Experiment No. 1
Analyze the Boston Housing dataset and apply appropriate Regression Technique
Date of Performance: 27/07/2023
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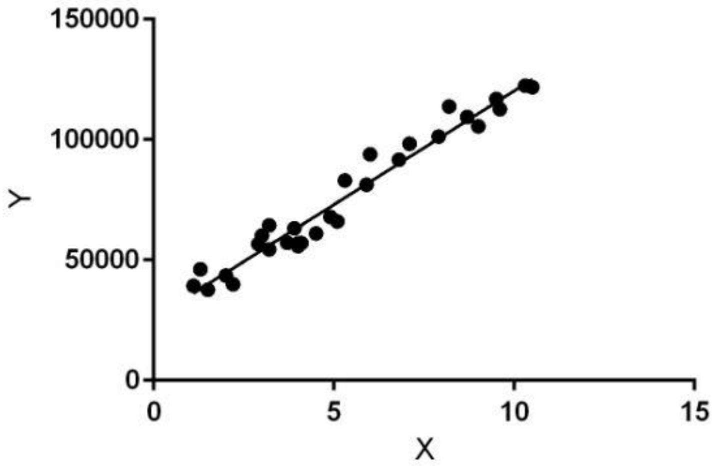
Aim: Analyze the Boston Housing dataset and apply appropriate Regression Technique.

Objective: Ablility to perform various feature engineering tasks, apply linear regression on the given dataset and minimise the error.

Theory:

Linear Regression is a machine learning algorithm based on supervised learning. It performs a regression task. Regression models a target prediction value based on independent variables. It is mostly used for finding out the relationship between variables and forecasting. Different regression models differ based on – the kind of relationship between dependent and independent variables they are considering, and the number of independent variables getting used.



Linear regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a linear relationship between x (input) and y(output). Hence, the name is Linear Regression.
In the figure above, X (input) is the work experience and Y (output) is the salary of a person. The regression line is the best fit line for our model.

Dataset:
The Boston Housing Dataset
The Boston Housing Dataset is a derived from information collected by the U.S. Census Service concerning housing in the area of Boston MA. The following describes the dataset columns:

CRIM - per capita crime rate by town

ZN - proportion of residential land zoned for lots over 25,000 sq.ft.

INDUS - proportion of non-retail business acres per town.

CHAS - Charles River dummy variable (1 if tract bounds river; 0 otherwise)

NOX - nitric oxides concentration (parts per 10 million)

RM - average number of rooms per dwelling

AGE - proportion of owner-occupied units built prior to 1940

DIS - weighted distances to five Boston employment centres

RAD - index of accessibility to radial highways

TAX - full-value property-tax rate per $10,000

PTRATIO - pupil-teacher ratio by town

B - 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town

LSTAT - % lower status of the population

MEDV - Median value of owner-occupied homes in $1000's

Code:

```
import numpy as np
import pandas as pd
import seaborn as sns
import sklearn
```

```
df = pd.read_csv('./boston.csv')
```

```
df.keys() #return all the keys of the dictionary
```

```
Index(['Unnamed: 0', 'CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS',
       'RAD', 'TAX', 'PTRATIO', 'B', 'LSTAT', 'Price'],
      dtype='object')
```

```
df.describe()
```

	Unnamed: 0	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506
mean	252.500000	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3
std	146.213884	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2
min	0.000000	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1
25%	126.250000	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2
50%	252.500000	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3
75%	378.750000	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5
max	505.000000	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 15 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  506 non-null    int64
 1   CRIM        506 non-null    float64
 2   ZN          506 non-null    float64
 3   INDUS       506 non-null    float64
 4   CHAS        506 non-null    float64
 5   NOX         506 non-null    float64
 6   RM          506 non-null    float64
 7   AGE         506 non-null    float64
 8   DIS         506 non-null    float64
 9   RAD         506 non-null    float64
 10  TAX         506 non-null    float64
 11  PTRATIO     506 non-null    float64
 12  B           506 non-null    float64
 13  LSTAT       506 non-null    float64
 14  Price       506 non-null    float64
dtypes: float64(14), int64(1)
memory usage: 59.4 KB
```

```
df.head(5)
```

	Unnamed: 0	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	Pri
0	0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98	2
1	1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14	2
2	2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03	3
3	3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94	3
4	4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33	3

Check if the dataset contains any null value or not

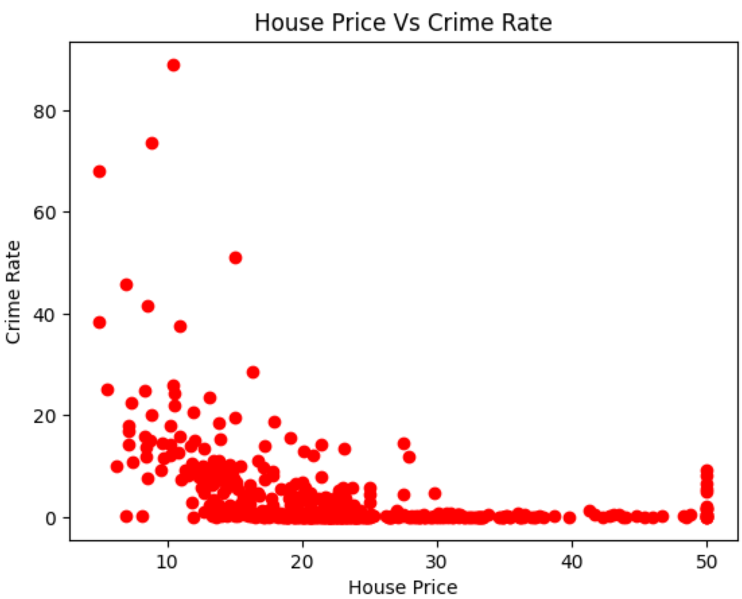
```
df.isnull()
```

	Unnamed: 0	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	Pr
0	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
1	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
2	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
3	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
4	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
501	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
502	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
503	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
504	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
505	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F

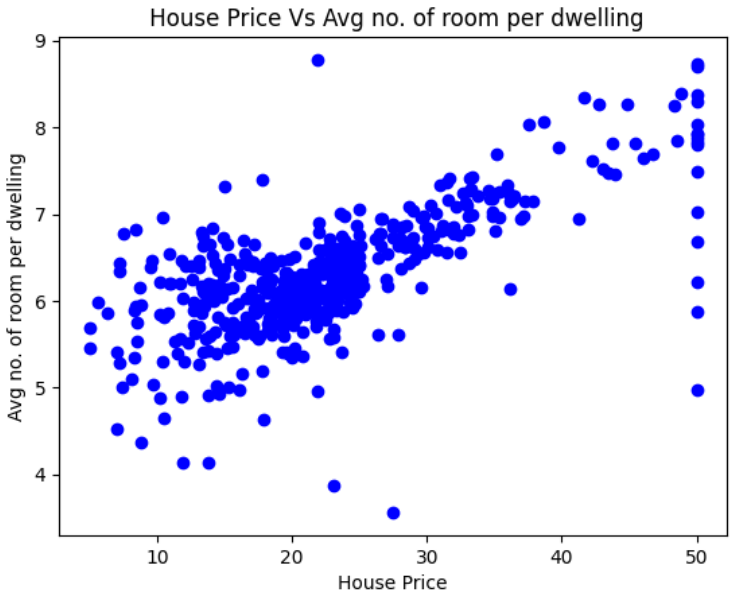
```
df.isnull().sum()
```

```
Unnamed: 0    0
CRIM          0
ZN            0
INDUS         0
CHAS          0
NOX           0
RM            0
AGE           0
DIS           0
RAD           0
TAX           0
PTRATIO       0
B             0
LSTAT         0
Price         0
dtype: int64
```

```
import matplotlib.pyplot as plt

plt.scatter(df['Price'],df['CRIM'], color='red')
plt.title(" House Price Vs Crime Rate ")
plt.xlabel("House Price")
plt.ylabel("Crime Rate")
plt.show()
```

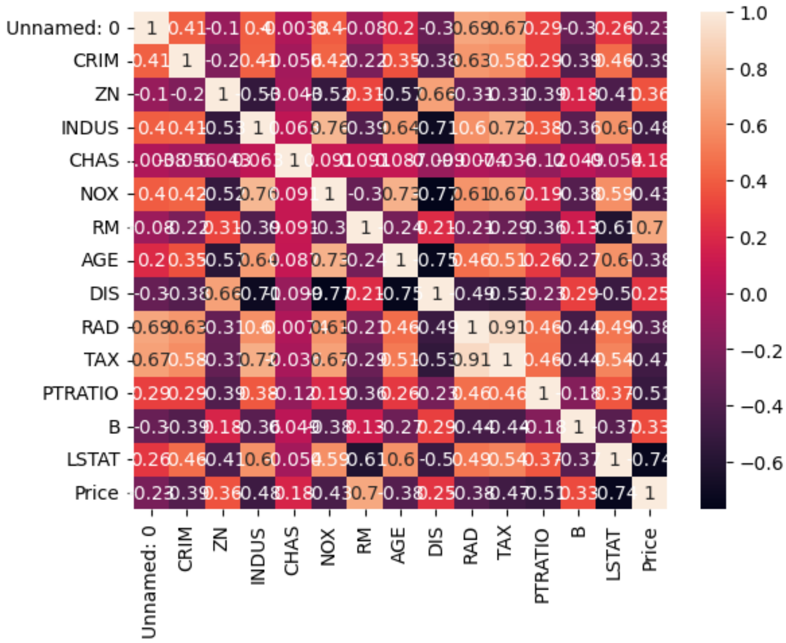



```
plt.scatter(df['Price'],df['RM'], color='blue')
plt.title(" House Price Vs Avg no. of room per dwelling")
plt.xlabel("House Price")
plt.ylabel("Avg no. of room per dwelling")
plt.show()
```




```
sns.heatmap(df.corr(), annot=True)
```

```
<Axes: >
```



We never train the model on all the data that we have, we split the data into two; one is training data and other is testing data to compare the result after traing the model with the testing data.

```
from sklearn.model_selection import train_test_split
```

```
X = df.drop(['Price'], axis=1)
```

```
Y = df['Price']
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.15, random_state=5)
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
```

```
(430, 14)
(76, 14)
(430,)
(76,)
```

Importing the linear regression model and train it on the training dataset

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
```

Fitting the model on the training data

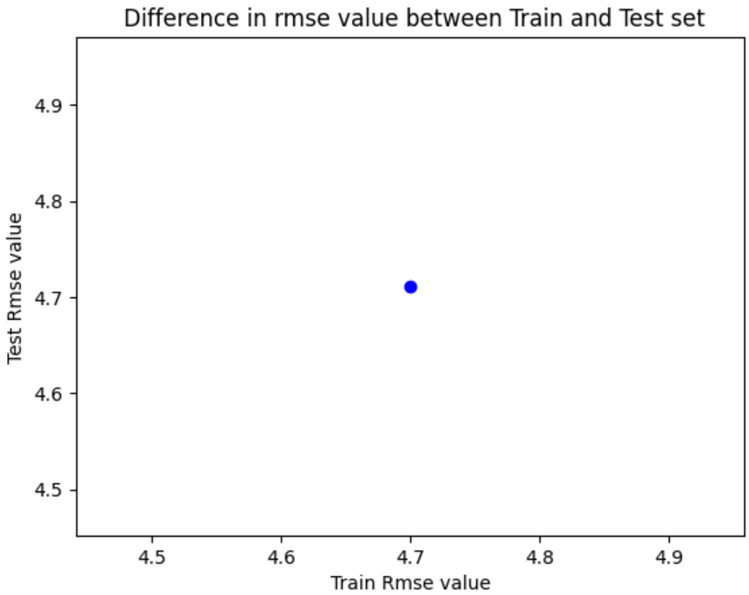
```
lin_model = LinearRegression()
lin_model.fit(X_train, Y_train)
```

```
▸ LinearRegression
```

```
y_train_predict = lin_model.predict(X_train)
rmse = (np.sqrt(mean_squared_error(Y_train, y_train_predict)))

print("The model performance for the training set")
print('RMSE is {}'.format(rmse))
print("\n")

#on testing set

y_test_predict = lin_model.predict(X_test)
rmsee = (np.sqrt(mean_squared_error(Y_test, y_test_predict)))

print("The model performance for the testing set")
print('RMSE is {}'.format(rmsee))
```

```
The model performance for the training set
RMSE is 4.700268480051523


The model performance for the testing set
RMSE is 4.711340264707373
```

```
plt.scatter(rmse, rmsee, color='blue')
plt.title(" Difference in rmse value between Train and Test set")
plt.xlabel("Train Rmse value")
plt.ylabel("Test Rmse value")
plt.show()
```



Conclusion:

1. What are features have been chosen to develop the model? Justify the features chosen to estimate the price of a house.

⇨ The features chosen to develop the model for estimating the price of a house are as follows:

i) CRIM - Per Capita Crime Rate by Town:
Justification: The crime rate in an area can affect the desirability and perceived safety of a neighborhood, which in turn can impact property values.

ii) ZN - Proportion of Residential Land Zoned for Large Lots:
Justification: The proportion of land zoned for larger lots may indicate a more spacious and upscale neighborhood, which can influence house prices.

iii) INDUS - Proportion of Non-Retail Business Acres per Town:
Justification: The industrial vs. residential balance in an area can affect the quality of life and demand for housing, potentially influencing prices.

iv) CHAS - Charles River Dummy Variable:
Justification: Being located near a river (Charles River in this case) can be an attractive feature, leading to higher property values.

v) NOX - Nitric Oxides Concentration:
Justification: Air quality is an important factor for homebuyers, and areas with lower pollution levels may have higher property values.

vi) RM - Average Number of Rooms per Dwelling:
Justification: The number of rooms directly relates to the size of the house and its potential for accommodating larger families, which can affect prices.

vii) AGE - Proportion of Owner-Occupied Units Built Prior to 1940:
Justification: Older homes may have historical significance or unique architecture, contributing to their value.

viii) DIS - Weighted Distances to Boston Employment Centers:

Justification: Proximity to employment centers can influence demand and, consequently, house prices.

ix) RAD - Index of Accessibility to Radial Highways:

Justification: Good highway access is convenient and can attract potential homebuyers, potentially leading to higher prices.

x) TAX - Full-Value Property-Tax Rate:

Justification: Property tax rates can impact the overall cost of homeownership and influence a buyer's decision.

xi) PTRATIO - Pupil-Teacher Ratio:

Justification: School quality is a significant factor for families, and a lower pupil-teacher ratio may be associated with better schools and higher home values.

xii) B - Proportion of Blacks by Town:

Justification: The B feature represents a complex interaction involving the proportion of blacks in the population. It could be related to socioeconomic factors that may impact housing values.

xiii) LSTAT - Percentage of Lower Status of the Population:

Justification: A higher percentage of a lower-status population might be associated with lower property values due to potential socioeconomic challenges.

2. Comment on the Mean Squared Error calculated.

⇨ RMSE for Training Set:

The RMSE value of 4.700268480051523 for the training set indicates that, on average, the model's predictions deviate from the actual values by approximately 4.70 units. This means that the model's predictions are fairly close to the actual values for the training data, with relatively low prediction errors.

RMSE for Testing Set:

The RMSE value of 4.711340264707373 for the testing set is slightly higher than the RMSE for the training set. This indicates that the model's performance on unseen data (testing set) is also relatively good, with predictions being, on average, off by about 4.71 units.

The RMSE for the testing set being close to the RMSE for the training set suggests that the model is not overfitting to the training data and is generalizing well to new data.