Project - 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.

1. Import pandas and load the file.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

In [2]:
```
#To remove warnings
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
data = pd.read_csv("googleplaystore.csv")
```

In [4]:
```
data.head()
```

Out[4]:

	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

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

In [5]:
```
data.isna().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
```

Rating, Type,Content Rating,Current Ver and Android version are showing null values. Hence, we will drop them

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

In [6]:
```
new_data = data.dropna()
```

In [7]:
```
new_data.isna()
```

Out[7]:

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Last Updated	Current Ver	Android Ver
0	False	False	False	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...
10834	False	False	False	False	False	False	False	False	False	False	False	False	False
10836	False	False	False	False	False	False	False	False	False	False	False	False	False
10837	False	False	False	False	False	False	False	False	False	False	False	False	False
10839	False	False	False	False	False	False	False	False	False	False	False	False	False
10840	False	False	False	False	False	False	False	False	False	False	False	False	False

9360 rows × 13 columns

After dropping null values, save the data into new variable names new_data

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.

4.1.1 Extract the numeric value from the column

In [8]:
```
new_data['Size'] = new_data.Size.replace("Varies with device",np.nan)
new_data['Size'] = new_data.Size.str.replace("M","000") # All size values became the kilobyte type.
new_data['Size'] = new_data.Size.str.replace("k","")
new_data['Size'] = new_data.Size.replace("1,000+",1000)
```

4.1.2 Multiply the value by 1,000, if size is mentioned in Mb

In [9]:
```
new_data['Size'] = new_data['Size'].astype(float)
new_data['Size'].dtype
```

Out[9]:
```
dtype('float64')
```

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

In [10]:
```
new_data["Reviews"] = new_data["Reviews"].astype(float)
new_data["Reviews"].dtype
```

Out[10]:
```
dtype('float64')
```

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

4.3.1 Treat 1,000,000+ as 1,000,000 and 4.3.2 remove '+', ',' from the field, convert it to integer

In [11]:
```
new_data["Installs"]=new_data.Installs.str.replace("+","")
new_data["Installs"]=new_data.Installs.str.replace(",","")
```

In [12]:
```
new_data["Installs"] = new_data["Installs"].astype(float)
new_data["Installs"].dtype
```

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

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

In [13]:
```
new_data["Price"]=new_data.Price.str.replace("$","")
```

In [14]:
```
new_data["Price"]=new_data["Price"].astype(float)
new_data["Price"].dtype
```

Out[14]:
```
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.

In [15]:
```
filter = (new_data.Rating<1) | (new_data.Rating>5)
print("Data Frame Size: ",new_data.shape, "Count of rows whose ratings are not between 1 and 5: ",filter.value_counts
())
```

```
Data Frame Size:  (9360, 13) Count of rows whose ratings are not between 1 and 5:  False    9360
Name: Rating, dtype: int64
```

There is no need to drop any rows as average rating is between 1 and 5

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.

In [16]:
```
new_data =new_data[new_data["Reviews"]<=new_data["Installs"]]
new_data.shape
```

Out[16]: (9353, 13)

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

In [17]:
```
new_data.loc[(new_data.Type=="Free") & (new_data.Price>0)]
```

Out[17]:

App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Last Updated	Current Ver	Android Ver

There are no values to drop, as for free apps, price is not greater than 0

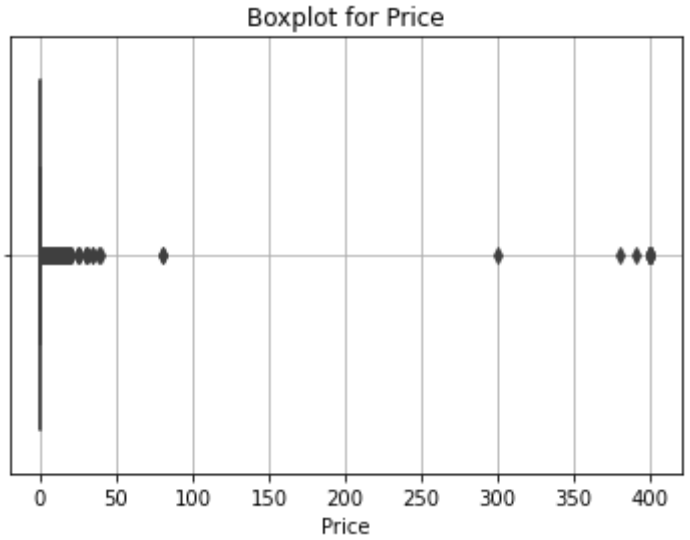
6. Performing univariate analysis:

6.1 Boxplot for Price

In [18]:
```
sns.boxplot(new_data.Price)

