Google Play Apps - Exploratory Analysis

June 22, 2019

1 Google Play Store Apps: An Exploratory Analysis

1.1 Introduction

The applications -or *apps*- offered in the Google Play store are in the millions and growing. As of the writing of this project, the Google Play store is estimated to hold 2.6 million applications. The creator of this dataset, Lavanya Gupta, was able to obtain data on 10,000 of these apps.

She obtained the dataset through scraping the store, which uses dynamic page loading. Dynamic page loading means that the store page displays the apps based on what Google knows about the user requesting the page, commonly known as *user behavior*. Scraping means that she wrote a script that runs through the dynamically-loaded page, reads the data, and outputs it into a structured file, such as the csv file I that will be working on for this project.

The data files include another file containing a sentiment analysis conducted on this sample of Google Play apps using the nltk Python library, which stands for Natural Language Toolkit. The objective of this analysis is to try to understand user reviews and what they convey about opinions of users of these apps.

1.1.1 Dataset Content

A. Main Dataset (googleplaystore.csv) This file contains data on the Google Play applications. It has 10,841 rows of data with the following columns:

- App Category: Category of the app. This could be beauty, business, entertainment, education...etc.
- Rating: How users rate the app out of 5, with 1 being the lowest rating and 5 being the highest.
- Reviews: The number of user reviews each app has received.
- Size: The memory size needed to install the application.
- Installs: The number of times each application has been installed by users.
- Type: Whether the app is free or a paid app.
- Price: The price of the app.
- Content Rating: This column specifies the intended audience for the app. Can be for teens, mature audience, or everyone.

- Genres: The sub-category for each app. Example: for the Education category, this could be Education: Pretend Play, for example.
- Last Updated: Release date of the most recent update for the app.
- Current Ver: The app's current version.
- Android Ver: The oldest version of Android OS supported by the app.

B. Sentiment Analysis (googleplaystore_user_reviews.csv) This file contains the result of the sentiment analysis conducted by the dataset creator. It has 64,295 rows of data with the following columns:

- App : Name of the app.
- Translated_Review: Either the original review in English, or a translated version if the orignal review is in another language.
- Sentiment: The result of the sentiment analysis conducted on a review. The value is either Positive, Neutral, or Negative.
- Sentiment_Polarity: A value indicating the positivity or negativity of the sentiment, values range from -1 (most negative) to 1 (most positive).
- Sentiment_Subjectivity: A value from 0 to 1 indicating the subjectivity of the review. Lower values indicate the review is based on factual information, and higher values indicate the review is based on personal or public opinions or judgements.

1.1.2 Analytic Questions:

Given what we have in the two datasets above, we should be able to answer the following questions:

1. **Which apps are most reviewed? Of these, which three have the highest rating?**
2. **How do these apps vary by rating, pricing, and the ratio of reviews-to-installs?**
3. **Do people review paid apps in the same way they review free apps?**

1.1.3 Limitations

The limitations of the Google Play Store Apps data are:

- The apps included are relevant to the dataset creator's activity on Google-related sites. She is a Machine Learning Software Developer based in India. It is most likely the applications generated are based on their popularity in the geographical region around India, while this analysis is intended for audience in the U.S or North America.
- With cloud-based storage available for Android users at little or no cost, app size may have no significant contribution to app popularity. Therefore the `Size` column will be removed.
- I am not sure if apps follow the same software versioning process, therefore I will assume the `Current Ver` column will be irrelevant to this analysis. Otherwise it would have been useful for measuring current support of the app by its developers.

- I will assume that the vast majority of users can upgrade their Android devices to the latest version. Based on that, the `Android Ver` column will also be excluded. Any limitations that may justify relying on older versions of Android most probably do not apply to the majority of the population.
- Scraping data off of a Google website is an unconventional way to obtain it, which may result in misplaced data. This largely depends on the scraper built by the dataset creator.
- The sentiment analysis result is limited by the abilities of Python's nltk library, which does not support all languages. Reviews with unsupported languages will not be translated,should have no values within the analysis, and therefore will be removed.

I will start by importing the csv files into two Pandas dataframes, one called `app_data` which contains the main data on the applications, and another called `sentiment_data` containing the sentiment analysis results on app reviews.

```
In [1]: import matplotlib.pyplot as plt
        import numpy as np
        import pandas as pd
        from scipy.stats import ttest_ind
        import warnings
        %matplotlib inline
        warnings.filterwarnings("ignore")
```

```
In [2]: # Import the googleplaystore.csv into a Pandas dataframe
        app_data = pd.read_csv(r"C:\Users\Mohammad's Pc\Documents\Thinkful\7.11 Capstone 1 Ana

        # Show the first 3 rows of the dataframe
        app_data.head(3)
```

```
Out[2]:                                                  App        Category  Rating  \
        0     Photo Editor & Candy Camera & Grid & ScrapBook  ART_AND_DESIGN     4.1
        1                                Coloring book moana  ART_AND_DESIGN     3.9
        2  U Launcher Lite   FREE Live Cool Themes, Hide ...  ART_AND_DESIGN     4.7

          Reviews  Size    Installs  Type Price Content Rating  \
        0     159   19M     10,000+  Free     0       Everyone
        1     967   14M    500,000+  Free     0       Everyone
        2   87510  8.7M  5,000,000+  Free     0       Everyone

                              Genres      Last Updated Current Ver   Android Ver
        0               Art & Design   January 7, 2018       1.0.0  4.0.3 and up
        1  Art & Design;Pretend Play  January 15, 2018       2.0.0  4.0.3 and up
        2               Art & Design    August 1, 2018       1.2.4  4.0.3 and up
```

With over 10,000 rows of data being obtained through a scraper, and rating and reviews being non-mandatory for users, we can expect some missing data in our columns. Let's construct a clear picture of what how many missing values we have in each column:

```
In [3]: # Header
        print ("Missing Values"+"\n"+"-"*15)

        # Print sum of null values per column
        app_data.isnull().sum()
```

```
Missing Values
---------------
```

```
Out[3]: App                  0
        Category             0
        Rating            1474
        Reviews              0
        Size                 0
        Installs             0
        Type                 1
        Price                0
        Content Rating       1
        Genres               0
        Last Updated         0
        Current Ver          8
        Android Ver          3
        dtype: int64
```

Except for the Rating column values, I would say we have a good dataset. Since answering our first question relies on having user-generated ratings rather than a mean we can calculate to substitute for missing values, these rows will be removed from the dataset.

Now, the rows are in their original sorting order. While the most popular apps are would still be most popular according to India and Lavanya's user behavior, they are still recognizable by North American audience due to their global offering, let's take a look at the most installed apps within this dataset:

```
In [4]: # Sort the original dataset by number of installs to see most popular apps first
        app_data = app_data.sort_values(by="Installs", ascending=False)
        app_data.head(4)
```

```
Out[4]:                                                    App           Category  \
        10472      Life Made WI-Fi Touchscreen Photo Frame                1.9
        420     UC Browser - Fast Download Private & Secure      COMMUNICATION
        474                        LINE: Free Calls & Messages      COMMUNICATION
        3767                      Flipboard: News For Our Time  NEWS_AND_MAGAZINES

               Rating   Reviews                Size       Installs  Type     Price  \
        10472    19.0      3.0M              1,000+           Free     0  Everyone
        420       4.5  17714850                 40M   500,000,000+  Free         0
        474       4.2  10790289  Varies with device   500,000,000+  Free         0
        3767      4.4   1284017  Varies with device   500,000,000+  Free         0
```

```
      Content Rating             Genres    Last Updated         Current Ver  \
10472            NaN  February 11, 2018          1.0.19          4.0 and up
420             Teen      Communication  August 2, 2018         12.8.5.1121
474         Everyone      Communication   July 26, 2018  Varies with device
3767    Everyone 10+   News & Magazines  August 3, 2018  Varies with device

             Android Ver
10472                NaN
420           4.0 and up
474     Varies with device
3767    Varies with device
```

