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POJECT WRITE-UP:

APP RATING PREDICTION...

Objectives:

The main goal of this project is to develop a model to predict app ratings using various features of the apps from the Google Play Store.

Problem Statement:

Google Play Store aims to enhance the visibility of promising apps through higher recommendations and search result rankings. This project aims to predict which apps will receive high ratings to help in identifying promising apps.

Given Dataset File Name

File: googleplaystore.csv

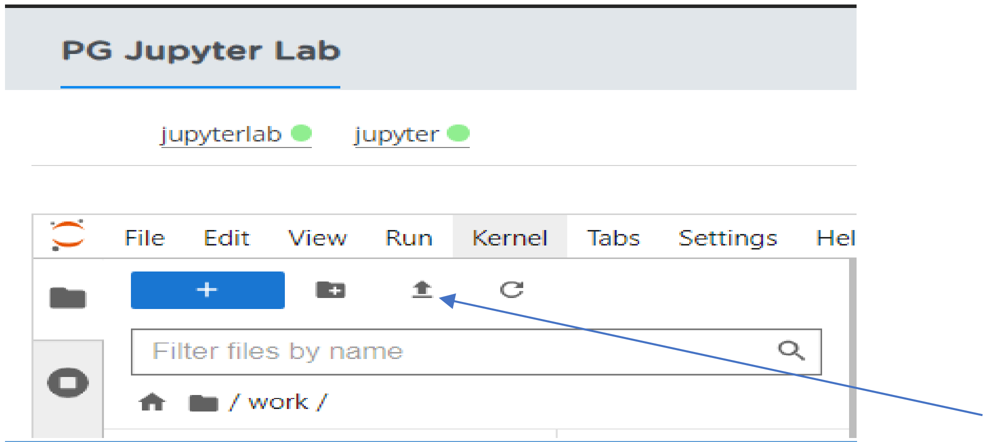
Dataset Description:

The dataset includes the following features: -

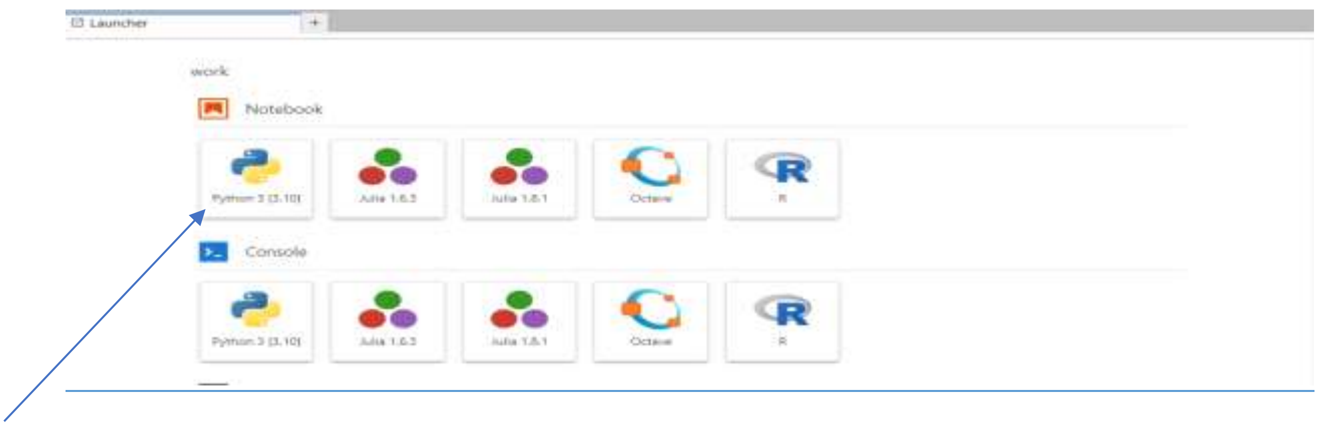
- **App**: Application name
- **Category**: Category to which the app belongs
- **Rating**: Overall user rating of the app
- **Reviews**: Number of user reviews for the app
- **Size**: Size of the app
- **Installs**: Number of user downloads/installs for the app
- **Type**: Paid or Free
- **Price**: Price of the app
- **Content Rating**: Age group the app is targeted at (Children / Mature 21+ / Adult)
- **Genres:** Multiple genres the app belongs to
- **Last Updated**: Date when the app was last updated on Play Store
- **Current Ver**: Current version of the app available on Play Store
- **Android Ver**: Minimum required Android version

Steps to Perform:

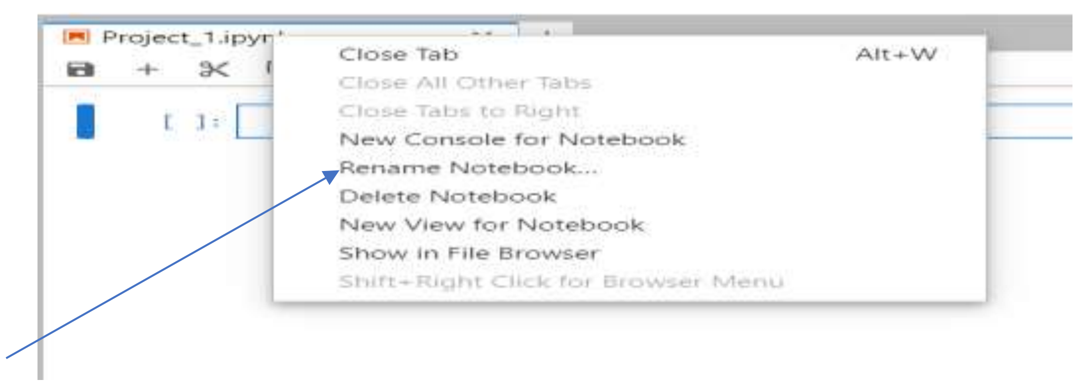
- Open the Jupiter lab then upload the given data file name googleplaystore.csv.