plt.title("Boxplot for Price")
plt.xlabel("Price")
plt.grid(linestyle = '-')

plt.show()
```



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

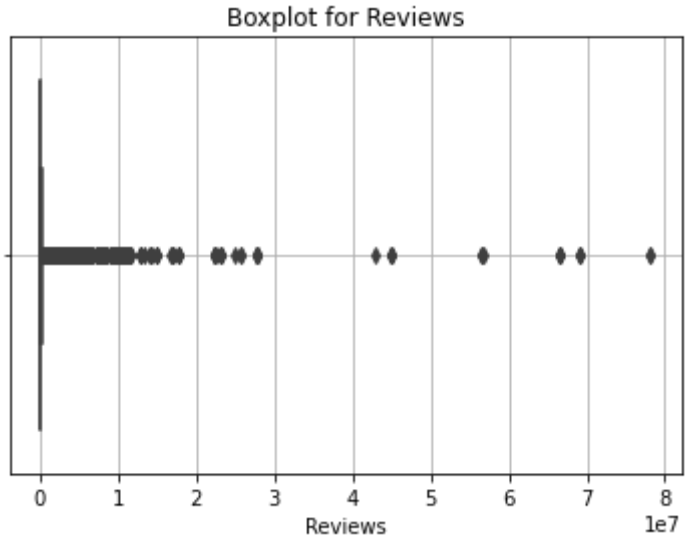
Yes there are outliers the rows with price greater than 250$ need to be removed.

6.2 Boxplot for Reviews

In [19]:
```
sns.boxplot(new_data.Reviews)

plt.title("Boxplot for Reviews")
plt.xlabel("Reviews")
plt.grid(linestyle = '-')

