In [1]:
```python
import requests
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
#Importing file from url.
url = 'https://raw.githubusercontent.com/Raghavagr/Laptop_Price_Prediction/main/laptop_data.csv'
res = requests.get(url, allow_redirects=True)
with open('laptop.csv','wb') as file:
    file.write(res.content)
```

In [2]:

Out[2]:

	Unnamed: 0	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price
1293	1293	Lenovo	Notebook	15.6	IPS Panel Full HD 1920x1080	Intel Core i7 6700HQ 2.6GHz	8GB	1TB HDD	Nvidia GeForce GTX 960M	Windows 10	2.6kg	47898.7200
1294	1294	HP	Notebook	15.6	Full HD 1920x1080	AMD A9-Series 9410 2.9GHz	6GB	1.0TB Hybrid	AMD Radeon R7 M440	Windows 10	2.04kg	29303.4672
1295	1295	Dell	Notebook	15.6	1366x768	Intel Core i7 7500U 2.7GHz	8GB	1TB HDD	AMD Radeon R5 M430	Linux	2.3kg	42943.1472
1296	1296	HP	Netbook	11.6	1366x768	Intel Celeron Dual Core N3060 1.6GHz	2GB	32GB Flash Storage	Intel HD Graphics 400	Windows 10	1.17kg	11135.5200
1297	1297	Asus	Notebook	15.6	1366x768	Intel Core i7 6500U 2.5GHz	4GB	500GB HDD	Nvidia GeForce 920M	Windows 10	2.2kg	38378.6496
1298	1298	Lenovo	2 in 1 Convertible	14.0	IPS Panel Full HD / Touchscreen 1920x1080	Intel Core i7 6500U 2.5GHz	4GB	128GB SSD	Intel HD Graphics 520	Windows 10	1.8kg	33992.6400
1299	1299	Lenovo	2 in 1 Convertible	13.3	IPS Panel Quad HD+ / Touchscreen 3200x1800	Intel Core i7 6500U 2.5GHz	16GB	512GB SSD	Intel HD Graphics 520	Windows 10	1.3kg	79866.7200
1300	1300	Lenovo	Notebook	14.0	1366x768	Intel Celeron Dual Core N3050 1.6GHz	2GB	64GB Flash Storage	Intel HD Graphics	Windows 10	1.5kg	12201.1200
1301	1301	HP	Notebook	15.6	1366x768	Intel Core i7 6500U 2.5GHz	6GB	1TB HDD	AMD Radeon R5 M330	Windows 10	2.19kg	40705.9200
1302	1302	Asus	Notebook	15.6	1366x768	Intel Celeron Dual Core N3050 1.6GHz	4GB	500GB HDD	Intel HD Graphics	Windows 10	2.2kg	19660.3200

In [3]:
```python
data.shape
```

Out[3]:
```
(1303, 12)
```

In [4]:
```python
#checking for null values.
data.isnull().sum()
```

Out[4]:
```
Unnamed: 0          0
Company             0
TypeName            0
Inches              0
ScreenResolution    0
Cpu                 0
Ram                 0
Memory              0
Gpu                 0
OpSys               0
Weight              0
Price               0
dtype: int64
```

In [5]:
```python
#opping unnecessary data.
data.drop(columns=['Unnamed: 0'],inplace=True)
```

Out[5]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price
0	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 2.3GHz	8GB	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37kg	71378.6832
1	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8GB	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34kg	47895.5232
2	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8GB	256GB SSD	Intel HD Graphics 620	No OS	1.86kg	30636.0000

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price
3	Apple	Ultrabook	15.4	IPS Panel Retina Display	Intel Core i7	16GB	512GB SSD	AMD Radeon Pro	macOS	1.83kg	135195.3360

In [6]:
```
#removing unitr return after ram,weight and converting them to numeric value.
data['Ram']=data['Ram'].str.replace("GB","")
data['Weight']=data['Weight'].str.replace("kg","")
data['Ram']=data['Ram'].astype('int32')
```

