We have to predict the house price - Boston DataSet

In [2]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from warnings import filterwarnings
filterwarnings('ignore')
```

In [3]:
```python
data = pd.read_csv("boston.csv")
data.head()
```

Out[3]:

	Unnamed: 0	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	Price
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	24.0
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	21.6
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	34.7
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	33.4
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	36.2

In [4]:
```python
data.columns
```

Out[4]:
```
Index(['Unnamed: 0', 'CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS',
       'RAD', 'TAX', 'PTRATIO', 'B', 'LSTAT', 'Price'],
      dtype='object')
```

In [9]:
```python
data = data.drop('Unnamed: 0',axis =1)
```

In [10]:
```python
data
```

Out[10]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	Price
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	24.0
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	21.6
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	34.7
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	33.4
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	36.2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0	391.99	9.67	22.4
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1.0	273.0	21.0	396.90	9.08	20.6
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0	396.90	5.64	23.9
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0	393.45	6.48	22.0
505	0.04741	0.0	11.93	0.0	0.573	6.030	80.8	2.5050	1.0	273.0	21.0	396.90	7.88	11.9

506 rows × 14 columns

1. CRIM

Full form: Per capita crime rate by town.

Meaning: The number of crimes per person in the town. Higher values → higher crime rate.

Impact: High crime usually decreases housing prices.

2. ZN

Full form: Proportion of residential land zoned for lots over 25,000 sq.ft.

Meaning: Percentage of land reserved for large residential plots.

Impact: Higher values suggest more spacious housing areas → prices tend to be higher.

3. INDUS

Full form: Proportion of non-retail business acres per town.

Meaning: Percentage of land used for industries.

Impact: Higher industrial land proportion often lowers housing prices.

4. CHAS

Full form: Charles River dummy variable (1 = tract bounds river; 0 = otherwise).

Meaning: Whether the property is near the Charles River.

Impact: Houses near the river (CHAS = 1) generally cost more.

5. NOX

Full form: Nitric oxide concentration (parts per 10 million).

Meaning: Measure of air pollution.

Impact: Higher NOX = more pollution → lower housing prices.

6. RM

Full form: Average number of rooms per dwelling.

Meaning: Average room count of houses in that area.

Impact: More rooms = bigger houses → higher price.

7. AGE

Full form: Proportion of owner-occupied units built before 1940.

Meaning: Share of older houses in the town.

Impact: High values = older houses, sometimes cheaper (but can vary with location).

8. DIS

Full form: Weighted distances to five Boston employment centers.

Meaning: Average distance to job centers.

Impact: Closer to jobs = higher housing prices.

9. RAD

Full form: Index of accessibility to radial highways.

Meaning: How well-connected the area is to highways.

Impact: Higher accessibility usually increases property value.

10. TAX

Full form: Full-value property-tax rate per $10,000.

Meaning: Local property tax rate.

Impact: Higher taxes may lower house prices.

11. PTRATIO

Full form: Pupil–teacher ratio by town.

Meaning: Number of students per teacher in schools.

Impact: Lower ratio (better education quality) → higher housing prices.

12. B

Formula: 1000 × (1 − 0.63 2) 1000×(1−0.63 2) where Bk Bk is the proportion of Black residents by town.

Meaning: A somewhat controversial proxy for racial diversity (outdated).

Impact: Historically used, but today considered socially inappropriate.

13. LSTAT

Full form: % lower status population.

Meaning: Percentage of residents with lower socioeconomic status.

Impact: Higher LSTAT → lower housing prices.

14. Price (MEDV)

Full form: Median value of owner-occupied homes (in $1000s).

Meaning: Target variable (the price we want to predict).

Impact: This is the output in regression tasks.

In [11]:
```
data.describe()
```

Out[11]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000
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
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000

In [13]:
```
data.shape
```

Out[13]: (506, 14)

In [14]:
```
data.tail()
```

Out[14]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	Price
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0	391.99	9.67	22.4
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1.0	273.0	21.0	396.90	9.08	20.6
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0	396.90	5.64	23.9
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0	393.45	6.48	22.0
505	0.04741	0.0	11.93	0.0	0.573	6.030	80.8	2.5050	1.0	273.0	21.0	396.90	7.88	11.9

In [16]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   CRIM     506 non-null    float64
 1   ZN       506 non-null    float64
 2   INDUS    506 non-null    float64
 3   CHAS     506 non-null    float64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      506 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    float64
 9   TAX      506 non-null    float64
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    506 non-null    float64
 13  Price    506 non-null    float64
dtypes: float64(14)
memory usage: 55.5 KB
```

