

# Simple Linear Regression

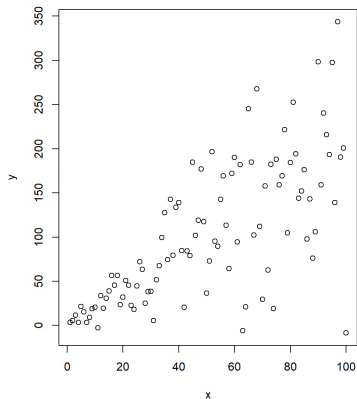
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# Introduction

Given 100 data points

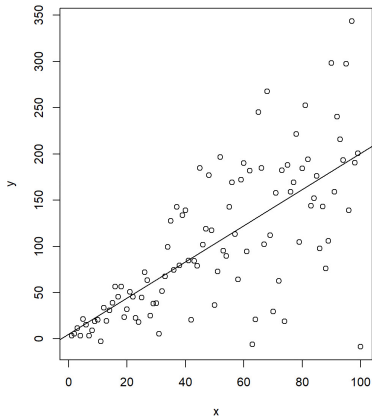
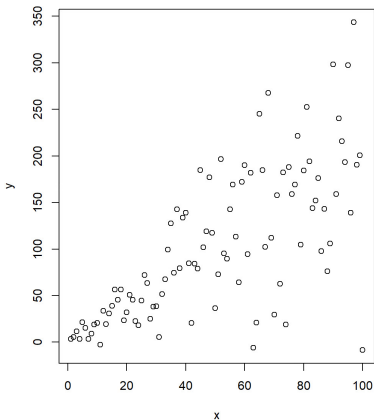
$$(x_1, y_1), (x_2, y_2), \dots, (x_{100}, y_{100})$$

we want to fit a line (or more generally an equation) to describe the relationship between  $x$  and  $y$ .



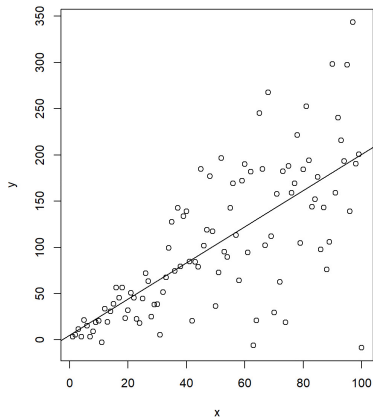
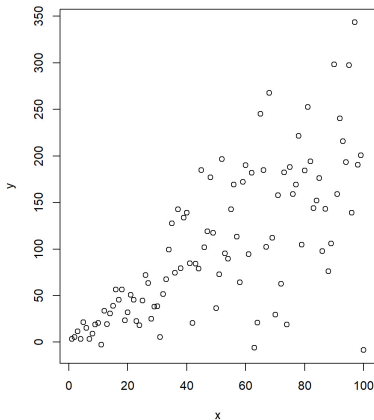
# Introduction

A **regression model** is a function that describes the relationship between the outcome (response)  $y$ , and the predictor (regressor)  $x$ .



# Simple Linear Regression (SLR)

The **simple linear regression model** is a model with a single predictor  $x$  that has a relationship with a outcome  $y$  that is a straight line.

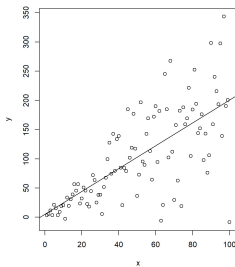
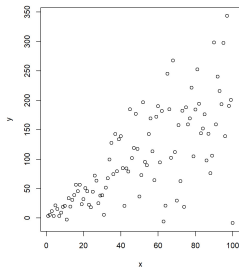


# Simple Linear Regression (SLR)

In SLR, the relationship between a response variable  $y$  and a predictor variable  $x$  is postulated as

$$y = \beta_0 + \beta_1 x + \epsilon$$

where  $\beta_0$  and  $\beta_1$  are constants called the *model regression coefficients*, and  $\epsilon$  is a random disturbance or error.



# Simple Linear Regression (SLR)

For data points  $(x_i, y_i)$ ,  $i = 1, 2, \dots, n$ , we write

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i$$

- (i)  $y_i$  is the value of the response variable in the  $i$ -th trial
- (ii)  $\beta_0$  and  $\beta_1$  are parameters
- (iii)  $x_i$  is a **known constant**, namely, the value of the predictor variable in the  $i$ -th trial
- (iv)  $\epsilon_i$  is a random error with

$$E(\epsilon_i) = 0 \quad \text{and} \quad \sigma^2(\epsilon_i) = \sigma^2$$

and  $\epsilon_i, \epsilon_j$  are uncorrelated so that their covariance is zero, i.e.  $\sigma(\epsilon_i, \epsilon_j) = 0$  for all  $i, j$ ,  $i \neq j$ ,  $i = 1, 2, \dots, n$ .

## Estimation of $\beta_0$ and $\beta_1$

The parameters  $\beta_0$  and  $\beta_1$  are unknown and must be estimated using sample data

$$(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$$

The **least squares method** is used to estimate  $\beta_0$  and  $\beta_1$ . To do this, from

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i$$

we write

$$\epsilon_i = y_i - (\beta_0 + \beta_1 x_i)$$

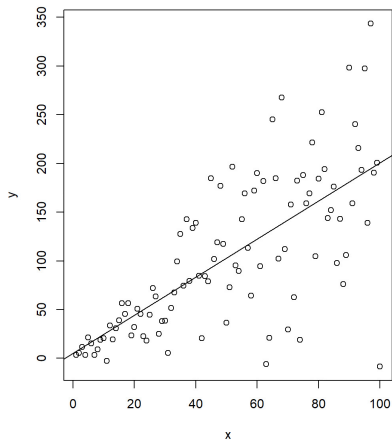
and call the following as

$$S(\beta_0, \beta_1) = \sum_{i=1}^n \epsilon_i^2 = \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2$$

the residual sum of squares.

## Estimation of $\beta_0$ and $\beta_1$

$$S(\beta_0, \beta_1) = \sum_{i=1}^n \epsilon_i^2 = \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2$$





## Estimation of $\beta_0$ and $\beta_1$

In the next video we will show how to estimate  $\beta_0$  and  $\beta_1$  by minimizing the residual sum of squares.