# Project : PRCP-1017-AutoPricePred

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Domain Analysis:

The project falls within the domain of automotive industry analytics, focusing on analyzing various attributes of vehicles, possibly for tasks such as predicting car prices, evaluating car performance, or categorizing vehicles based on features.

An automobile car price prediction system offers consumers the ability toforecast car prices accurately before making a purchase, facilitatinginformed decision-making and enhancing budget planning.

Implementation of such a tool can empower car buyers to make well□informed decisions, optimize savings, and reduce uncertainty associated with price negotiation.

Additionally, automotive dealerships and manufacturers can leverage this technology to improve pricing strategies, optimize inventory management,and enhance customer satisfaction.By dynamically adjusting pricing strategies based on predictive insights,dealerships can maximize revenue and profitability while maintaining competitiveness in the market.

Overall, an automobile car price prediction system represents a valuable asset for both consumers and automotive businesses ,facilitating efficiency and transparency in the car purchasing process.

Key Attributes: Car Specifications: Engine type, body style, drive wheels, fuel type. Performance Metrics: Horsepower, RPM, fuel efficiency. Physical Dimensions: Length, width, height, curb weight. Economic Factors: Price, fuel economy (mileage).

Potential Use Cases: Price Prediction: Using attributes to predict the market price of vehicles. Vehicle Categorization: Classifying cars into categories like economy, luxury, sports, etc. Market Analysis: Identifying trends in car features and performance over time

In [ ]:

```

```

# Importing Necessary Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import plotly.express as px
import warnings
warnings.filterwarnings('ignore')
import seaborn as sns
```

In [2]:
```
df=pd.read_csv('auto_imports.csv')
pd.set_option("display.max_columns",None)
```

In [3]:
```
df
```

Out[3]:

| | 3 | ? | alfa-romero | gas | std | two | convertible | rwd | front | 88.60 | 168.80 | 64.10 | 48.80 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 3 | ? | alfa-romero | gas | std | two | convertible | rwd | front | 88.6 | 168.8 | 64.1 | 48.8 |
| **1** | 1 | ? | alfa-romero | gas | std | two | hatchback | rwd | front | 94.5 | 171.2 | 65.5 | 52.4 |
| **2** | 2 | 164 | audi | gas | std | four | sedan | fwd | front | 99.8 | 176.6 | 66.2 | 54.3 |
| **3** | 2 | 164 | audi | gas | std | four | sedan | 4wd | front | 99.4 | 176.6 | 66.4 | 54.3 |
| **4** | 2 | ? | audi | gas | std | two | sedan | fwd | front | 99.8 | 177.3 | 66.3 | 53.1 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **195** | -1 | 95 | volvo | gas | std | four | sedan | rwd | front | 109.1 | 188.8 | 68.9 | 55.5 |
| **196** | -1 | 95 | volvo | gas | turbo | four | sedan | rwd | front | 109.1 | 188.8 | 68.8 | 55.5 |
| **197** | -1 | 95 | volvo | gas | std | four | sedan | rwd | front | 109.1 | 188.8 | 68.9 | 55.5 |
| **198** | -1 | 95 | volvo | diesel | turbo | four | sedan | rwd | front | 109.1 | 188.8 | 68.9 | 55.5 |
| **199** | -1 | 95 | volvo | gas | turbo | four | sedan | rwd | front | 109.1 | 188.8 | 68.9 | 55.5 |

200 rows × 26 columns

In [4]:
```
df.head(5)
```

Out[4]:

| | 3 | ? | alfa-romero | gas | std | two | convertible | rwd | front | 88.60 | 168.80 | 64.10 | 48.80 | 2548 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 3 | ? | alfa-romero | gas | std | two | convertible | rwd | front | 88.6 | 168.8 | 64.1 | 48.8 | 2548 |
| **1** | 1 | ? | alfa-romero | gas | std | two | hatchback | rwd | front | 94.5 | 171.2 | 65.5 | 52.4 | 2823 |
| **2** | 2 | 164 | audi | gas | std | four | sedan | fwd | front | 99.8 | 176.6 | 66.2 | 54.3 | 2337 |
| **3** | 2 | 164 | audi | gas | std | four | sedan | 4wd | front | 99.4 | 176.6 | 66.4 | 54.3 | 2824 |
| **4** | 2 | ? | audi | gas | std | two | sedan | fwd | front | 99.8 | 177.3 | 66.3 | 53.1 | 2507 |

In [5]:
```
headers = ["symboling","normalized-losses","make","fuel-type","aspirati
         "drive-wheels","engine-location","wheel-base", "length","widtl
         "num-of-cylinders", "engine-size","fuel-system","bore","stroke
         "peak-rpm","city-mpg","highway-mpg","price"]
print("headers\n", headers)
```

```
headers
 ['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration', 'nu
m-of-doors', 'body-style', 'drive-wheels', 'engine-location', 'wheel-bas
e', 'length', 'width', 'height', 'curb-weight', 'engine-type', 'num-of-cyl
inders', 'engine-size', 'fuel-system', 'bore', 'stroke', 'compression-rati
o', 'horsepower', 'peak-rpm', 'city-mpg', 'highway-mpg', 'price']
```

In [6]:
```
df.columns = headers
df.head(10)
```

Out[6]:

| | symboling | normalized-losses | make | fuel-type | aspiration | num-of-doors | body-style | drive-wheels | engine-location | wh b |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 3 | ? | alfa-romero | gas | std | two | convertible | rwd | front | 8 |
| **1** | 1 | ? | alfa-romero | gas | std | two | hatchback | rwd | front | 9 |
| **2** | 2 | 164 | audi | gas | std | four | sedan | fwd | front | 9 |
| **3** | 2 | 164 | audi | gas | std | four | sedan | 4wd | front | 9 |
| **4** | 2 | ? | audi | gas | std | two | sedan | fwd | front | 9 |
| **5** | 1 | 158 | audi | gas | std | four | sedan | fwd | front | 10 |
| **6** | 1 | ? | audi | gas | std | four | wagon | fwd | front | 10 |
| **7** | 1 | 158 | audi | gas | turbo | four | sedan | fwd | front | 10 |
| **8** | 2 | 192 | bmw | gas | std | two | sedan | rwd | front | 10 |
| **9** | 0 | 192 | bmw | gas | std | four | sedan | rwd | front | 10 |

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   symboling          200 non-null    int64  
 1   normalized-losses  200 non-null    object 
 2   make               200 non-null    object 
 3   fuel-type          200 non-null    object 
 4   aspiration         200 non-null    object 
 5   num-of-doors       200 non-null    object 
 6   body-style         200 non-null    object 
 7   drive-wheels       200 non-null    object 
 8   engine-location    200 non-null    object 
 9   wheel-base         200 non-null    float64
 10  length             200 non-null    float64
 11  width              200 non-null    float64
 12  height             200 non-null    float64
 13  curb-weight        200 non-null    int64  
 14  engine-type        200 non-null    object 
 15  num-of-cylinders   200 non-null    object 
 16  engine-size        200 non-null    int64  
 17  fuel-system        200 non-null    object 
 18  bore               200 non-null    object 
 19  stroke             200 non-null    object 
 20  compression-ratio  200 non-null    float64
 21  horsepower         200 non-null    object 
 22  peak-rpm           200 non-null    object 
 23  city-mpg           200 non-null    int64  
 24  highway-mpg        200 non-null    int64  
 25  price              200 non-null    int64  
dtypes: float64(5), int64(6), object(15)
memory usage: 40.8+ KB
```

In [8]:
```
df.describe(include="O")
```

Out[8]:

| | normalized-losses | make | fuel-type | aspiration | num-of-doors | body-style | drive-wheels | engine-location | engine-type | num cylind |
|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 200 | 200 | 200 | 200 | 200 | 200 | 200 | 200 | 200 | |
| **unique** | 52 | 22 | 2 | 2 | 3 | 5 | 3 | 2 | 6 | |
| **top** | ? | toyota | gas | std | four | sedan | fwd | front | ohc | |
| **freq** | 36 | 32 | 180 | 164 | 113 | 94 | 118 | 197 | 145 | |

In [9]:
```
df.describe()
```

Out[9]:

| | symboling | wheel-base | length | width | height | curb-weight | engine-size |
|---|---|---|---|---|---|---|---|
| **count** | 200.000000 | 200.000000 | 200.000000 | 200.000000 | 200.000000 | 200.000000 | 200.000000 |
| **mean** | 0.830000 | 98.848000 | 174.228000 | 65.898000 | 53.791500 | 2555.705000 | 126.860000 |
| **std** | 1.248557 | 6.038261 | 12.347132 | 2.102904 | 2.428449 | 518.594552 | 41.650501 |
| **min** | -2.000000 | 86.600000 | 141.100000 | 60.300000 | 47.800000 | 1488.000000 | 61.000000 |
| **25%** | 0.000000 | 94.500000 | 166.675000 | 64.175000 | 52.000000 | 2163.000000 | 97.750000 |
| **50%** | 1.000000 | 97.000000 | 173.200000 | 65.500000 | 54.100000 | 2414.000000 | 119.500000 |
| **75%** | 2.000000 | 102.400000 | 183.500000 | 66.675000 | 55.525000 | 2928.250000 | 142.000000 |
| **max** | 3.000000 | 120.900000 | 208.100000 | 72.000000 | 59.800000 | 4066.000000 | 326.000000 |

Insights : 1 Data has a variety of types.The main types stored in Pandas dataframes are object, float, int, bool and datetime64. 2 In this dataset have 16 discrete columns and 10 continues columns 3 In the dataset,90% of cars have gas as fuel-type 4 The lowest price of a vehicle is 5118 and highest is 45400

In [10]:
```
df["make"].value_counts()
```

Out[10]:
```
make
toyota           32
nissan           18
mazda            17
mitsubishi       13
honda            13
volkswagen       12
subaru           12
peugot           11
volvo            11
dodge             9
mercedes-benz     8
bmw               8
plymouth          7
audi              6
saab              6
porsche           4
jaguar            3
chevrolet         3
isuzu             2
renault           2
alfa-romero       2
mercury           1
Name: count, dtype: int64
```

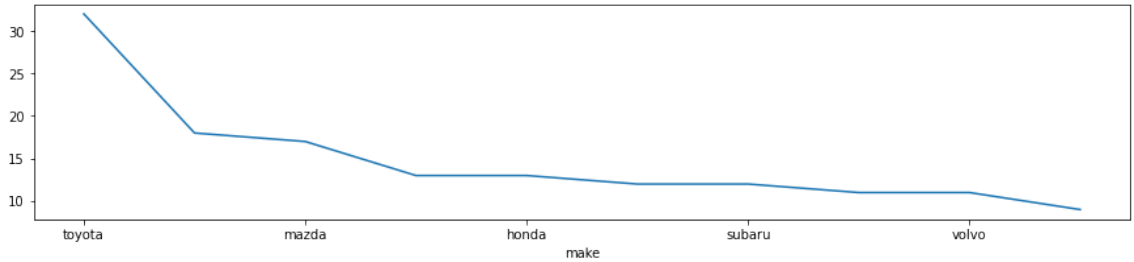
In [11]:
```
top10=df['make'].value_counts().sort_values(ascending=False) [:10]
```

In [12]:
```
top10
```

Out[12]:
```
make
toyota        32
nissan        18
mazda         17
mitsubishi    13
honda         13
volkswagen    12
subaru        12
peugot        11
volvo         11
dodge          9
Name: count, dtype: int64
```

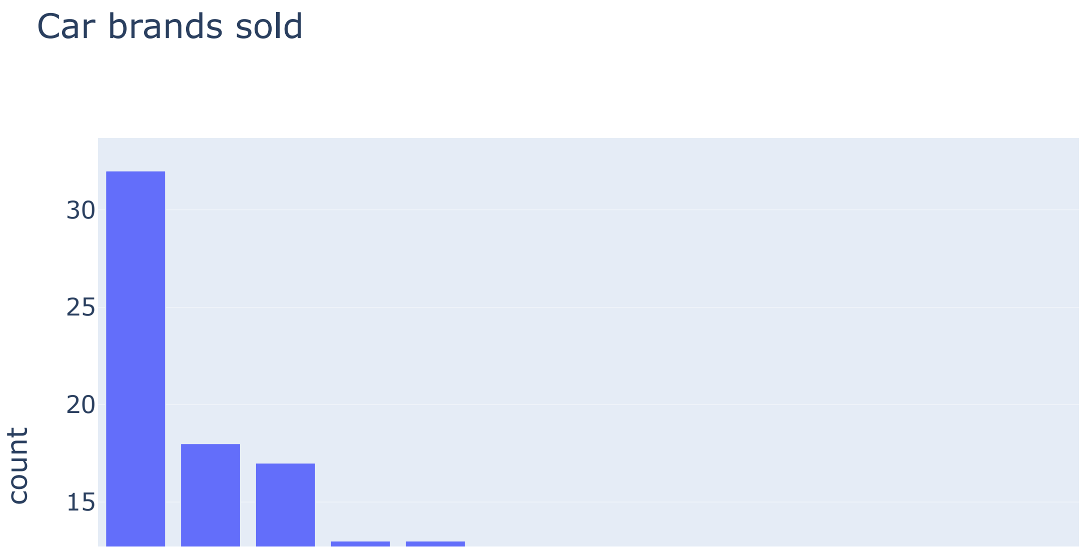
In [13]:
```
top10.plot(figsize= (15,3))
plt.show
```

