Project Name: Car Price Prediction

Mentor: Ms. Pooja Gupta

Submitted by: Mr. Deepesh Singh Suryavanshi

Hypothesis

Cars are being sold more than ever. Developing countries adopt the lease culture instead of buying a new car due to affordability. Therefore, the rise of used cars sales is exponentially increasing. Car sellers sometimes take advantage of this scenario by listing unrealistic prices owing to the demand. Therefore, arises a need for a model that can assign a price for a vehicle by evaluating its features taking the prices of other cars into consideration. In this paper, we use supervised learning method namely Random Forest to predict the prices of used cars. The model has been chosen after careful exploratory data analysis to determine the impact of each feature on price. A Random Forest was created to train the data. From experimental results, the linear regression accuracy was found out to be 64.377%, and the random forest accuracy was 70.437%. The model can predict the price of cars accurately by choosing the most correlated features.

Introduction

The prices of cars in the industry is fixed by the manufacturer with some additional costs incurred by the Government in the form of taxes. Therefore, customers buying a new car can be assured of the money they invest to be worthy. But due to the increased price of new cars and the incapability of customers to buy new cars due to the lack of funds, used cars sales are on a global increase.

Predicting the prices of cars is an interesting and much-needed problem to be addressed. Customers can be widely exploited by fixing unrealistic prices for the used cars and many falls into this trap. Therefore, rises an absolute necessity of a car price prediction system to effectively determine the worthiness of the car using a variety of features.

Due to the adverse pricing of cars and the nomadic nature of people in developed countries, the cars are mostly bought on a lease basis, where there is an agreement between the buyer and seller. These cars upon completion of the agreement are resold. Therefore, reselling has become an essential part of today's world.

Given the description of cars, the prediction of cars is not an easy task. There are a variety of features of a car like the age of the car, its make, the origin of the car (the original country of the manufacturer), its mileage (the number of kilometers it has run) and its horsepower. Due to rising fuel prices, fuel economy is also of prime importance. Other factors such as the type of fuel it uses, style, braking system, the volume of its cylinders (measured in cc), acceleration, the number of doors, safety index, size, weight, height, paint color, consumer reviews, prestigious awards won by the car manufacturer. Other options such as sound system, air conditioner, power steering, cosmic wheels, GPS navigator all may influence the price as well.

Project Data Introduction

This project is based on Predictive Analysis. This is a Python-based Project. This project was created via Spyder 3.3.5. IDE (Integrated Development Environment) using Python 3.7.3 and I python Console 7.4.0. The final outcome of this project is saved as a Jupyter Notebook v7.8.0. The libraries of python used in this project are:

1. NumPy
2. Pandas
3. Matplotlib
4. Seaborn
5. Statsmodels
6. Sci-kit Learn

This project is based on a data set provided by the teachers via GITHUB. The data used in the project is continuous, and hence, we are using LINEAR REGRESSION and RANDOM FOREST REGRESSION for predicting our data.

Here, the target variable is PRICE.

Data Set Dictionary:

Name of Column	Description	Type
Car_ID	Unique id of each observation	Numeric
Symboling	Its assigned insurance risk rating, A value of +3 indicates that the auto is risky, -3 that it is probably pretty safe.	Categorical
Company	Name of car company	Categorical
Fuel Type	Car fuel type i.e gas or diesel	Categorical
Aspiration	Aspiration used in a car	Categorical
Door Number	No of doors in a car	Categorical
Column Name	Description	Type
Car Body	Body of the car	Categorical
Drive wheel	Type of Drive Wheel	Categorical
Engine Location	Location of car engine	Categorical
Wheel Base	Wheel Base of the car	Categorical

Car Length	Length of car	Numeric
Car Width	Width of car	Numeric
Car Height	Height of car	Numeric
Car Volume	Volume of Car	Numeric
Curbweight	The weight of a car without occupants	Numeric
Engine Type	Type of engine in the car	Categorical
Cylinder Number	No of cylinders in the car	Categorical
Engine Size	Size of engine in the car	Numeric
Fuel System	Fuel system of car	Categorical
Bore Ratio	Bore ratio of the car	Numeric
Stroke	Stroke or volume inside the engine	Numeric
Compression Ratio	Compression Ratio of car	Numeric
Horse Power	Horse power of the car	Numeric
Peak RPM	Peak rpm of the car	Numeric
City MPG	City mpg of the car	Numeric

Highway MPG	Highway mpg of the car	Numeric
Fuel Economy	Fuel economy of the car	Numeric
Cars Range	Car Category	Categorical
Price (Dependent Variable)	Price of the car	Numeric

Data Set Size: 206 rows, 29 columns

Categorical Variables: [Company, carsrange, Symboling, fueltype, enginetype, carbody, doornumber, enginelocation, fuelsystem, cylindernumber, aspiration, drivewheel] = 12 features

Numeric Variables: [Car_ID, carlength, carwidth, carheight, carvolume, curbweight, Horsepower, Bore Ratio, Compression Ratio, Highway miles per gallon (mpg), Engine Size, Stroke, City Miles per gallon (mpg), Fuel economy, Peak Revolutions per Minute (rpm), Wheel Base, Price] = 17 Features

Exploratory Data Analysis (EDA)

In statistics, exploratory data analysis (EDA) is an approach to analysing data sets to summarize their main characteristics, often with visual methods. A statistical model can be used or not, but primarily EDA is for seeing what the data can tell us beyond the formal modeling or hypothesis testing task. Exploratory data analysis was promoted by many to encourage statisticians to explore the data, and possibly formulate hypotheses that could lead to new data collection and experiments. EDA is different from initial data analysis (IDA), which focuses more narrowly on checking assumptions required for model fitting and hypothesis testing, and handling missing values and making transformations of variables as needed. EDA encompasses IDA.

In this project, we used matplotlib, seaborn for EDA using python 3.7.3. It is as follows:

Firstly, I imported all the libraries initially required for EDA. Then, I imported the file saved in the repository link and displayed its data. Then, I used the describe() function to study the summary of the data(min, max, no of values etc.)

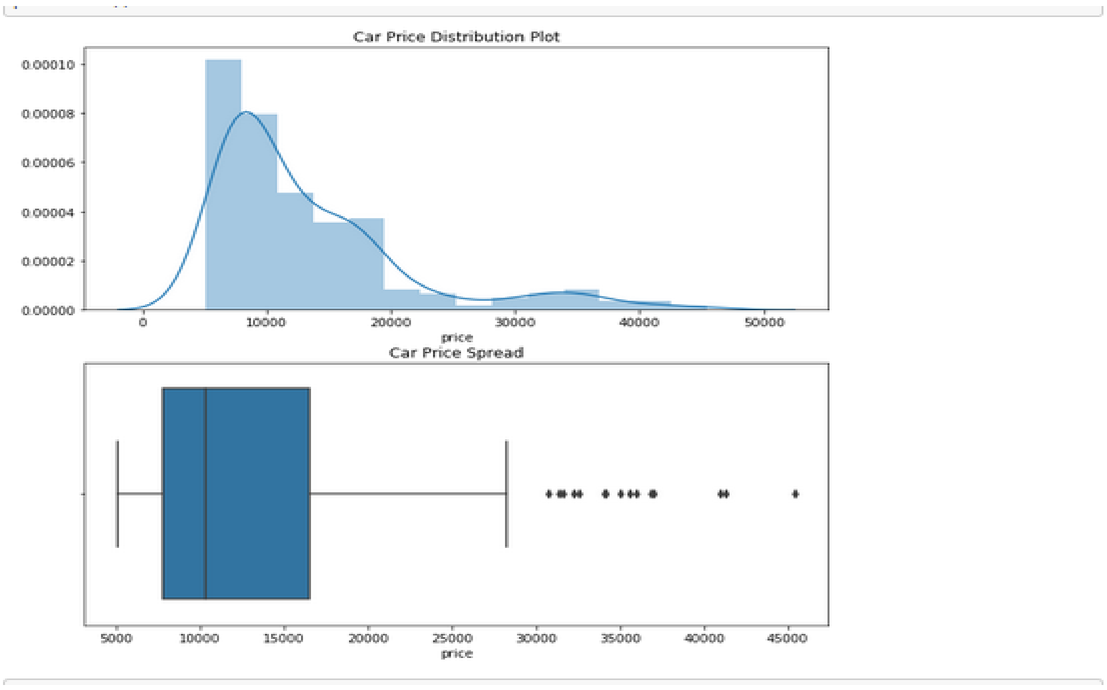
Data Cleaning, as the name suggests, is to clean the data of any irregularities. By performing this step, we prepare our data for analysis. For this, we check for any spelling errors, empty values and duplicate values. Now, we will check the columns created. Once this is done, we will move on to correcting the misspelled values.

Now, we can see that there are no duplicate values in our dataframe. Our data is officially clean. It’s time for the final step of EDA: Visualization.

Visualization

Visualization refers to the term that gives a picture to our information. We can describe our data by drawing graphs and charts to check different parameters that, in the end, might help us choose features for our analysis.In python, we use matplotlib and seaborn for visualization. These two libraries are efficient enough to give us an output that gives us an idea about our data set. The source code and output are :

```
plt.figure(figsize=(10,10)) #plot size according to scale 1 unit=72 pixels

plt.subplot(2,1,1) #2 rows, 1 column and index=1

plt.title('Car Price Distribution Plot') #title for the chart

sns.distplot(cars_data['price']) #distplot for price of cars


plt.subplot(2,1,2)

plt.title('Car Price Spread')

sns.boxplot(cars_data['price']) #distribution of price in the data

plt.show()
```



The distribution plot appears to be right-skewed. It means that most of the values in the dataframe are low, compared to the maximum value. Also, the data points are spread out far from the mean, which means that the data has high variance.

Now, we need to visualize our features to select the most significant of them for our analysis for better results. Hence, let’s first visualize the categorical variables.

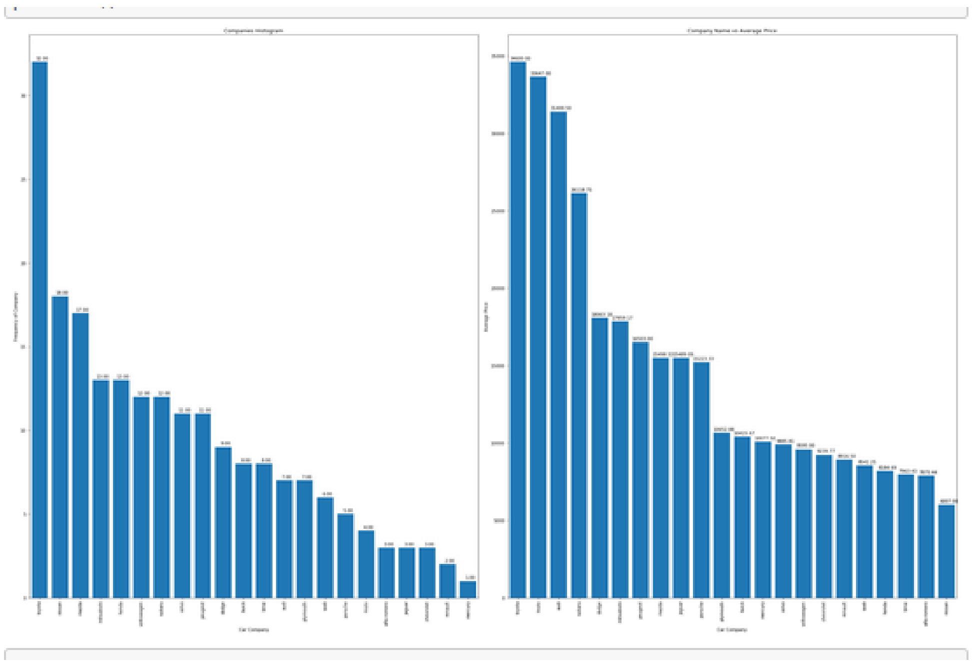
Categorical Variables: [Company, carsrange, Symboling, fueltype, enginetype, carbody, doornumber, enginelocation, fuelsystem, cylindernumber, aspiration, drivewheel] = 12 features

Car Company

First, lets check how many cars we have from each company. Then, we'll check the average price range for each company. Car companies are one of the most important feature while purchasing a car. The source code and output are:

```
plt.figure(figsize=(30, 20))


#plot 1


plt.subplot(1,2,1)
plt1 = cars_data['Company'].value_counts().plot('bar')
plt.title('Companies Histogram')
plt1.set(xlabel = 'Car Company', ylabel='Frequency of Company')


xs=cars_data['Company'].unique()
ys=cars_data['Company'].value_counts()
plt.bar(xs,ys)


for x,y in zip(xs,ys):
    label = "{:.2f}".format(y)
    plt.annotate(label,(x,y), textcoords="offset points",xytext=(5,5),ha='center')
plt.xticks(xs)


#plot 2
```

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

company_vs_price                                                          =
pd.DataFrame(cars_data.groupby(['Company'])['price'].mean().sort_values(ascending    =
False))

plt2=company_vs_price.index.value_counts().plot('bar')

plt.title('Company Name vs Average Price')

plt2.set(xlabel='Car Company', ylabel='Average Price')


xs=company_vs_price.index

ys=company_vs_price['price'].round(2)

plt.bar(xs,ys)


for x,y in zip(xs,ys):

    label = "{:.2f}".format(y)

    plt.annotate(label,(x,y), textcoords="offset points",xytext=(5,5),ha='center')

plt.xticks(xs)

plt.tight_layout()

plt.show()
```



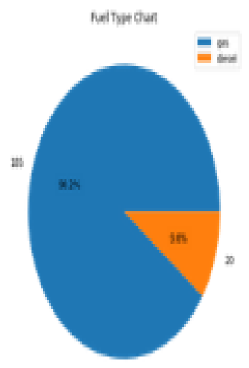
Toyota seems to be the most favored Company. Also, coincidentally, Toyota's average car price is highest as well.

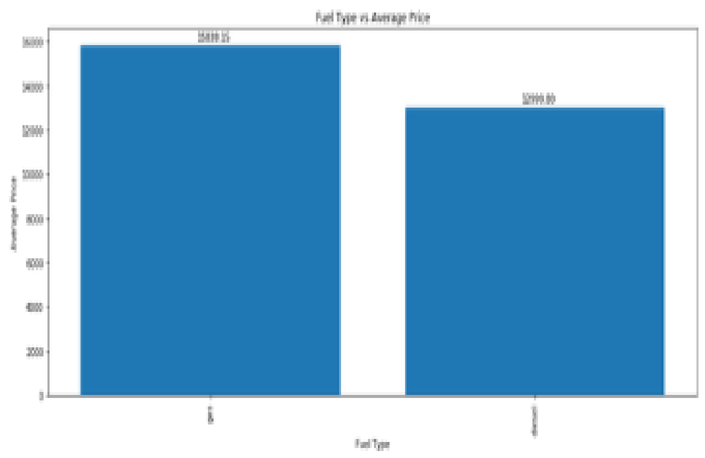
Fuel Type

Now, lets check which fuel type cars are preferred more, gas (petrol) or diesel. It is another important feature while purchasing a car. The source code and output are:

