APP RATING PREDICTION

Objective: Make a model to predict the app rating, with other information about the app provided.

Problem Statement:

Google Play Store team is about to launch a new feature wherein, certain apps that are promising, are boosted in visibility. The boost will manifest in multiple ways including higher priority in recommendations sections (“Similar apps”, “You might also like”, “New and updated games”). These will also get a boost in search results visibility. This feature will help bring more attention to newer apps that have the potential.

Steps to perform:

1.Load the data file using pandas

```
import pandas as pd

import numpy as np

import seaborn as sns

df=pd.read_csv("googleplaystore.csv")

df.head()
```

```
                                                 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

  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

                     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

    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
```

```
df.tail()
```

```
                                                 App
Category  \
10836                                Sya9a Maroc - FR
FAMILY
10837                Fr. Mike Schmitz Audio Teachings
FAMILY
10838                          Parkinson Exercices FR
MEDICAL
10839                   The SCP Foundation DB fr nn5n
BOOKS_AND_REFERENCE
10840  iHoroscope - 2018 Daily Horoscope & Astrology
LIFESTYLE

       Rating Reviews                Size     Installs  Type Price  \
10836     4.5      38                 53M       5,000+  Free     0
10837     5.0       4                3.6M         100+  Free     0
10838     NaN       3                9.5M       1,000+  Free     0
10839     4.5     114  Varies with device       1,000+  Free     0
10840     4.5  398307                 19M  10,000,000+  Free     0

      Content Rating            Genres      Last Updated
Current Ver  \
10836       Everyone         Education     July 25, 2017
1.48
10837       Everyone         Education      July 6, 2018
1.0
10838       Everyone           Medical  January 20, 2017
1.0
10839     Mature 17+  Books & Reference  January 19, 2015  Varies with
device
10840       Everyone         Lifestyle     July 25, 2018  Varies with
device

              Android Ver
10836          4.1 and up
10837          4.1 and up
10838          2.2 and up
10839  Varies with device
10840  Varies with device
```

2.Check for null values in the data. Get the number of null values for each column.

```
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
```

```
df.isnull().sum()
```

```
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
```

3.Drop records with nulls in any of the columns.

```
df.dropna(inplace=True)
df.isnull().sum()
```

```
App               0
Category          0
Rating            0
Reviews           0
Size              0
```

```
Installs          0
Type              0
Price             0
Content Rating    0
Genres            0
Last Updated      0
Current Ver       0
Android Ver       0
dtype: int64
```

4.Variables seem to have incorrect type and inconsistent formatting. You need to fix them:

4.1.Size column has sizes in Kb as well as Mb. To analyze, you'll need to convert these to numeric.

```
df['Size'].unique()
```

```
array(['19M', '14M', '8.7M', '25M', '2.8M', '5.6M', '29M', '33M',
'3.1M',
       '28M', '12M', '20M', '21M', '37M', '5.5M', '17M', '39M', '31M',
       '4.2M', '23M', '6.0M', '6.1M', '4.6M', '9.2M', '5.2M', '11M',
       '24M', 'Varies with device', '9.4M', '15M', '10M', '1.2M',
'26M',
       '8.0M', '7.9M', '56M', '57M', '35M', '54M', '201k', '3.6M',
'5.7M',
       '8.6M', '2.4M', '27M', '2.7M', '2.5M', '7.0M', '16M', '3.4M',
       '8.9M', '3.9M', '2.9M', '38M', '32M', '5.4M', '18M', '1.1M',
       '2.2M', '4.5M', '9.8M', '52M', '9.0M', '6.7M', '30M', '2.6M',
       '7.1M', '22M', '6.4M', '3.2M', '8.2M', '4.9M', '9.5M', '5.0M',
       '5.9M', '13M', '73M', '6.8M', '3.5M', '4.0M', '2.3M', '2.1M',
       '42M', '9.1M', '55M', '23k', '7.3M', '6.5M', '1.5M', '7.5M',
'51M',
       '41M', '48M', '8.5M', '46M', '8.3M', '4.3M', '4.7M', '3.3M',
'40M',
       '7.8M', '8.8M', '6.6M', '5.1M', '61M', '66M', '79k', '8.4M',
       '3.7M', '118k', '44M', '695k', '1.6M', '6.2M', '53M', '1.4M',
       '3.0M', '7.2M', '5.8M', '3.8M', '9.6M', '45M', '63M', '49M',
'77M',
       '4.4M', '70M', '9.3M', '8.1M', '36M', '6.9M', '7.4M', '84M',
'97M',
       '2.0M', '1.9M', '1.8M', '5.3M', '47M', '556k', '526k', '76M',
       '7.6M', '59M', '9.7M', '78M', '72M', '43M', '7.7M', '6.3M',
'334k',
       '93M', '65M', '79M', '100M', '58M', '50M', '68M', '64M', '34M',
       '67M', '60M', '94M', '9.9M', '232k', '99M', '624k', '95M',
'8.5k',
       '41k', '292k', '80M', '1.7M', '10.0M', '74M', '62M', '69M',
'75M',
       '98M', '85M', '82M', '96M', '87M', '71M', '86M', '91M', '81M',
       '92M', '83M', '88M', '704k', '862k', '899k', '378k', '4.8M',
       '266k', '375k', '1.3M', '975k', '980k', '4.1M', '89M', '696k',
```

```
       '544k', '525k', '920k', '779k', '853k', '720k', '713k', '772k',
       '318k', '58k', '241k', '196k', '857k', '51k', '953k', '865k',
       '251k', '930k', '540k', '313k', '746k', '203k', '26k', '314k',
       '239k', '371k', '220k', '730k', '756k', '91k', '293k', '17k',
       '74k', '14k', '317k', '78k', '924k', '818k', '81k', '939k',
'169k',
       '45k', '965k', '90M', '545k', '61k', '283k', '655k', '714k',
'93k',
       '872k', '121k', '322k', '976k', '206k', '954k', '444k', '717k',
       '210k', '609k', '308k', '306k', '175k', '350k', '383k', '454k',
       '1.0M', '70k', '812k', '442k', '842k', '417k', '412k', '459k',
       '478k', '335k', '782k', '721k', '430k', '429k', '192k', '460k',
       '728k', '496k', '816k', '414k', '506k', '887k', '613k', '778k',
       '683k', '592k', '186k', '840k', '647k', '373k', '437k', '598k',
       '716k', '585k', '982k', '219k', '55k', '323k', '691k', '511k',
       '951k', '963k', '25k', '554k', '351k', '27k', '82k', '208k',
       '551k', '29k', '103k', '116k', '153k', '209k', '499k', '173k',
       '597k', '809k', '122k', '411k', '400k', '801k', '787k', '50k',
       '643k', '986k', '516k', '837k', '780k', '20k', '498k', '600k',
       '656k', '221k', '228k', '176k', '34k', '259k', '164k', '458k',
       '629k', '28k', '288k', '775k', '785k', '636k', '916k', '994k',
       '309k', '485k', '914k', '903k', '608k', '500k', '54k', '562k',
       '847k', '948k', '811k', '270k', '48k', '523k', '784k', '280k',
       '24k', '892k', '154k', '18k', '33k', '860k', '364k', '387k',
       '626k', '161k', '879k', '39k', '170k', '141k', '160k', '144k',
       '143k', '190k', '376k', '193k', '473k', '246k', '73k', '253k',
       '957k', '420k', '72k', '404k', '470k', '226k', '240k', '89k',
       '234k', '257k', '861k', '467k', '676k', '552k', '582k',
'619k'],
      dtype=object)
```

```python
def change(Size):
    if 'M'in Size:
        x=Size[:-1]
        x=float(x)*1000
        return x

    elif 'K'in Size:
        x=Size[:-1]
        x=float(x)
        return x

    else:return None

df.Size=df.Size.map(change)
df.Size.value_counts()
```

```
14000.0    165
12000.0    161
11000.0    159
```

```
15000.0    159
13000.0    157
          ...
89000.0      9
84000.0      9
86000.0      8
90000.0      5
1000.0       4
Name: Size, Length: 181, dtype: int64
```

```
df['Size'].unique()
```

```
array([ 19000.,  14000.,   8700.,  25000.,   2800.,   5600.,  29000.,
        33000.,   3100.,  28000.,  12000.,  20000.,  21000.,  37000.,
         5500.,  17000.,  39000.,  31000.,   4200.,  23000.,   6000.,
         6100.,   4600.,   9200.,   5200.,  11000.,  24000.,     nan,
         9400.,  15000.,  10000.,   1200.,  26000.,   8000.,   7900.,
        56000.,  57000.,  35000.,  54000.,   3600.,   5700.,   8600.,
         2400.,  27000.,   2700.,   2500.,   7000.,  16000.,   3400.,
         8900.,   3900.,   2900.,  38000.,  32000.,   5400.,  18000.,
         1100.,   2200.,   4500.,   9800.,  52000.,   9000.,   6700.,
        30000.,   2600.,   7100.,  22000.,   6400.,   3200.,   8200.,
         4900.,   9500.,   5000.,   5900.,  13000.,  73000.,   6800.,
         3500.,   4000.,   2300.,   2100.,  42000.,   9100.,  55000.,
         7300.,   6500.,   1500.,   7500.,  51000.,  41000.,  48000.,
         8500.,  46000.,   8300.,   4300.,   4700.,   3300.,  40000.,
         7800.,   8800.,   6600.,   5100.,  61000.,  66000.,   8400.,
         3700.,  44000.,   1600.,   6200.,  53000.,   1400.,   3000.,
         7200.,   5800.,   3800.,   9600.,  45000.,  63000.,  49000.,
        77000.,   4400.,  70000.,   9300.,   8100.,  36000.,   6900.,
         7400.,  84000.,  97000.,   2000.,   1900.,   1800.,   5300.,
        47000.,  76000.,   7600.,  59000.,   9700.,  78000.,  72000.,
        43000.,   7700.,   6300.,  93000.,  65000.,  79000., 100000.,
        58000.,  50000.,  68000.,  64000.,  34000.,  67000.,  60000.,
        94000.,   9900.,  99000.,  95000.,  80000.,   1700.,  74000.,
        62000.,  69000.,  75000.,  98000.,  85000.,  82000.,  96000.,
        87000.,  71000.,  86000.,  91000.,  81000.,  92000.,  83000.,
        88000.,   4800.,   1300.,   4100.,  89000.,  90000.,   1000.])
```

