

Curve Fitting:- Sometimes a function may be defined in the form of an expression like

$$F(x) = Ax^m + Bx^{m-1} + Cx^{m-2} + \dots$$

In this particular case function may be defined and plotted easily and may be extended to required limit, and function is continuous so any point on the curve may be observed and calculated. But in some problems function is not defined directly but given in the form of a table, in that case we have to approximate the function such that the curve passes through maximum number of points. Such method of approximating the curves is called curve fitting.

In brief we can define curve fitting as the process of finding equations of approximating curves which fit the given set of data.

Let $F(x)$ is the approximated function

Let us suppose $x_1, x_2, x_3, \dots, x_n$ are the values of independent variable and $y_1, y_2, y_3, \dots, y_n$ are the values of dependent variables respectively that are the result of experiment.

Let $y' = F(x)$

$$D_1 = y_1 - F(x_1) = y_1 - y_1', D_2 = y_2 - F(x_2) = y_2 - y_2', \dots, D_n = y_n - F(x_n) = y_n - y_n'$$

The function is chosen in such a way that $D_1, D_2, D_3, \dots, D_n$ are small.

Different methods of minimization of errors may be

1. $\text{Min} \sum_{i=1}^n Di = \text{Min} \sum_{i=1}^n (y_i - F(x_i))$
2. $\text{Min} \sum_{i=1}^n |Di| = \text{Min} \sum_{i=1}^n |y_i - F(x_i)|$
3. $\text{Max}(Di) \leq \epsilon$
4. $\text{Min} \sum_{i=1}^n Di^2 = \text{Min} \sum_{i=1}^n (y_i - F(x_i))^2$

Method of least square Fitting:-

To fit the observe sample points the error can be minimized by computing the sum of square of deviation between the proposed curves of data points i.e. in this we use approach of equation 4.

Advantages of least square fitting:-

1. Small calculation and better result
2. The small errors should be neglected and larger differences should be highlighted and method of least square fitting perform the same.

3. The opposite differences cannot be cancelled each other so as to minimize the errors. In the method of least square fitting the same task is performed.

Linear Regression or straight line fitting:-

Let $F(x)$ is the approximated function. The experimental values are given in the Table:

x	y
X_1	Y_1
X_2	Y_2
X_n	Y_n

$$D_1 = y_1 - F(x_1)$$

$$D_2 = y_2 - F(x_2)$$

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$$D_n = y_n - F(x_n)$$

$$S = D_1^2 + D_2^2 + D_3^2 + \dots + D_n^2$$

Let $F(x) = a_0 + a_1x$ be the approximated function

$$D_1 = y_1 - (a_0 + a_1x_1)$$

$$D_2 = y_2 - (a_0 + a_1x_2)$$

|

|

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$$D_n = y_n - (a_0 + a_1x_n)$$

$$\text{Min } S = \text{Min} \sum_{i=1}^n (y_i - f(x_i))^2$$

Differentiating S partially w.r.t. a_0 and equating it to zero

$$\frac{\partial S}{\partial a_0} = \sum_{i=1}^n 2(y_i - (a_0 + a_1 x_i))(-1) = 0 \text{-----} \textcircled{1}$$

Now differentiating S partially w.r.t a₁

$$\frac{\partial S}{\partial a_1} = \sum_{i=1}^n 2(y_i - (a_0 + a_1 x_i))(-x_i) = 0 \text{-----} \textcircled{2}$$

On rearranging equations $\textcircled{1}$ & $\textcircled{2}$ we finally get

$$n a_0 + a_1 \sum_{i=1}^n x_i = \sum_{i=1}^n y_i \text{-----} \textcircled{3}$$

$$a_0 \sum_{i=1}^n x_i + a_1 \sum_{i=1}^n x_i^2 = \sum_{i=1}^n x_i y_i \text{-----} \textcircled{4}$$

On solving equations $\textcircled{3}$ & $\textcircled{4}$ we have

$$a_0 = \frac{\sum_{i=1}^n y_i \sum_{i=1}^n x_i^2 - \sum_{i=1}^n x_i \sum_{i=1}^n x_i y_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

$$a_1 = \frac{n \sum_{i=1}^n x_i y_i - \sum_{i=1}^n x_i \sum_{i=1}^n y_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

Polynomial Regression:-

Let us suppose $F(x) = a_0 + a_1 x + a_2 x^2$ be the polynomial

Let x_i 's and y_i 's are the data points where we want to fit this 2nd order polynomial.

