Problem Statement

The team at Google Play Store wants to develop a feature that would enable them to boost visibility for the most promising apps. Now, this analysis would require a preliminary understanding of the features that define a well-performing app. You can ask questions like:

- Does a higher size or price necessarily mean that an app would perform better than the other apps?
- Or does a higher number of installs give a clear picture of which app would have a better rating than others?

Exploratory Data Analysis

1. Import the necessary libraries
2. read the files (CSv or Excel)
3. Data inspection
4. check for null values in the rows
5. Data handling and cleaning
6. describe function
7. check for inconsistencies in your data (missing vales, NAN, incorrect spellings in the rows)
8. Impute these inconsistencies (missing data or NAN values , replace it with mean, median or mode statistics)
9. Visualize the data , check for outliers in each columns
10. Inferences in for the data (on your understanding of the data set)

In [2]:
```
# Importing necessary library
import numpy as np, pandas as pd
import seaborn as sns, matplotlib.pyplot as plt

import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
# Reading the csv file
data = pd.read_csv("googleplaystore_v2.csv")
data.head()
```

Out[3]:

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Conte Rati
0	Photo Editor & Candy Camera & Grid & ScrapBook	ART_AND_DESIGN	4.1	159	19000.0	10,000+	Free	0	Everyo
1	Coloring book moana	ART_AND_DESIGN	3.9	967	14000.0	500,000+	Free	0	Everyo
2	U Launcher Lite – FREE Live Cool Themes, Hide ...	ART_AND_DESIGN	4.7	87510	8700.0	5,000,000+	Free	0	Everyo
3	Sketch - Draw & Paint	ART_AND_DESIGN	4.5	215644	25000.0	50,000,000+	Free	0	Te
4	Pixel Draw - Number Art Coloring Book	ART_AND_DESIGN	4.3	967	2800.0	100,000+	Free	0	Everyo

In [4]:
```
# data inspection
data.shape
```

Out[4]:
```
(10841, 13)
```

In [5]:
```
# checking the rows for null values
data.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
```

Data handling and cleaning

The first few steps involve making sure that there are no **missing values** or **incorrect data types** before we proceed to the analysis stage. These aforementioned problems are handled as follows:

- For Missing Values: Some common techniques to treat this issue are
  - Dropping the rows containing the missing values
  - Imputing the missing values
  - Keep the missing values if they don't affect the analysis
- Incorrect Data Types:
  - Clean certain values
  - Clean and convert an entire column

In [7]:
```
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  float64
 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(2), object(11)
memory usage: 1.1+ MB
```

In [8]:
```
# Since Rating column has lot of missing values i will delete those rows
data = data[-data.Rating.isnull()]
data.shape
```

Out[8]:
```
(9367, 13)
```

In [9]:
```
# fetching the 3 null rows in the "Android Ver" column
data[data['Android Ver'].isnull()]
```

Out[9]:

	App	Category	Rating	Reviews	Size	Installs	Type	
4453	[substratum] Vacuum: P	PERSONALIZATION	4.4	230	11000.000000	1,000+	Paid	
4490	Pi Dark [substratum]	PERSONALIZATION	4.5	189	2100.000000	10,000+	Free	
10472	Life Made WI-Fi Touchscreen Photo Frame	1.9	19.0	3.0M	21516.529524	Free	0	Ever

In [10]:
```
# 10472 row is having shifted values so will drop this row
data.loc[10472,:]
data[(data['Android Ver'].isnull() & (data.Category == '1.9'))]
```

Out[10]:

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Co R
10472	Life Made WI-Fi Touchscreen Photo Frame	1.9	19.0	3.0M	21516.529524	Free	0	Everyone	

In [11]:
```
data = data[-(data['Android Ver'].isnull() & (data.Category == '1.9'))]
```

In [12]:
```
# Cross checking if its dropped
data[data['Android Ver'].isnull()]
```

Out[12]:

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Co R
4453	[substratum] Vacuum: P	PERSONALIZATION	4.4	230	11000.0	1,000+	Paid	$1.49	Eve
4490	Pi Dark [substratum]	PERSONALIZATION	4.5	189	2100.0	10,000+	Free	0	Eve

In [13]:
```
data["Android Ver"].value_counts()
```

Out[13]:
```
4.1 and up            2059
Varies with device    1319
4.0.3 and up          1240
4.0 and up            1131
4.4 and up             875
2.3 and up             582
5.0 and up             535
4.2 and up             338
2.3.3 and up           240
3.0 and up             211
2.2 and up             208
4.3 and up             207
2.1 and up             113
1.6 and up              87
6.0 and up              48
7.0 and up              41
3.2 and up              31
2.0 and up              27
5.1 and up              18
1.5 and up              16
3.1 and up               8
2.0.1 and up             7
4.4W and up              6
8.0 and up               5
7.1 and up               3
4.0.3 - 7.1.1            2
5.0 - 8.0                2
1.0 and up               2
7.0 - 7.1.1              1
4.1 - 7.1.1              1
5.0 - 6.0                1
Name: Android Ver, dtype: int64
```

Imputing the missing values using statistical techinique

For numerical columns we can use mean and median statistics

For categorical columns we use mode statistics

In [15]:
```
data["Android Ver"] = data["Android Ver"].fillna(data["Android Ver"].mode()[0])
```

In [16]:
```
data.isnull().sum()
```

Out[16]:
```
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       4
Android Ver       0
dtype: int64
```

In [17]:
```
data[data["Current Ver"].isnull()]
```

Out[17]:

	App	Category	Rating	Reviews	Size	Installs	Type	Price
15	Learn To Draw Kawaii Characters	ART_AND_DESIGN	3.2	55	2700.0	5,000+	Free	0
1553	Market Update Helper	LIBRARIES_AND_DEMO	4.1	20145	11.0	1,000,000+	Free	0
6322	Virtual DJ Sound Mixer	TOOLS	4.2	4010	8700.0	500,000+	Free	0
7333	Dots puzzle	FAMILY	4.0	179	14000.0	50,000+	Paid	$0.99

In [18]:
```
data["Current Ver"].value_counts()
```

Out[18]:
```
Varies with device    1415
1.0                    458
1.1                    195
1.2                    126
1.3                    120
                      ...
2.9.10                   1
3.18.5                   1
1.3.A.2.9                1
9.9.1.1910               1
0.3.4                    1
Name: Current Ver, Length: 2638, dtype: int64
```

In [19]:
```
data["Current Ver"] = data["Current Ver"].fillna(data["Current Ver"].mode()[0])
```

In [20]:
```
data.isnull().sum()
```

Out[20]:
```
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 [21]:
```
# Handling incorrect data types
data.dtypes
```

Out[21]:
```
App               object
Category          object
Rating           float64
Reviews           object
Size             float64
Installs          object
Type              object
Price             object
Content Rating    object
Genres            object
Last Updated      object
Current Ver       object
Android Ver       object
dtype: object
```

In [22]:
```
data.Price.value_counts()
```

Out[22]:
```
0          8719
$2.99       114
$0.99       107
$4.99        70
$1.99        59
           ...
$1.29         1
$299.99       1
$379.99       1
$37.99        1
$1.20         1
Name: Price, Length: 73, dtype: int64
```

In [23]:
```
data.Price = data.Price.apply(lambda x: 0 if x == '0' else float(x[1:]))
data.dtypes
```

Out[23]:
```
App                object
Category           object
Rating            float64
Reviews            object
Size              float64
Installs           object
Type               object
Price             float64
Content Rating     object
Genres             object
Last Updated       object
Current Ver        object
Android Ver        object
dtype: object
```

In [24]:
```
data.Reviews.value_counts()
```

Out[24]:
```
2         83
3         78
4         74
5         74
1         67
          ..
49657      1
41420      1
7146       1
44706      1
398307     1
Name: Reviews, Length: 5992, dtype: int64
```

In [25]:
```
data.Reviews = data.Reviews.astype("int32")
data.dtypes
```

Out[25]:
```
App                object
Category           object
Rating            float64
Reviews             int32
Size              float64
Installs           object
Type               object
Price             float64
Content Rating     object
Genres             object
Last Updated       object
Current Ver        object
Android Ver        object
dtype: object
```

In [26]:
```
data.Reviews.describe()
```

Out[26]:
```
count    9.366000e+03
mean     5.140498e+05
std      3.144042e+06
min      1.000000e+00
25%      1.862500e+02
50%      5.930500e+03
75%      8.153275e+04
max      7.815831e+07
Name: Reviews, dtype: float64
```

In [27]:
```
data.describe()
```

Out[27]:

	Rating	Reviews	Size	Price
count	9366.000000	9.366000e+03	9366.000000	9366.000000
mean	4.191757	5.140498e+05	22705.733753	0.960928
std	0.515219	3.144042e+06	21305.040123	15.816585
min	1.000000	1.000000e+00	8.500000	0.000000
25%	4.000000	1.862500e+02	6600.000000	0.000000
50%	4.300000	5.930500e+03	21000.000000	0.000000
75%	4.500000	8.153275e+04	27000.000000	0.000000
max	5.000000	7.815831e+07	100000.000000	400.000000

In [28]:
```
data.Installs.value_counts()
```

Out[28]:
```
1,000,000+        1577
10,000,000+       1252
100,000+          1150
10,000+           1010
5,000,000+         752
1,000+             713
500,000+           538
50,000+            467
5,000+             432
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
```

In [29]:
```
# clean function
def clean_installs(val):
    return int(val.replace(",", "").replace("+",""))
```

In [30]:
```
type(clean_installs("3,000+"))
data.Installs = data.Installs.apply(clean_installs)
```

In [31]:
```
data.Installs.value_counts()
```

Out[31]:
```
1000000       1577
10000000      1252
100000        1150
10000         1010
5000000        752
1000           713
500000         538
50000          467
5000           432
100000000      409
100            309
50000000       289
500            201
500000000       72
10              69
1000000000      58
50              56
5                9
1                3
Name: Installs, dtype: int64
```

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

Out[32]:

	Rating	Reviews	Size	Installs	Price
count	9366.000000	9.366000e+03	9366.000000	9.366000e+03	9366.000000
mean	4.191757	5.140498e+05	22705.733753	1.789744e+07	0.960928
std	0.515219	3.144042e+06	21305.040123	9.123822e+07	15.816585
min	1.000000	1.000000e+00	8.500000	1.000000e+00	0.000000
25%	4.000000	1.862500e+02	6600.000000	1.000000e+04	0.000000
50%	4.300000	5.930500e+03	21000.000000	5.000000e+05	0.000000
75%	4.500000	8.153275e+04	27000.000000	5.000000e+06	0.000000
max	5.000000	7.815831e+07	100000.000000	1.000000e+09	400.000000

In [33]:
```
data.dtypes
```

Out[33]:
```
App                object
Category           object
Rating            float64
Reviews             int32
Size              float64
Installs            int64
Type               object
Price             float64
Content Rating     object
Genres             object
Last Updated       object
Current Ver        object
Android Ver        object
dtype: object
```

In [34]:
```
data.Type.value_counts()
```

Out[34]:
```
Free    8719
Paid     647
Name: Type, dtype: int64
```

Lets do some sanity check

1. Ratings should have values 1 to 5
2. Reviews should be less than or equal to Installs
3. If Type column shows Free apps then should show 0 and paid should have some value in the Price column

In [36]:
```
data[(data.Type == "Free") & (data.Price > 0)].shape

