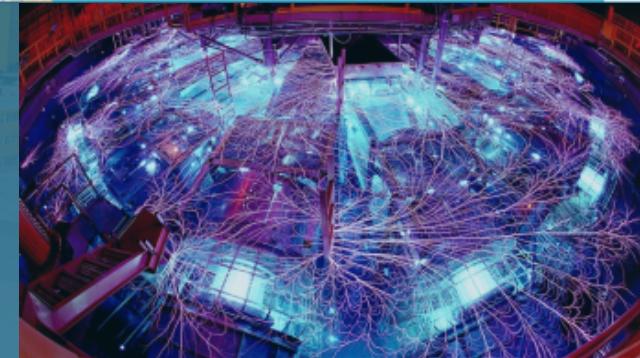




Sandia
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Optimization of Diagnostic Configurations in the presence of Uncertainty using Bayesian Inference and Optimization



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American Physical Society, Division of Plasma Physics

October 18, 2022

This work was done in collaboration with a large group

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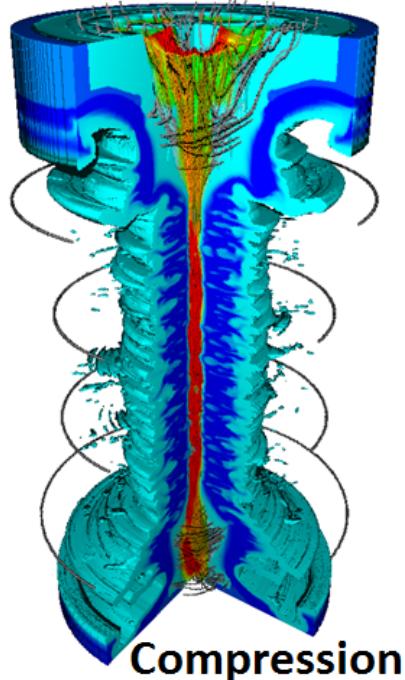
*current location, BNZ Energy Inc., Santa Fe NM



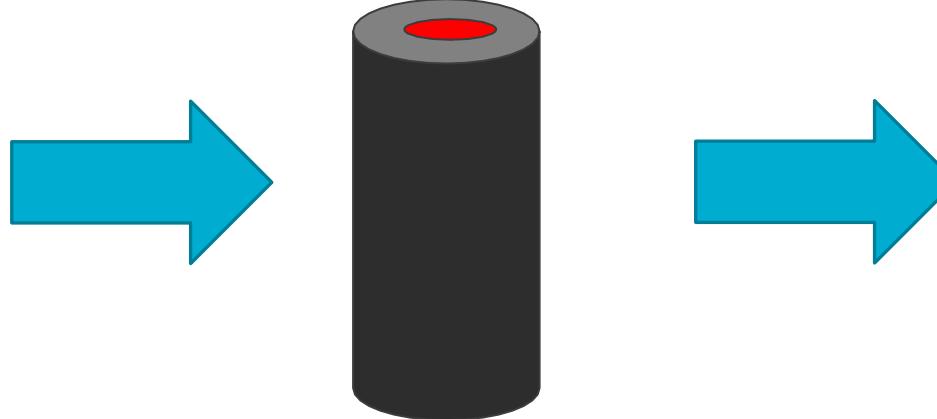
The models we use to analyze x-ray data in ICF experiments routinely make simplifying assumptions that can impact our interpretation



3D object, Evolving
in time



Uniform, stationary
plasma surrounded by
homogeneous liner



- Temperature
- Pressure
- ρR
- ...etc.

