60 Years

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Bayesian network evaluation at the example of neutron-induced cross sections of Fe-56

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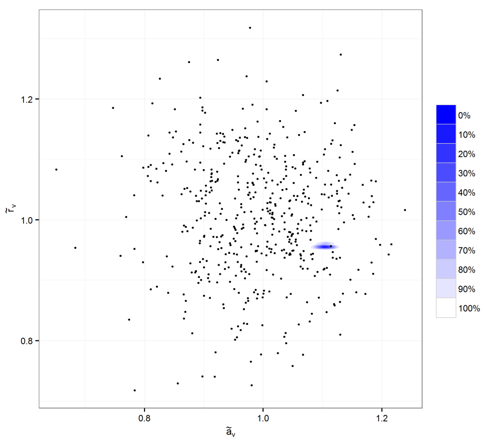
Outline

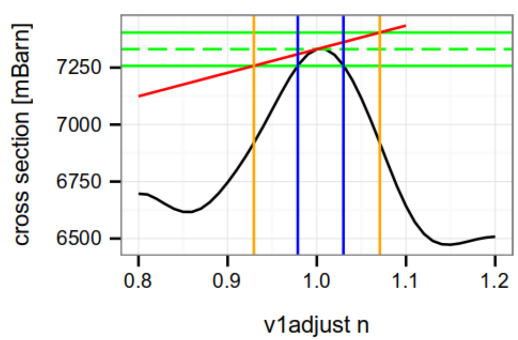
- Some words on Bayesian statistics
- Modeling options with Gaussian processes
- Bayesian networks
- Some words on example Fe-56 evaluation

Bayesian inference

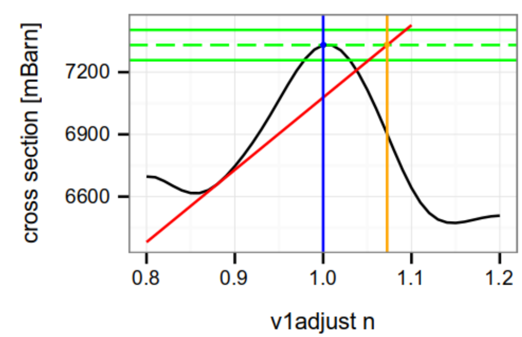
$$\pi(\vec{p}_{\mathrm{true}} \,|\, \vec{\sigma}_{\mathrm{exp}}, M) \propto f(\vec{\sigma}_{\mathrm{exp}} \,|\, \vec{p}_{\mathrm{true}}, M)\pi(\vec{p}_{\mathrm{true}} \,|\, M)$$



Monte Carlo



Optimization



GLS (sens.based)

Some ways to apply Gaussian processes

- Model defects[1] $\sigma_{\text{exp}} = f(\vec{p}) + \varepsilon_{\text{def}} + \varepsilon_{\text{exp}}$

$$\pi(\vec{p}, \varepsilon_{\text{def}}, \varepsilon_{\text{exp}} \,|\, \sigma_{\text{exp}}) \propto \pi(\sigma_{\text{exp}} \,|\, \vec{p}, \varepsilon_{\text{def}}, \varepsilon_{\text{exp}}) \pi(\vec{p})\, \pi(\varepsilon_{\text{def}})\, \pi(\varepsilon_{\text{exp}})$$

- Parameter modulation functions[2]

$$\sigma_{\text{exp}} = f(\vec{p}(E) + \vec{\varepsilon}_{\text{par}}(E)) + \varepsilon_{\text{exp}}$$

- Inconsistent experimental data[3]

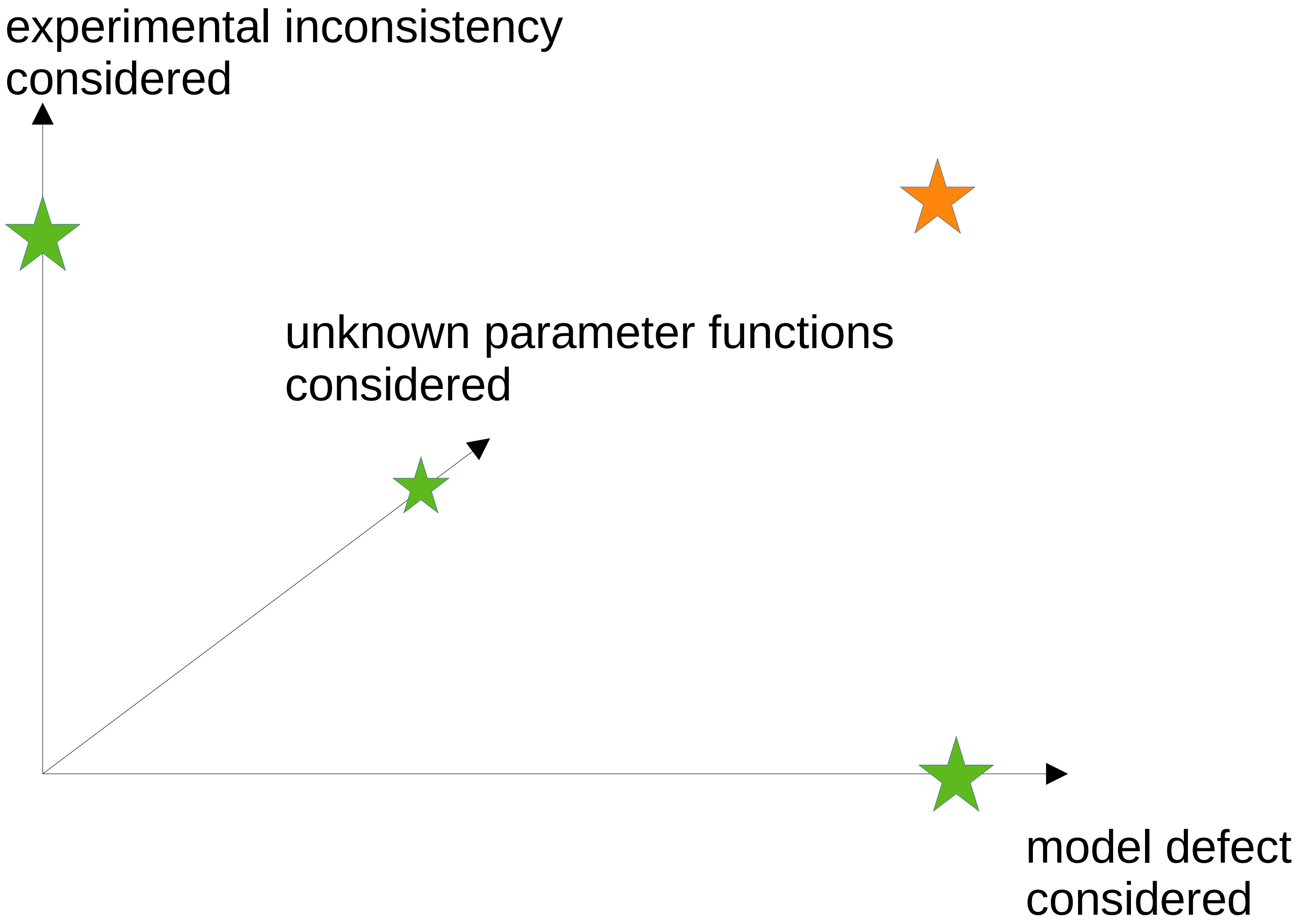
$$\sigma_{\text{exp}} = f(\vec{p}) + \varepsilon_{\text{exp}} + \varepsilon_{\text{usu}}$$

- Evaluations purely based on GPs[4]

Examples:

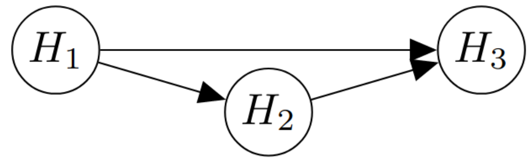
1) M.T. Pigni, H. Leeb, “Uncertainty Estimates of Evaluated 56Fe Cross Sections Based on Extensive Modelling at Energies Beyond 20 MeV”, Proc. Int. Workshop on Nuclear Data for the Transmutation of Nuclear Waste, 2003
2) P. Helgesson, H. Sjöstrand, “Treating model defects by fitting smoothly varying model parameters: Energy dependence in nuclear data evaluation”, Annals of Nuclear Energy, 2017
3) G. Schnabel, “Fitting and Analysis Technique for Inconsistent Nuclear Data”, M&C 2017
4) H. Iwamoto, “Generation of nuclear data using Gaussian process regression”, Journal of Nuclear Science & Technology, 2020

Exploring the possibility landscape

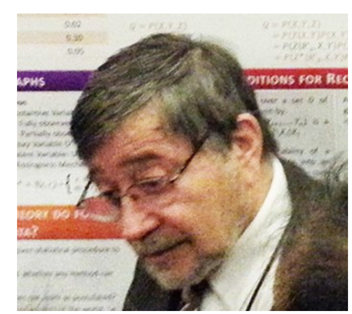


Bayesian networks

$$P(H_1, H_2, H_3) = P(H_1)P(H_2 \mid H_1)P(H_3 \mid H_1, H_2)$$



… build models by composing simple building blocks
… similar to how it is done for neural networks



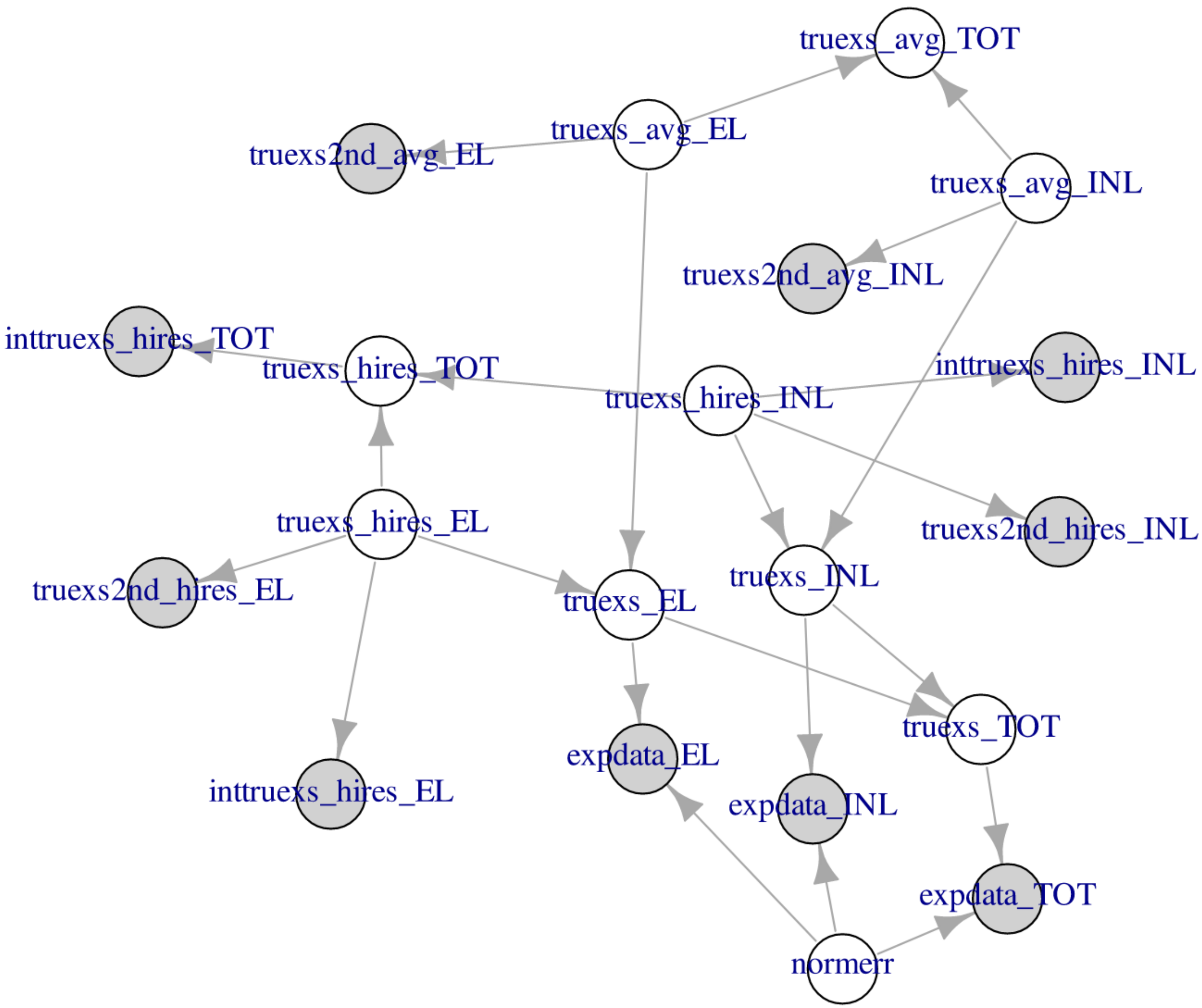
Judea Pearl*

* Image credit: Better Than Bacon – Judea Pearl at NIPS 2013

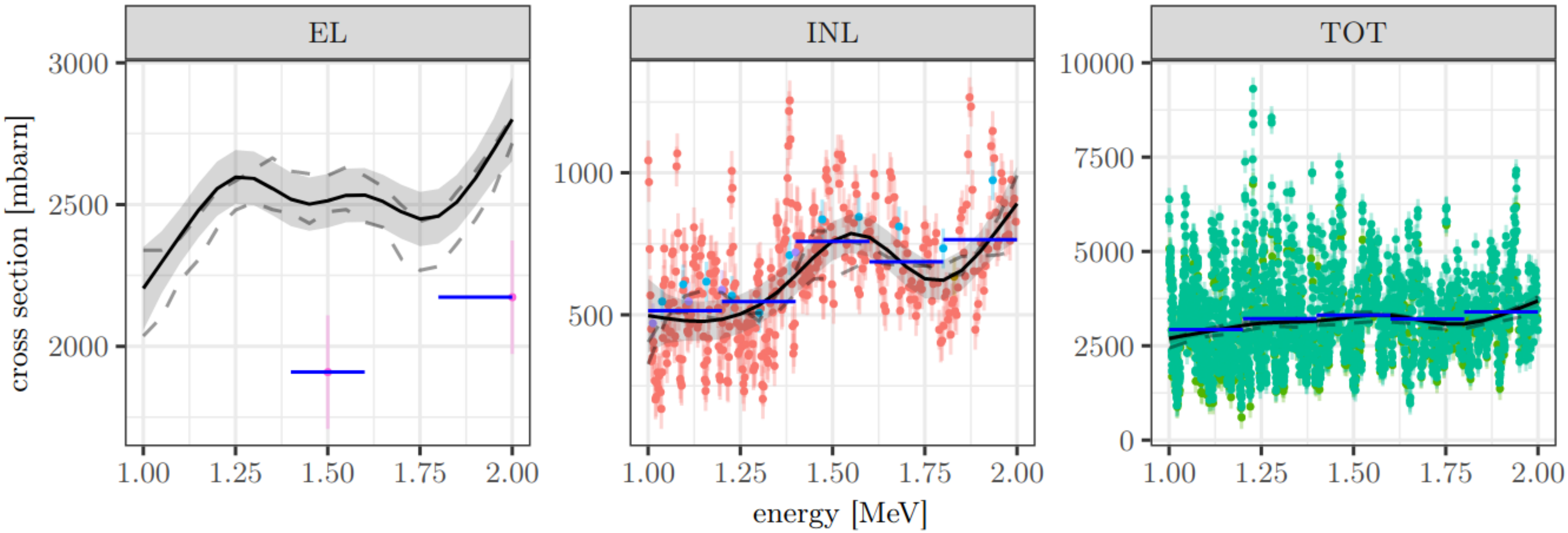
Fe-56 between 1 keV and 2 MeV

- Each channel xs is transformed sum of two GPs: average and high-freq component
- The transformation is given by a truncation (ReLU)
- The sum of average channel GPs gives average of (transformed) total xs
- The sum of high-freq channel GPs gives high-freq behavior of (transformed) total xs
- Folded channel xs (energy resolution) give experimental measurements up to normalization error

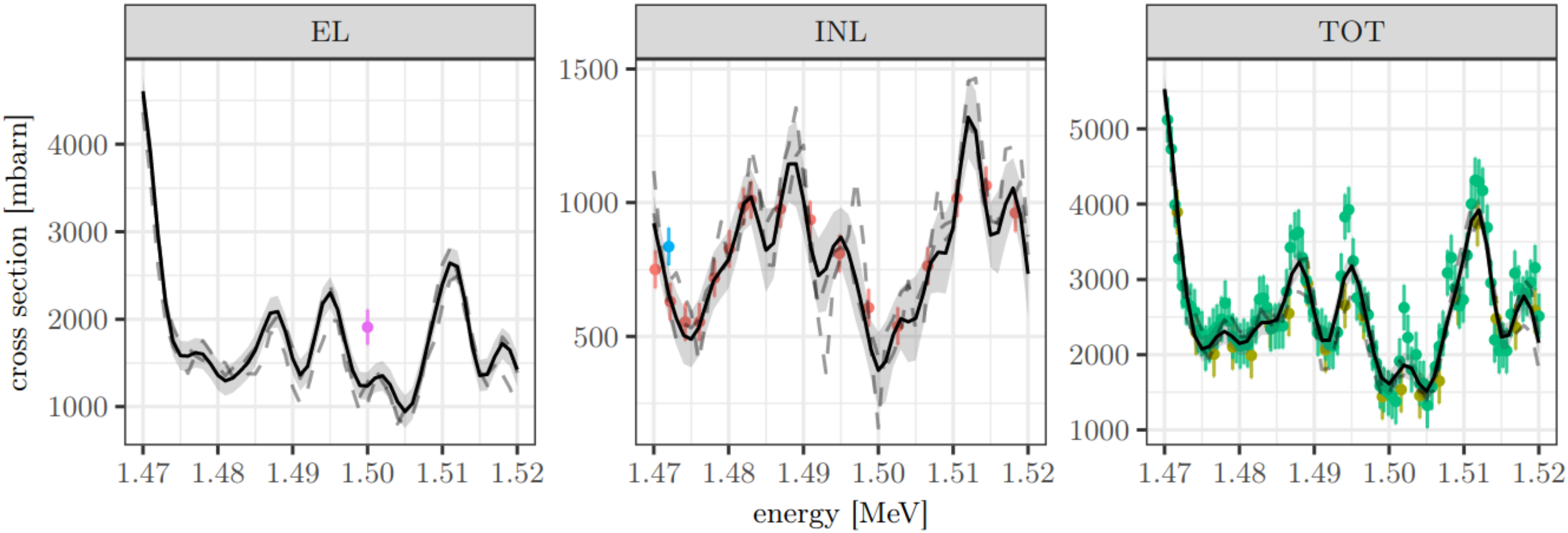
Bayesian network



Some results (average components)



Some results
(high-freq components)



Conclusions

- Bayesian networks are a powerful abstraction to build complex models using simple building blocks
- GPs can be used within Bayesian networks to represent unknown parameter functions, model defects or deal with inconsistent data
- Example evaluation for Fe-56 based on GPs, preserving sum rules and non-negative cross sections
- Mathematical details and two more examples (e.g., with model code TALYS and model defects) in:

  “Nuclear data evaluation with Bayesian networks”, arXiv:2110.10322

  GitHub repo: github.com/IAEA-NDS/nucdataBaynet