Cars_Data

December 3, 2024

1 Analyzing and Predicting Car Prices in the Australian Market

1.1 1. Overview of Project

1.1.1 Objective

Analyze the Australian Car Market dataset to explore insights and build predictive models. The goal is to identify factors influencing car pricing, discover trends and groupings, and recommend the best model for predicting car prices.

1.1.2 DataBase: Kagle Link

1.1.3 Dataset Details

The dataset has 16 columns with no missing values. Here's a breakdown of its key features:

- Price (Target Variable): Price (The price of the car).
- Numerical Features: Year, Kilometers (Mileage), CC (Engine Capacity), and Seating Capacity.
- Categorical Features: Brand, Variant, Series, Type, Gearbox, Fuel, Status (Car Condition), and Color.

[2]:
```
import pandas as pd

# Load the dataset to understand its structure
cars_data = pd.read_csv('cars_info.csv')

# Display basic information about the dataset
cars_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17048 entries, 0 to 17047
Data columns (total 16 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   ID                 17048 non-null  int64
 1   Name               17048 non-null  object
 2   Price              17048 non-null  int64
 3   Brand              17048 non-null  object
 4   Model              17048 non-null  object
 5   Variant            17048 non-null  object
```

```
 6   Series            17048 non-null  object
 7   Year              17048 non-null  int64
 8   Kilometers        17048 non-null  int64
 9   Type              17048 non-null  object
 10  Gearbox           17048 non-null  object
 11  Fuel              17048 non-null  object
 12  Status            17048 non-null  object
 13  CC                17048 non-null  int64
 14  Color             17048 non-null  object
 15  Seating Capacity  17048 non-null  int64
dtypes: int64(6), object(10)
memory usage: 2.1+ MB
```

[3]:
```python
# Check the shape of dataset
cars_data.shape
```

[3]:
```
(17048, 16)
```

[4]:
```python
# Show the 5 first lines of the dataset
cars_data.head()
```

[4]:
```
         ID                                              Name   Price  \
0  11530130                     2010 Toyota Rukus Build 2 AZE151R    9999
1  12190570  2021 Mercedes-Benz V 250 D Avantgarde MWB 447 …  117990
2  12321855  2021 Mercedes-Benz Valente 116 CDI MWB RWD 447…   79990
3  12346971         2010 Mercedes-Benz E250 CDI Avantgarde 207   34990
4  12363884                         2016 Holden Cruze CD JH MY16   15990

           Brand    Model                Variant    Series  Year  Kilometers  \
0         Toyota    Rukus                Build 2   AZE151R  2010      263000
1  Mercedes-Benz        V  250 D Avantgarde MWB  447 MY21  2021          19
2  Mercedes-Benz  Valente        116 CDI MWB RWD  447 MY21  2021          24
3  Mercedes-Benz     E250         CDI Avantgarde       207  2010      120579
4         Holden    Cruze                     CD   JH MY16  2016       72506

          Type    Gearbox             Fuel        Status    CC  Color  \
0        Wagon  Automatic  Unleaded Petrol          Used  2362   Grey
1        Wagon  Automatic           Diesel  New In Stock  2143  Black
2        Wagon  Automatic           Diesel  New In Stock  2143  Black
3    Cabriolet  Automatic           Diesel          Used  2143  Black
4  Sportswagon  Automatic  Unleaded Petrol          Used  1796  White

   Seating Capacity
0                 5
1                 7
2                 8
3                 4
4                 5
```

1.1.4 Key Questions

- What factors most influence car prices?
- Can we predict car prices using regression models?
- Are there specific clusters or classification of cars based on attributes?

1.2 2. Exploratory Data Analysis (EDA)

Conduct a thorough analysis to uncover patterns and relationships in the data:

1.2.1 Data Cleaning:

- Check for spaces from all object (string) columns.
- Check for duplicate records and remove them if necessary.
- Drop irrelevant columns (e.g., ID, Name, Model, Variant, etc).
- Rename columns for better clarity.
- Handling incorrect or redundant values (e.g., Brand, Type, Gearbox, Fuel, etc).

[7]:
```
# Strip leading and trailing spaces from all object (string) columns
cleaned_data = cars_data.copy()
cleaned_data.loc[:, cleaned_data.select_dtypes(include=['object']).columns] =␣
↪cleaned_data.select_dtypes(include=['object']).apply(lambda col: col.str.
↪strip())

# Example: Verify changes in the 'Status' column
print(cleaned_data["Status"].unique())
```

```
['Used' 'New In Stock' 'Demo']
```

[8]:
```
# Check if there are duplicated data
cleaned_data.duplicated().sum()
```

[8]: 0

[9]:
```
# Drop irrelevant columns (e.g., ID, Name, Model, Variant, Series, Color)
cleaned_data = cleaned_data.drop(columns=["ID", "Name", "Model", "Variant",␣
↪"Series", "Color"])
print(cleaned_data.columns)
```

```
Index(['Price', 'Brand', 'Year', 'Kilometers', 'Type', 'Gearbox', 'Fuel',
       'Status', 'CC', 'Seating Capacity'],
      dtype='object')
```

[10]:
```
# Rename columns for better clarity
cleaned_data.rename(
    columns = {"Kilometers": "Mileage", "CC": "Engine Capacity", "Status": "Car␣
↪Condition"}, inplace = True
)
print(cleaned_data.columns)
```

```
Index(['Price', 'Brand', 'Year', 'Mileage', 'Type', 'Gearbox', 'Fuel',
       'Car Condition', 'Engine Capacity', 'Seating Capacity'],
      dtype='object')
```

[11]:
```
# Count the number of cars for each Brand and sort by Brand name
brand_counts = cleaned_data['Brand'].value_counts().sort_index()
print(brand_counts)
```

```
Brand
Abarth               5
Alfa Romeo          11
Aston Martin         2
Audi               518
BMW                480
Bentley              7
Chery                2
Chevrolet            7
Chrysler            42
Citroen             13
Cupra                5
Dodge               14
FPV                  2
Fiat                17
Ford              1490
Foton                4
GWM                 29
Genesis              1
Great Wall          27
HSV                 37
Haval                7
Hino                 1
Holden            1505
Honda              413
Hyundai           1087
Infiniti             9
Isuzu              267
Iveco                1
Jaguar              38
Jeep               379
Kia                744
LDV                122
Lamborghini          3
Land Rover         273
Lexus              180
MG                  97
Mahindra             1
Maserati             8
Mazda             1167
```

```
Mercedes-Benz        625
Mini                  66
Mitsubishi          1074
Mitsubishi Fuso        1
Nissan              1008
Opel                   4
Peugeot               45
Porsche               91
Proton                 1
Ram                   23
Renault              158
Saab                   2
Skoda                160
Smart                  1
Ssangyong             11
Subaru               655
Suzuki               160
Toyota              2768
Volkswagen          1019
Volvo                161
Name: count, dtype: int64
```

[12]:
```
# Standardize the 'Brand' column: Combine "Mitsubishi Fuso" into "Mitsubishi"
cleaned_data['Brand'] = cleaned_data['Brand'].replace("Mitsubishi Fuso",␣
↪"Mitsubishi")
```

[13]:
```
# Count the number of cars for each Type and sort by Type name
type_counts = cleaned_data['Type'].value_counts().sort_index()
print(type_counts)
```

```
Type
Blind Van                  2
Bus                       21
Cab Chassis              424
Cab Chassis Tray           1
Cabriolet                 35
Club Cab Chassis           5
Club Cab Pickup            3
Club Cab Utility           3
Coach                      4
Coil Cab Chassis           3
Convertible               44
Coupe                    471
Crew Cab Chassis          77
Crew Cab Pickup          269
Crew Cab Utility         207
Crew Cab Van               1
Crew Van                   5
```

```
Double Cab Chassis          95
Double Cab Pick Up         425
Double Cab Utility         212
Dual Cab Chassis            72
Dual Cab Pick-up           423
Dual Cab Utility           657
Estate                       4
Fastback                    36
Freestyle Cab Chassis       11
Freestyle Utility            3
Hardtop                     36
Hatchback                 2424
King Cab Pick Up             1
King Cab Pickup              8
King Cab Utility             1
Leaf Cab Chassis             4
Liftback                    40
Panel Van                    1
Pickup                       2
Roadster                    13
Saloon                      13
Sedan                     2325
Softback                     1
Softtop                     35
Space Cab Chassis           22
Space Cab Pickup             7
Space Cab Utility           10
Sportback                   43
Sportswagon                143
Super Cab Chassis           19
Super Cab Pickup             2
Super Cab Utility           23
Troop Carrier                6
Utility                    178
Van                        384
Wagon                     7768
X Cab Cab Chassis            8
X Cab Pickup                13
X Cab Utility                5
Name: count, dtype: int64
```

