Laptop_data_Regression

July 2, 2024

1 Laptop Price Prediction

Objective: To develop a predictive model for estimating the price of laptops based on their specifications. By leveraging various supervised machine learning algorithms, we aim to identify the most accurate model for price prediction, providing valuable insights for both consumers and manufacturers in the laptop market.

About the Dataset: The dataset laptop_data.csv contains the following columns:

- Unnamed: 0: An index column.
- Company: The brand or manufacturer of the laptop (e.g., Dell, Apple, HP).
- TypeName: The type or category of the laptop (e.g., Ultrabook, Gaming, Notebook).
- Inches: The screen size of the laptop in inches.
- ScreenResolution: The resolution of the laptop screen (e.g., 1920x1080, 1366x768).
- Cpu: The central processing unit (CPU) model and speed of the laptop.
- Ram: The amount of random access memory (RAM) in the laptop, typically measured in GB.
- Memory: The storage capacity and type of the laptop (e.g., 256GB SSD, 1TB HDD).
- Gpu: The graphics processing unit (GPU) model in the laptop.
- OpSys: The operating system installed on the laptop (e.g., Windows, macOS, Linux).
- Weight: The weight of the laptop in kilograms.
- Price: The price of the laptop, which is the target variable for prediction.

Significance:

- Consumer Decision-Making: By predicting laptop prices based on specifications, consumers can make more informed purchasing decisions and find the best value for their money.
- Market Analysis: Manufacturers and retailers can use the model to analyze market trends, optimize pricing strategies, and understand the impact of various features on the overall price.
- Product Development: Insights gained from the model can guide manufacturers in designing laptops that meet consumer demands while maintaining competitive pricing.

By implementing and comparing various supervised machine learning algorithms, including Linear Regression, Ridge Regression, Lasso Regression, KNeighborsRegressor, DecisionTreeRegressor, SupportVectorRegressor, RandomForestRegressor, and Adaboost Regressor, we aim to identify the most effective model for accurate laptop price prediction.

1)Import required libraries

[3]:
```
import pandas as pd
import numpy as np
```

```
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import r2_score,mean_absolute_error
from sklearn.linear_model import LinearRegression,Ridge,Lasso
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,AdaBoostRegressor
from sklearn.svm import SVR
import pickle
import warnings
warnings.filterwarnings('ignore')
```

2 Exploratory Data Analysis

2)Read the dataset

[91]:
```
df=pd.read_csv('/content/drive/MyDrive/Datasets/laptop_data.csv')
df
```

[91]:

	Unnamed: 0	Company	TypeName	Inches	ScreenResolution
0	0	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600
1	1	Apple	Ultrabook	13.3	1440x900
2	2	HP	Notebook	15.6	Full HD 1920x1080
3	3	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800
4	4	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600
…	…	…	…	…	…
1298	1298	Lenovo	2 in 1 Convertible	14.0	IPS Panel Full HD / Touchscreen 1920x1080
1299	1299	Lenovo	2 in 1 Convertible	13.3	IPS Panel Quad HD+ / Touchscreen 3200x1800
1300	1300	Lenovo	Notebook	14.0	
1301	1301	HP	Notebook	15.6	
1302	1302	Asus	Notebook	15.6	

```
1300                                  1366x768
1301                                  1366x768
1302                                  1366x768

                                        Cpu   Ram               Memory  \
0                       Intel Core i5 2.3GHz   8GB            128GB SSD
1                       Intel Core i5 1.8GHz   8GB  128GB Flash Storage
2                  Intel Core i5 7200U 2.5GHz   8GB            256GB SSD
3                       Intel Core i7 2.7GHz  16GB            512GB SSD
4                       Intel Core i5 3.1GHz   8GB            256GB SSD
…                                        …    …                …
1298               Intel Core i7 6500U 2.5GHz   4GB            128GB SSD
1299               Intel Core i7 6500U 2.5GHz  16GB            512GB SSD
1300  Intel Celeron Dual Core N3050 1.6GHz   2GB   64GB Flash Storage
1301               Intel Core i7 6500U 2.5GHz   6GB              1TB HDD
1302  Intel Celeron Dual Core N3050 1.6GHz   4GB            500GB HDD

                                Gpu       OpSys  Weight        Price
0     Intel Iris Plus Graphics 640       macOS  1.37kg   71378.6832
1           Intel HD Graphics 6000       macOS  1.34kg   47895.5232
2            Intel HD Graphics 620       No OS  1.86kg   30636.0000
3               AMD Radeon Pro 455       macOS  1.83kg  135195.3360
4     Intel Iris Plus Graphics 650       macOS  1.37kg   96095.8080
…                              …         …     …           …
1298         Intel HD Graphics 520  Windows 10   1.8kg   33992.6400
1299         Intel HD Graphics 520  Windows 10   1.3kg   79866.7200
1300             Intel HD Graphics  Windows 10   1.5kg   12201.1200
1301            AMD Radeon R5 M330  Windows 10  2.19kg   40705.9200
1302             Intel HD Graphics  Windows 10   2.2kg   19660.3200

[1303 rows x 12 columns]
```

3) Statistical Analysis

[92]:
```
df.shape
```

[92]:
```
(1303, 12)
```

The dataset contains 1303 rows and 12 columns.

[93]:
```
df.describe()
```

[93]:
```
       Unnamed: 0       Inches         Price
count  1303.00000  1303.000000    1303.000000
mean    651.00000    15.017191   59870.042910
std     376.28801     1.426304   37243.201786
min       0.00000    10.100000    9270.720000
25%     325.50000    14.000000   31914.720000
```

```
50%     651.00000    15.600000   52054.560000
75%     976.50000    15.600000   79274.246400
max    1302.00000    18.400000  324954.720000
```

