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

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Date: 7/28/21

BUSINESS PROBLEM

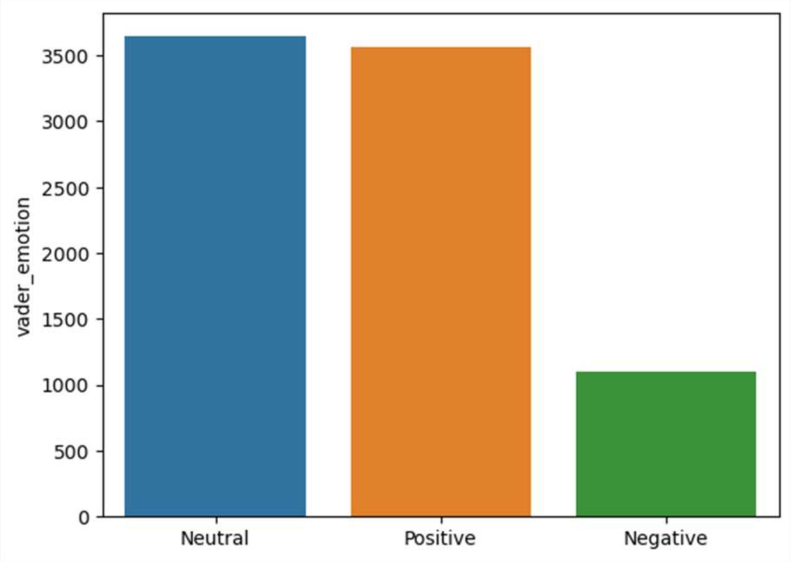
For better or worse, people's perception of tech giants have changed over time. A company that consults these large companies' PR teams have hired me to find how the consumers' sentiments have changed. To gather the necessary information, I am going to go to Twitter, and perform NLP sentiment analysis of the general public's sentiment towards these companies from the past and present.

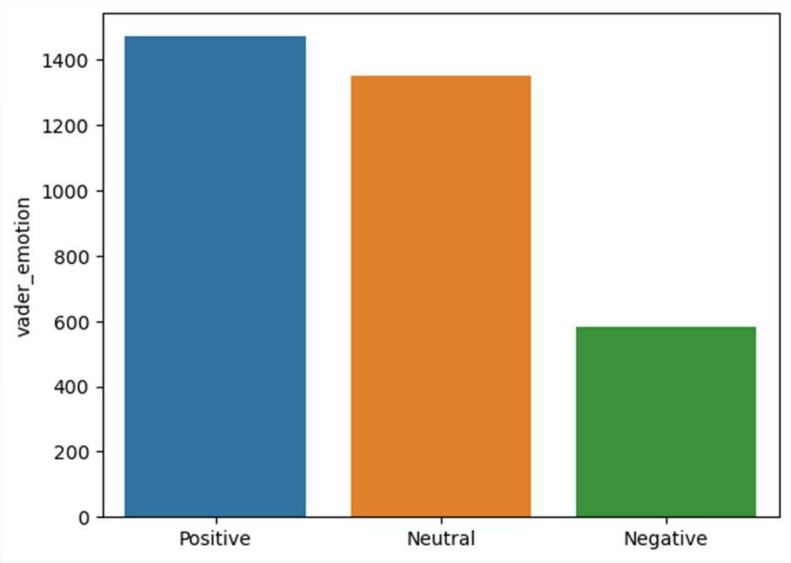
DATA COLLECTION

- Old Twitter data was gathered from https://data.world/crowdflower/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

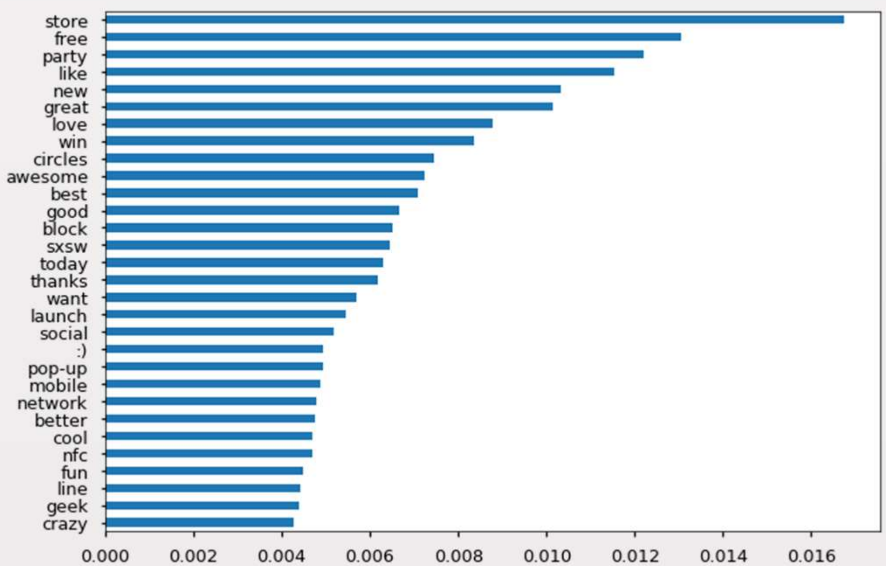
- For both the old tweets and new tweets, there was an imbalance in the number of the three sentiments.
- The top image represents the number of old tweets with the respective sentiments, and the bottom represents the new tweets with the respective sentiments.
- For both old and new tweets, the number of negative tweets were around a third of the size of the neutral tweets and positive tweets.



