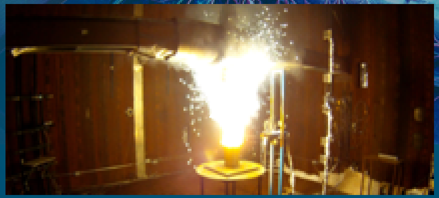
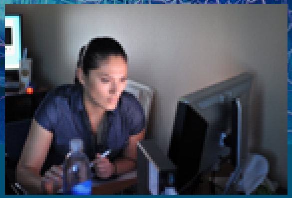
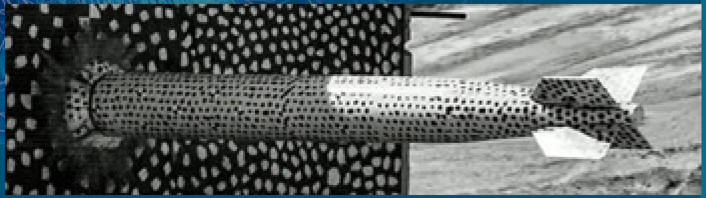
SAND2020-13267PE

Data Assimilation: Current use in MDD and path forward for the complex







PRESENTED BY

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2019 National Diagnostics Working Group

LLNL Livermore, CA

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What is Data assimilation?

Definition: "an approach for fusing data (observations) with prior knowledge (e.g. mathematical representations of physical laws; model output) to obtain an estimate of the distribution of the true state of a process"

-Wikle and Berliner, Physica D, 230 (2007)

A *useful* definition: Using multiple pieces of diagnostic information simultaneously to provide unbiased estimates of the parameters of a physical model from a single experiment or across an ensemble of experiments.

A canonical example: How do we measure the fuel pressure in fusion experiments?

$$P_{\mathrm{HS}} = (1 + \langle Z \rangle)\sqrt{\frac{2Y_{\mathrm{DD}}}{V\tau_b S(T)}}$$

$$S(T) = \frac{\langle \sigma v \rangle_{\mathrm{DD}}}{T_{\mathrm{i}}^2}$$

By assuming a uniform plasma in time and space we can estimate the pressure by inverting the yield equation

A canonical example: How do we measure the fuel pressure in fusion experiments?

$$P_{\mathrm{HS}} = (1 + \langle Z \rangle)\sqrt{\frac{2\boxed{Y_{\mathrm{DD}}}}{V\tau_b S(T)}}$$

Indium Activation measurement

$$S(T) = \frac{\langle \sigma v \rangle_{\mathrm{DD}}}{T_{\mathrm{i}}^2}$$

On Z, we measure the DD neutron yield using Indium activation

A canonical example: How do we measure the fuel pressure in fusion experiments?

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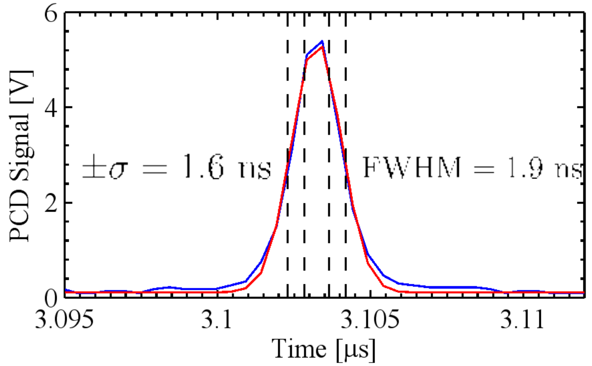

The burn duration is measured using the x-ray power history as a surrogate

We assume the FWHM of the x-ray pulse is a good stand in

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$$P_{\mathrm{HS}} = (1 + \langle Z \rangle)\sqrt{\frac{2Y_{\mathrm{DD}}}{\boxed{V}\tau_b S(T)}}$$

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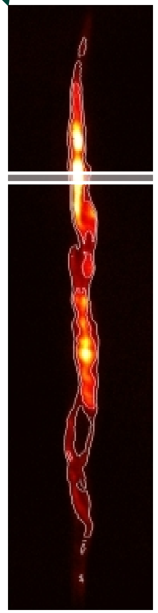
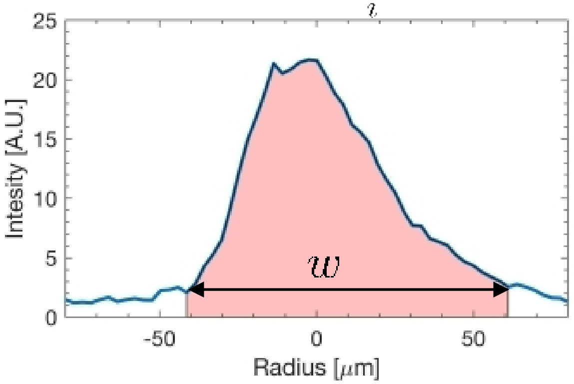


δh

$$V = \frac{1}{4}\pi\delta h \sum_i w_i^2$$



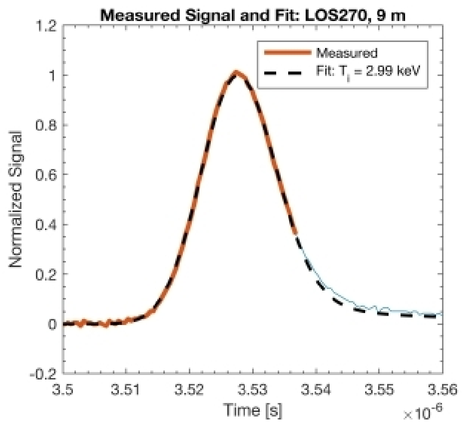
We estimate the volume using x-ray imaging

Assume the column is locally cylindrically symmetric and use the width containing 85% of the area under the curve to approximate the radius of the column

A canonical example: How do we measure the fuel pressure in fusion experiments?