- Click on the Python 3[3.10]:



- Rename the notebook file to "Project_1":



PROJECT TASKS:

Q.1 Load the data file using pandas.

Solution:

Load the Data: - Load the dataset using Pandas.

import pandas as pd

#Also run all the codes for preparing the environment for data analysis, visualization, and plotting, while ignoring future warnings.

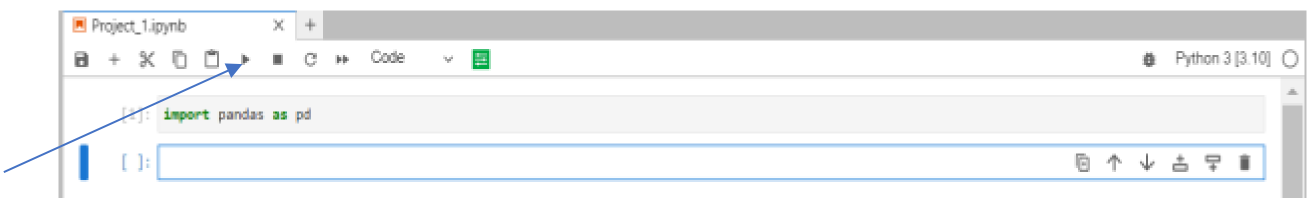
import numpy as np

import matplotlib.pyplot as plt, seaborn as sns

%matplotlib inline

import warnings

warnings.simplefilter(action='ignore', category=FutureWarning)




```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt, seaborn as sns
%matplotlib inline

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

data = pd.read_csv('googleplaystore.csv')

data.head()

```
[1]: data = pd.read_csv('googleplaystore.csv')
```

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

	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

```
[5]: data.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
```

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

Solution:

Check for Null Values: - Identify columns with null values and Sum them.

data.isnull().sum()

```
data.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
```

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

Solution:

Drop Records with Nulls: - Drop rows and columns with any null values.

Dropping the records with null ratings - this is done because ratings are our target variable

Why we drop null value- A null value represents an unknown or missing value in a dataset. It indicates that the data is absent or not applicable for a particular observation or record.

data.dropna(how ='any', inplace = True)

To check any null values: Confirming that the null records have been dropped

data.isnull().sum()

OR

data.isnull().any()

```
[70]: data.dropna(how ='any', inplace = True)

[71]: data.isnull().sum()

[71]: 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
```

```
[15]: data.isnull().any()

[15]: App               False
      Category          False
      Rating            False
      Reviews           False
      Size              False
      Installs          False
      Type              False
      Price             False
      Content Rating    False
      Genres            False
      Last Updated      False
      Current Ver       False
      Android Ver       False
      dtype: bool

[ ]:
```

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

Solution:

Data Type and Formatting Corrections: - Convert Size to numeric.

1. Size column has sizes in Kb as well as Mb. To analyze, you'll need to convert these to numeric.
    1. Extract the numeric value from the column
    2. Multiply the value by 1,000, if size is mentioned in Mb

Solution:

data.Size.describe()

```
def change_size(size):
    if 'M' in size:
        x = size[:-1]
        x = float(x)*1000
        return(x)
    elif 'k' == size[-1:]:
        x = size[:-1]
        x = float(x)
        return(x)
    else:
        return None
```

data["Size"] = data["Size"].map(change_size)

```
[11]: data.Size.describe()

[11]: count                   9360
      unique                   413
      top       Varies with device
      freq                    1637
      Name: Size, dtype: object

[12]: def change_size(size):
          if 'M' in size:
              x = size[:-1]
              x = float(x)*1000
              return(x)
          elif 'k' == size[-1:]:
              x = size[:-1]
              x = float(x)
              return(x)
          else:
              return None

[13]: data["Size"] = data["Size"].map(change_size)
```

data.Size.describe()

#filling Size which had NA

data.Size.fillna(method = 'ffill', inplace = True)

```
[19]: data.Size.describe()

[19]: count      7723.000000
      mean      22970.456105
      std       23449.628935
      min           8.500000
      25%        5300.000000
      50%       14000.000000
      75%       33000.000000
      max      100000.000000
      Name: Size, dtype: float64

[20]: data["Size"].isnull().sum()

[20]: 1637

[21]: #filling Size which had NA

      data.Size.fillna(method = 'ffill', inplace = True)

[22]: data.Size.describe()
```

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

Solution:

data.Reviews.describe()

data["Reviews"] = data["Reviews"].astype("int32")

data.Reviews.describe()

```
[23]: data.Reviews.describe() # object == categorical variable

[23]: count     9360
      unique    5990
      top          2
      freq        83
      Name: Reviews, dtype: object

[24]: data["Reviews"] = data["Reviews"].astype("int32")

[25]: data.Reviews.describe()

[25]: count    9.360000e+03
      mean     5.143767e+05
      std      3.145023e+06
      min      1.000000e+00
      25%      1.867500e+02
      50%      5.955000e+03
      75%      8.162750e+04
      max      7.815831e+07
      Name: Reviews, dtype: float64
```

object == categorical variable

3. Installs field is currently stored as string and has values like 1,000,000+.
   1. Treat 1,000,000+ as 1,000,000
   2. remove '+', ',' from the field, convert it to integer

Solution:

data.Installs.describe() # object == categorical variable

data.Installs.value_counts()