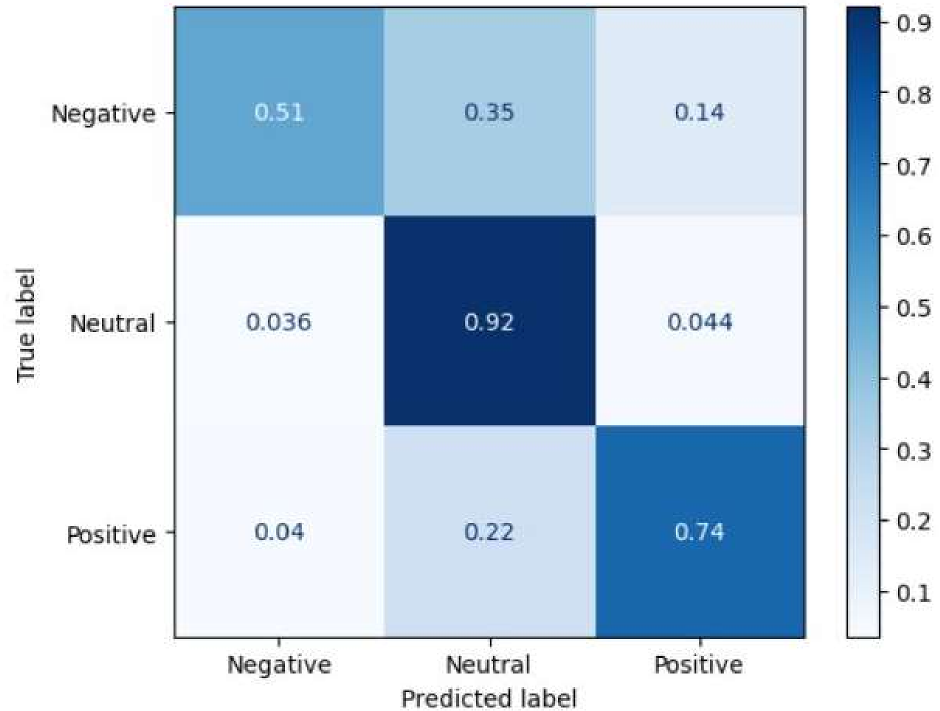


Random Forest
(Old Tweets)

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

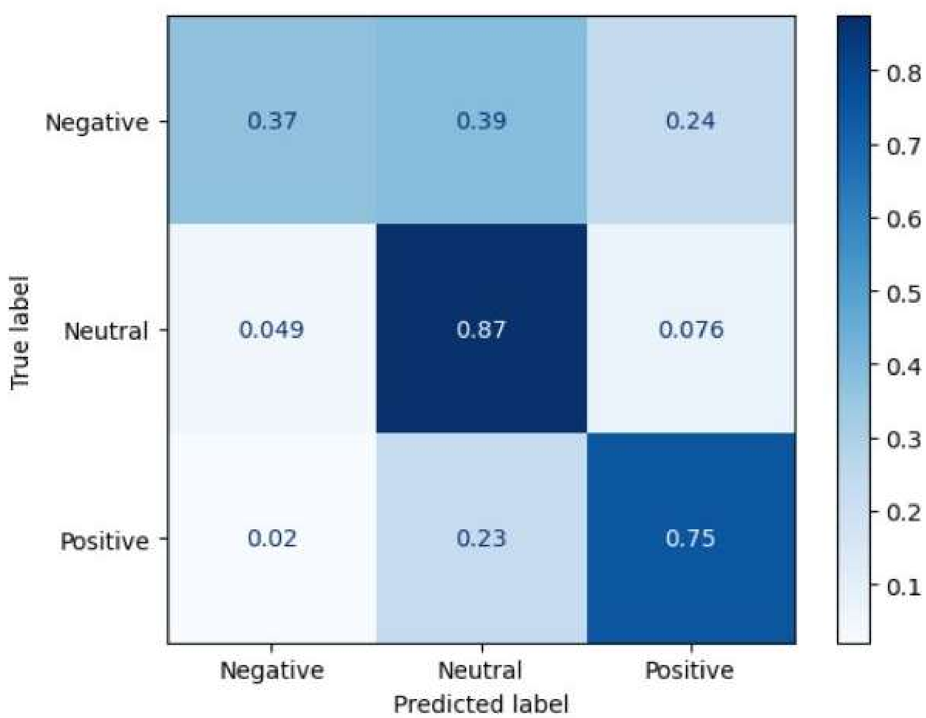



```
              precision    recall  f1-score   support

    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
```



