Amazon Case Study

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Amazon Case Study- Company Overview

- Amazon is a Global E-Commerce Giant. It is an Internet-based company that sells electronic goods, apparel, movie books and every good that can be sold online on its Platform Amazon.com. Amazon was founded by Jeff Bezos in 1994.
- Mobile phones have revolutionized the way we purchase products online, making all the information available at our fingertips. As
 the access to information becomes easier, more and more consumers will seek product information from other consumers apart
 from the information provided by the seller. Reviews and ratings submitted by consumers are examples of such of type of
 information and they have already become an integral part of customer's buying-decision process. The review and ratings
 platform provided by eCommerce players creates transparent system for consumers to take informed decision and feel confident
 about it.
- Amazon.com is a treasure trove of product reviews and their review system is accessible across all channels presenting reviews
 in an easy-to-use format. The product reviewer submits a rating on a scale of 1 to 5 and provides own viewpoint according to the
 whole experience. The mean value is calculated from all the ratings to arrive at the final product rating. Others can also mark yes
 or no to a review depending on its helpfulness adding credibility to the review and reviewer. In this study, we analysed more than
 400 thousand reviews of unlocked mobile phones sold on Amazon.com to find insights with respect to reviews, ratings, price and
 their relationships.

DATA

- We extracted the following information from the 'unlocked phone' category of Amzon.com:
- Product Title
- Brand
- Price
- Rating
- Review text
- · Number of people who found the review helpful

OUR GOAL

This statistical analysis had the following goals:

- · Perform exploratory analysis of ratings and reviews
- · Find out relationship between price and the number of reviews
- · Find out relationship between helpfulness of review and length of review
- · Find out relationship between review length and product price
- Find out relationship between review length and product rating
- · Find out relationship between product price and product rating
- Word cloud of most-used words
- Sentiment analysis

Loading the library

- library(tidyverse) <- The tidyverse is an opinionated collection of R packages designed for data science
- library(ggplot2) <- ggplot2 is a system for declaratively creating graphics, based on The Grammar of Graphics.
- library(ggthemes) <- Some extra themes, geoms, and scales for 'ggplot2'.
- library(tidytext) <- Using tidy data principles can make many text mining tasks easier, more effective, and consistent with tools already in wide use.
- library(plotly) <- Plotly's Python graphing library makes interactive, publication-quality graphs.
- library(readr) <- The goal of readr is to provide a fast and friendly way to read rectangular data (like csv, tsv, and fwf).
- library(extrafont) <- The extrafont package makes it easier to use fonts other than the basic PostScript fonts that R uses.
- library(stopwords) <- Provides multiple sources of stopwords, for use in text analysis and natural language processing.

```
library(tidyverse)
library(ggplot2)
library(ggthemes)
library(tidytext)
library(plotly)
library(readr)
library(extrafont)
library(stopwords)
```

Loading the datasets

```
items <- read_csv("C:\\Users\\Lenovo\\Downloads\\items.csv")
reviews <- read_csv("C:\\Users\\Lenovo\\Downloads\\20191226-reviews.csv\\reviews.csv")</pre>
```

Data

Exploring the datasets

To find missing values * If the value is NA the is.na() function return the value of true, otherwise, return to a value of false.

```
sapply(items, function(x) sum(is.na(x)))
##
            asin
                          brand
                                        title
                                                         url
                                                                      image
##
                              4
                                                                          0
          rating
                      reviewUrl totalReviews
##
                                                       price originalPrice
                              0
                                                           0
##
sapply(reviews, function(x) sum(is.na(x)))
                                                             verified
##
           asin
                                    rating
                                                    date
                                                                              title
                         name
##
                            1
                                         0
                                                       0
                                                                    0
                                                                                  2
           body helpfulVotes
##
##
             13
                        40771
```

• Dropping only NA's in items because 4 have not brand names

```
items <- na.omit(items)
max(items$rating)</pre>
```

```
## [1] 5
```

· Renaming the columns

```
names(reviews)[names(reviews)== "rating"] <- "reviewer_rating"
names(reviews)[names(reviews)=="title"] <- "review_title"
names(items)[names(items)=="rating"] <- "product_rating"
names(items)[names(items)=="title"] <- "product"</pre>
```