```
[26]: data.Installs.describe() # object == categorical variable

[26]: count           9360
      unique            19
      top       1,000,000+
      freq            1576
      Name: Installs, dtype: object

[27]: data.Installs.value_counts()

[27]: 1,000,000+        1576
      10,000,000+       1252
      100,000+          1150
      10,000+           1009
      5,000,000+         752
      1,000+             712
      500,000+           537
      50,000+            466
      5,000+             431
      100,000,000+       409
      100+               309
      50,000,000+        289
      500+               201
      500,000,000+        72
      10+                 69
      1,000,000,000+      58
      50+                 56
      5+                   9
      1+                   3
      Name: Installs, dtype: int64
```

def clean_Installs(Installs):

return int(Installs.replace(",", "").replace("+", ""))

data['Installs'] = data['Installs'].apply(clean_Installs)

data.Installs.describe()

data.Installs.value_counts()

```
[28]: def clean_Installs(Installs):
          return int(Installs.replace(",", "").replace("+", ""))

[29]: data['Installs'] = data['Installs'].apply(clean_Installs)

[31]: data.Installs.describe()

[31]: count    9.360000e+03
      mean     1.790875e+07
      std      9.126637e+07
      min      1.000000e+00
      25%      1.000000e+04
      50%      5.000000e+05
      75%      5.000000e+06
      max      1.000000e+09
      Name: Installs, dtype: float64

[31]: data.Installs.value_counts()

[21]: 1000000       1576
      10000000      1252
      100000        1150
      10000         1009
      5000000        752
      1000           712
      500000         537
      50000          466
      5000           431
      100000000      409
      100            309
```

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

Solution:

```
data.Price.describe()
data.Price.value_counts()[:5]
def clean_price(x):
    if '$' in x:
        x = x[1:]
        x = float(x)
        return(x)
    elif x == 0:
        x = float(x)
        return x
    else:
        return float(x)
data['Price'] = data.Price.map(clean_price)
data.Price.value_counts().head(5)
```

```
[32]: data.Price.describe()

[32]: count     9360
      unique      73
      top          0
      freq      8715
      Name: Price, dtype: object

[33]: data.Price.value_counts()[:5]

[33]: 0        8715
      $2.99     114
      $0.99     106
      $4.99      70
      $1.99      59
      Name: Price, dtype: int64

[34]: def clean_price(x):
          if '$' in x:
              x = x[1:]
              x = float(x)
              return(x)
          elif x == 0:
              x = float(x)
              return x
          else:
              return float(x)

[36]: data['Price'] = data.Price.map(clean_price)
```

```
data.Price.value_counts().head(5)
```

```
0.00    8715
2.99     114
0.99     106
4.99      70
1.99      59
Name: Price, dtype: int64
```

Q.5. Sanity checks:

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.

Solution:

- Ensure Rating is between 1 and 5.

data.loc[(data.Rating >= 1) & (data.Rating <= 5)]

print(data.Rating.describe())

```
[26]: data.loc[(data.Rating >= 1) & (data.Rating <= 5)]
      print(data.Rating.describe())
```

```
count    9360.000000
mean        4.191838
std         0.515263
min         1.000000
25%         4.000000
50%         4.300000
75%         4.500000
max         5.000000
Name: Rating, dtype: float64
```

Min is 1 and max is 5. Looks good.

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.

Solution:

print((data.Reviews > data.Installs).sum())

data.loc[data.Reviews > data.Installs]

```
[40]: print((data.Reviews > data.Installs).sum())
7
[41]: data.loc[data.Reviews > data.Installs]
```

[41]:

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Last Updated	Current Ver	Android Ver
2454	KBA-EZ Health Guide	MEDICAL	5.0	4	25000.0	1	Free	0.00	Everyone	Medical	August 2, 2018	1.0.72	4.0.3 and up
4663	Alarmy (Sleep If U Can) - Pro	LIFESTYLE	4.8	10249	30000.0	10000	Paid	2.49	Everyone	Lifestyle	July 30, 2018	Varies with device	Varies with device
5917	Ra Ga Ba	GAME	5.0	2	20000.0	1	Paid	1.49	Everyone	Arcade	February 8, 2017	1.0.4	2.3 and up
6700	Brick Breaker BR	GAME	5.0	7	19000.0	5	Free	0.00	Everyone	Arcade	July 23, 2018	1.0	4.1 and up
7402	Trovami se ci riesci	GAME	5.0	11	6100.0	10	Free	0.00	Everyone	Arcade	March 11, 2017	0.1	2.3 and up
8591	DN Blog	SOCIAL	5.0	20	4200.0	10	Free	0.00	Teen	Social	July 23, 2018	1.0	4.0 and up
10697	Mu.F.O.	GAME	5.0	2	16000.0	1	Paid	0.99	Everyone	Arcade	March 3, 2017	1.0	2.3 and up

retain that part of data where revives are less than installs

data.loc[data.Reviews <= data.Installs]

data.shape

