Task: Predict car prices based on features

Sub Tasks:

- Clean data, Summary and Visualizations
- Identify relevant features (both categorical and numerical)
- Create model
- Perform model performance evaluation
- Better Techniques

In [1]:

```
import pandas as pd # for dataframes
import numpy as np # for arrays
import seaborn as sns # for plots
from matplotlib import pyplot as plt # for plots
import statsmodels.api as sm # for regression
from sklearn.model_selection import train_test_split # for regression
import statistics
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

Import Data

In [2]:

```
cars = pd.read_csv("CarsData.csv")
```

Data Cleaning, Summary and Visualizations

Data Summary

In [3]:

```
cars.head()
```

Out[3]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	...	enginesize	fuelsy
0	1	3	alfa-romero giulia	gas	std	two	convertible	rwd	front	88.6	...	130	
1	2	3	alfa-romero stelvio	gas	std	two	convertible	rwd	front	88.6	...	130	
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	front	94.5	...	152	

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	...	enginesize	fuelsy
3	4	2	audi 100 ls	gas	std	four	sedan	fwd	front	99.8	...	109	
4	5	2	audi 100ls	gas	std	four	sedan	4wd	front	99.4	...	136	

5 rows × 26 columns

In [4]:

```
cars.describe()
```

Out[4]:

	car_ID	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	stroke	compressionrat
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.0000
mean	103.000000	0.834146	98.756585	174.049268	65.907805	53.724878	2555.565854	126.907317	3.329756	3.255415	10.1425
std	59.322565	1.245307	6.021776	12.337289	2.145204	2.443522	520.680204	41.642693	0.270844	0.313597	3.9720
min	1.000000	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000000	2.540000	2.070000	7.0000
25%	52.000000	0.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97.000000	3.150000	3.110000	8.6000
50%	103.000000	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.000000	3.310000	3.290000	9.0000
75%	154.000000	2.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	141.000000	3.580000	3.410000	9.4000
max	205.000000	3.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326.000000	3.940000	4.170000	23.0000

Inference: Data is has no NULL or NAs that we need to worry about

In [6]:

```
cars.columns
```

Out[6]:

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

Data Cleaning

Insight: All names have company brand names at start separated by a ' ' so we can fetch the brand name as brand will dictate the final price of the car. More luxurious the brand, the costlier the car.

In [8]:

```
# Retreive brand name from 'CarName'
cars['CarName'] = cars['CarName'].apply(lambda x : x.split(' ')[0])
cars['CarName']  = cars.CarName.str.lower()
```

Insight: There are some spelling inconsistencies as well. Like, 'maxda' and 'mazda'; 'porcshce' and 'porsche'; 'toyota' and 'toyouta'; 'vokswagen' and 'volkswagen'

In [9]:

```
# Correcting for spelling error
correct = ['mazda', 'porsche', 'toyota', 'volkswagen']
incorrect = ['maxda', 'porcshce', 'toyouta', 'vokswagen']
cars['CarName'].replace(incorrect, correct, inplace = True)
```

In [10]:

```
set(cars['CarName'])
```

Out[10]:

```
{'alfa-romero',
 'audi',
 'bmw',
 'buick',
 'chevrolet',
 'dodge',
 'honda',
 'isuzu',
 'jaguar',
 'mazda',
 'mercury',
 'mitsubishi',
 'nissan',
 'peugeot',
 'plymouth',
 'porsche',
 'renault',
 'saab',
 'subaru',
 'toyota',
 'volkswagen',
 'volvo',
 'vw'}
```

Data Visualizations

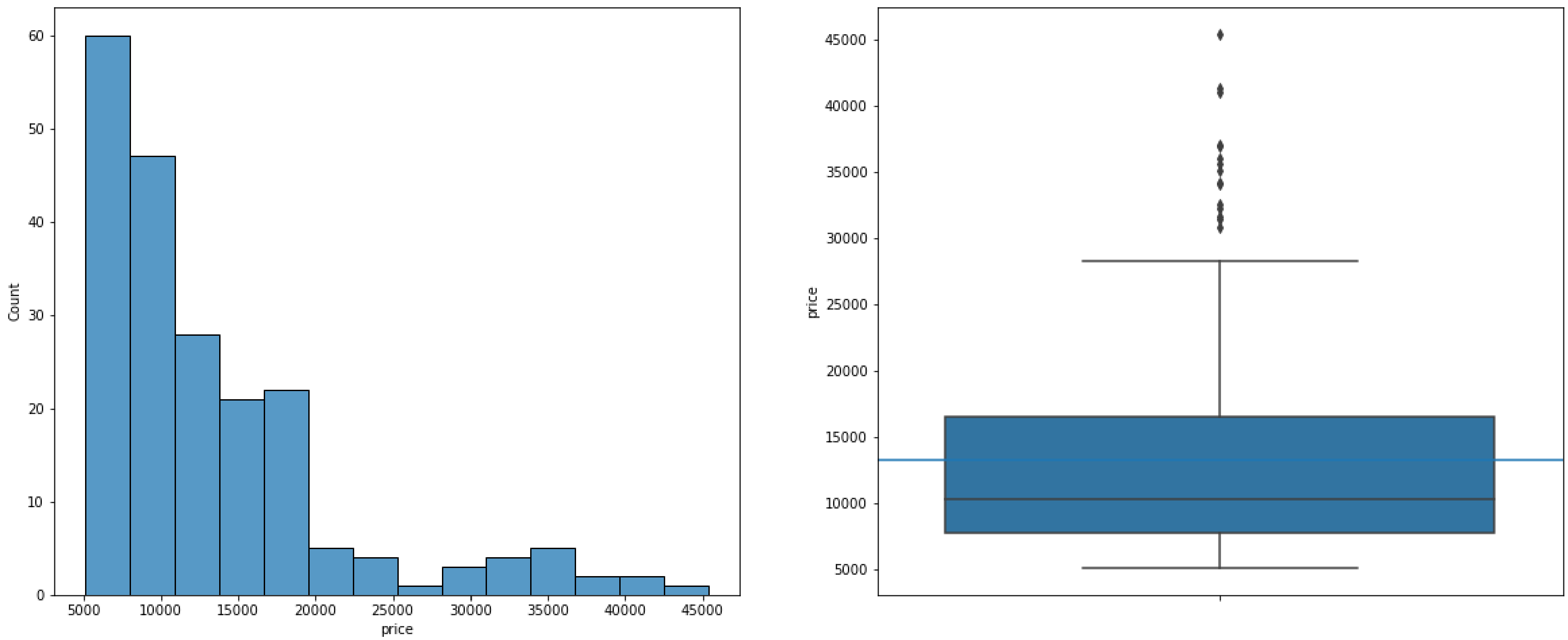
In [11]:

```
# Check distribution of label (price)
plt.figure(figsize=(20,8))

plt.subplot(1,2,1)
graph1 = sns.histplot(data = cars, x = 'price')

plt.subplot(1,2,2)
graph2 = sns.boxplot(data = cars, y = 'price')
graph2.axhline(np.mean(cars['price']))

plt.show()
```

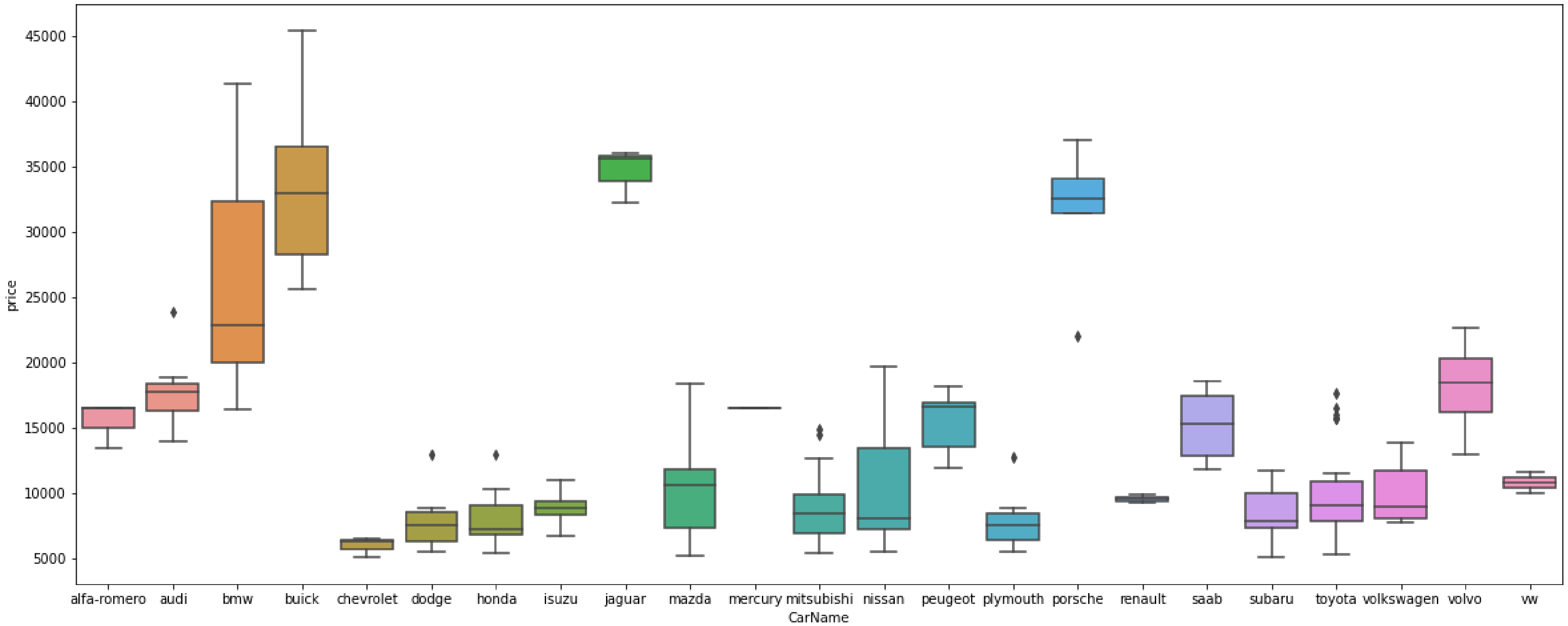


Insight: Plot is right-skewed. There are considerable number of values spread throughout, hence we do not need to take 'log' of price. We can considerable difference between mean and median. Variance is also high. The values are in range of 10000s so we will need to perform scaling later.

In [12]:

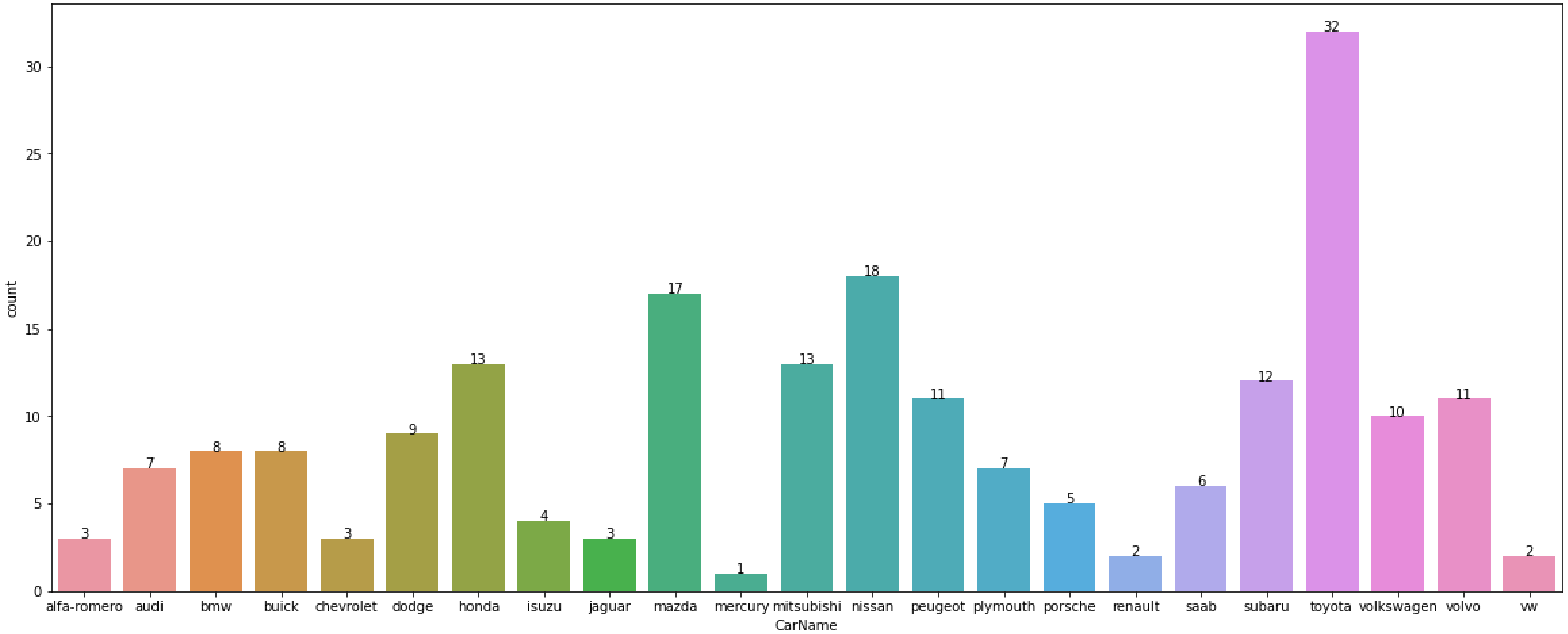
```
# Price Variation by Brand
plt.figure(figsize=(20,8))
sns.boxplot(data = cars, y = 'price', x = 'CarName', order = sorted(cars['CarName'].unique()))
# sns.catplot( data = cars, y = 'price', col = 'CarName', kind = 'box', col_wrap=6)
```

Out[12]: <AxesSubplot:xlabel='CarName', ylabel='price'>



In [13]:

```
plt.figure(figsize=(20,8))
# sns.histplot(data = cars, x = 'CarName')
graph = sns.countplot(data = cars, x = 'CarName', order = sorted(cars['CarName'].unique()))
data_labels = cars['CarName'].value_counts().reset_index().sort_values('index')['CarName']
for index, i in enumerate(data_labels):
    graph.annotate(text = str(i), xy = (index, i), horizontalalignment = 'center')
```



Insight: From the above two graphs we can see that 'CarName' should be a significant parameter. Price shows great variation across brands. We have brands like jaguar and porsche with high prices and low sales and bmw which has high variation. This implies some car prices vary largely with the brand they are associated with and some do not.
Also, do notice that our dataset is relatively small.

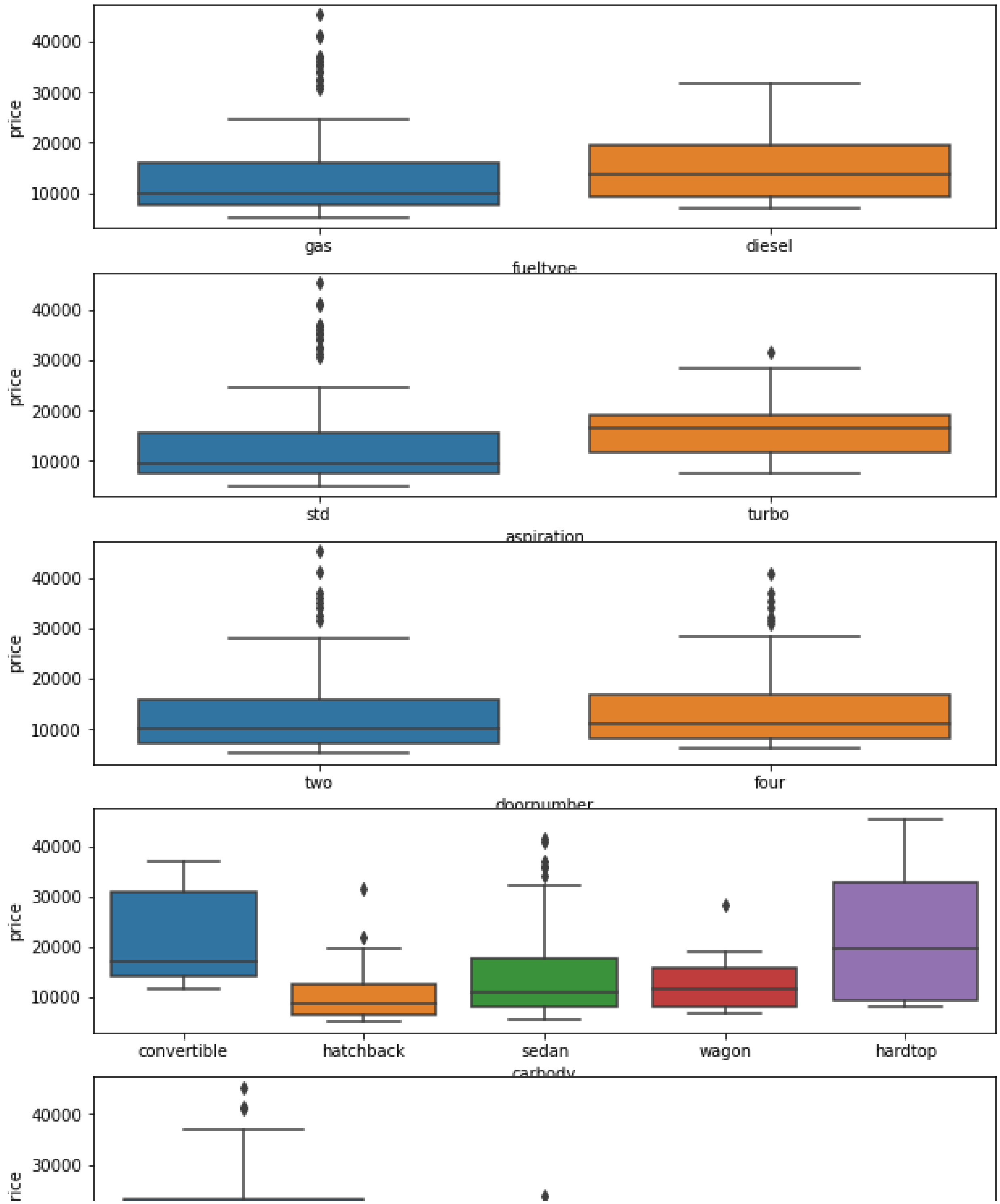
Price variation with respect to Categorical Variables

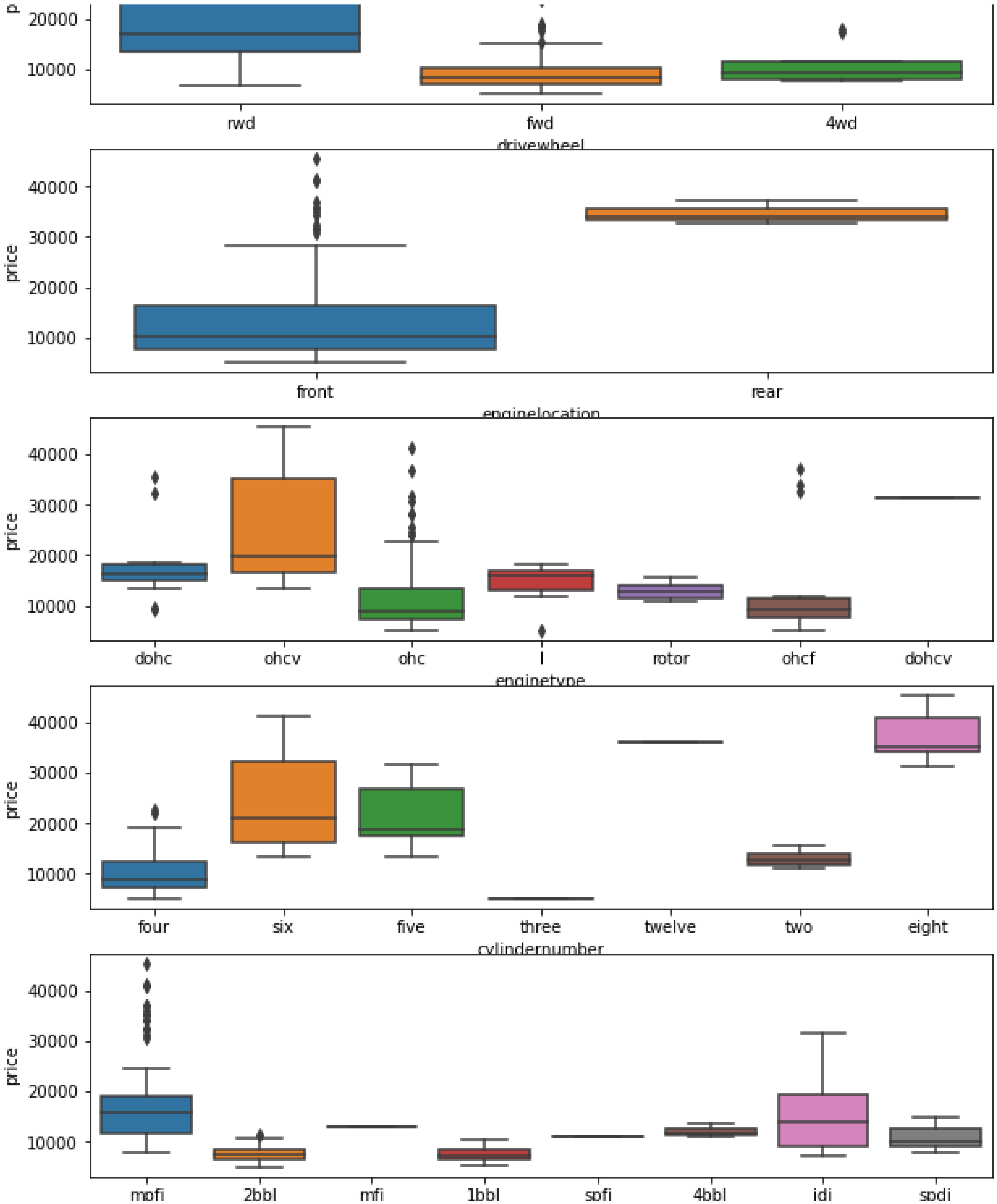
In [14]:

```
categorical_variables = ['CarName', 'fueltype', 'aspiration', 'doornumber', 'carbody', 'drivewheel', \
                        'enginelocation', 'enginetype', 'cylindernumber', 'fuelsystem']
row_number = len(categorical_variables)
col_number = np.max([len(set(cars[value])) for value in categorical_variables])
```

In [15]:

```
plt.figure(figsize=(10,30))
for index, value in enumerate(categorical_variables):
    if index == 0:
        continue
    plt.subplot(row_number,1,index+1)
    sns.boxplot(data = cars, y = 'price', x = value)
```


price
40000
30000
20000
10000
gas
diesel
fueltype
std
turbo
aspiration
two
four
doornumber
convertible
hatchback
sedan
wagon
hardtop
carbody



p
20000
10000
rwd
fwd
4wd
drivewheel
price
40000
30000
20000
10000
front
rear
enginelocation
price
dohc
ohcv
ohc
l
rotor
ohcf
dohcv
enginetype
price
four
six
five
three
twelve
two
eight
cylindernumber
price
mpfi
2bbl
mfi
1bbl
spfi
4bbl
idi
spdi

fuelsystem

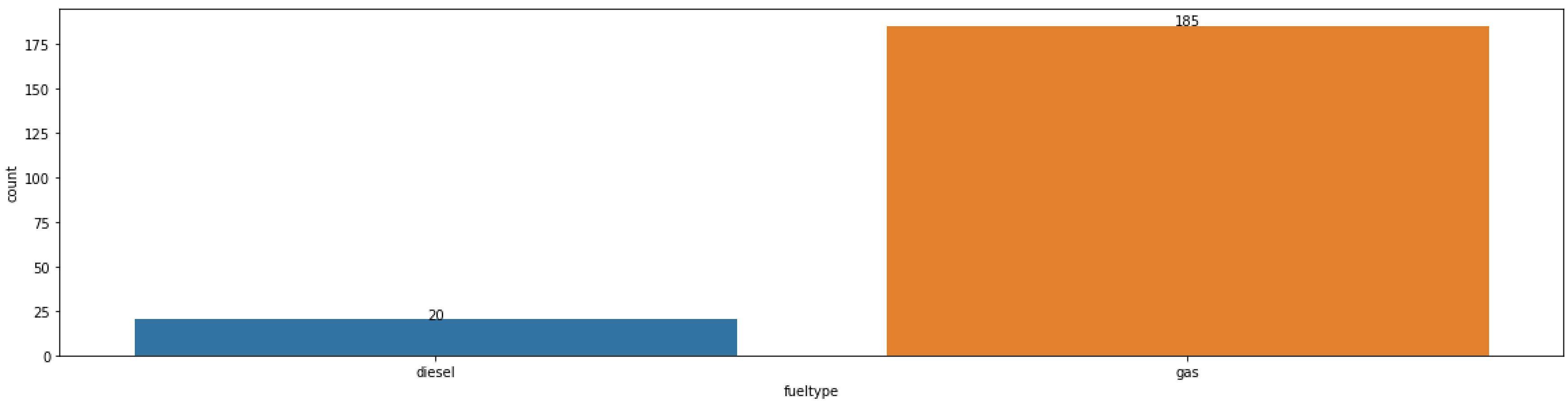
From the above boxplots, we can see that for categorical variables 'fueltype', 'aspiration', 'doornumber', variations in feature explain very little variation in label 'price'. Hence, we can drop these categorical variables.

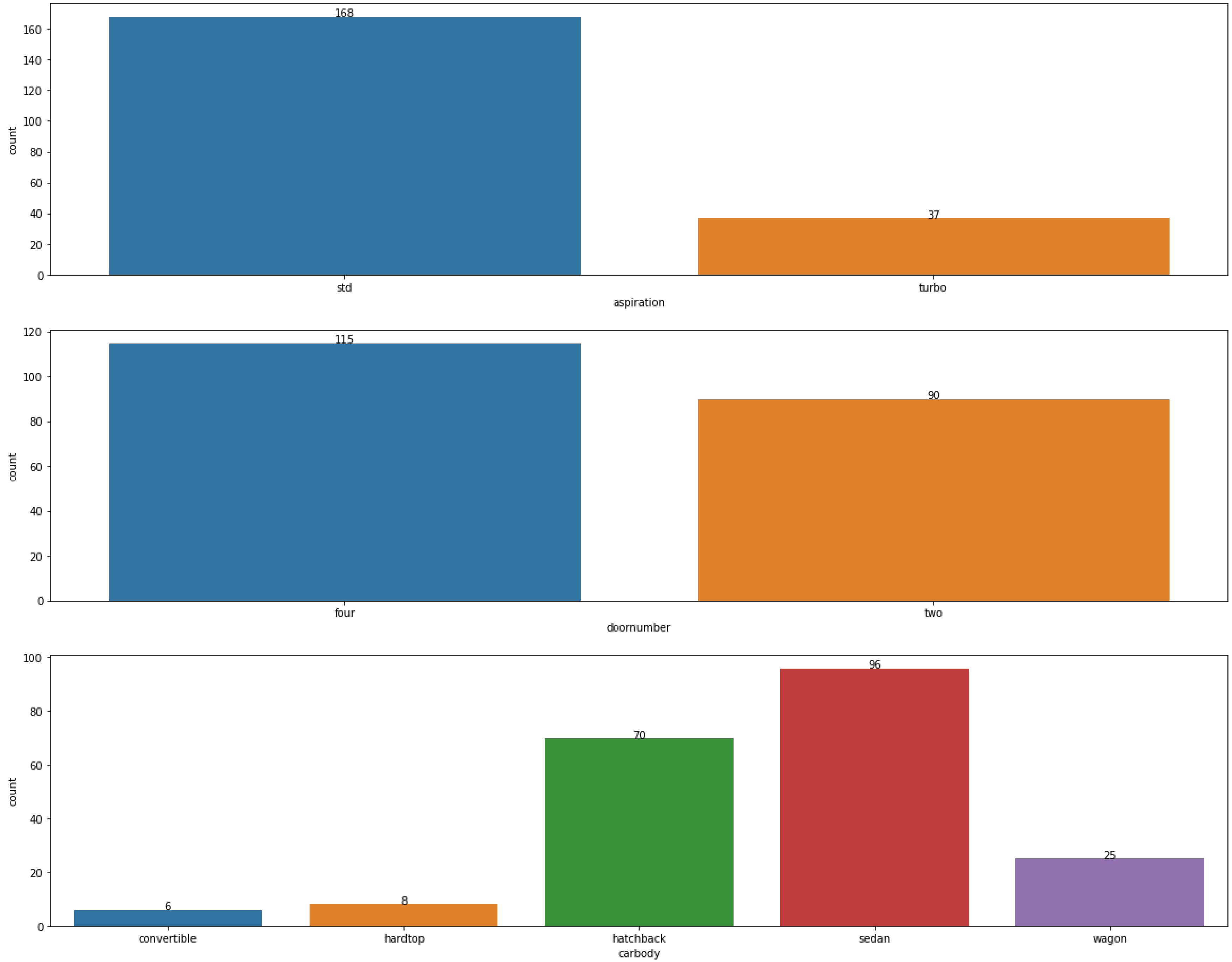
In [16]:

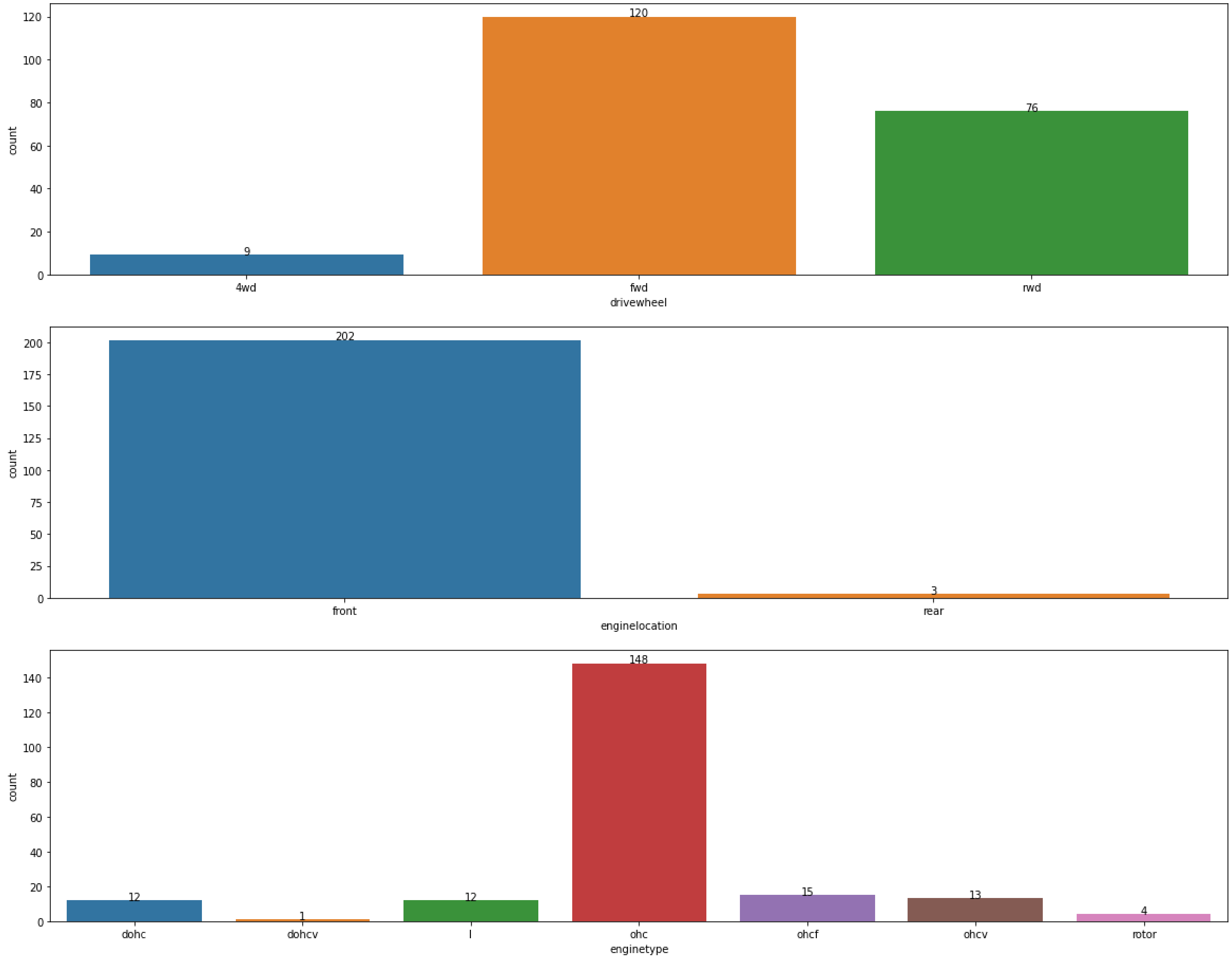
```
drop_categorical = ['fueltype', 'aspiration', 'doornumber', 'variations']
```

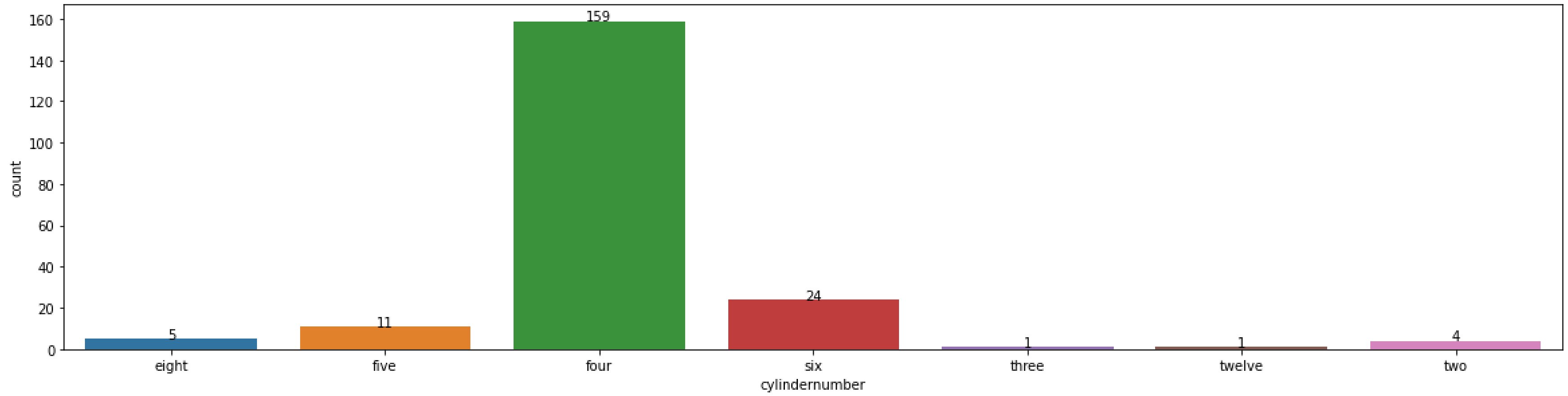
In [17]:

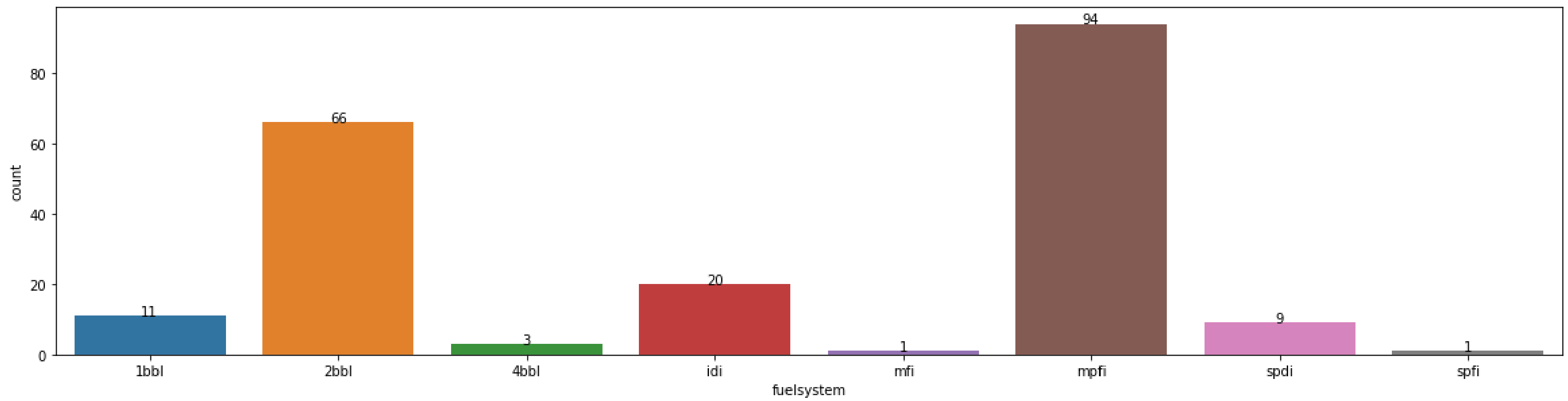
```
# Distribution of Categorical Variables
categorical_variables
for index, col_name in enumerate(categorical_variables):
    if col_name == 'CarName':
        continue
    plt.figure(figsize=(20,50))
    plt.subplot(len(categorical_variables)-1,1,index)
    graph = sns.countplot(data = cars, x = col_name, order = sorted(cars[col_name].unique()))
    data_labels = cars[col_name].value_counts().reset_index().sort_values('index')[col_name]
    for index, i in enumerate(data_labels):
        graph.annotate(text = str(i), xy = (index, i), horizontalalignment = 'center')
```




168
37
count
std
turbo
aspiration
115
90
count
four
two
doornumber
6
8
70
96
25
count
convertible
hardtop
hatchback
sedan
wagon
carbody


count
drivewheel
4wd
fwd
rwd
9
120
76
enginelocation
front
rear
202
3
enginetype
dohc
dohcv
l
ohc
ohcf
ohcv
rotor
12
1
12
148
15
13
4





INSIGHT: For 'enginelocation' there are very few points to make an inference. Hence, this feature will be insignificant too. Since most data is for 'fromt' engine we cannot make a reliable estimate of price based on this feature. Hence, we can drop this as well.

In [18]:
```
# Updated Categorical Variables with insignificant features removed
categorical_variables = ['CarName', 'carbody', 'drivewheel', 'enginetype']
```

In [19]:
```
print(categorical_variables)
drop_categorical
```

```
['CarName', 'carbody', 'drivewheel', 'enginetype']
```

Out[19]:
```
['fueltype', 'aspiration', 'doornumber', 'variations']
```

In [20]:
```
# Price Variation with respect to numerical variables
```

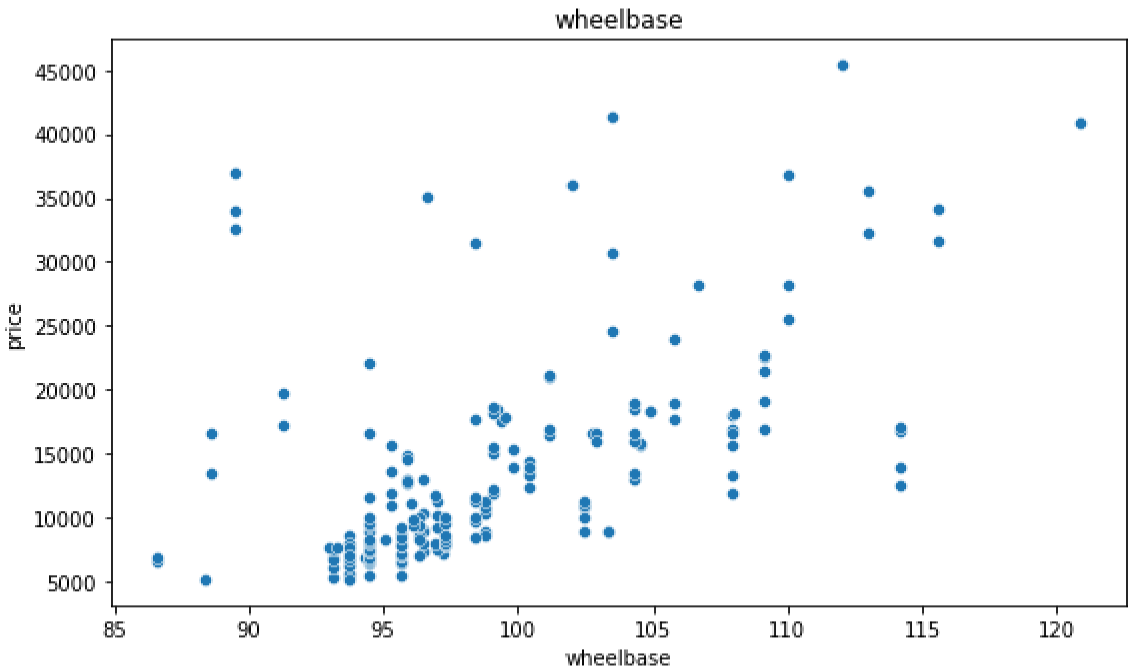
```
numerical_variables = ['wheelbase', 'carlength', 'carwidth', 'carheight', 'curbweight', 'enginesize', \
                       'boreratio', 'stroke', 'compressionratio', 'horsepower', 'peakrpm', 'citympg', \
                       'highwaympg']
row_number_var = len(numerical_variables)
```

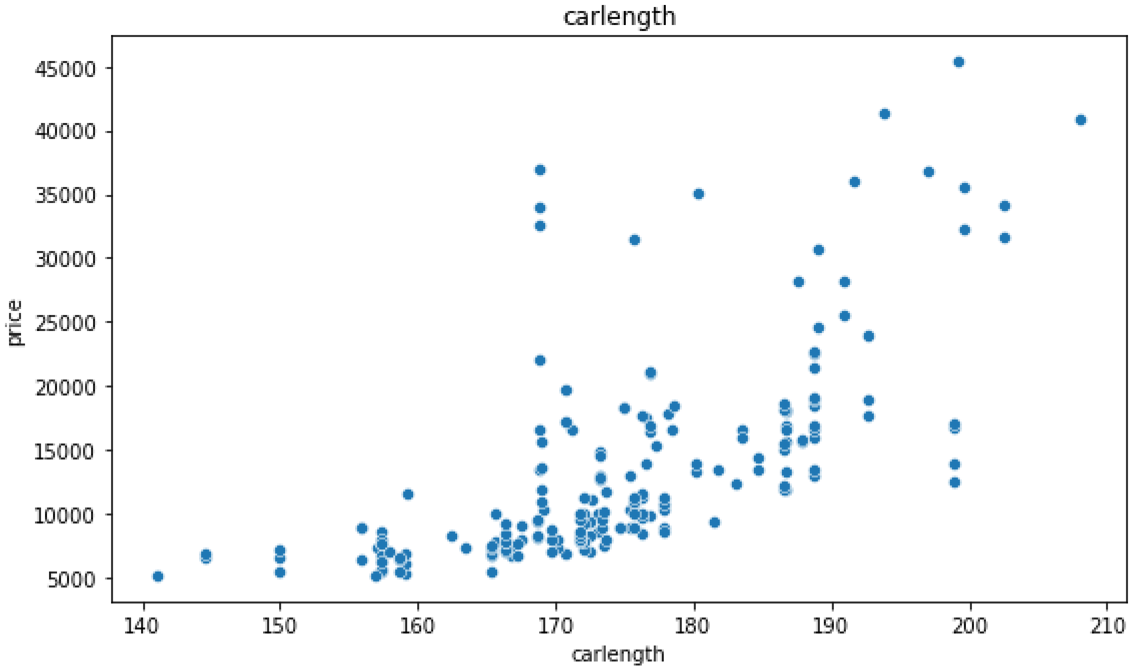
In [21]:

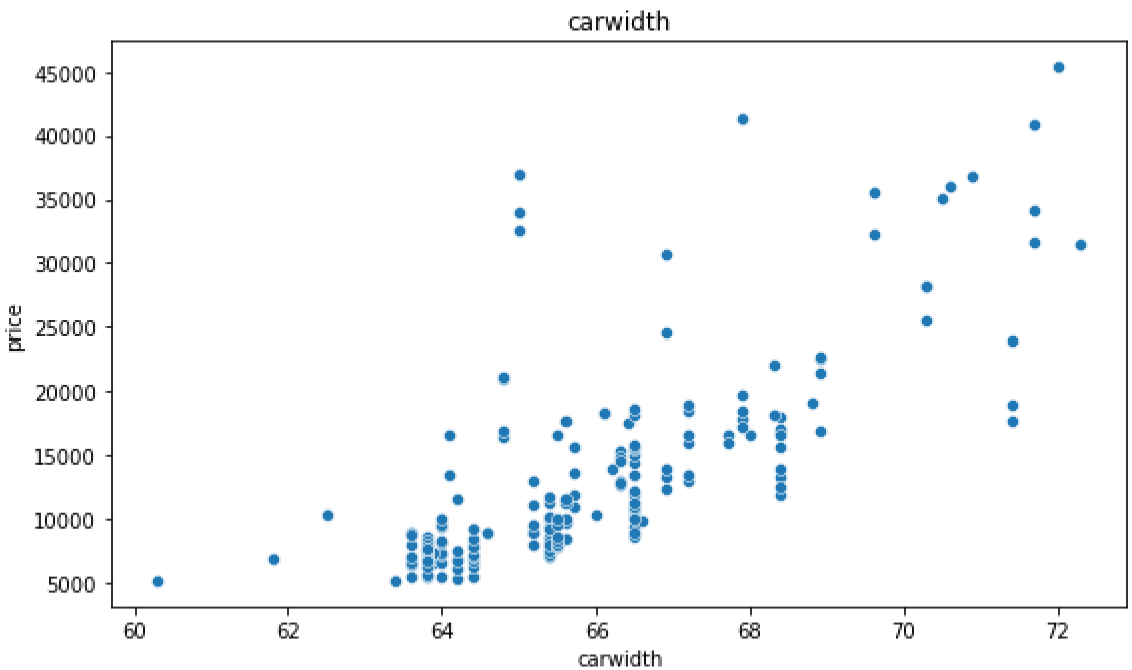
```
def make_plot(value, index):
    plt.figure(figsize=(20,80))
    plt.subplot(len(numerical_variables), 2, index)
    sns.scatterplot(data = cars, y = 'price', x = value).set_title(value)
```

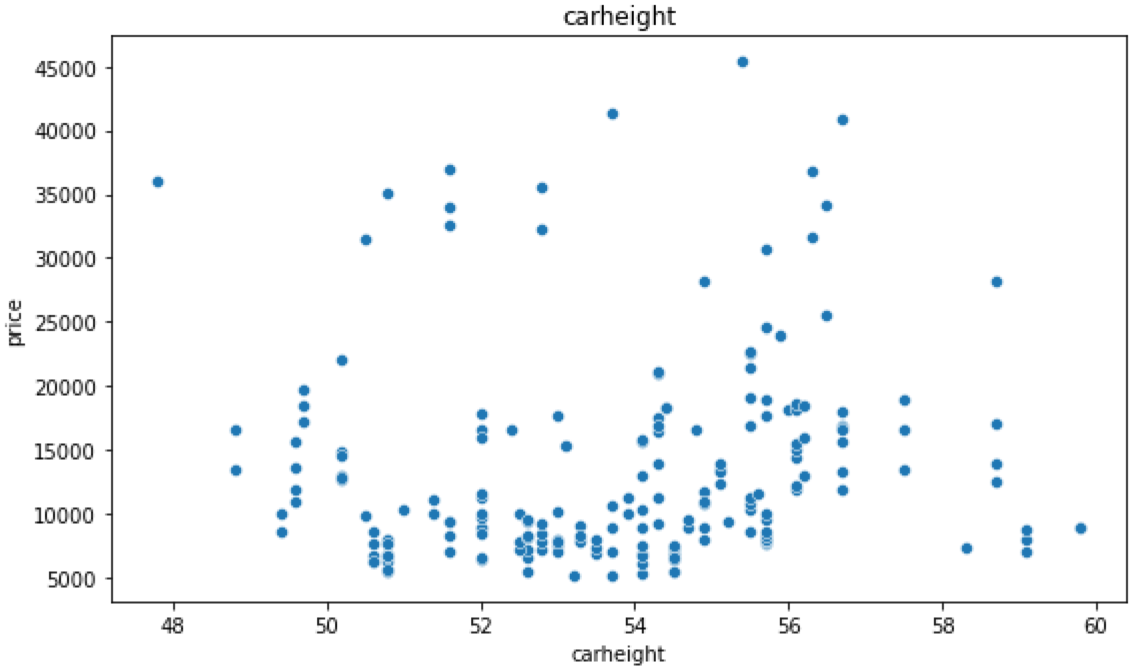
In [22]:

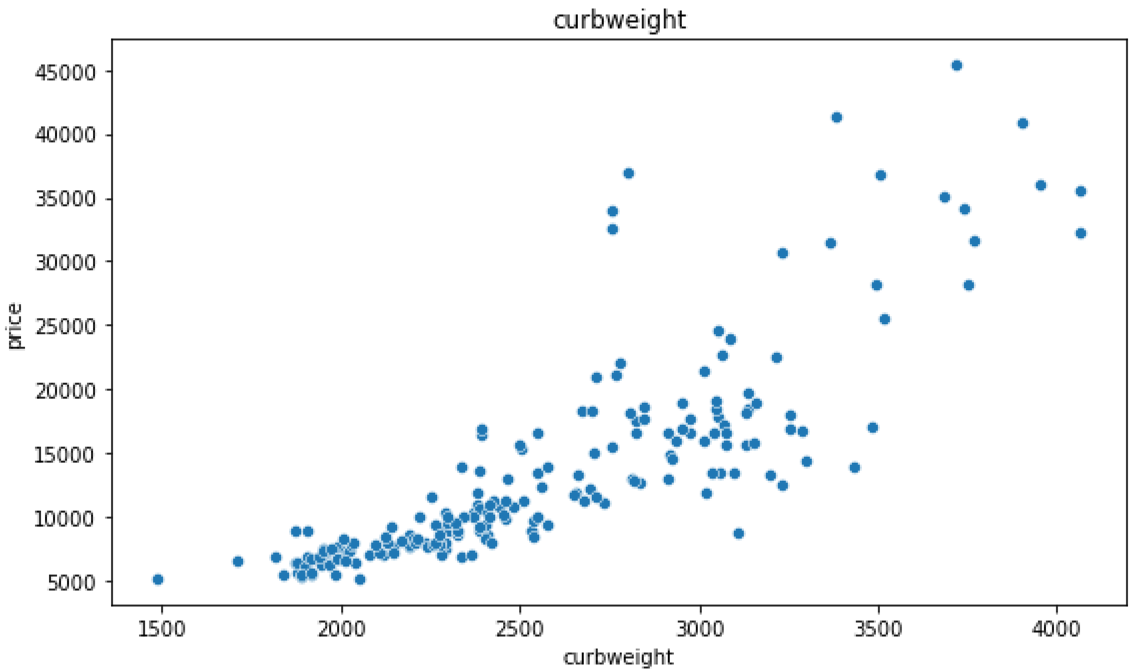
```
a = [make_plot(value, 1) for value in numerical_variables]
```

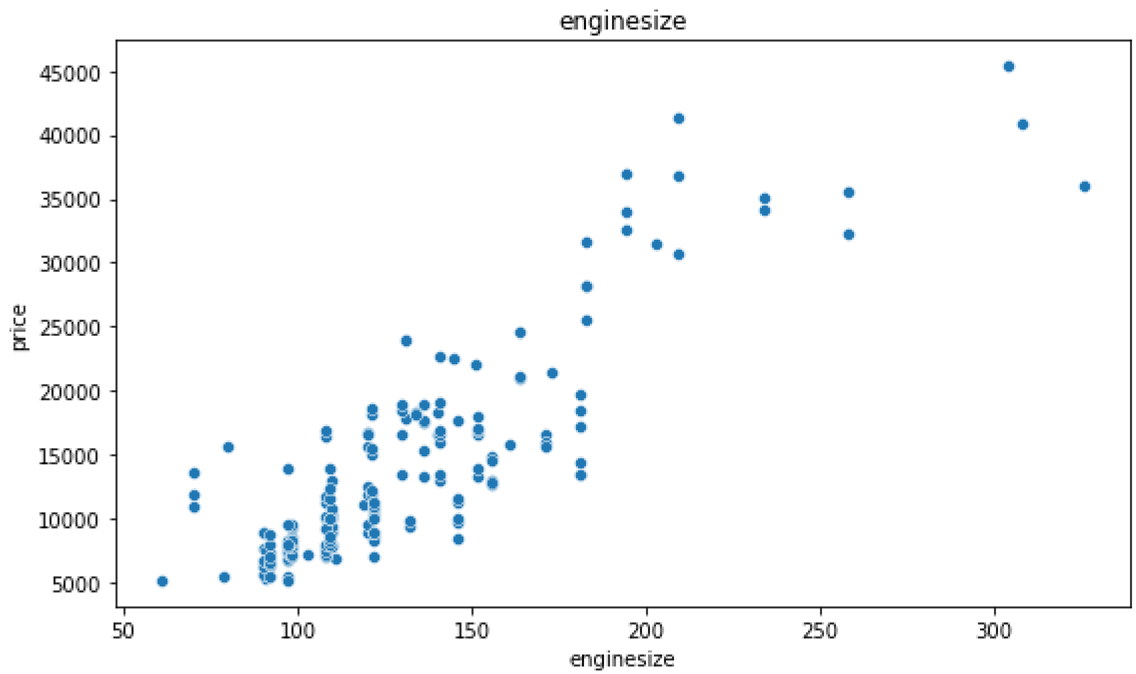


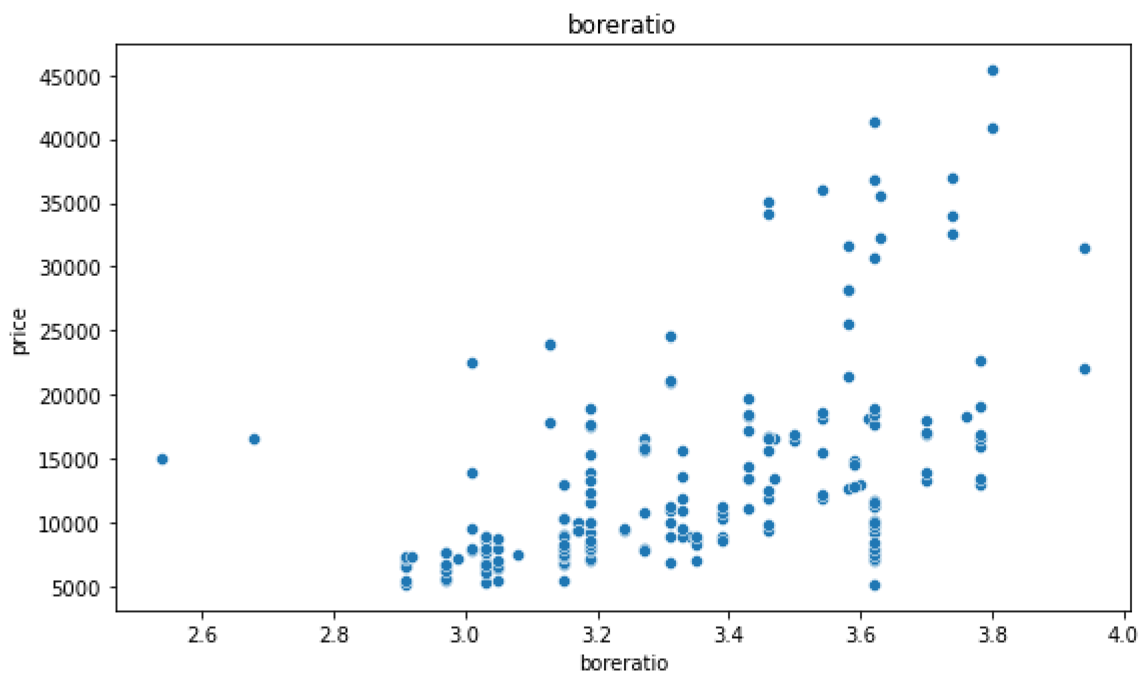

carlength
45000
40000
35000
30000
25000
20000
15000
10000
5000
price
140
150
160
170
180
190
200
210
carlength

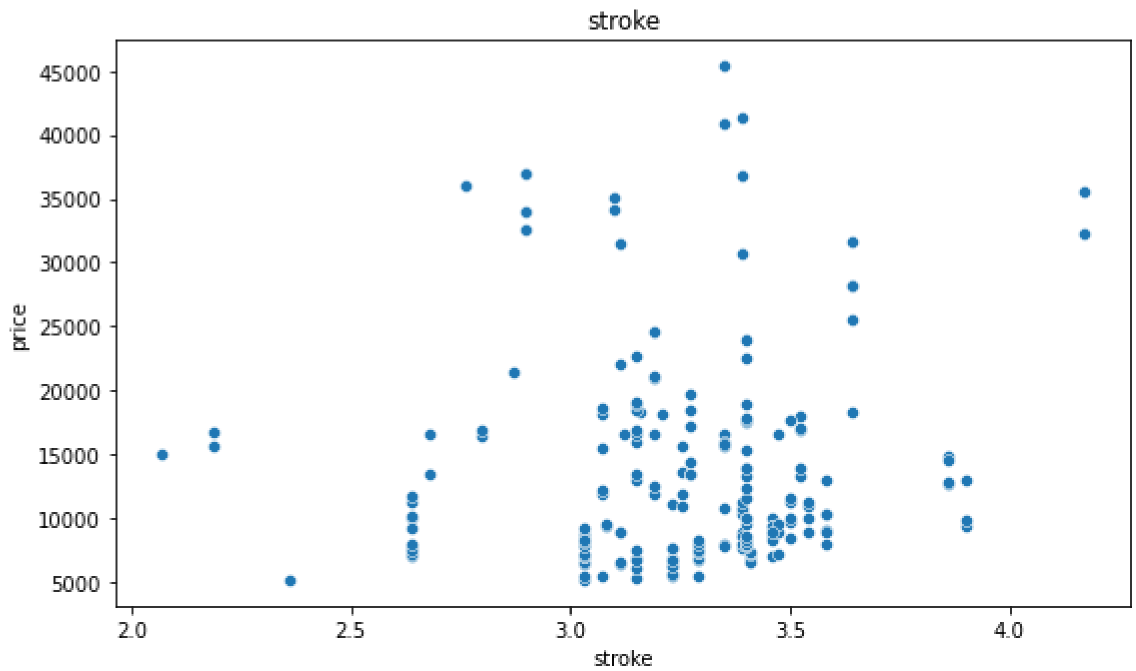

carwidth
45000
40000
35000
30000
25000
20000
15000
10000
5000
price
60
62
64
66
68
70
72
carwidth

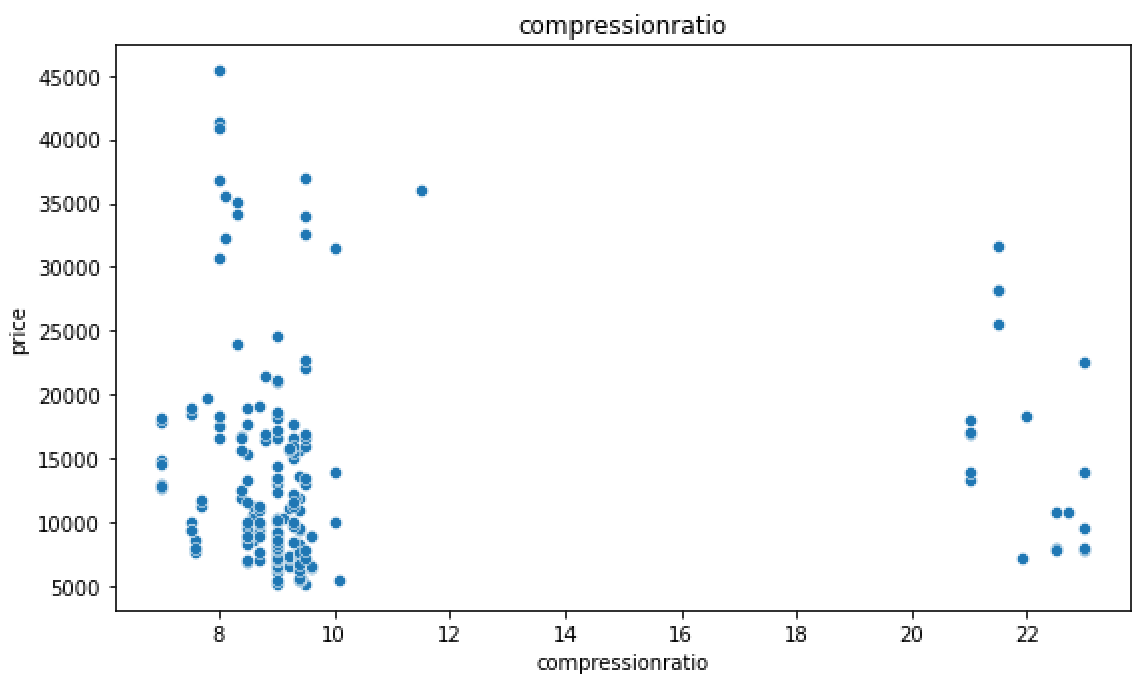

carheight
price
carheight

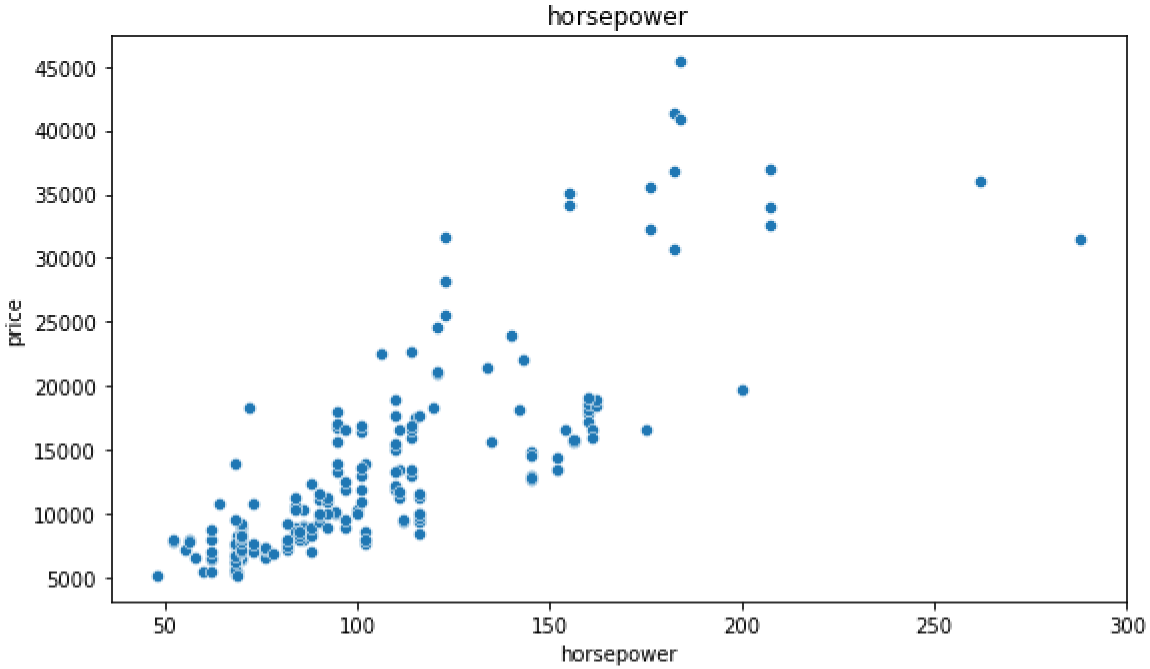

curbweight
price
curbweight

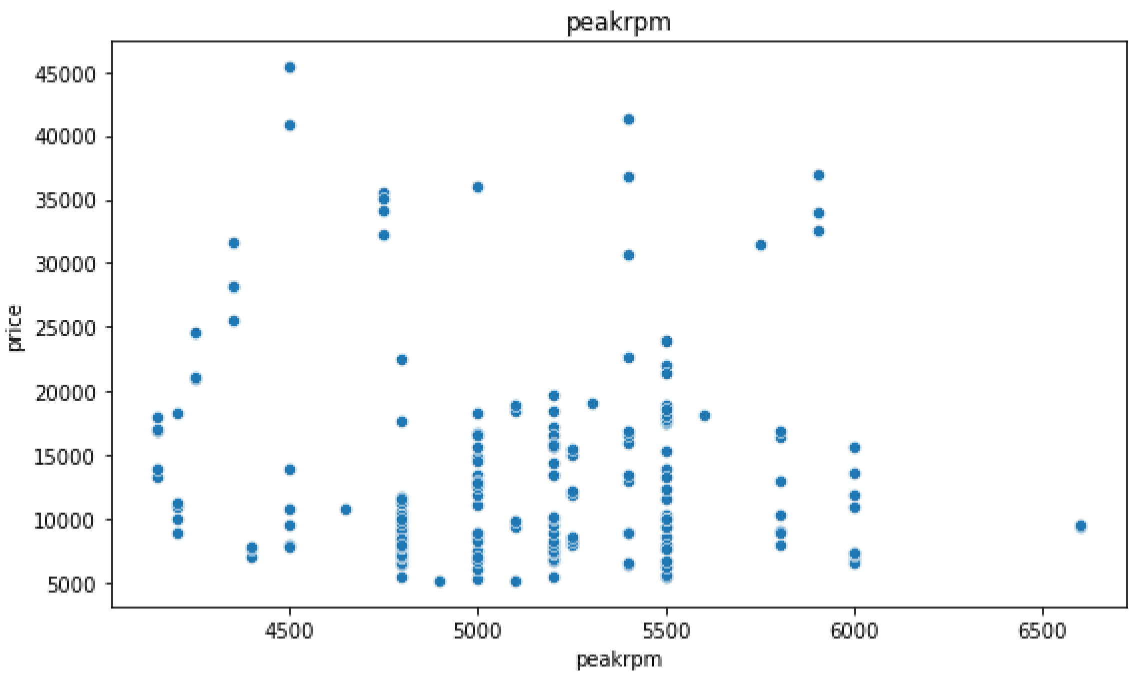

enginesize
price
45000
40000
35000
30000
25000
20000
15000
10000
5000
50
100
150
200
250
300
enginesize

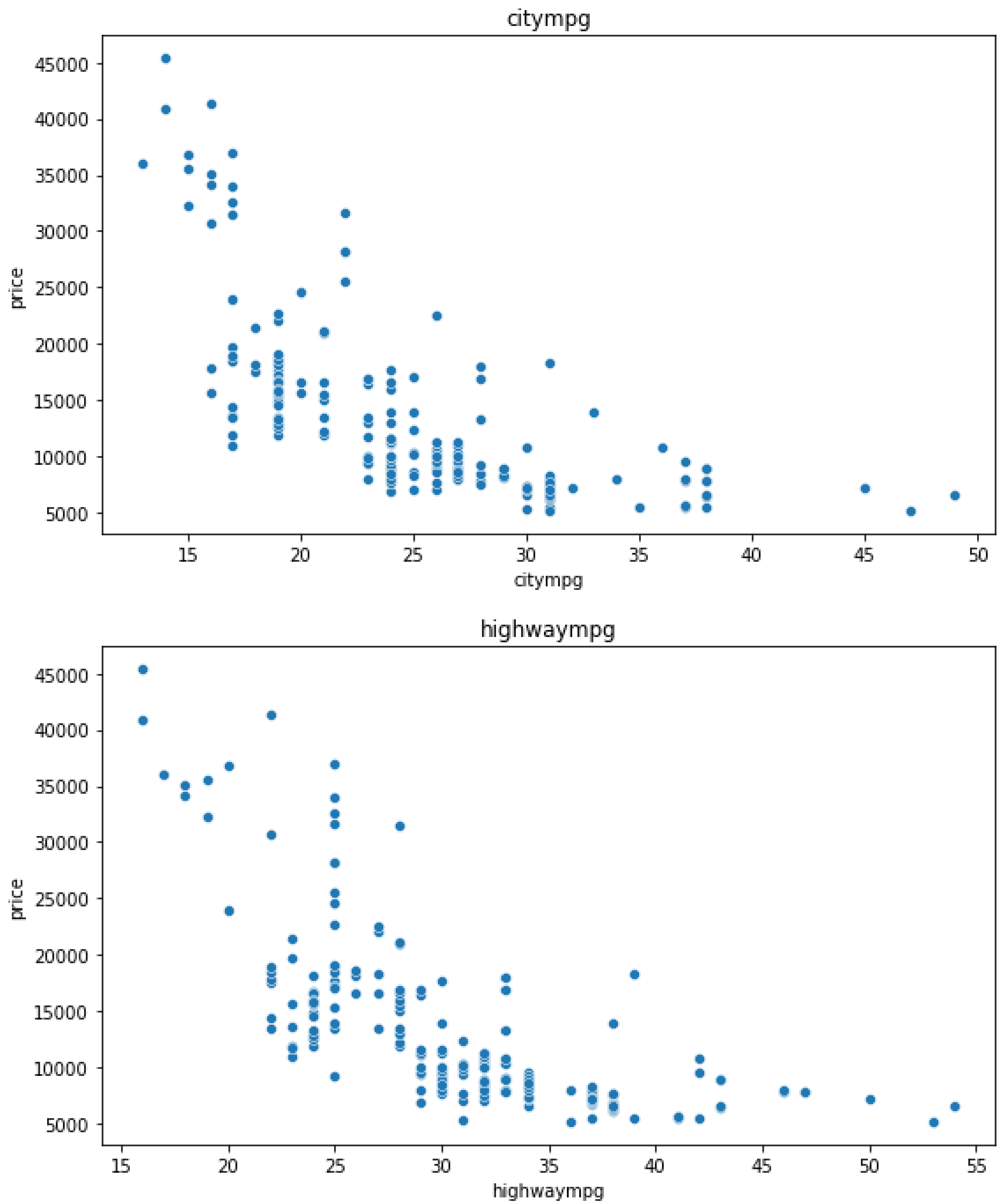

boreratio
price
45000
40000
35000
30000
25000
20000
15000
10000
5000
2.6
2.8
3.0
3.2
3.4
3.6
3.8
4.0
boreratio


stroke
price
45000
40000
35000
30000
25000
20000
15000
10000
5000
2.0
2.5
3.0
3.5
4.0
stroke


compressionratio
price
45000
40000
35000
30000
25000
20000
15000
10000
5000
8
10
12
14
16
18
20
22
compressionratio


horsepower
price
45000
40000
35000
30000
25000
20000
15000
10000
5000
50
100
150
200
250
300
horsepower


peakrpm
price
45000
40000
35000
30000
25000
20000
15000
10000
5000
4500
5000
5500
6000
6500
peakrpm



Insight: Most of the variables either have a positive or negative correlation with respect to price. However, from the graphs itself we cannot be sure about the exact correlation coefficient. Going, ahead we will calculate these numbers. For numerical features we will look at correlation matrix to drop features that are highliy correlated. Also, we look at VIF to examine multicollinearity and remove features that have multicollinearity.

Features 'carheight', 'stroke', 'peakrpm', 'compressionratio' have very low correlation with 'price' and can be removed.

In [23]:

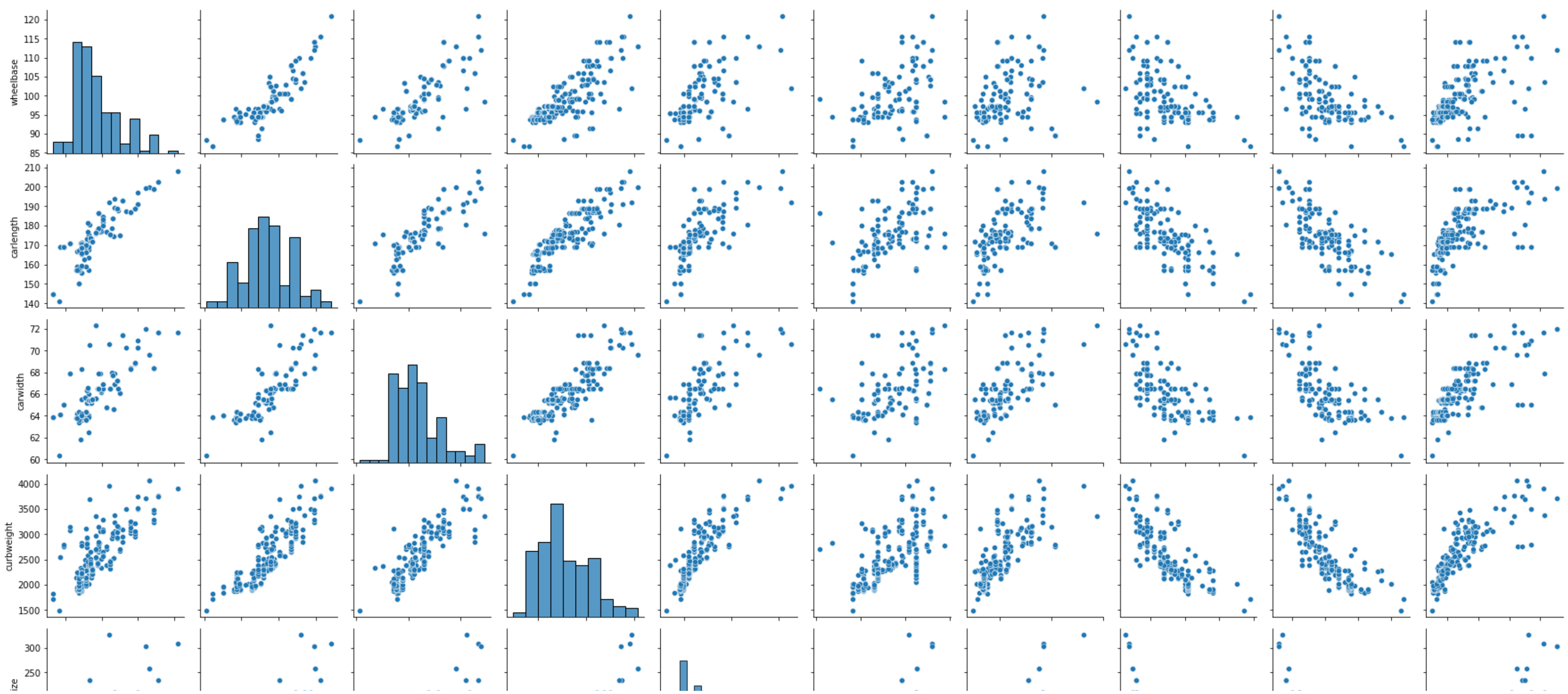
```
print(cars[['price','carheight', 'stroke', 'peakrpm', 'compressionratio']].corr(method = 'pearson'))
numerical_variables = ['wheelbase', 'carlength', 'carwidth', 'curbweight', 'enginesize', \
                       'boreratio', 'horsepower', 'citympg', 'highwaympg']
```

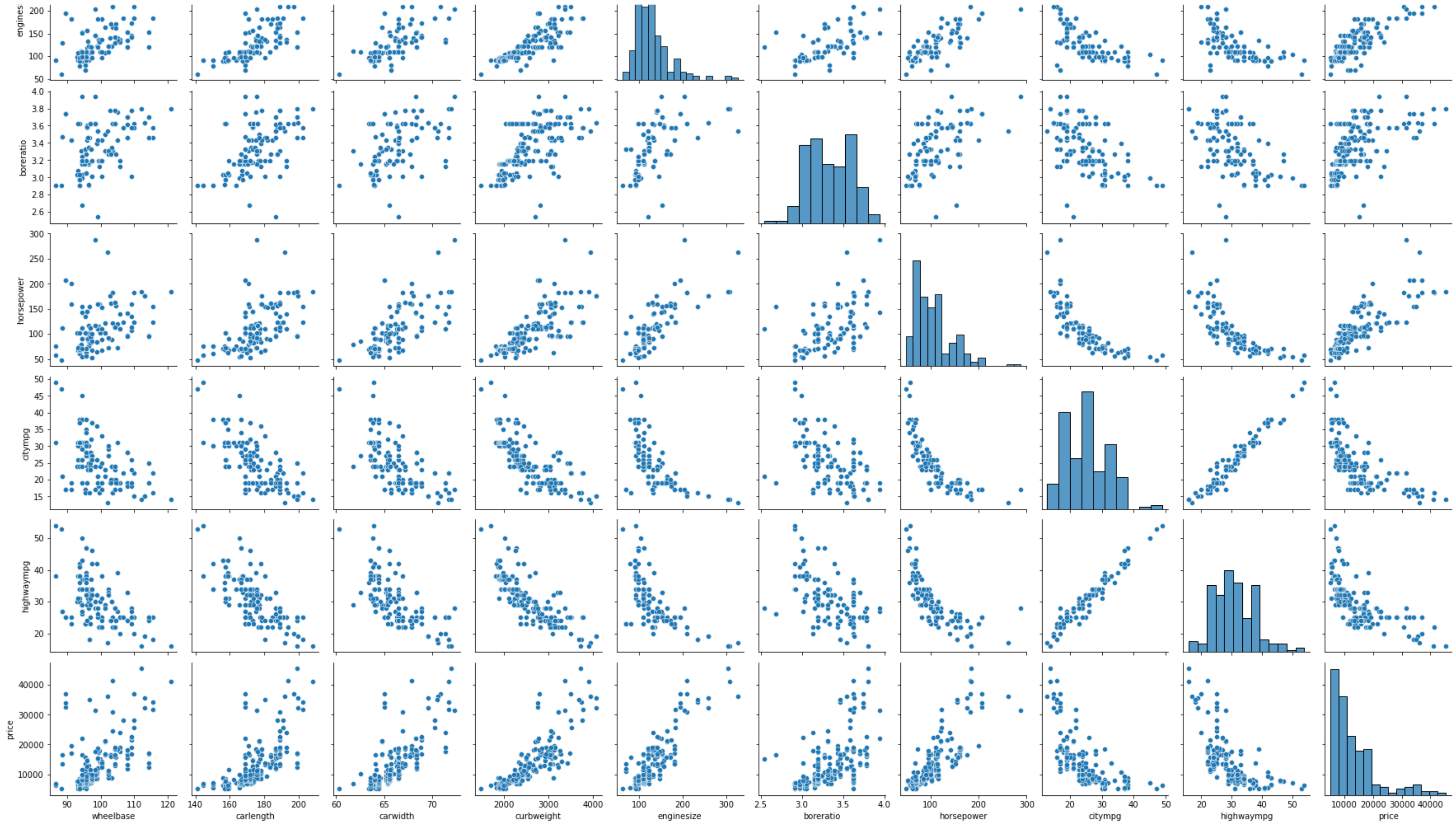
```
                     price  carheight    stroke   peakrpm  compressionratio
price             1.000000   0.119336  0.079443 -0.085267          0.067984
carheight         0.119336   1.000000 -0.055307 -0.320411          0.261214
stroke            0.079443  -0.055307  1.000000 -0.067964          0.186110
peakrpm          -0.085267  -0.320411 -0.067964  1.000000         -0.435741
compressionratio  0.067984   0.261214  0.186110 -0.435741          1.000000
```

In [24]:

```
sns.pairplot(cars[numerical_variables + ['price']])
```

Out[24]: <seaborn.axisgrid.PairGrid at 0x1ac0bb55dc0>





2. Identify relevant features (both categorical and numerical)

Feature Selection ||| Feature Selection 2

Numerical Variables

There are numerous ways of selecting numerical features

1. Low Variance Analysis
   This technique consists of observing features with low variance (typically less than 5%) and rejecting such features since these features have values that are very close to each other. We can say that the numerical values in these features are almost constant. However, low variance analysis does not answer how two features are related to each other. It is hard for model to learn from this feature.

2. Pearson Correlation Coefficient
   This technique relies on correlation between two features to eliminate one of them. An important underlying assumption of linear regression is that features must have very low correlation amongst them. We usually reject features that have correlation greater than 75% threshold for this project. The threshold might change as per various business scenarios. If features have high correlation then one feature can be expressed in the form of other which often leads to decrease in model performance. However, pearson correlation coefficient works best with data showcasing linear relationship what about data with non-linear relationship.
3. Spearman Rank Correlation Coefficient
   Spearman Rank Correlation Coefficient often comes in handy when handy when the relationship between label and feature follows a more non-linear behaviour. However,spearman rank correlation in Python yields a p-value for each variable which can be used to gauge the significance of the variable. If p-value is less than 5% we keep that variable else reject the variable.

The above mentioned techniques alone are not sufficient in finalizing the final parameter for prediction of label. This is because the interactions between the features and the label change as variables are added and removed. However, you can perform the above checks to finally ensure there are no p-values that are greater than threshold and no features are highly correlated or have low variance.

Low Variance

We will remove any features that variance lower than 1%.

In [25]:

```
var_dict = {value: statistics.variance(cars[value]) for value in numerical_variables}
var_dict
```

Out[25]:

```
{'wheelbase': 36.261782400765185,
 'carlength': 152.20868818747007,
 'carwidth': 4.601899569583935,
 'curbweight': 271107.8743185079,
 'enginesize': 1734.1139167862266,
 'boreratio': 0.07335631276901006,
 'horsepower': 1563.7411286465806,
 'citympg': 42.79961740793878,
 'highwaympg': 47.42309899569584}
```

There are no variances less than 1%.

Pearson Correlation Coefficient

Link

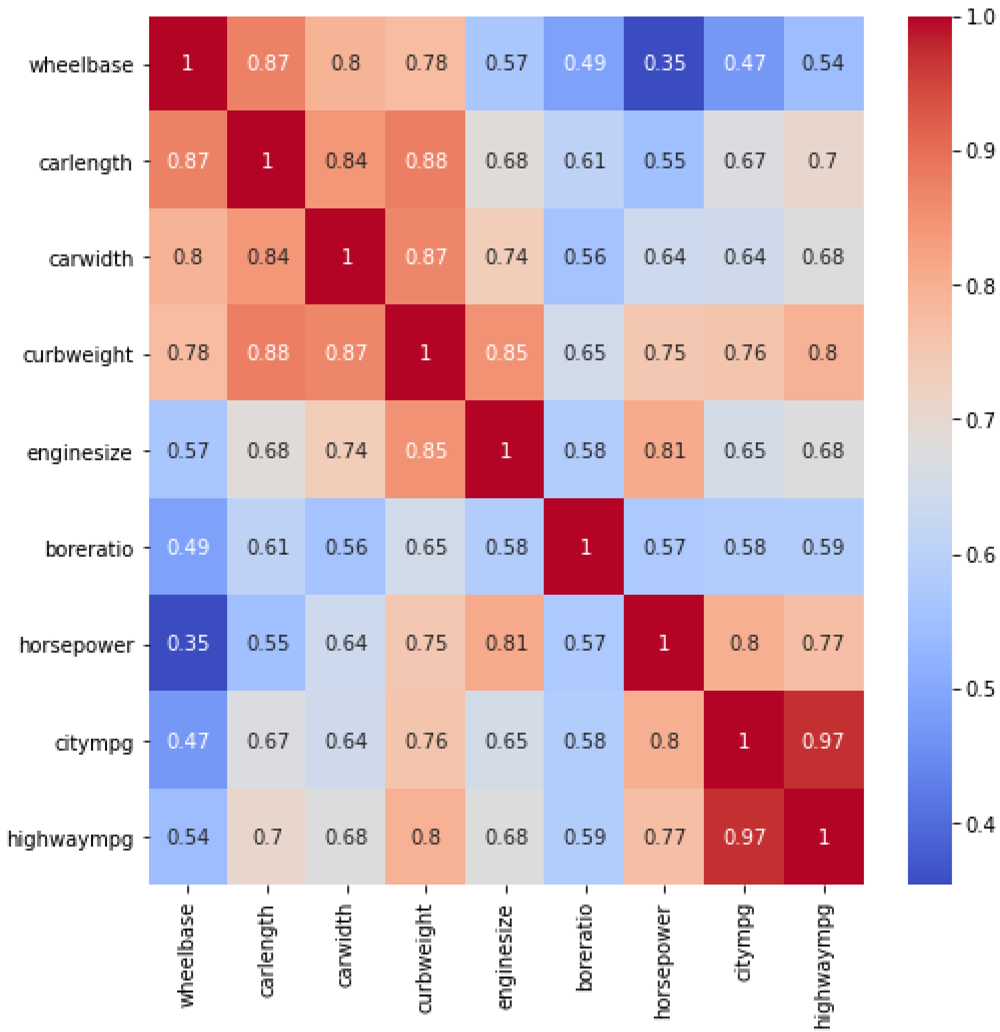
Pearson Correlation Coefficient oftens begs the question which feature to keep and which to remove. Answer, we should keep feature which has higher correlation with label.

In [26]:

```
# Create Correlation Matrix
```

```python
threshold = 0.85
correlation_matrix = cars[numerical_variables].corr(method = 'pearson').abs()
plt.figure(figsize=(8,8))
sns.heatmap(data = correlation_matrix, annot = True, cmap = 'coolwarm')
```

Out[26]: <AxesSubplot:>



[Variance Inflation Factor](https://statisticsbyjim.com/regression/multicollinearity-in-regression-analysis/#:~:text=Multicollinearity%20occurs%20when%20independent%20variables%20in%20a%20regression,you%20fit%20the%2

[Link1]

Variance Inflation Factor is used to detect the severity of multicollinearity in regression analysis. It varies between 1 and Inf and we usually reject feature if VIF is greater than 5.

In [27]:

```
# Variance Inflation Factor
def checkVIF(X):
    vif = pd.DataFrame()
    vif['Features'] = X.columns
    vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
    vif['VIF'] = round(vif['VIF'], 2)
    vif = vif.sort_values(by = "VIF", ascending = False)
    return(vif)

checkVIF(cars[numerical_variables])
```

Out[27]:

	Features	VIF
1	carlength	1753.38
0	wheelbase	1744.67
2	carwidth	1675.42
8	highwaympg	498.25
7	citympg	402.91
3	curbweight	272.49
5	boreratio	268.33
4	enginesize	55.00
6	horsepower	50.57

Encoding of Categorical Variables

In [ ]:

```
# Perform Encoding on Data
cars_modified = cars[numerical_variables + categorical_variables + ['price']]
cars_modified[categorical_variables] = cars_modified[categorical_variables].astype('category')
cars_combined = pd.get_dummies(data = cars_modified, drop_first=True)
categorical_variables_encoded = list(cars_combined.columns)[10:]
cars_combined = sm.add_constant(cars_combined)
```

Split data into training and test

In [29]:

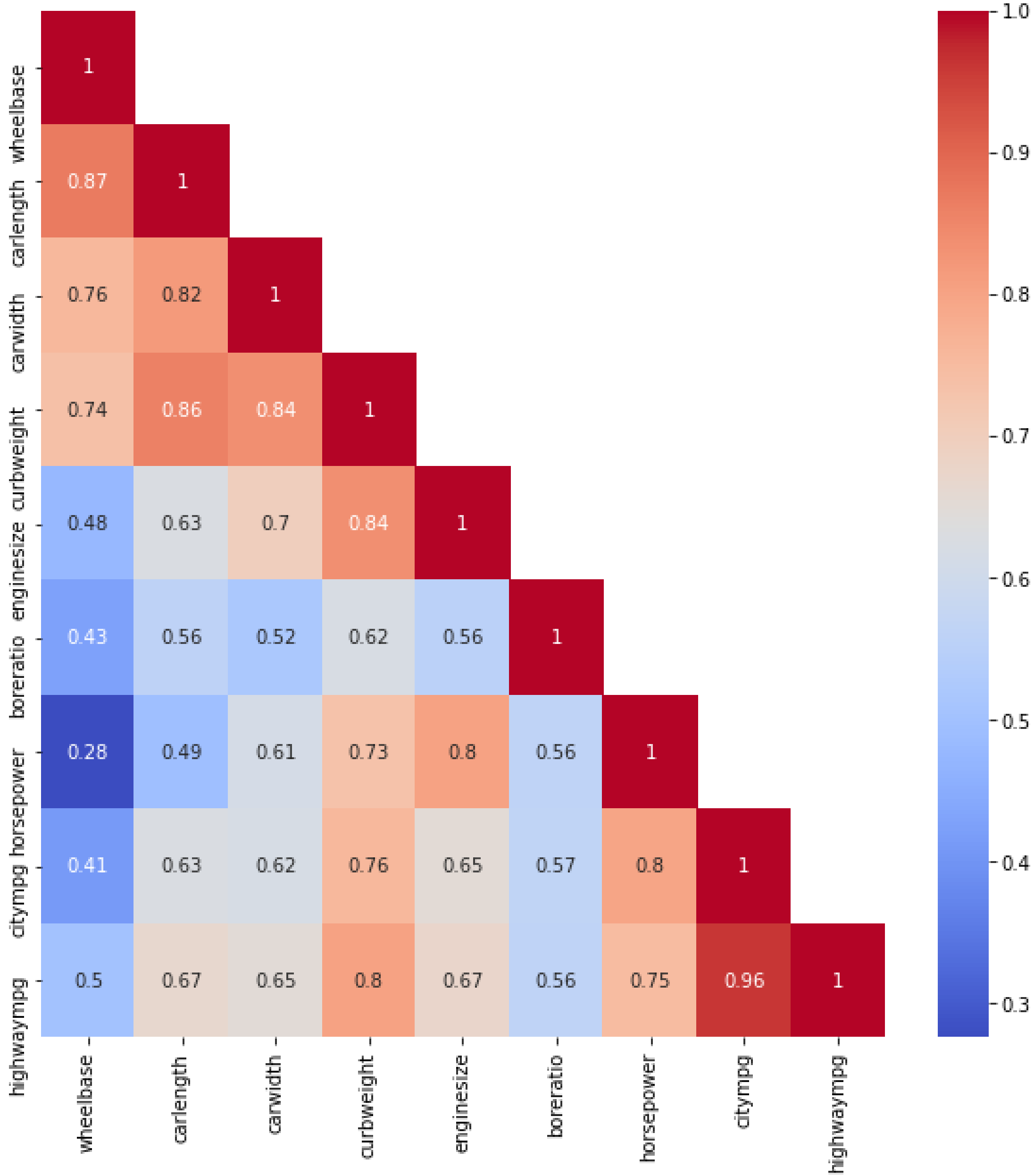
```
# Split data into train and test
cars_train, cars_test = train_test_split(cars_combined, train_size = 0.75, random_state = 42)
```

In [30]:

```
# Create correlation matrix
# MAKE THIS INTO FUNCTION
correlation_matrix = cars_train[numerical_variables].corr(method = 'pearson').abs()
lower_tri = correlation_matrix.where(np.tril(np.ones(correlation_matrix.shape)).astype(bool))
plt.figure(figsize=(10,10))
sns.heatmap(data = lower_tri, annot= True, cmap = 'coolwarm')
```

Out[30]:

```
<AxesSubplot:>
```



In [31]:

```
# Check VIF on training data
checkVIF(cars_train[numerical_variables])
```

Out[31]:

Features	VIF

	Features	VIF
1	carlength	1754.92
0	wheelbase	1702.77
2	carwidth	1533.97
8	highwaympg	464.10
7	citympg	370.83
3	curbweight	298.15
5	boreratio	251.79
4	enginesize	53.59
6	horsepower	47.27

Scaling is not performed on label

Note: Scaling is performed after splitting data since we want to standardize considering that test and train data are treated independently of each other.

In [32]:

```
# Perform feature scaling for Numerical Variables (Standardization)
def standardization_function(df, col_name):
    if df[col_name].dtype ==  'uint8':  # ignore cateforical variables
        return df[col_name]
    elif col_name == 'price' or col_name == 'const':  # ignore label
        return df[col_name]
    else:
        mu = np.mean(df[col_name])
        std_dev = statistics.stdev(df[col_name])
        scaled_column = (df[col_name] - mu)/std_dev
        return scaled_column

cars_train_scaled = pd.DataFrame()
for col_name in list(cars_train.columns):
    cars_train_scaled[col_name] = standardization_function(cars_train, col_name)
```

In [33]:

```
# Perform feature scaling for Test Data Numerical Variables (Standardization)
cars_test_scaled = pd.DataFrame()
```

```python
for col_name in list(cars_test.columns):
    cars_test_scaled[col_name] = standardization_function(cars_test, col_name)
```

Simulation 1: With All Features

In [34]:

```python
# Create model with all features
model_all_features = sm.OLS(cars_train_scaled['price'], cars_train_scaled[['const'] + numerical_variables + categorical_v
result = model_all_features.fit()
print(result.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.971
Model:                            OLS   Adj. R-squared:                  0.960
Method:                 Least Squares   F-statistic:                     87.78
Date:                Sat, 20 Nov 2021   Prob (F-statistic):           1.16e-67
Time:                        10:28:32   Log-Likelihood:                -1318.9
No. Observations:                 153   AIC:                             2724.
Df Residuals:                     110   BIC:                             2854.
Df Model:                          42
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
const                 1.904e+04   1786.030     10.661      0.000    1.55e+04    2.26e+04
wheelbase               41.6380    526.888      0.079      0.937   -1002.531    1085.807
carlength             -222.4221    608.003     -0.366      0.715   -1427.341     982.497
carwidth              1739.6147    442.800      3.929      0.000     862.089    2617.140
curbweight            1947.9419    668.168      2.915      0.004     623.790    3272.094
enginesize            1508.8725    604.734      2.495      0.014     310.431    2707.314
boreratio             -632.9943    276.627     -2.288      0.024   -1181.205     -84.784
horsepower            1703.2228    542.199      3.141      0.002     628.713    2777.733
citympg                584.2754    700.450      0.834      0.406    -803.853    1972.403
highwaympg            -283.2850    711.539     -0.398      0.691   -1693.388    1126.818
CarName_audi           209.4806   1630.837      0.128      0.898   -3022.456    3441.417
CarName_bmw           7615.5044   1629.365      4.674      0.000    4386.486    1.08e+04
CarName_buick         9798.0714   1795.184      5.458      0.000    6240.437    1.34e+04
CarName_chevrolet    -1936.1723   2127.583     -0.910      0.365   -6152.542    2280.198
CarName_dodge        -2041.4990   1505.865     -1.356      0.178   -5025.770     942.772
CarName_honda        -1862.1466   1425.854     -1.306      0.194   -4687.854     963.561
CarName_isuzu         -133.2736   1627.119     -0.082      0.935   -3357.841    3091.294
CarName_jaguar        4363.7173   2109.870      2.068      0.041     182.449    8544.985
CarName_mazda        -2118.1787   1402.349     -1.510      0.134   -4897.305     660.947
CarName_mercury      -1337.8031   2388.577     -0.560      0.577   -6071.402    3395.795
CarName_mitsubishi -3357.5336   1439.338     -2.333      0.021   -6209.963    -505.104
```

```
CarName_nissan     -1852.9786   1333.122     -1.390      0.167   -4494.914     788.957
CarName_peugeot    -1004.8647    826.040     -1.216      0.226   -2641.883     632.154
CarName_plymouth   -2394.8038   1466.011     -1.634      0.105   -5300.093     510.485
CarName_porsche     5761.1087   2361.199      2.440      0.016    1081.767    1.04e+04
CarName_renault    -3281.9926   1829.024     -1.794      0.075   -6906.689     342.703
CarName_saab         -30.9001   1557.385     -0.020      0.984   -3117.272    3055.472
CarName_subaru     -1.092e+04   3093.372     -3.532      0.001   -1.71e+04   -4794.490
CarName_toyota     -2466.1403   1288.652     -1.914      0.058   -5019.947      87.666
CarName_volkswagen -2039.3896   1429.798     -1.426      0.157   -4872.913     794.134
CarName_volvo       2147.0906   1712.123      1.254      0.212   -1245.936    5540.117
CarName_vw         -1215.3410   1681.600     -0.723      0.471   -4547.877    2117.195
carbody_hardtop    -1701.7887   1196.469     -1.422      0.158   -4072.909     669.332
carbody_hatchback  -3121.6591   1042.829     -2.993      0.003   -5188.301   -1055.017
carbody_sedan      -3016.1840   1109.705     -2.718      0.008   -5215.360    -817.008
carbody_wagon      -3847.6443   1246.688     -3.086      0.003   -6318.287   -1377.001
drivewheel_fwd      -891.5851   1083.648     -0.823      0.412   -3039.122    1255.952
drivewheel_rwd     -2052.1697   1197.688     -1.713      0.089   -4425.705     321.366
enginetype_dohcv   -4763.3649   2778.083     -1.715      0.089   -1.03e+04     742.143
enginetype_l       -1004.8647    826.040     -1.216      0.226   -2641.883     632.154
enginetype_ohc     -1005.4986    802.601     -1.253      0.213   -2596.066     585.069
enginetype_ohcf     7642.1390   2377.839      3.214      0.002    2929.820    1.24e+04
enginetype_ohcv    -2555.7953   1165.399     -2.193      0.030   -4865.343    -246.248
enginetype_rotor    4782.3030   1507.062      3.173      0.002    1795.660    7768.946
==============================================================================
Omnibus:                       20.024   Durbin-Watson:                   1.985
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               33.321
Skew:                           0.656   Prob(JB):                     5.81e-08
Kurtosis:                       4.873   Cond. No.                     1.35e+16
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 5.6e-30. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

In [35]:

```
# Predict price
y_pred = list(result.predict(cars_test_scaled[['const'] + numerical_variables + categorical_variables_encoded]))
y = list(cars_test_scaled['price'])
```

In [36]:

```
# Calculate rmse
def rmse(y, y_pred):
    sse = np.sum([(y[value] - y_pred[value])**2  for value in range(len(y))])
    rmse = np.sqrt(sse/len(y))
    return rmse
```

In [37]:

```
l_KPIs = [('None', 0,result.rsquared, result.fvalue, rmse(y, y_pred))]
l_KPIs
```

Out[37]:

```
[('None', 0, 0.9710267120765217, 87.77620286011167, 2945.624127266577)]
```

In [ ]:

```
# Loop on features to drop based on highest p-value
features = ['const'] + numerical_variables + categorical_variables_encoded
len(features)

while ( any(value > 0.05 for value in result.pvalues) ):
    # Identify feature to drop
    max_p_value = result.pvalues.max()
    feature_to_drop = list(result.pvalues[result.pvalues == max_p_value].index)[0]
    # Drop feature from data
    if feature_to_drop != 'const':
        features.remove(feature_to_drop)
        cars_train.drop(feature_to_drop, inplace = True, axis = 1)
        cars_test.drop(feature_to_drop, inplace = True, axis = 1)
        cars_train_scaled.drop(feature_to_drop, inplace = True, axis = 1)
        cars_test_scaled.drop(feature_to_drop, inplace = True, axis = 1)
    # Rerun the model
    model_all_features = sm.OLS(cars_train_scaled['price'], cars_train_scaled[features])
    result = model_all_features.fit()
    # Predict the values
    y_pred = list(result.predict(cars_test_scaled[features]))
    # Track the KPIs
    l_KPIs.append((feature_to_drop, max_p_value, result.rsquared, result.fvalue, rmse(y, y_pred)))
```

In [39]:

```
# After dropping all insignificant features summary looks as below
result.summary()
```

Out[39]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.961
Model:	OLS	**Adj. R-squared:**	0.956
Method:	Least Squares	**F-statistic:**	196.0
Date:	Sat, 20 Nov 2021	**Prob (F-statistic):**	3.11e-86
Time:	10:28:32	**Log-Likelihood:**	-1341.5
No. Observations:	153	**AIC:**	2719.

Df Residuals:	135	**BIC:**	2774.
Df Model:	17		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.576e+04	723.325	21.784	0.000	1.43e+04	1.72e+04
carwidth	1754.4165	298.605	5.875	0.000	1163.867	2344.966
curbweight	2812.8816	434.075	6.480	0.000	1954.414	3671.349
boreratio	-756.8864	227.540	-3.326	0.001	-1206.890	-306.883
horsepower	1713.6548	267.146	6.415	0.000	1185.323	2241.986
CarName_bmw	9563.5843	778.180	12.290	0.000	8024.583	1.11e+04
CarName_buick	1.138e+04	1056.724	10.767	0.000	9287.778	1.35e+04
CarName_jaguar	8672.4274	1184.930	7.319	0.000	6329.000	1.1e+04
CarName_mitsubishi	-1575.1248	595.946	-2.643	0.009	-2753.722	-396.528
CarName_porsche	6399.9902	1427.401	4.484	0.000	3577.031	9222.949
CarName_subaru	-9774.5006	1936.372	-5.048	0.000	-1.36e+04	-5944.953
CarName_volvo	3383.6776	703.146	4.812	0.000	1993.072	4774.284
carbody_hatchback	-3575.8633	721.590	-4.956	0.000	-5002.946	-2148.781
carbody_sedan	-3373.0925	717.513	-4.701	0.000	-4792.112	-1954.073
carbody_wagon	-4774.7252	833.176	-5.731	0.000	-6422.491	-3126.959
drivewheel_rwd	-1140.6562	505.675	-2.256	0.026	-2140.726	-140.587
enginetype_ohcf	1.004e+04	1743.525	5.761	0.000	6596.450	1.35e+04
enginetype_rotor	3389.1622	1048.668	3.232	0.002	1315.221	5463.104

Omnibus:	12.878	**Durbin-Watson:**	2.068
Prob(Omnibus):	0.002	**Jarque-Bera (JB):**	24.086
Skew:	0.363	**Prob(JB):**	5.89e-06
Kurtosis:	4.803	**Cond. No.**	37.0

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

In [40]:
```
# Create lists
KPI_data = []
feature_dropped = []
p_value = []
R_Squared = []
F_Score = []
RMSE = []

for i in range(len(l_KPIs)):
    feature_dropped.append(l_KPIs[i][0])
    p_value.append(l_KPIs[i][1])
    R_Squared.append(l_KPIs[i][2])
    F_Score.append(l_KPIs[i][3])
    RMSE.append(l_KPIs[i][4])
```

In [41]:
```
# Create dataframe with all KPIs
empty_dict = {'feature_dropped': feature_dropped,
              'p_value': p_value,
              'R_Squared': R_Squared,
              'F_Score': F_Score,
              'RMSE': RMSE
             }
metrics_df = pd.DataFrame(empty_dict)
metrics_df
```

Out[41]:

	feature_dropped	p_value	R_Squared	F_Score	RMSE
0	None	0.000000	0.971027	87.776203	2945.624127
1	CarName_saab	0.984206	0.971027	90.734180	2944.469882
2	wheelbase	0.934861	0.971025	93.834553	2949.646332
3	CarName_isuzu	0.945766	0.971024	97.095708	2949.844706
4	CarName_audi	0.804772	0.971008	100.476514	2951.141495

	feature_dropped	p_value	R_Squared	F_Score	RMSE
5	carlength	0.668916	0.970961	103.924699	2950.229538
6	highwaympg	0.637790	0.970905	107.525705	2943.984389
7	CarName_mercury	0.505891	0.970793	111.111911	2933.324597
8	CarName_vw	0.403988	0.970618	114.649301	2924.482190
9	CarName_chevrolet	0.330782	0.970381	118.140609	2911.551489
10	citympg	0.401591	0.970204	122.106856	2910.214754
11	drivewheel_fwd	0.258179	0.969884	125.702135	2911.178297
12	carbody_hardtop	0.131064	0.969309	128.434939	2982.604178
13	enginetype_dohcv	0.117832	0.968684	131.198668	2975.979492
14	enginetype_ohc	0.083242	0.967908	133.567417	3002.083879
15	CarName_peugeot	0.130310	0.967908	133.567417	3016.798469
16	enginetype_l	0.130310	0.967308	136.982499	3010.047098
17	enginetype_ohcv	0.063815	0.966393	139.354754	2978.581355
18	enginesize	0.070613	0.965506	142.193039	3120.683693
19	CarName_dodge	0.052124	0.964462	144.742018	3133.958244
20	CarName_honda	0.166782	0.963925	149.866502	3117.508313
21	CarName_nissan	0.192736	0.963446	155.744741	3136.572506
22	CarName_mazda	0.270417	0.963102	162.823108	3080.842415
23	CarName_plymouth	0.260981	0.962743	170.545834	3085.023714
24	CarName_renault	0.225106	0.962323	178.791235	3077.841908
25	CarName_volkswagen	0.233369	0.961917	188.036542	3087.049107
26	CarName_toyota	0.085190	0.961063	196.006219	3102.418694

In [42]:

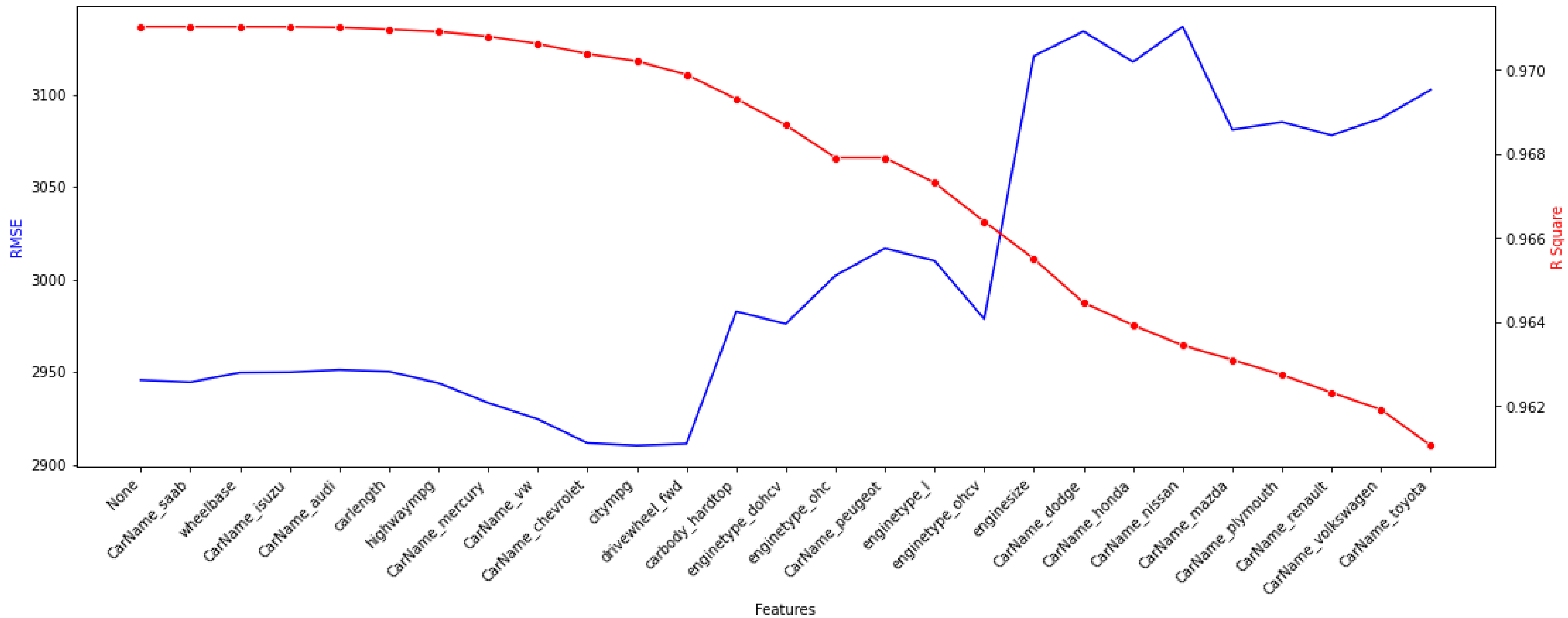
```
# Create plot to observe variation of RMSE and R_Square with each feature dropped
fig, ax1 = plt.subplots(figsize=(18,6)) # initializes figure and plots
```

```
ax2 = ax1.twinx() # applies twinx to ax2, which is the second y axis.

sns.lineplot(data = metrics_df, x = 'feature_dropped', y = 'RMSE', ax = ax1, color = 'blue') # plots the first set of dat
sns.lineplot(data = metrics_df, x = 'feature_dropped', y = 'R_Squared', marker = 'o', color = 'red', ax = ax2) # plots th

# these lines add the annotations for the plot.
ax1.set_xlabel('Features')
ax1.set_ylabel('RMSE', color='b')
ax2.set_ylabel('R Square', color='r')
ax1.set_xticklabels(labels = metrics_df.feature_dropped, rotation=45, horizontalalignment='right')
plt.show(); # shows the plot.
```

```
<ipython-input-42-b36af4757485>:13: UserWarning: FixedFormatter should only be used together with FixedLocator
  ax1.set_xticklabels(labels = metrics_df.feature_dropped, rotation=45, horizontalalignment='right')
```



From the above graph, we can see that RMSE is minimum when considering only fetures removed up to 'citympg'. Based on the business scenarios and model complexity we can either target a lower RMSE or go for a less complex model as done here which targets more significant variables. Also, we can see that dropping 'enginesize' greatly increases the MSE and it is not a best judgement call to drop features that increase MSE substantially.

Other techniques for creating linear models with best features are as belows. This implementation will be a part of separate project and same dataset as used here.

There are other techniques as well which can be used for feature selection specially . These are:

1. Forward Selection
   For this technique, we start with no features and insert features into the model one-by-one. First, the feature with the highest correlation is included. A disadvantage with forward selection is that a feature that makes it into the model is not dropped. It might happen that as newer features are added, the significance of existing features drops (or, p-value increases beyond 5%).
2. Backward Elimination
   For this technique, we start with all features in the model. The p-value is calculated as we remove regressors one at a time. In this case, the feature with the highest p-value is removed from the model ands the procedure continues until the largest p-value is smaller than the pre-selected cutoff value (5%), and terminates otherwise. This method sounds particularly appealing, when we'd like to see how each variable affects the model.
3. Recursive Feature Elimination (RFE)

https://stats.stackexchange.com/questions/138860/is-using-correlation-matrix-to-select-predictors-for-regression-correct