

Bayesian Monte-Carlo Framework: New Methods for Resonance Parameter Evaluation

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Assumptions or approximations used with Bayes' Theorem

1. The model and the prior PDF of data are assumed to be perfect
2. The model is approximated by its 1st order (linear) expansion
3. Prior and posterior PDFs are approximated by normal PDFs.

- We recognize that 1. is equivalent to constraining the posterior expectation values of δ , and of its covariance matrix, to 0:

$$z \equiv \begin{pmatrix} P \\ D \end{pmatrix}$$

$$\delta \equiv \delta(z, T(P)) \equiv T(P) - D$$

$$\langle \delta \rangle' = 0 \quad \Delta' \equiv \langle (\delta - \langle \delta \rangle')(\delta - \langle \delta \rangle')^\top \rangle' = \emptyset$$

- We remove 1. by letting evaluator choose values of $\langle \delta \rangle'$ and Δ'
- 2. and 3. can be removed by Metropolis-Hastings Monte Carlo

Overview of approximations used by ORNL codes

Code name	$\langle \delta \rangle'$	Δ'	Prior/Post PDF	Cost Function	Minimization
SAMMY	0	0	Normal/Normal	$\chi^2(z = (P, T(P)), \langle z \rangle, C)$	Linear, iterative
TSURFER	0	0	Normal/Normal	$- -$	Linear, 1 step
BMC	Any	Any	Any/any	$X^2(z, \langle z \rangle, C, T(P), \lambda, \Lambda)$	MHMC

- Bayes' theorem with arbitrary constraints:

$$p'(z|\beta, \gamma) = p'(z|\gamma, \beta) = N' \mathcal{L}(\beta|z, \gamma) \times p(z|\gamma)$$

$$\begin{aligned}\Lambda &= \Lambda(\langle \delta \rangle', \Delta', \langle z \rangle, C) \\ \lambda &= \lambda(\langle \delta \rangle', \Delta', \langle z \rangle, C)\end{aligned}$$

$$\mathcal{L}(\beta|z, \gamma) \leftarrow \mathcal{L}(\langle \delta \rangle', \Delta'|z, \gamma) = e^{-\frac{1}{2}(\delta - \lambda)^\dagger \Lambda^{-1} (\delta - \lambda)}$$

$\beta \leftarrow \{\text{any constraints on posteriors imposed by evaluator}\},$

$\gamma \leftarrow \{\text{any parameters needed to define the prior PDF, } p(z|\gamma)\}$

- GLS is recovered, i.e., $X^2 \rightarrow \chi^2$, for $(\Lambda = \lambda = 0) \leftarrow (\Delta' = \langle \delta \rangle' = 0)$.

