Project Title : Car Price Prediction Project

Problem Statement:

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. 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.

Business Goal:

We need to build a machine learning model. Before model building do all data pre-processing steps. Try different models with different hyper parameters and select the best model.

In [1]:

```
#importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sn
import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
#Loading the data-set
df=pd.read_csv("car_price_csv_merged.csv")
df.head(5)
```

Out[2]:

	Unnamed: 0	Unnamed: 0.1	Brand	Model	Variant	Year_of_Manufacturing	Transmission Type	Fu Ty
0	0	0	Maruti Suzuki	Swift Dzire	NaN	2018	Manual	Pet
1	1	1	Toyota	Innova	NaN	2013	Manual	Die
2	2	2	Hyundai	i10	NaN	2008	Manual	Pet
3	3	3	Maruti Suzuki	Swift Dzire	NaN	2015	Manual	Die
4	4	4	Maruti Suzuki	SX4	NaN	2007	Manual	Pet

```
#checking the shape of the data-set
df.shape
```

Out[3]:

```
(15950, 12)
```

Data Pre-Processing :

In [4]:

```
#checking the variant column
df['Variant'].value_counts()
```

Out[4]:

```
Series([], Name: Variant, dtype: int64)
```

Observations :

1. 'Variant' column doesnt have any data in it. so we can drop that column.

2. 'Unnamed: 0', 'Unnamed: 0.1' are 2 unwanted index columns.

In [5]:

```
#dropping the unwanted columns
df.drop(['Unnamed: 0', 'Unnamed: 0.1', 'Variant'], inplace=True, axis = 1)
df.head(5)
```

Out[5]:

	Brand	Model	Year_of_Manufacturing	Transmission Type	Fuel Type	Kilometers Driven	No of Owners	Pric
0	Maruti Suzuki	Swift Dzire	2018	Manual	Petrol	17,400 km	1st	6,90,00
1	Toyota	Innova	2013	Manual	Diesel	200,000 km	1st	6,80,00
2	Hyundai	i10	2008	Manual	Petrol	77,000 km	2nd	2,60,00
3	Maruti Suzuki	Swift Dzire	2015	Manual	Diesel	105,000 km	1st	5,49,00
4	Maruti Suzuki	SX4	2007	Manual	Petrol	98,000 km	2nd	2,10,00

```
##changing the dtype and striping the unwanted commas,words from the data

#Kilometers Driven
df['Kilometers Driven'] = df['Kilometers Driven'].str.replace('km','')
df['Kilometers Driven'] = df['Kilometers Driven'].str.replace(',','')
df['Kilometers Driven'] = df['Kilometers Driven'].str.replace('-','0')

#converting into int
df['Kilometers Driven'] = df['Kilometers Driven'].astype(int)
```

In [7]:

```
#finding mean for kms driven
kmsmean = df['Kilometers Driven'].mean()
kmsmean
```

Out[7]:

```
65577.26846394985
```

In [8]:

```
#Replacing 0 with mean value in kms driven
df['Kilometers Driven'] = df['Kilometers Driven'].apply(lambda x: x if x!=0 else kmsmea
n)
```

In [9]:

```
#Price
df['Price'] = df['Price'].str.strip()
df['Price'] = df['Price'].str.replace(',','')
df['Price'] = df['Price'].str.replace('-','0')

#converting into float
df['Price'] = df['Price'].astype(float)
```

In [10]:

```
#finding mean for kms driven
pricemean = df['Price'].mean()
pricemean
```

Out[10]:

```
641895.2333542319
```

In [11]:

```
#Replacing 0 with mean value in kms driven
df['Price'] = df['Price'].apply(lambda x: x if x!=0 else pricemean)
```

```
#Year_of_Manufacturing
df['Year_of_Manufacturing'] = df['Year_of_Manufacturing'].apply(lambda x: int(x.strip()
[0:4]) if x!='-' else 0)

# median year
median_year=df['Year_of_Manufacturing'].median()

#Replacing 0 with median value
df['Year_of_Manufacturing'] = df['Year_of_Manufacturing'].apply(lambda x: x if x!=0 els
e median_year)

#converting into int
df['Year_of_Manufacturing'] = df['Year_of_Manufacturing'].astype(int)
```

In [13]:

```
#No of Owners
df['No of Owners'] = df['No of Owners'].str.replace('1st','1').replace('2nd','2').repla
ce('3rd','3').replace('4th','4').replace('-','4+')
```

In [14]:

```
df['No of Owners'].value_counts()
```

Out[14]:

```
1     9310
2     4102
4+    1258
3     1057
4      223
Name: No of Owners, dtype: int64
```

In [15]:

```
# Fuel Type

df['Fuel Type'].value_counts()
```

Out[15]:

```
Diesel          7217
Petrol          7150
-                856
CNG & Hybrids    593
LPG              127
Electric           7
Name: Fuel Type, dtype: int64
```

```
# mode for fuel
Fuel_mode = df['Fuel Type'].mode()
Fuel_mode
```

Out[16]:

```
0    Diesel
dtype: object
```

In [17]:

```
# Fuel type
df['Fuel Type'] = df['Fuel Type'].apply(lambda x: x if x!='-' else 0)

#Replacing 0 with mode value
df['Fuel Type'] = df['Fuel Type'].apply(lambda x: x if x!=0 else "Diesel")

df['Fuel Type'].value_counts()
```

Out[17]:

```
Diesel          8073
Petrol          7150
CNG & Hybrids    593
LPG              127
Electric           7
Name: Fuel Type, dtype: int64
```

In [18]:

```
# Transmission Type
df['Transmission Type'].value_counts()
```

Out[18]:

```
Manual       11849
Automatic     2959
-             1142
Name: Transmission Type, dtype: int64
```

In [19]:

```
#replacing the "-" with manual
df['Transmission Type'] = df['Transmission Type'].apply(lambda x: x if x!='-' else 'Man
ual')

df['Transmission Type'].value_counts()
```

Out[19]:

```
Manual       12991
Automatic     2959
Name: Transmission Type, dtype: int64
```

```python
# Brand
df['Brand'].value_counts()
```

Out[20]:

```
Maruti Suzuki        4836
Hyundai              2565
Toyota               1263
Mahindra             1137
Honda                 922
-                     689
Tata                  685
Ford                  658
Volkswagen            540
Audi                  364
Mercedes-Benz         347
Renault               317
Chevrolet             276
Skoda                 248
BMW                   199
Nissan                183
Datsun                 87
Jeep                   80
Land Rover             75
Kia                    63
Jaguar                 56
Other Brands           52
Fiat                   41
Bajaj                  35
Volvo                  29
Ambassador             26
Mini                   24
Ashok Leyland          23
MG                     23
Mitsubishi             21
Force Motors           20
Porsche                19
Opel                   18
Isuzu                  16
Mahindra Renault        8
Premier                 5
Name: Brand, dtype: int64
```

```
#replacing the "-" with others
df['Brand'] = df['Brand'].apply(lambda x: x if x!='-' else 'others')
df['Brand'].value_counts()
```

Out[21]:

```
Maruti Suzuki       4836
Hyundai             2565
Toyota              1263
Mahindra            1137
Honda                922
others               689
Tata                 685
Ford                 658
Volkswagen           540
Audi                 364
Mercedes-Benz        347
Renault              317
Chevrolet            276
Skoda                248
BMW                  199
Nissan               183
Datsun                87
Jeep                  80
Land Rover            75
Kia                   63
Jaguar                56
Other Brands          52
Fiat                  41
Bajaj                 35
Volvo                 29
Ambassador            26
Mini                  24
MG                    23
Ashok Leyland         23
Mitsubishi            21
Force Motors          20
Porsche               19
Opel                  18
Isuzu                 16
Mahindra Renault       8
Premier                5
Name: Brand, dtype: int64
```

```python
# Model
df['Model'].value_counts()
```

Out[22]:

```
Swift           852
-               689
Swift Dzire     530
Innova          448
Wagon R         401
               ... 
Punto             2
Land Cruiser      2
XL6               2
Gypsy             2
Marshal           2
Name: Model, Length: 252, dtype: int64
```

In [23]:

```python
#replacing the "-" with others in Model
df['Model'] = df['Model'].apply(lambda x: x if x!='-' else 'others')
df['Model'].value_counts()
```

Out[23]:

```
Swift           852
others          689
Swift Dzire     530
Innova          448
Wagon R         401
               ... 
Land Cruiser      2
Punto             2
Marshal           2
XL6               2
Gypsy             2
Name: Model, Length: 252, dtype: int64
```

In [24]:

```python
# Location
df['Location'].value_counts()
```

Out[24]:

```
Delhi        3864
Mumbai       3202
Chennai      3185
karnataka    3102
kerala       2597
Name: Location, dtype: int64
```

```
df.dtypes
```

Out[25]:

```
Brand                     object
Model                     object
Year_of_Manufacturing      int32
Transmission Type         object
Fuel Type                 object
Kilometers Driven        float64
No of Owners              object
Price                    float64
Location                  object
dtype: object
```

In [26]:

```
df.head(10)
```

Out[26]:

	Brand	Model	Year_of_Manufacturing	Transmission Type	Fuel Type	Kilometers Driven	No of Owners	P
0	Maruti Suzuki	Swift Dzire	2018	Manual	Petrol	17400.0	1	69000
1	Toyota	Innova	2013	Manual	Diesel	200000.0	1	68000
2	Hyundai	i10	2008	Manual	Petrol	77000.0	2	26000
3	Maruti Suzuki	Swift Dzire	2015	Manual	Diesel	105000.0	1	54900
4	Maruti Suzuki	SX4	2007	Manual	Petrol	98000.0	2	21000
5	Mahindra	Xylo	2012	Manual	Diesel	150000.0	3	54000
6	Hyundai	Santro Xing	2010	Manual	Petrol	70000.0	1	18000
7	Maruti Suzuki	Eeco	2011	Manual	Petrol	82000.0	1	23000
8	Maruti Suzuki	Alto K10	2017	Manual	Petrol	19000.0	1	36000
9	Maruti Suzuki	Swift Dzire Tour	2018	Manual	Diesel	67000.0	1	57500

```
#checking all the column names
list(df.columns)
```

Out[27]:

```
['Brand',
 'Model',
 'Year_of_Manufacturing',
 'Transmission Type',
 'Fuel Type',
 'Kilometers Driven',
 'No of Owners',
 'Price',
 'Location']
```

In [28]:

```
# re-arranging the columns
df = df[['Brand', 'Model', 'Year_of_Manufacturing', 'Transmission Type', 'Fuel Type',
'Kilometers Driven', 'No of Owners', 'Location', 'Price']]
df.sample(5)
```

Out[28]:

	Brand	Model	Year_of_Manufacturing	Transmission Type	Fuel Type	Kilometers Driven	No of Owners
1154	Ford	Figo	2012	Manual	Diesel	84000.0	1
15589	Audi	A6	2014	Automatic	Diesel	75000.0	1
6152	Mahindra	Scorpio	2017	Manual	Diesel	58000.0	1
7566	Maruti Suzuki	Esteem	1995	Manual	Petrol	67989.0	2
6067	BMW	7 Series	2013	Automatic	Diesel	58000.0	1

