FLIP ROBO

CAR PRICE PREDICTION

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ACKNOWLEDGMENT

I would like to convey my heartfelt gratitude to Flip Robo Technologies for providing me with this wonderful opportunity to work on a Machine Learning project “Car Price Prediction Model” and also want to thank my SME “Mohd. Kashif” for providing the dataset and directions to complete this project. This project would not have been accomplished without their help and insights.

I would also like to thank my academic “Data Trained Education” and their team who has helped me to learn Machine Learning and how to work on it.

Working on this project was an incredible experience as I learnt more from this Project during completion.

INTRODUCTION

1. Business Problem Framing

One of our clients works with small traders, who sell used cars. With the change in market due to Covid-19 impact, our 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. This project contains two phases:

a. **Data Collection Phase**
b. **Model Building Phase**

2. Conceptual Background of the Domain Problem

With the Covid-19 impact in the market, we have seen 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. So, one of our clients works with small traders, who sell used cars due to Covid-19 impact, our 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.

3. Review of Literature

We have to made car price valuation model. This project contains two phases:

a. **Data Collection Phase**: We have scraped more than 6000 used cars data from websites: Olx and cardekho. We have fetched data for different locations. All types of cars are present in data for example- SUV, Sedans, Coupe, minivan, Hatchback.

b. **Model Building Phase**: After collecting the data, built a machine learning model. Before model building has done all data pre-processing steps. Tried different models with different hyper parameters and selected the best model. Followed the complete life cycle of data science. Include all the steps like.

1. Data Cleaning
2. Exploratory Data Analysis
3. Data Pre-processing
4. Model Building
5. Model Evaluation
6. Selecting the best model

4. Motivation for the Problem Undertaken

With the change in market due to Covid-19 impact, our 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

1. Mathematical/ Analytical Modeling of the Problem

1) Scrapped Data from websites: Cardekho, OLX and Cars24
2) Used Panda's Library to save data into csv file
3) Descriptive Statistics
4) Analyzed correlation
5) Detected Outliers and removed
6) Detected Skewness and removed
7) Scaled data using Standard Scalar
8) Removed Multi-co linearity

2. Data Sources and their formats

Scraped Data from websites: Cardekho, OLX and Cars24and used Panda's Library to save data into csv file: **car_price.csv**. Target and Features variables of this dataset are:

Target:

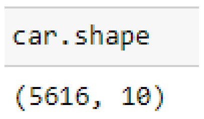
- **Car_Price:** Price of the used cars

Features:

- **Brand**
- **Model**
- **Variant**
- **Manufacturing_Year**
- **Driven_KiloMeters**
- **Fuel**
- **Number_of_Owners**
- **Location**

3. Data Pre-processing Done:

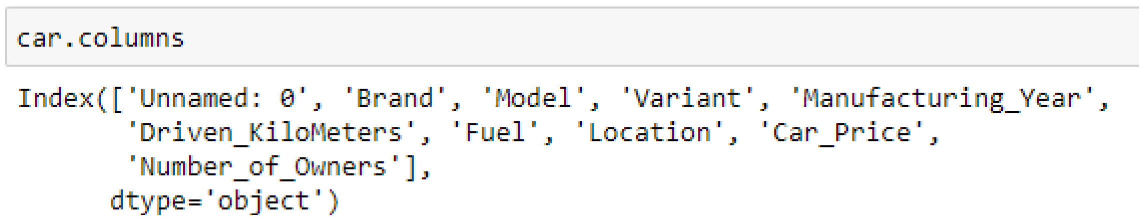
a) Checked Total Numbers of Rows and Column



```
car.shape
```

```
(5616, 10)
```

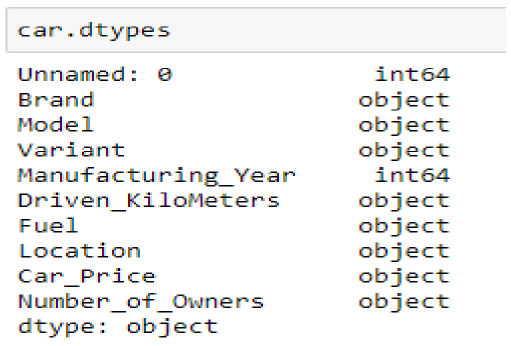
b) Checked All Column Name



```
car.columns
```

```
Index(['Unnamed: 0', 'Brand', 'Model', 'Variant', 'Manufacturing_Year',
       'Driven_KiloMeters', 'Fuel', 'Location', 'Car_Price',
       'Number_of_Owners'],
      dtype='object')
```

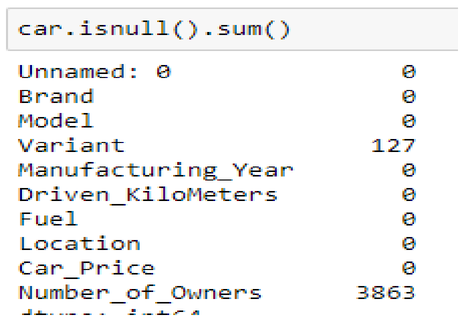
c) Checked Data Type of All Data



```
car.dtypes
```

```
Unnamed: 0             int64
Brand                 object
Model                 object
Variant               object
Manufacturing_Year     int64
Driven_KiloMeters     object
Fuel                  object
Location              object
Car_Price             object
Number_of_Owners      object
dtype: object
```

d) Checked for Null Values



```
car.isnull().sum()
```

```
Unnamed: 0               0
Brand                    0
Model                    0
Variant                127
Manufacturing_Year       0
Driven_KiloMeters        0
Fuel                     0
Location                 0
Car_Price                0
Number_of_Owners      3863
```

There is null value in the dataset.

e) Information about Data

```
car.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5483 entries, 0 to 5482
Data columns (total 8 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Brand                5483 non-null   object 
 1   Model                5483 non-null   object 
 2   Variant              5483 non-null   object 
 3   Manufacturing_Year   5483 non-null   int64  
 4   Driven_KiloMeters    5483 non-null   object 
 5   Fuel                 5483 non-null   object 
 6   Location             5483 non-null   object 
 7   Car_Price            5483 non-null   float64
dtypes: float64(1), int64(1), object(6)
memory usage: 342.8+ KB
```

f) Checked total number of unique values

```
car.nunique()
```

```
Unnamed: 0            5616
Brand                   29
Model                  243
Variant               1237
Manufacturing_Year      23
Driven_KiloMeters     2885
Fuel                     9
Location                73
Car_Price             2322
Number_of_Owners         3
dtype: int64
```

g) Data cleaning

- Column "Number_of_Owners" contains missing value (3863) which is more than 50%. So, dropped this column.

```
#Droping column "Number_of_Owners" as it contains most missing value(3863) which is more than 50%.
car.drop(columns=['Number_of_Owners'],inplace=True)
```

- Column 'Unnamed: 0' contains serial no, so dropped this column.

```
#Droping column "Unnamed: 0"
car.drop(columns=['Unnamed: 0'],inplace=True)
```

- Column "Variant" contains missing value (127) which is very less, less than 5%. So, we will keep this column and will drop those rows.

```
#We cannot fill any value in "Variant" as it is unique for each car model,
car.dropna(inplace = True)
```

- Checked all values of each column and replaced irrelevant value or data.

```
for i in car.columns:
    print(car[i].value_counts(),"\n\n", "-"*100, "\n\n")
```

Observation:

1. Brand column:
    - Brand "BMW" and "Bmw" both is same brand so we will replacing "Bmw" with "BMW"
    - Brand "KIA" and "Kia" both is same brand so we will replacing "Kia" with "KIA"
2. Driven_KiloMeters column:
    - Replacing "KM","kms", "km", "," and ".0" as these are not required and column name itself defines these are KM values
3. Fuel column:
    - Fuel "Petrol" and "PETROL" both are same so will replace "Petrol" with "PETROL"
    - Fuel "Diesel" and "DIESEL" both are same so will replace "Diesel" with "DIESEL"
4. Location column:
    - Location "Delhi" and "Delhi NCR" is same so will replace "Delhi NCR" with "Delhi"
5. Car_Price column:
    - Removing "₹", "." and ","
    - Replacing value "Lakh" with "000"
6. Car_Price is object type so wil convert it's datatype from object to integer datatype

```
#Brand column:
car["Brand"]= car["Brand"].str.replace('Bmw', 'BMW')
car["Brand"]= car["Brand"].str.replace('Kia', 'KIA')
```

```
#Driven_KiloMeters column:
car["Driven_KiloMeters"]= car["Driven_KiloMeters"].str.replace('KM', ' ')
```

```
car["Driven_KiloMeters"]= car["Driven_KiloMeters"].str.replace('kms', '')
```

```
car["Driven_KiloMeters"]= car["Driven_KiloMeters"].str.replace('km', '')
```

```
car["Driven_KiloMeters"]= car["Driven_KiloMeters"].str.replace(',', '')
```

```
car["Driven_KiloMeters"]= car["Driven_KiloMeters"].str.replace('.0', '')
```

```
#Fuel column:
car["Fuel"].replace('Petrol', 'PETROL',inplace=True)
```

```
#Fuel column:
car["Fuel"].replace('Diesel', 'DIESEL',inplace=True)
```

```
#Location column:
car["Location"].replace('Delhi NCR', 'Delhi',inplace=True)
```

```
#Car_Price column:
car["Car_Price"]= car["Car_Price"].str.replace('₹', '')
car["Car_Price"]= car["Car_Price"].str.replace('.', '')
car["Car_Price"]= car["Car_Price"].str.replace(',', '')
car["Car_Price"]= car["Car_Price"].str.replace(' Lakh', '000')
```

- Converted Data Type of column "Car_Price" as this column contains numeric values but its data type is object.

```
car['Car_Price']=pd.to_numeric(car['Car_Price'],errors='coerce')
```

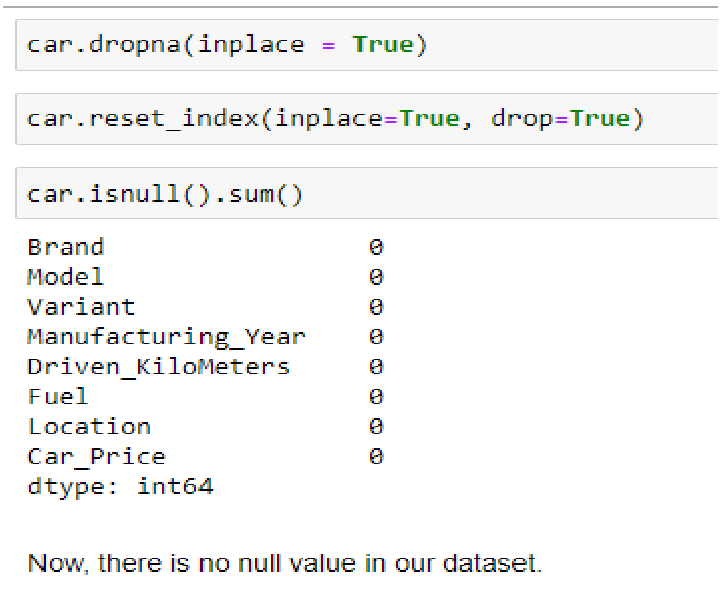
```
car.dtypes
```

```
Brand                  object
Model                  object
Variant                object
Manufacturing_Year      int64
Driven_KiloMeters      object
Fuel                   object
Location               object
Car_Price             float64
dtype: object
```

```
#Checking Null value again after conversion of datatype
car.isnull().sum()
```

```
Brand                 0
Model                 0
Variant               0
Manufacturing_Year    0
Driven_KiloMeters     0
Fuel                  0
Location              0
Car_Price             6
dtype: int64
```

- After conversion of Data type, we seen Car_Price column contains null values. So, dropped those rows only as total missing value is 6.



```
car.dropna(inplace = True)
```

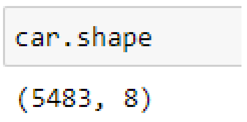
```
car.reset_index(inplace=True, drop=True)
```

```
car.isnull().sum()
```

```
Brand                   0
Model                   0
Variant                 0
Manufacturing_Year      0
Driven_KiloMeters       0
Fuel                    0
Location                0
Car_Price               0
dtype: int64
```

Now, there is no null value in our dataset.