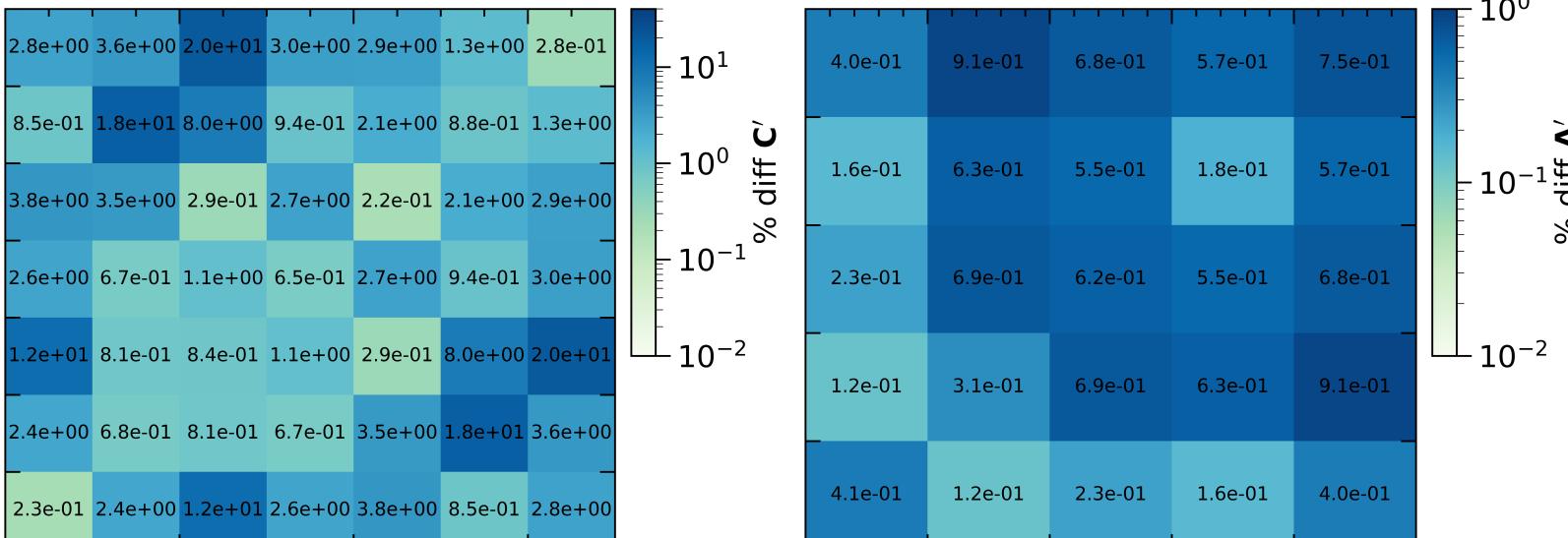
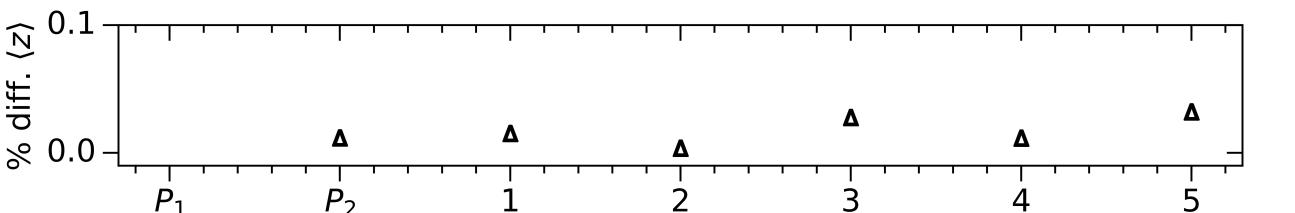
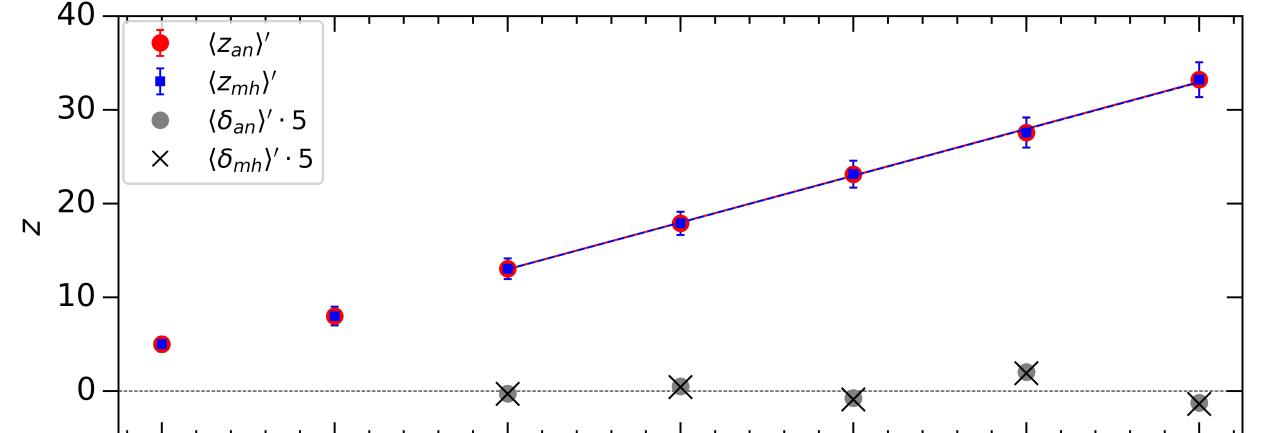
Metropolis Hastings Monte Carlo (MHMC) Algorithm

```
1:  $N \leftarrow$  iterations                                ▷ necessary number of iterations for convergence
2:  $i \leftarrow 0$ 
3:  $z_0 \leftarrow$  arbitrary values                      ▷  $z_i$  can be of arbitrary dimension
4: while  $i < (N + 1)$  do
5:   Generate random candidate sample  $z'$  from  $g(z'|z_i)$ 
6:    $A = \min\left(1, \frac{p(z')}{p(z_i)} \frac{g(z_i|z')}{g(z'|z_i)}\right)$ 
7:   Generate random value of  $u$  from uniform distribution between  $(0, 1)$ 
8:   if  $u < A$  then
9:      $z_{i+1} \leftarrow z'$ 
10:    else
11:       $z_{i+1} \leftarrow z_i$ 
12:     $i \leftarrow i + 1$ 
```

