SAND2021-13859C

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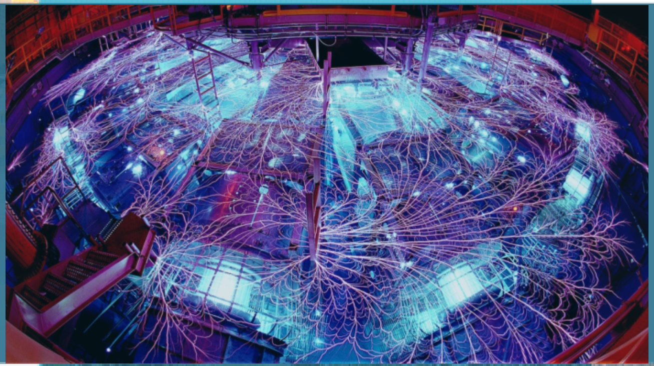
Bayesian Methods in Inertial Confinement Fusion Research: Embracing uncertainty and Learning More from our Data



Patrick F. Knapp

63rd Annual Meeting of the APS Division of Plasma Physics

Wednesday November 10, 2021

Pittsburgh, PA

U.S. DEPARTMENT OF ENERGY NNSA National Nuclear Security Administration

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Thanks to my many colleagues and contributors

[1]M.E. Glinsky, [1]W.E. Lewis, [1]M. A. Schaeuble, [1]C. A. Jennings, [1]E. C. Harding, [1]S. B. Hansen, [2]J. Gunning, [3]R. Joseph, [3]C.F.J. Wu, K. [1]Maupin, [1]A. J. Harvey-Thompson, [1]M. R. Gomez, [1]M. R. Weis, [1]P. F. Schmit, [1]D. E. Ruiz, [1]D. J. Ampleford, [5]M. Evans, [1]M. Geissel, [6]Shailaja Humane, [1]G.A. Chandler, [1,4]G. Cooper, [1]S. A. Slutz, [1]I.C. Smith, [1]T. J. Awe, K. Beckwith, [1]D. B. Sinars, [1]M. E. Cuneo, [1]M. Jones, [1]J. L. Porter, [1]G. A. Rochau, [1]K. J. Peterson, [1]T.R. Mattsson, [1]M. K. Matzen,[1] ***and many more…***

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[3]School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta,GA

[4]Nuclear Engineering Department, University of New Mexico, Albuquerque, NM

[5]Department of Physics and Astronomy, University of Rochester, Rochester, NY

[6]Nuclear Engineering & Radiological Sciences Department, University of Michigan, Ann Arbor, MI

Bayes' theorem provides us with a way to extract information from data with rigorously quantified uncertainties

$$\mathcal{P}(\overline{\mathbf{m}}|\overline{\mathbf{x}}, A)\mathcal{P}(\overline{\mathbf{x}}|A) = \mathcal{P}(\overline{\mathbf{x}}|\overline{\mathbf{m}}, A)\mathcal{P}(\overline{\mathbf{m}}|A)$$

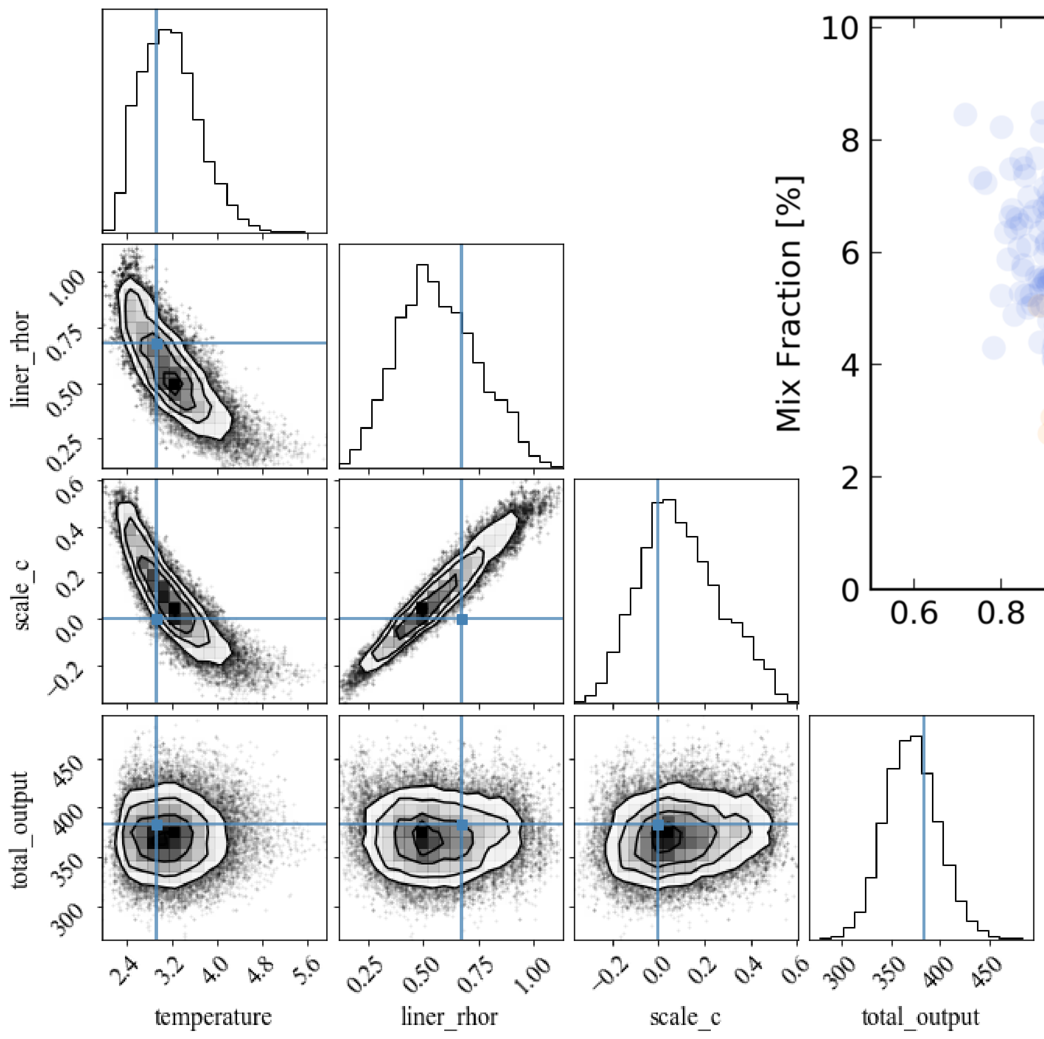
Likelihood: How well does a set of model parameters match the available data?

