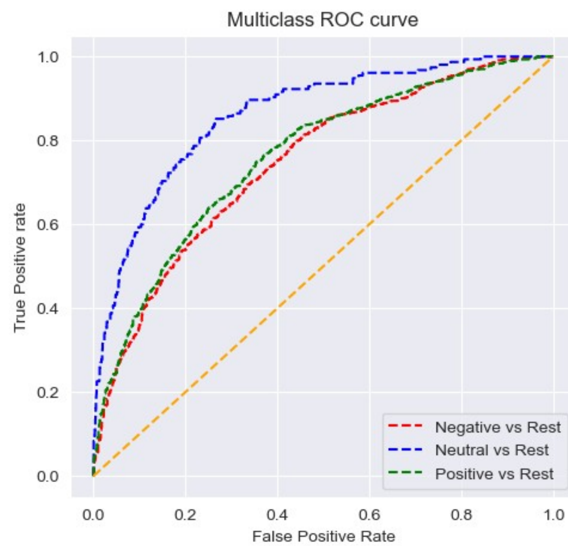
```
weighted avg       0.67      0.68      0.66      2229
```






```
Running... SGDClassifier Model
Cross Validation Score: 0.8258
Train Accuracy Score: 0.9053
Test Accuracy Score: 0.6577

Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.72      0.73      1335
           1       0.39      0.48      0.43       155
           2       0.57      0.58      0.58       739

    accuracy                           0.66      2229
   macro avg       0.57      0.59      0.58      2229
weighted avg       0.66      0.66      0.66      2229
```






```
                      Model  CV Score  Train Accuracy  Test Accuracy
Type
0  LogisticRegression    0.8320          0.9282         0.6662
Default
1       MultinomialNB    0.7932          0.9004         0.6178
Default
2        DecisionTree    0.8083          0.9580         0.5989
Default
3       GradientBoost    0.6453          0.7225         0.6101
Default
4         VectorClass    0.8624          0.9478         0.6774
Default
5       SGDClassifier    0.8258          0.9053         0.6577
Default
```

TUNING ALL THE MODELS

Model tuning was done in the Grid Search CV notebook.

Implementing Hyperparameter Tuning

```
def optimize_model(models, classifier, classifier_name, params):
    '''
    Uses optimal parameters from grid search to tune model's
hyperparameters.
    '''
    best_params = {}

    for param, values in params.items():
        parameter = param.replace('classifier__', '')
        best_params[parameter] = values
```

```
    models[classifier_name]['classifier'] = classifier(**best_params)

tuned_models = default_models.copy()
```

Logistic Regression

```
# Retrieving from the Grid Search Notebook
%store -r lr_best_params

optimize_model(tuned_models, LogisticRegression, 'LogisticRegression',
lr_best_params)
```

Multinomial Naive Bayes

```
# Retrieving from the Grid Search Notebook
%store -r mn_best_params

optimize_model(tuned_models, MultinomialNB, 'MultinomialNB',
mn_best_params)
```

Decision Tree

```
# Retrieving from the Grid Search Notebook
%store -r dt_best_params

optimize_model(tuned_models, DecisionTreeClassifier, 'DecisionTree',
dt_best_params)
```

GradientBoost

```
# Retrieving from the Grid Search Notebook
%store -r gb_best_params


optimize_model(tuned_models, GradientBoostingClassifier,
'GradientBoost', gb_best_params)
```

Vector Class

```
# Retrieving from the Grid Search Notebook
%store -r svc_best_params


optimize_model(tuned_models, SVC, 'VectorClass', svc_best_params)
```

SDG

```
# Retrieving from the Grid Search Notebook
%store -r sgd_best_params
```

```python
optimize_model(tuned_models, SGDClassifier, 'SGDClassifier',
sgd_best_params)
```

