

Least squares curve fitting is a data analysis tool to extract trends in data sets. Given a data set (x_i, y_i) , $i = 1, \dots, n$, the goal is to find the coefficients of a simple function $f(x)$ (often a polynomial) that follows a trend in the data. The *least squares* method minimizes the sum of the squares of the difference between the given y_i data and the fit function $f(x_i)$. Figure 1 shows two curve fits (dashed red curves) to data represented by blue dots.

Fitting a Line to Data

- To fit a line to data, the fit function is

$$f(x) = mx + b \quad (1)$$

where m is the slope and b .

- The goal of curve fitting is to find m and b so that Equation (1) does the best job of matching the given (x_i, y_i) data.
- Given a data set (x_i, y_i) , $i = 1, \dots, n$, the least squares method gives

$$m = \frac{n \sum x_i y_i - \sum x_i \sum y_i}{n \sum x_i^2 - (\sum x_i)^2} \quad (2)$$

$$b = \frac{\sum y_i - m \sum x_i}{n} \quad (3)$$

where all summations are for $i = 1, \dots, n$.

- The R^2 metric indicates how well the fit function matches the data. The value of R^2 is of the quality of the fit

$$R^2 = \frac{\sum (\hat{y}_i - \bar{y})^2}{\sum (y_i - \bar{y})^2} = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (4)$$

where $\hat{y}_i = f(x_i)$ is the fit function evaluated at the given data, and \bar{y} is the average of the y_i values. For any data set, $0 \leq R^2 \leq 1$.

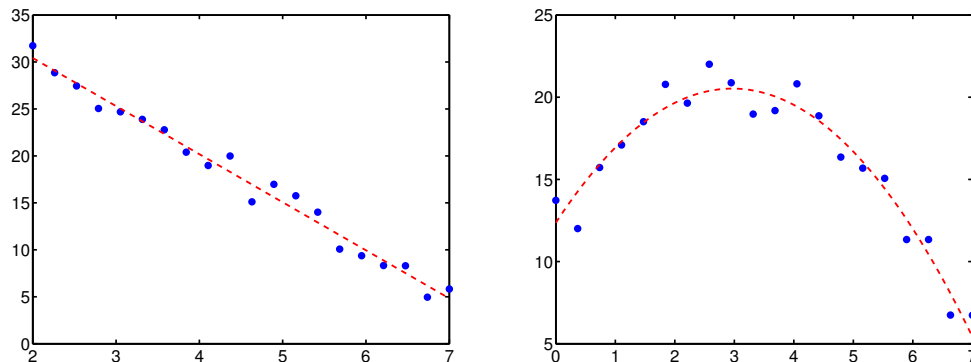


Figure 1: Linear (left) and quadratic (right) curve fits to data.

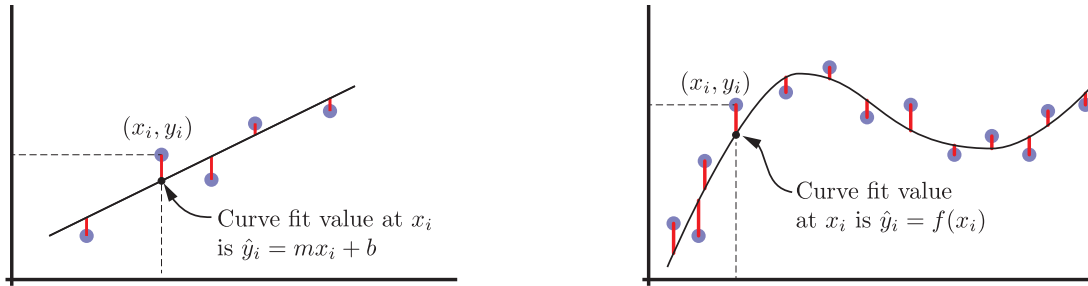


Figure 2: Geometry of a least squares fit: linear fit (left) and arbitrary $f(x)$ (right).

Geometry of a Least Squares Fit

The left side of Figure 2 shows the relationship between the original (x_i, y_i) data and a least squares line fit. For a given data set, the values of m and b in the fit function, $f(x) = mx + b$, are computed with Equation (2) and Equation (3).

The fit function can be evaluated at any x , which is just one advantage of obtaining the fit. We use $\hat{y}_i = f(x_i)$ to designate the value of the fit function at the discrete x_i values.

The right side of Figure 2 shows a least squares fit to an arbitrary $f(x)$, which could be a polynomial or some other function. As with the line fit, the fit function $f(x)$ can be evaluated at any x . The \hat{y}_i values are the fit function evaluated at the x_i from the given data set.

For both images in Figure 2, the vertical red bars are the vertical (y -direction) difference between the data and the fit function. The mathematical computations of the least squares method obtains the $f(x)$ that minimizes $(\hat{y}_i - y_i)^2$, i.e., the sum of the lengths of the red lines in Figure 2.

Fitting a Polynomial to Data

In some situations, a line does not adequately follow the trend in the data. The plot in the right hand side of Figure! 1 shows an example of a data set (blue dots) that cannot be fit by a line.

- To fit a polynomial to data, the fit function is

$$f(x) = c_{N+1}x^N + c_Nx^{N-1} + \dots + c_2x + c_1 \quad (5)$$

where c_j , $j = 1, \dots, N + 1$ are the coefficients of the degree N polynomial.

Examples:

$$f(x) = c_2x + c_1 \quad \text{linear fit} \quad (6)$$

$$f(x) = c_3x^2 + c_2x + c_1 \quad \text{quadratic fit} \quad (7)$$

$$f(x) = c_4x^3 + c_3x^2 + c_2x + c_1 \quad \text{cubic fit} \quad (8)$$

- The goal of curve fitting is to find values of the coefficients c_j , $j = 1, \dots, N + 1$ so that Equation (5) does the best job of matching the given (x_i, y_i) data.
- Given a data set (x_i, y_i) , $i = 1, \dots, n$, formulas for finding the c_j in Equation (5) are cumbersome for $N > 1$. Instead of writing explicit formulas, we use an *algorithm*, to compute the

c_j . The algorithm can be elegantly expressed in terms of linear algebra, but the details are beyond the scope of this brief document.

- The R^2 metric for a polynomial curve fit is computed with Equation (4). In other words, Equation (4) is the general expression for R^2 .

General Recommendations

- It is easy to make least squares curve fits with software like Excel, MATLAB, R and python. Avoid the temptation to use higher and higher degree polynomials just to increase the value of R^2 . In other words

Use the lowest degree polynomial that does an adequate job of fitting the data.

- R^2 is an indicator of how well the fit function matches the data, but there are cases where high values of R^2 can be misleading

Always plot the fit function with the original data to inspect the quality of the fit.

- To systematically compare curve fitting options, e.g., comparing fits with different degree polynomials, compute and plot the residuals of each fit. The residual is

$$r_i = f(x_i) - y_i \quad (9)$$

which is the difference (measured along the y axis) between the fit function and the given data¹. If the residual shows a pattern or trend, then a different fit function is warranted. When the plot of the residual looks random, further refinement of the fit, e.g., to high degree polynomial is not advantageous, even though a higher degree polynomial will further reduce R^2 .

¹The vertical red bars in Figure 2 have a length equal to $|r_i|$.