Social Media Analysis

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Abstract— This project tackles the issue of sentiment analysis in Twitter, which entails categorizing tweets into positive, negative, or neutral categories based on the sentiment expressed in them and providing suitable recommendations.

Twitter is a social networking and microblogging website that allows users to post short status updates of up to 140 characters. It is a rapidly growing service, with over 200 million registered users- of which 100 million are active users, with half of them logging in daily - and approximately 250 million tweets every day [1]. We intend to obtain a representation of public sentiment by analyzing the feelings conveyed in the tweets to gain some insights. As a use case we will analyze the consumer posts, comments, and reviews on Samsung Galaxy S8, iPhone 8, and iPhone X models to identify pre/post launch sentiment around these products and provide recommendations to companies on their next releases.

Keywords – Twitter Sentiment Analysis about Mobile phones.

1. Introduction

We opted Twitter because, in comparison to traditional online articles and web blogs, we believe it provides a better representation of popular sentiment. The reason behind this is because the amount of useful data on Twitter is substantially larger than on traditional blogging sites. Furthermore, the answer on Twitter is both faster and more general (because the number of users who tweet is significantly higher than the number of users who post daily web blogs). Public sentiment analysis is crucial in macro-scale socioeconomic phenomena such as anticipating a company's stock market rate. This could be accomplished by tracking overall public attitude toward the company over time and applying economics techniques to determine the relationship between public sentiment and stock market valuation. Firms can also assess how well their product is performing in the market, as well as which sections of the market are receiving positive feedback, and which are receiving bad feedback (thanks to Twitter's ability to download a stream of geo-tagged tweets for specific locations).[2] If companies can obtain this information, they can investigate the causes of geographically diverse responses and, as a result, sell their products more effectively by seeking out relevant solutions, such as the creation of appropriate market segments.

This work comes within the "Pattern Classification" and "Data Mining" areas, as it examines twitter attitudes. Both concepts are intimately related and intertwined, and they can be appropriately defined as the process of automatically (unsupervised) or semi automatically uncovering "useful" patterns in enormous volumes of data. The project would heavily rely on "Natural Language Processing" techniques for extracting significant patterns and features from the large dataset of tweets, as well as "Machine

Learning" techniques for accurately classifying individual unlabeled data samples (tweets) according to the pattern model that best describes them.[2]

The two primary types of features that can be used for modeling patterns and categorization are formal language-based features and informal blogging-based features.[3]

Language-based features include the prior sentiment polarity of individual words and phrases, as well as part of speech tagging of the sentence. Prior sentiment polarity describes the natural tendency of some words and phrases to express specific and specific sentiments in general. For example, the word "great" has a strong positive connotation, but the word "evil" has a strong negative connotation. As a result, whenever a positive-connotation word is included in a phrase, the entire statement is likely to be positive.

It's the process of a computer automatically determining which part of speech each word in a phrase belongs to, such as noun, pronoun, adverb, adjective, verb, interjection, and so on. The frequency distribution of these parts of speech (alone or in combination with another part of speech) in a certain class of labeled tweets can be used to find patterns. The features associated with Twitter are more casual, and they pertain to how people express themselves on online social networks and how they condense their thoughts into the short 140-character space provided by Twitter. Twitter hashtags, retweets, text capitalization, and word spacing are all examples.

Once the tweet data is cleaned it can be tokenized and later made available for sentiment classification analysis. Supervised vs. unsupervised, and non-adaptive vs. adaptive/reinforcement procedures are the two types of classification techniques.

For this case study, we will use Sentiment analysis tools such as TextBlob and VADER. We performed an analysis to determine which tool is the best for our scenario and further performed the analysis to determine the sentiment around the tweets and categorizing them into positive, neutral and negative sentiments. The most liked and disliked attributes of each phone were analyzed and we explored the reasoning for the identified attributes.

We would now evaluate our findings to uncover how each phone measures in its public opinion related to its price, quality, and value. These three attributes are the main components customers analyze on their own to determine whether or not to purchase a new device. We also dove into how the anticipation of the phone's release based on the announced features compares to the actual reaction to the phone once customers are able to test it out for themselves.

Based on all the analysis we performed on each breakdown of the sentiment analysis of each phone, we then make recommendations for each brand to take into consideration for development of future products. Since these datasets are from nearly five years ago, we are also able to see how these brands chose to continue development of these products and compare those directions to our recommendations.

2. Data Preparation and Exploratory Data Analysis

A. Data Collection

The Twitter data set was split into two comma-separated files. Each of these tweets was dated near the release launch dates of Samsung S8 and Iphone 8 and X models. Samsung S8 was launched on 29th March 2017. One of the CSV files has one month of tweets associated with Samsung products before the launch date of S8. This file also has 3 months of post-launch date tweets. On the other hand, the second CSV file has one month of pre-launch and 45 days of post-launch tweets for the iPhone which was launched on 22nd September 2017.