Merging dataset

```
amazon$verified <- as.factor(amazon$verified)</pre>
```

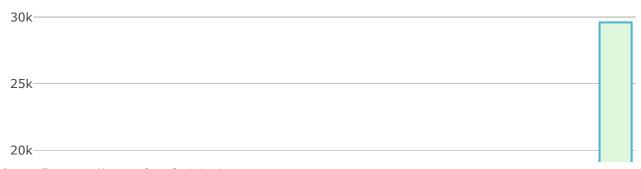
• Data Column into Daymonth and year (2 Columns) years between 2005-2018

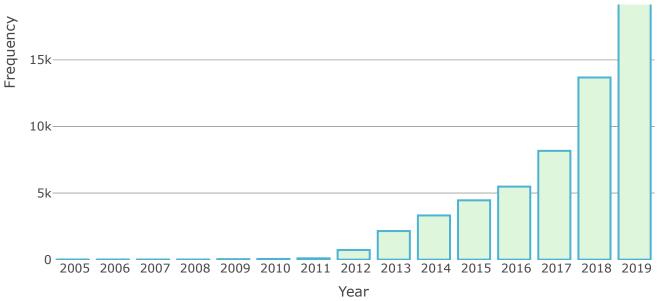
Descriptive Analysis

Q.1 Distiribution of Reviews by year

```
fig <- plot_ly(amazon, x=~year, type = "histogram",
    marker = list(color = "#def6dc",line = list(color = "#4eb2d2",width = 2))) %>%
    layout(title = "Distiribution of Reviews by year",
    yaxis = list(title = "Frequency",zeroline = FALSE),
    xaxis = list(title = "Year",zeroline = FALSE))
fig
```

Distiribution of Reviews by year





Q.2 Distribution of Price

```
amazonp <- amazon %>% filter(price != 0.00)

two <- ggplot(amazonp, aes(x = price)) +
        geom_density(alpha = 0.9,color="#4eb2d2", fill="#def6dc") +
        labs(x = "Price" , y = "Density") +
        theme_minimal() +
        theme(plot.title = element_text(hjust = 0.5 , color = "#37475A"),
        axis.title.x = element_text(color = "#37475A", size = 12,face = "bold",family="Arial"),
        axis.title.y = element_text(color = "#37475A", size = 12,face = "bold",family="Arial"),
        axis.text = element_text(size = 11 , color = "#37475A")) +
        ggtitle("Distribution of Price")

fig <- ggplotly(two)

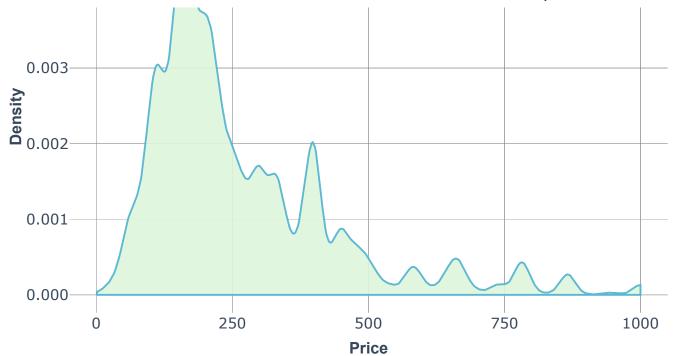
fig</pre>
```

Distribution of Price









Q.3 Grouping Price

```
amazonp <- amazonp %>%
    mutate(price_group = if_else(between(price, 0, 250), "Low price",
    if_else(between(price, 250, 450), "Medium price",
    if_else(price > 450, "High price","Unknown price"))),
    price_group = if_else(is.na(price_group), "Unknown price", price_group)) %>%
    rownames_to_column(var = "id")
```