In [7]:
```

```

Out[7]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price
0	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 2.3GHz	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832
1	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	47895.5232

In [8]:
```

#Data Preprocessing.
#We are creating touchscreen column which is a binary attribute one means touchscreen 0 no toucscreen.
data['Touchscreen'] = data['ScreenResolution'].apply(lambda x:1 if 'Touchscreen' in x else 0)
#extract IPS column
data['Ips'] = data['ScreenResolution'].apply(lambda x:1 if 'IPS' in x else 0)
#We will split resoluttion in x and y by first spllitting by space the spllitting by cross symbol
def findXresolution(s):
  return s.split()[-1].split("x")[0]
def findYresolution(s):
  return s.split()[-1].split("x")[1]
#finding the x_res and y_res from screen resolution
data['X_res'] = data['ScreenResolution'].apply(lambda x: findXresolution(x))
data['Y_res'] = data['ScreenResolution'].apply(lambda y: findYresolution(y))
#convert to numeric
data['X_res'] = data['X_res'].astype('int')
data['Y_res'] = data['Y_res'].astype('int')
```

Out[8]:
```
Price          1.000000
Ram            0.743007
X_res          0.556529
Y_res          0.552809
Ips            0.252208
Weight         0.210370
Touchscreen    0.191226
Inches         0.068197
Name: Price, dtype: float64
```

In [9]:
```
#Now we can see in the coorelation that Incehes is not correlated much while X_res ,Y_res is correlated much so we com
#WE will convert them to Pixel per inches(PPI) using standard formula.
data['ppi'] = (((data['X_res']**2) + (data['Y_res']**2))**0.5/data['Inches']).astype('float')
```

In [10]:
```
#Now we can see in the coorelation that Incehes is not correlated much while X_res ,Y_res is correlated much so we com
#WE will convert them to Pixel per inches(PPI) using standard formula.
data['ppi'] = (((data['X_res']**2) + (data['Y_res']**2))**0.5/data['Inches']).astype('float')
```

In [11]:
```
data.drop(columns = ['ScreenResolution', 'Inches','X_res','Y_res'], inplace=True)
```

In [12]:
```
#now we can see cpu column also contain many different values so will also split it.
def fetch_processor(x):
    cpu_name="".join(x.split()[0:3])
    if cpu_name=='Intel Core i7 'or cpu_name=='Intel Core i3'or cpu_name=='Intel Core i5':
        return cpu_name
    elif cpu_name.split()[0]=='Intel':
        return 'Other Intel Processor'
    else:
        return 'AMD Processor'
```

In [13]:
```
# Which brand GPU is in laptop
data['Gpu_brand'] = data['Gpu'].apply(lambda x:x.split()[0])
#there is only 1 row of ARM GPU so remove it
data = data[data['Gpu_brand'] != 'ARM']
```

In [15]:
```
#Get which OP sys
def cat_os(inp):
    if inp == 'Windows 10' or inp == 'Windows 7' or inp == 'Windows 10 S':
        return 'Windows'
    elif inp == 'macOS' or inp == 'Mac OS X':
        return 'Mac'
    else:
        return 'Others/No OS/Linux'
data['os'] = data['OpSys'].apply(cat_os)
```

