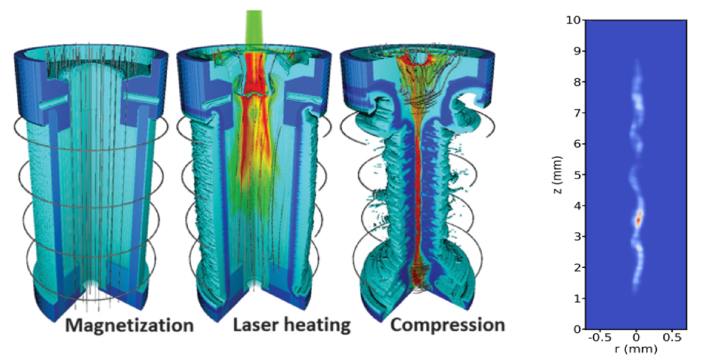
Sandia National Laboratories

Data-driven design and discovery for Magnetized Liner Inertial Fusion

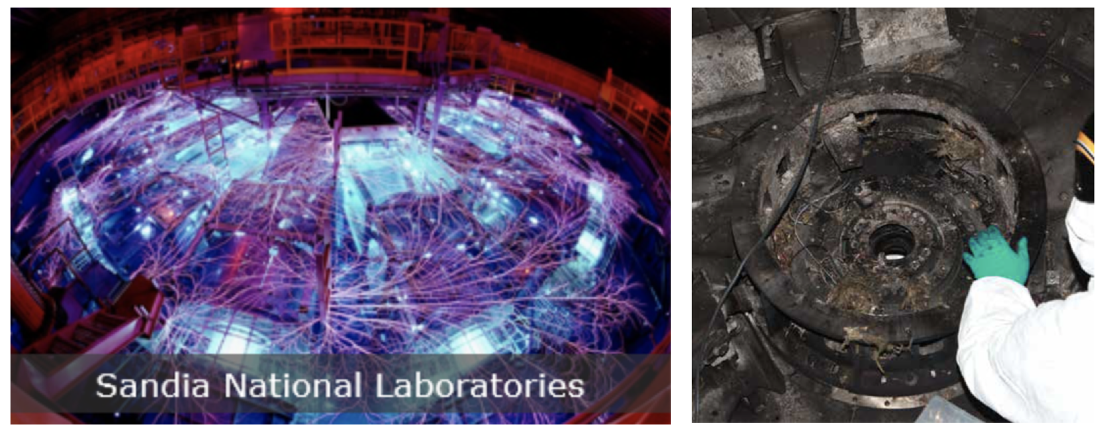
Presented by W. E. Lewis with contributions from P.F. Knapp *et al.*[1,2], J.R. Fein *et al.*[3], and the MagLIF Team

Introduction[4,5,6,7]

Magnetized Liner Inertial Fusion produces a hot (multi-keV), dense (~1 g/cc), and macroscopic (O(10mm) tall and O(0.1mm) diameter) cylindrical D_2 plasma. The fusion fuel at stagnation is well within the high energy density (HED) matter regime, with thermal pressures that can exceed 1Gbar.



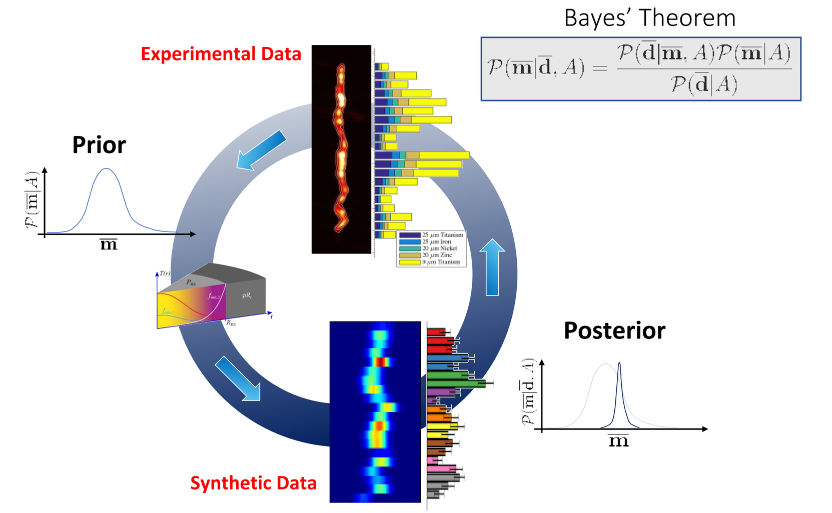
Extreme HED environments produced at Sandia's Z pulsed power facility place stringent constraints on diagnostic access and required robustness. Furthermore, experiments are costly, measurements are often highly spatially-spectrally- and/or temporally- integrated, and complex Multiphysics simulations are computationally expensive. These features represent significant challenges for experiment design and physics discovery.



