1 Capstone Project: Compare Consumer Sentiments of Apple, Google, and Android from Past to Present

Instructor: James Irving
Date:7/23/21

Business Problem: For better or worse, people's perception of tech giants have changed over time. A company that consults these large companies' PR teams have hired me to find how the consumers' sentiments have changed. To gather the necessary information, I am going to go to Twitter, and I will compare the public's emotion towards these companies using vader sentiment analysis.

In [417]:

```
import tweepy as tw
import os
import pandas as pd
import json
import csv
from datetime import date
from datetime import datetime
import time
import numpy as np
import re
import html
import matplotlib.pyplot as plt
import string
import streamlit as st
import plotly.express as px
from plotly.subplots import make_subplots
import plotly.graph_objects as go
import seaborn as sns

import nltk
from nltk import tokenize
from nltk.probability import FreqDist
from nltk.tokenize import TweetTokenizer, word_tokenize, wordpunct_tokenize
from nltk.corpus import stopwords, subjectivity
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.stem.porter import PorterStemmer
from nltk.corpus import subjectivity
from nltk.sentiment import SentimentAnalyzer
from nltk.sentiment.util import *
from nltk.sentiment.vader import SentimentIntensityAnalyzer
nltk.download('punkt')
nltk.download('vader_lexicon')
nltk.download('stopwords')
nltk.download('wordnet')


from wordcloud import WordCloud

import spacy
import sklearn
print(sklearn.__version__)
from sklearn import metrics
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.dummy import DummyClassifier
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import TfidfVectorizer,TfidfTransformer, CountVect
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import MultinomialNB, GaussianNB
from sklearn.linear_model import LogisticRegression, LogisticRegressionCV
```

executed in 208ms, finished 16:12:44 2021-07-28

```
0.24.1

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

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

In [418]:

```
# Add business problem and lay those things out so that I know what to talk about durir
# and what i should focus on
```

executed in 13ms, finished 16:12:44 2021-07-28

1.1 Data Cleaning

In [419]:

```
# Comment on what I did and why I did it ex) why I changed the column names
```

executed in 13ms, finished 16:12:44 2021-07-28

In [420]:

```
tweet=pd.read_csv('data/tweet.csv')
tweet.head()
```

executed in 46ms, finished 16:12:44 2021-07-28

Out[420]:

	created_at	id	id_string	full_text
0	Fri Jul 09 15:55:27 +0000 2021	1413527226071588868	1413527226071588868	the fact that apple doesn't sync the contacts you blocked on your phone to your mac is sick. this man messaged me and it came thru to my laptop and for the paat two days i've been debating cursing him out
1	Fri Jul 09 15:55:26 +0000 2021	1413527223252832257	1413527223252832257	j-armys doing the most for apple music yall pls stream there too https://t.co/8z0RSfJdlf
2	Fri Jul 09 15:55:26 +0000 2021	1413527223194226691	1413527223194226691	Here's some of the Draft picks made in the Combo's Court Mock Draft:\r\n\r\n1.) Pistons - Cade Cunningham\r\n\r\n6.) Thunder - James Bouknight \r\n\r\n9.) Kings - Jalen Johnson\r\n\r\nOdd Numbers Drafted by @dmurrayNBA \r\n\r\nEven Numbers Drafted by \r\n@comboscourt \r\n\r\nFull episode:\r\n\r\nhttps://t.co/1wQRaN7J8S
3	Fri Jul 09 15:55:26 +0000 2021	1413527222221111302	1413527222221111302	10 July 2021\r\nmidoukou128 got into bed.\r\nTime 00:55, Alarm set 6.5 hours of sleep\r\n#SleepMeister https://t.co/G6WANHNm1F
4	Fri Jul 09 15:55:26 +0000 2021	1413527222145724419	1413527222145724419	@Etrouse cinnamon apple!!!! I felt that

In [421]:

```
pd.set_option('max_colwidth', None)
tweet[['created_at', 'id_string','full_text']]
```

executed in 29ms, finished 16:12:45 2021-07-28

Out[421]:

	created_at	id_string	full_text
0	Fri Jul 09 15:55:27 +0000 2021	1413527226071588868	the fact that apple doesn’t sync the contacts you blocked on your phone to your mac is sick. this man messaged me and it came thru to my laptop and for the paat two days i’ve been debating cursing him out
1	Fri Jul 09 15:55:26 +0000 2021	1413527223252832257	j-armys doing the most for apple music yall pls stream there too https://t.co/8z0RSfJdlf
2	Fri Jul 09 15:55:26 +0000 2021	1413527223194226691	Here’s some of the Draft picks made in the Combo’s Court Mock Draft:\r\n\r\n1.) Pistons - Cade Cunningham\r\n\r\n6.) Thunder - James Bouknight \r\n\r\n9.) Kings - Jalen Johnson\r\n\r\nOdd Numbers Drafted by @dmurrayNBA \r\n\r\nEven Numbers Drafted by \r\n@comboscourt \r\n\r\nFull episode:\r\n\r\nhttps://t.co/1wQRaN7J8S
3	Fri Jul 09 15:55:26 +0000 2021	1413527222221111302	10 July 2021\r\nmidoukou128 got into bed.\r\nTime 00:55, Alarm set 6.5 hours of sleep\r\n#SleepMeister https://t.co/G6WANHNm1F
4	Fri Jul 09 15:55:26 +0000 2021	1413527222145724419	@Etrouse cinnamon apple!!!! I felt that
...	...	...	...
4495	Thu Jul 08 20:50:04 +0000 2021	1413238982574542848	#Samsung Galaxy now supported #revit #coronarender #android https://t.co/XSSKvJ1ZOI
4496	Thu Jul 08 20:49:00 +0000 2021	1413238713136648195	King Chase - Taking My Time Download the app on #Android \r\nComing soon to #ios #Cookupradio Repost\r\n your music when you see it. #IndependentArtist
4497	Thu Jul 08 20:48:50 +0000 2021	1413238670765740040	@Apple @Android ADD THIS EMOJI PLEASE!!! https://t.co/w7Gls1NaBI
4498	Thu Jul 08 20:48:32 +0000 2021	1413238594278465551	Charles Jenkins & Fellowship Chicago - He'll Make It Alright is #NowPlaying on #GospelMixRadio. [Download our app for #iOS and #Android]
4499	Thu Jul 08 20:48:31 +0000 2021	1413238590436429826	Want to help beta test the new release of BlastFort? @ us or email us at orion.studios.games@gmail.com to learn more and get an exclusive preview of what we've got planned! #construct2 #gamedev #betatesting #Steam #Android https://t.co/eoMS8atRDi

4500 rows × 3 columns

In [422]:

```
old_tweet_df=pd.read_csv('data/tweet_product_company.csv', encoding='latin_1')
old_tweet_df.head()
```

executed in 42ms, finished 16:12:45 2021-07-28

Out[422]:

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

In [423]:

```
# First we need to see if there are tweets that have no text and were able to find one
old_tweet_df.loc[old_tweet_df['tweet_text'].isna()]
```

executed in 14ms, finished 16:12:45 2021-07-28

Out[423]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_produ
6	NaN	NaN	No emotion toward brand or produ

In [424]:

```
1 old_tweet_df.dropna(subset=['tweet_text'], inplace=True)
2 old_tweet_df.info()
```

executed in 31ms, finished 16:12:45 2021-07-28

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9092 entries, 0 to 9092
Data columns (total 3 columns):
 #   Column                                              Non-Null Count  Dty
pe
---  ------                                              --------------  ---
--
 0   tweet_text                                          9092 non-null   obj
ect
 1   emotion_in_tweet_is_directed_at                     3291 non-null   obj
ect
 2   is_there_an_emotion_directed_at_a_brand_or_product  9092 non-null   obj
ect
dtypes: object(3)
memory usage: 284.1+ KB
```

In [425]:

```
#Changed the column names since they were long and seemed unnecessary
change_dict={'emotion_in_tweet_is_directed_at':'product or company',
             'is_there_an_emotion_directed_at_a_brand_or_product': 'emotion'}
old_tweet_df.rename(columns=change_dict, inplace=True)
old_tweet_df
```

executed in 14ms, finished 16:12:45 2021-07-28

Out[425]:

	tweet_text	product or company	emotion
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.	iPhone	Negative emotion
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	iPad or iPhone App	Positive emotion
2	@swonderlin Can not wait for #iPad 2 also. They should sale them down at #SXSW.	iPad	Positive emotion
3	@sxsw I hope this year's festival isn't as crashy as this year's iPhone app. #sxsw	iPad or iPhone App	Negative emotion
4	@sxtxstate great stuff on Fri #SXSW: Marissa Mayer (Google), Tim O'Reilly (tech books/conferences) & Matt Mullenweg (Wordpress)	Google	Positive emotion
...	...	...	...
9088	Ipad everywhere. #SXSW {link}	iPad	Positive emotion
9089	Wave, buzz... RT @mention We interrupt your regularly scheduled #sxsw geek programming with big news {link} #google #circles	NaN	No emotion toward brand or product
9090	Google's Zeiger, a physician never reported potential AE. Yet FDA relies on physicians. "We're operating w/out data." #sxsw #health2dev	NaN	No emotion toward brand or product
9091	Some Verizon iPhone customers complained their time fell back an hour this weekend. Of course they were the New Yorkers who attended #SXSW.	NaN	No emotion toward brand or product
9092	□Ï¡□Ïà□ü_□□Ê□□Î□□Ò□□£□□Á□ââ□□_□□£□□□□â_□ÛâRT @mention Google Tests □ÛÏCheck-in Offers□Û□ At #SXSW {link}	NaN	No emotion toward brand or product

9092 rows × 3 columns

In [426]:

```
# We want to know what kind of emotion and the number of emotions shown in the tweets
old_tweet_df['emotion'].value_counts()
```

executed in 14ms, finished 16:12:45 2021-07-28

Out[426]:

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

In [427]:

```
# Because the emotions were labeled as "I can't tell", pandas didn't recognize it as mi
old_tweet_df[old_tweet_df['emotion'].isna()]
```

executed in 14ms, finished 16:12:45 2021-07-28

Out[427]:

	tweet_text	product or company	emotion

In [428]:

```
# Here I wanted to see what companies and how many companies/brands there were per emot
old_tweet_df.groupby(by=['emotion', 'product or company'], dropna=False).count()

```

executed in 30ms, finished 16:12:45 2021-07-28

Out[428]:

		tweet_text
emotion	**product or company**	
I can't tell	**Apple**	2
	Google	1
	Other Google product or service	1
	iPad	4
	iPhone	1
	NaN	147
Negative emotion	**Android**	8
	Android App	8
	Apple	95
	Google	68
	Other Apple product or service	2
	Other Google product or service	47
	iPad	125
	iPad or iPhone App	63
	iPhone	103
	NaN	51
No emotion toward brand or product	**Android**	1
	Android App	1
	Apple	21
	Google	15
	Other Apple product or service	1
	Other Google product or service	9
	iPad	24
	iPad or iPhone App	10
	iPhone	9
	NaN	5297
Positive emotion	**Android**	69
	Android App	72
	Apple	543
	Google	346
	Other Apple product or service	32

emotion	product or company	tweet_text
	Other Google product or service	236
	iPad	793
	iPad or iPhone App	397
	iPhone	184
	NaN	306

In [429]:

```
#We are creating a dataframe that contains all duplications where the value for product
duplications=old_tweet_df.duplicated(subset=['tweet_text'], keep='first')
old_tweet_df[duplications]
```

executed in 29ms, finished 16:12:45 2021-07-28

Out[429]:

	tweet_text	product or company	emotion
468	Before It Even Begins, Apple Wins #SXSW {link}	Apple	Positive emotion
776	Google to Launch Major New Social Network Called Circles, Possibly Today {link} #sxsw	NaN	No emotion toward brand or product
2232	Marissa Mayer: Google Will Connect the Digital & Physical Worlds Through Mobile - {link} #sxsw	NaN	No emotion toward brand or product
2559	Counting down the days to #sxsw plus strong Canadian dollar means stock up on Apple gear	Apple	Positive emotion
3813	Win free ipad 2 from webdoc.com #sxsw RT	iPad	Positive emotion

In [430]:

```
clean_old_df=old_tweet_df.loc[~duplications].copy()
clean_old_df
```

executed in 14ms, finished 16:12:45 2021-07-28

Out[430]:

	tweet_text	product or company	emotion
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.	iPhone	Negative emotion
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	iPad or iPhone App	Positive emotion
2	@swonderlin Can not wait for #iPad 2 also. They should sale them down at #SXSW.	iPad	Positive emotion
3	@sxsw I hope this year's festival isn't as crashy as this year's iPhone app. #sxsw	iPad or iPhone App	Negative emotion
4	@sxtxstate great stuff on Fri #SXSW: Marissa Mayer (Google), Tim O'Reilly (tech books/conferences) & Matt Mullenweg (Wordpress)	Google	Positive emotion
...	...	...	...
9088	Ipad everywhere. #SXSW {link}	iPad	Positive emotion
9089	Wave, buzz... RT @mention We interrupt your regularly scheduled #sxsw geek programming with big news {link} #google #circles	NaN	No emotion toward brand or product
9090	Google's Zeiger, a physician never reported potential AE. Yet FDA relies on physicians. "We're operating w/out data." #sxsw #health2dev	NaN	No emotion toward brand or product
9091	Some Verizon iPhone customers complained their time fell back an hour this weekend. Of course they were the New Yorkers who attended #SXSW.	NaN	No emotion toward brand or product
9092	□Ï¡□Ïà□ü_□□Ê□□Î□□Ò□□£□□Á□ââ□□_□□£□□□□â_□ÛâRT @mention Google Tests □ÛÏCheck-in Offers□Û□ At #SXSW {link}	NaN	No emotion toward brand or product

9065 rows × 3 columns

In [431]:

```
# Tell why i did this
# Here I want to see the number of each emotions where the product or company's values
# Now we can see that most of the tweets that do not have a company show no emotion (ne
clean_old_df[clean_old_df['product or company'].isna()]['emotion'].value_counts()
```

executed in 14ms, finished 16:12:45 2021-07-28

Out[431]:

```
No emotion toward brand or product    5281
Positive emotion                       306
I can't tell                           147
Negative emotion                        51
Name: emotion, dtype: int64
```

In [432]:

```
# Lump apple products as Apple instead of having different products
# This is still cleaning for the older tweets
brands2={'Google':'Google', 'Apple' : 'Apple', 'Android': 'Android', 'iPad':'Apple', 'i
for key, values in brands2.items():
    clean_old_df.loc[clean_old_df['tweet_text'].str.contains(key, case=False), 'product
```

executed in 111ms, finished 16:12:45 2021-07-28

In [433]:

```
# After running the for loop above, we can see a clear decrease in the number of tweets
# that do not contain a company or product
clean_old_df[clean_old_df['product or company'].isna()]['emotion'].value_counts()
```

executed in 14ms, finished 16:12:45 2021-07-28

Out[433]:

```
No emotion toward brand or product    739
Positive emotion                       13
I can't tell                            6
Negative emotion                        1
Name: emotion, dtype: int64
```

In [434]:

```
1 clean_old_df
```

executed in 14ms, finished 16:12:45 2021-07-28

Out[434]:

	tweet_text	product or company	emotion
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.	Apple	Negative emotion
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	Apple	Positive emotion
2	@swonderlin Can not wait for #iPad 2 also. They should sale them down at #SXSW.	Apple	Positive emotion
3	@sxsw I hope this year's festival isn't as crashy as this year's iPhone app. #sxsw	Apple	Negative emotion
4	@sxtxstate great stuff on Fri #SXSW: Marissa Mayer (Google), Tim O'Reilly (tech books/conferences) & Matt Mullenweg (Wordpress)	Google	Positive emotion
...	...	...	...
9088	Ipad everywhere. #SXSW {link}	Apple	Positive emotion
9089	Wave, buzz... RT @mention We interrupt your regularly scheduled #sxsw geek programming with big news {link} #google #circles	Google	No emotion toward brand or product
9090	Google's Zeiger, a physician never reported potential AE. Yet FDA relies on physicians. "We're operating w/out data." #sxsw #health2dev	Google	No emotion toward brand or product
9091	Some Verizon iPhone customers complained their time fell back an hour this weekend. Of course they were the New Yorkers who attended #SXSW.	Apple	No emotion toward brand or product
9092	□Ï¡□Ïà□ü_□□Ê□□Î□□Ò□□£□□Á□ââ□□_□□£□□□□â_□ÛâRT @mention Google Tests □ÛÏCheck-in Offers□Û□ At #SXSW {link}	Google	No emotion toward brand or product

9065 rows × 3 columns

In [435]:

```
# Though I have already seen the total number of tweets without a product or company, I
# double check and make sure that the tweets indeed did not contain a company or produc
clean_old_df[clean_old_df['product or company'].isna()]
```

executed in 14ms, finished 16:12:45 2021-07-28

Out[435]:

	tweet_text	product or company	emotion
51	□ÛÏ@mention {link} <-- HELP ME FORWARD THIS DOC to all Anonymous accounts, techies,& ppl who can help us JAM #libya #SXSW	NaN	No emotion toward brand or product
52	□÷¼ WHAT? □÷_ {link} □ã_ #edchat #musedchat #sxsw #sxswi #classical #newTwitter	NaN	No emotion toward brand or product
53	.@mention @mention on the location-based 'fast, fun and future' - {link} (via @mention #sxsw	NaN	No emotion toward brand or product
66	At #sxsw? @mention / @mention wanna buy you a drink. 7pm at Fado on 4th. {link} Join us!	NaN	No emotion toward brand or product
	Chilcott: @mention #SXSW stand talking with Blogger staff. Too late		No emotion

In the next two lines of code, I am just repeating the above process but just looking at it in more detail for positive and negative emotions.

In [436]:

```
# tell what i was looking for/ why i did this for basically most of the lines
clean_old_df.loc[(clean_old_df['emotion']=='Positive emotion') & (clean_old_df['product
```

executed in 15ms, finished 16:12:45 2021-07-28

Out[436]:

	tweet_text	product or company	emotion
619	@mention hello! Enjoy #Sxsw and ride anywhere in Austin for $10 . download the #GroundLink app, {link} booth 437	NaN	Positive emotion
1366	@mention - spread the word, our #SXSW festival explorer App is live and free {link}	NaN	Positive emotion
2258	@mention be sure to use our FREE App for checking out the bands at #SXSW! {link}	NaN	Positive emotion
3034	Free iTunes Album, #SXSW Featured Artists, grab it if you missed it: {link}	NaN	Positive emotion
3747	{link} Coinsidence? Sounds like a good strategy to me. Wish I could go to #SXSW	NaN	Positive emotion
4237	@mention Luckily @mention has a pop up store at #SXSW!	NaN	Positive emotion
5613	RT @mention Check out the new @mention app {link} - this is gonna be HUGE next week at #sxsw and beyond.	NaN	Positive emotion
5746	RT @mention Free iTunes Album, #SXSW Featured Artists, grab it if you missed it: {link}	NaN	Positive emotion
6676	RT @mention Soundtrckr featured by @mention @mention as a Must-have for #SXSW {link}	NaN	Positive emotion
7825	Watch this @mention #sxsw - #ecademy @mention {link} >> fascinating & so true about maps saving itme - lots of it	NaN	Positive emotion
8196	Friends at #sxsw, can you take some 360 views with 360 Panorama - {link} - so I feel like I'm there? I'll gift you the app =)!	NaN	Positive emotion
8811	This #sxsw app by #MxM is made of AWESOME! -- {link} --{link}	NaN	Positive emotion
8835	Free #SXSW sampler on iTunes {link} #FreeMusic	NaN	Positive emotion

In [437]:

```
clean_old_df.loc[(clean_old_df['emotion']=='Negative emotion') & (clean_old_df['product
```

executed in 14ms, finished 16:12:45 2021-07-28

Out[437]:

	tweet_text	product or company	emotion
7561	Apps distract pubs, sez Khoi Vinh. Instead of focusing on reader exp, they're delivering same content 3 ways. #SXSW {link}	NaN	Negative emotion

In [438]:

```
# I have noticed that most of the tweets that used to contain a link had a {link} place
# However, I wasn't sure if all of the links were replaced with the place holder.
clean_old_df[clean_old_df['tweet_text'].str.contains("http[^ ]+|www\.[^ ]+")]
```

executed in 30ms, finished 16:12:45 2021-07-28

Out[438]:

	tweet_text	product or company	emotion
5	@teachntech00 New iPad Apps For #SpeechTherapy And Communication Are Showcased At The #SXSW Conference http://ht.ly/49n4M #iear #edchat #asd	Apple	No emotion toward brand or product
8	Beautifully smart and simple idea RT @madebymany @thenextweb wrote about our #hollergram iPad app for #sxsw! http://bit.ly/ieaVOB	Apple	Positive emotion
11	Find & Start Impromptu Parties at #SXSW With @HurricaneParty http://bit.ly/gVLrIn I can't wait til the Android app comes out.	Android	Positive emotion
12	Foursquare ups the game, just in time for #SXSW http://j.mp/grN7pK) - Still prefer @Gowalla by far, best looking Android app to date.	Android	Positive emotion
13	Gotta love this #SXSW Google Calendar featuring top parties/ show cases to check out. RT @hamsandwich via @ischafer =>http://bit.ly/aXZwxB	Google	Positive emotion

Unfortunately, my concern was true.
The next code will look for special characters as they will need to be replaced before performing the vader sentiment analysis.

