ML PROJECT - USED CAR PRICE PREDICTION

In this Project, I'm going to predict the Price of Used Cars using various features like Present_Price, Selling_Price, Kms_Driven, Fuel_Type, Year etc. The data used in this project was downloaded from Kaggle. To be able to predict used cars market value can help both buyers and sellers. There are lots of individuals who are interested in the used car market at some points in their life because they wanted to sell their car or buy a used car. In this process, it's a big corner to pay too much or sell less then it's market value.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns',None)
plt.style.use('fivethirtyeight')
```

```
df=pd.read_csv('/content/drive/MyDrive/ML_Project_Datasets/car data.csv')
df.head()
```

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

Data Preprocessing

```
df.describe(include='all')
```

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type
count	301	301.000000	301.000000	301.000000	301.000000	301
unique	98	NaN	NaN	NaN	NaN	3
top	city	NaN	NaN	NaN	NaN	Petrol
freq	26	NaN	NaN	NaN	NaN	239
mean	NaN	2013.627907	4.661296	7.628472	36947.205980	NaN
std	NaN	2.891554	5.082812	8.642584	38886.883882	NaN
min	NaN	2003.000000	0.100000	0.320000	500.000000	NaN
25%	NaN	2012.000000	0.900000	1.200000	15000.000000	NaN
50%	NaN	2014.000000	3.600000	6.400000	32000.000000	NaN
75%	NaN	2016.000000	6.000000	9.900000	48767.000000	NaN
max	NaN	2018.000000	35.000000	92.600000	500000.000000	NaN

```
df.isna().sum()
```

```
Car_Name         0
Year             0
Selling_Price    0
Present_Price    0
Driven_kms       0
Fuel_Type        0
Selling_type     0
Transmission     0
Owner            0
dtype: int64
```

```
df.dtypes
```

```
Car_Name          object
Year               int64
Selling_Price    float64
Present_Price    float64
Driven_kms         int64
Fuel_Type         object
```

```
Selling_type      object
Transmission      object
Owner              int64
dtype: object
```

```
df.ndim
```

```
2
```

```
df.shape
```

```
(301, 9)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Car_Name       301 non-null    object 
 1   Year           301 non-null    int64  
 2   Selling_Price  301 non-null    float64
 3   Present_Price  301 non-null    float64
 4   Driven_kms     301 non-null    int64  
 5   Fuel_Type      301 non-null    object 
 6   Selling_type   301 non-null    object 
 7   Transmission   301 non-null    object 
 8   Owner          301 non-null    int64  
dtypes: float64(2), int64(3), object(4)
memory usage: 21.3+ KB
```

```
# To check if there are any outliers
# Here we conclude that we don't have any outliers.
df.describe(percentiles=[0.25,0.5,0.75,0.9,0.95,0.99])
```

	Year	Selling_Price	Present_Price	Driven_kms	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	8.642584	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
90%	2017.000000	9.500000	14.790000	65000.000000	0.000000
95%	2017.000000	14.500000	22.780000	80000.000000	0.000000
99%	2017.000000	23.000000	35.960000	142000.000000	1.000000
max	2018.000000	35.000000	92.600000	500000.000000	3.000000

Feature Engineering

```
# Creating a new feature called 'Car_age', It's important to know how many years old the car is.
df['Car_age'] = 2023-df['Year']
df.drop('Year',axis=1,inplace=True)
```

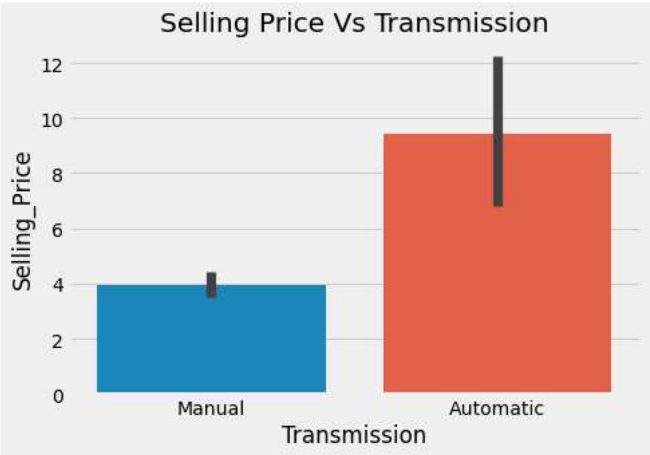
```
df.head()
```

	Car_Name	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner	Car_age
0	ritz	3.35	5.59	27000	Petrol	Dealer	Manual	0	9
1	sx4	4.75	9.54	43000	Diesel	Dealer	Manual	0	10
2	ciaz	7.25	9.85	6900	Petrol	Dealer	Manual	0	6
3	wagon r	2.85	4.15	5200	Petrol	Dealer	Manual	0	12
4	swift	4.60	6.87	42450	Diesel	Dealer	Manual	0	9

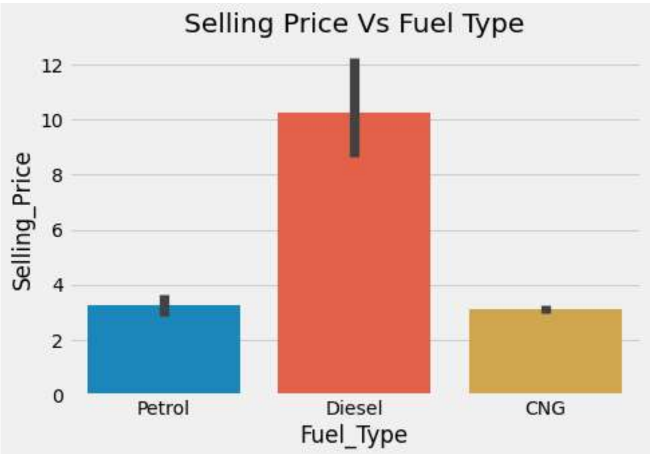
Exploratory Data Analysis

```
plt.figure(figsize=(15,10))
plt.subplot(2,2,1)
sns.barplot(data=df,x='Selling_type',y='Selling_Price')
plt.title('Selling Price Vs Seller Type')
plt.show()
```


```
plt.figure(figsize=(15,10))
plt.subplot(2,2,2)
sns.barplot(data=df,x='Transmission',y='Selling_Price')
plt.title('Selling Price Vs Transmission')
plt.show()
```

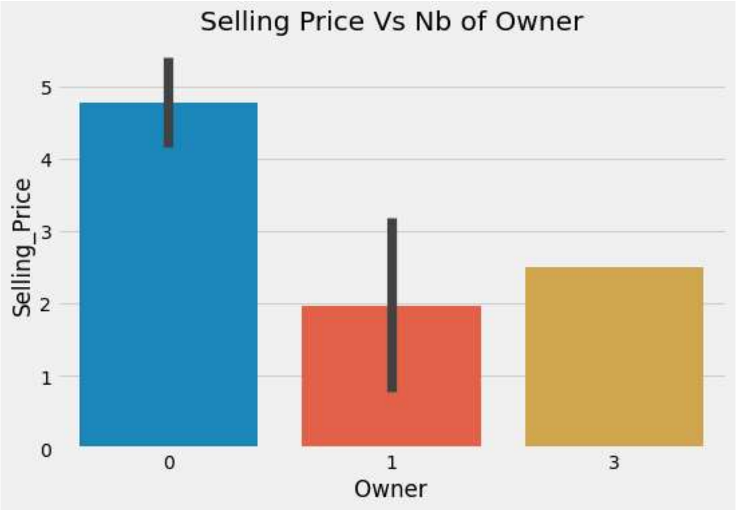



```
plt.figure(figsize=(15,10))
plt.subplot(2,2,3)
sns.barplot(data=df,x='Fuel_Type',y='Selling_Price')
plt.title('Selling Price Vs Fuel Type')
plt.show()
```




```
plt.figure(figsize=(15,10))
plt.subplot(2,2,4)
sns.barplot(data=df,x='Owner',y='Selling_Price')
plt.title('Selling Price Vs Nb of Owner')
```

```
plt.tight_layout()
plt.show()
```



Observations:

1.We have higher Selling Price when sold by Dealers compared to Individuals

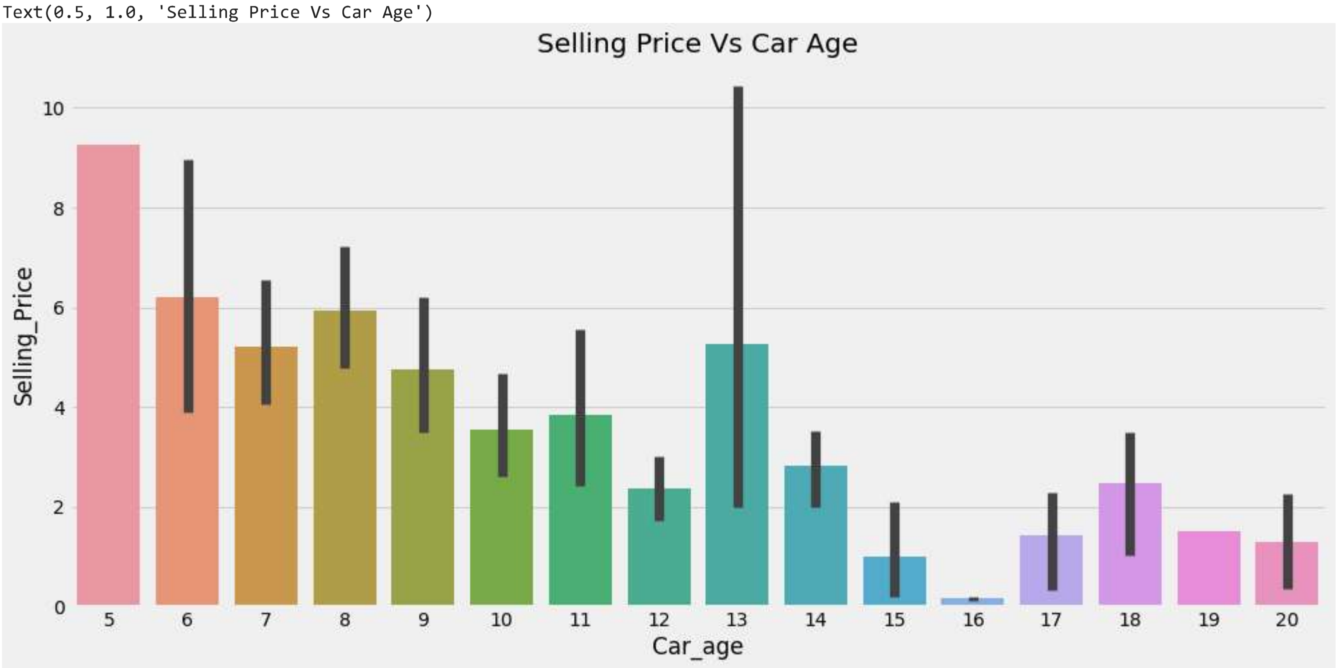
2.Selling Price would be higher for cars that are Automatic.

3.Selling Price of cars with Fuel Type of Diesel is higher than Petrol and CNG

4.Selling Price is high with less Owners used Cars

```
plt.figure(figsize=(15,7))
sns.barplot(data=df,x='Car_age',y='Selling_Price')
plt.title('Selling Price Vs Car Age')
```

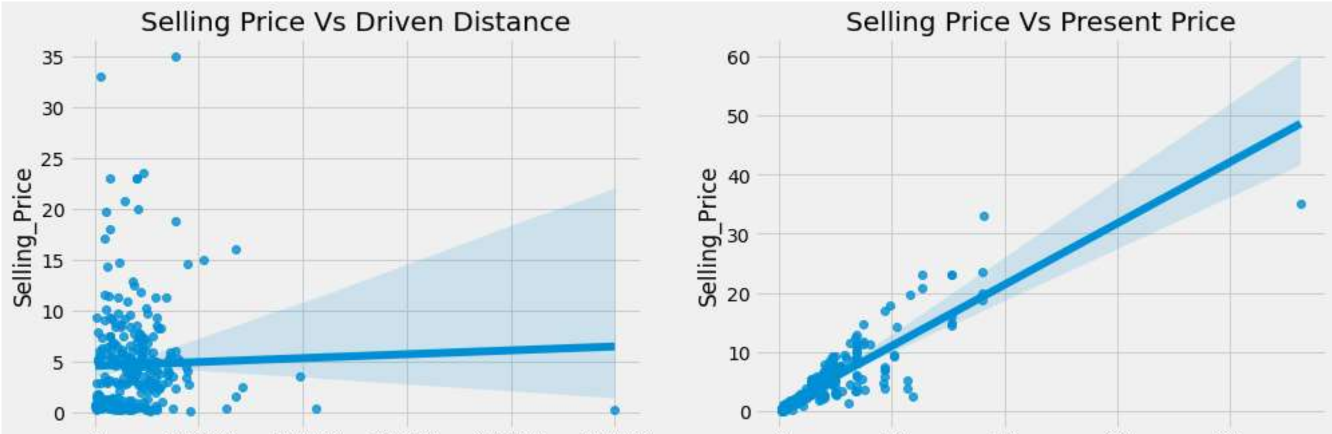
```
Text(0.5, 1.0, 'Selling Price Vs Car Age')
```



Observations: Selling Price of cars 5 years old would be high and gradually decreases with car of 20 years old

```
plt.figure(figsize=(15,5))
plt.subplot(1,2,1)
sns.regplot(data=df,x='Driven_kms',y='Selling_Price')
plt.title('Selling Price Vs Driven Distance')

plt.subplot(1,2,2)
sns.regplot(data=df,x='Present_Price',y='Selling_Price')
plt.title('Selling Price Vs Present Price')
plt.show()
```



Observations:

1. Lesser the driven distance, higher the Selling Price.
2. Selling Price tends to increase with increase in the Present Price of cars**

Dealing with Categorical Variables

```
cat_col = ['Fuel_Type','Selling_type','Transmission','Car_Name']
for i in cat_col:
    print(df[i].unique())
```

```
['Petrol' 'Diesel' 'CNG']
['Dealer' 'Individual']
['Manual' 'Automatic']
['ritz' 'sx4' 'ciaz' 'wagon r' 'swift' 'vitara brezza' 's cross'
 'alto 800' 'ertiga' 'dzire' 'alto k10' 'ignis' '800' 'baleno' 'omni'
 'fortuner' 'innova' 'corolla altis' 'etios cross' 'etios g' 'etios liva'
 'corolla' 'etios gd' 'camry' 'land cruiser' 'Royal Enfield Thunder 500'
 'UM Renegade Mojave' 'KTM RC200' 'Bajaj Dominar 400'
 'Royal Enfield Classic 350' 'KTM RC390' 'Hyosung GT250R'
 'Royal Enfield Thunder 350' 'KTM 390 Duke ' 'Mahindra Mojo XT300'
 'Bajaj Pulsar RS200' 'Royal Enfield Bullet 350'
 'Royal Enfield Classic 500' 'Bajaj Avenger 220' 'Bajaj Avenger 150'
 'Honda CB Hornet 160R' 'Yamaha FZ S V 2.0' 'Yamaha FZ 16'
 'TVS Apache RTR 160' 'Bajaj Pulsar 150' 'Honda CBR 150' 'Hero Extreme'
 'Bajaj Avenger 220 dtsi' 'Bajaj Avenger 150 street' 'Yamaha FZ  v 2.0'
 'Bajaj Pulsar  NS 200' 'Bajaj Pulsar 220 F' 'TVS Apache RTR 180'
 'Hero Passion X pro' 'Bajaj Pulsar NS 200' 'Yamaha Fazer '
 'Honda Activa 4G' 'TVS Sport ' 'Honda Dream Yuga '
 'Bajaj Avenger Street 220' 'Hero Splender iSmart' 'Activa 3g'
 'Hero Passion Pro' 'Honda CB Trigger' 'Yamaha FZ S '
 'Bajaj Pulsar 135 LS' 'Activa 4g' 'Honda CB Unicorn'
 'Hero Honda CBZ extreme' 'Honda Karizma' 'Honda Activa 125' 'TVS Jupyter'
 'Hero Honda Passion Pro' 'Hero Splender Plus' 'Honda CB Shine'
 'Bajaj Discover 100' 'Suzuki Access 125' 'TVS Wego' 'Honda CB twister'
 'Hero Glamour' 'Hero Super Splendor' 'Bajaj Discover 125' 'Hero Hunk'
 'Hero  Ignitor Disc' 'Hero  CBZ Xtreme' 'Bajaj  ct 100' 'i20' 'grand i10'
 'i10' 'eon' 'xcent' 'elantra' 'creta' 'verna' 'city' 'brio' 'amaze'
 'jazz']
```

```
# In Car Name column There are three hundred and twelve unique name.
# That's something really hard to implement and a regression that would mean more than 300 dummies, so we simply drop this column
df = df.drop(labels='Car_Name', axis=1)
```

```
# Dealing With Categorical Variables, creating dummie
col = ['Fuel_Type','Selling_type','Transmission']
df_new = pd.concat([df]+[pd.get_dummies(df[i],drop_first=True,prefix=i+'_') for i in col],axis=1)
df_new.drop(['Fuel_Type','Selling_type','Transmission'],axis=1,inplace=True)
df_new.head()
```

	Selling_Price	Present_Price	Driven_kms	Owner	Car_age	Fuel_Type__Diesel	Fuel_Type__Petrol	Selling_type__Individual	Transmi
0	3.35	5.59	27000	0	9	0	1	0	
1	4.75	9.54	43000	0	10	1	0	0	
2	7.25	9.85	6900	0	6	0	1	0	
3	2.85	4.15	5200	0	12	0	1	0	
4	4.60	6.87	42450	0	9	1	0	0	

Checking Multicollinearity Using VIF

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
variables = df_new[['Present_Price','Driven_kms','Owner','Car_age','Fuel_Type__Diesel','Fuel_Type__Petrol','Selling_type__Individual','Tr
vif = pd.DataFrame()
vif["VIF"] = [variance_inflation_factor(variables.values, i) for i in range(variables.shape[1])]
vif["Features"] = variables.columns
vif
```

	VIF	Features
0	3.211044	Present_Price
1	2.888998	Driven_kms
2	1.086964	Owner
3	16.194782	Car_age
4	5.395420	Fuel_Type__Diesel
5	16.933491	Fuel_Type__Petrol
6	2.231970	Selling_type__Individual
7	8.440614	Transmission__Manual

```
# Car_age and fuel_type_petrol feature has high VIF
df_no_multicolinearity = df_new.drop(['Driven_kms','Fuel_Type__Petrol'],axis=1)
```

```
# cheking again after removing some correlated feature
variables = df_new[['Present_Price','Driven_kms','Owner','Fuel_Type__Diesel','Selling_type__Individual','Transmission__Manual']]
vif = pd.DataFrame()
vif["VIF"] = [variance_inflation_factor(variables.values, i) for i in range(variables.shape[1])]
vif["Features"] = variables.columns
vif
```

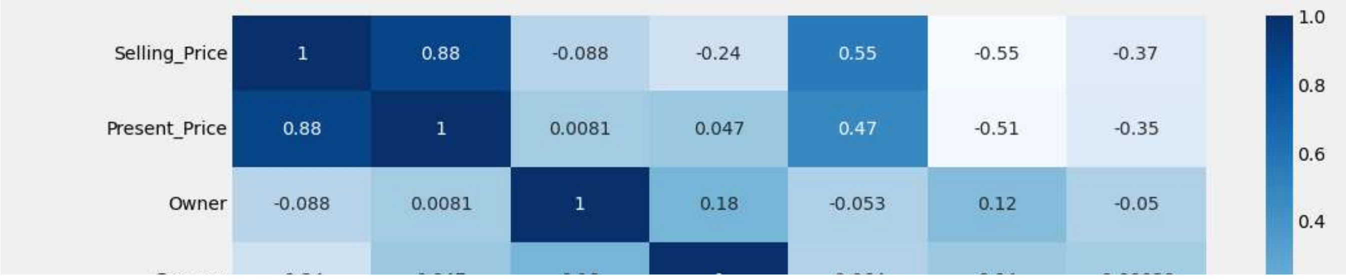
	VIF	Features
0	2.200856	Present_Price
1	1.883550	Driven_kms
2	1.065891	Owner
3	1.669331	Fuel_Type__Diesel
4	1.748706	Selling_type__Individual
5	2.465837	Transmission__Manual

Now we have VIF < 5 and hence there is no Multicollinearity occurrence in our model

Feature Selection: Feature selection simplified models, improves speed and prevent a series of unwanted issues arising from having many features

```
plt.figure(figsize=[15,7])
sns.heatmap(df_no_multicolinearity.corr(), annot=True,cmap='Blues')
```

```
<Axes: >
```



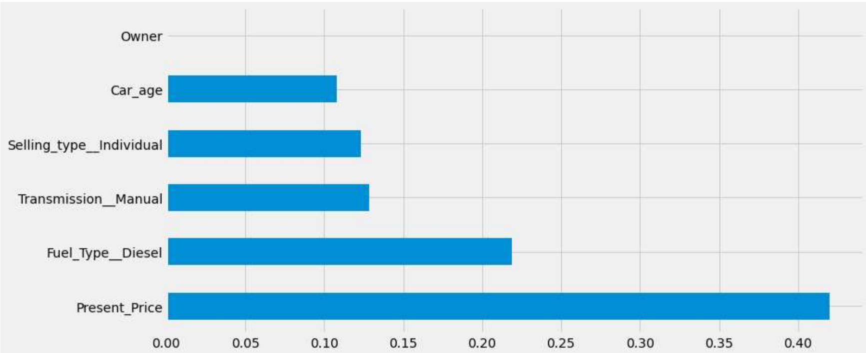
Feature Importance: Feature importance gives you a score for each feature of your data, the higher the score more important or relevant is the feature towards our Target variable.

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

```
# Important feature using ExtraTreesRegressor
from sklearn.ensemble import ExtraTreesRegressor
etree = ExtraTreesRegressor()
etree.fit(X,y)
```

```
▾ ExtraTreesRegressor
ExtraTreesRegressor()
```

```
# plot graph of feature importances for better visualization
plt.figure(figsize=[12,6])
feat_importances = pd.Series(etree.feature_importances_, index=X.columns)
feat_importances.nlargest(6).plot(kind='barh')
plt.show()
```




```
print(feat_importances.sort_values(ascending=False))
```

```
Present_Price               0.419832
Fuel_Type__Diesel           0.218754
Transmission__Manual        0.128481
Selling_type__Individual    0.123524
Car_age                     0.108105
Owner                       0.001304
dtype: float64
```

```
# Selecting useful features.
final_df = df_no_multicolinearity[['Selling_Price', 'Present_Price','Car_age','Fuel_Type__Diesel','Selling_type__Individual','Transmissic
final_df.head()
```

	Selling_Price	Present_Price	Car_age	Fuel_Type__Diesel	Selling_type__Individual	Transmission__Manual
0	3.35	5.59	9	0	0	1
1	4.75	9.54	10	1	0	1
2	7.25	9.85	6	0	0	1
3	2.85	4.15	12	0	0	1
4	4.60	6.87	9	1	0	1

Model Development

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

Feature Scaling

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit_transform(X[['Present_Price','Car_age']])
input_scaled = scaler.transform(X[['Present_Price','Car_age']])
scaled_data = pd.DataFrame(input_scaled, columns=['Present_Price','Car_age'])
```

```
X_scaled =scaled_data.join(X.drop(['Present_Price','Car_age'],axis=1))
```

```
#Training and Testing Data
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42)
X_train.shape,y_train.shape,X_test.shape,y_test.shape
```

```
((240, 5), (240,), (61, 5), (61,))
```

```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,GradientBoostingRegressor
from xgboost import XGBRegressor
from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error
```

```
res = pd.DataFrame()

lr = LinearRegression()
tree = DecisionTreeRegressor()
rf = RandomForestRegressor()
gb = GradientBoostingRegressor()
xgb = XGBRegressor()

Models = [lr,tree,rf,gb,xgb]

for model in Models:
    print('Model is: {}'.format(model))
    m = model.fit(X_train,y_train)
    print('Training score : {}'.format(m.score(X_train,y_train)))
    prediction = m.predict(X_test)
    print('Predictions are : {}'.format(prediction))

    r2score = r2_score(y_test,prediction)
    print('R2 score is : {}'.format(r2score))

    mae = mean_absolute_error(y_test,prediction)
    mse = mean_squared_error(y_test,prediction)
    rmse = np.sqrt(mean_squared_error(y_test,prediction))
    print('MAE : {}'.format(mae))
    print('MSE : {}'.format(mse))
    print('RMSE : {}'.format(rmse))

    model_dict = {'Model Name' : model, 'R2 score':r2score,'MAE' : mae,'MSE' : mse,'RMSE' : rmse}
    res = res.append(model_dict,ignore_index=True)
    print(res)
    print('='*80)
```

```
Model is: LinearRegression()
Training score : 0.8843830218270095
Predictions are : [ 2.85090216  8.12803353  6.41650528 -0.72103319  9.01800124  7.45747829
  1.32336542  0.65668224  1.34213912  7.4813302   9.09094746  0.49298142
  8.12866516  3.24051879  6.83169728  3.16976577  0.19714116 10.69155693
  1.75733112  2.3029391   0.17755181  8.07727328  6.41650528  2.38200739
  0.70357043  3.5644606   5.30530948  2.68891188  2.15374942  1.7513451
  0.20184841  9.20766793 -0.97424783  2.05714484  8.66976944  4.48435841
  7.34281425  7.35723323  2.96516278  7.7425873   3.60354714  4.10888459
  4.22860468  0.6268443   7.32533886  0.37789223  7.29764953 11.06720188
  3.04615146  5.30397652  6.58815672  2.15374942 20.47942208 16.80427774
  7.66208128  9.62400888  4.34541732  9.01503698  1.41857615  7.45010211
  0.11361337]
R2 score is : 0.8520804961634096
MAE : 1.207955719295842
MSE : 3.407412232827175
RMSE : 1.845917721033951
           Model Name  R2 score       MAE       MSE      RMSE
```

```
0  LinearRegression()   0.85208  1.207956  3.407412  1.845918
============================================================================
Model is: DecisionTreeRegressor()
Training score : 0.9987176853605171
Predictions are : [ 0.45       10.21666667  5.2         0.2         7.25        4.9
  1.13        0.4         0.475       7.2         7.25        1.
  7.5         0.465       5.95        2.35        0.9        18.
  0.475       1.65        0.38        8.75        5.2         2.35
  0.5         2.9         5.25        3.1         1.45        1.15
  0.38       11.25        0.52        2.25        7.75        3.9
  7.25        3.6         2.55        4.35        3.49        3.35
  5.4         0.6         4.9         0.65        8.73        9.45
  3.1         2.9         4.8         1.45       23.         20.75
  4.9        10.21666667  4.825       8.99        2.25        6.2
  0.25      ]
R2 score is : 0.9442622702784067
MAE : 0.662622950819672
MSE : 1.2839511839708557
RMSE : 1.1331156975220384
                Model Name  R2 score       MAE       MSE      RMSE
0       LinearRegression()  0.852080  1.207956  3.407412  1.845918
1  DecisionTreeRegressor()  0.944262  0.662623  1.283951  1.133116
============================================================================
Model is: RandomForestRegressor()
Training score : 0.9829456283572534
Predictions are : [ 0.45840762 10.24463571  5.137       0.24475     7.60988571  6.19
  1.1225781   0.49478524  0.46674095  6.71        7.6511      1.05334
  7.88133135  0.46018357  5.6475      2.807       1.1083     14.21191667
  0.47304762  1.5575      0.27161667  8.16579167  5.137       2.543
  0.53447738  3.59120357  5.346       3.0945      1.32        1.1617
  0.4102     10.75391667  0.466375    2.32        7.8285      4.08772619
  7.13246905  4.67496667  2.434625    5.78763333  4.09816667  3.542
  4.54471667  0.58911667  6.10583333  0.73113333  8.50034623  6.79533333
  2.92933333  3.654       4.9875      1.32       21.98080667 19.98763333
  6.482      10.78471905  4.8274875   9.2302      2.3225      6.29186667
  0.2464    ]
R2 score is : 0.9605520732118513
MAE : 0.5993053955243303
MSE : 0.908706051678621
RMSE : 0.9532607469515468
```

Model Comparison

```
models = ['LinearRegression','DecisionTreeRegressor','RandomForestRegressor','GradientBoostingRegressor','XGBRegressor']

result = pd.DataFrame({'Models':models})
result['R2 score'] = res['R2 score']
result['MAE'] = res['MAE']
result['MSE'] = res['MSE']
result['RMSE'] = res['RMSE']
result = result.sort_values(by='R2 score',ascending=False)
result
```

	Models	R2 score	MAE	MSE	RMSE
3	GradientBoostingRegressor	0.971354	0.498727	0.659878	0.812328
2	RandomForestRegressor	0.960552	0.599305	0.908706	0.953261
1	DecisionTreeRegressor	0.944262	0.662623	1.283951	1.133116
4	XGBRegressor	0.935905	0.653831	1.476469	1.215100
0	LinearRegression	0.852080	1.207956	3.407412	1.845918

```
#Trainning data with GradientBoostingRegressor
gb.fit(X_train,y_train)
y_pred = gb.predict(X_test)

out = pd.DataFrame({'Price_actual':y_test,'Price_pred':y_pred})
df_copy = df.copy()
res = df_copy.merge(out,left_index=True,right_index=True)
res.head(10)
```

	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner	Car_age	Price_actual	Price_pre
5	9.25	9.83	2071	Diesel	Dealer	Manual	0	5	9.25	8.22310
7	6.50	8.61	33429	Diesel	Dealer	Manual	0	8	6.50	6.73746
9	7.45	8.92	42367	Diesel	Dealer	Manual	0	8	7.45	6.55006
17	7.75	10.79	43000	Diesel	Dealer	Manual	0	7	7.75	8.34954

Conclusions:

1. Present price of a car plays an important role in predicting Selling Price, One increases the other gradually increases.
2. Car age is effecting negatively. As older the car lesser the Selling Price.
3. Selling Price of cars with Fuel type Diesel is higher.
4. Car of Manual type is of less priced whereas of Automatic type is high.
5. Cars sold by Individual tend to get less Selling Price when sold by Dealers.