[94]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1303 entries, 0 to 1302
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Unnamed: 0        1303 non-null   int64  
 1   Company           1303 non-null   object 
 2   TypeName          1303 non-null   object 
 3   Inches            1303 non-null   float64
 4   ScreenResolution  1303 non-null   object 
 5   Cpu               1303 non-null   object 
 6   Ram               1303 non-null   object 
 7   Memory            1303 non-null   object 
 8   Gpu               1303 non-null   object 
 9   OpSys             1303 non-null   object 
 10  Weight            1303 non-null   object 
 11  Price             1303 non-null   float64
dtypes: float64(2), int64(1), object(9)
memory usage: 122.3+ KB
```

[95]:
```
# to obtain unique elements in each columns.
df.nunique()
```

[95]:
```
Unnamed: 0          1303
Company               19
TypeName               6
Inches                18
ScreenResolution      40
Cpu                  118
Ram                    9
Memory                39
Gpu                  110
OpSys                  9
Weight               179
Price                791
dtype: int64
```

3 Data Cleaning

4) Handling Missing Values

[96]:
```
# To drop a column
df.drop(['Unnamed: 0'],axis=1,inplace=True)
df.drop_duplicates(inplace=True)
df.reset_index(drop=True,inplace=True)
df.head()
```

[96]:

	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
3	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16GB	512GB SSD	AMD Radeon Pro 455	macOS	1.83kg	135195.3360
4	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 3.1GHz	8GB	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37kg	96095.8080

[97]:
```
df.shape
```

[97]:
```
(1274, 11)
```

[98]:
```
# To check the missing values
df.isna().sum()
```

[98]:
```
Company             0
TypeName            0
Inches              0
ScreenResolution    0
Cpu                 0
Ram                 0
Memory              0
Gpu                 0
OpSys               0
Weight              0
Price               0
dtype: int64
```

There is no missing values in the dataset.

5)Datatype Conversion

[99]:
```
df.dtypes
```

[99]:
```
Company              object
TypeName             object
Inches              float64
ScreenResolution     object
Cpu                  object
Ram                  object
Memory               object
Gpu                  object
OpSys                object
Weight               object
Price               float64
dtype: object
```

[100]:
```
#to remove units of Ram and Weight
df['Ram']=df['Ram'].str.replace('GB',"")
df['Ram']=df['Ram'].astype(int)
df['Weight']=df['Weight'].str.replace('kg',"")
df['Weight']=df['Weight'].astype(float)
df.head()
```

[100]:

	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
2	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8	256GB SSD	Intel HD Graphics 620	No OS	1.86	30636.0000
3	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	135195.3360
4	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 3.1GHz	8	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37	96095.8080

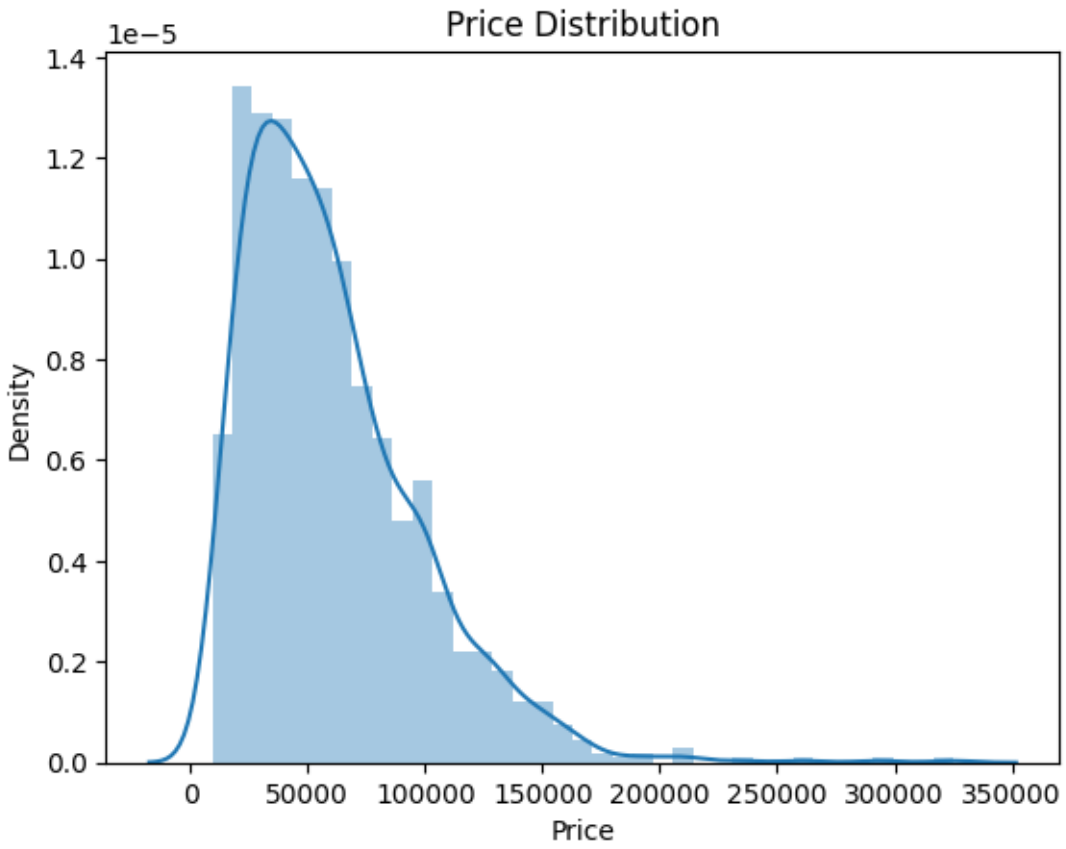
[101]:
```
df.dtypes
```

[101]:
```
Company              object
TypeName             object
Inches              float64
ScreenResolution     object
Cpu                  object
Ram                   int64
Memory               object
Gpu                  object
OpSys                object
Weight              float64
Price               float64
dtype: object
```

6)Data Visualization and Feature Engineering

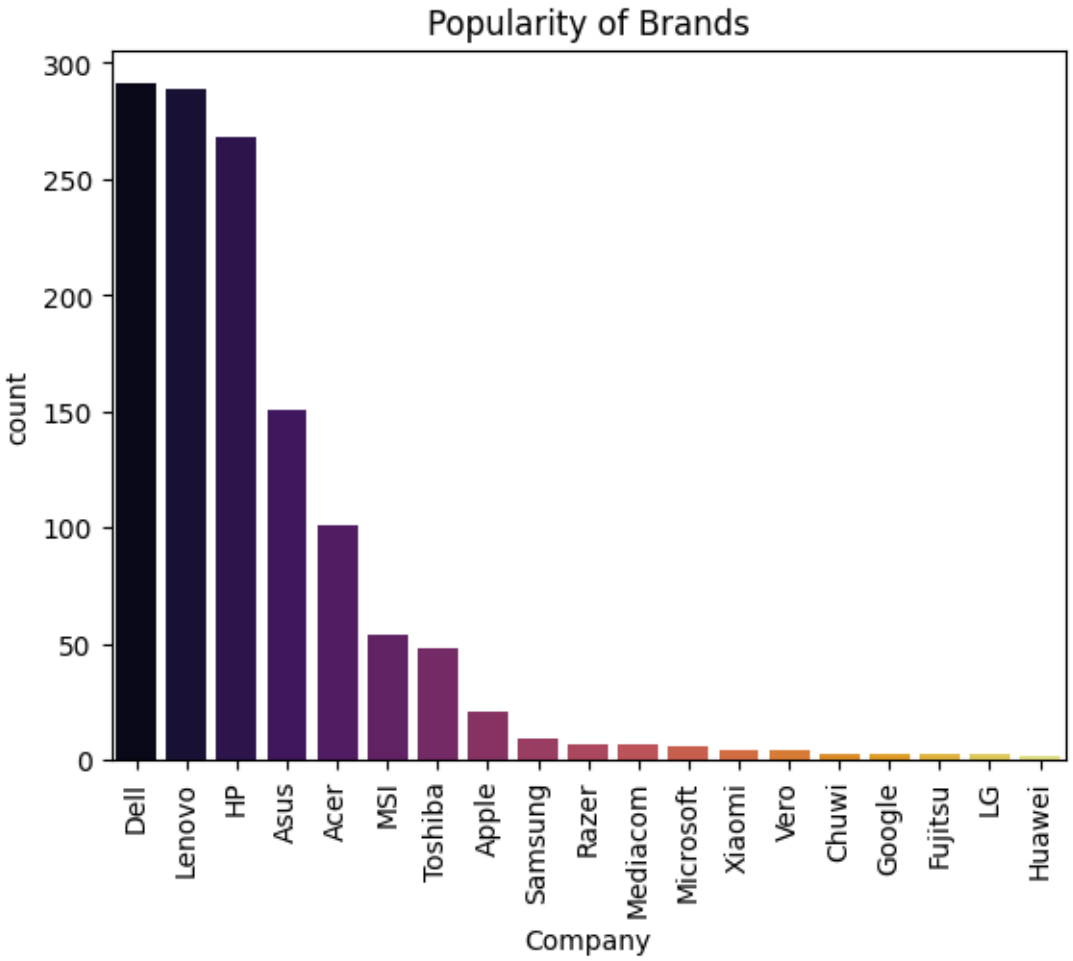
[102]:
```
sns.distplot(df['Price'])
plt.title('Price Distribution')
```

[102]:
```
Text(0.5, 1.0, 'Price Distribution')
```



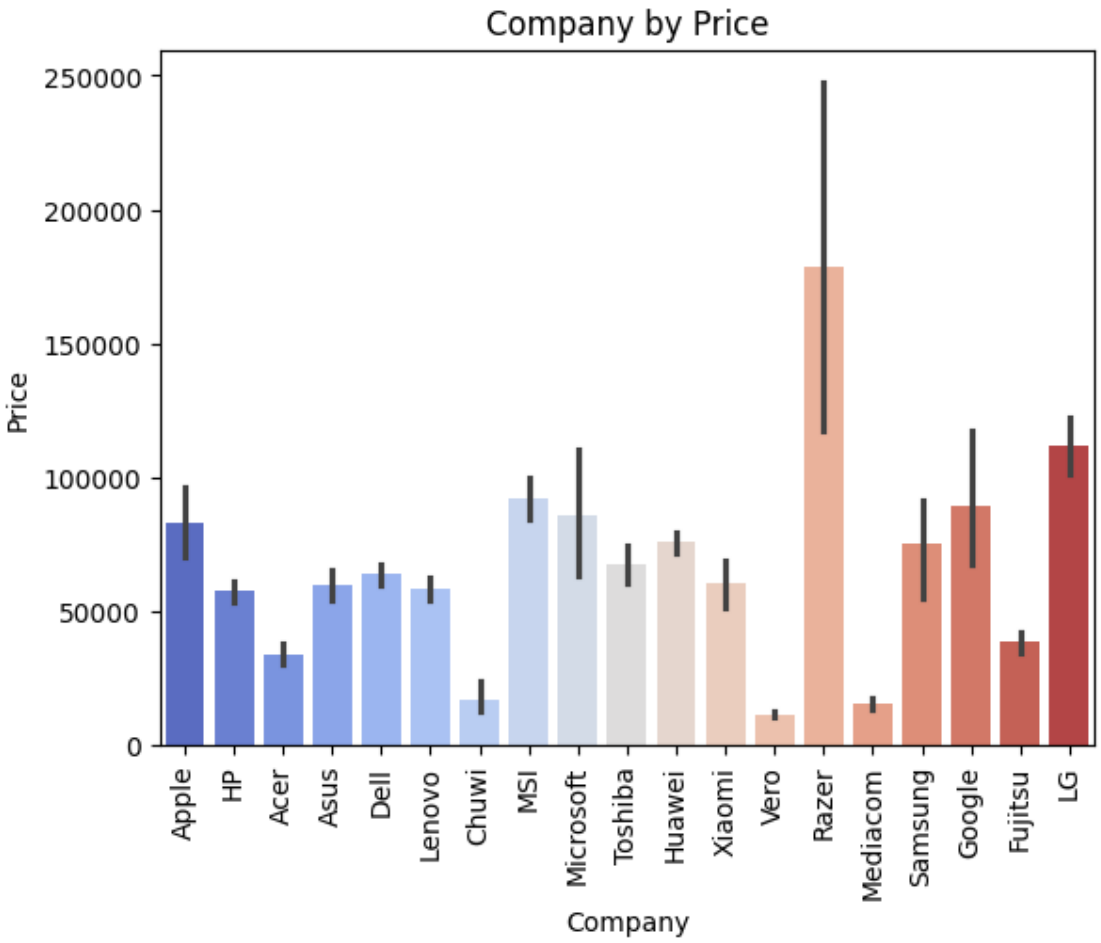
Insight: From the distplot, it is clear that the prices in range(0-50000) are more in count.

[103]:
```
sns.barplot(df['Company'].value_counts(),palette='inferno')
plt.xticks(rotation='vertical')
plt.title('Popularity of Brands')
plt.show()
```



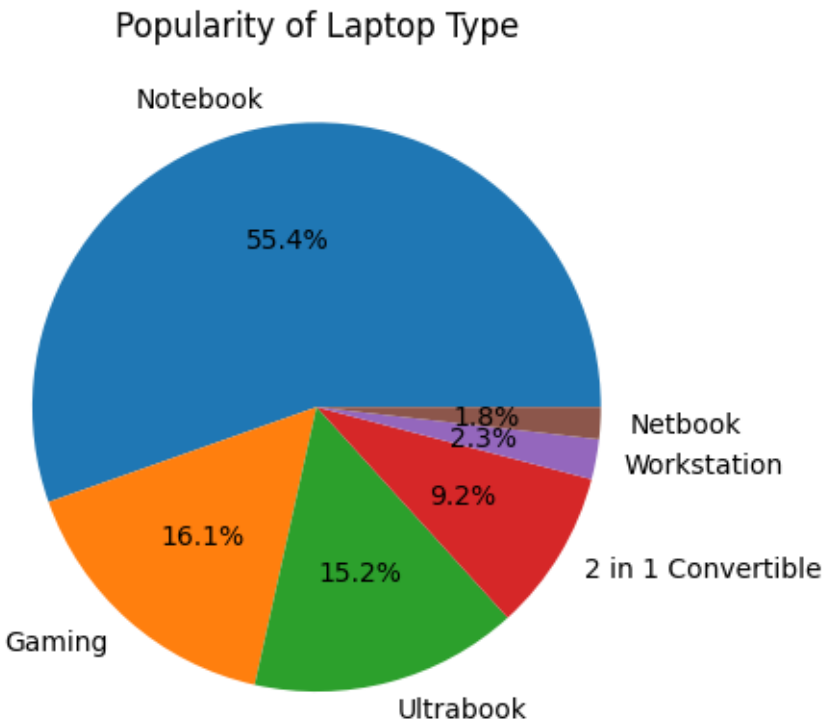
Insight: From the barplot, it is evident that majority of the laptops in the dataset are from Dell. Only few number of laptops are of Huawei.

[104]:
```
sns.barplot(x=df['Company'],y=df['Price'],palette='coolwarm')
plt.xticks(rotation='vertical')
plt.title('Company by Price')
plt.show()
```



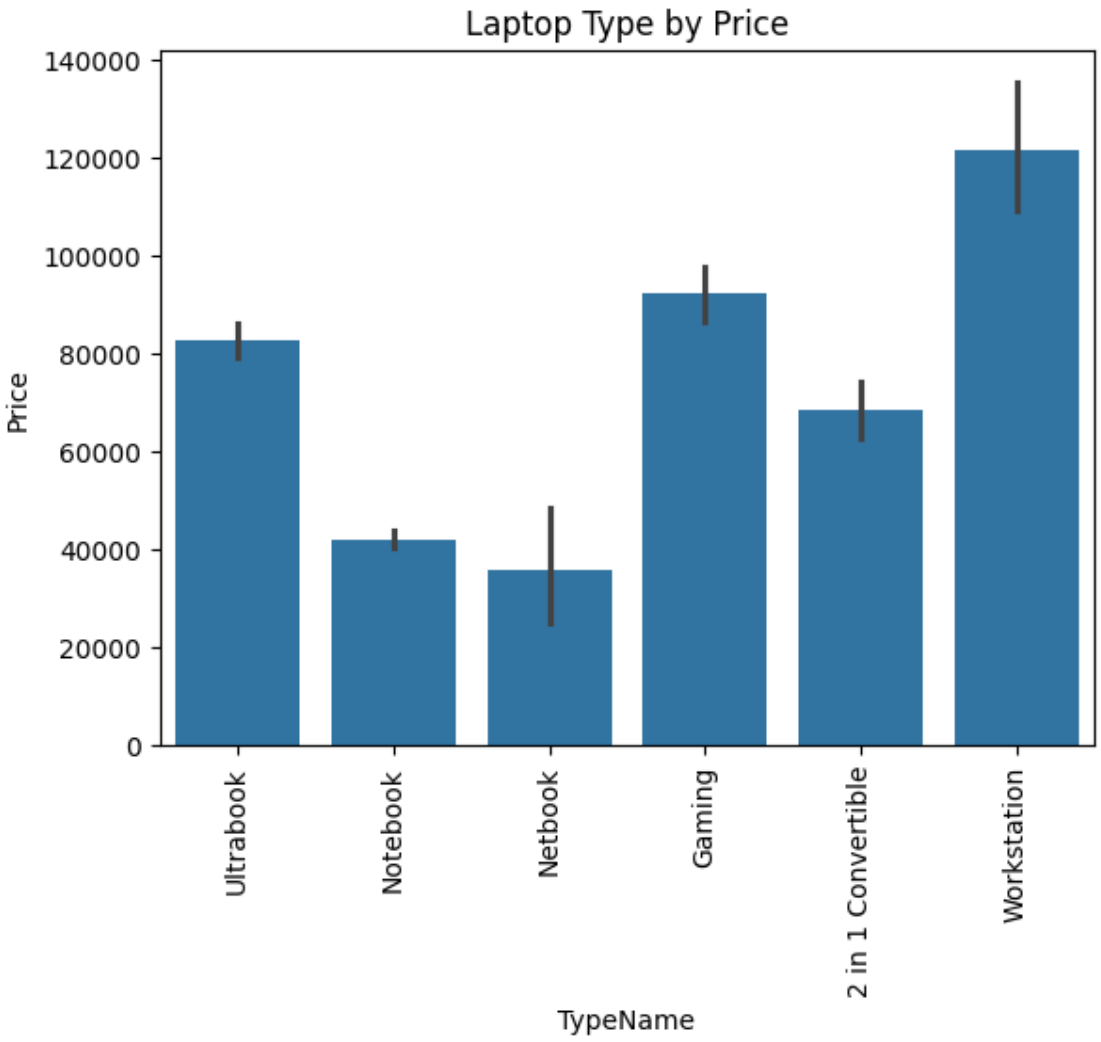
Insight: From the barplot, it is clear that Razer laptops are high in price. Whereas Vero brand has low price range.

[105]:
```
plt.pie(df['TypeName'].value_counts(),labels=df['TypeName'].value_counts().
  ↪index,
        autopct='%1.1f%%',textprops={'size': 'medium'}, radius=1)
plt.title('Popularity of Laptop Type')
plt.show()
```



Insight: From the piechart, it is evident that Notebook type of the laptop are more in count and Netbook type laptops are less in count.

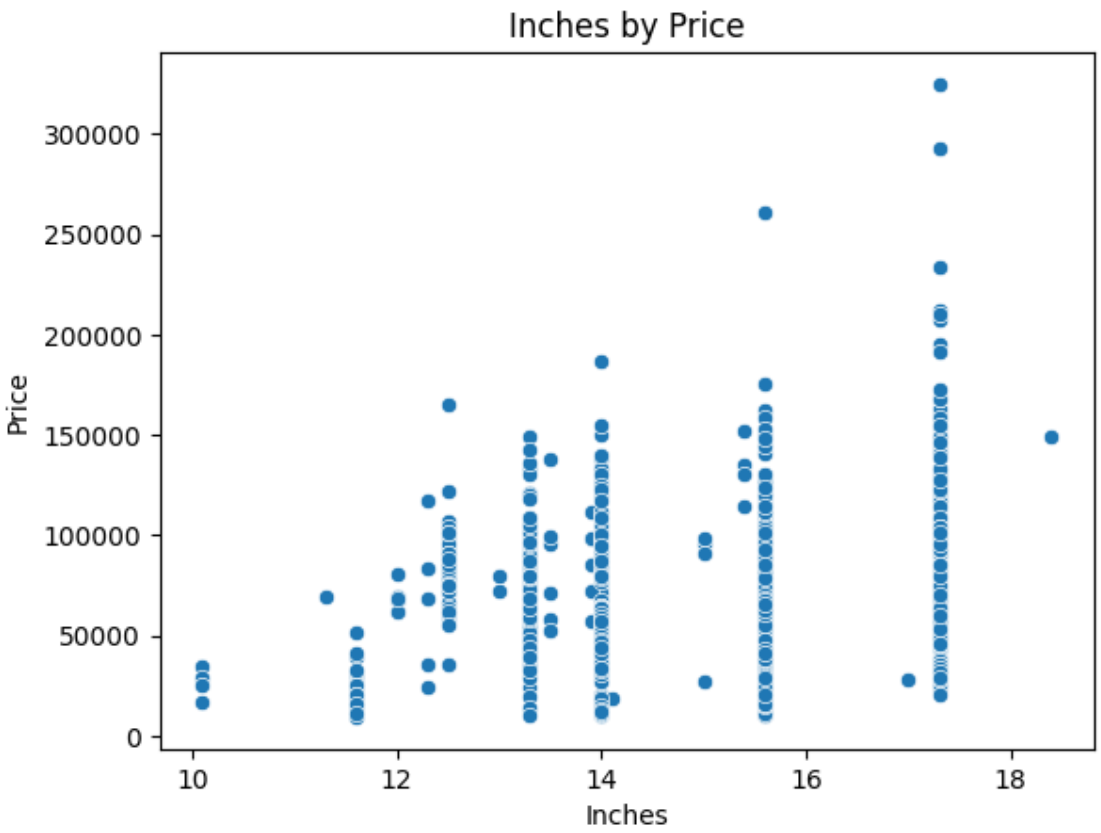
[106]:
```
sns.barplot(x=df['TypeName'],y=df['Price'])
plt.xticks(rotation='vertical')
plt.title('Laptop Type by Price')
plt.show()
```



Insight: From the barplot, it is clear that Price range is more for Workstation type laptops and less for Netbook type laptops.

[107]:
```
sns.scatterplot(x=df['Inches'],y=df['Price'])
plt.title('Inches by Price')
```

[107]:
```
Text(0.5, 1.0, 'Inches by Price')
```



Insight: From the scatterplot, it is clear that inches of range(16-18) have high price range.

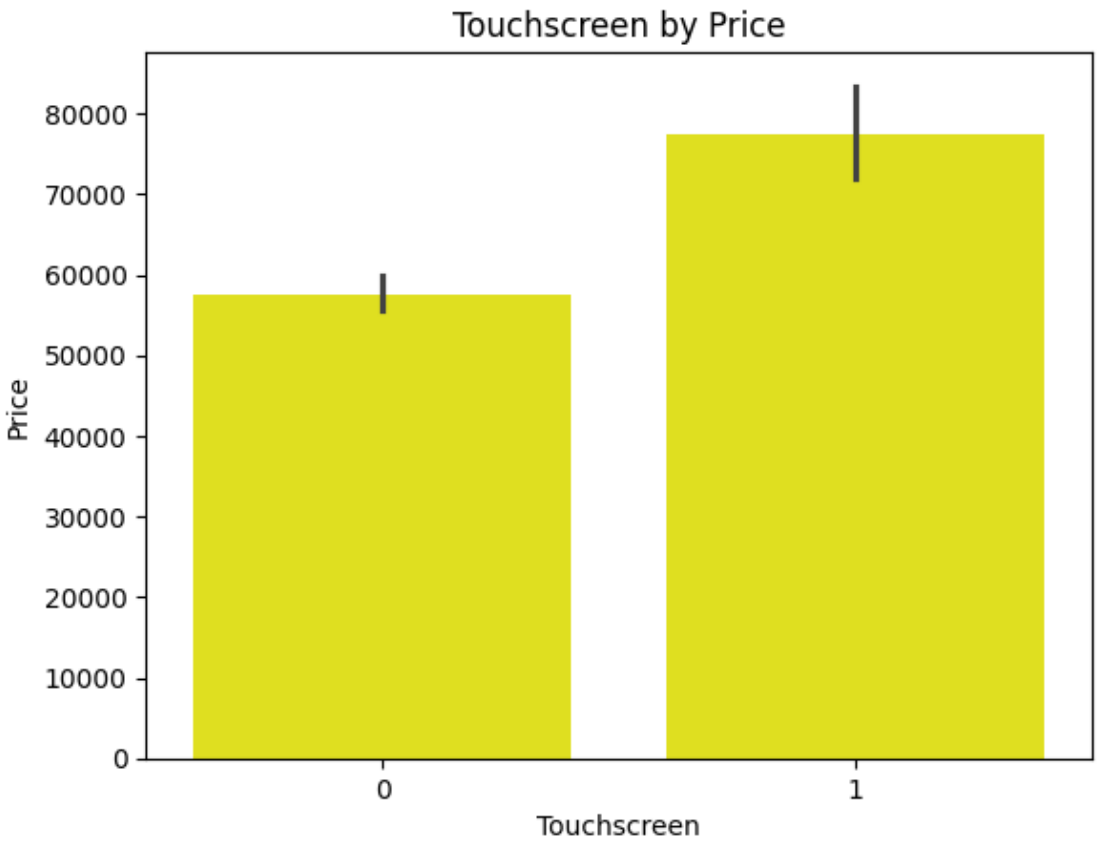
[108]:
```
df['ScreenResolution'].value_counts()
```

[108]:
```
ScreenResolution
Full HD 1920x1080                                505
1366x768                                         262
IPS Panel Full HD 1920x1080                      226
IPS Panel Full HD / Touchscreen 1920x1080         51
Full HD / Touchscreen 1920x1080                   47
1600x900                                          23
Touchscreen 1366x768                              16
Quad HD+ / Touchscreen 3200x1800                  15
IPS Panel 4K Ultra HD 3840x2160                   12
IPS Panel 4K Ultra HD / Touchscreen 3840x2160     11
4K Ultra HD / Touchscreen 3840x2160               10
4K Ultra HD 3840x2160                              7
Touchscreen 2560x1440                              7
IPS Panel 1366x768                                 7
IPS Panel Retina Display 2560x1600                 6
IPS Panel Retina Display 2304x1440                 6
```

```
Touchscreen 2256x1504                            6
IPS Panel Touchscreen 2560x1440                  5
IPS Panel Quad HD+ / Touchscreen 3200x1800       4
IPS Panel Touchscreen 1920x1200                  4
1440x900                                         4
IPS Panel Retina Display 2880x1800               4
IPS Panel 2560x1440                              4
2560x1440                                        3
Quad HD+ 3200x1800                               3
1920x1080                                        3
Touchscreen 2400x1600                            3
IPS Panel Quad HD+ 2560x1440                     3
IPS Panel Touchscreen 1366x768                   3
IPS Panel Touchscreen / 4K Ultra HD 3840x2160    2
IPS Panel Full HD 2160x1440                      2
IPS Panel Quad HD+ 3200x1800                     2
IPS Panel Retina Display 2736x1824               1
IPS Panel Full HD 1920x1200                      1
IPS Panel Full HD 2560x1440                      1
IPS Panel Full HD 1366x768                       1
Touchscreen / Full HD 1920x1080                  1
Touchscreen / Quad HD+ 3200x1800                 1
Touchscreen / 4K Ultra HD 3840x2160              1
IPS Panel Touchscreen 2400x1600                  1
Name: count, dtype: int64
```

[110]:
```
df['Touchscreen']=df['ScreenResolution'].apply(lambda x:1 if 'Touchscreen' in x␣
 ↪else 0)
sns.barplot(x=df['Touchscreen'],y=df['Price'],color='yellow')
plt.title('Touchscreen by Price')
```

[110]:
```
Text(0.5, 1.0, 'Touchscreen by Price')
```



Insight: From the barchart, it is clear that laptops with touchscreen have high price range.

[35]:
```
df['IPS']=df['ScreenResolution'].apply(lambda x:1 if 'IPS' in x else 0)
sns.barplot(x=df['IPS'],y=df['Price'])
plt.title('IPS by Price')
```

[35]:
```
Text(0.5, 1.0, 'IPS by Price')
```

Insight: From the barchart, it is evident that laptops with IPS Panel have high price range.

[36]:
```
temp=df['ScreenResolution'].str.split('x',n=1,expand=True)
```

[37]:
```
df['screen_width']=temp[0]
df['screen_height']=temp[1]
df.head()
```

[37]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory
0	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 2.3GHz	8	128GB SSD
1	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8	128GB Flash Storage
2	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8	256GB SSD
3	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16	512GB SSD
4	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600			

```
4        Intel Core i5 3.1GHz    8           256GB SSD

                            Gpu  OpSys  Weight        Price  Touchscreen  IPS  \
0  Intel Iris Plus Graphics 640  macOS    1.37   71378.6832            0    1
1        Intel HD Graphics 6000  macOS    1.34   47895.5232            0    0
2         Intel HD Graphics 620  No OS    1.86   30636.0000            0    0
3            AMD Radeon Pro 455  macOS    1.83  135195.3360            0    1
4  Intel Iris Plus Graphics 650  macOS    1.37   96095.8080            0    1

                    screen_width screen_height
0  IPS Panel Retina Display 2560          1600
1                        1440           900
2                   Full HD 1920          1080
3  IPS Panel Retina Display 2880          1800
4  IPS Panel Retina Display 2560          1600
```

[38]:
```
df['screen_width']=df['screen_width'].str.findall(r'(\d+\.?\d+)').apply(lambda
↪x:x[0])
df.head()
```

[38]:
```
  Company   TypeName  Inches                    ScreenResolution  \
0   Apple  Ultrabook    13.3  IPS Panel Retina Display 2560x1600
1   Apple  Ultrabook    13.3                          1440x900
2      HP   Notebook    15.6                 Full HD 1920x1080
3   Apple  Ultrabook    15.4  IPS Panel Retina Display 2880x1800
4   Apple  Ultrabook    13.3  IPS Panel Retina Display 2560x1600

                          Cpu  Ram               Memory  \
0        Intel Core i5 2.3GHz    8            128GB SSD
1        Intel Core i5 1.8GHz    8  128GB Flash Storage
2  Intel Core i5 7200U 2.5GHz    8            256GB SSD
3        Intel Core i7 2.7GHz   16            512GB SSD
4        Intel Core i5 3.1GHz    8            256GB SSD

                            Gpu  OpSys  Weight        Price  Touchscreen  IPS  \
0  Intel Iris Plus Graphics 640  macOS    1.37   71378.6832            0    1
1        Intel HD Graphics 6000  macOS    1.34   47895.5232            0    0
2         Intel HD Graphics 620  No OS    1.86   30636.0000            0    0
3            AMD Radeon Pro 455  macOS    1.83  135195.3360            0    1
4  Intel Iris Plus Graphics 650  macOS    1.37   96095.8080            0    1

  screen_width screen_height
0         2560          1600
1         1440           900
2         1920          1080
3         2880          1800
4         2560          1600
```

[39]:
```
df['screen_width']=df['screen_width'].astype(int)
df['screen_height']=df['screen_height'].astype(int)
```

[40]:
```
df['PPI']=(((df['screen_width']**2)+(df['screen_height']**2))**0.5/
 ↪df['Inches']).astype(float)
```

[41]:
```
df.dtypes
```

[41]:
```
Company              object
TypeName             object
Inches              float64
ScreenResolution     object
Cpu                  object
Ram                   int64
Memory               object
Gpu                  object
OpSys                object
Weight              float64
Price               float64
Touchscreen           int64
IPS                   int64
screen_width          int64
screen_height         int64
PPI                 float64
dtype: object
```

[42]:
```
df.
 ↪drop(['ScreenResolution','Inches','screen_width','screen_height'],axis=1,inplace=True)
df.head()
```

[42]:

	Company	TypeName	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	IPS	PPI
0	Apple	Ultrabook	Intel Core i5 2.3GHz	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	0	1	226.983005
1	Apple	Ultrabook	Intel Core i5 1.8GHz	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	47895.5232	0	0	127.677940
2	HP	Notebook	Intel Core i5 7200U 2.5GHz	8	256GB SSD	Intel HD Graphics 620	No OS	1.86	30636.0000	0	0	
3	Apple	Ultrabook	Intel Core i7 2.7GHz	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	135195.3360	0	1	
4	Apple	Ultrabook	Intel Core i5 3.1GHz	8	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37	96095.8080	0	1	

```
2  141.211998
3  220.534624
4  226.983005
```

[43]:
```
df['Cpu'].value_counts()
```

[43]:
```
Cpu
Intel Core i5 7200U 2.5GHz     190
Intel Core i7 7700HQ 2.8GHz    146
Intel Core i7 7500U 2.7GHz     132
Intel Core i7 8550U 1.8GHz      73
Intel Core i5 8250U 1.6GHz      72
                              ...
Intel Core M M3-6Y30 0.9GHz      1
AMD A9-Series 9420 2.9GHz        1
Intel Core i5 2.9GHz             1
AMD A6-Series 7310 2GHz          1
AMD A9-Series 9410 2.9GHz        1
Name: count, Length: 118, dtype: int64
```

[44]:
```
df['Cpu Name']=df['Cpu'].apply(lambda x:' '.join(x.split()[0:3]))
df.head()
```

[44]:
```
  Company   TypeName                         Cpu  Ram               Memory  \
0   Apple  Ultrabook       Intel Core i5 2.3GHz    8            128GB SSD
1   Apple  Ultrabook       Intel Core i5 1.8GHz    8  128GB Flash Storage
2      HP   Notebook  Intel Core i5 7200U 2.5GHz    8            256GB SSD
3   Apple  Ultrabook       Intel Core i7 2.7GHz   16            512GB SSD
4   Apple  Ultrabook       Intel Core i5 3.1GHz    8            256GB SSD

                           Gpu  OpSys  Weight        Price  Touchscreen  IPS  \
0  Intel Iris Plus Graphics 640  macOS    1.37   71378.6832            0    1
1        Intel HD Graphics 6000  macOS    1.34   47895.5232            0    0
2         Intel HD Graphics 620  No OS    1.86   30636.0000            0    0
3            AMD Radeon Pro 455  macOS    1.83  135195.3360            0    1
4  Intel Iris Plus Graphics 650  macOS    1.37   96095.8080            0    1

          PPI       Cpu Name
0  226.983005  Intel Core i5
1  127.677940  Intel Core i5
2  141.211998  Intel Core i5
3  220.534624  Intel Core i7
4  226.983005  Intel Core i5
```

[45]:
```
def Cpu_processor(text):
  if text=='Intel Core i7' or text=='Intel Core i5' or text=='Intel Core i3':
    return text
```

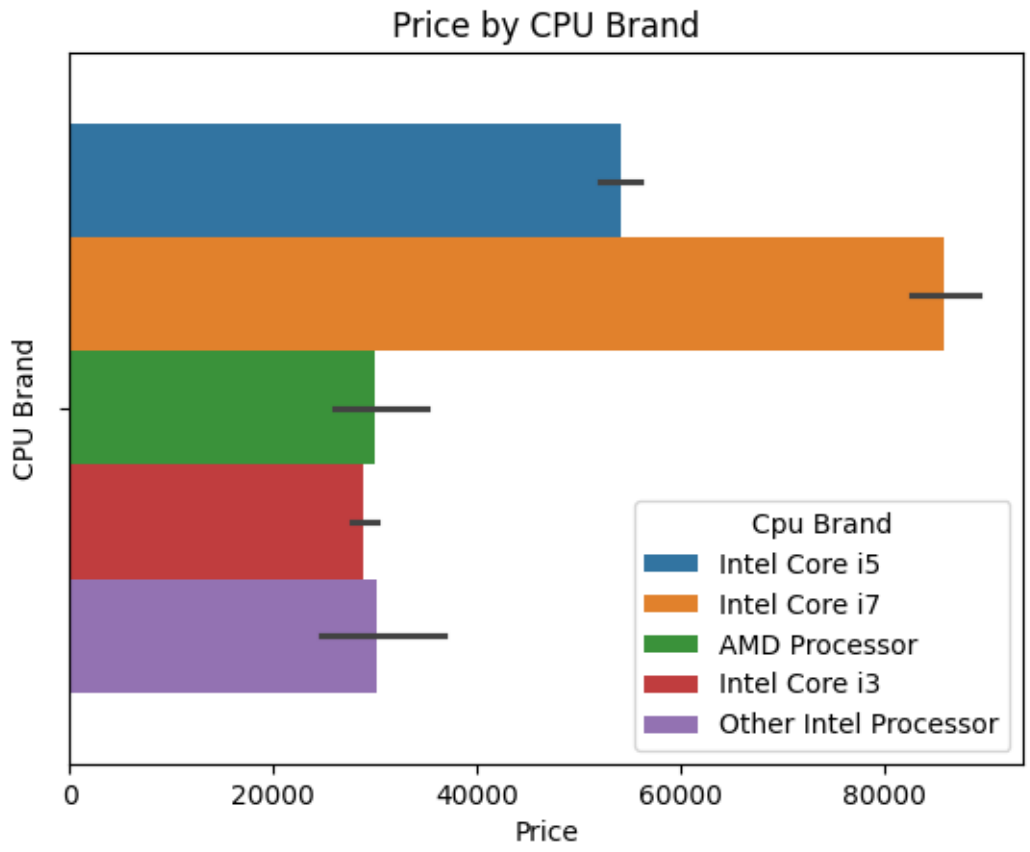
```
  else:
    if text.split()[0]=="Intel":
      return 'Other Intel Processor'
    else:
      return 'AMD Processor'
```

[46]:
```
df['Cpu Brand']=df['Cpu Name'].apply(Cpu_processor)
df.head()
```

[46]:

	Company	TypeName	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	IPS	PPI	Cpu Name	Cpu Brand
0	Apple	Ultrabook	Intel Core i5 2.3GHz	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	0	1	226.983005	Intel Core i5	Intel Core i5
1	Apple	Ultrabook	Intel Core i5 1.8GHz	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	47895.5232	0	0	127.677940	Intel Core i5	Intel Core i5
2	HP	Notebook	Intel Core i5 7200U 2.5GHz	8	256GB SSD	Intel HD Graphics 620	No OS	1.86	30636.0000	0	0	141.211998	Intel Core i5	Intel Core i5
3	Apple	Ultrabook	Intel Core i7 2.7GHz	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	135195.3360	0	1	220.534624	Intel Core i7	Intel Core i7
4	Apple	Ultrabook	Intel Core i5 3.1GHz	8	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37	96095.8080	0	1	226.983005	Intel Core i5	Intel Core i5

[48]:
```
sns.barplot(data=df,
            x='Price',
            hue='Cpu Brand')
plt.title('Price by CPU Brand')
plt.xlabel('Price')
plt.ylabel('CPU Brand')
plt.show()
```



Insight: From the barchart, it is evident that most of the laptops have intel core i7 processor.

[49]:
```
df.drop(['Cpu','Cpu Name'],axis=1,inplace=True)
df.head()
```

[49]:

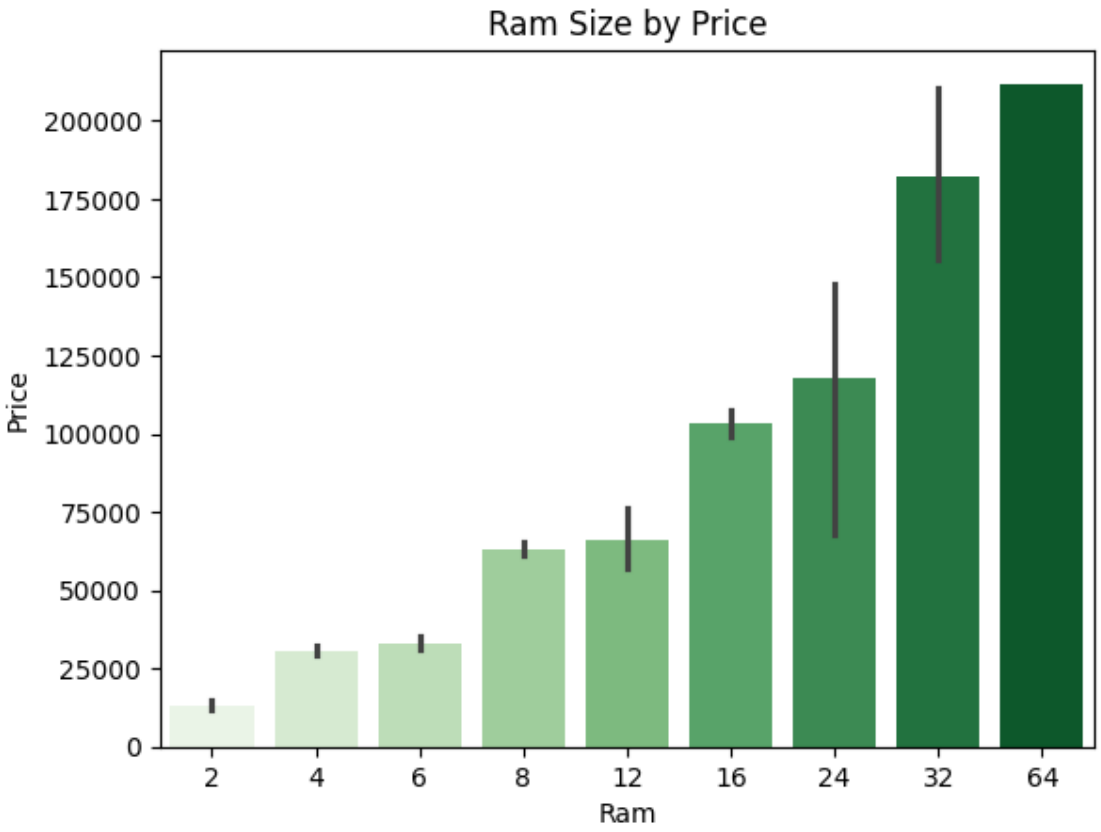
	Company	TypeName	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	IPS	PPI	Cpu Brand
0	Apple	Ultrabook	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	0	1	226.983005	Intel Core i5
1	Apple	Ultrabook	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	47895.5232	0	0	127.677940	Intel Core i5
2	HP	Notebook	8	256GB SSD	Intel HD Graphics 620	No OS	1.86	30636.0000	0	0	141.211998	Intel Core i5
3	Apple	Ultrabook	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	135195.3360	0	1	220.534624	Intel Core i7
4	Apple	Ultrabook	8	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37	96095.8080	0	1	226.983005	Intel Core i5

[50]:
```
df['Ram'].value_counts()
```

[50]:
```
Ram
8     613
4     366
16    198
6      35
12     25
32     17
2      16
24      3
64      1
Name: count, dtype: int64
```

[52]:
```
sns.barplot(x=df['Ram'],y=df['Price'],palette='Greens')
plt.title('Ram Size by Price')
```

[52]:
```
Text(0.5, 1.0, 'Ram Size by Price')
```



Insight: From the barchart, it is clear that most of the laptops have 64GB Ram.

[53]:
```
df['Memory'].value_counts()
```

[53]:
```
Memory
256GB SSD                        412
1TB HDD                          215
500GB HDD                        123
512GB SSD                        114
128GB SSD +  1TB HDD              94
128GB SSD                         74
256GB SSD +  1TB HDD              73
32GB Flash Storage                36
2TB HDD                           16
512GB SSD +  1TB HDD              14
1TB SSD                           14
64GB Flash Storage                13
256GB SSD +  2TB HDD              10
256GB Flash Storage                8
16GB Flash Storage                 7
1.0TB Hybrid                       7
32GB SSD                           6
180GB SSD                          5
128GB Flash Storage                4
512GB SSD +  2TB HDD               3
16GB SSD                           3
512GB Flash Storage                2
1TB SSD +  1TB HDD                 2
256GB SSD +  500GB HDD             2
128GB SSD +  2TB HDD               2
256GB SSD +  256GB SSD             2
512GB SSD +  256GB SSD             1
512GB SSD +  512GB SSD             1
64GB Flash Storage +  1TB HDD      1
1TB HDD +  1TB HDD                 1
32GB HDD                           1
64GB SSD                           1
128GB HDD                          1
240GB SSD                          1
8GB SSD                            1
508GB Hybrid                       1
1.0TB HDD                          1
512GB SSD +  1.0TB Hybrid          1
256GB SSD +  1.0TB Hybrid          1
Name: count, dtype: int64
```

[54]:
```
df['Memory'] = df['Memory'].astype(str).replace('\.0', '', regex=True)
df["Memory"] = df["Memory"].str.replace('GB', '')
df["Memory"] = df["Memory"].str.replace('TB', '000')
new = df["Memory"].str.split("+", n = 1, expand = True)
```

```
df["first"]= new[0]
df["second"]= new[1]
df.head()
```

[54]:

	Company	TypeName	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	IPS	PPI	Cpu Brand	first	second
0	Apple	Ultrabook	8	128 SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	0	1	226.983005	Intel Core i5	128 SSD	None
1	Apple	Ultrabook	8	128 Flash Storage	Intel HD Graphics 6000	macOS	1.34	47895.5232	0	0	127.677940	Intel Core i5	128 Flash Storage	None
2	HP	Notebook	8	256 SSD	Intel HD Graphics 620	No OS	1.86	30636.0000	0	0	141.211998	Intel Core i5	256 SSD	None
3	Apple	Ultrabook	16	512 SSD	AMD Radeon Pro 455	macOS	1.83	135195.3360	0	1	220.534624	Intel Core i7	512 SSD	None
4	Apple	Ultrabook	8	256 SSD	Intel Iris Plus Graphics 650	macOS	1.37	96095.8080	0	1	226.983005	Intel Core i5	256 SSD	None

[55]:
```
df['first'].value_counts()
```

[55]:
```
first
256 SSD              412
1000 HDD             216
500 HDD              123
512 SSD              114
128 SSD               96
256 SSD               88
128 SSD               74
32 Flash Storage      36
512 SSD               20
2000 HDD              16
1000 SSD              14
64 Flash Storage      13
256 Flash Storage      8
16 Flash Storage       7
1000 Hybrid            7
32 SSD                 6
180 SSD                5
128 Flash Storage      4
16 SSD                 3
```

```
1000 SSD                2
512 Flash Storage       2
64 SSD                  1
64 Flash Storage        1
1000 HDD                1
32 HDD                  1
128 HDD                 1
240 SSD                 1
8 SSD                   1
508 Hybrid              1
Name: count, dtype: int64
```

[56]:
```
df['second'].value_counts()
```

[56]:
```
second
  1000 HDD       185
  2000 HDD        15
  256 SSD          3
  500 HDD          2
  1000 Hybrid      2
  512 SSD          1
Name: count, dtype: int64
```

[57]:
```
df["Layer1HDD"] = df["first"].apply(lambda x: 1 if "HDD" in x else 0)
df["Layer1SSD"] = df["first"].apply(lambda x: 1 if "SSD" in x else 0)
df["Layer1Hybrid"] = df["first"].apply(lambda x: 1 if "Hybrid" in x else 0)
df["Layer1Flash_Storage"] = df["first"].apply(lambda x: 1 if "Flash Storage" in␣
 ↪x else 0)
df.head()
```

[57]:

	Company	TypeName	Ram	Memory	Gpu	\
0	Apple	Ultrabook	8	128 SSD	Intel Iris Plus Graphics 640	
1	Apple	Ultrabook	8	128 Flash Storage	Intel HD Graphics 6000	
2	HP	Notebook	8	256 SSD	Intel HD Graphics 620	
3	Apple	Ultrabook	16	512 SSD	AMD Radeon Pro 455	
4	Apple	Ultrabook	8	256 SSD	Intel Iris Plus Graphics 650	

	OpSys	Weight	Price	Touchscreen	IPS	PPI	Cpu Brand	\
0	macOS	1.37	71378.6832	0	1	226.983005	Intel Core i5	
1	macOS	1.34	47895.5232	0	0	127.677940	Intel Core i5	
2	No OS	1.86	30636.0000	0	0	141.211998	Intel Core i5	
3	macOS	1.83	135195.3360	0	1	220.534624	Intel Core i7	
4	macOS	1.37	96095.8080	0	1	226.983005	Intel Core i5	

	first	second	Layer1HDD	Layer1SSD	Layer1Hybrid	\
0	128 SSD	None	0	1	0	
1	128 Flash Storage	None	0	0	0	

```
2            256 SSD   None          0          1             0
3            512 SSD   None          0          1             0
4            256 SSD   None          0          1             0

   Layer1Flash_Storage
0                    0
1                    1
2                    0
3                    0
4                    0
```

[58]:
```
df['first'] = df['first'].str.findall(r'\d+').apply(lambda x:x[0])
df["second"].fillna("0", inplace = True)
df.head()
```

[58]:
```
  Company   TypeName  Ram             Memory                           Gpu  \
0   Apple  Ultrabook    8            128 SSD  Intel Iris Plus Graphics 640
1   Apple  Ultrabook    8  128 Flash Storage        Intel HD Graphics 6000
2      HP   Notebook    8            256 SSD         Intel HD Graphics 620
3   Apple  Ultrabook   16            512 SSD            AMD Radeon Pro 455
4   Apple  Ultrabook    8            256 SSD  Intel Iris Plus Graphics 650

   OpSys  Weight        Price  Touchscreen  IPS         PPI      Cpu Brand  \
0  macOS    1.37   71378.6832            0    1  226.983005  Intel Core i5
1  macOS    1.34   47895.5232            0    0  127.677940  Intel Core i5
2  No OS    1.86   30636.0000            0    0  141.211998  Intel Core i5
3  macOS    1.83  135195.3360            0    1  220.534624  Intel Core i7
4  macOS    1.37   96095.8080            0    1  226.983005  Intel Core i5

  first second  Layer1HDD  Layer1SSD  Layer1Hybrid  Layer1Flash_Storage
0   128      0          0          1             0                    0
1   128      0          0          0             0                    1
2   256      0          0          1             0                    0
3   512      0          0          1             0                    0
4   256      0          0          1             0                    0
```

[59]:
```
df["Layer2HDD"] = df["second"].apply(lambda x: 1 if "HDD" in x else 0)
df["Layer2SSD"] = df["second"].apply(lambda x: 1 if "SSD" in x else 0)
df["Layer2Hybrid"] = df["second"].apply(lambda x: 1 if "Hybrid" in x else 0)
df["Layer2Flash_Storage"] = df["second"].apply(lambda x: 1 if "Flash Storage"␣
 ↪in x else 0)
df.head()
```

[59]:
```
  Company   TypeName  Ram             Memory                           Gpu  \
0   Apple  Ultrabook    8            128 SSD  Intel Iris Plus Graphics 640
1   Apple  Ultrabook    8  128 Flash Storage        Intel HD Graphics 6000
2      HP   Notebook    8            256 SSD         Intel HD Graphics 620
```

```
3   Apple  Ultrabook   16            512 SSD            AMD Radeon Pro 455
4   Apple  Ultrabook    8            256 SSD  Intel Iris Plus Graphics 650

   OpSys  Weight        Price  Touchscreen  IPS  …  first second Layer1HDD  \
0  macOS    1.37   71378.6832            0    1  …    128      0         0
1  macOS    1.34   47895.5232            0    0  …    128      0         0
2  No OS    1.86   30636.0000            0    0  …    256      0         0
3  macOS    1.83  135195.3360            0    1  …    512      0         0
4  macOS    1.37   96095.8080            0    1  …    256      0         0

  Layer1SSD  Layer1Hybrid  Layer1Flash_Storage  Layer2HDD  Layer2SSD  \
0         1             0                    0          0          0
1         0             0                    1          0          0
2         1             0                    0          0          0
3         1             0                    0          0          0
4         1             0                    0          0          0

   Layer2Hybrid  Layer2Flash_Storage
0             0                    0
1             0                    0
2             0                    0
3             0                    0
4             0                    0

[5 rows x 22 columns]
```

[60]:
```
df['second'] = df['second'].str.findall(r'\d+').apply(lambda x:x[0])
df.head()
```

[60]:
```
  Company   TypeName  Ram              Memory                           Gpu  \
0   Apple  Ultrabook    8           128 SSD  Intel Iris Plus Graphics 640
1   Apple  Ultrabook    8  128 Flash Storage        Intel HD Graphics 6000
2      HP   Notebook    8           256 SSD         Intel HD Graphics 620
3   Apple  Ultrabook   16           512 SSD            AMD Radeon Pro 455
4   Apple  Ultrabook    8           256 SSD  Intel Iris Plus Graphics 650

   OpSys  Weight        Price  Touchscreen  IPS  …  first second Layer1HDD  \
0  macOS    1.37   71378.6832            0    1  …    128      0         0
1  macOS    1.34   47895.5232            0    0  …    128      0         0
2  No OS    1.86   30636.0000            0    0  …    256      0         0
3  macOS    1.83  135195.3360            0    1  …    512      0         0
4  macOS    1.37   96095.8080            0    1  …    256      0         0

  Layer1SSD  Layer1Hybrid  Layer1Flash_Storage  Layer2HDD  Layer2SSD  \
0         1             0                    0          0          0
1         0             0                    1          0          0
2         1             0                    0          0          0
```

```
3         1             0                    0          0          0
4         1             0                    0          0          0

   Layer2Hybrid  Layer2Flash_Storage
0             0                    0
1             0                    0
2             0                    0
3             0                    0
4             0                    0

[5 rows x 22 columns]
```

[61]:
```
df['first'].value_counts()
```

[61]:
```
first
256     508
1000    240
128     175
512     136
500     123
32       43
2000     16
64       15
16       10
180       5
240       1
8         1
508       1
Name: count, dtype: int64
```

[62]:
```
df['second'].value_counts()
```

[62]:
```
second
0       1066
1000     187
2000      15
256        3
500        2
512        1
Name: count, dtype: int64
```

[63]:
```
df["first"] = df["first"].astype(int)
df["second"] = df["second"].astype(int)
```

[64]:
```
df["HDD"]=(df["first"]*df["Layer1HDD"]+df["second"]*df["Layer2HDD"])
df["SSD"]=(df["first"]*df["Layer1SSD"]+df["second"]*df["Layer2SSD"])
df["Hybrid"]=(df["first"]*df["Layer1Hybrid"]+df["second"]*df["Layer2Hybrid"])
```

```
df["Flash_Storage"]=(df["first"]*df["Layer1Flash_Storage"]+df["second"]*df["Layer2Flash_Storag

df.drop(columns=['Memory','first', 'second', 'Layer1HDD', 'Layer1SSD',␣
↪'Layer1Hybrid',
       'Layer1Flash_Storage', 'Layer2HDD', 'Layer2SSD', 'Layer2Hybrid',
       'Layer2Flash_Storage'],inplace=True)
df.head()
```

[64]:

	Company	TypeName	Ram	Gpu	OpSys	Weight	Price	Touchscreen	IPS	PPI	Cpu Brand	HDD	SSD	Hybrid	Flash_Storage
0	Apple	Ultrabook	8	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	0	1	226.983005	Intel Core i5	0	128	0	0
1	Apple	Ultrabook	8	Intel HD Graphics 6000	macOS	1.34	47895.5232	0	0	127.677940	Intel Core i5	0	0	0	128
2	HP	Notebook	8	Intel HD Graphics 620	No OS	1.86	30636.0000	0	0	141.211998	Intel Core i5	0	256	0	0
3	Apple	Ultrabook	16	AMD Radeon Pro 455	macOS	1.83	135195.3360	0	1	220.534624	Intel Core i7	0	512	0	0
4	Apple	Ultrabook	8	Intel Iris Plus Graphics 650	macOS	1.37	96095.8080	0	1	226.983005	Intel Core i5	0	256	0	0

[65]:
```
df.corr(numeric_only=True)['Price']
```

[65]:
```
Ram              0.740106
Weight           0.212192
Price            1.000000
Touchscreen      0.188631
IPS              0.250358
PPI              0.469539
HDD             -0.098011
SSD              0.669957
Hybrid           0.022533
Flash_Storage   -0.037176
Name: Price, dtype: float64
```

[66]:
```
df.drop(['Hybrid','Flash_Storage'],axis=1,inplace=True)
df.head()
```

[66]:

	Company	TypeName	Ram	Gpu	OpSys	Weight	Price	Touchscreen	IPS	PPI	Cpu Brand	HDD	SSD
0	Apple	Ultrabook	8	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	0	1	226.983005	Intel Core i5	0	128
1	Apple	Ultrabook	8	Intel HD Graphics 6000	macOS	1.34	47895.5232	0	0	127.677940	Intel Core i5	0	0
2	HP	Notebook	8	Intel HD Graphics 620	No OS	1.86	30636.0000	0	0	141.211998	Intel Core i5	0	256
3	Apple	Ultrabook	16	AMD Radeon Pro 455	macOS	1.83	135195.3360	0	1	220.534624	Intel Core i7	0	512
4	Apple	Ultrabook	8	Intel Iris Plus Graphics 650	macOS	1.37	96095.8080	0	1	226.983005	Intel Core i5	0	256

[67]:
```
df['Gpu'].value_counts()
```

[67]:
```
Gpu
Intel HD Graphics 620      279
Intel HD Graphics 520      181
Intel UHD Graphics 620      68
Nvidia GeForce GTX 1050     66
Nvidia GeForce GTX 1060     48
                          ...
AMD Radeon R5 520            1
AMD Radeon R7                1
Intel HD Graphics 540        1
AMD Radeon 540               1
ARM Mali T860 MP4            1
Name: count, Length: 110, dtype: int64
```

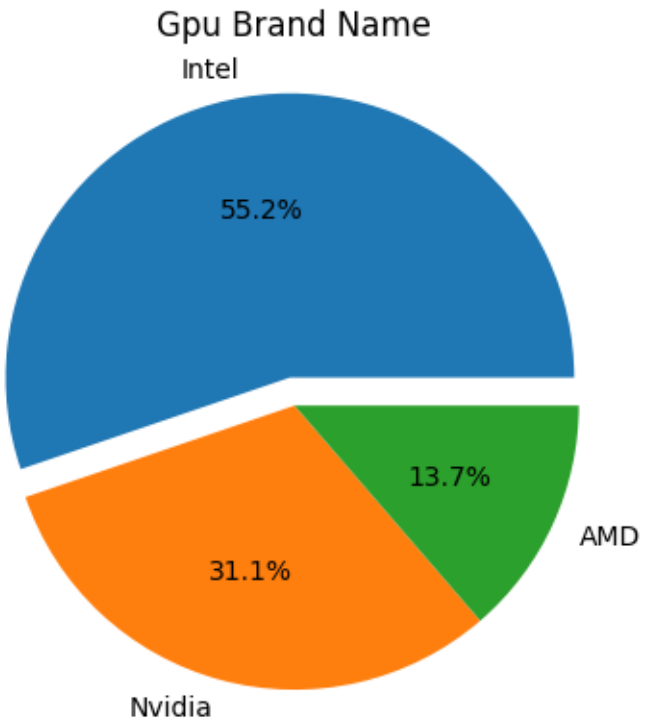
[68]:
```
df['Gpu Brand Name']=df['Gpu'].apply(lambda x:x.split()[0])
df=df[df['Gpu Brand Name']!='ARM']
df.drop('Gpu',axis=1,inplace=True)
df.head()
```

[68]:

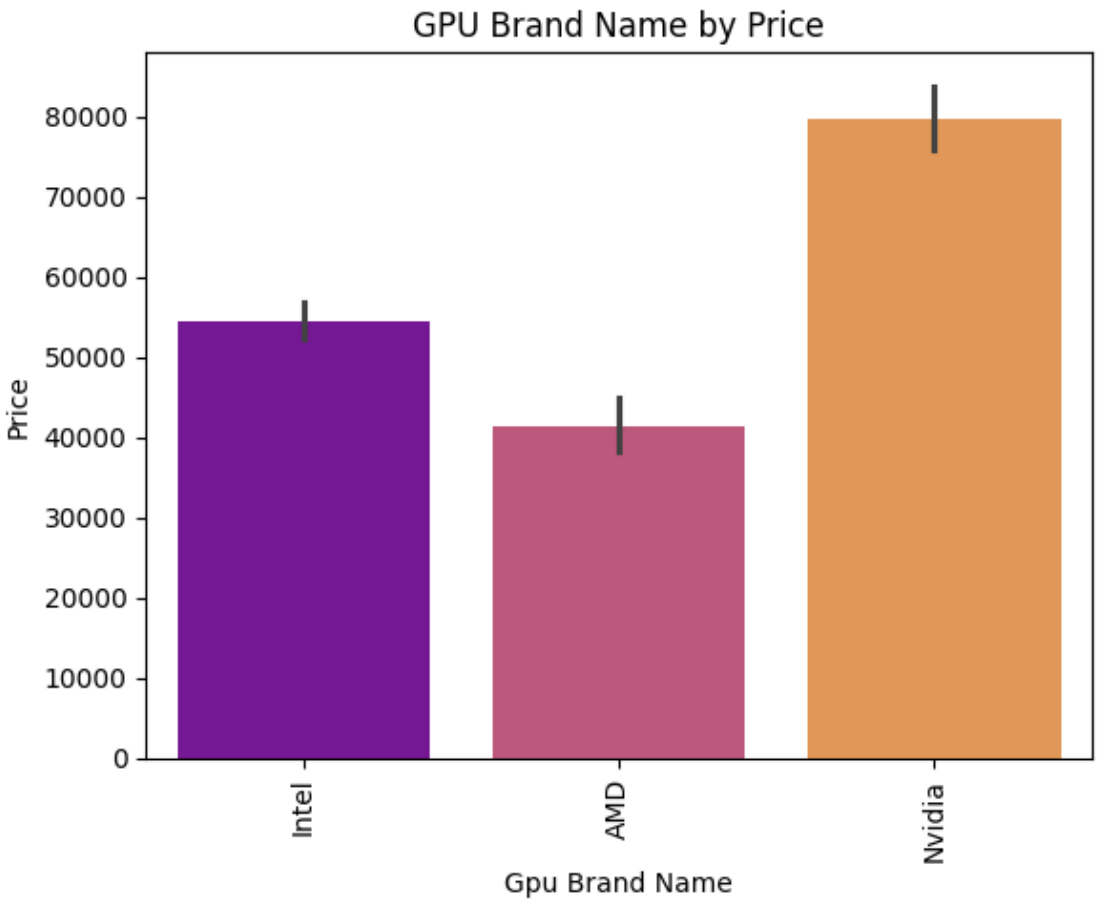
	Company	TypeName	Ram	OpSys	Weight	Price	Touchscreen	IPS	PPI	Cpu Brand	HDD	SSD	Gpu Brand Name
0	Apple	Ultrabook	8	macOS	1.37	71378.6832	0	1	226.983005	Intel Core i5	0	128	Intel
1	Apple	Ultrabook	8	macOS	1.34	47895.5232	0	0	127.677940	Intel Core i5	0	0	Intel
2	HP	Notebook	8	No OS	1.86	30636.0000	0	0	141.211998	Intel Core i5	0	256	Intel
3	Apple	Ultrabook	16	macOS	1.83	135195.3360	0	1	220.534624	Intel Core i7	0	512	AMD