B. Data Inspection

There were 41 properties in each of these CSV files, 11 of which were blank and 6 of which were sparsely populated. These would be deleted to simplify the computing processes required in the subsequent phases of data processing. We received around 50,008 tweets from Samsung between March 1, 2017, and June 30, 2017. From September 1st to October 31st, 2017, we received a total of 19,529 tweets for the iPhone. The pre-and post-launch split of tweets for Samsung was surprisingly skewed. Pre-launch, there were 42,520 tweets, while post-launch, there were just 7485. This is contradictory because we expect people to talk about a product more on social media channels once it is released.

C. Filtering Duplicates and Retweets

In Stage-1 we would clean up the tweets collected by removing the duplicate tweets and only considering the tweets that were original. We saw a drastic reduction in the overall population of the tweets available for our sentiment analysis after applying these elementary filtering stages. For the overall tweets for Samsung dropped by 43% after removing the duplicates it was further reduced by 21 % after removing the retweets. Likewise, for the iPhone we saw the tweets dropping by 55% and 32% after removing the duplicates and retweets. The following table shows the split of the records after Stage-1.

Table 1. Stage-1 Filtering Summary.

Filtering	Data Set	Records (before)	Records (after)
Duplicates	Samsung	50008	28494
Re-Tweets	Samsung	28494	22323
Duplicates	IPhone	19529	8894
Re-Tweets	IPhone	8894	6082

Table 2. Pre-Launch / Post-Launch Tweets Split

Filtering	Data Set	Pre/Post Split (before)	Pre/Post Split (after)
Duplicates	Samsung	42520/7485	23450/ 5044
Re-Tweets	Samsung	23450/5044	18163/4160
Duplicates	IPhone	9060/ 10469	4766/ 4128
Re-Tweets	IPhone	4766/ 4128	3311/ 2771

D. Filtering Influencers

Social media platforms are driven by influencers who promote an idea or a product as a part of their paid promotions. To understand this phenomenon we analyzed how tweets by these influencers might affect the overall sentiment associated with the product and later to remove any bias we would offset these tweets from our analysis. On profiling the Twitter accounts of our data set we found that about 75 percent of them have less than 2000 followers. On analyzing the remaining 25 percentile which we classify as potential influencers we saw an interesting behavior in the number of tweets in favor of Samsung phones. The following figure [Figure -1] shows the number of tweets by these influencers within the 30-day window of launch dates of Samsung's S8 and iPhone 8. There was a sudden spike in the number of tweets made by the Samsung influencers 30 days after the launch date of the Samsung S8. We believe the primary reason for this behavior could be the fact that the market was not very receptive to Samsung's phone especially after the S7 models faced heavy criticism on its safety issues.

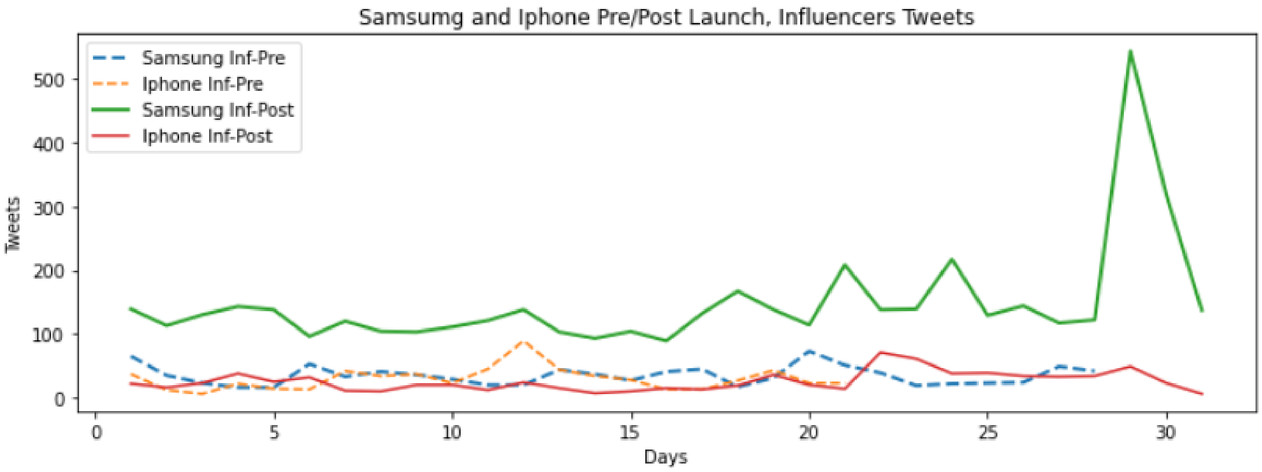


Figure -1. Samsung and IPhone Pre/Post launch, influencers Tweets

As a next step in our data preparation we decided to filter out the tweets made by individuals who have more than 2000 twitter followers and following were the results after this stage.

Table 3. Stage-2 Filtering Summary.

Filtering	Data Set	Records(before)	Records(after)
Influencers	Samsung	22323	16743
Influencers	I phone	6082	4670

Table 4. Pre-Launch / Post-Launch Tweets Split

Filtering	Data Set	Pre/Post Split (before)	Pre/Post Split (after)
Influencers	Samsung	23450/5044	13554/ 3160
Influencers	I phone	4766/ 4128	2521/2149

After this stage, the total number of available tweets reduces by 25% and 23% for Samsung and iPhone respectively.