In [439]:

```
clean_old_df[clean_old_df['tweet_text'].str.contains('[^\x00-\x7F]+')]
```

executed in 30ms, finished 16:12:45 2021-07-28

Out[439]:

	tweet_text	product or company	emotion
38	@mention - False Alarm: Google Circles Not Coming Now□ÛÒand Probably Not Ever? - {link} #Google #Circles #Social #SXSW	Google	Negative emotion
41	HootSuite - HootSuite Mobile for #SXSW ~ Updates for iPhone, BlackBerry & Android: Whether you□Ûªre getting friend... {link}	Apple	No emotion toward brand or product
42	Hey #SXSW - How long do you think it takes us to make an iPhone case? answer @mention using #zazzlesxsw and we□Ûªll make you one!	Apple	No emotion toward brand or product
45	#IPad2 's □Û÷#SmartCover□Ûª Opens to Instant Access - I should have waited to get one! - {link} #apple #SXSW	Apple	Positive emotion
46	Hand-Held □Û÷Hobo□Ûª: Drafthouse launches □Û÷Hobo With a Shotgun□Ûª iPhone app #SXSW {link}	Apple	Positive emotion
...	...	...	...
8925	umm that would be @mention □ÛÏ@mention I keep winning shit! Thanks @mention for the killer iPad case. #sxsw□Û□	Apple	Positive emotion
8945	FestivalExplorer iPhone App Finally Solves SXSW {link} #music #musica #musiek #musique #musik #app #sxsw #□Ù_¾¬â #□Ù_¾´_ #□□Î□¥É	Apple	Positive emotion
8963	Group #Texting War Heats Up: Fast Society Launches New Android App, Updates iPhone App: #SXSW□Û_ {link}	Apple	Positive emotion
8982	In case my fairy god mother = reading mail; my ÌÙ□±G wish this week is 2 go 2 #sxsw □Ï□ for the #Android □ÏÎ Dev □Ïà Meetup. @mention Hilton, Sat. 12:30PM	Android	No emotion toward brand or product
9092	□Ï¡□Ïà□ü_□□Ê□□Î□□Ò□□£□□Á□ââ□□_□□£□□□□â_□ÛâRT @mention Google Tests □ÛÏCheck-in Offers□Û□ At #SXSW {link}	Google	No emotion toward brand or product

483 rows × 3 columns

There were more number of tweets containing urls and special characters than I had initially expected. So I will need to create a function that will be able to remove special characters including emojis and other punctuation marks. The function will also replace all urls with the {link} place holder, but because I do not want the place holder to have an impact later on the word clouds, the place holders are will also be removed.

In [440]:

```
# Don't want any http or www. to have influence on word cloud later.
# First we will remove all non ascii characters
# Then we will remove the control characters
# Realized that standalone numbers should be removed as well
# Remove retweets, mentions, and hashtags
# Finally we have to remove unnecessary spaces

def text_cleaner(text):
    text=html.unescape(text)

    #remove links and urls
    links=re.findall("http[^ ]+|www\.[^ ]+", text)
    for link in links:
        text=str.replace(text, link, '{link}')
    text = re.sub('{link}', ' ', text)
    # this will remove all non-ascii
    text = re.sub(r'[^\x00-\x7F]+',' ', text)
    # remove control characters
    text = re.sub('[\x00-\x1F]',' ', text)
    # remove stand-alone numbers
#     text = ' '.join(word for word in text.split() if not word.isdigit())
    text= re.sub(r'\d', ' ', text)
    # retweets
    text = re.sub(r'RT [@]?\w*:',' ', text)
    text = re.sub('RT',' ', text)
    #mentions
    text = re.sub(r'\@\w*', ' ', text)
    # hashtags
    text = re.sub(r'\#\w*',' ', text)
    # remove unnecessary spaces
    text = re.sub(' +', ' ', text)
    return text
```

executed in 14ms, finished 16:12:45 2021-07-28

In [441]:

```
# For some reason, there was a period at the very front of the first tweet, and it was
# function. Because of this, I am just removing the period with the first line of code.
clean_old_df['tweet_text'][0]=clean_old_df['tweet_text'][0][1:]

# We are applying the text cleaner function using map lambda and creating a new column
# This column will be the same as the original text without special characters and othe
clean_old_df['clean_text'] = clean_old_df['tweet_text'].map(lambda x: text_cleaner(x))
```

executed in 206ms, finished 16:12:45 2021-07-28

In [442]:

```
# Now we want to make sure that our text cleaner function has performed its task
clean_old_df[clean_old_df['clean_text'].str.contains('[^\x00-\x7F]+')]
```

executed in 31ms, finished 16:12:45 2021-07-28

Out[442]:

tweet_text	product or company	emotion	clean_text

In [443]:

```
1 clean_old_df
```

executed in 15ms, finished 16:12:45 2021-07-28

Out[443]:

	tweet_text	product or company	emotion	clea
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.	Apple	Negative emotion	I have a G iF After hrs tw at , it was need to up Plugin static
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	Apple	Positive emotion	Know a Awe iPad/iPhor that you' appreciate design they're givir
2	@swonderlin Can not wait for #iPad 2 also. They should sale them down at #SXSW.	Apple	Positive emotion	Can not w also. They sale them do
3	@sxsw I hope this year's festival isn't as crashy as this year's iPhone app. #sxsw	Apple	Negative emotion	I hope this festival i crashy year's iPhon
4	@sxtxstate great stuff on Fri #SXSW: Marissa Mayer (Google), Tim O'Reilly (tech books/conferences) & Matt Mullenweg (Wordpress)	Google	Positive emotion	great stuff Marissa (Google O'Reilly books/confer & Matt Mull (Word
...	...	...	...	
9088	Ipad everywhere. #SXSW {link}	Apple	Positive emotion	Ipad every
9089	Wave, buzz... RT @mention We interrupt your regularly scheduled #sxsw geek programming with big news {link} #google #circles	Google	No emotion toward brand or product	Wave, buzz interrup regularly sche geek prograı with big
9090	Google's Zeiger, a physician never reported potential AE. Yet FDA relies on physicians. "We're operating w/out data." #sxsw #health2dev	Google	No emotion toward brand or product	Google's Ze physician reported pc AE. Yet FDA on phys "We're ope w/out data
9091	Some Verizon iPhone customers complained their time fell back an hour this weekend. Of course they were the New Yorkers who attended #SXSW.	Apple	No emotion toward brand or product	Some V iPhone cust complaine time fell b hour this wee Of cours were th Yorke atte

	tweet_text	product or company	emotion	clea
9092	□Ï¡□Ïà□ü_□□Ê□□Î□□Ò□□£□□Á□ââ□□_□□£□□□□â_□ÛâRT @mention Google Tests □ÛÏCheck-in Offers□Û□ At #SXSW {link}	Google	No emotion toward brand or product	_ _ _ Google Check-in Of

9065 rows × 4 columns

In [444]:

```
# Checking the percentage of tweets that do not contain a product or company since thes
# If the number of tweets missing a company is small enough, they will be dropped.
clean_old_df['product or company'].isna().sum()/len(clean_old_df)

```

executed in 15ms, finished 16:12:45 2021-07-28

Out[444]:

0.08372862658576945

In [445]:

```
1 no_company=clean_old_df['product or company'].isna()
2 clean_old_df[no_company]
```

executed in 14ms, finished 16:12:45 2021-07-28

Out[445]:

	tweet_text	product or company	emotion	clean_text
51	□ÛÏ@mention {link} <-- HELP ME FORWARD THIS DOC to all Anonymous accounts, techies,& ppl who can help us JAM #libya #SXSW	NaN	No emotion toward brand or product	<-- HELP ME FORWARD THIS DOC to all Anonymous accounts, techies,& ppl who can help us JAM
52	□÷¼ WHAT? □÷_ {link} □ã_ #edchat #musedchat #sxsw #sxswi #classical #newTwitter	NaN	No emotion toward brand or product	WHAT? _ _
53	.@mention @mention on the location-based 'fast, fun and future' - {link} (via @mention #sxsw	NaN	No emotion toward brand or product	. on the location-based 'fast, fun and future' - (via
66	At #sxsw? @mention / @mention wanna buy you a drink. 7pm at Fado on 4th. {link} Join us!	NaN	No emotion toward brand or product	At ? / wanna buy you a drink. pm at Fado on th. Join us!
71	Chilcott: @mention #SXSW stand talking with Blogger staff. Too late to win competition for best tweet mentioning @mention So no t-shirt.	NaN	No emotion toward brand or product	Chilcott: stand talking with Blogger staff. Too late to win competition for best tweet mentioning So no t-shirt.
...	...	...	...	...
8932	Z6: No News is Good News {link} [codes valid: 4:00-7:59:59p 03/11/11] #infektd #sxsw #zlf	NaN	No emotion toward brand or product	Z : No News is Good News [codes valid: : - : : p / /]
8936	CLIENT NEWS! @mention Releases "Dope Melodies & Heavy Bass" & Invades #SXSW -> {link}	NaN	No emotion toward brand or product	CLIENT NEWS! Releases "Dope Melodies & Heavy Bass" & Invades ->
8970	This is my 5th year downloading the #sxsw Music Torrent {link} ALL FREE and LEGAL! Great Music.	NaN	No emotion toward brand or product	This is my th year downloading the Music Torrent ALL FREE and LEGAL! Great Music.
9024	by the way, we're looking for a spanish-speaking trend scout based in Austin -> {link} #sxsw	NaN	No emotion toward brand or product	by the way, we're looking for a spanish-speaking trend scout based in Austin ->

	tweet_text	product or company	emotion	clean_text
9026	True story! RT @mention I just rated Amy's Ice Cream 5 stars. @mention "Best	NaN	No emotion toward	True story! I just rated Amy's Ice Cream stars. "Best ice

In [446]:

```
# Dropping rows without company or products as the number/percentage was small.
# Decreased from 9058 rows to 8301 rows.
clean_old_df2=clean_old_df[~no_company].copy()
clean_old_df2=clean_old_df2.drop(columns=['tweet_text'])
```

executed in 15ms, finished 16:12:45 2021-07-28

In [447]:

```
# Since there were multiple products that were related to the same company, the product
# to that of the main company's names so that comparing them would be easier.
brands={'iPad or iPhone App': 'Apple', 'Other Apple product or service': 'Apple',
        'Other Google product or service':'Google'}

for key, values in brands.items():
    clean_old_df2.loc[clean_old_df2['product or company'].str.contains(key), 'product c
```

executed in 30ms, finished 16:12:45 2021-07-28

In [448]:

```
for text in clean_old_df2['clean_text']:
    text=str.replace(text,'{link}', '')

#     text=re.sub('{link}','',text)
clean_old_df2['clean_text']
# clean_old_df2['clean_text']=re.sub('{link}', '',clean_old_df2['clean_text'])
```

executed in 23ms, finished 16:12:45 2021-07-28

Out[448]:

```
0                                                  I have a G iPhone. After hrs
tweeting at , it was dead! I need to upgrade. Plugin stations at .
1                          Know about ? Awesome iPad/iPhone app that you'll
likely appreciate for its design. Also, they're giving free Ts at
2
Can not wait for also. They should sale them down at .
3                                                                      I hop
e this year's festival isn't as crashy as this year's iPhone app.
4                               great stuff on Fri : Marissa Mayer (Google),
Tim O'Reilly (tech books/conferences) & Matt Mullenweg (Wordpress)
                                                                         ...
9088
Ipad everywhere.
9089                                                    Wave, buzz... We
interrupt your regularly scheduled geek programming with big news
9090                 Google's Zeiger, a physician never reported potential A
E. Yet FDA relies on physicians. "We're operating w/out data." dev
9091    Some Verizon iPhone customers complained their time fell back an hou
r this weekend. Of course they were the New Yorkers who attended .
9092
_ _ _ Google Tests Check-in Offers At
Name: clean_text, Length: 8306, dtype: object
```

New Tweet

Now we want to clean the newer tweets collected using tweepy.

In [449]:

```
# Adding company or products
# Similar to the previous cleaning process, we are assigning the actual company names t
brands2={'Google':'Google', 'Apple' : 'Apple', 'Android': 'Android', 'iPad':'Apple', 'i
for key, values in brands2.items():
    tweet.loc[tweet['full_text'].str.contains(key, case=False), 'product or company']=

```

executed in 76ms, finished 16:12:45 2021-07-28

In [450]:

```
# After company names have been assigned, we want to see the total number of tweets tha
# product or company names.
tweet['product or company'].isna().sum()
```

executed in 14ms, finished 16:12:45 2021-07-28

Out[450]:

```
1089
```

Out of the 4500 tweets that were collected, around a quarter of them do not contain product or company names. While it is a larger percentage of tweets, I believe that 3500 tweets is still a large enough number to show valid results.

In [451]:

```
missing_company2=tweet['product or company'].isna()
clean_new=tweet[~missing_company2].copy()
```

executed in 14ms, finished 16:12:46 2021-07-28

In [452]:

```
clean_new['clean_text'] = clean_new['full_text'].map(lambda x: text_cleaner(x))
clean_new.head()
```

executed in 110ms, finished 16:12:46 2021-07-28

Out[452]:

	created_at	id	id_string	full_text	product or company	clean_text
0	Fri Jul 09 15:55:27 +0000 2021	1413527226071588868	1413527226071588868	the fact that apple doesn’t sync the contacts you blocked on your phone to your mac is sick. this man messaged me and it came thru to my laptop and for the paat two days i’ve been debating cursing him out	Apple	the fact that apple doesn t sync the contacts you blocked on your phone to your mac is sick. this man messaged me and it came thru to my laptop and for the paat two days i ve

In [453]:

```
# Removing unrelated tweets
cinnamon=clean_new[clean_new['clean_text'].str.contains('cinnamon|pie')==True]
cinnamon
```

executed in 30ms, finished 16:12:46 2021-07-28

Out[453]:

	created_at	id	id_string	full_text	produ compa
4	Fri Jul 09 15:55:26 +0000 2021	1413527222145724419	1413527222145724419	@Etrouse cinnamon apple!!!! I felt that	Ap
156	Fri Jul 09 15:53:18 +0000 2021	1413526687095173121	1413526687095173121	Heard the drum fill from In the Air Tonight coming from the living room and thought my 2yo was a child prodigy, but she was just smashing ants around a piece of apple she left on the floor the other day	Ap
478	Fri Jul 09 15:49:35 +0000 2021	1413525749504647170	1413525749504647170	@Red__Glenn only if we can ask them to bring back the regular apple cinnamon pop tarts too	Ap
973	Fri Jul 09 15:42:32 +0000 2021	1413523977037877249	1413523977037877249	Whataburger apple pies slap	Ap
1187	Fri Jul 09 15:39:53 +0000 2021	1413523310915248129	1413523310915248129	That's my cinnamon apple https://t.co/pzpuXfxE03	Ap
1212	Fri Jul 09 15:39:31 +0000 2021	1413523216392495106	1413523216392495106	The 1998 Parent Trap to piercing your ears with an ice cube and an apple pipe line isn't discussed enough	Ap

	created_at	id	id_string	full_text	produ compa
1784	Fri Jul 09 15:52:19 +0000 2021	1413526436426756097	1413526436426756097	@DotKaffei @jon_british I had to Google stargazy pie.. I have never heard of it or seen it before.. Inverted teeth I'll give you but the pie you can poke up your arse xx	Goo
1897	Fri Jul 09 15:50:50 +0000 2021	1413526066325504003	1413526066325504003	since the #Google #Fitbit #LUXE high-fashion wrist personal #surveillance & data collection device is in the spotlight again, seems like a good moment to re-up the piece @hypervisible & I wrote for @_reallifemag this week about #LuxurySurveillance https://t.co/mg1cMAN3rH	Goo
2571	Fri Jul 09 15:40:56 +0000 2021	1413523574988681222	1413523574988681222	how to die and reincarnate as a bellybutton piercing @Google	Goo
3492	Fri Jul 09 11:44:53 +0000 2021	1413464168607461376	1413464168607461376	@UniverseIce Android doesn't copy alot of apples idea apple copies Androids. Widgets, cameras, size	Andr

	created_at	id	id_string	full_text	produ compa
4197	Fri Jul 09 02:15:31 +0000 2021	1413320885088423941	1413320885088423941	I have stood by the Apple iPhone for YEARS. Them taking the dapps out of @TrustWalletApp has me about to switch to Android 100% . Fuckin' crybaby pussy pieces of shit, jealous cause they can't take a cut of the crypto from us! Suck my dick Apple, this relationship is over! Darsh!	Ap
4448	Thu Jul 08 21:39:59 +0000 2021	1413251545018376198	1413251545018376198	Apple: acquires Dark Sky, kills Android app, plans to kill website, is in the process of slowly "breaking up" the iOS app in pieces for use in Apple Weather\r\n\r\nAlso Apple: https://t.co/5HzdsS2tBF	Andr

When collecting tweets, I didn't take into account 'Apple Cinnamon' or 'apple pies'. So we are selecting the few tweets that were unrelated and removed them

In [454]:

```
clean_new2=clean_new.drop(index=[4, 156, 478,973, 1187, 1212])
```

executed in 15ms, finished 16:12:46 2021-07-28

In [455]:

```
clean_new2=clean_new2.drop(columns=['full_text'])
```

executed in 14ms, finished 16:12:46 2021-07-28

1.2 Vader Sentiment Analysis

We will now use the vader sentiment analysis to determine the individual tweets' sentiment. The analysis produces four values: Compound, Positive, Neutral, and Negative; however, the last three components of the analysis does not provide the wanted information, so only the values of the compound will be used. All of the

values are between -1 and and 1. The values will first be stored in a list and later be incorporated into the data frames.

In [456]:

```
# Vader Sentiment Analysis
sid = SentimentIntensityAnalyzer()
old_tweet_sentiment=[]

for text in clean_old_df2['clean_text']:
    ss=sid.polarity_scores(text)
    old_tweet_sentiment.append(ss['compound'])
old_tweet_sentiment
```

executed in 1.70s, finished 16:12:47 2021-07-28

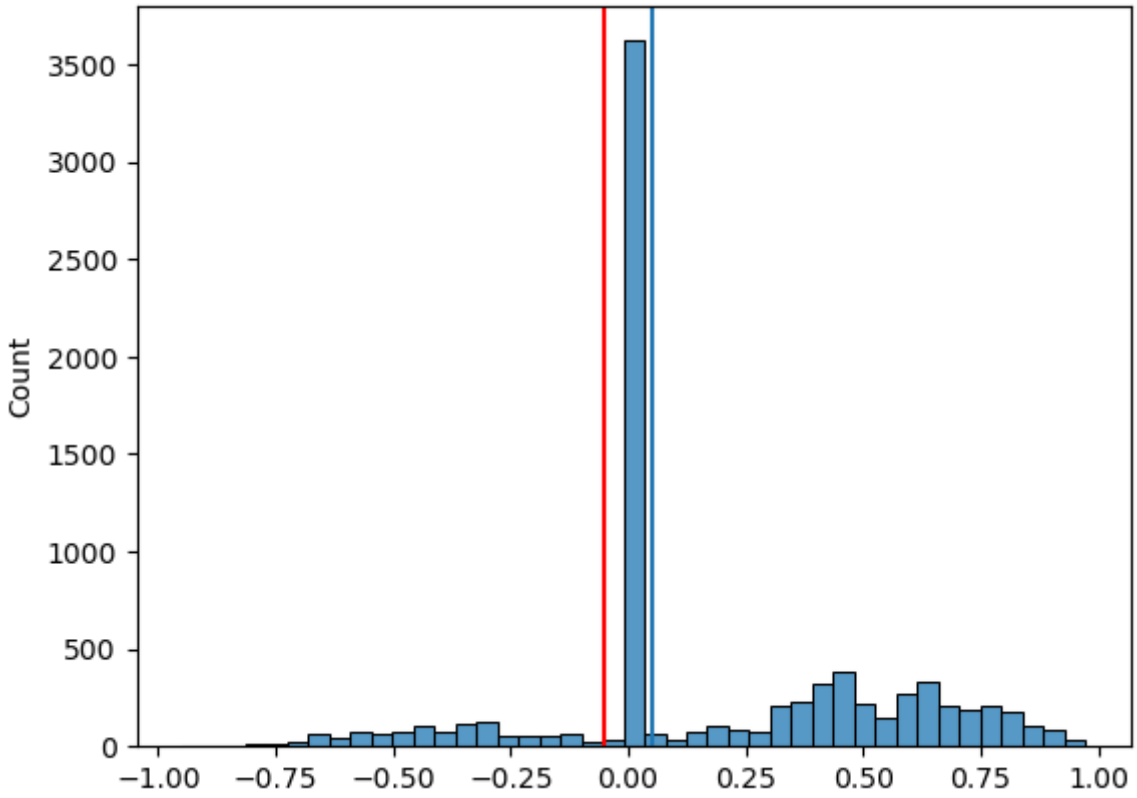
Out[456]:

```
[-0.68,
 0.91,
 0.0,
 0.7269,
 0.6249,
 0.0,
 0.6369,
 0.7712,
 0.5106,
 0.34,
 0.4019,
 0.6369,
 0.7184,
 0.6249,
 0.4588,
 0.0,
 0.0,
 0.4404,
```

In [457]:

```
# This graph shows the overall number and range of sentiments in the tweets. The two li
# of the cutoff between negative, neutral, and positive. All tweets on the left of the
# and all on the right side are positive. And between the two lines are the neutral twe

ax = sns.histplot(old_tweet_sentiment)
ax.axvline(-.05, color='r')
ax.axvline(.05)
plt.show()
```

executed in 252ms, finished 16:12:48 2021-07-28



Here we were able to observe that most common sentiment value shown in the tweets is 0.

