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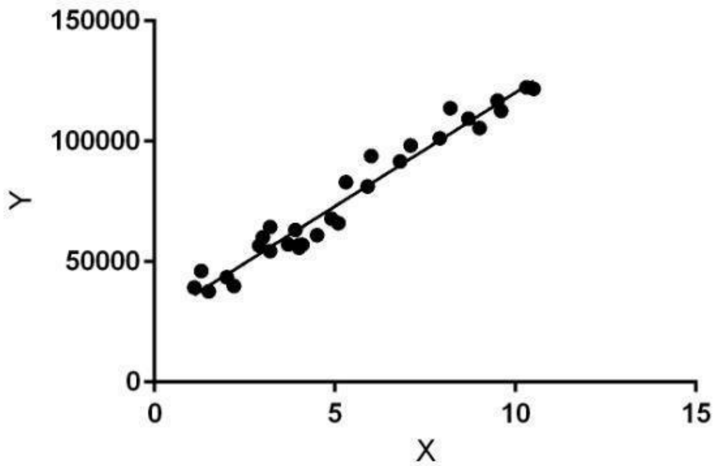
|---|
| Experiment No. 1 |
| Analyze the Boston Housing dataset and apply appropriate<br><br>Regression Technique |
| Date of Performance: 24—07—23 |
| Date of Submission: 07—08—23 |

**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:**

**Conclusion:**

The chosen feature set for predicting house prices comprises various attributes that encompass different aspects of towns, which have the potential to impact the median home value. These attributes encompass factors like crime rate, residential land proportion, nitric oxide concentration, average room count, highway accessibility, property-tax rate, and more. They collectively contribute to predicting the median value of homes in different neighborhoods.

Our primary focus is on the target variable, MEDV (Median Home Value), which serves as the central point of interest in our prediction model.

The Mean Squared Error (MSE) of 0.03415236861947717 quantifies the average squared difference between the predicted and actual house prices generated by the model. To assess the accuracy of these predictions, one can compare this MSE value to the range of actual house prices. This comparison helps determine whether the model's predictions are sufficiently accurate or not.

```
import numpy as np
import pandas as pd
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
```

```
data=pd.read_csv('/content/BostonHousing (1).csv')
```

```
pd.read_csv('/content/BostonHousing (1).csv')
```

| | crim | zn | indus | chas | nox | rm | age | dis | rad | tax | ptratio | b | lsta |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.00632 | 18.0 | 2.31 | 0 | 0.538 | 6.575 | 65.2 | 4.0900 | 1 | 296 | 15.3 | 396.90 | 4.9 |
| **1** | 0.02731 | 0.0 | 7.07 | 0 | 0.469 | 6.421 | 78.9 | 4.9671 | 2 | 242 | 17.8 | 396.90 | 9.1 |
| **2** | 0.02729 | 0.0 | 7.07 | 0 | 0.469 | 7.185 | 61.1 | 4.9671 | 2 | 242 | 17.8 | 392.83 | 4.0 |
| **3** | 0.03237 | 0.0 | 2.18 | 0 | 0.458 | 6.998 | 45.8 | 6.0622 | 3 | 222 | 18.7 | 394.63 | 2.9 |
| **4** | 0.06905 | 0.0 | 2.18 | 0 | 0.458 | 7.147 | 54.2 | 6.0622 | 3 | 222 | 18.7 | 396.90 | 5.3 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | . |
| **501** | 0.06263 | 0.0 | 11.93 | 0 | 0.573 | 6.593 | 69.1 | 2.4786 | 1 | 273 | 21.0 | 391.99 | 9.6 |
| **502** | 0.04527 | 0.0 | 11.93 | 0 | 0.573 | 6.120 | 76.7 | 2.2875 | 1 | 273 | 21.0 | 396.90 | 9.0 |
| **503** | 0.06076 | 0.0 | 11.93 | 0 | 0.573 | 6.976 | 91.0 | 2.1675 | 1 | 273 | 21.0 | 396.90 | 5.6 |
| **504** | 0.10959 | 0.0 | 11.93 | 0 | 0.573 | 6.794 | 89.3 | 2.3889 | 1 | 273 | 21.0 | 393.45 | 6.4 |
| **505** | 0.04741 | 0.0 | 11.93 | 0 | 0.573 | 6.030 | 80.8 | 2.5050 | 1 | 273 | 21.0 | 396.90 | 7.8 |