4.2.Reviews is a numeric field that is loaded as a string field. Convert it to numeric (int/float).

```
df.Reviews.dtype
```

```
dtype('O')
```

```
df['Reviews']=df.Reviews.replace('3.0M',3000000.0)
```

```
df['Reviews']=df['Reviews'].astype('int')
```

```
df.Reviews.dtype
```

```
dtype('int64')
```

4.3.Installs field is currently stored as string and has values like 1,000,000+.

```
df['Installs'].unique()
```

```
array(['10,000+', '500,000+', '5,000,000+', '50,000,000+', '100,000+',
       '50,000+', '1,000,000+', '10,000,000+', '5,000+',
'100,000,000+',
       '1,000,000,000+', '1,000+', '500,000,000+', '100+', '500+',
'10+',
       '5+', '50+', '1+'], dtype=object)
```

4.3.1.Treat 1,000,000+ as 1,000,000

```
df['Installs']=df.Installs.str.replace("+","")
df.Installs=df.Installs.str.replace('Free','0')
```

```
df['Installs'].unique()
```

```
array(['10,000', '500,000', '5,000,000', '50,000,000', '100,000',
       '50,000', '1,000,000', '10,000,000', '5,000', '100,000,000',
       '1,000,000,000', '1,000', '500,000,000', '100', '500', '10',
'5',
       '50', '1'], dtype=object)
```

4.3.2.remove '+', ',' from the field, convert it to integer

```
df['Installs']=df.Installs.str.replace(",","")
```

```
df.Installs=pd.to_numeric(df.Installs)
```

```
df.Installs.dtype
```

```
dtype('int64')
```

4.4.Price field is a string and has $ symbol. Remove '$' sign, and convert it to numeric.

```
df.Price=df.Price.str.replace('$','')
df.Price=df.Price.str.replace('Everyone','0')
```

```
df.Price=pd.to_numeric(df.Price)
```

```
df.Price.unique()
```

```
array([  0.  ,   4.99,   3.99,   6.99,   7.99,   5.99,   2.99,   3.49,
         1.99,   9.99,   7.49,   0.99,   9.  ,   5.49,  10.  ,  24.99,
        11.99,  79.99,  16.99,  14.99,  29.99,  12.99,   2.49,  10.99,
         1.5 ,  19.99,  15.99,  33.99,  39.99,   3.95,   4.49,   1.7 ,
         8.99,   1.49,   3.88, 399.99,  17.99, 400.  ,   3.02,   1.76,
         4.84,   4.77,   1.61,   2.5 ,   1.59,   6.49,   1.29, 299.99,
       379.99,  37.99,  18.99, 389.99,   8.49,   1.75,  14.  ,   2.  ,
         3.08,   2.59,  19.4 ,   3.9 ,   4.59,  15.46,   3.04,  13.99,
```

```
       4.29,   3.28,   4.6 ,   1.  ,   2.95,   2.9 ,   1.97,   2.56,
       1.2 ])
```

```
df.Price.dtype
```

```
dtype('float64')
```

5.Sanity checks:

5.1.Average rating should be between 1 and 5 as only these values are allowed on the play store. Drop the rows that have a value outside this range.

```
df=df[(df.Rating>=1)&(df.Rating<=5)]
```

```
df.Rating.value_counts()
```

```
4.4    1108
4.3    1076
4.5    1037
4.2     951
4.6     823
4.1     707
4.0     567
4.7     499
3.9     386
3.8     303
5.0     274
3.7     239
4.8     234
3.6     174
3.5     163
3.4     128
3.3     102
4.9      87
3.0      83
3.1      69
3.2      63
2.9      45
2.8      42
2.6      25
2.7      25
2.5      21
2.3      20
2.4      19
1.0      16
2.2      14
1.9      13
2.0      12
1.7       8
2.1       8
1.8       8
1.6       4
```

```
1.4       3
1.5       3
1.2       1
Name: Rating, dtype: int64
```

```
df['Rating'].unique()
```

```
array([4.1, 3.9, 4.7, 4.5, 4.3, 4.4, 3.8, 4.2, 4.6, 4. , 4.8, 4.9,
3.6,
       3.7, 3.2, 3.3, 3.4, 3.5, 3.1, 5. , 2.6, 3. , 1.9, 2.5, 2.8,
2.7,
       1. , 2.9, 2.3, 2.2, 1.7, 2. , 1.8, 2.4, 1.6, 2.1, 1.4, 1.5,
1.2])
```

