

Capstone Project: Comparing Consumer Sentiment of Apple, Google, and Android from the Past and Present on Twitter



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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 perform NLP sentiment analysis of the general public's sentiment towards these companies from the past and present.

DATA COLLECTION

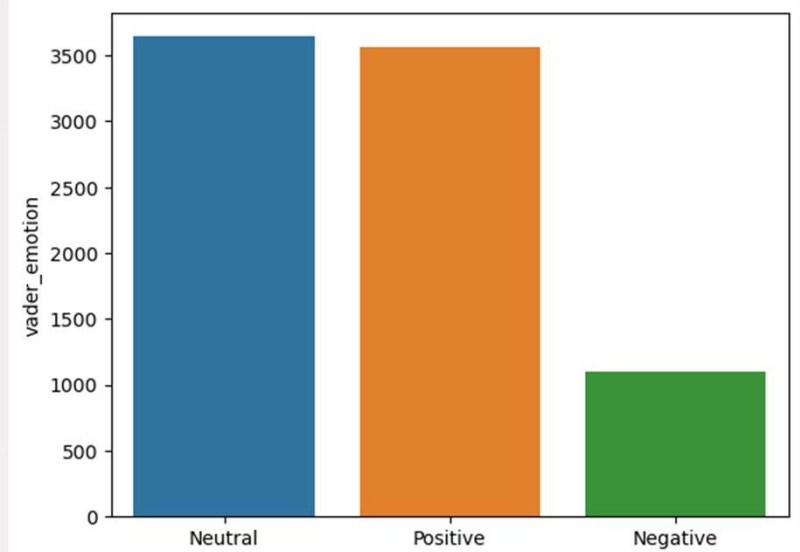
- Old Twitter data was gathered from <https://data.world/crowdfunder/brands-and-product-emotions>. After cleaning, 8,306 total tweets remained in the old Twitter data frame.
- Using Tweepy and Twitter's Developer API, I collected 1,500 tweets per company, but around 1/3 of the tweets were not related to the company.
- After cleaning, 3,405 tweets remained in the new Twitter data frame.



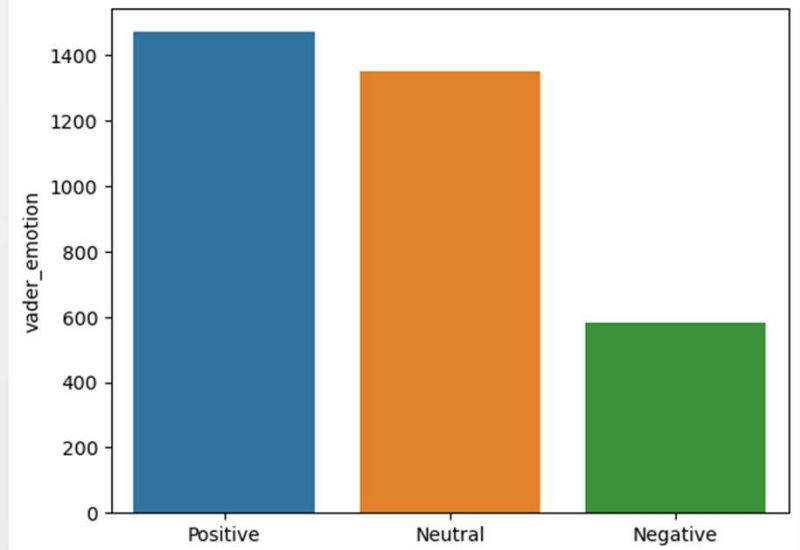
Data Imbalance

- There was an imbalance in the number of the three sentiments in both data frames.
- The number of negative tweets were around a third of the size of the neutral tweets and positive tweets.