506 rows × 14 columns

```
column_names = ['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX', 'PTRATIO', 'B', 'LSTAT', 'MEDV']
```

```
print(data.head(5))
```

```
      crim    zn  indus  chas    nox     rm   age     dis  rad  tax  ptratio  \
0  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296     15.3
1  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242     17.8
2  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242     17.8
3  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222     18.7
4  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222     18.7

        b  lstat  medv
0  396.90   4.98  24.0
1  396.90   9.14  21.6
2  392.83   4.03  34.7
3  394.63   2.94  33.4
4  396.90   5.33  36.2
```

```
print(np.shape(data))
```

```
(506, 14)
```

```
print(data.describe())
```

```
             crim          zn       indus        chas         nox          rm  \
count  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
std      8.601545   23.322453    6.860353    0.253994    0.115878    0.702617
min      0.006320    0.000000    0.460000    0.000000    0.385000    3.561000
25%      0.082045    0.000000    5.190000    0.000000    0.449000    5.885500
50%      0.256510    0.000000    9.690000    0.000000    0.538000    6.208500
75%      3.677083   12.500000   18.100000    0.000000    0.624000    6.623500
max     88.976200  100.000000   27.740000    1.000000    0.871000    8.780000

              age         dis         rad         tax     ptratio           b  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean    68.574901    3.795043    9.549407  408.237154   18.455534  356.674032
std     28.148861    2.105710    8.707259  168.537116    2.164946   91.294864
min      2.900000    1.129600    1.000000  187.000000   12.600000    0.320000
25%     45.025000    2.100175    4.000000  279.000000   17.400000  375.377500
```

```
50%     77.500000    3.207450    5.000000  330.000000   19.050000  391.440000
75%     94.075000    5.188425   24.000000  666.000000   20.200000  396.225000
max    100.000000   12.126500   24.000000  711.000000   22.000000  396.900000

            lstat        medv
count  506.000000  506.000000
mean    12.653063   22.532806
std      7.141062    9.197104
min      1.730000    5.000000
25%      6.950000   17.025000
50%     11.360000   21.200000
75%     16.955000   25.000000
max     37.970000   50.000000
```

```
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    int64  
 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    int64  
 9   tax      506 non-null    int64  
 10  ptratio  506 non-null    float64
 11  b        506 non-null    float64
 12  lstat    506 non-null    float64
 13  medv     506 non-null    float64
dtypes: float64(11), int64(3)
memory usage: 55.5 KB
```

```
linr = LinearRegression()
```

```
data['medv'] = np.log1p(data['medv'])
```

```
X = data.drop(['medv','b'], axis=1)
Y = data['medv']
```

```
print(X)
```

```
        crim    zn  indus  chas    nox     rm   age     dis  rad  tax  \
0    0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296   
1    0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242   
2    0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242   
3    0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222   
4    0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222   
..       ...   ...    ...   ...    ...    ...   ...     ...  ...  ...   
501  0.06263   0.0  11.93     0  0.573  6.593  69.1  2.4786    1  273   
502  0.04527   0.0  11.93     0  0.573  6.120  76.7  2.2875    1  273   
503  0.06076   0.0  11.93     0  0.573  6.976  91.0  2.1675    1  273   
504  0.10959   0.0  11.93     0  0.573  6.794  89.3  2.3889    1  273   
505  0.04741   0.0  11.93     0  0.573  6.030  80.8  2.5050    1  273   

     ptratio  lstat  
0       15.3   4.98  
1       17.8   9.14  
2       17.8   4.03  
3       18.7   2.94  
4       18.7   5.33  
..       ...    ...  
501     21.0   9.67  
502     21.0   9.08  
503     21.0   5.64  
504     21.0   6.48  
505     21.0   7.88  

[506 rows x 12 columns]
```

```
print(Y)
```

```
0      3.218876
1      3.117950
2      3.575151
3      3.538057
4      3.616309
         ...
501    3.152736
502    3.072693
503    3.214868
504    3.135494
505    2.557227
Name: medv, Length: 506, dtype: float64
```

```
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state=42, test_size=0.3)
```

```
print("x_train shape:",x_train.shape)
print("x_test shape:",x_test.shape)
print("y_train shape:",x_train.shape)
print("y_train shape:",x_test.shape)
```

```
x_train shape: (354, 12)
x_test shape: (152, 12)
y_train shape: (354, 12)
y_train shape: (152, 12)
```

```
linr.fit(x_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
y_pred = linr.predict(x_test)
```

```
print(mean_squared_error(y_test, y_pred))
```

```
0.03112933398095344
```

```
plt.scatter(y_test,y_pred,c ='blue')
plt.xlabel("value")
plt.ylabel("Predicted value")
plt.title("True value vs predicted value : Linear Regression")
plt.show()
```