5.2.Reviews should not be more than installs as only those who installed can review the app. If there are any such records, drop them.

```
df.Reviews
```

```
0           159
1           967
2         87510
3        215644
4           967
          ...
10834         7
10836        38
10837         4
10839       114
10840    398307
Name: Reviews, Length: 9360, dtype: int64
```

```
df.Installs
```

```
0           10000
1          500000
2         5000000
3        50000000
4          100000
           ...
10834         500
10836        5000
10837         100
10839        1000
10840    10000000
Name: Installs, Length: 9360, dtype: int64
```

```
len(df.Installs)
```

```
9360
```

```
len(df.Rating)
```

```
9360
```

5.3.For free apps (type = “Free”), the price should not be >0. Drop any such rows.

```
df.Type.value_counts()
```

```
Free    8715
Paid     645
Name: Type, dtype: int64
```

```
index_free_price_0=df.index[((df.Type=='Free')&(df.Price>0))]
if len(index_free_price_0)>0:
    print("Dropping such values",index_free_price_0)
    df.drop(index_free_price0,axis=0,inplace=True)
else:
    print("There has no apps price>0")
```

```
There has no apps price>0
```

1. Performing univariate analysis:

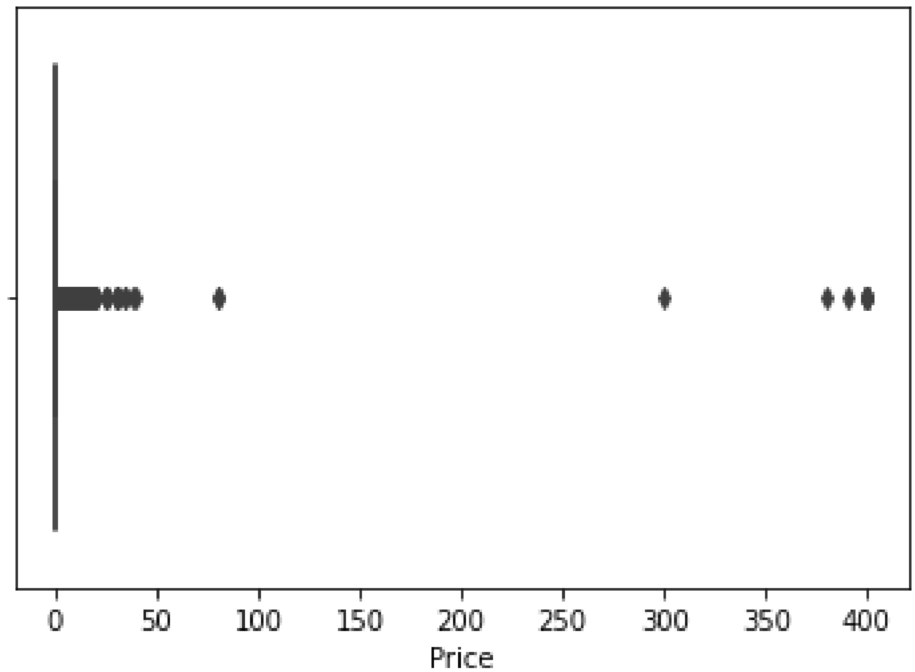
5.1.Boxplot for Price

5.1.Q.Are there any outliers? Think about the price of usual apps on Play Store.

```
sns.boxplot(df['Price'])
```

```
/usr/local/lib/python3.7/site-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  FutureWarning
```

```
<AxesSubplot:xlabel='Price'>
```



5.1.ANS.most of the price values are located in the range of 50. greater than 100 may be cansidered as outliers

```
import matplotlib.pyplot as plt
```

```
import statistics as stc
```

standard deviation of price

```
p_std=stc.stdev(df.Price)
print(p_std)
```

```
15.82164024735431
```

mean of price

```
p_mean=stc.mean(df.Price)
print(p_mean)
```

```
0.9612788461538462
```

price upper limit

```
price_up_lim=p_mean+3*p_std
print(price_up_lim)
```

```
48.426199588216775
```

```
len(df[df.Price>price_up_lim])
```

```
17
```

price lower limit

```
price_low_lim=p_mean-3*p_std
print(price_low_lim)
```

```
-46.503641895909084
```

```
len(df[df.Price<price_low_lim])
```

```
0
```

here i got 17 outliers

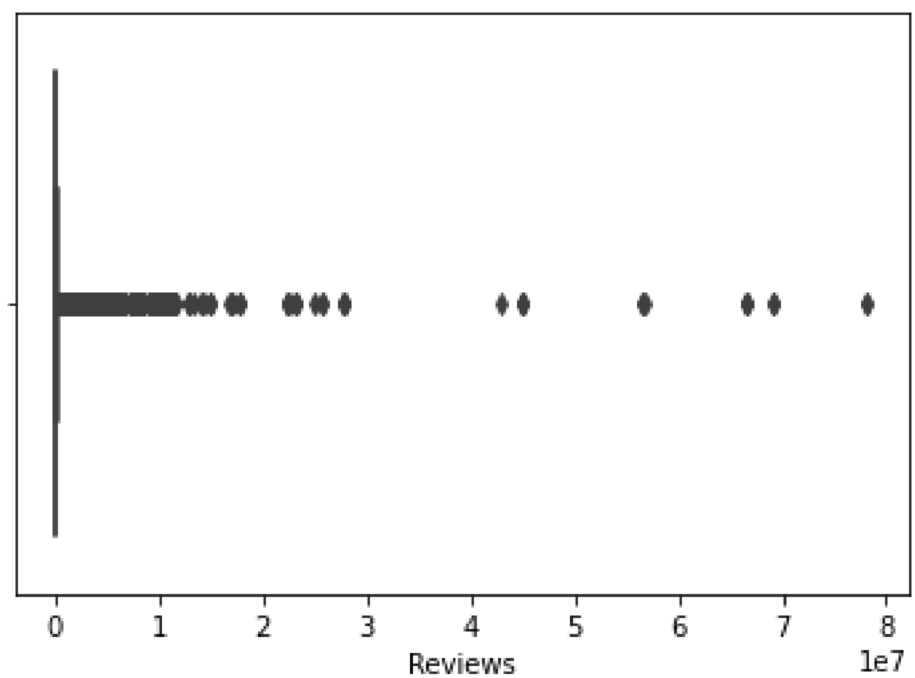
5.2.Boxplot for Reviews

5.2.Q.Are there any apps with very high number of reviews? Do the values seem right?

```
sns.boxplot(df['Reviews'])
```

```
/usr/local/lib/python3.7/site-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```

```
<AxesSubplot:xlabel='Reviews'>
```



5.2.ANS.here we can find out some outliers.

standard deviation reviews

