Cars Price Prediction Regression Model

Importing Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

sns.set_style('whitegrid')
plt.style.use("fivethirtyeight")
```

```
data = pd.read_csv('cars_price.csv')
```

```
data.head()
```

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine-size	fuel-system	bore	str
0	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	
1	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	

```
data.shape
```

```
(205, 26)
```

4 2 164 audi gas std four sedan 4wd front 99.4 ... 136 mpfi 3.19

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   symboling          205 non-null    int64
 1   normalized-losses  205 non-null    object
 2   make               205 non-null    object
 3   fuel-type          205 non-null    object
 4   aspiration         205 non-null    object
 5   num-of-doors       205 non-null    object
 6   body-style         205 non-null    object
 7   drive-wheels       205 non-null    object
 8   engine-location    205 non-null    object
 9   wheel-base         205 non-null    float64
 10  length             205 non-null    float64
 11  width              205 non-null    float64
 12  height             205 non-null    float64
 13  curb-weight        205 non-null    int64
 14  engine-type        205 non-null    object
 15  num-of-cylinders   205 non-null    object
 16  engine-size        205 non-null    int64
 17  fuel-system        205 non-null    object
```

```
 18  bore               205 non-null    object
 19  stroke             205 non-null    object
 20  compression-ratio  205 non-null    float64
 21  horsepower         205 non-null    object
 22  peak-rpm           205 non-null    object
 23  city-mpg           205 non-null    int64
 24  highway-mpg        205 non-null    int64
 25  price              205 non-null    object
dtypes: float64(5), int64(5), object(16)
memory usage: 41.8+ KB
```

```
data.describe()
```

	symboling	wheel-base	length	width	height	curb-weight	engine-size	compression-ratio	city-mpg	highway-mpg
count	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	10.142537	25.219512	30.751220
std	1.245307	6.021776	12.337289	2.145204	2.443522	520.680204	41.642693	3.972040	6.542142	6.886443
min	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000000	7.000000	13.000000	16.000000
25%	0.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97.000000	8.600000	19.000000	25.000000
50%	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.000000	9.000000	24.000000	30.000000
75%	2.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	141.000000	9.400000	30.000000	34.000000
max	3.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326.000000	23.000000	49.000000	54.000000

Cleaning Data

```
data['normalized-losses'].unique()
```

```
array(['?', '164', '158', '192', '188', '121', '98', '81', '118', '148',
       '110', '145', '137', '101', '78', '106', '85', '107', '104', '113',
```

```
       '150', '129', '115', '93', '142', '161', '153', '125', '128',
       '122', '103', '168', '108', '194', '231', '119', '154', '74',
       '186', '83', '102', '89', '87', '77', '91', '134', '65', '197',
       '90', '94', '256', '95'], dtype=object)
```

```
data.isnull().sum()
```

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

```
data.notnull().sum()
```

```
symboling            205
normalized-losses    205
```

```
make                 205
fuel-type            205
aspiration           205
num-of-doors         205
body-style           205
drive-wheels         205
engine-location      205
wheel-base           205
length               205
width                205
height               205
curb-weight          205
engine-type          205
num-of-cylinders     205
engine-size          205
fuel-system          205
bore                 205
stroke               205
compression-ratio    205
horsepower           205
peak-rpm             205
city-mpg             205
highway-mpg          205
price                205
dtype: int64
```

```
data.duplicated().sum()
```

```
0
```

```
cols = data.columns
cols
```

```
Index(['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration',
       'num-of-doors', 'body-style', 'drive-wheels', 'engine-location',
       'wheel-base', 'length', 'width', 'height', 'curb-weight', 'engine-type',
       'num-of-cylinders', 'engine-size', 'fuel-system', 'bore', 'stroke',
       'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg',
```

```
       'highway-mpg', 'price'],
      dtype='object')
```

```
for col in cols:

    print(col,data[col].nunique())
```

```
symboling 6
normalized-losses 52
make 22
fuel-type 2
aspiration 2
num-of-doors 3
body-style 5
drive-wheels 3
engine-location 2
wheel-base 53
length 75
width 44
height 49
curb-weight 171
engine-type 7
num-of-cylinders 7
engine-size 44
fuel-system 8
bore 39
stroke 37
compression-ratio 32
horsepower 60
peak-rpm 24
city-mpg 29
highway-mpg 30
price 187
```

```
for col in cols:

    print(col,data[col].unique())
```

```
 3750 3495 3770 3740 3685 3900 3715 2910 1918 1944 2004 2145 2370 2328
 2833 2921 2926 2365 2405 2403 1889 2017 1938 1951 2028 1971 2037 2008
```

```
 2324 2302 3095 3296 3060 3071 3139 3020 3197 3430 3075 3252 3285 3485
 3130 2818 2778 2756 2800 3366 2579 2460 2658 2695 2707 2758 2808 2847
 2050 2120 2240 2190 2340 2510 2290 2455 2420 2650 1985 2040 2015 2280
 3110 2081 2109 2275 2094 2122 2140 2169 2204 2265 2300 2540 2536 2551
 2679 2714 2975 2326 2480 2414 2458 2976 3016 3131 3151 2261 2209 2264
 2212 2319 2254 2221 2661 2563 2912 3034 2935 3042 3045 3157 2952 3049
 3012 3217 3062]
engine-type ['dohc' 'ohcv' 'ohc' 'l' 'rotor' 'ohcf' 'dohcv']
num-of-cylinders ['four' 'six' 'five' 'three' 'twelve' 'two' 'eight']
engine-size [130 152 109 136 131 108 164 209  61  90  98 122 156  92  79 110 111 119
 258 326  91  70  80 140 134 183 234 308 304  97 103 120 181 151 194 203
 132 121 146 171 161 141 173 145]
fuel-system ['mpfi' '2bbl' 'mfi' '1bbl' 'spfi' '4bbl' 'idi' 'spdi']
bore ['3.47' '2.68' '3.19' '3.13' '3.5' '3.31' '3.62' '2.91' '3.03' '2.97'
 '3.34' '3.6' '2.92' '3.15' '3.43' '3.63' '3.54' '3.08' '?' '3.39' '3.76'
 '3.58' '3.46' '3.8' '3.78' '3.17' '3.35' '3.59' '2.99' '3.33' '3.7'
 '3.61' '3.94' '3.74' '2.54' '3.05' '3.27' '3.24' '3.01']
stroke ['2.68' '3.47' '3.4' '2.8' '3.19' '3.39' '3.03' '3.11' '3.23' '3.46' '3.9'
 '3.41' '3.07' '3.58' '4.17' '2.76' '3.15' '?' '3.16' '3.64' '3.1' '3.35'
 '3.12' '3.86' '3.29' '3.27' '3.52' '2.19' '3.21' '2.9' '2.07' '2.36'
 '2.64' '3.08' '3.5' '3.54' '2.87']
compression-ratio [ 9.   10.    8.    8.5   8.3   7.    8.8   9.5   9.6   9.41  9.4   7.6
  9.2  10.1   9.1   8.1  11.5   8.6  22.7  22.   21.5   7.5  21.9   7.8
  8.4  21.    8.7   9.31  9.3   7.7  22.5  23.  ]
horsepower ['111' '154' '102' '115' '110' '140' '160' '101' '121' '182' '48' '70'
 '68' '88' '145' '58' '76' '60' '86' '100' '78' '90' '176' '262' '135'
 '84' '64' '120' '72' '123' '155' '184' '175' '116' '69' '55' '97' '152'
 '200' '95' '142' '143' '207' '288' '?' '73' '82' '94' '62' '56' '112'
 '92' '161' '156' '52' '85' '114' '162' '134' '106']
peak-rpm ['5000' '5500' '5800' '4250' '5400' '5100' '4800' '6000' '4750' '4650'
 '4200' '4350' '4500' '5200' '4150' '5600' '5900' '5750' '?' '5250' '4900'
 '4400' '6600' '5300']
city-mpg [21 19 24 18 17 16 23 20 15 47 38 37 31 49 30 27 25 13 26 36 22 14 45 28
 32 35 34 29 33]
highway-mpg [27 26 30 22 25 20 29 28 53 43 41 38 24 54 42 34 33 31 19 17 23 32 39 18
 16 37 50 36 47 46]
price ['13495' '16500' '13950' '17450' '15250' '17710' '18920' '23875' '?'
 '16430' '16925' '20970' '21105' '24565' '30760' '41315' '36880' '5151'
 '6295' '6575' '5572' '6377' '7957' '6229' '6692' '7609' '8558' '8921'
 '12964' '6479' '6855' '5399' '6529' '7129' '7295' '7895' '9095' '8845'
 '10295' '12945' '10345' '6785' '11048' '32250' '35550' '36000' '5195'
 '6095' '6795' '6695' '7395' '10945' '11845' '13645' '15645' '8495'
```

```
 '6095' '6795' '6695' '7395' '10945' '11845' '13645' '15645' '8495'
 '10595' '10245' '10795' '11245' '18280' '18344' '25552' '28248' '28176'
 '31600' '34184' '35056' '40960' '45400' '16503' '5389' '6189' '6669'
 '7689' '9959' '8499' '12629' '14869' '14489' '6989' '8189' '9279' '5499'
 '7099' '6649' '6849' '7349' '7299' '7799' '7499' '7999' '8249' '8949'
 '9549' '13499' '14399' '17199' '19699' '18399' '11900' '13200' '12440'
 '13860' '15580' '16900' '16695' '17075' '16630' '17950' '18150' '12764'
 '22018' '32528' '34028' '37028' '9295' '9895' '11850' '12170' '15040'
 '15510' '18620' '5118' '7053' '7603' '7126' '7775' '9960' '9233' '11259'
 '7463' '10198' '8013' '11694' '5348' '6338' '6488' '6918' '7898' '8778'
 '6938' '7198' '7788' '7738' '8358' '9258' '8058' '8238' '9298' '9538'
 '8449' '9639' '9989' '11199' '11549' '17669' '8948' '10698' '9988'
 '10898' '11248' '16558' '15998' '15690' '15750' '7975' '7995' '8195'
 '9495' '9995' '11595' '9980' '13295' '13845' '12290' '12940' '13415'
 '15985' '16515' '18420' '18950' '16845' '19045' '21485' '22470' '22625']
```

```
cl = ['normalized-losses','num-of-doors','bore', 'stroke','horsepower', 'peak-rpm', 'price']

for col in cl:
  print(data[col].value_counts())
```

```
106     2
176     2
55      1
262     1
134     1
115     1
140     1
48      1
58      1
60      1
78      1
135     1
200     1
64      1
120     1
72      1
154     1
288     1
143     1
142     1
175     1
```

```
175      1
106      1
Name: horsepower, dtype: int64
5500    37
4800    36
5000    27
5200    23
5400    13
6000     9
5250     7
4500     7
5800     7
4200     5
4150     5
4750     4
4350     4
5100     3
4250     3
5900     3
4400     3
?        2
6600     2
4650     1
5600     1
5750     1
4900     1
5300     1
Name: peak-rpm, dtype: int64
?        4
8921     2
18150    2
8845     2
8495     2
        ..
45400    1
16503    1
5389     1
6189     1
22625    1
```

```
for col in cl :
```

```
  data[col].replace({'?': np.nan},inplace = True)
```

```
data.head()
```

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine-size	fuel-system	bore	st
0	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	
1	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	
2	1	NaN	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...	152	mpfi	2.68	
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8	...	109	mpfi	3.19	
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4	...	136	mpfi	3.19	

5 rows × 26 columns

```
cl = ['normalized-losses','num-of-doors','bore', 'stroke','horsepower', 'peak-rpm', 'price']

for col in cl:
  print(data[col].unique())
```

```
[nan '164' '158' '192' '188' '121' '98' '81' '118' '148' '110' '145' '137'
 '101' '78' '106' '85' '107' '104' '113' '150' '129' '115' '93' '142'
 '161' '153' '125' '128' '122' '103' '168' '108' '194' '231' '119' '154'
 '74' '186' '83' '102' '89' '87' '77' '91' '134' '65' '197' '90' '94'
 '256' '95']
['two' 'four' nan]
['3.47' '2.68' '3.19' '3.13' '3.5' '3.31' '3.62' '2.91' '3.03' '2.97'
 '3.34' '3.6' '2.92' '3.15' '3.43' '3.63' '3.54' '3.08' nan '3.39' '3.76'
```

```
 '3.58' '3.46' '3.8' '3.78' '3.17' '3.35' '3.59' '2.99' '3.33' '3.7'
 '3.61' '3.94' '3.74' '2.54' '3.05' '3.27' '3.24' '3.01']
['2.68' '3.47' '3.4' '2.8' '3.19' '3.39' '3.03' '3.11' '3.23' '3.46' '3.9'
 '3.41' '3.07' '3.58' '4.17' '2.76' '3.15' nan '3.16' '3.64' '3.1' '3.35'
 '3.12' '3.86' '3.29' '3.27' '3.52' '2.19' '3.21' '2.9' '2.07' '2.36'
 '2.64' '3.08' '3.5' '3.54' '2.87']
['111' '154' '102' '115' '110' '140' '160' '101' '121' '182' '48' '70'
 '68' '88' '145' '58' '76' '60' '86' '100' '78' '90' '176' '262' '135'
 '84' '64' '120' '72' '123' '155' '184' '175' '116' '69' '55' '97' '152'
 '200' '95' '142' '143' '207' '288' nan '73' '82' '94' '62' '56' '112'
 '92' '161' '156' '52' '85' '114' '162' '134' '106']
['5000' '5500' '5800' '4250' '5400' '5100' '4800' '6000' '4750' '4650'
 '4200' '4350' '4500' '5200' '4150' '5600' '5900' '5750' nan '5250' '4900'
 '4400' '6600' '5300']
['13495' '16500' '13950' '17450' '15250' '17710' '18920' '23875' nan
 '16430' '16925' '20970' '21105' '24565' '30760' '41315' '36880' '5151'
 '6295' '6575' '5572' '6377' '7957' '6229' '6692' '7609' '8558' '8921'
 '12964' '6479' '6855' '5399' '6529' '7129' '7295' '7895' '9095' '8845'
 '10295' '12945' '10345' '6785' '11048' '32250' '35550' '36000' '5195'
 '6095' '6795' '6695' '7395' '10945' '11845' '13645' '15645' '8495'
 '10595' '10245' '10795' '11245' '18280' '18344' '25552' '28248' '28176'
 '31600' '34184' '35056' '40960' '45400' '16503' '5389' '6189' '6669'
 '7689' '9959' '8499' '12629' '14869' '14489' '6989' '8189' '9279' '5499'
 '7099' '6649' '6849' '7349' '7299' '7799' '7499' '7999' '8249' '8949'
 '9549' '13499' '14399' '17199' '19699' '18399' '11900' '13200' '12440'
 '13860' '15580' '16900' '16695' '17075' '16630' '17950' '18150' '12764'
 '22018' '32528' '34028' '37028' '9295' '9895' '11850' '12170' '15040'
 '15510' '18620' '5118' '7053' '7603' '7126' '7775' '9960' '9233' '11259'
 '7463' '10198' '8013' '11694' '5348' '6338' '6488' '6918' '7898' '8778'
 '6938' '7198' '7788' '7738' '8358' '9258' '8058' '8238' '9298' '9538'
 '8449' '9639' '9989' '11199' '11549' '17669' '8948' '10698' '9988'
 '10898' '11248' '16558' '15998' '15690' '15750' '7975' '7995' '8195'
 '9495' '9995' '11595' '9980' '13295' '13845' '12290' '12940' '13415'
 '15985' '16515' '18420' '18950' '16845' '19045' '21485' '22470' '22625']
```

```
data.isnull().sum()
```

```
symboling             0
normalized-losses    41
make                  0
```

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

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   symboling          205 non-null    int64 
 1   normalized-losses  164 non-null    object
 2   make               205 non-null    object
 3   fuel-type          205 non-null    object
 4   aspiration         205 non-null    object
 5   num-of-doors       203 non-null    object
 6   body-style         205 non-null    object
 7   drive-wheels       205 non-null    object
```

```
 8   engine-location    205 non-null    object
 9   wheel-base         205 non-null    float64
 10  length             205 non-null    float64
 11  width              205 non-null    float64
 12  height             205 non-null    float64
 13  curb-weight        205 non-null    int64
 14  engine-type        205 non-null    object
 15  num-of-cylinders   205 non-null    object
 16  engine-size        205 non-null    int64
 17  fuel-system        205 non-null    object
 18  bore               201 non-null    object
 19  stroke             201 non-null    object
 20  compression-ratio  205 non-null    float64
 21  horsepower         203 non-null    object
 22  peak-rpm           203 non-null    object
 23  city-mpg           205 non-null    int64
 24  highway-mpg        205 non-null    int64
 25  price              201 non-null    object
dtypes: float64(5), int64(5), object(16)
memory usage: 41.8+ KB
```

```
string = ['normalized-losses','horsepower','peak-rpm', 'price','bore', 'stroke']
#data['normalized-losses'] = data['normalized-losses'].astype(float)
# data['horsepower'] = data['horsepower'].astype(float)
# data['peak-rpm'] = data['peak-rpm'].astype(float)
# data['price'] = data['price'].astype(float)
# data['bore'] = data['bore'].astype(float)
# data['stroke'] = data['stroke'].astype(float)

for s in string:
  data[s] = data[s].astype(float)
```

```
for col in cols:
  print(col,data[col].unique())
```

```
curb-weight [2548 2823 2337 2824 2507 2844 2954 3086 3053 2395 2710 2765 3055 3230
 3380 3505 1488 1874 1909 1876 2128 1967 1989 2191 2535 2811 1713 1819
 1837 1940 1956 2010 2024 2236 2289 2304 2372 2465 2293 2734 4066 3950
```

```
 1890 1900 1905 1945 1950 2380 2385 2500 2410 2443 2425 2670 2700 3515
 3750 3495 3770 3740 3685 3900 3715 2910 1918 1944 2004 2145 2370 2328
 2833 2921 2926 2365 2405 2403 1889 2017 1938 1951 2028 1971 2037 2008
 2324 2302 3095 3296 3060 3071 3139 3020 3197 3430 3075 3252 3285 3485
 3130 2818 2778 2756 2800 3366 2579 2460 2658 2695 2707 2758 2808 2847
 2050 2120 2240 2190 2340 2510 2290 2455 2420 2650 1985 2040 2015 2280
 3110 2081 2109 2275 2094 2122 2140 2169 2204 2265 2300 2540 2536 2551
 2679 2714 2975 2326 2480 2414 2458 2976 3016 3131 3151 2261 2209 2264
 2212 2319 2254 2221 2661 2563 2912 3034 2935 3042 3045 3157 2952 3049
 3012 3217 3062]
engine-type ['dohc' 'ohcv' 'ohc' 'l' 'rotor' 'ohcf' 'dohcv']
num-of-cylinders ['four' 'six' 'five' 'three' 'twelve' 'two' 'eight']
engine-size [130 152 109 136 131 108 164 209  61  90  98 122 156  92  79 110 111 119
 258 326  91  70  80 140 134 183 234 308 304  97 103 120 181 151 194 203
 132 121 146 171 161 141 173 145]
fuel-system ['mpfi' '2bbl' 'mfi' '1bbl' 'spfi' '4bbl' 'idi' 'spdi']
bore [3.47 2.68 3.19 3.13 3.5  3.31 3.62 2.91 3.03 2.97 3.34 3.6  2.92 3.15
 3.43 3.63 3.54 3.08  nan 3.39 3.76 3.58 3.46 3.8  3.78 3.17 3.35 3.59
 2.99 3.33 3.7  3.61 3.94 3.74 2.54 3.05 3.27 3.24 3.01]
stroke [2.68 3.47 3.4  2.8  3.19 3.39 3.03 3.11 3.23 3.46 3.9  3.41 3.07 3.58
 4.17 2.76 3.15  nan 3.16 3.64 3.1  3.35 3.12 3.86 3.29 3.27 3.52 2.19
 3.21 2.9  2.07 2.36 2.64 3.08 3.5  3.54 2.87]
compression-ratio [ 9.   10.    8.    8.5   8.3   7.    8.8   9.5   9.6   9.41  9.4   7.6
  9.2  10.1   9.1   8.1  11.5   8.6  22.7  22.   21.5   7.5  21.9   7.8
  8.4  21.    8.7   9.31  9.3   7.7  22.5  23.  ]
horsepower [111. 154. 102. 115. 110. 140. 160. 101. 121. 182.  48.  70.  68.  88.
 145.  58.  76.  60.  86. 100.  78.  90. 176. 262. 135.  84.  64. 120.
  72. 123. 155. 184. 175. 116.  69.  55.  97. 152. 200.  95. 142. 143.
 207. 288.  nan  73.  82.  94.  62.  56. 112.  92. 161. 156.  52.  85.
 114. 162. 134. 106.]
peak-rpm [5000. 5500. 5800. 4250. 5400. 5100. 4800. 6000. 4750. 4650. 4200. 4350.
 4500. 5200. 4150. 5600. 5900. 5750.   nan 5250. 4900. 4400. 6600. 5300.]
city-mpg [21 19 24 18 17 16 23 20 15 47 38 37 31 49 30 27 25 13 26 36 22 14 45 28
 32 35 34 29 33]
highway-mpg [27 26 30 22 25 20 29 28 53 43 41 38 24 54 42 34 33 31 19 17 23 32 39 18
 16 37 50 36 47 46]
price [13495. 16500. 13950. 17450. 15250. 17710. 18920. 23875.    nan 16430.
 16925. 20970. 21105. 24565. 30760. 41315. 36880.  5151.  6295.  6575.
  5572.  6377.  7957.  6229.  6692.  7609.  8558.  8921. 12964.  6479.
  6855.  5399.  6529.  7129.  7295.  7895.  9095.  8845. 10295. 12945.
 10345.  6785. 11048. 32250. 35550. 36000.  5195.  6095.  6795.  6695.
```

```
  7395. 10945. 11845. 13645. 15645.  8495. 10595. 10245. 10795. 11245.
 18280. 18344. 25552. 28248. 28176. 31600. 34184. 35056. 40960. 45400.
 16503.  5389.  6189.  6669.  7689.  9959.  8499. 12629. 14869. 14489.
  6989.  8189.  9279.  5499.  7099.  6649.  6849.  7349.  7299.  7799.
  7499.  7999.  8249.  8949.  9549. 13499. 14399. 17199. 19699. 18399.
 11900. 13200. 12440. 13860. 15580. 16900. 16695. 17075. 16630. 17950.
 18150. 12764. 22018. 32528. 34028. 37028.  9295.  9895. 11850. 12170.
 15040. 15510. 18620.  5118.  7053.  7603.  7126.  7775.  9960.  9233.
 11259.  7463. 10198.  8013. 11694.  5348.  6338.  6488.  6918.  7898.
  8778.  6938.  7198.  7788.  7738.  8358.  9258.  8058.  8238.  9298.
  9538.  8449.  9639.  9989. 11199. 11549. 17669.  8948. 10698.  9988.
 10898. 11248. 16558. 15998. 15690. 15750.  7975.  7995.  8195.  9495.
  9995. 11595.  9980. 13295. 13845. 12290. 12940. 13415. 15985. 16515.
 18420. 18950. 16845. 19045. 21485. 22470. 22625.]
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   symboling          205 non-null    int64  
 1   normalized-losses  164 non-null    float64
 2   make               205 non-null    object 
 3   fuel-type          205 non-null    object 
 4   aspiration         205 non-null    object 
 5   num-of-doors       203 non-null    object 
 6   body-style         205 non-null    object 
 7   drive-wheels       205 non-null    object 
 8   engine-location    205 non-null    object 
 9   wheel-base         205 non-null    float64
 10  length             205 non-null    float64
 11  width              205 non-null    float64
 12  height             205 non-null    float64
 13  curb-weight        205 non-null    int64  
 14  engine-type        205 non-null    object 
 15  num-of-cylinders   205 non-null    object 
 16  engine-size        205 non-null    int64  
 17  fuel-system        205 non-null    object 
 18  bore               201 non-null    float64
```

```
 19  stroke             201 non-null    float64
 20  compression-ratio  205 non-null    float64
 21  horsepower         203 non-null    float64
 22  peak-rpm           203 non-null    float64
 23  city-mpg           205 non-null    int64
 24  highway-mpg        205 non-null    int64
 25  price              201 non-null    float64
dtypes: float64(11), int64(5), object(10)
memory usage: 41.8+ KB
```

```
data['normalized-losses'] = data['normalized-losses'].fillna(data['normalized-losses'].mean())
data['horsepower'] = data['horsepower'].fillna(data['horsepower'].mean())
data['peak-rpm'] = data['peak-rpm'].fillna(data['peak-rpm'].mean())
data['price'] = data['price'].fillna(data['price'].mean())
data['bore'] = data['bore'].fillna(data['bore'].mean())
data['stroke'] = data['stroke'].fillna(data['stroke'].mean())
#Replacing '4wd' with 'fwd' in 'drivewheel' column
data['drive-wheels'] = data['drive-wheels'].replace('4wd','fwd')
```

```
data.isnull().sum()
```

```
symboling            0
normalized-losses    0
make                 0
fuel-type            0
aspiration           0
num-of-doors         2
body-style           0
drive-wheels         0
engine-location      0
wheel-base           0
length               0
width                0
height               0
curb-weight          0
engine-type          0
num-of-cylinders     0
engine-size          0
```

```
fuel-system          0
bore                 0
stroke               0
compression-ratio    0
horsepower           0
peak-rpm             0
city-mpg             0
highway-mpg          0
price                0
dtype: int64
```

```
data['num-of-doors'].value_counts()
```

```
four    114
two      89
Name: num-of-doors, dtype: int64
```

```
data['num-of-doors'].replace({np.nan : 'two'},inplace = True)
```

```
data['drive-wheels'].unique()
```

```
array(['rwd', 'fwd'], dtype=object)
```

```
data.isnull().sum()
```

```
symboling            0
normalized-losses    0
make                 0
fuel-type            0
aspiration           0
num-of-doors         0
body-style           0
drive-wheels         0
engine-location      0
wheel-base           0
length               0
width                0
```

```
height               0
curb-weight          0
engine-type          0
num-of-cylinders     0
engine-size          0
fuel-system          0
bore                 0
stroke               0
compression-ratio    0
horsepower           0
peak-rpm             0
city-mpg             0
highway-mpg          0
price                0
dtype: int64
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   symboling          205 non-null    int64  
 1   normalized-losses  205 non-null    float64
 2   make               205 non-null    object 
 3   fuel-type          205 non-null    object 
 4   aspiration         205 non-null    object 
 5   num-of-doors       205 non-null    object 
 6   body-style         205 non-null    object 
 7   drive-wheels       205 non-null    object 
 8   engine-location    205 non-null    object 
 9   wheel-base         205 non-null    float64
 10  length             205 non-null    float64
 11  width              205 non-null    float64
 12  height             205 non-null    float64
 13  curb-weight        205 non-null    int64  
 14  engine-type        205 non-null    object 
 15  num-of-cylinders   205 non-null    object 
 16  engine-size        205 non-null    int64  
```

```
 17  fuel-system        205 non-null    object
 18  bore               205 non-null    float64
 19  stroke             205 non-null    float64
 20  compression-ratio  205 non-null    float64
 21  horsepower         205 non-null    float64
 22  peak-rpm           205 non-null    float64
 23  city-mpg           205 non-null    int64
 24  highway-mpg        205 non-null    int64
 25  price              205 non-null    float64
dtypes: float64(11), int64(5), object(10)
memory usage: 41.8+ KB
```

```
data.describe().style.background_gradient()
```

	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	engine-size	bore	stroke	cor
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	
mean	0.834146	122.000000	98.756585	174.049268	65.907805	53.724878	2555.565854	126.907317	3.329751	3.255423	
std	1.245307	31.681008	6.021776	12.337289	2.145204	2.443522	520.680204	41.642693	0.270844	0.313597	
min	-2.000000	65.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000000	2.540000	2.070000	
25%	0.000000	101.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97.000000	3.150000	3.110000	
50%	1.000000	122.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.000000	3.310000	3.290000	
75%	2.000000	137.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	141.000000	3.580000	3.410000	
max	3.000000	256.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326.000000	3.940000	4.170000	

```
data.head()
```

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine-size	fuel-system	bore	str
0	3	122.0	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	
1	3	122.0	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	
2	1	122.0	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...	152	mpfi	2.68	
3	2	164.0	audi	gas	std	four	sedan	fwd	front	99.8	...	109	mpfi	3.19	
4	2	164.0	audi	gas	std	four	sedan	fwd	front	99.4	...	136	mpfi	3.19	

5 rows × 26 columns

Handelling Outliers

- We can see that there are (205-88)= 117 records, which are outliers in the dataset.

```
# Finding outliers in all the numerical columns with 1.5 IQR rule and removing the outlier records
# #cul = ['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration',
#        'num-of-doors', 'body-style', 'drive-wheels', 'engine-location',
#        'wheel-base', 'length', 'width', 'height', 'curb-weight', 'engine-type',
#        'num-of-cylinders', 'engine-size', 'fuel-system', 'bore', 'stroke',
#        'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg',
#        'highway-mpg', 'price']

col_numeric = ['wheel-base','normalized-losses', 'length', 'width', 'height', 'curb-weight','engine-size','bore', 'stroke',
               'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg','highway-mpg', 'price']

for col in col_numeric:
    q1 = data[col].quantile(0.25)
    q3 = data[col].quantile(0.75)
```

```
    iqr = q3-q1
    range_low  = q1-1.5*iqr
    range_high = q3+1.5*iqr
    data = data.loc[(data[col] > range_low) & (data[col] < range_high)]

data.shape
```

```
(121, 26)
```

Checking Data Imbalance

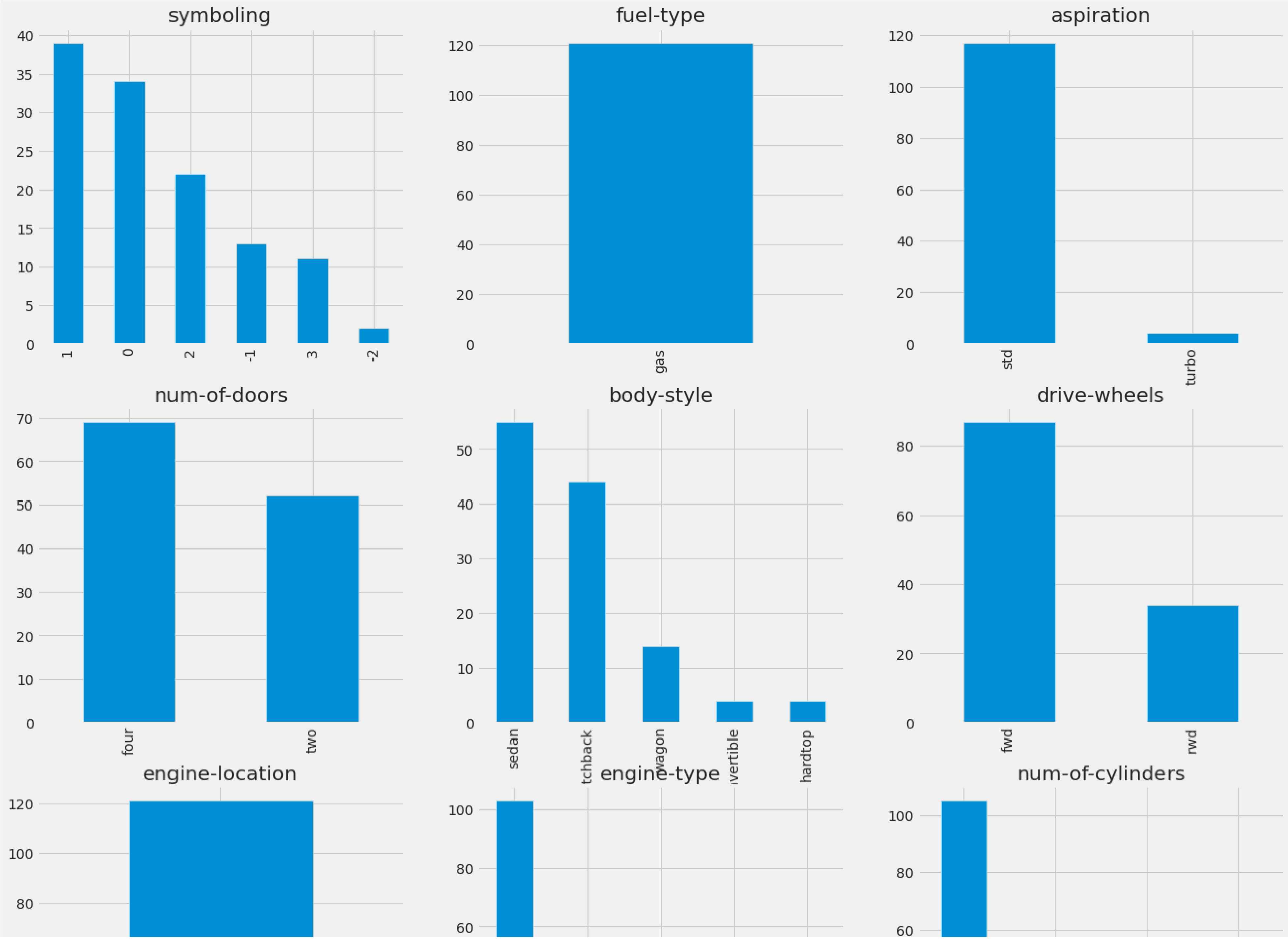
- We can see that there is data imbalance in below columns:-
    - symboling - There are very few with rating -2.
    - fuletype - All the cars fule type is Gas, as Diesel cars were removed while removing outliers..
    - aspiration - Lesser number of turbo than std.
    - engineloaction - All the engine location is in front, as all the rear engine cars were removed while removing outliers.
    - enginetype - Considerably more number of ohc than others.
    - cylindernumber - Large number of four cyliners than others.
    - fulesystem - mpfi and 2bbl fulesystem cars are more comparitavely others.
    - CarCompany - Most of the Toyata company cars were surveyed.

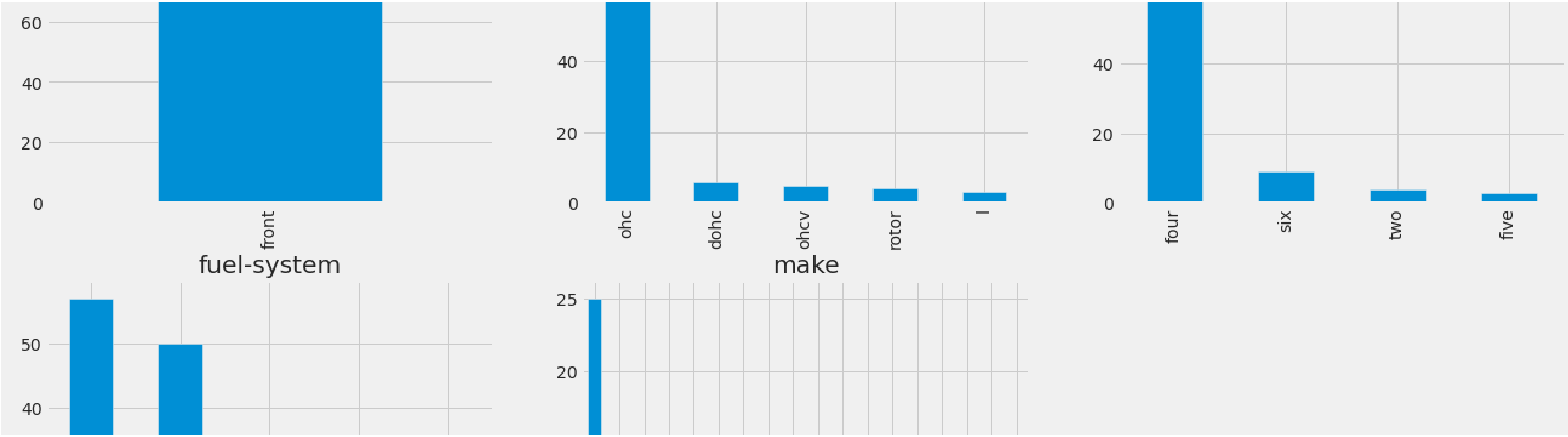
```
# Listing categorical columns for checking data imbalance and plotting them

# #cul = ['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration',
#        'num-of-doors', 'body-style', 'drive-wheels', 'engine-location',
#        'wheel-base', 'length', 'width', 'height', 'curb-weight', 'engine-type',
#        'num-of-cylinders', 'engine-size', 'fuel-system', 'bore', 'stroke',
#        'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg',
#        'highway-mpg', 'price']

col_category = ['symboling','fuel-type', 'aspiration','num-of-doors', 'body-style', 'drive-wheels', 'engine-location','engine-type',
           'num-of-cylinders','fuel-system','make']
```

```
k=0
plt.figure(figsize=(20,25))
for col in col_category:
    k=k+1
    plt.subplot(4, 3,k)
    data[col].value_counts().plot(kind='bar');
    plt.title(col)
```


symboling
fuel-type
aspiration
num-of-doors
body-style
drive-wheels
engine-location
engine-type
num-of-cylinders
1
0
2
-1
3
-2
gas
std
turbo
four
two
sedan
tchback
wagon
vertible
hardtop
fwd
rwd

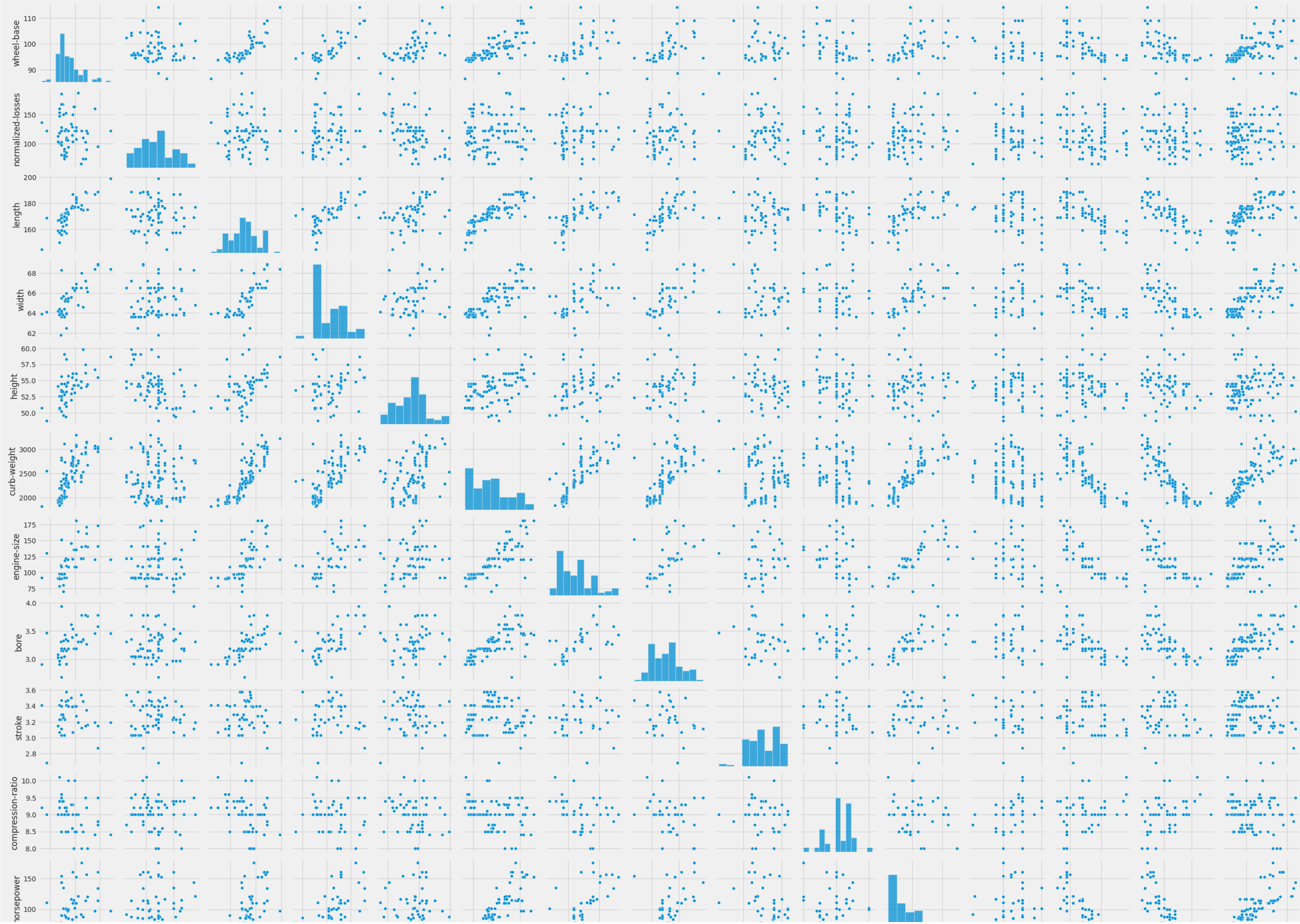


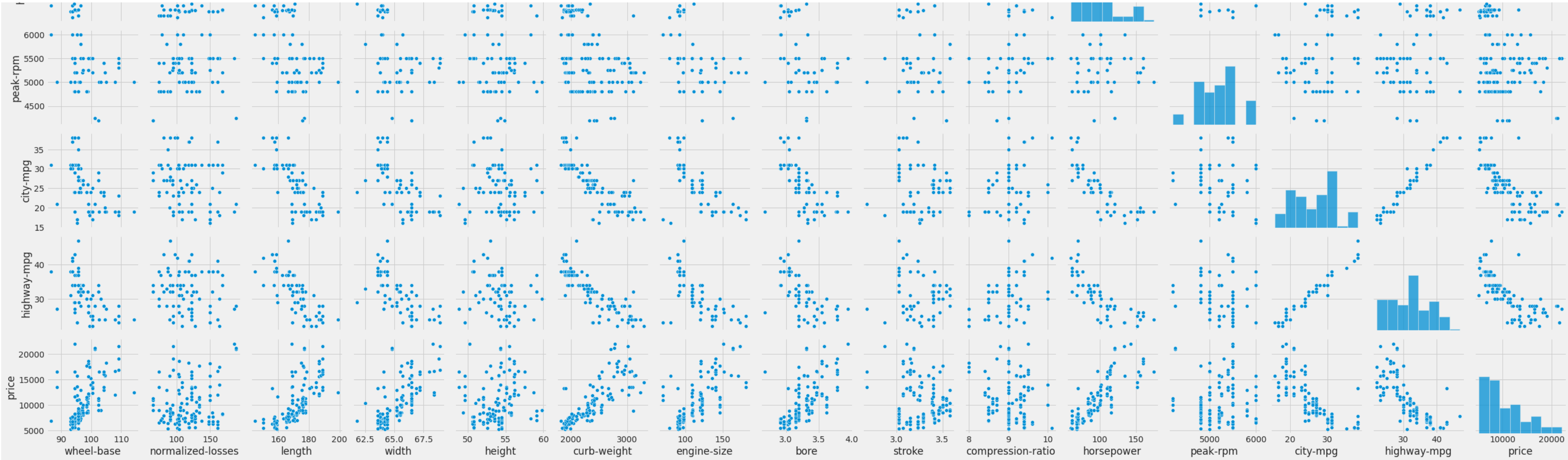
Visualising the data to check the possiblity of linear regression model

- We can see that there are few columns that have linear relationship with the target variable "price". So, we can build a linear regression model here.

```
# Visualising the numerical variables
plt.figure(figsize=(12,12))
sns.pairplot(data[col_numeric])
plt.show()
```

```
<Figure size 864x864 with 0 Axes>
```



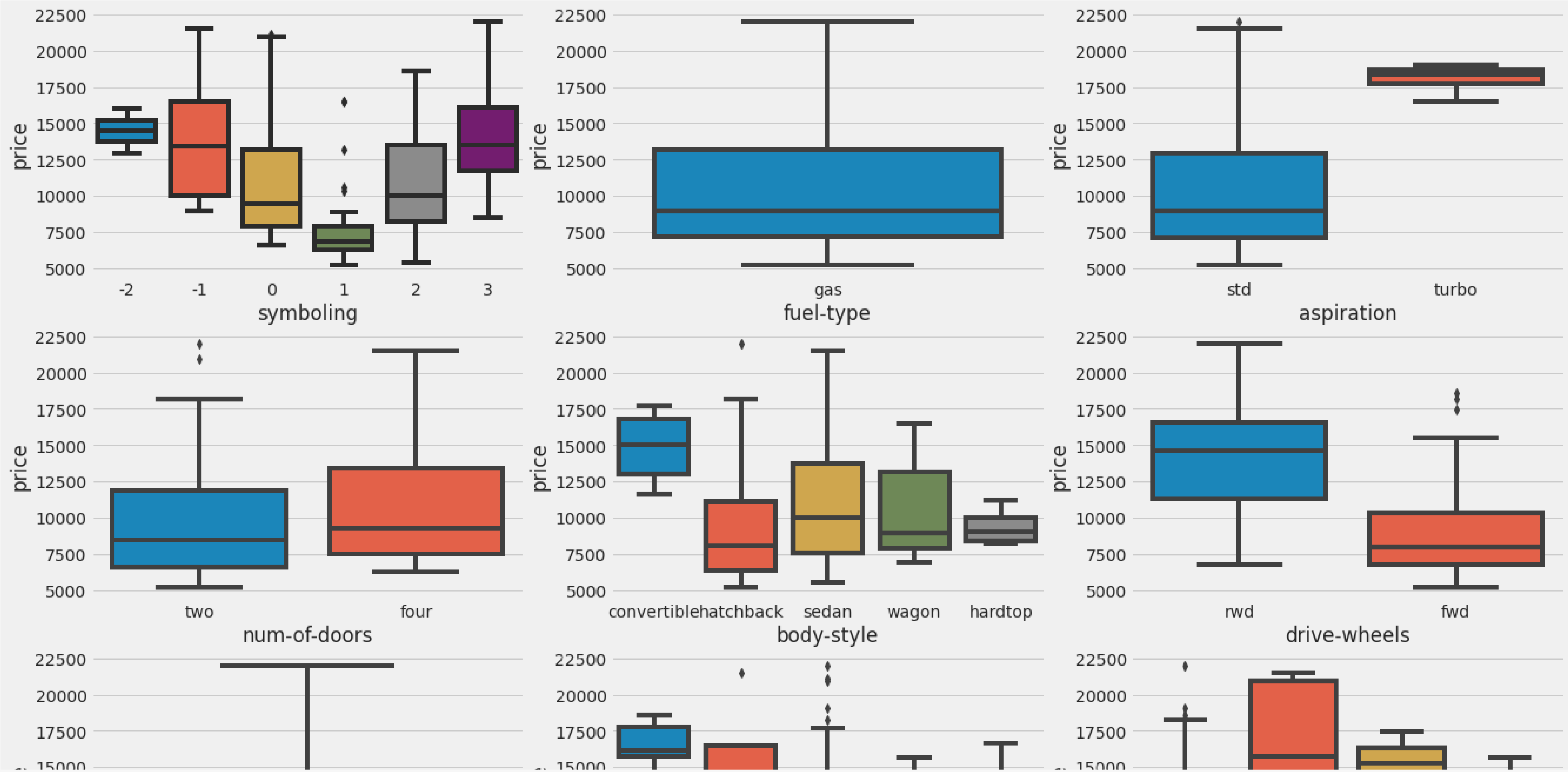


Visualising the categorical variables

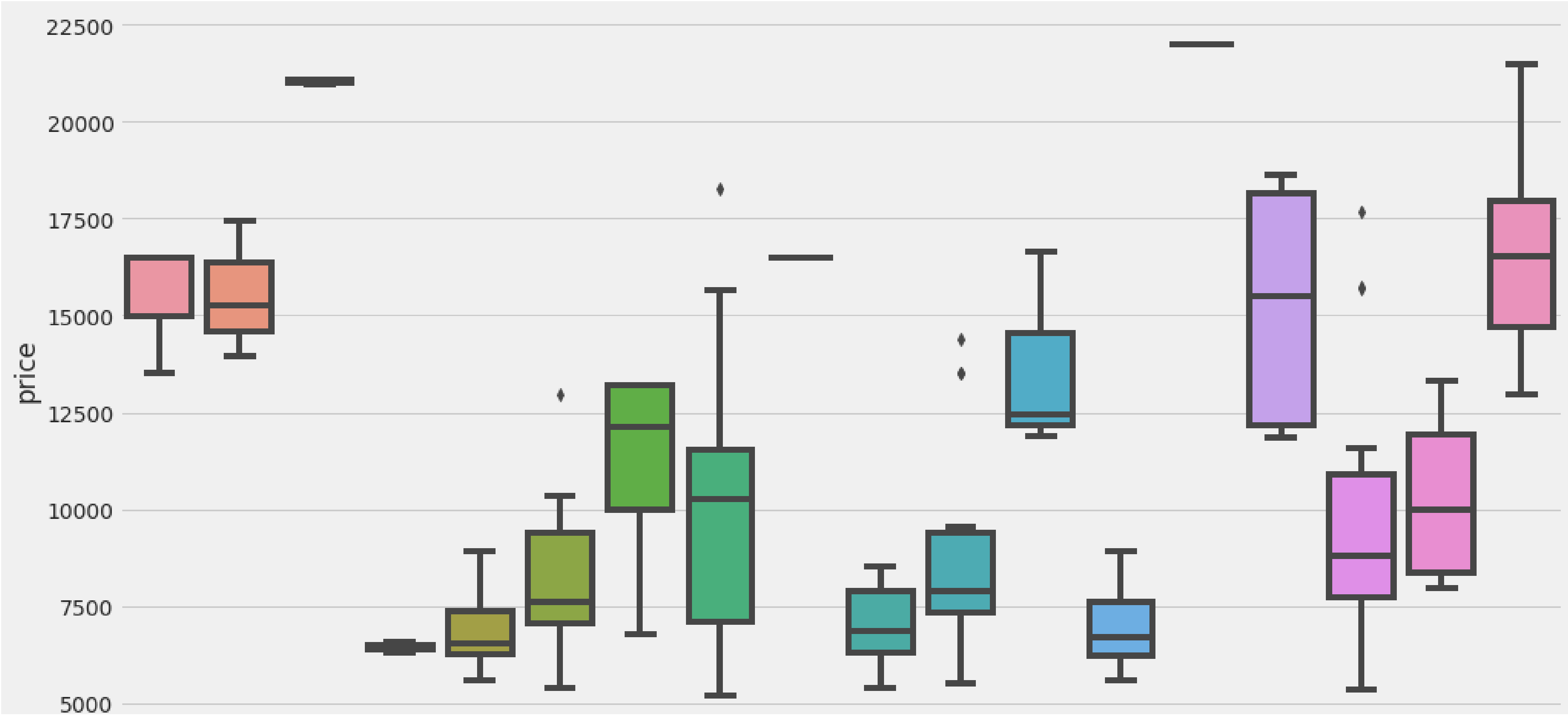
- CarCompany - Porsche has very high median price compared to other cars,though the number of Porsche cars is very less. Volvo, alfa-romero, audi and BMW are also high median price than others. Saab has wide rage of price, with high median price.
    - aspiration - std has lower median than turbo.
    - carbody - convertible has higher median that others.
    - symboling - -2 and -1 have higher median price than others.
    - enginelocation - rear has very high median price than fromt.
    - cylindernumber - Four has lower median than others.
    - fulesystem - 1bbl and 2bbl have lower median price than others.
- Now atleast we know that what are the variables have impact on the price. So as which variables are important for the model building.

```
# Boxplot for all categorical variables except CarCompany
```

```
# Boxplot for all categorical variables except CarCompany
# As X labels are not clearly visible for CarCompany. It is plotted in the next cell with bigger figure size.
k=0
plt.figure(figsize=(20,18))
for col in range (len(col_category)-1):
    k=k+1
    plt.subplot(4, 3, k)
    ax = sns.boxplot(x = col_category[col], y = 'price', data = data)
```




```
plt.figure(figsize=(15,8))
ax = sns.boxplot(x = 'make', y = 'price', data = data)
temp = ax.set_xticklabels(ax.get_xticklabels(), rotation = 45, horizontalalignment='right')
```



Step 2:- Preparing the data for model building

Encoding

- Converting categorical variables (fueltype, aspiration, doornumber, drivewheel, enginelocation) with two levels to binary variables.

```
data['fuel-type'].unique()
```

```
array(['gas'], dtype=object)
```

```
# fueltype
# Convert "gas" to 1 and "diesel" to 0
data['fuel-type'] = data['fuel-type'].map({'gas': 1, 'diesel': 0})
data.head()
```

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine-size	fuel-system	bore	st
0	3	122.0	alfa-romero	1	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	
1	3	122.0	alfa-romero	1	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	
2	1	122.0	alfa-romero	1	std	two	hatchback	rwd	front	94.5	...	152	mpfi	2.68	
3	2	164.0	audi	1	std	four	sedan	fwd	front	99.8	...	109	mpfi	3.19	
4	2	164.0	audi	1	std	four	sedan	fwd	front	99.4	...	136	mpfi	3.19	

5 rows × 26 columns

```
# aspiration
# Convert "std" to 1 and "turbo" to 0
data['aspiration'] = data['aspiration'].map({'std':1, 'turbo':0})
data.head()
```

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine-size	fuel-system	bore	st
0	3	122.0	alfa-romero	1	1	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	
1	3	122.0	alfa-romero	1	1	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	
2	1	122.0	alfa-romero	1	1	two	hatchback	rwd	front	94.5	...	152	mpfi	2.68	
3	2	164.0	audi	1	1	four	sedan	fwd	front	99.8	...	109	mpfi	3.19	
4	2	164.0	audi	1	1	four	sedan	fwd	front	99.4	...	136	mpfi	3.19	

```
# #cul = ['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration',
#        'num-of-doors', 'body-style', 'drive-wheels', 'engine-location',
#        'wheel-base', 'length', 'width', 'height', 'curb-weight', 'engine-type',
#        'num-of-cylinders', 'engine-size', 'fuel-system', 'bore', 'stroke',
#        'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg',
#        'highway-mpg', 'price']


data['num-of-doors'].unique()
```

```
array(['two', 'four'], dtype=object)
```

```
# doornumber
# Convert "four" to 1 and "two" to 0
data['num-of-doors'] = data['num-of-doors'].map({'four':1, 'two':0})
data.head()
```

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine-size	fuel-system	bore	st
0	3	122.0	alfa-romero	1	1	0	convertible	rwd	front	88.6	...	130	mpfi	3.47	
1	3	122.0	alfa-romero	1	1	0	convertible	rwd	front	88.6	...	130	mpfi	3.47	
2	1	122.0	alfa-romero	1	1	0	hatchback	rwd	front	94.5	...	152	mpfi	2.68	
3	2	164.0	audi	1	1	1	sedan	fwd	front	99.8	...	109	mpfi	3.19	
4	2	164.0	audi	1	1	1	sedan	fwd	front	99.4	...	136	mpfi	3.19	

5 rows × 26 columns

```
data['drive-wheels'].unique()
```

```
array(['rwd', 'fwd'], dtype=object)
```

```
# drivewheel
# Convert "fwd" to 1 and "rwd" to 0
data['drive-wheels'] = data['drive-wheels'].map({'fwd':1, 'rwd':0})
data.head()
```

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine-size	fuel-system	bore	st
0	3	122.0	alfa-romero	1	1	0	convertible	0	front	88.6	...	130	mpfi	3.47	
1	3	122.0	alfa-romero	1	1	0	convertible	0	front	88.6	...	130	mpfi	3.47	

```
data['engine-location'].unique()
```

```
array(['front'], dtype=object)
```

4	2	164.0	audi	1	1	1	sedan	1	front	99.4	...	136	mpfi	3.19

```
# enginelocation
# Convert "front" to 1 and "rear" to 0
data['engine-location'] = data['engine-location'].map({'front':1, 'rear':0})
data.head()
```

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-	body-style	drive-wheels	engine-location	wheel-base	...	engine-size	fuel-system	bore	st

Dummy variables

- Converting other categorical variables with more than two levels to dummy variables. We have to create (n-1) dummy variables by removing the base status. n is the number of levels of the variables.

romero

```
# Creating dummy variables for 'symboling'
# Dropping the redundant dummy variable (-2)
symboling_status = pd.get_dummies(data['symboling'],drop_first=True)
symboling_status.head()
```

	-1	0	1	2	3
0	0	0	0	0	1
1	0	0	0	0	1
2	0	0	1	0	0
3	0	0	0	1	0
4	0	0	0	1	0

```
# Renaming column names for better readability
symboling_status = symboling_status.rename(columns={-1:'symboling(-1)', 0:'symboling(0)', 1:'symboling(1)',2:'symboling(2)', 3:'symbo
symboling_status.head()
```

	symboling(-1)	symboling(0)	symboling(1)	symboling(2)	symboling(3)
0	0	0	0	0	1
1	0	0	0	0	1

```
# Concating the dummy dataframe with original dataframe
data = pd.concat([data,symboling_status], axis=1)
data.head()
```

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	horsepower	peak-rpm	city-mpg
0	3	122.0	alfa-romero	1	1	0	convertible	0	1	88.6	...	111.0	5000.0	21
1	3	122.0	alfa-romero	1	1	0	convertible	0	1	88.6	...	111.0	5000.0	21
2	1	122.0	alfa-romero	1	1	0	hatchback	0	1	94.5	...	154.0	5000.0	19
3	2	164.0	audi	1	1	1	sedan	1	1	99.8	...	102.0	5500.0	24
4	2	164.0	audi	1	1	1	sedan	1	1	99.4	...	115.0	5500.0	18

5 rows × 31 columns

```
# Dropping the 'symboling' column as we don't need it anymore
data = data.drop('symboling',axis=1)
data.head()
```

	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	...	horsepower	peak-rpm	city-mpg	hi
0	122.0	alfa-romero	1	1	0	convertible	0	1	88.6	168.8	...	111.0	5000.0	21	
1	122.0	alfa-romero	1	1	0	convertible	0	1	88.6	168.8	...	111.0	5000.0	21	
2	122.0	alfa-romero	1	1	0	hatchback	0	1	94.5	171.2	...	154.0	5000.0	19	
3	164.0	audi	1	1	1	sedan	1	1	99.8	176.6	...	102.0	5500.0	24	
4	164.0	audi	1	1	1	sedan	1	1	99.4	176.6	...	115.0	5500.0	18	

5 rows × 30 columns

```
# Creating dummy variables for 'carbody'
# Dropping the redundant dummy variable (convertible)
carbody_status = pd.get_dummies(data['body-style'],drop_first=True)
carbody_status.head()
```

	hardtop	hatchback	sedan	wagon
0	0	0	0	0
1	0	0	0	0
2	0	1	0	0
3	0	0	1	0
4	0	0	1	0

```
# Renaming column names for better readability
carbody_status = carbody_status.rename(columns={'hardtop':'carbody(hardtop)', 'hatchback':'carbody(hatchback)', 'sedan':'carbody(seda
carbody_status.head()
```

```
carbody_status.head()
```

	carbody(hardtop)	carbody(hatchback)	carbody(sedan)	carbody(wagon)
0	0	0	0	0
1	0	0	0	0
2	0	1	0	0
3	0	0	1	0
4	0	0	1	0

```
# Concating the dummy dataframe with original dataframe
data = pd.concat([data,carbody_status], axis=1)
data.head()
```

	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	...	price	symboling(-1)	symbo
0	122.0	alfa-romero	1	1	0	convertible	0	1	88.6	168.8	...	13495.0	0	
1	122.0	alfa-romero	1	1	0	convertible	0	1	88.6	168.8	...	16500.0	0	
2	122.0	alfa-romero	1	1	0	hatchback	0	1	94.5	171.2	...	16500.0	0	
3	164.0	audi	1	1	1	sedan	1	1	99.8	176.6	...	13950.0	0	
4	164.0	audi	1	1	1	sedan	1	1	99.4	176.6	...	17450.0	0	

5 rows × 34 columns

```
# Dropping the 'symboling' column as we don't need it
data = data.drop('body-style',axis=1)
data.head()
```

	normalized-losses	make	fuel-type	aspiration	num-of-doors	drive-wheels	engine-location	wheel-base	length	width	...	price	symboling(-1)	symbolin
0	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	13495.0	0	
1	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	16500.0	0	
2	122.0	alfa-romero	1	1	0	0	1	94.5	171.2	65.5	...	16500.0	0	
3	164.0	audi	1	1	1	1	1	99.8	176.6	66.2	...	13950.0	0	
4	164.0	audi	1	1	1	1	1	99.4	176.6	66.4	...	17450.0	0	

5 rows × 33 columns

cul = ['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration', 'num-of-doors', 'body-style', 'drive-wheels', 'engine-location', 'wheel-base', 'length', 'width', 'height', 'curb-weight', 'engine-type', 'num-of-cylinders', 'engine-size', 'fuel-system', 'bore', 'stroke', 'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg', 'highway-mpg', 'price']

```
# Creating dummy variables for 'enginetype'
# Dropping the redundant dummy variable (dohc)
enginetype_status = pd.get_dummies(data['engine-type'], drop_first=True)
enginetype_status.head()
```

	l	ohc	ohcv	rotor
0	0	0	0	0
1	0	0	0	0
2	0	0	1	0
3	0	1	0	0
4	0	1	0	0

```
# Renaming column name for better readability
enginetype_status = enginetype_status.rename(columns={'dohcv':'enginetype(dohcv)', 'l':'enginetype(l)', 'ohc':'enginetype(ohc)',
                                              'ohcf':'enginetype(ohcf)','ohcv':'enginetype(ohcv)' ,'rotor':'enginetype(rotor)
enginetype_status.head()
```

	enginetype(l)	enginetype(ohc)	enginetype(ohcv)	enginetype(rotor)
0	0	0	0	0
1	0	0	0	0
2	0	0	1	0
3	0	1	0	0
4	0	1	0	0

```
# Concating the dummy dataframe with original dataframe
data = pd.concat([data,enginetype_status], axis=1)
data.head()
```

	normalized-losses	make	fuel-type	aspiration	num-of-doors	drive-wheels	engine-location	wheel-base	length	width	...	symboling(2)	symboling(3)	carb
0	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	0	1	
1	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	0	1	
2	122.0	alfa-romero	1	1	0	0	1	94.5	171.2	65.5	...	0	0	
3	164.0	audi	1	1	1	1	1	99.8	176.6	66.2	...	1	0	

```
# Dropping the 'enginetype' column as we don't need it
data = data.drop('engine-type',axis=1)
data.head()
```

```
# Creating dummy variables for 'cylindernumber'
# Dropping the redundant dummy variable (eight)
cylindernumber_status = pd.get_dummies(data['num-of-cylinders'], drop_first=True)
cylindernumber_status.head()
```

	four	six	two
0	1	0	0
1	1	0	0
2	0	1	0
3	1	0	0
4	0	0	0

```
# Renaming column name for better readability
cylindernumber_status = cylindernumber_status.rename(columns={'five':'cylindernumber(five)', 'four':'cylindernumber(four)', 'six':'cy
                                                              'three':'cylindernumber(three)','twelve':'cylindernumber(twelve)' ,'two':'cylin
cylindernumber_status.head()
```

	cylindernumber(four)	cylindernumber(six)	cylindernumber(two)
0	1	0	0
1	1	0	0
2	0	1	0
3	1	0	0
4	0	0	0

```
# Concating the dummy dataframe with original dataframe
data = pd.concat([data,cylindernumber_status], axis=1)
data.head()
```

	normalized-losses	make	fuel-type	aspiration	num-of-doors	drive-wheels	engine-location	wheel-base	length	width	...	carbody(hatchback)	carbody(seda
0	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	0	
1	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	0	
2	122.0	alfa-romero	1	1	0	0	1	94.5	171.2	65.5	...	1	
3	164.0	audi	1	1	1	1	1	99.8	176.6	66.2	...	0	
4	164.0	audi	1	1	1	1	1	99.4	176.6	66.4	...	0	

5 rows × 39 columns

```
# Dropping the 'cylindernumber' column as we don't need it
data = data.drop('num-of-cylinders',axis=1)
data.head()
```

	normalized-losses	make	fuel-type	aspiration	num-of-doors	drive-wheels	engine-location	wheel-base	length	width	...	carbody(hatchback)	carbody(seda
0	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	0	
1	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	0	

```
# Creating dummy variables for 'fuelsystem'
# Dropping the redundant dummy variable (1bbl)
fuelsystem_status = pd.get_dummies(data['fuel-system'], drop_first=True)
fuelsystem_status.head()
```

	2bbl	4bbl	mpfi	spfi
0	0	0	1	0
1	0	0	1	0
2	0	0	1	0
3	0	0	1	0
4	0	0	1	0

```
# Renaming column name for better readability
fuelsystem_status = fuelsystem_status.rename(columns={'2bbl':'fuelsystem(2bbl)', '4bbl':'fuelsystem(4bbl)', 'idi':'fuelsystem(idi)',
                                                      'mfi':'fuelsystem(mfi)','mpfi':'fuelsystem(mpfi)' ,'spdi':'fuelsystem(spdi)',
                                                             'spfi':'fuelsystem(spfi)'})
fuelsystem_status.head()
```

	fuelsystem(2bbl)	fuelsystem(4bbl)	fuelsystem(mpfi)	fuelsystem(spfi)
0	0	0	1	0
1	0	0	1	0

```
# Concating the dummy dataframe with original dataframe
data = pd.concat([data,fuelsystem_status], axis=1)
data.head()
```

	normalized-losses	make	fuel-type	aspiration	num-of-doors	drive-wheels	engine-location	wheel-base	length	width	...	enginetype(ohc)	enginetype(ohcv
0	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	0	
1	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	0	
2	122.0	alfa-romero	1	1	0	0	1	94.5	171.2	65.5	...	0	
3	164.0	audi	1	1	1	1	1	99.8	176.6	66.2	...	1	
4	164.0	audi	1	1	1	1	1	99.4	176.6	66.4	...	1	

5 rows × 42 columns

```
# Dropping the 'fuelsystem' column as we don't need it
data = data.drop('fuel-system',axis=1)
data.head()
```

	normalized-losses	make	fuel-type	aspiration	num-of-doors	drive-wheels	engine-location	wheel-base	length	width	...	enginetype(ohc)	enginetype(ohcv
0	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	0	
1	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	0	
2	122.0	alfa-romero	1	1	0	0	1	94.5	171.2	65.5	...	0	
3	164.0	audi	1	1	1	1	1	99.8	176.6	66.2	...	1	
4	164.0	audi	1	1	1	1	1	99.4	176.6	66.4	...	1	

5 rows × 41 columns

```
# Creating dummy variables for 'CarCompany'
# Dropping the redundant dummy variable (alfa-romero)
CarCompany_status = pd.get_dummies(data['make'], drop_first=True)
CarCompany_status.head()
```

	audi	bmw	chevrolet	dodge	honda	isuzu	mazda	mercury	mitsubishi	nissan	peugot	plymouth	porsche	saab	toyota	volks
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

```
# Renaming column name for better readability
CarCompany_status = CarCompany_status.rename(columns={'audi':'CarCompany(audi)', 'bmw':'CarCompany(bmw)', 'buick':'CarCompany(buick)'
```

```
                                     'chevrolet':'CarCompany(chevrolet)','dodge':'CarCompany(dodge)' ,'honda':'CarCo
                                     'isuzu':'CarCompany(isuzu)','jaguar':'CarCompany(jaguar)','mazda':'CarCompany(m
                                     'mercury':'CarCompany(mercury)','mitsubishi':'CarCompany(mitsubishi)','nissan':
                                     'peugeot':'CarCompany(peugeot)','plymouth':'CarCompany(plymouth)','porsche':'Ca
                                     'renault':'CarCompany(renault)','saab':'CarCompany(saab)','subaru':'CarCompany(
                                     'toyota':'CarCompany(toyota)','volkswagen':'CarCompany(volkswagen)','volvo':'Ca

CarCompany_status.head()
```

	CarCompany(audi)	CarCompany(bmw)	CarCompany(chevrolet)	CarCompany(dodge)	CarCompany(honda)	CarCompany(isuzu)	CarCompan
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	0	0	0	0	
3	1	0	0	0	0	0	
4	1	0	0	0	0	0	

```
# Concating the dummy dataframe with original dataframe
data = pd.concat([data,CarCompany_status], axis=1)
data.head()
```

	normalized-losses	make	fuel-type	aspiration	num-of-doors	drive-wheels	engine-location	wheel-base	length	width	...	CarCompany(mercury)	CarCompany(
0	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	0	
1	122.0	alfa-romero	1	1	0	0	1	88.6	168.8	64.1	...	0	

```
# Dropping the 'CarCompany' column as we don't need it
data = data.drop('make',axis=1)
data.head()
```

	normalized-losses	fuel-type	aspiration	num-of-doors	drive-wheels	engine-location	wheel-base	length	width	height	...	CarCompany(mercury)	CarCompany(
0	122.0	1	1	0	0	1	88.6	168.8	64.1	48.8	...	0	
1	122.0	1	1	0	0	1	88.6	168.8	64.1	48.8	...	0	
2	122.0	1	1	0	0	1	94.5	171.2	65.5	52.4	...	0	
3	164.0	1	1	1	1	1	99.8	176.6	66.2	54.3	...	0	
4	164.0	1	1	1	1	1	99.4	176.6	66.4	54.3	...	0	

5 rows × 57 columns

```
x = data.loc[:,['normalized-losses', 'fuel-type', 'aspiration', 'num-of-doors',
       'drive-wheels', 'engine-location', 'wheel-base', 'length', 'width',
       'height', 'curb-weight', 'engine-size', 'bore', 'stroke',
       'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg',
       'highway-mpg','symboling(-1)', 'symboling(0)', 'symboling(1)',
```

```
       'symboling(2)', 'symboling(3)', 'carbody(hardtop)',
       'carbody(hatchback)', 'carbody(sedan)', 'carbody(wagon)',
       'enginetype(l)', 'enginetype(ohc)', 'enginetype(ohcv)',
       'enginetype(rotor)', 'cylindernumber(four)', 'cylindernumber(six)',
       'cylindernumber(two)', 'fuelsystem(2bbl)', 'fuelsystem(4bbl)',
       'fuelsystem(mpfi)', 'fuelsystem(spfi)', 'CarCompany(audi)',
       'CarCompany(bmw)', 'CarCompany(chevrolet)', 'CarCompany(dodge)',
       'CarCompany(honda)', 'CarCompany(isuzu)', 'CarCompany(mazda)',
       'CarCompany(mercury)', 'CarCompany(mitsubishi)', 'CarCompany(nissan)',
       'peugot', 'CarCompany(plymouth)', 'CarCompany(porsche)',
       'CarCompany(saab)', 'CarCompany(toyota)', 'CarCompany(volkswagen)',
       'CarCompany(volvo)']]

y = data.loc[:,'price']
```

```
x.head()
```

	normalized-losses	fuel-type	aspiration	num-of-doors	drive-wheels	engine-location	wheel-base	length	width	height	...	CarCompany(mercury)	CarCompany(
0	122.0	1	1	0	0	1	88.6	168.8	64.1	48.8	...	0	
1	122.0	1	1	0	0	1	88.6	168.8	64.1	48.8	...	0	
2	122.0	1	1	0	0	1	94.5	171.2	65.5	52.4	...	0	
3	164.0	1	1	1	1	1	99.8	176.6	66.2	54.3	...	0	
4	164.0	1	1	1	1	1	99.4	176.6	66.4	54.3	...	0	

5 rows × 56 columns

```
y.head()
```

```
0    13495.0
1    16500.0
2    16500.0
3    13950.0
4    17450.0
Name: price, dtype: float64
```

```
data.info()
```

```
 1   fuel-type              121 non-null    int64
 2   aspiration             121 non-null    int64
 3   num-of-doors           121 non-null    int64
 4   drive-wheels           121 non-null    int64
 5   engine-location        121 non-null    int64
 6   wheel-base             121 non-null    float64
 7   length                 121 non-null    float64
 8   width                  121 non-null    float64
 9   height                 121 non-null    float64
 10  curb-weight            121 non-null    int64
 11  engine-size            121 non-null    int64
 12  bore                   121 non-null    float64
 13  stroke                 121 non-null    float64
 14  compression-ratio      121 non-null    float64
 15  horsepower             121 non-null    float64
 16  peak-rpm               121 non-null    float64
 17  city-mpg               121 non-null    int64
 18  highway-mpg            121 non-null    int64
 19  price                  121 non-null    float64
 20  symboling(-1)          121 non-null    uint8
 21  symboling(0)           121 non-null    uint8
 22  symboling(1)           121 non-null    uint8
 23  symboling(2)           121 non-null    uint8
 24  symboling(3)           121 non-null    uint8
 25  carbody(hardtop)       121 non-null    uint8
 26  carbody(hatchback)     121 non-null    uint8
 27  carbody(sedan)         121 non-null    uint8
 28  carbody(wagon)         121 non-null    uint8
 29  enginetype(l)          121 non-null    uint8
 30  enginetype(ohc)        121 non-null    uint8
```

```
 31  enginetype(ohcv)        121 non-null    uint8
 32  enginetype(rotor)       121 non-null    uint8
 33  cylindernumber(four)    121 non-null    uint8
 34  cylindernumber(six)     121 non-null    uint8
 35  cylindernumber(two)     121 non-null    uint8
 36  fuelsystem(2bbl)        121 non-null    uint8
 37  fuelsystem(4bbl)        121 non-null    uint8
 38  fuelsystem(mpfi)        121 non-null    uint8
 39  fuelsystem(spfi)        121 non-null    uint8
 40  CarCompany(audi)        121 non-null    uint8
 41  CarCompany(bmw)         121 non-null    uint8
 42  CarCompany(chevrolet)   121 non-null    uint8
 43  CarCompany(dodge)       121 non-null    uint8
 44  CarCompany(honda)       121 non-null    uint8
 45  CarCompany(isuzu)       121 non-null    uint8
 46  CarCompany(mazda)       121 non-null    uint8
 47  CarCompany(mercury)     121 non-null    uint8
 48  CarCompany(mitsubishi)  121 non-null    uint8
 49  CarCompany(nissan)      121 non-null    uint8
 50  peugot                  121 non-null    uint8
 51  CarCompany(plymouth)    121 non-null    uint8
 52  CarCompany(porsche)     121 non-null    uint8
 53  CarCompany(saab)        121 non-null    uint8
 54  CarCompany(toyota)      121 non-null    uint8
 55  CarCompany(volkswagen)  121 non-null    uint8
 56  CarCompany(volvo)       121 non-null    uint8
dtypes: float64(11), int64(9), uint8(37)
memory usage: 28.3 KB
```

Splitting Data into Train and test

```
#Importing Model Building Libaries

# Train-test split
from sklearn.model_selection import train_test_split
# Min-max scling
from sklearn.preprocessing import MinMaxScaler
```

```
# Statsmodel
import statsmodels.api as sm
# VIF
from statsmodels.stats.outliers_influence import variance_inflation_factor
#R-squared
from sklearn.metrics import r2_score
# Label encoding
from sklearn.preprocessing import LabelEncoder
# Importing RFE
from sklearn.feature_selection import RFE
# Importing LinearRegression
from sklearn.linear_model import LinearRegression
# Supress warning
import warnings
warnings.filterwarnings('ignore')
```

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20, random_state=42)
```

```
from sklearn import metrics
from sklearn.model_selection import cross_val_score

def cross_val(model):
    pred = cross_val_score(model, x, y, cv=10)
    return pred.mean()

def print_evaluate(true, predicted):
    mae = metrics.mean_absolute_error(true, predicted)
    mse = metrics.mean_squared_error(true, predicted)
    rmse = np.sqrt(metrics.mean_squared_error(true, predicted))
    r2_square = metrics.r2_score(true, predicted)
    print('MAE:', mae)
    print('MSE:', mse)
    print('RMSE:', rmse)
    print('R2 Square', r2_square)
    print('__________________________________')

def evaluate(true, predicted):
```

```
def evaluate(true, predicted):
    mae = metrics.mean_absolute_error(true, predicted)
    mse = metrics.mean_squared_error(true, predicted)
    rmse = np.sqrt(metrics.mean_squared_error(true, predicted))
    r2_square = metrics.r2_score(true, predicted)
    return mae, mse, rmse, r2_square
```

```
scaler = MinMaxScaler()

x_train = scaler.fit_transform(x_train)

x_test = scaler.transform(x_test)
```

Model Creation Linear Regression

```
lin_reg = LinearRegression(normalize=True)
lin_reg.fit(x_train,y_train)
```

```
LinearRegression(normalize=True)
```

```
# print the intercept
print(lin_reg.intercept_)
```

```
12401.400923571686
```

```
coeff_df = pd.DataFrame(lin_reg.coef_, x.columns, columns=['Coefficient'])
coeff_df
```

	Coefficient
normalized-losses	5.364262e+02
fuel-type	4.911271e-11
aspiration	-7.135967e+02
num-of-doors	4.517465e+02
drive-wheels	-1.911465e+02
engine-location	-9.822543e-11
wheel-base	1.214284e+04
length	-4.232021e+03
width	2.269482e+03
height	-3.810101e+03
curb-weight	8.231102e+03
engine-size	-1.809028e+04
bore	1.584240e+04
stroke	4.138864e+03
compression-ratio	-6.888009e+02
horsepower	1.711234e+03
peak-rpm	1.221798e+04
city-mpg	-3.038019e+03
highway-mpg	5.841129e+03
symboling(-1)	6.174041e+02
symboling(0)	-2.006351e+03
symboling(1)	-1.546794e+03

symboling(2)	-1.557762e+03
symboling(3)	-1.043796e+03
carbody(hardtop)	-5.198632e+03
carbody(hatchback)	-3.961535e+03
carbody(sedan)	-3.077945e+03
carbody(wagon)	-3.113475e+03
enginetype(l)	-7.024955e+03
enginetype(ohc)	-1.134631e+03
enginetype(ohcv)	7.816698e+03
enginetype(rotor)	-6.064400e+03
cylindernumber(four)	-5.229821e+03
cylindernumber(six)	-3.517498e+03
cylindernumber(two)	-6.064400e+03
fuelsystem(2bbl)	1.171292e+03
fuelsystem(4bbl)	-6.064400e+03
fuelsystem(mpfi)	5.702351e+02
fuelsystem(spfi)	-3.637979e-11
CarCompany(audi)	-7.266831e+03
CarCompany(bmw)	1.257492e+04
CarCompany(chevrolet)	-1.097124e+04
CarCompany(dodge)	-1.218712e+04
CarCompany(honda)	-1.120816e+04
CarCompany(isuzu)	-5.549611e+03

CarCompany(mazda)	-6.300397e+03
CarCompany(mercury)	-7.275958e-12
CarCompany(mitsubishi)	-1.119795e+04
CarCompany(nissan)	-9.381603e+03
peugot	-7.024955e+03
CarCompany(plymouth)	-1.172562e+04
CarCompany(porsche)	-3.389551e+03
CarCompany(saab)	-7.219976e+03
CarCompany(toyota)	-5.800348e+03

Prediction from our model

```
pred = lin_reg.predict(x_test)
pred
```

```
array([10327.23884945, 23890.93919519, 16804.43226042,  6594.76993172,
       10174.6998297 ,  9426.91386408,  6884.37240061,  5043.34217433,
       18535.82106196,  8170.20742958,  7555.64493054,  6044.76139966,
        5080.18061249,  8262.77502563, 10495.33986194, 18173.83170366,
        9874.61397272, 16966.04542699,  8140.4676725 ,  9896.05780829,
       14324.84419744,  9527.24163496, 12199.6243466 , 11430.09044116,
       10327.23884945])
```

```
test_pred = lin_reg.predict(x_test)
train_pred = lin_reg.predict(x_train)

print('Test set evaluation:\n_____________________________________')
print_evaluate(y_test, test_pred)
print('Train set evaluation:\n_____________________________________')
print_evaluate(y_train, train_pred)
```

```
print_evaluate(y_train, train_pred)

results_df = pd.DataFrame(data=[["Linear Regression", *evaluate(y_test, test_pred) , cross_val(LinearRegression())]],
                          columns=['Model', 'MAE', 'MSE', 'RMSE', 'R2 Square', "Cross Validation"])
```

```
Test set evaluation:
_____________________________________
MAE: 1631.7548865140263
MSE: 5568857.322725073
RMSE: 2359.8426478740216
R2 Square 0.5950985663635897
__________________________________
Train set evaluation:
_____________________________________
MAE: 659.7588443098801
MSE: 671090.4995822677
RMSE: 819.2011349981565
R2 Square 0.9626935377493883
__________________________________
```

Robust Regression

Random Sample Consensus - RANSAC

```
from sklearn.linear_model import RANSACRegressor

model = RANSACRegressor(base_estimator=LinearRegression(), max_trials=100)
model.fit(x_train, y_train)

test_pred = model.predict(x_test)
train_pred = model.predict(x_train)

print('Test set evaluation:\n_____________________________________')
print_evaluate(y_test, test_pred)
print('====================================')
```

```
print('Train set evaluation:\n_____________________________________')
print_evaluate(y_train, train_pred)

results_df_2 = pd.DataFrame(data=[["Robust Regression", *evaluate(y_test, test_pred) , cross_val(RANSACRegressor())]],
                            columns=['Model', 'MAE', 'MSE', 'RMSE', 'R2 Square', "Cross Validation"])
results_df = results_df.append(results_df_2, ignore_index=True)
```

```
Test set evaluation:
_____________________________________
MAE: 2850.377532020369
MSE: 21900968.845926296
RMSE: 4679.8470964259395
R2 Square -0.5923794002685214
__________________________________
====================================
Train set evaluation:
_____________________________________
MAE: 1297.6926676300573
MSE: 11395141.908167949
RMSE: 3375.6691052542383
R2 Square 0.366534868692002
__________________________________
```

Ridge Regression

```
from sklearn.linear_model import Ridge

model = Ridge(alpha=100, solver='cholesky', tol=0.0001, random_state=42)
model.fit(x_train, y_train)
pred = model.predict(x_test)

test_pred = model.predict(x_test)
train_pred = model.predict(x_train)

print('Test set evaluation:\n_____________________________________')
print_evaluate(y_test, test_pred)
```

```
print_evaluate(y_test, test_pred)
print('====================================')
print('Train set evaluation:\n_____________________________________')
print_evaluate(y_train, train_pred)

results_df_2 = pd.DataFrame(data=[["Ridge Regression", *evaluate(y_test, test_pred) , cross_val(Ridge())]],
                            columns=['Model', 'MAE', 'MSE', 'RMSE', 'R2 Square', "Cross Validation"])
results_df = results_df.append(results_df_2, ignore_index=True)
```

```
Test set evaluation:
_____________________________________
MAE: 1869.0625915053417
MSE: 5144109.611156661
RMSE: 2268.0629645485287
R2 Square 0.6259811958477433
__________________________________
====================================
Train set evaluation:
_____________________________________
MAE: 2196.7318893822303
MSE: 8107280.544626266
RMSE: 2847.328668177642
R2 Square 0.5493097342586634
__________________________________
```

Lasso Regression

```
from sklearn.linear_model import Lasso

model = Lasso(alpha=0.1,
              precompute=True,
#               warm_start=True,
              positive=True,
              selection='random',
              random_state=42)
model.fit(x_train, y_train)
```

```
model.fit(X_train, y_train)

test_pred = model.predict(x_test)
train_pred = model.predict(x_train)

print('Test set evaluation:\n_____________________________________')
print_evaluate(y_test, test_pred)
print('====================================')
print('Train set evaluation:\n_____________________________________')
print_evaluate(y_train, train_pred)

results_df_2 = pd.DataFrame(data=[["Lasso Regression", *evaluate(y_test, test_pred) , cross_val(Lasso())]],
                            columns=['Model', 'MAE', 'MSE', 'RMSE', 'R2 Square', "Cross Validation"])
results_df = results_df.append(results_df_2, ignore_index=True)
```

```
Test set evaluation:
_____________________________________
MAE: 1086.3260714321107
MSE: 2140202.7459618445
RMSE: 1462.9431793346741
R2 Square 0.8443897715647555
__________________________________
====================================
Train set evaluation:
_____________________________________
MAE: 1072.5992746327288
MSE: 2072005.5320534536
RMSE: 1439.4462588278361
R2 Square 0.8848155409550171
__________________________________
```

Elastic Net

```
from sklearn.linear_model import ElasticNet

model = ElasticNet(alpha=0.1, l1_ratio=0.9, selection='random', random_state=42)
```

```
model.fit(x_train, y_train)

test_pred = model.predict(x_test)
train_pred = model.predict(x_train)

print('Test set evaluation:\n_____________________________________')
print_evaluate(y_test, test_pred)
print('====================================')
print('Train set evaluation:\n_____________________________________')
print_evaluate(y_train, train_pred)

results_df_2 = pd.DataFrame(data=[["Elastic Net Regression", *evaluate(y_test, test_pred) , cross_val(ElasticNet())]],
                            columns=['Model', 'MAE', 'MSE', 'RMSE', 'R2 Square', "Cross Validation"])
results_df = results_df.append(results_df_2, ignore_index=True)
```

```
Test set evaluation:
_____________________________________
MAE: 1207.3732628964087
MSE: 2418734.7579660695
RMSE: 1555.228201250887
R2 Square 0.8241382182498722
__________________________________
====================================
Train set evaluation:
_____________________________________
MAE: 1023.4487602922059
MSE: 1802685.98602198
RMSE: 1342.641421237249
R2 Square 0.8997872317830489
__________________________________
```

Polynomial Regression

```
from sklearn.preprocessing import PolynomialFeatures

poly_reg = PolynomialFeatures(degree=2)
```

```
poly_reg = PolynomialFeatures(degree=2)

x_train_2_d = poly_reg.fit_transform(x_train)
x_test_2_d = poly_reg.transform(x_test)

lin_reg = LinearRegression(normalize=True)
lin_reg.fit(x_train_2_d,y_train)

test_pred = lin_reg.predict(x_test_2_d)
train_pred = lin_reg.predict(x_train_2_d)

print('Test set evaluation:\n_____________________________________')
print_evaluate(y_test, test_pred)
print('====================================')
print('Train set evaluation:\n_____________________________________')
print_evaluate(y_train, train_pred)

results_df_2 = pd.DataFrame(data=[["Polynomail Regression", *evaluate(y_test, test_pred), 0]],
                            columns=['Model', 'MAE', 'MSE', 'RMSE', 'R2 Square', 'Cross Validation'])
results_df = results_df.append(results_df_2, ignore_index=True)
```

```
Test set evaluation:
_____________________________________
MAE: 5679253330676.771
MSE: 7.540490466357226e+25
RMSE: 8683599752612.522
R2 Square -5.48255274504984e+18
__________________________________
====================================
Train set evaluation:
_____________________________________
MAE: 37.48772090070482
MSE: 24549.048928726774
RMSE: 156.68136114013936
R2 Square 0.9986352985659639
__________________________________
```

Stochastic Gradient Descent

```
from sklearn.linear_model import SGDRegressor

sgd_reg = SGDRegressor(n_iter_no_change=250, penalty=None, eta0=0.0001, max_iter=100000)
sgd_reg.fit(x_train, y_train)

test_pred = sgd_reg.predict(x_test)
train_pred = sgd_reg.predict(x_train)

print('Test set evaluation:\n_____________________________________')
print_evaluate(y_test, test_pred)
print('====================================')
print('Train set evaluation:\n_____________________________________')
print_evaluate(y_train, train_pred)

results_df_2 = pd.DataFrame(data=[["Stochastic Gradient Descent", *evaluate(y_test, test_pred), 0]],
                            columns=['Model', 'MAE', 'MSE', 'RMSE', 'R2 Square', 'Cross Validation'])
results_df = results_df.append(results_df_2, ignore_index=True)
```

```
Test set evaluation:
_____________________________________
MAE: 1101.647249790968
MSE: 2469197.5754734827
RMSE: 1571.3680585634554
R2 Square 0.820469159056938
__________________________________
====================================
Train set evaluation:
_____________________________________
MAE: 1249.030230590947
MSE: 2604907.2553506363
RMSE: 1613.9725076192085
R2 Square 0.8551911042570646
__________________________________
```

Random Forest Regressor

```
from sklearn.ensemble import RandomForestRegressor

rf_reg = RandomForestRegressor(n_estimators=1000)
rf_reg.fit(x_train, y_train)

test_pred = rf_reg.predict(x_test)
train_pred = rf_reg.predict(x_train)

print('Test set evaluation:\n_____________________________________')
print_evaluate(y_test, test_pred)

print('Train set evaluation:\n_____________________________________')
print_evaluate(y_train, train_pred)

results_df_2 = pd.DataFrame(data=[["Random Forest Regressor", *evaluate(y_test, test_pred), 0]],
                            columns=['Model', 'MAE', 'MSE', 'RMSE', 'R2 Square', 'Cross Validation'])
results_df = results_df.append(results_df_2, ignore_index=True)
```

```
Test set evaluation:
_____________________________________
MAE: 862.9970688166312
MSE: 1519722.824088209
RMSE: 1232.7703857929948
R2 Square 0.889503732176392
__________________________________
Train set evaluation:
_____________________________________
MAE: 478.478963731933
MSE: 431517.79972999886
RMSE: 656.900144413136
R2 Square 0.9760115774010882
__________________________________
```

Support Vector Machine

```
from sklearn.svm import SVR

svm_reg = SVR(kernel='rbf', C=1000000, epsilon=0.001)
svm_reg.fit(x_train, y_train)

test_pred = svm_reg.predict(x_test)
train_pred = svm_reg.predict(x_train)

print('Test set evaluation:\n_____________________________________')
print_evaluate(y_test, test_pred)

print('Train set evaluation:\n_____________________________________')
print_evaluate(y_train, train_pred)

results_df_2 = pd.DataFrame(data=[["SVM Regressor", *evaluate(y_test, test_pred), 0]],
                            columns=['Model', 'MAE', 'MSE', 'RMSE', 'R2 Square', 'Cross Validation'])
results_df = results_df.append(results_df_2, ignore_index=True)
```

```
Test set evaluation:
_____________________________________
MAE: 1349.8107789830328
MSE: 3968916.7746342896
RMSE: 1992.2140383589033
R2 Square 0.7114273182264543
__________________________________
Train set evaluation:
_____________________________________
MAE: 174.7889295273078
MSE: 267005.22538857773
RMSE: 516.7254835873471
R2 Square 0.9851569641235043
__________________________________
```

```
results_df
```