plt.show()
```

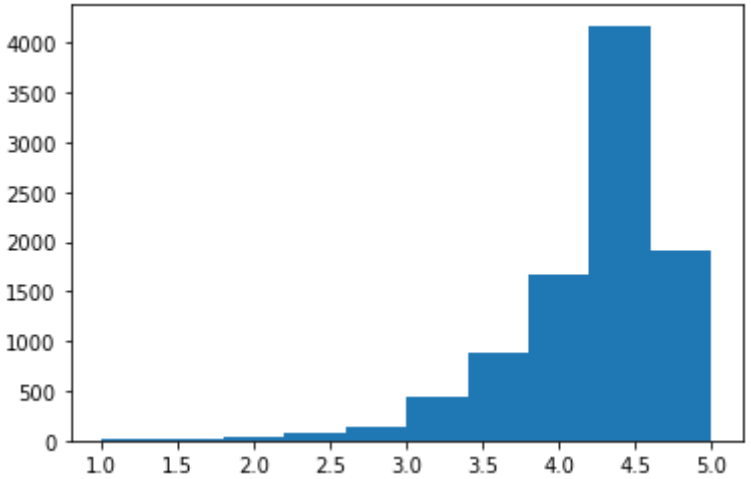


Are there any apps with very high number of reviews? Do the values seem right?

Certainly yes, there are apps which have high number of reviews. Mostly apps have reviews between 0 & 1

6.3 Histogram for Rating

In [20]:
```
plt.hist(new_data.Rating)
plt.show()
```

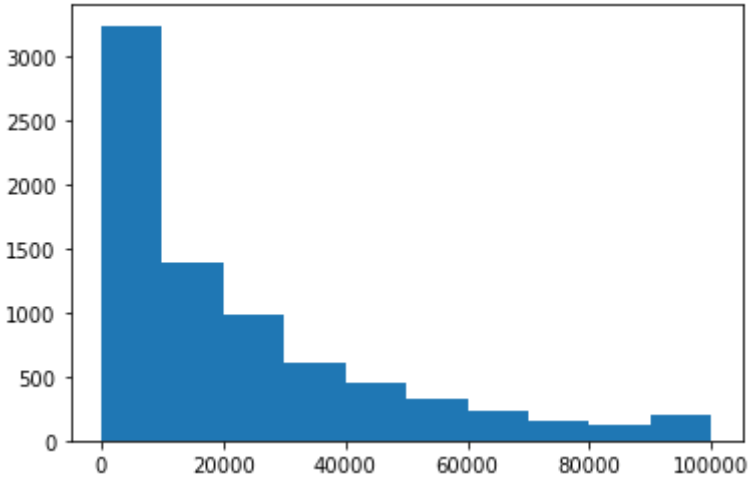


How are the ratings distributed? Is it more toward higher ratings?

Ratings Distribution is left skewed, as most off the data falls to the right of the mean. Yes,the ratings are towards higher rating

6.4 Histogram for Size

In [21]:
```
plt.hist(new_data.Size)
plt.show()
```



Note down your observations for the plots made above. Which of these seem to have outliers?

Size distribution is right or positively skewed, as most of the data is towards the left of the mean.

7. Outlier treatment:

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

Check out the records with very high price;Is 200 indeed a high price?;Drop these as most seem to be junk apps

In [22]:
```
