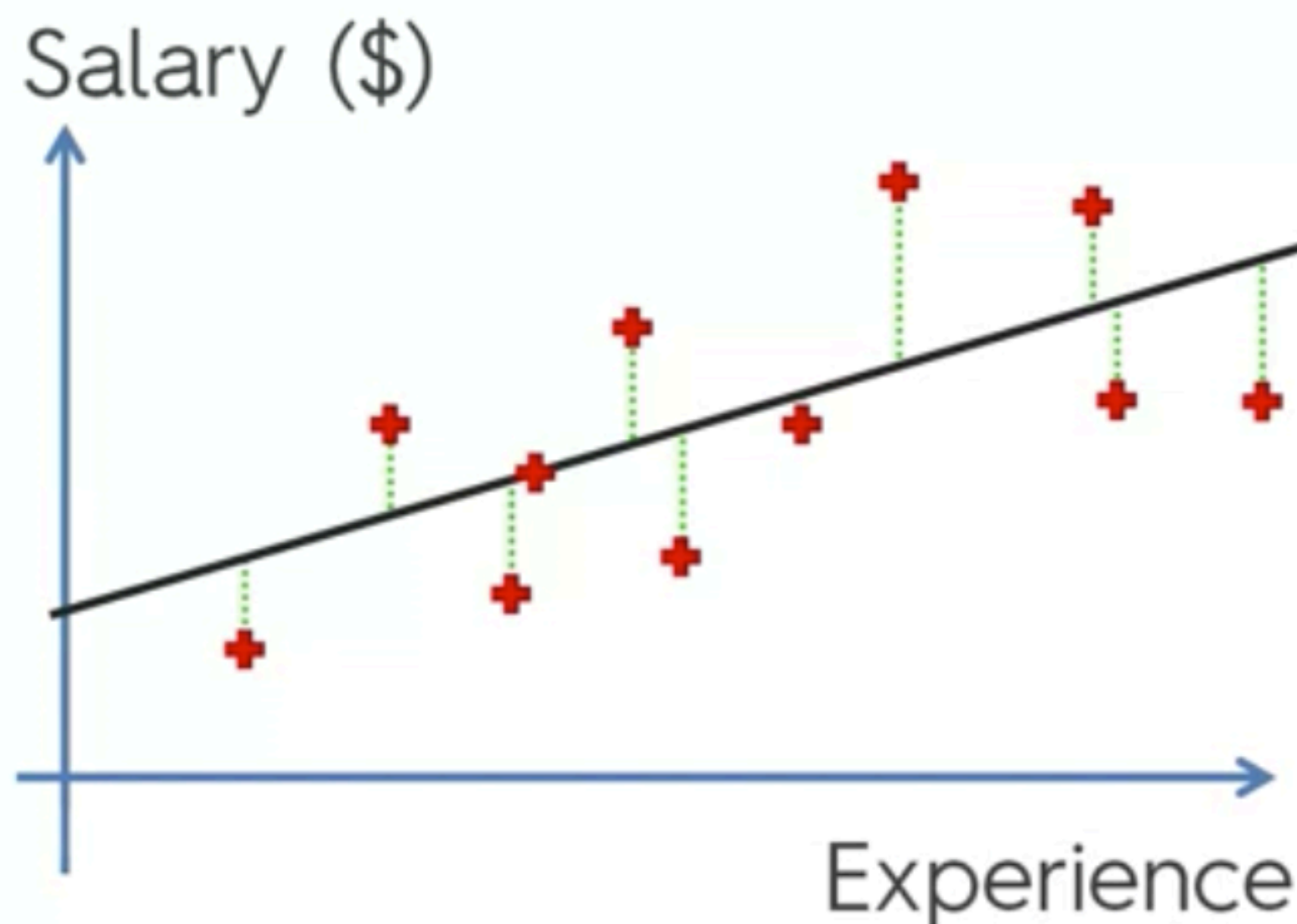


R Squared

Simple Linear Regression:



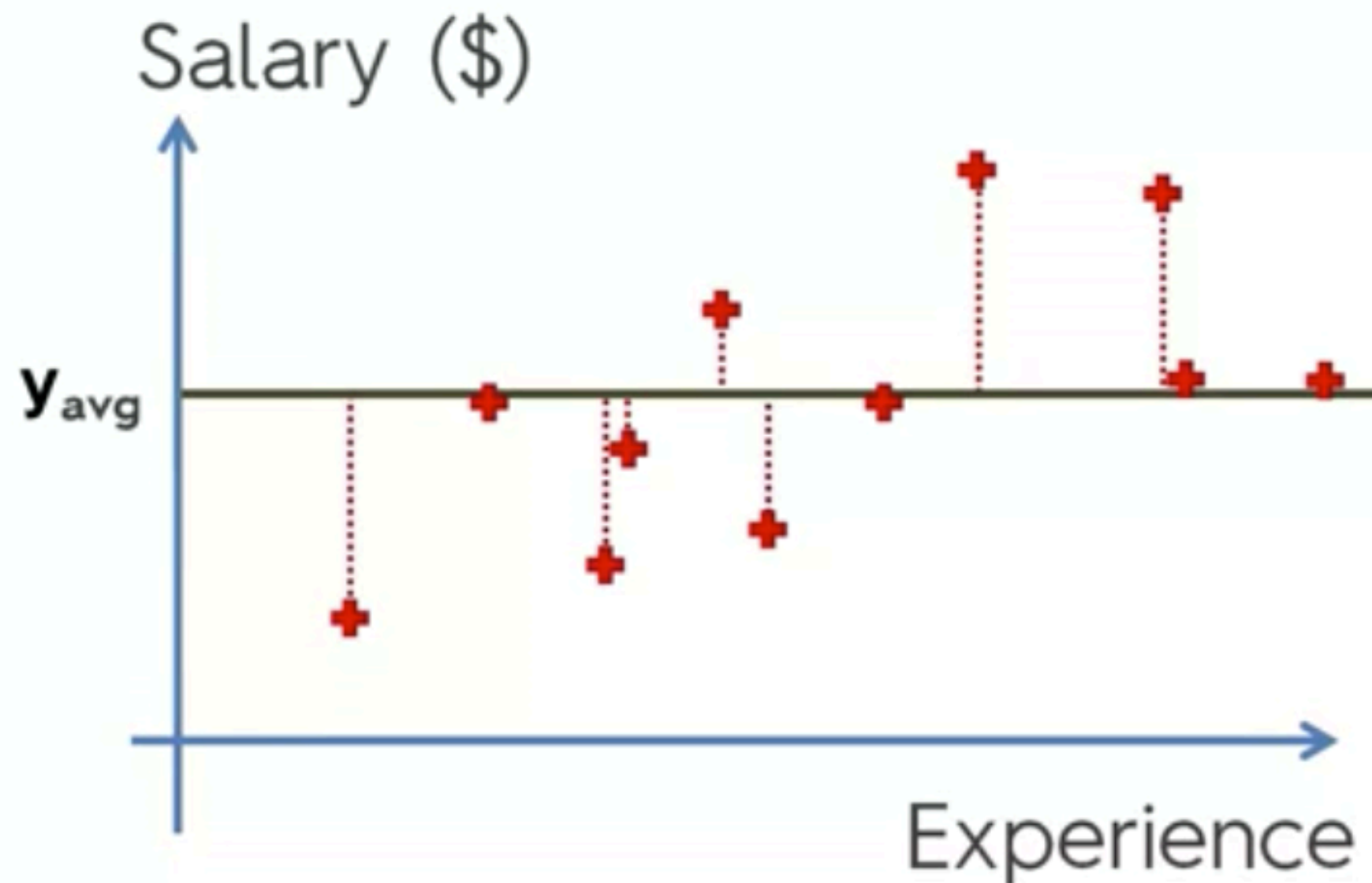
Sum of Squares of Residuals

$$SS_{\text{res}} = \text{SUM } (y_i - \hat{y}_i)^2$$

Predicted Value

R Squared

Simple Linear Regression:



$$SS_{res} = \text{SUM } (y_i - \hat{y}_i)^2$$

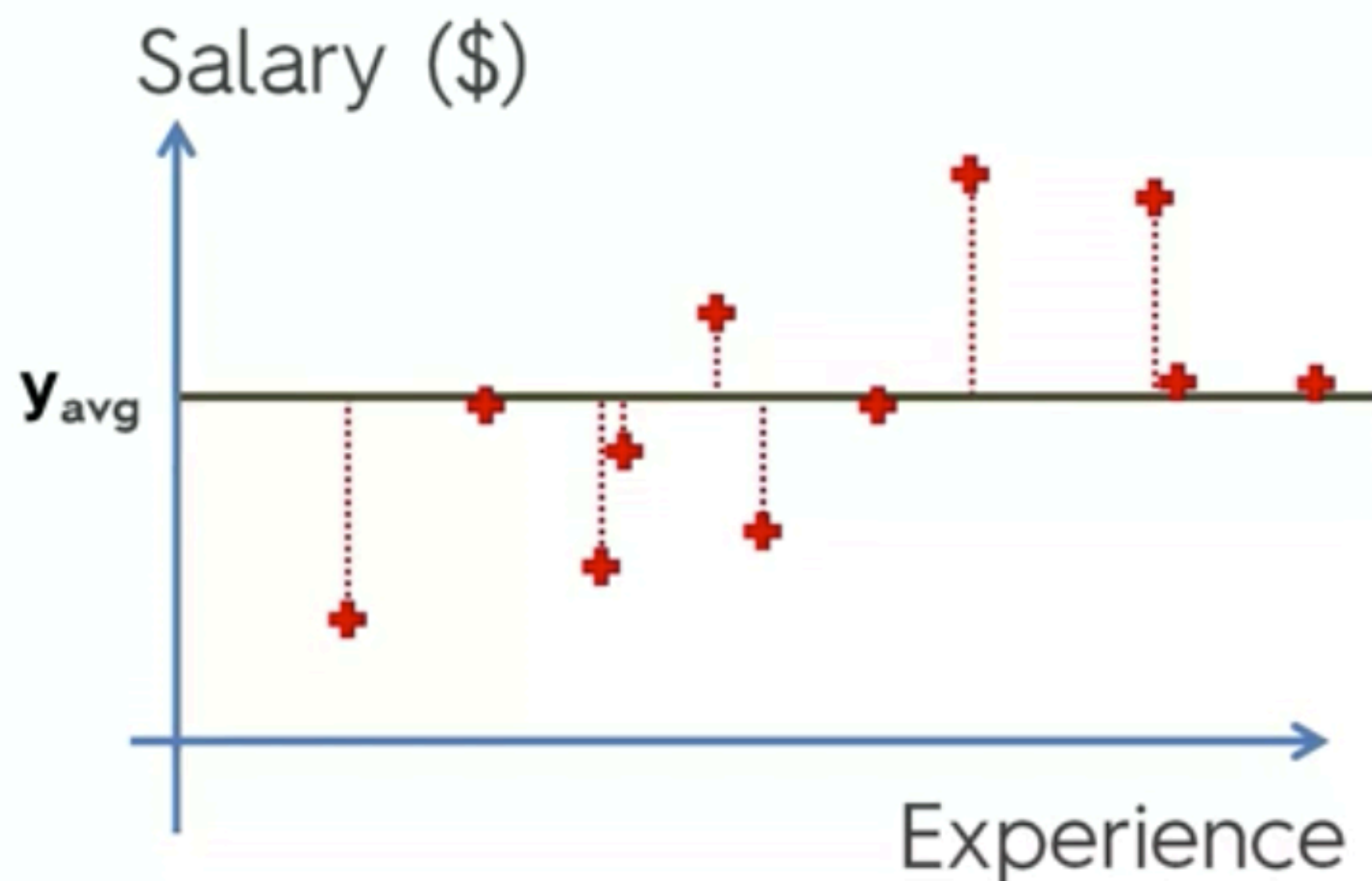
$$SS_{tot} = \text{SUM } (y_i - y_{avg})^2$$

↖ Total Sum of Squares

↑ Sample Mean Value

R Squared

Simple Linear Regression:



$$SS_{res} = \text{SUM } (y_i - \hat{y}_i)^2$$

$$SS_{tot} = \text{SUM } (y_i - y_{avg})^2$$

R2 means how good is the sloped line as compared to the horizontal line at the average.

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

While fitting, intention is to minimise SSres
Usually, $0 \leq R^2 \leq 1$, R2 tending to 1 is better
R2 can also be negative, we then go with avg.

Adjusted R²

$$R^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}}$$

R² – Goodness of fit
(greater is better)

$$y = b_0 + b_1 * x_1$$

$$y = b_0 + b_1 * x_1 + b_2 * x_2$$

Problem:

$$+ b_3 * x_3$$

$$SS_{\text{res}} \rightarrow \text{Min}$$

R² will never decrease

Adjusted R^2

$$R^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}}$$

$$\text{Adj } R^2 = 1 - (1 - R^2) \frac{n - 1}{n - p - 1}$$

p - number of regressors

n - sample size