```
review_std=stc.stdev(df.Reviews)
print(review_std)
```

```
3145023.255620224
```

mean of review

```
review_mean=stc.mean(df.Reviews)
print(review_mean)
```

```
514376.7052350427
```

review uper limit

```
review_up_lim=review_mean+3*review_std
print(review_up_lim)
```

```
9949446.472095715
```

```
len(df[df.Reviews>review_up_lim])
```

```
92
```

review lower limt

```
review_low_lim=review_mean-3*review_std
print(review_low_lim)
```

```
-8920693.061625628
```

```
len(df[df.Reviews<review_low_lim])
```

```
0
```

review column has 60 upper outlier.

removeing outlier

```
df.drop(df.index[(df.Reviews>review_up_lim)],inplace=True)
```

```
len(df[df.Reviews>review_up_lim])
```

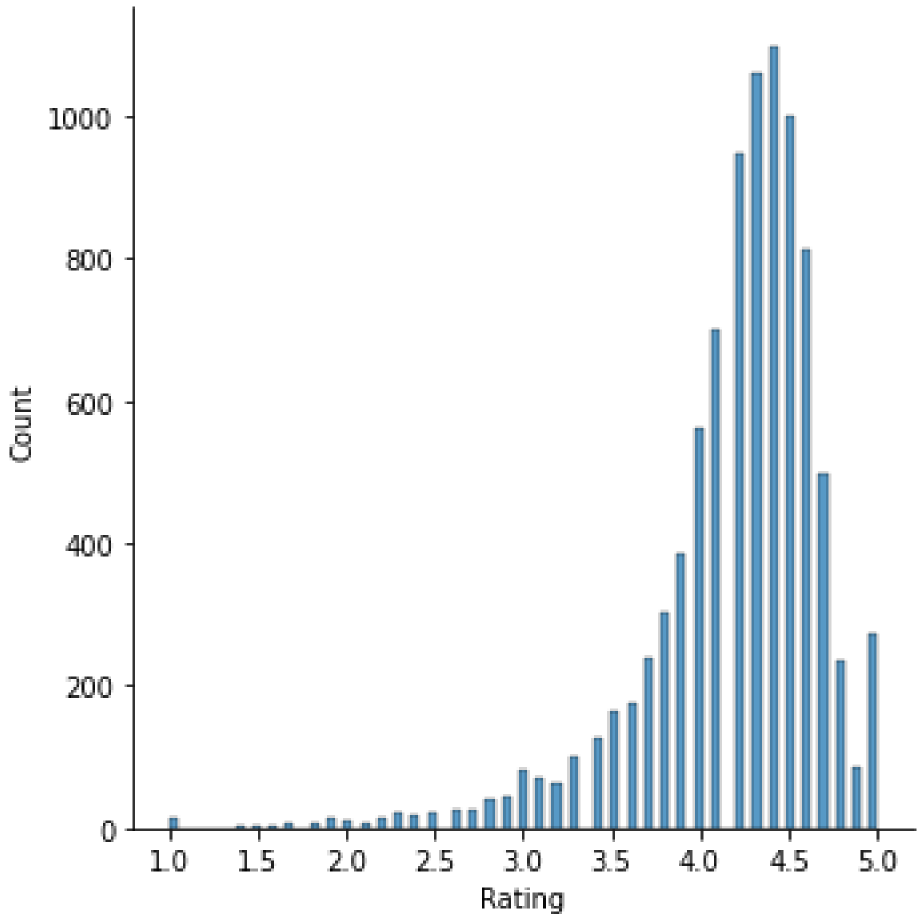
```
0
```

5.3.Histogram for Rating

5.3.Q.How are the ratings distributed? Is it more toward higher ratings?

```
sns.displot(df.Rating)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fa239ce70d0>
```



5.3.ans.this graph showing that 4.0 to 4.7 high variation(peak).it is a left skew plot.

define mean and standard deviation

```
rating_mean=np.mean(df.Rating)
rating_mean
```

```
4.189846784635309
```

```
rating_std=np.std(df.Rating)
rating_std
```

```
0.5170834870588434
```

define uper and lower outliers

```
rating_up_lim=rating_mean+3*rating_std
print(rating_up_lim)
```

```
5.741097245811839
```

```
len(df[df.Rating>rating_up_lim])
```

```
0
```

```
rating_low_lim=rating_mean-3*rating_std
rating_low_lim
```

```
2.6385963234587786
```

```
len(df[df.Rating<rating_low_lim])
```

```
175
```

removing outliers

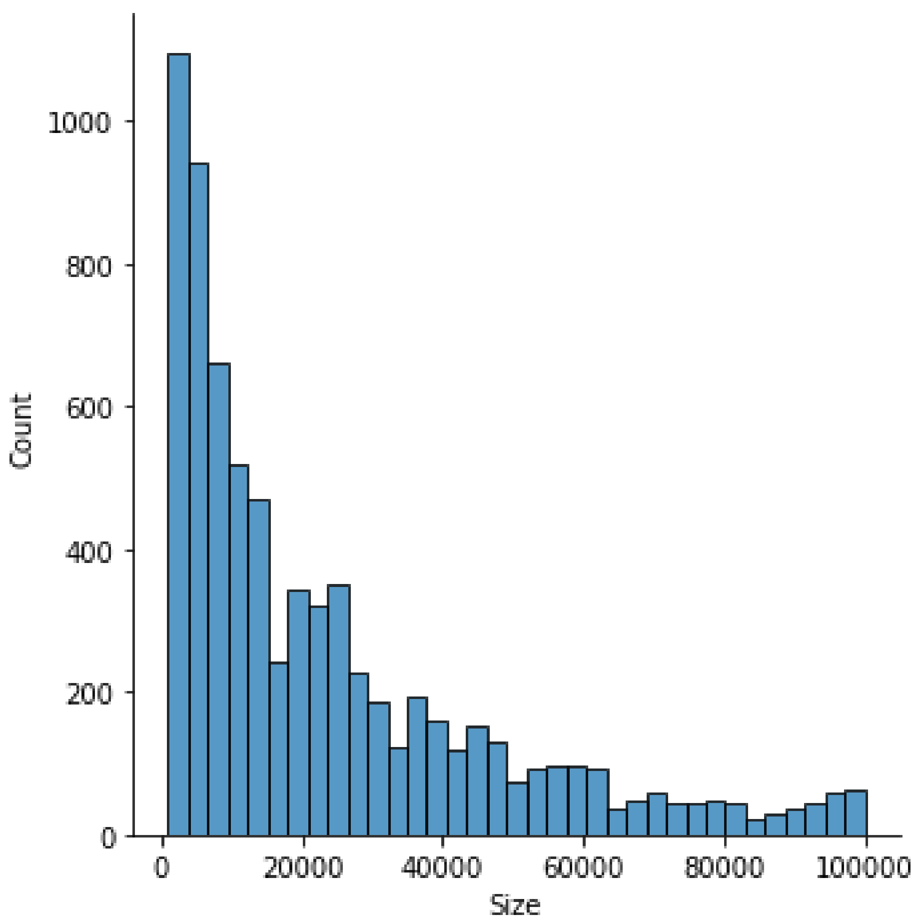
```
df.drop(df.index[df.Rating<rating_low_lim],inplace=True)
len(df[df.Rating<rating_low_lim])
```

```
0
```

5.4.Histogram for Size

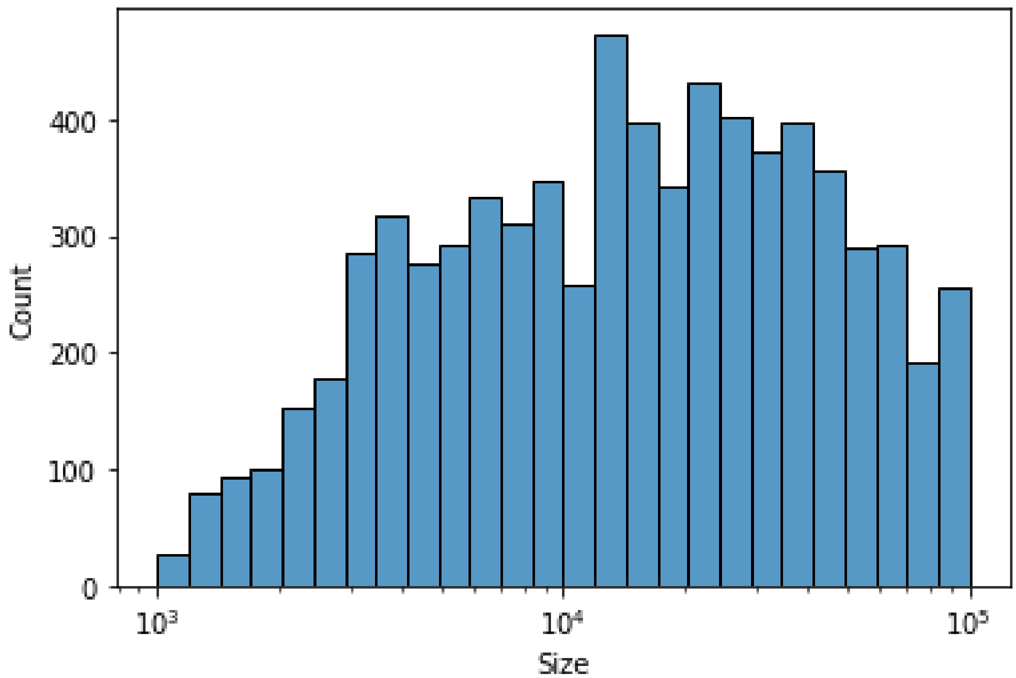
```
sns.displot(df.Size)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fa239912f90>
```




```
sns.histplot(x='Size',data=df,log_scale=True)
```

```
<AxesSubplot:xlabel='Size', ylabel='Count'>
```




```
size_mean=stc.mean(df.Size)
print(size_mean)
```

```
nan
```

```
size_std=stc.stdev(df.Size)
print(size_std)
```

```
nan
```

6.Outlier treatment:

6.1.Price: From the box plot, it seems like there are some apps with very high price. A price of $200 for an application on the Play Store is very high and suspicious!

6.1.1.Check out the records with very high price

```
df[df.Price>=200]
```

```
                                 App   Category  Rating  Reviews  
Size  \
4197         most expensive app (H)     FAMILY     4.3        6   
1500.0   
4362                      � I'm rich  LIFESTYLE     3.8      718  
26000.0   
4367       I'm Rich - Trump Edition  LIFESTYLE     3.6      275   
7300.0   
5351                      I am rich  LIFESTYLE     3.8     3547
```

```
1800.0
5354                  I am Rich Plus     FAMILY     4.0      856
8700.0
5355                   I am rich VIP  LIFESTYLE     3.8      411
2600.0
5356               I Am Rich Premium    FINANCE     4.1     1867
4700.0
5357             I am extremely Rich  LIFESTYLE     2.9       41
2900.0
5358                      I am Rich!    FINANCE     3.8       93
22000.0
5359              I am rich(premium)    FINANCE     3.5      472
NaN
5362                   I Am Rich Pro     FAMILY     4.4      201
2700.0
5364  I am rich (Most expensive app)    FINANCE     4.1      129
2700.0
5366                       I Am Rich     FAMILY     3.6      217
4900.0
5369                       I am Rich    FINANCE     4.3      180
3800.0
5373              I AM RICH PRO PLUS    FINANCE     4.0       36
41000.0

      Installs  Type   Price Content Rating         Genres       Last
Updated  \
4197       100  Paid  399.99       Everyone  Entertainment      July
16, 2018
4362     10000  Paid  399.99       Everyone      Lifestyle     March
11, 2018
4367     10000  Paid  400.00       Everyone      Lifestyle       May
3, 2018
5351    100000  Paid  399.99       Everyone      Lifestyle   January
12, 2018
5354     10000  Paid  399.99       Everyone  Entertainment       May
19, 2018
5355     10000  Paid  299.99       Everyone      Lifestyle      July
21, 2018
5356     50000  Paid  399.99       Everyone        Finance  November
12, 2017
5357      1000  Paid  379.99       Everyone      Lifestyle       July
1, 2018
5358      1000  Paid  399.99       Everyone        Finance  December
11, 2017
5359      5000  Paid  399.99       Everyone        Finance       May
1, 2017
5362      5000  Paid  399.99       Everyone  Entertainment       May
30, 2017
5364      1000  Paid  399.99           Teen        Finance   December
6, 2017
```

```
5366     10000  Paid  389.99       Everyone  Entertainment      June 
22, 2018
5369      5000  Paid  399.99       Everyone        Finance     March 
22, 2018
5373      1000  Paid  399.99       Everyone        Finance      June 
25, 2018

     Current Ver   Android Ver
4197         1.0    7.0 and up
4362       1.0.0    4.4 and up
4367       1.0.1    4.1 and up
5351         2.0  4.0.3 and up
5354         3.0    4.4 and up
5355       1.1.1    4.3 and up
5356         1.6    4.0 and up
5357         1.0    4.0 and up
5358         1.0    4.1 and up
5359         3.4    4.4 and up
5362        1.54    1.6 and up
5364           2  4.0.3 and up
5366         1.5    4.2 and up
5369         1.0    4.2 and up
5373       1.0.2    4.1 and up
```

```
a=len(df[df.Price>=200])
print(a,"apps are>200 ")
```

```
15 apps are>200
```

6.1.2.Drop these as most seem to be junk apps

```
df.drop(df.index[df.Price>=200],inplace=True)
len(df.Price)
```

```
9078
```

5.2.Reviews: Very few apps have very high number of reviews. These are all star apps that don’t help with the analysis and, in fact, will skew it. Drop records having more than 2 million reviews.

```
df.drop(df.index[df.Reviews>2000000],inplace=True)
len(df.index)
```

```
8717
```

6.3.Installs: There seems to be some outliers in this field too. Apps having very high number of installs should be dropped from the analysis.

6.3.1Find out the different percentiles – 10, 25, 50, 70, 90, 95, 99

```
installs_10_perc=np.percentile(df.Installs,10)
print(installs_10_perc)
```

```
1000.0
```

```
installs_25_perc=np.percentile(df.Installs,25)
installs_25_perc
```

```
10000.0
```

```
installs_50_perc=np.percentile(df.Installs,50)
installs_50_perc
```

```
500000.0
```

```
installs_75_perc=np.percentile(df.Installs,70)
installs_50_perc
```

```
500000.0
```

```
installs_90_perc=np.percentile(df.Installs,90)
installs_90_perc
```

```
10000000.0
```

```
installs_95_perc=np.percentile(df.Installs,95)
installs_95_perc
```

```
10000000.0
```

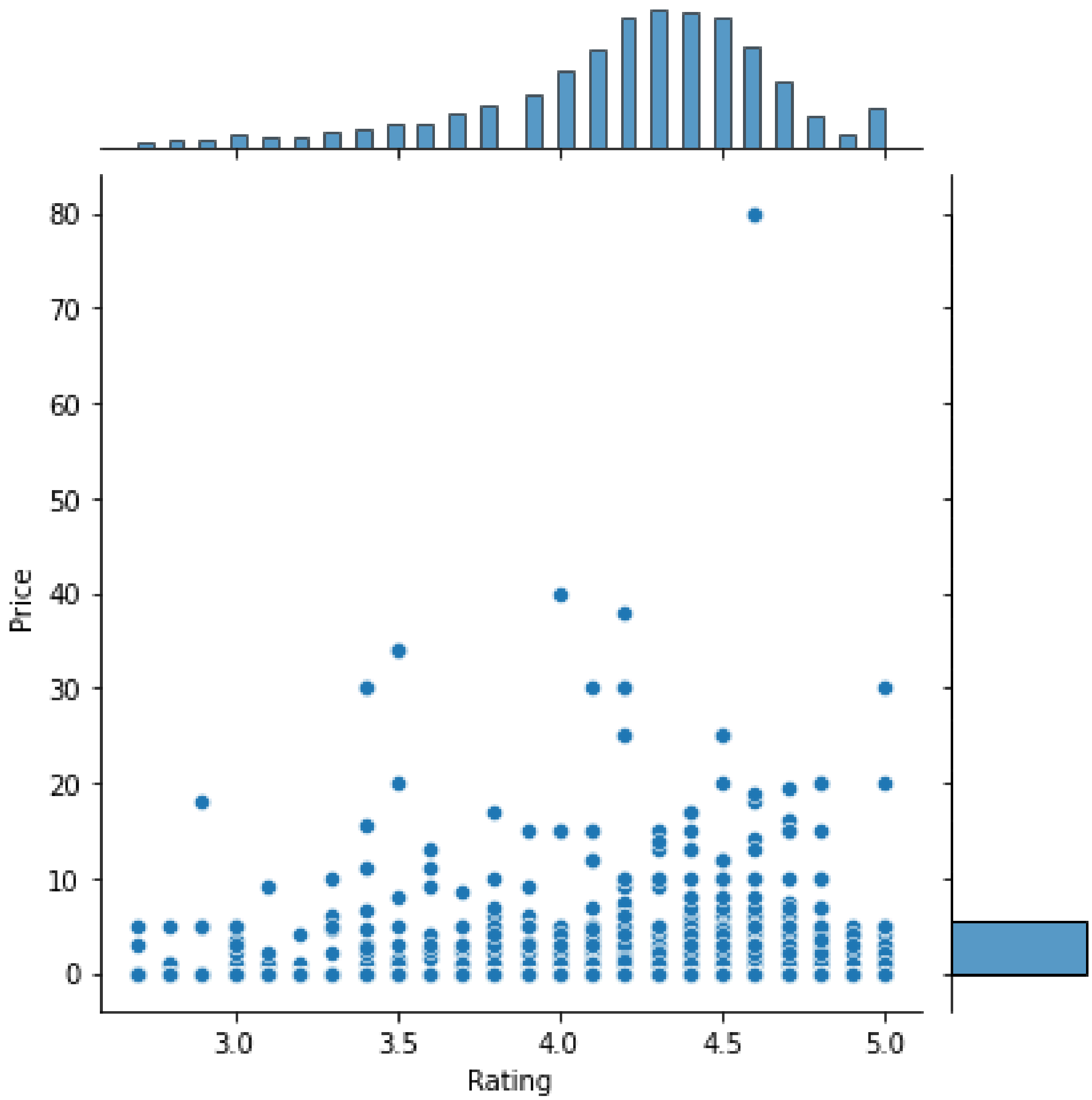
```
installs_99_perc=np.percentile(df.Installs,99)
installs_99_perc
```

```
100000000.0
```

1. Bivariate analysis: Let’s look at how the available predictors relate to the variable of interest, i.e., our target variable rating. Make scatter plots (for numeric features) and box plots (for character features) to assess the relations between rating and the other features.

7.1.Make scatter plot/joinplot for Rating vs. Price

```
joint_ch=sns.jointplot(data=df,x='Rating',y='Price')
```

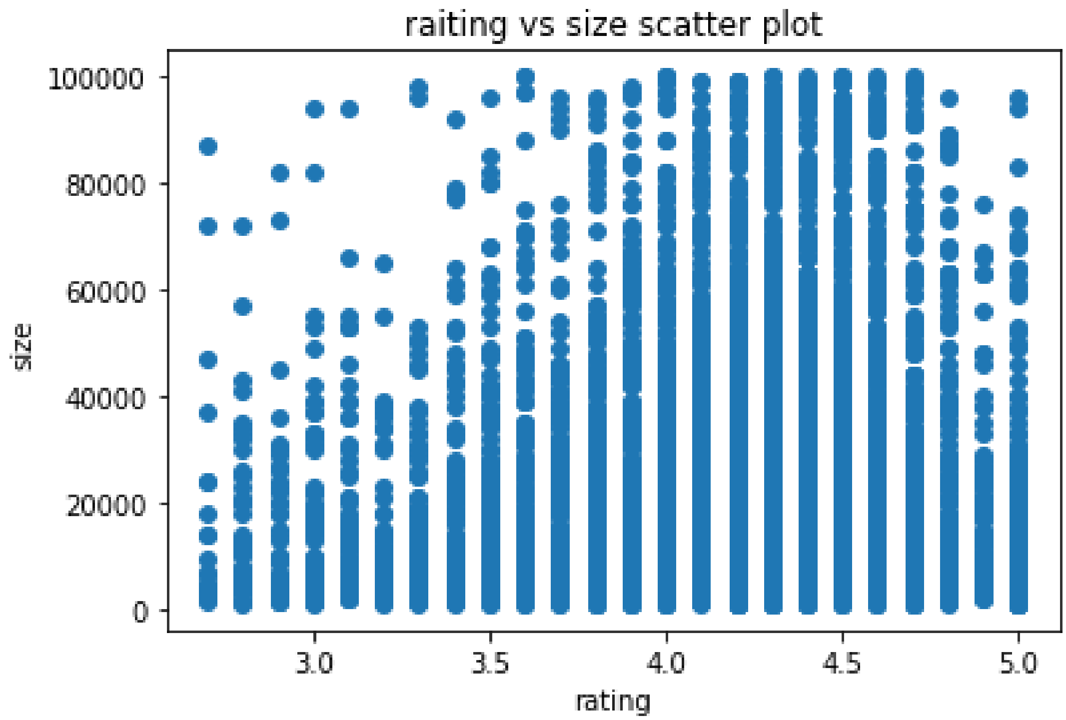


7.1.1.ans.What pattern do you observe? Does rating increase with price?

i observed that the rating and price are not in a good relationship. price has negatively impacted on rating or seems like price has limited impact on rating.

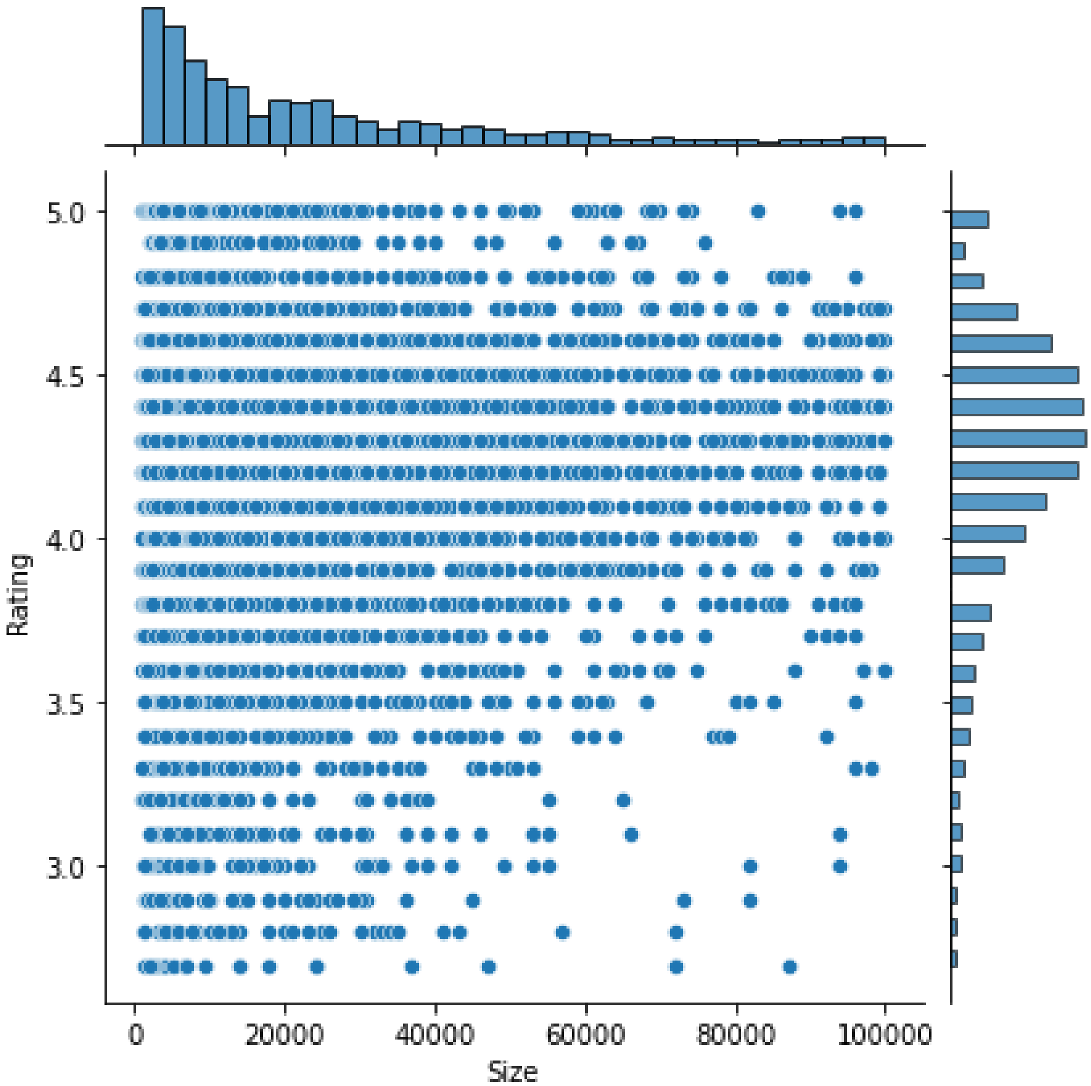
7.2.Make scatter plot/joinplot for Rating vs. Size

