Chapter 06.03
Linear Regression

After reading this chapter, you should be able to

1. *define regression,*
2. *use several minimizing of residual criteria to choose the right criterion,*
3. *derive the constants of a linear regression model based on least squares method criterion,*
4. *use in examples, the derived formulas for the constants of a linear regression model, and*
5. *prove that the constants of the linear regression model are unique and correspond to a minimum.*

Linear regression is the most popular regression model. In this model, we wish to predict response to n data points $(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)$ by a regression model given by

$$y = a_0 + a_1 x \qquad (1)$$

where a_0 and a_1 are the constants of the regression model.

A measure of goodness of fit, that is, how well $a_0 + a_1 x$ predicts the response variable y is the magnitude of the residual ε_i at each of the n data points.

$$E_i = y_i - (a_0 + a_1 x_i) \qquad (2)$$

Ideally, if all the residuals ε_i are zero, one may have found an equation in which all the points lie on the model. Thus, minimization of the residual is an objective of obtaining regression coefficients.

The most popular method to minimize the residual is the least squares methods, where the estimates of the constants of the models are chosen such that the sum of the squared residuals is minimized, that is minimize $\sum_{i=1}^{n} E_i^{\ 2}$.

Why minimize the sum of the square of the residuals? Why not, for instance, minimize the sum of the residual errors or the sum of the absolute values of the residuals? Alternatively, constants of the model can be chosen such that the average residual is zero without making individual residuals small. Will any of these criteria yield unbiased parameters with the smallest variance? All of these questions will be answered below. Look at the data in Table 1.

Table 1 Data points.

x	y
2.0	4.0
3.0	6.0
2.0	6.0
3.0	8.0

To explain this data by a straight line regression model,

$$y = a_0 + a_1 x \tag{3}$$

and using minimizing $\sum_{i=1}^{n} E_i$ as a criteria to find a_0 and a_1, we find that for (Figure 1)

$$y = 4x - 4 \tag{4}$$

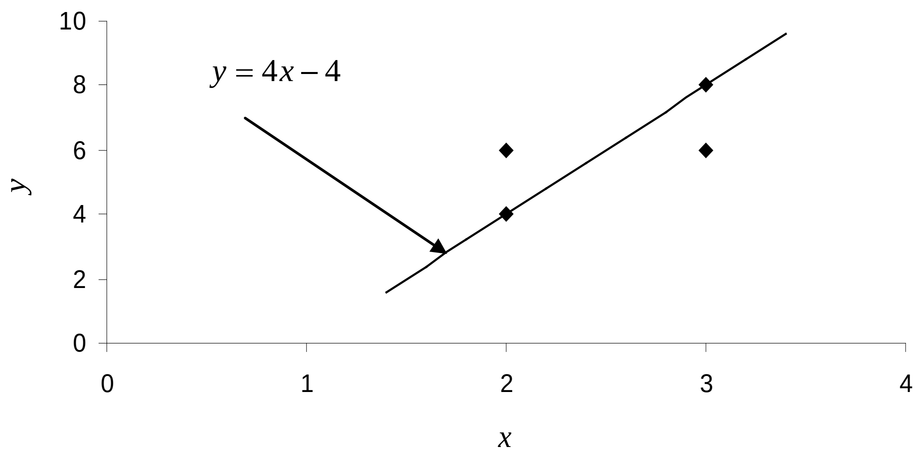

Figure 1 Regression curve $y = 4x - 4$ for y vs. x data.

the sum of the residuals, $\sum_{i=1}^{4} E_i = 0$ as shown in the Table 2.

Table 2 The residuals at each data point for regression model $y = 4x - 4$.

x	y	$y_{predicted}$	$\varepsilon = y - y_{predicted}$
2.0	4.0	4.0	0.0
3.0	6.0	8.0	-2.0
2.0	6.0	4.0	2.0
3.0	8.0	8.0	0.0
			$\sum_{i=1}^{4} \varepsilon_i = 0$

So does this give us the smallest error? It does as $\sum_{i=1}^{4} E_i = 0$. But it does not give unique values for the parameters of the model. A straight-line of the model

$$y = 6 \quad (5)$$

also makes $\sum_{i=1}^{4} E_i = 0$ as shown in the Table 3.

Table 3 The residuals at each data point for regression model $y = 6$

x	y	$y_{predicted}$	$\varepsilon = y - y_{predicted}$
2.0	4.0	6.0	-2.0
3.0	6.0	6.0	0.0
2.0	6.0	6.0	0.0
3.0	8.0	6.0	2.0
			$\sum_{i=1}^{4} E_i = 0$

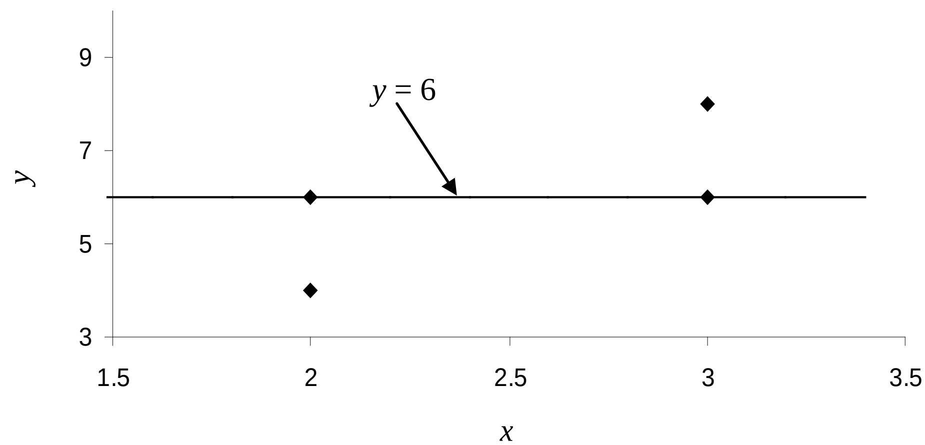

Figure 2 Regression curve $y = 6$ for y vs. x data.

Since this criterion does not give a unique regression model, it cannot be used for finding the regression coefficients. Let us see why we cannot use this criterion for any general data. We want to minimize

$$\sum_{i=1}^{n} E_i = \sum_{i=1}^{n} \left(y_i - a_0 - a_1 x_i \right) \quad (6)$$

Differentiating Equation (6) with respect to a_0 and a_1, we get

$$\frac{\partial \sum_{i=1}^{n} E_i}{\partial a_0} = -\sum_{i=1}^{n} 1 = -n \quad (7)$$

$$\frac{\partial \sum_{i=1}^{n} E_i}{\partial a_1} = -\sum_{i=1}^{n} x_i = -n\bar{x} \tag{8}$$

Putting these equations to zero, give $n = 0$ but that is not possible. Therefore, unique values of a_0 and a_1 do not exist.

You may think that the reason the minimization criterion $\sum_{i=1}^{n} E_i$ does not work is that negative residuals cancel with positive residuals. So is minimizing $\sum_{i=1}^{n} |E_i|$ better? Let us look at the data given in the Table 2 for equation $y = 4x - 4$. It makes $\sum_{i=1}^{4} |E_i| = 4$ as shown in the following table.

Table 4 The absolute residuals at each data point when employing $y = 4x - 4$.

x	y	$y_{predicted}$	$\varepsilon = y - y_{predicted}$
2.0	4.0	4.0	0.0
3.0	6.0	8.0	2.0
2.0	6.0	4.0	2.0
3.0	8.0	8.0	0.0
			$\sum_{i=1}^{4} \lvert\varepsilon_i\rvert = 4$

The value of $\sum_{i=1}^{4} |E_i| = 4$ also exists for the straight line model $y = 6$. No other straight line model for this data has $\sum_{i=1}^{4} |E_i| < 4$. Again, we find the regression coefficients are not unique, and hence this criterion also cannot be used for finding the regression model.

Let us use the least squares criterion where we minimize

$$S_r = \sum_{i=1}^{n} E_i^{\,2} = \sum_{i=1}^{n} \left(y_i - a_0 - a_1 x_i\right)^2 \tag{9}$$

S_r is called the sum of the square of the residuals.

To find a_0 and a_1, we minimize S_r with respect to a_0 and a_1.

$$\frac{\partial S_r}{\partial a_0} = 2\sum_{i=1}^{n} \left(y_i - a_0 - a_1 x_i\right)(-1) = 0 \tag{10}$$

$$\frac{\partial S_r}{\partial a_1} = 2\sum_{i=1}^{n} \left(y_i - a_0 - a_1 x_i\right)(-x_i) = 0 \tag{11}$$

giving

$$-\sum_{i=1}^{n} y_i + \sum_{i=1}^{n} a_0 + \sum_{i=1}^{n} a_1 x_i = 0 \tag{12}$$

$$-\sum_{i=1}^{n} y_i x_i + \sum_{i=1}^{n} a_0 x_i + \sum_{i=1}^{n} a_1 x_i^2 = 0 \tag{13}$$

Noting that $\sum_{i=1}^{n} a_0 = a_0 + a_0 + \ldots + a_0 = na_0$

$$na_0 + a_1 \sum_{i=1}^{n} x_i = \sum_{i=1}^{n} y_i \tag{14}$$

$$a_0 \sum_{i=1}^{n} x_i + a_1 \sum_{i=1}^{n} x_i^2 = \sum_{i=1}^{n} x_i y_i \tag{15}$$

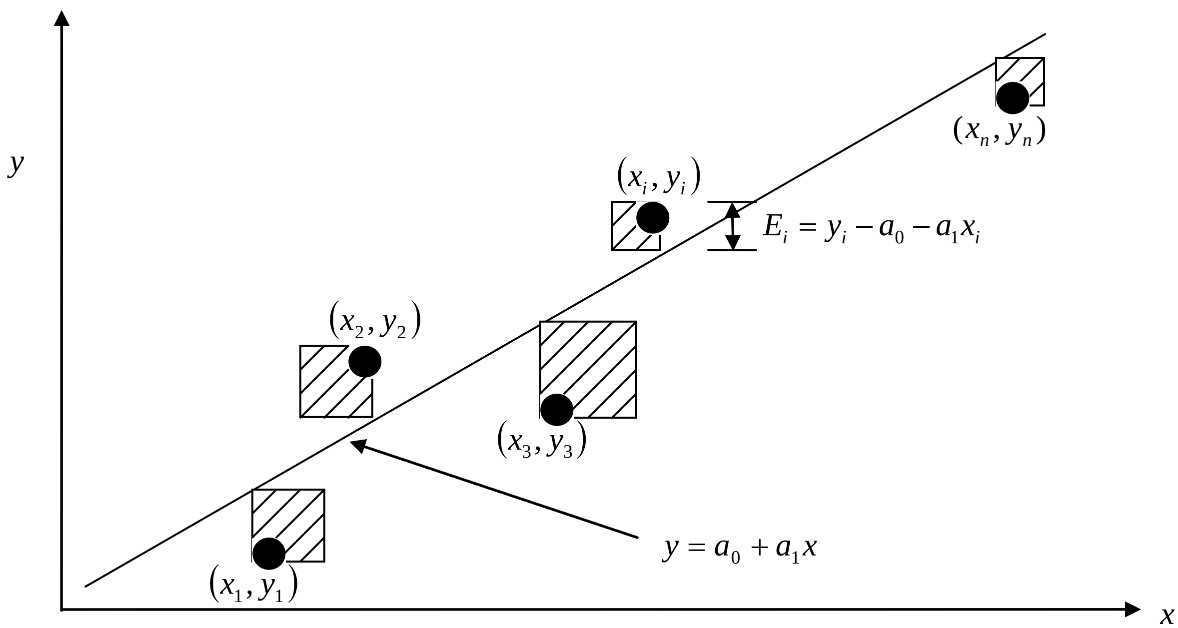

Figure 3 Linear regression of y vs. x data showing residuals and square of residual at a typical point, x_i.

Solving the above Equations (14) and (15) gives

$$a_1 = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \tag{16}$$

$$a_0 = \frac{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} x_i y_i}{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \tag{17}$$

Redefining

$$S_{xy} = \sum_{i=1}^{n} x_i y_i - n \bar{x} \bar{y} \tag{18}$$

$$S_{xx} = \sum_{i=1}^{n} x_i^2 - n \bar{x}^2 \tag{19}$$

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{20}$$

$$\bar{y} = \frac{\sum_{i=1}^{n} y_i}{n} \tag{21}$$

we can rewrite

$$a_1 = \frac{S_{xy}}{S_{xx}} \tag{22}$$

$$a_0 = \bar{y} - a_1 \bar{x} \tag{23}$$

Example 1

To simplify a model for a diode, it is approximated by a forward bias model consisting of DC voltage, V_d, and resistor R_d. Below are the current vs. voltage data that is collected for a small signal.

Table 5 Current versus voltage for a small signal.

V (volts)	I (amps)
0.6	0.01
0.7	0.05
0.8	0.20
0.9	0.70
1.0	2.00
1.1	4.00

The I vs. V data is regressed to $I = B_1 V + B_0$.

Once B_0 and B_1 are known, V_d and R_d can be computed as

$$V_d = -\frac{B_0}{B_1} \quad \text{and} \quad R_d = \frac{1}{B_1}$$

Find the value of V_d and R_d.

Solution

Table 6 shows the summations needed for the calculation of the constants of the regression model.

Table 6 Tabulation of data for calculation of needed summations.

i	V	I	V^2	$V \times I$
$-$	Volts	Amperes	Volts^2	Volt-Amps
1	0.6	0.01	0.36	0.006
2	0.7	0.05	0.49	0.035
3	0.8	0.20	0.64	0.160
4	0.9	0.70	0.81	0.630
5	1.0	2.00	1.00	2.000
6	1.1	4.00	1.21	4.400
$\sum_{i=1}^{6}$	5.1	6.96	4.51	7.231

$$n = 6$$

$$B_1 = \frac{n\sum_{i=1}^{6} V_i I_i - \sum_{i=1}^{6} V_i \sum_{i=1}^{6} I_i}{n\sum_{i=1}^{6} V_i^2 - \left(\sum_{i=1}^{6} V_i\right)^2}$$

$$= \frac{6(7.231) - (5.1)(6.96)}{6(4.51) - (5.1)^2}$$

$$= 7.5143 \text{ A/V}$$

$$\bar{I} = \frac{\sum_{i=1}^{6} I_i}{n}$$

$$= \frac{6.96}{6}$$

$$= 1.16 \text{ A}$$

$$\bar{V} = \frac{\sum_{i=1}^{6} V_i}{n}$$

$$= \frac{5.1}{6}$$

$$= 0.85 \text{ V}$$

$$B_0 = \bar{I} - B_1 \bar{V}$$

$$= 1.16 - (7.514)(0.85)$$
$$= -5.2269 \text{ A}$$

$$I = 7.514 \times V - 5.2269$$

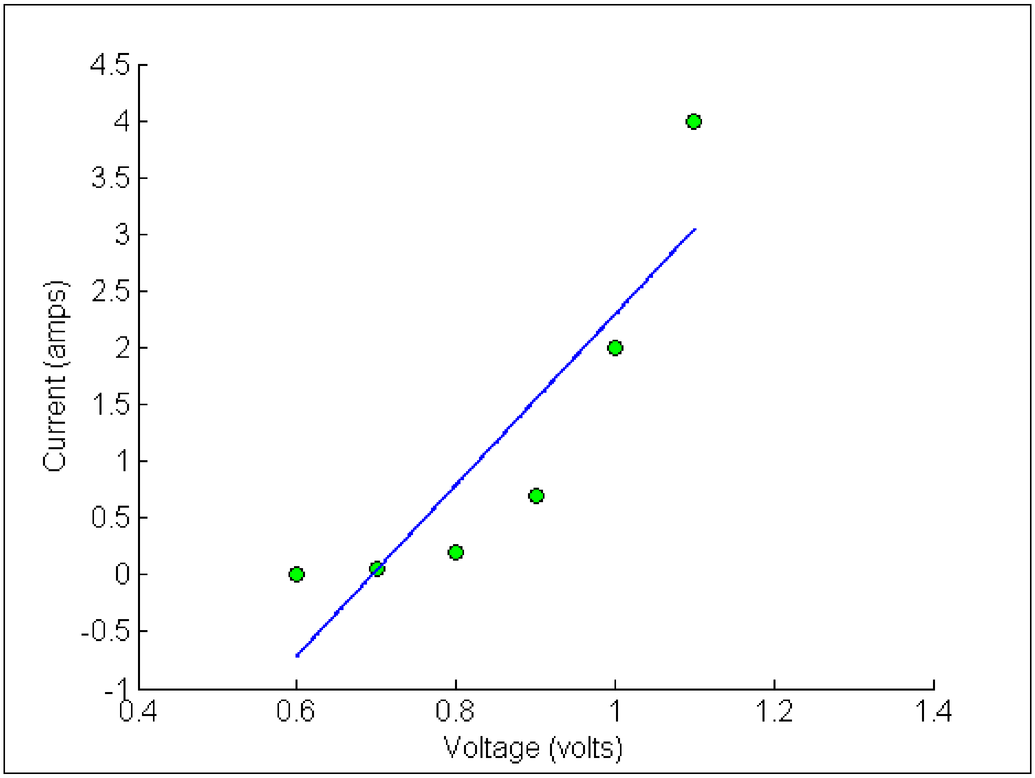

Figure 4 Linear regression of current vs. voltage

Solving for V_d and R_d:

$$V_d = -\frac{B_0}{B_1}$$
$$= -\left(\frac{-5.2269}{7.5143}\right)$$
$$= 0.69560 \text{ Volts}$$

$$R_d = \frac{1}{B_1}$$
$$= \frac{1}{7.5143}$$
$$= 0.13308 \text{ Ohms}$$

Example 2

To find the longitudinal modulus of a composite material, the following data, as given in Table 7, is collected.

Table 7 Stress vs. strain data for a composite material.

Strain (%)	Stress (MPa)
0	0
0.183	306
0.36	612
0.5324	917
0.702	1223
0.867	1529
1.0244	1835
1.1774	2140
1.329	2446
1.479	2752
1.5	2767
1.56	2896

Find the longitudinal modulus E using the regression model.

$$\sigma = E\varepsilon \tag{24}$$

Solution

Rewriting data from Table 7, stresses versus strain data in Table 8

Table 8 Stress vs strain data for a composite in SI system of units

Strain (m/m)	Stress (Pa)
0.0000	0.0000
1.8300×10^{-3}	3.0600×10^{8}
3.6000×10^{-3}	6.1200×10^{8}
5.3240×10^{-3}	9.1700×10^{8}
7.0200×10^{-3}	1.2230×10^{9}
8.6700×10^{-3}	1.5290×10^{9}
1.0244×10^{-2}	1.8350×10^{9}
1.1774×10^{-2}	2.1400×10^{9}
1.3290×10^{-2}	2.4460×10^{9}
1.4790×10^{-2}	2.7520×10^{9}
1.5000×10^{-2}	2.7670×10^{9}
1.5600×10^{-2}	2.8960×10^{9}

Applying the least square method, the residuals γ_i at each data point is

$$\gamma_i = \sigma_i - E\varepsilon_i$$

The sum of square of the residuals is

$$S_r = \sum_{i=1}^{n} \gamma_i^2$$

$$= \sum_{i=1}^{n} \left(\sigma_i - E\varepsilon_i\right)^2$$

Again, to find the constant E, we need to minimize S_r by differentiating with respect to E and then equating to zero

$$\frac{\partial S_r}{\partial E} = \sum_{i=1}^{n} 2\left(\sigma_i - E\varepsilon_i\right)\left(-\varepsilon_i\right) = 0$$

From there, we obtain

$$E = \frac{\sum_{i=1}^{n} \sigma_i \varepsilon_i}{\sum_{i=1}^{n} \varepsilon_i^{\ 2}} \qquad (25)$$

The summations used in Equation (25) are given in the Table 9.