# Here its showing 0 which means data points are sitting correctly
```

Out[36]:
```
(0, 13)
```

In [37]:
```
data[data.Reviews > data.Installs].shape
```

Out[37]:
```
(7, 13)
```

In [38]:
```
data.Rating.describe()
```

Out[38]:
```
count    9366.000000
mean        4.191757
std         0.515219
min         1.000000
25%         4.000000
50%         4.300000
75%         4.500000
max         5.000000
Name: Rating, dtype: float64
```

In [39]:
```
data[data["Reviews"] > data["Installs"]]
```

Out[39]:

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating
2454	KBA-EZ Health Guide	MEDICAL	5.0	4	25000.000000	1	Free	0.00	Everyone
4663	Alarmy (Sleep If U Can) - Pro	LIFESTYLE	4.8	10249	21516.529524	10000	Paid	2.49	Everyone
5917	Ra Ga Ba	GAME	5.0	2	20000.000000	1	Paid	1.49	Everyone
6700	Brick Breaker BR	GAME	5.0	7	19000.000000	5	Free	0.00	Everyone
7402	Trovami se ci riesci	GAME	5.0	11	6100.000000	10	Free	0.00	Everyone
8591	DN Blog	SOCIAL	5.0	20	4200.000000	10	Free	0.00	Teen
10697	Mu.F.O.	GAME	5.0	2	16000.000000	1	Paid	0.99	Everyone

In [40]:
```
condition = data["Reviews"] > data["Installs"]
data = data.drop(data[condition].index)
data.shape
```

Out[40]:
```
(9359, 13)
```

In [41]:
```
data[data["Reviews"] > data["Installs"]].shape
```

Out[41]:
```
(0, 13)
```

Data Visulizations

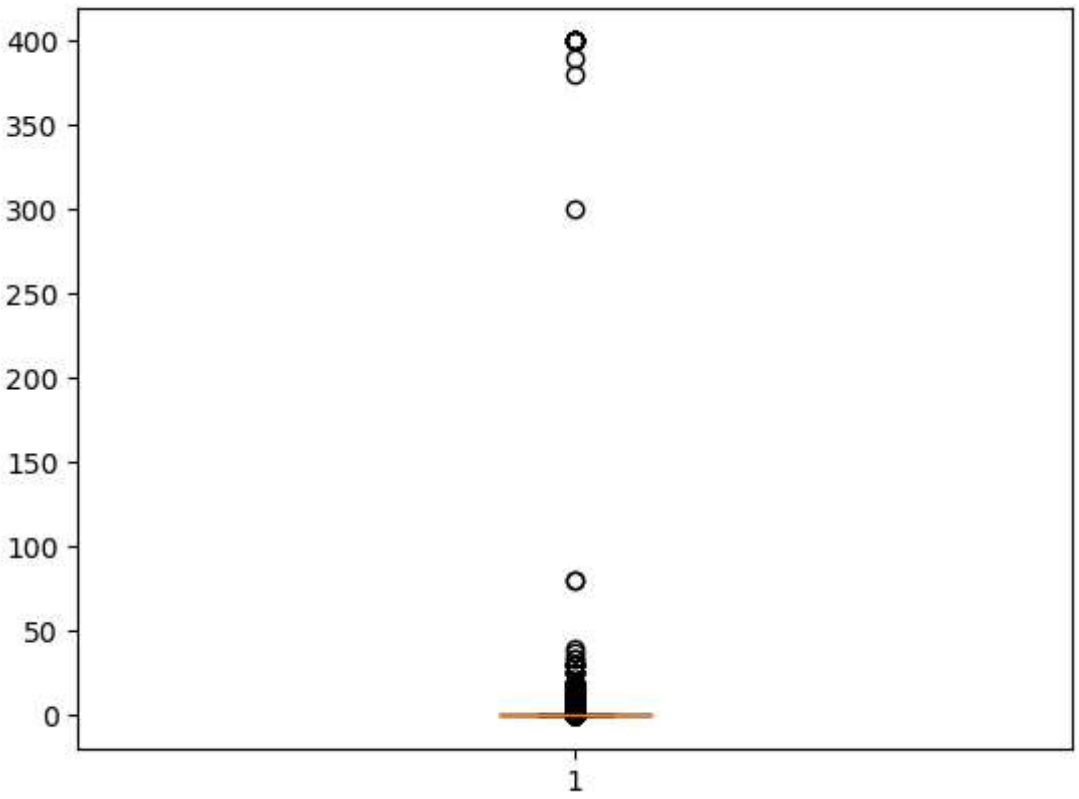
Univariate analysis

Now you need to start identifying and removing extreme values or **outliers** from our dataset. These values can tilt our analysis and often provide us with a biased perspective of the data available. This is where you'll start utilising visualisation to achieve your tasks. And the best visualisation to use here would be the box plot. Boxplots are one of the best ways of analysing the spread of a numeric variable

Using a box plot you can identify the outliers as follows: BoxPlots to Identify Outliers

- Outliers in data can arise due to genuine reasons or because of dubious entries. In the latter case, you should go ahead and remove such entries immediately. Use a boxplot to observe, analyse and remove them.
- In the former case, you should determine whether or not removing them would add value to your analysis procedure.
-
  - You can create a box plot directly from pandas dataframe or the matplotlib way as you learnt in the previous session. Check out their official documentation here:
    - https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.boxplot.html
    - https://matplotlib.org/3.1.1/api/_as_gen/matplotlib.pyplot.boxplot.html

In [43]:
```
# Outlier Analysis
plt.boxplot(data.Price)
plt.show()
```



In [44]:
```
data[data.Price>200].describe()
```

Out[44]:

	Rating	Reviews	Size	Installs	Price
count	15.000000	15.000000	15.000000	15.000000	15.000000
mean	3.866667	603.266667	8904.333333	14606.666667	391.324000
std	0.381101	943.841729	11580.105919	26563.521353	25.875398
min	2.900000	6.000000	965.000000	100.000000	299.990000
25%	3.700000	111.000000	2650.000000	1000.000000	399.990000
50%	3.800000	217.000000	3800.000000	5000.000000	399.990000
75%	4.100000	595.000000	8000.000000	10000.000000	399.990000
max	4.400000	3547.000000	41000.000000	100000.000000	400.000000

In [45]:
```
data[data.Price<200].describe()
```

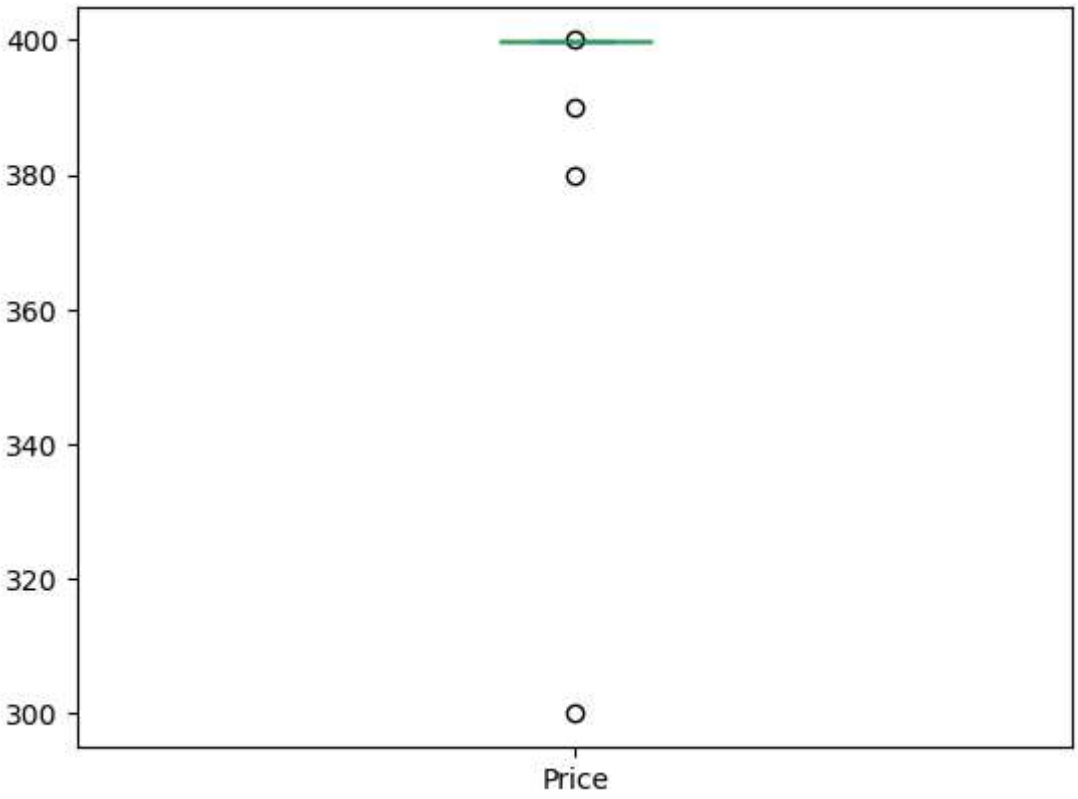
Out[45]:

	Rating	Reviews	Size	Installs	Price
count	9344.000000	9.344000e+03	9344.000000	9.344000e+03	9344.000000
mean	4.191695	5.152581e+05	22732.932449	1.793956e+07	0.334463
std	0.515004	3.147643e+06	21316.475007	9.134144e+07	2.169925
min	1.000000	1.000000e+00	8.500000	5.000000e+00	0.000000
25%	4.000000	1.880000e+02	6600.000000	1.000000e+04	0.000000
50%	4.300000	5.998500e+03	21000.000000	5.000000e+05	0.000000
75%	4.500000	8.222650e+04	27000.000000	5.000000e+06	0.000000
max	5.000000	7.815831e+07	100000.000000	1.000000e+09	79.990000

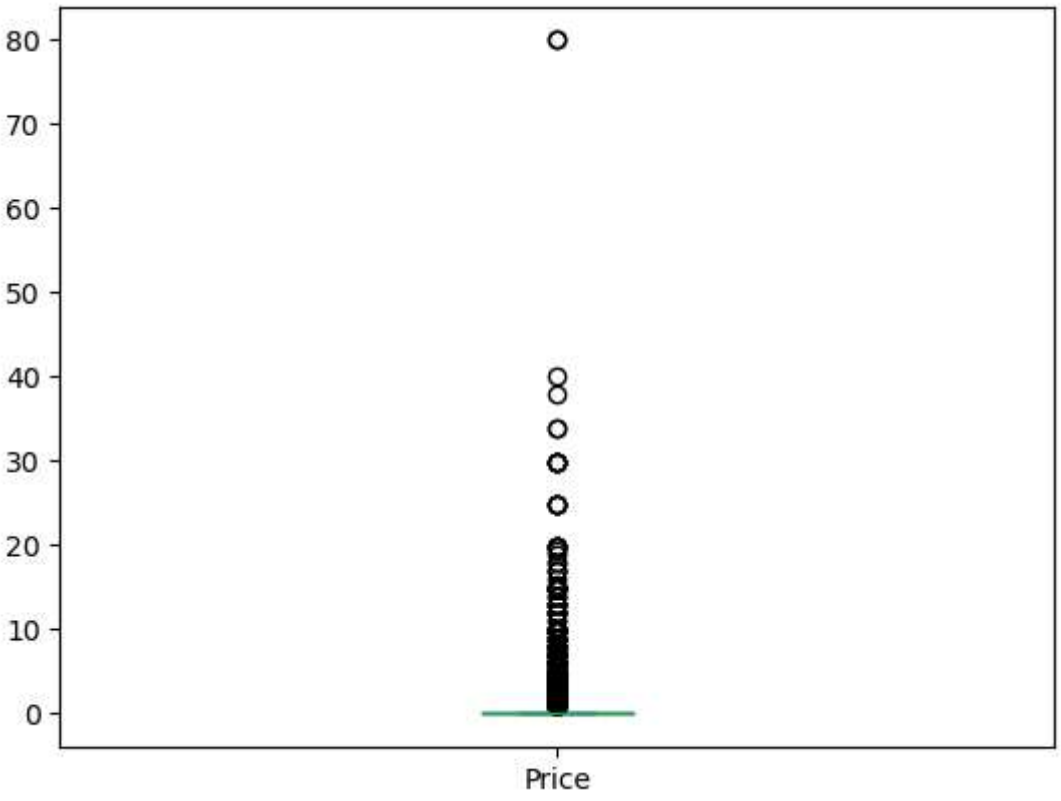
In [46]:
```
data.Price.describe()
```

Out[46]:
```
count    9359.000000
mean        0.961116
std        15.822478
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max       400.000000
Name: Price, dtype: float64
```

In [47]:
```
data[data.Price>200].Price.plot.box()
plt.show()
```



In [48]:
```
data[data.Price<200].Price.plot.box()
plt.show()
```



In [49]:
```
data[data.Price>30].shape
```

Out[49]: (21, 13)

In [50]:
```
data[data.Price>30].describe()
```

Out[50]:

	Rating	Reviews	Size	Installs	Price
count	21.000000	21.000000	21.000000	21.000000	21.000000
mean	3.923810	466.714286	16031.666667	10676.190476	294.085714
std	0.414614	821.064135	21178.196532	23119.708146	159.424893
min	2.900000	6.000000	965.000000	100.000000	33.990000
25%	3.600000	92.000000	2600.000000	1000.000000	79.990000
50%	4.000000	201.000000	4700.000000	1000.000000	399.990000
75%	4.200000	411.000000	26000.000000	10000.000000	399.990000
max	4.600000	3547.000000	68000.000000	100000.000000	400.000000

In [51]:
```
data[data.Price<=30].shape
```

Out[51]: (9338, 13)

In [52]:
```
data[data.Price<=30].describe()
```

Out[52]:

	Rating	Reviews	Size	Installs	Price
count	9338.000000	9.338000e+03	9338.000000	9.338000e+03	9338.000000
mean	4.191776	5.155891e+05	22725.789334	1.795108e+07	0.301915
std	0.515031	3.148627e+06	21310.340299	9.136965e+07	1.669887
min	1.000000	1.000000e+00	8.500000	5.000000e+00	0.000000
25%	4.000000	1.890000e+02	6600.000000	1.000000e+04	0.000000
50%	4.300000	6.011500e+03	21000.000000	5.000000e+05	0.000000
75%	4.500000	8.247100e+04	27000.000000	5.000000e+06	0.000000
max	5.000000	7.815831e+07	100000.000000	1.000000e+09	29.990000

Inference : Public choose to install applications from the Google Playstore that have nominal price.

Histograms

Histograms can also be used in conjuction with boxplots for data cleaning and data handling purposes. You can use it to check the spread of a numeric variable. Histograms generally work by bucketing the entire range of values that a particular variable takes to specific **bins.**

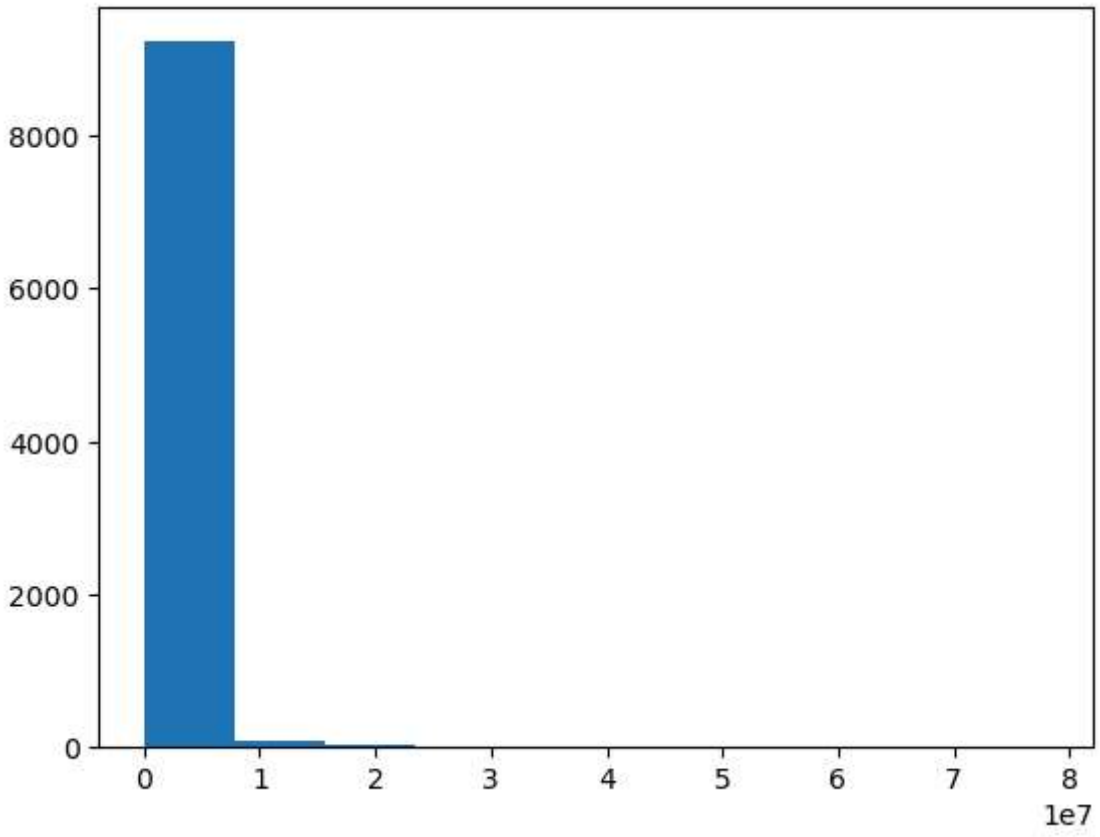
After that, it uses vertical bars to denote the total number of records in a specific bin, which is also known as its **frequency**.

Histogram

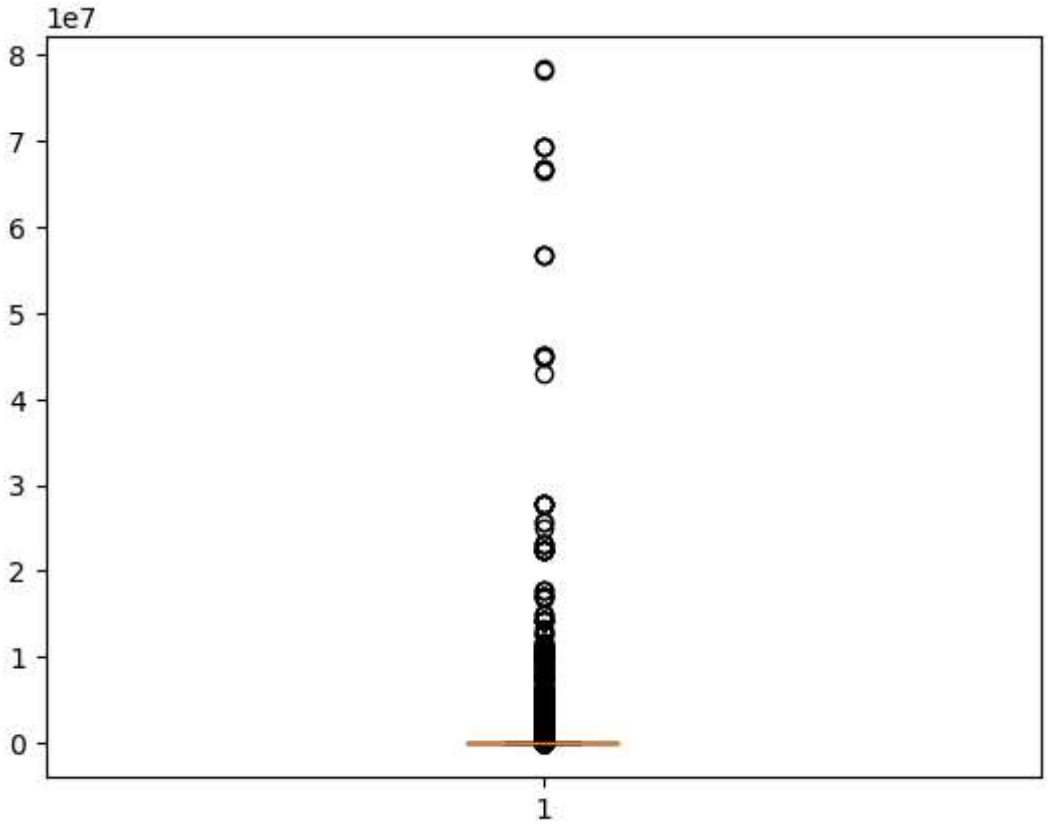
You can adjust the number of bins to improve its granularity Bins change

You'll be using plt.hist() to plot a histogram. Check out its official documentation:https://matplotlib.org/3.1.1/api/_as_gen/matplotlib.pyplot.hist.html

In [55]:
```
plt.hist(data.Reviews)
plt.show()
```



In [56]:
```
plt.boxplot(data.Reviews)
plt.show()
```



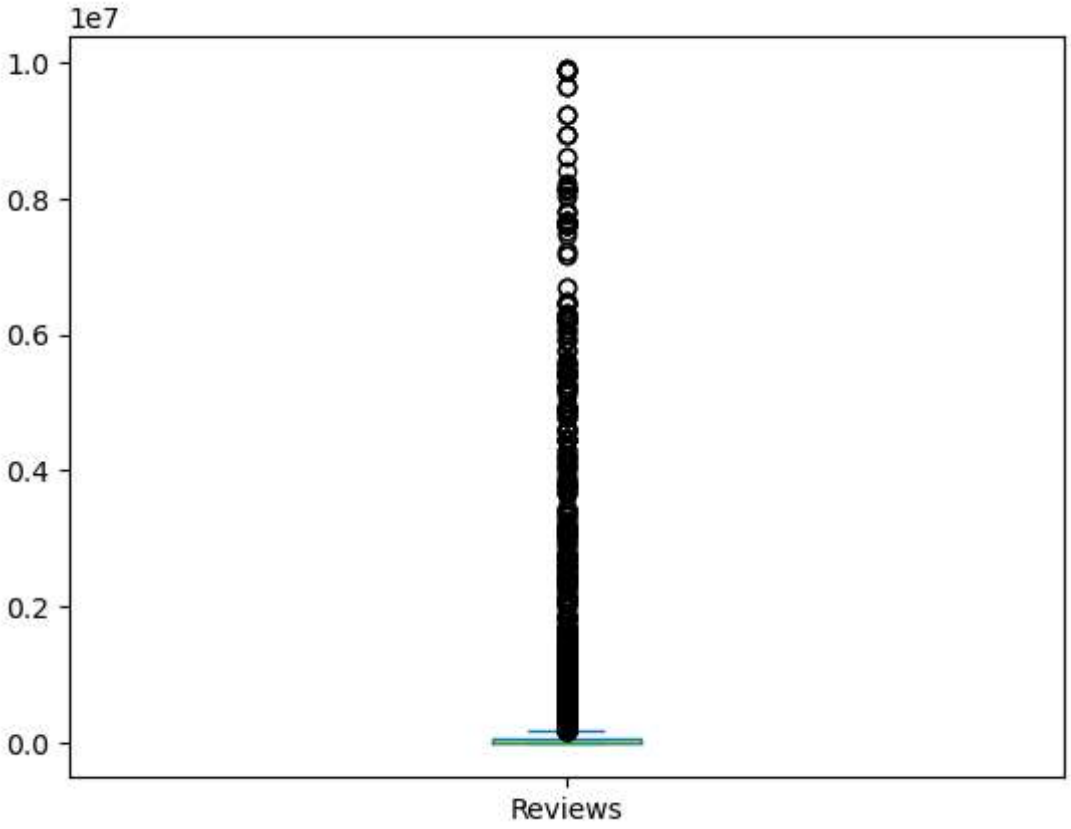
In [57]:
```
data[data.Reviews >= 10000000].shape
```

Out[57]: (92, 13)

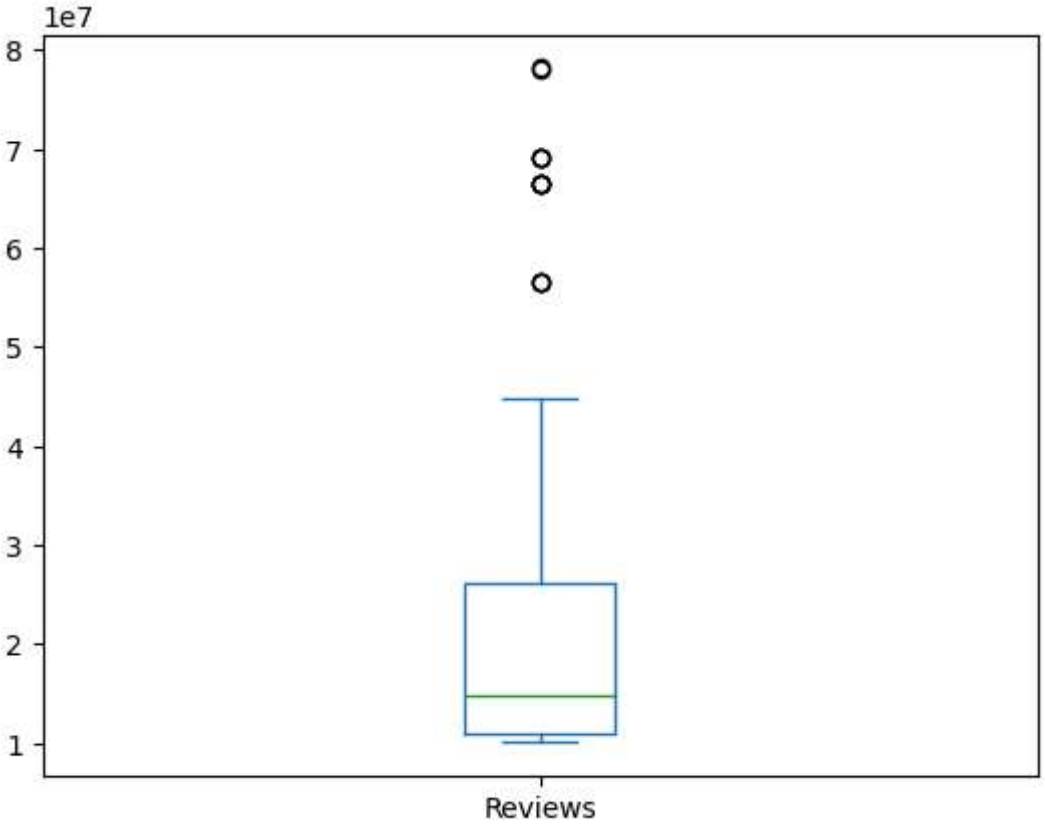
In [58]:
```
data[data.Reviews <= 10000000].shape
```

Out[58]: (9267, 13)

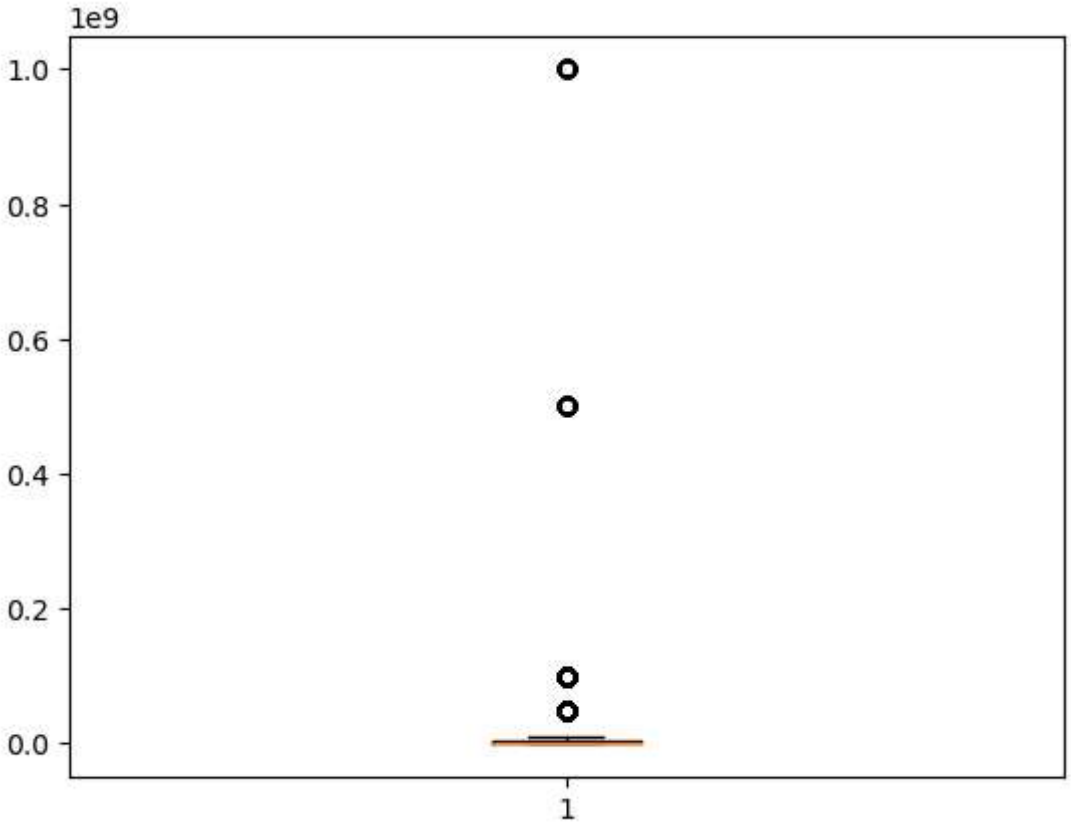
In [59]:
```
data[data.Reviews <= 10000000].Reviews.plot.box()
plt.show()
```



In [60]:
```
data[data.Reviews >= 10000000].Reviews.plot.box()
plt.show()
```



In [61]:
```
plt.boxplot(data.Installs)
plt.show()
```



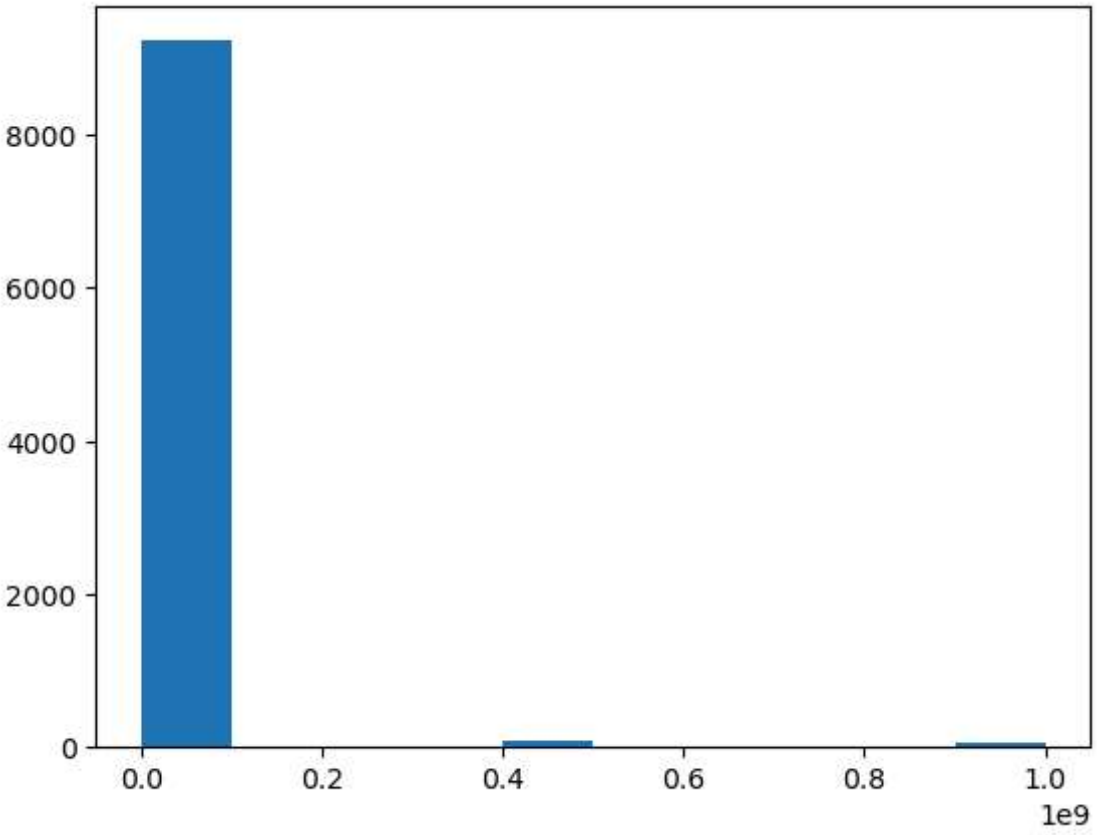
In [62]:
```
data.Installs.describe()
```

Out[62]:
```
count    9.359000e+03
mean     1.791083e+07
std      9.127102e+07
min      5.000000e+00
25%      1.000000e+04
50%      5.000000e+05
75%      5.000000e+06
max      1.000000e+09
Name: Installs, dtype: float64
```

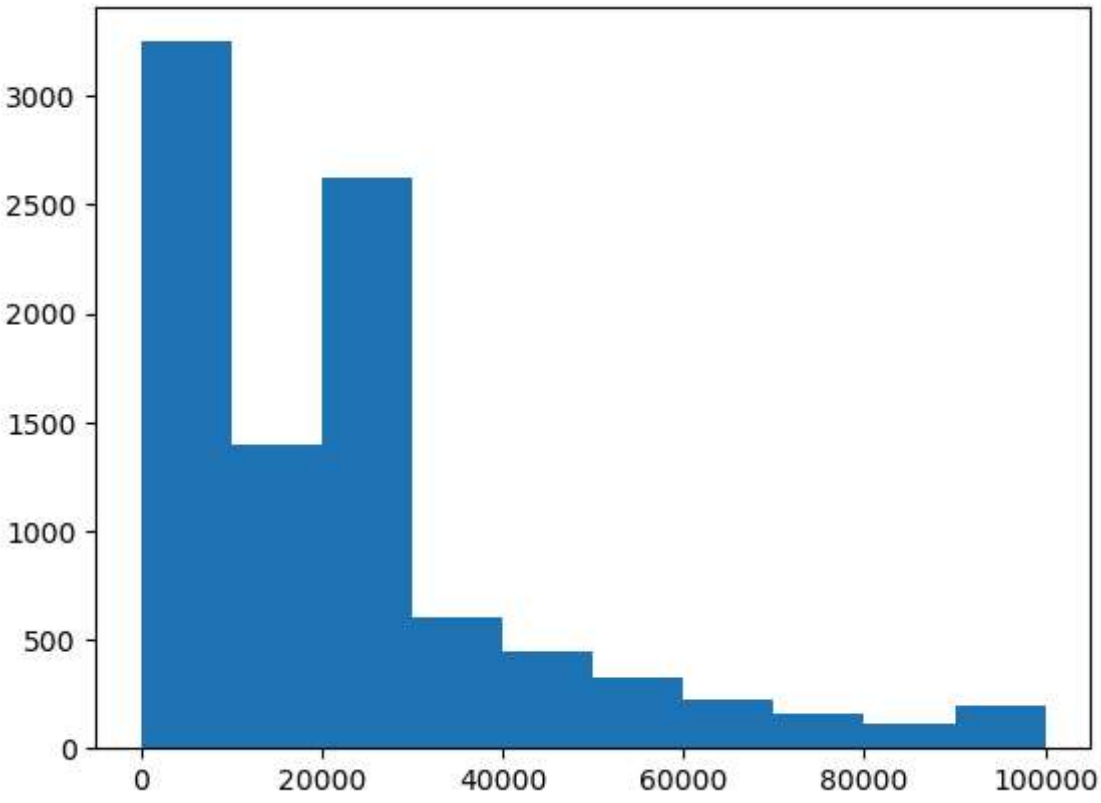
In [63]:
```
data[data.Installs <= 10000000].shape
```

Out[63]:
```
(8531, 13)
```

In [64]:
```
plt.hist(data.Installs)
plt.show()
```



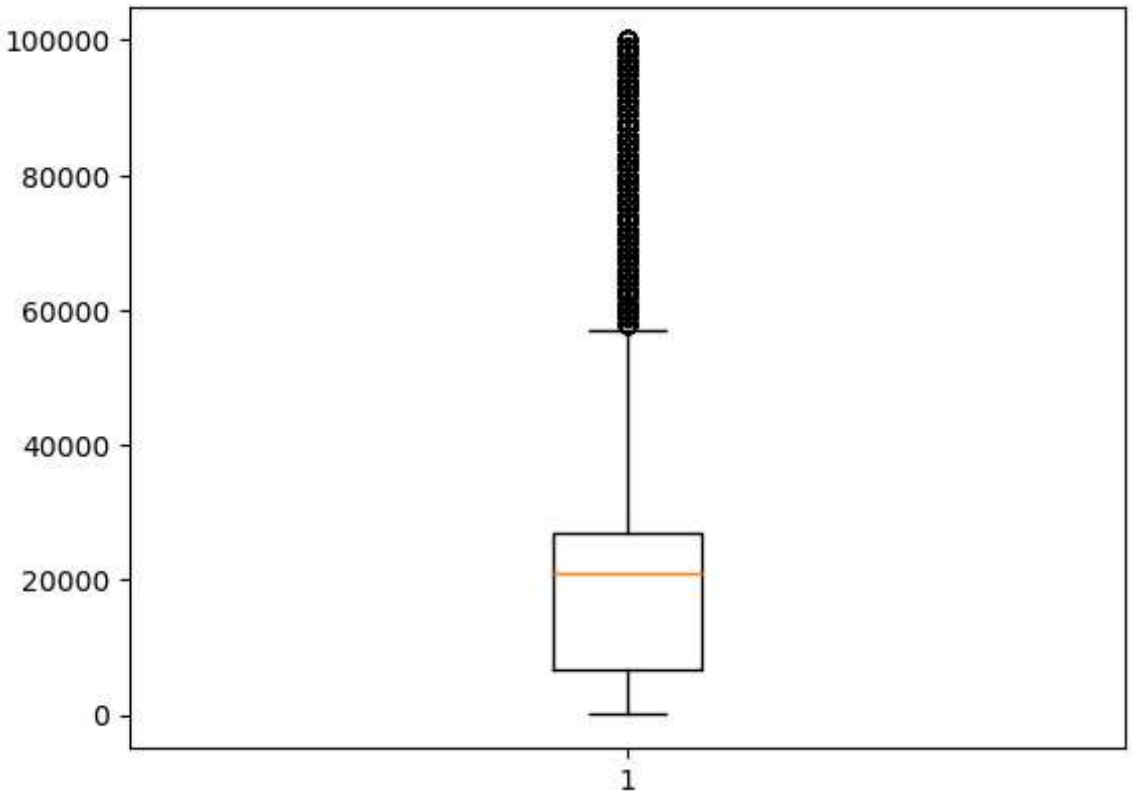
In [65]:
```
plt.hist(data.Size)
plt.show()
```



In [66]:
```
data.Size.describe()
```

Out[66]:
```
count      9359.000000
mean      22710.768864
std       21311.274234
min           8.500000
25%        6600.000000
50%       21000.000000
75%       27000.000000
max      100000.000000
Name: Size, dtype: float64
```

In [67]:
```
plt.boxplot(data.Size)
plt.show()
```



Styling Options

One of the biggest advantages of using Seaborn is that you can retain its aesthetic properties and also the Matplotlib functionalities to perform additional customisations. Before we continue with our case study analysis, let's study some styling options that are available in Seaborn.

In [69]:
```
plt.style.available
```

Out[69]:
```
['Solarize_Light2',
 '_classic_test_patch',
 '_mpl-gallery',
 '_mpl-gallery-nogrid',
 'bmh',
 'classic',
 'dark_background',
 'fast',
 'fivethirtyeight',
 'ggplot',
 'grayscale',
 'seaborn-v0_8',
 'seaborn-v0_8-bright',
 'seaborn-v0_8-colorblind',
 'seaborn-v0_8-dark',
 'seaborn-v0_8-dark-palette',
 'seaborn-v0_8-darkgrid',
 'seaborn-v0_8-deep',
 'seaborn-v0_8-muted',
 'seaborn-v0_8-notebook',
 'seaborn-v0_8-paper',
 'seaborn-v0_8-pastel',
 'seaborn-v0_8-poster',
 'seaborn-v0_8-talk',
 'seaborn-v0_8-ticks',
 'seaborn-v0_8-white',
 'seaborn-v0_8-whitegrid',
 'tableau-colorblind10']
```

Seaborn is Python library to create statistical graphs easily. It is built on top of matplotlib and closely integrated with pandas.

Functionalities of Seaborn :

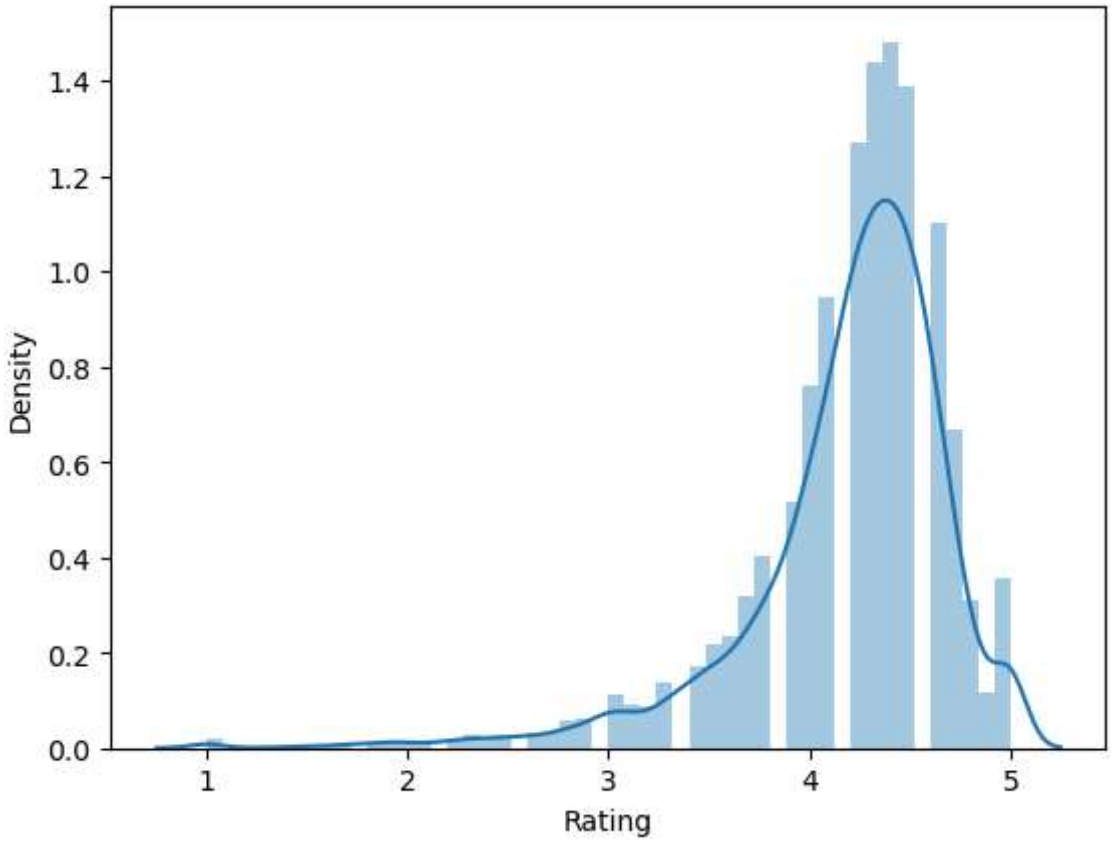
- Dataset oriented API
- Analysing univariate and bivariate distributions
- Automatic estimation and plotting of linear regression models
- Convenient views for complex datasets
- Concise control over style
- Colour palettes

A distribution plot is pretty similar to the histogram functionality in matplotlib. Instead of a frequency plot, it plots an approximate probability density for that rating bucket. And the curve (or the **KDE**) that gets drawn over the distribution is the approximate probability density curve.

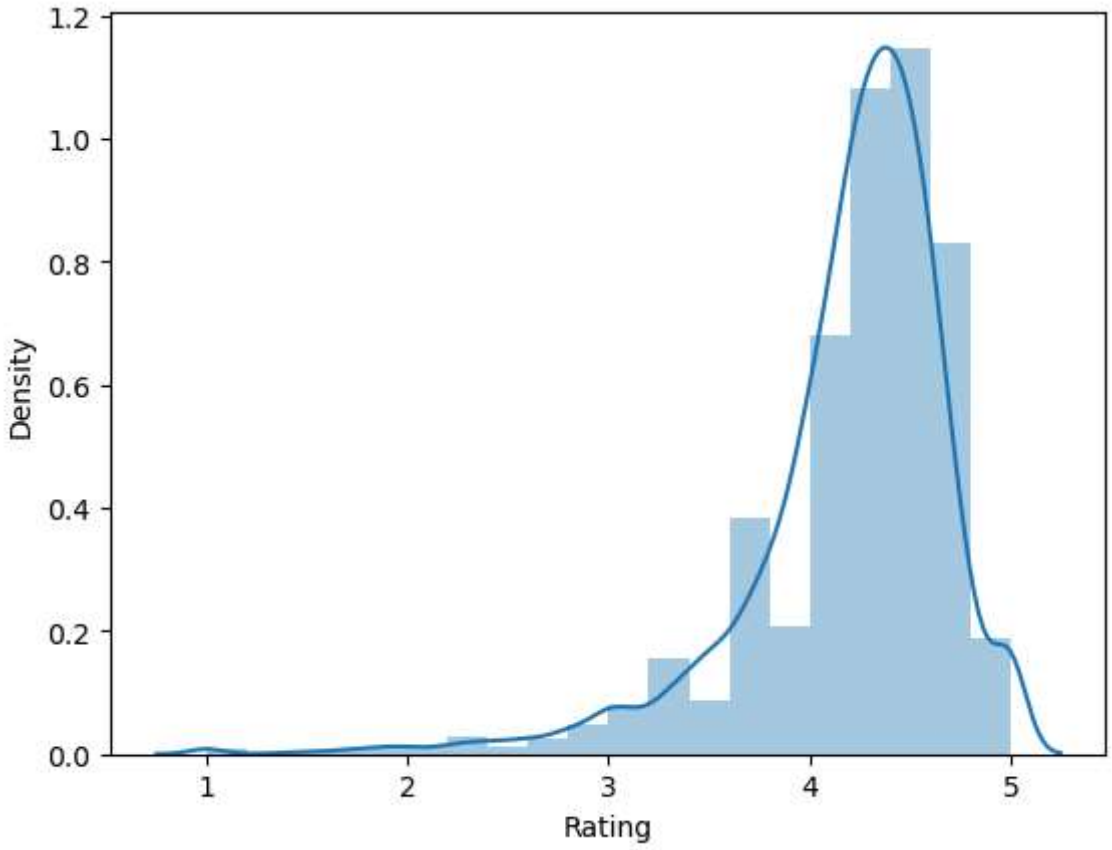
The following is an example of a distribution plot. Notice that now instead of frequency on the left axis, it has the density for each bin or bucket.

You'll be using sns.distplot for plotting a distribution plot. Check out its official documentation: https://seaborn.pydata.org/generated/seaborn.distplot.html

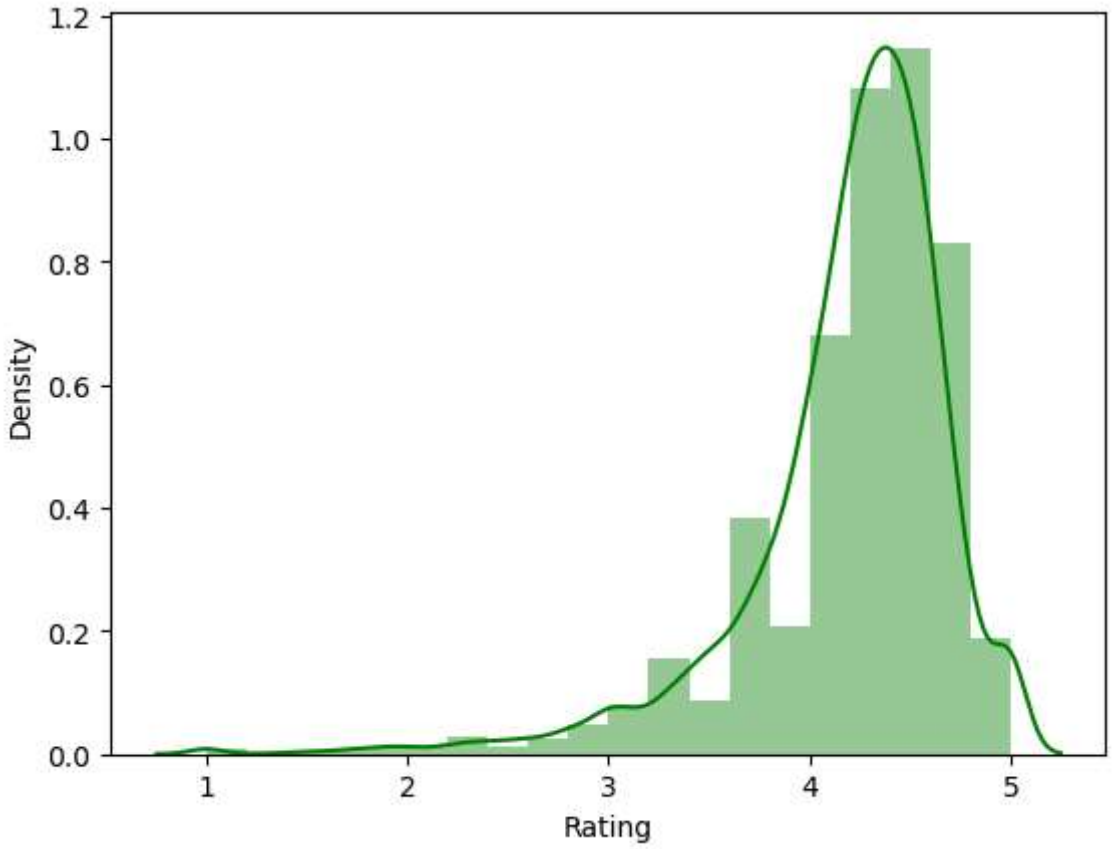
In [72]:
```
sns.distplot(data.Rating)
plt.show()
```



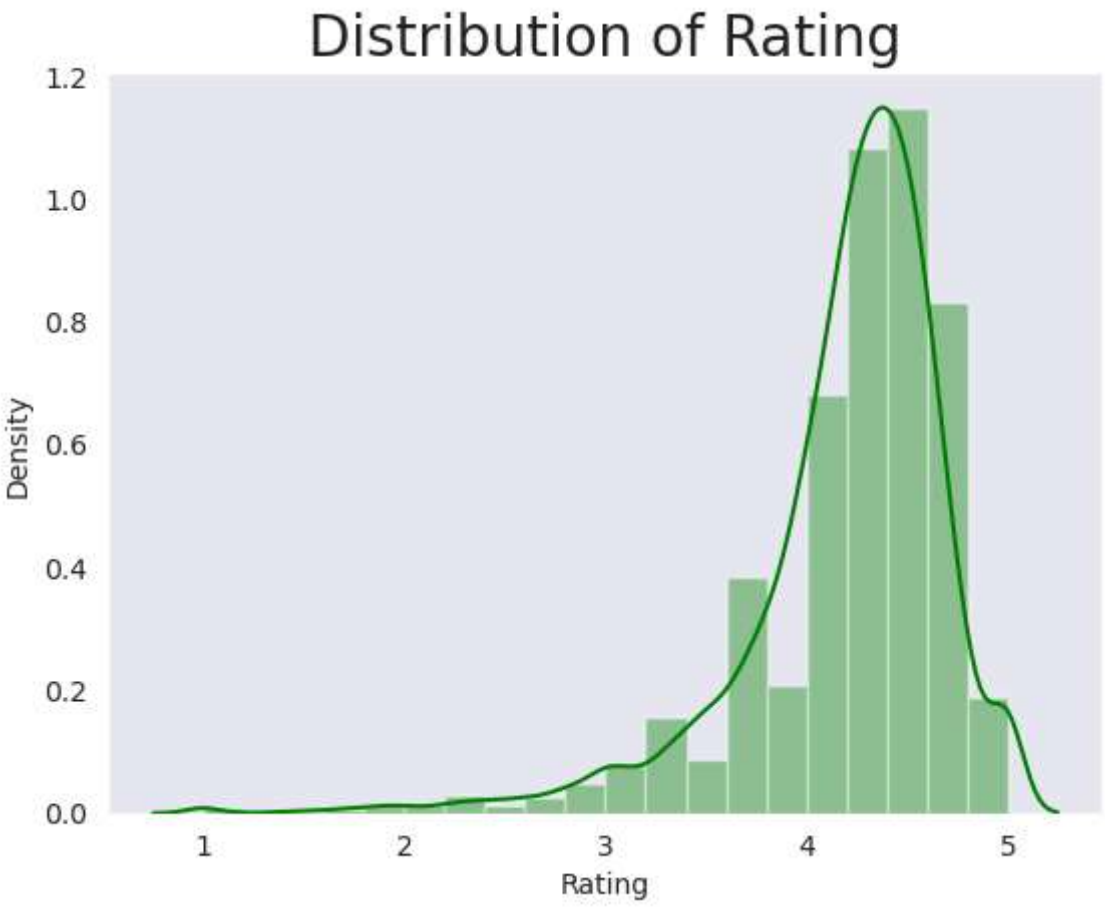
In [73]:
```
sns.distplot(data.Rating, bins = 20)
plt.show()
```



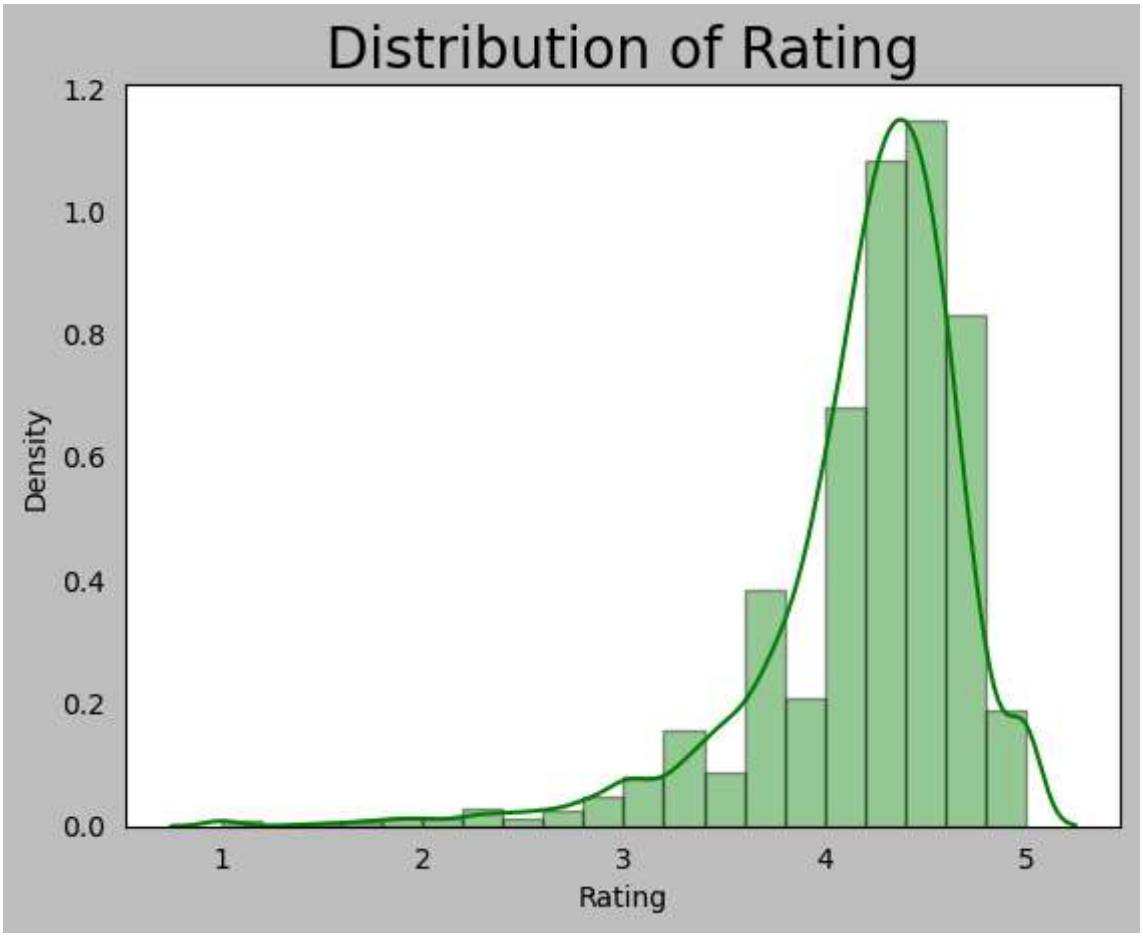
In [74]:
```
sns.distplot(data.Rating, bins = 20, color = 'g')
plt.show()
```



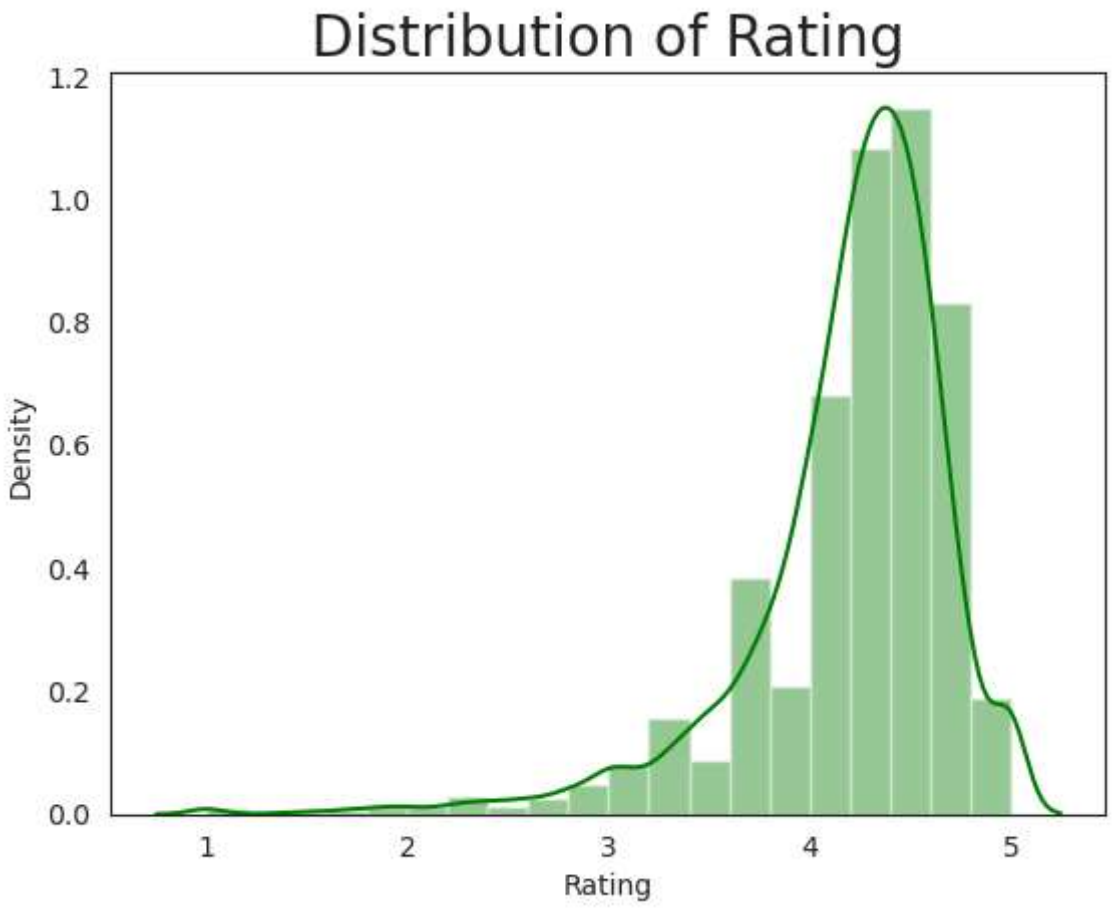
In [75]:
```
sns.set_style
sns.set_style("dark")
sns.distplot(data.Rating, bins = 20, color = 'g')
plt.title("Distribution of Rating", fontsize = 20)
plt.show()
```



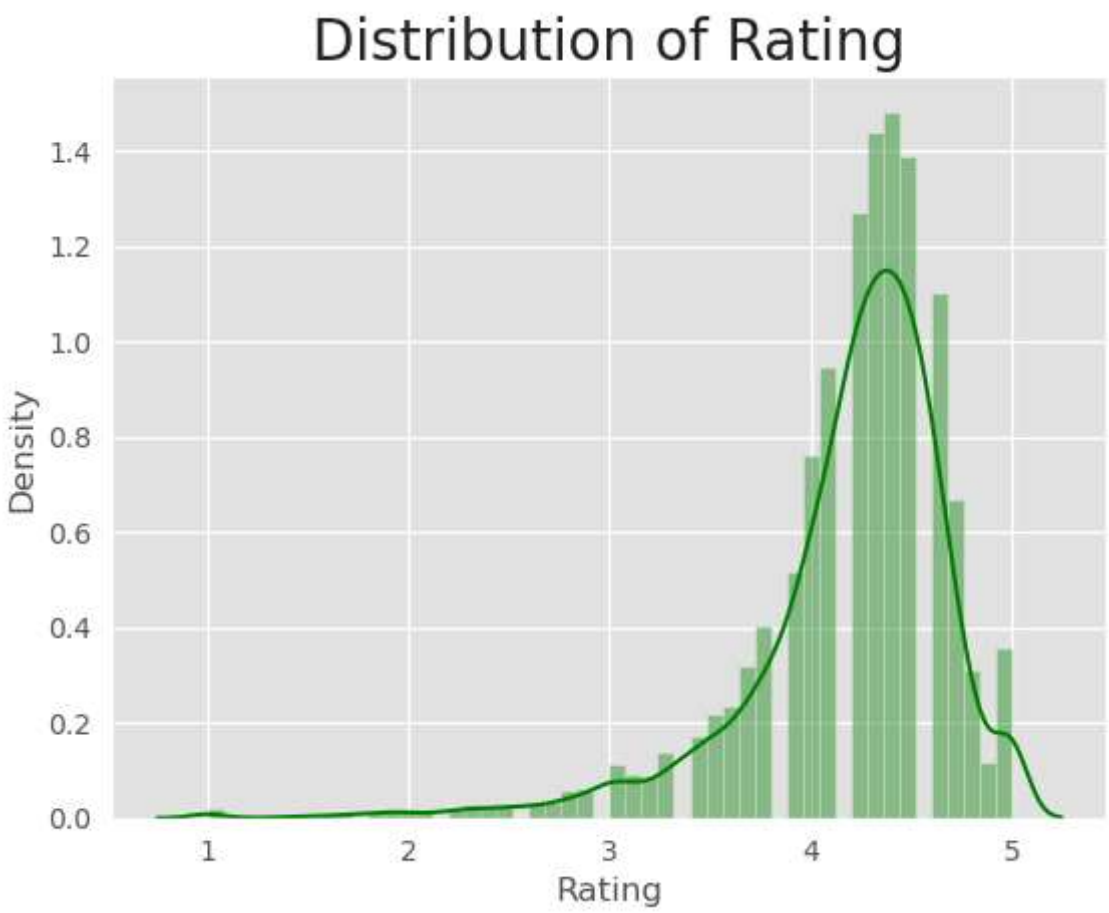
In [76]:
```
plt.style.use("grayscale")
sns.distplot(data.Rating, bins = 20, color = 'g')
plt.title("Distribution of Rating", fontsize = 20)
plt.show()
```



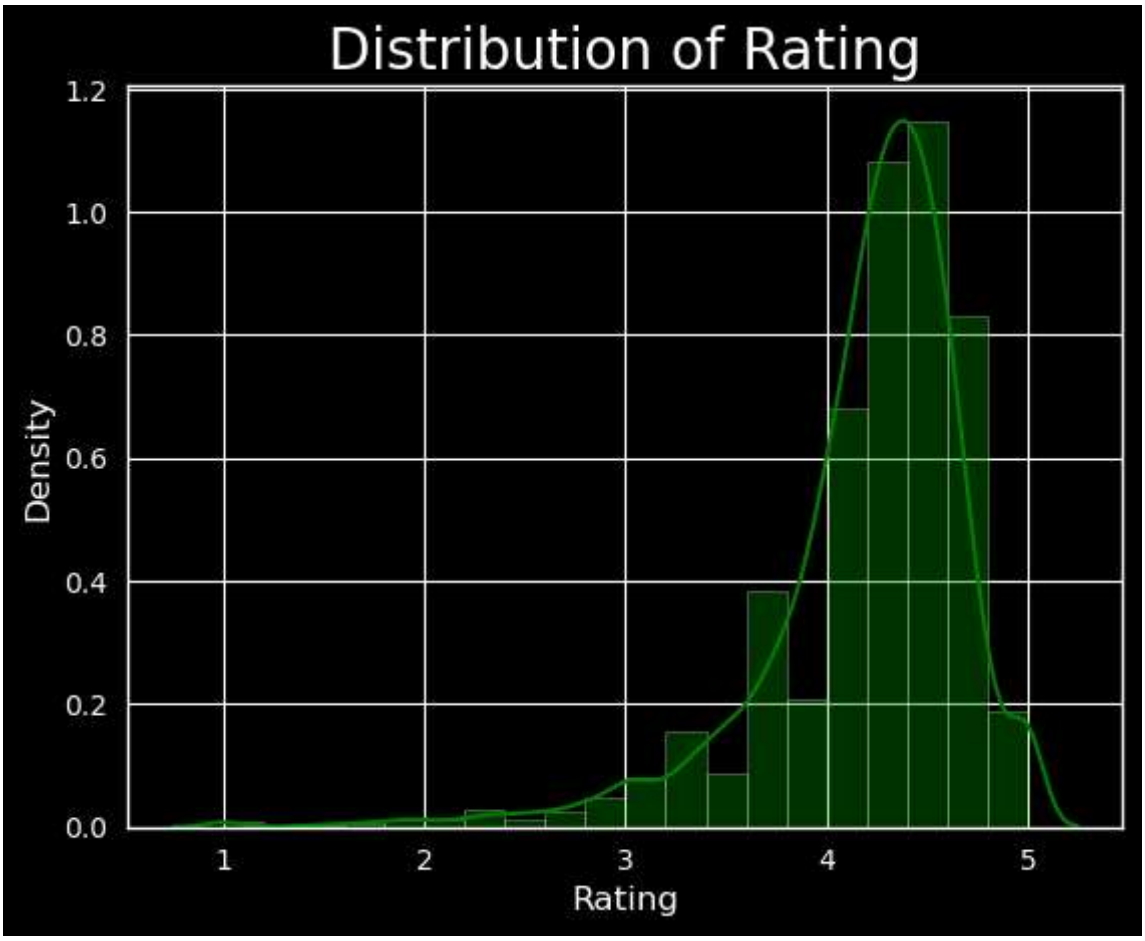
In [77]:
```
plt.style.use("grayscale")
sns.set_style("white")
sns.distplot(data.Rating, bins = 20, color = 'g')
plt.title("Distribution of Rating", fontsize = 20)
plt.show()
```



In [78]:
```
plt.style.use("ggplot")
#sns.set_style("white")
sns.distplot(data.Rating, color = 'g')
plt.title("Distribution of Rating", fontsize = 20)
plt.show()
```



In [79]:
```
plt.style.use("dark_background")