These simplifications can introduce bias into our analysis

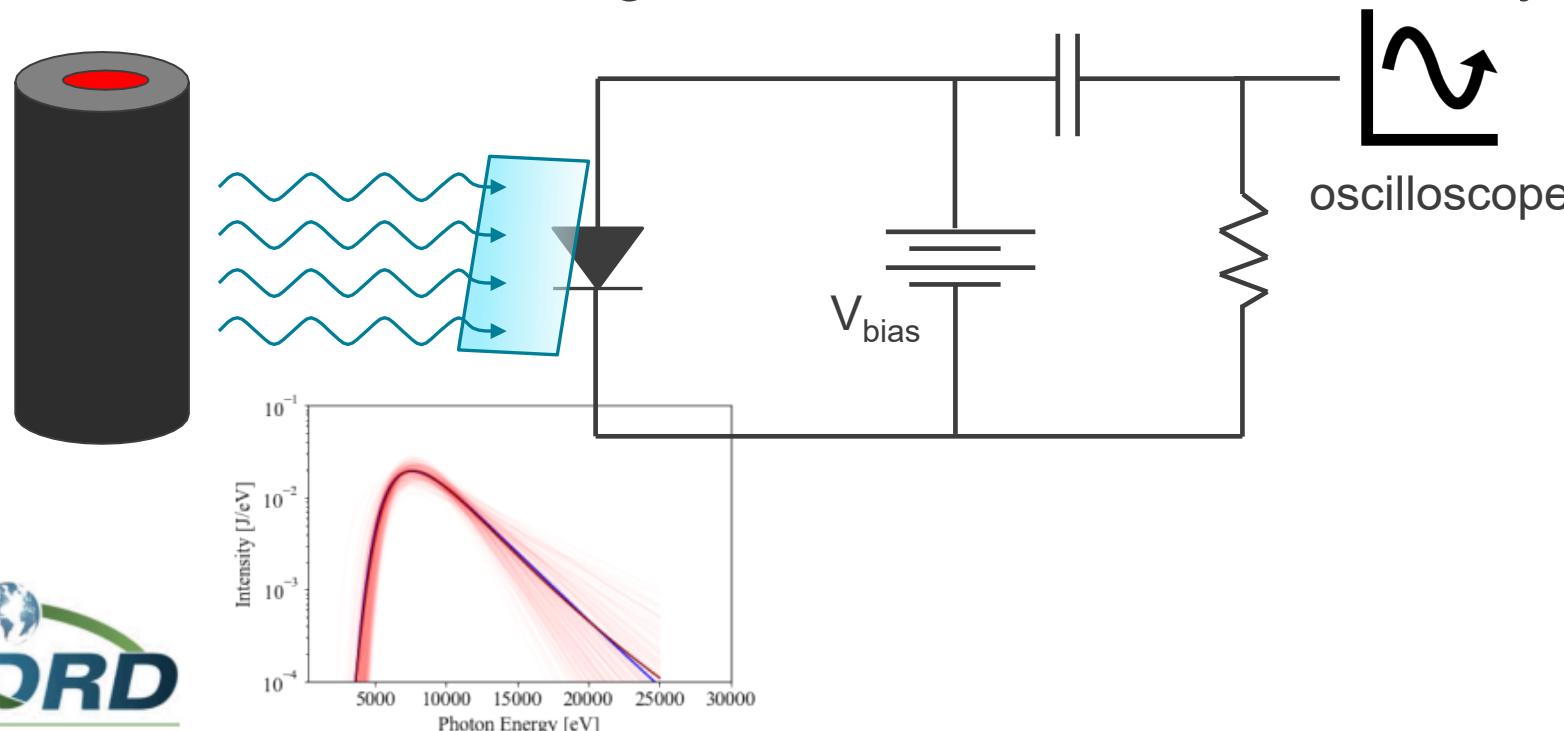
How do we configure an instrument to give us useful information in the face of this kind of bias?

We constructed a simplified problem to develop a method for optimizing filtered x-ray power detectors

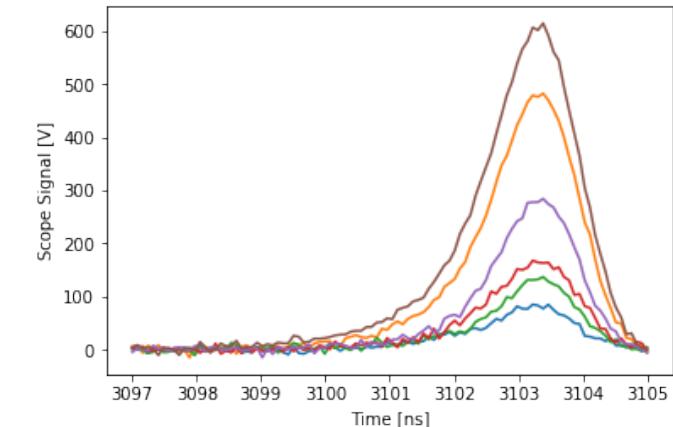


PCDs are a workhorse diagnostic on Z, but their highly integrating nature makes it difficult to extract source information

Using a database of 1D MagLIF simulations to optimize the detector and filter configurations to minimize uncertainty



Filtered Power Signals

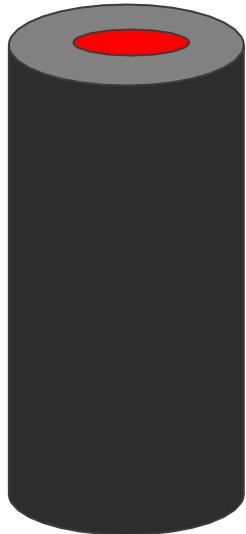


We use the fit to the reconstructed time-integrated spectrum as our optimization metric



There is no ambiguity in comparing a reconstructed spectrum to the simulation

Comparing physical quantities like temperature require a choice of mapping to the highly complex experiment