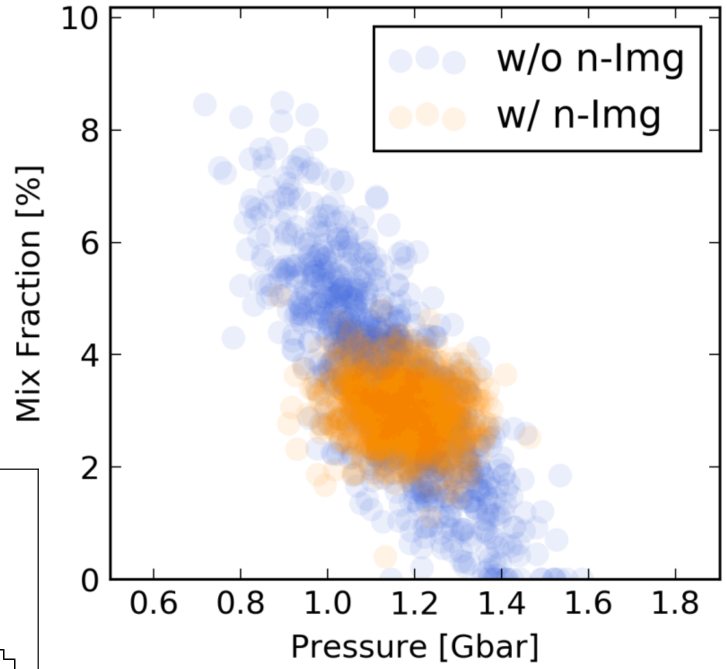
$$\boxed{\mathcal{P}(\overline{\mathbf{m}}|\overline{\mathbf{x}}, A)} = \frac{\boxed{\mathcal{P}(\overline{\mathbf{x}}|\overline{\mathbf{m}}, A)}\boxed{\mathcal{P}(\overline{\mathbf{m}}|A)}}{\mathcal{P}(\overline{\mathbf{x}}|A)}$$

Posterior (AKA the answer)

Prior: AKA the stuff we already know (e.g. pressure and temperature must be positive.)

The posterior distribution is much more than a point estimate of the parameters of interest





The full distribution provides estimates of the mean/median of various model parameters

Credible intervals

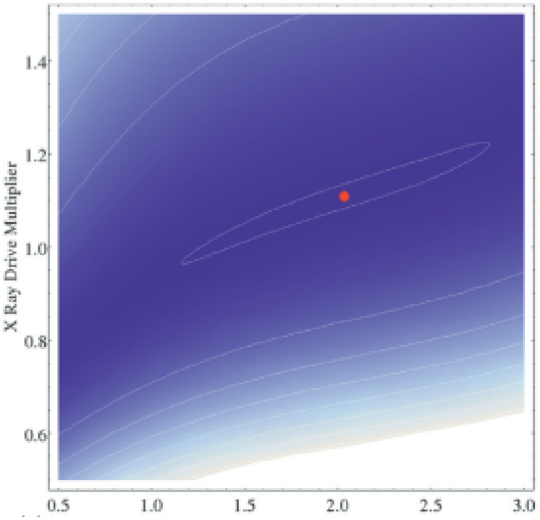
Correlations between parameters

Assess the information content contained in the posterior to

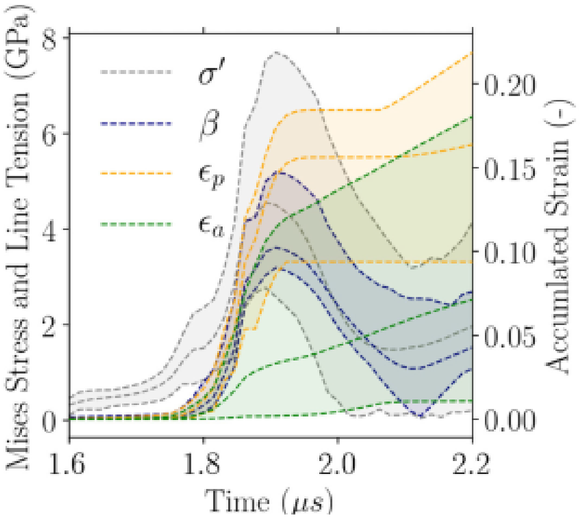
- Evaluate addition of new information
- Determine sensitivity to noise, calibration, model uncertainty, etc.

There are a wide variety of efforts in HED and ICF to exploit the power of Bayesian methods to better understand our data and models

Model Calibration



Gaffney et al. Nucl. Fusion 53 (2013)



S. Ali et al. J. Appl. Phys. 130, 055901 (2021)

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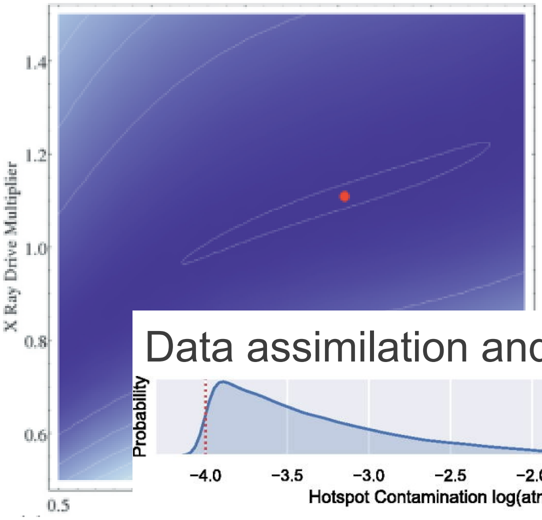

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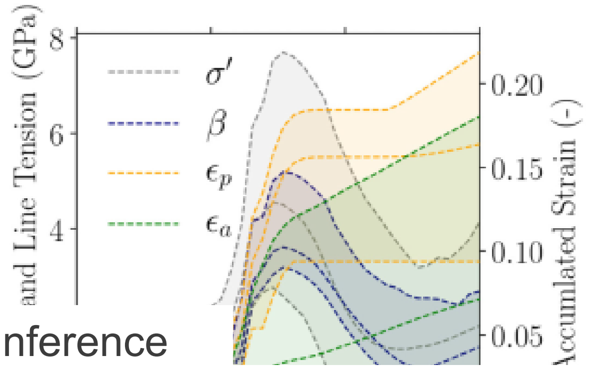
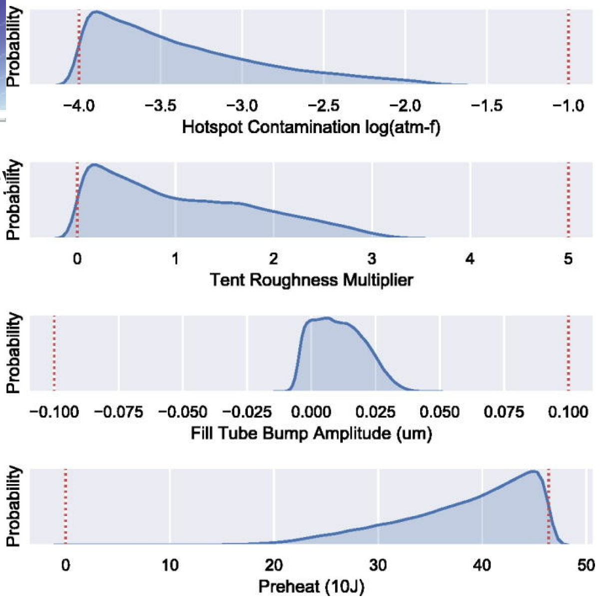
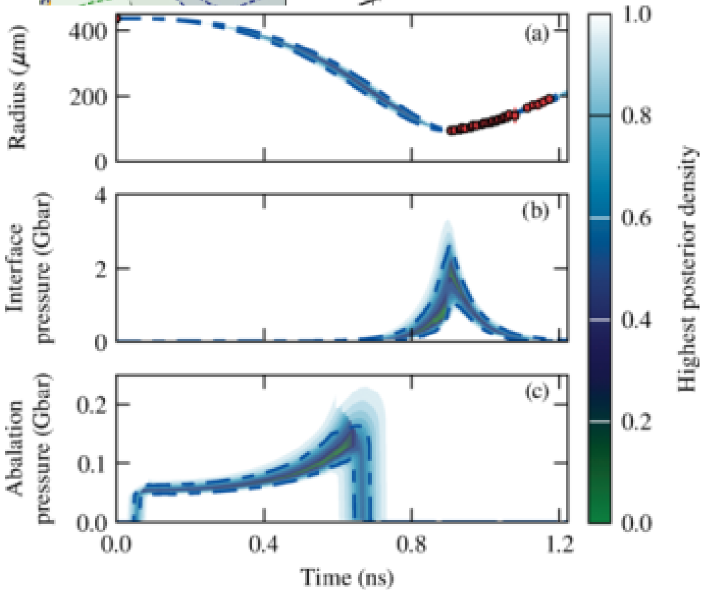
(2013)