sns.distplot(data.Rating, bins = 20,color = 'g')
plt.title("Distribution of Rating", fontsize = 20)
plt.show()
```



In [80]:
```
data["Content Rating"].value_counts()
```

Out[80]:
```
Everyone           7414
Teen               1083
Mature 17+          461
Everyone 10+        397
Adults only 18+       3
Unrated               1
Name: Content Rating, dtype: int64
```

In [81]:
```
data = data[-data["Content Rating"].isin(["Adults only 18+","Unrated"])]
```

In [82]:
```
data["Content Rating"].value_counts()
```

Out[82]:
```
Everyone        7414
Teen            1083
Mature 17+       461
Everyone 10+     397
Name: Content Rating, dtype: int64
```

In [83]:
```
data.shape
```

Out[83]:
```
(9355, 13)
```

In [84]:
```
data.reset_index(inplace = True, drop = True)
```

In [85]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9355 entries, 0 to 9354
Data columns (total 13 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   App             9355 non-null   object 
 1   Category        9355 non-null   object 
 2   Rating          9355 non-null   float64
 3   Reviews         9355 non-null   int32  
 4   Size            9355 non-null   float64
 5   Installs        9355 non-null   int64  
 6   Type            9355 non-null   object 
 7   Price           9355 non-null   float64
 8   Content Rating  9355 non-null   object 
 9   Genres          9355 non-null   object 
 10  Last Updated    9355 non-null   object 
 11  Current Ver     9355 non-null   object 
 12  Android Ver     9355 non-null   object 
dtypes: float64(3), int32(1), int64(1), object(8)
memory usage: 913.7+ KB
```

