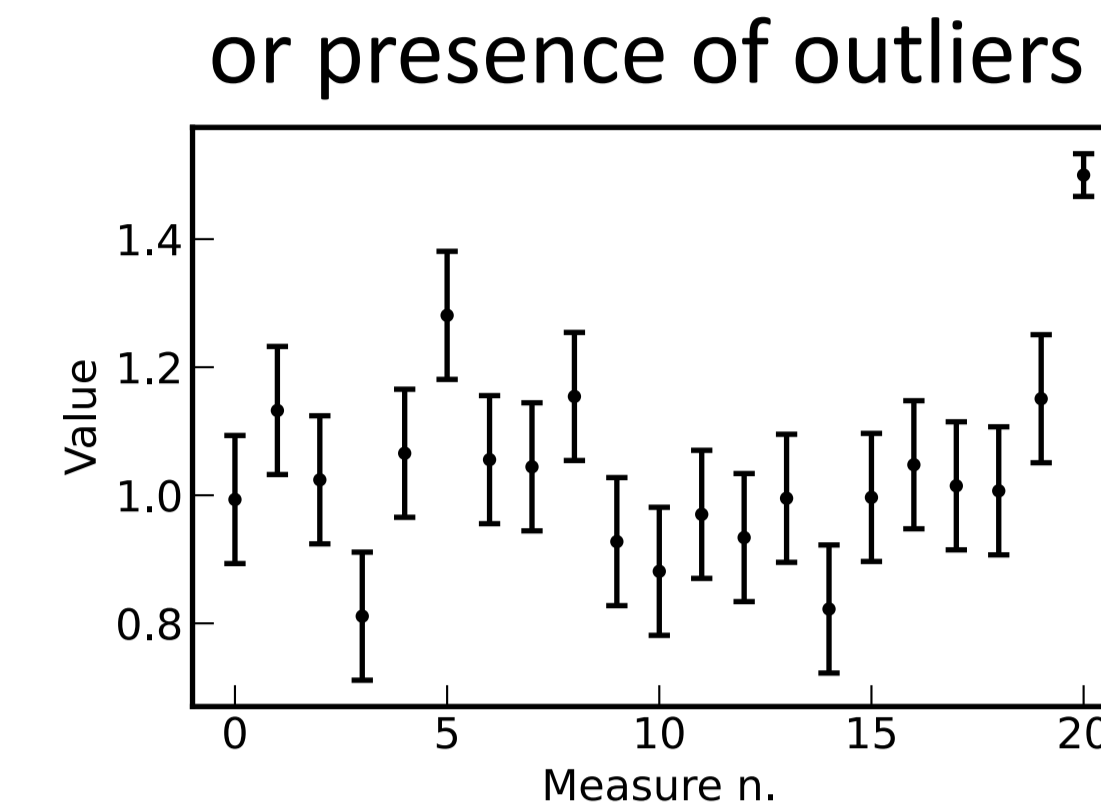