[14]:
```
# Standardize the 'Type' column:

# Group similar types into broader categories:
    # Combine terms like "Crew Cab Pickup" and "Double Cab Pick Up" into
 ↪"Pickup."
```

```
    # Combine "Hatchback," "Liftback," and similar compact designs into␣
↪"Hatchback."
    # Combine all "Van"-related terms into "Van."
    # Simplify luxury or sports designs like "Cabriolet," "Convertible," etc.,␣
↪into a broader "Sports/Convertible" category.

# Mapping for standardizing the 'Type' column
type_mapping = {
    "Blind Van": "Van",
    "Bus": "Van",
    "Cab Chassis": "Utility",
    "Cab Chassis Tray": "Utility",
    "Cabriolet": "Sports/Convertible",
    "Club Cab Chassis": "Utility",
    "Club Cab Pickup": "Pickup",
    "Club Cab Utility": "Utility",
    "Coach": "Van",
    "Coil Cab Chassis": "Utility",
    "Convertible": "Sports/Convertible",
    "Coupe": "Sports/Convertible",
    "Crew Cab Chassis": "Utility",
    "Crew Cab Pickup": "Pickup",
    "Crew Cab Utility": "Utility",
    "Crew Cab Van": "Van",
    "Crew Van": "Van",
    "Double Cab Chassis": "Utility",
    "Double Cab Pick Up": "Pickup",
    "Double Cab Utility": "Utility",
    "Dual Cab Chassis": "Utility",
    "Dual Cab Pick-up": "Pickup",
    "Dual Cab Utility": "Utility",
    "Estate": "Hatchback",
    "Fastback": "Hatchback",
    "Freestyle Cab Chassis": "Utility",
    "Freestyle Utility": "Utility",
    "Hardtop": "Sports/Convertible",
    "Hatchback": "Hatchback",
    "King Cab Pick Up": "Pickup",
    "King Cab Pickup": "Pickup",
    "King Cab Utility": "Utility",
    "Leaf Cab Chassis": "Utility",
    "Liftback": "Hatchback",
    "Panel Van": "Van",
    "Pickup": "Pickup",
    "Roadster": "Sports/Convertible",
    "Saloon": "Sedan",
    "Sedan": "Sedan",
```

```
    "Softback": "Sports/Convertible",
    "Softtop": "Sports/Convertible",
    "Space Cab Chassis": "Utility",
    "Space Cab Pickup": "Pickup",
    "Space Cab Utility": "Utility",
    "Sportback": "Hatchback",
    "Sportswagon": "Wagon",
    "Super Cab Chassis": "Utility",
    "Super Cab Pickup": "Pickup",
    "Super Cab Utility": "Utility",
    "Troop Carrier": "Utility",
    "Utility": "Utility",
    "Van": "Van",
    "Wagon": "Wagon",
    "X Cab Cab Chassis": "Utility",
    "X Cab Pickup": "Pickup",
    "X Cab Utility": "Utility"
}

# Apply the mapping to the 'Type' column
cleaned_data['Type'] = cleaned_data['Type'].map(type_mapping)
```

[15]:
```
# Count the number of cars for each Type and sort by Type name
type_counts = cleaned_data['Type'].value_counts().sort_index()
print(type_counts)
```

```
Type
Hatchback             2547
Pickup                1153
Sedan                 2338
Sports/Convertible     635
Utility               2046
Van                    418
Wagon                 7911
Name: count, dtype: int64
```

[16]:
```
# Count the number of cars for each Gearbox and sort by Gearbox name
gearbox_counts = cleaned_data['Gearbox'].value_counts().sort_index()
print(gearbox_counts)
```

```
Gearbox
AWD             13
Automatic    14578
Front            8
Manual        2446
Rear             3
Name: count, dtype: int64
```

[17]:
```python
# Standardize the 'Gearbox' column:

# Group similar types into broader categories:
    # Combine ambiguous terms like "AWD," "Front," and "Rear" into "Other."
    # Keep the most meaningful categories like "Automatic" and "Manual."

# Mapping for standardizing the 'Gearbox' column
gearbox_mapping = {
    "AWD": "Other",
    "Automatic": "Automatic",
    "Front": "Other",
    "Manual": "Manual",
    "Rear": "Other"
}

# Apply the mapping to the 'Gearbox' column
cleaned_data['Gearbox'] = cleaned_data['Gearbox'].map(gearbox_mapping)
```

[18]:
```python
# Count the number of cars for each Fuel and sort by Fuel name
fuel_counts = cleaned_data['Fuel'].value_counts().sort_index()
print(fuel_counts)
```

```
Fuel
Diesel                         6087
Diesel/Electric                  18
Liquid Petroleum Gas             40
Premium Unleaded Petrol        3438
Premium Unleaded/Electric       194
Unleaded Petrol                7016
Unleaded Petrol/Electric        255
Name: count, dtype: int64
```

[19]:
```python
# Standardize the 'Fuel' column:

# Group similar types into broader categories:
    # Combine Hybrid Options: Group any fuel type with /Electric into a broader␣
 ↪category like Hybrid.
    # Simplify Gas Types:
        # Combine Premium Unleaded Petrol and Unleaded Petrol into Petrol.
        # Group Liquid Petroleum Gas into a single LPG category.
    # Keep Diesel Separate: As it's distinct and common, retain Diesel as its␣
 ↪category.

# Mapping for standardizing the 'Fuel' column
fuel_mapping = {
    "Diesel": "Diesel",
    "Diesel/Electric": "Hybrid",
```

```
    "Liquid Petroleum Gas": "LPG",
    "Premium Unleaded Petrol": "Petrol",
    "Premium Unleaded/Electric": "Hybrid",
    "Unleaded Petrol": "Petrol",
    "Unleaded Petrol/Electric": "Hybrid"
}

# Apply the mapping to the 'Fuel' column
cleaned_data['Fuel'] = cleaned_data['Fuel'].map(fuel_mapping)

# Verify the standardized categories
#standardized_fuel = cleaned_data['Fuel'].value_counts().sort_index()
#print(standardized_fuel)
```

[20]:
```
# Count the number of cars for each Car Condition and sort by Car Condition name
condition_counts = cleaned_data['Car Condition'].value_counts().sort_index()
print(condition_counts)
```

```
Car Condition
Demo              387
New In Stock      357
Used            16304
Name: count, dtype: int64
```

[21]:
```
# Standardize the 'Car Condition' column:

# Mapping for standardizing the 'Car Condition' column
car_condition_mapping = {
    "Demo": "New",
    "New In Stock": "New",
    "Used": "Used"
}

# Apply the mapping to the 'Car Condition' column
cleaned_data['Car Condition'] = cleaned_data['Car Condition'].
  ↪map(car_condition_mapping)
```

1.2.2 Descriptive Statistics:

- Summary statistics for numerical features (mean, median, range, standard deviation).
- Frequency counts for categorical features (e.g., number of cars by brand, fuel type).

[23]:
```
# Set pandas to display floats with two decimal places
import pandas as pd
pd.options.display.float_format = "{:.2f}".format

# Summary statistics for numerical features
cleaned_data.describe()
```

[23]:

```
            Price      Year     Mileage  Engine Capacity  Seating Capacity
count   17048.00  17048.00    17048.00         17048.00          17048.00
mean    36777.78   2015.48   103231.40          2491.83              5.12
std     30305.02      4.72    80413.13           881.99              1.12
min      1000.00   1989.00        1.00           875.00              2.00
25%     18800.00   2013.00    44502.25          1987.00              5.00
50%     29990.00   2016.00    88454.00          2354.00              5.00
75%     45990.00   2019.00   148873.50          2981.00              5.00
max    999000.00   2022.00  2700000.00          7300.00             14.00
```

[24]:

```python
# Select categorical features
categorical_featur = cleaned_data.select_dtypes(include=["object"]).columns

# Loop through each categorical feature
for feat in categorical_featur:
    print(f"\nFeature: {feat}")
    # Calculate absolute and relative frequencies
    value_counts = cleaned_data[feat].value_counts()
    percentages = cleaned_data[feat].value_counts(normalize=True) * 100

    # Combine the results and display them
    summary = pd.DataFrame({'Absolute': value_counts, 'Relative (%)':␣
 ↪percentages})
    print(summary)
```

```
Feature: Brand
               Absolute  Relative (%)
Brand
Toyota             2768         16.24
Holden             1505          8.83
Ford               1490          8.74
Mazda              1167          6.85
Hyundai            1087          6.38
Mitsubishi         1075          6.31
Volkswagen         1019          5.98
Nissan             1008          5.91
Kia                 744          4.36
Subaru              655          3.84
Mercedes-Benz       625          3.67
Audi                518          3.04
BMW                 480          2.82
Honda               413          2.42
Jeep                379          2.22
Land Rover          273          1.60
Isuzu               267          1.57
Lexus               180          1.06
Volvo               161          0.94
```