Pie-Chart and Bar Chart

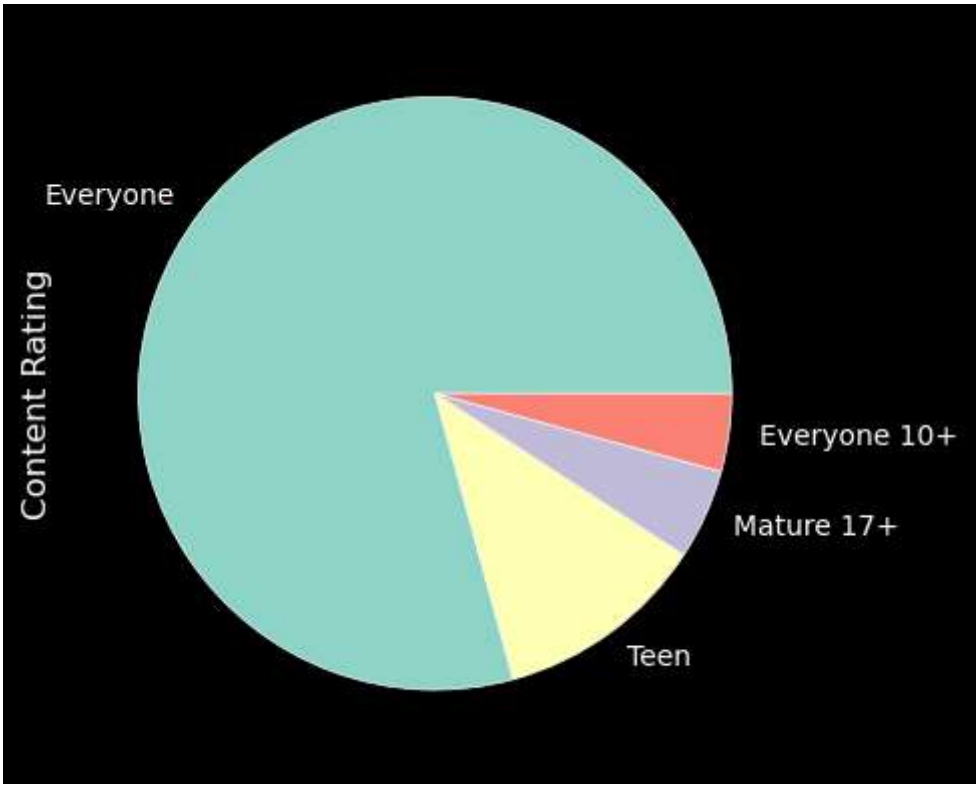
For analysing how a numeric variable changes across several categories of a categorical variable you utilise either a pie chart or a box plot

For example, if you want to visualise the responses of a marketing campaign, you can use the following views:  PieChart

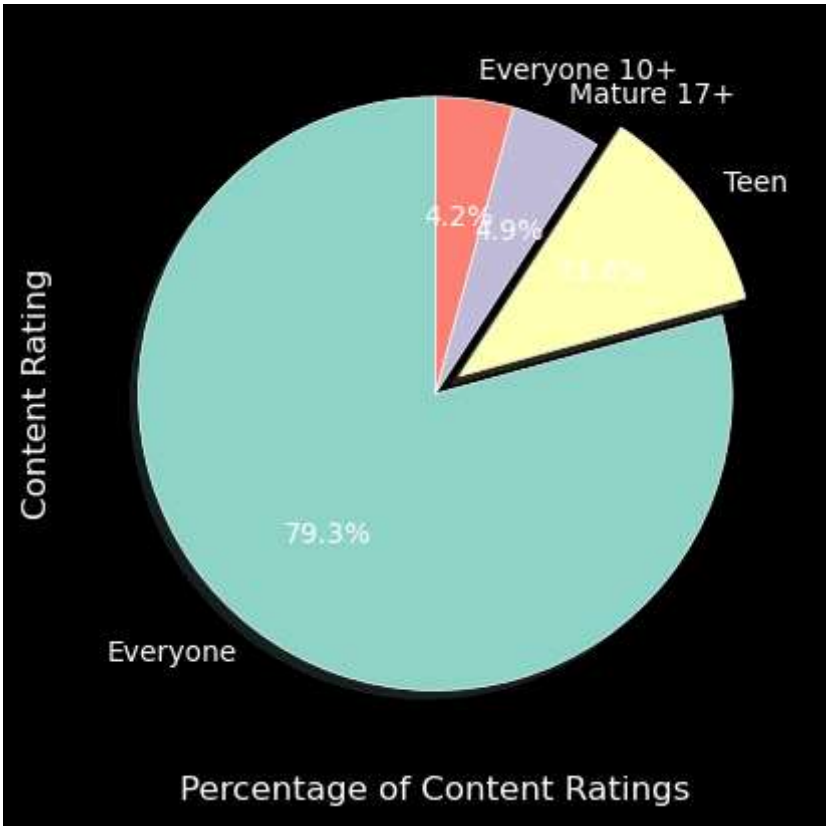
 barChart

- You'll be using the pandas method of plotting both a pie chart and a bar chart. Check out their official documentations:
  - https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.plot.bar.html
  - https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.plot.pie.html

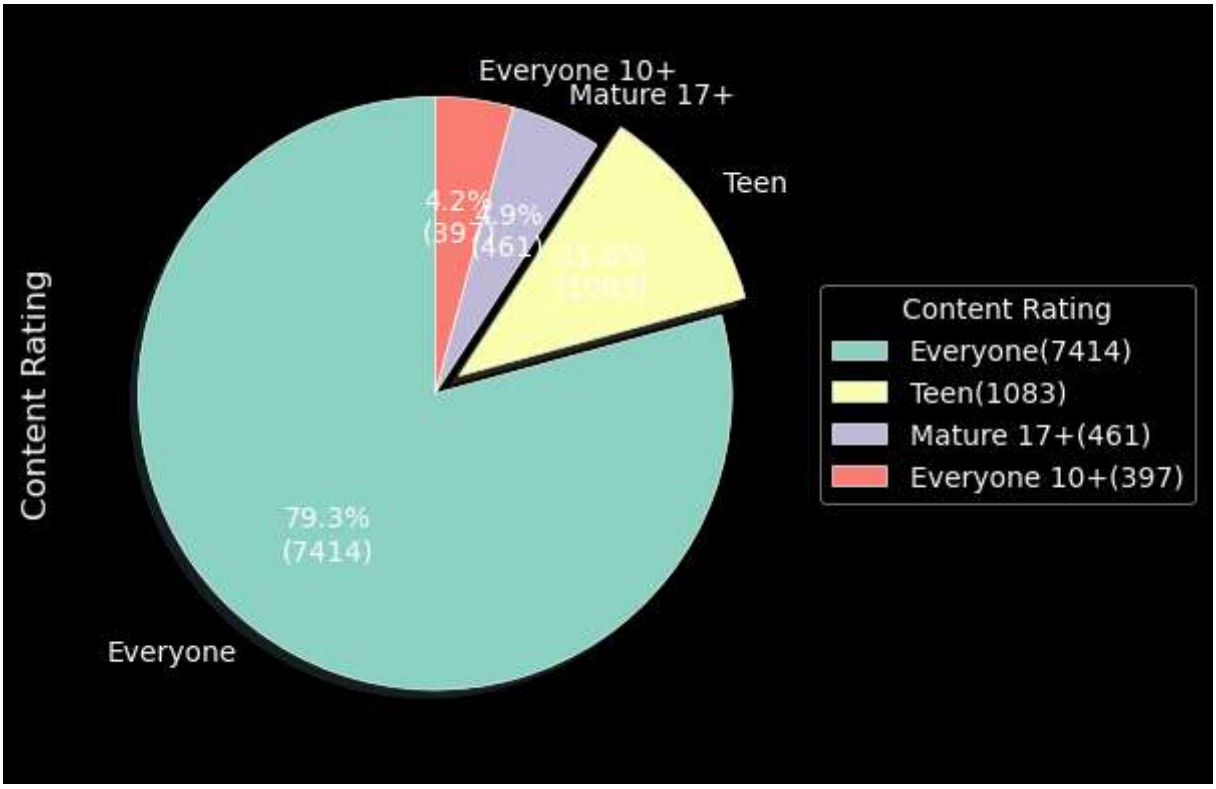
In [87]:
```
data["Content Rating"].value_counts().plot.pie()
plt.show()
```



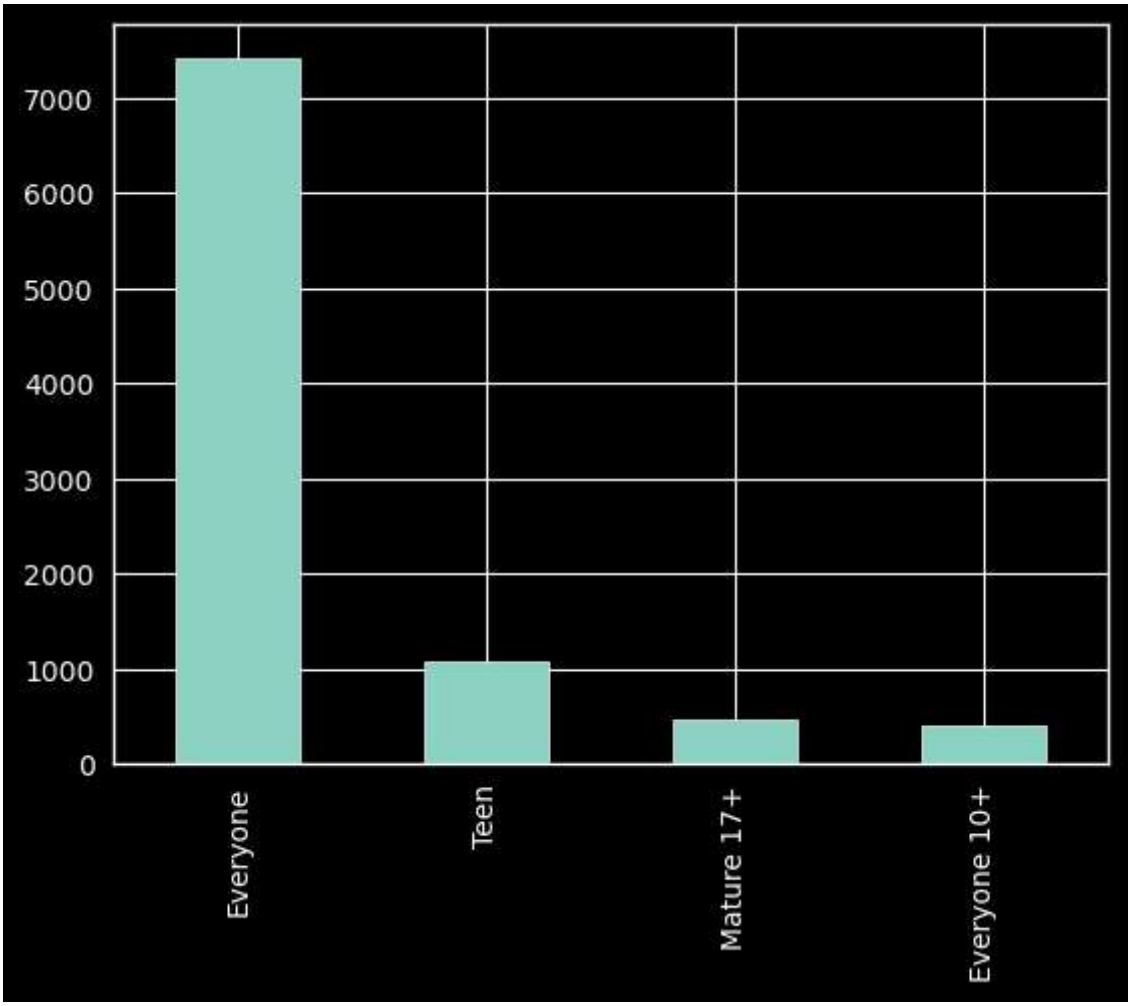
In [88]:
```
data["Content Rating"].value_counts().plot.pie(labels = data["Content Rating"].valu
                                               autopct = '%1.1f%%',
                                               explode = (0,0.1,0,0),
                                               startangle = 90,
                                               shadow = True)
plt.xlabel("Percentage of Content Ratings")

plt.show()
```



In [89]:
```
values = data["Content Rating"].value_counts()
total = values.sum()

def auctpct_format(pct):
    absolute = int(round(pct/100 * total))
    return f'{pct:.1f}%\n({absolute})'

values.plot.pie(
    labels = values.index,
    autopct = auctpct_format,
    explode = (0,0.1,0,0),
    startangle = 90,
    shadow = True)

plt.legend(
    labels = [f'{label}({count})' for label, count in zip(values.index,values)],
    title = 'Content Rating',
    loc = 'center left',
    bbox_to_anchor = (1,0.5)
)

plt.show()
```



In [90]:
```
data["Content Rating"].value_counts().plot.bar()
plt.show()
```



Scatter Plots

Scatterplots are perhaps one of the most commonly used as well one of the most powerful visualisations you can use in the field of machine learning. They are pretty crucial in revealing relationships between the data points and you can generally deduce some sort of trends in the data with the help of a scatter plot.

