



Formulation of Model Defects Suitable for the Resonance Regime

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Outline of the Presentation



- Motivation and Scope
- Bayesian Evaluation Technique
- Overview of previous considerations of Model Defects
- Model Defects in the Resonance Regime
- Formulation of a Covariance Matrix for the Model Error
- Summary and Conclusion



Motivation



Why considering model defects?

NO model is perfect!

Every model can describe certain apsects of a physical problem, but never the total reality

In nuclear physics:

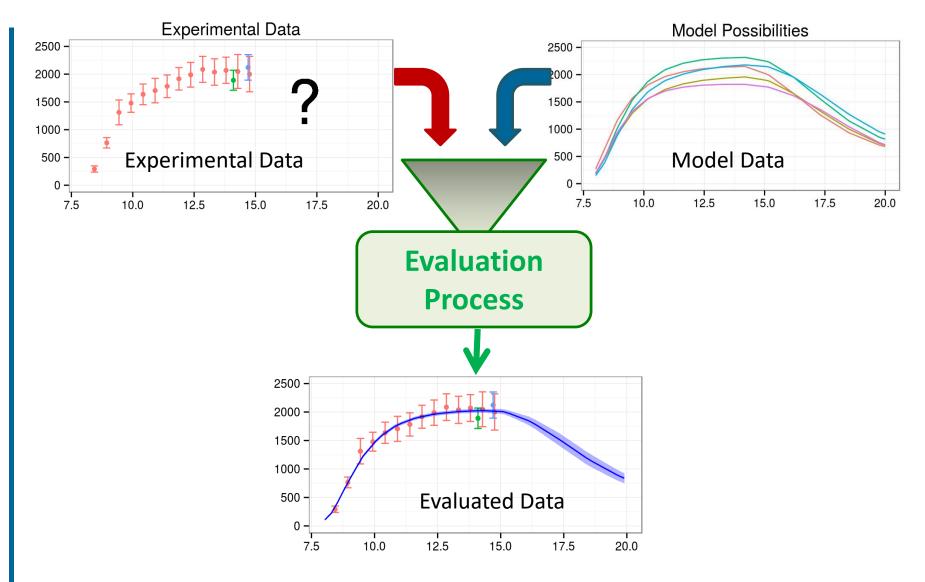
- Each nucleus consists of nucleons -> Many body problem
- Force between nucleons not exactly known

Up to now there exists no microscopic model that can predict quantitatively resonances in the cross section



Nuclear Data Evaluation





4



Bayesian Statistics



Bayes Theorem (1761):

$$\pi(\vec{p} \mid \vec{\sigma}_{\exp}) = \frac{1}{\int d^d p \, \ell(\vec{\sigma}_{\exp} \mid \vec{p}) \pi(\vec{p})} \, \ell(\vec{\sigma}_{\exp} \mid \vec{p}) \, \pi(\vec{p})$$

aposteriori distribution distribution of parameters taking a-priori and experimental info

likelihood

Experimental information

apriori distribution provides the apriori knowledge, e.g. the nuclear model

Evidence normalisation

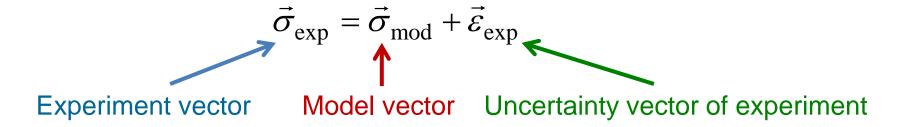


Evaluation Concept:



Standard Bayesian Evalution Techinque

Standard Evaluation:



Assumption: Model is perfect!

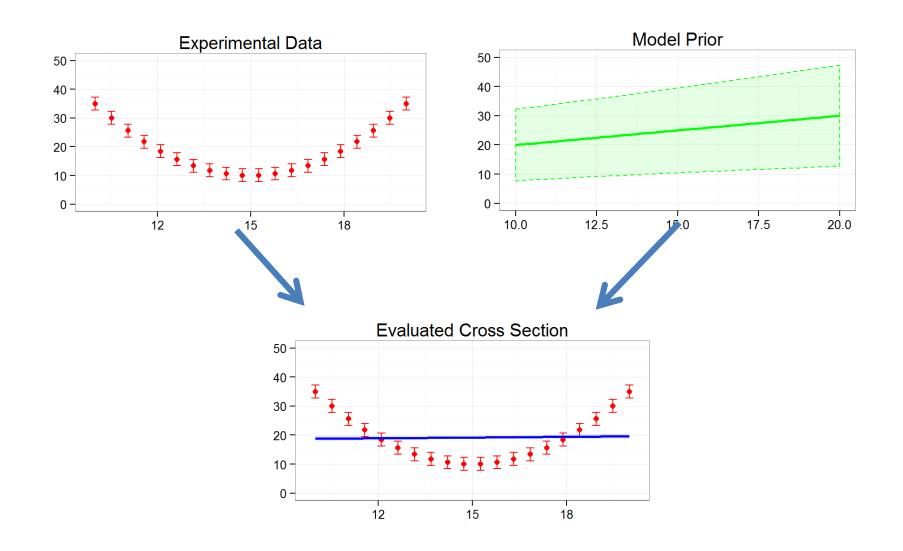
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A simple example:



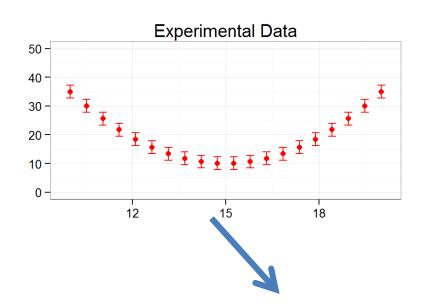
Evaluation without model defects...

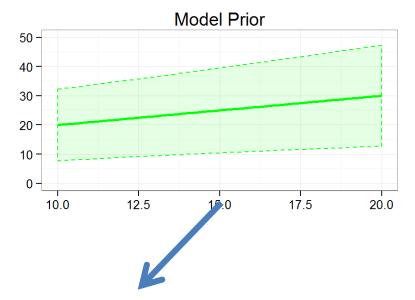


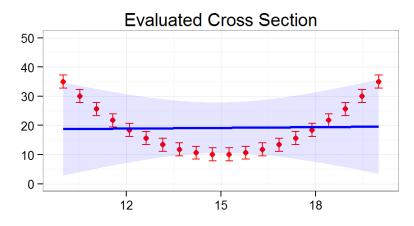




...and with model defects







8

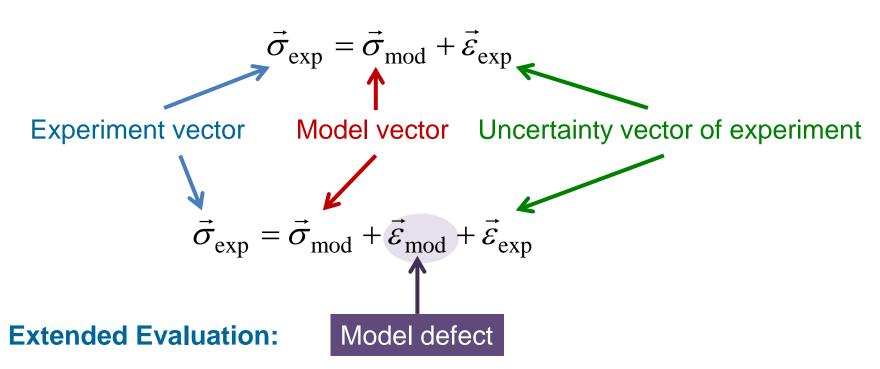


Evaluation Concept:



Statistically consistent Treatment of Model Defects

Standard Evaluation:



PhD thesis of Georg Schnabel (TU Wien, June 2015)

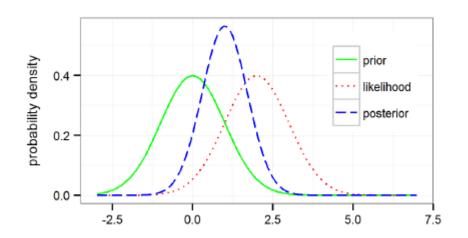


Normal Distributions



$$\rho(t) = \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2}(t - \langle t \rangle)^2\right]$$

 $\langle t \rangle$ mean value of the distribution



Generalisation: Multivariate normal distribution

$$\rho(\vec{t}) = \frac{1}{\sqrt{(2\pi)^d \|\mathbf{V}\|}} \exp\left[-\frac{1}{2}(\vec{t} - \langle \vec{t} \rangle)^T \mathbf{V}^{-1}(\vec{t} - \langle \vec{t} \rangle)\right] \qquad \qquad \vec{t} \sim N(\langle t \rangle, \mathbf{V})$$

$$p(t) \approx N(\langle t \rangle, \mathbf{V})$$

mean value $\langle t_i \rangle = \int dt_1 \cdots \int dt_d \ \rho(\vec{t}) \big(t_i - \langle t_i \rangle \big)$ covariance matrix $\mathbf{V} = \big(V_{i,j} \big) = \big(\int dt_1 \cdots \int dt_d \ \rho(\vec{t}) \big(t_i - \langle t_i \rangle \big) \big(t_j - \langle t_j \rangle \big)$



Multivariate Distributions and Bayesian Evaluation



Basic Assumptions:

$$\vec{\varepsilon}_{\text{exp}} \sim N(0, \mathbf{B})$$

$$\ell(\vec{\sigma}_{\text{exp}} \mid \vec{p}) \sim N(M(\vec{p}), \mathbf{B})$$

$$\pi(\vec{p}) \sim N(\vec{p}_{0}, \mathbf{A}_{0})$$

Multivariate normal distributions for experimental uncertainties, model parameters likelihood assumed

Bayesian Theorem

$$\log \pi (\vec{p} \mid \vec{\sigma}_{\exp}) = \log C + \log \ell (\vec{\sigma}_{\exp} \mid \vec{p}) + \log \pi (\vec{p})$$

$$= \log C - \frac{1}{2} (\vec{\sigma}_{\exp} - M(\vec{p}))^T \mathbf{B}^{-1} (\vec{\sigma}_{\exp} - M(\vec{p}))$$

$$- \frac{1}{2} (\vec{p} - \vec{p}_0)^T \mathbf{A}_0^{-1} (\vec{p} - \vec{p}_0)$$



Bayesian Update including model defects



Basic Assumptions:

$$\vec{\varepsilon}_{\text{exp}} \sim N(0, \mathbf{B})$$

$$\ell(\vec{\sigma}_{\text{exp}} \mid \vec{p}, \vec{\varepsilon}_{\text{mod}}) \sim N(M(\vec{p}) + \vec{\varepsilon}_{\text{mod}}, \mathbf{B})$$

 $\pi(\vec{p}) \sim N(\vec{p}_0, \mathbf{A}_0), \quad \pi(\vec{\varepsilon}_{\text{mod}}) = N(\vec{0}, \mathbf{K}_0)$

normal distributions for experimental uncertainties, model parameters likelihood assumed

a-priori independence of model parameters and model deficiency assumed

$$\log \pi \left(\vec{p} \vec{\varepsilon}_{\text{mod}} \mid \vec{\sigma}_{\text{exp}} \right) = \log \tilde{C} + \log \ell \left(\vec{\sigma}_{\text{exp}} \mid \vec{p} \vec{\varepsilon}_{\text{mod}} \right) + \log \pi \left(\vec{p} \right) + \log \pi \left(\vec{\varepsilon}_{\text{mod}} \right)$$

$$= \log \tilde{C} - \frac{1}{2} \left(\vec{\sigma}_{\text{exp}} - M \left(\vec{p} \right) - \vec{\varepsilon}_{\text{mod}} \right)^{T} \mathbf{B}^{-1} \left(\vec{\sigma}_{\text{exp}} - M \left(\vec{p} \right) - \vec{\varepsilon}_{\text{mod}} \right)$$

$$- \frac{1}{2} \left(\vec{p} - \vec{p}_{0} \right)^{T} \mathbf{A}_{0}^{-1} \left(\vec{p} - \vec{p}_{0} \right)$$

$$- \frac{1}{2} \left(\vec{\varepsilon}_{\text{mod}} \right)^{T} \mathbf{K}_{0}^{-1} \left(\vec{\varepsilon}_{\text{mod}} \right)$$

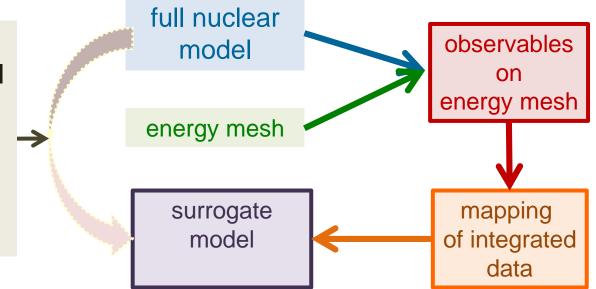


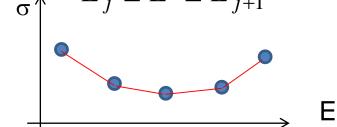
Surrogate Model: Mapping of Integrated Data



Main properties of nuclear model are transferred

- dominating eigenvalues
- summation properties





- value of observable at mesh point
- surrogate model



Overview of Model Defect Treatment



Up to now:

 Model defects formulated as Gaussian processes for cross sections smooth in energy

$$\mathbf{K}_{0}(E_{i}, E_{j}) = \sigma_{M}(E_{i})\sigma_{M}(E_{j}) \delta_{1}^{2} \cdot \exp \left[-\frac{1}{2\lambda_{1}^{2}} \left(E_{i} - E_{j}\right)^{2}\right]$$

Modell defects of angle-differential cross sections

But: This covariance matrix cannot be applied to the resonance regime





Setup:

- R-matrix example of n-¹⁶₈0 scattering up to 2.5 MeV
- Single channel R-matrix in three partial waves

$$R^{J\pi}(E) = \frac{{\gamma_{\lambda}}^2}{E_{\lambda} - E}$$

with parameters

J^{π}	E_{λ} [MeV]	γ _λ [MeV]
1/2+	0.70	0.20
3/2+	1.20	0.40
5/2-	2.00	0.30





Generation of experimental data

Applying an energy dependent deviation function to calculated data

$$d(E) = \alpha_d \cdot \frac{d\sigma_{calc}(E)}{dE}(E)$$

Experimental data are given by

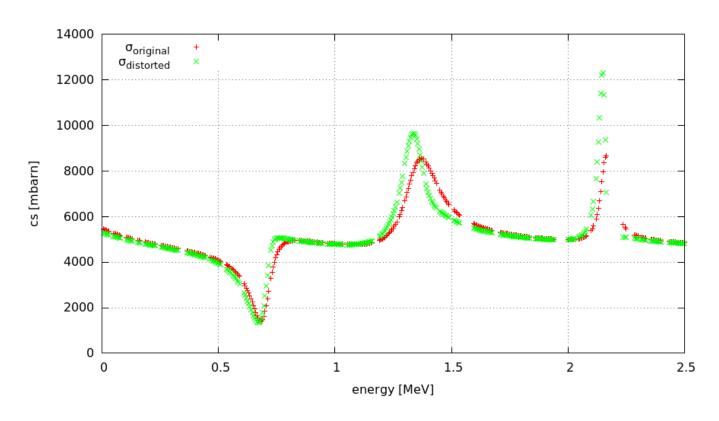
$$\sigma_{\text{exp}}(E) = [1 + d(E)]\sigma_{calc}(E)$$

on a grid of M energy points $(E_1, E_2, ..., E_M)$.





Comparison of calculated data and experimental data with $\alpha_d = 7 \times 10^{-6}$







The experimental data are fitted to get a best model parameter set

J^{π}	E_{λ} [MeV]	γ [MeV]
1/2+	0.686997	0.202074
3/2+	1.171064	0.383547
5/2-	1.933526	0.338253

• From these parameters $\sigma_M(E)$ is calculated on a N-point energy mesh, which contains the experimental grid as a subset





Calculation of the Prior

- The six best parameters $(E_1, \gamma_1, E_2, \gamma_2, E_3, \gamma_3)$ are varied n=200 times according to a normal distribution with $\sigma = 0.1$
- With each parameter set, a vector \vec{x}_k with k=1,...,n is calculated
- The prior covarinace matrix is given by

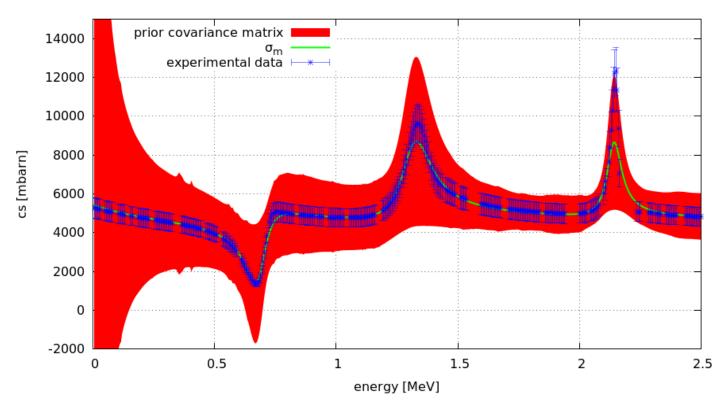
$$\mathbf{A}_0 = \frac{1}{N} \mathbf{U} \mathbf{U}^T$$

with
$$\mathbf{U} = (\vec{u}_1, \vec{u}_2, ..., \vec{u}_N)$$
 and $\vec{u}_k = \vec{x}_k - \vec{\sigma}_M$





Best parameter cross section with Prior A_0



All experimental points are contained in error band $\sqrt{A_0(E_i, E_i)}$

20





Prior covariance matrix of experimental data

• For the experimental data we assume a statistical errror ε_S =0.1 and a normalisation error ε_N =0.05

$$\sigma_{\text{exp}}(E_i) = (1 + \varepsilon_N) \sigma_i^{\text{exp}} N(1, \varepsilon_s)$$

with the normal distribution $N(1, \varepsilon_s)$

This leads to a prior covariance matrix

$$\mathbf{B} = \begin{pmatrix} (\sigma_{1}^{\text{exp}})^{2} [\varepsilon_{s}^{2} + \varepsilon_{N}^{2}] & \sigma_{1}^{\text{exp}} \sigma_{2}^{\text{exp}} \varepsilon_{N}^{2} & \cdots & \sigma_{1}^{\text{exp}} \sigma_{M}^{\text{exp}} \varepsilon_{N}^{2} \\ \sigma_{2}^{\text{exp}} \sigma_{1}^{\text{exp}} \varepsilon_{N}^{2} & (\sigma_{2}^{\text{exp}})^{2} [\varepsilon_{s}^{2} + \varepsilon_{N}^{2}] & \cdots & \sigma_{2}^{\text{exp}} \sigma_{M}^{\text{exp}} \varepsilon_{N}^{2} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{M}^{\text{exp}} \sigma_{1}^{\text{exp}} \varepsilon_{N}^{2} & \sigma_{M}^{\text{exp}} \sigma_{2}^{\text{exp}} \varepsilon_{N}^{2} & \cdots & (\sigma_{M}^{\text{exp}})^{2} [\varepsilon_{s}^{2} + \varepsilon_{N}^{2}] \end{pmatrix}$$





Including model error

$$\vec{\varepsilon}_{\text{mod}} \sim N(\vec{0}, \mathbf{K}_0)$$

Covariance matrix for the model error

$$\mathbf{K}_{0}(E_{i}, E_{j}) = \sigma_{M}(E_{i})\sigma_{M}(E_{j}) \, \delta_{1}^{2} \cdot \exp\left[-\frac{1}{2\lambda_{1}^{2}}\left(E_{i} - E_{j}\right)^{2}\right]$$

$$+\delta_{2}^{2} \cdot \alpha \frac{d\sigma_{M}}{dE}(E_{i}) \cdot \alpha \frac{d\sigma_{M}}{dE}(E_{j}) \cdot \exp\left[-\frac{1}{2\lambda_{2}^{2}}\left(E_{i} - E_{j}\right)^{2}\right]$$

δ_1	δ_{2}	α	λ_1	λ_{2}
0.05	1.5	0.22	0.5	0.1



Linearized Bayesian Update including model error



Using multivariate normal distributions allows linearization of Bayesian Theorem for update:

$$\vec{\sigma}_{1} = \vec{\sigma}_{0} + \mathbf{A}_{0}\mathbf{S}^{T} \left(\mathbf{S}\mathbf{A}_{0}\mathbf{S}^{T} + \mathbf{S}\mathbf{K}_{0}\mathbf{S}^{T} + \mathbf{B}\right)^{-1} \left(\vec{\sigma}_{\exp} - \mathbf{S}\vec{\sigma}_{M}\right)$$

$$\vec{\varepsilon}_{1} = \mathbf{K}_{0}\mathbf{S}^{T} \left(\mathbf{S}\mathbf{A}_{0}\mathbf{S}^{T} + \mathbf{S}\mathbf{K}_{0}\mathbf{S}^{T} + \mathbf{B}\right)^{-1} \left(\vec{\sigma}_{\exp} - \mathbf{S}\vec{\sigma}_{M}\right)$$

$$\mathbf{A}_{1} = \mathbf{A}_{0} - \mathbf{A}_{0}\mathbf{S}^{T} \left(\mathbf{S}\mathbf{A}_{0}\mathbf{S}^{T} + \mathbf{S}\mathbf{K}_{0}\mathbf{S}^{T} + \mathbf{B}\right)^{-1}\mathbf{S}\mathbf{A}_{0}$$

$$\mathbf{K}_{1} = \mathbf{K}_{0} - \mathbf{K}_{0}\mathbf{S}^{T} \left(\mathbf{S}\mathbf{A}_{0}\mathbf{S}^{T} + \mathbf{S}\mathbf{K}_{0}\mathbf{S}^{T} + \mathbf{B}\right)^{-1}\mathbf{S}\mathbf{K}_{0}$$



Linearized Bayesian Update including model error



We get the best estimate for the cross section

$$\vec{\sigma}_{true} = \vec{\sigma}_1 + \vec{\varepsilon}_1$$

and its covariance matrix

$$\mathbf{U}_{1} = \mathbf{U}_{0} - \mathbf{C}_{0} \left(\mathbf{S} \mathbf{A}_{0} \mathbf{S}^{T} + \mathbf{S} \mathbf{K}_{0} \mathbf{S}^{T} + \mathbf{B} \right)^{-1} \mathbf{C}_{0}^{T}$$

$$\mathbf{U}_0 = \mathbf{S}\mathbf{A}_0\mathbf{S}^T + \mathbf{K}_0$$

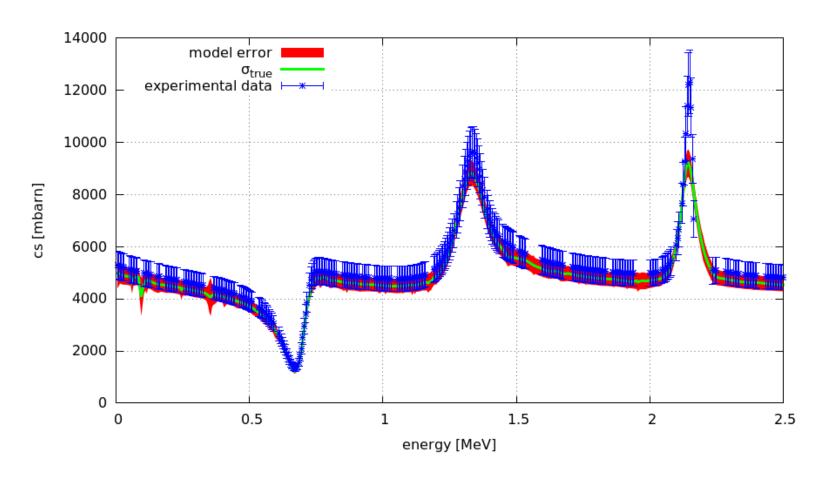
$$\mathbf{C}_0 = \mathbf{A}_0 \mathbf{S}^T + \mathbf{K}_0 \mathbf{S}^T$$