Amazon Case Study



Play

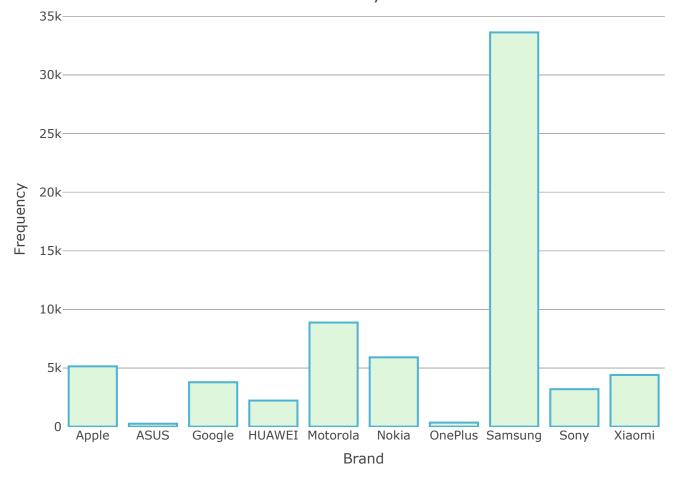
High price

Low price

Medium price

Q.4 Distribution of total reviews by brand

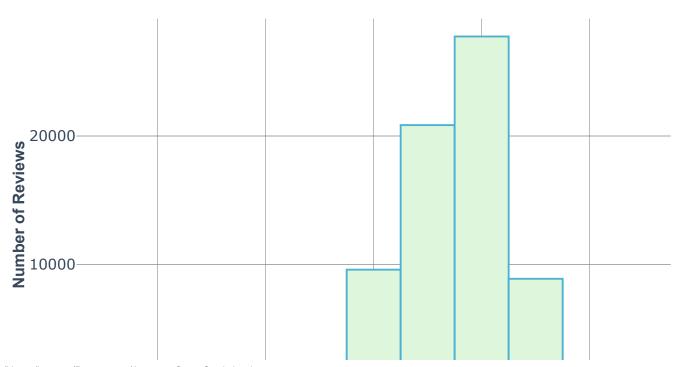




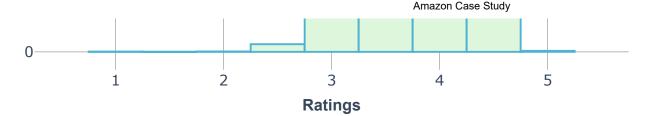
Exploratory Analysis based on Rating Distribution

- Q.5 Ratings vs. Number of reviews.
 - let's look at the distribution of ratings among the reviews. Most of the reviewers have given 4-star and 3-star rating with relatively very few giving 1-star rating.

Distribution of Product Ratings







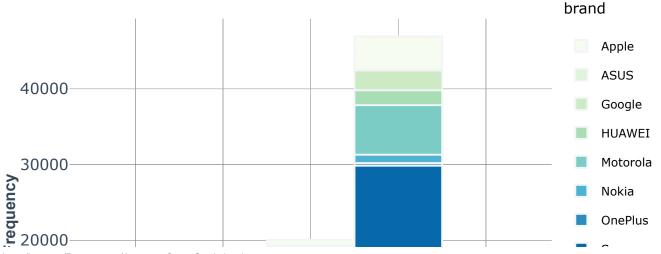
Conclusion

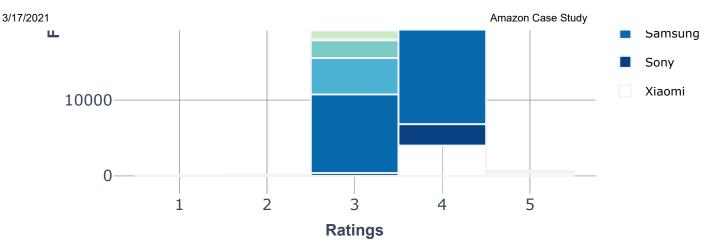
The mean value of all the ratings comes to 3.62.

