GoogleAppRating

July 9, 2024

[72]:
```
# Importing library
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
# Load the data file using pandas
df=pd.read_csv("googleplaystore.csv")
# Knowing the data
df.head()
# Checking for null Values count in each column
x=df.isnull().sum()
print(x)
# Droping the records with null in any of the column
df.dropna(inplace=True)
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
```

[72]:
```
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
```

[73]:
```
# Formatting the data
# converting categorical data types into numeric ones to facilitate analysis
# Extract the numeric value from the column & Multiply the value by 1,000, if␣
 ↪size is mentioned in Mb
df['Size'] = df['Size'].apply(lambda x: str(x).replace('M', '') if 'M' in␣
 ↪str(x) else x)
df['Size'] = df['Size'].apply(lambda x: str(x).replace('Varies with␣
 ↪device','nan') if 'Varies with device' in str(x) else x)
df['Size'] = df['Size'].apply(lambda x: float(str(x).replace('k', ''))/1000 if␣
 ↪'k' in str(x) else x)
df['Size'] = df['Size'].apply(lambda x : float(x))
df = df[pd.notnull(df['Size'])]
df['Size'].dtype
```

[73]:
```
dtype('float64')
```

[74]:
```
# Converting Reviews column into float type
df['Reviews']=df['Reviews'].astype("float")
df['Reviews'].dtype
```

[74]:
```
dtype('float64')
```

[75]:
```
# Treat 1,000,000+ as 1,000,000, remove '+', ',' from the field, convert it to␣
 ↪integer
df['Installs'] = df['Installs'].apply (lambda x: str(x).replace('+','') if '+'␣
 ↪in str(x) else x)
df['Installs'] = df['Installs'].apply(lambda x: str(x).replace(',', '') if ','␣
 ↪in str(x) else x)
df['Installs'] = df['Installs'].astype("int")
df['Installs'].dtype
```

[75]:
```
dtype('int64')
```

[76]:
```
# Price field is a string and has $ symbol. Remove '$' sign, and convert it to␣
 ↪numeric
df['Price'] = df['Price'].apply( lambda x: str(x).replace("$","") if "$" in␣
 ↪str(x) else x)
df['Price'] = df['Price'].astype("float")
```

```
df['Price'].dtype
```

[76]:
```
dtype('float64')
```

[77]:
```
# Average rating should be between 1 and 5 , Drop the rows that have a value␣
↪outside this range.
df[df['Rating']>5].shape[0]
```

[77]:
```
0
```

[78]:
```
# 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[df['Reviews']>df['Installs']].shape[0]
```

[78]:
```
6
```

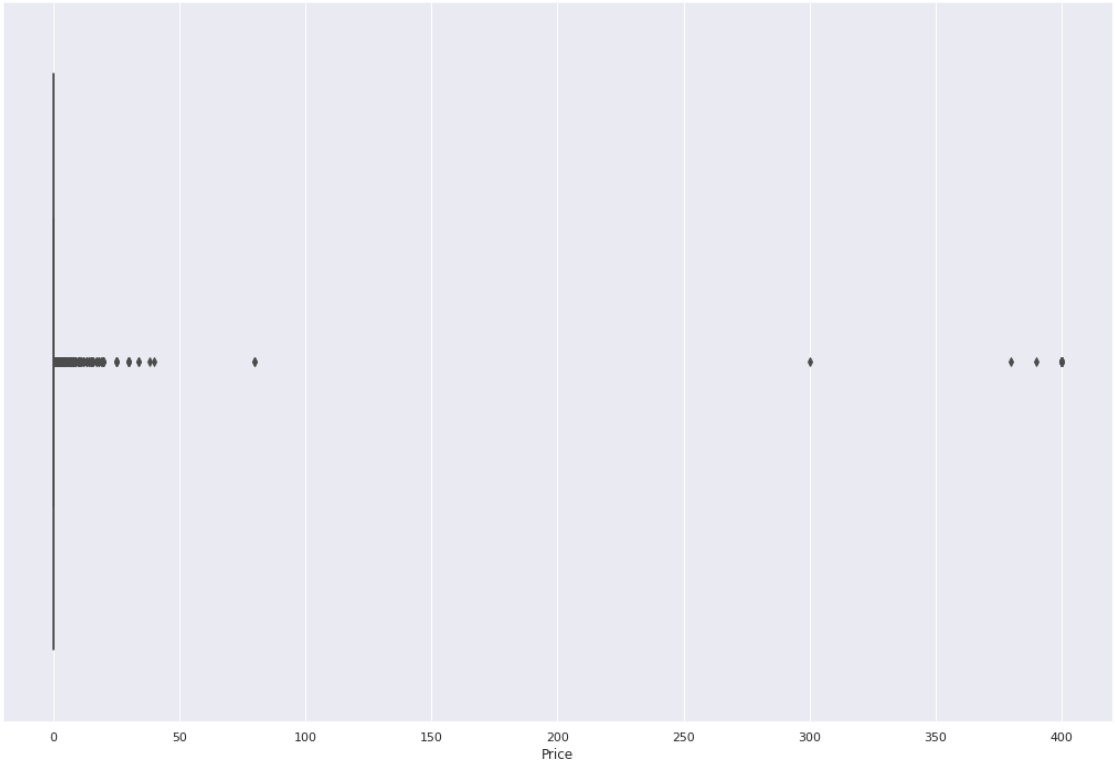
[79]:
```
df.drop(df[df['Reviews']>df['Installs']].index, inplace=True)
```