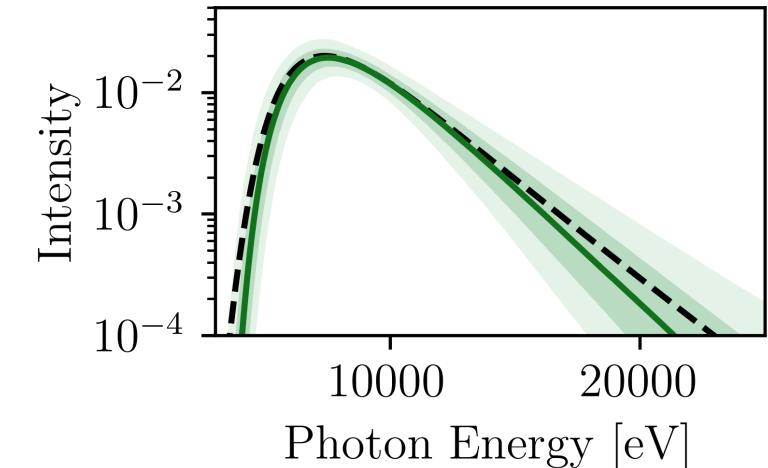
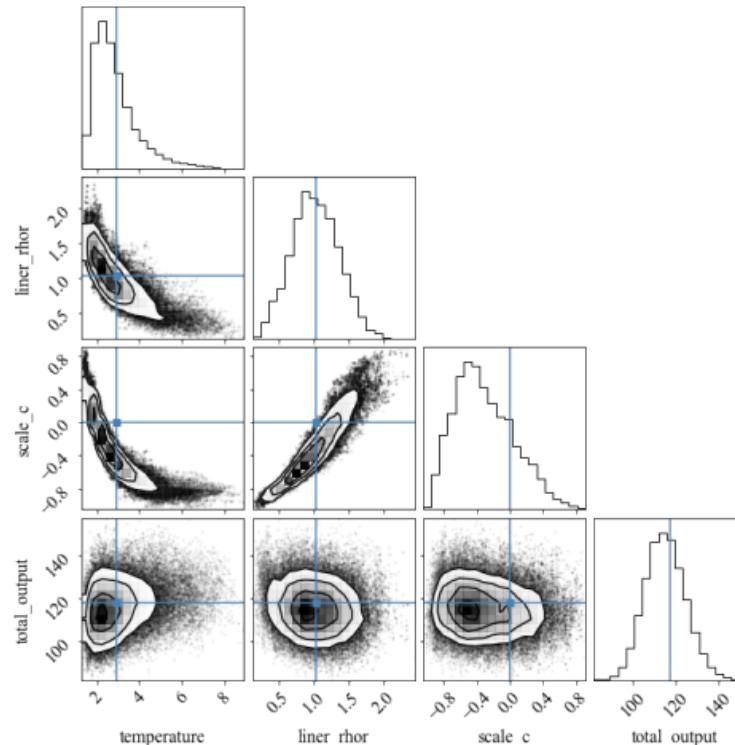


Parameters

$$T_e$$

$$\rho R_\ell$$

$$C$$



Quality of the inference
is quantified by the
MSE

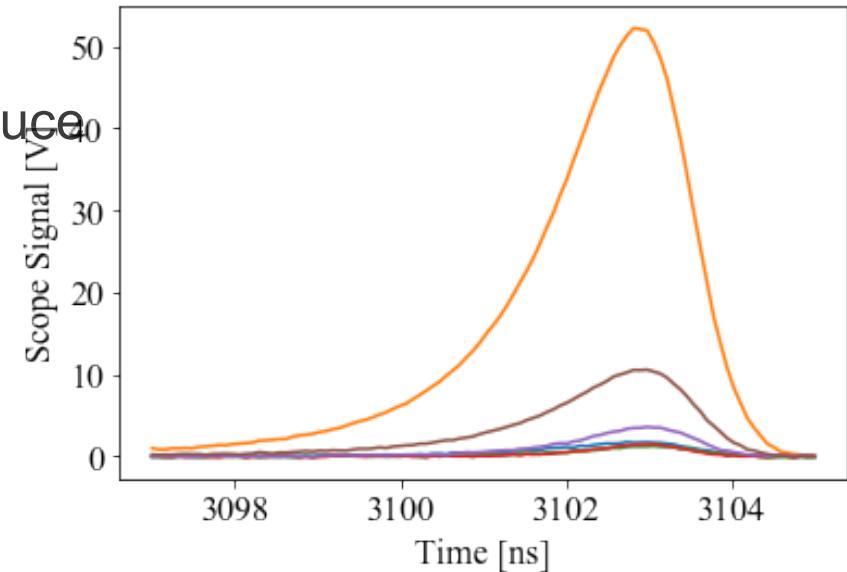
$$\text{MSE} = \frac{1}{N} \sum_{k=1}^{\#samples} \int d\nu (I_{\nu,k} - T_\nu)^2 = (\mathbb{E}(I_\nu) - T_\nu)^2 + \text{var}(I_\nu)$$

PCD's will saturate as the peak voltage approaches the bias voltage



- The form of our model does not allow us to explicitly account for this during the inference
 - PCD's measure power, our model produces an energy
- Accounting for this would require more physics be added to our model
- We must include a penalty term for configurations that produce signals with large amplitude

$$L = \exp\left(\frac{\max(V_{\text{peak},i})}{\alpha V_{\text{bias}}}\right) - 1$$