In [458]:

```
# Give values to sentiment compound and use the values to give word values to vader emo
clean_old_df2['sentiment_compound']=old_tweet_sentiment

clean_old_df2.loc[clean_old_df2['sentiment_compound']>=.05, 'vader_emotion']='Positive'
clean_old_df2.loc[clean_old_df2['sentiment_compound']<=-.05, 'vader_emotion']='Negative'
clean_old_df2.loc[(clean_old_df2['sentiment_compound']>-.05)&(clean_old_df2['sentiment_
```

executed in 14ms, finished 16:12:48 2021-07-28

In [459]:

```
# Here we can observe that the number of tweets with negative sentiments is a bit less
# positive or neutral tweets.
clean_old_df2['vader_emotion'].value_counts()
```

executed in 15ms, finished 16:12:48 2021-07-28

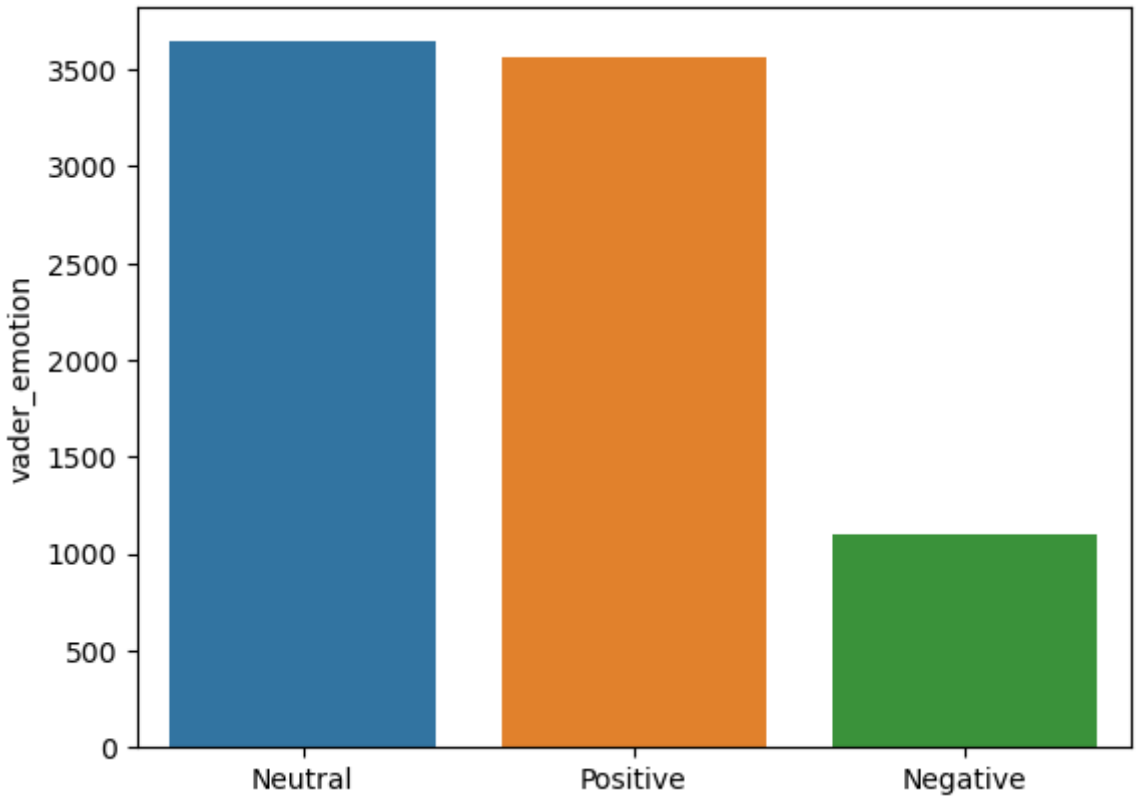
Out[459]:

```
Neutral     3643
Positive    3564
Negative    1099
Name: vader_emotion, dtype: int64
```

In [460]:

```
ax = sns.barplot(x=clean_old_df2['vader_emotion'].value_counts().index, y=clean_old_df2
plt.show()
```

executed in 124ms, finished 16:12:48 2021-07-28



In [461]:

```
clean_old_df2.head(15)
# show how many tweets did or didnt match
```

executed in 15ms, finished 16:12:48 2021-07-28

Out[461]:

	product or company	emotion	clean_text	sentiment_compound	vader_emotion
0	Apple	Negative emotion	I have a G iPhone. After hrs tweeting at , it was dead! I need to upgrade. Plugin stations at .	-0.6800	Negative
1	Apple	Positive emotion	Know about ? Awesome iPad/iPhone app that you'll likely appreciate for its design. Also, they're giving free Ts at	0.9100	Positive
2	Apple	Positive emotion	Can not wait for also. They should sale them down at .	0.0000	Neutral
3	Apple	Negative emotion	I hope this year's festival isn't as crashy as this year's iPhone app.	0.7269	Positive
4	Google	Positive emotion	great stuff on Fri : Marissa Mayer (Google), Tim O'Reilly (tech books/conferences) & Matt Mullenweg (Wordpress)	0.6249	Positive
5	Apple	No emotion toward brand or product	New iPad Apps For And Communication Are Showcased At The Conference	0.0000	Neutral
7	Android	Positive emotion	is just starting, is around the corner and is only a hop skip and a jump from there, good time to be an fan	0.6369	Positive
8	Apple	Positive emotion	Beautifully smart and simple idea wrote about our iPad app for !	0.7712	Positive
9	Apple	Positive emotion	Counting down the days to plus strong Canadian dollar means stock up on Apple gear	0.5106	Positive
10	Android	Positive emotion	Excited to meet the at so I can show them my Sprint Galaxy S still running Android . .	0.3400	Positive
11	Android	Positive emotion	Find & Start Impromptu Parties at With I can't wait til the Android app comes out.	0.4019	Positive
12	Android	Positive emotion	Foursquare ups the game, just in time for - Still prefer by far, best looking Android app to date.	0.6369	Positive
13	Google	Positive emotion	Gotta love this Google Calendar featuring top parties/ show cases to check out. via =>	0.7184	Positive
14	Apple	Positive emotion	Great ipad app from :	0.6249	Positive
15	Apple	Positive emotion	haha, awesomely rad iPad app by	0.4588	Positive

In [462]:

```
clean_old_df2[clean_old_df2['vader_emotion'].isna()]
```

executed in 14ms, finished 16:12:48 2021-07-28

Out[462]:

product or company	emotion	clean_text	sentiment_compound	vader_emotion

In [463]:

```
emotion_dict={'Positive emotion':'Positive', 'Negative emotion':'Negative', 'No emotion
for key, values in emotion_dict.items():
    clean_old_df2.loc[clean_old_df2['emotion'].str.contains(key, case=False), 'emotion'
```

executed in 30ms, finished 16:12:48 2021-07-28

In [464]:

```
# Try to find how many of these match
clean_old_df2['emotion_match'] = np.where(clean_old_df2['emotion'] == clean_old_df2['va
```

executed in 15ms, finished 16:12:48 2021-07-28

In [465]:

```
1 clean_old_df2
```

executed in 15ms, finished 16:12:48 2021-07-28

Out[465]:

	product or company	emotion	clean_text	sentiment_compound	vader_emotion	emotion_mat
0	Apple	Negative	I have a G iPhone. After hrs tweeting at , it was dead! I need to upgrade. Plugin stations at .	-0.6800	Negative	Tr
1	Apple	Positive	Know about ? Awesome iPad/iPhone app that you'll likely appreciate for its design. Also, they're giving free Ts at	0.9100	Positive	Tr
2	Apple	Positive	Can not wait for also. They should sale them down at .	0.0000	Neutral	Fal
3	Apple	Negative	I hope this year's festival isn't as crashy as this year's iPhone app.	0.7269	Positive	Fal
4	Google	Positive	great stuff on Fri : Marissa Mayer (Google), Tim O'Reilly (tech books/conferences) & Matt Mullenweg (Wordpress)	0.6249	Positive	Tr
...	...	...	...	...	...	
9088	Apple	Positive	Ipad everywhere.	0.0000	Neutral	Fal
9089	Google	Neutral	Wave, buzz... We interrupt your regularly scheduled geek programming with big news	-0.4939	Negative	Fal
9090	Google	Neutral	Google's Zeiger, a physician never reported potential AE. Yet FDA relies on physicians. "We're operating w/out data." dev	0.0000	Neutral	Tr
9091	Apple	Neutral	Some Verizon iPhone customers complained their time fell back an hour this weekend. Of course they were the New Yorkers who attended .	-0.4019	Negative	Fal
9092	Google	Neutral	_ _ _ Google Tests Check-in Offers At	0.0000	Neutral	Tr

8306 rows × 6 columns

In [466]:

```
print(clean_old_df2['emotion_match'].value_counts())
clean_old_df2['emotion_match'].groupby(clean_old_df2['vader_emotion']).value_counts()
```

executed in 14ms, finished 16:12:48 2021-07-28

```
True     4509
False    3797
Name: emotion_match, dtype: int64
```

Out[466]:

```
vader_emotion  emotion_match
Negative       False            880
               True             219
Neutral        True            2503
               False           1140
Positive       True            1787
               False           1777
Name: emotion_match, dtype: int64
```

We are able to observe that around half of the previous sentiment analysis matches with the new vader sentiment analysis. We can see that the previous sentiment analysis did a poor job of identifying negative sentiments, was half and half for positive sentiments, and was able to correctly idenitfy a bit more than two-thirds of neutral sentiments

New Tweets

In [467]:

```
new_tweet_sentiment=[]
for text in clean_new2['clean_text']:
    ss=sid.polarity_scores(text)
    new_tweet_sentiment.append(ss['compound'])
new_tweet_sentiment
```

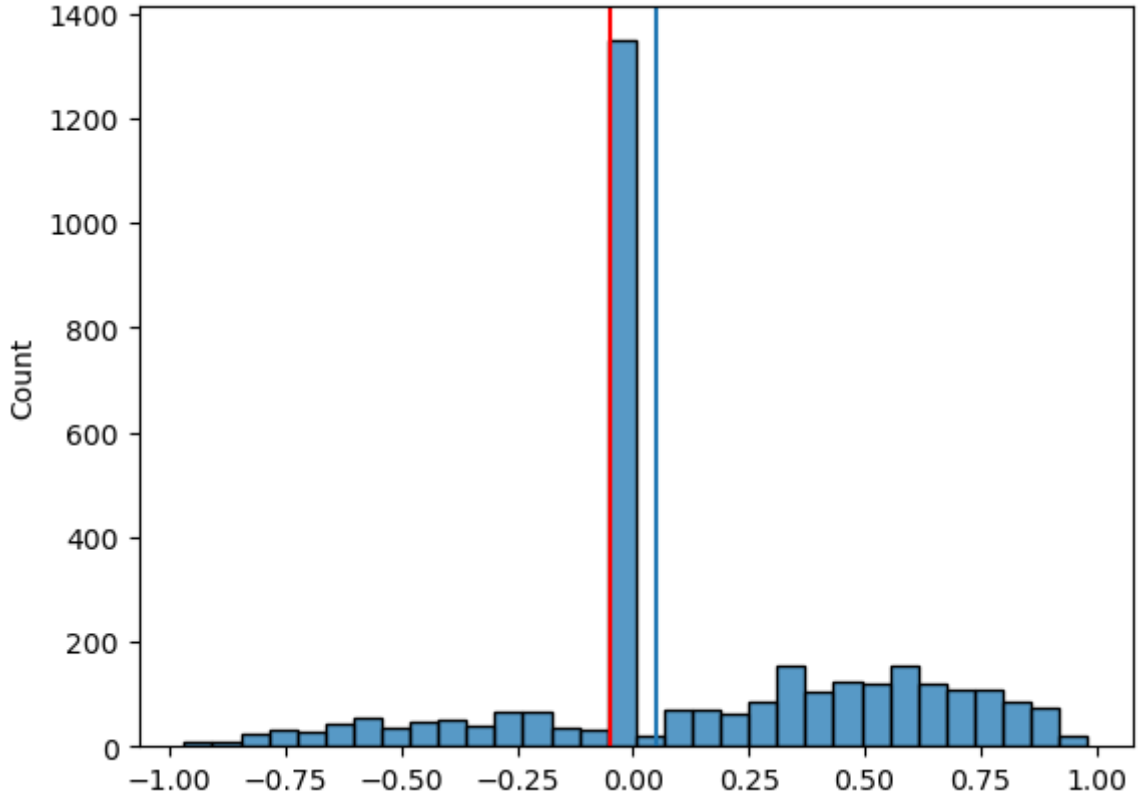
executed in 891ms, finished 16:12:49 2021-07-28

```
0.6249,
-0.2225,
0.0,
0.0,
0.8668,
0.0,
-0.7088,
0.0,
0.2714,
-0.3818,
0.7964,
0.0,
-0.4184,
0.4939,
0.9042,

0.4588,
0.0,
-0.2225,
0.2263,
-0.2987
```

In [468]:

```
ax = sns.histplot(new_tweet_sentiment)
ax.axvline(-.05, color='r')
ax.axvline(.05)
plt.show()
```

executed in 207ms, finished 16:12:49 2021-07-28



This graph also shows great similarity to the previous one where 0 is the most common sentiment value

In [469]:

```
# Give values to sentiment compound and use the values to give word values to vader emo
clean_new2['sentiment_compound']=new_tweet_sentiment

clean_new2.loc[clean_new2['sentiment_compound']>=.05, 'vader_emotion']='Positive'
clean_new2.loc[clean_new2['sentiment_compound']<=-.05, 'vader_emotion']='Negative'
clean_new2.loc[(clean_new2['sentiment_compound']>=-.05)&(clean_new2['sentiment_compound
```

executed in 14ms, finished 16:12:49 2021-07-28

In [470]:

```
1 clean_new2.head()
```

executed in 15ms, finished 16:12:49 2021-07-28

Out[470]:

	created_at	id	id_string	product or company	clean_text	sentiment_cc
0	Fri Jul 09 15:55:27 +0000 2021	1413527226071588868	1413527226071588868	Apple	the fact that apple doesn t sync the contacts you blocked on your phone to your mac is sick. this man messaged me and it came thru to my laptop and for the paat two days i ve been debating cursing him out	
1	Fri Jul 09 15:55:26 +0000 2021	1413527223252832257	1413527223252832257	Apple	j-armys doing the most for apple music yall pls stream there too	
5	Fri Jul 09 15:55:26 +0000 2021	1413527220727861251	1413527220727861251	Apple	Please, if you can, if it's okay on your schedule, do join on the listening parties! You just have to go to the site and log in with you Spotify/Apple Music account and you can join the listening party already!	
6	Fri Jul 09 15:55:24 +0000 2021	1413527212641423362	1413527212641423362	Apple	Due to I ll be blessing the first people that RETWEET & LIKE this tweet with — . Must have CashApp , Apple Pay or Zelle	

	created_at	id	id_string	product or company	clean_text	sentiment_cc
7	Fri Jul 09 15:55:23 +0000 2021	1413527209181126660	1413527209181126660	Apple	Opened Debris - Backlane request via iphone at A St SE Garbage piled in back lane.	

In [471]:

```
clean_new2['vader_emotion'].value_counts()
```

executed in 14ms, finished 16:12:49 2021-07-28

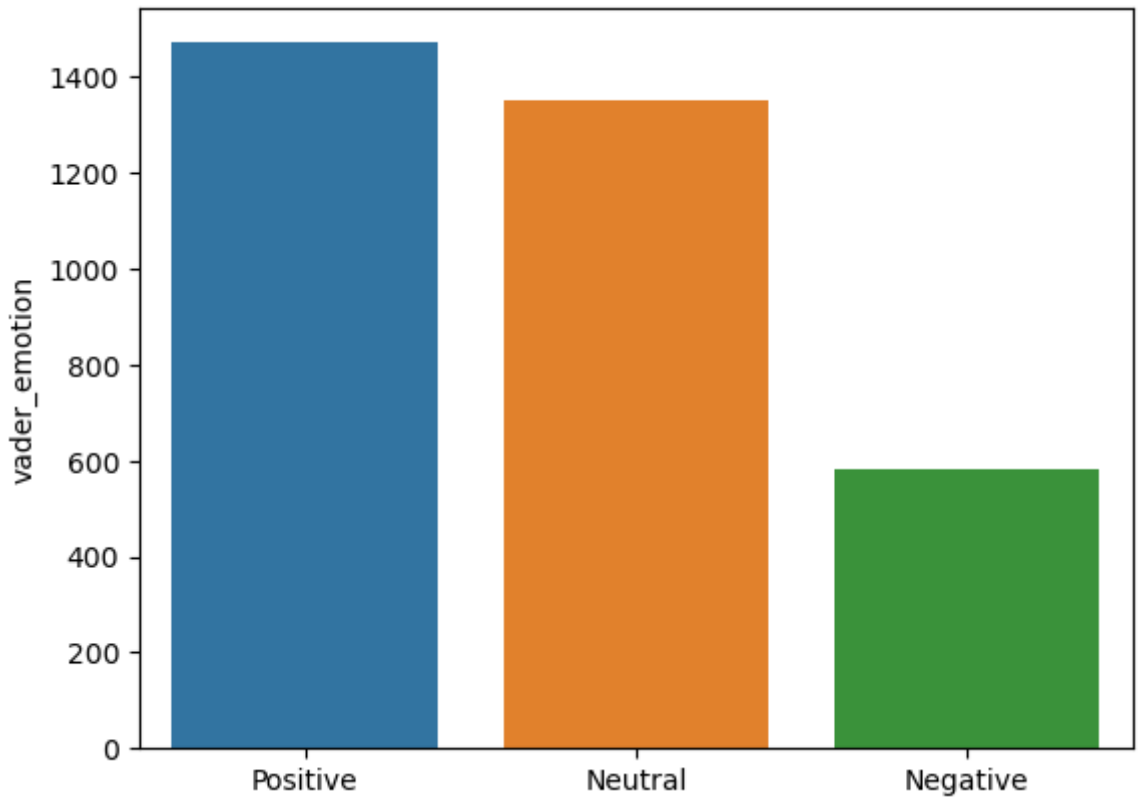
Out[471]:

```
Positive    1471
Neutral     1353
Negative     581
Name: vader_emotion, dtype: int64
```

In [472]:

```
ax = sns.barplot(x=clean_new2['vader_emotion'].value_counts().index, y=clean_new2['vade
plt.show()
```

executed in 126ms, finished 16:12:49 2021-07-28



The same can also be said of the individual emotions' value counts. Tweets with negative emotion are around a

third of both positve and neutral tweets

1.3 Tokenizing

Tokenizing is a process of splitting the tweet text into individual words and/or punctuation marks. This is considered one of the most important and foundational steps to performing NLP.

