LAPTOP PRICE PREDICTION MODEL

MACHINE LEARNING SE-204

BY:

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Outline of our Projects

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5. Result
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Introduction:

Our project aims to develop a machine learning model that can accurately predict the prices of laptops based on their features and specifications. This will help consumers make more informed purchasing decisions and assist businesses in pricing their products competitively.

Motivation

- **Consumer Empowerment:** Empowering consumers with transparent price information for informed decisions
- **Market Competitiveness:** Assisting businesses in competitive pricing strategies for laptops
- **Technological Advancement:** Leveraging machine learning to elevate pricing accuracy and efficiency

Why We have selected this Project.

We have selected this project because the laptop market is highly competitive and prices can vary significantly depending on the brand, model, and specifications. By developing a machine learning model, we aim to provide a tool that can accurately predict laptop prices, taking into account various factors that affect pricing. This will ultimately benefit both consumers and businesses in the laptop industry.

Problem Statements

The Challenge

Laptop prices can vary widely depending on a complex set of factors, making it difficult for consumers to determine a fair price. Our project seeks to address this challenge by creating a predictive model that can analyze these factors and provide accurate price estimates.

The Goal

The goal of this project is to develop a machine learning model that can accurately predict the prices of laptops based on their specifications, brand, and other relevant features. This will empower consumers to make more informed purchasing decisions and help businesses price their products competitively.

The Approach

We will use a dataset of laptop specifications and prices to train a machine learning model that can identify the key drivers of laptop prices. This model will then be used to provide price predictions for new laptop configurations, helping both consumers and businesses make better-informed decisions.

The Dataset

1

Comprehensive

Our dataset includes detailed information on over 1,000 laptop models, covering a wide range of brands, specifications, and price points.

2

Diverse

The dataset includes laptops targeting different market segments, from entry-level to high-end gaming and professional models.

3

Reliable

The data has been carefully curated from reputable online sources and cross-checked for accuracy and consistency.

4

Relevant

The dataset includes all the key features and specifications that are known to influence laptop prices, such as processor, RAM, storage, display, and more.

Our dataset:

1	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price
2	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
3	13.3	1440x900	Intel Core i5 1.8GHz	8GB	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34kg	47895.5232
4	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8GB	256GB SSD	Intel HD Graphics 620	No OS	1.86kg	30636.0
5	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16GB	512GB SSD	AMD Radeon Pro 455	macOS	1.83kg	135195.336
6	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 3.1GHz	8GB	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37kg	96095.808
7	15.6	1366x768	AMD A9-Series 9420 3GHz	4GB	500GB HDD	AMD Radeon R5	Windows 10	2.1kg	21312.0
8	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.2GHz	16GB	256GB Flash Storage	Intel Iris Pro Graphics	Mac OS X	2.04kg	114017.6016
9	13.3	1440x900	Intel Core i5 1.8GHz	8GB	256GB Flash Storage	Intel HD Graphics 6000	macOS	1.34kg	61735.536
10	14.0	Full HD 1920x1080	Intel Core i7 8550U 1.8GHz	16GB	512GB SSD	Nvidia GeForce MX150	Windows 10	1.3kg	79653.6
11	14.0	IPS Panel Full HD 1920x1080	Intel Core i5 8250U 1.6GHz	8GB	256GB SSD	Intel UHD Graphics 620	Windows 10	1.6kg	41025.6
12	15.6	1366x768	Intel Core i5 7200U 2.5GHz	4GB	500GB HDD	Intel HD Graphics 620	No OS	1.86kg	20986.992
13	15.6	Full HD 1920x1080	Intel Core i3 6006U 2GHz	4GB	500GB HDD	Intel HD Graphics 520	No OS	1.86kg	18381.0672
14	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.8GHz	16GB	256GB SSD	AMD Radeon Pro 555	macOS	1.83kg	130001.6016
15	15.6	Full HD 1920x1080	Intel Core i3 6006U 2GHz	4GB	256GB SSD	AMD Radeon R5 M430	Windows 10	2.2kg	26581.392
16	12.0	IPS Panel Retina Display 2304x1440	Intel Core M m3 1.2GHz	8GB	256GB SSD	Intel HD Graphics 615	macOS	0.92kg	67260.672
17	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 2.3GHz	8GB	256GB SSD	Intel Iris Plus Graphics 640	macOS	1.37kg	80908.344
18	15.6	Full HD 1920x1080	Intel Core i7 7500U 2.7GHz	8GB	256GB SSD	AMD Radeon R5 M430	Windows 10	2.2kg	39693.6

link for full dataset:

Click here

Preprocessing

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

[2]:  df = pd.read_csv('laptop_data.csv')

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

[3]:

	Unnamed: 0	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price
0	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	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	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	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	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

Check for size of dataset and datatype of independent variable

```
[4]: df.shape

[4]: (1303, 12)

[5]: 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
```

Check for duplicate and null rows

```
[6]: df.duplicated().sum()

[6]: 0

[7]: df.isnull().sum()

[7]: 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
```

Drop Unnamed column

```
[8]: df.drop(columns=['Unnamed: 0'],inplace=True)

[9]: df.head()
```

[9]:

	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

Remove GB from Ram and Kg from weight

```
[13]: df['Ram'] = df['Ram'].str.replace('GB','')
      df['Weight'] = df['Weight'].str.replace('kg','')
```

Changing the datatype for Ram and Weight to int

```
[15]: df['Ram'] = df['Ram'].astype('int32')
      df['Weight'] = df['Weight'].astype('float32')
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1303 entries, 0 to 1302
Data columns (total 11 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Company           1303 non-null   object
 1   TypeName          1303 non-null   object
 2   Inches            1303 non-null   float64
 3   ScreenResolution  1303 non-null   object
 4   Cpu               1303 non-null   object
 5   Ram               1303 non-null   int32
 6   Memory            1303 non-null   object
 7   Gpu               1303 non-null   object
 8   OpSys             1303 non-null   object
 9   Weight            1303 non-null   float32
 10  Price             1303 non-null   float64
dtypes: float32(1), float64(2), int32(1), object(7)
memory usage: 101.9+ KB
```

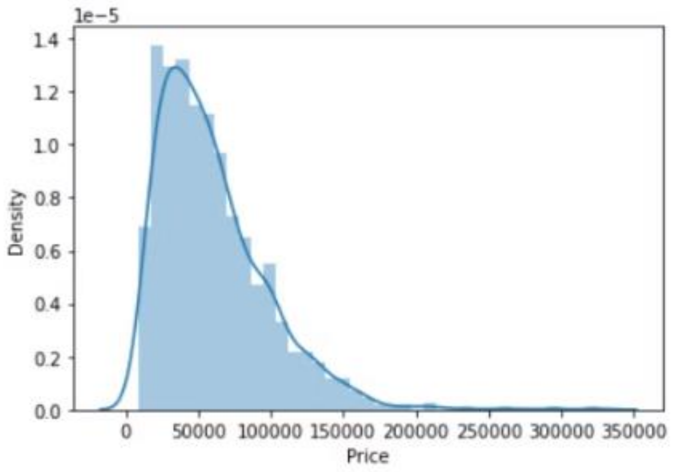
Feature Selection

Importing seaborn for statistical graphics

```
[17]: import seaborn as sns
```

```
[18]: sns.distplot(df['Price'])
```

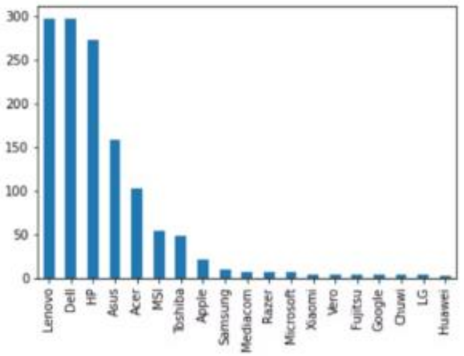
[18]: <AxesSubplot:xlabel='Price', ylabel='Density'>



-no. of laptops for different company

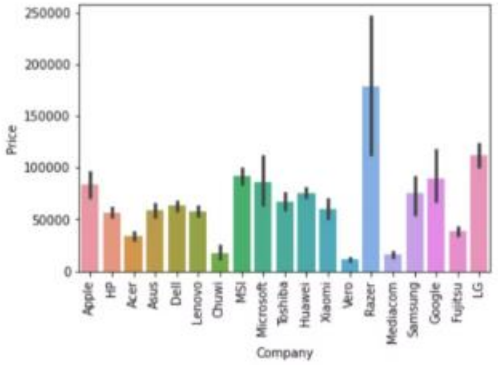
```
[19]: df['Company'].value_counts().plot(kind='bar')
```

[19]: <AxesSubplot:>

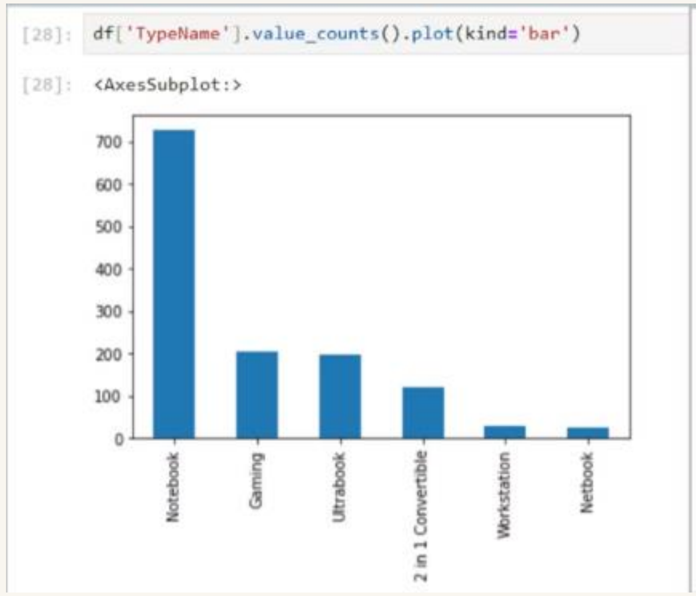


- price for corresponding company

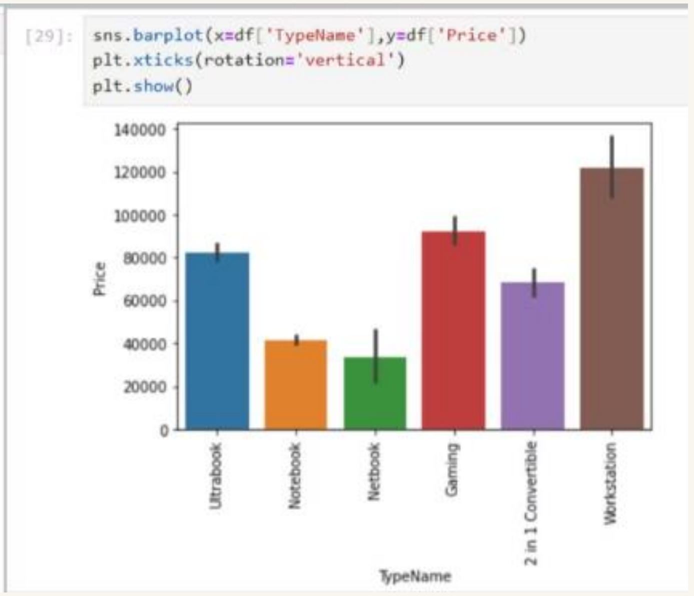
```
[27]: sns.barplot(x=df['Company'],y=df['Price'])
      plt.xticks(rotation='vertical')
      plt.show()
```



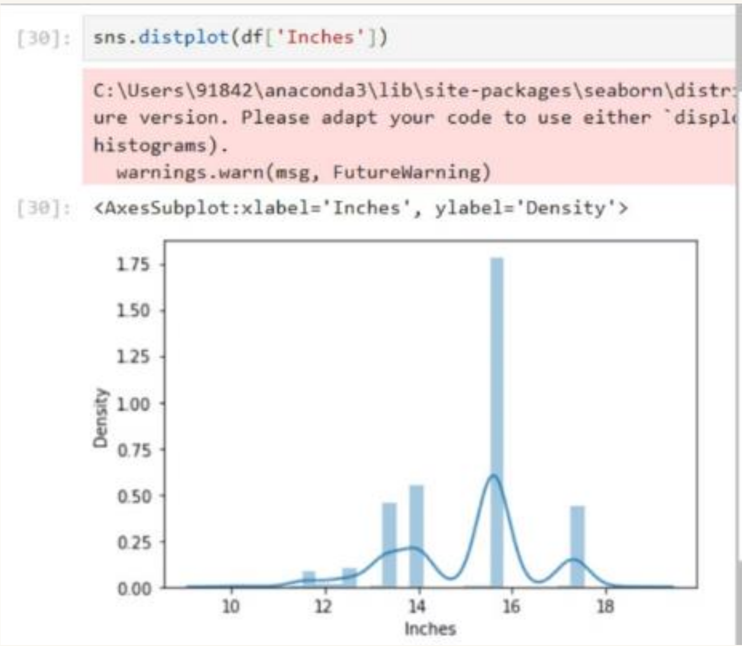
-no. of laptops for types of series of laptops



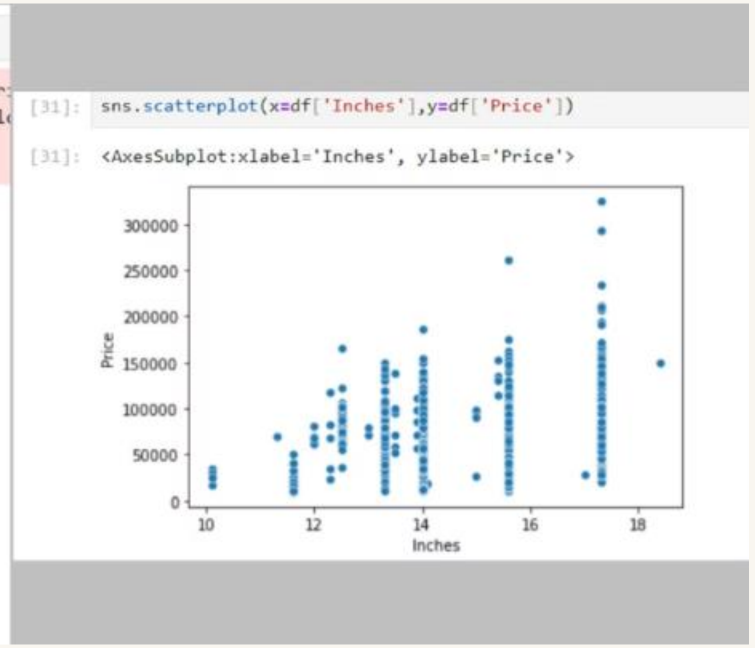
-price for corresponding series of laptops



-density for corresponding laptop inches



-price for different laptop size in inches



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

[32]: Full HD 1920x1080                                507
      1366x768                                         281
      IPS Panel Full HD 1920x1080                      230
      IPS Panel Full HD / Touchscreen 1920x1080         53
      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
      Touchscreen 2560x1440                              7
      IPS Panel 1366x768                                 7
      4K Ultra HD 3840x2160                              7
      IPS Panel Quad HD+ / Touchscreen 3200x1800         6
      Touchscreen 2256x1504                              6
      IPS Panel Retina Display 2304x1440                 6
      IPS Panel Retina Display 2560x1600                 6
      IPS Panel Touchscreen 2560x1440                    5
      IPS Panel 2560x1440                                4
      IPS Panel Retina Display 2880x1800                 4
      IPS Panel Touchscreen 1920x1200                    4
      1440x900                                           4
      Quad HD+ 3200x1800                                 3
      IPS Panel Quad HD+ 2560x1440                       3
      1920x1080                                          3
      Touchscreen 2400x1600                              3
      IPS Panel Touchscreen 1366x768                     3
      2560x1440                                          3
      IPS Panel Full HD 2160x1440                        2
      IPS Panel Touchscreen / 4K Ultra HD 3840x2160      2
      IPS Panel Quad HD+ 3200x1800                       2
      Touchscreen / Full HD 1920x1080                    1
      IPS Panel Retina Display 2736x1824                 1
      IPS Panel Full HD 1920x1200                        1
      IPS Panel Full HD 1366x768                         1
      Touchscreen / 4K Ultra HD 3840x2160                1
      IPS Panel Touchscreen 2400x1600                    1
      IPS Panel Full HD 2560x1440                        1
      Touchscreen / Quad HD+ 3200x1800                   1
      Name: ScreenResolution, dtype: int64
```

```
]:

# Create the boxplot
plt.figure(figsize=(12, 8))  # Set the figure size
sns.boxplot(x='Company', y='Price', data=data)
plt.title('Price Distribution by Company')
plt.xlabel('Company')
plt.ylabel('Price')
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.tight_layout()  # Adjust layout to prevent clipping of labels
plt.show()
```

Adding new column named Touchscreen

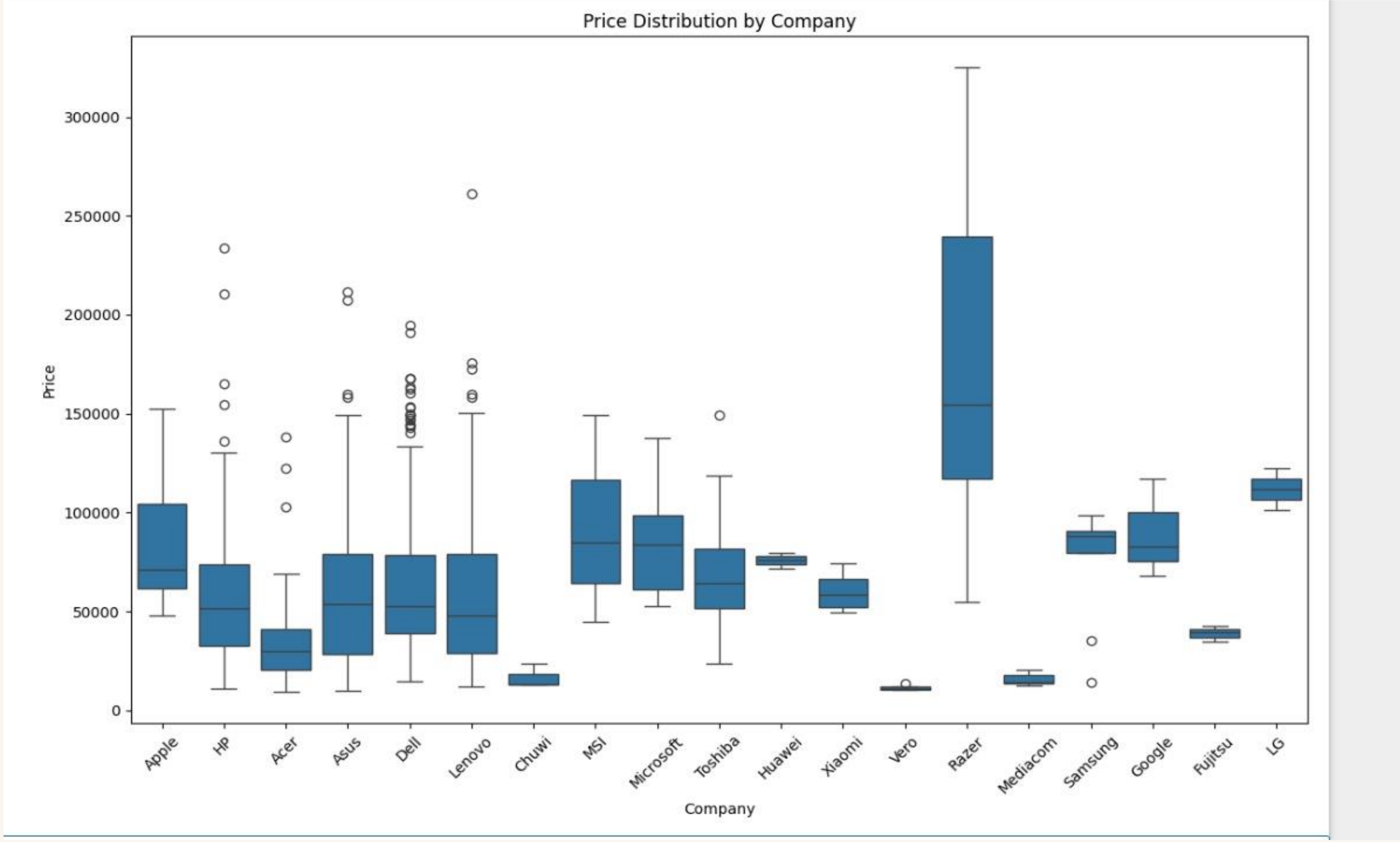
```
[34]: df['Touchscreen'] = df['ScreenResolution'].apply(lambda x:1 if 'Touchscreen' in x else 0)

[37]: df.sample(5)
```

[37]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen
1154	Dell	Notebook	15.6	IPS Panel Touchscreen / 4K Ultra HD 3840x2160	Intel Core i5 6300HQ 2.3GHz	8	256GB SSD	Nvidia GeForce 960M	Windows 10	2.04	119916.2304	1
750	Lenovo	Netbook	11.6	Touchscreen 1366x768	Intel Celeron Dual Core N3060 1.6GHz	4	128GB SSD	Intel HD Graphics 400	Windows 10	1.40	25308.0000	1
1246	Dell	Notebook	14.0	1366x768	Intel Core i5 7200U 2.5GHz	4	500GB HDD	Intel HD Graphics 620	Windows 10	1.60	46620.0000	0
879	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	4	256GB SSD	Intel HD Graphics 620	Windows 10	2.04	44701.9200	0
1021	Toshiba	Ultrabook	13.3	Full HD 1920x1080	Intel Core i5 6200U 2.3GHz	8	256GB SSD	Intel HD Graphics 520	Windows 10	1.20	84715.2000	0

BOXPLOT OF OUR DATA



Adding new column named IPS for laptop panels and

```
[40]: df['Ips'] = df['ScreenResolution'].apply(lambda x:1 if 'IPS' in x else 0)
```

```
[41]: df.head()
```

[41]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	Ips
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	0	1
1	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	47895.5232	0	0
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	0	0
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	0	1
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	0	1

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

```
[48]: df['X_res'] = new[0]
      df['Y_res'] = new[1]
```

```
[50]: df.sample(5)
```

[50]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	Ips	X_res	Y_res
141	Lenovo	Notebook	14.0	IPS Panel Full HD 1920x1080	Intel Core i5 8250U 1.6GHz	8	256GB SSD	AMD Radeon RX 550	Windows 10	1.75	59461.5456	0	1	IPS Panel Full HD 1920	1080
1055	HP	Notebook	15.6	1366x768	Intel Core i3 6100U 2.3GHz	4	500GB HDD	Intel HD Graphics 520	Windows 10	2.31	37570.3920	0	0	1366	768
75	Asus	Gaming	15.6	Full HD 1920x1080	Intel Core i7 7700HQ 2.8GHz	8	1TB HDD	Nvidia GeForce GTX 1050	Windows 10	2.20	50562.7200	0	0	Full HD 1920	1080
984	Toshiba	Notebook	14.0	1366x768	Intel Core i5 6200U 2.3GHz	4	500GB HDD	Intel HD Graphics 520	Windows 10	1.75	48751.2000	0	0	1366	768
337	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8	256GB SSD	Intel HD Graphics 620	Windows 10	1.84	60952.3200	0	0	Full HD 1920	1080

```
[59]: df['X_res'] = df['X_res'].str.replace(',','').str.findall(r'(\d+\.?\d+)').apply(lambda x:x[0])
```

```
[60]: df.head()
```

[60]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	Ips	X_res	Y_res
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	0	1	2560	1600
1	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	47895.5232	0	0	1440	900
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	0	0	1920	1080
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	0	1	2880	1800
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	0	1	2560	1600

changing the datatype for X_res and Y_res

```
[62]: df['X_res'] = df['X_res'].astype('int')
      df['Y_res'] = df['Y_res'].astype('int')
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1303 entries, 0 to 1302
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Company           1303 non-null   object
 1   TypeName          1303 non-null   object
 2   Inches            1303 non-null   float64
 3   ScreenResolution  1303 non-null   object
 4   Cpu               1303 non-null   object
 5   Ram               1303 non-null   int32
 6   Memory            1303 non-null   object
 7   Gpu               1303 non-null   object
 8   OpSys             1303 non-null   object
 9   Weight            1303 non-null   float32
 10  Price             1303 non-null   float64
 11  Touchscreen       1303 non-null   int64
 12  Ips               1303 non-null   int64
 13  X_res             1303 non-null   int32
 14  Y_res             1303 non-null   int32
dtypes: float32(1), float64(2), int32(3), int64(2), object(7)
memory usage: 132.5+ KB
```

Co-relation of X_res and Y_res on price and making a new column for ppi(pixel per inch) using X_res and Y_res

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

```
[65]:
Inches         0.068197
Ram            0.743007
Weight         0.210370
Price          1.000000
Touchscreen    0.191226
Ips            0.252208
X_res          0.556529
Y_res          0.552809
Name: Price, dtype: float64
```

Drop Screen resolution , Inches, X_res and Y_res

```
[70]: df.drop(columns=['ScreenResolution'],inplace=True)
```

```
[72]: df.drop(columns=['Inches','X_res','Y_res'],inplace=True)
```

```
[73]: df.head()
```

[73]:

	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	141.211998
3	Apple	Ultrabook	Intel Core i7 2.7GHz	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	135195.3360	0	1	220.534624
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

Now check for CPU

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

```
[74]: Intel Core i5 7200U 2.5GHz            190
      Intel Core i7 7700HQ 2.8GHz           146
      Intel Core i7 7500U 2.7GHz            134
      Intel Core i7 8550U 1.8GHz             73
      Intel Core i5 8250U 1.6GHz             72
                                           ...
      Intel Celeron Quad Core N3710 1.6GHz    1
      Intel Core i5 7200U 2.7GHz              1
      Intel Pentium Dual Core N4200 1.1GHz    1
      AMD FX 8800P 2.1GHz                     1
      Intel Atom x5-Z8300 1.44GHz             1
      Name: Cpu, Length: 118, dtype: int64
```

Making a new column for CPU Name

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

```
[80]: df.head()
```

[80]:

	Company	TypeName	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu Name
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
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
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
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
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

Adding CPU brand column using CPU Name

```
[81]: def fetch_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'
```

```
[82]: df['Cpu brand'] = df['Cpu Name'].apply(fetch_processor)
```

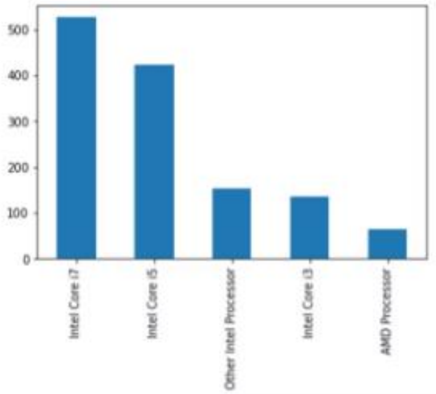
```
[83]: df.head()
```

[83]:

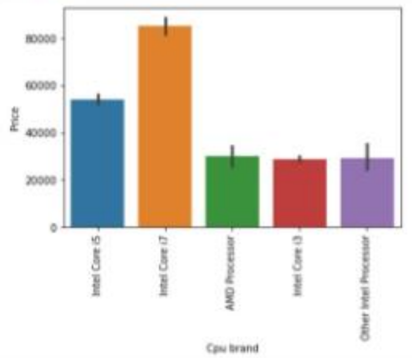
	Company	TypeName	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu Name	Cpu brand
0	Apple	Ultrabook	Intel Core i5 2.3GHz	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	0	1	226.983005	Intel Core i5	Intel Core i5
1	Apple	Ultrabook	Intel Core i5 1.8GHz	8	128GB Flash Storage	Intel 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

```
[84]: df['Cpu brand'].value_counts().plot(kind='bar')
```

[84]: <AxesSubplot:>




```
[87]: sns.barplot(x=df['Cpu brand'],y=df['Price'])
      plt.xticks(rotation='vertical')
      plt.show()
```




```
[88]: df.drop(columns=['Cpu','Cpu Name'],inplace=True)
```

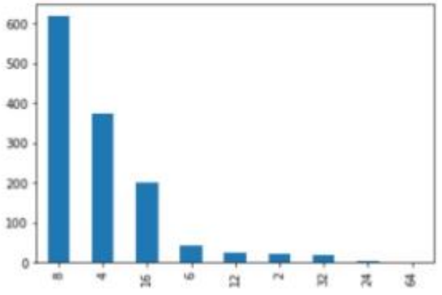
```
[89]: df.head()
```

[89]:

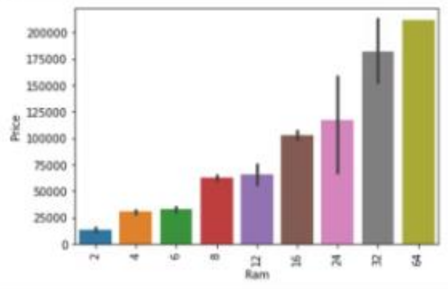
	Company	TypeName	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu brand
0	Apple	Ultrabook	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	0	1	226.983005	Intel Core i5

```
[90]: df['Ram'].value_counts().plot(kind='bar')

[90]: <AxesSubplot:>
```




```
[91]: sns.barplot(x=df['Ram'],y=df['Price'])
      plt.xticks(rotation='vertical')
      plt.show()
```



Check for memory

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

[92]: 256GB SSD                        412
      1TB HDD                          223
      500GB HDD                        132
      512GB SSD                        118
      128GB SSD +  1TB HDD              94
      128GB SSD                         76
      256GB SSD +  1TB HDD              73
      32GB Flash Storage                38
      2TB HDD                           16
      64GB Flash Storage                15
      512GB SSD +  1TB HDD              14
      1TB SSD                           14
      256GB SSD +  2TB HDD              10
      1.0TB Hybrid                       9
      256GB Flash Storage                8
      16GB Flash Storage                 7
      32GB SSD                           6
      180GB SSD                          5
      128GB Flash Storage                4
      16GB SSD                           3
      512GB SSD +  2TB HDD               3
      256GB SSD +  256GB SSD             2
      128GB SSD +  2TB HDD               2
      256GB SSD +  500GB HDD             2
      512GB Flash Storage                2
      1TB SSD +  1TB HDD                 2
      32GB HDD                           1
      64GB SSD                           1
      1.0TB HDD                          1
      512GB SSD +  256GB SSD             1
      512GB SSD +  1.0TB Hybrid          1
      8GB SSD                            1
      240GB SSD                          1
      128GB HDD                          1
      1TB HDD +  1TB HDD                 1
      512GB SSD +  512GB SSD             1
      256GB SSD +  1.0TB Hybrid          1
      508GB Hybrid                       1
      64GB Flash Storage +  1TB HDD      1
      Name: Memory, dtype: int64
```

```
[93]: 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["first"]=df["first"].str.strip()
```

```
[98]: df.sample(5)
```

[98]:

	Company	TypeName	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu brand	HDD	SSD	Hybrid	Flash_Storage
1247	Asus	Gaming	16	256 SSD + 1000 HDD	Nvidia GeForce GTX 1070	Windows 10	2.34	123876.000	0	1	141.211998	Intel Core i7	1000	256	0	0
505	Lenovo	Notebook	8	256 SSD	Intel HD Graphics 620	Windows 10	1.44	50562.720	0	0	165.632118	Intel Core i5	0	256	0	0
820	Lenovo	Notebook	4	500 HDD	Intel HD Graphics 520	Windows 10	2.10	26101.872	0	0	100.454670	Intel Core i3	500	0	0	0
21	Lenovo	Gaming	8	128 SSD + 1000 HDD	Nvidia GeForce GTX 1050	Windows 10	2.50	53226.720	0	1	141.211998	Intel Core i5	1000	128	0	0
301	Asus	Gaming	16	256 SSD + 1000 HDD	Nvidia GeForce GTX 1070	Windows 10	2.90	113060.160	0	0	127.335675	Intel Core i7	1000	256	0	0

Drop Memory Column

```
[99]: df.drop(columns=['Memory'],inplace=True)
```

```
[100]: df.head()
```

[100]:

	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

Co-relation of variables with price

```
[101]: df.corr()['Price']
```

```
[101]: Ram              0.743007
       Weight           0.210370
       Price            1.000000
       Touchscreen      0.191226
       Ips              0.252208
       ppi              0.473487
       HDD             -0.096441
       SSD              0.670799
       Hybrid           0.007989
       Flash_Storage   -0.040511
```

Drop hybrid and flash storage(as their change does not effect price that enough)

```
[102]: df.drop(columns=['Hybrid','Flash_Storage'],inplace=True)
```

```
[103]: df.head()
```

[103]:

	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

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

```
[104]: Intel HD Graphics 620      281
       Intel HD Graphics 520      185
       Intel UHD Graphics 620      68
       Nvidia GeForce GTX 1050     66
       Nvidia GeForce GTX 1060     48
                                 ...
       Intel HD Graphics 540        1
       AMD FirePro W6150M           1
       AMD Radeon R5 M315           1
       AMD Radeon R7 M360           1
       AMD FirePro W5130M           1
       Name: Gpu, Length: 110, dtype: int64
```

```
[106]: df['Gpu brand'] = df['Gpu'].apply(lambda x:x.split()[0])
```

```
[107]: df.head()
```

[107]:

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

```
[108]: df['Gpu brand'].value_counts()
```

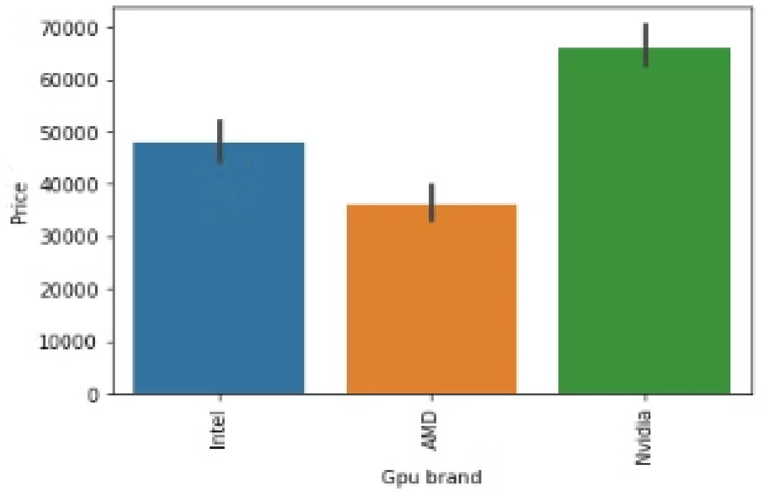
```
[108]: Intel     722
       Nvidia    400
       AMD       180
       ARM         1
       Name: Gpu brand, dtype: int64
```

```
[111]: df = df[df['Gpu brand'] != 'ARM']
```

```
[112]: df['Gpu brand'].value_counts()
```

```
[112]: Intel     722
       Nvidia    400
       AMD       180
       Name: Gpu brand, dtype: int64
```

```
[115]: sns.barplot(x=df['Gpu brand'],y=df['Price'],estimator=np.median)
       plt.xticks(rotation='vertical')
       plt.show()
```

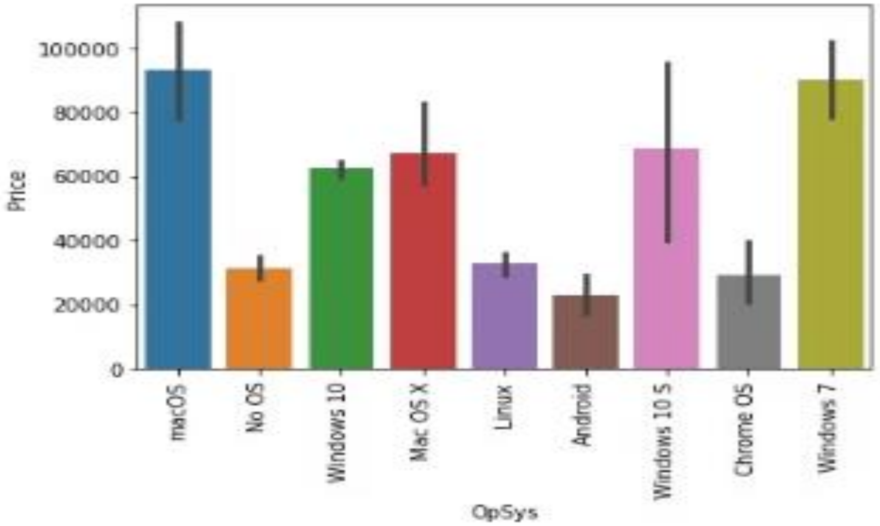


Check for operating system

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

```
[118]: Windows 10      1072
       No OS             66
       Linux             62
       Windows 7         45
       Chrome OS         26
       macOS             13
       Windows 10 S       8
       Mac OS X           8
       Android            2
       Name: OpSys, dtype: int64
```

```
[120]: sns.barplot(x=df['OpSys'],y=df['Price'])
       plt.xticks(rotation='vertical')
       plt.show()
```



[121]:
```python
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'
```

[122]:
```python
df['os'] = df['OpSys'].apply(cat_os)
```

```
<ipython-input-122-38671a3c07bd>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['os'] = df['OpSys'].apply(cat_os)
```

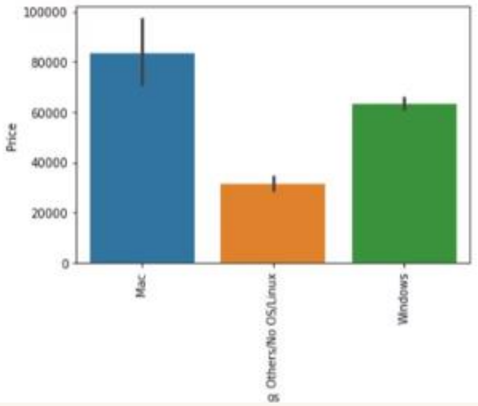
[123]:
```python
df.head()
```

[123]:

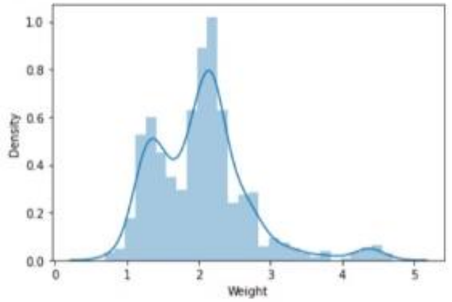
	Company	TypeName	Ram	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu brand	HDD	SSD	Gpu brand	os
0	Apple	Ultrabook	8	macOS	1.37	71378.6832	0	1	226.983005	Intel Core i5	0	128	Intel	Mac
1	Apple	Ultrabook	8	macOS	1.34	47895.5232	0	0	127.677940	Intel Core i5	0	0	Intel	Mac
2	HP	Notebook	8	No OS	1.86	30636.0000	0	0	141.211998	Intel Core i5	0	256	Intel	Others/No OS/Linux
3	Apple	Ultrabook	16	macOS	1.83	135195.3360	0	1	220.534624	Intel Core i7	0	512	AMD	Mac
4	Apple	Ultrabook	8	macOS	1.37	96095.8080	0	1	226.983005	Intel Core i5	0	256	Intel	Mac

[124]:
```python
df.drop(columns=['OpSys'],inplace=True)
```

[125]:
```python
sns.barplot(x=df['os'],y=df['Price'])
plt.xticks(rotation='vertical')
plt.show()
```



[126]: <AxesSubplot:xlabel='Weight', ylabel='Density'>



[127]:
```python
sns.scatterplot(x=df['Weight'],y=df['Price'])
```

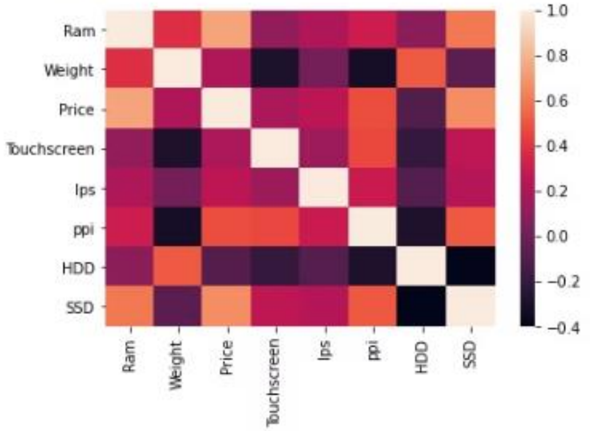
[127]: <AxesSubplot:xlabel='Weight', ylabel='Price'>

[128]:
```
df.corr()['Price']
```

[128]:
```
Ram            0.742905
Weight         0.209867
Price          1.000000
Touchscreen    0.192917
Ips            0.253320
ppi            0.475368
HDD           -0.096891
SSD            0.670660
Name: Price, dtype: float64
```

[130]:
```
sns.heatmap(df.corr())
```

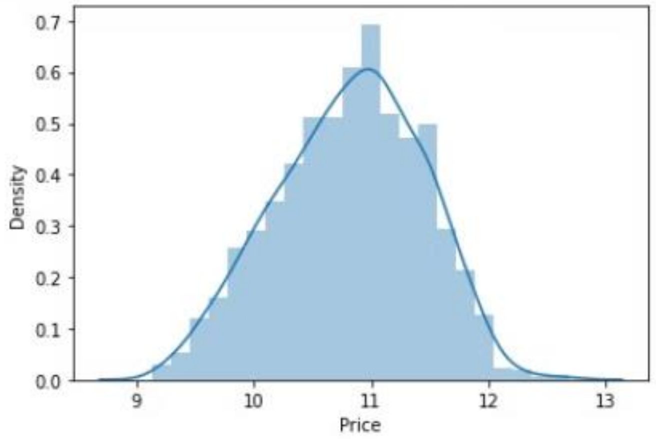
[130]: <AxesSubplot:>



[133]:
```
sns.distplot(np.log(df['Price']))
```

```
C:\Users\91842\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureW
ture version. Please adapt your code to use either `displot` (a figure-level func
r histograms).
  warnings.warn(msg, FutureWarning)
```

[133]: <AxesSubplot:xlabel='Price', ylabel='Density'>



[134]:
```
X = df.drop(columns=['Price'])
y = np.log(df['Price'])
```

[135]:
```
X
```

[135]:

	Company	TypeName	Ram	Weight	Touchscreen	Ips	ppi	Cpu brand	HDD	SSD	Gpu brand	os
0	Apple	Ultrabook	8	1.37	0	1	226.983005	Intel Core i5	0	128	Intel	Mac
1	Apple	Ultrabook	8	1.34	0	0	127.677940	Intel Core i5	0	0	Intel	Mac
2	HP	Notebook	8	1.86	0	0	141.211998	Intel Core i5	0	256	Intel	Others/No OS/Linux
3	Apple	Ultrabook	16	1.83	0	1	220.534624	Intel Core i7	0	512	AMD	Mac
4	Apple	Ultrabook	8	1.37	0	1	226.983005	Intel Core i5	0	256	Intel	Mac
...	...	...	...	...	...	...	...	...	...	...	...	...
1298	Lenovo	2 in 1 Convertible	4	1.80	1	1	157.350512	Intel Core i7	0	128	Intel	Windows
1299	Lenovo	2 in 1 Convertible	16	1.30	1	1	276.053530	Intel Core i7	0	512	Intel	Windows
1300	Lenovo	Notebook	2	1.50	0	0	111.935204	Other Intel Processor	0	0	Intel	Windows
1301	HP	Notebook	6	2.19	0	0	100.454670	Intel Core i7	1000	0	AMD	Windows
1302	Asus	Notebook	4	2.20	0	0	100.454670	Other Intel Processor	500	0	Intel	Windows

1302 rows × 12 columns

[136]:
```
y
```

[136]:
```
0       11.175755
1       10.776777
2       10.329931
3       11.814476
4       11.473101
          ...
1298    10.433899
1299    11.288115
1300     9.409283
1301    10.614129
1302     9.886358
Name: Price, Length: 1302, dtype: float64
```