- Checked again total no of rows and column



```
car.shape
```

```
(5483, 8)
```

h) Data Visualization

i. Uni-Variate Analysis
   - ➢ Used Count plot

ii. Bivariate Analysis
   (For comparison between each feature with target)
   - ➢ Used Cat plot and Scatter plot

iii. Multivariate Analysis
   (For comparison between all features with target)
   - ➢ Used Pair plot

4. Data Inputs- Logic- Output Relationships

i) Checking Correlation

```
car.corr()
```

	Brand	Model	Variant	Manufacturing_Year	Driven_KiloMeters	Fuel	Location	Car_Price
Brand	1.000000	0.984207	0.123862	0.129157	-0.028763	0.015162	0.000459	-0.003022
Model	0.984207	1.000000	0.106493	0.088589	-0.023588	-0.013179	0.044661	0.002470
Variant	0.123862	0.106493	1.000000	0.005068	-0.072386	0.169128	-0.073757	-0.086074
Manufacturing_Year	0.129157	0.088589	0.005068	1.000000	-0.160688	-0.005101	-0.151555	0.231122
Driven_KiloMeters	-0.028763	-0.023588	-0.072386	-0.160688	1.000000	-0.166733	-0.019620	-0.085451
Fuel	0.015162	-0.013179	0.169128	-0.005101	-0.166733	1.000000	-0.122324	-0.309870
Location	0.000459	0.044661	-0.073757	-0.151555	-0.019620	-0.122324	1.000000	0.032826
Car_Price	-0.003022	0.002470	-0.086074	0.231122	-0.085451	-0.309870	0.032826	1.000000

This gives the correlation between the denpendent and independent variables.

```
car.corr()["Car_Price"].sort_values()
```

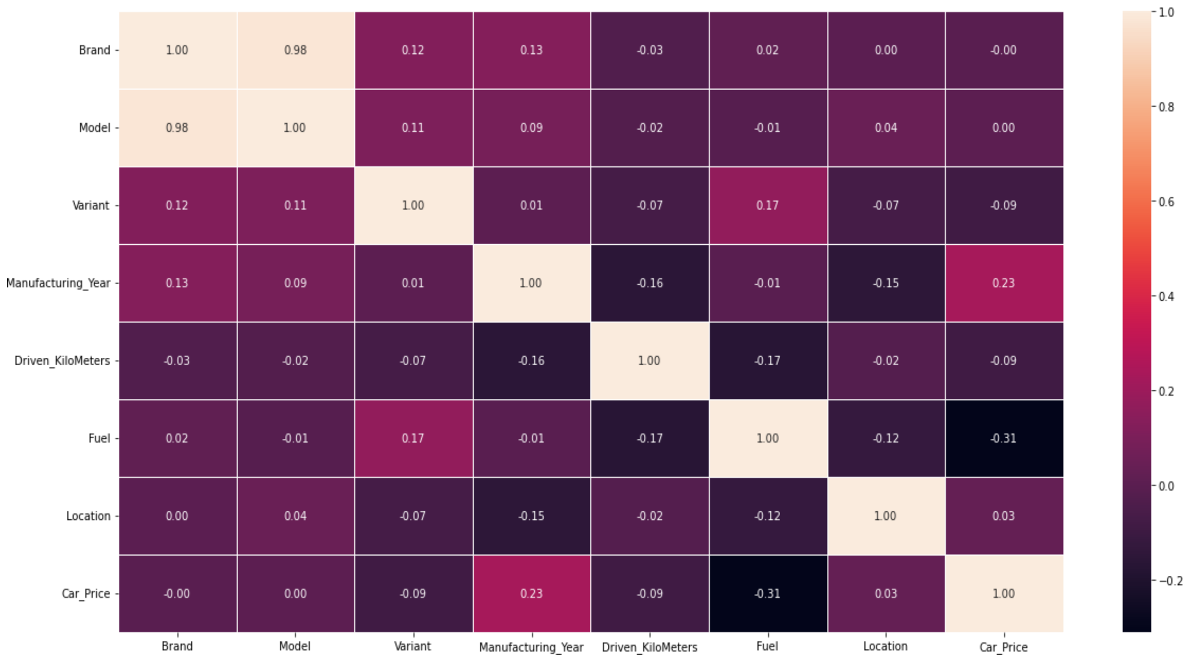
```
Fuel                 -0.309870
Variant              -0.086074
Driven_KiloMeters    -0.085451
Brand                -0.003022
Model                 0.002470
Location              0.032826
Manufacturing_Year    0.231122
Car_Price             1.000000
Name: Car_Price, dtype: float64
```

We can observe :

- All columns are sorted in ascending order showing least to strong correlation with target column.
- 3 columns are negatively correlated and 4 columns are positively correlated.
- Column 'Fuel' is highly positively correlated with Target column and Column 'Brand' is highly negatively correlated with Target column

Checking correlation with heatmap

```
plt.figure(figsize=(20,10))
sns.heatmap(car.corr(),annot=True,annot_kws= {"size": 10}, linewidth=0.5, linecolor='white', fmt='.2f')
```



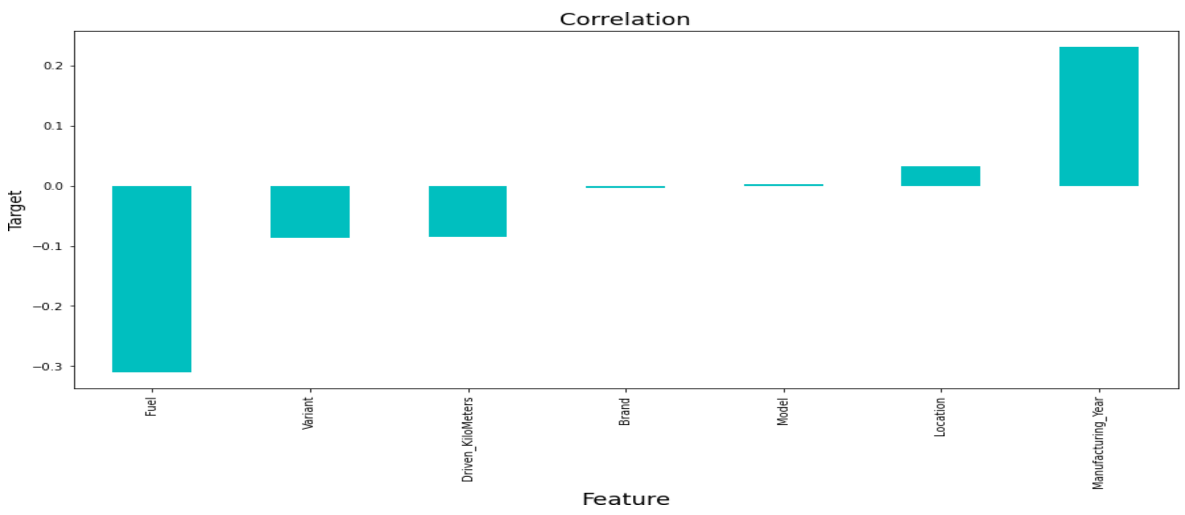
	Brand	Model	Variant	Manufacturing_Year	Driven_KiloMeters	Fuel	Location	Car_Price
Brand	1.00	0.98	0.12	0.13	-0.03	0.02	0.00	-0.00
Model	0.98	1.00	0.11	0.09	-0.02	-0.01	0.04	0.00
Variant	0.12	0.11	1.00	0.01	-0.07	0.17	-0.07	-0.09
Manufacturing_Year	0.13	0.09	0.01	1.00	-0.16	-0.01	-0.15	0.23
Driven_KiloMeters	-0.03	-0.02	-0.07	-0.16	1.00	-0.17	-0.02	-0.09
Fuel	0.02	-0.01	0.17	-0.01	-0.17	1.00	-0.12	-0.31
Location	0.00	0.04	-0.07	-0.15	-0.02	-0.12	1.00	0.03
Car_Price	-0.00	0.00	-0.09	0.23	-0.09	-0.31	0.03	1.00

Outcome of Correlation

- **Brand** has **-0 percent** correlation with the target column which can be considered as No correlation and is negatively correlated.
- **Model** has **-6 percent** correlation with the target column which can be considered as good correlation and negatively correlated.
- **Variant** has **10 percent** correlation with the target column which can be considered as good correlation and positively correlated.
- **Manufacturing_Year** has **29 percent** correlation with the target column which can be considered as good correlation and positively correlated.
- **Driven_KiloMeters** has **4 percent** correlation with the target column which can be considered as weak correlation and positively correlated.
- **Fuel** has **33 percent** correlation with the target column which can be considered as strong correlation and positively correlated.
- **Location** has **-21 percent** correlation with the target column which can be considered as weak correlation and negatively correlated.
  - Max correlation is with **Fuel**
  - Min correlation is with **Brand**