[80]:
```
# For free apps (type = "Free"), the price should not be >0. Drop any such rows
df[(df['Type']=="free") & (df['Price']>0)].shape[0]
```

[80]:
```
0
```

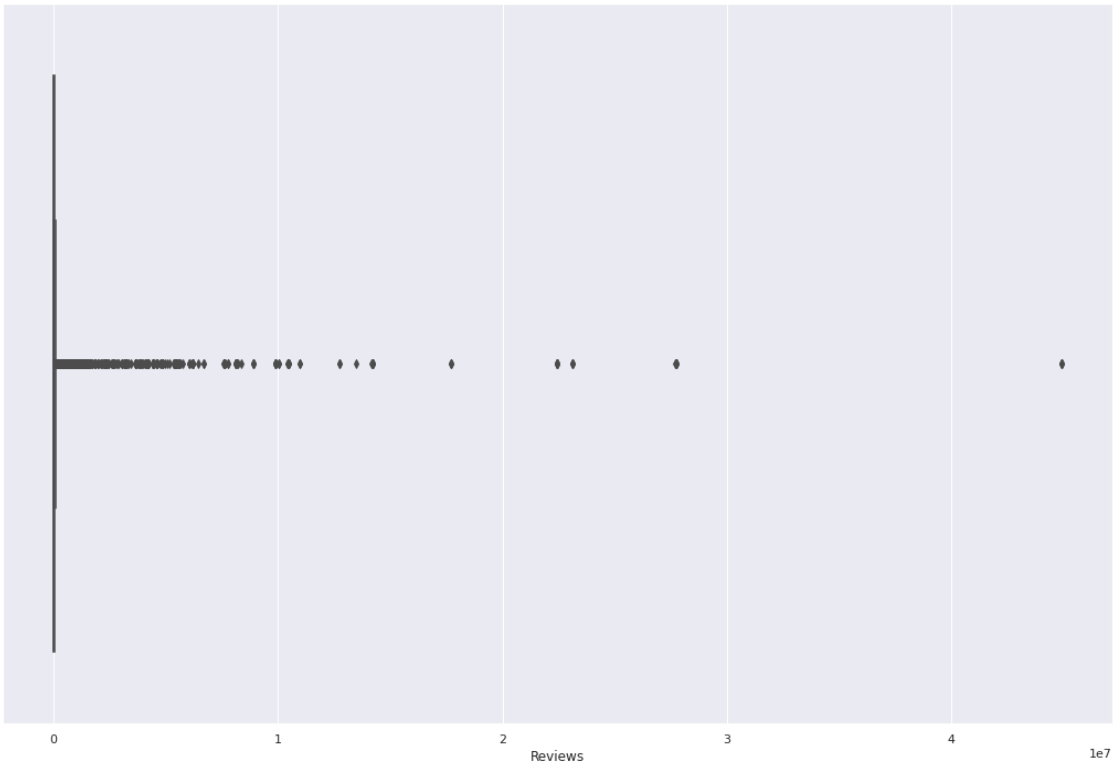
[81]:
```
# Univariate analysis
# Boxplots for price
sns.boxplot(data=df, x='Price')
```

[81]:
```
<AxesSubplot: xlabel='Price'>
```



[82]:
```
# Univariate analysis
# Boxplots for Reviews
sns.boxplot(data=df, x='Reviews')
```

