Using Twitter data to enhance the effectiveness of advertising for the iPhone 8

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Abstract

Apple today is a name commonly discussed in every household across the globe. They have changed the world and its future for eternity by making everything less demanding, straightforward, and productive. But among the entire portfolio of products that Apple offers, the iPhone has been the key product for the organization. It has changed Apple's business drastically.

iPhone sales have risen unequivocally over the years, from around 1.4 million iPhones sold in 2007 to more than 201 million units worldwide in 2016. [0.1]. However, according to a study published on the Business Insider website, the vendor saw a slight decrease in Year-over-Year growth of its share of the market notwithstanding solid rivalry from Samsung and Chinese sellers, for example, Huawei. [0.2]

With Apple having unveiled its iPhone 8 on September 12th, the tech giant will be in a full swing to surpass its historical sales records. In this paper, we make use of Twitter data to understand the consumer sentiments of iPhone 8 for different geographical markets and guide the timing and implementation of Apple's marketing to convert the greatest number Neutral sentiments to Positive sentiments.

Introduction

The first generation of Apple's iPhone was launched in 2007 and introduced exciting features to a more extensive group of audience. Since its introduction to the consumer market, Apple has released eighteen different iPhone models.

Models

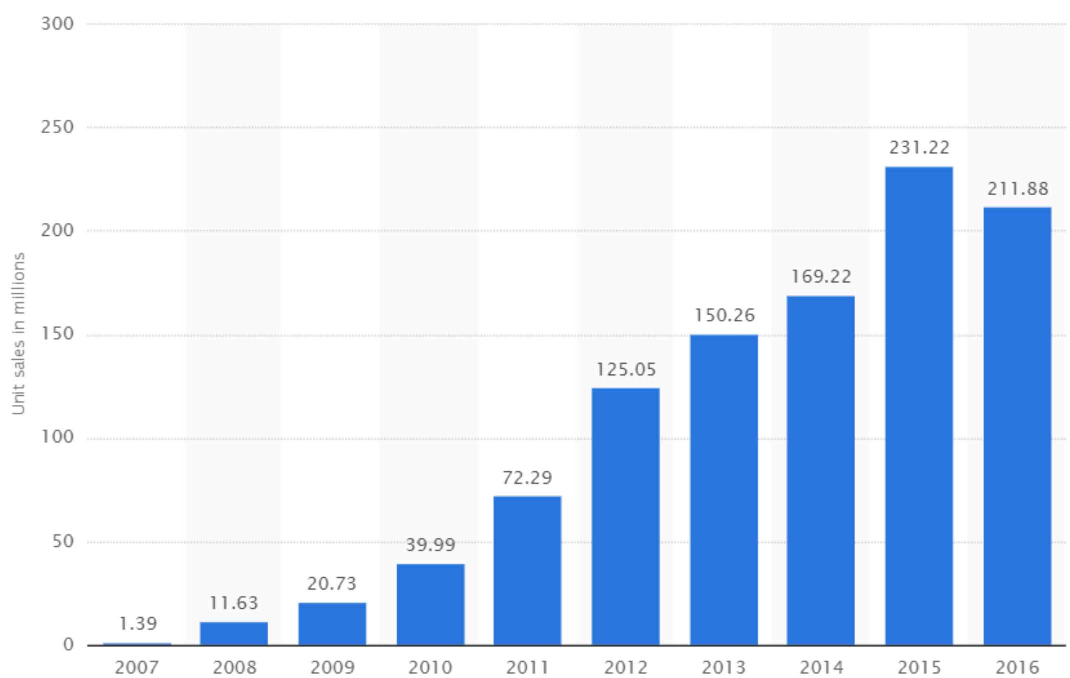
See also: iPhone model comparison

18 different iPhone models have been produced. The models in **bold** are the current flagship devices of the series:

- iPhone (2007–2008)
- iPhone 3G (2008–2010)
- iPhone 3GS (2009–2012)
- iPhone 4 (2010–2013)
- iPhone 4S (2011–2014)
- iPhone 5 (2012–2013)
- iPhone 5C (2013–2015)
- iPhone 5S (2013–2016)
- iPhone 6 (2014–2016)
- iPhone 6 Plus (2014–2016)
- iPhone 6S (2015–present)
- iPhone 6S Plus (2015–present)
- iPhone SE (2016–present)
- iPhone 7 (2016–present)
- iPhone 7 Plus (2016–present)
- **iPhone 8** (2017–present)
- **iPhone 8 Plus** (2017–present)
- **iPhone X** (2017–present)

Source: en.wikipedia.org/wiki/IPhone

In the first quarter of 2017, iPhone sales represented more than 69 percent of Apple's total revenue. **[0.1].** However, iPhone sales declined sharply post 2015, as visible in the graph below:



Source: https://www.statista.com/statistics/276306/global-apple-iphone-sales-since-fiscal-year-2007/

Also, according to the Business Insider study, Apple's growth in the developed markets has flatlined and a viable strategy that Apple is now planning is to target emerging markets such as India.