Updated cross section without including model defects

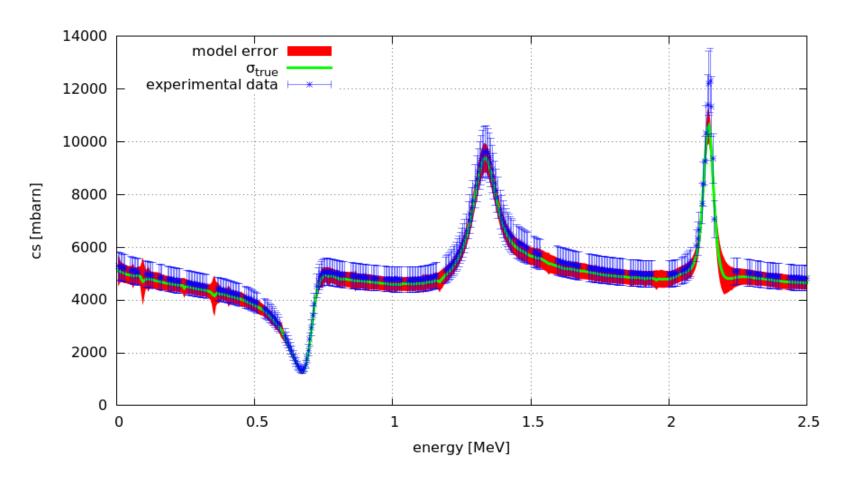








"True" cross section with model defects

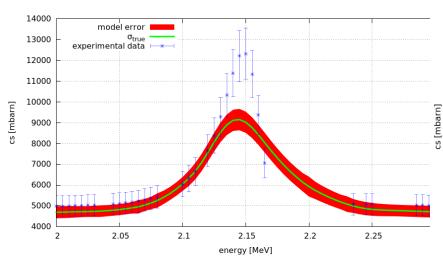


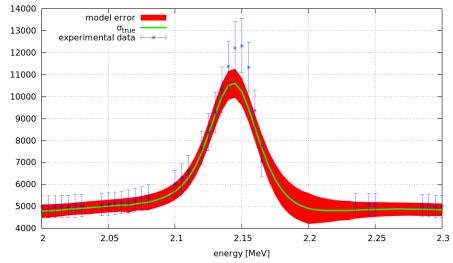






Without model defects - With model defects



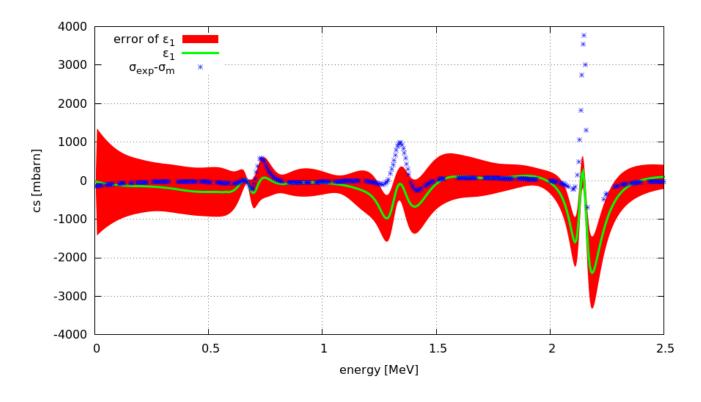








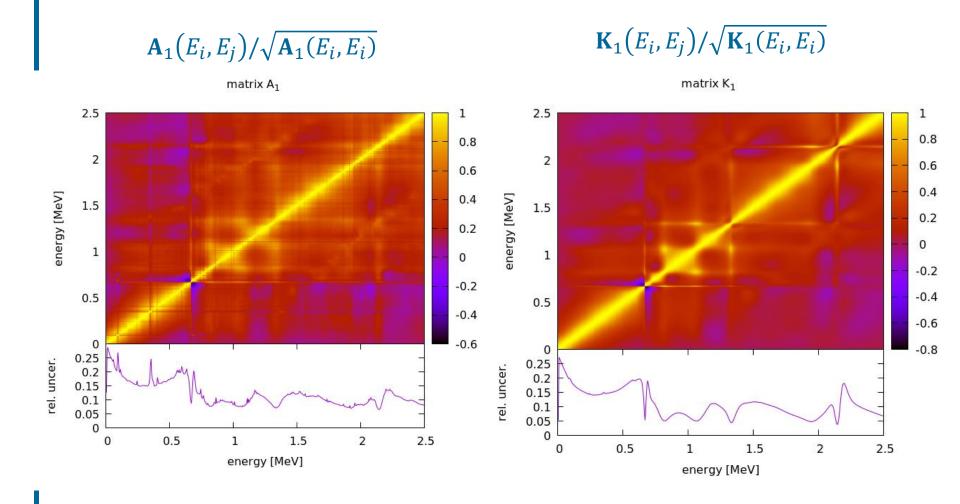
The model error – a comparison







Correlation matrices



29

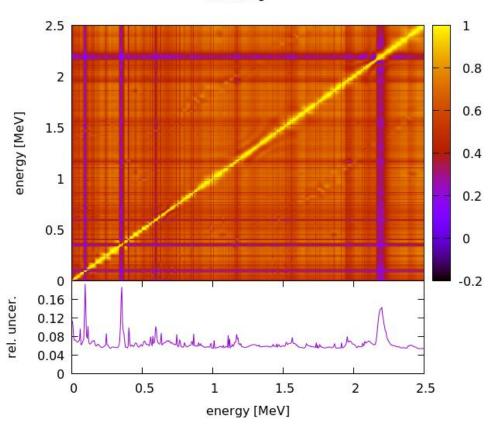




Correlation matrices









Summary and Conclusions



- We proposed a prior covariance matrix for the model error in the resonance regime for the first time.
- This is one possible form (but not the only one).
- Makes it possible to perform an evaluation with model defects for the total energy range up to 200 MeV including resonances at lower energies.
- The magnitude of the model error can explicitly be estimated.





Thank you for your attention