Out[13]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```




# Count Analysis

In [14]:
```
car_make = df['make'].value_counts()
px.bar(car_make,
 y = 'count',
 title = 'Car brands sold',
 )
```

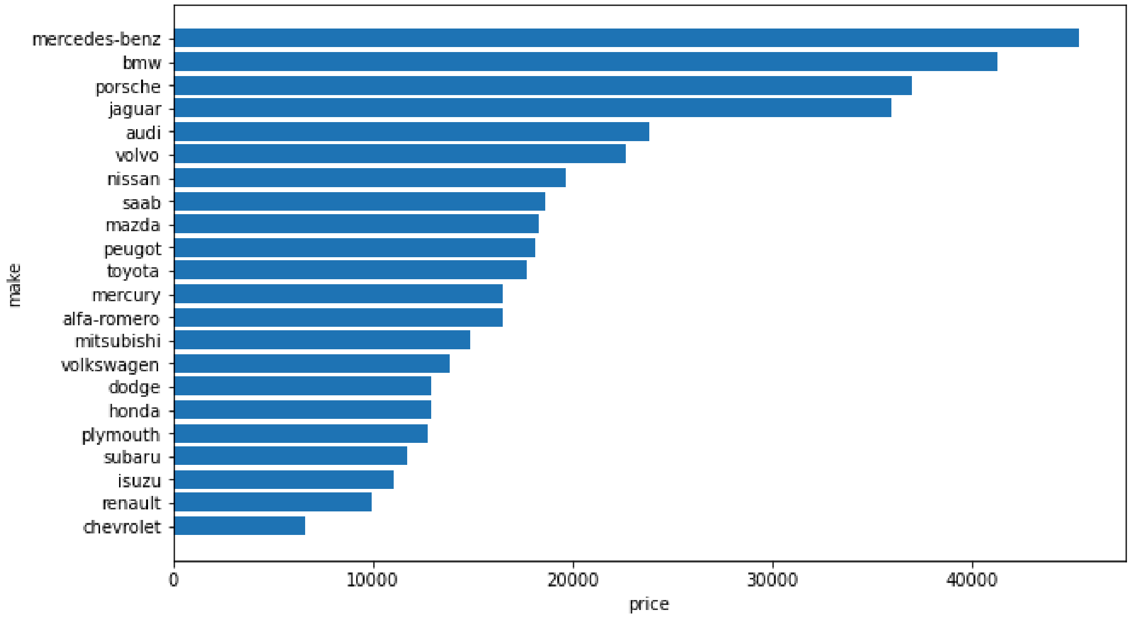



Insights 1 Toyota has the highest number of listings compared to other car brands in the dataset. 2 Mercury has the least number of listings comapred to other car brands in the dataset.

# Highest Price Make Analysis

In [15]:

```
lux_car=(df.sort_values(by=['price'],ascending=False))[:200]
plt.figure(figsize=(10,6))
plt.barh(lux_car['make'],lux_car['price'])
plt.xlabel('price')
plt.ylabel('make')
plt.gca().invert_yaxis()
plt.show()
```




In [16]:

```
df.loc[df["num-of-cylinders"]=="eight"]
```

Out[16]:

| | symboling | normalized-losses | make | fuel-type | aspiration | num-of-doors | body-style | drive-wheels | engine-location |
|---|---|---|---|---|---|---|---|---|---|
| **67** | -1 | ? | mercedes-benz | gas | std | four | sedan | rwd | front |
| **68** | 3 | 142 | mercedes-benz | gas | std | two | convertible | rwd | front |
| **69** | 0 | ? | mercedes-benz | gas | std | four | sedan | rwd | front |
| **70** | 1 | ? | mercedes-benz | gas | std | two | hardtop | rwd | front |

In [17]:

```
df.loc[df["city-mpg"]==49]
```

Out[17]:

| | symboling | normalized-losses | make | fuel-type | aspiration | num-of-doors | body-style | drive-wheels | engine-location | whe ba |
|---|---|---|---|---|---|---|---|---|---|---|
| **28** | 2 | 137 | honda | gas | std | two | hatchback | fwd | front | 8 |

# Insights

1 Mercedes-Benz stands out as the brand with the highest average vehicle prices. 2 Mercedes-benz,BMW and Porche are generally valued higher compared to other brand as it has highest vehcile price. 3 Chevrolet vehicles exhibit the highest average city miles per gallon (MPG) compared to other makes. 4 Chevrolet is the least priced vehicle make compared to others and it has the least horsepowerit has more city MPG.

# Univariate Analysis

In [18]:

```
df_num=df.select_dtypes(exclude='object')
df_var=df.select_dtypes(include='object')
```

In [19]:

```
df_num[["normalized-losses", 'make', 'bore', 'horsepower']] = df_var[[

df_num
```

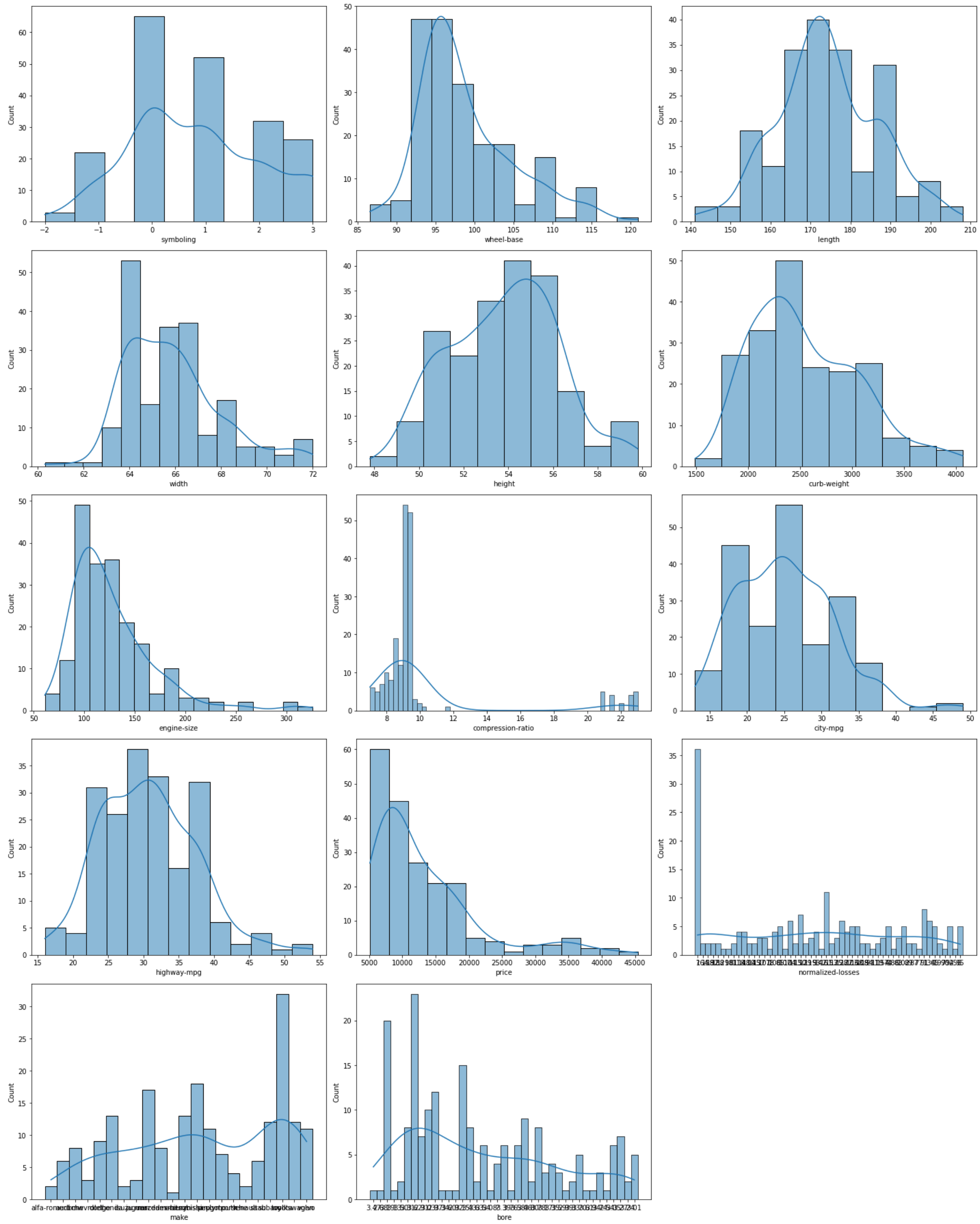
Out[19]:

| | symboling | wheel-base | length | width | height | curb-weight | engine-size | compression-ratio | city-mpg | highway mp |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 3 | 88.6 | 168.8 | 64.1 | 48.8 | 2548 | 130 | 9.0 | 21 | 2 |
| **1** | 1 | 94.5 | 171.2 | 65.5 | 52.4 | 2823 | 152 | 9.0 | 19 | 2 |
| **2** | 2 | 99.8 | 176.6 | 66.2 | 54.3 | 2337 | 109 | 10.0 | 24 | 3 |
| **3** | 2 | 99.4 | 176.6 | 66.4 | 54.3 | 2824 | 136 | 8.0 | 18 | 2 |
| **4** | 2 | 99.8 | 177.3 | 66.3 | 53.1 | 2507 | 136 | 8.5 | 19 | 2 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | . |
| **195** | -1 | 109.1 | 188.8 | 68.9 | 55.5 | 2952 | 141 | 9.5 | 23 | 2 |
| **196** | -1 | 109.1 | 188.8 | 68.8 | 55.5 | 3049 | 141 | 8.7 | 19 | 2 |
| **197** | -1 | 109.1 | 188.8 | 68.9 | 55.5 | 3012 | 173 | 8.8 | 18 | 2 |
| **198** | -1 | 109.1 | 188.8 | 68.9 | 55.5 | 3217 | 145 | 23.0 | 26 | 2 |
| **199** | -1 | 109.1 | 188.8 | 68.9 | 55.5 | 3062 | 141 | 9.5 | 19 | 2 |

200 rows × 15 columns

In [20]:

```
plt.figure(figsize=(20,25), facecolor='white')

plotnumber = 1  # Initialize plotnumber before the loop
for column in df_num:
    if plotnumber <= 14:
        plt.subplot(5, 3, plotnumber)  # Create a subplot
        sns.histplot(x=df_num[column], kde=True)  # Plot histogram wit
        plotnumber += 1  # Increment plotnumber after plotting

plt.tight_layout()  # Adjust layout to avoid overlap
plt.show()  # Ensure the figure is displayed
```




Insights 1 Wheel- base has a right skewed distribution and most of the vehicle opt the size of wheel between 95 to 100 2 The length distribution of vehicles is approximately normal, with most vehicles having lengths ranging from 170 to 190 units. 3 The majority of vehicles

achieve a city fuel efficiency of approximately 20 to 35 miles per gallon (mpg). 4 The highway fuel efficiency for most vehicles ranges from approximately 20 to 40 miles per gallon (mpg). 5 The majority of vehicle prices fall within the approximate range of 5,000 to 17,000

In [21]:

```
df_var1 = df_var.drop(['bore', 'stroke', 'horsepower', 'peak-rpm', 'nor
df_var1
```

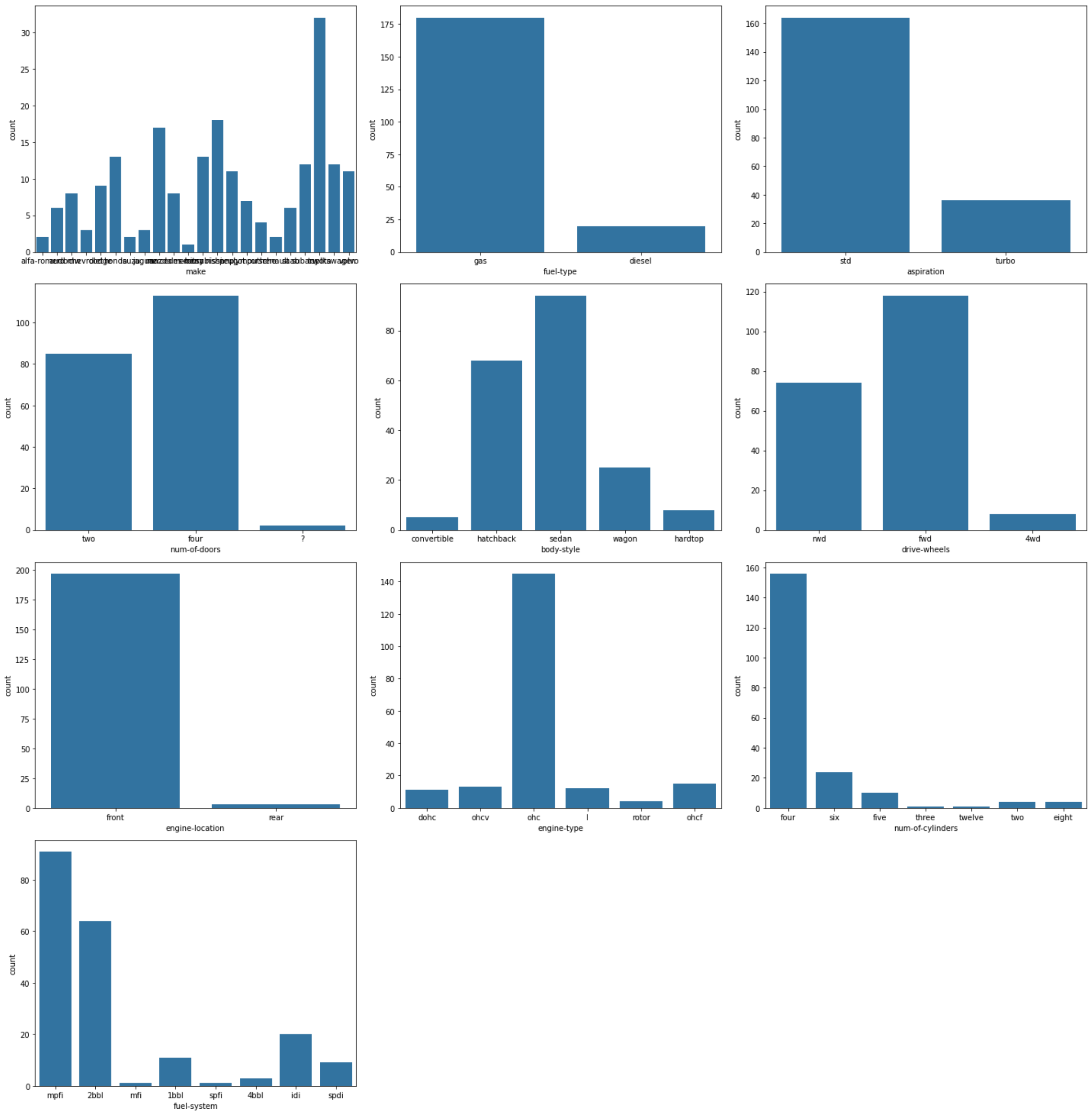
Out[21]:

| | make | fuel-type | aspiration | num-of-doors | body-style | drive-wheels | engine-location | engine-type | num-of-cylinders | fue syste |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | alfa-romero | gas | std | two | convertible | rwd | front | dohc | four | mr |
| **1** | alfa-romero | gas | std | two | hatchback | rwd | front | ohcv | six | mr |
| **2** | audi | gas | std | four | sedan | fwd | front | ohc | four | mr |
| **3** | audi | gas | std | four | sedan | 4wd | front | ohc | five | mr |
| **4** | audi | gas | std | two | sedan | fwd | front | ohc | five | mr |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **195** | volvo | gas | std | four | sedan | rwd | front | ohc | four | mr |
| **196** | volvo | gas | turbo | four | sedan | rwd | front | ohc | four | mr |
| **197** | volvo | gas | std | four | sedan | rwd | front | ohcv | six | mr |
| **198** | volvo | diesel | turbo | four | sedan | rwd | front | ohc | six | i |
| **199** | volvo | gas | turbo | four | sedan | rwd | front | ohc | four | mr |

200 rows × 10 columns

In [22]:

```python
plt.figure(figsize=(20, 25), facecolor='white')

plotnumber = 1
for column in df_var1:
    if plotnumber <= 14:
        plt.subplot(5, 3, plotnumber)
        sns.countplot(x=df_var1[column])
        plotnumber += 1

plt.tight_layout()
plt.show()

```




Toyota is the leading make, has the highest number of listings compared to other car brands in the dataset.

Mercury has the least number of listings comapred to other car brands in the dataset.

The analysis reveals that gasoline is the most prevalent fuel type, with a significantly higher count compared to diesel.

This suggests that the majority of vehicles prefer gasoline over diesel

The analysis indicates that the majority of vehicles are preferred with four doors.

The analysis indicates that the majority of vehicles have the engine located in the front.

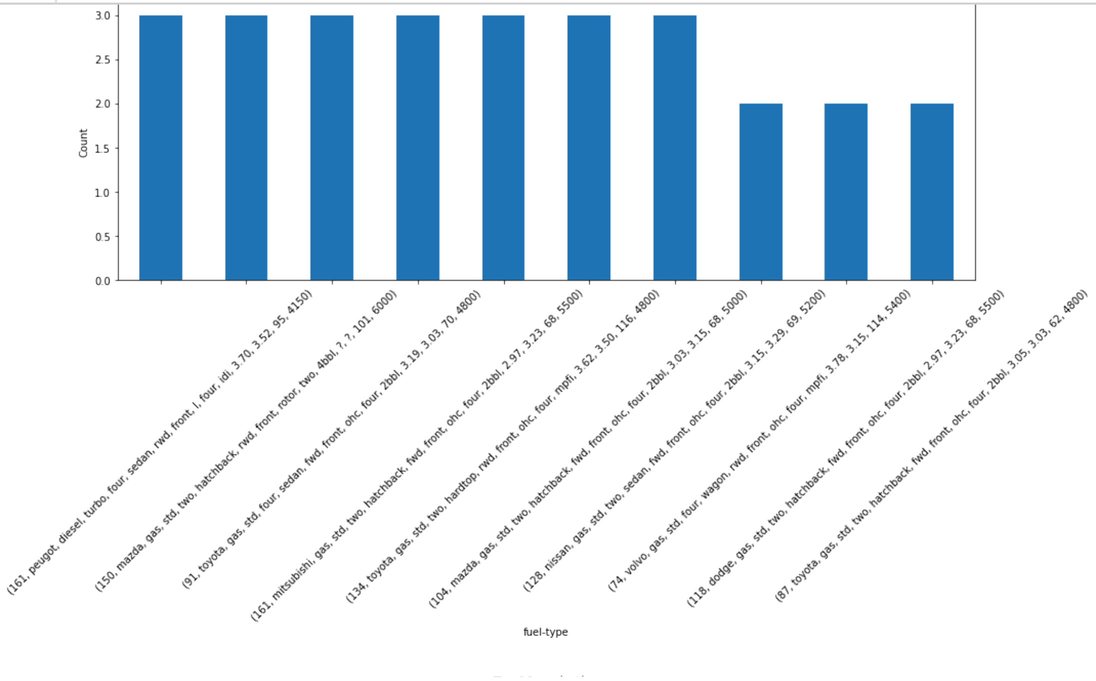
The predominance of front-engine layouts reflects a design standard that optimizes performance, safety, and cost-effectiveness for most vehicle manufacturers.

The Overhead Camshaft (OHC) engine type is widely used across all vehicle ranges.

This popularity is due to the OHC design offering several benefits, such as improved engine performance, higher efficiency, and better fuel economy compared to older engine types.

In [23]:

```python
for i in df_var:
    plt.figure(figsize=(15,5))
    var=df_var.value_counts()[:10]
    var.plot(kind="bar")
    plt.title(f'Top 10 {i}')
    plt.xlabel(i)
    plt.ylabel('Count')
    plt.xticks(rotation=45)
plt.show()
```

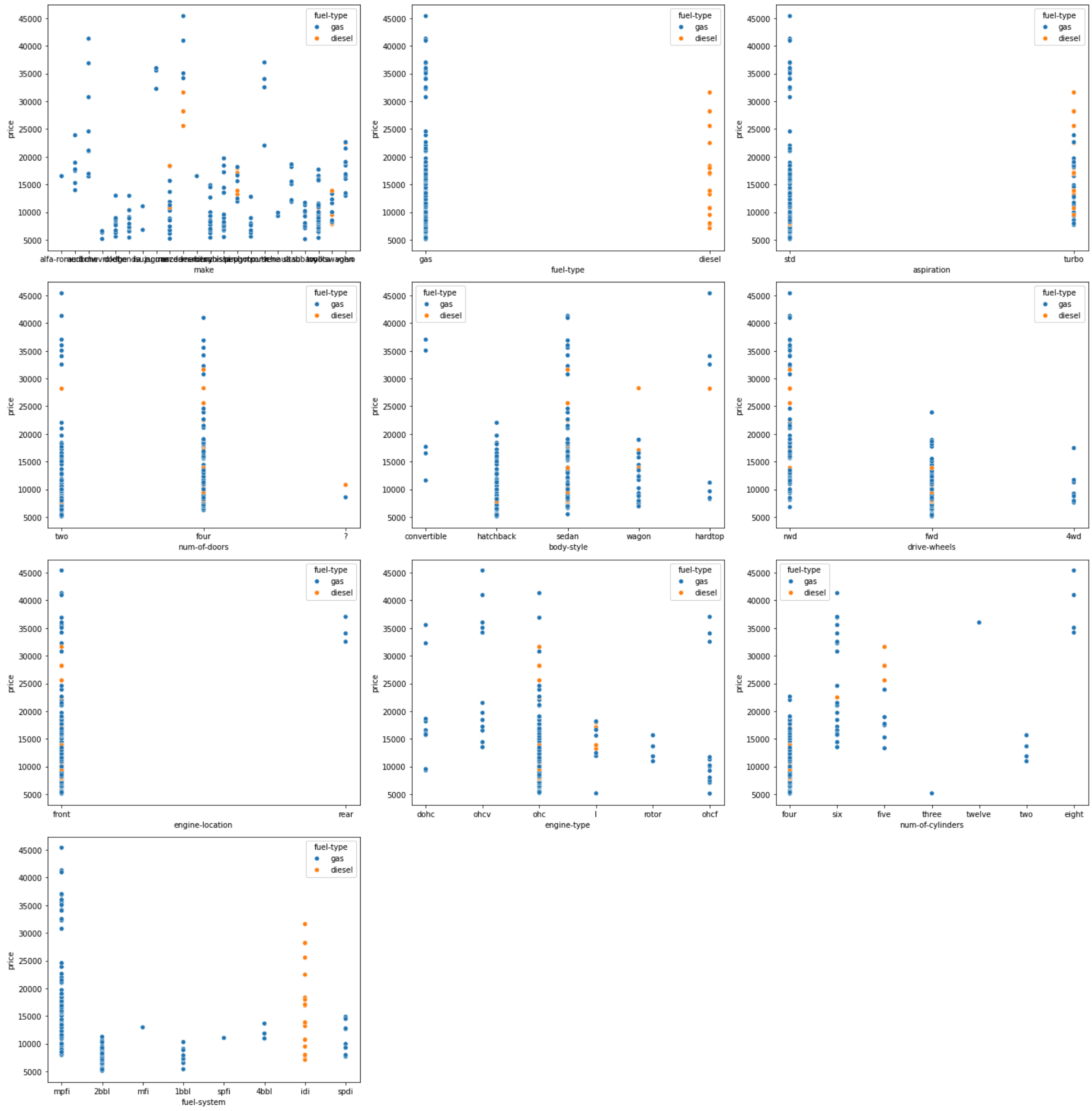



# Bivariate Analysis

In [24]:

```
plt.figure(figsize=(20,25),facecolor='white')
plotnumber = 1
for column in df_num:
    if plotnumber<=14:
        plt.subplot(5,3,plotnumber)
        sns.scatterplot(x=df_num[column],y="price",data=df,hue="fuel-ty
        plotnumber+=1
plt.tight_layout()
```

In [25]:
```
plt.figure(figsize=(20,25),facecolor='white')
plotnumber = 1
for column in df_var1:
    if plotnumber<=14:
        plt.subplot(5,3,plotnumber)
        sns.scatterplot(x=df_var1[column],y="price",data=df,hue="fuel-t
    plotnumber+=1
plt.tight_layout()
```



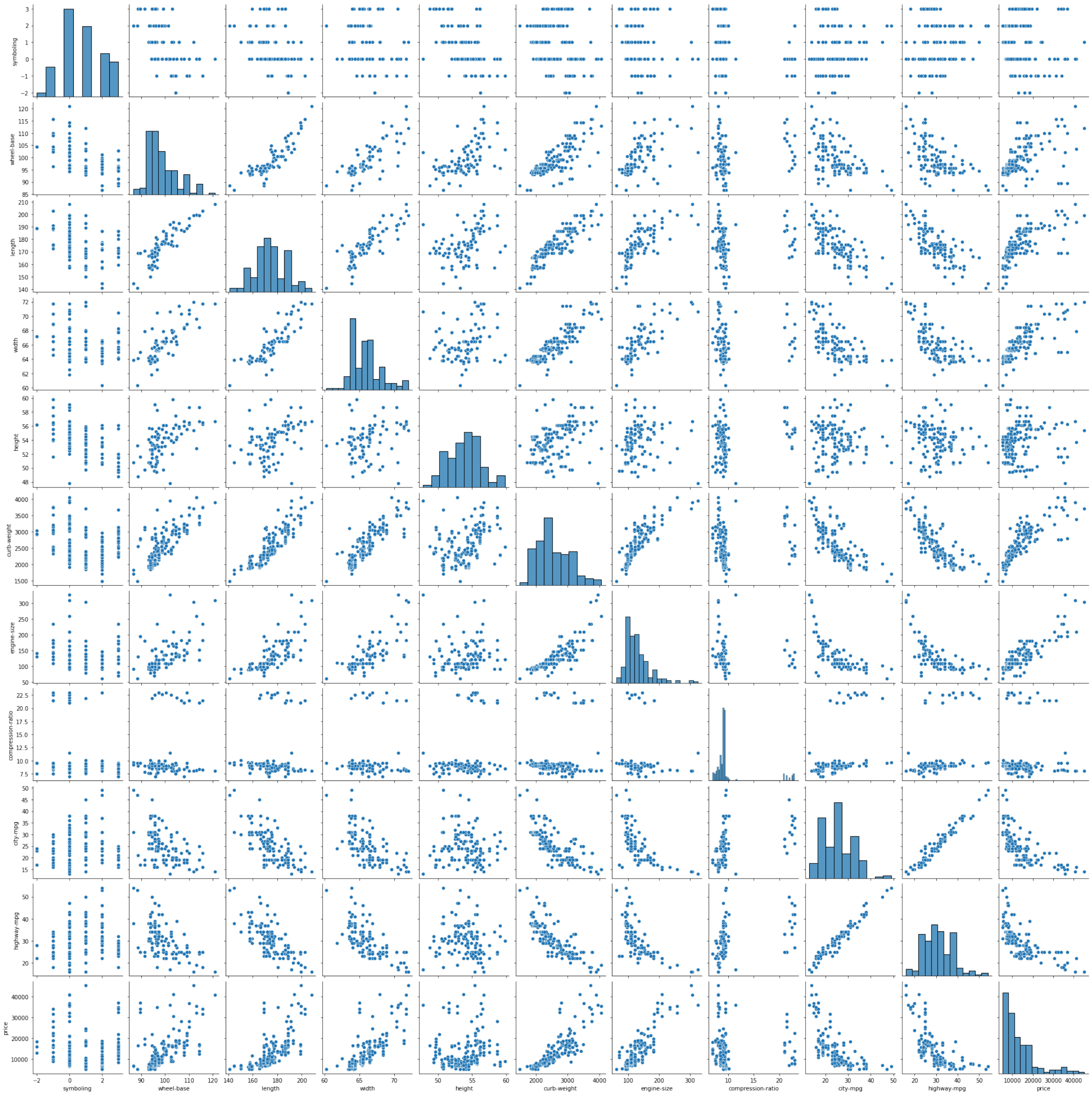

# Insights:

Vehicle with city-mpg range around 15 to 20 have higher car price. The gas fuel type has highest range of price. Vehicle with two door has highest price compared to others. Hardtop body style has highest priced vehicle . sedan body style as wide range of vehicle from lowest to highest price. The rear drive wheels encompasses a wide range of vehicles, from the lowest to the highest priced.

In [26]:
```
plt.figure(figsize=(100,100))
sns.pairplot(df)
```

Out[26]: <seaborn.axisgrid.PairGrid at 0x20300bf1e20>

<Figure size 7200x7200 with 0 Axes>




# Data Preprocessing

In [27]:
```
df.isnull().sum()
```

Out[27]:
```
symboling            0
normalized-losses    0
make                 0
fuel-type            0
aspiration           0
num-of-doors         0
body-style           0
drive-wheels         0
engine-location      0
wheel-base           0
length               0
width                0
height               0
curb-weight          0
engine-type          0
num-of-cylinders     0
engine-size          0
fuel-system          0
bore                 0
stroke               0
compression-ratio    0
horsepower           0
peak-rpm             0
city-mpg             0
highway-mpg          0
price                0
dtype: int64
```

In [28]:
```
df.duplicated().sum()
```

Out[28]:
```
0
```

In [29]:
```
qm_columns = df.isin(['?']).any()
qm_columns
```

Out[29]:
```
symboling            False
normalized-losses     True
make                 False
fuel-type            False
aspiration           False
num-of-doors          True
body-style           False
drive-wheels         False
engine-location      False
wheel-base           False
length               False
width                False
height               False
curb-weight          False
engine-type          False
num-of-cylinders     False
engine-size          False
fuel-system          False
bore                  True
stroke                True
compression-ratio    False
horsepower            True
peak-rpm              True
city-mpg             False
highway-mpg          False
price                False
dtype: bool
```

In [30]:
```
df.replace('?', pd.NA, inplace=True)
df
```

Out[30]:

| | symboling | normalized-losses | make | fuel-type | aspiration | num-of-doors | body-style | drive-wheels | engine-location |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 3 | <NA> | alfa-romero | gas | std | two | convertible | rwd | front |
| **1** | 1 | <NA> | alfa-romero | gas | std | two | hatchback | rwd | front |
| **2** | 2 | 164 | audi | gas | std | four | sedan | fwd | front |
| **3** | 2 | 164 | audi | gas | std | four | sedan | 4wd | front |
| **4** | 2 | <NA> | audi | gas | std | two | sedan | fwd | front |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **195** | -1 | 95 | volvo | gas | std | four | sedan | rwd | front |
| **196** | -1 | 95 | volvo | gas | turbo | four | sedan | rwd | front |
| **197** | -1 | 95 | volvo | gas | std | four | sedan | rwd | front |
| **198** | -1 | 95 | volvo | diesel | turbo | four | sedan | rwd | front |
| **199** | -1 | 95 | volvo | gas | turbo | four | sedan | rwd | front |

200 rows × 26 columns

In [31]:
```
df.isnull().sum()
```

Out[31]:
```
symboling             0
normalized-losses    36
make                  0
fuel-type             0
aspiration            0
num-of-doors          2
body-style            0
drive-wheels          0
engine-location       0
wheel-base            0
length                0
width                 0
height                0
curb-weight           0
engine-type           0
num-of-cylinders      0
engine-size           0
fuel-system           0
bore                  4
stroke                4
compression-ratio     0
horsepower            2
peak-rpm              2
city-mpg              0
highway-mpg           0
price                 0
dtype: int64
```

In [32]:
```
df["normalized-losses"].fillna(115,inplace=True)
```

In [33]:
```
df["num-of-doors"].fillna("four",inplace=True)
```

In [34]:
```
df["bore"].fillna(3.31,inplace=True)
```

In [35]:
```
df["stroke"].fillna(3.29,inplace=True)
```

In [36]:
```
df["horsepower"].fillna(95,inplace=True)
```

In [37]:
```
df["peak-rpm"].fillna(5200,inplace=True)
```

In [38]:
```
df.isnull().sum()
```

Out[38]:
```
symboling            0
normalized-losses    0
make                 0
fuel-type            0
aspiration           0
num-of-doors         0
body-style           0
drive-wheels         0
engine-location      0
wheel-base           0
length               0
width                0
height               0
curb-weight          0
engine-type          0
num-of-cylinders     0
engine-size          0
fuel-system          0
bore                 0
stroke               0
compression-ratio    0
horsepower           0
peak-rpm             0
city-mpg             0
highway-mpg          0
price                0
dtype: int64
```

In [39]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   symboling          200 non-null    int64  
 1   normalized-losses  200 non-null    object 
 2   make               200 non-null    object 
 3   fuel-type          200 non-null    object 
 4   aspiration         200 non-null    object 
 5   num-of-doors       200 non-null    object 
 6   body-style         200 non-null    object 
 7   drive-wheels       200 non-null    object 
 8   engine-location    200 non-null    object 
 9   wheel-base         200 non-null    float64
 10  length             200 non-null    float64
 11  width              200 non-null    float64
 12  height             200 non-null    float64
 13  curb-weight        200 non-null    int64  
 14  engine-type        200 non-null    object 
 15  num-of-cylinders   200 non-null    object 
 16  engine-size        200 non-null    int64  
 17  fuel-system        200 non-null    object 
 18  bore               200 non-null    object 
 19  stroke             200 non-null    object 
 20  compression-ratio  200 non-null    float64
 21  horsepower         200 non-null    object 
 22  peak-rpm           200 non-null    object 
 23  city-mpg           200 non-null    int64  
 24  highway-mpg        200 non-null    int64  
 25  price              200 non-null    int64  
dtypes: float64(5), int64(6), object(15)
memory usage: 40.8+ KB
```

In [40]:

```
df['bore'] = df['bore'].astype(float)
df['stroke'] = df['stroke'].astype(float)
df['horsepower'] = df['horsepower'].astype(int)
df['peak-rpm'] = df['peak-rpm'].astype(int)
df['normalized-losses'] = df['normalized-losses'].astype(int)
```

In [41]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   symboling          200 non-null    int64  
 1   normalized-losses  200 non-null    int32  
 2   make               200 non-null    object 
 3   fuel-type          200 non-null    object 
 4   aspiration         200 non-null    object 
 5   num-of-doors       200 non-null    object 
 6   body-style         200 non-null    object 
 7   drive-wheels       200 non-null    object 
 8   engine-location    200 non-null    object 
 9   wheel-base         200 non-null    float64
 10  length             200 non-null    float64
 11  width              200 non-null    float64
 12  height             200 non-null    float64
 13  curb-weight        200 non-null    int64  
 14  engine-type        200 non-null    object 
 15  num-of-cylinders   200 non-null    object 
 16  engine-size        200 non-null    int64  
 17  fuel-system        200 non-null    object 
 18  bore               200 non-null    float64
 19  stroke             200 non-null    float64
 20  compression-ratio  200 non-null    float64
 21  horsepower         200 non-null    int32  
 22  peak-rpm           200 non-null    int32  
 23  city-mpg           200 non-null    int64  
 24  highway-mpg        200 non-null    int64  
 25  price              200 non-null    int64  
dtypes: float64(7), int32(3), int64(6), object(10)
memory usage: 38.4+ KB
```

Insights: Changing the datatype of below mentioned five features as they all are in string datatype Converting "bore" , "stroke" to float64 datatype Converting "horsepower" and "peak-rpm ","normalized-losses" to int64 datatype

# Encoding

In [42]:
```
from sklearn.preprocessing import LabelEncoder
lc=LabelEncoder()
```

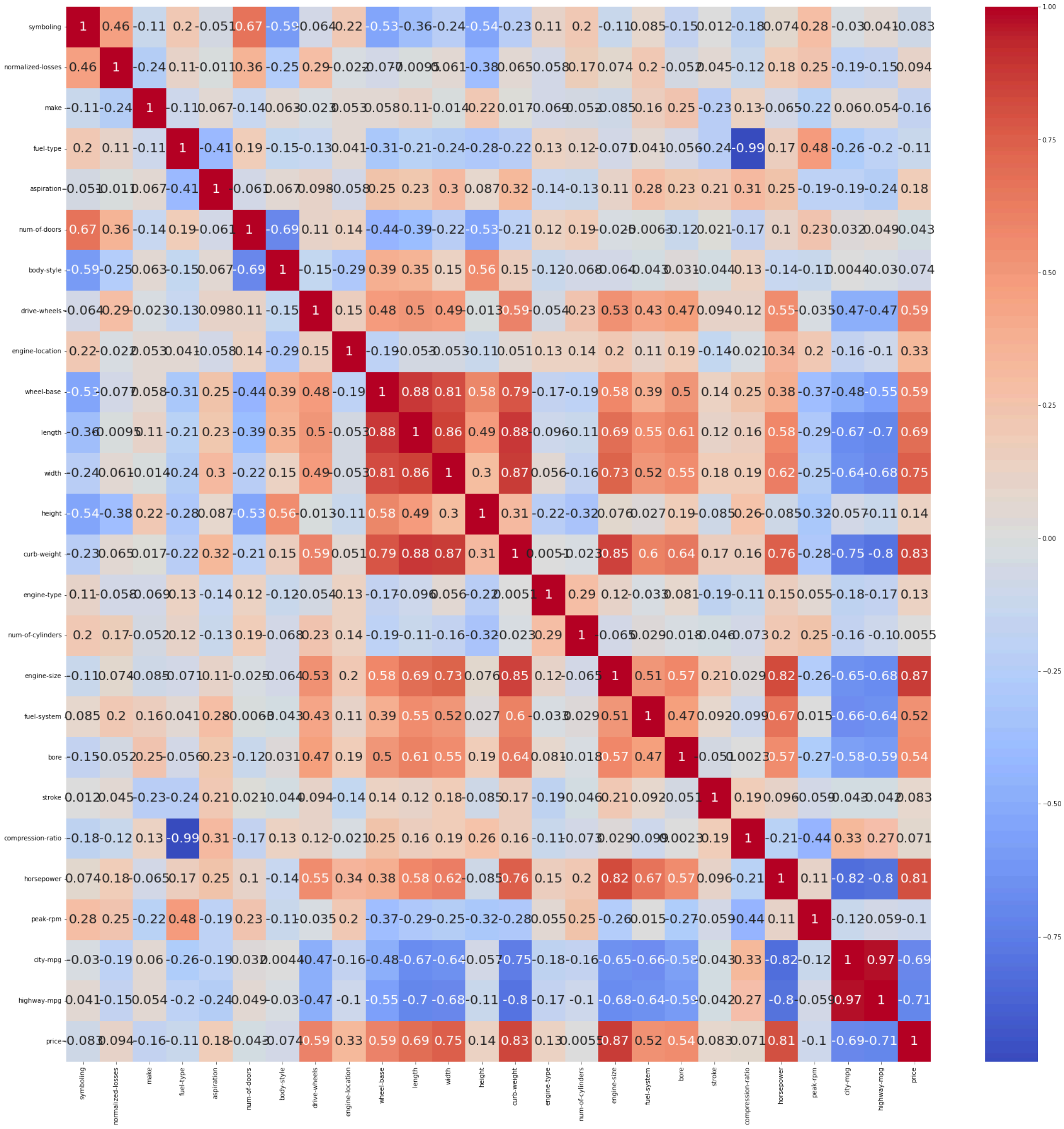
In [43]:
```
for i in df.select_dtypes(include="object"):
    df[i]=lc.fit_transform(df[i])
```

# Feature Selection

In [44]:
```
corr = df.corr()
```

In [45]:
```
plt.figure(figsize=(30,30))
sns.heatmap(df.corr(),annot=True,cmap="coolwarm",annot_kws={"size":20})
```

Out[45]: <Axes: >



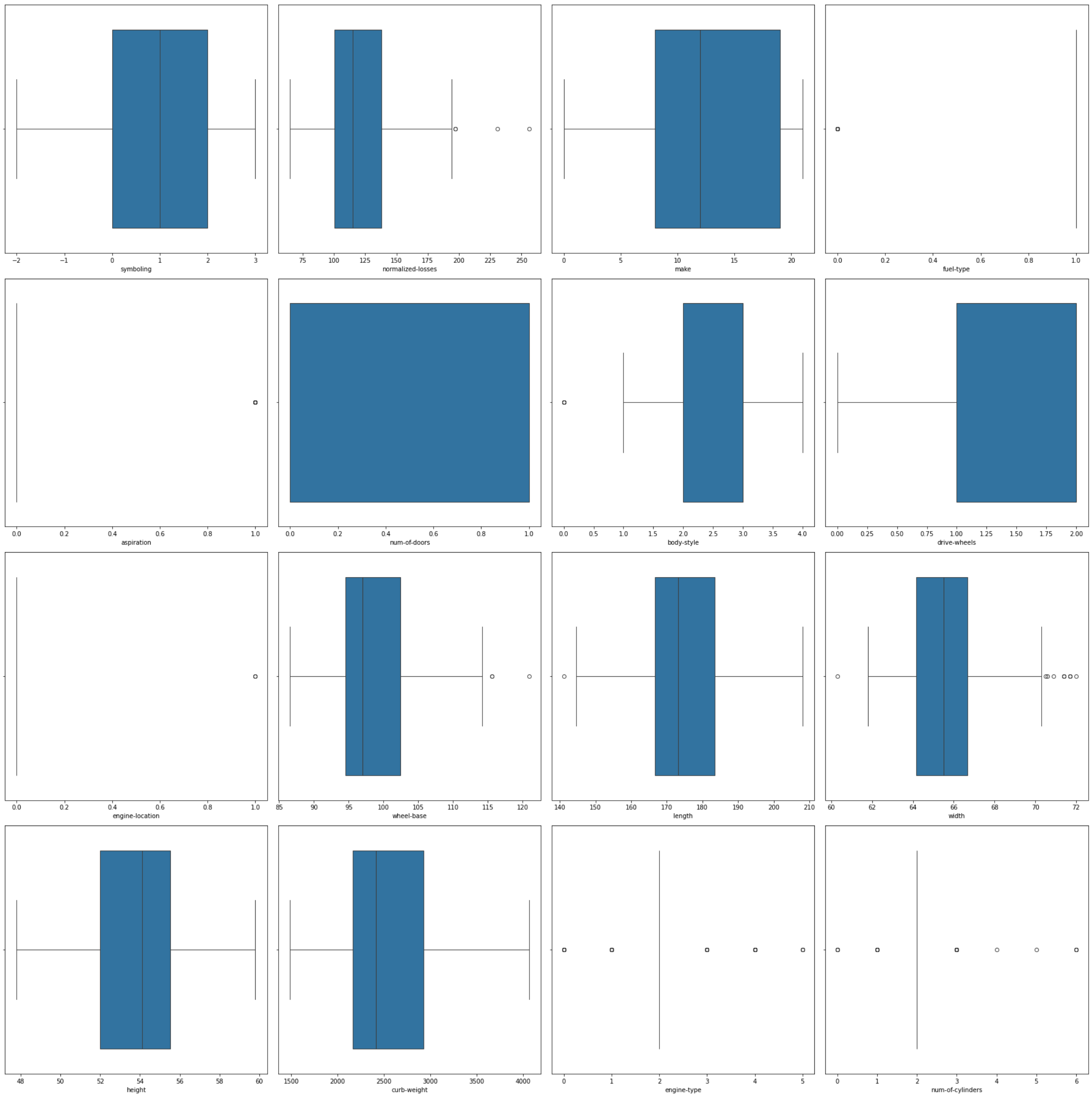
Insights: High correlation between length and wheel-base - 87% High correlation between width and length -85% High correlation between length and curbweight - 88% High correlation between width and curbweight - 86 High correlation between City mpg and high mpg -97 Horsepower and engine_size are highly correlated with price

# Outliers

In [46]:
```
df_num1=df.select_dtypes(exclude='object')
```

In [47]:

```
plt.figure(figsize=(25,25),facecolor='white')
plotnumber = 1
for column in df_num1:
    if plotnumber<=16:
        plt.subplot(4,4,plotnumber)
        sns.boxplot(x=df_num1[column])
        plt.xlabel(column)
    plotnumber+=1
plt.tight_layout()
```



In [48]:
```
Q1 = df_num1.quantile(0.25)
Q3 = df_num1.quantile(0.75)
IQR = Q3-Q1
min_value = Q1-1.5*IQR
max_value = Q3+1.5*IQR
outliers_count = ((df_num1>max_value) | (df_num1<min_value)).sum()
outliers_percentage = (outliers_count/len(df_num1))*100
print('\n Sum of outliers:\n',outliers_count)
print('\n Percentage of outliers:\n',outliers_percentage)
```

```
 Sum of outliers:
 symboling            0
normalized-losses     4
make                  0
fuel-type            20
aspiration           36
num-of-doors          0
body-style            5
drive-wheels          0
engine-location       3
wheel-base            3
length                1
width                11
height                0
curb-weight           0
engine-type          55
num-of-cylinders     44
engine-size          10
fuel-system           0
bore                  0
stroke               24
compression-ratio    27
horsepower            5
peak-rpm              2
city-mpg              2
highway-mpg           3
price                14
dtype: int64

 Percentage of outliers:
 symboling            0.0
normalized-losses     2.0
make                  0.0
fuel-type            10.0
aspiration           18.0
num-of-doors          0.0
body-style            2.5
drive-wheels          0.0
engine-location       1.5
wheel-base            1.5
length                0.5
width                 5.5
height                0.0
curb-weight           0.0
engine-type          27.5
num-of-cylinders     22.0
engine-size           5.0
fuel-system           0.0
bore                  0.0
stroke               12.0
compression-ratio    13.5
horsepower            2.5
peak-rpm              1.0
city-mpg              1.0
highway-mpg           1.5
price                 7.0
dtype: float64
```

In [49]:
```

Q1 = df["wheel-base"].quantile(0.25)
Q3 = df["wheel-base"].quantile(0.75)
IQR = Q3 - Q1

min_limit = Q1 - 1.5 * IQR
max_limit = Q3 + 1.5 * IQR

df.loc[(df["wheel-base"] < min_limit) | (df["wheel-base"] > max_limit),
```

In [50]:
```

Q1 = df.length.quantile(0.25)
Q3 = df.length.quantile(0.75)
IQR = Q3 - Q1

min_limit = Q1 - 1.5 * IQR
max_limit = Q3 + 1.5 * IQR

df.loc[(df.length < min_limit) | (df.length > max_limit), "length"] = d
```

In [51]:
```

Q1 = df.width.quantile(0.25)
Q3 = df.width.quantile(0.75)
IQR = Q3 - Q1
min_limit = Q1 - 1.5 * IQR
max_limit = Q3 + 1.5 * IQR
median_value = df.width.median()
df.loc[(df.width < min_limit) | (df.width > max_limit), "width"] = medi
```

In [52]:
```
# Calculate Q1, Q3, and IQR for the 'engine-size' column in the df data
Q1 = df["engine-size"].quantile(0.25)
Q3 = df["engine-size"].quantile(0.75)
IQR = Q3 - Q1

min_limit = Q1 - 1.5 * IQR
max_limit = Q3 + 1.5 * IQR
median_value = df["engine-size"].median()
df.loc[(df["engine-size"] < min_limit) | (df["engine-size"] > max_limit
```

In [53]:
```
# Calculate Q1, Q3, and IQR for the 'highway-mpg' column in the df data
Q1 = df["highway-mpg"].quantile(0.25)
Q3 = df["highway-mpg"].quantile(0.75)
IQR = Q3 - Q1
min_limit = Q1 - 1.5 * IQR
max_limit = Q3 + 1.5 * IQR
median_value = df["highway-mpg"].median()
df.loc[(df["highway-mpg"] < min_limit) | (df["highway-mpg"] > max_limit
```

In [54]:
```
# Calculate Q1, Q3, and IQR for the 'city-mpg' column in the df dataset
Q1 = df["city-mpg"].quantile(0.25)
Q3 = df["city-mpg"].quantile(0.75)
IQR = Q3 - Q1
min_limit = Q1 - 1.5 * IQR
max_limit = Q3 + 1.5 * IQR
median_value = df["city-mpg"].median()
df.loc[(df["city-mpg"] < min_limit) | (df["city-mpg"] > max_limit), "ci
```

Insights: The IQR is used to identify potential outliers in the fare data. Observations that fall below the first quartile (Q1 - 1.5 * IQR) or above the third quartile (Q3 + 1.5 * IQR) are considered outliers. These outliers may represent unusually high or low fare prices that deviate significantly from the typical range. I have use IQR Trimming method to handle outliers.

# Splitting the data

In [55]:
```
df
```

Out[55]:

| | symboling | normalized-losses | make | fuel-type | aspiration | num-of-doors | body-style | drive-wheels | engine-location | wheel-base |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 3 | 115 | 0 | 1 | 0 | 1 | 0 | 2 | 0 | 88.6 |
| **1** | 1 | 115 | 0 | 1 | 0 | 1 | 2 | 2 | 0 | 94.5 |
| **2** | 2 | 164 | 1 | 1 | 0 | 0 | 3 | 1 | 0 | 99.8 |
| **3** | 2 | 164 | 1 | 1 | 0 | 0 | 3 | 0 | 0 | 99.4 |
| **4** | 2 | 115 | 1 | 1 | 0 | 1 | 3 | 1 | 0 | 99.8 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **195** | -1 | 95 | 21 | 1 | 0 | 0 | 3 | 2 | 0 | 109.1 |
| **196** | -1 | 95 | 21 | 1 | 1 | 0 | 3 | 2 | 0 | 109.1 |
| **197** | -1 | 95 | 21 | 1 | 0 | 0 | 3 | 2 | 0 | 109.1 |
| **198** | -1 | 95 | 21 | 0 | 1 | 0 | 3 | 2 | 0 | 109.1 |
| **199** | -1 | 95 | 21 | 1 | 1 | 0 | 3 | 2 | 0 | 109.1 |

200 rows × 26 columns

In [56]:
```
x=df.drop('price',axis=1)
y=df.price
```

In [57]:
```
from sklearn.model_selection import train_test_split

# Split the data into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2
```

# Model Implementation

# Linear Regression

In [58]:
```
from sklearn.linear_model import LinearRegression
model_linear=LinearRegression()
model_linear.fit(x_train,y_train)
```

Out[58]:
```
▾ LinearRegression
LinearRegression()
```
(https://scikit-learn.org/1.5/modules/generated/sklearn.linear_model.LinearReg

In [59]:
```
y_pred_linear=model_linear.predict(x_test)
```

In [60]:
```
y_pred_linear
```

Out[60]:
```
array([ 9915.04916127, 31782.42292185,  7130.97208029,  7496.57366004,
       14111.25004028,  7108.59450565, 43046.95192822, 11359.03848107,
       17000.23028734, 47802.35939439, 25700.81094422, 10621.71240563,
       14230.34102249, 12464.31793577, 12868.35116601,  9785.8945048 ,
       10070.79873787,  6768.65658858,  9039.44469075, 36083.24232143,
       34114.87222211,  1779.46890469,  6010.74679761,  5615.26325975,
       24215.82114129, 10714.43853377, 12599.07457514, 37915.04059152,
        8758.29549748, 18131.31616503, 15113.79332728,  7215.2845387 ,
       10335.83579802,  8025.37480983, 11261.24614175, 16874.93502213,
        6942.34878448, 10225.18516926, 12833.7610831 , 10117.29189059])
```

In [61]:
```
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute
```

In [62]:
```
r2_score(y_test,y_pred_linear)
```

Out[62]:
```
0.9234115506357172
```

In [63]:
```
mae_l = mean_absolute_error(y_test,y_pred_linear)
mae_l
```

Out[63]:
```
2066.130558006506
```

In [64]:
```
mean_squared_error(y_test,y_pred_linear)
```

Out[64]:
```
8581598.230532113
```

# SVM

In [65]:
```
from sklearn.svm import SVR
model_svr=SVR(kernel="linear")
model_svr.fit(x_train,y_train)
```

Out[65]:
```
▾ SVR
SVR(kernel='linear')
```
(https://scikit-learn.org/1.5/modules/generated/sklearn.svm.SVR.html)

In [66]:
```
y_pred_svr=model_svr.predict(x_test)
```

In [67]:
```
y_pred_svr
```

Out[67]:
```
array([ 9873.0896059 , 25884.08776724,  5546.20664648,  7938.69019517,
       13491.40362223,  8766.93673316, 29432.62520394, 10059.47060175,
       17225.75420411, 33830.85400324, 22534.182018  ,  9809.27100996,
       12605.51621765, 15177.64359222, 11940.87736385,  8450.67466052,
       10460.82720189,  6908.75499466, 10106.77394456, 25025.74458465,
       16015.65810931,  2957.61078745,  8138.98319323,  6864.6836709 ,
       19843.23360352, 10592.84718596, 12049.81000312, 26156.07903772,
       11135.81172676, 17496.91479845, 12472.38432033,  6501.07654876,
       10346.9622465 ,  9450.52150694, 14795.64838875, 17526.86858774,
        7658.92213965,  8366.58055576, 11572.50482398, 11904.47819174])
```

# Model Evaluation

In [68]:
```
r2_score(y_test,y_pred_svr)
```

Out[68]:
```
0.7440620541678071
```

In [69]:
```
mae_svr = mean_absolute_error(y_test,y_pred_svr)
mae_svr
```

Out[69]:
```
3237.533880286669
```

# Decision Tree

In [70]:
```
from sklearn.tree import DecisionTreeRegressor
model_dt=DecisionTreeRegressor(random_state=2)
model_dt.fit(x_train,y_train)
y_pred_dt=model_dt.predict(x_test)
y_pred_dt
```

Out[70]:
```
array([ 9549., 35550.,  5572.,  8238., 15510.,  7957., 45400., 11248.,
       16558., 45400., 15690., 11395., 11549., 12764., 12290.,  7995.,
       10245.,  7799.,  6989., 14489., 33278.,  6479.,  7898.,  7349.,
       25552., 10595.,  9279., 16695., 11850., 18420., 16430.,  6295.,
       10595.,  7957., 18344., 17425.,  7898.,  7898.,  8449.,  9279.])
```

In [71]:
```
r2_score(y_test,y_pred_dt)
```

Out[71]:
```
0.7184633690609572
```

In [72]:
```
mae_dt = mean_absolute_error(y_test,y_pred_dt)
mae_dt
```

Out[72]:
```
2859.225
```

# Gradient Boosting

In [73]:
```
from sklearn.ensemble import GradientBoostingRegressor
model_gbm=GradientBoostingRegressor()
model_gbm.fit(x_train,y_train)
y_pred_gbm=model_gbm.predict(x_test)
y_pred_gbm
```

Out[73]:
```
array([ 9157.20446038, 35508.19318592,  6129.31856503,  8063.79628056,
       15071.90880431,  8629.38867512, 39339.60987859, 10795.68983724,
       16559.43266956, 42133.62714267, 24409.9083935 ,  8322.17082635,
       12920.2849253 , 13783.28300234, 13501.93891667,  8095.92424214,
       10200.24839399,  7473.88195197,  8390.95829959, 20711.58586633,
       33390.35791959,  6553.96078316,  7349.65785207,  7336.264734  ,
       21622.99608045, 10200.24839399,  9418.41025083, 23982.28522858,
       11378.38143081, 17536.84114124, 16069.88583153,  6279.36329758,
       10220.17885699,  8628.15056251, 12730.02753914, 17118.95992168,
        7289.60626941,  7893.41311095, 10550.11123097,  9781.76516211])
```

In [74]:
```
r2_score(y_test,y_pred_gbm)
```

Out[74]:
```
0.8832328172290832
```

In [75]:
```
mae_gb = mean_absolute_error(y_test,y_pred_gbm)
mae_gb
```

Out[75]:
```
2076.3513874205555
```

# XGB

In [76]:
```
#pip install xgboost
```

In [77]:
```
from xgboost import XGBRegressor
model_xgb=XGBRegressor(n_estimators=100)
model_xgb.fit(x_train,y_train)
y_pred_xgb=model_xgb.predict(x_test)
y_pred_xgb
```

Out[77]:
```
array([ 9921.649 , 37658.69  ,  5941.4136,  8266.301 , 15352.309 ,
        7985.8525, 41730.312 , 11000.06  , 16483.79  , 40500.08  ,
       17515.154 ,  9487.906 , 12829.441 , 14387.3545, 12566.081 ,
        7870.2964, 10250.673 ,  7679.751 ,  7921.738 , 21464.926 ,
       33529.68  ,  7134.045 ,  7644.1475,  7522.9526, 25330.305 ,
       10307.175 ,  9413.849 , 20536.064 , 11584.808 , 18246.033 ,
       15589.874 ,  6581.31  , 10591.991 ,  7976.533 , 14862.089 ,
       17527.266 ,  7169.25  ,  7620.946 ,  8881.352 ,  9158.242 ],
      dtype=float32)
```

In [78]:
```python
r2_score(y_test,y_pred_xgb)
```

Out[78]: 0.8422092199325562

In [79]:
```python
mae_xgb = mean_absolute_error(y_test,y_pred_xgb)
mae_xgb
```

Out[79]: 2251.9832763671875

# Bagging

In [80]:
```python
from sklearn.ensemble import BaggingRegressor
model_bag=BaggingRegressor(estimator=model_gbm,n_estimators=20)
model_bag.fit(x_train,y_train)

```

Out[80]:
```
▸ BaggingRegressor
(https://scikit-learn.org/1.5/modules/generated/sklearn.ensen
▸ estimator: GradientBoostingRegressor
  ▸ GradientBoostingRegressor
(https://scikit-learn.org/1.5/modules/generated/sklearn.ensemble.
```

In [81]:
```python
y_pred_bag=model_bag.predict(x_test)
```

# Model Evaluation

In [82]:
```python
r2_score(y_test,y_pred_bag)
```

Out[82]: 0.9116752771509442

In [83]:
```python
mae_b = mean_absolute_error(y_test,y_pred_bag)
mae_b
```

Out[83]: 1956.0755528062757

# Lasso

In [84]:
```python
from sklearn.linear_model import Lasso,Ridge
```

In [85]:
```python
lasso_model = Lasso(alpha=2.2)
# Fit the model to the training data
lasso_model.fit(x_train, y_train)
# Make predictions on the test data
y_pred_lasso = lasso_model.predict(x_test)
```

In [86]:
```
r2_score(y_test,y_pred_lasso)
```

Out[86]: 0.9265340513583995

In [87]:
```
mae_la = mean_absolute_error(y_test,y_pred_lasso)
mae_la
```

Out[87]: 2037.9742880251506

# Ridge

In [88]:
```
ridge_model = Ridge(alpha=0.011)
# Fit the model to the training data
ridge_model.fit(x_train, y_train)
# Make predictions on the test data
y_pred_ridge = ridge_model.predict(x_test)
```

In [89]:
```
r2_score(y_test,y_pred_ridge)
```

Out[89]: 0.924726685952573

In [90]:
```
mae_rid = mean_absolute_error(y_test,y_pred_ridge)
mae_rid
```

Out[90]: 2055.977491680604

# Hyperparameter Tuning

In [91]:
```
gbr = GradientBoostingRegressor()
# Define the parameter grid
from sklearn.model_selection import RandomizedSearchCV
param_grid = {
 'n_estimators': [100, 200, 300],
 'learning_rate': [0.001, 0.01, 0.1, 0.2],
 'max_depth': [3, 4, 5, 6],
 'min_samples_split': [2, 5, 10],
 'min_samples_leaf': [1, 2, 4],
 'subsample': [0.8, 0.9, 1.0]
}
# Set up the grid search with cross-validation
random_search = RandomizedSearchCV(estimator=gbr, param_distributions=p
                                   n_iter=100, cv=3, verbose=2, random_
# Fit the model
random_search.fit(x_train, y_train)
# Get the best parameters
best_params = random_search.best_params_
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
```

In [92]:
```
print(f"Best parameters found: {best_params}")
```

```
Best parameters found: {'subsample': 1.0, 'n_estimators': 200, 'min_sample
s_split': 5, 'min_samples_leaf': 1, 'max_depth': 3, 'learning_rate': 0.2}
```

In [93]:
```
best_gbr = GradientBoostingRegressor(**best_params)
best_gbr.fit(x_train, y_train)
# Make predictions on the test data
y_pred_gbrhyper = best_gbr.predict(x_test)
```

In [94]:
```
r2_score(y_test,y_pred_gbrhyper)
```

Out[94]:
```
0.8802673863183585
```

In [95]:
```
print("Feature Importances:", best_gbr.feature_importances_)
```

```
Feature Importances: [2.84261674e-03 1.06077081e-03 1.38845942e-02 3.11265
109e-06
 1.12838563e-02 1.21426654e-02 3.79049503e-03 1.36834128e-03
 0.00000000e+00 1.29201827e-02 6.38782382e-02 1.83758847e-02
 9.52495772e-03 4.89156956e-01 4.39231094e-05 9.17756612e-04
 4.41826569e-03 5.49343483e-04 1.61420245e-03 9.69600965e-03
 4.46153078e-03 3.11249504e-01 4.21861975e-03 1.94306855e-02
 3.16748678e-03]
```

# Decision Tree

In [96]:
```
dt_regressor = DecisionTreeRegressor()
# Define the parameter grid
params = {
 "criterion": ["mse", "friedman_mse", "mae"], # function to measure the
 "splitter": ["best", "random"], # strategy used to choose t
 "max_depth": list(range(1, 20)), # maximum depth of the tree
 "min_samples_split": [2, 3, 4], # minimum number of samples
 "min_samples_leaf": list(range(1, 20)), # minimum number of samples
}
random_search = RandomizedSearchCV(estimator=dt_regressor,
                                   param_distributions=params,
                                   n_iter=100, cv=3, verbose=2, random_

# Fit the grid search to the training data
random_search.fit(x_train, y_train)

# Get the best parameters
best_params = random_search.best_params_
print("Best Parameters:", best_params)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
Best Parameters: {'splitter': 'best', 'min_samples_split': 2, 'min_samples
_leaf': 5, 'max_depth': 3, 'criterion': 'friedman_mse'}
```

In [97]:
```
best_dt = DecisionTreeRegressor(**best_params)
best_dt.fit(x_train, y_train)
```

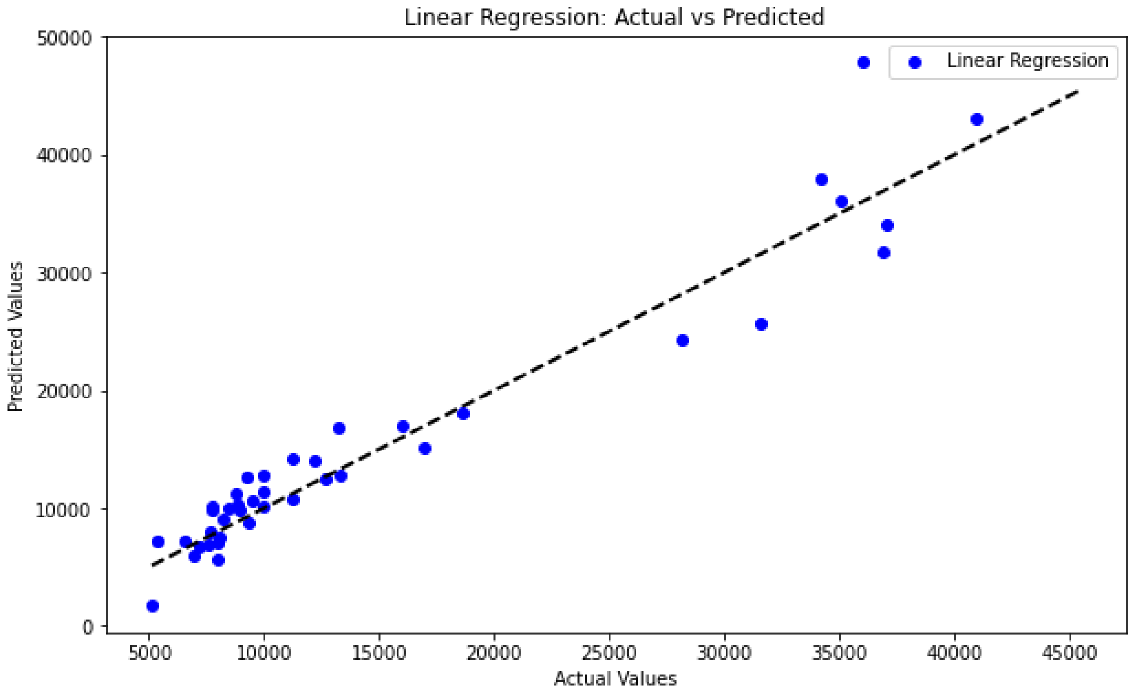
Out[97]:
```
DecisionTreeRegressor
DecisionTreeRegressor(criterion='friedman_mse', max_depth=3, min_samples_
leaf=5)
```

In [98]:
```
y_pred_dthyper = best_gbr.predict(x_test)
```

In [99]:
```
r2_score(y_test,y_pred_dthyper)
```

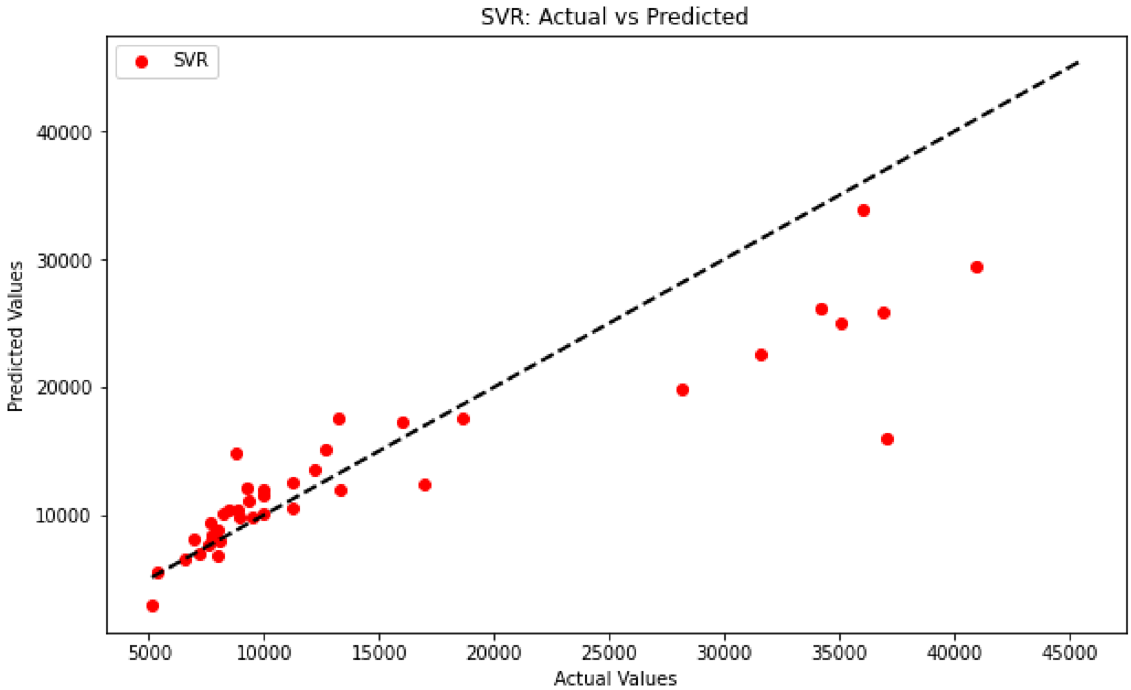
Out[99]: 0.8802673863183585

In [100]:
```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_linear, color='blue', label='Linear Regressi
plt.plot([y.min(),y.max()],[y.min(),y.max()],"k--",lw=2)
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Linear Regression: Actual vs Predicted')
plt.legend()
plt.show()

```



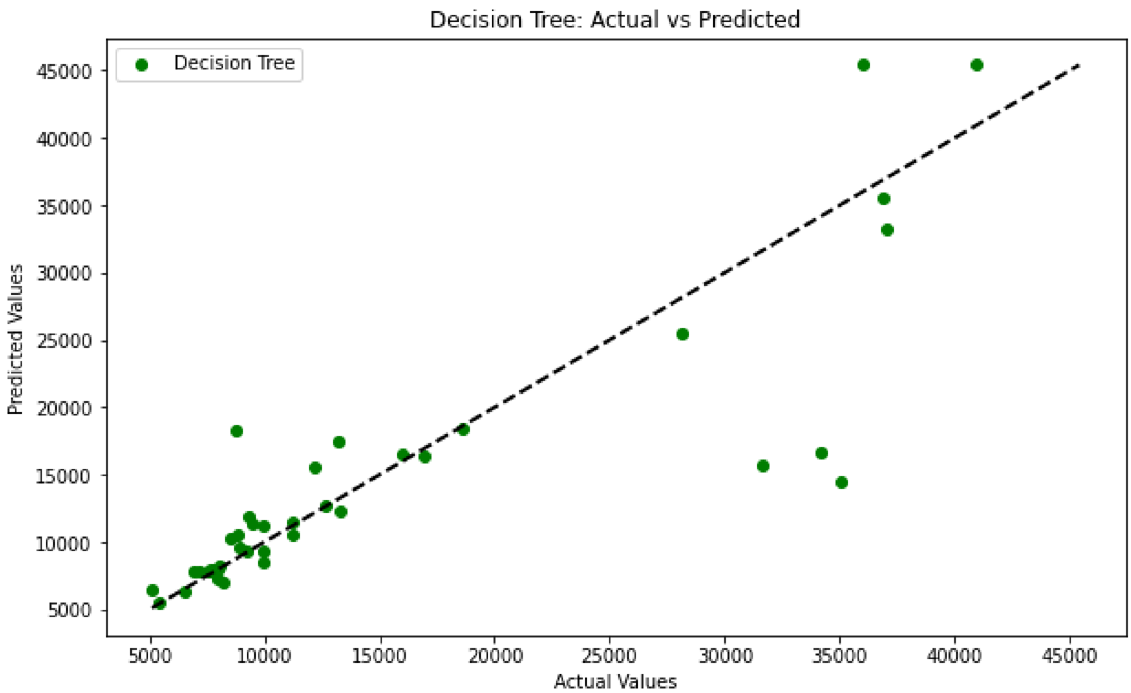
In [101]:

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_svr, color='red', label='SVR')
plt.plot([y.min(),y.max()],[y.min(),y.max()],"k--",lw=2)
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('SVR: Actual vs Predicted')
plt.legend()
plt.show()

```



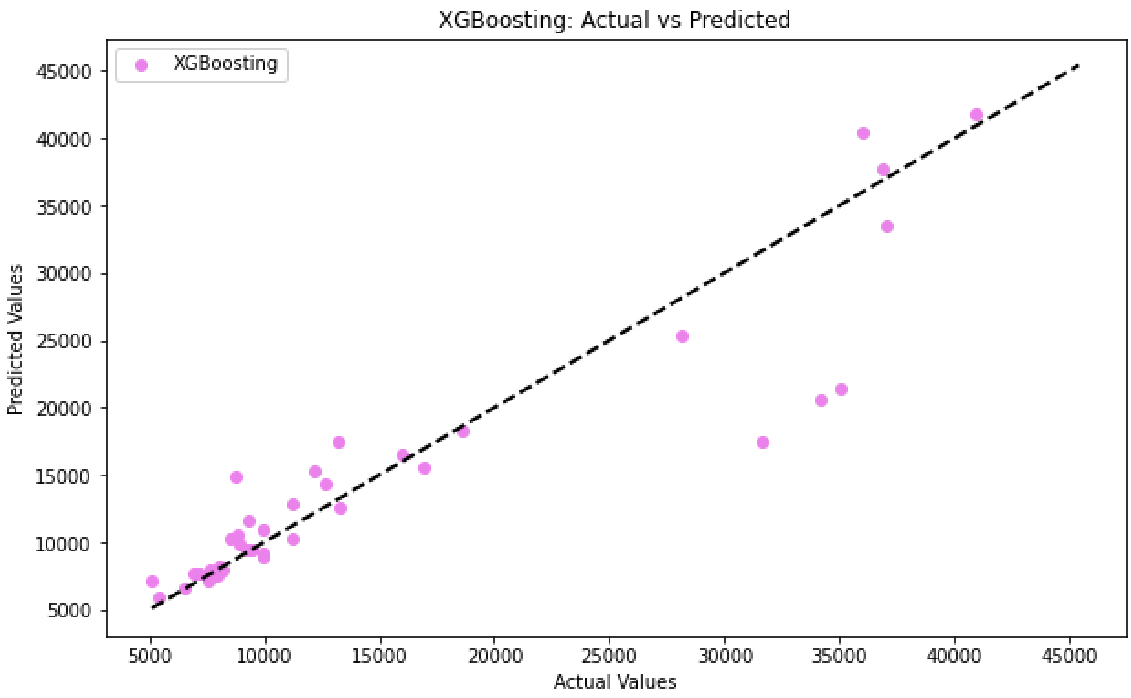
In [102]:

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_dt, color='green', label='Decision Tree')
plt.plot([y.min(),y.max()],[y.min(),y.max()],"k--",lw=2)
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Decision Tree: Actual vs Predicted')
plt.legend()
plt.show()

```



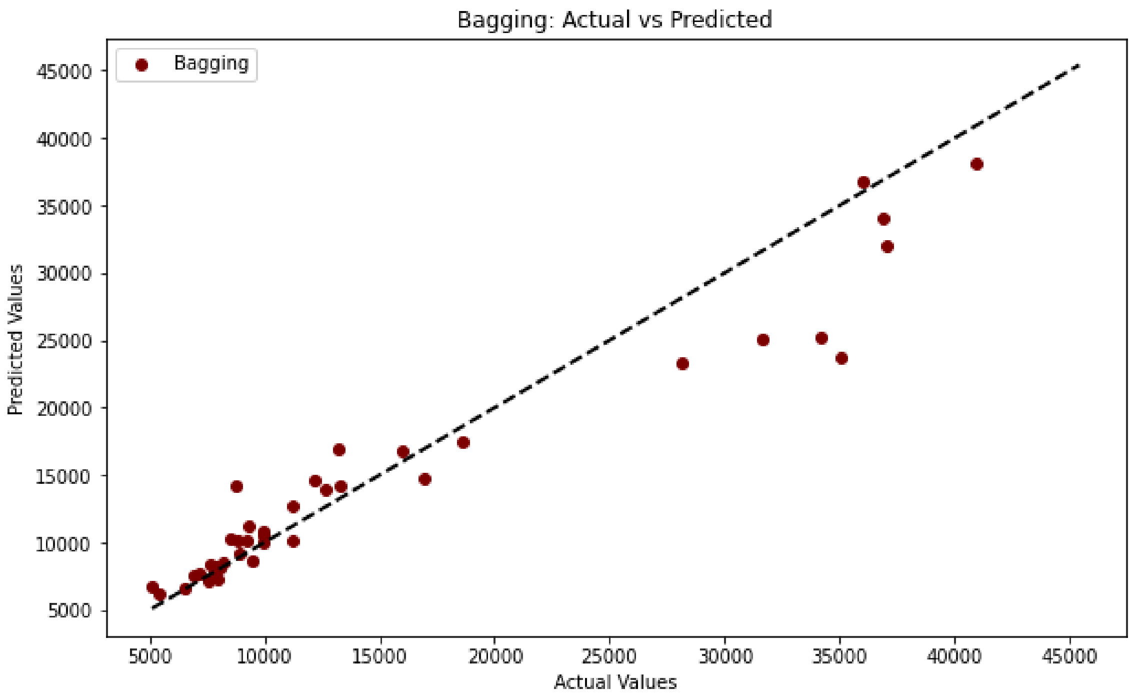
In [103]:

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_xgb, color='violet', label='XGBoosting')
plt.plot([y.min(),y.max()],[y.min(),y.max()],"k--",lw=2)
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('XGBoosting: Actual vs Predicted')
plt.legend()
plt.show()

```



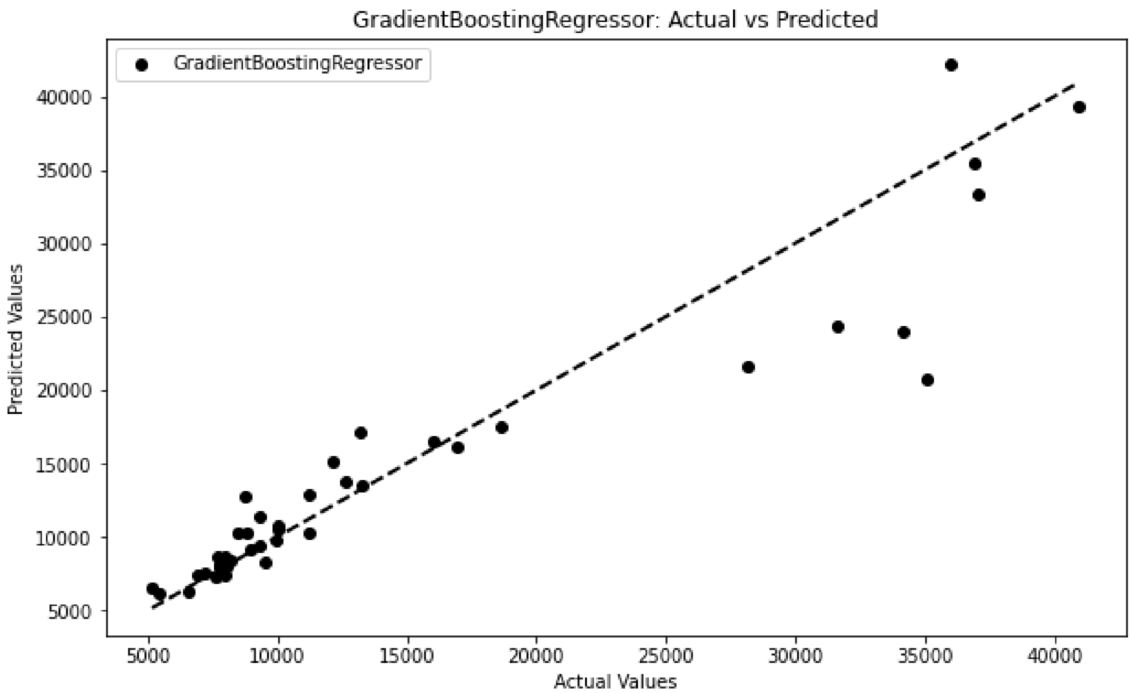
In [104]:

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_bag, color='maroon', label='Bagging')
plt.plot([y.min(),y.max()],[y.min(),y.max()],"k--",lw=2)
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Bagging: Actual vs Predicted')
plt.legend()
plt.show()

```



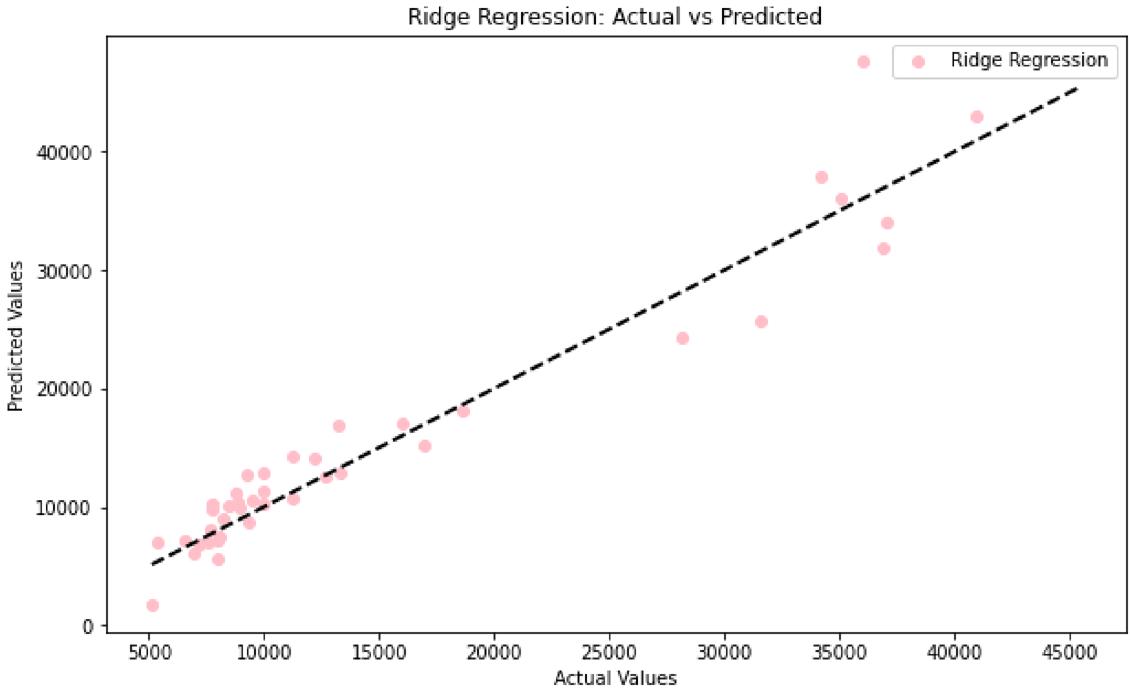
In [105]:

```

plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_gbm, color='black', label='GradientBoostingR
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], "k
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('GradientBoostingRegressor: Actual vs Predicted')
plt.legend()
plt.show()

```



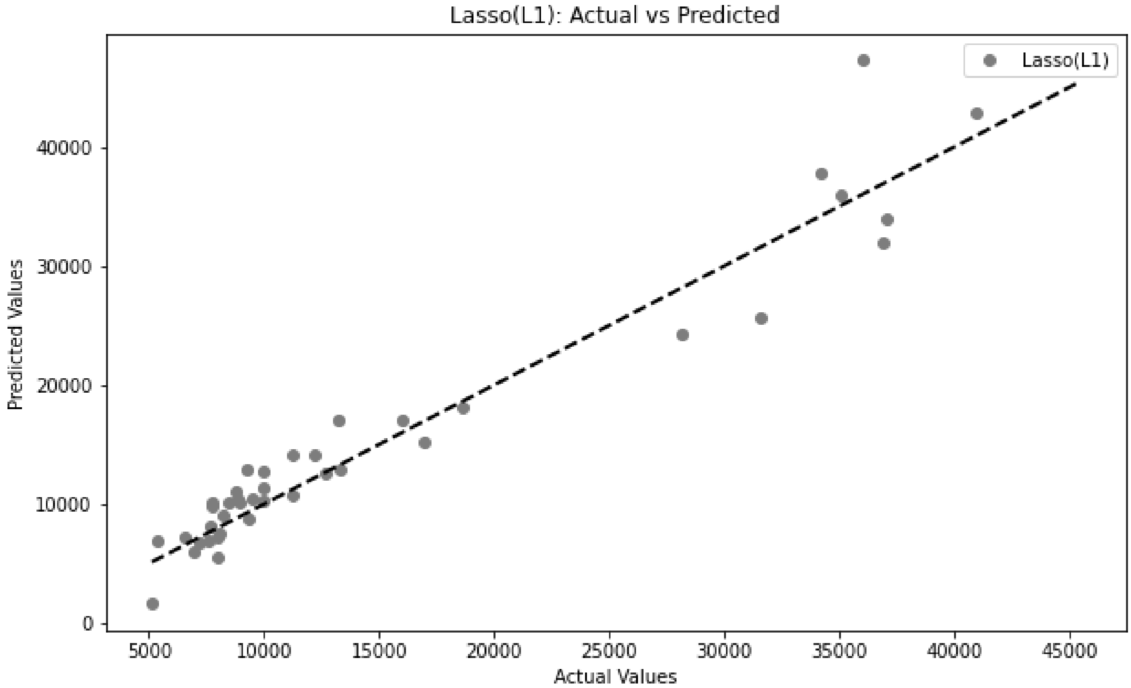
In [106]:

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_ridge, color='pink', label='Ridge Regressio
plt.plot([y.min(),y.max()],[y.min(),y.max()],"k--",lw=2)
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Ridge Regression: Actual vs Predicted')
plt.legend()
plt.show()
```



In [107]:

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_lasso, color='grey', label='Lasso(L1)')
plt.plot([y.min(),y.max()],[y.min(),y.max()],"k--",lw=2)
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Lasso(L1): Actual vs Predicted')
plt.legend()
plt.show()
```




Model comparison Report

1) Linear Regression: The Linear Regression model did not yield good accuracy,indicating poor accuracy and suboptimal performance 2) Support Vector Regressor: The Support Vector Regression (SVR) model yielded a low $R^2$ score and also did not yield good accuracy. While Support Vector Machines typically perform well with non-linear data, SVR did not perform well in this instance. 3) Decision Tree : The Decision Tree model demonstrated good accuracy in predicting car prices. Although Decision Trees are prone to overfitting, this issue was well-managed in this case, resulting in minimal overfitting. 4) Bagging : Bagging demonstrates strong performance compared to the previous models, yielding favorable accuracy results.

# Challenges Faced Report

A smaller dataset containing only 200 rows can contribute to model overfitting or inaccurate predictions, thereby compromising the efficacy of car price prediction models. Identifying unknown values represented by "?" in the dataset proved to be a challenging and laborious task. This process required extensive effort and attention to detail, as these unknown values could potentially introduce errors or inaccuracies into the analysis. Due to the dataset's limited size and absence of make, model year, and sale price year, the analysis faced challenges in extracting meaningful insights. Hyperparameter tuning proved to be a demanding endeavor, requiring thorough adjustment of parameters tailored to each model to enhance accuracy. Conclusion The strong performance of Gradient Bossting model suggests they are well-suited for this task, likely due to their ability to handle non-linear relationships and interactions within the dataset. This highlights their robustness and potential for delivering reliable predictions in similar applications. Automobile car price prediction encounters various challenges, spanning from data quality and availability to the intricate dynamics of pricing and vehicle specifications. Effectively tackling these hurdles demands a comprehensive approach, integrating collaborative data efforts, advanced modeling methodologies, and domain expertise

In [ ]:

```

```