Importing Libraries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error,accuracy_score
import warnings
warnings.filterwarnings('ignore')
import pickle
pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)
```

Dipak Mani

Importing the dataset

In [2]:

```
cars = pd.read_csv('car data.csv')
```

The datasets consist of several independent variables include:

Car_Name : This column should be filled with the name of the car.

Year : This column should be filled with the year in which the car was bought.

Selling_Price : This column should be filled with the price the owner wants to sell the car at.

Present_Price : This is the current ex-showroom price of the car.

Kms_Driven :This is the distance completed by the car in km.

Fuel_Type : Fuel type of the car i.e Diesel,Petrol,CNG

Seller_Type : Defines whether the seller is a dealer or an individual.

Transmission : Defines whether the car is manual or automatic.

Owner : Defines the number of owners the car has previously had.

In [3]:

```
#Top 5 rows
cars.head()
```

Out[3]:

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual	0
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual	0
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual	0
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual	0
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual	0

In [4]:

```
#last 5 rows
cars.tail()
```

Out[4]:

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner
296	city	2016	9.50	11.6	33988	Diesel	Dealer	Manual	0
297	brio	2015	4.00	5.9	60000	Petrol	Dealer	Manual	0
298	city	2009	3.35	11.0	87934	Petrol	Dealer	Manual	0
299	city	2017	11.50	12.5	9000	Diesel	Dealer	Manual	0
300	brio	2016	5.30	5.9	5464	Petrol	Dealer	Manual	0

In [5]:

```
# Check columns
cars.columns
```

Out[5]:

```
Index(['Car_Name', 'Year', 'Selling_Price', 'Present_Price', 'Kms_Driven', 'Fuel_Type', '
Seller_Type', 'Transmission', 'Owner'], dtype='object')
```

In [6]:

```
# Drop column Car_Name
cars.drop(['Car_Name'],axis=1,inplace = True)
```

In [7]:

```
# check rows and columns
cars.shape
```

Out[7]:

```
(301, 8)
```

In [8]:

```
cars.describe()
```

Out[8]:

	Year	Selling_Price	Present_Price	Kms_Driven	Owner
count	301.000000	301.000000	301.000000	301.000000	301.000000
mean	2013.627907	4.661296	7.628472	36947.205980	0.043189
std	2.891554	5.082812	8.644115	38886.883882	0.247915
min	2003.000000	0.100000	0.320000	500.000000	0.000000
25%	2012.000000	0.900000	1.200000	15000.000000	0.000000
50%	2014.000000	3.600000	6.400000	32000.000000	0.000000
75%	2016.000000	6.000000	9.900000	48767.000000	0.000000
max	2018.000000	35.000000	92.600000	500000.000000	3.000000

In [10]:

```
# Check how many duplicates
cars[cars.duplicated()]
```

Out[10]:

	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner
17	2016	7.75	10.79	43000	Diesel	Dealer	Manual	0
93	2015	23.00	30.61	40000	Diesel	Dealer	Automatic	0

In [11]:

```
# Check null and Dtypes
cars.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 8 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Year           301 non-null    int64  
 1   Selling_Price  301 non-null    float64
 2   Present_Price  301 non-null    float64
 3   Kms_Driven     301 non-null    int64  
 4   Fuel_Type      301 non-null    object 
 5   Seller_Type    301 non-null    object 
 6   Transmission   301 non-null    object 
 7   Owner          301 non-null    int64  
dtypes: float64(2), int64(3), object(3)
memory usage: 18.9+ KB
```

In [12]:

```
#check which column numerical, categorical
cars.dtypes
```

Out[12]:

```
Year               int64
Selling_Price    float64
Present_Price    float64
Kms_Driven         int64
Fuel_Type         object
Seller_Type       object
Transmission      object
Owner              int64
dtype: object
```

In [13]:

```
# Check missing values or not
cars.isnull().sum()
```

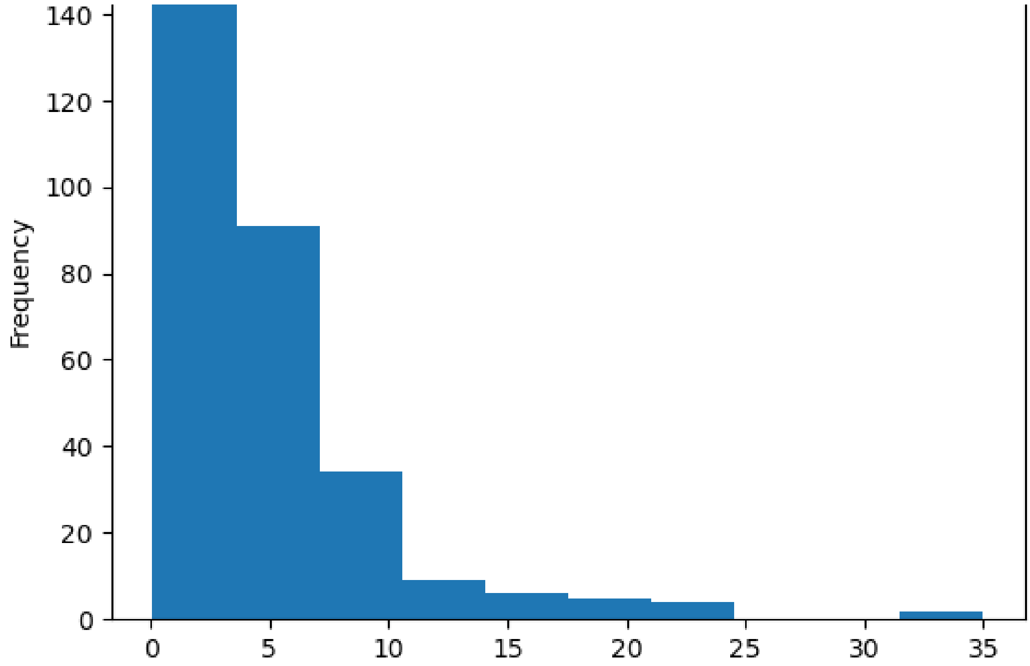
Out[13]:

```
Year             0
Selling_Price    0
Present_Price    0
Kms_Driven       0
Fuel_Type        0
Seller_Type      0
Transmission     0
Owner            0
dtype: int64
```

Plot the Target variable

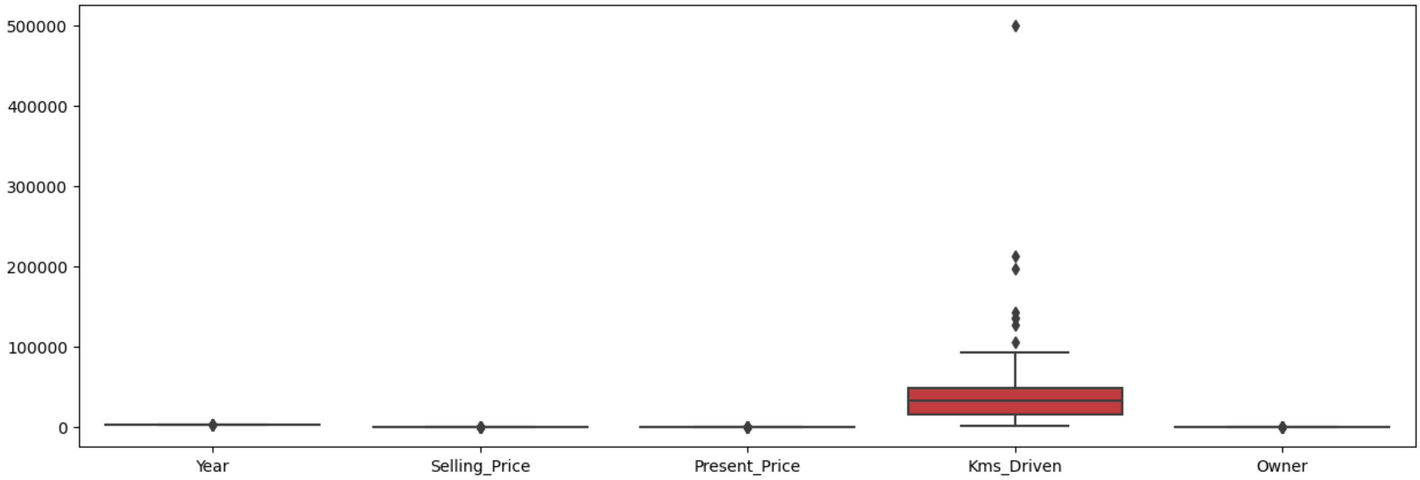
In [14]:

```
# Ploting a histogram
cars['Selling_Price'].plot(kind='hist')
plt.show()
```



In [15]:

```
# Year
plt.figure(figsize = (15,5))
sns.boxplot(data=cars)
plt.show()
```

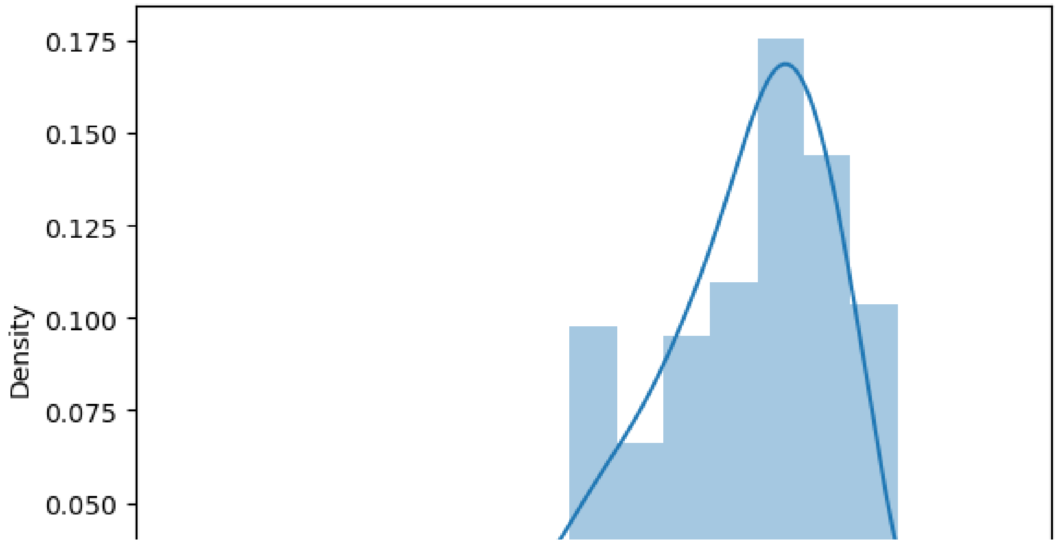


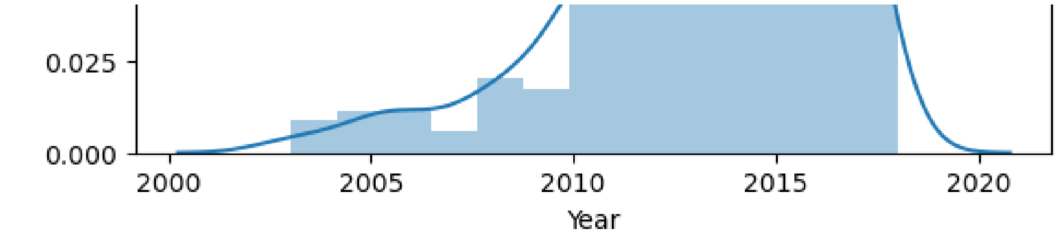
In [16]:

```
sns.distplot(cars['Year'])
```

Out[16]:

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



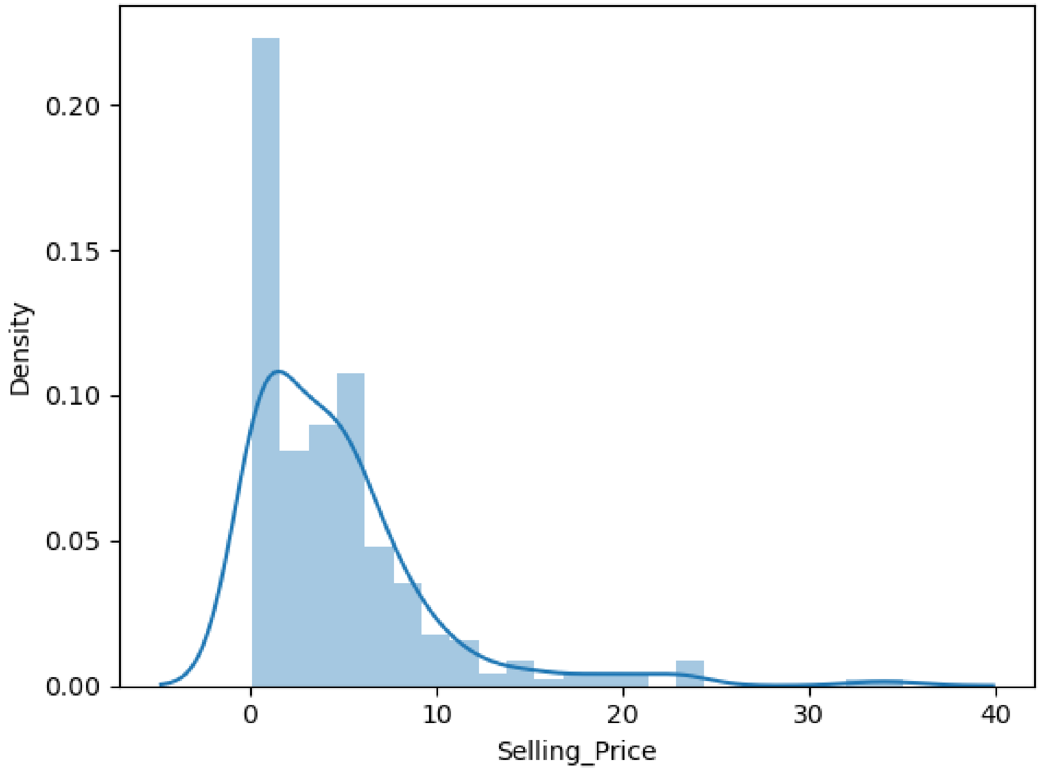


In [17]:

```
# The Years variable is left skewed
```

In [20]:

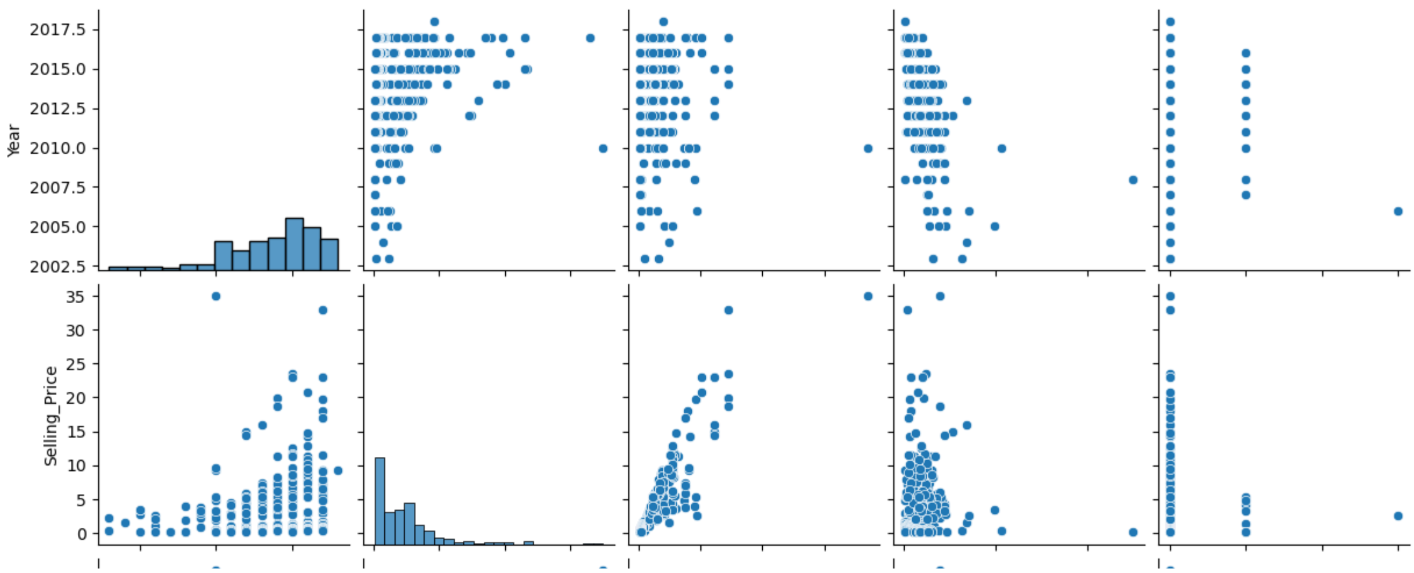
```
sns.distplot(cars['Selling_Price'])
plt.show()
```

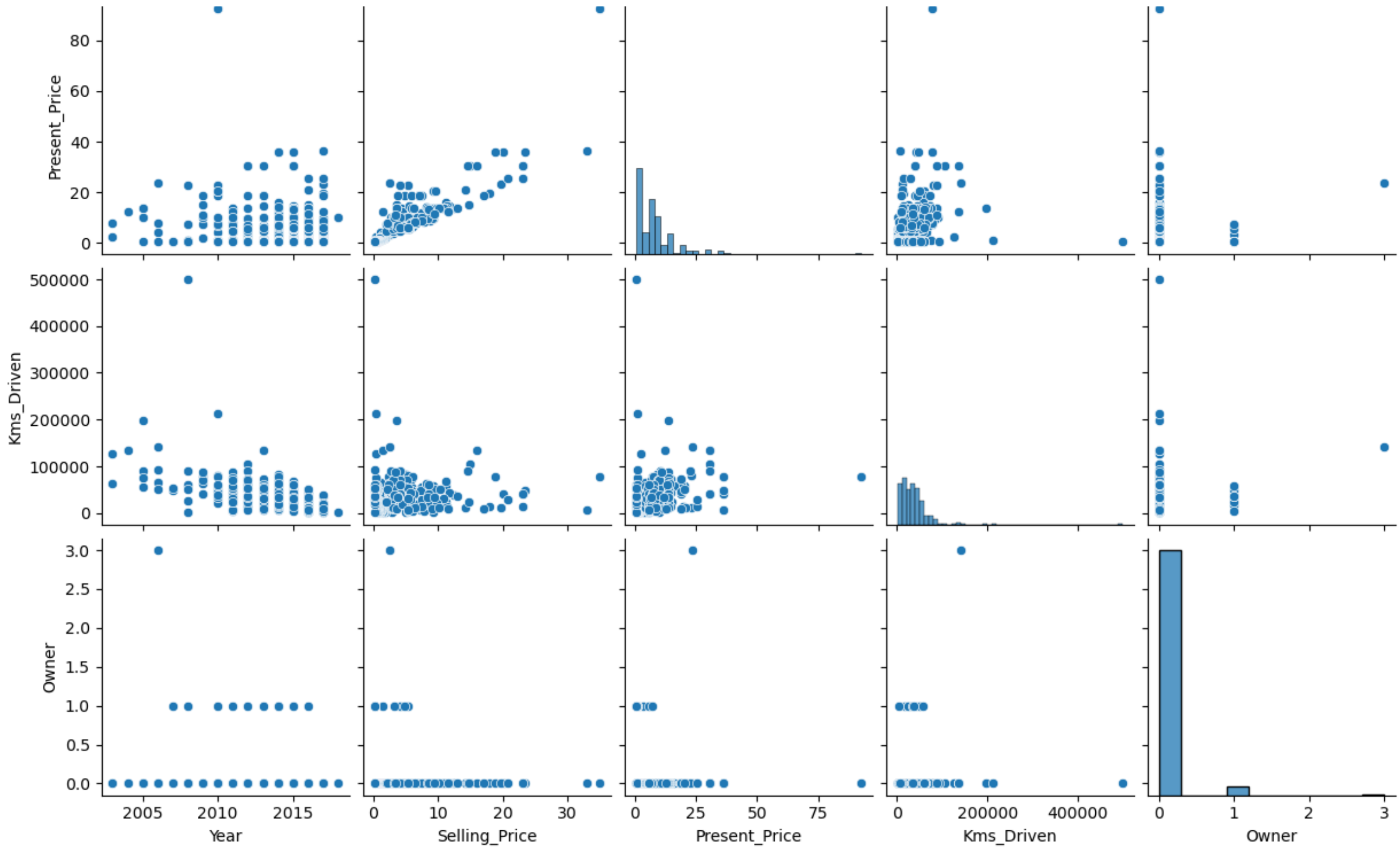


Create a pair plot of entire data

In [21]:

```
sns.pairplot(cars)
plt.show()
```





Present price and selling price has a strong relationship

Verify our observations finding the correlation of data

In [22]:

```
cars.corr()
```

Out[22]:

	Year	Selling_Price	Present_Price	Kms_Driven	Owner
Year	1.000000	0.236141	-0.047584	-0.524342	-0.182104
Selling_Price	0.236141	1.000000	0.878983	0.029187	-0.088344
Present_Price	-0.047584	0.878983	1.000000	0.203647	0.008057
Kms_Driven	-0.524342	0.029187	0.203647	1.000000	0.089216
Owner	-0.182104	-0.088344	0.008057	0.089216	1.000000

Converting categorical variables to dummy variables

In [23]:

```
#Fuel_Type

cars.Fuel_Type.value_counts()
```

Out[23]:

```
Petrol     239
Diesel      60
CNG          2
Name: Fuel_Type, dtype: int64
```

In [24]:

```
cars.Seller_Type.value_counts()
```

Out[24]:

```
Dealer        195
Individual    106
Name: Seller_Type, dtype: int64
```

In [25]:

```
cars.Transmission.value_counts()
```

Out[25]:

```
Manual       261
Automatic     40
Name: Transmission, dtype: int64
```

In [26]:

```
cars = pd.get_dummies(cars,columns=['Fuel_Type','Seller_Type','Transmission'],drop_first
=True)
```

In [27]:

```
cars.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 9 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Year                    301 non-null    int64  
 1   Selling_Price           301 non-null    float64
 2   Present_Price           301 non-null    float64
 3   Kms_Driven              301 non-null    int64  
 4   Owner                   301 non-null    int64  
 5   Fuel_Type_Diesel        301 non-null    uint8  
 6   Fuel_Type_Petrol        301 non-null    uint8  
 7   Seller_Type_Individual  301 non-null    uint8  
 8   Transmission_Manual     301 non-null    uint8  
dtypes: float64(2), int64(3), uint8(4)
memory usage: 13.1 KB
```

In [28]:

```
cars.shape
```

Out[28]:

```
(301, 9)
```

In [29]:

```
cars.head()
```

Out[29]:

	Year	Selling_Price	Present_Price	Kms_Driven	Owner	Fuel_Type_Diesel	Fuel_Type_Petrol	Seller_Type_Individual	Transmi
0	2014	3.35	5.59	27000	0	0	1	0	
1	2013	4.75	9.54	43000	0	1	0	0	
2	2017	7.25	9.85	6900	0	0	1	0	
3	2011	2.85	4.15	5200	0	0	1	0	
4	2014	4.60	6.87	42450	0	1	0	0	

Create a new feature which tells us how old the car is in terms of years

In [30]:

```
# Substracting the year by current year
cars['no_of_years'] = 2021 - cars['Year']
```

In [31]:

```
cars.head()
```

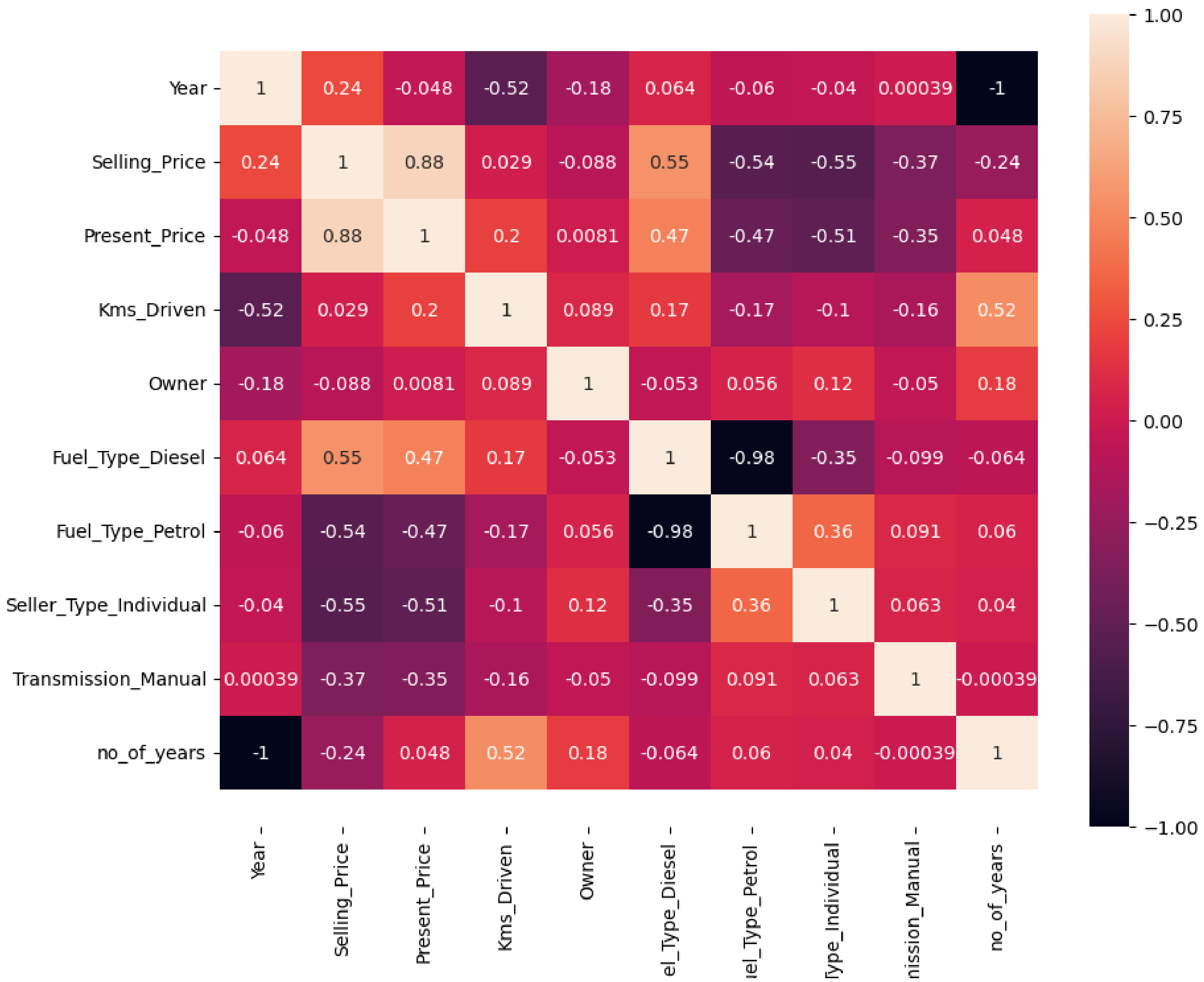
Out[31]:

	Year	Selling_Price	Present_Price	Kms_Driven	Owner	Fuel_Type_Diesel	Fuel_Type_Petrol	Seller_Type_Individual	Transmi
0	2014	3.35	5.59	27000	0	0	1	0	
1	2013	4.75	9.54	43000	0	1	0	0	
2	2017	7.25	9.85	6900	0	0	1	0	
3	2011	2.85	4.15	5200	0	0	1	0	
4	2014	4.60	6.87	42450	0	1	0	0	

In [32]:

```
#Heatmap to show the correlation between various variables of the dataset

plt.figure(figsize=(10, 8))
cor = cars.corr()
ax = sns.heatmap(cor,annot=True)
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
plt.show()
```



The target variable Selling Price is highly correlated with:

Present Price Fuel Type Seller Type

Linear Regression Model

In [33]:

```
y = cars['Selling_Price']
X = cars.drop(['Selling_Price'],axis=1)
```

In [34]:

```
#Splitting the data into train and test

from sklearn.model_selection import train_test_split

X_train ,X_test,y_train,y_test = train_test_split(X,y,test_size=0.30,random_state = 1)

print(X_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(210, 9)
(91, 9)
(91,)
```

In [35]:

```
#standardization of the data
from sklearn.preprocessing import StandardScaler

sc=StandardScaler()
X_train=sc.fit_transform(X_train)
X_train=pd.DataFrame(X_train,columns=X.columns)

X_test=sc.fit_transform(X_test)
```

In [36]:

```
#Building model using sklearn(Gradient Descent)

from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(X_train,y_train) # training the algorithm

# Getting the coefficients and intercept

print('coefficients:\n', lin_reg.coef_)
print('\n intercept:', lin_reg.intercept_)
#coeff_df = pd.DataFrame(lin_reg.coef_, X.columns, columns=['Coefficient'])
#print(coeff_df)

#Now predicting on the test data
y_pred = lin_reg.predict(X_test)
```

```
coefficients:
 [ 0.61446061  4.0342602  -0.18209819  0.07808457  0.87226802  0.17314277
 -0.52312819 -0.6032581  -0.61446061]

 intercept: 4.748809523809541
```

In [37]:

```python
# compare the actual output values for X_test with the predicted values

df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
df.reset_index(inplace=True,drop=True)
df
```

Out[37]:

	Actual	Predicted
0	7.40	8.139241
1	4.00	2.768482
2	0.50	-1.084232
3	3.15	4.108869
4	1.25	0.093750
5	5.75	6.058557
6	0.75	1.635044
7	2.65	2.401599
8	8.40	8.584556
9	0.48	0.542876
10	8.35	8.582469
11	3.45	3.434705
12	5.30	4.996272
13	4.10	4.551218
14	0.20	-3.016438
15	0.35	2.607288
16	6.85	8.435264
17	6.15	7.064520
18	5.11	7.153424
19	7.45	8.482777
20	6.00	4.594249
21	3.25	4.316855
22	5.25	12.908534
23	7.50	8.496530
24	2.50	10.692104
25	3.25	3.446563
26	3.35	4.090475
27	0.60	0.654310
28	0.30	-1.247878
29	0.35	-1.150567
30	0.30	-0.533153
31	0.16	-1.911068
32	4.40	4.267270
33	19.99	23.986891
34	23.00	21.478472
35	4.75	4.320773
36	3.75	3.499938
37	1.05	1.350338
38	0.20	-0.733307

	Actual	Predicted
39	4.50	5.745149
40	10.25	8.899823
41	12.90	10.771493
42	0.20	-0.242705
43	4.60	6.125878
44	3.95	5.839042
45	3.75	4.398146
46	7.20	7.755415
47	5.95	6.249034
48	7.25	8.735529
49	1.35	1.398198
50	3.35	3.777520
51	0.48	1.368213
52	2.00	2.285908
53	4.00	4.125913
54	1.10	1.199589
55	0.20	-4.244638
56	18.75	23.693895
57	0.50	0.245251
58	6.45	5.738649
59	5.65	5.917919
60	0.25	-0.035483
61	1.65	2.089498
62	14.73	11.586389
63	5.20	6.420132
64	0.45	-1.620540
65	0.75	0.571424
66	2.25	-0.003116
67	0.40	0.067561
68	3.80	8.498888
69	0.25	-0.587652
70	8.99	8.226796
71	7.75	9.163559
72	5.85	9.735197
73	0.40	0.448453
74	1.15	1.092675
75	1.95	1.762640
76	1.35	1.801642
77	10.11	9.205346
78	9.25	9.834452
79	4.50	4.288238
80	3.00	3.777792
81	1.20	1.635162
82	9.25	11.741139
83	11.45	11.191842

	Actual	Predicted
84	1.20	1.385490
85	5.50	6.762929
86	2.70	1.950740
87	0.60	1.061294
88	0.75	1.085983
89	7.90	6.665911
90	5.25	4.486496