$$P_{\mathrm{HS}} = (1 + \langle Z \rangle)\sqrt{\frac{2Y_{\mathrm{DD}}}{V\tau_b S(T)}}$$

$$\boxed{S(T) = \frac{\langle \sigma v \rangle_{\mathrm{DD}}}{T_{\mathrm{i}}^2}}$$



The ion temperature is measured using neutron time of flight (nTOF) assuming no contribution to residual velocity

A canonical example: How do we measure the fuel pressure in fusion experiments?

$$P_{\mathrm{HS}} = \boxed{(1 + \langle Z \rangle)} \sqrt{\frac{2Y_{\mathrm{DD}}}{V \tau_b S(T)}}$$

$$S(T) = \frac{\langle \sigma v \rangle_{\mathrm{DD}}}{T_{\mathrm{i}}^2}$$

The average ionization of the fuel is determined by mix

In this simple example we have no means of constraining this parameter

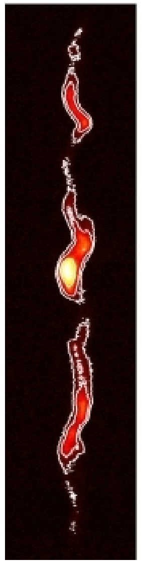
Assuming the mix species is fully ionized we have

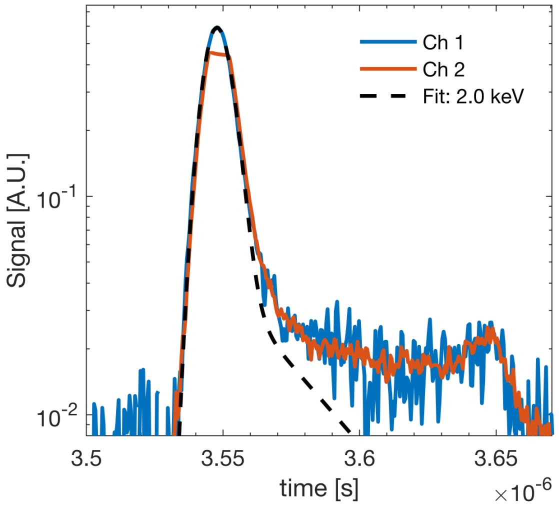
$$(1 + \langle Z \rangle) = 2 + f(Z_{\mathrm{mix}} - 1)$$

So for 0%-10% mix of Be we get a +/-7% uncertainty in the pressure

Putting this all together for two MagLIF experiment illustrates how this approach falls short

