Car Price Prediction - Supervised ML

Problem Statement:

A Chinese automobile company aspires to enter the US market by setting up their manufacturing unit there and producing cars locally to give competition to their US and European counterparts. They have contracted an automobile consulting company to understand the factors on which the pricing of cars depends. Specifically, they want to understand the factors affecting the pricing of cars in the American market, since those may be very different from the Chinese market.

You are required to model the price of cars with the available independent variables from given dataset. It will be used by the management to understand how exactly the prices vary with the independent variables. They can accordingly manipulate the design of the cars, the business strategy etc. to meet certain price levels. Further, the model will be a good way for the management to understand the pricing dynamics of a new market.

Essentially, the company wants to know:

- Which variables are significant in predicting the price of a car
- How well those variables describe the price of a car

Dataset: https://drive.google.com/file/d/1FHmYNLs9v0Enc-UExEMpitOFGsWvB2dP/view?usp=drive_link

IMPORTING GENERAL LIBRARIES

In [1]:
```
import numpy as np
import pandas as pd
pd.pandas.set_option('display.max_columns',None)
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set_theme(palette='flare')
import warnings
warnings.filterwarnings('ignore')
```

IMPORTING DATASET

In [2]:
```
df=pd.read_csv('CarPrice.csv')
```

INITIAL INFO ON DATASET

In [3]:
```
rows,cols=df.shape
print(f'Dataset has {rows} rows and {cols} columns')
```

```
Dataset has 205 rows and 26 columns
```

Columns in Dataset

In [4]:
```
print(f'Columns in dataset are\n\n{df.columns}')
```

```
Columns in dataset are

Index(['car_ID', 'symboling', 'CarName', 'fueltype', 'aspiration',
       'doornumber', 'carbody', 'drivewheel', 'enginelocation', 'wheelbase',
       'carlength', 'carwidth', 'carheight', 'curbweight', 'enginetype',
       'cylindernumber', 'enginesize', 'fuelsystem', 'boreratio', 'stroke',
       'compressionratio', 'horsepower', 'peakrpm', 'citympg', 'highwaympg',
       'price'],
      dtype='object')
```

Each car (row or entry) has 26 columns associated with it including the target, 'price'.

Displaying 5 Random Rows

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

Out[5]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drive
95	96	1	nissan juke	gas	std	two	hatchback	
193	194	0	volkswagen dasher	gas	std	four	wagon	
75	76	1	mercury cougar	gas	turbo	two	hatchback	
58	59	3	mazda glc 4	gas	std	two	hatchback	
111	112	0	peugeot 504	gas	std	four	sedan	

Dataset Info

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   car_ID            205 non-null    int64  
 1   symboling         205 non-null    int64  
 2   CarName           205 non-null    object 
 3   fueltype          205 non-null    object 
 4   aspiration        205 non-null    object 
 5   doornumber        205 non-null    object 
 6   carbody           205 non-null    object 
 7   drivewheel        205 non-null    object 
 8   enginelocation    205 non-null    object 
 9   wheelbase         205 non-null    float64
 10  carlength         205 non-null    float64
 11  carwidth          205 non-null    float64
 12  carheight         205 non-null    float64
 13  curbweight        205 non-null    int64  
 14  enginetype        205 non-null    object 
 15  cylindernumber    205 non-null    object 
 16  enginesize        205 non-null    int64  
 17  fuelsystem        205 non-null    object 
 18  boreratio         205 non-null    float64
 19  stroke            205 non-null    float64
 20  compressionratio  205 non-null    float64
 21  horsepower        205 non-null    int64  
 22  peakrpm           205 non-null    int64  
 23  citympg           205 non-null    int64  
 24  highwaympg        205 non-null    int64  
 25  price             205 non-null    float64
dtypes: float64(8), int64(8), object(10)
memory usage: 41.8+ KB
```

Sl. No.	Column	Description	Type
1	**car_ID**	unique car id	Numerical/Int64
2	**symboling**	insurance risk rating of car (-ve => low risk, +ve => high risk)	Numerical/Int64
3	**CarName**	make and model of car	Categorical/Object
4	**fueltype**	type of fuel (gas or diesel)	Categorical/Object
5	**aspiration**	type of engine aspiration (air intake)	Categorical/Object
6	**doornumber**	number of doors	Categorical/Object
7	**carbody**	body styles (convertible, hatchback, sedan, wagon etc.)	Categorical/Object
8	**drivewheel**	drivetrain configurations (RWD, FWD, 4WD etc.)	Categorical/Object
9	**enginelocation**	location of engine (front or rear)	Categorical/Object
10	**wheelbase**	distance between the center of the front wheels and the center of the rear wheels	Numerical/Float64
11	**carlength**	length of car in inches	Numerical/Float64
12	**carwidth**	width of car in inches	Numerical/Float64
13	**carheight**	height of car in inches	Numerical/Float64
14	**curbweight**	total weight of car without passengers, cargo, or any additional load	Numerical/Int64
15	**enginetype**	engine type (based on configuration and placement of the valves and camshaft)	Categorical/Object
16	**cylindernumber**	number of cylinders	Categorical/Object
17	**enginesize**	engine size in cubic inches	Numerical/Int64
18	**fuelsystem**	fuel system used in engine	Categorical/Object
19	**boreratio**	bore - diameter of engine cylinder in inches	Numerical/Float64
20	**stroke**	distance the piston travels within the cylinder in inches	Numerical/Float64
21	**compressionratio**	compression ratio (9.0 => 9:1)	Numerical/Float64
22	**horsepower**	engine horse power	Numerical/Int64
23	**peakrpm**	peak engine rpm	Numerical/Int64
24	**citympg**	mileage per gallon - city	Numerical/Int64
25	**highwaympg**	mileage per gallon - highway	Numerical/Int64
26	**price**	price in dollars ($)	Numerical/Float64

PREPARING DATASET

Checking for Null Values

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
car_ID              0
symboling           0
CarName             0
fueltype            0
aspiration          0
doornumber          0
carbody             0
drivewheel          0
enginelocation      0
wheelbase           0
carlength           0
carwidth            0
carheight           0
curbweight          0
enginetype          0
cylindernumber      0
enginesize          0
fuelsystem          0
boreratio           0
stroke              0
compressionratio    0
horsepower          0
peakrpm             0
citympg             0
highwaympg          0
price               0
dtype: int64
```

There are no entries with NaN or Null in any feature.

Checking for Duplicate Entries

In [8]:
```
df.duplicated().sum()
```

Out[8]:
```
0
```

There are no duplicate entries.

Seperating Numerical and Categorical Columns

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

Out[9]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drive
0	1	3	alfa-romero giulia	gas	std	two	convertible	
1	2	3	alfa-romero stelvio	gas	std	two	convertible	
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	
3	4	2	audi 100 ls	gas	std	four	sedan	
4	5	2	audi 100ls	gas	std	four	sedan	

In [10]:
```
df['symboling'].unique()
```

Out[10]:
```
array([ 3,  1,  2,  0, -1, -2], dtype=int64)
```

> Note:
>
> *it is better to convert column 'symboling' to type 'object'*

In [11]:
```
df['symboling'] = df['symboling'].astype('object')
```

In [12]:
```
numerical_columns = list(df.select_dtypes(include=['float64', 'int64']).columns)
categorical_columns=list(df.select_dtypes(include=['object']).columns)
```

Numerical Features

In [13]:
```
numerical_columns
```

Out[13]:
```
['car_ID',
 'wheelbase',
 'carlength',
 'carwidth',
 'carheight',
 'curbweight',
 'enginesize',
 'boreratio',
 'stroke',
 'compressionratio',
 'horsepower',
 'peakrpm',
 'citympg',
 'highwaympg',
 'price']
```

> Note:
>
> *The column 'car_ID' seems irrelevant and might have no role in determining the target*

In [14]:
```
df=df.drop(columns=['car_ID'], axis=1)
```

In [15]:
```
#rcreating a list of numerical features
numerical_features = numerical_columns.copy()
for feature in ['car_ID', 'price']:
    numerical_features.remove(feature)
```

In [16]:
```
 numerical_features
```

Out[16]:
```
['wheelbase',
 'carlength',
 'carwidth',
 'carheight',
 'curbweight',
 'enginesize',
 'boreratio',
 'stroke',
 'compressionratio',
 'horsepower',
 'peakrpm',
 'citympg',
 'highwaympg']
```

In [17]:
```
len(numerical_features)
```

Out[17]:
```
13
```

Categorical Features

In [18]:
```
categorical_columns
```

Out[18]:
```
['symboling',
 'CarName',
 'fueltype',
 'aspiration',
 'doornumber',
 'carbody',
 'drivewheel',
 'enginelocation',
 'enginetype',
 'cylindernumber',
 'fuelsystem']
```

In [19]:
```
for col in categorical_columns:
    print(df[col].value_counts(),"\n")
```

```
symboling
0     67
1     54
2     32
3     27
-1    22
-2     3
Name: count, dtype: int64

CarName
toyota corona           6
toyota corolla          6
peugeot 504             6
subaru dl               4
mitsubishi mirage g4    3
                       ..
mazda glc 4             1
mazda rx2 coupe         1
maxda glc deluxe        1
maxda rx3               1
volvo 246               1
Name: count, Length: 147, dtype: int64

fueltype
gas       185
diesel     20
Name: count, dtype: int64

aspiration
std      168
turbo     37
Name: count, dtype: int64

doornumber
four    115
two      90
Name: count, dtype: int64

carbody
sedan          96
hatchback      70
wagon          25
hardtop         8
convertible     6
Name: count, dtype: int64

drivewheel
fwd    120
rwd     76
4wd      9
Name: count, dtype: int64

enginelocation
front    202
rear       3
Name: count, dtype: int64

enginetype
ohc      148
ohcf      15
```

```
ohcv      13
dohc      12
l         12
rotor      4
dohcv      1
Name: count, dtype: int64

cylindernumber
four      159
six        24
five       11
eight       5
two         4
three       1
twelve      1
Name: count, dtype: int64

fuelsystem
mpfi    94
2bbl    66
idi     20
1bbl    11
spdi     9
4bbl     3
mfi      1
spfi     1
Name: count, dtype: int64
```

> ## Insight:
>
> *the column 'CarName' contains 147 unique values, which might increase the complexity of the project. Entries in 'CarName' appears to be in the format make[space]model. Extracting 'make' from the data might reduce the complexity while retaining significant information.*

In [20]:
```
#Extracting Make from 'CarName'
df['make'] = df['CarName'].apply(lambda x: x.split(' ')[0])
```

In [21]:
```
df['make'].value_counts()
```

Out[21]:
```
make
toyota         31
nissan         17
mazda          15
honda          13
mitsubishi     13
subaru         12
peugeot        11
volvo          11
volkswagen      9
dodge           9
buick           8
bmw             8
audi            7
plymouth        7
saab            6
isuzu           4
porsche         4
alfa-romero     3
chevrolet       3
jaguar          3
vw              2
maxda           2
renault         2
toyouta         1
vokswagen       1
Nissan          1
mercury         1
porcshce        1
Name: count, dtype: int64
```

In [22]:
```
df.make.nunique()
```

Out[22]:
```
28
```

In [23]:
```
df.make.unique()
```

Out[23]:
```
array(['alfa-romero', 'audi', 'bmw', 'chevrolet', 'dodge', 'honda',
       'isuzu', 'jaguar', 'maxda', 'mazda', 'buick', 'mercury',
       'mitsubishi', 'Nissan', 'nissan', 'peugeot', 'plymouth', 'porsche',
       'porcshce', 'renault', 'saab', 'subaru', 'toyota', 'toyouta',
       'vokswagen', 'volkswagen', 'vw', 'volvo'], dtype=object)
```

> ## Insight:
>
> *The derived feature 'make' contains misspelled make names and aliases*

In [24]:
```
#Correcting Misspelled Make Names and Replacing Aliases
df['make']=df['make'].replace({'maxda':'mazda', 'porcshce':'porsche', 'Nissan':'
```

In [25]:
```
df.make.nunique()
```

Out[25]:
```
22
```

In [26]:
```
df.make.unique()
```

Out[26]:
```
array(['alfa-romero', 'audi', 'bmw', 'chevrolet', 'dodge', 'honda',
       'isuzu', 'jaguar', 'mazda', 'buick', 'mercury', 'mitsubishi',
       'nissan', 'peugeot', 'plymouth', 'porsche', 'renault', 'saab',
       'subaru', 'toyota', 'volkswagen', 'volvo'], dtype=object)
```

In [27]:
```
#Dropping 'CarName' from dataset
df=df.drop(columns=['CarName'], axis=1)
```

In [28]:
```
#removing CarName from categorical features list
categorical_features = categorical_columns.copy()
categorical_features.remove('CarName')

#adding make to feature list
categorical_features.append('make')
```

Updated Dataset

In [29]:
```
df.shape
```

Out[29]:
```
(205, 25)
```

In [30]:
```
numerical_features
```

Out[30]:
```
['wheelbase',
 'carlength',
 'carwidth',
 'carheight',
 'curbweight',
 'enginesize',
 'boreratio',
 'stroke',
 'compressionratio',
 'horsepower',
 'peakrpm',
 'citympg',
 'highwaympg']
```

In [31]:
```
len(numerical_features)
```

Out[31]:
```
13
```

In [32]:
```
categorical_features
```

Out[32]:
```
['symboling',
 'fueltype',
 'aspiration',
 'doornumber',
 'carbody',
 'drivewheel',
 'enginelocation',
 'enginetype',
 'cylindernumber',
 'fuelsystem',
 'make']
```

In [33]:
```
len(categorical_features)
```

Out[33]: 11

There are total 13 *numerical features*, 11 *categorical features* and the target variable *price* in the updated dataset.

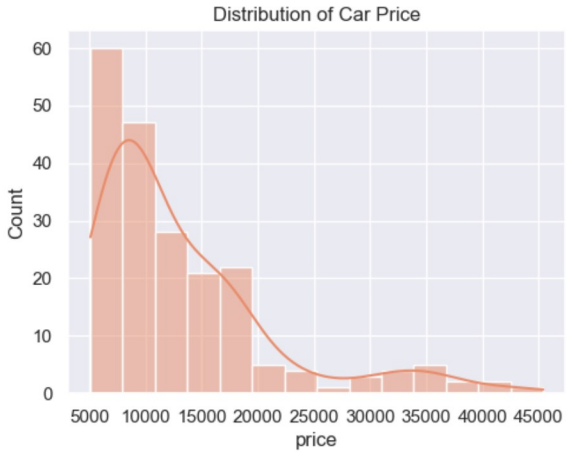
DATA EXPLORATION (EDA)

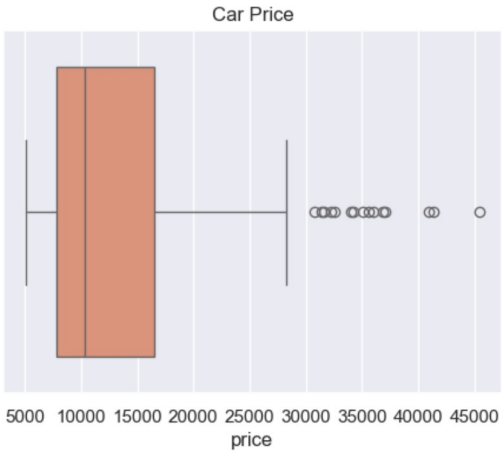
Target - Price

In [34]:
```
df['price'].describe()
```

Out[34]:
```
count      205.000000
mean     13276.710571
std       7988.852332
min       5118.000000
25%       7788.000000
50%      10295.000000
75%      16503.000000
max      45400.000000
Name: price, dtype: float64
```

In [35]:
```
plt.figure(figsize=(12,4))

#plotting histogram - price distribution
plt.subplot(1,2,1)
sns.histplot(data=df, x='price', kde=True)
plt.title('Distribution of Car Price')

#boxplot - price distribution
plt.subplot(1,2,2)
sns.boxplot(data=df, x='price',)
plt.title('Car Price')

plt.show()
```





In [36]:
```
print(f'Skewness: {df['price'].skew()}\nKurtosis:{df['price'].kurt()}')
```

```
Skewness: 1.7776781560914454
Kurtosis:3.051647871396399
```

Insights

- The plot or distribution of car price seems highly right skewed
- Most prices in the dataset are below 20000

Categorical Features

In [37]:
```
df[categorical_features].describe().T
```

Out[37]:

	count	unique	top	freq
symboling	205	6	0	67
fueltype	205	2	gas	185
aspiration	205	2	std	168
doornumber	205	2	four	115
carbody	205	5	sedan	96
drivewheel	205	3	fwd	120
enginelocation	205	2	front	202
enginetype	205	7	ohc	148
cylindernumber	205	7	four	159
fuelsystem	205	8	mpfi	94
make	205	22	toyota	32

