

# Mathematical Solution to Linear Regression

## 1. Simple Linear Regression

### Model

The model equation for simple linear regression is:

$$y = \theta_0 + \theta_1 x$$

where:

- $y$ : Dependent variable (output),
- $x$ : Independent variable (input),
- $\theta_0$ : Intercept,
- $\theta_1$ : Slope.

### Objective

The objective is to minimize the **Sum of Squared Errors (SSE)**:

$$SSE = \sum_{i=1}^n (y_i - (\theta_0 + \theta_1 x_i))^2$$

### Solution

The formulas for the coefficients are:

$$\theta_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$
$$\theta_0 = \bar{y} - \theta_1 \bar{x}$$

where  $\bar{x} = \frac{1}{n} \sum x_i$  and  $\bar{y} = \frac{1}{n} \sum y_i$  are the means of  $x$  and  $y$ , respectively.

## 2. Multiple Linear Regression

### Model

The model equation for multiple linear regression is:

$$y = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_p x_p$$

or equivalently, in matrix form:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\theta}$$

where:

- $\mathbf{y}$ :  $n \times 1$  vector of observed values,
- $\mathbf{X}$ :  $n \times (p + 1)$  matrix of predictors (first column is ones for  $\theta_0$ ),
- $\boldsymbol{\theta}$ :  $(p + 1) \times 1$  vector of coefficients.

### Objective

The objective is to minimize the **SSE**:

$$SSE = (\mathbf{y} - \mathbf{X}\boldsymbol{\theta})^T(\mathbf{y} - \mathbf{X}\boldsymbol{\theta})$$

### Solution

The formula for the coefficients is:

$$\boldsymbol{\theta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

## 3. Summary Table

The following table summarizes the key formulas for simple and multiple linear regression:

Aspect	Simple Linear Regression	Multiple Linear Regression
Model Equation	$y = \theta_0 + \theta_1 x$	$y = \theta_0 + \theta_1 x_1 + \cdots + \theta_p x_p$
Objective	$\min \sum_{i=1}^n (y_i - (\theta_0 + \theta_1 x_i))^2$	$\min(\mathbf{y} - \mathbf{X}\boldsymbol{\theta})^T(\mathbf{y} - \mathbf{X}\boldsymbol{\theta})$
Solution for Coefficients	$\theta_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$ $\theta_0 = \bar{y} - \theta_1 \bar{x}$	$\boldsymbol{\theta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$