Data assimilation and inference



Gaffney et al., *Physics of Plasmas* **26,** 082704 (2019)



JJ Ruby et al., *Phy. Rev. Letters* **125,** 215001 (2020)

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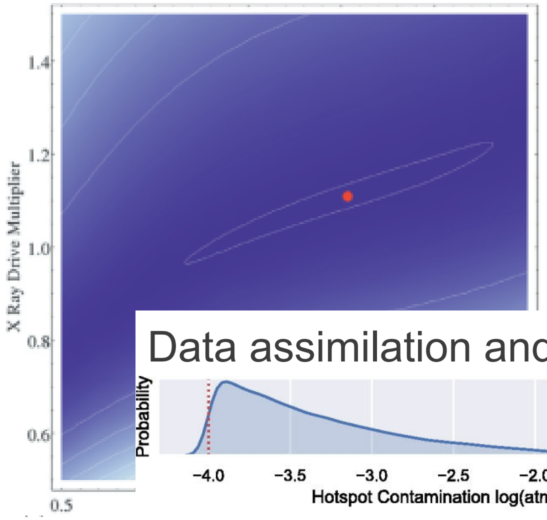

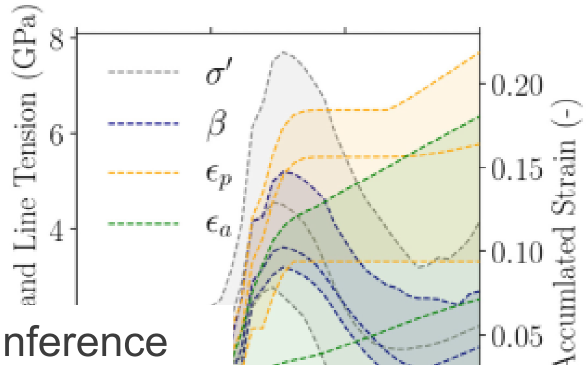

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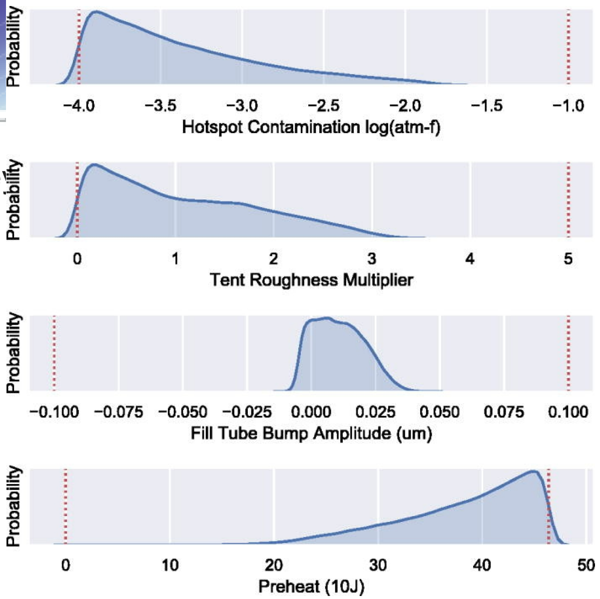

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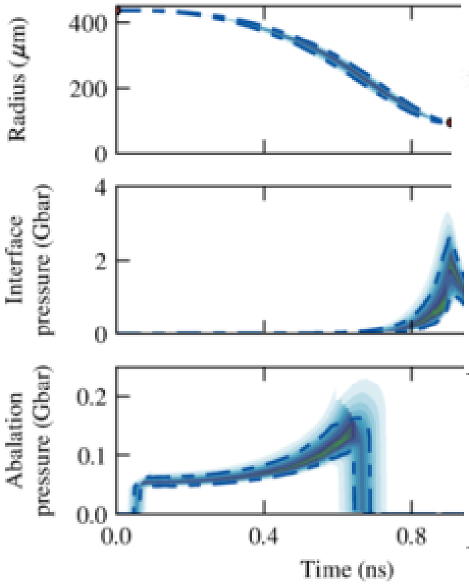

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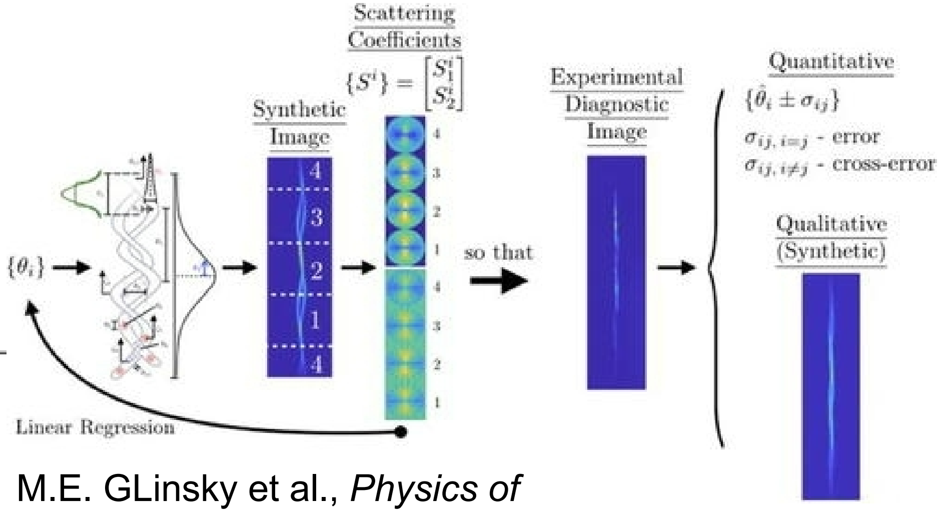
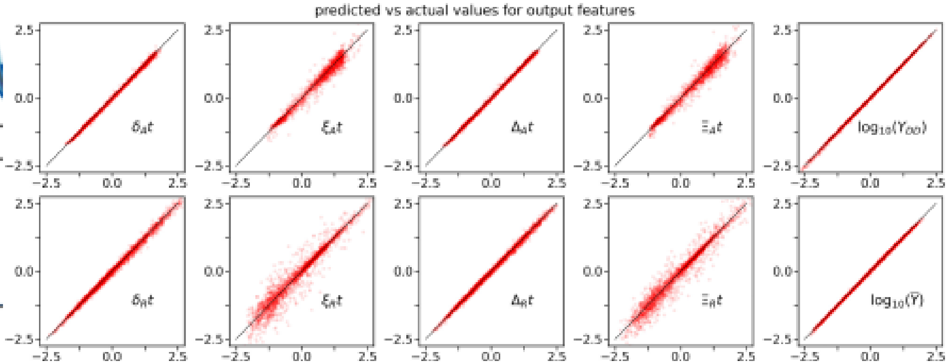
Bayesian Surrogate Modeling



M.E. GLinsky et al., *Physics of Plasmas* **27,** 112703 (2020)



W.E. Lewis et al., *Physics of Plasmas* **28,** 092701 (2021)

…And many more!

