Vidyavardhini's College of Engineering and Technology

Department of Artificial Intelligence & Data Science

AY: 2023-24

Class:	TE	**Semester:**	VI
Course Code:	CSL604	**Course Name:**	Machine Learning Lab

Name of Student:	Ojasi Prabhu
Roll No.:	43
Experiment No.:	2
Title of the Experiment:	Implementation of Linear Regression
Date of Performance:	
Date of Submission:	

Evaluation

Performance Indicator	Max. Marks	Marks Obtained
Performance	5	
Understanding	5	
Journal work and timely submission	10	
Total	20	

Performance Indicator	Exceed Expectations (EE)	Meet Expectations (ME)	Below Expectations (BE)
Performance	4-5	2-3	1
Understanding	4-5	2-3	1
Journal work and timely submission	8-10	5-8	1-4

Checked by

Name of Faculty : Mr Raunak Joshi

Signature :

Date :

Aim: Implementation of Linear Regression Algorithm.

Objective: To implement Linear Regression in order to build a model that studies the relationship between an independent and dependent variable. The model will be evaluated by using least square regression method where RMSE and R-squared will be the model evaluation parameters..

Theory:

The least-squares method is a crucial statistical method that is practiced to find a regression line or a best-fit line for the given pattern. This method is described by an equation with specific parameters. The method of least squares is generously used in evaluation and regression. In regression analysis, this method is said to be a standard approach for the approximation of sets of equations having more equations than the number of unknowns. The method of least squares actually defines the solution for the minimization of the sum of squares of deviations or the errors in the result of each equation. Find the formula for sum of squares of errors, which help to find the variation in observed data. The least-squares method is often applied in data fitting.

Least Squares Regression Example

Tom who is the owner of a retail shop, found the price of different T-shirts vs the number of T-shirts sold at his shop over a period of one week.

Price of T-shirts in dollars (x)	# of T-shirts sold (y)
2	4
3	5
5	7
7	10
9	15

Let us use the concept of least squares regression to find the line of best fit for the above data.

Step 1: Calculate the slope 'm' by using the following formula:

$$m = \frac{n\sum xy - (\Sigma x)(\Sigma y)}{n\Sigma x^2 - (\Sigma x)^2}$$

After you substitute the respective values, m = 1.518 approximately.

Step 2: Compute the y-intercept value

$$c = y - mx$$

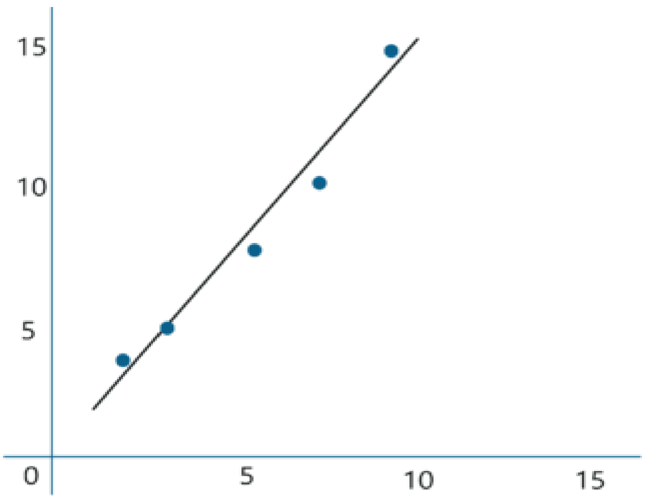
After you substitute the respective values, c = 0.305 approximately.

Step 3: Substitute the values in the final equation

$$y = mx + c$$

Price of T-shirts in dollars (x)	# of T-shirts sold (y)	Y=mx+c	error
2	4	3.3	-0.67
3	5	4.9	-0.14
5	7	7.9	0.89
7	10	10.9	0.93
9	15	13.9	-1.03

Let's construct a graph that represents the **y=mx + c** line of best fit:



Now Tom can use the above equation to estimate how many T-shirts of price $8 can he sell at the retail shop.

y = 1.518 x 8 + 0.305 = 12.45 T-shirts

This comes down to 13 T-shirts!

Dataset:

The data set contains the following variables:

- **Gender:** Male or female represented as binary variables
- **Age:** Age of an individual
- **Head size in cm^3:** An individuals head size in cm^3
- **Brain weight in grams:** The weight of an individual's brain measured in grams

These variables need to be analyzed in order to build a model that studies the relationship between the head size and brain weight of an individual.

Step 1: Import the required libraries

Step 2: Import the data set

Step 3: Assigning 'X' as independent variable and 'Y' as dependent variable

Step 4: Calculate the values of the slope and y-intercept

Step 5: Plotting the line of best fit

Step 6: Model Evaluation

Implementation:

Linear Regression

```
import numpy as np

class LinearRegression:
    def __init__ (self):
        self.b_0 = 0
        self.b_1 = 0

    def fit (self, X, y):
        X_mean = np.mean (X)
        y_mean = np.mean (y)
        ssxy, ssx = 0, 0
        for _ in range (len (X)):
            ssxy += (X[_]-X_mean)*(y[_]-y_mean)
            ssx += (X[_]-X_mean)**2

        self.b_1 = ssxy / ssx
        self.b_0 = y_mean - (self.b_1*X_mean)
        return self.b_0, self.b_1

    def predict (self, X):
        y_hat = self.b_0 + (X * self.b_1)
        return y_hat

if __name__ == '__main__':
    X = np.array ([173, 182, 165, 154, 170], ndmin=2)
    X = X.reshape(5, 1)
    y = np.array ([68, 79, 65, 57, 64])
    model = LinearRegression ()
    model.fit (X, y)
    y_pred = model.predict ([161])
    print (y_pred)
```

Linear Regression Output

```
(base) PS C:\Users\parth> python -u "c:\Users\parth\OneDrive\Desktop\ML LAB\linearRegression.py"
[60.85051546]
```

Multiple Linear Regression

```python
import numpy as np

class LinearRegression:
    def __init__ (self):
        self.params = np.zeros(int(np.random.random()), float)[:,np.newaxis]

    def fit (self, X, y):
        bias = np.ones (len (X))
        X_bias = np.c_[bias, X]
        lse = (np.linalg.inv (np.transpose(X_bias) @ X_bias) @ np.transpose (X_bias)) @ y
        self.params = lse
        return self.params

    def predict (self, X):
        bias_testing = np.ones (len (X))
        X_test = np.c_[bias_testing, X]
        y_hat = X_test @ self.params
        return y_hat

if __name__ == '__main__':
    X = np.array ([
        [1, 4],
        [2, 5],
        [3, 8],
        [4, 2]
    ])

    y = np.array ([1, 6, 8, 12])

    model = LinearRegression ()
    parameters = model.fit (X, y)
    print (f'The parameters for the model are : {parameters}')

    y_pred = model.predict ([[5, 3]])
    print (f'The predicted outcome is : {y_pred}')
```

Multiple Linear Regression Output

```
(base) PS C:\Users\parth> python -u "c:\Users\parth\OneDrive\Desktop\ML LAB\MultipleLinearRegression.py"
The parameters for the model are : [-1.69945355  3.48360656 -0.05464481]
The predicted outcome is : [15.55464481]
```

Conclusion:

To summarize, the Least Squares Method is a cornerstone in regression analysis, giving a simple and effective approach to estimate the parameters of a linear model. By minimizing the sum of squared residuals, it provides consistent coefficients with desirable statistical features. While its simplicity and effectiveness make it a popular choice, it is critical to confirm its assumptions and explore alternate methods for nonlinear connections.