```
plt.figure(figsize=(25, 6))

#plot 1
plt.subplot(1,2,1)
plt.title('Fuel Type Chart')
labels=cars_data['fueltype'].unique()
plt3 = cars_data['fueltype'].value_counts().tolist()
plt.pie(plt3,labels=plt3, autopct='%1.1f%%')
plt.legend(labels)

#plot 2
plt.subplot(1,2,2)
fuel_vs_price =
pd.DataFrame(cars_data.groupby(['fueltype'])['price'].mean().sort_values(ascending =
False))
plt4=fuel_vs_price.index.value_counts().plot('bar')
plt.title('Fuel Type vs Average Price')
plt4.set(xlabel='Fuel Type', ylabel='Average Price')
xs=fuel_vs_price.index
ys=fuel_vs_price['price'].round(2)
```

```
plt.bar(xs,ys)
for x,y in zip(xs,ys):
    label = "{:.2f}".format(y)
    plt.annotate(label,(x,y), textcoords="offset points",xytext=(5,5),ha='center')
plt.xticks(xs)
plt.tight_layout()
plt.show()
```





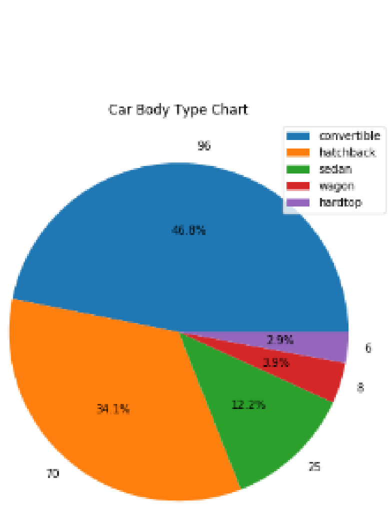
From the pie chart, we can see that gas cars more than diesel cars and subsequently, they cost more as well.

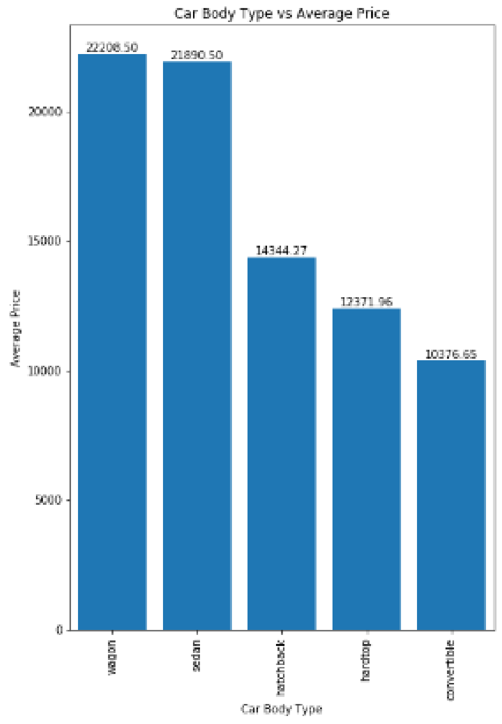
Car Body Type

There are different types of car bodies, all made for different purposes. Hence, it is important to know their distribution as well. So, let’s check which car body is most common in the data . The source code and output are:

```
plt.figure(figsize=(15,10))

#plot 1

plt.subplot(1,2,1)
plt.title('Car Body Type Chart')
labels=cars_data['carbody'].unique()
plt5 = cars_data['carbody'].value_counts().tolist()
plt.pie(plt5, labels=plt5, autopct='%1.1f%%')
plt.legend(labels, loc=1)

#plot 2

plt.subplot(1,2,2)
car_vs_price = pd.DataFrame(cars_data.groupby(['carbody'])['price'].mean().sort_values(ascending = False))
plt6=car_vs_price.index.value_counts().plot('bar')
plt.title('Car Body Type vs Average Price')
```

```
plt6.set(xlabel='Car Body Type', ylabel='Average Price')


xs=car_vs_price.index
ys=car_vs_price['price'].round(2)
plt.bar(xs,ys)


for x,y in zip(xs,ys):
    label = "{:.2f}".format(y)
    plt.annotate(label,(x,y), textcoords="offset points",xytext=(0,2),ha='center')
plt.xticks(xs)
plt.show()
```



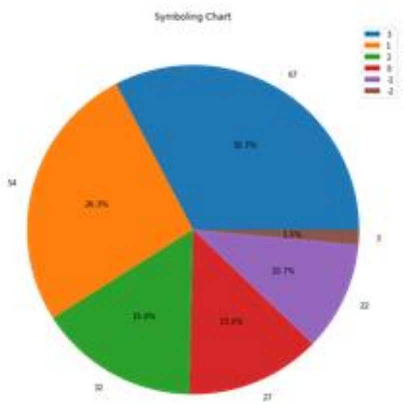


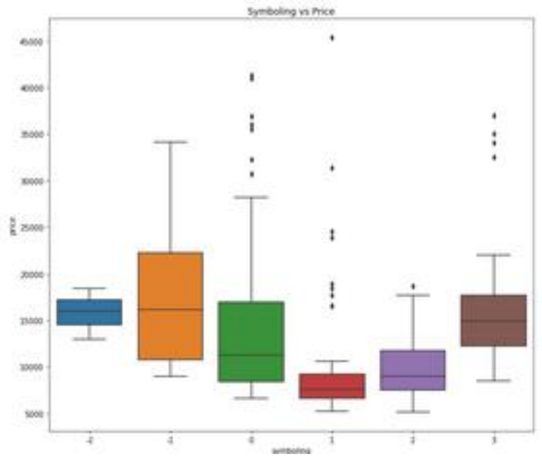
Clearly, the cars with car body convertible are more in the data. But, we have wagon cars having a higher price range.

Symboling

Symboling is a numerical value that describes our car’s insurance risk rating. Insurance is a must whenever you purchase a new asset, either for personal use or professional use. Hence, lets check what symboling has to offer. The code and output are:

```
plt.figure(figsize=(25,10))

#plot 1

plt.subplot(1,2,1)

plt.title('Symboling Chart')

labels=cars_data['symboling'].unique()

plt7 = cars_data['symboling'].value_counts().tolist()

plt.pie(plt7, labels=plt7, autopct='%1.1f%%')

plt.legend(labels, loc=1)


#plot 2

plt.subplot(1,2,2)

plt.title('Symboling vs Price')

sns.boxplot(x=cars_data['symboling'], y=cars_data['price'])

plt.show()
```



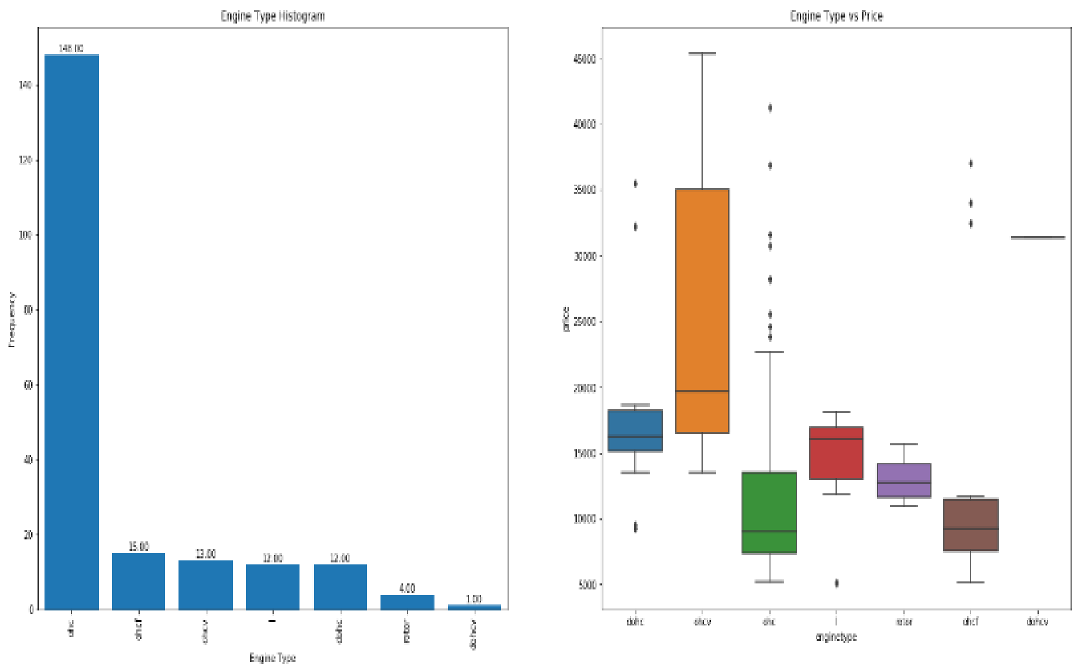


From the pie chart, it is clearly visible that symboling 3 and 1 are dominating the data. But, Cars with symboling -1 are sold at a relatively higher price than the others.

Engine Type

Engine also has a type. Hence, we need to check which engine type would be the best attribute for our car. So, lets check it out. The code and output are:

```
plt.figure(figsize=(25,10))


#plot 1

plt.subplot(1,2,1)

plt8 = cars_data['enginetype'].value_counts().plot('bar')

plt.title('Engine Type Histogram')

plt8.set(xlabel = 'Engine Type', ylabel='Frequency')

xs=cars_data['enginetype'].unique()

ys=cars_data['enginetype'].value_counts()

plt.bar(xs,ys)

for x,y in zip(xs,ys):

    label = "{:.2f}".format(y)

    plt.annotate(label,(x,y), textcoords="offset points",xytext=(0,2),ha='center')

plt.xticks(xs)


#plot 2

plt.subplot(1,2,2)

plt.title('Engine Type vs Price')

sns.boxplot(x=cars_data['enginetype'], y=cars_data['price'])

plt.show()
```



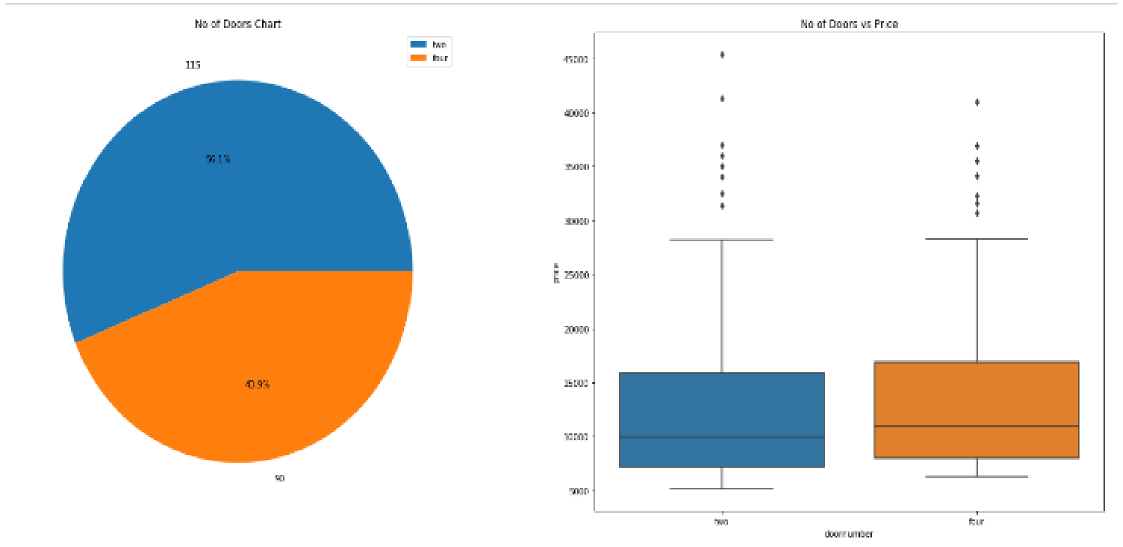
We can see that ‘ohc’ engine type is the most occurring engine type. But, ‘ohcv’ has a much higher price range, as depicted by the boxplot.

Door Number

Number of doors in the car doesn’t seem to be a very influencing factor, does it? However, for the analysis, we should leave no stone unturned. Hence, lets have a look at what the door number has to offer.

```
plt.figure(figsize=(25,10))

#plot 1

plt.subplot(1,2,1)

labels=cars_data['doornumber'].unique()
```

```
plt8 = cars_data['doornumber'].value_counts().tolist()

plt.title('No of Doors Chart')

plt.pie(plt8, labels=plt8, autopct='%1.1f%%')

plt.legend(labels, loc=1)


#plot 2

plt.subplot(1,2,2)

plt.title('No of Doors vs Price')

sns.boxplot(x=cars_data['doornumber'], y=cars_data['price'])

plt.show()
```

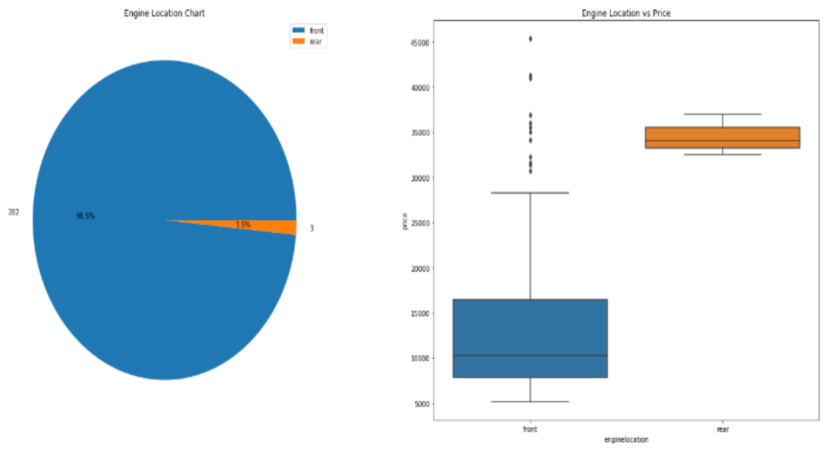


Cars with two doors are preferred over cars with four doors. However, it is not affecting the price much, as their distribution is almost the same.

Engine Location

Engine Location is a term most people would not think of, while purchasing a car. Since we are doing an analysis, we should run by it, just to be sure if it affects price at a higher rate or not. The code and output are:

```
plt.figure(figsize=(25,10))


#plot 1
plt.subplot(1,2,1)
labels=cars_data['enginelocation'].unique()
plt9 = cars_data['enginelocation'].value_counts().tolist()
plt.title('Engine Location Chart')
plt.pie(plt9, labels=plt9, autopct='%1.1f%%')
plt.legend(labels, loc=1)