Old Tweet



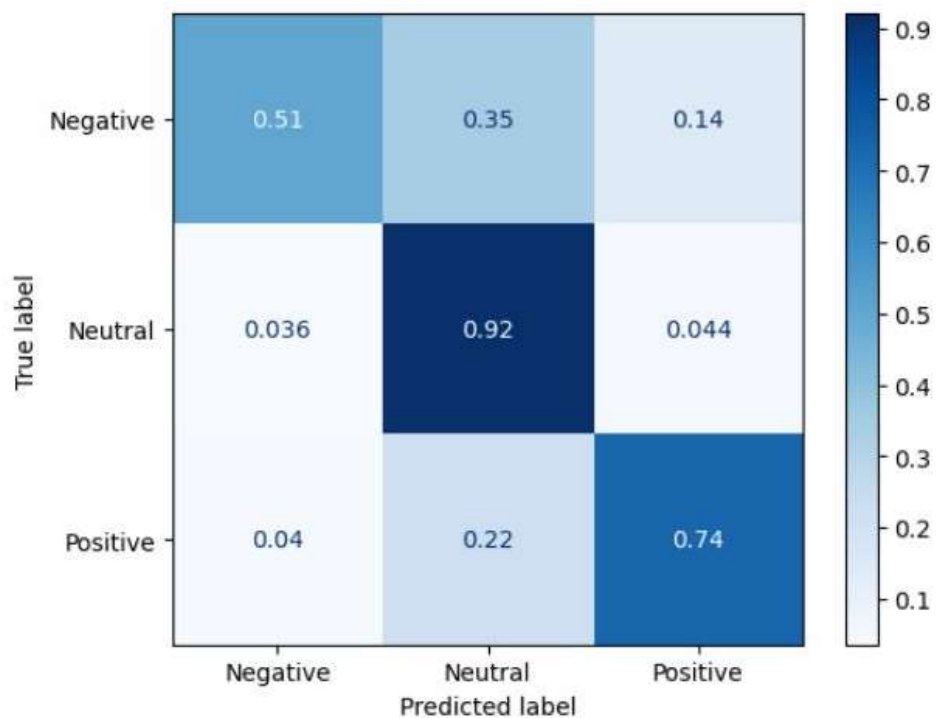
New Tweet



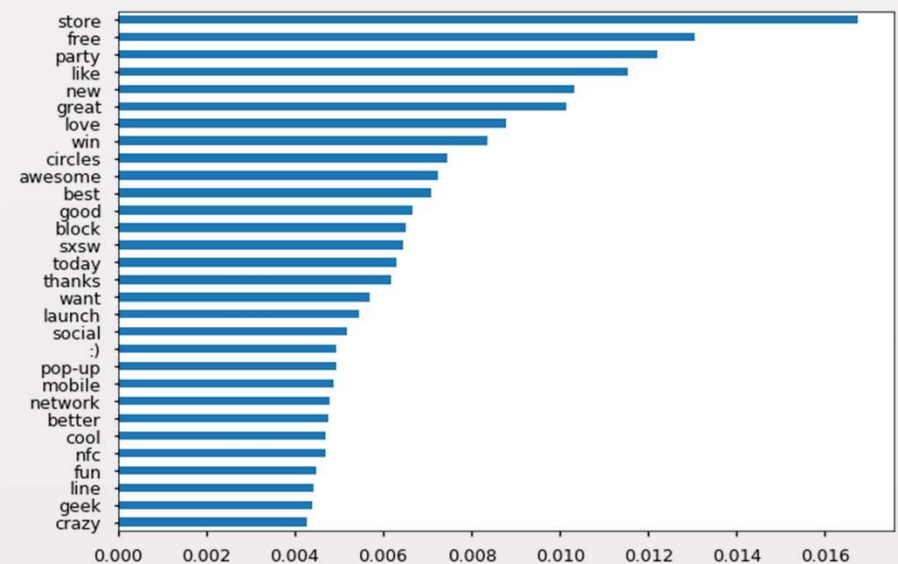
Random Forest (Old Tweets)

Training Score = 0.95

Test Score = 0.79

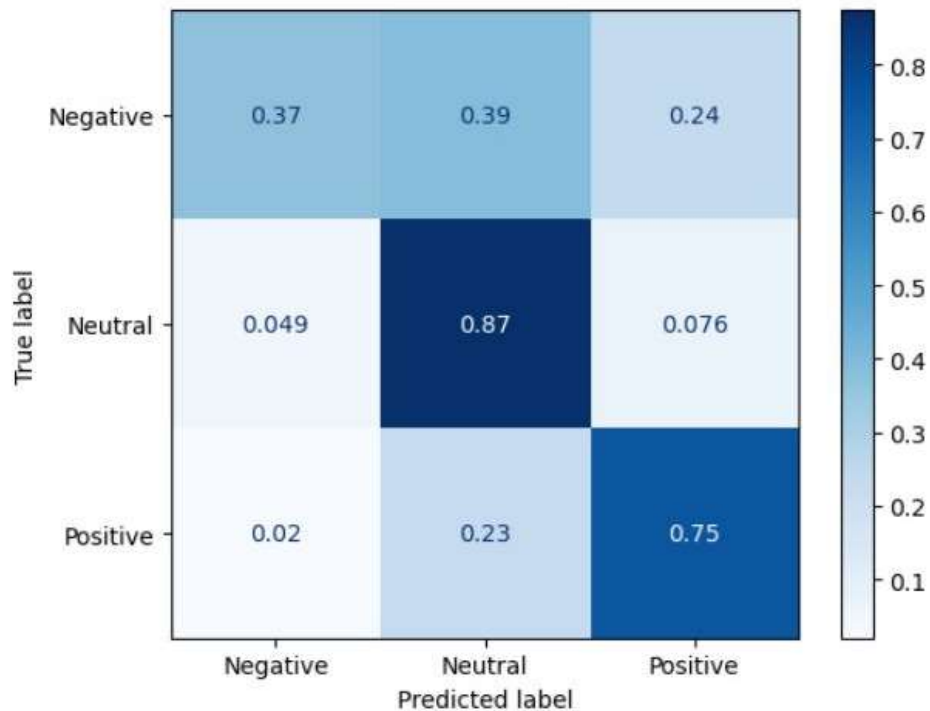


- Because of the small number of negative tweets, the recall score for 'Negative' is low.

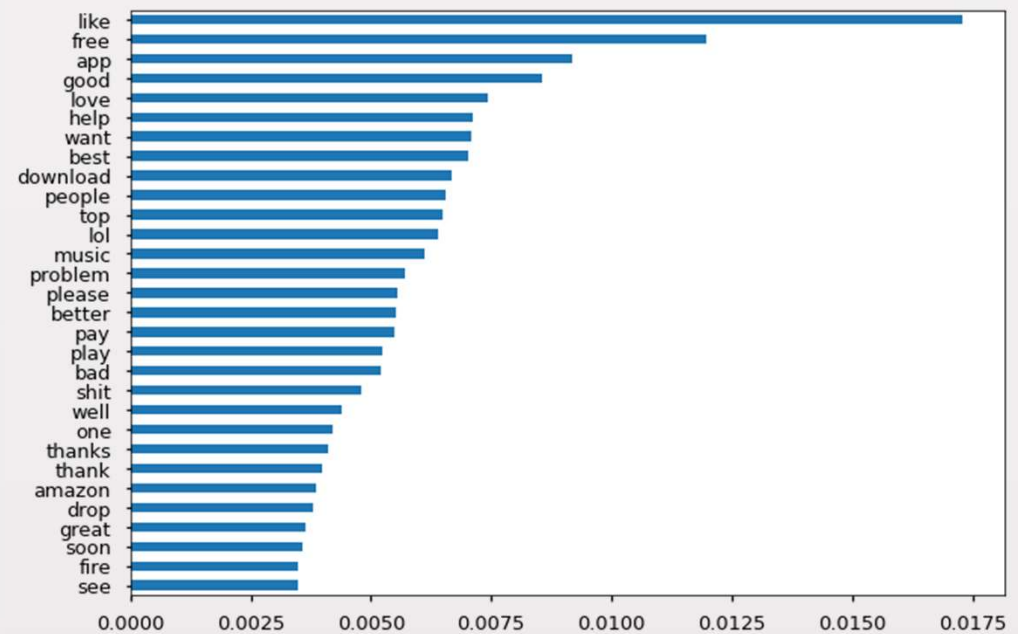


Random Forest with Grid Search (New Tweets)