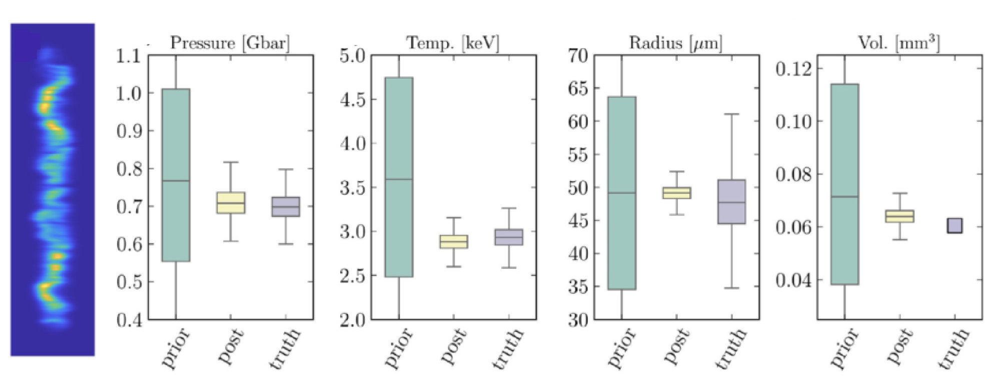
Data-driven approaches are being developed to accelerate discovery and improve automation, uncertainty quantification, and reproducibility. We highlight several published and ongoing projects demonstrating application to both experiment design and data analysis.

Bayesian Data Assimilation for Performance Metrics[1]

Combining disparate data sources with Bayes' theorem allows consistent inference

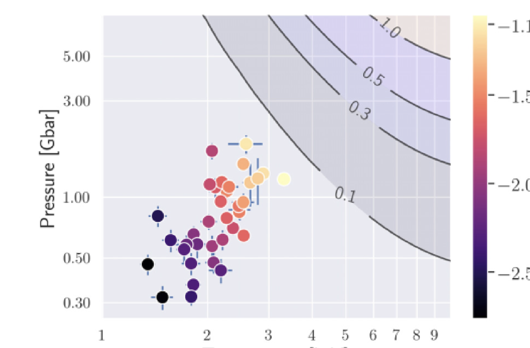


Validation on 3D simulation data indicates unbiased inference

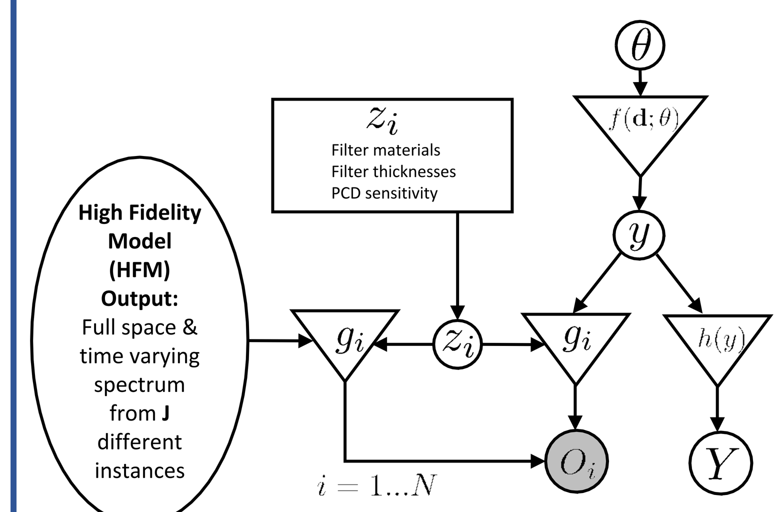


Resulted in first ever inference of Lawson parameter on MagLIF experiments

$$\chi = \frac{\varepsilon_\alpha}{24} P_{\mathrm{HS}} \tau_{\mathrm{E}} \frac{\langle \sigma v \rangle_{\mathrm{DT}}}{T^2}$$



Optimizing Experiment Design[2]

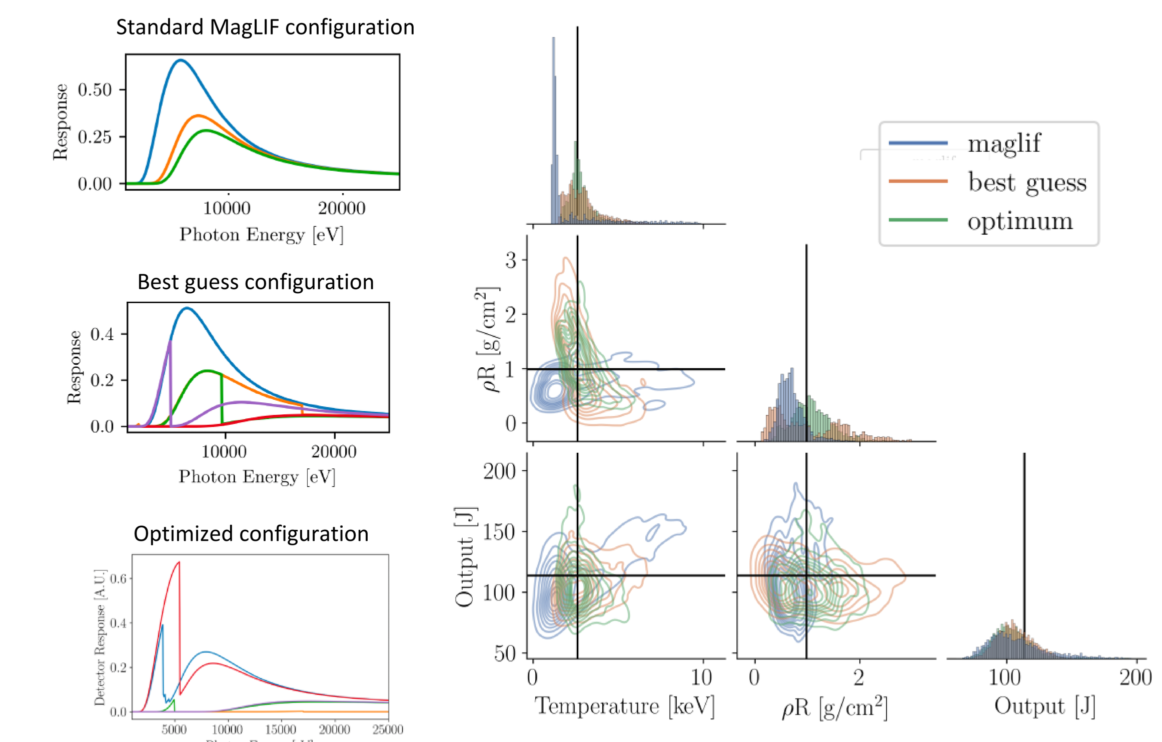


Procedure

1. Choose z_i
2. Create O_i from HFM
3. sample posterior
4. Compute MSE from posterior samples
5. Fit GP
6. Maximize EI
7. Repeat until stopping criterion

$$\mathcal{M} = \log(MSE + \lambda L) \qquad Z_{\mathrm{opt}} = \underset{z_i}{\mathrm{argmin}} \sum_{j=1}^{J} \mathcal{M}_j$$

Example: Optimize radiation detector filters to minimize bias and variance in inferences



Sparse-view Tomographic Reconstruction[3]

Basis function expansion:

$$f(x,y) = \sum_b^B a_b d_b(x,y) \Rightarrow \mathbf{f} = D\mathbf{a}$$

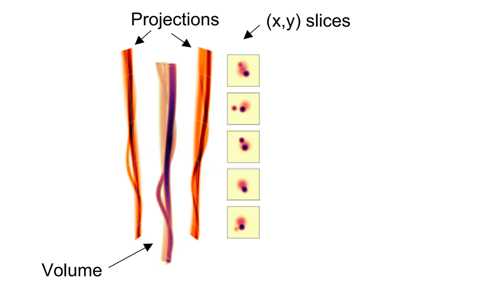
Coefficients; Basis functions

Reconstruction:

Minimize w.r.t. $\frac{1}{2}\|\mathbf{y} - AD\mathbf{a}\|^2$ s.t. $D\mathbf{a} = \mathbf{f} \geq 0$

Projection matrix; Projection measurements

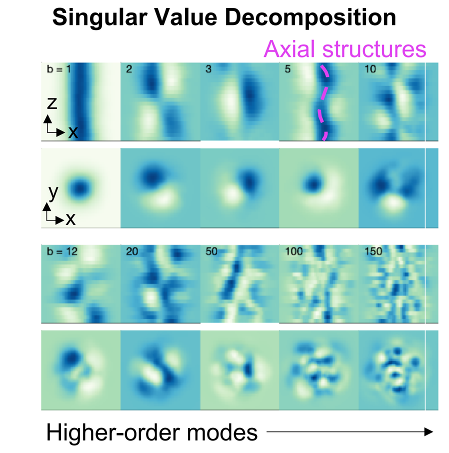
N=200 Training data volumes



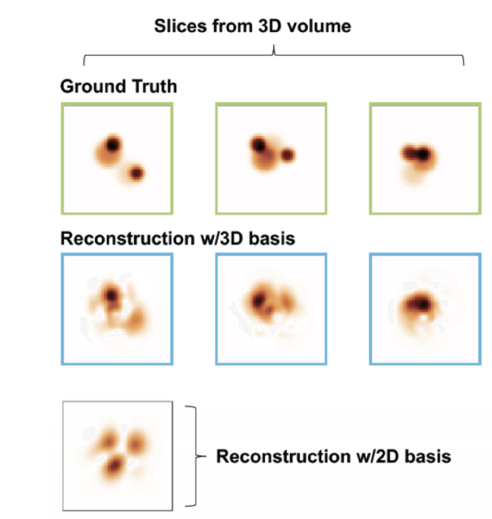
$X = U\Sigma V^T$

Left singular vectors = basis functions

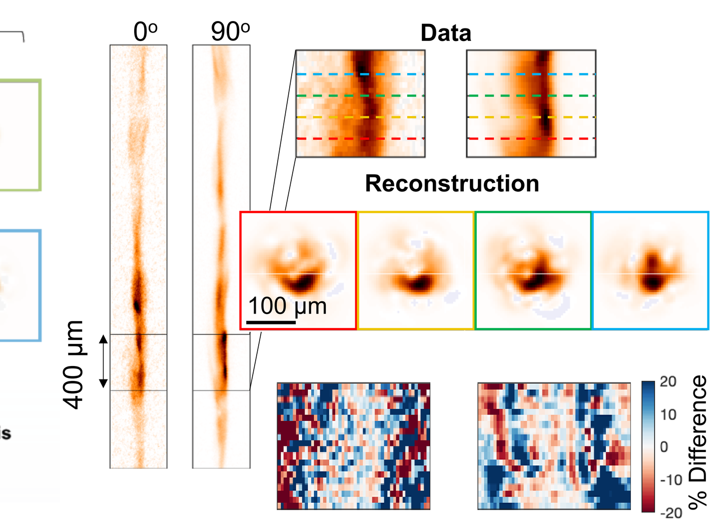
Singular Value Decomposition



Sparse-view tomography testing

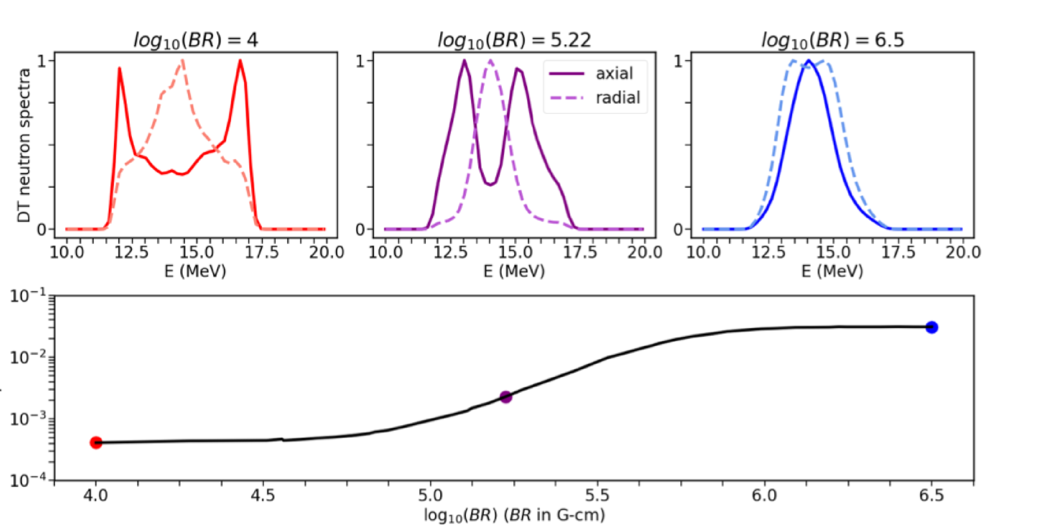


Orthogonal images from MagLIF shot z3479

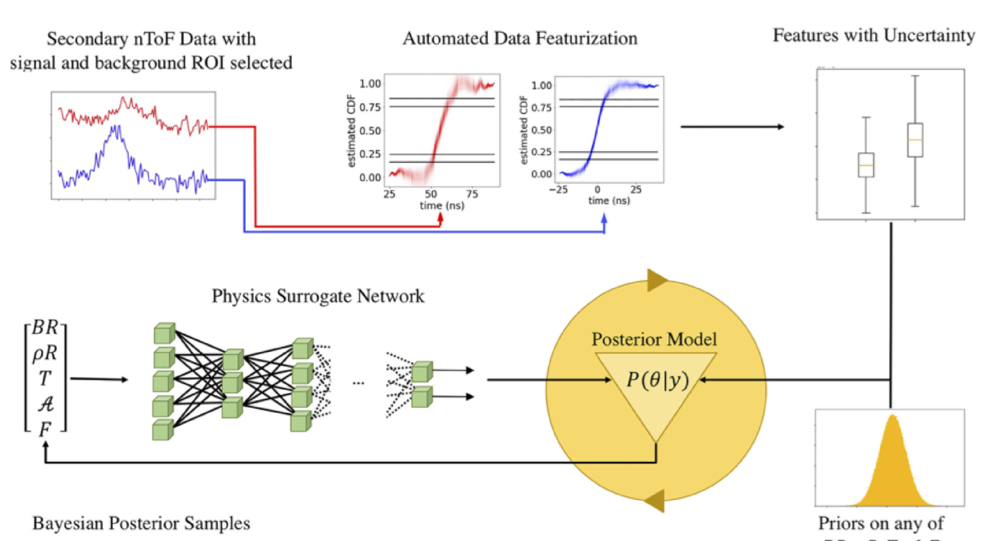


Deep-Learning-Enabled Bayesian Inference of Fuel Magnetization[6,8,9,10]

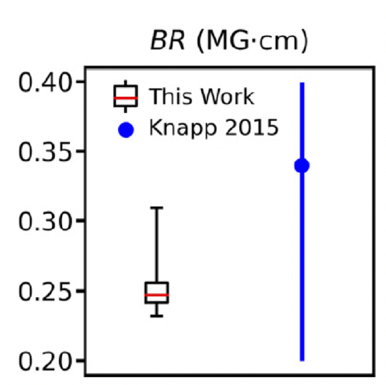
Nuclear diagnostics offer the only available method to characterize magnetic confinement parameter

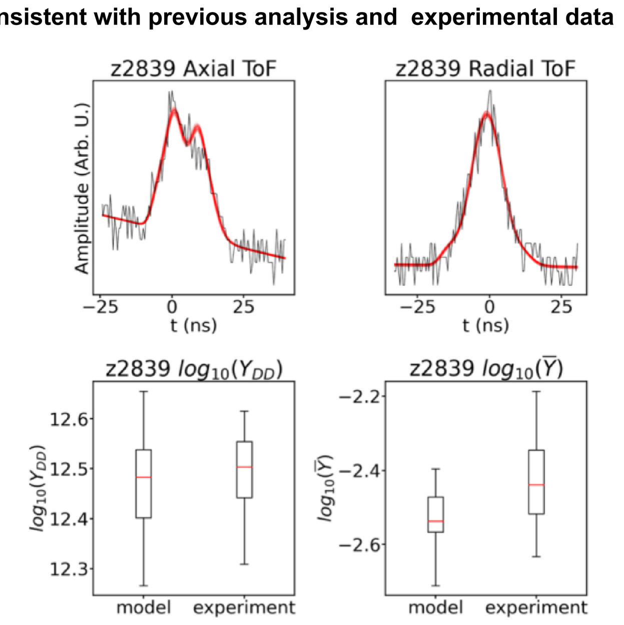


Forward model is expensive, so we use a neural network surrogate to enable inference

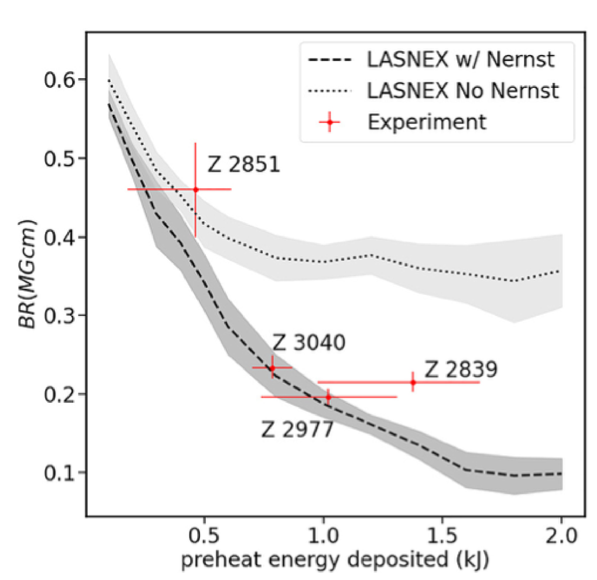


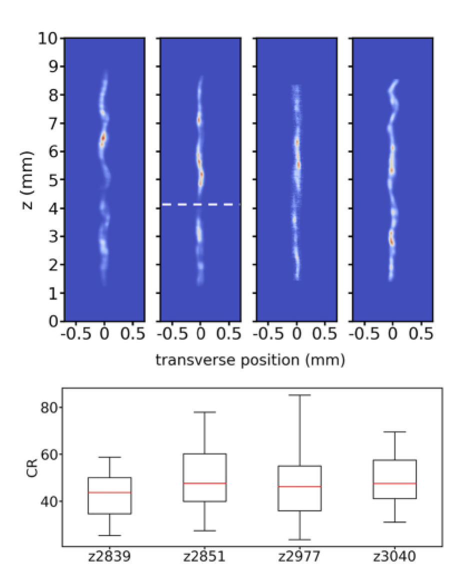
Posterior prediction intervals consistent with previous analysis and experimental data





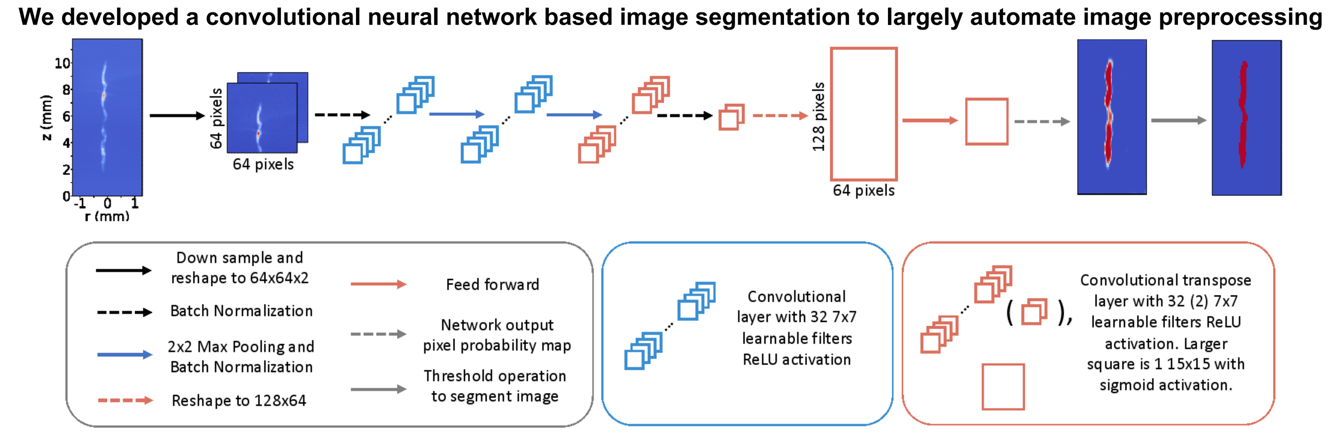
Fuel magnetization is consistent with flux loss via the Nernst effect



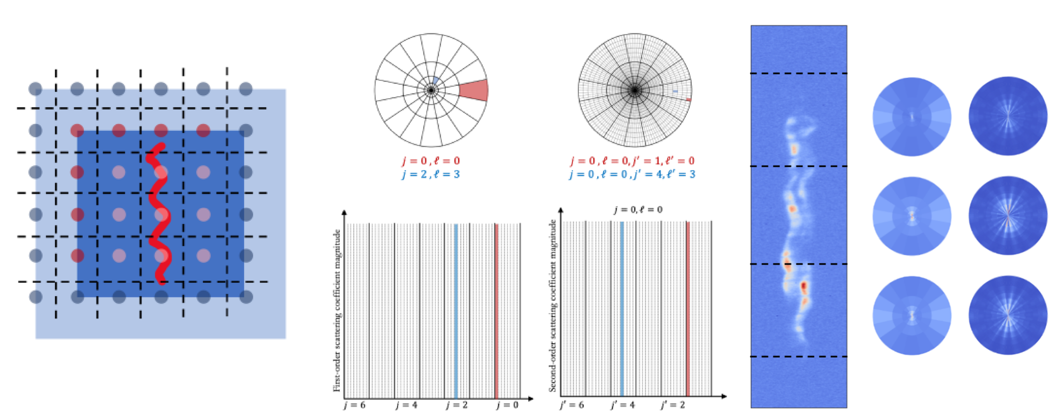


Automated Image Processing and Morphological Assessment[11,12,13,14,15]

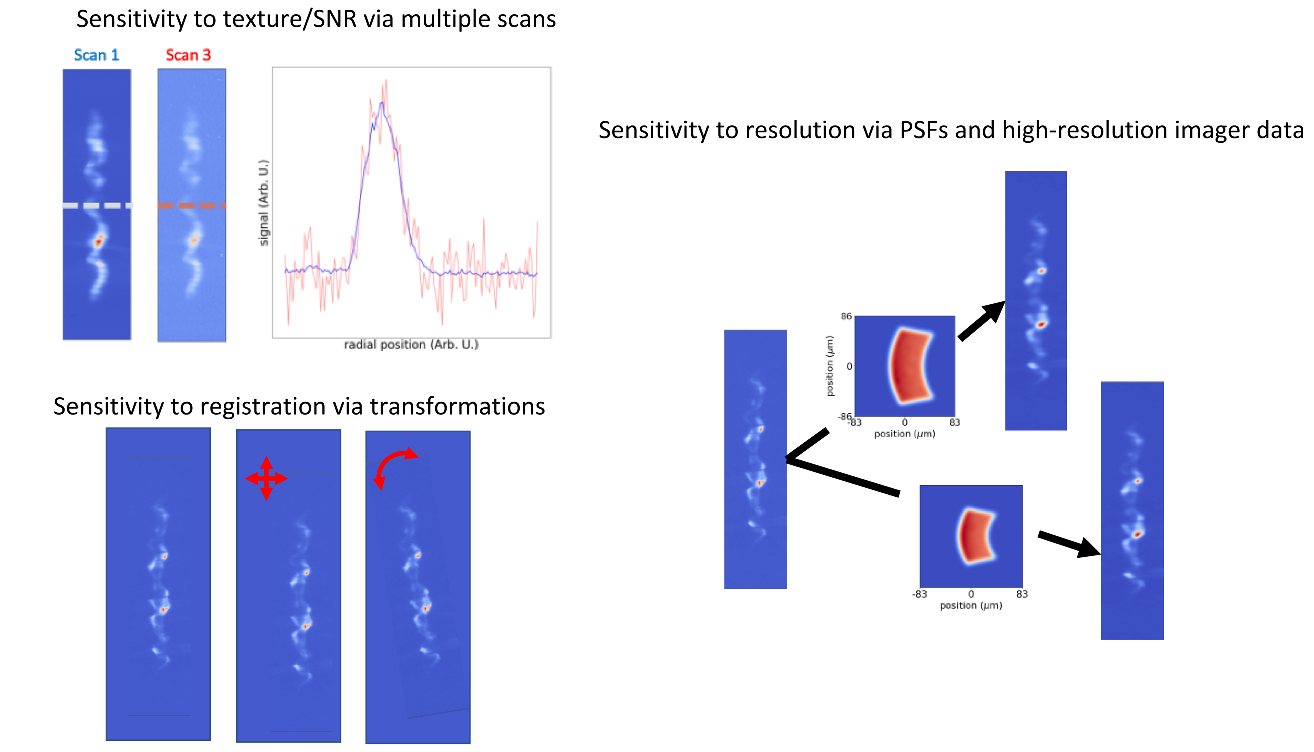
We developed a convolutional neural network based image segmentation to largely automate image preprocessing



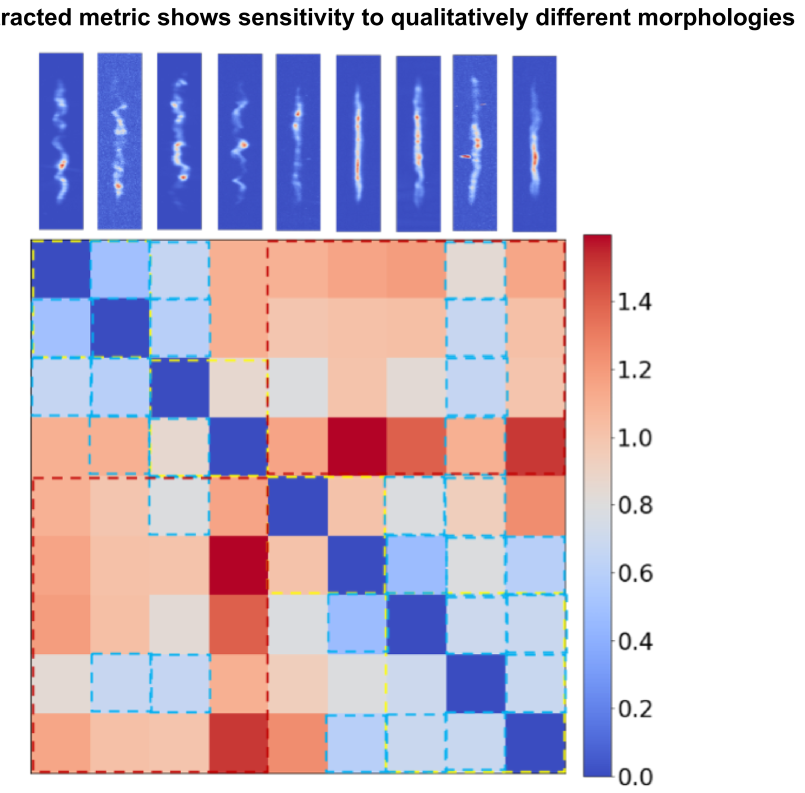
Wavelet based image metrics may provide a useful description of morphology



Experimental data offers a *model-free* approach to assess image metric sensitivities to realistic features



Texture subtracted metric shows sensitivity to qualitatively different morphologies



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[15] D.J. Ampleford *et al.*, In Preparation.