z3303: Y_{DD} = 3.5e12

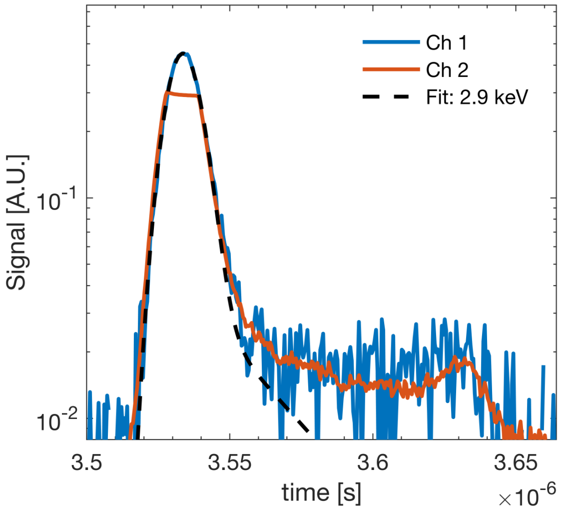




V = 1.4e-4 cm^3
τ_b = 1.9 ns
T_i = 2.4 keV

P = 0.6±0.15 Gbar

z3179: Y_{DD} = 5.5e12



V = 8.06e-5 cm^3
τ_b = 1.8 ns
T_i = 2.9 keV

P = 0.7±0.17 Gbar

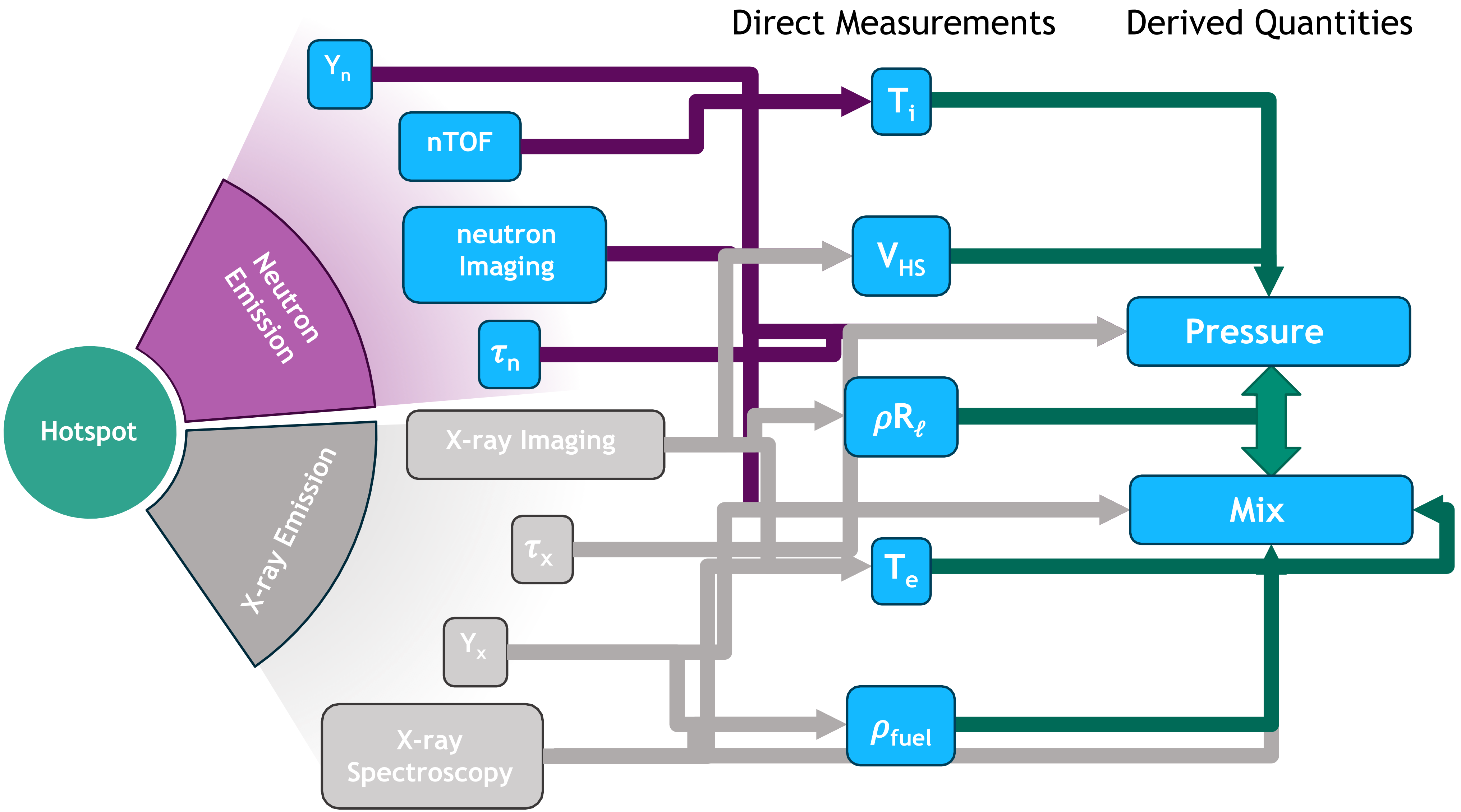
Error Analysis

$$\sigma_P \approx \frac{P_o}{2}\sqrt{\frac{4\sigma_Z^2}{(1+\langle Z\rangle)^2}+\frac{\sigma_Y^2}{Y^2}+\frac{\sigma_V^2}{V^2}+\frac{\sigma_\tau^2}{\tau^2}+(\eta-2)^2\frac{\sigma_T^2}{T^2}} \approx 25\%$$

Dominant sources of error are mix and temperature

With the data available this technique is not able to distinguish between these two experiments despite a 2x difference in yield!

We can do better by leveraging the fact that all of our diagnostics are different transformations of the emission from the same plasma



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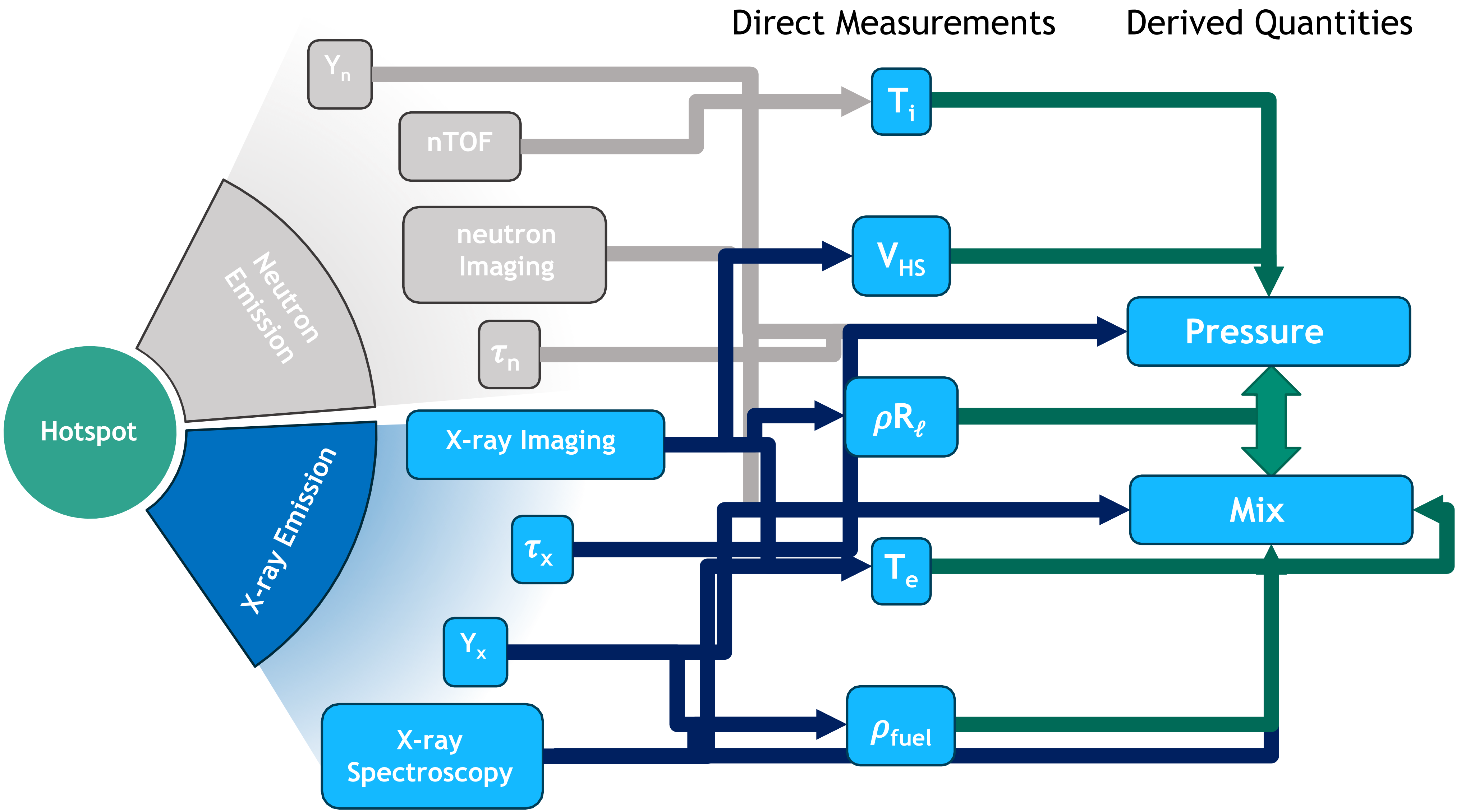