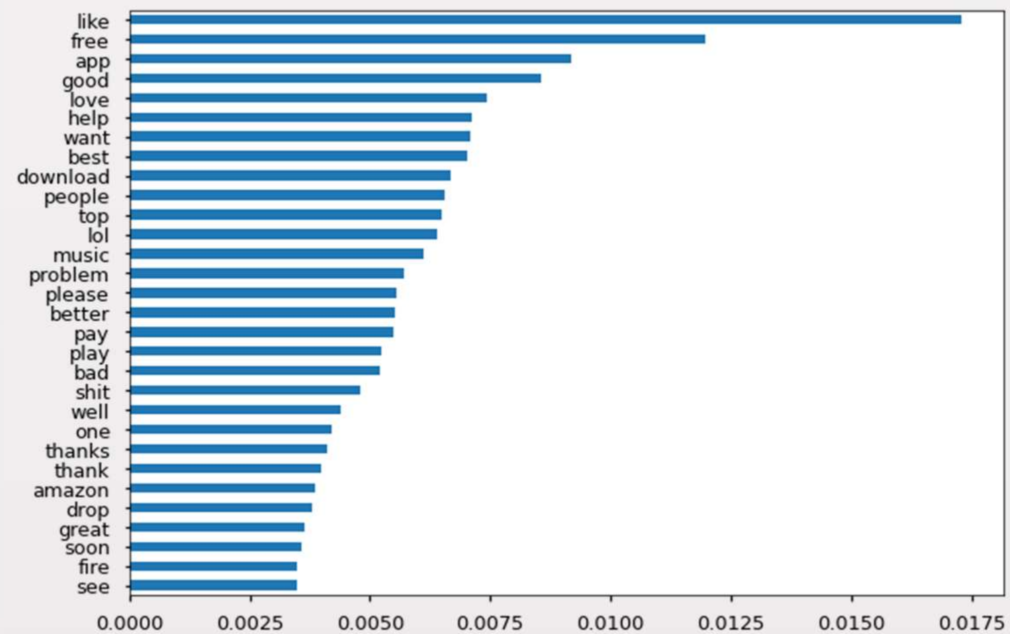
	precision	recall	f1-score	support
Negative	0.69	0.37	0.48	175
Neutral	0.68	0.87	0.76	406
Positive	0.82	0.75	0.78	441
accuracy			0.73	1022
macro avg	0.73	0.66	0.68	1022
weighted avg	0.74	0.73	0.72	1022

Training Score = 0.99
Test Score = 0.73



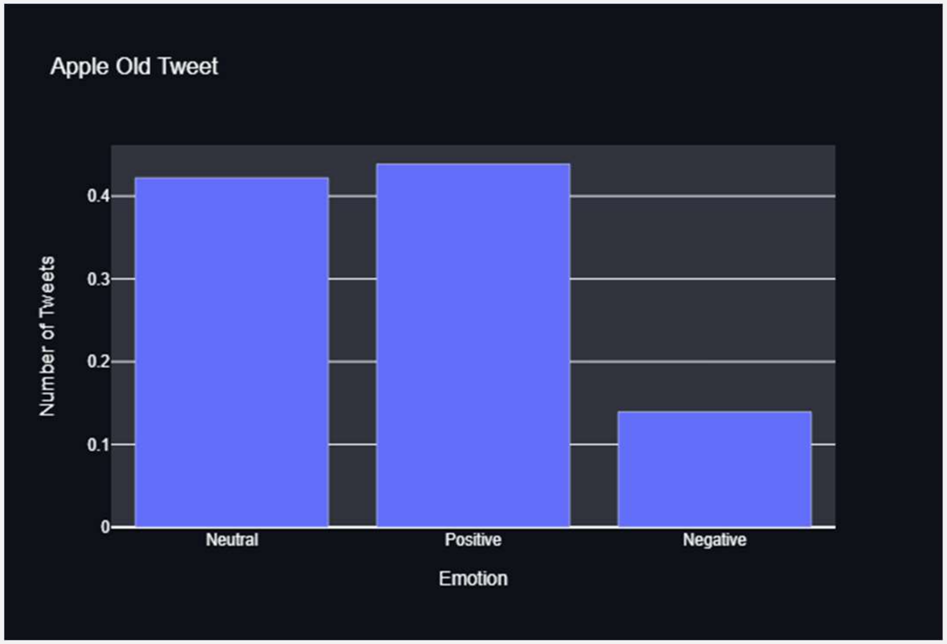
Random Forest with Grid Search (New Tweets)

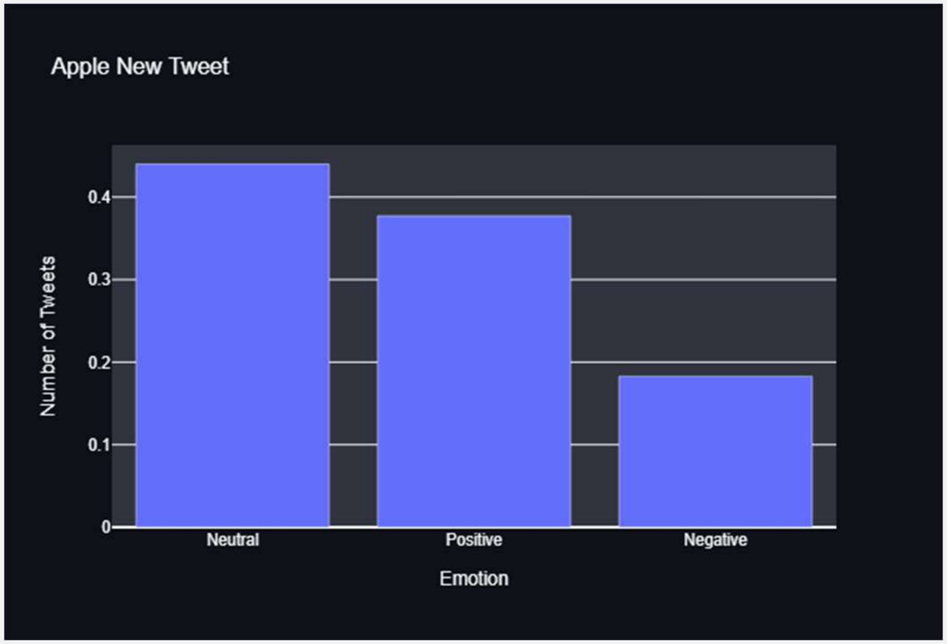
- Same problem as the old tweets
- Still recommended because it was able to maintain a relatively high recall scores while improving the recall score for the negative tweets.