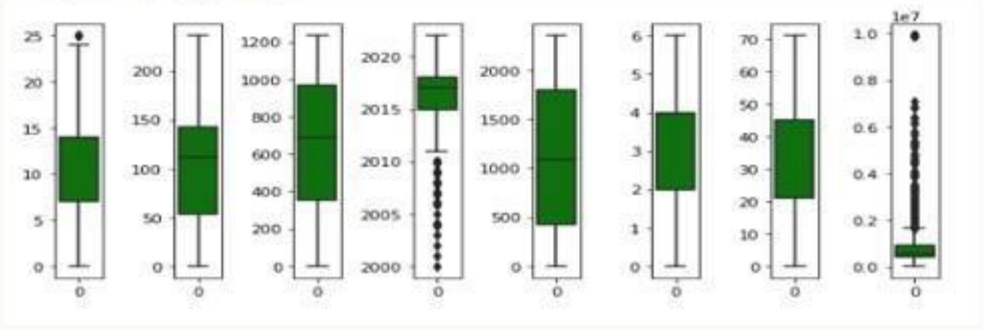
Checking correlation with barplot

```
plt.figure(figsize=(15,7))
car.corr()['Car_Price'].sort_values(ascending=True).drop(['Car_Price']).plot(kind='bar',color='c')
plt.xlabel('Feature',fontsize=18)
plt.ylabel('Target',fontsize=14)
plt.title('Correlation',fontsize=18)
plt.show()
```



CHECKING OUTLIERS

```
collist=car.columns.values
ncol=8
nrows=7
plt.figure(figsize=(ncol,3*ncol))
for i in range(0,len(collist)):
    plt.subplot(nrows,ncol,i+1)
    sns.boxplot(data=car[collist[i]],color='green',orient='v')
    plt.tight_layout()
```



Observation:

- **Outliers present in columns:** "Brand", "Manufacturing_Year" and "Car_Price".
- But we will not remove Outliers from "Brand" column as it is categorical column and from "Car_Price" column as it is a target column.
- **Outliers not present in columns:** 'Model', 'Variant','Driven_KiloMeters', 'Fuel' and 'Location'.

REMOVING OUTLIERS

- *Outliers are removed only from continuous features and not from target*

- **Checking two methods and compare between them which is give less percentage loss and then using that method for further process.**

1. **Zscore method using Scipy**
2. **IQR (Inter Quantile Range) method**

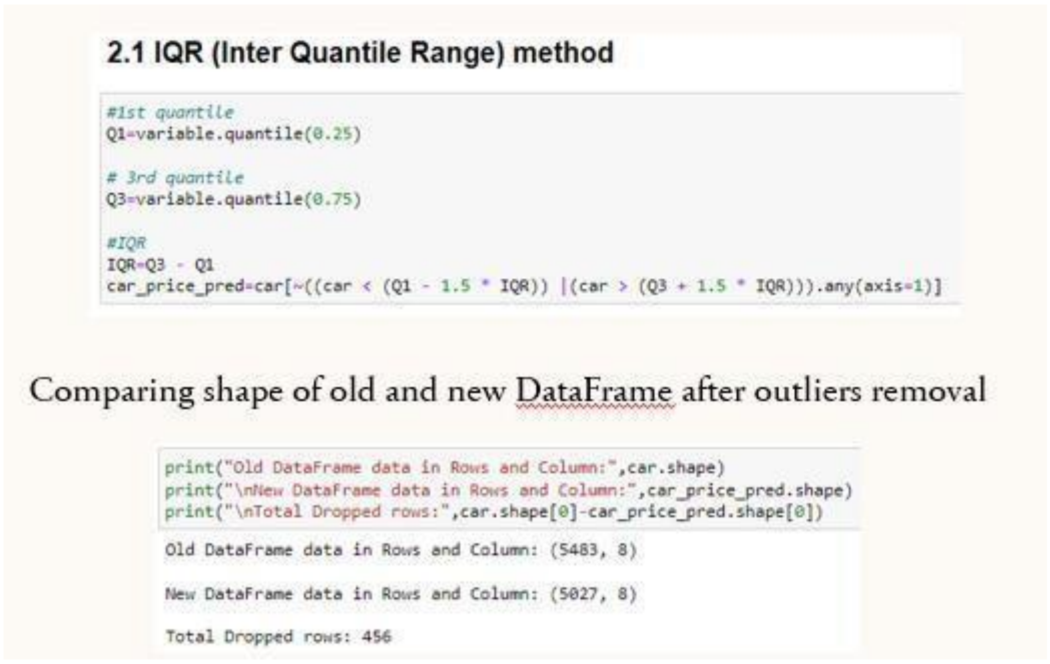
1.1 Zscore method using Scipy

```
#  Outliers will be removed only from Continuous column i.e; "Manufacturing_Year".
# We will not remove outliers from Categorical column i.e; "Brand".

variable = car[['Manufacturing_Year']]

z=np.abs(zscore(variable))

# Creating new dataframe
car_price = car[(z<3).all(axis=1)]
```

Comparing shape of old and new DataFrame after outliers removal

```
print("Old DataFrame data in Rows and Column:",car.shape)
print("New DataFrame data in Rows and Column:",car_price.shape)
print("Total Dropped rows:",car.shape[0]-car_price.shape[0])
```

```
Old DataFrame data in Rows and Column: (5483, 8)
New DataFrame data in Rows and Column: (5413, 8)
Total Dropped rows: 70
```



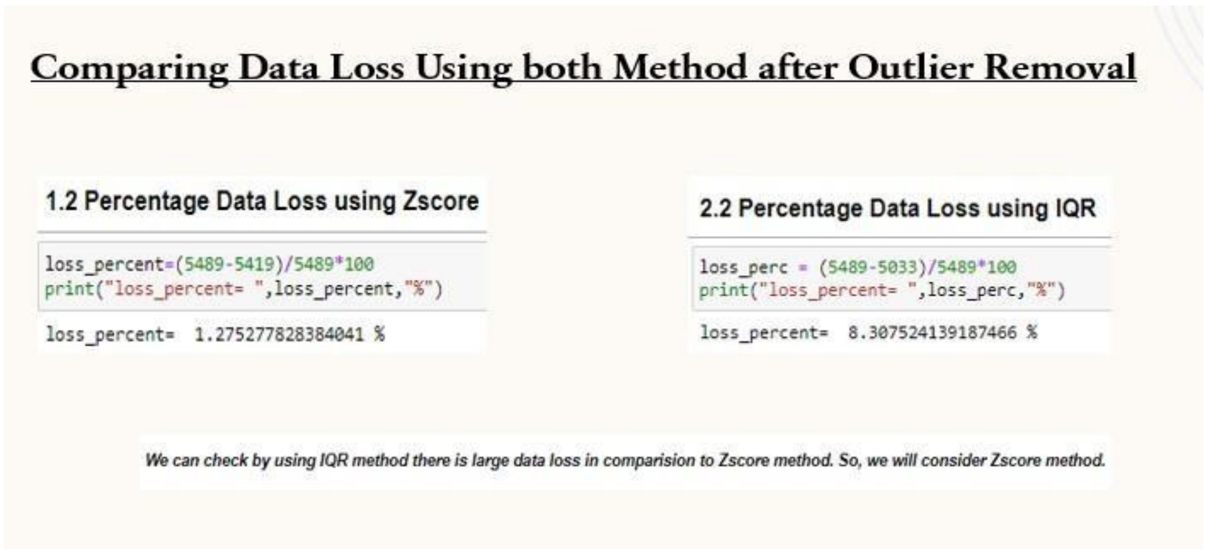
2.1 IQR (Inter Quantile Range) method

```
#1st quantile
Q1=variable.quantile(0.25)

# 3rd quantile
Q3=variable.quantile(0.75)

#IQR
IQR=Q3 - Q1
car_price_pred=car[~((car < (Q1 - 1.5 * IQR)) |(car > (Q3 + 1.5 * IQR))).any(axis=1)]
```

Comparing shape of old and new DataFrame after outliers removal

```
print("Old DataFrame data in Rows and Column:",car.shape)
print("\nNew DataFrame data in Rows and Column:",car_price_pred.shape)
print("\nTotal Dropped rows:",car.shape[0]-car_price_pred.shape[0])
```

```
Old DataFrame data in Rows and Column: (5483, 8)

New DataFrame data in Rows and Column: (5027, 8)

Total Dropped rows: 456
```



Comparing Data Loss Using both Method after Outlier Removal

1.2 Percentage Data Loss using Zscore

```
loss_percent=(5489-5419)/5489*100
print("loss_percent= ",loss_percent,"%")
```

```
loss_percent=  1.275277828384041 %
```

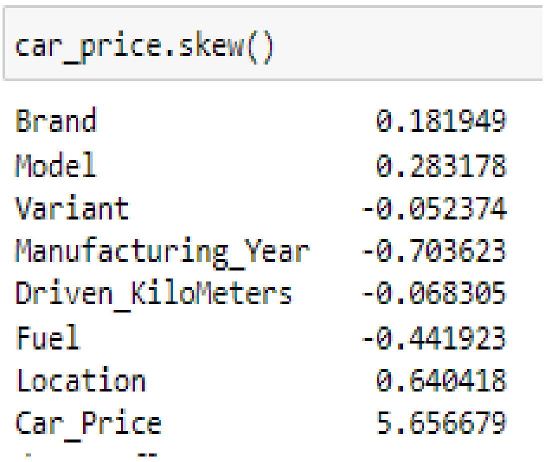
2.2 Percentage Data Loss using IQR

```
loss_perc = (5489-5033)/5489*100
print("loss_percent= ",loss_perc,"%")
```

```
loss_percent=  8.307524139187466 %
```

We can check by using IQR method there is large data loss in comparision to Zscore method. So, we will consider Zscore method.