`Life Made WI-Fi Touchscreen Photo Frame` is listed in the top, but is not a result of a huge amount of installs. This is probably due to an error in data entry that is attributed to the scraper used to get this dataset. However it is good that only one erroneous row exists beyond the true most-installed app rows. Since erroneous rows are likely to exist outside the range of *[0, maximum value]*, it is a must to check if such rows exist beyond rows with 0 installs as well:

In [5]:
```
# Re-sort the data in ascending order to show least installed apps first
app_data = app_data.sort_values(by="Installs")
app_data.head()
```

Out[5]:
```
                            App         Category  Rating Reviews  \
9148  Command & Conquer: Rivals           FAMILY     NaN       0
9337   EG | Explore Folegandros  TRAVEL_AND_LOCAL     NaN       0
9719               EP Cook Book          MEDICAL     NaN       0
6692              cronometra-br     PRODUCTIVITY     NaN       0
8081                 CX Network         BUSINESS     NaN       0

                    Size Installs  Type    Price Content Rating  \
9148  Varies with device        0   NaN        0   Everyone 10+
9337                 56M       0+  Paid    $3.99       Everyone
9719                3.2M       0+  Paid  $200.00       Everyone
6692                5.4M       0+  Paid  $154.99       Everyone
8081                 10M       0+  Free        0       Everyone

              Genres       Last Updated         Current Ver  \
9148        Strategy      June 28, 2018  Varies with device
9337  Travel & Local   January 22, 2017               1.1.1
9719         Medical      July 26, 2015                 1.0
6692    Productivity  November 24, 2017               1.0.0
8081        Business     August 6, 2018               1.3.1

             Android Ver
9148  Varies with device
9337          4.1 and up
9719          3.0 and up
6692          4.1 and up
8081          4.1 and up
```

This is good news, no erroneous rows exist below 0 for the `Installs` column. Therefore all we have to do is delete that one erroneous row. So far now we will delete from:

Rows: 1. That erroneous row, with an index number of `10472` 2. All rows with missing - or`NaN`- values in the `Rating` column.

Columns: 1. `Size` 2. `Current Ver` 3. `Andoird Ver`

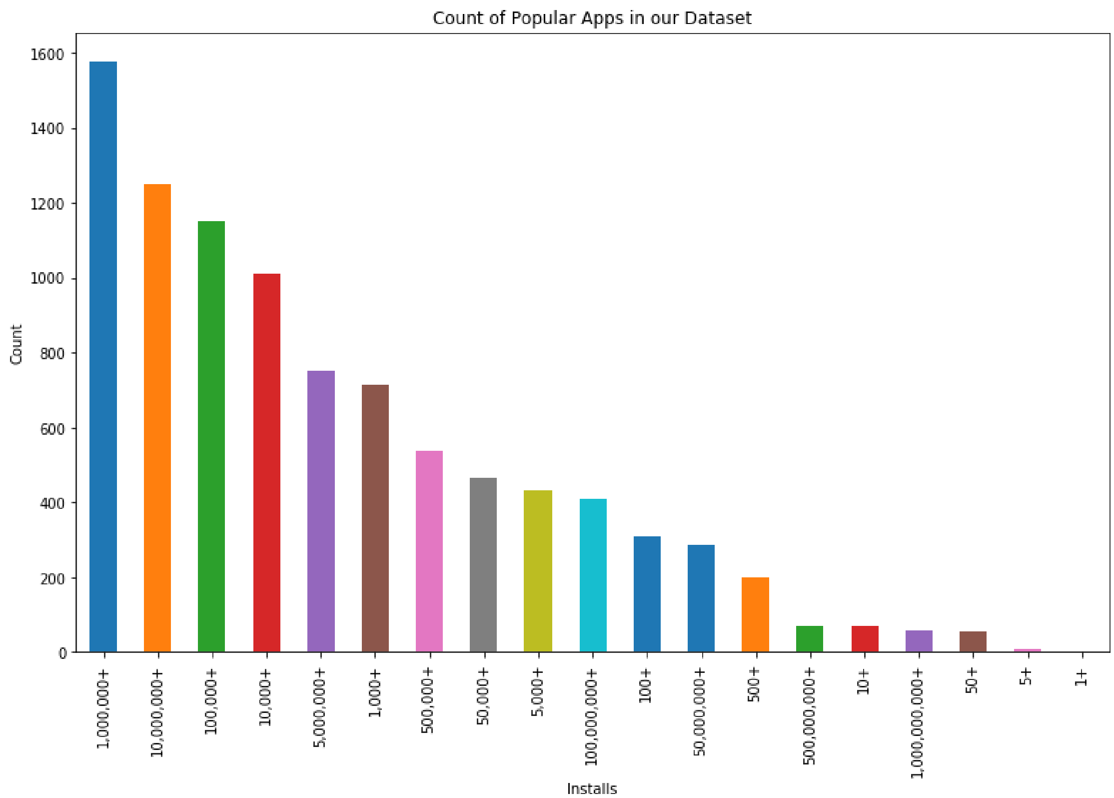
```
In [6]: # Get indexes of rows with NaN values for Rating column
        nan_rows = list(app_data[app_data["Rating"].isna()].index)

        # Add the index of the erroneous row
        nan_rows.append(10472)

        # Remove all rows with missing values
        app_data = app_data.drop(nan_rows, axis=0)

        # Remove unusable columns
        app_data = app_data.drop(columns=["Size", "Current Ver","Android Ver"])

        # Re-sort the data in descending order
        app_data = app_data.sort_values(by="Installs", ascending=False)
```

Having done initial cleaning of data, now we proceed to answer the first question in this document:

1.2 1. Which apps are most reviewed? Of these, which three have the highest rating?

To proceed in answering the first part of our first question *What apps are most reviewed?*, it is logical to assume the most installed apps have the most reviews. As mentioned above, the number of installs for each application is not an actual number, but a group or level of installs this app has reached (example: 50 million and up). Therefore we will call them **bins** throughout this document. Let's plot these bins of `Installs` that we have in our dataset:

```
In [7]: # Generate a series containing count of apps with each bin of number of installs

        # Plot each bin of installs with its frequency/occurrence/count in the dataset
        plt.figure(figsize=(13,8))
        app_data["Installs"].value_counts().plot(kind='bar')
        plt.title("Count of Popular Apps in our Dataset")
        plt.ylabel("Count")
        plt.xlabel("Installs")
        plt.show()
```



Many apps in our dataset have been installed over a million times, and over 10 million times resepectively. It only makes sense to compare apps that are in the same bin to each other in terms of reviews and ratings. However, this leaves us with about 20 bins, with many of these apps not being necessarily that popular. To get a better focus on popular apps, I will choose the top 10 bins for this analysis. Which bins are in the top 10?

In [8]:
```
# Get Unique values of all bins in the Installs column
top_10 = np.unique(app_data["Installs"])

# Sort the values by length and return the longest 10 values
top_10 = (sorted(top_10,key=len,reverse=True))[:10]

print(top_10)
del top_10
```

```
['1,000,000,000+', '100,000,000+', '500,000,000+', '10,000,000+', '50,000,000+', '1,000,000+',
```

The least known apps in our list of top 10 bins seem to be the ones with more than 10,000 installs. However, the sorting order is according to the length (len) of string values, which is why we see the 100 million+ value coming before the 500 million+. Since we have sliced the list to contain only the top 10, we can see that the last value is 10,000+, where it should be 50,000+. This will be easy to deal with after parsing those values to integers.