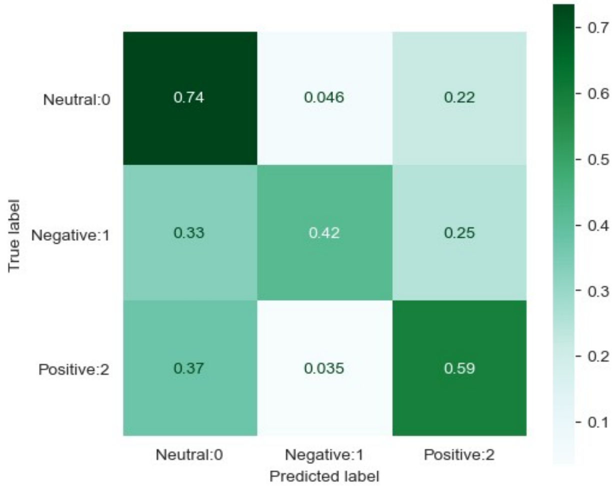
```python
tuned_models['VectorClass'] = {'classifier': SVC(C=1, degree = 1,
random_state=42, probability=True )}
tuned_models['SGDClassifier'] = {'classifier':
SGDClassifier(loss='log_loss', random_state= 42)}
tuned_models
```

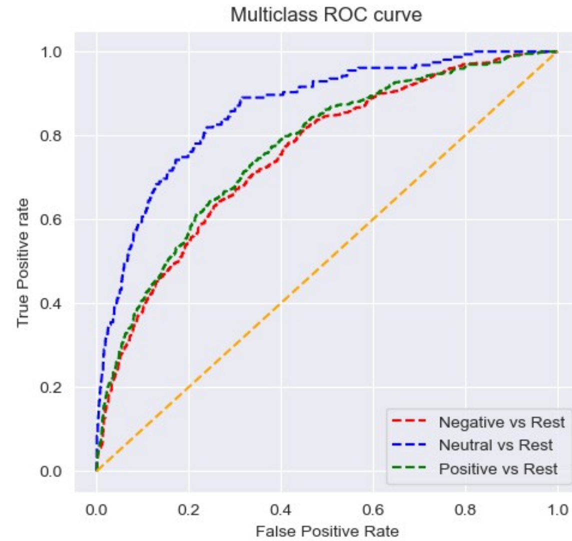
```
{'LogisticRegression': {'classifier': LogisticRegression(C=1)},
 'MultinomialNB': {'classifier': MultinomialNB(alpha=0.2)},
 'DecisionTree': {'classifier':
DecisionTreeClassifier(criterion='entropy', splitter='random')},
 'GradientBoost': {'classifier': GradientBoostingClassifier()},
 'VectorClass': {'classifier': SVC(C=1, degree=1, probability=True,
random_state=42)},
 'SGDClassifier': {'classifier': SGDClassifier(loss='log_loss',
random_state=42)}}
```

```python
tuned_metrics = run_model(tuned_models, 'Tuned', 'Purples')
tuned_metrics
```

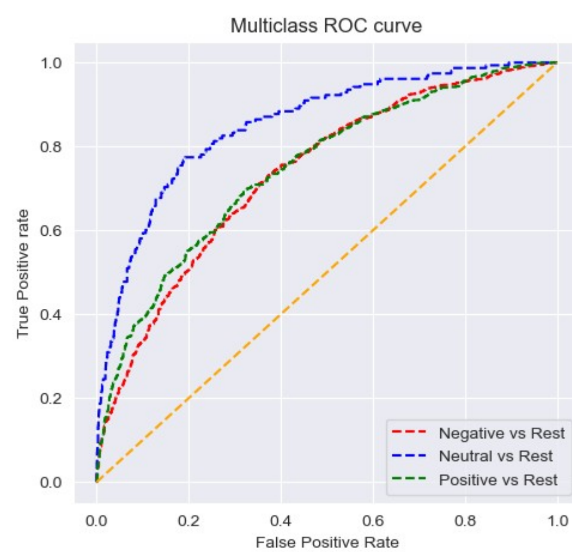
```
Running... LogisticRegression Model

c:\Users\rosew\anaconda3\envs\learn-env\lib\site-packages\sklearn\
linear_model\_logistic.py:460: ConvergenceWarning: lbfgs failed to
converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
c:\Users\rosew\anaconda3\envs\learn-env\lib\site-packages\sklearn\
linear_model\_logistic.py:460: ConvergenceWarning: lbfgs failed to
converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
c:\Users\rosew\anaconda3\envs\learn-env\lib\site-packages\sklearn\
```

```
linear_model\_logistic.py:460: ConvergenceWarning: lbfgs failed to
converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
c:\Users\rosew\anaconda3\envs\learn-env\lib\site-packages\sklearn\
linear_model\_logistic.py:460: ConvergenceWarning: lbfgs failed to
converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(

Cross Validation Score: 0.832
Train Accuracy Score: 0.9282
Test Accuracy Score: 0.6662

Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.74      0.74      1335
           1       0.42      0.42      0.42       155
           2       0.57      0.59      0.58       739

    accuracy                           0.67      2229
   macro avg       0.58      0.58      0.58      2229
weighted avg       0.67      0.67      0.67      2229
```