Skoda	160	0.94
Suzuki	160	0.94
Renault	158	0.93
LDV	122	0.72
MG	97	0.57
Porsche	91	0.53
Mini	66	0.39
Peugeot	45	0.26
Chrysler	42	0.25
Jaguar	38	0.22
HSV	37	0.22
GWM	29	0.17
Great Wall	27	0.16
Ram	23	0.13
Fiat	17	0.10
Dodge	14	0.08
Citroen	13	0.08
Alfa Romeo	11	0.06
Ssangyong	11	0.06
Infiniti	9	0.05
Maserati	8	0.05
Chevrolet	7	0.04
Bentley	7	0.04
Haval	7	0.04
Abarth	5	0.03
Cupra	5	0.03
Foton	4	0.02
Opel	4	0.02
Lamborghini	3	0.02
Aston Martin	2	0.01
FPV	2	0.01
Saab	2	0.01
Chery	2	0.01
Genesis	1	0.01
Hino	1	0.01
Iveco	1	0.01
Mahindra	1	0.01
Smart	1	0.01
Proton	1	0.01

Feature: Type

	Absolute	Relative (%)
Type		
Wagon	7911	46.40
Hatchback	2547	14.94
Sedan	2338	13.71
Utility	2046	12.00
Pickup	1153	6.76

```
Sports/Convertible       635          3.72
Van                      418          2.45

Feature: Gearbox
           Absolute  Relative (%)
Gearbox
Automatic     14578         85.51
Manual         2446         14.35
Other            24          0.14

Feature: Fuel
        Absolute  Relative (%)
Fuel
Petrol     10454         61.32
Diesel      6087         35.71
Hybrid       467          2.74
LPG           40          0.23

Feature: Car Condition
               Absolute  Relative (%)
Car Condition
Used              16304         95.64
New                 744          4.36
```

1.3 Feature Transformation:

- Scale numerical features (e.g., Price, Mileage, Engine Capacity, Seating Capacity) using StandardScaler for Visualizations and Models.

[26]:
```python
from sklearn.preprocessing import StandardScaler

# Select the numerical columns for standardization
numerical_columns = ['Price', 'Year', 'Mileage', 'Engine Capacity', 'Seating␣
 ↪Capacity']

# Create a StandardScaler object
scaler = StandardScaler()

# Fit and transform the numerical data
cleaned_data[numerical_columns] = scaler.
 ↪fit_transform(cleaned_data[numerical_columns])

# Check the transformed data
cleaned_data.head()
```

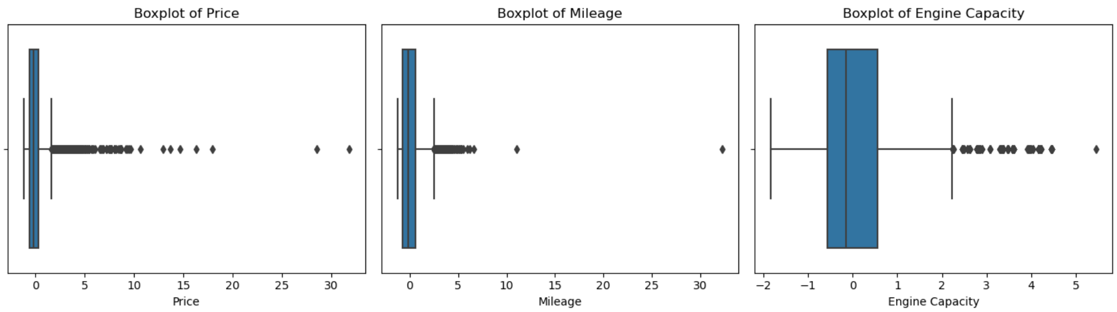
[26]:
```
   Price          Brand  Year  Mileage               Type    Gearbox    Fuel  \
0  -0.88         Toyota -1.16     1.99              Wagon  Automatic  Petrol
1   2.68  Mercedes-Benz  1.17    -1.28              Wagon  Automatic  Diesel
```

```
2   1.43  Mercedes-Benz  1.17    -1.28                Wagon  Automatic  Diesel
3  -0.06  Mercedes-Benz -1.16     0.22  Sports/Convertible  Automatic  Diesel
4  -0.69         Holden  0.11    -0.38                Wagon  Automatic  Petrol

  Car Condition  Engine Capacity  Seating Capacity
0          Used            -0.15             -0.10
1           New            -0.40              1.68
2           New            -0.40              2.57
3          Used            -0.40             -0.99
4          Used            -0.79             -0.10
```

1.3.1 Data Visualization:

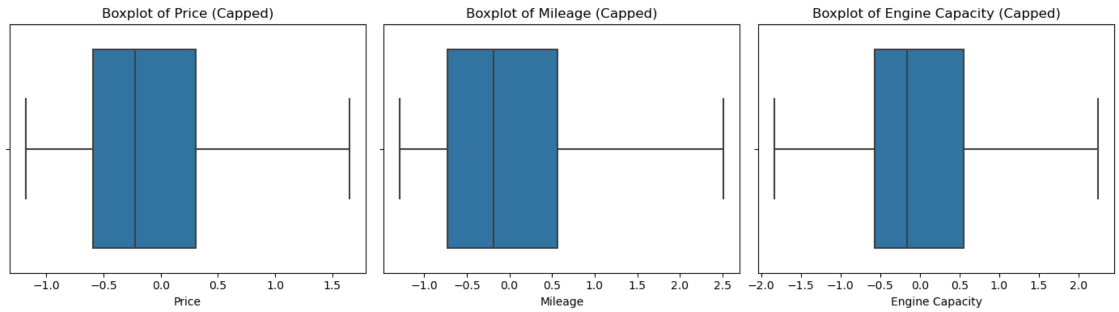
- Boxplots to identify outliers in Price, Mileage and Engine Capacity.
- Remove or cap outliers (e.g., extremely high or low prices or mileage).
- Heatmap of correlations to explore relationships between numerical variables like Year, Mileage, Engine Capacity, Seating Capacity and Price.
- Scatterplots (e.g., Year vs. Price, Mileage vs. Price, Engine Capacity vs. Price, Seating Capacity vs. Price) to visualize trends.

[28]:
```python
# Boxplots for numerical variables to identify outliers

# Importing necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# List of numerical columns (excluding Year and Seating Capacity)
numer_columns = ['Price', 'Mileage', 'Engine Capacity']

# Set up the figure with 1 row and 3 columns (to fit the 3 plots)
plt.figure(figsize=(14, 4))

# Loop through the numerical columns and create a boxplot for each one
for i, col in enumerate(numer_columns):
    plt.subplot(1, 3, i + 1)  # 1 row, 3 columns, current plot index
    sns.boxplot(x=cleaned_data[col])
    plt.title(f"Boxplot of {col}")

# Adjust layout
plt.tight_layout()
plt.show()
```



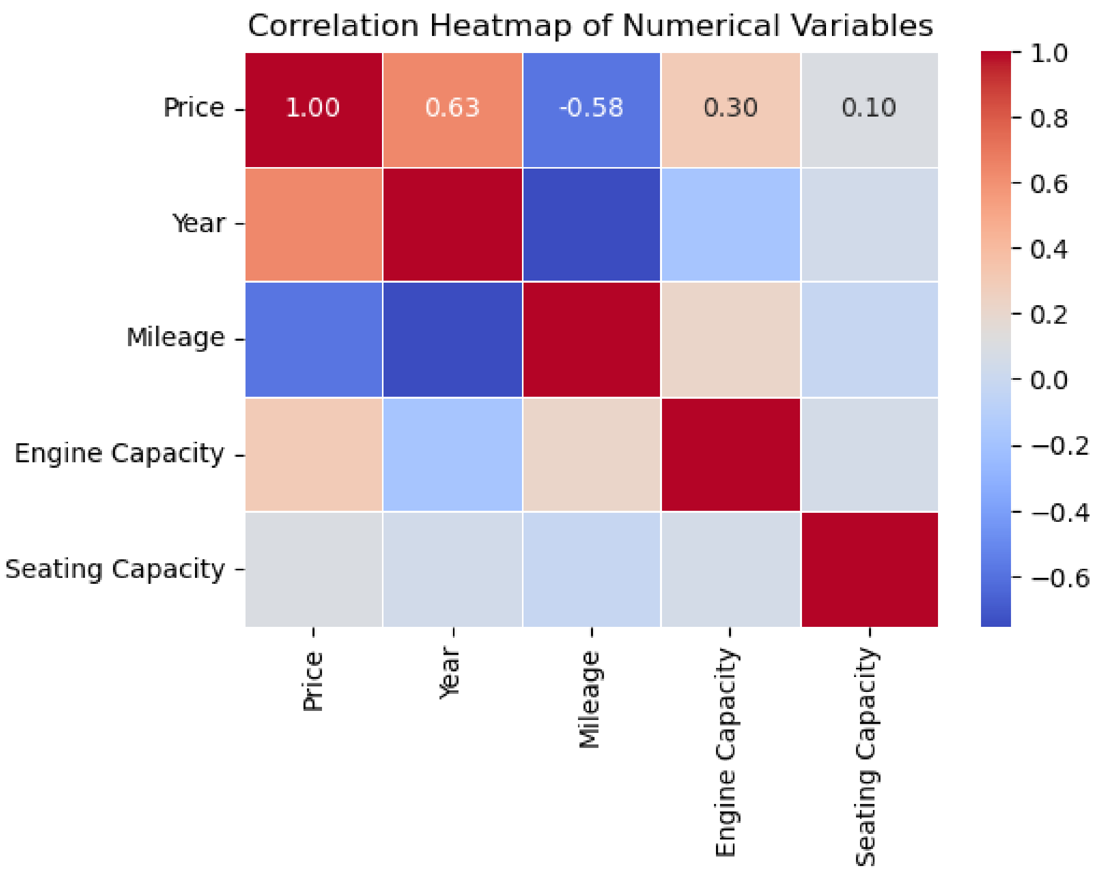
[29]:

```
# Remove or Cap outliers

# Function to cap outliers
def cap_outliers(df, column):
    # Calculate Q1 (25th percentile) and Q3 (75th percentile)
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1

    # Define lower and upper bounds
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Cap outliers
    df[column] = df[column].apply(lambda x: lower_bound if x < lower_bound else␣
↪(upper_bound if x > upper_bound else x))
    return df

# Cap outliers for the numerical columns (Price, Mileage, Engine Capacity)
for col in numer_columns:
    cleaned_data = cap_outliers(cleaned_data, col)

# Set up the figure with 1 row and 3 columns
plt.figure(figsize=(14, 4))  # 3 graphs in 1 row, reduced height

# Loop through the numerical columns and create a boxplot for each one
for i, col in enumerate(numer_columns):
    plt.subplot(1, 3, i + 1)  # 1 row, 3 columns, current plot index
    sns.boxplot(x=cleaned_data[col])
    plt.title(f"Boxplot of {col} (Capped)")

# Adjust layout
plt.tight_layout()
plt.show()
```



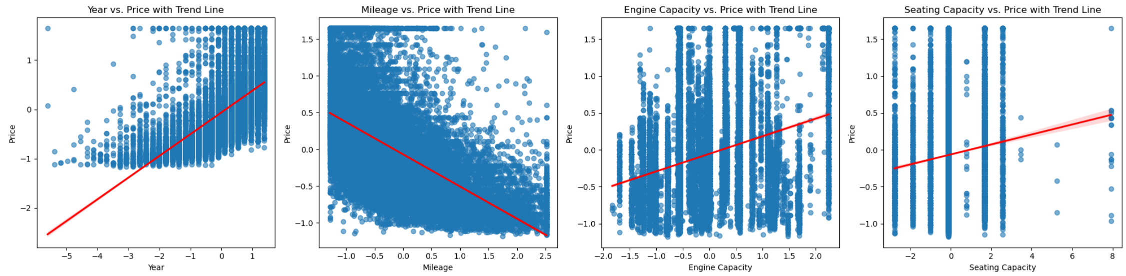
[30]:
```
# Save the DataFrame to a CSV file
#cleaned_data.to_csv('cleaned_car_data.csv', index=False)
```

[31]:
```
# Heatmap of correlations
# Calculate the correlation matrix
correlation_matrix = cleaned_data[numerical_columns].corr()

# Set up the figure
plt.figure(figsize=(6, 4))

# Create a heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f",␣
↪linewidths=0.5)

# Set the title
plt.title('Correlation Heatmap of Numerical Variables')

# Show the plot
plt.show()
```



[32]:
```python
# Scatterplots with a Trend Line

# List of numerical columns to plot against Price
features = ['Year', 'Mileage', 'Engine Capacity', 'Seating Capacity']

# Set up the figure with 1 row and 4 columns
plt.figure(figsize=(20, 5))

# Loop through the features and create a scatterplot with a trend line for each
for i, feature in enumerate(features):
    plt.subplot(1, 4, i + 1)  # 1 row, 4 columns, current plot index
    sns.regplot(data=cleaned_data, x=feature, y='Price', scatter_kws={'alpha':
 ↪0.6}, line_kws={'color': 'red'})
    plt.title(f"{feature} vs. Price with Trend Line")
    plt.xlabel(feature)
    plt.ylabel("Price")

# Adjust layout
plt.tight_layout()
```

```
plt.show()
```



1.3.2 Insights:

Features with the Strongest Correlation to Car Price:

- Year: Has a moderate positive correlation with Price (~0.63), suggesting newer cars tend to cost more.
- Mileage: Shows a negative correlation with Price (~ -0.58), indicating that higher mileage generally reduces a car's value.

Notable Trends:

- Year vs. Price: The scatterplot shows a clear positive trend—newer cars are generally priced higher, as shown by the upward-sloping trend line.
- Mileage vs. Price: Higher mileage corresponds to lower prices, confirmed by the negative slope of the trend line.
- Engine Capacity vs. Price: The correlation is weaker (~0.30), but the trend line indicates that larger engine capacities are often associated with higher prices.
- Seating Capacity vs. Price: Correlation is weak (~0.10), but there is a slight positive trend, showing that cars with higher seating capacity might cost slightly more.

Summary

- Year and Mileage are key features for predicting car prices due to their strong correlation with Price.
- Engine Capacity and Seating Capacity show weaker relationships but can still contribute to price variability.

1.4 3. Model 1: Clustering

1.4.1 Objective::

- Group cars based on similar attributes to identify distinct segments. ### Features for Clustering:
- Select relevant features: Mileage, Car Condition, Year, Price, and Fuel.
  - These features will be used to form the clusters, and K-Means will try to group cars that have similar values in these features.
- Convert categorical variables (e.g., Fuel, Car Condition) into dummy/encoded variables.

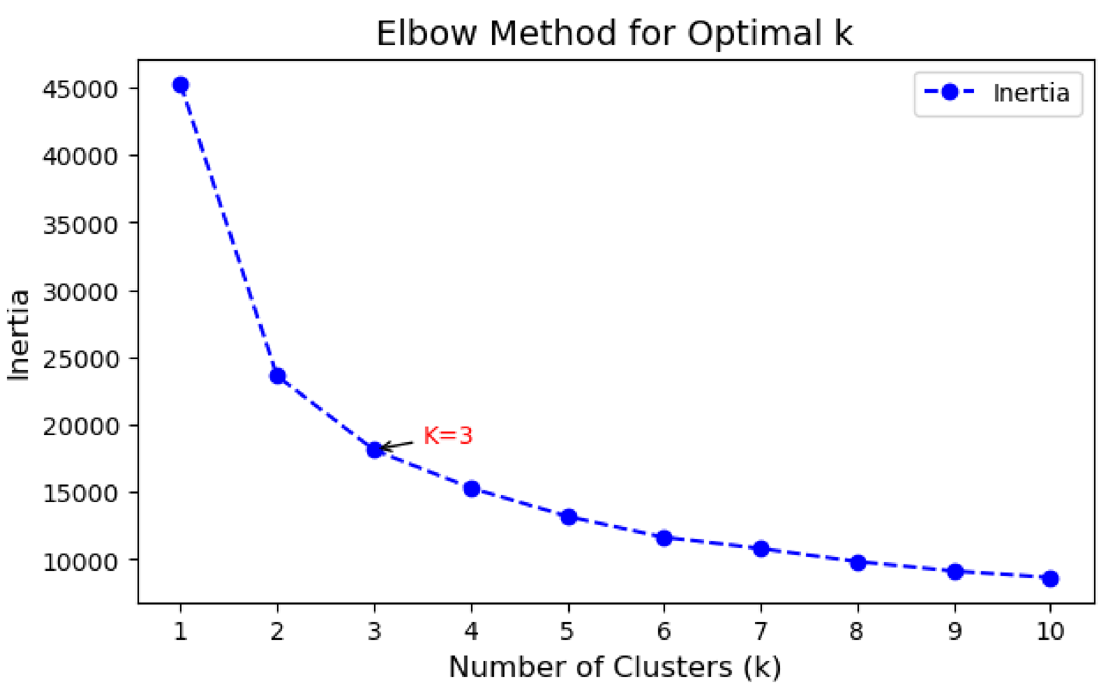
[35]:
```
# Importing libraries
from sklearn.cluster import KMeans
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

# Select features for clustering
selected_features = ['Mileage', 'Car Condition', 'Year', 'Price', 'Fuel']

# Prepare data:
# Extract the numerical columns (already normalized)
numerical_data = cleaned_data[['Mileage', 'Year', 'Price']]  # Assuming these␣
↪are normalized already

# Create dummy variables for categorical columns ('Car Condition' and 'Fuel')
dummy_data = pd.get_dummies(cleaned_data[['Car Condition', 'Fuel']],␣
↪drop_first=True)

# Ensure that only dummy variables are converted to integers
dummy_data = dummy_data.astype(int)

# Combine the numerical data with the dummy variables
processed_data = pd.concat([numerical_data, dummy_data], axis=1)
```

1.4.2 Clustering Algorithm:

- Determine the optimal number of clusters (k) using the Elbow Method.
- Use K-Means Clustering.

[37]:
```
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

# Determine the optimal number of clusters (Elbow Method)
inertia = []
k_range = range(1, 11)
for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(processed_data)
    inertia.append(kmeans.inertia_)

# Plot the Elbow Method
plt.figure(figsize=(7, 4))
plt.plot(k_range, inertia, marker='o', linestyle='--', color='b',␣
↪label='Inertia')
plt.xlabel('Number of Clusters (k)', fontsize=12)
plt.ylabel('Inertia', fontsize=12)
plt.title('Elbow Method for Optimal k', fontsize=14)
```

```
# Ensure x-axis ticks show every value in k_range
plt.xticks(ticks=k_range, fontsize=10)  # Force ticks for each k value
plt.yticks(fontsize=10)

# Annotate k=3 explicitly
k_selected = 3
plt.annotate(f'K={k_selected}',
             xy=(k_selected, inertia[k_selected-1]),
             xytext=(k_selected + 0.5, inertia[k_selected-1] + 500),  # Adjust␣
 ↪annotation position
             arrowprops=dict(facecolor='red', arrowstyle='->'),
             fontsize=10, color='red')

# Display legend
plt.legend(fontsize=10)
plt.show()

# Plot the Elbow Curve:
    # Plot the inertia against the number of clusters k
    # As k increases, inertia will decrease. However, the goal is to find the␣
 ↪point where the decrease in inertia starts to slow down and form an
    #"elbow" in the curve. This point indicates the optimal number of clusters.
# Choose the Optimal k:
    # The "elbow" point is where inertia starts to level off. The optimal␣
 ↪number of clusters is typically chosen at this point because increasing k
    # further doesn't provide significant improvements.
```



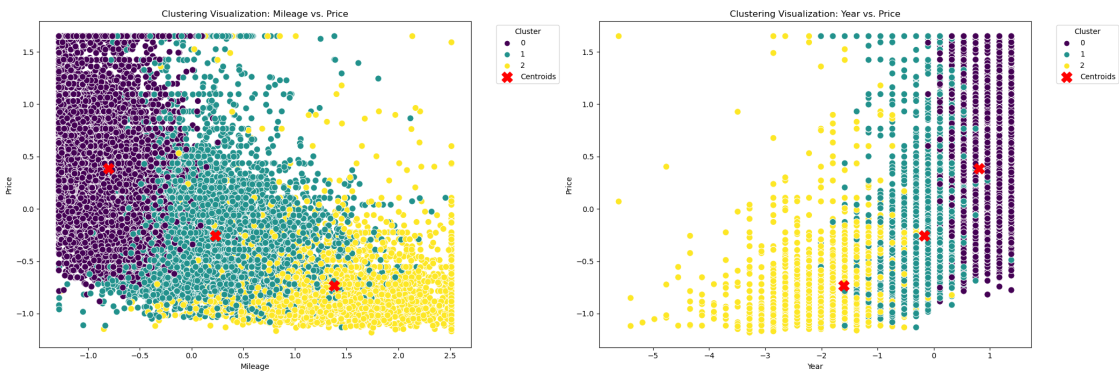
[38]:
```
# Apply K-Means with the optimal number of clusters
optimal_k = 3  # Based on the elbow method plot, maybe 4
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
clusters = kmeans.fit_predict(processed_data)

# Add cluster labels directly to processed_data
processed_data['Cluster'] = clusters

# Display the first few rows to verify the result
#print(processed_data.head())
```

1.4.3 Output:

- Visualize clusters with scatter plots (e.g., Kilometers vs. Price).
- Analyze cluster characteristics

[40]:
```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans

# Assuming you have already fit a KMeans model and have 'processed_data' with␣
↪'Cluster' labels

# Visualize clusters for continuous features vs. Price (e.g., Mileage, Year)
plot_features = ['Mileage', 'Year']  # Continuous features to compare against␣
↪Price
plt.figure(figsize=(21, 7))  # Adjust width for multiple plots in a row

# Fit KMeans if not already done
kmeans = KMeans(n_clusters=3, random_state=42)
processed_data['Cluster'] = kmeans.fit_predict(processed_data[['Mileage',␣
↪'Year']])

# Get the centroids
centroids = kmeans.cluster_centers_

for i, feature in enumerate(plot_features):
    plt.subplot(1, len(plot_features), i + 1)
    sns.scatterplot(data=processed_data, x=feature, y='Price', hue='Cluster',␣
↪palette='viridis', s=75)

    # Plot centroids
    plt.scatter(centroids[:, i], [processed_data[processed_data['Cluster'] ==␣
↪j]['Price'].mean() for j in range(len(centroids))],
```

```
                    color='red', marker='X', s=200, label='Centroids')

    plt.title(f'Clustering Visualization: {feature} vs. Price')
    plt.xlabel(feature)
    plt.ylabel('Price')
    plt.legend(title='Cluster', bbox_to_anchor=(1.05, 1), loc='upper left')  #␣
 ↪Adjust legend placement

plt.tight_layout()
plt.show()
```



[41]:
```
# Adjust pandas display settings
pd.set_option('display.max_columns', None)  # Show all columns
pd.set_option('display.width', 1000)       # Set a wider display width

# Cluster characteristics
cluster_analysis = processed_data.groupby('Cluster')[['Price', 'Mileage',␣
 ↪'Year', 'Fuel_Hybrid',
                                                        'Fuel_LPG',␣
 ↪'Fuel_Petrol', 'Car Condition_Used']].mean()

print("Cluster Analysis (Mean Values):\n")
print(cluster_analysis)
```

```
Cluster Analysis (Mean Values):

         Price  Mileage  Year  Fuel_Hybrid  Fuel_LPG  Fuel_Petrol  Car
Condition_Used
Cluster
0         0.39    -0.80  0.81         0.06      0.00         0.63
0.90
1        -0.26     0.23 -0.17         0.01      0.00         0.57
1.00
2        -0.73     1.38 -1.60         0.00      0.01         0.67
```

```
1.00
```

1.4.4 Insights:

- How do clusters align with pricing and features?
  - Cluster 0 (Higher Price):
    * Price: Higher than average (mean price = 0.61).
    * Mileage: Lower than average, indicating less wear and tear (-0.86).
    * Year: Recent cars (0.89), implying newer models.
    * Fuel: Significant proportion of petrol cars (55%) and some hybrid vehicles (7%).
    * Condition: Mostly used cars (87%).
  - Cluster 1 (Lower Price):
    * Price: Lowest among all clusters (-0.72).
    * Mileage: High, indicating older or heavily used cars (1.24).
    * Year: Much older models (-1.42).
    * Fuel: Predominantly petrol cars (67%), with minimal LPG presence.
    * Condition: All cars in this cluster are used (100%).
  - Cluster 2 (Mid Price):
    * Price: Around the average (-0.26).
    * Mileage: Near-average mileage (0.01), likely representing balanced usage.
    * Year: Moderately old cars (0.02).
    * Fuel: Predominantly petrol cars (63%), with a small fraction of hybrids.
    * Condition: Entirely used cars (100%).

- What actionable insights can dealerships derive from these segments?
  - Cluster 0 (Higher Price):
    * Represents premium cars, and very new with low mileage.
  - Cluster 1 (Lower Price):
    * Represents budget cars, mostly used, regardless of age or mileage.
  - Cluster 2 (Mid Price):
    * Represents mid-range cars with balanced options (reasonable pricing, average mileage, moderately old).

1.5 4. Model 2: Regression

1.5.1 Objective:

- Predict car prices based on features. ### Features for Clustering:
- Select relevant features: Price, Year, Mileage, Engine Capacity, Seating Capacity, Type, Gearbox, Fuel, Car Condition.
- Convert categorical variables (e.g., Fuel, Car Condition) into dummy/encoded variables.

[44]:
```
# Install the xgboost library:
!pip install xgboost
```

```
Requirement already satisfied: xgboost in c:\users\xisko\anaconda3\lib\site-
packages (2.1.3)
Requirement already satisfied: numpy in c:\users\xisko\anaconda3\lib\site-
packages (from xgboost) (1.26.4)
```

```
Requirement already satisfied: scipy in c:\users\xisko\anaconda3\lib\site-
packages (from xgboost) (1.11.4)
```

[45]:
```
# Import libraries
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.pipeline import Pipeline
import statsmodels.api as sm

# Features for regression
categorical_features = ['Type', 'Gearbox', 'Fuel', 'Car Condition']
numerical_features = ['Year', 'Mileage', 'Engine Capacity', 'Seating Capacity']
target = 'Price'

# Separate features and target
X = cleaned_data[categorical_features + numerical_features]
y = cleaned_data[target]

# Convert categorical variables: One-hot encode categorical variables
preprocessor = ColumnTransformer(
    transformers=[('cat', OneHotEncoder(drop='first'), categorical_features)],
    remainder='passthrough'  # Keep numerical features as is
)

# Apply the transformations to get the encoded data
X_encoded = preprocessor.fit_transform(X)
```

1.5.2 Train-Test Split:

- Split the dataset into training and testing sets (e.g., 80-20 split).

[47]:
```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=0.
 ↪2, random_state=42)
```

1.5.3 Regression Algorithms:

- Linear Regression as a baseline model.
- Random Forest Regressor or Gradient Boosting (XGBoost) for non-linear relationships.

[49]:
```
# Define models
models = {
    'Linear Regression': LinearRegression(),
    'Random Forest': RandomForestRegressor(random_state=42),
    'XGBoost': XGBRegressor(random_state=42)
```

```
}

# Function to calculate Adjusted R²
def adjusted_r2_score(y_true, y_pred, n, p):
    r2 = r2_score(y_true, y_pred)
    return 1 - (1 - r2) * (n - 1) / (n - p - 1)
```

1.5.4 Evaluation:

- Cross-validate to ensure robustness.
- Metrics: Use R^2, Mean Absolute Error (MAE), and Mean Squared Error (MSE).
- Compare models and choose the best-performing one

[51]:
```
# Train and evaluate models
results = []
for name, model in models.items():
    # Create a pipeline with preprocessor and model
    pipeline = Pipeline(steps=[
        ('regressor', model)
    ])

    # Cross-validation scores
    cv_scores = cross_val_score(pipeline, X_train, y_train, cv=5, scoring='r2')

    # Fit and predict
    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)

    # Calculate adjusted R²
    n = len(y_test)  # Number of test samples
    p = X_train.shape[1]  # Number of features
    adj_r2 = adjusted_r2_score(y_test, y_pred, n, p)

    # Evaluate model
    mse = mean_squared_error(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    results.append({
        'Model': name,
        'R² (CV Mean)': np.mean(cv_scores),
        'R² (Test)': r2,
        'Adjusted R² (Test)': adj_r2,
        'MSE': mse,
        'MAE': mae
    })
```

```
# Convert results to DataFrame for display
results_df = pd.DataFrame(results)

# Display results
print("Model Evaluation Results:\n")
print(results_df)
```

```
Model Evaluation Results:

               Model  R² (CV Mean)  R² (Test)  Adjusted R² (Test)  MSE  MAE
0  Linear Regression          0.68       0.69                0.69 0.15 0.30
1      Random Forest          0.86       0.86                0.86 0.07 0.17
2            XGBoost          0.88       0.89                0.89 0.05 0.16
```

- Best Model Selection:
  - R^2 (Test): Measures how well the model explains the variance in the data. XGBoost has the highest R^2 (0.89), indicating it explains 89% of the variance.
  - Adjusted R^2 (Test): Adjusts R^2 to penalize for the number of predictors. XGBoost retains the highest value (0.89), meaning its complexity is justified.
  - MSE (Mean Squared Error): Measures the average squared difference between actual and predicted values. Lower is better, and XGBoost achieves the lowest MSE (0.05).
  - MAE (Mean Absolute Error): Measures the average absolute error. Again, XGBoost performs the best (0.16).
- Conslusion:
  - XGBoost is the best-performing model overall, excelling in all metrics: R^2, Adjusted R^2, MSE, and MAE.
  - XGBoost's advanced boosting techniques allow it to capture complex relationships in the data better than simpler models like Linear Regression or Random Forest, which makes it a robust choice.

1.5.5 Most Significant Variables:

- Identify which features have the greatest impact on car prices.

[54]:
```
# Statistical significance for Linear Regression

# Get the feature names for categorical columns after one-hot encoding
categorical_columns = preprocessor.transformers_[0][1].
 ↪get_feature_names_out(categorical_features)
numerical_columns = numerical_features  # The numerical columns are unchanged

# Combine the feature names
feature_names = ['const'] + list(categorical_columns) + numerical_columns  #␣
 ↪Include 'const' for intercept

# Add intercept (constant term)
X_encoded_with_intercept = sm.add_constant(X_encoded)
```

```python
# Fit the OLS regression model
linear_model = sm.OLS(y, X_encoded_with_intercept).fit()

# Assign correct names to the summary
linear_model.model.data.xnames = feature_names  # Ensure the real names are␣
↪used in the output

# Print the full summary
print("Linear Regression Full Summary (Statsmodels):\n")
print(linear_model.summary())
```

```
Linear Regression Full Summary (Statsmodels):

                            OLS Regression Results
==============================================================================
Dep. Variable:                  Price   R-squared:                       0.684
Model:                            OLS   Adj. R-squared:                  0.684
Method:                 Least Squares   F-statistic:                     2304.
Date:                Tue, 03 Dec 2024   Prob (F-statistic):               0.00
Time:                        19:56:09   Log-Likelihood:                -8227.7
No. Observations:               17048   AIC:                         1.649e+04
Df Residuals:                   17031   BIC:                         1.662e+04
Df Model:                          16
Covariance Type:            nonrobust
================================================================================
===========
                              coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----------
const                       0.2251      0.020     11.409      0.000       0.186
0.264
Type_Pickup                 0.0850      0.017      5.123      0.000       0.052
0.117
Type_Sedan                  0.0092      0.012      0.773      0.440      -0.014
0.033
Type_Sports/Convertible     0.4653      0.018     25.393      0.000       0.429
0.501
Type_Utility               -0.0754      0.016     -4.861      0.000      -0.106
-0.045
Type_Van                    0.0501      0.023      2.164      0.031       0.005
0.096
Type_Wagon                  0.0545      0.010      5.445      0.000       0.035
0.074
Gearbox_Manual              0.0219      0.009      2.327      0.020       0.003
0.040
Gearbox_Other               0.6662      0.081      8.255      0.000       0.508
0.824
```

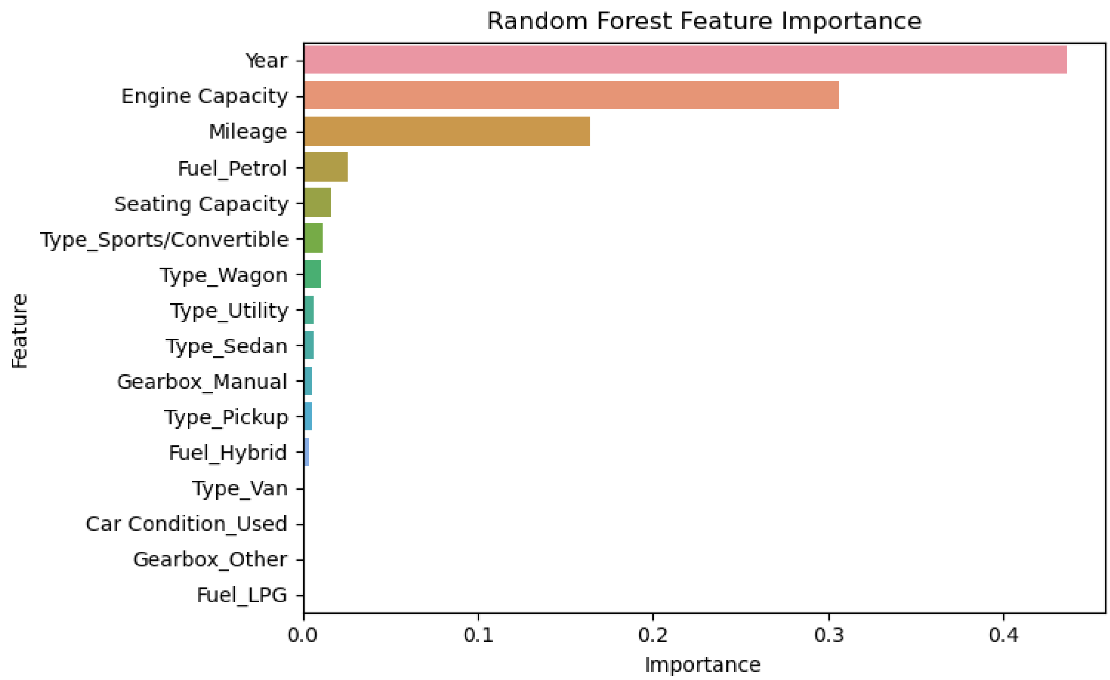
```
Fuel_Hybrid                     0.0533      0.020      2.665      0.008       0.014
0.093
Fuel_LPG                       -0.6128      0.063     -9.707      0.000      -0.736
-0.489
Fuel_Petrol                    -0.3185      0.008    -38.267      0.000      -0.335
-0.302
Car Condition_Used             -0.1349      0.016     -8.668      0.000      -0.165
-0.104
Year                            0.2626      0.005     52.173      0.000       0.253
0.273
Mileage                        -0.2825      0.005    -53.080      0.000      -0.293
-0.272
Engine Capacity                 0.3301      0.004     82.691      0.000       0.322
0.338
Seating Capacity                0.0231      0.004      6.024      0.000       0.016
0.031
==============================================================================
Omnibus:                     2640.653   Durbin-Watson:                   1.846
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4772.790
Skew:                           0.995   Prob(JB):                         0.00
Kurtosis:                       4.662   Cond. No.                         43.6
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

[55]:

```python
# Significant Features for tree-based models
for name, model in models.items():
    if name in ['Random Forest', 'XGBoost']:
        # Fit the model again for feature importance
        pipeline = Pipeline(steps=[
            ('regressor', model)
        ])
        pipeline.fit(X_train, y_train)

        # Extract feature names
        feature_names = preprocessor.named_transformers_['cat'].
 ↪get_feature_names_out(categorical_features)
        feature_names = list(feature_names) + numerical_features

        # Extract features most important
        importance = pipeline.named_steps['regressor'].feature_importances_
        importance_df = pd.DataFrame({
            'Feature': feature_names,
            'Importance': importance
        }).sort_values(by='Importance', ascending=False)
```

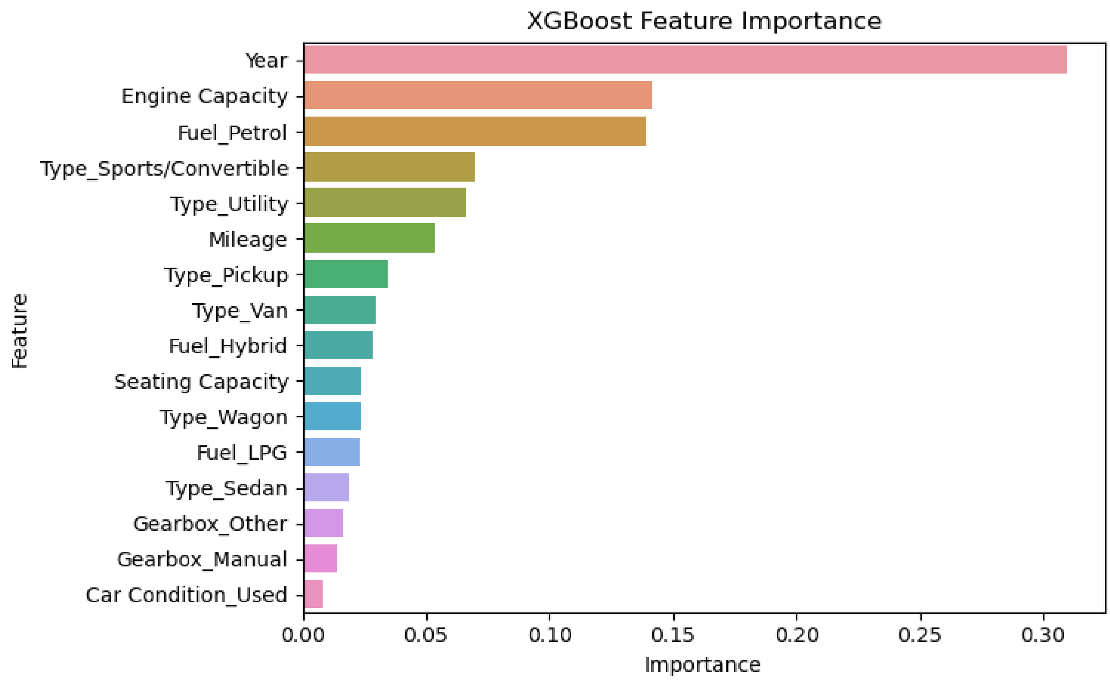
```python
# Print and plot features most important
print(f"\n{name} Feature Importance:\n")
print(importance_df)

plt.figure(figsize=(7, 5))
sns.barplot(x='Importance', y='Feature', data=importance_df)
plt.title(f'\n{name} Feature Importance')
plt.show()
```

```
Random Forest Feature Importance:

                      Feature  Importance
12                       Year        0.44
14            Engine Capacity        0.31
13                    Mileage        0.16
10                Fuel_Petrol        0.03
15           Seating Capacity        0.02
2    Type_Sports/Convertible        0.01
5                  Type_Wagon        0.01
3                Type_Utility        0.01
1                  Type_Sedan        0.01
6              Gearbox_Manual        0.01
0                 Type_Pickup        0.00
8                 Fuel_Hybrid        0.00
4                    Type_Van        0.00
11         Car Condition_Used        0.00
7               Gearbox_Other        0.00
9                    Fuel_LPG        0.00
```



XGBoost Feature Importance:

	Feature	Importance
12	Year	0.31
14	Engine Capacity	0.14
10	Fuel_Petrol	0.14
2	Type_Sports/Convertible	0.07
3	Type_Utility	0.07
13	Mileage	0.05
0	Type_Pickup	0.03
4	Type_Van	0.03
8	Fuel_Hybrid	0.03
15	Seating Capacity	0.02
5	Type_Wagon	0.02
9	Fuel_LPG	0.02
1	Type_Sedan	0.02
7	Gearbox_Other	0.02
6	Gearbox_Manual	0.01
11	Car Condition_Used	0.01



1.6 5. Model 3: Classification

1.6.1 Objective:

- Classify cars into price ranges (e.g., low, medium, high). ### Create price ranges using quantiles

[57]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, precision_score, recall_score
from sklearn.preprocessing import LabelEncoder

# Create price ranges using quantiles
quantiles = cleaned_data['Price'].quantile([0.33, 0.66]).values
cleaned_data['Price_Range'] = pd.cut(cleaned_data['Price'],␣
↪bins=[-float('inf'), quantiles[0], quantiles[1], float('inf')],
                                     labels=['Low', 'Medium', 'High'])
```

1.6.2 Prepare features and target

[59]:
```
# Prepare features and target
X = cleaned_data.drop(['Price', 'Price_Range'], axis=1)  # Drop the target and␣
↪Price columns
y = cleaned_data['Price_Range']
```

```python
# Encode categorical features using one-hot encoding
categorical_features = X.select_dtypes(include=["object"]).columns
X_encoded = pd.get_dummies(X, columns=categorical_features, drop_first=True)

# Label encode the target variable
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)
```

1.6.3 Train-Test Split:

- Split the dataset into training and testing sets (e.g., 80-20 split).

[61]:
```python
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y_encoded,␣
↪test_size=0.2, random_state=42)
```

1.6.4 Method for Classification:

- Use Decision Trees
- Use Naïve Bayes

[63]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB

# Decision Tree
# Fit Decision Tree
dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train, y_train)
dt_y_pred = dt_model.predict(X_test)

# Evaluate Decision Tree
dt_accuracy = accuracy_score(y_test, dt_y_pred)
dt_precision = precision_score(y_test, dt_y_pred, average='weighted')
dt_recall = recall_score(y_test, dt_y_pred, average='weighted')

# Naive Bayes
# Fit Naive Bayes
nb_model = GaussianNB()
nb_model.fit(X_train, y_train)
nb_y_pred = nb_model.predict(X_test)

# Evaluate Naive Bayes
nb_accuracy = accuracy_score(y_test, nb_y_pred)
nb_precision = precision_score(y_test, nb_y_pred, average='weighted')
nb_recall = recall_score(y_test, nb_y_pred, average='weighted')
```

```python
# Random Forest
# Fit Random Forest
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
rf_y_pred = rf_model.predict(X_test)

# Evaluate Random Forest
rf_accuracy = accuracy_score(y_test, rf_y_pred)
rf_precision = precision_score(y_test, rf_y_pred, average='weighted')
rf_recall = recall_score(y_test, rf_y_pred, average='weighted')
```

1.6.5 Evaluation of methods:

- Evaluate accuracy, precision, and recall metrics.

[65]:
```python
# Create a DataFrame for comparing the methods
comparison_df = pd.DataFrame({
    'Model': ['Decision Tree', 'Naive Bayes', 'Random Forest'],
    'Accuracy': [dt_accuracy, nb_accuracy, rf_accuracy],
    'Precision': [dt_precision, nb_precision, rf_precision],
    'Recall': [dt_recall, nb_recall, rf_recall]
})

# Display comparison
print(comparison_df)
```

```
           Model  Accuracy  Precision  Recall
0  Decision Tree      0.83       0.83    0.83
1    Naive Bayes      0.40       0.69    0.40
2  Random Forest      0.86       0.86    0.86
```

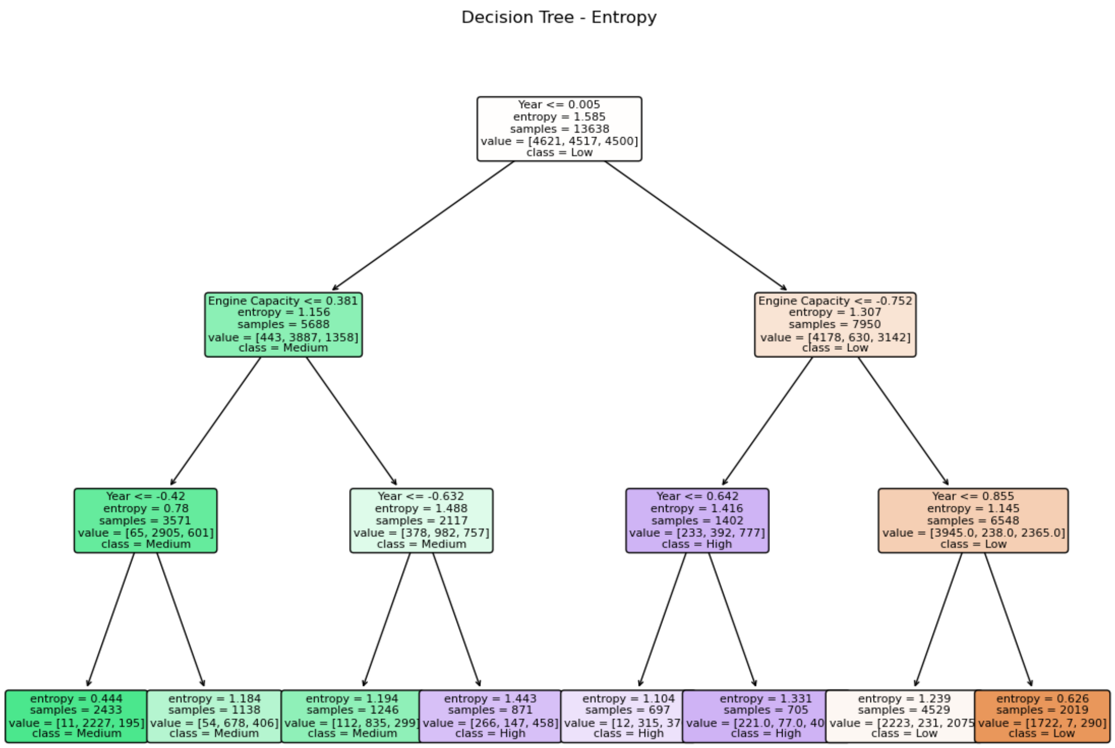
- Best Model Selection:
  - Decision Tree:
    - Accuracy: 0.83 — This indicates that the model correctly classified 83% of the test instances.
    - Precision: 0.83 — The model is quite good at identifying true positive predictions compared to all positive predictions.
    - Recall: 0.83 — The model also does well in identifying all actual positive cases, with 83% of them correctly classified.
  - Naive Bayes:
    - Accuracy: 0.40 — The Naive Bayes model is underperforming, with only 40% of the test instances correctly classified.
    - Precision: 0.69 — This suggests that when the Naive Bayes model predicts a positive outcome, it is correct 69% of the time, which is relatively higher than its recall.
    - Recall: 0.40 — The recall is very low, meaning that the Naive Bayes model is missing a large number of actual positive cases.
  - Random Forest
    - Accuracy: 0.86 — very strogn model

    * Precision: 0.86 — The model is good at identifying true positive predictions compared to all positive predictions.
    * Recall: 0.86 — The model also does well in identifying all actual positive cases, with 86% of them correctly classified.

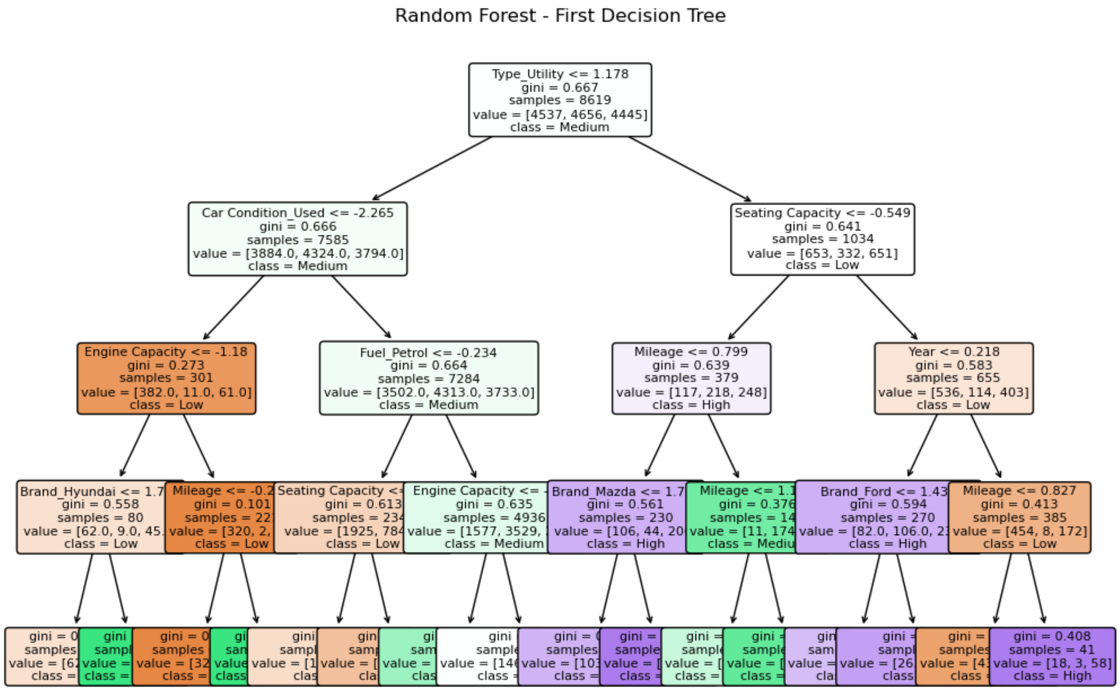
- Conclusion:
  - The Decision Random Forest is performing much better across all metrics than the Other models. It has a much higher accuracy, precision, and recall, making it the better choice for this classification task.

[67]:
```python
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Select features and target variable
features = ['Brand', 'Year', 'Mileage', 'Type', 'Gearbox', 'Fuel', 'Car␣
↪Condition', 'Engine Capacity', 'Seating Capacity']

# Define the features (X) and target (y)
X = cleaned_data[features]
y = cleaned_data['Price_Range']

# Encode categorical variables using One-Hot Encoding
X = pd.get_dummies(X, columns=['Brand', 'Type', 'Gearbox', 'Fuel', 'Car␣
↪Condition'], drop_first=True)

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Standardize features to improve model performance
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Create and train the Decision Tree
dtree = DecisionTreeClassifier(criterion='entropy', max_depth=3,␣
↪random_state=42)
dtree.fit(X_train, y_train)

# Make predictions and calculate accuracy and confusion matrix for the Decision␣
↪Tree
dtree_pred = dtree.predict(X_test)
dtree_accuracy = accuracy_score(y_test, dtree_pred)
```

```python
dtree_conf_matrix = confusion_matrix(y_test, dtree_pred)

# Plot the Decision Tree with smaller font size
plt.figure(figsize=(14, 10))
plot_tree(dtree, feature_names=X.columns, class_names=['Low', 'Medium', 
 ↪'High'], filled=True, rounded=True, fontsize=8)
plt.title("Decision Tree - Entropy")
plt.show()

# Print Decision Tree accuracy and confusion matrix
print(f"Decision Tree Accuracy: {dtree_accuracy:.4f}")
print("Decision Tree Confusion Matrix:")
print(dtree_conf_matrix)

# Create and train the Random Forest model
rf = RandomForestClassifier(n_estimators=100, max_depth=4, random_state=42)
rf.fit(X_train, y_train)

# Make predictions and calculate accuracy and confusion matrix for the Random 
 ↪Forest
rf_pred = rf.predict(X_test)
rf_accuracy = accuracy_score(y_test, rf_pred)
rf_conf_matrix = confusion_matrix(y_test, rf_pred)

# Plot a single tree from the Random Forest with smaller font size
plt.figure(figsize=(12, 8))
plot_tree(rf.estimators_[0], feature_names=X.columns, class_names=['Low', 
 ↪'Medium', 'High'], filled=True, rounded=True, fontsize=8)
plt.title("Random Forest - First Decision Tree")
plt.show()

# Print Random Forest accuracy and confusion matrix
print(f"Random Forest Accuracy: {rf_accuracy:.4f}")
print("Random Forest Confusion Matrix:")
print(rf_conf_matrix)
```




```
Decision Tree Accuracy: 0.6499
Decision Tree Confusion Matrix:
[[1010   33  132]
 [  65  922  125]
 [ 612  227  284]]
```




```
Random Forest Accuracy: 0.7405
Random Forest Confusion Matrix:
[[1003   67  105]
 [  17  963  132]
 [ 308  256  559]]
```

1.7 6. Final Conclusion

The project successfully analyzed the Australian car market dataset and identified key factors influencing car prices. Through EDA and modeling, Year, Mileage, and Engine Capacity emerged as the most significant predictors of car price.

Among the models evaluated:

- XGBoost was the most robust for regression tasks, achieving the highest R^2 and lowest error metrics.
- Decision Trees were the best for classification, correctly categorizing cars into price ranges with high accuracy, precision, and recall.

Clustering analysis added value by segmenting cars into meaningful groups, aiding market targeting and pricing strategies. The integration of multiple methods—EDA, clustering, regression, and classification—provided a holistic view of the dataset and addressed the project's objectives effectively.