Table 9 Tabulation for Example 2 for needed summations

i	ε	σ	ε^2	$\varepsilon\sigma$
1	0.0000	0.0000	0.0000	0.0000
2	1.8300×10^{-3}	3.0600×10^{8}	3.3489×10^{-6}	5.5998×10^{5}
3	3.6000×10^{-3}	6.1200×10^{8}	1.2960×10^{-5}	2.2032×10^{6}
4	5.3240×10^{-3}	9.1700×10^{8}	2.8345×10^{-5}	4.8821×10^{6}
5	7.0200×10^{-3}	1.2230×10^{9}	4.9280×10^{-5}	8.5855×10^{6}
6	8.6700×10^{-3}	1.5290×10^{9}	7.5169×10^{-5}	1.3256×10^{7}
7	1.0244×10^{-2}	1.8350×10^{9}	1.0494×10^{-4}	1.8798×10^{7}
8	1.1774×10^{-2}	2.1400×10^{9}	1.3863×10^{-4}	2.5196×10^{7}
9	1.3290×10^{-2}	2.4460×10^{9}	1.7662×10^{-4}	3.2507×10^{7}
10	1.4790×10^{-2}	2.7520×10^{9}	2.1874×10^{-4}	4.0702×10^{7}
11	1.5000×10^{-2}	2.7670×10^{9}	2.2500×10^{-4}	4.1505×10^{7}
12	1.5600×10^{-2}	2.8960×10^{9}	2.4336×10^{-4}	4.5178×10^{7}
$\sum_{i=1}^{12}$			1.2764×10^{-3}	2.3337×10^{8}

$$n = 12$$

$$\sum_{i=1}^{12} \varepsilon_i^2 = 1.2764\times10^{-3}$$

$$\sum_{i=1}^{12} \sigma_i \varepsilon_i = 2.3337\times10^{8}$$

$$E = \frac{\sum_{i=1}^{12} \sigma_i \varepsilon_i}{\sum_{i=1}^{12} \varepsilon_i^{\ 2}}$$
$$= \frac{2.3337 \times 10^{8}}{1.2764 \times 10^{-3}}$$
$$= 182.84 \text{ GPa}$$

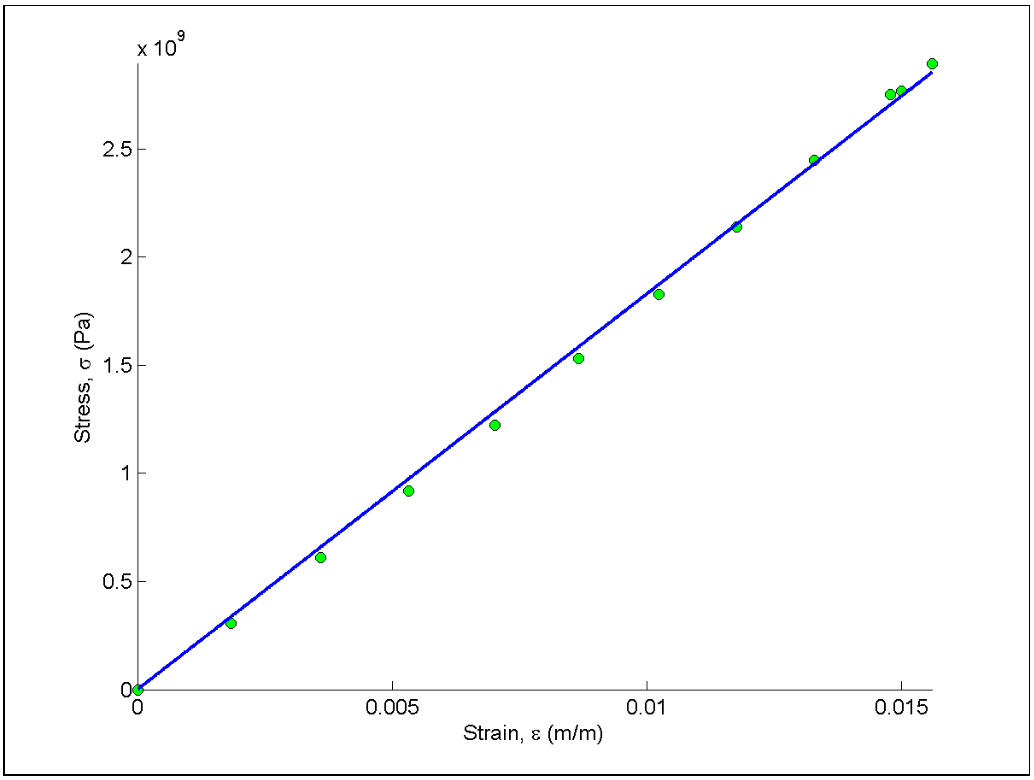

Figure 5 Linear regression model of stress vs. strain for a composite material.

Appendix

Do the values of the constants of the least squares straight-line regression model correspond to a minimum? Is the straight line unique?

ANSWER:

Given n data pairs, $(x_1, y_1), \ldots, (x_n, y_n)$, the best fit for the straight line regression model

$$y = a_0 + a_1 x \tag{A.1}$$

is found by the method of least squares.

Starting with the sum of the square of the residuals S_r, we get

$$S_r = \sum_{i=1}^{n} (y_i - a_0 - a_1 x_i)^2 \tag{A.2}$$

and using

$$\frac{\partial S_r}{\partial a_0} = 0 \qquad (A.3)$$

$$\frac{\partial S_r}{\partial a_1} = 0 \qquad (A.4)$$

gives two simultaneous linear equations whose solution is

$$a_1 = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \qquad (A.5a)$$

$$a_0 = \frac{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} x_i y_i}{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \qquad (A.5b)$$

But does this give the minimum of value of S_r? The first derivative only tells us about a local extreme, not whether it is a minimum or a maximum.

We need to conduct a second derivative test to find out whether the point (a_0, a_1) from Equation (A.5) gives the minimum or maximum of S_r.

What is the second derivative test for a minimum if we have a function of two variables?

If you have a function $f(x,y)$ and we found a critical point (a,b) from the first derivative test, then (a,b) is a minimum point if

$$\frac{\partial^2 f}{\partial x^2}\frac{\partial^2 f}{\partial y^2} - \left(\frac{\partial^2 f}{\partial x \partial y}\right)^2 > 0 \text{, and} \qquad (A.6)$$

$$\frac{\partial^2 f}{\partial x^2} > 0 \text{ OR } \frac{\partial^2 f}{\partial y^2} > 0 \qquad (A.7)$$

From Equation (2)

$$\begin{aligned}\frac{\partial S_r}{\partial a_0} &= \sum_{i=1}^{n} 2(y_i - a_0 - a_1 x_i)(-1) \\ &= -2\sum_{i=1}^{n}(y_i - a_0 - a_1 x_i)\end{aligned} \qquad (A.8)$$

$$\begin{aligned}\frac{\partial S_r}{\partial a_1} &= \sum_{i=1}^{n} 2(y_i - a_0 - a_1 x_i)(-x_i) \\ &= -2\sum_{i=1}^{n}(x_i y_i - a_0 x_i - a_1 x_i^2)\end{aligned} \qquad (A.9)$$

then

$$\frac{\partial^2 S_r}{\partial a_0^2} = -2\sum_{i=1}^{n} -1$$

$$= 2n \tag{A.10}$$

$$\frac{\partial^2 S_r}{\partial a_1^2} = 2\sum_{i=1}^{n} x_i^2 \tag{A.11}$$

$$\frac{\partial^2 S_r}{\partial a_0 \partial a_1} = 2\sum_{i=1}^{n} x_i \tag{A.12}$$

So we satisfy condition (A.7) as from Equation (A.10), $2n$ is a positive number and from Equation (A.11) $2\sum_{i=1}^{n} x_i^2$ is a positive number as assuming that all data points are NOT zero is reasonable.

Is the other condition for being a minimum as given by Equation (A.6) met? Yes, we can show (*the proof is not given*)

$$\frac{\partial^2 S_r}{\partial a_0^2}\frac{\partial^2 S_r}{\partial a_1^2} - \left(\frac{\partial^2 S_r}{\partial a_0 \partial a_1}\right) = (2n)\left(2\sum_{i=1}^{n} x_i^2\right) - \left(2\sum_{i=1}^{n} x_i\right)^2$$

$$= 4\left[n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2\right] > 0 \tag{A.13}$$

So the values of a_0 and a_1 that we have in Equations (A.5a) and (A.5b), are in fact a minimum. Also, this minimum is an absolute minimum because the first derivative is zero for only one point as given by Equations (A.5a) and (A.5b). Hence, this also makes the straight-line regression model unique.

LINEAR REGRESSION	
Topic	Linear Regression
Summary	Textbook notes of Linear Regression
Major	Electrical Engineering
Authors	Egwu Kalu, Autar Kaw, Cuong Nguyen
Date	September 10, 2009
Web Site	http://numericalmethods.eng.usf.edu