

PHYS 232

March 25, 2024

- ✓ - Assignment #6 due April 5 @ 11am
- ✓ - Formal Report due Apr. 10 @ 11am
- ✓ - Bring Exp't #5 notebooks to class on Wednesday, April 3 @ 11:00am
- ✓ - If needed, sign up for make up labs today

Last Time: Nonlinear fits

$$\chi^2 = \sum_{i=1}^n \left(\frac{y_i - y(x_i)}{\sigma_i} \right)^2$$

Goal is to minimize χ^2 by adjusting the parameters in $y(x_i; a_1, a_2, \dots, a_m)$

Achieved by:

① Selecting a range of values for each a_k

$$a_{k,\min} < a_k < a_{k,\max}$$

② Select a step size Δa_k for each parameter

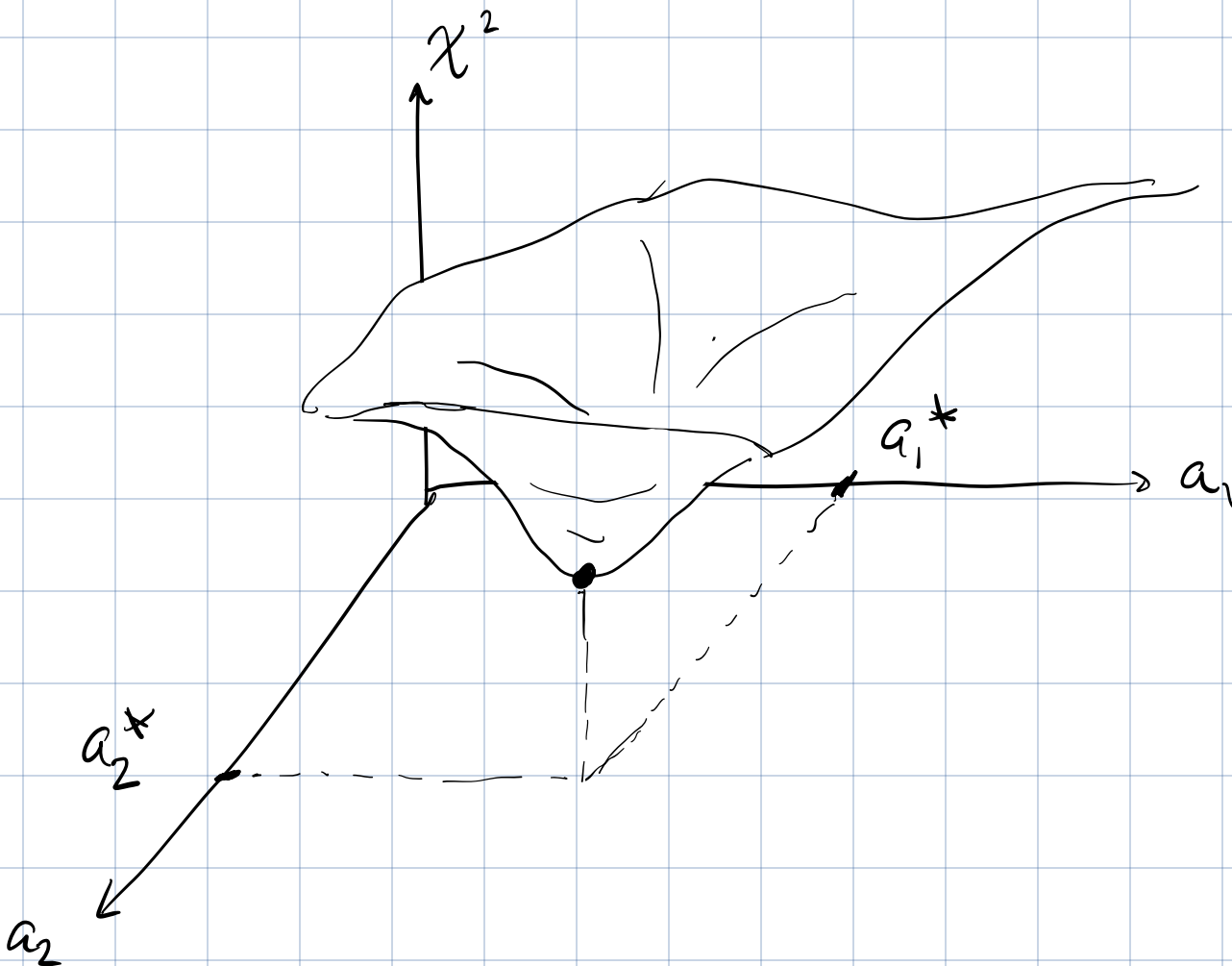
a_k values are then:

$$a_{k,\min}, a_{k,\min} + \Delta a_k, a_{k,\min} + 2\Delta a_k$$

$$\dots, a_{k,\max} - \Delta a_k, a_{k,\max}$$

③ Evaluate χ^2 at all combinations of a_k values

Eg. for a two-parameter fit.



