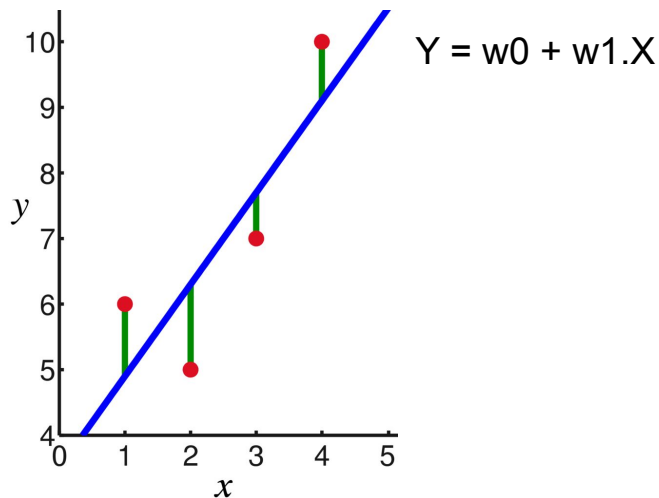


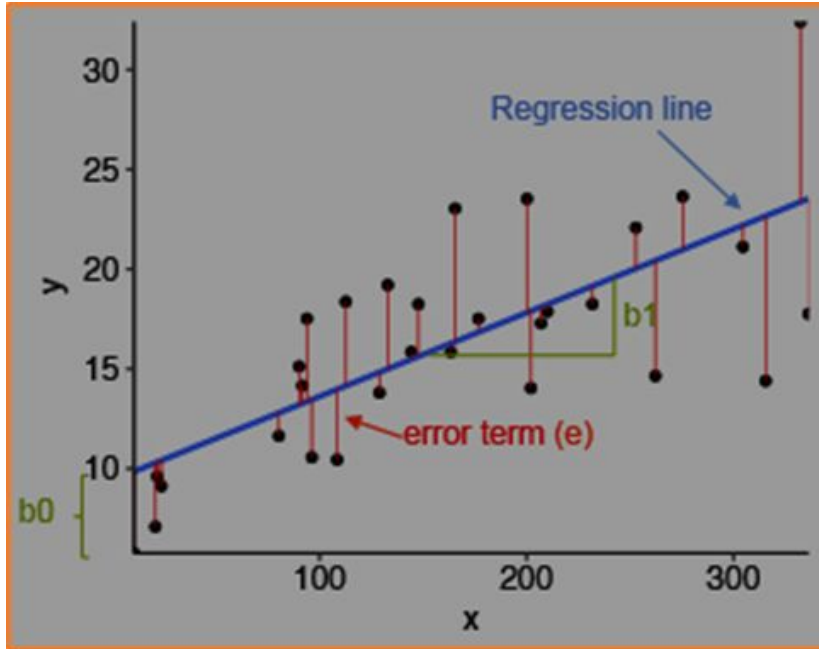
Linear Regression Model

Linear Regression

- LinearRegression fits a linear model with coefficients $w = (w_1, \dots, w_p)$ to minimize the residual sum of squares between the observed targets in the dataset, and the targets predicted by the linear approximation.



Linear Regression



Estimated (or predicted) y value

Estimate of the regression intercept

Estimate of the regression slope

Independent variable

Error term

$$y_i = b_0 + b_1 x + e$$

Linear Regression

$$\boxed{\hat{y}} = \boxed{\beta_0 + \beta_1} \boxed{X} + \boxed{\epsilon}$$

target coefficients input random error

The diagram illustrates the linear regression equation $\hat{y} = \beta_0 + \beta_1 X + \epsilon$. Each term is enclosed in a colored box: \hat{y} is in a pink box, $\beta_0 + \beta_1$ is in a grey box, X is in a blue box, and ϵ is in a green box. Arrows point from these boxes to labels below: a pink arrow from \hat{y} to 'target', a grey arrow from $\beta_0 + \beta_1$ to 'coefficients', a blue arrow from X to 'input', and a green arrow from ϵ to 'random error'.

$$y = \alpha + \beta x,$$

$$y_i = \alpha + \beta x_i + \varepsilon_i.$$

$$\hat{\varepsilon}_i = y_i - \alpha - \beta x_i.$$

In other words, $\hat{\alpha}$ and $\hat{\beta}$ solve the following minimization problem:

$$\text{Find } \min_{\alpha, \beta} Q(\alpha, \beta), \quad \text{for } Q(\alpha, \beta) = \sum_{i=1}^n \hat{\varepsilon}_i^2 = \sum_{i=1}^n (y_i - \alpha - \beta x_i)^2.$$

By expanding to get a quadratic expression in α and β , we can derive values of α and β that minimize the objective function Q (these minimizing values are denoted $\hat{\alpha}$ and $\hat{\beta}$).[‡]

$$\hat{\alpha} = \bar{y} - (\hat{\beta} \bar{x}),$$

$$\hat{\beta} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

Coeficiente de Determinação

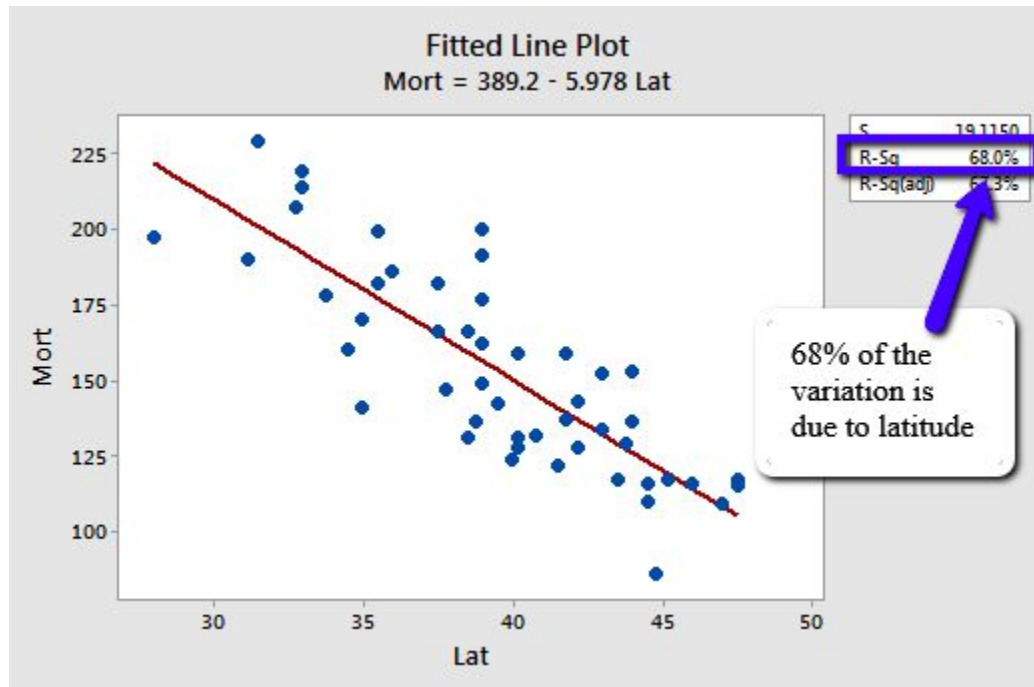
In regression, the R^2 coefficient of determination is a statistical measure of how well the regression predictions approximate the real data points. An R^2 of 1 indicates that the regression predictions perfectly fit the data.

$$R^2 = 1 - \frac{RSS}{TSS}$$

$$RSS = \sum_{i=1}^n (y_i - f(x_i))^2$$

$$TSS = \sum_{i=1}^n (y_i - \bar{y})^2$$

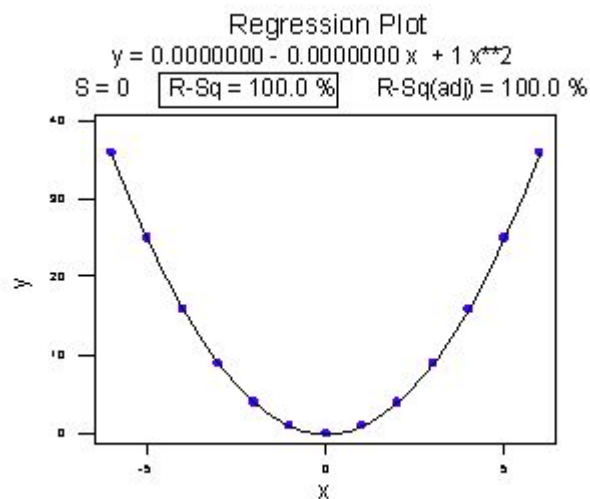
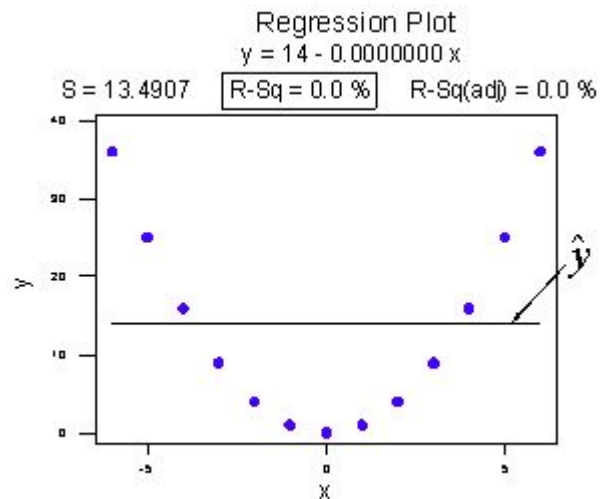
R-squared



Caution #1

The coefficient of determination r^2 and the correlation coefficient r quantify the strength of a *linear* relationship. It is possible that $r^2 = 0\%$ and $r = 0$, suggesting there is no linear relation between x and y , and yet a perfect curved (or "curvilinear" relationship) exists.

Caution #1



Caution #2

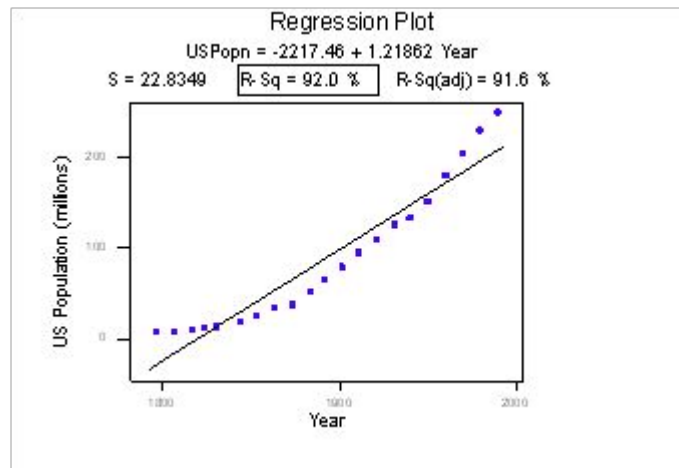
A large r^2 value should not be interpreted as meaning that the estimated regression line fits the data well. Another function might better describe the trend in the data.

$r^2 \times 100$ percent of the variation in y is reduced by taking into account predictor x "

or:

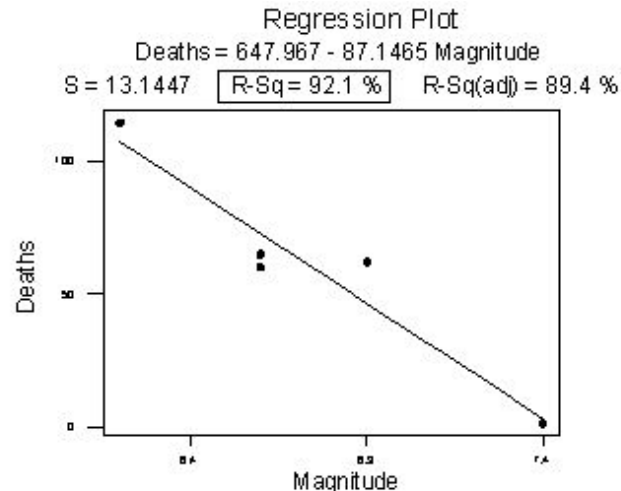
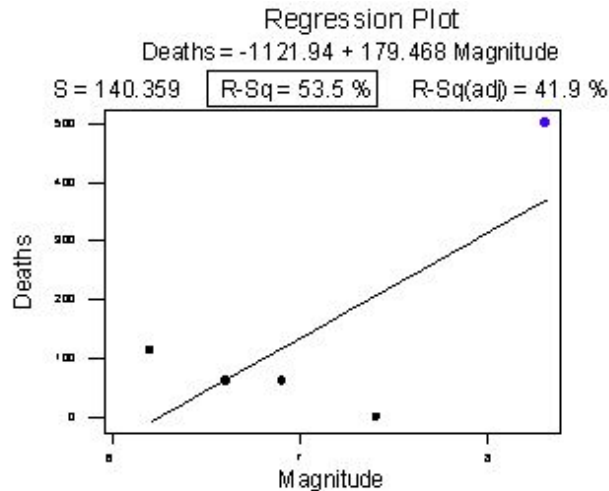
$r^2 \times 100$ percent of the variation in y is 'explained by' the variation in predictor x ."

Caution #2



Caution #3

The coefficient of determination r^2 and the correlation coefficient r can both be greatly affected by just one data point (or a few data points).



Caution #4

Correlation (or association) does not imply causation.