Training Score = 0.99
Test Score = 0.73



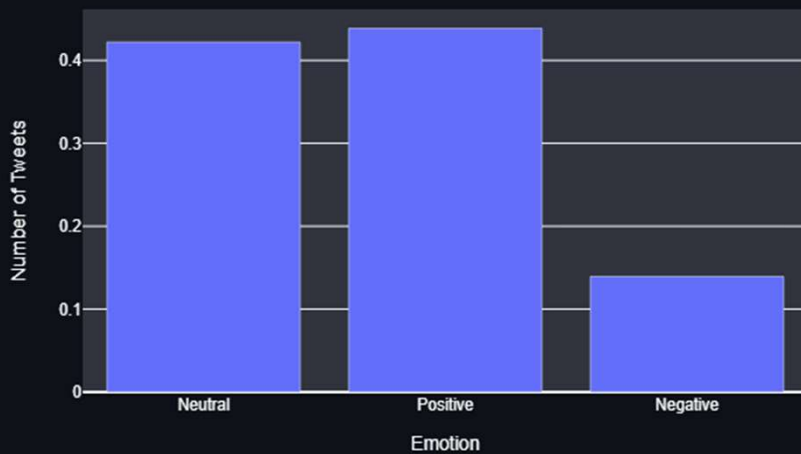
- Same problem as the old tweets
- Still recommended because it was able to maintain a relatively high recall scores while improving the recall score for the negative tweets.



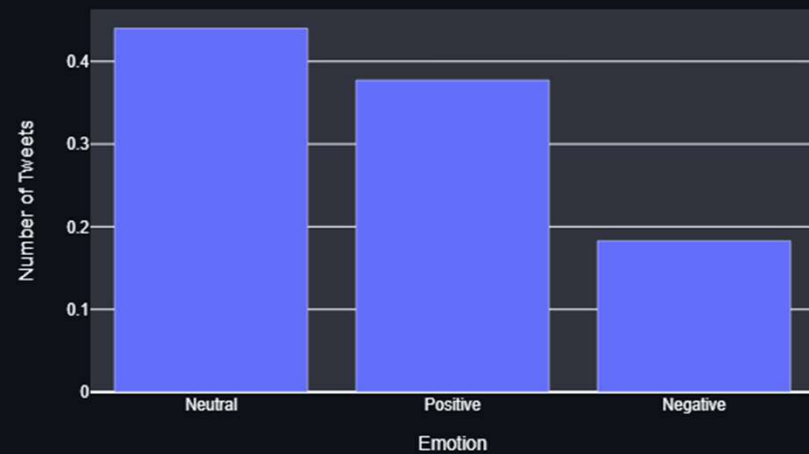
APPLE

- When comparing the user sentiments generated from the old tweets to the newer tweets, we can see an increase in the ratio of negative tweets.

Apple Old Tweet



Apple New Tweet



- Old Tweet: store, app, line, opening, win, great, Thank, want
- New Tweet: music, like, phone, Spotify, want, Watch
- Words associated with positive sentiment seems to change from one's experience at the Apple store or using their product apps such as Apple Music or Spotify.

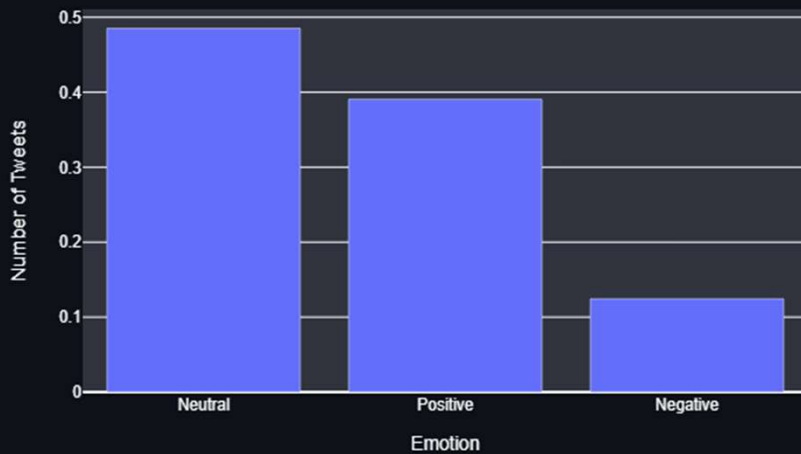
[illegible][illegible]

- Old Tweet: store, line, block, need, crazy
- New Tweet: price yet, people text, problem, stop, minutes drop
- As with before, the negative sentiment towards Apple has shifted from the Apple experience to people's discontent towards Apple's products and prices.
- Cashtag, get paid, cashtag name are all from advertisements that use an app called Cashpay. PayPal also seems to be associated with advertisements.

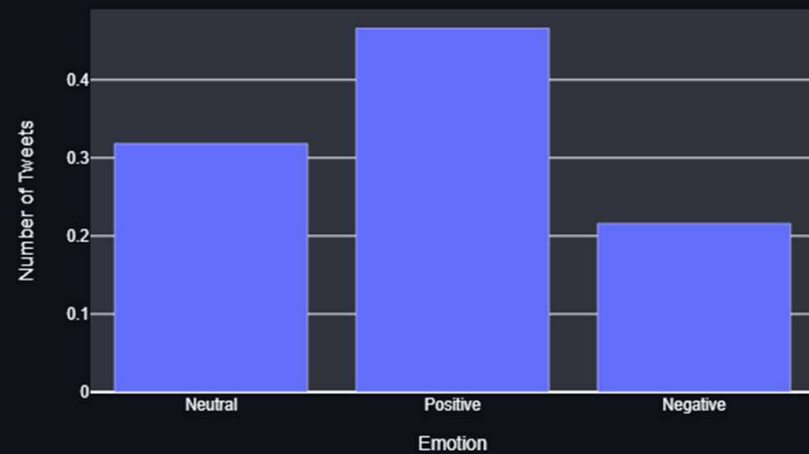
Google

- Sentiment towards Google has increased.
- The ratio of positive tweets have increased significantly. T
- he ratio of neutral sentiments decreased while the ratio of negative sentiments did not show too much change.