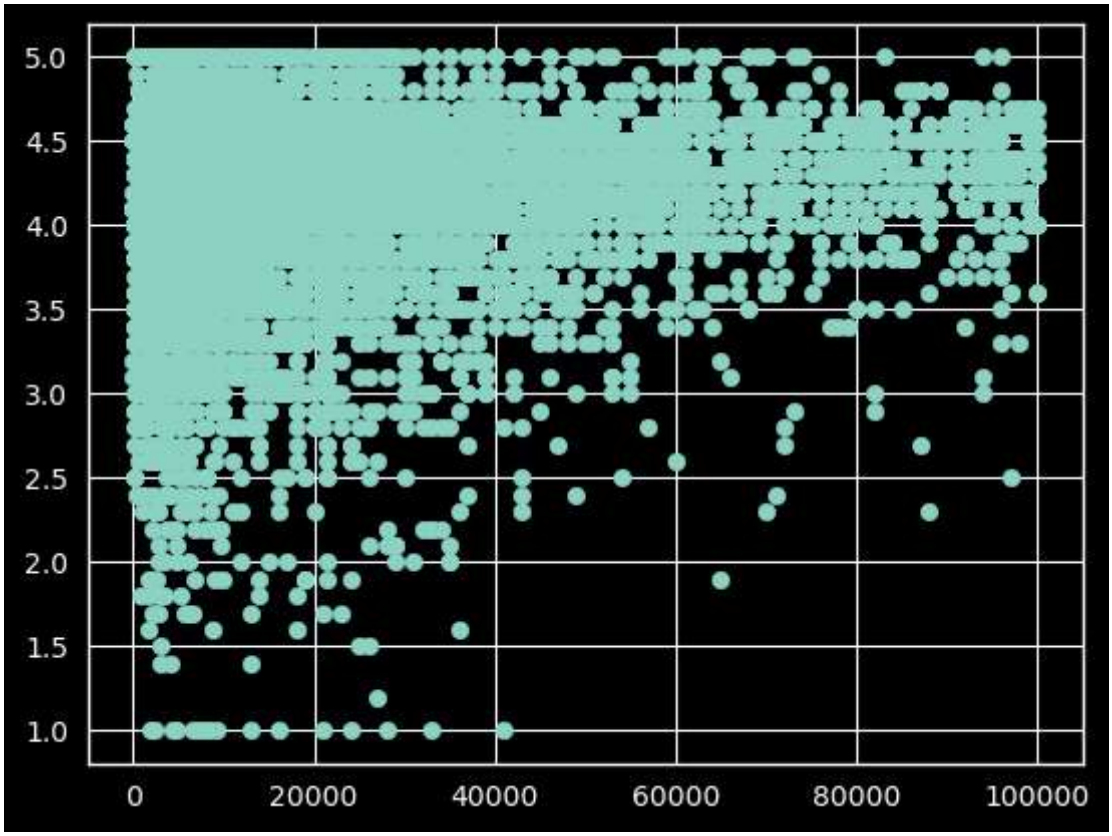
- They're pretty useful in regression problems to check whether a linear trend exists in the data or not. For example, in the image below, creating a linear model in the first case makes far more sense since a clear straight line trend is visible.

- - Also, they help in observing **naturally occuring clusters**. In the following image, the marks of students in Maths and Biology has been plotted.You can clearly group the students to 4 clusters now. Cluster 1 are students who score very well in Biology but very poorly in Maths, Cluster 2 are students who score equally well in both the subjects and so on.

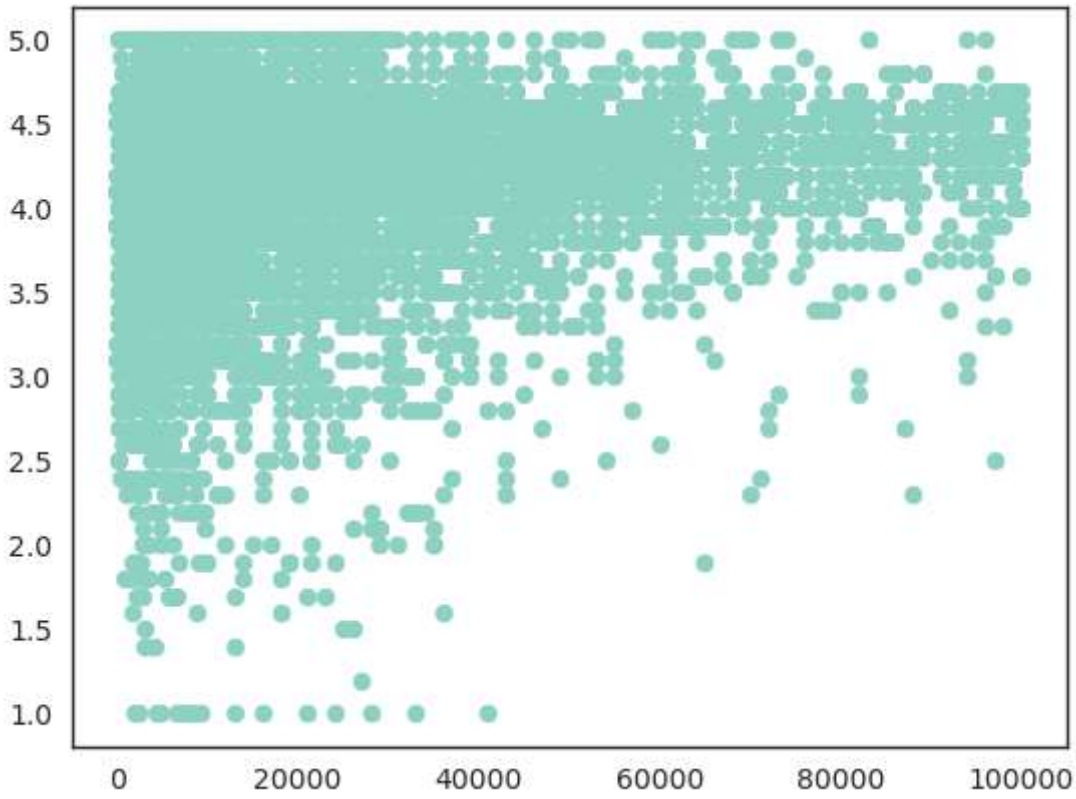
- **Note**: You'll be studying about both Regression and Clustering in greater detail in the machine learning modules
- You'll be using **sns.jointplot()** for creating a scatter plot. Check out its documentation:

https://seaborn.pydata.org/generated/seaborn.jointplot.html

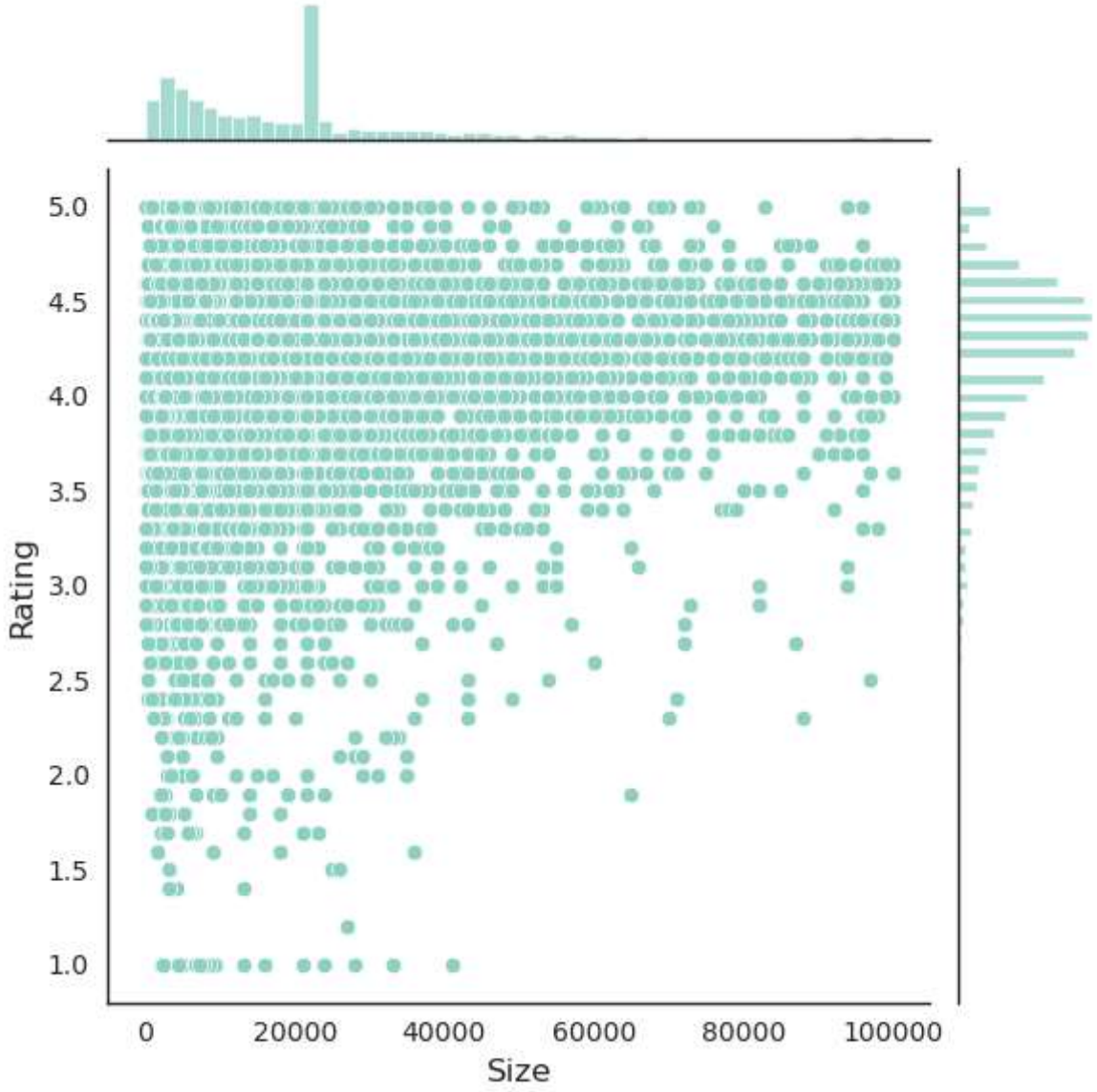
In [92]:
```
# Bivariate Analysis

plt.scatter(data.Size, data.Rating)
plt.show()
```



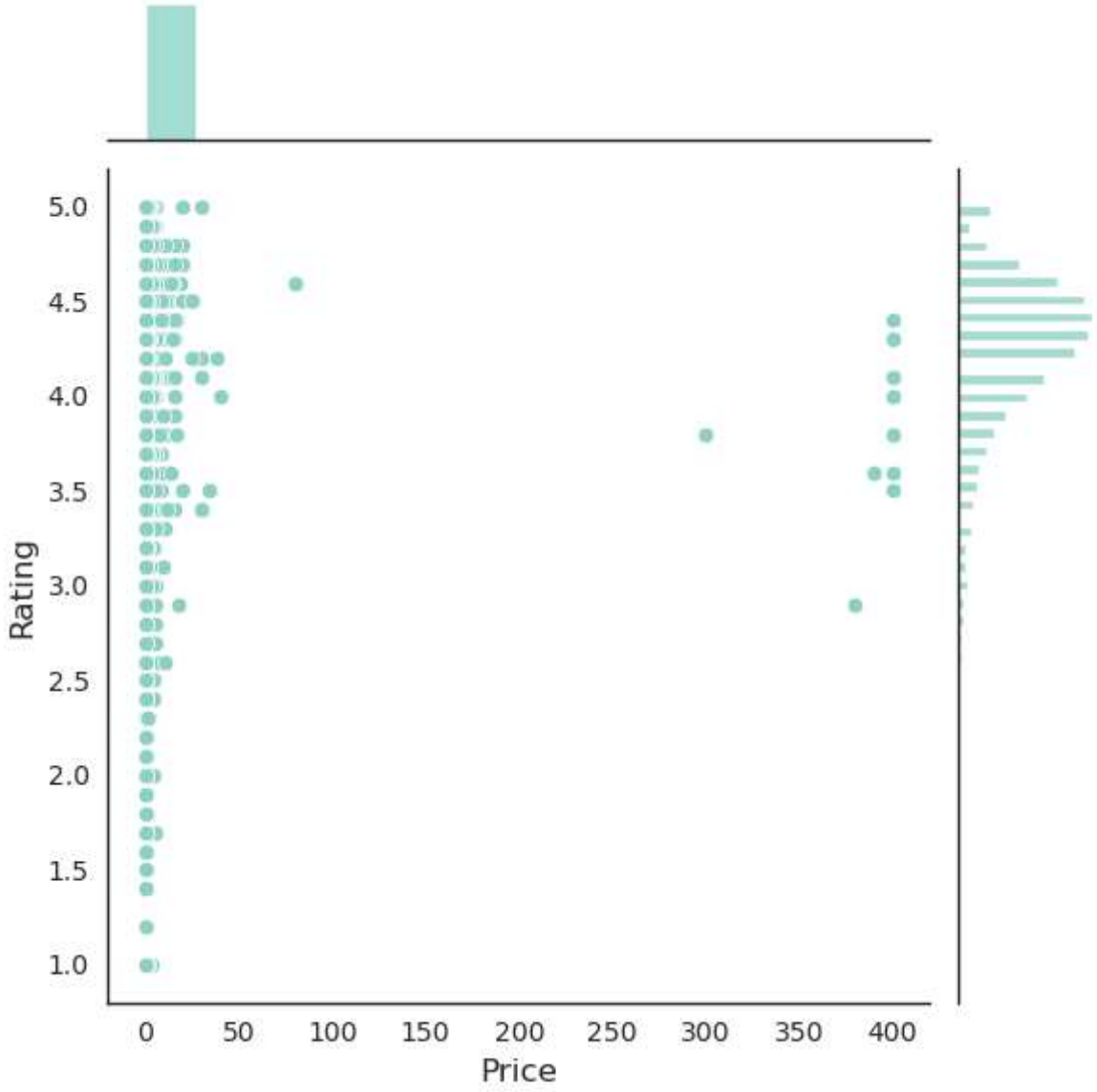
In [93]:
```
sns.set_style("white")

plt.scatter(data.Size, data.Rating)
plt.show()
```



In [94]:
```
sns.jointplot(x= 'Size', y = 'Rating', data = data)
plt.show()
```



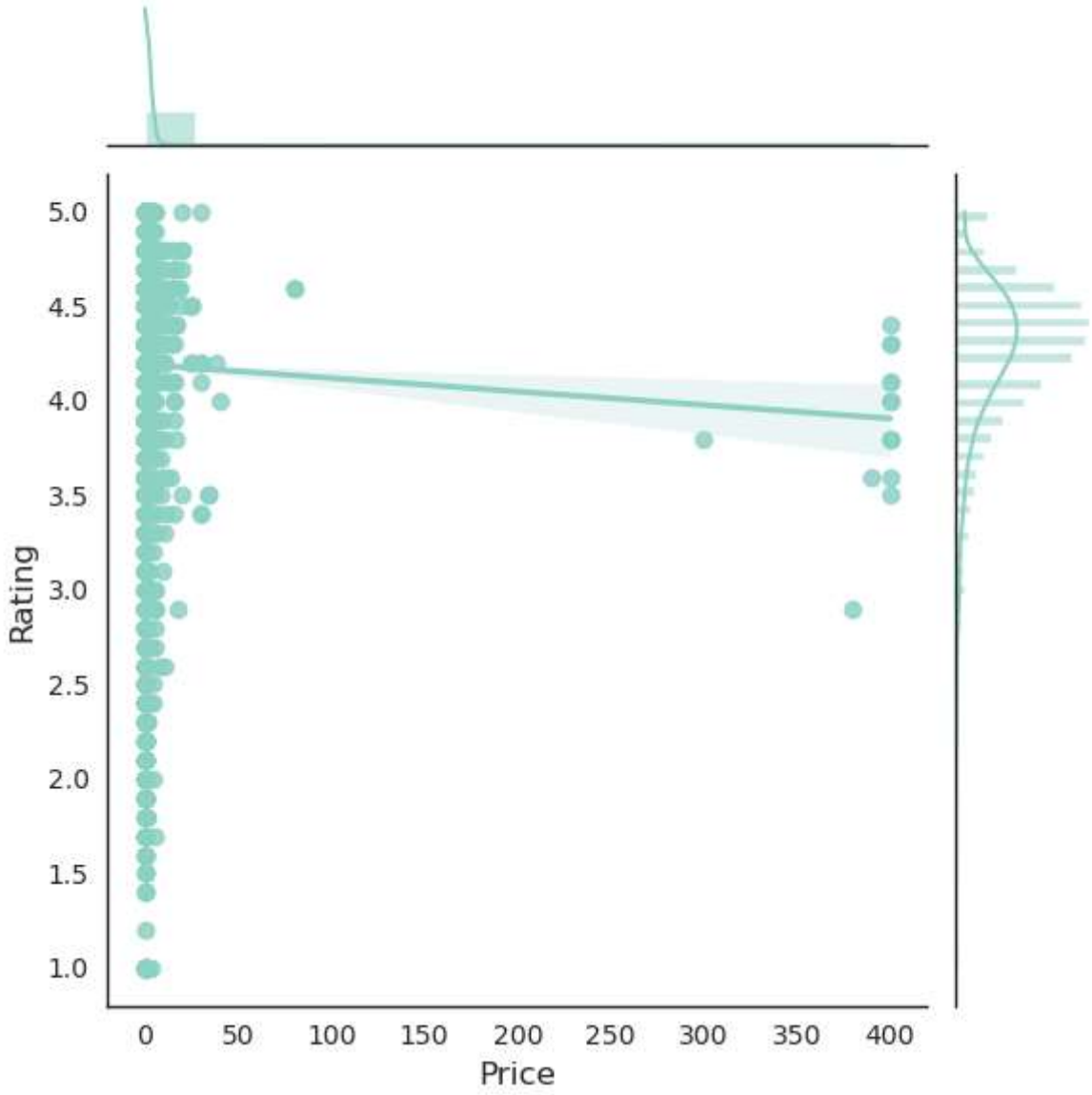
In [95]:
```
sns.jointplot(x= 'Price', y = 'Rating', data = data)
plt.show()
```



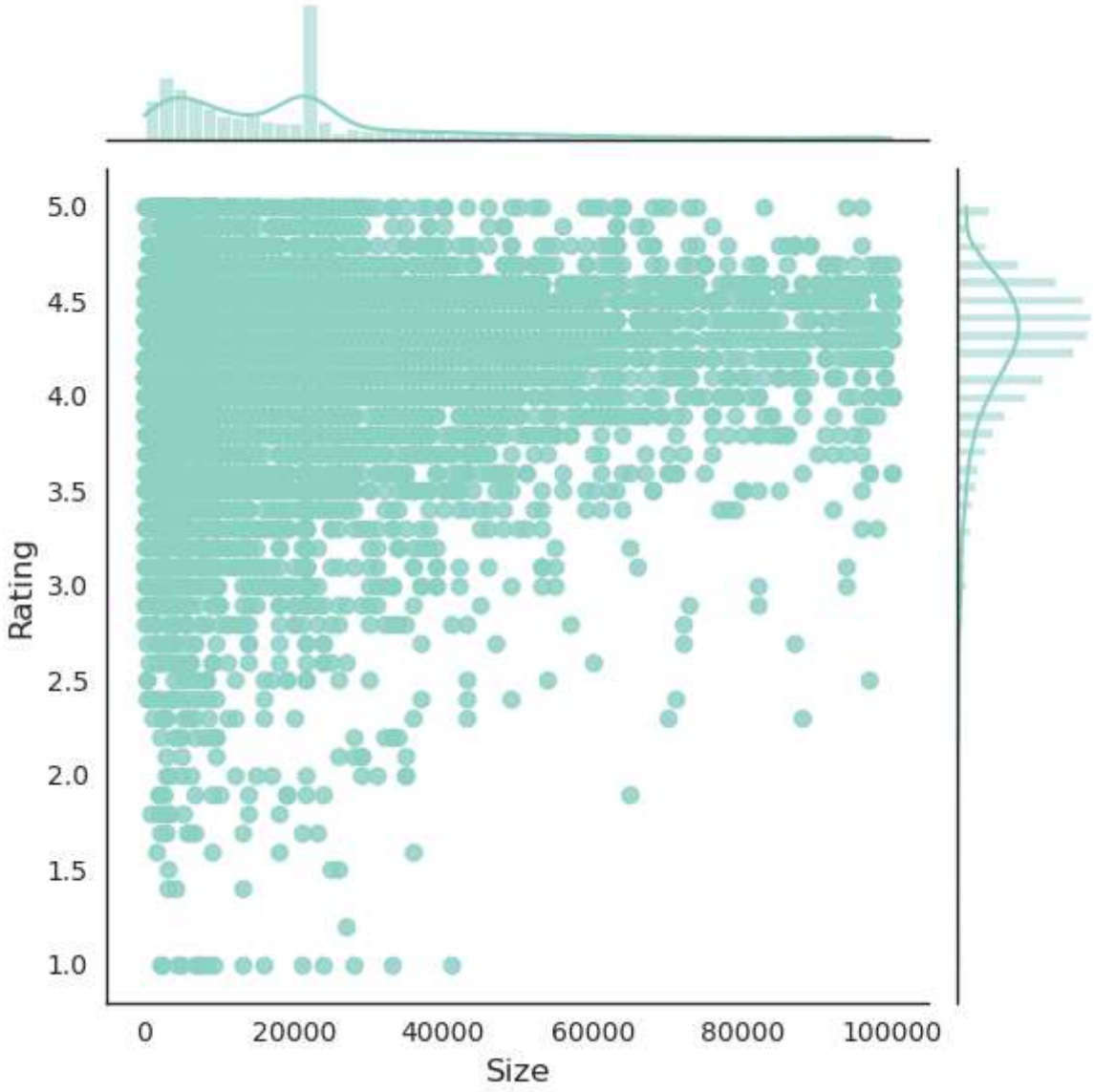
Reg Plots

These are an extension to the jointplots, where a regression line is added to the view

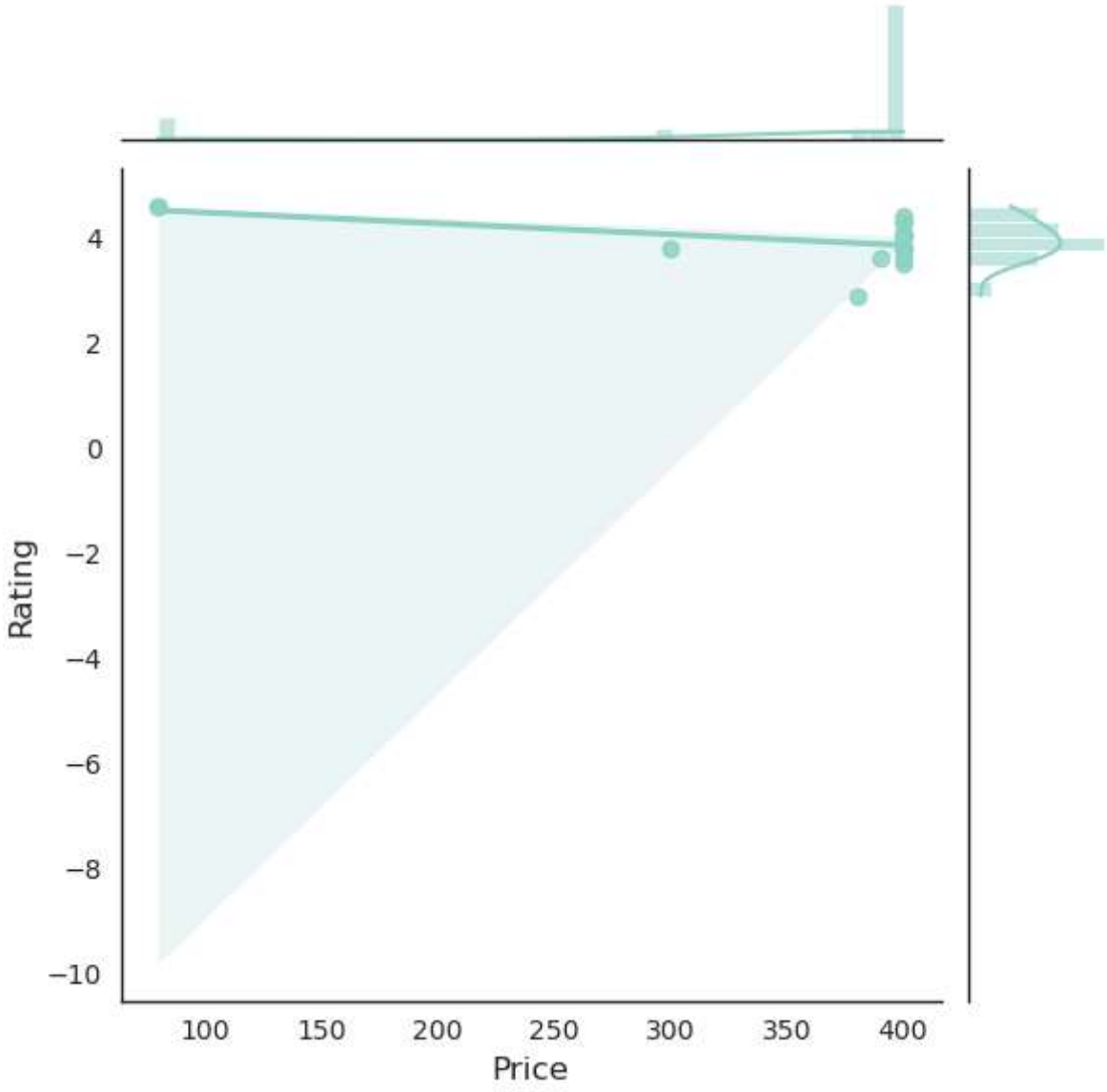
In [97]:
```
sns.jointplot(x= 'Price', y = 'Rating', data = data, kind = 'reg')
plt.show()
```



