In [1]: import

import numpy as np
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model\_selection import train\_test\_split
from sklearn.linear\_model import LinearRegression

In [2]:

df = pd.read\_csv("mobile.csv")
df

Out[2]:

t[2]:		Phone Name	Rating ?/5	Number of Ratings	RAM	ROM/Storage	Back/Rare Camera	Front Camera	Battery	Processor	Price in INR
	0	POCO C50 (Royal Blue, 32 GB)	4.2	33,561	2 GB RAM	32 GB ROM	8MP Dual Camera	5MP Front Camera	5000 mAh	Mediatek Helio A22 Processor, Upto 2.0 GHz Pro	₹5,649
	1	POCO M4 5G (Cool Blue, 64 GB)	4.2	77,128	4 GB RAM	64 GB ROM	50MP + 2MP	8MP Front Camera	5000 mAh	Mediatek Dimensity 700 Processor	₹11,999
	2	POCO C51 (Royal Blue, 64 GB)	4.3	15,175	4 GB RAM	64 GB ROM	8MP Dual Rear Camera	5MP Front Camera	5000 mAh	Helio G36 Processor	₹6,999
	3	POCO C55 (Cool Blue, 64 GB)	4.2	22,621	4 GB RAM	64 GB ROM	50MP Dual Rear Camera	5MP Front Camera	5000 mAh	Mediatek Helio G85 Processor	₹7,749
	4	POCO C51 (Power Black, 64 GB)	4.3	15,175	4 GB RAM	64 GB ROM	8MP Dual Rear Camera	5MP Front Camera	5000 mAh	Helio G36 Processor	₹6,999
	•••										
1	1831	Infinix Note 7 (Forest Green, 64 GB)	4.3	25,582	4 GB RAM	64 GB ROM	48MP + 2MP + 2MP + Al Lens Camera	16MP Front Camera	5000 mAh	MediaTek Helio G70 Processor	₹14,999
1	1832	Infinix Note 7 (Bolivia Blue, 64 GB)	4.3	25,582	4 GB RAM	64 GB ROM	48MP + 2MP + 2MP + Al Lens Camera	16MP Front Camera	5000 mAh	MediaTek Helio G70 Processor	₹14,999

	Phone Name	Rating ?/5	Number of Ratings	RAM	ROM/Storage	Back/Rare Camera	Front Camera	Battery	Processor	Price in INR
1833	Infinix Note 7 (Aether Black, 64 GB)	4.3	25,582	4 GB RAM	64 GB ROM	48MP + 2MP + 2MP + Al Lens Camera	16MP Front Camera	5000 mAh	MediaTek Helio G70 Processor	₹14,999
1834	Infinix Zero 8i (Silver Diamond, 128 GB)	4.2	7,117	8 GB RAM	128 GB ROM	48MP + 8MP + 2MP + Al Lens Camera	16MP + 8MP Dual Front Camera	4500 mAh	MediaTek Helio G90T Processor	₹18,999
1835	Infinix S5 (Quetzal Cyan, 64 GB)	4.3	15,701	4 GB RAM	64 GB ROM	16MP + 5MP + 2MP + Low Light Sensor	32MP Front Camera	4000 mAh	Helio P22 (MTK6762) Processor	₹10,999

1836 rows × 11 columns

In [3]: | df.head()

Out[3]:

	Phone Name	Rating ?/5	Number of Ratings	RAM	ROM/Storage	Back/Rare Camera	Front Camera	Battery	Processor	Price in INR	Dat Scra <sub>l</sub>
0	POCO C50 (Royal Blue, 32 GB)	4.2	33,561	2 GB RAM	32 GB ROM	8MP Dual Camera	5MP Front Camera	5000 mAh	Mediatek Helio A22 Processor, Upto 2.0 GHz Pro	₹5,649	2023
1	POCO M4 5G (Cool Blue, 64 GB)	4.2	77,128	4 GB RAM	64 GB ROM	50MP + 2MP	8MP Front Camera	5000 mAh	Mediatek Dimensity 700 Processor	₹11,999	2023
2	POCO C51 (Royal Blue, 64 GB)	4.3	15,175	4 GB RAM	64 GB ROM	8MP Dual Rear Camera	5MP Front Camera	5000 mAh	Helio G36 Processor	₹6,999	2023
3	POCO C55 (Cool Blue, 64 GB)	4.2	22,621	4 GB RAM	64 GB ROM	50MP Dual Rear Camera	5MP Front Camera	5000 mAh	Mediatek Helio G85 Processor	₹7,749	2023
4	POCO C51 (Power Black, 64 GB)	4.3	15,175	4 GB RAM	64 GB ROM	8MP Dual Rear Camera	5MP Front Camera	5000 mAh	Helio G36 Processor	₹6,999	2023

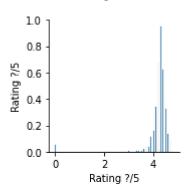
## Data cleaning and pre processing

```
In [4]:
         df.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 1836 entries, 0 to 1835
        Data columns (total 11 columns):
             Column
                                Non-Null Count Dtype
                                -----
         0
             Phone Name
                                1836 non-null
                                               object
             Rating ?/5
                                1836 non-null
                                                float64
         1
         2
             Number of Ratings 1836 non-null
                                               object
         3
                                               object
                                1836 non-null
             ROM/Storage
                                1662 non-null
                                               object
         5
             Back/Rare Camera 1827 non-null
                                               object
         6
             Front Camera
                                1435 non-null
                                               object
         7
             Battery
                                1826 non-null
                                                object
         8
             Processor
                                1781 non-null
                                                object
             Price in INR
         9
                              1836 non-null
                                                object
         10 Date of Scraping 1836 non-null
                                                object
        dtypes: float64(1), object(10)
        memory usage: 157.9+ KB
In [5]:
         df.describe()
Out[5]:
                Rating ?/5
        count 1836.000000
        mean
                 4.210512
          std
                 0.543912
          min
                 0.000000
         25%
                 4.200000
         50%
                 4.300000
         75%
                 4.400000
                 4.800000
         max
In [6]:
         df.columns
Out[6]: Index(['Phone Name', 'Rating ?/5', 'Number of Ratings', 'RAM', 'ROM/Storage',
               'Back/Rare Camera', 'Front Camera', 'Battery', 'Processor',
               'Price in INR', 'Date of Scraping'],
              dtype='object')
```

## **EDA and VISUALIZATION**

```
In [7]: sns.pairplot(df)
```

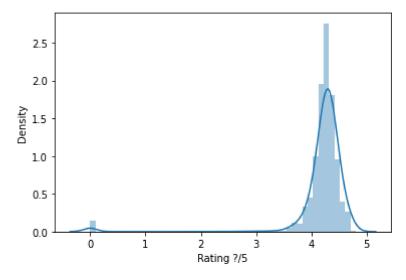
Out[7]: <seaborn.axisgrid.PairGrid at 0x1495a28ca00>



```
In [8]: sns.distplot(df["Rating ?/5"])
```

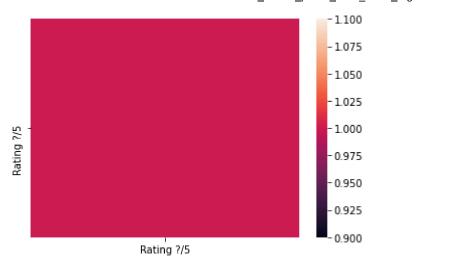
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning:
 distplot` is a deprecated function and will be removed in a future version. Please adap
 t your code to use either `displot` (a figure-level function with similar flexibility) o
 r `histplot` (an axes-level function for histograms).
 warnings.warn(msg, FutureWarning)

Out[8]: <AxesSubplot:xlabel='Rating ?/5', ylabel='Density'>



```
In [10]: sns.heatmap(df1.corr())
```

Out[10]: <AxesSubplot:>



```
In [11]:     x = df1[['Rating ?/5','Rating ?/5']]
     y = df1['Rating ?/5']
```

## split the data into training and test data

```
In [12]:
          x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.3)
In [13]:
          lr = LinearRegression()
          lr.fit(x train, y train)
Out[13]: LinearRegression()
In [14]:
          lr.intercept
         -2.6645352591003757e-15
Out[14]:
In [15]:
           coeff = pd.DataFrame(lr.coef_, x.columns, columns =['Co-efficient'])
           coeff
Out[15]:
                    Co-efficient
          Rating ?/5
                           0.5
          Rating ?/5
                           0.5
In [16]:
           prediction = lr.predict(x_test)
          plt.scatter(y_test, prediction)
Out[16]: <matplotlib.collections.PathCollection at 0x1495aed12e0>
```

```
4
          3
          2
          1
          0
In [17]:
          lr.score(x_test,y_test)
Out[17]: 1.0
In [18]:
          from sklearn.linear_model import Ridge,Lasso
In [19]:
          rr=Ridge(alpha=10)
          rr.fit(x_train,y_train)
          rr.score(x_test,y_test)
```

```
rr.score(x_train,y_train)
```

```
Out[19]:
         0.9998643503417138
```

```
In [20]:
          rr.score(x_test,y_test)
```

Out[20]: 0.9998642822291992

```
In [21]:
          la = Lasso(alpha=10)
          la.fit(x_train,y_train)
```

Out[21]: Lasso(alpha=10)

```
In [22]:
          la.score(x_test,y_test)
```

-0.0005021207975841602 Out[22]:

```
In [23]:
          from sklearn.linear_model import ElasticNet
          en = ElasticNet()
          en.fit(x_train,y_train)
```

Out[23]: ElasticNet()

```
In [24]:
           print(en.coef_)
```

```
[0. 0.]
```

In [25]:

print(en.intercept\_)

4.20739299610895

In [26]:

print(en.predict(x\_test))

```
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In [27]:
         print(en.score(x test,y test))
```

-0.0005021207975841602

## **Evaluation Metrics**

```
In [28]: from sklearn import metrics
In [29]: print("Mean Absolute Error:",metrics.mean_absolute_error(y_test,prediction))
    Mean Absolute Error: 1.1767155106734871e-16
In [30]: print("Mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
    Mean Squared Error: 1.3601050090017446e-31
In [32]: print("Root Mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction))
```

Root Mean Squared Error: 3.6879601529866676e-16