new_data.Price.unique()
```

Out[22]:
```
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 ])
```

There are records with very high price; so we need to drop them

In [23]:
```
new_data = new_data.loc[(new_data.Price<200)]
new_data.shape
```

Out[23]:
```
(9338, 13)
```

7.2 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.

In [24]:
```
new_data= new_data.loc[(new_data.Reviews<2000000)]
new_data.shape
```

Out[24]:
```
(8885, 13)
```

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

Find out the different percentiles – 10, 25, 50, 70, 90, 95, 99;Decide a threshold as cutoff for outlier and drop records having values more than that

In [25]:
```
new_data.Installs.quantile([0.10, 0.25, 0.50, 0.70, 0.90, 0.95, 0.99])
```

Out[25]:
```
0.10         1000.0
0.25        10000.0
0.50       500000.0
0.70      1000000.0
0.90     10000000.0
0.95     10000000.0
0.99    100000000.0
Name: Installs, dtype: float64
```

In [26]:
```
new_data= new_data.loc[(new_data.Installs<10000000)]
```

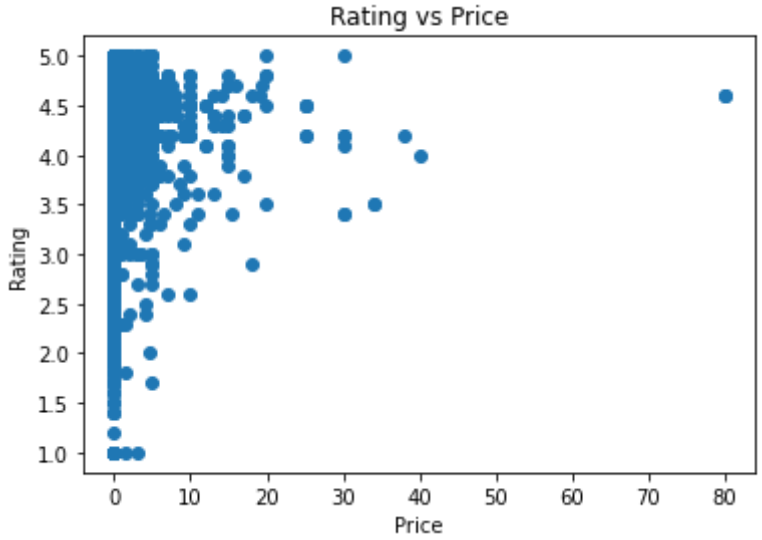