CHECKING SKEWNESS

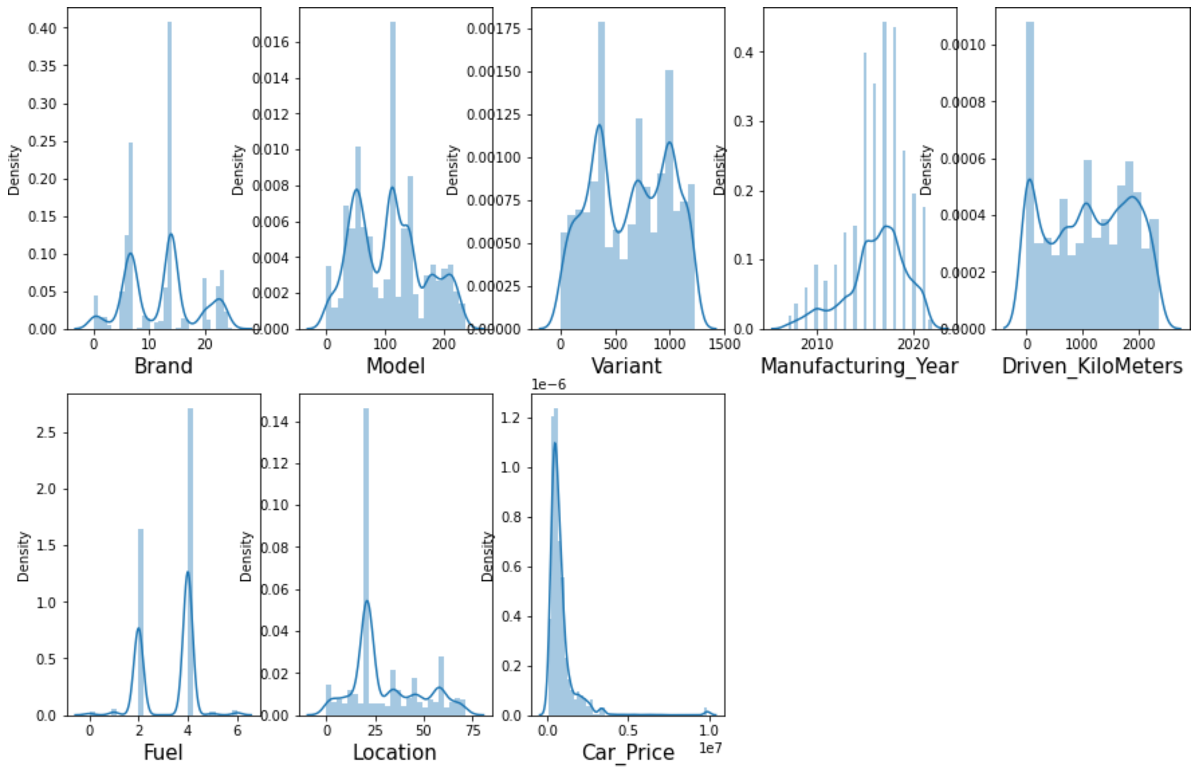


```
car_price.skew()
```

```
Brand                 0.181949
Model                 0.283178
Variant              -0.052374
Manufacturing_Year   -0.703623
Driven_KiloMeters    -0.068305
Fuel                 -0.441923
Location              0.640418
Car_Price             5.656679
```

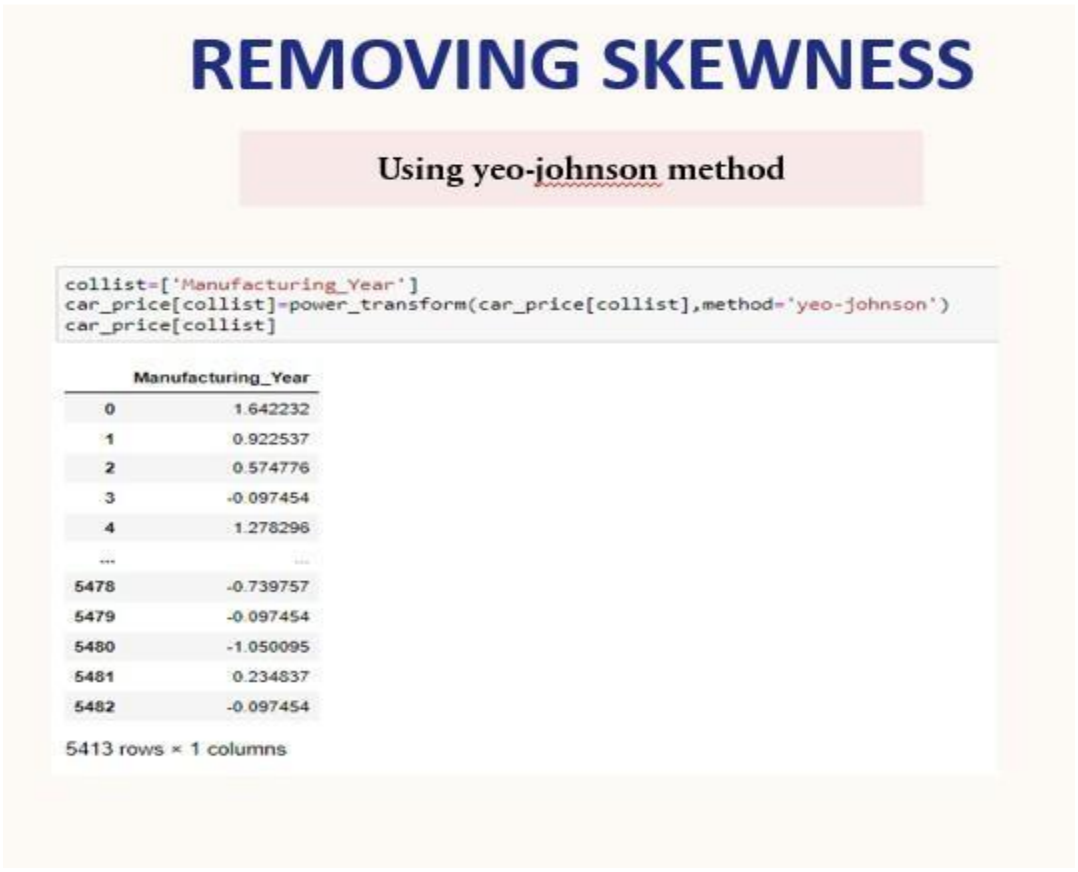
Checking skweness through Data Visualization also

```
plt.figure(figsize=(15,15), facecolor='white')
plotnumber = 1

for column in car_price:
    if plotnumber<=15:
        ax = plt.subplot(3,5,plotnumber)
        sns.distplot(car_price[column])
        plt.xlabel(column,fontsize=15)
    plotnumber+=1
plt.show()
```



Observation:

- Skewness threshold taken is +/-0.25
- All the columns are not normallly distributed, they are skewed.
- Columns which are having skewness: 'Brand', 'Model', 'Manufacturing_Year', 'Fuel', 'Car_Price'.
- The 'Fuel' column data is negatively highly skewed and 'Location' is positively highly skewed
- Since 'Brand', 'Model', 'Fuel' are categorical column so we will not remove skewness and 'Car_Price' is Target Column so we can not remove skewness.
- So we will remove skewness from Manufacturing_Year column as it contains continuous data.



REMOVING SKEWNESS

Using yeo-johnson method

```
collist=['Manufacturing_Year']
car_price[collist]=power_transform(car_price[collist],method='yeo-johnson')
car_price[collist]
```

	Manufacturing_Year
0	1.642232
1	0.922537
2	0.574776
3	-0.097454
4	1.278296
...	...
5478	-0.739757
5479	-0.097454
5480	-1.050095
5481	0.234837
5482	-0.097454

5413 rows × 1 columns

CHECKING SKEWNESS AFTER REMOVAL

```
car_price.skew()
```

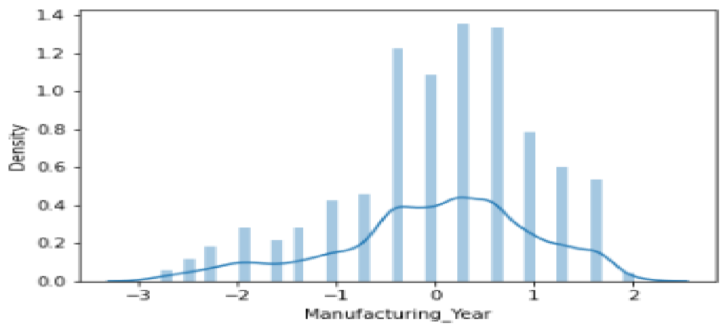
```
Brand                   0.181949
Model                   0.283178
Variant                -0.052374
Manufacturing_Year     -0.521735
Driven_KiloMeters      -0.068305
Fuel                   -0.441923
Location                0.640418
Car_Price               5.656679
dtype: float64
```

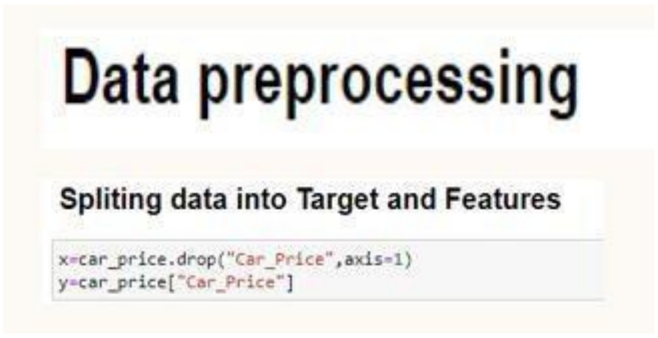
Still we can see skewness is present but from earlier it is removed.

Checking through Visualization

```
sns.distplot(car_price['Manufacturing_Year'])
```

```
<AxesSubplot:xlabel='Manufacturing_Year', ylabel='Density'>
```





Data preprocessing

Spliting data into Target and Features

```
x=car_price.drop("Car_Price",axis=1)
y=car_price["Car_Price"]
```

```
x.head()
```

	Brand	Model	Variant	Manufacturing_Year	Driven_KiloMeters	Fuel	Location
0	7	71	625	1.642232	75	4	2
1	10	90	639	0.922537	332	4	2
2	20	176	751	0.574776	804	4	2
3	6	46	1211	-0.097454	549	4	2
4	3	28	917	1.278296	483	4	2

```
y.head()
```

```
0    2300000.0
1    1553000.0
2     711000.0
3     733000.0
4     381000.0
Name: Car_Price, dtype: float64
```

```
x.shape, y.shape
```

```
((5413, 7), (5413,))
```

Scaling data using Standard Scaler

```
scaler = StandardScaler()
x = pd.DataFrame(scaler.fit_transform(x), columns = x.columns)
```

```
x.head()
```

	Brand	Model	Variant	Manufacturing_Year	Driven_KiloMeters	Fuel	Location
0	-0.810184	-0.610846	-0.039789	1.642232	-1.413423	0.723823	-1.601946
1	-0.328258	-0.288392	0.000313	0.922537	-1.062234	0.723823	-1.601946
2	1.278161	1.171135	0.321125	0.574776	-0.417250	0.723823	-1.601946
3	-0.970826	-1.035127	1.638746	-0.097454	-0.765705	0.723823	-1.601946
4	-1.452752	-1.340609	0.796614	1.278296	-0.855894	0.723823	-1.601946

Checking for Multicolinearity

VIF (Variance Inflation factor)

```
vif = pd.DataFrame()
vif['VIF values']= [variance_inflation_factor(x.values,i) for i in range(len(x.columns))]
vif['Features'] = x.columns
vif
```

	VIF values	Features
0	36.587438	Brand
1	36.172661	Model
2	1.047921	Variant
3	1.140527	Manufacturing_Year
4	1.075751	Driven_KiloMeters
5	1.090563	Fuel
6	1.096371	Location

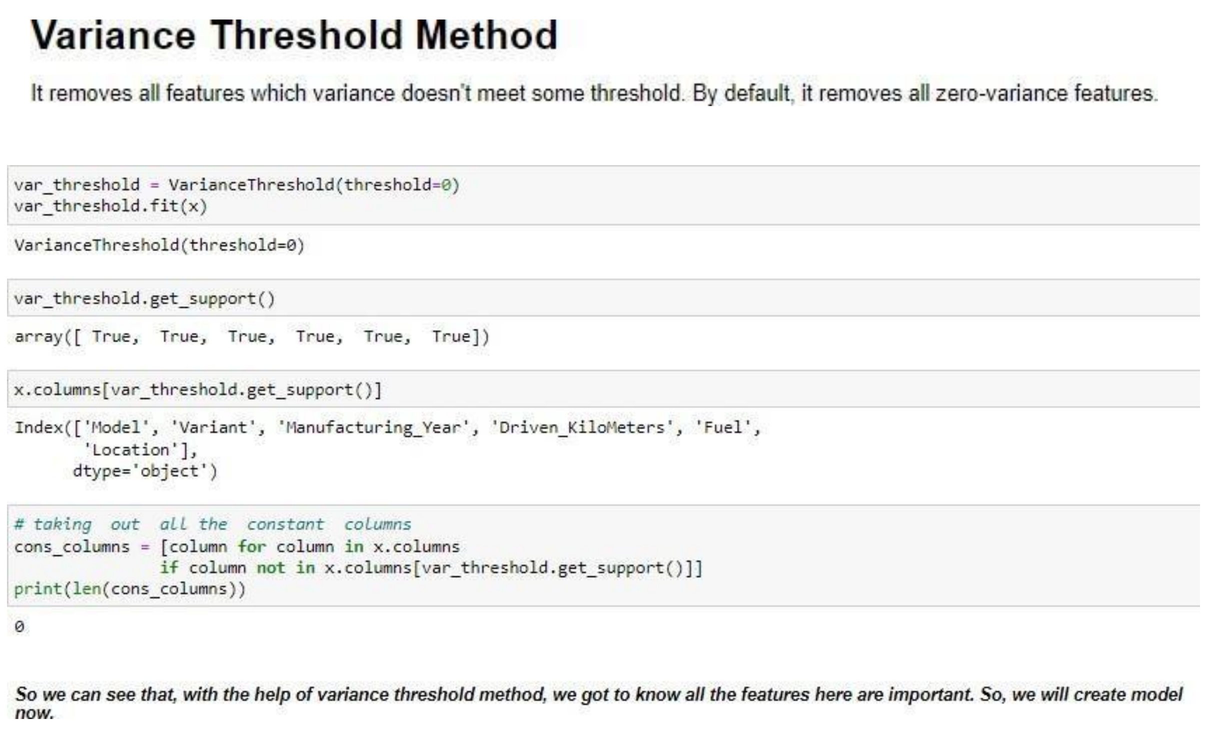
The VIF value is more than 10 in the columns 'Brand', 'Model'. But column 'Brand' is having highest VIF value. So, we will drop column 'Brand'.

```
x = x.drop(['Brand'],axis=1)
```

```
#Checking again Multicolinearity using VIF
vif = pd.DataFrame()
vif['VIF values']= [variance_inflation_factor(x.values,i) for i in range(len(x.columns))]
vif['Features'] = x.columns
vif
```

	VIF values	Features
0	1.035566	Model
1	1.043016	Variant
2	1.090540	Manufacturing_Year
3	1.073187	Driven_KiloMeters
4	1.071377	Fuel
5	1.052502	Location

Now, we can check Multicolinearity is removed from the columns as VIF value of all columns are less than 10.



Variance Threshold Method

It removes all features which variance doesn't meet some threshold. By default, it removes all zero-variance features.

```
var_threshold = VarianceThreshold(threshold=0)
var_threshold.fit(x)
```

```
VarianceThreshold(threshold=0)
```

```
var_threshold.get_support()
```

```
array([ True,  True,  True,  True,  True,  True])
```

```
x.columns[var_threshold.get_support()]
```

```
Index(['Model', 'Variant', 'Manufacturing_Year', 'Driven_KiloMeters', 'Fuel',
       'Location'],
      dtype='object')
```

```
# taking  out  all the  constant  columns
cons_columns = [column for column in x.columns
                if column not in x.columns[var_threshold.get_support()]]
print(len(cons_columns))
```

```
0
```

So we can see that, with the help of variance threshold method, we got to know all the features here are important. So, we will create model now.

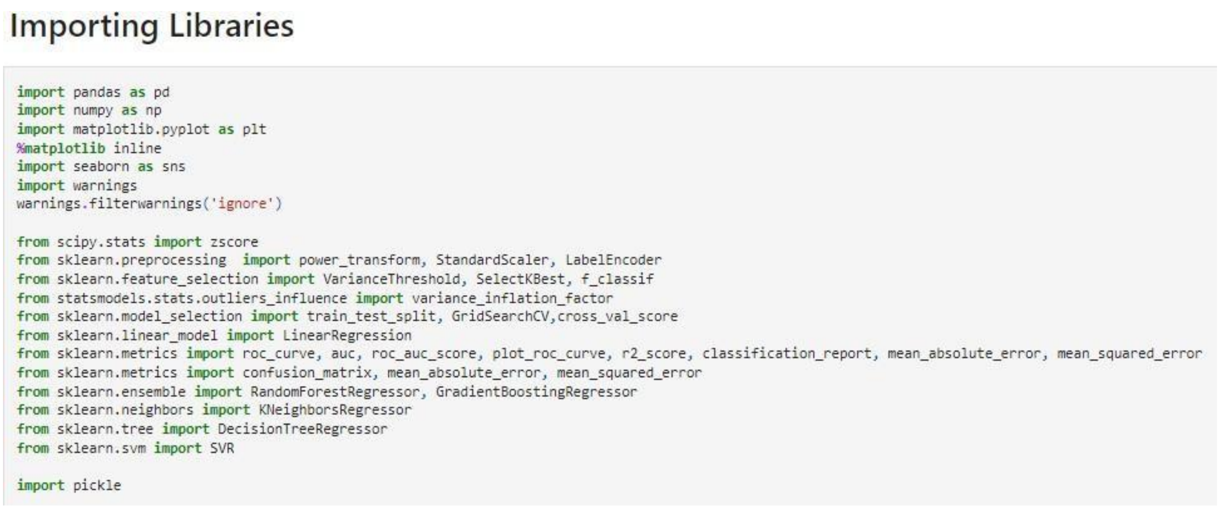
5. State the set of assumptions (if any) related to the problem under consideration

- By observing Target Variable "label" it is already assumed that it is a Regression Problem and to understand it have to use Regression model.
- Also, it was observed that there is one column "Unnamed 0" which is irrelevant column as it contains serial no so have to drop this column.
- Have to convert data type of "Car_Price" column.

6. Hardware and Software Requirements and Tools Used

- **Hardware used:**
  - **Processor**: 11th Gen Intel(R) Core(TM) i3-1125G4 @ 2.00GHz 2.00 GHz
  - **System Type**: 64-bit OS
- **Software used:**
  - **Anaconda** for 64-bit OS
  - **Jupyter** notebook

- **Tools, Libraries and Packages used:**



Importing Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

from scipy.stats import zscore
from sklearn.preprocessing  import power_transform, StandardScaler, LabelEncoder
from sklearn.feature_selection import VarianceThreshold, SelectKBest, f_classif
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import train_test_split, GridSearchCV,cross_val_score
from sklearn.linear_model import LinearRegression
from sklearn.metrics import roc_curve, auc, roc_auc_score, plot_roc_curve, r2_score, classification_report, mean_absolute_error, mean_squared_error
from sklearn.metrics import confusion_matrix, mean_absolute_error, mean_squared_error
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR

import pickle
```

Model/s Development and Evaluation

1. Identification of possible problem-solving approaches (methods)

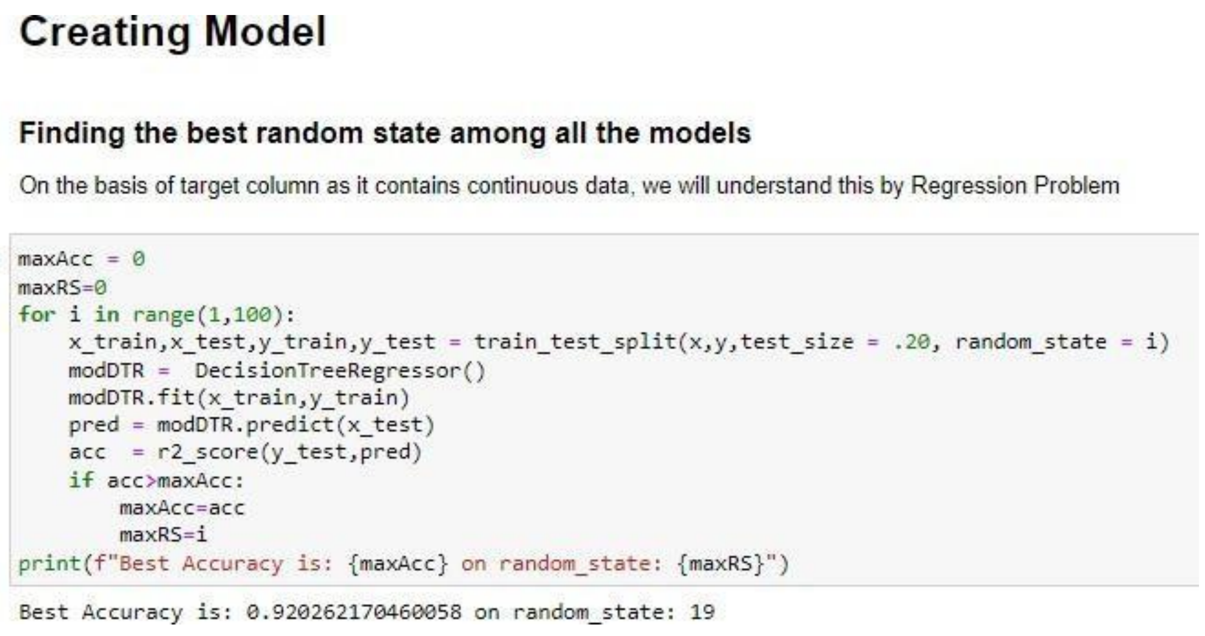
In this project, we want to predict the micro-credit defaulter and for this we have used these approaches:

- Checked Total Numbers of Rows and Column
- Checked All Column Name
- Checked Data Type of All Data
- Checked for Null Values
- Checked for special character present in dataset or not
- Checked total number of unique values
- Dropped irrelevant Features
- Replaced duplicate values, special characters and irrelevant data
- Checked all features through visualization.
- Information about Data
- Checked correlation of features with target
- Detected Outliers and removed
- Checked skewness and removed
- Scaled data using Standard Scalar
- Checked Multi co-linearity
- Used Feature Selection Method: Variance threshold method

Testing of Identified Approaches (Algorithms)

1. Linear Regression
2. Random Forest Regressor
3. KNN Regressor
4. Gradient Boosting Regressor
5. Decision Tree Regressor

2. Run and evaluate selected models



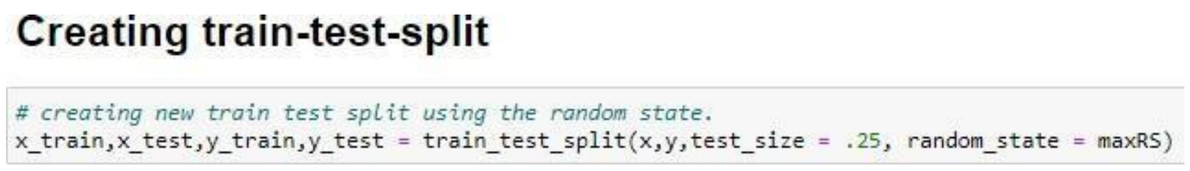
Creating Model

Finding the best random state among all the models

On the basis of target column as it contains continuous data, we will understand this by Regression Problem

```
maxAcc = 0
maxRS=0
for i in range(1,100):
    x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = .20, random_state = i)
    modDTR =  DecisionTreeRegressor()
    modDTR.fit(x_train,y_train)
    pred = modDTR.predict(x_test)
    acc  = r2_score(y_test,pred)
    if acc>maxAcc:
        maxAcc=acc
        maxRS=i
print(f"Best Accuracy is: {maxAcc} on random_state: {maxRS}")
```

```
Best Accuracy is: 0.920262170460058 on random_state: 19
```

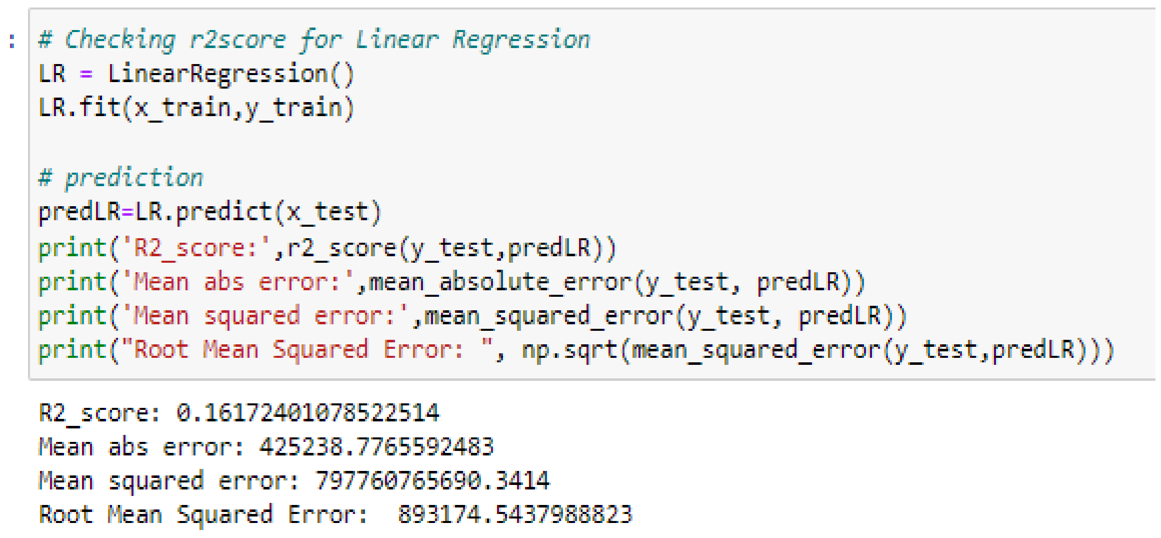


Creating train-test-split

```
# creating new train test split using the random state.
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = .25, random_state = maxRS)
```

Regression Algorithm

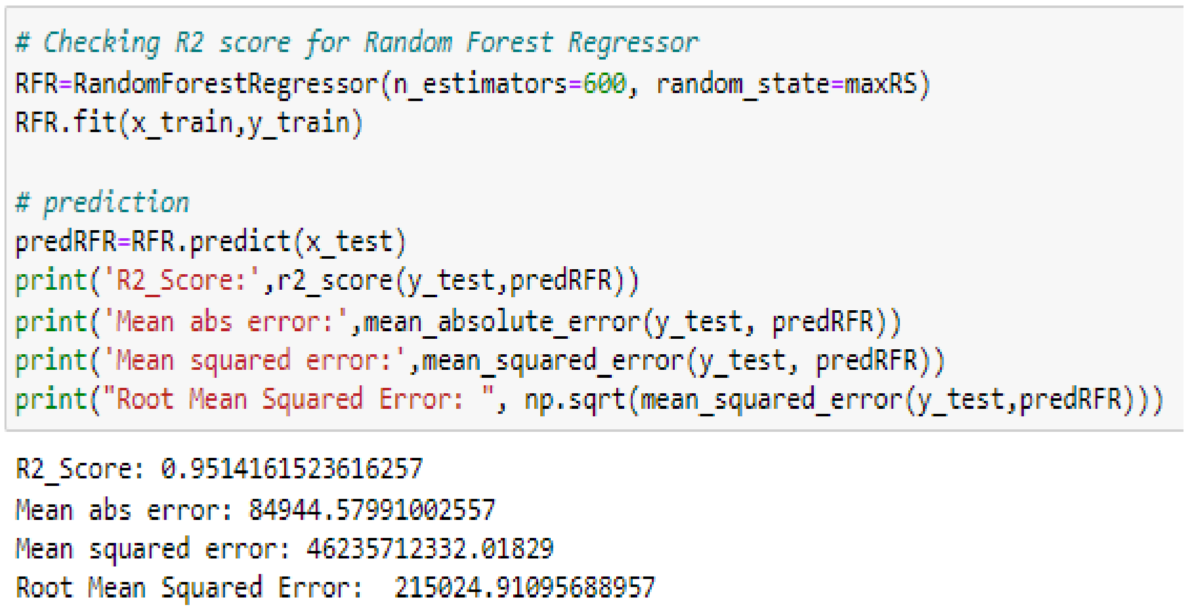
1. Linear Regression



```
# Checking r2score for Linear Regression
LR = LinearRegression()
LR.fit(x_train,y_train)

# prediction
predLR=LR.predict(x_test)
print('R2_score:',r2_score(y_test,predLR))
print('Mean abs error:',mean_absolute_error(y_test, predLR))
print('Mean squared error:',mean_squared_error(y_test, predLR))
print("Root Mean Squared Error: ", np.sqrt(mean_squared_error(y_test,predLR)))
```

```
R2_score: 0.16172401078522514
Mean abs error: 425238.7765592483
Mean squared error: 797760765690.3414
Root Mean Squared Error:  893174.5437988823
```

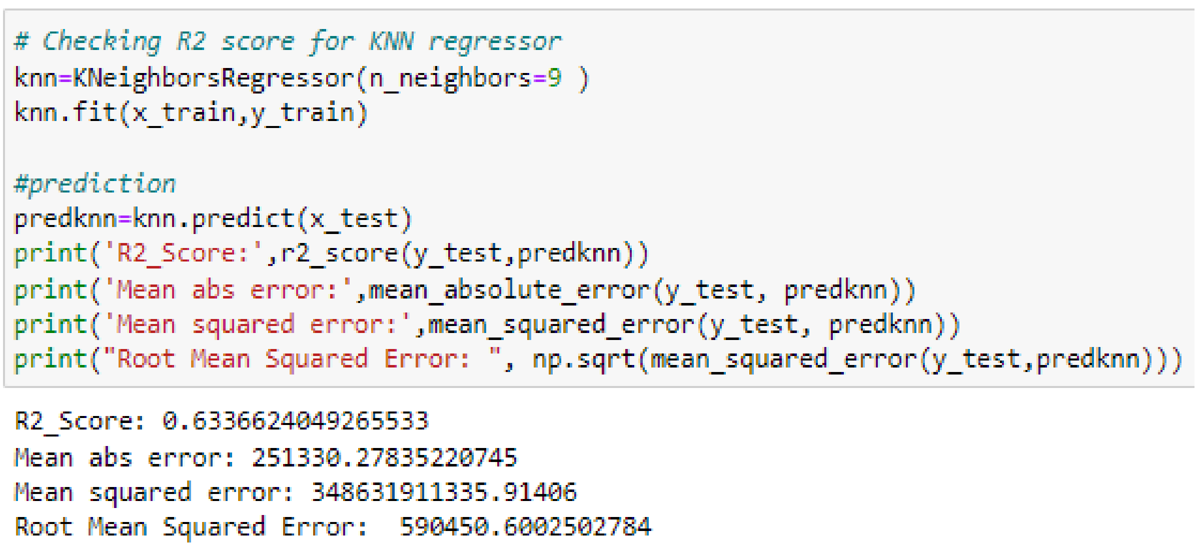
2. Random forest Regression Model



```
# Checking R2 score for Random Forest Regressor
RFR=RandomForestRegressor(n_estimators=600, random_state=maxRS)
RFR.fit(x_train,y_train)

# prediction
predRFR=RFR.predict(x_test)
print('R2_Score:',r2_score(y_test,predRFR))
print('Mean abs error:',mean_absolute_error(y_test, predRFR))
print('Mean squared error:',mean_squared_error(y_test, predRFR))
print("Root Mean Squared Error: ", np.sqrt(mean_squared_error(y_test,predRFR)))
```

```
R2_Score: 0.9514161523616257
Mean abs error: 84944.57991002557
Mean squared error: 46235712332.01829
Root Mean Squared Error:  215024.91095688957
```

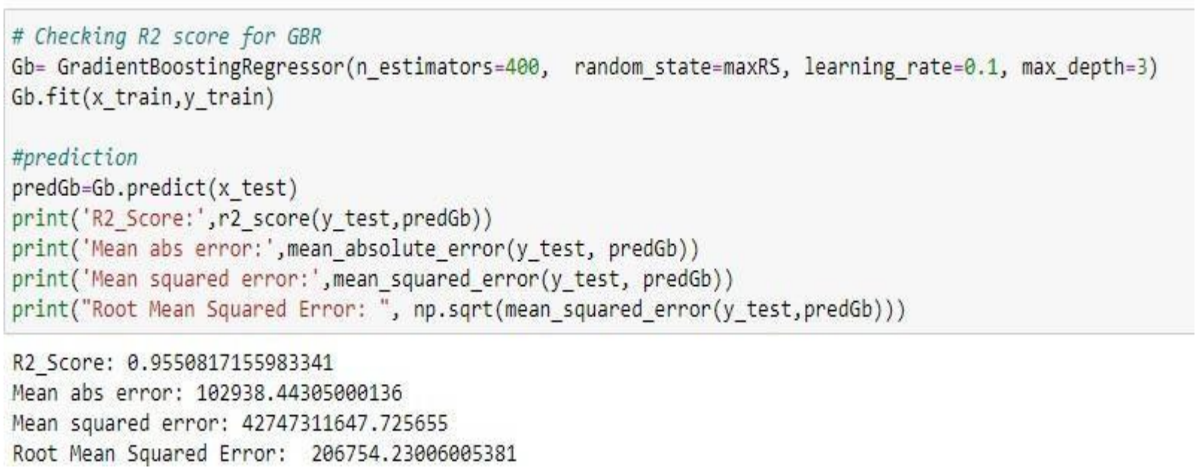
3. KNN Regressor



```
# Checking R2 score for KNN regressor
knn=KNeighborsRegressor(n_neighbors=9 )
knn.fit(x_train,y_train)

#prediction
predknn=knn.predict(x_test)
print('R2_Score:',r2_score(y_test,predknn))
print('Mean abs error:',mean_absolute_error(y_test, predknn))
print('Mean squared error:',mean_squared_error(y_test, predknn))
print("Root Mean Squared Error: ", np.sqrt(mean_squared_error(y_test,predknn)))
```

```
R2_Score: 0.6336624049265533
Mean abs error: 251330.27835220745
Mean squared error: 348631911335.91406
Root Mean Squared Error:  590450.6002502784
```

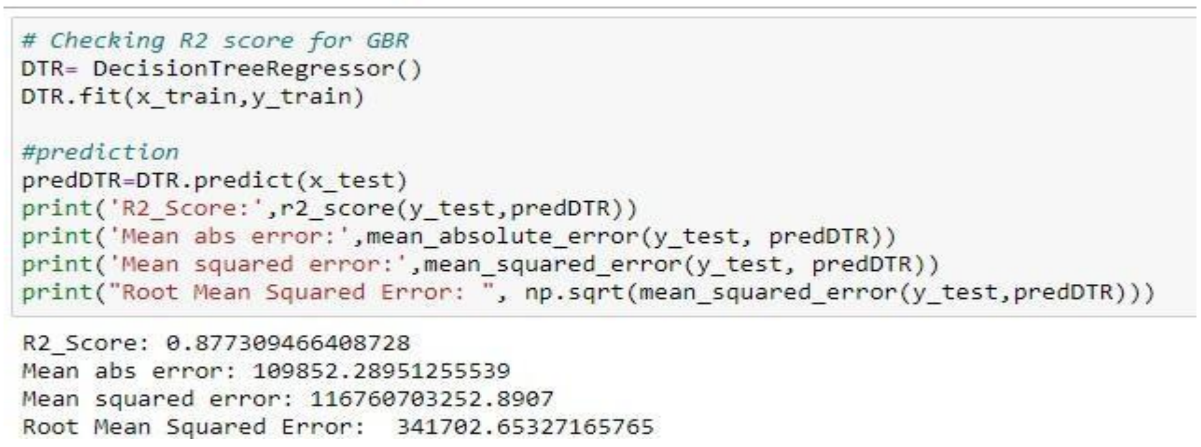
4. Gradient boosting Regressor



```
# Checking R2 score for GBR
Gb= GradientBoostingRegressor(n_estimators=400,  random_state=maxRS, learning_rate=0.1, max_depth=3)
Gb.fit(x_train,y_train)

#prediction
predGb=Gb.predict(x_test)
print('R2_Score:',r2_score(y_test,predGb))
print('Mean abs error:',mean_absolute_error(y_test, predGb))
print('Mean squared error:',mean_squared_error(y_test, predGb))
print("Root Mean Squared Error: ", np.sqrt(mean_squared_error(y_test,predGb)))
```

```
R2_Score: 0.9550817155983341
Mean abs error: 102938.44305000136
Mean squared error: 42747311647.725655
Root Mean Squared Error:  206754.23006005381
```

5. Decision Tree Regressor



```
# Checking R2 score for GBR
DTR= DecisionTreeRegressor()
DTR.fit(x_train,y_train)

#prediction
predDTR=DTR.predict(x_test)
print('R2_Score:',r2_score(y_test,predDTR))
print('Mean abs error:',mean_absolute_error(y_test, predDTR))
print('Mean squared error:',mean_squared_error(y_test, predDTR))
print("Root Mean Squared Error: ", np.sqrt(mean_squared_error(y_test,predDTR)))
```

```
R2_Score: 0.877309466408728
Mean abs error: 109852.28951255539
Mean squared error: 116760703252.8907
Root Mean Squared Error:  341702.65327165765
```

Cross Validation Score for all the model

```
#CV Score for Linear Regression
print('CV score for Linear Regression: ',cross_val_score(LR,x,y,cv=5).mean())

#CV Score for Random Forest Regression
print('CV score for Random forest Regression: ',cross_val_score(RFR,x,y,cv=5).mean())

#CV Score for KNN Regression
print('CV score for KNN Regression: ',cross_val_score(knn,x,y,cv=5).mean())

#CV Score for Gradient Boosting Regression
print('CV score for Gradient Boosting Regression: ',cross_val_score(Gb,x,y,cv=5).mean())

#CV Score for Decision Tree Regression
print('CV score for Decision Tree Regression: ',cross_val_score(DTR,x,y,cv=5).mean())
```

```
CV score for Linear Regression:  0.15707215392115464
CV score for Random forest Regression:  0.7464943437285952
CV score for KNN Regression:  0.32119277110194466
CV score for Gradient Boosting Regression:  0.7509483931060308
CV score for Decision Tree Regression:  0.5074509918030621
```

Hyper Parameter Tuning

The Gradient boosting regressor with GridsearchCV

```
parameter = {'n_estimators':[100,200,300,400],
             'learning_rate':[0.1,0.01,0.001,1],
             'subsample': [0.1,0.2,0.3,0.5,1],
             'max_depth':[1,2,3,4],
             'alpha':[0.1,0.01,0.001,1]}
```

```
CV_GBR = GridSearchCV(GradientBoostingRegressor(),parameter,cv=6,n_jobs = 3,verbose = 2)
```

```
CV_GBR.fit(x_train,y_train)
```

```
Fitting 6 folds for each of 1280 candidates, totalling 7680 fits

GridSearchCV(cv=6, estimator=GradientBoostingRegressor(), n_jobs=3,
             param_grid={'alpha': [0.1, 0.01, 0.001, 1],
                         'learning_rate': [0.1, 0.01, 0.001, 1],
                         'max_depth': [1, 2, 3, 4],
                         'n_estimators': [100, 200, 300, 400],
                         'subsample': [0.1, 0.2, 0.3, 0.5, 1]},
             verbose=2)
```

```
CV_GBR.best_params_
```

```
{'alpha': 0.001,
 'learning_rate': 0.1,
 'max_depth': 4,
 'n_estimators': 400,
 'subsample': 0.5}
```

Creating Regressor Model with Gradient Boosting Regressor

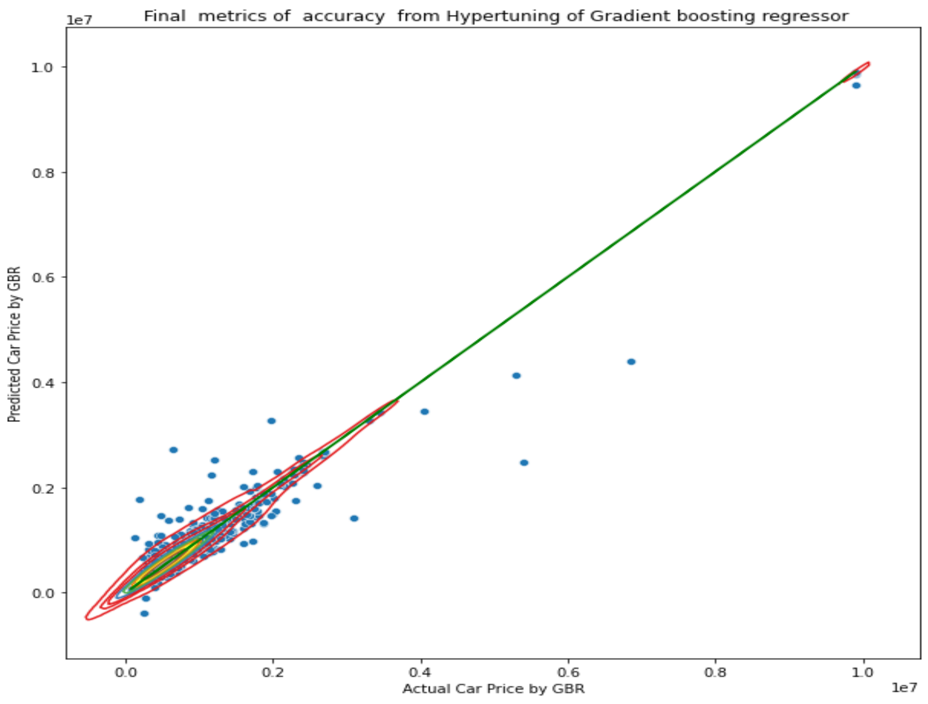
```
GBR = GradientBoostingRegressor(n_estimators=400, alpha=0.001,learning_rate= 0.1, max_depth= 4, subsample = 0.5)
GBR.fit(x_train, y_train)
```

```
GradientBoostingRegressor(alpha=0.001, max_depth=4, n_estimators=400,
                          subsample=0.5)
```

```
#prediction
GBRpred = GBR.predict(x_test)
#R2 score
acc = r2_score(y_test,GBRpred)
print(acc*100)
```

```
95.60799200909335
```

```
#Verifying the final  performance of the model by graph
plt.figure(figsize=(10,10))
sns.scatterplot(x=y_test,y=GBRpred,palette='Set2')
sns.kdeplot(x=y_test,y=GBRpred, cmap='Set1')
plt.plot(y_test,y_test,color='g')
#Verifying the performance of the model by graph
plt.xlabel("Actual Car Price by GBR")
plt.ylabel("Predicted Car Price by GBR")
plt.title(" Final  metrics of  accuracy  from Hypertuning of Gradient boosting regressor")
plt.show()
```



Saving The Predictive Model

