PREDICTION OF AUTOMOBILE

IMPORTING THE LIBRARIES

In [1]:

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
from sklearn.feature_selection import RFE
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
import warnings
warnings.filterwarnings('ignore')
```

DATA PROCESSING

In [3]:

```
c_df=pd.read_csv("C:/Users/yuvak/OneDrive/Desktop/ML PROJECTS 1&2 FROM BI/AutoData (1).csv")
```

In [4]:

```
c_df.head()
```

Out[4]:

	symboling	make	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	carlength	...	enginesize	fuelsystem	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	highwaympg	price
0	3	alfa-romero giulia	gas	std	two	convertible	rwd	front	88.6	168.8	...	130	mpfi	3.47	2.68	9.0	111	5000	21	27	13495.0
1	3	alfa-romero stelvio	gas	std	two	convertible	rwd	front	88.6	168.8	...	130	mpfi	3.47	2.68	9.0	111	5000	21	27	16500.0
2	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	front	94.5	171.2	...	152	mpfi	2.68	3.47	9.0	154	5000	19	26	16500.0
3	2	audi 100 ls	gas	std	four	sedan	fwd	front	99.8	176.6	...	109	mpfi	3.19	3.40	10.0	102	5500	24	30	13950.0
4	2	audi 100ls	gas	std	four	sedan	4wd	front	99.4	176.6	...	136	mpfi	3.19	3.40	8.0	115	5500	18	22	17450.0

5 rows × 25 columns

In [5]:

```
c_df.tail()
```

Out[5]:

	symboling	make	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	carlength	...	enginesize	fuelsystem	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	highwaympg	price
200	-1	volvo 145e (sw)	gas	std	four	sedan	rwd	front	109.1	188.8	...	141	mpfi	3.78	3.15	9.5	114	5400	23	28	16845.0
201	-1	volvo 144ea	gas	turbo	four	sedan	rwd	front	109.1	188.8	...	141	mpfi	3.78	3.15	8.7	160	5300	19	25	19045.0
202	-1	volvo 244dl	gas	std	four	sedan	rwd	front	109.1	188.8	...	173	mpfi	3.58	2.87	8.8	134	5500	18	23	21485.0
203	-1	volvo	diesel	turbo	four	sedan	rwd	front	109.1	188.8	...	145	idi	3.01	3.40	23.0	106	4800	26	27	2247

	symboling	make	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	carlength	...	enginesize	fuelsystem	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	highwaympg	price
		246																			0.0
204	-1	volvo 264gl	gas	turbo	four	sedan	rwd	front	109.1	188.8	...	141	mpfi	3.78	3.15	9.5	114	5400	19	25	22625.0

5 rows × 25 columns

In [7]:

```
c_df.shape
```

Out[7]:

```
(205, 25)
```

In [8]:

```
c_df.dtypes
```

Out[8]:

```
symboling             int64
make                 object
fueltype             object
aspiration           object
doornumber           object
carbody              object
drivewheel           object
enginelocation       object
wheelbase           float64
carlength           float64
carwidth            float64
carheight           float64
```

```
curbweight            int64
enginetype           object
cylindernumber       object
enginesize            int64
fuelsystem           object
boreratio           float64
stroke              float64
compressionratio    float64
horsepower            int64
peakrpm               int64
citympg               int64
highwaympg            int64
price               float64
dtype: object
```

In [9]:

c_df.info()

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

```
 22   citympg            205 non-null    int64  
 23   highwaympg         205 non-null    int64  
 24   price              205 non-null    float64
dtypes: float64(8), int64(7), object(10)
memory usage: 40.2+ KB
```

In [10]:

```
c_df.describe()
```

Out[10]:

	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	highwaympg	price
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000
mean	0.834146	98.756585	174.049268	65.907805	53.724878	2555.565854	126.907317	3.329756	3.255415	10.142537	104.117073	5125.121951	25.219512	30.751220	13276.710571
std	1.245307	6.021776	12.337289	2.145204	2.443522	520.680204	41.642693	0.270844	0.313597	3.972040	39.544167	476.985643	6.542142	6.886443	7988.852332
min	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000000	2.540000	2.070000	7.000000	48.000000	4150.000000	13.000000	16.000000	5118.000000
25%	0.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97.000000	3.150000	3.110000	8.600000	70.000000	4800.000000	19.000000	25.000000	7788.000000
50%	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.000000	3.310000	3.290000	9.000000	95.000000	5200.000000	24.000000	30.000000	10295.000000
75%	2.000000	102.40	183.10	66.900000	55.500000	2935.00	141.00	3.580000	3.410000	9.400000	116.000000	5500.00	30.000000	34.000000	16503.000000

	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	highwaympg	price
		0000	0000			0000	0000					0000			
max	3.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326.000000	3.940000	4.170000	23.000000	288.000000	6600.000000	49.000000	54.000000	45400.000000

DATA CLEANING

In [11]:

```
c_df.duplicated().sum()
```

Out[11]:

```
0
```

In [15]:

```
c_df.isnull().sum()
```

Out[15]:

```
symboling           0
make                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
```

In [16]:

```
c_df['symboling'].value_counts()
```

Out[16]:

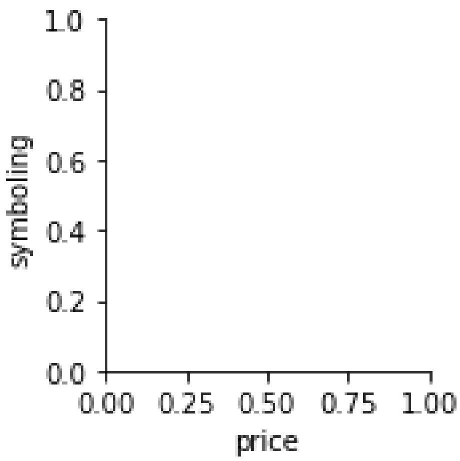
```
 0    67
 1    54
 2    32
 3    27
-1    22
-2     3
Name: symboling, dtype: int64
```

In [25]:

```
sns.pairplot(y_vars = 'symboling', x_vars = 'price' ,data=c_df)
```

Out[25]:

```
<seaborn.axisgrid.PairGrid at 0x11771b787f0>
```



In [26]:

```
c_df['make'].value_counts()
```

Out[26]:

```
peugeot 504            6
toyota corolla         6
toyota corona          6
subaru dl              4
mitsubishi g4          3
                      ..
plymouth duster        1
mitsubishi mirage      1
porsche boxter         1
audi fox               1
dodge coronet custom   1
Name: make, Length: 147, dtype: int64
```

In [27]:

```
c_df['car_company'] = c_df['make'].apply(lambda x:x.split(' ')[0])
```

In [28]:

```
c_df.head()
```

Out[28]:

	symboling	make	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	carlength	...	fuelsystem	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	highwaympg	price	car_company
0	3	alfa-romero giulia	gas	std	two	convertible	rwd	front	88.6	168.8	...	mpfi	3.47	2.68	9.0	111	5000	21	27	13495.0	alfa-romero

	symboling	make	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	carlength	...	fuelsystem	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	highwaympg	price	car_company
1	3	alfa-romero stelvio	gas	std	two	convertible	rwd	front	88.6	168.8	...	mpfi	3.47	2.68	9.0	111	5000	21	27	16500.0	alfa-romero
2	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	front	94.5	171.2	...	mpfi	2.68	3.47	9.0	154	5000	19	26	16500.0	alfa-romero
3	2	audi 100 ls	gas	std	four	sedan	fwd	front	99.8	176.6	...	mpfi	3.19	3.40	10.0	102	5500	24	30	13950.0	audi
4	2	audi 100ls	gas	std	four	sedan	4wd	front	99.4	176.6	...	mpfi	3.19	3.40	8.0	115	5500	18	22	17450.0	audi

5 rows × 26 columns

In [29]:

```
c_df = c_df.drop(['make'], axis =1)
```

In [30]:

```
c_df['car_company'].value_counts()
```

Out[30]:

```
toyota          31
nissan          17
mazda           15
mitsubishi      13
honda           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
maxda            2
vw               2
renault          2
Nissan           1
vokswagen        1
toyouta          1
mercury          1
porcshce         1
Name: car_company, dtype: int64
```

In [32]:

```
c_df['car_company'].replace('toyouta', 'toyota',inplace=True)
c_df['car_company'].replace('Nissan', 'nissan',inplace=True)
c_df['car_company'].replace('maxda', 'mazda',inplace=True)
c_df['car_company'].replace('vokswagen', 'volkswagen',inplace=True)
c_df['car_company'].replace('vw', 'volkswagen',inplace=True)
c_df['car_company'].replace('porcshce', 'porsche',inplace=True)
```

In [33]:

```
c_df['car_company'].value_counts()
```

Out[33]:

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

mistakes are re-summerized

In [34]:

```
c_df['fueltype'].value_counts()
```

Out[34]:

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

In [35]:

```
c_df['aspiration'].value_counts()
```

Out[35]:

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

In [36]:

c_df['doornumber'].value_counts()

Out[36]:

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

In [37]:

c_df['carbody'].value_counts()

Out[37]:

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

In [38]:

c_df['drivewheel'].value_counts()

Out[38]:

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

In [39]:

c_df['enginelocation'].value_counts()

Out[39]:

```
front     202
```

```
rear          3
Name: enginelocation, dtype: int64
```

In [40]:

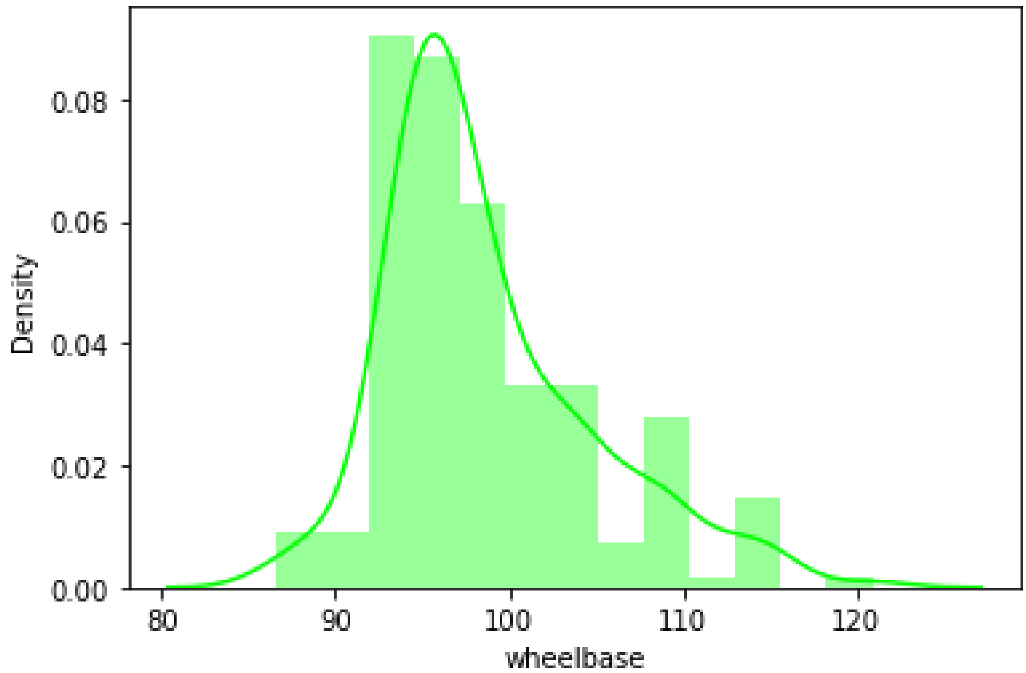
```
c_df['wheelbase'].value_counts().head()
```

Out[40]:

```
94.5    21
93.7    20
95.7    13
96.5     8
98.4     7
Name: wheelbase, dtype: int64
```

In [41]:

```
sns.distplot(c_df['wheelbase'],color="lime")
plt.show()
```



In [42]:

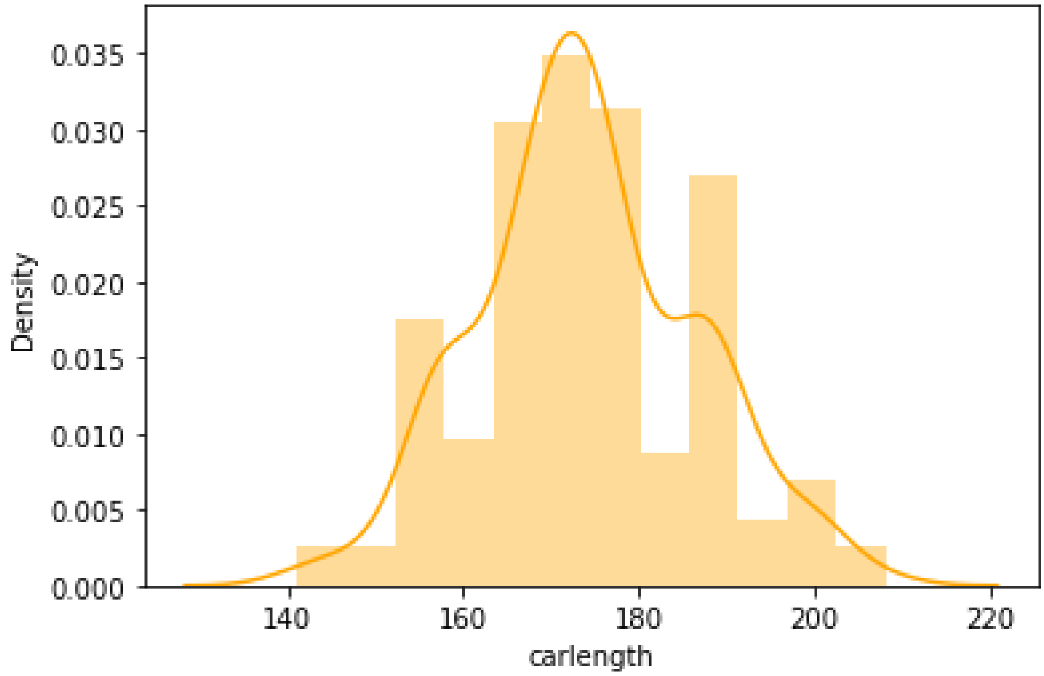
```
c_df['carlength'].value_counts().head()
```

Out[42]:

```
157.3    15
188.8    11
166.3     7
171.7     7
186.7     7
Name: carlength, dtype: int64
```

In [43]:

```
sns.distplot(c_df['carlength'],color="orange")
plt.show()
```



In [44]:

```
c_df['enginetype'].value_counts()
```

Out[44]:

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

In [45]:

```
c_df['cylindernumber'].value_counts()
```

Out[45]:

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

In [46]:

```
def number(x):
  return x.map({'four':4,'six':6,'five':5,'eight':8,'two':2,'three':3,'twelve':12})
c_df['cylindernumber']=c_df[['cylindernumber']].apply(number)
```

In [47]:

```
c_df['cylindernumber'].value_counts()
```

Out[47]:

```
4      159
6       24
5       11
8        5
2        4
12       1
3        1
Name: cylindernumber, dtype: int64
```

In [48]:

```
c_df['fuelsystem'].value_counts()
```

Out[48]:

```
mpfi     94
```

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

Data Visulaization:

In [52]:

```
c_num = c_df.select_dtypes(include =['int64','float64'])
```

In [53]:

```
c_num.head()
```

Out[53]:

	symboling	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	highwaympg	price
0	3	88.6	168.8	64.1	48.8	2548	4	130	3.47	2.68	9.0	111	5000	21	27	13495.0
1	3	88.6	168.8	64.1	48.8	2548	4	130	3.47	2.68	9.0	111	5000	21	27	16500.0
2	1	94.5	171.2	65.5	52.4	2823	6	152	2.68	3.47	9.0	154	5000	19	26	16500.0
3	2	99.8	176.6	66.2	54.3	2337	4	109	3.19	3.40	10.0	102	5500	24	30	13950.0

	symboling	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	highwaympg	price
4	2	99.4	176.6	66.4	54.3	2824	5	136	3.19	3.40	8.0	115	5500	18	22	17450.0

In [54]:

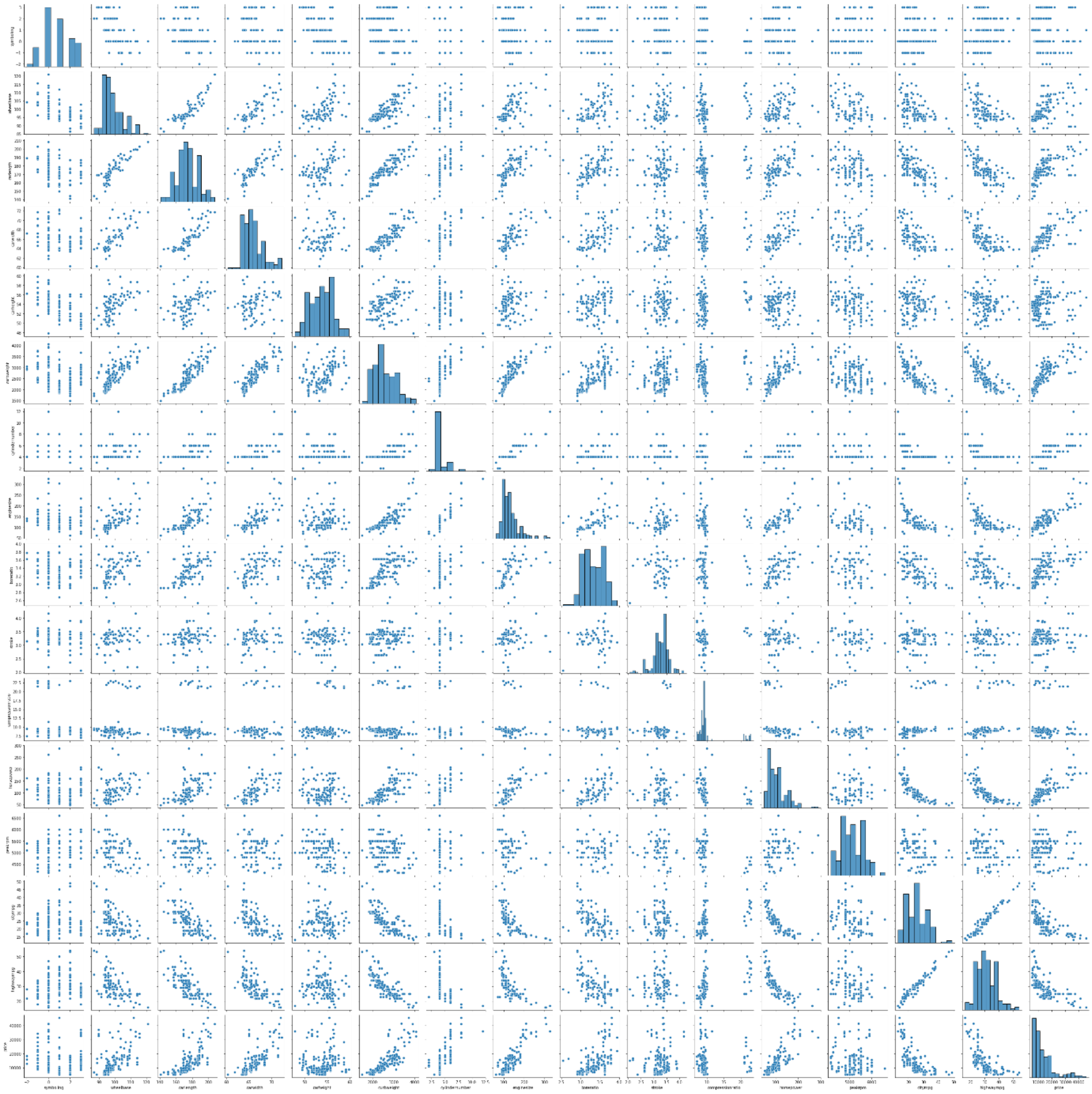
```
c_num.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   symboling         205 non-null    int64  
 1   wheelbase         205 non-null    float64
 2   carlength         205 non-null    float64
 3   carwidth          205 non-null    float64
 4   carheight         205 non-null    float64
 5   curbweight        205 non-null    int64  
 6   cylindernumber    205 non-null    int64  
 7   enginesize        205 non-null    int64  
 8   boreratio         205 non-null    float64
 9   stroke            205 non-null    float64
 10  compressionratio  205 non-null    float64
 11  horsepower        205 non-null    int64  
 12  peakrpm           205 non-null    int64  
 13  citympg           205 non-null    int64  
 14  highwaympg        205 non-null    int64  
 15  price             205 non-null    float64
dtypes: float64(8), int64(8)
memory usage: 25.8 KB
```

In [57]:

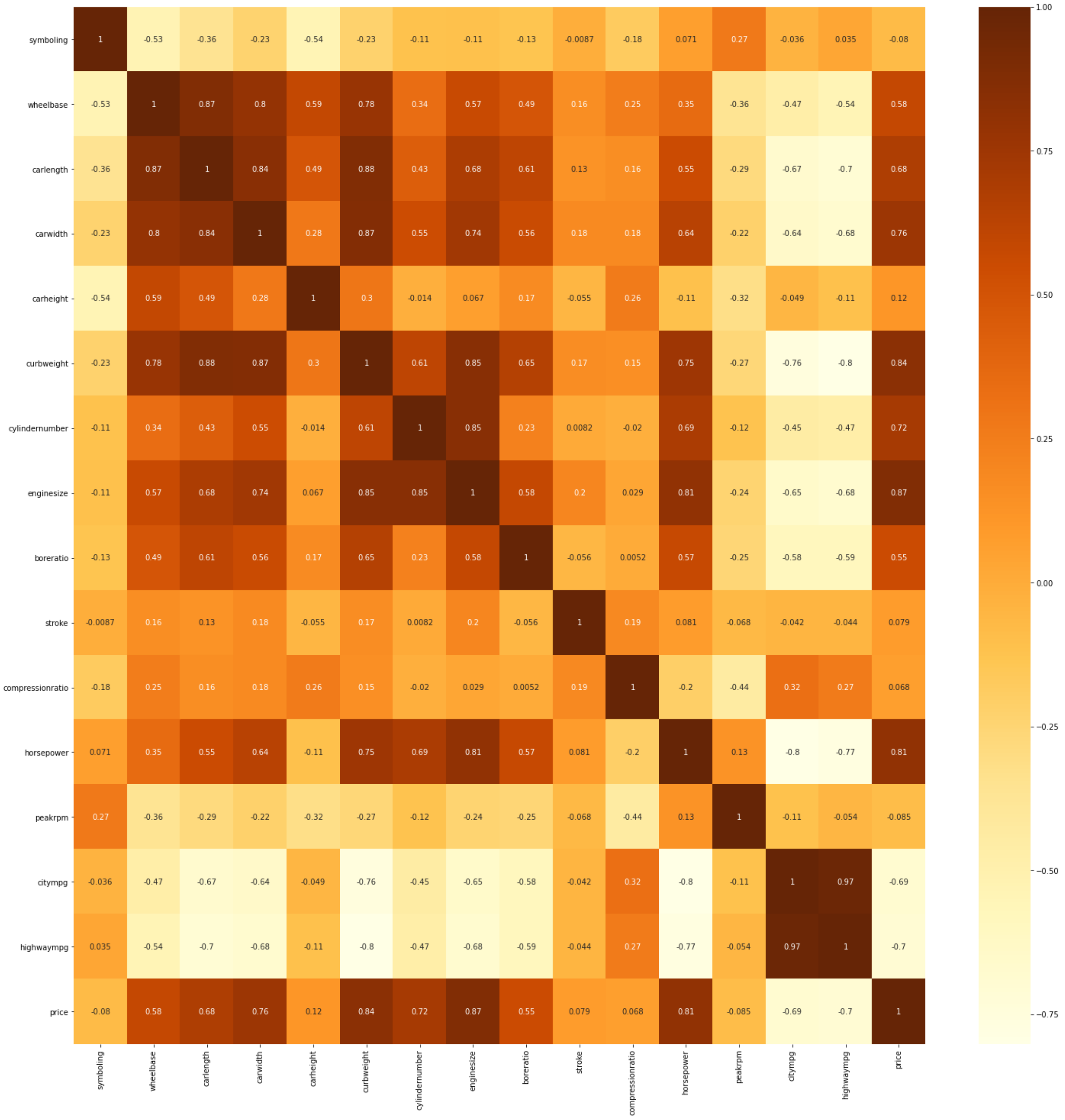
```
plt.figure(figsize = (25,25))
sns.pairplot(c_num)
plt.show()
```

```
<Figure size 1800x1800 with 0 Axes>
```



In [61]:

```
plt.figure(figsize = (25,25))
sns.heatmap(c_df.corr(), annot = True ,cmap = 'YlOrBr')
plt.show()
```



-Price is highly (positively) correlated with wheelbase, carlength, carwidth, curbweight, enginesize, horsepower.

-Price is negatively correlated to symboling, citympg and highwaympg.

-This suggest that cars having high mileage may fall in the 'economy' cars category, and are priced lower.

-There are many independent variables which are highly correlated: wheelbase, carlength, curbweight, enginesize etc.. all are positively correlated.

In [62]:

```
categorical_cols = c_df.select_dtypes(include = ['object'])
```

```
categorical_cols.head()
```

Out[62]:

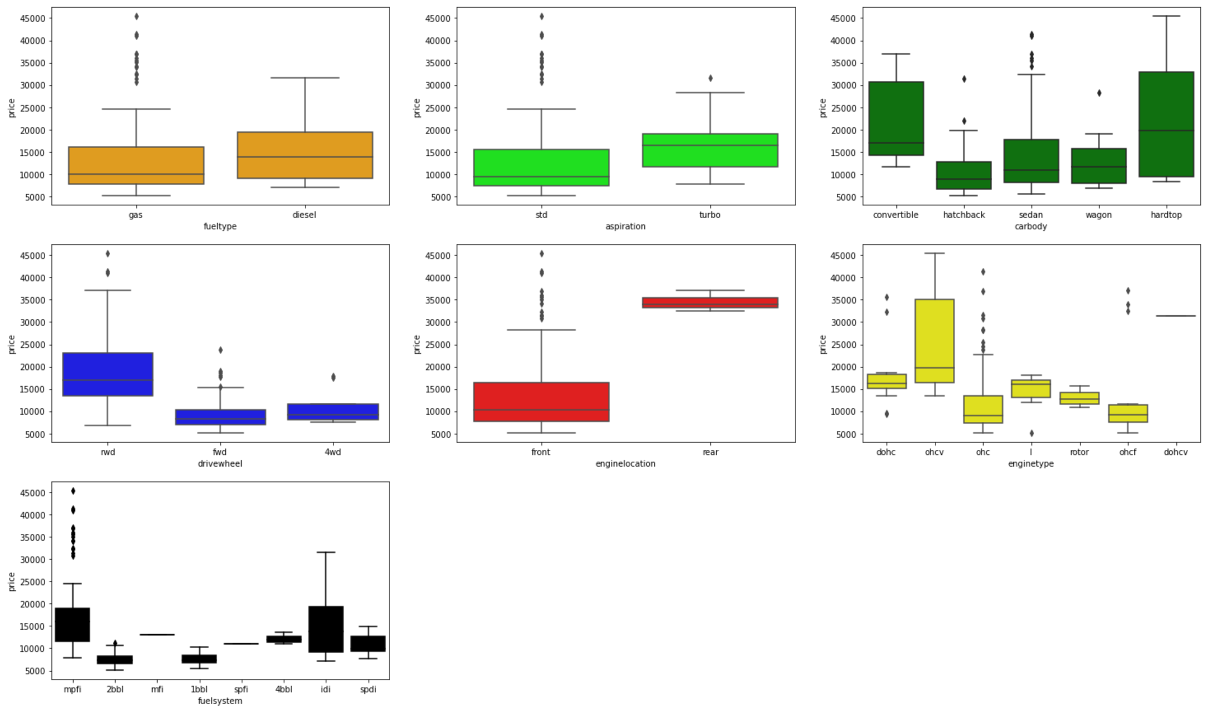
	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	enginetype	fuelsystem	car_company
0	gas	std	two	convertible	rwd	front	dohc	mpfi	alfa-romero
1	gas	std	two	convertible	rwd	front	dohc	mpfi	alfa-romero
2	gas	std	two	hatchback	rwd	front	ohcv	mpfi	alfa-romero
3	gas	std	four	sedan	fwd	front	ohc	mpfi	audi
4	gas	std	four	sedan	4wd	front	ohc	mpfi	audi

In [64]:

```
plt.figure(figsize = (25,15))
plt.subplot(3,3,1)
sns.boxplot(x = 'fueltype', y = 'price', data = c_df,color="orange")
plt.subplot(3,3,2)
sns.boxplot(x = 'aspiration', y = 'price', data = c_df,color="lime")
plt.subplot(3,3,3)
sns.boxplot(x = 'carbody', y = 'price', data = c_df,color="green")
plt.subplot(3,3,4)
sns.boxplot(x = 'drivewheel', y = 'price', data = c_df,color="blue")
plt.subplot(3,3,5)
sns.boxplot(x = 'enginelocation', y = 'price', data = c_df,color="red")
plt.subplot(3,3,6)
sns.boxplot(x = 'enginetype', y = 'price', data = c_df,color="yellow")
plt.subplot(3,3,7)
sns.boxplot(x = 'fuelsystem', y = 'price', data = c_df,color="black")
```

Out[64]:

```
<AxesSubplot:xlabel='fuelsystem', ylabel='price'>
```

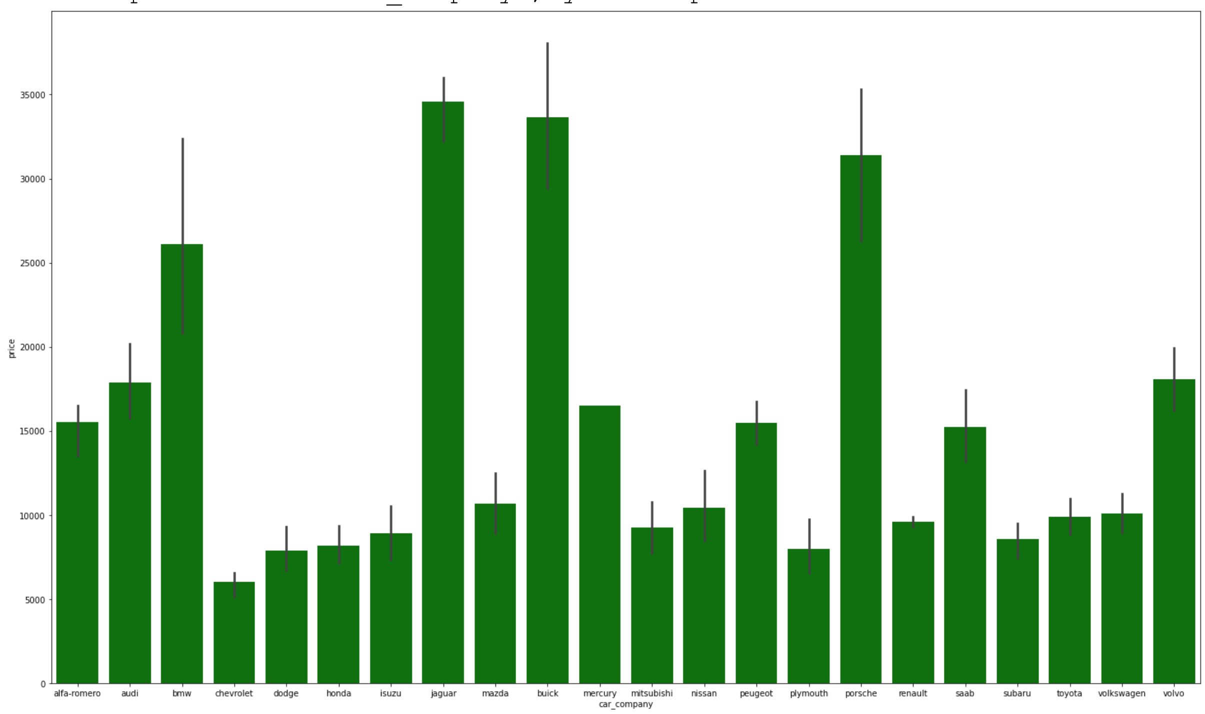


In [71]:

```
plt.figure(figsize = (25,15))
sns.barplot(x = 'car_company', y = 'price', data = c_df,color="green")
```

Out[71]:

```
<AxesSubplot:xlabel='car_company', ylabel='price'>
```



1. From the price boxplot it is clear that The brands with the most expensive vehicles in the dataset belong to Bmw,Buick,Jaguar and porsche.

2. Whereas the lower priced cars belong to chevrolet
3. The median price of gas vehicles is lower than that of Diesel Vehicles.
4. 75th percentile of standard aspirated vehicles have a price lower than the median price of turbo aspirated vehicles.
5. Two and four Door vehicles are almost equally priced. There are however some outliers in the price of two-door vehicles.
6. Hatchback vehicles have the lowest median price of vehicles in the data set whereas hardtop vehicles have the highest median price.
7. The price of vehicles with rear placed engines is significantly higher than the price of vehicles with front placed engines.
8. Almost all vehicles in the dataset have engines placed in the front of the vehicle. However, the price of vehicles with rear placed engines is significantly higher than the price of vehicles with front placed engines.
9. The median cost of eight cylinder vehicles is higher than other cylinder categories.
10. It is clear that vehicles Multi-port Fuel Injection [MPFI] fuelsystem have the highest median price. There are also some outliers on the higher price side having MPFI systems.
11. Vehicles with OHCV engine type falls under higher price range.

Extract Features and Target

In [461]:

```
c_df
```

Out[461]:

	symboling	doornumber	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	...	car_company_nissan	car_company_peugeot	car_company_plymouth	car_company_porsche	car_company_renault	car_company_saab	car_company_subaru	car_company_toyota	car_company_volkswagen	car_company_volvo
0	3	two	0.058309	0.413433	0.316667	48.8	0.411171	4	0.260377	0.664286	...	0	0	0	0	0	0	0	0	0	0
1	3	two	0.058309	0.413433	0.316667	48.8	0.411171	4	0.260377	0.664286	...	0	0	0	0	0	0	0	0	0	0

	symboling	doornumber	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	...	car_company_nissan	car_company_peugeot	car_company_plymouth	car_company_porsche	car_company_renault	car_company_saab	car_company_subaru	car_company_toyota	car_company_volkswagen	car_company_volvo
2	1	two	0.230321	0.449254	0.433333	52.4	0.517843	6	0.343396	0.100000	...	0	0	0	0	0	0	0	0	0	0
3	2	four	0.384840	0.529851	0.491667	54.3	0.329325	4	0.181132	0.464286	...	0	0	0	0	0	0	0	0	0	0
4	2	four	0.373178	0.529851	0.508333	54.3	0.518231	5	0.283019	0.464286	...	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
200	-1	four	0.655977	0.711940	0.716667	55.5	0.567882	4	0.301887	0.885714	...	0	0	0	0	0	0	0	0	0	1
201	-1	four	0.6559	0.7119	0.7083	55.5	0.6055	4	0.3018	0.8857	...	0	0	0	0	0	0	0	0	0	1

	symboling	doornumber	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	...	car_company_nissan	car_company_peugeot	car_company_plymouth	car_company_porsche	car_company_renault	car_company_saab	car_company_subaru	car_company_toyota	car_company_volkswagen	car_company_volvo
			77	40	33		08		87	14											
202	-1	four	0.655977	0.711940	0.716667	55.5	0.591156	6	0.422642	0.742857	...	0	0	0	0	0	0	0	0	0	1
203	-1	four	0.655977	0.711940	0.716667	55.5	0.670675	6	0.316981	0.335714	...	0	0	0	0	0	0	0	0	0	1
204	-1	four	0.655977	0.711940	0.716667	55.5	0.610551	4	0.301887	0.885714	...	0	0	0	0	0	0	0	0	0	1

205 rows × 61 columns

In [462]:

```
y=c_df["price"]
```

In [463]:

```
X=c_df.drop("price",axis="columns")
```

In [464]:

X

Out[464]:

	symboling	doornumber	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	...	car_company_nissan	car_company_peugeot	car_company_plymouth	car_company_porsche	car_company_renault	car_company_saab	car_company_subaru	car_company_toyota	car_company_volkswagen	car_company_volvo
0	3	two	0.058309	0.413433	0.316667	48.8	0.411171	4	0.260377	0.664286	...	0	0	0	0	0	0	0	0	0	0
1	3	two	0.058309	0.413433	0.316667	48.8	0.411171	4	0.260377	0.664286	...	0	0	0	0	0	0	0	0	0	0
2	1	two	0.230321	0.449254	0.433333	52.4	0.517843	6	0.343396	0.100000	...	0	0	0	0	0	0	0	0	0	0
3	2	four	0.384840	0.529851	0.491667	54.3	0.329325	4	0.181132	0.464286	...	0	0	0	0	0	0	0	0	0	0

	symboling	doornumber	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	...	car_company_nissan	car_company_peugeot	car_company_plymouth	car_company_porsche	car_company_renault	car_company_saab	car_company_subaru	car_company_toyota	car_company_volkswagen	car_company_volvo
4	2	four	0.373178	0.529851	0.508333	54.3	0.518231	5	0.283019	0.464286	...	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
200	-1	four	0.655977	0.711940	0.716667	55.5	0.567882	4	0.301887	0.885714	...	0	0	0	0	0	0	0	0	0	1
201	-1	four	0.655977	0.711940	0.708333	55.5	0.605508	4	0.301887	0.885714	...	0	0	0	0	0	0	0	0	0	1
202	-1	four	0.655977	0.711940	0.716667	55.5	0.591156	6	0.422642	0.742857	...	0	0	0	0	0	0	0	0	0	1
203	-1	four	0.6559	0.7119	0.7166	55.5	0.6706	6	0.3169	0.3357	...	0	0	0	0	0	0	0	0	0	1

	symboling	doornumber	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	...	car_company_nissan	car_company_peugeot	car_company_plymouth	car_company_porsche	car_company_renault	car_company_saab	car_company_subaru	car_company_toyota	car_company_volkswagen	car_company_volvo
			77	40	67		75		81	14											
204	-1	four	0.655977	0.711940	0.716667	55.5	0.610551	4	0.301887	0.885714	...	0	0	0	0	0	0	0	0	0	1

205 rows × 60 columns

Features should be of numeric nature:

In [465]:

```
c_df.dtypes
```

Out[465]:

```
symboling                  int64
doornumber                object
wheelbase                float64
carlength                float64
carwidth                 float64
                          ...
car_company_saab           uint8
car_company_subaru         uint8
car_company_toyota         uint8
car_company_volkswagen     uint8
car_company_volvo          uint8
Length: 61, dtype: object
```

In [466]:

```
NonNumericColumns=X.columns[X.dtypes=="object"]
```

In [467]:

```
NonNumericColumns
```

Out[467]:

```
Index(['doornumber'], dtype='object')
```

In [468]:

```
X=pd.get_dummies(X,columns=NonNumericColumns,drop_first=True)
```

Features should be of type array/ dataframe:

In [469]:

```
type(X)
```

Out[469]:

```
pandas.core.frame.DataFrame
```

Features should have some rows and some columns:

In [470]:

```
X.shape
```

Out[470]:

```
(205, 60)
```

Split the dataset- training and testing:

In [471]:

```
from sklearn.model_selection import train_test_split
```

In [472]:

```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=4)
```

Features should be on the same scale:

In [473]:

```
X.describe()
```

Out[473]:

	symboling	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	stroke	...	car_company_peugeot	car_company_plymouth	car_company_porsche	car_company_renault	car_company_saab	car_company_subaru	car_company_toyota	car_company_volkswagen	car_company_volvo	doornumber_two
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	...	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000
mean	0.834146	0.354419	0.491780	0.467317	53.724878	0.414106	4.380488	0.248707	0.564111	0.255415	...	0.053659	0.034146	0.024390	0.009756	0.029268	0.058537	0.156098	0.058537	0.053659	0.439024
std	1.245307	0.175562	0.184139	0.178767	2.443522	0.201971	1.080854	0.157142	0.193460	0.313597	...	0.225894	0.182050	0.154635	0.098531	0.168970	0.235330	0.363836	0.235330	0.225894	0.497483

	symboling	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	stroke	...	car_company_peugeot	car_company_plymouth	car_company_porsche	car_company_renault	car_company_saab	car_company_subaru	car_company_toyota	car_company_volkswagen	car_company_volvo	doornumber_two
min	-2.000000	0.000000	0.000000	0.000000	47.800000	0.000000	2.000000	0.000000	0.000000	2.070000	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.230321	0.376119	0.316667	52.000000	0.254849	4.000000	0.135849	0.435714	3.110000	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	1.000000	0.303207	0.479104	0.433333	54.100000	0.359193	4.000000	0.222642	0.550000	3.290000	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	2.000000	0.460641	0.626866	0.550000	55.500000	0.561288	4.000000	0.301887	0.742857	3.410000	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000
max	3.000000	1.000000	1.000000	1.000000	59.800000	1.000000	12.000000	1.000000	1.000000	4.170000	...	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

symboling	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	stroke	...	car_company_peugeot	car_company_plymouth	car_company_porsche	car_company_renault	car_company_saab	car_company_subaru	car_company_toyota	car_company_volkswagen	car_company_volvo	doornumber_two
0	0	0	0	0	0	0	0	0	0											
0	0	0	0	0	0	0	0	0	0											

8 rows × 60 columns

In [474]:

```
from sklearn.preprocessing import MinMaxScaler
```

In [475]:

```
scaler=MinMaxScaler()
```

In [476]:

```
X_train=scaler.fit_transform(X_train)
```

In [477]:

```
X_test=scaler.transform(X_test)
```

Train the model on the training dataset:

In [478]:

```
X.shape
```

Out[478]:

```
(205, 60)
```

In [479]:

```python
from sklearn.feature_selection import RFE
```

In [480]:

```python
from sklearn.linear_model import LinearRegression
```

In [481]:

```python
model=LinearRegression()
```

In [482]:

```python
rfe_model=RFE(model,15)
```

In [483]:

```python
rfe_model.fit(X_train,y_train)
```

Out[483]:

```
RFE(estimator=LinearRegression(), n_features_to_select=15)
```

In [484]:

```python
rfe_model.support_
```

Out[484]:

```
array([False, False, False,  True, False,  True,  True,  True,  True,
        True, False,  True, False, False, False, False, False, False,
       False, False, False, False, False, False,  True,  True, False,
       False, False, False, False, False, False, False, False, False,
       False, False,  True,  True,  True, False, False, False, False,
```

```
        True, False, False, False, False, False, False,  True, False,
       False, False, False, False,  True, False])
```

In [485]:

```
X.columns
```

Out[485]:

```
Index(['symboling', 'wheelbase', 'carlength', 'carwidth', 'carheight',
       'curbweight', 'cylindernumber', 'enginesize', 'boreratio', 'stroke',
       'compressionratio', 'horsepower', 'peakrpm', 'citympg', 'highwaympg'
,
       'fueltype_gas', 'aspiration_turbo', 'doornumber_two', 'carbody_hardt
op',
       'carbody_hatchback', 'carbody_sedan', 'carbody_wagon', 'drivewheel_f
wd',
       'drivewheel_rwd', 'enginelocation_rear', 'enginetype_dohcv',
       'enginetype_l', 'enginetype_ohc', 'enginetype_ohcf', 'enginetype_ohc
v',
       'enginetype_rotor', 'fuelsystem_2bbl', 'fuelsystem_4bbl',
       'fuelsystem_idi', 'fuelsystem_mfi', 'fuelsystem_mpfi',
       'fuelsystem_spdi', 'fuelsystem_spfi', 'car_company_audi',
       'car_company_bmw', 'car_company_buick', 'car_company_chevrolet',
       'car_company_dodge', 'car_company_honda', 'car_company_isuzu',
       'car_company_jaguar', 'car_company_mazda', 'car_company_mercury',
       'car_company_mitsubishi', 'car_company_nissan', 'car_company_peugeot
',
       'car_company_plymouth', 'car_company_porsche', 'car_company_renault'
,
       'car_company_saab', 'car_company_subaru', 'car_company_toyota',
       'car_company_volkswagen', 'car_company_volvo', 'doornumber_two'],
      dtype='object')
```

In [486]:

```
Top15Columns=X.columns[rfe_model.support_]
```

In [487]:

```
Top15Columns
```

Out[487]:

```
Index(['carwidth', 'curbweight', 'cylindernumber', 'enginesize', 'boreratio
',
       'stroke', 'horsepower', 'enginelocation_rear', 'enginetype_dohcv',
       'car_company_audi', 'car_company_bmw', 'car_company_buick',
       'car_company_jaguar', 'car_company_porsche', 'car_company_volvo'],
      dtype='object')
```

In [488]:

```
X_train=pd.DataFrame(X_train,columns=X.columns)
```

In [489]:

```
X_test=pd.DataFrame(X_test,columns=X.columns)
```

In [490]:

```
X_train=X_train[Top15Columns]
```

In [491]:

```
X_test=X_test[Top15Columns]
```

In [492]:

```
import statsmodels.api as sm
```

In [493]:

```
X_train
```

Out[493]:

	carwidth	curbweight	cylindernumber	enginesize	boreratio	stroke	horsepower	enginelocation_rear	enginetype_dohcv	car_company_audi	car_company_bmw	car_company_buick	car_company_jaguar	car_company_porsche	car_company_volvo
0	0.342857	0.183595	0.2	0.148438	0.746032	0.227273	0.127119	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.190476	0.117297	0.2	0.078125	0.230159	0.525253	0.067797	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.247619	0.098173	0.2	0.085937	0.230159	0.525253	0.067797	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.352381	0.234169	0.2	0.105469	0.261905	0.611111	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.190476	0.087123	0.2	0.078125	0.230159	0.525253	0.067797	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
159	1.000000	0.702507	0.6	0.519531	1.000000	0.464646	1.000000	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0
160	0.514286	0.564811	0.2	0.277344	0.873016	0.484848	0.262712	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
161	0.352381	0.210795	0.2	0.152344	0.404762	0.611111	0.139831	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

	carwidth	curbweight	cylindernumber	enginesize	boreratio	stroke	horsepower	enginelocation_rear	enginetype_dohcv	car_company_audi	car_company_bmw	car_company_buick	car_company_jaguar	car_company_porsche	car_company_volvo
162	0.447619	0.325967	0.2	0.156250	0.468254	0.585859	0.088983	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
163	0.190476	0.203145	0.2	0.109375	0.230159	0.525253	0.067797	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

164 rows × 15 columns

In [494]:

```
y_train=pd.DataFrame(y_train).reset_index(drop=True)
```

In [495]:

```
y_train
```

Out[495]:

	price
0	0.049849
1	0.061839
2	0.026588
3	0.071421
4	0.011271
...	...

	price
159	0.652463
160	0.282930
161	0.070925
162	0.138523
163	0.061839

164 rows × 1 columns

In [496]:

```
pvalues=sm.OLS(y_train,X_train).fit()
```

In [497]:

```
pvalues.summary()
```

Out[497]:

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.971
Model:	OLS	**Adj. R-squared (uncentered):**	0.968
Method:	Least Squares	**F-statistic:**	327.3
Date:	Thu, 27 Jan 2022	**Prob (F-statistic):**	8.07e-106
Time:	09:26:34	**Log-Likelihood:**	261.59
No. Observations:	164	**AIC:**	-493.2
Df Residuals:	149	**BIC:**	-446.7
Df Model:	15		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]

carwidth	0.2120	0.048	4.381	0.000	0.116	0.308
curbweight	0.1875	0.052	3.596	0.000	0.084	0.290
cylindernumber	-0.1643	0.061	-2.694	0.008	-0.285	-0.044
enginesize	0.3026	0.081	3.742	0.000	0.143	0.462
boreratio	-0.0840	0.024	-3.437	0.001	-0.132	-0.036
stroke	-0.0392	0.020	-1.926	0.056	-0.079	0.001
horsepower	0.2397	0.053	4.546	0.000	0.135	0.344
enginelocation_rear	0.2773	0.063	4.390	0.000	0.153	0.402
enginetype_dohcv	-0.0377	0.079	-0.476	0.635	-0.194	0.119
car_company_audi	0.0607	0.025	2.474	0.014	0.012	0.109
car_company_bmw	0.2757	0.024	11.414	0.000	0.228	0.323
car_company_buick	0.2533	0.032	7.948	0.000	0.190	0.316
car_company_jaguar	0.1792	0.048	3.734	0.000	0.084	0.274
car_company_porsche	0.1503	0.054	2.795	0.006	0.044	0.257
car_company_volvo	0.0635	0.022	2.914	0.004	0.020	0.107

Omnibus:	38.901	**Durbin-Watson:**	2.128
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	100.672
Skew:	0.967	**Prob(JB):**	1.38e-22
Kurtosis:	6.315	**Cond. No.**	27.8

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [498]:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [499]:

```
list(range(0,len(X_train.columns)))
```

Out[499]:

```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14]
```

In [500]:

```
VIF=[]
for i in range(len(X_train.columns)):
    vifvalue=variance_inflation_factor(X_train.values,i)
    VIF.append(vifvalue)
results=pd.DataFrame()
results["Features"]=X_train.columns
results["VIF"]=VIF
results.sort_values("VIF",ascending=False)
```

Out[500]:

	Features	VIF
3	enginesize	30.339968
1	curbweight	28.574975
0	carwidth	27.252337
2	cylindernumber	15.862157
6	horsepower	13.584559
4	boreratio	11.514555

	Features	VIF
5	stroke	7.957269
13	car_company_porsche	5.449883
7	enginelocation_rear	4.512491
8	enginetype_dohcv	2.362695
11	car_company_buick	2.297328
12	car_company_jaguar	1.735591
9	car_company_audi	1.363560
10	car_company_bmw	1.319310
14	car_company_volvo	1.254465

In [501]:

```
results
```

Out[501]:

	Features	VIF
0	carwidth	27.252337
1	curbweight	28.574975
2	cylindernumber	15.862157
3	enginesize	30.339968
4	boreratio	11.514555
5	stroke	7.957269

	Features	VIF
6	horsepower	13.584559
7	enginelocation_rear	4.512491
8	enginetype_dohcv	2.362695
9	car_company_audi	1.363560
10	car_company_bmw	1.319310
11	car_company_buick	2.297328
12	car_company_jaguar	1.735591
13	car_company_porsche	5.449883
14	car_company_volvo	1.254465

In [502]:

```
X_train=X_train.drop("boreratio",axis="columns")
```

In [503]:

```
X_test=X_test.drop("boreratio",axis="columns")
```

In [504]:

```
X_train.shape
```

Out[504]:

```
(164, 14)
```

In [505]:

```
X_test.shape
```

Out[505]:

```
(41, 14)
```

In [506]:

```
pvalues=sm.OLS(y_train,X_train).fit()
pvalues.summary()
```

Out[506]:

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.968
Model:	OLS	**Adj. R-squared (uncentered):**	0.965
Method:	Least Squares	**F-statistic:**	326.3
Date:	Thu, 27 Jan 2022	**Prob (F-statistic):**	1.27e-104
Time:	09:28:30	**Log-Likelihood:**	255.34
No. Observations:	164	**AIC:**	-482.7
Df Residuals:	150	**BIC:**	-439.3
Df Model:	14		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
carwidth	0.1668	0.048	3.460	0.001	0.072	0.262
curbweight	0.1558	0.053	2.933	0.004	0.051	0.261
cylindernumber	-0.1610	0.063	-2.551	0.012	-0.286	-0.036
enginesize	0.2718	0.083	3.266	0.001	0.107	0.436
stroke	-0.0546	0.021	-2.662	0.009	-0.095	-0.014
horsepower	0.2345	0.055	4.297	0.000	0.127	0.342

enginelocation_rear	0.2806	0.065	4.291	0.000	0.151	0.410
enginetype_dohcv	-0.0044	0.081	-0.055	0.957	-0.165	0.156
car_company_audi	0.0877	0.024	3.642	0.000	0.040	0.135
car_company_bmw	0.2814	0.025	11.282	0.000	0.232	0.331
car_company_buick	0.2868	0.031	9.131	0.000	0.225	0.349
car_company_jaguar	0.2235	0.048	4.671	0.000	0.129	0.318
car_company_porsche	0.1269	0.055	2.298	0.023	0.018	0.236
car_company_volvo	0.0643	0.023	2.848	0.005	0.020	0.109

Omnibus:	36.709	**Durbin-Watson:**	2.045
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	93.492
Skew:	0.916	**Prob(JB):**	4.99e-21
Kurtosis:	6.213	**Cond. No.**	23.9

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [508]:

```
VIF=[]
for i in range(len(X_train.columns)):
   vifvalue=variance_inflation_factor(X_train.values,i)
   VIF.append(vifvalue)
results=pd.DataFrame()
results["Features"]=X_train.columns
results["VIF"]=VIF
results.sort_values("VIF",ascending=False)
```

Out[508]:

	Features	VIF
3	enginesize	29.967218
1	curbweight	27.683483
0	carwidth	25.240891
2	cylindernumber	15.858262
5	horsepower	13.573386
4	stroke	7.566429
12	car_company_porsche	5.362649
6	enginelocation_rear	4.511440
7	enginetype_dohcv	2.327402
10	car_company_buick	2.082103
11	car_company_jaguar	1.610138
9	car_company_bmw	1.312935
13	car_company_volvo	1.254343
8	car_company_audi	1.224016

In [509]:

```
X_train=X_train.drop("stroke",axis="columns")
X_test=X_test.drop("stroke",axis="columns")
```

In [510]:

```
pvalues=sm.OLS(y_train,X_train).fit()
pvalues.summary()
```

Out[510]:

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.967
Model:	OLS	**Adj. R-squared (uncentered):**	0.964
Method:	Least Squares	**F-statistic:**	337.2
Date:	Thu, 27 Jan 2022	**Prob (F-statistic):**	2.14e-104
Time:	09:30:59	**Log-Likelihood:**	251.55
No. Observations:	164	**AIC:**	-477.1
Df Residuals:	151	**BIC:**	-436.8
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
carwidth	0.1193	0.046	2.611	0.010	0.029	0.210
curbweight	0.1502	0.054	2.774	0.006	0.043	0.257
cylindernumber	-0.2329	0.058	-4.003	0.000	-0.348	-0.118
enginesize	0.2982	0.084	3.539	0.001	0.132	0.465
horsepower	0.2396	0.056	4.307	0.000	0.130	0.350
enginelocation_rear	0.2800	0.067	4.198	0.000	0.148	0.412
enginetype_dohcv	0.0353	0.082	0.433	0.666	-0.126	0.196
car_company_audi	0.0988	0.024	4.085	0.000	0.051	0.147
car_company_bmw	0.2913	0.025	11.574	0.000	0.242	0.341

car_company_buick	0.3123	0.031	10.229	0.000	0.252	0.373
car_company_jaguar	0.2551	0.047	5.396	0.000	0.162	0.349
car_company_porsche	0.1375	0.056	2.448	0.016	0.027	0.249
car_company_volvo	0.0779	0.022	3.476	0.001	0.034	0.122

Omnibus:	35.032	**Durbin-Watson:**	2.024
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	90.028
Skew:	0.869	**Prob(JB):**	2.82e-20
Kurtosis:	6.187	**Cond. No.**	19.6

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [511]:

```
VIF=[]
for i in range(len(X_train.columns)):
  vifvalue=variance_inflation_factor(X_train.values,i)
  VIF.append(vifvalue)
results=pd.DataFrame()
results["Features"]=X_train.columns
results["VIF"]=VIF
results.sort_values("VIF",ascending=False)
```

Out[511]:

	Features	VIF
3	enginesize	29.540020
1	curbweight	27.639910
0	carwidth	21.779889

	Features	VIF
4	horsepower	13.556504
2	cylindernumber	12.953959
11	car_company_porsche	5.334717
5	enginelocation_rear	4.511385
6	enginetype_dohcv	2.248999
9	car_company_buick	1.889715
10	car_company_jaguar	1.510843
8	car_company_bmw	1.284272
12	car_company_volvo	1.189612
7	car_company_audi	1.187264

In [513]:

```
X_train=X_train.drop("cylindernumber",axis="columns")
X_test=X_test.drop("cylindernumber",axis="columns")
```

In [514]:

```
pvalues=sm.OLS(y_train,X_train).fit()
pvalues.summary()
```

Out[514]:

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.963
Model:	OLS	**Adj. R-squared (uncentered):**	0.960

Method:	Least Squares	**F-statistic:**	331.3
Date:	Thu, 27 Jan 2022	**Prob (F-statistic):**	2.28e-102
Time:	09:34:19	**Log-Likelihood:**	243.28
No. Observations:	164	**AIC:**	-462.6
Df Residuals:	152	**BIC:**	-425.4
Df Model:	12		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
carwidth	0.0519	0.045	1.166	0.246	-0.036	0.140
curbweight	0.1954	0.056	3.520	0.001	0.086	0.305
enginesize	0.0990	0.071	1.389	0.167	-0.042	0.240
horsepower	0.2431	0.058	4.169	0.000	0.128	0.358
enginelocation_rear	0.2449	0.069	3.534	0.001	0.108	0.382
enginetype_dohcv	-0.0051	0.085	-0.060	0.952	-0.173	0.163
car_company_audi	0.0991	0.025	3.909	0.000	0.049	0.149
car_company_bmw	0.2945	0.026	11.170	0.000	0.242	0.347
car_company_buick	0.3535	0.030	11.735	0.000	0.294	0.413
car_company_jaguar	0.2716	0.049	5.501	0.000	0.174	0.369
car_company_porsche	0.1739	0.058	2.993	0.003	0.059	0.289
car_company_volvo	0.0869	0.023	3.716	0.000	0.041	0.133

Omnibus:	55.065	**Durbin-Watson:**	2.054
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	172.858

Skew:	1.308	**Prob(JB):**	2.91e-38
Kurtosis:	7.295	**Cond. No.**	17.6

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [515]:

```
VIF=[]
for i in range(len(X_train.columns)):
  vifvalue=variance_inflation_factor(X_train.values,i)
  VIF.append(vifvalue)
results=pd.DataFrame()
results["Features"]=X_train.columns
results["VIF"]=VIF
results.sort_values("VIF",ascending=False)
```

Out[515]:

	Features	VIF
1	curbweight	26.439464
2	enginesize	19.238065
0	carwidth	18.820871
3	horsepower	13.553243
10	car_company_porsche	5.195056
4	enginelocation_rear	4.433400
5	enginetype_dohcv	2.214503
8	car_company_buick	1.674605
9	car_company_jaguar	1.499397

	Features	VIF
7	car_company_bmw	1.282924
6	car_company_audi	1.187254
11	car_company_volvo	1.177738

In [518]:

```
X_train=X_train.drop("enginesize",axis="columns")
X_test=X_test.drop("enginesize",axis="columns")
```

In [519]:

```
pvalues=sm.OLS(y_train,X_train).fit()
pvalues.summary()
```

Out[519]:

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.963
Model:	OLS	**Adj. R-squared (uncentered):**	0.960
Method:	Least Squares	**F-statistic:**	359.0
Date:	Thu, 27 Jan 2022	**Prob (F-statistic):**	3.05e-103
Time:	09:37:11	**Log-Likelihood:**	242.25
No. Observations:	164	**AIC:**	-462.5
Df Residuals:	153	**BIC:**	-428.4
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
carwidth	0.0634	0.044	1.446	0.150	-0.023	0.150
curbweight	0.2165	0.054	4.043	0.000	0.111	0.322

horsepower	0.2808	0.052	5.427	0.000	0.179	0.383
enginelocation_rear	0.2550	0.069	3.688	0.000	0.118	0.392
enginetype_dohcv	-0.0179	0.085	-0.211	0.833	-0.185	0.149
car_company_audi	0.0942	0.025	3.739	0.000	0.044	0.144
car_company_bmw	0.3037	0.026	11.863	0.000	0.253	0.354
car_company_buick	0.3727	0.027	13.877	0.000	0.320	0.426
car_company_jaguar	0.3011	0.045	6.732	0.000	0.213	0.389
car_company_porsche	0.1740	0.058	2.985	0.003	0.059	0.289
car_company_volvo	0.0829	0.023	3.560	0.000	0.037	0.129

Omnibus:	59.438	**Durbin-Watson:**	2.091
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	225.933
Skew:	1.339	**Prob(JB):**	8.70e-50
Kurtosis:	8.088	**Cond. No.**	16.3

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [520]:

```
VIF=[]
for i in range(len(X_train.columns)):
   vifvalue=variance_inflation_factor(X_train.values,i)
   VIF.append(vifvalue)
results=pd.DataFrame()
results["Features"]=X_train.columns
results["VIF"]=VIF
```

```
results.sort_values("VIF",ascending=False)
```

Out[520]:

	Features	VIF
1	curbweight	24.457594
0	carwidth	18.166648
2	horsepower	10.610975
9	car_company_porsche	5.195050
3	enginelocation_rear	4.384744
4	enginetype_dohcv	2.188629
7	car_company_buick	1.323009
8	car_company_jaguar	1.222734
6	car_company_bmw	1.202203
5	car_company_audi	1.163552
10	car_company_volvo	1.159505

In [521]:

```
X_train=X_train.drop("curbweight",axis="columns")
X_test=X_test.drop("curbweight",axis="columns")
```

In [522]:

```
pvalues=sm.OLS(y_train,X_train).fit()
pvalues.summary()
```

Out[522]:

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.959
Model:	OLS	**Adj. R-squared (uncentered):**	0.956
Method:	Least Squares	**F-statistic:**	357.7
Date:	Thu, 27 Jan 2022	**Prob (F-statistic):**	3.63e-101
Time:	09:38:37	**Log-Likelihood:**	233.93
No. Observations:	164	**AIC:**	-447.9
Df Residuals:	154	**BIC:**	-416.9
Df Model:	10		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
carwidth	0.2034	0.028	7.197	0.000	0.148	0.259
horsepower	0.3807	0.048	7.985	0.000	0.287	0.475
enginelocation_rear	0.2712	0.072	3.747	0.000	0.128	0.414
enginetype_dohcv	-0.0785	0.087	-0.899	0.370	-0.251	0.094
car_company_audi	0.0774	0.026	2.971	0.003	0.026	0.129
car_company_bmw	0.3161	0.027	11.860	0.000	0.263	0.369
car_company_buick	0.3929	0.028	14.201	0.000	0.338	0.448
car_company_jaguar	0.3309	0.046	7.155	0.000	0.240	0.422
car_company_porsche	0.1469	0.061	2.418	0.017	0.027	0.267
car_company_volvo	0.0902	0.024	3.708	0.000	0.042	0.138

Omnibus:	52.980	**Durbin-Watson:**	2.236
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	154.272
Skew:	1.287	**Prob(JB):**	3.16e-34

Kurtosis:	6.994	**Cond. No.**	12.9

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [524]:

```
VIF=[]
for i in range(len(X_train.columns)):
   vifvalue=variance_inflation_factor(X_train.values,i)
   VIF.append(vifvalue)
results=pd.DataFrame()
results["Features"]=X_train.columns
results["VIF"]=VIF
results.sort_values("VIF",ascending=False)
```

Out[524]:

	Features	VIF
1	horsepower	8.191734
0	carwidth	6.854279
8	car_company_porsche	5.126040
2	enginelocation_rear	4.369984
3	enginetype_dohcv	2.119965
6	car_company_buick	1.277027
7	car_company_jaguar	1.189413
5	car_company_bmw	1.184970
9	car_company_volvo	1.152389
4	car_company_audi	1.132036

In [552]:

```
X_train=X_train.drop("carwidth",axis="columns")
X_test=X_test.drop("carwidth",axis="columns")
```

In [553]:

```
pvalues=sm.OLS(y_train,X_train).fit()
pvalues.summary()
```

Out[553]:

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.936
Model:	OLS	**Adj. R-squared (uncentered):**	0.933
Method:	Least Squares	**F-statistic:**	325.6
Date:	Thu, 27 Jan 2022	**Prob (F-statistic):**	4.90e-90
Time:	10:05:33	**Log-Likelihood:**	197.40
No. Observations:	164	**AIC:**	-380.8
Df Residuals:	157	**BIC:**	-359.1
Df Model:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
horsepower	0.7376	0.027	27.243	0.000	0.684	0.791
enginelocation_rear	0.1105	0.086	1.285	0.201	-0.059	0.280
enginetype_dohcv	-0.2203	0.106	-2.073	0.040	-0.430	-0.010
car_company_bmw	0.2653	0.032	8.226	0.000	0.202	0.329
car_company_buick	0.4265	0.032	13.219	0.000	0.363	0.490
car_company_jaguar	0.2391	0.056	4.280	0.000	0.129	0.349

car_company_porsche	0.1351	0.075	1.803	0.073	-0.013	0.283

Omnibus:	32.059	**Durbin-Watson:**	2.198
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	49.111
Skew:	1.031	**Prob(JB):**	2.17e-11
Kurtosis:	4.714	**Cond. No.**	7.53

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [554]:

```
VIF=[]
for i in range(len(X_train.columns)):
   vifvalue=variance_inflation_factor(X_train.values,i)
   VIF.append(vifvalue)
results=pd.DataFrame()
results["Features"]=X_train.columns
results["VIF"]=VIF
results.sort_values("VIF",ascending=False)
```

Out[554]:

	Features	VIF
6	car_company_porsche	5.098936
1	enginelocation_rear	4.029362
2	enginetype_dohcv	2.050239
0	horsepower	1.724928
4	car_company_buick	1.133970
5	car_company_jaguar	1.133280

	Features	VIF
3	car_company_bmw	1.132587

In [557]:

```
VIF=[]
for i in range(len(X_train.columns)):
  vifvalue=variance_inflation_factor(X_train.values,i)
  VIF.append(vifvalue)
results=pd.DataFrame()
results["Features"]=X_train.columns
results["VIF"]=VIF
results.sort_values("VIF",ascending=False)
```

Out[557]:

	Features	VIF
6	car_company_porsche	5.098936
1	enginelocation_rear	4.029362
2	enginetype_dohcv	2.050239
0	horsepower	1.724928
4	car_company_buick	1.133970
5	car_company_jaguar	1.133280
3	car_company_bmw	1.132587

In [558]:

```
X_train.columns
```

Out[558]:

```
Index(['horsepower', 'enginelocation_rear', 'enginetype_dohcv',
       'car_company_bmw', 'car_company_buick', 'car_company_jaguar',
```

```
 'car_company_porsche'],
dtype='object')
```

In [559]:

```
c_df.head()
```

Out[559]:

	symboling	doornumber	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	...	car_company_nissan	car_company_peugeot	car_company_plymouth	car_company_porsche	car_company_renault	car_company_saab	car_company_subaru	car_company_toyota	car_company_volkswagen	car_company_volvo
0	3	two	0.058309	0.413433	0.316667	48.8	0.411171	4	0.260377	0.664286	...	0	0	0	0	0	0	0	0	0	0
1	3	two	0.058309	0.413433	0.316667	48.8	0.411171	4	0.260377	0.664286	...	0	0	0	0	0	0	0	0	0	0
2	1	two	0.230321	0.449254	0.433333	52.4	0.517843	6	0.343396	0.100000	...	0	0	0	0	0	0	0	0	0	0
3	2	four	0.384840	0.529851	0.491667	54.3	0.329325	4	0.181132	0.464286	...	0	0	0	0	0	0	0	0	0	0

	symboling	doornumber	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	...	car_company_nissan	car_company_peugeot	car_company_plymouth	car_company_porsche	car_company_renault	car_company_saab	car_company_subaru	car_company_toyota	car_company_volkswagen	car_company_volvo
4	2	four	0.373178	0.529851	0.508333	54.3	0.518231	5	0.283019	0.464286	...	0	0	0	0	0	0	0	0	0	0

5 rows × 61 columns

In [560]:

```
model=LinearRegression()
```

In [561]:

```
model.fit(X_train,y_train)
```

Out[561]:

```
LinearRegression()
```

In [562]:

```
model.coef_
```

Out[562]:

```
array([[ 0.68554384,  0.12465035, -0.18828237,  0.27183568,  0.4332186 ,
         0.2613242 ,  0.14057525]])
```

In [563]:

```
results=pd.DataFrame()
results["Features"]=X_train.columns
```

In [564]:

```
X_train.columns
```

Out[564]:

```
Index(['horsepower', 'enginelocation_rear', 'enginetype_dohcv',
       'car_company_bmw', 'car_company_buick', 'car_company_jaguar',
       'car_company_porsche'],
      dtype='object')
```

In [565]:

```
X_train.columns
```

Out[565]:

```
Index(['horsepower', 'enginelocation_rear', 'enginetype_dohcv',
       'car_company_bmw', 'car_company_buick', 'car_company_jaguar',
       'car_company_porsche'],
      dtype='object')
```

In [568]:

```
results["Importance"]=model.coef_.reshape(7,)
```

In [569]:

```
results.sort_values(by="Importance",ascending=False)
```

Out[569]:

	Features	Importance
0	horsepower	0.685544
4	car_company_buick	0.433219

	Features	Importance
3	car_company_bmw	0.271836
5	car_company_jaguar	0.261324
6	car_company_porsche	0.140575
1	enginelocation_rear	0.124650
2	enginetype_dohcv	-0.188282

Here, above are the features that makes car price huge among all car drives.