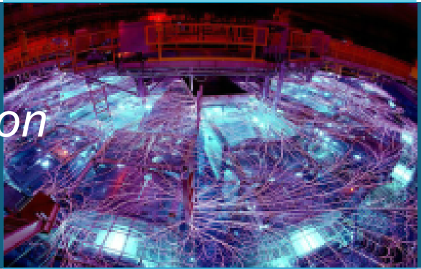
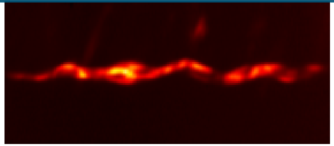
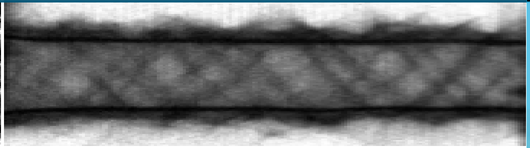
Sandia National Laboratories

SAND2020-11855C

Deep Learning Enabled Bayesian Inference of Fuel Magnetization in Magnetized Liner Inertial Fusion Experiments on Z







PRESENTED BY

William Lewis

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Contributors

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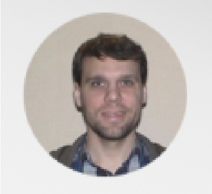
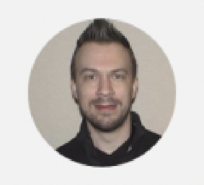
Matt Gomez

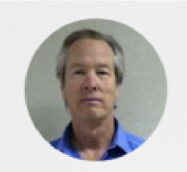


Adam
Harvey-Thompson

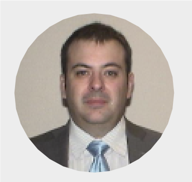
Paul Schmit



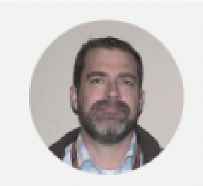
Steve Slutz



Kris Beckwith

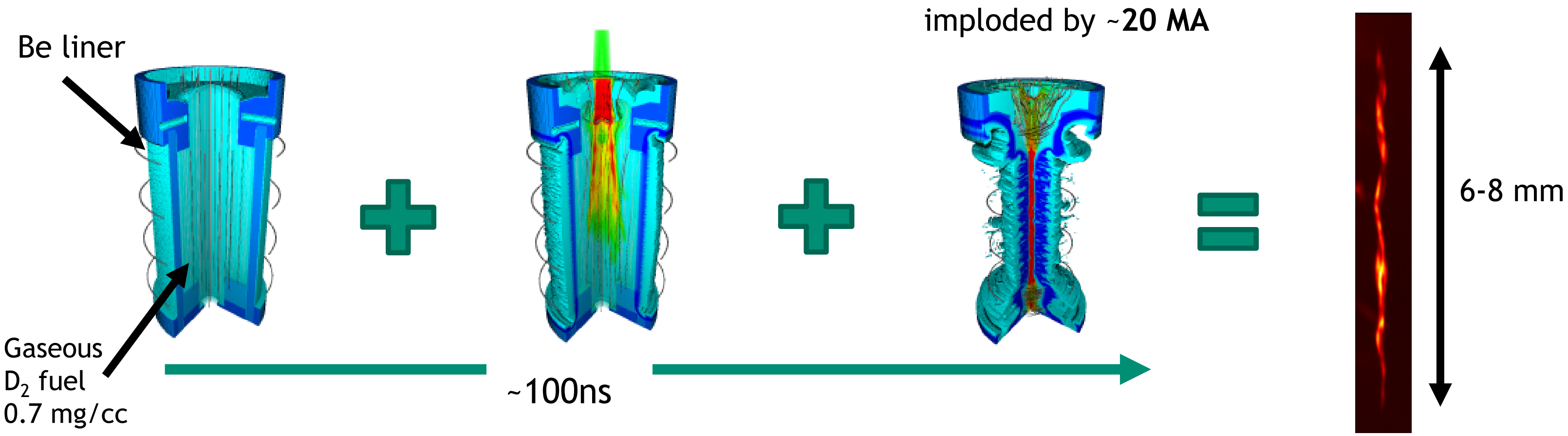


Dave Ampleford



And plenty of others!

Magnetized liner inertial fusion relies on three stages to reach fusion relevant conditions.



Apply External Magnetic Field

- Will suppress radial thermal conduction losses starting in next step.

Preheat

- Increase fuel adiabat to limit required convergence
- Ionize fuel to lock in B-field

Implosion

- PdV work to heat fuel
- Amplify B-field through flux compression

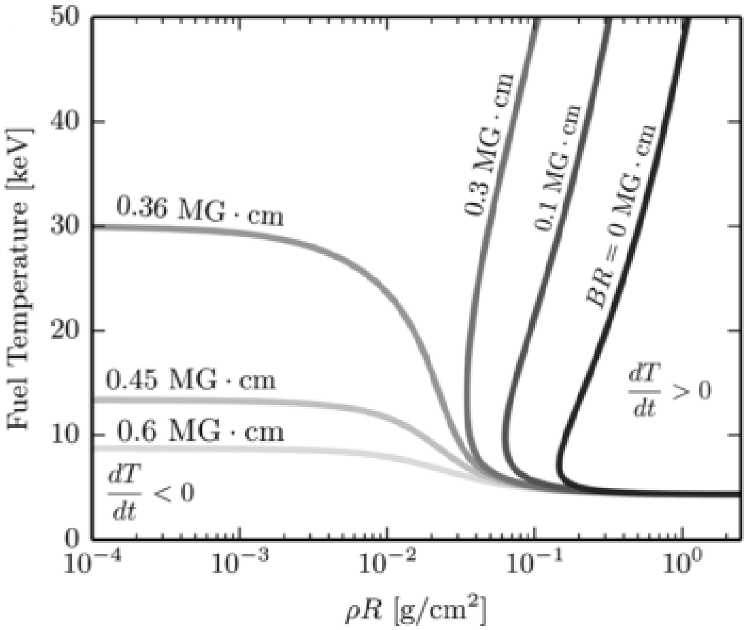
Stagnation

- Several keV temperatures
- Several kT B-field to trap charged fusion products

Don't miss Paul Schmit's MIF review talk on Friday at 8am! YR01.00001

S.A. Slutz *et. al.*, PoP (2010)

parameter, but must be measured via nuclear measurement.



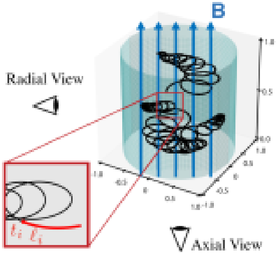
$$\text{Primary}: D + D \rightarrow \begin{cases} n + {}^{3}\text{He} & 2.45\ \text{MeV} \\ p + T, & 1.01\ \text{MeV} \end{cases}$$

$$\text{Secondary}: D + T \rightarrow n + \alpha. \quad 11.8\text{–}17.1\ \text{MeV}$$

$$\mathcal{P}_{L.} \propto \langle \rho_D \ell \rangle \sigma_{DT} \xrightarrow{\text{Magnetized}} \ell \propto f(BR)$$

$Y_{DD}, Y_{DT},$

$\Delta_A \text{nToF}, \Delta_R nToF$



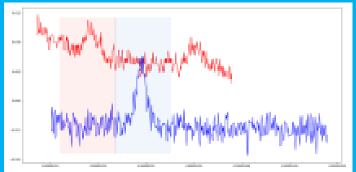
P.F. Knapp *et. al.*, PoP (2015)

Our analysis is based on a Bayesian inference which makes use of NN surrogate for speedup of physics model.

Stage requiring minimal human input with low impact on results

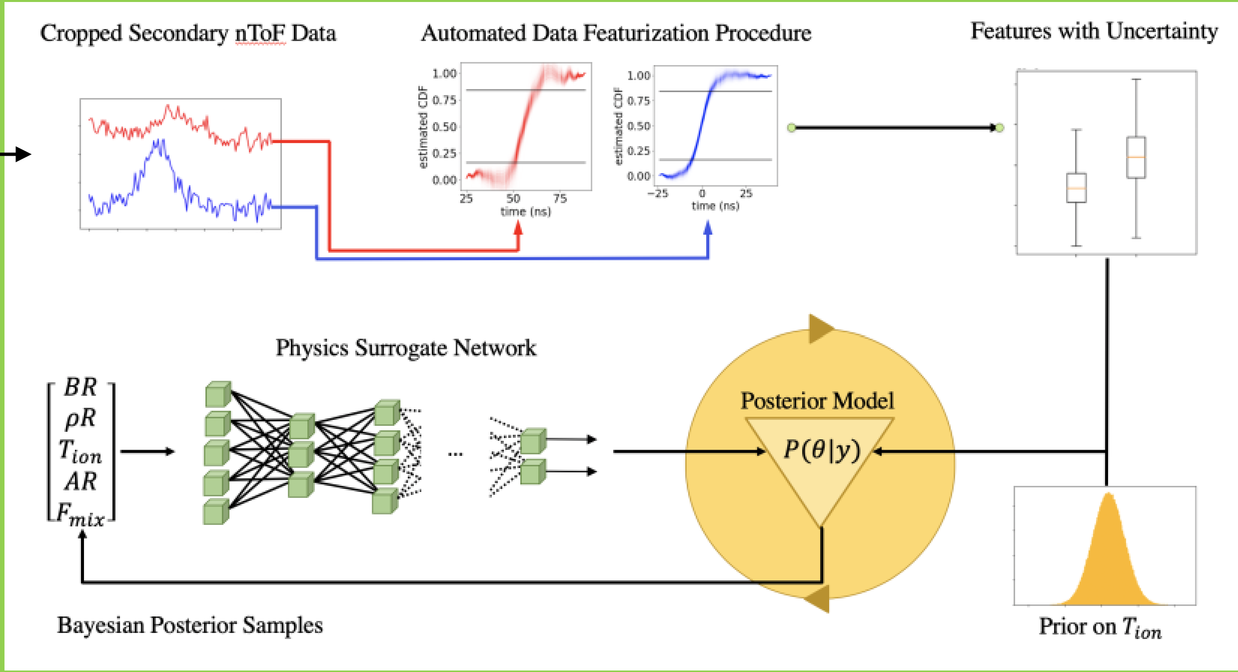
Machine learning and Bayesian inference with no human input

Obtain secondary neutron signals



Select Signal and background ROIs

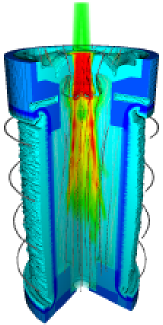
Provide DT and DD yields with uncertainty as well as nToF



Experiments show trend consistent with Nernst effect.

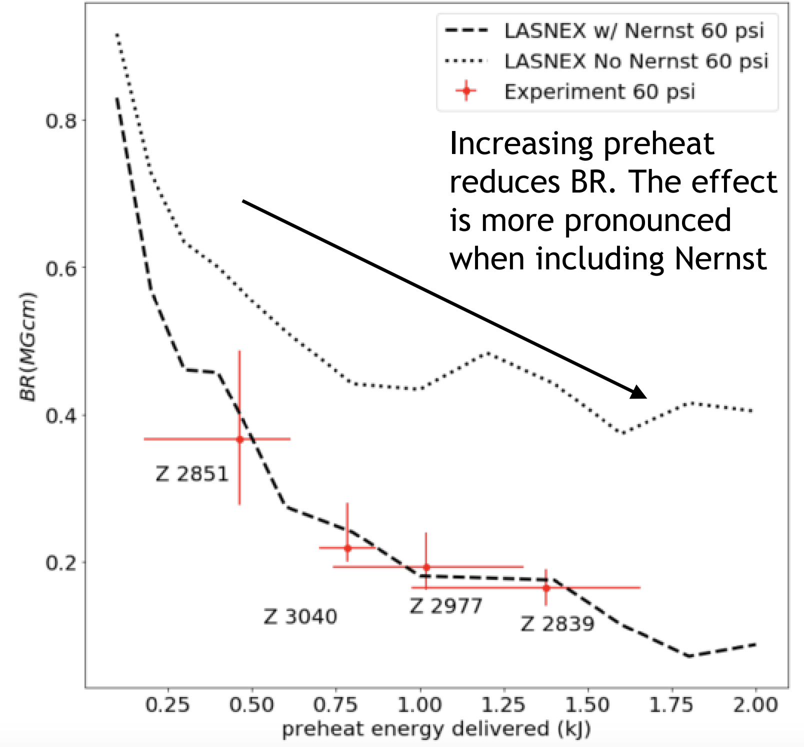
Nernst effect:

B-field locked into plasma by warm electrons, so electronic thermal transport perpendicular to magnetic field will transport flux.



$$v_{Nernst} = \frac{\beta_{\wedge} \nabla_{\perp} T_e}{eB}$$

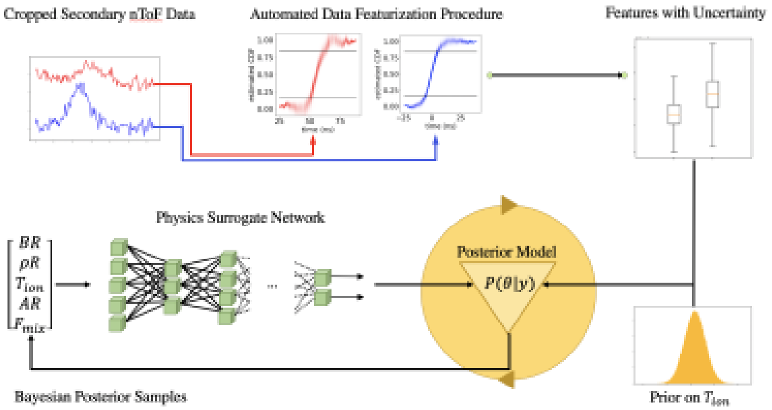
Greater preheat will establish stronger radial temperature gradient and applied magnetic field is axial, so as preheat is increased, Nernst effect is expected to become more significant.

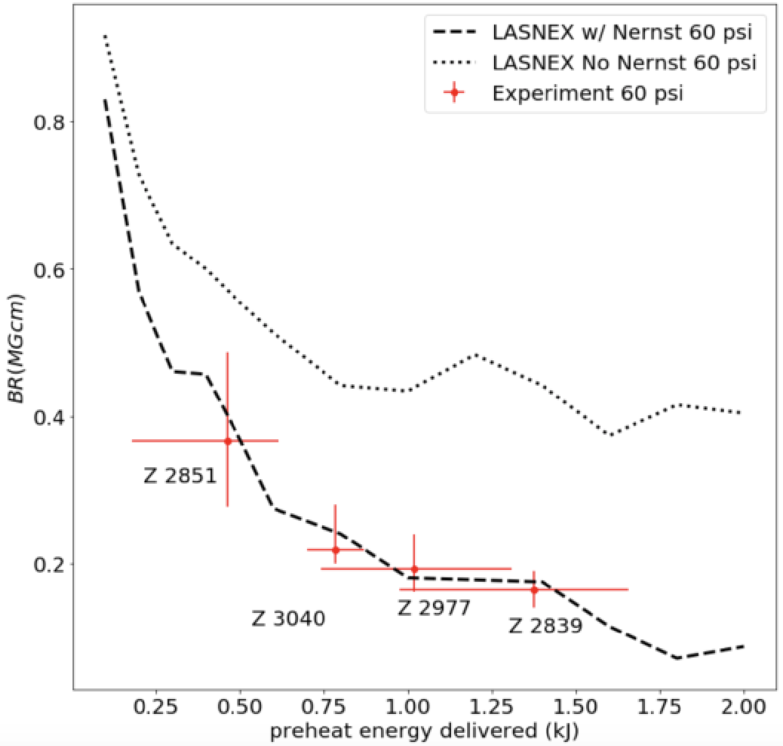


Note: Preheat error bars (x-axis) are provided by experiment, while BR error bars (y-axis) are inferred from Bayesian analysis

Closing remarks

- DL enabled Bayesian inference of BR for MagLIF shots
- Want to develop a database of BR for MagLIF shots to mine for trends
  - Already see interesting physics consistent with Nernst effect
- Plans to investigate
  - 3D nature of plasma
  - Instabilities
  - Mix
  - Fill density (already early indications?)
  - Impact of uncertainty
  - Scaling aspects of Nernst effect

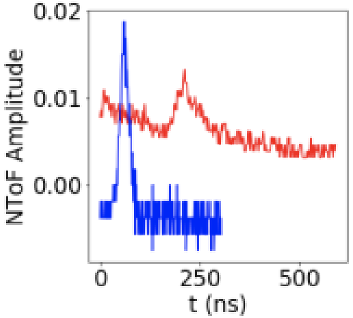




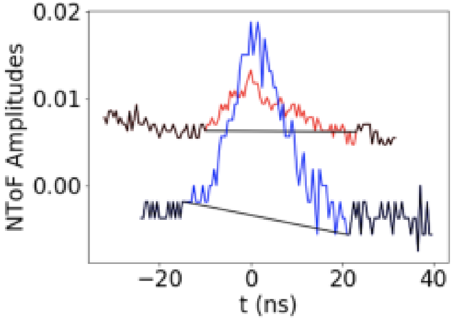
Backup

Experimental data exhibit significant noise which should be captured in uncertainty of features extracted.

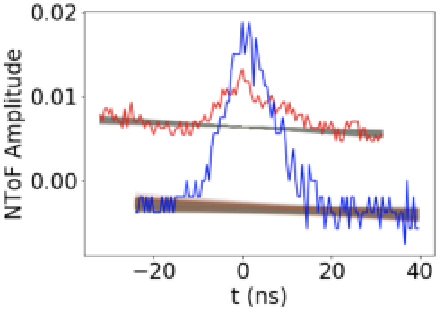
Step 1: collect data from experiment



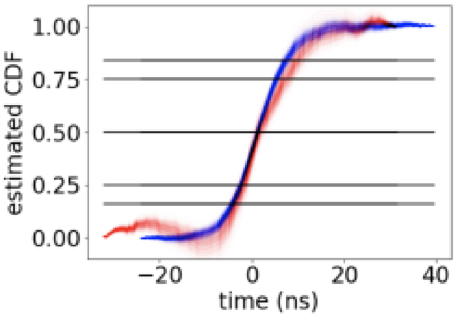
Step 2: crop and select background ROI



Step 3: Bayesian Background fit



Step 4: Compute CDFs after subtraction



Step 5: Compute Quantile Features with Uncertainty

75%-25%

(75%-50%)-(50%-25%)

84%-16%

(84%-50%)-(50%-16%)

Our Bayesian model incorporates models for most sources of uncertainty.

- Uncertainty in forward model due to use of surrogate

$$\vec{y}_{nn}(\theta) = \vec{y}(\theta) + N(0, \Sigma_{OOS})$$

- Uncertainty in observed values (DD yield, DT yield, quantile features)

$$\vec{y}_{feats} = \vec{y}(\theta) + N(0, cov[\vec{y}_{feats}, \vec{y}_{feats}])$$

- Not included:
  - Possible systematic uncertainty from model (would need to assess performance of different models)
  - Doesn't contain uncertainty in NN parameters (in principle possible, but not likely to be dominant source)