```
[47]: # retain that part of data where revives are less than installs
      data.loc[data.Reviews <= data.Installs]
```

[47]:

	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	19000.0	10000	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	14000.0	500000	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	8700.0	5000000	Free	0.0	Everyone	Art & Design	August 1, 2018	1.2.4	4.0.3 and up
3	Sketch - Draw & Paint	ART_AND_DESIGN	4.5	215644	25000.0	50000000	Free	0.0	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	2800.0	100000	Free	0.0	Everyone	Art & Design;Creativity	June 20, 2018	1.1	4.4 and up
...	...	...	...	...	...	...	...	...	...	...	...	...	...
10834	FR Calculator	FAMILY	4.0	7	2600.0	500	Free	0.0	Everyone	Education	June 18, 2017	1.0.0	4.1 and up
10836	Sya9a Maroc - FR	FAMILY	4.5	38	53000.0	5000	Free	0.0	Everyone	Education	July 25, 2017	1.48	4.1 and up
10837	Fr. Mike Schmitz Audio Teachings	FAMILY	5.0	4	3600.0	100	Free	0.0	Everyone	Education	July 6, 2018	1.0	4.1 and up
10839	The SCP Foundation DB fr nn5n	BOOKS_AND_REFERENCE	4.5	114	3800.0	1000	Free	0.0	Mature 17+	Books & Reference	January 19, 2015	Varies with device	Varies with device

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

Solution:

len(data[(data.Type == "Free") & (data.Price > 0)])

```
[45]: len(data[(data.Type == "Free") & (data.Price > 0)])
[45]: 0
```

Q.5.A. Performing univariate analysis:

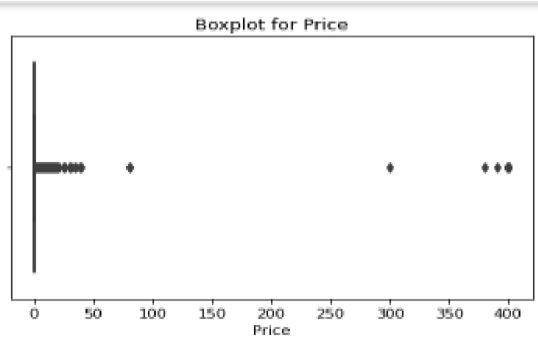
-Boxplot for Price

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

Solution:

sns.boxplot(x=data.Price).set(title = "Boxplot for Price");

```
sns.boxplot(x=data.Price).set(title = "Boxplot for Price");
```



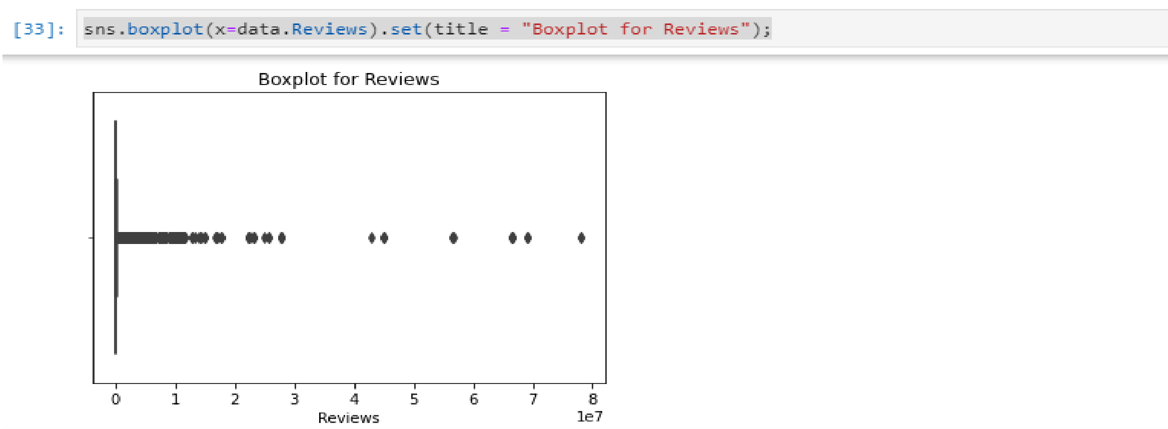
Yes, there are outliers in the price data for apps on the Play Store. These outliers are likely apps that are significantly more expensive than the usual apps, which typically fall within a much lower price range. This suggests that while most apps are priced affordably, a few are priced much higher, possibly due to offering premium features or being targeted at a niche market. The line inside the box represents the median price of the apps. If you think about the usual apps on the Play Store, most of them are free or have a low price, so these outliers represent the few that are priced unusually high.

-Boxplot for Reviews

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

Solution:

sns.boxplot(x=data.Reviews).set(title = "Boxplot for Reviews");



Yes, some apps have a very high number of reviews, compared to other apps. These are shown as outliers in the boxplot, far from the main group of apps with fewer reviews. These values seem correct, as it's normal for a few very popular apps to get many more reviews than others.

-Histogram for Rating

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

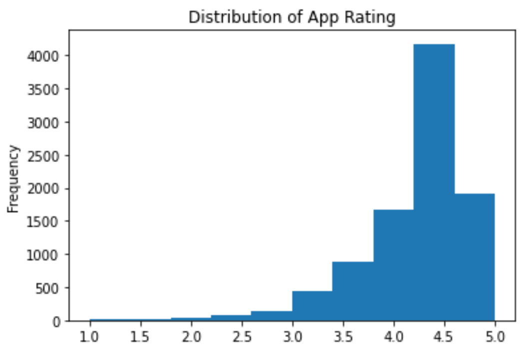
Solution:

data.Rating.plot.hist(). set(title = "Distribution of App Rating");

plt.show()

```
[46]: data.Rating.plot.hist(). set(title = "Distribution of App Rating");

plt.show()
```



Yes, the majority of the app ratings are clustered towards the higher end, particularly between 4.0 and 4.5. The highest frequency of ratings is observed around the 4.5 mark.

Lower Ratings are below 3.0, indicating that most users are generally satisfied with the apps.

In summary, the ratings are indeed skewed towards higher values, suggesting that most users rate the apps positively.

-Histogram for Size

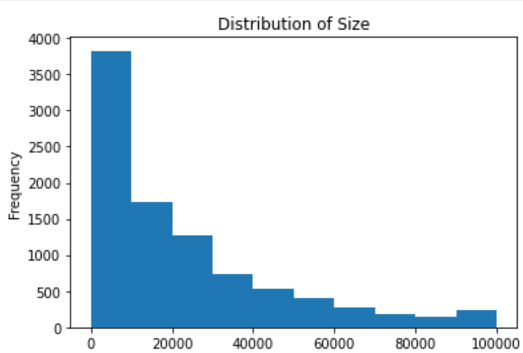
Solution:

data.Size.plot.hist(). set(title = "Distribution of Size");

plt.show()

```
[47]: data.Size.plot.hist(). set(title = "Distribution of Size");

plt.show()
```



The histogram plot shows the distribution of the variable "Size.

The distribution is highly right-skewed, meaning most of the values are concentrated on the left side (lower sizes), with fewer and fewer observations as the size increases.¶

Q.6. Outlier treatment:

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!

   a. Check out the records with very high price i. Is 200 indeed a high price?

   b. Drop these as most seem to be junk apps

Solution:

len(data[data['Price'] > 200])

ata[data.Price > 200]

```
[36]: len(data[data['Price'] > 200])
[36]: 15
[37]: data[data.Price > 200]
```

[37]:

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Last Updated	Current Ver	Android Ver
4197	most expensive app (H)	FAMILY	4.3	6.0	1500.0	100	Paid	399.99	Everyone	Entertainment	July 16, 2018	1.0	7.0 and up
4362	💎 I'm rich	LIFESTYLE	3.8	718.0	26000.0	10000	Paid	399.99	Everyone	Lifestyle	March 11, 2018	1.0.0	4.4 and up
4367	I'm Rich - Trump Edition	LIFESTYLE	3.6	275.0	7300.0	10000	Paid	400.00	Everyone	Lifestyle	May 3, 2018	1.0.1	4.1 and up
5351	I am rich	LIFESTYLE	3.8	3547.0	1800.0	100000	Paid	399.99	Everyone	Lifestyle	January 12, 2018	2.0	4.0.3 and up
5354	I am Rich Plus	FAMILY	4.0	856.0	8700.0	10000	Paid	399.99	Everyone	Entertainment	May 19, 2018	3.0	4.4 and up
5355	I am rich VIP	LIFESTYLE	3.8	411.0	2600.0	10000	Paid	299.99	Everyone	Lifestyle	July 21, 2018	1.1.1	4.3 and up
5356	I Am Rich Premium	FINANCE	4.1	1867.0	4700.0	50000	Paid	399.99	Everyone	Finance	November 12, 2017	1.6	4.0 and up
5357	I am extremely Rich	LIFESTYLE	2.9	41.0	2900.0	1000	Paid	379.99	Everyone	Lifestyle	July 1, 2018	1.0	4.0 and up
5358	I am Rich!	FINANCE	3.8	93.0	22000.0	1000	Paid	399.99	Everyone	Finance	December 11, 2017	1.0	4.1 and up
5359	I am rich(premium)	FINANCE	3.5	472.0	22000.0	5000	Paid	399.99	Everyone	Finance	May 1, 2017	3.4	4.4 and up
5362	I Am Rich Pro	FAMILY	4.4	201.0	2700.0	5000	Paid	399.99	Everyone	Entertainment	May 30, 2017	1.54	1.6 and up
5364	I am rich (Most expensive app)	FINANCE	4.1	129.0	2700.0	1000	Paid	399.99	Teen	Finance	December 6, 2017	2	4.0.3 and up
5366	I Am Rich	FAMILY	3.6	217.0	4900.0	10000	Paid	389.99	Everyone	Entertainment	June 22, 2018	1.5	4.2 and up

data = data[data.Price <= 200].copy()

data.shape

```
[133]: data = data[data.Price <= 200].copy()

       data.shape

[133]: (9345, 13)
```

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.

Solution:

data = data[data.Reviews <= 2000000].copy()

data.shape

```
[135]: data = data[data.Reviews <= 2000000].copy()

       data.shape

[135]: (8892, 13)
```

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.

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

   b. Decide a threshold as cutoff for outlier and drop records having values more than that

Solution:

```
data.Installs.quantile([0.1, 0.25, 0.5, 0.70, 0.9, 0.95, 0.99])
```

```
[136]: data.Installs.quantile([0.1, 0.25, 0.5, 0.70, 0.9, 0.95, 0.99])

[136]: 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
```

check how many row have installs greater than corresponding to 99 percentile.

```
percentile_99 = data.Installs.quantile(0.99)

count = (data.Installs >= percentile_99).sum()

print(count)
```

```
[46]: # check how many row have installs greater than corresponding to 99 percentile.

      percentile_99 = data.Installs.quantile(0.99)

      count = (data.Installs >= percentile_99).sum()
      print(count)

      142
```

retain installs less than corresponding to 99 percentile. check shape

```
data = data[data.Installs < percentile_99]

print(data.shape)
```

```
[139]: # retain installs less than corresponding to 99 percentile. check shape

       data = data[data.Installs < percentile_99]
       print(data.shape)

       (8750, 13)
```

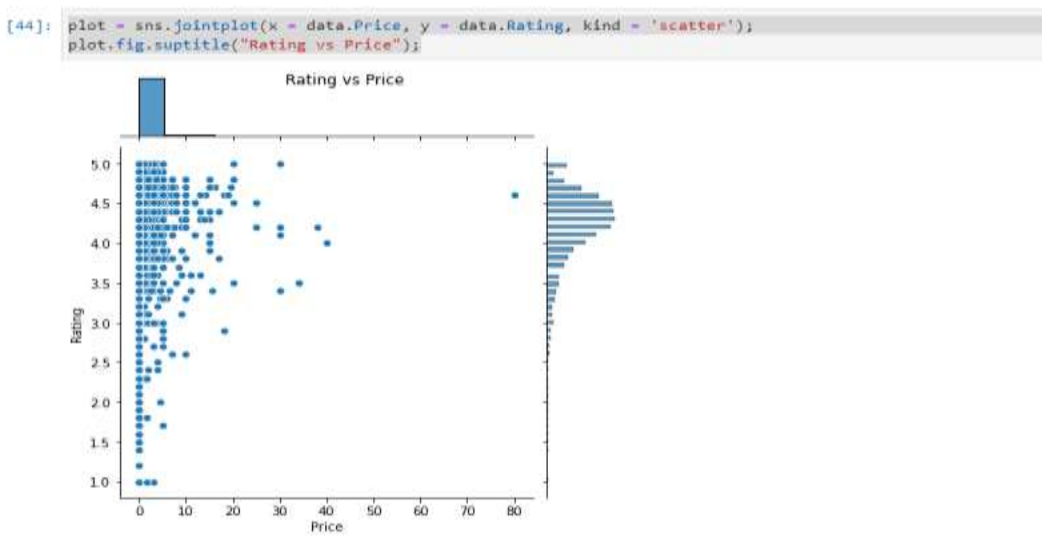
Q.7. Bivariate analysis: Let’s look at how the available predictors relate to the variable of interest, i.e., our target variable rating. Make scatter plots (for numeric features) and box plots (for character features) to assess the relations between rating and the other features.

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

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

Solution:

```
plot = sns.jointplot(x = data.Price, y = data.Rating, kind = 'scatter');
plot.fig.suptitle("Rating vs Price");
```



The scatter plot shows the relationship between the Rating and Price variables. The x-axis represents Price, and the y-axis represents Rating. Most of the ratings appear to be concentrated in the range of 3 to 4.5, regardless of the price.

Based on the scatter plot, it appears that the rating does not consistently increase with the price. Instead, ratings are dispersed across various price points, indicating that price alone may not be a strong predictor of the rating.¶

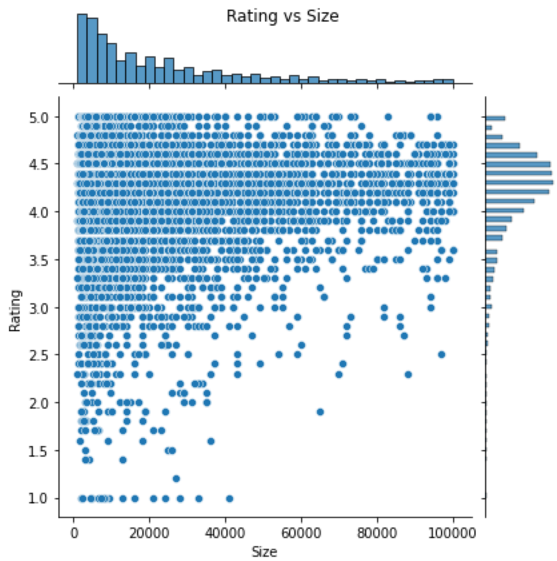
2. Make scatter plot/joinplot for Rating vs. Size

   a. Are heavier apps rated better?

Solution:

```
plot = sns.jointplot(x = data.Size, y = data.Rating, kind = 'scatter');
plot.fig.suptitle("Rating vs Size");
```

```
[45]: plot = sns.jointplot(x = data.Size, y = data.Rating, kind = 'scatter');
      plot.fig.suptitle("Rating vs Size");
```



No, heavier apps are not consistently rated better. The scatter plot shows no clear relationship between app size and ratings, with high and low ratings distributed across various app sizes.

3. Make scatter plot/joinplot for Rating vs. Reviews

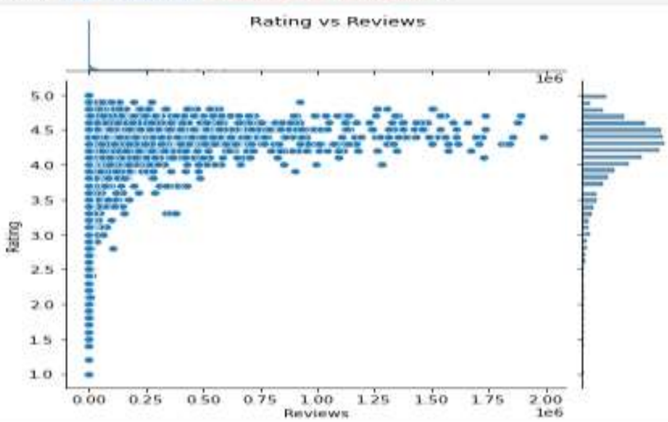
   a. Does more review mean a better rating always?

Solution:

plot = sns.jointplot(x = data.Reviews, y = data.Rating, kind = 'scatter');

plot.fig.suptitle("Rating vs Reviews");

```
[46]: plot = sns.jointplot(x = data.Reviews, y = data.Rating, kind = 'scatter');
      plot.fig.suptitle("Rating vs Reviews");
```



No, more reviews do not always mean a better rating. The scatter plot indicates that there is no consistent trend showing that a higher number of reviews correlates directly with higher ratings. Ratings vary regardless of the number of reviews.

4. Make boxplot for Rating vs. Content Rating

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

Solution:

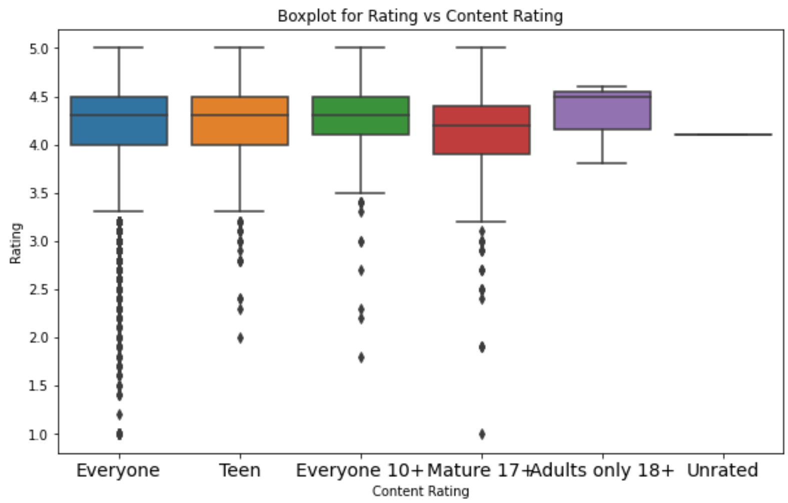
plt.figure(figsize=(10, 6))

sns.boxplot(y=data.Rating, x=data["Content Rating"]).set(title="Boxplot for Rating vs Content Rating")

plt.xticks(fontsize=14)

plt.show()

```
[47]: plt.figure(figsize=(10, 6))
sns.boxplot(y=data.Rating, x=data["Content Rating"]).set(title="Boxplot for Rating vs Content Rating")
plt.xticks(fontsize=14)
plt.show()
```



There are some differences in the ratings across content rating categories, but they are not extremely pronounced. The median ratings are fairly similar, though some categories, like Everyone and Teen, have a broader range of ratings, indicating more variability. Categories such as Adults only 18+ and Unrated seem to be rated slightly better on average, but these categories might have fewer apps, which can affect the overall rating trend.

5. Make boxplot for Ratings vs. Category

a. Which genre has the best ratings?

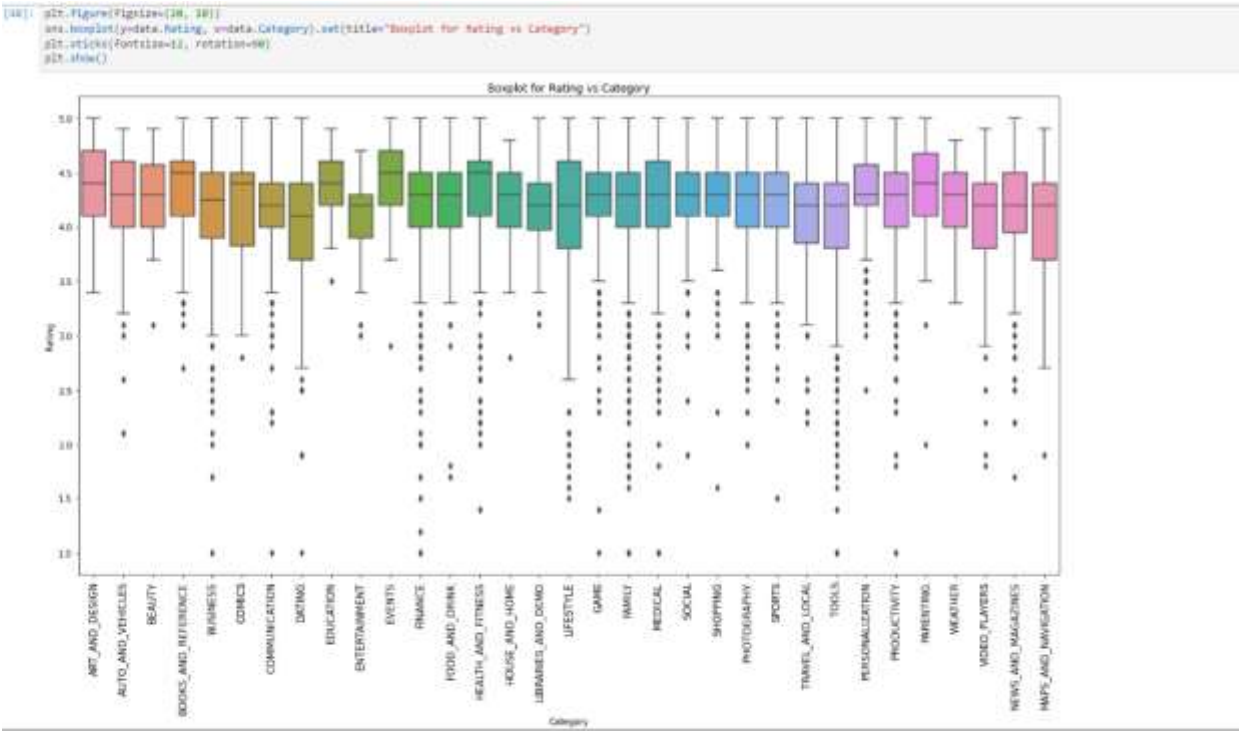
Solution:

plt.figure(figsize=(20, 10))

sns.boxplot(y=data.Rating, x=data.Category).set(title="Boxplot for Rating vs Category")

plt.xticks(fontsize=12, rotation=90)

plt.show()



The genre with the best ratings appears to be "EVENTS," as it has a higher median rating and less variability compared to other categories. The ratings in this category seem to be consistently high, with fewer outliers below 4.0 compared to other categories.

Q.8 Data preprocessing

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

Making a copy of the dataset

Solution:

inp1 = data.copy()

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.

Solution:

check describe for installs

print(inp1.Installs.describe())

inp1.Installs = inp1.Installs.apply(np.log1p)

inp1.Reviews = inp1.Reviews.apply(np.log1p)