APPLE

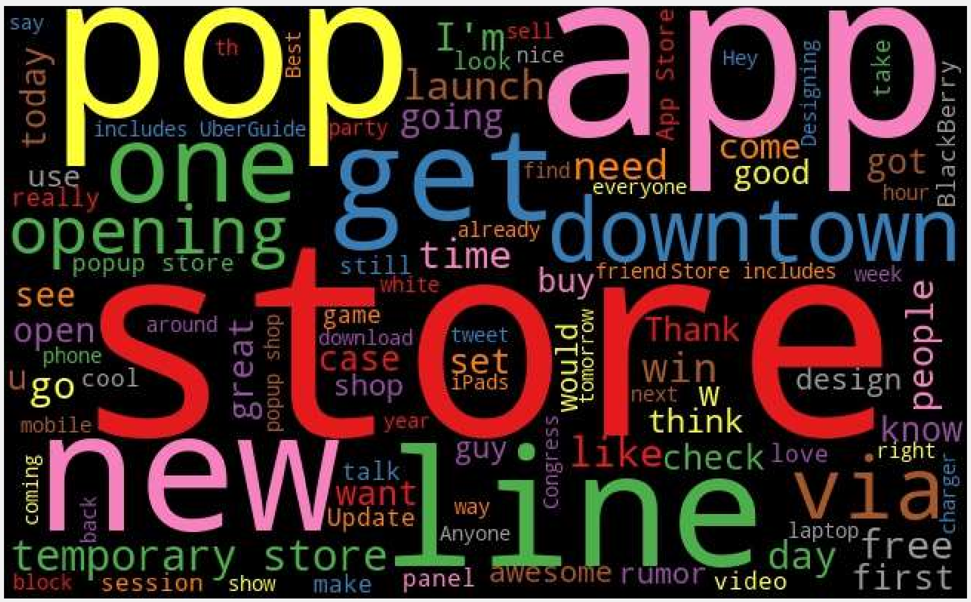
- When comparing the user sentiments generated from the old tweets to the newer tweets, we can see an increase in the ratio of negative tweets.





Word Cloud Comparison: Apple

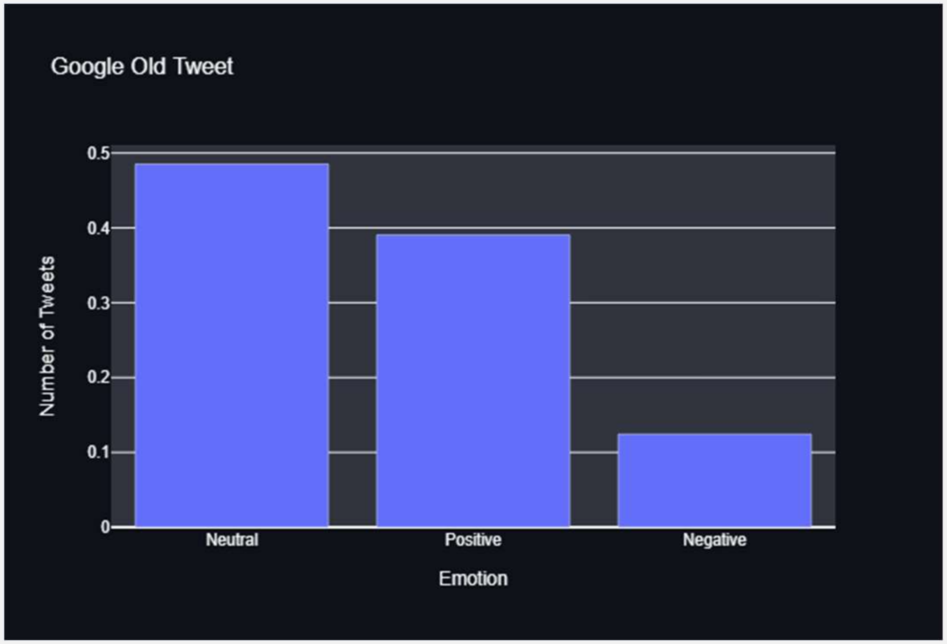
Old

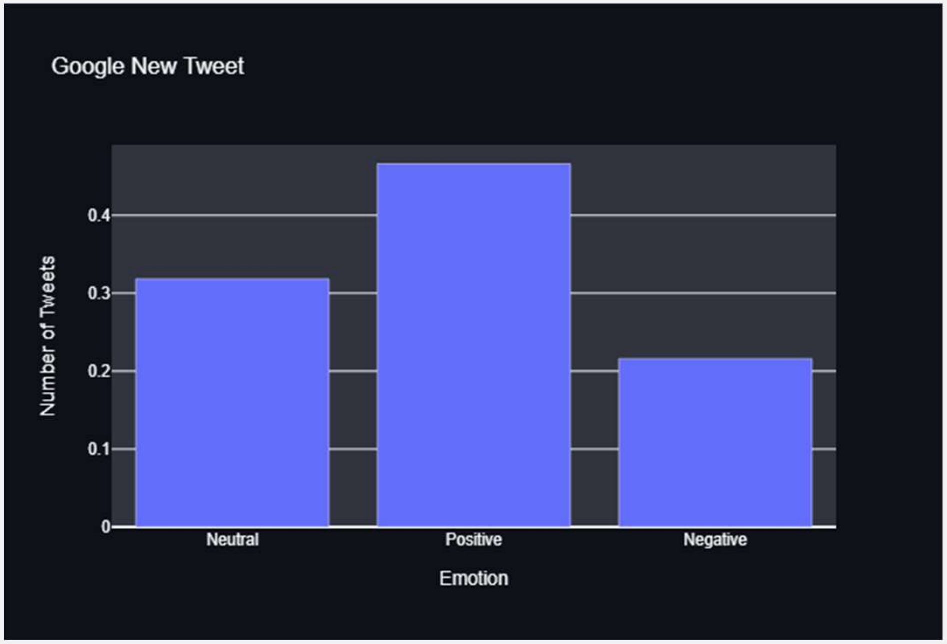


New

Google

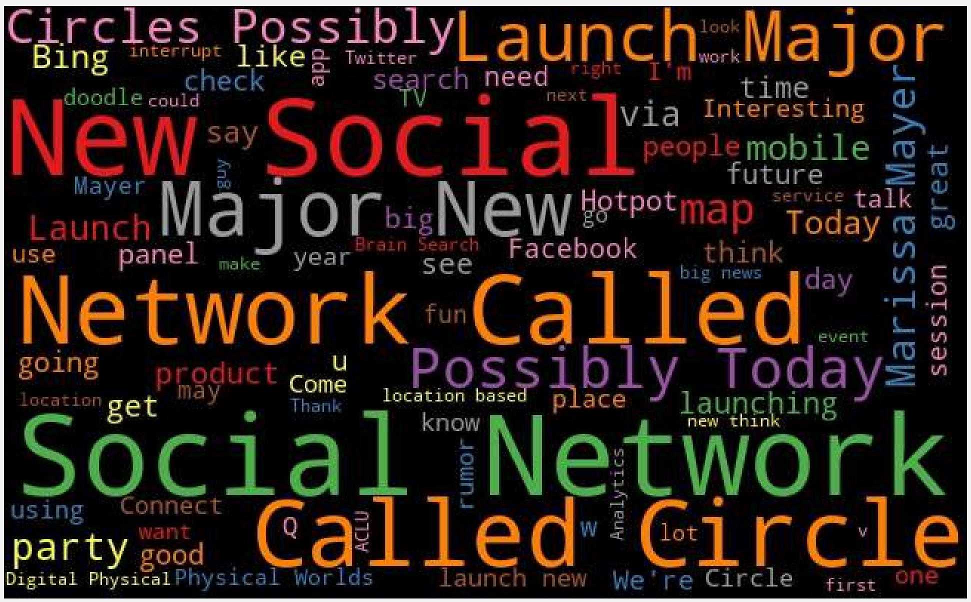
- Sentiment towards Google also became slightly worse.
- While the graphs may seem to represent a positive change, the ratio of negative to positive comments have increased by nearly two-fold.



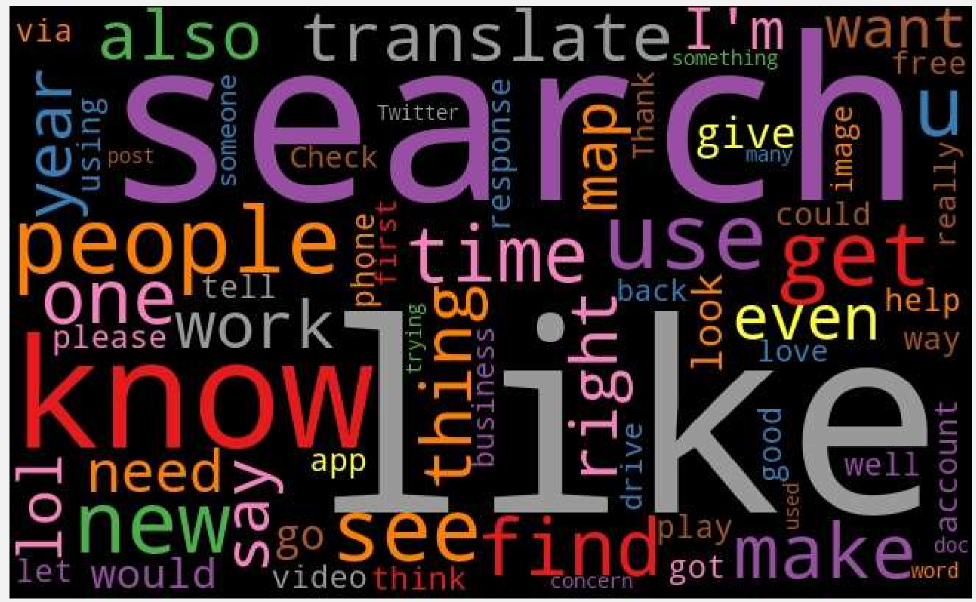


Word Cloud Comparison: Google

Old

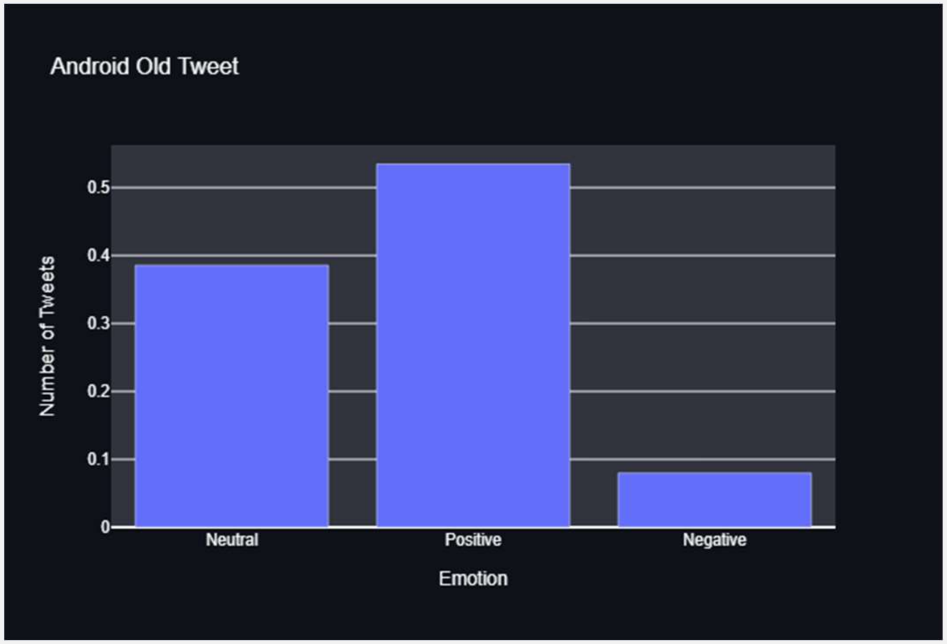


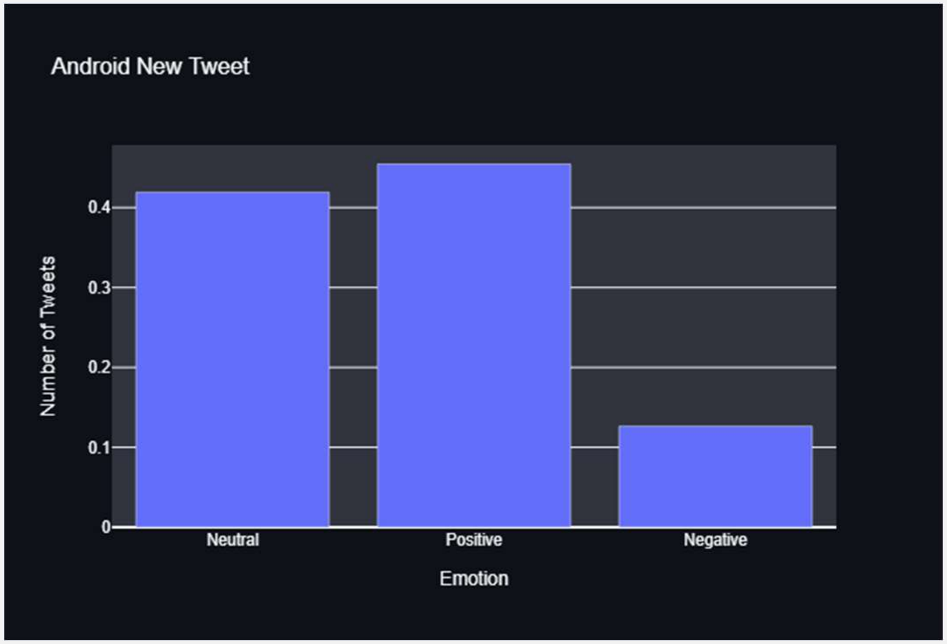
New



Android

- User's sentiment towards Android has improved significantly.
- The graph may seem to show similar sentiment, the ratio of negative to positive sentiments are not too different, but the total number of positive sentiments has increased.





Word Cloud Comparison: Android

Old

New

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

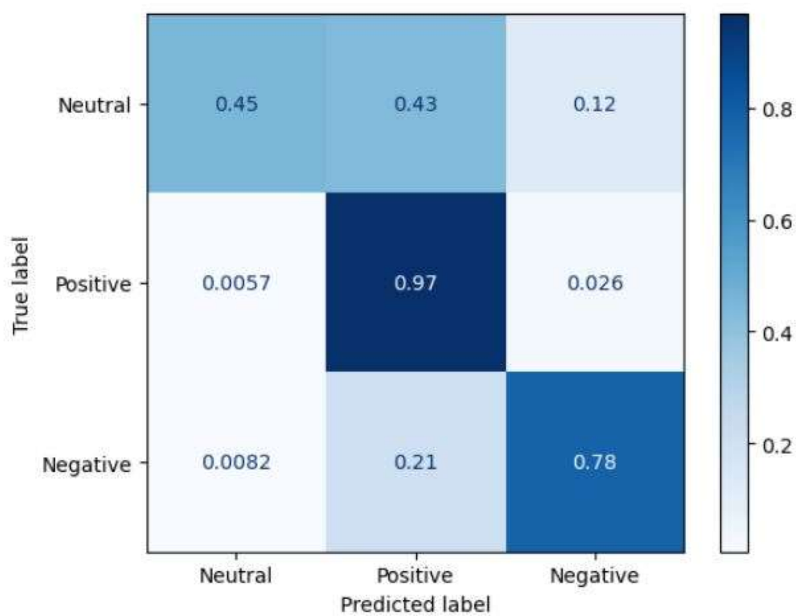
Q&A

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

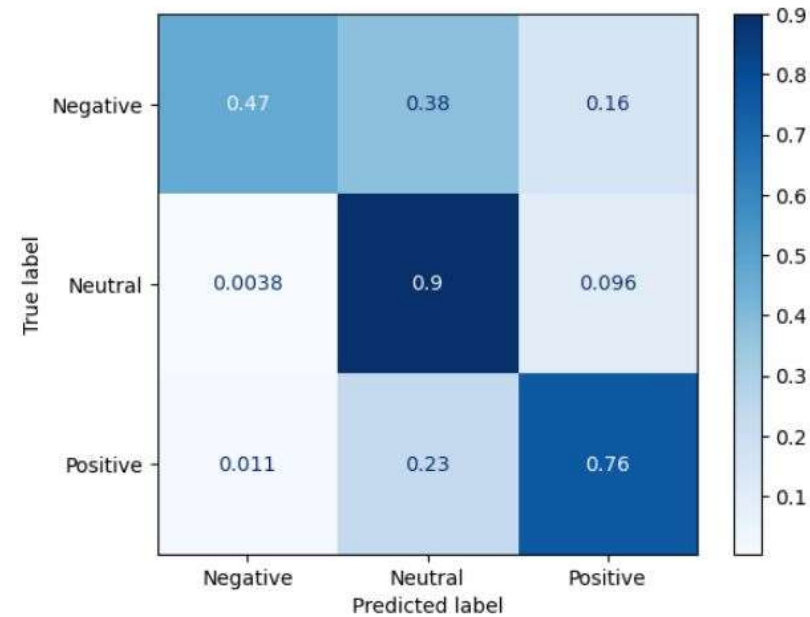
Training Score = 1.00
Test Score = 0.81



Piepeline

	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

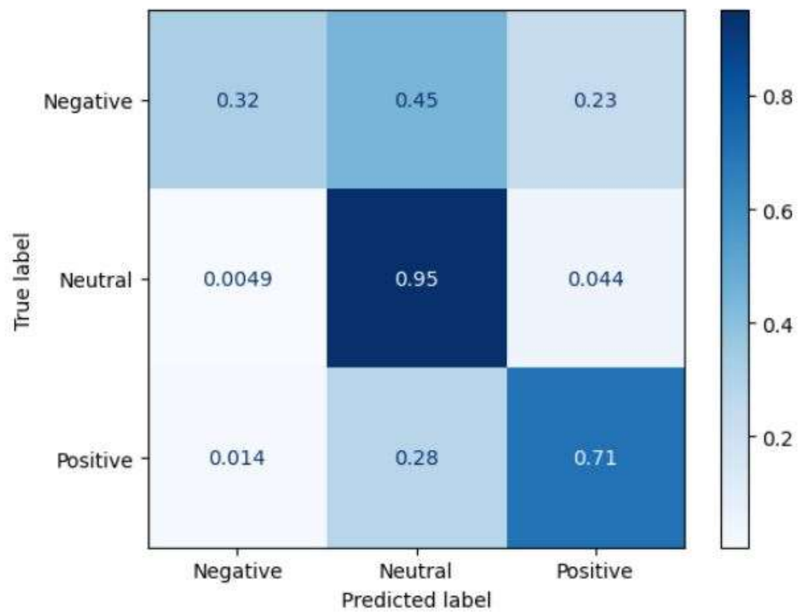
Training Score = 1.00
Test Score = 0.78



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

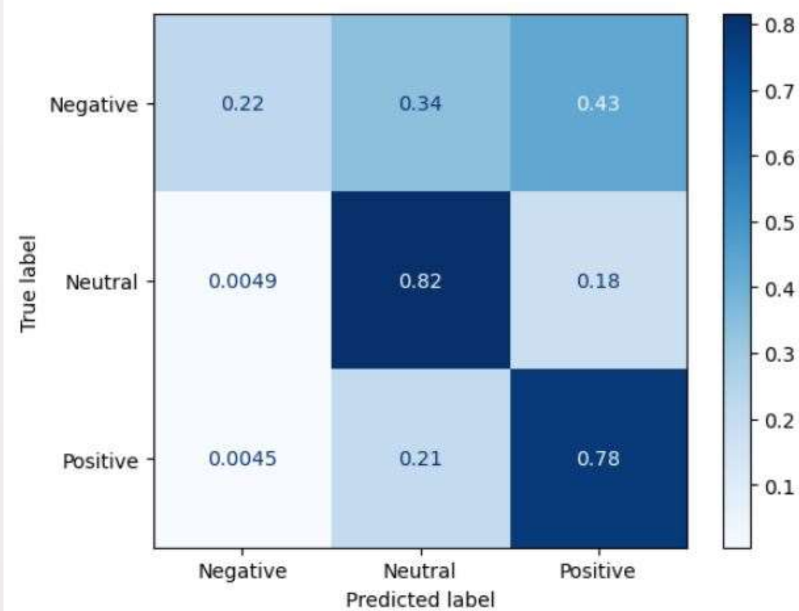
Base

```
              precision    recall  f1-score   support

    Negative       0.88      0.32      0.47       175
     Neutral       0.66      0.95      0.78       406
    Positive       0.84      0.71      0.77       441

    accuracy                           0.74      1022
   macro avg       0.79      0.66      0.67      1022
weighted avg       0.77      0.74      0.72      1022

Training Score = 1.00
Test Score = 0.74
```



Piepeline

```
              precision    recall  f1-score   support

    Negative       0.91      0.22      0.36       175
     Neutral       0.68      0.82      0.74       406
    Positive       0.70      0.78      0.74       441

    accuracy                           0.70      1022
   macro avg       0.76      0.61      0.61      1022
weighted avg       0.73      0.70      0.67      1022

Training Score = 1.00
Test Score = 0.70
```

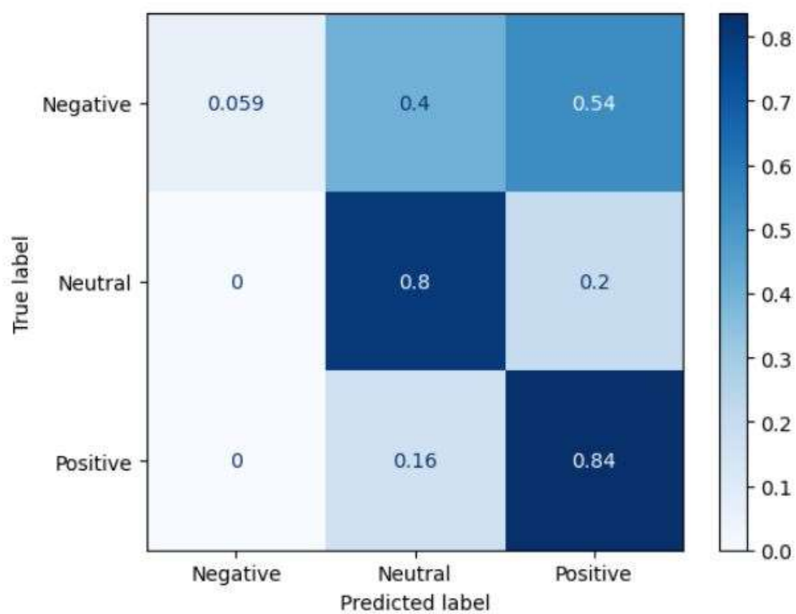


Appendx: Naïve Bayesian Base model and Grid Search (Old Tweet)

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

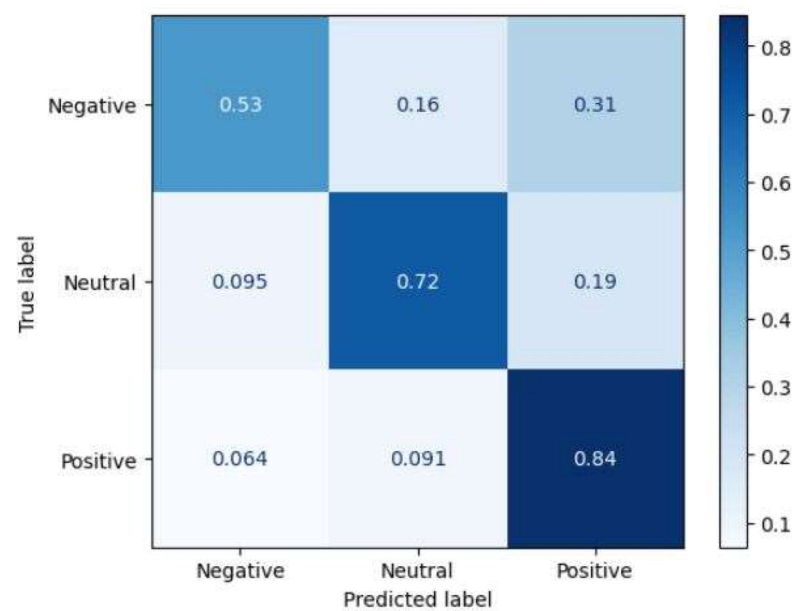
Training Score = 0.81
Test Score = 0.72



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

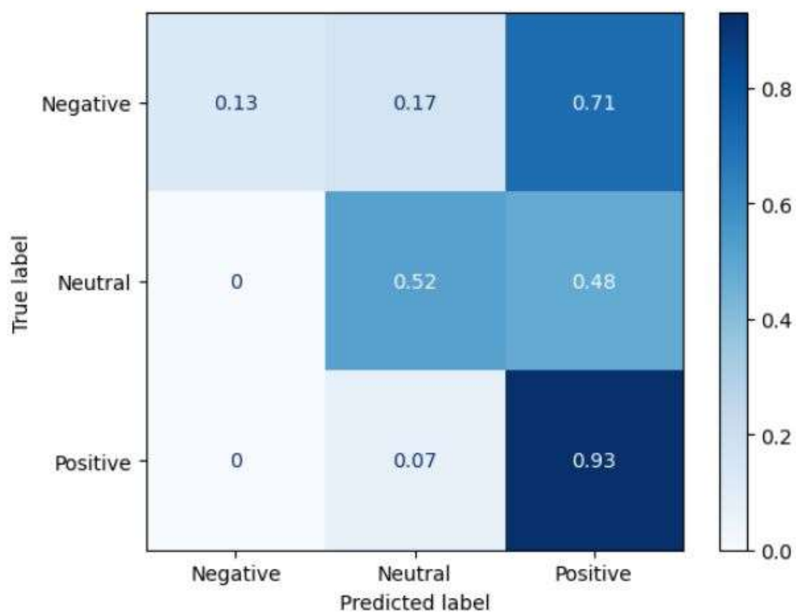


Appendx: Naïve Bayesian Base model and Grid Search (New Tweet)

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