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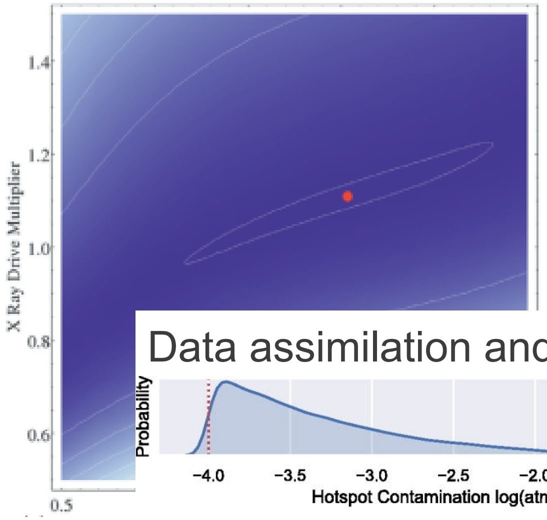

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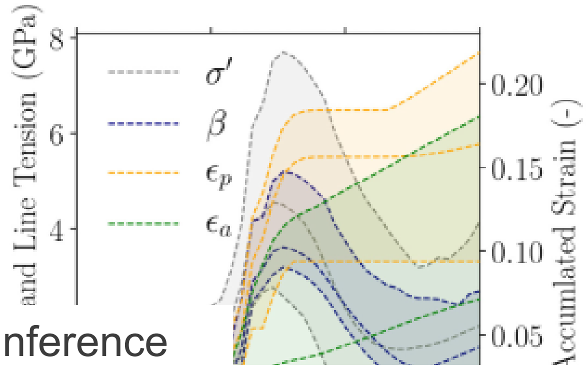

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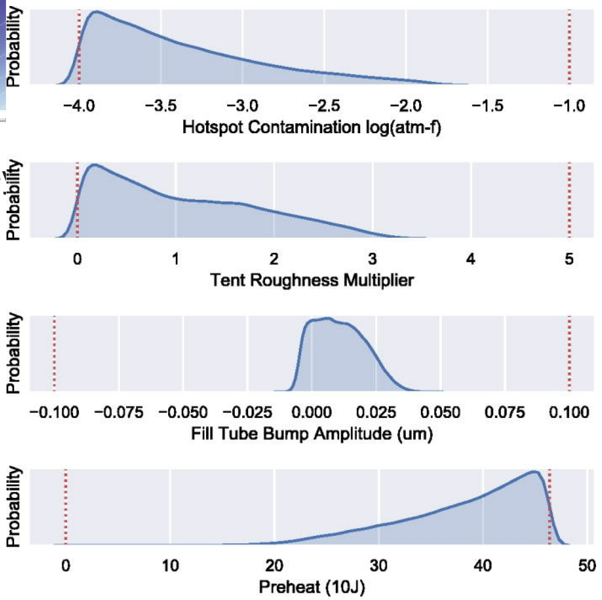

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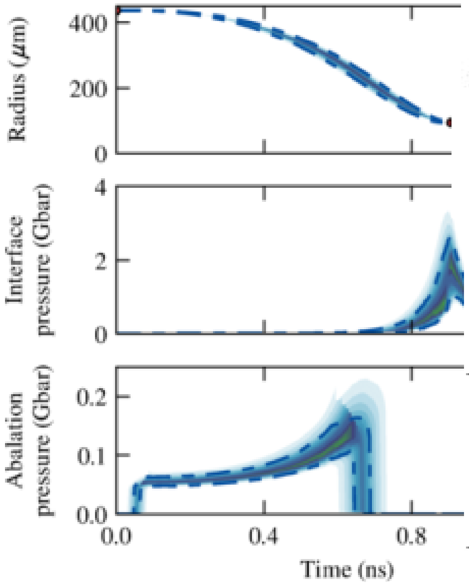

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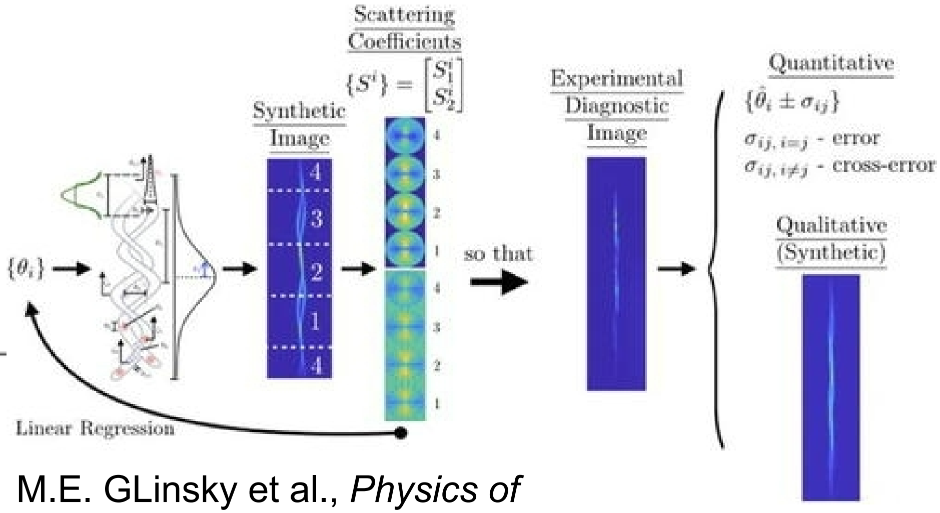

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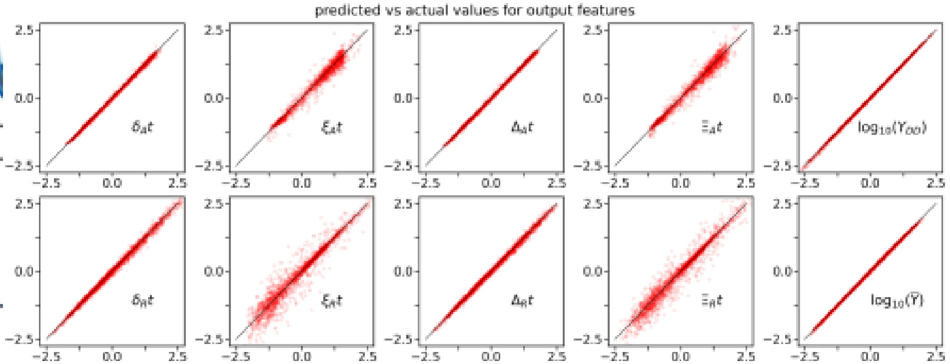

