

(Linear Regression with Least Squares)

The technique of regression, in particular linear regression, is one of the most popular statistical tool. A major purpose of regression is to explore the dependence of one variable on others. There are all forms of regression: linear, nonlinear, simple, multiple, parametric, nonparametric, etc. The word *regression* is used in statistics to signify a relationship of a target variable (say, y_i) between other variables (say, $x_{i,p}$). More generally, we have a relationship of the form

$$y_{n \times 1} = \mathbf{f}(X_{p \times n}) + \epsilon_{n \times 1},$$

where n is the realization of the observable random variables, and the \mathbf{f} is an arbitrary function; $\epsilon_{1 \times n}$ is the random vector describes the deviations or errors. It is also common to suppose it has zeros mean $\mathbb{E}(\epsilon) = 0$; that is

$$\mathbb{E}(y|X) = \mathbf{f}(X).$$

When we refer to *regression that is linear* (more precisely, affine), we mean that the conditional expectation of Y given X is a linear function of X (*i.e.* the term linear regression refers to a specification that is *linear in the parameters*). Hence we have the linear model

$$y_{n \times 1} = X_{n \times p+1} \beta_{p+1 \times 1} + \epsilon_{n \times 1} = \begin{pmatrix} 1 & x_{11} & x_{12} & \dots & x_{1,p} \\ 1 & x_{21} & x_{22} & \dots & x_{2,p} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} & \dots & x_{n,p} \end{pmatrix} \beta_{p+1 \times 1} + \epsilon_{n \times 1},$$

where the all-ones column represents the intercept. Now we shall derive the estimator for β , as well as accurately describe what a "good" estimator is. A very common way is to use the least squares criterion; that is

$$\hat{\beta} = \arg \min_{\beta} (Y - X\beta)^T (Y - X\beta) = \arg \min_{\beta} (\epsilon^T \epsilon).$$

We can differentiate $\epsilon^T \epsilon$ to get

$$\hat{\beta} = (X^T X)^{-1} X^T y,$$

such that

$$\hat{y} = X \hat{\beta},$$

where it can be shown that $X^T X$ is nonsingular if and only if the rank of X equals $p + 1$. Otherwise, we can take the pseudo-inverse of $X^T X$.

Now we define the minimum deviations as the *residual sum of squares (RSS)* or the *unexplained variation* by

$$\text{RSS} = \sum_{i=1}^n (y_i - \hat{y}_i)^2.$$

In addition, we define *total variation* as $\sum_{i=1}^n (y_i - \bar{y})^2$; explained variation as $\sum_{i=1}^n (\hat{y}_i - \bar{y})^2$. Hence,

$$\begin{aligned} \sum_{i=1}^n (y_i - \bar{y})^2 &= \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 + \sum_{i=1}^n (y_i - \hat{y}_i)^2 \\ \text{total variation} &= \text{explained variation} + \text{unexplained variation}. \end{aligned}$$

The *coefficient of determination* is r^2 :

$$r^2 = \frac{\text{explained variation}}{\text{total variation}}.$$

The coefficient of determination increases with the proportion of explained variation by the linear relation above. In the extreme cases where $r^2 = 1$, all of the variation is explained by the linear regression. The other extreme, $r^2 = 0$, is where the empirical covariance of X and y is zero. However, the coefficient of determination is influenced by the number of regressors p . For a given sample size n , the r^2 value will increase by adding more regressors into the linear model. The value of r^2 may therefore be high even if possibly irrelevant regressors are included. A corrected coefficient of determination for p regressors and a constant intercept ($p+1$ parameters) is

$$r_{\text{adj}}^2 = r^2 - \frac{p(1 - r^2)}{n - (p + 1)}.$$

Now we consider a data set consisting of 10 measurements of 4 variables. The story: A textile shop manager is studying the sales of “classic blue” pullovers over 10 periods. He uses three different marketing methods and hopes to understand his sales as a fit of these variables using statistics. The variables measured are

- X_1 : Numbers of sold pullovers,
- X_2 : Price (in EUR),
- X_3 : Advertisement costs in local newspapers (in EUR),
- X_4 : Presence of a sales assistant (in hours per period).

	Sales	Price	Advert.	Ass. Hours
1	230	125	200	109
2	181	99	55	107
3	165	97	105	98
4	150	115	85	71
5	97	120	0	82
6	192	100	150	103
7	181	80	85	111
8	189	90	120	93
9	172	95	110	86
10	170	125	130	78

Now please answer the following questions

- (a) Find the least square estimate $\hat{\beta}$.
- (b) Find the coefficient of determination.
- (c) Find the corrected coefficient of determination.