In [1]:
```
import pandas as pd
import numpy as np
import os
import re
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split as split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error as mse
```

In [2]:
```
#Step 1. Load the data using pandas.
appdata = pd.read_csv('/Users/priya/Pravat/Simplilearn Data Analytics/Class2/project/googleplaystore.csv')
appdata.head(5)
```

Out[2]:

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Last Updated	Current Ver	Android Ver
0	Photo Editor & Candy Camera & Grid & ScrapBook	ART_AND_DESIGN	4.1	159	19M	10,000+	Free	0	Everyone	Art & Design	January 7, 2018	1.0.0	4.0.3 and up
1	Coloring book moana	ART_AND_DESIGN	3.9	967	14M	500,000+	Free	0	Everyone	Art & Design;Pretend Play	January 15, 2018	2.0.0	4.0.3 and up
2	U Launcher Lite – FREE Live Cool Themes, Hide ...	ART_AND_DESIGN	4.7	87510	8.7M	5,000,000+	Free	0	Everyone	Art & Design	August 1, 2018	1.2.4	4.0.3 and up
3	Sketch - Draw & Paint	ART_AND_DESIGN	4.5	215644	25M	50,000,000+	Free	0	Teen	Art & Design	June 8, 2018	Varies with device	4.2 and up
4	Pixel Draw - Number Art Coloring Book	ART_AND_DESIGN	4.3	967	2.8M	100,000+	Free	0	Everyone	Art & Design;Creativity	June 20, 2018	1.1	4.4 and up

In [3]:
```
appdata.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
```

In [4]:
```
appdata.columns
```

Out[4]:
```
Index(['App', 'Category', 'Rating', 'Reviews', 'Size', 'Installs', 'Type',
       'Price', 'Content Rating', 'Genres', 'Last Updated', 'Current Ver',
       'Android Ver'],
      dtype='object')
```

In [5]:
```
#Step 2. Check for null values in the data. Get the number of null values for each column.
appdata.isnull().sum()
```

Out[5]:
```
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
```

In [6]:
```
#Step 3. Drop records with nulls in any of the columns.
appdata.dropna(axis = 0, inplace=True)
```

In [7]:
```
#verify
appdata.isna().sum()
```

Out[7]:
```
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
```

In [8]:
```
appdata.shape
```

Out[8]:
```
(9360, 13)
```

In [9]:
```
#Step 4. Fix incorrect type and inconsistent formatting.
appdata['Size']
```

Out[9]:
```
0                     19M
1                     14M
2                    8.7M
3                     25M
4                    2.8M
                ...
10834                2.6M
10836                 53M
10837                3.6M
10839    Varies with device
10840                 19M
Name: Size, Length: 9360, dtype: object
```

In [10]:
```
appdata['Size'].unique()
```

Out[10]:
```
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)
```

In [11]:
```
#Format Size coloumn
```

```
appdata['Size'] = appdata.Size.replace('Varies with device','0k')
appdata['Size'] = appdata.Size.str.replace('M','000')
appdata['Size'] = appdata.Size.str.replace('k','')
appdata['Size'] = appdata.Size.replace('1,000+',1000)
appdata['Size'] = appdata['Size'].astype(float)
```

In [12]:
```
#verify
appdata['Size'].dtype
```

Out[12]:
```
dtype('float64')
```

In [13]:
```
#verify
appdata['Size']
```

Out[13]:
```
0        19000.0
1        14000.0
2            8.7
3        25000.0
4            2.8
          ...
10834        2.6
10836    53000.0
10837        3.6
10839        0.0
10840    19000.0
Name: Size, Length: 9360, dtype: float64
```

In [14]:
```
#change datatype for Reviews column to float
appdata['Reviews']= appdata['Reviews'].astype(float)
```

In [15]:
```
#Check Installs coloumn
appdata['Installs'].unique()
```

Out[15]:
```
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)
```

In [16]:
```
#Format Installs coloumn
appdata['Installs'] = appdata.Installs.str.replace(',','')
appdata['Installs'] = appdata.Installs.str.replace('+','')
appdata['Installs'] = appdata.Installs.str.replace('Free','')
appdata['Installs'] = appdata['Installs'].astype(float)
appdata['Installs'] = appdata['Installs'].astype(float)
```

In [17]:
```
#verify data type for the coloumn
appdata['Installs'].dtype
```

Out[17]:
```
dtype('float64')
```

In [18]:
```
appdata.Installs
```

Out[18]:
```
0           10000.0
1          500000.0
2         5000000.0
3        50000000.0
4          100000.0
             ...
10834         500.0
10836        5000.0
10837         100.0
10839        1000.0
10840    10000000.0
Name: Installs, Length: 9360, dtype: float64
```

In [19]:
```
#Check Price coloumn
appdata['Price'].unique()
```

Out[19]:
```
array(['0', '$4.99', '$3.99', '$6.99', '$7.99', '$5.99', '$2.99', '$3.49',
       '$1.99', '$9.99', '$7.49', '$0.99', '$9.00', '$5.49', '$10.00',
       '$24.99', '$11.99', '$79.99', '$16.99', '$14.99', '$29.99',
       '$12.99', '$2.49', '$10.99', '$1.50', '$19.99', '$15.99', '$33.99',
       '$39.99', '$3.95', '$4.49', '$1.70', '$8.99', '$1.49', '$3.88',
       '$399.99', '$17.99', '$400.00', '$3.02', '$1.76', '$4.84', '$4.77',
       '$1.61', '$2.50', '$1.59', '$6.49', '$1.29', '$299.99', '$379.99',
       '$37.99', '$18.99', '$389.99', '$8.49', '$1.75', '$14.00', '$2.00',
       '$3.08', '$2.59', '$19.40', '$3.90', '$4.59', '$15.46', '$3.04',
       '$13.99', '$4.29', '$3.28', '$4.60', '$1.00', '$2.95', '$2.90',
       '$1.97', '$2.56', '$1.20'], dtype=object)
```

In [20]:
```
#Format Price coloumn
appdata['Price'] = appdata.Price.str.replace('$','').astype(float)
```

In [21]:
```
#verify
appdata['Price'].dtype
```

Out[21]:
```
dtype('float64')
```

In [22]:
```
appdata.Price
```

Out[22]:
```
0        0.0
1        0.0
2        0.0
3        0.0
4        0.0
        ...
10834    0.0
10836    0.0
10837    0.0
10839    0.0
10840    0.0
Name: Price, Length: 9360, dtype: float64
```

In [23]:
```
#Step 5. Sanity checks:
# all ratings are between 1 to 5
appdata['Rating'].unique()
```

Out[23]:
```
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])
```

In [24]:
```
appdata['Rating'].dtype
```

Out[24]:
```
dtype('float64')
```

In [25]:
```
# drop all rows with Ratings outside the 1-5 range
RatingOut = appdata[(appdata['Rating'] < 0) & (appdata['Rating'] > 5)].index
appdata.drop(RatingOut , inplace = True)
```

In [26]:
```
#verify the rows and coloumns
appdata.shape
```

Out[26]:
```
(9360, 13)
```

In [27]:
```
#Reviews should not be more than installs as only those who installed can review the app. If there are any such records
appdata = appdata[appdata['Reviews'] <= appdata['Installs']]
```