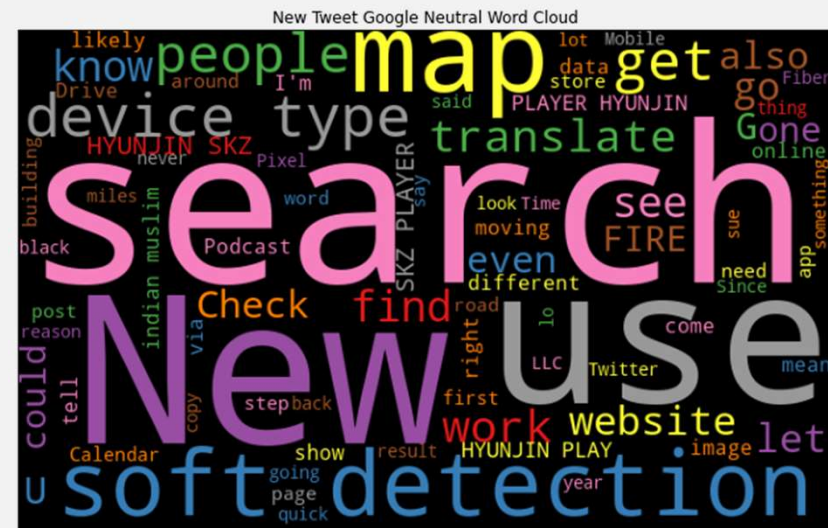
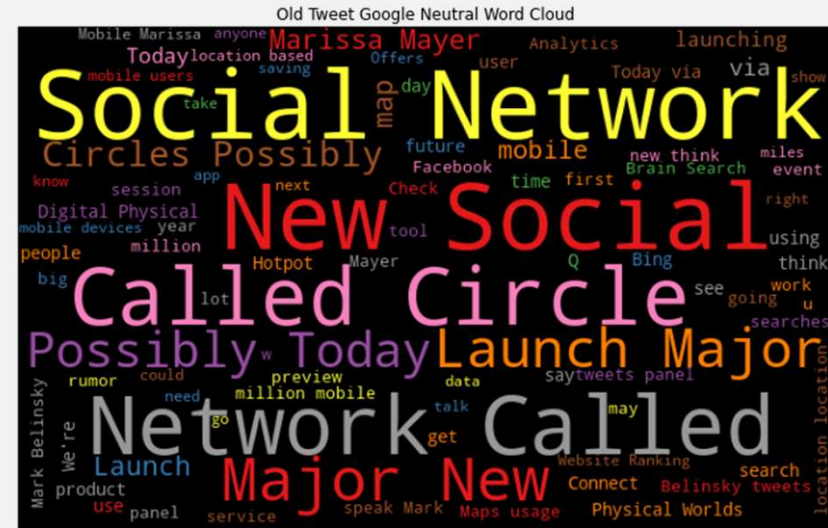
Google Old Tweet



Google New Tweet

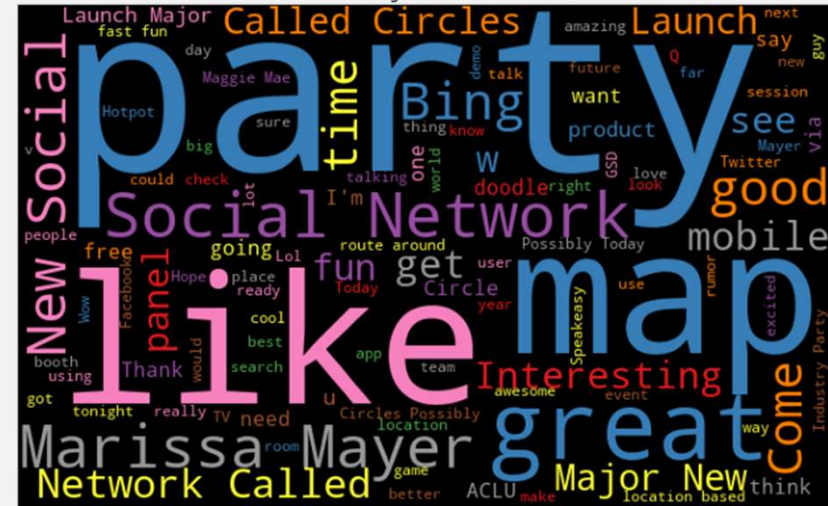


- Old Tweet: Social Network, Major New, Possibly Today, Launch
- New Tweet: Search, New, use, map, soft detection, translate
- Neutral sentiment towards Google seems to have shifted from texts relating to social media to general uses of the Google search engine.



- Old Tweet: New Social, map, great, party, Social Network
- New Tweet: like, know, use, see, help, search, find
- Overall, the number of words related to positive sentiment towards Google seems to have decreased.
- Similar to the tweets with neutral sentiment, new tweets seem to be more related to the Google's search engine rather than Google as a company.