Analytical solutions: Linear model

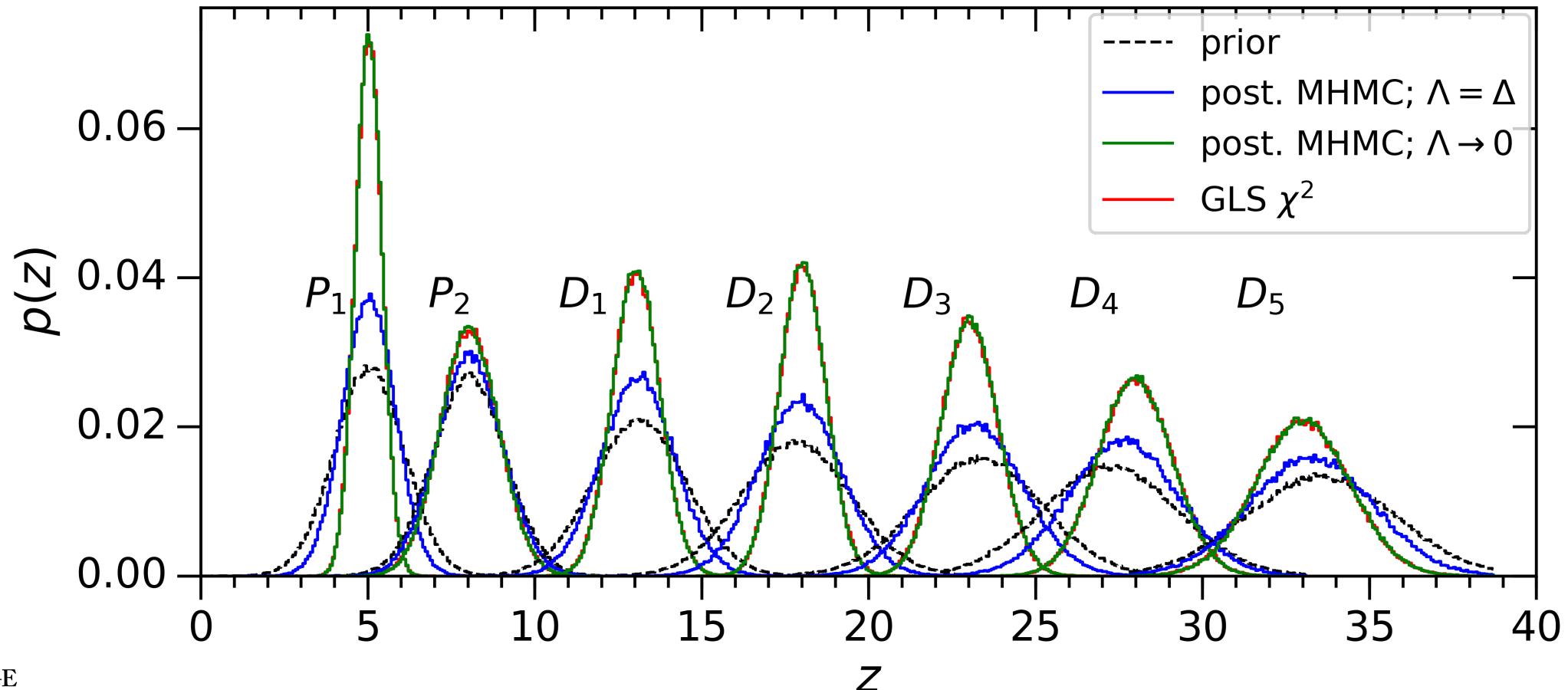
$$T(P) = P_1 x + P_2$$

- We validate the framework with linear models
- The upper plot shows the perfect (within statistical uncertainty) agreement between the analytical and MHMC values for $\langle z \rangle'$ and $\langle \delta \rangle'$
- The lower plot shows that the difference between the analytical and MHMC $\langle z \rangle'$ is not $> 0.06\%$ for any element of z
- Diagonal of C' matches analytical to within $< 0.6\%$, off-diagonal requires more iterations
- Δ' matches well throughout



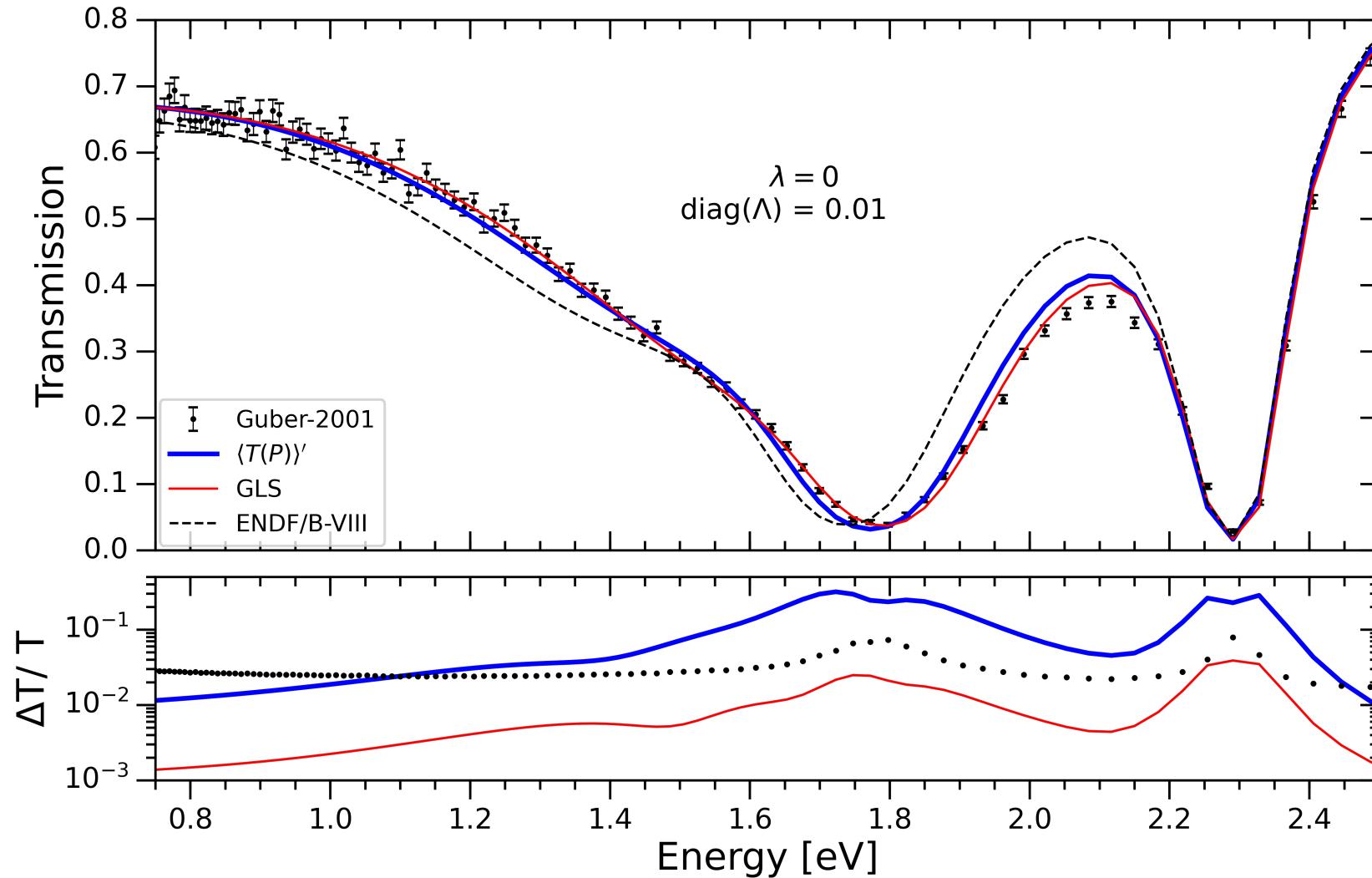
Comparison to GLS: Linear Model

- Case $\Lambda = \Delta$: solves for $\Delta' = \Delta/2$ and $\langle \delta \rangle' = \langle \delta \rangle/2$ by using $\Lambda = \Delta$ and $\lambda = 0$
- Case $\Lambda \rightarrow 0$: solves for $\Delta' = 0$ and $\langle \delta \rangle' = 0$ by using $\Lambda \rightarrow 0$ and $\lambda \rightarrow 0$ (matches GLS)
 - Demonstrates the effect of the GLS assumption: $\langle \delta \rangle' = 0, \Delta' = 0$