Old Tweets

In [473]:

```
# Create a list of all the common words in the old tweet
corpus_old = clean_old_df2['clean_text'].to_list()
token_list_old= word_tokenize(', '.join(corpus_old))
```

executed in 1.08s, finished 16:12:50 2021-07-28

In [474]:

```
freq_dist=FreqDist(token_list_old)
freq_dist.most_common(10)
```

executed in 126ms, finished 16:12:50 2021-07-28

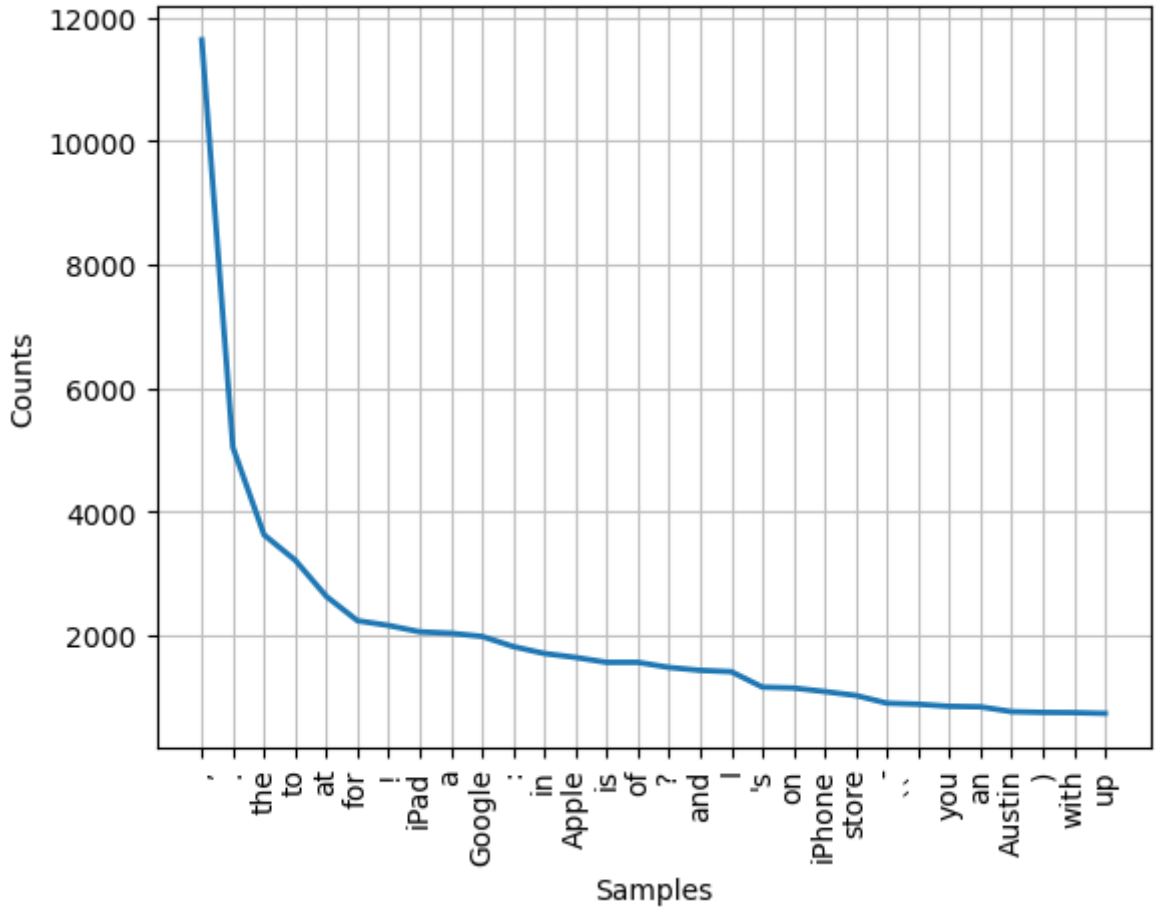
Out[474]:

```
[(',', 11638),
 ('.', 5044),
 ('the', 3628),
 ('to', 3218),
 ('at', 2632),
 ('for', 2238),
 ('!', 2161),
 ('iPad', 2058),
 ('a', 2035),
 ('Google', 1984)]
```

In [475]:

```
1 freq_dist.plot(30)
```

executed in 266ms, finished 16:12:51 2021-07-28



Out[475]:

<AxesSubplot:xlabel='Samples', ylabel='Counts'>

In [476]:

```
# Create a horizontal distribution of the most common words in the list
def common_word_hdist(word_list, n=30, figsize=(12,5)):
    freq_df = pd.DataFrame(word_list.most_common(100), columns=['Common Words','count']
    freq_df.set_index('Common Words').tail(n).plot(kind='barh', figsize=(12,5))
    plt.show()
```

executed in 13ms, finished 16:12:51 2021-07-28

In [477]:

```
# Create a list of all the common words in the newer tweets
corpus_new = clean_new2['clean_text'].to_list()
token_list_new= word_tokenize(', '.join(corpus_new))

freq_dist_new=FreqDist(token_list_new)
```

executed in 570ms, finished 16:12:51 2021-07-28

In [478]:

```
freq_df_new = pd.DataFrame(freq_dist_new.most_common(100), columns=['Common Words','cou
```

executed in 14ms, finished 16:12:51 2021-07-28

I wanted to see which words were the most common in the tweets as well as which words should be included in the stopwords list. So after creating frequency distribution of the combination of both old and new tweets' clean text, I created a distribution plot of the most common words/characters

In [479]:

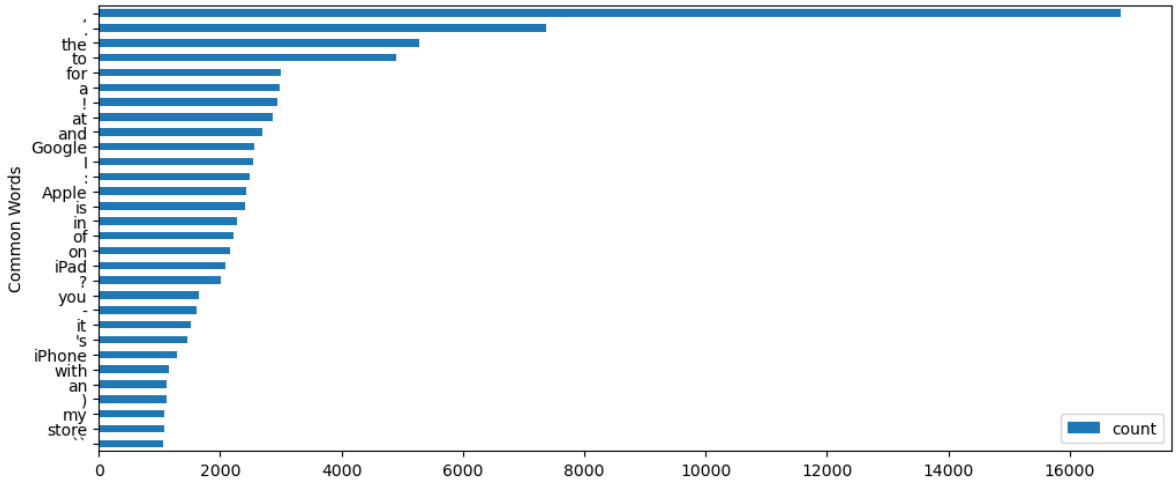
```
corpus_total = pd.concat([clean_old_df2['clean_text'],clean_new2['clean_text']]).to_lis
total_tokenlist = word_tokenize(', '.join(corpus_total))
freq_total = FreqDist(total_tokenlist)

```

executed in 1.74s, finished 16:12:53 2021-07-28

In [480]:

```
# frequency distribution of the most common words/characters in both tweets
common_word_hdist(freq_total)
```

executed in 330ms, finished 16:12:53 2021-07-28



In both the old and new tweets, punctuation marks were always on the top 30 most common characters. Other common words included the companies' names and products. I determined that these words/characters should be included in the stopwords list

Stop Words

In [481]:

```
#Stop words
stop_words=stopwords.words('english')
stop_words.sort()
stop_words
```

executed in 14ms, finished 16:12:53 2021-07-28

. . .

In [482]:

```
# First I am including punctuation marks, common twitter phrases such as rt and mentior
# Quotation marks were also included since they were not part of the string.punctuatior
# Finally, posessives such as 's and the company names and products were included in th
stop_words.extend(string.punctuation)
stop_words.extend(['RT', 'mention','SXSW','link'])
stop_words.extend(['“','”','...',"''",'’','``'])
stop_words.extend(["'s","n't"])
stop_words.extend(['apple','google','android','apple','ipad','i-pad','iphone'])
```

executed in 14ms, finished 16:12:53 2021-07-28

In [483]:

```
# only have 1 dist plt and then use the stopwords to show which words were actually use
# Then display the dist plot for the new and old tweets
```

executed in 14ms, finished 16:12:53 2021-07-28

In [484]:

```
#Create new word cloud stop word list
wordcloud_stopwords=stop_words.copy()
```

executed in 14ms, finished 16:12:53 2021-07-28

In [497]:

```
# Removing stopwords from token lists
stopwords_removed_old = [x.lower() for x in token_list_old if x.lower() not in stop_wor
stopwords_removed_new = [x.lower() for x in token_list_new if x.lower() not in stop_wor
stopwords_removed_total = [x.lower() for x in total_tokenlist if x.lower() not in stop_
```

executed in 1.10s, finished 16:16:00 2021-07-28

In [498]:

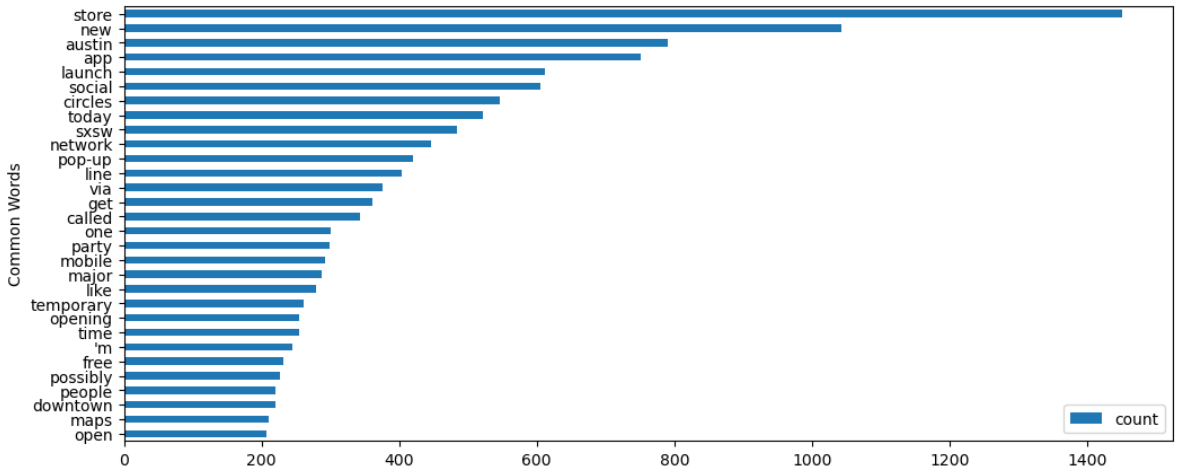
```
sw_freq_old = FreqDist(stopwords_removed_old)
sw_freq_new = FreqDist(stopwords_removed_new)
sw_freq_total = FreqDist(stopwords_removed_new)
```

executed in 122ms, finished 16:16:01 2021-07-28

In [499]:

```
common_word_hdist(sw_freq_old)
```

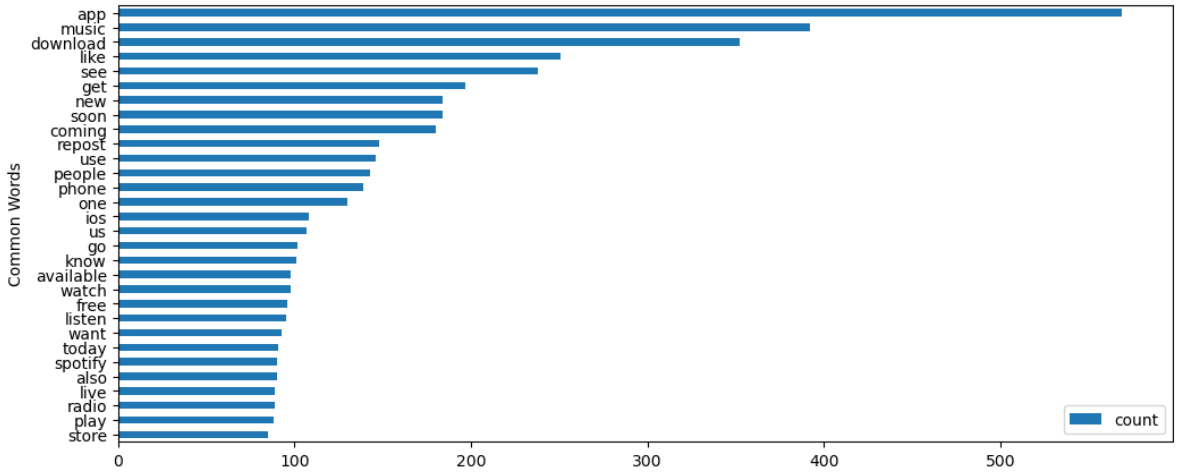
executed in 328ms, finished 16:16:01 2021-07-28



In [500]:

```
1 common_word_hdist(sw_freq_new)
```

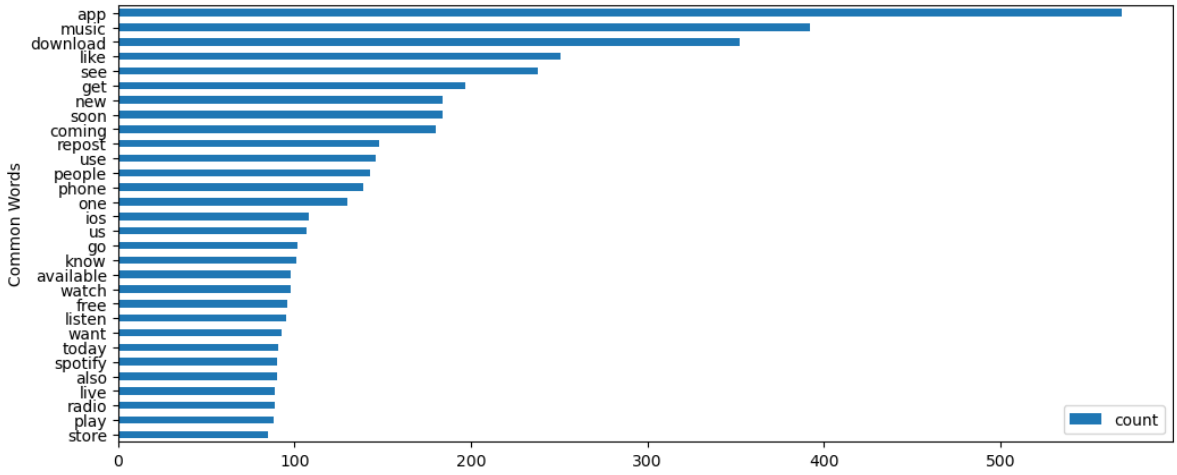
executed in 332ms, finished 16:16:01 2021-07-28



In [502]:

```
1 common_word_hdist(sw_freq_total)
```

executed in 307ms, finished 16:16:28 2021-07-28



In [317]:

```
t_tokenizer=TweetTokenizer(strip_handles=True, reduce_len=True)
t_token=[]
# for token in token_list:
for text in clean_old_df2['clean_text']:
    t_token.extend(t_tokenizer.tokenize(text))
# t_token
```

executed in 838ms, finished 12:15:53 2021-07-28

1.3.1 Lemmatization

Old Tweets

In [318]:

```
lemmatizer = WordNetLemmatizer()
lemmatized_old_tweet = [lemmatizer.lemmatize(x) for x in token_list_old]
lemmatized_old_tweet[:5]
```

executed in 629ms, finished 12:15:54 2021-07-28

Out[318]:

```
['I', 'have', 'a', 'G', 'iPhone']
```

New Tweets

In [319]:

```
lemmatized_new_tweet = [lemmatizer.lemmatize(x) for x in token_list_new]
lemmatized_new_tweet[:5]
```

executed in 330ms, finished 12:15:54 2021-07-28

Out[319]:

```
['the', 'fact', 'that', 'apple', 'doesn']
```

In [320]:

```
# Vectorizer for modeling. it will do tokenizing for you. scikitlearn.vectorizer
# for twitter say tokenizer=tweettokenizer

# Using the compound(from vader), give sentiment first then create word clouds for posi

```

executed in 14ms, finished 12:15:54 2021-07-28

1.4 Old Tweet Modeling

1.4.1 Preprocessing

In [321]:

```
old_X = clean_old_df2['clean_text'].copy()
old_y = clean_old_df2['vader_emotion'].copy()
```

executed in 13ms, finished 12:15:54 2021-07-28

In [322]:

```
old_X_train , old_X_test , old_y_train , old_y_test = train_test_split(old_X, old_y, te
```

executed in 15ms, finished 12:15:54 2021-07-28

In [323]:

```
old_X_train
```

executed in 14ms, finished 12:15:54 2021-07-28

Out[323]:

```
749                                                          Google
no lanzara ningun producto en South by SouthWest
6767                                  The session is changing my mind ab
out my future kid's relationship with the iPhone.
7022
Am I the only one left with an iPad
3927                                                Playing with my fave
new iPhone app, Wow, this will rock at next week!
921                                       HootSuite News: HootSuite Mobi
le for ~ Updates for iPhone, BlackBerry & Android
                                                                    ...
2938             Lol at : "apple comes up with cool technology no one's e
ver heard of because they don't go to conferences"
8508                                                 P.S. and Google th
row a b!tchin' party. Shout out to The Spazmatics
108                                                 opens "Mobile Park"
& Content Incubator at constructs "pop-up" store
7370                                                                 V
erizon IPhone at = bars, baby. Suck on that, AT&T!
1273    There are two apple stores in ATX!! The iPad goes on sale next Fri
day...the Austin Apple Store is going to be busy!
Name: clean_text, Length: 5814, dtype: object
```

In [324]:

```
old_y_train.isna().sum()
```

executed in 13ms, finished 12:15:54 2021-07-28

Out[324]:

```
0
```

1.4.2 Vectorization

In [325]:

```
vectorizer =TfidfVectorizer(tokenizer=t_tokenizer.tokenize,stop_words=stop_words)
old_X_train_tfidf = vectorizer.fit_transform(old_X_train)
old_X_test_tfidf = vectorizer.transform(old_X_test)
old_X_train_tfidf
```

executed in 946ms, finished 12:15:55 2021-07-28

```
F:\Anaconda3\envs\learn-env\lib\site-packages\sklearn\feature_extraction\tex
t.py:388: UserWarning:

Your stop_words may be inconsistent with your preprocessing. Tokenizing the
stop words generated tokens ['rt', 'sxsw'] not in stop_words.
```

Out[325]:

```
<5814x6934 sparse matrix of type '<class 'numpy.float64'>'
        with 44646 stored elements in Compressed Sparse Row format>
```

In [326]:

```
len(vectorizer.vocabulary_)
```

executed in 15ms, finished 12:15:55 2021-07-28

Out[326]:

```
6934
```

In [327]:

```
print(old_y_train.unique())
```

executed in 14ms, finished 12:15:55 2021-07-28

```
['Negative' 'Neutral' 'Positive']
```

1.4.3 Random Forest

In [328]:

```
# Random Forest Modeling
rand_f=RandomForestClassifier(class_weight='balanced')
rand_f.fit(old_X_train_tfidf, old_y_train)
```

executed in 3.83s, finished 12:15:59 2021-07-28

Out[328]:

```
RandomForestClassifier(class_weight='balanced')
```

In [329]:

```
# give model score.
# model = sckitlearn model type

def model_score(model, X_test_tfidf, y_test, cmap='Blues', normalize='true', class_name
                X_train=None, y_train=None):
    # predictions and classification report
    print(metrics.classification_report(y_test, model.predict(X_test_tfidf), target_nar

    # Confusion Matrix
#     fig, ax= plt.subplots(ncols=len(class_names), figsize=figsize)
    metrics.plot_confusion_matrix(model, X_test_tfidf, y_test, cmap=cmap, normalize=nor
                                  display_labels=class_names)#, ax=ax[0])

    if (X_train is not None) & (y_train is not None):
        print(f"Training Score = {model.score(X_train,y_train):.2f}")
        print(f"Test Score = {model.score(X_test_tfidf,y_test):.2f}")
    plt.show()
```

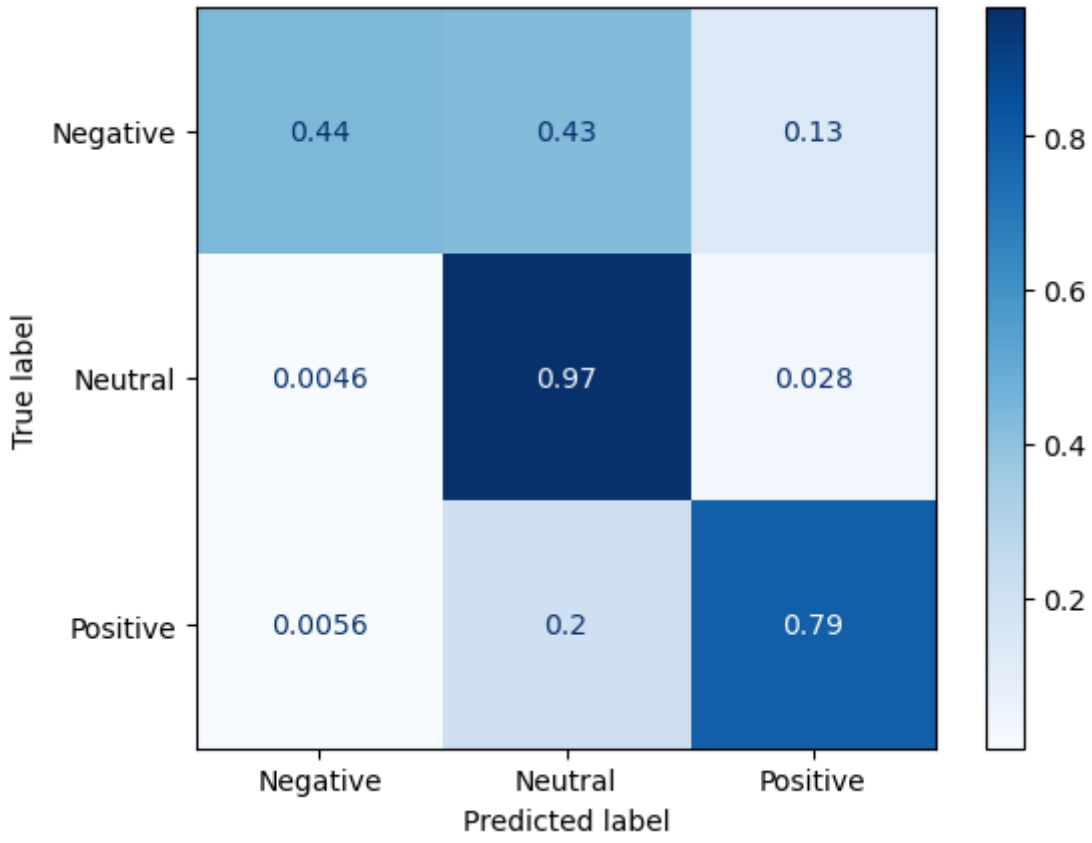
executed in 15ms, finished 12:15:59 2021-07-28

In [330]:

```
model_score(rand_f, old_X_test_tfidf, old_y_test, class_names=None,#old_y_train.unique(
            X_train=old_X_train_tfidf, y_train=old_y_train)
```

executed in 946ms, finished 12:16:00 2021-07-28

```
              precision    recall  f1-score   support

    Negative       0.93      0.44      0.60       338
     Neutral       0.75      0.97      0.84      1091
    Positive       0.92      0.79      0.85      1063

    accuracy                           0.82      2492
   macro avg       0.87      0.73      0.76      2492
weighted avg       0.84      0.82      0.81      2492

Training Score = 1.00
Test Score = 0.82
```



Tweets with neutral sentiments were most well identified. I believe that this is the case because of the small range given to neutral sentiments in vader sentiment analysis.

