```
In [ ]: Name:Abhishek V Sutrave
        Batch: MARCH P-1
        Role:Data Science Intern
        Company:OASIS INFOBYTE

        Objective:Examine the impact of different factors on car prices and apply Machine learning methods in Python to predict car prices

        TASK3 : CAR PRICE PREDICTION WITH MACHINE LEARNING
```

```
In [1]: #Importing required libraries
        import pandas as pd
        import numpy as np
        import warnings
        warnings.filterwarnings('ignore')
        #Importing libraries for data visualization
        import matplotlib.pyplot as plt
        from matplotlib import style
        import seaborn as sns
```

```
In [ ]: #Loading The Dataset
        data =pd.read_csv(r"C:/Users/Abhishek/Desktop/OASIS INFOBYTE/car data.csv")
```

Conducting exploratory analysis to comprehend the variables and their associated values

```
In [17]: #Analyzing the structure of dataset
         data.shape
```

```
Out[17]: (301, 9)
```

```
In [18]: #Exploring the dataset variables
         data.info
```

```
Out[18]: <bound method DataFrame.info of     Car_Name  Year  Selling_Price  Present_Price  Driven_kms Fuel_Type  \
0       ritz  2014           3.35           5.59       27000    Petrol
1        sx4  2013           4.75           9.54       43000    Diesel
2       ciaz  2017           7.25           9.85        6900    Petrol
3    wagon r  2011           2.85           4.15        5200    Petrol
4      swift  2014           4.60           6.87       42450    Diesel
..       ...   ...            ...            ...         ...       ...
296     city  2016           9.50          11.60       33988    Diesel
297     brio  2015           4.00           5.90       60000    Petrol
298     city  2009           3.35          11.00       87934    Petrol
299     city  2017          11.50          12.50        9000    Diesel
300     brio  2016           5.30           5.90        5464    Petrol

    Selling_type Transmission  Owner
0         Dealer       Manual      0
1         Dealer       Manual      0
2         Dealer       Manual      0
3         Dealer       Manual      0
4         Dealer       Manual      0
..           ...          ...    ...
296       Dealer       Manual      0
297       Dealer       Manual      0
298       Dealer       Manual      0
299       Dealer       Manual      0
300       Dealer       Manual      0

[301 rows x 9 columns]>
```

```
In [20]: #Display the first 5 rows of the dataset
         data.head(5)
```

Out[20]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_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 [21]: #Conducting summary statistics analysis
         data.describe()
```

Out[21]:

	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
max	2018.000000	35.000000	92.600000	500000.000000	3.000000

```
In [26]: #Identifying missing values in the dataset
         data.isnull().sum()
```

```
Out[26]: 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
```

```
In [27]: #Removing unecessary columns from the dataset
         data.drop(columns=['Owner'],inplace=True)
```

```
In [29]: #Extracting categorical features from the dataset
         data_cat=data.select_dtypes(exclude=['float64', 'int64'])
         print(data_cat.columns)

Index(['Car_Name', 'Fuel_Type', 'Selling_type', 'Transmission'], dtype='object')
```

```
In [30]: #Extracting numerical features from dataset
         data_num=data.select_dtypes(include=['float64','int64'])
         #Display the columns for numerical data
         print(data_num.columns)

Index(['Year', 'Selling_Price', 'Present_Price', 'Driven_kms'], dtype='object')
```

```
In [67]: #Identifying distinct values in each categorical feature
         categorical_columns=['Car_Name', 'Year', 'Selling_Price', 'Present_Price', 'Driven_kms',
                'Fuel_Type', 'Selling_type', 'Transmission']

         def print_value_counts():
            for col in categorical_columns:
                 print('Column Name :', col)
                 print(data[col].value_counts())
         print_value_counts()

Column Name : Car_Name
Car_Name
city                   26
corolla altis          16
verna                  14
fortuner               11
brio                   10
                       ..
Honda Activa 125        1
Hero Hunk               1
Hero  Ignitor Disc      1
Hero  CBZ Xtreme        1
Bajaj  ct 100           1
Name: count, Length: 98, dtype: int64
Column Name : Year
Year
2015    61
2016    50
2014    38
2017    35
2013    33
2012    23
2011    19
2010    15
2008     7
2009     6
2005     4
2006     4
2007     2
2003     2
2018     1
2004     1
Name: count, dtype: int64
Column Name : Selling_Price
Selling_Price
0.45     8
0.60     8
4.50     7
5.25     7
4.75     6
        ..
10.11    1
6.40     1
8.55     1
9.50     1
11.50    1
Name: count, Length: 156, dtype: int64
Column Name : Present_Price
Present_Price
9.40     14
13.60    13
5.70      8
1.47      7
4.43      6
         ..
6.10      1
13.09     1
11.60     1
11.00     1
12.50     1
Name: count, Length: 148, dtype: int64
Column Name : Driven_kms
Driven_kms
15000    9
45000    9
40000    5
25000    5
50000    5
        ..
60076    1
33988    1
87934    1
9000     1
5464     1
Name: count, Length: 206, dtype: int64
Column Name : Fuel_Type
Fuel_Type
Petrol    239
Diesel     60
CNG         2
Name: count, dtype: int64
Column Name : Selling_type
Selling_type
Dealer        195
Individual    106
Name: count, dtype: int64
Column Name : Transmission
Transmission
Manual       261
Automatic     40
Name: count, dtype: int64
```

Visualising Data

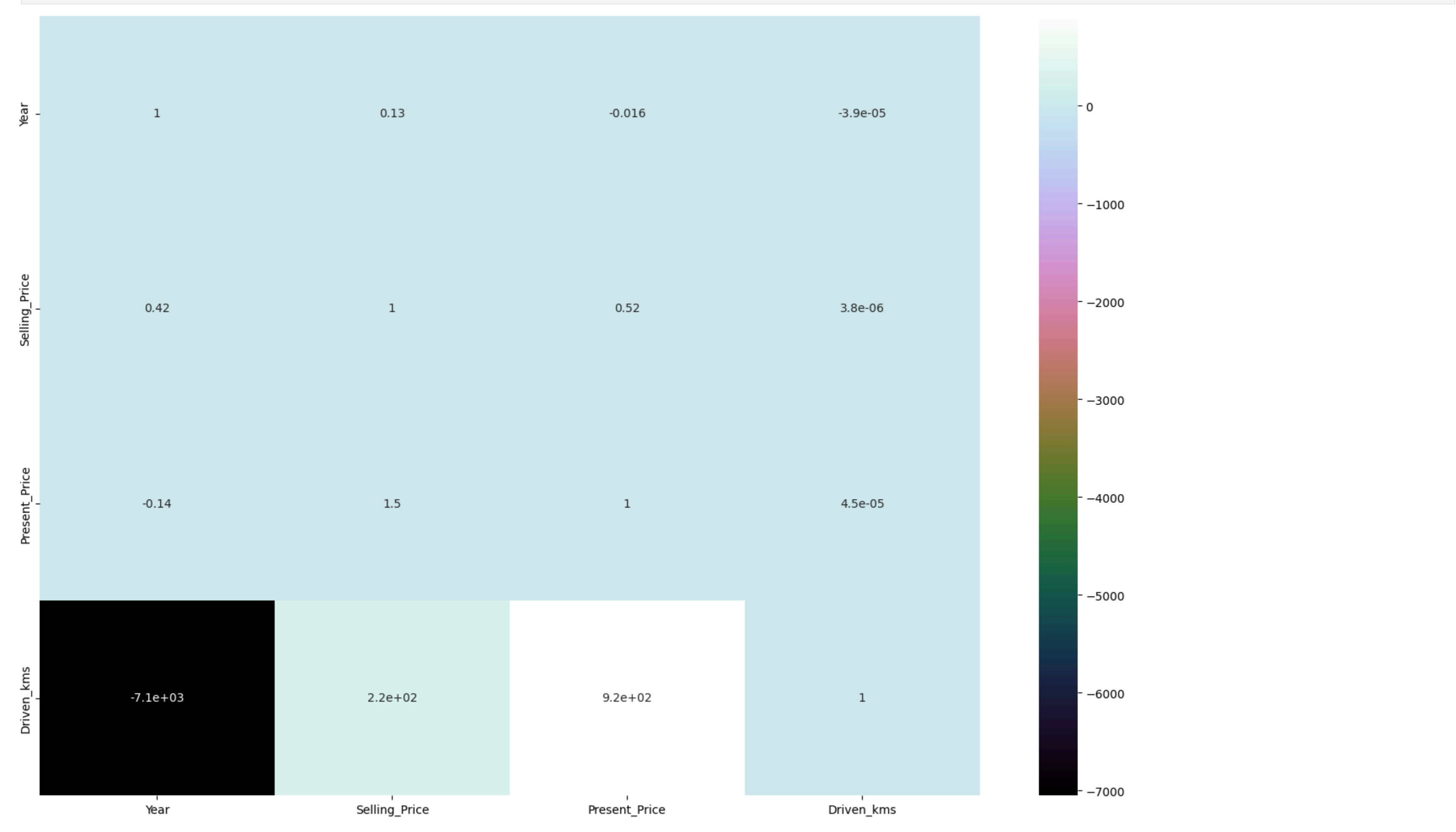
Data visualisation helps illustrate how various factors influence the price variable

HEATMAP

```
In [54]: #Compute correlations between variables in the dataset for heatmap visualization
         numeric_data =data.select_dtypes(include=['float64', 'int64'])
         data_corr = numeric_data.cov() / (numeric_data.std() * numeric_data.std())
         print(data_corr)

                      Year  Selling_Price  Present_Price  Driven_kms
Year              1.000000       0.134338      -0.015789   -0.000039
Selling_Price     0.415092       1.000000       0.516901    0.000004
Present_Price    -0.141054       1.494467       1.000000    0.000045
Driven_kms    -7051.580968     223.300627     916.168064    1.000000
```

```
In [65]: #Set the size of the plot
         plt.figure(figsize=(18,12))
         #Create a heatmap with annotations and a color map
         sns.heatmap(data_corr,annot=True,cmap="cubehelix")
         #Display the plot
         plt.show()
```

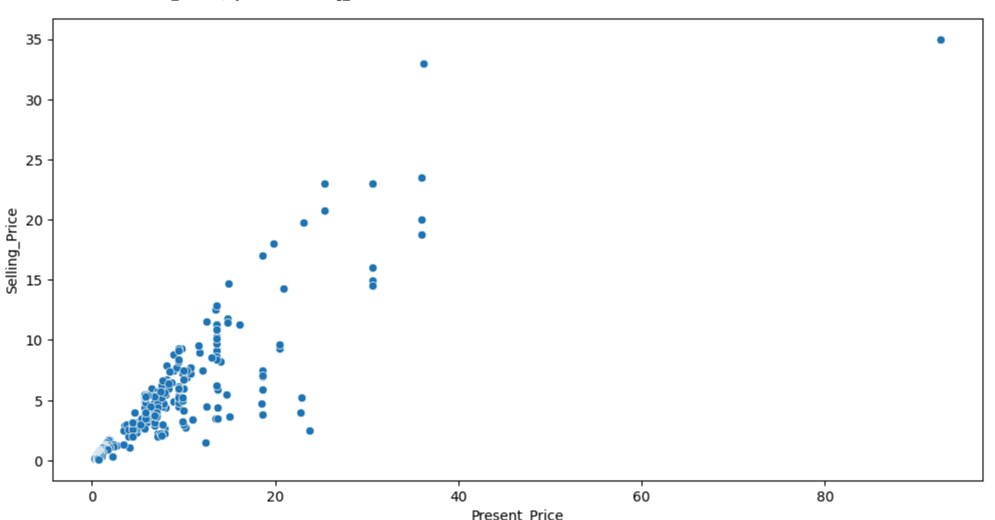


Variables Selling_Price and Present_Price have a strong correlation(around 1.5) indicating direct relationship

Present_Price shows a good correlation with Selling_Price(0.52),making it a key factor in price prediction

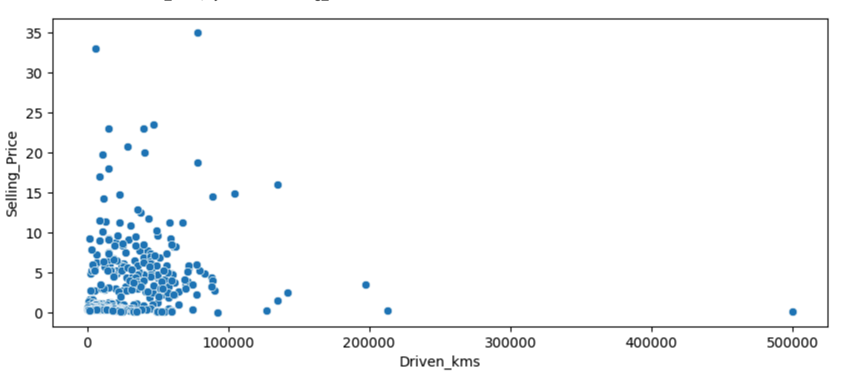
```
In [71]: #Using a scatter plot to analyze the relationship between different factors and Selling_Price
         #Scatter plot: Present_Price vs Selling_Price
         plt.figure(figsize=(12,6))
         sns.scatterplot(data=data,x=data['Present_Price'],y=data['Selling_Price'])

Out[71]: <Axes: xlabel='Present_Price', ylabel='Selling_Price'>
```



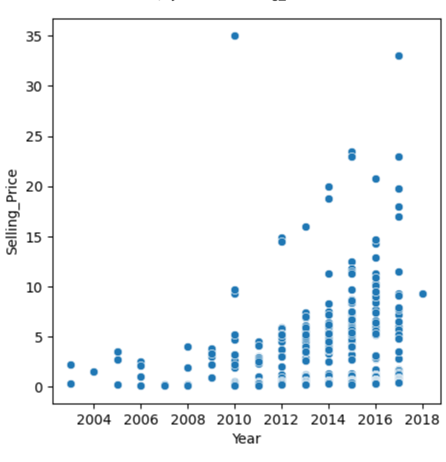

```
In [73]: #Scatter plot:Driven_kms vs Selling_Price
         plt.figure(figsize=(10,4))
         sns.scatterplot(data=data ,x=data['Driven_kms'],y=data['Selling_Price'])

Out[73]: <Axes: xlabel='Driven_kms', ylabel='Selling_Price'>
```




```
In [75]: #Scatter plot: Year vs Selling_Price
         plt.figure(figsize=(5,5))
         sns.scatterplot(data=data,x=data['Year'],y=data['Selling_Price'])

Out[75]: <Axes: xlabel='Year', ylabel='Selling_Price'>
```



The plots indicate that Present_Price has a strong positive correlation with Selling_Price ,while Driven_kms and Year show more dispersed trends

```
In [78]: #Encoding Categorical Variables into Numeric representations
         from sklearn.preprocessing import LabelEncoder
         # Create a LabelEncoder object
         encoder=LabelEncoder()
         #Encode categorical columns
         for col in ['Car_Name', 'Year', 'Selling_Price', 'Present_Price', 'Driven_kms',
                'Fuel_Type', 'Selling_type', 'Transmission']:
               data[col]=encoder.fit_transform(data[col])
         data.head(5)
```

Out[78]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission
0	90	11	59	58	86	2	0	1
1	93	10	78	105	135	1	0	1
2	68	14	112	107	26	2	0	1
3	96	8	52	49	18	2	0	1
4	92	11	76	74	134	1	0	1

Model Development

```
In [84]: #Importing train-test split function
         from sklearn.model_selection import train_test_split
         #Defining independent variables and dependent variables
         Z,a=data.drop(columns=['Car_Name','Selling_Price']),data['Selling_Price']
```

```
In [86]: #Dividing the dataset into training and testing sets
         #75% of the data is used for training ,and 25% for testing
         M_train,M_test,n_train,n_test =train_test_split(Z,a,train_size=0.75)
         #Displaying the dimensions of testing and training sets
         print('Testing data shape:',M_test.shape)
         print('Training data shape:',M_train.shape)
         print('Target variable for testing:',n_test.shape)
         print('Target variable for training :',n_train.shape)

Testing data shape: (76, 6)
Training data shape: (225, 6)
Target variable for testing: (76,)
Target variable for training : (225,)
```

Train the model using the training dataset

```
In [87]: #Importing the LinearRegression class from the sklearn library
         from sklearn.linear_model import LinearRegression
```

```
In [88]: #Implementing a linear Regression model(a type of supervised learning algorithm)
         #This model establishes a linear relationship between input features and the target variable
         lr=LinearRegression()
```

```
In [89]: #Training the Linear Regression model using the training dataset
         lr.fit(M_train,n_train)
```

```
Out[89]: ▾ LinearRegression
         LinearRegression()
```

Estimating the Car's Selling_Price

```
In [90]: #Estimating the car price using test data
         predicted_values=lr.predict(M_test)
         predicted_values
```

```
Out[90]: array([ -1.66899934, -28.85538041,  49.45422095, 120.09578631,
         50.48543916,  29.95295306,  41.70394455,   7.77790945,
        110.37214594,  68.53437654,  48.74505193,  65.89796374,
         50.30653758, 116.33125113,  93.46917833,  37.93940937,
         98.45342407, 116.56098259,  49.17897966,  88.8745717 ,
         -0.80746228, 119.92496051,  35.77323185,   8.97615947,
        115.70974167, 126.28083961, -10.42299225,  32.68310162,
         40.7619644 , 105.95788527,  78.3107891 ,  42.7331129 ,
         93.08398342,  68.65153089,  77.72481968, 112.69143243,
         33.63289772,  49.18911018,  65.16027895,  89.14794317,
         12.324184  ,  67.86881249,  23.36862129,  29.62859965,
         84.11007896,  19.62233235,  69.53846172,  51.89563976,
         24.08820971,  76.49667821, 119.36518742,  82.47275953,
        104.29194908, 110.54671545,  41.14458603,  48.39882967,
         37.88594945, 113.27386528, 105.81837091,  41.97064469,
        158.26034401,  59.91409086, 122.58182416,  40.1061163 ,
         40.71009386, 105.67365322,  49.37442326, 100.23434096,
         -2.04538863,  15.93774473,  70.05237205,  95.73822788,
         16.39006856, 103.313972  ,  39.12012748, 134.93866709])
```

Evaluate model's performance

```
In [91]: #Importing the mean squared error metric from sklearn
         from sklearn.metrics import mean_squared_error
```

```
In [95]: #Evaluating the difference between actual and predicted values
         mse_value=mean_squared_error(n_test,predicted_values)
         print("Mean Squared Error:",mse_value)

Mean Squared Error: 154.55398880529572
```

In [98]:

```
#Bringing in the function to measure the model's goodness of fit
from sklearn.metrics import r2_score as determination_coefficient
r2_value=determination_coefficient(n_test,predicted_values)
print("r-squared:",r2_value)
```

```
r-squared: 0.914833386376817
```