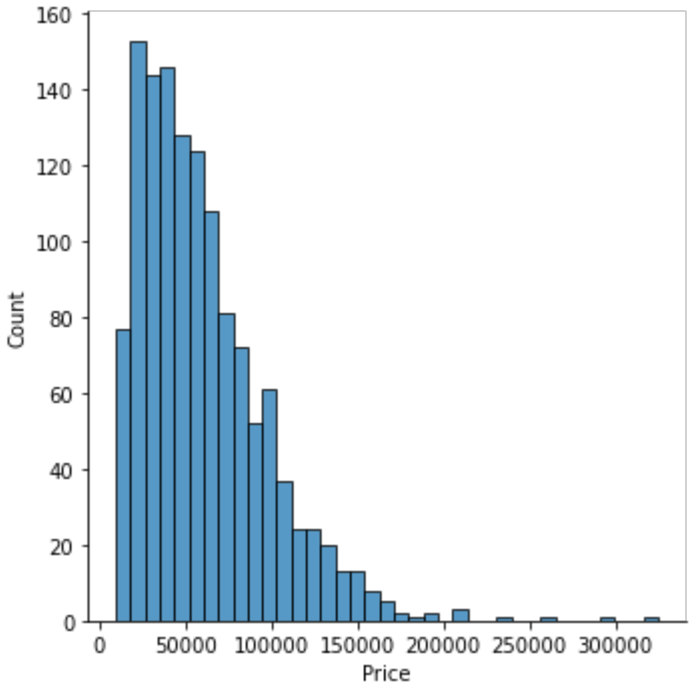
In [16]:
```

```

Out[16]:

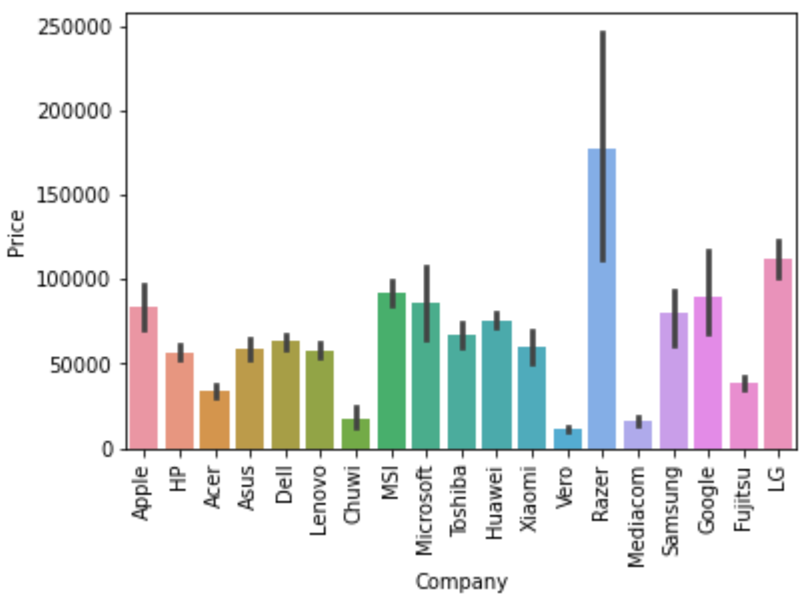
	Company	TypeName	Cpu	Ram	Memory	Weight	Price	Touchscreen	Ips	ppi	cpu_brand	Gpu_brand	os

	Company	TypeName	Cpu	Ram	Memory	Weight	Price	Touchscreen	Ips	ppi	cpu_brand	Gpu_brand	os
0	Apple	Ultrabook	Intel Core i5 2.3GHz	8	128GB SSD	1.37	71378.6832	0	1	226.983005	AMD Processor	Intel	Mac
1	Apple	Ultrabook	Intel Core i5 1.8GHz	8	128GB Flash Storage	1.34	47895.5232	0	0	127.677940	AMD Processor	Intel	Mac
2	HP	Notebook	Intel Core i5 7200U 2.5GHz	8	256GB SSD	1.86	30636.0000	0	0	141.211998	AMD Processor	Intel	Others/No OS/Linux
3	Apple	Ultrabook	Intel Core i7 2.7GHz	16	512GB SSD	1.83	135195.3360	0	1	220.534624	AMD Processor	AMD	Mac
			Intel Core		256GB						AMD		

In [17]:
```
#We will now see distribution of our target column that is price.
sns.displot(data['Price'])
plt.show()
#the disrtibution is skewed towards left showing that more laptops at lower price because lower price laptop are sold
```