Random Forest GridSearch and NLP Pipeline

In [332]:

```
tweet_pipeline = Pipeline(steps=[('count_vectorizer',CountVectorizer()),
                                 ('tf_transformer',TfidfTransformer(use_idf=True))])
tweet_pipeline
```

executed in 14ms, finished 12:16:06 2021-07-28

Out[332]:

```
Pipeline(steps=[('count_vectorizer', CountVectorizer()),
                ('tf_transformer', TfidfTransformer())])
```

In [333]:

```
old_X_train_pipe= tweet_pipeline.fit_transform(old_X_train)
old_X_test_pipe= tweet_pipeline.transform(old_X_test)
old_X_train_pipe
```

executed in 142ms, finished 12:16:06 2021-07-28

Out[333]:

```
<5814x6772 sparse matrix of type '<class 'numpy.float64'>'
        with 76494 stored elements in Compressed Sparse Row format>
```

In [334]:

```
model_pipeline=Pipeline([('tweet_pipe', tweet_pipeline),
                         ('clf', RandomForestClassifier(class_weight='balanced'))])
model_pipeline
```

executed in 15ms, finished 12:16:06 2021-07-28

Out[334]:

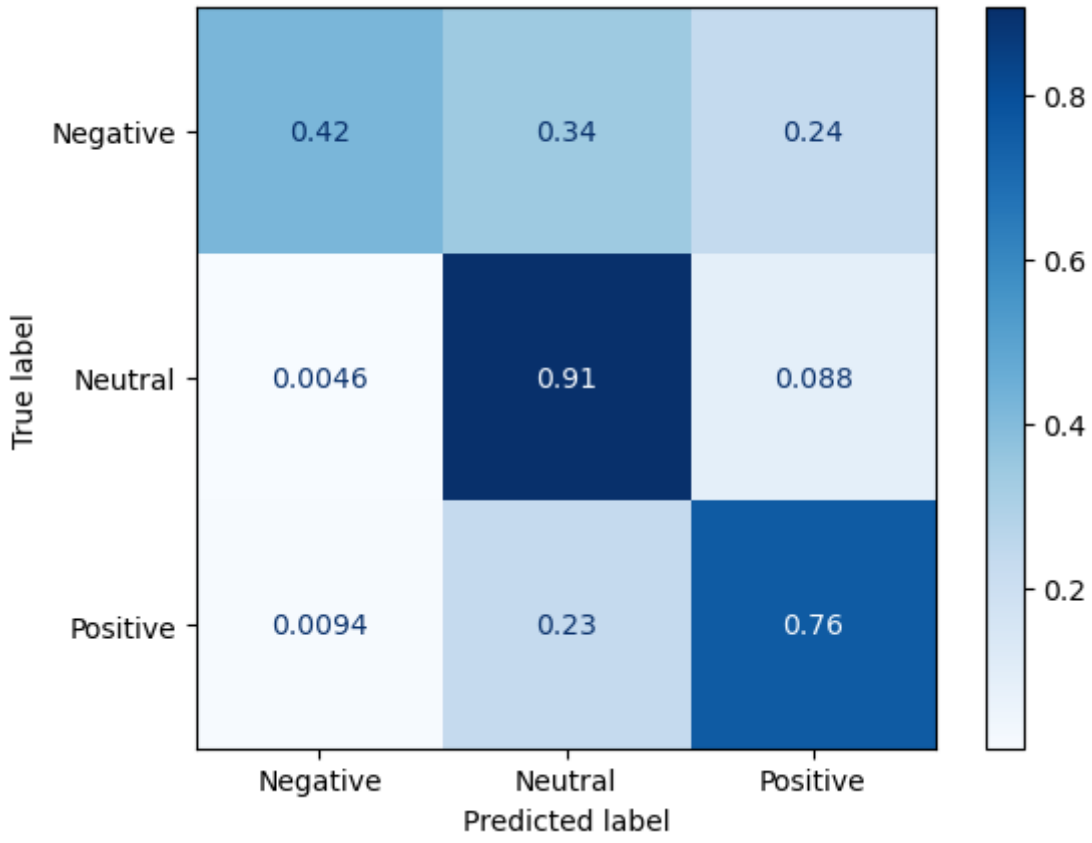
```
Pipeline(steps=[('tweet_pipe',
                 Pipeline(steps=[('count_vectorizer', CountVectorizer()),
                                 ('tf_transformer', TfidfTransformer())])),
                ('clf', RandomForestClassifier(class_weight='balanced'))])
```

In [335]:

```
1 model_pipeline.fit(old_X_train, old_y_train)
2 model_score(model_pipeline, old_X_test, old_y_test, X_train=old_X_train, y_train= old_y
```

executed in 5.37s, finished 12:16:11 2021-07-28

```
              precision    recall  f1-score   support

    Negative       0.91      0.42      0.58       338
     Neutral       0.73      0.91      0.81      1091
    Positive       0.82      0.76      0.79      1063

    accuracy                           0.78      2492
   macro avg       0.82      0.70      0.72      2492
weighted avg       0.79      0.78      0.77      2492

Training Score = 1.00
Test Score = 0.78
```



After performing the pipeline, we see that the performance has decreased for the model.

In [337]:

```
params = {'tweet_pipe__tf_transformer__use_idf':[True,False],
          'tweet_pipe__tf_transformer__norm':['l2','l1'],
          'tweet_pipe__tf_transformer__smooth_idf':[True,False],
          'tweet_pipe__count_vectorizer__stop_words':[stop_words,None],
          'clf__criterion':['gini','entropy'],
          'clf__max_depth':[None, 10, 30, 50, 75]
         }
```

executed in 15ms, finished 12:16:11 2021-07-28

In [338]:

```
gs= GridSearchCV(model_pipeline, params, cv=3, scoring='recall_macro', n_jobs=-1, verbo
gs.fit(old_X_train, old_y_train)
gs.best_params_
```

executed in 1m 26.9s, finished 12:17:38 2021-07-28

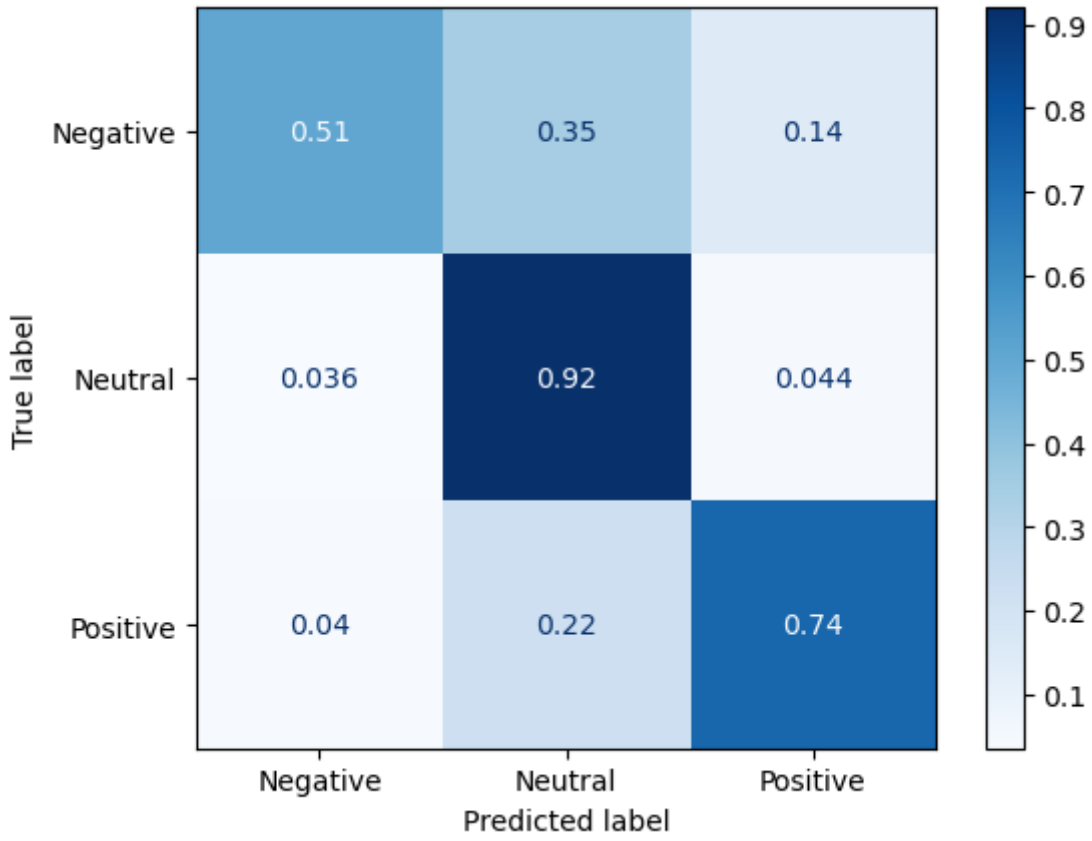
```
Your stop_words may be inconsistent with your preprocessing. Tokenizing th
e stop words generated tokens ['pad', 'rt', 'sxsw'] not in stop_words.
```

In [339]:

```
1 model_score(gs.best_estimator_, old_X_test, old_y_test, X_train= old_X_train, y_train=
```

executed in 767ms, finished 12:17:39 2021-07-28

```
              precision    recall  f1-score   support

    Negative       0.68      0.51      0.58       338
     Neutral       0.74      0.92      0.82      1091
    Positive       0.89      0.74      0.81      1063

    accuracy                           0.79      2492
   macro avg       0.77      0.72      0.74      2492
weighted avg       0.80      0.79      0.78      2492

Training Score = 0.95
Test Score = 0.79
```



The gridsearch helped improve identifying tweets with negative sentiments, but the recall score for the neutral and positive tweets have decreased by nearly identical amount. However, I believe that this is the best model for the old tweets' sentiment analysis as the recall score for both the neutral and positive sentiments were

acceptable, and the recall score for negative sentiments were above .5

1.4.4 Naive Bayesian Classification

In [340]:

```
# n_bayes = GaussianNB()
n_bayes = MultinomialNB()
n_bayes.fit(old_X_train_pipe, old_y_train)
```

executed in 30ms, finished 12:17:39 2021-07-28

Out[340]:

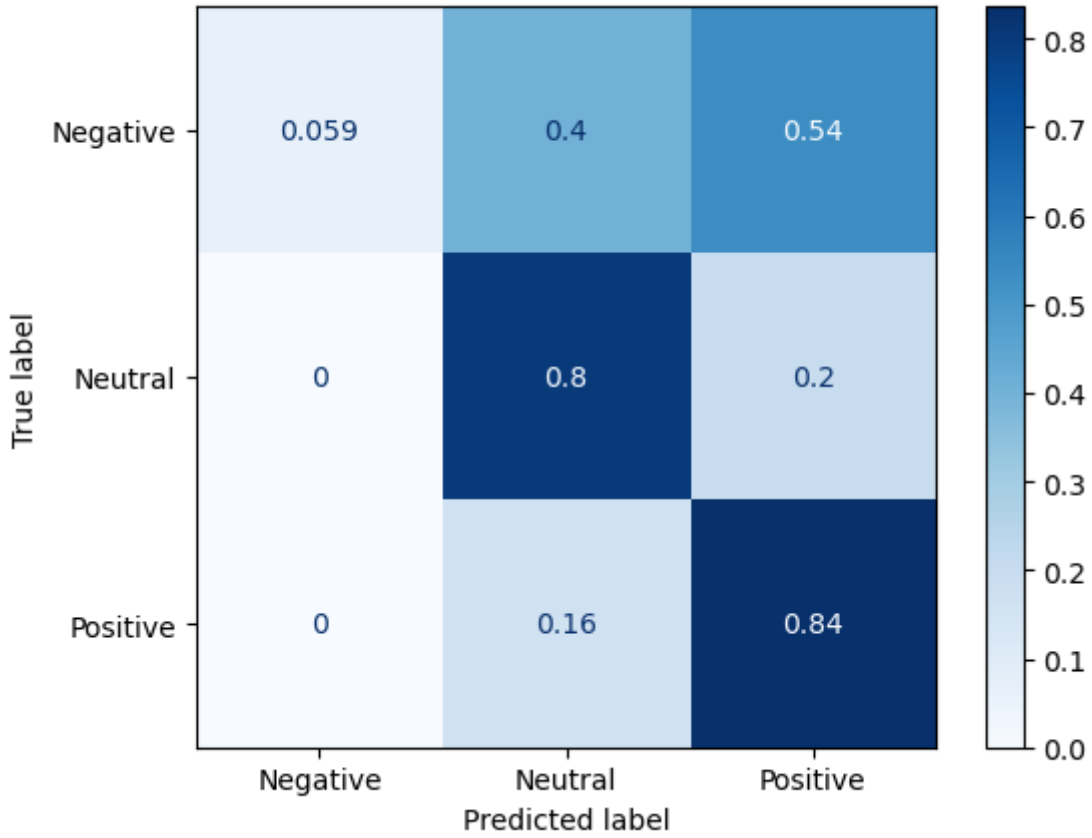
```
MultinomialNB()
```

In [341]:

```
model_score(n_bayes, old_X_test_pipe, old_y_test, X_train= old_X_train_pipe, y_train= o
```

executed in 265ms, finished 12:17:39 2021-07-28

```
              precision    recall  f1-score   support

    Negative       1.00      0.06      0.11       338
     Neutral       0.74      0.80      0.77      1091
    Positive       0.69      0.84      0.76      1063

    accuracy                           0.72      2492
   macro avg       0.81      0.57      0.55      2492
weighted avg       0.75      0.72      0.67      2492

Training Score = 0.81
Test Score = 0.72
```



Compared to the random forest model, the naive bayesian model performed significantly worse, especially for tweets with negative sentiments. Even with the smaller size of the negative tweets, the low recall rate of .059 seems to be extraneous.

In [342]:

```
bayes_pipeline= Pipeline(steps=[('tweet_pipe', tweet_pipeline), ('clf', MultinomialNB()

params = {'tweet_pipe__tf_transformer__use_idf':[True, False],
          'tweet_pipe__tf_transformer__norm':['l2','l1'],
          'tweet_pipe__tf_transformer__use_idf':[True,False],
          'tweet_pipe__tf_transformer__smooth_idf':[True,False],
#           'tweet_pipe__count_vectorizer__tokenizer':[
# #               None,
#               TweetTokenizer(preserve_case=True).tokenize,
#               TweetTokenizer(preserve_case=False).tokenize],

          'tweet_pipe__count_vectorizer__stop_words':[None,stop_words],
#           'tweet_pipe__count_vectorizer__max_df':[1.0,0.95,0.9],
#           'ttweet_pipe__count_vectorizer__min_df':[1,2,3],

         'clf__alpha':[0, 1],
         'clf__fit_prior':[True,False]}
gs = GridSearchCV(bayes_pipeline, params, cv=3, scoring = 'recall_macro', n_jobs=-1, ve
gs.fit(old_X_train, old_y_train)
gs.best_params_
```

executed in 3.19s, finished 12:17:42 2021-07-28

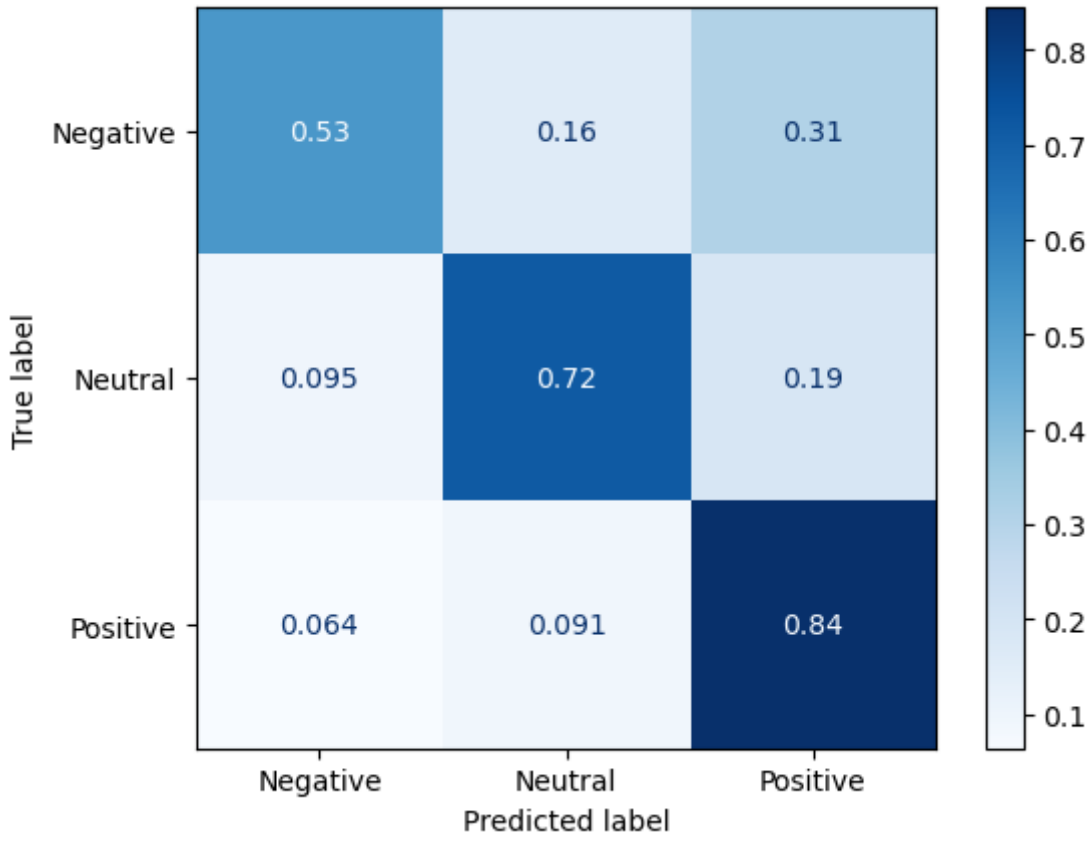
```
Fitting 3 folds for each of 64 candidates, totalling 192 fits

F:\Anaconda3\envs\learn-env\lib\site-packages\sklearn\feature_extraction\t
ext.py:388: UserWarning:

Your stop_words may be inconsistent with your preprocessing. Tokenizing th
e stop words generated tokens ['pad', 'rt', 'sxsw'] not in stop_words.

F:\Anaconda3\envs\learn-env\lib\site-packages\sklearn\naive_bayes.py:508:
UserWarning:

alpha too small will result in numeric errors, setting alpha = 1.0e-10
```

In [343]:

```
1 model_score(gs.best_estimator_, old_X_test, old_y_test, X_train= old_X_train, y_train =
```

executed in 415ms, finished 12:17:43 2021-07-28

```
              precision    recall  f1-score   support

    Negative       0.51      0.53      0.52       338
     Neutral       0.84      0.72      0.77      1091
    Positive       0.74      0.84      0.79      1063

    accuracy                           0.75      2492
   macro avg       0.70      0.70      0.70      2492
weighted avg       0.75      0.75      0.75      2492

Training Score = 0.95
Test Score = 0.75
```



After performing the grid search for the naive bayesian model, the results improved dramatically. The recall score for the negative tweets were slightly better than the random forest models, but the overall recall scores were lower than the rf models

1.5 New Tweet Modeling

1.5.1 Preprocessing

In [344]:

```
# move for each new tweet old tweet. move x and y above the models
```

executed in 15ms, finished 12:17:43 2021-07-28

In [345]:

```
new_X = clean_new2['clean_text'].copy()
new_y = clean_new2['vader_emotion'].copy()
```

executed in 14ms, finished 12:17:43 2021-07-28

In [346]:

```
new_X_train , new_X_test , new_y_train , new_y_test = train_test_split(new_X, new_y, te
new_X_train
```

executed in 14ms, finished 12:17:43 2021-07-28

Out[346]:

```
4421
Homescreen for Today Kggm Material for Kwgt by Wallpaper by Hishoot Templa
te by
1542             I just google things. You can always rely on google to te
ll you anything. And YouTube! So many times that had saved me by giving me
a visual walkthrough!
3041
YouTube TV Picks Up Three New Add-On Channels For $ . Each
4127
Make your case!
659                                                                      D
amn. Apple is gonna bring the hammer down. Shifts will go from to hours at
their overseas plant.

...
151
Glad today my last day with this fucked up ass iPhone
3727
Nirvana - Come As You Are Listen KILPOP RADIO APP
1905                                    Coronavirus Delta Variant Cripples
Bangladesh in Third COVID- Wave - The Great Courses Daily News - "indian m
uslims" - Google News
1282
apple
1861    Vergecast! joins to talk about the big Google antitrust suit and m
ore. I talk a bit more about my Switch OLED model hands on. And has emotio
ns about Jeep drones.
Name: clean_text, Length: 2383, dtype: object
```

1.5.2 Vectorization

In [347]:

```
new_vectorizer = TfidfVectorizer(tokenizer=t_tokenizer.tokenize,stop_words=stop_words)
new_X_train_tfidf = new_vectorizer.fit_transform(new_X_train)
new_X_test_tfidf = new_vectorizer.transform(new_X_test)
new_X_train_tfidf
```

executed in 496ms, finished 12:17:43 2021-07-28

```
F:\Anaconda3\envs\learn-env\lib\site-packages\sklearn\feature_extraction\tex
t.py:388: UserWarning:

Your stop_words may be inconsistent with your preprocessing. Tokenizing the
stop words generated tokens ['rt', 'sxsw'] not in stop_words.
```

Out[347]:

```
<2383x6758 sparse matrix of type '<class 'numpy.float64'>'
        with 23360 stored elements in Compressed Sparse Row format>
```

In [348]:

```
new_y_train.unique()
```

executed in 14ms, finished 12:17:43 2021-07-28

Out[348]:

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

1.5.3 Random Forest

In [349]:

```
rand_f2=RandomForestClassifier(class_weight='balanced')
rand_f2.fit(new_X_train_tfidf, new_y_train)
```

executed in 1.16s, finished 12:17:44 2021-07-28

Out[349]:

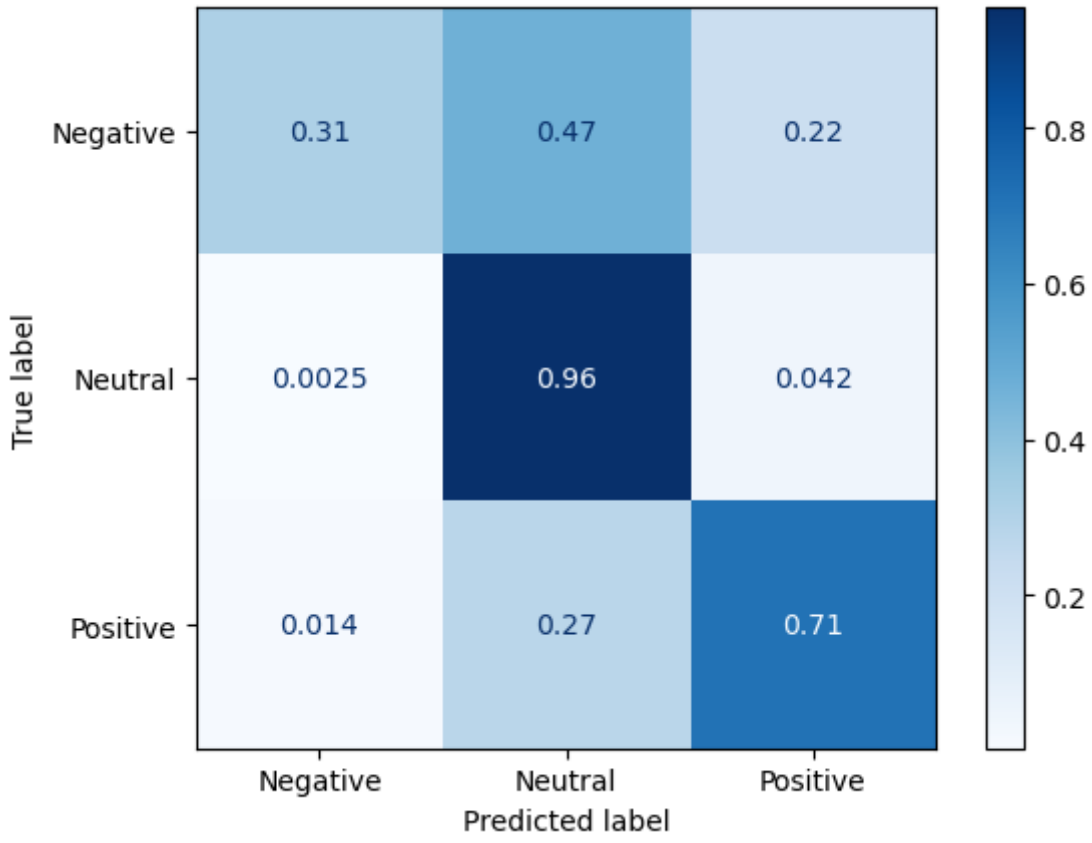
```
RandomForestClassifier(class_weight='balanced')
```

In [388]:

```
model_score(rand_f2, new_X_test_tfidf, new_y_test, class_names=None,
            X_train = new_X_train_tfidf, y_train = new_y_train)
```

executed in 526ms, finished 13:10:52 2021-07-28

```
              precision    recall  f1-score   support

    Negative       0.89      0.31      0.46       175
     Neutral       0.66      0.96      0.78       406
    Positive       0.85      0.71      0.78       441

    accuracy                           0.74      1022
   macro avg       0.80      0.66      0.67      1022
weighted avg       0.78      0.74      0.72      1022

Training Score = 1.00
Test Score = 0.74
```



The number of tweets with negative sentiments were also mirrored with the older tweets (a third of positive or neutral), and the results are also similar with the highest recal score for neutral tweets.

Pipeline

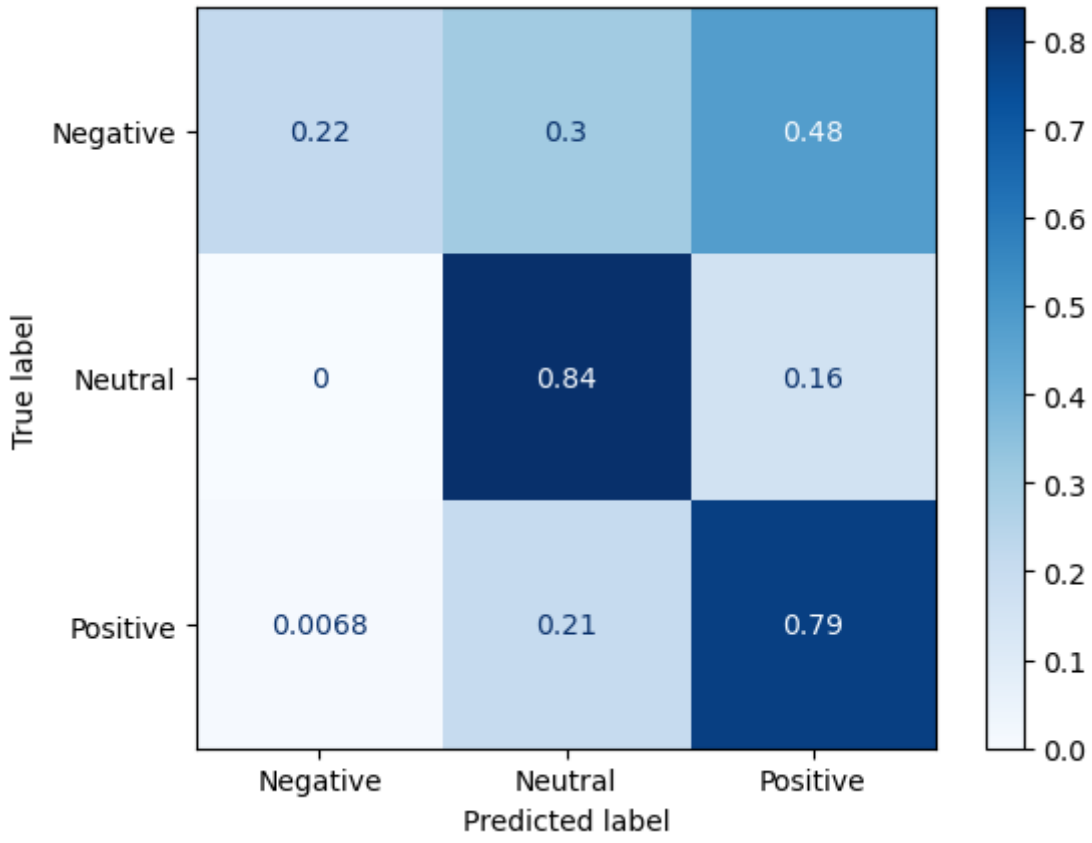
In [352]:

```
tweet_pipeline_new = Pipeline(steps=[('count_vectorizer',CountVectorizer()),
                            ('tf_transformer',TfidfTransformer(use_idf=True))])


new_X_train_pipe= tweet_pipeline.fit_transform(new_X_train)
new_X_test_pipe= tweet_pipeline.transform(new_X_test)


model_pipeline_new=Pipeline([('tweet_pipe', tweet_pipeline),
                         ('clf', RandomForestClassifier(class_weight='balanced'))])


model_pipeline_new.fit(new_X_train, new_y_train)
model_score(model_pipeline_new, new_X_test, new_y_test, X_train=new_X_train, y_train= r
```

executed in 1.91s, finished 12:17:52 2021-07-28

	precision	recall	f1-score	support
Negative	0.93	0.22	0.35	175
Neutral	0.70	0.84	0.76	406
Positive	0.70	0.79	0.74	441
accuracy			0.71	1022
macro avg	0.78	0.61	0.62	1022
weighted avg	0.74	0.71	0.68	1022

Training Score = 1.00
Test Score = 0.71



Compared to the old tweets' random forest model with pipeline, there is a slight increase in the recall score for tweets with positive sentiment. However, like in the old tweets' model, the overall performance has decreased compared to the rf model without pipelining.

GridSearch CV

In [391]:

```
params = {'tweet_pipe__tf_transformer__use_idf':[True,False],
          'tweet_pipe__tf_transformer__norm':['l2','l1'],
          'tweet_pipe__tf_transformer__smooth_idf':[True,False],
          'tweet_pipe__count_vectorizer__stop_words':[stop_words,None],
          'tweet_pipe__count_vectorizer__max_df':[1.0,0.95],
          'tweet_pipe__count_vectorizer__min_df':[1,2,3],
          'clf__criterion':['gini','entropy'],
          'clf__max_depth':[None, 10, 30, 50, 75]
         }

gs_new= GridSearchCV(model_pipeline_new, params, cv=3, scoring='recall_macro', n_jobs=-
# SCORING RECALL MACRO IF I GET ALL THE NANS
gs_new.fit(new_X_train, new_y_train)
gs_new.best_params_
```

executed in 3m 26s, finished 13:18:33 2021-07-28

Out[391]:

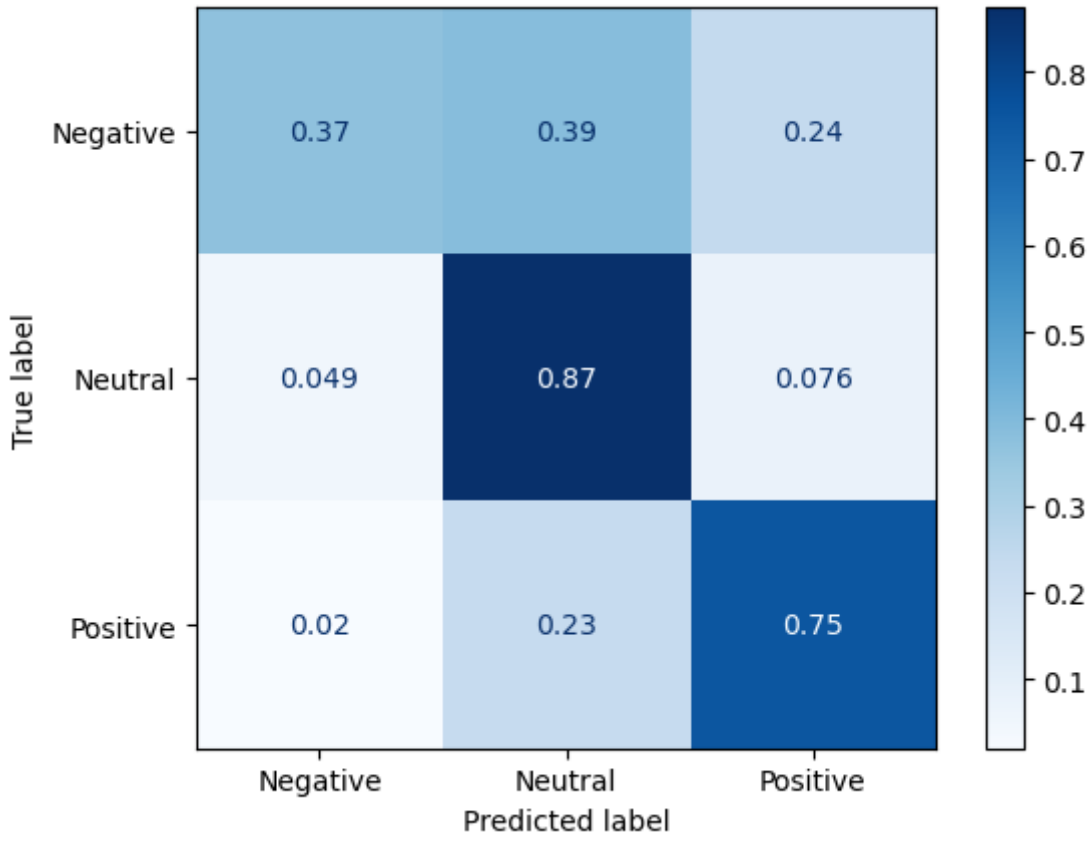
```
{'clf__criterion': 'entropy',
 'clf__max_depth': None,
 'tweet_pipe__count_vectorizer__max_df': 0.95,
 'tweet_pipe__count_vectorizer__min_df': 3,
 'tweet_pipe__count_vectorizer__stop_words': ['a',
```

In [392]:

```
1 model_score(gs_new.best_estimator_, new_X_test, new_y_test, X_train= new_X_train, y_tra
```

executed in 595ms, finished 13:18:34 2021-07-28

```
              precision    recall  f1-score   support

    Negative       0.69      0.37      0.48       175
     Neutral       0.68      0.87      0.76       406
    Positive       0.82      0.75      0.78       441

    accuracy                           0.73      1022
   macro avg       0.73      0.66      0.68      1022
weighted avg       0.74      0.73      0.72      1022

Training Score = 0.99
Test Score = 0.73
```



The recall scores for negative tweets has slightly improved compared to the original rf model of the new tweets, but the recall scores of the other tweets have decreased by a similar amount to that increase. However, like the rf models of the old tweets, I believe that the rf models after the gridsearch are the best because it maintains a relatively high recall score for the positive and neutral tweets while improving the recall score for the negative tweets.

1.5.4 Naive Bayesian

In [355]:

```
1 n_bayes_new = MultinomialNB()
2 n_bayes_new.fit(new_X_train_pipe, new_y_train)
```

executed in 14ms, finished 12:21:13 2021-07-28

Out[355]:

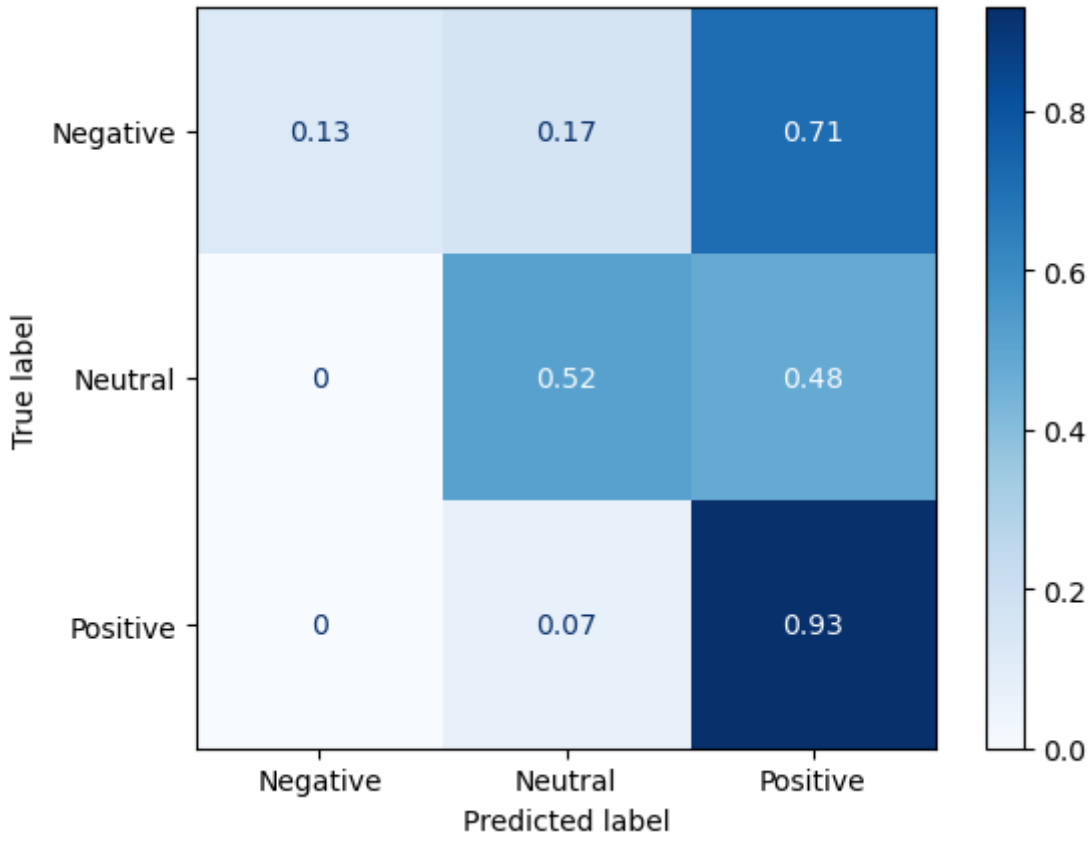
```
MultinomialNB()
```

In [356]:

```
1 model_score(n_bayes_new, new_X_test_pipe, new_y_test, X_train= new_X_train_pipe, y_trai
```

executed in 223ms, finished 12:21:13 2021-07-28

```
              precision    recall  f1-score   support

    Negative       1.00      0.13      0.22       175
     Neutral       0.78      0.52      0.62       406
    Positive       0.56      0.93      0.70       441

    accuracy                           0.63      1022
   macro avg       0.78      0.52      0.51      1022
weighted avg       0.72      0.63      0.59      1022

Training Score = 0.77
Test Score = 0.63
```



The recall score for the negative and neutral tweets are far lower than those from the random forest model. Overall, the naive bayesian models did not perform well before performing the gridsearch.