E. Labeling and Categorizing Tweets

The tweets collected were for Samsung and Iphone so we need to add one more step of filtering only those tweets that were relevant to specific products in this case, it was Samsung's S8 and Iphone's 8 and X models. We carry out this filtering by looking for terms related to these models in the tweets. The following table shows the results of this stage.

Table 5. Stage-3 Filtering Summary.

Filtering	**Data Set**	**Records(before)**	**Records(after)**
By Product	Samsung	16743	12086
By Product	I phone	4670	4221

After this stage, the total number of available tweets reduces by 27 % and 9 % for Samsung and iPhone respectively. In the end the number of tweets for each product type is shown in the following table. However after categorizing we observe there are not many tweets available for Iphone X.

Table 6. Tweets by Product:

Product	**Records**
Samsung S8	12086
Iphone 8	3583
Iphone X	638

F. Text Clean up

After the filtering stage, we carry out the sequential steps of cleaning the data before it can be tokenized for the sentiment analysis. A clean-up stage is essential because the raw tweets are susceptible to nonuniform language patterns which could be miss classified by our analyzer. The following table presents different text cleanup operations on nonuniform patterns in the tweet data that should need to be performed before sentiment analysis.

Clean-up Operations

Clean up Task	**PreCleanup**	**Post Cleanup**
Lowering Case	IPhoNe	iphone
Expand Contractions	don’t	do not
Remove URL	website http://web.com is broken	website is broken
Remove White Space	i like s8 phone	i like s8 phone
Remove Hashtags	#mkbhd loves it	loves it
Remove Emoticons	:) X0 iphone rocks <3<3	iphone rocks
Frequent Words	s8 best samsung s8	best

[Table -6]

Each of these cleanup tasks is chained sequentially in the order mentioned in the above table. Our text clean-up task has been designed in a modular way where all the above steps are applied to the entire tweet population in a single pass. by calling the function “text cleanup” as illustrated in the following figure[Figure 2]. The resulting dataset is stored in a data frame named “combined_df” and is ready to be tokenized for sentiment analysis.

```
combined_df['Sound Bite Text'].apply(textcleanup)
```

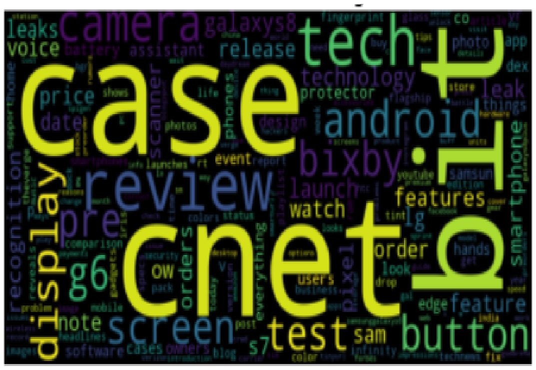
3. Sentiment Analysis

Sentiment Analysis is the process of computationally determining whether a piece of writing is positive, negative or neutral. It's also known as opinion mining, deriving the opinion or attitude of a speaker, author, or writer.

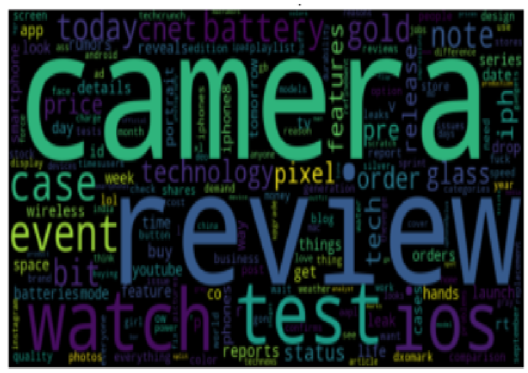
A. WordCloud distributions for each phone

A quick overview of the most-commonly used words in the tweets was identified by performing the Word-Cloud distribution for each of the phones. This step helped us in getting an overview of the buzz, general topics and features being spoken by the crowd about the products.

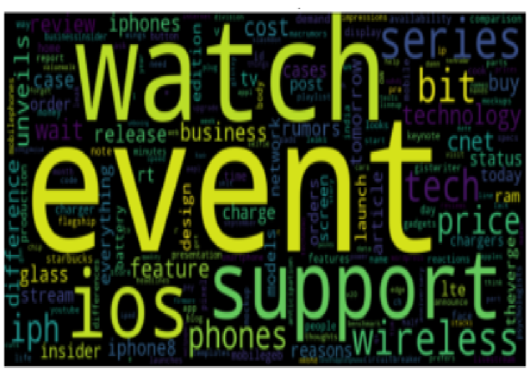
Word cloud for Samsung S8:



Word cloud for IPhone 8:



Word cloud for IPhone X:



B. Selection of Sentiment Analysis tools

A detailed research on sentiment analysis tools such as TextBlob and VADER was done to select the best of the two for the provided use-case. Below are some of the interesting findings from the analysis.

TextBlob -TextBlob is a Python (2 and 3) library for processing textual data. It provides a simple API for diving into common natural language processing (NLP) tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, translation, and more.
TextBlob works better with blog posts which are longer and have more formal language.