In [38]:
```
def visualize_categorical(df, feature):
    plt.figure(figsize=(12,4))

    print(df[feature].value_counts())
```

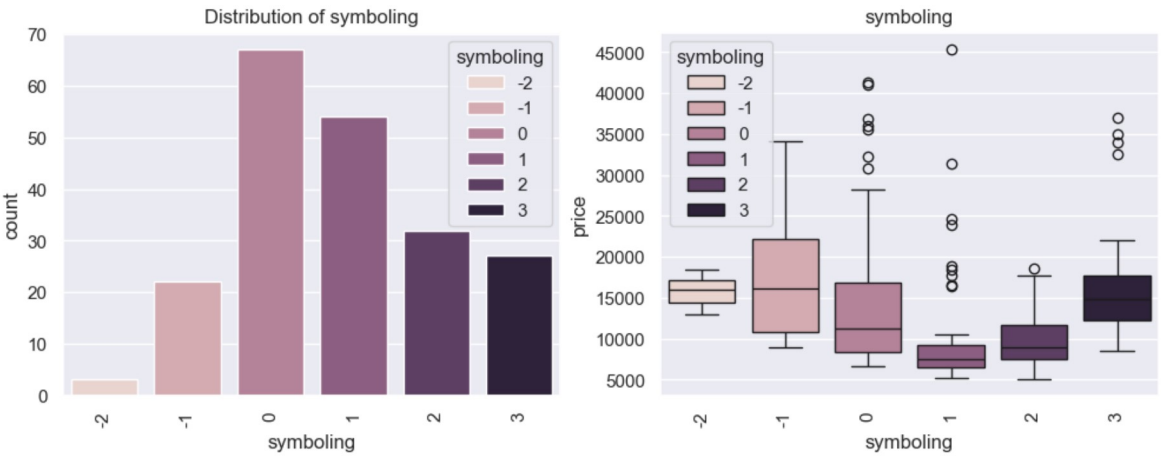
```
    #countplot
    plt.subplot(1,2,1)
    sns.countplot(data=df, x=feature, hue=feature)
    plt.title(f'Distribution of {feature}')
    plt.xticks(rotation=90)

    #boxplot
    plt.subplot(1,2,2)
    sns.boxplot(data=df, x=feature, y='price', hue=feature)
    plt.title(f'{feature}')
    plt.xticks(rotation=90)

    plt.show()
```

In [39]:
```
categorical_features
```

Out[39]:
```
['symboling',
 'fueltype',
 'aspiration',
 'doornumber',
 'carbody',
 'drivewheel',
 'enginelocation',
 'enginetype',
 'cylindernumber',
 'fuelsystem',
 'make']
```

In [40]:
```
visualize_categorical(df,'symboling')
```

```
symboling
0     67
1     54
2     32
3     27
-1    22
-2     3
Name: count, dtype: int64
```



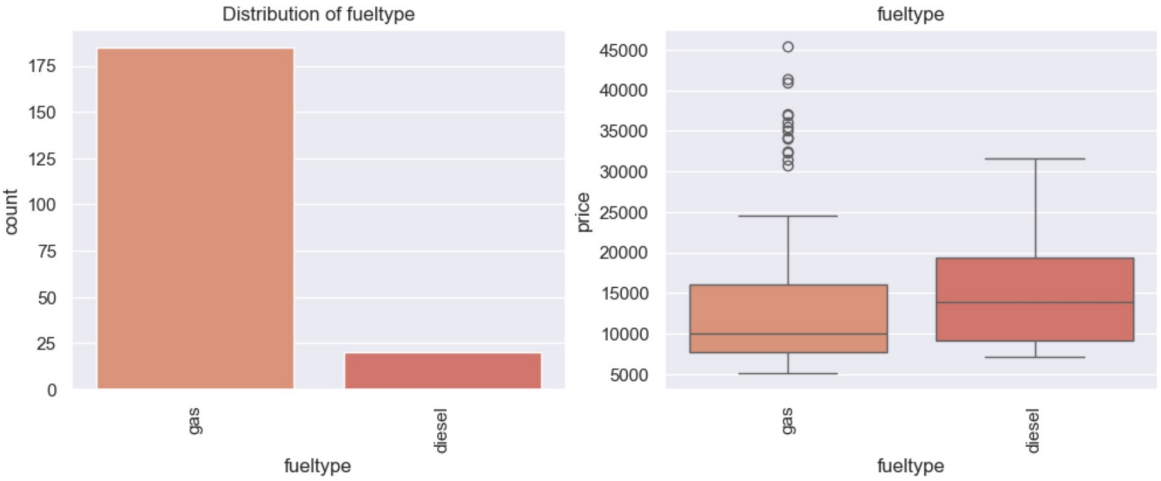
Insights

- Cars with symboling or insurance risk rating **0** and **1** (low insurance risk) are most sold.
- Cars with symboling **-1** and **-2** are high priced.

- Cars with symboling **3** have a similar price to that of -2 and -1, which is odd.

In [41]:
```
visualize_categorical(df,'fueltype')
```

```
fueltype
gas       185
diesel     20
Name: count, dtype: int64
```

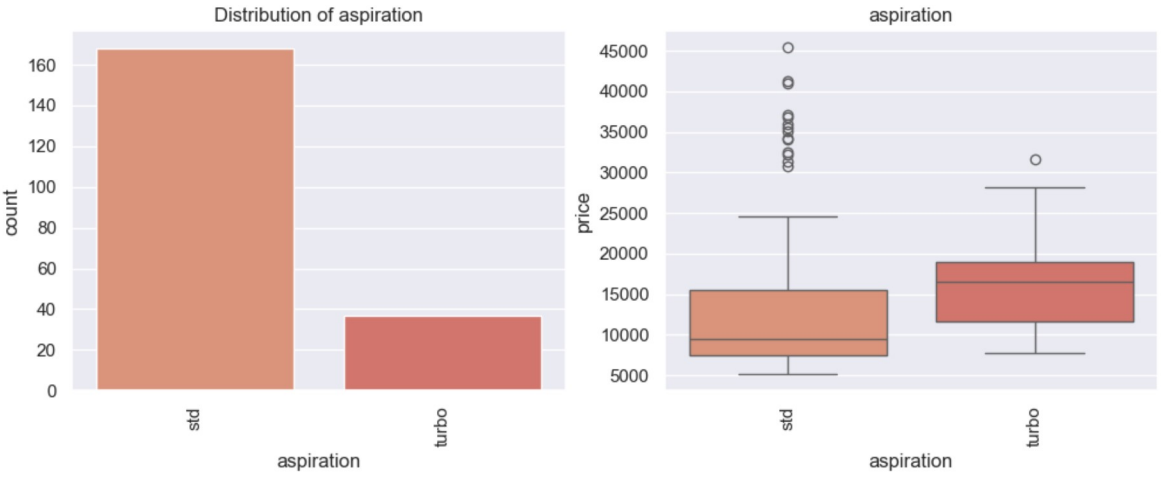


Insights

- Cars that run on **gas** are most sold.
- Cars that run on **diesel** are comparatively expensive than cars run on gas.

In [42]:
```
visualize_categorical(df,'aspiration')
```

```
aspiration
std      168
turbo     37
Name: count, dtype: int64
```

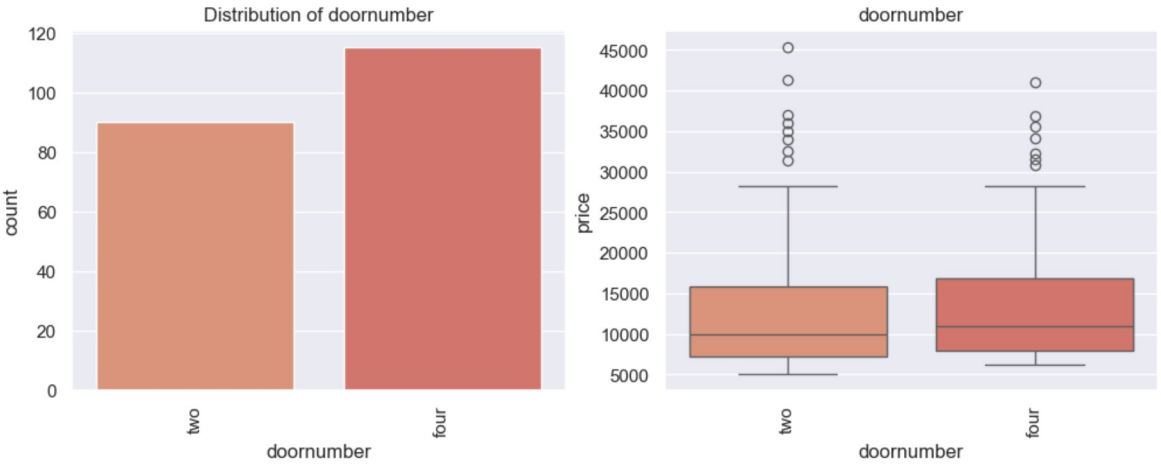


Insights

- Cars with **standards** aspiration are most sold.
- Cars with **turbo** aspiration are comparatively expensive than cars with standard aspiration.

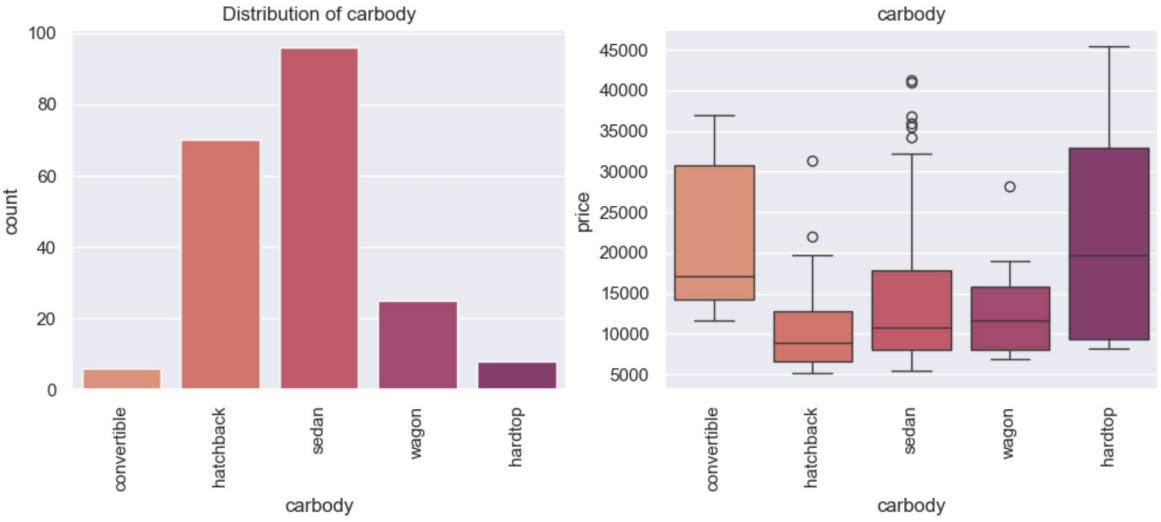
In [43]:
```
visualize_categorical(df,'doornumber')
```

```
doornumber
four    115
two      90
Name: count, dtype: int64
```



In [44]:
```
visualize_categorical(df,'carbody')
```

```
carbody
sedan          96
hatchback      70
wagon          25
hardtop         8
convertible     6
Name: count, dtype: int64
```

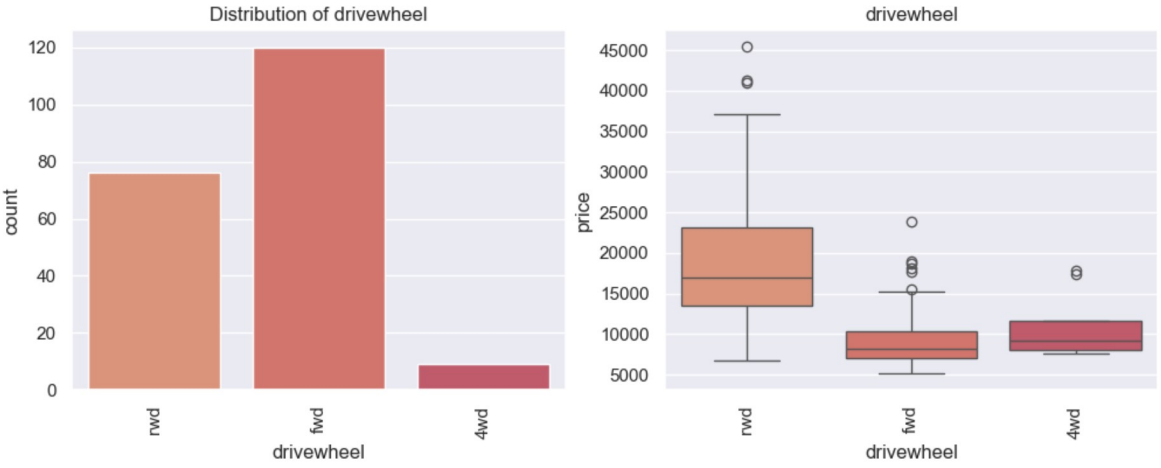


Insights

- **Sedans** are the most sold body type
- **convertibles** and **hardtops** have higher average prices and are availiable in a wider price range.

In [45]:
```
visualize_categorical(df,'drivewheel')
```

```
drivewheel
fwd    120
rwd     76
4wd      9
Name: count, dtype: int64
```

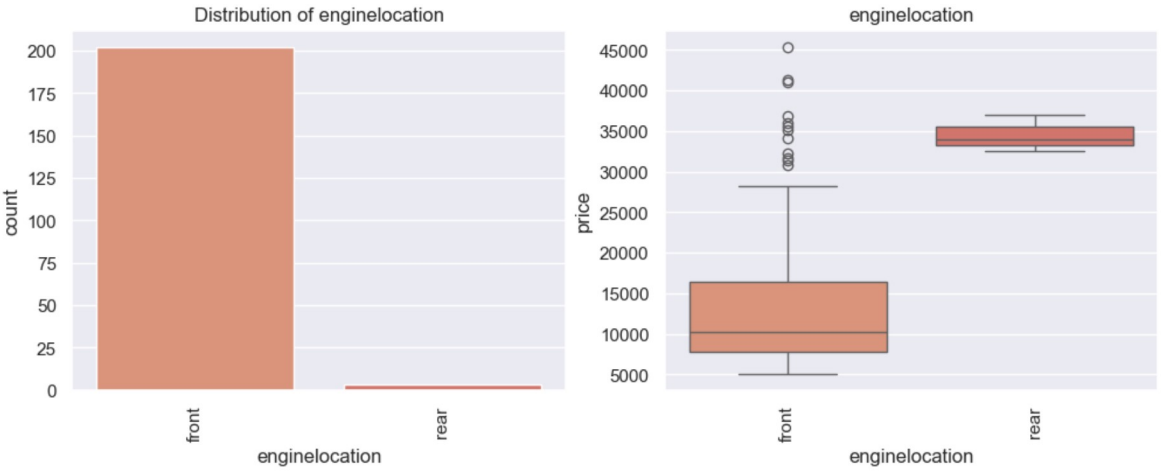


Insights

- Cars with **FWD** are the most sold, which is obvious.

In [46]:
```
visualize_categorical(df,'enginelocation')
```

```
enginelocation
front    202
rear       3
Name: count, dtype: int64
```

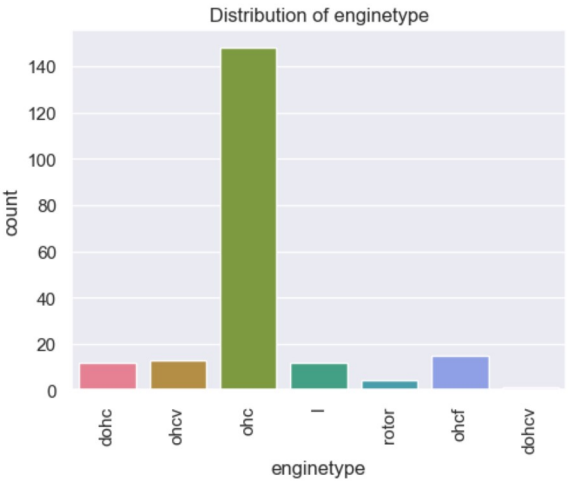


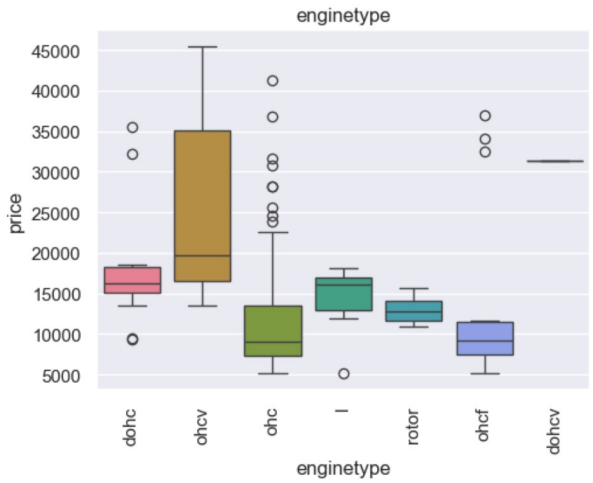
Insights

- Cars in which engines are located at **rear** comes at a significantly higher price range

In [47]:
```
visualize_categorical(df,'enginetype')
```

```
enginetype
ohc       148
ohcf       15
ohcv       13
dohc       12
l          12
rotor       4
dohcv       1
Name: count, dtype: int64
```



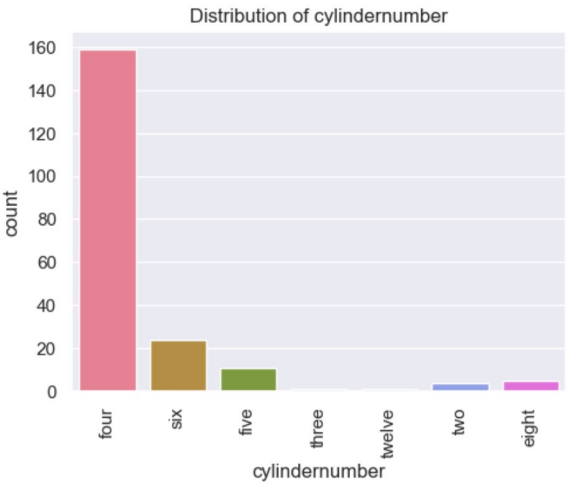


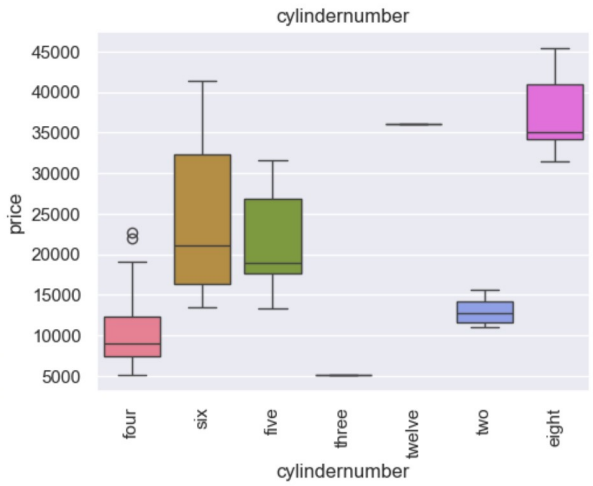
Insights

- Cars with **ohcv** mechanism are the most sold and are offered in a wider price change.

In [48]:
```
visualize_categorical(df,'cylindernumber')
```

```
cylindernumber
four      159
six        24
five       11
eight       5
two         4
three       1
twelve      1
Name: count, dtype: int64
```



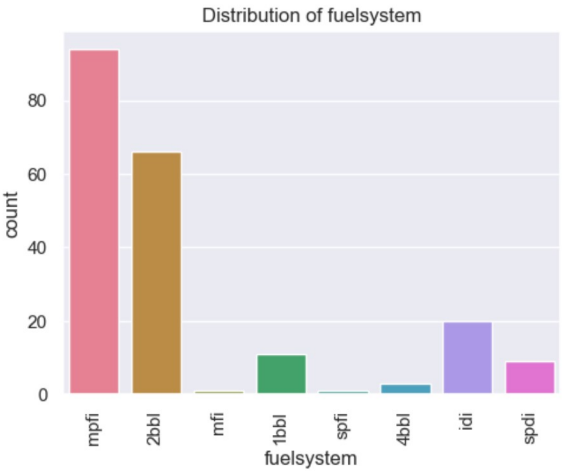


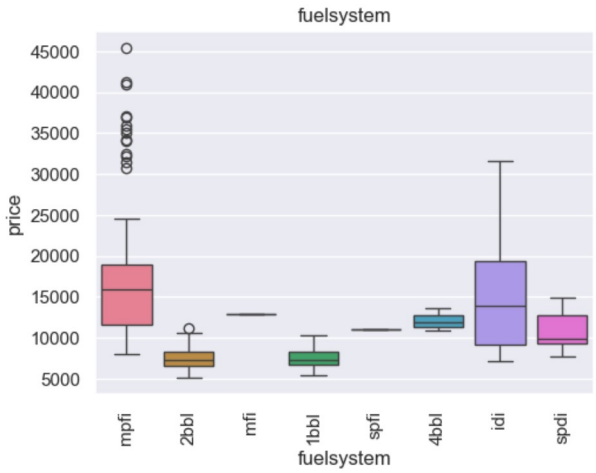
Insights

- Cars with 8 and 12 cylinders comes at a higher price point.

In [49]:
```
visualize_categorical(df,'fuelsystem')
```

```
fuelsystem
mpfi    94
2bbl    66
idi     20
1bbl    11
spdi     9
4bbl     3
mfi      1
spfi     1
Name: count, dtype: int64
```



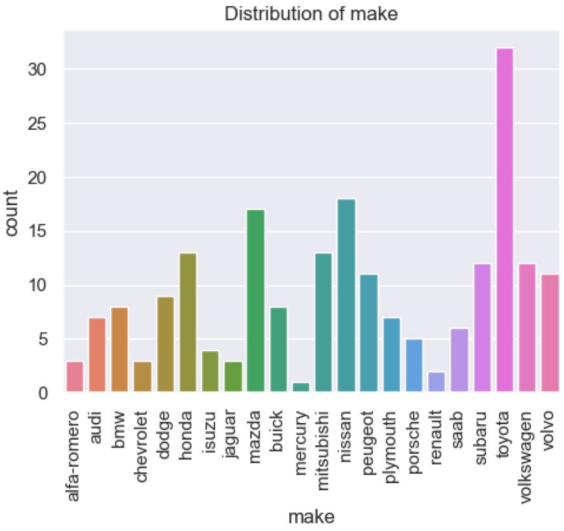


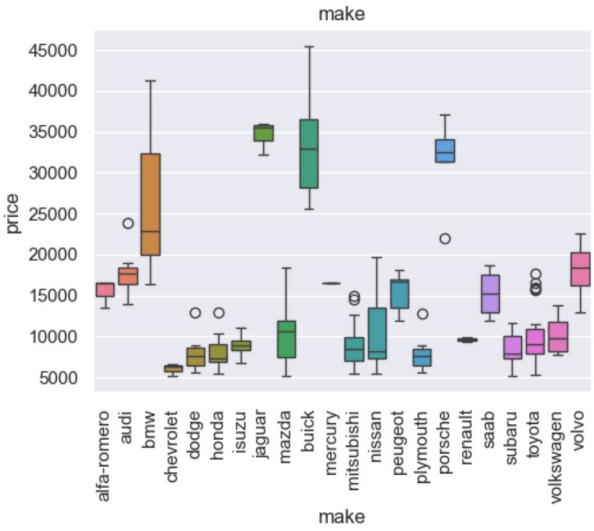
Insights

- **mpfi** and **2bbl** are most common fuel systems and cars with mpfi system have higher average price.

In [50]:
```
visualize_categorical(df,'make')
```

```
make
toyota          32
nissan          18
mazda           17
mitsubishi      13
honda           13
volkswagen      12
subaru          12
peugeot         11
volvo           11
dodge            9
buick            8
bmw              8
audi             7
plymouth         7
saab             6
porsche          5
isuzu            4
jaguar           3
chevrolet        3
alfa-romero      3
renault          2
mercury          1
Name: count, dtype: int64
```





Insights

- **Toyota** appears to be the most preferred car brand.
- **Jaguar**, **Buick** and **Porsche** have higher average price.

Numerical Features

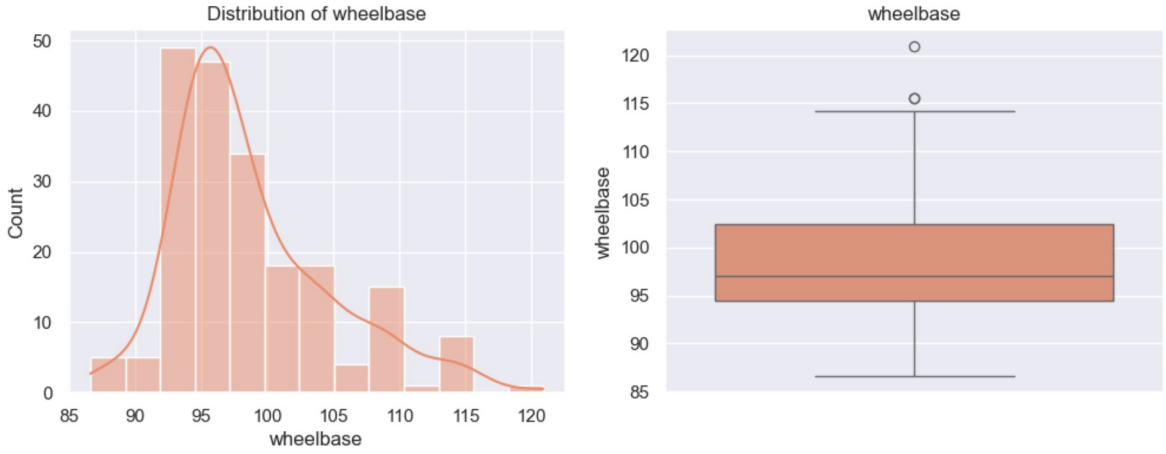
In [51]:
```
def visualize_numerical(df, feature):
    plt.figure(figsize=(12,4))

    #histogram
    plt.subplot(1,2,1)
```

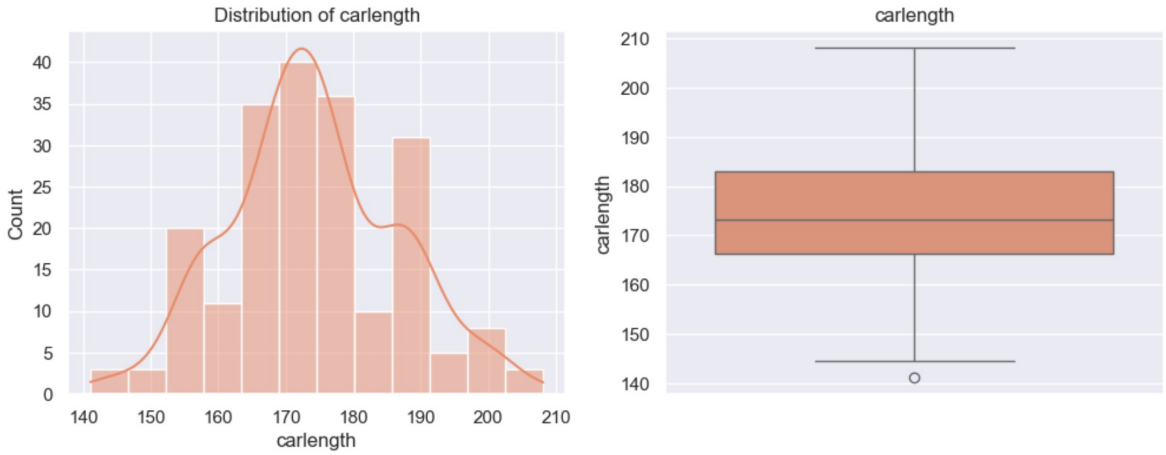
```
    sns.histplot(data=df, x=feature, kde=True)
    plt.title(f'Distribution of {feature}')

    #boxplot
    plt.subplot(1,2,2)
    sns.boxplot(data=df, y=feature)
    plt.title(f'{feature}')

    plt.show()
```

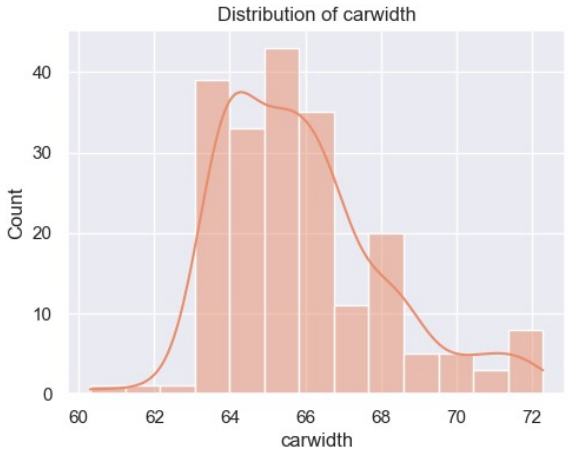
In [52]:
```
numerical_features
```

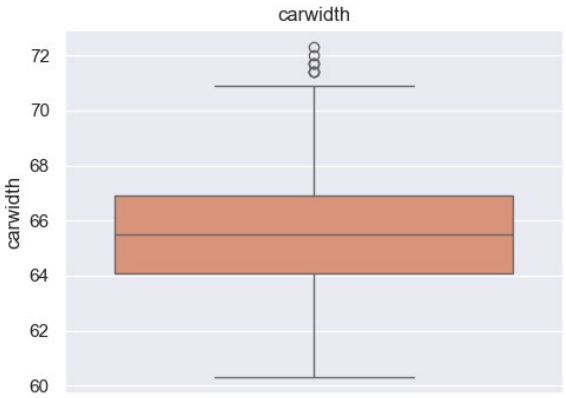
Out[52]:
```
['wheelbase',
 'carlength',
 'carwidth',
 'carheight',
 'curbweight',
 'enginesize',
 'boreratio',
 'stroke',
 'compressionratio',
 'horsepower',
 'peakrpm',
 'citympg',
 'highwaympg']
```

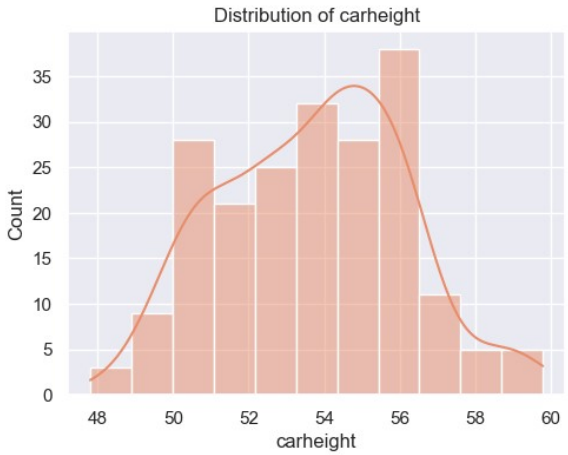
In [53]:
```
for feature in numerical_features:
    visualize_numerical(df, feature)
```

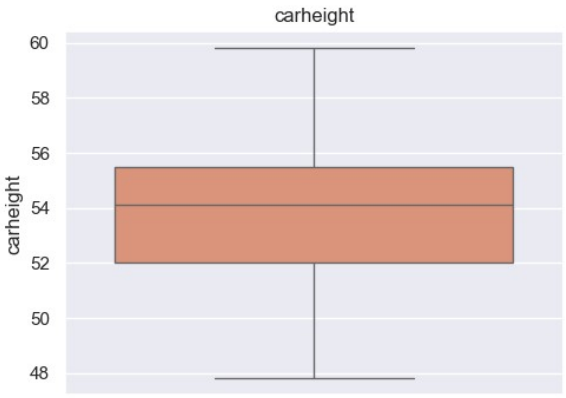


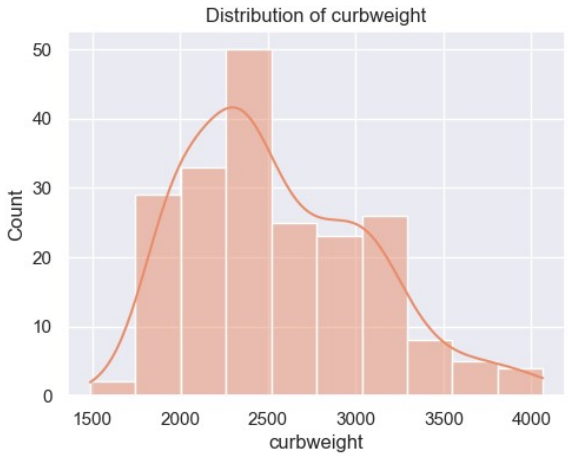


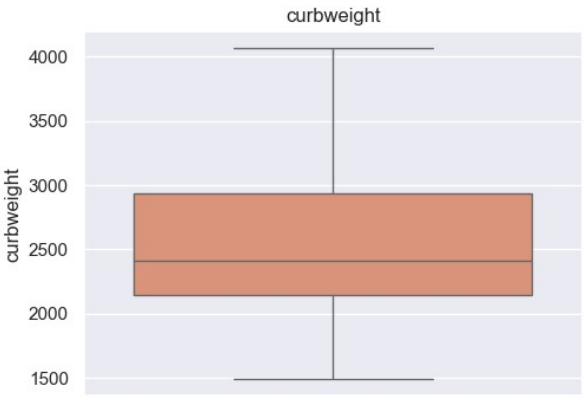

Distribution of carwidth
Count
carwidth

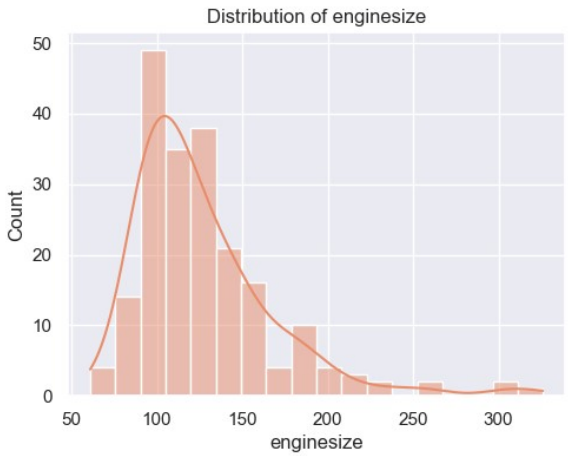

carwidth

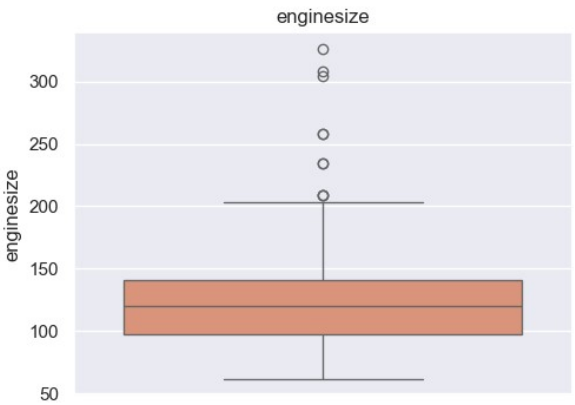

Distribution of carheight
Count
carheight

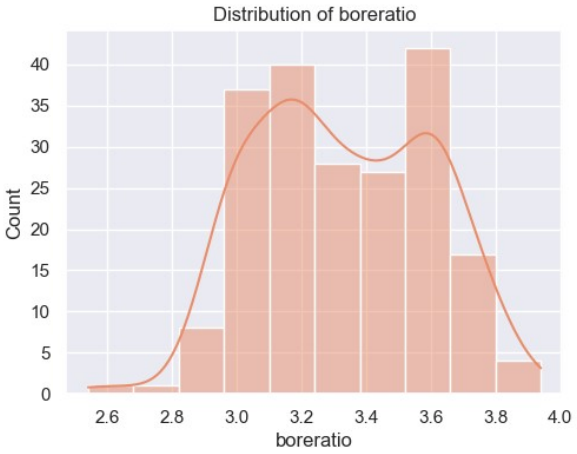

carheight

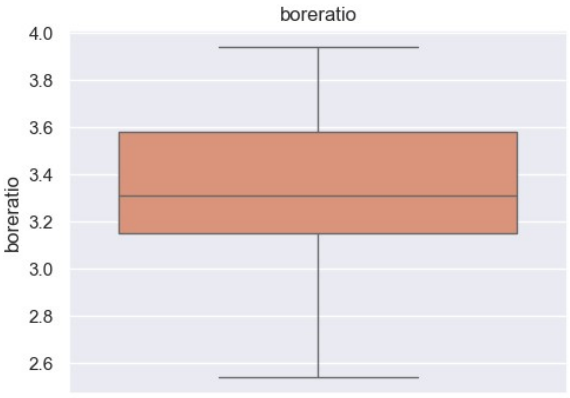

Distribution of curbweight
Count
curbweight

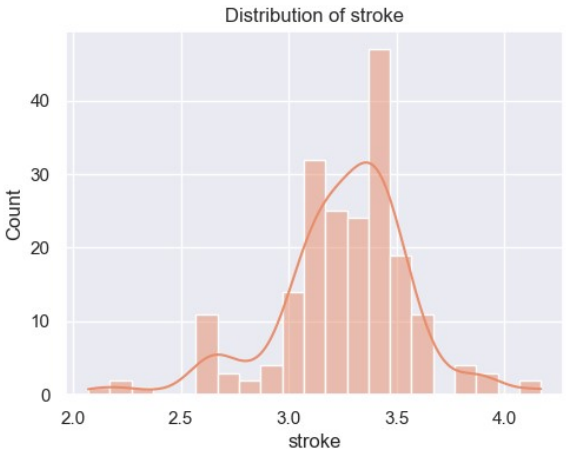

curbweight

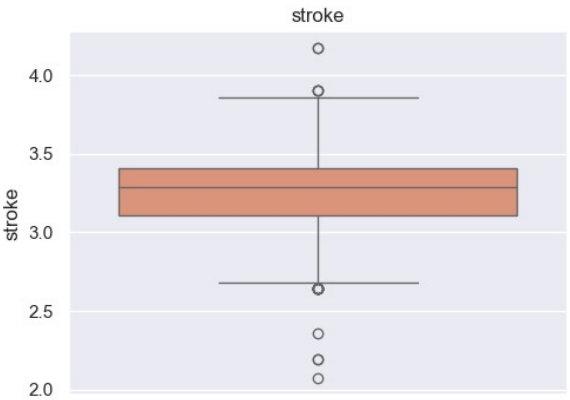

Distribution of enginesize
Count
enginesize

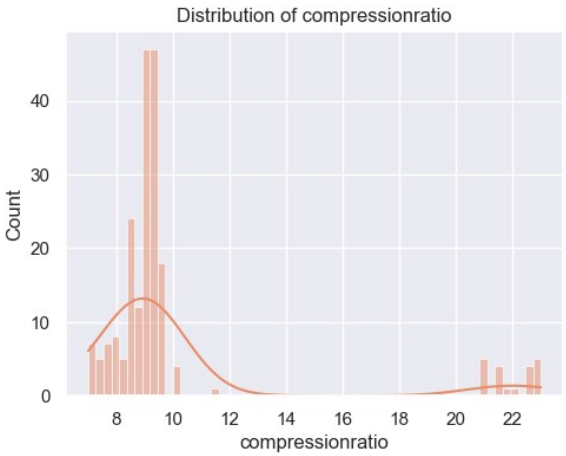

enginesize

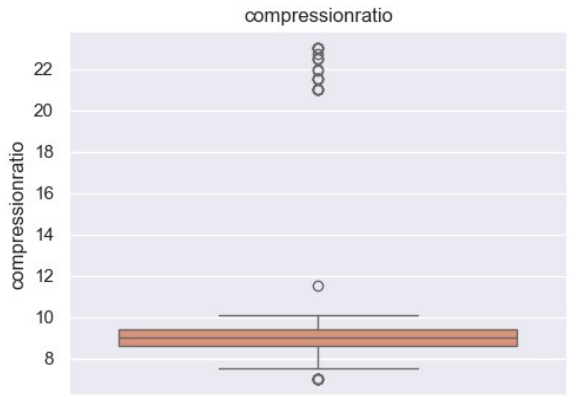

Distribution of boreratio
Count
boreratio

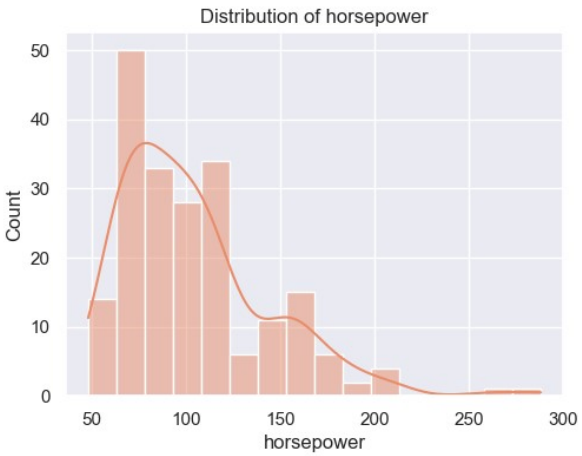

boreratio
boreratio

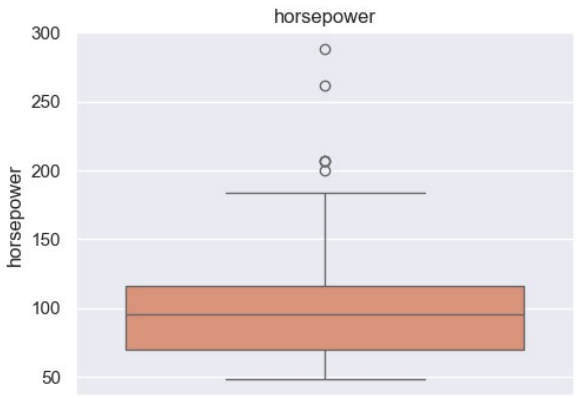

Distribution of stroke
Count
stroke

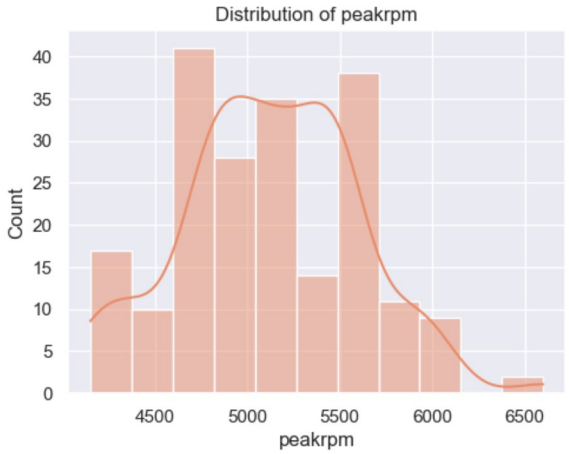

stroke
stroke

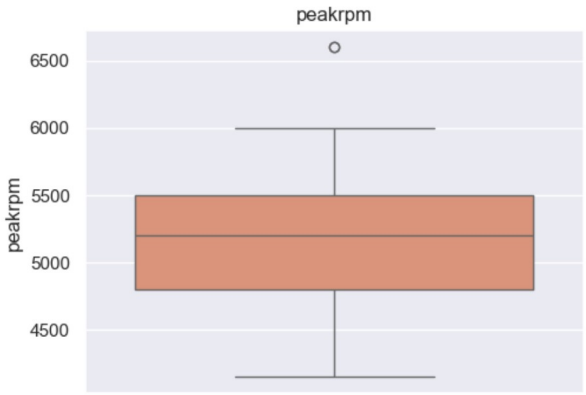

Distribution of compressionratio
Count
compressionratio

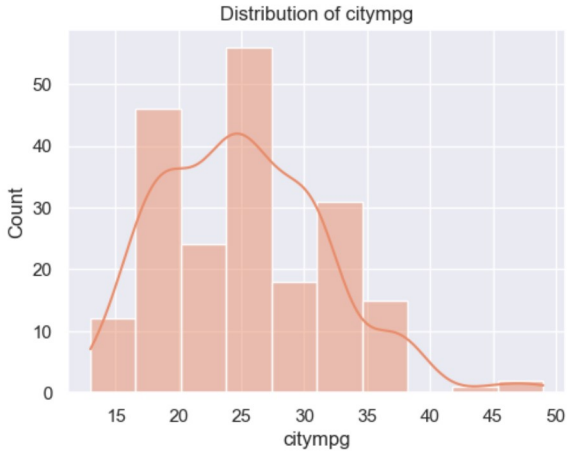

compressionratio
compressionratio

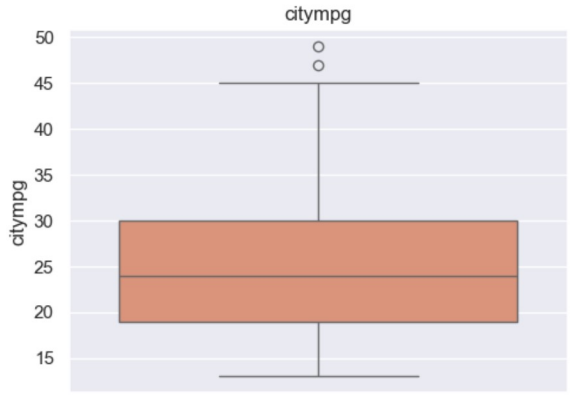

Distribution of horsepower
Count
horsepower

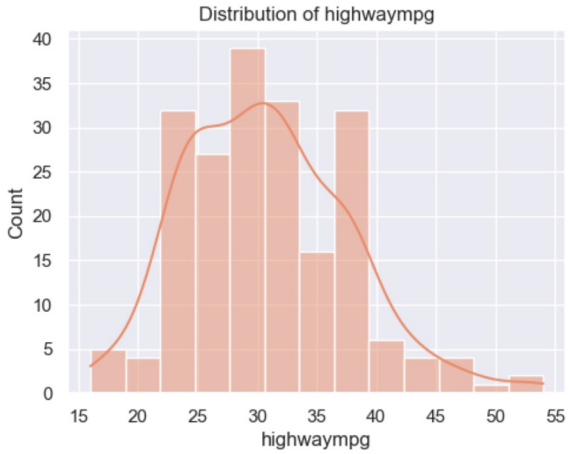

horsepower
horsepower

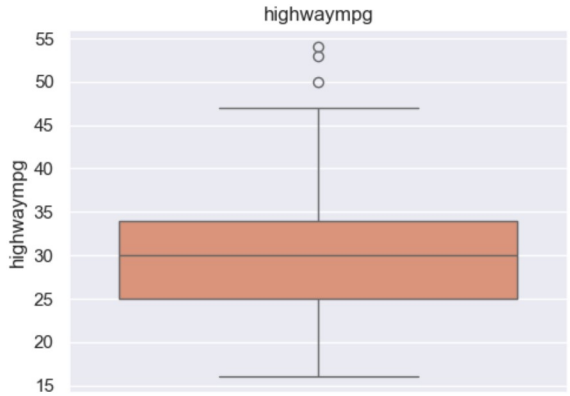












In [54]:
```
#defining function to create skewness kurtosis report


def create_skew_kurt_report(df, features):
    skew_values = []
    skew_types = []
    skew_levels = []
    kurt_values = []
    kurt_types = []
    for feature in features:
        skew = df[feature].skew()
        kurt = df[feature].kurt()
        skew_values.append(skew)
        kurt_values.append(kurt)

        #determining skewness type (+ve or -ve)
        if skew >= 0:
```

```
            skew_types.append('Positive')
        else:
            skew_types.append('Negative')

        #determining skewness level (low, moderate or high)
        if skew == 0:
            skew_levels.append('Symmetrical')
        elif skew < -1 or skew > 1:
            skew_levels.append('High')
        elif (skew >= -1 and skew <= -0.5) or (skew >= 0.5 and skew <= 1):
            skew_levels.append('Moderate')
        else:
            skew_levels.append('Low')

        #determining kurtosis type (Platykurtic, Leptokurtic, Mesokurtic)
        if kurt < 3:
            kurt_types.append('Platykurtic')
        elif kurt > 3:
            kurt_types.append('Leptokurtic')
        else:
            kurt_types.append('Mesokurtic')

    report = pd.DataFrame({
        'Feature': features,
        'Skewness': skew_values,
        'Skewness Type': skew_types,
        'Skewness Level': skew_levels,
        'Kurtosis': kurt_values,
        'Kurtosis Type': kurt_types
    })

    report.set_index('Feature', inplace=True)

    return report
```

In [55]:
```
report = create_skew_kurt_report(df, numerical_features)
```

In [56]:
```
#function to highlight 'Skewness Level' cell
def highlight_cells(val):
    if val == 'High':
        color = '#f5b7b1'
    elif val == 'Moderate':
        color = '#f9e79f'
    else:
        color = '#abebc6'

    return f'background-color: {color}'
```

In [57]:
```
report = report.style.applymap(highlight_cells, subset=['Skewness Level'])
```

In [58]:
```
report
```

Out[58]:

Feature	Skewness	Skewness Type	Skewness Level	Kurtosis	Kurtosis Type
wheelbase	1.050214	Positive	High	1.017039	Platykurtic
carlength	0.155954	Positive	Low	-0.082895	Platykurtic
carwidth	0.904003	Positive	Moderate	0.702764	Platykurtic
carheight	0.063123	Positive	Low	-0.443812	Platykurtic
curbweight	0.681398	Positive	Moderate	-0.042854	Platykurtic
enginesize	1.947655	Positive	High	5.305682	Leptokurtic
boreratio	0.020156	Positive	Low	-0.785042	Platykurtic
stroke	-0.689705	Negative	Moderate	2.174396	Platykurtic
compressionratio	2.610862	Positive	High	5.233054	Leptokurtic
horsepower	1.405310	Positive	High	2.684006	Platykurtic
peakrpm	0.075159	Positive	Low	0.086756	Platykurtic
citympg	0.663704	Positive	Moderate	0.578648	Platykurtic
highwaympg	0.539997	Positive	Moderate	0.440070	Platykurtic

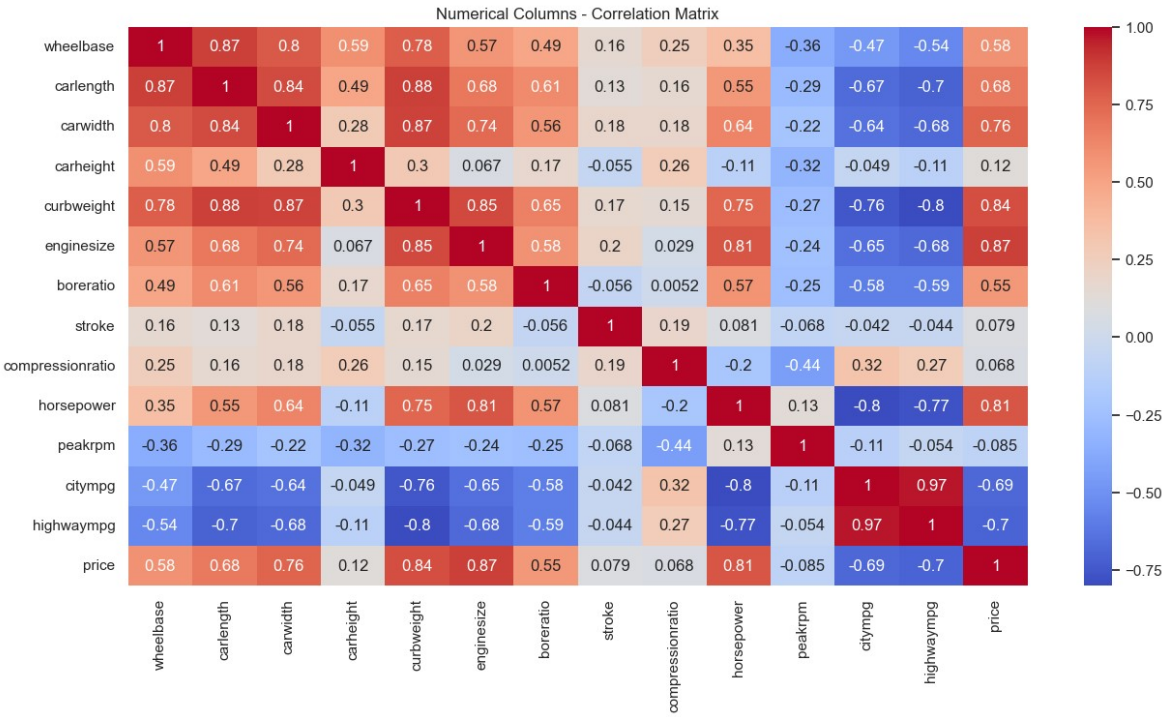
> ### Insight:
>
> *Most features follow a near-normal distribution and have considerable number of outliers. There are 4 highly skewed features, 5 moderately skewed features and 4 features with low skewness. The features with moderate and high skewness will be transformed.*

In [59]:
```
cols_to_transform = ['wheelbase', 'carwidth', 'curbweight', 'enginesize', 'strok
```

Correlation Analysis - Before Scaling

In [60]:
```
correlation_matrix = df[numerical_features+['price']].corr()
```

In [61]:
```
plt.figure(figsize=(15, 7.5))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Numerical Columns - Correlation Matrix')
plt.show()
```



Insights

- carwidth (0.76), curbweight (0.84), enginesize (0.87) and horsepower (0.81) are highly correlated with **car price**
- citympg (-0.69) and highwaympg (0.7) have high negative correlation with **car price**

Interpretation

- Car width: Wider cars may indicate more spacious vehicle, which often comes with higher price range.
- Curb weight: Heavier vehicles might be associated with better build quality or larger engines, which can result in higher price.
- Engine size: larger engines offer more power, which typically leads to a higher price.
- Horsepower: Higher horsepower is associated with better performance, which contribute to higher price range.
- City and Highway MPG: Fuel efficiency is typically higher affordable or economy cars, while larger or luxury vehicles often trade fuel economy off for performance or comfort, leading to a higher price.

There are a number of independent features with high correlation (0.7 to 0.99 and -0.7 to -0.99)

Column 1	Column 2	Correlation
citympg	highwaympg	0.97
carlength	curbweight	0.88
carlength	wheelbase	0.87
carwidth	curbweight	0.87
curbweight	enginesize	0.85
carlength	carwidth	0.84
enginesize	horsepower	0.81
carwidth	wheelbase	0.80
curbweight	wheelbase	0.78
curbweight	horsepower	0.75
carwidth	enginesize	0.74
highwaympg	carlength	-0.70
citympg	curbweight	-0.76
highwaympg	horsepower	-0.77
citympg	horsepower	-0.80
highwaympg	curbweight	-0.80

DATA PREPROCESSING

Transforming Numerical Features

log transformation failed to produce desired results. Went for box-cox transformation, which is useful for stabilizing variance and making the data more normally distributed, particularly when dealing with skewed data.

In [62]:
```
#removed 'carwidth' from cols to transform since box-cox transformation ended up
cols_to_transform = ['wheelbase', 'curbweight', 'enginesize', 'stroke', 'compres
```

In [63]:
```
#checking for non-positive values
df[numerical_features].describe().loc['min']
```

Out[63]:
```
wheelbase             86.60
carlength            141.10
carwidth              60.30
carheight             47.80
curbweight          1488.00
enginesize            61.00
boreratio              2.54
stroke                 2.07
compressionratio       7.00
horsepower            48.00
peakrpm             4150.00
citympg               13.00
highwaympg            16.00
Name: min, dtype: float64
```

In [64]:
```
from scipy import stats
df_transformed = df.copy()
#box-cox transformation on specific columns
for col in cols_to_transform:
    df_transformed[col] = np.where(df_transformed[col] > 0, stats.boxcox(df_tran
```

In [76]:
```
#repeated cuberoot transformation worked for 'carwidth'(x9)
df_transformed['carwidth'] = np.where(df_transformed['carwidth'] > 0,np.cbrt(df_
```

In [77]:
```
report1 = create_skew_kurt_report(df_transformed, numerical_features)
```

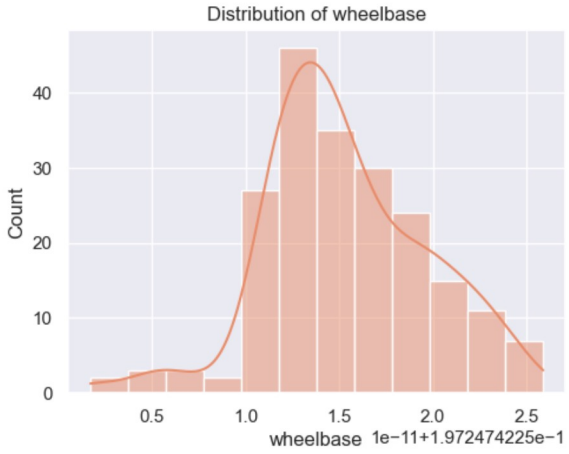
In [78]:
```
report1 = report1.style.applymap(highlight_cells, subset=['Skewness Level'])
```

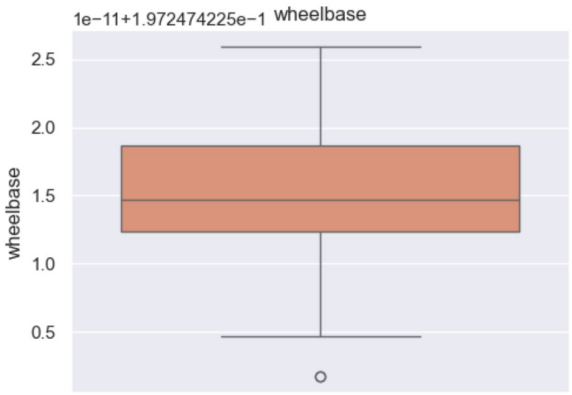
In [79]:
```
report1
```

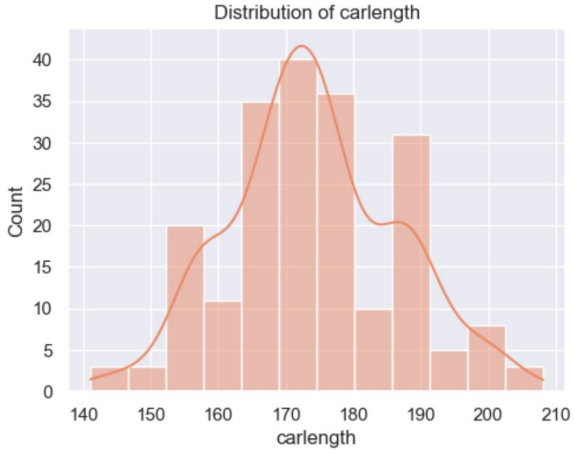
Out[79]:

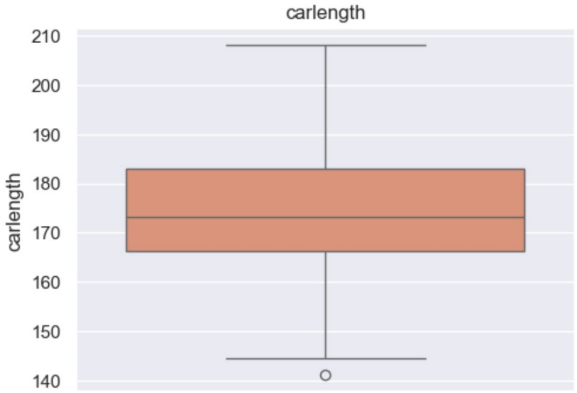
Feature	Skewness	Skewness Type	Skewness Level	Kurtosis	Kurtosis Type
wheelbase	0.000000	Positive	Symmetrical	0.000000	Platykurtic
carlength	0.155954	Positive	Low	-0.082895	Platykurtic
carwidth	0.000000	Positive	Symmetrical	0.562316	Platykurtic
carheight	0.063123	Positive	Low	-0.443812	Platykurtic
curbweight	0.024852	Positive	Low	-0.574375	Platykurtic
enginesize	-0.003190	Negative	Low	0.311933	Platykurtic
boreratio	0.020156	Positive	Low	-0.785042	Platykurtic
stroke	0.120019	Positive	Low	1.849909	Platykurtic
compressionratio	0.008026	Positive	Low	1.679051	Platykurtic
horsepower	0.048363	Positive	Low	-0.655894	Platykurtic
peakrpm	0.075159	Positive	Low	0.086756	Platykurtic
citympg	0.000188	Positive	Low	-0.431435	Platykurtic
highwaympg	-0.000576	Negative	Low	-0.013221	Platykurtic

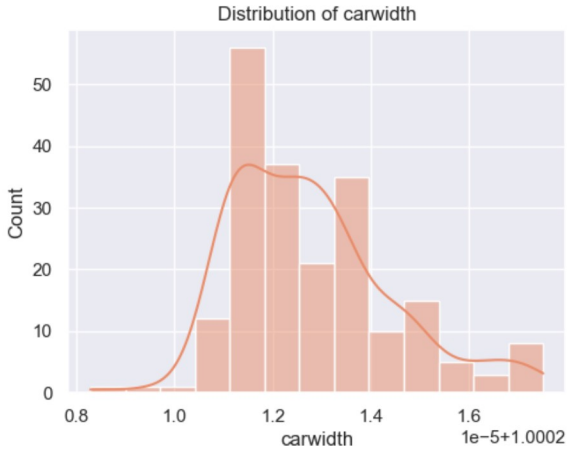
In [80]:
```
for feature in numerical_features:
    visualize_numerical(df_transformed, feature)
```

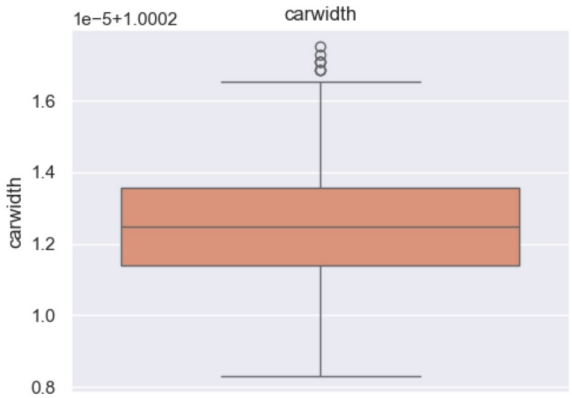


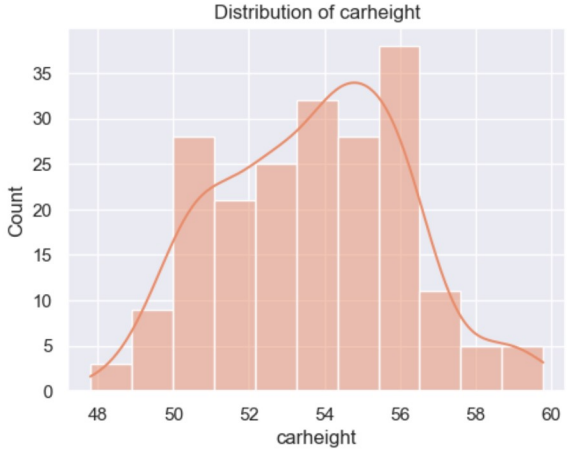


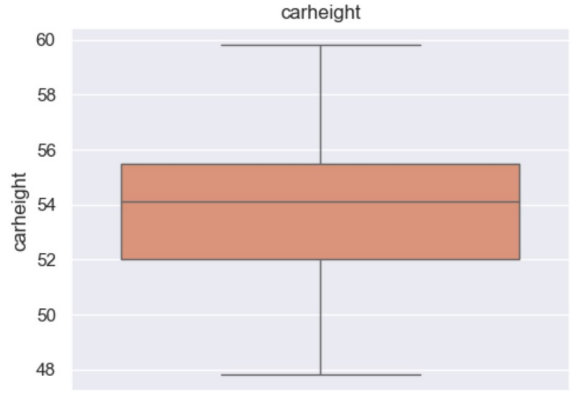


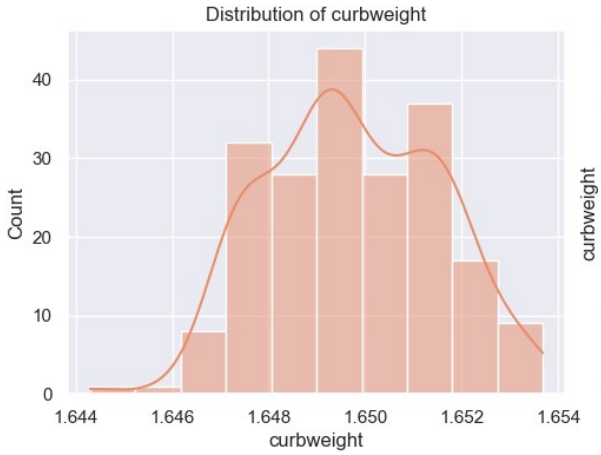


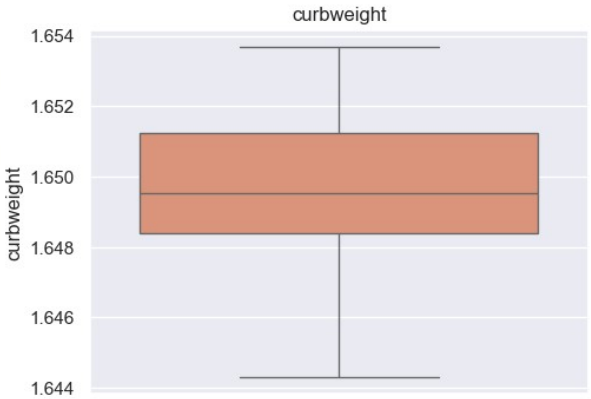


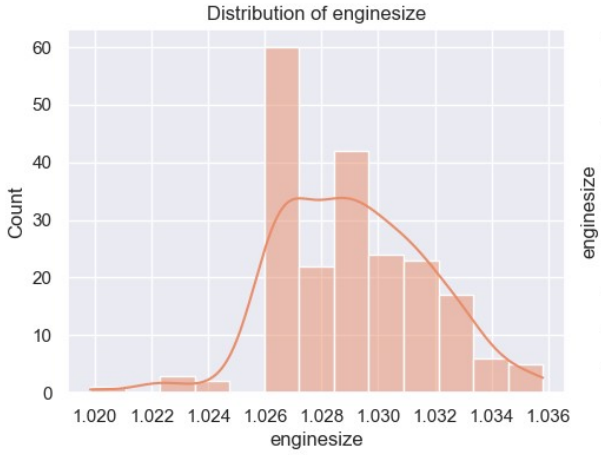


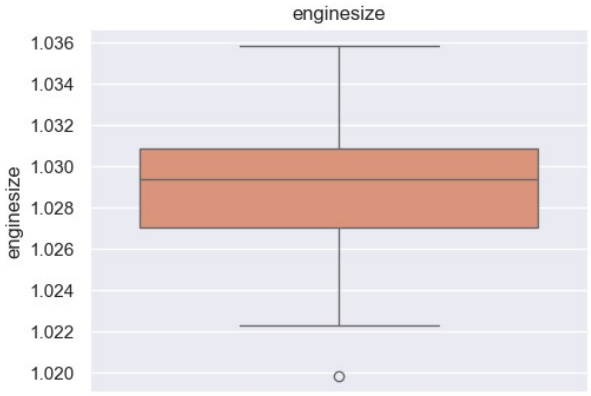


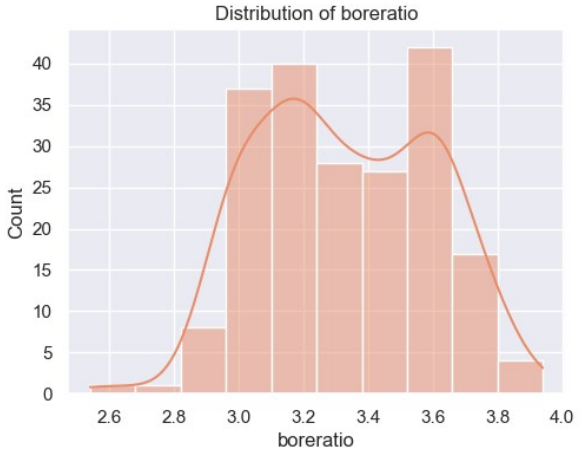


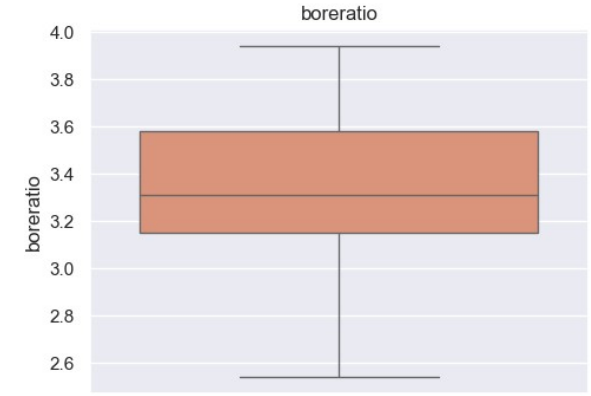

Distribution of curbweight
Count
curbweight
0
10
20
30
40
1.644
1.646
1.648
1.650
1.652
1.654

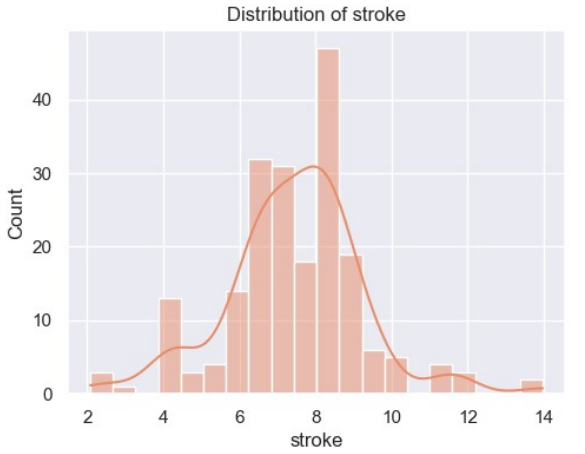

curbweight
curbweight
1.644
1.646
1.648
1.650
1.652
1.654


Distribution of enginesize
Count
enginesize
0
10
20
30
40
50
60
1.020
1.022
1.024
1.026
1.028
1.030
1.032
1.034
1.036

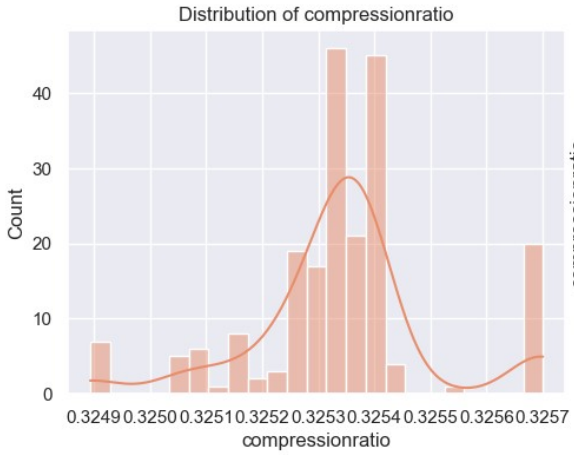

enginesize
enginesize
1.020
1.022
1.024
1.026
1.028
1.030
1.032
1.034
1.036

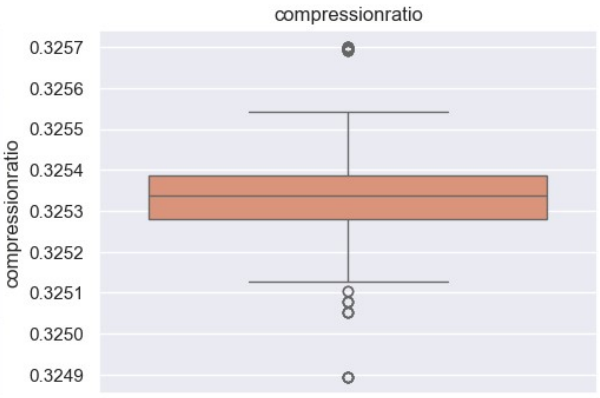

Distribution of boreratio
Count
boreratio
0
5
10
15
20
25
30
35
40
2.6
2.8
3.0
3.2
3.4
3.6
3.8
4.0

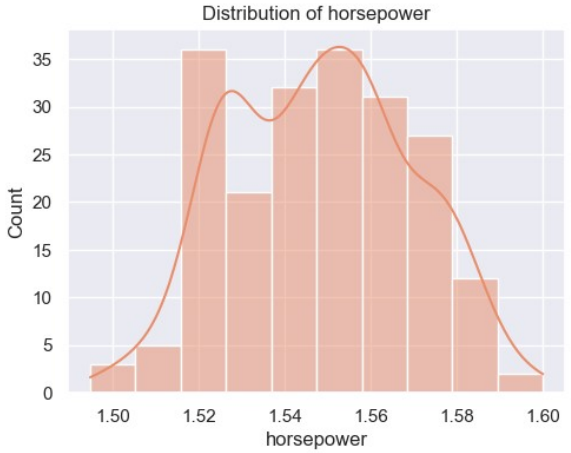

boreratio
boreratio
2.6
2.8
3.0
3.2
3.4
3.6
3.8
4.0

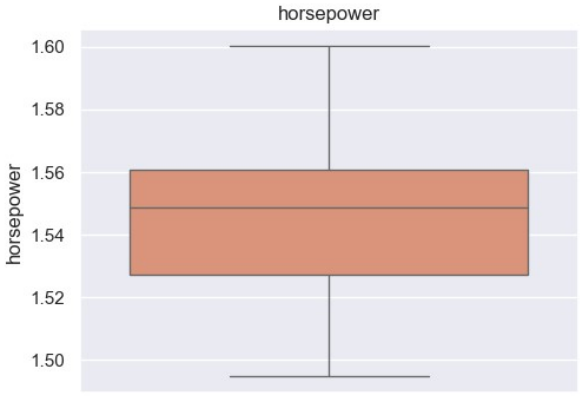

Distribution of stroke
Count
stroke
0
10
20
30
40
2
4
6
8
10
12
14

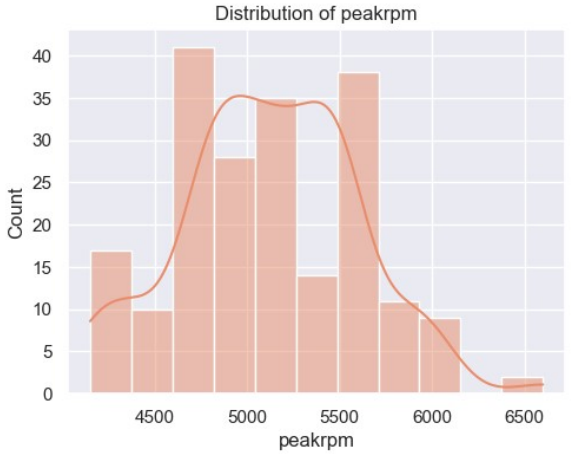

stroke
stroke
2
4
6
8
10
12
14

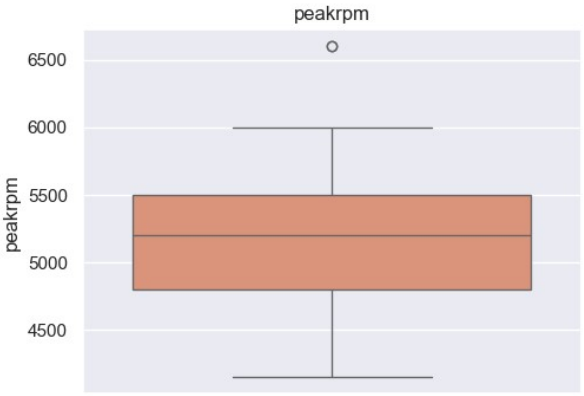

Distribution of compressionratio
Count
compressionratio
0.3249 0.3250 0.3251 0.3252 0.3253 0.3254 0.3255 0.3256 0.3257

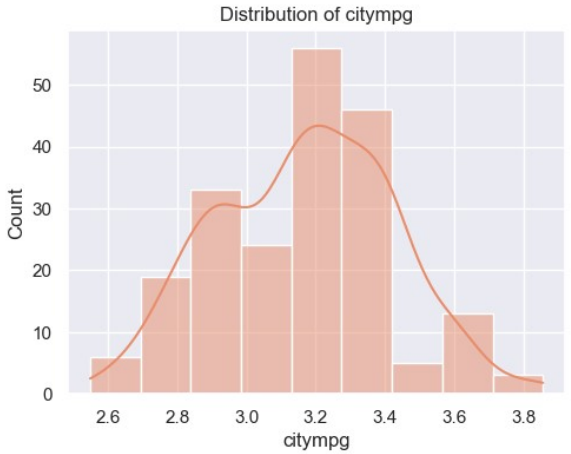

compressionratio
compressionratio
0.3257
0.3256
0.3255
0.3254
0.3253
0.3252
0.3251
0.3250
0.3249

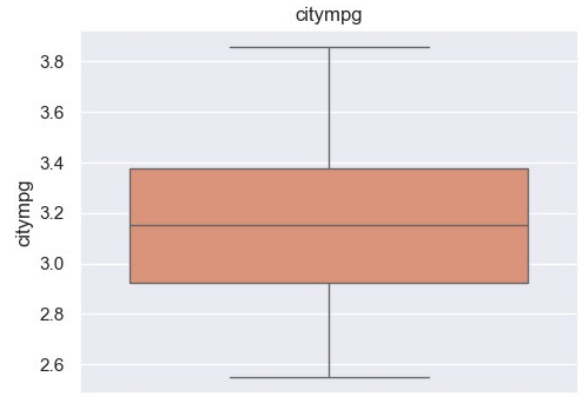

Distribution of horsepower
Count
horsepower
1.50 1.52 1.54 1.56 1.58 1.60

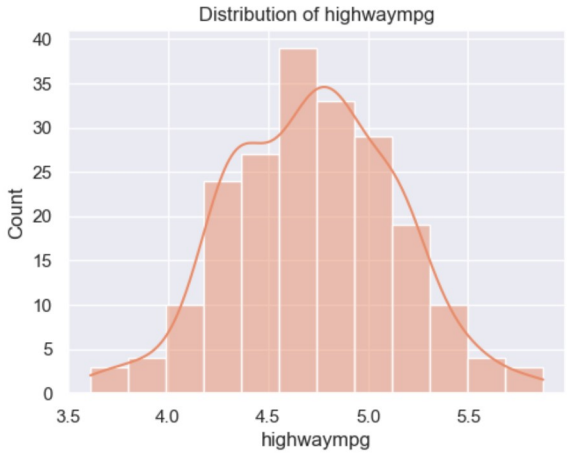

horsepower
horsepower
1.60
1.58
1.56
1.54
1.52
1.50

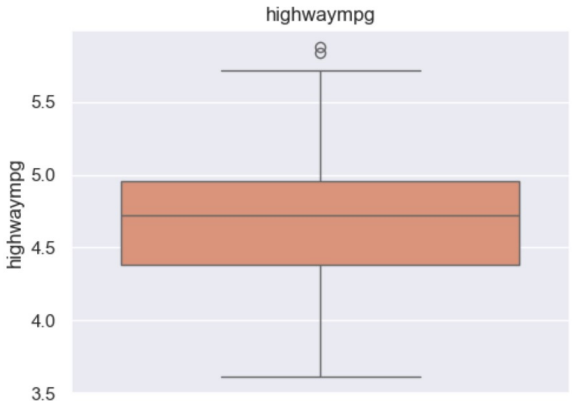

Distribution of peakrpm
Count
peakrpm
4500 5000 5500 6000 6500


peakrpm
peakrpm
6500
6000
5500
5000
4500


Distribution of citympg
Count
citympg
2.6 2.8 3.0 3.2 3.4 3.6 3.8


citympg
citympg
3.8
3.6
3.4
3.2
3.0
2.8
2.6





Transforming 'price'

In [81]:
```
df_transformed['price'] = stats.boxcox(df_transformed[col])[0]
```

In [82]:
```
visualize_numerical(df_transformed, 'price')
```

In [83]:
```
df_transformed['price'].skew()
```

Out[83]: -0.0012603104458931151

In [84]:
```
df_transformed['price'].kurt()
```

Out[84]: -0.013135237464321659

> Note:
>
> *There are minimal outliers after transformations. Outliers are not capped or removed since we use models that are sensitive and not sensitive to outliers.*

Encoding Categorical Columns (OHE)

In [85]:
```
categorical_features
```

Out[85]:
```
['symboling',
 'fueltype',
 'aspiration',
 'doornumber',
 'carbody',
 'drivewheel',
 'enginelocation',
 'enginetype',
 'cylindernumber',
 'fuelsystem',
 'make']
```

In [86]:
```
df_encoded = pd.get_dummies(df_transformed, columns=categorical_features, drop_f
```

In [87]:
```
df_encoded.columns
```

Out[87]:
```
Index(['wheelbase', 'carlength', 'carwidth', 'carheight', 'curbweight',
       'enginesize', 'boreratio', 'stroke', 'compressionratio', 'horsepower',
       'peakrpm', 'citympg', 'highwaympg', 'price', 'symboling_-1',
       'symboling_0', 'symboling_1', 'symboling_2', 'symboling_3',
       'fueltype_gas', 'aspiration_turbo', 'doornumber_two', 'carbody_hardtop',
       'carbody_hatchback', 'carbody_sedan', 'carbody_wagon', 'drivewheel_fwd',
       'drivewheel_rwd', 'enginelocation_rear', 'enginetype_dohcv',
       'enginetype_l', 'enginetype_ohc', 'enginetype_ohcf', 'enginetype_ohcv',
       'enginetype_rotor', 'cylindernumber_five', 'cylindernumber_four',
       'cylindernumber_six', 'cylindernumber_three', 'cylindernumber_twelve',
       'cylindernumber_two', 'fuelsystem_2bbl', 'fuelsystem_4bbl',
       'fuelsystem_idi', 'fuelsystem_mfi', 'fuelsystem_mpfi',
       'fuelsystem_spdi', 'fuelsystem_spfi', 'make_audi', 'make_bmw',
       'make_buick', 'make_chevrolet', 'make_dodge', 'make_honda',
       'make_isuzu', 'make_jaguar', 'make_mazda', 'make_mercury',
       'make_mitsubishi', 'make_nissan', 'make_peugeot', 'make_plymouth',
       'make_porsche', 'make_renault', 'make_saab', 'make_subaru',
       'make_toyota', 'make_volkswagen', 'make_volvo'],
      dtype='object')
```

In [88]:
```
df_transformed.shape
```

Out[88]:
```
(205, 25)
```

In [89]:
```
df_encoded.shape
```

Out[89]:
```
(205, 69)
```

In [90]:
```
df_transformed.head(1)
```

Out[90]:

	symboling	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation
0	3	gas	std	two	convertible	rwd	front

In [91]:
```
df_encoded.head(1)
```

Out[91]:

	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	stro
0	0.197247	168.8	1.000211	48.8	1.650015	1.030153	3.47	4.3369

In [92]:
```
df_encoded = df_encoded.replace({False:0, True:1})
```

In [93]:
```
df_encoded.head(1)
```

Out[93]:

	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	stro
0	0.197247	168.8	1.000211	48.8	1.650015	1.030153	3.47	4.3369

Scaling Features

we will use robust scaler that scales the data according to the median and the interquartile range (IQR), making it more robust against outliers.

In [94]:
```
X = df_encoded.drop('price', axis=1) #features
y = df_encoded['price'] #target
```

In [95]:
```
numerical_features
```

Out[95]:
```
['wheelbase',
 'carlength',
 'carwidth',
 'carheight',
 'curbweight',
 'enginesize',
 'boreratio',
 'stroke',
 'compressionratio',
 'horsepower',
 'peakrpm',
 'citympg',
 'highwaympg']
```

In [96]:
```
X_scaled = X.copy()
```

In [97]:
```
from sklearn.preprocessing import RobustScaler

scaler = RobustScaler()
X_scaled[numerical_features] = scaler.fit_transform(X_scaled[numerical_features]
```

In [98]:
```
X.head(1)
```

Out[98]:

	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	stro
0	0.197247	168.8	1.000211	48.8	1.650015	1.030153	3.47	4.3369

In [99]:
```
X_scaled.head(1)
```

Out[99]:

	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	str
0	-1.526907	-0.261905	-0.505344	-1.514286	0.173246	0.199842	0.372093	-1.78

Correlation Analysis - After Scaling

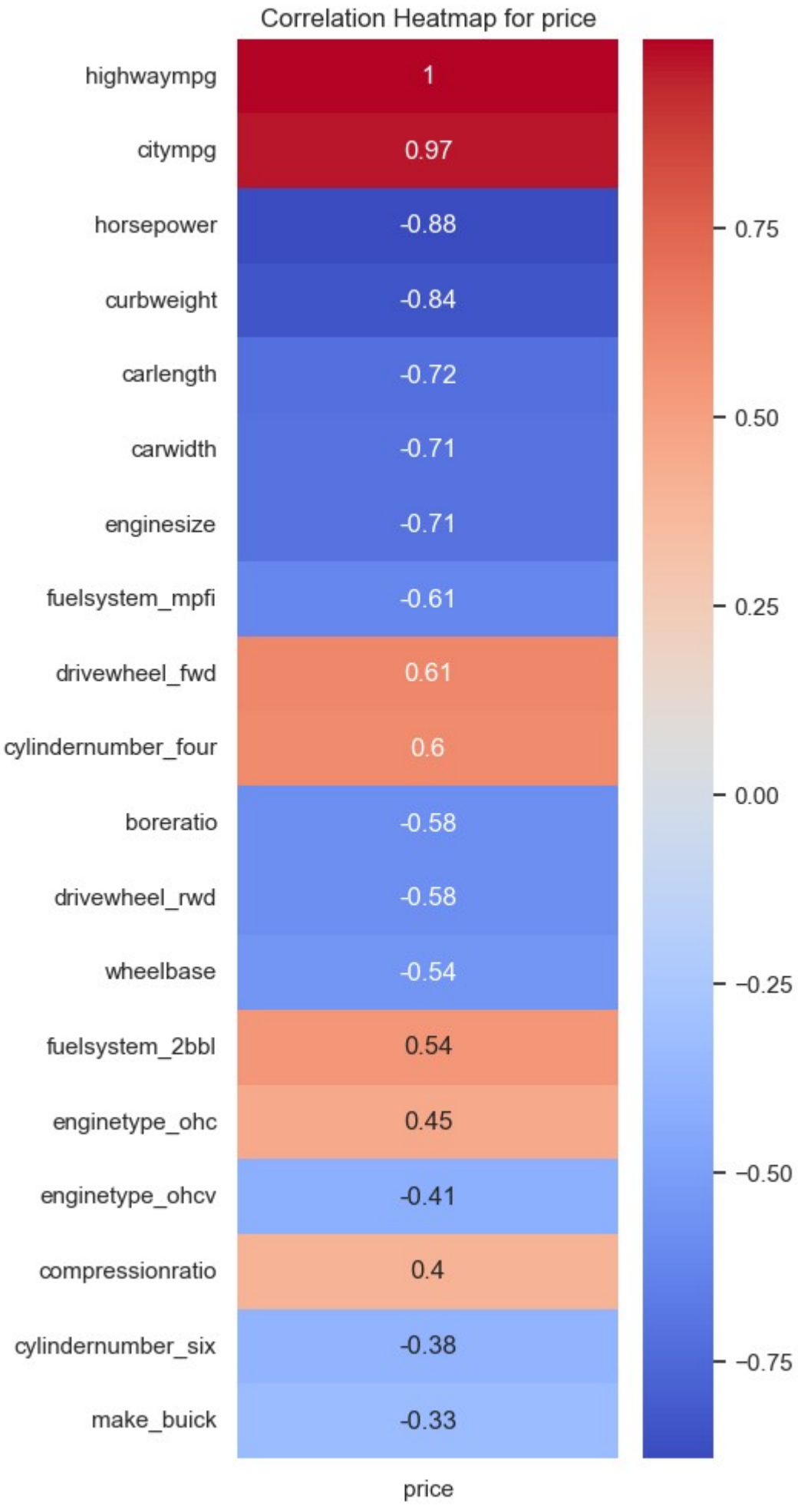
In [100…
```
correlation_matrix1 = pd.merge(X_scaled, y, right_index=True, left_index=True).c
```

In [101…
```
price_correlation = correlation_matrix1[['price']]
```

In [102…
```
sorted_top20_corr = price_correlation.reindex(price_correlation['price'].abs().s
```

In [105…
```
sorted_top20_corr.drop(index='price', inplace=True)
```

In [106…
```
plt.figure(figsize=(4, 12))
sns.heatmap(sorted_top20_corr, annot=True, cmap='coolwarm', cbar=True)
plt.title(f'Correlation Heatmap for price')
plt.show()
```


Correlation Heatmap for price
highwaympg
citympg
horsepower
curbweight
carlength
carwidth
enginesize
fuelsystem_mpfi
drivewheel_fwd
cylindernumber_four
boreratio
drivewheel_rwd
wheelbase
fuelsystem_2bbl
enginetype_ohc
enginetype_ohcv
compressionratio
cylindernumber_six
make_buick
1
0.97
-0.88
-0.84
-0.72
-0.71
-0.71
-0.61
0.61
0.6
-0.58
-0.58
-0.54
0.54
0.45
-0.41
0.4
-0.38
-0.33
price
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

Splitting Train - Test Data

In [107…
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2)
```

In [108…
```
X_train.shape
```

Out[108… (164, 68)

In [109…
```
X_test.shape
```

Out[109… (41, 68)

In [110…
```
y_train.shape
```

Out[110… (164,)

In [111…
```
y_test.shape
```

Out[111… (41,)

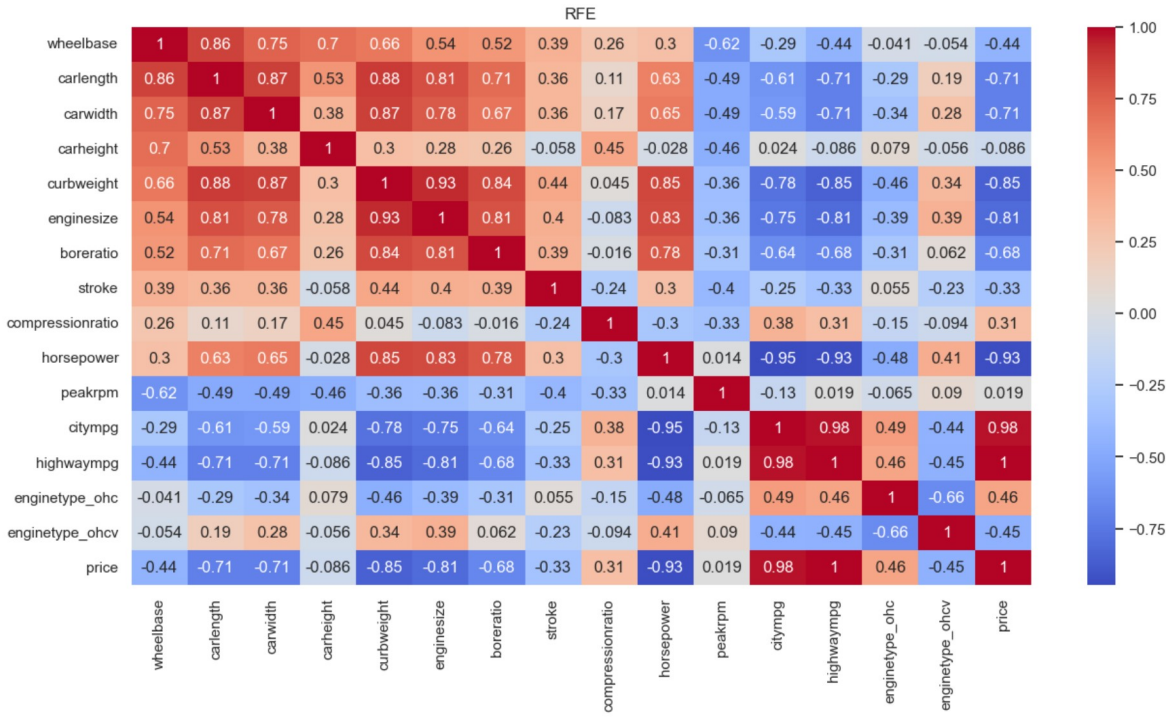
Feature Selection

In [115…
```
from sklearn.feature_selection import RFE
from sklearn.ensemble import RandomForestRegressor

rfe = RFE(estimator=RandomForestRegressor(), n_features_to_select=15)
rfe.fit(X_train, y_train)
selected_features = X_train.columns[rfe.support_]
X_RFE=X_train[selected_features]
print(selected_features)
```

```
Index(['wheelbase', 'carlength', 'carwidth', 'carheight', 'curbweight',
       'enginesize', 'boreratio', 'stroke', 'compressionratio', 'horsepower',
       'peakrpm', 'citympg', 'highwaympg', 'enginetype_ohc',
       'enginetype_ohcv'],
      dtype='object')
```

In [116…
```
RFE_corr = pd.merge(X_test[selected_features], df_encoded[['price']], left_index
```

In [117…
```
plt.figure(figsize=(15, 7.5))
sns.heatmap(RFE_corr, annot=True, cmap='coolwarm')
plt.title('RFE')
plt.show()
```



In [118…
```
X_train_final = X_RFE.copy()
```

In [119…
```
X_train_final.shape
```

Out[119… (164, 15)

In [120…
```
X_test_final = X_test[selected_features]
```

In [121…
```
X_test_final.shape
```

Out[121… (41, 15)

MODEL IMPLEMENTATION

Linear Regression

In [122…
```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
```

Decision Tree Regressor

In [123…
```
from sklearn.tree import DecisionTreeRegressor
dt = DecisionTreeRegressor()
```

Random Forest Regressor

In [124…
```
from sklearn.ensemble import RandomForestRegressor
```

```
rf = RandomForestRegressor()
```

Gradient Boosting Regressor

In [125…
```
from sklearn.ensemble import GradientBoostingRegressor
gbr = GradientBoostingRegressor()
```

Support Vector Regressor

In [126…
```
from sklearn.svm import SVR
svr = SVR()
```

MODEL EVALUATION

In [127…
```
models=[lr, dt, rf, gbr, svr]
```

In [128…
```
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error

model_names = {}
r2_scores = {}
mse_train = {}
mse_test = {}
mae_train = {}
mae_test = {}

for model in models:
    model_names[model] = model.__class__.__name__
    model.fit(X_train_final, y_train)
    y_pred = model.predict(X_test_final)
    r2_scores[model] = r2_score(y_test, y_pred)
    mse_train[model] = mean_squared_error(y_train, model.predict(X_train_final))
    mse_test[model] = mean_squared_error(y_test, y_pred)
    mae_train[model] = mean_absolute_error(y_train, model.predict(X_train_final))
    mae_test[model] = mean_absolute_error(y_test, y_pred)
```

In [129…
```
df_model_scores = pd.DataFrame({
    'Model': model_names.values(),
    'R2 Score': r2_scores.values(),
    'MSE - Train': mse_train.values(),
    'MSE - Test': mse_test.values(),
    'MAE - Train': mae_train.values(),
    'MAE - Test': mae_test.values()
})
```

In [130…
```
df_model_scores
```

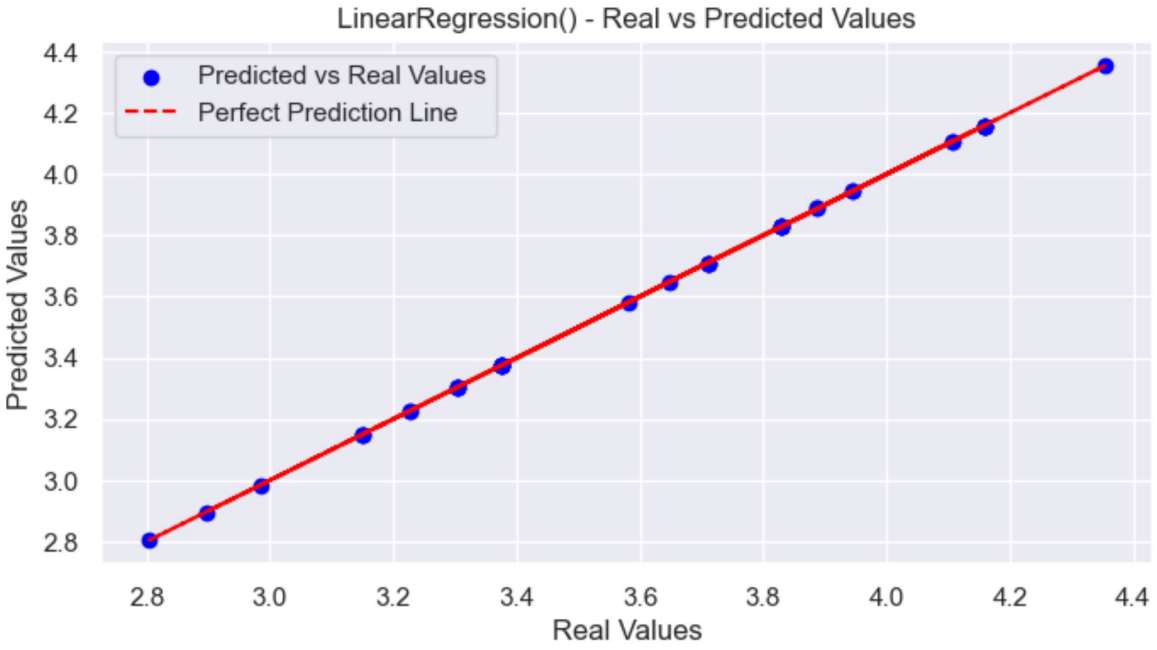
Out[130…

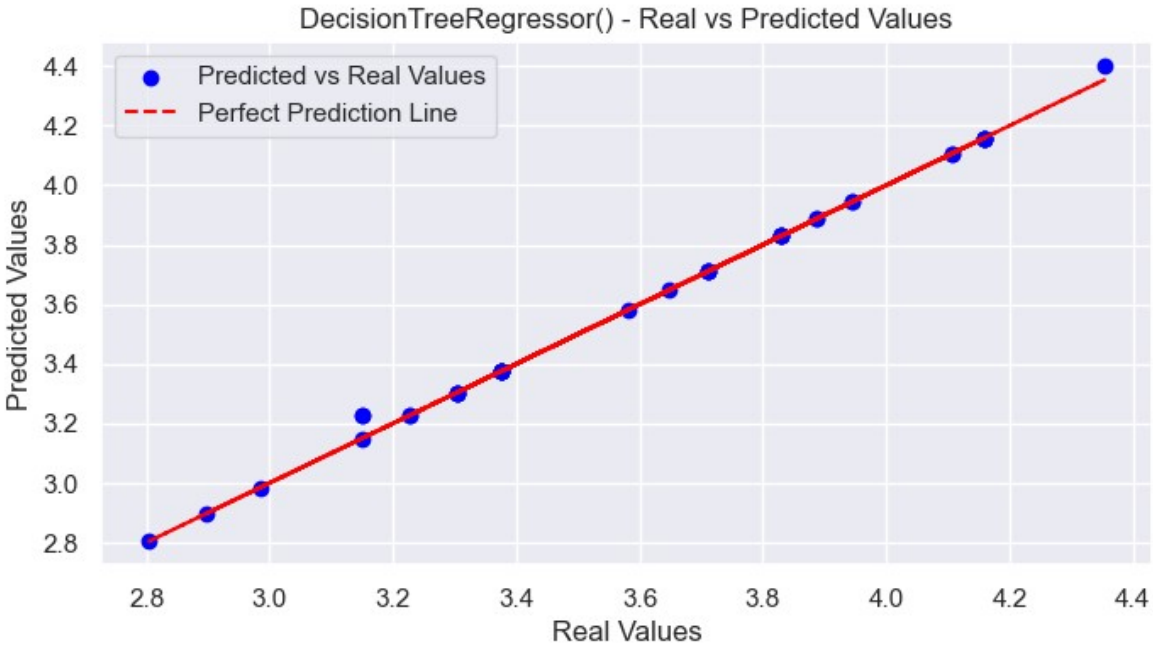
	Model	R2 Score	MSE - Train	MSE - Test	MAE - Train	MAE Tes
0	LinearRegression	1.000000	3.139167e-09	3.773687e-09	3.947233e-05	0.00004
1	DecisionTreeRegressor	0.997741	3.968355e-31	3.519840e-04	4.440892e-16	0.00495
2	RandomForestRegressor	0.998186	1.558388e-04	2.826120e-04	5.075101e-03	0.00748
3	GradientBoostingRegressor	0.999608	3.288592e-10	6.106170e-05	1.219890e-05	0.00192
4	SVR	0.964415	4.584117e-03	5.545339e-03	5.802713e-02	0.06075

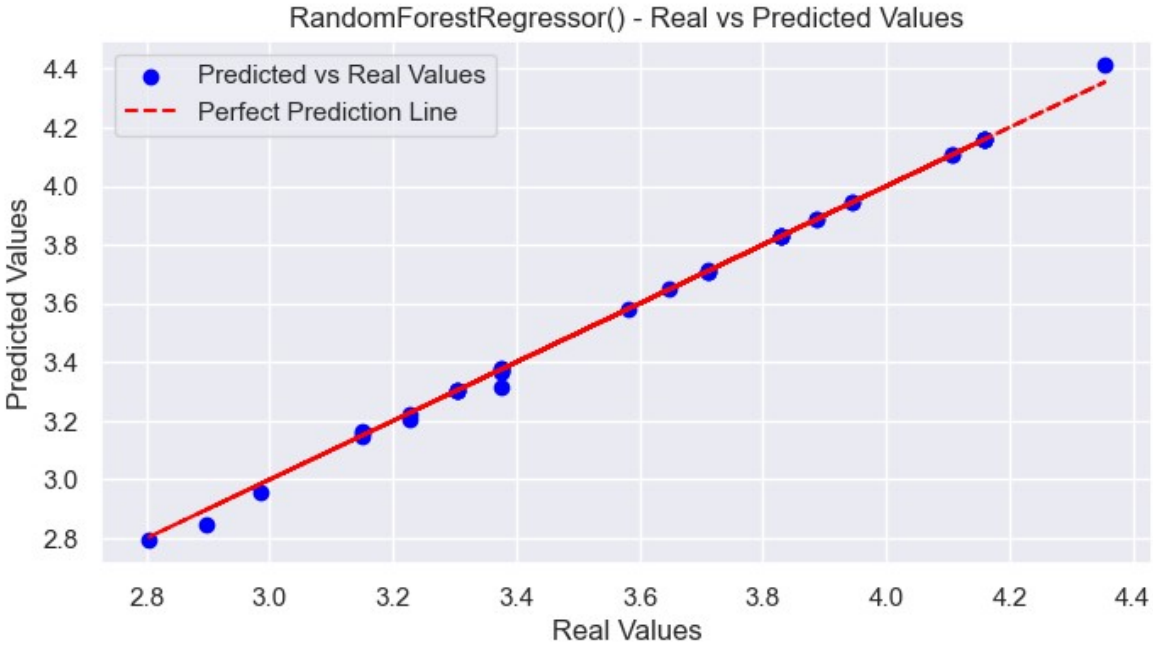
Predicted vs Real Values

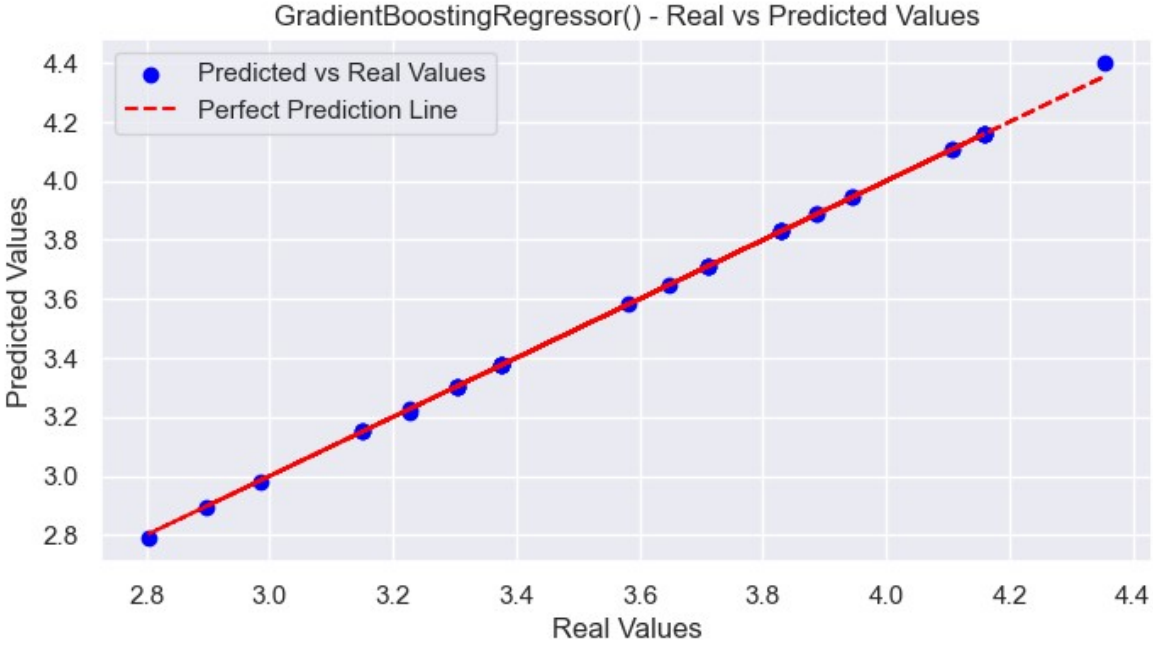
In [131…

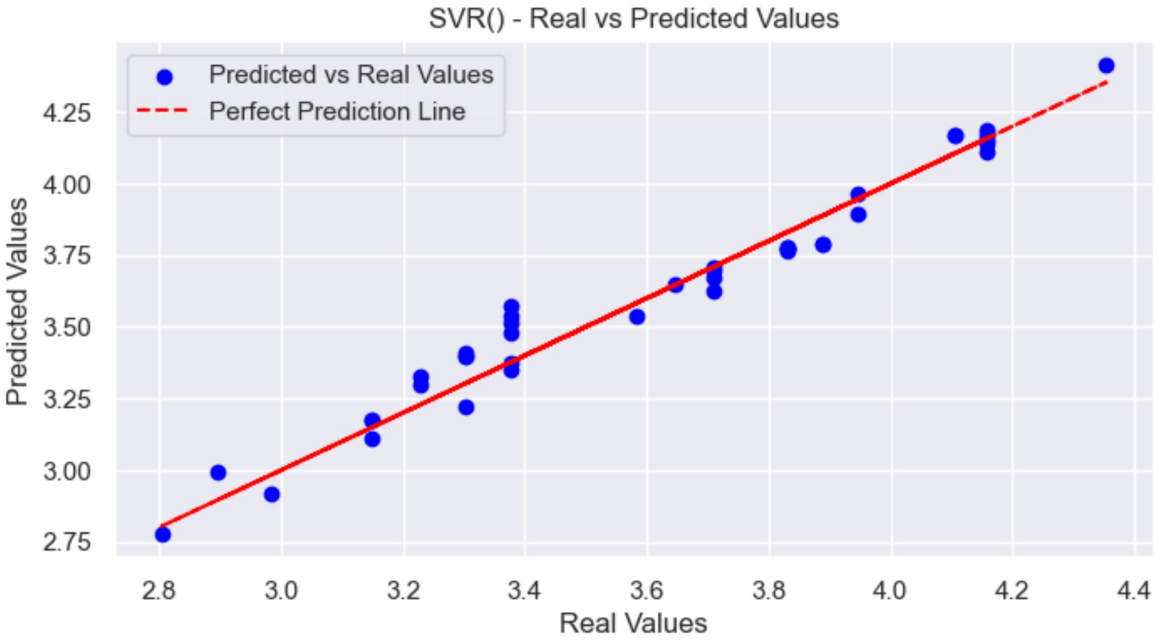
```
for model in models:
    y_pred = model.predict(X_test_final)

    #real values vs predicted values
    plt.figure(figsize=(8, 4))
    plt.scatter(y_test, y_pred, color='blue', label='Predicted vs Real Values')
    plt.plot(y_test, y_test, color='red', linestyle='--', label='Perfect Predict
    plt.title(f'{model} - Real vs Predicted Values')
    plt.xlabel('Real Values')
    plt.ylabel('Predicted Values')
    plt.legend()
    plt.show()
```




DecisionTreeRegressor() - Real vs Predicted Values
Predicted vs Real Values
Perfect Prediction Line
Predicted Values
Real Values
2.8
3.0
3.2
3.4
3.6
3.8
4.0
4.2
4.4


RandomForestRegressor() - Real vs Predicted Values
Predicted vs Real Values
Perfect Prediction Line
Predicted Values
Real Values
2.8
3.0
3.2
3.4
3.6
3.8
4.0
4.2
4.4


GradientBoostingRegressor() - Real vs Predicted Values
Predicted vs Real Values
Perfect Prediction Line
Predicted Values
Real Values
2.8
3.0
3.2
3.4
3.6
3.8
4.0
4.2
4.4



K-fold Cross Validation

In [142…

```
from sklearn.model_selection import cross_val_score, KFold

kf = KFold(n_splits=5, shuffle=True, random_state=42)

for model in models:
    scores = cross_val_score(model, X_scaled[selected_features], y, cv=kf, scori
    print(f'{model.__class__.__name__}: Mean MSE = {np.mean(scores):.4f}, Std =
```

```
LinearRegression: Mean MSE = -0.0000, Std = 0.0000
DecisionTreeRegressor: Mean MSE = -0.0021, Std = 0.0018
RandomForestRegressor: Mean MSE = -0.0014, Std = 0.0013
GradientBoostingRegressor: Mean MSE = -0.0004, Std = 0.0004
SVR: Mean MSE = -0.0193, Std = 0.0163
```

Hyperparameter Tuning

In [132…

```
from sklearn.model_selection import GridSearchCV
```

In [137…

```
models_and_params = {
    'LinearRegression': (LinearRegression(), {}),

    'DecisionTreeRegressor': (
        DecisionTreeRegressor(),
        {
            'max_depth': [None, 5, 10, 15],
            'min_samples_split': [2, 5, 10],
            'min_samples_leaf': [1, 2, 4]
        }
    ),

    'RandomForestRegressor': (
        RandomForestRegressor(),
```

```
        {
            'n_estimators': [50, 100, 200],
            'max_depth': [None, 10, 20],
            'min_samples_split': [2, 5],
            'min_samples_leaf': [1, 2, 4]
        }
    ),

    'GradientBoostingRegressor': (
        GradientBoostingRegressor(),
        {
            'n_estimators': [50, 100],
            'learning_rate': [0.01, 0.1, 0.2],
            'max_depth': [3, 5, 7],
            'min_samples_split': [2, 5],
            'min_samples_leaf': [1, 2, 4]
        }
    ),

    'SVR': (
        SVR(),
        {
            'kernel': ['linear', 'rbf', 'poly'],
            'C': [0.1, 1, 10],
            'gamma': ['scale', 'auto']
        }
    )
}


results = {}

#hyperparameter tuning
for model_name, (model, params) in models_and_params.items():
    print(f"Tuning hyperparameters for {model_name}...")

    if model_name == 'LinearRegression':
        model.fit(X_train_final, y_train)
        y_pred = model.predict(X_test_final)
        mse = mean_squared_error(y_test, y_pred)
        r2 = r2_score(y_test, y_pred)
        best_params = {}
    else:
        grid_search = GridSearchCV(model, params, cv=5, scoring='neg_mean_square
        grid_search.fit(X_train_final, y_train)

        best_model = grid_search.best_estimator_
        best_params = grid_search.best_params_

        y_pred = best_model.predict(X_test_final)
        mse = mean_squared_error(y_test, y_pred)
        r2 = r2_score(y_test, y_pred)

    results[model_name] = {'Best Params': best_params,
                           'MSE': mse,
                           'R2': r2}


resultss = pd.DataFrame(results).T
print("\nHyperparameter tuning results:")
```

```
print(resultss)
```

```
Tuning hyperparameters for LinearRegression...
Tuning hyperparameters for DecisionTreeRegressor...
Tuning hyperparameters for RandomForestRegressor...
Tuning hyperparameters for GradientBoostingRegressor...
Tuning hyperparameters for SVR...

Hyperparameter tuning results:
                                                          Best Params  \
LinearRegression                                                    {}
DecisionTreeRegressor      {'max_depth': 10, 'min_samples_leaf': 1, 'min_...
RandomForestRegressor      {'max_depth': None, 'min_samples_leaf': 1, 'mi...
GradientBoostingRegressor  {'learning_rate': 0.2, 'max_depth': 3, 'min_sa...
SVR                           {'C': 1, 'gamma': 'scale', 'kernel': 'linear'}

                                MSE        R2
LinearRegression                0.0       1.0
DecisionTreeRegressor      0.000448  0.997126
RandomForestRegressor      0.000451  0.997107
GradientBoostingRegressor  0.000116  0.999255
SVR                        0.002357  0.984873
```

In [136…
```
df_model_scores.round(6)
```

Out[136…

	Model	R2 Score	MSE - Train	MSE - Test	MAE - Train	MAE - Test
0	LinearRegression	1.000000	0.000000	0.000000	0.000039	0.000043
1	DecisionTreeRegressor	0.997741	0.000000	0.000352	0.000000	0.004955
2	RandomForestRegressor	0.998186	0.000156	0.000283	0.005075	0.007489
3	GradientBoostingRegressor	0.999608	0.000000	0.000061	0.000012	0.001925
4	SVR	0.964415	0.004584	0.005545	0.058027	0.060754

Hyperparameter tuning increased test MSE for all models except linear regression and SVR. It reduced R2 score of the same models.

> The best-performing model based on the provided metrics is *Linear Regression*. It has the highest R^2 score (1.000000), the lowest Mean Squared Error (MSE) for testing set, and the lowest Mean Absolute Error (MAE) for testing set.

In [138…
```
feature_coeffs = pd.DataFrame({
    'feature': X_train_final.columns,
    'coeff': lr.coef_
})
```

In [139…
```
feature_coeffs.sort_values(by='coeff', ascending=False).head(10)
```

Out[139...

	feature	coeff
12	highwaympg	5.679268e-01
9	horsepower	3.418241e-05
0	wheelbase	3.046114e-05
13	enginetype_ohc	2.869889e-05
6	boreratio	1.035714e-05
3	carheight	9.559380e-06
5	enginesize	8.442164e-06
10	peakrpm	8.257660e-06
8	compressionratio	7.780121e-06
4	curbweight	-4.000023e-07

OBSERVATIONS

- highwaympg has the largest positive coefficient (0.5679), meaning that as highway mileage increases, the predicted target variable (likely car price or some performance measure) increases significantly. This is the most influential feature in the model.
- horsepower, wheelbase, and enginetype_ohc also have small positive coefficients, though their impact is much smaller compared to highwaympg.
- curbweight has a small negative coefficient (-4.000e-07), meaning that as curb weight increases, it slightly reduces the target variable. However, this influence is very minimal.

CONCLUSION

- highwaympg is by far the most important feature in the model, strongly driving the target variable in a positive direction.
- Other features like horsepower, wheelbase, and enginetype_ohc also have a positive but much weaker influence.
- The negative coefficient of curbweight indicates a very slight negative relationship, but its impact is negligible compared to highwaympg.

NOTE

The popular car options in current US market are mentioned below

- insurance risk rating : 0,1
- fuel type : gas
- body type : hatchback, sedan
- no. of cylinders : 4
- valve mechanism : ohc

If the company aims to launch cars at a higher price range focus on spacious and well built cars with a higher performance