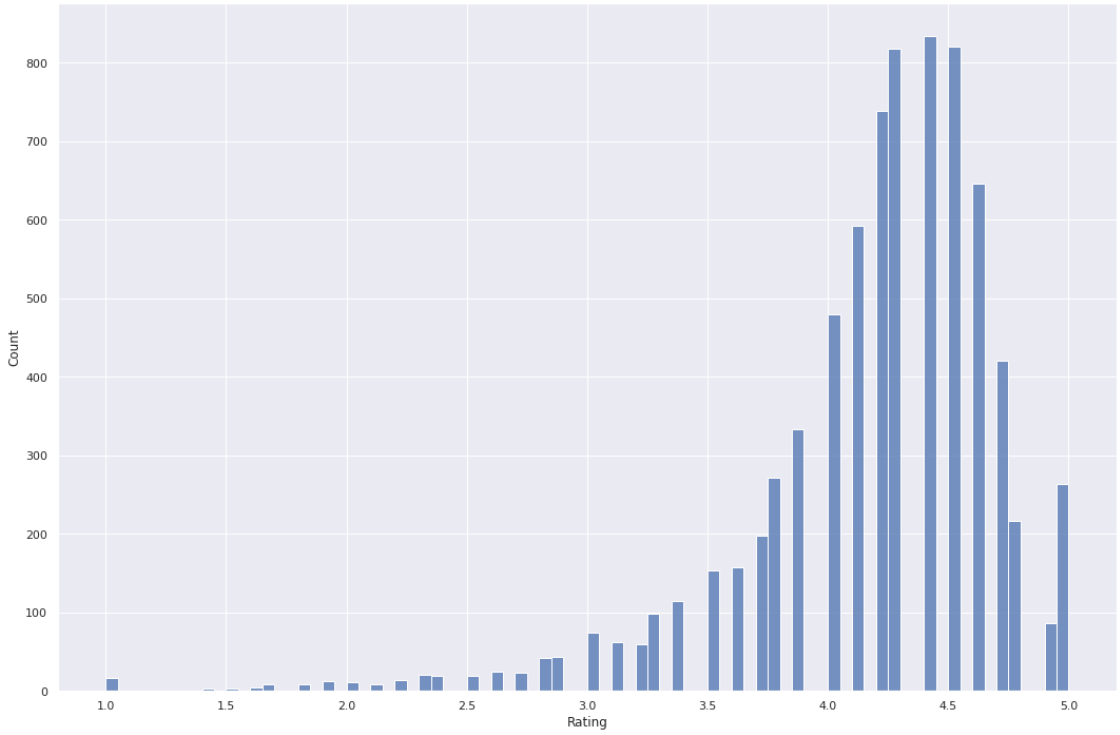
[82]: <AxesSubplot: xlabel='Reviews'>



[83]:
```
# There are some outliers in the Price column
# There are some apps whose price is more than usual apps on the Googleplaystore
# Indeed there are some apps that have very high number of Review
```

[84]:
```
# Univariate analysis
# Histplots for Rating
sns.histplot(data=df,x='Rating')
```

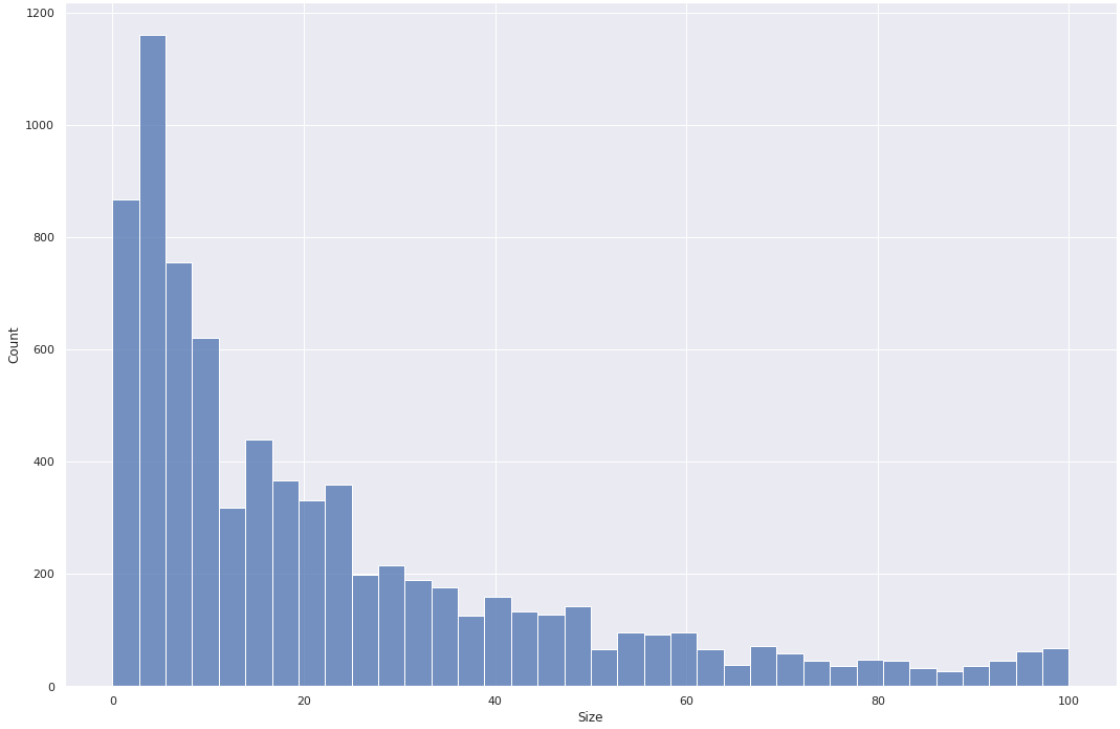
[84]: <AxesSubplot: xlabel='Rating', ylabel='Count'>



[85]:
```
# There is a Negative skewness(left- skewed) some apps seem to have higher␣
↪Ratings than usual
```

[86]:
```
# Univariate analysis
# Histplot for Size
sns.histplot(data=df,x='Size')
```