In [27]:
```
new_data.shape
```

Out[27]:
```
(7258, 13)
```

8. 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.

8.1 Make scatter plot/joinplot for Rating vs. Price

In [28]:
```
plt.scatter(x =new_data.Price, y =new_data.Rating)
plt.xlabel("Price")
plt.ylabel("Rating")
plt.title("Rating vs Price")
plt.show()
```

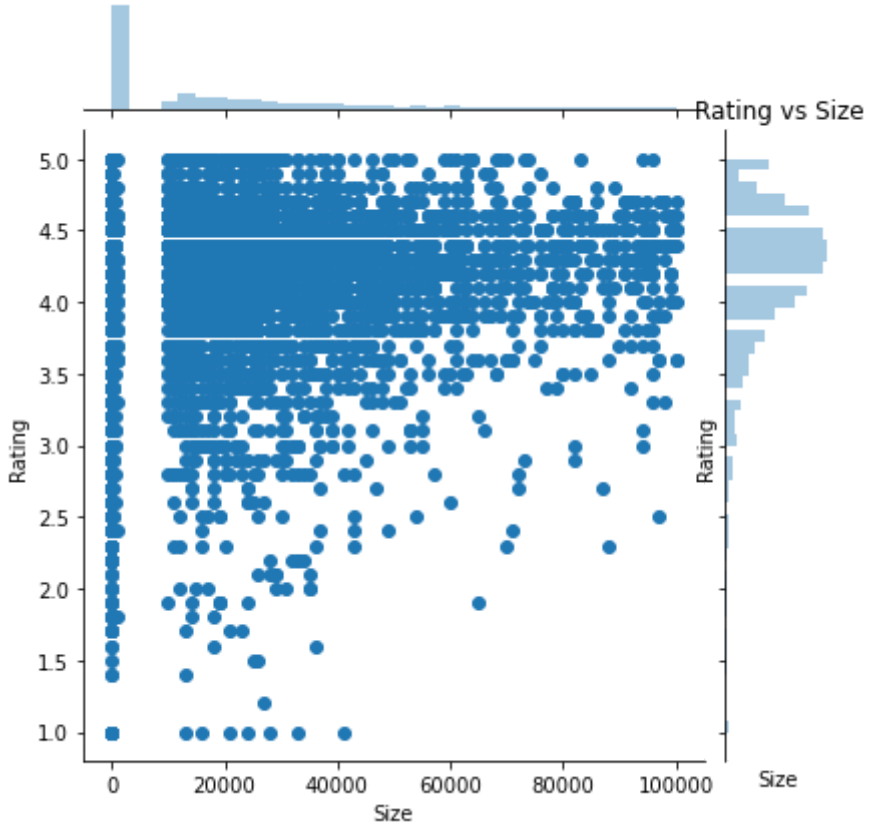


What pattern do you observe? Does rating increase with price?

No,Ratings does not increase with price

8.2 Make scatter plot/joinplot for Rating vs. Size

In [29]:
```
sns.jointplot(x ='Size', y ='Rating', data = new_data, kind ='scatter')
plt.xlabel("Size")
plt.ylabel("Rating")
plt.title("Rating vs Size")
plt.show()
```



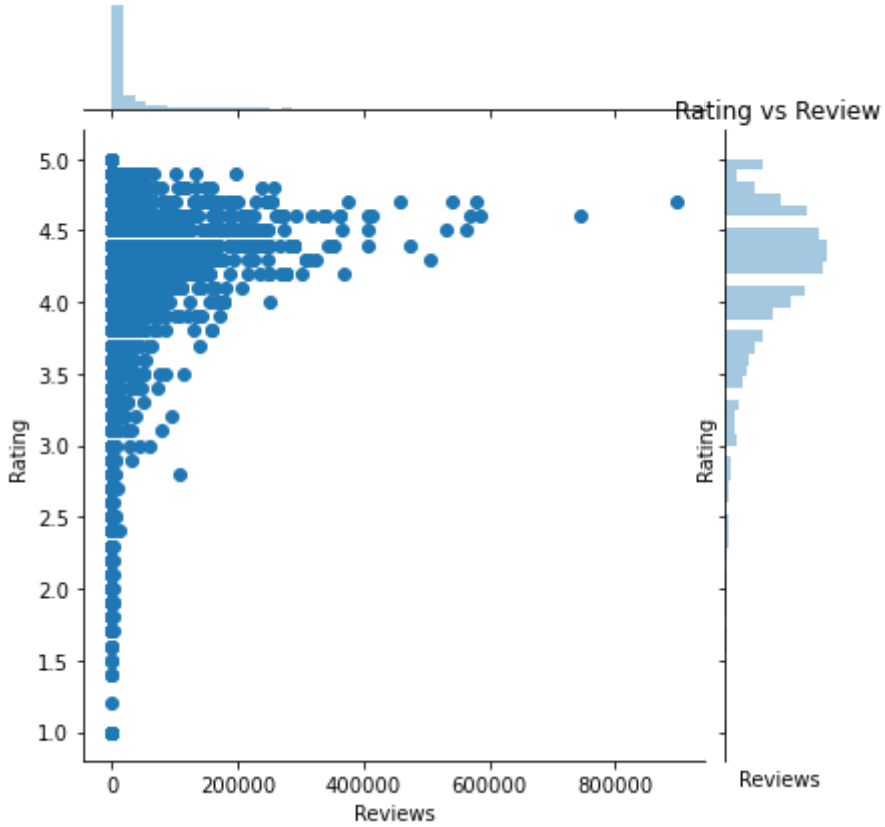
Are heavier apps rated better?

We can observe that heavier apps are having higher rating

8.3 Make scatter plot/joinplot for Rating vs. Reviews

In [30]:
```
sns.jointplot(x ='Reviews', y ='Rating', data = new_data,kind ='scatter')
plt.xlabel("Reviews")
plt.ylabel("Rating")
plt.title("Rating vs Review")