By using method of least square fitting

$$S = \sum_{i=1}^n (y_i - F(x_i))^2$$

$$\text{Min } S = \text{Min} \sum_{i=1}^n (y_i - (a_0 + a_1 x_i + a_2 x_i^2))^2$$

To apply the criteria of least square fitting we differentiate S w.r.t a₀, a₁ & a₂ and equate them to zero

$$\frac{\partial S}{\partial a_0} = \sum_{i=1}^n 2(y_i - (a_0 + a_1 x_i + a_2 x_i^2)) = 0 \text{-----} \textcircled{1}$$

$$\frac{\partial S}{\partial a_1} = \sum_{i=1}^n 2(y_i - (a_0 + a_1 x_i + a_2 x_i^2))(-x_i) = 0 \text{ --- (2)}$$

$$\frac{\partial S}{\partial a_2} = \sum_{i=1}^n 2(y_i - (a_0 + a_1 x_i + a_2 x_i^2))(-x_i^2) = 0 \text{ --- (3)}$$

On rearranging equation (1), (2) & (3)

$$n a_0 + a_1 \sum_{i=1}^n x_i + a_2 \sum_{i=1}^n x_i^2 = \sum_{i=1}^n y_i \text{ --- (4)}$$

$$a_0 \sum_{i=1}^n x_i + a_1 \sum_{i=1}^n x_i^2 + a_2 \sum_{i=1}^n x_i^3 = \sum_{i=1}^n x_i y_i \text{ --- (5)}$$

$$a_0 \sum_{i=1}^n x_i^2 + a_1 \sum_{i=1}^n x_i^3 + a_2 \sum_{i=1}^n x_i^4 = \sum_{i=1}^n x_i^2 y_i \text{ --- (6)}$$

Equations (4), (5) & (6) are three linear equations with three unknowns. These equations are called normal equations for quadratic regression. These may be solved by Gauss Elimination Method.

Exponential Regression:-

Fitting of an exponential curve to a given problem.

The basic assumption in picking up least square error criteria for curve fitting is that for linear functions $F(x)$, this leads to optimum fit.

This assumption is no more valid for nonlinear curve, inspite of that we use least square method due to its ease of implementation.

Let $y = a_0 e^{a_1 x}$ be the function to be fitted by using method of least square

$$y = a_0 e^{a_1 x} \text{ --- (1)}$$

Taking Log of equation (1)

$$\log y = \log(a_0 e^{a_1 x})$$

$$\log y = \log a_0 + a_1 x \text{ --- (2)}$$

$$\text{Let } \log y = z, \log a_0 = b_0, a_1 = b_1 \text{ --- (3)}$$

By putting these assumption from equations (3) into equation (2), we get

$$Z = b_0 + b_1 x \text{-----} \textcircled{4}$$

Equation $\textcircled{4}$ is linear and we can use the normal equations for linear regression and obtain

$$b_0 = \frac{\sum_{i=1}^n z_i \sum_{i=1}^n x_i^2 - \sum_{i=1}^n x_i z_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

$$b_0 = \frac{\sum_{i=1}^n \log y_i \sum_{i=1}^n x_i^2 - \sum_{i=1}^n x_i \log y_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

$$b_1 = \frac{n \sum_{i=1}^n x_i z_i - \sum_{i=1}^n x_i \sum_{i=1}^n z_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

$$b_1 = \frac{n \sum_{i=1}^n x_i \log y_i - \sum_{i=1}^n x_i \sum_{i=1}^n \log y_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

$$a_0 = e^{b_0}$$

$$a_1 = b_1$$

Hyperbolic Regression:-

Fitting of a hyperbolic curve

$$y = \frac{1}{a + bx}$$

$$z = a + bx$$

$$a = \frac{\sum_{i=1}^n x_i \sum_{i=1}^n z_i - \sum_{i=1}^n x_i \sum_{i=1}^n x_i z_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

$$a = \frac{\sum_{i=1}^n x_i^2 \sum_{i=1}^n \frac{1}{y_i} - \sum_{i=1}^n x_i \sum_{i=1}^n \frac{x_i}{y_i}}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

$$b = \frac{n \sum_{i=1}^n x_i z_i - \sum_{i=1}^n x_i \sum_{i=1}^n z_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

$$b = \frac{n \sum_{i=1}^n \frac{x_i}{y_i} - \sum_{i=1}^n x_i \sum_{i=1}^n \frac{1}{y_i}}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$