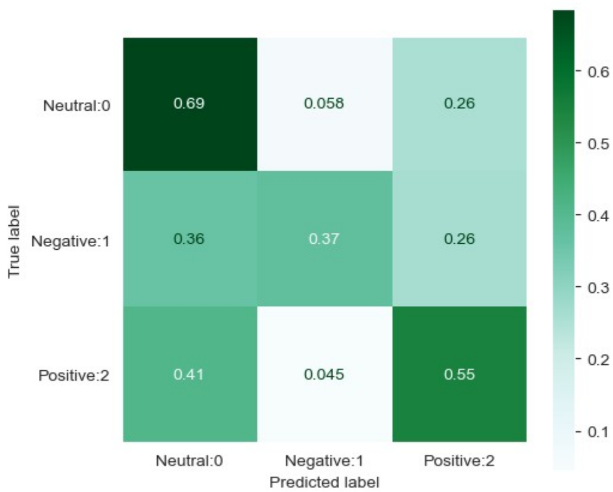


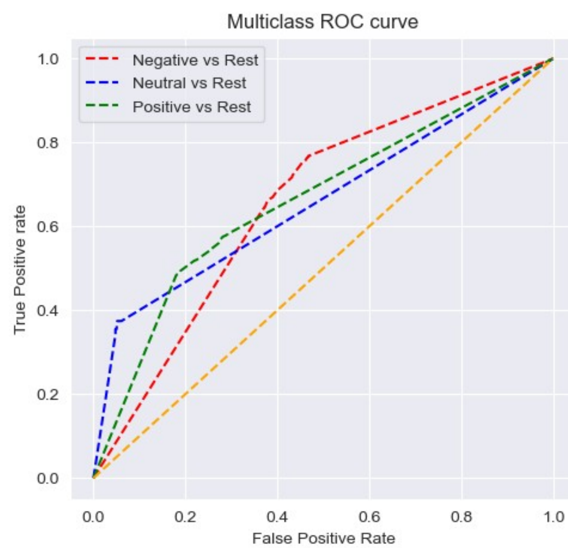



```
Running... MultinomialNB Model
Cross Validation Score: 0.8169
Train Accuracy Score: 0.9264
Test Accuracy Score: 0.6375

Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.67      0.71      1335
           1       0.34      0.50      0.41       155
           2       0.55      0.60      0.57       739

    accuracy                           0.64      2229
   macro avg       0.55      0.59      0.56      2229
weighted avg       0.66      0.64      0.64      2229
```



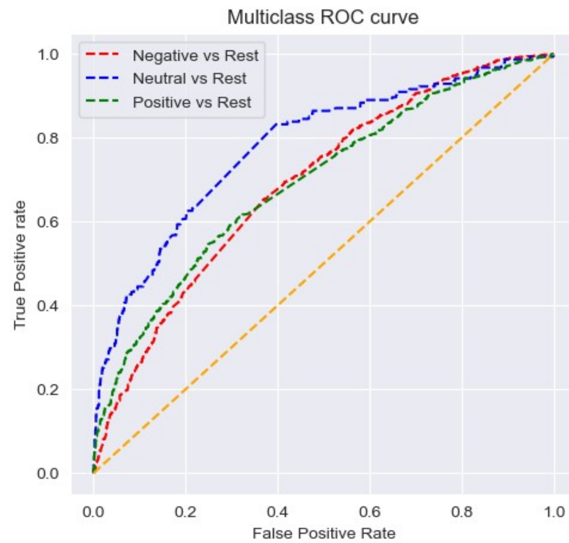
```
Running... DecisionTree Model
Cross Validation Score: 0.8167
Train Accuracy Score: 0.958
Test Accuracy Score: 0.6182

Classification Report:
              precision    recall  f1-score   support

           0       0.72      0.69      0.70      1335
           1       0.35      0.37      0.36       155
           2       0.51      0.55      0.53       739

    accuracy                           0.62      2229
   macro avg       0.53      0.54      0.53      2229
weighted avg       0.62      0.62      0.62      2229
```