plt.show()
```

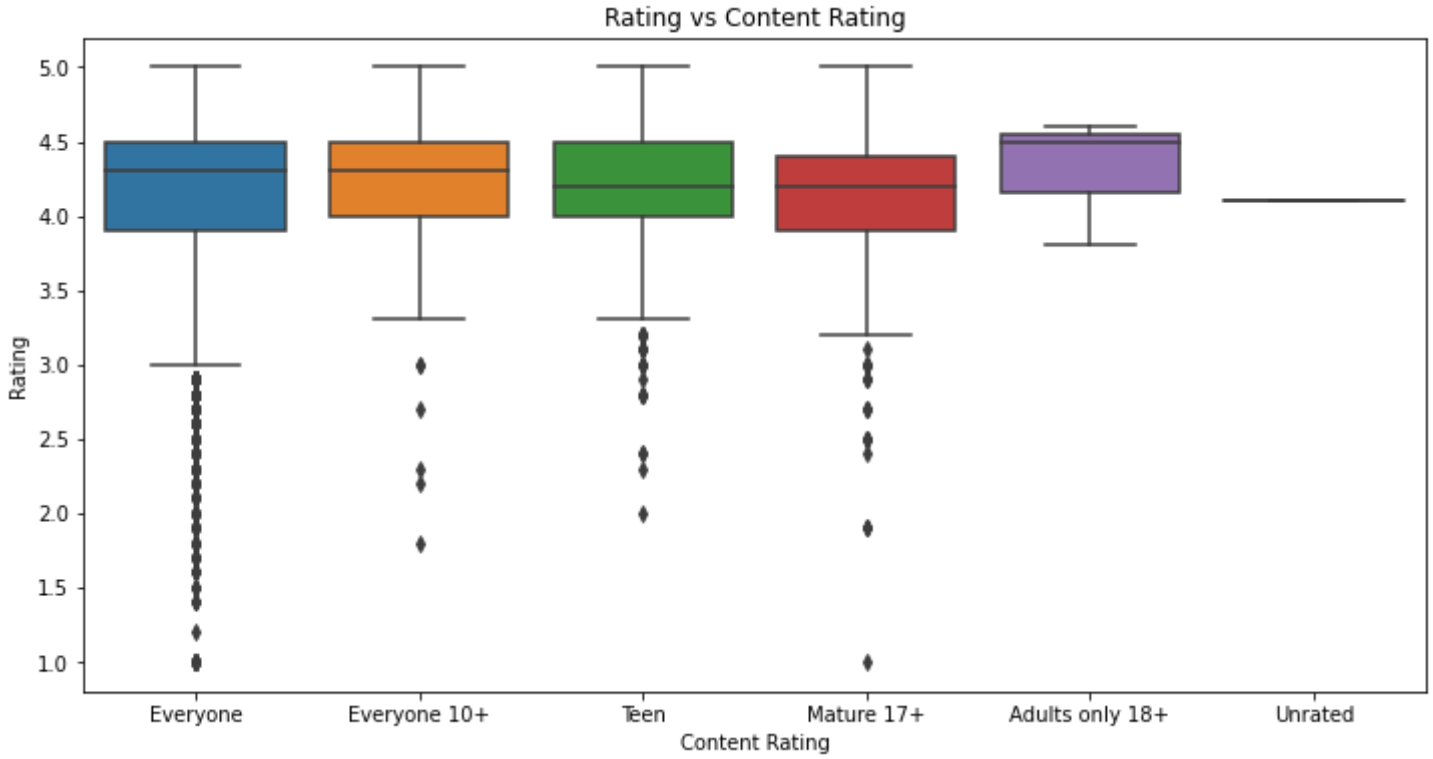


Does more review mean a better rating always?

Scatter plot indicate higher rating for apps having Max reviews. But this cannot be always it could be an outlier

8.4 Make boxplot for Rating vs. Content Rating

In [31]:
```
plt.figure(figsize=[12,6])
sns.boxplot(y= "Rating", x= "Content Rating", data=new_data)
plt.title("Rating vs Content Rating")
plt.show()
```



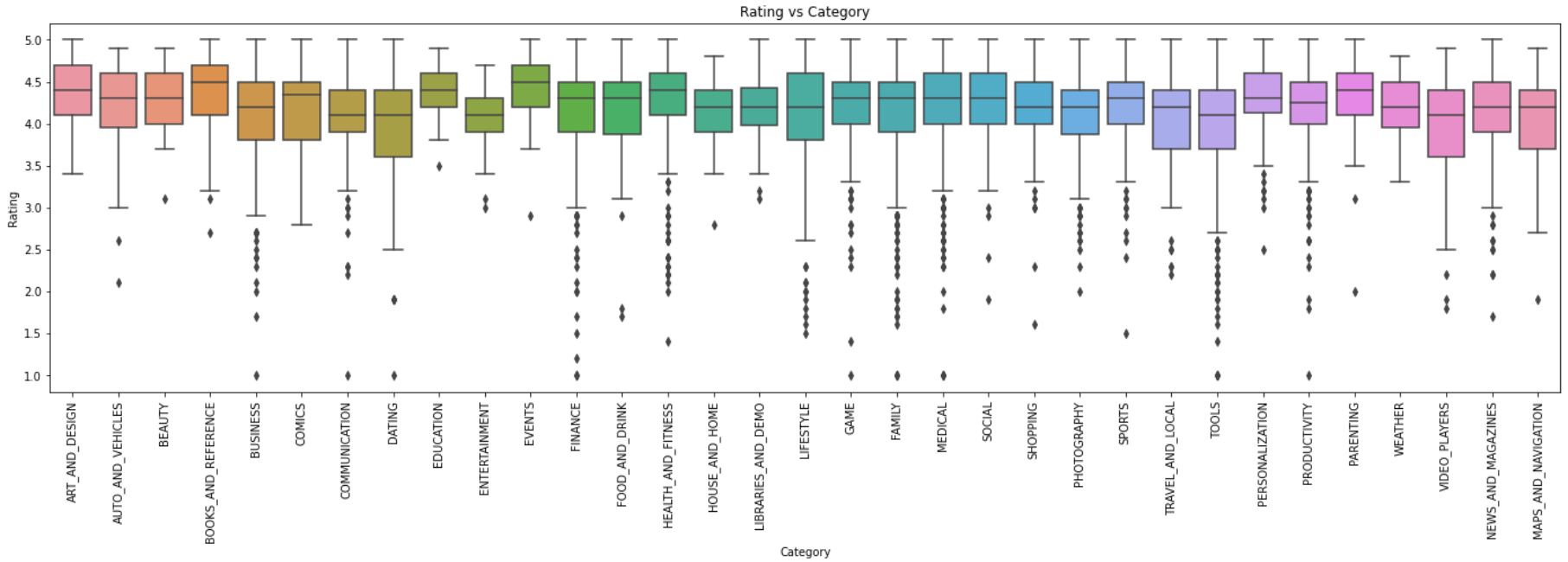
Is there any difference in the ratings? Are some types liked better?

Not much conclusion could be drawn as the plot is almost same for Content Ratings.

8.5 Make boxplot for Ratings vs. Category

In [32]:
```
plt.subplots(figsize=(24,6))

