```
## Importing essential libraries
import pandas as pd # to load the data,
import numpy as np # mathematical intitution

import seaborn as sns # ploting
import matplotlib.pyplot as plt # ploting


## Importing datasets
df = pd.read_csv('car_price.csv')


## To see top 5 rows of dataset
df.head()

## To see bottom 5 rows of dataset
df.tail()

## To see random 5 rows of dataset
df.sample(5)
```

Unnamed: 0	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type	Mileage	Engine	Power	Seats	New_Price

```
df.Owner_Type.value_counts()
```

```
First             4929
Second             968
Third              113
Fourth & Above       9
Name: Owner_Type, dtype: int64
```

CNG km/kg CC bhp

```
df['Name'].value_counts().any()
```

```
True
```

CRDi kmpl CC bhp

```
## To see the dataset information i.e column names, type of column, how many non-null values are present in the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6019 entries, 0 to 6018
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Unnamed: 0         6019 non-null   int64  
 1   Name               6019 non-null   object 
 2   Location           6019 non-null   object 
 3   Year               6019 non-null   int64  
 4   Kilometers_Driven  6019 non-null   int64  
 5   Fuel_Type          6019 non-null   object 
 6   Transmission       6019 non-null   object 
 7   Owner_Type         6019 non-null   object 
 8   Mileage            6017 non-null   object 
 9   Engine             5983 non-null   object 
 10  Power              5983 non-null   object 
 11  Seats              5977 non-null   float64
 12  New_Price          824 non-null    object 
 13  Price              6019 non-null   float64
dtypes: float64(2), int64(3), object(9)
memory usage: 658.5+ KB
```

```
df.columns
```

```
Index(['Unnamed: 0', 'Name', 'Location', 'Year', 'Kilometers_Driven',
       'Fuel_Type', 'Transmission', 'Owner_Type', 'Mileage', 'Engine', 'Power',
```

```
           'Seats', 'New_Price', 'Price'],
          dtype='object')
```

```
#We can see that in first column there is only index number given so its better to delete it
df=df.drop('Unnamed: 0',axis=1)
```

```
df.shape
```

```
(6019, 13)
```

```
## To get how many different types of data types are present in dataset
print("Unique Data type :",len(set(df.dtypes)))
print("Different types of datatypes in dataset are",set(df.dtypes))
```

```
Unique Data type : 3
Different types of datatypes in dataset are {dtype('float64'), dtype('int64'), dtype('O')}
```

```
## The car name with one frequency does not work for modeling purpose
df=df.groupby('Name').filter(lambda x : (x['Name'].value_counts()>1).any())
```

```
df.shape
```

```
(5177, 13)
```

```
## we know that mileage , power and Engine featurea are numeric but in dataset its units are also given So its datatype is object
## We will convert object type to data type
df["Engine"] = df["Engine"].str.replace(' CC','')
df['Power'] = df['Power'].str.replace('bhp', '')
df['Mileage'] = df['Mileage'].str.replace('kmpl', '')
df['Mileage'] = df['Mileage'].str.replace('km/kg', '')
```

```
## Now for numeric columns we can compute its description
df.describe()
```

	Year	Kilometers_Driven	Seats	Price
count	5177.000000	5.177000e+03	5147.000000	5177.000000
mean	2013.477303	5.857074e+04	5.271032	9.319218
std	3.106109	9.671200e+04	0.766693	10.469339
min	1998.000000	1.710000e+02	2.000000	0.440000
25%	2012.000000	3.401000e+04	5.000000	3.500000
75%	2016.000000	7.200000e+04	5.000000	9.990000

Missing Value

```
df.isnull().sum()
```

```
Name                 0
Location             0
Year                 0
Kilometers_Driven    0
Fuel_Type            0
Transmission         0
Owner_Type           0
Mileage              0
Engine              26
Power               26
Seats               30
New_Price         4490
Price                0
dtype: int64
```

```
## In this column we have seen how many missing values are present in data
round(df.isnull().sum()/6019,2)
```

```
Name                 0.00
Location             0.00
Year                 0.00
Kilometers_Driven    0.00
Fuel_Type            0.00
Transmission         0.00
Owner_Type           0.00
Mileage              0.00
Engine               0.00
Power                0.00
Seats                0.00
New_Price            0.75
```

```
Price                0.00
dtype: float64
```

```
## This command is used to delete column from the dataframe
df=df.drop("New_Price",axis=1)
```

```
st = 'null'
st.replace('null', '74')
```

```
'74'
```

```
## Power column contain 'null' values which was not detected using isnull syntax
df['Power']=df.Power.replace('null ',df.Power.mode()[0])
```

```
## Mileage is a numeric variable which contain only 2 missing values so we are replacing it by median
df["Mileage"].fillna(df.Mileage.mode(), inplace=True)
```

```
df.shape
```

```
(5177, 12)
```

```
## Our data is big enough so we can delete missing values by using following syntax
df=df.dropna()
df.shape
```

```
(5147, 12)
```

Duplicate Values

```
df = df.drop_duplicates()
df.shape
```

```
(5147, 12)
```

We can see that dataset does not contain duplicate values

Outlier Detection

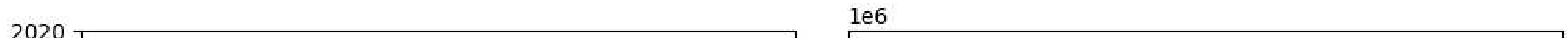
```
## Outliers are present in numeric type column only so we are going to list numeric type columns
num_type = list(df.select_dtypes(include=['int64','float64']).columns)
print("Numbers of numeric type columns in data are" ,len(num_type))
print("Numeric type columns are " ,num_type)
```

```
Numbers of numeric type columns in data are 4
Numeric type columns are  ['Year', 'Kilometers_Driven', 'Seats', 'Price']
```

```
## To visualize numeric type column boxplot is best way
num_features=['Year', 'Kilometers_Driven']

n = 1
plt.figure(figsize=(20,15))

for column in num_features:
    plt.subplot(4,4,n)
    n = n+1
    sns.boxplot(df[column])
    plt.tight_layout()
```




```
# df.Kilometers_Driven
q1 = np.percentile(df.Kilometers_Driven,25)
q3 = np.percentile(df.Kilometers_Driven,75)
iqr=q3-q1
print(iqr)
upper_limit=q3+1.5*iqr
print(upper_limit)
print(max(df.Kilometers_Driven))
print(q1-1.5*iqr)
min(df.Kilometers_Driven)
```

```
38000.0
129000.0
6500000
-23000.0
171
```

```
def outlier(column_name):
    """Outlier detection using Interquartile range"""
    q1=np.percentile(df[column_name],25)
    q3=np.percentile(df[column_name],75)
    iqr=q3-q1
    upper_limit=q3+1.5*iqr
    lower_limit=q1-1.5*iqr
    return upper_limit,lower_limit
```

```
## for year feature from boxplot we can see that outliers are only present in left side
upper_limit,lower_limit=outlier("Year")
##So replacing outliers by 2003
df.loc[df.Year < lower_limit, 'Year'] = 2006
## for Kilometers_Driven feature from boxplot we can see that outliers are only present in right side
upper_limit,lower_limit=outlier("Kilometers_Driven")
##So replacing outliers by its upper_limit
df.loc[df.Kilometers_Driven > upper_limit, 'Kilometers_Driven'] = upper_limit
```

```
df.shape
```

```
(5147, 12)
```

Linear regression assumptions

- Multicollinearity

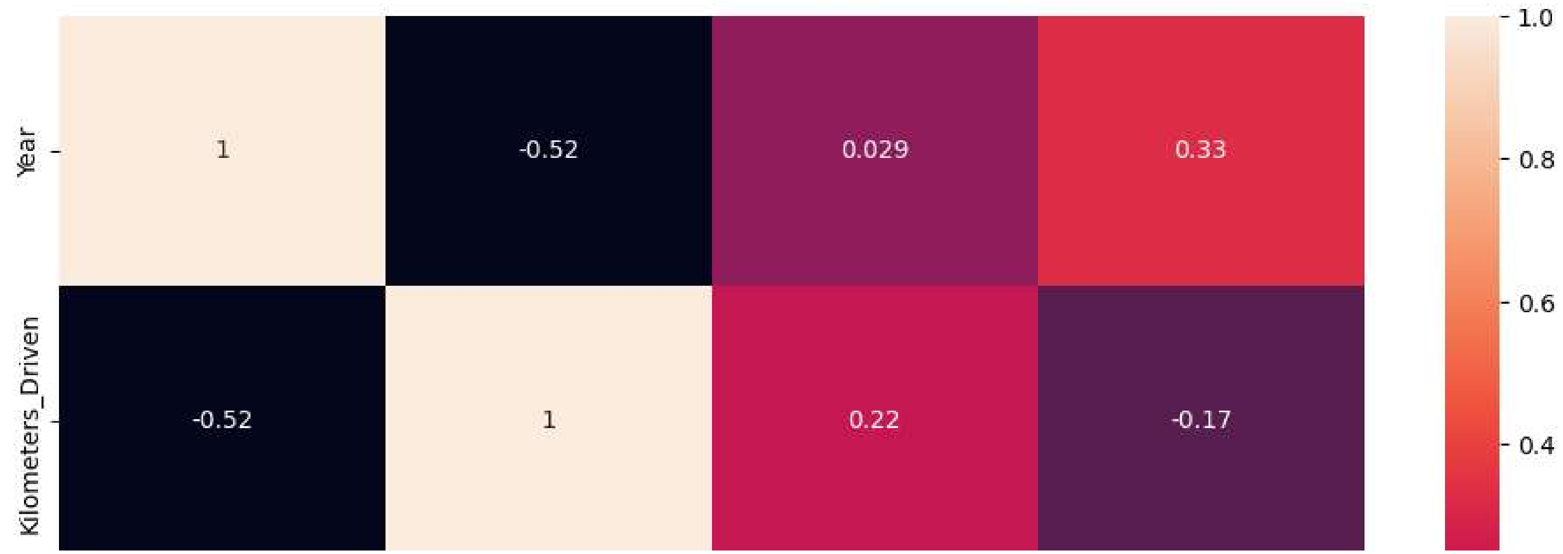
```
df.corr()
```

```
<ipython-input-82-2f6f6606aa2c>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version
  df.corr()
```

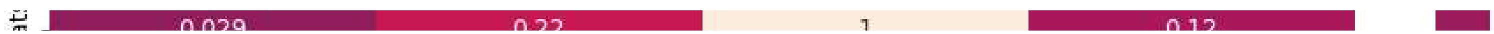
	Year	Kilometers_Driven	Seats	Price
Year	1.000000	-0.515433	0.029315	0.329268
Kilometers_Driven	-0.515433	1.000000	0.222979	-0.168231
Seats	0.029315	0.222979	1.000000	0.117809
Price	0.329268	-0.168231	0.117809	1.000000

```
## Plot the heatmap to see correlation with columns
fig, ax = plt.subplots(figsize=(12,8))
sns.heatmap(df.corr(), annot=True, ax=ax);
```

```
<ipython-input-83-ef9627669b90>:3: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version
  sns.heatmap(df.corr(), annot=True, ax=ax);
```



We can observe that All auto correlations are less than 0.60 . So using auto correlation function we can say there is no multicollinearity. But still we are going to check using VIF.



```
## To check Multicollinearity here we are using VIF
from statsmodels.stats.outliers_influence import variance_inflation_factor

X = df[list(df.select_dtypes(include=['int64','float64']).columns)]
# Price feature is dependent or o/p feature so we are deleting
X=X.drop('Price',axis=1)

# VIF dataframe
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns

# calculating VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                          for i in range(len(X.columns))]

print(vif_data)
```

```
             feature        VIF
0               Year  48.416808
1  Kilometers_Driven   4.868823
2              Seats  50.944503
```

here we will delete seats feature

```
df=df.drop('Seats',axis=1)
```

```
X = df[list(df.select_dtypes(include=['int64','float64']).columns)]
X=X.drop('Price',axis=1)

# VIF dataframe
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns

# calculating VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                          for i in range(len(X.columns))]

print(vif_data)
```

```
              feature       VIF
0                Year  4.615981
1   Kilometers_Driven  4.615981
```

Now all VIF values are less than 10 after deleting Seats column.So no multicollinearity present in data.

Converting Categorical variables to Numerical

LabelEncoder one hot enoding | dummy variable

one way

1st obs--> location_hyd= 1 | location_pune=0 | location_mum=0 | location_delhi=0 2nd obs--> location_hyd= 0 | location_pune=0 | location_mum=0 | location_delhi=1

2nd way

1st obs--> 1 2nd obs--> 4

method 1 - label encoding

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

```
## Name column has lots of unique values so we are lable encoding here
df['Name']=le.fit_transform(df['Name'])
df['Engine']=le.fit_transform(df['Engine'])
df['Mileage']=le.fit_transform(df['Mileage'])
```

method 2 - one hot enoding or dummy variable

```
## creating list of column names with dtype object
categorical_features = list(df.columns[df.dtypes == object])
categorical_features
```

```
['Location', 'Fuel_Type', 'Transmission', 'Owner_Type', 'Power']
```

```
## All other columns are nominal type so converting categorical variable to numeric using get_dummy
df=pd.get_dummies(df, columns = categorical_features)
df.head()
```

	Name	Year	Kilometers_Driven	Mileage	Engine	Price	Location_Ahmedabad	Location_Bangalore	Location_Chennai	Location_Coimbatore
0	688	2010	72000	322	103	1.75	0	0	0	0
1	293	2015	41000	218	33	12.50	0	0	0	0
2	277	2011	46000	182	11	4.50	0	0	1	0
3	597	2012	87000	243	12	6.00	0	0	1	0
4	12	2013	40670	101	49	17.74	0	0	0	1

5 rows × 309 columns

```
df.sample(5)
```

	Name	Year	Kilometers_Driven	Mileage	Engine	Price	Location_Ahmedabad	Location_Bangalore	Location_Chennai	Location_Coimbator
5493	410	2012	57184	228	9	3.09	0	0	0	
5001	802	2014	40206	201	25	7.22	0	0	0	
1482	945	2009	92000	21	86	8.90	0	0	0	
2859	825	2018	4126	264	104	4.80	0	0	0	
5138	446	2015	118211	276	22	5.90	0	0	0	

5 rows × 309 columns

```
df.shape
```

```
(5147, 309)
```

Train Test Split

```
from sklearn.model_selection import train_test_split
```

```
x=df.drop('Price',axis=1)
y=df['Price']
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size =0.1)
```

```
##Standardization of data means convering values in between 0-1. In regression Standardization is important because model is sensitive to outl
## Standardizing the data
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X_train = sc_X.fit_transform(x_train)
X_test = sc_X.transform(x_test)
```

```
print('x_train',x_train.shape)
print('y_train',y_train.shape)
print('x_test',x_test.shape)
print('y_test',y_test.shape)
```

```
x_train (4632, 308)
y_train (4632,)
x_test (515, 308)
y_test (515,)
```

Model Building

```
from sklearn.linear_model import LinearRegression
model= LinearRegression()
```

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

```
▾ LinearRegression
LinearRegression()
```

R square :It is statistical measure of how close the data are to the fitted regression line.

```
r_sq = model.score(x_train , y_train)
print('coefficient of determination:', r_sq)
```

```
coefficient of determination: 0.9051356527183352
```

```
## It will give output of x_test
y_pred = model.predict(x_test)
```

```
# importing r2_score module
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
# predicting the accuracy score
score=r2_score(y_pred,y_test)
print('r2 socre is' ,score)
print('mean_sqrd_error is==',mean_squared_error(y_test,y_pred))
print('root_mean_squared error of is==',np.sqrt(mean_squared_error(y_test,y_pred)))
```

```
r2 socre is 0.8270434640323016
mean_sqrd_error is== 15.527551483429425
root_mean_squared error of is== 3.9405014253809663
```