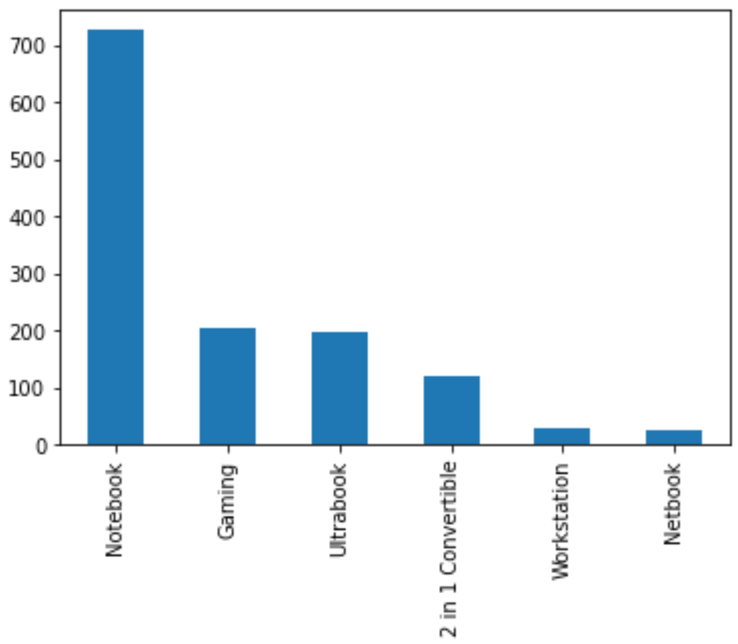


In [18]:
```
#A bar plat to check whether brand name affect price of laptop.
sns.barplot(x=data['Company'], y=data['Price'])
plt.xticks(rotation="vertical")

plt.show()
#we can se from the plot that Razer, Apple, LG, Microsoft, Google, MSI laptops are expensive, and others are in the bu
```



In [19]:

Out[19]: <AxesSubplot:>



In [20]:

```
#checking corelation between various attributes.
data.corr()
```

Out[20]:

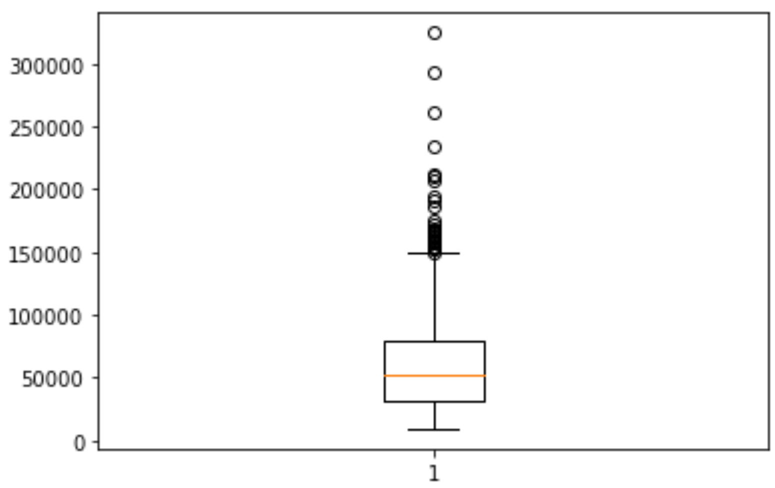
```
Ram            0.742905
Weight         0.209867
Price          1.000000
Touchscreen    0.192917
Ips            0.253320
ppi            0.475368
Name: Price, dtype: float64
```

In [21]:

```
#We can se few laptop price is exceedling high so they are shown as outlier in box plot this is very common a s some e
plt.boxplot(data['Price'])
```

Out[21]:

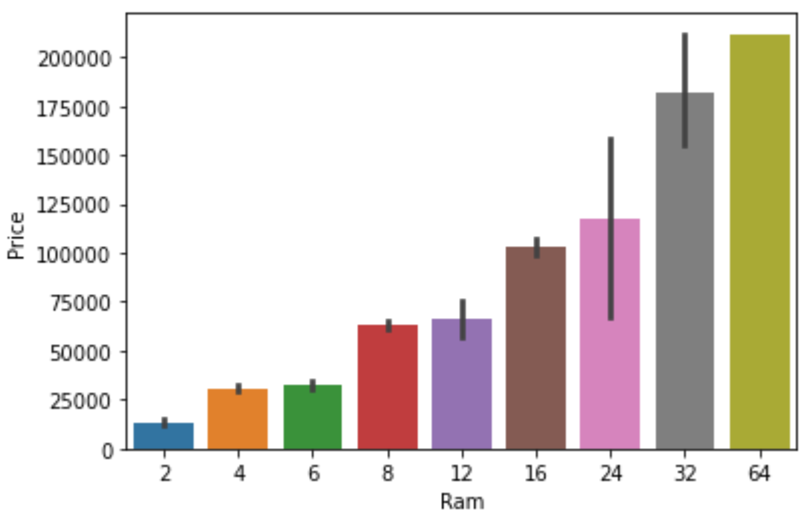
```
{'whiskers': [<matplotlib.lines.Line2D at 0x212646f96d0>,
  <matplotlib.lines.Line2D at 0x212646f99a0>],
 'caps': [<matplotlib.lines.Line2D at 0x212646f9d60>,
  <matplotlib.lines.Line2D at 0x21264705130>],
 'boxes': [<matplotlib.lines.Line2D at 0x212646f9310>],
 'medians': [<matplotlib.lines.Line2D at 0x212647054c0>],
 'fliers': [<matplotlib.lines.Line2D at 0x21264705850>],
 'means': []}
```