VADER stands for (Valence Aware Dictionary and Sentiment Reasoner). It is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media. It is an open-source python library under the name vaderSentiment.
VADER is optimized for social media data and things like slangs, and emojis. In addition to general text-processing tools that identify parts of speech, root words, VADER is also optimized to capture some the features as below:

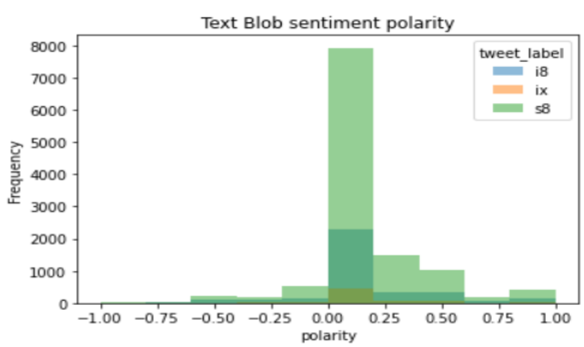
- understanding many sentiment-laden slang words as modifiers such as 'uber' or 'friggin' or 'kinda'
- understanding many sentiment-laden emoticons such as :) and :D
- translating utf-8 encoded emojis such as and 💘 and 😁
- understanding sentiment-laden initialisms and acronyms (for example: 'lol')

C. Sentiment Polarity distribution - TextBlob vs VADER

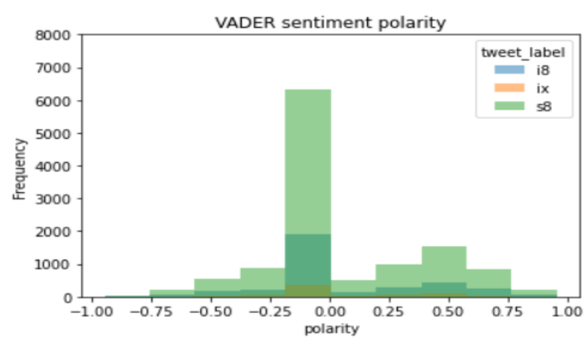
Both the tools provide sentiment polarity for each of the text (tweets) data in the range [-1, 1]. In textblob, the polarity is obtained by calling the method TextBlob().sentiment.polarity[5][6]. Similarly, VADER provides a compound score that can be accessed by SentimentIntensityAnalyzer().polarity_scores[4][7].

The polarity <0 is classified as 'negative', polarity >0 is classified as 'positive' and polarity=0 is 'neutral'. Using both the tools the sentiment polarity distribution was plotted for the given dataset to observe the sentiment intensity being captured. The distributions are as follows:

Text Blob Sentiment polarity distribution

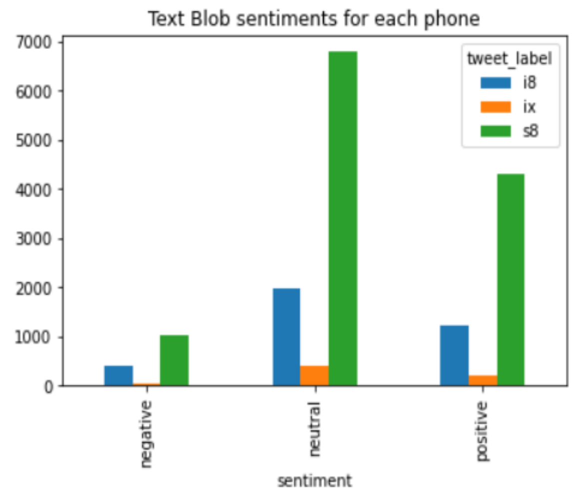


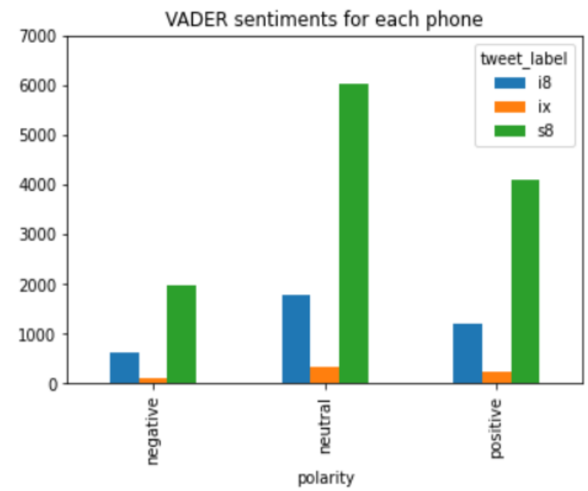
VADER Sentiment polarity distribution



Important findings:
VADER histogram has peaks in the region 0.50 to 0.75 and -0.5 to -0.25 in comparison to TextBlob histogram.
VADER was able to capture the sentiments from the tweets and not categorize them as neutral. In specific, VADER classified the tweets as non-negative as compared to TextBlob by ~6.14%.

A further drill-down analysis for each of the phones in order to identify which of the phones had a difference in sentiment and the counts was performed. The results are as follows:





From the above plots, we identified that ~1000 additional S8 tweets were categorized as negative sentiment as compared to TextBlob. It was clear that VADER was the most suitable tool for further analysis as it was able to better pick up the sentiment from the tweets.