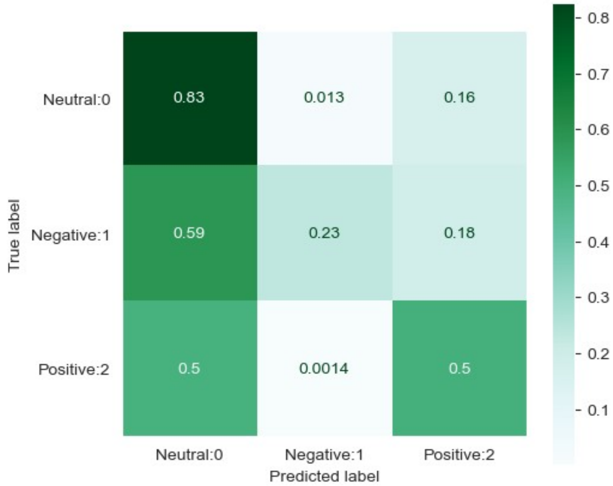


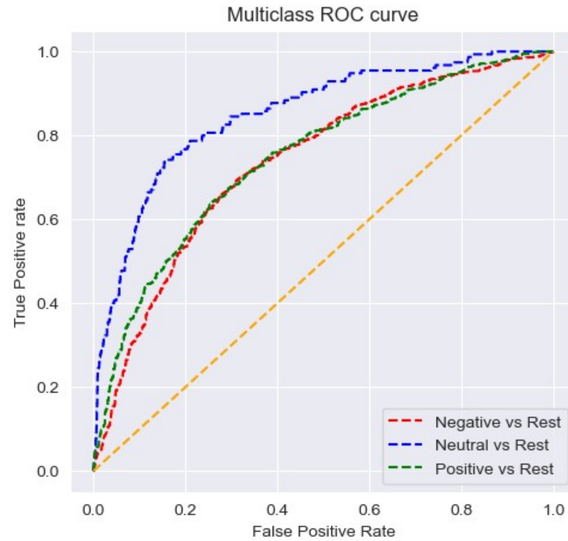

```
Running... GradientBoost Model
Cross Validation Score: 0.6465
Train Accuracy Score: 0.7233
Test Accuracy Score: 0.6092

Classification Report:
              precision    recall  f1-score   support

           0       0.70      0.71      0.71      1335
           1       0.27      0.43      0.34       155
           2       0.54      0.46      0.50       739

    accuracy                           0.61      2229
   macro avg       0.51      0.54      0.51      2229
```

```
weighted avg       0.62      0.61      0.61      2229
```