In [22]:

```
#As price is having very strong corelation with ram we will plot it
sns.barplot(data['Ram'], data['Price'])
```

```
C:\Users\sawan\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables as
keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



In [23]:
```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
```

In [24]:
```python
le={}
for col in set(data.columns).difference({'Price'}):
    le[col] = LabelEncoder()
    data[col]  = le[col].fit_transform(data[col])
```

Out[24]:

	Company	TypeName	Cpu	Ram	Memory	Weight	Price	Touchscreen	Ips	ppi	cpu_brand	Gpu_brand	os
0	1	4	65	3	4	37	71378.6832	0	1	29	0	1	0
1	1	4	63	3	2	34	47895.5232	0	0	10	0	1	0
2	7	3	74	3	16	72	30636.0000	0	0	12	0	1	1
3	1	4	85	5	29	69	135195.3360	0	1	25	0	0	0
4	1	4	67	3	16	37	96095.8080	0	1	29	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1298	10	0	89	1	4	68	33992.6400	1	1	14	0	1	2
1299	10	0	89	5	29	31	79866.7200	1	1	34	0	1	2
1300	10	3	34	0	35	49	12201.1200	0	0	5	0	1	2
1301	7	3	89	2	10	100	40705.9200	0	0	1	0	0	2
1302	2	3	34	1	26	102	19660.3200	0	0	1	0	1	2

1302 rows × 13 columns

In [25]:
```python
def normalize_col(col_name):
      return (data[col_name] -data[col_name].min())/(data[col_name].max()-data[col_name].min())
for col in ['Price']:
     data[col]=normalize_col(col)
```

Out[25]:

	Company	TypeName	Cpu	Ram	Memory	Weight	Price	Touchscreen	Ips	ppi	cpu_brand	Gpu_brand	os
0	1	4	65	3	4	37	0.196741	0	1	29	0	1	0
1	1	4	63	3	2	34	0.122353	0	0	10	0	1	0
2	7	3	74	3	16	72	0.067679	0	0	12	0	1	1
3	1	4	85	5	29	69	0.398895	0	1	25	0	0	0
4	1	4	67	3	16	37	0.275038	0	1	29	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1298	10	0	89	1	4	68	0.078312	1	1	14	0	1	2
1299	10	0	89	5	29	31	0.223629	1	1	34	0	1	2
1300	10	3	34	0	35	49	0.009283	0	0	5	0	1	2
1301	7	3	89	2	10	100	0.099578	0	0	1	0	0	2
1302	2	3	34	1	26	102	0.032911	0	0	1	0	1	2

1302 rows × 13 columns

In [26]:
```python
#x=df.drop('Price_euros',axis=1)
#y=df.Price_euros
x = data.drop(columns=['Price'])
y =  data['Price']
```

In [39]:

Out[39]:

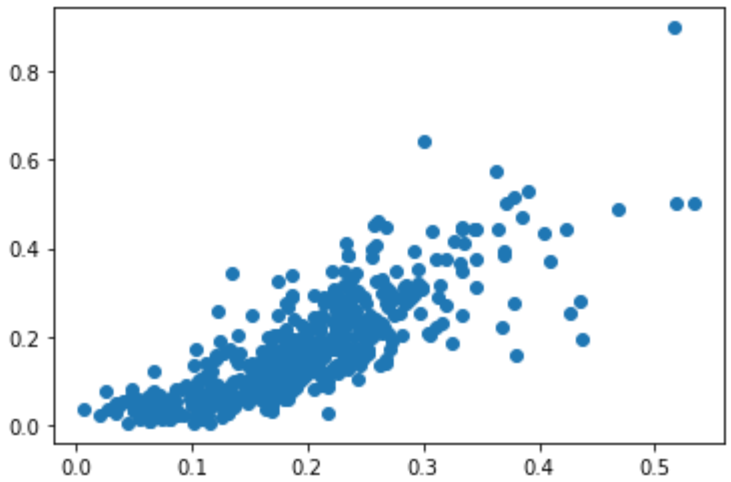
	Company	TypeName	Cpu	Ram	Memory	Weight	Touchscreen	Ips	ppi	cpu_brand	Gpu_brand	os
935	7	2	68	3	16	27	0	0	19	0	1	2
11	7	3	56	1	26	72	0	0	12	0	1	1
835	4	1	102	5	18	146	0	0	12	0	2	2
332	2	3	97	3	18	84	0	0	14	0	1	2
963	16	4	97	3	29	10	1	0	19	0	1	2
553	7	3	56	3	10	128	0	0	2	0	1	2
1251	7	3	8	1	26	72	0	0	1	0	0	2
54	0	3	59	1	10	117	0	0	1	0	1	2
663	7	3	56	2	10	87	0	0	12	0	0	2
233	4	3	74	3	16	55	0	0	14	0	1	2

In [ ]:
```python
pip install sckit learn
```

In [27]:
```
#training our model o n SVm
from sklearn.svm import SVR
regressor = SVR(kernel = 'rbf')
```

In [38]:
```
#Evaluating our SVM Model
y1pred=models2.predict(x_test)
plt.scatter(ypred,y_test)

print('R2 score',r2_score(y_test,y1pred))
```

```
R2 score 0.610653311893592
MAE 0.05827611660340891
```



In [29]:
```
numerical_cols=data.select_dtypes(exclude=['object']).columns
data1=data[numerical_cols]
```

Out[29]:

	Company	TypeName	Cpu	Ram	Memory	Weight	Price	Touchscreen	Ips	ppi	cpu_brand	Gpu_brand	os
0	1	4	65	3	4	37	0.196741	0	1	29	0	1	0
1	1	4	63	3	2	34	0.122353	0	0	10	0	1	0

In [30]:
```
#Applying linear  regression on numerical data.
x2= data1.drop(columns=['Price'])