```
4  226.983005  Intel Core i5    0  256          Intel
```

[74]:
```
explode = [0.1,0,0]
df['Gpu Brand Name'].value_counts()
top10_price = df['Gpu Brand Name'].value_counts()
plt.pie(top10_price,
        labels=top10_price.index,
        explode=explode,
        autopct='%1.1f%%')
plt.title('Gpu Brand Name')
plt.show()
```



[75]:
```
sns.barplot(x=df['Gpu Brand Name'],y=df['Price'],palette='plasma')
plt.xticks(rotation='vertical')
plt.title('GPU Brand Name by Price')
plt.show()
```



Insight: From the barchart, it is clear that price range is high for laptops having Nvidia Gpu Processor.

[76]:
```
df['OpSys'].value_counts()
```

[76]:
```
OpSys
Windows 10      1047
No OS             66
Linux             58
Windows 7         45
Chrome OS         26
macOS             13
Mac OS X           8
Windows 10 S       8
Android            2
Name: count, dtype: int64
```

[77]:
```
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'
```

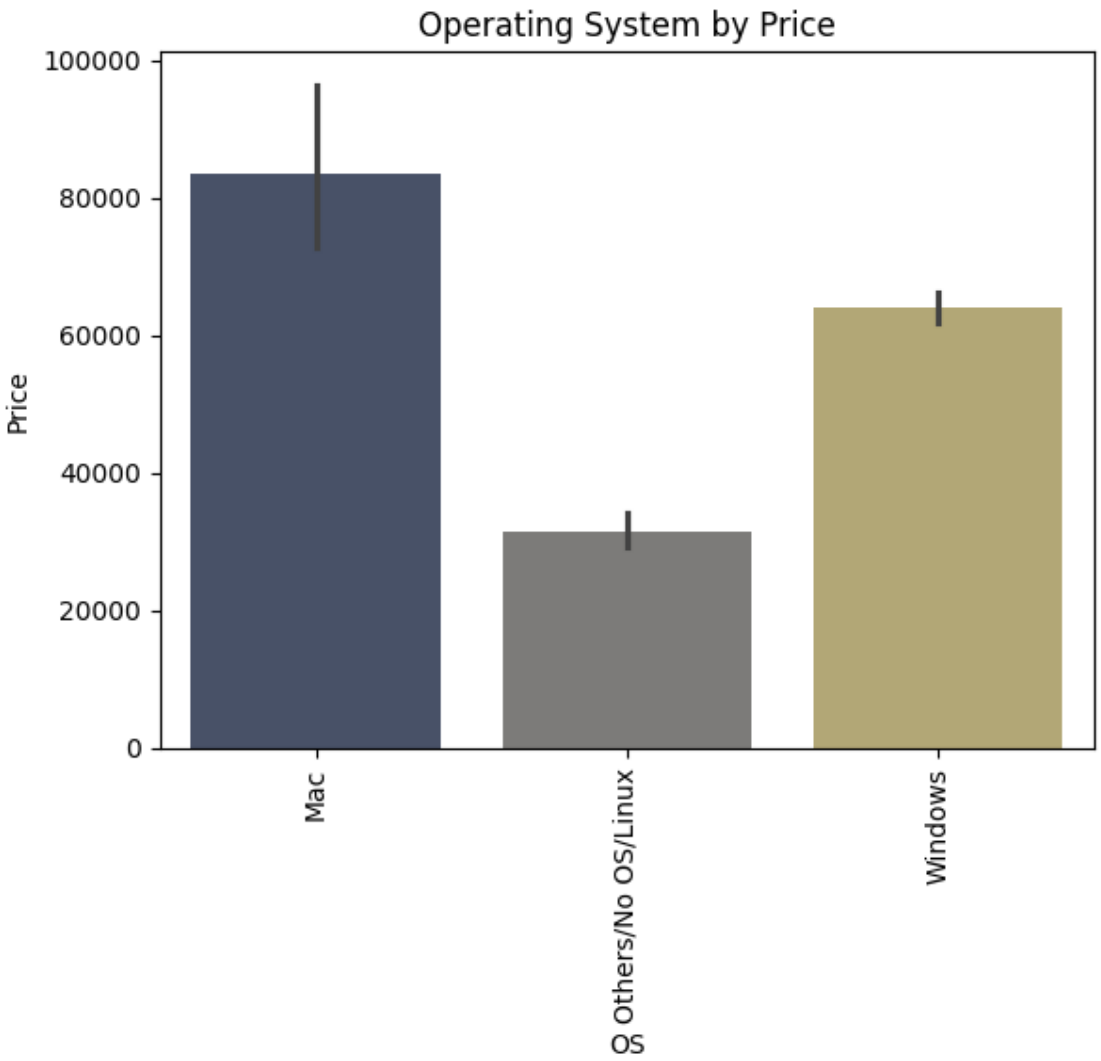
[78]:
```
df['OS'] = df['OpSys'].apply(cat_os)
df.drop('OpSys',axis=1,inplace=True)
df.head()
```

[78]:

	Company	TypeName	Ram	Weight	Price	Touchscreen	IPS	PPI	\
0	Apple	Ultrabook	8	1.37	71378.6832	0	1	226.983005	
1	Apple	Ultrabook	8	1.34	47895.5232	0	0	127.677940	
2	HP	Notebook	8	1.86	30636.0000	0	0	141.211998	
3	Apple	Ultrabook	16	1.83	135195.3360	0	1	220.534624	
4	Apple	Ultrabook	8	1.37	96095.8080	0	1	226.983005	

	Cpu Brand	HDD	SSD	Gpu Brand	Name	OS
0	Intel Core i5	0	128	Intel		Mac
1	Intel Core i5	0	0	Intel		Mac
2	Intel Core i5	0	256	Intel		Others/No OS/Linux
3	Intel Core i7	0	512	AMD		Mac
4	Intel Core i5	0	256	Intel		Mac

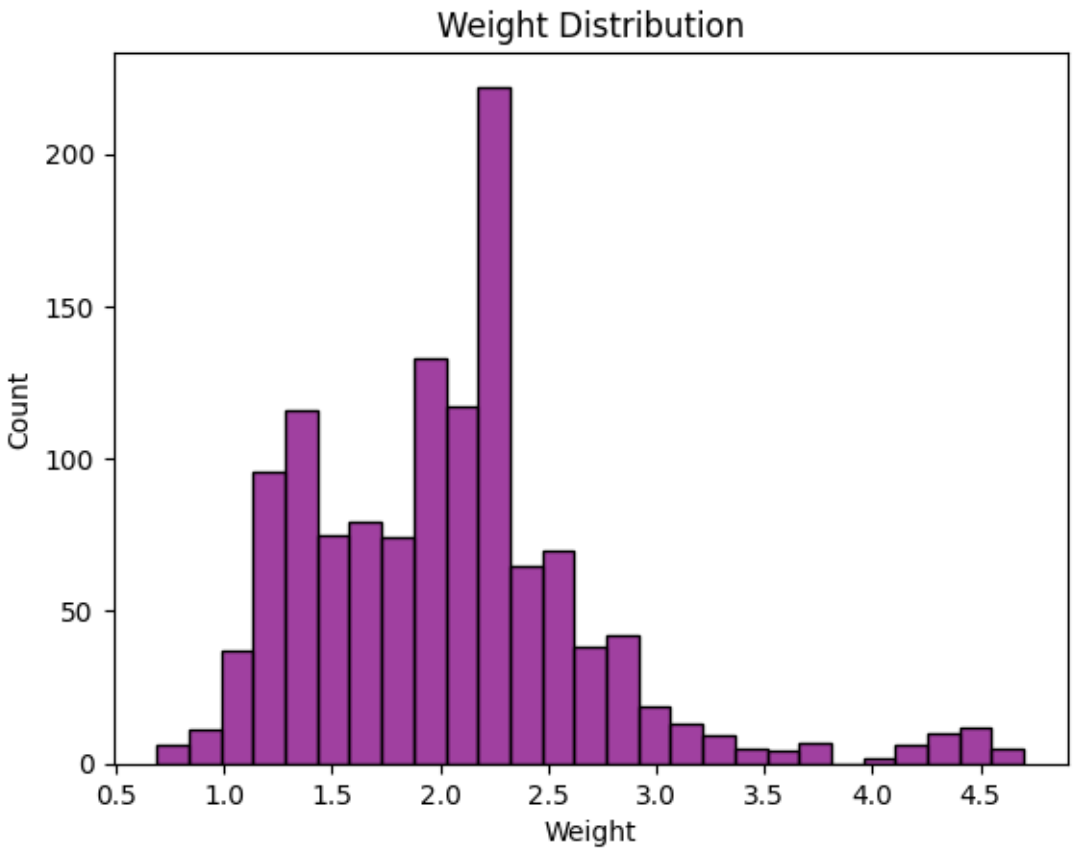
[80]:
```
sns.barplot(x=df['OS'],y=df['Price'],palette='cividis')
plt.xticks(rotation='vertical')
plt.title('Operating System by Price')
plt.show()
```



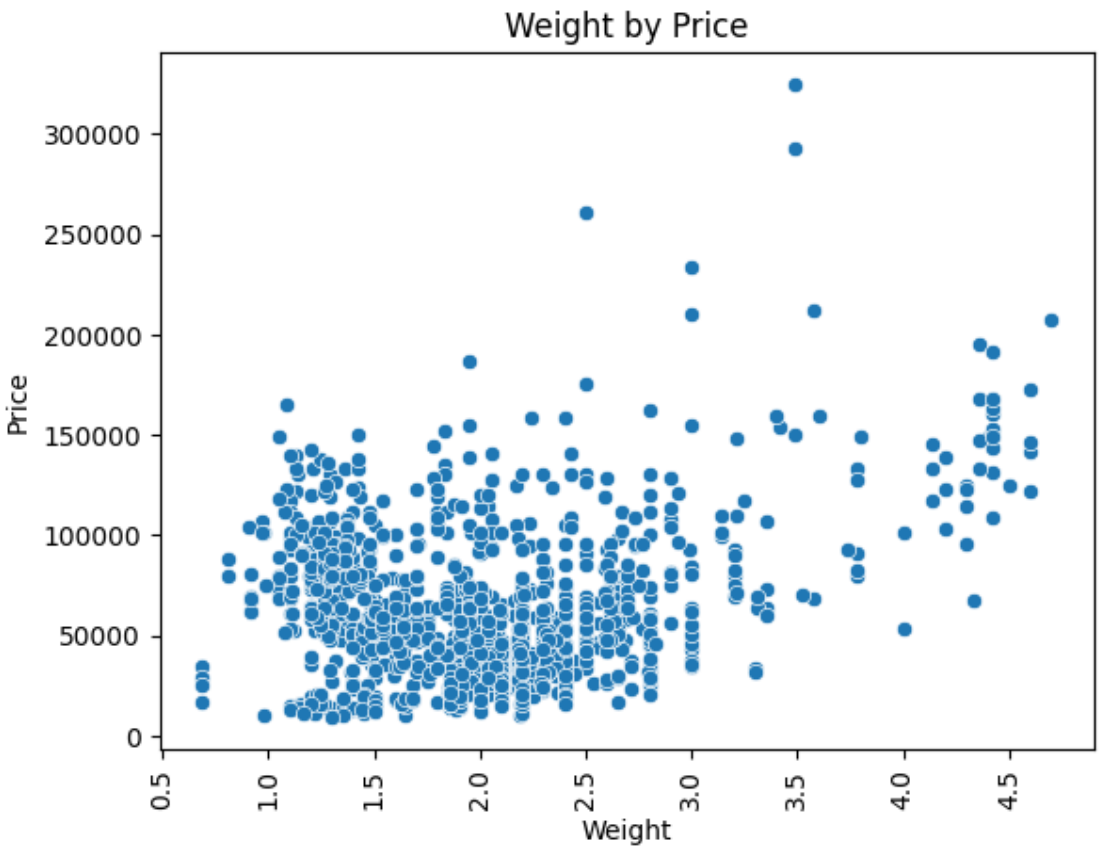
Insight: From the barchart, it is evident that price range is high for laptops having Mac OS.

[81]:
```
sns.histplot(df['Weight'],color='purple')
plt.title('Weight Distribution')
```

[81]:
```
Text(0.5, 1.0, 'Weight Distribution')
```

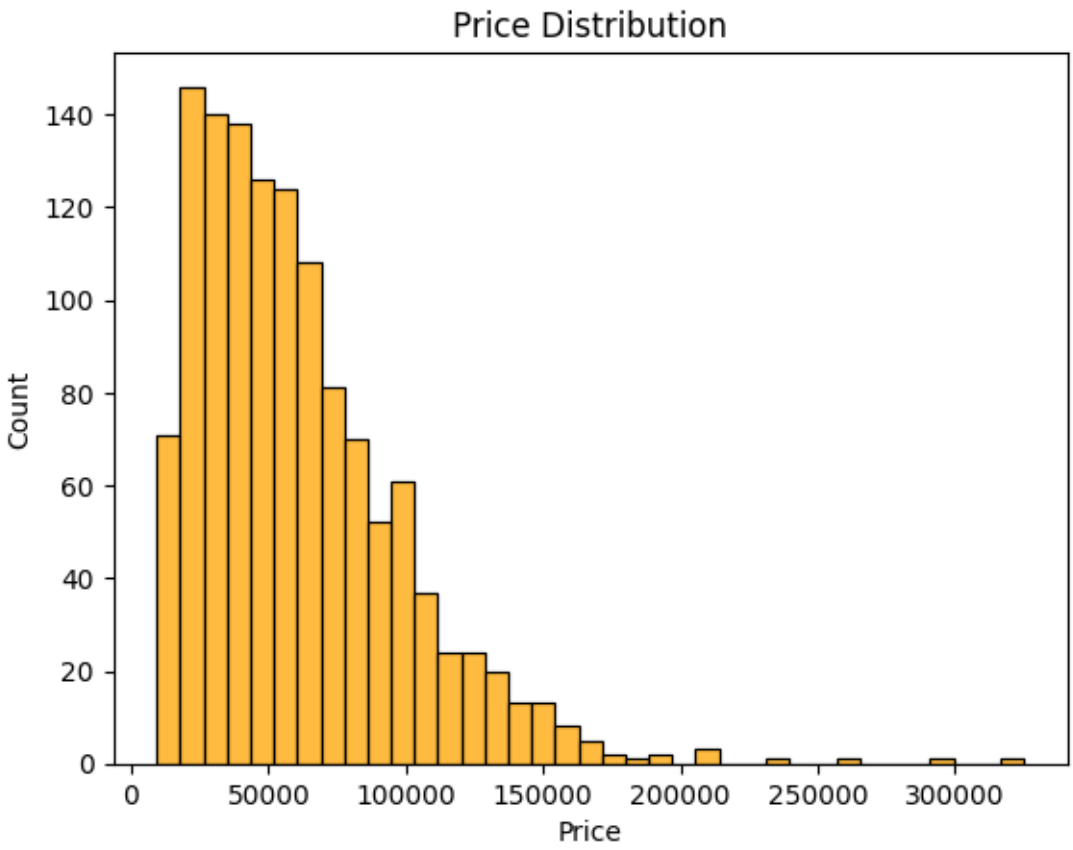


[82]:
```
sns.scatterplot(x=df['Weight'],y=df['Price'])
plt.xticks(rotation='vertical')
plt.title('Weight by Price')
plt.show()
```



[88]:
```
sns.histplot(df['Price'],color='orange')
plt.title('Price Distribution')
```

[88]: Text(0.5, 1.0, 'Price Distribution')



[89]:
```
sns.histplot(np.log(df['Price']),color='orange')
plt.title('Price Distribution')
```

[89]: Text(0.5, 1.0, 'Price Distribution')

7) Feature Correlation

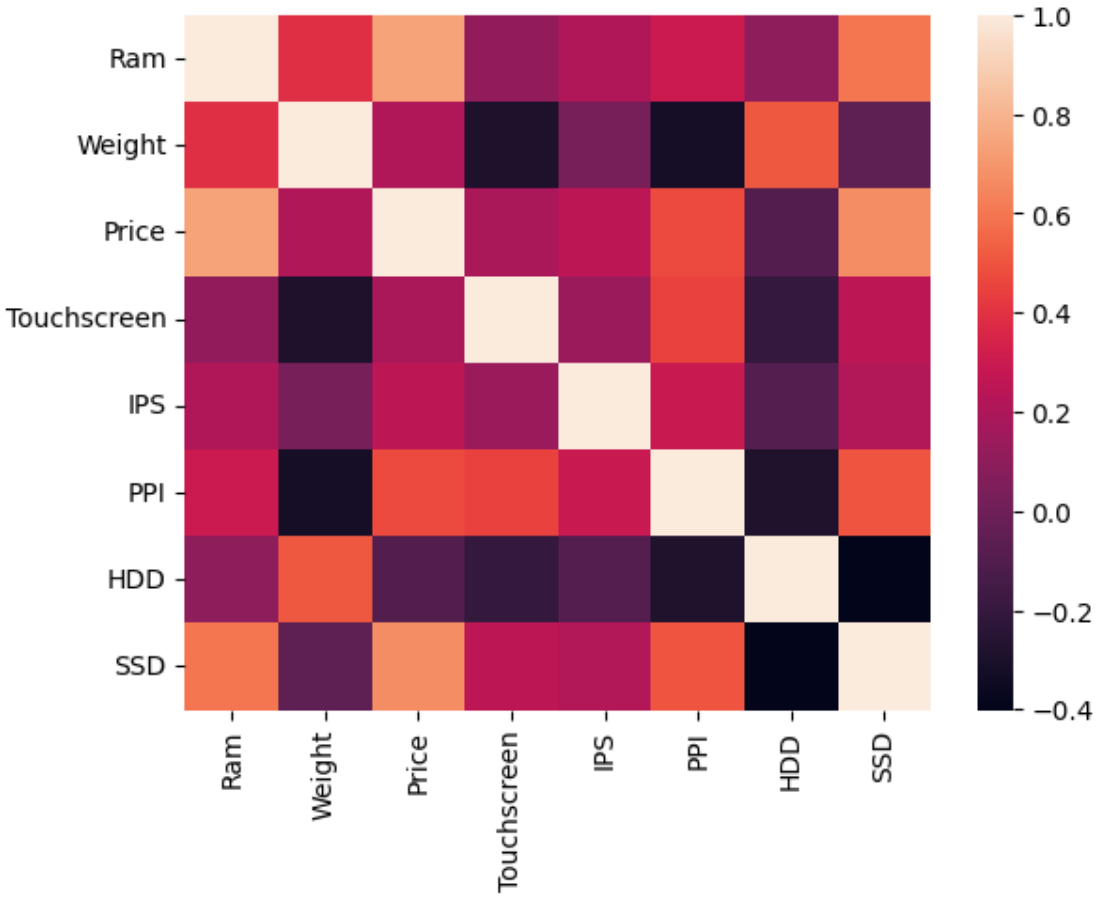
[ ]:
```
df.corr(numeric_only=True)
```

[ ]:
```
                   Ram    Weight     Price  Touchscreen       IPS       PPI  \
Ram           1.000000  0.389134  0.739996     0.113316  0.202809  0.294927
Weight        0.389134  1.000000  0.211667    -0.292288  0.023966 -0.319499
Price         0.739996  0.211667  1.000000     0.190382  0.251514  0.471481
Touchscreen   0.113316 -0.292288  0.190382     1.000000  0.136973  0.452107
IPS           0.202809  0.023966  0.251514     0.136973  1.000000  0.288833
PPI           0.294927 -0.319499  0.471481     0.452107  0.288833  1.000000
HDD           0.097340  0.510876 -0.098481    -0.205105 -0.090411 -0.290774
SSD           0.599552 -0.056985  0.669808     0.252142  0.215197  0.499899