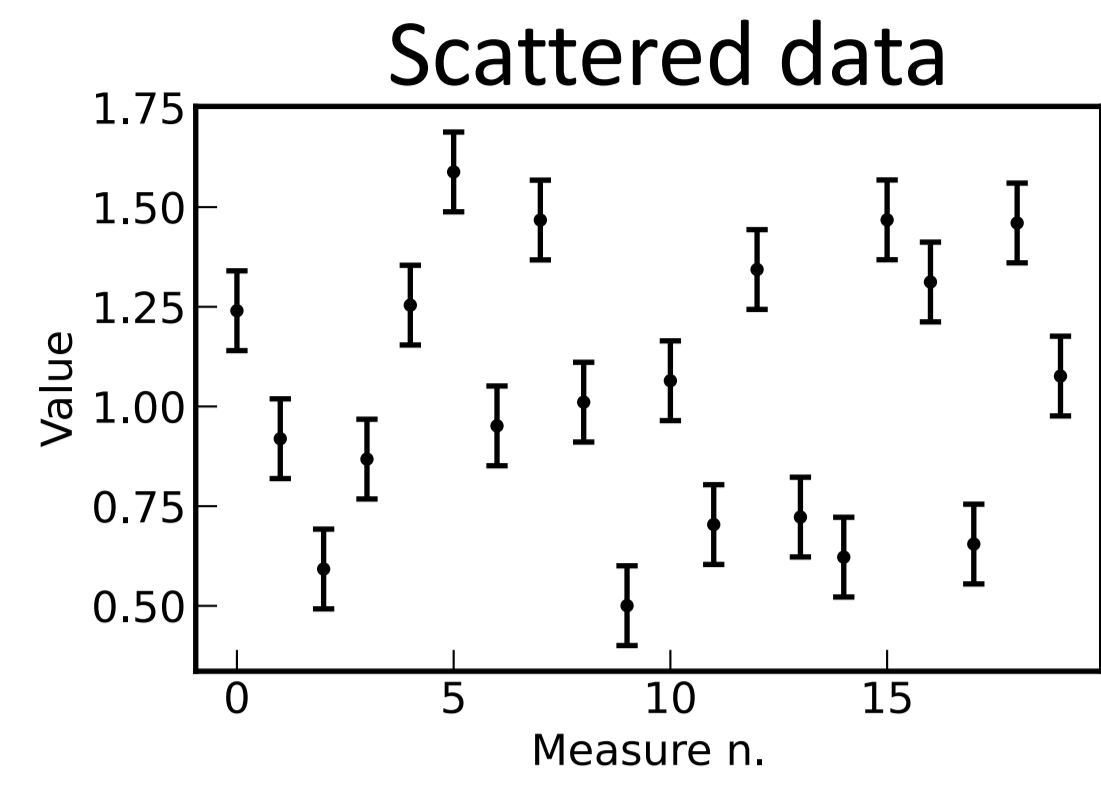