In [28]:
```
#verify the rows and coloumns after drop
appdata.shape
```

Out[28]:
```
(9353, 13)
```

In [29]:
```
#For free apps (type = “Free”), the price should not be >0. Drop any such rows.
#get indexes where free Types have a price over 0
priceindexOut = appdata[(appdata['Price'] >= 0.1) & (appdata['Type'] == 'Free')].index
# drop these row
appdata.drop(priceindexOut ,inplace = True)
```

In [30]:
```
#verify after drop
appdata.shape
```

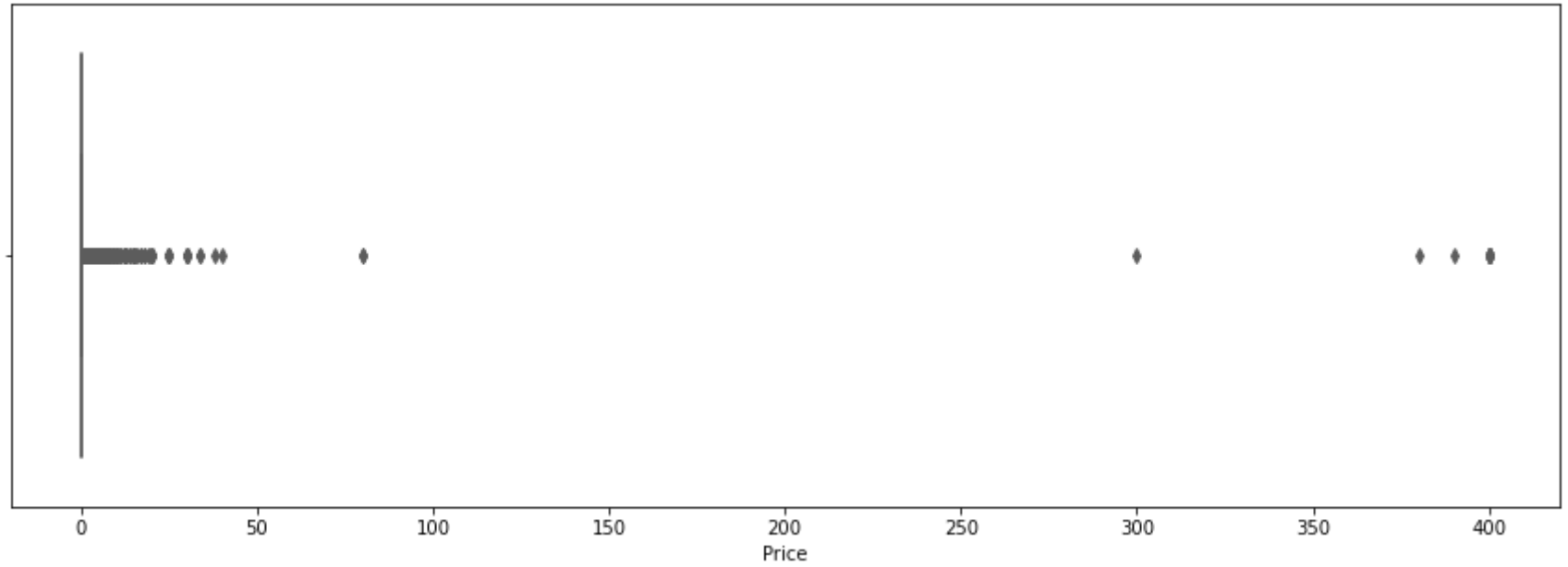
Out[30]:
```
(9353, 13)
```

In [31]:
```
#Step 6. Performing univariate analysis:
#find possible outliers in Price colomns and Review columns using Box Plot
```

In [32]:
```
appdata['Price'].describe()
```

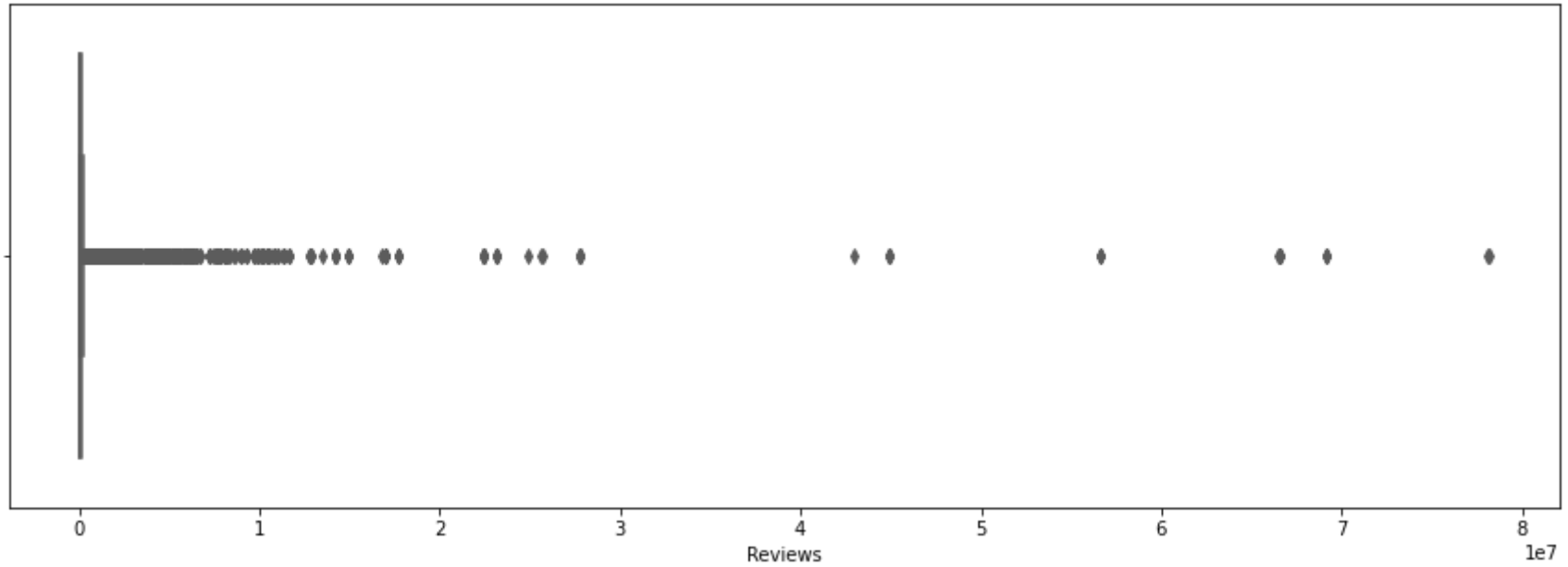
Out[32]:
```
count    9353.000000
mean        0.961467
std        15.827539
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max       400.000000
Name: Price, dtype: float64
```

In [33]:
```
#Boxplot for Price
plt.figure(figsize= (15, 5))
sns.boxplot(x = appdata.Price, color = 'mediumaquamarine',)
plt.show()
```



- From the statistical analysis table and price box plot it is observed that apps over $100 are outliers.

In [34]:
```
#Boxplot for Review
plt.figure(figsize= (15, 5))
sns.boxplot(x = appdata.Reviews, color = 'mediumaquamarine',)
plt.show()
```

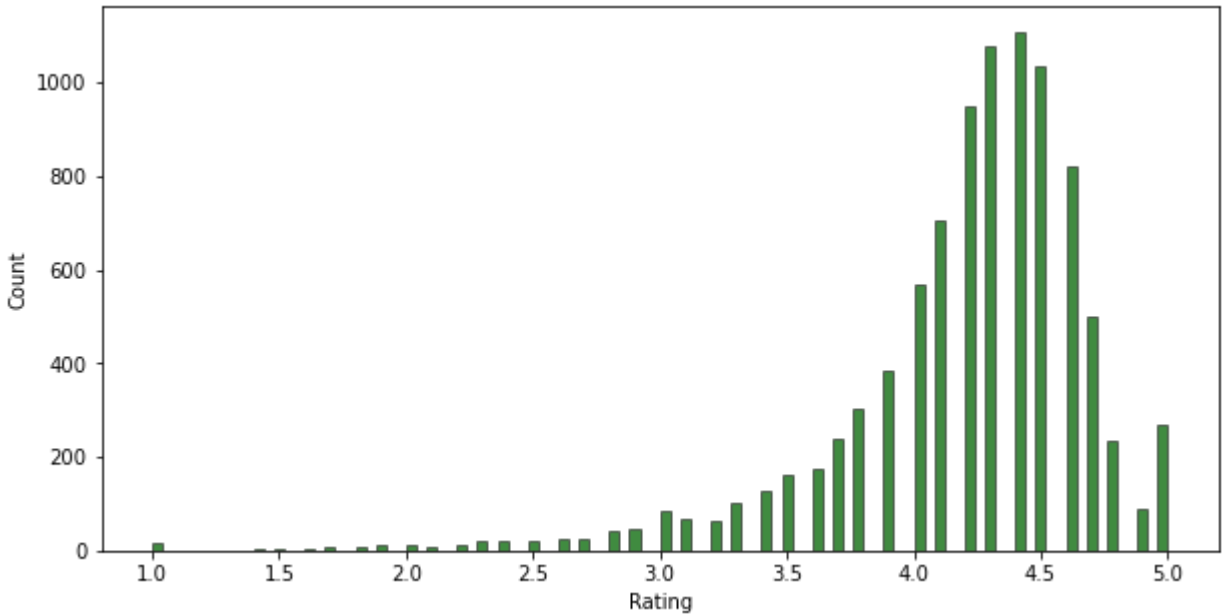


In [35]:
```
appdata['Reviews'].describe()
```

Out[35]:
```
count    9.353000e+03
mean     5.147606e+05
std      3.146169e+06
min      1.000000e+00
25%      1.870000e+02
50%      5.967000e+03
75%      8.174700e+04
max      7.815831e+07
Name: Reviews, dtype: float64
```

- From the statistcial analysis table and box plot, it is observed that the averge number of reviews are 5,14,760 with a standard deviation of 31,46,169 between values. This deviation is due to several outliers in reviews column.

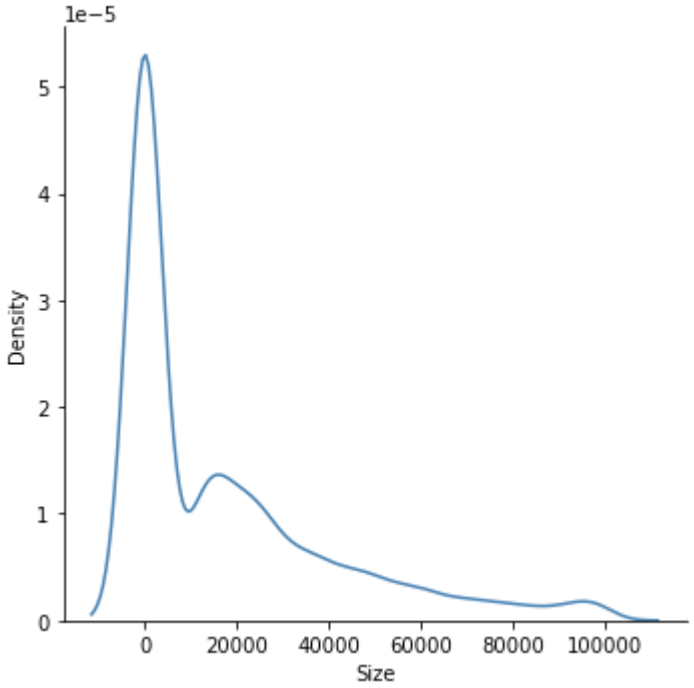
In [36]:
```
#Histogram for Rating
plt.figure(figsize= (10,5))
sns.histplot(appdata.Rating, bins = 100, color =  'darkgreen', edgecolor = 'black')
plt.show()
```



- From the rating histogram it is observed that most apps lean/skewed towards high ratings.

In [37]:
```
#Histogram for Size
plt.figure(figsize= (10,5))
sns.displot(appdata.Size, kind = 'kde', color= 'steelblue')
plt.show()
```

```
<Figure size 720x360 with 0 Axes>
```



- From the size displot histogram, it is observed that most apps size are below 20,000 kb.

In [38]:
```
#Step 7. Outlier treatment:
```

In [39]:
```
#drop Price rows which are above 200
appdata = appdata[appdata['Price'] < 200]
#verify
appdata.shape
```

Out[39]: (9338, 13)

In [40]:
```
#Drop Review rows with over 2 million reviews
appdata = appdata[appdata['Reviews'] <= 2000000]
#verify
appdata.shape
```

Out[40]: (8885, 13)

In [41]:
```
#Apps having very high number of installs should be dropped from the analysis so drop rows with 100,000,000 and more In
```

```
appdata = appdata[appdata['Installs'] <= 100000000]
#verify
appdata.shape
```

Out[41]: (8865, 13)

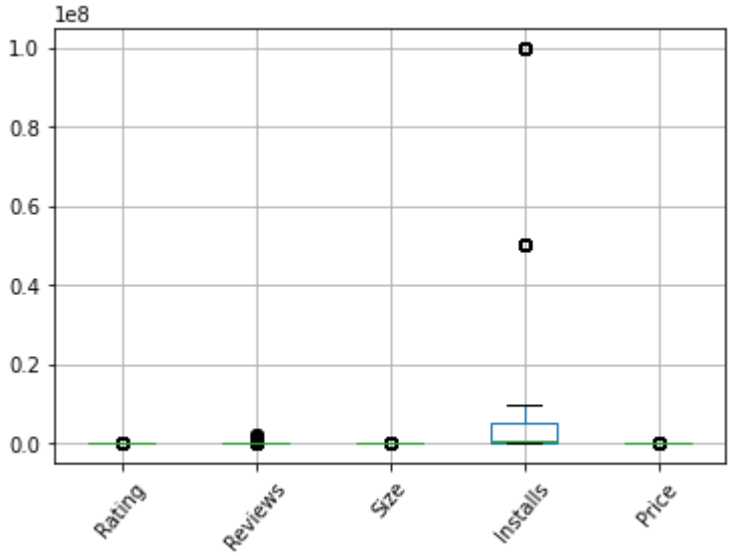
In [42]:
```
#Find out the different percentiles – 10, 25, 50, 70, 90, 95, 99
percentiles = appdata[['Rating','Reviews','Size','Installs','Price']]
```

In [43]:
```
#10, 25, 50, 70, 90, 95, 99 percentiles
print("10th percentile : ",
       np.percentile(percentiles, 10))
print("25th percentile : ",
       np.percentile(percentiles, 25))
print("50th percentile : ",
       np.percentile(percentiles, 50))
print("70th percentile : ",
       np.percentile(percentiles, 70))
print("90th percentile : ",
       np.percentile(percentiles, 90))
print("95th percentile : ",
       np.percentile(percentiles, 95))
print("99th percentile  : ",
       np.percentile(percentiles, 99))
```

```
10th percentile :  0.0
25th percentile :  2.99
50th percentile :  8.5
70th percentile :  14000.0
90th percentile :  549517.5999999993
95th percentile :  5000000.0
99th percentile  :  10000000.0
```

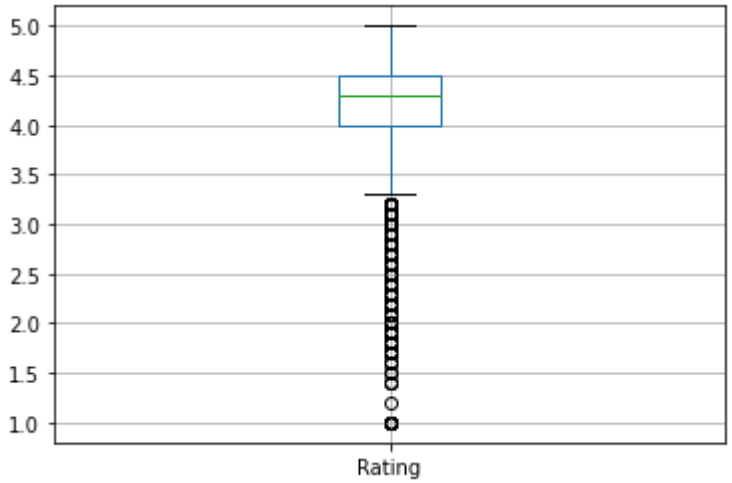
In [44]:
```
#find out remining outliers with boxplots
percentiles.boxplot(rot = 50)
```

Out[44]: <AxesSubplot:>



In [45]:
```
#zoomed into Rating box plot to find out outliers
percentiles.boxplot(column=['Rating'])
```

Out[45]: <AxesSubplot:>



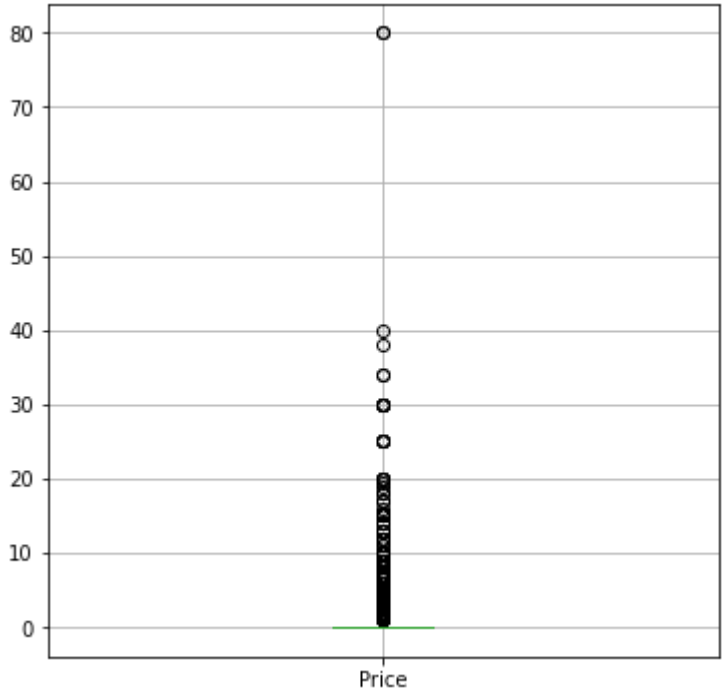
In [46]:
```
#remove outliers from Ratings
RatingOut1 = appdata[(appdata['Rating'] < 3.5) ].index
appdata.drop(RatingOut1 , inplace = True)
```

In [47]:
```
appdata.shape
```

Out[47]:
```
(8134, 13)
```

In [48]:
```
#zoomed into outliers from price coloumn
percentiles.boxplot(column = ['Price'], figsize = (6,6))
```

Out[48]:
```
<AxesSubplot:>
```

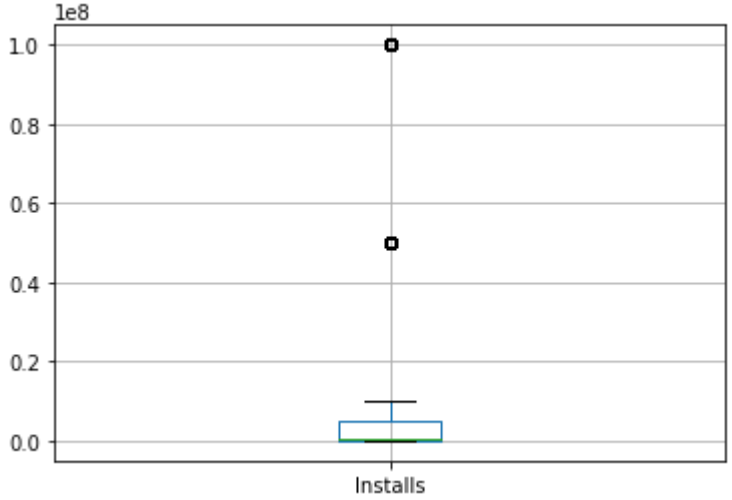


In [49]:
```
#remove outliers from price coloumn, anything above $40 seems outliers
PriceOut = appdata[(appdata['Price'] > 40)].index
appdata.drop(PriceOut , inplace = True)
#verify
appdata.shape
```

Out[49]:
```
(8132, 13)
```

In [50]:
```
#zoomed into outliers in Installs coloumn
percentiles.boxplot(column = ['Installs'])
```

Out[50]: <AxesSubplot:>

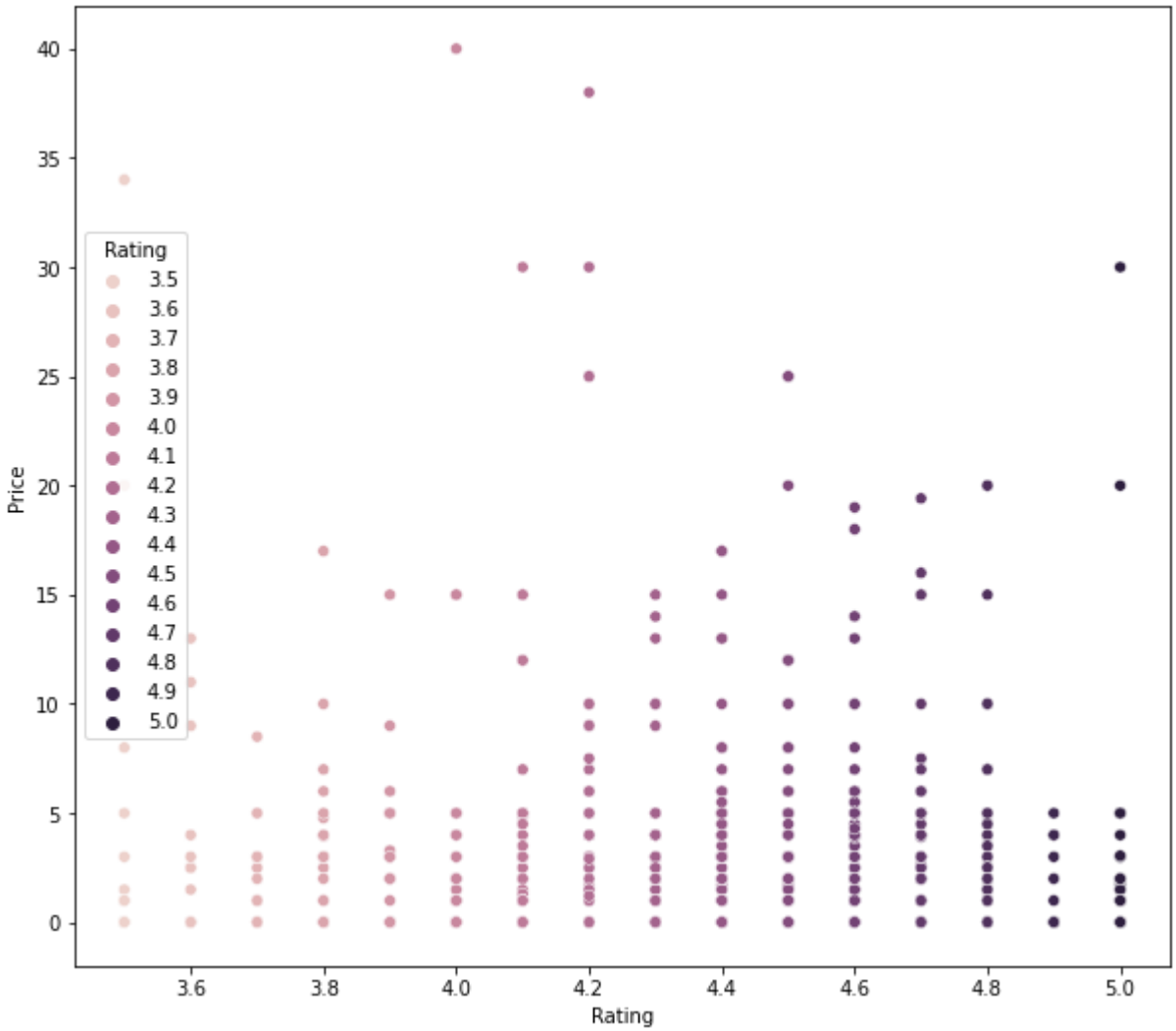


In [51]:
```
#remove outliers from Installs coloumns
Installsout = appdata[(appdata['Installs'] >= 100000000)].index
appdata.drop(Installsout , inplace = True)
#verify
appdata.shape
```

Out[51]: (8010, 13)

In [52]:
```
#Step 8. Bivariate analysis
#Scatter plot for Rating vs. Price
plt.figure(figsize=(10, 9))
sns.scatterplot(
    data=appdata, x="Rating", y="Price", hue="Rating",
    sizes=(20, 200),  legend="full")
```

Out[52]: <AxesSubplot:xlabel='Rating', ylabel='Price'>



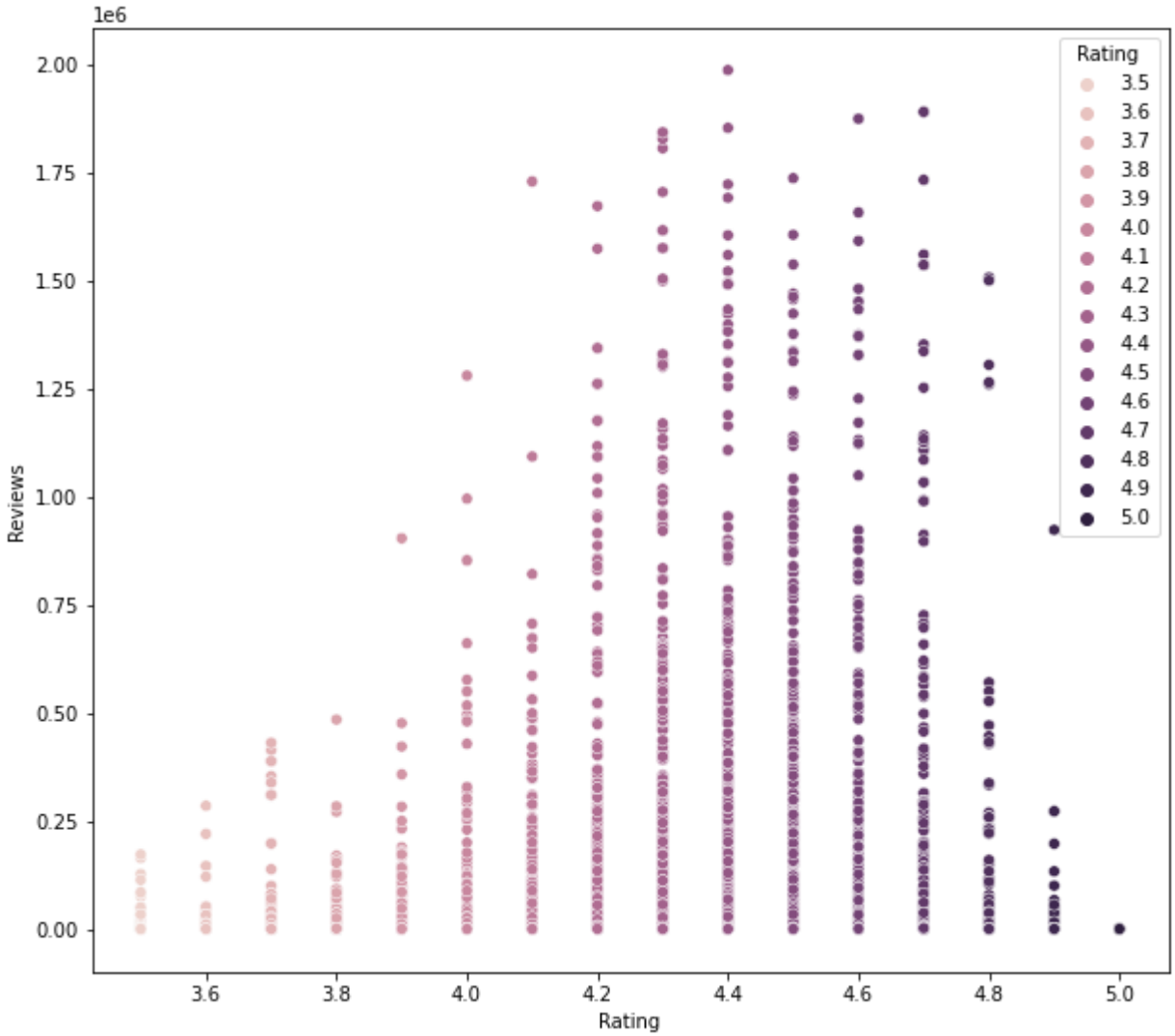
observation in Rating vs Price:

- Most Ratings for the apps are with in 4.4 to 5.0 and apps Prices are between 0 and $10. It is also observed that higher Price apps does not mean better ratings.

