# Least Squares Regression

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#### 1 Derivation

the model can be described as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \epsilon$$

where y is the dependent variable,  $x_1, x_2, \dots, x_k$  are the independent variables,  $\beta_0, \beta_1, \beta_2, \dots, \beta_k$  are the parameters, and  $\epsilon$  is the error term. The object is to estimate the parameters. We can arrange n observations in matrix / vector form as follows:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & x_{12} & x_{13} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & x_{23} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} & x_{n3} & \cdots & x_{nk} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

which can be simplified as follows:

$$Y = X\beta + \epsilon$$

the vector of parameter estimates is denoted  $\hat{\beta}$ . To calculate the parameter estimates we want to minimize the sum of the squared errors. The vector of errors is:

$$\epsilon = Y - X\hat{\beta}$$

and hence the sum of the squared errors is:

$$\epsilon^T \epsilon = (Y - X\hat{\beta})^T (Y - X\hat{\beta})$$

to find the minimum of the sum of the squared errors we differentiate the above expression with respect to  $\hat{\beta}$ :

$$\begin{split} \frac{\partial}{\partial \hat{\beta}} \epsilon^T \epsilon &= \frac{\partial}{\partial \hat{\beta}} (Y - X \hat{\beta})^T (Y - X \hat{\beta}) \\ &= \frac{\partial}{\partial \hat{\beta}} (Y^T - \hat{\beta}^T X^T) (Y - X \hat{\beta}) \\ &= \frac{\partial}{\partial \hat{\beta}} (Y^T Y - Y^T X \hat{\beta} - \hat{\beta}^T X^T Y + \hat{\beta}^T X^T X \hat{\beta}) \\ &= \frac{\partial}{\partial \hat{\beta}} (Y^T Y - 2 \hat{\beta}^T X^T Y + \hat{\beta}^T X^T X \hat{\beta}) \\ &= -2 X^T Y + 2 X^T X \hat{\beta} \end{split}$$

setting this equal to zero we get:

$$-2X^{T}Y + 2X^{T}X\hat{\beta} = 0$$
 
$$2X^{T}X\hat{\beta} = 2X^{T}Y$$
 
$$X^{T}X\hat{\beta} = X^{T}Y$$
 
$$\hat{\beta} = (X^{T}X)^{-1}X^{T}Y$$

#### 2 Estimation

we can now estimate the parameters with real data using the previously derived equation:

#### head(data)

```
##
             jpi aptitude
                            tol technical general
     empid
                    43.83 55.92
                                              43.58
         1 45.52
                                     51.82
                                              51.03
## 2
         2 40.10
                    32.71 32.56
                                     51.49
         3 50.61
                    56.64 54.84
                                     52.29
                                             52.47
## 4
         4 38.97
                    51.53 59.69
                                     47.48
                                             47.69
                                             45.77
         5 41.87
                    51.35 51.50
                                     47.59
         6 38.71
                    39.60 43.63
                                     48.34
                                              42.06
## 6
```

we construct our X matrix using the independent variables with a column of 1s for the intercept:

```
X <- cbind(rep(1, nrow(data)), as.matrix(data[, c("aptitude", "tol", "technical", "general")]))
head(X)</pre>
```

```
##
          aptitude
                   tol technical general
## [1,] 1
             43.83 55.92
                             51.82
                                     43.58
## [2,] 1
             32.71 32.56
                             51.49
                                     51.03
## [3,] 1
             56.64 54.84
                             52.29
                                     52.47
## [4,] 1
             51.53 59.69
                             47.48
                                     47.69
## [5,] 1
             51.35 51.50
                             47.59
                                     45.77
## [6,] 1
             39.60 43.63
                             48.34
                                     42.06
```

next we construct our Y vector from the dependent variable:

```
Y <- as.matrix(data[, "jpi"])
head(Y)

## [,1]
## [1,] 45.52
## [2,] 40.10
## [3,] 50.61
## [4,] 38.97
## [5,] 41.87
## [6,] 38.71
```

and finally we solve for our  $\hat{\beta}$  vector of estimated parameters using our expression derived earlier:

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

```
B <- solve(t(X) %*% X) %*% t(X) %*% Y
round(B[, 1], 5)

## aptitude tol technical general
## -54.28225  0.32356  0.03337  1.09547  0.53683</pre>
```

here we use the *solve* function to get the inverse of a matrix, and the t function to get the transpose of a vector or matrix. Lets compare our parameters with the parameter estimates using the standard lm function:

```
lm(jpi ~ aptitude + tol + technical + general, data = data)

##
## Call:
## lm(formula = jpi ~ aptitude + tol + technical + general, data = data)
##
## Coefficients:
## (Intercept) aptitude tol technical general
## -54.28225 0.32356 0.03337 1.09547 0.53683
```