```
x=(df['Rating'])
y=(df['Size'])
plt.scatter(x,y)
plt.xlabel('rating')
plt.ylabel('size')
plt.title('raiting vs size scatter plot')
plt.show()
```




```
sns.jointplot(data=df,x='Size',y='Rating')
```

```
<seaborn.axisgrid.JointGrid at 0x7fa239391e50>
```



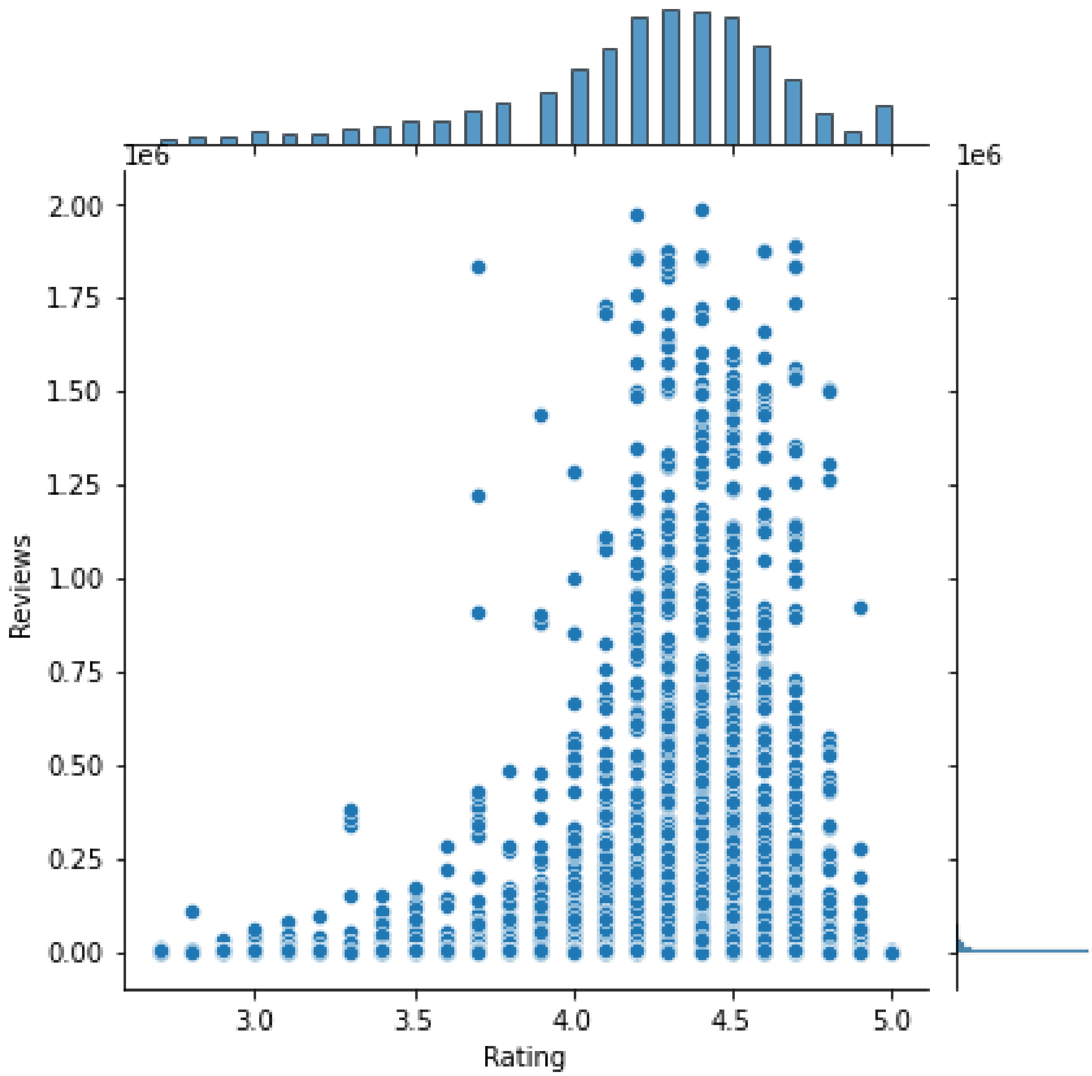
7.2.1. Are heavier apps rated better?

this plot showing us that most of apps raited between (3.5 to 5.0) almost data distributed evenly. but relationship of this two variable unconvinced.

Make scatter plot/joinplot for Rating vs. Reviews