D. Most liked attributes for each phone

To determine the most liked attributes for each phone, the tokenized tweets after data pre-processing were used. The most frequently occurring nouns and adjectives were captured and a combination of them were analyzed. Also, the words such as samsung, s8, apple, iphone and others were excluded from the list.

Below are the lists of words that occurred as the most liked attributes for each phone:

Samsung S8: [review, case, tech, camera, screen, g6, technology, best, free, black, red, live, full, facial]
IPhone 8 : [best, top, big, goof, unboxing, open, live, first, great, camera, case, gold, battery, pixel]
IPhone X: [live, unveils, best, wireless, better, upgrade, aapl, specs, premium, top, event, watch, support, cost]

Insights:

1. Among the attributes, Camera and screen appeared as one of the top most liked attributes for Samsung S8. Samsung had launched the infinity display feature for the first time. It included some of the unique features such as notifications on sidebars. This attribute seems to be well received by the audience. Also, the camera features were upgraded compared to previous models.
2. Apple has always been very creative and aims to provide a unique experience for its users even during unboxing. Unboxing word appearing on top reflects the user's excitement and curiosity to experience the product.
3. iPhoneX was the first phone without a button on the front face. It was unique and also came with an upgrade to its wireless charging technology. The keywords wireless, premium, best, better, upgrade appears to be indicative of the above features.

E. Most disliked attributes for each phone

Below are the lists of words that occurred as the most liked attributes for each phone:

Samsung S8: [iris, leak, red, mashable, facial, bixby, bad, screen, scanner, button, reveals, drop, display, photos, massive]

IPhone 8: [small, hard, lower, touch, screen, low, upgrade, leak, drop, battery, glass, demand, status]
IPhone X: [leak, september, expected, gamble, poor, production, watch, charger, rumors, code, series, release, smaller]

Insights:

1. Iris, bixby, scanner were some of the top attributes that were disliked by the audience for Samsung S8. Samsung started to include an iris scanner for facial recognition for the first time which was not well appreciated. Also, the new virtual assistant feature Bixby was loaded with a ton of features which were a point of concern for the company.
2. IPhone 8 was the first phone to have a glass back. The glass keyword in disliked attributed seems to reflect the fact that this inclusion was a cause of concern for the users as the phone glass would shatter on both front and back on dropping the phone. The users need to be extra careful while handling the phone.
3. For Iphone X: There were initial plans to release a gold iphone, which was a highly favored color option in the previous models but it was put on hold due to production issues
4. The iPhone 7 and 8 both came with a plus option to get a larger version of the phone. The iPhone X did not have that option and instead opted for a size slightly bigger than the smaller version of the 7 and 8.
5. The wireless charger wasn't included in the box and the users had to separately buy it for iPhone X

4. Evaluating Price, Value, and Quality

A. Data Categorization

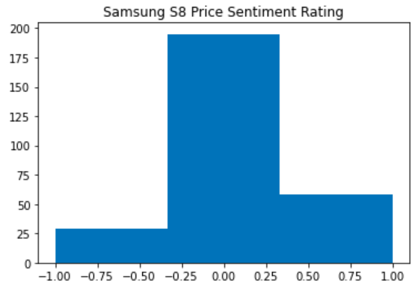
The process began by building lists of words related to the attributes we were trying to analyze, which were price, quality and value. We did our best to choose unbiased words in relation to our attributes, or key words a customer would use in their judgment of that specific attribute.

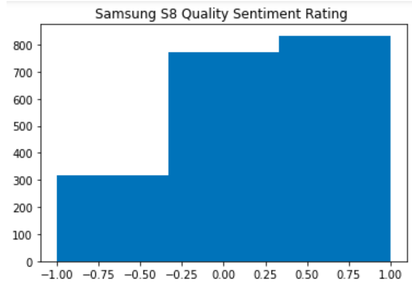
For example, for the word "price," the list included other words such as cost, pricey, cheap, and expensive. These were words we found by scanning the tweets in the dataset and we added words as we continued analysis in order to improve the accuracy of our tagging system.

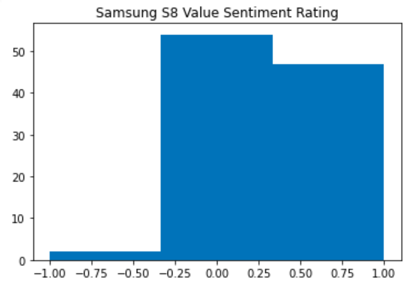
Given these lists of words for each attribute, each tweet was tested on whether it contained any of the words in the given list and tagged with the boolean value of whether it was a price-related tweet (True) or not (False). There was overlap in tweets being labeled as related to more than one of the three attributes, so there were tweets marked "True" for all three.

B. Evaluating Price, Quality, and Value for Samsung

Below are the distributions for the sentiment about price, quality, and value of the Samsung S8. There is a noticeably lower number of tweets for each category, so separated histograms seemed to be the best way to understand the distribution for each individual attribute.