In [98]:
```
sns.jointplot(x= 'Size', y = 'Rating', data = data, kind = 'reg')
plt.show()
```

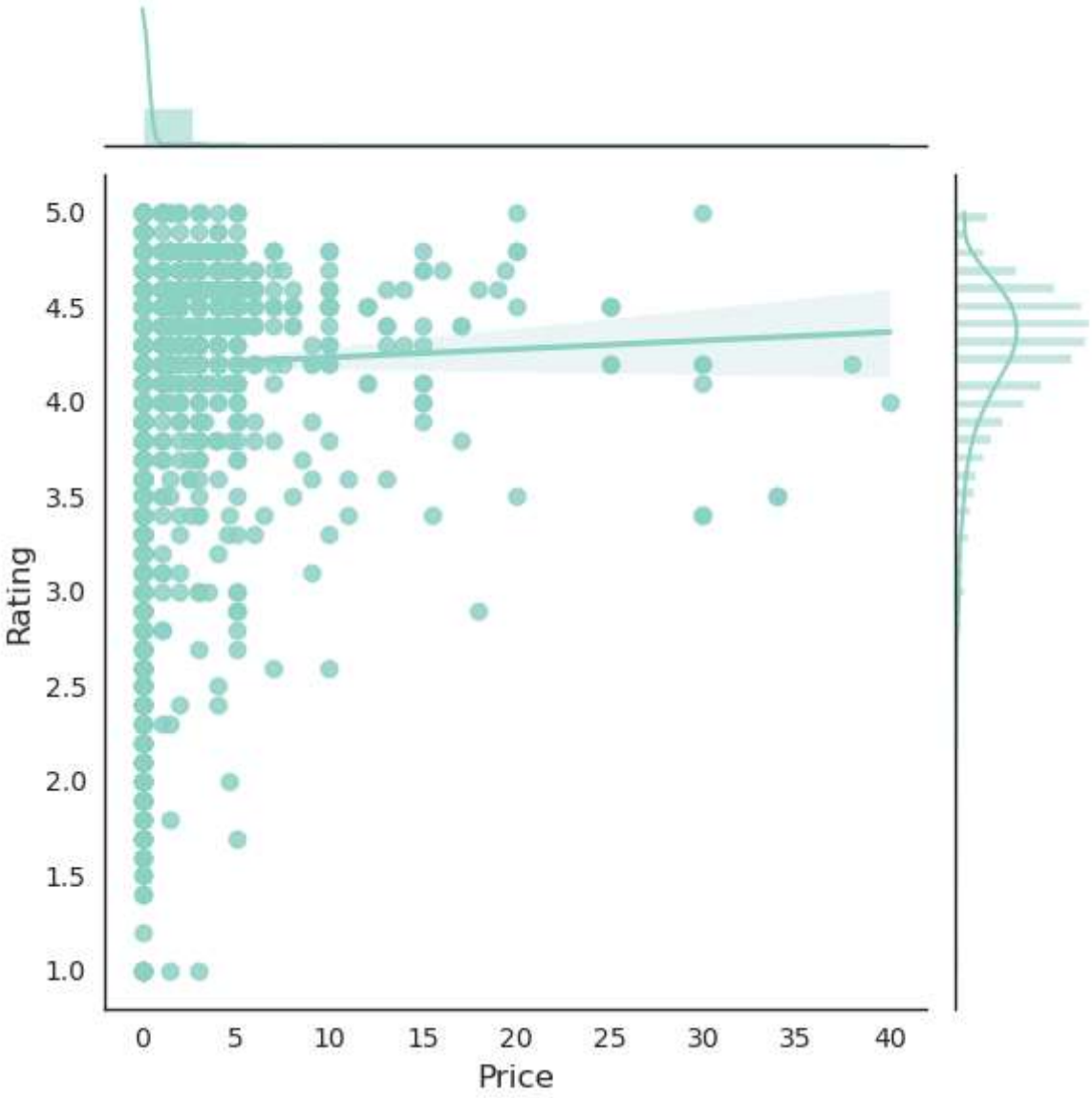


In [99]:
```
sns.jointplot(x= 'Price', y = 'Rating', data = data[data.Price>50], kind = 'reg')
plt.show()
```



In [100…

```
sns.jointplot(x= 'Price', y = 'Rating', data = data[data.Price<50], kind = 'reg')
plt.show()
```



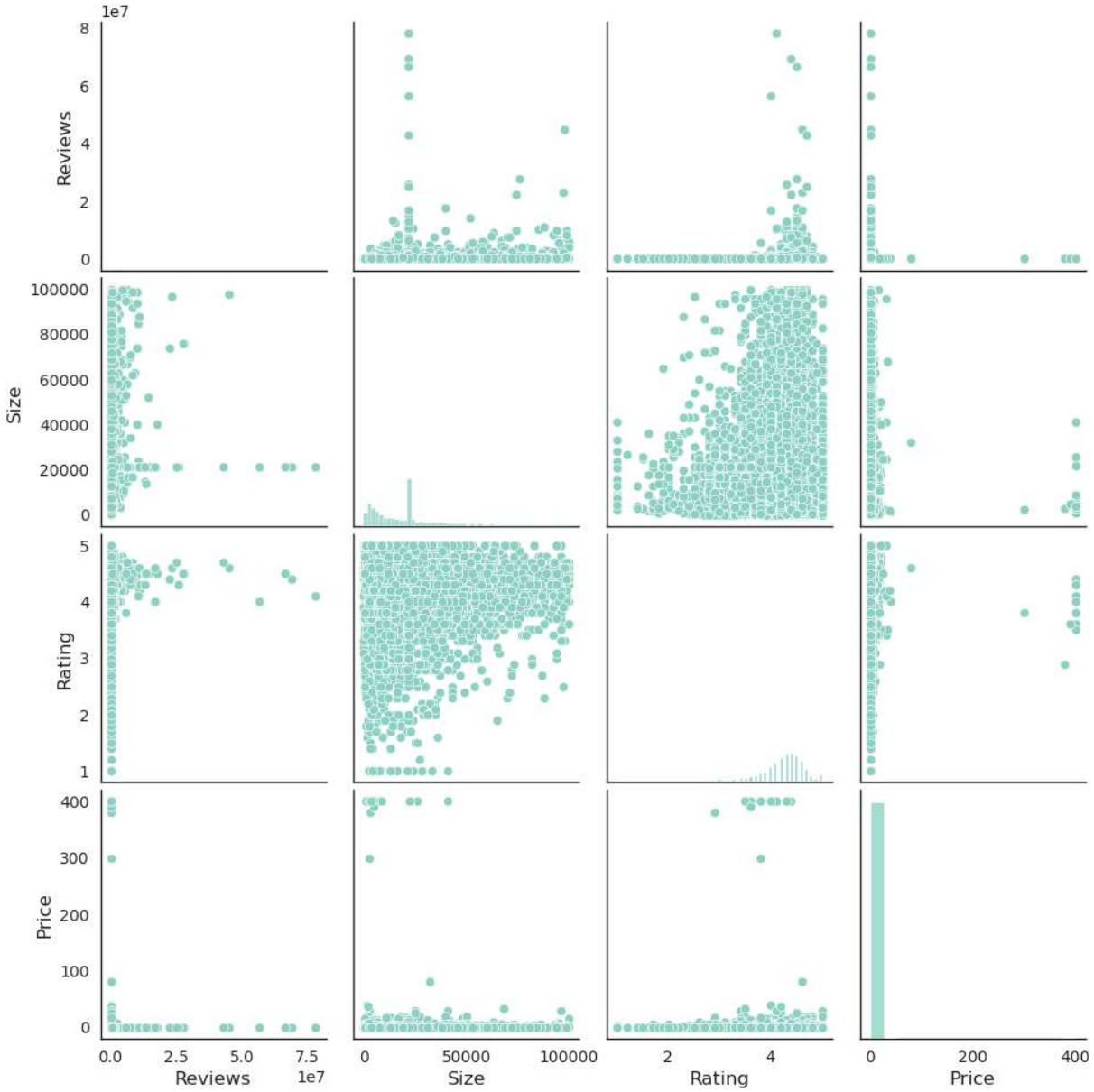
Pair Plots

- When you have several numeric variables, making multiple scatter plots becomes rather tedious. Therefore, a pair plot visualisation is preferred where all the scatter plots are in a single view in the form of a matrix
- For the non-diagonal views, it plots a **scatter plot** between 2 numeric variables
- For the diagonal views, it plots a **histogram**
- Pair Plots help in identifying the trends between a target variable and the predictor variables pretty quickly. For example, say you want to predict how your company's profits are affected by three different factors. In order to choose which you created a pair plot containing profits and the three different factors as the variables. Here are the scatterplots of profits vs the three variables that you obtained from the pair plot.

- It is clearly visible that the left-most factor is the most prominently related to the profits, given how linearly scattered the points are and how randomly scattered the rest two factors are.
- You'll be using **sns.pairplot()** for this visualisation. Check out its official documentation:https://seaborn.pydata.org/generated/seaborn.pairplot.html

In [102…

```
# Pairplots
sns.pairplot(data[["Reviews", "Size","Rating","Price"]])
plt.show()
```

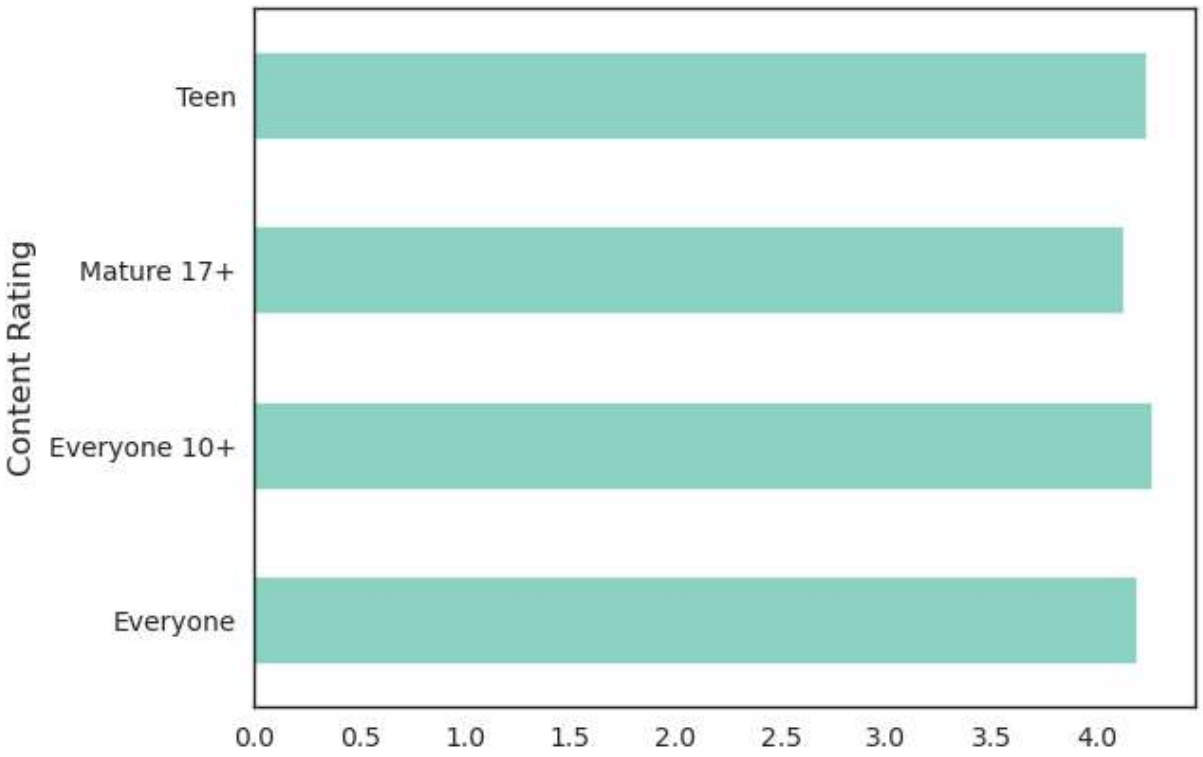


Bar Charts Revisited

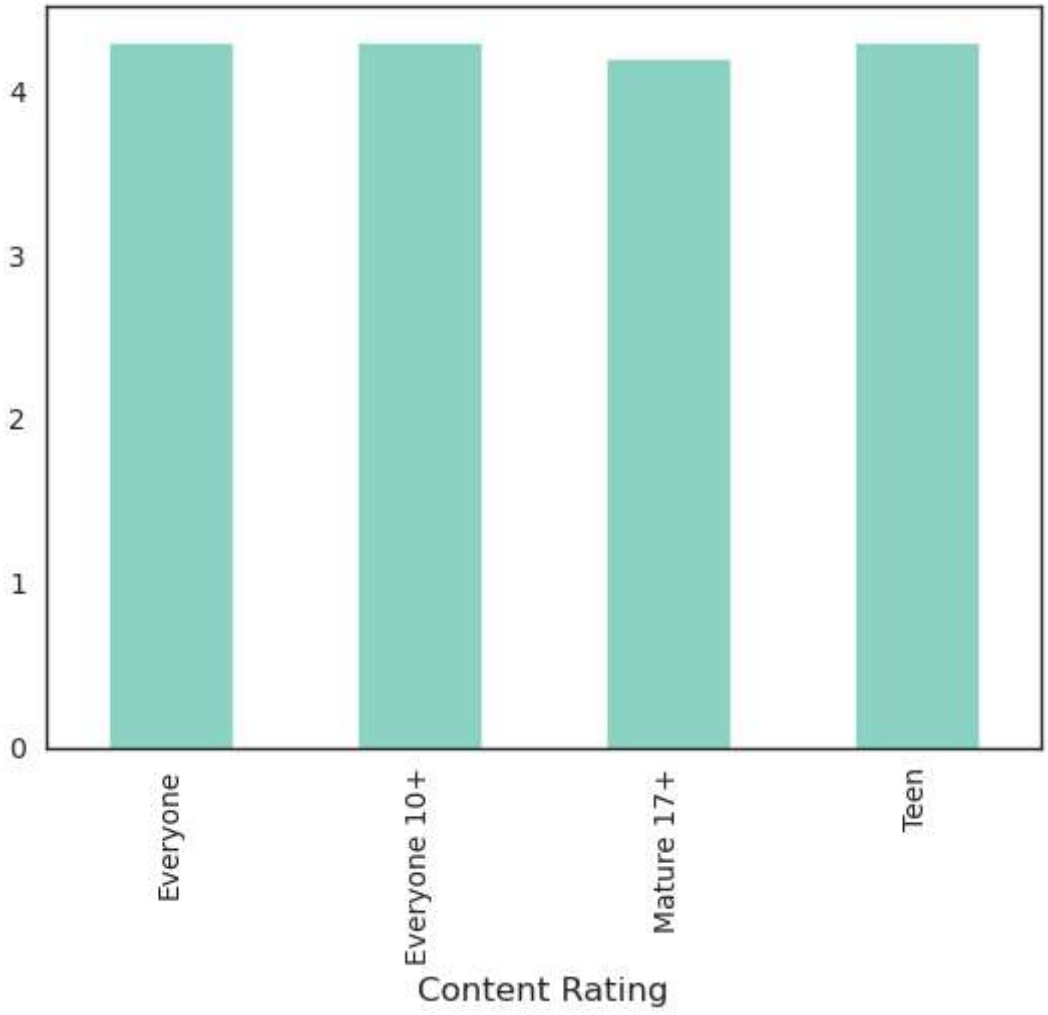
- Here, you'll be using bar charts once again, this time using the **sns.barplot()** function. Check out its official documentation:https://seaborn.pydata.org/generated/seaborn.barplot.html

- You can modify the **estimator** parameter to change the aggregation value of your barplot

In [104…
```
data.groupby(["Content Rating"])["Rating"].mean().plot.barh()
plt.show()
```

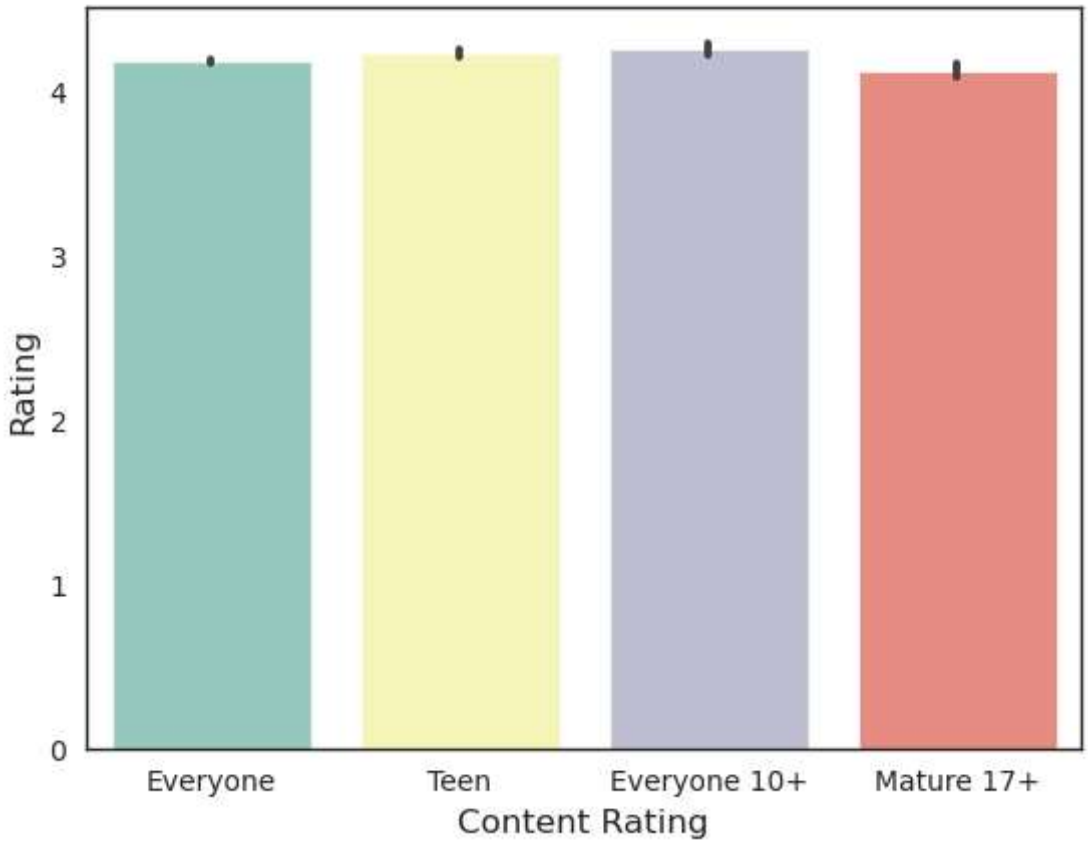


In [105…
```
data.groupby(["Content Rating"])["Rating"].median().plot.bar()
plt.show()
```



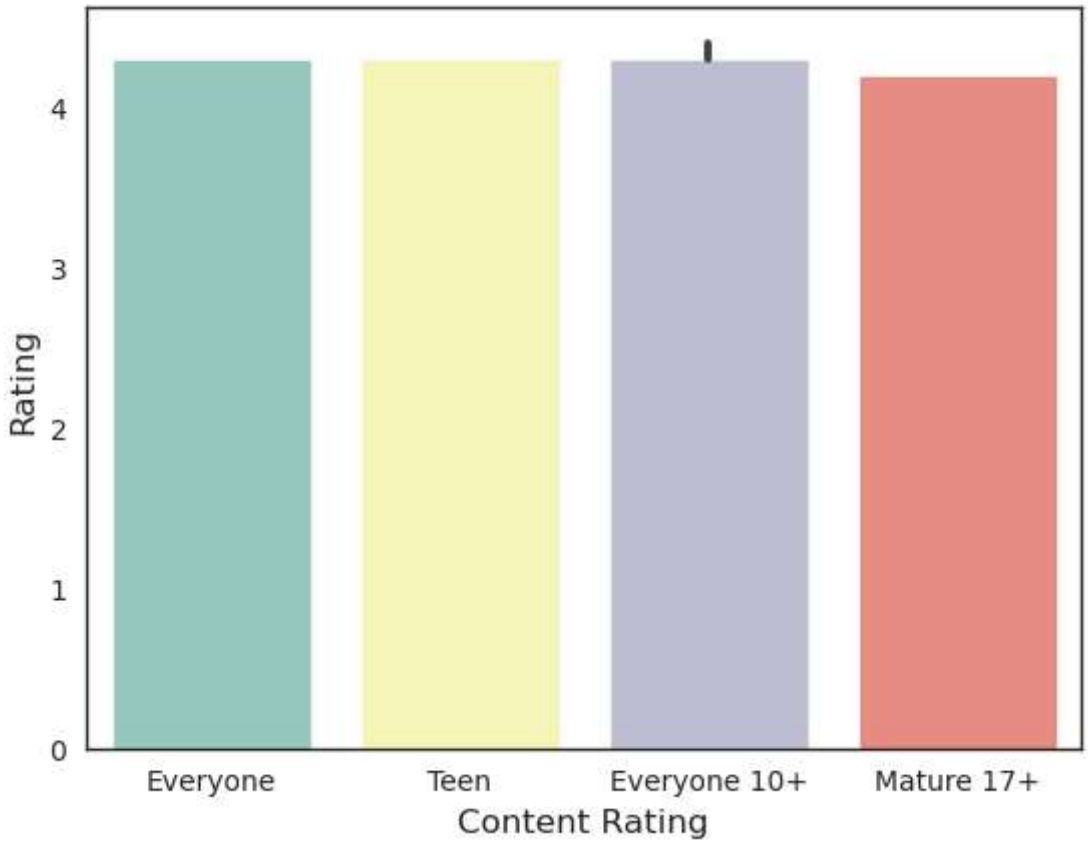
In [106…

```
sns.barplot(data = data , x = "Content Rating", y = "Rating")
plt.show()
```