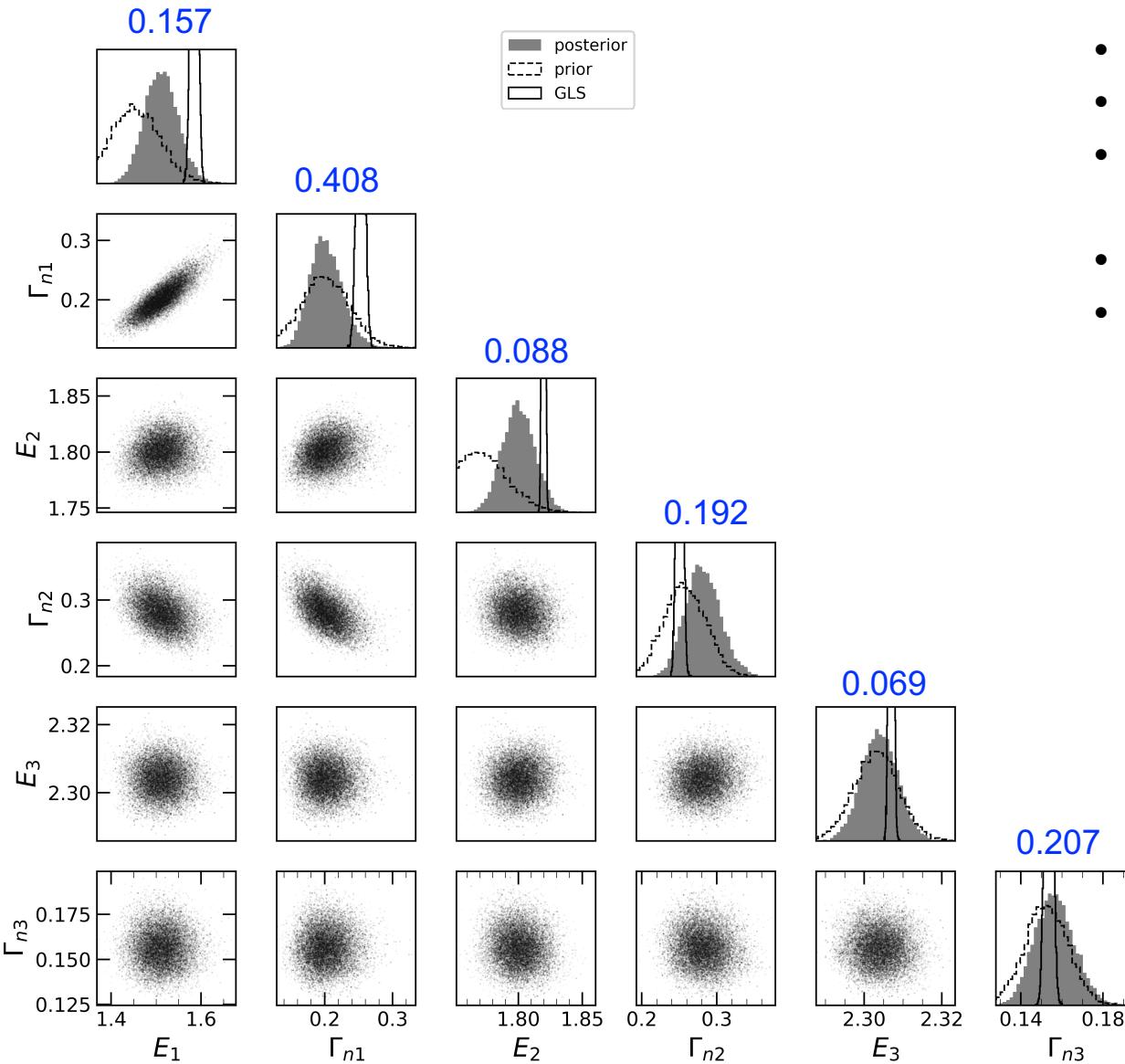


Application to RRR evaluation: U-233

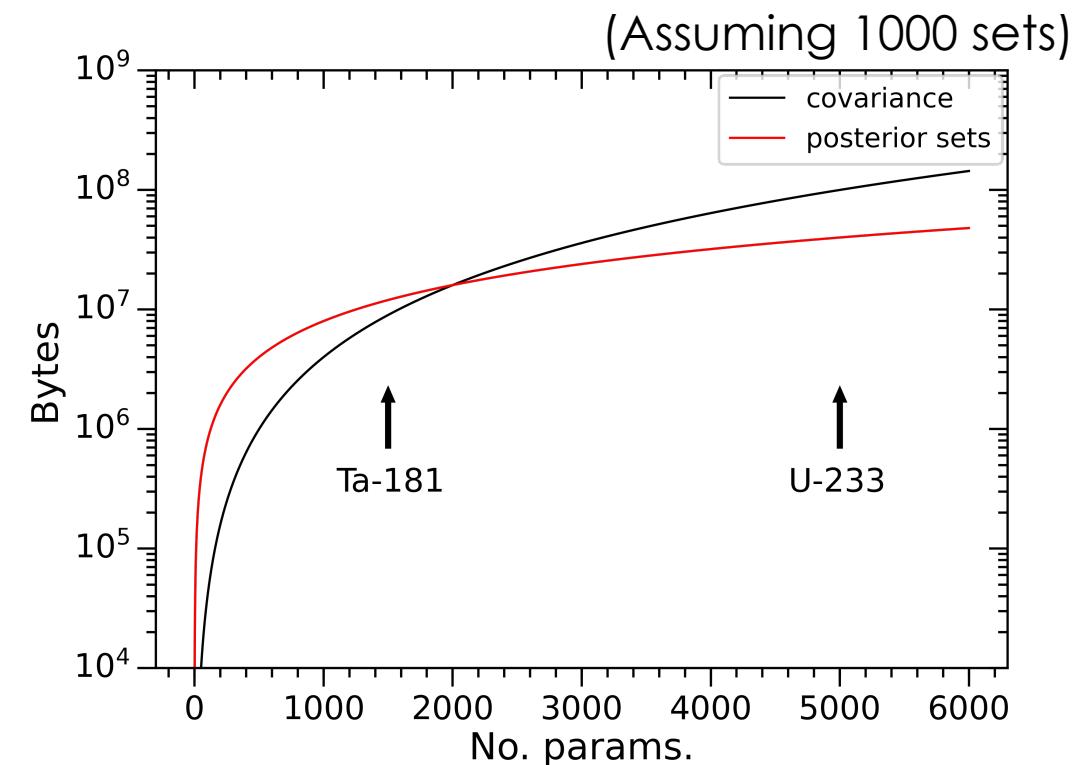
- Fit 3 resonances allowing the energy eigenvalues and neutron widths to vary
- The explicit application of $\Delta' \neq 0$ gives the evaluator control over model/data defects (background, normalization, etc.)
- Uncertainty on model now envelopes the data



Uncertainty analysis: covariance and beyond



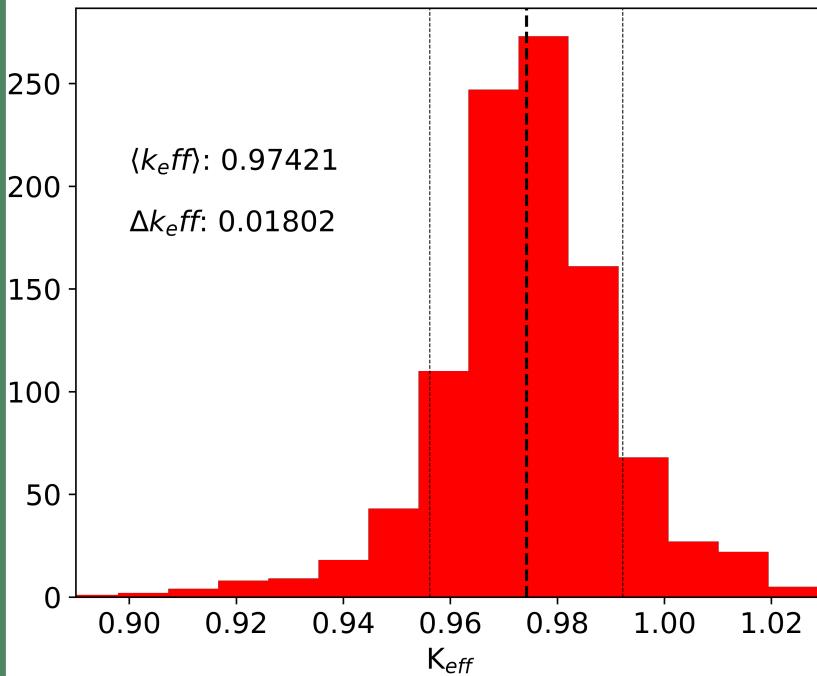
- 6 resonance parameters
- ~30,000 posterior sets make up PDF
- Posterior PDFs compared to GLS (black) and prior (black-dashed) PDFs
- Instead of storing covariance, store posterior sets
- All PDFs are positively skewed (blue)



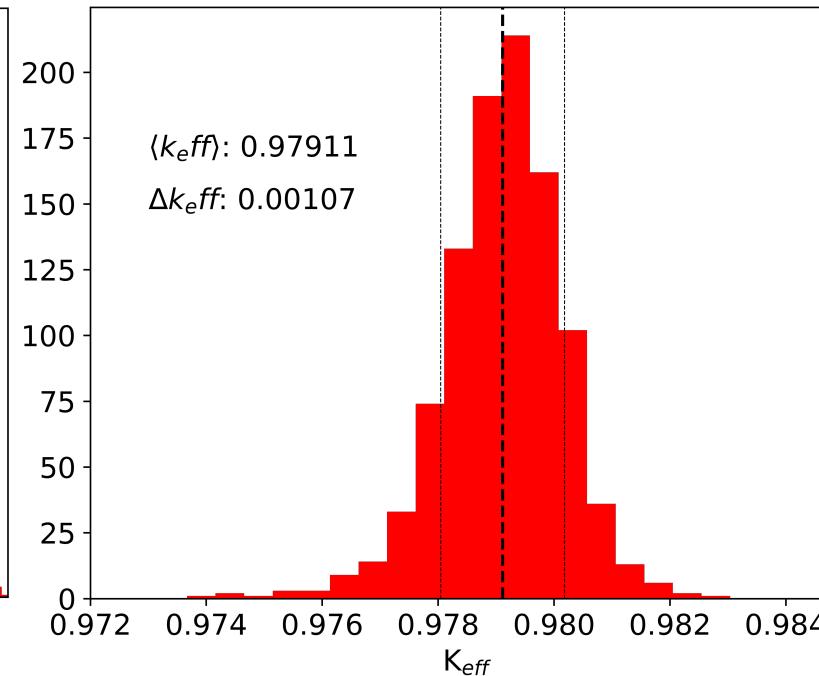
The Impact on Reactors

- Example: U233-SOL-INTER-001
- We randomly sample ENDF/B-VIII.0 File 32
- Issues exposed: non-linearity (sensitivities), non-normality (PDFs)
- Take-away: small change in RP uncertainty can lead to large changes in Δk_{eff}

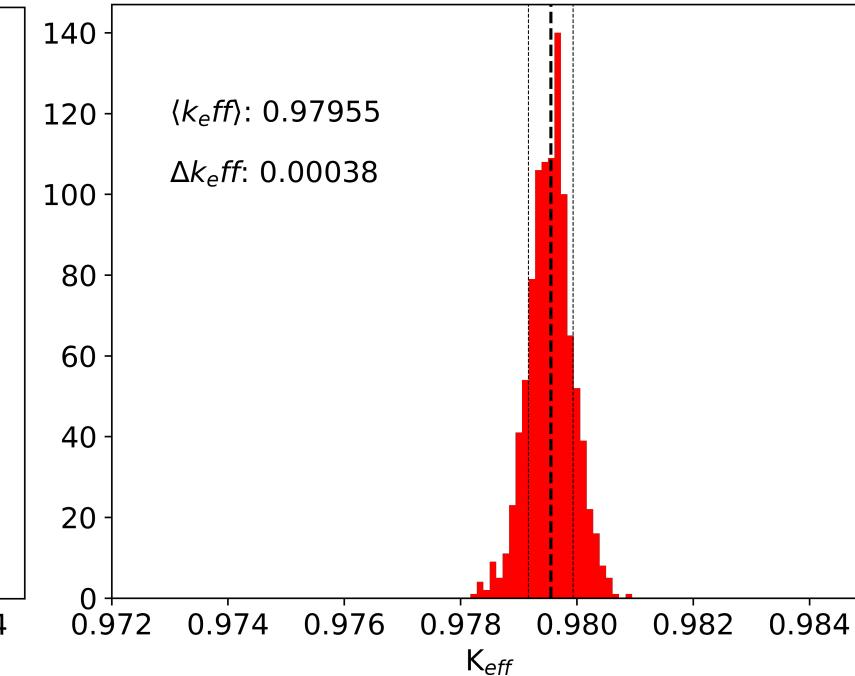
MC samples from: File 32,



File 32 divided by 4,



File 32 divided by 8



k_{eff} uncertainty is decreasing significantly faster than linear scaling would imply

Considerations

- BMC evaluation is a tool to address:
 - **Imperfect data & models**
 - **non-linear models**
 - **non-normal PDFs**
- ENDF-6 format does not allow non-normal parameter PDFs
 - Storing posterior sets allows for: variance, covariance, skewness, etc.
- To better predict criticality we could:
 - Document non-normal parameter PDFs (i.e. asymmetric uncertainty)
 - Consider non-linear sensitivity of k_{eff} to resonance parameters
 - Reduce uncertainty in key resonance parameters

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Additional Slides

MC vs. linear approx. for Δk_{eff} of U233-SOL-INTER-001-001

- MC reveals large deviation from non-linearity for ENDF/B-VIII.0 U-233 File 32