With iPhone 8 at the forefront, the idea of analyzing customer sentiments in not just the United States of America, but also in two major cities of significant geographical markets i.e. UK and India, motivated us to conduct this study.

The data we collected is based on observations two days prior and three days post iPhone 8 launch, including the day of launch. Additionally, we derived some interesting features by collecting and comparing tweets that came from iOS vs the Android devices.

As we proceed further, all relevant problem statements related to the case study are answered sequentially and cover details pertaining to data gathering and data analysis.

Problem 1: Sampling Twitter Data with Streaming API about iPhone 8

Based on the keyword "iPhone8", we collected data from three cities, i.e. New York, Mumbai and London several days in a row. Since the release date of the new iPhone is in one of this days, we could analyze people's attitude toward the smartphone by filtering sentiment sentences pre and post launch. The function of twitter API search.tweets[1.1] has the argument of geocode to help limit the scale of tweets we collect. Then we divide the tweets into two categories, the tweets texted from android and IOS, to carry out deeper analysis.

We store those tweets in a JSON file by implementing the JSON.dump[1.2] function.

Problem 2: Analyzing Tweets and Tweet Entities with Frequency Analysis

In our analyzing process, we get the top 30 popular words without meaningless words, the most popular tweets in the data set and the most popular tweet entities in the data set. We use some Python modules to help us analyze the data, including NLTK, Matplotlib and PrettyTable. Here are the steps for our data analysis.

1) Add the content of "text" attribute of the data set to a list.
2) Create a function named unwantedWords to return list of all non-sense words, punctuations and stop words.
3) Count words not in unwanted words list to get the top 30 popular words.
4) Plot the result by Matplotlib to show the trends of top 30 popular words.
5) Count the tweets with the largest number of retweet counts
6) Count the top 10 hashtags, top 10 user mentions that are the most popular

Here is the result.

1) Sample of the top 30 popular words

Word	Count
#AppleEvent	1640
#iPhoneX	1620
X	1620
win	1600

2) Sample of top 10 tweets that are the most popular

Retweet Count	Screen Name	Text
1089	techdotdeals	RT @techdotdeals: GIVEAWAY | RT and follow for a chance to win the iPhone X upon release. #iPhoneX #iphone8 #AppleEvent #fifa18 #win https…
63	marketing_birds	RT @marketing_birds: Apple unveiled #iPhone8 and #iPhoneX, here are the best memes from the #AppleEvent! (via: 9GAG) 😹😹 What do you think a…
60	robboma24	RT @robboma24: BREAKING: PSG put #Neymar and #Mbappe on the transfer list as they look to purchase the new #iPhone8

3) Sample of top 10 hashtags and top 10 user mentions

User Mentions	Count
Tech Dot (V)	1580
Marketing Birds	40
Three UK	40

Hashtags	Count
AppleEvent	1700
iPhoneX	1680
iphone8	1660

Problem 3: Getting "All" friends and "All" followers of John Cena in twitter¶

For this problem, our team selected the Twitter verified account of John Cena. John Cena is an American professional wrestler, rapper, actor, and reality television show host. [3.1] His Twitter account indicates he has 10.1 million followers.

First, a brief review of the Twitter relationship model. Twitter can be thought of as a global text messaging service, limited to 140 characters, where each message, or Tweet, is delivered at the "speed of thought" [3.2]. Twitters service allows anyone with an account to be aware of the latest events or communications from any other Twitter user, even if the other Twitter user does not follow you back. Twitter's following model is simple but exploits a fundamental aspect of what makes us human: our curiosity [3.3].

Before we get into the details of the findings for John Cena's Followers and Friends it may be useful to first review what exactly is a 'Friend' versus a 'Follower' in within the Twitter following model. In simple terms, a follower is someone who follows you (or in this case someone who follows John Cena). A friend is someone who you follow (or in this case someone who John Cena follows).

Collecting these populations of 'Friends' and 'Followers' can be useful for processing with set-wise operations, like intersection or difference, for finding mutual relationships, one-way relationships, etc.

Our first endeavor was to collect twenty Friends of John Cena and plot the data in an ASCII table for convenient review. Using the twitter_api object defined in Problem 1, we gathered twenty Friends and stored their IDs and Names in a Python list. We then iterated through the list of Friends and with the help of the Python library prettytable we plotted the list in an ASCII table. A sample list of twenty Friends is shown below:

```
+--------------------+----------------------+
| Friends Id         |     Friends Name     |
+--------------------+----------------------+
| 23504870           |      South Park      |
| 16222584           |    Official DWTS     |
| 39625388           |      Chad Gable      |
+--------------------+----------------------+
```

The process was repeated for collecting twenty Followers of John Cena. We gathered twenty Followers and stored their IDs and Names in a Python list. We then iterated through the list of Followers and plotted the list in an ASCII table. A sample list of twenty Followers is shown below:

```
+--------------------+----------------------+
| Followers Id       |    Followers Name    |
+--------------------+----------------------+|
| 908897926629310465 |      Saroj Shah      |
| 893005961660571649 | MD. SHAHANUR GAZI SH |
| 908898860701020160 |    Raymond Wyatt     |
+--------------------+----------------------+
```

The final task for Problem 3 was to compute the mutual friends within the two groups (i.e. the users who are in both friend list and follower list) and plot their ID numbers and screen names in an ASCII table. As mentioned earlier, set-wise operations can be applied against these groups in order to identify the Twitter users who follow John Cena, and are followed by John Cena.