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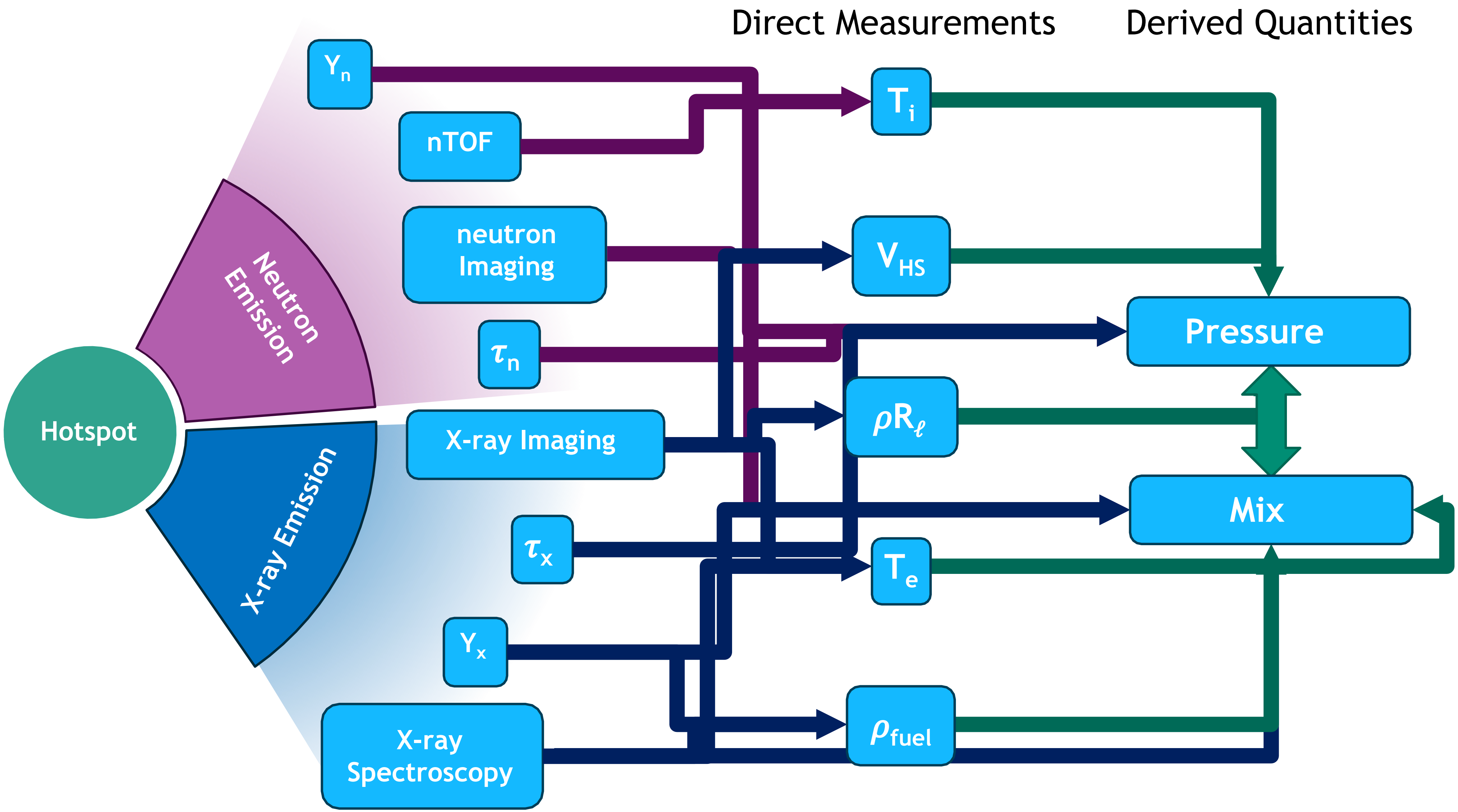


Bayesian data assimilation provides a statistical framework with which to carry out this analysis