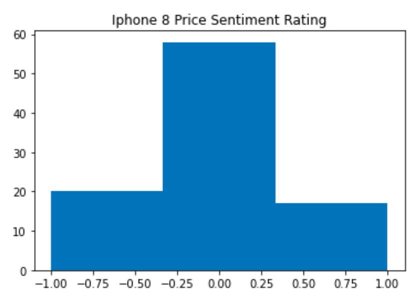


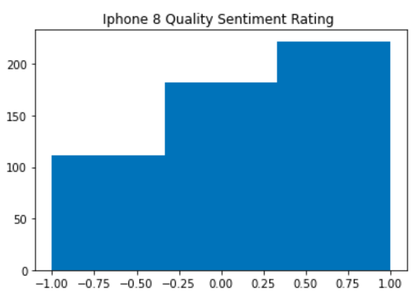
Samsung's distributions for quality and value were unsurprising because the general brand perception for Samsung is that their phones are dependable and consistent. Rarely do arguments against Androids ever attack the quality of the phone itself. Popular arguments for opposition to Android smartphones typically have more to do with the big difference in the look of the interface compared to iOS and the "green text bubble" effect. The "green text bubble effect" is a social media trend surrounding the dissatisfaction with the differing color of the message bubbles when an Apple product is sending a message to another Apple product or to an Android device.

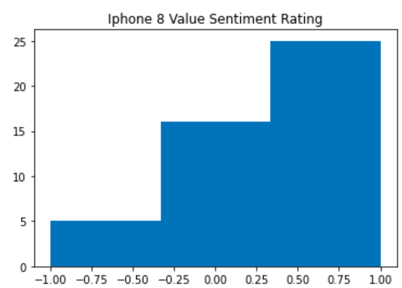
It is a well known fact that the price point is lower than that of an Apple smartphone, which is often a point of argument in the popular Apple vs Android debate. The slight positive skew in the price sentiment is likely because of that same fact, but it didn't have much buzz because it's an inevitability at this point.

C. Evaluating Price, Quality, and Value for iPhone 8

Below are the distributions for the sentiment about price, quality, and value of the iPhone 8. There were more tweets relating to quality than price and value, but there were still at least 50 tweets for each.



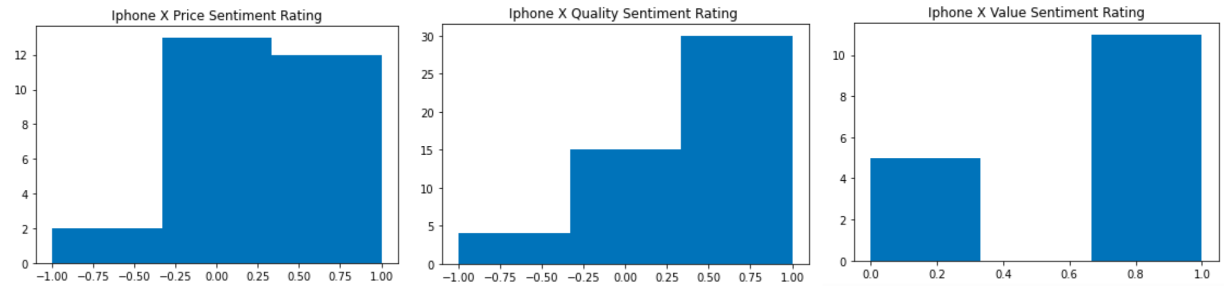




There was a strong positive sentiment for both quality and value, but mostly neutral with a slightly negative sentiment for the price.

It's a well known fact that iPhones are on the more expensive side of smartphones, so it makes sense that there wasn't much buzz complaining about that to create a strong negative sentiment about price. There is an overarching upset from Apple users about the ever increasing prices as each new model is released, which is likely what informs the slight negative sentiment.

D. Evaluating Price, Quality, and Value for iPhone X



The strong positive sentiment about the price of the iPhone x is surprising, because it was by far the most expensive iPhone ever released at that point, with even higher price points internationally. We assume it might be related to the complete redesign of the look of the phone and the large set of new features released with it as well.

The iPhone X was very well received by customers due to the drastic improvement in camera quality and appreciation for the new facial recognition feature.

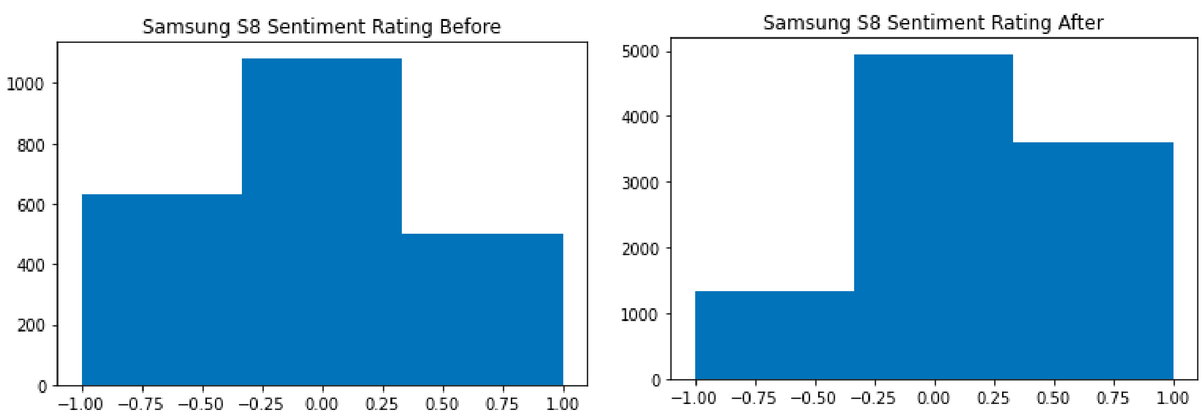
Both the iPhone x and iPhone 8 had strong positive sentiment for quality and value, which makes sense due to the very strong customer base for the apple ecosystem.

