

Suppose we have a data set $\{(x_i, y_i)\}_{i=1}^N$, where $x_i, y_i \in \mathbb{R}$.
We derive the formula for the best linear fit $y = Ax + B$ for this dataset.

We assume that there is noise in our y -values, such that the $\{y_i\}_{i=1}^N$ are normally distributed around the "true" values, $A + Bx_i$, and that the normal distribution has the same variance σ^2 for each datapoint i :

$$y_i \sim \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_i - A - Bx_i)^2}{2\sigma^2}}$$

We now wish to choose A and B to maximize the probability that we observe $\{y_i\}_{i=1}^N$ given $\{x_i\}_{i=1}^N$.

The probability of observing $\{y_i\}_{i=1}^N$ given $\{x_i\}_{i=1}^N$, A , and B is given by

$$P(y_1, \dots, y_N | x_1, \dots, x_N, A, B) =$$

$$P(y_1 | x_1, A, B) \cdots P(y_N | x_N, A, B) =$$

$$\frac{1}{(2\pi\sigma^2)^{N/2}} e^{-\frac{1}{2\sigma^2} \sum_i (y_i - A - Bx_i)^2}$$

We now maximize this quantity with respect to A, B .

$$\frac{\partial \rho}{\partial A} = \frac{1}{(2\pi\sigma^2)^{N/2}} e^{-\frac{1}{2\sigma^2} \sum_i (y_i - A - Bx_i)^2} \cdot \left(-\frac{1}{\sigma^2}\right).$$

$$\sum_i 2(y_i - A - Bx_i) \cdot (-1) = 0 \iff$$

$$NA + B \sum_i x_i = \sum_i y_i.$$

$$\frac{\partial \rho}{\partial B} = \frac{1}{(2\pi\sigma^2)^{N/2}} e^{-\frac{1}{2\sigma^2} \sum_i (y_i - A - Bx_i)^2} \cdot \left(-\frac{1}{\sigma^2}\right).$$

$$\sum_i 2(y_i - A - Bx_i)(-x_i) = 0 \iff$$

$$\sum_i Ax_i + Bx_i^2 = \sum_i x_i y_i.$$

These equations can now be rewritten

$$\begin{pmatrix} N & \sum_i x_i \\ \sum_i x_i & \sum_i x_i^2 \end{pmatrix} \begin{pmatrix} A \\ B \end{pmatrix} = \begin{pmatrix} \sum_i y_i \\ \sum_i x_i y_i \end{pmatrix} \iff$$

$$A = \frac{1}{N \sum_i x_i^2 - (\sum_i x_i)^2} \begin{pmatrix} \sum_i x_i^2 & -\sum_i x_i \\ -\sum_i x_i & N \end{pmatrix} \begin{pmatrix} \sum_i y_i \\ \sum_i x_i y_i \end{pmatrix}_1$$

$$\rightarrow A = \frac{1}{N \sum_i x_i^2 - (\sum_i x_i)^2} \left[\sum_i x_i^2 \sum_j y_j - \sum_i x_i \sum_j x_j y_j \right]$$

$$B = \frac{1}{N \sum_i x_i^2 - (\sum_i x_i)^2} \begin{pmatrix} \sum_i x_i^2 & -\sum_i x_i \\ -\sum_i x_i & N \end{pmatrix} \begin{pmatrix} \sum_i y_i \\ \sum_i x_i y_i \end{pmatrix}_2$$

$$\rightarrow B = \frac{1}{N \sum_i x_i^2 - (\sum_i x_i)^2} \left[-\sum_i x_i \sum_j y_j + N \sum_i x_i y_i \right]$$

(Source: Taylor, Error Analysis, p. 182-184)