FLIP ROBO

A

Data science

Project

on

"Used Car Price Prediction"

Submitted by:

Santosh Arvind Dharam

ACKNOWLEDGMENT

I feel great pleasure to present the Project entitled "Used Car Price Prediction". But it would be unfair on our part if I do not acknowledge efforts of some of the people without the support of whom, this Project would not have been a success. First and for most I am very much thankful to my respected SME 'shrishti Maan' for his leading guidance in this Project. Also he has been persistent source of inspiration to me. I would like to express my sincere thanks and appreciation to 'flip robo' for their valuable support. Most importantly I would like to express our sincere gratitude towards my Friend & Family for always being there when I needed them most.

Mr. Santosh Arvind Dharam

INTRODUCTION

We have to get at least 5000 used cars data. We can get more data as well; more the data better the model .In this section we need to scrape the data of used cars from websites (Olx, cardekho, Cars24 etc.) we have to fetch data for different locations. The number of columns for data doesn’t have limit, generally, these columns are Brand, model, variant, manufacturing year, driven kilometres, fuel, number of owners, location and at last target variable Price of the car. This data is to give you a hint about important variables in used car model. You can make changes to it, you can add or you can remove some columns, it completely depends on the website from where you are fetching the data. Include all types of cars in your data for example- SUV, Sedans, Coupe, minivan,

PROBLEM STATEMENT

With the Covid-19 impact in the market, we saw lot of changes in the car market. Now some cars are in demand hence making them costly and some are not in demand hence cheaper. One of clients works with small traders, who sell used cars. With the change in market due to Covid-19 impact, client is facing problems with their previous car price valuation machine learning models. So, they are looking for new machine learning models from new data. We have to make car price valuation model.

Analytical Problem Framing

EDA steps:

1) import necessary libraries:

first we will import all the necessary libraries which will be usefull for analysis of data

In [1]:
```
#import all libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error
from sklearn.linear_model import LogisticRegression,Lasso,LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import AdaBoostRegressor,GradientBoostingRegressor
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.decomposition import PCA
from scipy.stats import zscore
from sklearn.model_selection import cross_val_score
```

in this case we have to import all the necessary library that are usefull for data analysis in jupyter notebook

2)extract the dataset in jupyter notebook:

now lets we will extract the data by pandas library

In [2]:
```
data=pd.read_excel("C:\\Users\\SAI BABA\\Desktop\\used car.xlsx")
data.head()
```

Out[2]:

	Sr.No.	Car Brand	Model	Price	Model Year	Location	Fuel	Driven (Kms)	Gear	Ownership	EMI (monthly)
0	0	Hyundai	EonERA PLUS	330399	2016	Hyderabad	Petrol	10674	Manual	2	7350
1	1	Maruti	Wagon R 1.0LXI	350199	2011	Hyderabad	Petrol	20979	Manual	1	7790
2	2	Maruti	Alto K10LXI	229199	2011	Hyderabad	Petrol	47330	Manual	2	5098
3	3	Maruti	RitzVXI BS IV	306399	2011	Hyderabad	Petrol	19662	Manual	1	6816
4	4	Tata	NanoTWIST XTA	208699	2015	Hyderabad	Petrol	11256	Automatic	1	4642

now as the column Sr.No. has not that much importance so lets we will drop that column

Data is extracted for further analysis in jupyter notebook

4)checking null values:

In this case we have to find out the null values present in our data set if yes it is required to remove it in our data set it has some null values it is also shown by heat map

```
In [6]: data.isnull().sum()

Out[6]: Car Brand         0
        Model           265
        Price             0
        Model Year        0
        Location          0
        Fuel              0
        Driven (Kms)      0
        Gear            265
        Ownership         0
        EMI (monthly)     0
        dtype: int64
```

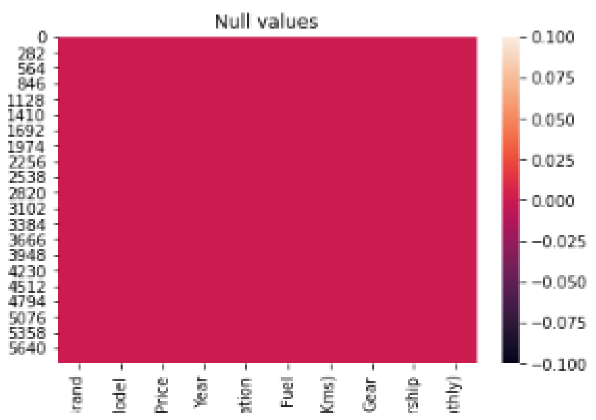
dataset contains null values in column Model and Gear so lets we will remove it further

```
In [7]: data['Model']=data['Model'].fillna(data['Model'].mode()[0])
        data['Gear']=data['Gear'].fillna(data['Gear'].mode()[0])
```

```
In [8]: data.isnull().sum()

Out[8]: Car Brand        0
        Model            0
        Price            0
        Model Year       0
        Location         0
        Fuel             0
        Driven (Kms)     0
        Gear             0
        Ownership        0
        EMI (monthly)    0
        dtype: int64
```

so dataset does not contains any null values now

```
In [9]: sns.heatmap(data.isnull())
        plt.title("Null values")
        plt.show()
```



3)Encoding the dataset:

In this case as our data contains some categorical column having object type of data it is necessary to convert it into numerical form by LabelEncoder

DATA ENCODING

In [11]:
```
from sklearn.preprocessing import LabelEncoder
```

In [12]:
```
le=LabelEncoder()
label=le.fit_transform(data["Location"])
label
le.classes_
data=data.drop("Location",axis='columns')
data["Location"]=label
le=LabelEncoder()
label=le.fit_transform(data["Fuel"])
label
le.classes_
data=data.drop("Fuel",axis='columns')
data["Fuel"]=label
le=LabelEncoder()
label=le.fit_transform(data["Gear"])
label
le.classes_
data=data.drop("Gear",axis='columns')
data["Gear"]=label
le=LabelEncoder()
label=le.fit_transform(data["Car Brand"])
label
le.classes_
data=data.drop("Car Brand",axis='columns')
data["Car Brand"]=label
data
```

Out[12]:

	Model	Price	Model Year	Driven (Kms)	Ownership	EMI (monthly)	Location	Fuel	Gear	Car Brand
0	EonERA PLUS	330399	2016	10674	2	7350	3	2	1	7
1	Wagon R 1.0LXI	350199	2011	20979	1	7790	3	2	1	15
2	Alto K10LXI	229199	2011	47330	2	5098	3	2	1	15
3	RitzVXI BS IV	306399	2011	19662	1	6816	3	2	1	15
4	NanoTWIST XTA	208699	2015	11256	1	4642	3	2	0	23
...	...	...	...	...	...	...	...	...	...	...

Data contains 10 columns and 5918 rows

6) Data Description:

In this case data is described in detail which helping us for detail analysis

In [20]:
```
data.describe()
```

Out[20]:

	Price	Model Year	Driven (Kms)	Ownership	EMI (monthly)	Location	Fuel	Gear	Car Brand	Model
count	5.918000e+03	5918.000000	5918.000000	5918.000000	5918.000000	5918.000000	5918.000000	5918.000000	5918.000000	5918.000000
mean	5.180530e+05	2014.547651	60842.778979	1.285738	11523.801284	2.282528	1.366847	0.902332	13.085333	441.238087
std	3.224695e+05	2.905185	42362.990292	0.532820	7173.156118	1.355988	0.981886	0.296890	5.642913	298.032009
min	9.100000e+04	2007.000000	179.000000	1.000000	2024.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	3.205240e+05	2012.000000	30856.000000	1.000000	7129.750000	2.000000	0.000000	1.000000	7.000000	152.000000
50%	4.303990e+05	2015.000000	53514.000000	1.000000	9574.000000	2.000000	2.000000	1.000000	15.000000	423.500000
75%	6.157990e+05	2017.000000	81979.250000	1.000000	13698.000000	4.000000	2.000000	1.000000	15.000000	708.000000
max	6.500000e+06	2021.000000	912380.000000	4.000000	144589.000000	4.000000	4.000000	1.000000	26.000000	901.000000

it shows the total count of every column also the minimum to maximum values present in our dataset with its std and mean values nowif we see the data it is seen that column location,fuel,gear,car brand,model contains zero values in its min row so lets remove that

In [21]:
```
#replacing zero values with mean of column
data['Location']=data['Location'].replace(0,data['Location'].mean())
data['Fuel']=data['Fuel'].replace(0,data['Fuel'].mean())
data['Gear']=data['Gear'].replace(0,data['Gear'].mean())
data['Car Brand']=data['Car Brand'].replace(0,data['Car Brand'].mean())
data['Model']=data['Model'].replace(0,data['Model'].mean())
```

In [22]:
```
data.describe()
```

Out[22]:

	Price	Model Year	Driven (Kms)	Ownership	EMI (monthly)	Location	Fuel	Gear	Car Brand	Model
count	5.918000e+03	5918.000000	5918.000000	5918.000000	5918.000000	5918.000000	5918.000000	5918.000000	5918.000000	5918.000000
mean	5.180530e+05	2014.547651	60842.778979	1.285738	11523.801284	2.599567	1.820461	0.990461	13.140611	441.312646
std	3.224695e+05	2.905185	42362.990292	0.532820	7173.156118	1.007174	0.371717	0.028997	5.578169	297.976793
min	9.100000e+04	2007.000000	179.000000	1.000000	2024.000000	1.000000	1.000000	0.902332	1.000000	1.000000
25%	3.205240e+05	2012.000000	30856.000000	1.000000	7129.750000	2.000000	1.366847	1.000000	7.000000	152.250000
50%	4.303990e+05	2015.000000	53514.000000	1.000000	9574.000000	2.282528	2.000000	1.000000	15.000000	424.500000

It is found from data description in some column min row consist of zero values in it so practically it is not possible so it is necessary to remove it ,so we have removed it

7) Data Correlation:

Heat Map-

now lets we will plot heat map to find the correlation between target variable and sucessive column

In [23]:
```
#heat map
plt.figure(figsize=(30,20))
sns.heatmap(data.corr(),annot=True,linewidths=0.2,linecolor='black',fmt='0.2f')
```

Out[23]: <AxesSubplot:>

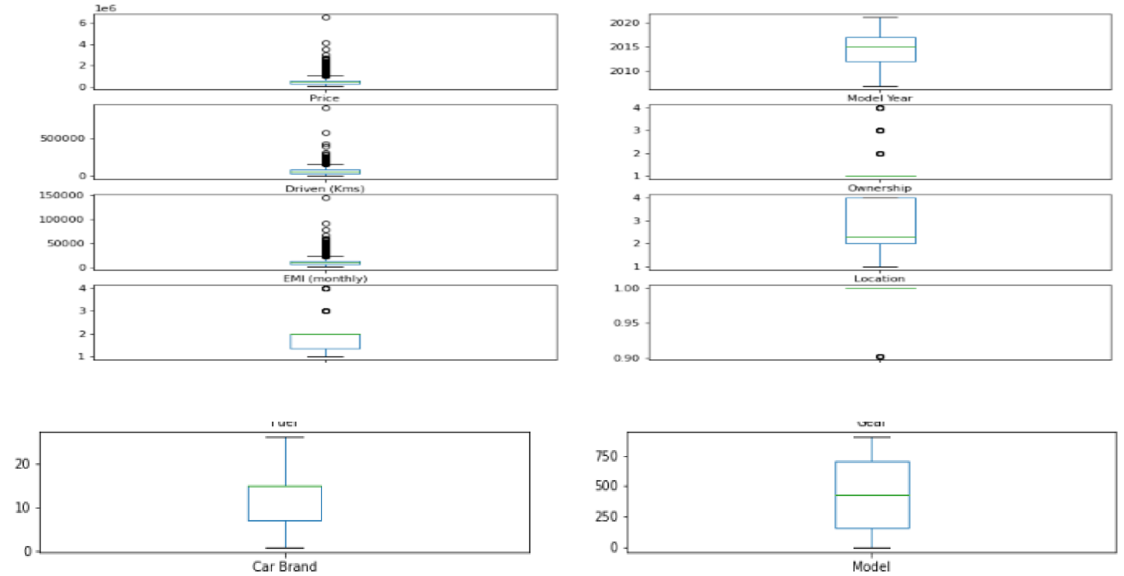
it shows that column EMI(monthly),Model Year has maximum correlation with the price now lets we will find the outliers present in the dataset with the box plot

Data is correlated with other column data and also with its own it also gives the positive negative correlation of data with respective one another. it shows that column EMI(monthly),Model Year has maximum correlation with the price now lets we will find the outliers present in the dataset with the box plot

7)Checking of Outliers:

In [24]:
```python
#plotting the boxplot of each column to check the outliers
data.plot(kind='box',subplots = True,layout=(5,2),figsize = (15,10))
```

Out[24]:
```
Price               AxesSubplot(0.125,0.749828;0.352273x0.130172)
Model Year       AxesSubplot(0.547727,0.749828;0.352273x0.130172)
Driven (Kms)        AxesSubplot(0.125,0.593621;0.352273x0.130172)
Ownership        AxesSubplot(0.547727,0.593621;0.352273x0.130172)
EMI (monthly)       AxesSubplot(0.125,0.437414;0.352273x0.130172)
Location         AxesSubplot(0.547727,0.437414;0.352273x0.130172)
Fuel                AxesSubplot(0.125,0.281207;0.352273x0.130172)
Gear             AxesSubplot(0.547727,0.281207;0.352273x0.130172)
Car Brand             AxesSubplot(0.125,0.125;0.352273x0.130172)
Model              AxesSubplot(0.547727,0.125;0.352273x0.130172)
dtype: object
```



price.Driven(Kms),EMI(monthly) has contains some outliers lets we will remove it

price.Driven(Kms),EMI(monthly) has contains some outliers lets we will remove it.

7)Removing outliers:

In [25]:
```python
#calculate the zscore
z = np.abs(zscore(data))
print(z)
```

```
[[0.58197695 0.49995839 1.18435969 ... 0.32899802 1.10092213 0.44743052]
 [0.52057061 1.22124798 0.94108436 ... 0.32899802 0.33336147 1.24076304]
 [0.89583158 1.22124798 0.319003   ... 0.32899802 0.33336147 1.37711166]
 ...
 [0.4238091  0.18852416 0.85411431 ... 0.32899802 0.33336147 1.24747554]
 [0.64245289 1.22124798 0.72436746 ... 0.32899802 1.10092213 1.48576926]
 [1.11044364 2.59821308 0.2265324  ... 0.32899802 0.33336147 1.27096929]]
```

In [26]:
```python
threshold=3
print(np.where(z<3))
print(data.shape)
```

```
(array([   0,    0,    0, ..., 5917, 5917, 5917], dtype=int64), array([0, 1, 2, ..., 7, 8, 9], dtype=int64))
(5918, 10)
```

In [27]:
```python
#Assign the value to df_new which are less the threshold value and removing the outliers
data_new=data[(z<3).all(axis = 1)]
```

In [28]:
```python
print(data.shape)
print(data_new.shape)
data = data_new
print('Shape after removing outlires',data.shape)
```

```
(5918, 10)
(4882, 10)
Shape after removing outlires (4882, 10)
```

So after removing the outliers we have 4882 rows and 10 column remaining

8) Finding the skewness:

now lets check whether our data set contains skewness in it .if yes then lets we will remove it

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

Out[30]: Price            1.319401
         Model Year      -0.195612
         Driven (Kms)     0.795508
         Ownership        1.371186
         EMI (monthly)    1.319404
         Location         0.367108
         Fuel            -0.698649
         Gear             0.000000
         Car Brand        0.175365
         Model           -0.059945
         dtype: float64
```

so column Driven(Kms),Ownership,EMI(monthly) has some skewness so lets remove it by sqrt

```
In [31]: #remove skewness
         data['Driven (Kms)']=np.sqrt(data['Driven (Kms)'])
         data['Ownership']=np.sqrt(data['Ownership'])
         data['EMI (monthly)']=np.sqrt(data['EMI (monthly)'])
```

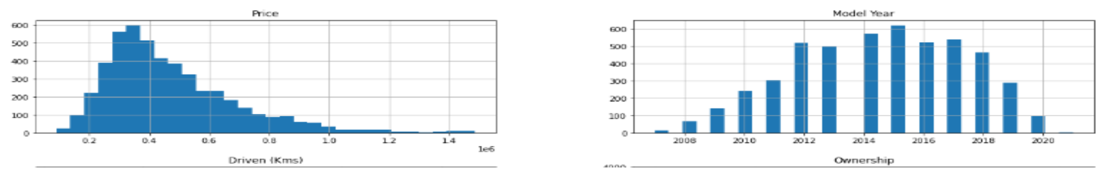
```
In [32]: data.skew()

Out[32]: Price            1.319401
         Model Year      -0.195612
         Driven (Kms)     0.025614
         Ownership        1.371186
         EMI (monthly)    0.680639
         Location         0.367108
         Fuel            -0.698649
         Gear             0.000000
         Car Brand        0.175365
         Model           -0.059945
         dtype: float64
```

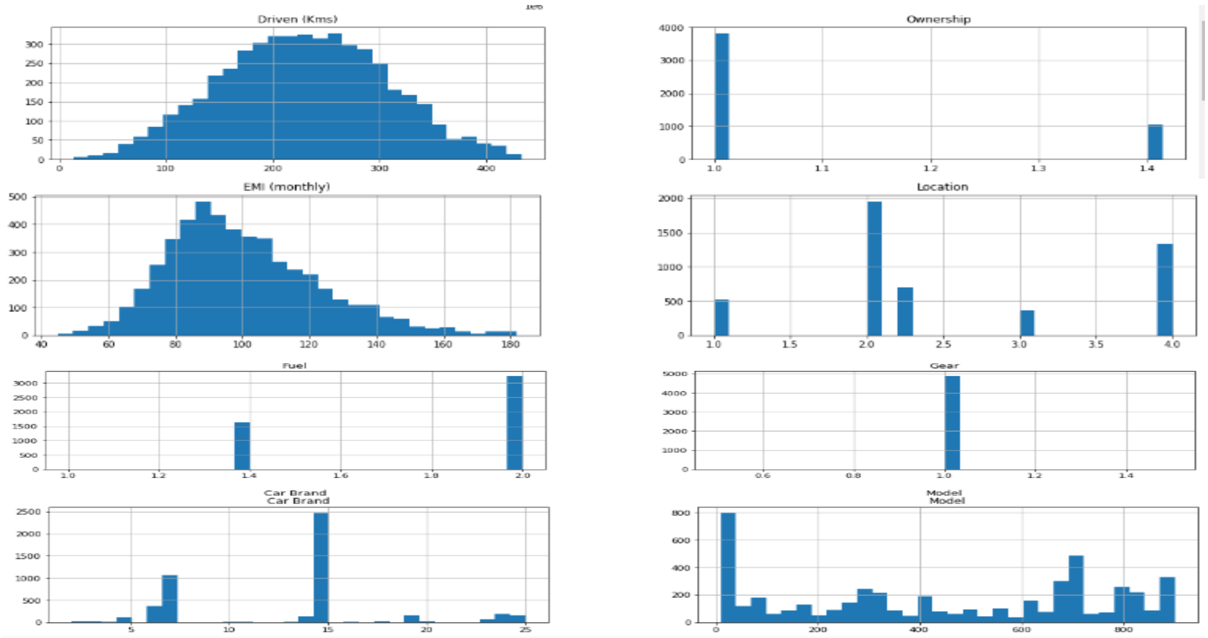
So column driven km ,ownership,EMI(monthly)has some skewness so we have removed it

9) Graphical Representation of Data:

Now let will check whether data is uniformely distributed or not

```
In [33]: #plotting histogram for univariate analysis and checking the Normal Distribution
         data.hist(figsize=(20,20), grid = True, layout = (5,2), bins = 30)
        [<AxesSubplot:title={'center':'EMI (monthly)'}>,
         <AxesSubplot:title={'center':'Location'}>],
        [<AxesSubplot:title={'center':'Fuel'}>,
         <AxesSubplot:title={'center':'Gear'}>],
        [<AxesSubplot:title={'center':'Car Brand'}>,
         <AxesSubplot:title={'center':'Model'}>]], dtype=object)
```





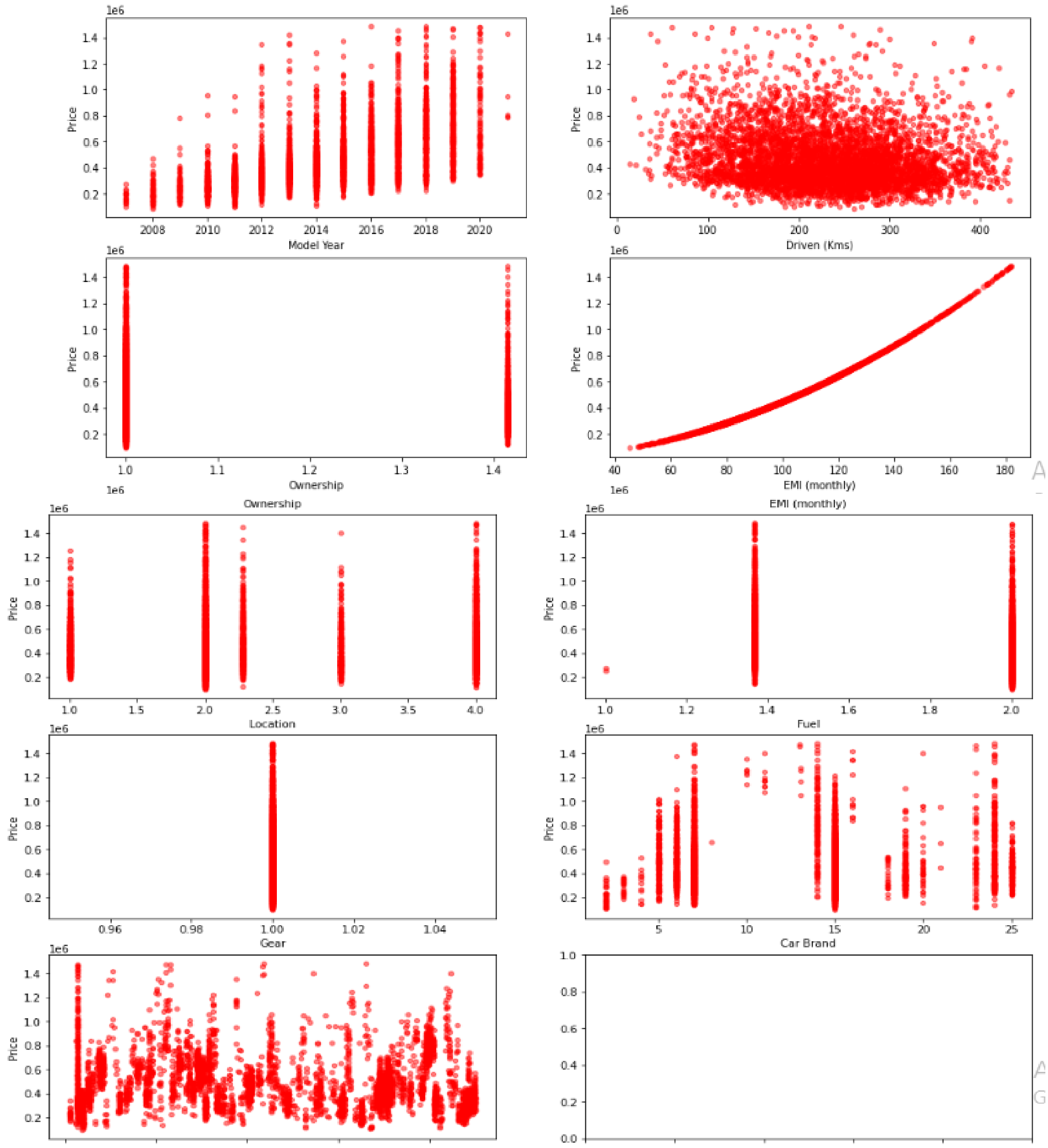
it shows that data is uniformely distributed within column

It shows that data is uniformely distributed

9) Scatter Plot:

scatter plot shows that how the data is distributed with respective the target variable

In [34]:
```
# setup figure
fig, axes = plt.subplots(nrows=5, ncols=2, figsize=(16, 20))

# iterate and plot subplots
for xcol, ax in zip(data.columns[1:], [x for v in axes for x in v]):
    data.plot.scatter(x=xcol, y='Price', ax=ax, alpha=0.5, color='r')
```



10)Divide dataset:

```
In [37]: from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error
         from sklearn.linear_model import LogisticRegression,Lasso,LinearRegression
         from sklearn.neighbors import KNeighborsRegressor
         from sklearn.svm import SVR
         from sklearn.tree import DecisionTreeRegressor
         from sklearn.ensemble import AdaBoostRegressor,GradientBoostingRegressor
         from sklearn.preprocessing import LabelEncoder,StandardScaler
         from sklearn.model_selection import train_test_split,GridSearchCV
         from sklearn.decomposition import PCA
         from scipy.stats import zscore
         from sklearn.model_selection import cross_val_score
```

```
In [38]: #devide data set into feature and label
         y=data['Price']
         x=data.drop(['Price'],axis=1)
```

```
In [39]: from sklearn.preprocessing import LabelEncoder,StandardScaler
```

```
In [40]: #Standardize the value of x so that mean will 0 and SD will become 1 , and make the data as normal distributed
         sc = StandardScaler()
         sc.fit_transform(x)
         x = pd.DataFrame(x,columns=x.columns)
```

11)multiple Algorithms:

```
In [41]: #Now by using multiple Algorithms we are calculating the best Algo which suit best for our data set

         model = [DecisionTreeRegressor(),KNeighborsRegressor(),AdaBoostRegressor(),LinearRegression(),GradientBoostingRegressor()]
         max_r2_score = 0
         for r_state in range(40,90):
             train_x,test_x,train_y,test_y = train_test_split(x,y,random_state = r_state,test_size = 0.33)
             for i in model:
                 i.fit(train_x,train_y)
                 pre = i.predict(test_x)
                 r2_sc = r2_score(test_y,pre)
                 print("R2 score correspond to random state " ,r_state ,"is", r2_sc)
                 if r2_sc> max_r2_score:
                     max_r2_score=r2_sc
                     final_state = r_state
                     final_model = i

         print()
         print()
         print()
         print()
         print("max R2 score correspond to random state " ,final_state , "is" , max_r2_score ,"and model is",final_model)
```

```
R2 score correspond to random state  40 is 0.9999446153499179
R2 score correspond to random state  40 is 0.8978131883304017
R2 score correspond to random state  40 is 0.9939147623344393
R2 score correspond to random state  40 is 0.9810857057767612
R2 score correspond to random state  40 is 0.9998949966287864
R2 score correspond to random state  41 is 0.9999324690232877
R2 score correspond to random state  41 is 0.9181991559761051
R2 score correspond to random state  41 is 0.9951423380060272
R2 score correspond to random state  41 is 0.9818125566579295
```

So by using the various alogorith we found that we have maximum accuracy for DecisionTreeRegressor with accuracy of 99.99% for the random state of 65

12)Cross Validation:

Now lets we will do the cross validation of our model to confirm the accuracy of model

cross validation

```
In [47]: from sklearn.model_selection import cross_val_score
```

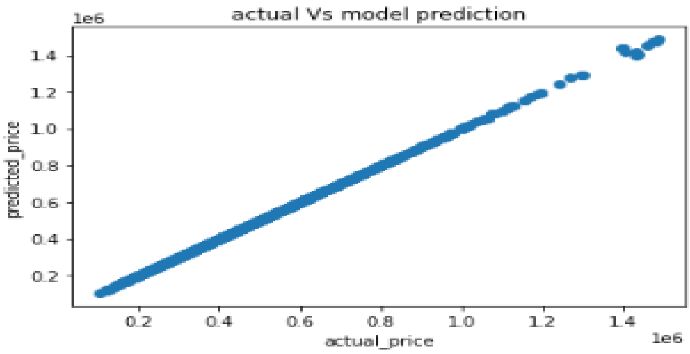
```
In [48]: for i in range(2,10):
             cv=cross_val_score(dtr,x,y,cv=i)
             print(dtr,cv.mean())

DecisionTreeRegressor() 0.9998893552539054
DecisionTreeRegressor() 0.9999532251523348
DecisionTreeRegressor() 0.9999282616825487
DecisionTreeRegressor() 0.9999649593266223
DecisionTreeRegressor() 0.9999528736700632
DecisionTreeRegressor() 0.9999554497283593
DecisionTreeRegressor() 0.9999592578102496
DecisionTreeRegressor() 0.9999693618224739
```

We have done cross validation of model in that case also we got it 99.99%

13)Visualization:

```
In [49]: #lets plot and visualize
         y_pred=dtr.predict(x_test)
         y_pred

Out[49]: array([ 831999.,  360000., 1194399., ...,  638699.,  397299.,  408099.])
```

```
In [50]: plt.scatter(y_test,y_pred)
         plt.xlabel('actual_price')
         plt.ylabel('predicted_price')
         plt.title('actual Vs model prediction')
         plt.show()
```



it gives the actual verses predicted price of vehicle

14)Regularization:

Regularization

In [51]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
import warnings
from sklearn.linear_model import Lasso
warnings.filterwarnings('ignore')
```

In [52]:
```
parameters={'alpha':[.0001,0.001,.01,.1,1,10],'random_state':list(range(0,30))}
ls=Lasso()
clf=GridSearchCV(ls,parameters)
clf.fit(x_train,y_train)
print(clf.best_params_)
```

```
{'alpha': 10, 'random_state': 0}
```

In [53]:
```
from sklearn.metrics import r2_score
```

In [54]:
```
ls=Lasso(alpha=10,random_state=0)
ls.fit(x_train,y_train)
ls.score(x_train,y_train)
pred_ls=ls.predict(x_test)
lss=r2_score(y_test,pred_ls)
lss
```

Out[54]:
```
0.9803354614896415
```

In [55]:
```
cv_score=cross_val_score(ls,x,y,cv=5)
cv_mean=cv_score.mean()
cv_mean
```

Out[55]:
```
0.9799043663968952
```

15)Ensemble technique:

Ensemble technique

In [56]:
```
from sklearn.model_selection import GridSearchCV
```

In [57]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [58]:
```
parameters={'criterion':['mse','mae'],'max_features':['auto','sqrt','log2']}
rf=RandomForestRegressor()
clf=GridSearchCV(rf,parameters)
clf.fit(x_train,y_train)
print(clf.best_params_)
```

```
{'criterion': 'mae', 'max_features': 'auto'}
```

In [59]:
```
rf=RandomForestRegressor(criterion='mse',max_features='auto')
rf.fit(x_train,y_train)
rf.score(x_train,y_train)
pred_decision=rf.predict(x_test)
rfs=r2_score(y_test,pred_decision)
print('R2score:',rfs*100)
rfscore=cross_val_score(rf,x,y,cv=5)
rfc=rfscore.mean()
print('cross val score:',rfc*100)
```

```
R2score: 99.9979771532304
cross val score: 99.99817426189661
```

16)Saving Model:

As we have tested out our selected model through various process lets we will save the given model

Saving Model

```
In [60]: #saving model
         import joblib
         joblib.dump(dtr,'used_car_price_prediction')

Out[60]: ['used_car_price_prediction']
```

CONCLUSION

So we found the following conclusion from the saved model

conclusion

```
In [61]: loaded_model=joblib.load('used_car_price_prediction')
         result=loaded_model.score(x_test,y_test)
         print(result)

0.9999228289407224
```

so in this way we have sucessfully saved model and also drawn a score with the saved model

We observed that data was filled with some outliers it is removed, also there some encoding is done now data is uniformly distributed in column. it is also observed from subplot, we have saved model and also predicted the result with help of saved model .model is ready for the future data prediction