5. Evaluating Pre-Launch vs Post Launch Sentiment

As stated earlier, the two given data sets were distinguished as being for the pre and post launch tweet for Samsung S8 and those of the iPhone 8 and X. Each tweet was categorized as before or after the launch date. These tags were used to create subsets of the data to analyze for pre and post launch sentiment, results of which will be detailed below.

A. Evaluating Pre and Post Launch Sentiment for Samsung S8

Below are the sentiment distributions for the Samsung S8 before and after its launch.

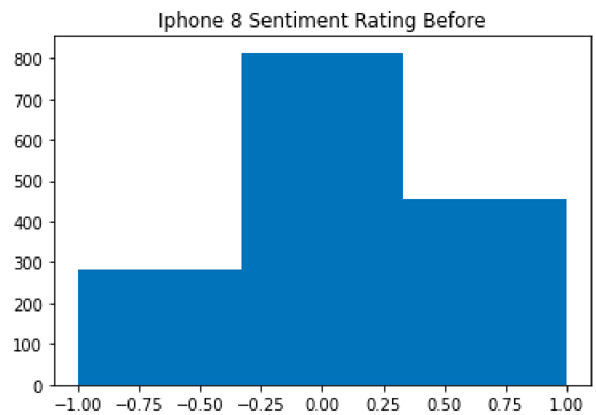


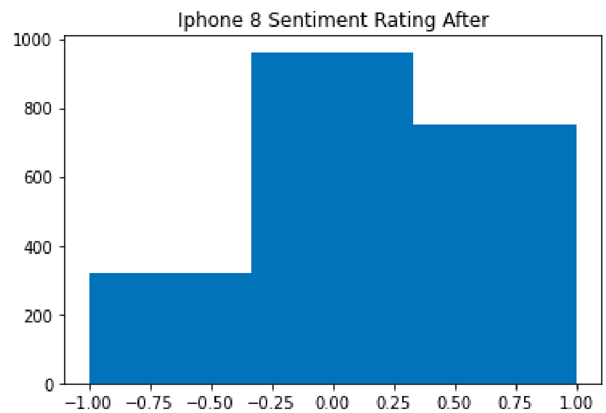
We can see there was a noticeable difference in sentiment before and after launch. There was a negative skew before the launch, but then a definitive positive sentiment after launch. There were a lot of negative reactions to the previous S7 model, so the anticipation of the new model going the same way is likely what informed the negative sentiment before the launch.

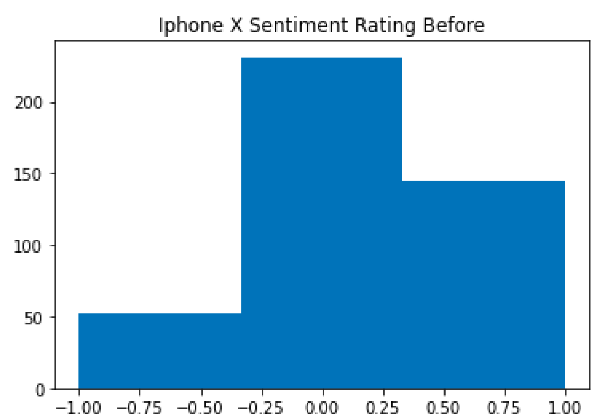
The phone was very well received by critics and customers, which shows in the significant bump in positive sentiment after the launch. As mentioned before, there was a strong appreciation for the new infinity display, boosting screen and video quality on the phone.

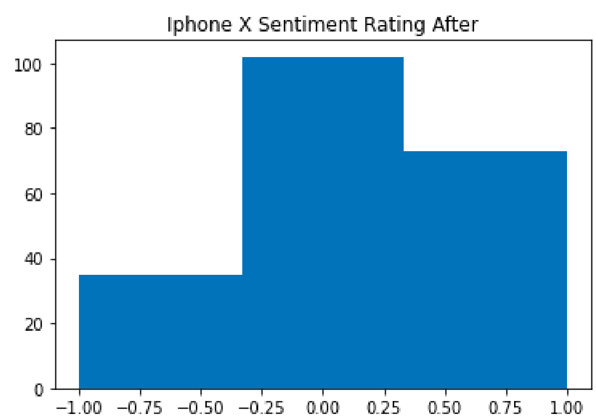
B. Evaluating Pre and Post Launch Sentiment for iPhone 8 and X

Below are the sentiment distributions for the iPhone 8 and iPhone X before and after their launch. The data pulled for both phones was from the same time period and the distributions are very similar, which is why they have been grouped together for analysis of pre and post launch sentiment.