```
[144]: # check describe for installs

       print(inp1.Installs.describe())

       count    8.750000e+03
       mean     3.484077e+06
       std      8.656515e+06
       min      1.000000e+00
       25%      1.000000e+04
       50%      1.000000e+05
       75%      5.000000e+06
       max      5.000000e+07
       Name: Installs, dtype: float64

[145]: inp1.Installs = inp1.Installs.apply(np.log1p)

[146]: inp1.Reviews = inp1.Reviews.apply(np.log1p)
```

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

Solution:

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

inp1.shape

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

[148]: inp1.shape

[148]: (8750, 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.

Solution:

check types

inp1.dtypes

inp2 = pd.get_dummies(inp1, drop_first=True)

```
[149]: # check types

inp1.dtypes

[149]: Category          object
       Rating           float64
       Reviews          float64
       Size             float64
       Installs         float64
       Type              object
       Price            float64
       Content Rating    object
       Genres            object
       dtype: object

[150]: inp2 = pd.get_dummies(inp1, drop_first=True)
```

display col names

print(inp2.columns)

inp2.shape

```
[151]: # display col names

print(inp2.columns)

Index(['Rating', 'Reviews', 'Size', 'Installs', 'Price',
       'Category_AUTO_AND_VEHICLES', 'Category_BEAUTY',
       'Category_BOOKS_AND_REFERENCE', 'Category_BUSINESS', 'Category_COMICS',
       ...
       'Genres_Tools', 'Genres_Tools;Education', 'Genres_Travel & Local',
       'Genres_Travel & Local;Action & Adventure', 'Genres_Trivia',
       'Genres_Video Players & Editors',
       'Genres_Video Players & Editors;Creativity',
       'Genres_Video Players & Editors;Music & Video', 'Genres_Weather',
       'Genres_Word'],
      dtype='object', length=157)

[152]: inp2.shape

[152]: (8750, 157)
```

Q. 9. Train test split and apply 70-30 split. Name the new dataframes df_train and df_test.¶

Train - test split

Solution:

from sklearn.model_selection import train_test_split

?train_test_split

df_train, df_test = train_test_split(inp2, train_size = 0.7, random_state = 100)

df_train.shape, df_test.shape

```
[153]: from sklearn.model_selection import train_test_split

       ?train_test_split

[155]: df_train, df_test = train_test_split(inp2, train_size = 0.7, random_state = 100)

[156]: df_train.shape, df_test.shape

[156]: ((6125, 157), (2625, 157))
```

Q. 10. Separate the dataframes into X_train, y_train, X_test, and y_test.

Solution:

y_train = df_train.pop("Rating")

X_train = df_train

y_train

y_test = df_test.pop("Rating")

X_test = df_test

print(X_train.shape)

print(y_train.shape)

print(X_test.shape)

print(y_test.shape)

```
[157]: y_train = df_train.pop("Rating")
       X_train = df_train

[158]: y_train

[158]: 9028     4.2
       6547     4.4
       9069     3.0
       3209     4.2
       10151    3.0
               ...
       399      4.3
       81       4.4
       9862     4.5
       8511     4.7
       6787     3.6
       Name: Rating, Length: 6125, dtype: float64

[159]: y_test = df_test.pop("Rating")
       X_test = df_test

[160]: print(X_train.shape)
       print(y_train.shape)
       print(X_test.shape)
       print(y_test.shape)

       (6125, 156)
       (6125,)
       (2625, 156)
       (2625,)
```

11 . Model building

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

Solution:

#Build a linear regression model.

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

model = LinearRegression()
model.fit(X_train, y_train)
train_predictions = model.predict(X_train)
print(f'R2 on train set: {r2_score(y_train, train_predictions)}')
```

```
[161]: #Build a linear regression model.

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

```
[162]: model = LinearRegression()
model.fit(X_train, y_train)
train_predictions = model.predict(X_train)
print(f'R2 on train set: {r2_score(y_train, train_predictions)}')

R2 on train set: 0.1687854505316947
```

Q.12. Make predictions on test set and report R2.

Solution:

Predict on the test set and report R2.

```
test_predictions = model.predict(X_test)
print(f'R2 on test set: {r2_score(y_test, test_predictions)}')
```

```
[163]: # Predict on the test set and report R2.

test_predictions = model.predict(X_test)
print(f'R2 on test set: {r2_score(y_test, test_predictions)}')

R2 on test set: 0.13387130861282437

[ ]:
```