Google PlayStore Data

Complete Exploratory Data Analysis

- `Author`
  Shariq Nauman

- `E-mail`
  shariqnaumann@gmail.com

About Dataset

- `Source`
  This dataset was taken from Kaggle using the following link:
  https://www.kaggle.com/datasets/lava18/google-play-store-apps?resource=download

- `Context`
  While many public datasets (on Kaggle and the like) provide Apple App Store data, there are not many counterpart datasets available for Google Play Store apps anywhere on the web. On digging deeper, I found out that iTunes App Store page deploys a nicely indexed appendix-like structure to allow for simple and easy web scraping. On the other hand, Google Play Store uses sophisticated modern-day techniques (like dynamic page load) using JQuery making scraping more challenging.

- `Content`
  Each app (row) has values for catergory, rating, size, and more.

- `Acknowledgements`
  This information is scraped from the Google Play Store. This app information would not be available without it.

- `Inspiration`
  The Play Store apps data has enormous potential to drive app-making businesses to success. Actionable insights can be drawn for developers to work on and capture the Android market!

Importing Libraries

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

```
# This is for jupyter notebook to show the plot in the notebook itself instead of o
%matplotlib inline
```

Data Exploration & Cleaning

↪ Load the csv file with the pandas library.

↪ Creating the dataframe and understanding the data present in the dataset using pandas.

↪ Dealing with the missing data, outliers and the incorrect records.

In [2]:
```
df = pd.read_csv('googleplaystore.csv')
```

- Viewing the first five Rows of the data.

In [3]:
```
df.head(5)
```

Out[3]:

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating
0	Photo Editor & Candy Camera & Grid & ScrapBook	ART_AND_DESIGN	4.1	159	19M	10,000+	Free	0	Everyone
1	Coloring book moana	ART_AND_DESIGN	3.9	967	14M	500,000+	Free	0	Everyone
2	U Launcher Lite – FREE Live Cool Themes, Hide ...	ART_AND_DESIGN	4.7	87510	8.7M	5,000,000+	Free	0	Everyone
3	Sketch - Draw & Paint	ART_AND_DESIGN	4.5	215644	25M	50,000,000+	Free	0	Teen
4	Pixel Draw - Number Art Coloring Book	ART_AND_DESIGN	4.3	967	2.8M	100,000+	Free	0	Everyone

> **Note**: Sometimes, the notebook does not present the complete output, therefore we can increase the limit of columns view and row view by using these commands:

In [4]:

```
# Enabling the maximum rows & columns display option
pd.set_option('display.max_columns', None) # This is to display all the columns in
pd.set_option('display.max_rows', None) # This is to display all the rows in the da

# Disabling any unnecassary warnings for better representation
import warnings
warnings.filterwarnings('ignore')
```

- Lets see the exact column names which can be easily copied later on from Google Playstore Dataset.

In [5]:

```
columns = ''
for i in range(len(df.columns)):
    columns += df.columns[i] + ', '
print(f"The names of the columns are as follows: {columns[:len(columns)-2]}.")
```

```
The names of the columns are as follows: App, Category, Rating, Reviews, Size, Insta
lls, Type, Price, Content Rating, Genres, Last Updated, Current Ver, Android Ver.
```

- Lets have a look on the shape of the dataset.

In [6]:

```
print(f"This dataset contains {df.shape[0]} rows & {df.shape[1]} columns.")
```

```
This dataset contains 10841 rows & 13 columns.
```

- Not enough, lets have a look on the columns and their data types using detailed info function.

In [7]:

```
df.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        10840 non-null  object 
 2   Rating          9367 non-null   float64
 3   Reviews         10841 non-null  int64  
 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  10841 non-null  object 
 9   Genres          10840 non-null  object 
 10  Last Updated    10841 non-null  object 
 11  Current Ver     10833 non-null  object 
 12  Android Ver     10839 non-null  object 
dtypes: float64(1), int64(1), object(11)
memory usage: 1.1+ MB
```

Observations

---

1. There are 10841 rows and 13 columns in the dataset.
2. The columns are of different data types.
3. The columns in the datasets are:
   - `'App', 'Category', 'Rating', 'Reviews', 'Size', 'Installs', 'Type', 'Price', 'Content Rating', 'Genres', 'Last Updated', 'Current Ver', 'Android Ver'`
4. There are some missing values in the dataset which we will read in detail and deal later on in the notebook.
5. There are some columns which are of object data type but they should be of numeric data type, we will convert them later on in the notebook.
   - `'Size', 'Installs', 'Price'`

In [8]:
```
df.describe()
```

Out[8]:

	Rating	Reviews
count	9367.000000	1.084100e+04
mean	4.191513	4.441119e+05
std	0.515735	2.927629e+06
min	1.000000	0.000000e+00
25%	4.000000	3.800000e+01
50%	4.300000	2.094000e+03
75%	4.500000	5.476800e+04
max	5.000000	7.815831e+07

Observations

- We have only 2 columns as numeric data type, rest all are object data type (according to python), but we can see that `'Size', 'Installs', 'Price'` are also numeric, we must convert them to numeric data type in data wrangling process.

- Let's clean the `Size` column first

In [9]:

```
# Counting the number of missing values in the column
df['Size'].isnull().sum()
```

Out[9]:

```
np.int64(0)
```

- There are no missing values, so we are good to go.

In [10]:

```
# Check unique values
df['Size'].unique()
```

```
Out[10]: array(['19M', '14M', '8.7M', '25M', '2.8M', '5.6M', '29M', '33M', '3.1M',
       '28M', '12M', '20M', '21M', '37M', '2.7M', '5.5M', '17M', '39M',
       '31M', '4.2M', '7.0M', '23M', '6.0M', '6.1M', '4.6M', '9.2M',
       '5.2M', '11M', '24M', 'Varies with device', '9.4M', '15M', '10M',
       '1.2M', '26M', '8.0M', '7.9M', '56M', '57M', '35M', '54M', '201k',
       '3.6M', '5.7M', '8.6M', '2.4M', '27M', '2.5M', '16M', '3.4M',
       '8.9M', '3.9M', '2.9M', '38M', '32M', '5.4M', '18M', '1.1M',
       '2.2M', '4.5M', '9.8M', '52M', '9.0M', '6.7M', '30M', '2.6M',
       '7.1M', '3.7M', '22M', '7.4M', '6.4M', '3.2M', '8.2M', '9.9M',
       '4.9M', '9.5M', '5.0M', '5.9M', '13M', '73M', '6.8M', '3.5M',
       '4.0M', '2.3M', '7.2M', '2.1M', '42M', '7.3M', '9.1M', '55M',
       '23k', '6.5M', '1.5M', '7.5M', '51M', '41M', '48M', '8.5M', '46M',
       '8.3M', '4.3M', '4.7M', '3.3M', '40M', '7.8M', '8.8M', '6.6M',
       '5.1M', '61M', '66M', '79k', '8.4M', '118k', '44M', '695k', '1.6M',
       '6.2M', '18k', '53M', '1.4M', '3.0M', '5.8M', '3.8M', '9.6M',
       '45M', '63M', '49M', '77M', '4.4M', '4.8M', '70M', '6.9M', '9.3M',
       '10.0M', '8.1M', '36M', '84M', '97M', '2.0M', '1.9M', '1.8M',
       '5.3M', '47M', '556k', '526k', '76M', '7.6M', '59M', '9.7M', '78M',
       '72M', '43M', '7.7M', '6.3M', '334k', '34M', '93M', '65M', '79M',
       '100M', '58M', '50M', '68M', '64M', '67M', '60M', '94M', '232k',
       '99M', '624k', '95M', '8.5k', '41k', '292k', '11k', '80M', '1.7M',
       '74M', '62M', '69M', '75M', '98M', '85M', '82M', '96M', '87M',
       '71M', '86M', '91M', '81M', '92M', '83M', '88M', '704k', '862k',
       '899k', '378k', '266k', '375k', '1.3M', '975k', '980k', '4.1M',
       '89M', '696k', '544k', '525k', '920k', '779k', '853k', '720k',
       '713k', '772k', '318k', '58k', '241k', '196k', '857k', '51k',
       '953k', '865k', '251k', '930k', '540k', '313k', '746k', '203k',
       '26k', '314k', '239k', '371k', '220k', '730k', '756k', '91k',
       '293k', '17k', '74k', '14k', '317k', '78k', '924k', '902k', '818k',
       '81k', '939k', '169k', '45k', '475k', '965k', '90M', '545k', '61k',
       '283k', '655k', '714k', '93k', '872k', '121k', '322k', '1.0M',
       '976k', '172k', '238k', '549k', '206k', '954k', '444k', '717k',
       '210k', '609k', '308k', '705k', '306k', '904k', '473k', '175k',
       '350k', '383k', '454k', '421k', '70k', '812k', '442k', '842k',
       '417k', '412k', '459k', '478k', '335k', '782k', '721k', '430k',
       '429k', '192k', '200k', '460k', '728k', '496k', '816k', '414k',
       '506k', '887k', '613k', '243k', '569k', '778k', '683k', '592k',
       '319k', '186k', '840k', '647k', '191k', '373k', '437k', '598k',
       '716k', '585k', '982k', '222k', '219k', '55k', '948k', '323k',
       '691k', '511k', '951k', '963k', '25k', '554k', '351k', '27k',
       '82k', '208k', '913k', '514k', '551k', '29k', '103k', '898k',
       '743k', '116k', '153k', '209k', '353k', '499k', '173k', '597k',
       '809k', '122k', '411k', '400k', '801k', '787k', '237k', '50k',
       '643k', '986k', '97k', '516k', '837k', '780k', '961k', '269k',
       '20k', '498k', '600k', '749k', '642k', '881k', '72k', '656k',
       '601k', '221k', '228k', '108k', '940k', '176k', '33k', '663k',
       '34k', '942k', '259k', '164k', '458k', '245k', '629k', '28k',
       '288k', '775k', '785k', '636k', '916k', '994k', '309k', '485k',
       '914k', '903k', '608k', '500k', '54k', '562k', '847k', '957k',
       '688k', '811k', '270k', '48k', '329k', '523k', '921k', '874k',
       '981k', '784k', '280k', '24k', '518k', '754k', '892k', '154k',
       '860k', '364k', '387k', '626k', '161k', '879k', '39k', '970k',
       '170k', '141k', '160k', '144k', '143k', '190k', '376k', '193k',
       '246k', '73k', '658k', '992k', '253k', '420k', '404k', '470k',
       '226k', '240k', '89k', '234k', '257k', '861k', '467k', '157k',
```

```
 '44k', '676k', '67k', '552k', '885k', '1020k', '582k', '619k'],
dtype=object)
```

- There are several uniques values in the `Size` column, we have to first convert each unit into one common unit (megabytes) for all values, and then remove the `M` and `k` from the values and convert them into numeric data type.

In [11]:
```
# Counting the number of values that contain 'k' in them
df['Size'].loc[df['Size'].str.contains('k')].value_counts().sum()
```

Out[11]:
```
np.int64(316)
```

In [12]:
```
# Counting the number of values that contain 'M' in them
df['Size'].loc[df['Size'].str.contains('M')].value_counts().sum()
```

Out[12]:
```
np.int64(8830)
```

In [13]:
```
# Counting the number of values that contain 'Varies with device' in them
df['Size'].loc[df['Size'].str.contains('Varies with device')].value_counts().sum()
```

Out[13]:
```
np.int64(1695)
```

In [14]:
```
# Taking sum of all the values in size column which has 'M', 'K' and 'varies with d
316+8830+1695 == len(df)
```

Out[14]:
```
True
```

- We have `8830` values that have `M` unit.
- We have `316` values that have `k` unit.
- We have `1695` values of `Varies with device`.

> Let's convert the `k` units into megabytes and then remove the `M` and `k` from the values and convert them into numeric data type.

In [15]:
```
# Convert the size column to numeric by dividing the values with 1024 if it has 'k'
def convert_to_mb(size):
    if 'k' in size:
        return float(size.replace('k', '')) / 1024
    elif 'M' in size:
        return float(size.replace('M', ''))
    else:
        return np.nan  # Return NaN for unknown values

# Applying the convert function to the Size column
df['Size'] = df['Size'].apply(convert_to_mb)
```

In [16]:
```
# Converting the object data type into numeric (float) data type
df['Size'] = pd.to_numeric(df['Size'], errors='coerce')
df['Size'].dtype
```

Out[16]: dtype('float64')

In [17]:
```
# Renaming the Size column
df.rename(columns={'Size': 'Size (MB)'}, inplace=True)
```

- Now we have converted every value into megabytes and removed the `M` and `K` from the values and converted them into numeric data type.
- 'Varies with device' was a string value, therefore we intentionally converted them into null values, which we can fill later on according to our needs.

- Lets have a look on the `Installs` column.

In [18]:
```
# Check the unique values in size column
df['Installs'].unique()
```

Out[18]:
```
array(['10,000+', '500,000+', '5,000,000+', '50,000,000+', '100,000+',
       '50,000+', '1,000,000+', '10,000,000+', '5,000+', '100,000,000+',
       '1,000,000,000+', '1,000+', '500,000,000+', '50+', '100+', '500+',
       '10+', '1+', '5+', '0+', '0'], dtype=object)
```

In [19]:
```
# Lets have a values counts
df['Installs'].value_counts()
```

Out[19]:
```
Installs
1,000,000+        1579
10,000,000+       1252
100,000+          1169
10,000+           1054
1,000+             908
5,000,000+         752
100+               719
500,000+           539
50,000+            479
5,000+             477
100,000,000+       409
10+                386
500+               330
50,000,000+        289
50+                205
5+                  82
500,000,000+        72
1+                  67
1,000,000,000+      58
0+                  14
0                    1
Name: count, dtype: int64
```

In [20]:
```
# Counting the number of missing values in the column
df['Installs'].isnull().sum()
```

Out[20]: np.int64(0)

In [21]:
```python
# Find how many values has '+' in it
df['Installs'].loc[df['Installs'].str.contains('\+')].value_counts().sum()
```

Out[21]: `np.int64(10840)`

- The only problem I see here is the `+` and `,` signs.
- The total values in the `Installs` column are `10841` and there are no null values in the column.
- However, one value `0` has no plus sign.
- Let's remove the plus sign `+` and `,` from the values and convert them into numeric data type

In [22]:
```python
# Remove the plus sign from install column and convert it to numeric
df['Installs'] = df['Installs'].str.replace('+', '')
# Also remove the commas from the install column
df['Installs'] = df['Installs'].str.replace(',', '')
# convert the install column to numeric (integers because this is the number of ins
df['Installs'] = df['Installs'].astype('int64')
```

- Lets verify if the datatype has been changed and the `+` and `,` sign have been removed.

In [23]:
```python
df.head() # Check the head of the dataframe
```

Out[23]:

	App	Category	Rating	Reviews	Size (MB)	Installs	Type	Price	Content Rating
0	Photo Editor & Candy Camera & Grid & ScrapBook	ART_AND_DESIGN	4.1	159	19.0	10000	Free	0	Everyone
1	Coloring book moana	ART_AND_DESIGN	3.9	967	14.0	500000	Free	0	Everyone
2	U Launcher Lite – FREE Live Cool Themes, Hide ...	ART_AND_DESIGN	4.7	87510	8.7	5000000	Free	0	Everyone
3	Sketch - Draw & Paint	ART_AND_DESIGN	4.5	215644	25.0	50000000	Free	0	Teen
4	Pixel Draw - Number Art Coloring Book	ART_AND_DESIGN	4.3	967	2.8	100000	Free	0	Everyone

In [24]:

```
df['Installs'].dtype # This will show the data type of the column
```

Out[24]:

```
dtype('int64')
```

- We can generate a new column based on the installation values, which will be helpful in our analysis.

In [25]:

```
df['Installs'].max() # This will show the maximum value of the column
```

Out[25]:

```
np.int64(1000000000)
```

In [26]:

```
# Binning the Installs column to make categories and storing them in a new column '
bins = [-1, 0, 100, 1000, 10000, 100000, 1000000, 10000000, 100000000, 1000000000]
labels = ['Zero', 'Very Low', 'Low', 'Medium', 'High', 'Very High', 'Extreme High',
df['Installs_Category'] = pd.cut(df['Installs'], bins=bins, labels=labels)
```

In [27]:

```
# Lets have a values counts of each category in 'Installs_Category'
df['Installs_Category'].value_counts()
```

Out[27]:
```
Installs_Category
Very High        2118
Extreme High     2004
High             1648
Medium           1531
Very Low         1459
Low              1238
Ultra High        698
Huge              130
Zero               15
Name: count, dtype: int64
```

- Lets a look at the `Price` column.

In [28]:
```
# Check the unique values in the column
df['Price'].unique()
```

Out[28]:
```
array(['0', '$4.99', '$3.99', '$6.99', '$1.49', '$2.99', '$7.99', '$5.99',
       '$3.49', '$1.99', '$9.99', '$7.49', '$0.99', '$9.00', '$5.49',
       '$10.00', '$24.99', '$11.99', '$79.99', '$16.99', '$14.99',
       '$1.00', '$29.99', '$12.99', '$2.49', '$10.99', '$1.50', '$19.99',
       '$15.99', '$33.99', '$74.99', '$39.99', '$3.95', '$4.49', '$1.70',
       '$8.99', '$2.00', '$3.88', '$25.99', '$399.99', '$17.99',
       '$400.00', '$3.02', '$1.76', '$4.84', '$4.77', '$1.61', '$2.50',
       '$1.59', '$6.49', '$1.29', '$5.00', '$13.99', '$299.99', '$379.99',
       '$37.99', '$18.99', '$389.99', '$19.90', '$8.49', '$1.75',
       '$14.00', '$4.85', '$46.99', '$109.99', '$154.99', '$3.08',
       '$2.59', '$4.80', '$1.96', '$19.40', '$3.90', '$4.59', '$15.46',
       '$3.04', '$4.29', '$2.60', '$3.28', '$4.60', '$28.99', '$2.95',
       '$2.90', '$1.97', '$200.00', '$89.99', '$2.56', '$30.99', '$3.61',
       '$394.99', '$1.26', '$1.20', '$1.04'], dtype=object)
```

In [29]:
```
# Counting the number of missing values in the column
df['Price'].isnull().sum()
```

Out[29]:
```
np.int64(0)
```

- There no missing/null values so we are good to go.

In [30]:
```
# Check the value counts of the column
df['Price'].value_counts()
```

```
Out[30]: Price
0          10041
$0.99        148
$2.99        129
$1.99         73
$4.99         72
$3.99         63
$1.49         46
$5.99         30
$2.49         26
$9.99         21
$6.99         13
$399.99       12
$14.99        11
$4.49          9
$29.99         7
$3.49          7
$7.99          7
$24.99         7
$5.49          6
$19.99         6
$6.49          5
$8.99          5
$12.99         5
$11.99         5
$10.00         3
$1.00          3
$16.99         3
$2.00          3
$17.99         2
$10.99         2
$9.00          2
$79.99         2
$7.49          2
$3.95          2
$33.99         2
$1.70          2
$13.99         2
$8.49          2
$39.99         2
$1.50          1
$25.99         1
$74.99         1
$15.99         1
$3.88          1
$1.76          1
$3.02          1
$400.00        1
$4.84          1
$2.50          1
$1.59          1
$1.61          1
$4.77          1
$5.00          1
$1.29          1
$379.99        1
```

```
$299.99        1
$37.99         1
$18.99         1
$389.99        1
$19.90         1
$1.75          1
$14.00         1
$4.85          1
$46.99         1
$109.99        1
$154.99        1
$3.08          1
$2.59          1
$4.80          1
$1.96          1
$19.40         1
$3.90          1
$4.59          1
$15.46         1
$3.04          1
$4.29          1
$2.60          1
$3.28          1
$4.60          1
$28.99         1
$2.95          1
$2.90          1
$1.97          1
$200.00        1
$89.99         1
$2.56          1
$30.99         1
$3.61          1
$394.99        1
$1.26          1
$1.20          1
$1.04          1
Name: count, dtype: int64
```

- We need to confirm if the values in the `Price` column are only with $ sign or not.

In [31]:
```python
# Counting the number of values in the 'Price' column that have $ in it
df['Price'].str.startswith('$').sum()
```

Out[31]:
```
np.int64(800)
```

In [32]:
```python
# Counting the number of values in the 'Price' column that do not have $ in it
df['Price'].str.startswith('0').sum()
```

Out[32]:
```
np.int64(10041)
```

- Now we can confirm that the only currency used is `$` in the `Price` column, as `800+10041=10841 values`, which is equal to the total number of rows in the dataframe.

- The only problem is $ sign let's remove it and convert the column into numeric data type.

In [33]:
```
# Removing the $ sign from the 'Price' column and converting it to numeric (float)
df['Price'] = df['Price'].str.replace('$', '')
df['Price'] = df['Price'].astype('float64')
```

In [34]:
```
# Check the data type of the column
df['Price'].dtype
```

Out[34]:
```
dtype('float64')
```

In [35]:
```
# Displaying the minimum, maximum and average (mean) price of the apps
df['Price'].agg(['min', 'max', 'mean'])
```

Out[35]:
```
min       0.000000
max     400.000000
mean      1.027273
Name: Price, dtype: float64
```

Descriptive Statistics

In [36]:
```
df.describe()
```

Out[36]:

	Rating	Reviews	Size (MB)	Installs	Price
count	9367.000000	1.084100e+04	9146.000000	1.084100e+04	10841.000000
mean	4.191513	4.441119e+05	21.514141	1.546291e+07	1.027273
std	0.515735	2.927629e+06	22.588679	8.502557e+07	15.948971
min	1.000000	0.000000e+00	0.008301	0.000000e+00	0.000000
25%	4.000000	3.800000e+01	4.900000	1.000000e+03	0.000000
50%	4.300000	2.094000e+03	13.000000	1.000000e+05	0.000000
75%	4.500000	5.476800e+04	30.000000	5.000000e+06	0.000000
max	5.000000	7.815831e+07	100.000000	1.000000e+09	400.000000

Observations

- Now, we have only 5 columns as numeric data type.
- We can observe their descriptive statistics. and make tons of observations as per our hypotheses.
- We can see that the `Rating` column has a minimum value of `1` and a maximum value of `5`, which is the range of rating, and the mean is `4.19` which is a good rating. On an average people give this rating.

- We can see that the `Reviews` column has a minimum value of `0` and a maximum value of `78,158,306` (78+ Million), which is the range of reviews, and the mean is `444,111.93` which is a good number of reviews. On an average people give this number of reviews to the apps. But it does not make sense to us, as we have different categories of apps.
- Similarly, we can observe the other columns as well.

Therefore, the most important thing is to classify as app based on the correlation matrix and then observe the descriptive statistics of the app category and number of installs, reviews, ratings, etc.

But even before that we have to think about the missing values in the dataset.

Dealing with missing values

Dealing with the missing values is one of the most important part of the data wrangling process, we must deal with the missing values in order to get the correct insights from the data.

- Lets have a look on the missing values in the dataset.

In [37]:
```
# Counting the number of missing values in each column of the dataframe and display
df.isnull().sum().sort_values(ascending=False)
```

Out[37]:
```
Size (MB)           1695
Rating              1474
Current Ver            8
Android Ver            2
Category               1
Type                   1
Genres                 1
Installs               0
App                    0
Reviews                0
Content Rating         0
Price                  0
Last Updated           0
Installs_Category      0
dtype: int64
```

In [38]:
```
# Total number of missing values in the dataframe
df.isnull().sum().sum()
```

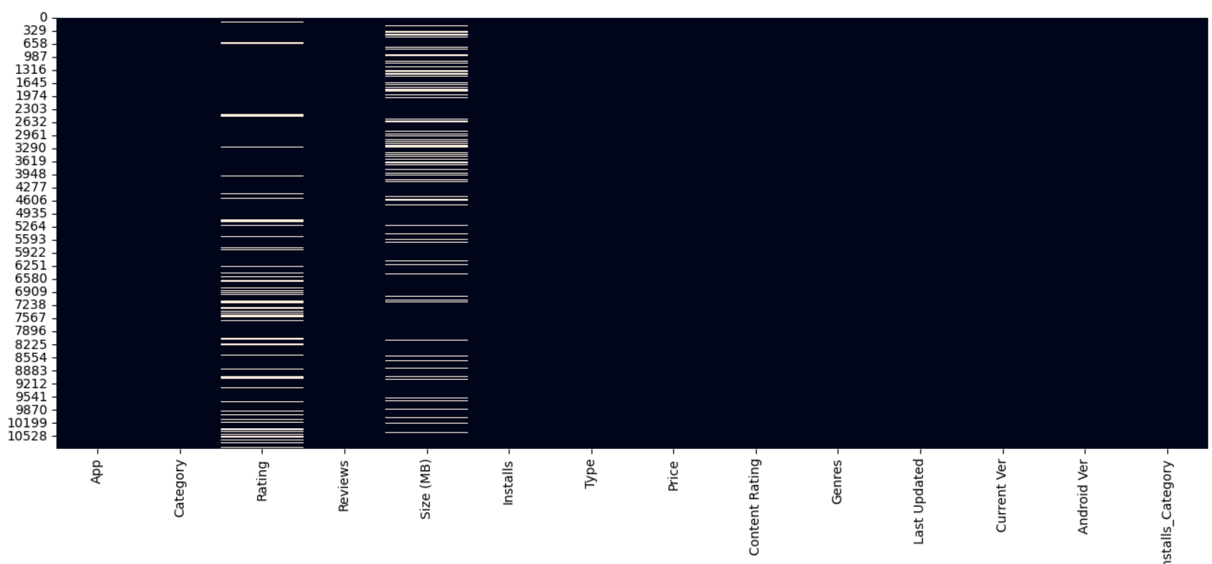
Out[38]:
```
np.int64(3182)
```

In [39]:
```
# Percentage of missing values in each column and displaying them in descending ord
(df.isnull().sum() / len(df) * 100).sort_values(ascending=False)
```

Out[39]:
```
Size (MB)            15.635089
Rating               13.596532
Current Ver           0.073794
Android Ver           0.018448
Category              0.009224
Type                  0.009224
Genres                0.009224
Installs              0.000000
App                   0.000000
Reviews               0.000000
Content Rating        0.000000
Price                 0.000000
Last Updated          0.000000
Installs_Category     0.000000
dtype: float64
```

- Lets plot the missing values on a heatmap.

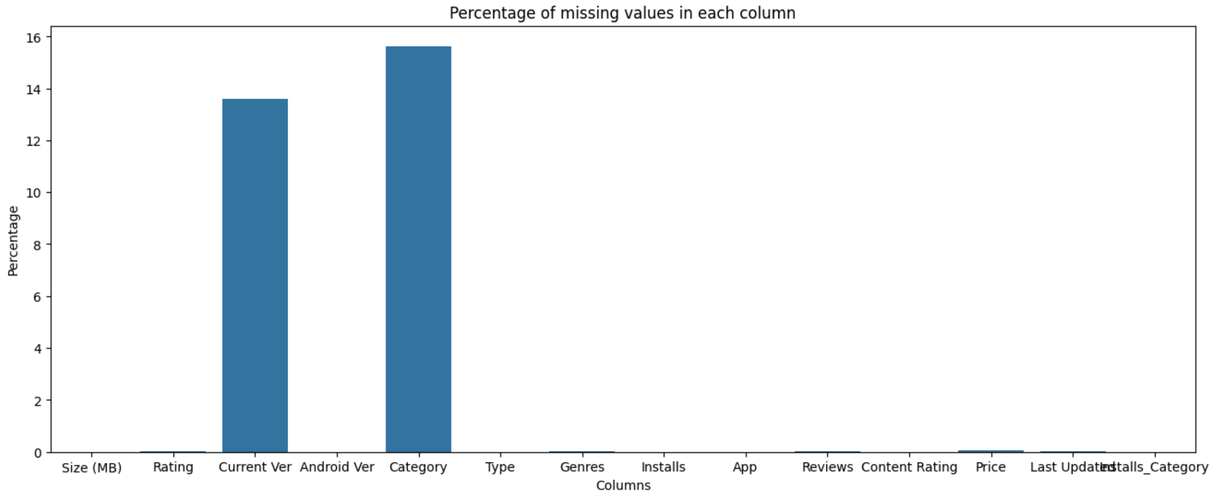
In [40]:
```
# setting the figure size
plt.figure(figsize=(16, 6))
# plotting the missing values on a heatmap using seaborn
sns.heatmap(df.isnull(), cbar=False)
# displaying the plot
plt.show()
```



- Now, lets plot the missing values by their percentage on a bar plot.

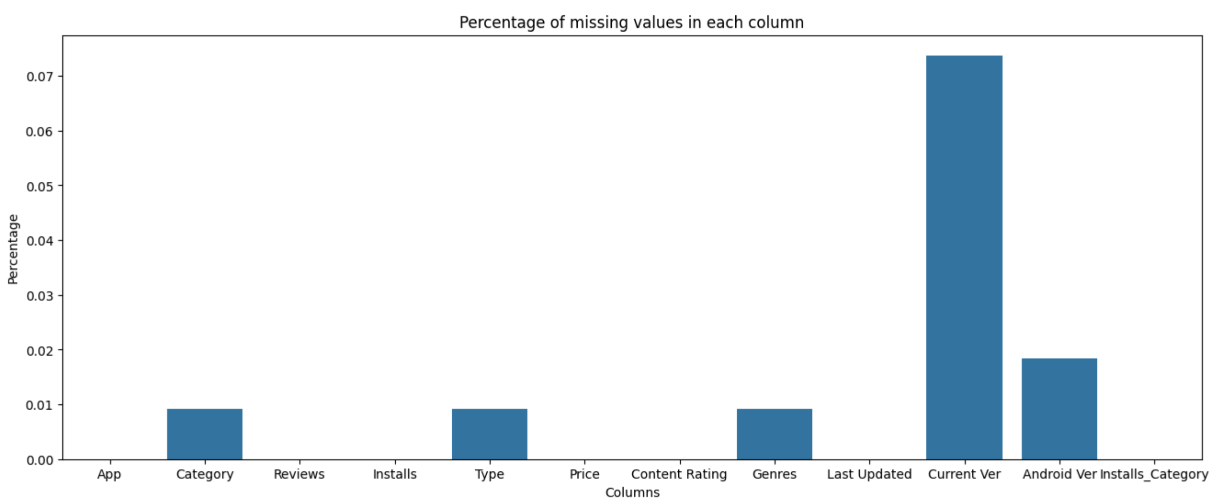
In [41]:
```
# setting figure size
plt.figure(figsize=(16, 6))
# plotting the missing values by their percentage on a bar plot
sns.barplot(x=(df.isnull().sum() / len(df) * 100).sort_values(ascending=False).inde
plt.xlabel('Columns')
plt.ylabel('Percentage')
plt.title('Percentage of missing values in each column')
```

```python
# displaying the plot
plt.show()
```



- We have missing percentage columns that have less than one percent of missing values, we will plot them as follows:

In [42]:
```python
# setting the figure size
plt.figure(figsize=(16, 6))
# plotting the missing values of the columns that have percentage less than 1 on a
sns.barplot(x=(df.isnull().sum() / len(df) * 100)[(df.isnull().sum() / len(df) * 10
plt.xlabel('Columns')
plt.ylabel('Percentage')
plt.title('Percentage of missing values in each column')
# displaying the plot
plt.show()
```



Observations

- We have 1695 missing values in the `'Size_in_bytes'` and `'Size_in_Mb'` columns, which is 15.6% of the total values in the column.

- We have 1474 missing values in the `'Rating'` column, which is 13.6% of the total values in the column.
- We have 8 missing value in the `'Current Ver'` column, which is 0.07% of the total values in the column.
- We have 2 missing values in the `'Android Ver'` column, which is 0.01% of the total values in the column.
- We have only 1 missing value in `Category`, `Type` and `Genres` columns, which is 0.009% of the total values in the column.

- We can not impute the `Rating` column as it is directly linked with the `Installs` column. To test this Hypothesis, we need to plot the `Rating` column with the `Installs` and `Size` columns and statistically test it using `pearson correlation test`.

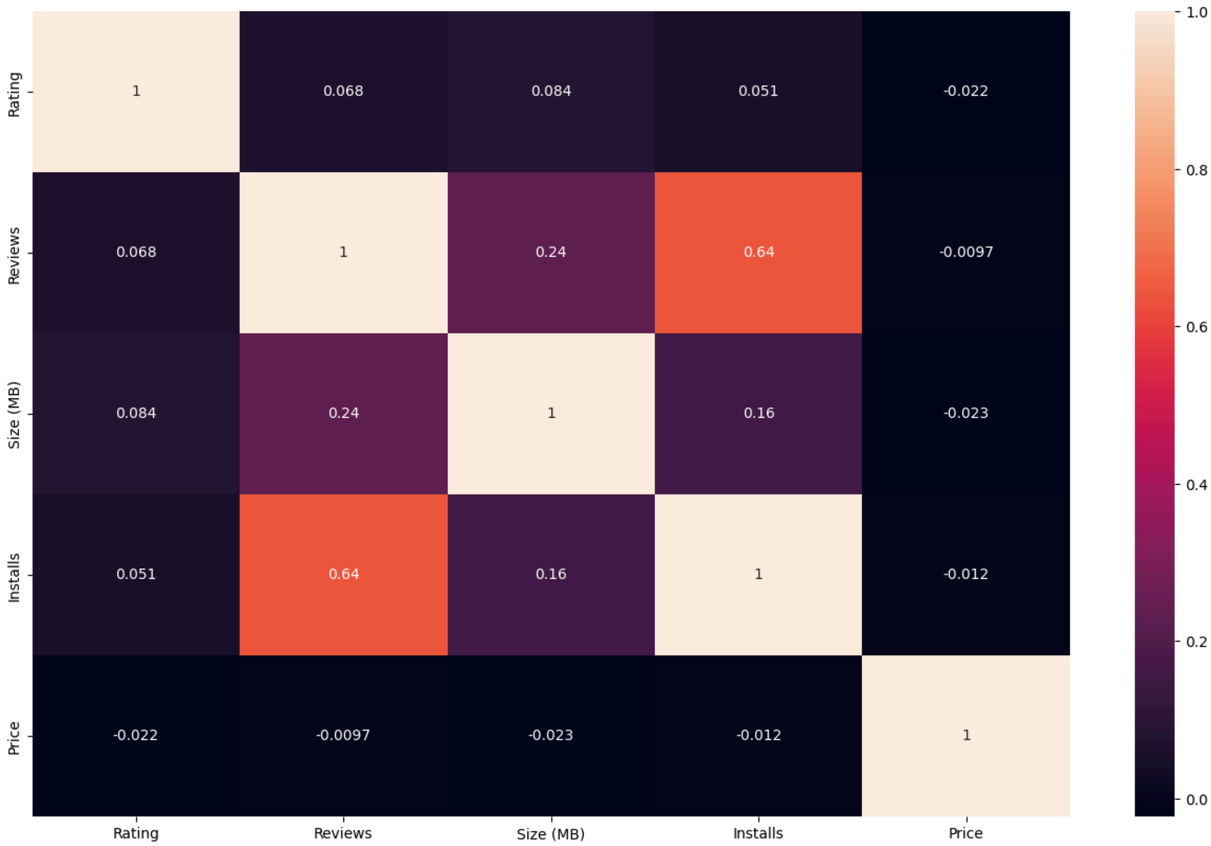
- Lets run the correlations.

In [43]:
```
# Displays the numeric columns with their summary statistics
df.describe()
```

Out[43]:

	Rating	Reviews	Size (MB)	Installs	Price
count	9367.000000	1.084100e+04	9146.000000	1.084100e+04	10841.000000
mean	4.191513	4.441119e+05	21.514141	1.546291e+07	1.027273
std	0.515735	2.927629e+06	22.588679	8.502557e+07	15.948971
min	1.000000	0.000000e+00	0.008301	0.000000e+00	0.000000
25%	4.000000	3.800000e+01	4.900000	1.000000e+03	0.000000
50%	4.300000	2.094000e+03	13.000000	1.000000e+05	0.000000
75%	4.500000	5.476800e+04	30.000000	5.000000e+06	0.000000
max	5.000000	7.815831e+07	100.000000	1.000000e+09	400.000000

In [44]:
```
# Making a correlation matrix of numeric columns on a heatmap
plt.figure(figsize=(16, 10))
sns.heatmap(df.select_dtypes(include='number').corr(), annot=True)
plt.show()
```



In [45]:

```
# Displaying the correlation matrix in the tabulated format
df.select_dtypes(include='number').corr()
```

Out[45]:

	Rating	Reviews	Size (MB)	Installs	Price
Rating	1.000000	0.068147	0.084098	0.051393	-0.021851
Reviews	0.068147	1.000000	0.238218	0.643123	-0.009666
Size (MB)	0.084098	0.238218	1.000000	0.164794	-0.023000
Installs	0.051393	0.643123	0.164794	1.000000	-0.011688
Price	-0.021851	-0.009666	-0.023000	-0.011688	1.000000

In [46]:

```
# We can calculate the pearson correlation coefficient using scipy
from scipy import stats

# Remove rows containing NaN or infinite values (Important to calculate Pearson's R
df_clean = df.dropna()

# calculate Pearson's R between Rating and Installs
pearson_r, _ = stats.pearsonr(df_clean['Reviews'], df_clean['Installs'])
print(f"Pearson's R between Reviews and Installs: {pearson_r:.4f}")
```

```
Pearson's R between Reviews and Installs: 0.6262
```

Observations

- Lighter color shows the high correlation and darker color shows the low correlation.
- We can see that the `Reviews` column has a high correlation with the `Installs` column, which is `0.64` according to corr(), which is quite good.
  - This shows that the more the reviews the more the installs are for one app. If in any case we need to impute reviews we have to think of number of install.
  - If we have an app with `2` installs and we impute the reviews with `1000` or via average reviews then it will be wrong.
- Installs is slightly correlated with `Size (MB)`, which is `0.16`, this also shows us the importance of Size and Installs. But we can not depend on it as the Pearson correlation is very low.

- Before going ahead, let's remove the rows with missing values in the `Current Ver`, `Android Ver`, `Category`, `Type` and `Genres` columns, as they are very less in number and will not affect our analysis.

In [47]:
```
# Length beofre removing the null values
print(f"Length of the dataframe before removing the null values: {len(df)}")
```

```
Length of the dataframe before removing the null values: 10841
```

In [48]:
```
# Removing the rows having null values in 'Cureent Ver', 'Android Ver', 'Genres', '
df.dropna(subset=['Current Ver', 'Android Ver', 'Genres', 'Category', 'Type'], inpl
```

In [49]:
```
# Length after removing the null values
print(f"Length of the dataframe after removing the null values: {len(df)}")
```

```
Length of the dataframe after removing the null values: 10829
```

- We have removed `12` rows having null values in the `Current Ver`, `Android Ver`, `Category`, `Type` and `Genres` columns.

In [50]:
```
# Lets check the null values again
df.isnull().sum().sort_values(ascending=False)
```

Out[50]:
```
Size (MB)            1694
Rating               1469
Category                0
App                     0
Reviews                 0
Installs                0
Type                    0
Price                   0
Content Rating          0
Genres                  0
Last Updated            0
Current Ver             0
Android Ver             0
Installs_Category       0
dtype: int64
```

Observations

- Only `Rating` and `Size (MB)` columns are left with missing values.
  - We know that we have to be carefull while deadling with `Rating` column, as it is directly linked with the `Installs` column.
  - In Size columns, we already know about `Varies with device` values, which we have converted into null values, we do not need to impute at the moment, as every app has different size and nobody can predict that as accurately as possible.

In [51]:
```
df.columns
```

Out[51]:
```
Index(['App', 'Category', 'Rating', 'Reviews', 'Size (MB)', 'Installs', 'Type',
       'Price', 'Content Rating', 'Genres', 'Last Updated', 'Current Ver',
       'Android Ver', 'Installs_Category'],
      dtype='object')
```

In [52]:
```
# Find the trend of 'Rating' in each 'Insalls_Category'
df.groupby('Installs_Category')['Rating'].describe()
```

Out[52]:

Installs_Category	count	mean	std	min	25%	50%	75%	max
Zero	0.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Very Low	446.0	4.420179	0.878608	1.0	4.2	4.8	5.0	5.0
Low	913.0	4.090581	0.789222	1.0	3.8	4.3	4.7	5.0
Medium	1440.0	4.035417	0.604428	1.4	3.8	4.2	4.5	5.0
High	1616.0	4.093255	0.505619	1.6	3.9	4.2	4.5	4.9
Very High	2113.0	4.207525	0.376594	1.8	4.0	4.3	4.5	4.9
Extreme High	2004.0	4.287076	0.294902	2.0	4.1	4.3	4.5	4.9
Ultra High	698.0	4.386533	0.192817	3.1	4.3	4.4	4.5	4.8
Huge	130.0	4.309231	0.186126	3.7	4.2	4.3	4.4	4.7

In [53]:
```
df['Rating'].isnull().sum()
```

Out[53]:
```
np.int64(1469)
```

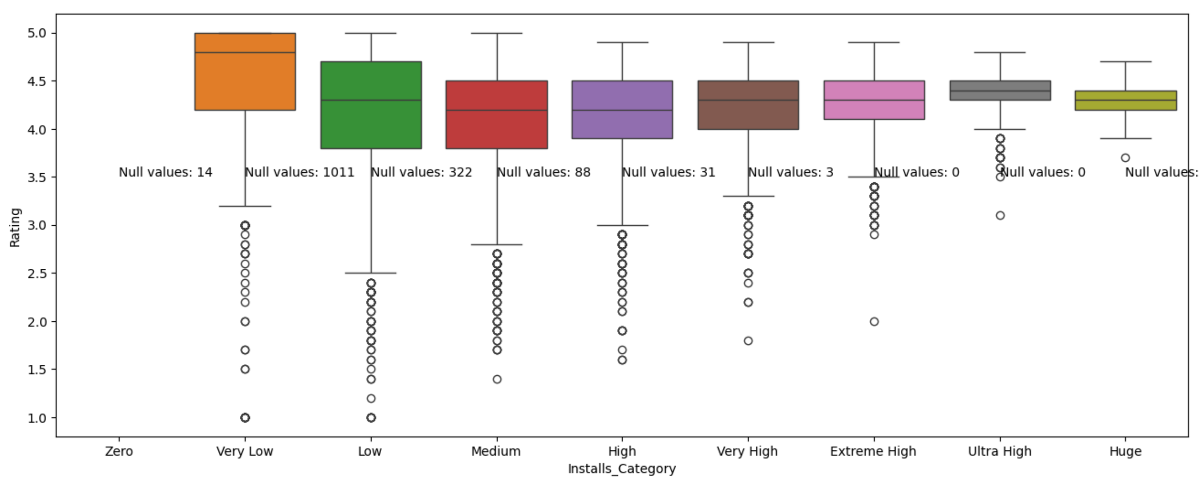
In [54]:
```
# In which Install_category the Rating has NaN values
df['Installs_Category'].loc[df['Rating'].isnull()].value_counts()
```

Out[54]:
```
Installs_Category
Very Low          1011
Low                322
Medium              88
High                31
Zero                14
Very High            3
Extreme High         0
Ultra High           0
Huge                 0
Name: count, dtype: int64
```

- Let's plot this and have a look.

In [55]:
```python
# Plot the boxplot of Rating in each Installs_category
plt.figure(figsize=(16, 6)) # make figure size
sns.boxplot(x='Installs_Category', y='Rating', hue='Installs_Category', data=df) #

# Add the text of number of null values in each category
plt.text(0, 3.5, 'Null values: 14')
plt.text(1, 3.5, 'Null values: 1011')
plt.text(2, 3.5, 'Null values: 322')
plt.text(3, 3.5, 'Null values: 88')
plt.text(4, 3.5, 'Null values: 31')
plt.text(5, 3.5, 'Null values: 3')
plt.text(6, 3.5, 'Null values: 0')
plt.text(7, 3.5, 'Null values: 0')
plt.text(8, 3.5, 'Null values: 0')
```

Out[55]: `Text(8, 3.5, 'Null values: 0')`



- Let's check if there is any similar link with Reviews as well

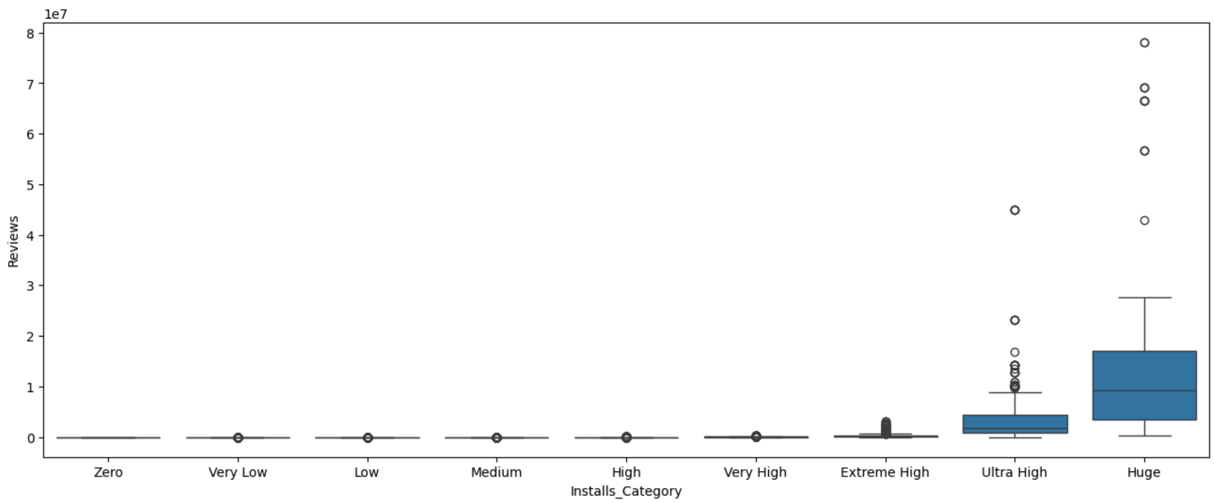
In [56]:
```python
# In which Install_category the Reviews has NaN values
df['Installs_Category'].loc[df['Reviews'].isnull()].value_counts()
```

Out[56]:
```
Installs_Category
Zero              0
Very Low          0
Low               0
Medium            0
High              0
Very High         0
Extreme High      0
Ultra High        0
Huge              0
Name: count, dtype: int64
```

- There are no Null values in Reviews.

In [57]:
```
# Let's plot the same plots for Reviews column as well
plt.figure(figsize=(16, 6)) # make figure size
sns.boxplot(x='Installs_Category', y= 'Reviews', data=df) # plot the boxplot
```

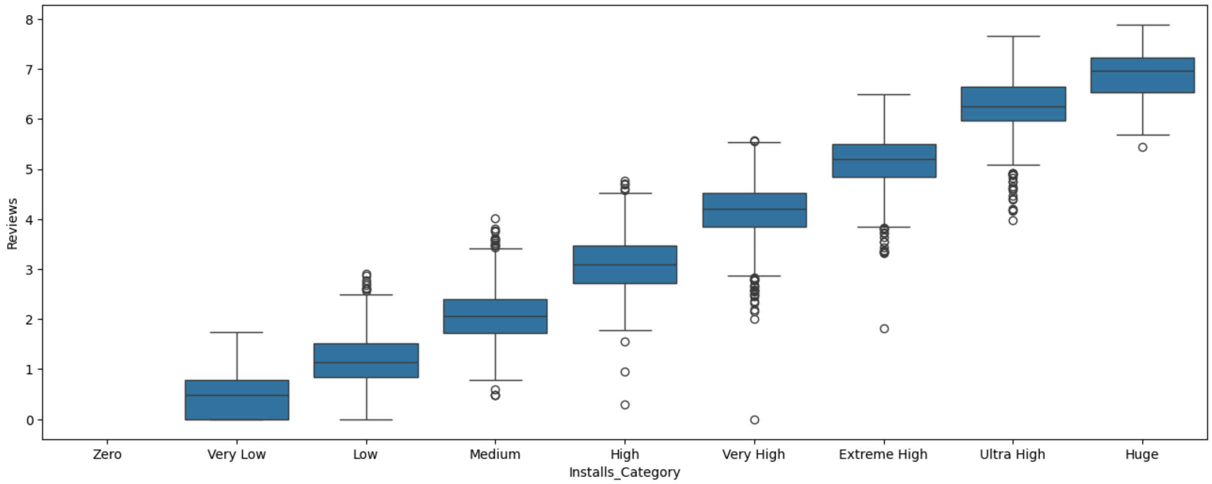
Out[57]:
```
<Axes: xlabel='Installs_Category', ylabel='Reviews'>
```



- The data looks really imbalance, let's normalize the data using log transformation.

In [58]:
```
plt.figure(figsize=(16, 6)) # make figure size
sns.boxplot(x='Installs_Category', y= np.log10(df['Reviews']), data=df) # plot the
```

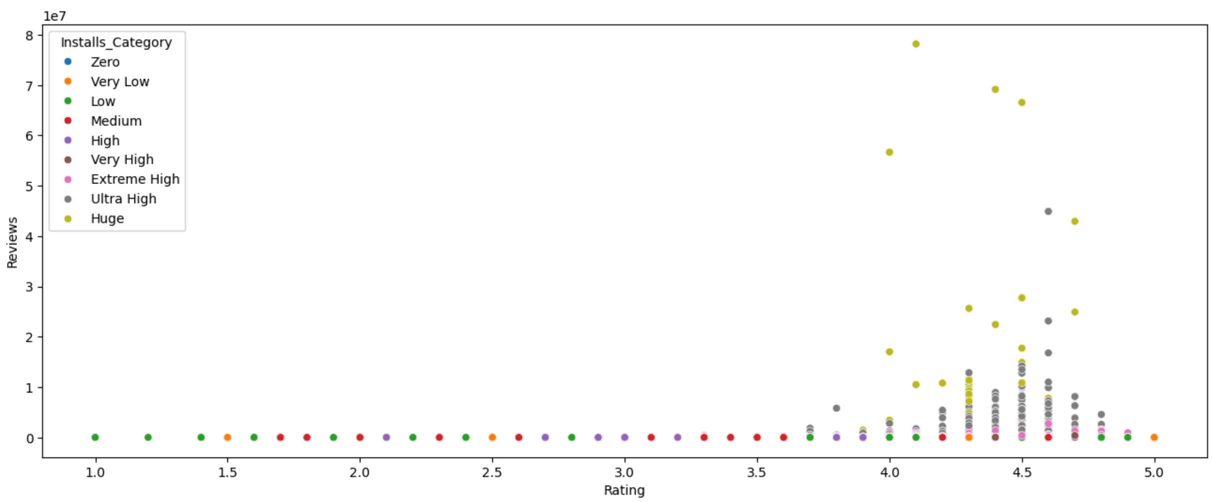
Out[58]:
```
<Axes: xlabel='Installs_Category', ylabel='Reviews'>
```



- We also draw the scatter plot of the `Rating` and `Review` columns with the `Installs` column.

In [59]:
```python
# Draw a scatter plot between Rating, Reviews and Installs
plt.figure(figsize=(16, 6)) # make figure size
sns.scatterplot(x='Rating', y='Reviews', hue='Installs_Category', data=df) # plot t
```

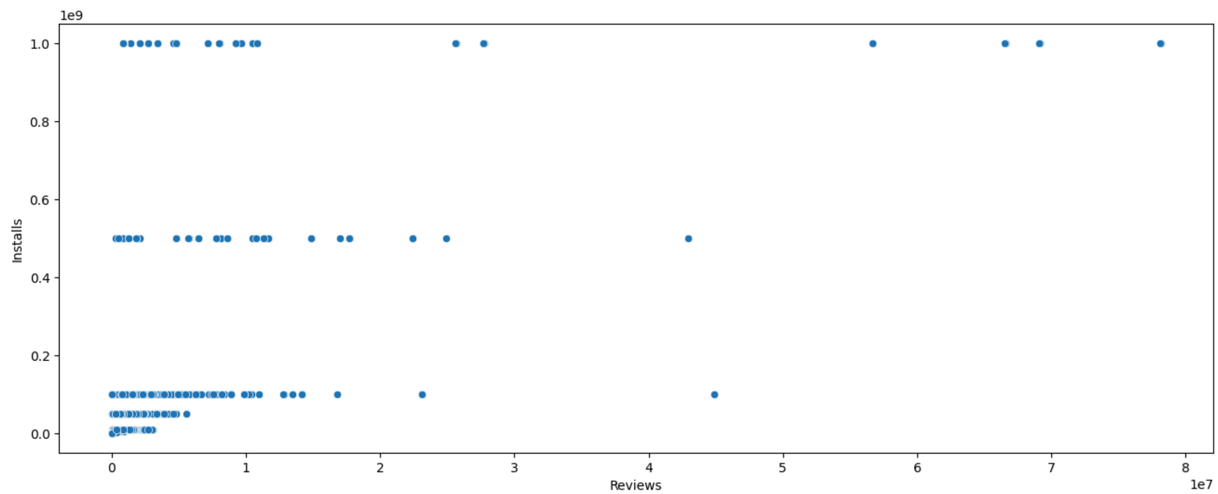
Out[59]: `<Axes: xlabel='Rating', ylabel='Reviews'>`



- It doesn't show any trend, because, you should know that Rating is a categorical variable (Ordinal) and Reviews is a continuous variable, therefore, we can not plot them together.
- Let's try with Reviews and Installs

In [60]:
```python
# Plot reviews and installs in a scatter plot
plt.figure(figsize=(16, 6)) # make figure size
sns.scatterplot(x='Reviews', y='Installs', data=df) # plot the scatter plot
```

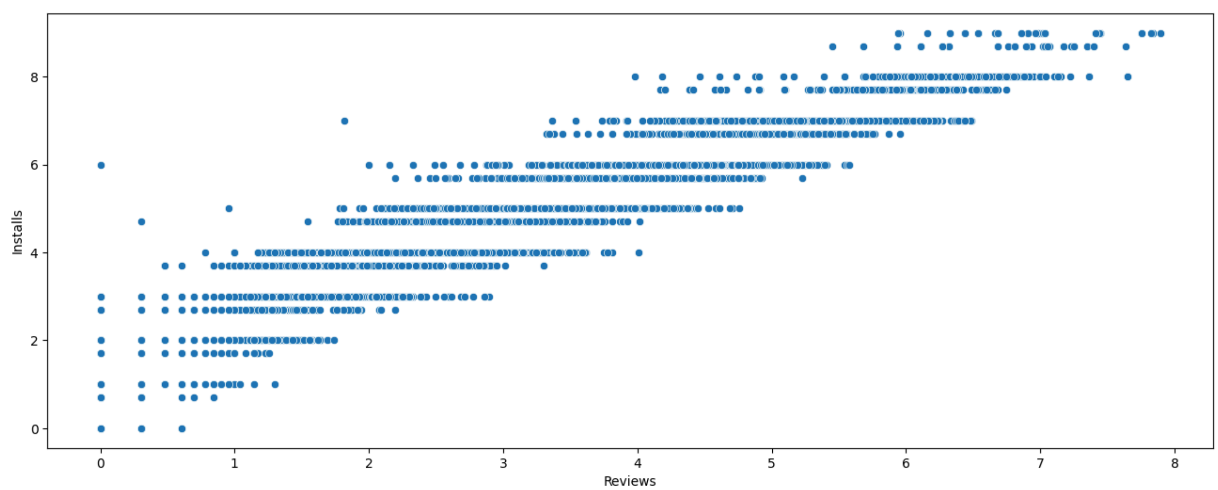
Out[60]: `<Axes: xlabel='Reviews', ylabel='Installs'>`



- We did not see any trend and the issue is we need to normalize the data before plotting it, let's try with log transformation.

In [61]:
```
# Plot reviews and installs in a scatter plot
plt.figure(figsize=(16, 6)) # make figure size
sns.scatterplot(x=np.log10(df['Reviews']), y=np.log10(df['Installs']), data=df) # p
```

Out[61]: `<Axes: xlabel='Reviews', ylabel='Installs'>`

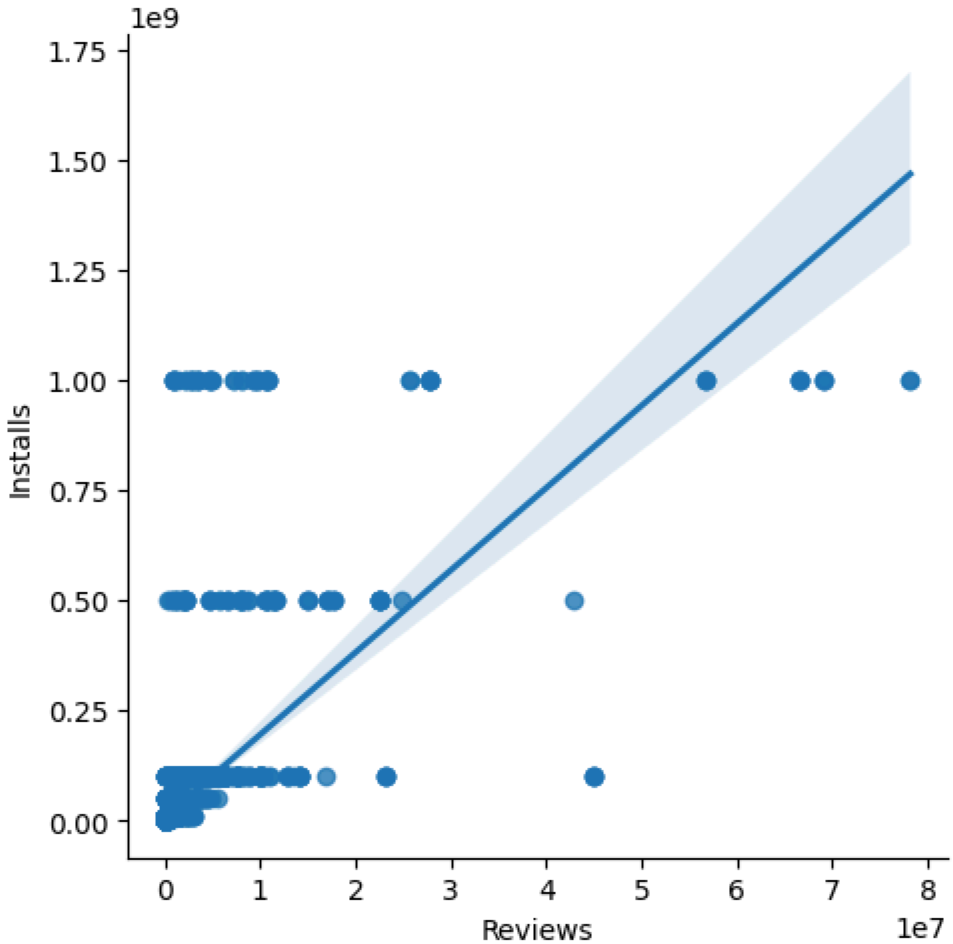


- Now we see a slight trend but still the issue is installs were given in a factorial manner such as 10+, 20+, 1000+ etc, and these are not continuous, instead they are discrete, therefore, we can only see a slight trend here. Let's plot a line plot to see the trend.

In [62]:
```
# Plot reviews and installs in a scatter plot with trend line
plt.figure(figsize=(16, 6)) # make figure size
sns.lmplot(x='Reviews', y='Installs', data=df) # plot the scatter plot with trend l
```

Out[62]: `<seaborn.axisgrid.FacetGrid at 0x17e8cb567b0>`

```
<Figure size 1600x600 with 0 Axes>
```



- Here, we can see a nice trend, which shows that number of Reviews increases with the number of Installs, which is quite obvious.

Observation

- We can see that most of the null values from `Rating` column are No - Moderate Installation apps, which make sense that if the app has less installations, it has less Rating and Reviews.

- But wait, we have to check for the duplicates as well, as they can affect our analysis.

Duplicates

- Removing duplicates is one of the most important part of the data wrangling process, we must remove the duplicates in order to get the correct insights from the data.
- If you do not remove duplicates from a dataset, it can lead to incorrect insights and analysis.

- Duplicates can skew statistical measures such as mean, median, and standard deviation, and can also lead to over-representation of certain data points.
- It is important to remove duplicates to ensure the accuracy and reliability of your data analysis.

In [63]:
```
# Find duplicate if any
df.duplicated().sum()
```

Out[63]:
```
np.int64(483)
```

This shows us total duplicates, but we can also check based on the app name, as we know that every app has a unique name.

In [64]:
```
# Find duplicate if any in the 'App' column
df['App'].duplicated().sum()
```

Out[64]:
```
np.int64(1181)
```

- Oops! we have 1181 dupicate app names.
- Can we find a column which can help us to remove the duplicates?

Let's check for number of duplicates in each column using a for loop and print the output.

In [65]:
```
# Let's check for number of duplicates
for col in df.columns:
    print(f"Number of duplicates in {col} column are: {df[col].duplicated().sum()}"
```

```
Number of duplicates in App column are: 1181
Number of duplicates in Category column are: 10796
Number of duplicates in Rating column are: 10789
Number of duplicates in Reviews column are: 4830
Number of duplicates in Size (MB) column are: 10373
Number of duplicates in Installs column are: 10809
Number of duplicates in Type column are: 10827
Number of duplicates in Price column are: 10737
Number of duplicates in Content Rating column are: 10823
Number of duplicates in Genres column are: 10710
Number of duplicates in Last Updated column are: 9453
Number of duplicates in Current Ver column are: 7998
Number of duplicates in Android Ver column are: 10796
Number of duplicates in Installs_Category column are: 10820
```

- Find and watch all duplicates if they are real!

In [66]:
```
# Find exact duplicates and print them
df[df['App'].duplicated(keep=False)].sort_values(by='App').head(19)
```

Out[66]:

	App	Category	Rating	Reviews	Size (MB)	Installs	Type	Price
1393	10 Best Foods for You	HEALTH_AND_FITNESS	4.0	2490	3.8	500000	Free	0.00
1407	10 Best Foods for You	HEALTH_AND_FITNESS	4.0	2490	3.8	500000	Free	0.00
2543	1800 Contacts - Lens Store	MEDICAL	4.7	23160	26.0	1000000	Free	0.00
2322	1800 Contacts - Lens Store	MEDICAL	4.7	23160	26.0	1000000	Free	0.00
2385	2017 EMRA Antibiotic Guide	MEDICAL	4.4	12	3.8	1000	Paid	16.99
2256	2017 EMRA Antibiotic Guide	MEDICAL	4.4	12	3.8	1000	Paid	16.99
1337	21-Day Meditation Experience	HEALTH_AND_FITNESS	4.4	11506	15.0	100000	Free	0.00
1434	21-Day Meditation Experience	HEALTH_AND_FITNESS	4.4	11506	15.0	100000	Free	0.00
3083	365Scores - Live Scores	SPORTS	4.6	666521	25.0	10000000	Free	0.00
5415	365Scores - Live Scores	SPORTS	4.6	666246	25.0	10000000	Free	0.00
7035	420 BZ Budeze Delivery	MEDICAL	5.0	2	11.0	100	Free	0.00
2522	420 BZ Budeze Delivery	MEDICAL	5.0	2	11.0	100	Free	0.00
3953	8 Ball Pool	SPORTS	4.5	14184910	52.0	100000000	Free	0.00
1970	8 Ball Pool	GAME	4.5	14201604	52.0	100000000	Free	0.00

	App	Category	Rating	Reviews	Size (MB)	Installs	Type	Price
1844	8 Ball Pool	GAME	4.5	14200550	52.0	100000000	Free	0.00
1755	8 Ball Pool	GAME	4.5	14200344	52.0	100000000	Free	0.00
1703	8 Ball Pool	GAME	4.5	14198602	52.0	100000000	Free	0.00
1675	8 Ball Pool	GAME	4.5	14198297	52.0	100000000	Free	0.00
1871	8 Ball Pool	GAME	4.5	14201891	52.0	100000000	Free	0.00

- Remove Duplicates.

In [67]:
```
# Remove the duplicates from app column
df.drop_duplicates(subset='App', keep='first', inplace=True)
```

In [68]:
```
# Print the number of rows and columns after removing duplicates
print(f"Number of rows after removing duplicates: {df.shape[0]}")
```

```
Number of rows after removing duplicates: 9648
```

- Now we have removed 1181 duplicates from the dataset, and have 9648 rows left.

Insights from Data

1. Which category has the highest number of apps?

In [69]:
```
# Which category has highest number of apps
df['Category'].value_counts().head(10) # this will show the top 10 categories with
```

Out[69]:
```
Category
FAMILY             1828
GAME                959
TOOLS               825
BUSINESS            420
MEDICAL             395
PRODUCTIVITY        374
PERSONALIZATION     374
LIFESTYLE           369
FINANCE             345
SPORTS              325
Name: count, dtype: int64
```

2. Which category has the highest number of installs?

In [70]:
```
# Category with highest number of Installs
df.groupby('Category')['Installs'].sum().sort_values(ascending=False).head(10)
```

Out[70]:
```
Category
GAME                   13878924415
COMMUNICATION          11038276251
TOOLS                   8001271905
PRODUCTIVITY            5793091369
SOCIAL                  5487867902
PHOTOGRAPHY             4649147655
FAMILY                  4427881405
VIDEO_PLAYERS           3926902720
TRAVEL_AND_LOCAL        2894887146
NEWS_AND_MAGAZINES      2369217760
Name: Installs, dtype: int64
```

3. Which category has the highest number of reviews?

In [71]:
```
# Category with highest number of Reviews
df.groupby('Category')['Reviews'].sum().sort_values(ascending=False).head(10)
```

Out[71]:
```
Category
GAME                622298709
COMMUNICATION       285811368
TOOLS               229352567
SOCIAL              227927801
FAMILY              143825265
PHOTOGRAPHY         105351270
VIDEO_PLAYERS        67484568
PRODUCTIVITY         55590649
PERSONALIZATION      53542661
SHOPPING             44551730
Name: Reviews, dtype: int64
```

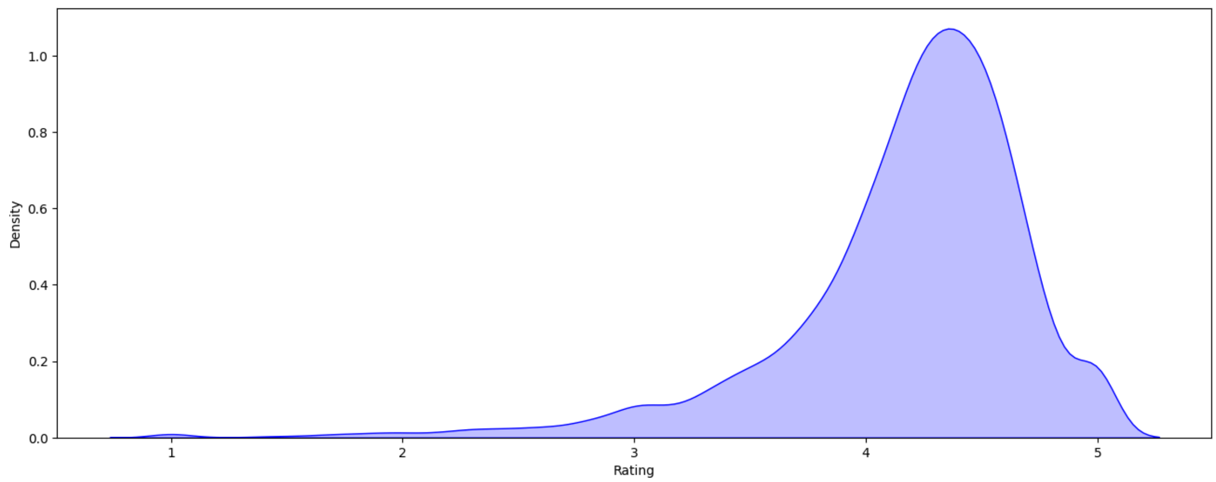
4. Which category has the highest rating?

In [72]:
```
# Category with highest average Rating
df.groupby('Category')['Rating'].mean().sort_values(ascending=False).head(10)
```

```
Out[72]: Category
EVENTS                 4.435556
ART_AND_DESIGN         4.376667
EDUCATION              4.364407
BOOKS_AND_REFERENCE    4.344970
PERSONALIZATION        4.331419
PARENTING              4.300000
BEAUTY                 4.278571
GAME                   4.247368
SOCIAL                 4.247291
WEATHER                4.243056
Name: Rating, dtype: float64
```

```
In [73]: # Plot the rating distribution
plt.figure(figsize=(16, 6)) # make figure size
sns.kdeplot(df['Rating'], color="blue", shade=True) # plot the distribution plot
```

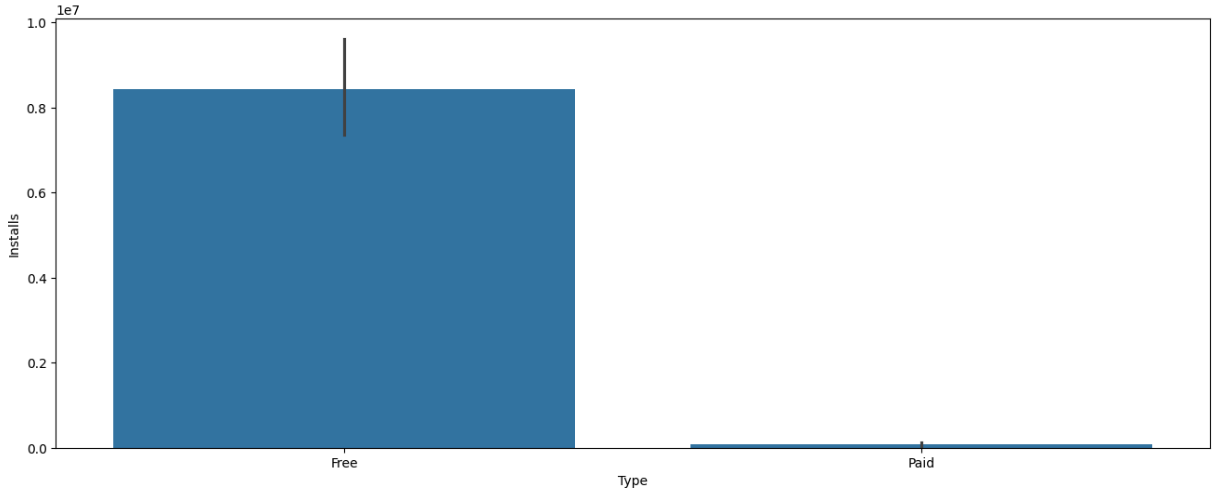
```
Out[73]: <Axes: xlabel='Rating', ylabel='Density'>
```

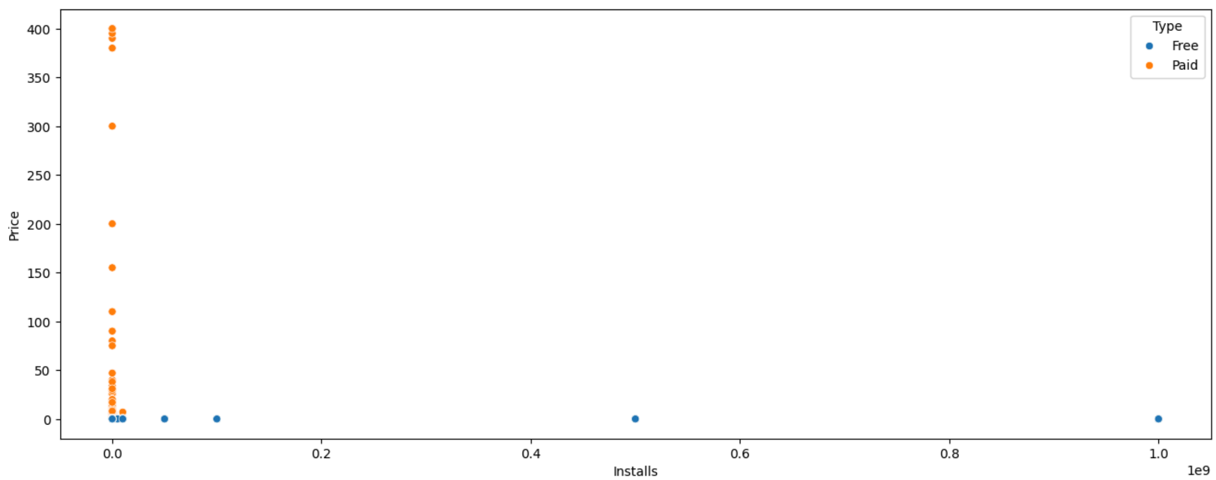


5. Which type has more number of installs?

```
In [74]: # Plot number of installs for free vs paid apps on a bar plot
plt.figure(figsize=(16, 6)) # make figure sizeccc
sns.barplot(x='Type', y='Installs', data=df) # plot the bar plot

# Show scatter plot as well where x-axis is Installs and y-axis is Price and hue is
plt.figure(figsize=(16, 6)) # make figure size
sns.scatterplot(x='Installs', y='Price', hue='Type', data=df) # plot the scatter pl
```

```
Out[74]: <Axes: xlabel='Installs', ylabel='Price'>
```

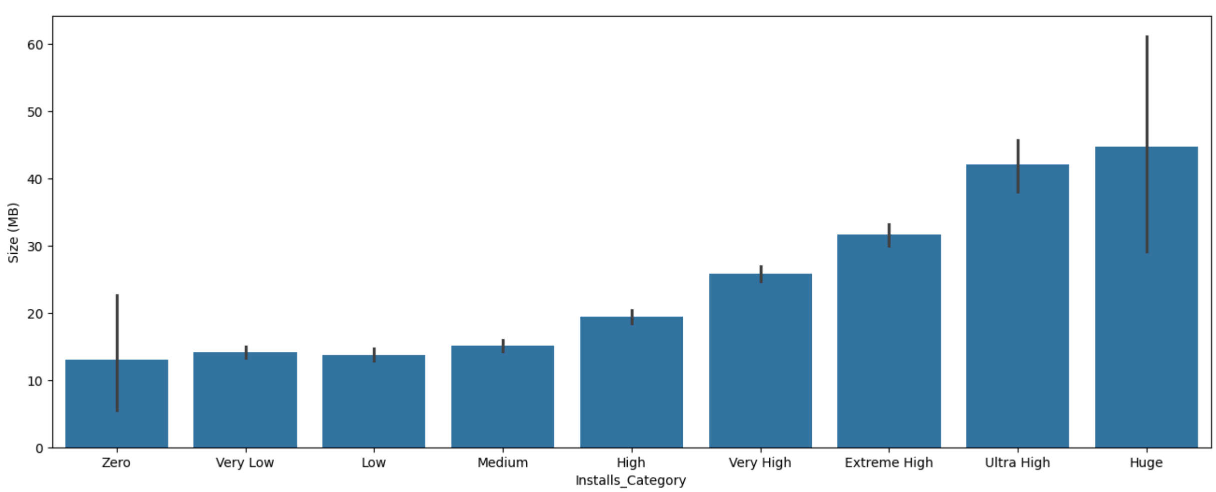




6. Which installs' category has the greatest size in megabytes?

In [75]:
```
# Make a bar plot of Size (MB) vs Installs_Category
plt.figure(figsize=(16, 6)) # make figure size
sns.barplot(x='Installs_Category', y='Size (MB)', data=df) # plot the bar plot
```

Out[75]: <Axes: xlabel='Installs_Category', ylabel='Size (MB)'>



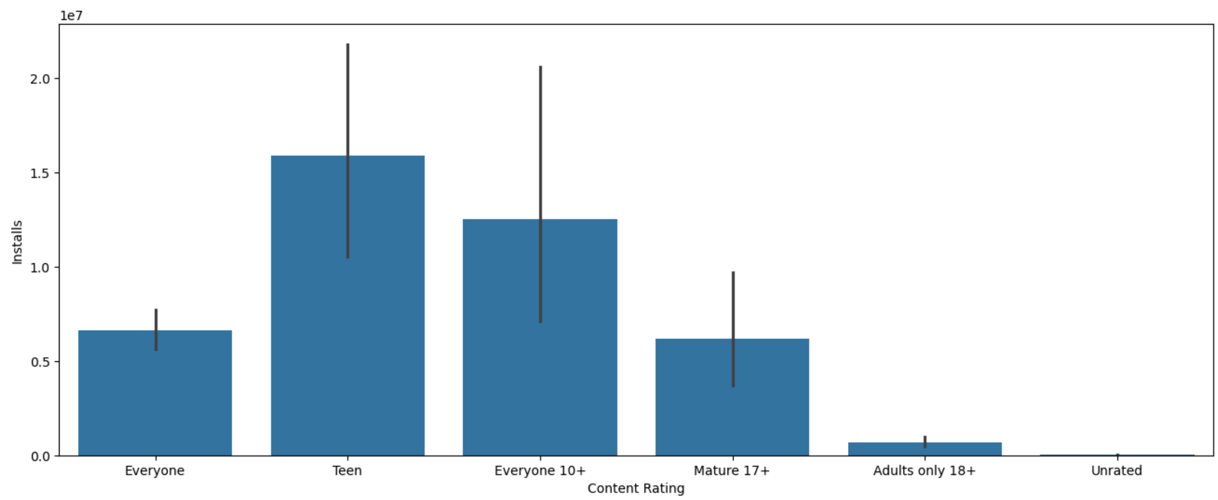
7. Which content rating is the most popular?

In [76]:
```
df['Content Rating'].value_counts() # this will show the value counts of each conte
```

Out[76]:
```
Content Rating
Everyone          7893
Teen              1036
Mature 17+         393
Everyone 10+       321
Adults only 18+      3
Unrated              2
Name: count, dtype: int64
```

In [77]:
```
# Plot the bar plot of Content Rating vs Installs
plt.figure(figsize=(16, 6)) # make figure size
sns.barplot(x='Content Rating', y='Installs', data=df) # plot the bar plot
```

Out[77]:
```
<Axes: xlabel='Content Rating', ylabel='Installs'>
```



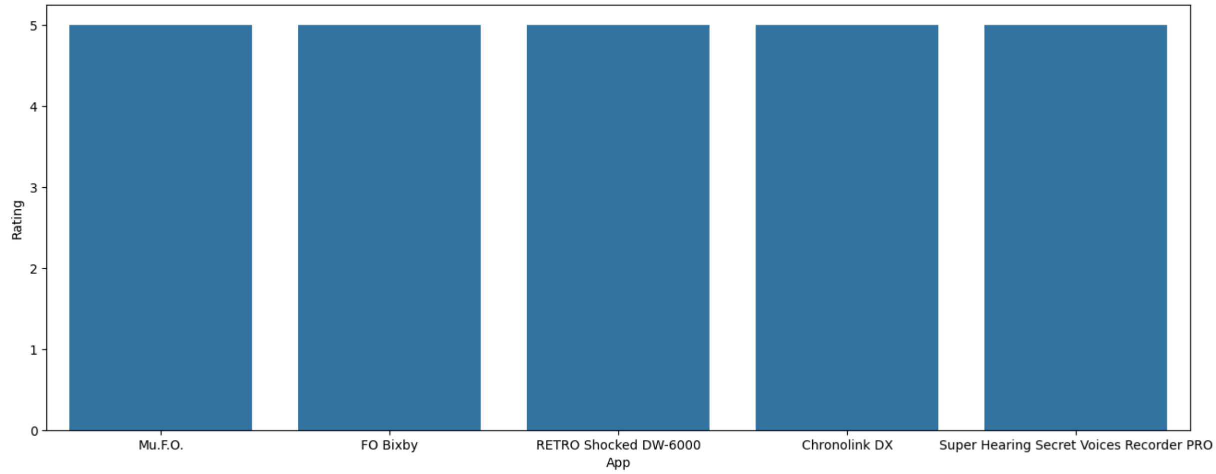
In [78]:
```
# Find how many apps in each category are there in Everyone content rating
df['Category'].loc[df['Content Rating'] == 'Everyone'].value_counts()
```

Out[78]:
```
Category
FAMILY                 1428
TOOLS                   817
GAME                    493
BUSINESS                405
MEDICAL                 377
PRODUCTIVITY            363
FINANCE                 340
LIFESTYLE               333
PERSONALIZATION         309
SPORTS                  300
COMMUNICATION           280
PHOTOGRAPHY             268
HEALTH_AND_FITNESS      258
TRAVEL_AND_LOCAL        212
BOOKS_AND_REFERENCE     197
SHOPPING                172
NEWS_AND_MAGAZINES      168
VIDEO_PLAYERS           137
MAPS_AND_NAVIGATION     127
EDUCATION               112
FOOD_AND_DRINK          102
SOCIAL                   87
AUTO_AND_VEHICLES        83
LIBRARIES_AND_DEMO       83
WEATHER                  75
HOUSE_AND_HOME           72
ART_AND_DESIGN           59
PARENTING                58
EVENTS                   53
BEAUTY                   45
ENTERTAINMENT            37
COMICS                   26
DATING                   17
Name: count, dtype: int64
```

8. What are the top 5 rated paid apps?

In [79]:
```
# Plot top 5 rated paid apps
plt.figure(figsize=(16, 6)) # make figure size
sns.barplot(x='App', y='Rating', data=df[df['Type'] == 'Paid'].sort_values(by='Rati
```

Out[79]:
```
<Axes: xlabel='App', ylabel='Rating'>
```



In [80]:
```
df[df['Type'] == 'Paid'].sort_values(by='Rating', ascending=False).head(5)
```

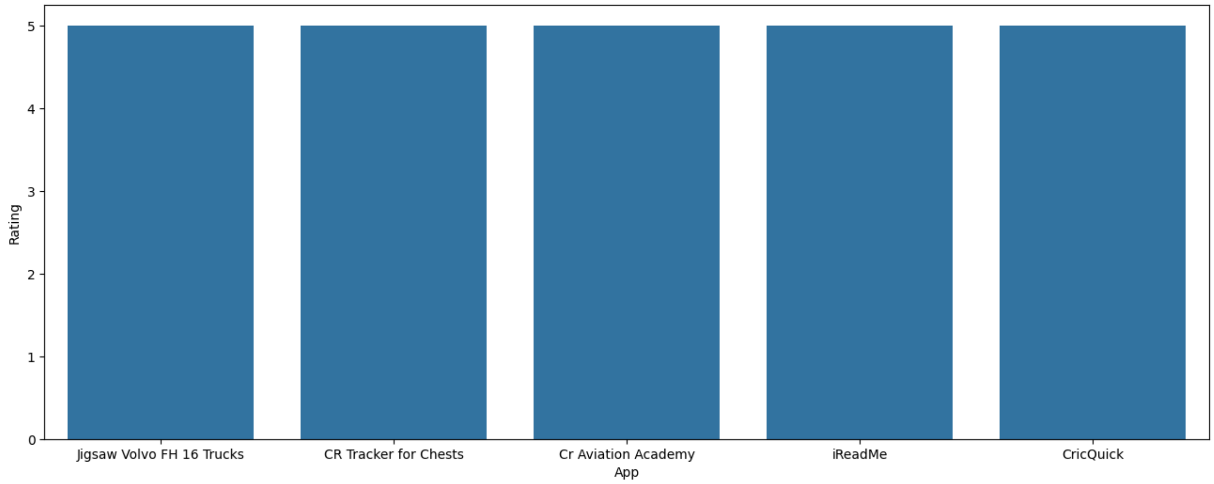
Out[80]:

	App	Category	Rating	Reviews	Size (MB)	Installs	Type	Price	C
10697	Mu.F.O.	GAME	5.0	2	16.000000	1	Paid	0.99	Ev
10690	FO Bixby	PERSONALIZATION	5.0	5	0.840820	100	Paid	0.99	Ev
9010	RETRO Shocked DW-6000	PERSONALIZATION	5.0	13	0.488281	100	Paid	1.49	Ev
9039	Chronolink DX	FAMILY	5.0	7	73.000000	10	Paid	0.99	Ev
2262	Super Hearing Secret Voices Recorder PRO	MEDICAL	5.0	3	23.000000	100	Paid	2.99	Ev

9. What are the top 5 rated free apps?

In [81]:
```
# Plot top rated 5 apps in free category
plt.figure(figsize=(16, 6)) # make figure size
sns.barplot(x='App', y='Rating', data=df[df['Type'] == 'Free'].sort_values(by='Rati
```

Out[81]: <Axes: xlabel='App', ylabel='Rating'>



In [82]:
```python
df[df['Type'] == 'Free'].sort_values(by='Rating', ascending=False).head(5)
```

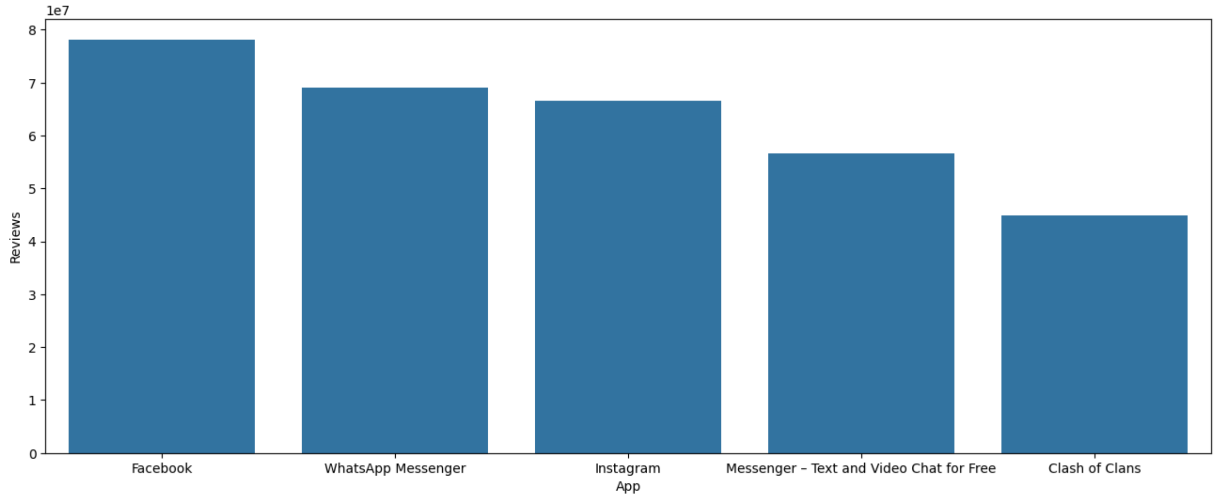
Out[82]:

	App	Category	Rating	Reviews	Size (MB)	Installs	Type	Price	Content Rating	
10407	Jigsaw Volvo FH 16 Trucks	FAMILY	5.0	5	8.1	1000	Free	0.0	Teen	
7805	CR Tracker for Chests	TOOLS	5.0	6	4.5	50	Free	0.0	Everyone	
7799	Cr Aviation Academy	FAMILY	5.0	7	22.0	100	Free	0.0	Everyone	
7756	iReadMe	PRODUCTIVITY	5.0	8	22.0	100	Free	0.0	Everyone	Pr
7754	CricQuick	SPORTS	5.0	17	1.5	50	Free	0.0	Everyone	

10. What are the top 5 free and paid apps with highest number of reviews?

In [83]:
```python
# Plot top 5 FREE apps with highest number of reviews
plt.figure(figsize=(16, 6)) # make figure size
sns.barplot(x='App', y='Reviews', data=df[df['Type'] == 'Free'].sort_values(by='Rev
```

Out[83]: <Axes: xlabel='App', ylabel='Reviews'>



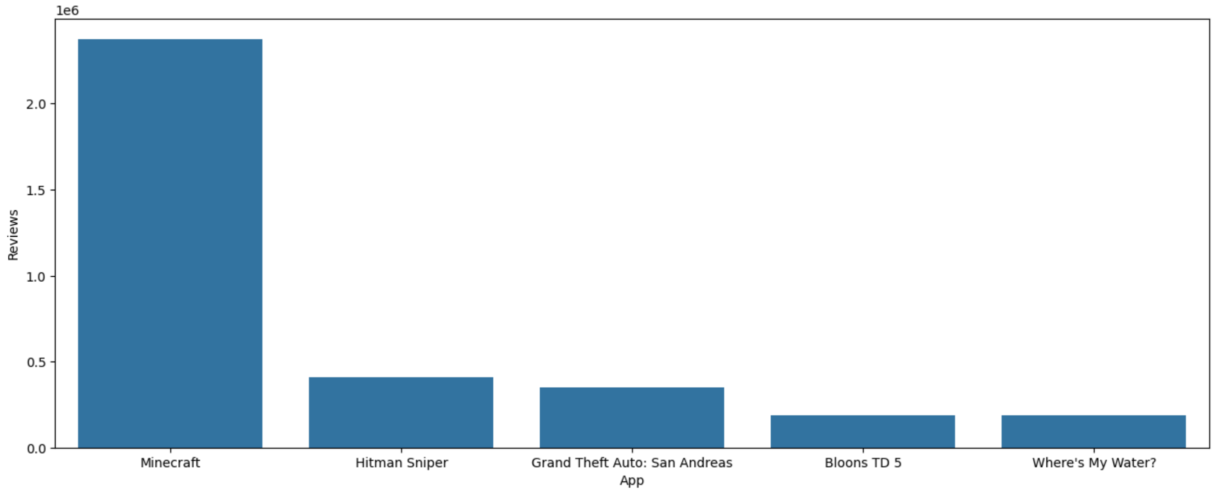
In [84]:
```
df[df['Type'] == 'Free'].sort_values(by='Reviews', ascending=False).head(5)
```

Out[84]:

	App	Category	Rating	Reviews	Size (MB)	Installs	Type	Price	Co R
2544	Facebook	SOCIAL	4.1	78158306	NaN	1000000000	Free	0.0	
336	WhatsApp Messenger	COMMUNICATION	4.4	69119316	NaN	1000000000	Free	0.0	Eve
2545	Instagram	SOCIAL	4.5	66577313	NaN	1000000000	Free	0.0	
335	Messenger – Text and Video Chat for Free	COMMUNICATION	4.0	56642847	NaN	1000000000	Free	0.0	Eve
1670	Clash of Clans	GAME	4.6	44891723	98.0	100000000	Free	0.0	Eve

In [85]:
```
# Plot top 5 Paid apps with highest number of reviews
plt.figure(figsize=(16, 6)) # make figure size
sns.barplot(x='App', y='Reviews', data=df[df['Type'] == 'Paid'].sort_values(by='Rev
```

Out[85]: <Axes: xlabel='App', ylabel='Reviews'>



Machine Learning: Predicting App Ratings

Building upon our data exploration and cleaning, we'll now use this preprocessed data to create a machine learning model that predicts app ratings. This will allow us to identify which features are most important in determining an app's rating.

In [86]:
```
# Import additional libraries for machine learning
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, r2_score
```

Feature Selection and Model Preparation

In [87]:
```
# Check for NaN values
print("Columns with NaN values:")
print(df.isna().sum())

df['Rating'].fillna(df['Rating'].mean(), inplace=True)
df['Size (MB)'].fillna(df['Size (MB)'].mean(), inplace=True)

# Log transforming skewed features
df['Reviews_log'] = np.log1p(df['Reviews'])
df['Installs_log'] = np.log1p(df['Installs'])
df['Price_log'] = np.log1p(df['Price'])

# Adding interaction terms
df['Reviews_Installs'] = df['Reviews'] * df['Installs']

# Feature Selection
features = ['Category', 'Reviews', 'Size (MB)', 'Installs', 'Type', 'Price', 'Conte
X = pd.get_dummies(df[features], columns=['Category', 'Type', 'Content Rating', 'Ge
y = df['Rating']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

```
# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

print(f"\nTraining set shape: {X_train.shape}")
print(f"Testing set shape: {X_test.shape}")
```

```
Columns with NaN values:
App                    0
Category               0
Rating              1458
Reviews                0
Size (MB)           1226
Installs               0
Type                   0
Price                  0
Content Rating         0
Genres                 0
Last Updated           0
Current Ver            0
Android Ver            0
Installs_Category      0
dtype: int64

Training set shape: (7718, 163)
Testing set shape: (1930, 163)
```

Observations:

- We checked for and handled any remaining NaN values in the 'Rating' column.
- We've selected relevant features for our model, including both numerical and categorical variables.
- Categorical variables have been one-hot encoded to be usable in our model.
- The data has been split into training (80%) and testing (20%) sets.
- Features have been scaled to ensure all variables are on the same scale, which is important for many machine learning algorithms.

Model Training

In [88]:

```
# 4. Model Training
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

rf = RandomForestRegressor(random_state=42)
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, n_jobs=-1, ve
grid_search.fit(X_train_scaled, y_train)
```

```
print("Model training completed.")
```

```
Fitting 5 folds for each of 81 candidates, totalling 405 fits
Model training completed.
```

Observations:

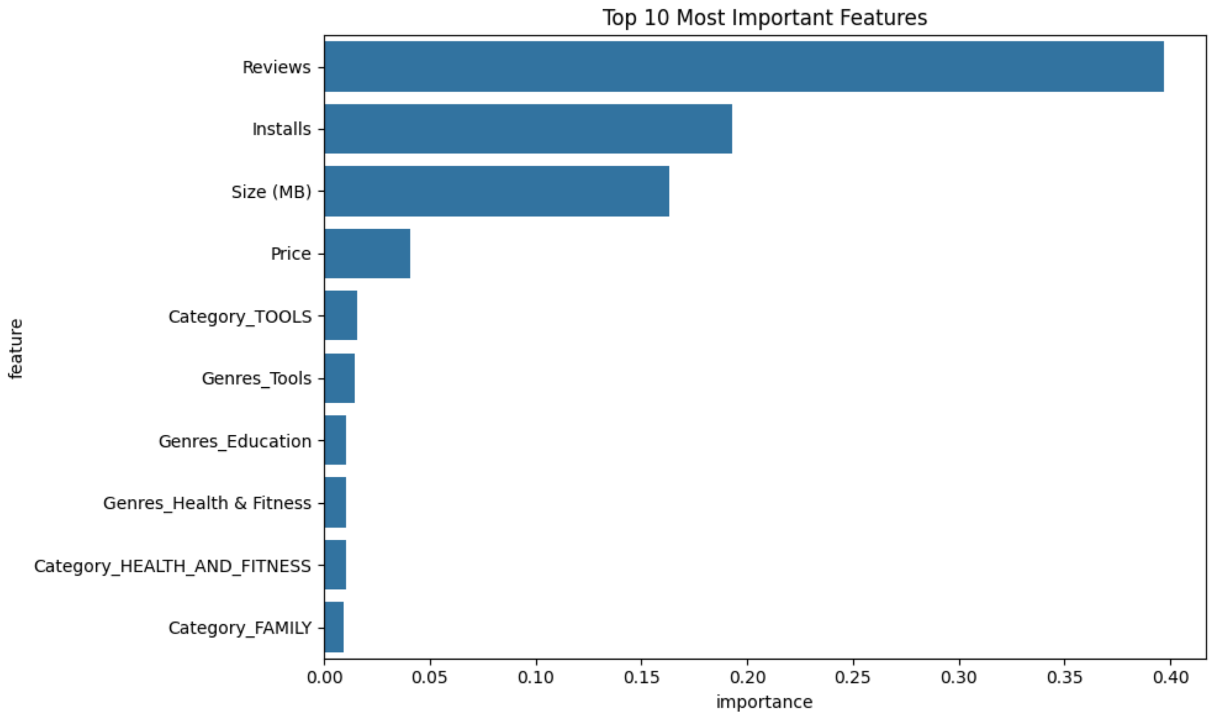
- We've used a Random Forest Regressor with 100 trees.
- Random Forests are ensemble learning methods that operate by constructing multiple decision trees and outputting the mean prediction of the individual trees.
- They're known for their high accuracy and ability to handle large datasets with higher dimensionality.

Model Evaluation

In [89]:

```
# 5. Model Evaluation
best_rf = grid_search.best_estimator_
y_pred = best_rf.predict(X_test_scaled)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Squared Error: {mse:.4f}")
print(f"R-squared Score: {r2:.4f}")

# Feature Importance
feature_importance = pd.DataFrame({'feature': X.columns, 'importance': best_rf.feat
feature_importance = feature_importance.sort_values('importance', ascending=False).
print("\nTop 10 Most Important Features:")
print(feature_importance)

# Visualize feature importance
plt.figure(figsize=(10, 6))
sns.barplot(x='importance', y='feature', data=feature_importance)
plt.title('Top 10 Most Important Features')
plt.tight_layout()
plt.show()
```

```
Mean Squared Error: 0.2101
R-squared Score: 0.1136

Top 10 Most Important Features:
                          feature  importance
0                         Reviews    0.396945
2                        Installs    0.192922
1                       Size (MB)    0.163419
3                           Price    0.040479
33                 Category_TOOLS    0.015448
152                  Genres_Tools    0.014380
83               Genres_Education    0.010502
106       Genres_Health & Fitness    0.010466
19   Category_HEALTH_AND_FITNESS    0.010367
15                Category_FAMILY    0.009181
```



Observations:

- Reviews, Installs, and Size (MB) are the most influential features in the model, with Reviews having the highest impact.
- The Mean Squared Error (MSE) of 0.2101 indicates a moderate level of prediction accuracy.
- The low R-squared score of 0.1136 suggests that the model explains only a small portion of the target's variance, indicating room for improvement.
- Specific app categories and genres like "Tools" and "Health & Fitness" contribute to predictions, but their impact is relatively minor compared to the top features.

Conclusion

This exploratory data analysis provided valuable insights into the characteristics and user engagement of apps on the Google Play Store. Key findings reveal that while high ratings are common, the number of reviews varies widely, potentially indicating varying levels of user satisfaction or popularity. Additionally, the predominance of free apps and "Everyone"-rated apps suggest a broad and accessible app ecosystem. These insights lay the groundwork for further analysis, such as predictive modeling or deeper trend analysis, to understand factors that influence app success on the Google Play Store.