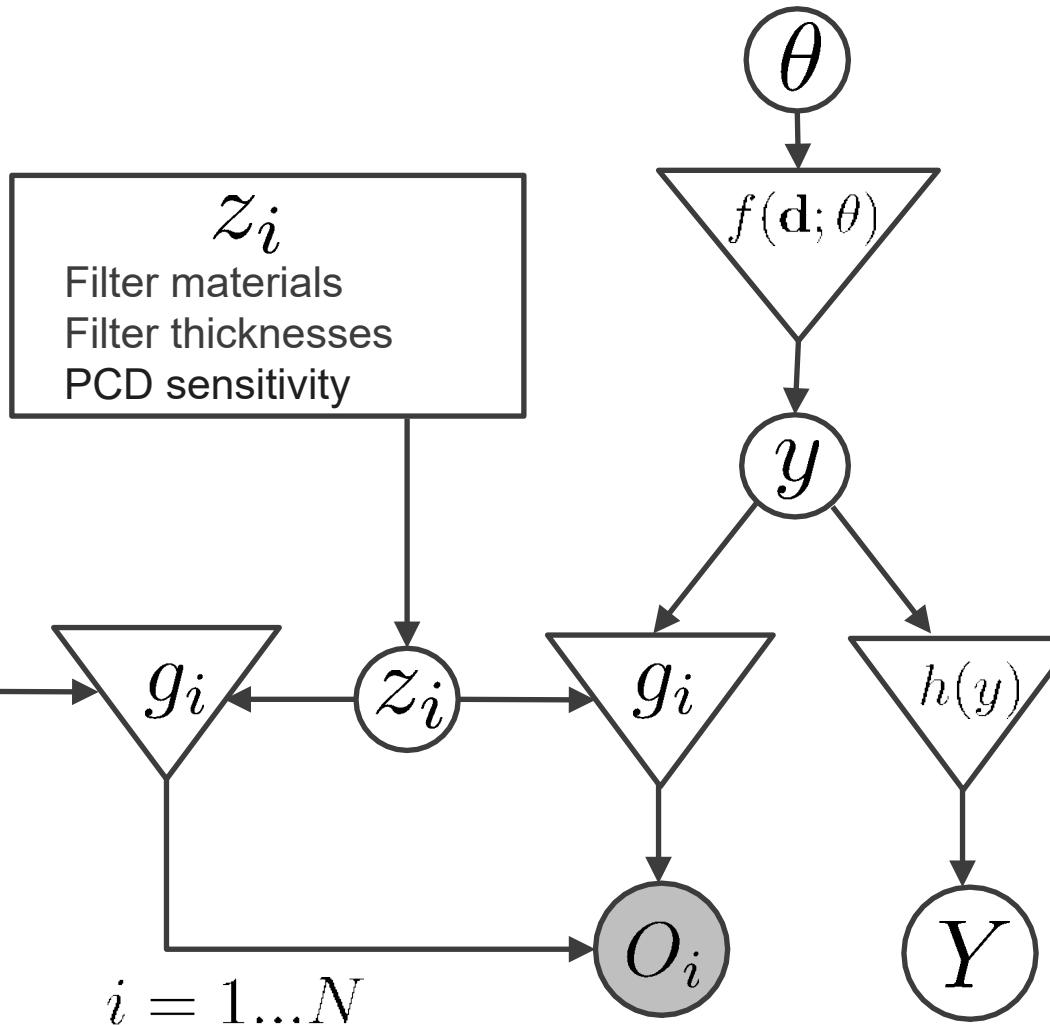
$$\mathcal{M} = \log(MSE + \lambda L)$$

Optimization metric

Our goal is to find the set of PCD filters and sensitivities that provide optimal reconstruction of the emitted spectrum



High Fidelity Model (HFM) Output:
Full space & time varying spectrum from J different instances

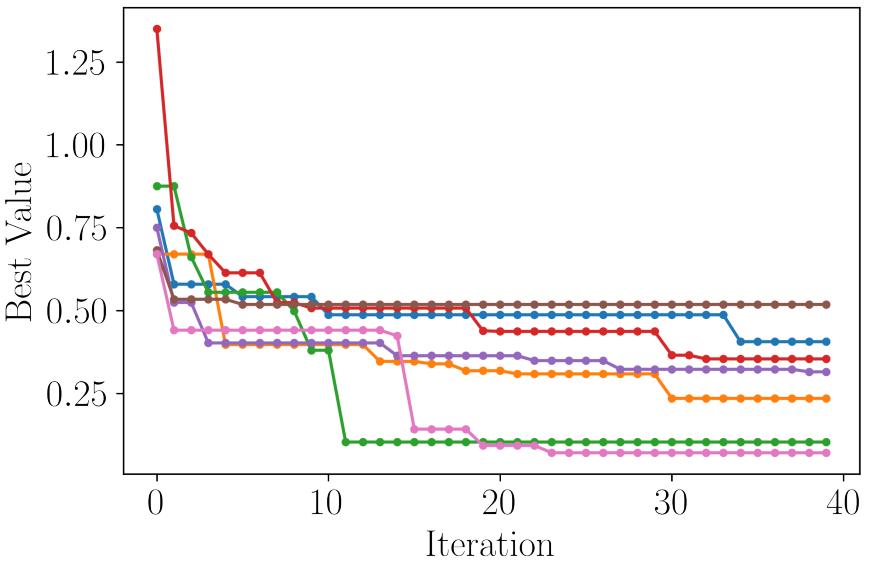
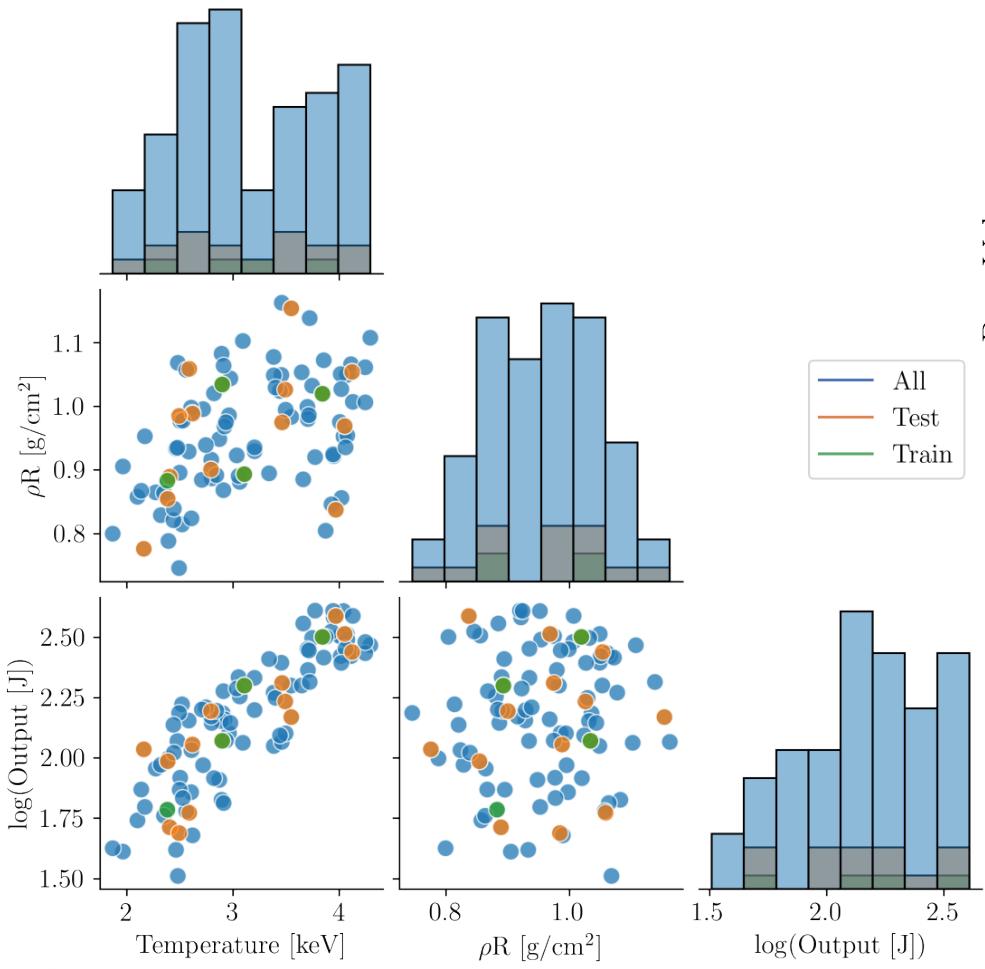


Procedure

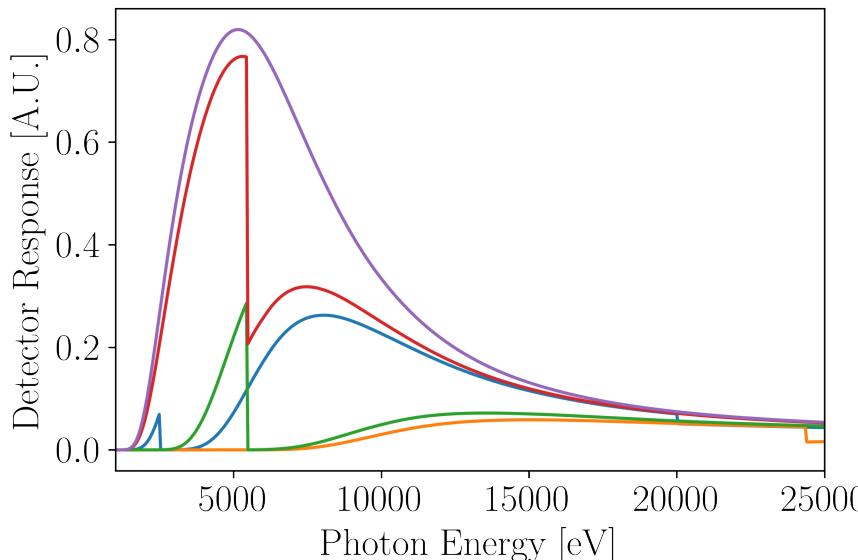
1. Choose z_i (filter material and thickness for each element)
2. Create O_i from HFM output for each element with chosen configuration
3. sample posterior with chosen configuration and new O_i
4. Compute MSE from posterior samples
5. Fit GP and compute EI to select new point
6. Go back to (1) with new choice, iterate until stopping criterion is reached

$$\mathcal{M} = \log(MSE + \lambda L) \quad Z_{\text{opt}} = \operatorname{argmin}_{z_i} \sum_{j=1}^J \mathcal{M}_j$$

We leverage an ensemble of TD-Arakawa magnetohydrodynamic calculations to train and validate our optimization procedure

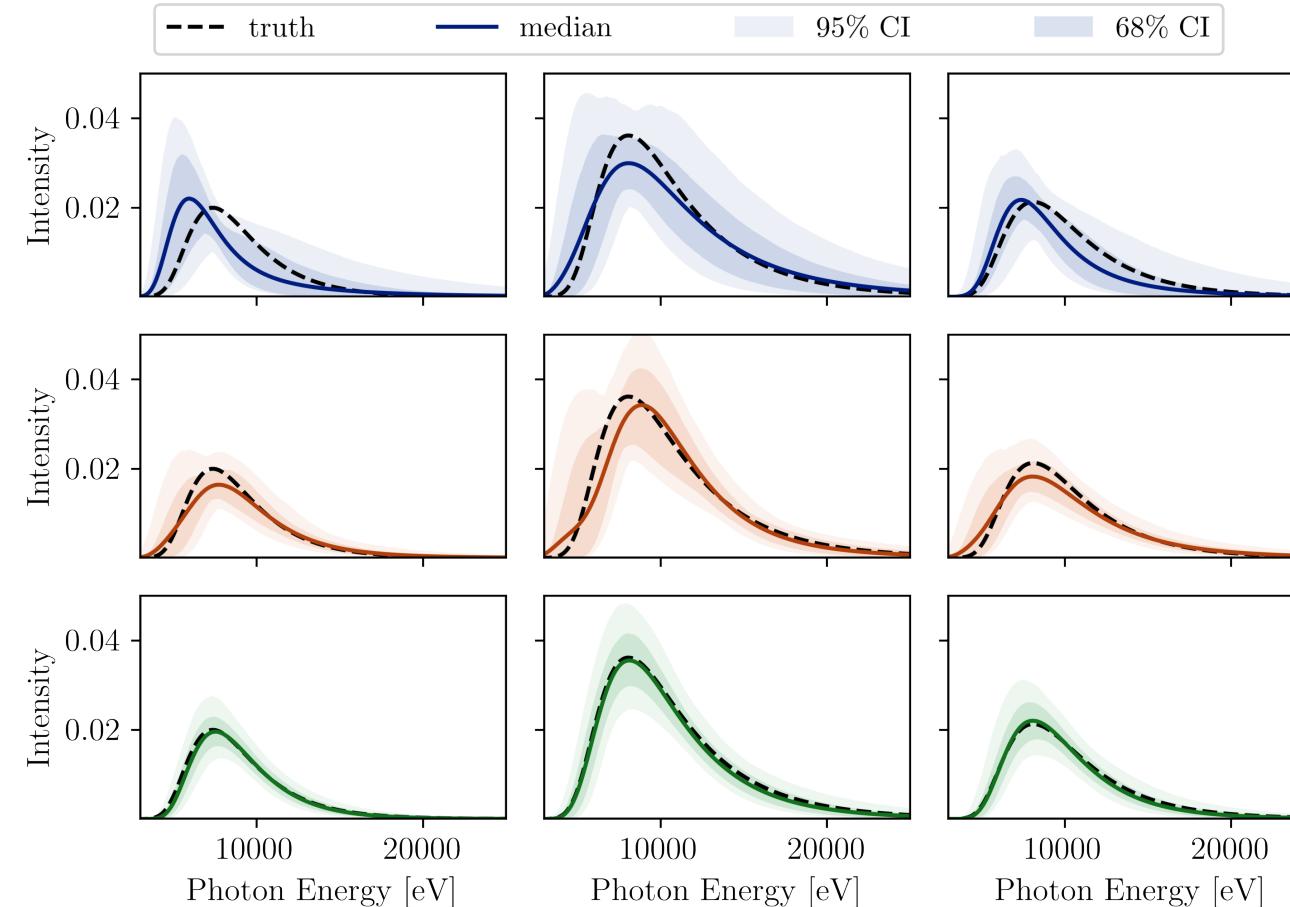
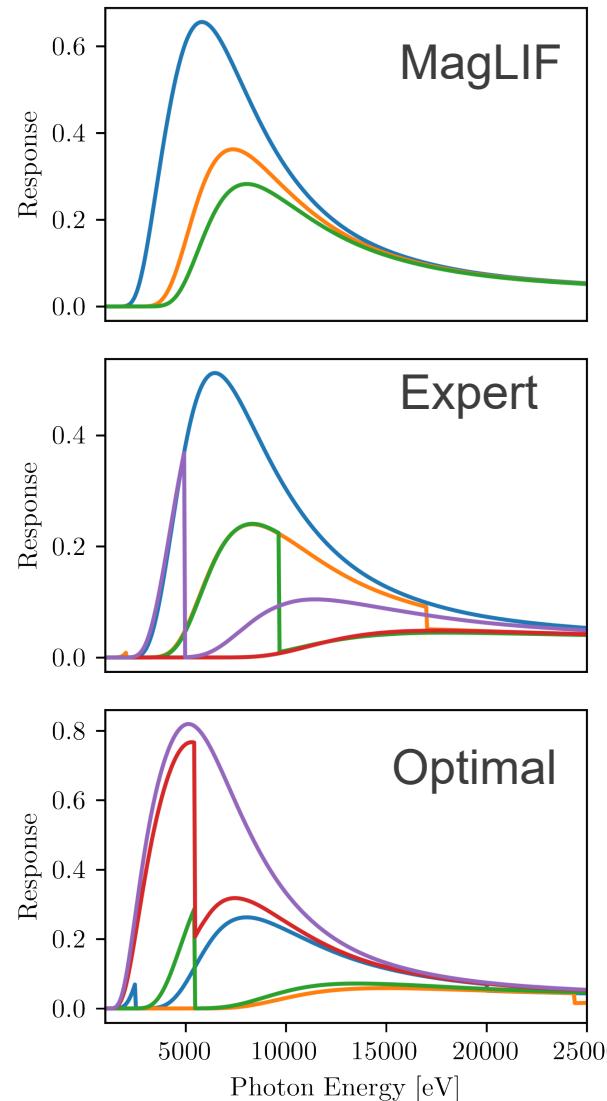


Due computational cost, only 4 training and 16 validation points were selected from the ensemble



Support points were used to ensure the samples represent the distribution

The performance of the optimum was compared against two reference cases



Total log(MSE)

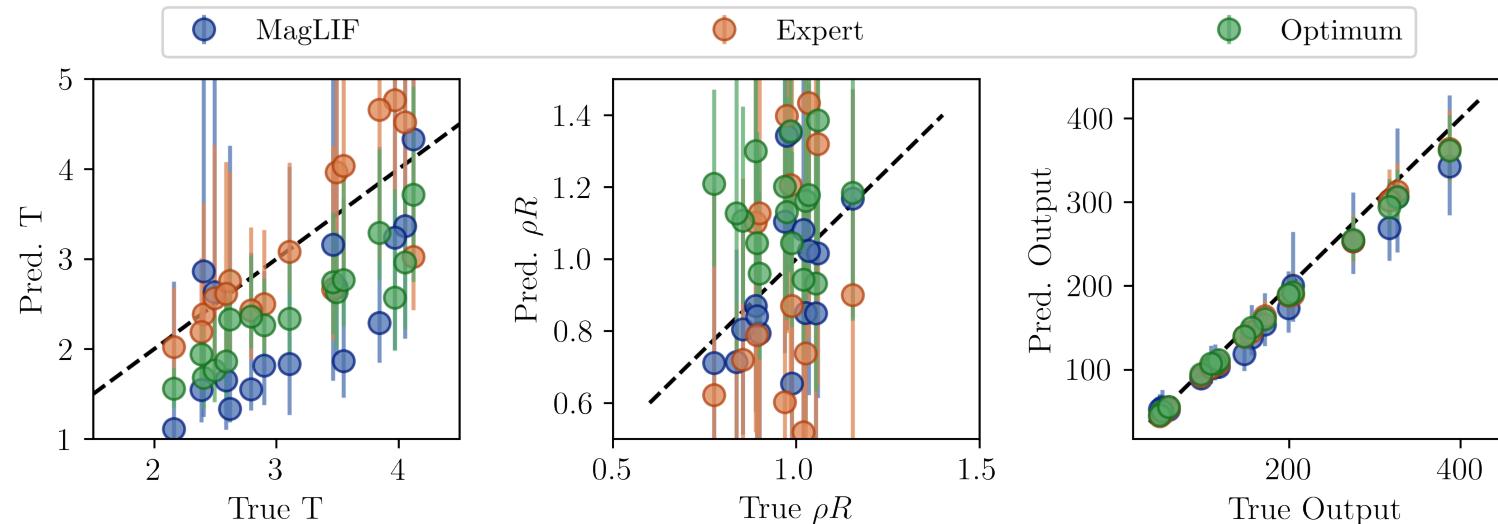
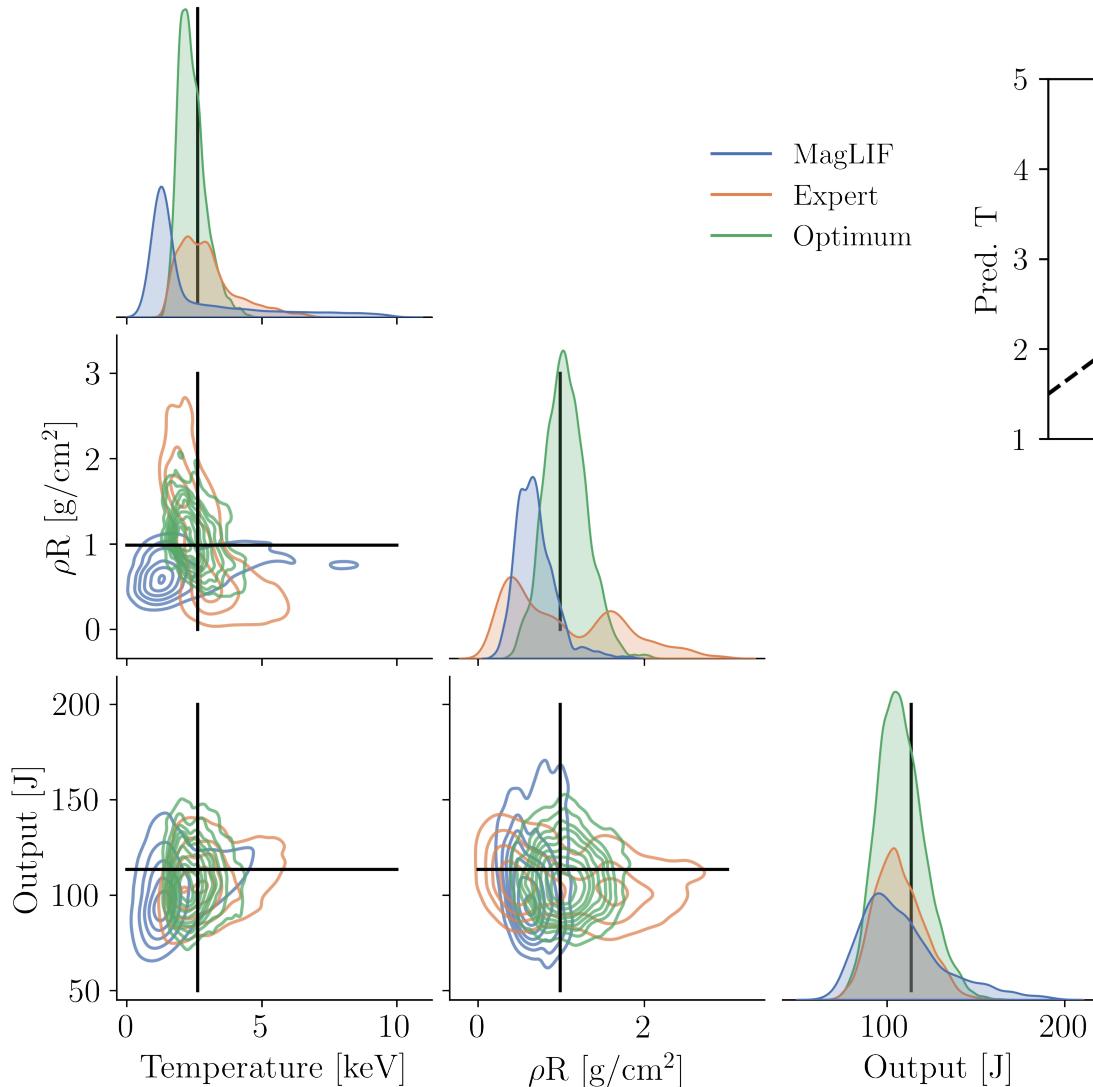
2.13

2.5

-0.22

Our optimal configuration performs markedly better on the validation set

Our optimized configuration also performs better on some of the physical parameters



The posterior is narrower with the optimal configuration

Liner ρR is poorly constrained in all cases

The temperature is biased somewhat low, but is inferred with better precision

The output is constrained more tightly and with less bias

Summary



- We have demonstrated a general method to optimize instrumental configurations to produce inferences with low combined variance and bias
- The metric utilizes the full posterior leveraging the uncertainty in the optimization
- The method explicitly acknowledges the impact of model assumptions in the interpretation of data
- Future work will look at:
 - Optimizing additional metrics
 - Pareto optimization to examine tradeoffs between e.g. bias and variance
 - Incorporation of more instruments
- Ultimately, this technique can be used to assess the value of new data and optimize proposed new instruments before they are built