```
#saving the model at local file system
filename='Car_price_prediction.pickle'
pickle.dump(CV_GBR,open(filename,'wb'))
#prediction using the saved model
loaded_model = pickle.load(open(filename, 'rb'))
loaded_model.predict(x_test)
```

3. Key Metrics for success in solving problem under consideration

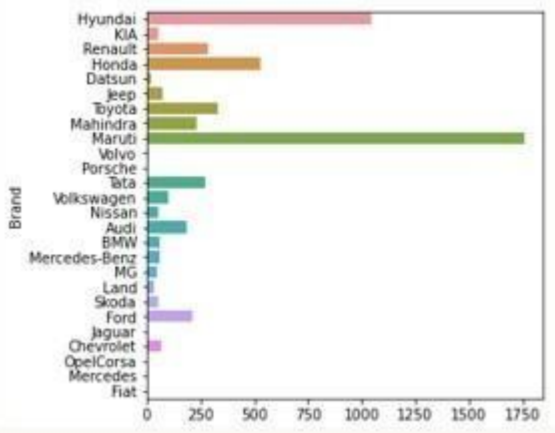
- R2 Score, Mean abs error, Mean squared error, Root Mean Squared Error, CV score are used for success.

4. Visualization

- Uni-Variate Analysis
    - ➢ Using Count plot

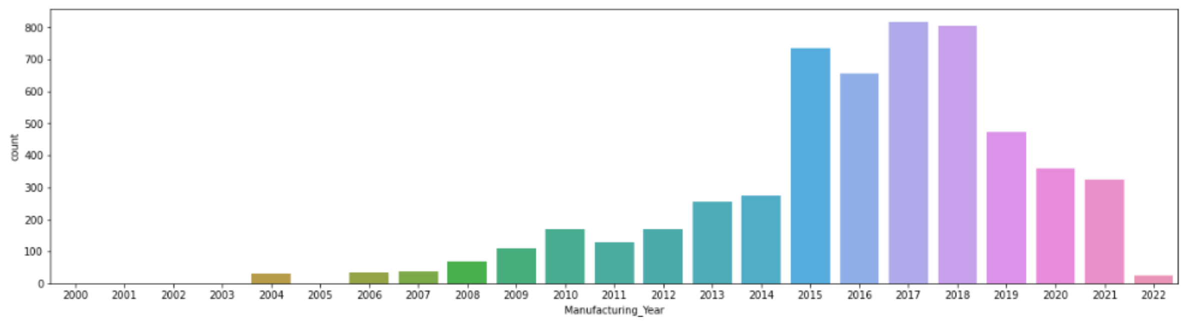
```
#Count Plot for "Brand" column
plt.figure(figsize=(5,5))
sns.countplot(y="Brand",data=car)
```

```
<AxesSubplot:xlabel='count', ylabel='Brand'>
```



```
#Count Plot for "Manufacturing_Year" column
plt.figure(figsize=(20,5))
sns.countplot(x="Manufacturing_Year",data=car)
```

```
<AxesSubplot:xlabel='Manufacturing_Year', ylabel='count'>
```



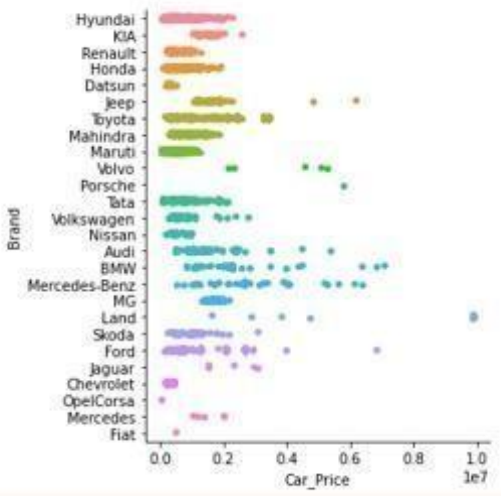
- Bivariate Analysis

  (For comparison between each feature with target)

  - Using Cat plot

```
plt.figure(figsize=(25,20))
sns.catplot(x='Car_Price', y= 'Brand', data = car)
plt.show()
```

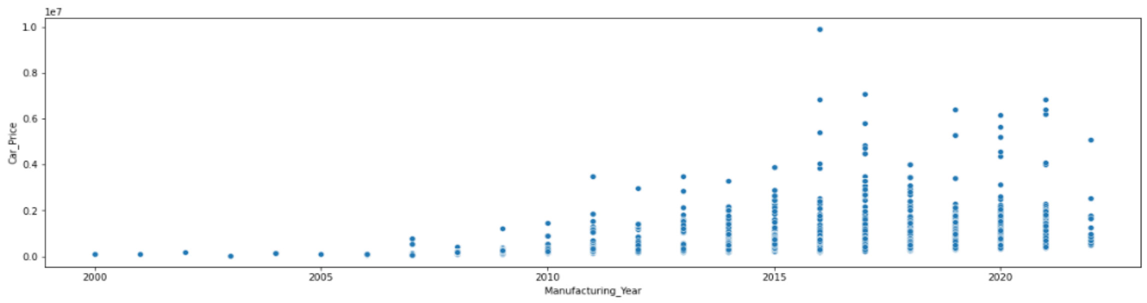
```
<Figure size 1800x1440 with 0 Axes>
```



  - Using Scatter plot

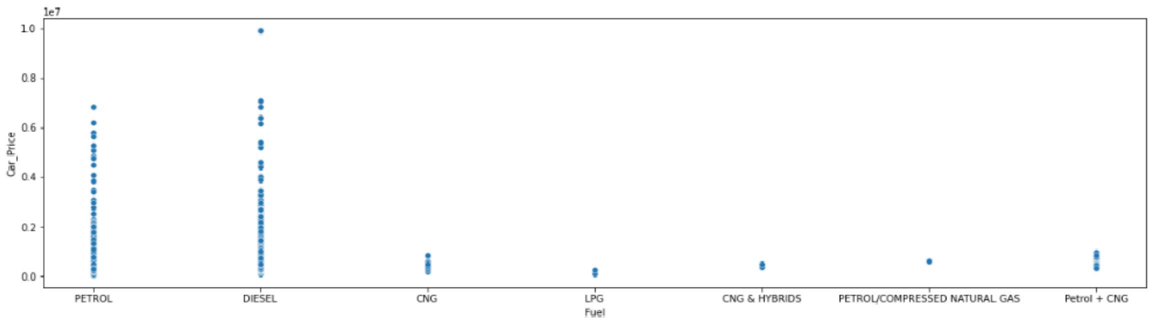
```
#scatterplot for comparision between "Manufacturing_Year" and "Car_Price" column
plt.figure(figsize=(20,5))
sns.scatterplot(x="Manufacturing_Year",data=car, y='Car_Price')
```

```
<AxesSubplot:xlabel='Manufacturing_Year', ylabel='Car_Price'>
```



```
#scatterplot for comparision between "Fuel" and "Car_Price" column
plt.figure(figsize=(20,5))
sns.scatterplot(x="Fuel",data=car, y='Car_Price')
```

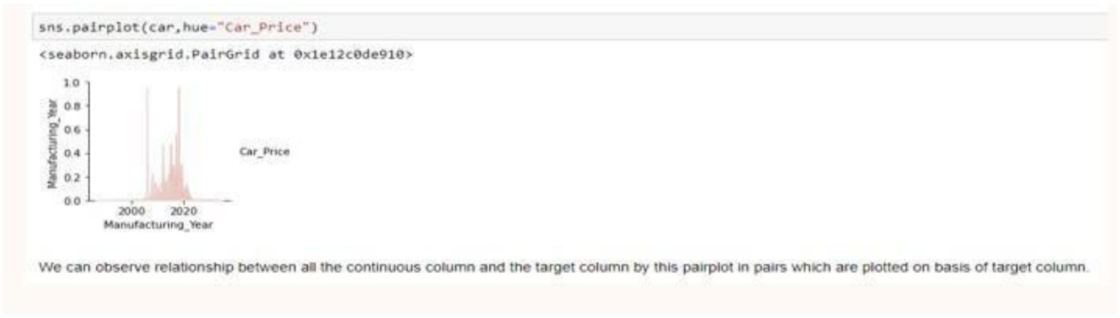
```
<AxesSubplot:xlabel='Fuel', ylabel='Car_Price'>
```



- Multivariate Analysis

  (For comparison between all features with target)

  - Using Pair plot



```
sns.pairplot(car,hue="Car_Price")
<seaborn.axisgrid.PairGrid at 0x1e12c0de910>
```

We can observe relationship between all the continuous column and the target column by this pairplot in pairs which are plotted on basis of target column.

5. Interpretation of the Results

- Through Visualization it is interpreted that Data is skewed due to presence of outliers in Dataset.
- Through Pre-processing it is interpretive that outliers & skewness was present in dataset, data was improper scaled, Multi co-linearity was present.
- By creating/building model we get best model: Gradient Boosting Regressor.

CONCLUSION

1. Key Findings and Conclusions of the Study

Here we have made a new car price valuation model as due to Covid-19 impact previous car price valuation machine learning models is not working well because some cars are in demand hence making them costly and some are not in demand hence cheaper.

For new car price valuation model, we have done prediction on basis of Data using EDA, Data Cleaning, Data Visualization, Data Pre-processing, Checked Correlation, removed irrelevant features, Removed Outliers, Removed Skewness and at last train our data by splitting our data through train-test split process.

Built our model using 5 models and finally selected best model which was giving best accuracy that is Gradient Boosting Regressor. Then tuned our model through Hyper Tuning using GridSearchCV. And at last compared our predicted and Actual Price of Car. Thus, our project is completed.

2. Learning Outcomes of the Study in respect of Data Science

- This project has demonstrated the importance of scrapping data then converting that data of those data into csv and then using that csv file built a model to predict on data.
- Through different powerful tools of visualization, we were able to analyze and interpret different hidden insights about the data.
- Through data cleaning we were able to remove unnecessary columns and outliers from our dataset due to which our model would have suffered from over fitting or under fitting.

The few challenges while working on this project were: -

- Improper scaling: scaled it to a single scale using Standard Scalar
- Too many features: 10 features were present in the dataset, after data cleaning 2 features were reduced due to no relation with target variable and last after removing Multi co-linearity; we were able to reduce 1 more feature.
- Converted data type of target column
- Replaced irrelevant values or data from features
- Skewed data due to outliers: Removed using power transformer 'yeo-johnson' method and outliers was removed through Z-score.

3. Limitations of this work and Scope for Future Work

While we couldn’t reach out goal of 100% accuracy in detecting defaulter but created a system that made data get very close to that goal. This project allows multiple algorithms to be integrated together to combine modules and their results to increase the accuracy of the final result. This model can further be improved with the addition of more algorithms into it. However, the output of these algorithms needs to be in the same format as the others which will make modules easy to add as done in the code.