[86]: <AxesSubplot: xlabel='Size', ylabel='Count'>



[87]:
```
# positive skewness Right Skewed
# As per the above observation of plots, there seems to be some outliers in the␣
 ↪Price & Reviews column, In the Installs column as well
```

[88]:
```
# Check out the records with very high price
df[df['Price']>200].shape[0]
```

[88]: 15

[89]:
```
# Drop these as most seem to be junk apps
df.drop(df[df['Price']>200].index, inplace=True)
```

[90]:
```
df.drop(df[df['Reviews']>2000000].index, inplace= True)
df.shape
```

[90]: (7483, 13)

[91]:
```
# Find out the different percentiles - 10, 25, 50, 70, 90, 95, 99
df.quantile([0.1,0.25,0.5,0.7,0.9,0.95,0.99], axis=0)
```

```
/tmp/ipykernel_341/3150743028.py:2: FutureWarning: The default value of
numeric_only in DataFrame.quantile is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
```

```
to silence this warning.
  df.quantile([0.1,0.25,0.5,0.7,0.9,0.95,0.99], axis=0)
```

[91]:

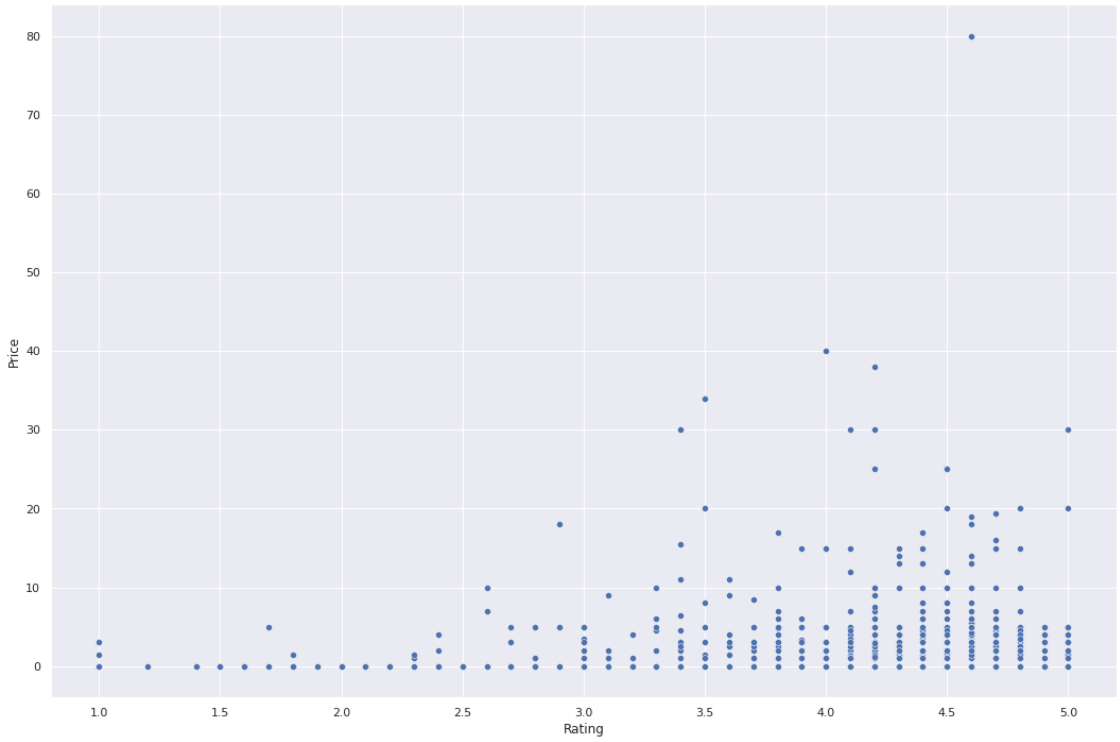
	Rating	Reviews	Size	Installs	Price
0.10	3.5	13.00	2.5	1000.0	0.00
0.25	4.0	99.00	5.1	10000.0	0.00
0.50	4.3	2026.00	14.0	100000.0	0.00
0.70	4.5	20295.60	26.0	1000000.0	0.00
0.90	4.7	180385.40	56.0	10000000.0	0.00
0.95	4.8	407660.30	72.9	10000000.0	1.99
0.99	5.0	1242884.16	96.0	50000000.0	8.99

[92]:
```
# Find out the different percentiles - 10, 25, 50, 70, 90, 95, 99
df.drop(df[df['Installs']>10000000].index, inplace= True)
```

[93]:
```
# Make scatter plots (for numeric features) and box plots (for character␣
↪features)
# to assess the relations between rating and the other features
```