In [18]:
```
data.dtypes
```

```
Out[18]: CRIM       float64
         ZN         float64
         INDUS      float64
         CHAS       float64
         NOX        float64
         RM         float64
         AGE        float64
         DIS        float64
         RAD        float64
         TAX        float64
         PTRATIO    float64
         B          float64
         LSTAT      float64
         Price      float64
         dtype: object
```

```
In [20]: data.isnull().sum()
```

```
Out[20]: 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
```

Data Cleaning is not required here

Single Linear Regerssion for one variable and Target

Now we are going to do Linear Regerssion with 1 variable -> Ind = LSTAT and Dep = Price

```
In [25]: df_1data = data[['LSTAT','Price']]
         df_1data .head()
```

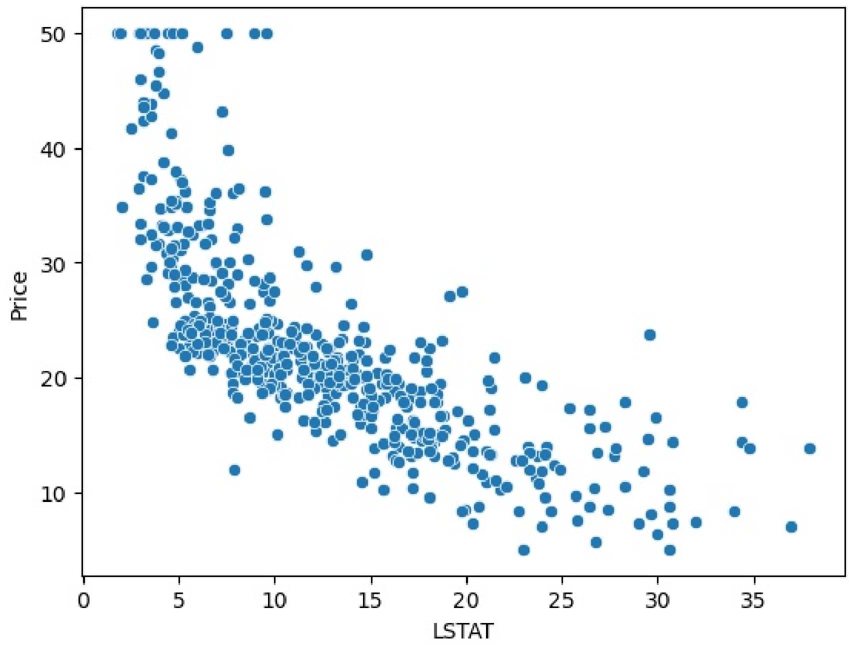
Out[25]:

	LSTAT	Price
0	4.98	24.0
1	9.14	21.6
2	4.03	34.7
3	2.94	33.4
4	5.33	36.2

find the relation b/w to one variable and target suing SCATTER PLOT

```
In [27]: sns.scatterplot(x= data.LSTAT,y=data.Price)
```

```
Out[27]: <Axes: xlabel='LSTAT', ylabel='Price'>
```



Segregating the Dependant and Independant Variables

In [28]:
```
X = pd.DataFrame(df_1data['LSTAT'])
y = pd.DataFrame(df_1data['Price'])
```

Devide the dataset into train & test

In [29]:
```
from sklearn.model_selection import train_test_split
```

In [32]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=42)
```

In [33]:
```
print(f"X Train Shape is :{X_train.shape}")
print(f"y Train Shape is : {y_train.shape}")
print("-"*30)
print(f"X Test Shape is : {X_test.shape}")
print(f"y Test Shape is : {y_test.shape}")
```

```
X Train Shape is :(404, 1)
y Train Shape is : (404, 1)
------------------------------
X Test Shape is : (102, 1)
y Test Shape is : (102, 1)
```

Create The Model

In [35]:
```
from sklearn.linear_model import LinearRegression
```

In [38]:
```
model = LinearRegression()
model
```

Out[38]:
```
▾ LinearRegression
LinearRegression()
```

Fit the model - > Linear Regression

"fit" = train the model on given data

In [39]:
```
model.fit(X_train,y_train) # finding the pattern
```

Out[39]:
```
▾ LinearRegression
LinearRegression()
```

coefficent or slope

In [40]:
```
print(model.coef_) # coefficent/slope
```

```
[[-0.9665309]]
```

why its negative value because its negative slope m =-0.9665309

Intrecept or constant

In [41]:
```
print(model.intercept_)
```

```
[34.83694982]
```

Predictions we have the coefficent and we have the intercept

In [43]:
```
y_pred = model.predict(X_test) # only pass the X_test
# y_test are not going to give beacuse
#if you give the y_test already giving the actual value you need to test
y_pred = pd.DataFrame(y_pred, columns=['Predicted'])
```

In [44]:
```
y_pred
```

Out[44]:

	Predicted
0	26.099510
1	31.425096
2	17.371736
3	29.501699
4	18.144961
...	...
97	1.617283
98	17.391067
99	14.327164
100	22.407362
101	26.196164

102 rows × 1 columns

How do you know our predicted model is good or bad

we learned about 3 errors

- Mean Squared Error (MSE)
- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- R squared
- Adj R Squared

In [45]:
```
y_test # actual error
```

Out[45]:

	Price
173	23.6
274	32.4
491	13.6
72	22.8
452	16.1
...	...
412	17.9
436	9.6
411	17.2
86	22.5
75	21.4

102 rows × 1 columns

So here Already we can see that some errors

Here we are going to find the errors

In [50]:
```
from sklearn.metrics import mean_absolute_error,mean_squared_error,root_mean_squared_error,r2_score
```

In [51]:
```
print("Mean Absolute Error :",mean_absolute_error(y_test,y_pred))
print("Mean Squared Error :",mean_squared_error(y_test,y_pred))
print("Root Mean Squared Error :",np.sqrt(root_mean_squared_error(y_test,y_pred)))

print("R Squared :",r2_score(y_test,y_pred))
```

```
Mean Absolute Error : 4.184807930623361
Mean Squared Error : 33.51954917268488
Root Mean Squared Error : 2.4061602183547923
R Squared : 0.5429180422970386
```

Multiple Linear Regerssion

same way what we done in one feature only thing is segregate portion

In [70]:
```
X = pd.DataFrame(data.iloc[:,:-1])  # data.drop('Price',axis =1)
y = pd.DataFrame(data.iloc[:,-1])
```

In [66]:
```
data.shape
```

Out[66]:
```
(506, 14)
```

In [68]:
```
data.iloc[:,-1]
```

Out[68]:
```
0      24.0
1      21.6
2      34.7
3      33.4
4      36.2
       ... 
501    22.4
502    20.6
503    23.9
504    22.0
505    11.9
Name: Price, Length: 506, dtype: float64
```

divide the dataset

In [71]:
```
X_train ,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=42)
```

In [87]:
```
print(f"X Train Shape is :{X_train.shape}")
print(f"y Train Shape is : {y_train.shape}")
print("-"*30)
print(f"X Test Shape is : {X_test.shape}")
print(f"y Test Shape is : {y_test.shape}")
```

```
X Train Shape is :(404, 13)
y Train Shape is : (404, 1)
------------------------------
X Test Shape is : (102, 13)
y Test Shape is : (102, 1)
```

create the Model

In [73]:
```
lr =LinearRegression()
lr
```

Out[73]:
```
▾ LinearRegression
LinearRegression()
```

In [74]:
```
lr.fit(X_train,y_train)
```

Out[74]:
```
▾ LinearRegression
LinearRegression()
```

In [75]:
```
print(lr.coef_)
```

```
[[-1.13055924e-01  3.01104641e-02  4.03807204e-02  2.78443820e+00
  -1.72026334e+01  4.43883520e+00 -6.29636221e-03 -1.44786537e+00
   2.62429736e-01 -1.06467863e-02 -9.15456240e-01  1.23513347e-02
  -5.08571424e-01]]
```

In [76]:
```
print(lr.intercept_)
```

```
[30.24675099]
```

In [79]:
```
y_pred = lr.predict(X_test)
y_pred = pd.DataFrame(y_pred,columns=['Predicted'])
y_pred
```

Out[79]:

	Predicted
0	28.996724
1	36.025565
2	14.816944
3	25.031979
4	18.769880
...	...
97	-0.164237
98	13.684867
99	16.183597
100	22.276220
101	24.479024

102 rows × 1 columns

In [80]:
```
y_test
```

Out[80]:

	Price
173	23.6
274	32.4
491	13.6
72	22.8
452	16.1
...	...
412	17.9
436	9.6
411	17.2
86	22.5
75	21.4

102 rows × 1 columns

Errors

In [88]:

```
from sklearn.metrics import mean_absolute_error,mean_squared_error,root_mean_squared_error,r2_score
```

In [86]:

```
print("Mean Absolute Error : ",mean_absolute_error(y_test,y_pred))
print("Mean Squared Error : ",mean_squared_error(y_test,y_pred))
print("Root Mean Squared Error : ",np.sqrt(root_mean_squared_error(y_test,y_pred)))
print("R squared : ",r2_score(y_test,y_pred))
```

```
Mean Absolute Error :  3.189091965887843
Mean Squared Error :  24.29111947497345
Root Mean Squared Error :  4.92860218266533
R squared :  0.6687594935356329
```