

Matrix Approach to Simple Linear Regression Analysis

Least squared estimation

The simple linear regression model can be formed in the matrix form as

$$Y = X \beta + \varepsilon, \quad E(\varepsilon) = 0, \text{Var}(\varepsilon) = \sigma^2 I,$$

where

$$\mathbf{Y}_{n \times 1} = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} \quad \mathbf{X}_{n \times 2} = \begin{bmatrix} 1 & X_1 \\ 1 & X_2 \\ \vdots & \vdots \\ 1 & X_n \end{bmatrix} \quad \boldsymbol{\beta}_{2 \times 1} = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} \quad \boldsymbol{\varepsilon}_{n \times 1} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

Now, we apply the least squared method to

to find the estimation of the vector β as follows:

$$Q = \sum_{i=1}^n e_i^2 = e'e = (Y - X\beta)'(Y - X\beta)$$

Expanding, we obtain:

$$Q = Y'Y - \beta'X'Y - Y'X\beta + \beta'X'X\beta$$

since $(X\beta)' = \beta'X'$ Note now that $Y'X\beta$ is 1×1 , hence is equal to its transpose, is $\beta'X'Y$. Thus, we find:

$$Q = Y'Y - 2\beta'X'Y + \beta'X'X\beta$$

To find the value of β that minimizes Q , we differentiate with respect to β_0 and β_1 . Let:

$$\frac{\partial}{\partial \beta}(Q) = \begin{bmatrix} \frac{\partial Q}{\partial \beta_0} \\ \frac{\partial Q}{\partial \beta_1} \end{bmatrix}$$

Then it follows that:

$$\frac{\partial}{\partial \beta}(Q) = -2X'Y + 2X'X\beta$$

Equating to the zero vector, we get

$$b = \begin{bmatrix} b_0 \\ b_1 \end{bmatrix} = \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{bmatrix} = \hat{\beta} = (X'X)^{-1}X'Y$$

where

$$(\mathbf{X}'\mathbf{X})^{-1}_{2 \times 2} = \begin{bmatrix} \frac{\sum X_i^2}{n \sum (X_i - \bar{X})^2} & \frac{-\sum X_i}{n \sum (X_i - \bar{X})^2} \\ \frac{-\sum X_i}{n \sum (X_i - \bar{X})^2} & \frac{n}{n \sum (X_i - \bar{X})^2} \end{bmatrix}$$

$$\mathbf{X}'\mathbf{Y}_{2 \times 1} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ X_1 & X_2 & \cdots & X_n \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} \sum Y_i \\ \sum X_i Y_i \end{bmatrix}$$

Example

We shall use matrix methods to obtain the estimated regression coefficients for the Toluca Company example. The data On the Y and X Variables. Using these data, we define the Y observations vector and the X matrix as follows:

$$\mathbf{Y} = \begin{bmatrix} 399 \\ 121 \\ \vdots \\ 323 \end{bmatrix} \quad \mathbf{X} = \begin{bmatrix} 1 & 80 \\ 1 & 30 \\ \vdots & \vdots \\ 1 & 70 \end{bmatrix}$$

We now require the following matrix products:

$$\mathbf{X}'\mathbf{X} = \begin{bmatrix} 1 & 1 & \dots & 1 \\ 80 & 30 & \dots & 70 \end{bmatrix} \begin{bmatrix} 1 & 80 \\ 1 & 30 \\ \vdots & \vdots \\ 1 & 70 \end{bmatrix} = \begin{bmatrix} 25 & 1,750 \\ 1,750 & 142,300 \end{bmatrix}$$

we find the inverse of $\mathbf{X}'\mathbf{X}$:

$$(\mathbf{X}'\mathbf{X})^{-1} = \begin{bmatrix} .287475 & -.003535 \\ -.003535 & .00005051 \end{bmatrix}$$

In subsequent matrix calculations utilizing this inverse matrix and other matrix results, we shall actually utilize more digits for the matrix elements than are shown.

$$\begin{aligned} \mathbf{b} = \begin{bmatrix} b_0 \\ b_1 \end{bmatrix} &= (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{Y} = \begin{bmatrix} .287475 & -.003535 \\ -.003535 & .00005051 \end{bmatrix} \begin{bmatrix} 7,807 \\ 617,180 \end{bmatrix} \\ &= \begin{bmatrix} 62.37 \\ 3.5702 \end{bmatrix} \end{aligned}$$

or $b_0 = 62.37$ and $b_1 = 3.5702$. These results agree with the ones in Chapter 1. Any differences would have been due to rounding effects.

One can use R code direct to get the estimates as:

```
mat <- scan('a.txt')
```

```
mat <- matrix(mat, ncol = 2, byrow = TRUE)
```

```
mat[,1]
```

```
mat[,2]
```

```
length(mat[,1])
```

```
one=as.vector(rep(1, 25))
```

```
x=cbind(one,mat[,1])
```

```
y=mat[,2]
```

```
b=solve(t(x)%*%x)%*%t(x)%*%y
```

```
b
```