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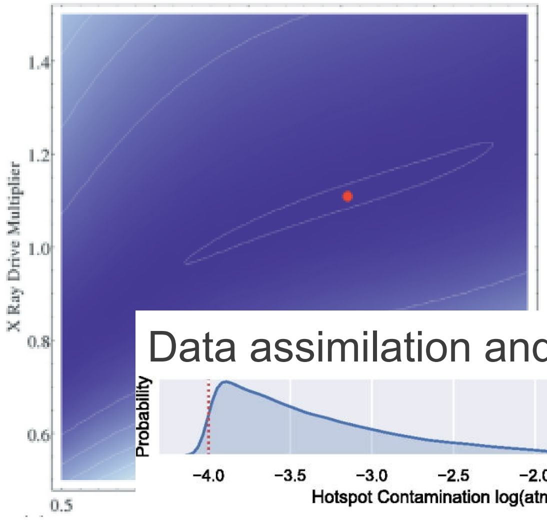

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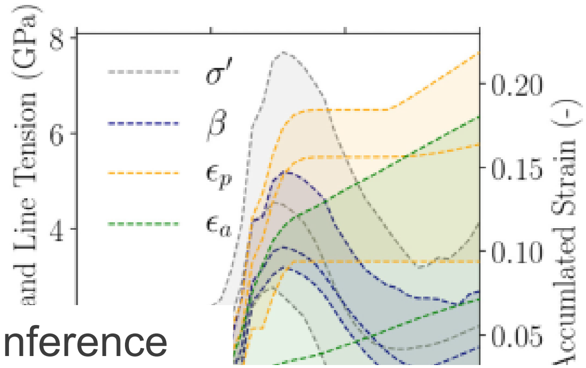

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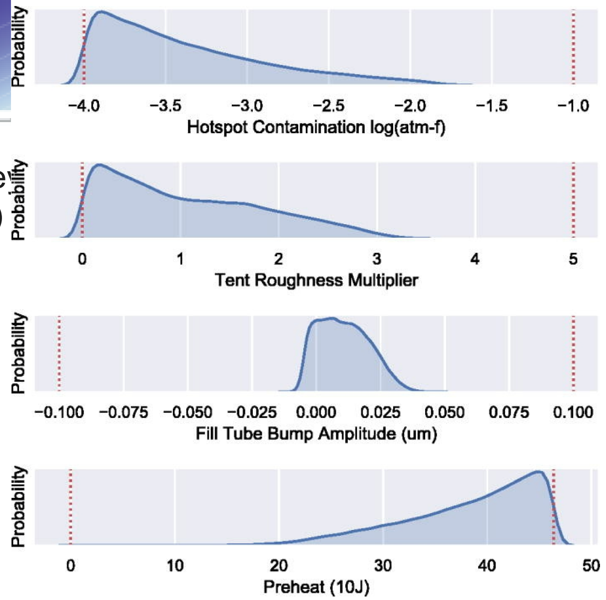

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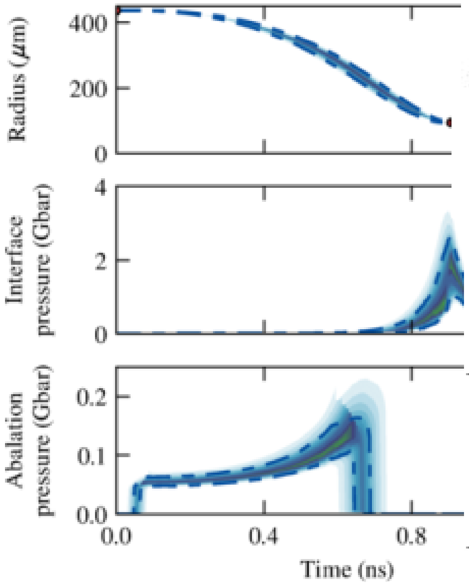

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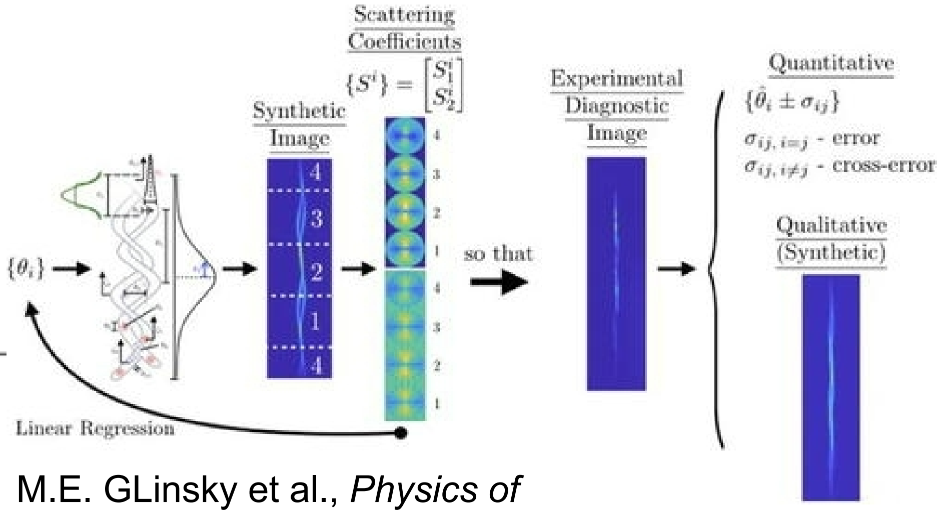

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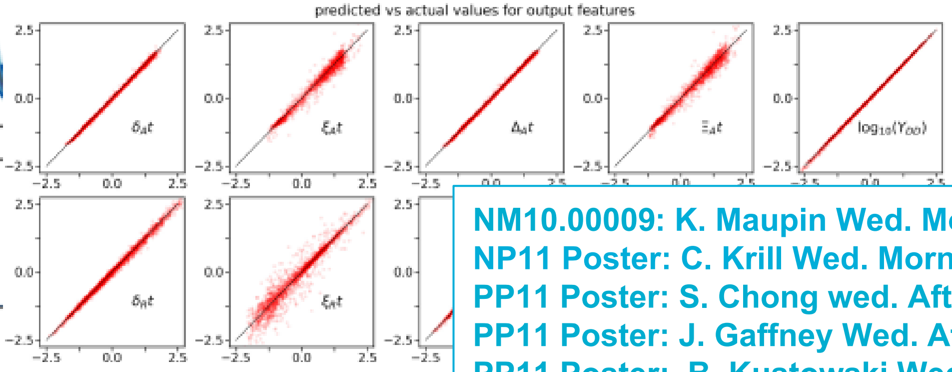


W.E. Lewis et al., *Physic* *Plasmas* **28,** 092701 (2

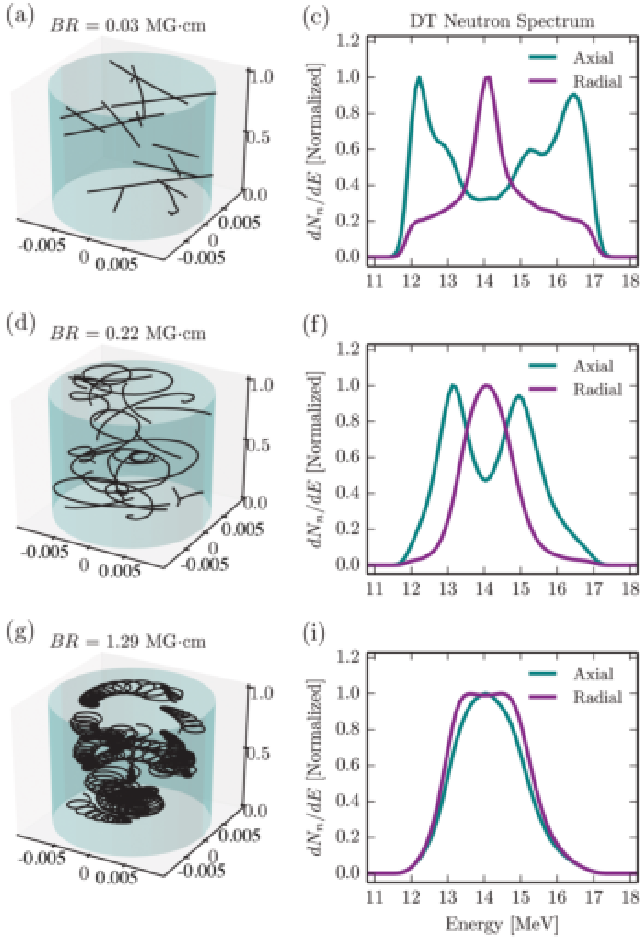
NM10.00009: K. Maupin Wed. Morning
NP11 Poster: C. Krill Wed. Morning
PP11 Poster: S. Chong wed. Afternoon
PP11 Poster: J. Gaffney Wed. Afternoon
PP11 Poster: B. Kustowski Wed. Afternoon
TO07.00007: J. Gaffney Thurs. Morning
TO07.00009: J.L. Peterson Thurs. Morning
…And many more

Bayesian methods can be applied to a variety of tasks in the physical sciences to greatly improve how well we use the available information

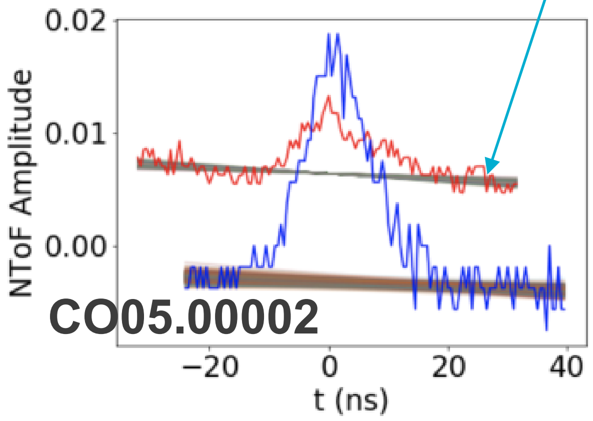
- **Automated feature extraction**
  - reduce raw data to useful quantities with quantified uncertainties
- **Data Assimilation**
  - Combine experimental data from disparate sources for a self-consistent description of the processes under study
  - Mathematically rigorous uncertainties propagated from all sources (model, experiment, surrogate, etc.)
- **Experiment design and optimization**
  - Utilize the full posterior to guide the design of instruments and experiments to maximize information gain

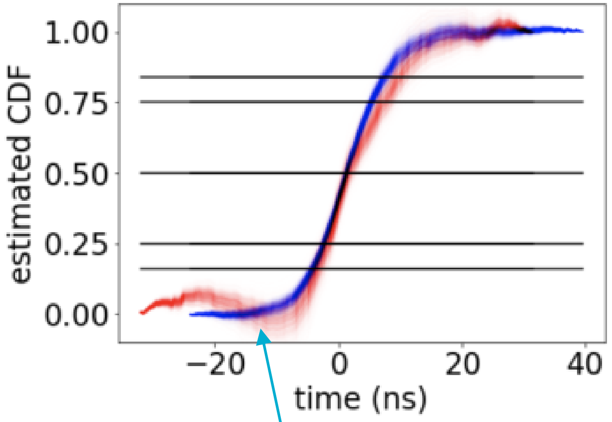
Bayesian fits to experimental data provide a means to extract features with rigorous uncertainties

In this application the width and asymmetry of the neutron time of flight signal is sensitive to magnetization in MagLIF experiments



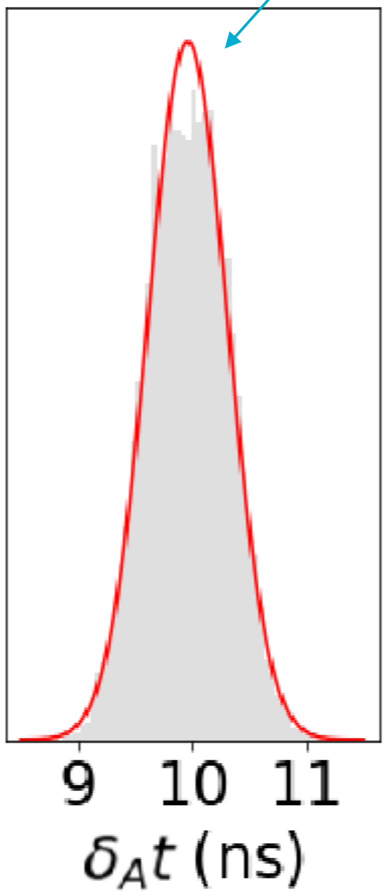
Bayesian Background fits





Posterior CDF's

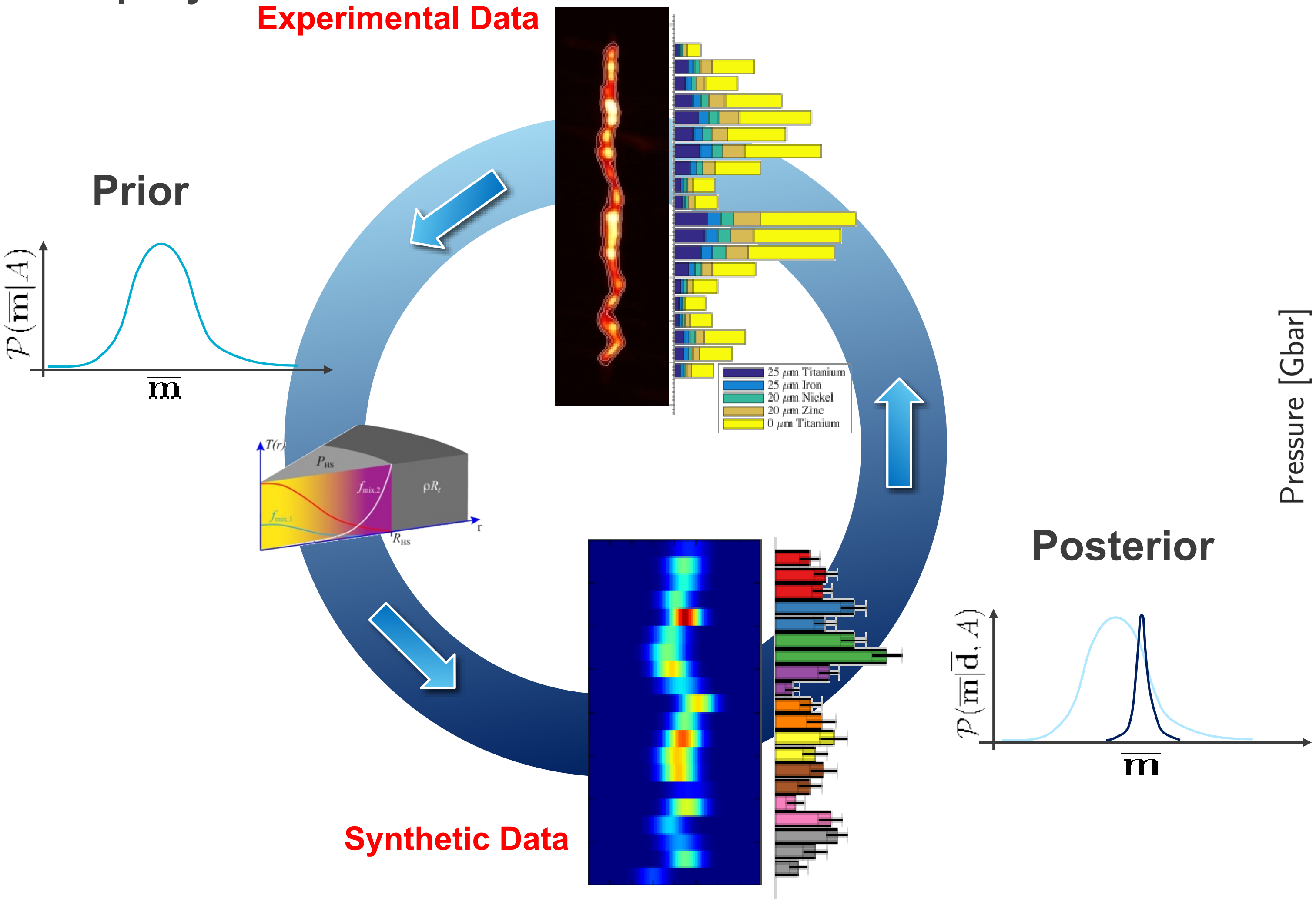
Posterior feature distribution

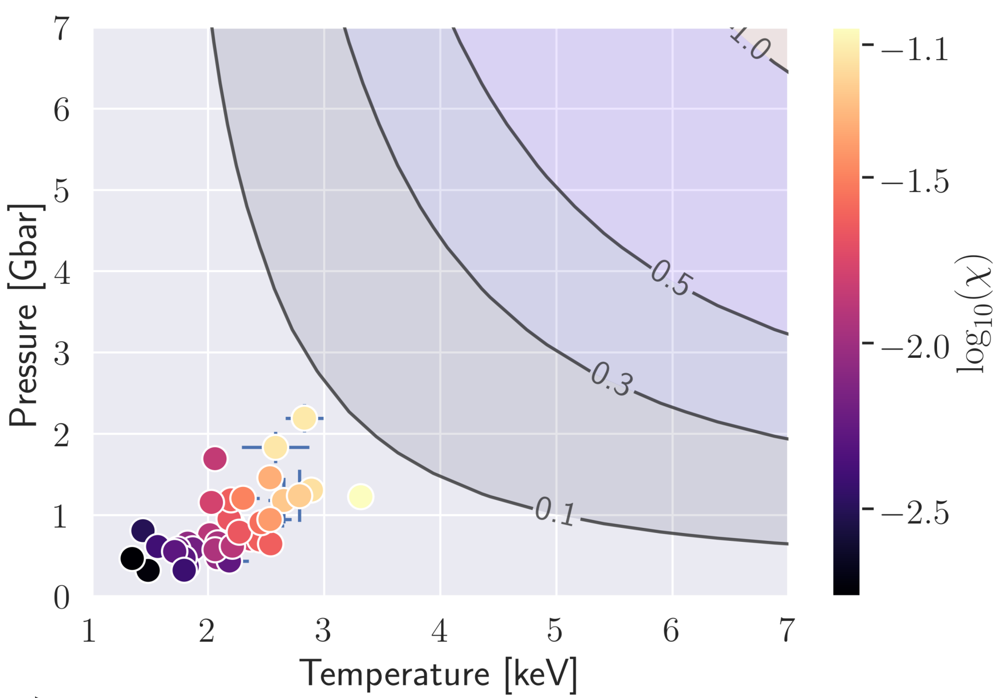


W.E. Lewis et al., *Physics of Plasmas* **28,** 092701 (2021)

CO05.00002 : W.E. Lewis Mon. Afternoon

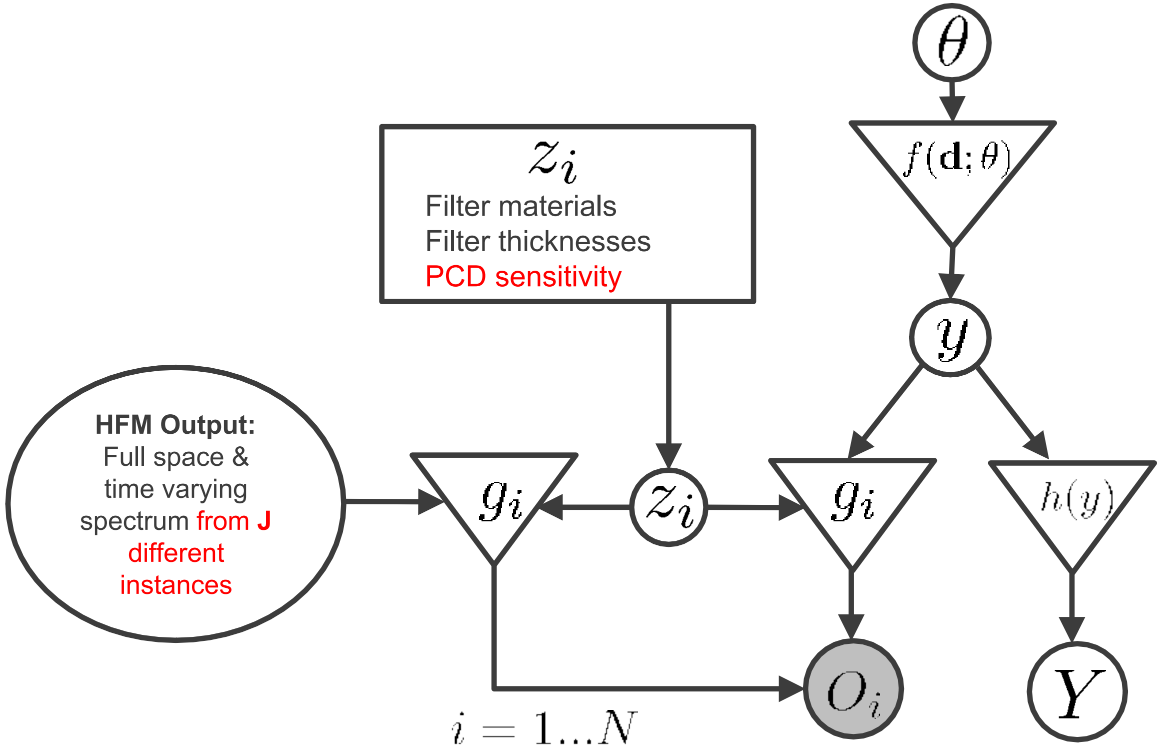
Bayesian data assimilation provides a means to self-consistently integrate multiple sources of diagnostic information through a physical model



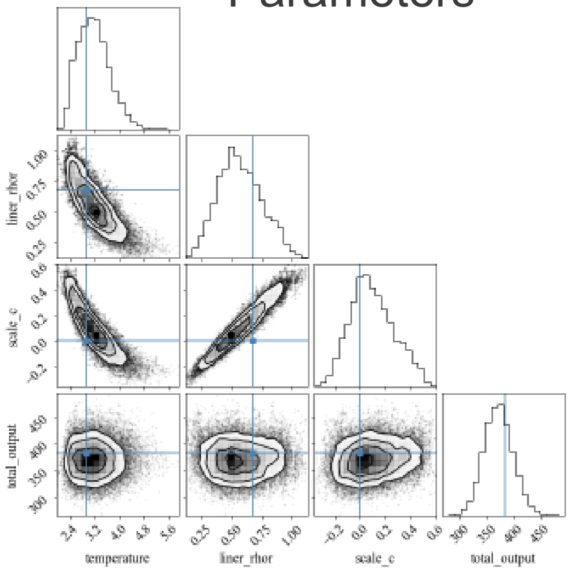


A well constructed posterior provides us with rigorous metrics we can use to find optimal experiment designs

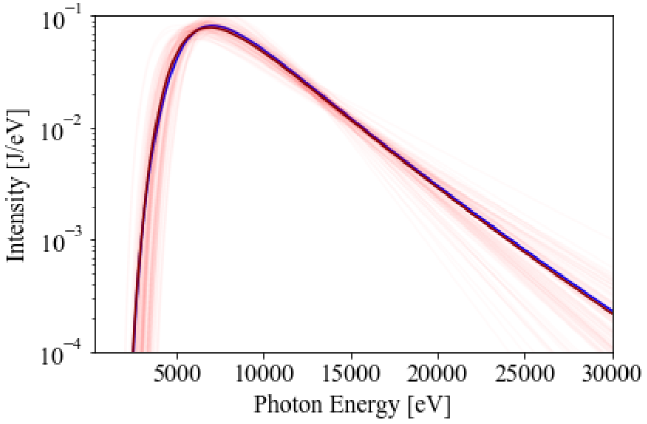
We want to use synthetic data to find the best set of radiation detectors and filters to optimally constrain the source spectrum over a range of possible outcomes



Posterior of Model Parameters



Posterior Output Spectrum

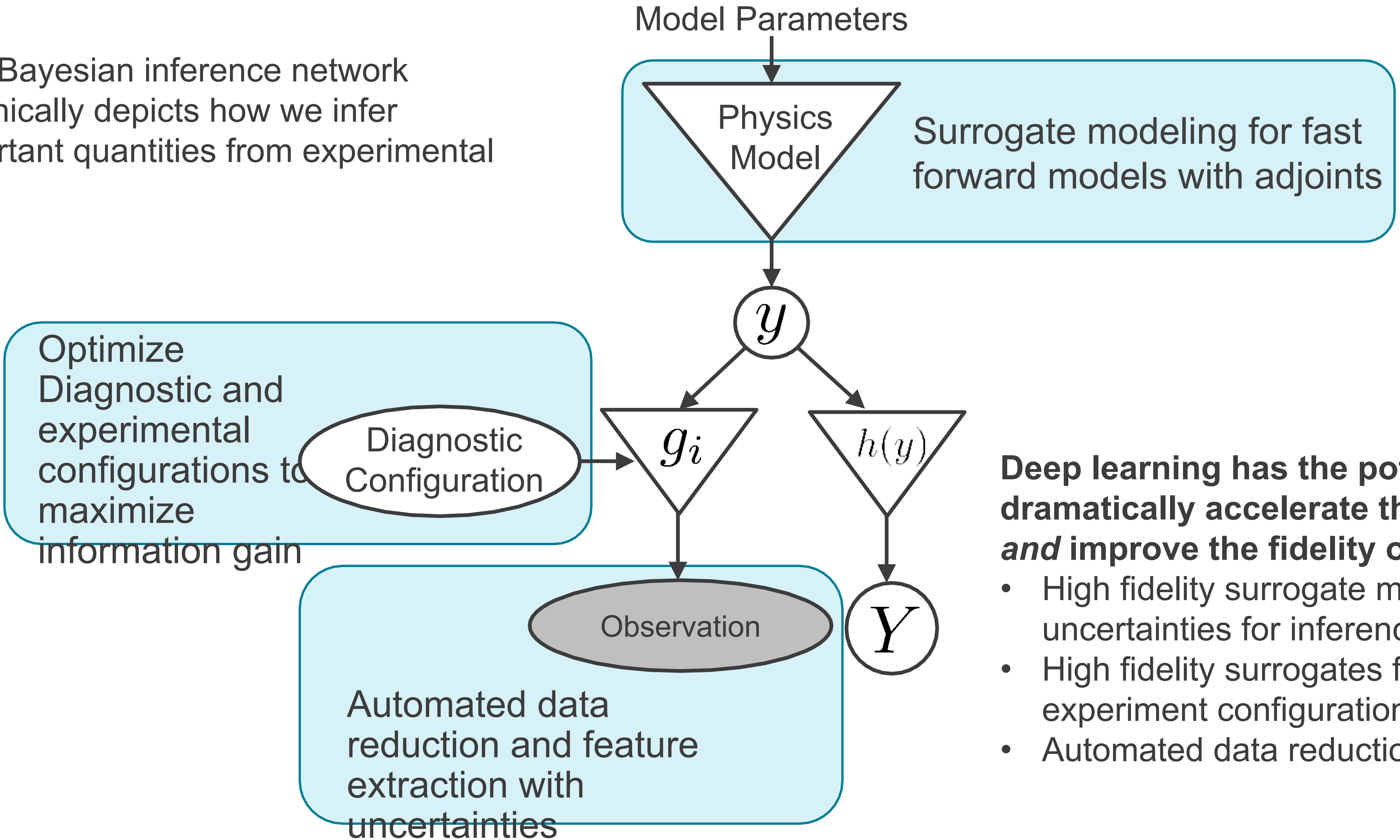


Bayesian Optimization

$$\mathcal{M} = \log(MSE) + \lambda\left(\frac{1}{N_{\mathrm{PCD}}}\sum_{n=1}^{N_{\mathrm{PCD}}}\exp\left(\frac{2V_{\mathrm{peak},n}}{V_{\mathrm{bias}}}\right) - 1\right)$$

These examples provide a model for an end-to-end fully Bayesian design, analysis, and integration loop

This Bayesian inference network graphically depicts how we infer important quantities from experimental data



Deep learning has the potential to dramatically accelerate this process *and* improve the fidelity of our work

- High fidelity surrogate models with uncertainties for inference
- High fidelity surrogates for sampling experiment configurations
- Automated data reduction pipelines