

RETTE MINIMI QUADRATI

(1)

$$\min \left[\sum_{i=1}^N (y_i - (A + Bx_i))^2 \right]$$

$$\sigma_x^2 \ll \sigma_y^2$$



La funzione $(A + Bx_i)$ deve essere tale da minimizzare la somma dei quadrati delle distanze tra i dati MISURATI e quelli della forma funzionale $(A + Bx_i)$

Minimizzare tale funzione vuol dire DERIVARE rispetto ad A e B e porre $= \phi$

$$\frac{\partial}{\partial A} \left[\sum_{i=1}^N (y_i - (A + Bx_i))^2 \right] = 2(-1) \left[\sum_{i=1}^N y_i - NA - B \sum_{i=1}^N x_i \right]$$

$$NA + B \sum_{i=1}^N x_i - \sum_{i=1}^N y_i = \phi$$

PRIMA EQ. NORMALE

$$\frac{\partial}{\partial B} \left[\sum_{i=1}^N (y_i - (A + Bx_i))^2 \right] = 2 \left[\sum_{i=1}^N (y_i x_i - Ax_i - Bx_i^2) \right]$$

$$2 \sum_{i=1}^N x_i y_i - 2A \sum_{i=1}^N x_i - 2B \sum_{i=1}^N x_i^2 = \phi$$

$$\sum_{i=1}^N x_i A + \sum_{i=1}^N x_i^2 B = \sum_{i=1}^N x_i y_i$$

SECONDA EQ. NORMALE

$$\begin{cases} NA + \sum_{i=1}^N x_i B = \sum_{i=1}^N y_i \\ \sum_{i=1}^N x_i A + \sum_{i=1}^N x_i^2 B = \sum_{i=1}^N x_i y_i \end{cases}$$

Soluzioni
mediante
metodo di Cramer

$$A = \frac{\begin{vmatrix} \sum y_i & \sum x_i \\ \sum x_i y_i & \sum x_i^2 \end{vmatrix}}{\Delta} = \frac{\sum y_i \sum x_i^2 - \sum x_i \sum x_i y_i}{\Delta}$$

dove $\Delta = N \sum_{i=1}^N x_i^2 - \left(\sum_{i=1}^N x_i\right)^2$

$$B = \frac{\begin{vmatrix} N & \sum y_i \\ \sum x_i & \sum x_i y_i \end{vmatrix}}{\Delta} = \frac{N \sum x_i y_i - \sum x_i \sum y_i}{\Delta}$$

Trovati A e B possiamo valutare le incertizze su questi due valori σ_A e σ_B propagando l'incertizza σ_y su A e B. Per fare ciò utilizzeremo la relazione:

$$\sigma_A^2 = \sum_{j=1}^N \left(\frac{\partial A}{\partial y_j}\right)^2 \sigma_y^2 \quad e \quad \sigma_B^2 = \sum_{j=1}^N \left(\frac{\partial B}{\partial y_j}\right)^2 \sigma_y^2$$

prima però valutiamo le grandezze

$$\frac{\partial A}{\partial y_j} \quad e \quad \frac{\partial B}{\partial y_j}$$

$$\frac{\partial A}{\partial y_j} = \frac{\sum_{i=1}^N x_i^2 - x_j \sum_{i=1}^N x_i}{\Delta}$$

$$\frac{\partial B}{\partial y_j} = \frac{N x_j - \sum_{i=1}^N x_i}{\Delta}$$

Calcoliamo

$$\begin{aligned} \sigma_A^2 &= \sum_{j=1}^N \left(\frac{\sum_{i=1}^N x_i^2 - x_j \sum_{i=1}^N x_i}{\Delta} \right)^2 \sigma_y^2 \\ &= \frac{\sigma_y^2}{\Delta^2} \sum_{j=1}^N \left(\left(\sum_{i=1}^N x_i^2 \right)^2 - 2 x_j \sum_{i=1}^N x_i \sum_{i=1}^N x_i^2 + x_j^2 \left(\sum_{i=1}^N x_i \right)^2 \right) \\ &= \frac{\sigma_y^2}{\Delta^2} \left[N \left(\sum_{i=1}^N x_i^2 \right)^2 - 2 \sum_{j=1}^N x_j \sum_{i=1}^N x_i \sum_{i=1}^N x_i^2 + \sum_{j=1}^N x_j^2 \left(\sum_{i=1}^N x_i \right)^2 \right] \end{aligned}$$

$$= \frac{\sigma_y^2}{\Delta^2} \left[N \left(\sum_{i=1}^N x_i^2 \right)^2 - \sum_{i=1}^N x_i^2 \left(\sum_{i=1}^N x_i \right)^2 \right]$$

$$= \frac{\sigma_y^2}{\Delta^2} \left(\sum_{i=1}^N x_i^2 \right) \left[\underbrace{N \sum_{i=1}^N x_i^2 - \left(\sum_{i=1}^N x_i \right)^2}_{\text{raccolgiamo questo termine}} \right]$$

$$\Rightarrow \sigma_A^2 = \frac{\sigma_y^2}{\Delta^2} \sum_{i=1}^N x_i^2 \cdot \Delta = \frac{\sigma_y^2}{\Delta} \sum_{i=1}^N x_i^2$$

Calcoliamo σ_B^2

④

$$\begin{aligned}\sigma_B^2 &= \sum_{j=1}^N \left(\frac{Nx_j - \sum_{i=1}^N x_i}{\Delta} \right)^2 \sigma_y^2 \\ &= \frac{\sigma_y^2}{\Delta^2} \sum_{j=1}^N \left(Nx_j^2 - 2Nx_j \sum_{i=1}^N x_i + \left(\sum_{i=1}^N x_i \right)^2 \right) \\ &= \frac{\sigma_y^2}{\Delta^2} \left[N^2 \sum_{j=1}^N x_j^2 - 2N \sum_{j=1}^N x_j \sum_{i=1}^N x_i + N \left(\sum_{i=1}^N x_i \right)^2 \right] \\ &= \frac{\sigma_y^2}{\Delta^2} N \left[N \sum_{i=1}^N x_i^2 - \left(\sum_{i=1}^N x_i \right)^2 \right] \left(\sum_{i=1}^N x_i \right)^2\end{aligned}$$

$$\Rightarrow \sigma_B^2 = \frac{\sigma_y^2}{\Delta^2} \cdot N \cdot \Delta = \frac{N}{\Delta} \sigma_y^2$$

In conclusione la forma funzionale che approssima meglio il vostro set di punti sperimentali sarà:

$$y = (A \pm \sigma_A) + (B \pm \sigma_B) \cdot x$$