Old Tweet Google Positive Word Cloud



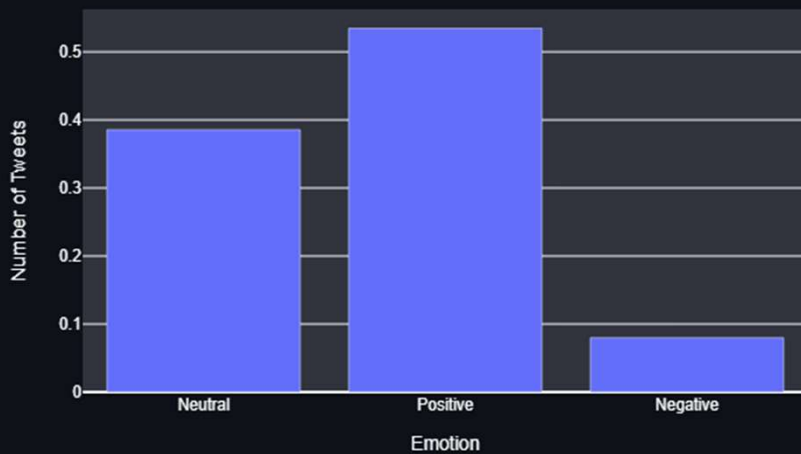
New Tweet Google Positive Word Cloud



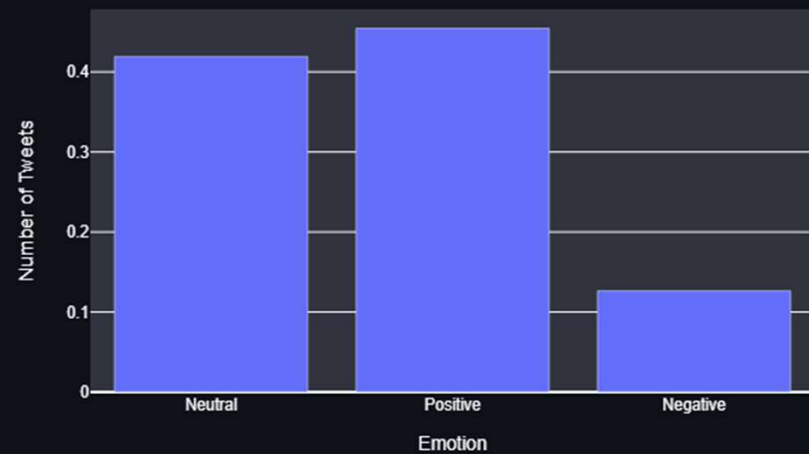
Android

- User's sentiment towards Android has more or less remained the same.
- The ratio of all sentiments in the new tweets do not differ too much from those of the old tweets.

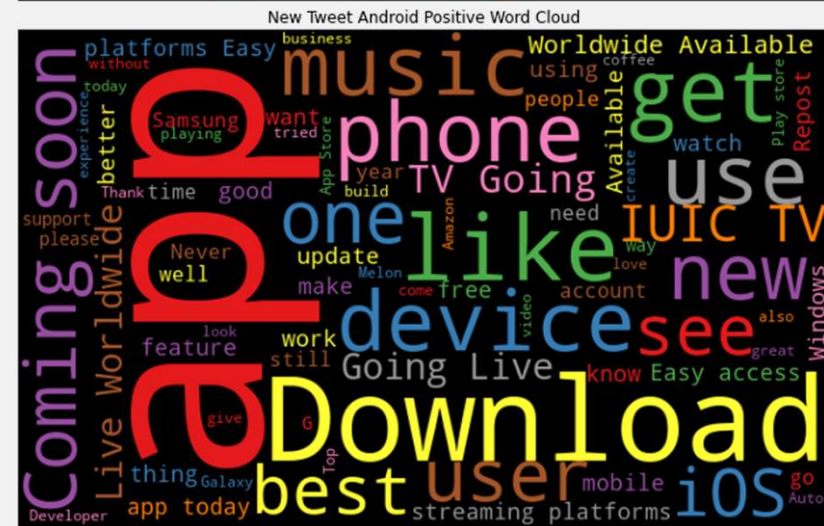
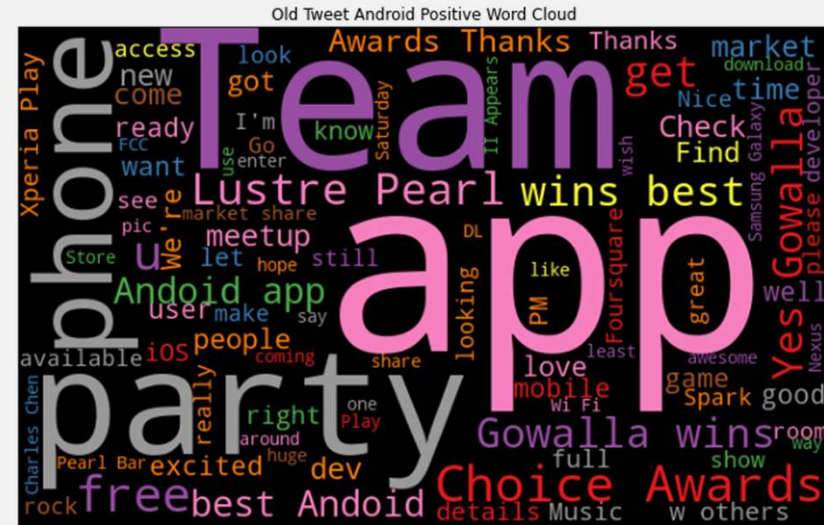
Android Old Tweet