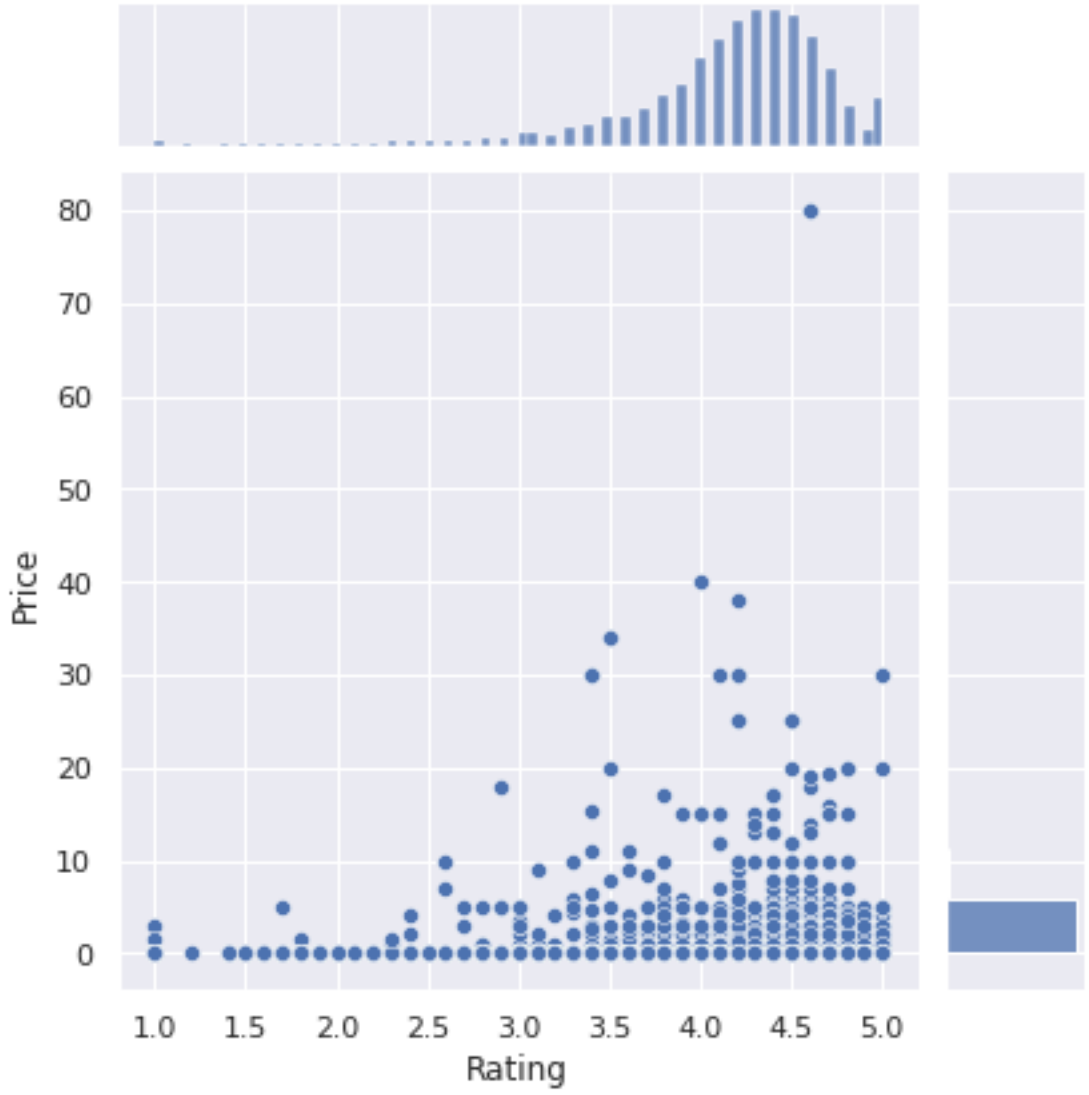
[94]:
```
sns.scatterplot(data=df, x='Rating',y='Price')
```

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



[95]:
```
sns.jointplot(x= 'Rating',y= 'Price',data= df)
```

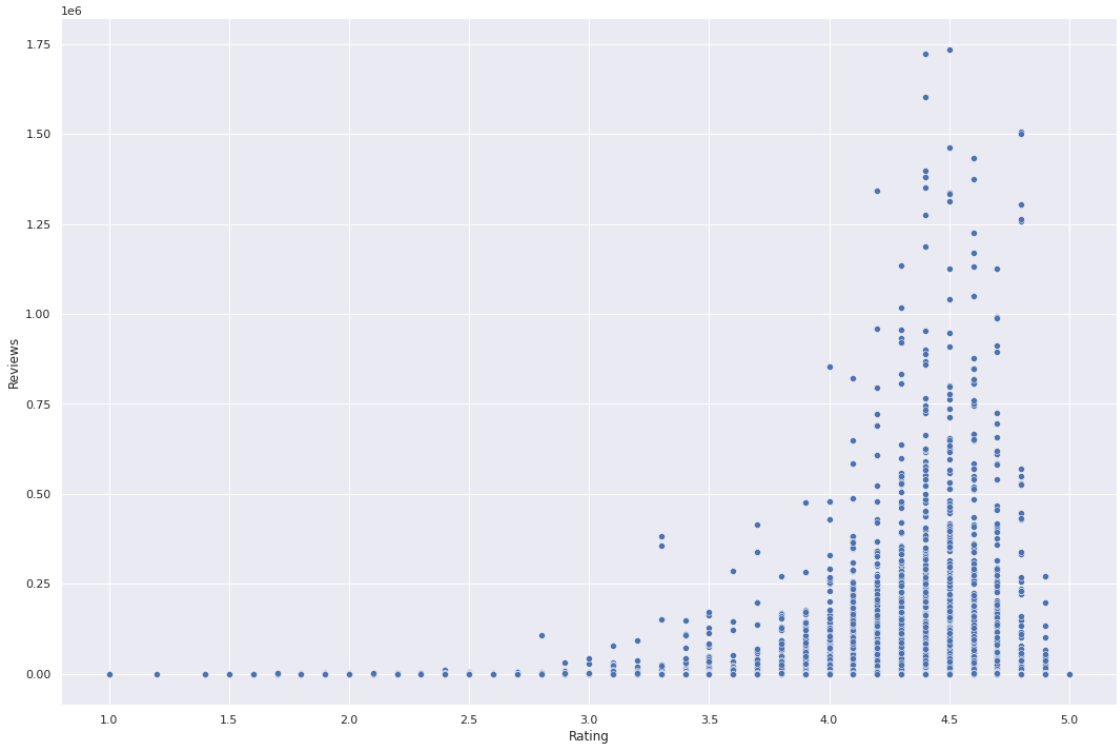
[95]: <seaborn.axisgrid.JointGrid at 0x7efd34cb8e80>



[96]:
```
# Both the plots show a positive linear relationship; as the price of an app␣
 ↪increases its rating also increases.
# That states the paid apps have the highest of Ratings
```

[113]:
```
sns.scatterplot(x= 'Rating',y= 'Reviews', data= df)
```

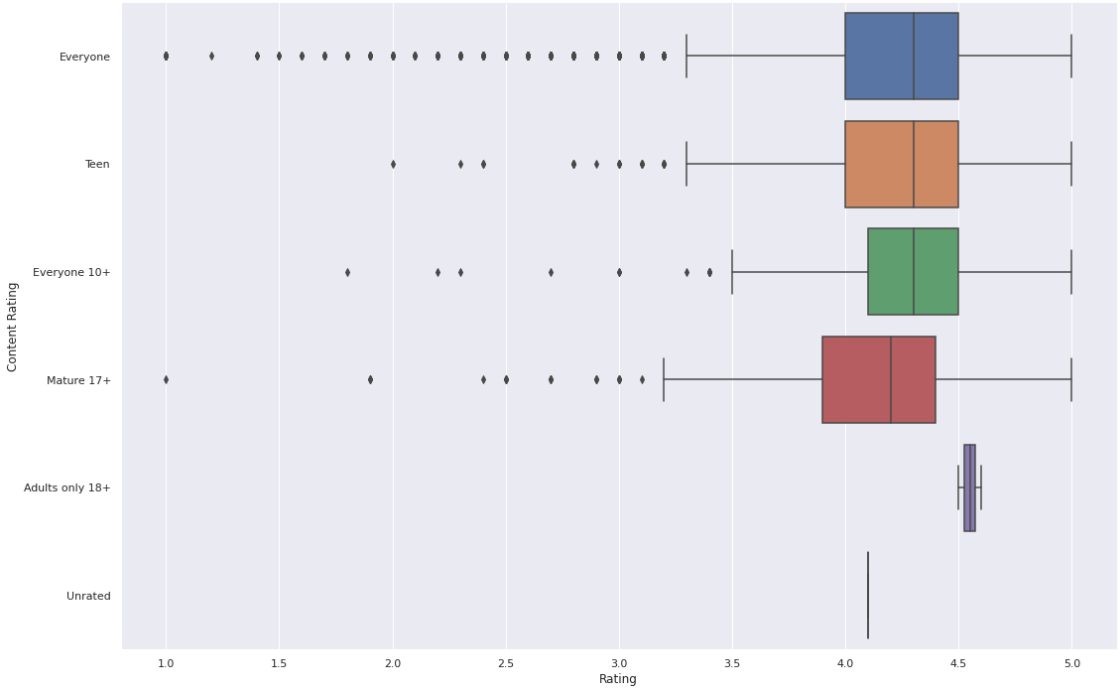
[113]: <AxesSubplot: xlabel='Rating', ylabel='Reviews'>



[ ]:
```
# The plot shows a positive linear relationship between Ratings and Reviews.␣
↪More reviews mean better ratings indeed
```

[97]:
```
sns.boxplot(data=df, x='Rating',y='Content Rating')
```

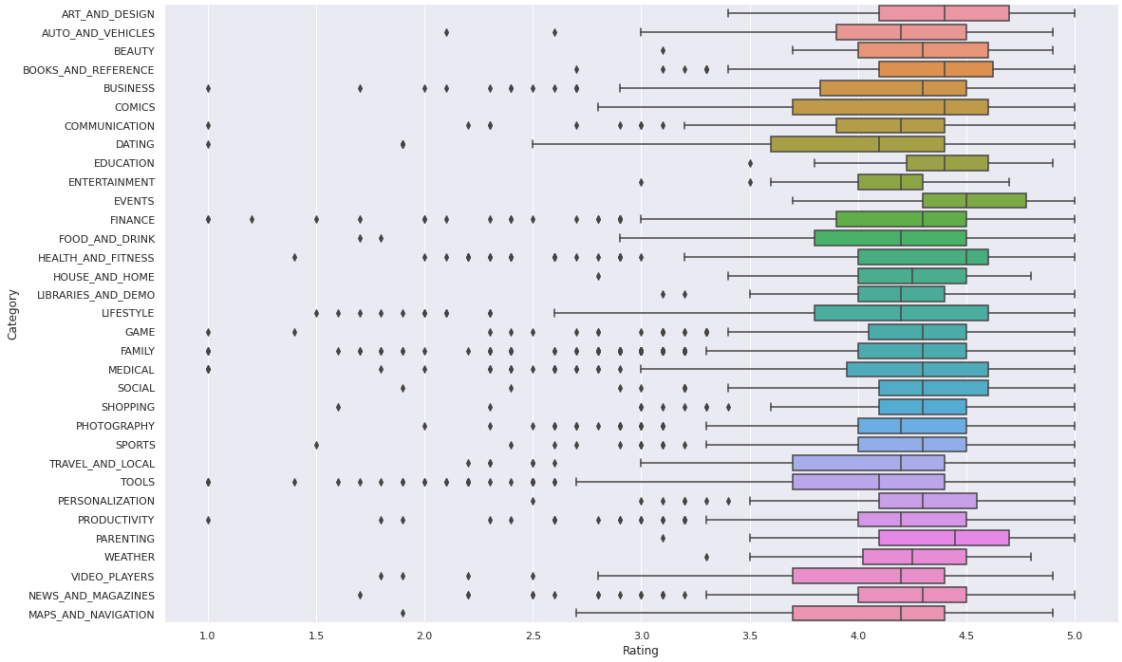
[97]:
```
<AxesSubplot: xlabel='Rating', ylabel='Content Rating'>
```



[98]:
```
# The above plot shows the apps for Everyone is worst rated as it contain the␣
↪highest number of outliers followed by apps for Mature 17+ and Everyone 10+␣
↪along with Teen.
# The catergory Adults only 18+ is rated better and falls under most liked type
```

[99]:
```
sns.set(rc={'figure.figsize':(18,12)})
sns.boxplot(data=df, x='Rating',y='Category')
```

[99]:
```
<AxesSubplot: xlabel='Rating', ylabel='Category'>
```



[100]:
```
# creating a copy of the data(df) to make all edits
inp1=df.copy()
inp1.head()

# Reviews and Installs column still have some relatively high values
# before building the linear regression model we need to reduce the skew;␣
 ↪columns needs log transformation
inp1.skew()
```

```
/tmp/ipykernel_341/2343976428.py:7: FutureWarning: The default value of
numeric_only in DataFrame.skew is deprecated. In a future version, it will
default to False. In addition, specifying 'numeric_only=None' is deprecated.
Select only valid columns or specify the value of numeric_only to silence this
warning.
  inp1.skew()
```

[100]:
```
Rating      -1.692510
Reviews      5.305328
Size         1.533259
Installs     1.922597
Price       15.724184
dtype: float64
```

[101]:
```
# apply log transformation to Reviews
reviews_skew = np.log1p(inp1['Reviews'])
inp1['Reviews']= reviews_skew
```

```
reviews_skew.skew()
```

[101]:
```
-0.06808430177422468
```

[102]:
```
# apply log transformation to Installs
Installs_skew = np.log1p(inp1['Installs'])
inp1['Installs']
Installs_skew.skew()
```

[102]:
```
-0.3930918801065247
```

[103]:
```
# Dropping the columns- App, Last Updated, Current Ver, Type, & Andriod Ver as␣
 ↪these won't be useful for our model
inp1.drop(['App','Last Updated','Current Ver','Android Ver','Type'], axis= 1,␣
 ↪inplace = True)
```

[104]:
```
# create a copy of dataframe
inp2=inp1

# As Model does not understand any Catergorical variable hence these need to be␣
 ↪converted to numerical
# Dummy Encoding is one way to convert these columns into numerical
x = inp2[['Category']]
del inp2['Category']
dummies = pd.get_dummies(x, prefix = 'Category')
inp2 = pd.concat([inp2,dummies], axis=1)
inp2.head()
```

[104]:
```
   Rating    Reviews  Size  Installs  Price Content Rating  \
0     4.1   5.075174  19.0     10000    0.0       Everyone
1     3.9   6.875232  14.0    500000    0.0       Everyone
2     4.7  11.379520   8.7   5000000    0.0       Everyone
4     4.3   6.875232   2.8    100000    0.0       Everyone
5     4.4   5.123964   5.6     50000    0.0       Everyone

                      Genres  Category_ART_AND_DESIGN  \
0               Art & Design                        1
1  Art & Design;Pretend Play                        1
2               Art & Design                        1
4    Art & Design;Creativity                        1
5               Art & Design                        1

   Category_AUTO_AND_VEHICLES  Category_BEAUTY  …  Category_PERSONALIZATION  \
0                           0                0  …                         0
1                           0                0  …                         0
2                           0                0  …                         0
4                           0                0  …                         0
```

```
5                           0                 0  …                           0

   Category_PHOTOGRAPHY  Category_PRODUCTIVITY  Category_SHOPPING  \
0                     0                      0                  0
1                     0                      0                  0
2                     0                      0                  0
4                     0                      0                  0
5                     0                      0                  0

   Category_SOCIAL  Category_SPORTS  Category_TOOLS  \
0                0                0               0
1                0                0               0
2                0                0               0
4                0                0               0
5                0                0               0

   Category_TRAVEL_AND_LOCAL  Category_VIDEO_PLAYERS  Category_WEATHER
0                          0                       0                 0
1                          0                       0                 0
2                          0                       0                 0
4                          0                       0                 0
5                          0                       0                 0

[5 rows x 40 columns]
```

[105]:
```
# There are too many categories under Genres.
# we will reduce some categories which have very few samples under them and put␣
 ↪them under one new common category i.e. "Other"
lists = []
for i in inp2.Genres.value_counts().index:
    if inp2.Genres.value_counts()[i]<20:
        lists.append(i)

#Storing the genres column into x varible and delete the genres col from␣
 ↪dataframe inp2
#And concat the encoded cols to the dataframe inp2

inp2.Genres = ['Other' if i in lists else i for i in inp2.Genres]
x = inp2[["Genres"]]
del inp2['Genres']
dummies = pd.get_dummies(x, prefix = 'Genres')
inp2 = pd.concat([inp2,dummies], axis=1)
```

[106]:
```
#Applying one hot encoding
#Storing the Content Rating column into x varible and delete the Content Rating␣
 ↪col from dataframe inp2
#And concat the encoded cols to the dataframe inp2
```

```
x = inp2[['Content Rating']]
del inp2['Content Rating']
dummies = pd.get_dummies(x, prefix = 'Content Rating')
inp2 = pd.concat([inp2,dummies], axis=1)
inp2.head()
```

[106]:

	Rating	Reviews	Size	Installs	Price	Category_ART_AND_DESIGN	\
0	4.1	5.075174	19.0	10000	0.0	1	
1	3.9	6.875232	14.0	500000	0.0	1	
2	4.7	11.379520	8.7	5000000	0.0	1	
4	4.3	6.875232	2.8	100000	0.0	1	
5	4.4	5.123964	5.6	50000	0.0	1	

	Category_AUTO_AND_VEHICLES	Category_BEAUTY	Category_BOOKS_AND_REFERENCE	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
4	0	0	0	
5	0	0	0	

	Category_BUSINESS	…	Genres_Trivia	Genres_Video Players & Editors	\
0	0	…	0	0	
1	0	…	0	0	
2	0	…	0	0	
4	0	…	0	0	
5	0	…	0	0	

	Genres_Weather	Genres_Word	Content Rating_Adults only 18+	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
4	0	0	0	
5	0	0	0	

	Content Rating_Everyone	Content Rating_Everyone 10+	\
0	1	0	
1	1	0	
2	1	0	
4	1	0	
5	1	0	

	Content Rating_Mature 17+	Content Rating_Teen	Content Rating_Unrated
0	0	0	0
1	0	0	0
2	0	0	0
4	0	0	0

```
5                          0                          0                          0

[5 rows x 95 columns]
```

[107]:
```
#importing the neccessary libraries from sklearn to split the data and and for␣
 ↪model building

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error as mse
from sklearn import metrics
```

[108]:
```
#Creating the variable X and Y which contains the X features as independent␣
 ↪features and Y is the target feature

df2 = inp2
X = df2.drop('Rating',axis=1)
y = df2['Rating']
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.
 ↪3,random_state=5)
```

[109]:
```
#Create a linear reggression obj by calling the linear reggressor algorithm

lm = LinearRegression()
lm.fit(X_train,y_train)
```

[109]:
```
LinearRegression()
```

[110]:
```
# r2 value for training set

R2_train = round(lm.score(X_train,y_train),3)
print("The R2 value of the Training Set is : {}".format(R2_train))
```

```
The R2 value of the Training Set is : 0.068
```

[111]:
```
# r2 value for testing set

R2_test = round(lm.score(X_test,y_test),3)
print("The R2 value of the Testing Set is : {}".format(R2_test))
```

```
The R2 value of the Testing Set is : 0.058
```

[112]:
```
# predict test

y_hat = lm.predict(X_test)
R2_test_data =metrics.r2_score(y_test,y_hat)
R2_test_data
```

[112]: 0.057753700325213764