sns.boxplot(y="Rating",x="Category",data=new_data)
plt.title("Rating vs Category")
plt.xticks(rotation = 90)
plt.show()
```



Which genre has the best ratings?

9. Data preprocessing

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

In [33]:
```
inp1 = new_data.copy()
inp1.head()
```

Out[33]:

	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
2	U Launcher Lite – FREE Live Cool Themes, Hide ...	ART_AND_DESIGN	4.7	87510.0	8.7	5000000.0	Free	0.0	Everyone	Art & Design	August 1, 2018	1.2.4	4.0.3 and up
4	Pixel Draw - Number Art Coloring Book	ART_AND_DESIGN	4.3	967.0	2.8	100000.0	Free	0.0	Everyone	Art & Design;Creativity	June 20, 2018	1.1	4.4 and up
5	Paper flowers instructions	ART_AND_DESIGN	4.4	167.0	5.6	50000.0	Free	0.0	Everyone	Art & Design	March 26, 2017	1.0	2.3 and up

9.1 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.

In [34]:
```
inp1['Reviews'] = np.log1p(inp1['Reviews'])
inp1['Installs'] = np.log1p(inp1['Installs'])
inp1.head()
```

Out[34]:

	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	5.075174	19000.0	9.210440	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	6.875232	14000.0	13.122365	Free	0.0	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	11.379520	8.7	15.424949	Free	0.0	Everyone	Art & Design	August 1, 2018	1.2.4	4.0.3 and up
4	Pixel Draw - Number Art Coloring Book	ART_AND_DESIGN	4.3	6.875232	2.8	11.512935	Free	0.0	Everyone	Art & Design;Creativity	June 20, 2018	1.1	4.4 and up
5	Paper flowers instructions	ART_AND_DESIGN	4.4	5.123964	5.6	10.819798	Free	0.0	Everyone	Art & Design	March 26, 2017	1.0	2.3 and up

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

In [35]:
```
inp1.drop(["App", "Last Updated", "Current Ver", "Android Ver"],axis=1,inplace=True)
inp1.head()
```

Out[35]:

	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
2	ART_AND_DESIGN	4.7	11.379520	8.7	15.424949	Free	0.0	Everyone	Art & Design
4	ART_AND_DESIGN	4.3	6.875232	2.8	11.512935	Free	0.0	Everyone	Art & Design;Creativity
5	ART_AND_DESIGN	4.4	5.123964	5.6	10.819798	Free	0.0	Everyone	Art & Design

9.3 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.

In [36]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

In [37]:
```
cat=inp1[['Category','Genres','Content Rating','Type']].apply(le.fit_transform)
inp1.drop(["Category","Genres","Content Rating","Type"],axis=1,inplace=True)
inp2 = pd.concat([inp1,cat],axis=1).copy()
inp2.head()
```

Out[37]:

	Rating	Reviews	Size	Installs	Price	Category	Genres	Content Rating	Type
0	4.1	5.075174	19000.0	9.210440	0.0	0	8	1	0
1	3.9	6.875232	14000.0	13.122365	0.0	0	10	1	0
2	4.7	11.379520	8.7	15.424949	0.0	0	8	1	0
4	4.3	6.875232	2.8	11.512935	0.0	0	9	1	0
5	4.4	5.123964	5.6	10.819798	0.0	0	8	1	0

In [38]:
```
inp2.isna().sum()
```

Out[38]:
```
Rating             0
Reviews            0
Size             769
Installs           0
Price              0
Category           0
Genres             0
Content Rating     0
Type               0
dtype: int64
```

In [39]:
```
inp2 = inp2.dropna()
```

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

In [40]:
```
from sklearn.model_selection import train_test_split
df_train,df_test=train_test_split(inp2,test_size = 0.30,random_state=40)
```

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

In [41]:
```
y_train=df_train.pop('Rating')
X_train=df_train
y_test=df_test.pop('Rating')
X_test=df_test
```

12. Model building

Use linear regression as the technique Report the R2 on the train set

In [42]:
```
from sklearn.linear_model import LinearRegression
lm=LinearRegression()
lm.fit(X_train,y_train)

from sklearn.metrics import r2_score
y_train_predict=lm.predict(X_train)
r2_score(y_train,y_train_predict)
```

Out[42]: 0.09995364825387587

13. Make predictions on test set and report R2.

In [43]:
```
X_test_prect=lm.predict(X_test)
r2_score(y_test,X_test_prect)
```

Out[43]: 0.10509051754196752

In [ ]: