### Practical No.: 04

Create a Linear Regression Model using Python/R to predict home prices using Boston Housing Dataset (https://www.kaggle.com/c/boston-housing). The Boston Housing dataset contains information about various houses in Boston through different parameters. There are 506 samples and 14 feature variables in this dataset.

The objective is to predict the value of prices of the house using the given features

### Import libraries

x.info()

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.model_selection import train_test_split
         from sklearn.linear_model import LinearRegression
        from sklearn.metrics import mean_squared_error, mean_absolute_error
        from sklearn.preprocessing import StandardScaler
        boston = pd.read_csv(r"C:\Users\shreyash\Documents\DSBDA\A4\boston_csv")
        boston.head()
                    ZN INDUS CHAS
                                                            DIS RAD
                                                                       TAX PTRATIO BLACK LSTAT MEDV
             CRIM
                                        NOX
                                               RM AGE
         0.00632
                    18.0
                           2.31
                                                                                                        24.0
                                     0 0.538 6.575
                                                    65.2 4.0900
                                                                      296.0
                                                                                 15.3
                                                                                       396.90
                                                                                                 4.98
         1 0.02731
                           7.07
                                                    78.9 4.9671
                                                                    2 242.0
                                                                                       396.90
                                                                                                        21.6
                     0.0
                                     0 0.469
                                             6.421
                                                                                 17.8
                                                                                                 9.14
         2 0.02729
                     0.0
                           7.07
                                     0 0.469 7.185
                                                    61.1 4.9671
                                                                    2 242.0
                                                                                 17.8
                                                                                       392.83
                                                                                                 4.03
                                                                                                        34.7
         3 0.03237
                     0.0
                           2.18
                                     0 0.458
                                             6.998
                                                    45.8 6.0622
                                                                    3 222.0
                                                                                 18.7
                                                                                       394.63
                                                                                                 2.94
                                                                                                        33.4
          4 0.06905
                     0.0
                           2.18
                                     0 0.458 7.147
                                                    54.2 6.0622
                                                                    3 222.0
                                                                                 18.7
                                                                                       396.90
                                                                                                 5.33
                                                                                                        36.2
        x = boston.drop(columns=["MEDV"], axis=1)
          boston.MEDV
        x.head()
                     ZN INDUS CHAS
                                        NOX
                                               RM AGE
                                                            DIS RAD
                                                                       TAX PTRATIO BLACK LSTAT
             CRIM
Out[4]:
         0.00632
                           2.31
                                     0 0.538 6.575
                                                    65.2 4.0900
                                                                      296.0
                                                                                       396.90
                                                                                                 4.98
         1 0.02731
                     0.0
                           7.07
                                      0.469
                                             6.421
                                                    78.9
                                                         4.9671
                                                                    2 242.0
                                                                                 17.8
                                                                                       396.90
                                                                                                 9.14
                                                                    2 242.0
         2 0.02729
                           7.07
                                     0 0.469 7.185
                                                    61.1 4.9671
                                                                                 17.8
                                                                                       392.83
                                                                                                 4.03
                     0.0
         3 0.03237
                     0.0
                           2.18
                                       0.458
                                             6.998
                                                    45.8
                                                         6.0622
                                                                    3
                                                                      222.0
                                                                                 18.7
                                                                                       394.63
                                                                                                 2.94
         4 0.06905
                     0.0
                           2.18
                                     0 0.458 7.147 54.2 6.0622
                                                                    3 222.0
                                                                                 18.7
                                                                                       396.90
                                                                                                 5.33
        x.shape, y.shape
out[5]: ((506, 13), (506,))
        Basic stats
```

0 CR IM 506 non-null float64 1 ΖN 506 non-nu**ll** float64 2 INDUS 506 non-nu**ll** float64 3 **CHAS** 506 non-nu**ll** int64 4 NOX 506 non-nu**ll** float64 5 RM506 non-null float64 6 AGE 506 non-null float64 DIS 506 non-null float64 8 RAD 506 non-null int64 9 TAX 506 non-nu**ll** float64 10 PTRATIO 506 non-null float64 **BLACK** 506 non-nu**ll** float64 12 LSTAT 506 non-nu**ll** float64 dtypes: float64(11), int64(2) memory usage: 51.5 KB x.describe() Out[7]: CRIM ΖN **INDUS CHAS** NOX RMAGE DIS RAD TAX **count** 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 5 9.549407 408.237154 mean 3.613524 11.363636 11.136779 0.069170 0.554695 6.284634 68.574901 3.795043 std 8.601545 23.322453 6.860353 0.253994 0.115878 0.702617 28.148861 2.105710 8.707259 168.537116 1.000000 187.000000 0.006320 0.000000 0.460000 0.000000 0.385000 3.561000 2.900000 1.129600 min 25% 0.082045 0.000000 5.190000 0.000000 0.449000 5.885500 45.025000 2.100175 4.000000 279.000000 50% 0.256510 0.000000 9.690000 0.000000 0.538000 6.208500 77.500000 3.207450 5.000000 330.000000 75% 3.677083 12.500000 18.100000 0.000000 0.624000 6.623500 94.075000 5.188425 24.000000 666.000000 88.976200 100.000000 24.000000 711.000000 27.740000 1.000000 0.871000 8.780000 100.000000 12.126500 max 4 y.info() <class 'pandas.core.series.Series'> RangeIndex: 506 entries, 0 to 505 Series name: MEDV Non-Null Count Dtype float64 506 non-nu**ll** dtypes: float64(1) memory usage: 4.1 KB y.describe() 506.000000 count Out[9]: 22.532806 mean std 9.197104 min 5.000000 25% 17.025000 50% 21.200000 75% 25.000000 max 50.000000 Name: MEDV, dtype: float64 x.isnull().sum() Out[10]: CRIM 0 ΖN 0 **INDUS** 0 **CHAS** 0 NOX 0 RM0 **AGE** 0 DIS 0 RAD 0 TAX 0 PTRAT I O 0 **BLACK** 0 **LSTAT** 0 dtype: int64 y.isnull().sum()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 13 columns):

Non-Null Count Dtype

Column

#

Out[11]: 0

```
df = x
df["target"] = y
df.head()
    CRIM
            ZN INDUS CHAS
                               NOX
                                      RM AGE
                                                   DIS RAD
                                                              TAX PTRATIO BLACK LSTAT target
0 0.00632
           18.0
                  2.31
                            0 0.538 6.575
                                           65.2 4.0900
                                                           1 296.0
                                                                              396.90
                                                                                        4.98
                                                                                               24.0
1 0.02731
            0.0
                  7.07
                            0 0.469
                                     6.421
                                           78.9 4.9671
                                                           2 242.0
                                                                        17.8
                                                                              396.90
                                                                                        9.14
                                                                                               21.6
                  7.07
2 0.02729
           0.0
                            0 0.469 7.185 61.1 4.9671
                                                           2 242.0
                                                                        17.8
                                                                              392.83
                                                                                        4.03
                                                                                               34.7
3 0.03237
            0.0
                  2.18
                            0 0.458 6.998 45.8 6.0622
                                                           3 222.0
                                                                        18.7
                                                                              394.63
                                                                                        2.94
                                                                                               33.4
4 0.06905
           0.0
                  2.18
                            0 \quad 0.458 \quad 7.147 \quad 54.2 \quad 6.0622
                                                           3 222.0
                                                                        18.7
                                                                              396.90
                                                                                        5.33
                                                                                               36.2
Considering only 'RM' and 'LSTAT' by considering correlation and multi-collinearity of other
```

features

```
df = df[["RM", "LSTAT", "target"]]
x = df[["RM", "LSTAT"]]
y = df["target"]
```

### Scale the data

```
scaler = StandardScaler()
x = scaler.fit_transform(x)
```

# Split the data

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, shuffle=True)
         x_train.shape, x_test.shape, y_train.shape, y_test.shape
Out[18]: ((354, 2), (152, 2), (354,), (152,))
```

## Linear Regression Modelling

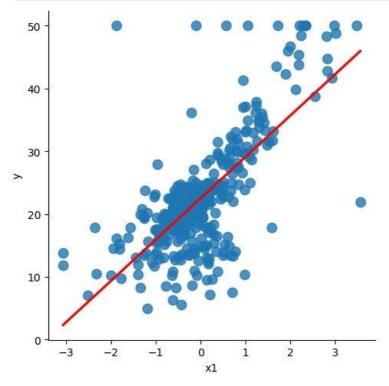
```
model = LinearRegression(n_jobs=-1)
         model.fit(x_train, y_train)
Out[20]:
              LinearRegression 🕛 🤇
         LinearRegression(n_jobs=-1)
```

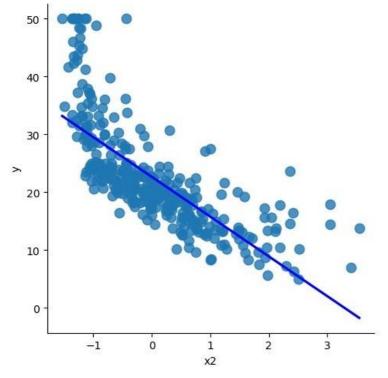
## Make predictions

df = pd.DataFrame(data)

```
y_pred = model.predict(x_test)
         mean_absolute_error(y_test, y_pred)
Out[22]: 3.951764544904325
         mean_squared_error(y_test, y_pred)
Out[23]: 30.569387567982456
In [24]:
         import pandas as pd
         import seaborn as sns
         import matplotlib.pyplot as plt
         \# Assuming x_train[0], x_train[1], and y_train are your variables
         # Create a DataFrame containing your variables
         data = { "x1": x_train[:,0], "x2": x_train[:,1], "y": y_train}
```

```
# Plot the regression line for y vs x1 and x2
sns.Implot(x="x1", y="y", data=df, ci=None, scatter_kws={"s": 80}, line_kws={"color": "red"})
sns.Implot(x="x2", y="y", data=df, ci=None, scatter_kws={"s": 80}, line_kws={"color": "blue"})
plt.show()
```





```
In [25]: df.head()
```

Out[25]:		<b>x</b> 1	x2	у
	364	3.555044	-1.032108	21.9
	40	1.053344	-1.496084	34.9
	449	0.188576	0.933128	13.0
	179	0.990659	-1.067152	37.2
	189	1.282714	-1.018091	34.9

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