

# Data Analysis-II

Least square fit and extrapolation

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# Table of Contents

- 1 Least Square Fit
  - Maximum likelihood
  
- 2 Least-square Fit to a Straight Line

# General Description

- Based on some theoretical grounds or assumption
  - if we know that a quantity  $y$  is a function of  $x$  with  $m$  parameters  $a_1, a_2, \dots, a_m$ .
  - $\Rightarrow y = f(a_1, a_2, \dots, a_m; x)$ .
- $\Rightarrow$  find the values of parameters that give the best description to a set of measured values of  $y$  (data obtained from experiments or simulations).

# Maximum likelihood

- Maximum likelihood  $\Rightarrow$  canonical ensembles in statistical physics.
- Let  $y_i$  be the measured value of  $y$  at  $x = x_i$  in the set of data  $\{(x_i, y_i)\}$ .
- Due to the uncertainties or experimental or systematic errors and so on:
  - $y_i$  is likely to be different from what we expected if we repeat the measurement
  - By the central limit theorem

$$p(y_i)dy_i = \frac{1}{\sigma_i\sqrt{2\pi}}e^{-(y_i-f_i)^2/2\sigma_i^2}dy_i \quad (1)$$

where

$$f_i = f(a_1, a_2, \dots, a_m; x_i)$$

and  $\sigma_i^2$  is the variance.

# Maximum likelihood

## Def.: Likelihood Function

The likelihood function for  $\{y_i\}$  is defined as

$$\begin{aligned}\mathcal{L}(a_1, a_2, \dots, a_m) &= \prod_{i=1}^N p(y_i) \\ &= \prod_{i=1}^N \frac{1}{\sigma_i \sqrt{2\pi}} e^{(y_i - f_i)^2 / 2\sigma_i^2} \\ &= \left\{ \prod_{i=1}^N \frac{1}{\sigma_i \sqrt{2\pi}} \right\} \exp \left[ -\frac{1}{2} \sum_{i=1}^N \left( \frac{y_i - f_i}{\sigma_i} \right)^2 \right] \quad (2)\end{aligned}$$

# Maximum likelihood

Def.:  $\chi^2$

$$\chi^2 \equiv \sum_{i=1}^N \left( \frac{y_i - f_i}{\sigma_i} \right)^2 \quad (3)$$

Minimize  $\chi^2$  in the parameter space

$$\frac{\partial \chi^2}{\partial a_k} = -2 \sum_{i=1}^N \left( \frac{y_i - f_i}{\sigma_i^2} \right) \frac{\partial f_i}{\partial a_k} = 0 \quad (4)$$

where  $k = 1, 2, \dots, m$ .

# Least-square Fit to a Straight Line

Let

$$a_1 = a, \quad a_2 = b$$

Then

$$f(a, b; x) = a + bx$$

and

$$\frac{\partial f}{\partial a} = 1, \quad \text{and} \quad \frac{\partial f}{\partial b} = x$$

From Eq. (4)

$$\sum_{i=1}^N \left( \frac{y_i - f_i}{\sigma_i^2} \right) = 0, \quad \text{and} \quad \sum_{i=1}^N \left( \frac{y_i - f_i}{\sigma_i^2} \right) x_i = 0$$

# Least-square Fit to a Straight Line

Or using  $f_i = a + bx_i$

$$a \sum_{i=1}^N \frac{1}{\sigma_i^2} + b \sum_{i=1}^N \frac{x_i}{\sigma_i^2} = \sum_{i=1}^N \frac{y_i}{\sigma_i^2}$$

$$a \sum_{i=1}^N \frac{1}{\sigma_i^2} + b \sum_{i=1}^N \frac{x_i^2}{\sigma_i^2} = \sum_{i=1}^N \frac{x_i y_i}{\sigma_i^2}$$



# Least-square Fit to a Straight Line

In the matrix form

$$\begin{pmatrix} \alpha & \beta \\ \gamma & \delta \end{pmatrix} \begin{pmatrix} a \\ b \end{pmatrix} = \begin{pmatrix} \theta \\ \phi \end{pmatrix}$$

where

$$\alpha = \sum_{i=1}^N \frac{1}{\sigma_i^2}, \quad \beta = \sum_{i=1}^N \frac{x_i}{\sigma_i^2}, \quad \gamma = \beta$$

$$\delta = \sum_{i=1}^N \frac{x_i^2}{\sigma_i^2}, \quad \theta = \sum_{i=1}^N \frac{y_i}{\sigma_i^2}, \quad \phi = \sum_{i=1}^N \frac{x_i y_i}{\sigma_i^2}$$

# Least-square Fit to a Straight Line

What we have to calculate are

$$a = \frac{1}{D} \begin{vmatrix} \theta & \beta \\ \phi & \delta \end{vmatrix} = \frac{1}{D}(\theta\delta - \beta\phi)$$

$$b = \frac{1}{D} \begin{vmatrix} \alpha & \theta \\ \gamma & \phi \end{vmatrix} = \frac{1}{D}(\alpha\phi - \gamma\theta)$$

where  $D$  is the value of the determinant

$$D = \begin{vmatrix} \alpha & \beta \\ \gamma & \delta \end{vmatrix} = \alpha\delta - \beta\gamma = \alpha\delta - \beta^2$$

# Least-square Fit to a Straight Line

## Errors: Uncertainties in the parameters

Error propagation:

$$\sigma_a^2 = \sum_{i=1}^N \left\{ \left( \frac{\partial a}{\partial y_i} \right)^2 \sigma_i^2 \right\} \quad \sigma_b^2 = \sum_{i=1}^N \left\{ \left( \frac{\partial b}{\partial y_i} \right)^2 \sigma_i^2 \right\} \quad (5)$$

From the calculation of  $a$ ,  $b$ , and  $D$

$$\frac{\partial a}{\partial y_i} = \frac{1}{D} \left( \frac{1}{\sigma_i^2} \delta - \frac{x_i}{\sigma_i^2} \beta \right), \quad \frac{\partial b}{\partial y_i} = \frac{1}{D} \left( \frac{x_i}{\sigma_i^2} \alpha - \frac{1}{\sigma_i^2} \gamma \right) \quad (6)$$

# Least-square Fit to a Straight Line

Errors: Uncertainties in the parameters

Inserting Eq. (6) into Eq. (5)

$$\begin{aligned}\sigma_a^2 &= \frac{1}{D^2} \sum_{i=1}^N \left\{ \sigma_i^2 \left( \frac{1}{\sigma_i^2} \delta - \frac{x_i}{\sigma_i^2} \beta \right)^2 \right\} \\ &= \frac{\delta}{D}\end{aligned}\tag{7}$$

$$\begin{aligned}\sigma_b^2 &= \frac{1}{D^2} \sum_{i=1}^N \left\{ \sigma_i^2 \left( \frac{x_i}{\sigma_i^2} \alpha - \frac{1}{\sigma_i^2} \gamma \right)^2 \right\} \\ &= \frac{\alpha}{D}\end{aligned}\tag{8}$$