LAPTOP PRICE PREDICTOR:

In [ ]:

```

```

Ignore all warnings :

In [567]:

```
import warnings
warnings.filterwarnings('ignore')
```

In [ ]:

```

```

LOAD SOME LIBRARIES INITIALLY:

In [568]:

```
import numpy as np
import pandas as pd

import seaborn as sns
import matplotlib.pyplot as plt
```

In [ ]:

```

```

LOAD THE DATASET:

In [569]:

```
df = pd.read_csv("laptop_data.csv")
```

In [570]:

```
df.head()
```

Out[570]:

	Unnamed: 0	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Pric
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	71378.68
1	1	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8GB	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34kg	47895.52
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	30636.00
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	135195.33

	Unnamed: 0	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Pri
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	96095.80

In [ ]:

DETAILED INFORMATION ABOUT THE DATASET:

In [571]:

```
df.duplicated().sum()
```

Out[571]:

```
np.int64(0)
```

In [572]:

```
df.shape
```

Out[572]:

```
(1303, 12)
```

In [573]:

```
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
```

In [574]:

```
df.describe()
```

Out[574]:

	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

	Unnamed: 0	Inches	Price
max	1302.000000	18.400000	324954.720000

In [575]:

```
df.isnull().sum()
```

Out[575]:

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

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

DATA CLEANING:

In [576]:

```
df.head()
```

Out[576]:

	Unnamed: 0	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Pri
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	71378.68
1	1	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8GB	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34kg	47895.52
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	30636.00
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	135195.33
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	96095.80

In [ ]:

In [577]:

```
df.drop(columns=["Unnamed: 0"],inplace=True)
df["Ram"] = df["Ram"].str.replace("GB","")
df["Weight"] = df["Weight"].str.replace("kg","")

df["Ram"] = df["Ram"].astype(int)
df["Weight"] = df["Weight"].astype(float)
df["Inches"] = df["Inches"].astype(float)
df["Price"] = df["Price"].astype(float)
```

In [578]:

```
df.head()
```

Out[578]:

	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

In [579]:

```
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   int64  
 6   Memory            1303 non-null   object 
 7   Gpu               1303 non-null   object 
 8   OpSys             1303 non-null   object 
 9   Weight            1303 non-null   float64
 10  Price             1303 non-null   float64
dtypes: float64(3), int64(1), object(7)
memory usage: 112.1+ KB
```

In [ ]:

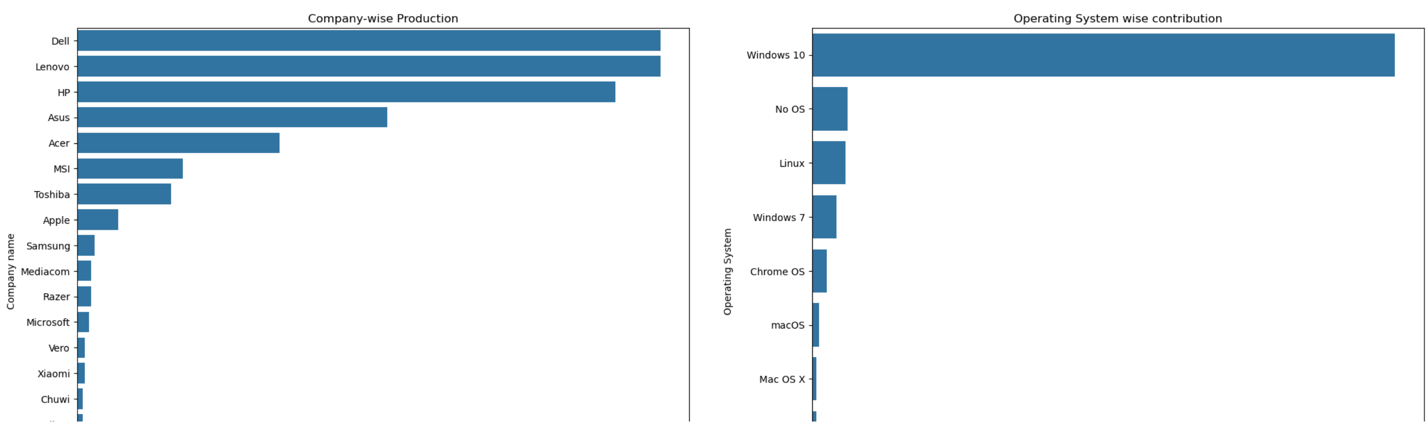
In [ ]:

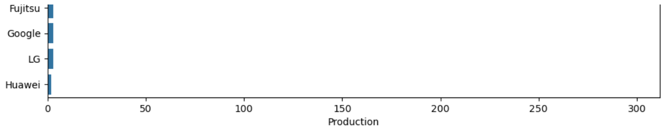
EDA , FEATURE ENGINEERING AND DATA TRANSFORMATION Section:

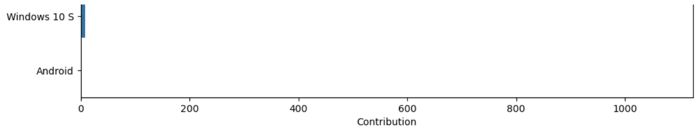
In [580]:

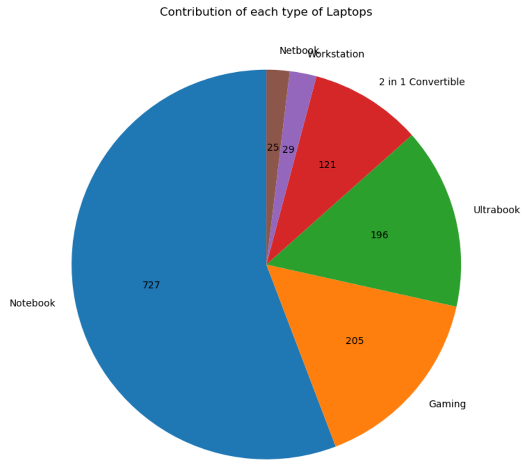
```
plt.figure(figsize=(25, 20))

data1 = df["Company"].value_counts().reset_index()

data2 = df["OpSys"].value_counts().reset_index()

plt.suptitle(
    "Exploratory Data Analysis of Laptop Dataset (Part - 1)",
    fontsize=24,
    fontweight="bold",
    y=0.98
)
plt.subplot(2,2,1)
sns.barplot(x="count",y="Company",data=data1.reset_index())
plt.xlabel("Production")
plt.ylabel("Company name")
plt.title("Company-wise Production")




#Each operating-system's contribution:

plt.subplot(2,2,2)
sns.barplot(x="count",y="OpSys",data=data2.reset_index())
plt.xlabel("Contribution")
plt.ylabel("Operating System")
plt.title("Operating System wise contribution")



plt.subplot(2,2,3)
data = df["TypeName"].value_counts()
plt.pie(x=data,labels=data.index,autopct=lambda p: f'{int(p*sum(data)/100)}',
    startangle=90)
plt.title("Contribution of each type of Laptops")

plt.subplot(2,2,4)
sns.distplot(df["Price"])
plt.title("Price Distribution of all laptops")




plt.show()
```

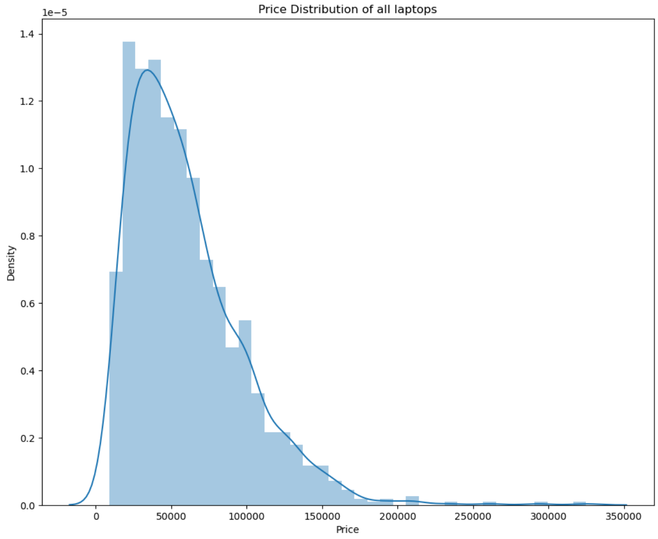
Exploratory Data Analysis of Laptop Dataset (Part - 1)





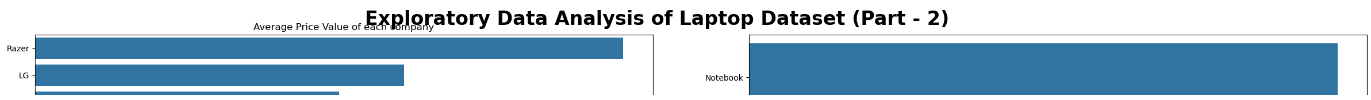


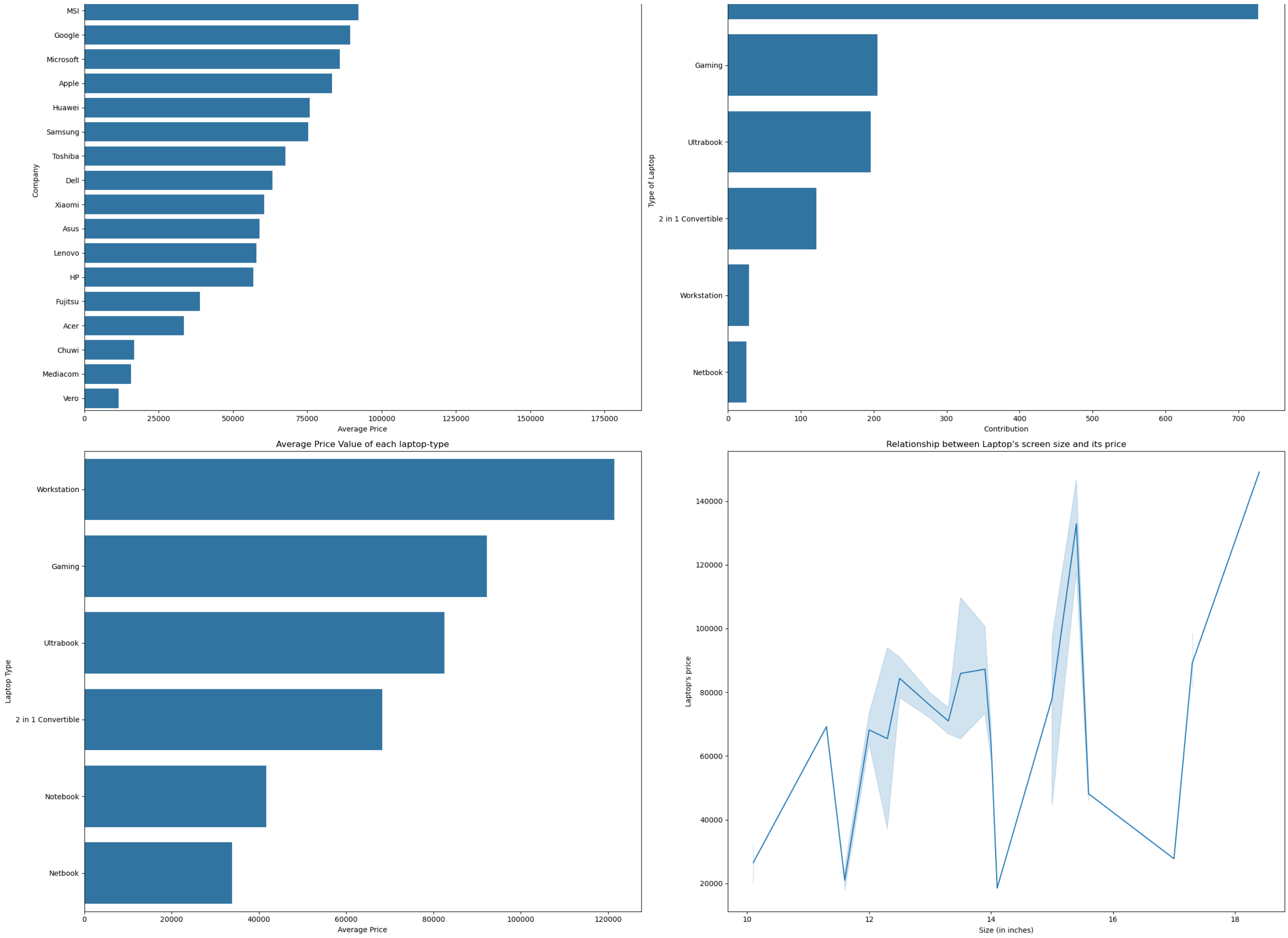




In [581]:

```
plt.figure(figsize=(25,20))
plt.suptitle(
    "Exploratory Data Analysis of Laptop Dataset (Part - 2)",
    fontsize=24,
    fontweight="bold",
    y=0.98
)

plt.tight_layout()
plt.subplot(2,2,1)
data = df.groupby("Company")["Price"].mean().reset_index().sort_values(by="Price",ascend
ing=False)
sns.barplot(y="Company",x="Price",data=data)
plt.title("Average Price Value of each company")
plt.xlabel("Average Price")
plt.ylabel("Company")



plt.subplot(2,2,2)
data = df["TypeName"].value_counts().reset_index()
sns.barplot(y="TypeName",x="count",data=data)
plt.xlabel("Contribution")
plt.ylabel("Type of Laptop")


plt.subplot(2,2,3)
data = df.groupby("TypeName")["Price"].mean().reset_index().sort_values(by="Price",ascen
ding=False)
sns.barplot(y="TypeName",x="Price",data=data)
plt.title("Average Price Value of each laptop-type")
plt.xlabel("Average Price")
plt.ylabel("Laptop Type")
plt.tight_layout()

plt.subplot(2,2,4)
sns.lineplot(x=df["Inches"],y=df["Price"])
plt.title("Relationship between Laptop's screen size and its price")
plt.xlabel("Size (in inches)")
plt.ylabel("Laptop's price")
plt.tight_layout()
plt.show()
```





In [ ]:

In [ ]:

Now we will determine how many laptops are touch screen and how many arent :

(for this we will do feature engineering (i.e. create a new column named as: 'Touchscreen'))

In [582]:

```
df["ScreenResolution"].value_counts()
```

Out[582]:

```
ScreenResolution
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
IPS Panel 1366x768                                 7
Touchscreen 2560x1440                              7
4K Ultra HD 3840x2160                              7
IPS Panel Retina Display 2304x1440                 6
```

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

In [583]:

```
# 0 if not touchscreen and 1 if touchscreen:
df["Touchscreen"] = df["ScreenResolution"].apply(lambda x: 1 if 'Touchscreen' in x else
0)
```

In [584]:

```
#inspect first 5 rows of the dataframe:
df.head()
```

Out[584]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscr
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	

In [585]:

```
#take a sample of any 5 rows:
df.sample(5)
```

Out[585]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchsc
31	Asus	Notebook	14.0	1366x768	AMD E-Series E2-6110 1.5GHz	2	32GB Flash Storage	AMD Radeon R2	Windows 10	1.65	10602.72	
557	Lenovo	Notebook	17.3	1600x900	Intel Core i7 7500U 2.7GHz	6	128GB SSD + 1TB HDD	Nvidia GeForce 940MX	Windows 10	2.80	50562.72	
842	HP	Notebook	17.3	1600x900	Intel Core i5 7200U 2.5GHz	8	1TB HDD	Nvidia GeForce 930MX	Windows 10	2.63	48484.80	
105	HP	Notebook	14.0	IPS Panel Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	6	256GB SSD	Nvidia GeForce 940MX	Windows 10	1.58	35111.52	
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	50562.72	

In [ ]:

In [586]:

```
df["Touchscreen"].value_counts().reset_index()
```

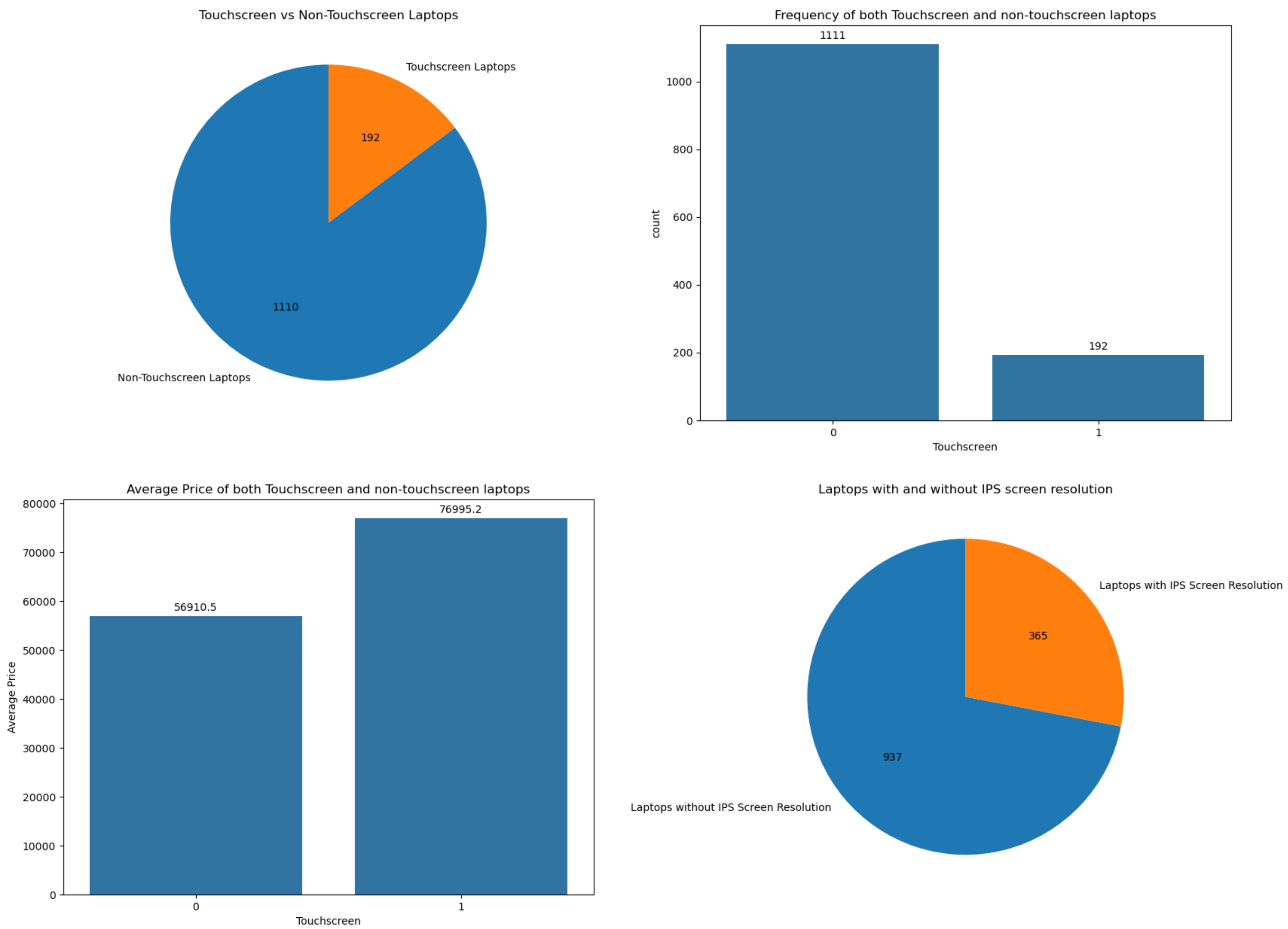
Out[586]:

	Touchscreen	count
0	0	1111
1	1	192

In [587]:

```
plt.figure(figsize=(20,15))

plt.suptitle(
    "Exploratory Data Analysis of Laptop Dataset (Part - 3)",
    fontsize=24,
    fontweight="bold",
    y=0.98
)




plt.subplot(2,2,1)
data = df["Touchscreen"].value_counts().reset_index()

labels = data["Touchscreen"].map({
    0: "Non-Touchscreen Laptops",
    1: "Touchscreen Laptops"
})

plt.pie(
    data["count"],
    labels=labels,
    autopct=lambda p: f'{int(p*sum(data["count"])/100)}',
    startangle=90
)
```

```
plt.title("Touchscreen vs Non-Touchscreen Laptops")

plt.subplot(2,2,2)
plt.title("Frequency of both Touchscreen and non-touchscreen laptops")
sns.barplot(x="Touchscreen", y="count", data=data)


for c in plt.gca().containers:
    plt.gca().bar_label(c, padding=3)

plt.subplot(2,2,3)
plt.title("Average Price of both Touchscreen and non-touchscreen laptops")
### _Now we will see average prices of both touch-screen and non-touchscreen laptops:_
data = df.groupby("Touchscreen")["Price"].mean().reset_index(name = "Average Price")
sns.barplot(y="Average Price",x="Touchscreen",data=data)
for c in plt.gca().containers:
    plt.gca().bar_label(c, padding=3)

plt.subplot(2,2,4)
plt.title("Laptops with and without IPS screen resolution")
df["Ips"] = df["ScreenResolution"].apply(lambda x:1 if 'IPS' in x else 0)
data = df["Ips"].value_counts().reset_index()

labels = data["Ips"].map({
    0: "Laptops without IPS Screen Resolution",
    1: "Laptops with IPS Screen Resolution"
})
plt.pie(
    data["count"],
    labels=labels,
    autopct=lambda p: f'{int(p*sum(data["count"])/100)}',
    startangle=90
)
plt.show()
```



In [ ]:

```

```

Extract screen-resoution's size (means x and y (in inches)) from 'ScreenResolution' column:

In [588]:

```
df.head()
```

Out[588]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscr
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	Intel Core i5	8	256GB SSD	Intel Iris Plus Graphics	macOS	1.37	96095.8080	

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscr

In [589]:

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

In [590]:

```
df["X_res"] = new[0]
df["Y_res"] = new[1]
```

In [591]:

```
df.head()
```

Out[591]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscr
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	

In [592]:

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

In [593]:

```
df.head()
```

Out[593]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscr
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	

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscr
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	

In [594]:

```
df["X_res"]=df["X_res"].apply(int)
df["Y_res"]=df["Y_res"].apply(int)
```

In [595]:

```
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   int64
 6   Memory            1303 non-null   object
 7   Gpu               1303 non-null   object
 8   OpSys             1303 non-null   object
 9   Weight            1303 non-null   float64
 10  Price             1303 non-null   float64
 11  Touchscreen       1303 non-null   int64
 12  Ips               1303 non-null   int64
 13  X_res             1303 non-null   int64
 14  Y_res             1303 non-null   int64
dtypes: float64(3), int64(5), object(7)
memory usage: 152.8+ KB
```

In [596]:

```
#Correlation of all numeric columns with respect to 'Price' column:
df.corr(numeric_only=True)['Price']
```

Out[596]:

```
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
```

Prepare a new-column named 'PPI' (stands for Pixels-Per-Inches):

In [597]:

```
df["ppi"] = (((df['X_res']**2) + (df['Y_res']**2))**0.5 / df['Inches']).astype('float')
```

In [598]:

```
df.head()
```

Out[598]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscr
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	

In [599]:

```
#Correlation of all numeric columns with respect to 'Price' column:
df.corr(numeric_only=True)['Price']
```

Out[599]:

```
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
ppi            0.473487
Name: Price, dtype: float64
```

In [600]:

```
# Drop 'ScreenResolution' column:
df.drop(columns='ScreenResolution',inplace=True)
```

In [601]:

```
df.columns
```

Out[601]:

```
Index(['Company', 'TypeName', 'Inches', 'Cpu', 'Ram', 'Memory', 'Gpu', 'OpSys',
       'Weight', 'Price', 'Touchscreen', 'Ips', 'X_res', 'Y_res', 'ppi'],
      dtype='object')
```

In [602]:

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

In [603]:

```
df.columns
```

Out[603]:

```
Index(['Company', 'TypeName', 'Cpu', 'Ram', 'Memory', 'Gpu', 'OpSys', 'Weight',
       'Price', 'Touchscreen', 'Ips', 'ppi'],
      dtype='object')
```

In [ ]:

```

```

In [604]:

```
#simplify the 'Cpu' column:

#step 1) extract first 3 words of all the values:
df["Cpu Name"] = df["Cpu"].apply(lambda x:" ".join(x.split()[0:3]))
```

In [605]:

```
df.head()
```

Out[605]:

	Company	TypeName	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cp Nam
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	Inte Cor i
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	Inte Cor i
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	Inte Cor i
3	Apple	Ultrabook	Intel Core i7 2.7GHz	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	135195.3360	0	1	220.534624	Inte Cor i
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	Inte Cor i

In [606]:

```
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'
```

In [607]:

```
df["Cpu brand"] = df["Cpu Name"].apply(fetch_processor)
```

In [608]:

```
df.head()
```

Out[608]:

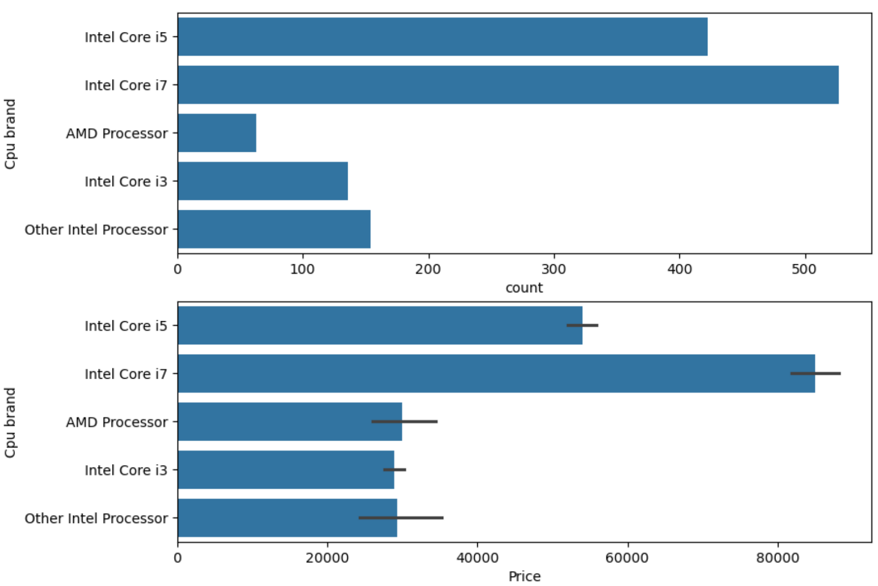
	Company	TypeName	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cp Nam
0	Apple	Ultrabook	Intel Core i5 2.3GHz	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	0	1	226.983005	Inte Cor i
			Intel		128GB	Intel HD							Inte

	Company	TypeName	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu Nam
1	Apple	Ultrabook	Core i5 1.8GHz	8	Flash Storage	Graphics 6000	macOS	1.34	47895.5232	0	0	127.677940	Cor
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	Inte Cor i
3	Apple	Ultrabook	Intel Core i7 2.7GHz	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	135195.3360	0	1	220.534624	Inte Cor i
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	Inte Cor i

In [609]:

```
plt.figure(figsize=(20,7))

plt.suptitle(
    "Exploratory Data Analysis of Laptop Dataset (Part - 4)",
    fontsize=24,
    fontweight="bold",
    y=0.98
)

plt.subplot(2,2,1)
sns.countplot(df["Cpu brand"])

plt.subplot(2,2,3)
sns.barplot(y="Cpu brand",x="Price",data=df)

plt.show()
```

Exploratory Data Analysis of Laptop Dataset (Part - 4)



In [ ]:

```

```

In [610]:

```
# Drop 'Cpu' and 'Cpu Name' columns (as they arent required now):
df.drop(columns=["Cpu","Cpu Name"],inplace=True)
```

In [611]:

```
df.head()
```

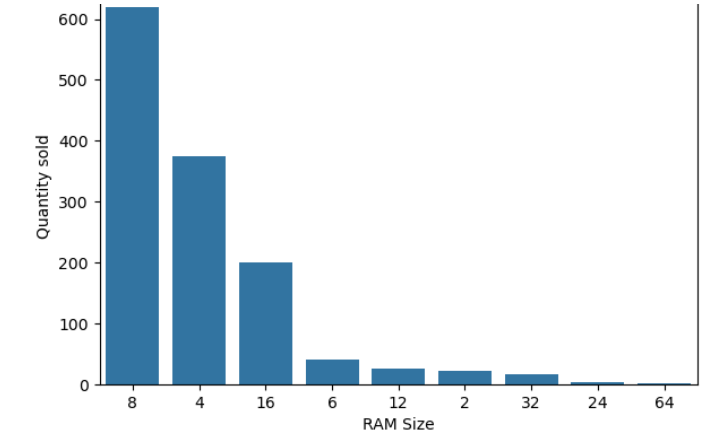
Out[611]:

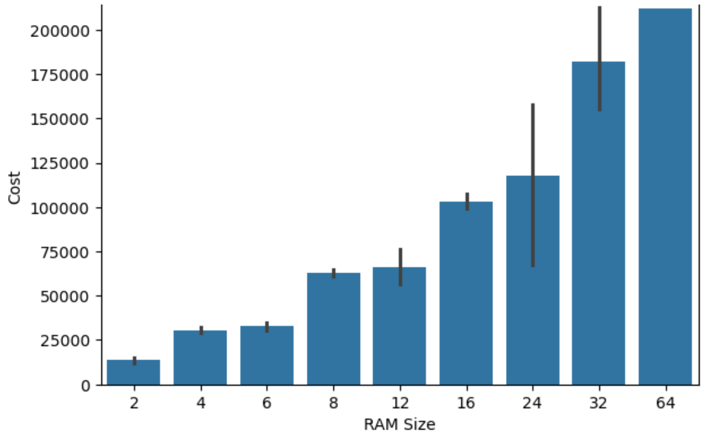
	Company	TypeName	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu brand
0	Apple	Ultrabook	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	0	1	226.983005	Intel Core i5
1	Apple	Ultrabook	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	47895.5232	0	0	127.677940	Intel Core 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

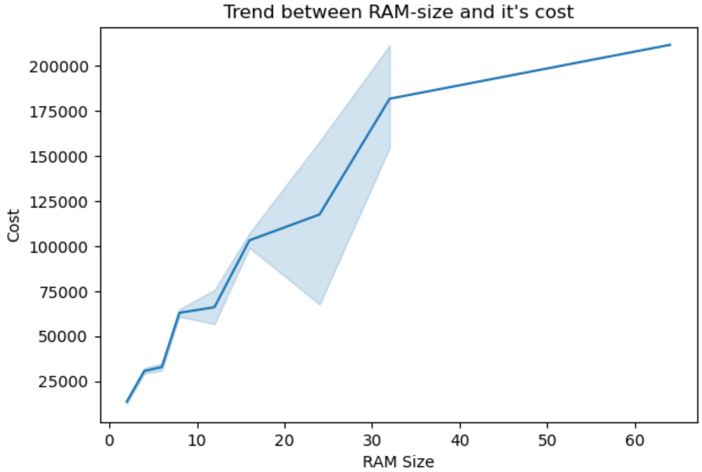
In [ ]:

In [612]:

```
plt.figure(figsize=(15,10))



plt.suptitle(
    "Exploratory Data Analysis of Laptop Dataset (Part - 5)",
    fontsize=24,
    fontweight="bold",
    y=0.98
)


# Which Ram is mostly soled in the market:
plt.subplot(2,2,1)
order = df['Ram'].value_counts().index
plt.title("Most sold RAM")
sns.countplot(x="Ram",data=df,order=order)
plt.xlabel("RAM Size")
plt.ylabel("Quantity sold")


# Which Ram is most costly?
plt.subplot(2,2,2)
sns.barplot(x="Ram",y="Price",data=df)
plt.title("RAM-size and it's cost")
plt.xlabel("RAM Size")
plt.ylabel("Cost")


# Trend between RAM-size and it's cost:
plt.subplot(2,2,3)
sns.lineplot(x="Ram",y="Price",data=df)
plt.title("Trend between RAM-size and it's cost")
plt.xlabel("RAM Size")
plt.ylabel("Cost")
plt.show()
```







In [ ]:

```

```

In [ ]:

```

```

In [613]:

```
df.head()
```

Out[613]:

	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

In [614]:

```
df["Memory"].value_counts()
```

Out[614]:

```
Memory
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
1TB SSD                           14
512GB SSD +  1TB HDD              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
128GB SSD +  2TB HDD               2
256GB SSD +  256GB SSD             2
512GB Flash Storage                2
1TB SSD +  1TB HDD                 2
256GB SSD +  500GB HDD             2
64GB SSD                           1
512GB SSD +  512GB SSD             1
64GB Flash Storage +  1TB HDD      1
1TB HDD +  1TB HDD                 1
512GB SSD +  256GB SSD             1
32GB HDD                           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
```

NOW WE WILL DO EDA ON 'Memory' COLUMN:

EARLIER:

In [615]:

```
df.head(1)
```

Out[615]:

	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

NOW AFTER TRANSFORMATION:

In [616]:

```
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()
df["second"] = new[1]

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["first"] = df["first"].str.replace(r"\D", "")

df["second"].fillna("0", inplace=True)

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["second"] = df["second"].str.replace(r"\D", "")

df["first"] = (
    df["first"]
    .str.extract(r"(\d+)", expand=False)
    .astype(int)
)

df["second"] = (
    df["second"]
    .str.extract(r"(\d+)", expand=False)
    .fillna(0)
    .astype(int)
)


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_Storage"]
)

df.drop(
    columns=[
        "first", "second",
        "Layer1HDD", "Layer1SSD", "Layer1Hybrid", "Layer1Flash_Storage",
        "Layer2HDD", "Layer2SSD", "Layer2Hybrid", "Layer2Flash_Storage"
    ],
    inplace=True
)
```

In [617]:

```
df.head()
```

Out[617]:

	Company	TypeName	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu brand	HDD
0	Apple	Ultrabook	8	128 SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	0	1	226.983005	Intel Core i5	0
1	Apple	Ultrabook	8	128 Flash	Intel HD Graphics	macOS	1.34	47895.5232	0	0	127.677940	Intel Core	0

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

In [618]:

```
#Drop the 'Memory' column since it isn't required now:
df.drop(columns=["Memory"],inplace=True)
```

In [619]:

```
df.head()
```

Out[619]:

	Company	TypeName	Ram	Gpu	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu brand	HDD	SSD	Hyt
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	

In [620]:

```
#See correlation of all columns with respect to the 'Price' column:
df.corr(numeric_only=True)['Price']
```

Out[620]:

```
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
Name: Price, dtype: float64
```

In [621]:

```
#Drop the columns 'Hybrid','Flash_Storage' since they serve no purpose:
```

```
df.drop(columns=["Hybrid","Flash_Storage"],inplace=True)
```

Now do eda on 'Gpu' and 'OpSys' columns:

In [622]:

```
df["Gpu"].value_counts().reset_index()
```

Out[622]:

	Gpu	count
0	Intel HD Graphics 620	281
1	Intel HD Graphics 520	185
2	Intel UHD Graphics 620	68
3	Nvidia GeForce GTX 1050	66
4	Nvidia GeForce GTX 1060	48
...	...	...
105	Nvidia Quadro M500M	1
106	AMD Radeon R7 M360	1
107	Nvidia Quadro M3000M	1
108	Nvidia GeForce 960M	1
109	ARM Mali T860 MP4	1

110 rows × 2 columns

In [623]:

```
df["OpSys"].value_counts().reset_index()
```

Out[623]:

	OpSys	count
0	Windows 10	1072
1	No OS	66
2	Linux	62
3	Windows 7	45
4	Chrome OS	27
5	macOS	13
6	Mac OS X	8
7	Windows 10 S	8
8	Android	2

In [624]:

```
df.head()
```

Out[624]:

	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
				Intel HD							Intel		

	Company	TypeName	Ram	Gpu	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu brand	HDD	SSD
1	Apple	Ultrabook	8	Graphics 6000	macOS	1.34	47895.5232	0	0	127.677940	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

In [625]:

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

In [626]:

```
df.head()
```

Out[626]:

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

In [627]:

```
df["Gpu brand"].value_counts().reset_index()
```

Out[627]:

	Gpu brand	count
0	Intel	722
1	Nvidia	400
2	AMD	180
3	ARM	1

In [628]:

```
df[df["Gpu brand"] == 'ARM']
```

Out[628]:

	Company	TypeName	Ram	Gpu	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu brand	HDD	SSD	Gp bran

	Company	TypeName	Ram	Gpu	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu brand	HDD	SSD	Gpu brar
1191	Samsung	2 in 1 Convertible	4	ARM Mali T860 MP4	Chrome OS	1.15	35111.52	1	1	234.5074	AMD Processor	0	0	AR

In [629]:

```python
df = df[df["Gpu brand"] != 'ARM']
```

In [630]:

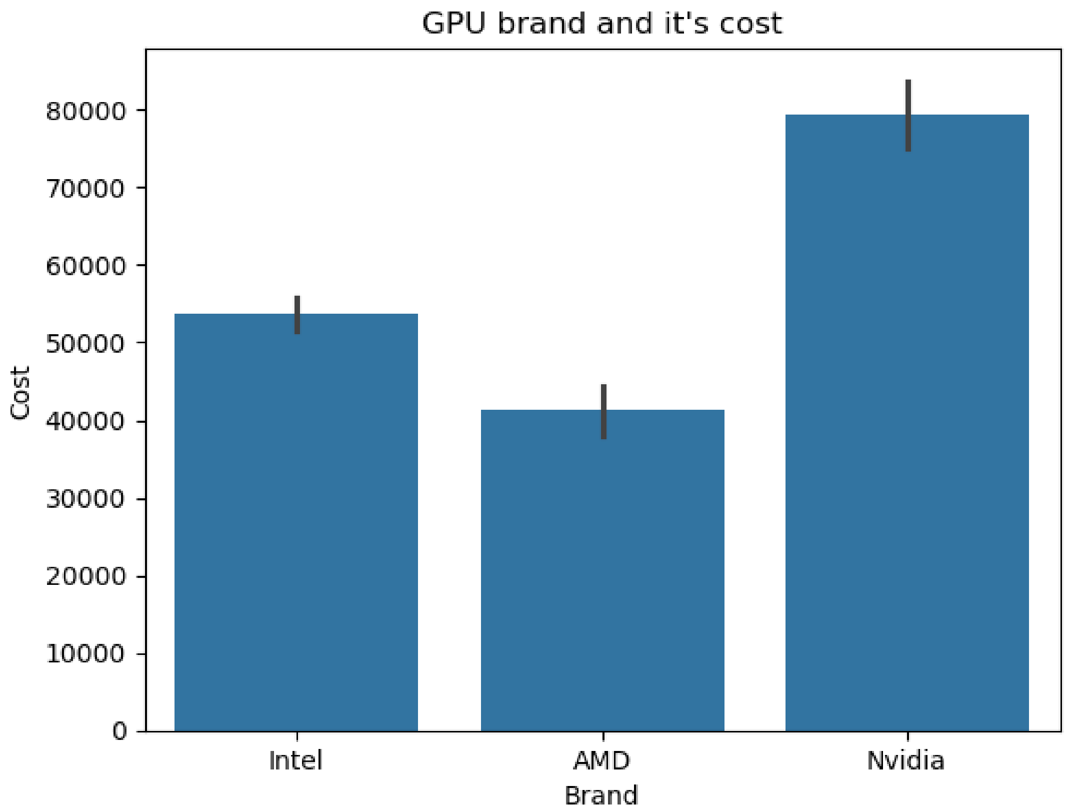
```python
df["Gpu brand"].value_counts().reset_index()
```

Out[630]:

	Gpu brand	count
0	Intel	722
1	Nvidia	400
2	AMD	180

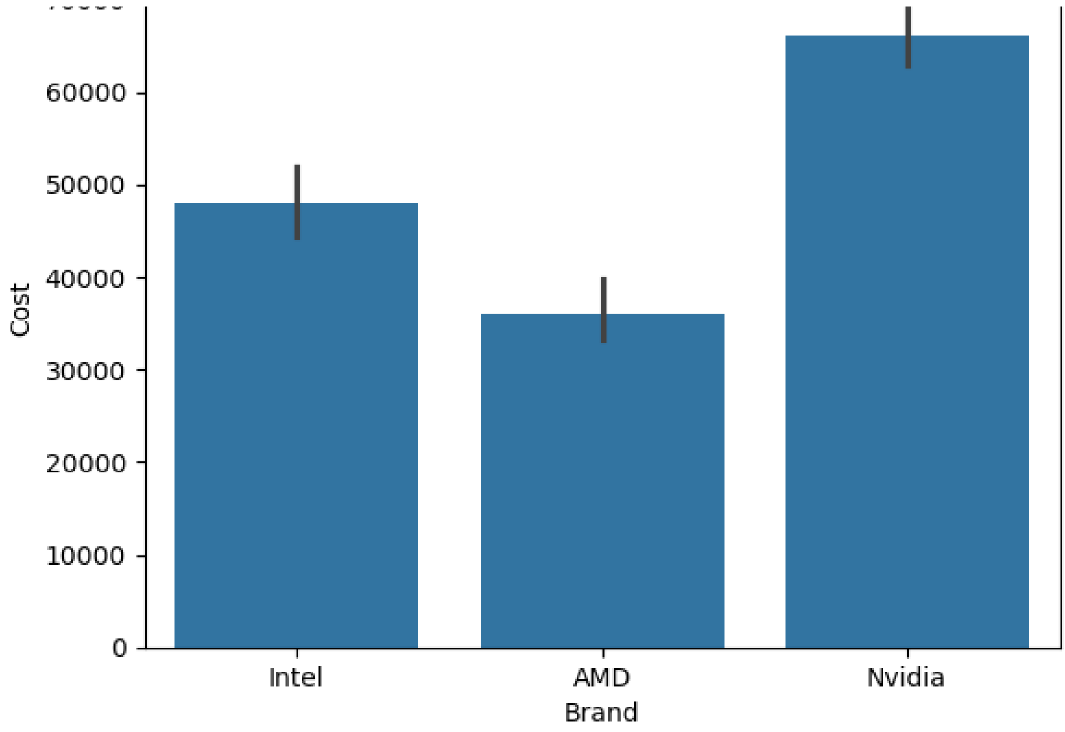
In [631]:

```python
sns.barplot(x="Gpu brand",y="Price",data=df)
plt.title("GPU brand and it's cost")
plt.xlabel("Brand")
plt.ylabel("Cost")
plt.show()
```



In [632]:

```python
sns.barplot(x="Gpu brand",y="Price",data=df,estimator=np.median)
plt.title("GPU brand and it's cost")
plt.xlabel("Brand")
plt.ylabel("Cost")
plt.show()
```



In [633]:

```
#Drop 'Gpu' column since it is not required now:
df.drop(columns="Gpu",inplace=True)
```

In [634]:

```
df.head()
```

Out[634]:

	Company	TypeName	Ram	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu brand	HDD	SSD	Gpu brand
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	Apple	Ultrabook	8	macOS	1.37	96095.8080	0	1	226.983005	Intel Core i5	0	256	Intel

In [ ]:

In [ ]:

Now we will do EDA On 'OpSys'(i.e. Operating System) and 'Weight' columns:

In [635]:

```
df["OpSys"].value_counts().reset_index()
```

Out[635]:

	OpSys	count

	OpSys	count
0	Windows 10	1072
1	No OS	66
2	Linux	62
3	Windows 7	45
4	Chrome OS	26
5	macOS	13
6	Mac OS X	8
7	Windows 10 S	8
8	Android	2

In [636]:

```
df["Weight"].value_counts().reset_index()
```

Out[636]:

	Weight	count
0	2.200	126
1	2.100	58
2	2.000	45
3	2.400	44
4	2.300	41
...	...	...
166	0.990	1
167	2.591	1
168	2.210	1
169	2.191	1
170	2.340	1

171 rows × 2 columns

In [637]:

```
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"

df["os"] = df["OpSys"].apply(cat_os)
```

In [638]:

```
df.head()
```

Out[638]:

	Company	TypeName	Ram	OpSys	Weight	Price	Touchscreen	Ips	ppi	Cpu brand	HDD	SSD	Gpu brand	
0	Apple	Ultrabook	8	macOS	1.37	71378.6832	0	1	226.983005	Intel Core i5	0	128	Intel	I
1	Apple	Ultrabook	8	macOS	1.34	47895.5232	0	0	127.677940	Intel Core i5	0	0	Intel	I

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

In [639]:

```
df.drop(columns=["OpSys"],inplace=True)
```

In [640]:

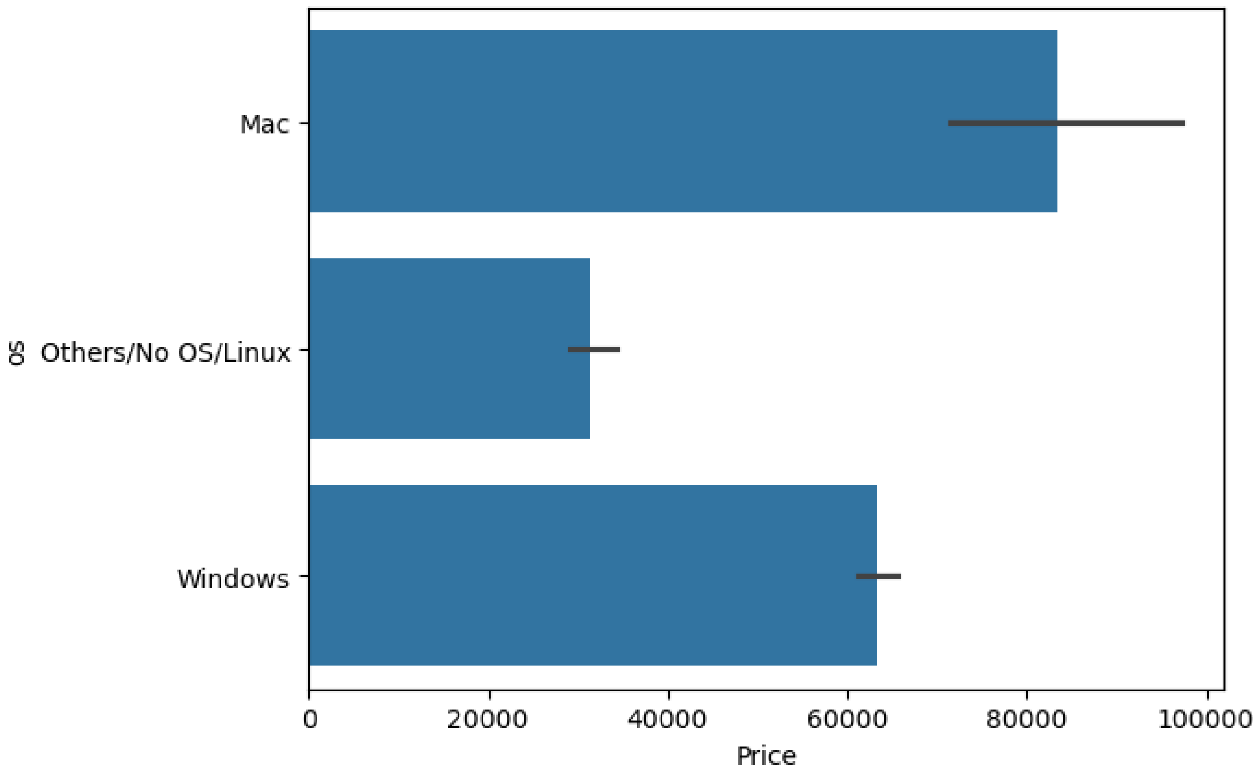
```
df.head()
```

Out[640]:

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

In [641]:

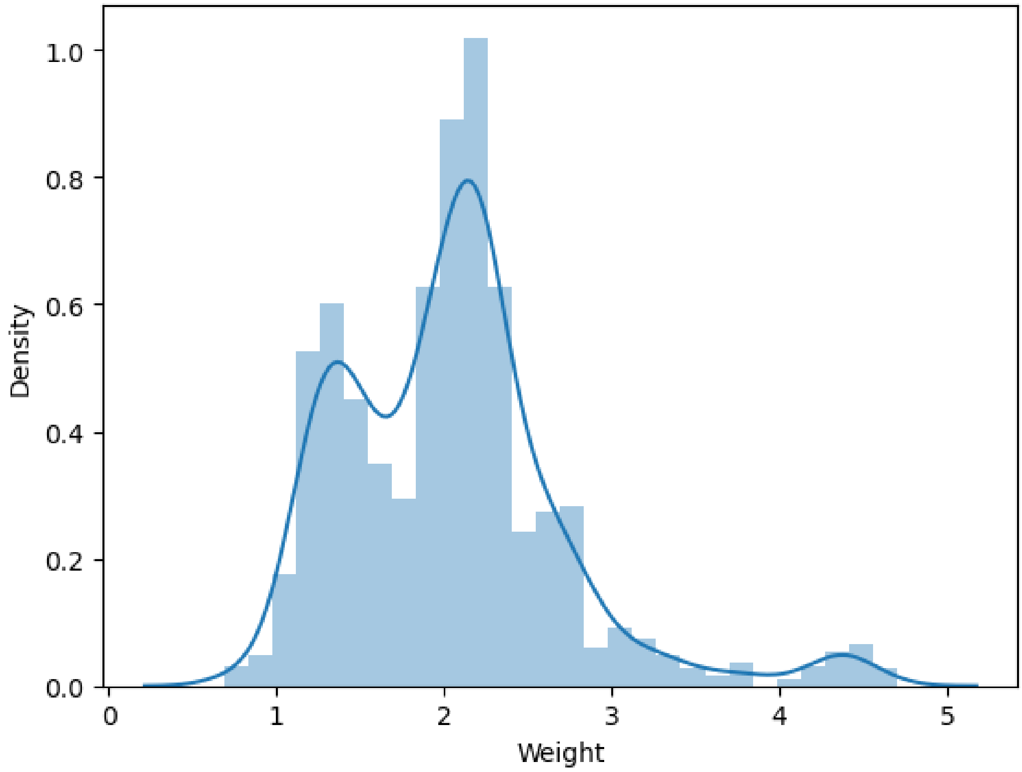
```
sns.barplot(y="os",x="Price",data=df)
plt.show()
```



Now we will do EDA on 'Weight' column:

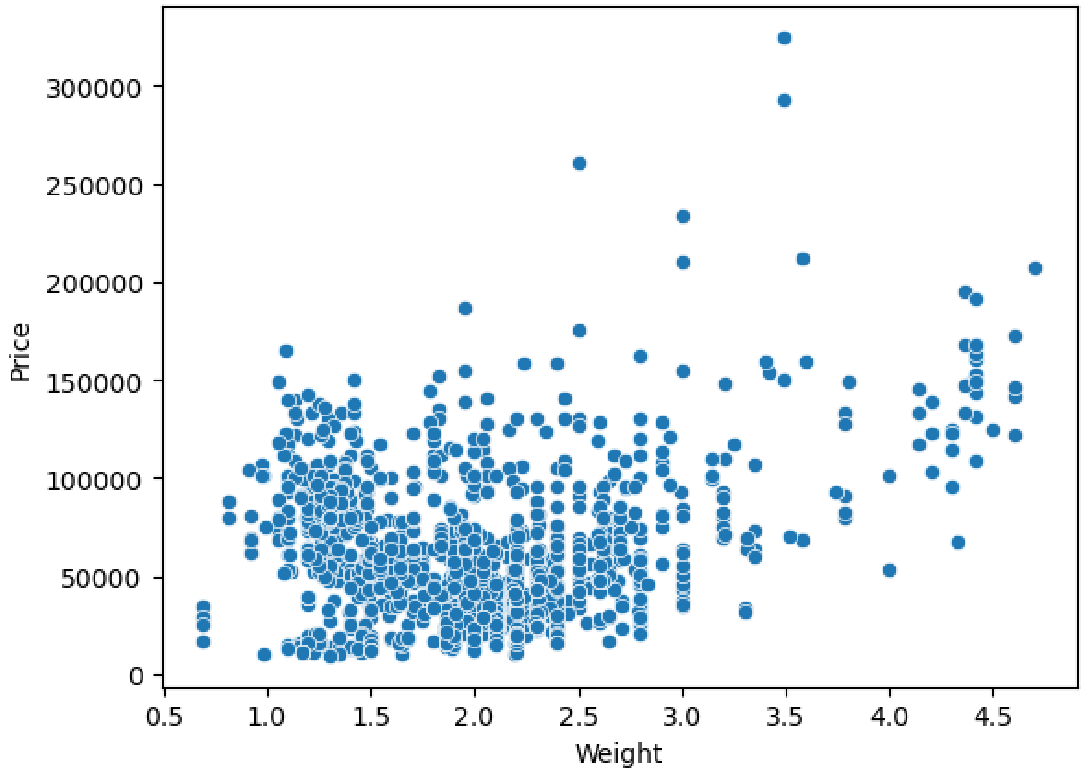
In [642]:

```
#Distribution of all values in the 'Weight' column:
sns.distplot(df["Weight"])
plt.show()
```



In [643]:

```
sns.scatterplot(x="Weight",y="Price",data=df)
plt.show()
```



In [644]:

```
#Correlation of all numeric columns with respect to 'Price' column:
df.corr(numeric_only=True)["Price"].reset_index()
```

Out[644]:

Out[644]:

	index	Price
0	Ram	0.742905
1	Weight	0.209867
2	Price	1.000000
3	Touchscreen	0.192917
4	Ips	0.253320
5	ppi	0.475368
6	HDD	-0.096891
7	SSD	0.670660

In [ ]:

In [ ]:

In [645]:

```
#Correlation of all columns with respect to all other columns:
df.corr(numeric_only=True)
```

Out[645]:

	Ram	Weight	Price	Touchscreen	Ips	ppi	HDD	SSD
Ram	1.000000	0.383362	0.742905	0.118875	0.207949	0.305688	0.095808	0.603379
Weight	0.383362	1.000000	0.209867	-0.293004	0.018643	-0.321883	0.514147	-0.063818
Price	0.742905	0.209867	1.000000	0.192917	0.253320	0.475368	-0.096891	0.670660
Touchscreen	0.118875	-0.293004	0.192917	1.000000	0.148026	0.458571	-0.208766	0.257577
Ips	0.207949	0.018643	0.253320	0.148026	1.000000	0.299142	-0.093588	0.225311
ppi	0.305688	-0.321883	0.475368	0.458571	0.299142	1.000000	-0.294698	0.509437
HDD	0.095808	0.514147	-0.096891	-0.208766	-0.093588	-0.294698	1.000000	-0.400750
SSD	0.603379	-0.063818	0.670660	0.257577	0.225311	0.509437	-0.400750	1.000000

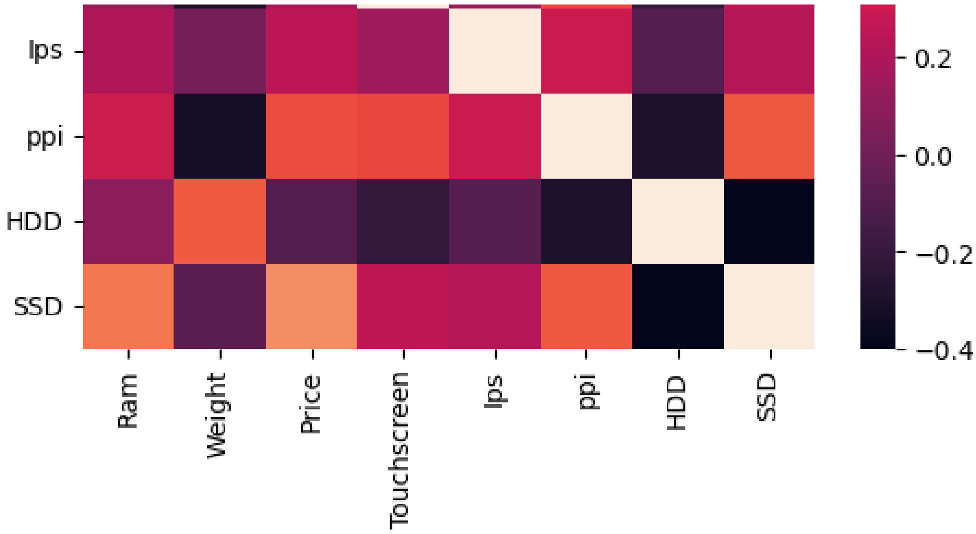
Above result on a heatmap:

In [646]:

```
#Correlation of all columns with respect to all other columns:
sns.heatmap(df.corr(numeric_only=True))
```

Out[646]:

<Axes: >



In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

Now we will do EDA on 'Price' column:

In [647]:

```
X = df.drop(columns=["Price"])
y = np.log(df["Price"])
```

In [648]:

```
X
```

Out[648]:

	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

In [649]:

```
y
```

Out[649]:

```
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
```

In [650]:

```
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)

from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline


#load all models to check which algorithm will perform best (since we dont know which it
would be):
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor, AdaBoostRe
gressor, ExtraTreesRegressor
from sklearn.svm import SVR
from xgboost import XGBRegressor
from sklearn.metrics import r2_score,mean_absolute_error


#Create a column transformer:
from sklearn.preprocessing import OneHotEncoder
step1 = ColumnTransformer(
    transformers=[
        ("col_tnf", OneHotEncoder(sparse_output=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  =  0.8073277450155012
MAE    =  0.21017827953019166
```

Now start testing all algorithms and see whch algorithm gives the best result:

LINEAR REGRESSION:

In [651]:

```
# Same preprocessing: OneHotEncode specific columns, keep the rest
step1 = ColumnTransformer(
    transformers=[
        ('col_tnf', OneHotEncoder(sparse_output=False, drop='first'), [0, 1, 7, 10, 11])
    ],
    remainder='passthrough'
)

# Step 2: Ordinary Linear Regression (no regularization)
step2 = LinearRegression()

# Create the pipeline
pipe = Pipeline([
    ('step1', step1),
    ('step2', step2)
])

# Train the model
pipe.fit(X_train, y_train)

# Predictions
y_pred = pipe.predict(X_test)

# Evaluation
print('R2 score:', r2_score(y_test, y_pred))
print('MAE:', mean_absolute_error(y_test, y_pred))
```

```
R2 score: 0.8073277450155012
MAE: 0.21017827953019166
```

RIDGE REGRESSION:

In [652]:

```
step1 = ColumnTransformer(
    transformers=[
        ('col_tnf', OneHotEncoder(sparse_output=False, drop='first'), [0, 1, 7, 10, 11])
    ],
    remainder='passthrough'   # keep all other columns unchanged
)

# Step 2: Ridge regression with alpha=10
step2 = Ridge(alpha=10)

# Create the pipeline
pipe = Pipeline([
    ('step1', step1),
    ('step2', step2)
])

# Split data (assuming you have X_train, X_test, y_train, y_test already)
# If not, use train_test_split
pipe.fit(X_train, y_train)

# Predictions
y_pred = pipe.predict(X_test)

# Evaluation
print('R2 score:', r2_score(y_test, y_pred))
print('MAE:', mean_absolute_error(y_test, y_pred))
```

```
R2 score: 0.8127331033739459
MAE: 0.20926802210371442
```

LASSO REGRESSION:

In [653]:

```
step1 = ColumnTransformer(
    transformers=[
        ('col_tnf', OneHotEncoder(sparse_output=False, drop='first'), [0, 1, 7, 10, 11])
    ],
    remainder='passthrough'  # numerical columns pass through unchanged
)

# Step 2: Lasso regression with alpha=0.001
step2 = Lasso(alpha=0.001)

# Create the pipeline
pipe = Pipeline([
    ('step1', step1),
    ('step2', step2)
])

# Train the model
pipe.fit(X_train, y_train)

# Predictions on test set
y_pred = pipe.predict(X_test)

# Evaluation
print('R2 score:', r2_score(y_test, y_pred))
print('MAE:', mean_absolute_error(y_test, y_pred))
```

```
R2 score: 0.8071853947620582
MAE: 0.21114361575113458
```

KNN:

In [654]:

```
step1 = ColumnTransformer(
    transformers=[
        ('col_tnf', OneHotEncoder(sparse_output=False, drop='first'), [0, 1, 7, 10, 11])
    ],
    remainder='passthrough'  # numerical columns pass through as is
)

# Step 2: K-Nearest Neighbors Regressor with 3 neighbors
step2 = KNeighborsRegressor(n_neighbors=3)

# Create the pipeline
pipe = Pipeline([
    ('step1', step1),
    ('step2', step2)
])

# Train the model
pipe.fit(X_train, y_train)

# Predictions on test set
y_pred = pipe.predict(X_test)

# Evaluation (optional but recommended)
print('R2 score:', r2_score(y_test, y_pred))
print('MAE:', mean_absolute_error(y_test, y_pred))
```

```
R2 score: 0.8031008164264897
MAE: 0.19268746498695286
```

DECISION TREE:

In [655]:

```
step1 = ColumnTransformer(
```

```
step1 = ColumnTransformer(
    transformers=[
        ('col_tnf', OneHotEncoder(sparse_output=False, drop='first'), [0, 1, 7, 10, 11])
    ],
    remainder='passthrough'  # numerical columns pass through as is
)

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: 0.8426084411425243
MAE: 0.18107155164530095
```

SVM:

In [656]:

```
step1 = ColumnTransformer(
    transformers=[
        ('col_tnf', OneHotEncoder(sparse_output=False, drop='first'), [0, 1, 7, 10, 11])
    ],
    remainder='passthrough'  # numerical features pass through as is
)

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

# Create the pipeline
pipe = Pipeline([
    ('step1', step1),
    ('step2', step2)
])

# Train the model
pipe.fit(X_train, y_train)

# Predictions on test set
y_pred = pipe.predict(X_test)

# Evaluation
print('R2 score:', r2_score(y_test, y_pred))
print('MAE:', mean_absolute_error(y_test, y_pred))
```

```
R2 score: 0.8083168388457612
MAE: 0.20239400567814725
```

RANDOM FOREST:

In [657]:

```
step1 = ColumnTransformer(
    transformers=[
        ('col_tnf', OneHotEncoder(sparse_output=False, drop='first'), [0, 1, 7, 10, 11])
    ],
    remainder='passthrough'  # numerical features pass through as is
)

# Step 2: Random Forest Regressor with specified hyperparameters
step2 = RandomForestRegressor(
    n_estimators=100,
```

```
    random_state=3,
    max_samples=0.5,
    max_features=0.75,
    max_depth=15
)

# Create the pipeline
pipe = Pipeline([
    ('step1', step1),
    ('step2', step2)
])

# Train the model
pipe.fit(X_train, y_train)

# Predictions on test set
y_pred = pipe.predict(X_test)

# Evaluation
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
```

EXTRATREES:

In [658]:

```
step1 = ColumnTransformer(
    transformers=[
        ('col_tnf', OneHotEncoder(sparse_output=False, drop='first'), [0, 1, 7, 10, 11])
    ],
    remainder='passthrough'  # numerical features pass through as is
)

# Step 2: ExtraTrees Regressor with specified hyperparameters
step2 = ExtraTreesRegressor(
    n_estimators=100,
    random_state=3,
    max_samples=0.5,
    max_features=0.75,
    max_depth=15,
    bootstrap=True  # required when using max_samples < 1.0
)

# Create the pipeline
pipe = Pipeline([
    ('step1', step1),
    ('step2', step2)
])

# Train the model
pipe.fit(X_train, y_train)

# Predictions on test set
y_pred = pipe.predict(X_test)

# Evaluation
print('R2 score:', r2_score(y_test, y_pred))
print('MAE:', mean_absolute_error(y_test, y_pred))
```

```
R2 score: 0.8850720167552375
MAE: 0.16154538000217084
```

ADABOOST:

In [659]:

```
step1 = ColumnTransformer(
```

```
step1 = ColumnTransformer(
    transformers=[
        ('col_tnf', OneHotEncoder(sparse_output=False, drop='first'), [0, 1, 7, 10, 11])
    ],
    remainder='passthrough'   # numerical features pass through as is
)


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

# Create the pipeline
pipe = Pipeline([
    ('step1', step1),
    ('step2', step2)
])

# Train the model
pipe.fit(X_train, y_train)

# Predictions on test set
y_pred = pipe.predict(X_test)

# Evaluation
print('R2 score:', r2_score(y_test, y_pred))
print('MAE:', mean_absolute_error(y_test, y_pred))
```

```
R2 score: 0.8020965600051384
MAE: 0.2211495197113982
```

GRADIENT BOOST:

In [660]:

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf', OneHotEncoder(sparse_output=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 0.8815819094071498
MAE 0.15966219871732804
```

XG BOOST:

In [661]:

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf', OneHotEncoder(sparse_output=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 0.8771404806375557
MAE 0.16262936288951352
```

VOTING REGRESSOR:

In [662]:

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

# Fixed: Added bootstrap=True for both RF and ET when using max_samples
rf = RandomForestRegressor(
    n_estimators=350,
    random_state=3,
    max_samples=0.5,            # subsample 50% of data per tree
    max_features=0.75,
    max_depth=15,
    bootstrap=True              # REQUIRED when max_samples is set
)

gbdt = GradientBoostingRegressor(n_estimators=100, max_features=0.5)

xgb = XGBRegressor(n_estimators=25, learning_rate=0.3, max_depth=5)

et = ExtraTreesRegressor(
    n_estimators=100,
    random_state=3,
    max_samples=0.5,            # subsample 50% of data per tree
    max_features=0.75,
    max_depth=15,
    bootstrap=True              # REQUIRED when max_samples is set
)

step2 = VotingRegressor(
    estimators=[('rf', rf), ('gbdt', gbdt), ('xgb', xgb), ('et', et)],
    weights=[5, 1, 1, 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: 0.8906299333066894
MAE: 0.15721405706647654
```

STACKING:

In [663]:

```
from sklearn.ensemble import VotingRegressor, StackingRegressor


step1 = ColumnTransformer(transformers=[
    ('col_tnf', OneHotEncoder(sparse_output=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, bootstrap=True)),
    ('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)

# Optional evaluation
from sklearn.metrics import r2_score, mean_absolute_error
print('R2 score:', r2_score(y_test, y_pred))
print('MAE:', mean_absolute_error(y_test, y_pred))
```

```
R2 score: 0.8788531484462075
MAE: 0.166733576119004
```

In [ ]:

```

```

In [ ]:

```

```

CONCLUSION FROM THE ML ALGORITHMS]

RandomForest performs the best hence we will use this model in our website which we are going to deploy for predicting Laptop Prices based on Laptop's configurations.

We will also export our dataframe which will be used in the dropdowns of our website"

In [664]:

```
df.head()
```

Out[664]:

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

In [665]:

```
import pickle
pickle.dump(df,open('df.pkl','wb'))
pickle.dump(pipe,open('pipe.pkl','wb'))
```

In [ ]:

```

```