

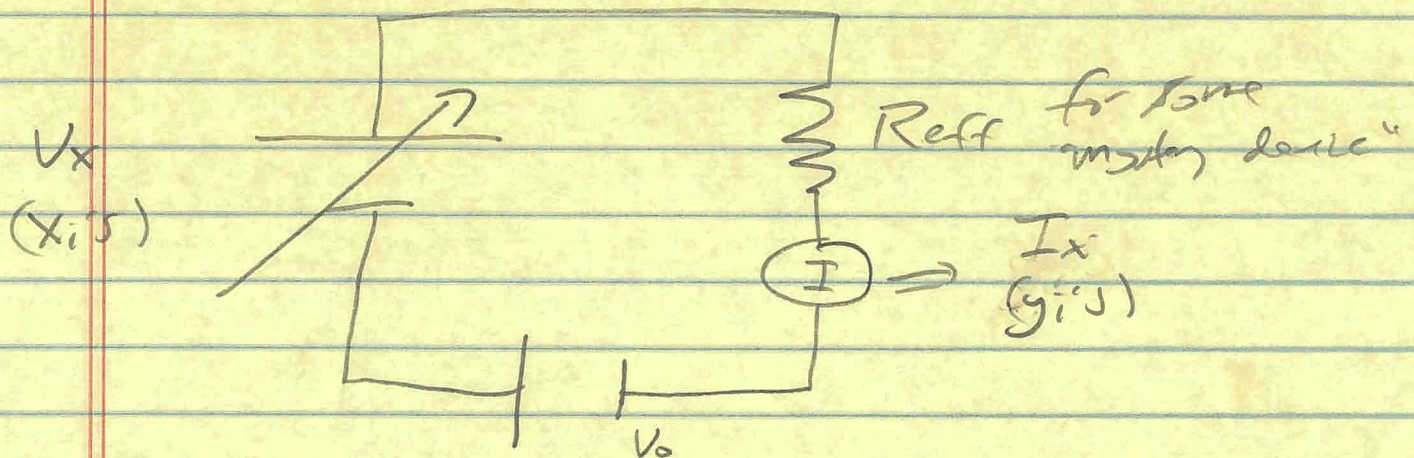
391
F16
LS.1

1) LS fitting

2) a bit of Astrophysics (w/ caveats)

1) have N responses from experiment with y_i responses from x_i (manipulated) inputs. (Cheng's x)

for example.



our goal is to determine R_{eff}

assume Ohm's Law applies $V = IR_{eff} = V_x + V_0$

$$\text{solve for } I = \frac{V_0}{R_{eff}} + \frac{V_x}{R_{eff}}$$

of form $y_i = A + Bx_i$ ($A = \frac{V_0}{R_{eff}}$ $B = \frac{1}{R_{eff}}$)

3π
≠ 16
15.2

writing $y_i = A + Bx_i$ could imply a pair A, B for each pair (x_i, y_i)

or in $y_i = A_i + B_i x_i$

note, this would \Rightarrow
a bunch of A, B
pairs useful?

our goal, however, is to determine one pair A, B that provide a "best fit" for all (x_i, y_i) pairs.

"optimal"

to start, consider a set of \bar{Y}_i 's corresponding to x_i 's w/ $\bar{Y}_i \neq y_i$ b/c of stochastic

we also assume that each observed y_i is normally distributed about its respective \bar{Y}_i

$$\text{So: } P_{\bar{Y}_i}(y_i) = \frac{1}{\sigma_y} e^{-\frac{[y_i - \bar{Y}_i]^2}{2\sigma_y^2}}$$

and, for one pair (x_i, y_i)

$$= \frac{1}{\sigma_y} e^{-\frac{[y_i - (A + Bx_i)]^2}{2\sigma_y^2}}$$

to recap, we have assumed there is a set of optimal \bar{Y}_i 's, generated from $\bar{Y}_i = A + Bx_i$, and that our observed y_i 's are normally distributed about these \bar{Y}_i 's

So think + share "question": "what is probability of observing our N y_i 's for our x_i 's?"

The Joint Probability is

$$JP \propto \frac{1}{(\sigma_y)^N} e^{-\frac{\chi^2}{2}}$$

with $\chi^2 = \sum_{i=1}^N \frac{[y_i - A - Bx_i]^2}{\sigma_y^2}$

↑
"chi-squared", sum of residuals

as per usual, want to maximize JP \Rightarrow min. χ^2

~~So $\frac{\partial}{\partial A} (JP) = 0$
 $\frac{\partial}{\partial B} (JP) = 0 \Rightarrow$ best A + B~~

(next)

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 Fl6
 LS (5)

As per usual, we want to maximize the JIP (find the true Ψ 's).
 This means minimizing χ^2 (negative exp)

for example, set

$$\left. \begin{array}{l} \frac{\partial \text{JIP}}{\partial A} = 0 \text{ and solve} \\ \text{also } \frac{\partial \text{JIP}}{\partial B} = 0 \end{array} \right\} 2 \text{ eqns}$$

this gives:

$$\begin{array}{l} A N + B \sum x_i = \sum y_i \\ A \sum x_i + B \sum x_i^2 = \sum x_i y_i \end{array}$$

2 eqns, 2 unknowns, but wait!
 This is a job for linear algebra

Write this as $\vec{M} \cdot \vec{F} = \vec{K}$
 matrix \vec{F} \vec{K} vectors

$$\vec{M} \rightarrow \begin{pmatrix} N & \sum x_i \\ \sum x_i & \sum x_i^2 \end{pmatrix} \cdot \begin{pmatrix} A \\ B \end{pmatrix} = \begin{pmatrix} \sum y_i \\ \sum x_i y_i \end{pmatrix}$$

vector of unknowns \vec{K}

solve by "dividing" both sides by \vec{M}

2) continued

$$\vec{F} = \text{inv}(\vec{M}) \cdot \vec{K}$$

(Matlab L3 F5.m poly01.m)

what if variances vary eg $\sigma_{y1}^2 \neq \sigma_{y2}^2$ etc.

$$w_i = \frac{1}{\sigma_i^2}$$

then weight individual y_i pieces of χ^2 by their own variances

$$\chi^2 = \sum_{i=1}^N \frac{(y_i - A - Bx_i)^2}{\sigma_i^2}$$

that defn

as with weighted sums, define $w_i = \frac{1}{\sigma_i^2}$

$$\Rightarrow \vec{M} = \begin{pmatrix} \sum w_i & \sum w_i x_i \\ \sum w_i x_i & \sum w_i x_i^2 \end{pmatrix}$$

$$\vec{K} = \begin{pmatrix} \sum w_i y_i \\ \sum w_i x_i y_i \end{pmatrix}$$

easy to fix in ML (python)

(poly01_wst.m)

hope ~~for~~ comments & help

2) cont'd

with them
=>

finally, what about higher order or other "fit" functions?

quad.
fit
fctn

define $Y_i = A + Bx_i + Cx_i^2$

$$JP \propto e^{-\frac{\chi^2}{2}}$$

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

($w_i = \frac{1}{\sigma_i^2}$ as before)

then minimize $\chi^2 \Rightarrow A, B, C$

set $\left. \begin{matrix} \frac{\partial \chi^2}{\partial A} = 0, \text{ solve} \\ \frac{\partial \chi^2}{\partial B} = 0, \text{ solve} \\ \frac{\partial \chi^2}{\partial C} = 0, \text{ solve} \end{matrix} \right\} \Rightarrow 3 \text{ eqns for 3 unknowns } (A, B, C)$

again, solve using linear eqns

show polyod wgt