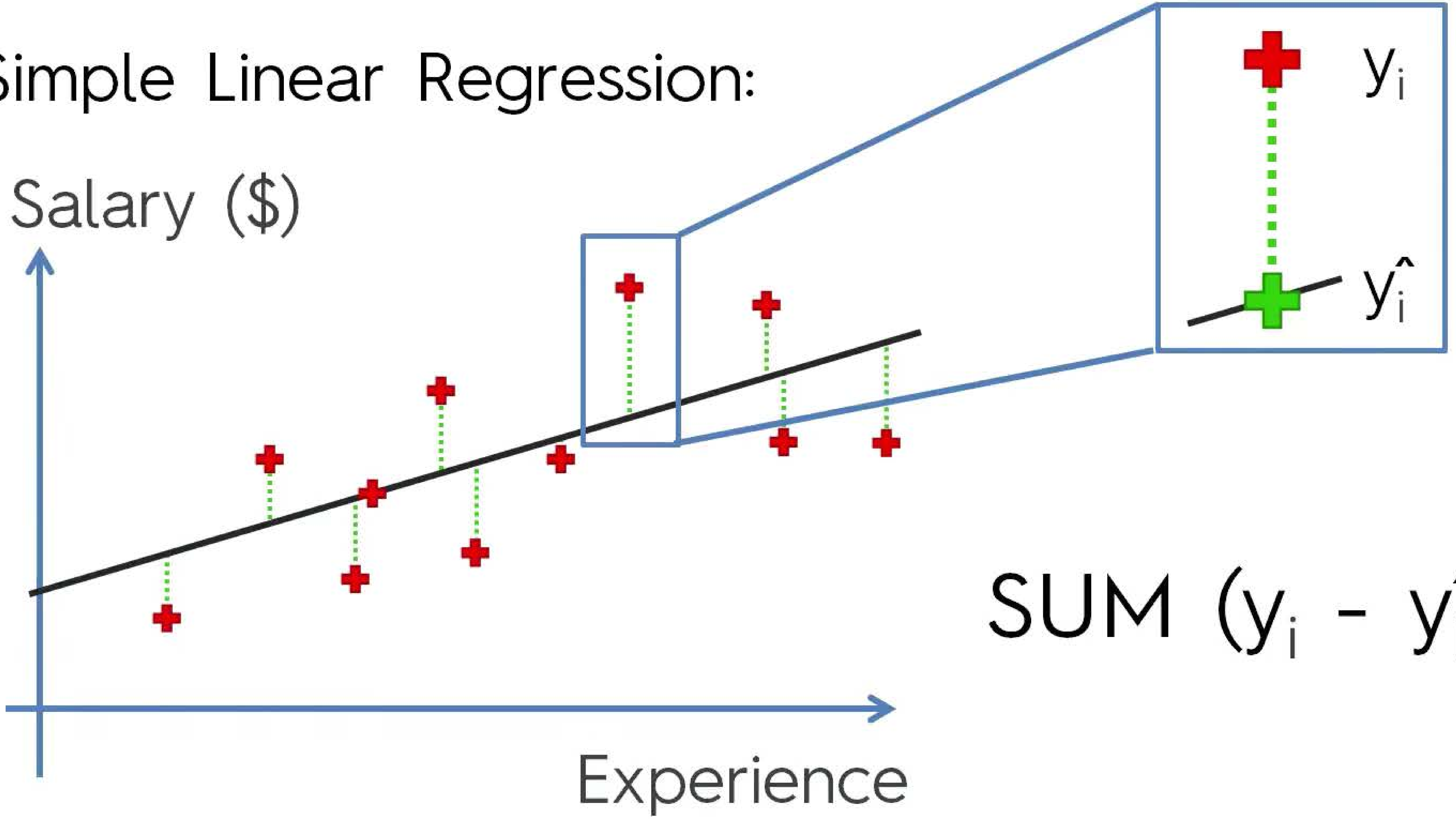
R Squared
Intuition

R Squared

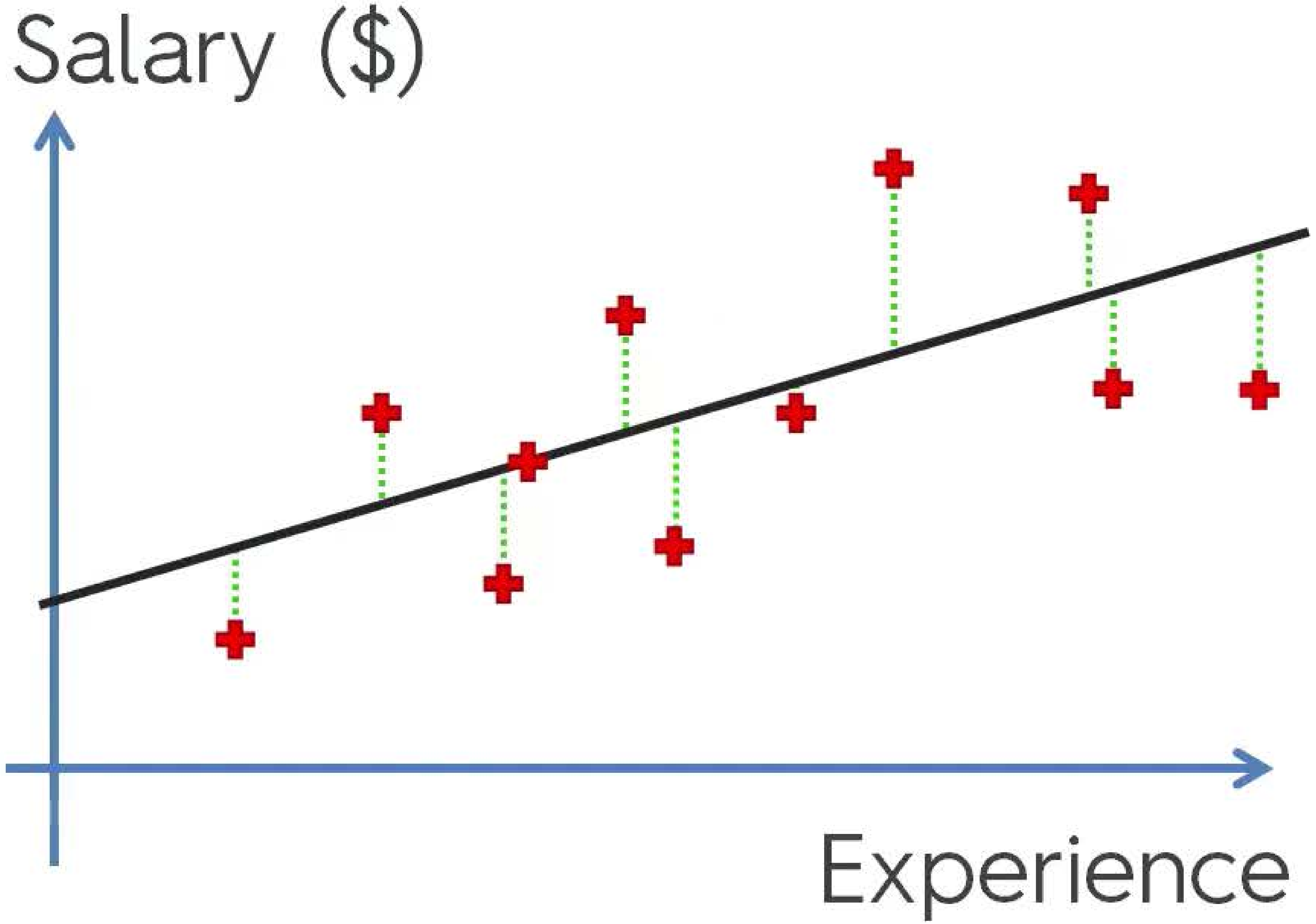
Simple Linear Regression:



$$\text{SUM } (y_i - \hat{y}_i)^2 \rightarrow \min$$

R Squared

Simple Linear Regression:

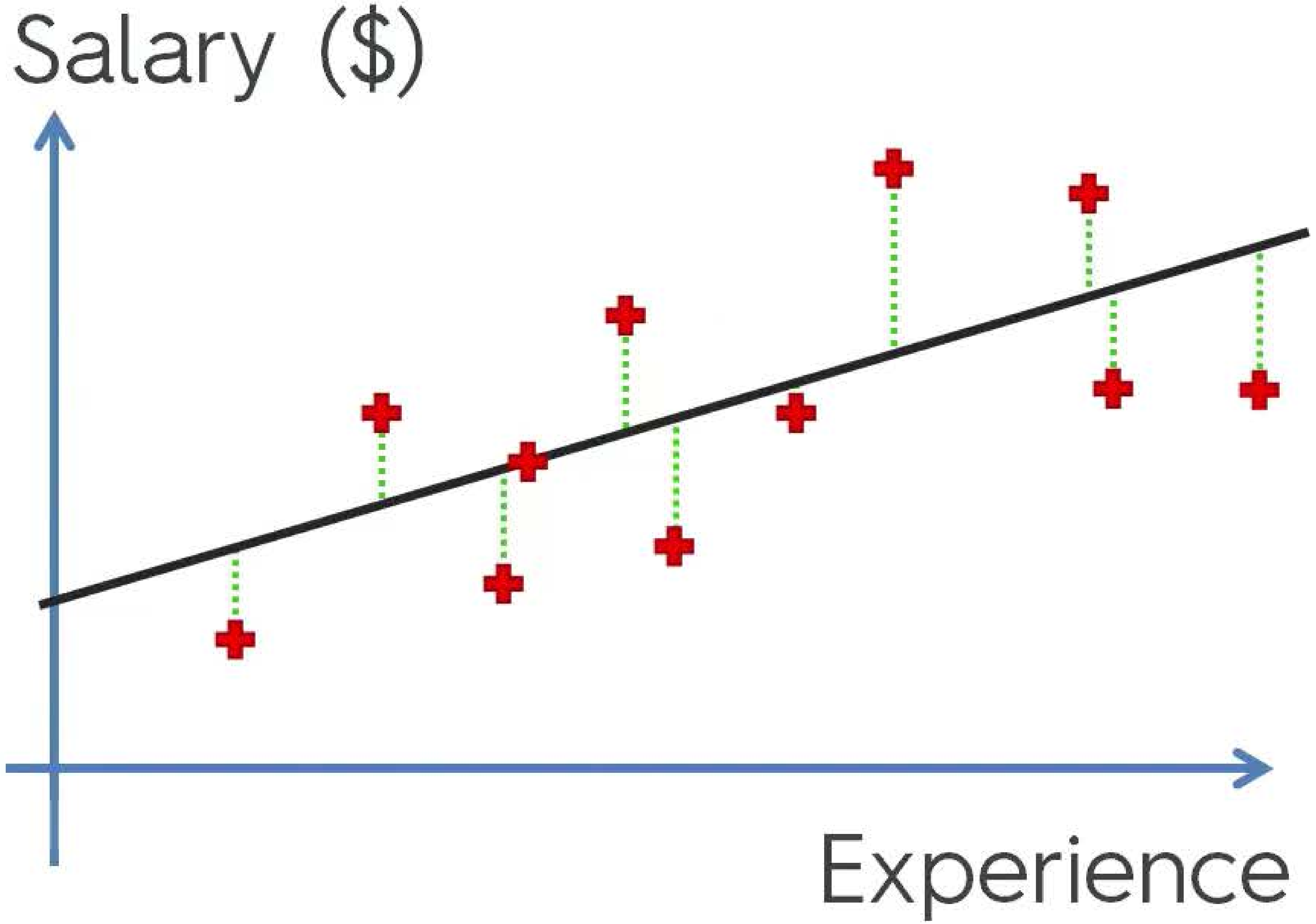


SUM $(y_i - \hat{y}_i)^2$

R Squared

Simple Linear Regression:

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



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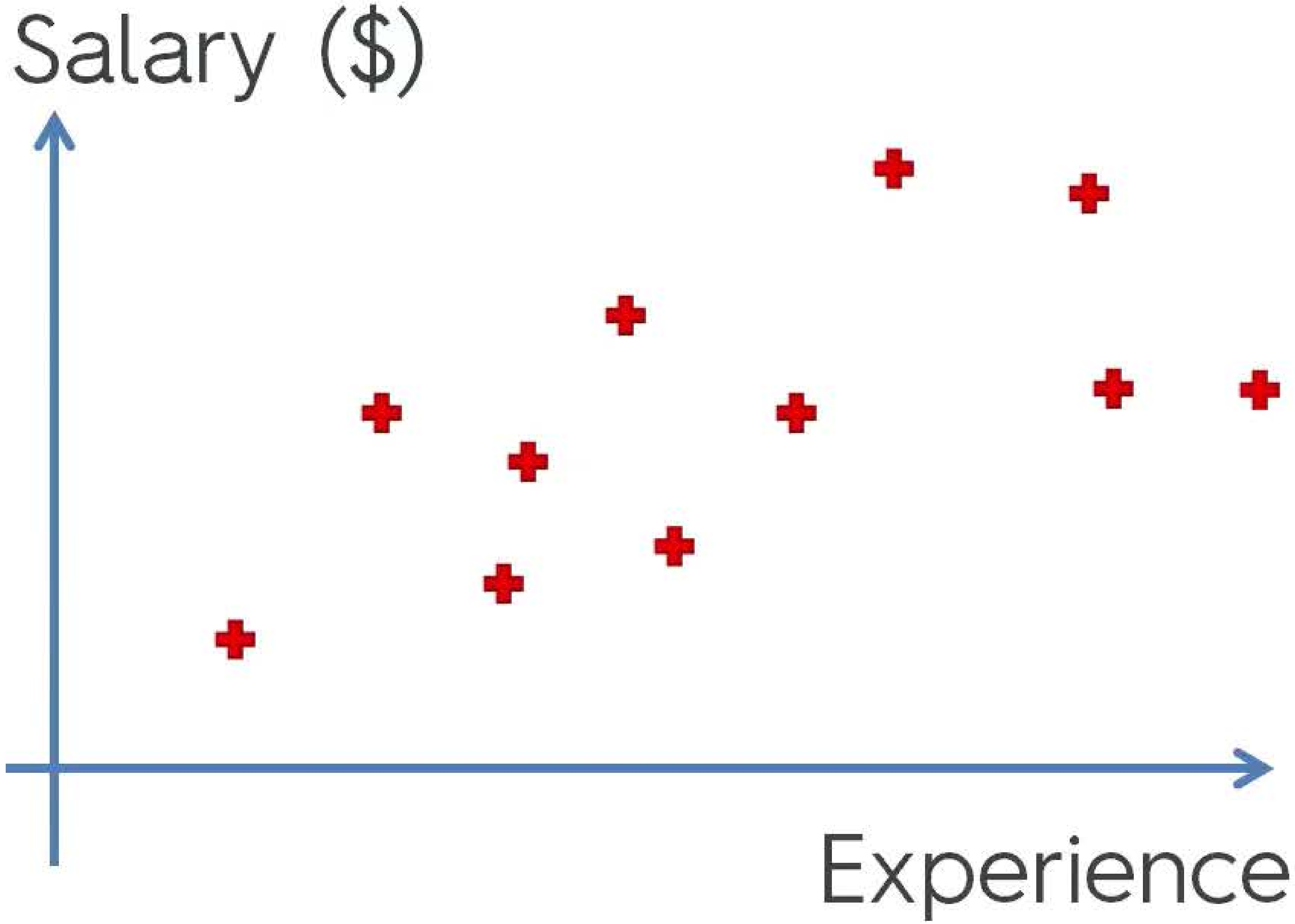

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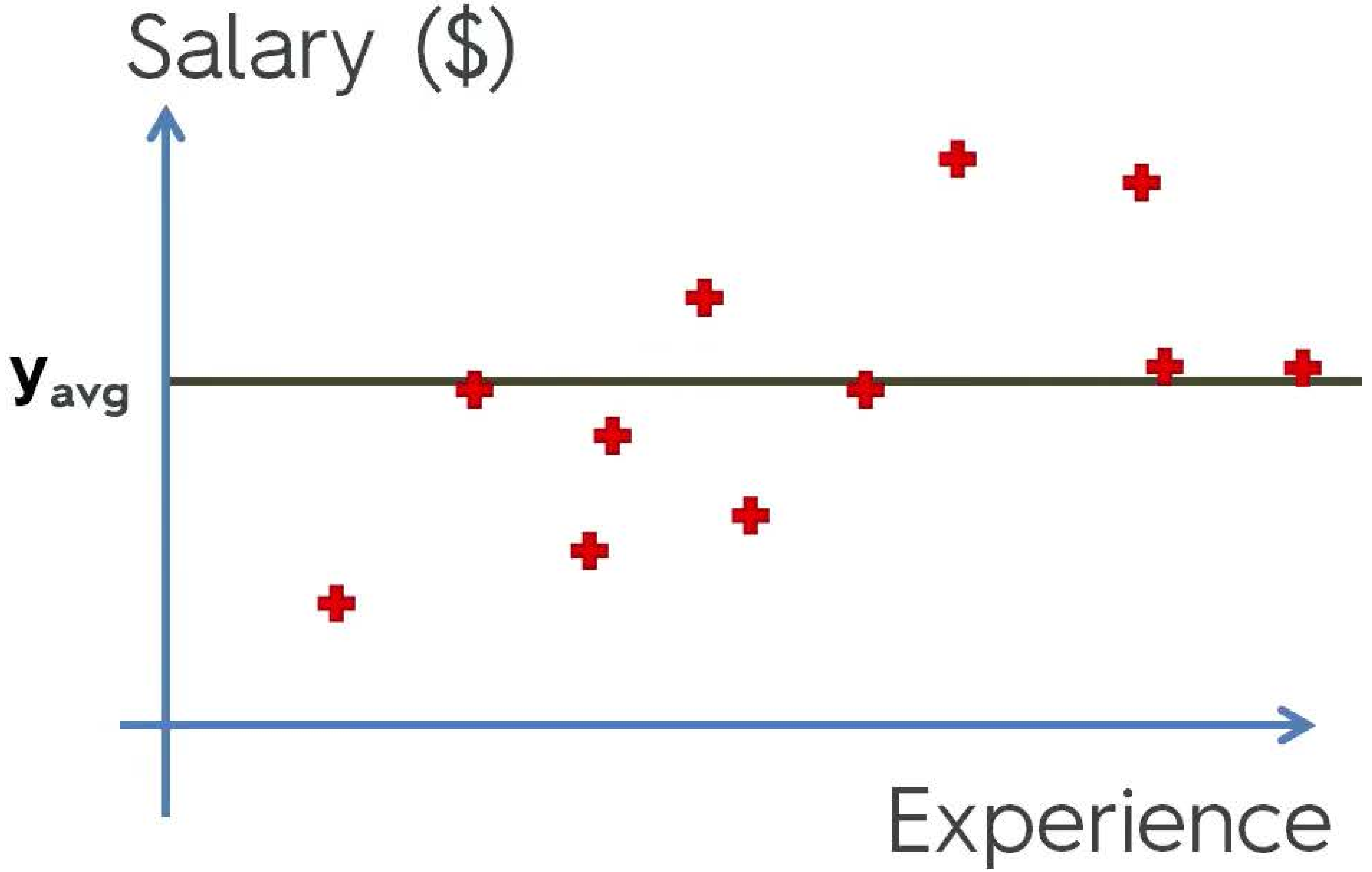

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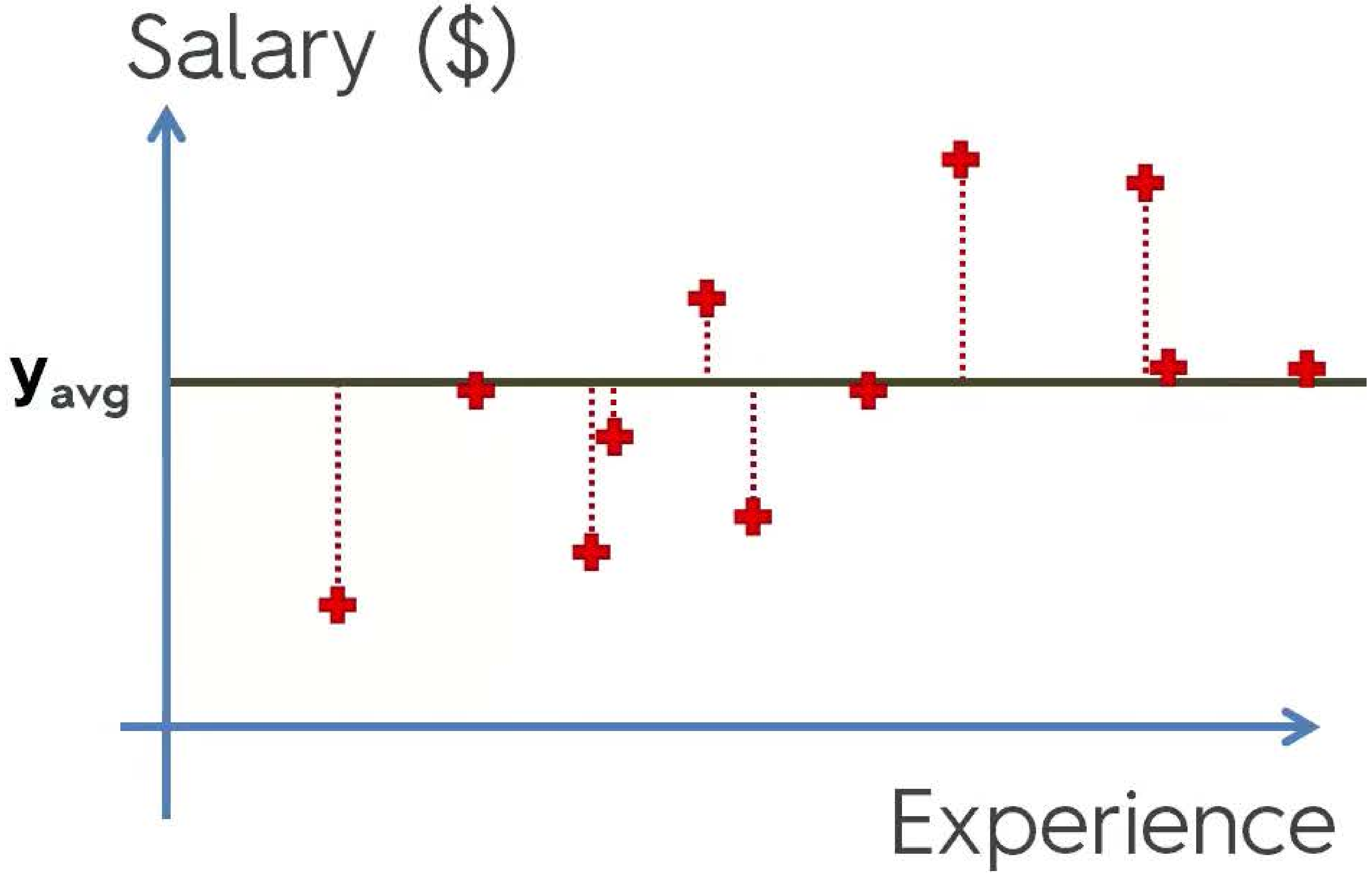

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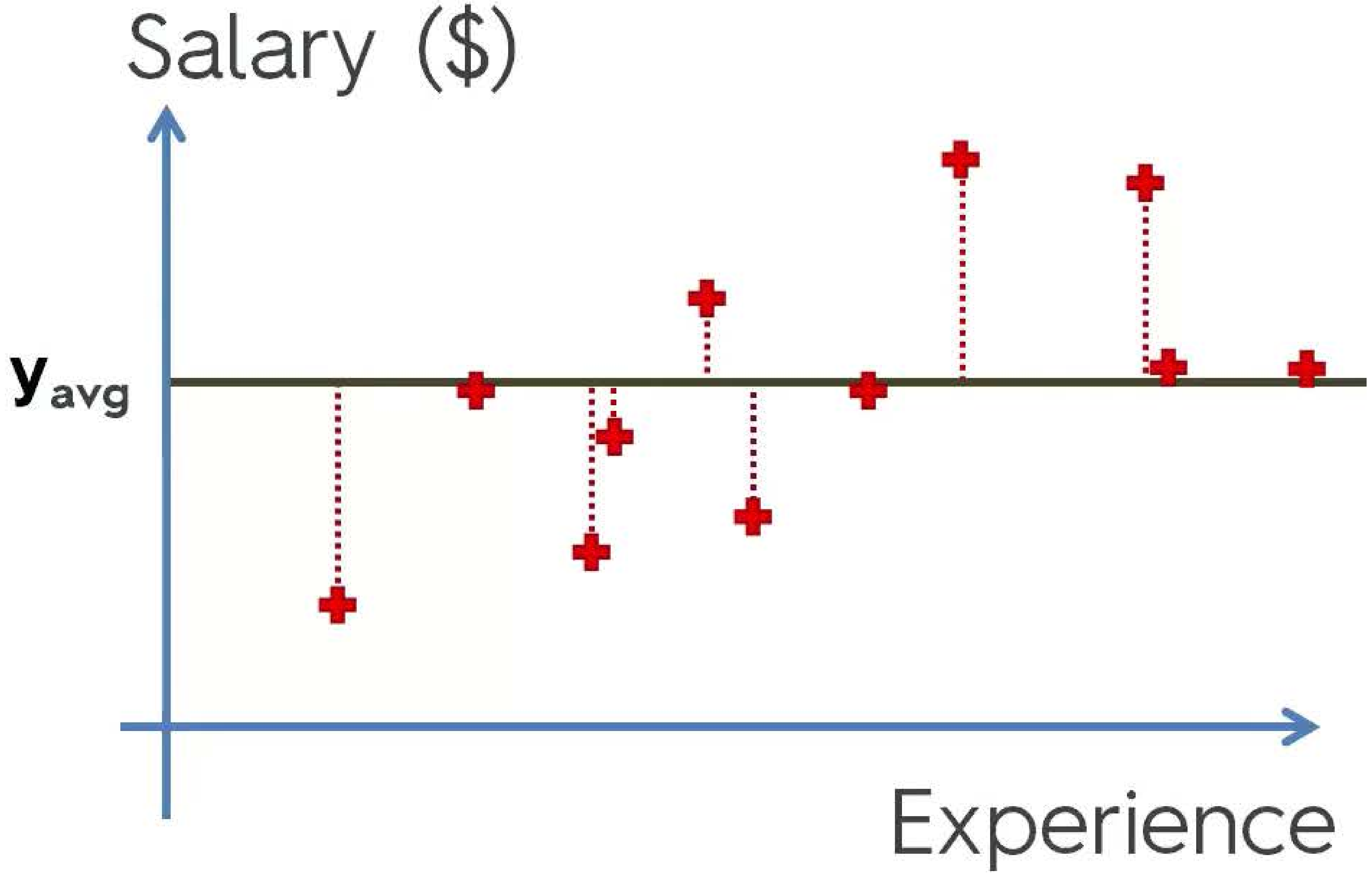
Simple Linear Regression:

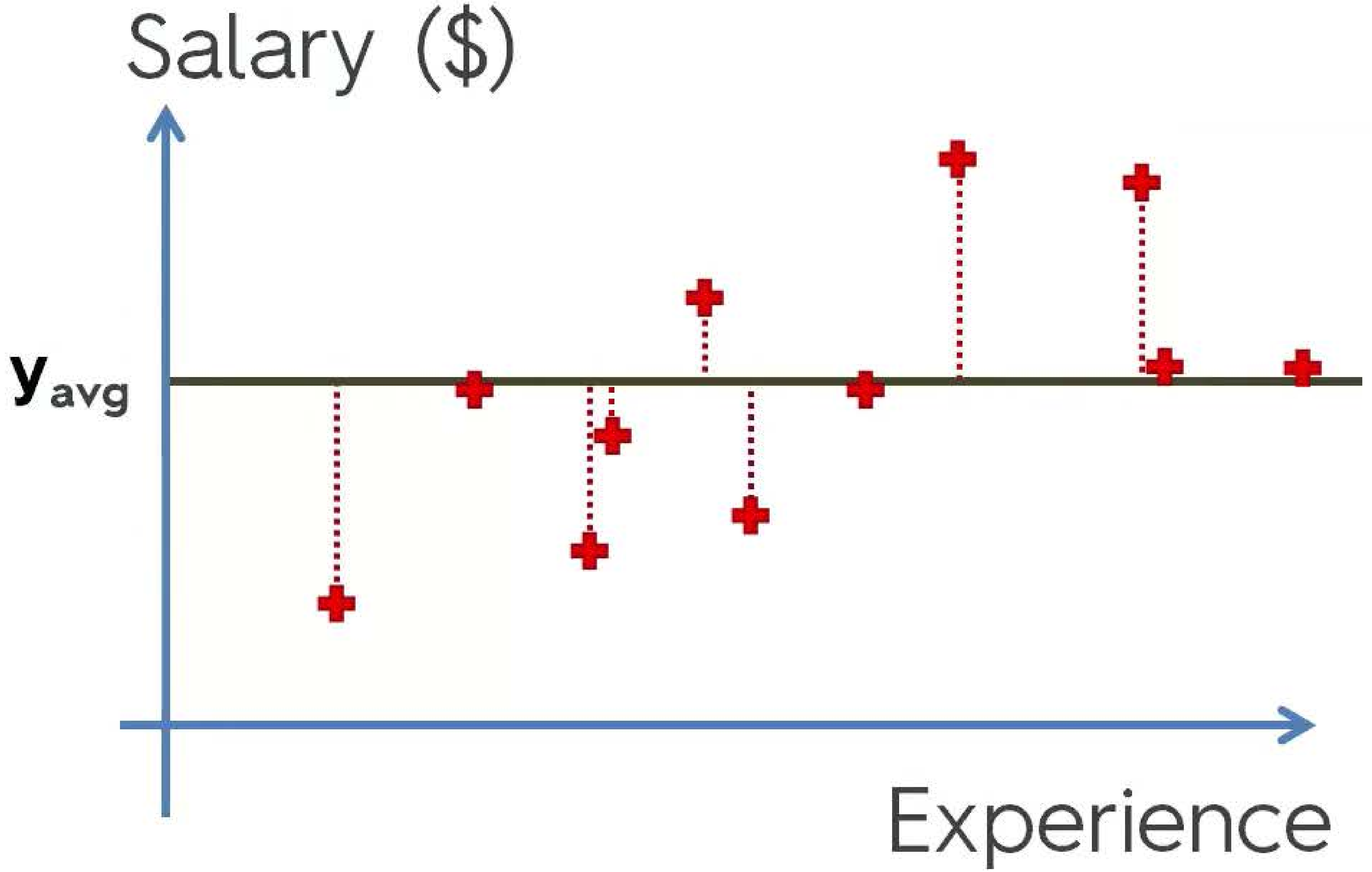


$$SS_{res} = SUM\ (y_i - \hat{y}_i)^2$$

$$SUM\ (y_i - y_{avg})^2$$

R Squared

Simple Linear Regression:

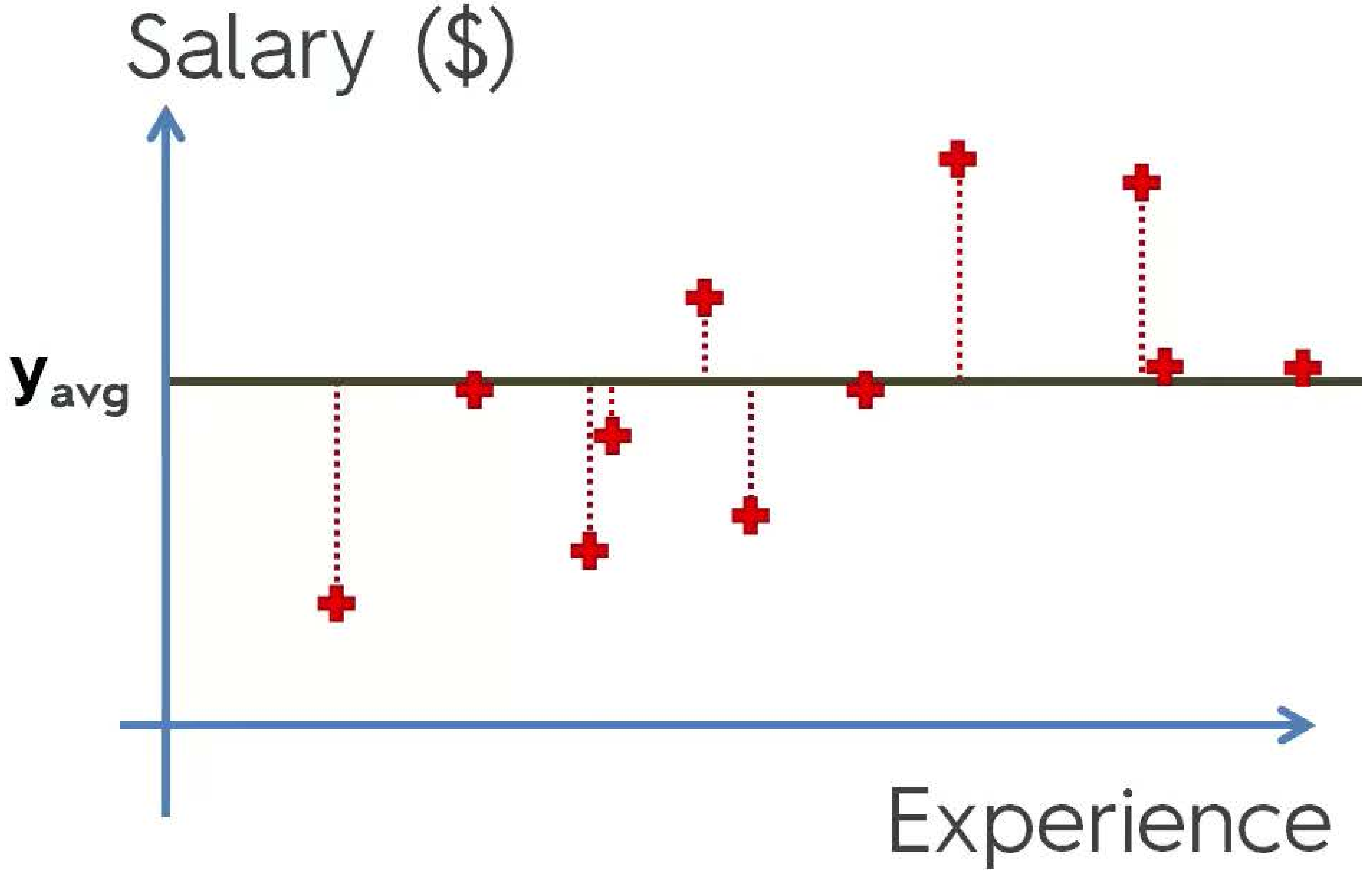


$$SS_{res} = SUM\ (y_i - \hat{y}_i)^2$$

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

R Squared

Simple Linear Regression:



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

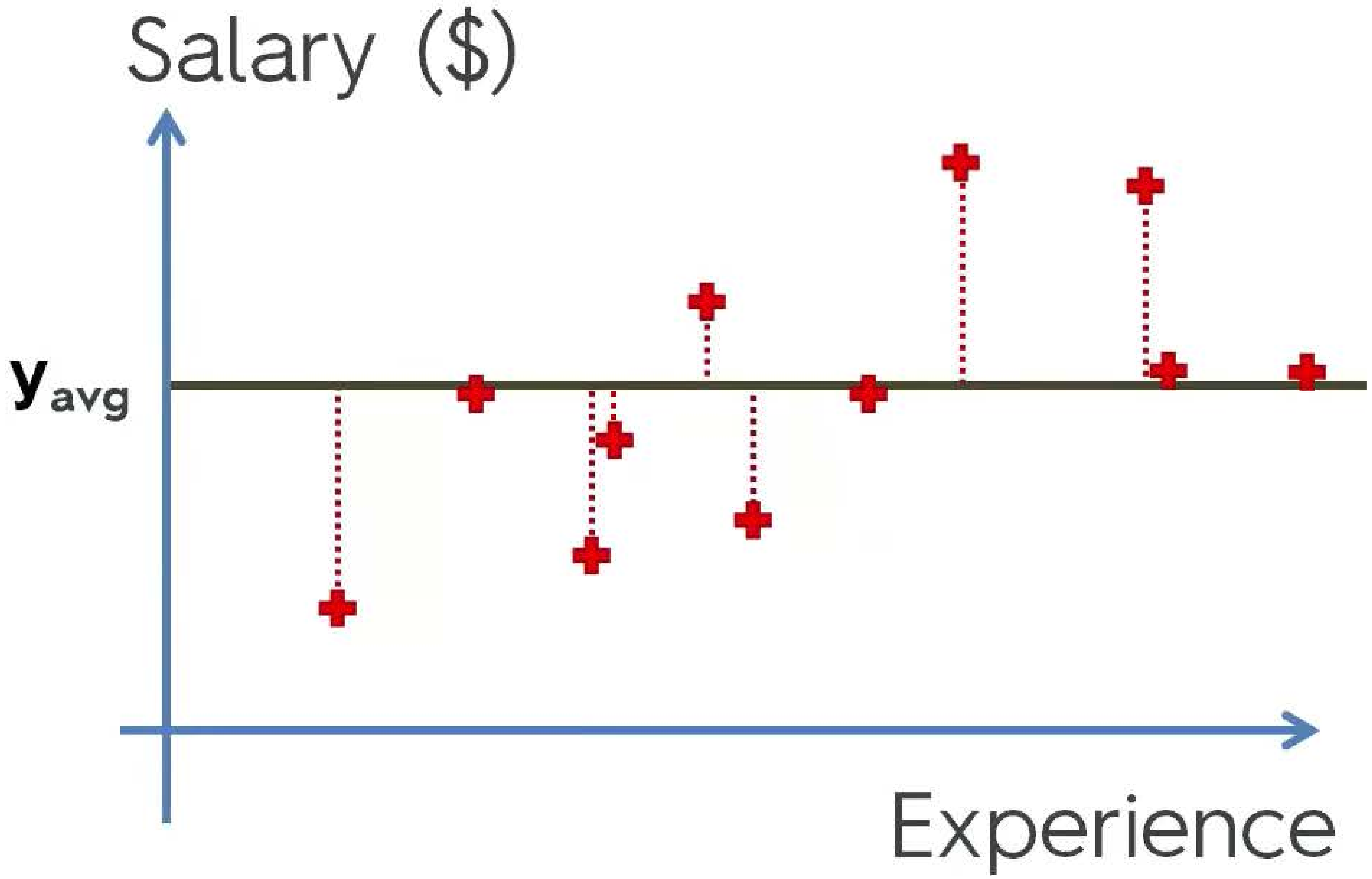
$$SS_{tot} = SUM\ (y_i - y_{avg})^2$$

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

Adjusted R Squared Intuition

Adjusted R^2

Simple Linear Regression:



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

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

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

Adjusted R^2

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

$$y = b_0 + b_1 * x_1$$

Adjusted R^2

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

$$y = b_0 + b_1 * x_1$$

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

Adjusted R^2

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

$$y = b_0 + b_1{*}x_1$$

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

SS_{res} -> Min

Adjusted R^2

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

R^2 – Goodness of fit
(greater is better)

$y = b_0 + b_1 * x_1$

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

SS_{res} -> Min

Adjusted R^2

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

R^2 – Goodness of fit

(greater is better)

$y = b_0 + b_1 * x_1$

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

$SS_{res} \text{->} \text{Min}$

Problem:

Adjusted R^2

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

R^2 – Goodness of fit
(greater is better)

$y = b_0 + b_1{*}x_1$

$y = b_0 + b_1{*}x_1 + b_2{*}x_2 \leftarrow \boxed{+\ b_3{*}x_3}$

Problem:

SS_{res} -> Min

Adjusted R^2

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

R^2 – Goodness of fit
(greater is better)

$y = b_0 + b_1{*}x_1$

Problem:

$y = b_0 + b_1{*}x_1 + b_2{*}x_2$ ← $\boxed{+ b_3{*}x_3}$

SS_{res} -> Min → R^2 will never decrease

Adjusted R^2

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

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

Adjusted R^2

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

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

p - number of regressors

n - sample size