Importing Libraries

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

In [2]:
```
df = pd.read_csv('laptop_price.csv',encoding='latin1')
```

The file was not read by utf-8. Then 'latin1' was used for encoding.

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

Out[3]:

	laptop_ID	Company	Product	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys
0	1	Apple	MacBook Pro	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 2.3GHz	8GB	128GB SSD	Intel Iris Plus Graphics 640	macOS
1	2	Apple	Macbook Air	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8GB	128GB Flash Storage	Intel HD Graphics 6000	macOS
2	3	HP	250 G6	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8GB	256GB SSD	Intel HD Graphics 620	No OS
3	4	Apple	MacBook Pro	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16GB	512GB SSD	AMD Radeon Pro 455	macOS
4	5	Apple	MacBook Pro	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 3.1GHz	8GB	256GB SSD	Intel Iris Plus Graphics 650	macOS

The dataset consists of several features related with computers. Let's explore the dataset!

In [4]:
```
df.count()
```

Out[4]:
```
laptop_ID           1303
Company             1303
Product             1303
TypeName            1303
Inches              1303
ScreenResolution    1303
Cpu                 1303
Ram                 1303
Memory              1303
Gpu                 1303
OpSys               1303
Weight              1303
Price_euros         1303
dtype: int64
```

There is no missing value, great! Thus, there is no need to fill or drop data.

In [5]:
```
df.nunique()
```

Out[5]:
```
laptop_ID           1303
Company               19
Product              618
TypeName               6
Inches                18
ScreenResolution      40
Cpu                  118
Ram                    9
Memory                39
Gpu                  110
OpSys                  9
Weight               179
Price_euros          791
dtype: int64
```

There is no problem to use continues features because they can be used directly as inputs after standardization. However we need to work on catagorical features carefully. It seems very hard to work on product name because there are 618 unique product name which is too many for our dataset. Let's drop it.

In [6]:
```
df.drop('Product',axis =1,inplace=True)
```

Also, we cannot use Laptop ID as feature because every ID is distinct. From now on, we will use them as index.

In [7]:
```
df.set_index('laptop_ID',inplace = True)
```

In [8]:
```
df.head()
```

Out[8]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Pric
laptop_ID											
1	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	
2	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8GB	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34kg	
3	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8GB	256GB SSD	Intel HD Graphics 620	No OS	1.86kg	
4	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16GB	512GB SSD	AMD Radeon Pro 455	macOS	1.83kg	
5	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	

Company name, type name and OpSys can be used as dummy variable but we should turn Ram, Weight, Memory and ScreenResolution to numerical value because they carry important numerical informations for our model while they are currently seen as catagories. So, we will preprocess them one by one. How about starting with the easiest one: 'weight'.

In [9]:
```
weight = df["Weight"].iloc[0]
weight[:-2]
```

Out[9]: '1.37'

As you see, weight info can be captured easily by simple slicing operation. However, its type is still string. Therefore, the result should be type casted to float.

In [10]:
```
float(weight[:-2])
```

Out[10]:
```
1.37
```

We managed to convert a single weight info to continuous value. Now, it is time to turn this operation to function in order to apply it to whole column of the dataframe.

In [11]:
```
def weight_extraction(name):
    return float(name[:-2])
```

In [12]:
```
df["Weight"] = df["Weight"].apply(weight_extraction)
```

In [13]:
```
df.head()
```

Out[13]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Pric
laptop_ID											
1	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 2.3GHz	8GB	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	
2	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8GB	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	
3	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8GB	256GB SSD	Intel HD Graphics 620	No OS	1.86	
4	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16GB	512GB SSD	AMD Radeon Pro 455	macOS	1.83	
5	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 3.1GHz	8GB	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37	

Yeeyyy it works! We do not need 'kg' unit anymore because all the data is in same unit.

Now it is time to move on 'Ram'. It is similar to weight column. So, let's directly dive into the function.

In [14]:
```
def ram_extraction(name):
    return int(name[:-2])
```

In [15]:
```
df["Ram"] = df["Ram"].apply(ram_extraction)
```

In [16]:
```
df.head()
```

Out[16]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price
laptop_ID											
1	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	1
2	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	
3	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8	256GB SSD	Intel HD Graphics 620	No OS	1.86	
4	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	2
5	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	1

We got rid of GB in Ram also and we use the Ram category directly as continuous value.

In [17]:
```
df['Cpu'].value_counts()
```

Out[17]:
```
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 Core M M3-6Y30 0.9GHz        1
AMD A9-Series 9420 2.9GHz          1
Intel Core i3 6006U 2.2GHz         1
AMD A6-Series 7310 2GHz            1
Intel Xeon E3-1535M v6 3.1GHz      1
Name: Cpu, Length: 118, dtype: int64
```

There are 118 type of processor here. It is very hard to get sensible ML model with all these processor models. So, we will only get the clock speed from 'Cpu' feature. It is seen that in every row, the clock speed is located at the end in the feature. Hence, we can extract it by splitting the data to its parts and we can store the last part.

In [18]:
```
clock = df['Cpu'].iloc[15]
speed = clock.split()[-1]
speed
```

Out[18]:
```
'2.3GHz'
```

Great but we do not want any string in the result. So, our function should only get the numbers. By running a for loop, we can store the clock speed value if the iteration stops before a 'G' of 'GHz' appear.

In [19]:
```
value = ''
for character in speed:
    if character == 'G':
        break
    else:
        value+=character
print(float(value))
```

```
2.3
```

It works great! Let's turn this into function again.

In [20]:
```
def cpu_clockspeed(name):
    speed = name.split()[-1]
    value = ''
    for character in speed:
        if character == 'G':
            break
        else:
            value+=character

    return float(value)
```

In [21]:
```
df['ClockSpeed'] = df['Cpu'].apply(cpu_clockspeed)
```

In [22]:
```
df['ClockSpeed'].value_counts()
```

Out[22]:
```
2.50    293
2.70    166
2.80    165
1.60    134
2.30     86
2.00     86
1.80     78
2.60     76
1.10     53
2.40     52
2.90     21
3.00     19
1.20     15
1.44     12
2.20     11
1.50     10
1.30      6
3.60      5
0.90      4
```

In [23]:
```
df.head()
```

Out[23]:

laptop_ID	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price_
1	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	1
2	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	
3	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8	256GB SSD	Intel HD Graphics 620	No OS	1.86	
4	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	2
5	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	1

We successed to get the clockspeed information from 'Cpu' feature. So, we do not need 'Cpu' catagory anymore.

In [24]:
```
df.drop('Cpu',axis =1,inplace =True)
```

In [25]:
```
df.head()
```

Out[25]:

laptop_ID	Company	TypeName	Inches	ScreenResolution	Ram	Memory	Gpu	OpSys	Weight	Price_euros
1	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	1339.69
2	Apple	Ultrabook	13.3	1440x900	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	898.94
3	HP	Notebook	15.6	Full HD 1920x1080	8	256GB SSD	Intel HD Graphics 620	No OS	1.86	575.00
4	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	2537.45
5	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	8	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37	1803.60

In [26]:
```
df['ScreenResolution'].value_counts()
```

Out[26]:
```
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
4K Ultra HD 3840x2160                            7
Touchscreen 2560x1440                            7
IPS Panel 1366x768                               7
IPS Panel Quad HD+ / Touchscreen 3200x1800       6
IPS Panel Retina Display 2560x1600               6
IPS Panel Retina Display 2304x1440               6
Touchscreen 2256x1504                            6
IPS Panel Touchscreen 2560x1440                  5
```

There are many type of screen info. It is very hard to differantiate them. However, it is possible to get the resolution value info from this feature. If you examine them carefuly, it can be seen that the resolution part is the last portion in all rows. So, we can split this feature to its parts and get the pixel values.

In [27]:
```
resolution = df['ScreenResolution'].iloc[40]
quality = resolution.split()[-1]
quality
```

Out[27]:
```
'1920x1080'
```

Now, we managed to get the resolution info. To process it in our model, ww need to seperate it to width and height pixel values.

In [28]:
```
def width(screen):

    quality = screen.split()[-1]
    result = int(quality.split('x')[0])

    return result
```

In [29]:
```
def height(screen):

    quality = screen.split()[-1]
    result = int(quality.split('x')[1])

    return result
```

In [30]:
```
df['Width'] = df['ScreenResolution'].apply(width)
```

In [31]:
```
df['Height'] = df['ScreenResolution'].apply(height)
```

Image quality is a product of width and height pixel values.

In [32]:
```
df['Pixel'] = df['Width'] * df['Height']
```

In [33]:
```
df['Pixel'].value_counts()
```

Out[33]:
```
2073600    841
1049088    308
8294400     43
5760000     27
3686400     23
1440000     23
4096000      6
3317760      6
3393024      6
2304000      5
1296000      4
5184000      4
3840000      4
3110400      2
4990464      1
Name: Pixel, dtype: int64
```

The higher the pixel value, the better theimage quality. We got the pixel value of the display so we can drop ScreenResolution feature.

In [34]:
```
df.drop('ScreenResolution',axis =1,inplace =True)
```

In [35]:
```
df.head()
```

Out[35]:

laptop_ID	Company	TypeName	Inches	Ram	Memory	Gpu	OpSys	Weight	Price_euros	ClockSpeed	Width
1	Apple	Ultrabook	13.3	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	1339.69	2.3	2560
2	Apple	Ultrabook	13.3	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	898.94	1.8	1440
3	HP	Notebook	15.6	8	256GB SSD	Intel HD Graphics 620	No OS	1.86	575.00	2.5	1920
4	Apple	Ultrabook	15.4	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	2537.45	2.7	2880
5	Apple	Ultrabook	13.3	8	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37	1803.60	3.1	2560

Let's check the correlation between features and price.

In [36]:
```
df.corr()['Price_euros'].sort_values(ascending=False)
```

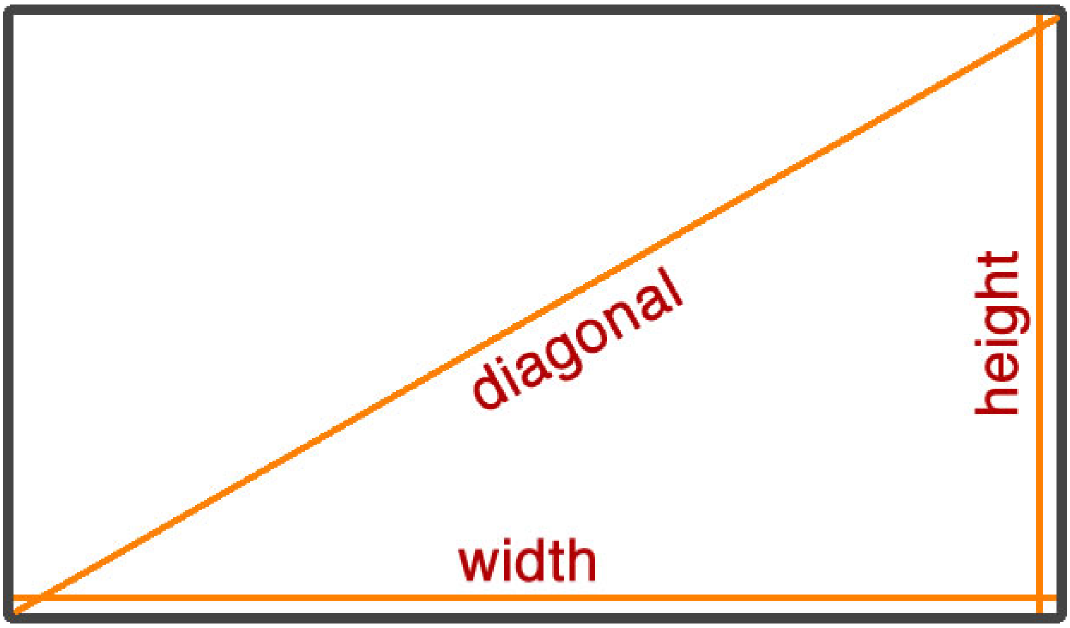
Out[36]:
```
Price_euros    1.000000
Ram            0.743007
Width          0.556529
Height         0.552809
Pixel          0.515486
ClockSpeed     0.430293
Weight         0.210370
Inches         0.068197
Name: Price_euros, dtype: float64
```

Only inch value has little effect on price, lets try to add another parameter.

In [37]:
```
df['PPI'] = ((df['Width'])**2 + (df['Height'])**2)**0.5/df['Inches']
df['PPI'] = round(df['PPI'],2)
```

PPI stands for Pixel per Inches. It shows the density of pixels in a screen. The formula is below:

$$\text{diagonal} = \sqrt{\text{width}^2 + \text{height}^2}$$



$$\text{PPI} = \frac{\text{diagonal in pixels}}{\text{diagonal in inches}}$$

In [38]:
```
df.head()
```

Out[38]:

laptop_ID	Company	TypeName	Inches	Ram	Memory	Gpu	OpSys	Weight	Price_euros	ClockSpeed	Width
1	Apple	Ultrabook	13.3	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	1339.69	2.3	2560
2	Apple	Ultrabook	13.3	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	898.94	1.8	1440
3	HP	Notebook	15.6	8	256GB SSD	Intel HD Graphics 620	No OS	1.86	575.00	2.5	1920
4	Apple	Ultrabook	15.4	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	2537.45	2.7	2880
5	Apple	Ultrabook	13.3	8	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37	1803.60	3.1	2560

In [39]:
```
df.corr()['Price_euros'].sort_values(ascending=False)
```

Out[39]:
```
Price_euros    1.000000
Ram            0.743007
Width          0.556529
Height         0.552809
Pixel          0.515486
PPI            0.473506
ClockSpeed     0.430293
Weight         0.210370
Inches         0.068197
Name: Price_euros, dtype: float64
```

So, the PPI value is also an important feature for us. The 'Pixel' and 'PPI' features contain already enough information for us. For this reason, we can drop 'Width' and 'Height'.

In [40]:
```
df.drop(['Width','Height'],axis = 1, inplace=True)
```

Now we can work on Memory and GPU, then we can move on to transforming every catagoric feature to OHE.

In [41]:
```
df['Gpu'].value_counts()
```

Out[41]:
```
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
                          ... 
AMD Radeon R5 520            1
AMD Radeon R7                1
Intel HD Graphics 540        1
AMD Radeon 540               1
ARM Mali T860 MP4            1
Name: Gpu, Length: 110, dtype: int64
```

There are many GPU models as well but at least we can extract GPU Brand for comparison. It is possible that some brands more expensive than others.

In [42]:
```
def gpu_brand(name):
    brand = name.split()[0]

    return brand
```

In [43]:
```
df['GPU_Brand'] = df['Gpu'].apply(gpu_brand)
```

In [44]:
```
df['GPU_Brand'].unique()
```

Out[44]:
```
array(['Intel', 'AMD', 'Nvidia', 'ARM'], dtype=object)
```

We extracted the brands from GPU. Thus, the Gpu feature is no longer necessary for us.

In [45]:
```
df.drop('Gpu',axis = 1, inplace=True)
df.head()
```

Out[45]:

laptop_ID	Company	TypeName	Inches	Ram	Memory	OpSys	Weight	Price_euros	ClockSpeed	Pixel	PPI
1	Apple	Ultrabook	13.3	8	128GB SSD	macOS	1.37	1339.69	2.3	4096000	226.98
2	Apple	Ultrabook	13.3	8	128GB Flash Storage	macOS	1.34	898.94	1.8	1296000	127.68
3	HP	Notebook	15.6	8	256GB SSD	No OS	1.86	575.00	2.5	2073600	141.21
4	Apple	Ultrabook	15.4	16	512GB SSD	macOS	1.83	2537.45	2.7	5184000	220.53
5	Apple	Ultrabook	13.3	8	256GB SSD	macOS	1.37	1803.60	3.1	4096000	226.98

Now, it is time to work on 'Memory'. For device memory, both the capacity and the speed of the storage are important.

In [46]:
```
df['Memory'].value_counts()
```

Out[46]:
```
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
```

There are many type of memory we must work on here. We can extract the amount of the storage by extracting the values from the feature. The speed of the storage cannot be found from this dataset however we can identify the technologies.

In [47]:
```
re.findall(r'\d+', "256GB SSD +  2TB HDD")
```

Out[47]:
```
['256', '2']
```

This built-in function can detect positive numbers. However, we should be careful about GB and TB. 1 TB equals to 1024 GB.

In [48]:
```
def storage(name):
    storage = name.split()
    amount = 0

    for element in storage:
        if 'GB' in element:
            amount += int(element[:-2])
        elif 'TB' in element:
            amount += float(element[:-2])*1024

    return int(amount)
```

Let's try our function with some examples.

In [49]:
```
storage('256GB SSD +  256GB SSD')
```

Out[49]:
```
512
```

In [50]:
```
storage('1.0TB HDD +  1TB HDD')
```

Out[50]:
```
2048
```

It works well. For next step, we need to detect the storage tech. There are 3 storage type in our feature. They are HDD, SSD and Flash Storage. It is commonly known that SSDs and Flash are usually faster than HDD. They can be used alone or can be used collectively which is called 'Hybrid' in computer world. Hybrids are usually cheaper than pure SSD storage while faster and more expesive than pure HDD storage.

In [51]:
```
def storage_type(name):
    storage = name.split()
    tech = []

    for element in storage:
        if element=='SSD' or element=='HDD' or element=='Flash':
            tech.append(element)
        elif element=='Hybrid':
            tech.append(element)

    if len(tech) > 1:
        return 'Hybrid'
    else:
        return tech[0]
```

Let's try this function with some examples as well.

In [52]:
```
storage_type('512GB SSD +  1.0TB Hybrid')
```

Out[52]:
```
'Hybrid'
```

In [53]:
```
storage_type('64GB Flash Storage +  1TB HDD')
```

Out[53]:
```
'Hybrid'
```

In [54]:
```
storage_type('240GB SSD')
```

Out[54]:
```
'SSD'
```

It is time to apply functions to dataset.

In [55]:
```
df['Total_Storage'] = df['Memory'].apply(storage)
df['Storage_Type'] = df['Memory'].apply(storage_type)
```

In [56]:
```
df.drop('Memory',axis = 1, inplace=True)
df.head()
```

Out[56]:

	Company	TypeName	Inches	Ram	OpSys	Weight	Price_euros	ClockSpeed	Pixel	PPI	GPU_Br
laptop_ID											
1	Apple	Ultrabook	13.3	8	macOS	1.37	1339.69	2.3	4096000	226.98	
2	Apple	Ultrabook	13.3	8	macOS	1.34	898.94	1.8	1296000	127.68	
3	HP	Notebook	15.6	8	No OS	1.86	575.00	2.5	2073600	141.21	
4	Apple	Ultrabook	15.4	16	macOS	1.83	2537.45	2.7	5184000	220.53	A
5	Apple	Ultrabook	13.3	8	macOS	1.37	1803.60	3.1	4096000	226.98	

In [57]:
```
df.corr()['Price_euros'].sort_values(ascending=False)
```

Out[57]:
```
Price_euros      1.000000
Ram              0.743007
Pixel            0.515486
PPI              0.473506
ClockSpeed       0.430293
Weight           0.210370
Total_Storage    0.157830
Inches           0.068197
Name: Price_euros, dtype: float64
```

Total_Storage has a slight influance on price but i am pretty sure that when combined with the Storage_Type, they hold valuable information for price.

In [58]:
```
df['OpSys'].value_counts()
```

Out[58]:
```
Windows 10      1072
No OS             66
Linux             62
Windows 7         45
Chrome OS         27
macOS             13
Mac OS X           8
Windows 10 S       8
Android            2
Name: OpSys, dtype: int64
```

In [59]:
```
df['TypeName'].value_counts()
```

Out[59]:
```
Notebook              727
Gaming                205
Ultrabook             196
2 in 1 Convertible    121
Workstation            29
Netbook                25
Name: TypeName, dtype: int64
```

We are pretty close to finish preprocessing. Let's turn categorical features to dummy variables.

In [60]:
```
df = df.join(pd.get_dummies(df.Company)).drop(['Company'],axis = 1)
df = df.join(pd.get_dummies(df.TypeName)).drop(['TypeName'],axis = 1)
df = df.join(pd.get_dummies(df.OpSys)).drop(['OpSys'],axis = 1)
df = df.join(pd.get_dummies(df.Storage_Type)).drop(['Storage_Type'],axis = 1)
df = df.join(pd.get_dummies(df.GPU_Brand)).drop(['GPU_Brand'],axis = 1)
```

In [61]:
```
df.head()
```

Out[61]:

	Inches	Ram	Weight	Price_euros	ClockSpeed	Pixel	PPI	Total_Storage	Acer	Apple	...	Windo
laptop_ID												
1	13.3	8	1.37	1339.69	2.3	4096000	226.98	128	0	1	...	
2	13.3	8	1.34	898.94	1.8	1296000	127.68	128	0	1	...	
3	15.6	8	1.86	575.00	2.5	2073600	141.21	256	0	0	...	
4	15.4	16	1.83	2537.45	2.7	5184000	220.53	512	0	1	...	
5	13.3	8	1.37	1803.60	3.1	4096000	226.98	256	0	1	...	

5 rows × 50 columns

In [62]:
```
len(df.columns)
```

Out[62]:
```
50
```

50 columns? Phew! It is better to filter some to get a generalized model.

In [63]:
```
df.corr()['Price_euros'].sort_values(ascending=False)
```

Out[63]:
```
Price_euros           1.000000
Ram                   0.743007
Pixel                 0.515486
PPI                   0.473506
ClockSpeed            0.430293
Gaming                0.375789
Nvidia                0.348797
Hybrid                0.294630
SSD                   0.264977
Ultrabook             0.255658
Workstation           0.249752
Razer                 0.233756
Weight                0.210370
MSI                   0.180100
Total_Storage         0.157830
Windows 7             0.152381
Windows 10            0.137048
macOS                 0.089928
Apple                 0.080688
```

Some features can have a negative correlation as above. Therefore, we must filter the features according to their absolute correlation.

In [64]:
```
correlated_features = abs(df.corr()['Price_euros']).sort_values(ascending=False)
correlated_features
```

Out[64]:
```
Price_euros          1.000000
Ram                  0.743007
Notebook             0.549248
Pixel                0.515486
PPI                  0.473506
ClockSpeed           0.430293
HDD                  0.425241
Gaming               0.375789
Nvidia               0.348797
Hybrid               0.294630
SSD                  0.264977
Ultrabook            0.255658
Workstation          0.249752
Razer                0.233756
Flash                0.216282
Weight               0.210370
Acer                 0.208349
AMD                  0.199415
Intel                0.184205
```

In [65]:
```
selected_features = correlated_features[:26].index
selected_features
```

Out[65]:
```
Index(['Price_euros', 'Ram', 'Notebook', 'Pixel', 'PPI', 'ClockSpeed', 'HDD',
       'Gaming', 'Nvidia', 'Hybrid', 'SSD', 'Ultrabook', 'Workstation',
       'Razer', 'Flash', 'Weight', 'Acer', 'AMD', 'Intel', 'MSI', 'No OS',
       'Linux', 'Total_Storage', 'Windows 7', 'Windows 10', 'Chrome OS'],
      dtype='object')
```

In [66]:
```
df = df[selected_features]
```

We filtered most important 25 features in the dataframe.

In [67]:
```
df
```

Out[67]:

laptop_ID	Price_euros	Ram	Notebook	Pixel	PPI	ClockSpeed	HDD	Gaming	Nvidia	Hybrid	...	Acer
1	1339.69	8	0	4096000	226.98	2.3	0	0	0	0	...	0
2	898.94	8	0	1296000	127.68	1.8	0	0	0	0	...	0
3	575.00	8	1	2073600	141.21	2.5	0	0	0	0	...	0
4	2537.45	16	0	5184000	220.53	2.7	0	0	0	0	...	0
5	1803.60	8	0	4096000	226.98	3.1	0	0	0	0	...	0
...	...	...	...	...	...	...	...	...	...	...	...	...
1316	638.00	4	0	2073600	157.35	2.5	0	0	0	0	...	0
1317	1499.00	16	0	5760000	276.05	2.5	0	0	0	0	...	0
1318	229.00	2	1	1049088	111.94	1.6	0	0	0	0	...	0

Now, we are done with preprocessing. It is time for separeting the dataframe to input and target vectors.

In [68]:
```
X = df.drop('Price_euros',axis = 1)
y = df['Price_euros']
```

In [69]:
```
X.columns
```

Out[69]:
```
Index(['Ram', 'Notebook', 'Pixel', 'PPI', 'ClockSpeed', 'HDD', 'Gaming',
       'Nvidia', 'Hybrid', 'SSD', 'Ultrabook', 'Workstation', 'Razer', 'Flash',
       'Weight', 'Acer', 'AMD', 'Intel', 'MSI', 'No OS', 'Linux',
       'Total_Storage', 'Windows 7', 'Windows 10', 'Chrome OS'],
      dtype='object')
```

In [70]:
```
y
```

Out[70]:
```
laptop_ID
1       1339.69
2        898.94
3        575.00
4       2537.45
5       1803.60
          ...
1316     638.00
1317    1499.00
1318     229.00
1319     764.00
1320     369.00
Name: Price_euros, Length: 1303, dtype: float64
```

To reach optimum weights, scaling input variables is crucial. For scaling, standard scaler is prefered in this study.

In [71]:
```
continues_features = ['Ram','Weight','ClockSpeed','Pixel','PPI','Total_Storage']
```

There is no need to scale dummy variables because their range is already 0 and 1.

In [72]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X[continues_features] = scaler.fit_transform(X[continues_features])
```

In [73]:
```
X
```

Out[73]:

	Ram	Notebook	Pixel	PPI	ClockSpeed	HDD	Gaming	Nvidia	Hybrid	SSD	...	Acer	A
laptop_ID													
1	-0.075195	0	1.385714	1.863955	0.002426	0	0	0	0	1	...	0	
2	-0.075195	0	-0.627576	-0.439733	-0.985431	0	0	0	0	0	...	0	
3	-0.075195	1	-0.068457	-0.125847	0.397569	0	0	0	0	1	...	0	
4	1.498767	0	2.168021	1.714320	0.792712	0	0	0	0	1	...	0	
5	-0.075195	0	1.385714	1.863955	1.582997	0	0	0	0	1	...	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
1316	-0.862176	0	-0.068457	0.248590	0.397569	0	0	0	0	1	...	0	
1317	1.498767	0	2.582183	3.002344	0.397569	0	0	0	0	1	...	0	
1318	-1.255667	1	-0.805114	-0.804889	-1.380574	0	0	0	0	0	...	0	
1319	-0.468686	1	-0.805114	-1.071449	0.397569	1	0	0	0	0	...	0	
1320	-0.862176	1	-0.805114	-1.071449	-1.380574	1	0	0	0	0	...	0	

1303 rows × 25 columns

Our inputs are scaled now. We can split the data to train and test sets. Due to a few data we have, we will split the train and test set as 85%-15%.

In [74]:
```
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=30)
```

There are many catagories in our model. In these kind of situations, random forest works well because it is made of many decision trees. It can estimate the target value by votes of majority.

In [75]:
```
from sklearn.ensemble import RandomForestRegressor
# Fitting Random Forest Regression to the dataset
random_forest = RandomForestRegressor()

# Fit the regressor with x and y data
random_forest.fit(X_train, y_train)
```

Out[75]:
```
RandomForestRegressor()
```

In [76]:
```
from sklearn.metrics import mean_squared_error, r2_score
```

In [77]:
```
# Making predictions on the testing set
forest_predictions = random_forest.predict(X_test)

# Evaluating the model on testing set
mse = mean_squared_error(y_test, forest_predictions)
rmse = mse**0.5
r2 = r2_score(y_test, forest_predictions)

print(f'Mean Squared Error: {mse:.2f}, R-squared: {r2:.2f}, Root Mean Squared Error: {rmse:.2
```

```
Mean Squared Error: 121391.26, R-squared: 0.80, Root Mean Squared Error: 348.41
```

Our model works well. In order to make sure that the model did not overfit, we should check for cross validation.

In [78]:
```
from sklearn.model_selection import cross_val_score

scores = cross_val_score(random_forest, X, y, cv=5)  # 5-fold cross-validation
```

In [79]:
```
print(f"CV Scores: {scores:}")
print(f"Average CV Score: {scores.mean():.2f}")
print(f"Standard Deviation of CV Scores: {scores.std():.2f}")
```

```
CV Scores: [0.81985148 0.81455062 0.81506524 0.74544757 0.72414901]
Average CV Score: 0.78
Standard Deviation of CV Scores: 0.04
```

Our avarage score is 0.78 and standard deviation is 0.04. It is not the best but still relatively good model to use. For further improvement, working with wider range of data would provide us more accurate and generalized model. Also, other ML models can be tried for comparison. Thank you for reading until here!