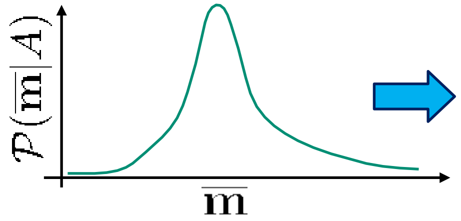
Bayes' Theorem

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

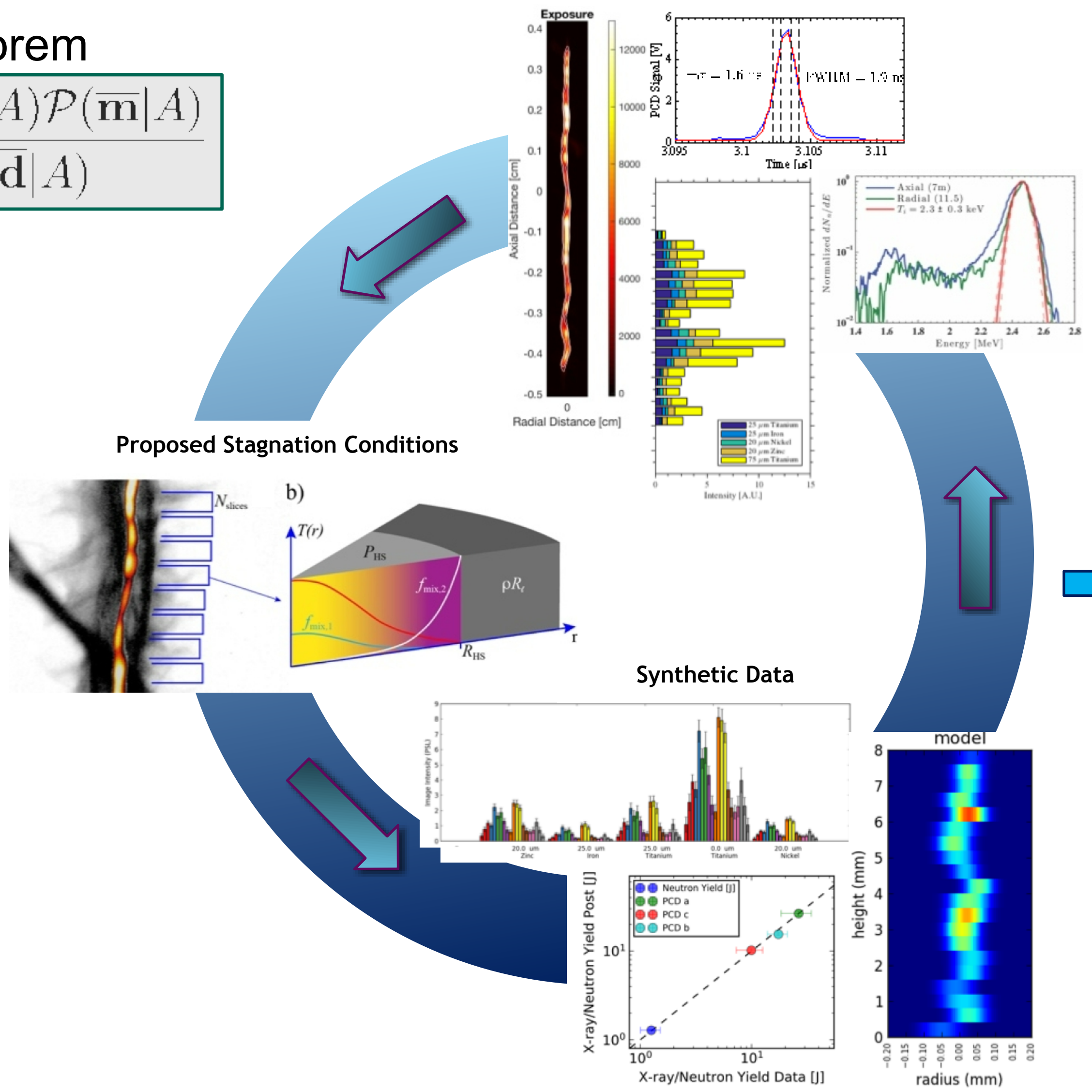
Likelihood

$$\mathcal{P}(\overline{\mathbf{x}}|\overline{\mathbf{m}}, \mathcal{A}) \propto \prod_{i=1}^{N} \exp\left(-\frac{(\mathcal{F}_i(\overline{\mathbf{m}}) - x_i)^2}{2\sigma_i^2}\right)$$

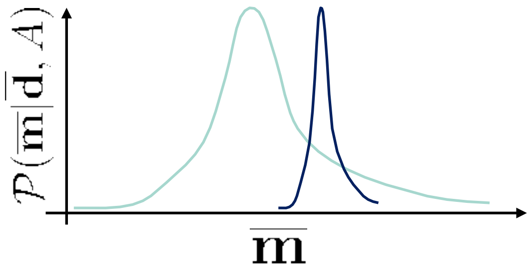
Prior Distribution



Experimental Data



Posterior Distribution



Model Parameters

$$\overline{\mathbf{m}} = \begin{cases} P_{\mathrm{HS}} \\ T \\ f_{\mathrm{mix}} \\ R_{\mathrm{HS}} \\ \rho R_\ell \end{cases}$$

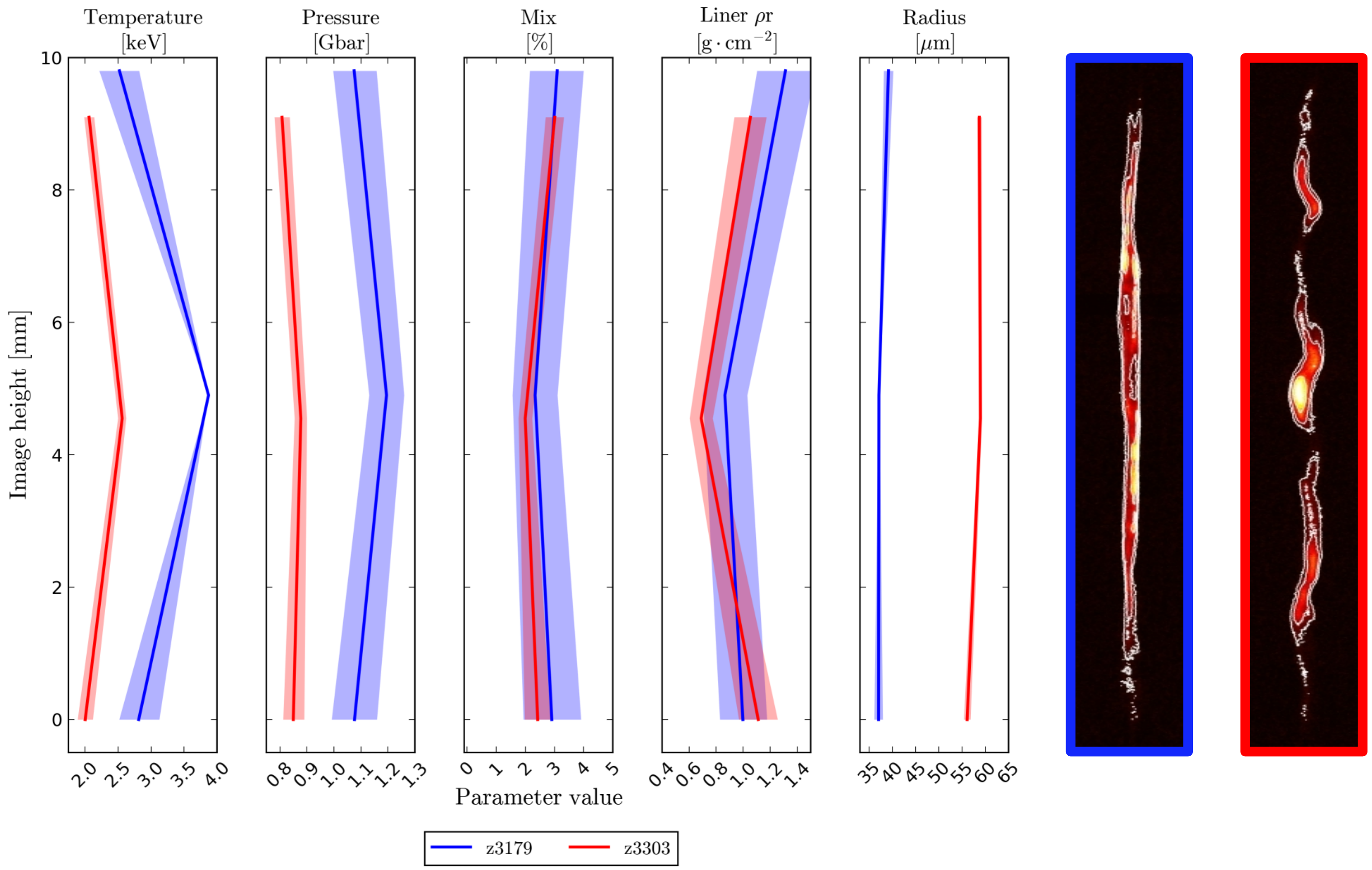
Outputs/Benefits:

- **most likely parameter values**
- **confidence intervals**
- **correlations**
- **Value of information**

Comparing the same two experiments using our Bayesian model allows us to look deeper into the data set with more confidence

We are able to leverage more information from both x-ray and neutron diagnostics

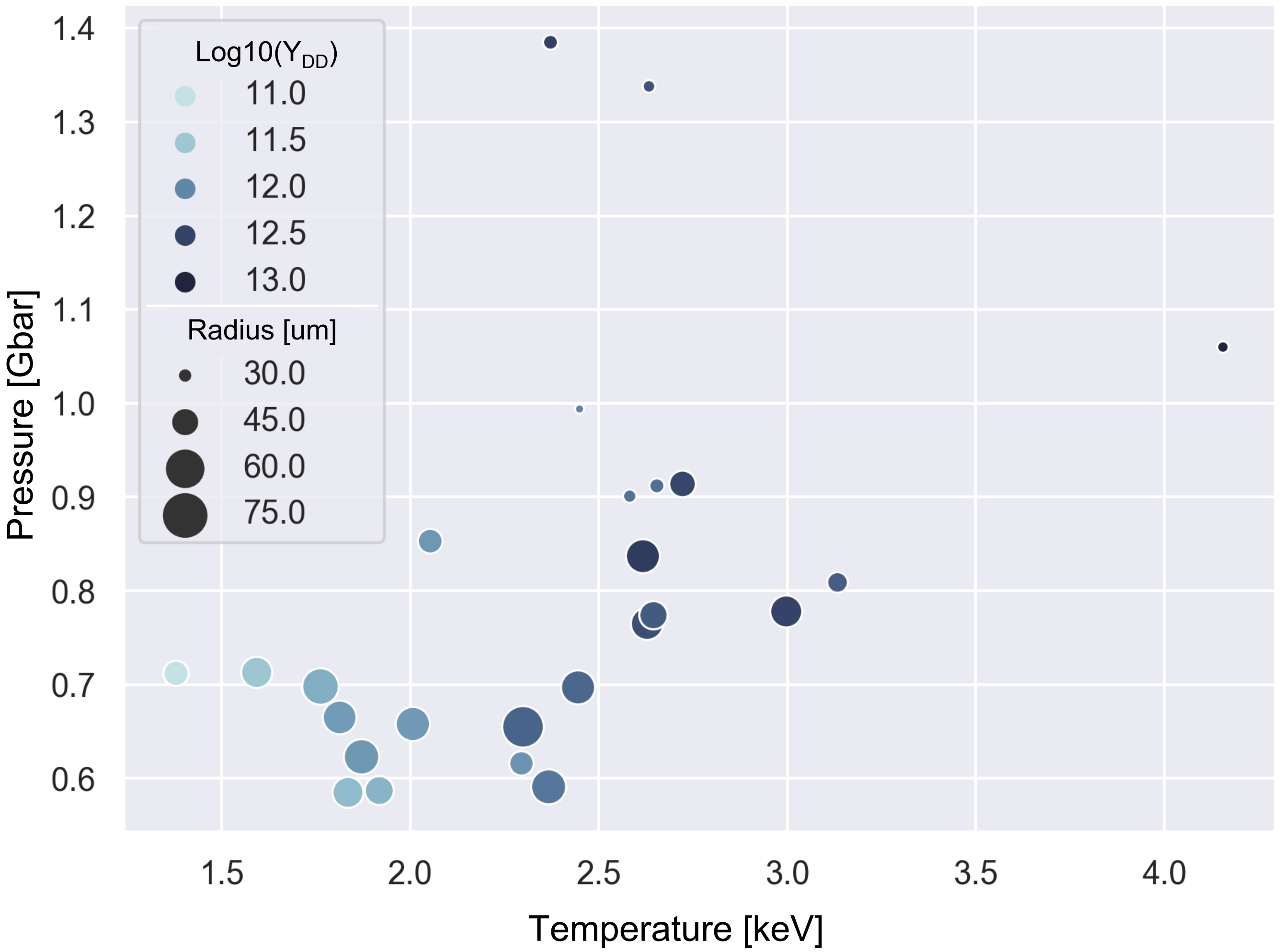
Our model requires consistency between x-rays and neutrons providing additional constraints and adding value to each piece of data



The amount of information we can get out is currently limited by the complexity of our model

- The plasma model assumes local cylindrical symmetry which limits the analysis to “bulk” properties and gross variations
- Capturing the morphology so that we can relate structure to conditions is the ultimate goal

With this technique we begin mining data from a large database of MagLIF experiments



By determining all of the various model parameters simultaneously we can begin to examine trends across experiments

We see from this dataset that there are multiple ways to get the same yield e.g.

- moderate pressure, high temperature
- High pressure, moderate temperature

Central temperatures below ~2.3 keV are always associated with low performance

We are currently developing tools to bring the power of data assimilation to a variety of applications on Z

Improving measurements of x-ray output on Z by integrating

- X-ray power detectors (PCD’s, XRD’s, etc.)
- Total x-ray yield measurements (Calorimeter, bolometer)
- X-ray spectra from multiple independent instruments
- Driven by Radiation Effects Sciences (RES) needs

Use our knowledge of the Z circuit to constrain power delivery to the load and losses

- Electrical measurements at multiple points in the Z circuit
- Load current velocimetry constrained by the circuit model and implosion model
- Driven by a need for better post-shot simulation capability and understanding of powerflow for scaling

Use the Bayesian formalism to design new diagnostics and optimize existing ones

- Output statistics give VOI which can be used to assess how much impact each diagnostic has on each parameter
- Synthetic data from simulation can be used to test new diagnostics to see which will have the most impact on the parameters of interest

What is the path forward?

In order to start the discussion on this question we held the first workshop on Bayesian Methods in ICF and HED on Nov. 6th at SNL

We had presentations by
- Michael Glinsky (SNL)
- Varchas Gopalaswamy (LLE)
- Jim Gaffney (LLNL)
- Ben Tobias (LANL)

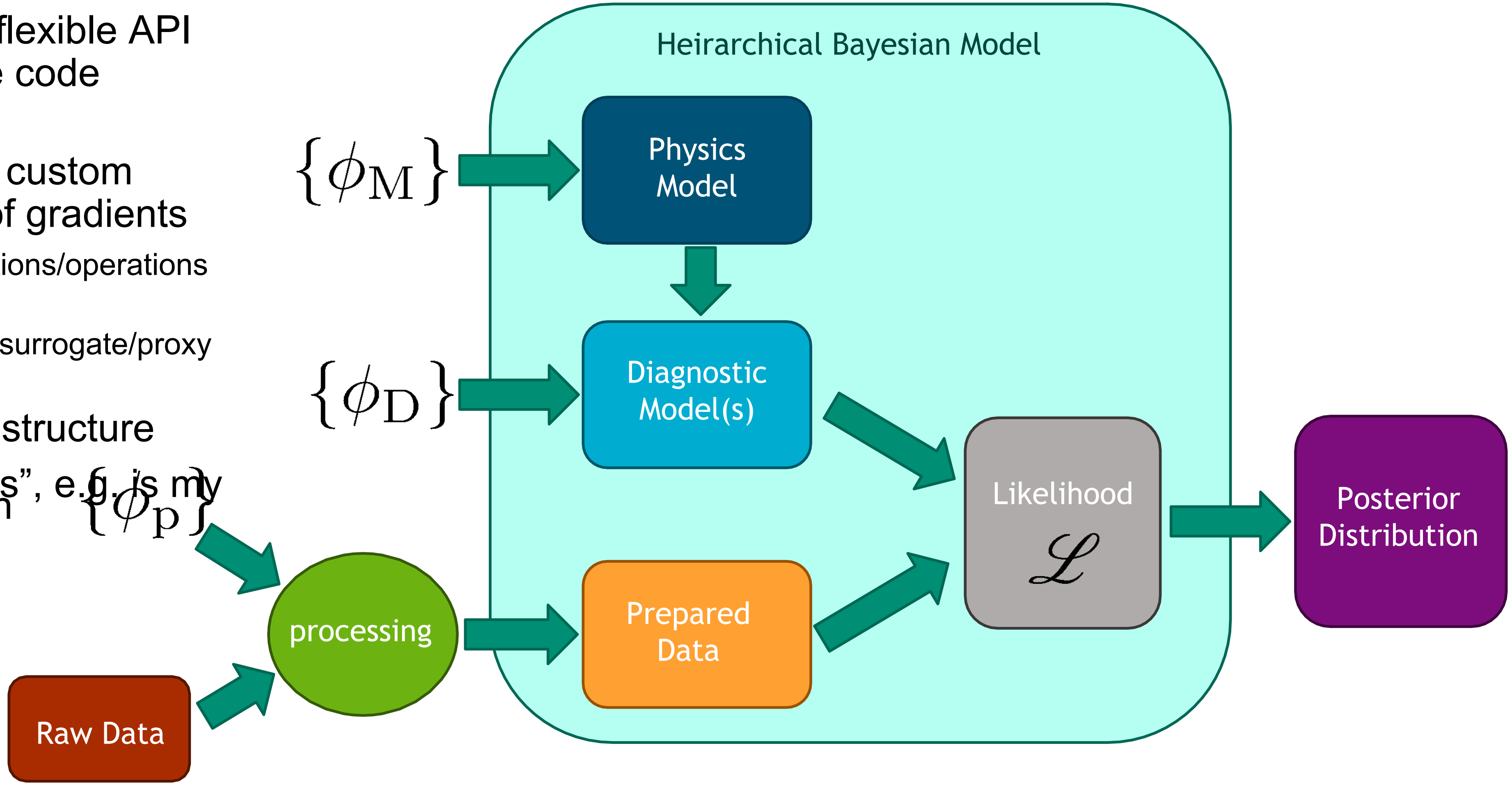
There were ~18 attendees: Michael Glinsky, Will Lewis, Pat Knapp, Marc Schaeuble, Brandon Klein(r), Alex Zylstra, Prav Patel, Jim Gaffney(r), Nino Landen(r), Dan Thorn, Paul Springer, Duc Cao, Varchas Gopalaswamy(r), John Kline, Ben Tobias, Codie Fiedler Kawaguchi, Mike Grosskopf

What is the path forward?

Current methods are limited in sophistication due to computational complexity of the physics model and inefficiency of sampling algorithms

There is a desire to develop a software tool for Hierarchical Bayesian Data Assimilation that:

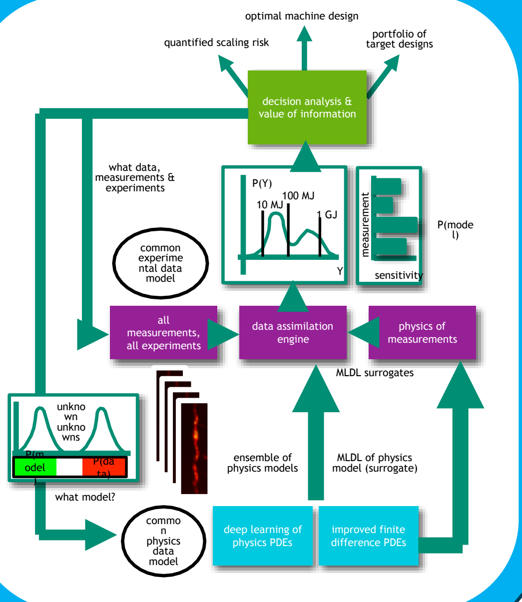
- Has a straightforward and flexible API (python based to maximize code portability)
- Allows the incorporation of custom models taking advantage of gradients
  - A library of common transformations/operations with defined gradients
  - Development and integration of surrogate/proxy models
- Interfaces with a data lake structure
- Support for "causal analysis", e.g., is my model complete?
- State of the art optimization and sampling algorithms



Currently, each of the sites are doing pieces of our “wish list”, we would like to unify that effort

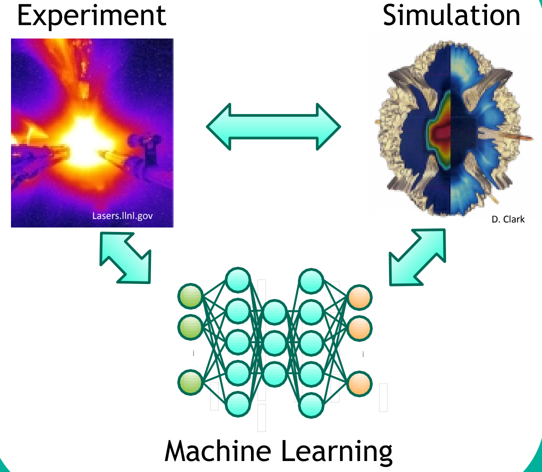
SNL

Vision:
Bayesian data assimilation at the heart of physics informed decisions for e.g. diagnostic dev., facility investments, etc.



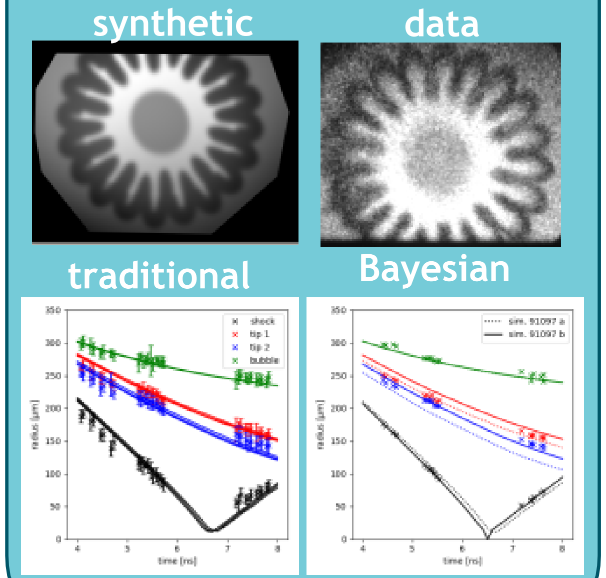
LLNL

Integration of experiment, simulation and deep learning to improve predictive modeling and quantify prediction uncertainties



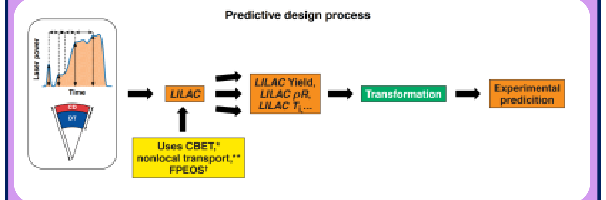
LANL

Bayesian data analysis to provide reduced confidence intervals and rigorous statistical comparison between models and data



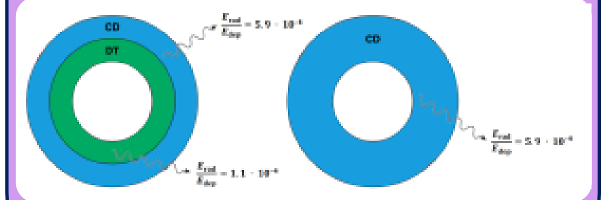
LLE

Predictive design



Data Assimilation

Using hard x-ray signatures from different, but complimentary experiments to constrain hot electron population in cryo-DT experiments



Conclusions and future outlook

At Sandia we are developing a Bayesian data assimilation engine that is providing deeper insight into MagLIF experiments

- Currently limited by simple assumptions in the physics model and computational complexity of more physics-rich models
- We are expanding the data assimilation engine to other applications (x-ray output for RES, power coupling to loads on Z, physics-based decision making)

A workshop was organized bringing people from all four sites (LLE, LANL, LLNL, SNL) together to discuss what we are doing in the area of Bayesian methods

- There is a lot of overlap and there could be tremendous benefit to all from a more cooperative approach
- There is a shared interest in developing a common tool to enable better transfer of information and tools
- Management of and access to data is a key issue that needs to be addressed at all sites