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

In [2]:
```
df=pd.read_csv(r"C:\Users\user\Downloads\12_mobile_prices_2023.csv")
df.fillna(0,inplace=True)
df
```

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Out[2]:

	Phone Name	Rating ?/5	Number of Ratings	RAM	ROM/Storage	Back/Rare Camera	Front Camera	Battery	Processor	Pı
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...	₹
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	₹
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	₹
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	₹
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	₹
...	...	...	...	...	...	...	...	...	...	
1831	Infinix Note 7 (Forest Green, 64 GB)	4.3	25,582	4 GB RAM	64 GB ROM	48MP + 2MP + 2MP + AI Lens Camera	16MP Front Camera	5000 mAh	MediaTek Helio G70 Processor	₹1
1832	Infinix Note 7 (Bolivia Blue, 64 GB)	4.3	25,582	4 GB RAM	64 GB ROM	48MP + 2MP + 2MP + AI Lens Camera	16MP Front Camera	5000 mAh	MediaTek Helio G70 Processor	₹1
1833	Infinix Note 7 (Aether Black, 64 GB)	4.3	25,582	4 GB RAM	64 GB ROM	48MP + 2MP + 2MP + AI Lens Camera	16MP Front Camera	5000 mAh	MediaTek Helio G70 Processor	₹1
1834	Infinix Zero 8i (Silver Diamond, 128 GB)	4.2	7,117	8 GB RAM	128 GB ROM	48MP + 8MP + 2MP + AI Lens Camera	16MP + 8MP Dual Front Camera	4500 mAh	MediaTek Helio G90T Processor	₹1
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	₹1

1836 rows × 11 columns

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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
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

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 
 1   Rating ?/5         1836 non-null   float64
 2   Number of Ratings  1836 non-null   object 
 3   RAM                1836 non-null   object 
 4   ROM/Storage        1836 non-null   object 
 5   Back/Rare Camera   1836 non-null   object 
 6   Front Camera       1836 non-null   object 
 7   Battery            1836 non-null   object 
 8   Processor          1836 non-null   object 
 9   Price in INR       1836 non-null   object 
 10  Date of Scraping   1836 non-null   object 
dtypes: float64(1), object(10)
memory usage: 157.9+ KB
```

In [5]:
```
import seaborn as sns
```

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In [6]:
```
df.describe()
```

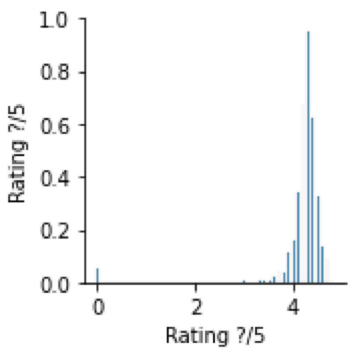
Out[6]:

	Rating ?/5
count	1836.000000
mean	4.210512
std	0.543912
min	0.000000
25%	4.200000
50%	4.300000
75%	4.400000
max	4.800000

In [ ]:

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

Out[7]: <seaborn.axisgrid.PairGrid at 0x2023ebc3a30>



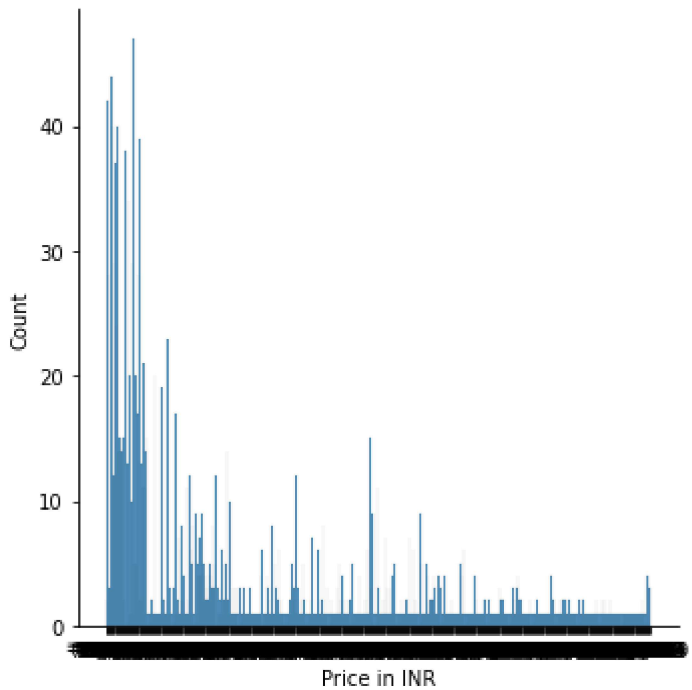
In [8]:
```
df1=df.drop(['Battery'],axis=1)
df1
df1=df1.drop(df1.index[1537:])
df1.isna().sum()
```

Out[8]:
```
Phone Name           0
Rating ?/5           0
Number of Ratings    0
RAM                  0
ROM/Storage          0
Back/Rare Camera     0
Front Camera         0
Processor            0
Price in INR         0
Date of Scraping     0
dtype: int64
```

Loading [MathJax]/jax/output/HTML-CSS/fonts/STIX-Web/fontdata.js

In [9]:
```
sns.displot(df['Price in INR'])
```

Out[9]: <seaborn.axisgrid.FacetGrid at 0x2023bdd9f10>



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

Out[10]: <AxesSubplot:>

In [11]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

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In [12]:
```
df1.isna().sum()
```

Out[12]:
```
Phone Name           0
Rating ?/5           0
Number of Ratings    0
RAM                  0
ROM/Storage          0
Back/Rare Camera     0
Front Camera         0
Processor            0
Price in INR         0
Date of Scraping     0
dtype: int64
```

In [13]:
```
y=df1['Rating ?/5']
x=df1.drop(['Phone Name','ROM/Storage','RAM','Back/Rare Camera','Front Camera',
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
print(x_train)
```

```
      Rating ?/5
1417        3.8
1003        4.3
264         4.3
1053        4.3
490         4.6
...         ...
1051        4.4
529         4.2
1347        3.9
612         4.3
1227        4.3

[1075 rows x 1 columns]
```

In [14]:
```
model=LinearRegression()
model.fit(x_train,y_train)
model.intercept_
```

Out[14]:
```
1.0658141036401503e-14
```

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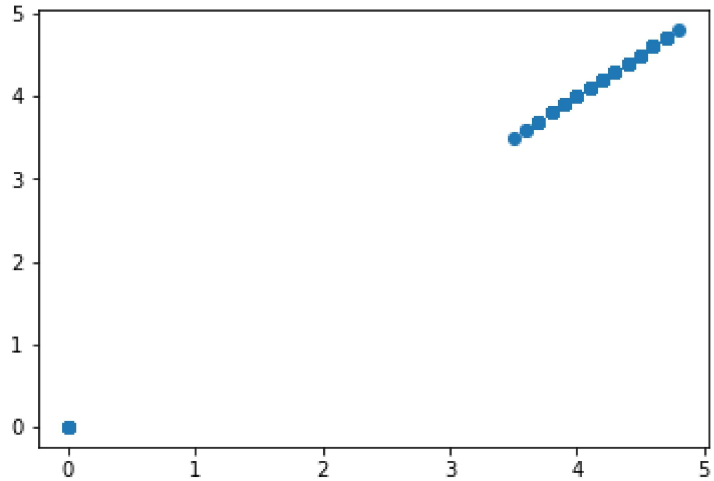
In [15]:
```
prediction=model.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[15]: <matplotlib.collections.PathCollection at 0x20242871c40>



In [16]:
```
model.score(x_test,y_test)
```

Out[16]: 1.0

In [17]:
```
from sklearn.linear_model import Ridge,Lasso
```

In [18]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[18]: Ridge(alpha=10)

In [19]:
```
rr.score(x_test,y_test)
```

Out[19]: 0.9978250643987941

In [20]:
```
la =Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[20]: Lasso(alpha=10)

In [21]:
```
la.score(x_test,y_test)
```

Out[21]: -0.0076789222100206445

In [22]:
```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[22]: ElasticNet()

In [23]:
```
print(en.coef_)
```

```
[0.]
```

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

```
4.254325581395348
```

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In [25]:
```
print(en.predict(x_test))
```

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```
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```

In [26]:
```
print(en.score(x_test,y_test))
```

```
-0.007678922100206445
```

In [27]:
```
from sklearn import metrics
```

In [28]:
```
print("Mean Absolute Error:",metrics.mean_absolute_error(y_test,prediction))
```

```
Mean Absolute Error: 4.719649394726856e-16
```

In [29]:
```
print("Mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
```

```
Mean Squared Error: 2.063076166089367e-30
```

In [30]:
```
print("Root Mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,prec
```

```
Root Mean Squared Error: 1.4363412429117834e-15
```