Q.6 Ratings fill by brand

```
six <- ggplot(amazon, aes(x = product_rating,fill = `brand` )) +
    geom_histogram (binwidth = 1, col = "#f2f4f7" , stat="bin") +
    labs(x = "Ratings", y = "Frequency",title = "Distribution of the Product Ratings amongst Brands") +
    scale_x_continuous(breaks = c(1,2, 3,4, 5)) +
    scale_fill_brewer(palette="GnBu") +
        theme_minimal() +
        theme(plot.title = element_text(hjust = 0.5 , color = "#37475A"),
        axis.title.x = element_text(color = "#37475A", size = 12,face = "bold",family="Arial"),
        axis.title.y = element_text(color = "#37475A", size = 12,face = "bold",family="Arial"),
        axis.text = element_text(size = 11.5 , color = "#37475A"))</pre>
```



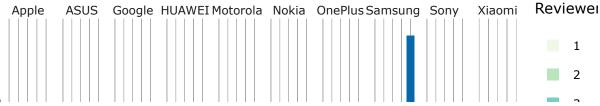




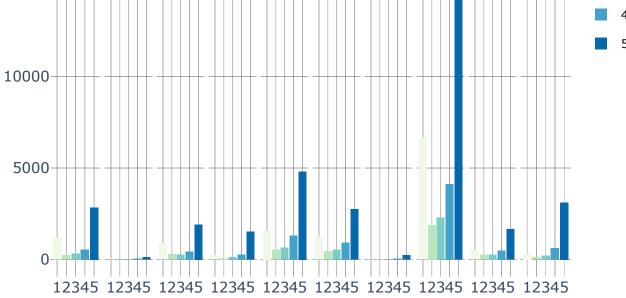
"IF YOU WANT TO CONTROL YOUR BRAND PRESENCE ONLINE YOU HAVE TO CONTROL WHAT IT LOOKS LIKE ON AMAZON."

Q.7 Reviewer Ratings by Brand

Reviewer Ratings by Brand



TOUU



Conclusion

- When consumers pay more for a product, they also expect better quality and sellers need to meet this expectation.
- It can be considered that with cost the product quality increases, which in turn leads to higher rating.

```
price <- amazonp %>%
    mutate(rating_group = if_else(between(product_rating, 0, 1), "1",
    if_else(between(product_rating, 1, 2), "2",
    if_else(between(product_rating, 2, 3), "3",
    if_else(between(product_rating, 3, 4), "4",
    if_else(product_rating > 5, "5","5"))))),
    rating_group = if_else(is.na(rating_group), "", rating_group)) %>%
    rownames_to_column(var = "idd")
```

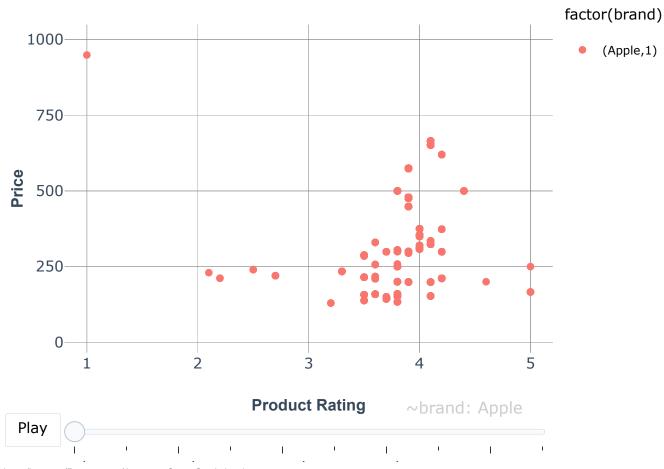
```
price <- na.omit(price)</pre>
```

Q.8 Price and Brand**

• Let's now try to explore correlation between product price and number of reviews.

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This will help us answer questions like: Do expensive products receive more number of reviews?



Apple Google Motorola OnePlus Sony

Conclusion

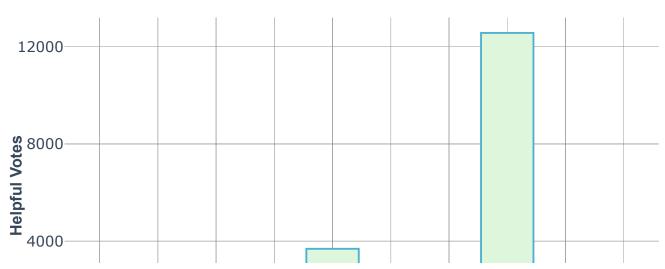
- The scatter above says not necessarily.
- So there is no relationship between price and the number of reviews it gets.