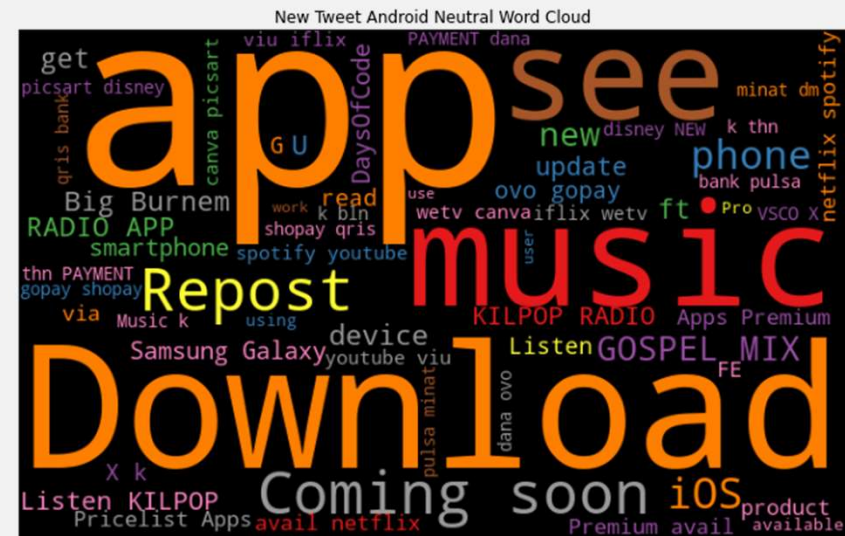
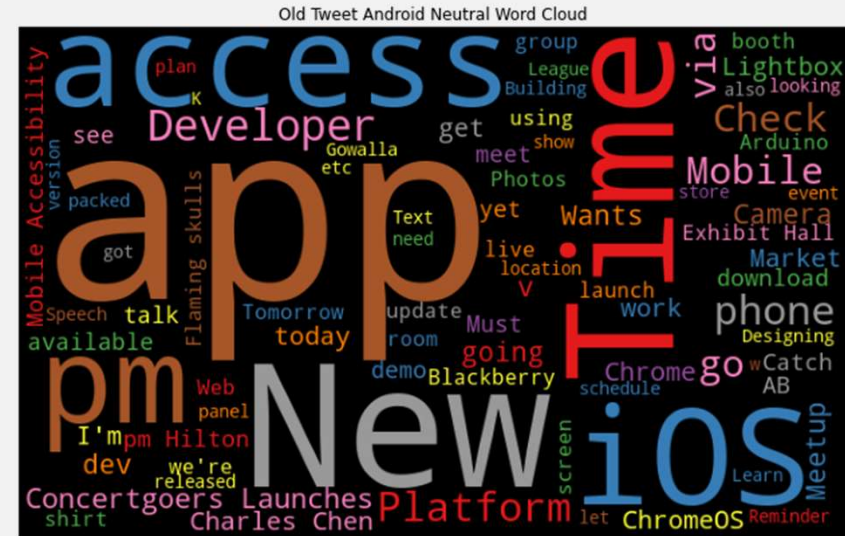
Android New Tweet



- Old Tweet: Team, App, wins best, phone, best Android
- New Tweet: app, music phone, device, Easy access
- Like the tweets about Apple, people seem to use their phones for music apps more.
- From the wording in the old tweets, there is a rivalry between the users of Android phones and iPhone users, which we can no longer observe in the new tweets.



- Old Tweet: app, New, Time, iOS, access, Platform, ChromeOS
- New Tweet: app, music, Download, RADIO APP, iOS
- Both old and new tweets seem to focus on Android apps, and judging from the word iOS, these tweets seem to either compare the type of apps or show the availability in both the Google Play Store and the iOS App Store.



Recommendation



- I recommend using the Random Forest model with gridsearch.
- This model was able to improve on the low recall score for tweets with negative sentiments while maintaining the relatively high recall scores for other tweets.
- Given that the consumer's sentiment towards some of these companies have turned more negative, it could be recommended that these companies start paying more attention to their consumers to retain/improve their relationships with their customers.

Future Works

- Create a timeline that displays continuous changes in public's sentiment towards these companies.
- Add important events to the timelines to have a better understanding of what end consumers' wants and needs.
- Add monthly/quarterly/annual earnings to show the relationship between the rate of increase in earnings to public sentiment.
- Add companies that have continuously improved its relations with the end consumers and report on the changes in their earnings.





Thank You

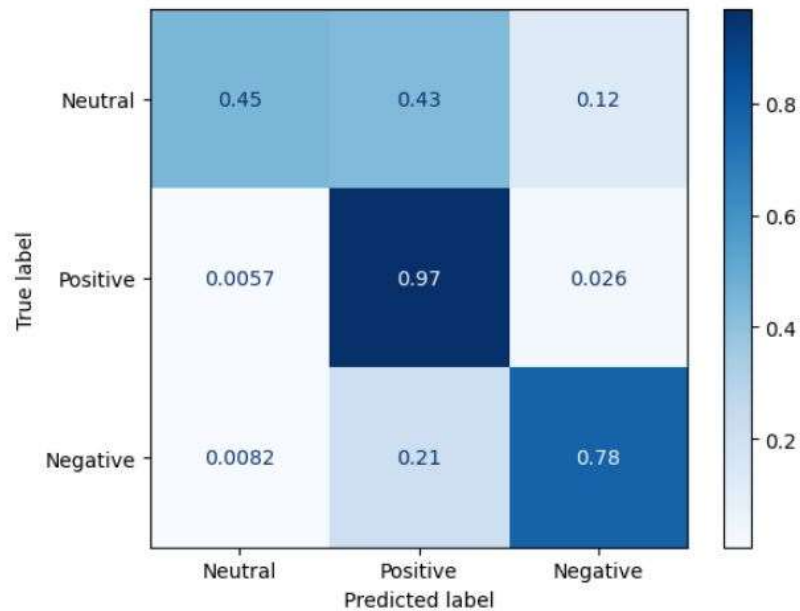
Q&A

Appendx: Random Forest Base model and Pipeline (Old Tweet)

Base

	precision	recall	f1-score	support
Neutral	0.91	0.45	0.60	343
Positive	0.73	0.97	0.83	1050
Negative	0.93	0.78	0.85	1098
accuracy			0.81	2491
macro avg	0.85	0.73	0.76	2491
weighted avg	0.84	0.81	0.81	2491

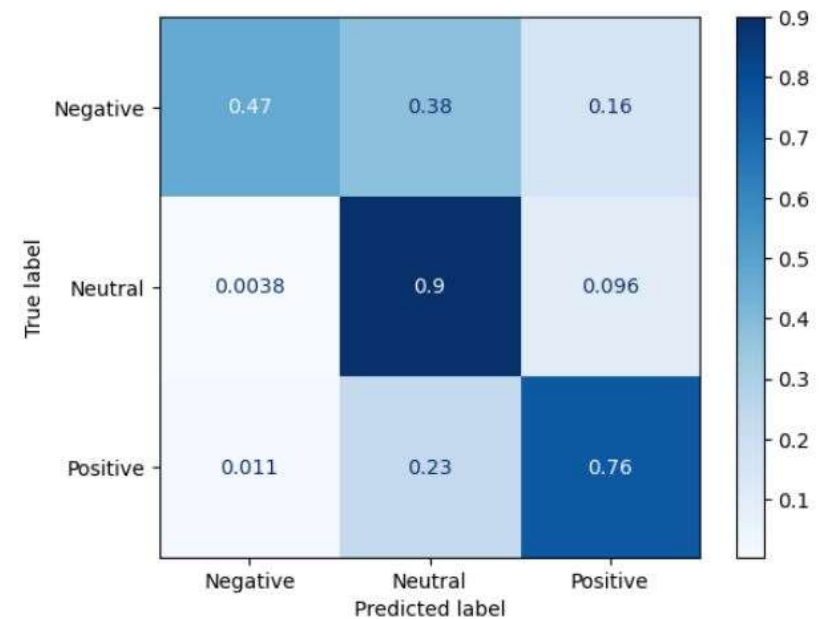
Training Score = 1.00
Test Score = 0.81



Pipeline

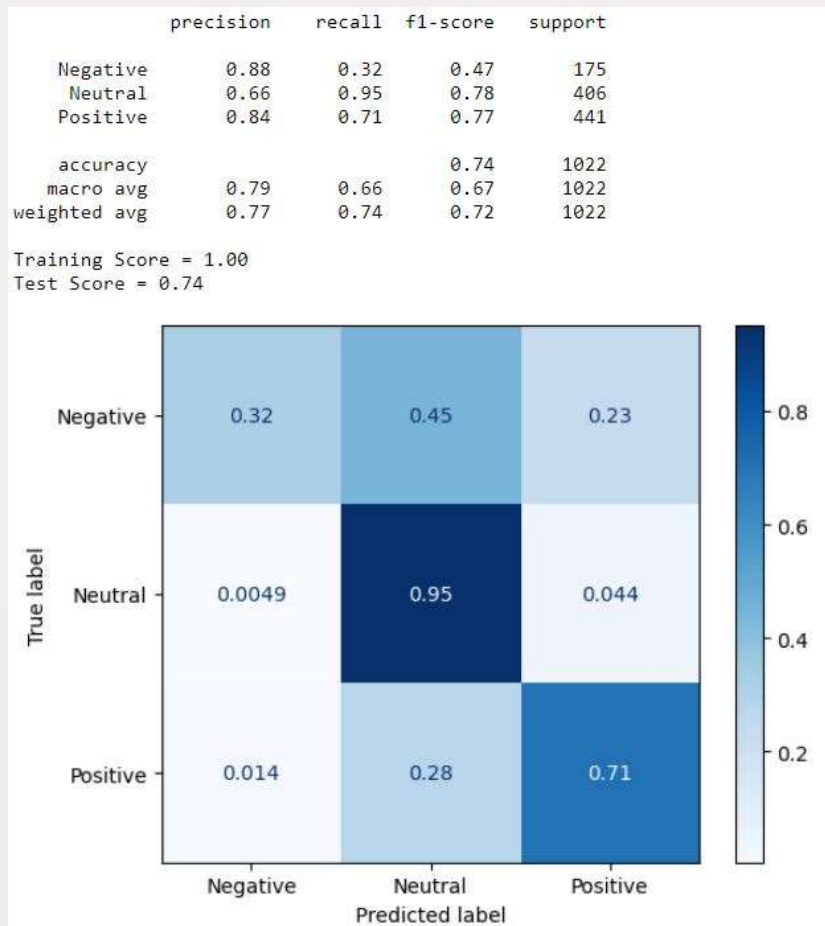
	precision	recall	f1-score	support
Negative	0.91	0.47	0.62	343
Neutral	0.71	0.90	0.80	1050
Positive	0.84	0.76	0.80	1098
accuracy			0.78	2491
macro avg	0.82	0.71	0.74	2491
weighted avg	0.80	0.78	0.77	2491