```
sns.jointplot(data=df,x='Rating',y='Reviews')
```

```
<seaborn.axisgrid.JointGrid at 0x7fa239416cd0>
```



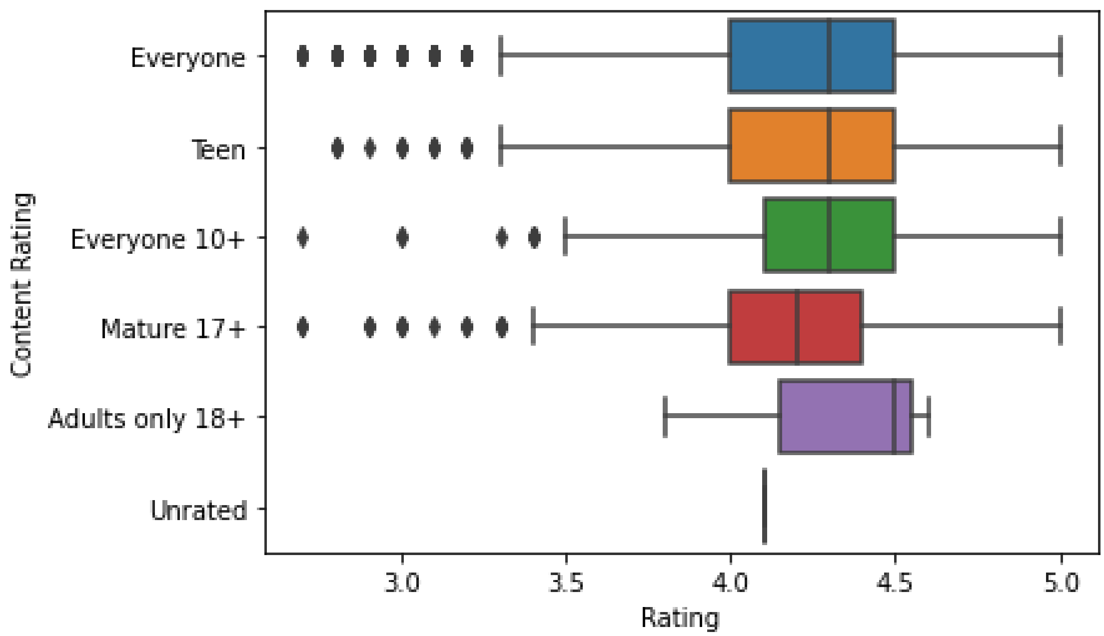
7.3.1.Does more review mean a better rating always?

this plot shown some relation between rating and review.this is left skew plot.high rating having high reviews.

7.4.Make boxplot for Rating vs. Content Rating

```
sns.boxplot(data=df,x='Rating',y='Content Rating')
```

```
<AxesSubplot:xlabel='Rating', ylabel='Content Rating'>
```



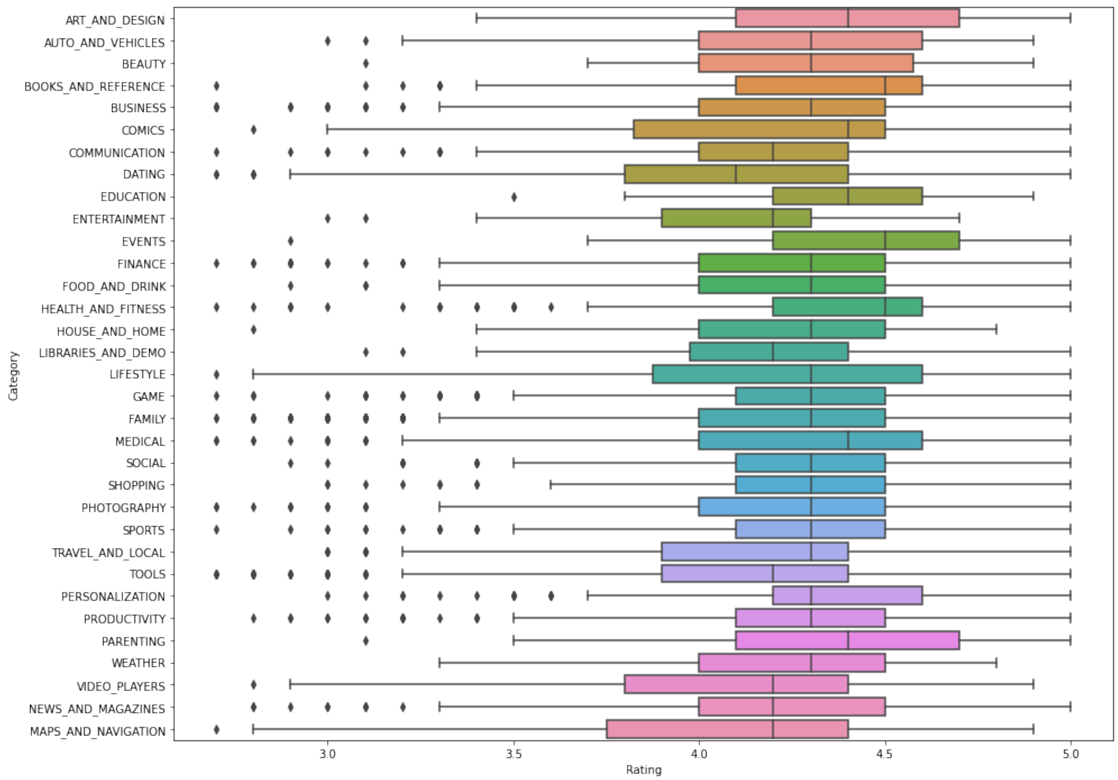
7.4.1.Is there any difference in the ratings? Are some types liked better?

Adult only 18+ has slightly higher rating. others content rating are seems as same.

7.5.Make boxplot for Ratings vs. Category

```
dim_box=(15,12)
plt.subplots(figsize=dim_box)
sns.boxplot(data=df,x='Rating',y='Category')
```

```
<AxesSubplot:xlabel='Rating', ylabel='Category'>
```




```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
```

8. Data preprocessing

For the steps below, create a copy of the dataframe to make all the edits. Name it inp1.

8.1.Reviews and Install have some values that are still relatively very high. Before building a linear regression model, you need to reduce the skew. Apply log transformation (np.log1p) to Reviews and Installs.

```
mod_1=df.copy()
mod_1.Reviews=mod_1.Reviews.apply(np.log1p)
mod_1.Installs=mod_1.Installs.apply(np.log1p)
```

8.2.Drop columns App, Last Updated, Current Ver, and Android Ver. These variables are not useful for our task.

```
mod_1.drop(columns=['App','Last Updated','Current Ver','Android Ver'],inplace=True)
```

```
mod_1.shape
```

```
(7069, 9)
```

8.3.Get dummy columns for Category, Genres, and Content Rating. This needs to be done as the models do not understand categorical data, and all data should be numeric. Dummy encoding is one way to convert character- fields to numeric. Name of dataframe should be inp2.

```
inp2=pd.get_dummies(mod_1)
```

```
inp2.shape
```

```
(7069, 158)
```

1. Train test split and apply 70-30 split. Name the new dataframes df_train and df_test.

```
data=inp2.drop(columns='Rating')
data.shape
```

```
(7069, 157)
```

```
target=pd.DataFrame(inp2.Rating)
target.shape
```

```
(7069, 1)
```

1. Separate the dataframes into X_train, y_train, X_test, and y_test.

```
x_train,x_test,y_train,y_test=train_test_split(data,target,test_size=0
.30,random_state=32)
print("x_train =",x_train.shape)
print('x_test =',x_test.shape)
print("y_train =",y_train.shape)
print('y_test =',y_test.shape)
```

```
x_train = (4948, 157)
x_test = (2121, 157)
y_train = (4948, 1)
y_test = (2121, 1)
```

11 . Model building Use linear regression as the technique Report the R2 on the train set

```
regression=LinearRegression()
regression.fit(x_train,y_train)
```

```
LinearRegression()
```

```
train_pred=regression.predict(x_train)
print('r2 value of train set is',r2_score(y_train,train_pred))
```

```
r2 value of train set is 0.19371992182920217
```

1. Make predictions on test set and report R2.

```
test_pred=regression.predict(x_test)
print('r2 value of train set is',r2_score(y_test,test_pred))
```

```
r2 value of train set is 0.14603814020909311
```