SDAIA BOOTCAMP PROJECT - Google Play Store

January 12, 2022

1 1. Introduction

With technology dominating the modern world; the app industry has become a high thriving. New apps are coming to the market every while. Indeed, app usage is still growing at a steady rate, but some are higher than others. There are different demands for different apps based on several features. Data science potentials can be utilized to drive app-making businesses and app developers to the right road.

2 2. Dataset Description

Google Play Store is a big digital distribution service that provides apps supported by Android-certified devices and Chrome OS. We found a dataset on Kaggle that contains data of 10k Play Store apps for analyzing the Android market. The dataset has 13 columns -which will be shown in the following subsection- and 10842 rows. It is aiming to use these apps' statistics to predict which apps are more likely to be installed or get a high rate.

2.1 2.1. Sneak Peek on the Dataset

This is the link to the dataset on Kaggle (https://www.kaggle.com/lava18/google-play-store-apps)

2.1.1 2.1.1. Importing Libraries and the Dataset

[1]:
```
#import the libraries
import numpy as np
import pandas as pd

#read the dataset
df = pd.read_csv('googleplaystore.csv')
df.head(10)
```

[1]:
```
                                                 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
3                              Sketch - Draw & Paint  ART_AND_DESIGN     4.5
4              Pixel Draw - Number Art Coloring Book  ART_AND_DESIGN     4.3
5                         Paper flowers instructions  ART_AND_DESIGN     4.4
6            Smoke Effect Photo Maker - Smoke Editor  ART_AND_DESIGN     3.8
```

```
7                                   Infinite Painter  ART_AND_DESIGN     4.1
8                               Garden Coloring Book  ART_AND_DESIGN     4.4
9                     Kids Paint Free - Drawing Fun  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
3  215644   25M  50,000,000+  Free     0           Teen
4     967  2.8M     100,000+  Free     0       Everyone
5     167  5.6M      50,000+  Free     0       Everyone
6     178   19M      50,000+  Free     0       Everyone
7   36815   29M   1,000,000+  Free     0       Everyone
8   13791   33M   1,000,000+  Free     0       Everyone
9     121  3.1M      10,000+  Free     0       Everyone

                     Genres      Last Updated         Current Ver  \
0              Art & Design     January 7, 2018               1.0.0
1  Art & Design;Pretend Play    January 15, 2018              2.0.0
2              Art & Design      August 1, 2018               1.2.4
3              Art & Design        June 8, 2018  Varies with device
4    Art & Design;Creativity       June 20, 2018                 1.1
5              Art & Design      March 26, 2017                 1.0
6              Art & Design      April 26, 2018                 1.1
7              Art & Design       June 14, 2018            6.1.61.1
8              Art & Design  September 20, 2017               2.9.2
9    Art & Design;Creativity        July 3, 2018                 2.8

   Android Ver
0  4.0.3 and up
1  4.0.3 and up
2  4.0.3 and up
3    4.2 and up
4    4.4 and up
5    2.3 and up
6  4.0.3 and up
7    4.2 and up
8    3.0 and up
9  4.0.3 and up
```

[2]:
```
df.shape
```

[2]:
```
(10841, 13)
```

2.2 2.2. Features Explanation

[3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10841 entries, 0 to 10840
Data columns (total 13 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   App             10841 non-null  object
 1   Category        10841 non-null  object
 2   Rating          9367 non-null   float64
 3   Reviews         10841 non-null  object
 4   Size            10841 non-null  object
 5   Installs        10841 non-null  object
 6   Type            10840 non-null  object
 7   Price           10841 non-null  object
 8   Content Rating  10840 non-null  object
 9   Genres          10841 non-null  object
 10  Last Updated    10841 non-null  object
 11  Current Ver     10833 non-null  object
 12  Android Ver     10838 non-null  object
dtypes: float64(1), object(12)
memory usage: 1.1+ MB
```

1. App: is for the name of the app.
2. Category: means the category of a certain app
3. Rating: displays the rating of the app in Google Play Store on 5 Point numerical rating scale.
4. Reviews: this shows the number of reviews given to the app.
5. Size: shows the size of the app in megabytes.
6. Installs: shows the number of times the app got installed
7. Type: this shows if the app is free or paid.
8. Price: shows the price of the app in dollars. If the app is free the value will be 0.
9. Content Rating: shows the rating of the content if it's for everyone or specified for a specific audience.
10. Genres: means the genre of a certain app (it appears to be the same as the Category feature)
11. Last Updated: shows the date of the last update of the app.
12. Current Ver: shows the number of the current version of the app.
13. Android Ver: shows the number of Android versions that the app support.

3 3. Purpose of the Project

There are two principle goals for this project. The first goal is to classify apps based on their Installs and Rating, taking into consideration other features like Category, Type, Price and Content Rating. We're aiming to run many experiments with different classifier models and many trails to discover their effect on the accuracy scores. The second goal of this project is to predict Rating based on set of app features like Category, Reviews, Size, Installs, Type, Price and Content Rating. We're aiming to build a regression model that can predict the app rating.

4 4. Data Cleaning

We plan to perform basic cleaning for the dataset and analyze some features. We will try to drop columns that will appear to be irrelevant to our analysis.

4.1 4.1. Removing Duplicates

[4]:
```python
df[df.duplicated(subset='App')]
```

[4]:
```
                                   App       Category  Rating Reviews  \
229         Quick PDF Scanner + OCR FREE       BUSINESS     4.2   80805
236                                  Box       BUSINESS     4.2  159872
239                   Google My Business       BUSINESS     4.4   70991
256                  ZOOM Cloud Meetings       BUSINESS     4.4   31614
261            join.me - Simple Meetings       BUSINESS     4.0    6989
…                                    …            …     …       …
10715                 FarmersOnly Dating         DATING     3.0    1145
10720  Firefox Focus: The privacy browser  COMMUNICATION     4.4   36981
10730                        FP Notebook        MEDICAL     4.5     410
10753      Slickdeals: Coupons & Shopping       SHOPPING     4.5   33599
10768                               AAFP        MEDICAL     3.8      63

                     Size     Installs  Type Price Content Rating  \
229    Varies with device   5,000,000+  Free     0       Everyone
236    Varies with device  10,000,000+  Free     0       Everyone
239    Varies with device   5,000,000+  Free     0       Everyone
256                   37M  10,000,000+  Free     0       Everyone
261    Varies with device   1,000,000+  Free     0       Everyone
…                    …          …   …   …             …
10715                1.4M     100,000+  Free     0     Mature 17+
10720                4.0M   1,000,000+  Free     0       Everyone
10730                 60M      50,000+  Free     0       Everyone
10753                 12M   1,000,000+  Free     0       Everyone
10768                 24M      10,000+  Free     0       Everyone

              Genres       Last Updated         Current Ver  \
229         Business  February 26, 2018  Varies with device
236         Business      July 31, 2018  Varies with device
239         Business      July 24, 2018    2.19.0.204537701
256         Business      July 20, 2018      4.1.28165.0716
261         Business      July 16, 2018           4.3.0.508
…                …                …                 …
10715         Dating  February 25, 2016                 2.2
10720  Communication       July 6, 2018                 5.2
10730        Medical     March 24, 2018           2.1.0.372
10753       Shopping      July 30, 2018                 3.9
10768        Medical      June 22, 2018               2.3.1
```

```
               Android Ver
229         4.0.3 and up
236   Varies with device
239           4.4 and up
256           4.0 and up
261           4.4 and up
…                    …
10715         4.0 and up
10720         5.0 and up
10730         4.4 and up
10753         4.4 and up
10768         5.0 and up

[1181 rows x 13 columns]
```

There are 1181 duplicated apps apparently. They need to be dropped.

[5]:
```
df.drop_duplicates(subset='App', inplace=True, ignore_index=True)
```

4.2 4.2. Dropping Irrelevant Columns

From looking at the head of the table, we can notice that "Category" and "Genres" features are a little similar.

[6]:
```
df[['Category', 'Genres']]
```

[6]:
```
                Category                     Genres
0         ART_AND_DESIGN               Art & Design
1         ART_AND_DESIGN  Art & Design;Pretend Play
2         ART_AND_DESIGN               Art & Design
3         ART_AND_DESIGN               Art & Design
4         ART_AND_DESIGN    Art & Design;Creativity
…                    …                          …
9655              FAMILY                  Education
9656              FAMILY                  Education
9657             MEDICAL                    Medical
9658  BOOKS_AND_REFERENCE         Books & Reference
9659           LIFESTYLE                  Lifestyle

[9660 rows x 2 columns]
```

[7]:
```
print(df['Category'].nunique())
print(df['Genres'].nunique())
```

```
34
119
```

From the above, we can notice that "Category" is more abstract than the "Genres" feature. The "Genres" has more values as it takes into consideration more than one genre to the app. We want to be exclusive as possible so we will work on the "Category" column and ignore the "Genres" column.

For our classification and regression models, we consider "App", "Last Updated", "Current Ver", and "Android Ver" in addition to "Genres" as irrelevant features. So, we need to drop all these irrelevant columns

[8]:
```
df = df.drop(['App', 'Genres', 'Last Updated', 'Current Ver', 'Android Ver'],␣
↪axis = 1)
```

[9]:
```
df.head(3)
```

[9]:

	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating
0	ART_AND_DESIGN	4.1	159	19M	10,000+	Free	0	Everyone
1	ART_AND_DESIGN	3.9	967	14M	500,000+	Free	0	Everyone
2	ART_AND_DESIGN	4.7	87510	8.7M	5,000,000+	Free	0	Everyone

4.3 4.3. Handling Missing Values

[10]:
```
#Detecting missing values
df.isna().sum()
```

[10]:
```
Category             0
Rating            1463
Reviews              0
Size                 0
Installs             0
Type                 1
Price                0
Content Rating       1
dtype: int64
```

We can see that 'Rating' has a large number of rows with missing values. So, instead of dropping these rows, we will fill them with the mean value of the 'Rating'.

[11]:
```
#Filling missing values with mean
RatingMean = df['Rating'].mean()
df['Rating'] = df['Rating'].fillna(RatingMean)
```

As we have seen, 'Type' and 'Content Rating' have only one missing value for each, so, we will drop these rows.

[12]:
```
#Dropping missing values
df = df.dropna(subset=['Type'])
df = df.dropna(subset=['Content Rating'])
```

[13]:
```
df.isna().sum()
```

[13]:
```
Category          0
Rating            0
Reviews           0
Size              0
Installs          0
Type              0
Price             0
Content Rating    0
dtype: int64
```

4.4 4.4. Changing Features Data Type

From the info of the features, we know that some features have 'object' Dtype with numeric valuse. So, we need to convert these features to 'float' dtaype.

We noticed from the table shown that 'Price' column has '$' symbol, so this need to be dropped before converting 'Price' to float.

[14]:
```
#Drop the $ sign from Price values
df['Price'] = df['Price'].str.replace('$', '')
```

```
/var/folders/gy/jsxj5kgx6xj644yvj9136j480000gn/T/ipykernel_43877/2481516221.py:2
: FutureWarning: The default value of regex will change from True to False in a
future version. In addition, single character regular expressions will *not* be
treated as literal strings when regex=True.
  df['Price'] = df['Price'].str.replace('$', '')
```

[15]:
```
#Converting Price to float
df['Price'] = df['Price'].astype(float)
```

We also noticed from the table shown that "Installs" column has '+' and ',' symbols, so these need to be dropped before converting 'Installs' to float.

[16]:
```
#Drop the + and , sign from Installs values
df['Installs'] = df['Installs'].str.replace('+', '')
df['Installs'] = df['Installs'].str.replace(',', '')
df[['Installs']]
```

```
/var/folders/gy/jsxj5kgx6xj644yvj9136j480000gn/T/ipykernel_43877/283116142.py:2:
FutureWarning: The default value of regex will change from True to False in a
future version. In addition, single character regular expressions will *not* be
treated as literal strings when regex=True.
  df['Installs'] = df['Installs'].str.replace('+', '')
```

[16]:
```
      Installs
0        10000
```

```
1        500000
2       5000000
3      50000000
4        100000
…           …
9655       5000
9656        100
9657       1000
9658       1000
9659   10000000

[9658 rows x 1 columns]
```

[17]:
```
#Converting Installs to float
df['Installs'] = df['Installs'].astype(float)
```

[18]:
```
#Converting Reviews to float
df['Reviews'] = df['Reviews'].astype(float)
```

We also noticed from the table shown that "Size" column has 'Varies with device'. This will be replaced with NaN in order to fill it with mean value later

[19]:
```
df['Size'] = df['Size'].replace('Varies with device', 'NaN', regex=True)
```

Moreover, some apps have a size in K (kilobyte) and some have it in M (megabyte). We will convert the sizes to KB and MB. And we will convert the type to float

[20]:
```
df['Size'] = (df['Size'].replace(r'[kM]+$','', regex=True).astype(float) *
                         df['Size'].str.extract(r'[\d\.]+([kM]+)', expand=False)
              .fillna(1).replace(['k','M'], [10**3, 10**6]).astype(int))
```

[21]:
```
#Filling missing values with mean
SizegMean = df['Size'].mean()
df['Size'] = df['Size'].fillna(SizegMean)
```

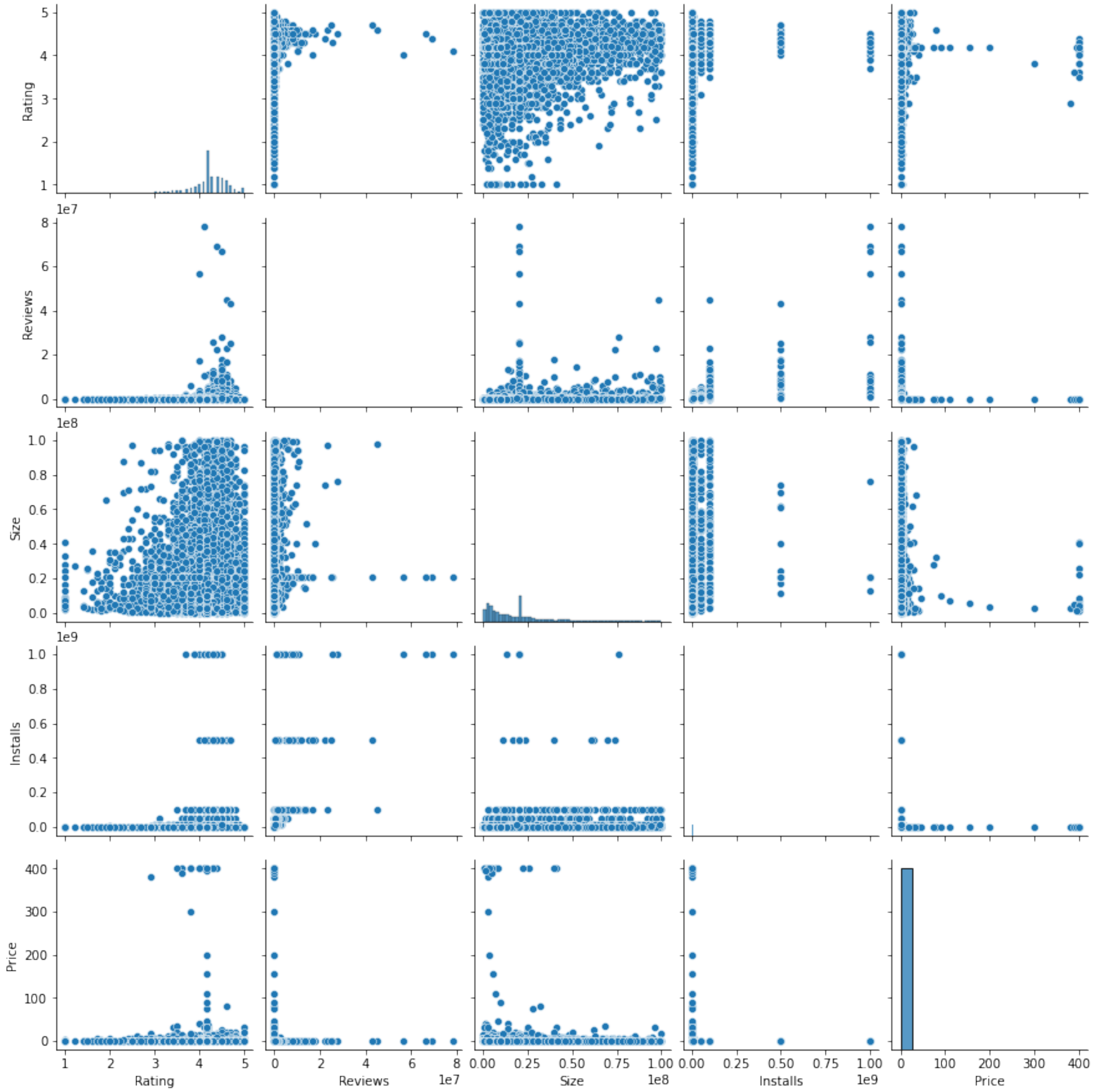
5 5. Visualalization

We will take a glance into tha dataset in visuals.

[22]:
```
#import visualization libraries
import seaborn as sns
import matplotlib.pyplot as plt
```

Lest's first create a pairplot for the remainig numeric features of the dataset.

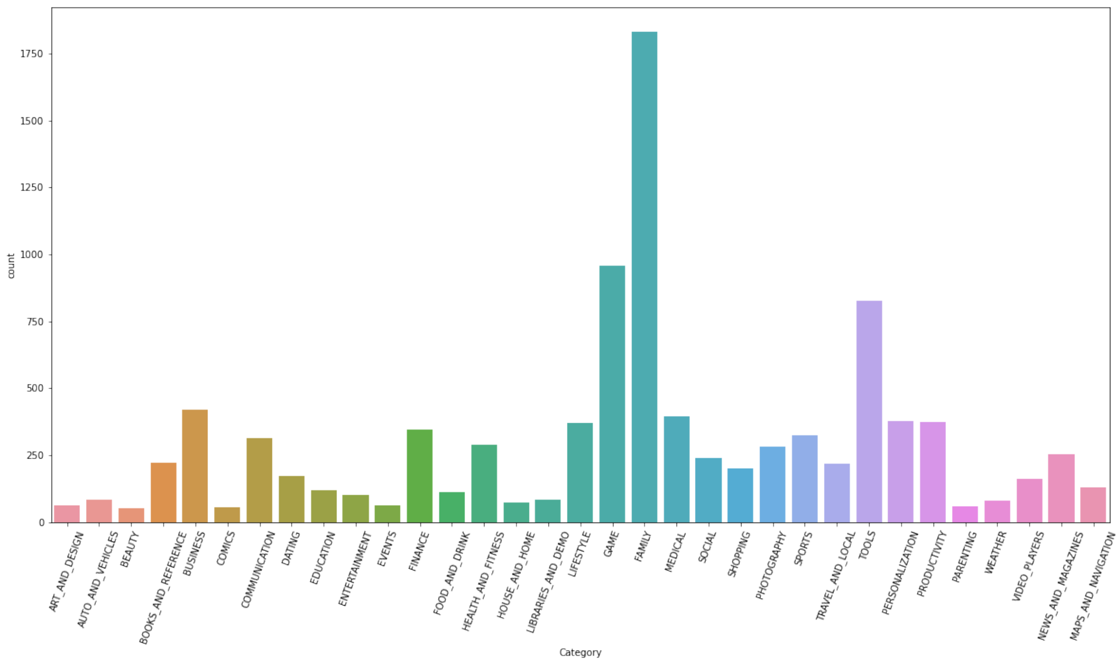
[23]:
```
sns.pairplot(df);
```



Now we want ro see the distribution of each column and the count of its categories.

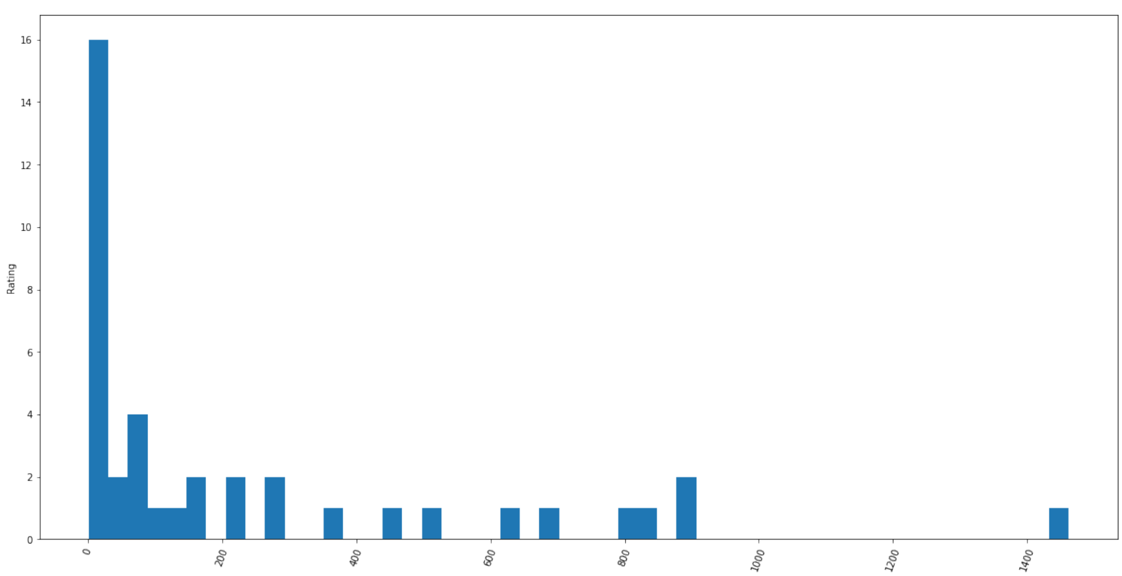
5.0.1 Category

[24]:
```
plt.rcParams['figure.figsize'] = (20, 10)
sns.countplot(x='Category',data=df)
plt.xticks(rotation=70);
```



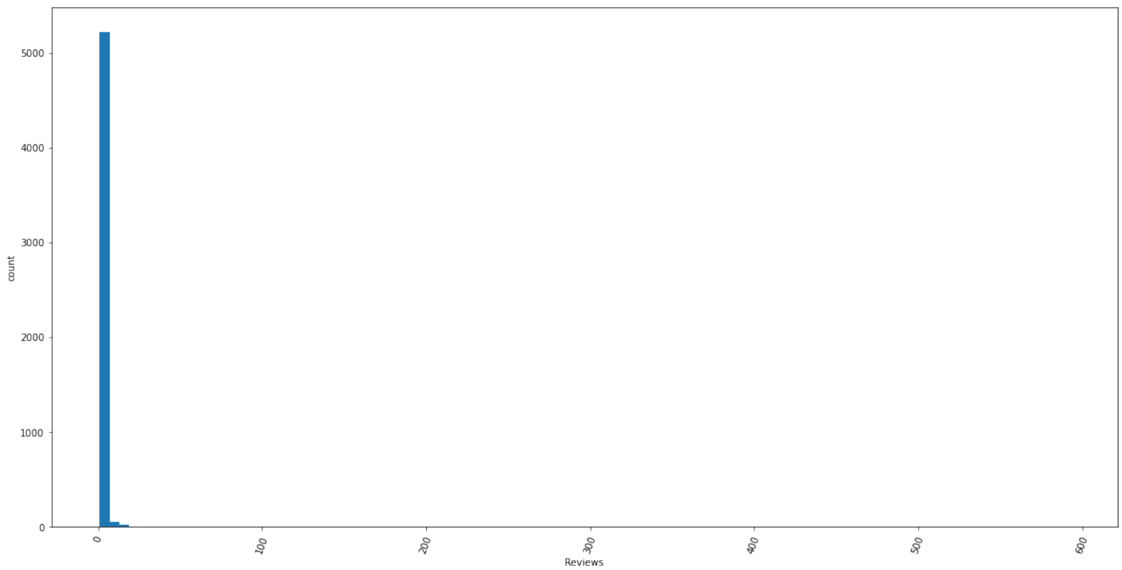
5.0.2 Rating

[25]:
```
plt.rcParams['figure.figsize'] = (20, 10)
RA = df['Rating'].value_counts()
plt.hist(RA,50)
plt.xlabel('Count')
plt.ylabel('Rating')
plt.xticks(rotation=70);
```



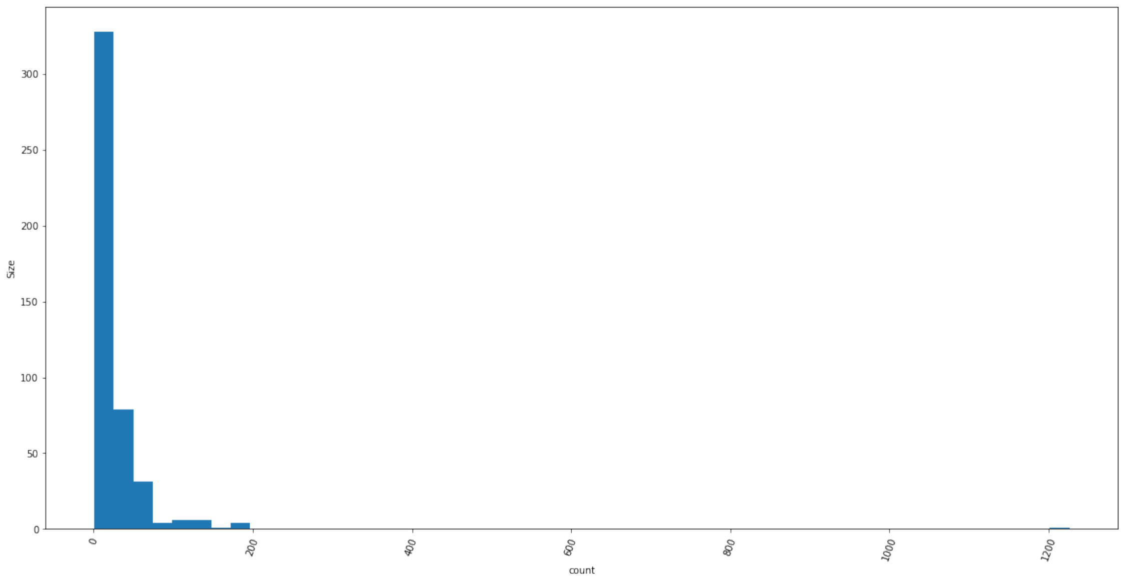
5.0.3 Reviews

[26]:
```
plt.rcParams['figure.figsize'] = (20, 10)
R = df['Reviews'].value_counts()
plt.hist(R, 100)
plt.xlabel('Reviews')
plt.ylabel('count')
plt.xticks(rotation=70);
```



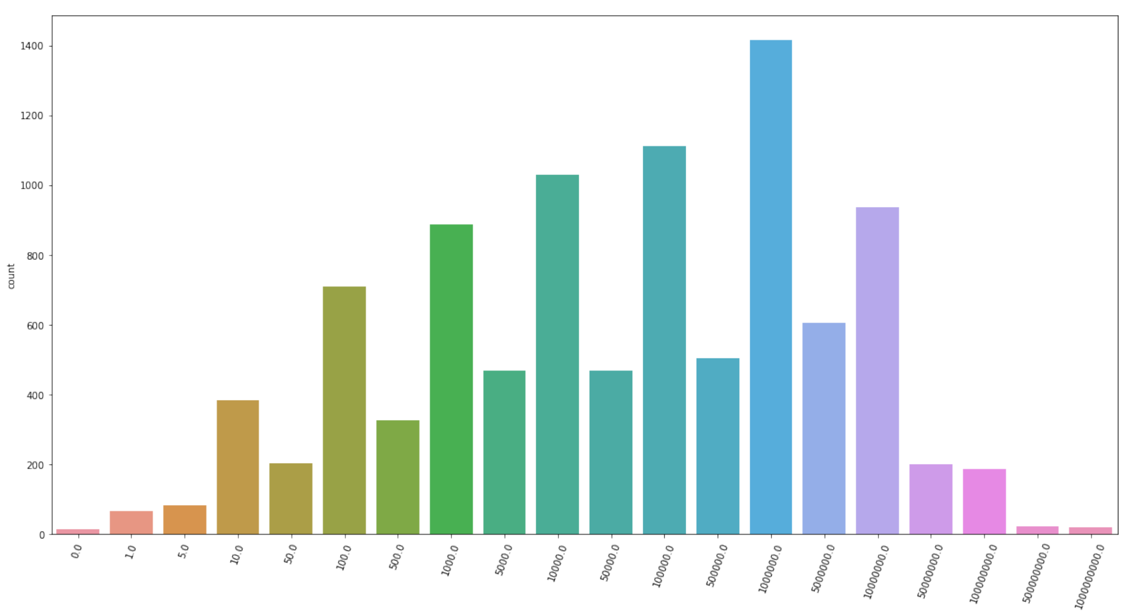
5.0.4 Size

[27]:
```
plt.rcParams['figure.figsize'] = (20, 10)
S= df['Size'].value_counts()
plt.hist(S, 50)
plt.xlabel('count')
plt.ylabel('Size')
plt.xticks(rotation=70);
```



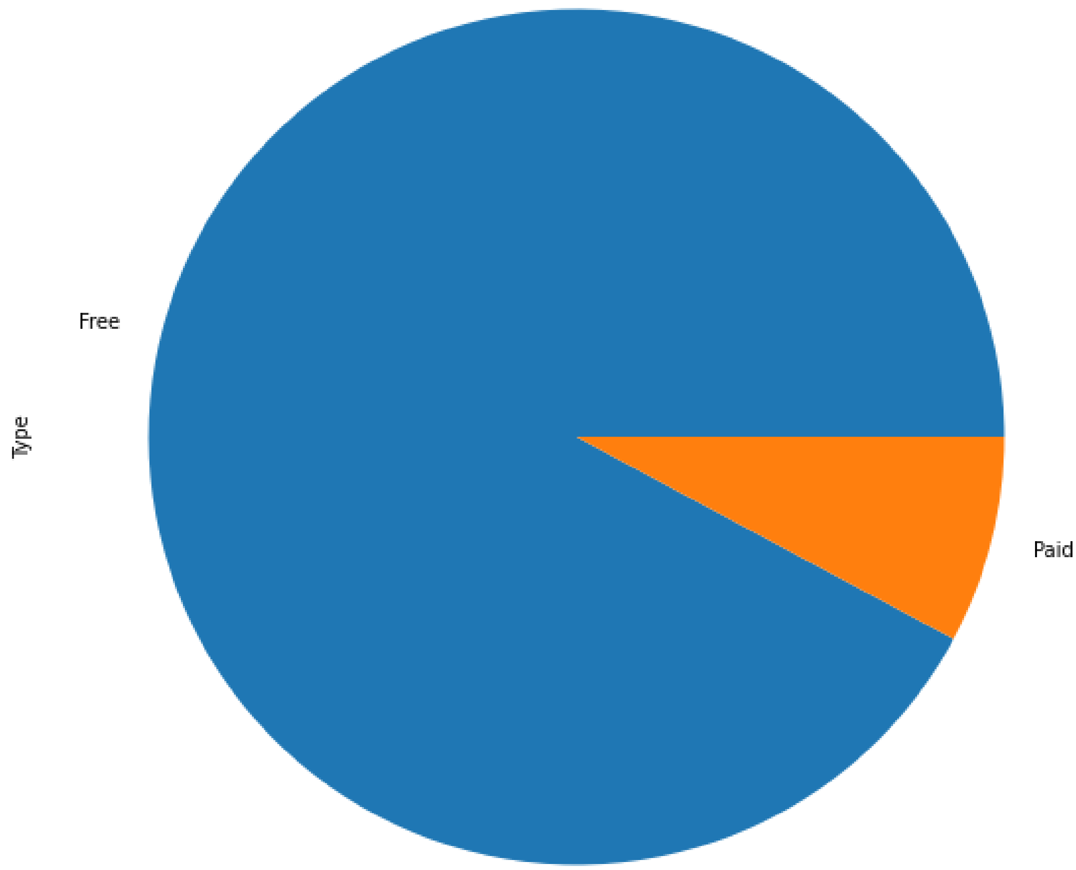
5.0.5 Installs

[28]:
```
plt.rcParams['figure.figsize'] = (20, 10)
sns.countplot(x='Installs',data=df)
plt.xticks(rotation=70);
```



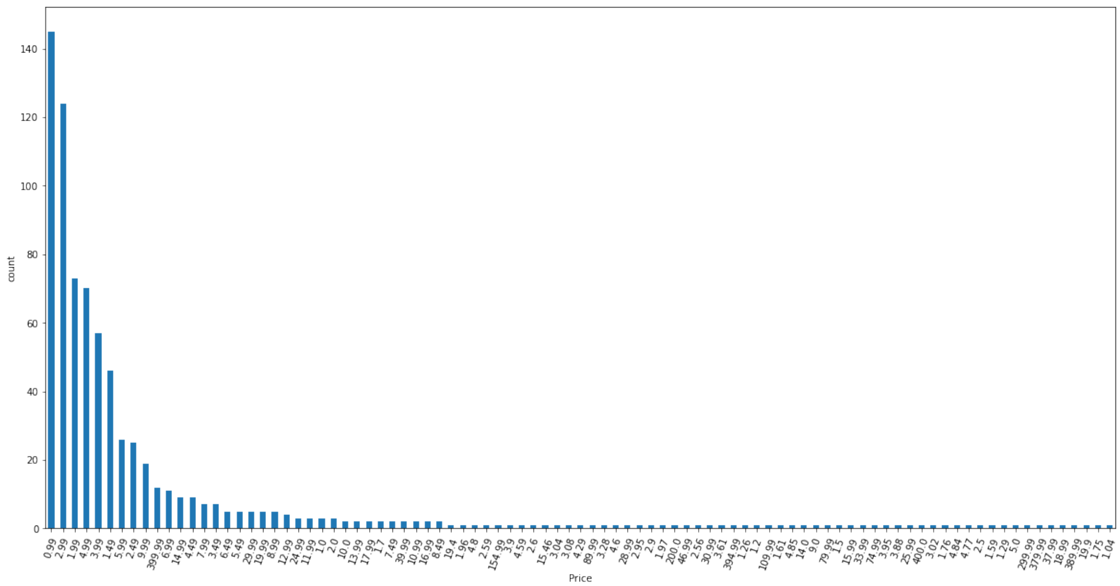
5.0.6 Type

[29]:
```
plt.rcParams['figure.figsize'] = (20, 10)
df['Type'].value_counts().plot.pie()
plt.xticks(rotation=70);
```



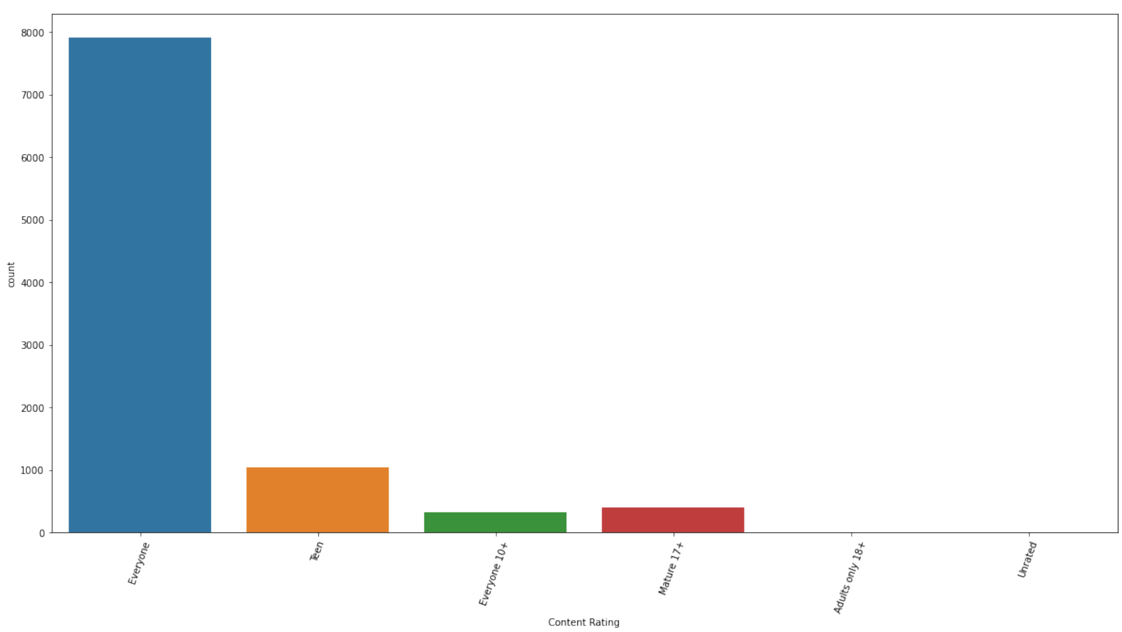
5.0.7 Price

[30]:
```
plt.rcParams['figure.figsize'] = (20, 10)
P = df.loc[(df.Type == 'Paid')]
P['Price'].value_counts().plot.bar()
plt.xlabel('Price')
plt.ylabel('count')
plt.xticks(rotation=70);
```



5.0.8 Content Rating

[31]:
```python
plt.rcParams['figure.figsize'] = (20, 10)
sns.countplot(x='Content Rating',data=df)
plt.xticks(rotation=70);
```



6 6. Feature Engineering

We want to add a new column called (App_Demand) engineered engineered from the 'Installs' and 'Rating' features. The column will have 7 categories ('very_high_demand' , 'high_demand', 'on_demand', 'moderate_demand', 'low_demand','very_low_demand','no_demand') which represent the demand on a certain app based on its installs and rating.

6.1 6.1. Calculations Related to New Column

We will compute maximum, average and minimum 'Installs' values, and average and minimum 'Rating' values using max(), mean(), and min() methods respectively. The approach compares the 'Installs' number and 'Rating' of each app with Maximum, Average, and Minimum Installs values and assigns the appropriate category for each app. These methods will be applied to the 'Installs' and 'Rating' features. In addition, we defined two variables (lowrRateIN) which denotes the average 'Installs' value between the minimum and average values. And (highRateIN) which denotes the average 'Installs' value between the maximum and average values.

[32]:
```
avgIN = round(df['Installs'].mean(), 2)
maxiIN = round(df['Installs'].max(), 2)
miniIN = round(df['Installs'].min(), 2)

print ("Mean Value:", avgIN)
print ("Max Value:", maxiIN)
print ("Min Value:", miniIN)

lowRateIN = round((miniIN+avgIN)/2, 2)
print ("Below Average App - Cutoff:", lowRateIN)
highRateIN = round((avgIN+maxiIN)/2, 2)
print ("Above Average App - Cutoff:", highRateIN)
```

```
Mean Value: 7778312.02
Max Value: 1000000000.0
Min Value: 0.0
Below Average App - Cutoff: 3889156.01
Above Average App - Cutoff: 503889156.01
```

[33]:
```
avgR = round(df['Rating'].mean(), 2)
miniR = round(df['Rating'].min(), 2)

print ("Mean Value:", avgR)
print ("Min Value:", miniR)
```

```
Mean Value: 4.17
Min Value: 1.0
```

6.2 6.2. Inserting the New Column

We want to classify apps into seven categories. First, the 'very_high_demand' apps are the app with the installs number between maximum and highRateIN values. Second, the 'high_demand' apps are the app with the installs number between highRateIN and average value and rating value above average value. Third, the 'on_demand' apps are the app with the installs number between highRateIN and average values and rating value below average value. Fourth, the 'moderate_demand' apps are the app with the installs number between average and lowrRateIN values. Fifth, 'low_demand' apps are the app with the installs number between lowrRateIN and minimum values and rating value above average value. Sixth, 'very_low_demand' apps are the app with the installs number between lowrRateIN and minimum values and rating value below average value. The last category, 'no_demand' apps are the app with the installs number equal to minimum values. The result is stored in a new column called (App_Demand) that is added to the dataset.

[34]:
```
conditions = [
    (df['Installs'] <= maxiIN) & (df['Installs'] >= highRateIN),
    (df['Installs'] < highRateIN) & (df['Installs'] >= avgIN) & (df['Rating'] >␣
 ↪avgR),
    (df['Installs'] < highRateIN) & (df['Installs'] >= avgIN) & (df['Rating']␣
 ↪<= avgR),
    (df['Installs'] < avgIN) & (df['Installs'] >= lowRateIN),
    (df['Installs'] < lowRateIN) & (df['Installs'] > miniIN) & (df['Rating'] >␣
 ↪avgR),
    (df['Installs'] < lowRateIN) & (df['Installs'] > miniIN)& (df['Rating'] <=␣
 ↪avgR),
    (df['Installs'] == miniIN)]
categories = ['very_high_demand' , 'high_demand', 'on_demand',␣
 ↪'moderate_demand', 'low_demand','very_low_demand',
              'no_demand']
df['App_Demand'] = np.select(conditions, categories)

#lets show the new column on the first 15 rows
df.head(15)
```

[34]:
```
         Category  Rating   Reviews        Size     Installs  Type  Price  \
0   ART_AND_DESIGN     4.1     159.0  19000000.0     10000.0  Free    0.0
1   ART_AND_DESIGN     3.9     967.0  14000000.0    500000.0  Free    0.0
2   ART_AND_DESIGN     4.7   87510.0   8700000.0   5000000.0  Free    0.0
3   ART_AND_DESIGN     4.5  215644.0  25000000.0  50000000.0  Free    0.0
4   ART_AND_DESIGN     4.3     967.0   2800000.0    100000.0  Free    0.0
5   ART_AND_DESIGN     4.4     167.0   5600000.0     50000.0  Free    0.0
6   ART_AND_DESIGN     3.8     178.0  19000000.0     50000.0  Free    0.0
7   ART_AND_DESIGN     4.1   36815.0  29000000.0   1000000.0  Free    0.0
8   ART_AND_DESIGN     4.4   13791.0  33000000.0   1000000.0  Free    0.0
9   ART_AND_DESIGN     4.7     121.0   3100000.0     10000.0  Free    0.0
10  ART_AND_DESIGN     4.4   13880.0  28000000.0   1000000.0  Free    0.0
11  ART_AND_DESIGN     4.4    8788.0  12000000.0   1000000.0  Free    0.0
12  ART_AND_DESIGN     4.2   44829.0  20000000.0  10000000.0  Free    0.0
13  ART_AND_DESIGN     4.6    4326.0  21000000.0    100000.0  Free    0.0
14  ART_AND_DESIGN     4.4    1518.0  37000000.0    100000.0  Free    0.0
```

```
   Content Rating        App_Demand
0        Everyone   very_low_demand
1        Everyone   very_low_demand
2        Everyone   moderate_demand
3            Teen       high_demand
4        Everyone        low_demand
5        Everyone        low_demand
6        Everyone   very_low_demand
7        Everyone   very_low_demand
8        Everyone        low_demand
9        Everyone        low_demand
10       Everyone        low_demand
11       Everyone        low_demand
12           Teen       high_demand
13       Everyone        low_demand
14       Everyone        low_demand
```

As we have seen, the new 'App_Demand' column is added to our dataset.

[35]:
```
#Use loc function to test the results
df.loc[(df['Installs'] <= maxiIN) & (df['Installs'] >= highRateIN)].head(3)
```

[35]:
```
                Category  Rating     Reviews          Size      Installs  \
152  BOOKS_AND_REFERENCE     3.9   1433233.0  2.039529e+07  1.000000e+09
299        COMMUNICATION     4.0  56642847.0  2.039529e+07  1.000000e+09
300        COMMUNICATION     4.4  69119316.0  2.039529e+07  1.000000e+09

     Type  Price Content Rating        App_Demand
152  Free    0.0           Teen  very_high_demand
299  Free    0.0       Everyone  very_high_demand
300  Free    0.0       Everyone  very_high_demand
```

6.3 6.3. Visualization of the Distribution

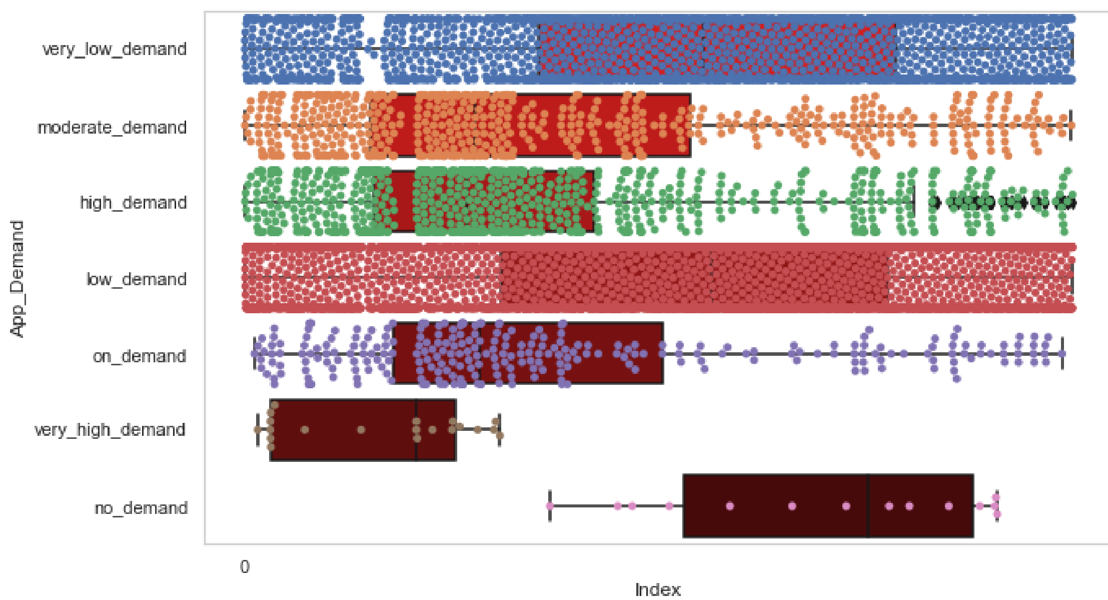
Now we will display the distribution of the apps as per their categories of demand.

[36]:
```
plt.figure(figsize=(10,6))
sns.set(context='notebook', style='whitegrid')
df['Index'] = df.index #converting index into column
sns.boxplot(x= 'Index', y= 'App_Demand', data= df, palette= 'flag')
sns.boxplot()
sns.swarmplot(x = 'Index', y= 'App_Demand', data= df, linewidth= 0)
```

```
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/seaborn/categorical.py:1296: UserWarning: 72.3% of the points cannot be
placed; you may want to decrease the size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
```

```
packages/seaborn/categorical.py:1296: UserWarning: 32.3% of the points cannot be
placed; you may want to decrease the size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/seaborn/categorical.py:1296: UserWarning: 58.5% of the points cannot be
placed; you may want to decrease the size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/seaborn/categorical.py:1296: UserWarning: 85.0% of the points cannot be
placed; you may want to decrease the size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/seaborn/categorical.py:1296: UserWarning: 15.0% of the points cannot be
placed; you may want to decrease the size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
```

[36]:
```
<AxesSubplot:xlabel='Index', ylabel='App_Demand'>
```



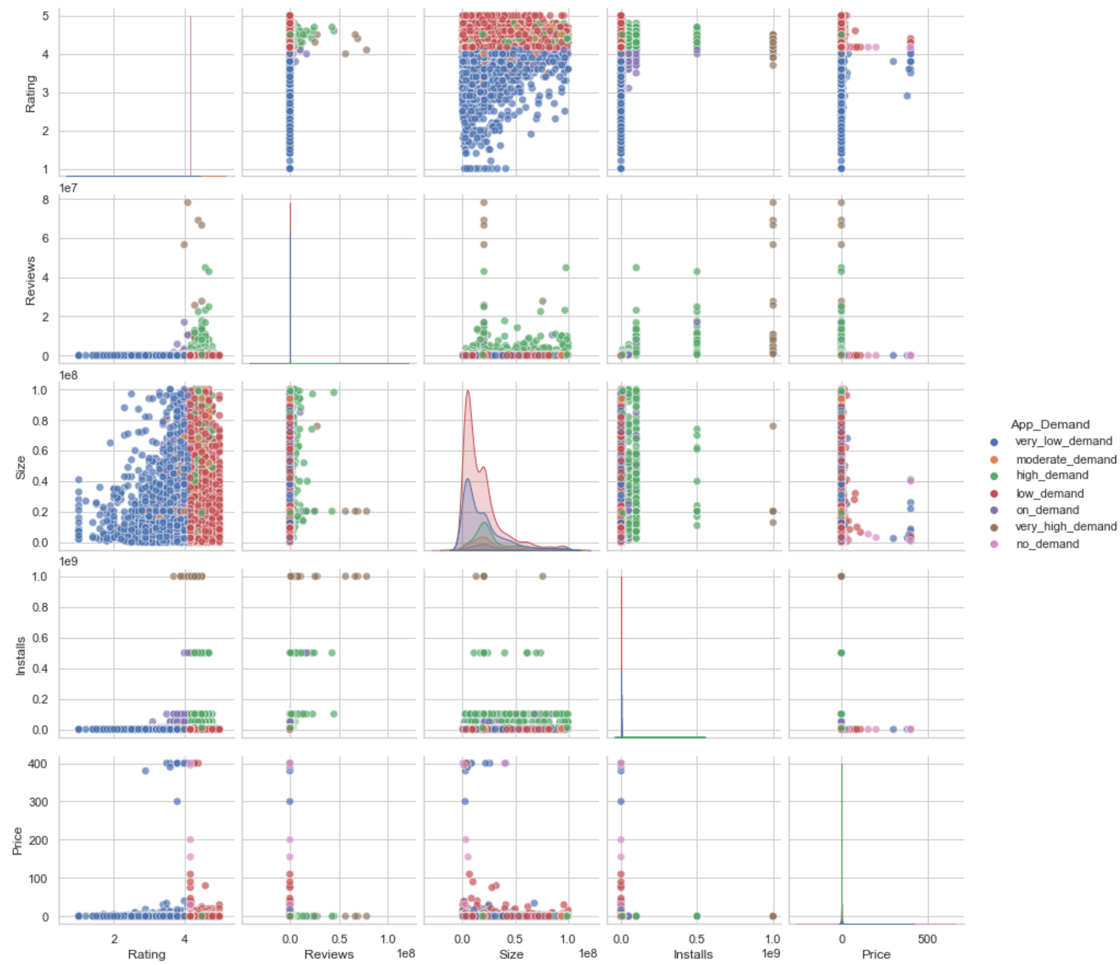
We will drop the 'Index' as we no longer need it.

[37]:
```
df = df.drop(['Index'], axis = 1)
```

Lets see a pair plot of the dataset with the target App_Demand

[38]:
```
sns.pairplot(data = df,hue = 'App_Demand', plot_kws={'alpha':0.7 , 's':50})
```

[38]:
```
<seaborn.axisgrid.PairGrid at 0x7fb7d1165f40>
```



7 7. Data Transformation

We know that we have some features with string values. Let's take a look into those distinguish values

[39]:
```
print(df['Category'].value_counts())
```

```
FAMILY                 1831
GAME                    959
TOOLS                   827
BUSINESS                420
MEDICAL                 395
PERSONALIZATION         376
PRODUCTIVITY            374
LIFESTYLE               369
FINANCE                 345
SPORTS                  325
```

```
COMMUNICATION           315
HEALTH_AND_FITNESS      288
PHOTOGRAPHY             281
NEWS_AND_MAGAZINES      254
SOCIAL                  239
BOOKS_AND_REFERENCE     222
TRAVEL_AND_LOCAL        219
SHOPPING                202
DATING                  171
VIDEO_PLAYERS           163
MAPS_AND_NAVIGATION     131
EDUCATION               119
FOOD_AND_DRINK          112
ENTERTAINMENT           102
AUTO_AND_VEHICLES        85
LIBRARIES_AND_DEMO       84
WEATHER                  79
HOUSE_AND_HOME           74
EVENTS                   64
ART_AND_DESIGN           64
PARENTING                60
COMICS                   56
BEAUTY                   53
Name: Category, dtype: int64
```

[40]:
```
print(df['Type'].value_counts())
```

```
Free    8902
Paid     756
Name: Type, dtype: int64
```

[41]:
```
print(df['Content Rating'].value_counts())
```

```
Everyone           7903
Teen               1036
Mature 17+          393
Everyone 10+        321
Adults only 18+       3
Unrated               2
Name: Content Rating, dtype: int64
```

[42]:
```
print(df['App_Demand'].value_counts())
```

```
low_demand          5103
very_low_demand     2563
high_demand         1071
moderate_demand      607
on_demand            280
```

```
very_high_demand      20
no_demand             14
Name: App_Demand, dtype: int64
```

It is now important to encode categorical labels into numerical values. So, the values/labels in the 'Category', 'Type', 'Content Rating' and 'App_Demand' need to be transformed and normalized, such that they contain only numerical values. For instance, 'App_Demand' will contain only values between 0 and 6. For this purpose, we use the LabelEncoder from sklearn.preprocessing library and fit the categories on it to get the numeric values.

[43]:
```
from sklearn.preprocessing import LabelEncoder
encode = LabelEncoder()

df['Category'] = encode.fit_transform(df['Category'])

df['Type'] = encode.fit_transform(df['Type'])

df['Content Rating'] = encode.fit_transform(df['Content Rating'])

df['App_Demand'] = encode.fit_transform(df['App_Demand'])
```

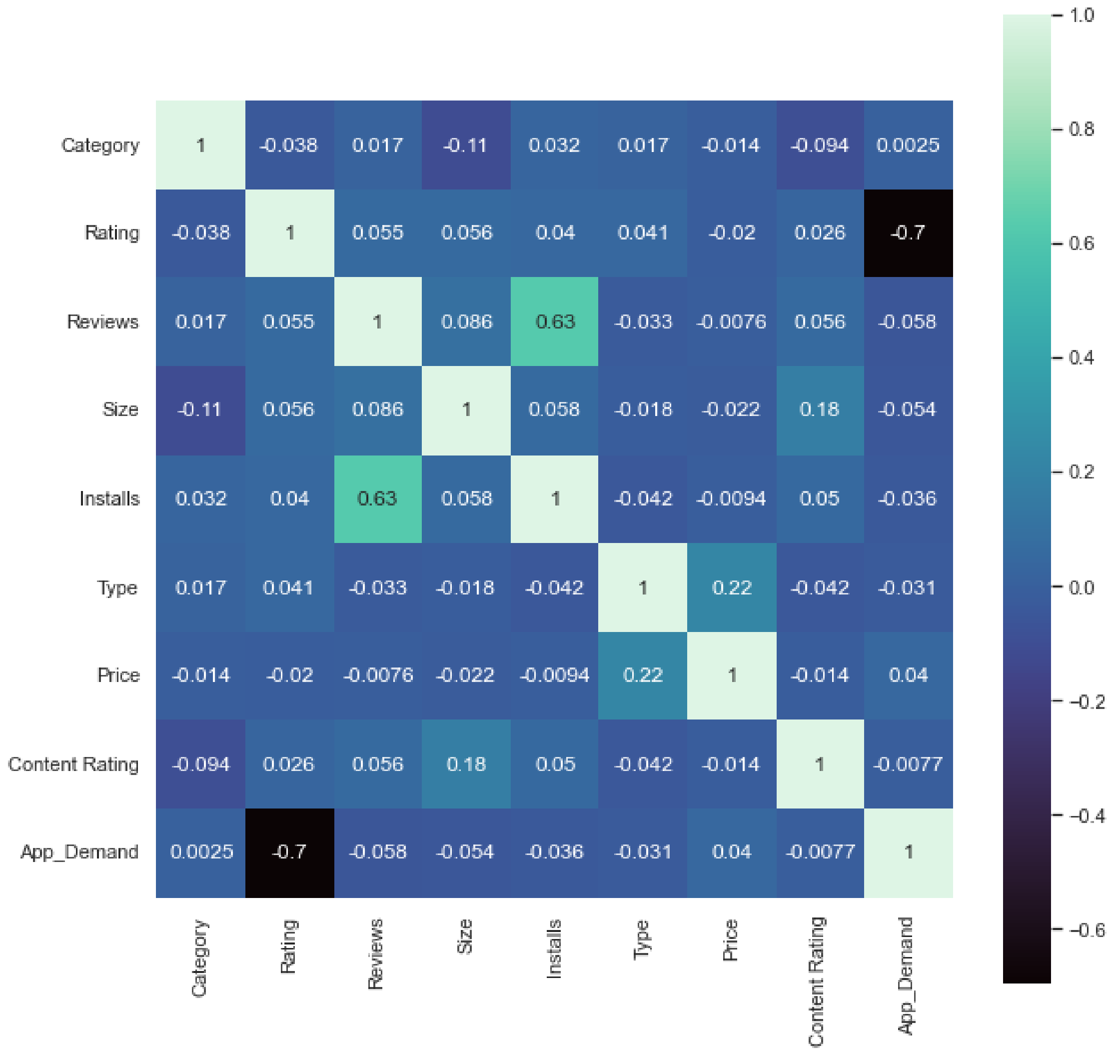
[44]:
```
df.head(3)
```

[44]:
```
   Category  Rating  Reviews        Size   Installs  Type  Price  \
0         0     4.1    159.0  19000000.0    10000.0     0    0.0
1         0     3.9    967.0  14000000.0   500000.0     0    0.0
2         0     4.7  87510.0   8700000.0  5000000.0     0    0.0

   Content Rating  App_Demand
0               1           6
1               1           6
2               1           2
```

8 8. Correlation Matrix

[45]:
```
plt.figure(figsize=(10,10))
cormat = df.corr()
sns.heatmap(cormat, annot= True, cmap='mako', square= True);
```



We can notice that almost all the features have no relationship with the target of classification 'App_Demand'. We can already assume that the classification models won't work. But we will continue and see the results.

We can also see that the target of regression model 'Rating' has low relationship with the other features. We can also assume that we will have bad regression.

9 9. Building the Models

First, we plan to develop K-Nearest Neighbor and Random Forrest Classifier models for classifying the apps into categories based on their demand. Second, we plan to develop a Random Forrest Regression model to predict the app rating.

9.1 9.1. Imorting the Libraries

[46]:
```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import RandomForestRegressor
```

[47]:
```
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import mean_squared_error
from sklearn.metrics import confusion_matrix
```

9.2 9.2. Classification Goal

9.2.1 9.2.1. Set Features and Target

We will specify X set of features and y feature which is the target. We will use features ('Category', 'Type', 'Price', 'Content Rating') as input variables, and the new feature (App_Demand) will be generated as output for our classification models. X will take all rows, and ('Category', 'Type', 'Price', 'Content Rating') columns. And y will take all rows, and only the last column 'App_Demand'.

[48]:
```
X = df[['Category', 'Type', 'Price', 'Content Rating']]
y = df.iloc[:, -1]
```

[49]:
```
X.head()
```

[49]:
```
   Category  Type  Price  Content Rating
0         0     0    0.0               1
1         0     0    0.0               1
2         0     0    0.0               1
3         0     0    0.0               4
4         0     0    0.0               1
```

[50]:
```
y.head()
```

[50]:
```
0    6
1    6
2    2
3    0
4    1
Name: App_Demand, dtype: int64
```

9.2.2 9.2.2. Splitting the Dataset

The dataset must be split into a training set and testing set. We will use the train_test_split() method to do splitting. We will set the test_size parameter 0.30.

[51]:
```python
#hold out 30% of the data for final testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.30,␣
↪random_state=42, stratify=y)
```

9.2.3 9.2.3. Feature Scaling

Before fitting the model, we need to scales and translates each feature on the training set to be in range between 0 and 1.

[52]:
```python
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
```

[53]:
```python
scaler.fit(X_train)
```

[53]:
```
MinMaxScaler()
```

9.2.4 9.2.4. Training and Evaluating the Models

9.2.5 9.2.4.1. K-Nearest Neighbor Classifier

Best Value of K Tuning Using Cross-Validation

[54]:
```python
#search for an optimal value of K for KNN
from sklearn.model_selection import cross_val_score

neighbors = list(range(0, 300, 5))
k_scores = []
for k in neighbors:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X_train, y_train, cv=10, scoring='accuracy')
    k_scores.append(scores.mean())
print(k_scores)
```

```
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py:615: FitFailedWarning: Estimator
fit failed. The score on this train-test partition for these parameters will be
set to nan. Details:
Traceback (most recent call last):
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py", line 598, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_classification.py", line 179, in fit
    return self._fit(X, y)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_base.py", line 514, in _fit
    raise ValueError(
ValueError: Expected n_neighbors > 0. Got 0
```

```
  warnings.warn("Estimator fit failed. The score on this train-test"
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py:615: FitFailedWarning: Estimator
fit failed. The score on this train-test partition for these parameters will be
set to nan. Details:
Traceback (most recent call last):
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
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    estimator.fit(X_train, y_train, **fit_params)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
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set to nan. Details:
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packages/sklearn/model_selection/_validation.py", line 598, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_classification.py", line 179, in fit
    return self._fit(X, y)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_base.py", line 514, in _fit
    raise ValueError(
ValueError: Expected n_neighbors > 0. Got 0

  warnings.warn("Estimator fit failed. The score on this train-test"
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py:615: FitFailedWarning: Estimator
fit failed. The score on this train-test partition for these parameters will be
set to nan. Details:
Traceback (most recent call last):
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py", line 598, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_classification.py", line 179, in fit
    return self._fit(X, y)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_base.py", line 514, in _fit
```

```
    raise ValueError(
ValueError: Expected n_neighbors > 0. Got 0

  warnings.warn("Estimator fit failed. The score on this train-test"
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py:615: FitFailedWarning: Estimator
fit failed. The score on this train-test partition for these parameters will be
set to nan. Details:
Traceback (most recent call last):
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py", line 598, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_classification.py", line 179, in fit
    return self._fit(X, y)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_base.py", line 514, in _fit
    raise ValueError(
ValueError: Expected n_neighbors > 0. Got 0

  warnings.warn("Estimator fit failed. The score on this train-test"
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py:615: FitFailedWarning: Estimator
fit failed. The score on this train-test partition for these parameters will be
set to nan. Details:
Traceback (most recent call last):
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  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_classification.py", line 179, in fit
    return self._fit(X, y)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_base.py", line 514, in _fit
    raise ValueError(
ValueError: Expected n_neighbors > 0. Got 0

  warnings.warn("Estimator fit failed. The score on this train-test"
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py:615: FitFailedWarning: Estimator
fit failed. The score on this train-test partition for these parameters will be
set to nan. Details:
Traceback (most recent call last):
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py", line 598, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_classification.py", line 179, in fit
```

```
    return self._fit(X, y)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_base.py", line 514, in _fit
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ValueError: Expected n_neighbors > 0. Got 0

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/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py:615: FitFailedWarning: Estimator
fit failed. The score on this train-test partition for these parameters will be
set to nan. Details:
Traceback (most recent call last):
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py", line 598, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_classification.py", line 179, in fit
    return self._fit(X, y)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_base.py", line 514, in _fit
    raise ValueError(
ValueError: Expected n_neighbors > 0. Got 0

  warnings.warn("Estimator fit failed. The score on this train-test"
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py:615: FitFailedWarning: Estimator
fit failed. The score on this train-test partition for these parameters will be
set to nan. Details:
Traceback (most recent call last):
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packages/sklearn/model_selection/_validation.py", line 598, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
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packages/sklearn/neighbors/_base.py", line 514, in _fit
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ValueError: Expected n_neighbors > 0. Got 0

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/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py:615: FitFailedWarning: Estimator
fit failed. The score on this train-test partition for these parameters will be
set to nan. Details:
Traceback (most recent call last):
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py", line 598, in _fit_and_score
```
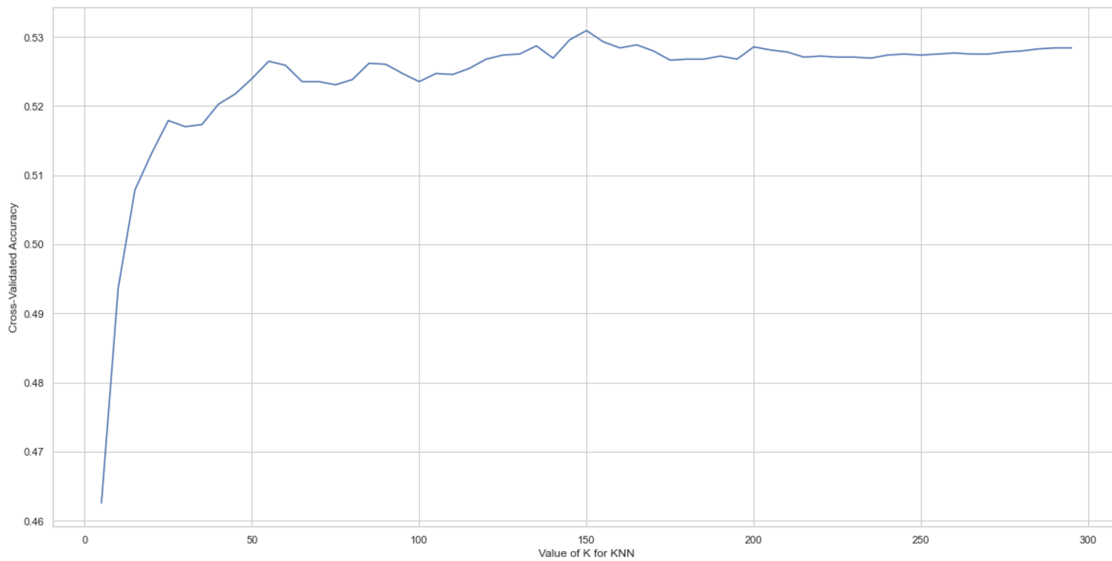

```
    estimator.fit(X_train, y_train, **fit_params)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_classification.py", line 179, in fit
    return self._fit(X, y)
  File "/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/neighbors/_base.py", line 514, in _fit
    raise ValueError(
ValueError: Expected n_neighbors > 0. Got 0

  warnings.warn("Estimator fit failed. The score on this train-test"
```

```
[nan, 0.4625739644970414, 0.4936390532544378, 0.5078402366863906,
0.5131656804733727, 0.5178994082840236, 0.5170118343195267, 0.5173076923076924,
0.5202662721893491, 0.5217455621301774, 0.5239644970414201, 0.5264792899408283,
0.525887573964497, 0.5235207100591716, 0.5235207100591717, 0.5230769230769232,
0.5238165680473373, 0.5261834319526627, 0.5260355029585798, 0.5247041420118344,
0.5235207100591716, 0.5247041420118344, 0.5245562130177515, 0.5254437869822484,
0.5267751479289939, 0.5273668639053255, 0.5275147928994082, 0.528698224852071,
0.5269230769230768, 0.5295857988165681, 0.5309171597633137, 0.5292899408284024,
0.5284023668639053, 0.5288461538461539, 0.5279585798816567, 0.5266272189349113,
0.5267751479289939, 0.526775147928994, 0.5272189349112426, 0.5267751479289942,
0.5285502958579882, 0.5281065088757397, 0.5278106508875741, 0.5270710059171598,
0.5272189349112427, 0.5270710059171598, 0.5270710059171598, 0.526923076923077,
0.5273668639053255, 0.5275147928994084, 0.5273668639053255, 0.5275147928994084,
0.5276627218934913, 0.5275147928994084, 0.5275147928994084, 0.5278106508875741,
0.527958579881657, 0.5282544378698226, 0.5284023668639054, 0.5284023668639054]
```

[55]:
```python
# plot the value of K for KNN (x-axis) versus the cross-validated accuracy␣
↪(y-axis)
import matplotlib.pyplot as plt
plt.plot(neighbors, k_scores)
plt.xlabel('Value of K for KNN')
plt.ylabel('Cross-Validated Accuracy')
```

[55]:
```
Text(0, 0.5, 'Cross-Validated Accuracy')
```



The best result is nearly at k=145

Building the Model (1st Trial)

[56]:
```
knn1 = KNeighborsClassifier(n_neighbors=150)
knn1.fit(X_train, y_train)
```

[56]:
```
KNeighborsClassifier(n_neighbors=150)
```

[57]:
```
y_predknn1 = knn1.predict(X_test)
```

[58]:
```
knn1.predict([[4, 1, 3, 2]])
```

[58]:
```
array([1])
```

Evaluating the 1st Trial

[59]:
```
print("KNN Training Set Accuracy:", metrics.accuracy_score(y_train, knn1.
 ↪predict(X_train)))
print("KNN Testing Set Accuracy:", metrics.accuracy_score(y_test, y_predknn1))
print("Classification Report of KNN:\n", classification_report(y_test,␣
 ↪y_predknn1))
print("Confusion Matrix of KNN:\n", confusion_matrix(y_test, y_predknn1))
```

```
KNN Training Set Accuracy: 0.531508875739645
KNN Testing Set Accuracy: 0.525879917184265
Classification Report of KNN:
               precision    recall  f1-score   support

           0       0.27      0.10      0.15       322
```

```
             1       0.54      0.97      0.69      1531
             2       0.00      0.00      0.00       182
             3       0.00      0.00      0.00         4
             4       0.00      0.00      0.00        84
             5       0.00      0.00      0.00         6
             6       0.00      0.00      0.00       769

      accuracy                           0.53      2898
     macro avg       0.12      0.15      0.12      2898
  weighted avg       0.31      0.53      0.38      2898

Confusion Matrix of KNN:
 [[  33  289    0    0    0    0    0]
 [  38 1491    0    0    0    0    2]
 [   9  173    0    0    0    0    0]
 [   0    4    0    0    0    0    0]
 [   7   77    0    0    0    0    0]
 [   1    5    0    0    0    0    0]
 [  35  734    0    0    0    0    0]]
```

```
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/metrics/_classification.py:1248: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/metrics/_classification.py:1248: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/metrics/_classification.py:1248: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

As shown in the confusion matrix; there is clearly a bias towards the class of 1. Which means that the dataset is maybe imbalanced.

Rsampling the Dataset Using SMOTE - Synthetic Minority Oversampling TEchnique
Let's take a look to the target class of our dataset

[60]:
```
y.value_counts()
```

[60]:
```
1    5103
6    2563
0    1071
2     607
```

```
4     280
5      20
3      14
Name: App_Demand, dtype: int64
```

[61]:
```
y_train.value_counts()
```

[61]:
```
1    3572
6    1794
0     749
2     425
4     196
5      14
3      10
Name: App_Demand, dtype: int64
```

We can notice that clearly the dataset is imbalanced. We will apply SMOTE - Synthetic Minority Oversampling TEchnique on the imbalanced dataset to resample it.

[62]:
```
from imblearn.over_sampling import SMOTE
sm=SMOTE(random_state=42)
X_smoted, y_smoted =sm.fit_resample(X_train,y_train)
```

Now let's check the target class value counts

[63]:
```
y_smoted.value_counts()
```

[63]:
```
6    3572
2    3572
1    3572
4    3572
0    3572
5    3572
3    3572
Name: App_Demand, dtype: int64
```

Best Value of K Tuning Using Cross-Validation

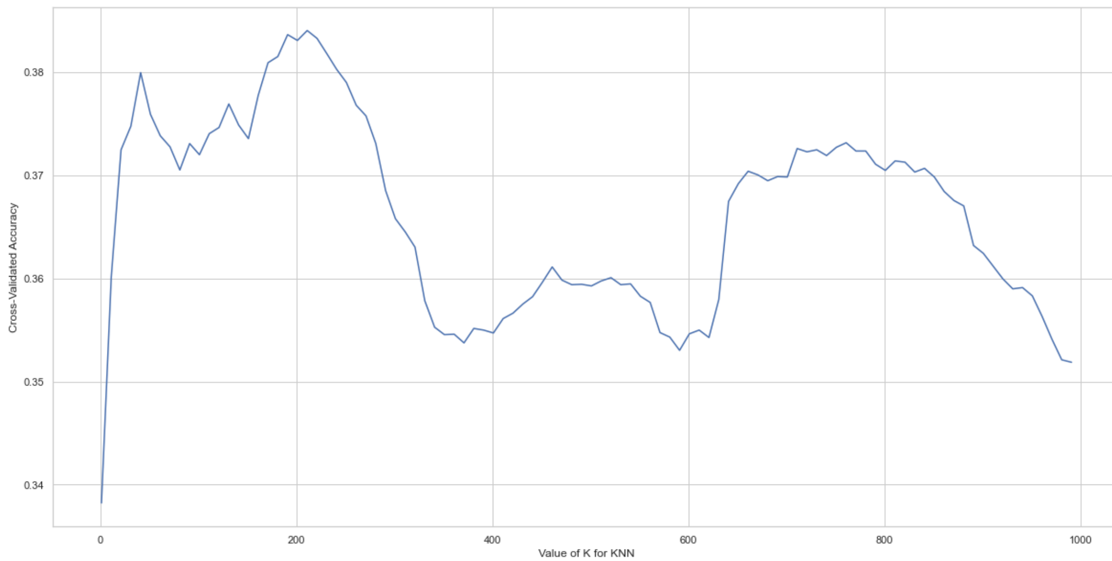
[64]:
```
#search for an optimal value of K for KNN
neighbors = list(range(1, 1000, 10))
k_scores = []
for k in neighbors:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X_smoted, y_smoted, cv=10, scoring='accuracy')
    k_scores.append(scores.mean())
print(k_scores)
```

```
[0.3382266613354658, 0.360103606557377, 0.37246163934426224,
```

```
0.37474159136345464, 0.3799400719712115, 0.3759011275489804,
0.37382175129948025, 0.3727418632546981, 0.3705019432227109, 0.373061287485006,
0.37198117552978804, 0.3740205357856857, 0.3746204398240704,
0.37690026389444226, 0.37486040783686525, 0.3735405517792883,
0.3777398320671731, 0.3808987604958016, 0.3814993522590963, 0.3836189044382247,
0.383058856457417, 0.3840186005597761, 0.3832587445021991, 0.3817790323870452,
0.380259112355058, 0.37897903238704517, 0.37677964014394244, 0.3757395761695322,
0.3730601999200319, 0.3685009036385446, 0.3657812235105958, 0.36450136745301875,
0.3630215753698521, 0.35782261495401835, 0.3552629348260696, 0.3545431267493003,
0.3545830787684926, 0.35374311075569775, 0.3551427588964414, 0.3549828868452619,
0.35470299880047984, 0.35610287085165926, 0.35662267892842864,
0.35750240703718517, 0.35822253498600554, 0.3596225349860056,
0.36110266293482607, 0.3598229028388644, 0.35938293482606953,
0.3594229348260696, 0.35926295081967213, 0.3597426949220312, 0.360062662934826,
0.3593828068772491, 0.35946271091563375, 0.35826266293482606,
0.35766312674930034, 0.35474322271091563, 0.35430347860855654,
0.3530235425829668, 0.3546232227109156, 0.35498315873650543,
0.35426341463414635, 0.35794251899240304, 0.367460343862455, 0.3691807277089164,
0.3703809676129548, 0.37002087165133946, 0.3694609676129548, 0.3698609356257497,
0.36982083966413437, 0.37258042383046786, 0.37226058376649335,
0.37246067972810876, 0.3719010475809676, 0.3727005517792883, 0.3731403758496601,
0.37234048780487805, 0.37234063174730114, 0.3710608716513395,
0.3704610155937625, 0.37138061575369846, 0.3712605677728909, 0.3703004238304678,
0.37066034386245506, 0.3698202798880447, 0.36842042383046775,
0.36754035985605754, 0.36702029588164736, 0.36318167133146745,
0.3624216393442623, 0.36118192722910836, 0.35994187924830073,
0.35898203918432625, 0.35910223110755696, 0.3583021031587365,
0.35630259896041583, 0.3541028388644542, 0.3521029668132747,
0.35186296681327467]
```

[65]:
```
# plot the value of K for KNN (x-axis) versus the cross-validated accuracy␣
↪(y-axis)
import matplotlib.pyplot as plt
plt.plot(neighbors, k_scores)
plt.xlabel('Value of K for KNN')
plt.ylabel('Cross-Validated Accuracy')
```

[65]: Text(0, 0.5, 'Cross-Validated Accuracy')



Building the Model (2nd Trial) We will build the model now using resampled dataset

[66]:
```
knn2 = KNeighborsClassifier(n_neighbors=220)
knn2.fit(X_smoted, y_smoted)
```

[66]:
```
KNeighborsClassifier(n_neighbors=220)
```

[67]:
```
y_predknn2 = knn2.predict(X_test)
```

Evaluating the 2nd Trial

[68]:
```
print("KNN Training Set Accuracy:", metrics.accuracy_score(y_smoted, knn2.
 ↪predict(X_smoted)))
print("KNN Testing Set Accuracy:", metrics.accuracy_score(y_test, y_predknn2))
print("Classification Report of KNN:\n", classification_report(y_test,␣
 ↪y_predknn2))
print("Confusion Matrix of KNN:\n", confusion_matrix(y_test, y_predknn2))
```

```
KNN Training Set Accuracy: 0.3874980003199488
KNN Testing Set Accuracy: 0.3053830227743271
Classification Report of KNN:
               precision    recall  f1-score   support

           0       0.19      0.61      0.28       322
           1       0.61      0.41      0.49      1531
           2       0.09      0.17      0.12       182
           3       0.01      0.75      0.03         4
           4       0.04      0.02      0.03        84
           5       0.01      0.17      0.02         6
```

```
           6       0.32      0.04      0.07       769

    accuracy                           0.31      2898
   macro avg       0.18      0.31      0.15      2898
weighted avg       0.43      0.31      0.32      2898

Confusion Matrix of KNN:
 [[196  49  44   1   9  20   3]
 [445 623 176 170  16  47  54]
 [ 78  52  31   0   7  11   3]
 [  0   0   0   3   0   0   1]
 [ 47  19   9   0   2   7   0]
 [  4   1   0   0   0   1   0]
 [287 282  95  42  11  23  29]]
```

We somhow fixed the imbalance of the dataset, but the the accuracy is worse.

9.2.6 9.2.4.2. Random Forrest Classifier

Building the Model (1st Trial)

[69]:
```python
RF1 = RandomForestClassifier(n_estimators = 1000, criterion = 'entropy',␣
↪random_state = 42)
RF1.fit(X_train, y_train)
```

[69]:
```
RandomForestClassifier(criterion='entropy', n_estimators=1000, random_state=42)
```

[71]:
```python
y_predRF1 = RF1.predict(X_test)
```

Evaluating the 1st Trial

[72]:
```python
print("RF Training Set Accuracy:", metrics.accuracy_score(y_train, RF1.
↪predict(X_train)))
print("RF Testing Set Accuracy:", metrics.accuracy_score(y_test, y_predRF1))
print("Classification Report of RF:\n", classification_report(y_test,␣
↪y_predRF1))
print("Confusion Matrix of RF:\n", confusion_matrix(y_test, y_predRF1))
```

```
RF Training Set Accuracy: 0.5455621301775148
RF Testing Set Accuracy: 0.5158730158730159
Classification Report of RF:
               precision    recall  f1-score   support

           0       0.25      0.12      0.16       322
           1       0.54      0.92      0.68      1531
           2       0.00      0.00      0.00       182
           3       0.00      0.00      0.00         4
           4       0.00      0.00      0.00        84
           5       0.00      0.00      0.00         6
```

```
           6       0.31      0.06      0.10       769

    accuracy                           0.52      2898
   macro avg       0.16      0.16      0.14      2898
weighted avg       0.40      0.52      0.41      2898

Confusion Matrix of RF:
 [[  39  266    1    0    0    0   16]
 [  51 1411    1    0    0    0   68]
 [  14  155    0    0    0    0   13]
 [   0    4    0    0    0    0    0]
 [  13   66    0    0    0    0    5]
 [   2    4    0    0    0    0    0]
 [  40  683    1    0    0    0   45]]
```

```
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/metrics/_classification.py:1248: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/metrics/_classification.py:1248: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/hessaalhamad/opt/anaconda3/lib/python3.9/site-
packages/sklearn/metrics/_classification.py:1248: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

The Random Forrest performed almost as acccurate as KNN but with no bias towards the class of 1. But still, there are some missing classes. So, the model must be build on balanced dataset.

Building the Model (2nd Trial) We will use (class weight) in Random Forest classifier to see if it solve the problem of imbalanced dataset

[73]:
```
RF2 = RandomForestClassifier(n_estimators = 1000, criterion = 'entropy',␣
 ↪random_state = 42, class_weight= 'balanced')
RF2.fit(X_train, y_train)
```

[73]:
```
RandomForestClassifier(class_weight='balanced', criterion='entropy',
                       n_estimators=1000, random_state=42)
```

[74]:
```
y_predRF2 = RF2.predict(X_test)
```

Evaluating the 2nd Trial

```
[75]: print("RF Training Set Accuracy:", metrics.accuracy_score(y_train, RF2.
        ↪predict(X_train)))
      print("RF Testing Set Accuracy:", metrics.accuracy_score(y_test, y_predRF2))
      print("Classification Report of RF:\n", classification_report(y_test,␣
        ↪y_predRF2))
      print("Confusion Matrix of RF:\n", confusion_matrix(y_test, y_predRF2))
```

```
RF Training Set Accuracy: 0.28816568047337277
RF Testing Set Accuracy: 0.25086266390614215
Classification Report of RF:
               precision    recall  f1-score   support

           0       0.25      0.43      0.32       322
           1       0.73      0.21      0.33      1531
           2       0.07      0.13      0.09       182
           3       0.00      0.00      0.00         4
           4       0.05      0.24      0.08        84
           5       0.02      0.50      0.03         6
           6       0.29      0.29      0.29       769

    accuracy                           0.25      2898
   macro avg       0.20      0.26      0.16      2898
weighted avg       0.50      0.25      0.29      2898

Confusion Matrix of RF:
 [[139   8  51   4  51  30  39]
 [217 321 179 125 191  62 436]
 [ 40   9  24   4  32  27  46]
 [  0   3   0   0   0   0   1]
 [ 25   3   9   1  20  10  16]
 [  2   0   0   0   1   3   0]
 [129  96  80  52 138  54 220]]
```

We somhow fixed the imbalance of the dataset, but the the accuracy is also worse.

Building the Model (3rd Trial) We will build the model now using resampled dataset

```
[76]: RF3 = RandomForestClassifier(n_estimators = 1000, criterion = 'entropy',␣
        ↪random_state = 42)
      RF3.fit(X_smoted, y_smoted)
```

