Multiple linear regression

وصف البيانات Descriptive data

Data typically consist of n observations on the dependent variable y and m independent variables $(X_1, X_2, ..., X_m)$. The data is arranged as in the following table:

رقم المشاهدة	y_i	X_1	X_2	•••	$X_{\scriptscriptstyle m}$
1	\mathcal{Y}_1	<i>x</i> ₁₁	<i>x</i> ₁₂		\mathcal{X}_{1m}
2	y_2	<i>x</i> ₂₁	<i>x</i> ₂₂		x_{2m}
3	<i>y</i> ₃	<i>x</i> ₃₁	<i>x</i> ₃₂	•••	X_{3m}
:	:	:	÷		:
n	\mathcal{Y}_n	X_{n1}	X_{n2}		\mathcal{X}_{nm}

Graphical representation

The graph of a multiple linear regression equation is a dimensional surface (m+1) Where m is the number of independent variables. If there are two independent variables (m=2). The appropriate surface for the data is a three-dimensional surface that is best represented by points:

$$(x_{11}, x_{12}, y_1), (x_{21}, x_{22}, y_2), \dots, (x_{n1}, x_{n2}, y_n)$$

Whereas (x_{i1}, x_{i2}, y_i) represent values X_1, X_2, y_i For observation i of the sample.

Therefore, the multiple regression equation in this case is a surface that represents the average of the y values for different values X_1, X_2 , that is, the model

$$y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + e_i$$

It can be represented by a three-dimensional surface, as shown in Figure (1).

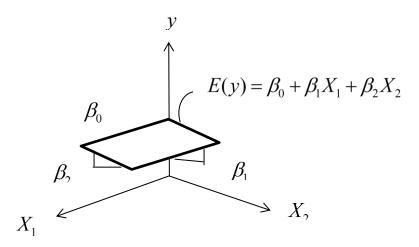


Figure (1): Graphical representation of the three-dimensional regression equation

Mathematical model

The significant relationship between the variable y and the independent variables X_{is} in multiple regression analysis can be expressed as a linear function as follows:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_m x_{im} + e_i, i = 1, 2, \dots, n$$

That is:

$$y = X\beta + e$$

whereas:

 y_i : is the value of the dependent variable or response variable.

 $x_{i1}, x_{i2}, \dots, x_{im}$: they are fixed values of m of independent variables.

 $\beta_0, \beta_1, ..., \beta_m$: they are constants or parameters of the regression equation.

whereas:

 β_0 : It is the location of the intersection of the slope plane with the y-axis, and β_1 gives the average response when the values of x_{is} are equal to zero.

 β_i It is the partial regression coefficient of y on X_i . When the rest of the independent variables are held constant. It also represents the amount of change in y for a one-unit increase in X_i when the rest of the independent variables are constant.

 e_i it is a random or residual error.

The previous equation is called multiple because it contains more than one independent variable, and it is linear because each of the parameters $\beta_0, \beta_1, \ldots, \beta_m$ as well as the independent variables X_1, X_2, \ldots, X_m It is of first order, meaning it has a power equal to one.

Analysis assumptions

1. The dependent variable y is a random variable and its values are statistically independent from one another and distributed normally with an arithmetic mean of $\mu_{y/x_1,\dots,x_m}$ and variance $\sigma^2_{y/x_1,\dots,x_m} = \sigma^2$ that is, the average y is a linear function

$$\mu_{y/X_1,...,X_m} = E(y_i) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_m X_m$$

and the variance of y is

$$\sigma_{y/X_1,\dots,X_m}^2 = \sigma_{\beta_0+\beta_1X_1+\beta_2X_2+\dots+\beta_mX_m}^2 = \sigma_e^2 = \sigma_I^2$$

This property is called homoscedasticity, i.e. homogeneity of error

2. The error term e_i is a random error distributed normally with an arithmetic mean of zero, that is E(e) = 0, and a variance of the amount $\sigma_e^2 = \sigma_I^2$ that is $E(e'e) = \sigma_I^2$.

The covariance between is $cov(e_ie_i) = 0$ because we assume that there is no correlation between the values e_i .

3. There is no specific or complete linear relationship between the independent variables.