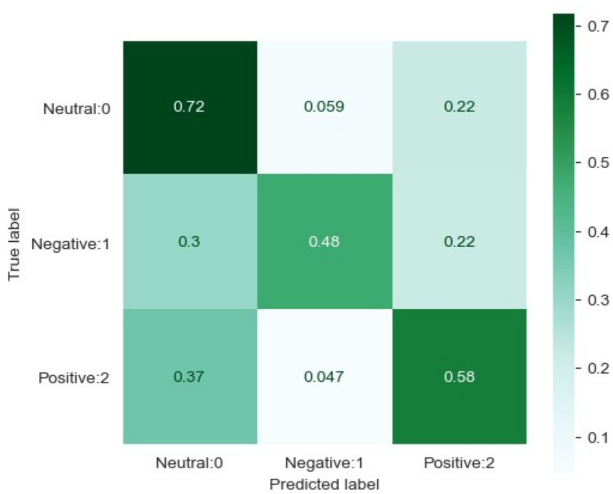


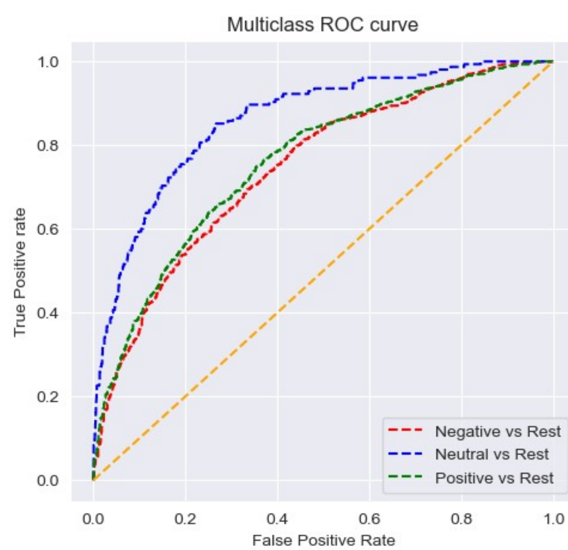

```
Running... VectorClass Model
Cross Validation Score: 0.8624
Train Accuracy Score: 0.9478
Test Accuracy Score: 0.6774

Classification Report:
              precision    recall  f1-score   support

           0       0.71      0.83      0.76      1335
           1       0.65      0.23      0.34       155
           2       0.61      0.50      0.55       739

    accuracy                           0.68      2229
   macro avg       0.66      0.52      0.55      2229
weighted avg       0.67      0.68      0.66      2229
```






```
Running... SGDClassifier Model
Cross Validation Score: 0.8258
Train Accuracy Score: 0.9053
Test Accuracy Score: 0.6577

Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.72      0.73      1335
           1       0.39      0.48      0.43       155
           2       0.57      0.58      0.58       739

    accuracy                           0.66      2229
   macro avg       0.57      0.59      0.58      2229
weighted avg       0.66      0.66      0.66      2229
```





```
                 Model  CV Score  Train Accuracy  Test Accuracy   Type
0   LogisticRegression    0.8320          0.9282         0.6662  Tuned
1        MultinomialNB    0.8169          0.9264         0.6375  Tuned
2         DecisionTree    0.8167          0.9580         0.6182  Tuned
3        GradientBoost    0.6465          0.7233         0.6092  Tuned
4          VectorClass    0.8624          0.9478         0.6774  Tuned
5        SGDClassifier    0.8258          0.9053         0.6577  Tuned
```