Training Score = 1.00
Test Score = 0.78

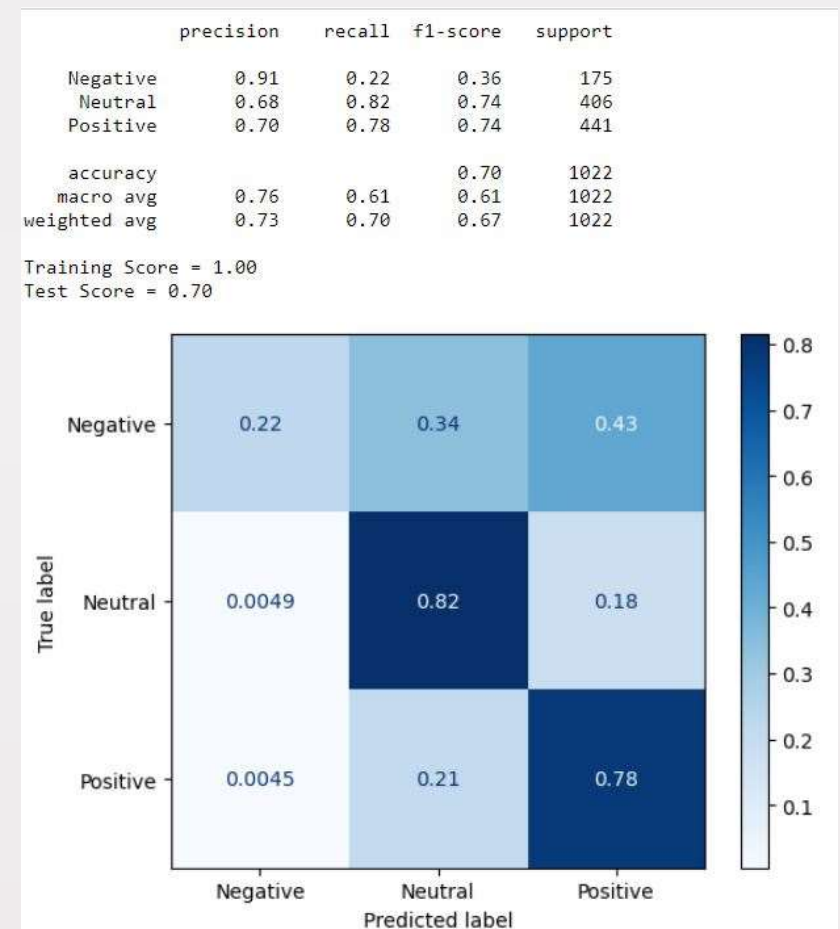


Appendx: Random Forest Base model and Pipeline (New Tweet)

Base



Pipeline



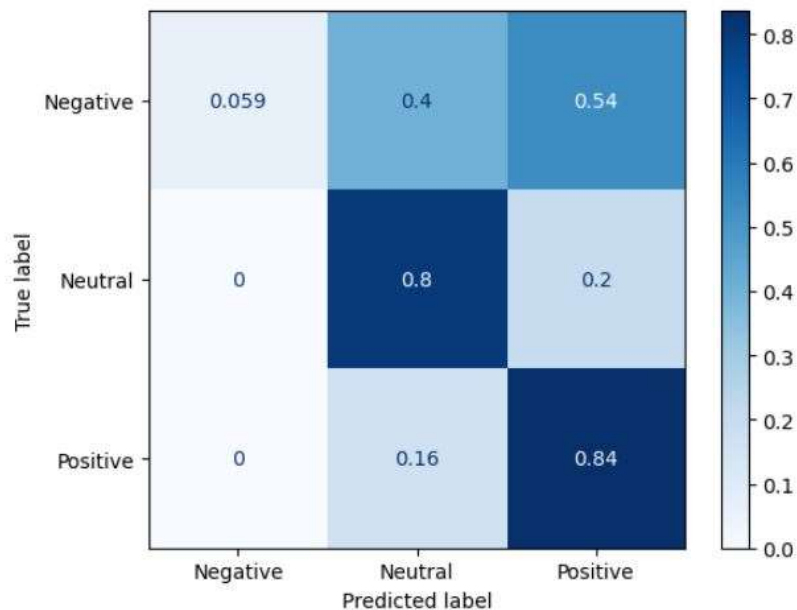
Appendx: Naïve Bayesian Base model and Grid Search (Old Tweet)

Base

	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

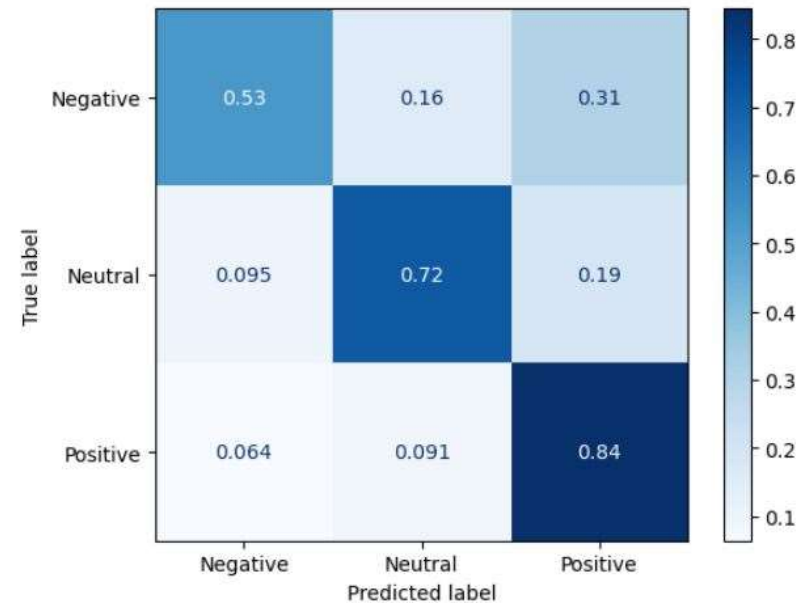


Grid Search

	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

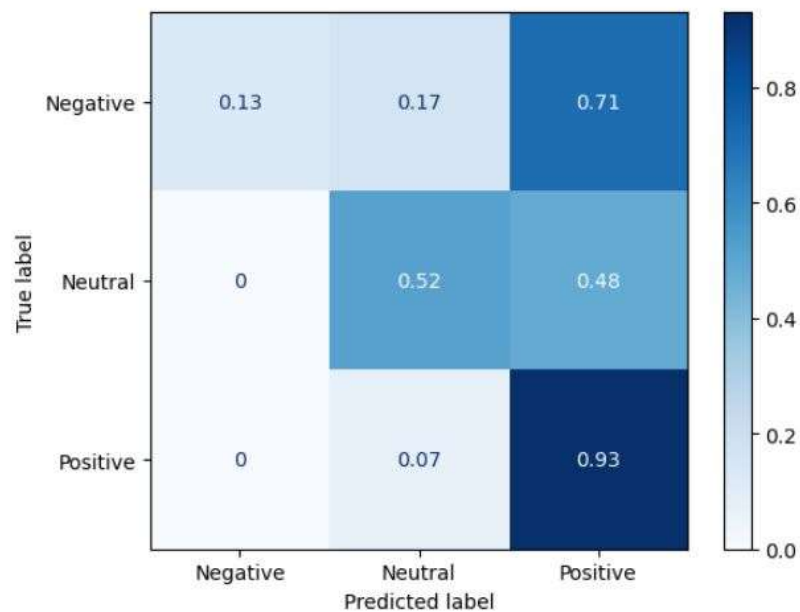


Appendx: Naïve Bayesian Base model and Grid Search (New Tweet)

Base

	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



Grid Search

	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