Naive Bayesian GridSearch

In [357]:

```
bayes_pipeline_new= Pipeline(steps=[('tweet_pipe', tweet_pipeline), ('clf', Multinomial

params = {'tweet_pipe__tf_transformer__use_idf':[True, False],
          'tweet_pipe__tf_transformer__norm':['l2','l1'],
          'tweet_pipe__tf_transformer__use_idf':[True,False],
          'tweet_pipe__tf_transformer__smooth_idf':[True,False],
          'tweet_pipe__count_vectorizer__stop_words':[None,stop_words],
         'clf__alpha':[0, 1],
         'clf__fit_prior':[True,False]}
gs_new = GridSearchCV(bayes_pipeline_new, params, cv=3, scoring = 'recall_macro', n_jo
gs_new.fit(new_X_train, new_y_train)
gs_new.best_params_
```

executed in 1.86s, finished 12:21:15 2021-07-28

```
Fitting 3 folds for each of 64 candidates, totalling 192 fits

F:\Anaconda3\envs\learn-env\lib\site-packages\sklearn\naive_bayes.py:508: Us
erWarning:

alpha too small will result in numeric errors, setting alpha = 1.0e-10
```

Out[357]:

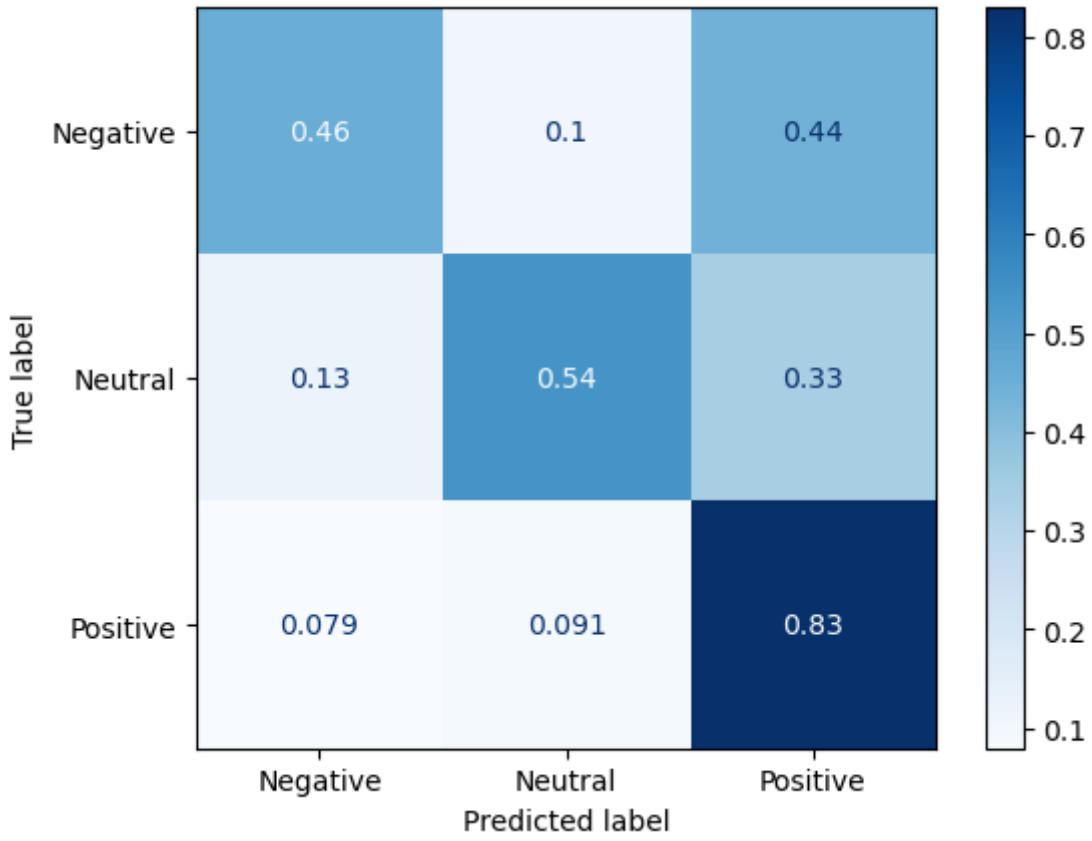
```
{'clf__alpha': 0,
 'clf__fit_prior': False,
 'tweet_pipe__count_vectorizer__stop_words': None,
 'tweet_pipe__tf_transformer__norm': 'l2',
 'tweet_pipe__tf_transformer__smooth_idf': True,
 'tweet_pipe__tf_transformer__use_idf': False}
```

In [358]:

```
1 model_score(gs_new.best_estimator_, new_X_test, new_y_test, X_train= new_X_train, y_tra
```

executed in 330ms, finished 12:21:15 2021-07-28

```
              precision    recall  f1-score   support

    Negative       0.48      0.46      0.47       175
     Neutral       0.79      0.54      0.64       406
    Positive       0.63      0.83      0.72       441

    accuracy                           0.65      1022
   macro avg       0.63      0.61      0.61      1022
weighted avg       0.67      0.65      0.64      1022

Training Score = 0.98
Test Score = 0.65
```



While the recall scores have improved prior to the gridsearch, the recalls core for the neutral tweets are still far too low considering the number of neutral tweets.

1.6 Word Cloud

Move this section to above the modeling section

In [359]:

```
# Wordcloud Generator
def wordcloud_generator(text, cmap, stopwords=None, min_font=12, n_grams=True, title='W
    cloud = WordCloud(colormap=cmap, stopwords=stop_words, width=650, height=400, min_f
                      collocations=n_grams).generate(' '.join(text))#generate_from_text
    fig, ax = plt.subplots(figsize=(12,7))
    ax.imshow(cloud)
    ax.set_axis_off()
    ax.set_title=(title)
    ax.margins(x=0, y=0)
    ax.axis('off')
    plt.show()
```

executed in 15ms, finished 12:21:15 2021-07-28

In [360]:

```
# generate word clouds for each negative positive neutral. compare what words have chag
```

executed in 13ms, finished 12:21:15 2021-07-28

In [361]:

```
old_positive = clean_old_df2.loc[clean_old_df2['vader_emotion']=='Positive'].copy()
old_negative = clean_old_df2.loc[clean_old_df2['vader_emotion']=='Negative'].copy()
old_neutral = clean_old_df2.loc[clean_old_df2['vader_emotion']=='Neutral'].copy()
```

executed in 15ms, finished 12:21:15 2021-07-28

In [362]:

```
1 old_positive
```

executed in 31ms, finished 12:21:15 2021-07-28

Out[362]:

	product or company	emotion	clean_text	sentiment_compound	vader_emotion	emotion_n
1	Apple	Positive	Know about ? Awesome iPad/iPhone app that you'll likely appreciate for its design. Also, they're giving free Ts at	0.9100	Positive	
3	Apple	Negative	I hope this year's festival isn't as crashy as this year's iPhone app.	0.7269	Positive	
4	Google	Positive	great stuff on Fri : Marissa Mayer (Google), Tim O'Reilly (tech books/conferences) & Matt Mullenweg (Wordpress)	0.6249	Positive	
7	Android	Positive	is just starting, is around the corner and is only a hop skip and a jump from there, good time to be an fan	0.6369	Positive	
8	Apple	Positive	Beautifully smart and simple idea wrote about our iPad app for !	0.7712	Positive	
...	...	...	...	...	...	
9073	Apple	Neutral	At your iphone charger is your best friend.	0.8126	Positive	
9077	Apple	Positive	your PR guy just convinced me to switch back to iPhone. Great coverage.	0.7783	Positive	
9079	Apple	Positive	"papyrus...sort of like the ipad" - nice! Lol! Lavelle	0.8264	Positive	
9080	Google	Negative	Diller says Google TV "might be run over by the PlayStation and the Xbox, which are essentially ready today."	0.3612	Positive	

	product or company	emotion	clean_text	sentiment_compound	vader_emotion	emotion_n
9086	Google	Neutral	Google says: want to give a lightning talk to a ckers audience at tonight? Email ben.mcgraw gmail.com for a spot on stage.	0.0772	Positive	

3564 rows × 6 columns

In [363]:

```
new_positive = clean_new2.loc[clean_new2['vader_emotion']=='Positive'].copy()
new_negative = clean_new2.loc[clean_new2['vader_emotion']=='Negative'].copy()
new_neutral = clean_new2.loc[clean_new2['vader_emotion']=='Neutral'].copy()
```

executed in 15ms, finished 12:21:15 2021-07-28

1.6.1 No Stop Words Old Twitter

In [364]:

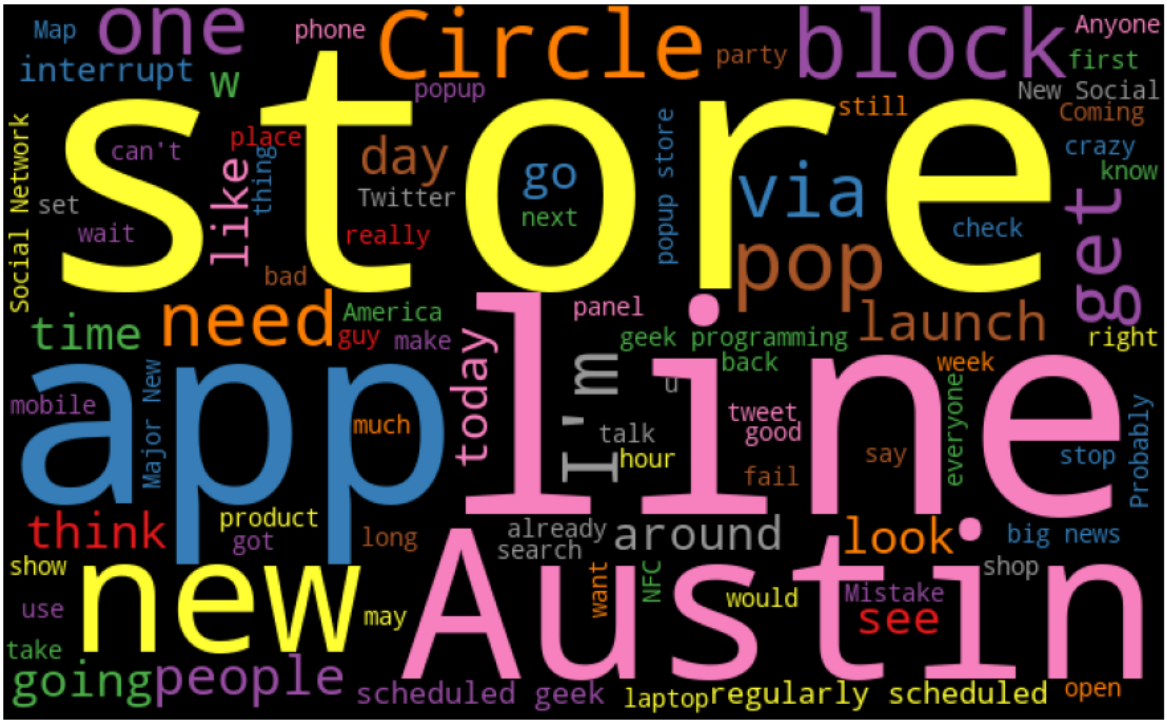
```
old_pos_wc=wordcloud_generator(text=old_positive['clean_text'], cmap='Set1', stopwords=
old_pos_wc
```

executed in 634ms, finished 12:21:16 2021-07-28

In [365]:

```
1 old_neg_wc=wordcloud_generator(text=old_negative['clean_text'], cmap='Set1', stopwords=
2 old_neg_wc
```

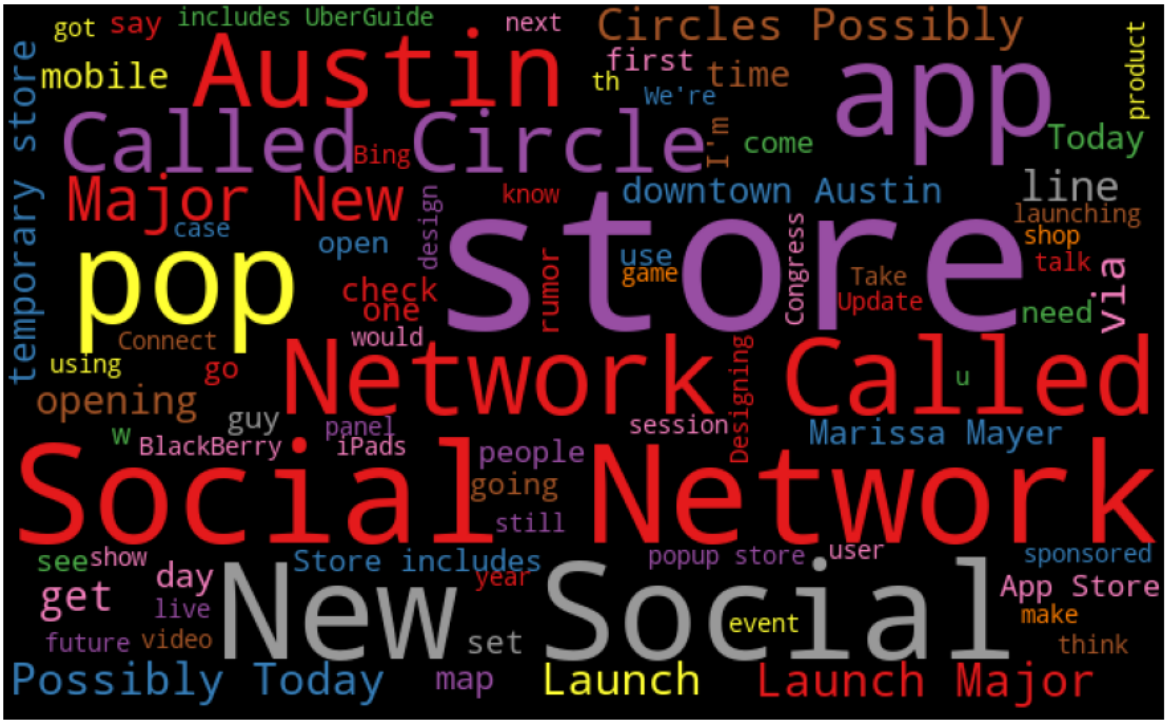
executed in 532ms, finished 12:21:17 2021-07-28



In [366]:

```
1 old_neut_wc=wordcloud_generator(text=old_neutral['clean_text'], cmap='Set1', stopwords=
2 old_neut_wc
```

executed in 620ms, finished 12:21:17 2021-07-28

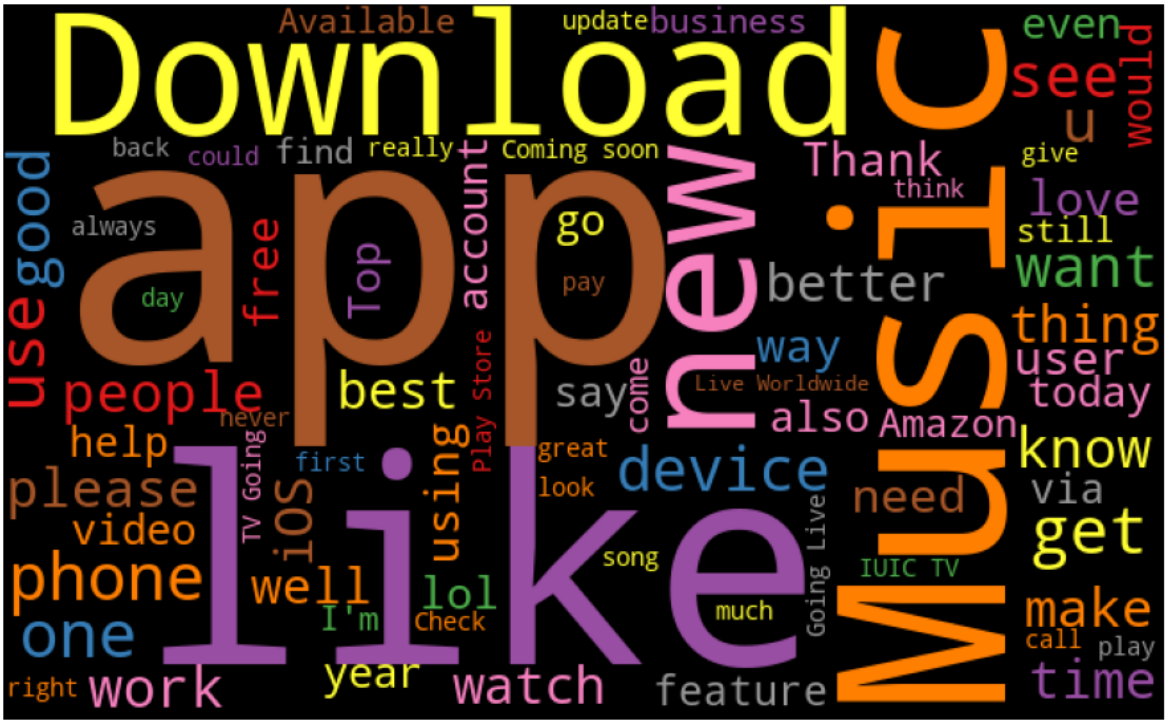


1.6.2 No Stop Words New Twitter

In [370]:

```
new_pos_wc=wordcloud_generator(text=new_positive['clean_text'], cmap='Set1', stopwords=
new_pos_wc
```

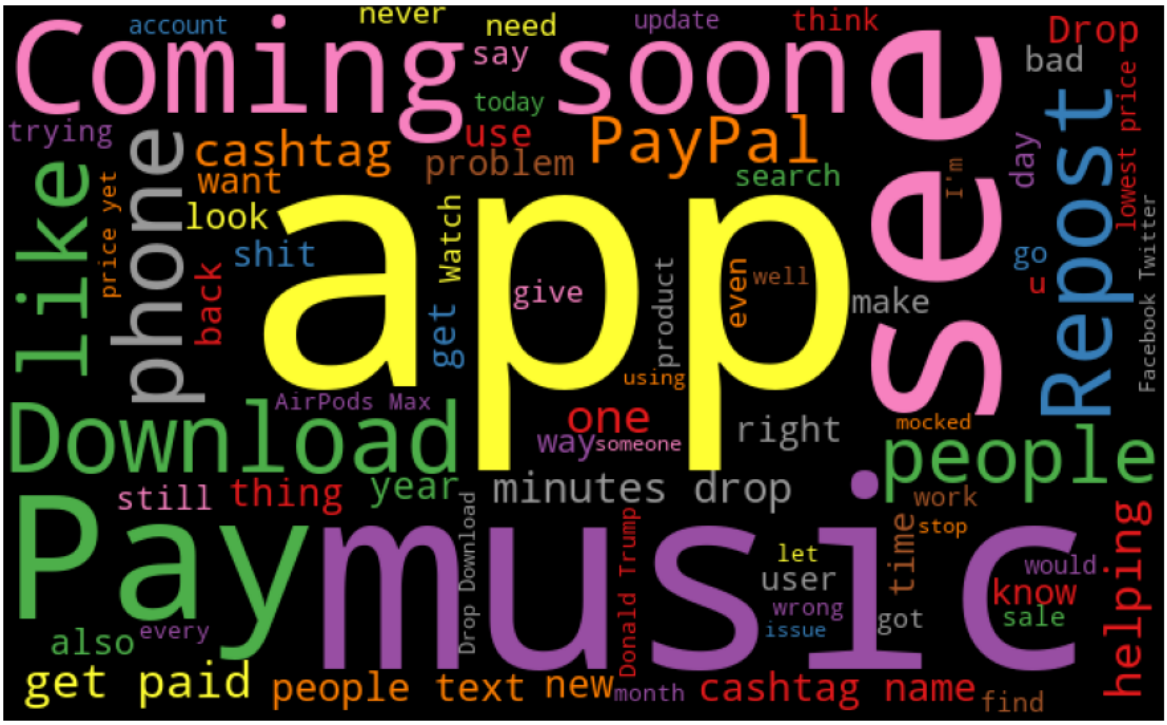
executed in 588ms, finished 12:21:20 2021-07-28



In [371]:

```
new_neg_wc=wordcloud_generator(text=new_negative['clean_text'], cmap='Set1', stopwords=
new_neg_wc
```