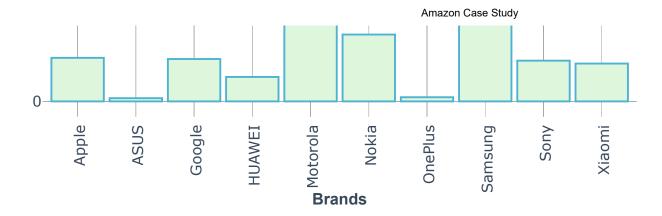
Q.9 Helpful Votes by Brand

```
a <- amazon %>% select(brand, helpfulVotes) %>% na.omit()
```

```
elev <- ggplot(a, aes(factor(brand))) +
    geom_bar(position = "dodge", color="#4eb2d2", fill="#def6dc") +
    ylab("Helpful Votes")+ xlab("Brands") + labs(title = "Helpful Votes by Brand")+
    theme_minimal() +
    theme(plot.title = element_text(hjust = 0.5 , color = "#37475A"),
    axis.title.x = element_text(color = "#37475A", size = 12, face = "bold", family="Arial"),
    axis.title.y = element_text(color = "#37475A", size = 12, face = "bold", family="Arial"),
    axis.text.y = element_text(size = 11 , color = "#37475A"),
    axis.text.x = element_text(size = 11 , color = "#37475A", angle = 90))</pre>
fig <- ggplotly(elev)
fig
```

Helpful Votes by Brand



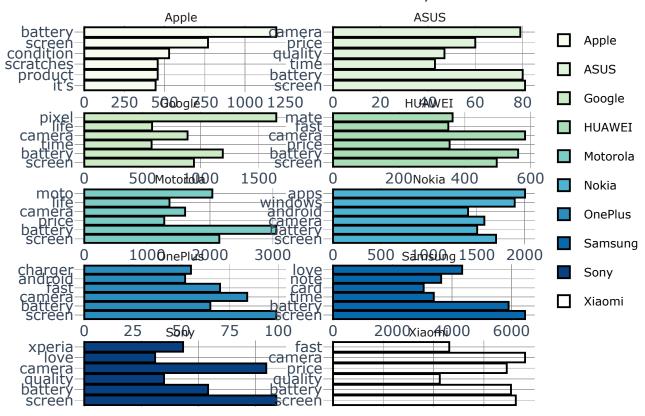


```
amazon_clean2 <- amazon_clean %>% anti_join(stop_words)
```

```
## Joining, by = "word"
```

Q.10 Most common words by brand

Most Common Words in Reviews by Brand



```
amazon_clean_rank2 <- amazon_clean_rank %>% anti_join(stop_words)
```

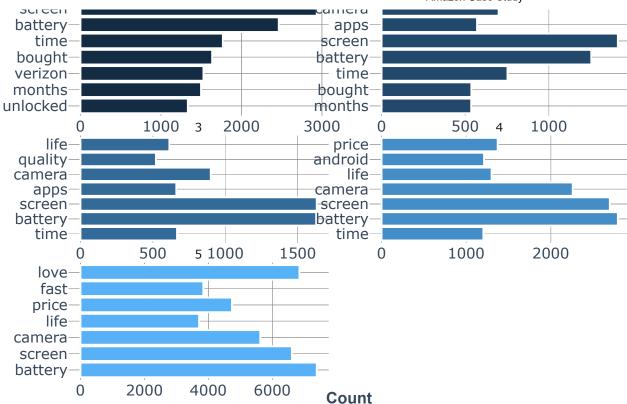
```
## Joining, by = "word"
```

Q.11 Most common words all reviews

- We segregated the reviews according to their ratings positive reviews (4 or 5 star) and negative reviews (1 or 2 star).
- In both type of reviews there are certain common words like "work", "battery" and "screen". The most frequently used words in positive reviews are: "great", "good", "camera", "price", "excellent", etc. In case of negative reviews words such as "return", "back", "problem", "charge" are prevalent.