#plot 2
plt.subplot(1,2,2)
plt.title('Engine Location vs Price')
sns.boxplot(x=cars_data['enginelocation'], y=cars_data['price'])
plt.show()
```



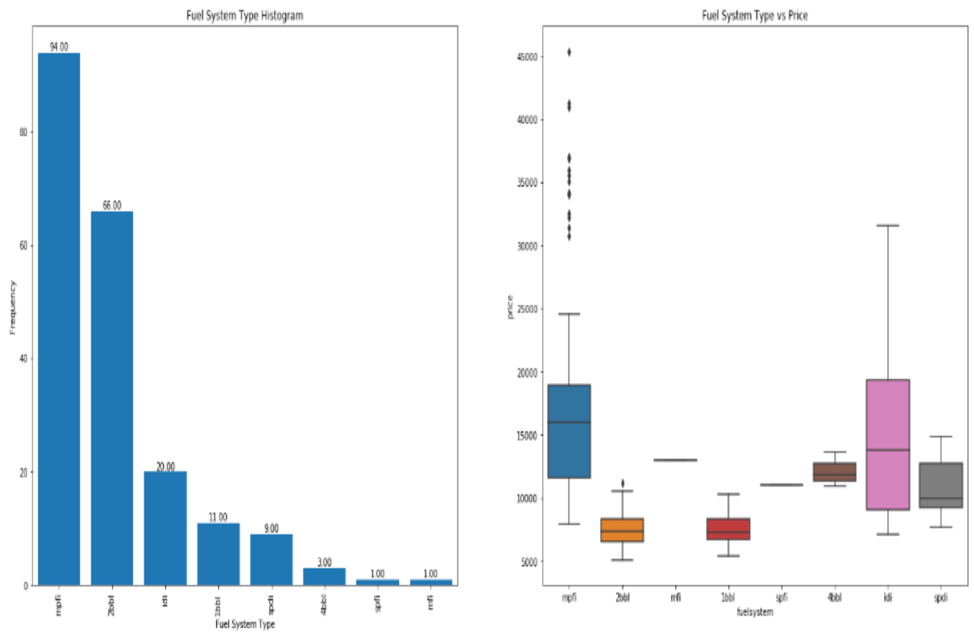
As expected, engine location is not a significant variable for price. The boxplot shows it and the pie chart shows the domination of front engines.

Fuel System

Fuel System is another technical term that most people are not aware of, when they purchase a car. But, lets check what brings to the table. The code and output are:

```
plt.figure(figsize=(25,10))


#plot 1

plt.subplot(1,2,1)

plt10 = cars_data['fuelsystem'].value_counts().plot('bar')

plt.title('Fuel System Type Histogram')

plt10.set(xlabel = 'Fuel System Type', ylabel='Frequency')

xs=cars_data['fuelsystem'].unique()

ys=cars_data['fuelsystem'].value_counts()

plt.bar(xs,ys)
```

```
for x,y in zip(xs,ys):
    label = "{:.2f}".format(y)
    plt.annotate(label,(x,y), textcoords="offset points",xytext=(0,2),ha='center')
plt.xticks(xs)


#plot 2
plt.subplot(1,2,2)
plt.title('Fuel System Type vs Price')
sns.boxplot(x=cars_data['fuelsystem'], y=cars_data['price'])
plt.show()
```



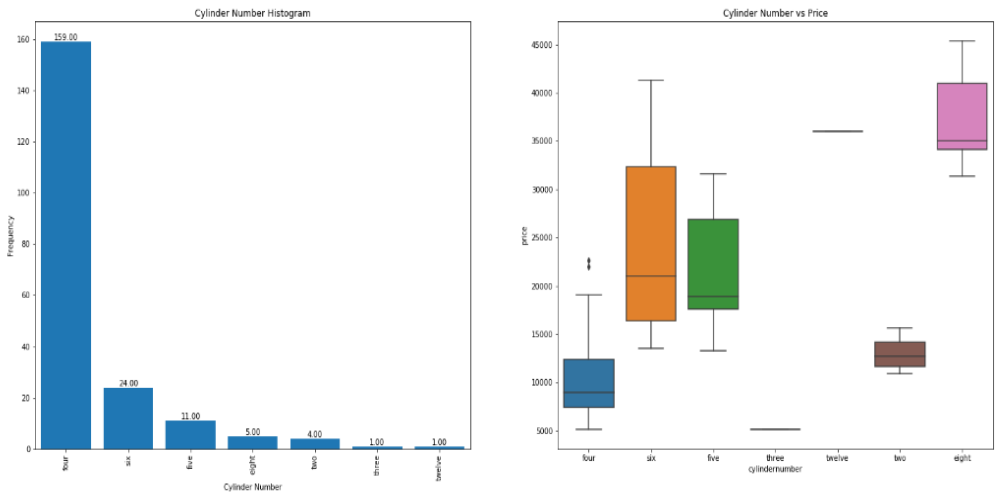
From the plots, we can say that mpfi is the most preferred fuel system. But, idi is having a high price range.

Cylinder Number

Number of cylinders can be another important factor, because it increases the power of the car, its stroke and bore ratio respectively. A car can have upto 12 cylinders ! So, let's check what our data tells us. The code and output are:

```
plt.figure(figsize=(25,10))


#plot 1
plt.subplot(1,2,1)
plt11 = cars_data['cylindernumber'].value_counts().plot('bar')
plt.title('Cylinder Number Histogram')
plt11.set(xlabel = 'Cylinder Number', ylabel='Frequency')
xs=cars_data['cylindernumber'].unique()
ys=cars_data['cylindernumber'].value_counts()
plt.bar(xs,ys)
for x,y in zip(xs,ys):
    label = "{:.2f}".format(y)
    plt.annotate(label,(x,y), textcoords="offset points",xytext=(0,2),ha='center')
plt.xticks(xs)


#plot 2
plt.subplot(1,2,2)
plt.title('Cylinder Number vs Price')
sns.boxplot(x=cars_data['cylindernumber'], y=cars_data['price'])
```

```
plt.show()
```

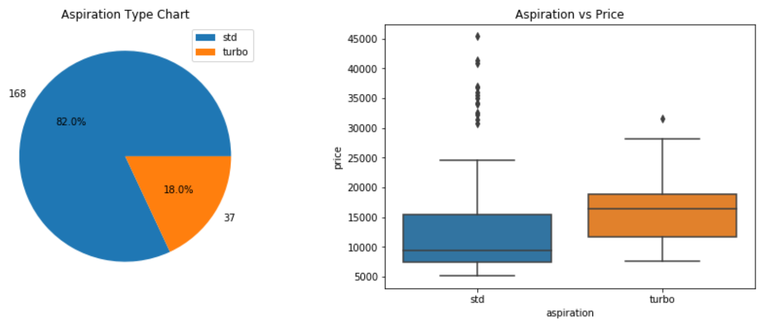


From the plots, we can infer that cars with four cylinders are the most favorable ones. Though, cars with eight cylinders have the highest car range.

Aspiration

Aspiration is another one of those features that people don’t know about. Still, we need to check for aspiration as well. Remember, leave no stone unturned ! The code and output are:

```
plt.figure(figsize=(15,5))


#plot 1

plt.subplot(1,2,1)

labels=cars_data['aspiration'].unique()

plt12 = cars_data['aspiration'].value_counts().tolist()

plt.title('Aspiration Type Chart')

plt.pie(plt12, labels=plt12, autopct='%1.1f%%')

plt.legend(labels, loc=1)


#plot 2

plt.subplot(1,2,2)

plt.title('Aspiration vs Price')

sns.boxplot(x=cars_data['aspiration'], y=cars_data['price'])

plt.show()
```

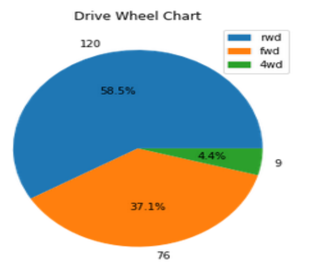


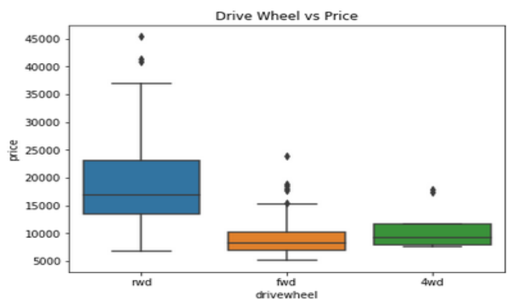
std aspiration is much more common than turbo, that is why it has been distributed better than turbo, which, in turn has higher price range.

Drivewheel

Drivewheel is another uncommon characteristic of cars that usually gets ignored when price is talked about. However, little or high, we need to check if it affects price in high rate or not. Hence, the code and output are:

```
plt.figure(figsize=(15,5))

#plot 1

plt.subplot(1,2,1)

labels=cars_data['drivewheel'].unique()

plt13 = cars_data['drivewheel'].value_counts().tolist()

plt.title('Drive Wheel Chart')

plt.pie(plt13, labels=plt13, autopct='%1.1f%%')

plt.legend(labels, loc=1)


#plot 2

plt.subplot(1,2,2)

plt.title('Drive Wheel vs Price')

sns.boxplot(x=cars_data['drivewheel'], y=cars_data['price'])

plt.show()
```





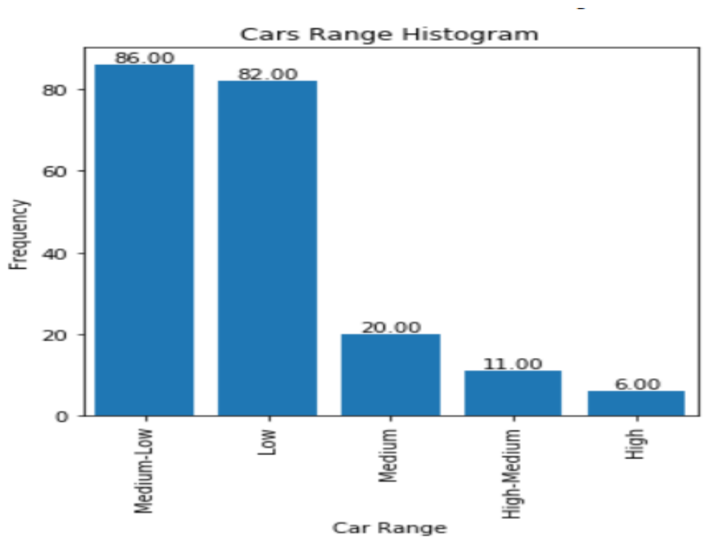
Most cars have rwd drivewheel, but it is not affecting price on a higher scale. As expected, it is not that significant variable, but can be taken for analysis.

Cars Range

This is one variable we didn’t have from the starting. Now, lets create a cars range column and check our variable. Code and Output is:

```
price=cars_data['price'].tolist()

price


carsrange=[]


for i in cars_data['price']:

    if (i>0 and i<9000): carsrange.append('Low')

    elif (i>9000 and i<18000): carsrange.append('Medium-Low')

    elif (i>18000 and i<27000): carsrange.append('Medium')

    elif(i>27000 and i<36000): carsrange.append('High-Medium')

    else : carsrange.append('High')


cars_data['carsrange']=carsrange

cars_data['carsrange'].unique()


#plot


plt.figure(figsize=(5,5))


plt14 = cars_data['carsrange'].value_counts().plot('bar')
```

```
plt.title('Cars Range Histogram')

plt14.set(xlabel = 'Car Range', ylabel='Frequency')

xs=cars_data['carsrange'].unique()

ys=cars_data['carsrange'].value_counts()

plt.bar(xs,ys)


for x,y in zip(xs,ys):

    label = "{:.2f}".format(y)

    plt.annotate(label,(x,y), textcoords="offset points",xytext=(0,2),ha='center')

plt.xticks(xs)
```



With this, our categorical visualization is complete. Now, let’s move on to the numeric data.

Numeric Variables : [Car_ID, carlength, carwidth, carheight, carvolume, curbweight, Horsepower, Bore Ratio, Compression Ratio, Highway miles per gallon (mpg), Engine Size, Stroke, City Miles per gallon (mpg), Fuel economy, Peak Revolutions per Minute (rpm), Wheel Base, Price] = 17 Features

For numeric data, we will be using scatterplot and pairplots to understand the distribution of data points better. Hence, lets make a function scatterplot to use when we need to.

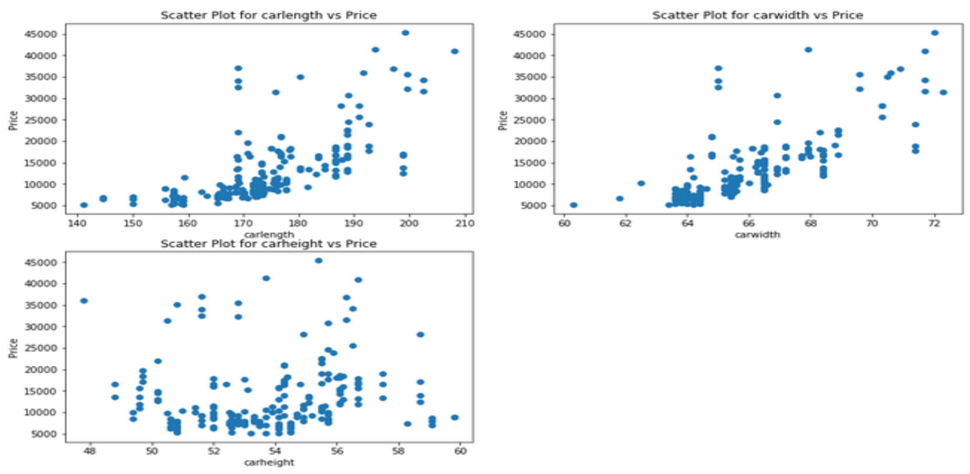
```
def scatterplot(df,var):

    plt.scatter(df[var],df['price'])
    plt.xlabel(var); plt.ylabel('Price')
    plt.title('Scatter Plot for '+var+' vs Price')
```

Now, lets make some scatterplots. Let’s start with car length, width and height.

Car Length, Width and Height

```
plt.figure(figsize=(15,20))
plt.subplot(4,2,1)
scatterplot(cars_data,'carlength')
plt.subplot(4,2,2)
scatterplot(cars_data,'carwidth')
```

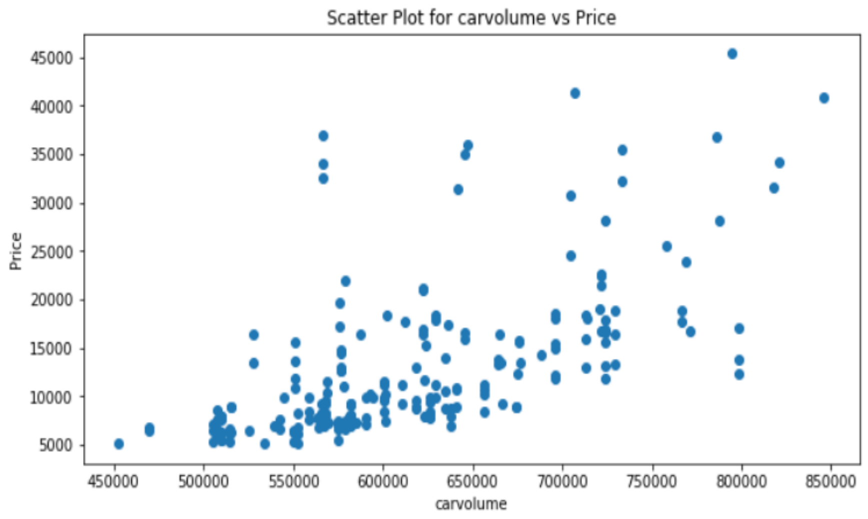
```
plt.subplot(4,2,3)

scatterplot(cars_data,'carheight')

plt.show()

plt.tight_layout()
```



Car length and width seem to have a significant trend with price, whereas car height is not that influencing on it. Now, let’s combine these to make a new variable carvolume.

Car Volume

Initially, car volume is not a part of our data. But, after studying it so much, we felt like adding it to the columns. So, let’s add car volume to our dataframe and make a scatterplot for it. The code and output are:



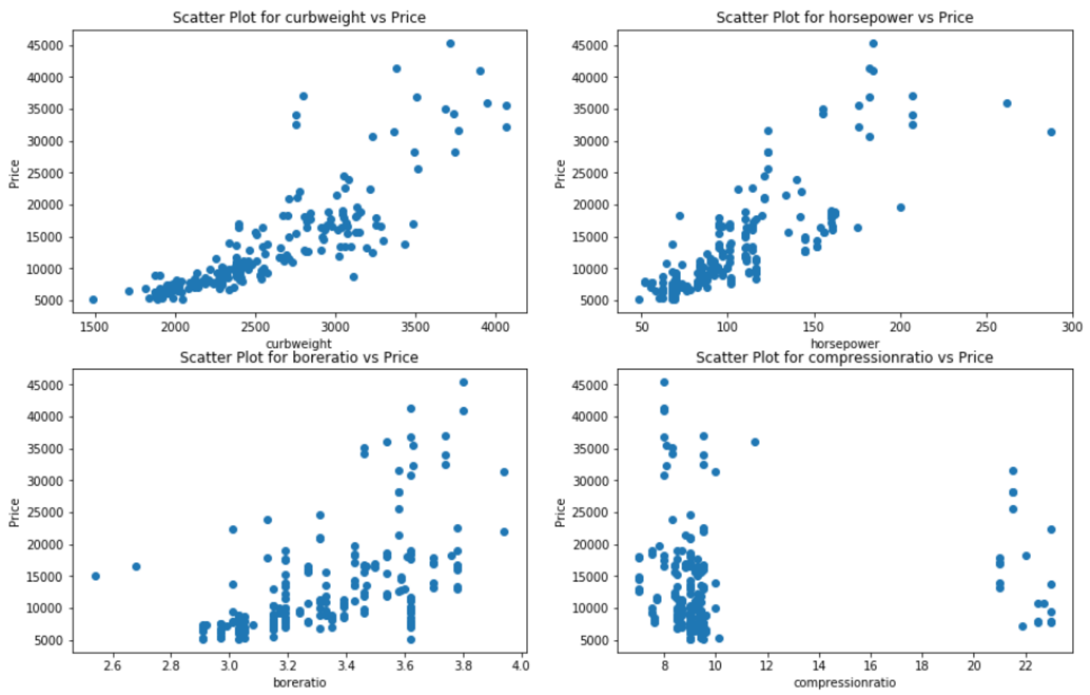
Car volume also seems to have a trend with price.

Curbweight, Horsepower, Bore ratio and Compression Ratio

All these features are significant in deciding the power of the car and as a result, its efficiency. Hence, we need to plot them as well. The code and output are:

```
plt.figure(figsize=(15,20))

plt.subplot(4,2,1)

scatterplot(cars_data,'curbweight')

plt.subplot(4,2,2)

scatterplot(cars_data,'horsepower')

plt.subplot(4,2,3)
```

```
scatterplot(cars_data,'boreratio')

plt.subplot(4,2,4)

scatterplot(cars_data,'compressionratio')

plt.show()

plt.tight_layout()
```

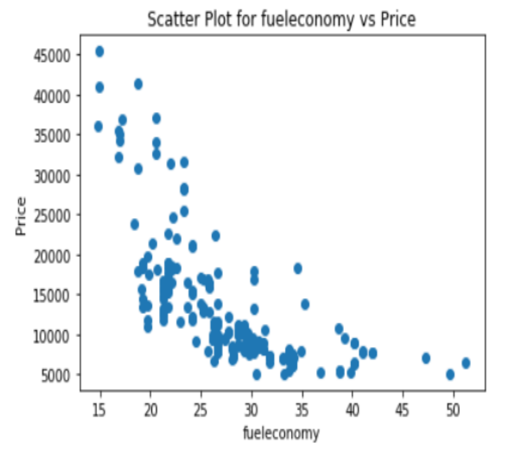


Clearly, Curb Weight, Horsepower and Bore Ratio have a significant trend with price. Compression Ratio does not affect price that much.

Fuel Economy

We did not have fuel economy as an original column. We created this column to get another important variable for our analysis. Let’s create it and plot a scatter plot for the same. The code and output are:

```
cars_data['fueleconomy']=(cars_data['citympg']*0.55)+(cars_data['highwaympg']*0.45)


cars_data['fueleconomy'].unique()

scatterplot(cars_data,'fueleconomy')
```

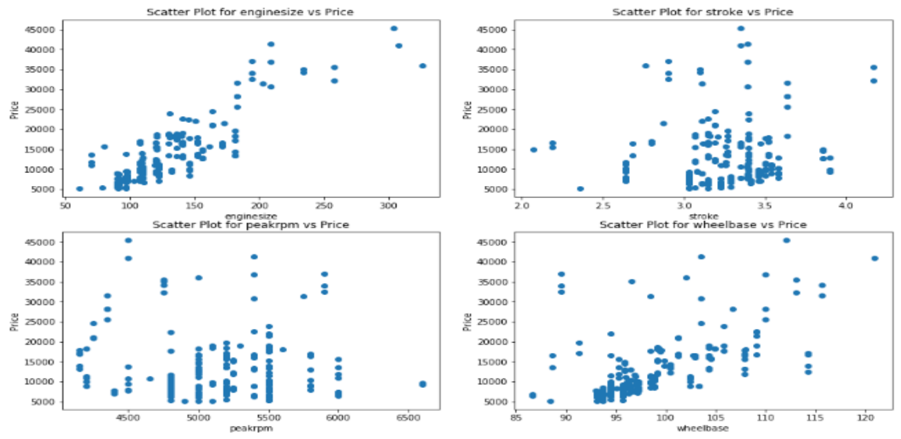


Fuel economy has a nice trend with price. Looks like we did the right thing to include it to our columns.

Engine Size, Stroke, RPM and Wheel Base

Lets wind up our numeric visualization with the last remaining 4 variables. We need to see if they influence price in a strong way or not. Lets check it out. The code and output are:

```
plt.figure(figsize=(15,20))
plt.subplot(4,2,1)

scatterplot(cars_data,'enginesize')

plt.subplot(4,2,2)

scatterplot(cars_data,'stroke')

plt.subplot(4,2,3)

scatterplot(cars_data,'peakrpm')

plt.subplot(4,2,4)

scatterplot(cars_data,'wheelbase')

plt.show()

plt.tight_layout()
```

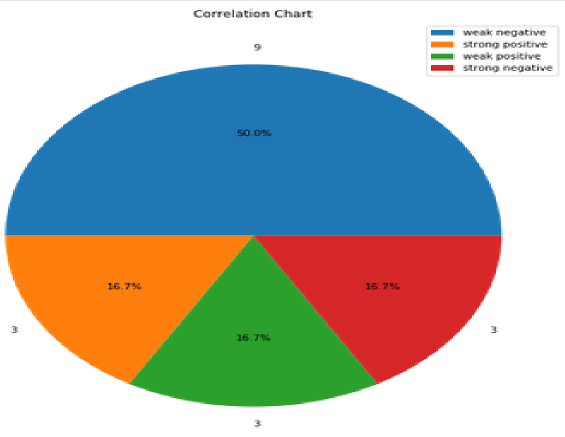


Well, we can see a positive correlation for wheelbase and enginesize with price. Hence, the other two are rested.

With this, our numeric visualization is complete. To check correlation more specifically, lets make a correlation data set and check our results.

```
corr=cars_data.corr().round(3).loc['price']

corr=pd.DataFrame(corr)

corr

result=[]


for i in corr['price']:

        if (i>-1 and i<-0.4): result.append('strong negative')

        elif (i>-0.4 and i<-0.2): result.append('moderate negative')

        elif (i>-0.2 and i<0): result.append('weak negative')

        elif(i>0 and i<0.2): result.append('weak positive')

        elif(i>0.2 and i<0.5): result.append('moderate positive')

        else : result.append('strong positive')


corr['correlation']=result

corr['correlation'].value_counts()


plt.figure(figsize=(10,10))

plt.title('Correlation Chart')

labels=corr['correlation'].unique()

plt15 = corr['correlation'].value_counts().tolist()

plt.pie(plt15, labels=plt15, autopct='%1.1f%%')

plt.legend(labels, loc=1)

plt.show()
```

corr.loc[:,'correlation']



```
Out[31]: car_ID                weak negative
         symboling             weak negative
         wheelbase           strong positive
         carlength           strong positive
         carwidth            strong positive
         carheight             weak positive
         curbweight          strong positive
         enginesize          strong positive
         boreratio           strong positive
         stroke                weak positive
         compressionratio      weak positive
         horsepower          strong positive
         peakrpm               weak negative
         citympg             strong negative
         highwaympg          strong negative
         price               strong positive
         carvolume           strong positive
         fueleconomy         strong negative
         Name: correlation, dtype: object
```

Hence, we can clearly say that the highly correlated variables with price are:

1. Wheel Base
2. Car Length
3. Car Width
4. Curb Weight
5. Engine Size
6. Bore Ratio
7. Horsepower
8. Car Volume
9. Fuel Economy
10. Cars Range
11. Car Body
12. Fuel Type
13. Engine Type
14. Aspiration
15. Cylinder Number
16. Drivewheel

These variables are the features with which we will do our prediction.

Model Building

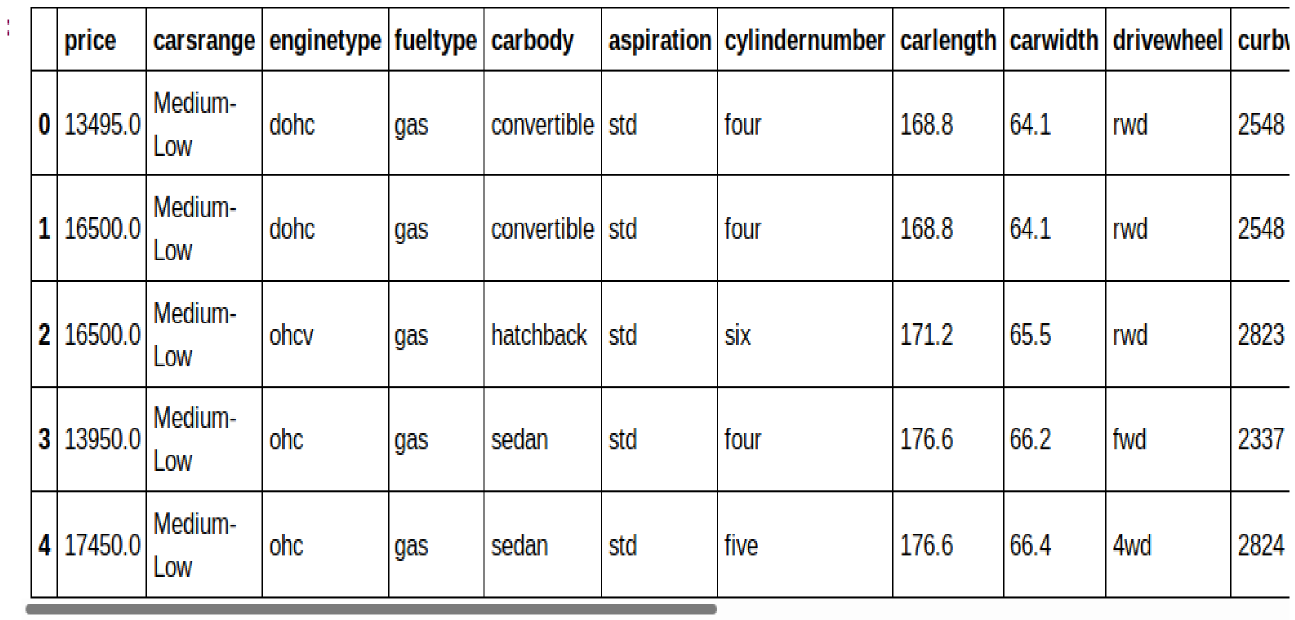
Now that we have selected which features to be chosen, it is time to make a model for our analysis. First of all, what is a model?

A statistical model is usually specified as a mathematical relationship between one or more random variables and other non-random variables. As such, a statistical model is "a formal representation of a theory."

Now, to be precise, we need to create a model. For that, we need a data set that has only values of the features we selected through visualization. Let's do that. The code and output are:

```
cars=cars_data[['price','carsrange','enginetype','fueltype','carbody','aspiration','cylindernumber','carlength','carwidth','drivewheel','curbweight','carvolume','enginesize','boreratio','horsepower','wheelbase','fueleconomy']]
```

```
cars.head()
```



	price	carsrange	enginetype	fueltype	carbody	aspiration	cylindernumber	carlength	carwidth	drivewheel	curbw
0	13495.0	Medium-Low	dohc	gas	convertible	std	four	168.8	64.1	rwd	2548
1	16500.0	Medium-Low	dohc	gas	convertible	std	four	168.8	64.1	rwd	2548
2	16500.0	Medium-Low	ohcv	gas	hatchback	std	six	171.2	65.5	rwd	2823
3	13950.0	Medium-Low	ohc	gas	sedan	std	four	176.6	66.2	fwd	2337
4	17450.0	Medium-Low	ohc	gas	sedan	std	five	176.6	66.4	4wd	2824

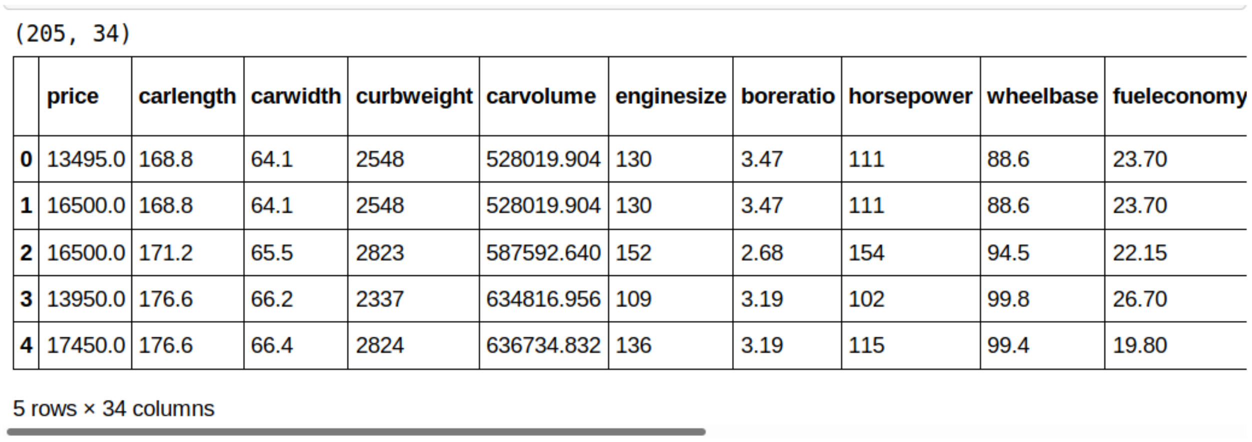
This is the data set, that we need to work on. We now need to have a pairplot of our whole data set, just to have an idea.

Dummy variables: A dummy variable is one that takes the value 0 or 1 to indicate the absence or presence of some categorical effect that may be expected to shift the outcome. Dummy variables are used as devices to sort data into mutually exclusive categories

Now, lets create these dummy variables. Remember, we need to create dummy variable for categorical variables only. Lets do this.

```
def dummies(x,df):


var=pd.get_dummies(df[x], drop_first=True)

    df=pd.concat([df,var], axis=1)

    df.drop([x], axis=1, inplace=True)

    return df

cars = dummies('fueltype',cars)

cars = dummies('aspiration',cars)

cars = dummies('carbody',cars)

cars = dummies('drivewheel',cars)

cars = dummies('enginetype',cars)

cars = dummies('cylindernumber',cars)

cars = dummies('carsrange',cars)


print(cars.shape)
```

cars.head()



```
(205, 34)
```

	price	carlength	carwidth	curbweight	carvolume	enginesize	boreratio	horsepower	wheelbase	fueleconomy
0	13495.0	168.8	64.1	2548	528019.904	130	3.47	111	88.6	23.70
1	16500.0	168.8	64.1	2548	528019.904	130	3.47	111	88.6	23.70
2	16500.0	171.2	65.5	2823	587592.640	152	2.68	154	94.5	22.15
3	13950.0	176.6	66.2	2337	634816.956	109	3.19	102	99.8	26.70
4	17450.0	176.6	66.4	2824	636734.832	136	3.19	115	99.4	19.80

5 rows × 34 columns

(205,34) is the shape of the data set now. It means that we have 34 variables to select from, for our analysis. Why select the variables again? Because when we run our analysis, we take an optimum amount of features to get the best results. We can let the model do that, or we can choose by ourselves.

Now comes the most important part. We will be splitting our data set into training set and test set. What are these sets? Why do we do this? Split the data set?

Firstly, if you run the model on the whole data set and predict from the same, you will get accuracy too high, which would be invalid because your dependent variable will be included in the data set in which you are predicting your values.

Secondly, if the model fails, the data set has to be re-loaded from the beginning. Hence, we first train our model with the training set, and when our model runs perfectly, we use it on our test set to predict values. Remember, training set should always be greater than test set. The more you train your model, the better it will predict. Let’s do this.

```
from sklearn.model_selection import train_test_split

np.random.seed(0)
```

```
df_train, df_test=train_test_split(cars, train_size=0.6, test_size=0.4, random_state=100)


df_train.head() #training set

df_test.head() #test set


from sklearn.preprocessing import MinMaxScaler #feature scaling

scaler=MinMaxScaler()


high_corr=df_train.corr().loc[df_train.corr()['price']>0.75]['price']      #highly   correlated
values with price

high=high_corr.index.drop('price').tolist()


low_corr=df_train.corr().loc[df_train.corr()['price']<-0.45]['price']

low=low_corr.index.tolist()


num_vars=high+low

num_vars

df_train[num_vars] = scaler.fit_transform(df_train[num_vars])


df_train.head()

df_train.describe().round(2)


#splitting into x and y
```

```
y_train=df_train.pop('price')

x_train=df_train
```

Now, after splitting the data set, we used a function MinMaxScaler(). This is because we may have very high values and very low values in our data set, and hence it scales down all those values to values that do not vary much. Remember, not to take your target variable (price) in this function, or your predicted values will also be scaled down values. Then, we split our training set into x (response variable) and y (target variable).

Now, it is time to build our model. For that, we use RFE (Recursive Feature Engineering) to select ‘n’ no. of variables from our already selected variables. Lets do that.

RFE selects ‘n’ no. of variables for your model on its own. You don’t need to select the variables. However, if you want to, you can do it by not using RFE. I have used it because it selects variables after running some tests on those variables.

Now, lets create our model.

```
from sklearn.feature_selection import RFE

from sklearn.linear_model import LinearRegression

from statsmodels.stats.outliers_influence import variance_inflation_factor


model=LinearRegression()

model.fit(x_train, y_train)

rfe=RFE(model,15)

rfe=rfe.fit(x_train, y_train)

selected_features=list(zip(x_train.columns,rfe.support_,rfe.ranking_)) #checking the selected features
```

```
selected_features


index=x_train.columns[rfe.support_]

x_train_new=x_train[index]

x_train_new.head()


def buildmodel(x,y):

    x=sm.add_constant(x)

    model=sm.OLS(y,x).fit()

    print(model.summary())

    return x
```

Linear regression

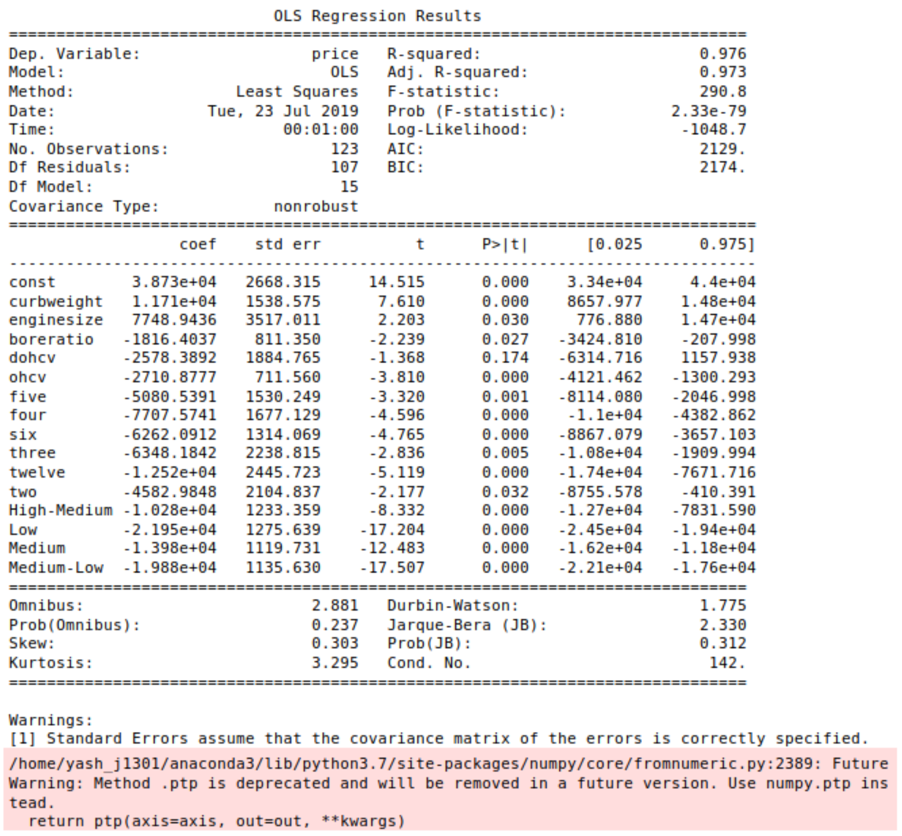
In statistics, linear regression is a linear approach to modeling the relationship between a scalar response (or dependent variable) and one or more explanatory variables (or independent variables). We use linear regression because our data is continuous, as I mentioned in the ‘Project Data Introduction’, and we have to predict continuous values.

Now, let’s start running our models.

RUNNING REGRESSION MODELS

Model 1

model_1=buildmodel(x_train_new,y_train)



```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.976
Model:                            OLS   Adj. R-squared:                  0.973
Method:                 Least Squares   F-statistic:                     290.8
Date:                Tue, 23 Jul 2019   Prob (F-statistic):           2.33e-79
Time:                        00:01:00   Log-Likelihood:                -1048.7
No. Observations:                 123   AIC:                             2129.
Df Residuals:                     107   BIC:                             2174.
Df Model:                          15
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        3.873e+04   2668.315     14.515      0.000    3.34e+04     4.4e+04
curbweight   1.171e+04   1538.575      7.610      0.000    8657.977    1.48e+04
enginesize   7748.9436   3517.011      2.203      0.030     776.880    1.47e+04
boreratio   -1816.4037    811.350     -2.239      0.027   -3424.810    -207.998
dohcv       -2578.3892   1884.765     -1.368      0.174   -6314.716    1157.938
ohcv        -2710.8777    711.560     -3.810      0.000   -4121.462   -1300.293
five        -5080.5391   1530.249     -3.320      0.001   -8114.080   -2046.998
four        -7707.5741   1677.129     -4.596      0.000    -1.1e+04   -4382.862
six         -6262.0912   1314.069     -4.765      0.000   -8867.079   -3657.103
three       -6348.1842   2238.815     -2.836      0.005   -1.08e+04   -1909.994
twelve      -1.252e+04   2445.723     -5.119      0.000   -1.74e+04   -7671.716
two         -4582.9848   2104.837     -2.177      0.032   -8755.578    -410.391
High-Medium -1.028e+04   1233.359     -8.332      0.000   -1.27e+04   -7831.590
Low         -2.195e+04   1275.639    -17.204      0.000   -2.45e+04   -1.94e+04
Medium      -1.398e+04   1119.731    -12.483      0.000   -1.62e+04   -1.18e+04
Medium-Low  -1.988e+04   1135.630    -17.507      0.000   -2.21e+04   -1.76e+04
==============================================================================
Omnibus:                        2.881   Durbin-Watson:                   1.775
Prob(Omnibus):                  0.237   Jarque-Bera (JB):                2.330
Skew:                           0.303   Prob(JB):                        0.312
Kurtosis:                       3.295   Cond. No.                         142.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
/home/yash_j1301/anaconda3/lib/python3.7/site-packages/numpy/core/fromnumeric.py:2389: Future
Warning: Method .ptp is deprecated and will be removed in a future version. Use numpy.ptp ins
tead.
  return ptp(axis=axis, out=out, **kwargs)
```

This is our Model Report. Notice at a column p>[t]. This column gives us the p-value. What is the p-value? It is a probability value that, when p>0.05, tells us to reject the null hypothesis and adopt alternate hypothesis.

Null hypothesis is a general statement or default position that there is nothing new happening, like there is no relationship between two measured phenomena, or no association among groups. Everytime we run our model, we need to check our p-value and delete those variables with p>0.05. We need to do this until all our variables have p-value less than 0.05.

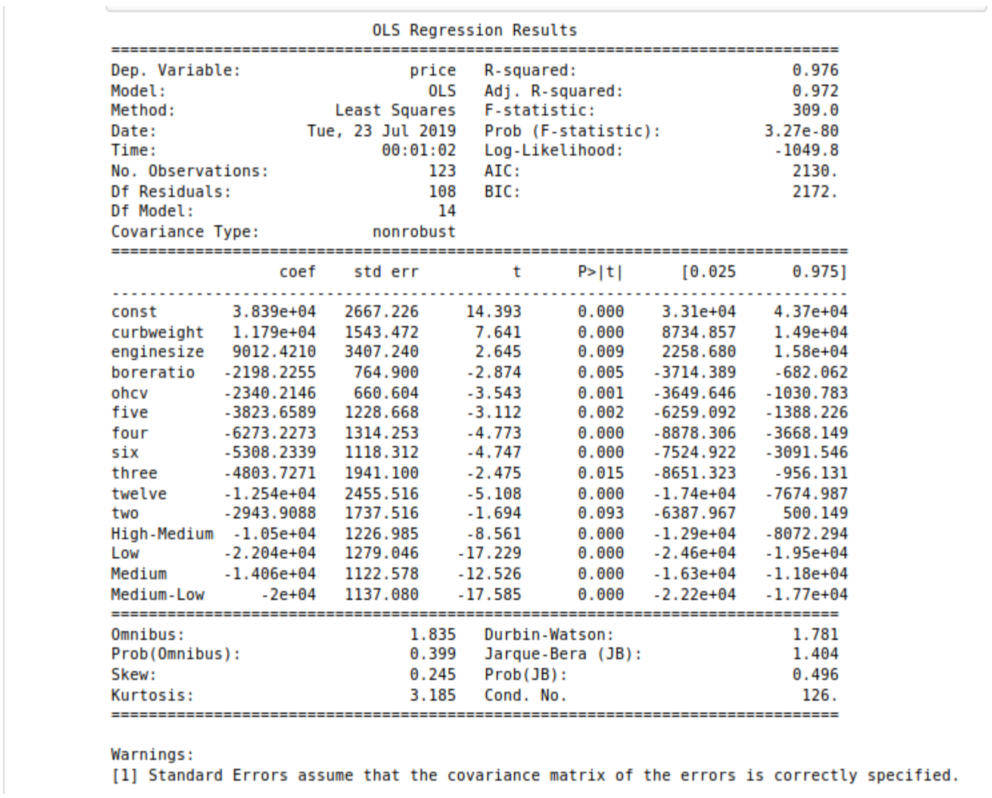
Now, in the report, 'dohcv' is having p>0.05. Let us remove this and run a new model.

```
x_train_new=x_train_new.drop(['dohcv'], axis=1)
```

Model 2

```
model_2=buildmodel(x_train_new, y_train)
```

Lets run the model and see the report now.



```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.976
Model:                            OLS   Adj. R-squared:                  0.972
Method:                 Least Squares   F-statistic:                     309.0
Date:                Tue, 23 Jul 2019   Prob (F-statistic):           3.27e-80
Time:                        00:01:02   Log-Likelihood:                -1049.8
No. Observations:                 123   AIC:                             2130.
Df Residuals:                     108   BIC:                             2172.
Df Model:                          14
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        3.839e+04   2667.226     14.393      0.000    3.31e+04    4.37e+04
curbweight   1.179e+04   1543.472      7.641      0.000    8734.857    1.49e+04
enginesize   9012.4210   3407.240      2.645      0.009    2258.680    1.58e+04
boreratio   -2198.2255    764.900     -2.874      0.005   -3714.389    -682.062
ohcv        -2340.2146    660.604     -3.543      0.001   -3649.646   -1030.783
five        -3823.6589   1228.668     -3.112      0.002   -6259.092   -1388.226
four        -6273.2273   1314.253     -4.773      0.000   -8878.306   -3668.149
six         -5308.2339   1118.312     -4.747      0.000   -7524.922   -3091.546
three       -4803.7271   1941.100     -2.475      0.015   -8651.323    -956.131
twelve      -1.254e+04   2455.516     -5.108      0.000   -1.74e+04   -7674.987
two         -2943.9088   1737.516     -1.694      0.093   -6387.967     500.149
High-Medium  -1.05e+04   1226.985     -8.561      0.000   -1.29e+04   -8072.294
Low         -2.204e+04   1279.046    -17.229      0.000   -2.46e+04   -1.95e+04
Medium      -1.406e+04   1122.578    -12.526      0.000   -1.63e+04   -1.18e+04
Medium-Low       -2e+04   1137.080    -17.585      0.000   -2.22e+04   -1.77e+04
==============================================================================
Omnibus:                        1.835   Durbin-Watson:                   1.781
Prob(Omnibus):                  0.399   Jarque-Bera (JB):                1.404
Skew:                           0.245   Prob(JB):                        0.496
Kurtosis:                       3.185   Cond. No.                         126.
==============================================================================

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

Now, we can see that ‘two’ has p>0.05. Let’s drop it and run the new model.

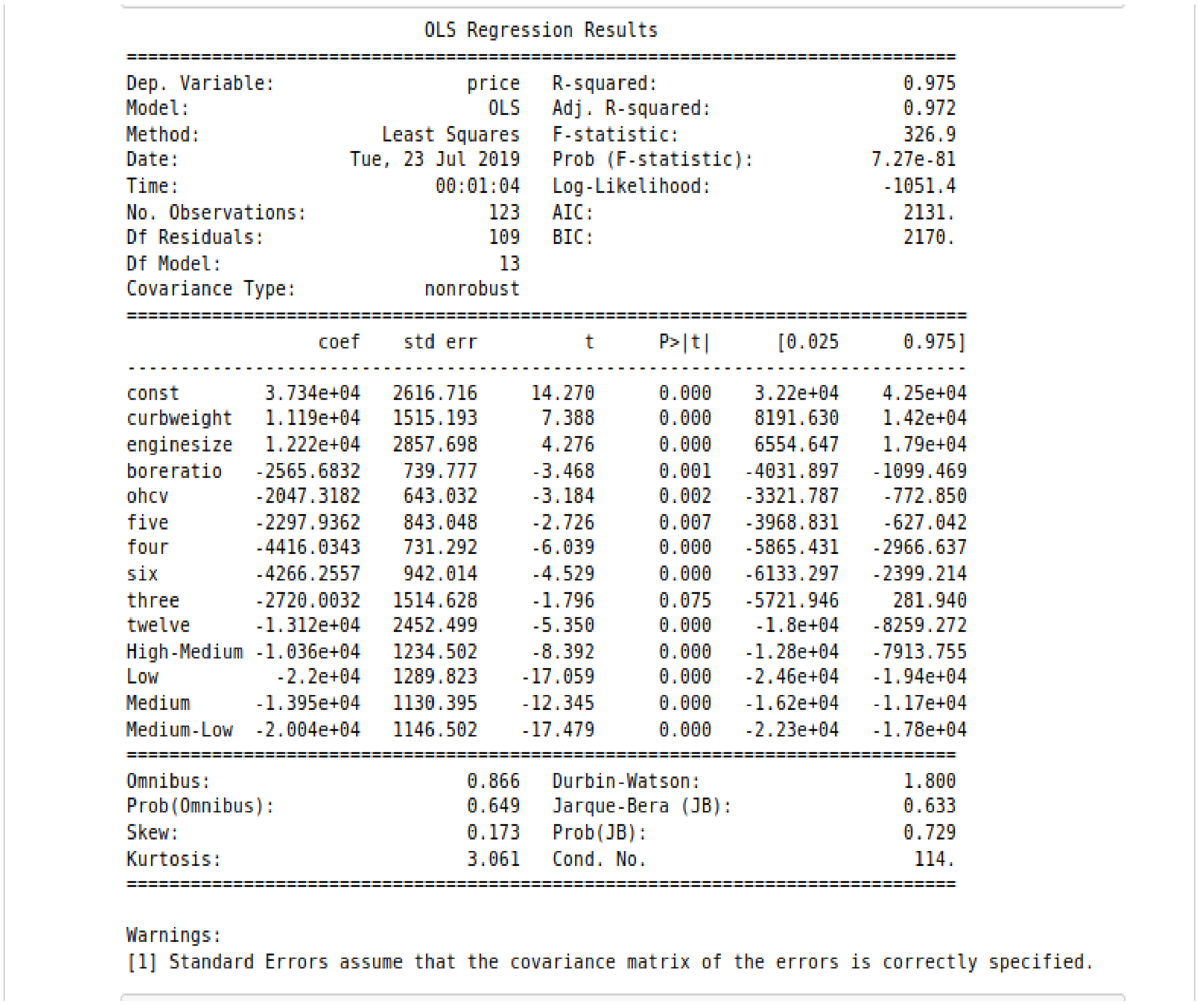
x_train_new=x_train_new.drop(['two'],axis=1)

Now, create a new model and run it.

Model 3

model_3=buildmodel(x_train_new, y_train)

Let us run this model and check our results.



```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.975
Model:                            OLS   Adj. R-squared:                  0.972
Method:                 Least Squares   F-statistic:                     326.9
Date:                Tue, 23 Jul 2019   Prob (F-statistic):           7.27e-81
Time:                        00:01:04   Log-Likelihood:                -1051.4
No. Observations:                 123   AIC:                             2131.
Df Residuals:                     109   BIC:                             2170.
Df Model:                          13
Covariance Type:            nonrobust
================================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const        3.734e+04   2616.716     14.270      0.000    3.22e+04    4.25e+04
curbweight   1.119e+04   1515.193      7.388      0.000    8191.630    1.42e+04
enginesize   1.222e+04   2857.698      4.276      0.000    6554.647    1.79e+04
boreratio   -2565.6832    739.777     -3.468      0.001   -4031.897   -1099.469
ohcv        -2047.3182    643.032     -3.184      0.002   -3321.787    -772.850
five        -2297.9362    843.048     -2.726      0.007   -3968.831    -627.042
four        -4416.0343    731.292     -6.039      0.000   -5865.431   -2966.637
six         -4266.2557    942.014     -4.529      0.000   -6133.297   -2399.214
three       -2720.0032   1514.628     -1.796      0.075   -5721.946     281.940
twelve      -1.312e+04   2452.499     -5.350      0.000    -1.8e+04   -8259.272
High-Medium -1.036e+04   1234.502     -8.392      0.000   -1.28e+04   -7913.755
Low           -2.2e+04   1289.823    -17.059      0.000   -2.46e+04   -1.94e+04
Medium      -1.395e+04   1130.395    -12.345      0.000   -1.62e+04   -1.17e+04
Medium-Low  -2.004e+04   1146.502    -17.479      0.000   -2.23e+04   -1.78e+04
==============================================================================
Omnibus:                        0.866   Durbin-Watson:                   1.800
Prob(Omnibus):                  0.649   Jarque-Bera (JB):                0.633
Skew:                           0.173   Prob(JB):                        0.729
Kurtosis:                       3.061   Cond. No.                         114.
==============================================================================

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

This time, ‘three’ has p>0.05. Let us drop it and run a new model.

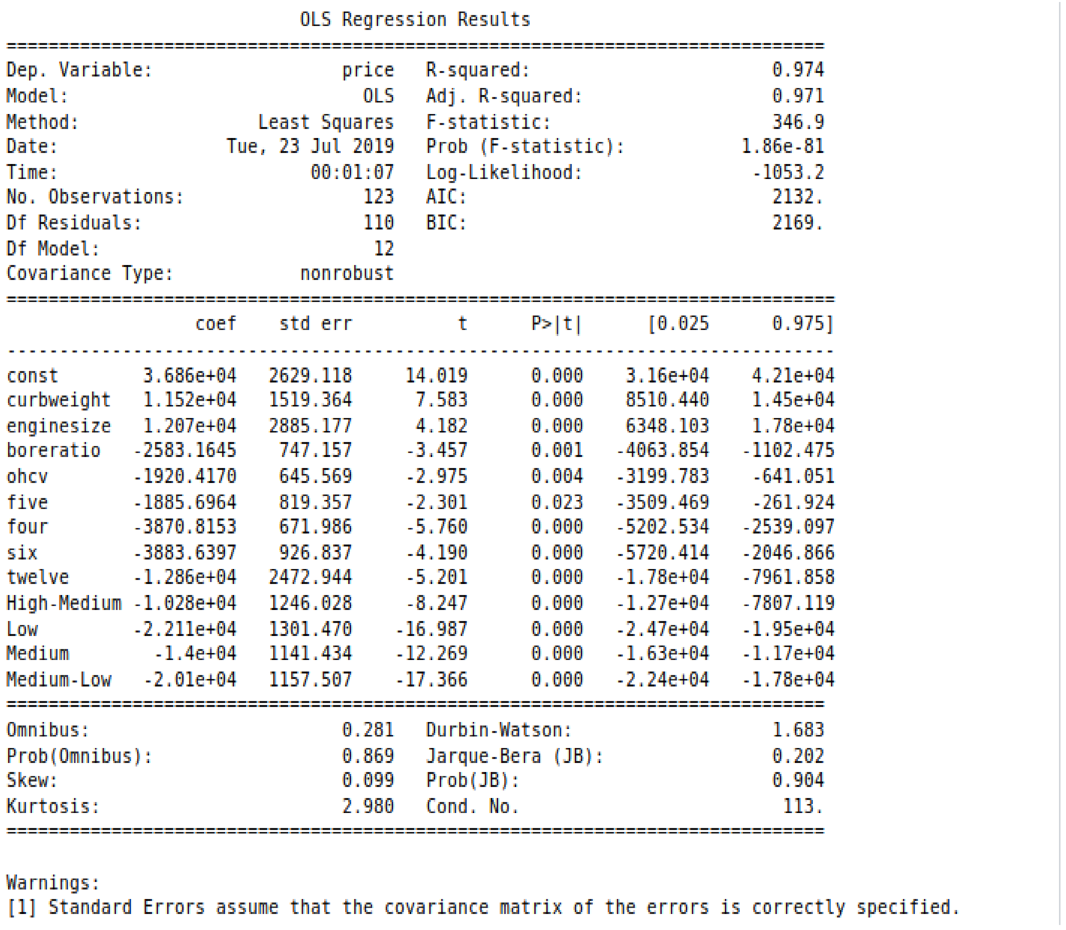
```
x_train_new=x_train_new.drop(['three'],axis=1)
```

Now, create a new model and run it.

Model 4

```
model_4=buildmodel(x_train_new,y_train)
```

Lets run this model and check the results.



```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.974
Model:                            OLS   Adj. R-squared:                  0.971
Method:                 Least Squares   F-statistic:                     346.9
Date:                Tue, 23 Jul 2019   Prob (F-statistic):           1.86e-81
Time:                        00:01:07   Log-Likelihood:                -1053.2
No. Observations:                 123   AIC:                             2132.
Df Residuals:                     110   BIC:                             2169.
Df Model:                          12
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        3.686e+04   2629.118     14.019      0.000    3.16e+04    4.21e+04
curbweight   1.152e+04   1519.364      7.583      0.000    8510.440    1.45e+04
enginesize   1.207e+04   2885.177      4.182      0.000    6348.103    1.78e+04
boreratio   -2583.1645    747.157     -3.457      0.001   -4063.854   -1102.475
ohcv        -1920.4170    645.569     -2.975      0.004   -3199.783    -641.051
five        -1885.6964    819.357     -2.301      0.023   -3509.469    -261.924
four        -3870.8153    671.986     -5.760      0.000   -5202.534   -2539.097
six         -3883.6397    926.837     -4.190      0.000   -5720.414   -2046.866
twelve      -1.286e+04   2472.944     -5.201      0.000   -1.78e+04   -7961.858
High-Medium -1.028e+04   1246.028     -8.247      0.000   -1.27e+04   -7807.119
Low         -2.211e+04   1301.470    -16.987      0.000   -2.47e+04   -1.95e+04
Medium         -1.4e+04   1141.434    -12.269      0.000   -1.63e+04   -1.17e+04
Medium-Low   -2.01e+04   1157.507    -17.366      0.000   -2.24e+04   -1.78e+04
==============================================================================
Omnibus:                        0.281   Durbin-Watson:                   1.683
Prob(Omnibus):                  0.869   Jarque-Bera (JB):                0.202
Skew:                           0.099   Prob(JB):                        0.904
Kurtosis:                       2.980   Cond. No.                         113.
==============================================================================

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

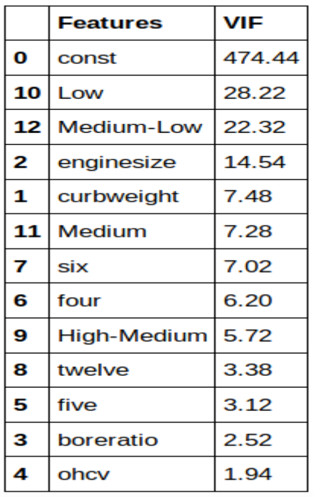
This is our trained model. Let it be f_model.

```
f_model=model_4
```

VIF Value

In statistics, the variance inflation factor (VIF) is the ratio of variance in a model with multiple terms, divided by the variance of a model with one term alone. It needs to be under control.

```
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(model_4)
```



	Features	VIF
0	const	474.44
10	Low	28.22
12	Medium-Low	22.32
2	enginesize	14.54
1	curbweight	7.48
11	Medium	7.28
7	six	7.02
6	four	6.20
9	High-Medium	5.72
8	twelve	3.38
5	five	3.12
3	boreratio	2.52
4	ohcv	1.94

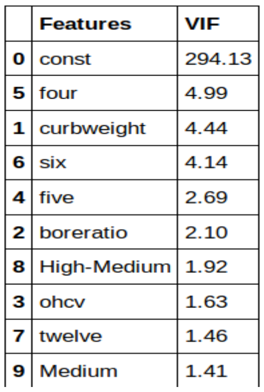
The VIF Value for Low, Medium-Low and enginesize is very high. Let us drop it and run a new model. Remember, check the p-value and the vif value both.

model_new=model_4.drop(['Low','Medium-Low','enginesize'], axis=1)

model_5=buildmodel(model_new, y_train) #checking OLS Results

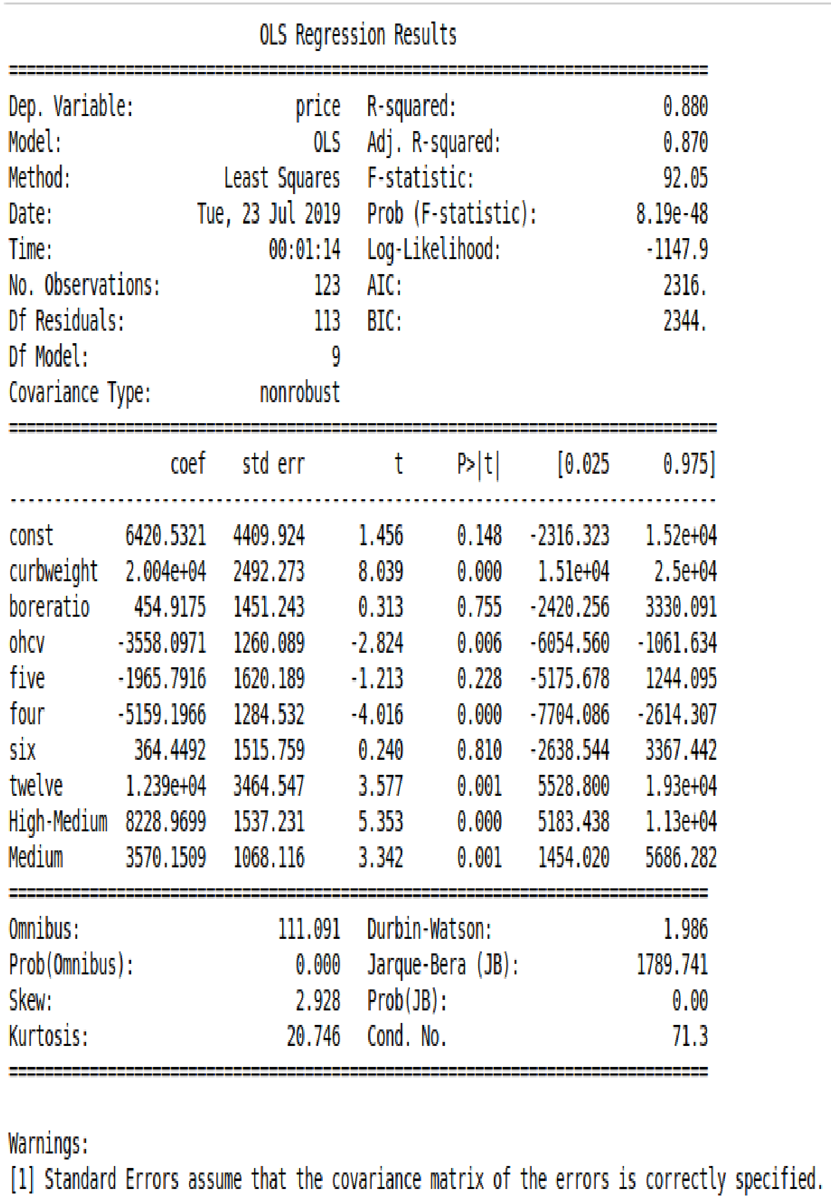
checkVIF(model_5) #checking vif value

Let us see the VIF Value and Regression Results:



	Features	VIF
0	const	294.13
5	four	4.99
1	curbweight	4.44
6	six	4.14
4	five	2.69
2	boreratio	2.10
8	High-Medium	1.92
3	ohcv	1.63
7	twelve	1.46
9	Medium	1.41

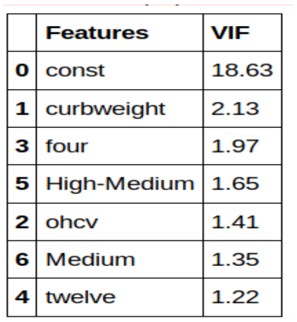
VIF Value is not very high. Let us check the regression results:



```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.880
Model:                            OLS   Adj. R-squared:                  0.870
Method:                 Least Squares   F-statistic:                     92.05
Date:                Tue, 23 Jul 2019   Prob (F-statistic):           8.19e-48
Time:                        00:01:14   Log-Likelihood:                -1147.9
No. Observations:                 123   AIC:                             2316.
Df Residuals:                     113   BIC:                             2344.
Df Model:                           9
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        6420.5321   4409.924      1.456      0.148   -2316.323    1.52e+04
curbweight   2.004e+04   2492.273      8.039      0.000    1.51e+04     2.5e+04
boreratio     454.9175   1451.243      0.313      0.755   -2420.256    3330.091
ohcv        -3558.0971   1260.089     -2.824      0.006   -6054.560   -1061.634
five        -1965.7916   1620.189     -1.213      0.228   -5175.678    1244.095
four        -5159.1966   1284.532     -4.016      0.000   -7704.086   -2614.307
six           364.4492   1515.759      0.240      0.810   -2638.544    3367.442
twelve       1.239e+04   3464.547      3.577      0.001    5528.800    1.93e+04
High-Medium  8228.9699   1537.231      5.353      0.000    5183.438    1.13e+04
Medium       3570.1509   1068.116      3.342      0.001    1454.020    5686.282
==============================================================================
Omnibus:                      111.091   Durbin-Watson:                   1.986
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1789.741
Skew:                           2.928   Prob(JB):                         0.00
Kurtosis:                      20.746   Cond. No.                         71.3
==============================================================================

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

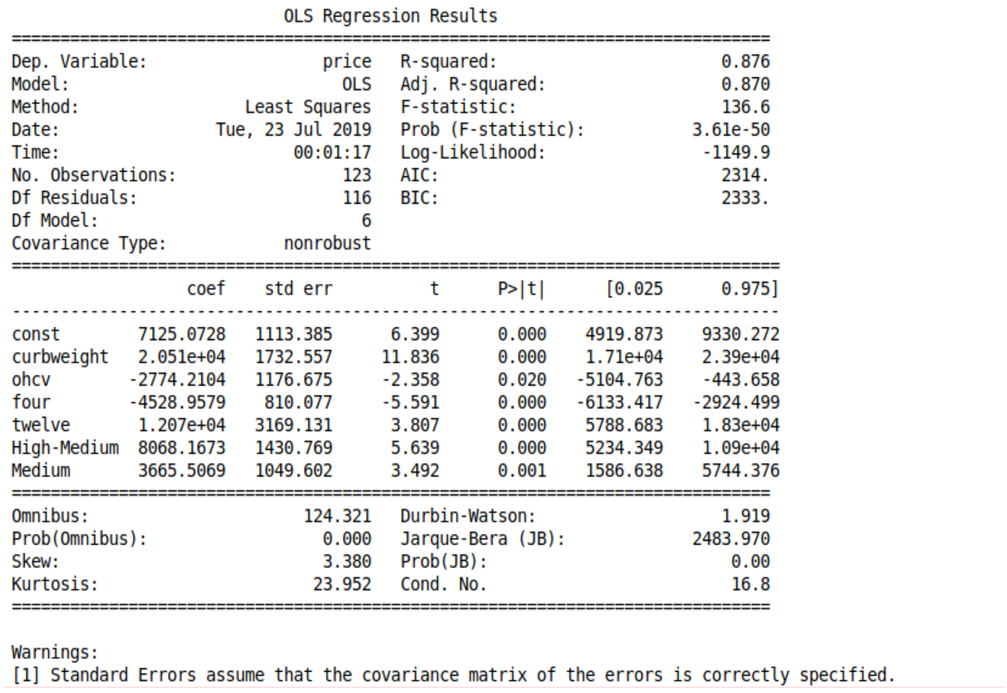
Looks like the p-value of boreratio, five and six is greater than 0.05. Let us remove them and run a new model.

```
model_new=model_new.drop(['boreratio','five','six'], axis=1)

model_6=buildmodel(model_new,y_train)

checkVIF(model_6)
```



	Features	VIF
0	const	18.63
1	curbweight	2.13
3	four	1.97
5	High-Medium	1.65
2	ohcv	1.41
6	Medium	1.35
4	twelve	1.22

VIF Value is under control. Let us check the regression results:



```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.876
Model:                            OLS   Adj. R-squared:                  0.870
Method:                 Least Squares   F-statistic:                     136.6
Date:                Tue, 23 Jul 2019   Prob (F-statistic):           3.61e-50
Time:                        00:01:17   Log-Likelihood:                -1149.9
No. Observations:                 123   AIC:                             2314.
Df Residuals:                     116   BIC:                             2333.
Df Model:                           6
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        7125.0728   1113.385      6.399      0.000    4919.873    9330.272
curbweight   2.051e+04   1732.557     11.836      0.000     1.71e+04    2.39e+04
ohcv        -2774.2104   1176.675     -2.358      0.020   -5104.763    -443.658
four        -4528.9579    810.077     -5.591      0.000   -6133.417   -2924.499
twelve       1.207e+04   3169.131      3.807      0.000    5788.683    1.83e+04
High-Medium  8068.1673   1430.769      5.639      0.000    5234.349    1.09e+04
Medium       3665.5069   1049.602      3.492      0.001    1586.638    5744.376
==============================================================================
Omnibus:                      124.321   Durbin-Watson:                   1.919
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2483.970
Skew:                           3.380   Prob(JB):                         0.00
Kurtosis:                      23.952   Cond. No.                         16.8
==============================================================================

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

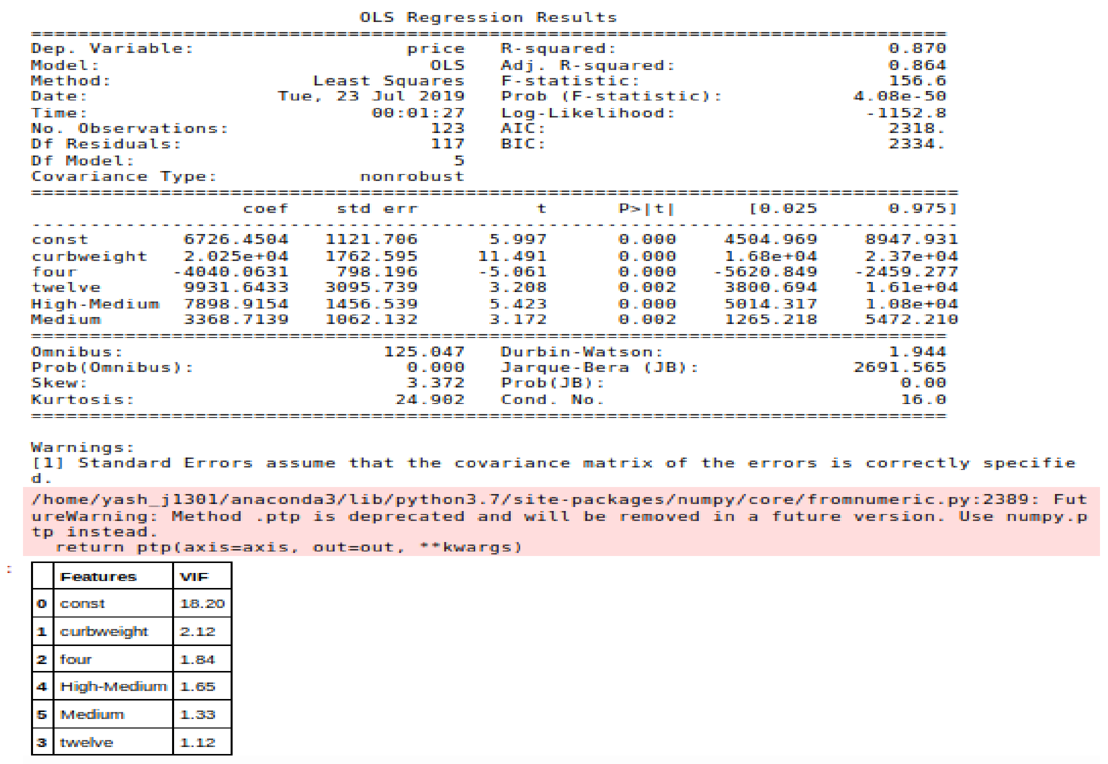
p-value is under control. Hence, it is our regression model. Let us name it as final_rm.

final_rm=model_6

Now, we need to check errors in our model. For that, we will drop any one variable, and see what are the results.

```
model_check=model_6.drop(['ohcv'], axis=1)

model_check=buildmodel(model_check, y_train)

checkVIF(model_check)
```

Now, lets check the VIF value and regression results.

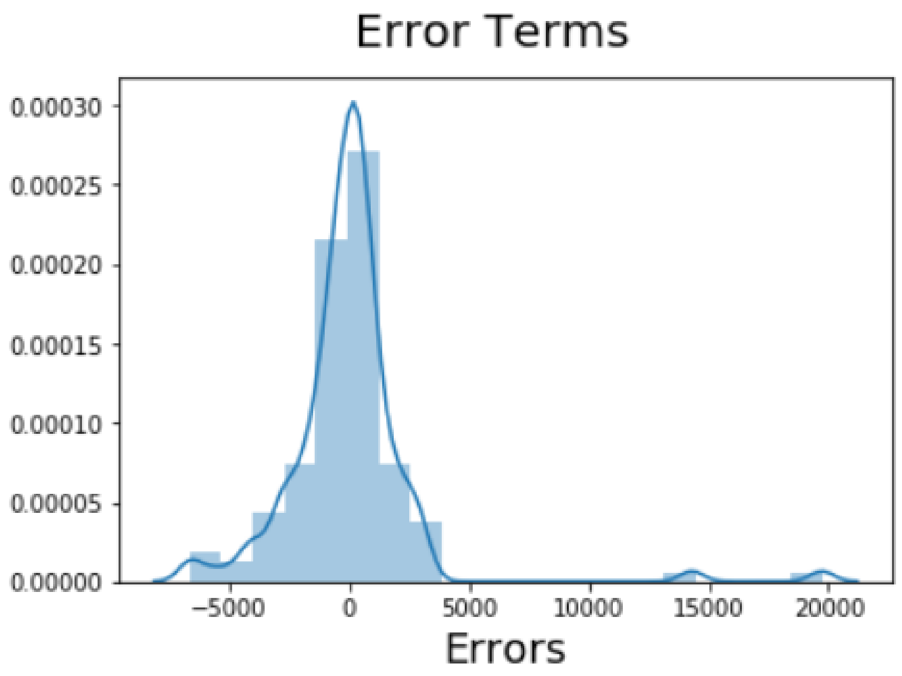


```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.870
Model:                            OLS   Adj. R-squared:                  0.864
Method:                 Least Squares   F-statistic:                     156.6
Date:                Tue, 23 Jul 2019   Prob (F-statistic):           4.08e-50
Time:                        00:01:27   Log-Likelihood:                -1152.8
No. Observations:                 123   AIC:                             2318.
Df Residuals:                     117   BIC:                             2334.
Df Model:                           5
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        6726.4504   1121.706      5.997      0.000    4504.969    8947.931
curbweight   2.025e+04   1762.595     11.491      0.000    1.68e+04    2.37e+04
four        -4040.0631    798.196     -5.061      0.000   -5620.849   -2459.277
twelve       9931.6433   3095.739      3.208      0.002    3800.694    1.61e+04
High-Medium  7898.9154   1456.539      5.423      0.000    5014.317    1.08e+04
Medium       3368.7139   1062.132      3.172      0.002    1265.218    5472.210
==============================================================================
Omnibus:                      125.047   Durbin-Watson:                   1.944
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2691.565
Skew:                           3.372   Prob(JB):                         0.00
Kurtosis:                      24.902   Cond. No.                         16.0
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifie
d.
/home/yash_j1301/anaconda3/lib/python3.7/site-packages/numpy/core/fromnumeric.py:2389: Fut
ureWarning: Method .ptp is deprecated and will be removed in a future version. Use numpy.p
tp instead.
  return ptp(axis=axis, out=out, **kwargs)
```

	Features	VIF
0	const	18.20
1	curbweight	2.12
2	four	1.84
4	High-Medium	1.65
5	Medium	1.33
3	twelve	1.12

Both the p-value and vif values are under control. Hence, there is not much error. Let us plot a graph to just be sure.

```
lm=sm.OLS(y_train,model_check).fit()

y_train_price=lm.predict(model_check)

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)

plt.show()
```



Prediction and Evaluation

We are at the final stage of our project. Time to predict values! First, let us select the features in our training set. Then, split into x and y.

```
#selecting the highly correlated values

df_test[num_vars] = scaler.fit_transform(df_test[num_vars])


#splitting into x and y

y_test=df_test.pop('price')

x_test=df_test
```

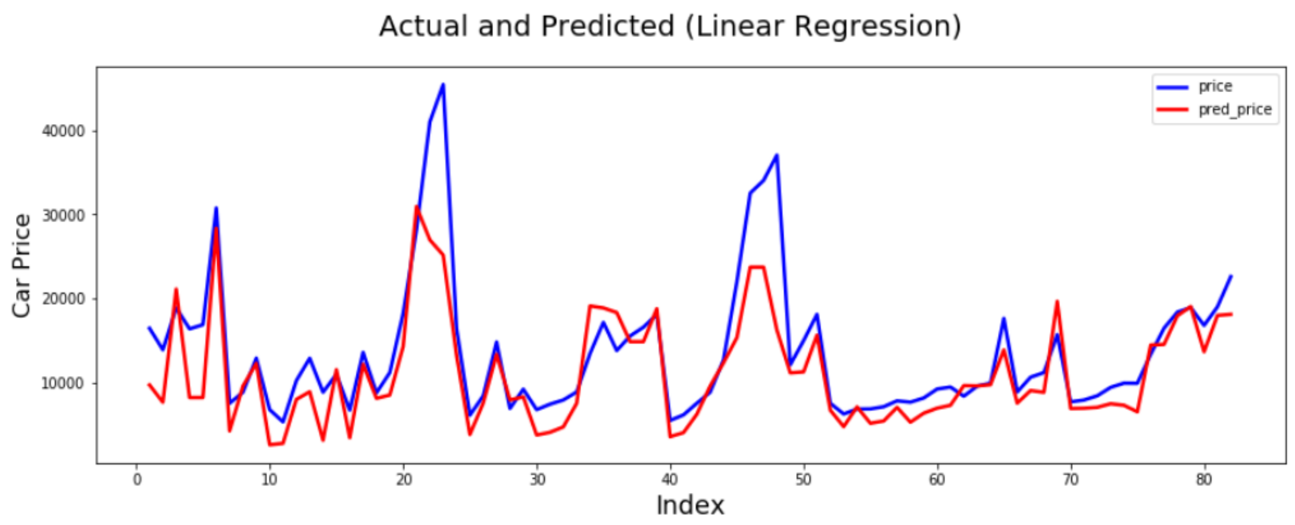
Now that we have declared our test variables, it is time to predict. Let us use our model to predict.

```
X_train_new = model_check.drop('const',axis=1)

# Creating X_test_new dataframe by dropping variables from X_test

X_test_new = x_test[X_train_new.columns]

# Adding a constant variable

X_test_new = sm.add_constant(X_test_new)
```

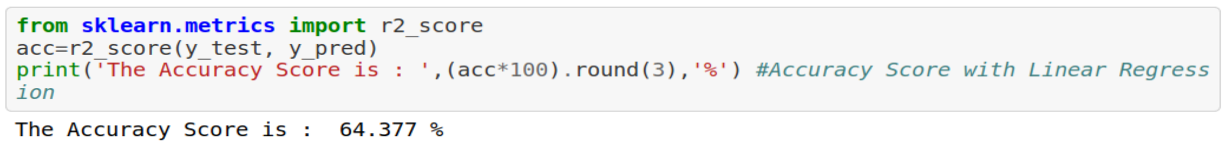
Now, let us predict values for our test set. Then, plot them in a line graph to show the variation.

```
y_pred=lm.predict(X_test_new)


price=pd.concat([y_test,y_pred.round(2)],axis=1)

price=price.rename(columns={0:'pred_price'}) #price prediction using linear regression

price=price.sort_index()

price=price.reset_index(0)
```

```
c= [i for i in range(1,83,1)] # generating index

fig = plt.figure(figsize=(15,5))

plt.plot(c,price['price'], color="blue", linewidth=2.5, linestyle="-") #Plotting Actual

plt.plot(c,price['pred_price'],   color="red",     linewidth=2.5,   linestyle="-")   #Plotting
predicted

fig.suptitle('Actual and Predicted (Linear Regression)', fontsize=20)          # Plot heading

plt.xlabel('Index', fontsize=18)                              # X-label

plt.ylabel('Car Price', fontsize=16)                        # Y-label

plt.legend()

plt.show()
```



This is the variation in the predicted price. Barring a few irregularities, the prediction seems to work fine. Let’s check how accurate we are.



```
from sklearn.metrics import r2_score
acc=r2_score(y_test, y_pred)
print('The Accuracy Score is : ',(acc*100).round(3),'%') #Accuracy Score with Linear Regress
ion
The Accuracy Score is :  64.377 %
```

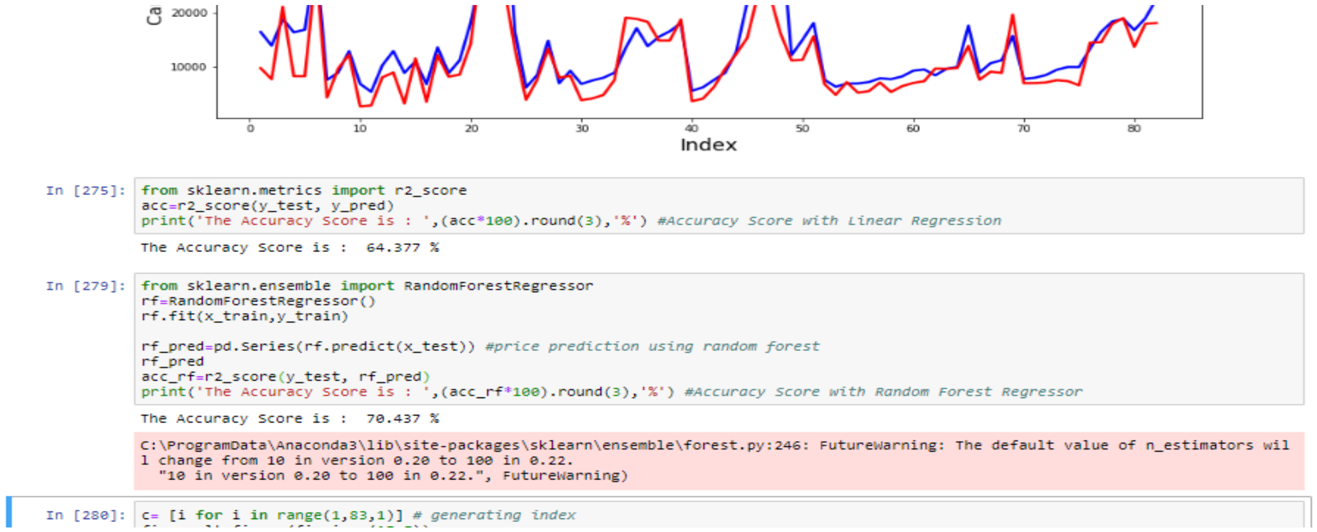
The accuracy is 64.377 %. It is a little bit low, according to me. Let us use Random Forest Regressor to fine tune our analysis.

Random Forest

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

Now, let us use Random Forest for our regression.

```
from sklearn.ensemble import RandomForestRegressor

rf=RandomForestRegressor()

rf.fit(x_train,y_train)


rf_pred=pd.Series(rf.predict(x_test)) #price prediction using random forest

rf_pred

acc_rf=r2_score(y_test, rf_pred)

print('The Accuracy Score is : ',(acc_rf*100).round(3),'%') #Accuracy Score with Random Forest Regressor
```



```
In [275]: from sklearn.metrics import r2_score
          acc=r2_score(y_test, y_pred)
          print('The Accuracy Score is : ',(acc*100).round(3),'%') #Accuracy Score with Linear Regression

          The Accuracy Score is :  64.377 %

In [279]: from sklearn.ensemble import RandomForestRegressor
          rf=RandomForestRegressor()
          rf.fit(x_train,y_train)

          rf_pred=pd.Series(rf.predict(x_test)) #price prediction using random forest
          rf_pred
          acc_rf=r2_score(y_test, rf_pred)
          print('The Accuracy Score is : ',(acc_rf*100).round(3),'%') #Accuracy Score with Random Forest Regressor

          The Accuracy Score is :  70.437 %

          C:\ProgramData\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:246: FutureWarning: The default value of n_estimators wil
          l change from 10 in version 0.20 to 100 in 0.22.
            "10 in version 0.20 to 100 in 0.22.", FutureWarning)

In [280]: c= [i for i in range(1,83,1)] # generating index
```

Now, we get an accuracy of 70.437%, which is more than enough for prediction. Let us plot the price and predicted price line graph to check the difference.

c= [i for i in range(1,83,1)] # generating index

fig = plt.figure(figsize=(15,5))

plt.plot(c,y_test, color="blue", linewidth=2.5, linestyle="-", label='price') #Plotting Actual

plt.plot(c,rf_pred, color="red", linewidth=2.5, linestyle="-", label='pred_price') #Plotting predicted

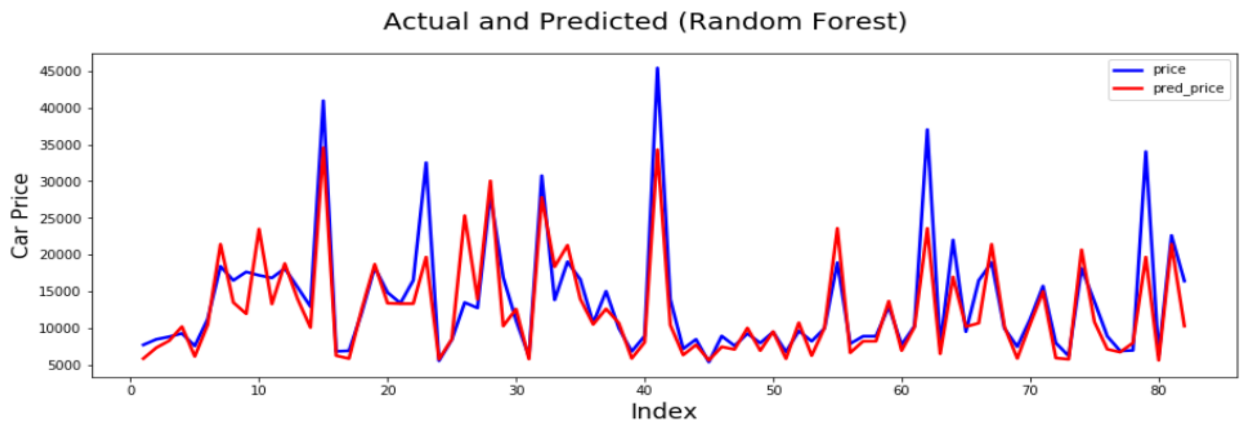
fig.suptitle('Actual and Predicted (Random Forest)', fontsize=20) # Plot heading

plt.xlabel('Index', fontsize=18) # X-label

plt.ylabel('Car Price', fontsize=16) # Y-label

plt.legend()

plt.show()



Not bad, though. This was our predictive analysis model. Let us check the price spread between actual and predicted price for both random forest and linear regression.

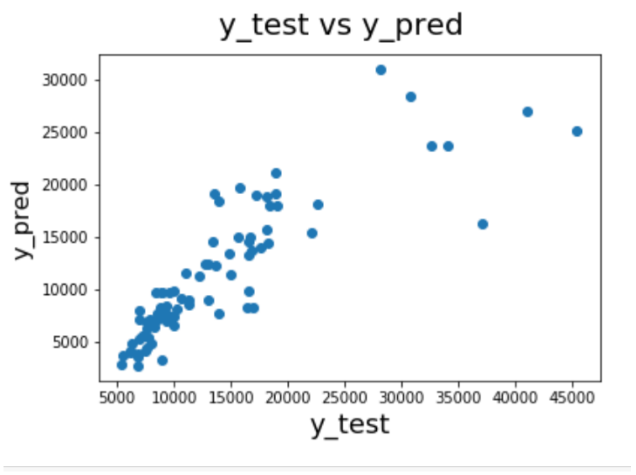
fig = plt.figure()

plt.scatter(y_test,y_pred)

fig.suptitle('y_test vs y_pred', fontsize=20)   # Plot heading

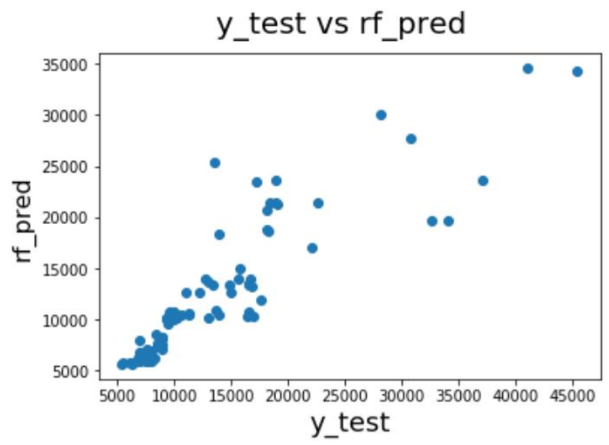
plt.xlabel('y_test', fontsize=18)   # X-label

plt.ylabel('y_pred', fontsize=16)



Now, lets check with random forest. This would be the final part of the project.

```
fig = plt.figure()

plt.scatter(y_test,rf_pred)

fig.suptitle('y_test vs rf_pred', fontsize=20)            # Plot heading

plt.xlabel('y_test', fontsize=18)                         # X-label

plt.ylabel('rf_pred', fontsize=16)                        # Y-label
```



Bibliography

https://arxiv.org/pdf/1711.06970.pdf

https://github.com/akjadon/Finalprojects_DS/tree/master/Car_pricing_prediction

https://en.wikipedia.org/wiki/Dummy_variable_(statistics)

https://en.wikipedia.org/wiki/Linear_regression

https://en.wikipedia.org/wiki/Variance_inflation_factor

https://www.kaggle.com/goyalshalini93/car-price-prediction-linear-regression-rfe

https://en.wikipedia.org/wiki/Random_forest

https://www.kaggle.com/jshih7/car-price-prediction