In [29]:

```
(df['Brand'] == 'others').sum()
```

Out[29]:

```
689
```

In [30]:

```
df.shape
```

Out[30]:

```
(15950, 9)
```

In [31]:

```
#df.drop(df[df['Age'] < 25].index, inplace = True)
```

```
drop689 = df[df['Brand'] == 'others'].index
df.drop(drop689, inplace = True)
```

In [33]:

```
df.shape
```

Out[33]:

```
(15261, 9)
```

In [34]:

```
(df['Brand'] == 'others').sum()
```

Out[34]:

```
0
```

In [35]:

```
#checking the data type and null values of the variables in the data-set
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15261 entries, 0 to 15938
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Brand                 15261 non-null  object 
 1   Model                 15261 non-null  object 
 2   Year_of_Manufacturing 15261 non-null  int32  
 3   Transmission Type     15261 non-null  object 
 4   Fuel Type             15261 non-null  object 
 5   Kilometers Driven     15261 non-null  float64
 6   No of Owners          15261 non-null  object 
 7   Location              15261 non-null  object 
 8   Price                 15261 non-null  float64
dtypes: float64(2), int32(1), object(6)
memory usage: 1.1+ MB
```

In [36]:

```
df.describe().T
```

Out[36]:

	count	mean	std	min	25%	50%
Year_of_Manufacturing	15261.0	2013.142848	4.542378	1980.0	2011.0	2014.0
Kilometers Driven	15261.0	68890.293429	54723.587433	1.0	40123.0	64000.0
Price	15261.0	670875.366752	886589.207986	15000.0	260000.0	450000.0

```
# Describing object types
df.describe(include='object').T
```

Out[37]:

	count	unique	top	freq
Brand	15261	35	Maruti Suzuki	4836
Model	15261	251	Swift	852
Transmission Type	15261	2	Manual	12302
Fuel Type	15261	5	Diesel	7384
No of Owners	15261	5	1	9310
Location	15261	5	Delhi	3690

Handling the Null Values :

In [38]:

```
#checking the null values
for col in df.columns:print("\nTitle :",col,"\nNaN val:",df[col].isnull().sum())
```

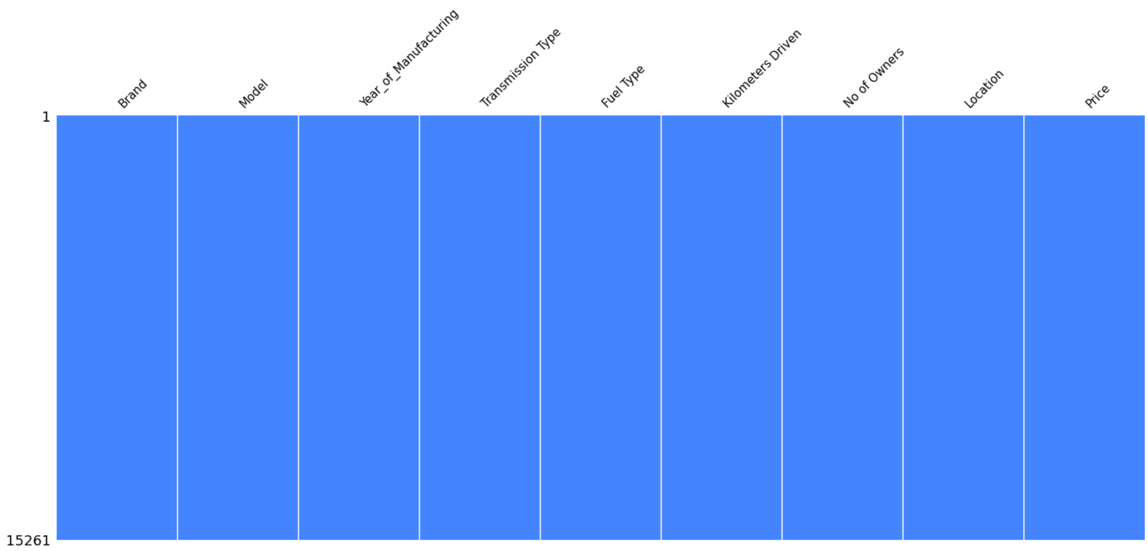
```
Title : Brand
NaN val: 0

Title : Model
NaN val: 0

Title : Year_of_Manufacturing
NaN val: 0

Title : Transmission Type
NaN val: 0

Title : Fuel Type
NaN val: 0

Title : Kilometers Driven
NaN val: 0

Title : No of Owners
NaN val: 0

Title : Location
NaN val: 0

Title : Price
NaN val: 0
```

In [39]:

```
# Program to visualize missing values in dataset
# Importing the libraries
import missingno as msno
# Visualize missing values as a matrix
msno.matrix(df,labels=True, sparkline=False, figsize=(25,10), fontsize=15, color=(0.27, 0.52, 1.0))
```

Out[39]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f2fcfd0b20>
```



Catagorical Variables :

In [40]:

```
cat_List = [x for x in df.columns if df[x].dtype==object]
list (cat_List)
```

Out[40]:

```
['Brand',
 'Model',
 'Transmission Type',
 'Fuel Type',
 'No of Owners',
 'Location']
```

Continous Variables :

In [41]:

```
num_List = [x for x in df.columns if x not in cat_List]
list (num_List)
```

Out[41]:

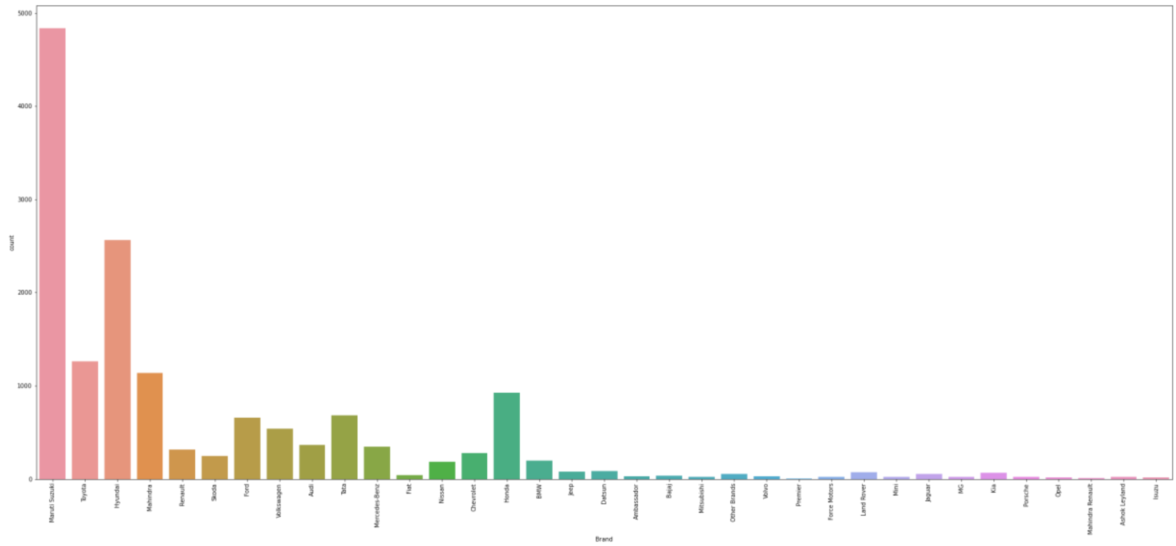
```
['Year_of_Manufacturing', 'Kilometers Driven', 'Price']
```

DATA VISUALIZATION :

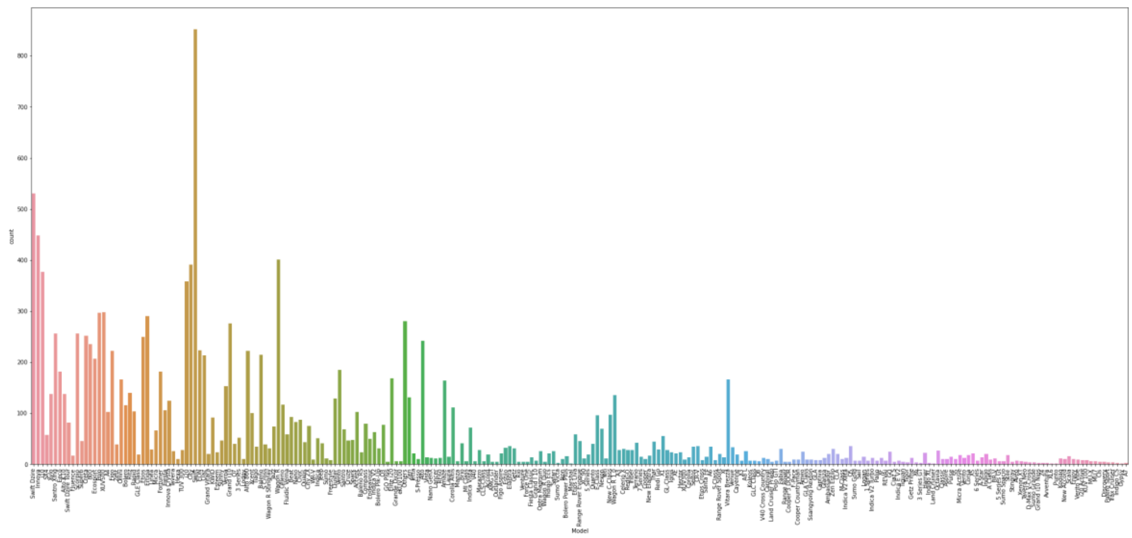
UNI-VARIATE ANALYSIS :

In [42]:

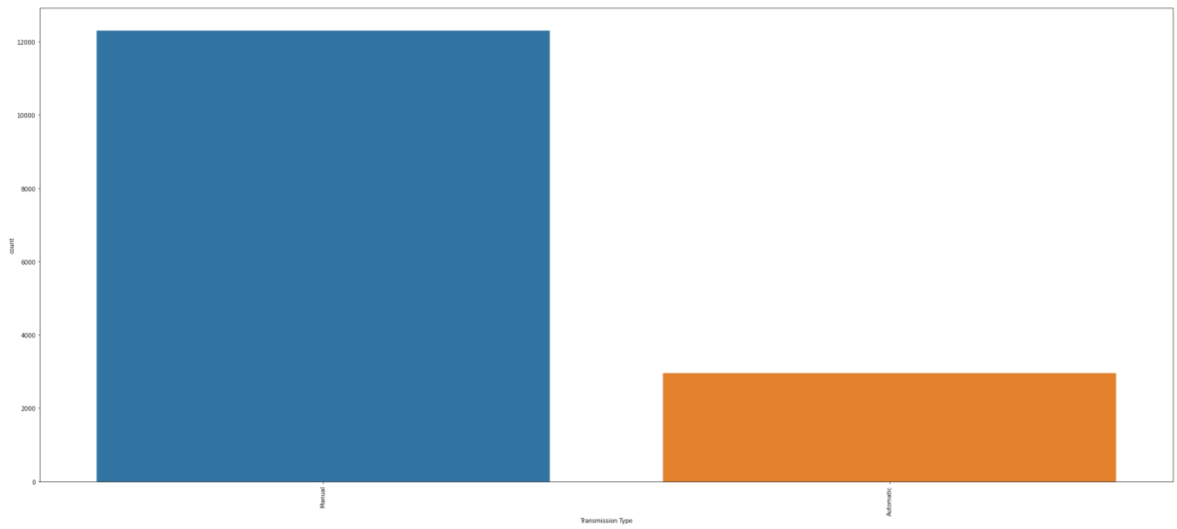
```
for i in cat_List:
    plt.figure(figsize=(35,15))
    sn.countplot(df[i])
    plt.xticks(rotation=90)
    plt.show()
```



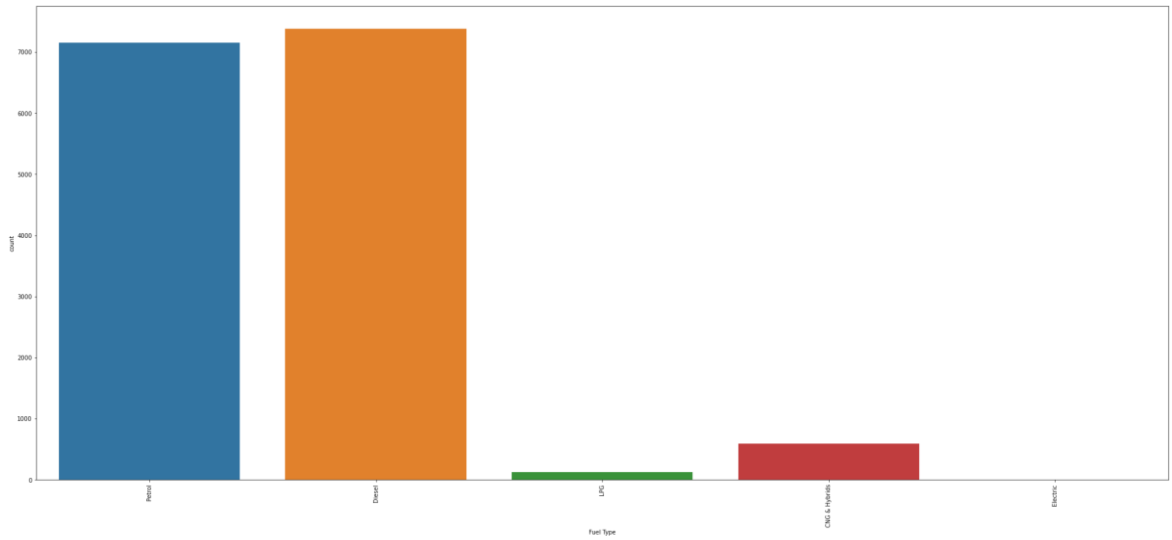
count
Brand
Maruti Suzuki
Toyota
Hyundai
Mahindra
Renault
Skoda
Ford
Volkswagen
Audi
Tata
Mercedes-Benz
Fiat
Nissan
Chevrolet
Honda
BMW
Jeep
Datsun
Ambassador
Bajaj
Mitsubishi
Other Brands
Volvo
Premier
Force Motors
Land Rover
Mini
Jaguar
MG
Kia
Porsche
Opel
Mahindra Renault
Ashok Leyland
Isuzu



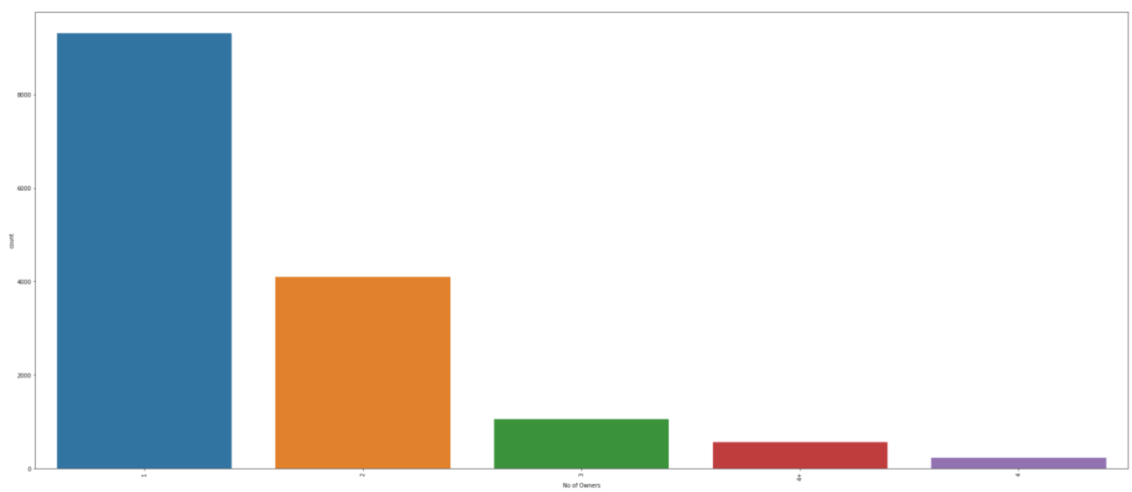
count
Model



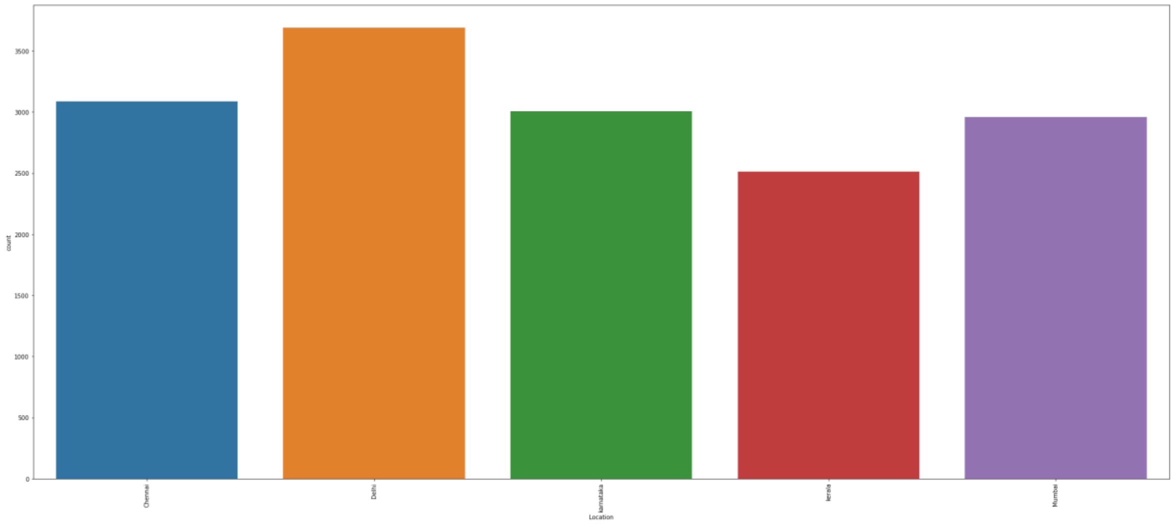
count
Manual
Automatic
Transmission Type



count
Petrol
Diesel
LPG
CNG & Hybrids
Electric
Fuel Type



count
No of Owners

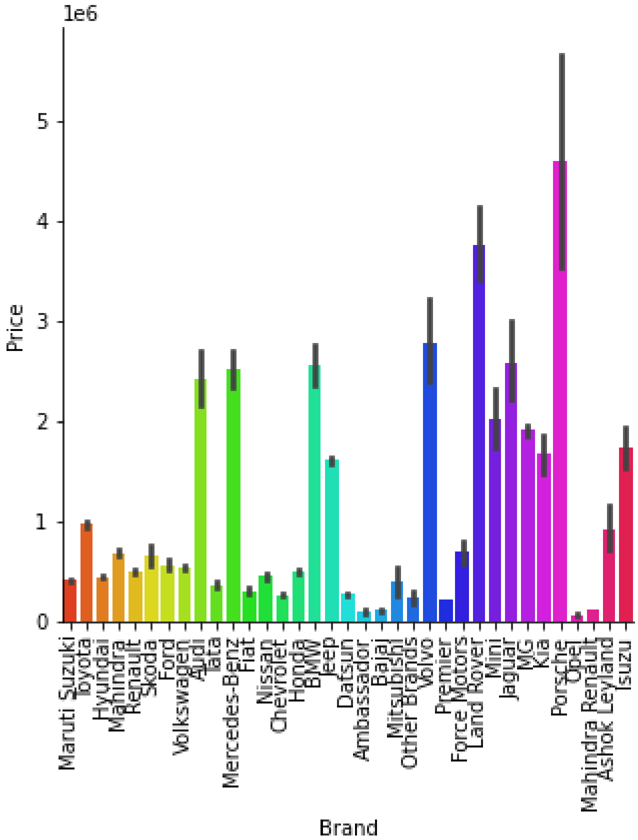


BI-VARIATE ANALYSIS :

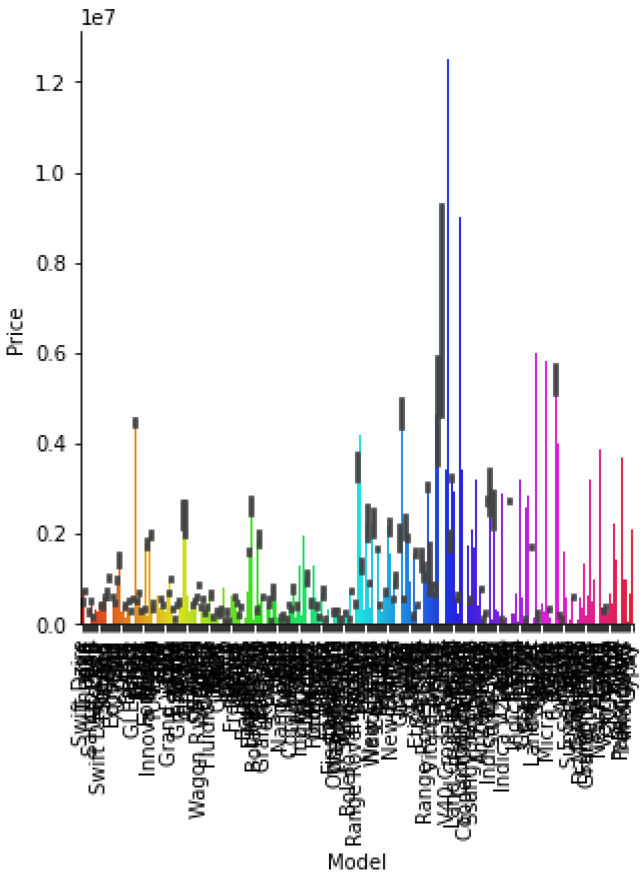
In [43]:

```
for i in cat_List:
    plt.figure(figsize=(30,25))
    sn.catplot(y='Price',x=i,data=df,kind="bar",palette="hsv")
    plt.xticks(rotation=90)
    plt.show()
```

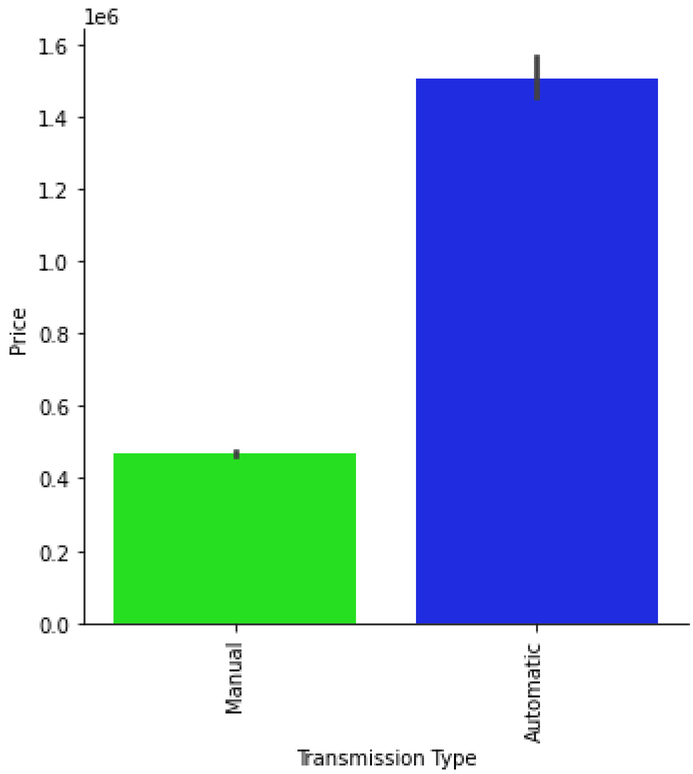
<Figure size 2160x1800 with 0 Axes>



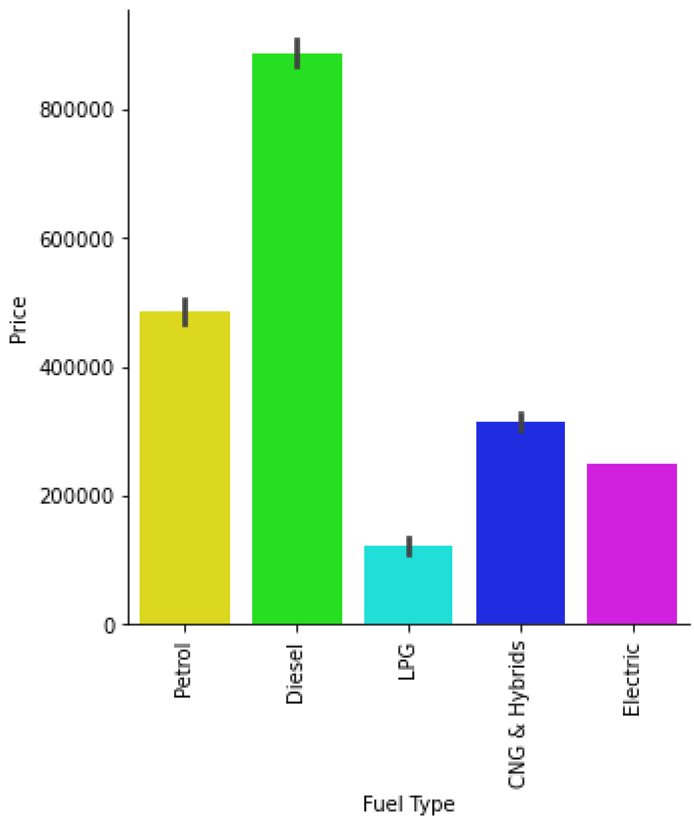
<Figure size 2160x1800 with 0 Axes>



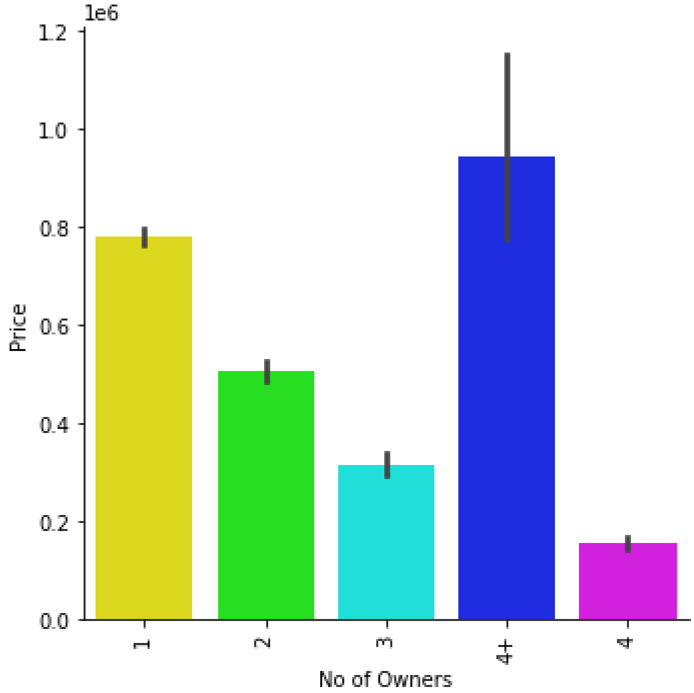
<Figure size 2160x1800 with 0 Axes>



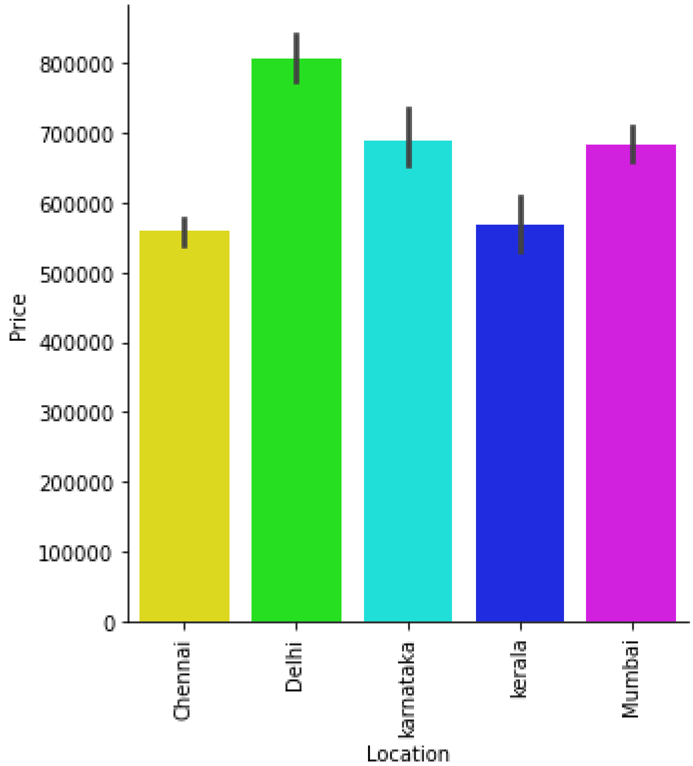
<Figure size 2160x1800 with 0 Axes>



<Figure size 2160x1800 with 0 Axes>

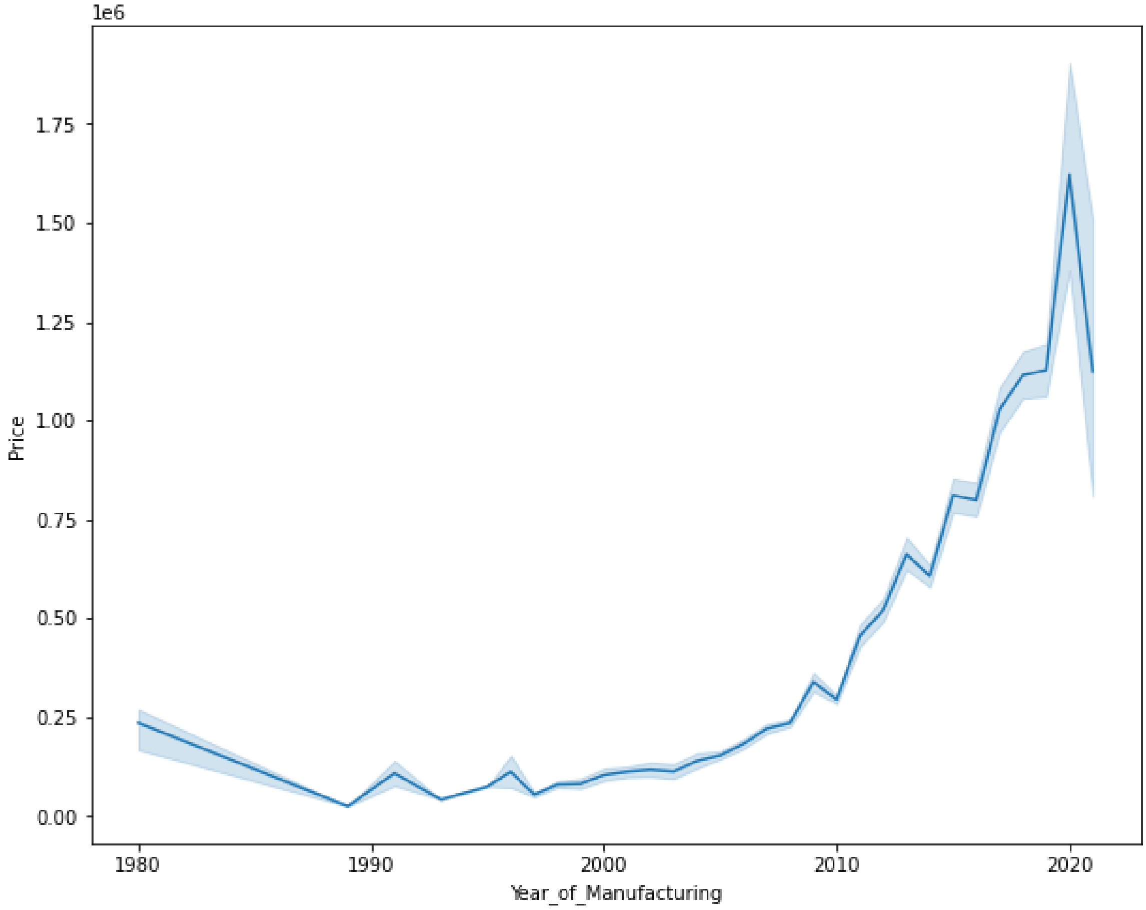


<Figure size 2160x1800 with 0 Axes>



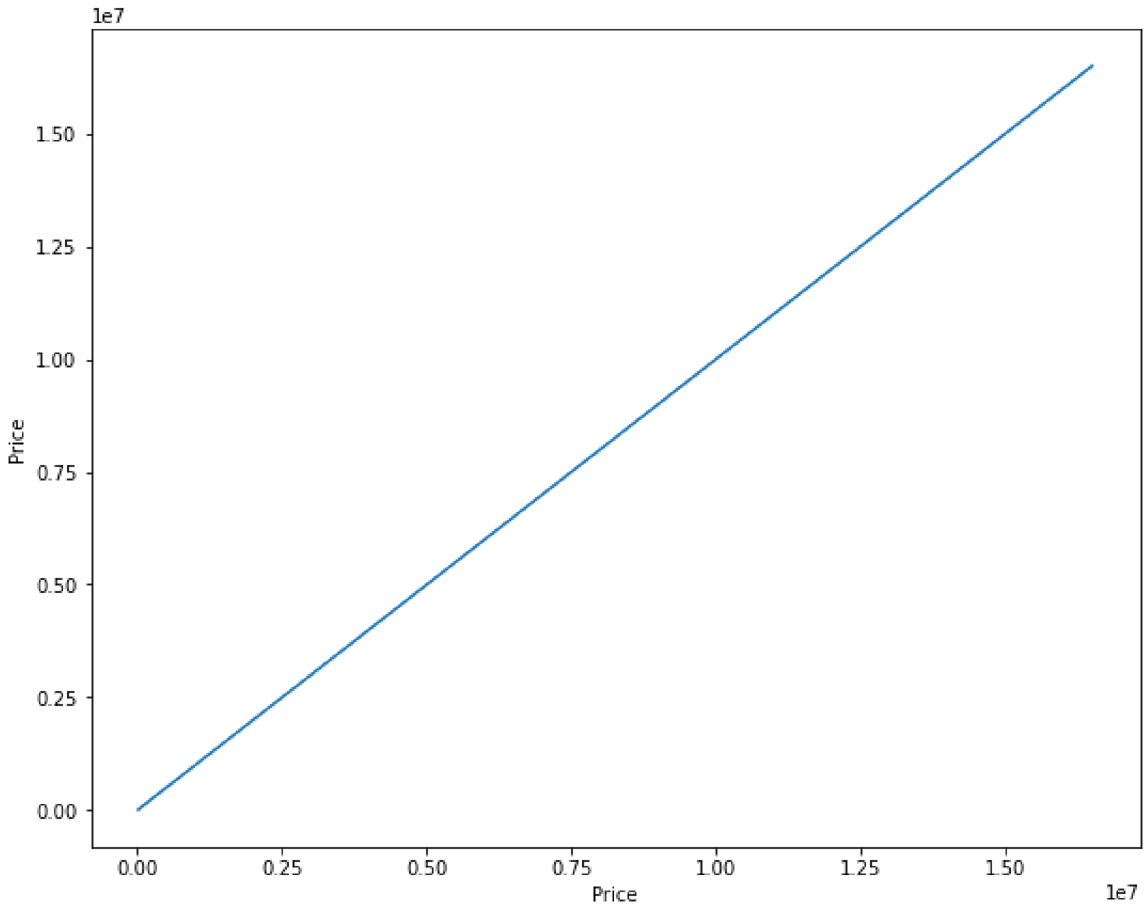
In [44]:

```
for i in num_List:
    plt.figure(figsize=(10,8))
    sn.lineplot(y='Price',x=i,data=df)
    plt.show()
```



1e6
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Price
1980
1990
2000
2010
2020
Year_of_Manufacturing

1e7
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Price
0.0
0.2
0.4
0.6
0.8
1.0
1e6
Kilometers Driven



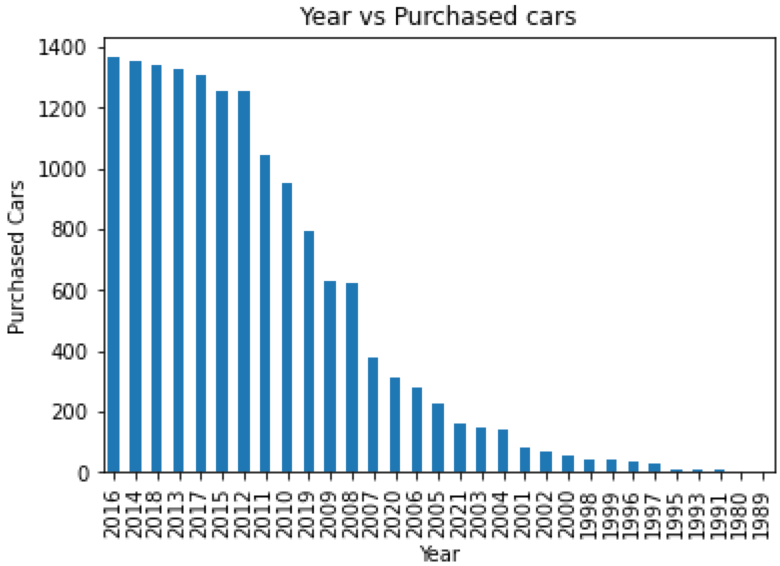
In [45]:

```
df.head(0)
```

Out[45]:

Brand	Model	Year_of_Manufacturing	Transmission Type	Fuel Type	Kilometers Driven	No of Owners	Location

```
#Plotting year vs no of cars
purchased_car_per_year = df['Year_of_Manufacturing'].value_counts()
purchased_car_per_year.plot(kind='bar')
plt.xlabel("Year")
plt.ylabel("Purchased Cars")
plt.title("Year vs Purchased cars")
plt.show()
```



Feature Engineering:

Now we will use Label Encoder to change catagorical values to Numerical values.

LabelEncoder

```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for i in cat_List:
    df[i] = le.fit_transform(df[i].astype(str))
print (df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15261 entries, 0 to 15938
Data columns (total 9 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Brand                  15261 non-null  int32
 1   Model                  15261 non-null  int32
 2   Year_of_Manufacturing  15261 non-null  int32
 3   Transmission Type      15261 non-null  int32
 4   Fuel Type              15261 non-null  int32
 5   Kilometers Driven      15261 non-null  float64
 6   No of Owners           15261 non-null  int32
 7   Location               15261 non-null  int32
 8   Price                  15261 non-null  float64
dtypes: float64(2), int32(7)
memory usage: 1.4 MB
None
```

In [48]:

```python
#Checking the dataset
df.head()
```

Out[48]:

	Brand	Model	Year_of_Manufacturing	Transmission Type	Fuel Type	Kilometers Driven	No of Owners	Location
0	20	201	2018	1	4	17400.0	0	0
1	32	118	2013	1	1	200000.0	0	0
2	11	248	2008	1	4	77000.0	1	0
3	20	201	2015	1	1	105000.0	0	0
4	20	180	2007	1	4	98000.0	1	0

```python
#Statistical summary of the dataset
df.describe()
```

Out[49]:

	Brand	Model	Year_of_Manufacturing	Transmission Type	Fuel Type	K
count	15261.000000	15261.000000	15261.000000	15261.000000	15261.000000	152
mean	18.435424	129.137933	2013.142848	0.806107	2.383789	688
std	8.365009	76.940928	4.542378	0.395359	1.540947	547
min	0.000000	0.000000	1980.000000	0.000000	0.000000	
25%	11.000000	62.000000	2011.000000	1.000000	1.000000	401
50%	20.000000	124.000000	2014.000000	1.000000	1.000000	640
75%	20.000000	200.000000	2017.000000	1.000000	4.000000	850
max	34.000000	250.000000	2021.000000	1.000000	4.000000	9700

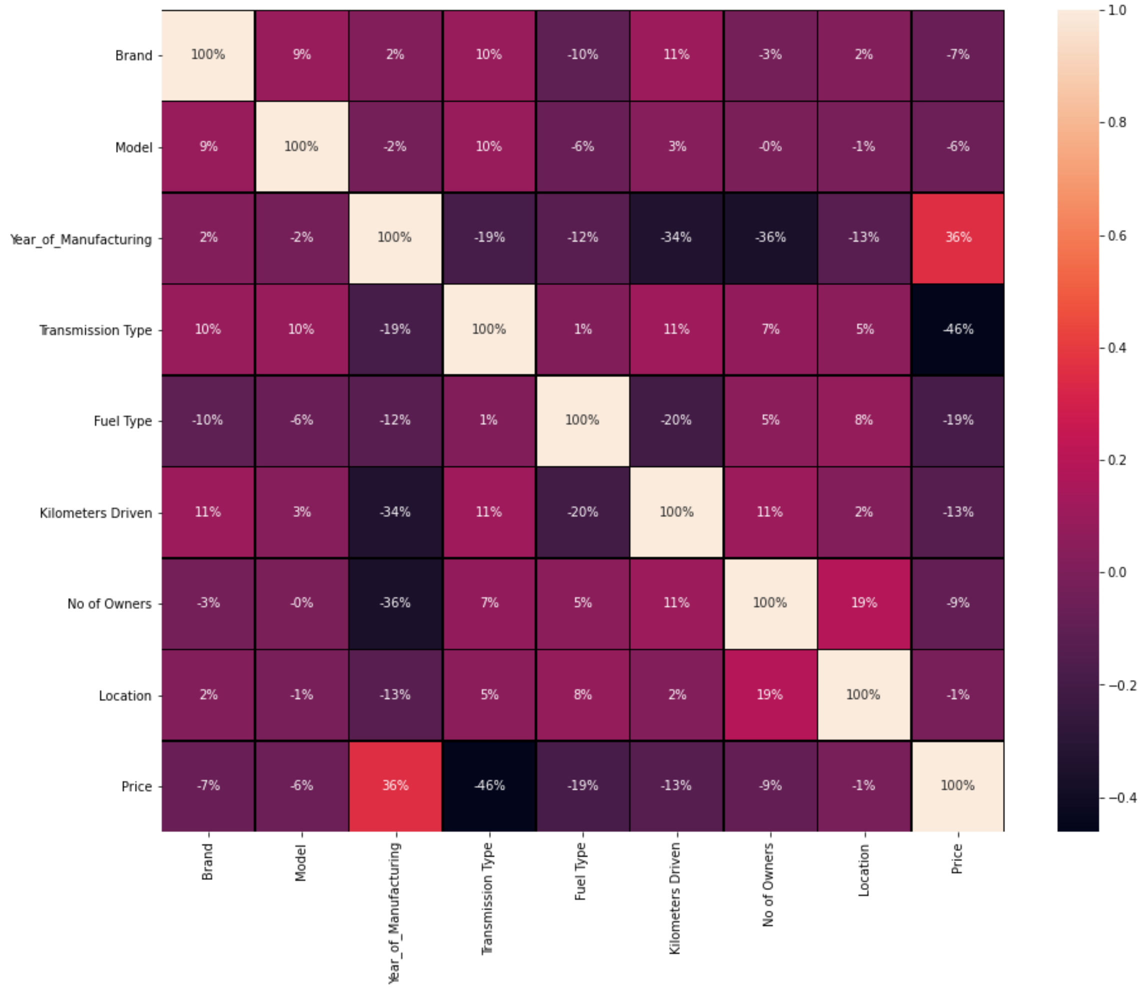
In [50]:

```python
#Checking correlation of the dataset
corr=df.corr()  #corr() function provides the correlation value of each column
corr
```

Out[50]:

	Brand	Model	Year_of_Manufacturing	Transmission Type	Fuel Type
Brand	1.000000	0.093857	0.022042	0.096803	-0.103890
Model	0.093857	1.000000	-0.023385	0.096246	-0.063901
Year_of_Manufacturing	0.022042	-0.023385	1.000000	-0.188992	-0.123867
Transmission Type	0.096803	0.096246	-0.188992	1.000000	0.012115
Fuel Type	-0.103890	-0.063901	-0.123867	0.012115	1.000000
Kilometers Driven	0.105912	0.033045	-0.335421	0.114207	-0.203454
No of Owners	-0.027054	-0.004554	-0.361461	0.072182	0.052104
Location	0.022794	-0.011801	-0.125976	0.051440	0.080874
Price	-0.067410	-0.058917	0.355400	-0.462308	-0.187129

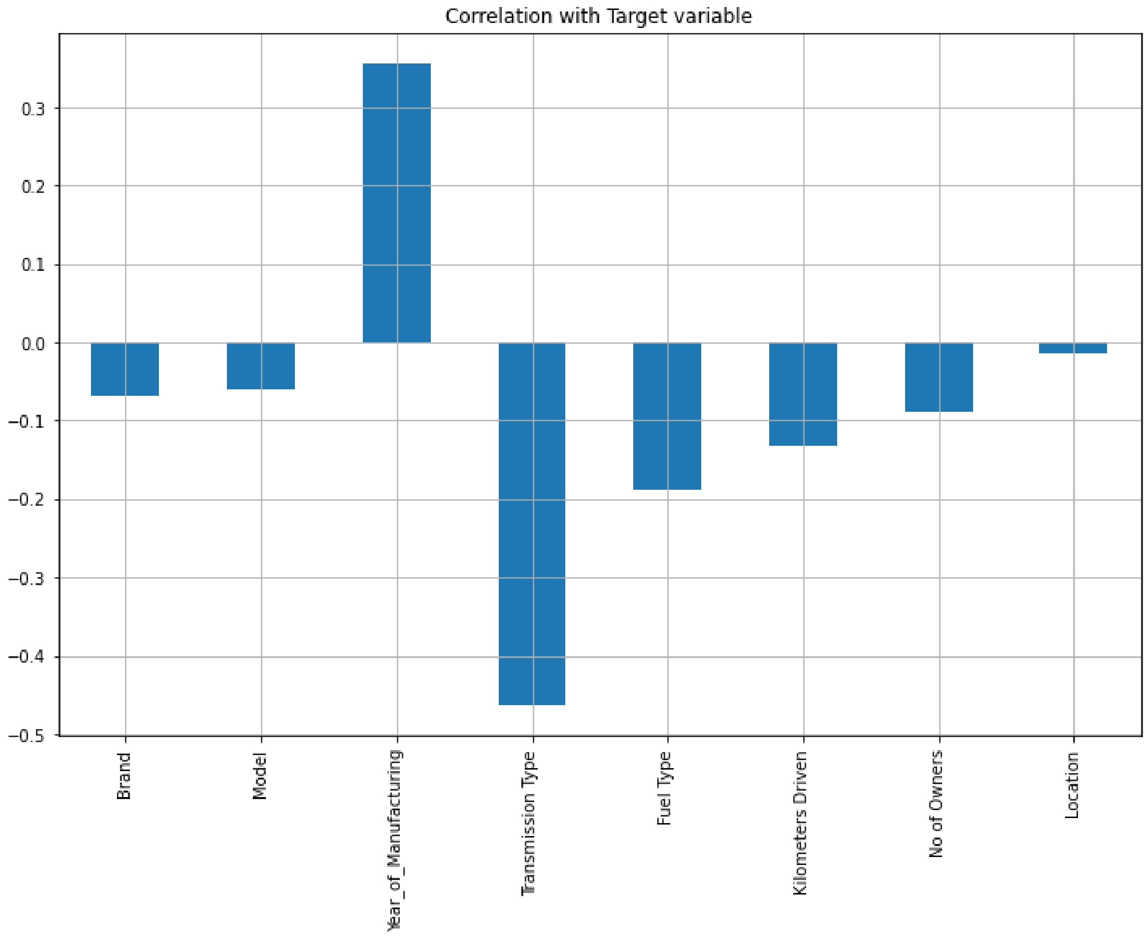
```
#Plotting heatmap for visualizing the correlation
plt.figure(figsize=(15,12))
sn.heatmap(corr,linewidth=0.5,linecolor='black',fmt='.0%',annot=True)
plt.show()
```



```
#Correlation with target variable
plt.figure(figsize=(12,8))
df.drop('Price',axis=1).corrwith(df['Price']).plot(kind='bar',grid=True)
plt.title('Correlation with Target variable')
```

Out[52]:

```
Text(0.5, 1.0, 'Correlation with Target variable')
```



Checking skewness :

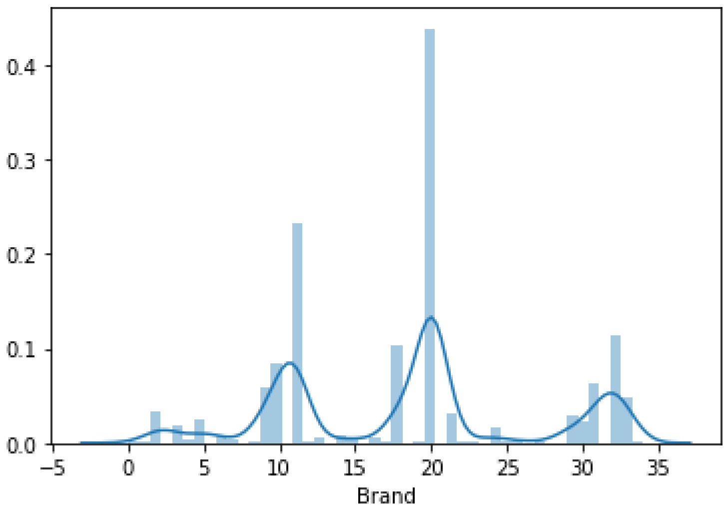
```
#checking the skewness
df.skew()
```

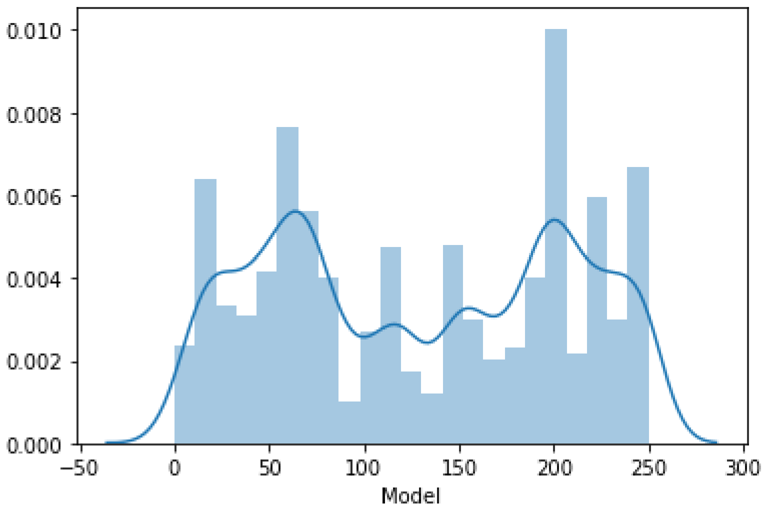
Out[53]:

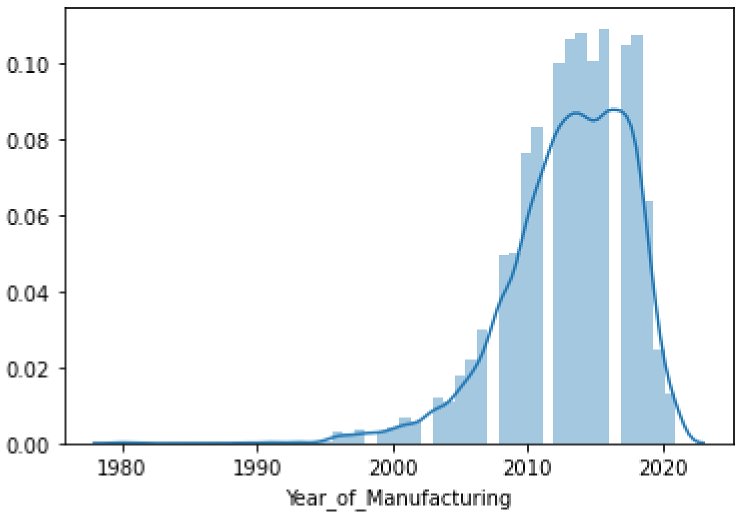
```
Brand                     0.146203
Model                     0.012543
Year_of_Manufacturing    -1.025200
Transmission Type        -1.548705
Fuel Type                 0.046864
Kilometers Driven         6.569194
No of Owners              1.995361
Location                  0.129712
Price                     6.262688
dtype: float64
```

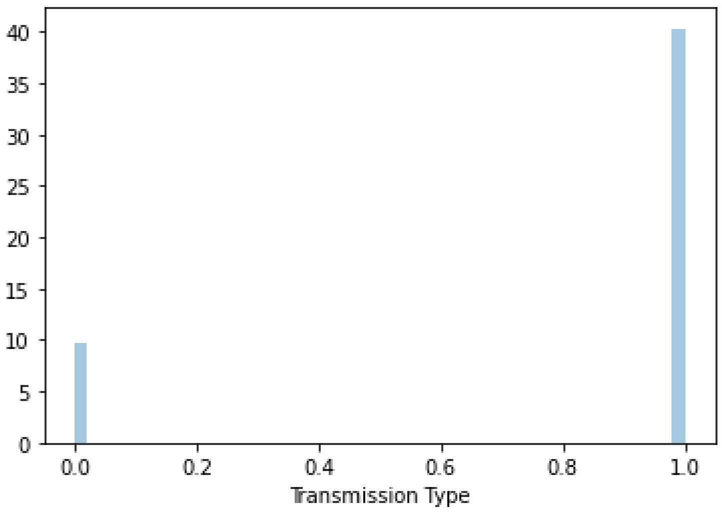
In [54]:

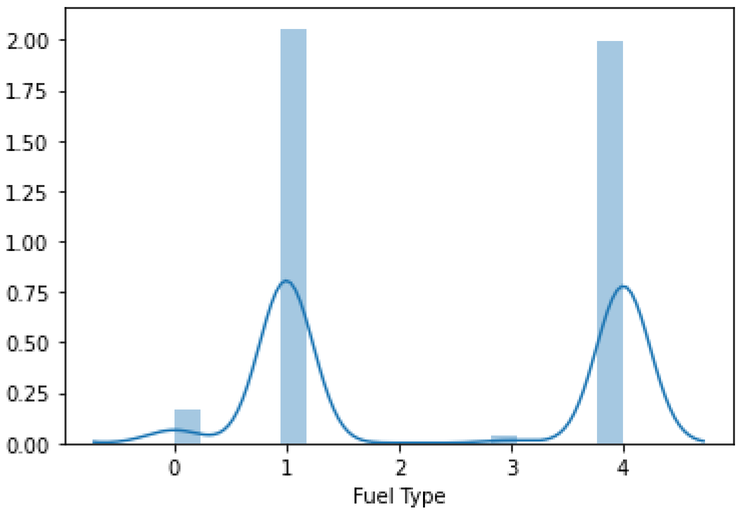
```
#Plotting distplot for checking the distribution of skewness
for col in df.describe().columns:
    sn.distplot(df[col])
    plt.show()
```

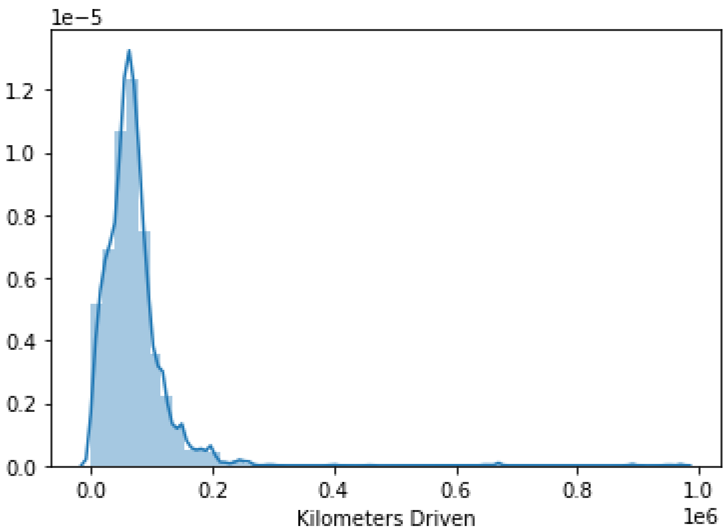

0.4
0.3
0.2
0.1
0.0
−5
0
5
10
15
20
25
30
35
Brand

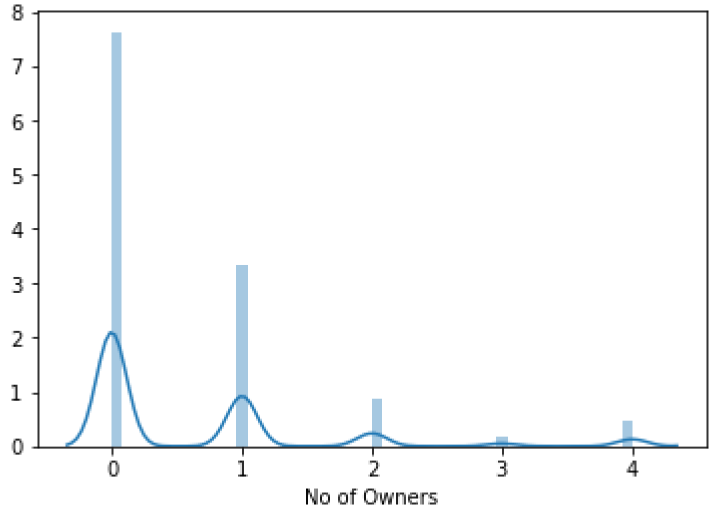

0.010
0.008
0.006
0.004
0.002
0.000
−50
0
50
100
150
200
250
300
Model

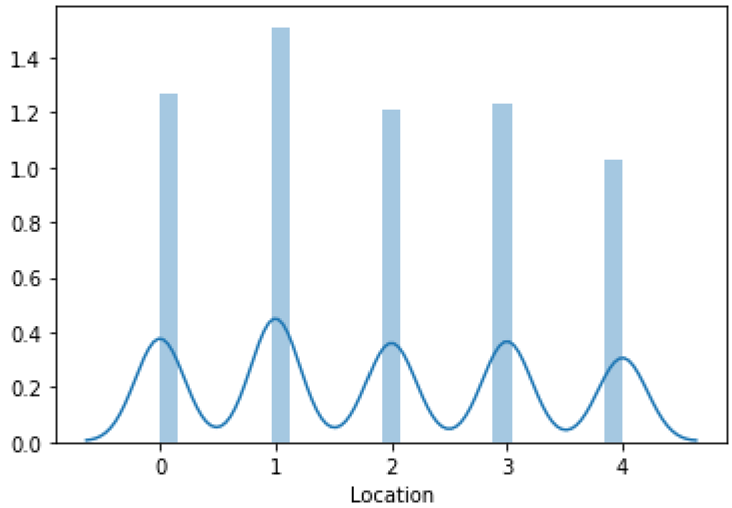

0.10
0.08
0.06
0.04
0.02
0.00
1980
1990
2000
2010
2020
Year_of_Manufacturing

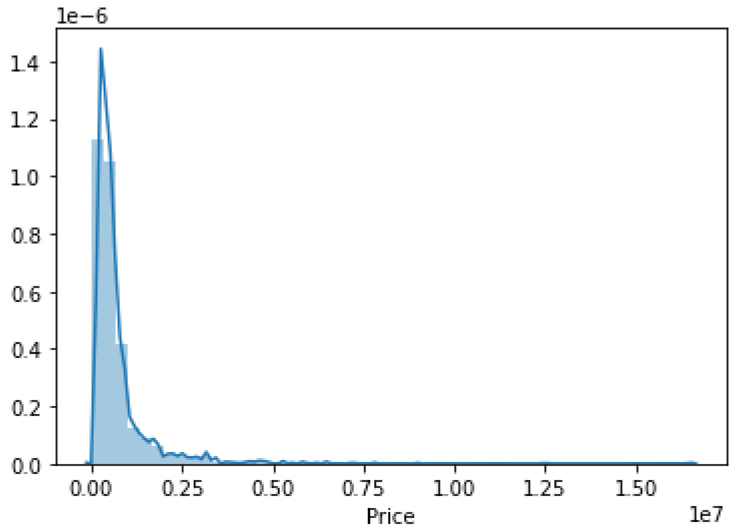

40
35
30
25
20
15
10
5
0
0.0
0.2
0.4
0.6
0.8
1.0
Transmission Type


2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0
1
2
3
4
Fuel Type


1e−5
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
1e6
Kilometers Driven

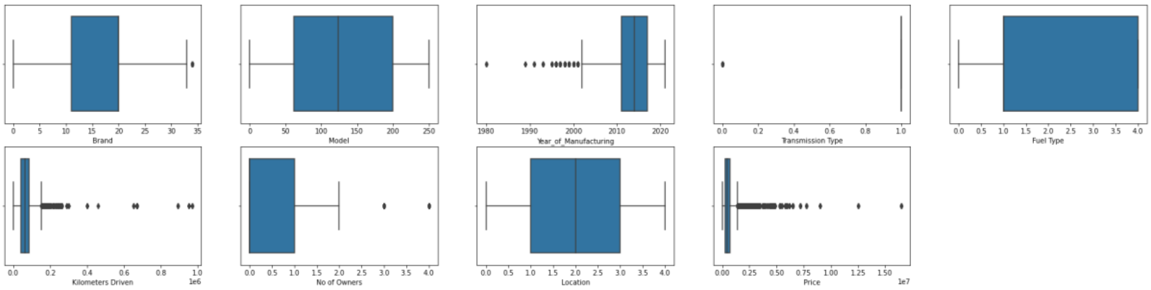






Checking outliers :

```
collist=df.columns.values
ncol=5
nrow=8
plt.figure(figsize=(30,30))
for i in range(0,len(collist)):
    plt.subplot(nrow,ncol,i+1)
    sn.boxplot(df[collist[i]])
```



Handling outliers by using z-score method :

In [56]:

```
from scipy.stats import zscore
import numpy as np
z=np.abs(zscore(df))    #converting all values into absolute values
threshold=3     #setting up a threshold
np.where(z>3)
```

Out[56]:

```
(array([   32,    71,   112, ..., 15223, 15226, 15249], dtype=int64),
 array([8, 8, 8, ..., 6, 6, 6], dtype=int64))
```

```
#Removing outliers
df_new=df[(z<3).all(axis=1)]
df_new
```

Out[57]:

	Brand	Model	Year_of_Manufacturing	Transmission Type	Fuel Type	Kilometers Driven	No of Owners	Loca
0	20	201	2018	1	4	17400.0	0	
1	32	118	2013	1	1	200000.0	0	
2	11	248	2008	1	4	77000.0	1	
3	20	201	2015	1	1	105000.0	0	
4	20	180	2007	1	4	98000.0	1	
...	...	...	...	...	...	...	...	
15934	7	131	2013	1	4	28000.0	0	
15935	11	248	2009	1	4	30214.0	0	
15936	26	152	2012	0	1	100000.0	0	
15937	9	78	2010	1	1	132000.0	2	
15938	11	239	2019	1	0	70000.0	0	

14188 rows × 9 columns

In [58]:

```
#Original data dimensions
df.shape
```

Out[58]:

```
(15261, 9)
```

In [59]:

```
#New data dimensions
df_new.shape
```

Out[59]:

```
(14188, 9)
```

Percentage loss of data after removing outliers :

```
dfshape = 15261
dfnewshape = 14188
total = dfshape-dfnewshape
percentage_loss=((total)/dfshape)*100
print(percentage_loss)
```

7.030994037088003

Preparing dataset for model training :

In [61]:

```
df_x=df_new.drop('Price',axis=1) #Independent variables
y=df_new['Price'] #Target Variable
```

In [62]:

```
#Checking x data
df_x.head()
```

Out[62]:

	Brand	Model	Year_of_Manufacturing	Transmission Type	Fuel Type	Kilometers Driven	No of Owners	Location
0	20	201	2018	1	4	17400.0	0	0
1	32	118	2013	1	1	200000.0	0	0
2	11	248	2008	1	4	77000.0	1	0
3	20	201	2015	1	1	105000.0	0	0
4	20	180	2007	1	4	98000.0	1	0

In [63]:

```
#Checking y data after splitting
y.head()
```

Out[63]:

```
0    690000.0
1    680000.0
2    260000.0
3    549000.0
4    210000.0
Name: Price, dtype: float64
```

Treating skewness :

```python
#We are treating skewness by using square root transform
for col in df_x.skew().index:
    if col in df_x.describe().columns:
        if df_x[col].skew()>0.55:
            df_x[col]=np.sqrt(df_x[col])
        if df_x[col].skew()<-0.55:
            df_x[col]=np.sqrt(df_x[col])
```

In [65]:

```python
#Checking skewness after treating it
df_x.skew()
```

Out[65]:

```
Brand                     0.174927
Model                     0.011186
Year_of_Manufacturing    -0.589082
Transmission Type        -1.624313
Fuel Type                 0.047233
Kilometers Driven        -0.311203
No of Owners              0.765074
Location                  0.165007
dtype: float64
```

Scaling the data :

```
#Scaling the dataset using StandardScaler
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
x=sc.fit_transform(df_x)
x=pd.DataFrame(x,columns=df_x.columns)
x
```

Out[66]:

	Brand	Model	Year_of_Manufacturing	Transmission Type	Fuel Type	Kilometers Driven	O
0	0.186902	0.926805	1.139861	0.476129	1.048835	-1.449619	-0.7
1	1.630887	-0.151864	-0.075589	0.476129	-0.894345	2.545513	-0.7
2	-0.896087	1.537618	-1.292550	0.476129	1.048835	0.394979	1.0
3	0.186902	0.926805	0.410772	0.476129	-0.894345	0.984779	-0.7
4	0.186902	0.653889	-1.536124	0.476129	1.048835	0.845559	1.0
...	...	...	...	...	...	...	
14183	-1.377416	0.017084	-0.075589	0.476129	1.048835	-1.000785	-0.7
14184	-0.896087	1.537618	-1.049037	0.476129	1.048835	-0.918556	-0.7
14185	0.908894	0.290000	-0.318860	-2.100271	-0.894345	0.885830	-0.7
14186	-1.136752	-0.671705	-0.805584	0.476129	-0.894345	1.482497	1.8
14187	-0.896087	1.420654	1.382770	0.476129	-1.542071	0.231354	-0.7

14188 rows × 8 columns

Model Building :

In [67]:

```
#Importing required metrices and model for the dataset
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.linear_model import LinearRegression,Lasso,ElasticNet,Ridge
from sklearn.metrics import r2_score, mean_absolute_error,mean_squared_error
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor, GradientBoosting
Regressor
from sklearn.model_selection import GridSearchCV
```

```
#Finding the best random state and r2_score
for i in range(42,100):
    x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.20,random_state=i)
    lr=LinearRegression()
    lr.fit(x_train,y_train)
    pred_train=lr.predict(x_train)
    pred_test=lr.predict(x_test)
    if round(r2_score(y_train,pred_train)*100,1)==round(r2_score(y_test,pred_test)*100,
1):
        print('At random state',i,',the model performs well')
        print('Training r2_score is: ',r2_score(y_train,pred_train)*100)
        print('Testing r2_score is: ',r2_score(y_test,pred_test)*100)
```

```
At random state 69 ,the model performs well
Training r2_score is:  43.73940831897944
Testing r2_score is:  43.67352543221313
```

In [69]:

```
#Creating train_test_split using best random_state
x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=69,test_size=.20)
```

Finding the best model :

In [70]:

```
LR=LinearRegression()
l=Lasso()
en=ElasticNet()
rd=Ridge()
dtr=DecisionTreeRegressor()
knr=KNeighborsRegressor()
rf=RandomForestRegressor()
ab=AdaBoostRegressor()
gb=GradientBoostingRegressor()
```

In [71]:

```
models= []
models.append(('Linear Regression',LR))
models.append(('Lasso Regression',l))
models.append(('Elastic Net Regression',en))
models.append(('Ridge Regression',rd))
models.append(('Decision Tree Regressor',dtr))
models.append(('KNeighbors Regressor',knr))
models.append(('RandomForestRegressor',rf))
models.append(('AdaBoostRegressor',ab))
models.append(('GradientBoostingRegressor',gb))
```

In [72]:

```
#Finding the required metrices for all models together using a for loop
Model=[]
score=[]
cvs=[]
sd=[]
mae=[]
mse=[]
rmse=[]
for name,model in models:
    print('******************************',name,'***************************')
    print('\n')
    Model.append(name)
    model.fit(x_train,y_train)
    print(model)
    pre=model.predict(x_test)
    print('\n')
    AS=r2_score(y_test,pre)
    print('r2_score: ',AS)
    score.append(AS*100)
    print('\n')
    std=cross_val_score(model,x,y,cv=5,scoring='r2').std()
    print('Standard Deviation: ',std)
    sd.append(std)
    print('\n')
    MAE=mean_absolute_error(y_test,pre)
    print('Mean Absolute Error: ',MAE)
    mae.append(MAE)
    print('\n')
    MSE=mean_squared_error(y_test,pre)
    print('Mean Squared Error: ',MSE)
    mse.append(MSE)
    print('\n')
    RMSE=np.sqrt(mean_squared_error(y_test,pre))
    print('Root Mean Squared Error: ',RMSE)
    rmse.append(RMSE)
    print('\n\n')
```

```
****************************** Linear Regression *************************
**

LinearRegression()

r2_score:  0.43673525432213134

Standard Deviation:  0.07993052305828376

Mean Absolute Error:  265196.85040908016

Mean Squared Error:  164380872360.56992

Root Mean Squared Error:  405439.1105462939


****************************** Lasso Regression **************************
*

Lasso()

r2_score:  0.4367355125258132

Standard Deviation:  0.07992978140800723

Mean Absolute Error:  265196.2309892308

Mean Squared Error:  164380797007.4668

Root Mean Squared Error:  405439.01761851535


****************************** Elastic Net Regression ********************
*******

ElasticNet()

r2_score:  0.40558560486431716

Standard Deviation:  0.05036260545124671

Mean Absolute Error:  260420.23601405346
```

```
Mean Squared Error:  173471458254.48953

Root Mean Squared Error:  416499.049524113


****************************** Ridge Regression *************************
*

Ridge()

r2_score:  0.4367366727908023

Standard Deviation:  0.07991809291983559

Mean Absolute Error:  265192.14856179355

Mean Squared Error:  164380458400.49283

Root Mean Squared Error:  405438.60003765405


****************************** Decision Tree Regressor ******************
********

DecisionTreeRegressor()

r2_score:  0.9947437784676423

Standard Deviation:  0.35896037756020915

Mean Absolute Error:  1630.6987900225215

Mean Squared Error:  1533954126.2600467

Root Mean Squared Error:  39165.726423239576


****************************** KNeighbors Regressor *********************
*****

KNeighborsRegressor()
```

```
r2_score:  0.9640688921591424

Standard Deviation:  0.3546862406462319

Mean Absolute Error:  32057.47843551797

Mean Squared Error:  10485987090.588768

Root Mean Squared Error:  102401.10883476198


****************************** RandomForestRegressor *********************
******

RandomForestRegressor()

r2_score:  0.9951960959479162

Standard Deviation:  0.18210592081438265

Mean Absolute Error:  6003.390685727501

Mean Squared Error:  1401951648.6295717

Root Mean Squared Error:  37442.64478678785


****************************** AdaBoostRegressor *************************
**

AdaBoostRegressor()

r2_score:  0.45249011284625007

Standard Deviation:  0.18138411646664038

Mean Absolute Error:  283913.3473493897

Mean Squared Error:  159783039089.47595

Root Mean Squared Error:  399728.7068618864
```

```
****************************** GradientBoostingRegressor ****************
**********

GradientBoostingRegressor()

r2_score:  0.8102034380625738

Standard Deviation:  0.06696334137026888

Mean Absolute Error:  152251.57921475024

Mean Squared Error:  55389449919.79623

Root Mean Squared Error:  235349.63335385977
```

In [73]:

```
#Finalizing the result
result=pd.DataFrame({'Model':Model, 'r2_score': score, 'Standard_deviation':sd,
                     'Mean_absolute_error':mae, 'Mean_squared_error':mse, 'Root_Mean_Squ
ared_error':rmse})
result
```

Out[73]:

	Model	r2_score	Standard_deviation	Mean_absolute_error	Mean_squar
0	Linear Regression	43.673525	0.079931	265196.850409	1.64
1	Lasso Regression	43.673551	0.079930	265196.230989	1.64
2	Elastic Net Regression	40.558560	0.050363	260420.236014	1.73
3	Ridge Regression	43.673667	0.079918	265192.148562	1.64
4	Decision Tree Regressor	99.474378	0.358960	1630.698790	1.53
5	KNeighbors Regressor	96.406889	0.354686	32057.478436	1.04
6	RandomForestRegressor	99.519610	0.182106	6003.390686	1.40
7	AdaBoostRegressor	45.249011	0.181384	283913.347349	1.59
8	GradientBoostingRegressor	81.020344	0.066963	152251.579215	5.53

Hyperparameter Tuning :

Random Forest Regressor

```
#Creating parameter list to pass in GridSearchCV
parameters={'criterion':['mse','mae'],'n_estimators':[50,100,500],'max_features':['aut
o','sqrt','log2']}
```

In [75]:

```
#Using GridSearchCV to run the parameters and checking final accuracy
rf=RandomForestRegressor()
grid=GridSearchCV(rf,parameters,cv=5,scoring='r2')
grid.fit(x_train,y_train)
print(grid.best_params_)  #Printing the best parameters obtained
print(grid.best_score_) #Mean cross-validated score of best_estimator
```

```
{'criterion': 'mse', 'max_features': 'log2', 'n_estimators': 500}
0.995169643223543
```

In [76]:

```
#Using the best parameters obtained
RF=RandomForestRegressor(random_state=48, n_estimators=500, criterion='mse', max_featur
es='log2')
RF.fit(x_train,y_train)
pred=RF.predict(x_test)
print('r2_score: ',r2_score(y_test,pred)*100)
print('Standard deviation: ',cross_val_score(RF,x,y,cv=5,scoring='r2').std())
print('Mean absolute error: ',mean_absolute_error(y_test,pred))
print('Mean squared error: ',mean_squared_error(y_test,pred))
print('Root Mean squared error: ',np.sqrt(mean_squared_error(y_test,pred)))
```

```
r2_score:  99.8748045053894
Standard deviation:  0.12100305463610382
Mean absolute error:  4984.192319008198
Mean squared error:  365365394.8275357
Root Mean squared error:  19114.53360214514
```

Finalizing the model :

In [77]:

```
rf_prediction=RF.predict(x)
print('Predictions of Random Forest Regressor: ',rf_prediction)
```

```
Predictions of Random Forest Regressor:  [689524.  684006.13113826 259850.
........................................280274.276
 232438.         564307.43517949]
```

In [78]:

```
#Comparing actual and predicted values with the help of a dataframe
predictions=pd.DataFrame({'Original_price':y, 'Predicted_price':rf_prediction})
predictions
```

Out[78]:

	Original_price	Predicted_price
0	690000.0	689524.000000
1	680000.0	684006.131138
2	260000.0	259850.000000
3	549000.0	549000.000000
4	210000.0	210000.000000
...	...	...
15934	375000.0	372044.000000
15935	188000.0	188632.000000
15936	150000.0	280274.276000
15937	231000.0	232438.000000
15938	550000.0	564307.435179

14188 rows × 2 columns

Saving the model :

In [79]:

```
#Saving the model
import pickle
filename='Car_Price_Prediction.pkl'    #Specifying the filename
pickle.dump(RF,open(filename,'wb'))
```

In [80]:

```
#Saving the predicted values
results=pd.DataFrame(rf_prediction)
results.to_csv('Car_Price_Prediction_Results.csv')
```

CONCLUSION :

- ***The increased prices of new cars and the financial incapability of the customers to buy them, Used Car sales are on a global increase. Therefore, there is an urgent need for a Used Car Price Prediction system which effectively determines the worthiness of the car using a variety of features. The proposed system will help to determine the accurate price of used car price prediction.***

FUTURE SCOPE :

- ***In future this machine learning model may bind with various website which can provide real time data for price prediction. Also we may add large historical data of car price which can help to improve accuracy of the machine learning model. We can build an android app as user interface for interacting with user. For better performance, we plan to judiciously design deep learning network structures, use adaptive learning rates and train on clusters of data rather than the whole dataset.***

In [ ]:

```

```