The Twitter API presented some challenges when requesting significant amounts of Friend and Follower data. We were forced to limit the number of records returned in order to avoid the frustrating error "HTTP Error 429: Too Many Requests:"

Given these challenges, we were able to collect only a few examples of mutual friends. However, the nature of these mutual friends made it easy to verify that our code did indeed find the set-wise intersection of the two groups. The mutual friends were captured in separate events and are shown below:

Mutual Id	Mutual Name
86188401	Rip Rogers

Mutual Id	Mutual Name
202116088	Mission Hills China

Viewing the Twitter account for Rip Rogers reveals that he is a retired wrestler. His real name is Mark Sciarra and he was better known by his ring name, Rip Rogers [3.4]. Since John Cena is currently a professional wrestler it is plausible that they would be mutual friends given their shared background in professional wrestling.

A similar investigation of Mission Hills China reveals that this account is associated with a non-person entity. According to their website, they are the owner and operator of Mission Hills Shenzhen and Mission Hills Resort Hainan, and a notable player in China's young sports and leisure industry [3.5]. Some additional investigation shows that Mission Hill China and the WWE (to which John Cena is signed and a free agent) have partnered to bring a WWE wrestling event to Shenzhen China.

According to the WWE website, "Mission Hills, the largest golf club in the world, is excited and proud to partner with WWE, a global entertainment company, to bring WWE Live to China," said Tenniel Chu, Vice Chairman of Mission Hills Group. "Together we are bringing the excitement and family-friendly entertainment of WWE Live to fans here in Shenzhen for the very first time." [3.6]

To circumvent the issue of "HTTP Error 429" with the API, our team decided to collect Twitter data for a different 'famous' entity with far fewer followers than John Cena. We decided to use Hefty (@Hefty) because of its affiliation with John Cena so the data collected in our first attempt would remain relevant. Hefty is a brand name of household products such as trash bags and trash cans, disposable tableware, children's disposable tableware, slider closure food storage and freezer bags, plastic storage bins, and disposable cookware. [3.7] John Cena is currently starring in a series of advertising campaigns for Hefty.

Using the same libraries and methods covered earlier with John Cena's Twitter account, we collected Friend and Follower data for Hefty. Here is a sample of Friends of Followers into tables as shown below:

Friends Id	Friends Name
27786584	Tracy Donatelli
369238299	Jaclyn Hill
197962366	Buffer

Followers Id	Followers Name
4282881733	Todd Shelite
756395383727779840	thefutureishere
157182825	Laura Linderman

We then computed the mutual friends within the two groups (i.e. the users who are in both friend list and follower list) and stored the IDs in a variable. This time, we could collect thousands of IDs of mutual friends for Hefty but we again encountered the "HTTP Error 429" when using the API to resolve the IDs to Screen Names. As a result, we were once again able to produce only a partial list of mutual friends due to the error associated with too many requests. Sample of mutual friends for Hefty which we could compile is shown below:

Friends Id	Friends Name
2492826637	Jessica Davis
65130553	Tableofferings ™
37079283	Jennifer Sikora
94558801	Dollar Tree

Problem 4: Business question

Question: How can Twitter data be used to guide the timing and implementation of Apple's marketing of the iPhone8 in order to convert the greatest number Neutral sentiments to Positive sentiments?

We find this question compelling because we believe there is valuable information associated with Tweets due to the array of metadata associated with each message. Tweets are a resource waiting to be exploited and the price of admission is having resolve and knowing just enough Python to be dangerous.

Determined to unlock this value, our team collected Tweets regarding the iPhone8 before and after Apple's official product launch (September 12, 2017) with multiple attributes that we believe may influence sentiment towards the iPhone8. We propose that a review of the sentiment, timing and attributes of these Tweets, and how they might relate to reach other, could reveal opportunities for Apple to change sentiment from Neutral to Positive.