y2 = data1['Price']
```

In [31]:

Out[31]:

	Company	TypeName	Cpu	Ram	Memory	Weight	Touchscreen	Ips	ppi	cpu_brand	Gpu_brand	os
0	1	4	65	3	4	37	0	1	29	0	1	0
1	1	4	63	3	2	34	0	0	10	0	1	0
2	7	3	74	3	16	72	0	0	12	0	1	1
3	1	4	85	5	29	69	0	1	25	0	0	0
4	1	4	67	3	16	37	0	1	29	0	1	0

In [32]:
```
lg=LinearRegression()
model=lg.fit(x2train,y2train)
```

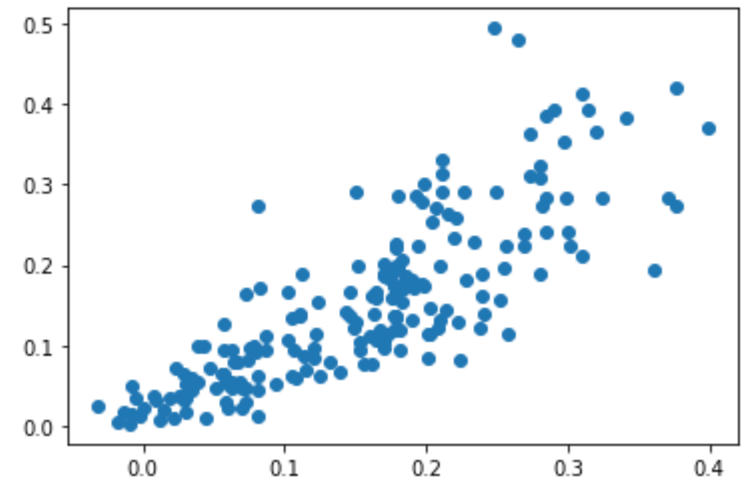
In [33]:

Out[33]: 0.6573348144299724

In [34]:
```
#Evaluation of linaer regression
from sklearn.metrics import r2_score
print('R2 score',r2_score(y2test,y2pred))
print('MAE',mean_absolute_error(y2test,y2pred))
```

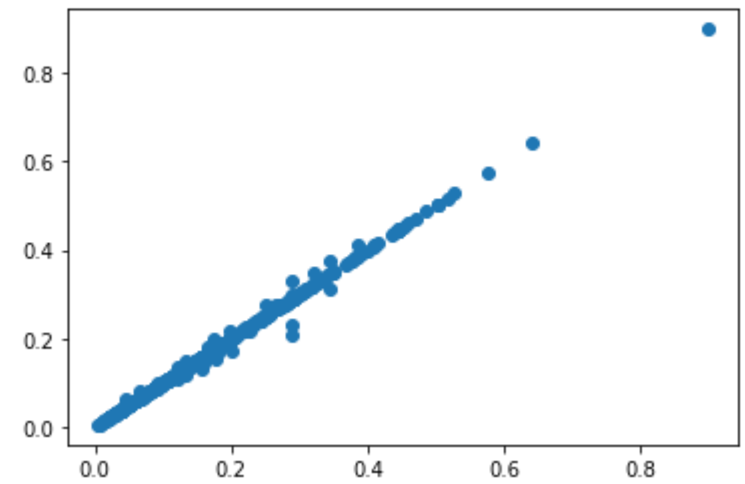
```
R2 score 0.6573348144299724
MAE 0.046044067856167006
```

Out[34]: <matplotlib.collections.PathCollection at 0x21264f4a700>



In [35]:
```
#Aplying DecisiontreeRegressor
from sklearn.tree import DecisionTreeRegressor
decision = DecisionTreeRegressor(random_state = 45)
decision.fit(x,y)
y3pred=decision.predict(x_test)
```

Out[35]: <matplotlib.collections.PathCollection at 0x21264728f70>



In [37]:
```
#Evaluatiing decision tree regressor.
print('R2 score',r2_score(y_test,y3pred))
```

```
R2 score 0.9969123656945321
MAE 0.0014372803572055256
```

In [61]:

Out[61]: array([0.11561181])

In [62]:
```
#As we can our oredicted and actual price is very similar hence decision tree regression is best for our dataset.
```

Out[62]:
```
Company          4.000000
TypeName         3.000000
Cpu             74.000000
Ram              3.000000
Memory          16.000000
Weight          55.000000
Price            0.115612
Touchscreen      0.000000
Ips              0.000000
ppi             14.000000
cpu_brand        0.000000
Gpu_brand        1.000000
os               2.000000
Name: 233, dtype: float64
```

In [ ]: