

# Fits to combined datasets

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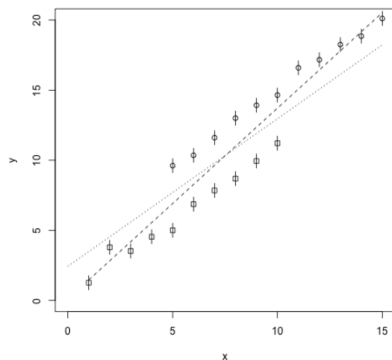


# The problem

Fitting a function to data which share a systematic error within experiments. (Or data-taking runs. Or tracker-modules. Or...)

Ignoring systematics gives wrong answer (dashed line)

Need to include them for correct (dotted) line



## The puzzle

There are two different ways to do it. Which should you use?

# The Question

Which of two Methods should you use?

Using  $i, j, \dots$  to index the data and  $r$  to index the experiments

$a$  represents the fitting parameters

Individual measurement errors  $\sigma_i$  and systematic errors  $S_r$

## Invert the Covariance matrix

Adjust  $a$  to minimise  $\chi^2$

$$\sum_{i,j} (y_i - f(x_i, a)) \mathbf{V}_{ij}^{-1} (y_j - f(x_j, a))$$

$$V_{ij} = \delta_{ij} \sigma_i^2 + \delta_{r_i r_j} S_{r_i}^2$$

Need to invert a (very) large matrix

## Introduce and fit deviations $z_r$

Adjust  $a$  and  $z$  to minimise  $\chi^2$

$$\sum_r \sum_{i \in r} \left( \frac{y_i - f(x_i, a) - z_r}{\sigma_i} \right)^2 + \left( \frac{z_r}{S_r} \right)^2$$

Minimisation space has (several) extra parameters

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## The answer

It doesn't matter. They are equivalent

# Inverting the matrix

$$\begin{pmatrix} \sigma_1^2 + S_1^2 & S_1^2 & S_1^2 & S_1^2 & 0 & 0 & 0 & \dots \\ S_1^2 & \sigma_2^2 + S_1^2 & S_1^2 & S_1^2 & 0 & 0 & 0 & \dots \\ S_1^2 & S_1^2 & \sigma_3^2 + S_1^2 & S_1^2 & 0 & 0 & 0 & \dots \\ S_1^2 & S_1^2 & S_1^2 & \sigma_4^2 + S_1^2 & 0 & 0 & 0 & \dots \\ 0 & 0 & 0 & 0 & \sigma_5^2 + S_2^2 & S_2^2 & S_2^2 & \dots \\ 0 & 0 & 0 & 0 & S_2^2 & \sigma_6^2 + S_2^2 & S_2^2 & \dots \\ 0 & 0 & 0 & 0 & S_2^2 & S_2^2 & \sigma_7^2 + S_2^2 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

$\mathbf{V}$  is block diagonal,  $\text{diag}\{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots\}$  so  $\mathbf{V}^{-1}$  is also block diagonal  $\text{diag}\{\mathbf{v}_1^{-1}, \mathbf{v}_2^{-1}, \mathbf{v}_3^{-1}, \dots\}$

Consider case where all  $\sigma_i$  the same  $\mathbf{v} = \sigma^2 \mathbf{I} + S^2 \mathbf{U}$

$\mathbf{U}$  is matrix of ones. Note  $\mathbf{U}^2 = n\mathbf{U}$

$$\mathbf{v}^{-1} = \frac{1}{\sigma^2} \mathbf{I} - \frac{S^2}{\sigma^2(\sigma^2 + nS^2)} \mathbf{U}$$

$$\text{Now generalise } v_{ij}^{-1} = \frac{\delta_{ij}}{\sigma_i^2} + \frac{S_r^2}{1 + \sum_{k \in E_r} \frac{S_r^2}{\sigma_k^2}} \frac{1}{\sigma_i^2 \sigma_j^2}$$

$$\text{Minimise } \chi^2 = \sum_r \sum_{i \in E_r} \frac{\Delta_i^2}{\sigma_i^2} - \sum_r \frac{S_r^2}{1 + \sum_{k \in E_r} \frac{S_r^2}{\sigma_k^2}} \sum_{i \in E_r} \sum_{j \in E_r} \frac{\Delta_i \Delta_j}{\sigma_i^2 \sigma_j^2}$$

## Fitting the extra parameters

$$\text{Minimise } \chi^2 = \sum_r \sum_{i \in E_r} \left( \frac{\Delta_i - z_r}{\sigma_i} \right)^2 + \left( \frac{z_r}{S_r} \right)^2$$

$$\frac{\partial \chi^2}{\partial z_r} = 0 = -2 \sum_{i \in E_r} \frac{\Delta_i - z_r}{\sigma_i^2} + 2 \frac{z_r}{S_r^2}$$

$$z_r = \frac{\sum_{j \in E_r} \Delta_j / \sigma_j^2}{1/S_r^2 + \sum_{k \in E_r} \frac{1}{\sigma_k^2}}$$

Put these back into the expression for  $\chi^2$  and get

$$\sum_r \sum_{i \in E_r} \left( \frac{\Delta_i - \frac{\sum_{j \in E_r} \Delta_j / \sigma_j^2}{1/S_r^2 + \sum_{k \in E_r} \frac{1}{\sigma_k^2}}}{\sigma_i} \right)^2 + S_r^2 \left( \frac{\sum_{j \in E_r} \Delta_j / \sigma_j^2}{1 + \sum_{k \in E_r} \frac{S_r^2}{\sigma_k^2}} \right)^2$$

Multiply out and collect terms in  $\Delta_i^2$  and  $\Delta_i \Delta_j$  and get

$$\sum_r \sum_{i \in E_r} \frac{\Delta_i^2}{\sigma_i^2} - \sum_r \frac{S_r^2}{1 + \sum_{k \in E_r} \frac{S_r^2}{\sigma_k^2}} \sum_{i \in E_r} \sum_{j \in E_r} \frac{\Delta_i \Delta_j}{\sigma_i^2 \sigma_j^2}$$

We've seen that before

# The two methods are equivalent

Maybe surprising. Maybe obvious.

## Which to choose?

Doesn't matter.

Second method gives offsets, which may or may not be useful.

First method gives direct (non-iterative) solution for linear function.

Minimisation in second method requires care as there is a direction in parameter space adjusting  $c$  and all the  $z_r$  with small  $\chi^2$  dependence (Rosenbrock's Valley). Scrutinise 'solutions' from minimiser, or solve for  $z_r$  as you go.

# Multiplicative Systematics

More common. Experiments have uncertainty in efficiency, or luminosity...

Matrix  $V_{ij} = \delta_{ij}\sigma_i^2 + \xi_r^2 y_i y_j$

where  $\xi_r$  is shared fractional error

Or can minimise values scaled by  $z_r$ , and add  $\left(\frac{z_r-1}{\xi_r}\right)^2$  to  $\chi^2$

Ambiguity: do we scale  $y_i$  or  $f(x_i)$ ?

Scaling the  $y_i$  gives the same results as the matrix inversion (similar algebra to last time)

But this has a problem...



# "D'Agostini Bias"

Combining correlated results gives a biased result

## Simple illustration

Two measurements  $x_1, x_2$  of the same quantity  $a$  with a shared error  $\xi$

$$V = \begin{pmatrix} \sigma_1^2 + \xi^2 x_1^2 & \xi^2 x_1 x_2 \\ \xi^2 x_1 x_2 & \sigma_2^2 + \xi^2 x_2^2 \end{pmatrix}$$

$$\chi^2 \propto (x_1 - a, x_2 - a) \begin{pmatrix} \sigma_2^2 + \xi^2 x_2^2 & -\xi^2 x_1 x_2 \\ -\xi^2 x_1 x_2 & \sigma_1^2 + \xi^2 x_1^2 \end{pmatrix} \begin{pmatrix} x_1 - a \\ x_2 - a \end{pmatrix}$$

$$\hat{a} = \frac{\sigma_2^2 x_1 + \sigma_1^2 x_2}{\sigma_1^2 + \sigma_2^2 + \xi^2 (x_1 - x_2)^2}$$

$$\langle \hat{a} \rangle < a$$

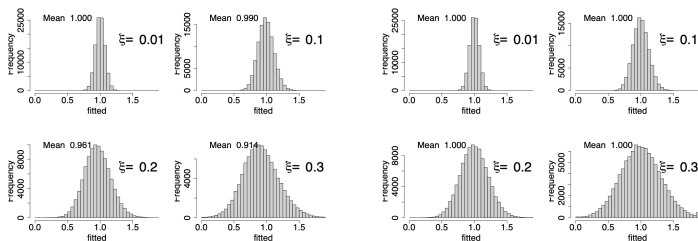
Bias is not due to correlation - but to multiplicative errors

## Simple question

How should you average  $90 \pm 10\%$  and  $110 \pm 10\%$ ?

If you apply the  $z_r$  to the  $f_i$  (or use  $V_{ij} = \xi_r^2 f(x_i)f(x_j)$ ) the bias is removed.

Toy MC results of averaging 2 correlated values using  $\xi^2 y_i y_j$  (LEFT) and  $\xi^2 f_i f_j$  (RIGHT)



# Conclusions

Nucl. Instrum. and Meth. **A987** 164864 (2021) ,arXiv:1701.03701

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Two early Christmas presents