2024

LAPTOP PRICE ANALYSIS

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1 Laptop Price Analysis

[23]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

1.0.1 Loading Data Set

[2]:
```
df=pd.read_csv('C:\\Users\\progr\\OneDrive\\Desktop\\data_Sets\\laptop-price.
↪csv' , index_col=0)
```

[3]:
```
df
```

[3]:
```
         Company            TypeName  Ram  Weight        Price  Touchscreen  Ips  \
index
0          Apple           Ultrabook    8    1.37   71378.6832            0    1
1          Apple           Ultrabook    8    1.34   47895.5232            0    0
2             HP            Notebook    8    1.86   30636.0000            0    0
3          Apple           Ultrabook   16    1.83  135195.3360            0    1
4          Apple           Ultrabook    8    1.37   96095.8080            0    1
…            …                 …   …     …       …              …   …
1298      Lenovo  2 in 1 Convertible    4    1.80   33992.6400            1    1
1299      Lenovo  2 in 1 Convertible   16    1.30   79866.7200            1    1
1300      Lenovo            Notebook    2    1.50   12201.1200            0    0
1301          HP            Notebook    6    2.19   40705.9200            0    0
1302        Asus            Notebook    4    2.20   19660.3200            0    0

              ppi            Cpu brand  HDD  SSD  Hybrid  Flash_Storage  \
index
0      226.983005        Intel Core i5    0  128       0              0
1      127.677940        Intel Core i5    0    0       0            128
2      141.211998        Intel Core i5    0  256       0              0
3      220.534624        Intel Core i7    0  512       0              0
4      226.983005        Intel Core i5    0  256       0              0
…             …                    …   …  …    …              …
1298   157.350512        Intel Core i7    0  128       0              0
1299   276.053530        Intel Core i7    0  512       0              0
```

```
1300   111.935204  Other Intel Processor     0     0        0             64
1301   100.454670          Intel Core i7  1000     0        0              0
1302   100.454670  Other Intel Processor   500     0        0              0

      Gpu brand                 os
index
0         Intel                Mac
1         Intel                Mac
2         Intel  Others/No OS/Linux
3           AMD                Mac
4         Intel                Mac
…           …                  …
1298      Intel            Windows
1299      Intel            Windows
1300      Intel            Windows
1301        AMD            Windows
1302      Intel            Windows

[1268 rows x 15 columns]
```

1.0.2 Summary Statistics

[8]:
```python
df.columns
```

[8]:
```
Index(['Company', 'TypeName', 'Ram', 'Weight', 'Price', 'Touchscreen', 'Ips',
       'ppi', 'Cpu brand', 'HDD', 'SSD', 'Hybrid', 'Flash_Storage',
       'Gpu brand', 'os'],
      dtype='object')
```

[9]:
```python
df.shape
```

[9]:
```
(1268, 15)
```

[6]:
```python
df.describe()
```

[6]:
```
               Ram       Weight          Price  Touchscreen          Ips  \
count  1268.000000  1268.000000    1268.000000  1268.000000  1268.000000
mean      8.461356     2.080047   59924.981175     0.145110     0.282334
std       5.569898     0.806482   37340.350650     0.352351     0.450313
min       1.000000     0.690000    9270.720000     0.000000     0.000000
25%       4.000000     1.500000   31914.720000     0.000000     0.000000
50%       8.000000     2.040000   52107.840000     0.000000     0.000000
75%       8.000000     2.320000   79346.840400     0.000000     1.000000
max      64.000000    11.100000  324954.720000     1.000000     1.000000

               ppi          HDD          SSD       Hybrid  Flash_Storage
count  1268.000000  1268.000000  1268.000000  1268.000000    1268.000000
```

```
mean    145.935819   415.741325   183.634069     9.075710       4.580442
std      43.445969   517.152677   186.641125    93.825228      30.615945
min      44.019462     0.000000     0.000000     0.000000       0.000000
25%     127.335675     0.000000     0.000000     0.000000       0.000000
50%     141.211998     0.000000   256.000000     0.000000       0.000000
75%     157.350512  1000.000000   256.000000     0.000000       0.000000
max     352.465147  2000.000000  1024.000000  1000.000000     512.000000
```

[7]:
```
df.dtypes
```

[7]:
```
Company           object
TypeName          object
Ram                int64
Weight           float64
Price            float64
Touchscreen        int64
Ips                int64
ppi              float64
Cpu brand         object
HDD                int64
SSD                int64
Hybrid             int64
Flash_Storage      int64
Gpu brand         object
os                object
dtype: object
```

1.0.3 checking null values

[30]:
```
df.isnull().sum()
```

[30]:
```
Company          0
TypeName         0
Ram              0
Weight           0
Price            0
Touchscreen      0
Ips              0
ppi              0
Cpu brand        0
HDD              0
SSD              0
Hybrid           0
Flash_Storage    0
Gpu brand        0
os               0
dtype: int64
```

2 Exploratory Data Analysis (EDA)

2.0.1 Price Correction

- Since price is in INR we have to Convert it into PKR
- 1 INR is Equal to 3.28 PKR

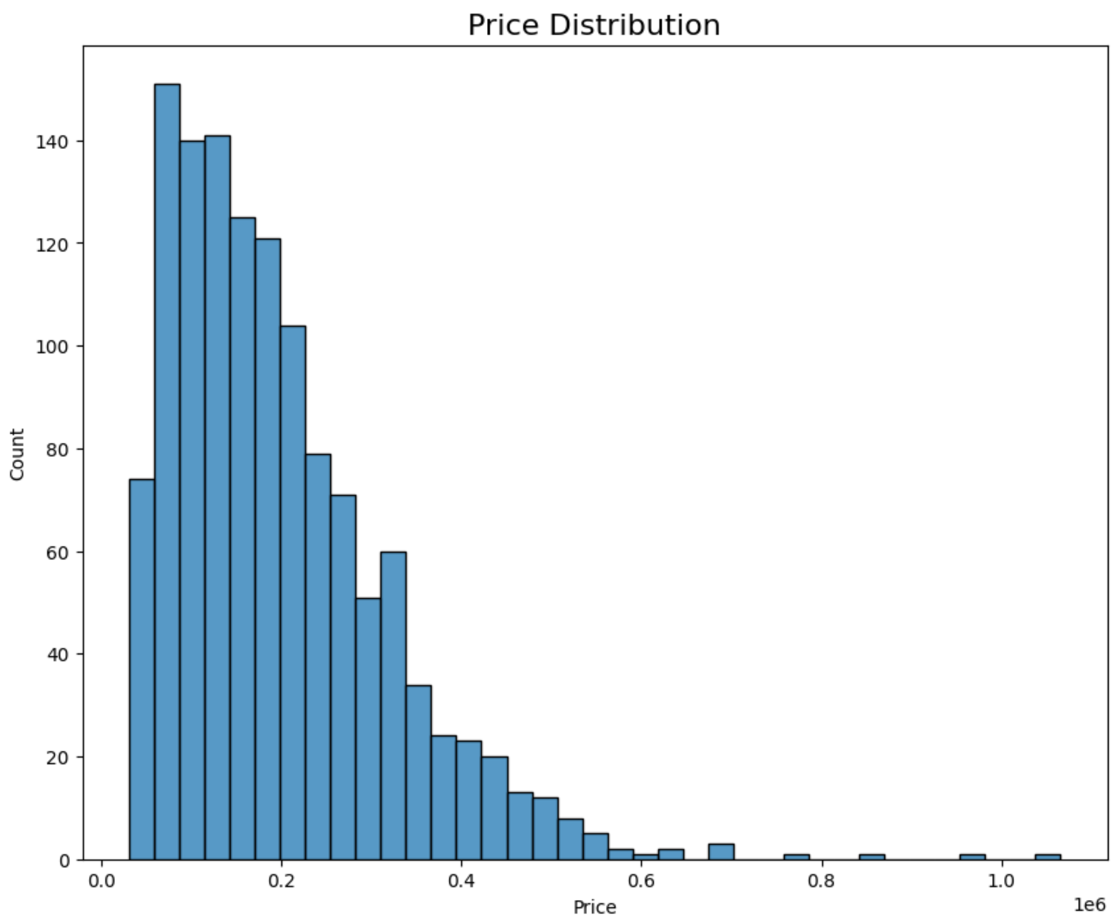
[10]:
```
df['Price']=df['Price'] * 3.28
```

[11]:
```
df.head()
```

[11]:
```
      Company   TypeName  Ram  Weight          Price  Touchscreen  Ips  \
index
0       Apple  Ultrabook    8    1.37  234122.080896            0    1
1       Apple  Ultrabook    8    1.34  157097.316096            0    0
2          HP   Notebook    8    1.86  100486.080000            0    0
3       Apple  Ultrabook   16    1.83  443440.702080            0    1
4       Apple  Ultrabook    8    1.37  315194.250240            0    1

              ppi      Cpu brand  HDD  SSD  Hybrid  Flash_Storage Gpu brand  \
index
0      226.983005  Intel Core i5    0  128       0              0     Intel
1      127.677940  Intel Core i5    0    0       0            128     Intel
2      141.211998  Intel Core i5    0  256       0              0     Intel
3      220.534624  Intel Core i7    0  512       0              0       AMD
4      226.983005  Intel Core i5    0  256       0              0     Intel

                      os
index
0                    Mac
1                    Mac
2      Others/No OS/Linux
3                    Mac
4                    Mac
```

2.0.2 Price Distribution

[12]:
```
plt.figure(figsize=(10,8))
sns.histplot(
    data=df,
    x='Price'
)
plt.title('Price Distribution' ,fontsize=16)
plt.show()
```



[13]:
```
#most expensive laptops

most_expensive = df.loc[df['Price'].idxmax()]
print(most_expensive[['Company' , 'Price']])
```

```
Company           Razer
Price      1065851.4816
Name: 196, dtype: object
```

[14]:
```
# most cheapest Laptop

most_cheapest=df.loc[df['Price'].idxmin()]
print(most_cheapest[['Company' , 'Price']])
```

```
Company          Acer
Price      30407.9616
Name: 1215, dtype: object
```

2.0.3 Checking for outliers

[15]:
```python
Q1 =  df['Price'].quantile(0.25)
Q3 =  df['Price'].quantile(0.75)

Iqr = Q3 - Q1

Lower_bound=Q1 - 1.5 * Iqr
Upper_bound=Q3 + 1.5 * Iqr

outliers = df[(df['Price'] < Lower_bound) | (df['Price'] > Upper_bound)]

print('Outliers are ')
print(outliers)
```

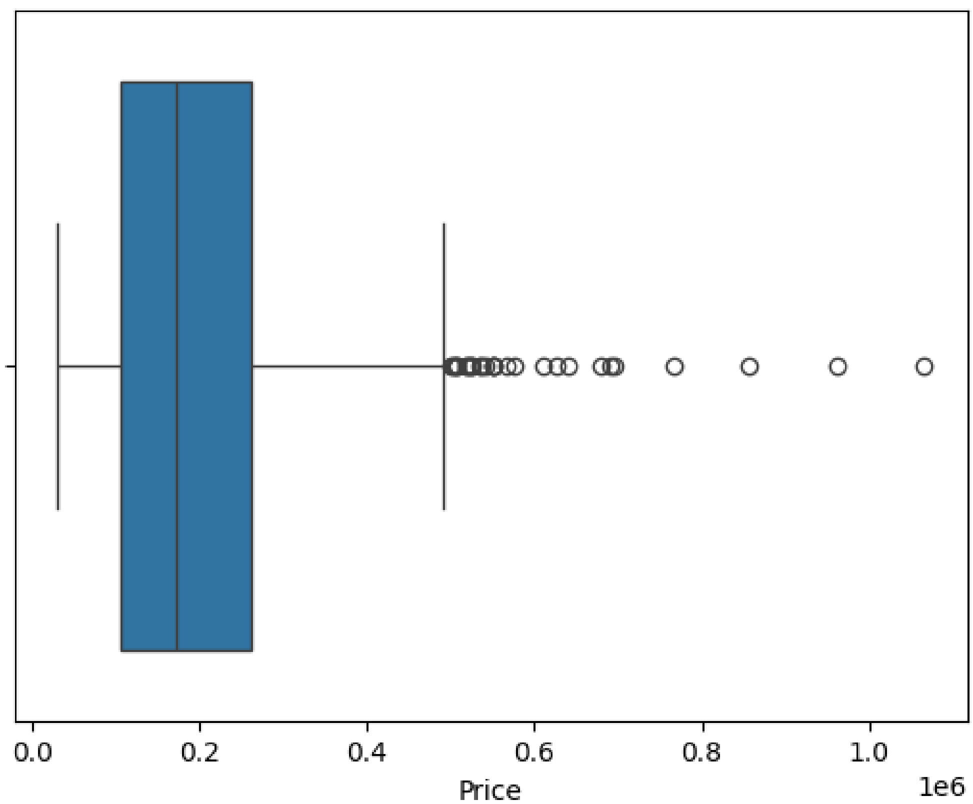
```
Outliers are 
      Company     TypeName  Ram  Weight         Price  Touchscreen  Ips  \
index                                                                     
17      Apple    Ultrabook   16    1.83  4.994595e+05            0    1   
196     Razer       Gaming   32    3.49  1.065851e+06            1    0   
204      Dell  Workstation   16    2.80  5.338869e+05            0    0   
238      Asus       Gaming   32    4.70  6.798102e+05            0    0   
247      Asus       Gaming   16    3.60  5.241004e+05            0    0   
297      Dell  Workstation   16    3.42  5.041535e+05            0    0   
517      Asus       Gaming   24    2.24  5.186829e+05            0    0   
530      Dell       Gaming   16    4.42  5.265069e+05            0    1   
563    Lenovo     Notebook    8    3.40  5.241004e+05            0    1   
610    Lenovo     Notebook   32    2.50  8.561414e+05            0    1   
659      Dell       Gaming   32    4.42  5.500293e+05            0    1   
723      Dell       Gaming   32    4.36  6.395109e+05            0    0   
744    Lenovo  Workstation   16    2.50  5.765280e+05            0    1   
749        HP  Workstation   16    3.00  7.670146e+05            0    1   
758      Dell       Gaming   16    4.42  5.013801e+05            0    1   
778     Razer       Gaming   16    1.95  5.066246e+05            0    0   
780      Dell       Gaming   32    4.42  6.271729e+05            0    1   
830     Razer       Gaming   32    3.49  9.609964e+05            1    0   
841      Dell       Gaming   32    4.42  5.370133e+05            0    1   
911        HP    Ultrabook    8    1.09  5.417510e+05            1    0   
955      Dell       Gaming   16    4.36  5.511880e+05            0    1   
968      Dell       Gaming   32    4.42  5.503142e+05            0    1   
1017   Lenovo     Notebook   16    2.40  5.186829e+05            0    1   
1066     Asus       Gaming   64    3.58  6.946646e+05            0    1   
1081   Lenovo       Gaming   32    4.60  5.662172e+05            0    1   
1103       HP  Workstation    8    3.00  5.066246e+05            0    1   
1136       HP  Workstation    8    3.00  6.901908e+05            0    1   
1231    Razer       Gaming   16    1.95  6.114796e+05            0    0   

              ppi                Cpu brand   HDD   SSD  Hybrid  Flash_Storage  \
```

index						
17	220.534624	Intel Core i7	0	512	0	0
196	254.671349	Intel Core i7	0	1000	0	0
204	282.423996	Other Intel Processor	1000	256	0	0
238	127.335675	Intel Core i7	1000	512	0	0
247	127.335675	Intel Core i7	0	256	0	0
297	127.335675	Intel Core i7	0	256	0	0
517	141.211998	Intel Core i7	0	512	0	0
530	127.335675	Intel Core i7	1000	128	0	0
563	127.335675	Intel Core i7	0	256	0	0
610	282.423996	Other Intel Processor	0	1000	0	0
659	254.671349	Intel Core i7	1000	512	0	0
723	254.671349	Intel Core i7	1000	1000	0	0
744	282.423996	Intel Core i7	0	1000	0	0
749	127.335675	Other Intel Processor	0	256	0	0
758	282.423996	Intel Core i7	1000	256	0	0
778	157.350512	Intel Core i7	0	512	0	0
780	127.335675	Intel Core i7	1000	1000	0	0
830	254.671349	Intel Core i7	0	512	0	0
841	127.335675	Intel Core i7	1000	512	0	0
911	352.465147	Other Intel Processor	0	240	0	0
955	254.671349	Intel Core i7	1000	512	0	0
968	127.335675	Intel Core i7	1000	256	0	0
1017	254.671349	Intel Core i7	0	512	0	0
1066	127.335675	Intel Core i7	0	1000	0	0
1081	127.335675	Intel Core i7	0	512	1000	0
1103	127.335675	Intel Core i7	1000	0	0	0
1136	127.335675	Intel Core i7	0	256	0	0
1231	157.350512	Intel Core i7	0	1000	0	0

index	Gpu brand	os
17	AMD	Mac
196	Nvidia	Windows
204	Nvidia	Windows
238	Nvidia	Windows
247	Nvidia	Windows
297	Nvidia	Windows
517	Nvidia	Windows
530	Nvidia	Windows
563	Nvidia	Windows
610	Nvidia	Windows
659	Nvidia	Windows
723	Nvidia	Windows
744	Nvidia	Windows
749	Nvidia	Windows
758	Nvidia	Windows
778	Nvidia	Windows

```
780       Nvidia  Windows
830       Nvidia  Windows
841       Nvidia  Windows
911        Intel  Windows
955       Nvidia  Windows
968       Nvidia  Windows
1017      Nvidia  Windows
1066      Nvidia  Windows
1081      Nvidia  Windows
1103         AMD  Windows
1136      Nvidia  Windows
1231      Nvidia  Windows
```

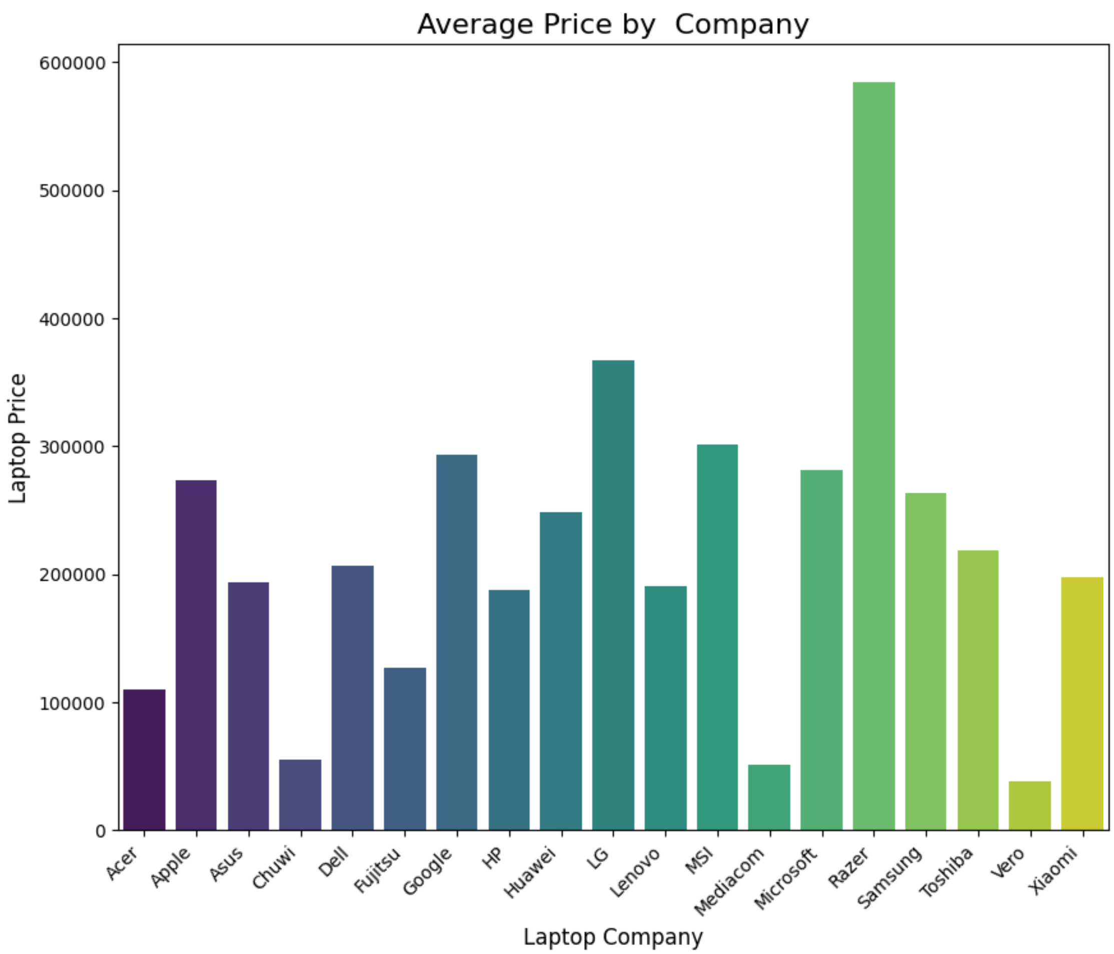
[16]:
```python
sns.boxplot(
    x=df['Price']
)
plt.show()
```



2.0.4 Average Price Company

[70]:
```
avrg_price=df.groupby('Company')['Price'].mean().reset_index()

plt.figure(figsize=(10,8))

sns.barplot(
    data=avrg_price,
    x='Company',
    y='Price',
    palette='viridis'
)

plt.title('Average Price by  Company' , fontsize=16)
plt.xlabel('Laptop Company' , fontsize=12)
plt.ylabel('Laptop Price',fontsize=12)

plt.xticks(rotation=45, ha='right')

plt.show()
```

```
C:\Users\progr\AppData\Local\Temp\ipykernel_7464\373912292.py:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(
```



2.0.5 Most Common Specification

[77]:
```
most_common_ram=df['Ram'].value_counts()
most_common_ssd=df['SSD'].value_counts()

print('Most common Ram')
print(most_common_ram)
print('\nMost common SSD')
print(most_common_ssd)
```

```
Most common Ram
Ram
8      598
4      366
16     193
6       40
12      25
```

```
2      22
32     17
64      3
24      3
1       1
Name: count, dtype: int64

Most common SSD
SSD
256     483
0       448
128     168
512     136
1000     15
32        6
180       4
16        3
64        1
1024      1
768       1
240       1
8         1
Name: count, dtype: int64
```

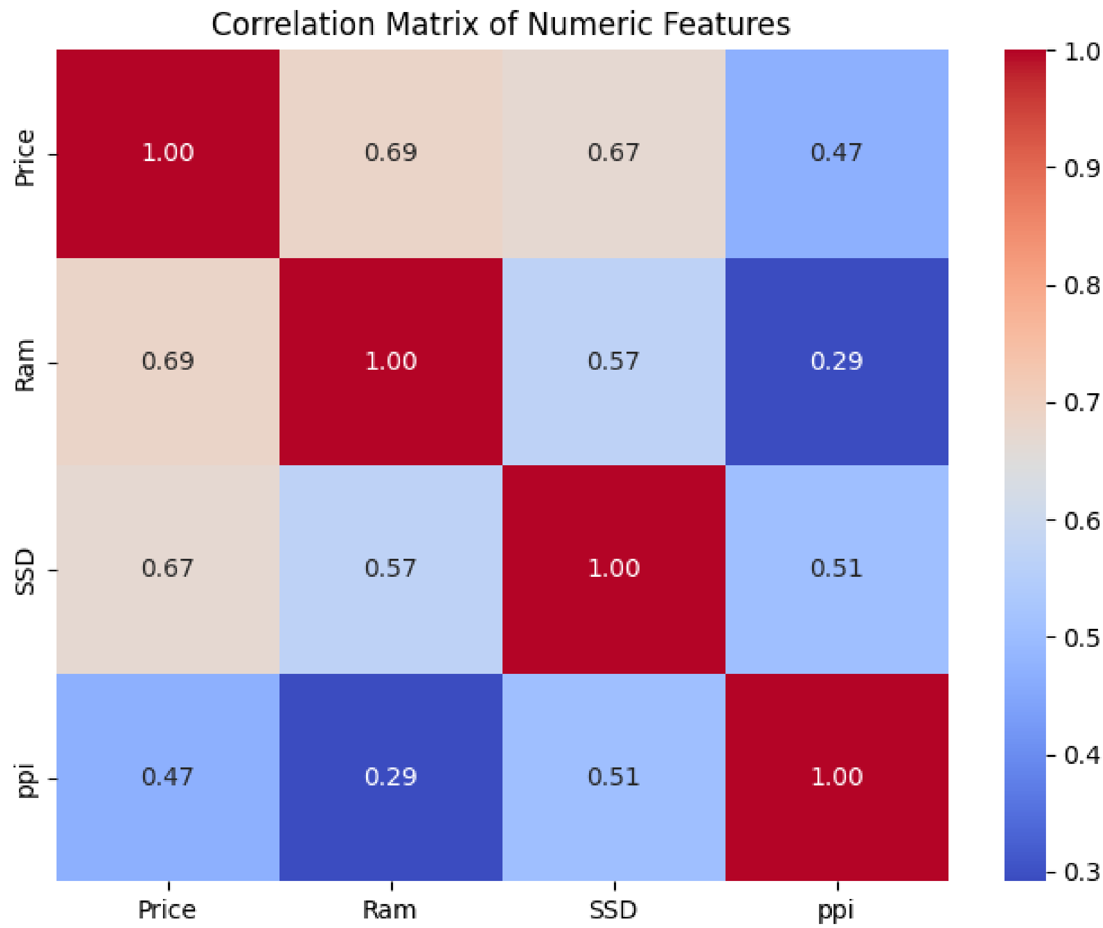
2.0.6 Correlation b/w Variables :

- **Correlation** helps measure the relationship between variables, showing how one variable changes concerning another.
- I am analyzing the correlation between laptop features (like Price, RAM, SSD, and PPI) to understand their impact on price and identify significant trends or patterns.

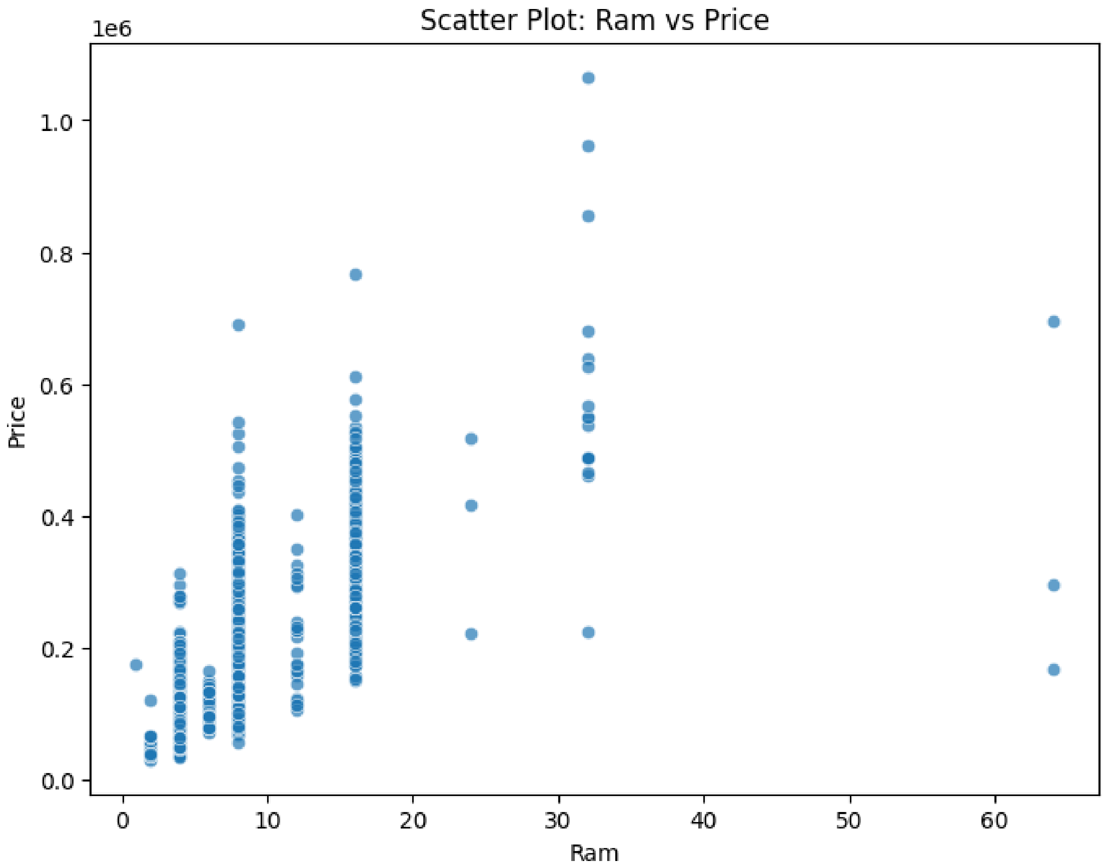
[24]:
```
from sklearn.preprocessing import LabelEncoder

# Correlation Analysis for numeric features
numeric_features = ['Price', 'Ram', 'SSD', 'ppi']
correlation_matrix = df[numeric_features].corr()

print("Correlation Matrix:")
print(correlation_matrix)

# Visualize the correlation matrix
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Matrix of Numeric Features")
plt.show()
```

```
Correlation Matrix:
          Price       Ram       SSD       ppi
```

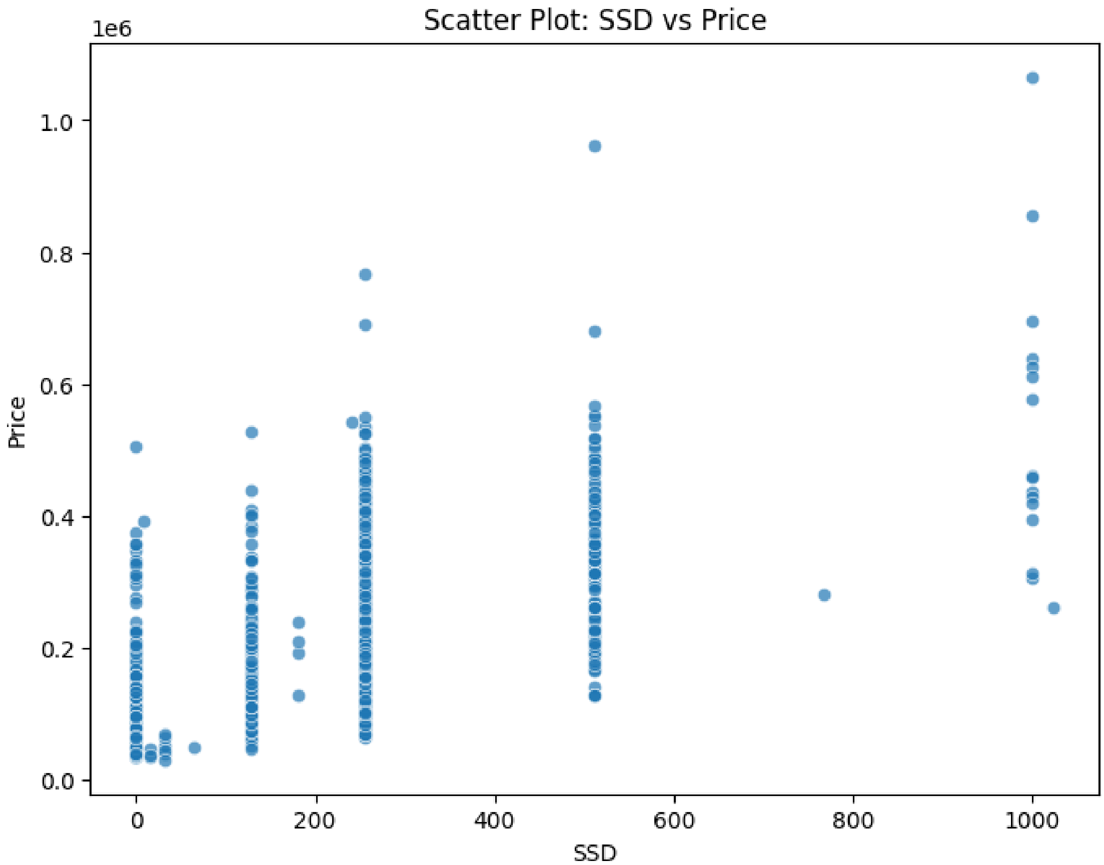
Price	1.000000	0.687127	0.668765	0.471284
Ram	0.687127	1.000000	0.570047	0.291502
SSD	0.668765	0.570047	1.000000	0.506248
ppi	0.471284	0.291502	0.506248	1.000000

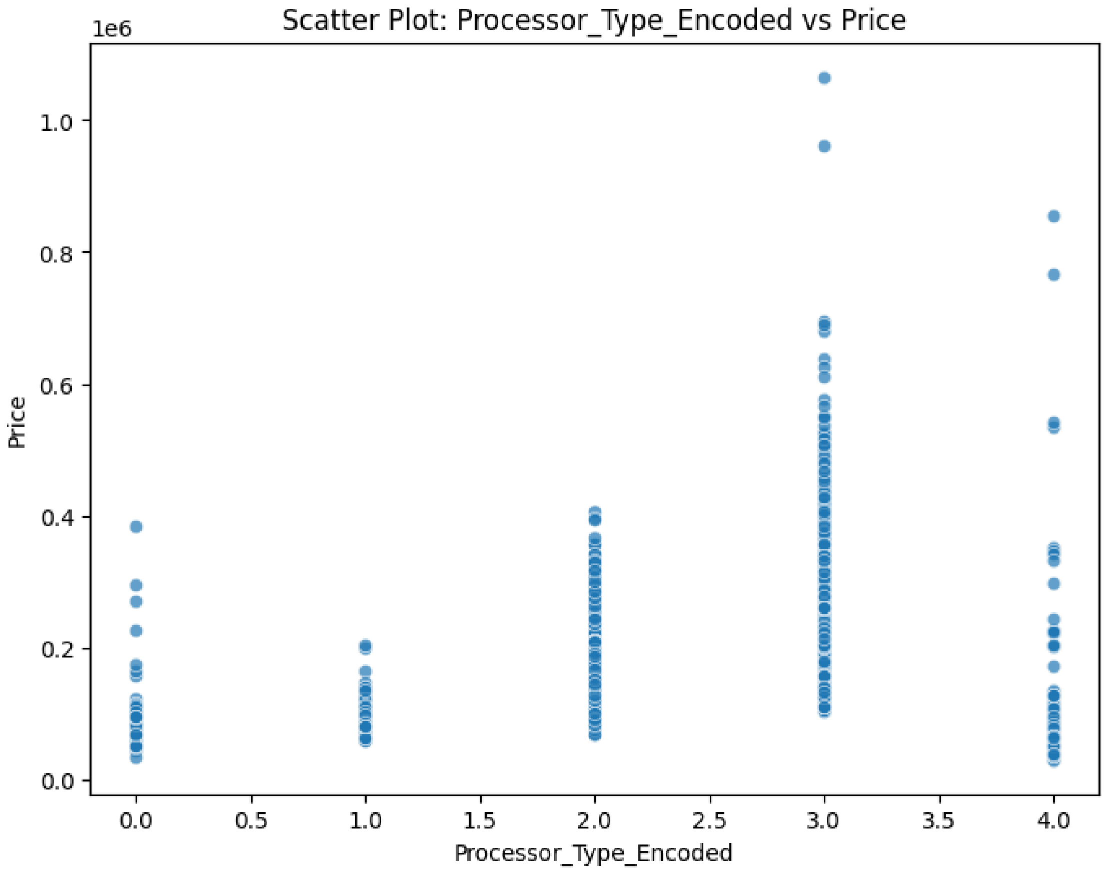


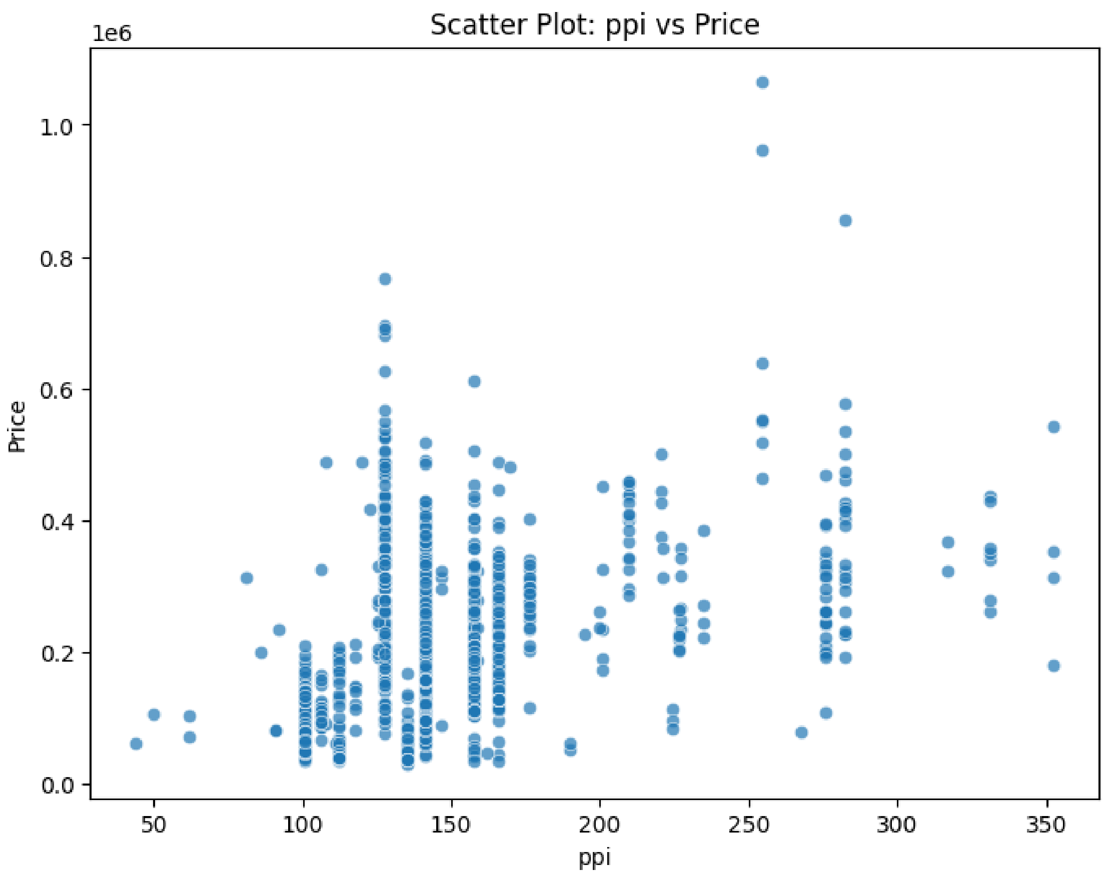
[25]:
```python
# Encoding categorical data (e.g., Processor_Type)
label_encoder = LabelEncoder()
df['Processor_Type_Encoded'] = label_encoder.fit_transform(df['Cpu brand'])

# Scatter Plots
features_to_plot = ['Ram', 'SSD', 'Processor_Type_Encoded', 'ppi']
for feature in features_to_plot:
    plt.figure(figsize=(8, 6))
    sns.scatterplot(data=df, x=feature, y='Price', alpha=0.7)
    plt.title(f"Scatter Plot: {feature} vs Price")
    plt.xlabel(feature)
    plt.ylabel('Price')
    plt.show()
```



Scatter Plot: Ram vs Price
1e6
1.0
0.8
0.6
0.4
0.2
0.0
Price
0
10
20
30
40
50
60
Ram


Scatter Plot: SSD vs Price
1e6
1.0
0.8
0.6
0.4
0.2
0.0
Price
0
200
400
600
800
1000
SSD

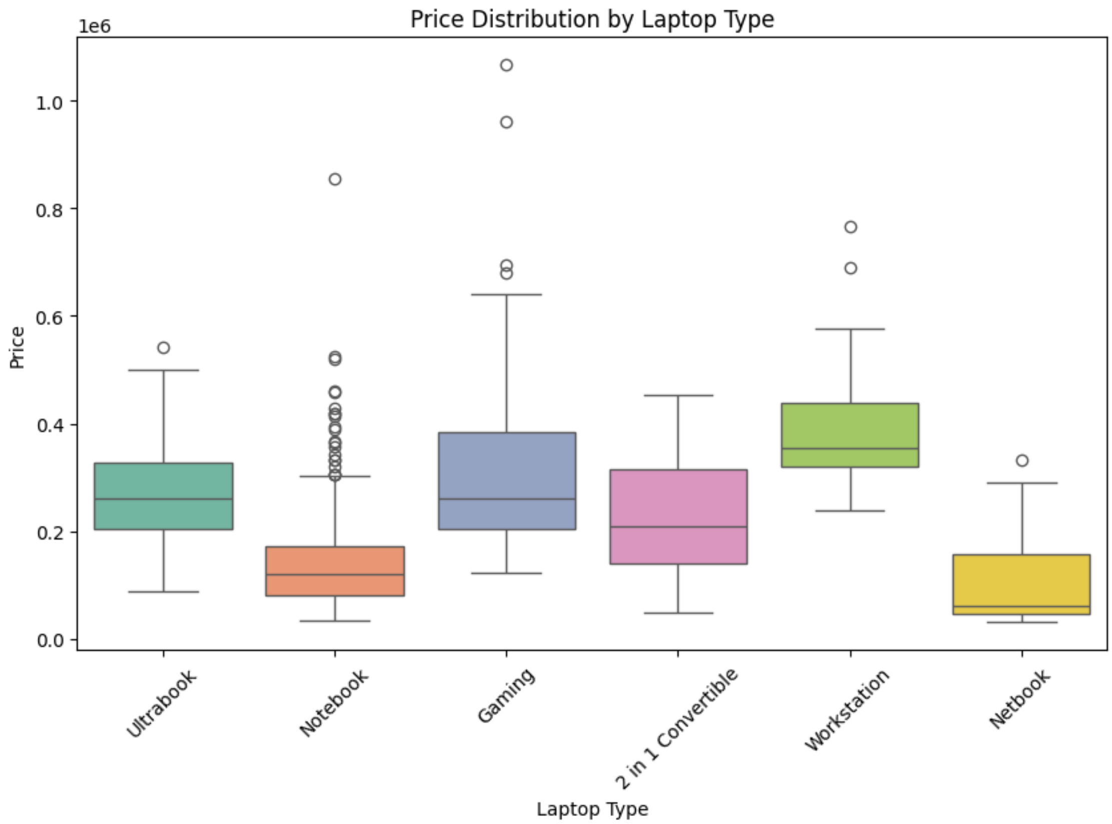

Scatter Plot: Processor_Type_Encoded vs Price
1e6
1.0
0.8
0.6
0.4
0.2
0.0
Price
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Processor_Type_Encoded



2.0.7 Laptop price according to it's Type

[26]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(data=df, x='TypeName', y='Price', palette='Set2')
plt.title("Price Distribution by Laptop Type")
plt.xlabel("Laptop Type")
plt.ylabel("Price")
plt.xticks(rotation=45)
plt.show()
```

```
C:\Users\progr\AppData\Local\Temp\ipykernel_6612\1586278336.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(data=df, x='TypeName', y='Price', palette='Set2')
```



2.1 Advance Analysis

- Advanced analysis involves evaluating price-performance ratios, calculating value-for-money scores, and comparing brands based on key features like RAM, SSD, and processor efficiency to identify the best options for consumers.

2.2 Value For Money

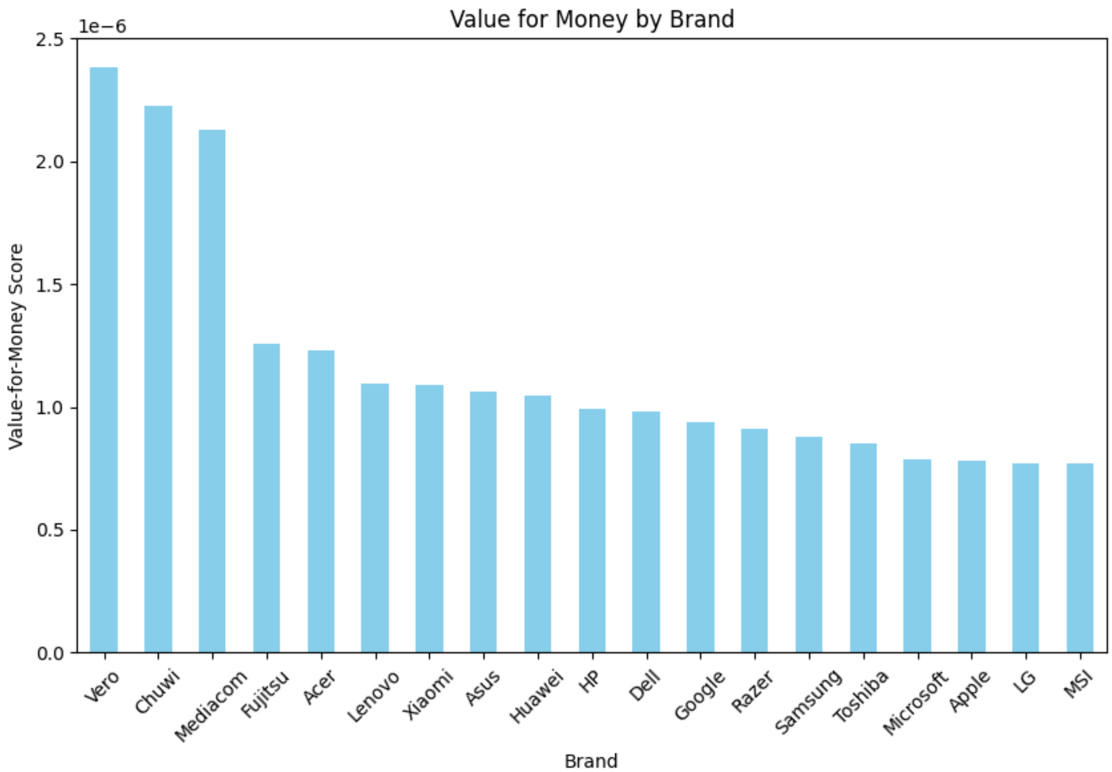
[28]:
```
from sklearn.preprocessing import MinMaxScaler

# Features to consider for performance
performance_features = ['Ram', 'SSD', 'ppi', 'Weight']

# Normalize performance features
scaler = MinMaxScaler()
df[performance_features] = scaler.fit_transform(df[performance_features])

# Calculate a performance score (weighted sum of features)
df['Performance_Score'] = (
    0.4 * df['Ram'] +         # Weight RAM higher
    0.3 * df['SSD'] +         # Weight SSD slightly lower
```

```
    0.2 * df['ppi'] +          # Add ppi
    0.1 * df['Weight']         # Add weight
)

# Calculate value-for-money score
df['Value_for_Money'] = df['Performance_Score'] / df['Price']

# Average value-for-money score by brand
value_for_money_by_brand = df.groupby('Company')['Value_for_Money'].mean().
 ↪sort_values(ascending=False)

print("Value for Money by Brand:")
print(value_for_money_by_brand)
```

```
Value for Money by Brand:
Company
Vero         2.381985e-06
Chuwi        2.224923e-06
Mediacom     2.129407e-06
Fujitsu      1.254794e-06
Acer         1.229873e-06
Lenovo       1.096187e-06
Xiaomi       1.087026e-06
Asus         1.063890e-06
Huawei       1.045139e-06
HP           9.936190e-07
Dell         9.825570e-07
Google       9.386005e-07
Razer        9.108398e-07
Samsung      8.762972e-07
Toshiba      8.529378e-07
Microsoft    7.866187e-07
Apple        7.835930e-07
LG           7.722339e-07
MSI          7.679958e-07
Name: Value_for_Money, dtype: float64
```

Bar plot for Value for Money Score

[29]:
```
plt.figure(figsize=(10, 6))
value_for_money_by_brand.plot(kind='bar', color='skyblue')
plt.title("Value for Money by Brand")
plt.xlabel("Brand")
plt.ylabel("Value-for-Money Score")
plt.xticks(rotation=45)
plt.show()
```

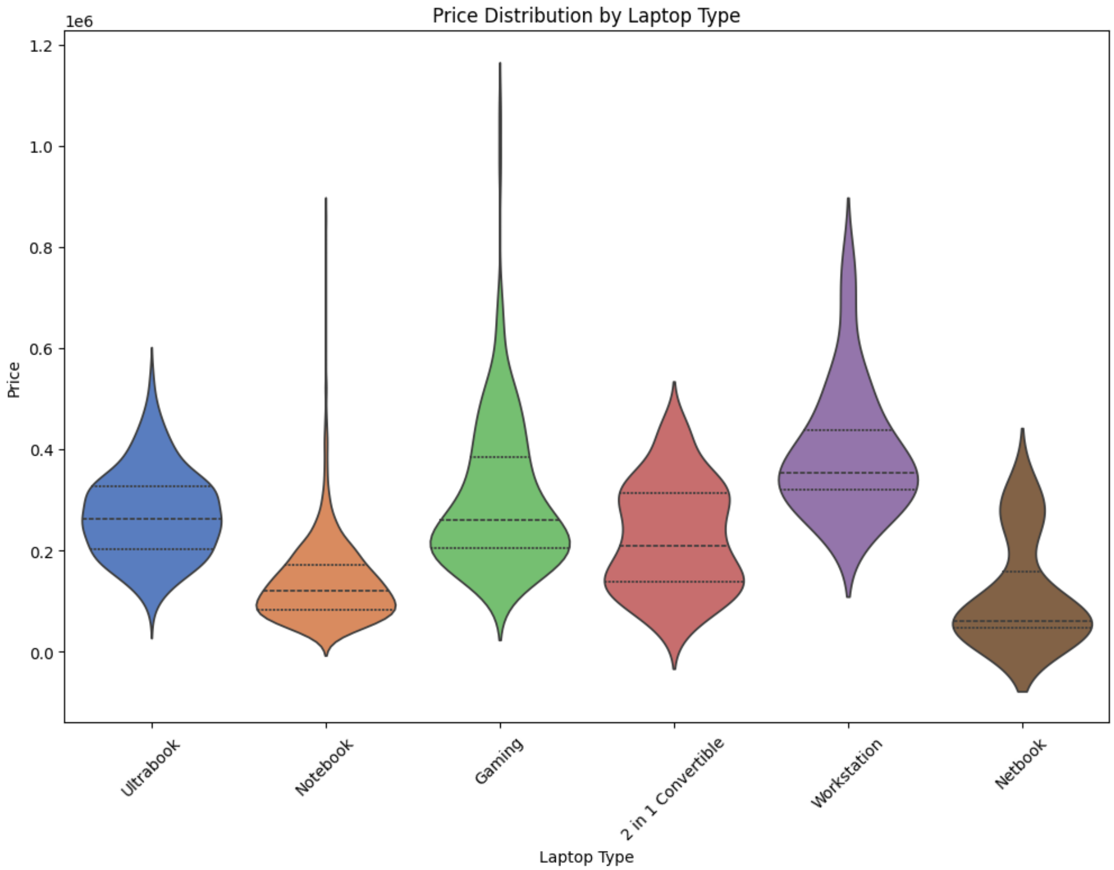


2.3 Visualizing Some Insights

[32]:
```
avg_price_by_brand = df.groupby('Company')['Price'].mean().
 ↪sort_values(ascending=False)

top_5_brands = avg_price_by_brand.head(5)

plt.figure(figsize=(10, 6))
top_5_brands.plot(kind='bar', color='lightgreen')
plt.title("Top 5 Brands by Average Laptop Price")
plt.xlabel("Brand")
plt.ylabel("Average Price")
plt.xticks(rotation=45)
plt.show()
```

[33]:
```
# Violin plot for price distribution by configurations (e.g., Laptop Type)
plt.figure(figsize=(12, 8))
sns.violinplot(data=df, x='TypeName', y='Price', palette='muted',␣
↪inner='quartile')
plt.title("Price Distribution by Laptop Type")
plt.xlabel("Laptop Type")
plt.ylabel("Price")
plt.xticks(rotation=45)
plt.show()
```

```
C:\Users\progr\AppData\Local\Temp\ipykernel_6612\211881395.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.violinplot(data=df, x='TypeName', y='Price', palette='muted',
inner='quartile')
```



2.3.1 Price Distribution by Operating System

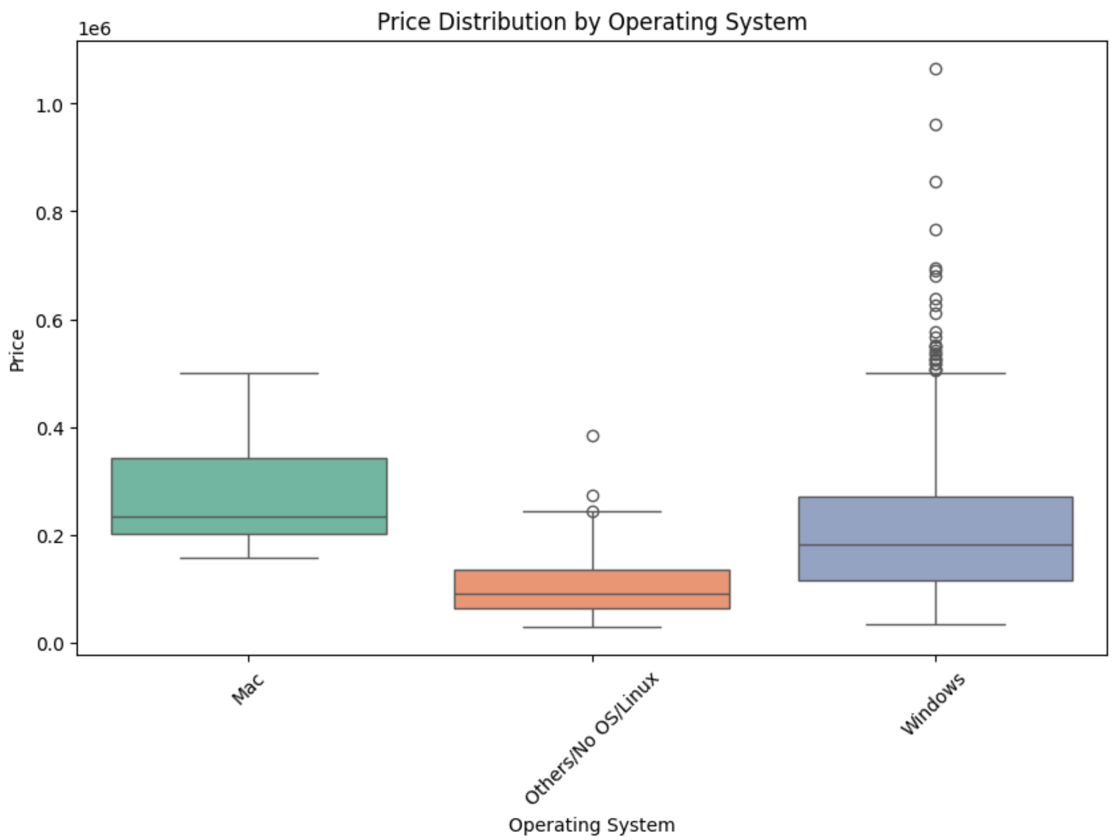
[35]:
```
os_price_stats = df.groupby('os')['Price'].agg(['min', 'max', 'mean', 'std']).
  ↪sort_values(by='mean', ascending=False)

print("Price Statistics by Operating System:")
print(os_price_stats)
```

```
Price Statistics by Operating System:
                            min           max           mean            std
os
Mac                   157097.316096  4.994595e+05  273356.839625   98148.440936
Windows                34252.646400  1.065851e+06  207773.879705  123960.439337
Others/No OS/Linux     30407.961600  3.842937e+05  104435.284211   54389.323718
```

[36]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(data=df, x='os', y='Price', palette='Set2')
plt.title("Price Distribution by Operating System")
plt.xlabel("Operating System")
```

```
plt.ylabel("Price")
plt.xticks(rotation=45)
plt.show()
```

```
C:\Users\progr\AppData\Local\Temp\ipykernel_6612\1232078340.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(data=df, x='os', y='Price', palette='Set2')
```



2.3.2 Conclusion

From the analysis of the laptop dataset, several key insights about the laptop market have been identified:

1. **Price Influencers**:
    - **RAM, SSD, and Processor Brand** significantly impact laptop prices, with higher configurations leading to higher costs.
    - **Touchscreen** and **IPS displays** add to the price, indicating these features are associ-

ated with premium laptops.

2. **Performance and Value**:
   - Brands offering laptops with better price-performance ratios (e.g., a balanced combination of RAM, SSD, and processor power) stand out as better value for money.
   - **PPI (pixels per inch)** and **Weight** have minor but noticeable impacts on pricing, with lighter, high-resolution laptops tending to be more expensive.
3. **Trends by Type and OS**:
   - **Gaming laptops** with dedicated GPUs are priced higher due to their performance-oriented specifications.
   - Laptops with **Windows OS** are more diverse in price range compared to macOS, which targets the premium segment.
4. **Storage Trends**:
   - **SSD storage** is preferred over HDDs, as it correlates with higher prices and better performance.
   - Hybrid and flash storage laptops cater to users requiring both speed and capacity, balancing price and storage needs.
5. **Brand Insights**:
   - Premium brands like Apple and Dell dominate the higher price range.
   - Cost-effective options are available in brands like Acer and Asus for budget-conscious buyers.

2.3.3 Recommendations

1. **For Budget Buyers**:
   - Consider brands like **Acer** or **Asus** for laptops offering competitive specifications at lower prices.
   - Focus on configurations with **8GB RAM** and **256GB SSD**, which provide good performance for everyday tasks.
2. **For Gamers**:
   - **Dell and MSI** laptops with dedicated **GPU brands (e.g., NVIDIA)** offer the best options for gaming.
   - Invest in at least **16GB RAM**, **512GB SSD**, and a high refresh rate display for optimal gaming experiences.
3. **For Professionals**:
   - Look for **Touchscreen** and **IPS displays** for tasks requiring high-quality visuals (e.g., content creation or design).
   - **Lenovo ThinkPads** are excellent for productivity due to their build quality and balanced specs.
4. **For Portability**:
   - Choose lightweight laptops with **SSD storage** and high **ppi** for travel-friendly options.
   - **MacBooks** excel in this category for their combination of lightweight design and battery efficiency.
5. **Storage Needs**:
   - Opt for laptops with **SSD storage** for faster performance, especially if multitasking is a priority.
   - For users needing extensive storage, consider laptops with a combination of **SSD +**

HDD (hybrid storage).