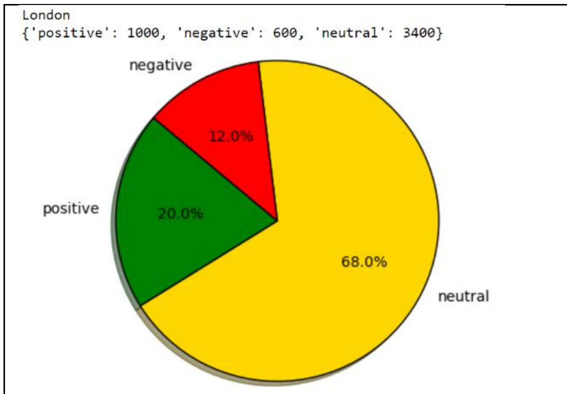
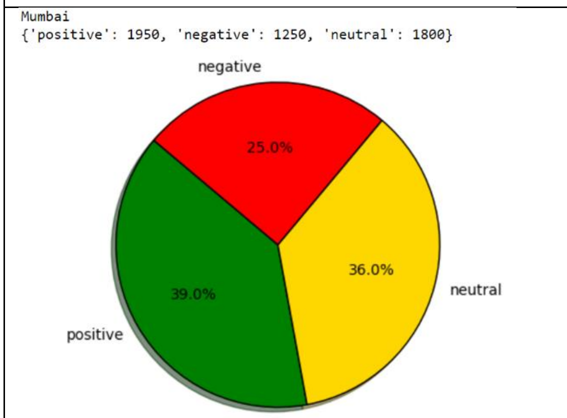
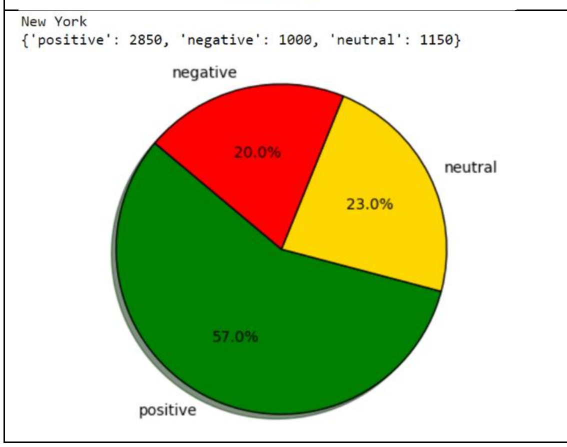
There are some key assumptions that frame our analysis and they are articulated here:

- We assume that people who expressed Negative sentiment towards the iPhone8 are entrenched in their views and will not change to a Neutral or Positive sentiment. They should not be targeted with advertising.
- We assume that people who expressed a Neutral sentiment toward the iPhone8 have a pliable sentiment and can be targeted with advertising to change their sentiment to Positive towards the iPhone8.
- We assume that that people who expressed a Positive sentiment towards the iPhone8 will generally remain positive. They do not need to be targeted with advertising in order to maintain their Positive sentiment towards the iPhone8.
- We assume that people who already express a Positive sentiment towards the iPhone8 are most likely to purchase the product when it is available.
- We assume each Tweet represents one actual person.
- Twitter data for London is representative of the United Kingdom.
- Twitter data for Mumbai is representative of the India.
- Twitter data for New York is representative of the United States of America.
- The percentages for each sentiment remain the same at larger scales. In other words, if the percentages for Negative, Neutral and Positive sentiment are 30%, 40% and 30% respectively for a sample size of 5000 Tweets, those same percentages would hold true for 500,000 Tweets or 50,000,000 Tweets.

So, the overall the strategy will be to target Apple's advertising to the greatest number of people who expressed a neutral sentiment so we can convert them to a positive sentiment thereby making them more likely to purchase the new iPhone8.

We first explored the attribute of geographic location of a Tweet and its potential influence on sentiment towards the iPhone8. Our team collected Tweets with a geographic attribute for Mumbai (India), London (United Kingdom), and New York (United States). The NLTK library was imported to perform natural language processing and compute an overall sentiment category of Negative or Neutral or Positive. The JSON library was also used to enhance readability of the data and provide a convenient mechanism for file write operations.

All Tweets for each geographic location were then processed using the MATPLOTLIB library and a pie chart indicating sentiment was created for each location. The charts are shown below for comparison:

TWEET SENTIMENT BY CITY	COUNTRY ASSOCIATED WITH EACH CITY
	UK Population = 65.64 million (2016) The UK presents a Neutral sentiment equivalent of approximately 44.64 million people *(0.68 X 65.64M = 44.64 Million)*
	India Population = 1.324 billion (2016) India presents a Neutral sentiment equivalent of approximately 476.64 million people *(0.36 X 1,324M = 476.64 Million)*
	United States Population = 323.1 million (2016) The United States presents a Neutral sentiment equivalent of approximately 74.31 million people *(0.23 X 323.1M = 74.31 Million)*

Some relationships between location and sentiment are readily apparent when we compare these charts. Some of these observations are:

- Tweets from New York had the largest percentage of Positive Tweets.
- Tweets from London had the smallest percentage of Negative tweets *and* the largest percentage of Neutral Tweets.
- Tweets from Mumbai had a somewhat balanced portion for each sentiment.

A case could be made for focusing advertising on the London market because it presents the largest percentage of Neutral Tweets (68%) when compared against Mumbai (36%) and New York (23%). It's also noteworthy that London exhibits the smallest percentage of Negative sentiment (12%) compared to Mumbai (25%) and New York (20%); not many Londoners dislike Apple.

It is tempting to arrive at a conclusion that London presents the best opportunity for deploying targeted advertising in order to convert sentiment from Neutral to Positive. However, when we consider how these percentages translate to individuals head counts we realize the best opportunity lies elsewhere. When the sentiment percentages are extrapolated to the UK's population, it provides an opportunity of only <u>45</u> million people for targeted advertising due to Neutral sentiment.

In absolute numbers of individuals, Mumbai represents the largest opportunity for targeted advertising. While only 36% of Mumbai Tweets were of Neutral sentiment, if extrapolated to India's population, that potentially represents <u>477</u> million people; that is more than the entire population of the United States and the United Kingdom combined.

If the intent of Apple's advertising effort is to convert Neutral sentiment to Positive sentiment, because we assume a person with Positive sentiment is most likely to purchase the iPhone8, then advertising efforts should focus on the Mumbai and greater Indian market first. Logically, it would then make sense to choose advertising methods that promote the iPhone8 to the largest number of people as efficiently as possible.

Television is a proven medium for reaching many people in an efficient manner [4.1] and additional research reveals that shows like Kaun Banega Crorepati and Chakravartin Ashoka Samrat are very popular in India [4.2]. Shows such as these enjoy high viewership and offer Apple an opportunity to target their advertising to maximize Neutral-to-Positive sentiment conversion which in turn would maximize the conversion from Positive sentiment to product purchase of the iPhone8.

Rounding out the analysis we consider the New York geographic market. While New York Tweets presented the largest percentage of Positive sentiment at 57%, there is still opportunity with the Neutral sentiment segment which accounted for 23% of all New York Tweets. If we extrapolate the percentage of Neutral Tweets against the US population we find that the Neutral sentiment representation is equivalent to approximately <u>75</u> million people.

So, if we consider the three geographic markets of:

- London – which we consider representative of the UK
- Mumbai – which we consider representative of the India
- New York – which we consider representative of the United States

And we consider how the percentages for each geographic markets sentiment translates to individuals, we see that each location presents a significantly different number of potential customers:

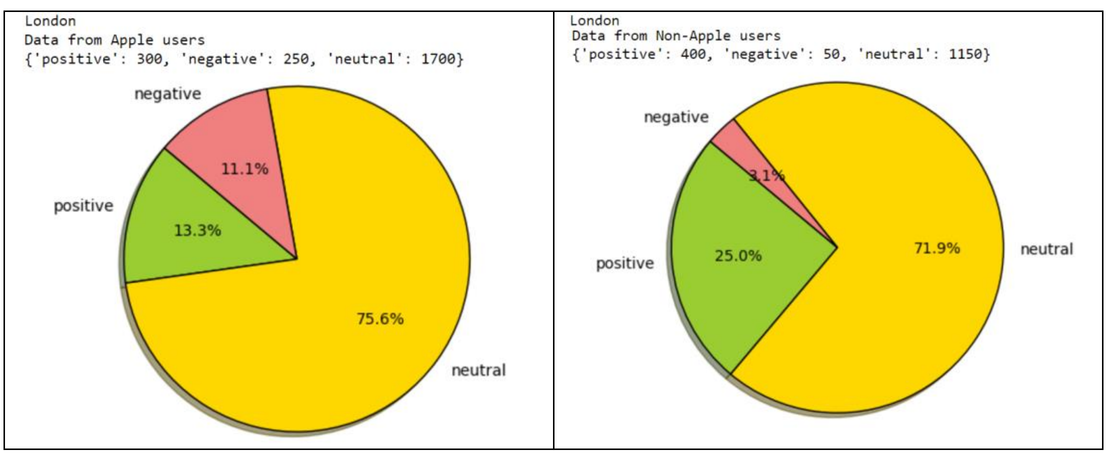
- Mumbai – 477 Million people of Neutral sentiment towards the iPhone8
- New York – 75 Million people of Neutral sentiment towards the iPhone8
- London – 45 Million people of Neutral sentiment towards the iPhone8

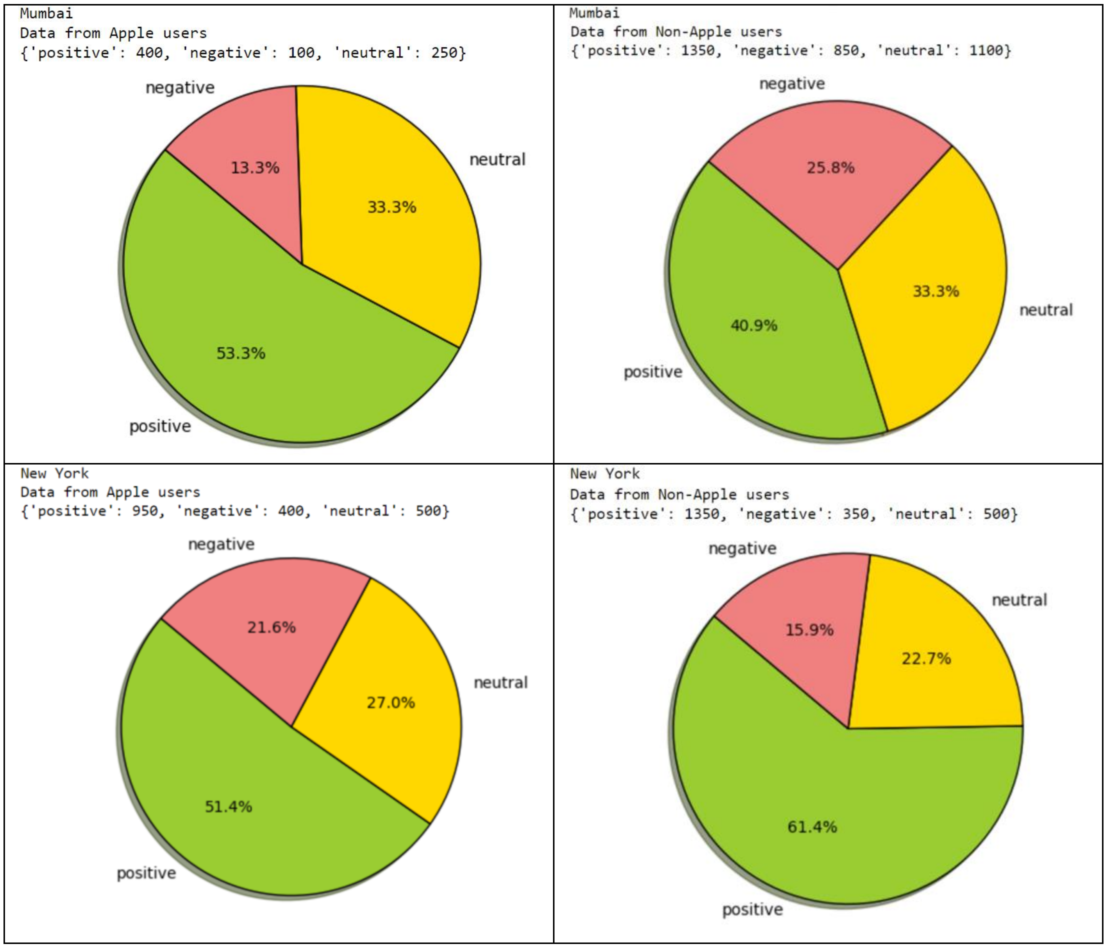
As stated earlier, Television is a proven medium for reaching many people in an efficient manner. The process outlined earlier for India can also be applied to London and New York. Popular television shows can be identified for each geographic market which will allow Apple to target their advertising and maximize Neutral-to-Positive sentiment conversions. If there are budget constraints for advertising then the potential population of Neutral sentiments within each market can be factored into the decision process.

Next, we explored the attributes of location and device type and their combined, potential influence on sentiment. Our team collected Tweets with geographic attributes for Mumbai (India), London (United Kingdom), and New York (United States) and each was classified by the type of device from which the Twitter originated; Apple or Non-Apple devices.

Once again, the NLTK library was imported to perform natural language processing and compute an overall sentiment category of Negative or Neutral or Positive. The JSON library was also used again for readability and file write operations.

All Tweets for each geographic location and device type were then processed using the MATPLOTLIB library and a pie chart indicating sentiment and device type was created for each location. The charts are shown below for comparison:





London Tweets with a Neutral sentiment were roughly the same percentage for Apple and Non-Apple devices. London Apple users were also nearly evenly split between Positive and Negative sentiment yet the Non-Apple users were nearly twice as likely to express a Positive sentiment. Regardless of device type, 74% the London market expressed a Neutral sentiment towards the iPhone8.

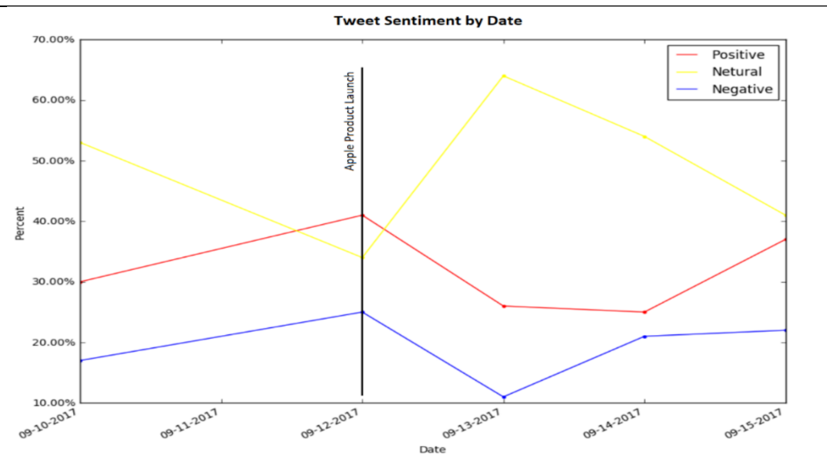
For Mumbai, the percentage of Neutral sentiment Tweets were roughly the same between Apple and Non-Apple devices. We also see that Non-Apple users in Mumbai were about thirteen percent less likely to express a Positive sentiment towards the iPhone8. Is this due to a regional preference for Non-apple devices or is there some other factor?

New York Tweets show the largest difference between Apple and Non-Apple devices for the Positive sentiment category. Interestingly, that difference was in favor of the Non-Apple device segment; 61.4% expressed a Positive sentiment towards the iPhone8 compared to 51.4% of Apple device users expressing a Positive sentiment. This market could also benefit from further investigation in order to determine why Non-Apple users would have a more Positive sentiment towards the iPhone8 compared to users who actually Tweeted from Apple devices.

Are New York Apple users harder to please? Or do they simply expect more from new Apple products? Are Non-Apple users expressing their desire to "jump ship" from their own devices by heaping praise upon the iPhone8? Advertising to the New York market warrants further investigation into these observations.

Finally, we consider the influence of time on sentiment; what were the attitudes towards the iPhone8 before and after the official product launch. Specifically, we tracked sentiment computed from Tweets collected at two instances before product launch and three instances after product launch (September 12, 2017). The Tweets were processed using the PANDAS and MATPLOTLIB libraries. By plotting the change in sentiment before and after product launch, we could see that there were indeed significant changes in sentiment relative to the product launch date.

The first chart plots the sentiment percentages by date for our three focus cities of London (UK), Mumbai (India) and New York (United States) combined.



Date	Positive	Neutral	Negative
9/10/2017	0.3	0.53	0.17
9/12/2017	0.41	0.34	0.25
9/13/2017	0.26	0.64	0.11
9/14/2017	0.25	0.54	0.21
9/15/2017	0.37	0.41	0.22

The chart indicates distinct changes in trajectory for all three sentiment categories after the product launch. We shall examine each sentiment and note the changes for each and posit theories and pose questions regarding the cause of sentiment change.

The Neutral sentiment was computed as 35% just prior to product launch. A day after product launch the Neutral sentiment was computed as 65%. Did the product launch reveal details on pricing or features that caused people to change sentiment? For example, did the launch confirm the presence of desirable features thereby shifting Negative sentiments into the Neutral sentiment category? Or did the opposite occur and the launch revealed details about price that made people question the value proposition of an iPhone8, causing their sentiment to slip from a Positive sentiment into the Neutral sentiment category?

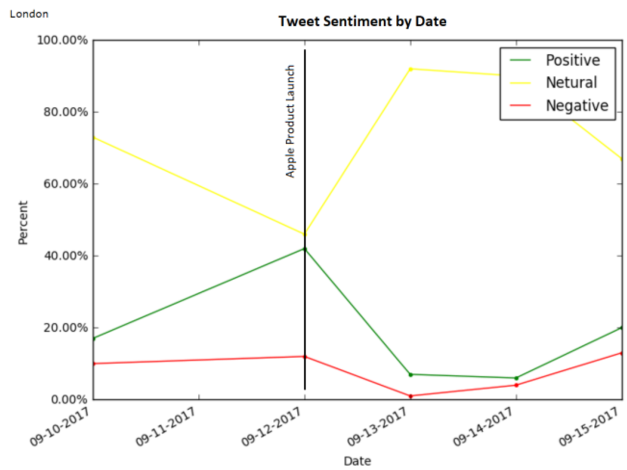
Overall, we can see there was a significant shift to the Neutral sentiment after product launch and as we stated earlier, people who expressed a Neutral sentiment are the intended targets for Apple advertising. So, it stands to reason that the deployment of advertising targeted at the Neutral sentiment population should occur after product launch since that segment reach peaked growth one day after product launch. Again, the goal is to convert Neutral sentiment users to Positive sentiment users thereby making them more likely to purchase the new iPhone8.

The Positive sentiment category experienced a drop from 41% to 26% immediately after the product launch. Why were fewer Twitter users expressing a Positive sentiment about the iPhone8 after the product launch? Was there disappointment over price or features which changed their sentiment? Or were expectations too high among potential consumers? Perhaps there was a sense of deflation after the product launch over what were perceived as evolutionary changes, and not revolutionary changes, to the iPhone8?

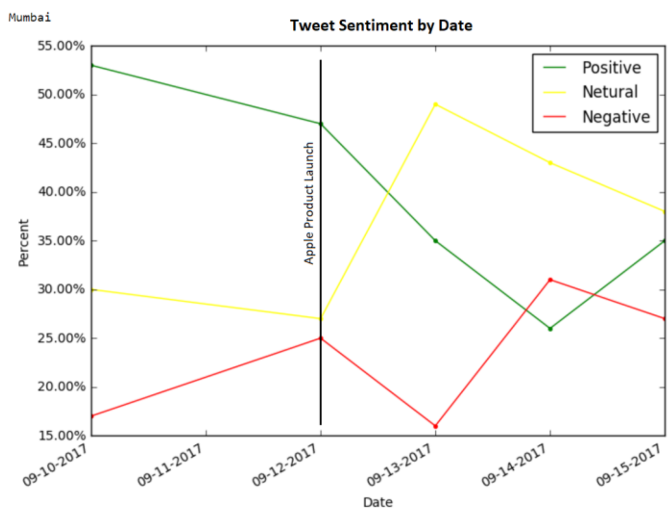
The Negative sentiment category also experienced a drop after product launch. Negative sentiment was computed as 25% prior to product launch and dropped to 11% just one day after product launch. Perhaps the same set of theories and questions for changes in Positive sentiment apply here but in an inverse manner. Why were fewer Twitter users expressing a Negative sentiment about the iPhone8 after the product launch? Was there collective relief over price or features which changed their sentiment? Or were expectations too low among potential consumers? Perhaps there was a sense of excitement after the product launch and the iPhone8 was perceived as a revolutionary product?

We also explored the potential effect of geographic location and time on sentiment; what were the attitudes towards the iPhone8 before and after the official product launch within each city. Consider the following Tweet data collected as JSON files, converted to a CSV file, then plotted using the MATPLOTLIB library:

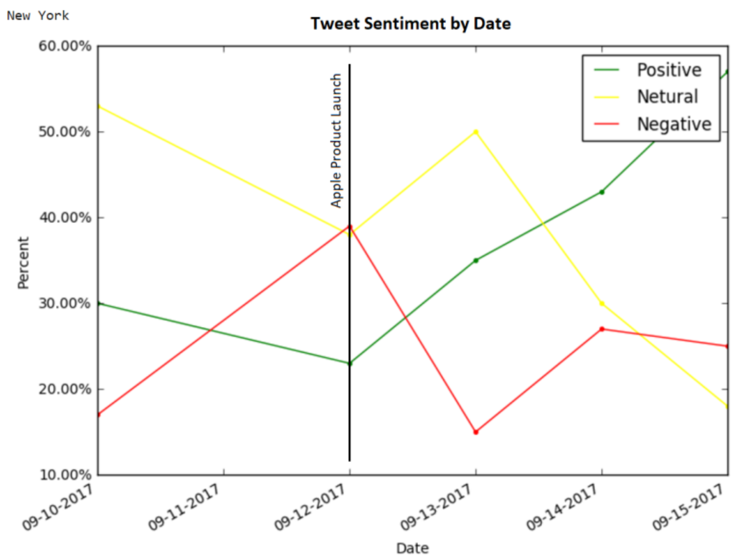
Date	Mumbai Positive	Mumbai Neutral	Mumbai Negative	London Positive	London Neutral	London Negative	New York Positive	New York Neutral	New York Negative
9/10/2017	0.53	0.3	0.17	0.17	0.73	0.1	0.3	0.53	0.17
9/12/2017	0.47	0.27	0.25	0.42	0.46	0.12	0.23	0.38	0.39
9/13/2017	0.35	0.49	0.16	0.07	0.92	0.01	0.35	0.5	0.15
9/14/2017	0.26	0.43	0.31	0.06	0.9	0.04	0.43	0.3	0.27
9/15/2017	0.35	0.38	0.27	0.2	0.67	0.13	0.57	0.18	0.25



Sentiment over time for London was very similar to the sentiment over time for all the three cities combined. Positive and Negative sentiment declined after product launch but experienced recovery towards pre-launch levels by the third day after product launch. Neutral sentiment grew from 46% to 92% one day after product launch.



Sentiment over time for Mumbai was unique. Positive sentiment was already on a slight decline as the product launch date approached. After product launch, Positive sentiment declined steeply to a low of 26% but then recovered to 35% by the third day after launch. Negative sentiment fluctuated after product launch before landing at 27% three days after product launch. Neutral sentiment grew from 27% to 49% one day after product launch.



Sentiment over time for New York was also unique. Positive sentiment was on a slight decline before the product launch but increased in a nearly linear fashion after product launch. New Yorkers were clearly receptive to the iPhone8 after launch. Negative sentiment fluctuated after product launch and settled to a lower 25% compared to 39% just before launch. Neutral sentiment experienced an increase one day after product launch, rising from 38% to 50%.

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