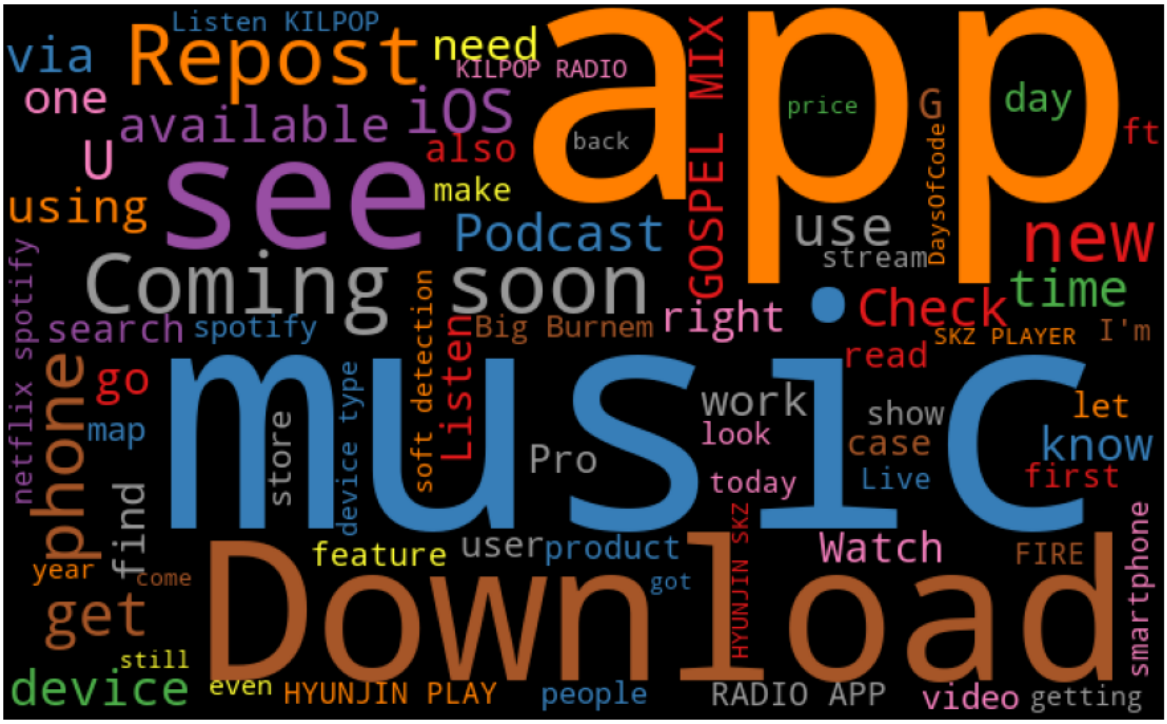
executed in 499ms, finished 12:21:20 2021-07-28



In [372]:

```
new_neut_wc=wordcloud_generator(text=new_neutral['clean_text'], cmap='Set1', stopwords=
new_neut_wc
```

executed in 504ms, finished 12:21:21 2021-07-28

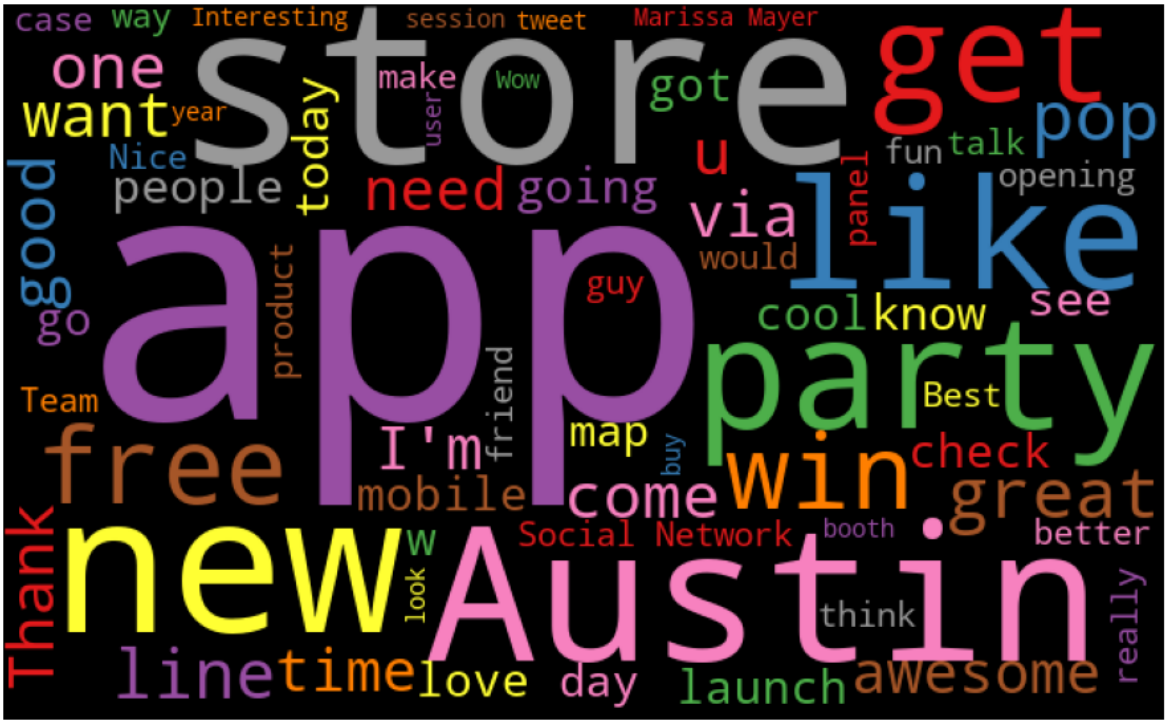


1.6.3 With Stop Words Old Twitter

In [367]:

```
1 old_pos_wc=wordcloud_generator(text=old_positive['clean_text'], cmap='Set1', stopwords=
2 old_pos_wc
```

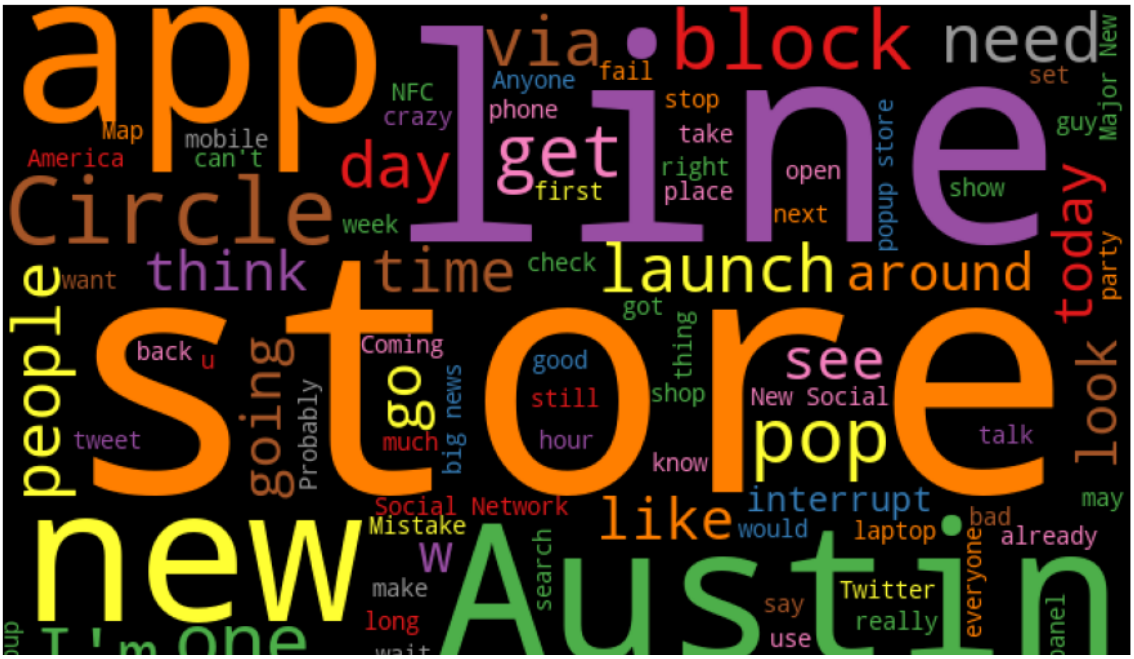
executed in 605ms, finished 12:21:18 2021-07-28



In [368]:

```
1 old_neg_wc=wordcloud_generator(text=old_negative['clean_text'], cmap='Set1', stopwords=
2 old_neg_wc
```

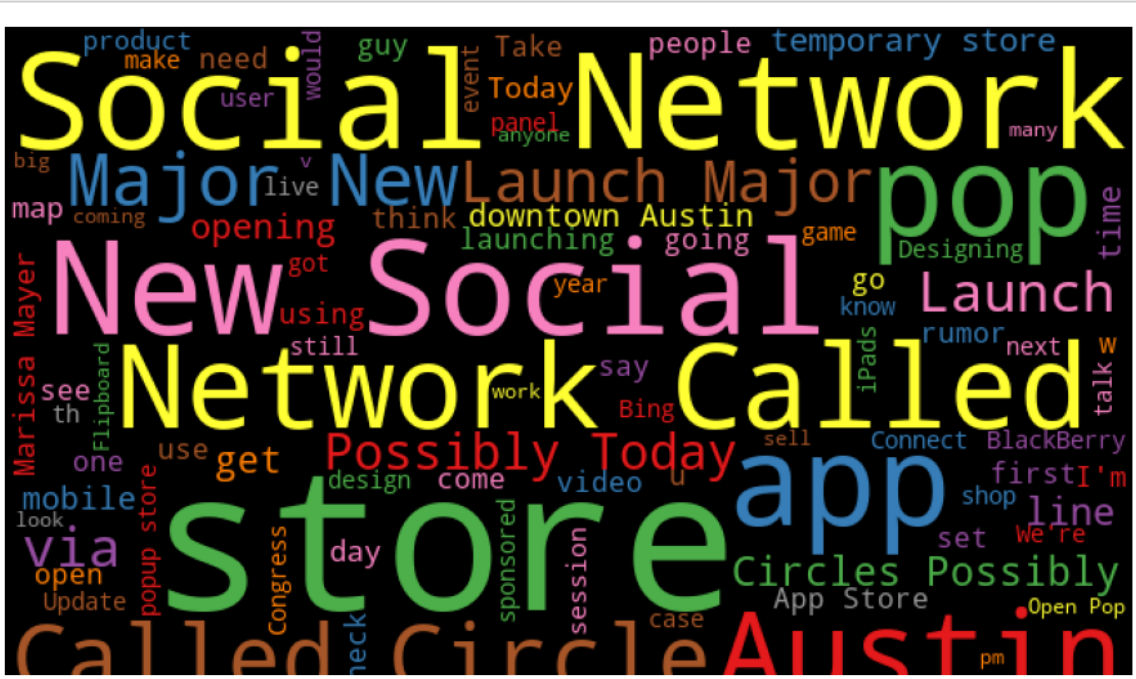
executed in 801ms, finished 12:21:19 2021-07-28



In [369]:

```
old_neut_wc=wordcloud_generator(text=old_neutral['clean_text'], cmap='Set1', stopwords=
old_neut_wc
```

executed in 664ms, finished 12:21:19 2021-07-28



1.6.4 With Stop Words New Twitter

In [373]:

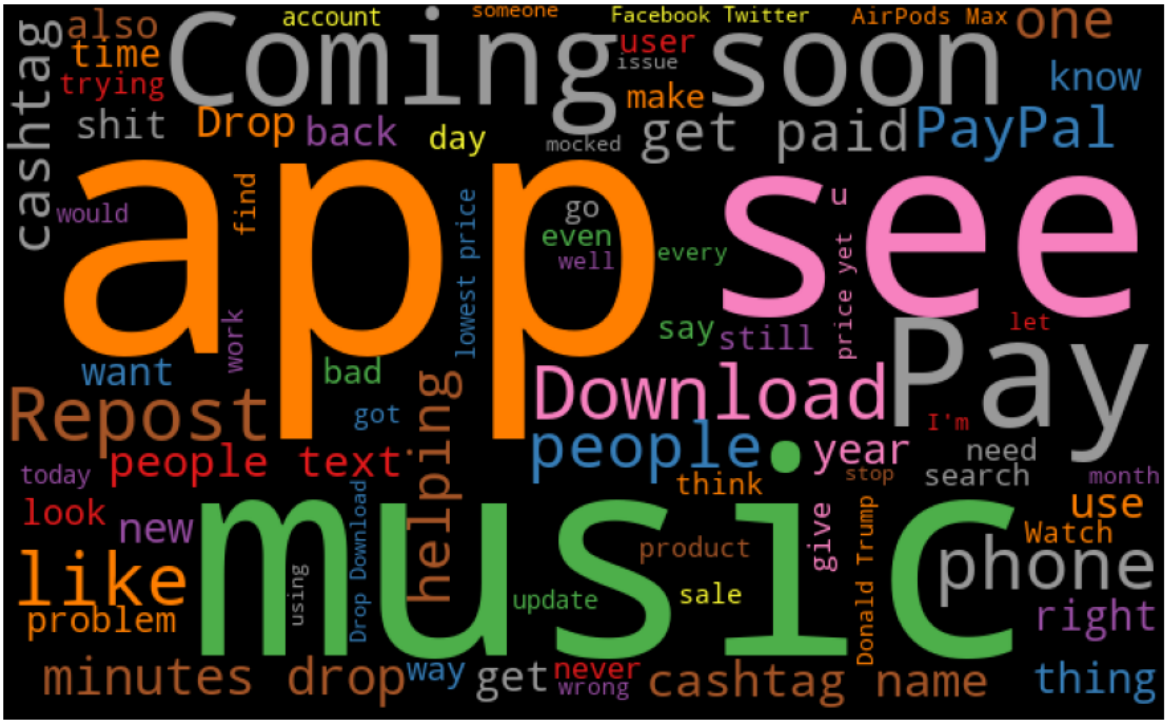
```
new_pos_wc=wordcloud_generator(text=new_positive['clean_text'], cmap='Set1', stopwords=
new_pos_wc
```

executed in 593ms, finished 12:21:21 2021-07-28

In [374]:

```
new_neg_wc=wordcloud_generator(text=new_negative['clean_text'], cmap='Set1', stopwords=
new_neg_wc
```

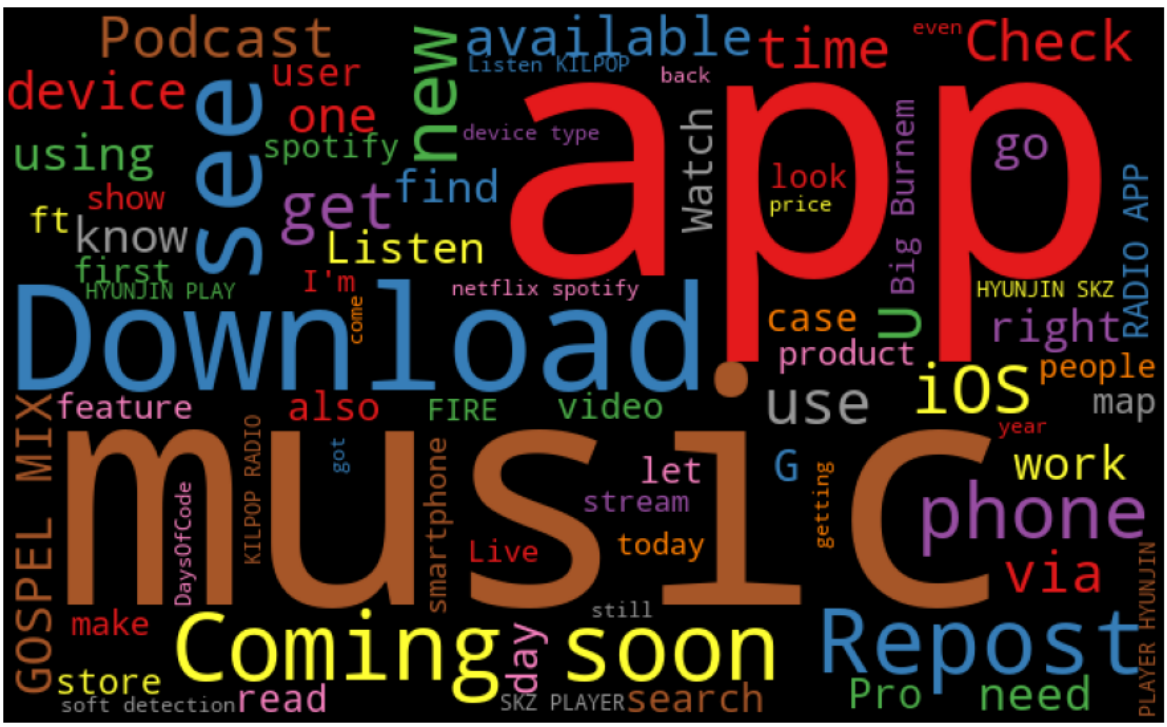
executed in 473ms, finished 12:21:22 2021-07-28



In [375]:

```
new_neut_wc=wordcloud_generator(text=new_neutral['clean_text'], cmap='Set1', stopwords=
new_neut_wc
```

executed in 506ms, finished 12:21:22 2021-07-28



1.7 Model Recommendation

For both of the tweets, the Random Forest models after the gridsearch performed the best. The random forest models before the pipeline and the models after performing the grid search performed similarly; however, because the low recall score for the negative tweets were improved to that of the original random forest models while maintaining the relatively high recall scores for the neutral and positive tweets, I recommend the **Random Forest models using gridsearch**. As mentioned before, the number of tweets with negative sentiments were only a third of the size of either the positive or neutral neutral tweets which led to the poor recall rate of negative tweets for all models.

1.8 Conclusion

1.8.1 Future Work

There are many things that I would like to incorporate into this project that I did not have the necessary skills or time to perform, but given the chance I would like to do these for the future:

1. Collect similar amounts of tweets for all three sentiments
    - This would help improve the recall scores for the models and maybe give an insight as to why the naive bayesian models did not perform as well before gridsearch.
2. Create a time line of sentiments and events.
    - By collecting tweets from the past throughout to the present, I would be able to show how the sentiment trends gradually changes.
    - Incorporating events from the past could also help understand the sentiment trends and highlight specific actions that the company had taken that negatively or positively impacted the public's sentiment.
3. Add the companies' earnings.
    - Adding the companies' earnings and comparing the relationship between the rate of increase in earnings to change in public sentiment shows a definitive reason to pay more attention to the public's wants/needs.
    - Adding a company that has continuously bettered its relationship with its end consumers and how their earnings have changed along with the public sentiment could show the difference that good public relationship can have on the company's earnings.

1.8.2 Final thoughts

This project was an adventure from the start as I had to learn how to collect my own data. Another aspect that I had not experienced before was the lengthy text cleaning that came with using tweets. And while the old tweet data were provided, I had to use the vader sentiment analysis as I had noticed much of the tweets did not correctly represent the tweet's sentiment. The aspect that most intrigued me about the Twitter sentiment towards these large companies is the obviously smaller number of negative emotion towards the companies and the overwhelming number of neutral sentiments towards them as well. I had initially expected to see a large increase in negative sentiment towards companies such as Apple as they have become less consumer friendly in their product designs. And as mentioned above in the future works section, I believe that creating a time line of the sentiment changes and events could help paint a clearer picture of how much these companies have changed in their policies and in the eyes of the consumers.

2 Dashboard

In [410]:

```
clean_old_df2.to_csv('old_twitter')
clean_new2.to_csv('new_twitter')
```

executed in 75ms, finished 14:52:16 2021-07-28

In [411]:

```
old_positive.to_csv('old_pos')
old_negative.to_csv('old_neg')
old_neutral.to_csv('old_neut')
new_positive.to_csv('new_pos')
new_negative.to_csv('new_neg')
new_neutral.to_csv('new_neut')
```

executed in 81ms, finished 14:52:16 2021-07-28

In [380]:

```
pd.DataFrame(wordcloud_stopwords).to_csv('wordcloud_stopwords')
```

executed in 15ms, finished 12:21:23 2021-07-28

In [415]:

```
from IPython.display import display, Markdown
with open('my_app.py') as file:
    display(Markdown("```python\n"+file.read()+'\n```'))
```

executed in 11ms, finished 15:49:17 2021-07-28

```
            text=""
            text2 = text1.loc[text1['vader_emotion']==status].copy()
            # print(type(' '.join(text2['clean_text'])))
            text += ','.join(text2['clean_text'])
            wordcloud_generator(text, cmap='Set1')
    elif select_time == 'New':
        text1 = new_tweet[(new_tweet['product or company']==select_company
)].copy()
        for status in select_status:
            text=""
            text2 = text1.loc[text1['vader_emotion']==status].copy()

            text += ','.join(text2['clean_text'])
            wordcloud_generator(text, cmap='Set1')
# def get_data(sentiment=select_status, companies=select_company, time=sel
ect_time):
#     data=[[sentiment], [ companies], [time]]
```