RESULTS AND RECOMMENDATION

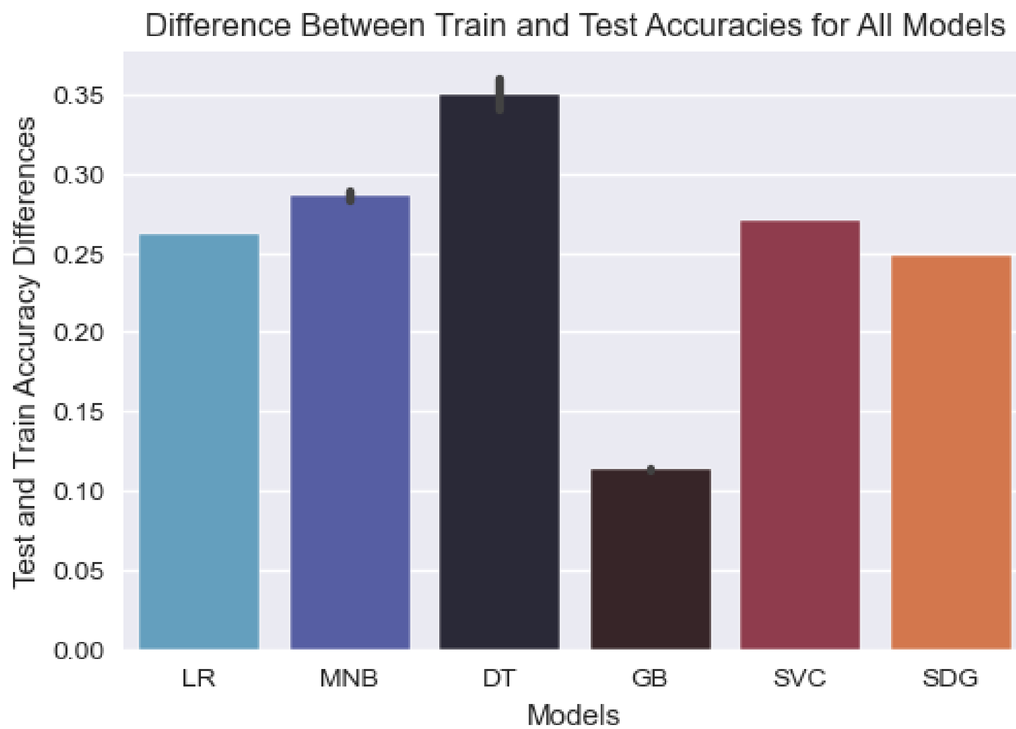
Model Performance:

```
all_models = pd.concat([default_metrics, tuned_metrics],
ignore_index=True)

all_models

                 Model  CV Score  Train Accuracy  Test Accuracy
Type
0   LogisticRegression    0.8320          0.9282         0.6662
Default
1        MultinomialNB    0.7932          0.9004         0.6178
Default
2         DecisionTree    0.8083          0.9580         0.5989
Default
3        GradientBoost    0.6453          0.7225         0.6101
Default
4          VectorClass    0.8624          0.9478         0.6774
Default
5        SGDClassifier    0.8258          0.9053         0.6577
Default
6   LogisticRegression    0.8320          0.9282         0.6662
Tuned
7        MultinomialNB    0.8169          0.9264         0.6375
Tuned
8         DecisionTree    0.8167          0.9580         0.6182
Tuned
9        GradientBoost    0.6465          0.7233         0.6092
Tuned
10         VectorClass    0.8624          0.9478         0.6774
Tuned
11       SGDClassifier    0.8258          0.9053         0.6577
Tuned


import seaborn as sns
all_models['accuracy_differences'] = all_models['Train Accuracy'] -
all_models['Test Accuracy']
```

```
plt.figure(figsize = (6,4))

bp_accuracies = sns.barplot(data=all_models, x = all_models['Model'],
y = all_models['accuracy_differences'], palette='icefire')
bp_accuracies.set_ylabel('Test and Train Accuracy Differences')
bp_accuracies.set_xlabel('Models')
bp_accuracies.set(xticklabels=["LR", "MNB", "DT", "GB", 'SVC', 'SDG'])
bp_accuracies.set_title("Difference Between Train and Test Accuracies
for All Models");
all_models
```

```
                 Model  CV Score  Train Accuracy  Test Accuracy
Type  \
0   LogisticRegression    0.8320          0.9282         0.6662
Default
1        MultinomialNB    0.7932          0.9004         0.6178
Default
2         DecisionTree    0.8083          0.9580         0.5989
Default
3        GradientBoost    0.6453          0.7225         0.6101
Default
4          VectorClass    0.8624          0.9478         0.6774
Default
5        SGDClassifier    0.8258          0.9053         0.6577
Default
6   LogisticRegression    0.8320          0.9282         0.6662
Tuned
7        MultinomialNB    0.8169          0.9264         0.6375
Tuned
8         DecisionTree    0.8167          0.9580         0.6182
Tuned
9        GradientBoost    0.6465          0.7233         0.6092
Tuned
10         VectorClass    0.8624          0.9478         0.6774
Tuned
11       SGDClassifier    0.8258          0.9053         0.6577
Tuned

    accuracy_differences
0                 0.2620
1                 0.2826
2                 0.3591
3                 0.1124
4                 0.2704
5                 0.2476
6                 0.2620
7                 0.2889
8                 0.3398
9                 0.1141
```

```
10                  0.2704
11                  0.2476
```



From the visualization above, initial the Gradient Boost model is the least overfit since it has the least difference between the train and test data (0.1124).