The estimate of the best-fit parameters is given by the set of parameters (a_1^*, a_2^*) that gives the smallest value for χ^2 .

Today: Develop a method for estimating the uncertainty in the best-fit parameters.

Imagine that perform an experiment $\{ \text{meas} (x_i, y_i \pm \sigma_i) \}_{i=1..N}$.

Fit our data to a model $y = y(x; a_1, a_2, \dots, a_m)$ that depends on parameters $a_k \quad k=1..m$.

Find set of parameters that minimizes

$$\chi^2 = \sum_{i=1}^N \left(\frac{y_i - y(x_i)}{\sigma_i} \right)^2$$

Recall that χ^2 come from fact that prob. of obtaining a set of data $(x_i, y_i \pm \sigma_i)$ from

parameters a_1, a_2, \dots, a_m is given by:

$$P(a_1, a_2, \dots, a_m) = P_1 P_2 P_3 \dots P_N$$

$$= \prod_{i=1}^N P_i = \prod_{i=1}^N \left[\frac{\Delta y}{\sigma_i \sqrt{2\pi}} \exp \left\{ -\frac{1}{2} \left(\frac{y_i - y(x_i)}{\sigma_i} \right)^2 \right\} \right]$$

$$= \prod_{i=1}^N \left[\frac{\Delta y}{\sigma_i \sqrt{2\pi}} \right] \exp \left\{ -\frac{1}{2} \underbrace{\sum_{i=1}^N \left(\frac{y_i - y(x_i)}{\sigma_i} \right)^2}_{\equiv \chi^2} \right\}$$

$$P(a_1, a_2, \dots, a_m) = \prod_{i=1}^N \left[\frac{\Delta y}{\sigma_i \sqrt{2\pi}} \right] \exp \left\{ -\frac{1}{2} \chi^2 \right\}$$

(#)

Try to determine the shape of χ^2 near its minimum.

Minimization of χ^2 .

$$y = (a_1, a_2, \dots, a_m; x)$$

$$\chi^2 = \sum_{i=1}^N \left(\frac{y_i - y(x_i)}{\sigma_i} \right)^2$$

Taylor series expansion of χ^2 about its minimum w.r.t. one of the a parameters $\rightarrow a_j$.

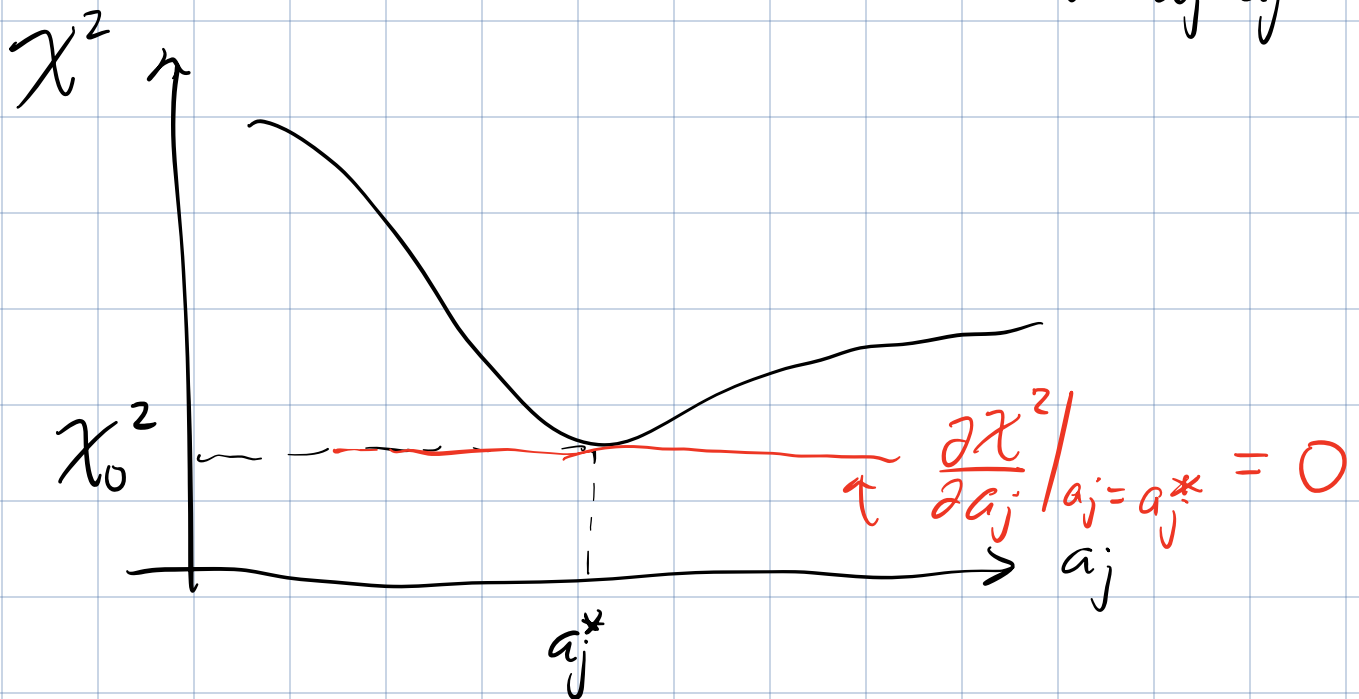
χ_0^2 (minimum of χ^2) $j = 1 \dots m$

$$\chi^2 \approx \chi^2 \Big|_{a_j = a_j^*} + (a_j - a_j^*) \frac{\partial \chi^2}{\partial a_j} \Big|_{a_j = a_j^*}$$

Value of a_j that minimize χ^2

$$+ \frac{1}{2} (a_j - a_j^*)^2 \frac{\partial^2 \chi^2}{\partial a_j^2} \Big|_{a_j = a_j^*} + \dots$$

At the minimum of χ^2 , require $\frac{\partial \chi^2}{\partial a_j} \Big|_{a_j=a_j^*} = 0$



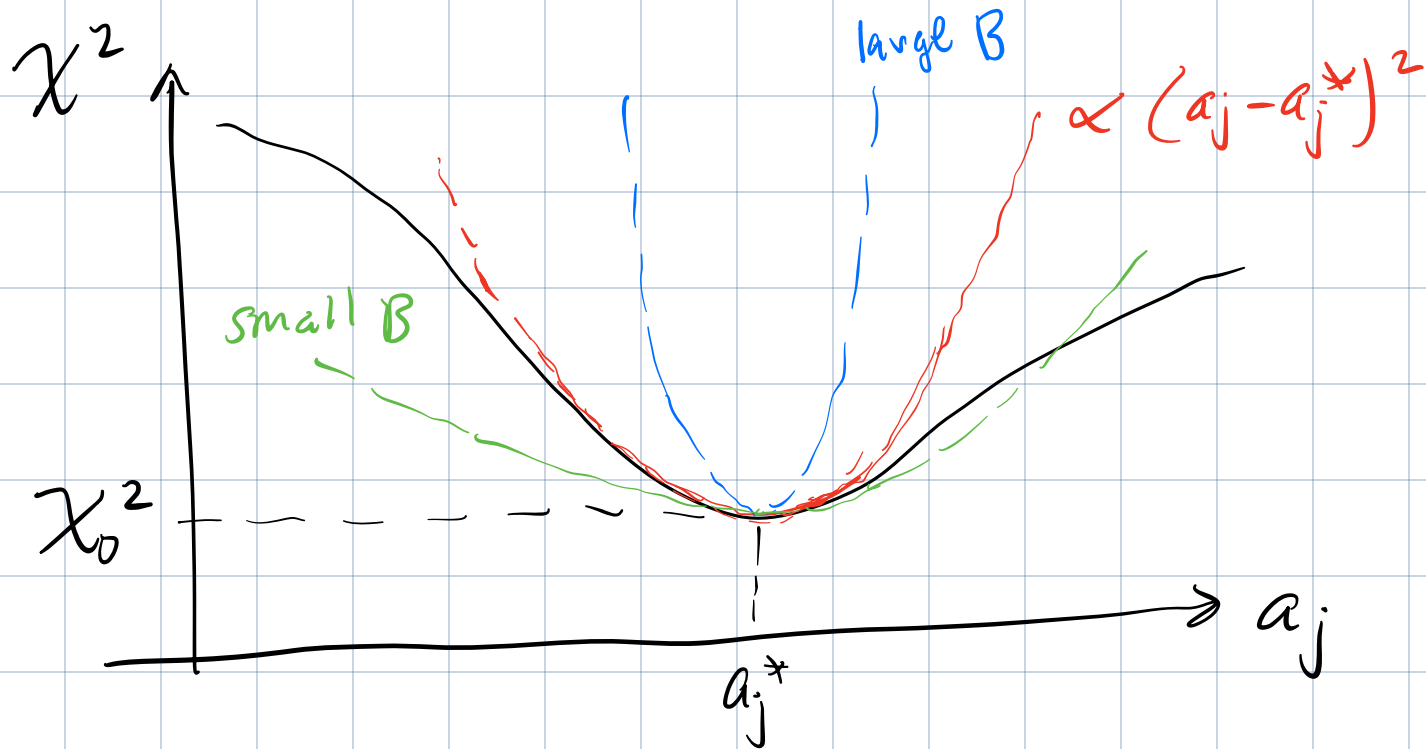
$$\therefore \chi^2 \approx \chi_0^2 + \underbrace{\left(\frac{1}{2} \frac{\partial^2 \chi^2}{\partial a_j^2} \Big|_{a_j=a_j^*} \right)}_{= B} (a_j - a_j^*)^2$$

$$\chi^2 \approx \chi_0^2 + B (a_j - a_j^*)^2$$

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unknowns.

χ^2 looks quadratic near its minimum.

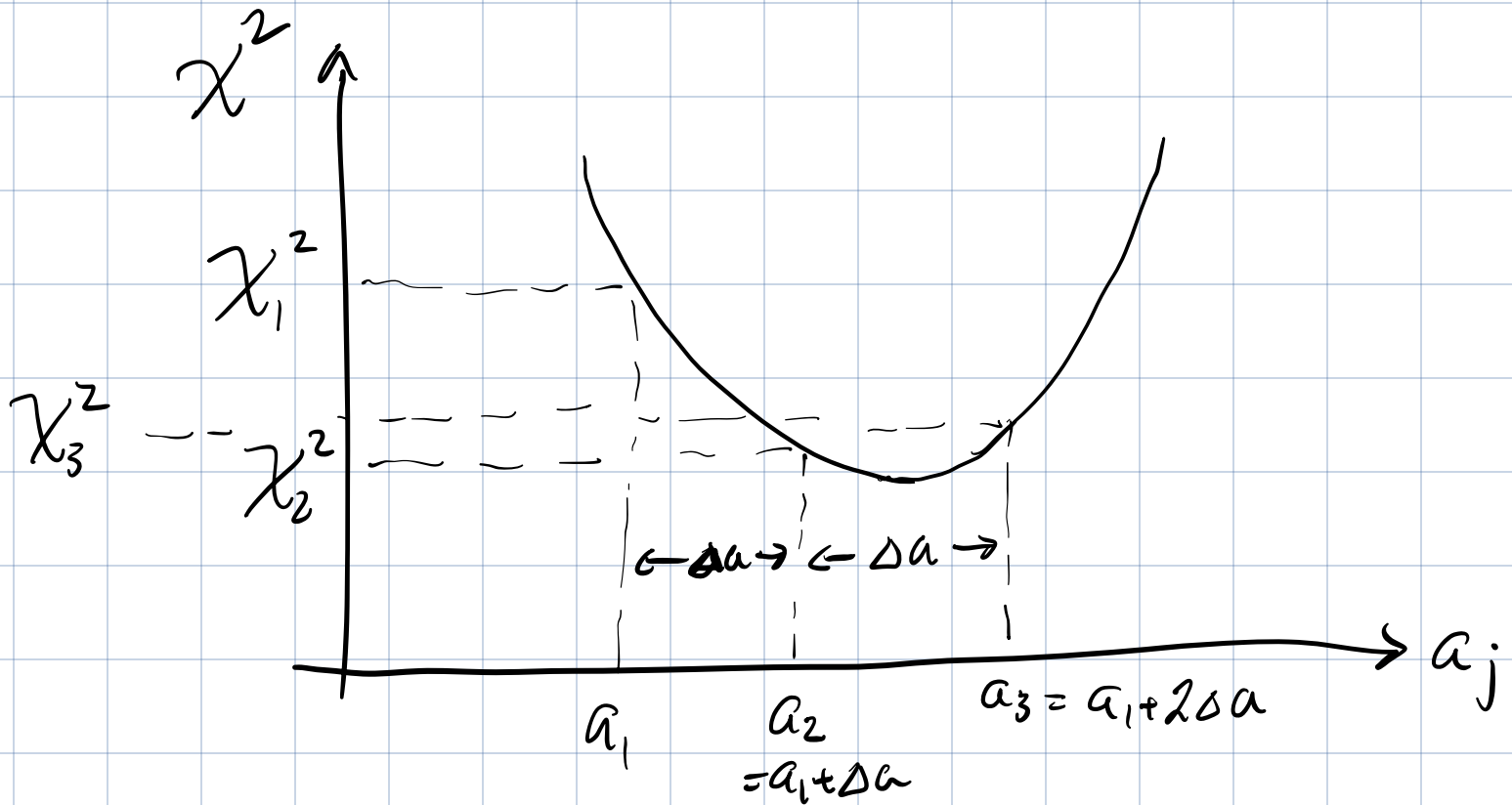


When B is large, the range of a_j values that minimize χ^2 is narrow
 $\rightarrow a_j^*$ precisely known
 σ_{a_j} small.

When B is small, large range of a_j values to come close to minimizing χ^2
 $\rightarrow a_j^*$ poorly known
 σ_{a_j} large.

Expect that σ_{a_j} is, in some way, inversely prop. to B .

In principle, (if in practice) if we know value of χ^2 at 3 points of a_j near the minimum, can determine the three unknowns: χ_0^2 , a_j^* , B .



Pick 3 values of a_j .

$$\begin{aligned} a_1 \\ a_2 &= a_1 + \Delta a \\ a_3 &= a_1 + 2\Delta a \end{aligned}$$

Write $\chi_1^2 = \chi_0^2 + B(a_1 - a^*)^2$
 $= \chi_0^2 + B(a_3 - 2\Delta a - a^*)^2$
 ①. $= \chi_0^2 + B((a_3 - a^*) - 2\Delta a)^2$

$\chi_2^2 = \chi_0^2 + B(a_2 - a^*)^2$
 ②. $= \chi_0^2 + B((a_3 - a^*) - \Delta a)^2$

③. $\chi_3^2 = \chi_0^2 + B(a_3 - a^*)^2$

Can solve this system of 3 eqns for the 3 unknowns. Important result is:

$$B = \frac{\chi_1^2 - 2\chi_2^2 + \chi_3^2}{2(\Delta a)^2}$$

Return to likelihood prob. $\textcircled{\#}$:

$$P(a_1, a_2, \dots, a_m) = \prod_{i=1}^N \left[\frac{\Delta y}{\sigma_i \sqrt{2\pi}} \right] \exp \left\{ -\frac{1}{2} \chi^2 \right\}$$

sub in $\textcircled{*}$ $\chi^2 = \chi_0^2 + B(a_j - a_j^*)^2$
near the minimum of χ^2 .

$$P(a_1, \dots, a_m) \approx \underbrace{\prod_{i=1}^N \left[\frac{\Delta y}{\sigma_i \sqrt{2\pi}} \right]}_{\equiv A} \exp \left\{ -\frac{1}{2} \left[\chi_0^2 + B(a_j - a_j^*)^2 \right] \right\}$$

$$\approx \underbrace{A \exp \left\{ -\frac{1}{2} \chi_0^2 \right\}}_{\equiv A'} \exp \left\{ -\frac{B(a_j - a_j^*)^2}{2} \right\}$$

$$P(a_1, \dots, a_m) = A' \exp \left\{ -\frac{(a_j - a_j^*)^2}{2B^{-1}} \right\}$$

Is of the form of a Gaussian dist'n

$$f_G = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Likelihood fun becomes a Gaussian fun of each parameter a_j .

$$\sigma_j^2 = B^{-1}$$

or

$$\sigma_j = \frac{1}{\sqrt{B}} \quad \text{uncertainty in parameter } a_j$$

where:

$$B = \frac{\chi_1^2 - 2\chi_2^2 + \chi_3^2}{2(\Delta a)^2}$$