In [53]:
```
#Scatter plot for Rating vs. Reviews
plt.figure(figsize=(10, 9))
sns.scatterplot(
```

```
    data=appdata, x="Rating", y="Reviews", hue="Rating",
    sizes=(20, 200), legend="full")
```

Out[53]: <AxesSubplot:xlabel='Rating', ylabel='Reviews'>

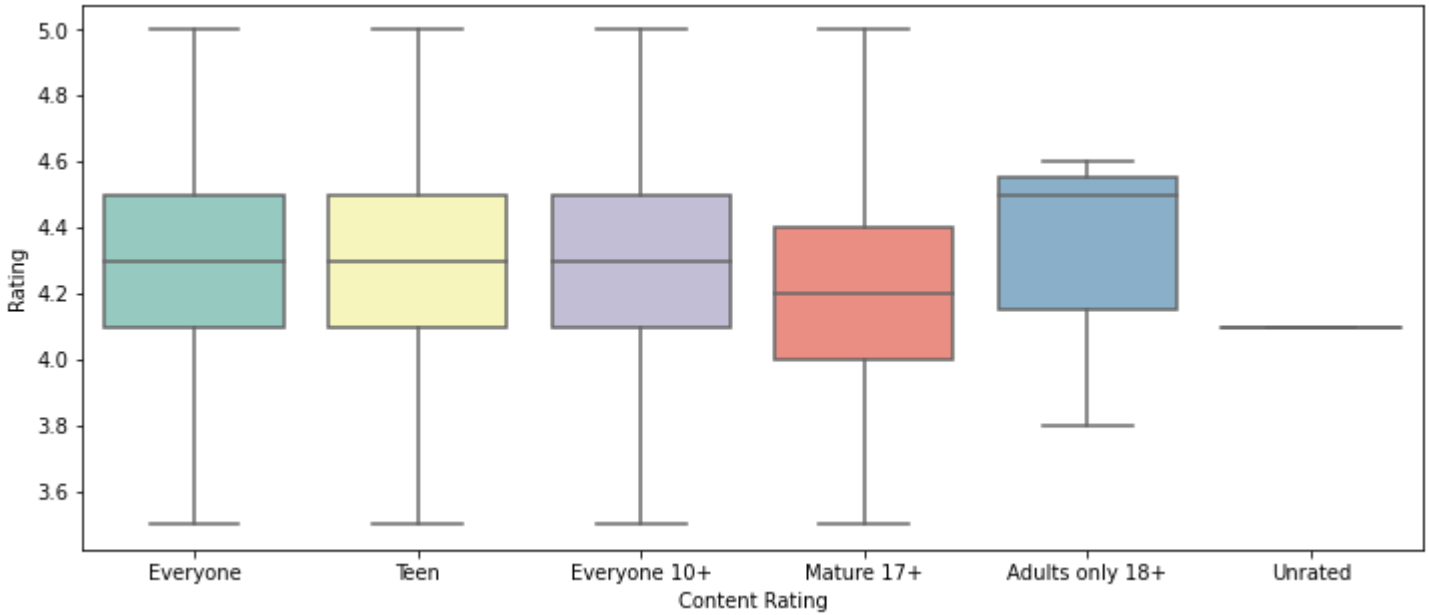


Observation in Rating vs Reviews:

- Better ratings apps have most reviews although not everytime is the case.

In [54]:
```
#Box plot for Rating vs. Content Rating
```

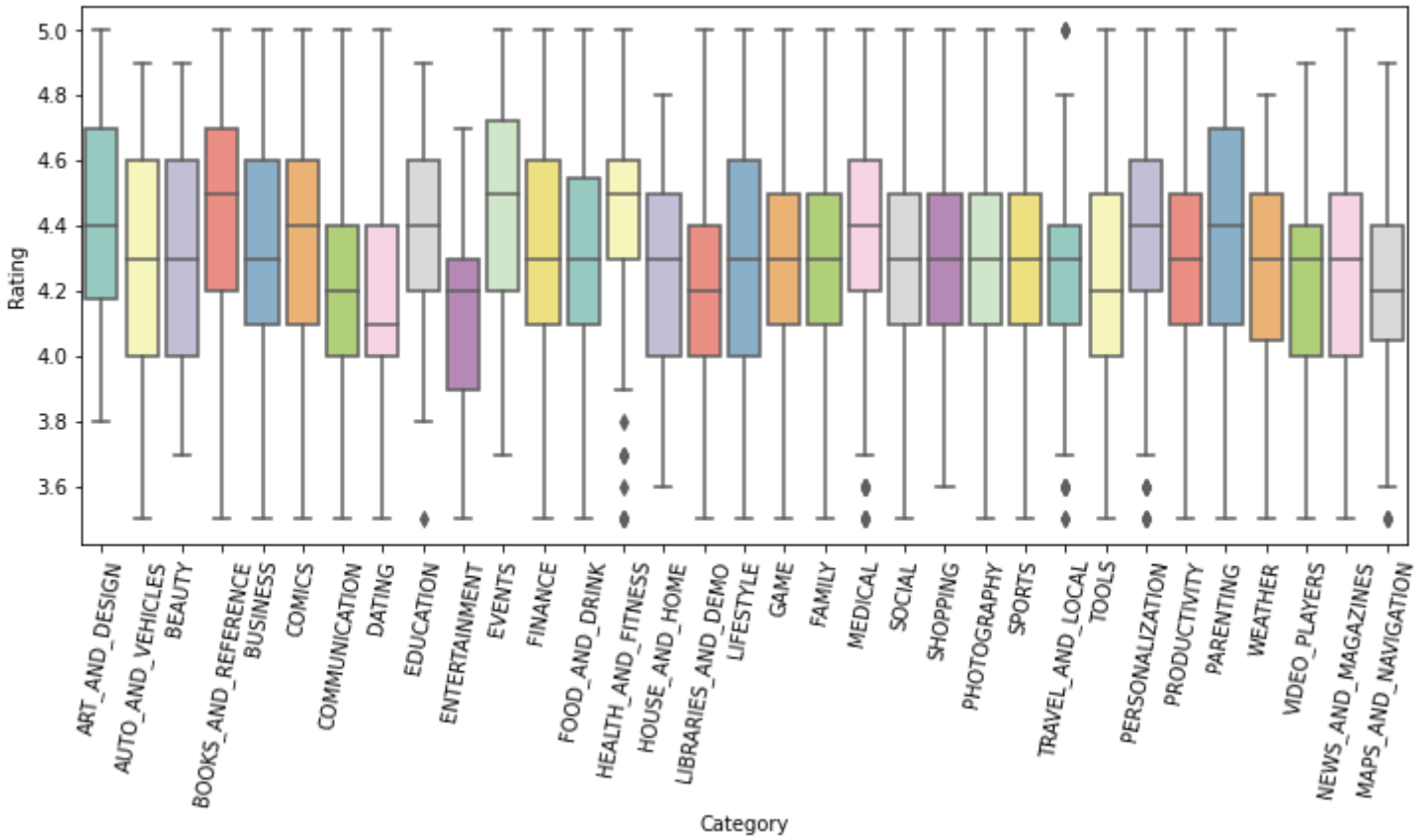
```
plt.figure(figsize=(12, 5))
rvcr = sns.boxplot(data = appdata,x ='Content Rating', y ='Rating', palette ='Set3')
```



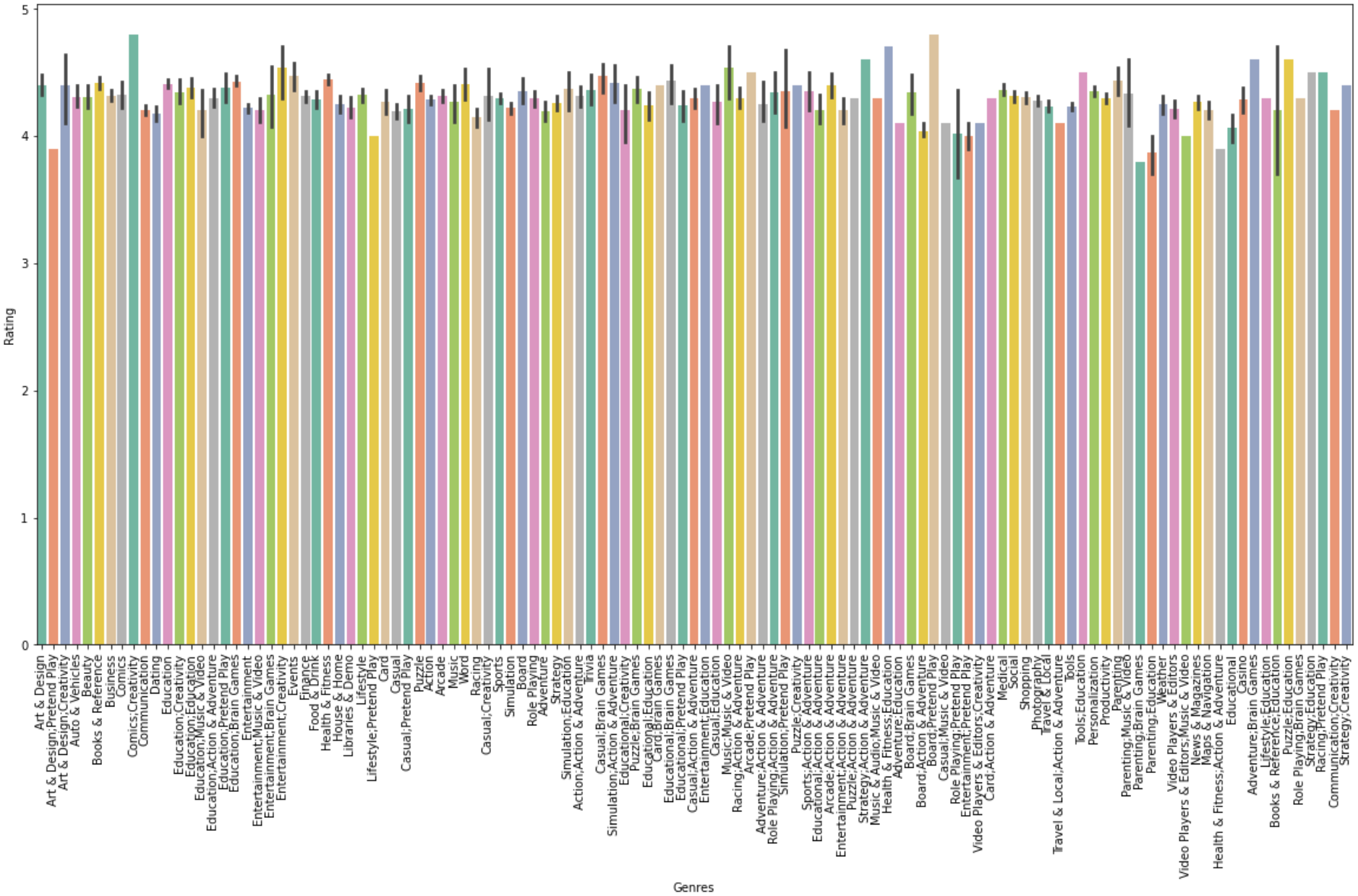
Observation in Rating vs Content Ratings:

- From the box plot, there does not seem to be much difference between Content Ratings in relation to Ratings.

In [55]:
```
#Box plot for Rating vs. Category
plt.figure(figsize=(12, 5))
rvca = sns.boxplot(data = appdata,x ='Category', y ='Rating', palette ='Set3')
plt.show(plt.setp(rvca.get_xticklabels(), rotation = 80))
```



In [56]:
```
#categorical data in relation to Genres
plt.figure(figsize=(20, 10))
cgen = sns.barplot(data = appdata, x ='Genres', y ='Rating', palette ='Set2')
plt.show (plt.setp(cgen.get_xticklabels(), rotation=90))
```



Box plot for Rating vs. Genres

- Comics;Creativity and Board Pretend Play has rate best ratings.

In [57]:
```
#Step 9.Data preprocessing
```

In [58]:
```
inp1 = appdata.copy()
```

In [59]:
```
inp1.head(2)
```

Out[59]:

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Last Updated	Current Ver	Android Ver
0	Photo Editor & Candy Camera & Grid & ScrapBook	ART_AND_DESIGN	4.1	159.0	19000.0	10000.0	Free	0.0	Everyone	Art & Design	January 7, 2018	1.0.0	4.0.3 and up
1	Coloring book moana	ART_AND_DESIGN	3.9	967.0	14000.0	500000.0	Free	0.0	Everyone	Art & Design;Pretend Play	January 15, 2018	2.0.0	4.0.3 and up

In [60]:
```
inp1.describe()
```

Out[60]:

	Rating	Reviews	Size	Installs	Price
count	8010.000000	8.010000e+03	8010.000000	8.010000e+03	8010.000000
mean	4.294931	9.734010e+04	17388.392559	3.755792e+06	0.334087
std	0.335667	2.408202e+05	23634.134319	8.968026e+06	1.866648
min	3.500000	1.000000e+00	0.000000	5.000000e+00	0.000000
25%	4.100000	2.110000e+02	3.300000	1.000000e+04	0.000000
50%	4.300000	6.030500e+03	861.500000	5.000000e+05	0.000000
75%	4.500000	6.122275e+04	27000.000000	5.000000e+06	0.000000
max	5.000000	1.986068e+06	100000.000000	5.000000e+07	39.990000

In [61]:
```
# Apply log transformation to reduce the skew in Reviews and Installs.
inp1.Reviews = np.log1p(inp1.Reviews.values)
inp1.Installs = np.log1p(inp1.Installs.values)
```

In [62]:
```
#verify after apply log transformation.
inp1.describe()
```

Out[62]:

	Rating	Reviews	Size	Installs	Price
count	8010.000000	8010.000000	8010.000000	8010.000000	8010.000000
mean	4.294931	8.192454	17388.392559	12.088349	0.334087
std	0.335667	3.489351	23634.134319	3.526139	1.866648
min	3.500000	0.693147	0.000000	1.791759	0.000000
25%	4.100000	5.356586	3.300000	9.210440	0.000000
50%	4.300000	8.704751	861.500000	13.122365	0.000000
75%	4.500000	11.022290	27000.000000	15.424949	0.000000
max	5.000000	14.501668	100000.000000	17.727534	39.990000

In [63]:
```
#Drop columns App, Last Updated, Current Ver, and Android Ver.
inp1 = inp1.drop(['App', 'Last Updated', 'Current Ver', 'Android Ver'], axis = 1)
```

In [64]:
```
#verify
inp1.head(2)
```

Out[64]:

	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres
0	ART_AND_DESIGN	4.1	5.075174	19000.0	9.210440	Free	0.0	Everyone	Art & Design
1	ART_AND_DESIGN	3.9	6.875232	14000.0	13.122365	Free	0.0	Everyone	Art & Design;Pretend Play

In [65]:
```
## convert the object type variable and convert them to dumies
inp2 = pd.get_dummies(inp1, columns = ['Category','Type','Content Rating','Genres'])
```

In [66]:
```
inp2
```

Out[66]:

	Rating	Reviews	Size	Installs	Price	Category_ART_AND_DESIGN	Category_AUTO_AND_VEHICLES	Category_BEAUTY	Category_
0	4.1	5.075174	19000.0	9.210440	0.0	1	0	0	
1	3.9	6.875232	14000.0	13.122365	0.0	1	0	0	
2	4.7	11.379520	8.7	15.424949	0.0	1	0	0	

	Rating	Reviews	Size	Installs	Price	Category_ART_AND_DESIGN	Category_AUTO_AND_VEHICLES	Category_BEAUTY	Category_
3	4.5	12.281389	25000.0	17.727534	0.0	1	0	0	
4	4.3	6.875232	2.8	11.512935	0.0	1	0	0	
...	...	...	...	...	...	...	...	...	
10834	4.0	2.079442	2.6	6.216606	0.0	0	0	0	
10836	4.5	3.663562	53000.0	8.517393	0.0	0	0	0	
10837	5.0	1.609438	3.6	4.615121	0.0	0	0	0	
10839	4.5	4.744932	0.0	6.908755	0.0	0	0	0	
10840	4.5	12.894981	19000.0	16.118096	0.0	0	0	0	

8010 rows × 161 columns

In [67]:
```
#Step 10. Train test split  and apply 70-30 split. Name the new dataframes df_train and df_test
df_train, df_test = split(inp2, test_size = 0.30, random_state = 12)
```

In [68]:
```
df_train.shape
```

Out[68]:
```
(5607, 161)
```

In [69]:
```
df_test.shape
```

Out[69]:
```
(2403, 161)
```

In [70]:
```
#Step 11. Model bulding
lm = LinearRegression()
```

In [71]:
```
# fit the model
X = df_train.drop(columns=['Rating'])
Y = df_train.Rating
lm = lm.fit(X,Y)
```

In [72]:
```
lm.coef_
```

Out[72]:
```
array([ 1.25377279e-01, -1.96994216e-07, -1.29919784e-01, -6.73259942e-03,
        2.85896314e-01,  1.20982219e-02,  2.21857947e-02,  4.39740520e-02,
       -5.12960310e-03,  1.74879339e-01, -6.09064501e-02, -5.90037866e-02,
       -4.08333449e-02, -1.25718155e-01,  8.03342238e-02, -3.62643100e-02,
       -1.43024208e-02, -3.86428067e-03,  1.61136374e-01,  4.89036100e-02,
       -1.87843171e-02, -4.08525665e-02, -7.95022343e-02, -7.80563309e-02,
        1.67663827e-02, -2.53218613e-02, -5.27299070e-02,  1.25476805e-03,
       -5.56277442e-03, -1.56147917e-02, -6.96197399e-03, -1.64395714e-02,
       -9.36158870e-04, -3.75960020e-02, -6.69146404e-02, -3.62807411e-02,
       -1.98528581e-02,  2.58650111e-02, -2.58650111e-02,  1.71864220e-01,
        2.41072631e-02, -1.27049668e-02, -1.30084282e-02, -4.64355218e-03,
       -1.65614536e-01, -2.20725433e-01,  3.40191251e-02, -3.42138163e-01,
       -5.40113359e-02,  2.08143226e-01, -2.10932826e-01, -1.55038241e-01,
        7.39169510e-02,  2.03241021e-01, -1.71455176e-01, -4.90520273e-02,
       -2.62704839e-01,  1.20982219e-02,  2.21857947e-02, -2.09811765e-01,
       -1.97106423e-01,  3.98780038e-02,  4.17689836e-01,  4.39740520e-02,
       -1.72266591e-01, -5.12960310e-03, -2.49920786e-01,  2.37240783e-14,
        1.08607567e-13, -2.58050277e-01, -1.11871161e-01,  6.77896636e-02,
        2.27012270e-01,  3.10776786e-02,  1.61773609e-02,  2.87958921e-02,
       -4.07660072e-02, -1.91896450e-01,  3.66775789e-01, -6.09064501e-02,
       -1.69309011e-15, -5.90037866e-02,  1.07016745e-01,  1.19049549e-01,
        6.60694916e-02,  2.61886016e-01,  1.70393576e-01,  1.08573651e-01,
        1.91767755e-01, -2.02568746e-01,  4.37720491e-02,  5.05066276e-01,
        1.81189634e-01,  7.69906736e-02,  2.00655042e-03, -3.29278806e-02,
       -1.17923833e-01,  4.71959836e-02,  3.12081543e-01, -5.84254867e-15,
        2.36000827e-02, -3.08572251e-01,  8.03342238e-02, -1.43024208e-02,
       -3.86428067e-03,  4.89036100e-02, -5.46611367e-15,  2.06843461e-01,
       -1.87843171e-02, -4.08525665e-02,  9.68226894e-02, -6.08439391e-02,
       -1.76324924e-01, -7.80563309e-02,  1.67663827e-02, -1.44745533e-01,
        2.52523397e-01, -9.21489355e-02, -2.53218613e-02,  2.23108457e-01,
       -2.62610091e-01, -2.31480919e-01,  2.18252646e-01,  1.25476805e-03,
       -5.56277442e-03, -1.56147917e-02,  2.13730574e-02,  3.06612461e-02,
        9.61820795e-02, -4.60863916e-02,  0.00000000e+00, -2.73393824e-01,
        8.60842490e-02,  4.97513945e-01, -1.11120093e-01, -4.57271982e-02,
        6.24700352e-02, -1.43312323e-01, -6.96197399e-03, -4.97579456e-02,
        1.30538288e-01, -8.74851314e-02, -2.64823687e-01, -1.64395714e-02,
       -5.69859825e-02,  3.73578765e-02, -9.85850735e-02,  3.25545482e-01,
        0.00000000e+00,  4.09471972e-01, -3.75960020e-02,  0.00000000e+00,
        5.06883920e-03, -7.19834796e-02, -1.20714740e-01, -6.48362231e-02,
       -2.40332750e-01, -1.81375275e-01, -1.98528581e-02, -6.38469067e-02])
```

In [73]:
```
lm.intercept_
```

Out[73]:
```
4.8330797658206865
```

In [74]:
```
lm.score(X,Y)  # R squared value for the df_train data
```

Out[74]:
```
0.2094384482453281
```

In [75]:
```
#ycap that is prediction for the df_train data
ycap = lm.predict(X)
print(ycap)
```

```
[4.53689204 4.32417326 4.27046062 ... 4.34424434 4.28856167 4.27971385]
```

In [76]:
```
#Step 12. Make predictions for df_test data
df_test_x = df_test.drop(columns = ['Rating'])
```

In [77]:
```
y_pred = lm.predict(df_test_x)
print (y_pred)
```

```
[4.42758805 4.23124602 4.1869629  ... 4.16990709 4.20954689 4.17562067]
```

In [78]:
```
mse(y_true = df_test.Rating, y_pred = y_pred, squared = False) #MSE value for df_test data
```

Out[78]:
```
0.3055338383580272
```