

## Linear Regression

### Intro

Linear regression is an algorithm used to determine the relationship between a continuous dependent variable and one or more independent variables. This is done through fitting the line of best fit which uses beta coefficients that minimize the sum of squared residuals.

### Definitions

**Beta Coefficient:** the degree of change in the outcome variable for each unit of change in the predictor variable(s)

$$y = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n$$

where  $\beta_0$  is the intercept,  $\beta_n$  is the coefficient, and  $X_n$  is the independent variable

**Residuals:** the difference between the predicted value of a dependent variable and the actual value of that dependent variable (loss function)

$$(y - \hat{y})$$

where  $y$  is the actual value and  $\hat{y}$  is the predicted value

**Sum of Squared Residuals:** the sum of all residuals squared (cost function)

$$RSS = \sum_{i=0}^n (y_i - \hat{y}_i)^2$$

### Derivation

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

Solving for  $\varepsilon_i$ :

$$\varepsilon_i = y_i - \beta_0 - \beta_1 x_i$$

Letting  $E$  stand for the sum of squared errors:

$$E = \sum_{i=1}^n \varepsilon_i^2 = \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2$$

To find the line of "best fit", we need to find a pair of  $(\beta_0, \beta_1)$  which will minimize  $E$

Solving for  $\beta_1$ 's:  
derivative  $\frac{\partial E}{\partial \beta_1} = \sum_{i=1}^n 2(y_i - \beta_0 - \beta_1 x_i)(-1)(x_i)$

$$0 = \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)(x_i)$$

$$0 = \sum_{i=1}^n y_i x_i - \beta_0 \sum_{i=1}^n x_i - \beta_1 \sum_{i=1}^n x_i^2$$

$$\text{Let } v = \sum_{i=1}^n x_i \text{ and } u = \sum_{i=1}^n x_i^2$$

$$\textcircled{1} \quad 0 = \sum_{i=1}^n y_i x_i - \beta_0 v - \beta_1 u$$

Solving for  $\beta_0$ 's:  
derivative  $\frac{\partial E}{\partial \beta_0} = \sum_{i=1}^n 2(y_i - \beta_0 - \beta_1 x_i)(-1)$

$$0 = \sum_{i=1}^n y_i - \sum_{i=1}^n \beta_0 - \sum_{i=1}^n \beta_1 x_i$$

$$\text{Let } \sum_{i=1}^n 1 = n \text{ and } v = \sum_{i=1}^n x_i$$

$$\textcircled{2} \quad 0 = \sum_{i=1}^n y_i - n\beta_0 - v\beta_1$$



Using equations (2) and (1)

$$(2) \sum_{i=1}^n y_i = n\beta_0 + v\beta_1$$

$$(1) \sum_{i=1}^n y_i x_i = v\beta_0 + u\beta_1$$

If we multiply equation (2) by  $v$ , and equation (1) by  $n$ , we can isolate  $\beta_1$

$$v \sum_{i=1}^n y_i = nv\beta_0 + v^2\beta_1$$

$$n \sum_{i=1}^n y_i x_i = nv\beta_0 + nu\beta_1$$

Subtracting results in:

$$v \sum_{i=1}^n y_i - n \sum_{i=1}^n y_i x_i = v^2\beta_1 - nu\beta_1$$

$$\frac{v \sum_{i=1}^n y_i - n \sum_{i=1}^n y_i x_i}{(v^2 - nu)} = \beta_1 \quad (3)$$

Using equation (2) we can substitute equation (3) for  $\beta_1$ , and solve for  $\beta_0$

$$\beta_0 = \frac{\sum_{i=1}^n y_i}{n} - \frac{v\beta_1}{n}$$

$$\beta_0 = \frac{\sum_{i=1}^n y_i}{n} - \frac{v \left( \frac{v \sum_{i=1}^n y_i - n \sum_{i=1}^n y_i x_i}{v^2 - nu} \right)}{n}$$

Simplifying and reducing results in:

$$\beta_0 = \frac{v^2 \sum_{i=1}^n y - n u \sum_{i=1}^n y - v^2 \sum_{i=1}^n y + v n \sum_{i=1}^n y_i x_i}{n v^2 - n u}$$

$$\beta_0 = \frac{-n u \sum_{i=1}^n y + v n \sum y x}{n v^2 - n u} \quad (4)$$



$\beta_0$  can be re-written using prior definitions of  $\bar{y}$  and  $\bar{x}$ :

$$\beta_0 = \frac{-n \sum_{i=1}^n x_i^2 \bar{y} + \sum_{i=1}^n x_i n \sum_{i=1}^n y_i x_i}{n \left( \sum_{i=1}^n x_i \right)^2 - n \sum_{i=1}^n x_i^2}$$

Multiplication of  $-1/n^2$  to numerator and denominator can further reduce the equation

$$\beta_0 = \frac{\sum_{i=1}^n x_i^2 \bar{y}_n - \sum_{i=1}^n y_i x_i (\bar{x}_n)}{\sum x_i^2 (1/n) - \bar{x} \left( \sum_{i=1}^n x_i \right)}$$

Following the same steps above for  $\beta_1$ :

$$\beta_1 = \frac{\sum_{i=1}^n x_i \sum_{i=1}^n y_i - n \sum_{i=1}^n y_i x_i}{\left( \sum_{i=1}^n x_i \right)^2 - n \sum_{i=1}^n x_i^2}$$

Using  $1/n^2$  rather than  $-1/n^2$ :

$$\beta_1 = \frac{\bar{x}_n \bar{y}_n - \left( \sum_{i=1}^n y_i x_i \right) (1/n)}{\bar{x}_n^2 - \left( \sum_{i=1}^n x_i^2 \right) (1/n)}$$