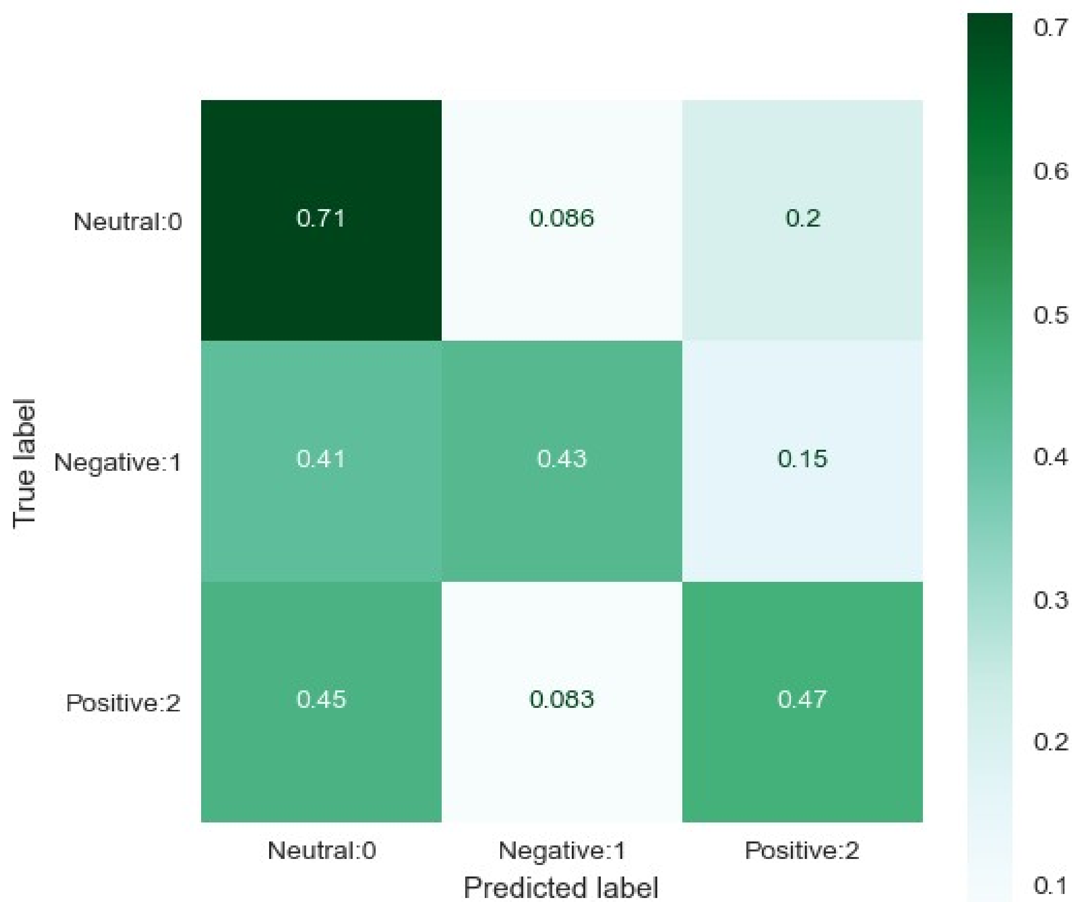
Comparing the earlier confusion matrices of the models above, the final model that I chose for this problem is the original GradientBoost model. Even though the VectorClass model has the highest test accuracy score and the Multinomial Naive Bayes models have better true negative and true positive rates, they are extremely overfit and therefore, do not generalize well to real world data. It is important that our model performs well when presented with data that it has not yet seen. The true positive and negative rates of our final model are also somewhat high, which is indicates good overall performance.

- The misclassification of the negative sentiments can be more costly to the conference organizers and companies featured at the events if more negative sentiments are spread online and missed.
- The correct classification of positive sentiments can be more beneficial to understand and provide satisfaction to the attendees.

The **Final Model** has a True Negatives value of 0.43 and a True Positives value of 0.47, Also, it has an accuracy score of 62% and only misclassifies 15% of the negative sentiments as positive.

```
final = Pipeline(steps=[('tfifd', tfidf), ('final_model',
GradientBoostingClassifier(random_state=42))])
# an alpha level of 0.2 was the optimal one after tuning
```

```
final.fit(X_train_res, y_train_res)

final_pred = final.predict(X_test)
accuracy_score(y_test, final_pred)

0.6101390758187528


plt.style.use('seaborn')
fig, ax = plt.subplots(figsize=(6,6))


# plot the confusion matrix of the final model

ConfusionMatrixDisplay.from_predictions(y_test, final.predict(X_test),
display_labels=['Neutral:0', 'Negative:1', 'Positive:2'],
                                                ax=ax,
normalize='true', cmap='BuGn')

ax.grid(False)
plt.show()
```



Recommendations

The model is recommended for use since it is fairly accurate in classifying tweet sentiments, especially compared to doing so by hand. As a result, Apple's product team can use this sentiment analyzer to target neutral consumers and convert them to buyers.

While the model improved from the first iteration, it still does not distinguish non-neutral tweets from neutral ones very well. Furthermore, the sentiment analysis only looked at tweets, while consumers post about Apple from other platforms as well.

Moving forward, it would be interesting to try and implement sentiment anaylysis from other platforms as well to gauge consumers.

Also, having more explicit sentiment labels could provide more insight into the customers' sentiments.

FURTHER RESEARCH

For further research, the data should be updated with more recent tweets, and more advanced models should be explored, such as the recent transformers.