Most Common Words in Reviews by Rating

1 2



CONCLUSION

- Amazon's product review platform shows that most of the reviewers have given 4-star and 3-star ratings to unlocked mobile phones.
- We also uncovered that lengthier reviews tend to be more helpful and there is a positive correlation between price & rating. Sentiment analysis shows that positive sentiment is prevalent among the reviews and in terms of emotions, 'trust', 'anticipation' and 'joy' have highest scores.
- It'd be interesting to perform further analysis based on the brand (example: Samsung vs. Apple).
- We can also look at building a model to predict the helpfulness of the review and the rating based on the review text.
- Corpus-based and knowledge-based methods can be used to determine the semantic similarity of review text.
- There are many insights to be unveiled from the Amazon reviews.

Samsung Vs. Apple

```
samsung <- amazon %>% filter(brand == "Samsung")

samsung2 <- amazon %>% filter(year >= 2017)

samsung_apple <- amazon %>% filter(brand == "Samsung" | brand== "Apple")

samsung_apple %>% filter(year >= 2017)
```

```
[1] asin
                                       reviewer rating daynmonth
                       name
## [5] year
                       verified
                                       review_title
                                                       body
                                       product
                                                       url
## [9] helpfulVotes
                       brand
## [13] image
                       product_rating reviewUrl
                                                       totalReviews
## [17] price
                       originalPrice
## <0 rows> (or 0-length row.names)
```

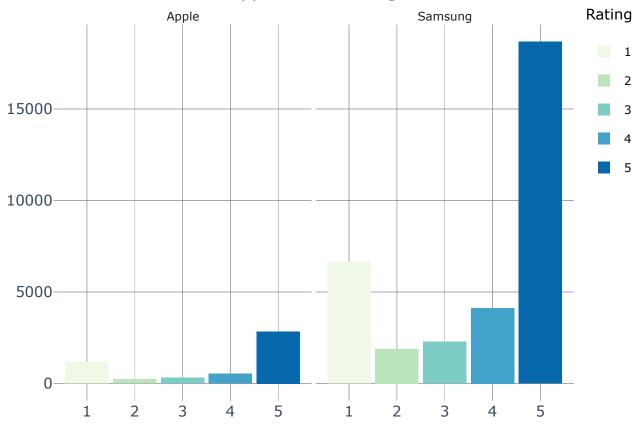
```
samsung_apple %>% select(brand) %>% distinct()
```

```
## brand
## 1 Samsung
## 2 Apple
```

```
samsung_apple<- samsung_apple %>%
mutate(price_group = if_else(between(price, 0, 250), "Low price",
if_else(between(price, 250, 450), "Medium price",
if_else(price > 450, "High price","Unknown price"))),
price_group = if_else(is.na(price_group), "Unknown price", price_group)) %>%
rownames_to_column(var = "id")
```

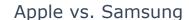
Product Rating

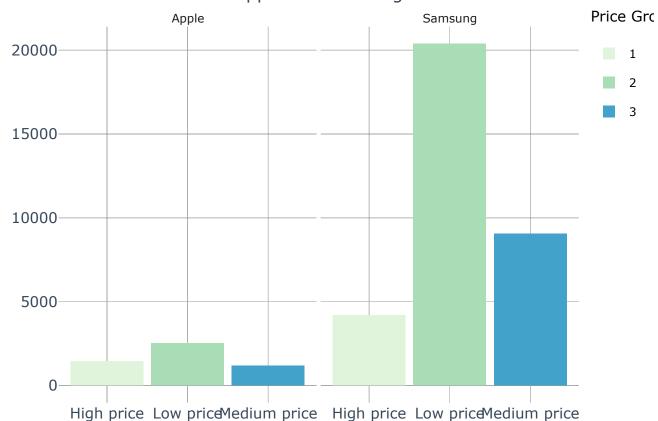




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Distribution of Price Groups





```
samsung_apple_clear<- samsung_apple %>%
  select(brand,body) %>%
  unnest_tokens(input=body,output=word) %>%
  count(brand,word,sort=T) %>%
  filter(nchar(word)>3) %>%
  filter(!word %in% stopwords_phone) %>%
  group_by(brand)
```

```
samsung_apple_clear2 <- samsung_apple_clear %>%
anti_join(stop_words)
```

```
## Joining, by = "word"
```

Most Common Words in Reviews by Brand

Most Common Words in Reviews by Brand

