Used Cars Analysis - Capstone Project

Import Necessary Libraries

In [1]:
```
#Import packages
import numpy as np
import pandas as pd
import statsmodels.api as sm
import scipy.stats as stats
from matplotlib import pyplot as plt
from scipy import stats
from statsmodels.formula.api import ols
import matplotlib.pyplot as plt
from matplotlib.lines import Line2D
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
import random
from math import sqrt
import seaborn as sns
import warnings
from scipy.stats import norm
warnings.filterwarnings("ignore")
%matplotlib inline
plt.style.use('seaborn')
```

Data Understanding

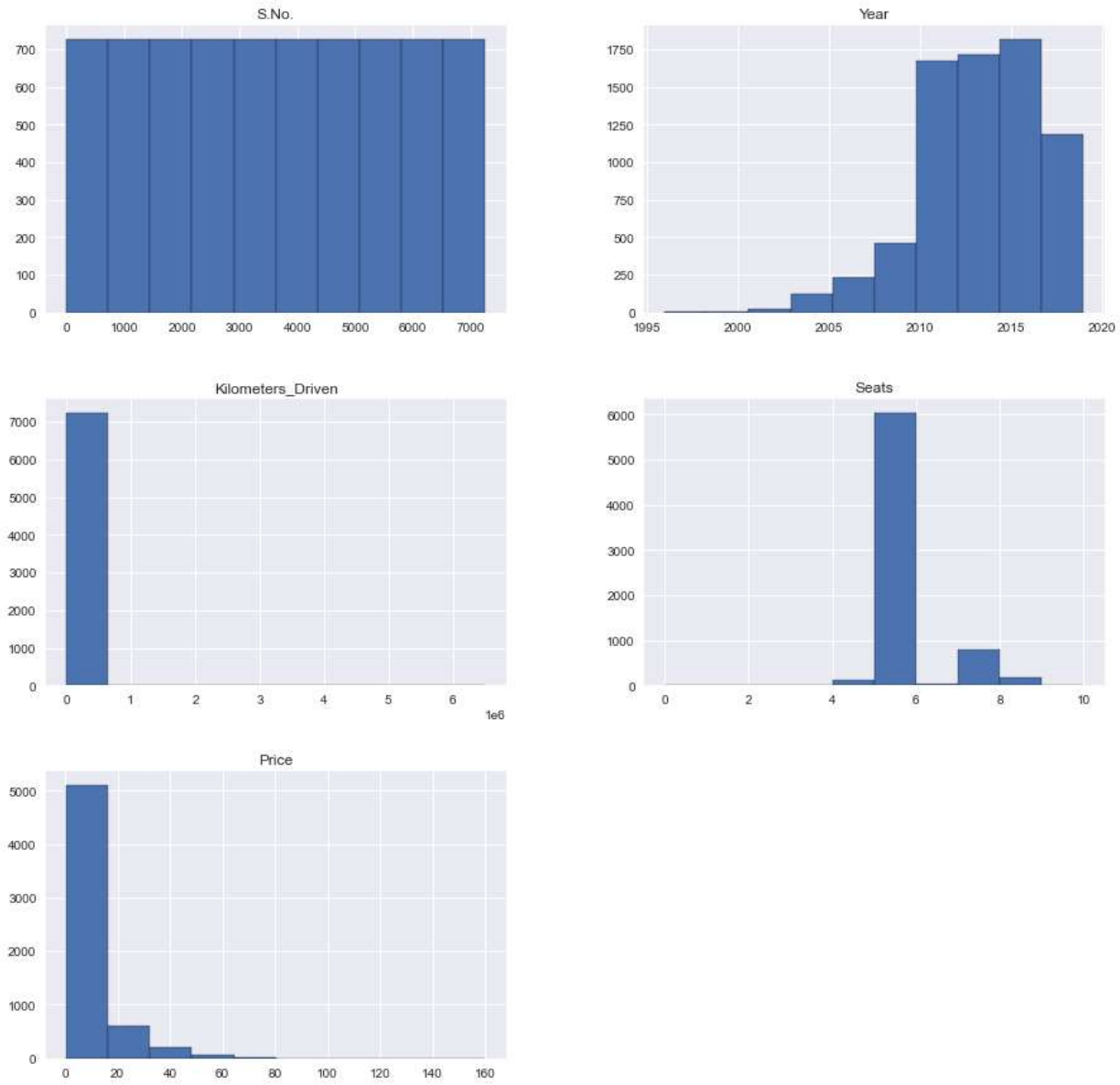
In [2]:
```
#Review the dataset
data = pd.read_csv('data\\used_cars_data.csv')
```

In [3]:
```
#Load the first rows
data.head()
```

Out[3]:

	S.No.	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type	M
0	0	Maruti Wagon R LXI CNG	Mumbai	2010	72000	CNG	Manual	First	
1	1	Hyundai Creta 1.6 CRDi SX Option	Pune	2015	41000	Diesel	Manual	First	
2	2	Honda Jazz V	Chennai	2011	46000	Petrol	Manual	First	
3	3	Maruti Ertiga VDI	Chennai	2012	87000	Diesel	Manual	First	
4	4	Audi A4 New 2.0 TDI Multitronic	Coimbatore	2013	40670	Diesel	Automatic	Second	

In [4]:
```
#Distribution visualization
data.hist(figsize=(15,15), edgecolor = 'black');
```



Data Preparation

In [5]:
```
#Dropping the first column as its an ID place holder
data.drop(['S.No.'],axis=1,inplace=True)
```

In [6]:
```
#Drop the New Price column - no need for 2 Pricing structures
data.drop(['New_Price'],axis=1, inplace=True)
```

In [7]:
```
#Specify data columns with null values to remove
from scipy.stats import norm
num_col = data.select_dtypes(include=np.number).columns.tolist()

for col in num_col:
    data[col]=data[col].replace(0.0,np.nan)
```

In [8]:
```
#list categorical columns
num_col
```

Out[8]:
```
['Year', 'Kilometers_Driven', 'Seats', 'Price']
```

In [9]:
```
#loop will add all the columns we want to change obj to string to use for a list
num_values = []

for colname in data.columns[data.dtypes == 'object']:  # only need to focus on st
    if data[colname].str.endswith('pl').any() or data[colname].str.endswith('kg')
        # using `.str` to use an element-wise string method to select the require
        num_values.append(colname)

print(num_values)
```

```
['Mileage', 'Engine', 'Power']
```

In [10]:
```
#Formulating a function to split the string from the numerical values in the colu
##the string and converts to float (see data head for values)
def obj_to_num(n):
    if isinstance(n,str): #checks if the column is a string
        if n.endswith('kmpl'):
            return float(n.split('kmpl')[0])
        elif n.endswith('km/kg'):
            return float(n.split('km/kg')[0])
        elif n.endswith('CC'):
            return float(n.split('CC')[0])
        elif n.startswith('null'):     #changes str values from 'null bhp' to Nar
            return(np.nan)
        elif n.endswith('bhp'):
             return float(n.split('bhp')[0])
    else:
        return np.nan

for colname in num_values:
    data[colname] = data[colname].apply(obj_to_num)#applying above function to th
    data[colname]=data[colname].replace(0.0,np.nan)
```

Transform categorical columns for use in Linear Regression model

In [11]:
```
#Creating category
data["Name"]=data["Name"].astype("category")
data["Location"]=data["Location"].astype("category")
data["Fuel_Type"]=data["Fuel_Type"].astype("category")
data["Transmission"]=data["Transmission"].astype("category")
data["Owner_Type"]=data["Owner_Type"].astype("category")
```

In [12]:
```
#Checking dataset for non-null values, types, totals
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7253 entries, 0 to 7252
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype   
---  ------             --------------  -----   
 0   Name               7253 non-null   category
 1   Location           7253 non-null   category
 2   Year               7253 non-null   int64   
 3   Kilometers_Driven  7253 non-null   int64   
 4   Fuel_Type          7253 non-null   category
 5   Transmission       7253 non-null   category
 6   Owner_Type         7253 non-null   category
 7   Mileage            7170 non-null   float64 
 8   Engine             7207 non-null   float64 
 9   Power              7078 non-null   float64 
 10  Seats              7199 non-null   float64 
 11  Price              6019 non-null   float64 
dtypes: category(5), float64(5), int64(2)
memory usage: 520.7 KB
```

In [13]:
```
#Creating category dataframe whilst viewing statistics
data.describe(include=["category"]).T
```

Out[13]:

	count	unique	top	freq
Name	7253	2041	Mahindra XUV500 W8 2WD	55
Location	7253	11	Mumbai	949
Fuel_Type	7253	5	Diesel	3852
Transmission	7253	2	Manual	5204
Owner_Type	7253	4	First	5952

OBSERVATIONS: -Mumbai sold the most cars -Preference of vehicle by fuel choice is diesel -Manual transmission sold most -First time owners purchased a second hand car the most in this dataset

In [14]:
```
#Split brand and the car model
data[['Car_Brand','Model']] = data.Name.str.split(n=1,expand=True)
```

In [15]:
```
#Model names are unique to the Car Brands
Brand_name=data['Car_Brand'].unique()
Model=data['Model'].unique()
```

In [16]:
```
#Revising names
data['Car_Brand']=data['Car_Brand'].replace('Land','Land_Rover')
data['Car_Brand']=data['Car_Brand'].replace('ISUZU','Isuzu')
data['Car_Brand'].value_counts()
```

Out[16]:
```
Maruti           1444
Hyundai          1340
Honda             743
Toyota            507
Mercedes-Benz     380
Volkswagen        374
Ford              351
Mahindra          331
BMW               312
Audi              285
Tata              228
Skoda             202
Renault           170
Chevrolet         151
Nissan            117
Land_Rover         67
Jaguar             48
Fiat               38
Mitsubishi         36
Mini               31
Volvo              28
Porsche            19
Jeep               19
Datsun             17
Isuzu               5
Force               3
Bentley             2
Smart               1
Ambassador          1
Lamborghini         1
Hindustan           1
OpelCorsa           1
Name: Car_Brand, dtype: int64
```

In [17]:
```
#Creating num columns
numeric_columns = data.select_dtypes(include=np.number).columns.tolist()
numeric_columns
```

Out[17]:
```
['Year', 'Kilometers_Driven', 'Mileage', 'Engine', 'Power', 'Seats', 'Price']
```

In [18]:
```
#Creating dependant variables using lambda function
numeric_columns.remove('Price')
medianFiller = lambda x: x.fillna(x.median())
data[numeric_columns] = data[numeric_columns].apply(medianFiller,axis=0)
```

In [19]:
```
#list for column data
Median1=[]
for i in range(len(Brand_name)):
    x=data['Price'][data['Car_Brand']==Brand_name[i]].median()
    Median1.append(x)
```

In [20]:
```
#Plotting second empty list to display median price of cars per Car model for vis
Median2=[]
for i in range(len(Model)):
    x=data['Price'][data['Model']==Model[i]].median()
    Median2.append(x)
```

In [21]:
```
#Adding float amount 0.00 to missing data values in modified data
data['Price']= data['Price'].fillna(0.0)
```

In [22]:
```
#Running a loop to check every row in data dataset
for i in range(len(data)):
    if data.Price[i]==0.00:
        for j in range(len(Model)):
            if data.Model[i]==Model[j]:  #Comparing the Car model  names in both
                data.Price[i]=Median2[j]  #replacing the Price of the car with th
```

In [23]:
```
#Additional check for df types and confirming non-null values
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7253 entries, 0 to 7252
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype   
---  ------             --------------  -----   
 0   Name               7253 non-null   category
 1   Location           7253 non-null   category
 2   Year               7253 non-null   int64   
 3   Kilometers_Driven  7253 non-null   int64   
 4   Fuel_Type          7253 non-null   category
 5   Transmission       7253 non-null   category
 6   Owner_Type         7253 non-null   category
 7   Mileage            7253 non-null   float64 
 8   Engine             7253 non-null   float64 
 9   Power              7253 non-null   float64 
 10  Seats              7253 non-null   float64 
 11  Price              7075 non-null   float64 
 12  Car_Brand          7253 non-null   object  
 13  Model              7253 non-null   object  
dtypes: category(5), float64(5), int64(2), object(2)
memory usage: 634.0+ KB
```

In [24]:
```
#Checking for all Price values containing NaN's in df
data[data['Price'].isna()]
```

Out[24]:

	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type	Mileage
6021	Toyota Innova Crysta Touring Sport 2.4 MT	Mumbai	2017	34000	Diesel	Manual	First	13.68
6037	Maruti Swift AMT ZXI	Kochi	2019	15409	Petrol	Automatic	First	22.00
6042	Skoda Laura 1.8 TSI Ambition	Bangalore	2009	72000	Petrol	Manual	Second	17.50
6043	Honda Civic 2010-2013 1.8 S MT Inspire	Bangalore	2011	40000	Petrol	Manual	Second	15.50
6076	Toyota Etios Liva 1.4 VXD	Pune	2016	104350	Diesel	Manual	First	23.59
...	...	...	...	...	...	...	...	..
7225	Skoda Superb Petrol Ambition	Delhi	2010	40000	Petrol	Manual	First	13.10
7228	Tata Tiago 1.05 Revotorq XT Option	Pune	2016	41413	Diesel	Manual	First	27.28
7231	Ford EcoSport 1.5 Petrol Ambiente	Kochi	2017	39015	Petrol	Manual	First	17.00
7232	Jeep Compass 1.4 Sport	Mumbai	2018	6000	Petrol	Manual	First	16.00
7236	Hyundai Elite i20 Magna Plus	Kochi	2018	23955	Petrol	Manual	First	18.60

178 rows × 14 columns

In [25]:
```
#Replacing the missing values with float 0.0
data['Price']= data['Price'].fillna(0.0)
#running a loop to check row in dataset
for i in range(len(data)):
    if data.Price[i]==0.00:
        for j in range(len(Brand_name)):
            if data.Car_Brand[i]==Brand_name[j]:  #Comparing the brand names in b
                data.Price[i]=Median1[j]          #replacing with corresponding m
```

In [26]:
```
#Checking NaN Price values
data[data['Price'].isna()]
```

Out[26]:

	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type	Milea
6216	Hindustan Motors Contessa 2.0 DSL	Pune	1996	65000	Diesel	Manual	Second	14
7067	OpelCorsa 1.4Gsi	Hyderabad	2005	50000	Petrol	Manual	Second	14

In [27]:
```
#Dropping the cars in above df - (as they are rare, do not want to impact overall
data.dropna(axis=0,inplace=True)
```

In [28]:
```
#checking the shape
data.shape
```

Out[28]:
```
(7251, 14)
```

In [29]:
```
#Lambda function for float values and transpose data frame output
pd.set_option('display.float_format', lambda x: '%.3f' % x)
data.describe().T
```

Out[29]:

	count	mean	std	min	25%	50%	75%	
Year	7251.000	2013.369	3.247	1998.000	2011.000	2014.000	2016.000	2
Kilometers_Driven	7251.000	58699.394	84439.271	171.000	34000.000	53416.000	73000.000	650
Mileage	7251.000	18.346	4.134	6.400	15.400	18.200	21.100	
Engine	7251.000	1615.769	593.534	72.000	1198.000	1493.000	1968.000	5
Power	7251.000	112.318	52.929	34.200	77.000	94.000	138.030	
Seats	7251.000	5.278	0.807	2.000	5.000	5.000	5.000	
Price	7251.000	9.328	10.863	0.000	3.500	5.500	9.750	

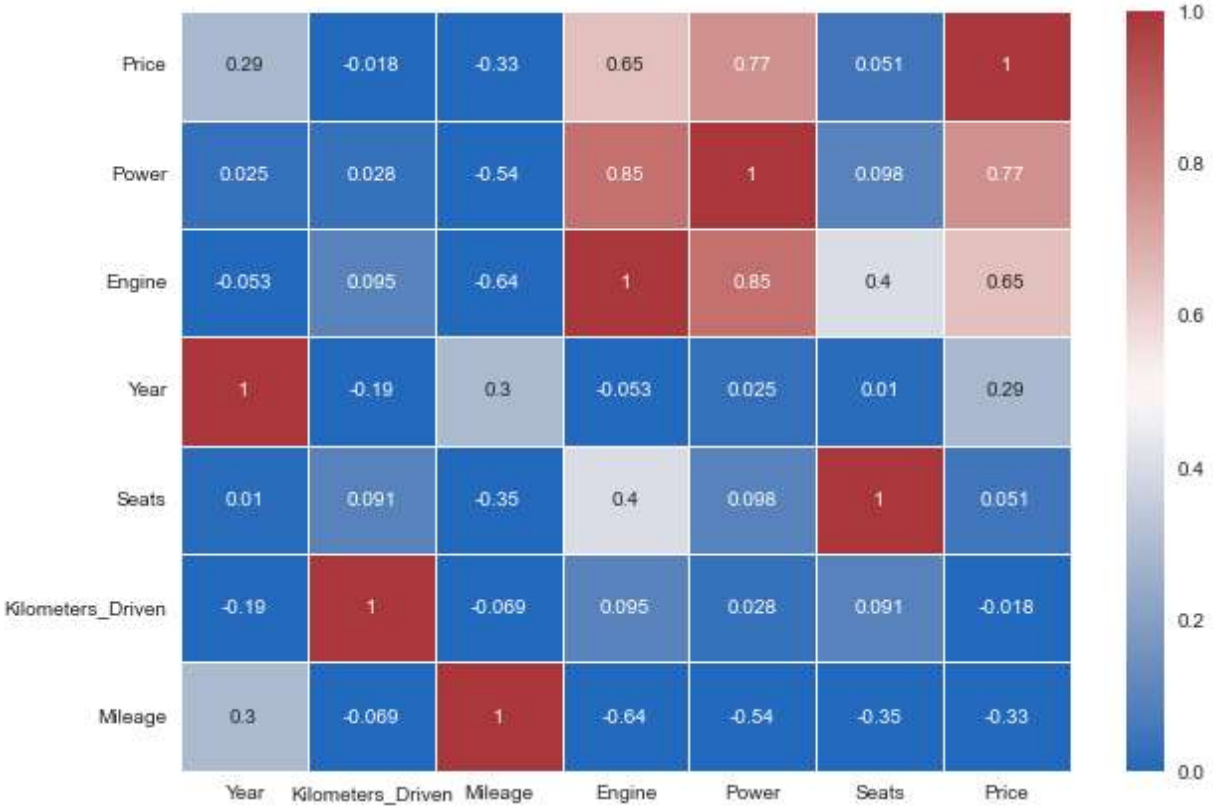
Correlation Visualization

In [30]:
```
data.corr()
```

Out[30]:

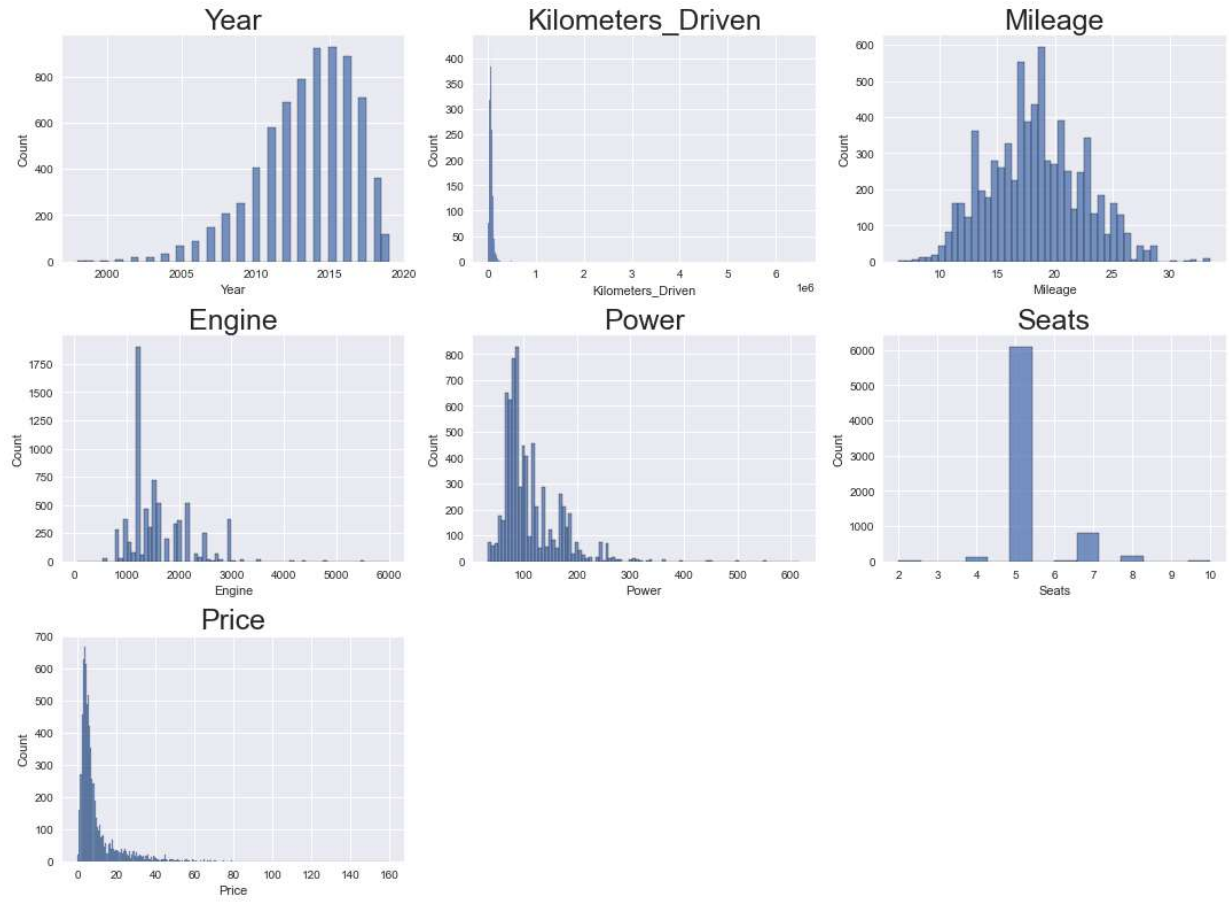
	Year	Kilometers_Driven	Mileage	Engine	Power	Seats	Price
Year	1.000	-0.188	0.295	-0.053	0.025	0.010	0.292
Kilometers_Driven	-0.188	1.000	-0.069	0.095	0.028	0.091	-0.018
Mileage	0.295	-0.069	1.000	-0.638	-0.543	-0.348	-0.325
Engine	-0.053	0.095	-0.638	1.000	0.855	0.403	0.652
Power	0.025	0.028	-0.543	0.855	1.000	0.098	0.767
Seats	0.010	0.091	-0.348	0.403	0.098	1.000	0.051
Price	0.292	-0.018	-0.325	0.652	0.767	0.051	1.000

In [31]:
```
#heat map showing strongest correlations
corr= data.corr().sort_values(by=['Price'],ascending=False)
plt.figure(figsize=(10,7))
sns.heatmap(corr,annot= True,vmin=0,vmax=1, cmap='vlag',linewidths=0.75)
plt.show()
#Price & Power = .77
#Power & Engine = .85
```



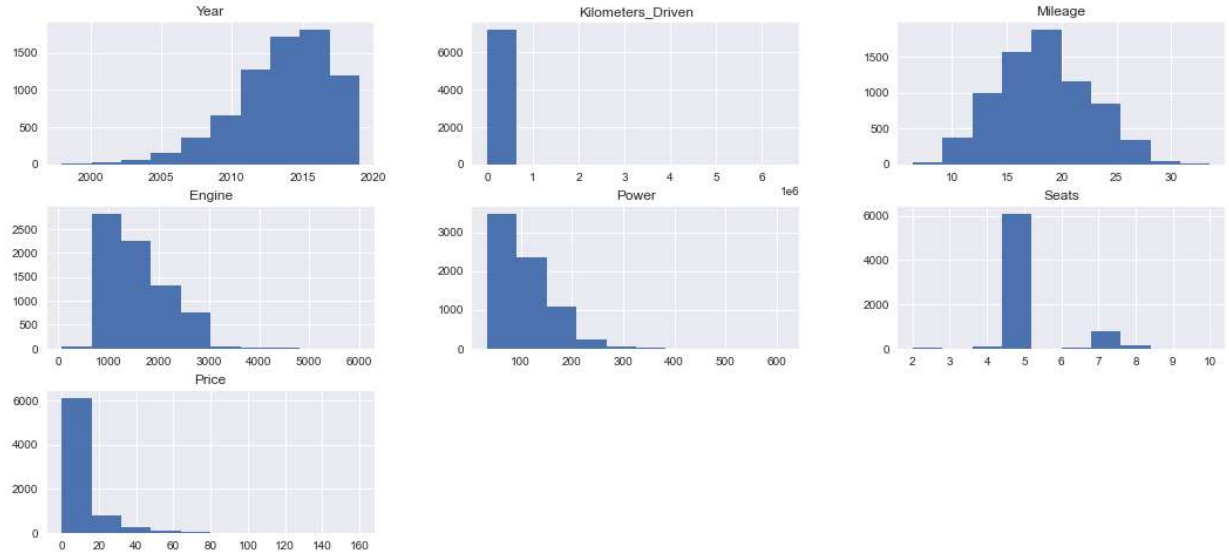
Univariate Analysis to Plot histograms to check the distributions of the predictors

In [32]:
```
#Plotting histogram for distribution
Uni_num = data.select_dtypes(include=np.number).columns.tolist()
plt.figure(figsize=(15,65))
 #creating a loop that will show the plots for the columns in one plot
for i in range(len(Uni_num)):
    plt.subplot(18,3,i+1)
    sns.histplot(data[Uni_num[i]],kde=False)
    plt.tight_layout()
    plt.title(Uni_num[i],fontsize=25)

plt.show()
```

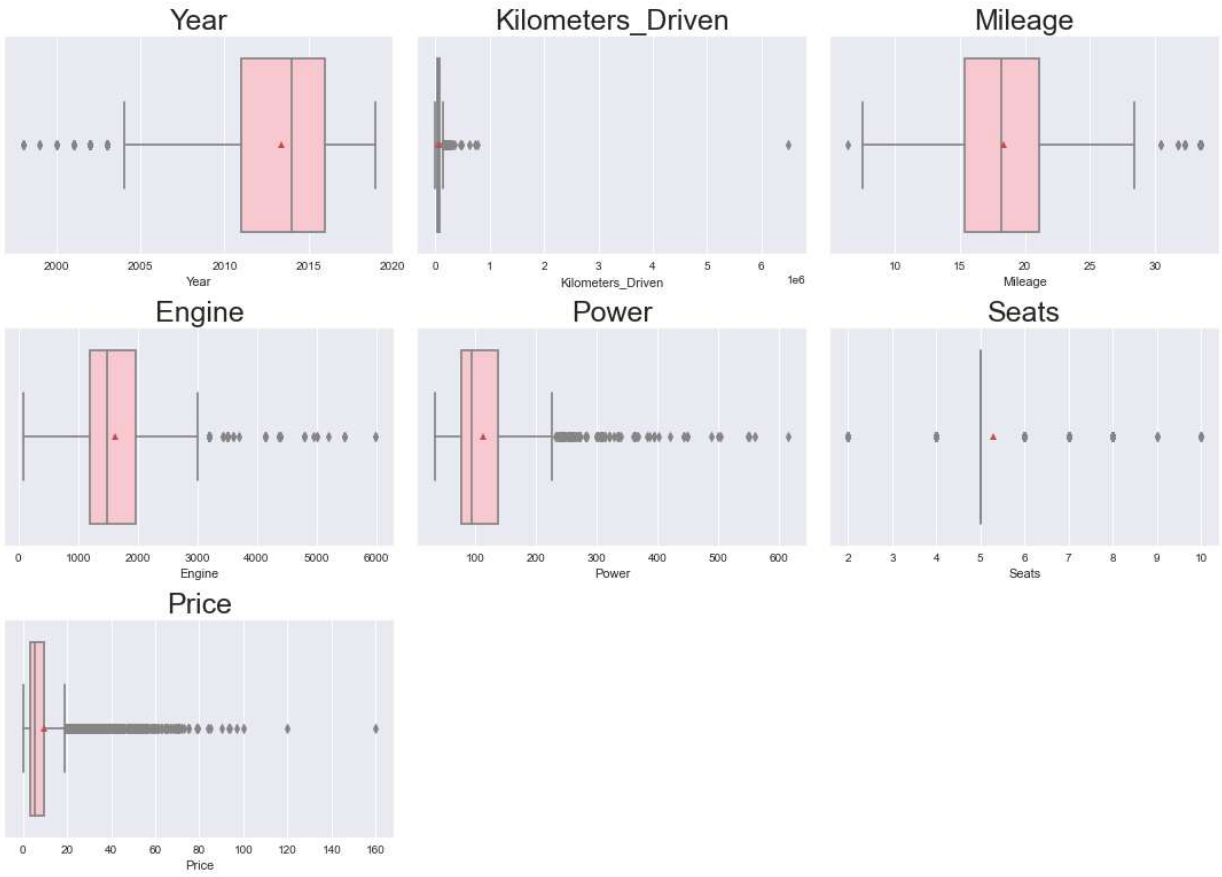


Analsyis of above and the below visualisations Year: Left Skewed Kilometers driven: Right skewed spike Mileage: Normal distribution Engine:Right skewed Power: Right skewed Seats: Right Skewed

In [33]:
```
#Useful histogram to view any variances and understand the data set - note mileag
import warnings
warnings.filterwarnings('ignore')
fig = plt.figure(figsize = (18,8))
ax = fig.gca()
data.hist(ax = ax);
```



In [34]:
```
#Plotting a box plot to confirm preconceived assumptions
plt.figure(figsize=(15,35))
for i in range(len(Uni_num)):
    plt.subplot(10,3,i+1)
    sns.boxplot(data[Uni_num[i]],showmeans=True, color='pink')
    plt.tight_layout()
    plt.title(Uni_num[i],fontsize=25)
plt.show()
```



More Data Preparation is required for categorical values

In [35]:
```
#Creating region lists
regions ={'Delhi':'North','Jaipur':'North',
          'Chennai':'South','Coimbatore':'South','Hyderabad':'South','Bangalore':
         'Kolkata':'East',
          'Mumbai':'West','Pune':'West','Ahmedabad':'West'}
data['Region']=data['Location'].replace(regions)
```

In [36]:
```
#Dropping unnecessary models  & counting valid car type values to classify by lev
data.drop(["Car_Brand","Model"],axis=1,inplace=True)
data['Car_Type'] = pd.cut(data['Price'],[-np.inf,5.5,10.5,20.5,45.0,75.0,np.inf],
                          labels=["Level1","Level2","Level3","Level4","Level5","Leve

data['Car_Type'].value_counts()

## LEVELS = CAR_TYPE Level 1 is low grade(economical less expensive car) to Level
## Owner Type = First second cars, second card, third car, etc.
```

Out[36]:
```
Level1    3638
Level2    1916
Level3     896
Level4     669
Level5     120
Level6      12
Name: Car_Type, dtype: int64
```

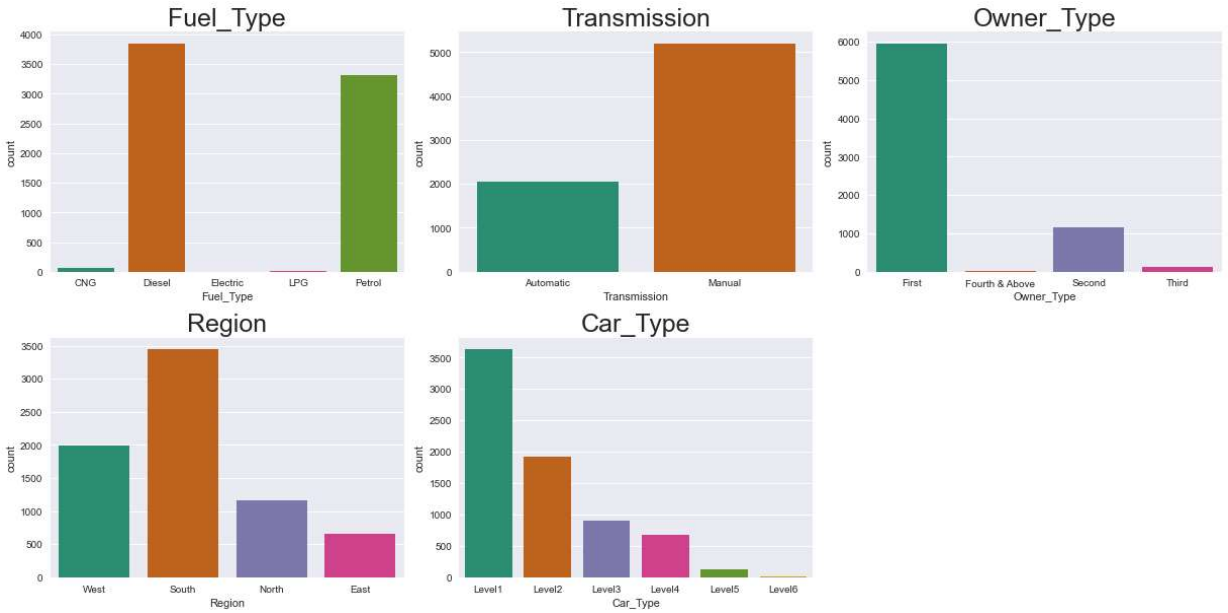
In [37]:
```
#View sample of Level 3 type vehicle below
data.sample()
```

Out[37]:

	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type	Mileage
3762	Skoda Superb Elegance 1.8 TSI AT	Mumbai	2009	35000	Petrol	Automatic	Second	13.700

In [38]:
```
#Set categorical values to populate column list
categorical_val = data.select_dtypes(exclude=np.number).columns.tolist()
categorical_val.remove('Name')
categorical_val.remove('Location')
```

In [39]:
```
#visual bar graph
plt.figure(figsize=(17,75))
for i in range(len(categorical_val)):
    plt.subplot(18,3,i+1)
    ax=sns.countplot(data[categorical_val[i]],palette='Dark2')
    plt.tight_layout()
    plt.title(categorical_val[i],fontsize=25)
    total = len (data[categorical_val[i]])
    for p in ax.patches:
        x = p.get_x() + (p.get_width() / 2)-0.1
        y = p.get_y() + p.get_height()
plt.show()
```

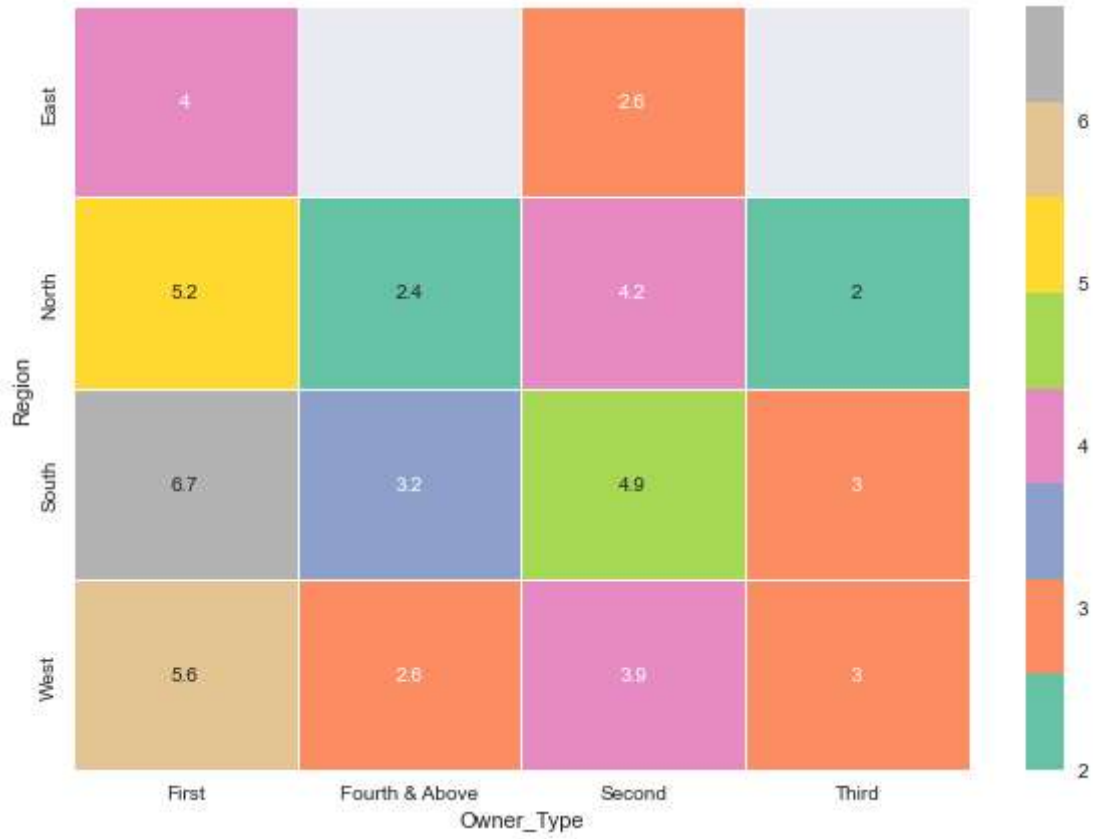


In [40]:
```
#Reviewing dataset for electric cars
data[data['Fuel_Type']=='Electric']
```

Out[40]:

	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type	Mileage
4446	Mahindra E Verito D4	Chennai	2016	50000	Electric	Automatic	First	18.200
4904	Toyota Prius 2009-2016 Z4	Mumbai	2011	44000	Electric	Automatic	First	18.200

In [41]:
```
#Does type of ownership affect Car price?
df_hm =data.pivot_table(index = 'Region',columns ='Owner_Type',values ="Price",ag
# Heatmap to display
plt.subplots(figsize=(10,7))
sns.heatmap(df_hm,cmap='Set2',linewidths=.5, annot=True);
#south Region purchases more second hand cars
```



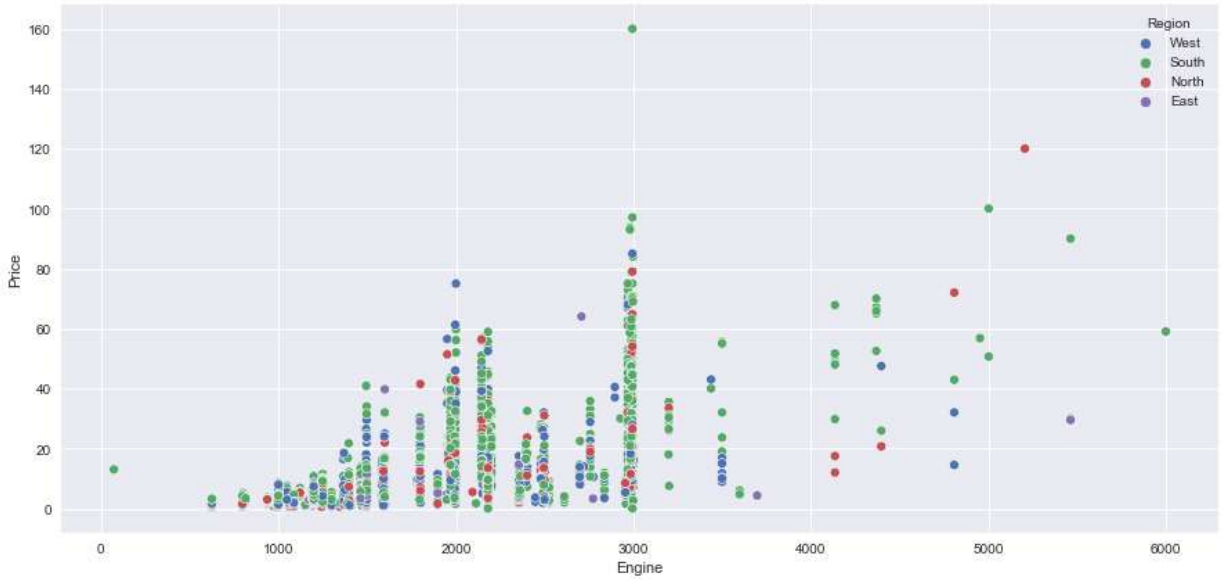
Linear Regression Assumption Checks with Visualisations

Using scatterplots, heatmaps, bar graphs to plot each predictor against the target variable

1. Linearity
2. Normality (residuals)
3. Homoscedasticity

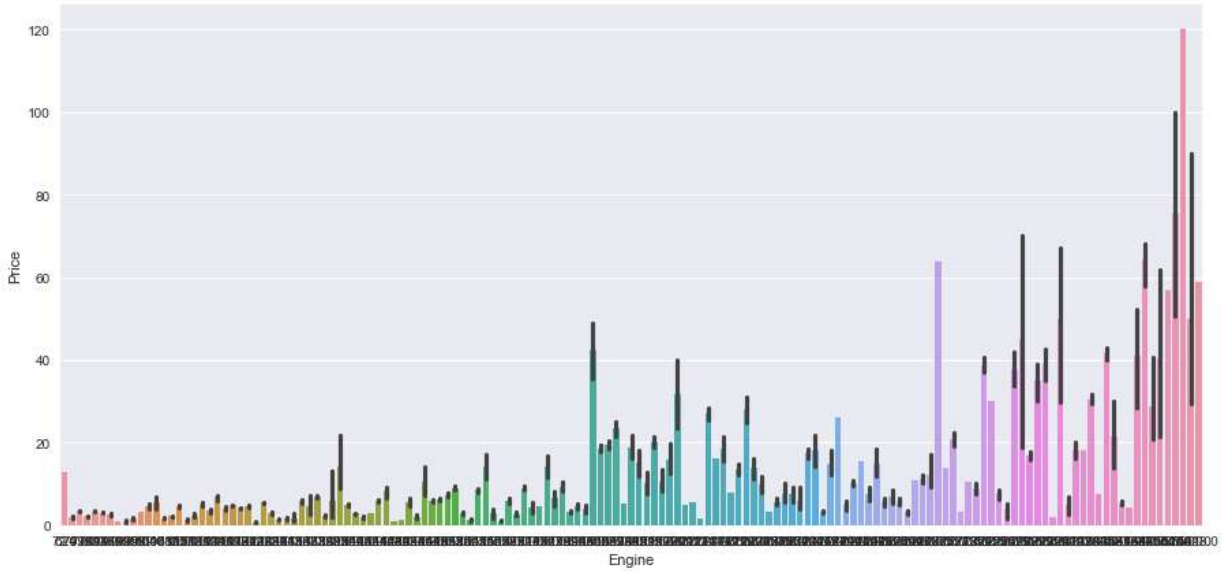
additional detail further incorporating test data

In [42]:
```
#Analysis of variables that have high correlation with Price
#Price Vs Engine Vs Region
plt.figure(figsize=(15,7))
sns.scatterplot(data=data,y='Price',x='Engine',hue='Region')
plt.show()
```



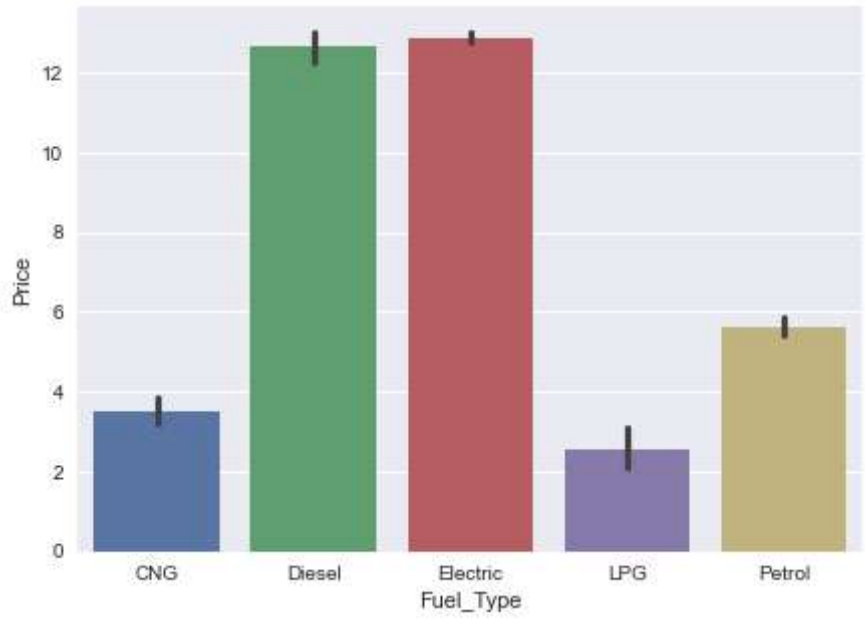
In [43]:
```
#Does type of Fuel affect car price?
plt.figure(figsize=(15,7))
sns.barplot(data=data,x='Engine',y='Price')
```

Out[43]: <AxesSubplot:xlabel='Engine', ylabel='Price'>



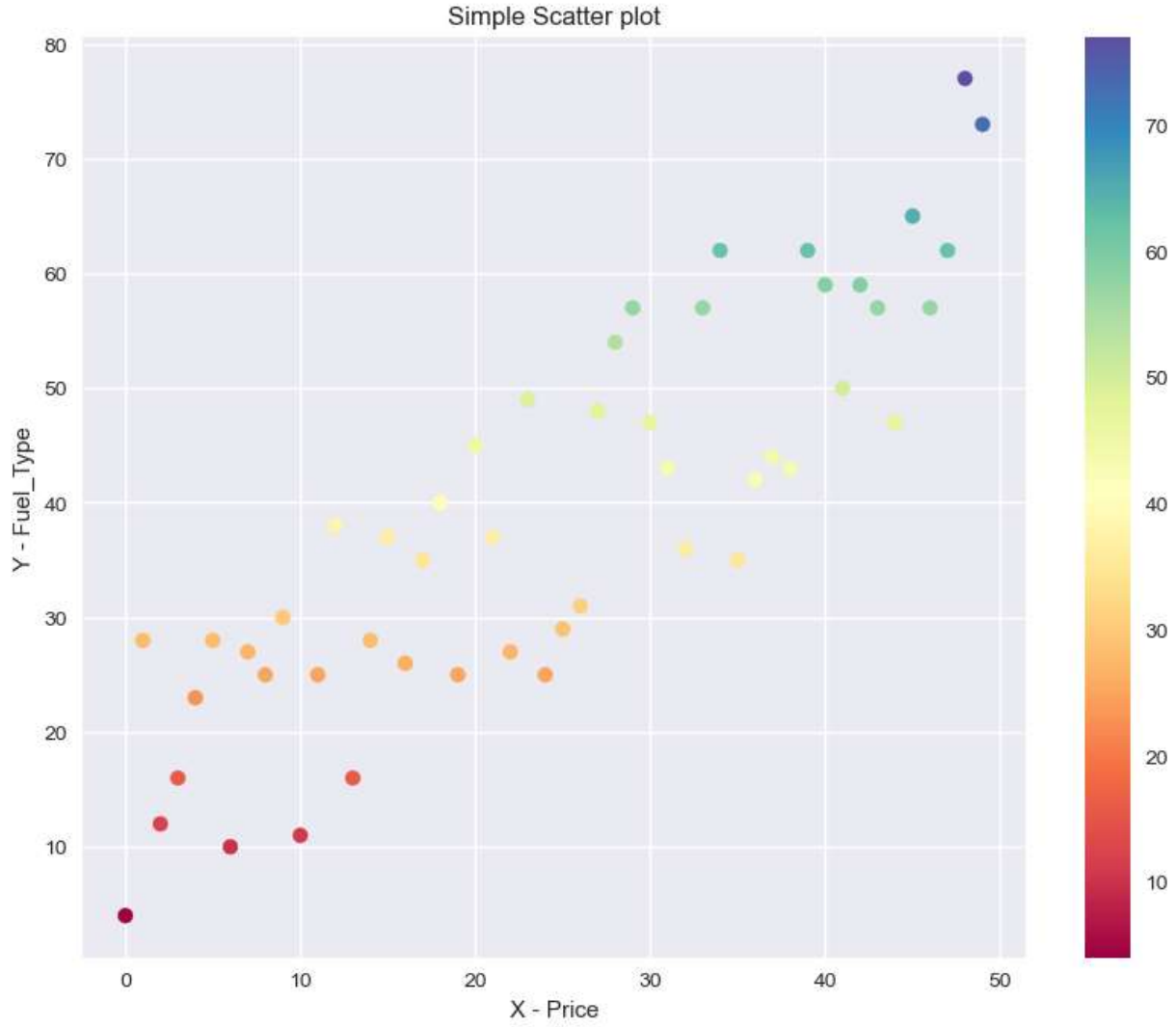
In [44]:
```
#Does type of Fuel affect car price?
plt.figure(figsize=(7,5))
sns.barplot(data=data,x='Fuel_Type',y='Price')
```

Out[44]: <AxesSubplot:xlabel='Fuel_Type', ylabel='Price'>



Visualize the error term for variance and heteroscedasticity

In [45]:
```
# Simple Scatterplot with colored points
x = range(50)
y = range(50) + np.random.randint(0,30,50)
plt.rcParams.update({'figure.figsize':(10,8), 'figure.dpi':100})
plt.scatter(x, y, c=y, cmap='Spectral')
plt.colorbar()
plt.title('Simple Scatter plot')
plt.xlabel('X - Price')
plt.ylabel('Y - Fuel_Type')
plt.show()
```



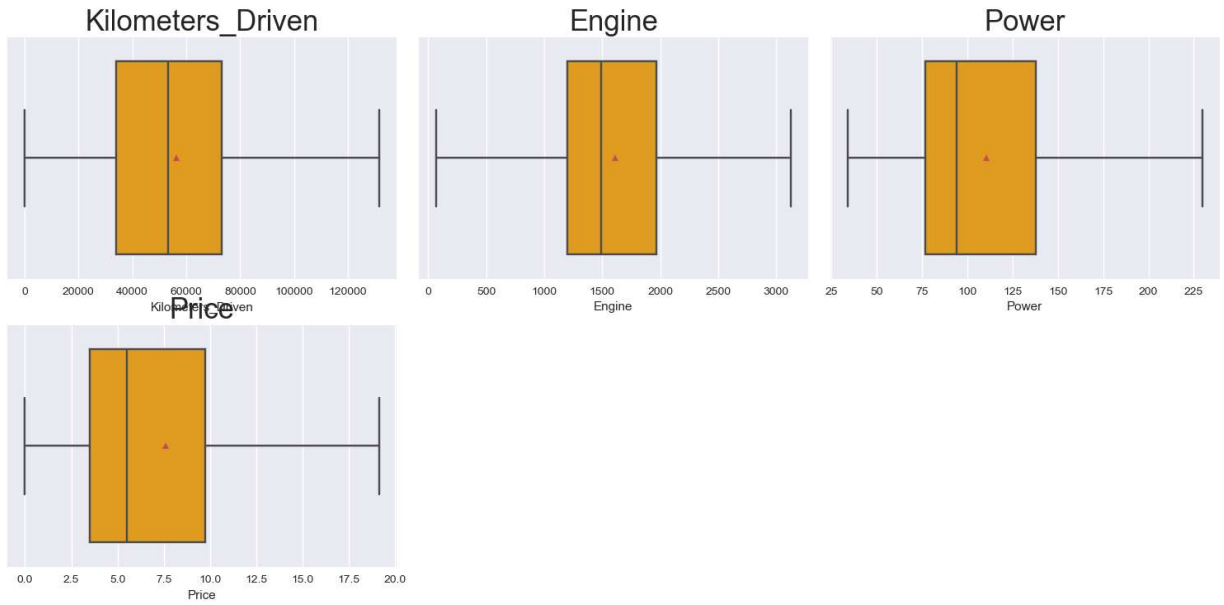
In [46]:
```
#Dealing with outliers utilisng the 25th & 75th quantiles
def treat_outliers(data,col):

    Q1=data[col].quantile(0.25) # 25th quantile
    Q3=data[col].quantile(0.75)  # 75th quantile
    IQR=Q3-Q1
    Lower_Whisker = Q1 - 1.5*IQR
    Upper_Whisker = Q3 + 1.5*IQR
    data[col] = np.clip(data[col], Lower_Whisker, Upper_Whisker)

    return data

def treat_outliers_all(data, col_list):

    for c in col_list:
        data = treat_outliers(data,c)
    return data
```

In [47]:
```
#making a first copy & dropping Year, mileage and seats outliers as irrelevant
df2=data.copy()
numerical_col = df2.select_dtypes(include=np.number).columns.tolist()
numerical_col.remove('Year')
numerical_col.remove('Mileage')
numerical_col.remove('Seats')
numerical_col
```

Out[47]:
```
['Kilometers_Driven', 'Engine', 'Power', 'Price']
```

In [48]:
```
#dealing with outliers
df2 = treat_outliers_all(df2,numerical_col)
```

In [49]:
```
#checking if the outliers have applied
plt.figure(figsize=(15,35))
for i in range(len(numerical_col)):
    plt.subplot(10,3,i+1)
    sns.boxplot(df2[numerical_col[i]],showmeans=True, color='orange')
    plt.tight_layout()
    plt.title(numerical_col[i],fontsize=25)
plt.show()
```



In [50]:
```
#Reviewing data head
df2.head()
```

Out[50]:

	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type	Mileage
0	Maruti Wagon R LXI CNG	Mumbai	2010	72000.000	CNG	Manual	First	26.600
1	Hyundai Creta 1.6 CRDi SX Option	Pune	2015	41000.000	Diesel	Manual	First	19.670
2	Honda Jazz V	Chennai	2011	46000.000	Petrol	Manual	First	18.200
3	Maruti Ertiga VDI	Chennai	2012	87000.000	Diesel	Manual	First	20.770
4	Audi A4 New 2.0 TDI Multitronic	Coimbatore	2013	40670.000	Diesel	Automatic	Second	15.200

In [51]:
```
#dropping Name as we have created a bin called: Car_Type
#dropping Fuel_Type
X = df2.drop(['Name','Fuel_Type','Location','Price'], axis=1)
y = df2[['Price']]
#Reviewing new data shape
print(X.shape)
print(y.shape)
```

```
(7251, 10)
(7251, 1)
```

In [52]:
```
##pd.set_option('display.float_format', lambda x: '%.3f' % x) # to display number
##data.describe().T
```

In [53]:
```
#Creating Dummy Variabls for the Categorical Columns
#Dummy variable will be used as independent variables and will not impose any rar
X = pd.get_dummies(X, columns=['Transmission','Owner_Type','Region','Car_Type'],
X.head()
```

Out[53]:

	Year	Kilometers_Driven	Mileage	Engine	Power	Seats	Transmission_Manual	Owner_Type_ &
0	2010	72000.000	26.600	998.000	58.160	5.000	1	
1	2015	41000.000	19.670	1582.000	126.200	5.000	1	
2	2011	46000.000	18.200	1199.000	88.700	5.000	1	
3	2012	87000.000	20.770	1248.000	88.760	7.000	1	
4	2013	40670.000	15.200	1968.000	140.800	5.000	0	

In [54]:
```
#split the data into train and test
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_s
X_train.head()
```

Out[54]:

	Year	Kilometers_Driven	Mileage	Engine	Power	Seats	Transmission_Manual	Owner_Ty
1928	2016	55100.000	17.010	1582.000	126.200	5.000	0	
6278	2012	90000.000	23.590	1364.000	94.000	5.000	1	
22	2015	55985.000	13.530	1984.000	177.010	5.000	0	
5925	2010	85000.000	17.500	1798.000	94.000	5.000	1	
5762	2014	51000.000	27.030	1969.000	190.000	5.000	0	

In [55]:
```
#Fitting linear model
from sklearn.linear_model import LinearRegression
linearregression = LinearRegression()
linearregression.fit(X_train, y_train)
print("Intercept of the linear equation:", linearregression.intercept_)
for idx, col_name in enumerate(X_train.columns):
    print("The coefficient for {} is {}".format(col_name, linearregression.coef_[
```

```
Intercept of the linear equation: [-404.87654936]
The coefficient for Year is 0.2014249816152108
The coefficient for Kilometers_Driven is -1.6203755332221522e-06
The coefficient for Mileage is 0.04349748263039035
The coefficient for Engine is 0.0007955011277483669
The coefficient for Power is 0.016005440241528498
The coefficient for Seats is 0.07091913468838472
The coefficient for Transmission_Manual is -0.7422961502300802
The coefficient for Owner_Type_Fourth & Above is 0.5406481259194158
The coefficient for Owner_Type_Second is -0.09782155395636072
The coefficient for Owner_Type_Third is -0.23169983508213976
The coefficient for Region_North is 0.21245763647508623
The coefficient for Region_South is 0.3898811409975626
The coefficient for Region_West is 0.26965728280936585
The coefficient for Car_Type_Level2 is 2.6033256086328653
The coefficient for Car_Type_Level3 is 8.598665328915168
The coefficient for Car_Type_Level4 is 12.04933176079081
The coefficient for Car_Type_Level5 is 10.894805905199384
The coefficient for Car_Type_Level6 is 10.584283476822167
```

In [56]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
pred = linearregression.predict(X_test)
```

In [57]:
```
# Mean Absolute Error on test
mean_absolute_error(y_test, pred)
```

Out[57]: 0.8903015607952957

In [58]:
```
# RMSE on test data
mean_squared_error(y_test, pred)**0.5
```

Out[58]: 1.215184412886623

In [59]:
```
# R-squared on test rather than log transformation as data is not highly skewed
r2_score(y_test, pred)
```

Out[59]: 0.9536193921069149

In [60]:
```
#Calculating train score
linearregression.score(X_train, y_train)  # 70 % data
```

Out[60]: 0.9520061630151408

In [61]:
```
#Calculating Test Score
linearregression.score(X_test, y_test) # unseen data
```

Out[61]: 0.9536193921069149

In [62]:
```
#Creating another copy of df
df3=data.copy()
df3.head()
```

Out[62]:

	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type	Mileage
0	Maruti Wagon R LXI CNG	Mumbai	2010	72000	CNG	Manual	First	26.600
1	Hyundai Creta 1.6 CRDi SX Option	Pune	2015	41000	Diesel	Manual	First	19.670
2	Honda Jazz V	Chennai	2011	46000	Petrol	Manual	First	18.200
3	Maruti Ertiga VDI	Chennai	2012	87000	Diesel	Manual	First	20.770
4	Audi A4 New 2.0 TDI Multitronic	Coimbatore	2013	40670	Diesel	Automatic	Second	15.200

In [63]:
```
#Creating additional variable to drop unnecessary columns
X1 = df3.drop(['Name','Fuel_Type','Location','Price'], axis=1)
y1 = df3[['Price']]

print(X1.shape)
print(y1.shape)
```

```
(7251, 10)
(7251, 1)
```

In [64]:
```
#Creating Dummy Variables for categorical columns
X1 = pd.get_dummies(X1, columns=['Region','Car_Type','Transmission','Owner_Type'])
X1.head()
```

Out[64]:

	Year	Kilometers_Driven	Mileage	Engine	Power	Seats	Region_North	Region_South	Regi
0	2010	72000	26.600	998.000	58.160	5.000	0	0	
1	2015	41000	19.670	1582.000	126.200	5.000	0	0	
2	2011	46000	18.200	1199.000	88.700	5.000	0	1	
3	2012	87000	20.770	1248.000	88.760	7.000	0	1	
4	2013	40670	15.200	1968.000	140.800	5.000	0	1	

In [65]:
```
#split the data into train and test
from sklearn.model_selection import train_test_split
X1_train, X1_test, y1_train, y1_test = train_test_split(X1, y1, test_size=0.3, ra
X1_train.head()
```

Out[65]:

	Year	Kilometers_Driven	Mileage	Engine	Power	Seats	Region_North	Region_South	R
1928	2016	55100	17.010	1582.000	126.200	5.000	0	0	
6278	2012	90000	23.590	1364.000	94.000	5.000	0	1	
22	2015	55985	13.530	1984.000	177.010	5.000	0	0	
5925	2010	85000	17.500	1798.000	94.000	5.000	0	0	
5762	2014	51000	27.030	1969.000	190.000	5.000	0	1	

In [66]:
```
#Fitting linear model
from sklearn.linear_model import LinearRegression
linearregression = LinearRegression()
linearregression.fit(X1_train, y1_train)
print('Intercept of the linear equation:', linearregression.intercept_)
for idx, col_name in enumerate(X1_train.columns):
    print("The coefficient for {} is {}".format(col_name, linearregression.coef_[
```

```
Intercept of the linear equation: [-559.64477119]
The coefficient for Year is 0.27815207711649104
The coefficient for Kilometers_Driven is -3.933049214243794e-06
The coefficient for Mileage is 0.041173020980351936
The coefficient for Engine is 0.0012536524615097344
The coefficient for Power is 0.021857197060797674
The coefficient for Seats is -0.10443213439518366
The coefficient for Region_North is 0.43423501867368897
The coefficient for Region_South is 0.6551430985061976
The coefficient for Region_West is 0.3849291968220981
The coefficient for Car_Type_Level2 is 2.18734590987969
The coefficient for Car_Type_Level3 is 7.852889631704657
The coefficient for Car_Type_Level4 is 21.448157673682097
The coefficient for Car_Type_Level5 is 45.73101094812465
The coefficient for Car_Type_Level6 is 77.34107051395367
The coefficient for Transmission_Manual is -0.5553857640064356
The coefficient for Owner_Type_Fourth & Above is 1.060293629823952
The coefficient for Owner_Type_Second is -0.012176133022344845
The coefficient for Owner_Type_Third is 0.19972117592182498
```

In [67]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
pred1 = linearregression.predict(X1_test)
```

In [68]:
```
# Calculate MAE
mean_absolute_error(y1_test, pred1)
```

Out[68]:
```
1.5128627827869912
```

In [69]:
```
#Calculate RMSE
mean_squared_error(y1_test, pred1)**0.5
```

Out[69]: 3.093684570463301

In [70]:
```
#Calculate R2 Score
r2_score(y1_test, pred1)
```

Out[70]: 0.921506918435542

In [71]:
```
#Calculate training lr Score based on 70% training data
linearregression.score(X1_train, y1_train)
```

Out[71]: 0.9450553498559194

The above appears to be a good fit to model predictions at 94%

In [72]:
```
#calculate lr score
linearregression.score(X1_test, y1_test)
```

Out[72]: 0.921506918435542

Run a OLS regression in Statsmodels with multiple variables in test data

In [73]:
```
# Builing first OLS stats model
import statsmodels.api as sm
X = sm.add_constant(X)
X_train1, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_

olsmod0 = sm.OLS(y_train, X_train1)
olsres0 = olsmod0.fit()
print(olsres0.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                  Price   R-squared:                       0.95
2
Model:                            OLS   Adj. R-squared:                  0.95
2
Method:                 Least Squares   F-statistic:                     557
2.
Date:                Sat, 11 Jun 2022   Prob (F-statistic):               0.0
0
Time:                        23:08:58   Log-Likelihood:                -8236.
5
No. Observations:                5075   AIC:                          1.651e+0
4
Df Residuals:                    5056   BIC:                          1.664e+0
4
Df Model:                          18
Covariance Type:            nonrobust
==============================================================================
================
                                coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
----------------
const                       -404.8765     15.837    -25.565      0.000    -43
5.924    -373.829
Year                           0.2014      0.008     25.530      0.000
0.186       0.217
Kilometers_Driven          -1.62e-06   7.42e-07     -2.183      0.029   -3.08
e-06   -1.65e-07
Mileage                        0.0435      0.006      7.141      0.000
0.032       0.055
Engine                         0.0008   7.79e-05     10.216      0.000
0.001       0.001
Power                          0.0160      0.001     16.028      0.000
0.014       0.018
Seats                          0.0709      0.029      2.463      0.014
0.014       0.127
Transmission_Manual           -0.7423      0.056    -13.312      0.000      -
0.852      -0.633
Owner_Type_Fourth & Above      0.5406      0.412      1.311      0.190      -
0.268       1.349
Owner_Type_Second             -0.0978      0.051     -1.917      0.055      -
0.198       0.002
Owner_Type_Third              -0.2317      0.132     -1.754      0.079      -
0.491       0.027
Region_North                   0.2125      0.074      2.869      0.004
```

```
0.067       0.358
Region_South                  0.3899      0.066      5.909      0.000
0.261       0.519
Region_West                   0.2697      0.068      3.940      0.000
0.135       0.404
Car_Type_Level2               2.6033      0.050     51.616      0.000
2.504       2.702
Car_Type_Level3               8.5987      0.079    108.186      0.000
8.443       8.754
Car_Type_Level4              12.0493      0.104    116.153      0.000      1
1.846      12.253
Car_Type_Level5              10.8948      0.180     60.663      0.000      1
0.543      11.247
Car_Type_Level6              10.5843      0.411     25.764      0.000
9.779      11.390
==============================================================================
=
Omnibus:                      358.893   Durbin-Watson:                   1.99
8
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1743.73
5
Skew:                           0.123   Prob(JB):                         0.0
0
Kurtosis:                       5.861   Cond. No.                     5.85e+0
7
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 5.85e+07. This might indicate that there a
re
strong multicollinearity or other numerical problems.
```

In [74]:
```
#statsmodels.stats.outliers_influence.variance - A measure for multicollinearity
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif_series1 = pd.Series([variance_inflation_factor(X_train1.values,i) for i in ra
print('Train Model 1: \n\n{}\n'.format(vif_series1))
```

```
Train Model 1:

const                          843215.673
Year                                2.198
Kilometers_Driven                   1.688
Mileage                             2.122
Engine                              6.520
Power                               7.102
Seats                               1.818
Transmission_Manual                 2.120
Owner_Type_Fourth & Above           1.013
Owner_Type_Second                   1.139
Owner_Type_Third                    1.077
Region_North                        2.482
Region_South                        3.654
Region_West                         3.109
Car_Type_Level2                     1.669
Car_Type_Level3                     2.284
Car_Type_Level4                     3.052
Car_Type_Level5                     1.641
Car_Type_Level6                     1.116
dtype: float64
```

In [75]:
```
#training second model to display values
X_train2 = X_train1.drop('Power', axis=1)
vif_series2 = pd.Series([variance_inflation_factor(X_train2.values,i) for i in ra
print('Train Model 2: \n\n{}\n'.format(vif_series2))
```

```
Train Model 2:

const                         841255.110
Year                               2.194
Kilometers_Driven                  1.688
Mileage                            2.093
Engine                             3.925
Seats                              1.625
Transmission_Manual                1.957
Owner_Type_Fourth & Above          1.012
Owner_Type_Second                  1.138
Owner_Type_Third                   1.077
Region_North                       2.480
Region_South                       3.638
Region_West                        3.106
Car_Type_Level2                    1.586
Car_Type_Level3                    2.077
Car_Type_Level4                    2.577
Car_Type_Level5                    1.532
Car_Type_Level6                    1.107
dtype: float64
```

Get Regression Diagnostics Summary

In [76]:
```
#OLS model - depicting values
olsmod1 = sm.OLS(y_train, X_train2)
olsres1 = olsmod1.fit()
print(olsres1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Price   R-squared:                       0.950
Model:                            OLS   Adj. R-squared:                  0.949
Method:                 Least Squares   F-statistic:                     5601.
Date:                Sat, 11 Jun 2022   Prob (F-statistic):               0.00
Time:                        23:08:58   Log-Likelihood:                -8362.3
No. Observations:                5075   AIC:                         1.676e+04
Df Residuals:                    5057   BIC:                         1.688e+04
Df Model:                          17
Covariance Type:            nonrobust
==============================================================================
                                 coef    std err          t      P>|t|      [0.0
25      0.975]
------------------------------------------------------------------------------
--------------
const                       -392.6371     16.214    -24.216      0.000    -424.4
23    -360.851
Year                           0.1961      0.008     24.274      0.000       0.1
80       0.212
Kilometers_Driven         -1.718e-06   7.61e-07     -2.258      0.024   -3.21e-
06   -2.27e-07
Mileage                        0.0320      0.006      5.160      0.000       0.0
20       0.044
Engine                         0.0016   6.19e-05     25.561      0.000       0.0
01       0.002
Seats                         -0.0793      0.028     -2.844      0.004      -0.1
34      -0.025
Transmission_Manual           -0.9898      0.055    -18.024      0.000      -1.0
97      -0.882
Owner_Type_Fourth & Above      0.4341      0.423      1.027      0.304      -0.3
95       1.263
Owner_Type_Second             -0.0778      0.052     -1.488      0.137      -0.1
80       0.025
Owner_Type_Third              -0.2048      0.135     -1.513      0.130      -0.4
70       0.061
Region_North                   0.1776      0.076      2.340      0.019       0.0
29       0.326
Region_South                   0.3221      0.067      4.772      0.000       0.1
90       0.454
Region_West                    0.2395      0.070      3.415      0.001       0.1
02       0.377
Car_Type_Level2                2.7833      0.050     55.226      0.000       2.6
85       2.882
Car_Type_Level3                8.9825      0.078    115.632      0.000       8.8
30       9.135
Car_Type_Level4               12.7053      0.098    130.038      0.000      12.5
14      12.897
Car_Type_Level5               11.6370      0.178     65.427      0.000      11.2
88      11.986
Car_Type_Level6               11.1725      0.419     26.639      0.000      10.3
```

```
50      11.995
==============================================================================
Omnibus:                      299.978   Durbin-Watson:                   2.007
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1076.358
Skew:                           0.199   Prob(JB):                    1.87e-234
Kurtosis:                       5.221   Cond. No.                     5.85e+07
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctl
y specified.
[2] The condition number is large, 5.85e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [77]:
```
#Running third model - depicting values
X_train3 = X_train1.drop('Engine', axis=1)
vif_series3 = pd.Series([variance_inflation_factor(X_train3.values,i) for i in ra
print('Train Model 3: \n\n{}\n'.format(vif_series3))
```

```
Train Model 3:

const                        841834.515
Year                              2.195
Kilometers_Driven                 1.625
Mileage                           2.013
Power                             4.275
Seats                             1.401
Transmission_Manual               2.114
Owner_Type_Fourth & Above         1.012
Owner_Type_Second                 1.138
Owner_Type_Third                  1.077
Region_North                      2.478
Region_South                      3.647
Region_West                       3.102
Car_Type_Level2                   1.647
Car_Type_Level3                   2.235
Car_Type_Level4                   3.010
Car_Type_Level5                   1.590
Car_Type_Level6                   1.096
dtype: float64
```

In [78]:
```
#Running OLS
olsmod2 = sm.OLS(y_train, X_train3)
olsres2 = olsmod2.fit()
print(olsres2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Price   R-squared:                       0.951
Model:                            OLS   Adj. R-squared:                  0.951
Method:                 Least Squares   F-statistic:                     5775.
Date:                Sat, 11 Jun 2022   Prob (F-statistic):               0.00
Time:                        23:08:58   Log-Likelihood:                -8288.4
No. Observations:                5075   AIC:                         1.661e+04
Df Residuals:                    5057   BIC:                         1.673e+04
Df Model:                          17
Covariance Type:            nonrobust
==============================================================================
                                 coef    std err          t      P>|t|      [0.0
25      0.975]
------------------------------------------------------------------------------
const                       -398.3288     15.985    -24.919      0.000    -429.6
66    -366.992
Year                           0.1982      0.008     24.883      0.000       0.1
83       0.214
Kilometers_Driven         -1.577e-07   7.36e-07     -0.214      0.830    -1.6e-
06    1.28e-06
Mileage                        0.0293      0.006      4.898      0.000       0.0
18       0.041
Power                          0.0224      0.001     28.673      0.000       0.0
21       0.024
Seats                          0.2117      0.026      8.292      0.000       0.1
62       0.262
Transmission_Manual           -0.7115      0.056    -12.650      0.000      -0.8
22      -0.601
Owner_Type_Fourth & Above      0.5719      0.417      1.373      0.170      -0.2
45       1.389
Owner_Type_Second             -0.1023      0.052     -1.984      0.047      -0.2
03      -0.001
Owner_Type_Third              -0.2410      0.133     -1.807      0.071      -0.5
03       0.021
Region_North                   0.1822      0.075      2.437      0.015       0.0
36       0.329
Region_South                   0.3623      0.067      5.440      0.000       0.2
32       0.493
Region_West                    0.2376      0.069      3.439      0.001       0.1
02       0.373
Car_Type_Level2                2.6626      0.051     52.608      0.000       2.5
63       2.762
Car_Type_Level3                8.7180      0.079    109.775      0.000       8.5
62       8.874
Car_Type_Level4               12.1741      0.104    116.988      0.000      11.9
70      12.378
Car_Type_Level5               11.2187      0.179     62.824      0.000      10.8
69      11.569
Car_Type_Level6               11.1487      0.411     27.111      0.000      10.3
```

```
42      11.955
==============================================================================
Omnibus:                      363.497   Durbin-Watson:                   1.998
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1637.494
Skew:                           0.189   Prob(JB):                         0.00
Kurtosis:                       5.757   Cond. No.                     5.85e+07
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctl
y specified.
[2] The condition number is large, 5.85e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [79]:
```
#Running OLS
X_train4 = X_train3.drop('Kilometers_Driven', axis=1)
olsmod3 = sm.OLS(y_train, X_train4)
olsres3 = olsmod3.fit()
print(olsres3.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Price   R-squared:                       0.951
Model:                            OLS   Adj. R-squared:                  0.951
Method:                 Least Squares   F-statistic:                     6137.
Date:                Sat, 11 Jun 2022   Prob (F-statistic):               0.00
Time:                        23:08:58   Log-Likelihood:                -8288.4
No. Observations:                5075   AIC:                         1.661e+04
Df Residuals:                    5058   BIC:                         1.672e+04
Df Model:                          16
Covariance Type:            nonrobust
==============================================================================
                                 coef    std err          t      P>|t|      [0.0
25      0.975]
------------------------------------------------------------------------------
const                       -399.9048     14.192    -28.179      0.000    -427.7
27    -372.083
Year                           0.1989      0.007     28.150      0.000       0.1
85       0.213
Mileage                        0.0292      0.006      4.917      0.000       0.0
18       0.041
Power                          0.0224      0.001     28.968      0.000       0.0
21       0.024
Seats                          0.2103      0.025      8.520      0.000       0.1
62       0.259
Transmission_Manual           -0.7123      0.056    -12.697      0.000      -0.8
22      -0.602
Owner_Type_Fourth & Above      0.5712      0.417      1.371      0.170      -0.2
46       1.388
Owner_Type_Second             -0.1027      0.052     -1.993      0.046      -0.2
04      -0.002
Owner_Type_Third              -0.2410      0.133     -1.807      0.071      -0.5
03       0.021
Region_North                   0.1794      0.074      2.437      0.015       0.0
35       0.324
Region_South                   0.3593      0.065      5.519      0.000       0.2
32       0.487
Region_West                    0.2356      0.068      3.442      0.001       0.1
01       0.370
Car_Type_Level2                2.6630      0.051     52.663      0.000       2.5
64       2.762
Car_Type_Level3                8.7183      0.079    109.813      0.000       8.5
63       8.874
Car_Type_Level4               12.1763      0.104    117.588      0.000      11.9
73      12.379
Car_Type_Level5               11.2217      0.178     63.042      0.000      10.8
73      11.571
Car_Type_Level6               11.1522      0.411     27.144      0.000      10.3
47      11.958
```

```
==============================================================================
Omnibus:                      363.483   Durbin-Watson:                   1.998
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1637.000
Skew:                           0.189   Prob(JB):                         0.00
Kurtosis:                       5.757   Cond. No.                     1.64e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctl
y specified.
[2] The condition number is large, 1.64e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [80]:
```
residual= olsres3.resid
np.mean(residual)
```

Out[80]:
```
-1.3657719946781153e-12
```

In [81]:
```
#predicted values
residual=olsres3.resid
fitted=olsres3.fittedvalues
```

Regression Results: Adjusted. R-squared: Model fit between the range of 0 to 1 A high Adjusted R-Squared value of 0.953 indicates good fit.

Const coefficient is the Y-intercept with -40.48 Std err: coefficients reflect high accuracy P >|t|: It is p-value.

This shows that for each independent feature there is a null hypothesis and alternate hypothesis

Ho : Independent variable is not significant

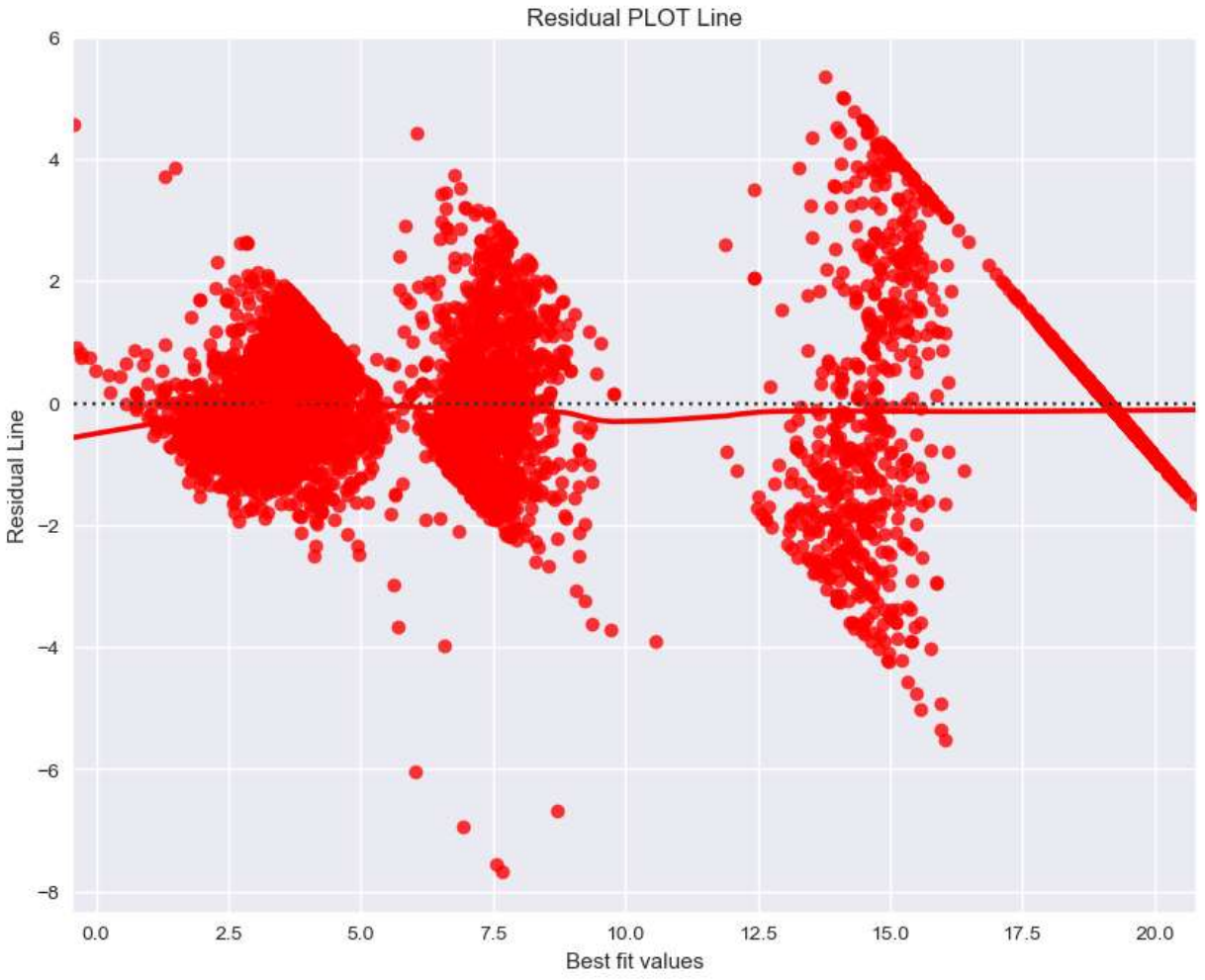
Ha : Independent variable is significant

If p-value is less than 0.05 , then the variable is considered to be statistically significant.

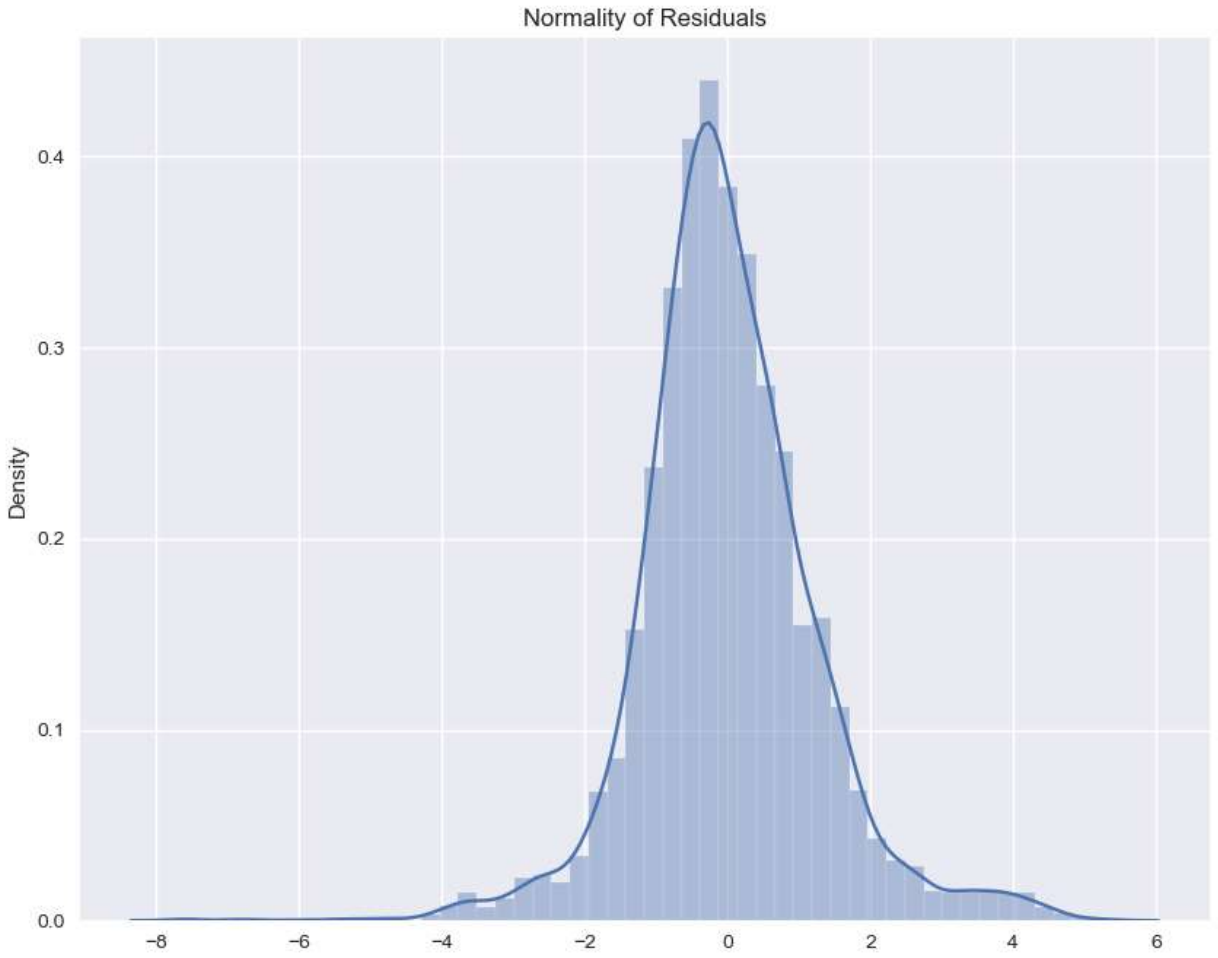
Confidence Interval 95%: It represents the range in which our coefficients are likely to fall.

Draw a prediction line with data points on a scatter plot Showing Residuals Best Fit

In [82]:
```
#Graph mapping residual best plot / line of fit
sns.set_style("darkgrid")
sns.residplot(fitted,residual,color="red",lowess=True)
plt.xlabel("Best fit values")
plt.ylabel("Residual Line")
plt.title("Residual PLOT Line")
plt.show()
```



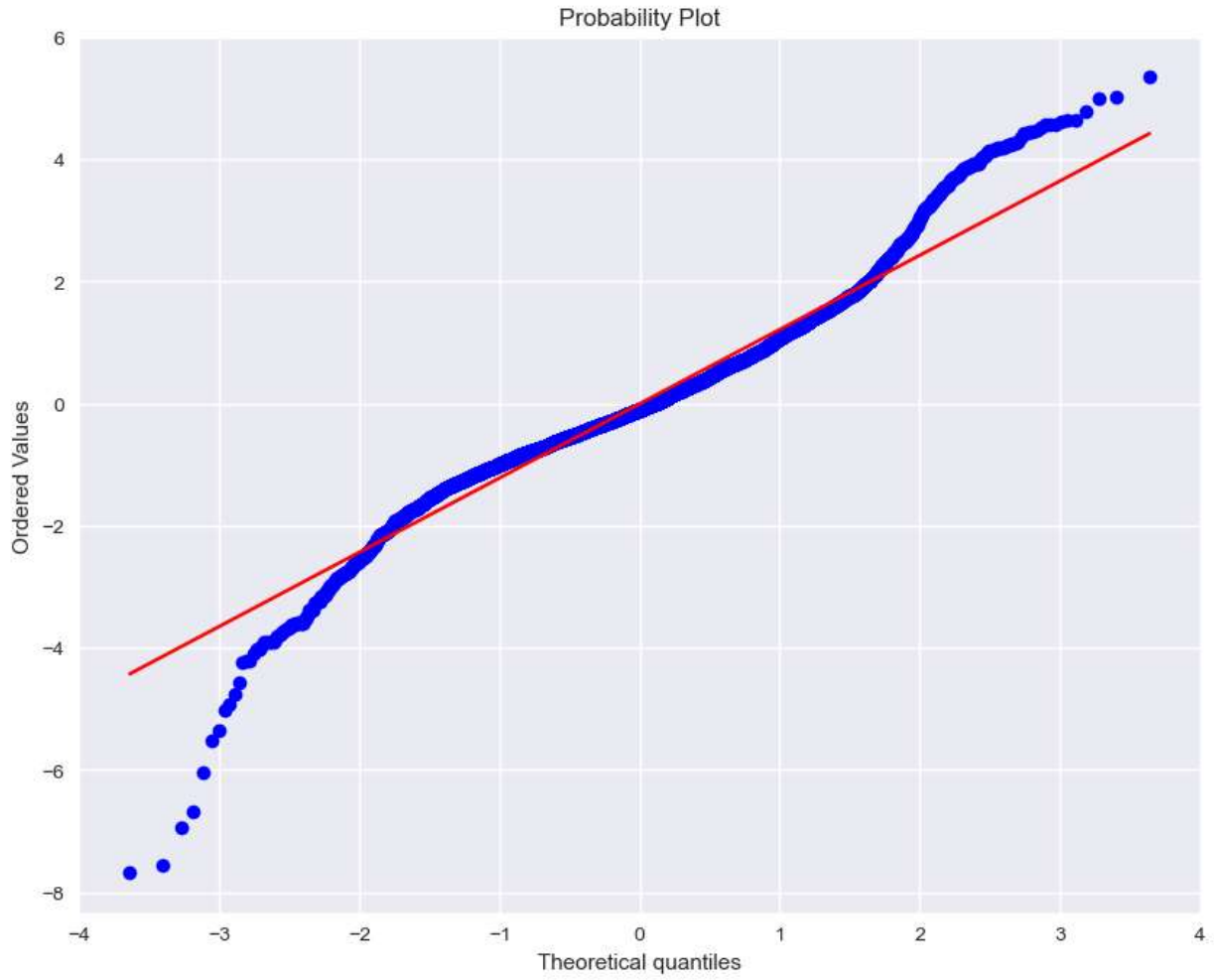
In [84]:
```
#Histogram of Residuals
sns.distplot(residual)
plt.title('Normality of Residuals')
plt.show()
```



Check the normality assumptions by creating a QQ-plot

QQ Plot shows linearity see below

In [85]:
```
# Q-Q plot to check the normal probability of residuals.
import pylab
import scipy.stats as stats
stats.probplot(residual,dist="norm",plot=pylab)
plt.show()
```



In [86]:
```
#Obtain F statistic and P values
import statsmodels.stats.api as sms
from statsmodels.compat import lzip
name = ['F statistic', 'p-value']
test = sms.het_goldfeldquandt(residual, X_train4)
lzip(name, test)
```

Out[86]:
```
[('F statistic', 1.033807218416428), ('p-value', 0.20199670346246976)]
```

Model Data for Prediction

In [87]:
```
#Clarify x train column detail
X_train4.columns
```

Out[87]:
```
Index(['const', 'Year', 'Mileage', 'Power', 'Seats', 'Transmission_Manual',
       'Owner_Type_Fourth & Above', 'Owner_Type_Second', 'Owner_Type_Third',
       'Region_North', 'Region_South', 'Region_West', 'Car_Type_Level2',
       'Car_Type_Level3', 'Car_Type_Level4', 'Car_Type_Level5',
       'Car_Type_Level6'],
      dtype='object')
```

In [88]:
```
#Print x train head
X_test_final = X_test[X_train4.columns]
X_test_final.head()
```

Out[88]:

	const	Year	Mileage	Power	Seats	Transmission_Manual	Owner_Type_Fourth & Above	Owner_Typ
1083	1.000	2015	21.430	87.200	5.000	1	0	
4601	1.000	2019	20.680	190.000	5.000	0	0	
1969	1.000	2011	12.400	132.000	8.000	1	0	
5344	1.000	2015	18.600	81.830	5.000	1	0	
2056	1.000	2015	16.770	229.575	5.000	0	0	

In [89]:
```
#set variable predictor value
y_pred = olsres3.predict(X_test_final)
```

Cross Validation Using Sci-kit Learn

In [90]:
```
#Checking root mean squared error for train and test set
rms = np.sqrt(mean_squared_error(y_train, fitted))
print('Train error:',rms)
rms1 = np.sqrt(mean_squared_error(y_test, y_pred))
print('Test error:',rms1)
```

```
Train error: 1.2389217848929732
Test error: 1.2327474340985183
```

Train and test values are very low, yet is not over / under fitting.

In [91]:
```
#final train test
olsmodtest = sm.OLS(y_test, X_test_final)
olsrestest = olsmodtest.fit()
print(olsrestest.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Price   R-squared:                       0.953
Model:                            OLS   Adj. R-squared:                  0.952
Method:                 Least Squares   F-statistic:                     2720.
Date:                Sat, 11 Jun 2022   Prob (F-statistic):               0.00
Time:                        23:09:44   Log-Likelihood:                -3532.1
No. Observations:                2176   AIC:                             7098.
Df Residuals:                    2159   BIC:                             7195.
Df Model:                          16
Covariance Type:            nonrobust
==============================================================================
==============
                                 coef    std err          t      P>|t|      [0.0
25      0.975]
------------------------------------------------------------------------------
--------------
const                       -415.2947     21.617    -19.212      0.000    -457.6
87    -372.903
Year                           0.2061      0.011     19.132      0.000       0.1
85       0.227
Mileage                        0.0388      0.009      4.209      0.000       0.0
21       0.057
Power                          0.0237      0.001     20.555      0.000       0.0
21       0.026
Seats                          0.3157      0.038      8.271      0.000       0.2
41       0.391
Transmission_Manual           -0.7067      0.084     -8.402      0.000      -0.8
72      -0.542
Owner_Type_Fourth & Above     -0.0296      0.716     -0.041      0.967      -1.4
35       1.375
Owner_Type_Second             -0.1154      0.076     -1.526      0.127      -0.2
64       0.033
Owner_Type_Third              -0.4693      0.201     -2.338      0.019      -0.8
63      -0.076
Region_North                   0.2735      0.111      2.468      0.014       0.0
56       0.491
Region_South                   0.5520      0.098      5.605      0.000       0.3
59       0.745
Region_West                    0.2863      0.102      2.803      0.005       0.0
86       0.487
Car_Type_Level2                2.6065      0.077     33.879      0.000       2.4
56       2.757
Car_Type_Level3                8.6726      0.117     74.426      0.000       8.4
44       8.901
Car_Type_Level4               12.0980      0.154     78.776      0.000      11.7
97      12.399
Car_Type_Level5               11.2200      0.247     45.392      0.000      10.7
35      11.705
Car_Type_Level6               11.4906      0.890     12.905      0.000       9.7
44      13.237
==============================================================================
```

Omnibus:	197.434	Durbin-Watson:	1.967
Prob(Omnibus):	0.000	Jarque-Bera (JB):	495.288
Skew:	0.521	Prob(JB):	2.82e-108
Kurtosis:	5.092	Cond. No.	1.65e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.65e+06. This might indicate that there are strong multicollinearity or other numerical problems.

In [92]:
```
#print trained OLS model
print(olsres3.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Price   R-squared:                       0.95
1
Model:                            OLS   Adj. R-squared:                  0.95
1
Method:                 Least Squares   F-statistic:                     613
7.
Date:                Sat, 11 Jun 2022   Prob (F-statistic):               0.0
0
Time:                        23:09:44   Log-Likelihood:                -8288.
4
No. Observations:                5075   AIC:                          1.661e+0
4
Df Residuals:                    5058   BIC:                          1.672e+0
4
Df Model:                          16
Covariance Type:            nonrobust
================================================================================
================
                                 coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
----------------
const                       -399.9048     14.192    -28.179      0.000    -42
7.727    -372.083
Year                           0.1989      0.007     28.150      0.000
0.185       0.213
Mileage                        0.0292      0.006      4.917      0.000
0.018       0.041
Power                          0.0224      0.001     28.968      0.000
0.021       0.024
Seats                          0.2103      0.025      8.520      0.000
0.162       0.259
Transmission_Manual           -0.7123      0.056    -12.697      0.000      -
0.822      -0.602
Owner_Type_Fourth & Above      0.5712      0.417      1.371      0.170      -
0.246       1.388
Owner_Type_Second             -0.1027      0.052     -1.993      0.046      -
0.204      -0.002
Owner_Type_Third              -0.2410      0.133     -1.807      0.071      -
0.503       0.021
Region_North                   0.1794      0.074      2.437      0.015
0.035       0.324
Region_South                   0.3593      0.065      5.519      0.000
0.232       0.487
Region_West                    0.2356      0.068      3.442      0.001
0.101       0.370
Car_Type_Level2                2.6630      0.051     52.663      0.000
2.564       2.762
Car_Type_Level3                8.7183      0.079    109.813      0.000
8.563       8.874
Car_Type_Level4               12.1763      0.104    117.588      0.000      1
```

```
1.973      12.379
Car_Type_Level5              11.2217      0.178     63.042      0.000      1
0.873      11.571
Car_Type_Level6              11.1522      0.411     27.144      0.000      1
0.347      11.958
==============================================================================
=
Omnibus:                      363.483   Durbin-Watson:                   1.99
8
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1637.00
0
Skew:                           0.189   Prob(JB):                         0.0
0
Kurtosis:                       5.757   Cond. No.                     1.64e+0
6
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 1.64e+06. This might indicate that there a
re
strong multicollinearity or other numerical problems.
```

In [93]:
```
outcome = 'Price'
x_cols = ['Fuel_Type', 'Engine', 'Region', 'Power']
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=data).fit()
model.summary()
```

Out[93]:

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.614
Model:	OLS	**Adj. R-squared:**	0.613
Method:	Least Squares	**F-statistic:**	1279.
Date:	Sat, 11 Jun 2022	**Prob (F-statistic):**	0.00
Time:	23:09:44	**Log-Likelihood:**	-24134.
No. Observations:	7251	**AIC:**	4.829e+04
Df Residuals:	7241	**BIC:**	4.836e+04
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-6.6071	0.915	-7.224	0.000	-8.400	-4.814
Fuel_Type[T.Diesel]	-0.2810	0.875	-0.321	0.748	-1.995	1.433
Fuel_Type[T.Electric]	9.8674	4.852	2.033	0.042	0.355	19.380
Fuel_Type[T.LPG]	-1.2034	2.131	-0.565	0.572	-5.381	2.974
Fuel_Type[T.Petrol]	-3.0664	0.869	-3.530	0.000	-4.769	-1.364
Region[T.North]	1.1058	0.331	3.341	0.001	0.457	1.755
Region[T.South]	2.9338	0.289	10.141	0.000	2.367	3.501
Region[T.West]	0.7971	0.306	2.608	0.009	0.198	1.396
Engine	-0.0019	0.000	-6.814	0.000	-0.002	-0.001
Power	0.1669	0.003	56.914	0.000	0.161	0.173

Omnibus:	4492.122	**Durbin-Watson:**	2.029
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	241621.728
Skew:	2.277	**Prob(JB):**	0.00
Kurtosis:	30.911	**Cond. No.**	1.06e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.06e+05. This might indicate that there are strong multicollinearity or other numerical problems.

##Conclusion:

Main impacts to buying Used cars:

-The Ordinary Least Squares is a good model for prediction and inference at 95.1% adjusted Rsquared value. -Transmission and Owner type depict negative correlation to Price. -Automatic transmissions tend to be more expensive and manuals sell for less according to this model. -The year, mileage, power and number of seats have shown a positive assosiation with sale price.