                   HDD       SSD
Ram           0.097340  0.599552
Weight        0.510876 -0.056985
Price        -0.098481  0.669808
Touchscreen  -0.205105  0.252142
IPS          -0.090411  0.215197
```

```
PPI          -0.290774  0.499899
HDD           1.000000 -0.400625
SSD          -0.400625  1.000000
```

[ ]:
```
sns.heatmap(df.corr(numeric_only=True))
```

[ ]: <Axes: >



8) Splitting data to X and y

[ ]:
```
Ind_var=df.drop(columns=['Price'])
Ind_var
```

[ ]:
```
      Company            TypeName  Ram  Weight  Touchscreen  IPS         PPI  \
0       Apple          Ultrabook    8    1.37            0    1  226.983005
1       Apple          Ultrabook    8    1.34            0    0  127.677940
2          HP           Notebook    8    1.86            0    0  141.211998
3       Apple          Ultrabook   16    1.83            0    1  220.534624
4       Apple          Ultrabook    8    1.37            0    1  226.983005
```

```
…      …                  …  …     …           …  …          …
1269    Asus            Notebook    4    2.20            0    0  100.454670
1270  Lenovo  2 in 1 Convertible    4    1.80            1    1  157.350512
1271  Lenovo  2 in 1 Convertible   16    1.30            1    1  276.053530
1272  Lenovo            Notebook    2    1.50            0    0  111.935204
1273      HP            Notebook    6    2.19            0    0  100.454670

                    Cpu Brand   HDD  SSD Gpu Brand Name                 OS
0              Intel Core i5     0  128          Intel                Mac
1              Intel Core i5     0    0          Intel                Mac
2              Intel Core i5     0  256          Intel  Others/No OS/Linux
3              Intel Core i7     0  512            AMD                Mac
4              Intel Core i5     0  256          Intel                Mac
…                        …   …  …            …                  …
1269           Intel Core i7   500    0         Nvidia            Windows
1270           Intel Core i7     0  128          Intel            Windows
1271           Intel Core i7     0  512          Intel            Windows
1272  Other Intel Processor     0    0          Intel            Windows
1273           Intel Core i7  1000    0            AMD            Windows

[1273 rows x 12 columns]
```

[ ]:
```
Dep_var=np.log(df['Price'])
Dep_var
```

[ ]:
```
0       11.175755
1       10.776777
2       10.329931
3       11.814476
4       11.473101
          …
1269    10.555257
1270    10.433899
1271    11.288115
1272     9.409283
1273    10.614129
Name: Price, Length: 1273, dtype: float64
```

9) Splitting data to train data and test data

[ ]:
```
X_train,X_test,y_train,y_test=train_test_split(Ind_var,Dep_var,test_size=0.
↪10,random_state=2)
```

4 Building ML models

[ ]:
```
step1 =␣
 ↪ColumnTransformer(transformers=[('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,
lr=LinearRegression()
rg=Ridge(alpha=10,random_state=42)
ls=Lasso(alpha=0.001,random_state=42)
knn=KNeighborsRegressor(n_neighbors=3)
dt=DecisionTreeRegressor(max_depth=8,random_state=42)
sv=SVR(kernel='rbf')
rf=RandomForestRegressor(n_estimators=100,random_state=42,max_samples=0.
 ↪5,max_features=0.75,max_depth=15)
ad=AdaBoostRegressor(n_estimators=15,random_state=42)

step2 = [lr,rg,ls,knn,dt,sv,rf,ad]
for i in step2:
  print('_'*50,i,'_'*50)
  pipe = Pipeline([('step1',step1),('step2',i)])
  pipe.fit(X_train,y_train)
  y_pred = pipe.predict(X_test)
  print('R2 Score',r2_score(y_test,y_pred))
  print('MAE',mean_absolute_error(y_test,y_pred))
```