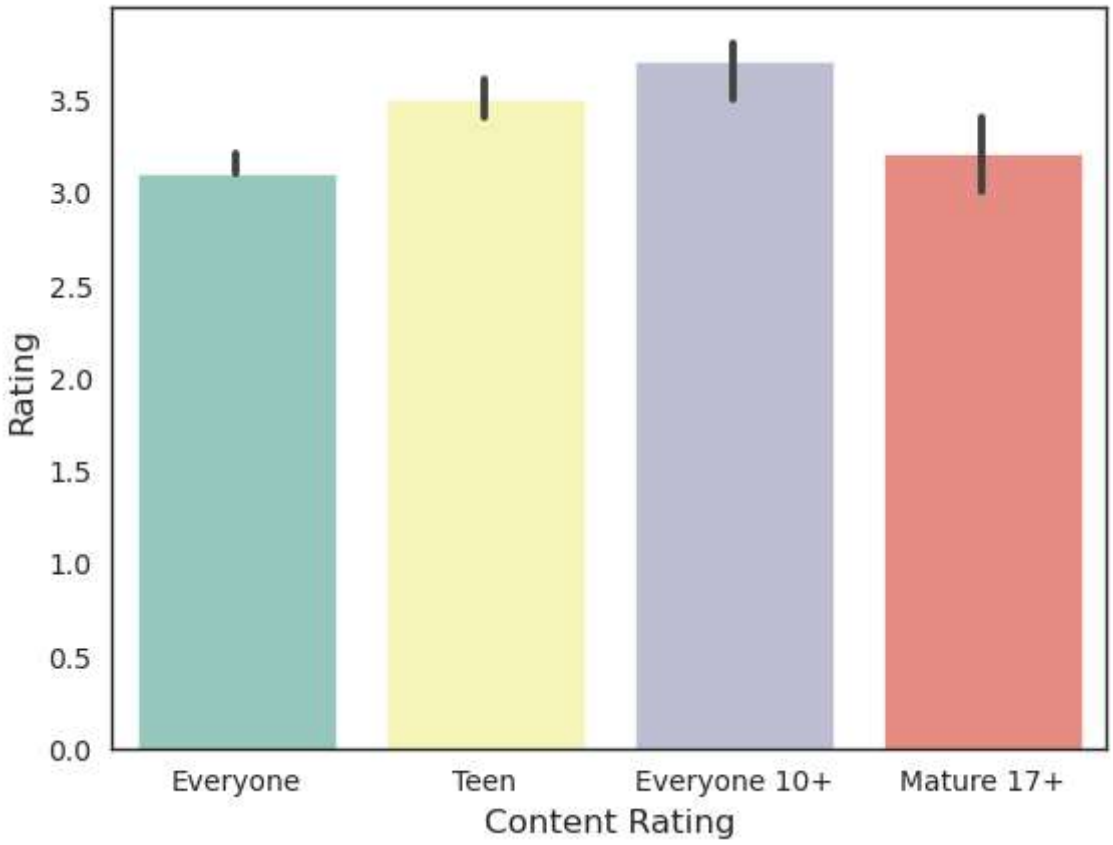


In [107…

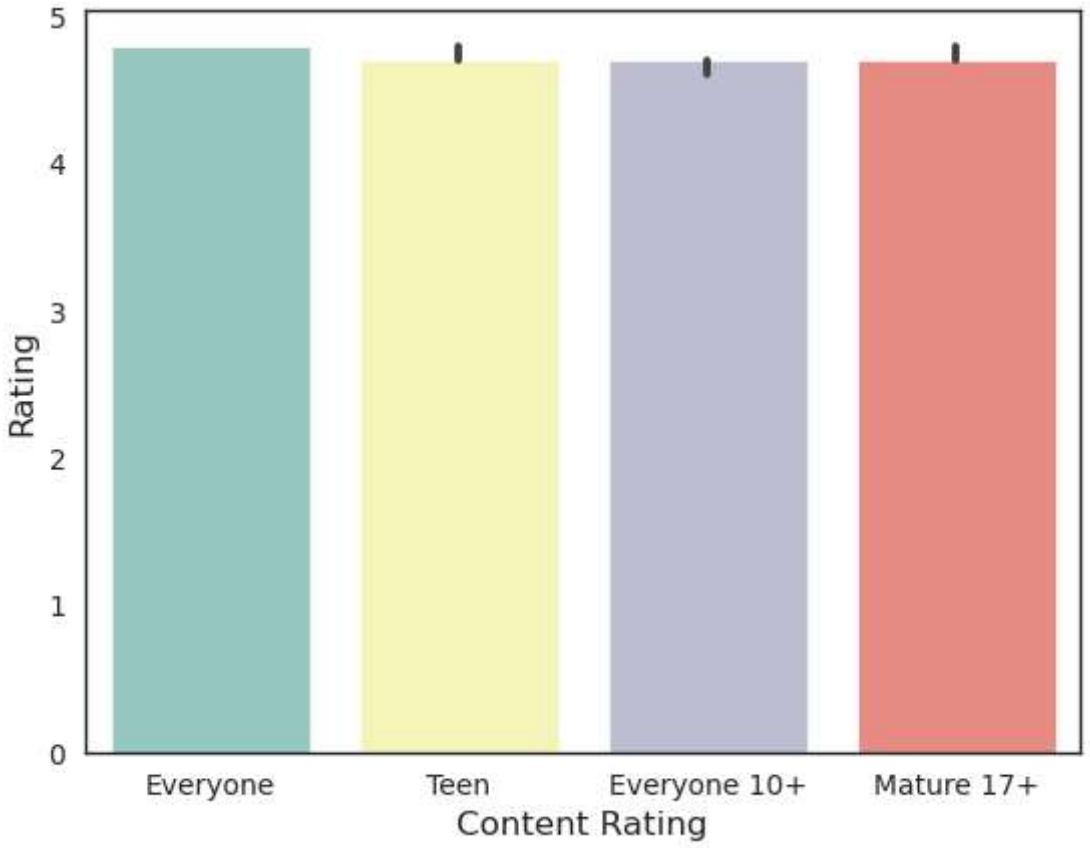
```
sns.barplot(data = data , x = "Content Rating", y = "Rating", estimator = np.median
plt.show()
```



In [108…
```
sns.barplot(data = data , x = "Content Rating", y = "Rating", estimator = lambda x
plt.show()
```

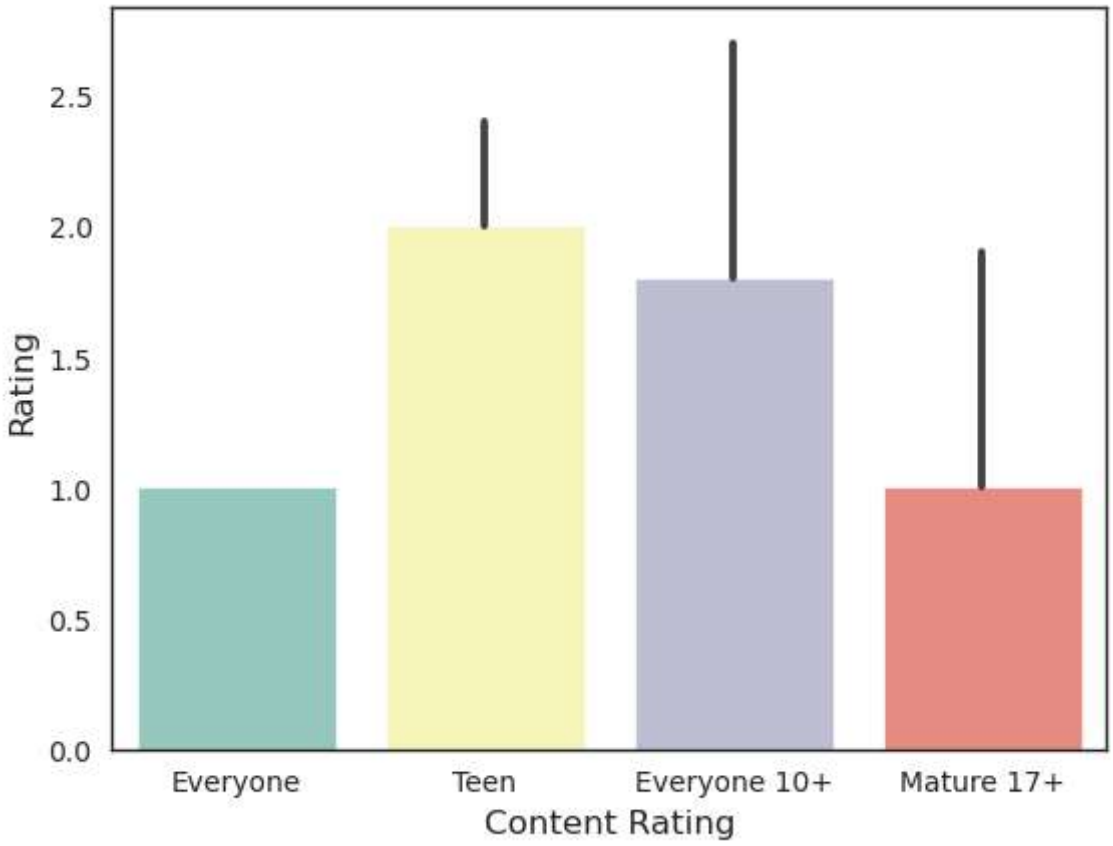


In [109…
```
sns.barplot(data = data , x = "Content Rating", y = "Rating", estimator = lambda x
plt.show()
```

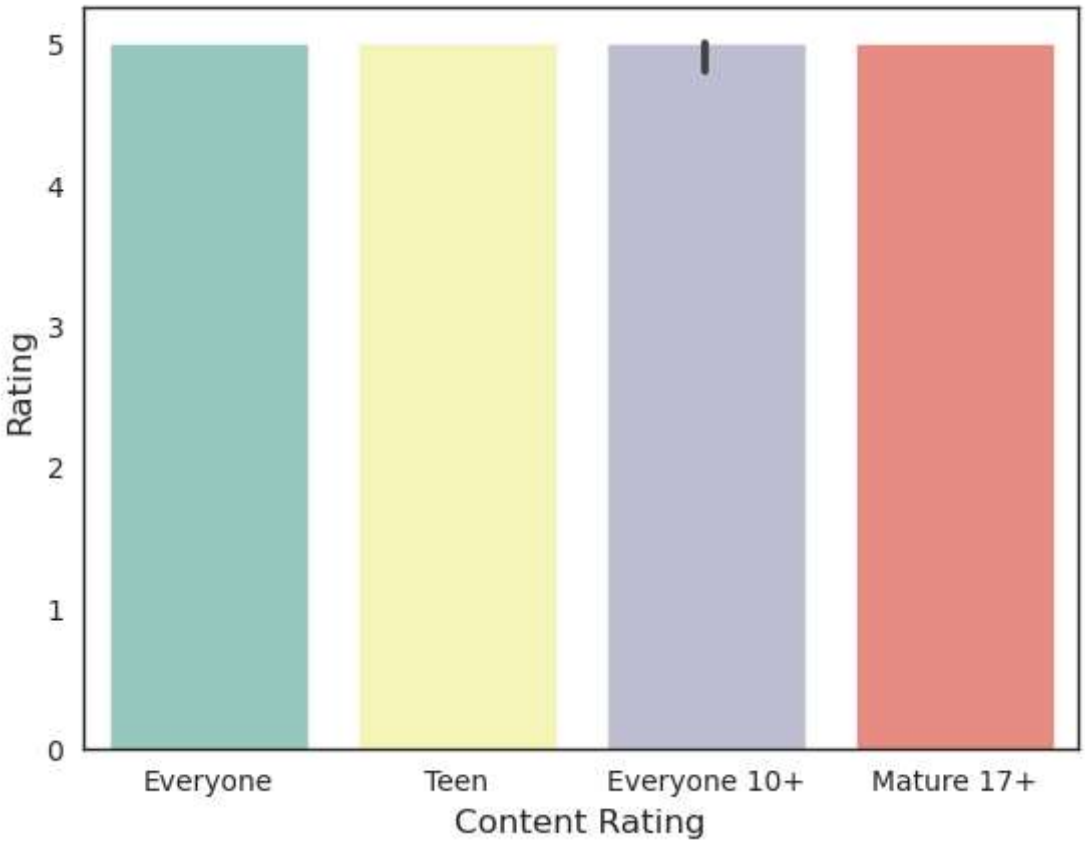


In [110…

```
sns.barplot(data = data , x = "Content Rating", y = "Rating", estimator = np.min)
plt.show()
```



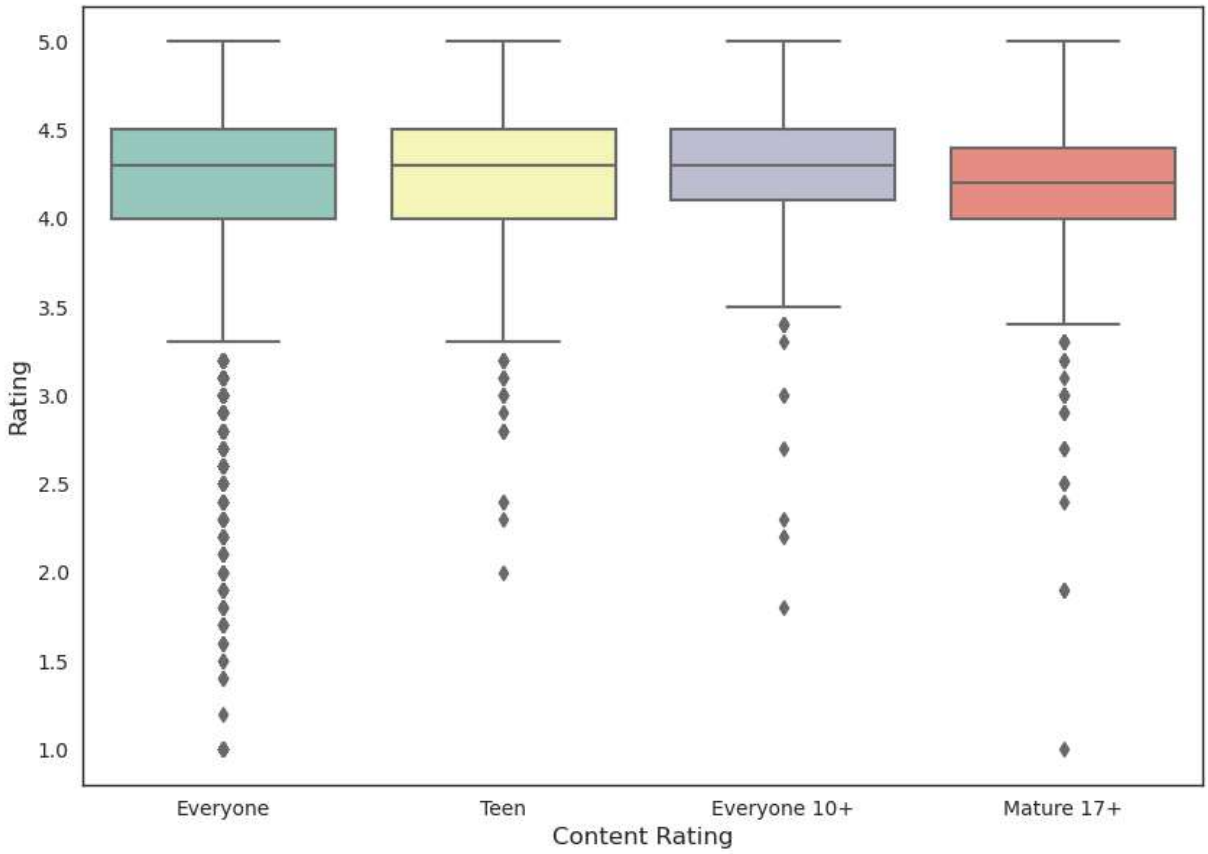
In [111…
```
sns.barplot(data = data , x = "Content Rating", y = "Rating", estimator = np.max)
plt.show()
```



Box Plots Revisited

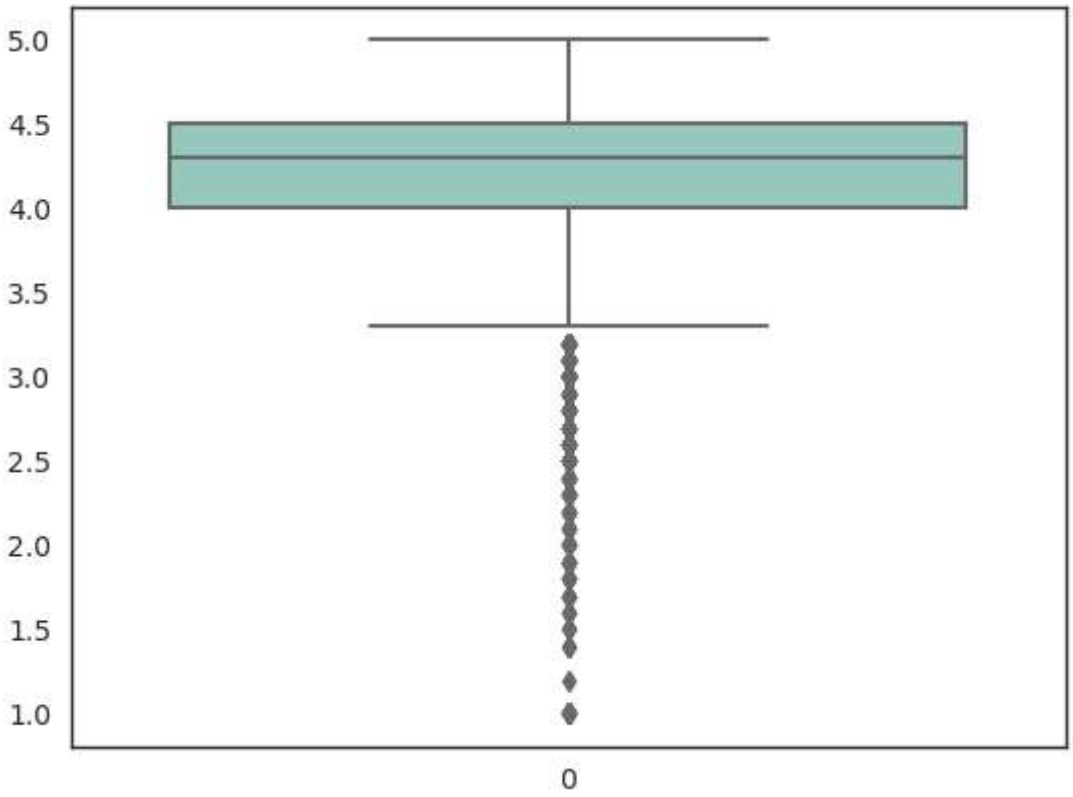
- Apart from outlier analysis, box plots are great at comparing the spread and analysing a numerical variable across several categories
- Here you'll be using **sns.boxplot()** function to plot the visualisation. Check out its documentation: https://seaborn.pydata.org/generated/seaborn.boxplot.html

In [113…
```
# revist box plots

plt.figure(figsize=[10,7])
sns.boxplot(x='Content Rating',y='Rating',data = data)
plt.show()
```



In [114…

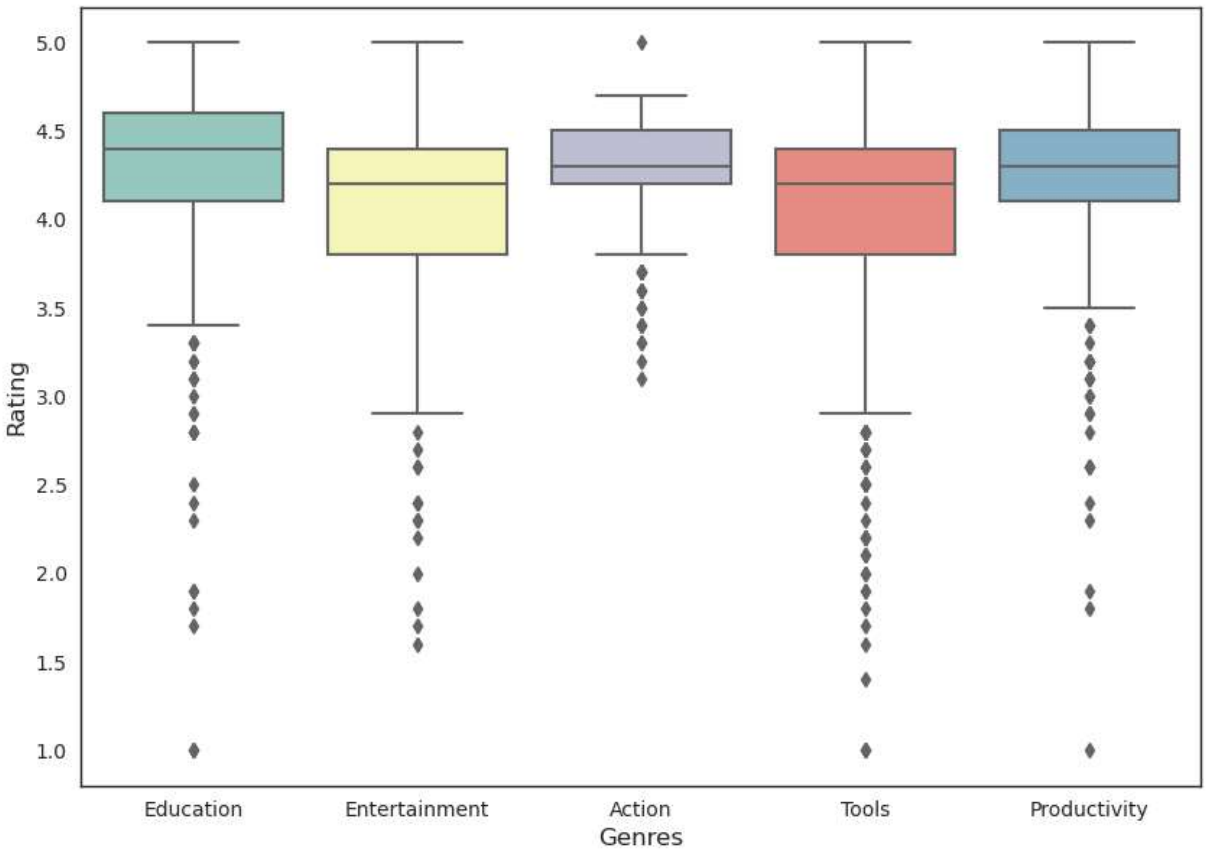
```
sns.boxplot(data.Rating)
plt.show()
```



In [115…
```
# Geners
data['Genres'].value_counts()
```

Out[115…
```
Tools                        732
Entertainment                533
Education                    468
Action                       358
Productivity                 351
                            ...
Parenting;Brain Games          1
Card;Brain Games               1
Tools;Education                1
Entertainment;Education        1
Strategy;Creativity            1
Name: Genres, Length: 115, dtype: int64
```

In [116…
```
plt.figure(figsize=[10,7])
a = ['Tools','Entertainment','Education','Action','Productivity']
data1 = data[data['Genres'].isin(a)]
sns.boxplot(x = data1['Genres'], y= data.Rating)
plt.show()
```



In [117…
```
# Heat Maps

# Rating Vs Size Vs Content Rating

# Prepare buckets for Size column using pd.qcut
data['Size_Bucket'] = pd.qcut(data.Size, [0,0.2,0.4,0.6,0.8,1],["VL","L","M","H","V
```

In [118…
```
data.head()
```

Out[118…

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating
0	Photo Editor & Candy Camera & Grid & ScrapBook	ART_AND_DESIGN	4.1	159	19000.0	10000	Free	0.0	Everyone
1	Coloring book moana	ART_AND_DESIGN	3.9	967	14000.0	500000	Free	0.0	Everyone
2	U Launcher Lite – FREE Live Cool Themes, Hide ...	ART_AND_DESIGN	4.7	87510	8700.0	5000000	Free	0.0	Everyone
3	Sketch - Draw & Paint	ART_AND_DESIGN	4.5	215644	25000.0	50000000	Free	0.0	Teen
4	Pixel Draw - Number Art Coloring Book	ART_AND_DESIGN	4.3	967	2800.0	100000	Free	0.0	Everyone

In [119…
```
pd.pivot_table(data = data, index = 'Content Rating',columns = 'Size_Bucket',values
```

Out[119…

Size_Bucket	VL	L	M	H	VH
Content Rating					
Everyone	4.112653	4.167516	4.254010	4.164042	4.220790
Everyone 10+	4.189474	4.251282	4.253153	4.226761	4.283439
Mature 17+	4.112281	4.057292	4.098592	4.174603	4.194175
Teen	4.198165	4.221893	4.207101	4.228462	4.276855

In [120…
```
pd.pivot_table(data = data, index = 'Content Rating',columns = 'Size_Bucket',values
```