Anything below 50,000 installs will be removed from consideration in answering our questions. The next step is to parse column bins into integer numbers so we can select rows with only those bins in a Pythonic way:

```
In [9]: # Remove "+" and "," from Installs column values & Put new values in a variable
        installs = [np.int(i.replace("+", "").replace(",","")) for i in app_data["Installs"]]

        # Replace the installs column with the new integer values
        app_data["Installs"] = [i for i in installs]

        del installs
```

Now to the final step in finalizing a dataframe that has the necessary data to answer the first question, selecting rows that belong in the top 10 bins:

```
In [10]: # A new dataframe containing rows in top 10 bins
         top_10_df = app_data[app_data["Installs"] >= 50000]

         # How much does this data represent of the original data?
         print (str(round(len(top_10_df)/len(app_data)*100,0))+"%")

70.0%
```

Now to see the most reviewed apps. Apps in each bin will be compared based on the ratio of number of reviews to number of installs, which I will call `ReviewRatio`, calculated using the formula:

$$ReviewRatio = \frac{Reviews}{Installs}$$

The `Review` column data type is still string, therefore it will be converted to integer first.

```
In [11]: # Parse review column values to integers
         top_10_df["Reviews"] = [int(value) for value in top_10_df["Reviews"]]

         # Add a new column containing review ratios
         top_10_df["ReviewRatio"] = top_10_df["Reviews"]/top_10_df["Installs"]
```

Let's take a look at how the review ratios look for our top 10 bins. For each bin, we will take the app with the highest `ReviewRatio`:

```
In [12]: # A dataframe to contain the most reviewed app from each bin:
         most_reviewed = pd.DataFrame()

         # Get the most reviewed app from each bin and add it to the most_reviewed dataframe
         for bins in np.unique(top_10_df["Installs"]):
             top_row = top_10_df[top_10_df["Installs"] == bins]
             top_row = top_row.sort_values(by="ReviewRatio", ascending=False)
             top_row = top_row.head(1)
```

```
    most_reviewed = most_reviewed.append(top_row)

# Clear this dataframe of irrelevant columns for enhanced visibility
most_reviewed = most_reviewed.drop(columns=["Category","Type","Price","Content Rating"
most_reviewed
```

Out[12]:

```
                                        App  Rating   Reviews  \
6181           Shadow Fight 2 Special Edition     4.5     10440
9627             ai.type keyboard Plus + Emoji     4.5     57076
7766   CR & CoC Private Server - Clash Barbarians PRO     4.6    167974
10809       Castle Clash: RPG War and Strategy FR     4.7    376223
4242          Fame Boom for Real Followers, Likes     4.7    896118
1888                                Homescapes     4.6   3093932
6551                                Boom Beach     4.5   5591653
1879                            Clash of Clans     4.6  44893888
4005      Clean Master- Space Cleaner & Antivirus     4.7  42916526
2544                                  Facebook     4.1  78158306

         Installs  ReviewRatio
6181        50000     0.208800
9627       100000     0.570760
7766       500000     0.335948
10809     1000000     0.376223
4242      5000000     0.179224
1888     10000000     0.309393
6551     50000000     0.111833
1879    100000000     0.448939
4005    500000000     0.085833
2544   1000000000     0.078158
```

And there it is! The most reviewed app from each bin of installs. Being the most reviewed does not mean the highest rated, as in the Facebook app's case, but it certainly gives more credibility to the rating.

Now to the second part of our question, what are the top 3 rated apps from these top 10?

In [13]:

```
# Sort by rating descending and get the top 3
highest_rated = most_reviewed.sort_values(by="Rating", ascending=False).head(3)
highest_rated
```

Out[13]:

```
                                          App  Rating   Reviews   Installs  \
10809     Castle Clash: RPG War and Strategy FR     4.7    376223    1000000
4242        Fame Boom for Real Followers, Likes     4.7    896118    5000000
4005   Clean Master- Space Cleaner & Antivirus     4.7  42916526  500000000

       ReviewRatio
10809     0.376223
4242      0.179224
4005      0.085833
```

In terms of rating, the top 3 apps tie on 4.7 out of 5.0!

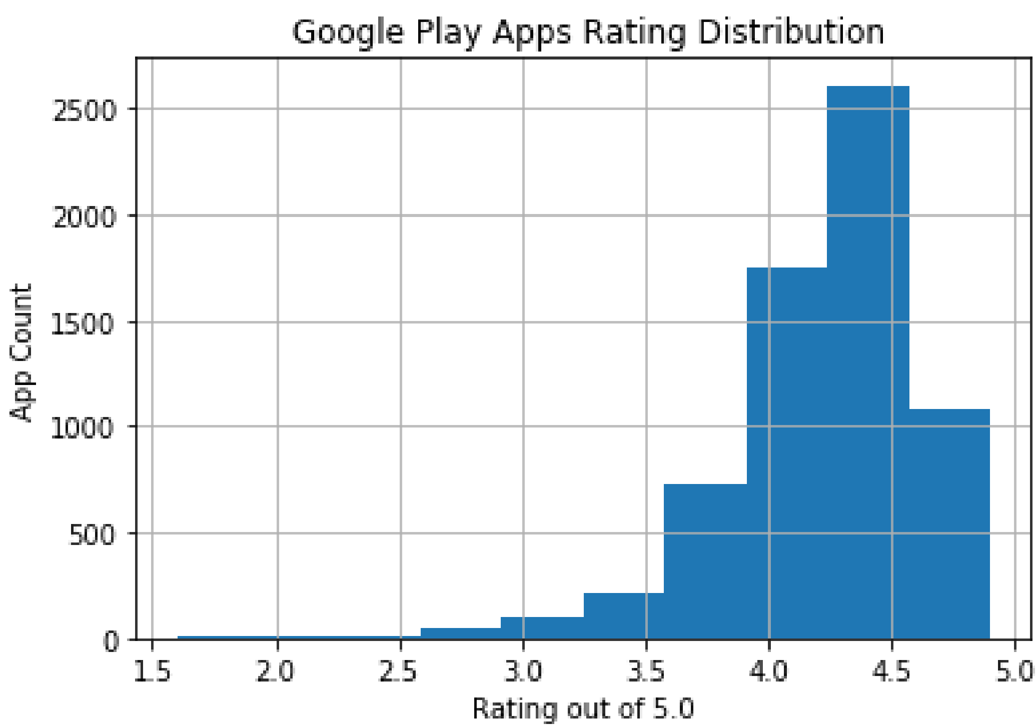
1.3 2. How do these apps vary by rating, pricing, and the ratio of reviews based on number of installs?

1.3.1 A. Rating

We have seen that apps with the highest review ratios for the top 10 bins had maximum ratings of 4.7 out of 5, and a minimum of 4.1, but that is only for apps with the highest review ratios.

What about other apps in the top 10 bins? To have a clearer idea, let's plot the rating column from our dataset:

```
In [14]: #Plot a histogram from the Rating column
         top_10_df["Rating"].hist()
         plt.title(" Google Play Apps Rating Distribution")
         plt.ylabel("App Count")
         plt.xlabel("Rating out of 5.0")
         plt.show()
```



Over 2500 of the apps in the top 10 bins have a rating of over 4.2 to a nudge over 4.5, maybe 4.6. And almost 1000 apps have been rated higher than that. To get our numbers right, let's see a quick descriptive summary of ratings:

```
In [15]: top_10_df["Rating"].describe()

Out[15]: count    6564.000000
         mean        4.224680
         std         0.384961
```

```
min          1.600000
25%          4.100000
50%          4.300000
75%          4.500000
max          4.900000
Name: Rating, dtype: float64
```

In our previous question, the most reviewed apps scored maximum ratings of 4.7. We see here that other apps in the top 10 bins do have higher ratings, how many of them are there?

```
In [16]: len(top_10_df[top_10_df["Rating"] > 4.7])
```

```
Out[16]: 129
```

We have 129 apps with ratings higher than 4.7. Let's take a look at the top 5, sorted descending by Rating and Review Ratio:

```
In [17]: top_10_df[top_10_df["Rating"] > 4.7].sort_values(by=["Rating","ReviewRatio"],ascending
```

```
Out[17]:                                                    App           Category  \
         1833                               The Room: Old Sins               GAME
         79                              Tickets + PDA 2018 Exam  AUTO_AND_VEHICLES
         10254                                        FC Porto             SPORTS
         712     Learn Japanese, Korean, Chinese Offline & Free          EDUCATION
         4332                               EXO-L Amino for EXO Fans             SOCIAL

                Rating  Reviews  Installs  Type  Price Content Rating  \
         1833      4.9    21119    100000  Paid  $4.99       Everyone
         79        4.9   197136   1000000  Free      0       Everyone
         10254     4.9    15883    100000  Free      0       Everyone
         712       4.9   133136   1000000  Free      0       Everyone
         4332      4.9     5677     50000  Free      0           Teen

                              Genres    Last Updated  ReviewRatio
         1833                 Puzzle  April 18, 2018     0.211190
         79          Auto & Vehicles   July 15, 2018     0.197136
         10254                Sports   June 19, 2018     0.158830
         712     Education;Education   July 20, 2018     0.133136
         4332                 Social   July 13, 2018     0.113540
```

The Room: Old Sins seems like a great game to be played, especially since it is a paid app, costing $4.99, and still scoring a 4.9 out of 5. The second app Tickets + PDA 2018 Exam is for the PDA proficiency test, a test for engineers working high strain dynamic foundations. FC Porto is a Portuguese soccer team, for which the ratings may have been biased due to fan bias towards their favorite sports team.

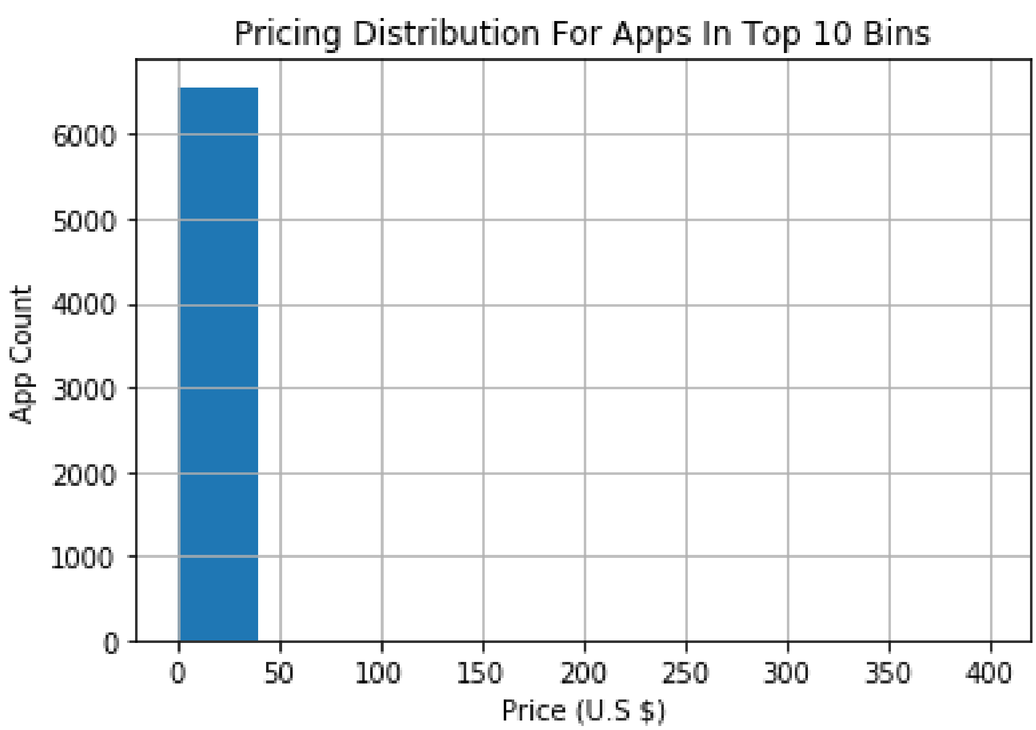
The fourth app on the list, Learn Japanese, Korean, Chinese Offline & Free, seems to have done a great job educating users on these 3 languages, given that many other apps do require an internet connection. And the last application on the list is meant for fans of a Kpop group called Exo, again for which fans may have rated based on bias or love for content they can surely find elsewhere.

1.3.2 B. Price

Many apps in the Google Play store are for free. Still, let's take a look at how app pricing looks in general:

```
In [18]: # Function to remove the $ prefix and parse price values to floats
         def usd_2_float(value):
             if value == "0":
                 return 0
             return float(value[1:])

         # Call function on the Price column values
         top_10_df["Price"] = [usd_2_float(value) for value in top_10_df["Price"]]
```

```
In [19]: #First, the paid_apps variable will contain ALL apps, even free ones
         #Plot a histogram of the Price column values
         paid_apps = top_10_df["Price"]
         paid_apps.hist()
         plt.title("Pricing Distribution For Apps In Top 10 Bins")
         plt.ylabel("App Count")
         plt.xlabel("Price (U.S $)")
         plt.show()
```



This plot shows that paid apps in the top 10 bins mostly cost less than $50, but nothing else. How about seeing if there are outliers to this range?

What interests me in finding out this answer is knowing what kind of apps cost more than $50 USD *AND* were downloaded over 50,000 times at least? They might either be something of high value to many users, or an outlier with a very interesting reason to land in the top 10 bins:

```
In [20]: #Pick apps with a price higher than zero
         paid_apps = top_10_df[top_10_df["Price"] > 0]

         #Pick apps with a price higher than $50
         paid_apps[paid_apps["Price"] > 50]
```

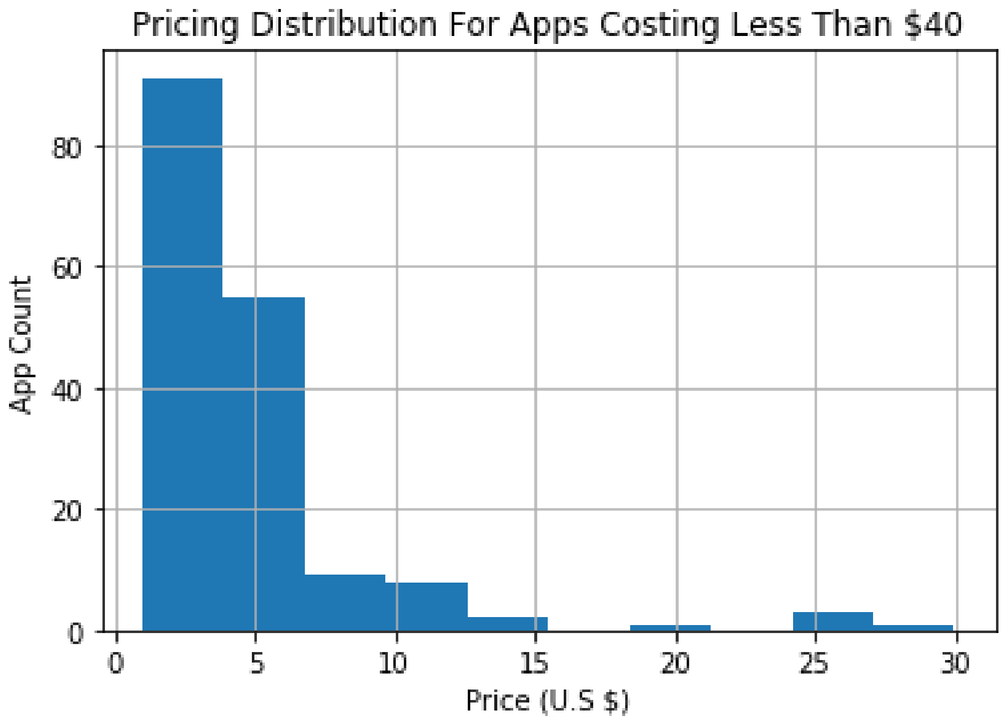
```
Out[20]:                    App   Category  Rating  Reviews  Installs  Type   Price  \
         5356  I Am Rich Premium    FINANCE     4.1     1867     50000  Paid  399.99
         5351          I am rich  LIFESTYLE     3.8     3547    100000  Paid  399.99

              Content Rating     Genres       Last Updated  ReviewRatio
         5356       Everyone    Finance  November 12, 2017      0.03734
         5351       Everyone  Lifestyle   January 12, 2018      0.03547
```

After looking these apps up on their Google Play page, it turns out their developer kept changing prices and the apps are there to show others you are rich, with no other use of real value. This may explain people buying or installing these apps at low prices, maybe knowing these apps rise in price and they can use that information later to show off!

Now I will get back to most paid apps and see how they range, this time limiting the price to something a little less than $40:

```
In [21]: paid_apps[paid_apps["Price"]<40]["Price"].hist()
         plt.title("Pricing Distribution For Apps Costing Less Than $40")
         plt.ylabel("App Count")
         plt.xlabel("Price (U.S $)")
```

```
Out[21]: Text(0.5, 0, 'Price (U.S $)')
```



Most apps cost less than \$5 (or even \$3, estimating through visuals). As would usually be expected, the amount of apps that cost more than that significantly decrease as we go up through the pricing, and two noticeable gaps can be seen between about \$16 to almost \$23 for apps in the top 10 bins.

The competition in app development is at its top at the moment, with many alternatives developed to almost every app and are only based on human creativity plus the ability to code, lowering entry barriers for more competition. Therefore, pricing an app significantly higher than the market will certainly require significant, sustainable competitive advantage.

Finally, what is the minimum price for paid apps within the top 10 bins?

```
In [22]: print("$ {}".format(paid_apps["Price"].min()))
```

```
$ 0.99
```

1.3.3 C. Review Ratio

Our choice of only the top 10 bins is most suitable for exploring the ratio of reviews-to-installs, since apps in lower bins can be biased either by fake reviews, an individual developer's family and friends, or other factors. First, let's look at apps with review ratios where reviews surpass the amount of downloads:

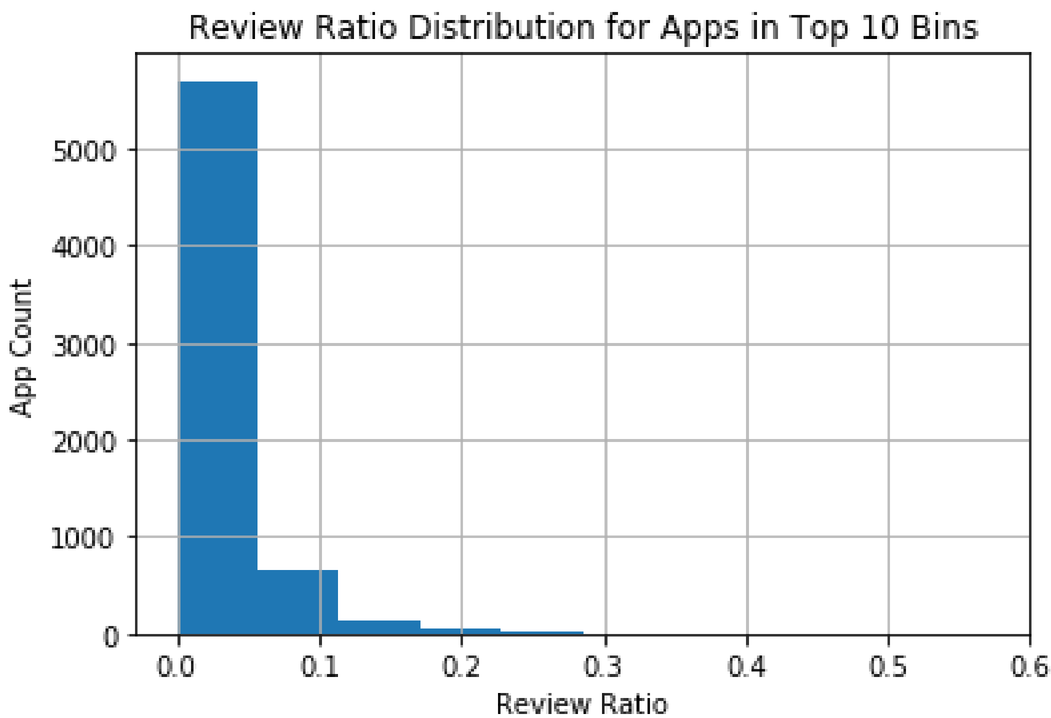
```
In [23]: top_10_df[top_10_df["ReviewRatio"] > 1]
```

```
Out[23]: Empty DataFrame
         Columns: [App, Category, Rating, Reviews, Installs, Type, Price, Content Rating, Genr
         Index: []
```

No apps in the top 10 bins have review ratios over 1, even though that could have been the case since a hypothetical app in the 50,000 bin could have actual amount of installs of 52,000 with 51,000 reviews, which in the case of bins is counted as 51,000 reviews over 50,000 (the bin amount, not the actual amount). However, that is clearly not the case in the real world as we have seen in this dataset.

Knowing that real-world reviews usually do not come close to the amount of installs, how does the distribution for the review ratio look like for the top 10 bins?

```
In [24]: top_10_df["ReviewRatio"].hist()
         plt.title("Review Ratio Distribution for Apps in Top 10 Bins")
         plt.xlabel("Review Ratio")
         plt.ylabel("App Count")
         plt.show()
```



So, most review ratios are less than 0.1 of the amount of installs, and the highest of them seem to approach 0.3, all judged visually. Let's take a look at the actual numbers, this time using percentiles:

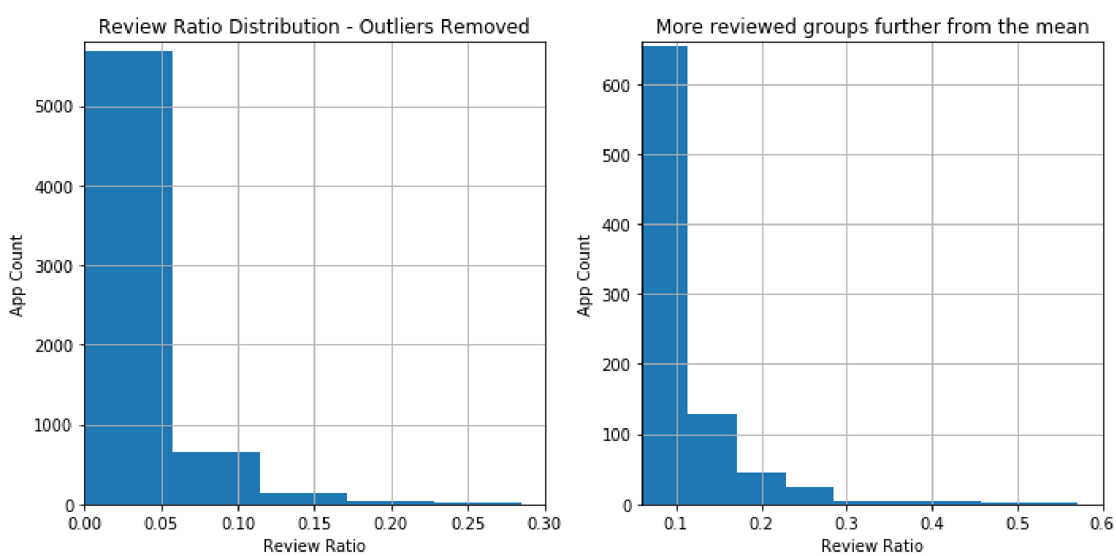
```
In [25]: #Print percentiles at the borders of 1st, 2nd, and 3rd standard deviations, along wit
         print("68th: {}".format(round(np.percentile(top_10_df["ReviewRatio"], 68),4)))
         print("95th: {}".format(round(np.percentile(top_10_df["ReviewRatio"], 95),4)))
         print("99th: {}".format(round(np.percentile(top_10_df["ReviewRatio"], 99),4)))
         print("Max: {}".format(max(top_10_df["ReviewRatio"])))
```

```
68th: 0.0305
95th: 0.0972
```

```
99th: 0.1906
Max: 0.57076
```

The maximum point is a unique outlier, especially given the jump from 0.19 to 0.57, which is longer than the range for values below the 99th percentiles! For this purpose, let's explore the ratios depending on what we just found here:

```
In [26]: plt.figure(figsize=(10, 5))

         plt.subplot(1, 2, 1)
         top_10_df["ReviewRatio"].hist()
         plt.title("Review Ratio Distribution - Outliers Removed")
         plt.xlabel("Review Ratio")
         plt.ylabel("App Count")
         plt.xlim(0,0.3)
         plt.ylim(0,5800)

         plt.subplot(1, 2, 2)
         top_10_df["ReviewRatio"].hist()
         plt.title("More reviewed groups further from the mean")
         plt.xlabel("Review Ratio")
         plt.ylabel("App Count")
         plt.xlim(0.06,0.6)
         plt.ylim(0,660)

         plt.tight_layout()
         plt.show()
```



The first plot shows most review ratios with only the maximum value removed, so it contains more than 99% of the data. We can see that most apps get reviewed about 0.06 times as much as they get installed or less (image on the left), while a much smaller percentage of apps get the opportunity to get reviewed 0.25 times their number of installs.

The second plot is there to zoom in on groups of fewer count but higher reveiw ratio. The first thing seen here is that the second plot looks kind of similar to the first one, even though it clearly has different limitations for x and y ticks. This leads to a question, *Is there a correlation between the number of installs and reviews?*

```
In [27]: top_10_df["Installs"].corr(top_10_df["Reviews"])

Out[27]: 0.6367889269753078
```

A positive correlation of about 0.64 confirms that reviews do increase with the amount of installs, but not concurrently. While this number does explain how reviews grow with increased app installs, having a solid number of installs per app -versus the bins we have here- would give a more accurate correlation between the two.

1.4 3. Do people review paid apps in the same way they review free apps?

In addition to the original dataset, the dataset creator also collected reviews for these apps and conducted a sentiment analysis using Python's nltk library, which I am lucky to have since it will be answering a very interesting question, *do people review paid apps in the same way they review free apps?*

Aside from the name of the app, the review, and the sentiment that the analysis concluded, this dataset relied in its results on two columns that the nltk library, or the field of Natural Language Processing in general, use for analyzing text and concluding sentiments: `Sentiment_Polarity` and `Sentiment_Subjectivity`. These will be explained in their own sections below.

Now on to loading the sentiment analysis data:

```
In [28]: # Import the csv file
         sentiment_data = pd.read_csv(r"C:\Users\Mohammad's Pc\Documents\Thinkful\7.11 Capstone

         # Drop null values
         sentiment_data = sentiment_data.dropna()
         sentiment_data.head()

Out[28]:                        App                                     Translated_Review  \
         0  10 Best Foods for You  I like eat delicious food. That's I'm cooking ...
         1  10 Best Foods for You    This help eating healthy exercise regular basis
         3  10 Best Foods for You          Works great especially going grocery store
         4  10 Best Foods for You                                          Best idea us
         5  10 Best Foods for You                                              Best way

           Sentiment  Sentiment_Polarity  Sentiment_Subjectivity
         0  Positive                1.00                0.533333
         1  Positive                0.25                0.288462
         3  Positive                0.40                0.875000
         4  Positive                1.00                0.300000
         5  Positive                1.00                0.300000
```

Good. Now we have a dataframe containing what we need on the side of sentiment analysis, but in order to compare free and paid apps, referred to here as `Type`, we need to get these types from the dataframe we used above, `app_data`.

Some of the apps included in the `sentiment_data` dataframe are not in the `app_data` dataframe, and therefore I will perform an inner join to add values from the `Type` column where both dataframes have the same app names in the `App` columns:

```
In [29]: # Take a slice of the original dataset containing app name and type, and merge it wit
         sentiment_data = pd.merge(sentiment_data, app_data[["App","Type"]] , how='inner', on=

         # Drop null values from sentiment data
         sentiment_data = sentiment_data.dropna()

         sentiment_data.head()
```

```
Out[29]:                       App                                     Translated_Review  \
         0  10 Best Foods for You  I like eat delicious food. That's I'm cooking ...
         1  10 Best Foods for You  I like eat delicious food. That's I'm cooking ...
         2  10 Best Foods for You    This help eating healthy exercise regular basis
         3  10 Best Foods for You    This help eating healthy exercise regular basis
         4  10 Best Foods for You         Works great especially going grocery store

           Sentiment  Sentiment_Polarity  Sentiment_Subjectivity  Type
         0  Positive                1.00                0.533333  Free
         1  Positive                1.00                0.533333  Free
         2  Positive                0.25                0.288462  Free
         3  Positive                0.25                0.288462  Free
         4  Positive                0.40                0.875000  Free
```

Now that we have our dataframe containing the data we need to answer the analysis, let's see how many apps of each type we have:

```
In [30]: # Generate counts of each unique values and print them
         (values,counts)= np.unique(sentiment_data["Type"], return_counts=True)

         for index in range(len(values)):
             print("{}: {}".format(values[index],counts[index]))
```

```
Free: 71784
Paid: 782
```

The sample size of free apps is close to 90 times the size of paid ones. This would give us the expectation that the statistics we are about to pull for free apps can be generalized of the population of free apps with more confidence than in the case of paid apps.

What I can do before comparing equal sample sizes is calculate the percentage of positive, neutral, and negative reviews for each dataset, which I will do right after creating their respective dataframes:

```
In [31]: # A dataframe for each app type
         free_apps = sentiment_data[sentiment_data["Type"] == "Free"]
         paid_apps = sentiment_data[sentiment_data["Type"] == "Paid"]
```

```
In [32]: # Return normalized values (percentages) of each value's occurrence & display them
         print("Free Apps - Sentiment Percentage \n"+"-"*30+"\n{}\n\n".format(free_apps['Senti
         print("Paid Apps - Sentiment Percentage \n"+"-"*30+"\n{}".format(paid_apps['Sentiment
```

```
Free Apps - Sentiment Percentage
------------------------------
Positive    63.437535
Negative    25.097515
Neutral     11.464950
Name: Sentiment, dtype: float64


Paid Apps - Sentiment Percentage
------------------------------
Positive    80.051151
Negative    14.578005
Neutral      5.370844
Name: Sentiment, dtype: float64
```

The percentage of positive sentiments in paid apps is significantly higher than that of free apps. This can be due to several reasons, the most visible of which are that many paid apps have some kind of advantage that many free apps do not, such as providing a service that company x is known for, or executing a process based on proprietary technology. With that in mind, such apps usually have more support, including more frequent security and user interface updates, which results in higher user statisfaction. Another reason may be the notion of having invested an amount of money into this app, and therefore a user may reinforce their satisfaction with this investment by providing a positive review.

Again, confidence in these percentages is higher for free apps than paid apps. If a paid apps sample of size equal to that of free apps was provided, the number may converge to a lower or a higher value.

When creating dataframes for each data type, indexes were moved along other data from the original dataframe, resulting in an index of unorganized integers. Due to the huge inequality of the count of free apps versus paid apps, I will be using index names to pick a random sample from free apps in order to perform head-to-head comparison. This calls for resetting the index for each of these dataframes:

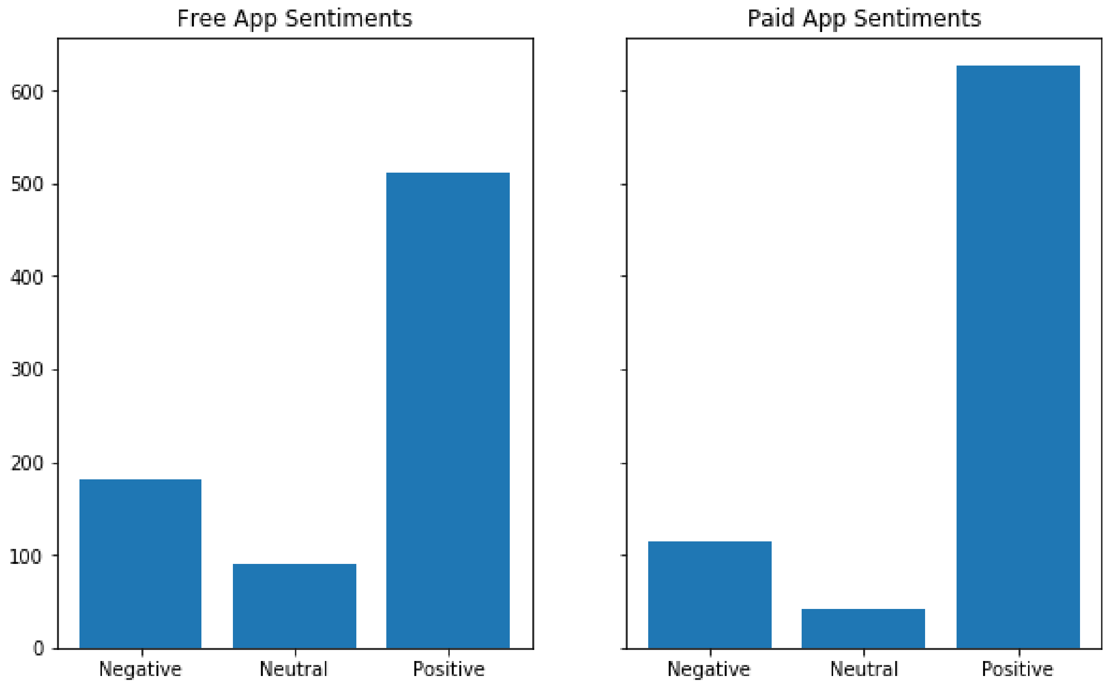
```
In [33]: # Make random, consistent choice of rows from free apps
         np.random.seed(777)

         # Reset index, then drop the old index column when it is moved to the right as a new
         paid_apps = paid_apps.reset_index().drop(columns=["index"])
         free_apps = free_apps.reset_index().drop(columns=["index"])

         # Generate a list of random indexes applicable to free_apps
```

```
random_indexes = np.random.choice(len(free_apps)-1, len(paid_apps), replace=False)

# Shorten free_apps to the same size of paid_apps & using a random selection
free_apps = free_apps.iloc[random_indexes]

# Reset index of free_apps
free_apps = free_apps.reset_index().drop(columns=["index"])


len(free_apps)
```

Out[33]: 782

Great, now we have two samples of equal size for both app types, which will allow for better comparison of sentiments. I move on to plotting counts of sentiments in each app type:

```
In [34]: # Generate values & counts for Sentiment columns in our dataframes & put them in dict
         val_ct_free = np.unique(free_apps['Sentiment'],return_counts=True)
         free_data = {value: count for value, count in zip(val_ct_free[0],val_ct_free[1])}
         val_ct_paid = np.unique(paid_apps['Sentiment'],return_counts=True)
         paid_data = {value: count for value, count in zip(val_ct_paid[0],val_ct_paid[1])}


         # Put values and counts each in a different variable for use in plots, taken from dic
         free_names = list(free_data.keys())
         free_values = list(free_data.values())
         paid_names = list(paid_data.keys())
         paid_values = list(paid_data.values())


         # Create a figure containing plots for each app type, sharing the y-axis for comparis
         fig, axs = plt.subplots(1, 2, figsize=(10, 6),sharey=True)
         axs[0].bar(free_names, free_values)
         axs[0].set_title("Free App Sentiments")
         axs[1].bar(paid_names, paid_values)
         axs[1].set_title("Paid App Sentiments")
         plt.show()
```



After we have taken a sample of free apps of equal size to paid apps, the plots show us where the difference in positive sentiments is distributed; free apps have more negative and neutral reviews, indicating higher variance of sentiments for free apps.

This subject requires more clarification, which we will see in the next sections; polarity and subjectivity.

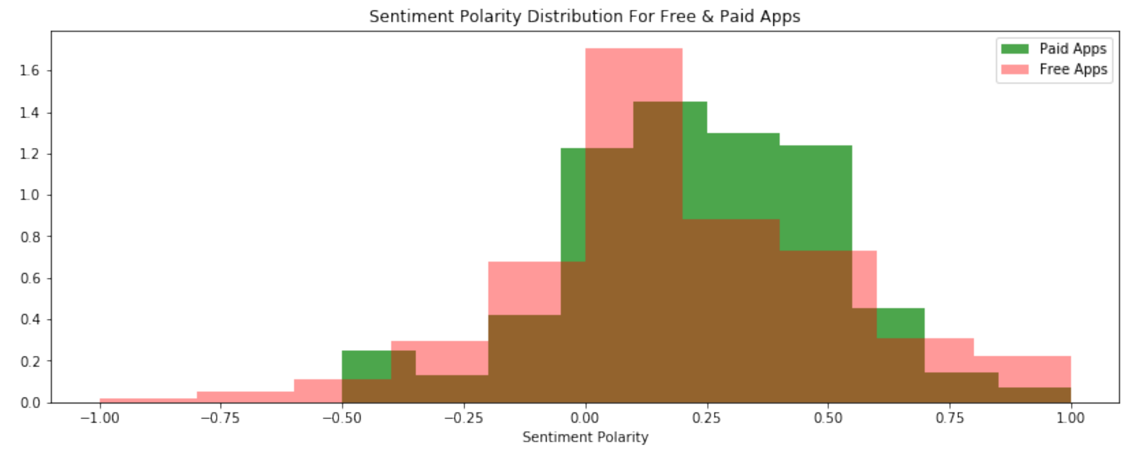
1.4.1 3.1. Sentiment Polarity

The polarity of a sentiment measures how negative or positive the context is, regardless of other factors. In the sentiment analysis data that I have, the polarity ranges from -1 (most negative) to +1 (most positive). In general, polarity can indicate whether people have strong opinions about a certain topic.

In this case, I expect polarity to be more extreme towards either positive or negative opinions in the case of free apps, because of relatively low entry barrier for developing and publishing apps through the Android market. Let's find out by plotting polarity for both app types:

```
In [35]: # Define variables that contain sentiment polarity for each app type
         polarity_paid = paid_apps["Sentiment_Polarity"]
         polarity_free = free_apps["Sentiment_Polarity"]

         # Plot two histograms showing sentiment polarity of each app type
         plt.figure(figsize=(14,5))
         plt.hist(polarity_paid, normed=True, color="green",alpha=.7, label="Paid Apps")
         plt.hist(polarity_free, normed=True,color="red",alpha=.4, label="Free Apps")
         plt.title('Sentiment Polarity Distribution For Free & Paid Apps')
         plt.xlabel('Sentiment Polarity')
```

```
plt.legend(loc='upper right')
plt.show()
```



Seeing this plot, I notice more neutral polarity in free apps, seen through the larger red area right above the 0.00 on the x axis. However, there is also more extreme positive polarity for free apps, shown in the area from 0.5 to 1.00 on the x axis, the extremity is also evident for free apps in negative polarity extending from -0.50 to -1. The majority of sentiments for free apps is concentrated around neutral and mildly positive. Polarity of sentiments for free apps has more spread around 0.

As for paid apps, most sentiments are focused in between a bit less than 0 and 0.5. Some sentiments do extend towards extremely positive, but none extend to below -0.5, indicating more general satisfaction with paid apps, and proving a minimum limitation for negative sentiments.

Let's take a look on solid numbers and see how these two samples compare:

```
In [36]: print("Mean polarity of free apps : {}".format(round(polarity_free.mean(),3)))
         print("Mean polarity of paid apps : {}".format(round(polarity_paid.mean(),3)))
         print("Polarity std. deviation of free apps : {}".format(round(polarity_free.std(),3)
         print("Polarity std. deviation of paid apps : {}".format(round(polarity_paid.std(),3)
```

```
Mean polarity of free apps : 0.183
Mean polarity of paid apps : 0.228
Polarity std. deviation of free apps : 0.33
Polarity std. deviation of paid apps : 0.265
```

The polarity mean difference between two samples is 0.045 within a range of 2 (from -1 to 1), which is considered a small difference. A slightly higher standard deviation can be seen for free apps, which is causing the wider spread of observations around their polarity mean. This also may be the reason for paid app polarity observations being a bit more clustered around their mean.

Several reasons can provide justification for both **A.** having a higher standard deviation for polarity of free apps and **B.** paid app polarity being at a visible minimum of -0.5. One cause that jumps to mind and can justify both phenoma, is that free apps have looser terms and conditions for being published; an android developer can code an app in a relatively short time and put it on the market for free without having to have established real value for app users. On the other side, paid apps -who are able to compete in the Google Play store- are expected to have more robust value-producing technology within the app, which convinces the user of purchasing.

```
In [37]: # Test similarity of samples with a t-value & a p-value
         sample_comparison = list(ttest_ind(polarity_paid,polarity_free, equal_var=False))
         sample_comparison = [round(value,3) for value in sample_comparison]
         print("t-value: {}\np-value: {}".format(sample_comparison[0],sample_comparison[1]))
```

```
t-value: 2.993
p-value: 0.003
```

This t-value indicates that the difference between means sentiment polarity of free apps and polarity of paid apps is about 3 times as high as the variances within each type of app. This difference is verified with a really small p-value of 0.003, which means that the difference is most probably comes from difference in the the populations of paid and free apps, and not from noise in the data.

In summary, this means that there is some difference in user's extremity of opinions towards paid and free apps, and that the sentiment polarity of reviews of each type of app is likely to follow the distribution of its respective histogram plotted above.

1.4.2 3.2. Sentiment Subjectivity

The subjectivitiy of a sentiment is how likely that sentiment is to be based on factual information, versus personal opinions or public notions. The lower the subjectivity, the more the sentiment is based on data or factual information. For this sentiment analysis, subjectivity values range from 0 (least subjective) to 1 (most subjective).

```
In [38]: # Define variables that contain sentiment subjectivity for each app type
         subjectivity_paid = paid_apps["Sentiment_Subjectivity"]
         subjectivity_free = free_apps["Sentiment_Subjectivity"]

         # Plot two histograms showing sentiment subjectivity of each app type
         plt.figure(figsize=(14,5))
         plt.hist(subjectivity_paid, normed=True, color="green",alpha=.7, label="Paid Apps")
         plt.hist(subjectivity_free, normed=True,color="red",alpha=.4, label="Free Apps")
         plt.title('Sentiment Subjectivity Distribution For Free & Paid Apps')
         plt.xlabel('Sentiment Subjectivity')
         plt.legend(loc='upper right')
         plt.show()
```

Both paid and free apps seem to have a distribution of sentiment subjectivity that is very close to a normal distribution, although paid apps have more data around the mean. The overall subjectivity of reviews of paid apps seem to be slightly lower than that of paid apps.

```
In [39]: print("Mean subjectivity of free apps : {}".format(round(subjectivity_free.mean(),3)))
         print("Mean subjectivity of paid apps : {}".format(round(subjectivity_paid.mean(),3)))
         print("Subjectivity std. deviation of free apps : {}".format(round(subjectivity_free.s
         print("Subjectivity std. deviation of paid apps : {}".format(round(subjectivity_paid.s
```

```
Mean subjectivity of free apps : 0.506
Mean subjectivity of paid apps : 0.521
Subjectivity std. deviation of free apps : 0.237
Subjectivity std. deviation of paid apps : 0.21
```

As can be visually inferred from the histogram plot above, sentiment subjectivity in reviews for both types of apps is similar. The means of both samples are very close to each other, and the standard deviatons are also similar. This indicates that user subjectivity is expected to be the same when reviewing free and paid apps. This hints that a developer should not expect more or less subjectivity from general users of either app type.

Let us validate our inference with a t-test:

```
In [40]: # Test similarity of samples with a t-value & a p-value
         sample_comparison = list(ttest_ind(subjectivity_paid,subjectivity_free, equal_var=Fals
         sample_comparison = [round(value,2) for value in sample_comparison]
         print("t-value: {}\np-value: {}".format(sample_comparison[0],sample_comparison[1]))
```

```
t-value: 1.34
p-value: 0.18
```

The t-value of 1.34 says that that statistically, these two samples are not significantly different. In other words, it says that this difference found in paid apps, for example, is not unusual to find in free apps. That is because the difference is almost equal to the variance *within* paid apps or free apps alike, and therefore may expectedly be reproduced if we re-do the test using a different random sample from the free apps population.

The p-value of 0.18 indicates that this t-value is somewhat likely to have been caused by noise in the data rather than by actual difference in sentiment subjectivity towards either type of app.

1.4.3 Conclusion Of Sentiment Analysis

In terms of polarity, the mean difference between the two groups is higher, relative to the variance, and the mean difference is close in terms of subjectivity, based on t-values. I conclude the polarity is statistically significantly different between paid and free apps, given the polarity p-value is really small, and that subjectivity may need a larger sample size to confirm that the subjectivity is not significantly differnt, given its p-value of 0.18. This tells that people may maintain the same subjectivity in general when posting reviews for either type of app, but do tend to be somewhat more extreme when writing reviews on free apps.

1.5 Proposal Of Further Research

Based on findings in this document, a summary of points that would help validate our understand of the results are:

- The segmentational nature of Google Store's app listing requires more sample collection from users with different behaviors, including professions, favorite content categories, browsing and online-shopping habits, especially on websites owned by Google.
- It would further enhance our findings of user sentiments if we had samples from users in different geographical locations.
- A sentiment analysis performed on reviews in languages other than English would help understand user sentiments over a wider geographic area, and possibly globally.
- A solid sub-categorization of apps, as could have been seen in the `Genres` column, would help us rank apps from each category, and identify gaps in the Google Play store and the app market in general.
- Should any of the first 3 points of this proposal of further research be carried out, the sample size of paid apps would be larger and therefore an equally larger sample of free apps would help clear the fog off the result of our analysis on sentiment subjectivity.