```
[76]: RandomForestClassifier(criterion='entropy', n_estimators=1000, random_state=42)
```

```
[77]: y_predRF3 = RF3.predict(X_test)
```

Evaluating the 3rd Trial

[78]:
```
print("RF Training Set Accuracy:", metrics.accuracy_score(y_smoted, RF2.
 ↪predict(X_smoted)))
print("RF Testing Set Accuracy:", metrics.accuracy_score(y_test, y_predRF3))
print("Classification Report of RF:\n", classification_report(y_test,␣
 ↪y_predRF3))
print("Confusion Matrix of RF:\n", confusion_matrix(y_test, y_predRF3))
```

```
RF Training Set Accuracy: 0.28943369060950247
RF Testing Set Accuracy: 0.28778467908902694
Classification Report of RF:
               precision    recall  f1-score   support

           0       0.25      0.42      0.31       322
           1       0.71      0.28      0.40      1531
           2       0.07      0.13      0.09       182
           3       0.11      0.75      0.19         4
           4       0.06      0.29      0.09        84
           5       0.02      0.50      0.03         6
           6       0.29      0.28      0.29       769

    accuracy                           0.29      2898
   macro avg       0.21      0.38      0.20      2898
weighted avg       0.49      0.29      0.33      2898

Confusion Matrix of RF:
 [[135  12  53   2  51  34  35]
 [219 429 181  18 183  72 429]
 [ 43  14  24   0  34  22  45]
 [  0   1   0   3   0   0   0]
 [ 23   3   9   0  24   9  16]
 [  1   0   1   0   1   3   0]
 [129 141  79   4 143  57 216]]
```

Although the testing set performed better than the second trial; the results are still not good.

9.3 9.3. Regression Goal

Data Transformation Before building the regression model, we need to log-transform the 'Installs' column, in order to make it more 'Normal'. Since there are apps with 0 installs, we wil transform it with log(x+1) transform.

[79]:
```
df['Installs']=np.log(df['Installs'] + 1)
```

Target Values Now, let's check the value counts of the 'Rating' column

[80]:
```
df['Rating'].value_counts()
```

[80]:
```
4.175052    1462
4.300000     897
4.400000     895
4.500000     848
4.200000     810
4.600000     683
4.100000     621
4.000000     513
4.700000     442
3.900000     359
3.800000     286
5.000000     271
3.700000     224
4.800000     221
3.600000     167
3.500000     156
3.400000     126
3.300000     100
4.900000      85
3.000000      81
3.100000      69
3.200000      63
2.900000      45
2.800000      40
2.600000      24
2.700000      23
2.500000      20
2.300000      20
2.400000      19
1.000000      16
2.200000      14
2.000000      12
1.900000      11
1.700000       8
1.800000       8
2.100000       8
1.600000       4
1.400000       3
1.500000       3
1.200000       1
Name: Rating, dtype: int64
```

There is only one data point with the value '1.200000'. This could make the learning model bias and not fit. So, we need to drop it.

[81]:
```
#We need to locate it
df.loc[(df['Rating'] == 1.200000)]
```

[81]:
```
      Category  Rating  Reviews        Size  Installs  Type  Price  \
8922        12     1.2     44.0  27000000.0  6.908755     0    0.0

      Content Rating  App_Demand
8922               1           6
```

[82]:
```
#Need to be dropped
df= df.drop(8922)
```

[83]:
```
#Check the value counts again
df['Rating'].value_counts()
```

[83]:
```
4.175052    1462
4.300000     897
4.400000     895
4.500000     848
4.200000     810
4.600000     683
4.100000     621
4.000000     513
4.700000     442
3.900000     359
3.800000     286
5.000000     271
3.700000     224
4.800000     221
3.600000     167
3.500000     156
3.400000     126
3.300000     100
4.900000      85
3.000000      81
3.100000      69
3.200000      63
2.900000      45
2.800000      40
2.600000      24
2.700000      23
2.500000      20
2.300000      20
2.400000      19
1.000000      16
2.200000      14
2.000000      12
1.900000      11
1.700000       8
1.800000       8
```

```
2.100000        8
1.600000        4
1.400000        3
1.500000        3
Name: Rating, dtype: int64
```

9.3.1 9.3.1. Set Features and Target

We will specify X set of fetures and y feature which is the target. We will all remaining features exept ('Rating' and 'App_Demand') as input variables, and the feature (Rating) will be generated as output for our regression model. X will take all rows, and all columns expect tha new one 'App_Demand' and the 'Rating' column because it's the output(y). And y will take all rows, and only the column 'Rating'.

[84]:
```
X1 =df.drop(['Rating','App_Demand'] , axis = 1)
y1 =df['Rating']
```

9.3.2 9.3.2. Splitting the Dataset

The dataset must be split into a training set and testing set. We will use the train_test_split() method to do splitting. We will set the test_size parameter 0.30 for now, later on, we will run many experiments with different amounts of the test_size parameter.

[85]:
```
#hold out 30% of the data for final testing
X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, test_size=.30,␣
↪random_state=42)
```

9.3.3 9.3.3. Features Scaling

Before fitting the model, we need to scales and translates each feature on the training set to be in range between 0 and 1.

[86]:
```
scaler = MinMaxScaler()
```

[87]:
```
scaler.fit(X_train1)
```

[87]:
```
MinMaxScaler()
```

[89]:
```
X_train1 = scaler.transform(X_train1)
X_test1 = scaler.transform(X_test1)
```

9.3.4 9.3.4. Training and Evaluating the Models

Building the Model

[90]:
```
RFR1 = RandomForestRegressor()
RFR1.fit(X_train1,y_train1)
```

[90]: RandomForestRegressor()

[91]:
```
y_predRFR1 = RFR1.predict(X_test1)
```

[92]:
```
RFR1.predict([[4, 3, 4, 50000, 1, 3, 2]])
```

[92]: array([4.427])

Evaluating the Model

[93]:
```
mseRFR1 = mean_squared_error(y_test1, y_predRFR1)
print("RMSE using RFR: ", np.sqrt(mseRFR1))
```

```
RMSE using RFR:  0.46971027534528054
```

9.3.5 9.3.5. Different Splitting of the Dataset.

In these experiments, we will change the dataset split size for the regression model each time to see if the results are affected by the way of split or not.

Training set > Testing set (15)

[96]:
```
#hold out 15% of the data for final testing
X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, test_size=.15,␣
↪random_state=42)
```

[97]:
```
X_train1 = scaler.transform(X_train1)
X_test1 = scaler.transform(X_test1)
```

[98]:
```
RFR2 = RandomForestRegressor()
RFR2.fit(X_train1,y_train1)
```

[98]: RandomForestRegressor()

[99]:
```
y_predRFR2 = RFR2.predict(X_test1)
```

[100]:
```
mseRFR2 = mean_squared_error(y_test1, y_predRFR2)
print("RMSE using RFR: ", np.sqrt(mseRFR2))
```

```
RMSE using RFR:  0.45493198981234695
```

Training set = Testing set (50)

[101]:
```
#hold out 50% of the data for final testing
X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, test_size=.50,␣
↪random_state=42)
```

[102]:
```
X_train1 = scaler.transform(X_train1)
X_test1 = scaler.transform(X_test1)
```

[103]:
```
RFR3 = RandomForestRegressor()
RFR3.fit(X_train1,y_train1)
```

[103]:
```
RandomForestRegressor()
```

[104]:
```
y_predRFR3 = RFR3.predict(X_test1)
```

[105]:
```
mseRFR3 = mean_squared_error(y_test1, y_predRFR3)
print("RMSE using RFR: ", np.sqrt(mseRFR3))
```

```
RMSE using RFR:  0.49064546580455526
```

Training set < Testing set (75)

[106]:
```
#hold out 75% of the data for final testing
X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, test_size=.75,␣
↪random_state=42)
```

[107]:
```
X_train1 = scaler.transform(X_train1)
X_test1 = scaler.transform(X_test1)
```

[108]:
```
RFR4 = RandomForestRegressor()
RFR4.fit(X_train1,y_train1)
```

[108]:
```
RandomForestRegressor()
```

[109]:
```
y_predRFR4 = RFR4.predict(X_test1)
```

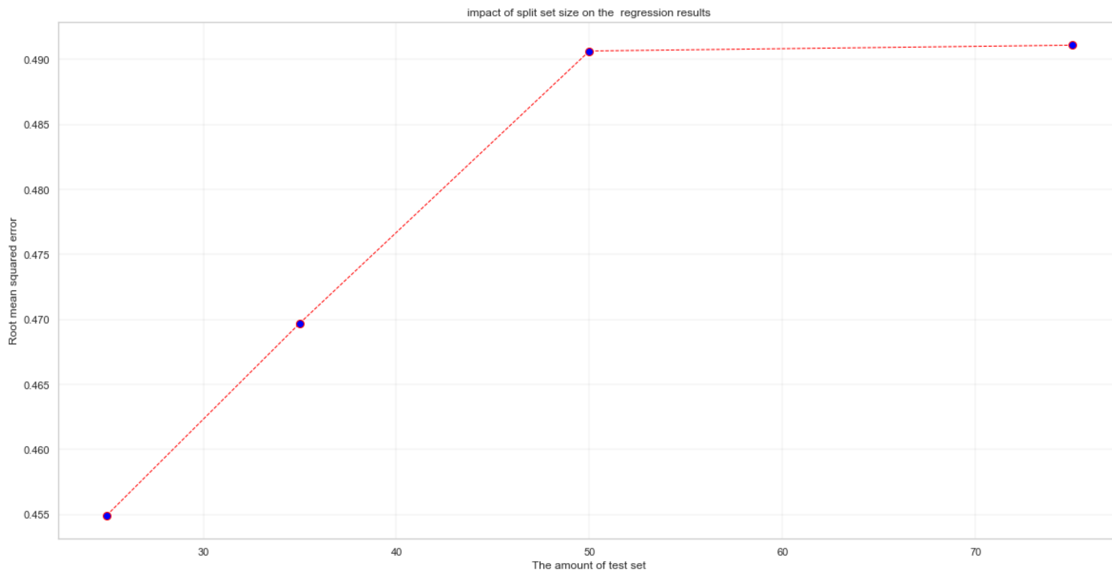
[110]:
```
mseRFR4 = mean_squared_error(y_test1, y_predRFR4)
print("RMSE using RFR: ", np.sqrt(mseRFR4))
```

```
RMSE using RFR:  0.49109259386519327
```

Now let's visulize the testing set size VS. regression RMSE

[111]:
```
# x axis values
a = [25, 35, 50, 75] #the test set size
#corresponding y axis values
b = [np.sqrt(mseRFR2), np.sqrt(mseRFR1), np.sqrt(mseRFR3), np.sqrt(mseRFR4)]␣
↪#refression results



plt.grid(color='grey', linestyle='-', linewidth=0.25, alpha=0.5)

plt.plot(a, b, color='red', linestyle='dashed', linewidth = 1,
         marker='o', markerfacecolor='blue', markersize=8)

#naming the x axis
```

```python
plt.xlabel('The amount of test set')
# naming the y axis
plt.ylabel('Root mean squared error')

#giving a title to my graph
plt.title('impact of split set size on the  regression results')

#function to show the plot
plt.show()
```



The above figure shows that the RMSE is at its lowest at the less test size which means that it gave the best regression.

10 10. Tools

In this project, we used the following tools: - Anaconda Navigator 2.1.1/ Jupyter Notebook 6.4.5 for implementing both algorithms and creating the models. - Set of libraries for modeling and visualization. In principle we are going to import these libraries : (Panda, Numpy, Matpoltlib, Seaborn, Scikit-learn).

11 11. Conclusions

Depending on this dataset we could not predict the demand of apps based on their category, type, price and content rating. We attribute that to some reasons:

- The dataset is highly imbalanced.
- There were no strong relationships among features.

Regarding the predicting of the rating, we –somehow- reach some reasonable results. For further, we suggest building different regression algorithms to find the best result.