

## Car Price Prediction

**Develop a model that predicts the probability of a used car in addition to predicting the price Based on the factors of external as well as internal factors of the car**

```
In [1]: import pandas as pd  
import numpy as np  
import matplotlib.pyplot as plt  
import seaborn as sns
```

```
In [2]: cars_data=pd.read_csv("Car details v3.csv")
```

```
In [3]: cars_data
```

Out[3]:

		name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	n
0		Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner	
1		Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner	
2		Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual	Third Owner	
3		Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual	First Owner	
4		Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual	First Owner	
...	...	...	...	...	...	...	...	...	...	...
8123		Hyundai i20 Magna	2013	320000	110000	Petrol	Individual	Manual	First Owner	
8124		Hyundai Verna CRDi SX	2007	135000	119000	Diesel	Individual	Manual	Fourth & Above Owner	
8125		Maruti Swift Dzire ZDi	2009	382000	120000	Diesel	Individual	Manual	First Owner	
8126		Tata Indigo CR4	2013	290000	25000	Diesel	Individual	Manual	First Owner	
8127		Tata Indigo CR4	2013	290000	25000	Diesel	Individual	Manual	First Owner	

8128 rows × 13 columns



In [4]: cars\_data.nunique()

```
Out[4]: name      2058  
year        29  
selling_price    677  
km_driven     921  
fuel          4  
seller_type     3  
transmission     2  
owner         5  
mileage       393  
engine        121  
max_power     322  
torque        441  
seats          9  
dtype: int64
```

```
In [5]: cars_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 8128 entries, 0 to 8127  
Data columns (total 13 columns):  
 #   Column      Non-Null Count  Dtype     
 ---  --          -----            
 0   name        8128 non-null   object    
 1   year        8128 non-null   int64     
 2   selling_price 8128 non-null   int64    
 3   km_driven    8128 non-null   int64    
 4   fuel         8128 non-null   object    
 5   seller_type   8128 non-null   object    
 6   transmission  8128 non-null   object    
 7   owner        8128 non-null   object    
 8   mileage       7907 non-null   object    
 9   engine        7907 non-null   object    
 10  max_power     7913 non-null   object    
 11  torque        7906 non-null   object    
 12  seats         7907 non-null   float64  
dtypes: float64(1), int64(3), object(9)  
memory usage: 825.6+ KB
```

```
In [6]: cars_data.describe()
```

Out[6]:

	year	selling_price	km_driven	seats
<b>count</b>	8128.000000	8.128000e+03	8.128000e+03	7907.000000
<b>mean</b>	2013.804011	6.382718e+05	6.981951e+04	5.416719
<b>std</b>	4.044249	8.062534e+05	5.655055e+04	0.959588
<b>min</b>	1983.000000	2.999900e+04	1.000000e+00	2.000000
<b>25%</b>	2011.000000	2.549990e+05	3.500000e+04	5.000000
<b>50%</b>	2015.000000	4.500000e+05	6.000000e+04	5.000000
<b>75%</b>	2017.000000	6.750000e+05	9.800000e+04	5.000000
<b>max</b>	2020.000000	1.000000e+07	2.360457e+06	14.000000

In [7]: `cars_data.isna().sum()`Out[7]:  
name 0  
year 0  
selling\_price 0  
km\_driven 0  
fuel 0  
seller\_type 0  
transmission 0  
owner 0  
mileage 221  
engine 221  
max\_power 215  
torque 222  
seats 221  
dtype: int64In [8]: `cars_data.duplicated().sum()`

Out[8]: 1202

In [9]: `cars_data.drop_duplicates(inplace=True)`In [10]: `cars_data`

Out[10]:

		name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	n
0		Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner	
1		Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner	
2		Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual	Third Owner	
3		Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual	First Owner	
4		Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual	First Owner	
...	...	...	...	...	...	...	...	...	...	...
8121		Maruti Wagon R VXI BS IV with ABS	2013	260000	50000	Petrol	Individual	Manual	Second Owner	
8122		Hyundai i20 Magna 1.4 CRDi	2014	475000	80000	Diesel	Individual	Manual	Second Owner	
8123		Hyundai i20 Magna	2013	320000	110000	Petrol	Individual	Manual	First Owner	
8124		Hyundai Verna CRDi SX	2007	135000	119000	Diesel	Individual	Manual	Fourth & Above Owner	
8125		Maruti Swift Dzire ZDi	2009	382000	120000	Diesel	Individual	Manual	First Owner	

6926 rows × 13 columns



In [11]: cars\_data[['mileage(kmpl)', 'column2']] = cars\_data['mileage'].str.split(' ', expand=True)

```
In [12]: cars_data.drop("column2", inplace=True, axis=1)
```

```
In [13]: cars_data
```

Out[13]:

		name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	n
0		Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner	
1		Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner	
2		Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual	Third Owner	
3		Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual	First Owner	
4		Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual	First Owner	
...	...	...	...	...	...	...	...	...	...	...
8121		Maruti Wagon R VXI BS IV with ABS	2013	260000	50000	Petrol	Individual	Manual	Second Owner	
8122		Hyundai i20 Magna 1.4 CRDi	2014	475000	80000	Diesel	Individual	Manual	Second Owner	
8123		Hyundai i20 Magna	2013	320000	110000	Petrol	Individual	Manual	First Owner	
8124		Hyundai Verna CRDi SX	2007	135000	119000	Diesel	Individual	Manual	Fourth & Above Owner	
8125		Maruti Swift Dzire ZDi	2009	382000	120000	Diesel	Individual	Manual	First Owner	

6926 rows × 14 columns



In [14]: cars\_data[['engine(CC)', 'column2']] = cars\_data['engine'].str.split(' ', expand=True)

```
In [15]: cars_data.drop("column2", inplace=True, axis=1)
```

```
In [16]: cars_data
```

Out[16]:

		name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	n
0		Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner	
1		Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner	
2		Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual	Third Owner	
3		Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual	First Owner	
4		Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual	First Owner	
...	...	...	...	...	...	...	...	...	...	...
8121		Maruti Wagon R VXI BS IV with ABS	2013	260000	50000	Petrol	Individual	Manual	Second Owner	
8122		Hyundai i20 Magna 1.4 CRDi	2014	475000	80000	Diesel	Individual	Manual	Second Owner	
8123		Hyundai i20 Magna	2013	320000	110000	Petrol	Individual	Manual	First Owner	
8124		Hyundai Verna CRDi SX	2007	135000	119000	Diesel	Individual	Manual	Fourth & Above Owner	
8125		Maruti Swift Dzire ZDi	2009	382000	120000	Diesel	Individual	Manual	First Owner	

6926 rows × 15 columns



In [17]: cars\_data["max\_power"].isna().sum()

Out[17]: 205

In [18]: cars\_data["max\_power"].value\_counts()

```
Out[18]: max_power
74 bhp      324
88.5 bhp    177
46.3 bhp    158
67 bhp      152
67.1 bhp    141
...
265 bhp      1
55.23 bhp   1
156 bhp     1
181.04 bhp  1
135.1 bhp   1
Name: count, Length: 322, dtype: int64
```

In [19]: cars\_data["max\_power"].fillna("74 bhp", inplace=True)

C:\Users\Lenovo\_Ideapad\_slim3\AppData\Local\Temp\ipykernel\_10328\3144470996.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an `inplace` method.

The behavior will change in pandas 3.0. This `inplace` method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing `'df[col].method(value, inplace=True)'`, try using `'df.method({col: value}, inplace=True)'` or `df[col] = df[col].method(value)` instead, to perform the operation `inplace` on the original object.

cars\_data["max\_power"].fillna("74 bhp", inplace=True)

In [20]: cars\_data["max\_power"].isna().sum()

Out[20]: 0

In [21]: cars\_data[['max\_power(bhp)', 'column2']] = cars\_data['max\_power'].str.split(' ', ex

In [22]: cars\_data.drop("column2", inplace=True, axis=1)

In [23]: cars\_data

Out[23]:

		name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	n
0		Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner	
1		Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner	
2		Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual	Third Owner	
3		Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual	First Owner	
4		Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual	First Owner	
...	...	...	...	...	...	...	...	...	...	...
8121		Maruti Wagon R VXI BS IV with ABS	2013	260000	50000	Petrol	Individual	Manual	Second Owner	
8122		Hyundai i20 Magna 1.4 CRDi	2014	475000	80000	Diesel	Individual	Manual	Second Owner	
8123		Hyundai i20 Magna	2013	320000	110000	Petrol	Individual	Manual	First Owner	
8124		Hyundai Verna CRDi SX	2007	135000	119000	Diesel	Individual	Manual	Fourth & Above Owner	
8125		Maruti Swift Dzire ZDi	2009	382000	120000	Diesel	Individual	Manual	First Owner	

6926 rows × 16 columns



In [24]: cars\_data.drop(["mileage", "engine", "max\_power"], axis=1, inplace=True)

```
In [25]: data=cars_data.drop("selling_price",axis=1)
```

```
In [26]: cars_data=pd.merge(data,cars_data)
```

```
In [27]: cars_data
```

Out[27]:

	<b>name</b>	<b>year</b>	<b>km_driven</b>	<b>fuel</b>	<b>seller_type</b>	<b>transmission</b>	<b>owner</b>	<b>torque</b>	<b>se</b>
<b>0</b>	Maruti Swift Dzire VDI	2014	145500	Diesel	Individual	Manual	First Owner	190Nm@ 2000rpm	
<b>1</b>	Skoda Rapid 1.5 TDI Ambition	2014	120000	Diesel	Individual	Manual	Second Owner	250Nm@ 1500-2500rpm	
<b>2</b>	Honda City 2017-2020 EXi	2006	140000	Petrol	Individual	Manual	Third Owner	12.7@ 2,700(kgm@ rpm)	
<b>3</b>	Honda City 2017-2020 EXi	2006	140000	Petrol	Individual	Manual	Third Owner	12.7@ 2,700(kgm@ rpm)	
<b>4</b>	Hyundai i20 Sportz Diesel	2010	127000	Diesel	Individual	Manual	First Owner	22.4 kgm at 1750-2750rpm	
...	...	...	...	...	...	...	...	...	...
<b>7407</b>	Maruti Wagon R VXI BS IV with ABS	2013	50000	Petrol	Individual	Manual	Second Owner	90Nm@ 3500rpm	
<b>7408</b>	Hyundai i20 Magna 1.4 CRDi	2014	80000	Diesel	Individual	Manual	Second Owner	219.7Nm@ 1500-2750rpm	
<b>7409</b>	Hyundai i20 Magna	2013	110000	Petrol	Individual	Manual	First Owner	113.7Nm@ 4000rpm	
<b>7410</b>	Hyundai Verna CRDi SX	2007	119000	Diesel	Individual	Manual	Fourth & Above Owner	24@ 1,900-2,750(kgm@ rpm)	
<b>7411</b>	Maruti Swift Dzire ZDi	2009	120000	Diesel	Individual	Manual	First Owner	190Nm@ 2000rpm	

7412 rows × 13 columns



In [28]: cars\_data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7412 entries, 0 to 7411
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   name              7412 non-null    object  
 1   year              7412 non-null    int64  
 2   km_driven         7412 non-null    int64  
 3   fuel              7412 non-null    object  
 4   seller_type       7412 non-null    object  
 5   transmission      7412 non-null    object  
 6   owner             7412 non-null    object  
 7   torque            7195 non-null    object  
 8   seats              7196 non-null    float64 
 9   mileage(kmpl)    7196 non-null    object  
 10  engine(CC)        7196 non-null    object  
 11  max_power(bhp)   7412 non-null    object  
 12  selling_price    7412 non-null    int64  
dtypes: float64(1), int64(3), object(9)
memory usage: 752.9+ KB
```

```
In [29]: cars_data["mileage(kmpl)"] = cars_data["mileage(kmpl)"].astype(float)
```

```
In [30]: cars_data["engine(CC)"] = cars_data["engine(CC)"].astype(float)
```

```
In [31]: cars_data["max_power(bhp)"].isna().sum()
```

```
Out[31]: 0
```

```
In [32]: cars_data['max_power(bhp)'] = pd.to_numeric(cars_data['max_power(bhp)'])
```

```
In [33]: cars_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7412 entries, 0 to 7411
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   name              7412 non-null    object  
 1   year              7412 non-null    int64  
 2   km_driven         7412 non-null    int64  
 3   fuel              7412 non-null    object  
 4   seller_type       7412 non-null    object  
 5   transmission      7412 non-null    object  
 6   owner             7412 non-null    object  
 7   torque            7195 non-null    object  
 8   seats              7196 non-null    float64 
 9   mileage(kmpl)    7196 non-null    float64 
 10  engine(CC)        7196 non-null    float64 
 11  max_power(bhp)   7411 non-null    float64 
 12  selling_price    7412 non-null    int64  
dtypes: float64(4), int64(3), object(6)
memory usage: 752.9+ KB
```

```
In [34]: cars_data.isna().sum()
```

```
Out[34]: name      0
year       0
km_driven 0
fuel       0
seller_type 0
transmission 0
owner      0
torque     217
seats      216
mileage(kmpl) 216
engine(CC)   216
max_power(bhp) 1
selling_price 0
dtype: int64
```

```
In [35]: cars_data.loc[cars_data["max_power(bhp)"].isna()]
```

```
Out[35]:    name  year  km_driven  fuel  seller_type  transmission  owner  torque  seats  mil
4581  Maruti  Omni  2000      100000  CNG  Individual  Manual  Second
          CNG           Owner      NaN      8.0
```



```
In [36]: cars_data["max_power(bhp)"].fillna(cars_data["max_power(bhp)"].median(), inplace=True)
```

C:\Users\Lenovo\_Ideapad\_slim3\AppData\Local\Temp\ipykernel\_10328\3549038377.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an `inplace` method.

The behavior will change in pandas 3.0. This `inplace` method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing `'df[col].method(value, inplace=True)'`, try using `'df.method({col: value}, inplace=True)'` or `df[col] = df[col].method(value)` instead, to perform the operation `inplace` on the original object.

```
cars_data["max_power(bhp)"].fillna(cars_data["max_power(bhp)"].median(), inplace=True)
```

```
In [37]: cars_data.loc[cars_data["max_power(bhp)"].isna()]
```

```
Out[37]:    name  year  km_driven  fuel  seller_type  transmission  owner  torque  seats  mileage(km)
4581  Maruti  Omni  2000      100000  CNG  Individual  Manual  Second
          CNG           Owner      NaN      8.0
```



```
In [38]: cars_data["engine(CC)"].fillna(cars_data["engine(CC)"].median(), inplace=True)
```

```
C:\Users\Lenovo_Ideapad_slim3\AppData\Local\Temp\ipykernel_10328\3135933936.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.  
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
cars_data["engine(CC)"].fillna(cars_data["engine(CC)"].median(), inplace=True)
```

```
In [39]: cars_data["mileage(kmpl)"].fillna(cars_data["mileage(kmpl)"].median(), inplace=True)
```

```
C:\Users\Lenovo_Ideapad_slim3\AppData\Local\Temp\ipykernel_10328\2365437972.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
```

The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
cars_data["mileage(kmpl)"].fillna(cars_data["mileage(kmpl)"].median(), inplace=True)
```

```
In [40]: cars_data["seats"].value_counts()
```

```
Out[40]: seats  
5.0      5658  
7.0      1020  
8.0       232  
4.0       130  
9.0        76  
6.0        59  
10.0       18  
2.0         2  
14.0       1  
Name: count, dtype: int64
```

```
In [41]: cars_data["seats"].fillna(5.0, inplace=True)
```

```
C:\Users\Lenovo_Ideapad_slim3\AppData\Local\Temp\ipykernel_10328\1096849628.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.  
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
cars_data["seats"].fillna(5.0,inplace=True)
```

```
In [42]: cars_data["torque"].value_counts()
```

```
Out[42]: torque  
190Nm@ 2000rpm      556  
200Nm@ 1750rpm      426  
90Nm@ 3500rpm       371  
62Nm@ 3000rpm        180  
114Nm@ 4000rpm       160  
...  
11.4@ 4,000(kgm@ rpm)    1  
25.5@ 1,500-3,000(kgm@ rpm) 1  
202Nm@ 3600-5200rpm     1  
128Nm@ 3100rpm         1  
96 Nm at 3000 rpm       1  
Name: count, Length: 441, dtype: int64
```

```
In [43]: cars_data["torque"].fillna("190Nm@ 2000rpm ",inplace=True)
```

```
C:\Users\Lenovo_Ideapad_slim3\AppData\Local\Temp\ipykernel_10328\481521205.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.  
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
cars_data["torque"].fillna("190Nm@ 2000rpm ",inplace=True)
```

```
In [44]: cars_data.isna().sum()
```

```
Out[44]: name      0  
year       0  
km_driven  0  
fuel        0  
seller_type 0  
transmission 0  
owner       0  
torque      0  
seats        0  
mileage(kmpl) 0  
engine(CC)   0  
max_power(bhp) 0  
selling_price 0  
dtype: int64
```

```
In [92]: num_data=cars_data.select_dtypes(exclude="object")
```

```
In [94]: cars_data
```

Out[94]:

	<b>name</b>	<b>year</b>	<b>km_driven</b>	<b>fuel</b>	<b>seller_type</b>	<b>transmission</b>	<b>owner</b>	<b>torque</b>	<b>se</b>
<b>0</b>	Maruti Swift Dzire VDI	2014	145500	Diesel	Individual	Manual	First Owner	190Nm@ 2000rpm	
<b>1</b>	Skoda Rapid 1.5 TDI Ambition	2014	120000	Diesel	Individual	Manual	Second Owner	250Nm@ 1500- 2500rpm	
<b>2</b>	Honda City 2017- 2020 EXi	2006	140000	Petrol	Individual	Manual	Third Owner	12.7@ 2,700(kgm@ rpm)	
<b>3</b>	Honda City 2017- 2020 EXi	2006	140000	Petrol	Individual	Manual	Third Owner	12.7@ 2,700(kgm@ rpm)	
<b>4</b>	Hyundai i20 Sportz Diesel	2010	127000	Diesel	Individual	Manual	First Owner	22.4 kgm at 1750- 2750rpm	
...	...	...	...	...	...	...	...	...	...
<b>7407</b>	Maruti Wagon R VXI BS IV with ABS	2013	50000	Petrol	Individual	Manual	Second Owner	90Nm@ 3500rpm	
<b>7408</b>	Hyundai i20 Magna 1.4 CRDi	2014	80000	Diesel	Individual	Manual	Second Owner	219.7Nm@ 1500- 2750rpm	
<b>7409</b>	Hyundai i20 Magna	2013	110000	Petrol	Individual	Manual	First Owner	113.7Nm@ 4000rpm	
<b>7410</b>	Hyundai Verna CRDi SX	2007	119000	Diesel	Individual	Manual	Fourth & Above Owner	24@ 1,900- 2,750(kgm@ rpm)	
<b>7411</b>	Maruti Swift Dzire ZDi	2009	120000	Diesel	Individual	Manual	First Owner	190Nm@ 2000rpm	

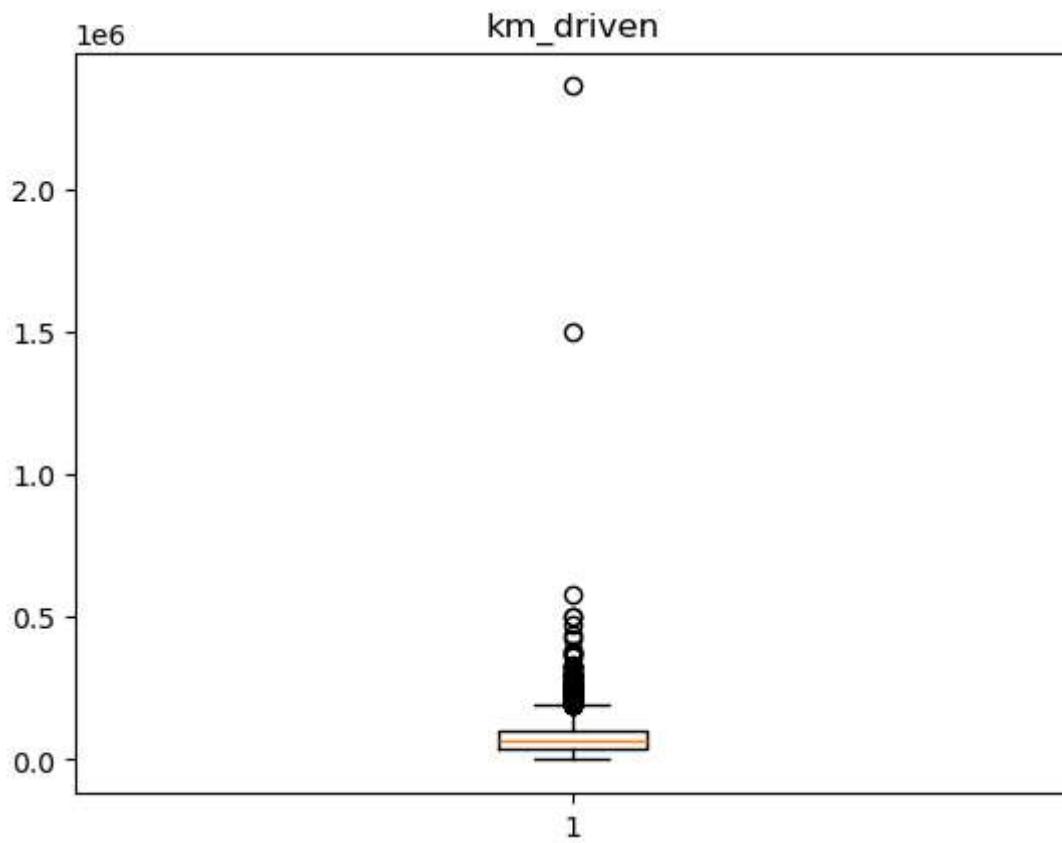
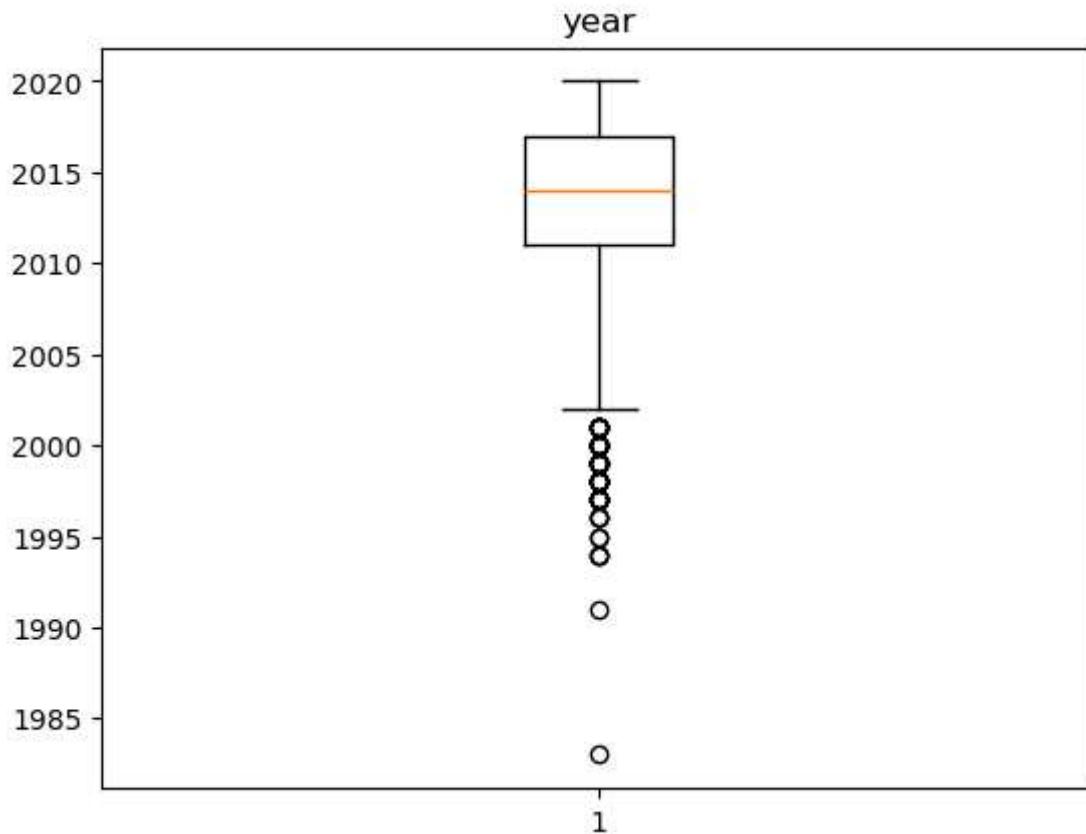
7412 rows × 13 columns

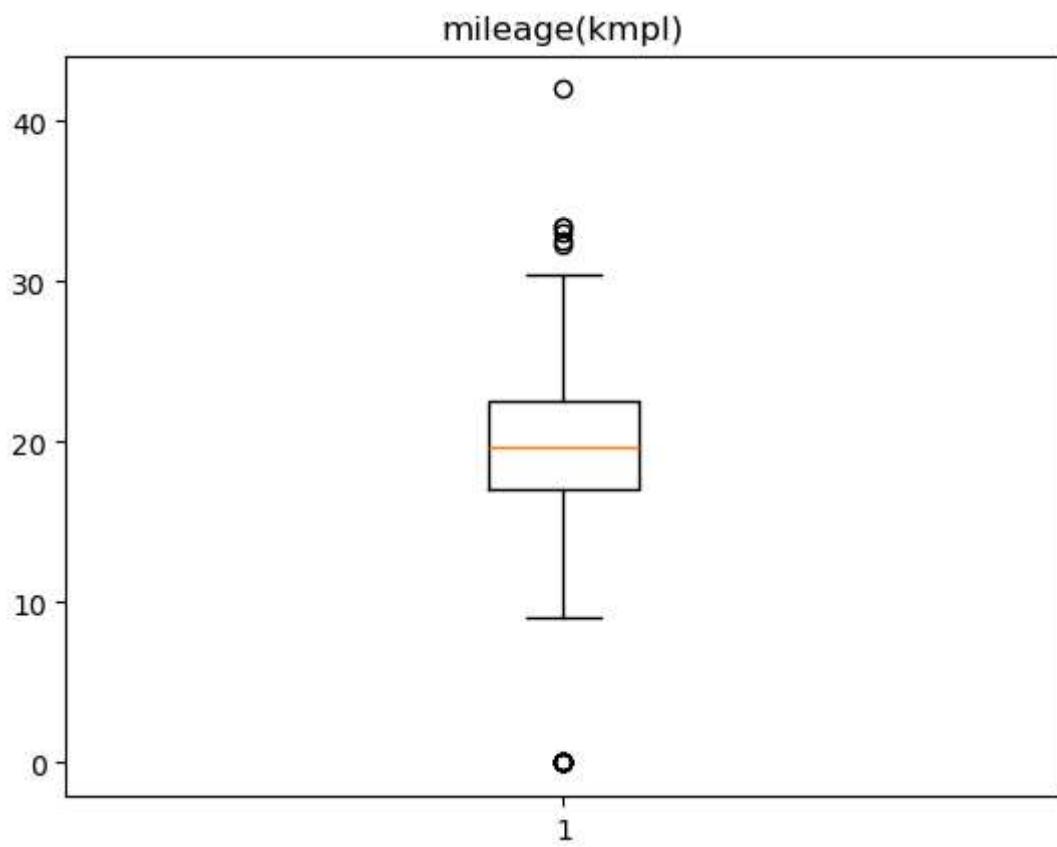
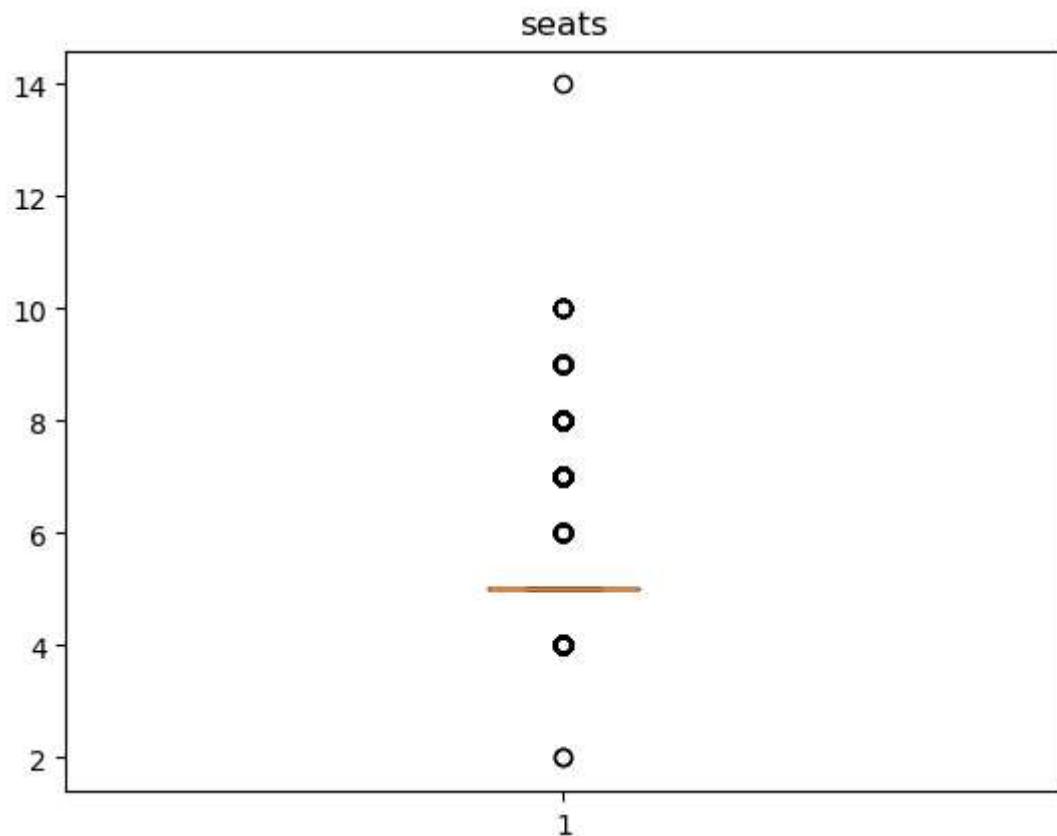


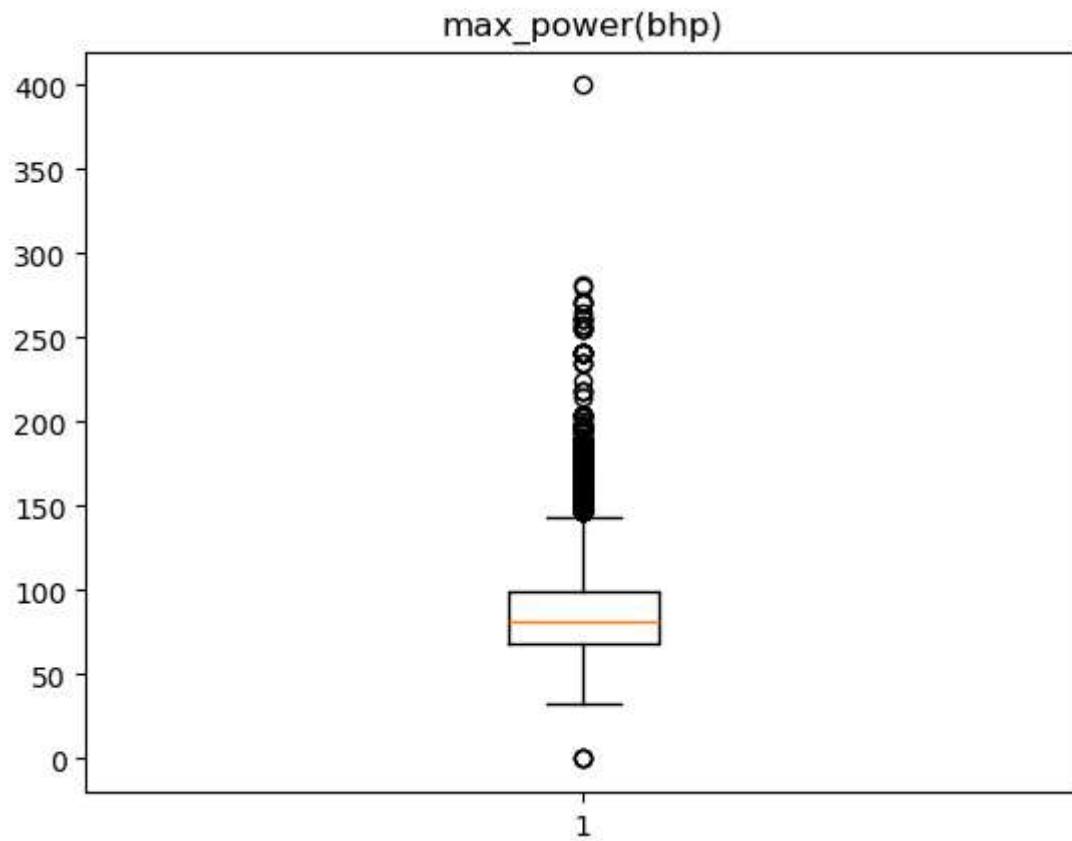
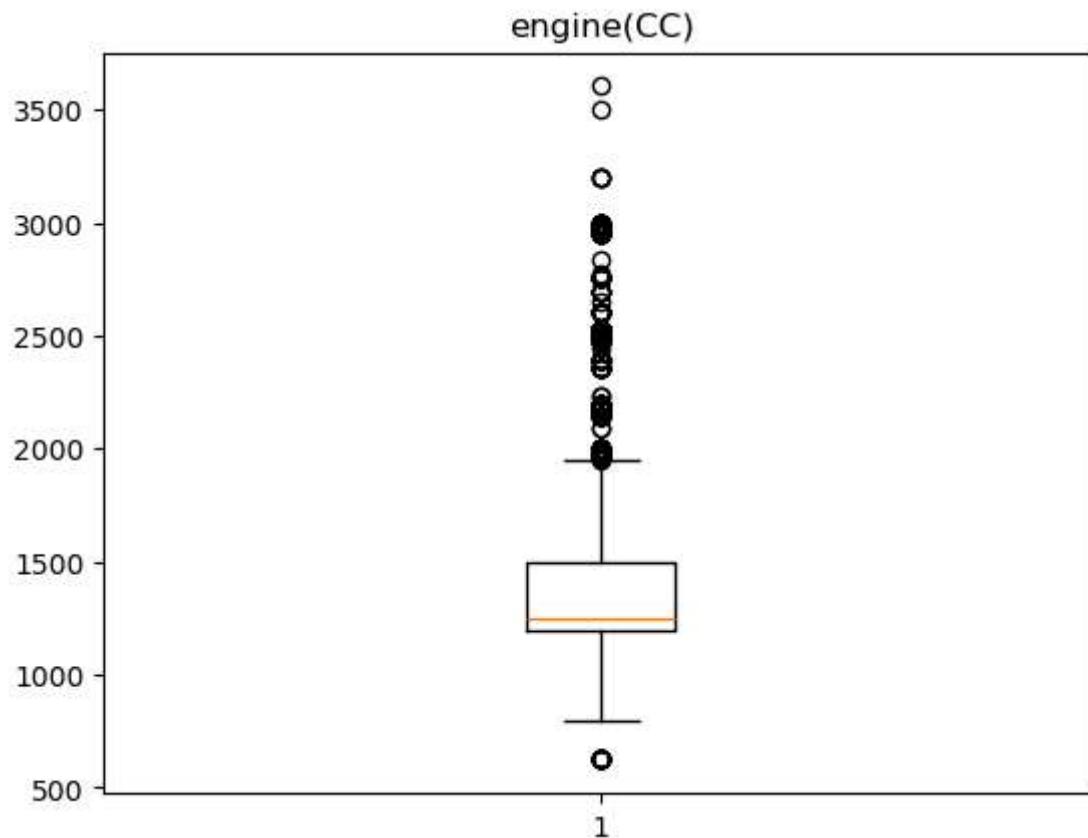
In [47]:

```
for i in num_data:
    plt.boxplot(num_data[i])
```

```
plt.title(i)  
plt.show()
```









```
In [48]: outliers=["year","km_driven","seats","mileage(kmpl)","engine(CC)","max_power(bhp)"]
```

```
In [49]: for i in cars_data:  
    print(cars_data[i].value_counts())  
    print(50*"*")
```

```
name
Maruti Swift Dzire VDI           168
Maruti Alto 800 LXI              92
Maruti Alto LXi                 77
Maruti Swift VDI BSIV            68
Maruti Swift VDI                 66
...
Skoda Rapid 1.6 MPI AT Ambition BSIV    1
Ford Fiesta 1.6 ZXi ABS             1
Honda Jazz 1.5 E i DTEC            1
Mahindra Bolero 2011-2019 DI BSIII   1
Toyota Innova 2.5 GX (Diesel) 8 Seater BS IV  1
Name: count, Length: 2058, dtype: int64
*****
year
2017    882
2016    741
2015    735
2012    660
2018    650
2014    645
2013    594
2011    584
2010    400
2019    365
2009    254
2008    211
2007    184
2006    133
2005    95
2020    65
2004    62
2003    49
2002    26
2000    20
1999    17
1997    11
1998    10
2001     9
1996     3
1994     3
1995     2
1983     1
1991     1
Name: count, dtype: int64
*****
km_driven
120000   565
70000    502
80000    457
60000    436
50000    383
...
87237     1
62960     1
26634     1
```

```
163720      1
191000      1
Name: count, Length: 921, dtype: int64
*****
fuel
Diesel     4025
Petrol     3291
CNG        58
LPG         38
Name: count, dtype: int64
*****
seller_type
Individual    6698
Dealer        687
Trustmark Dealer    27
Name: count, dtype: int64
*****
transmission
Manual       6814
Automatic    598
Name: count, dtype: int64
*****
owner
First Owner   4562
Second Owner  2126
Third Owner   548
Fourth & Above Owner  171
Test Drive Car  5
Name: count, dtype: int64
*****
torque
190Nm@ 2000rpm      556
200Nm@ 1750rpm      426
90Nm@ 3500rpm       371
190Nm@ 2000rpm      217
62Nm@ 3000rpm       180
...
11.4@ 4,000(kgm@ rpm)  1
25.5@ 1,500-3,000(kgm@ rpm)  1
202Nm@ 3600-5200rpm  1
128Nm@ 3100rpm       1
96 Nm at 3000 rpm    1
Name: count, Length: 442, dtype: int64
*****
seats
5.0      5874
7.0      1020
8.0      232
4.0      130
9.0      76
6.0      59
10.0     18
2.0      2
14.0     1
Name: count, dtype: int64
*****
```

```
mileage(kmpl)
19.70      404
18.90      230
18.60      162
21.10      161
17.00      130
...
15.63      1
11.88      1
12.12      1
14.66      1
16.51      1
Name: count, Length: 381, dtype: int64
*****
engine(CC)
1248.0     1235
1197.0     746
796.0      471
998.0      418
1498.0     358
...
1489.0     1
1422.0     1
2496.0     1
3604.0     1
1950.0     1
Name: count, Length: 121, dtype: int64
*****
max_power(bhp)
74.00      601
88.50      207
46.30      178
67.00      172
47.30      155
...
86.79      1
80.80      1
138.08     1
179.50     1
135.10     1
Name: count, Length: 319, dtype: int64
*****
selling_price
300000     226
350000     212
600000     181
400000     177
550000     175
...
801000     1
317000     1
493000     1
236000     1
386000     1
Name: count, Length: 677, dtype: int64
*****
```

```
In [50]: #handling outliers
```

```
Q1=num_data["year"].quantile(0.25)
Q3=num_data["year"].quantile(0.75)
IQR=Q3-Q1
UB=Q3+(1.5*IQR)
LB=Q1-(1.5*IQR)
print(UB)
print(LB)
```

```
2026.0
```

```
2002.0
```

```
In [51]: cars_data.loc[cars_data["year"]>UB]
```

```
Out[51]: name  year  km_driven  fuel  seller_type  transmission  owner  torque  seats  mileage(ki
```



```
In [52]: cars_data.loc[cars_data["year"]<LB]
```

Out[52]:

		name	year	km_driven	fuel	seller_type	transmission	owner	torque	seat
8		Maruti 800 DX BSII	2001	5000	Petrol	Individual	Manual	Second Owner	59Nm@ 2500rpm	4.0
192		Maruti 800 Std	1999	40000	Petrol	Individual	Manual	Second Owner	59Nm@ 2500rpm	4.0
202		Daewoo Matiz SD	2000	60000	Petrol	Individual	Manual	First Owner	71Nm@ 3500rpm	5.0
341		Mahindra Willys CJ 3B 4X4	1983	10000	Diesel	Individual	Manual	Third Owner	190Nm@ 2000rpm	5.0
785		Hyundai Santro GLS I - Euro I	1999	110000	Petrol	Individual	Manual	Second Owner	190Nm@ 2000rpm	5.0
...	...	...	...	...	...	...	...	...	...	.
7259		Maruti Alto LX	2000	90000	Petrol	Individual	Manual	Second Owner	62Nm@ 3000rpm	5.0
7277		Hyundai Santro LS zipPlus	2000	50000	Petrol	Individual	Manual	Second Owner	190Nm@ 2000rpm	5.0
7308		Maruti 800 AC	1998	40000	Petrol	Individual	Manual	Second Owner	59Nm@ 2500rpm	4.0
7325		Maruti Gypsy King Soft Top	1997	186388	Petrol	Individual	Manual	Second Owner	103Nm@ 4500rpm	8.0
7402		Maruti 800 AC	1997	120000	Petrol	Individual	Manual	First Owner	59Nm@ 2500rpm	4.0

77 rows × 13 columns



In [53]: cars\_data.loc[cars\_data["year"] &lt; LB, "year"] = LB

In [54]: cars\_data.loc[cars\_data["year"] &gt; LB]

Out[54]: name year km\_driven fuel seller\_type transmission owner torque seats mileage(km)



In [55]: #handling outliers

Q1=num\_data["km\_driven"].quantile(0.25)

Q3=num\_data["km\_driven"].quantile(0.75)

IQR=Q3-Q1

```
UB=Q3+(1.5*IQR)
LB=Q1-(1.5*IQR)
print(UB)
print(LB)
```

190000.0  
-50000.0

In [56]: cars\_data.loc[cars\_data["km\_driven"]<LB]

Out[56]: name year km\_driven fuel seller\_type transmission owner torque seats mileage(ki



In [57]: cars\_data.loc[cars\_data["km\_driven"]>UB]

Out[57]:

		name	year	km_driven	fuel	seller_type	transmission	owner	torque	...
297		Maruti Swift Dzire ZDi	2012	193000	Diesel	Individual	Manual	First Owner	190Nm@2000rpm	
312		Mahindra Bolero DI DX 7 Seater	2007	207890	Diesel	Individual	Manual	Second Owner	180 Nm at 1440-1500rpm	
418		Toyota Innova 2.5 G1 Diesel 8-seater	2005	240000	Diesel	Individual	Manual	Third Owner	20.4@1400-3400(kgm@ rpm)	
420		Hyundai Verna XXi ABS (Petrol)	2009	214000	Petrol	Individual	Manual	Second Owner	14.9@3,000(kgm@ rpm)	
421		Hyundai Verna CRDi SX	2009	214000	Diesel	Individual	Manual	Second Owner	24@ 1,900-2,750(kgm@ rpm)	
...	...	...	...	...	...	...	...	...	...	...
7316		Hyundai Verna 1.6 SX	2012	200000	Diesel	Individual	Manual	Second Owner	259.8Nm@1900-2750rpm	
7356		Toyota Innova 2.5 V Diesel 7-seater	2010	200000	Diesel	Individual	Manual	Second Owner	20.4@1400-3400(kgm@ rpm)	
7362		Toyota Innova 2.5 E 7 STR	2009	250000	Diesel	Individual	Manual	First Owner	20.4@1400-3400(kgm@ rpm)	
7380		Ford Figo Diesel Titanium	2012	194000	Diesel	Individual	Manual	First Owner	160Nm@2000rpm	
7406		Hyundai Santro Xing GLS	2008	191000	Petrol	Individual	Manual	First Owner	96.1Nm@3000rpm	

171 rows × 13 columns



In [58]: cars\_data.loc[cars\_data["km\_driven"] &gt; UB, "km\_driven"] = UB

```
In [59]: cars_data.loc[cars_data["km_driven"]>UB]
```

```
Out[59]:   name  year  km_driven  fuel  seller_type  transmission  owner  torque  seats  mileage(km)
```



```
In [67]: #handling outliers
```

```
Q1=num_data["mileage(kmpl)"].quantile(0.25)
Q3=num_data["mileage(kmpl)"].quantile(0.75)
IQR=Q3-Q1
UB=Q3+(1.5*IQR)
LB=Q1-(1.5*IQR)
print(UB)
print(LB)
```

30.849999999999998

8.690000000000001

```
In [68]: cars_data.loc[cars_data["mileage(kmpl)"]>UB]
```

```
Out[68]:   name  year  km_driven  fuel  seller_type  transmission  owner  torque  seats  mileage(km)
```

39	Maruti Alto 800 CNG LXI Optional	2019	10000	CNG	Individual	Manual	Second Owner	60Nm@3500rpm	4.
183	Volvo XC90 T8 Excellence BSIV	2017	30000	Petrol	Individual	Automatic	First Owner	640Nm@1740rpm	4.
2277	Maruti Wagon R CNG LXI	2013	80000	CNG	Individual	Manual	Second Owner	78Nm@3500rpm	5.
3765	Maruti Alto 800 CNG LXI	2017	67000	CNG	Individual	Manual	First Owner	60Nm@3500rpm	4.
5379	Maruti Alto K10 LXI CNG	2019	20000	CNG	Individual	Manual	First Owner	78Nm@3500rpm	4.
5408	Maruti Alto 800 LXI CNG	2020	16000	CNG	Individual	Manual	First Owner	69Nm@3500rpm	5.



```
In [69]: cars_data.loc[cars_data["mileage(kmpl)"]>UB,"mileage(kmpl)"]=UB
```

```
In [70]: cars_data.loc[cars_data["mileage(kmpl)"]>UB]
```

```
Out[70]:    name  year  km_driven  fuel  seller_type  transmission  owner  torque  seats  mileage(km)
```



```
In [71]: cars_data.loc[cars_data["mileage(kmp1)"] < LB]
```

Out[71]:

		<b>name</b>	<b>year</b>	<b>km_driven</b>	<b>fuel</b>	<b>seller_type</b>	<b>transmission</b>	<b>owner</b>	<b>torque</b>
669		Tata Indica Vista Aura Safire Anniversary Edition	2009	28900	Petrol	Individual	Manual	Second Owner	9.8@ 3,000(kgm@ rpm)
797		Hyundai Santro Xing GL	2009	90000	Petrol	Individual	Manual	Second Owner	96.1Nm@ 3000rpm
1624		Hyundai Santro Xing GL	2008	128000	Petrol	Individual	Manual	First Owner	96.1Nm@ 3000rpm
1652		Mercedes-Benz M-Class ML 350 4Matic	2011	110000	Diesel	Individual	Automatic	Third Owner	510@ 1600-2400
2091		Land Rover Freelander 2 TD4 HSE	2013	64788	Diesel	Dealer	Automatic	First Owner	400 Nm /2000 rpm
2327		Hyundai Santro Xing (Non-AC)	2010	80000	Petrol	Individual	Manual	Second Owner	96.1Nm@ 3000rpm
2674		Hyundai Santro Xing (Non-AC)	2013	15000	Petrol	Individual	Manual	First Owner	96.1Nm@ 3000rpm
4882		Hyundai Santro Xing GL	2008	40000	Petrol	Individual	Manual	First Owner	96.1Nm@ 3000rpm
5442		Volkswagen Polo GT TSI BSIV	2014	28080	Petrol	Dealer	Automatic	First Owner	175nm@ 1500-4100rpm
5445		Volkswagen Polo GT TSI BSIV	2014	28100	Petrol	Dealer	Automatic	First Owner	175nm@ 1500-4100rpm
5499		Mahindra Bolero Pik-Up FB 1.7T	2020	5000	Diesel	Individual	Manual	First Owner	200Nm@ 1400-2200rpm
6049		Hyundai Santro Xing GL	2010	110000	Petrol	Individual	Manual	First Owner	96.1Nm@ 3000rpm
6106		Mahindra Bolero Pik-Up CBC 1.7T	2019	80000	Diesel	Individual	Manual	First Owner	200Nm@ 1400-2200rpm

		name	year	km_driven	fuel	seller_type	transmission	owner	torque
6292		Hyundai Santro Xing GL	2011	40000	Petrol	Individual	Manual	Fourth & Above Owner	96.1Nm@ 3000rpm
6778		Mercedes-Benz GLC 220d 4MATIC	2017	60000	Diesel	Dealer	Automatic	First Owner	400nm@ 2800rpm

In [72]: `cars_data.loc[cars_data["mileage(kmpl)"]<LB,"mileage(kmpl)"]=LB`

In [73]: `cars_data.loc[cars_data["mileage(kmpl)"]>UB]`

Out[73]: `name year km_driven fuel seller_type transmission owner torque seats mileage(km`



In [74]: `#handling outliers`

```
Q1=num_data["max_power(bhp)"].quantile(0.25)
Q3=num_data["max_power(bhp)"].quantile(0.75)
IQR=Q3-Q1
UB=Q3+(1.5*IQR)
LB=Q1-(1.5*IQR)
print(UB)
print(LB)
```

145.39999999999998

21.56000000000001

In [75]: `cars_data.loc[cars_data["max_power(bhp)"]>UB]`

Out[75]:

		name	year	km_driven	fuel	seller_type	transmission	owner	torque	seats
45	Jeep Compass 1.4 Limited Plus BSIV	2019	5000	Petrol	Individual	Automatic	First Owner	250Nm@ 1750-2500rpm		
51	Toyota Fortuner 4x4 MT	2014	77000	Diesel	Dealer	Manual	First Owner	343Nm@ 1400-3400rpm		
55	Mitsubishi Pajero Sport 4X4	2013	151000	Diesel	Dealer	Manual	First Owner	400Nm@ 2000-2500rpm		
59	Toyota Innova Crysta 2.8 ZX AT BSIV	2016	127700	Diesel	Dealer	Automatic	Second Owner	360Nm@ 1200-3400rpm		
61	Audi A6 2.0 TDI Technology	2013	33900	Diesel	Dealer	Automatic	Second Owner	380Nm@ 1750-2500rpm		
...										
7335	Honda CR-V 2.4L 4WD AT	2012	50171	Petrol	Dealer	Automatic	First Owner	218Nm@ 4200rpm		
7340	Honda Accord 2.4 A/T	2013	50000	Petrol	Dealer	Automatic	First Owner	222Nm@ 4300rpm		
7341	Audi A3 40 TFSI Premium	2017	8000	Petrol	Dealer	Automatic	First Owner	250Nm@ 1250-5000rpm		
7368	Chevrolet Captiva LT	2008	100000	Diesel	Individual	Manual	Second Owner	320Nm@ 2000rpm		
7370	Chevrolet Cruze LT	2011	40000	Diesel	Individual	Manual	First Owner	327Nm@ 2600rpm		

377 rows × 13 columns



In [76]: cars\_data.loc[cars\_data["max\_power(bhp)"] &gt; UB, "max\_power(bhp)"] = UB

In [77]: cars\_data.loc[cars\_data["max\_power(bhp)"] &gt; UB]

Out[77]: name year km\_driven fuel seller\_type transmission owner torque seats mileage(km)



In [78]: cars\_data.loc[cars\_data["max\_power(bhp)"]<LB]

Out[78]:

		name	year	km_driven	fuel	seller_type	transmission	owner	torque	seats
597		Maruti Alto K10 LXI	2011	97500	Petrol	Individual	Manual	First Owner	190Nm@ 2000rpm	5.0
1408		Maruti Swift Dzire VDI Optional	2017	41232	Diesel	Dealer	Manual	First Owner	190Nm@ 2000rpm	5.0
2523		Tata Indica Vista Quadrajet LS	2012	70000	Diesel	Individual	Manual	First Owner	190Nm@ 2000rpm	5.0



In [79]: cars\_data.loc[cars\_data["max\_power(bhp)"]<LB,"max\_power(bhp)"]=LB

In [80]: cars\_data.loc[cars\_data["max\_power(bhp)"]<LB]

Out[80]:

	name	year	km_driven	fuel	seller_type	transmission	owner	torque	seats	mileage(km)
597	Maruti Alto K10 LXI	2011	97500	Petrol	Individual	Manual	First Owner	190Nm@ 2000rpm	5.0	1949.5
1408	Maruti Swift Dzire VDI Optional	2017	41232	Diesel	Dealer	Manual	First Owner	190Nm@ 2000rpm	5.0	745.5



In [81]: #handling outliers

```
Q1=num_data["engine(CC)"].quantile(0.25)
Q3=num_data["engine(CC)"].quantile(0.75)
IQR=Q3-Q1
UB=Q3+(1.5*IQR)
LB=Q1-(1.5*IQR)
print(UB)
print(LB)
```

1949.5

745.5

In [82]: cars\_data.loc[cars\_data["engine(CC)"]>UB]

Out[82]:

		name	year	km_driven	fuel	seller_type	transmission	owner	torque	s
43	Tata Safari DICOR 2.2 LX 4x2	2011	60000	Diesel	Individual	Manual	Second Owner	320Nm@ 1700-2700rpm		
51	Toyota Fortuner 4x4 MT	2014	77000	Diesel	Dealer	Manual	First Owner	343Nm@ 1400-3400rpm		
52	Toyota Innova 2.5 G (Diesel) 7 Seater BS IV	2013	99000	Diesel	Dealer	Manual	First Owner	200Nm@ 1400-3400rpm		
53	Mercedes-Benz B Class B180	2014	27800	Diesel	Dealer	Automatic	Second Owner	200Nm@ 1250-4000rpm		
55	Mitsubishi Pajero Sport 4X4	2013	151000	Diesel	Dealer	Manual	First Owner	400Nm@ 2000-2500rpm		
...	...	...	...	...	...	...	...	...	...	...
7365	Tata New Safari DICOR 2.2 EX 4x2	2010	100000	Diesel	Individual	Manual	First Owner	320Nm@ 1700-2700rpm		
7368	Chevrolet Captiva LT	2008	100000	Diesel	Individual	Manual	Second Owner	320Nm@ 2000rpm		
7370	Chevrolet Cruze LT	2011	40000	Diesel	Individual	Manual	First Owner	327Nm@ 2600rpm		
7384	Mahindra XUV500 W8 2WD	2013	120000	Diesel	Individual	Manual	First Owner	330Nm@ 1600-2800rpm		
7400	Toyota Innova 2.5 GX (Diesel) 8 Seater BS IV	2010	129000	Diesel	Individual	Manual	First Owner	20.4@ 1400-3400(kgm@ rpm)		

1232 rows × 13 columns



In [83]: cars\_data.loc[cars\_data["engine(CC)"] &gt; UB, "engine(CC)"] = UB

In [84]: cars\_data.loc[cars\_data["engine(CC)"] &gt; UB]

```
Out[84]:    name  year  km_driven  fuel  seller_type  transmission  owner  torque  seats  mileage(ki
```



```
In [85]: cars_data.loc[cars_data["engine(CC)"]<LB]
```

Out[85]:

		<b>name</b>	<b>year</b>	<b>km_driven</b>	<b>fuel</b>	<b>seller_type</b>	<b>transmission</b>	<b>owner</b>	<b>torque</b>
389		Tata Nano STD	2012	18000	Petrol	Dealer	Manual	First Owner	51Nm@ 4000rpm
716		Tata Nano Cx	2011	10000	Petrol	Individual	Manual	Third Owner	48Nm@ 3000rpm
1176		Tata Nano CX	2013	30000	Petrol	Individual	Manual	First Owner	51Nm@ 4000+/-500rpm
1177		Tata Nano CX	2013	30000	Petrol	Individual	Manual	First Owner	51Nm@ 4000+/-500rpm
1227		Tata Nano Cx BSIV	2010	50000	Petrol	Individual	Manual	Third Owner	48@ 3,000+/-500(NM@ rpm)
1391		Tata Nano XTA	2015	20000	Petrol	Individual	Automatic	First Owner	51Nm@ 4000rpm
2226		Tata Nano CX	2013	30000	Petrol	Individual	Manual	First Owner	51Nm@ 4000+/-500rpm
2227		Tata Nano CX	2013	30000	Petrol	Individual	Manual	First Owner	51Nm@ 4000+/-500rpm
2386		Tata Nano LX	2015	60000	Petrol	Individual	Manual	First Owner	51Nm@ 4000+/-500rpm
2419		Tata Nano Lx BSIV	2010	26432	Petrol	Dealer	Manual	First Owner	51Nm@ 4000+/-500rpm
2720		Tata Nano Cx	2009	15000	Petrol	Individual	Manual	First Owner	48Nm@ 3000rpm
2802		Tata Nano Twist XT	2015	25000	Petrol	Individual	Manual	First Owner	51Nm@ 4000+/-500rpm
3576		Tata Nano XE	2017	70000	Petrol	Individual	Manual	Third Owner	51Nm@ 4000rpm

	<b>name</b>	<b>year</b>	<b>km_driven</b>	<b>fuel</b>	<b>seller_type</b>	<b>transmission</b>	<b>owner</b>	<b>torque</b>
3796	Tata Nano Cx BSIII	2012	40000	Petrol	Individual	Manual	Second Owner	51Nm@ 4000+/-500rpm
4116	Tata Nano XTA	2018	55000	Petrol	Dealer	Automatic	First Owner	51Nm@ 4000rpm
4240	Tata Nano XE	2015	60000	Petrol	Individual	Manual	First Owner	51Nm@ 4000rpm
4535	Tata Nano XTA	2016	22000	Petrol	Individual	Automatic	First Owner	51Nm@ 4000rpm
4835	Tata Nano Cx BSIII	2012	45000	Petrol	Individual	Manual	First Owner	51Nm@ 4000+/-500rpm
5286	Tata Nano Twist XE	2015	15000	Petrol	Individual	Manual	First Owner	51Nm@ 4000+/-500rpm
5476	Tata Nano Lx	2011	40000	Petrol	Individual	Manual	First Owner	4.8kgm@ 3000rpm
6047	Tata Nano Twist XT	2014	50000	Petrol	Individual	Manual	Second Owner	51Nm@ 4000+/-500rpm
6198	Tata Nano Lx BSIV	2010	30400	Petrol	Individual	Manual	Fourth & Above Owner	48@ 3,000+/-500(NM@ rpm)
6285	Tata Nano Lx BSIV	2012	90000	Petrol	Individual	Manual	First Owner	51Nm@ 4000+/-500rpm
6996	Tata Nano Lx BSIV	2012	50000	Petrol	Individual	Manual	Second Owner	51Nm@ 4000+/-500rpm
7004	Tata Nano Cx	2011	80000	Petrol	Individual	Manual	First Owner	48Nm@ 3000rpm

		<b>name</b>	<b>year</b>	<b>km_driven</b>	<b>fuel</b>	<b>seller_type</b>	<b>transmission</b>	<b>owner</b>	<b>torque</b>
<b>7167</b>	Tata Nano LX SE	2012	28000	Petrol	Individual		Manual	Second Owner	51Nm@ 4000+/-500rpm
<b>7374</b>	Tata Cx	2011	25000	Petrol	Individual		Manual	Second Owner	48Nm@ 3000rpm

In [86]: `cars_data.loc[cars_data["engine(CC)"]<LB,"engine(CC)"]=LB`

In [87]: `cars_data.loc[cars_data["engine(CC)"]<LB]`

Out[87]: `name year km_driven fuel seller_type transmission owner torque seats mileage(km)`

◀ ▶

In [92]: `cars_data["transmission"]=cars_data["transmission"].map({"Manual":1,"Automatic":0})`

In [93]: `cars_data["transmission"].value_counts()`

Out[93]: `transmission`  
 1 6814  
 0 598  
 Name: count, dtype: int64

In [94]: `cars_data=pd.get_dummies(cars_data,columns=["fuel"])`

In [95]: `cars_data[["fuel_CNG","fuel_Diesel","fuel_LPG","fuel_Petrol"]]=cars_data[["fuel_CNG`

In [96]: `cars_data`

Out[96]:

	<b>name</b>	<b>year</b>	<b>km_driven</b>	<b>seller_type</b>	<b>transmission</b>	<b>owner</b>	<b>torque</b>	<b>seats</b>	<b>m</b>
<b>0</b>	Maruti Swift Dzire VDI	2014	145500	Individual		1 First Owner	190Nm@ 2000rpm	5.0	
<b>1</b>	Skoda Rapid 1.5 TDI Ambition	2014	120000	Individual		1 Second Owner	250Nm@ 1500- 2500rpm	5.0	
<b>2</b>	Honda City 2017- 2020 EXi	2006	140000	Individual		1 Third Owner	12.7@ 2,700(kgm@ rpm)	5.0	
<b>3</b>	Honda City 2017- 2020 EXi	2006	140000	Individual		1 Third Owner	12.7@ 2,700(kgm@ rpm)	5.0	
<b>4</b>	Hyundai i20 Sportz Diesel	2010	127000	Individual		1 First Owner	22.4 kgm at 1750- 2750rpm	5.0	
...	...	...	...	...		...	...	...	...
<b>7407</b>	Maruti Wagon R VXI BS IV with ABS	2013	50000	Individual		1 Second Owner	90Nm@ 3500rpm	5.0	
<b>7408</b>	Hyundai i20 Magna 1.4 CRDi	2014	80000	Individual		1 Second Owner	219.7Nm@ 1500- 2750rpm	5.0	
<b>7409</b>	Hyundai i20 Magna	2013	110000	Individual		1 First Owner	113.7Nm@ 4000rpm	5.0	
<b>7410</b>	Hyundai Verna CRDi SX	2007	119000	Individual		1 Fourth & Above Owner	24@ 1,900- 2,750(kgm@ rpm)	5.0	
<b>7411</b>	Maruti Swift Dzire ZDi	2009	120000	Individual		1 First Owner	190Nm@ 2000rpm	5.0	

7412 rows × 16 columns



In [97]: cars\_data

Out[97]:

		name	year	km_driven	seller_type	transmission	owner	torque	seats	m
0		Maruti Swift Dzire VDI	2014	145500	Individual		1	First Owner	190Nm@ 2000rpm	5.0
1		Skoda Rapid 1.5 TDI Ambition	2014	120000	Individual		1	Second Owner	250Nm@ 1500- 2500rpm	5.0
2		Honda City 2017- 2020 EXi	2006	140000	Individual		1	Third Owner	12.7@ 2,700(kgm@ rpm)	5.0
3		Honda City 2017- 2020 EXi	2006	140000	Individual		1	Third Owner	12.7@ 2,700(kgm@ rpm)	5.0
4		Hyundai i20 Sportz Diesel	2010	127000	Individual		1	First Owner	22.4 kgm at 1750- 2750rpm	5.0
...	...	...	...	...	...		...	...	...	...
7407		Maruti Wagon R VXI BS IV with ABS	2013	50000	Individual		1	Second Owner	90Nm@ 3500rpm	5.0
7408		Hyundai i20 Magna 1.4 CRDi	2014	80000	Individual		1	Second Owner	219.7Nm@ 1500- 2750rpm	5.0
7409		Hyundai i20 Magna	2013	110000	Individual		1	First Owner	113.7Nm@ 4000rpm	5.0
7410		Hyundai Verna CRDi SX	2007	119000	Individual		1	Fourth & Above Owner	24@ 1,900- 2,750(kgm@ rpm)	5.0
7411		Maruti Swift Dzire ZDi	2009	120000	Individual		1	First Owner	190Nm@ 2000rpm	5.0

7412 rows × 16 columns



In [98]: cars\_data=pd.get\_dummies(cars\_data,columns=["seller\_type"])

```
In [99]: cars_data[["seller_type_Dealer","seller_type_Individual","seller_type_Trustmark Dea
```

```
In [100... cars_data
```

Out[100...]

		name	year	km_driven	transmission	owner	torque	seats	mileage(kmpl)
0		Maruti Swift Dzire VDI	2014	145500		1 First Owner	190Nm@ 2000rpm	5.0	23.40
1		Skoda Rapid 1.5 TDI Ambition	2014	120000		1 Second Owner	250Nm@ 1500- 2500rpm	5.0	21.14
2		Honda City 2017- 2020 EXi	2006	140000		1 Third Owner	12.7@ 2,700(kgm@ rpm)	5.0	17.70
3		Honda City 2017- 2020 EXi	2006	140000		1 Third Owner	12.7@ 2,700(kgm@ rpm)	5.0	17.70
4		Hyundai i20 Sportz Diesel	2010	127000		1 First Owner	22.4 kgm at 1750- 2750rpm	5.0	23.00
...	...	...	...	...	...	...	...	...	...
7407		Maruti Wagon R VXI BS IV with ABS	2013	50000		1 Second Owner	90Nm@ 3500rpm	5.0	18.90
7408		Hyundai i20 Magna 1.4 CRDi	2014	80000		1 Second Owner	219.7Nm@ 1500- 2750rpm	5.0	22.54
7409		Hyundai i20 Magna	2013	110000		1 First Owner	113.7Nm@ 4000rpm	5.0	18.50
7410		Hyundai Verna CRDi SX	2007	119000		1 Fourth & Above Owner	24@ 1,900- 2,750(kgm@ rpm)	5.0	16.80
7411		Maruti Swift Dzire ZDi	2009	120000		1 First Owner	190Nm@ 2000rpm	5.0	19.30

7412 rows × 18 columns



```
In [101... cars_data=pd.get_dummies(cars_data,columns=[ "owner"])
```

```
In [102... cars_data[["owner_First Owner","owner_Fourth & Above Owner","owner_Second Owner","o
```

```
In [103... cars_data
```

Out[103...]

		name	year	km_driven	transmission	torque	seats	mileage(kmpl)	engine
0		Maruti Swift Dzire VDI	2014	145500	1	190Nm@ 2000rpm	5.0	23.40	12
1		Skoda Rapid 1.5 TDI Ambition	2014	120000	1	250Nm@ 1500- 2500rpm	5.0	21.14	14
2		Honda City 2017- 2020 EXi	2006	140000	1	12.7@ 2,700(kgm@ rpm)	5.0	17.70	14
3		Honda City 2017- 2020 EXi	2006	140000	1	12.7@ 2,700(kgm@ rpm)	5.0	17.70	14
4		Hyundai i20 Sportz Diesel	2010	127000	1	22.4 kgm at 1750- 2750rpm	5.0	23.00	13
...	...	...	...	...	...	...	...	...	...
7407		Maruti Wagon R VXI BS IV with ABS	2013	50000	1	90Nm@ 3500rpm	5.0	18.90	9
7408		Hyundai i20 Magna 1.4 CRDi	2014	80000	1	219.7Nm@ 1500- 2750rpm	5.0	22.54	13
7409		Hyundai i20 Magna	2013	110000	1	113.7Nm@ 4000rpm	5.0	18.50	11
7410		Hyundai Verna CRDi SX	2007	119000	1	24@ 1,900- 2,750(kgm@ rpm)	5.0	16.80	14
7411		Maruti Swift Dzire ZDi	2009	120000	1	190Nm@ 2000rpm	5.0	19.30	12

7412 rows × 22 columns



```
In [104... cars_data.drop(["fuel_CNG","seller_type_Trustmark Dealer","owner_First Owner"],axis=1)
```

```
In [105... cars_data.value_counts().sum()
```

```
Out[105... 7412
```

```
In [106... cars_data
```

Out[106...]

		name	year	km_driven	transmission	torque	seats	mileage(kmpl)	engine
0		Maruti Swift Dzire VDI	2014	145500	1	190Nm@ 2000rpm	5.0	23.40	12
1		Skoda Rapid 1.5 TDI Ambition	2014	120000	1	250Nm@ 1500- 2500rpm	5.0	21.14	14
2		Honda City 2017- 2020 EXi	2006	140000	1	12.7@ 2,700(kgm@ rpm)	5.0	17.70	14
3		Honda City 2017- 2020 EXi	2006	140000	1	12.7@ 2,700(kgm@ rpm)	5.0	17.70	14
4		Hyundai i20 Sportz Diesel	2010	127000	1	22.4 kgm at 1750- 2750rpm	5.0	23.00	13
...	...	...	...	...	...	...	...	...	...
7407		Maruti Wagon R VXI BS IV with ABS	2013	50000	1	90Nm@ 3500rpm	5.0	18.90	9
7408		Hyundai i20 Magna 1.4 CRDi	2014	80000	1	219.7Nm@ 1500- 2750rpm	5.0	22.54	13
7409		Hyundai i20 Magna	2013	110000	1	113.7Nm@ 4000rpm	5.0	18.50	11
7410		Hyundai Verna CRDi SX	2007	119000	1	24@ 1,900- 2,750(kgm@ rpm)	5.0	16.80	14
7411		Maruti Swift Dzire ZDi	2009	120000	1	190Nm@ 2000rpm	5.0	19.30	12

7412 rows × 19 columns



```
In [107... cars=cars_data.drop("name",axis=1)
```

```
In [108... cars_df=cars.drop("torque",axis=1)
```

```
In [109... cars_df
```

```
Out[109...
```

	year	km_driven	transmission	seats	mileage(kmpl)	engine(CC)	max_power(bhp)
--	------	-----------	--------------	-------	---------------	------------	----------------

<b>0</b>	2014	145500		1	5.0	23.40	1248.0	74.00
<b>1</b>	2014	120000		1	5.0	21.14	1498.0	103.52
<b>2</b>	2006	140000		1	5.0	17.70	1497.0	78.00
<b>3</b>	2006	140000		1	5.0	17.70	1497.0	78.00
<b>4</b>	2010	127000		1	5.0	23.00	1396.0	90.00
...	...	...		...	...	...	...	...
<b>7407</b>	2013	50000		1	5.0	18.90	998.0	67.10
<b>7408</b>	2014	80000		1	5.0	22.54	1396.0	88.73
<b>7409</b>	2013	110000		1	5.0	18.50	1197.0	82.85
<b>7410</b>	2007	119000		1	5.0	16.80	1493.0	110.00
<b>7411</b>	2009	120000		1	5.0	19.30	1248.0	73.90

7412 rows × 17 columns



```
In [110... cars_df.corr()
```

Out[110...]

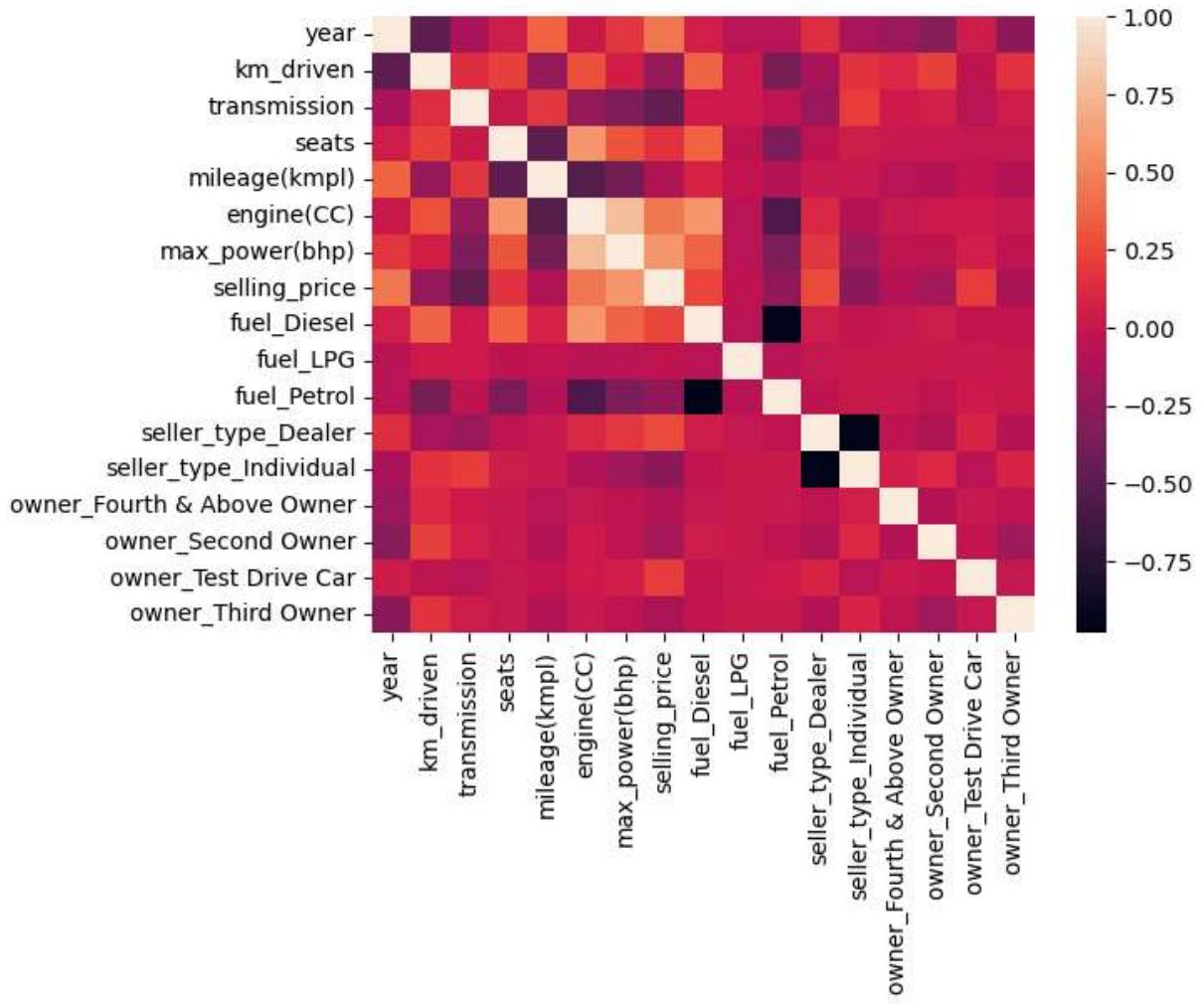
	year	km_driven	transmission	seats	mileage(kmpl)	engine(CC)
<b>year</b>	1.000000	-0.491126	-0.141002	0.040739	0.351974	0.01
<b>km_driven</b>	-0.491126	1.000000	0.147025	0.227081	-0.226650	0.28
<b>transmission</b>	-0.141002	0.147025	1.000000	0.017018	0.177826	-0.21
<b>seats</b>	0.040739	0.227081	0.017018	1.000000	-0.472994	0.58
<b>mileage(kmpl)</b>	0.351974	-0.226650	0.177826	-0.472994	1.000000	-0.53
<b>engine(CC)</b>	0.012544	0.289517	-0.216039	0.583609	-0.536935	1.00
<b>max_power(bhp)</b>	0.178667	0.065085	-0.351034	0.308126	-0.387527	0.77
<b>selling_price</b>	0.439045	-0.217106	-0.461970	0.166751	-0.118252	0.44
<b>fuel_Diesel</b>	0.061161	0.359095	0.020622	0.352886	0.080548	0.58
<b>fuel_LPG</b>	-0.064399	0.023961	0.021266	-0.030833	-0.017087	-0.06
<b>fuel_Petrol</b>	-0.056323	-0.361894	-0.028398	-0.343170	-0.094442	-0.56
<b>seller_type_Dealer</b>	0.140861	-0.146448	-0.209389	-0.029897	-0.003708	0.09
<b>seller_type_Individual</b>	-0.147784	0.154167	0.218938	0.033737	0.005862	-0.09
<b>owner_Fourth &amp; Above Owner</b>	-0.208398	0.112121	0.029026	0.002203	-0.081258	-0.00
<b>owner_Second Owner</b>	-0.299049	0.233386	0.058627	0.003015	-0.102291	0.02
<b>owner_Test Drive Car</b>	0.036673	-0.034635	-0.068623	-0.011159	-0.017855	0.02
<b>owner_Third Owner</b>	-0.271993	0.169863	0.040161	-0.009856	-0.104961	0.00



In [111...]

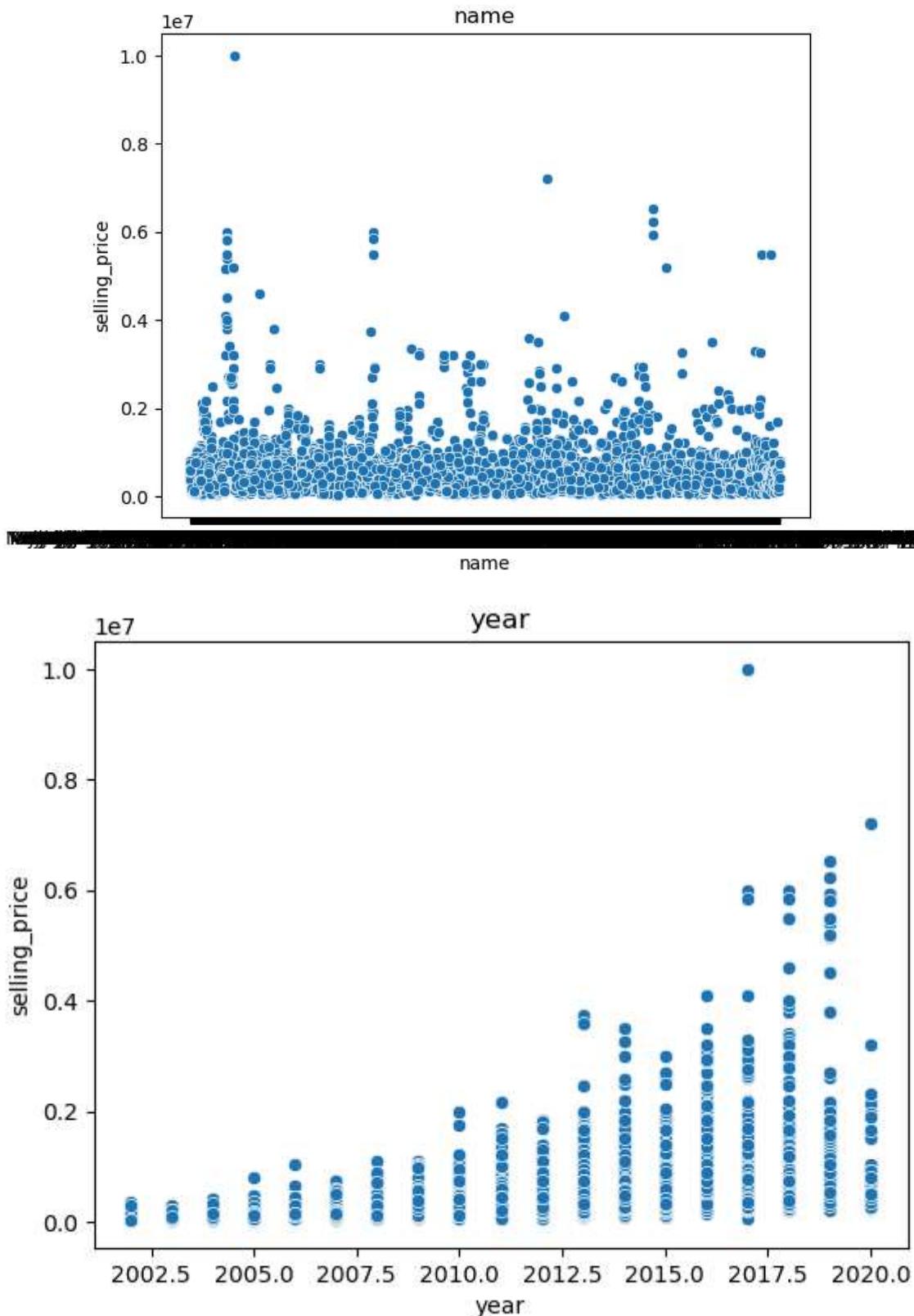
sns.heatmap(cars\_df.corr())

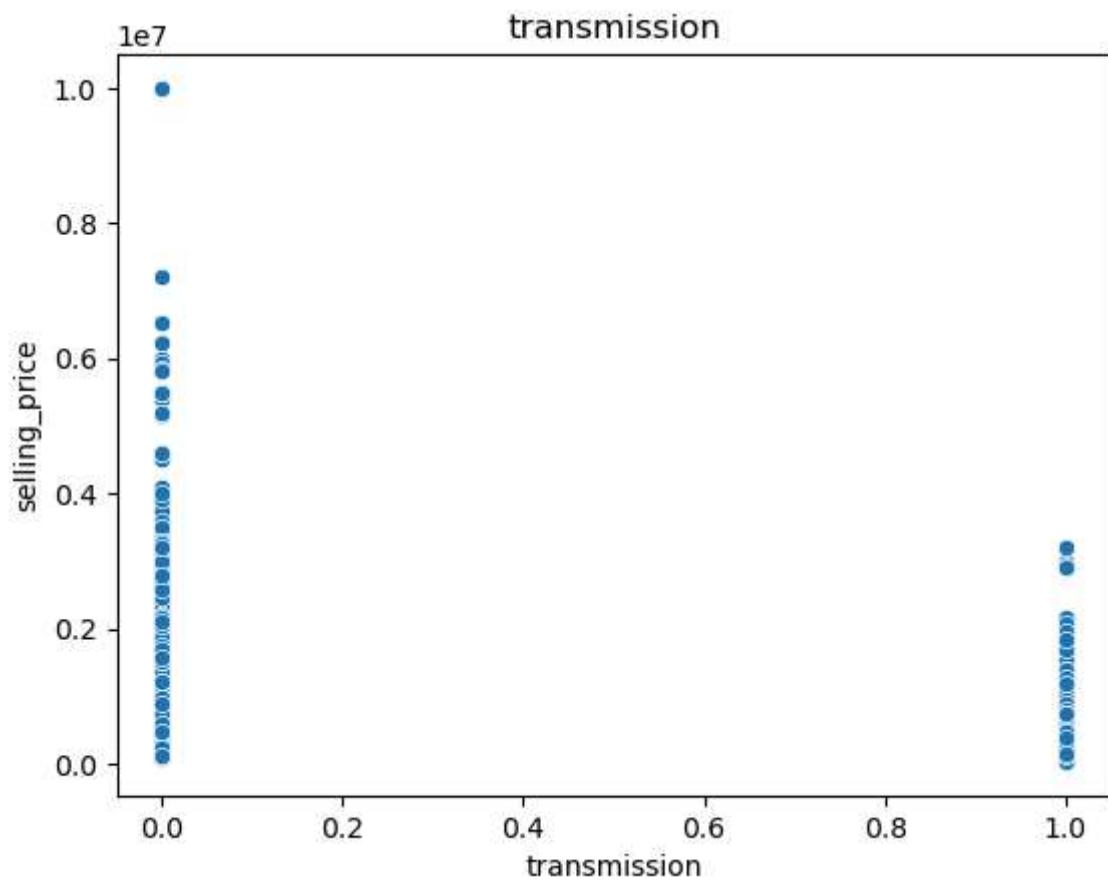
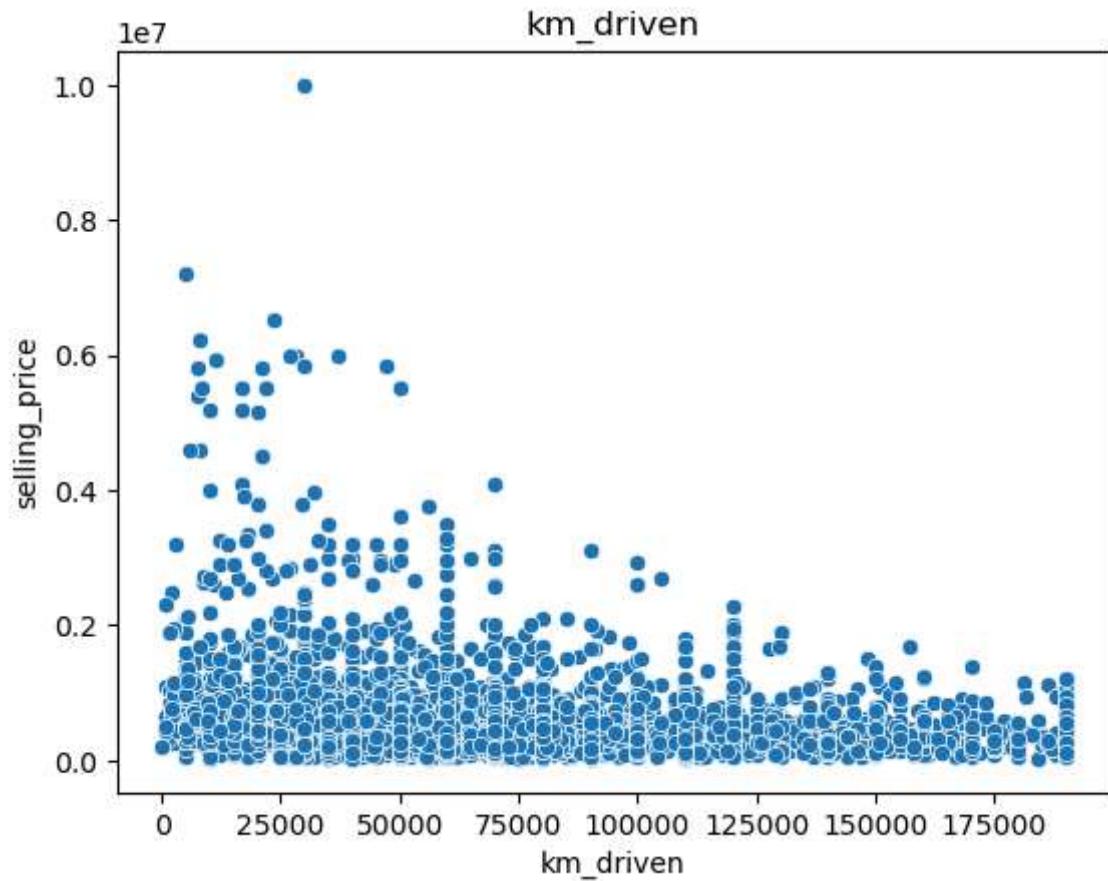
Out[111...]: &lt;Axes: &gt;

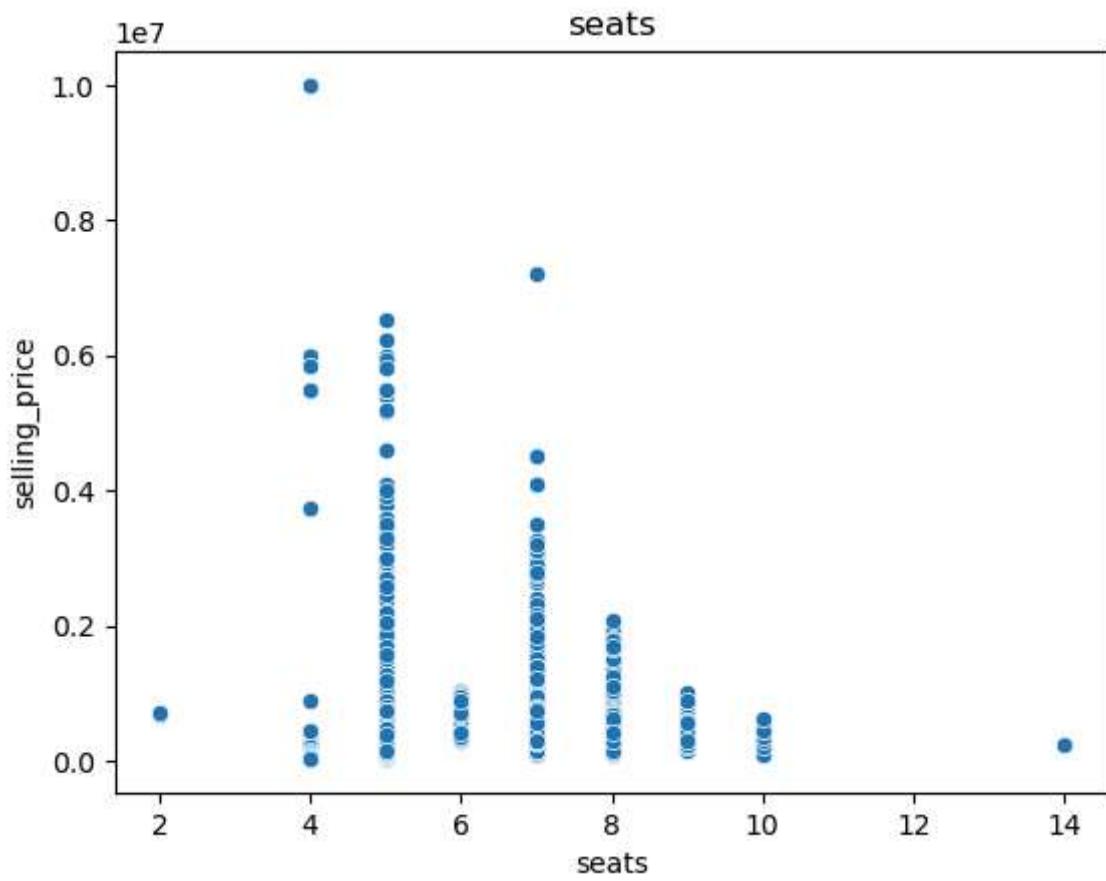
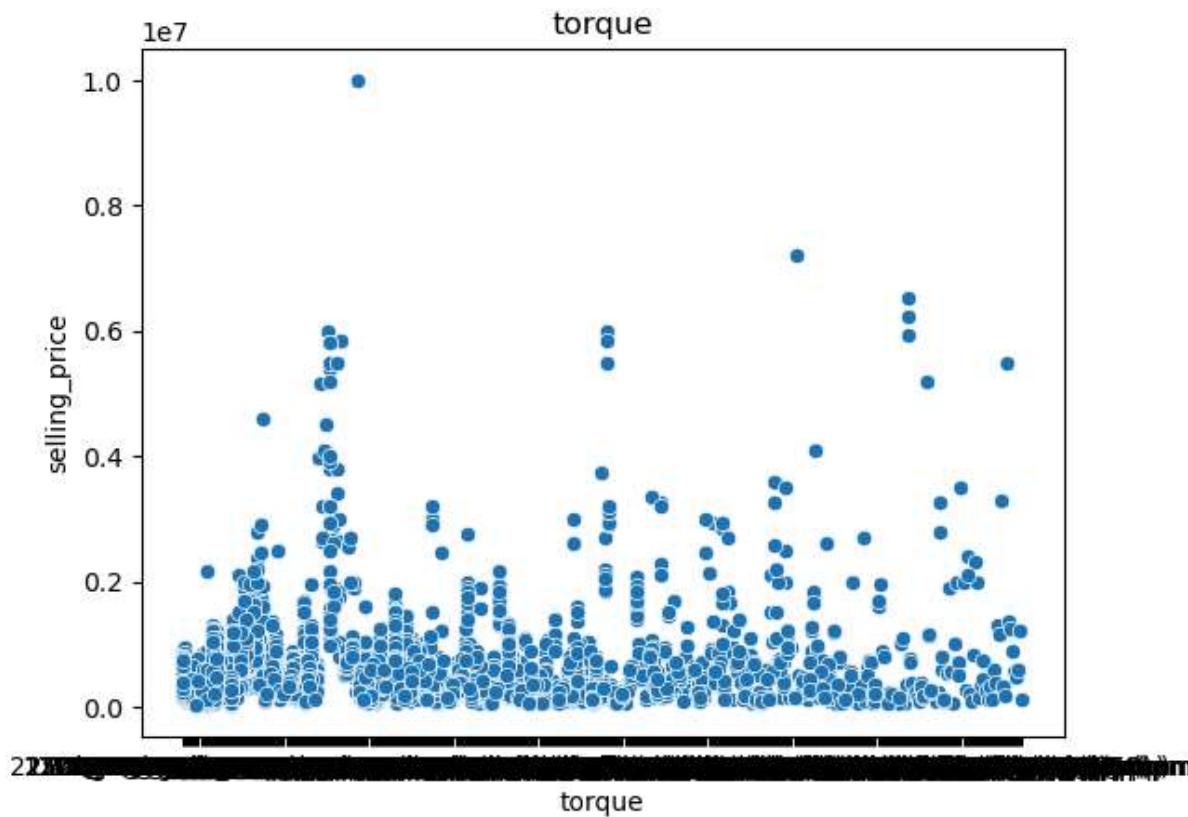


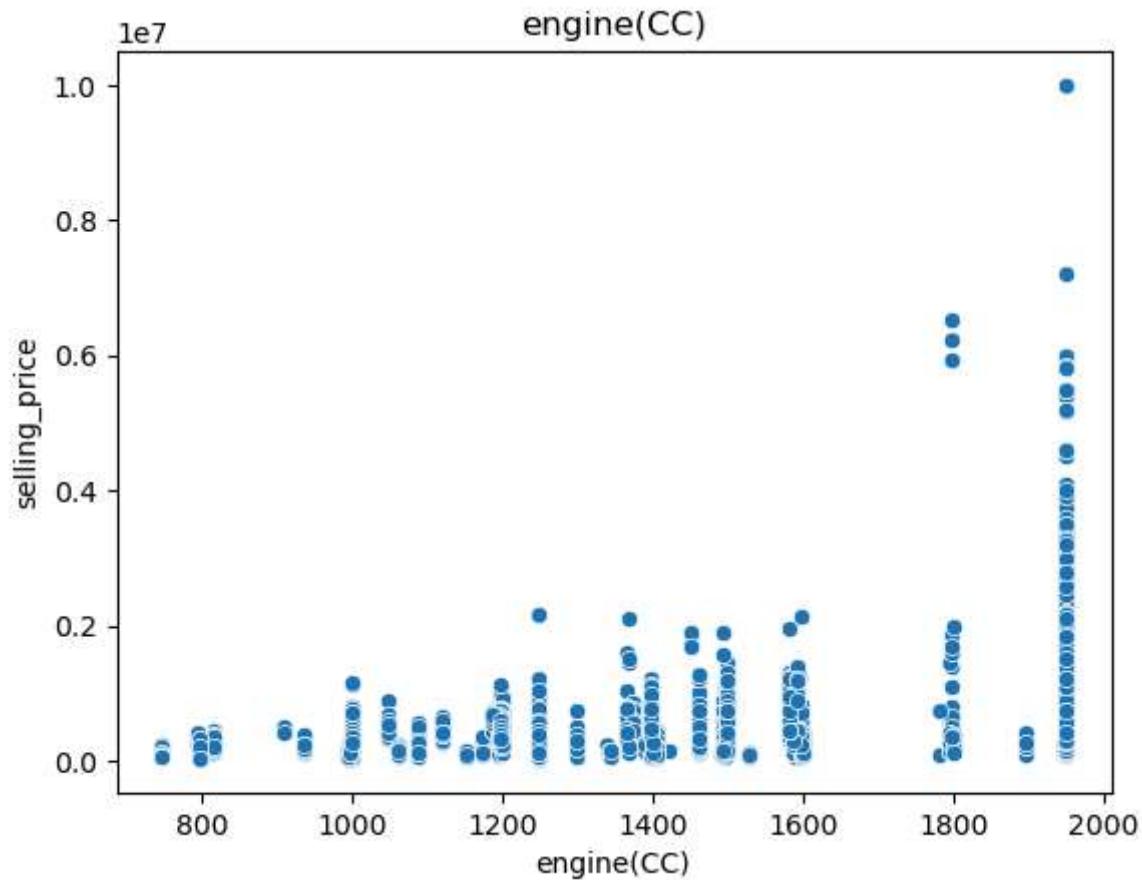
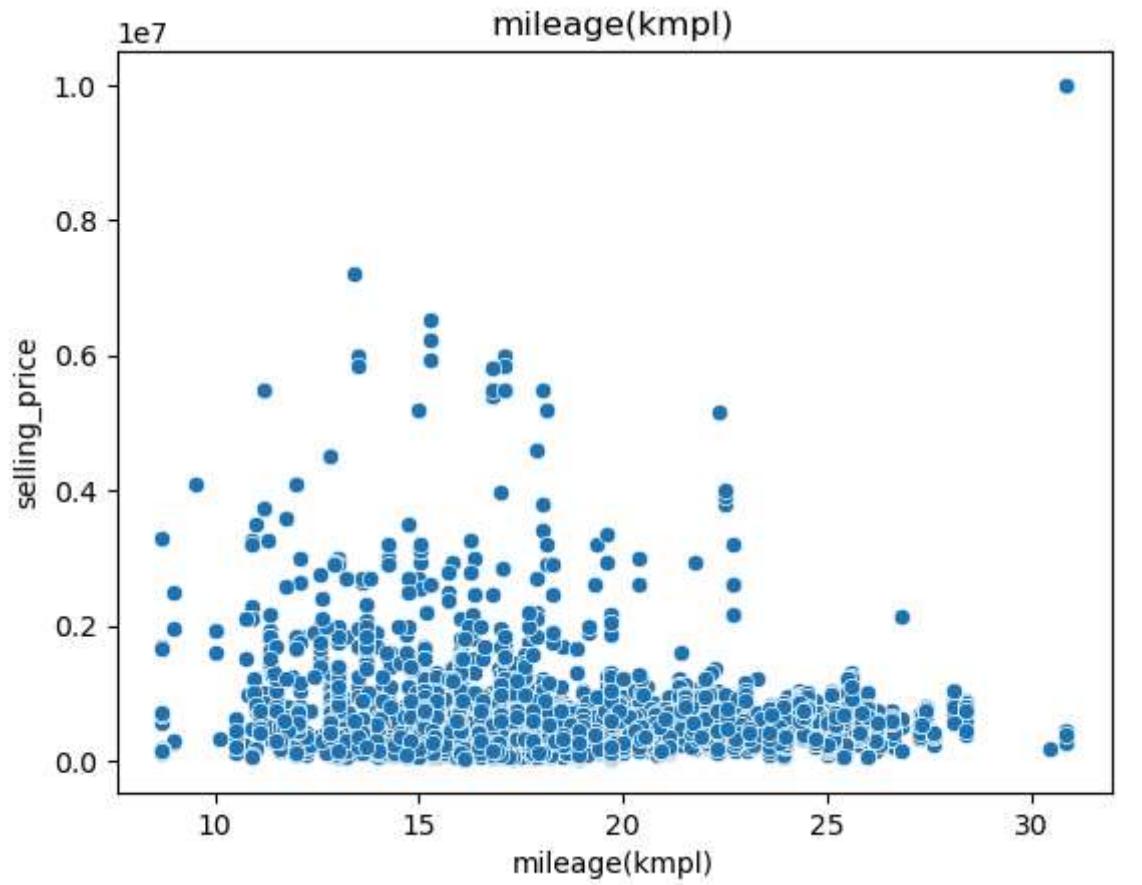
In [112...]

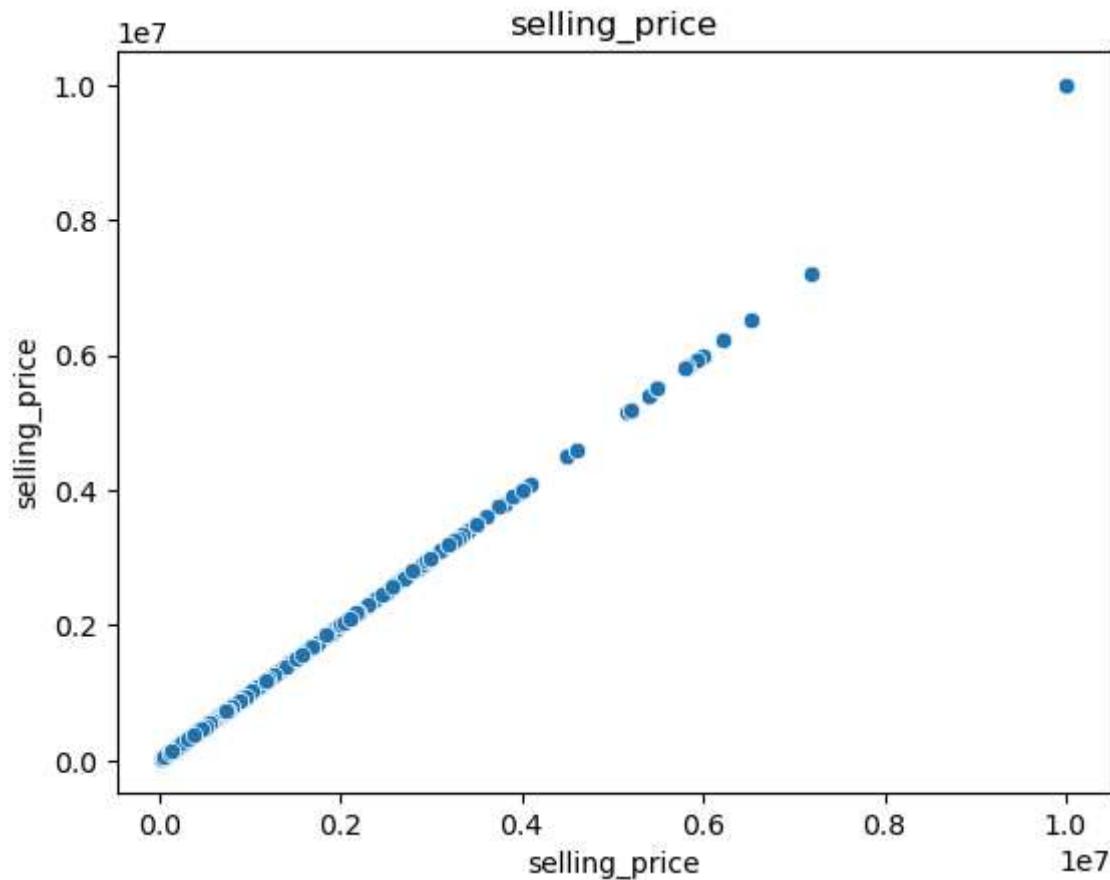
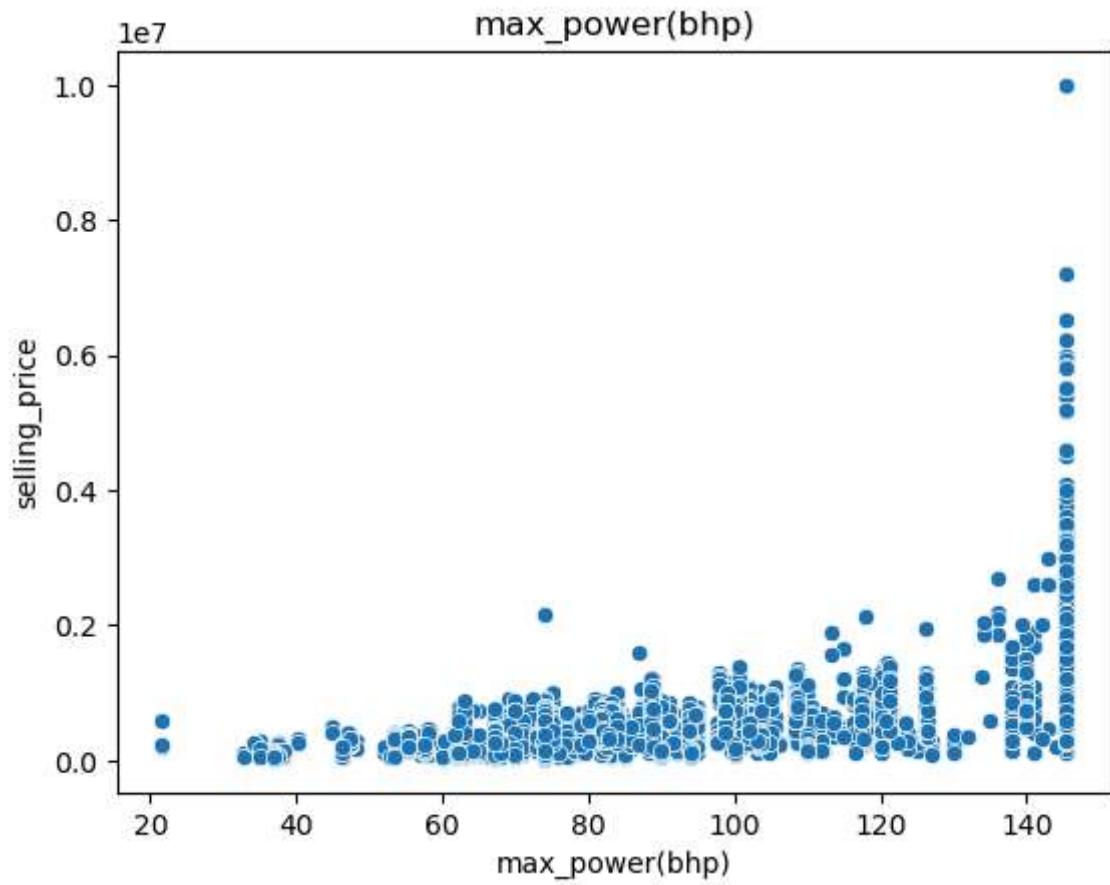
```
for i in cars_data:  
    sns.scatterplot(cars_data,x=cars_data[i],y="selling_price")  
    plt.title(i)  
    plt.show()
```

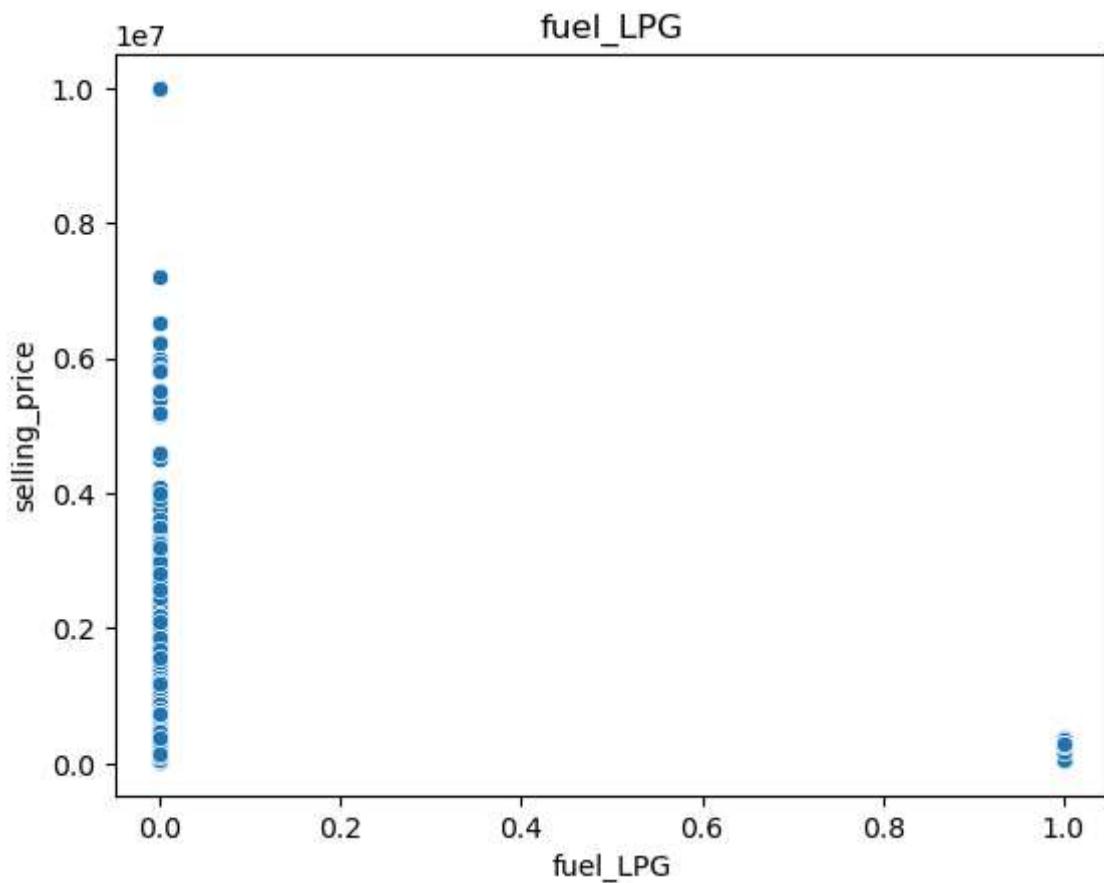
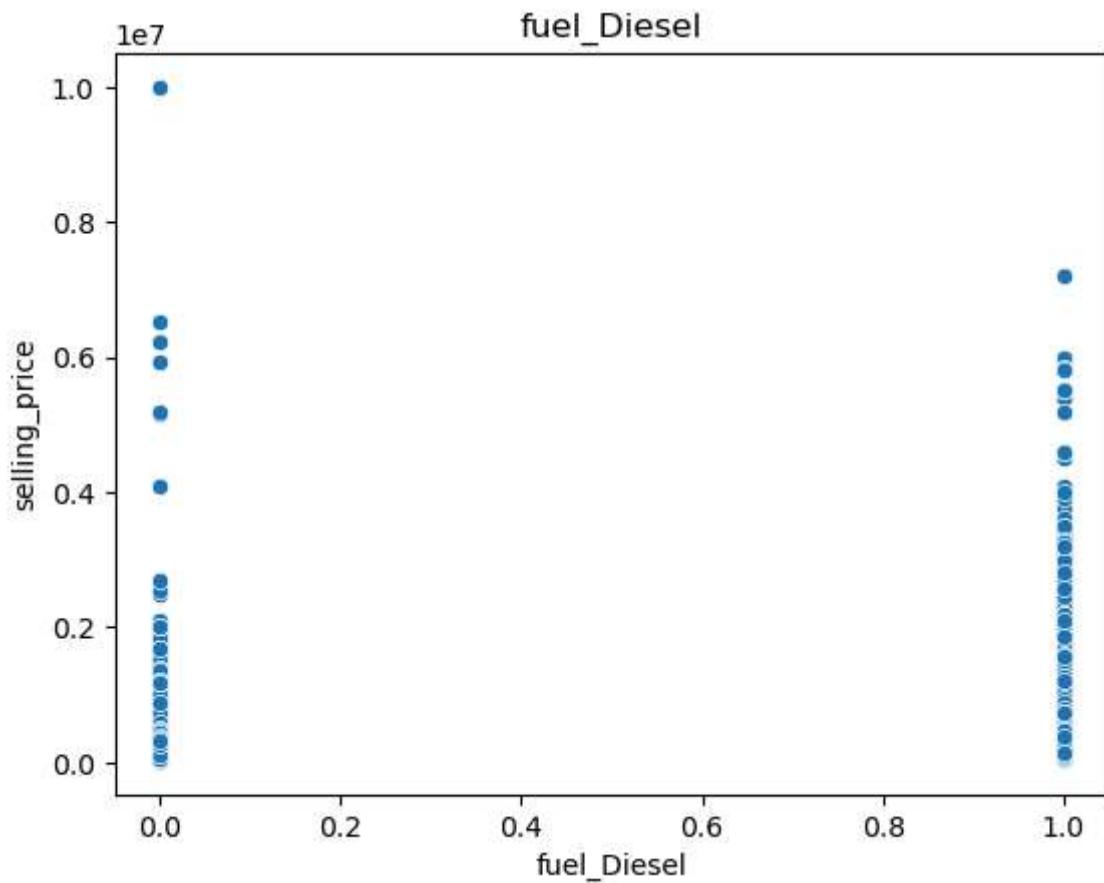


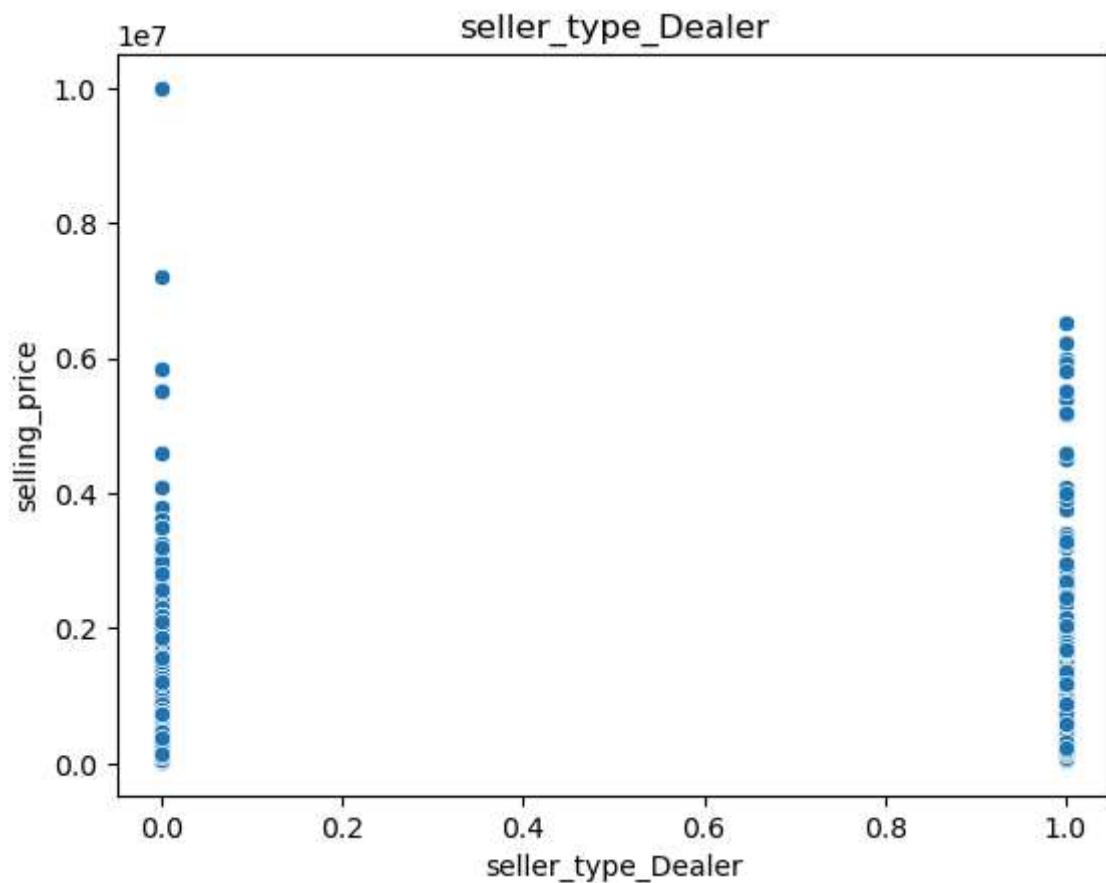
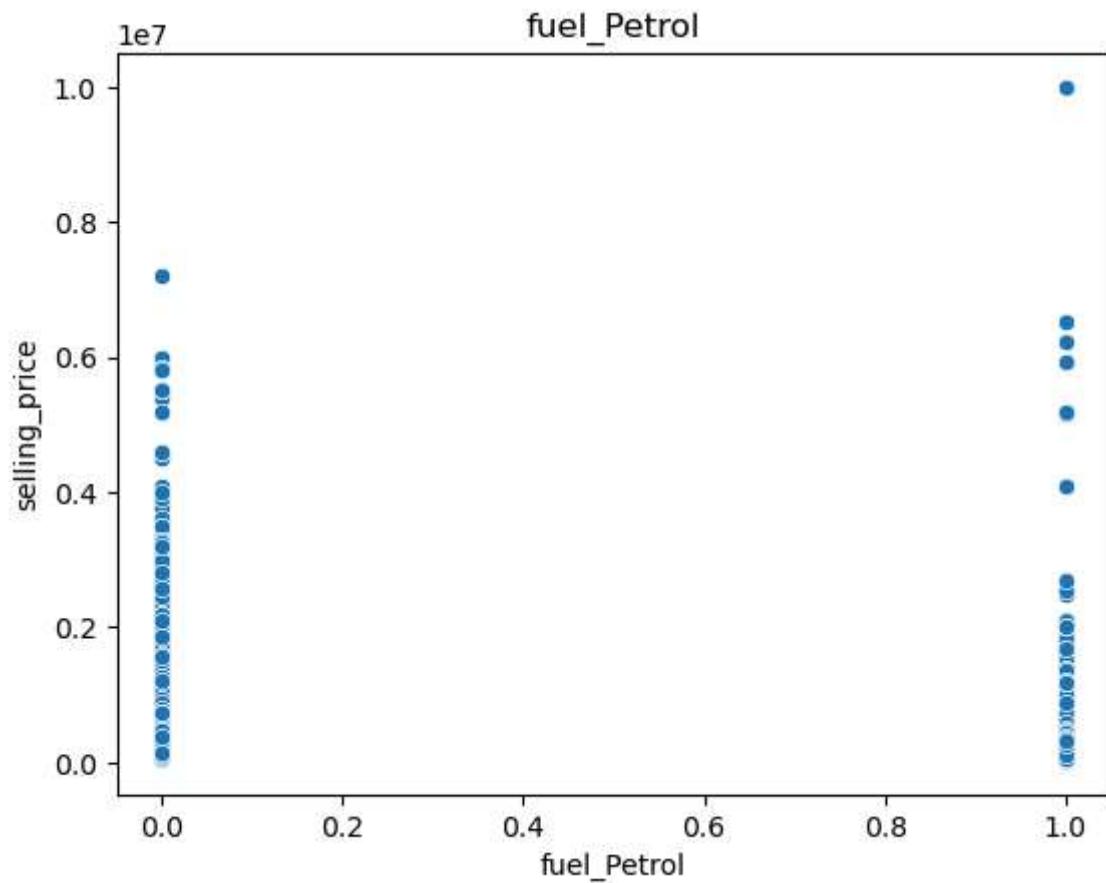


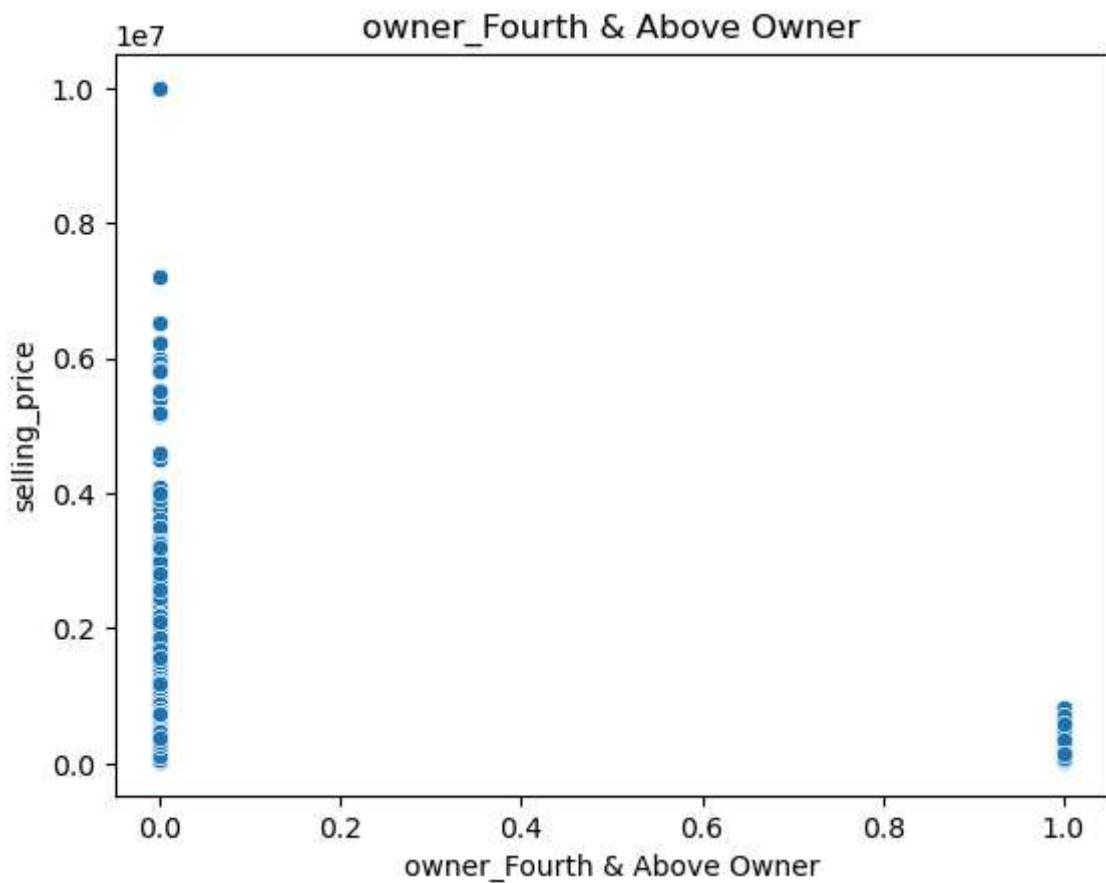
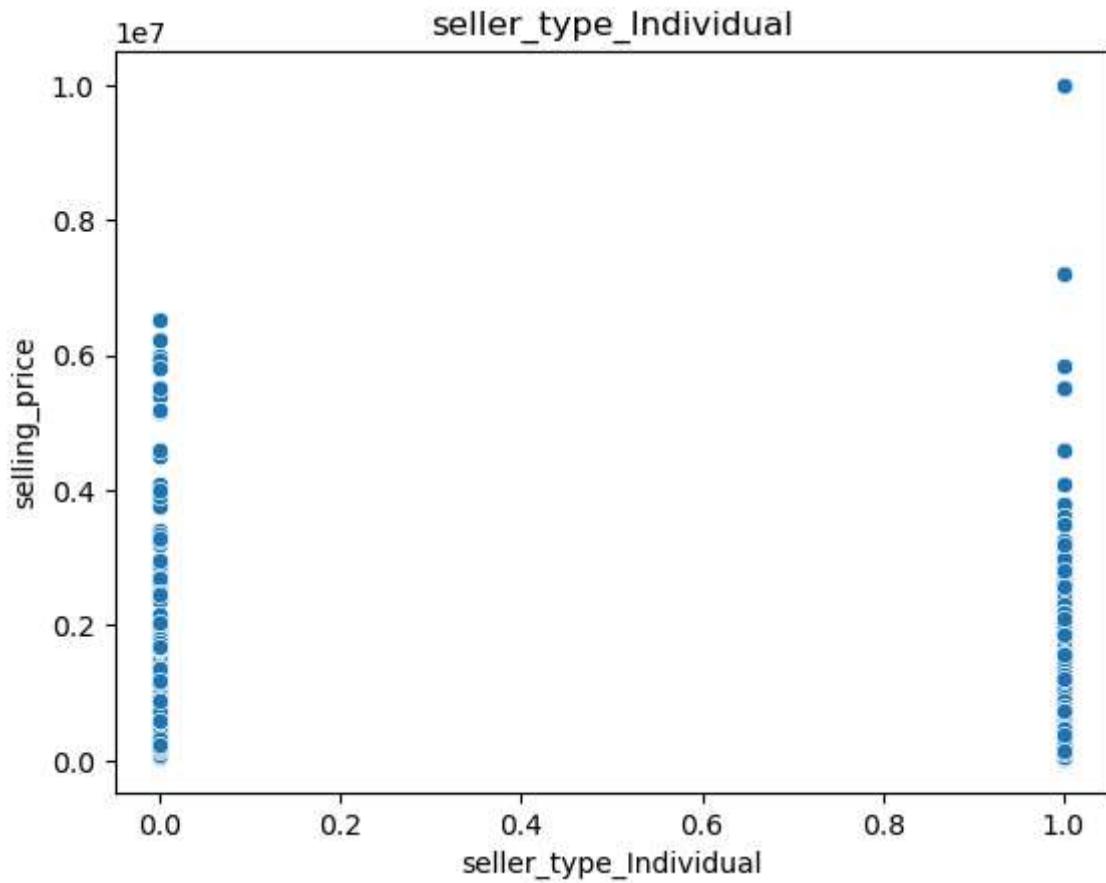


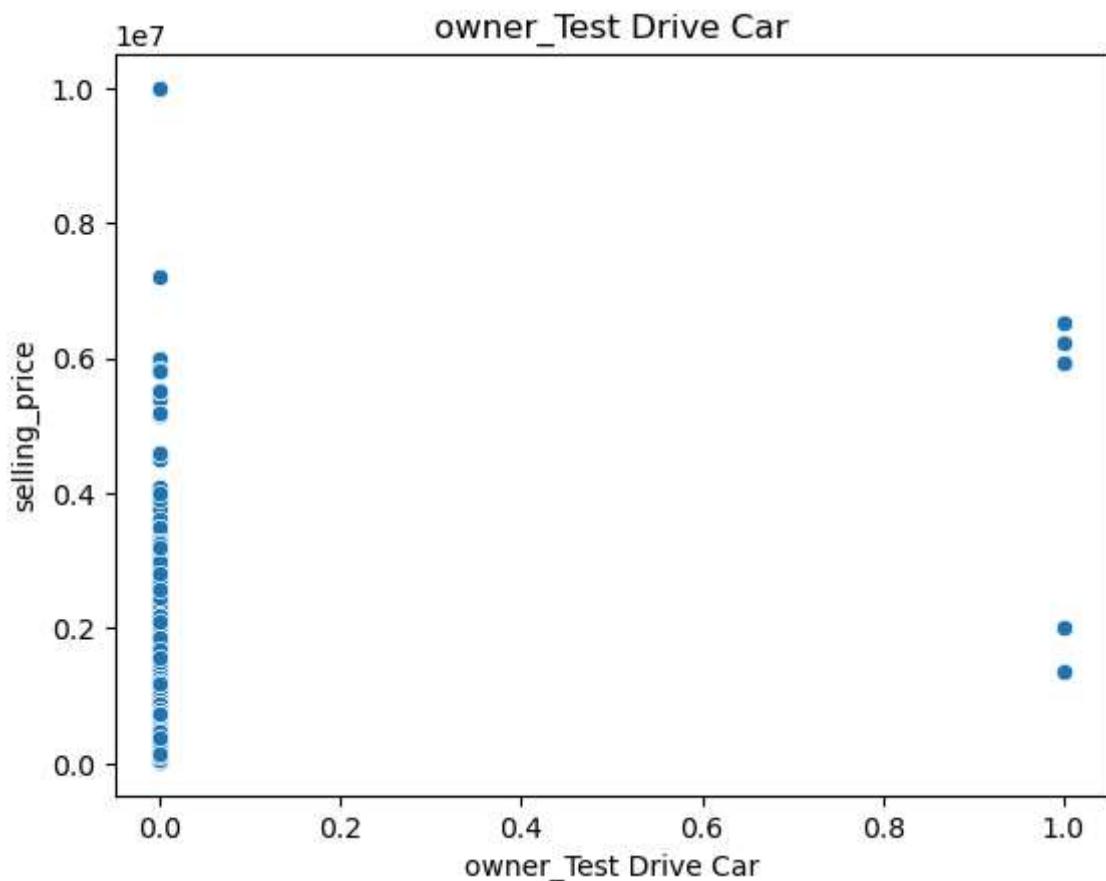
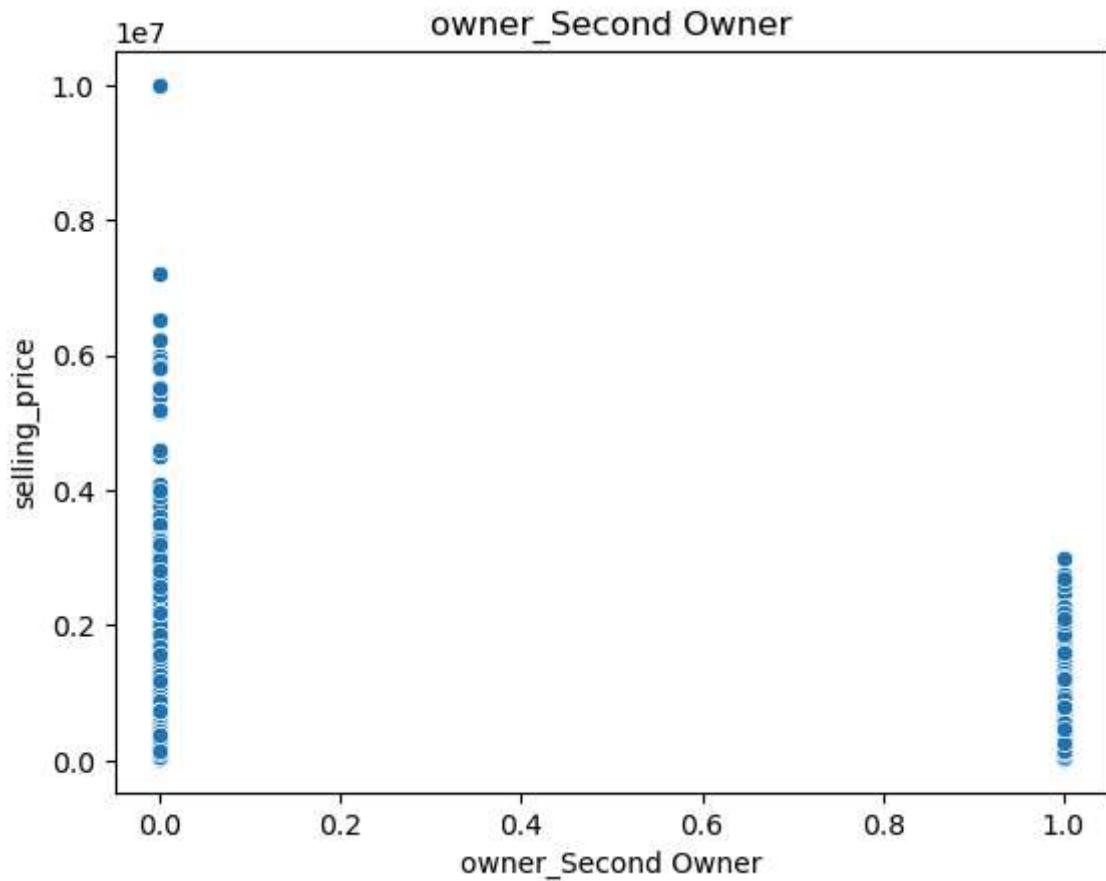


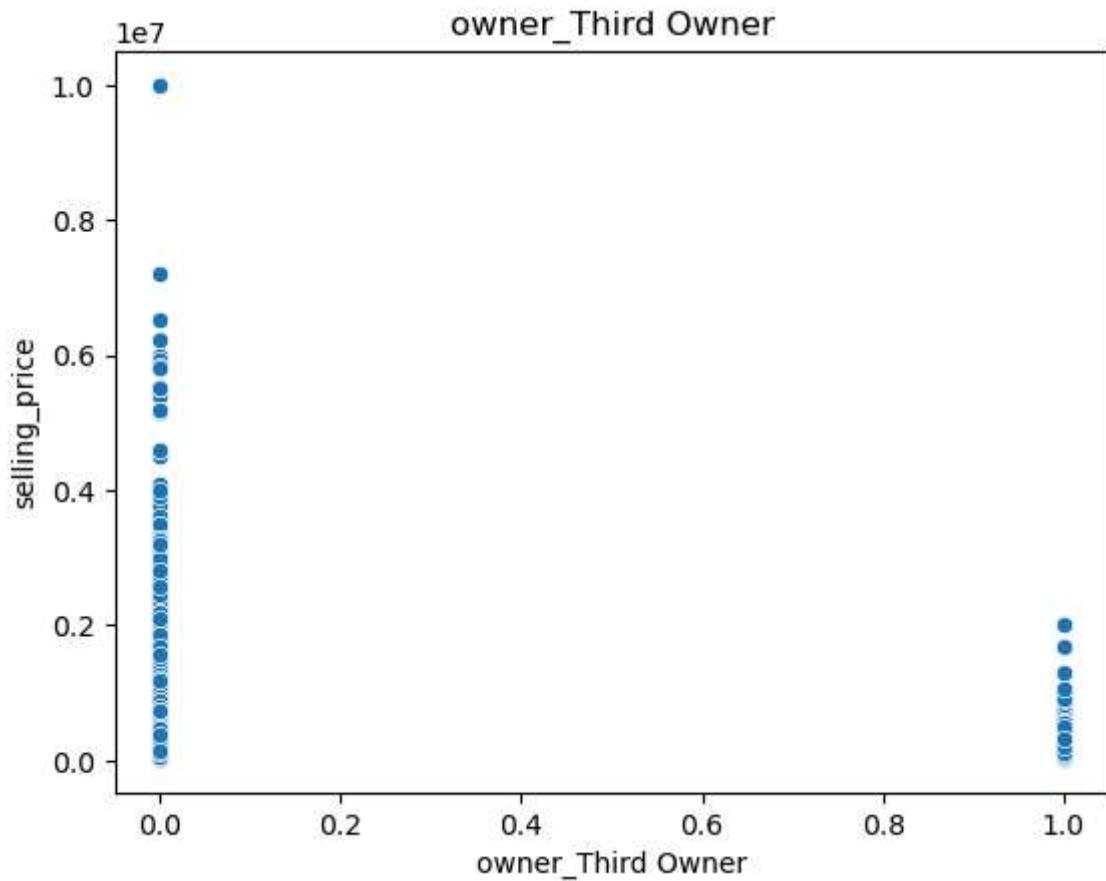












In [113]: cars\_df

Out[113...]

	year	km_driven	transmission	seats	mileage(kmpl)	engine(CC)	max_power(bhp)
<b>0</b>	2014	145500		1	5.0	23.40	1248.0
<b>1</b>	2014	120000		1	5.0	21.14	1498.0
<b>2</b>	2006	140000		1	5.0	17.70	1497.0
<b>3</b>	2006	140000		1	5.0	17.70	1497.0
<b>4</b>	2010	127000		1	5.0	23.00	1396.0
...	...	...		...	...	...	...
<b>7407</b>	2013	50000		1	5.0	18.90	998.0
<b>7408</b>	2014	80000		1	5.0	22.54	1396.0
<b>7409</b>	2013	110000		1	5.0	18.50	1197.0
<b>7410</b>	2007	119000		1	5.0	16.80	1493.0
<b>7411</b>	2009	120000		1	5.0	19.30	1248.0

7412 rows × 17 columns



In [114...]

```
from scipy.stats import skew
for i in cars_df:
    print(i,"--->",skew(cars_df[i]))
```

year ---> -0.7461174623555729  
km\_driven ---> 0.6784934306557338  
transmission ---> -3.0793520946026725  
seats ---> 1.9894636002537804  
mileage(kmpl) ---> -0.02841761678291445  
engine(CC) ---> 0.41984853633131897  
max\_power(bhp) ---> 0.7211438728578453  
selling\_price ---> 5.6620513032462  
fuel\_Diesel ---> -0.17279458878736642  
fuel\_LPG ---> 13.858491433776791  
fuel\_Petrol ---> 0.22537868673879413  
seller\_type\_Dealer ---> 2.80910903007586  
seller\_type\_Individual ---> -2.736339044366389  
owner\_Fourth & Above Owner ---> 6.353632406937305  
owner\_Second Owner ---> 0.9426313363533518  
owner\_Test Drive Car ---> 38.46297797931313  
owner\_Third Owner ---> 3.2565908977168614

In [115...]

```
cars_df["seats"] = np.log(cars_df["seats"])
```

In [116...]

```
skew(cars_df["seats"])
```

Out[116...]

1.5955771452180667

```
In [117... cars_df["selling_price"] = np.log(cars_df["selling_price"])

In [118... skew(cars_df["selling_price"])

Out[118... -0.16025239145848685

In [119... x=cars_df.drop("selling_price",axis=1)
y=cars_df["selling_price"]

In [120... from sklearn.preprocessing import StandardScaler

In [121... SS=StandardScaler()

In [122... for features in x:
    x[features]=SS.fit_transform(x[[features]])

In [123... from sklearn.model_selection import train_test_split

In [124... x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=3)

In [125... from sklearn.linear_model import LinearRegression

In [126... lr=LinearRegression()

In [127... model=lr.fit(x_train,y_train)

In [128... y_predict=model.predict(x_test)
y_predict

Out[128... array([12.96052547, 13.11780698, 12.97053987, ..., 13.31099445,
       10.96576274, 12.71306938])

In [129... residual=y_test-y_predict
residual

Out[129... 1119   -0.194837
      513    0.282188
     2683    0.366935
     6045    0.065745
     1409   -0.219459
      ...
     2103   -0.335188
      945    0.204966
     7355   -0.387084
     5064   -0.369128
     3066    0.186150
Name: selling_price, Length: 2224, dtype: float64

In [130... model.intercept_

Out[130... 12.860938202573392
```

In [131... model.coef\_

```
Out[131... array([ 0.42873913, -0.03066301, -0.08065135,  0.04924791,  0.0255519 ,
   0.09685216,  0.25432804,  0.10445275,  0.01071395,  0.0094515 ,
   0.00125968, -0.02950426, -0.01406452, -0.03354937,  0.01650622,
  -0.03000076])
```

In [132... from sklearn.metrics import mean\_absolute\_error,mean\_squared\_error,r2\_score

In [133... y\_pred=model.predict(x\_train)

```
mse=mean_squared_error(y_train,y_pred)
print("mean_squared_error",mse)
print(50**")
```

```
rmse=np.sqrt(mse)
print("rmse",rmse)
print(50**")
```

```
mae=mean_absolute_error(y_train,y_pred)
print("mean_absolute_error",mae)
print(50**")
```

```
r_squared_value=r2_score(y_train,y_pred)
print("r2_score",r_squared_value)
print(50**")
```

```
adj_r2=1-(((1-r_squared_value) * (x_train.shape[0]-1)) / (x_train.shape[0] - x_train.shape[0]))
print("adj_r2",adj_r2)
```

mean\_squared\_error 0.09608462982187943

\*\*\*\*\*

rmse 0.3099752083987999

\*\*\*\*\*

mean\_absolute\_error 0.23664104801643782

\*\*\*\*\*

r2\_score 0.8322251215402573

\*\*\*\*\*

adj\_r2 0.8317059960219135

In [134... y\_pred=model.predict(x\_test)

```
mse=mean_squared_error(y_test,y_pred)
print("mean_squared_error",mse)
print(50**")
```

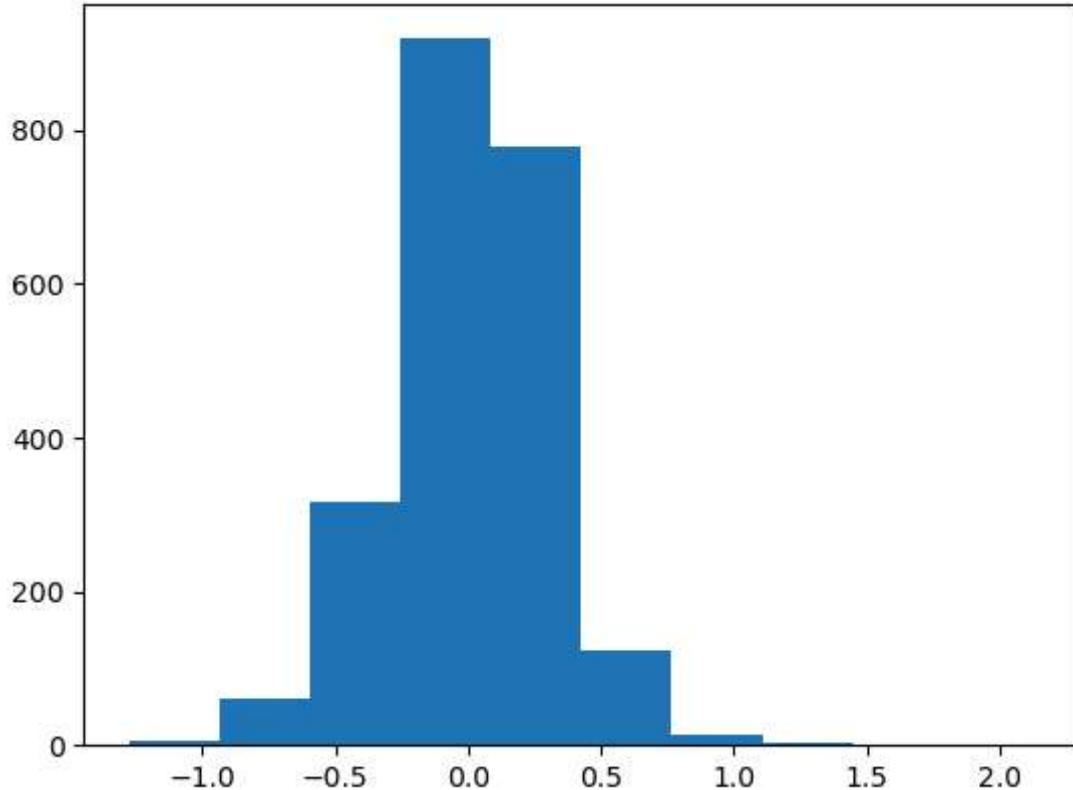
```
rmse=np.sqrt(mse)
print("rmse",rmse)
print(50**")
```

```
mae=mean_absolute_error(y_test,y_pred)
print("mean_absolute_error",mae)
print(50**")
```

```
r_squared_value=r2_score(y_test,y_pred)
print("r2_score",r_squared_value)
```

```
print(50**"")  
  
adj_r2=1-(((1-r_squared_value) * (x_test.shape[0]-1)) / (x_test.shape[0] - x_test.s  
print("adj_r2",adj_r2)  
  
mean_squared_error 0.09308639156388164  
*****  
rmse 0.30510062530889975  
*****  
mean_absolute_error 0.23242717203455002  
*****  
r2_score 0.8361574486133551  
*****  
adj_r2 0.8349696457940591
```

In [135... #normalized residual  
plt.hist(residual)  
plt.show()



In [136... model.score(x\_train,y\_train)

Out[136... 0.8322251215402573

In [137... model.score(x\_test,y\_test)

Out[137... 0.8361574486133551

In [138... from sklearn.tree import DecisionTreeRegressor, plot\_tree

In [139... DTC=DecisionTreeRegressor(random\_state=11)

In [140... DTC.fit(x\_train, y\_train)

Out[140... ▾ DecisionTreeRegressor ⓘ ?

DecisionTreeRegressor(random\_state=11)

In [141... y\_pred\_train=DTC.predict(x\_train)

```
mse=mean_squared_error(y_train,y_pred_train)
print("mean_squared_error",mse)
print(50**")
```

```
rmse=np.sqrt(mse)
print("rmse",rmse)
print(50**")
```

```
mae=mean_absolute_error(y_train,y_pred_train)
print("mean_absolute_error",mae)
print(50**")
```

```
r_squared_value=r2_score(y_train,y_pred_train)
print("r2_score",r_squared_value)
print(50**")
```

```
adj_r2=1-(((1-r_squared_value) * (x_train.shape[0]-1)) / (x_train.shape[0] - x_train.shape[0]))
print("adj_r2",adj_r2)
```

mean\_squared\_error 0.002150051744759462

\*\*\*\*\*

rmse 0.04636865045221245

\*\*\*\*\*

mean\_absolute\_error 0.01308662711197939

\*\*\*\*\*

r2\_score 0.9962457609419125

\*\*\*\*\*

adj\_r2 0.9962341446539742

In [142... y\_pred=DTC.predict(x\_test)

```
mse=mean_squared_error(y_test,y_pred)
print("mean_squared_error",mse)
print(50**")
```

```
rmse=np.sqrt(mse)
print("rmse",rmse)
print(50**")
```

```
mae=mean_absolute_error(y_test,y_pred)
print("mean_absolute_error",mae)
print(50**")
```

```
r_squared_value=r2_score(y_test,y_pred)
print("r2_score",r_squared_value)
print(50**")
```

```
adj_r2=1-(((1-r_squared_value) * (x_test.shape[0]-1)) / (x_test.shape[0] - x_test.shape[0]))
print("adj_r2",adj_r2)

mean_squared_error 0.0960045504265881
*****
rmse 0.30984601082890856
*****
mean_absolute_error 0.21449366399824402
*****
r2_score 0.8310211597811764
*****
adj_r2 0.8297961206133009

In [143... DTC.score(x_train,y_train)

Out[143... 0.9962457609419125

In [144... DTC.score(x_test,y_test)

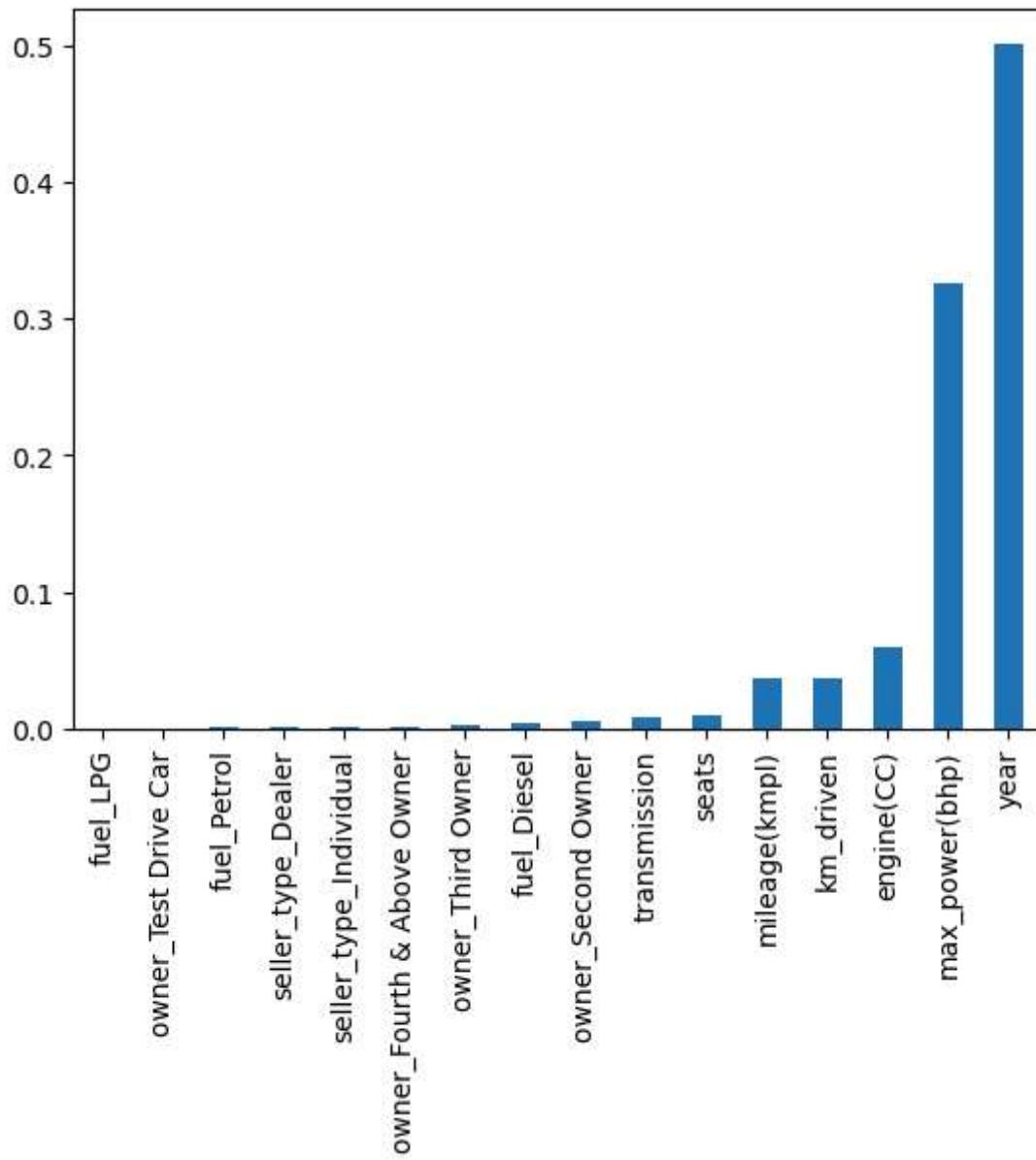
Out[144... 0.8310211597811764

In [145... array=DTC.feature_importances_
array

Out[145... array([5.01359386e-01, 3.74025633e-02, 8.94503272e-03, 9.84604634e-03,
       3.73191701e-02, 6.03568982e-02, 3.25661670e-01, 4.61139065e-03,
       3.24945707e-04, 1.17620317e-03, 1.23847165e-03, 1.24688725e-03,
       1.54349583e-03, 6.23279960e-03, 5.07523452e-04, 2.22751597e-03])

In [146... s1=pd.Series(array,index=x.columns)
s1.sort_values().plot(kind="bar")

Out[146... <Axes: >
```



```
In [147]: from sklearn.model_selection import GridSearchCV
```

```
In [294]: hyperparameter={"criterion": ["squared_error"],
                    "max_depth": np.arange(3, 9),
                    "min_samples_split": np.arange(2, 20),
                    "min_samples_leaf": np.arange(2, 15)}
```

```
In [296]: gscv=GridSearchCV(DTC,hyperparameter, cv=5)
```

```
In [298]: gscv.fit(x_train,y_train)
```

```
Out[298]: 
▶      GridSearchCV ⓘ ? 
▶ estimator: DecisionTreeRegressor 
    ▶ DecisionTreeRegressor ⓘ
```

In [300... gscv.best\_estimator\_

Out[300... ▾ DecisionTreeRegressor

```
DecisionTreeRegressor(max_depth=8, min_samples_leaf=7, min_samples_split=1
6,
                     random_state=11)
```

In [302... DT\_REG = gscv.best\_estimator\_
DT\_REG.fit(x\_train, y\_train)

Out[302... ▾ DecisionTreeRegressor

```
DecisionTreeRegressor(max_depth=8, min_samples_leaf=7, min_samples_split=1
6,
                     random_state=11)
```

In [304... y\_pred\_train=DT\_REG.predict(x\_train)

```
mse=mean_squared_error(y_train,y_pred_train)
print("mean_squared_error",mse)
print(50**")
```

```
rmse=np.sqrt(mse)
print("rmse",rmse)
print(50**")
```

```
mae=mean_absolute_error(y_train,y_pred_train)
print("mean_absolute_error",mae)
print(50**")
```

```
r_squared_value=r2_score(y_train,y_pred_train)
print("r2_score",r_squared_value)
print(50**")
```

```
adj_r2=1-(((1-r_squared_value) * (x_train.shape[0]-1)) / (x_train.shape[0] - x_train.shape[0]))
print("adj_r2",adj_r2)
```

mean\_squared\_error 0.057553353249635175

\*\*\*\*\*

rmse 0.23990279958690597

\*\*\*\*\*

mean\_absolute\_error 0.17769891283170988

\*\*\*\*\*

r2\_score 0.8995051876214919

\*\*\*\*\*

adj\_r2 0.8991942386758226

In [306... y\_pred=DT\_REG.predict(x\_test)

```
mse=mean_squared_error(y_test,y_pred)
print("mean_squared_error",mse)
```

```

print(50**"")
rmse=np.sqrt(mse)
print("rmse",rmse)
print(50**"")
mae=mean_absolute_error(y_test,y_pred)
print("mean_absolute_error",mae)
print(50**"")
r_squared_value=r2_score(y_test,y_pred)
print("r2_score",r_squared_value)
print(50**"")
adj_r2=1-(((1-r_squared_value) * (x_test.shape[0]-1)) / (x_test.shape[0] - x_test.s
print("adj_r2",adj_r2)

mean_squared_error 0.07076923181002191
*****
rmse 0.26602487066066194
*****
mean_absolute_error 0.1874138062277255
*****
r2_score 0.875438167656658
*****
adj_r2 0.8745351367017449

```

In [308]: DT\_REG.score(x\_train,y\_train)

Out[308]: 0.8995051876214919

In [310]: DT\_REG.score(x\_test,y\_test)

Out[310]: 0.875438167656658

In [312]: from sklearn.ensemble import RandomForestRegressor

In [314]: RF=RandomForestRegressor()

In [316]: RF.fit(x\_train,y\_train)

Out[316]: ▾ RandomForestRegressor ⓘ ?

RandomForestRegressor()

In [317]: y\_pred\_train=RF.predict(x\_train)

```

mse=mean_squared_error(y_train,y_pred_train)
print("mean_squared_error",mse)
print(50**"")

```

```

rmse=np.sqrt(mse)
print("rmse",rmse)
print(50**"")

```

```

mae=mean_absolute_error(y_train,y_pred_train)
print("mean_absolute_error",mae)
print(50**"")
r_squared_value=r2_score(y_train,y_pred_train)
print("r2_score",r_squared_value)
print(50**"")
adj_r2=1-(((1-r_squared_value) * (x_train.shape[0]-1)) / (x_train.shape[0] - x_train.shape[0]))
print("adj_r2",adj_r2)

```

```

mean_squared_error 0.00940512882785531
*****
rmse 0.09698004345150249
*****
mean_absolute_error 0.06876844102061556
*****
r2_score 0.9835775571085945
*****
adj_r2 0.9835267431294294

```

In [318...]

```

y_pred=RF.predict(x_test)

mse=mean_squared_error(y_test,y_pred)
print("mean_squared_error",mse)
print(50**"")
rmse=np.sqrt(mse)
print("rmse",rmse)
print(50**"")
mae=mean_absolute_error(y_test,y_pred)
print("mean_absolute_error",mae)
print(50**"")
r_squared_value=r2_score(y_test,y_pred)
print("r2_score",r_squared_value)
print(50**"")
adj_r2=1-(((1-r_squared_value) * (x_test.shape[0]-1)) / (x_test.shape[0] - x_test.shape[0]))
print("adj_r2",adj_r2)

```

```

mean_squared_error 0.055596546225683725
*****
rmse 0.2357891987044439
*****
mean_absolute_error 0.1666716823589742
*****
r2_score 0.9021438061045652
*****
adj_r2 0.9014343819530805

```

In [320...]

```
RF.score(x_train,y_train)
```

Out[320...]

0.9835775571085945

```
In [324]: RF.score(x_test,y_test)
```

```
Out[324]: 0.9021438061045652
```

```
In [ ]:
```

```
In [ ]:
```

```
In [ ]:
```