Out[120…

Size_Bucket	VL	L	M	H	VH
Content Rating					
Everyone	4.2	4.3	4.3	4.30	4.3
Everyone 10+	4.1	4.3	4.3	4.30	4.4
Mature 17+	4.3	4.2	4.2	4.20	4.2
Teen	4.3	4.3	4.3	4.25	4.3

In [121…

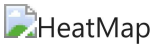
```
# Suppose you want to see the 20th percentile
pd.pivot_table(data = data, index = 'Content Rating',columns = 'Size_Bucket',values
```

Out[121…

Size_Bucket	VL	L	M	H	VH
Content Rating					
Everyone	3.80	3.80	4.1	3.8	4.00
Everyone 10+	3.86	4.06	4.1	4.0	4.02
Mature 17+	3.42	3.60	4.0	3.9	4.00
Teen	3.80	3.90	4.0	4.0	4.00

Heat Maps

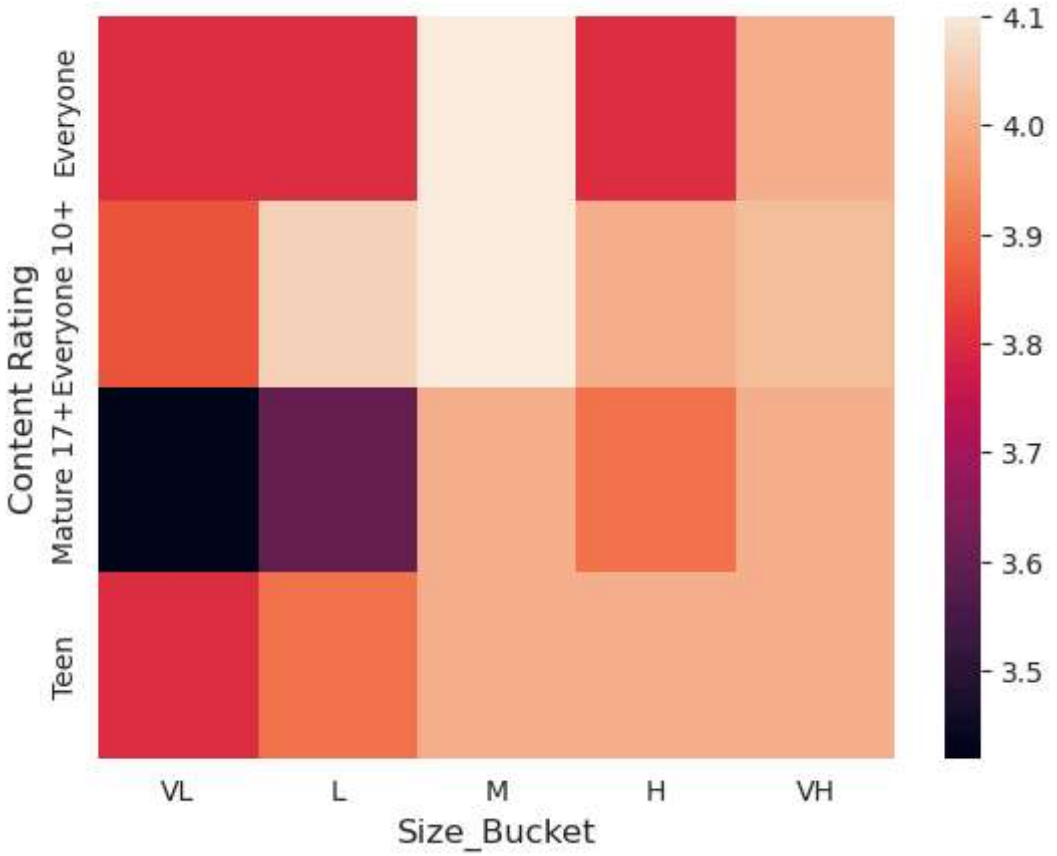
Heat mapsutilise the concept of using colours and colour intensities to visualise a range of values. You must have seen heat maps in cricket or football broadcasts on television to denote the players' areas of strength and weakness.

 HeatMap

- In python, you can create a heat map whenever you have a rectangular grid or table of numbers analysing any two features
- - You'll be using **sns.heatmap()** to plot the visualisation. Checkout its official documentation :https://seaborn.pydata.org/generated/seaborn.heatmap.html

In [123…

```
result = pd.pivot_table(data = data, index = 'Content Rating',columns = 'Size_Bucke
sns.heatmap(result)
plt.show()
```

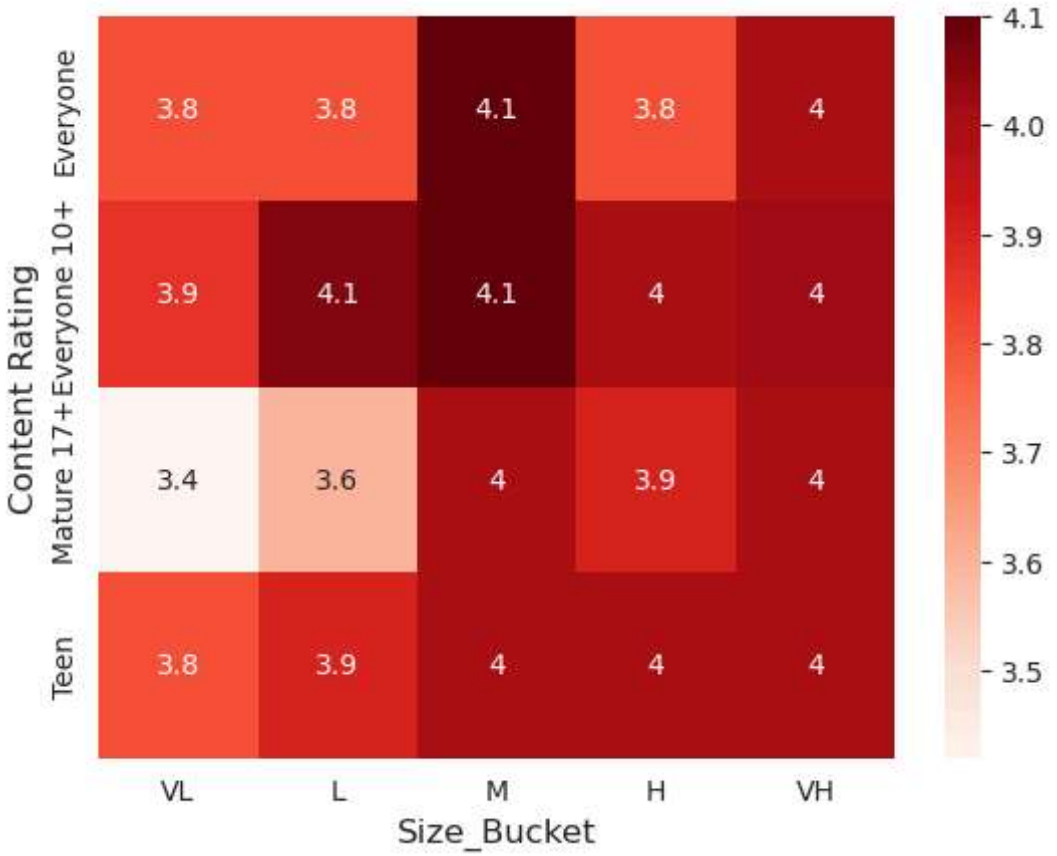


In [124…

```
result = pd.pivot_table(data = data, index = 'Content Rating',columns = 'Size_Bucke
sns.heatmap(result, annot = True)
plt.show()
```

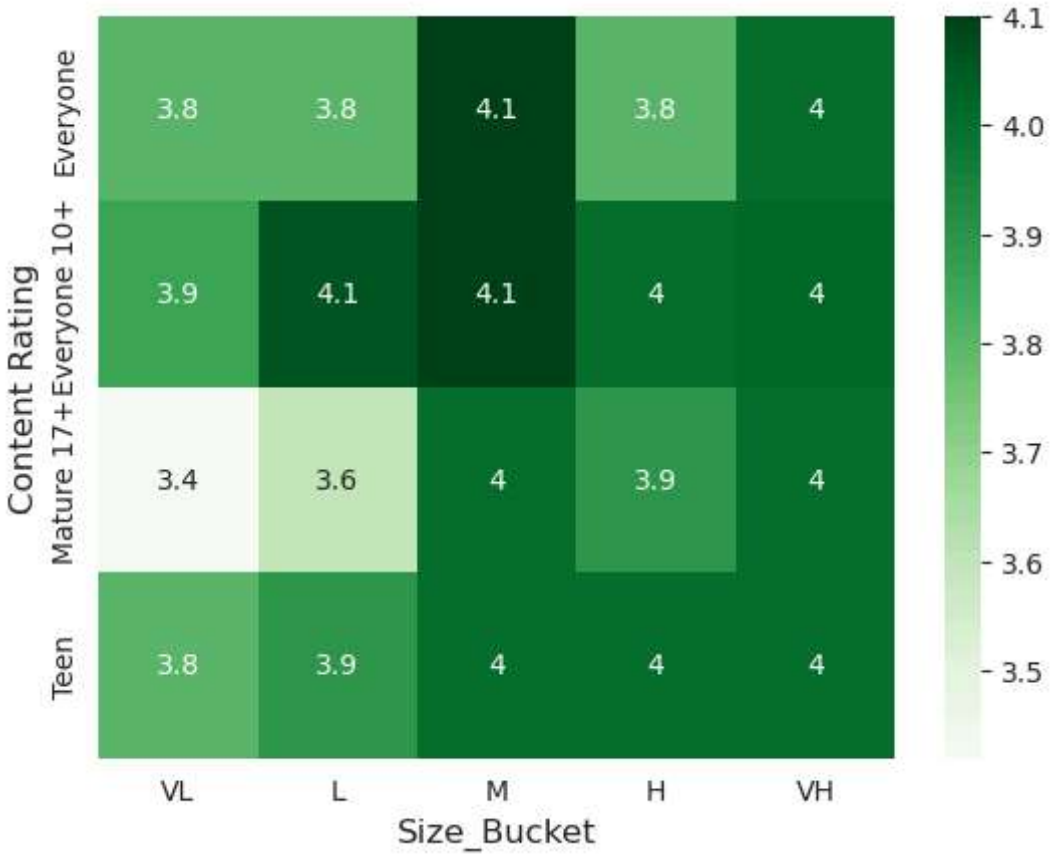
In [125…

```
result = pd.pivot_table(data = data, index = 'Content Rating',columns = 'Size_Bucke
sns.heatmap(result, annot = True, cmap = 'Reds')
plt.show()
```



In [126…

```
result = pd.pivot_table(data = data, index = 'Content Rating',columns = 'Size_Bucke
sns.heatmap(result, annot = True, cmap = 'Greens')
plt.show()
```



In [127…
```
# Line Graphs

data['Last Updated'].head()
```

Out[127…
```
0     January 7, 2018
1    January 15, 2018
2      August 1, 2018
3        June 8, 2018
4       June 20, 2018
Name: Last Updated, dtype: object
```

In [128…
```
data['Last_Updated_Month'] = pd.to_datetime(data['Last Updated']).dt.month
data.groupby(['Last_Updated_Month'])['Rating'].mean()
```

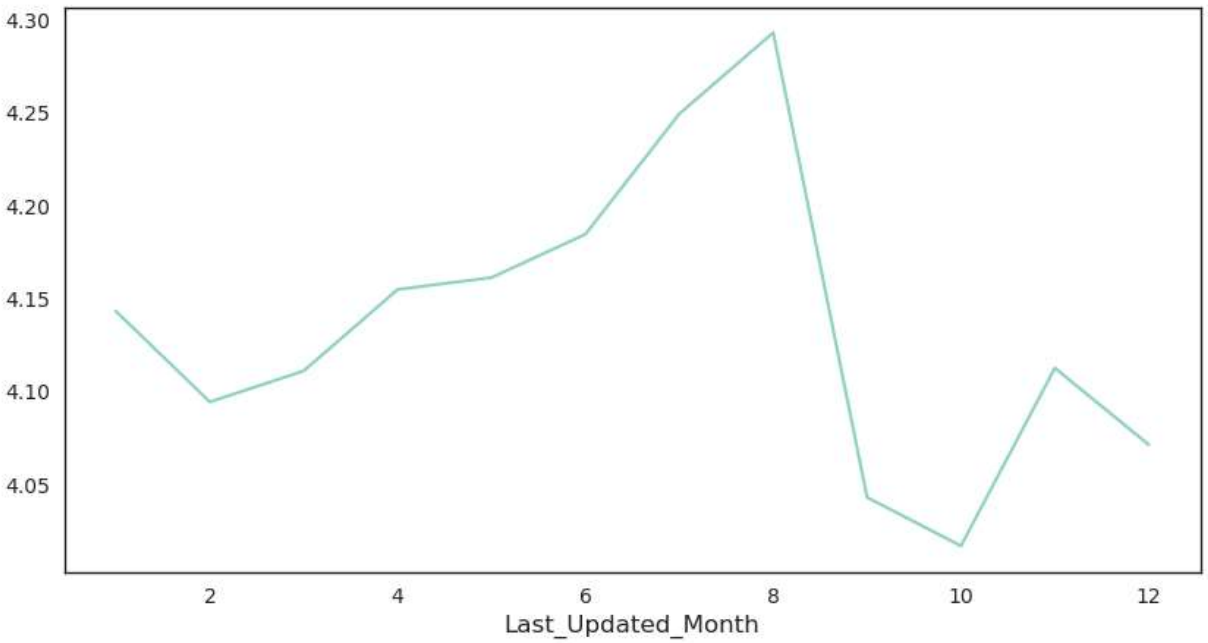
Out[128…
```
Last_Updated_Month
1     4.142892
2     4.094048
3     4.110766
4     4.154600
5     4.161031
6     4.184372
7     4.249206
8     4.292963
9     4.042636
10    4.016460
11    4.112298
12    4.071006
Name: Rating, dtype: float64
```

Session 3: Additional Visualisations

- A line plot tries to observe trends using time dependent data.
- For this part, you'll be using **pd.to_datetime()** function. Check out its documentation:https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.to_datetime.html

In [130…

```
plt.figure(figsize = [10,5])
data.groupby(['Last_Updated_Month'])['Rating'].mean().plot()
plt.show()
```



In [131…

```
# Stacked Bars
pd.pivot_table(data = data , values = 'Installs', index = 'Last_Updated_Month',colu
```

Out[131…

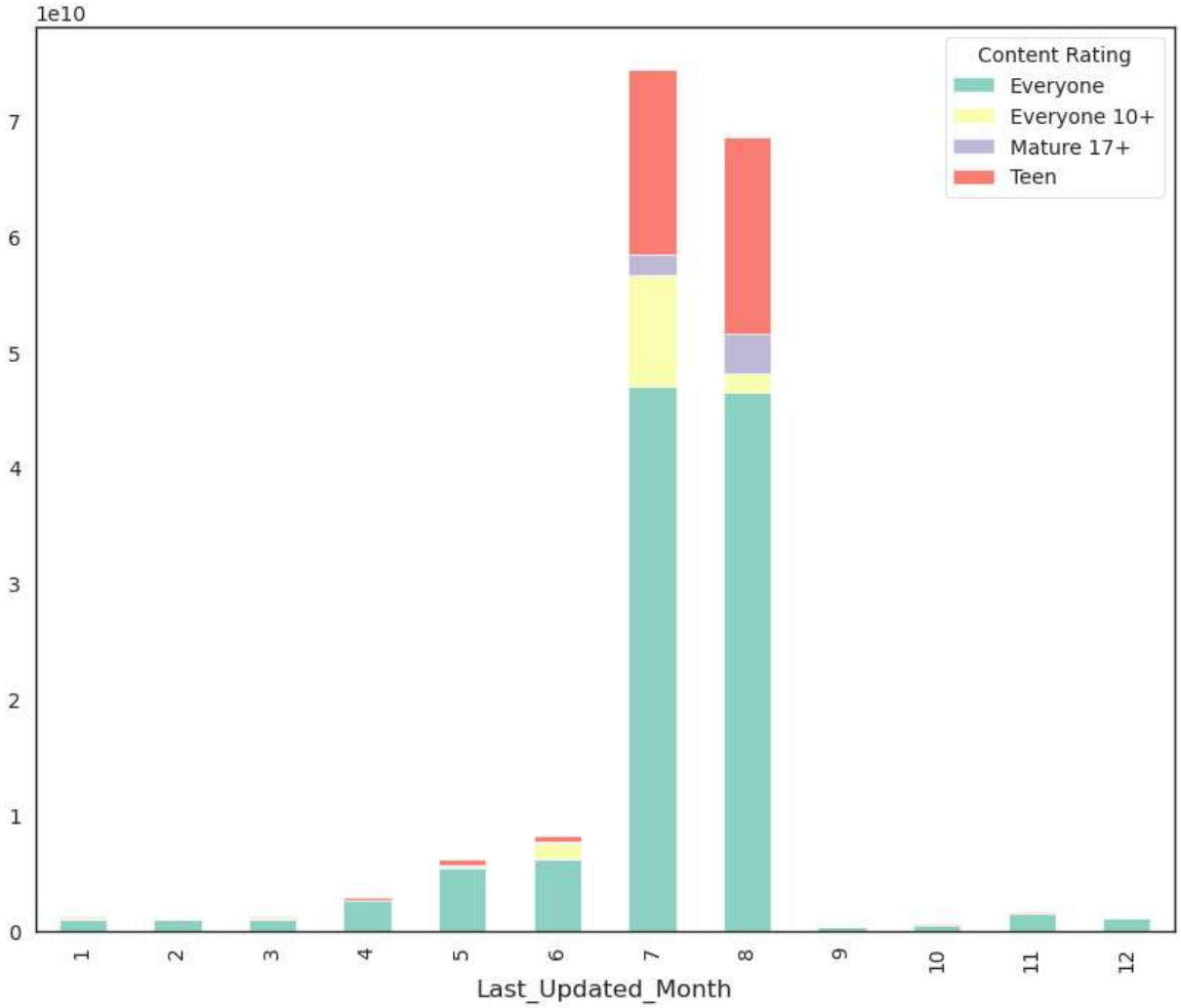
Content Rating	Everyone	Everyone 10+	Mature 17+	Teen
Last_Updated_Month				
1	1025487390	105282000	9701210	44159010
2	945372005	19821000	13021500	39597710
3	1045380520	30322510	9111100	99850310
4	2593371280	23300000	5259000	271619410
5	5431097800	128173500	110140100	562689600
6	6157183505	1367727100	155257200	505716600
7	46991121780	9726556000	1739491910	15983556800
8	46490943320	1715821000	3462981700	16997855650
9	410340410	24931100	2201010	22483100
10	508281680	23101000	3160000	55629210
11	1475474710	60310000	1070100	81261100
12	1077106770	8410000	12960100	51708100

Stacked Bar Charts

- A stacked bar chart breaks down each bar of the bar chart on the basis of a different category
- For example, for the Campaign Response bar chart you saw earlier, the stacked bar chart is also showing the Gender bifurcation as well
- Stacked

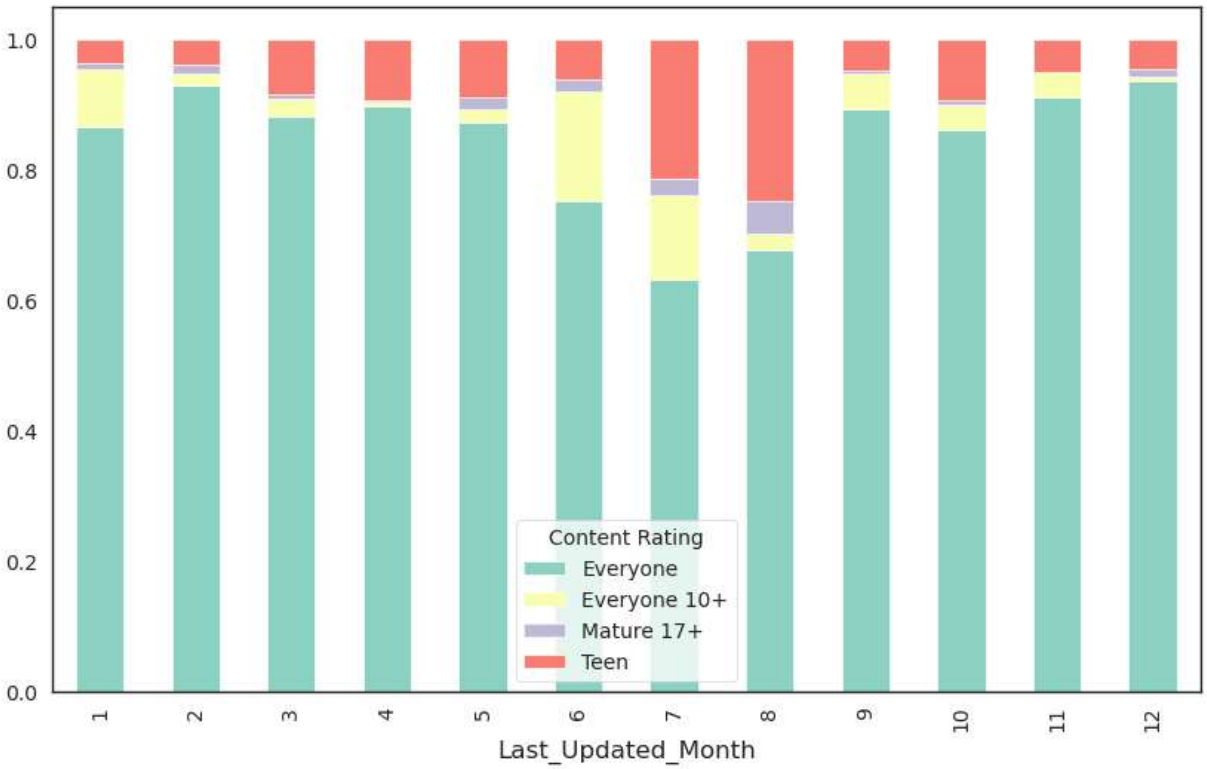
In [133…

```
monthly = pd.pivot_table(data = data , values = 'Installs', index = 'Last_Updated_M
monthly.plot(kind = 'bar', stacked = 'True', figsize=[10,8])
plt.show()
```



In [134…

```
monthly_precent = monthly[["Everyone", "Everyone 10+", "Mature 17+","Teen"]].apply(
monthly_precent.plot(kind = 'bar', stacked = 'True', figsize = [10,6])
plt.show()
```



In [135…
```
# plotly library


res = data.groupby(["Last_Updated_Month"])[["Rating"]].mean()
res.reset_index(inplace = True)
print(res)
```

```
    Last_Updated_Month    Rating
0                    1  4.142892
1                    2  4.094048
2                    3  4.110766
3                    4  4.154600
4                    5  4.161031
5                    6  4.184372
6                    7  4.249206
7                    8  4.292963
8                    9  4.042636
9                   10  4.016460
10                  11  4.112298
11                  12  4.071006
```

Plotly

Plotly is a Python library used for creating interactive visual charts. You can take a look at how you can use it to create aesthetic looking plots with a lot of user-friendly functionalities like hover, zoom, etc.

Check out this link for installation and documentation:https://plot.ly/python/getting-started/

In [137…
```
import plotly.express as px
fig = px.line(res, x = 'Last_Updated_Month', y = 'Rating', title = 'Monthly Average
```

```
fig.show()
```

In [138…

```
fig = px.bar(res, x = 'Last_Updated_Month', y = 'Rating', title = 'Monthly Average
fig.show()
```

In [139…

```
fig = px.box(res, x = 'Last_Updated_Month', y = 'Rating', title = 'Monthly Average
fig.show()
```

In [140…

```
fig = px.histogram(res, x = 'Last_Updated_Month', y = 'Rating', title = 'Monthly Av
fig.show()
```

In [141…

```
fig = px.scatter(res, x = 'Last_Updated_Month', y = 'Rating', title = 'Monthly Aver
fig.show()
```

In [ ]: