Importing Libraries

In [1]:
```
#Importing Pandas and NumPy
import pandas as pd
import numpy as np

#Importing seaborn
import seaborn as sns

#Importing matplotlib
from matplotlib import pyplot as plt
%matplotlib inline

#Suppressing Warnings
import warnings
warnings.filterwarnings('ignore')
```

Reading and Understanding Data

In [2]:
```
#Reading the data
data = pd.read_csv("D:\Data Science\Machine Learning\CarPrice_Assignment.csv")
data.head()
```

Out[2]:

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

5 rows × 26 columns

In [3]:
```
#Checking the dimension of dataframe
data.shape
```

Out[3]: (205, 26)

In [4]:
```
#Checking the statistical aspects of dataframe
data.describe()
```

Out[4]:

	car_ID	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000

	car_ID	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize
mean	103.000000	0.834146	98.756585	174.049268	65.907805	53.724878	2555.565854	126.907317
std	59.322565	1.245307	6.021776	12.337289	2.145204	2.443522	520.680204	41.642693
min	1.000000	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000000
25%	52.000000	0.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97.000000
50%	103.000000	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.000000
75%	154.000000	2.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	141.000000
max	205.000000	3.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326.000000

In [5]:
```
#Checking the type of each column
data.info()
```

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

In [6]:
```
#No null values found from above, checking for duplicate values
data.duplicated().unique()
```

Out[6]:
```
array([False])
```

Data Preparation

Since in the question its given to consider the company name as independent variable, we first split the CarName and store the company Name in another dummy variable and drop the orginal variable

In [7]:
```
#Splitting the CarName into dummy variable
data['companyname']=data['CarName'].apply(lambda x:(x.split(' ')[0]))

#Dropping the variable CarName
data=data.drop(['CarName'],axis='columns')

data
```

Out[7]:

	car_ID	symboling	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	whe
0	1	3	gas	std	two	convertible	rwd	front	
1	2	3	gas	std	two	convertible	rwd	front	
2	3	1	gas	std	two	hatchback	rwd	front	
3	4	2	gas	std	four	sedan	fwd	front	
4	5	2	gas	std	four	sedan	4wd	front	
...	...	...	...	...	...	...	...	...	
200	201	-1	gas	std	four	sedan	rwd	front	
201	202	-1	gas	turbo	four	sedan	rwd	front	
202	203	-1	gas	std	four	sedan	rwd	front	
203	204	-1	diesel	turbo	four	sedan	rwd	front	
204	205	-1	gas	turbo	four	sedan	rwd	front	

205 rows × 26 columns

In [8]:
```
data['companyname'].unique()
```

Out[8]:
```
array(['alfa-romero', 'audi', 'bmw', 'chevrolet', 'dodge', 'honda',
       'isuzu', 'jaguar', 'maxda', 'mazda', 'buick', 'mercury',
       'mitsubishi', 'Nissan', 'nissan', 'peugeot', 'plymouth', 'porsche',
       'porcshce', 'renault', 'saab', 'subaru', 'toyota', 'toyouta',
       'vokswagen', 'volkswagen', 'vw', 'volvo'], dtype=object)
```

In [9]:
```
#Merging the mispelled Company Names
data['companyname'].replace('maxda','mazda',inplace=True)
data['companyname'].replace('Nissan','nissan',inplace=True)
data['companyname'].replace('porcshce','porsche',inplace=True)
data['companyname'].replace('toyouta','toyota',inplace=True)
data['companyname'].replace(['vokswagen','vw'],'volkswagen',inplace=True)

data['companyname'].unique()
```

Out[9]:
```
array(['alfa-romero', 'audi', 'bmw', 'chevrolet', 'dodge', 'honda',
```

```
'isuzu', 'jaguar', 'mazda', 'buick', 'mercury', 'mitsubishi',
'nissan', 'peugeot', 'plymouth', 'porsche', 'renault', 'saab',
'subaru', 'toyota', 'volkswagen', 'volvo'], dtype=object)
```

From the information we can drop car_ID as it has no relation in determining the car price

In [10]:
```
data.drop(['car_ID'],axis = 1, inplace = True)
```

In [11]:
```
data.head()
```

Out[11]:

	symboling	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	ca
0	3	gas	std	two	convertible	rwd	front	88.6	
1	3	gas	std	two	convertible	rwd	front	88.6	
2	1	gas	std	two	hatchback	rwd	front	94.5	
3	2	gas	std	four	sedan	fwd	front	99.8	
4	2	gas	std	four	sedan	4wd	front	99.4	

5 rows × 25 columns

To create a regression line, we need numeric data. Therefore, we create dummy variable for categorical variables with more than 2 levels.

In [12]:
```
#Creating dummy variables for categorical variables and dropping the first column
dummies = pd.get_dummies(data[['fueltype','aspiration','doornumber','carbody','drivewhe

#Merging the results to orginal dataframe
data = pd.concat([data,dummies],axis=1)

#Dropping the orginal variables from dataframe
data.drop(['fueltype','aspiration','doornumber','carbody','drivewheel','enginelocation'
```

In [13]:
```
data.head()
```

Out[13]:

	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	stroke	cc
0	3	88.6	168.8	64.1	48.8	2548	130	3.47	2.68	
1	3	88.6	168.8	64.1	48.8	2548	130	3.47	2.68	
2	1	94.5	171.2	65.5	52.4	2823	152	2.68	3.47	
3	2	99.8	176.6	66.2	54.3	2337	109	3.19	3.40	
4	2	99.4	176.6	66.4	54.3	2824	136	3.19	3.40	

5 rows × 65 columns

In [14]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 65 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   symboling               205 non-null    int64  
 1   wheelbase               205 non-null    float64
 2   carlength               205 non-null    float64
 3   carwidth                205 non-null    float64
 4   carheight               205 non-null    float64
 5   curbweight              205 non-null    int64  
 6   enginesize              205 non-null    int64  
 7   boreratio               205 non-null    float64
 8   stroke                  205 non-null    float64
 9   compressionratio        205 non-null    float64
 10  horsepower              205 non-null    int64  
 11  peakrpm                 205 non-null    int64  
 12  citympg                 205 non-null    int64  
 13  highwaympg              205 non-null    int64  
 14  price                   205 non-null    float64
 15  fueltype_gas            205 non-null    uint8  
 16  aspiration_turbo        205 non-null    uint8  
 17  doornumber_two          205 non-null    uint8  
 18  carbody_hardtop         205 non-null    uint8  
 19  carbody_hatchback       205 non-null    uint8  
 20  carbody_sedan           205 non-null    uint8  
 21  carbody_wagon           205 non-null    uint8  
 22  drivewheel_fwd          205 non-null    uint8  
 23  drivewheel_rwd          205 non-null    uint8  
 24  enginelocation_rear     205 non-null    uint8  
 25  enginetype_dohcv        205 non-null    uint8  
 26  enginetype_l            205 non-null    uint8  
 27  enginetype_ohc          205 non-null    uint8  
 28  enginetype_ohcf         205 non-null    uint8  
 29  enginetype_ohcv         205 non-null    uint8  
 30  enginetype_rotor        205 non-null    uint8  
 31  cylindernumber_five     205 non-null    uint8  
 32  cylindernumber_four     205 non-null    uint8  
 33  cylindernumber_six      205 non-null    uint8  
 34  cylindernumber_three    205 non-null    uint8  
 35  cylindernumber_twelve   205 non-null    uint8  
 36  cylindernumber_two      205 non-null    uint8  
 37  fuelsystem_2bbl         205 non-null    uint8  
 38  fuelsystem_4bbl         205 non-null    uint8  
 39  fuelsystem_idi          205 non-null    uint8  
 40  fuelsystem_mfi          205 non-null    uint8  
 41  fuelsystem_mpfi         205 non-null    uint8  
 42  fuelsystem_spdi         205 non-null    uint8  
 43  fuelsystem_spfi         205 non-null    uint8  
 44  companyname_audi        205 non-null    uint8  
 45  companyname_bmw         205 non-null    uint8  
 46  companyname_buick       205 non-null    uint8  
 47  companyname_chevrolet   205 non-null    uint8  
 48  companyname_dodge       205 non-null    uint8  
 49  companyname_honda       205 non-null    uint8  
 50  companyname_isuzu       205 non-null    uint8  
 51  companyname_jaguar      205 non-null    uint8  
 52  companyname_mazda       205 non-null    uint8  
 53  companyname_mercury     205 non-null    uint8  
 54  companyname_mitsubishi  205 non-null    uint8  
 55  companyname_nissan      205 non-null    uint8  
 56  companyname_peugeot     205 non-null    uint8  
```

```
 57  companyname_plymouth    205 non-null    uint8
 58  companyname_porsche     205 non-null    uint8
 59  companyname_renault     205 non-null    uint8
 60  companyname_saab        205 non-null    uint8
 61  companyname_subaru      205 non-null    uint8
 62  companyname_toyota      205 non-null    uint8
 63  companyname_volkswagen  205 non-null    uint8
 64  companyname_volvo       205 non-null    uint8
dtypes: float64(8), int64(7), uint8(50)
memory usage: 34.2 KB
```

Feature Scaling

In [15]:
```
from sklearn.preprocessing import MinMaxScaler
```

In [16]:
```
scaler = MinMaxScaler()
```

In [17]:
```
# Apply scaler() to all the columns except for dummy variables
num_var = ['symboling','horsepower','wheelbase','curbweight', 'enginesize', 'boreratio'

data[num_var] = scaler.fit_transform(data[num_var])
data.head()
```

Out[17]:

	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	stroke
0	1.0	0.058309	0.413433	0.316667	0.083333	0.411171	0.260377	0.664286	0.290476
1	1.0	0.058309	0.413433	0.316667	0.083333	0.411171	0.260377	0.664286	0.290476
2	0.6	0.230321	0.449254	0.433333	0.383333	0.517843	0.343396	0.100000	0.666667
3	0.8	0.384840	0.529851	0.491667	0.541667	0.329325	0.181132	0.464286	0.633333
4	0.8	0.373178	0.529851	0.508333	0.541667	0.518231	0.283019	0.464286	0.633333

5 rows × 65 columns

Splitting Data into Test and Training Data

In [18]:
```
# Importing library for splitting
from sklearn.model_selection import train_test_split
```

In [19]:
```
#Independent variables
X = data.drop('price',axis = 1)

X.head()
```

Out[19]:

	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	stroke
0	1.0	0.058309	0.413433	0.316667	0.083333	0.411171	0.260377	0.664286	0.290476
1	1.0	0.058309	0.413433	0.316667	0.083333	0.411171	0.260377	0.664286	0.290476

	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	stroke
2	0.6	0.230321	0.449254	0.433333	0.383333	0.517843	0.343396	0.100000	0.666667
3	0.8	0.384840	0.529851	0.491667	0.541667	0.329325	0.181132	0.464286	0.633333
4	0.8	0.373178	0.529851	0.508333	0.541667	0.518231	0.283019	0.464286	0.633333

5 rows × 64 columns

In [20]:
```
#Dependent variable
Y = data.price

Y.head()
```

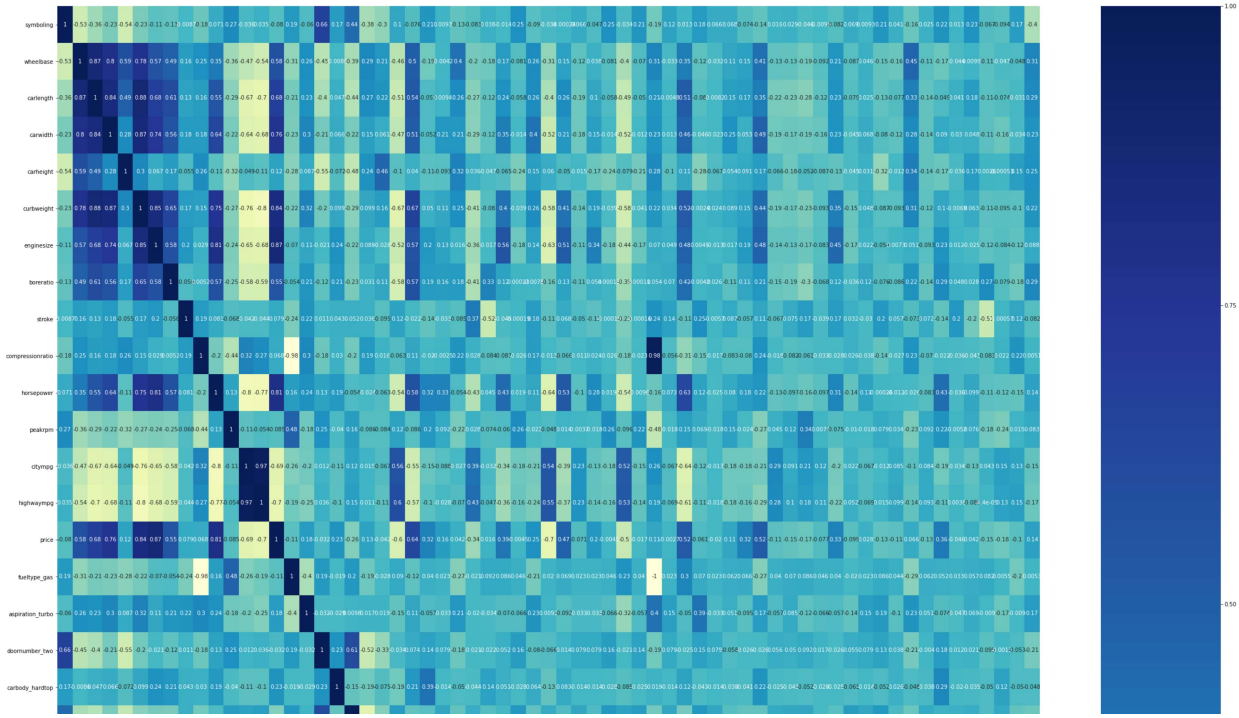
Out[20]:
```
0    0.207959
1    0.282558
2    0.282558
3    0.219254
4    0.306142
Name: price, dtype: float64
```

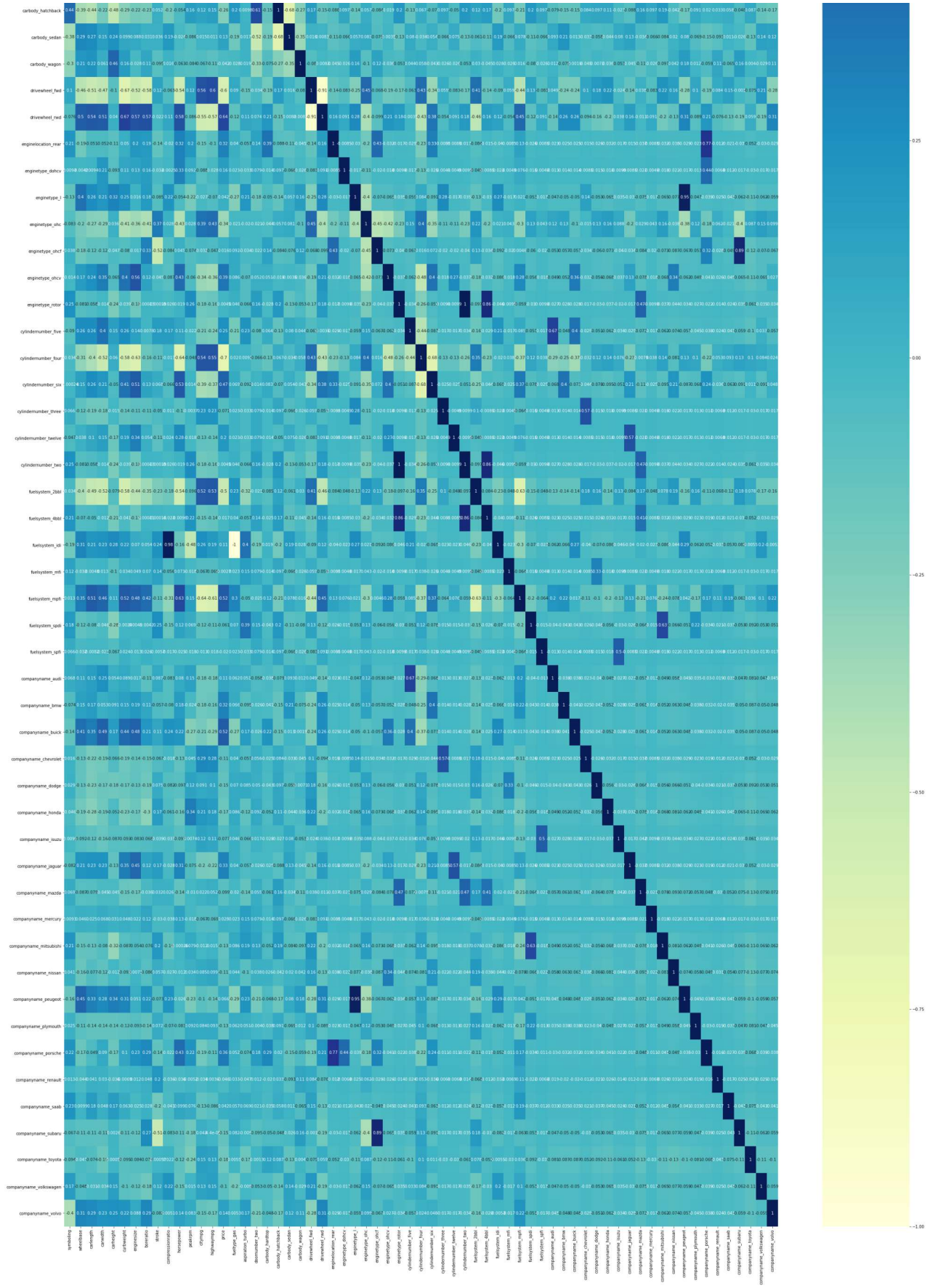
In [21]:
```
# Splitting the data into train and test
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, train_size=0.7, test_size=0.3
```

Correlation Matrix

In [22]:
```
# Checking correlation coeffiecients to see which variables are highly correlted

plt.figure(figsize = (40,80))
sns.heatmap(data.corr(), annot = True, cmap = 'YlGnBu')
plt.show()
```





Model Building

In [23]:
```
import statsmodels.api as sm
```

```
# Add a constant otherwise it will be straight line from zero
X_train_mlr = sm.add_constant(X_train)

# Create a first fitted model
mlr_1 = sm.OLS(Y_train, X_train_mlr).fit()
```

In [24]:
```
mlr_1.summary()
```

Out[24]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.975
Model:	OLS	**Adj. R-squared:**	0.958
Method:	Least Squares	**F-statistic:**	57.59
Date:	Mon, 16 May 2022	**Prob (F-statistic):**	1.40e-49
Time:	16:09:41	**Log-Likelihood:**	295.32
No. Observations:	143	**AIC:**	-474.6
Df Residuals:	85	**BIC:**	-302.8
Df Model:	57		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0960	0.136	-0.704	0.483	-0.367	0.175
symboling	-0.0089	0.033	-0.265	0.792	-0.075	0.058
wheelbase	0.2517	0.099	2.542	0.013	0.055	0.449
carlength	-0.1715	0.098	-1.747	0.084	-0.367	0.024
carwidth	0.2334	0.090	2.581	0.012	0.054	0.413
carheight	-0.1682	0.050	-3.341	0.001	-0.268	-0.068
curbweight	0.2958	0.117	2.521	0.014	0.063	0.529
enginesize	1.8066	0.417	4.333	0.000	0.978	2.635
boreratio	-0.6205	0.170	-3.660	0.000	-0.958	-0.283
stroke	-0.1728	0.079	-2.174	0.032	-0.331	-0.015
compressionratio	-0.3246	0.243	-1.334	0.186	-0.808	0.159
horsepower	-0.1802	0.188	-0.958	0.341	-0.554	0.194
peakrpm	0.1688	0.046	3.688	0.000	0.078	0.260
citympg	-0.0463	0.138	-0.335	0.738	-0.321	0.228
highwaympg	0.1175	0.128	0.918	0.361	-0.137	0.372
fueltype_gas	-0.1716	0.083	-2.064	0.042	-0.337	-0.006
aspiration_turbo	0.0729	0.026	2.778	0.007	0.021	0.125
doornumber_two	-0.0114	0.014	-0.841	0.403	-0.038	0.016

carbody_hardtop	-0.0873	0.051	-1.704	0.092	-0.189	0.015
carbody_hatchback	-0.0951	0.040	-2.386	0.019	-0.174	-0.016
carbody_sedan	-0.0779	0.042	-1.838	0.070	-0.162	0.006
carbody_wagon	-0.0608	0.045	-1.343	0.183	-0.151	0.029
drivewheel_fwd	-0.0031	0.022	-0.140	0.889	-0.047	0.041
drivewheel_rwd	0.0236	0.031	0.757	0.451	-0.038	0.086
enginelocation_rear	0.1779	0.062	2.890	0.005	0.056	0.300
enginetype_dohcv	0.2137	0.151	1.415	0.161	-0.087	0.514
enginetype_l	0.1861	0.074	2.528	0.013	0.040	0.332
enginetype_ohc	0.0009	0.040	0.023	0.981	-0.079	0.081
enginetype_ohcf	0.1487	0.037	4.032	0.000	0.075	0.222
enginetype_ohcv	-0.0247	0.035	-0.702	0.485	-0.095	0.045
enginetype_rotor	0.3559	0.104	3.438	0.001	0.150	0.562
cylindernumber_five	0.2395	0.127	1.885	0.063	-0.013	0.492
cylindernumber_four	0.3941	0.165	2.391	0.019	0.066	0.722
cylindernumber_six	0.1068	0.093	1.154	0.252	-0.077	0.291
cylindernumber_three	0.4452	0.112	3.992	0.000	0.223	0.667
cylindernumber_twelve	-0.3202	0.161	-1.992	0.050	-0.640	-0.001
cylindernumber_two	0.3559	0.104	3.438	0.001	0.150	0.562
fuelsystem_2bbl	0.0209	0.050	0.416	0.679	-0.079	0.121
fuelsystem_4bbl	-0.0439	0.071	-0.616	0.540	-0.185	0.098
fuelsystem_idi	0.0756	0.154	0.492	0.624	-0.230	0.381
fuelsystem_mfi	7.343e-16	1.94e-16	3.783	0.000	3.48e-16	1.12e-15
fuelsystem_mpfi	-0.0145	0.055	-0.262	0.794	-0.124	0.095
fuelsystem_spdi	-0.0235	0.059	-0.399	0.691	-0.141	0.094
fuelsystem_spfi	-4.053e-15	1.16e-15	-3.495	0.001	-6.36e-15	-1.75e-15
companyname_audi	0.0626	0.077	0.812	0.419	-0.091	0.216
companyname_bmw	0.3052	0.083	3.664	0.000	0.140	0.471
companyname_buick	0.0443	0.080	0.554	0.581	-0.115	0.203
companyname_chevrolet	-0.0469	0.071	-0.665	0.508	-0.187	0.093
companyname_dodge	-0.0979	0.059	-1.655	0.102	-0.216	0.020
companyname_honda	-0.0619	0.074	-0.836	0.406	-0.209	0.085
companyname_isuzu	0.0021	0.066	0.031	0.975	-0.130	0.134
companyname_jaguar	-0.1197	0.080	-1.492	0.139	-0.279	0.040
companyname_mazda	0.0220	0.059	0.370	0.712	-0.096	0.140

companyname_mercury	1.593e-16	5.18e-17	3.075	0.003	5.63e-17	2.62e-16
companyname_mitsubishi	-0.1144	0.060	-1.899	0.061	-0.234	0.005
companyname_nissan	0.0241	0.061	0.396	0.693	-0.097	0.145
companyname_peugeot	-0.2592	0.055	-4.719	0.000	-0.368	-0.150
companyname_plymouth	-0.1011	0.057	-1.758	0.082	-0.215	0.013
companyname_porsche	0.2369	0.100	2.367	0.020	0.038	0.436
companyname_renault	-0.0098	0.071	-0.138	0.891	-0.151	0.131
companyname_saab	0.2030	0.078	2.608	0.011	0.048	0.358
companyname_subaru	-0.0293	0.061	-0.479	0.633	-0.151	0.092
companyname_toyota	0.0148	0.056	0.263	0.794	-0.097	0.127
companyname_volkswagen	0.0205	0.058	0.356	0.723	-0.094	0.135
companyname_volvo	0.0961	0.083	1.164	0.247	-0.068	0.260

Omnibus:	34.574	**Durbin-Watson:**	1.863
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	162.755
Skew:	0.707	**Prob(JB):**	4.55e-36
Kurtosis:	8.032	**Cond. No.**	1.09e+16

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 8.3e-30. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

Feature Selection using RFE

In [25]:
```
from sklearn.feature_selection import RFE
from sklearn.ensemble import RandomForestRegressor
forest = RandomForestRegressor()
#Init the transformer
rfe = RFE(estimator=RandomForestRegressor(), n_features_to_select=15)

#Fit to the training data
rfe = rfe.fit(X_train_mlr, Y_train)
```

In [26]:
```
list(zip(X_train.columns, rfe.support_,rfe.ranking_))
```

Out[26]:
```
[('symboling', False, 51),
 ('wheelbase', True, 1),
 ('carlength', True, 1),
 ('carwidth', True, 1),
 ('carheight', True, 1),
 ('curbweight', True, 1),
```

```
('enginesize', True, 1),
('boreratio', True, 1),
('stroke', True, 1),
('compressionratio', True, 1),
('horsepower', True, 1),
('peakrpm', True, 1),
('citympg', True, 1),
('highwaympg', True, 1),
('fueltype_gas', True, 1),
('aspiration_turbo', False, 15),
('doornumber_two', False, 3),
('carbody_hardtop', False, 14),
('carbody_hatchback', False, 30),
('carbody_sedan', False, 9),
('carbody_wagon', False, 6),
('drivewheel_fwd', False, 18),
('drivewheel_rwd', False, 7),
('enginelocation_rear', False, 2),
('enginetype_dohcv', False, 45),
('enginetype_l', False, 47),
('enginetype_ohc', False, 43),
('enginetype_ohcf', False, 5),
('enginetype_ohcv', False, 36),
('enginetype_rotor', False, 22),
('cylindernumber_five', False, 39),
('cylindernumber_four', False, 17),
('cylindernumber_six', False, 8),
('cylindernumber_three', False, 16),
('cylindernumber_twelve', False, 46),
('cylindernumber_two', False, 41),
('fuelsystem_2bbl', False, 26),
('fuelsystem_4bbl', False, 11),
('fuelsystem_idi', False, 25),
('fuelsystem_mfi', False, 13),
('fuelsystem_mpfi', False, 50),
('fuelsystem_spdi', False, 4),
('fuelsystem_spfi', False, 32),
('companyname_audi', False, 49),
('companyname_bmw', False, 23),
('companyname_buick', True, 1),
('companyname_chevrolet', False, 38),
('companyname_dodge', False, 27),
('companyname_honda', False, 37),
('companyname_isuzu', False, 42),
('companyname_jaguar', False, 12),
('companyname_mazda', False, 34),
('companyname_mercury', False, 33),
('companyname_mitsubishi', False, 48),
('companyname_nissan', False, 24),
('companyname_peugeot', False, 31),
('companyname_plymouth', False, 21),
('companyname_porsche', False, 44),
('companyname_renault', False, 28),
('companyname_saab', False, 29),
('companyname_subaru', False, 35),
('companyname_toyota', False, 40),
('companyname_volkswagen', False, 10),
('companyname_volvo', False, 19)]
```

In [27]:
```
rfe.support_[1:]
```

Out[27]:
```
array([ True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
```

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

In [28]:
```
col = X_train.columns[rfe.support_[1:]]
col
```

Out[28]:
```
Index(['symboling', 'wheelbase', 'carlength', 'carwidth', 'carheight',
       'curbweight', 'enginesize', 'boreratio', 'stroke', 'compressionratio',
       'horsepower', 'peakrpm', 'citympg', 'highwaympg', 'companyname_bmw'],
      dtype='object')
```

In [29]:
```
X_train.columns[~rfe.support_[1:]]
```

Out[29]:
```
Index(['fueltype_gas', 'aspiration_turbo', 'doornumber_two', 'carbody_hardtop',
       'carbody_hatchback', 'carbody_sedan', 'carbody_wagon', 'drivewheel_fwd',
       'drivewheel_rwd', 'enginelocation_rear', 'enginetype_dohcv',
       'enginetype_l', 'enginetype_ohc', 'enginetype_ohcf', 'enginetype_ohcv',
       'enginetype_rotor', 'cylindernumber_five', 'cylindernumber_four',
       'cylindernumber_six', 'cylindernumber_three', 'cylindernumber_twelve',
       'cylindernumber_two', 'fuelsystem_2bbl', 'fuelsystem_4bbl',
       'fuelsystem_idi', 'fuelsystem_mfi', 'fuelsystem_mpfi',
       'fuelsystem_spdi', 'fuelsystem_spfi', 'companyname_audi',
       'companyname_buick', 'companyname_chevrolet', 'companyname_dodge',
       'companyname_honda', 'companyname_isuzu', 'companyname_jaguar',
       'companyname_mazda', 'companyname_mercury', 'companyname_mitsubishi',
       'companyname_nissan', 'companyname_peugeot', 'companyname_plymouth',
       'companyname_porsche', 'companyname_renault', 'companyname_saab',
       'companyname_subaru', 'companyname_toyota', 'companyname_volkswagen',
       'companyname_volvo'],
      dtype='object')
```

Updating the model after dropping features

In [30]:
```
# Building the second model
X_train_mlr_1 = sm.add_constant(X_train[col])
mlr_2 = sm.OLS(Y_train, X_train_mlr_1).fit()
mlr_2.summary()
```

Out[30]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.892
Model:	OLS	**Adj. R-squared:**	0.880
Method:	Least Squares	**F-statistic:**	70.10
Date:	Mon, 16 May 2022	**Prob (F-statistic):**	7.15e-54
Time:	16:10:48	**Log-Likelihood:**	191.52
No. Observations:	143	**AIC:**	-351.0
Df Residuals:	127	**BIC:**	-303.6
Df Model:	15		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.1708	0.075	-2.287	0.024	-0.319	-0.023
symboling	0.0374	0.033	1.138	0.257	-0.028	0.102
wheelbase	-0.0111	0.095	-0.116	0.908	-0.199	0.177
carlength	-0.1715	0.095	-1.802	0.074	-0.360	0.017
carwidth	0.3002	0.078	3.838	0.000	0.145	0.455
carheight	0.0162	0.043	0.380	0.705	-0.068	0.101
curbweight	0.3516	0.117	3.012	0.003	0.121	0.583
enginesize	0.4706	0.105	4.490	0.000	0.263	0.678
boreratio	-0.0263	0.046	-0.572	0.568	-0.117	0.065
stroke	-0.0940	0.046	-2.053	0.042	-0.185	-0.003
compressionratio	0.0911	0.036	2.533	0.013	0.020	0.162
horsepower	0.0978	0.101	0.968	0.335	-0.102	0.298
peakrpm	0.1253	0.042	2.952	0.004	0.041	0.209
citympg	0.0010	0.168	0.006	0.995	-0.331	0.333
highwaympg	-0.0059	0.161	-0.037	0.971	-0.324	0.312
companyname_bmw	0.2308	0.031	7.351	0.000	0.169	0.293

Omnibus:	25.927	**Durbin-Watson:**	2.118
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	55.121
Skew:	0.769	**Prob(JB):**	1.07e-12
Kurtosis:	5.624	**Cond. No.**	77.4

Notes:

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

Checking VIFs

In [31]:
```
#Importing VIF
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [32]:
```
# Create a dataframe that will contain the names of all the feature variables and their
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[32]:

	Features	VIF
13	highwaympg	150.10
12	citympg	128.23
5	curbweight	84.43
2	carlength	72.97
3	carwidth	47.74
1	wheelbase	43.09
6	enginesize	28.17
10	horsepower	25.38
8	stroke	20.37
7	boreratio	19.33
4	carheight	14.92
0	symboling	10.34
11	peakrpm	9.61
9	compressionratio	3.28
14	companyname_bmw	1.30

There are variables with very high VIF. We check the VIF along with their p value. In the first case highwaympg has the highest VIF and p-value. So, drop highwaympg.

In [33]:
```
col = col.drop('highwaympg', 1)
col
```

Out[33]:
```
Index(['symboling', 'wheelbase', 'carlength', 'carwidth', 'carheight',
       'curbweight', 'enginesize', 'boreratio', 'stroke', 'compressionratio',
       'horsepower', 'peakrpm', 'citympg', 'companyname_bmw'],
      dtype='object')
```

Updating the model after dropping features

In [34]:
```
#Building the third model
X_train_mlr_1 = sm.add_constant(X_train[col])
mlr_3 = sm.OLS(Y_train, X_train_mlr_1).fit()
mlr_3.summary()
```

Out[34]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.892
Model:	OLS	**Adj. R-squared:**	0.880
Method:	Least Squares	**F-statistic:**	75.69
Date:	Mon, 16 May 2022	**Prob (F-statistic):**	8.05e-55
Time:	16:14:39	**Log-Likelihood:**	191.52
No. Observations:	143	**AIC:**	-353.0

Df Residuals:	128	**BIC:**	-308.6
Df Model:	14		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.1712	0.074	-2.316	0.022	-0.317	-0.025
symboling	0.0374	0.033	1.142	0.255	-0.027	0.102
wheelbase	-0.0105	0.094	-0.112	0.911	-0.196	0.175
carlength	-0.1722	0.093	-1.843	0.068	-0.357	0.013
carwidth	0.3002	0.078	3.853	0.000	0.146	0.454
carheight	0.0163	0.042	0.384	0.702	-0.068	0.100
curbweight	0.3525	0.113	3.110	0.002	0.128	0.577
enginesize	0.4710	0.104	4.539	0.000	0.266	0.676
boreratio	-0.0265	0.045	-0.586	0.559	-0.116	0.063
stroke	-0.0944	0.044	-2.135	0.035	-0.182	-0.007
compressionratio	0.0911	0.036	2.546	0.012	0.020	0.162
horsepower	0.0971	0.099	0.985	0.326	-0.098	0.292
peakrpm	0.1254	0.042	2.972	0.004	0.042	0.209
citympg	-0.0045	0.076	-0.059	0.953	-0.156	0.147
companyname_bmw	0.2307	0.031	7.442	0.000	0.169	0.292

Omnibus:	25.870	**Durbin-Watson:**	2.118
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	54.922
Skew:	0.768	**Prob(JB):**	1.19e-12
Kurtosis:	5.619	**Cond. No.**	47.6

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

In [35]:
```
#Checking the VIFs again
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[35]:

	Features	VIF

	Features	VIF
5	curbweight	81.06
2	carlength	69.91
3	carwidth	47.74
1	wheelbase	41.89
6	enginesize	27.73
10	horsepower	24.19
8	stroke	18.59
7	boreratio	18.54
4	carheight	14.91
12	citympg	11.85
0	symboling	10.31
11	peakrpm	9.61
9	compressionratio	3.28
13	companyname_bmw	1.28

Though curbweight has very high VIF, their p-value is closer to zero. Hence we go for the next feature with high VIF and p-value ie carlength

In [36]:
```
col = col.drop('carlength', 1)
col
```

Out[36]:
```
Index(['symboling', 'wheelbase', 'carwidth', 'carheight', 'curbweight',
       'enginesize', 'boreratio', 'stroke', 'compressionratio', 'horsepower',
       'peakrpm', 'citympg', 'companyname_bmw'],
      dtype='object')
```

Updating the model after dropping features

In [37]:
```
#Building the fourth model
X_train_mlr_1 = sm.add_constant(X_train[col])
mlr_4 = sm.OLS(Y_train, X_train_mlr_1).fit()
mlr_4.summary()
```

Out[37]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.889
Model:	OLS	**Adj. R-squared:**	0.878
Method:	Least Squares	**F-statistic:**	79.77
Date:	Mon, 16 May 2022	**Prob (F-statistic):**	4.62e-55
Time:	16:17:23	**Log-Likelihood:**	189.65
No. Observations:	143	**AIC:**	-351.3
Df Residuals:	129	**BIC:**	-309.8

Df Model:	13
Covariance Type:	nonrobust

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.2046	0.072	-2.830	0.005	-0.348	-0.062
symboling	0.0406	0.033	1.229	0.221	-0.025	0.106
wheelbase	-0.0690	0.089	-0.776	0.439	-0.245	0.107
carwidth	0.2689	0.077	3.503	0.001	0.117	0.421
carheight	-0.0013	0.042	-0.032	0.975	-0.084	0.081
curbweight	0.3156	0.113	2.803	0.006	0.093	0.538
enginesize	0.4576	0.104	4.381	0.000	0.251	0.664
boreratio	-0.0433	0.045	-0.967	0.335	-0.132	0.045
stroke	-0.0966	0.045	-2.165	0.032	-0.185	-0.008
compressionratio	0.0904	0.036	2.505	0.014	0.019	0.162
horsepower	0.1240	0.098	1.261	0.210	-0.071	0.319
peakrpm	0.1264	0.043	2.969	0.004	0.042	0.211
citympg	0.0372	0.074	0.505	0.615	-0.109	0.183
companyname_bmw	0.2262	0.031	7.255	0.000	0.165	0.288

Omnibus:	22.988	**Durbin-Watson:**	2.099
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	45.608
Skew:	0.706	**Prob(JB):**	1.25e-10
Kurtosis:	5.380	**Cond. No.**	45.6

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

In [38]:
```
#Checking the VIFs again
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[38]:

	Features	VIF
4	curbweight	75.92
2	carwidth	45.35

	Features	VIF
1	wheelbase	37.18
5	enginesize	27.68
9	horsepower	23.78
7	stroke	18.32
6	boreratio	16.50
3	carheight	13.67
11	citympg	11.49
0	symboling	10.27
10	peakrpm	9.53
8	compressionratio	3.25
12	companyname_bmw	1.26

Though curbweight and carwidth has high VIF, they have low p value. Dropping next feature with high VIF and p-value,ie wheelbase

In [39]:
```
col = col.drop('wheelbase', 1)
col
```

Out[39]:
```
Index(['symboling', 'carwidth', 'carheight', 'curbweight', 'enginesize',
       'boreratio', 'stroke', 'compressionratio', 'horsepower', 'peakrpm',
       'citympg', 'companyname_bmw'],
      dtype='object')
```

Updating the model after dropping features

In [40]:
```
#Building the fifth model
X_train_mlr_1 = sm.add_constant(X_train[col])
mlr_5 = sm.OLS(Y_train, X_train_mlr_1).fit()
mlr_5.summary()
```

Out[40]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.889
Model:	OLS	**Adj. R-squared:**	0.879
Method:	Least Squares	**F-statistic:**	86.63
Date:	Mon, 16 May 2022	**Prob (F-statistic):**	6.53e-56
Time:	16:19:46	**Log-Likelihood:**	189.32
No. Observations:	143	**AIC:**	-352.6
Df Residuals:	130	**BIC:**	-314.1
Df Model:	12		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.2061	0.072	-2.856	0.005	-0.349	-0.063
symboling	0.0505	0.030	1.660	0.099	-0.010	0.111
carwidth	0.2396	0.067	3.589	0.000	0.108	0.372
carheight	-0.0087	0.041	-0.215	0.830	-0.089	0.072
curbweight	0.2807	0.103	2.723	0.007	0.077	0.485
enginesize	0.4618	0.104	4.433	0.000	0.256	0.668
boreratio	-0.0446	0.045	-1.000	0.319	-0.133	0.044
stroke	-0.1005	0.044	-2.272	0.025	-0.188	-0.013
compressionratio	0.0915	0.036	2.541	0.012	0.020	0.163
horsepower	0.1512	0.092	1.648	0.102	-0.030	0.333
peakrpm	0.1232	0.042	2.911	0.004	0.039	0.207
citympg	0.0381	0.074	0.518	0.605	-0.107	0.184
companyname_bmw	0.2206	0.030	7.287	0.000	0.161	0.280

Omnibus:	22.484	**Durbin-Watson:**	2.127
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	45.385
Skew:	0.683	**Prob(JB):**	1.40e-10
Kurtosis:	5.398	**Cond. No.**	43.6

Notes:

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

In [41]:

```
#Checking the VIFs again
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[41]:

	Features	VIF
3	curbweight	62.08
1	carwidth	34.35
4	enginesize	27.60
8	horsepower	20.77
6	stroke	18.00
5	boreratio	16.44

	Features	VIF
2	carheight	12.86
10	citympg	11.49
9	peakrpm	9.40
0	symboling	8.50
7	compressionratio	3.24
11	companyname_bmw	1.19

Dropping horsepower with high VIF and p-value

In [42]:
```
col = col.drop('horsepower', 1)
col
```

Out[42]:
```
Index(['symboling', 'carwidth', 'carheight', 'curbweight', 'enginesize',
       'boreratio', 'stroke', 'compressionratio', 'peakrpm', 'citympg',
       'companyname_bmw'],
      dtype='object')
```

Updating model after dropping features

In [43]:
```
#Building the sixth model
X_train_mlr_1 = sm.add_constant(X_train[col])
mlr_6 = sm.OLS(Y_train, X_train_mlr_1).fit()
mlr_6.summary()
```

Out[43]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.887
Model:	OLS	**Adj. R-squared:**	0.877
Method:	Least Squares	**F-statistic:**	93.04
Date:	Mon, 16 May 2022	**Prob (F-statistic):**	2.50e-56
Time:	16:21:22	**Log-Likelihood:**	187.84
No. Observations:	143	**AIC:**	-351.7
Df Residuals:	131	**BIC:**	-316.1
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.2002	0.073	-2.760	0.007	-0.344	-0.057
symboling	0.0542	0.031	1.777	0.078	-0.006	0.115
carwidth	0.2484	0.067	3.707	0.000	0.116	0.381
carheight	-0.0259	0.039	-0.655	0.513	-0.104	0.052
curbweight	0.3032	0.103	2.948	0.004	0.100	0.507

enginesize	0.5514	0.089	6.165	0.000	0.374	0.728
boreratio	-0.0383	0.045	-0.856	0.393	-0.127	0.050
stroke	-0.1117	0.044	-2.537	0.012	-0.199	-0.025
compressionratio	0.0871	0.036	2.411	0.017	0.016	0.159
peakrpm	0.1530	0.038	3.977	0.000	0.077	0.229
citympg	0.0131	0.072	0.181	0.857	-0.130	0.156
companyname_bmw	0.2229	0.030	7.323	0.000	0.163	0.283

Omnibus:	26.032	**Durbin-Watson:**	2.158
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	57.448
Skew:	0.757	**Prob(JB):**	3.35e-13
Kurtosis:	5.711	**Cond. No.**	41.8

Notes:

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

In [44]:
```
#Checking the VIFs again
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[44]:

	Features	VIF
3	curbweight	60.51
1	carwidth	34.11
4	enginesize	20.13
6	stroke	17.62
5	boreratio	16.19
2	carheight	12.03
9	citympg	10.75
0	symboling	8.40
8	peakrpm	7.16
7	compressionratio	3.21
10	companyname_bmw	1.19

Dropping boreratio with high VIF and p-value

In [45]:
```
col = col.drop('boreratio', 1)
col
```

Out[45]:
```
Index(['symboling', 'carwidth', 'carheight', 'curbweight', 'enginesize',
       'stroke', 'compressionratio', 'peakrpm', 'citympg', 'companyname_bmw'],
      dtype='object')
```

Updating model after dropping feature

In [46]:
```
#Building the seventh model
X_train_mlr_1 = sm.add_constant(X_train[col])
mlr_7 = sm.OLS(Y_train, X_train_mlr_1).fit()
mlr_7.summary()
```

Out[46]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.886
Model:	OLS	**Adj. R-squared:**	0.877
Method:	Least Squares	**F-statistic:**	102.5
Date:	Mon, 16 May 2022	**Prob (F-statistic):**	3.45e-57
Time:	16:22:22	**Log-Likelihood:**	187.44
No. Observations:	143	**AIC:**	-352.9
Df Residuals:	132	**BIC:**	-320.3
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.2294	0.064	-3.585	0.000	-0.356	-0.103
symboling	0.0530	0.030	1.740	0.084	-0.007	0.113
carwidth	0.2394	0.066	3.621	0.000	0.109	0.370
carheight	-0.0259	0.039	-0.657	0.513	-0.104	0.052
curbweight	0.3008	0.103	2.928	0.004	0.098	0.504
enginesize	0.5465	0.089	6.129	0.000	0.370	0.723
stroke	-0.0975	0.041	-2.393	0.018	-0.178	-0.017
compressionratio	0.0844	0.036	2.348	0.020	0.013	0.156
peakrpm	0.1609	0.037	4.313	0.000	0.087	0.235
citympg	0.0263	0.071	0.372	0.710	-0.113	0.166
companyname_bmw	0.2241	0.030	7.379	0.000	0.164	0.284

Omnibus:	21.888	**Durbin-Watson:**	2.136
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	42.354
Skew:	0.681	**Prob(JB):**	6.35e-10

Kurtosis:	5.292	**Cond. No.**	39.2

Notes:

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

In [47]:
```
#Checking the VIFs again
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[47]:

	Features	VIF
3	curbweight	57.23
1	carwidth	32.47
4	enginesize	20.12
5	stroke	16.52
2	carheight	11.75
8	citympg	10.12
0	symboling	7.45
7	peakrpm	7.16
6	compressionratio	3.18
9	companyname_bmw	1.19

Dropping carheight with high VIF and p-value

In [48]:
```
col = col.drop('carheight', 1)
col
```

Out[48]:
```
Index(['symboling', 'carwidth', 'curbweight', 'enginesize', 'stroke',
       'compressionratio', 'peakrpm', 'citympg', 'companyname_bmw'],
      dtype='object')
```

Updating model after dropping feature

In [49]:
```
#Building the eighth model
X_train_mlr_1 = sm.add_constant(X_train[col])
mlr_8 = sm.OLS(Y_train, X_train_mlr_1).fit()
mlr_8.summary()
```

Out[49]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.886
Model:	OLS	**Adj. R-squared:**	0.878

Method:	Least Squares	**F-statistic:**	114.3
Date:	Mon, 16 May 2022	**Prob (F-statistic):**	3.87e-58
Time:	16:23:29	**Log-Likelihood:**	187.21
No. Observations:	143	**AIC:**	-354.4
Df Residuals:	133	**BIC:**	-324.8
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.2426	0.061	-4.002	0.000	-0.362	-0.123
symboling	0.0614	0.028	2.233	0.027	0.007	0.116
carwidth	0.2375	0.066	3.603	0.000	0.107	0.368
curbweight	0.2784	0.097	2.879	0.005	0.087	0.470
enginesize	0.5729	0.079	7.211	0.000	0.416	0.730
stroke	-0.0975	0.041	-2.398	0.018	-0.178	-0.017
compressionratio	0.0860	0.036	2.399	0.018	0.015	0.157
peakrpm	0.1652	0.037	4.508	0.000	0.093	0.238
citympg	0.0199	0.070	0.285	0.776	-0.118	0.158
companyname_bmw	0.2207	0.030	7.390	0.000	0.162	0.280

Omnibus:	19.353	**Durbin-Watson:**	2.140
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	34.972
Skew:	0.627	**Prob(JB):**	2.55e-08
Kurtosis:	5.073	**Cond. No.**	35.7

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

In [50]:
```
#Checking the VIFs again
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[50]:

	Features	VIF
2	curbweight	40.98
1	carwidth	32.11

	Features	VIF
4	stroke	16.42
3	enginesize	15.12
6	peakrpm	7.13
0	symboling	6.70
7	citympg	6.43
5	compressionratio	3.04
8	companyname_bmw	1.13

Dropping citympg with high VIF and p-value

In [51]:
```
col = col.drop('citympg', 1)
col
```

Out[51]:
```
Index(['symboling', 'carwidth', 'curbweight', 'enginesize', 'stroke',
       'compressionratio', 'peakrpm', 'companyname_bmw'],
      dtype='object')
```

Updating the model after dropping features

In [52]:
```
#Building the ninth model
X_train_mlr_1 = sm.add_constant(X_train[col])
mlr_9 = sm.OLS(Y_train, X_train_mlr_1).fit()
mlr_9.summary()
```

Out[52]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.885
Model:	OLS	**Adj. R-squared:**	0.879
Method:	Least Squares	**F-statistic:**	129.5
Date:	Mon, 16 May 2022	**Prob (F-statistic):**	3.42e-59
Time:	16:25:14	**Log-Likelihood:**	187.16
No. Observations:	143	**AIC:**	-356.3
Df Residuals:	134	**BIC:**	-329.7
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.2279	0.032	-7.174	0.000	-0.291	-0.165
symboling	0.0591	0.026	2.260	0.025	0.007	0.111
carwidth	0.2356	0.065	3.605	0.000	0.106	0.365
curbweight	0.2606	0.074	3.541	0.001	0.115	0.406
enginesize	0.5781	0.077	7.507	0.000	0.426	0.730

stroke	-0.0970	0.040	-2.396	0.018	-0.177	-0.017
compressionratio	0.0919	0.029	3.166	0.002	0.034	0.149
peakrpm	0.1626	0.035	4.595	0.000	0.093	0.233
companyname_bmw	0.2197	0.030	7.436	0.000	0.161	0.278

Omnibus:	19.081	**Durbin-Watson:**	2.144
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	33.786
Skew:	0.626	**Prob(JB):**	4.61e-08
Kurtosis:	5.025	**Cond. No.**	26.8

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

In [53]:
```
#Checking the VIFs again
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[53]:

	Features	VIF
2	curbweight	35.63
1	carwidth	31.56
3	enginesize	15.09
4	stroke	12.60
6	peakrpm	6.98
0	symboling	6.34
5	compressionratio	2.36
7	companyname_bmw	1.13

Since p-values are all in range, we will be making predictions in this training set

Residual Analysis

To check if the error terms are normally distributed.

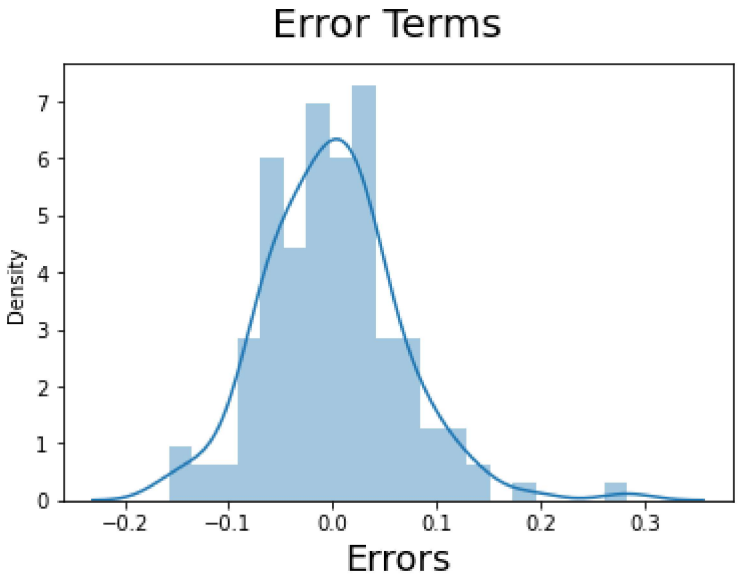
In [54]:
```
Y_train_price = mlr_9.predict(X_train_mlr_1)
```

In [56]:
```
Y_train_price.head()
```

Out[56]:
```
122    0.077896
125    0.370946
166    0.172796
1      0.203226
199    0.254713
dtype: float64
```

In [57]:
```
#Plotting the histogram of the error terms
fig = plt.figure()
sns.distplot((Y_train - Y_train_price), bins = 20)
fig.suptitle('Error Terms', fontsize = 20)                  # Plot heading
plt.xlabel('Errors', fontsize = 18)                         # X-label
```

Out[57]:
```
Text(0.5, 0, 'Errors')
```



Making Predictions based on Model

In [58]:
```
x_test_try = sm.add_constant(X_test[col])
```

In [59]:
```
y_prediction = mlr_9.predict(x_test_try)
```

In [60]:
```
y_prediction.head()
```

Out[60]:
```
160    0.028528
186    0.128824
59     0.144415
165    0.169258
140    0.066687
dtype: float64
```

Predicted Values

In [70]:
```
pred_df=pd.DataFrame({'Actual Value':Y_test,'Predicted Value':y_prediction,'Difference'
pred_df.head()
```

Out[70]:

	Actual Value	Predicted Value	Difference
160	0.065041	0.028528	0.036513
186	0.083834	0.128824	-0.044990
59	0.092523	0.144415	-0.051892
165	0.103768	0.169258	-0.065489
140	0.061690	0.066687	-0.004997

Model Evaluation

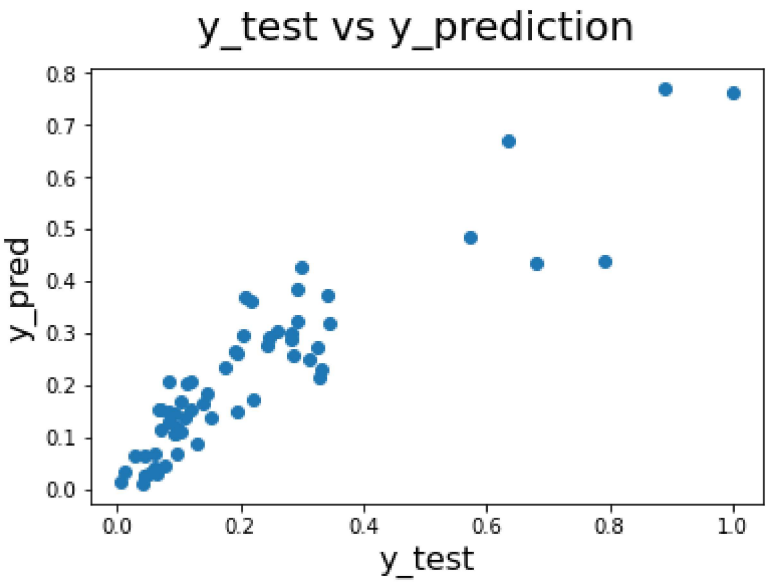
In [71]:
```
#Checking the accuracy of the test data
from sklearn.metrics import r2_score
score = r2_score(Y_test,y_prediction)
score
```

Out[71]: 0.821939463293434

Plotting results

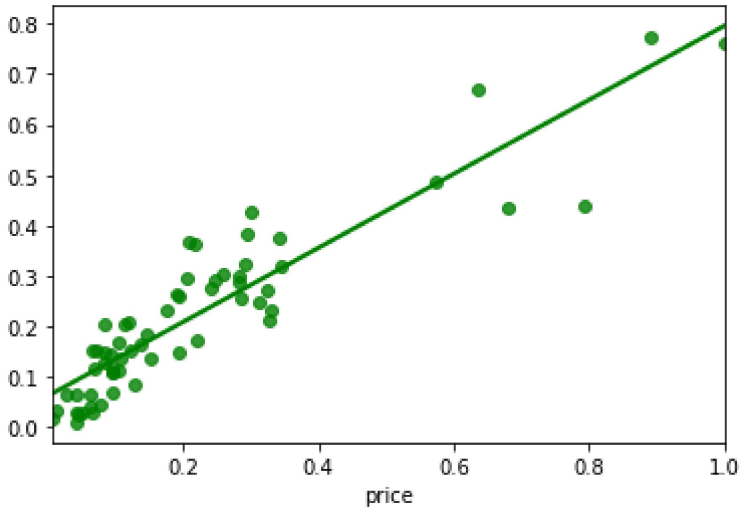
In [72]:
```
#Plotting the graph between actual price vs predicted values
fig = plt.figure()
plt.scatter(Y_test, y_prediction)
fig.suptitle('y_test vs y_prediction', fontsize = 20) # Plot heading
plt.xlabel('y_test', fontsize = 16) # X-Label
plt.ylabel('y_pred', fontsize = 16)  # Y-Label
```

Out[72]: Text(0, 0.5, 'y_pred')



In [73]:
```
#Plotting the regression line
sns.regplot(x=Y_test,y=y_prediction,ci=None,color ='green')
```

Out[73]: <AxesSubplot:xlabel='price'>



Therefore the model is built with important features that helps in predicting the price of a car and the accuracy of the test data set is found to be 82.19%

The equation of the best fitted line is: price = -0.2279 + 0.0591*symboling* + *0.2356*carwidth + 0.2606*curbweight* + *0.5781*enginesize - 0.0970*stroke* + *0.0919*compressionratio + 0.1626*peakrpm* + *0.2197*companyname_bmw