We can see there was very little change from before and after the launch for both the iPhone 8 and X. There was a slight increase in positive tweets, from the excitement of the new look of the phones and new features and apps that are released with each model. Apple products, specifically iPhones, have a very consistent customer base. When most people enter the Apple ecosystem, it's very difficult to leave due to the cross-device integration and specialized chargers enticing people to stay loyal to one brand for all their technology.

6. Recommendations

After drawing our insights from all the above analysis, we are able to make some recommendations for each brand to take into consideration for their next models. We do this by drawing from the most liked and disliked attributes of each phone and identifying areas of growth and improvement. Each brand is aiming to maintain not only positive brand perception but also positive reception to each model that comes out. Since these phones came out nearly five years ago, we are also able to see what their next moves were following these models and compare them to our recommendations.

A. Recommendations and Outcomes for Samsung S8

The most promising features we singled out for the Samsung S8 were the fact that a high percentage of Android apps are free, the new screen with infinity display, and dual sim card support. The difference of pricing for apps between Apple and Android products is a frequent argument in the popular Apple vs Android debate. Apple has more restrictions on the apps put on their app store, and developers have less freedom with the capabilities of the app itself because Apple likes to maintain control of its operating system and key features. The S8 included a new screen with an infinity display, which was very well received by customers excited about the improved video watching experience. Especially for customers who need two phones (one for work, one for personal use), being able to consolidate into one phone was a large convenience.

The most disliked features were Bixby, the new iris scanner, and the poor placement of the fingerprint sensor near the camera. The S8 included a new set of voice assistant features named Bixby. Bixby was described as “lackluster” and left many customers unimpressed with the change. There was also a new iris scanner, which was Samsung’s attempt at facial recognition with their phone. The new scanner was not well received. In addition to the constant smudging of the camera with the placement of the fingerprint sensor next to the camera, both authentication methods that came with the phone left customers dissatisfied.

The recommendations we have for Samsung are to move the fingerprint sensor and to improve on Bixby. We can actually see that the new Samsung S9 had the fingerprint sensor placed below the camera as opposed to the side, which improved the experience for customers. Both Google and Apple have notable voice assistants heavily tied with the success of their products. It would be in Samsung’s best interests to improve upon Bixby to make it a drawing feature for new customers to buy into the Android smartphones as opposed to the Apple counterparts.

B. Recommendations and Outcomes for iPhone 8 and X

The most promising features for the iPhone X (since it was the later release of the two) were the camera, wireless charging capability, and improved battery life. The continuous improvement of camera quality with each iPhone release is a large draw for many customers, especially those interested in creating digital content. Though earlier models also support wireless charging, the iPhone X was the first to promote its capability to do so.

The most disliked features for iPhones in general are the different adapters required for all the devices and the overall high price point for all the products. Especially since Apple changes the laptop charging port every few models, customers are left with multiple now useless chargers and are forced to buy new adapters for all other external ports they need. Although most customers choose to stay within the Apple ecosystem because of the high convenience of use, there is always pushback on the rapidly increasing prices with new product that comes out.

We recommend Apple work on reducing the number of different chargers for each product and to offer a lower price tier for certain products. We suggest focusing on the new adoption of USB-C as the new charging standard for their devices. Although the most recent Macbook has reverted to Magsafe chargers, previous Macbooks and all recent iPad releases have been using a USB-C charger. We think it would be best to also change the iPhone charging port to USB-C as well so customers can consolidate their charging cords and minimize the number of necessary adapters. We can see that Apple ended up releasing the iPhone SE 2nd generation, which was a lower price iPhone they released in 2020 as a redesign of the iPhone SE they released in 2016.

References

1. Wikipedia, Sentiment Analysis
   https://en.wikipedia.org/wiki/Sentiment_analysis
2. Shashank Gupta, Sentiment Analysis: Concept, Analysis and Applications, 7th January, 2018
   https://towardsdatascience.com/sentiment-analysis-concept-analysis-and-applications-6c94d6f58c17
3. Lex Analytics, Sentiment Analysis Explained, 2nd May, 2020
   https://www.lexalytics.com/technology/sentiment-analysis
4. NLTK Vader Documentation
   https://www.nltk.org/_modules/nltk/sentiment/vader.html
5. Nikhil Kumar, Twitter Sentiment Analysis using python, 22 July, 2021
   https://www.geeksforgeeks.org/twitter-sentiment-analysis-using-python/
6. TextBlob: Simplified Text Processing, Release v0.16.0
   https://textblob.readthedocs.io/en/dev/
7. Aditya Beri, Sentiment analysis using VADER, May 27, 2020
   https://towardsdatascience.com/sentimental-analysis-using-vader-a3415fef7664
8. Admin. “26 Nov Apple Ecosystem Leads User Retention.” VentureDNA. AppleInsider, November 26, 1970.
   https://www.venturedna.com/apple-ecosystem-helps-iphone–lead-user-retention/