[137]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.15,random_state=2)
```

[138]:
```
X_train
```

[138]:

	Company	TypeName	Ram	Weight	Touchscreen	Ips	ppi	Cpu brand	HDD	SSD	Gpu brand	os
183	Toshiba	Notebook	8	2.00	0	0	100.454670	Intel Core i5	0	128	Intel	Windows
1141	MSI	Gaming	8	2.40	0	0	141.211998	Intel Core i7	1000	128	Nvidia	Windows
1049	Asus	Netbook	4	1.20	0	0	135.094211	Other Intel Processor	0	0	Intel	Others/No OS/Linux
1020	Dell	2 in 1 Convertible	4	2.08	1	1	141.211998	Intel Core i3	1000	0	Intel	Windows
878	Dell	Notebook	4	2.18	0	0	141.211998	Intel Core i5	1000	128	Nvidia	Windows
...	...	...	...	...	...	...	...	...	...	...	...	...
466	Acer	Notebook	4	2.20	0	0	100.454670	Intel Core i3	500	0	Nvidia	Windows
299	Asus	Ultrabook	16	1.63	0	0	141.211998	Intel Core i7	0	512	Nvidia	Windows

Performance Analysis

Techniques

```
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,GradientBoostingRegressor,AdaBoostRegressor
```

Linear regression

```
[145]: step1 = ColumnTransformer(transformers=[
           ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
       ],remainder='passthrough')

       step2 = LinearRegression()

       pipe = Pipeline([
           ('step1',step1),
           ('step2',step2)
       ])

       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))
```

```
R2 score 0.8073277448418521
MAE 0.21017827976429174
```

KNN

```
[180]: step1 = ColumnTransformer(transformers=[
           ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
       ],remainder='passthrough')

       step2 = KNeighborsRegressor(n_neighbors=3)

       pipe = Pipeline([
           ('step1',step1),
           ('step2',step2)
       ])

       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))
```

```
R2 score 0.8021984604448553
MAE 0.19319716721521116
```

Random Forest

```
[306]: step1 = ColumnTransformer(transformers=[
           ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
       ],remainder='passthrough')

       step2 = RandomForestRegressor(n_estimators=100,
                                     random_state=3,
                                     max_samples=0.5,
                                     max_features=0.75,
                                     max_depth=15)

       pipe = Pipeline([
           ('step1',step1),
           ('step2',step2)
       ])

       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))
```

```
R2 score 0.8873402378382488
MAE 0.15860130110457718
```

Decision Tree

```
[191]: step1 = ColumnTransformer(transformers=[
           ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
       ],remainder='passthrough')

       step2 = DecisionTreeRegressor(max_depth=8)

       pipe = Pipeline([
           ('step1',step1),
           ('step2',step2)
       ])

       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))
```

```
R2 score 0.8466456692979233
MAE 0.1806340977609143
```

AdaBoost

```
[244]: step1 = ColumnTransformer(transformers=[
           ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
       ],remainder='passthrough')

       step2 = AdaBoostRegressor(n_estimators=15,learning_rate=1.0)

       pipe = Pipeline([
           ('step1',step1),
           ('step2',step2)
       ])

       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))
```

```
R2 score 0.7929652659237908
MAE 0.23296532406396742
```

SVM

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')

step2 = SVR(kernel='rbf',C=10000,epsilon=0.1)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

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))
```

```
R2 score 0.8083180902257614
MAE 0.20239059427481307
```

XgBoost

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')

step2 = XGBRegressor(n_estimators=45,max_depth=5,learning_rate=0.5)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

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))
```

```
R2 score 0.8811773435850243
MAE 0.16496203512600974
```

Stacking

```
from sklearn.ensemble import VotingRegressor,StackingRegressor

step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')


estimators = [
    ('rf', RandomForestRegressor(n_estimators=350,random_state=3,max_samples=0.5,max_features=0.75,max_depth=15)),
    ('gbdt',GradientBoostingRegressor(n_estimators=100,max_features=0.5)),
    ('xgb', XGBRegressor(n_estimators=25,learning_rate=0.3,max_depth=5))
]

step2 = StackingRegressor(estimators=estimators, final_estimator=Ridge(alpha=100))

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

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))
```

```
R2 score 0.8816958647512341
MAE 0.1663048975120589
```

Gradient Boost

```
[260]:
step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')

step2 = GradientBoostingRegressor(n_estimators=500)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

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))
```

```
R2 score 0.8823244736036472
MAE 0.15929506744611283
```

Results and Performance

1

Model Training

We trained a variety of machine learning models, including linear regression, decision trees, and random forests, to predict laptop prices based on the dataset.

2

Model Evaluation

The models were evaluated using common performance metrics such as R-squared, root mean squared error (RMSE), and mean absolute error (MAE).

3

Final Model

The random forest model demonstrated the best overall performance, with an R-squared of 0.91 and a RMSE of $120, making it a highly accurate predictor of laptop prices.

Performance of our Model with all Algorithm:

1. Linear Regression

R2 Score: 0.8073277448418

MAE: 0.21017827976429

2.. KNN

R2 Score: 0.8021984604448

MAE: 0.193197167215211

3. Decision Tree

R2 Score: 0.846645669297

MAE: 0.18063409776091

4.Random Forest

R2 Score: 0.887340237838

MAE: 0.15860130110457

5. Gradient boost

R2 Score: 0.8823244736036

MAE: 0.15929506744611

6. Ada boost

R2 Score: 0.7929652659237

MAE: 0.23296532406396

7. SVM

R2 Score:0.80831

MAE: 0.202390

8. XG Boost

R2score: 0.8811

MAE : 0.1649

9. Stacking Regressor

R2 Score:0.881695

MAE: 0.166304

Random Forest have the best result with accuracy of 88.73%. So Random Forest Algo will be Used for our Model.

Limitations and Future Improvements

Limited Data Scope

Our dataset, while comprehensive, may not capture the full diversity of the laptop market, particularly for newer or more specialized models.

Changing Market Conditions

Laptop prices and features can evolve rapidly, so the model's accuracy may degrade over time without regular retraining and updates.

Unexplained Factors

There may be additional factors, such as brand reputation or customer reviews, that influence laptop prices but are not captured in the current dataset.

Future Enhancements

Future work could include expanding the dataset, incorporating real-time market data, and exploring more advanced machine learning techniques to further improve the model's accuracy and robustness.

Conclusion

1

2

3

Accurate Predictions

Our machine learning model has demonstrated the ability to accurately predict laptop prices based on their key features and specifications.

Empowered Consumers

This tool can help consumers make more informed purchasing decisions by providing reliable price estimates for different laptop configurations.

Competitive Pricing

Businesses can also leverage the model to price their laptop offerings more competitively and better understand market trends.

Overall, this project has the potential to transform the way consumers and businesses approach laptop purchases, leading to more informed decisions and a more efficient laptop market.

Comparing all the algo, Random Forest with accuracy of 88.23% will be best fit for our Model.

References:

1. Books
2. Youtube
3. Githhub
4. kaggle,.com
5. Wikipedia
6. Geeks for geeks