The problem of averages of inconsistent data

What to do with inconsistent sets of data?



Standard procedure:

inverse-invariance weighted average

$$\hat{\mu} = \frac{\sum_i x_i / \sigma_i^2}{\sum_i 1 / \sigma_i^2} \quad \sigma_{\hat{\mu}} = \sqrt{\frac{1}{\sum_i 1 / \sigma_i^2}}$$

BUT $\sigma_{\hat{\mu}}$ does not depend on the data spread, only on the uncertainties!!

with $\hat{\mu}$ maximising $p(\mu | \{x_i, \sigma_i\}) = \prod_i p(x_i | \mu, \sigma_i)$ ← Gaussian (normal) distribution assumed
and with $\sigma_{\hat{\mu}} = \frac{\partial^2}{\partial \mu^2} \log[p(\mu | \{x_i, \sigma_i\})] \Big|_{\mu=\hat{\mu}}$

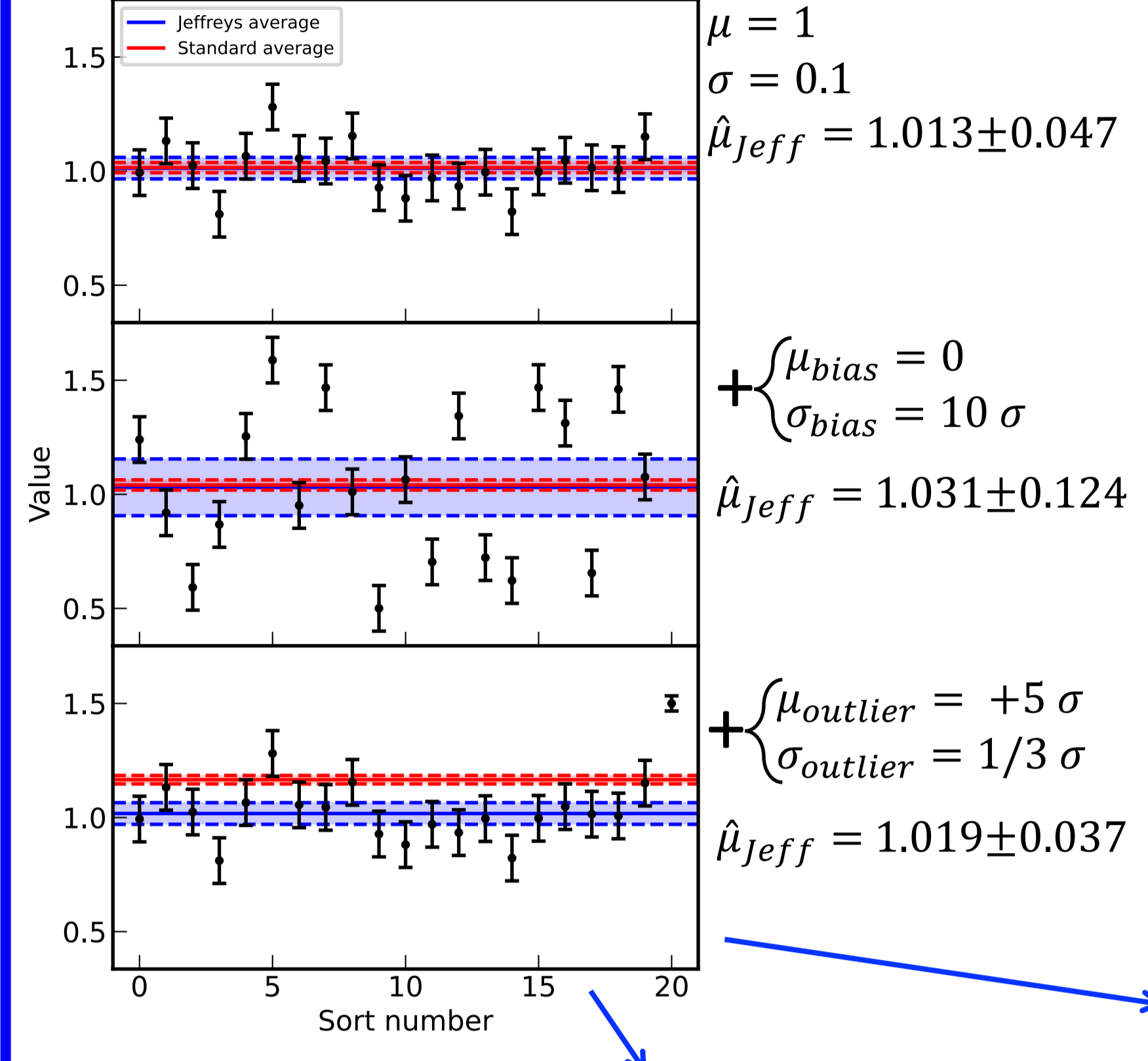
Proposed alternative averages

- Increase all uncertainties to have a final $\chi^2_{\text{red}} \approx 1$ (Birge ratio [1])

$$R_{\text{Birge}} = \sqrt{\frac{1}{n-1} \sum_i \frac{(x_i - \hat{\mu})^2}{\sigma_i^2}}$$
 But global adjustment, not adapted to inter-laboratory comparisons!!
- Evaluate the unknown uncertainty from the final spread [2,3]

$$\hat{\mu} = \frac{\sum_{i=1}^m \frac{1}{\sqrt{d_i^2 + \hat{\sigma}_i^2}} x_i}{\sum_{i=1}^m \frac{1}{\sqrt{d_i^2 + \hat{\sigma}_i^2}}}$$
 with $d_i = x_i - \hat{\mu}$
 But adjustment a posteriori
- More complex modelling of the missing systematic effects ...

Tests and analyses Simulations



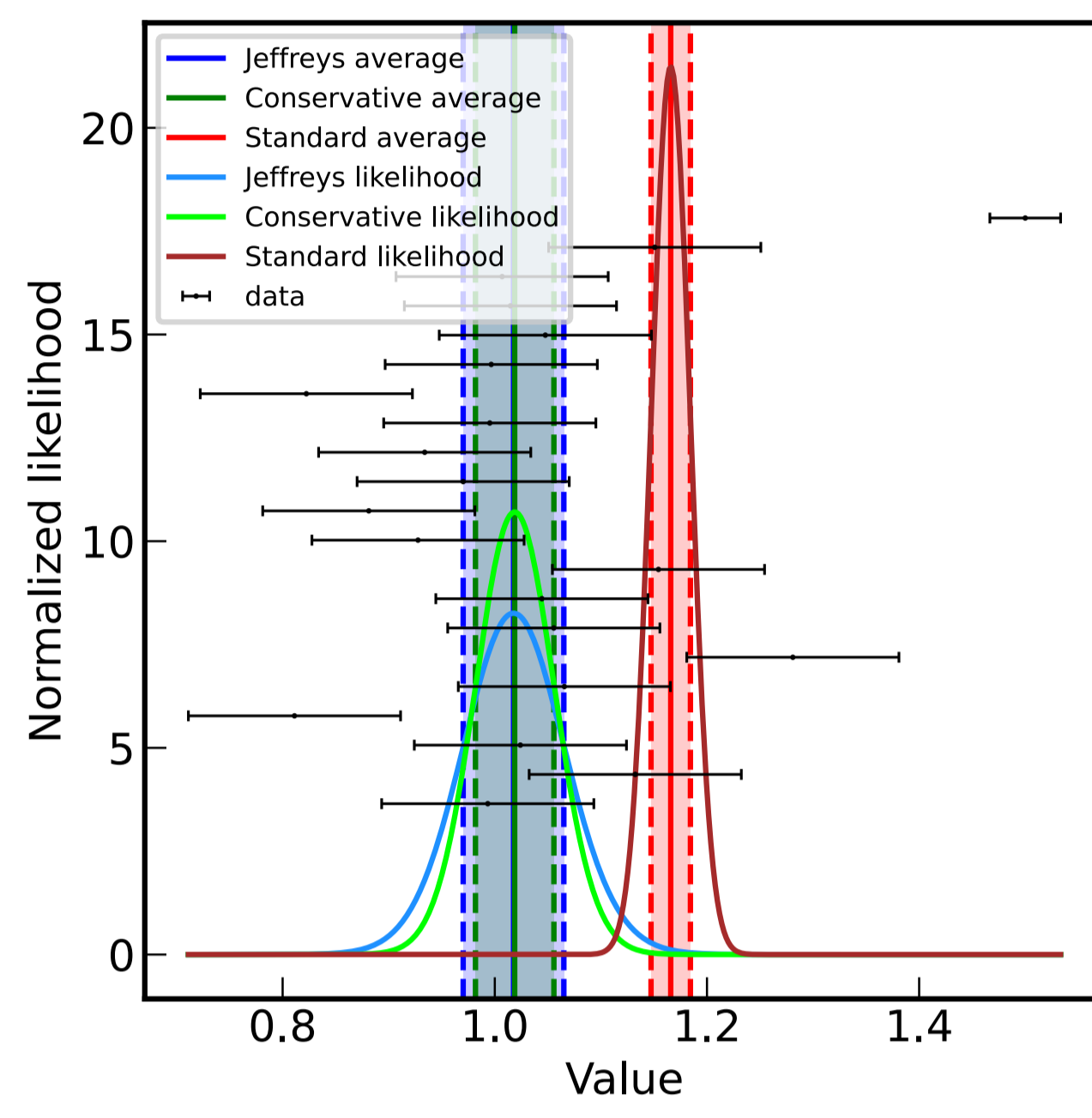
The outlier case

Weighted average type	Average $\hat{\mu}$	Unc. $\sigma_{\hat{\mu}}$
Inverse-variance (standard)	1.166	0.019
Inverse-variance with Birge ratio	1.166	0.054 ^a
Jeffreys' prior	1.018	0.047
Conservative	1.019	0.037

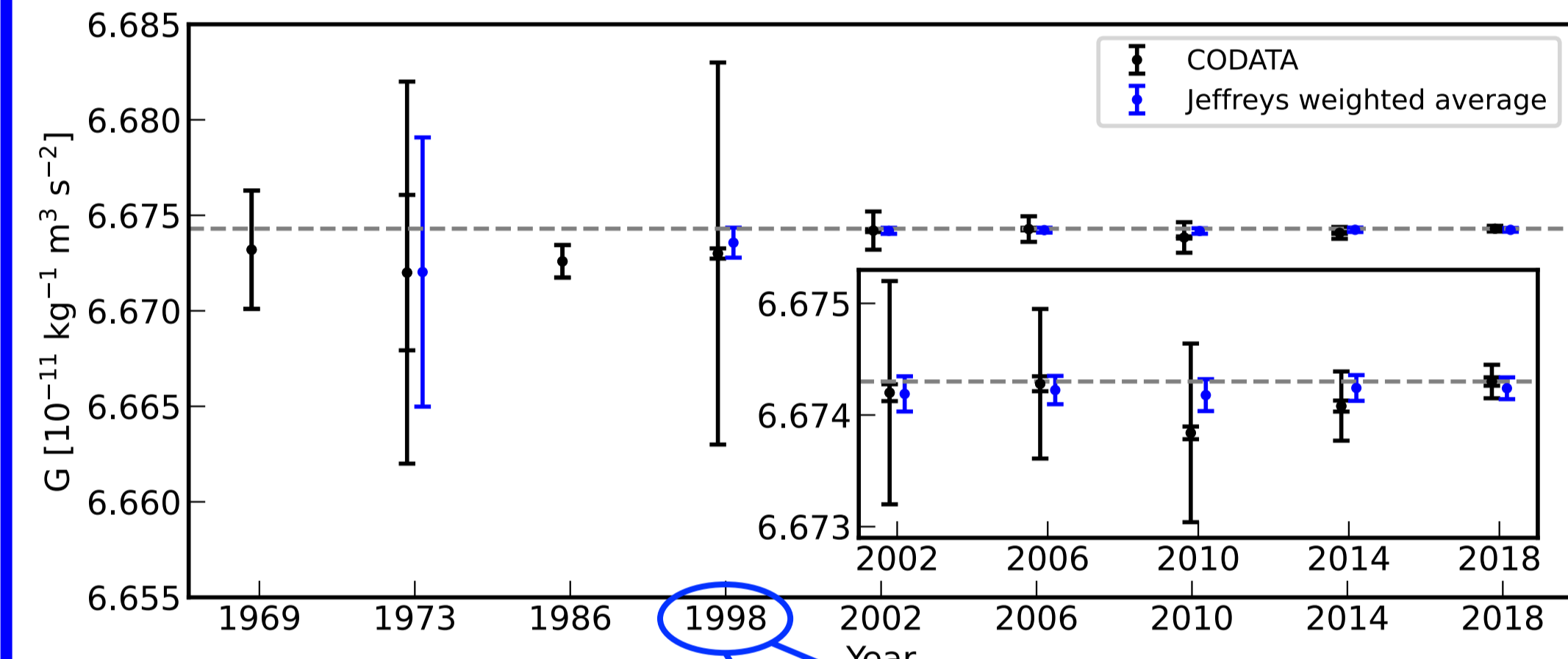
^aBirge ratio equal to 2.9

Jeffreys' prior weighted average:

- Systematically larger uncertainty
- Reproducing the data spread
- Much more robust to outliers



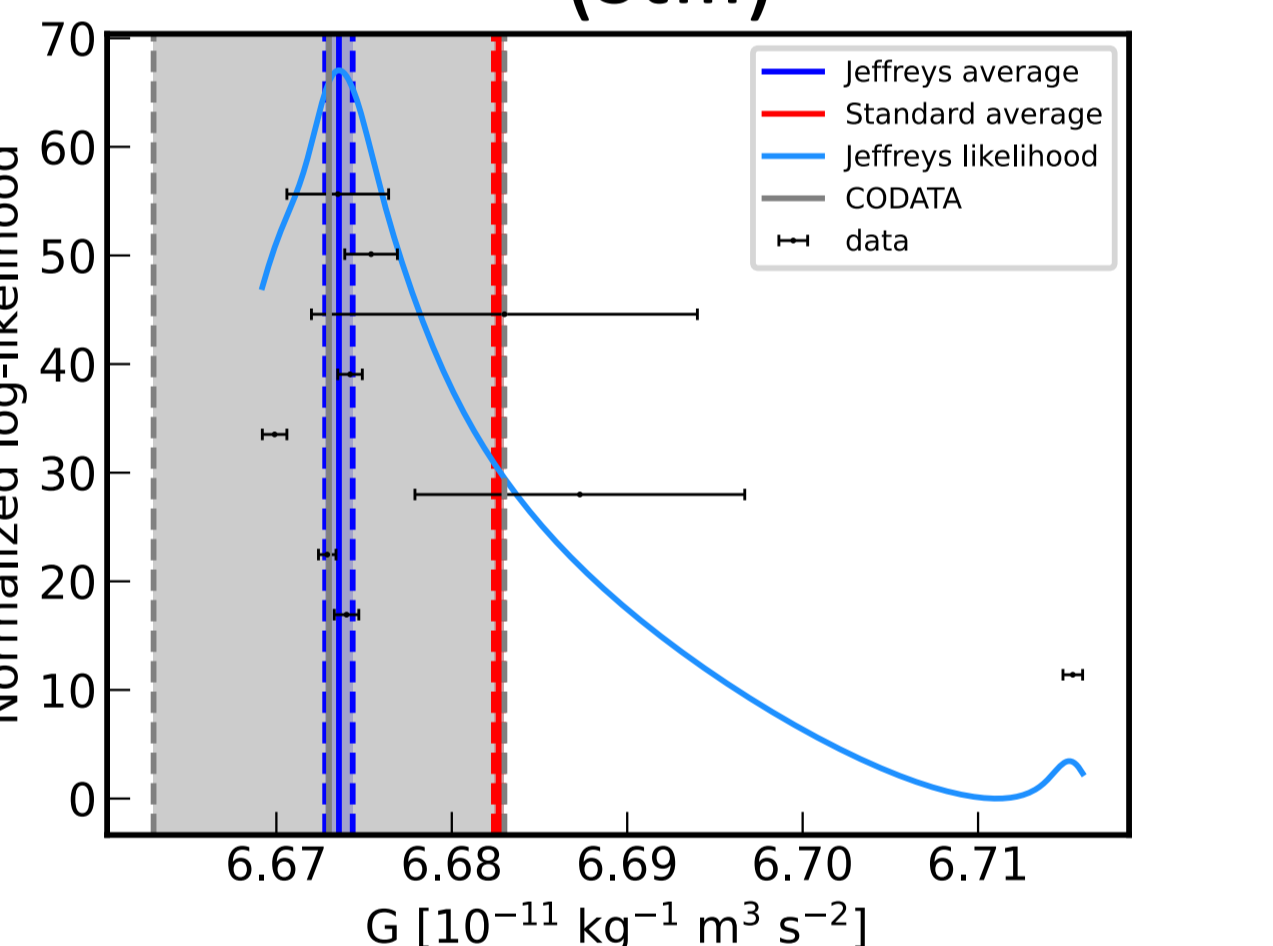
The Newtonian constant of gravity from CODATA



1998: a difficult case

Weighted average type	Average $\hat{\mu}$	Unc. $\sigma_{\hat{\mu}}$
Inverse-variance (standard)	6.6827	0.0003
Inverse-variance with Birge ratio	6.6827	0.0063 ^a
Conservative	6.6735	0.0006
Jeffreys' prior	6.6736	0.0008
CODATA 1998 [21]	6.673	0.010 ^b

^aBirge ratio equal to 23.6
^bCorresponding scale factor equal to 37



- Always consistent with the most recent value
- Good built-in estimation of the uncertainty
- Robust to outliers (still)

A Bayesian minimalistic approach

The simplest possible (and pessimistic) assumption [4]: my uncertainty is only a lower-bound estimation of the real one

Marginalization over the unknown variable

$$p(x_i | \mu, \sigma_i) = \int_{\sigma_i}^{\infty} p(x_i | \mu, \sigma'_i) p(\sigma'_i | \sigma_i) d\sigma'_i$$

What to choose for $p(\sigma'_i | \sigma_i)$?

The "natural" choice: a non-informative (Jeffreys') prior:

Invariant over parameter transformation

$$p(\sigma'_i | \sigma_i) = \frac{1}{\log(\sigma_i^{\text{max}} / \sigma_i)} \frac{1}{\sigma'_i} \quad \text{for } \sigma'_i \leq \sigma_i \leq \sigma_i^{\text{max}},$$

$$0 \quad \text{otherwise.}$$

but additional parameters σ_i^{max} to add, not normalizable otherwise

Possible solution:

Sivia conservative prior [4]: $p(\sigma'_i | \sigma_i) = \frac{\sigma_i}{(\sigma'_i)^2}$

$$p(x_i | \mu, \sigma_i) = \frac{\sigma_i}{\sqrt{2\pi}} \left[\frac{1 - e^{-\frac{(x_i - \mu)^2}{2\sigma_i^2}}}{(x_i - \mu)^2} \right]$$

No more a Gaussian distribution but not a non-informative prior

Our solution:

Jeffreys' prior + marginalization

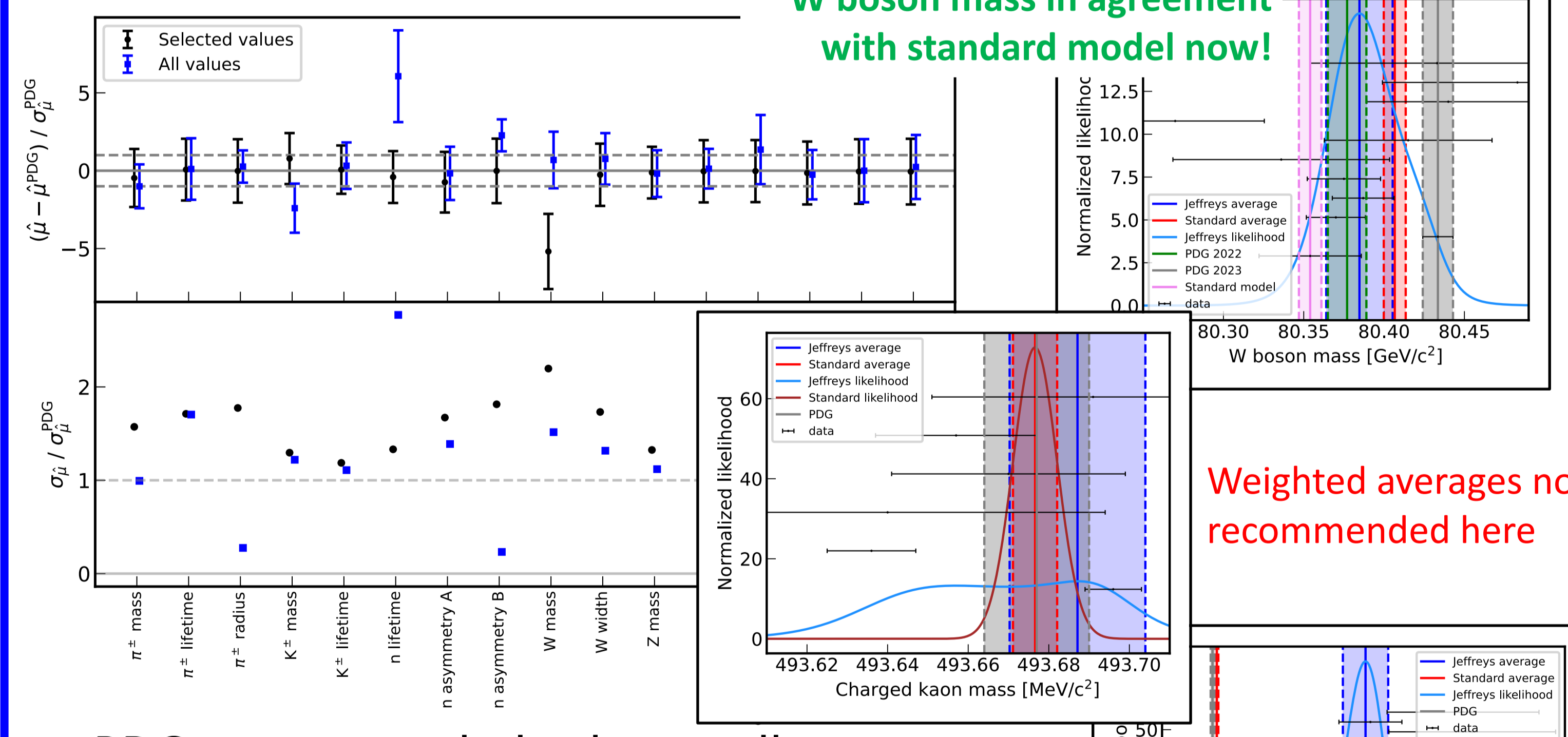
$$p(x_i | \mu, \sigma_i) = \frac{1}{\log(\sigma_i^{\text{max}} / \sigma_i)} \frac{\text{erf}\left(\frac{x_i - \mu}{\sqrt{2}\sigma_i}\right) - \text{erf}\left(\frac{x_i - \mu}{\sqrt{2}\sigma_i^{\text{max}}}\right)}{2(x_i - \mu)}$$

Limit case:

$$\log[p(\mu | \{x_i, \sigma_i\})] = \lim_{\sigma_i^{\text{max}} \rightarrow \infty} \log[p(\mu | \{x_i, \sigma_i, \sigma_i^{\text{max}}\})] = \sum_i \log \left[\frac{\text{erf}\left(\frac{x_i - \mu}{\sqrt{2}\sigma_i}\right)}{2(x_i - \mu)} \right] - C^{\infty}$$

No more additional parameters, and maximum and second derivative still well defined

Particle properties



W boson mass in agreement with standard model now!

Weighted averages not recommended here

- PDG recommended values well reproduced for (almost) all selected cases
- Critical cases easily detectable

Proton puzzle is still a puzzle!!

The Python library

- Easily installable via pip: `pip install bayesian_average`
- Freely available in GitHub: https://github.com/martinit18/bayesian_average
- Different average type proposed
- Plot representation of the final probability distribution with the input data

[1] R.T. Birge, Phys. Rev. **40**, 207-227 (1932)

[2] I. Lira, Metrologia **44**, 415 (2007)

[3] H. Huang, Metrologia **55**, 106 (2018)

[4] D.S. Sivia and J. Skilling., *Data analysis: a Bayesian tutorial*. Second ed. 2006: Oxford University Press