```
_____ LinearRegression()
_____
R2 Score 0.7926901156667799
MAE 0.22065476517716653
_____ Ridge(alpha=10,
random_state=42) _____
R2 Score 0.7927938535467675
MAE 0.2235451409312221
_____ Lasso(alpha=0.001,
random_state=42) _____
R2 Score 0.7911292878893352
MAE 0.22399649007048428

_____
KNeighborsRegressor(n_neighbors=3)

_____
R2 Score 0.7486634726488367
MAE 0.2154187555553761

_____
DecisionTreeRegressor(max_depth=8, random_state=42)

_____
R2 Score 0.8019037046093079
MAE 0.2164088620174775
_____ SVR()
_____
```

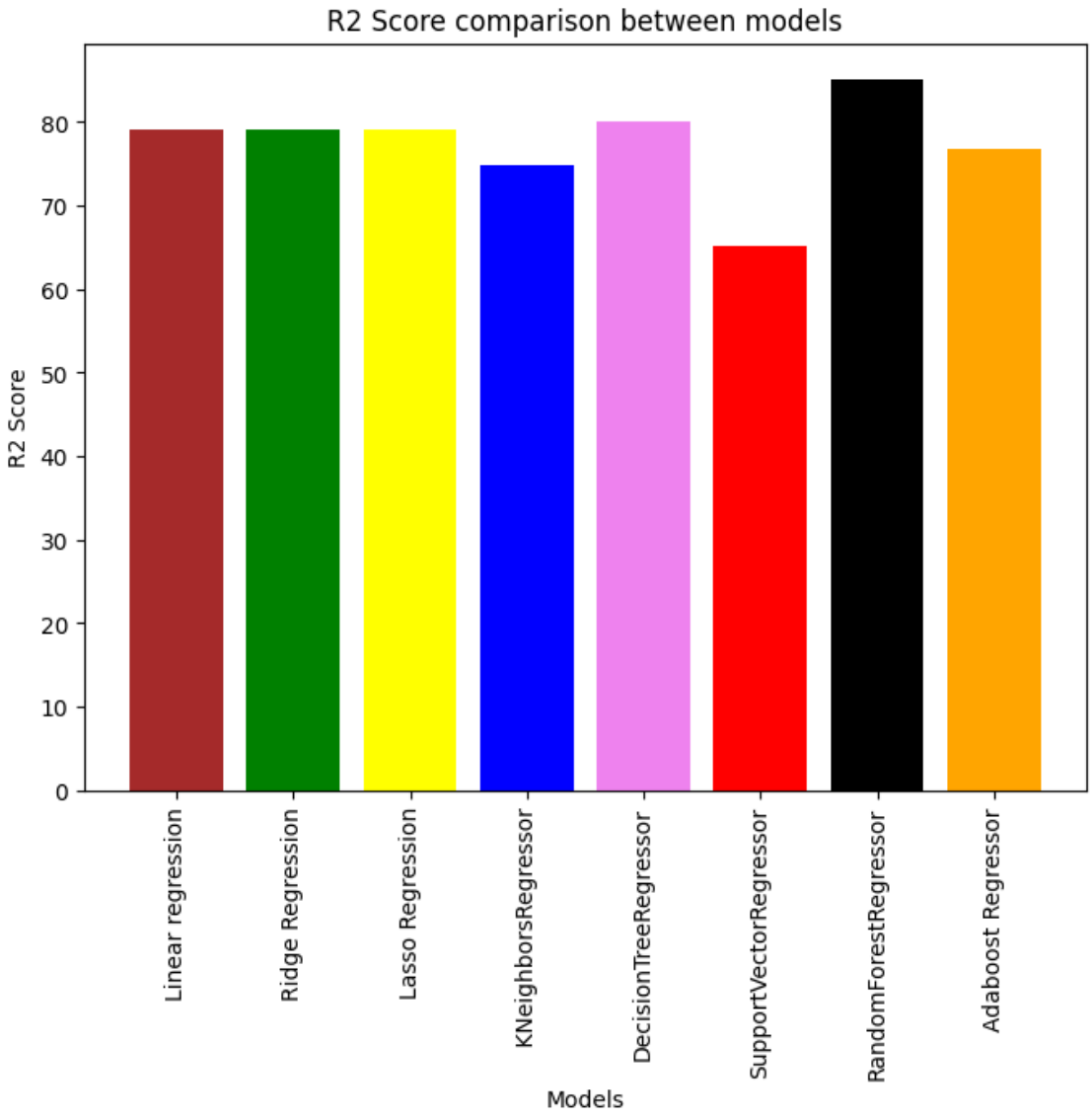
```
R2 Score 0.6515291902558747
MAE 0.26461314868916874

--------------------------------------------------
RandomForestRegressor(max_depth=15, max_features=0.75, max_samples=0.5,
                      random_state=42)

--------------------------------------------------
R2 Score 0.8525464607117873
MAE 0.1794891533537441

--------------------------------------------------
AdaBoostRegressor(n_estimators=15, random_state=42)

--------------------------------------------------
R2 Score 0.7688691453495048
MAE 0.2500654165508208
```

[ ]:
```
# Accuracy Comparison
Table=pd.DataFrame({'Model':['Linear regression','Ridge Regression','Lasso␣
 ↪Regression','␣
 ↪KNeighborsRegressor','DecisionTreeRegressor','SupportVectorRegressor','RandomForestRegresso
 ↪Regressor'],'R2 Score':[0.792,0.792,0.791,0.748,0.801,0.651,0.852,0.768],
                      'MAE':[0.220,0.223,0.223,0.215,0.216,0.264,0.179,0.250]})
Table['R2 Score']=Table['R2 Score']*100
Table
```

[ ]:

	Model	R2 Score	MAE
0	Linear regression	79.2	0.220
1	Ridge Regression	79.2	0.223
2	Lasso Regression	79.1	0.223
3	KNeighborsRegressor	74.8	0.215
4	DecisionTreeRegressor	80.1	0.216
5	SupportVectorRegressor	65.1	0.264
6	RandomForestRegressor	85.2	0.179
7	Adaboost Regressor	76.8	0.250

[ ]:
```
# Plotting Accuracy of Models
plt.figure(figsize=(8,6))
Models=['Linear regression','Ridge Regression','Lasso Regression','␣
 ↪KNeighborsRegressor','DecisionTreeRegressor','SupportVectorRegressor','RandomForestRegresso
 ↪Regressor']
r2_score=[79.2,79.2,79.1,74.8,80.1,65.1,85.2,76.8]
plt.title('R2 Score comparison between models')
plt.xlabel('Models')
plt.ylabel('R2 Score')
plt.
 ↪bar(Models,r2_score,color=['brown','green','yellow','blue','violet','red','black','orange']
plt.xticks(rotation='vertical')
plt.show()
```



Insight: From the bar chart, it is evident that Random Forest Regressor model has high R2 Score and low MAE.

Predicting the Laptop Price

[ ]:
```
# Selecting the best performing model and training it again with data for␣
 ↪prediction
best_model = RandomForestRegressor(n_estimators=100, random_state=3,␣
 ↪max_samples=0.5, max_features=0.75, max_depth=15)
rf_pipe = Pipeline([('step1', step1), ('step2', best_model)])
rf_pipe.fit(X_train, y_train)
```

```
[ ]: Pipeline(steps=[('step1',
                      ColumnTransformer(remainder='passthrough',
                                        transformers=[('col_tnf',
                                                       OneHotEncoder(drop='first',
                                                                     sparse=False),
                                                       [0, 1, 7, 10, 11])])),
                     ('step2',
                      RandomForestRegressor(max_depth=15, max_features=0.75,
                                            max_samples=0.5, random_state=3))])
```

```
[ ]: sample = pd.DataFrame([['Apple', 'Ultrabook', '8', '1.37', '0', '1', '226.
     ↪983005', 'Intel Core i5', '0', '128', 'Intel', 'Mac']],
                              columns=['Company', 'TypeName', 'Ram', 'Weight',␣
     ↪'Touchscreen', 'IPS', 'PPI', 'Cpu Brand', 'HDD', 'SSD', 'Gpu Brand Name',␣
     ↪'OS'])
     y_new = rf_pipe.predict(sample)
     print('Predicted Price:', y_new)
```

```
Predicted Price: [11.13052688]
```

```
[ ]: Price=np.exp(y_new)
     print("The predicted price of this configuration is ",Price)
```

```
The predicted price of this configuration is  [68222.3074989]
```

Exporting the model

```
[ ]: pickle.dump(rf_pipe,open('rf_pipe.pkl','wb'))
     pickle.dump(df,open('df.pkl','wb'))
```

Deploying the model using Stremlit

```
[ ]: !pip install streamlit -q
```

```
                                 8.6/8.6 MB
19.7 MB/s eta 0:00:00
                                 207.3/207.3
kB 17.6 MB/s eta 0:00:00
                                 6.9/6.9 MB
43.2 MB/s eta 0:00:00
                                 83.0/83.0 kB
8.1 MB/s eta 0:00:00
                                 62.7/62.7 kB
6.7 MB/s eta 0:00:00
```

```
[ ]: %%writefile app.py
     import streamlit as st
```

```
from PIL import Image
import pickle
import numpy as np

# Custom CSS to set background color and font color
page_bg_img = '''
<style>
body {
    background-color: #000000;
    color: #ffffff;
}
/* Style for select boxes */
div[data-baseweb="select"] > div:first-child, .st-ct {
    background-color: #000000 !important;
    color: #ffffff !important;
}

/* Style for number input */
.stNumberInput input {
    background-color: #000000;
    color: #ffffff;
}
</style>
'''
st.markdown(page_bg_img, unsafe_allow_html=True)

# import the model
pipe = pickle.load(open('/content/drive/MyDrive/saved models/rf_pipe.pkl','rb'))
df = pickle.load(open('/content/drive/MyDrive/saved models/df.pkl','rb'))

st.title("Laptop Price Predictor")
st.subheader("Welcome! Here you can find out the price of your desired Laptop.")
image=Image.open('/content/drive/MyDrive/laptop_img.jpeg')
st.image(image, width=800)

st.subheader("Fill in the fields")

# brand
company = st.selectbox('Brand',df['Company'].unique())

# type of laptop
typename = st.selectbox('Type',df['TypeName'].unique())

# Ram
ram = st.selectbox('RAM(in GB)',[2,4,6,8,12,16,24,32,64])

# weight
```

```
weight = st.number_input('Weight of the Laptop')

# Touchscreen
touchscreen = st.selectbox('Touchscreen',['No','Yes'])

# IPS
ips = st.selectbox('IPS',['No','Yes'])

# screen size
inches = st.number_input('Screen Size')

# resolution
screen_resolution = st.selectbox('Screen␣
 ↪Resolution',['1920x1080','1366x768','1600x900','3840x2160','3200x1800','2880x1800','2560x16

#cpu
cpu = st.selectbox('CPU',df['Cpu Brand'].unique())

hdd = st.selectbox('HDD(in GB)',[0,128,256,512,1024,2048])

ssd = st.selectbox('SSD(in GB)',[0,8,128,256,512,1024])

gpu = st.selectbox('GPU',df['Gpu Brand Name'].unique())

os = st.selectbox('OS',df['OS'].unique())

if st.button('Predict Price'):

    if touchscreen == 'Yes':
        touchscreen = 1
    else:
        touchscreen = 0

    if ips == 'Yes':
        ips = 1
    else:
        ips = 0

    screen_width= int(screen_resolution.split('x')[0])
    screen_height= int(screen_resolution.split('x')[1])
    ppi = ((screen_width**2) + (screen_height**2))**0.5/inches

    # create the query array
    query = np.
 ↪array([company,typename,ram,weight,touchscreen,ips,ppi,cpu,hdd,ssd,gpu,os],dtype=object).
 ↪reshape(1, -1)
```

```
    # make the prediction
    predicted_price = int(np.exp(pipe.predict(query)[0]))
    st.title(f"The predicted price of this configuration is {predicted_price}")
```

```
Writing app.py
```

[ ]:
```
!wget -q -O - ipv4.icanhazip.com
```

```
34.168.116.153
```

[ ]:
```
! streamlit run app.py & npx localtunnel --port 8501
```

```
Collecting usage statistics. To deactivate, set browser.gatherUsageStats to
false.


  You can now view your Streamlit app in your browser.

  Local URL: http://localhost:8501
  Network URL: http://172.28.0.12:8501
  External URL: http://34.168.116.153:8501

npx: installed 22 in 7.044s
your url is: https://common-masks-punch.loca.lt
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does
not have valid feature names, but OneHotEncoder was fitted with feature names
  warnings.warn(
  Stopping…
^C
```