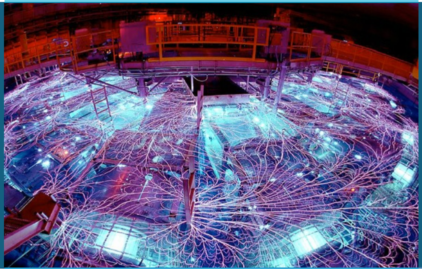
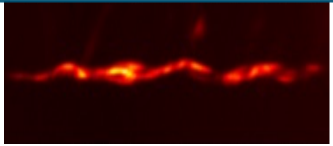
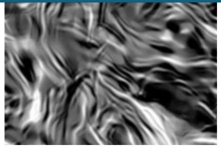
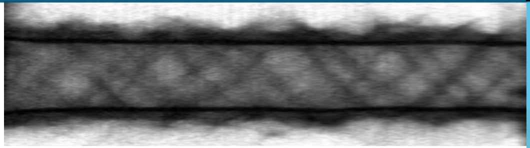
SAND2023-11670C

Developing data-driven approaches to design and discovery for extreme physics on the Z Machine









PRESENTED BY

William Lewis

LANL Seminar 2/2/23

SAND2023-####

Today I'll be representing the work of a large group of talented and dedicated colleagues at the intersection of data science and HEDP.

- **Center 1600 (Pulsed Power Sciences)**: L. Stanek, M. A. Schaeuble, J.R. Fein, A.J. Porwitzky , J.L. Brown, O.M. Mannion, E. C. Harding, S. B. Hansen, T. Nagayama, M.B. Adams, J.M. Woolstrum, C. A. Jennings, A. J. Harvey-Thompson, C. Tyler, M. R. Gomez, M. R. Weis, D. E. Ruiz, D. J. Ampleford, M. Geissel, M. Mangan, G.A. Chandler, G. Cooper, K. Blaha , S. Fields, S. A. Slutz, I.C. Smith, T. J. Awe, K. Beckwith, L. Schulenburger, D. B. Sinars, M. Jones, G. A. Rochau, K. J. Peterson, T.R. Mattsson, *P.F. Knapp, **M.E. Glinsky, ***P. F. Schmit

Our team is growing!

Center 1600's first Maxwell fellow, Luke Stanek

Actively recruiting and seeking collaborations

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

*current location, Los Alamos National Laboratory, Los Alamos NM

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

***current location, Lawrence Livermore National Laboratory, Livermore CA

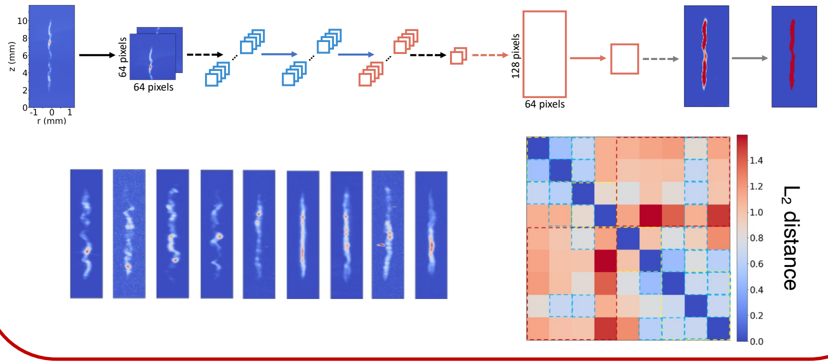
LABORATORY DIRECTED RESEARCH & DEVELOPMENT

WHERE INNOVATION BEGINS

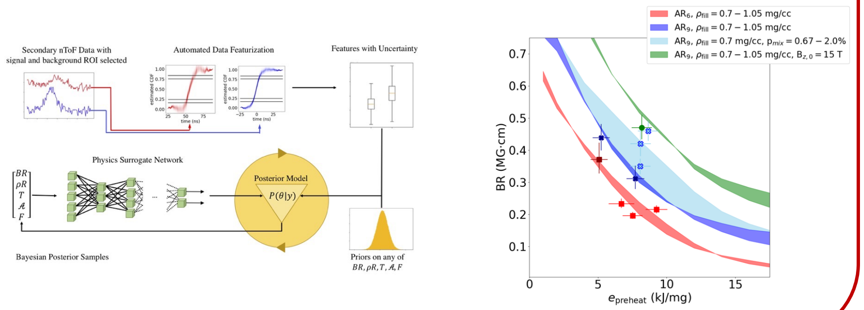
Talk overview

- Introduction
  - Sandia's Z Pulsed Power Facility
  - Magnetized Liner Inertial Fusion
- Exemplars of applied data science for MagLIF
  - stagnation image analysis
  - fuel magnetization parameter analysis
  - future directions and collaboration opportunities!
- Overview of other efforts and concluding remarks

Image analysis



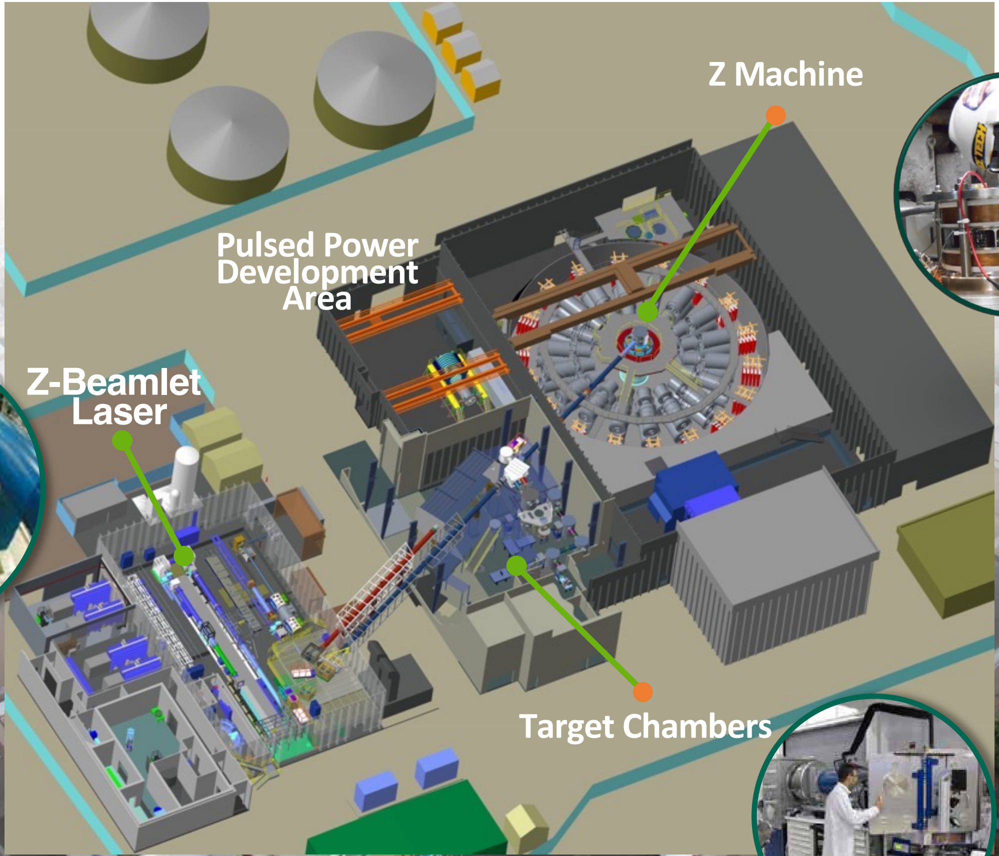
Fuel magnetization



Sandia's Z Pulsed Power Facility

The Earth's largest pulsed power machine

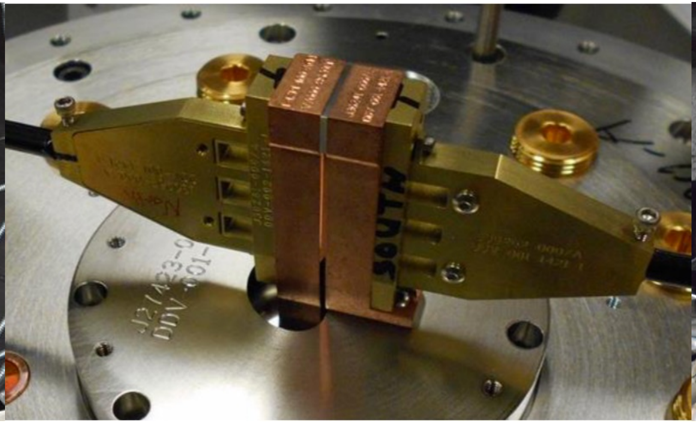
Sandia's Z Pulsed Power Facility



Capabilities

- 20 MA peak current
- 4 kJ, 1 TW laser
- 2 MJ's soft x-ray
- kJ's warm x-rays
- kJ's fusion yield
- Mbar's planar drive

As a world class facility, Z provides a powerful resource for investigating critical national security questions and exciting fundamental science.



Radiation Science

- Weapon survivability
- Laboratory Astrophysics

Dynamic Material Properties

- Pu aging and manufacturing
- Planetary science

Inertial Confinement Fusion

- Thermonuclear burn
- Basic fusion research

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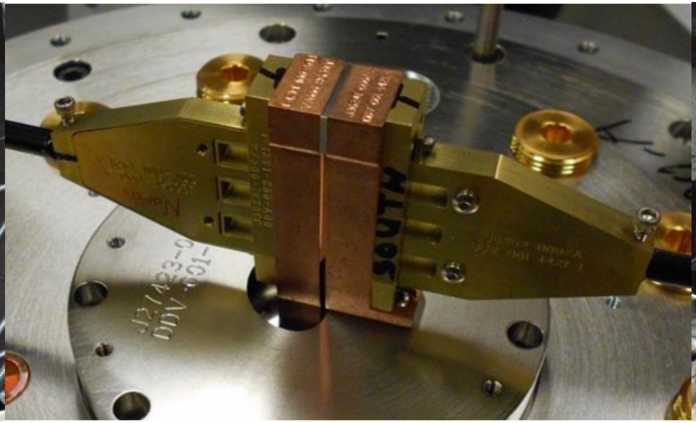

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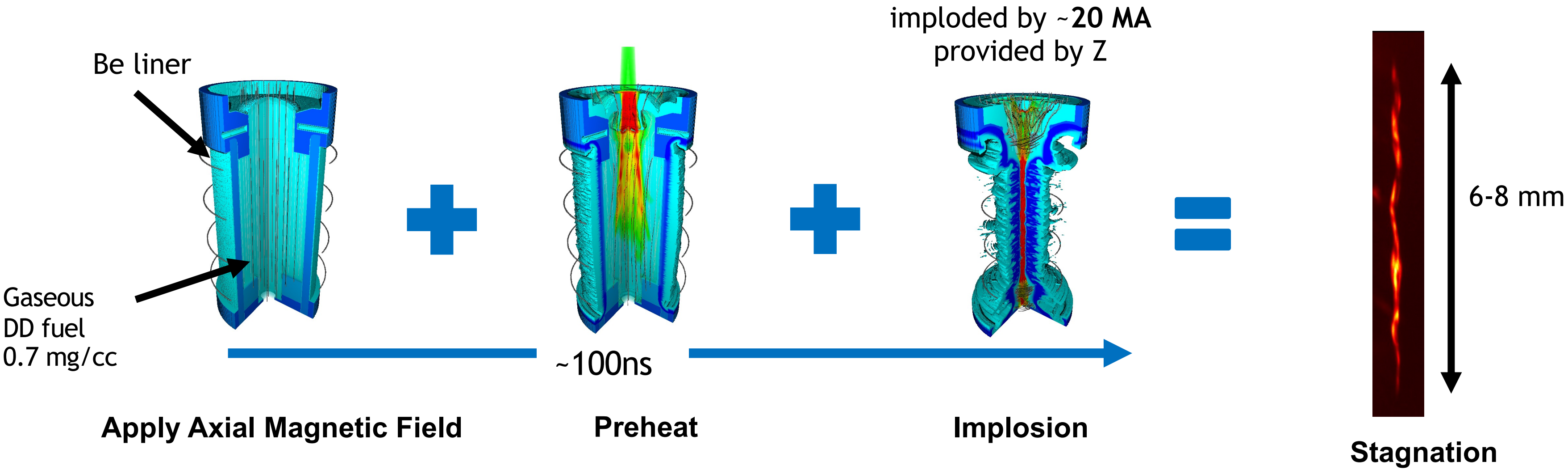
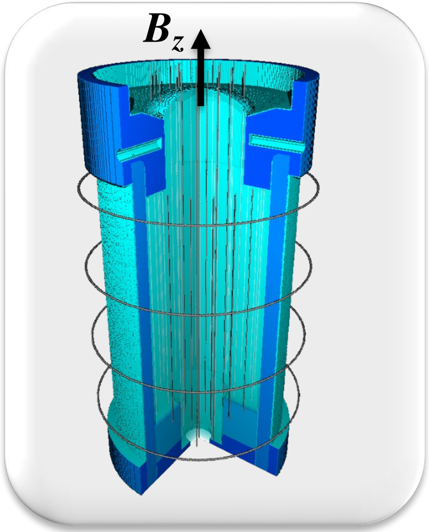
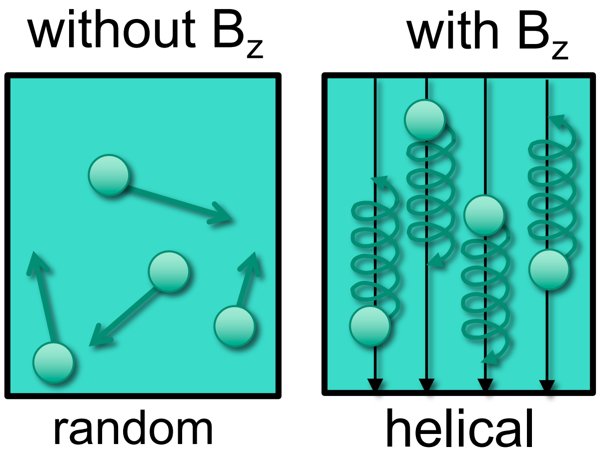
The Magnetized Liner Inertial Fusion (MagLIF) concept relies on three stages to reach fusion relevant conditions.

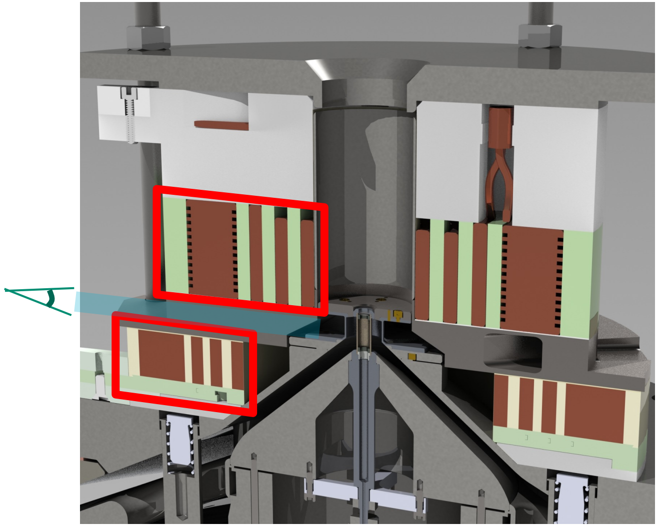


S.A. Slutz *et. al.*, Phys. Plasmas **17**, 056303 (2010).
M.R. Gomez *et al*. Phys. Rev. Lett. **113**, 155003 (2014).

Helmholtz-like coils are used to premagnetize the MagLIF load





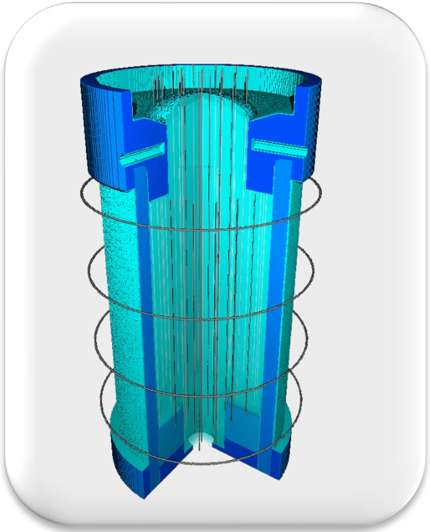


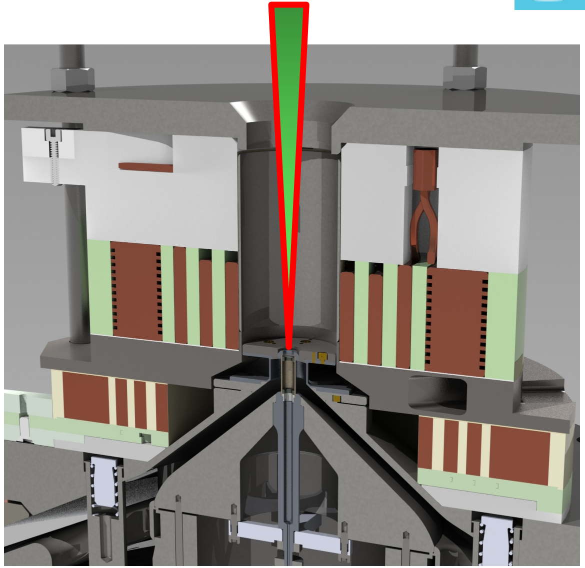
D. C. Rovang *et al.*, Rev. Sci. Instrum. **85**, 124701 (2014).

Premagnetize fuel

- embed 7-20 T in ~ms timescale
- reduce radial thermal conduction
- compress + traps fusion products

Z Beamlet laser preheats the fuel establishing a higher adiabat



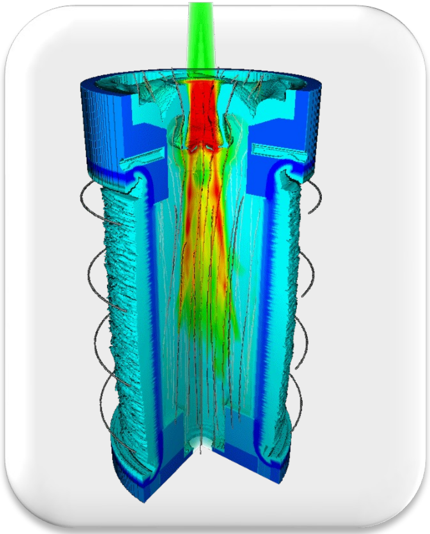


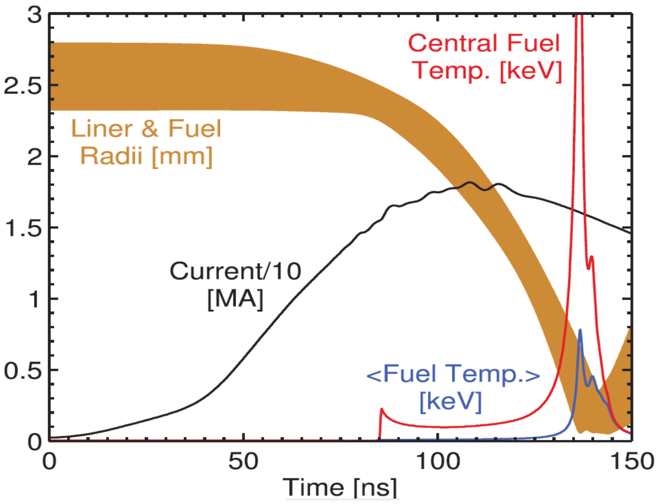
Preheat the fuel

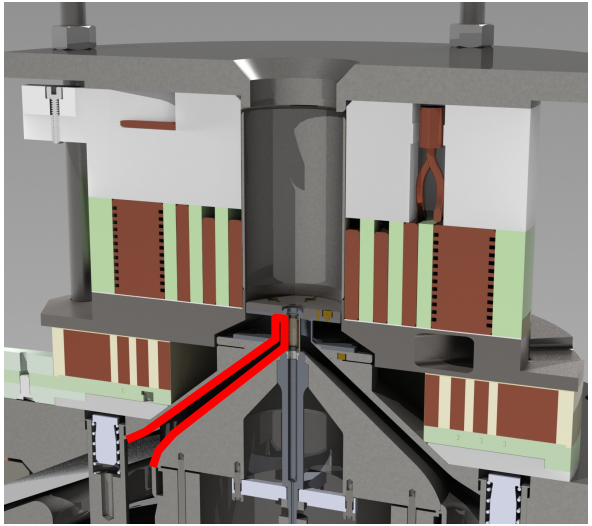
- Z-Beamlet laser delivers ~2-3 kJ to the Z chamber.
- Laser heats fuel through Inverse Bremsstrahlung (~100-200 eV, 1-2 kJ)
- Laser preheat sets the adiabat of the implosion.

M. R. Weis, *et al.*, Phys. Plasmas **28,** 012705 (2021).
A. J. Harvey-Thompson, *et al.*, Phys. Plasmas **27,** 113301 (2020).
A. J. Harvey-Thompson, *et al.*, Phys. Plasmas **26**, 032707 (2019).
A. J. Harvey-Thompson, *et al.*, Phys. Plasmas **25**, 112705 (2018).
M. Geissel, *et al.*, Phys. Plasmas **25**, 022706 (2018).
A. J. Harvey-Thompson, *et al.*, Phys. Rev. E **94**, 051201 (2016).
A. J. Harvey-Thompson, *et al.*, Phys. Plasmas **22**, 122708 (2015).

Current from the Z pulsed power generator provides a magnetic pressure driving the liner to implode compressing the fuel





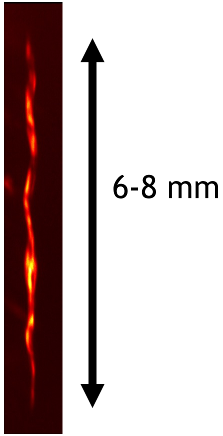


Compress liner and fuel

- Lorentz force accelerated the liner.
- Fuel is then quasi-adiabatically compressed.
- Liner implosion leads to flux compression, amplifying B-field

R. McBride et al., Phys. Plasmas **23**, 012705 (2016).
3D implosion movie courtesy of C. Jennings.

When thermal pressure exceeds magnetic pressure, the liner decelerates resulting in stagnation



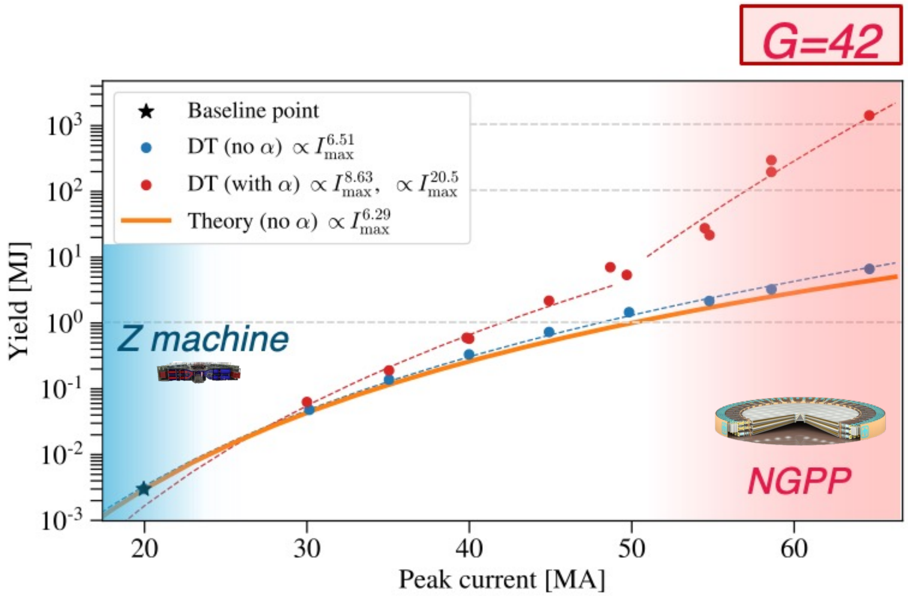
Stagnation

Shot ID	z3289
$\dot{R}_{max}$	70 km/s
R_{burn}	50 um
T_{burn}	2.7 keV
p_{burn}	1.9 Gbar
BR	0.2-0.5 MG·cm
τ_{bw}	2 ns
Y (DT equivalent)	2 kJ

S.A. Slutz *et. al.*, Phys. Plasmas **17**, 056303 (2010).
M.R. Gomez *et al*. Phys. Rev. Lett. **113**, 155003 (2014).

MagLIF offers a rich physics platform with paths to high yield at a next generation pulsed power (NGPP) facility.

- Physics:
  - magnetized HED plasmas
  - fusion relevant temperatures and densities
  - thermonuclear neutron generation
- NNSA Stockpile Stewardship Program
  - Y>100MJ in controlled fashion in the lab
  - NGPP may help achieve this goal
- May provide route to fusion-energy on the grid*
  - high-yield pulsed-power ICF has relevant gain factor
    - need G~100

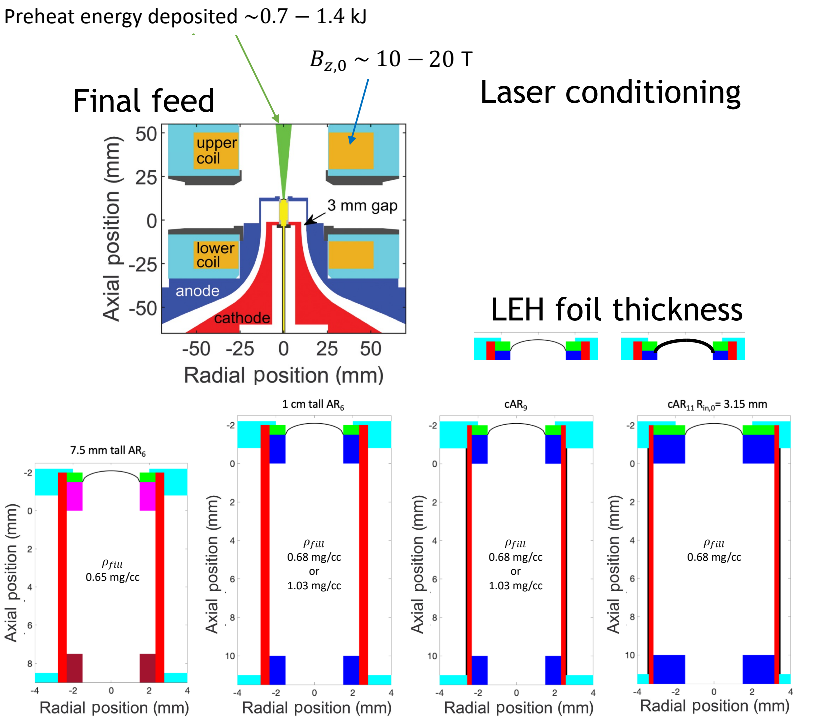


*S. Atzeni and J. Meyer-ter Vehn, *The Physics of Inertial Fusion*, (Oxford University Press Inc., New York, 2009).

D.E. Ruiz *et. al.*, (Submitted) Phys. Plasmas.

A critical aspect of confidently scaling to NGPP is to ensure we understand and characterize the physics of MagLIF on Z today.

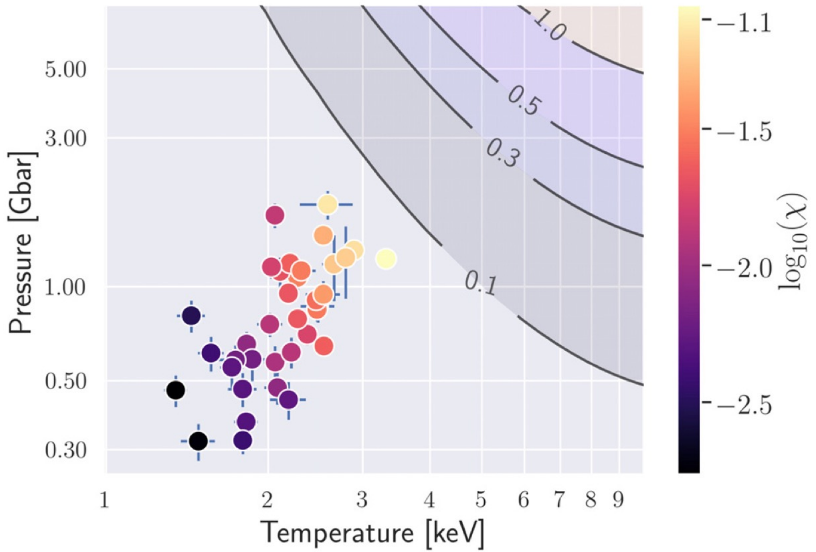
Experimental input conditions



A.J. Harvey-Thompson *et al*. Phys. Plasmas **25**, 112705 (2018).
D.A. Yager-Elorriaga *et al*. Nucl. Fusion **62**, 042015 (2022).
W.E. Lewis *et al*. Phys. Plasmas (Submitted).

Experimental performance

$$\chi = \frac{2}{3}\frac{f_D f_T}{(1+\langle Z\rangle)^2}\frac{\varepsilon_\alpha \tau_E}{V_{HS}}\int_V P_{HS}\frac{\langle\sigma v\rangle_{DT}}{T^2}dV$$



P.F. Knapp *et al.*, Phys. Plasmas **29**, 052711 (2022).

Data-driven methods paired with physics insight, theory, and simulation are playing a key role in this effort.

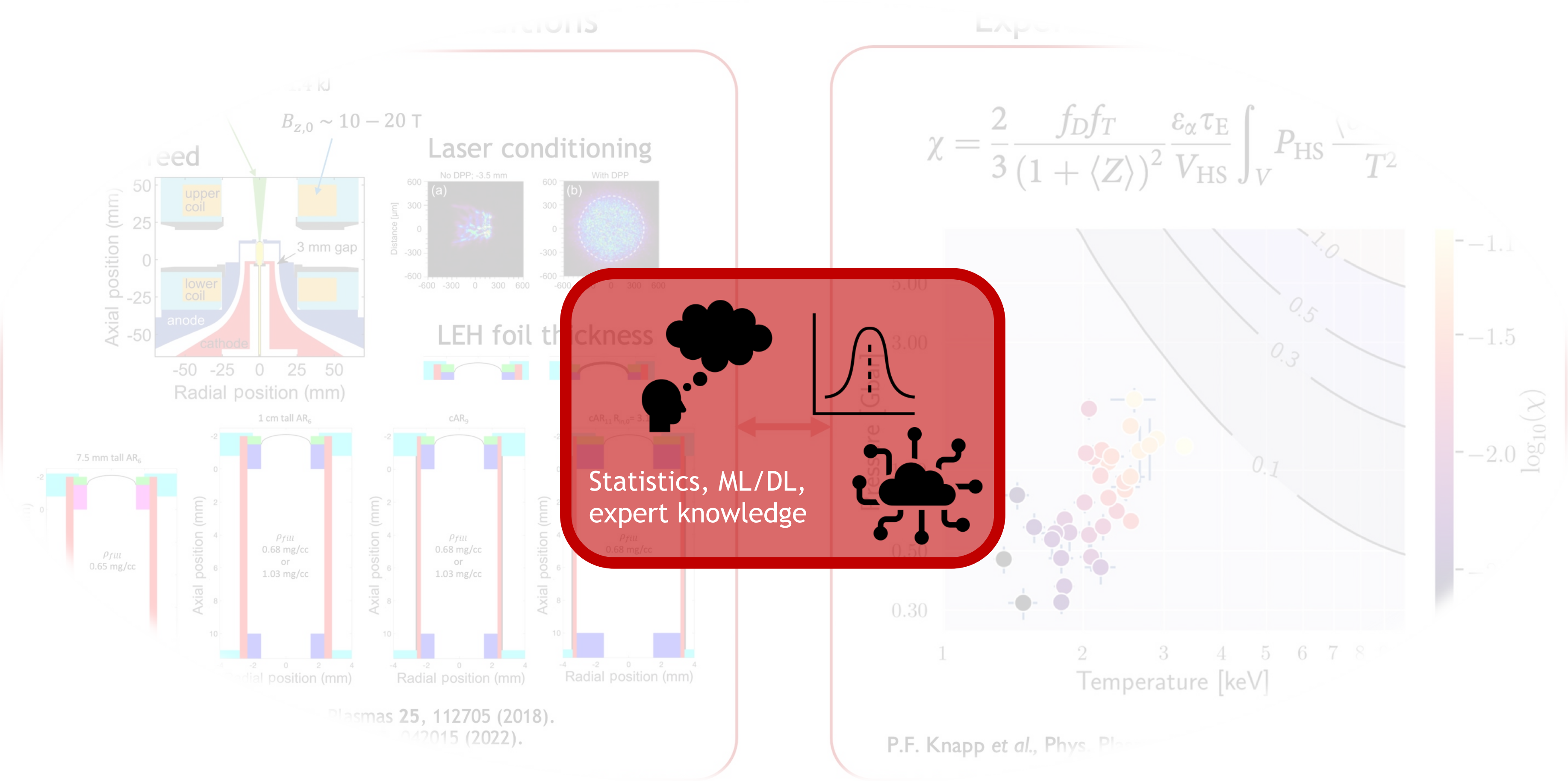


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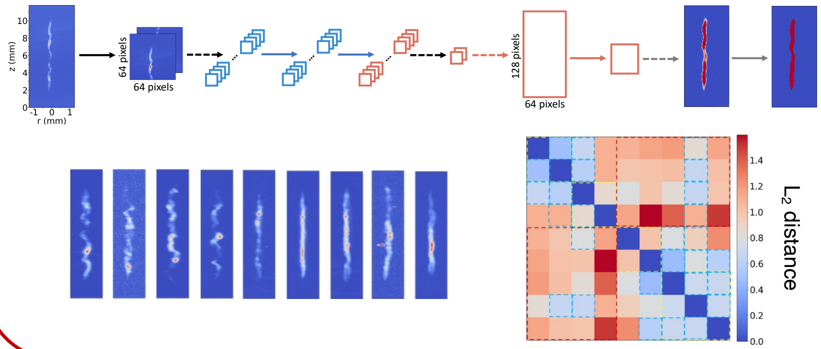
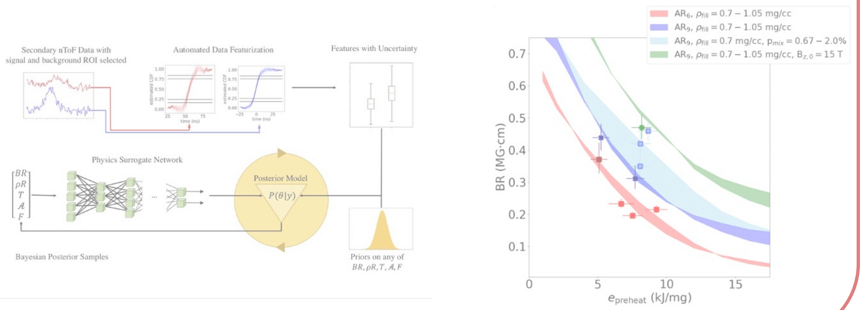
Image analysis

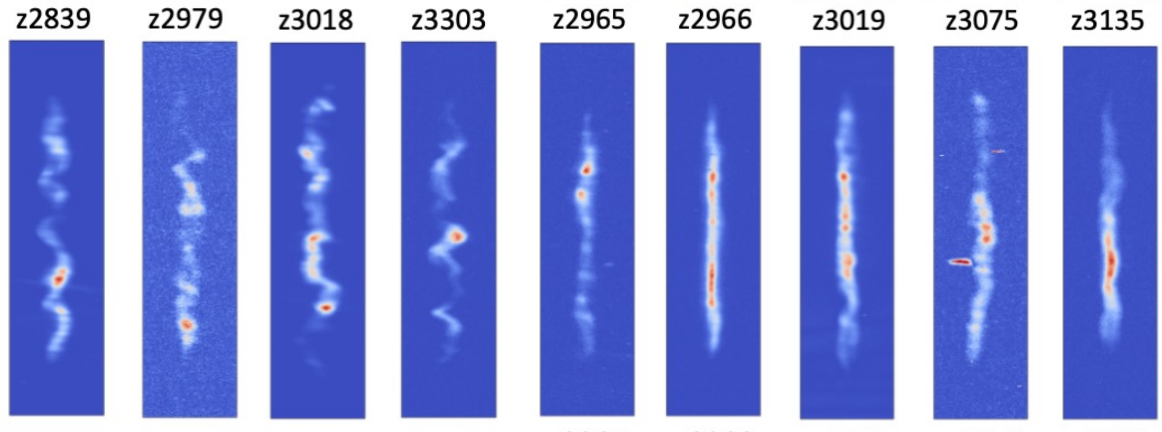


Fuel magnetization



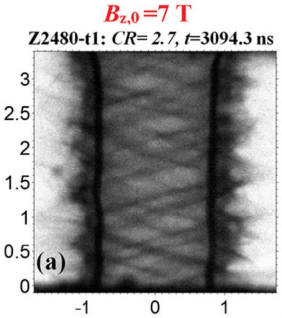
Stagnation morphology is a complex but important piece of the puzzle of understanding performance and reproducibility

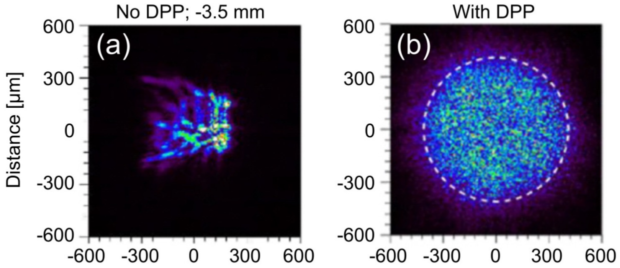
- MagLIF stagnation images show significant variance

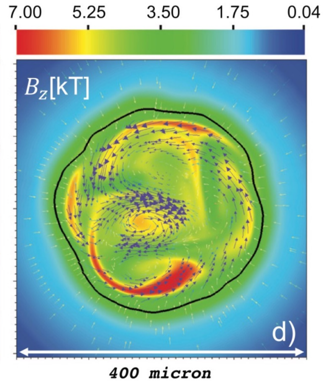


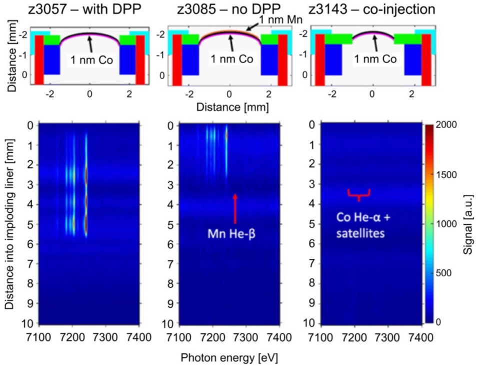
Stagnation morphology is a complex but important piece of the puzzle of understanding performance and reproducibility

- Wish to understand sources of variance e.g.
  - magneto-Rayleigh Taylor and deceleration instabilities
    - feedthrough
    - seed mechanism(s)
    - relation to mix
  - preheat induced mix
  - preheat induced vorticity





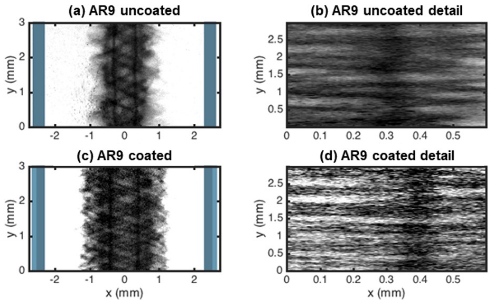


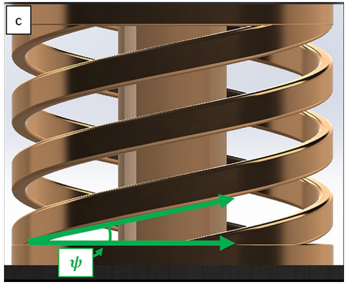


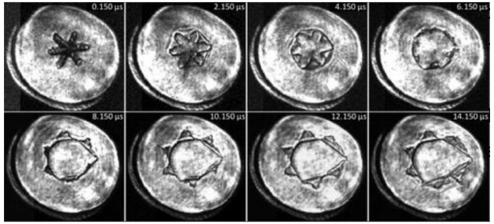
T.J. Awe *et al*. Phys. Rev. Lett. **111**, 235005 (2013).
A.J. Harvey-Thompson *et al*. Phys. Plasmas **25**, 112705 (2018).
M.R. Weis *et. al*., Phys. Plasmas **28**, 012705 (2021).
D.A. Yager-Elorriaga *et al*. Nucl. Fusion **62**, 042015 (2022).

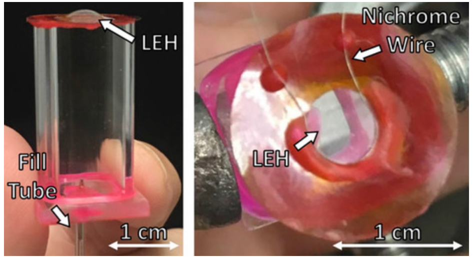
Stagnation morphology is a complex but important piece of the puzzle of understanding performance and reproducibility

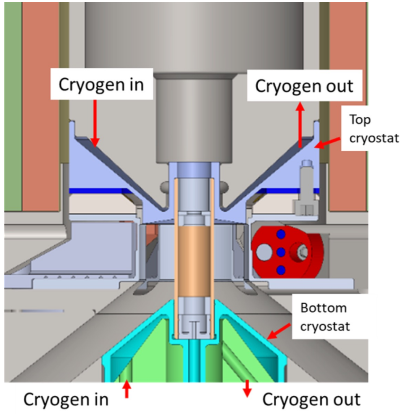
- Want to investigate mitigation mechanisms
  - dielectric coatings
  - dynamic screw pinch
  - laser gate
  - cryogenic cooling







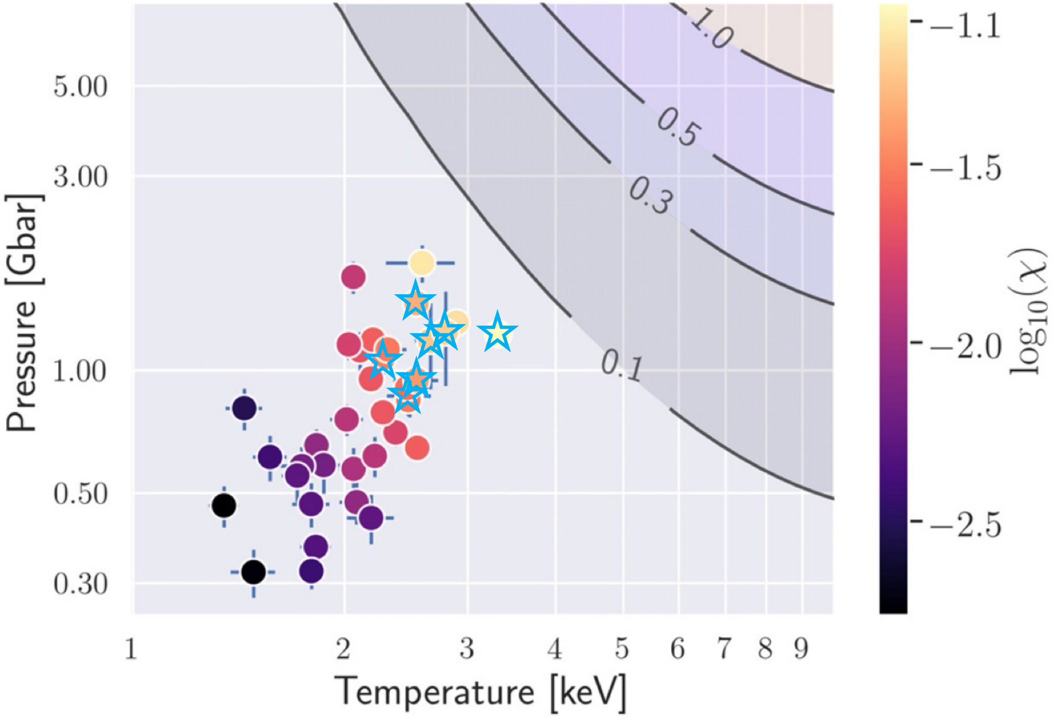




P.F. Schmit *et al*. Phys. Rev. Lett. **117**, 205001 (2016).
A.J. Harvey-Thompson *et al*. Phys. Plasmas **25**, 112705 (2018).
G.A. Shipley *et al*. Phys. Plasmas **26**, 102702 (2019).
S.M Miller *et al*. Rev. Sci. Instrum. **91**, 063507 (2020).
B.R. Galloway *et al*. Phys. Plasmas **28**, 112703 (2021).
A.J. Harvey-Thompson *et al*. Rev. Sci. Instrum. (Submitted).
D.J. Ampleford, D.A. Yager-Elorriaga *et al*. (In Preparation).

Stagnation morphology is a complex but important piece of the puzzle of understanding performance and reproducibility

- Can we characterize relation to variance in performance?
  - 7 of top 10 performers coated
  - 1 of bottom 10 performers coated
- Improved morphology partially responsible?

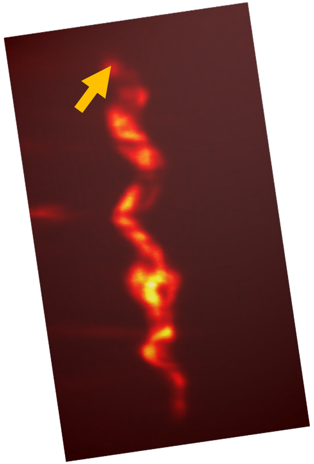


P.F. Knapp *et al.*, Phys. Plasmas **29**, 052711 (2022).

Several challenges make addressing these questions difficult.

Challenge

- Bespoke tools
  - Time consuming
  - possible variation from user to user



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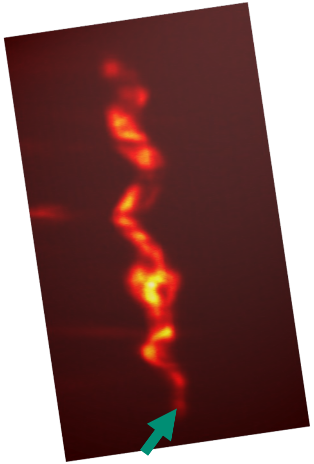

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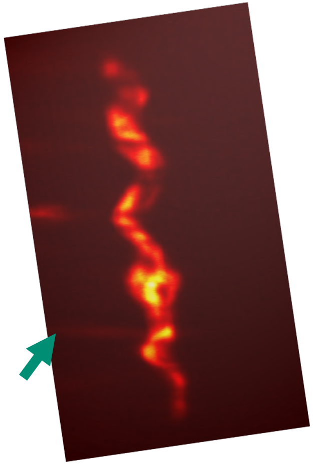

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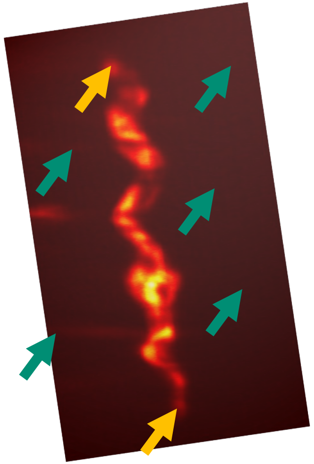
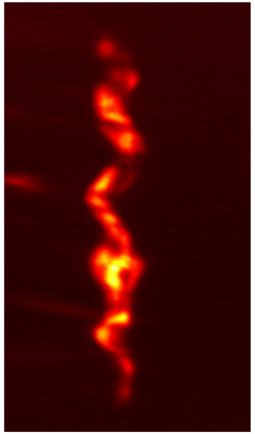
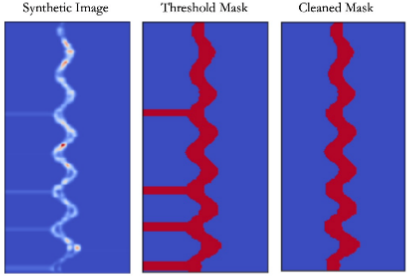


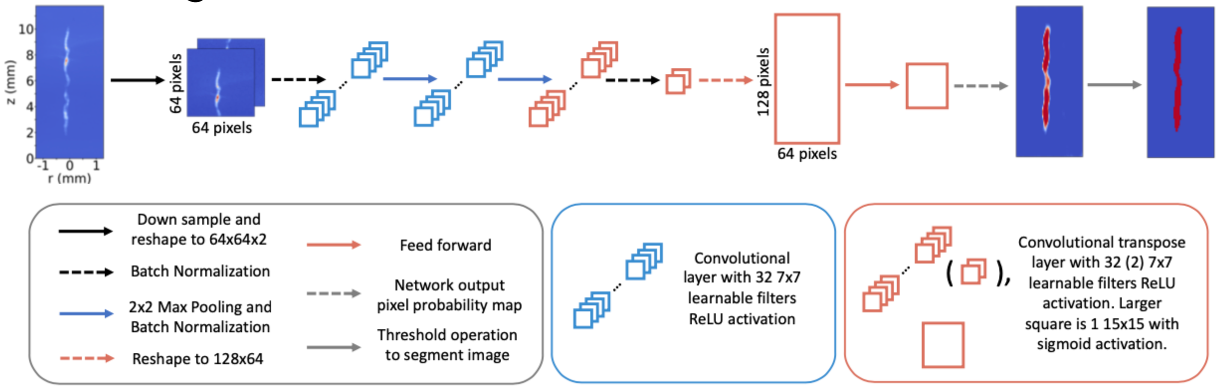


Machine learning provides a route towards automating preprocessing steps improving reproducibility and data throughput.

Synthetic training data

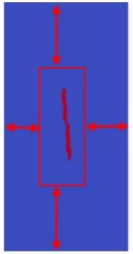


Segmentation convolutional neural network

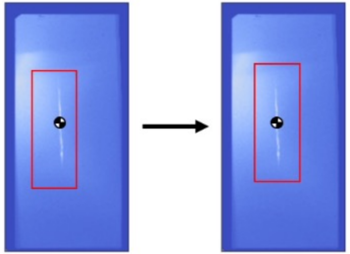


Registration and background subtraction pipeline

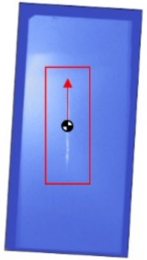
Zero pad probability map



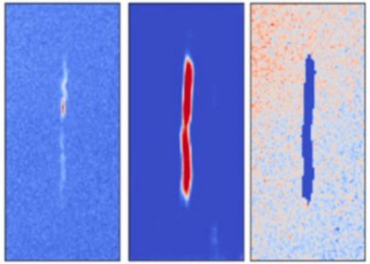
Translate image and probability map



Rotate image and probability map



Use segmentation to extract and fit slowly varying background

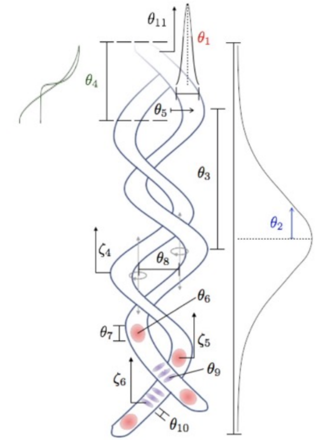


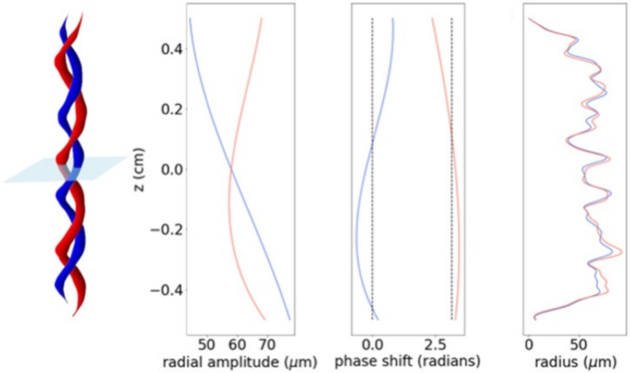
W.E. Lewis *et al.*, J. Plasmas Phys. **88**, 895880501 (2022).

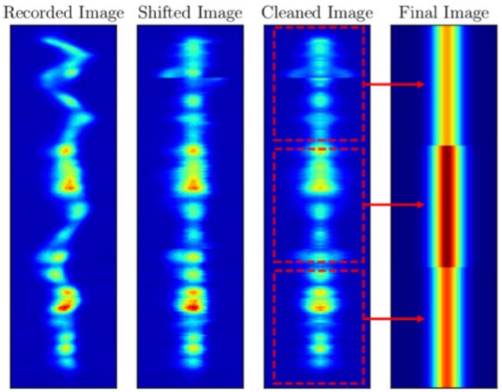
Several challenges make addressing these questions difficult.

Challenge

- Need statistics on image noise, background, and structure
  - E.g. for Bayesian inference or ML synthetic training data



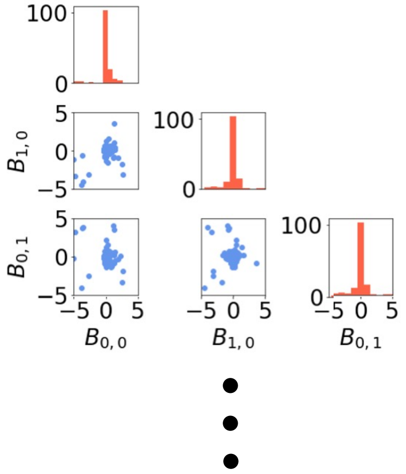


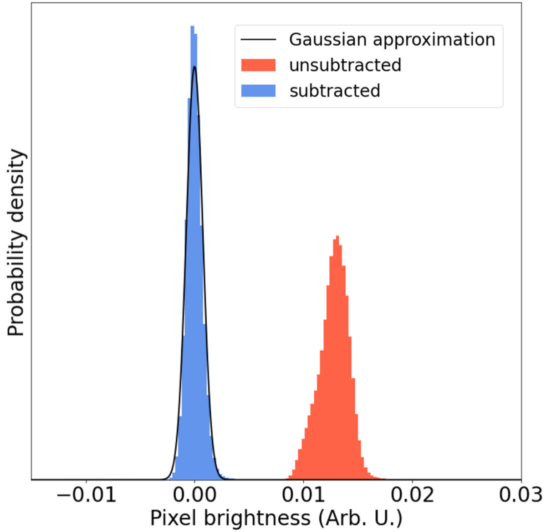


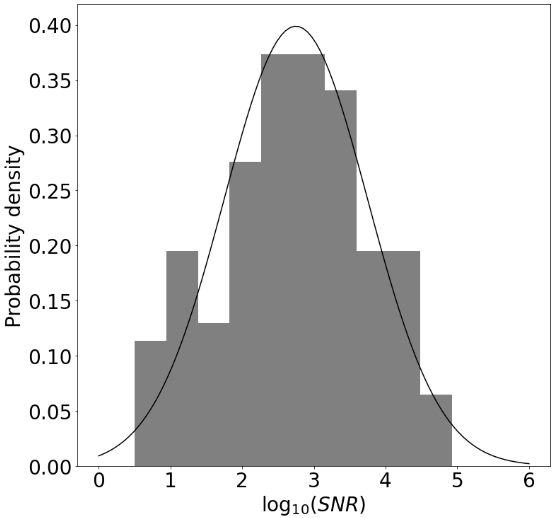
M.E. Glinsky *et al.,* Phys. Plasmas **27**, 112703 (2020).
P.F. Knapp *et al.,* Phys. Plasmas **29**, 052711 (2022).
W.E. Lewis *et al.,* J. Plasma Phys. **88**, 895880501 (2022).

Machine learning aided pipelines enable "large-scale" analysis and statistical characterization

Statistical characterization of slowly varying background, noise, and signal levels







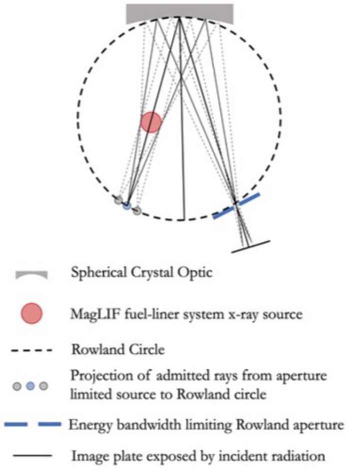
W.E. Lewis *et al.*, J. Plasmas Phys. **88**, 895880501 (2022).

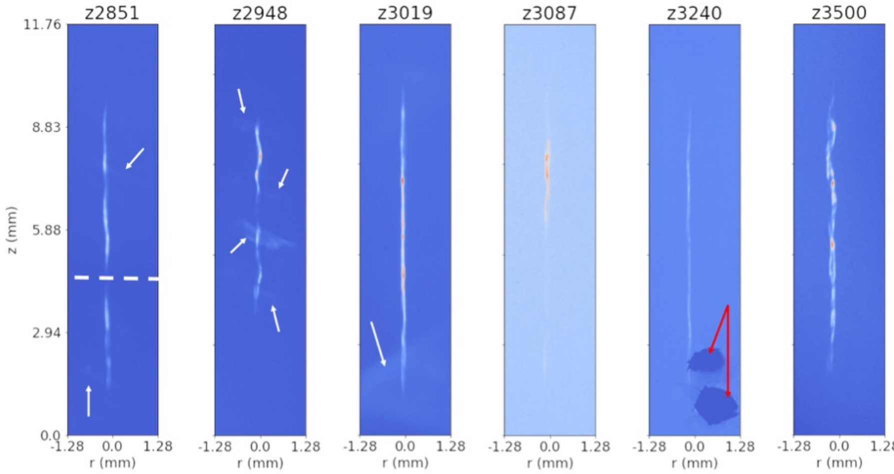
Several challenges make addressing these questions difficult.

Challenge

- Unspecified experiment dependent SNR
- Multiple distinct spherical crystal imaging modalities
  - Continuum vs spectral lines
  - Resolution
  - Views
- Typically no spatial fiducial
  - Registration

Imager	Configuration	Resolution [μm^2]
Argon Imager(Ar-Imager)	single	15×85
Continuum X-ray Imager (CXI)	single	59×83
High Resolution Continuum X-ray (CXI)	single	15×16
Dual Continuum X-ray (DCXI)	dual	Ch1 54×120 Ch2 46×84
Iron K-α_1 (IKA1)	dual	Ch1 79×82 Ch2 64×66
Iron Helium-β (IHEB)	dual	Ch1 63×66 Ch2 50×53
Cobalt He-w (CHEWI)	dual/orthogonal	Ch1 61×66 Ch2 73×72



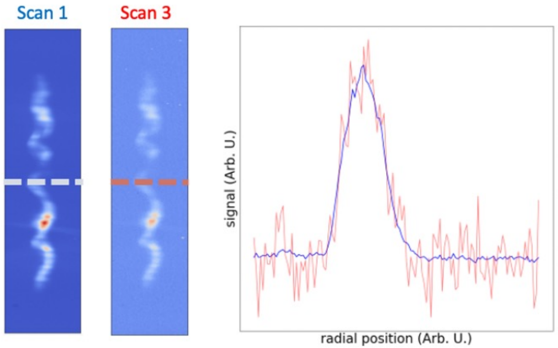


E.C. Harding *et. al.*, (Submitted).
W.E. Lewis *et al.*, J. Plasmas Phys. **88**, 895880501 (2022).

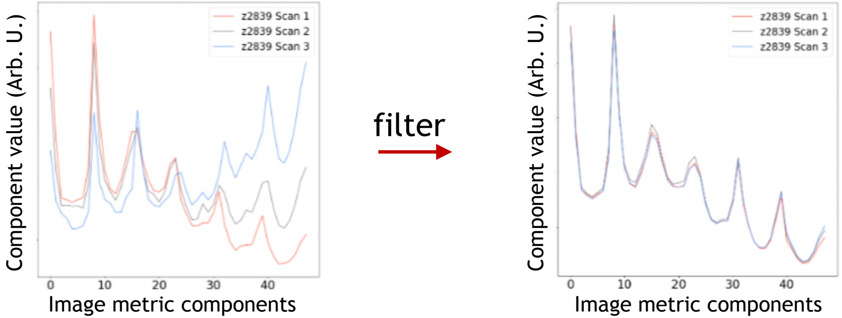
We can turn this to our advantage using ideas of data augmentation common in training machine learning algorithms

"Model-free" data augmentation help understand sensitivities and engineer metrics

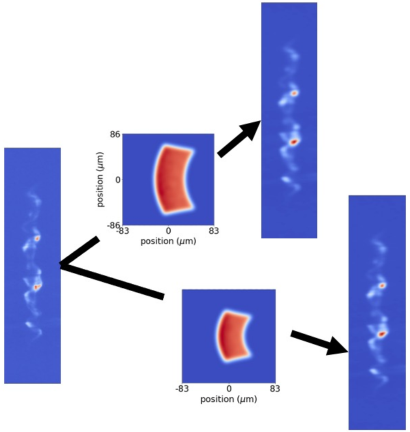
Sensitivity to texture/SNR via multiple scans

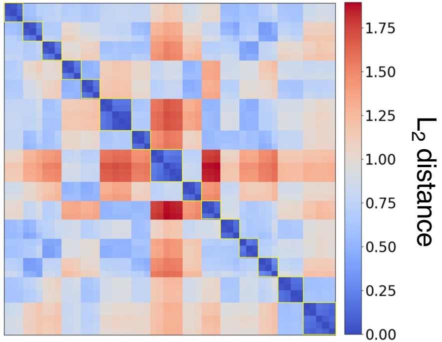


Noise filtering can remove unwanted sensitivity to SNR



Sensitivity to resolution via PSFs and high-resolution imager data





<u>Note:</u> Diagonal compares image to itself

= similar

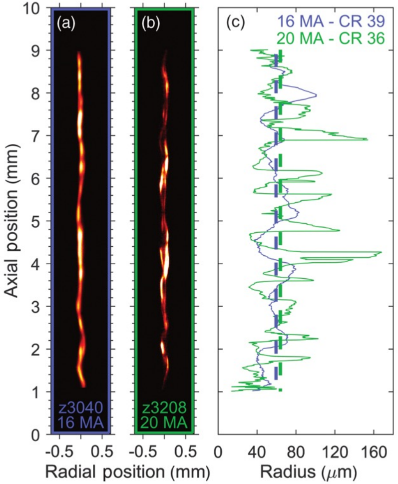
= different

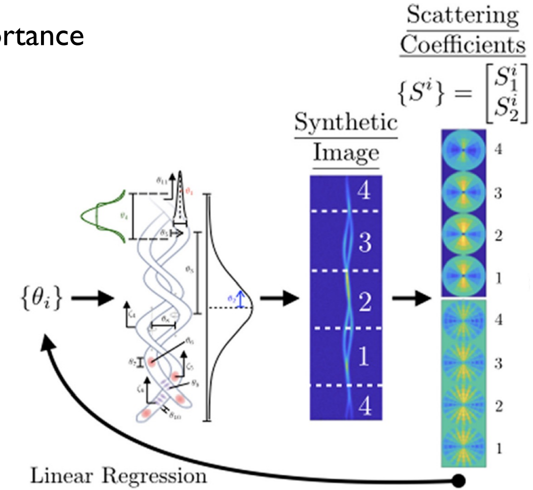
Invited paper ICDDPS-4 W.E. Lewis *et al.*, (In Preparation).

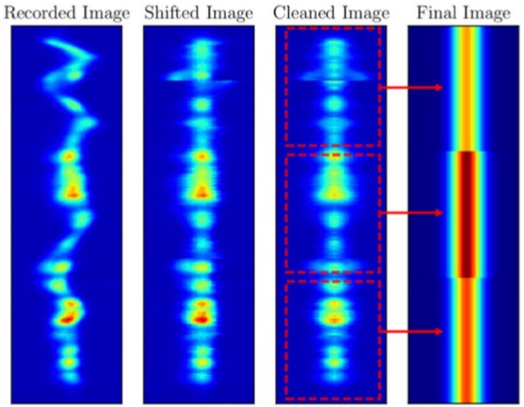
Characterizing stagnation morphology is a complex but important part of comparing experiments understanding performance

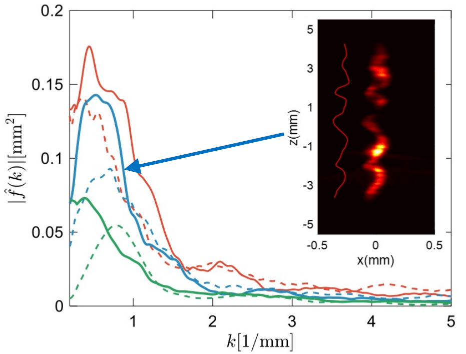
Challenge

- Image metrics may vary between practitioners and studies
  - Uncertain how sensitive metrics are to previous factors
  - Need statistical studies to understand importance





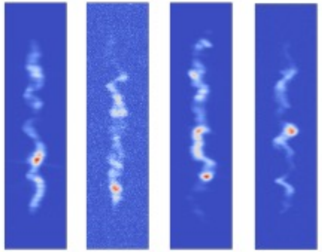




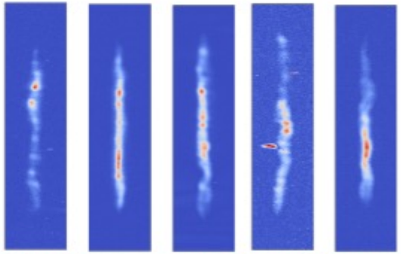
M.R. Gomez *et al.*, Phys. Rev. Lett. **125**, 155002 (2020).
M.E. Glinsky *et al.*, Phys. Plasmas **27**, 112703 (2020).
P.F. Knapp *et al.*, Phys. Plasmas **29**, 052711 (2022).
D.J. Ampleford, D.A. Yager-Elorriaga *et al.* (In Preparation).

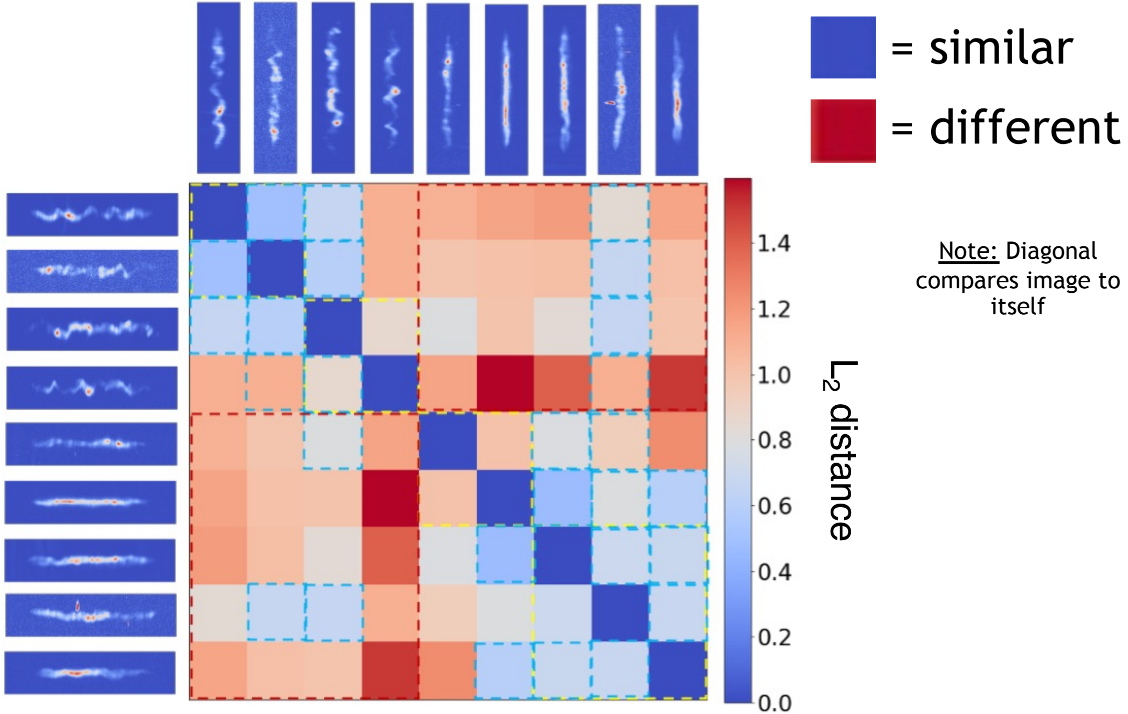
Data-driven methods are enabling metric exploration that is building to more detailed understanding of important features.

Randomly selected uncoated targets



Randomly selected coated targets



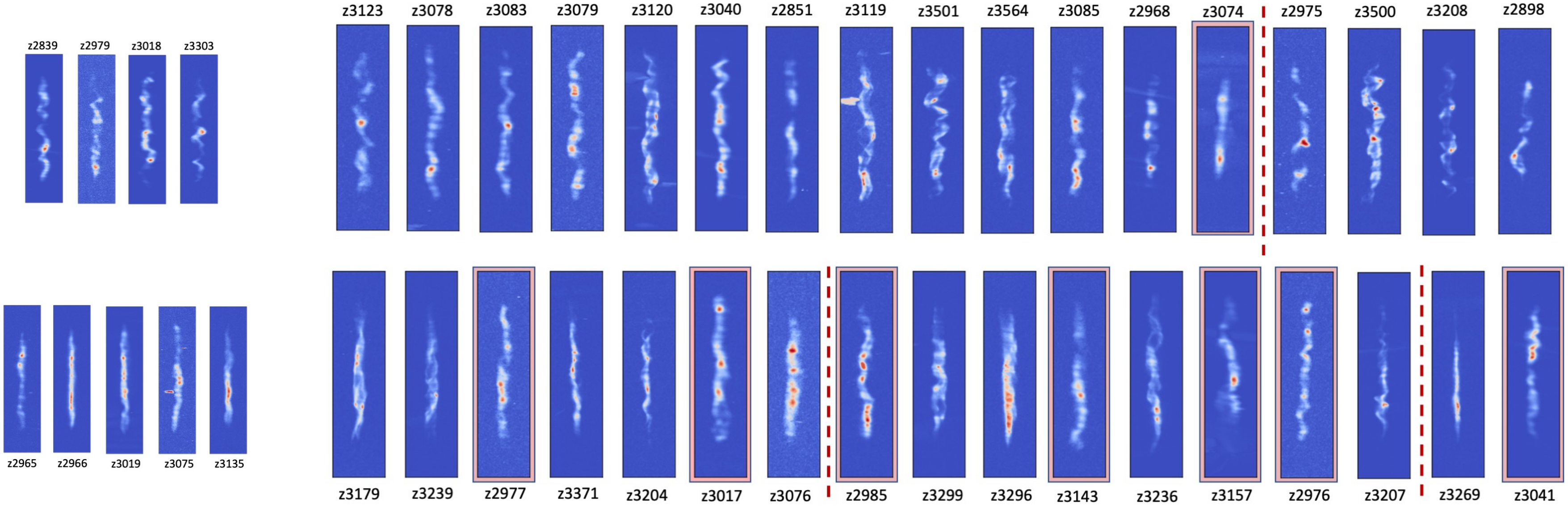


Note: Diagonal compares image to itself

Invited paper at ICDDPS-4 W.E. Lewis *et al.,* (In Preparation).

Data-driven methods are enabling metric exploration that is building to more detailed understanding of important features.

Large-scale studies can aid in investigating non-obvious structure in our data



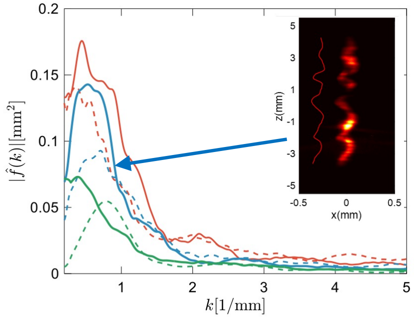
random	u	c
$\tilde{u}$	0.74 ± 0.06	0.74 ± 0.11
$\tilde{c}$	0.26 ± 0.06	0.26 ± 0.11

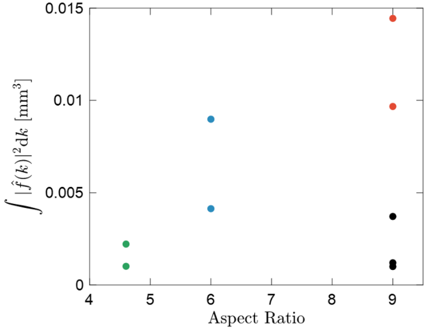
MST	u	c
$\tilde{u}$	0.84	0.47
$\tilde{c}$	0.16	0.53

Invited paper at ICDDPS-4 W.E. Lewis *et al.,* (In Preparation).

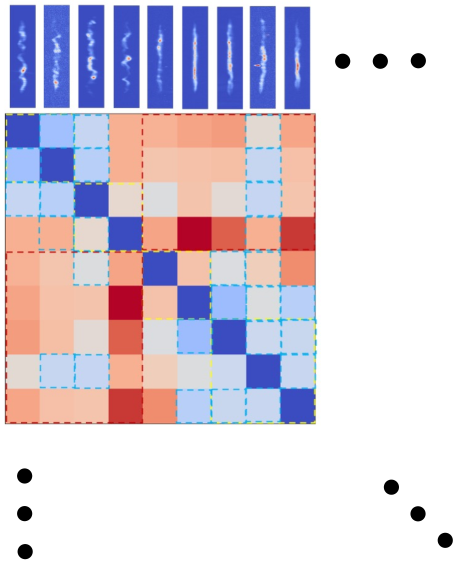
Future directions and potential for collaboration

- Identification of features determining similarity
  - E.g. axial brightness variation frequency, helical excursion, mean and variance of strand radius/CR, etc.
    - May try to answer by studying correlations across full image database





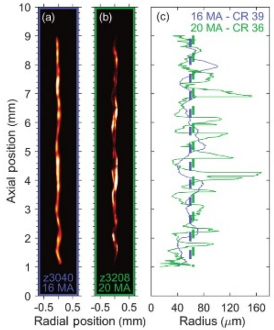
Extend to larger database and study correlations

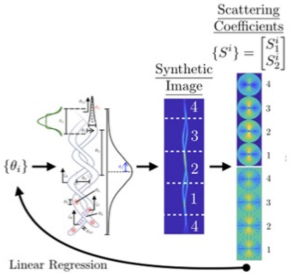


D.J. Ampleford, D.A. Yager-Elorriaga *et al*. (In Preparation).

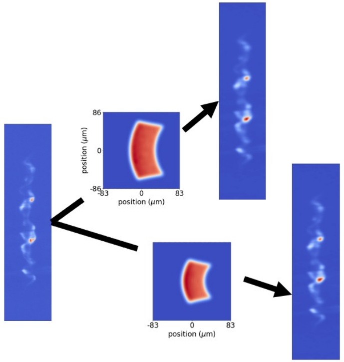
Future directions and potential for collaboration

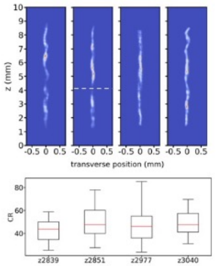
- Extension of sensitivity study to alternate metrics

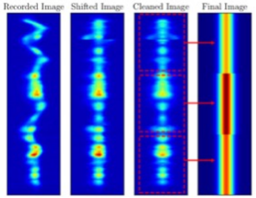


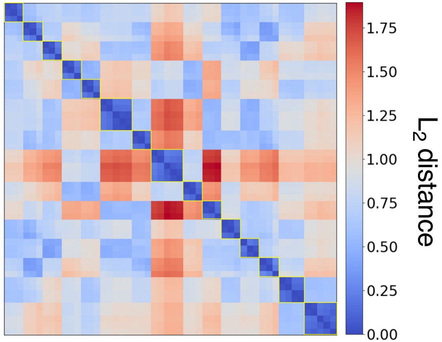


Apply model free data-augmentations and understand sensitivities









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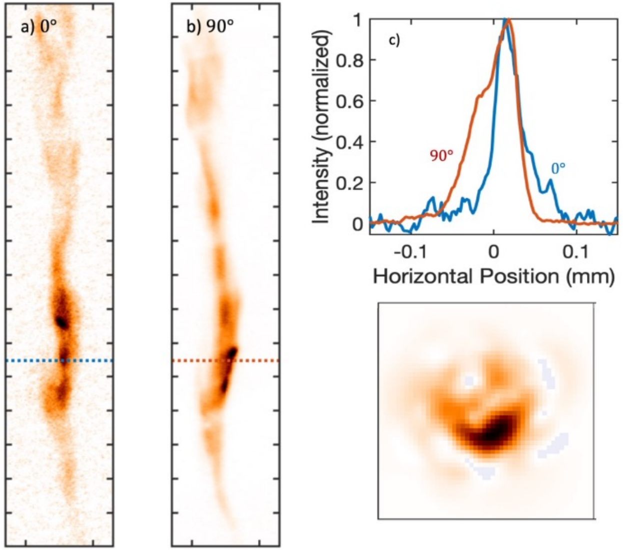
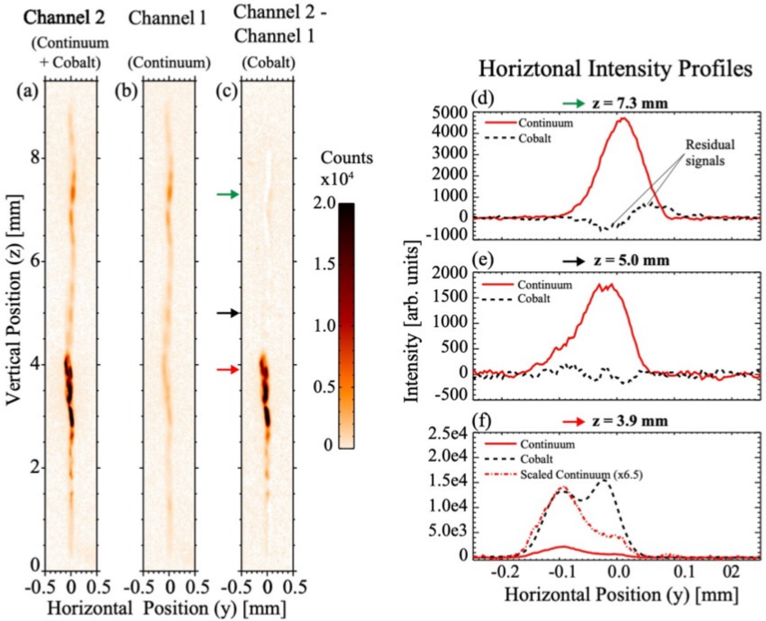
D.J. Ampleford, D.A. Yager-Elorriaga *et al.* (In Preparation).

Future directions and potential for collaboration

- Multiple view angles
  - Do differences in image metric between multiple views contain valuable "integrated" information?
    - E.g. value even if tomographic inversion ill-posed
- Quantifying mix morphology, liner opacity impact

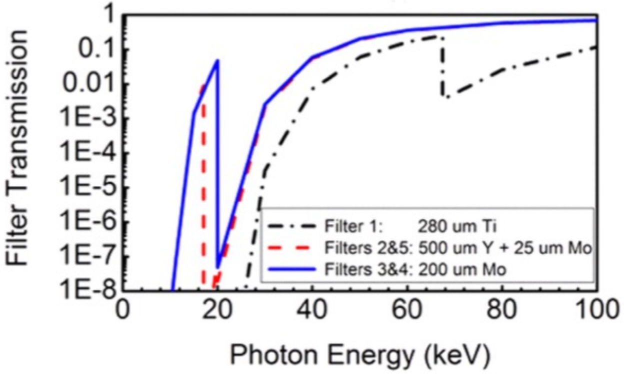


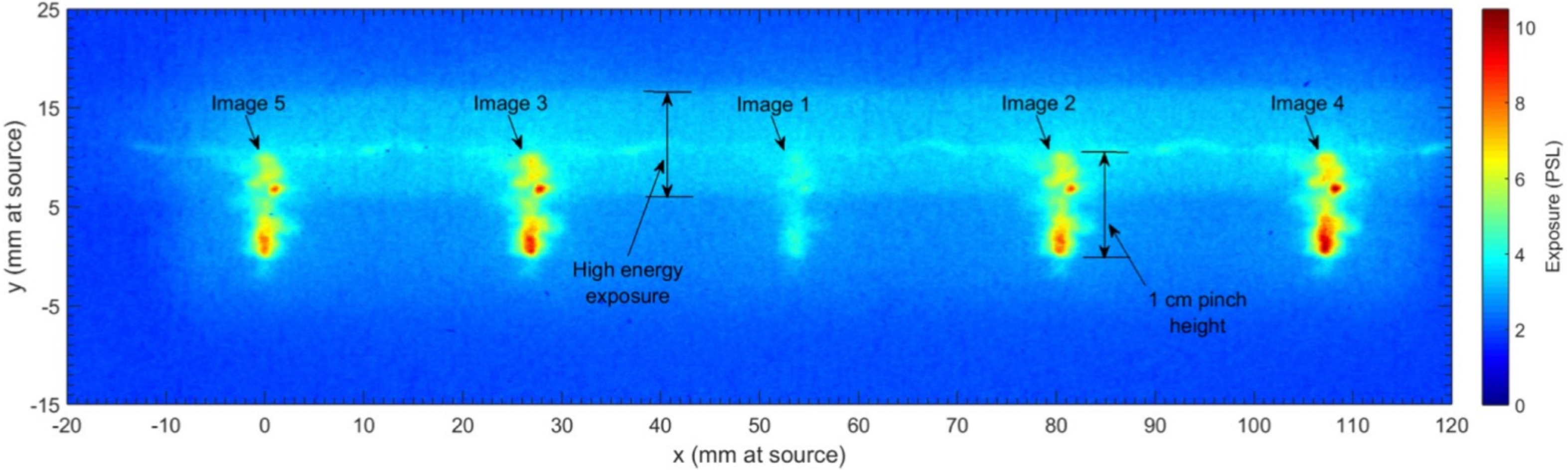


E.C. Harding *et al.* (Submitted to RSI).
J.R. Fein *et al.*, (In Preparation).

Future directions and potential for collaboration

- Extension to other imaging diagnostics/platforms
  - e.g. pinhole camera, radiography, *etc.*
  - wire arrays, gas puffs, *etc.*



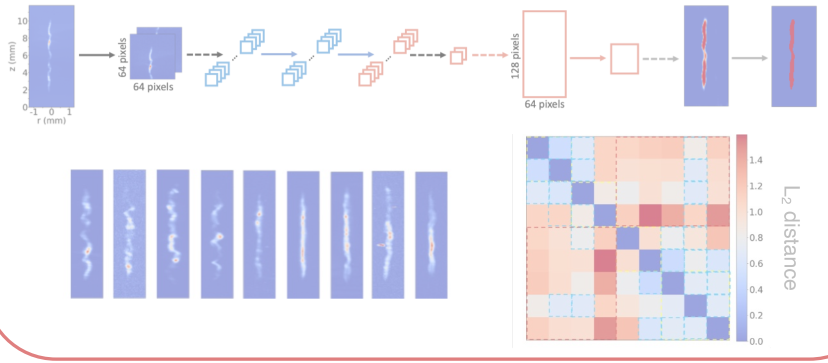


L.A. McPherson *et al.* Rev. Sci. Instrum. **87**, 063502 (2016).

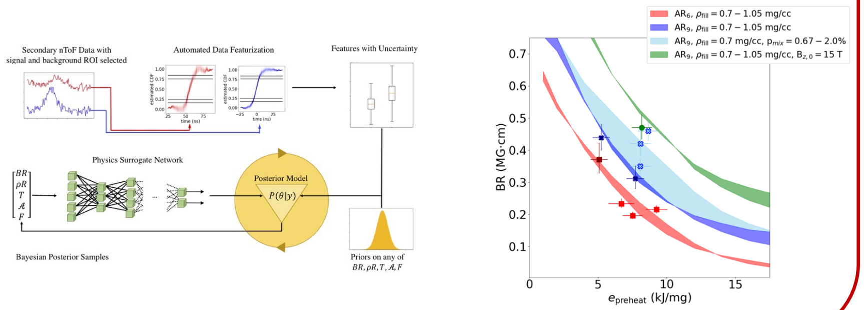
Talk overview

- Introduction
  - Sandia's Z Pulsed Power Facility
  - Magnetized Liner Inertial Fusion
- Exemplars of applied data science for MagLIF
  - stagnation image analysis
  - fuel magnetization parameter analysis
  - future directions and collaboration opportunities!
- Overview of other efforts and concluding remarks

Image analysis



Fuel magnetization



The magnetic field-fuel radius product (BR), determines charged fusion product confinement and electron thermal conduction losses.

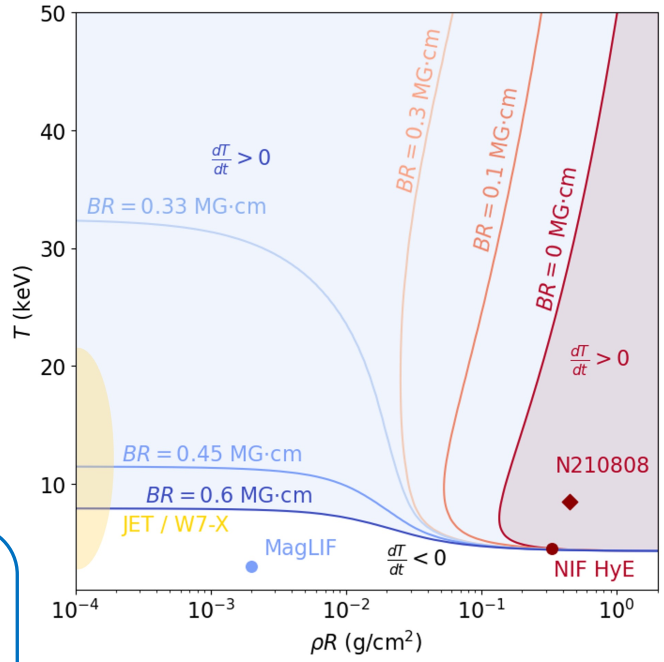
Effective BR for $B_z(r)$ profile:

$$\overline{BR} = \frac{\Phi_R}{\pi R} = \frac{2}{R}\int_0^R rB_z(r)dr$$

$\overline{\text{BR}}$ determines trapping of fast charged particles:

trapping condition for particles born at r=0

$$\overline{BR} \geq \sqrt{\frac{8mE_\perp}{q^2}}$$

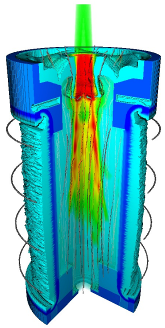


W.E. Lewis *et. al.*, PoP (Submitted)

A variety of plasma transport effects will modify the flux compression process. Measuring BR could provide insights into these effects.

- Ideal flux compression ~1000x B-field amplification
  - trapping of fusion products and reduction of electron heat conduction
- Physical mechanisms leading to flux loss
  - Resistive diffusion
  - Nernst advection

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

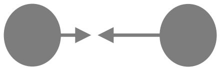


Resistive diffusion

- Current disrupted by collisions
  - Allows magnetic field diffusion

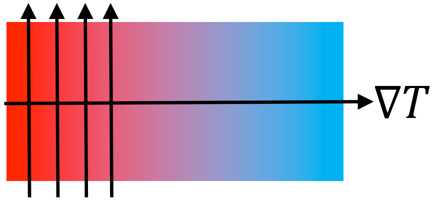
$$\tau_D \sim \mu_0 \sigma L^2$$

$$\sigma \propto \tau_{coll}$$



Nernst effect

- B-field locked into warm electrons
- Thermal transport perpendicular to B transports flux



- Increased preheat $\propto \nabla_{\perp}T_e$ increases Nernst
- Increased B_z decreases Nernst
- What about geometry?
- Fill density?
- Impact of mix throughout implosion
- Measurements needed to study effects
  - **can't do proton deflectometry/radiography**
    - **O(50 MG) fields driving Z-pinch!**

Radially and axially viewed secondary DT neutron spectra and yield ratio $\bar{Y} = Y_{DT}/Y_{DD}$ are sensitive to fuel magnetization.

- Pure Deuterium fuel
  - ~1.01 MeV tritons produced by DD fusion

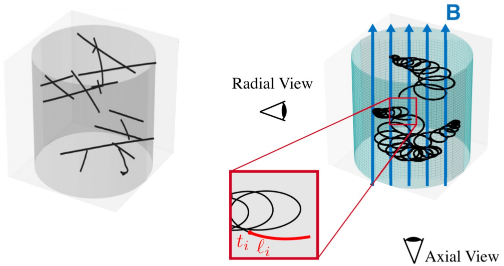
$$\text{Primary:}\quad D + D \rightarrow \begin{cases} n\ (2.45\text{MeV}) + {}^3He \\ p + T\ (1.01\text{MeV}) \end{cases}$$

$$\text{Secondary:}\quad D + T \rightarrow n\ (14.1\text{MeV}) + \alpha$$

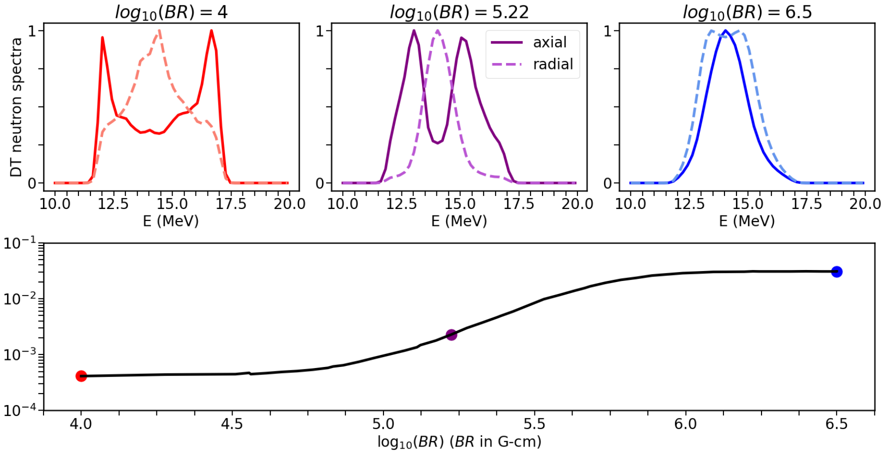
$$\mathcal{P}_{DT} \propto \langle \rho_D \ell \rangle \sigma_{DT} \xrightarrow{\text{Magnetized}} \ell \propto f(BR)$$

$$\rho R \longrightarrow \rho Z$$

P.F. Schmit *et al.*, PRL (2014)
P.F. Knapp *et. al.*, PoP (2015)



Increase in P_{DT} increases $\bar{Y}$



- Surrogacy of tritons for $\alpha's$
  - similar Larmor radius
  - 3.5 MeV α stopping length ~ 0.5x1.01 MeV tritons

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

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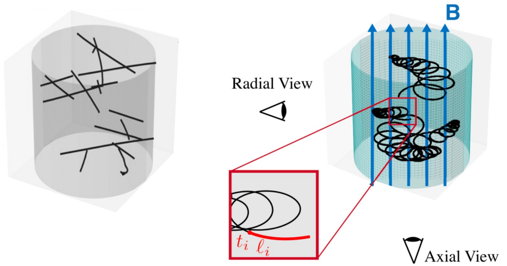

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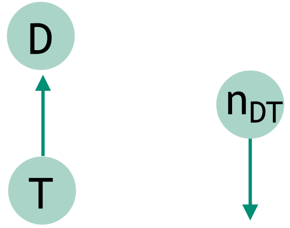
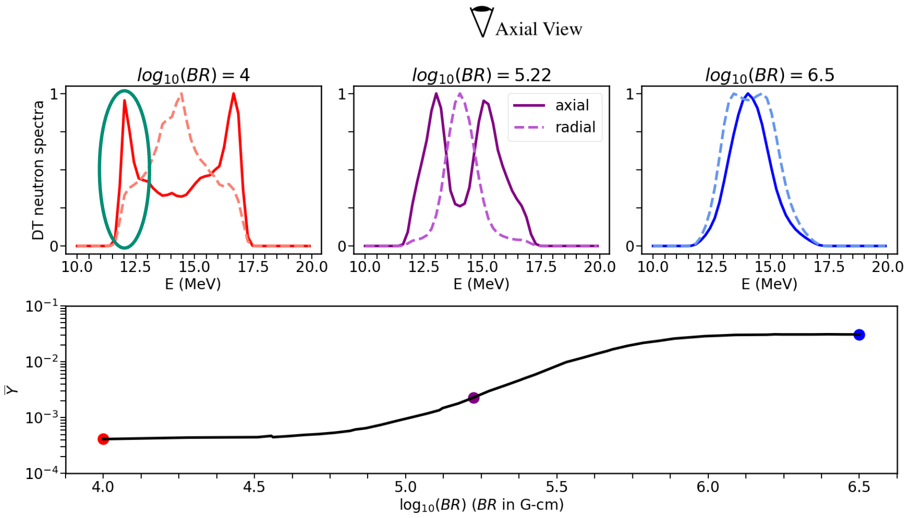


14 MeV in CM
Doppler down shift



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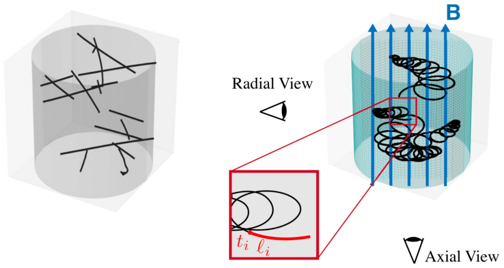

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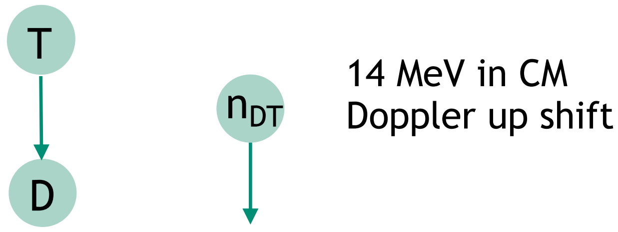

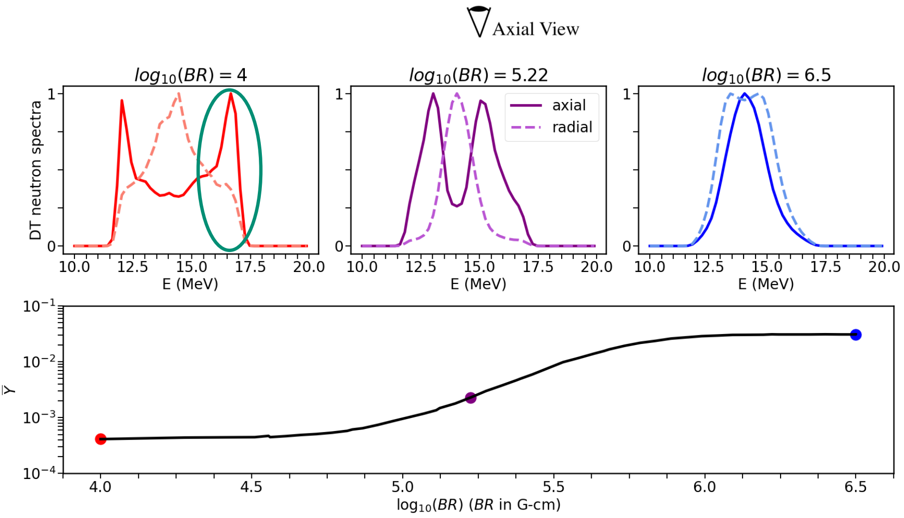

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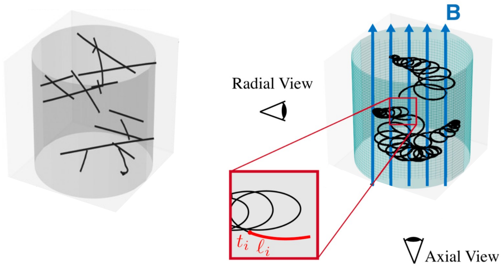

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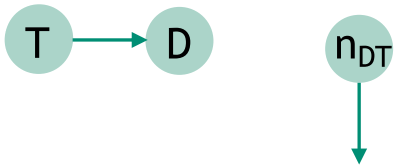
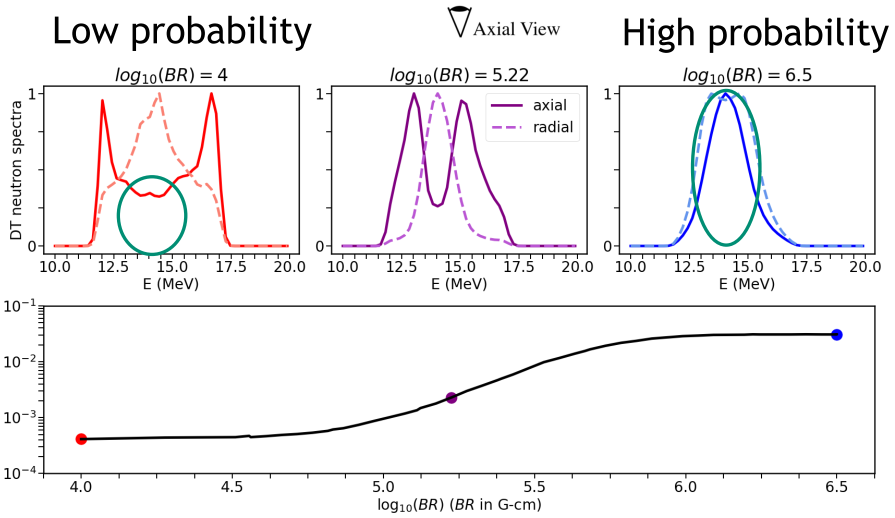


14 MeV in CM
No Doppler shift
B_z ~ probability

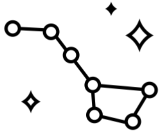


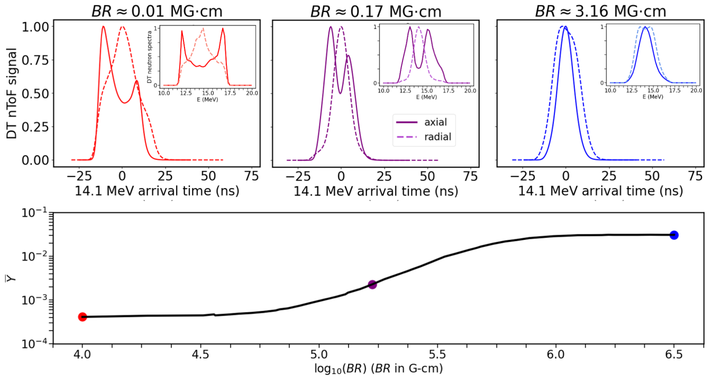
W.E. Lewis *et al.*, Phys. Plasmas **28**, 092701 (2021).

Characterizing stagnation morphology is a complex but important part of comparing experiments understanding performance

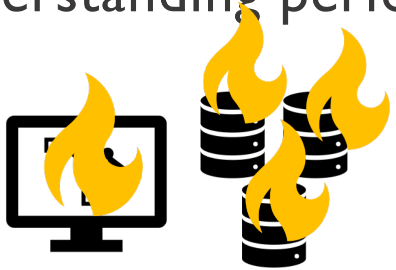
Challenge

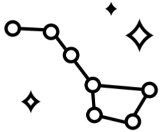
- Computational cost of forward physics model
  - O(10-100) CPU hours evaluation on a high-performance cluster





Characterizing stagnation morphology is a complex but important part of comparing experiments understanding performance

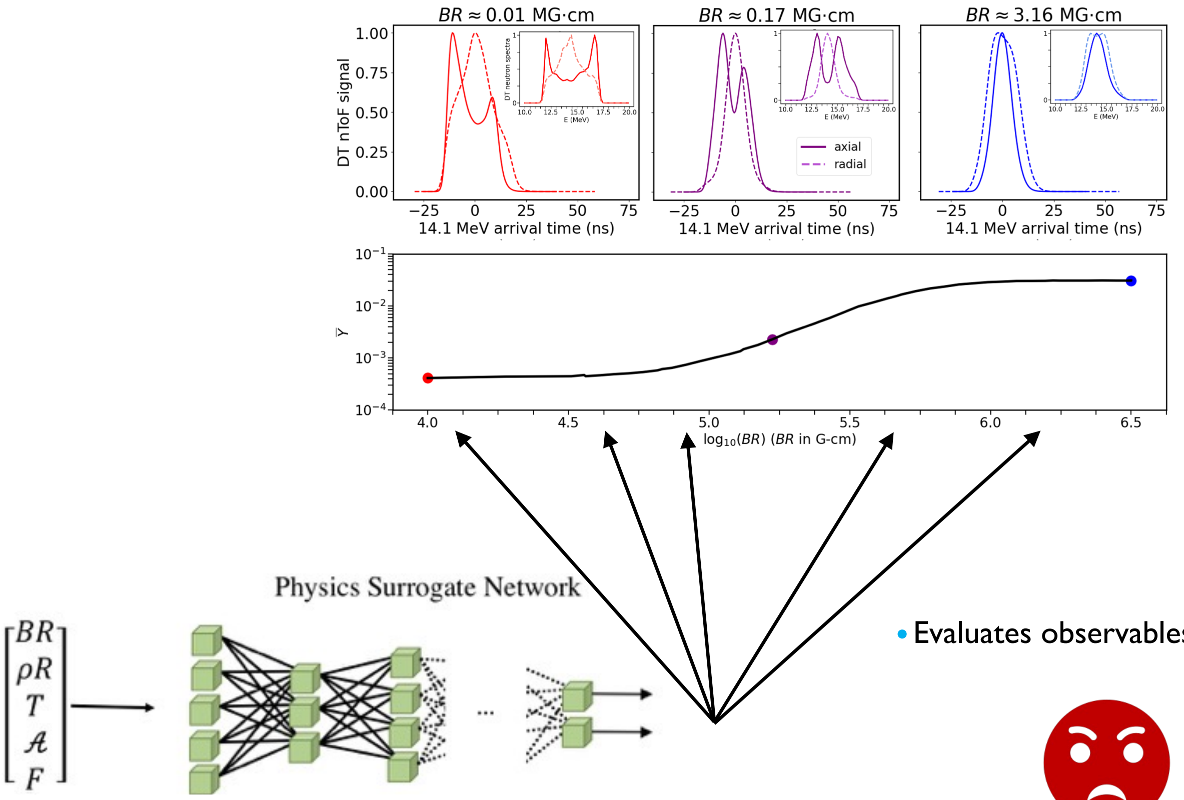




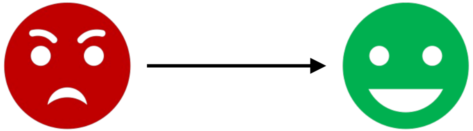
Challenge

- Computational cost of forward physics model
  - O(10-100) CPU hours evaluation on a high-performance cluster
  - 10k-100k + evaluations per experiment for inference and uncertainty quantification

Machine learning offers a route to avoiding repeat calculations by interpolating/surrogating results from representative simulations.



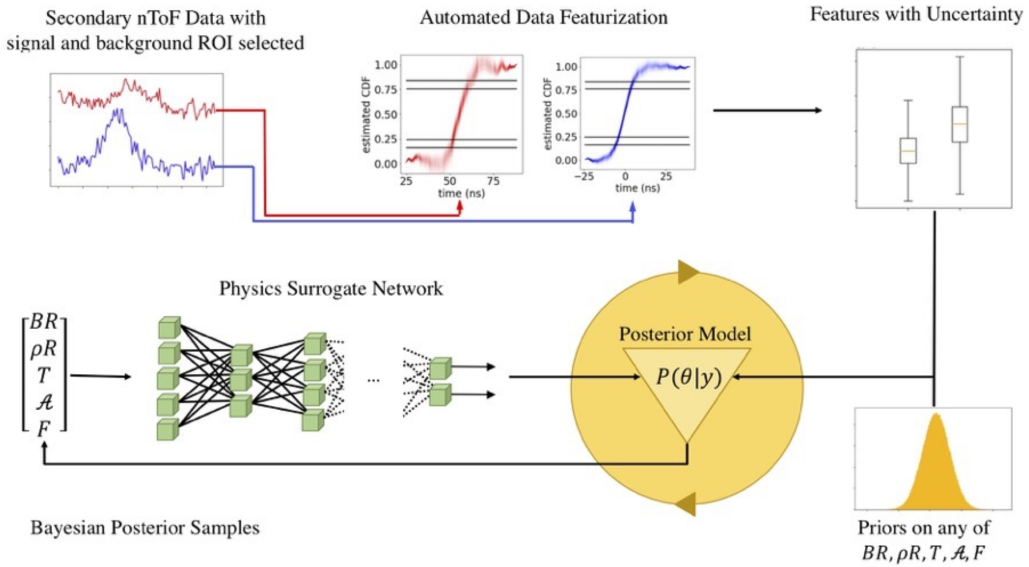
- Evaluates observables in sub millisecond times on a laptop



W.E. Lewis *et al.*, J. Plasmas Phys. **88**, 895880501 (2022).

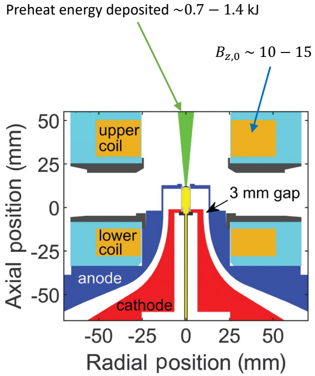
Machine learning enables rigorously defined UQ through coupling into a Bayesian inference framework.

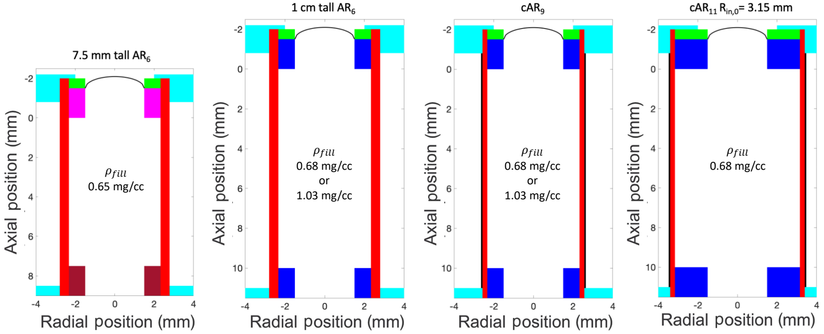
- First systematic study of magnetic confinement properties of any neutron producing magneto-inertial fusion platform
  - Enabled by deep-learning and Bayesian inference

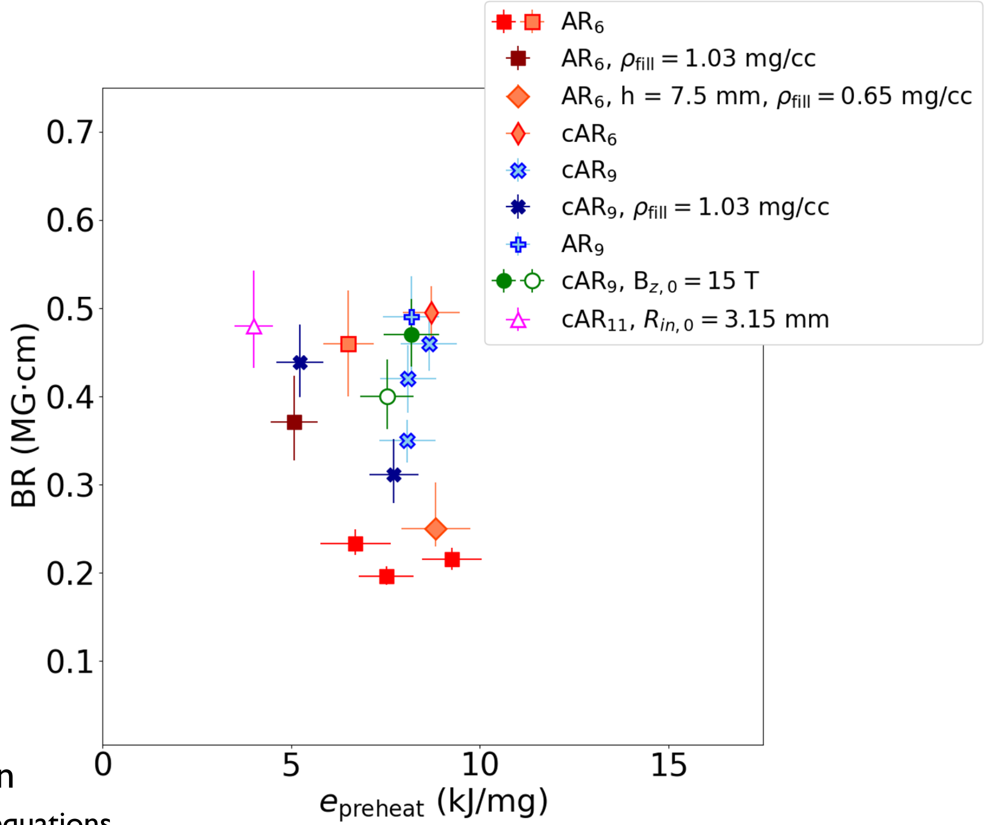


W.E. Lewis *et al.*, Phys. Plasmas **28**, 092701 (2021).

We can use our deep-learning based inference tool discover the larger story behind the physics of magnetic confinement in MagLIF







- 1D resistive radMHD code Kraken* for comparison
  - C.A. Jennings implementation of GORGON system of MHD equations

W.E. Lewis *et al.*, Phys. Plasmas (Submitted).

Indeed, there are physics arguments that can explain the variance in the data and capture the results for all but two experimental cases.

- Nernst advection leads to significant decay of $(BR)_f$ with $e_{preheat}$

$$e_{preheat} = \frac{E_{preheat}}{m_{fuel}}$$

$$\langle T_{preheat} \rangle \propto e_{preheat}$$

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

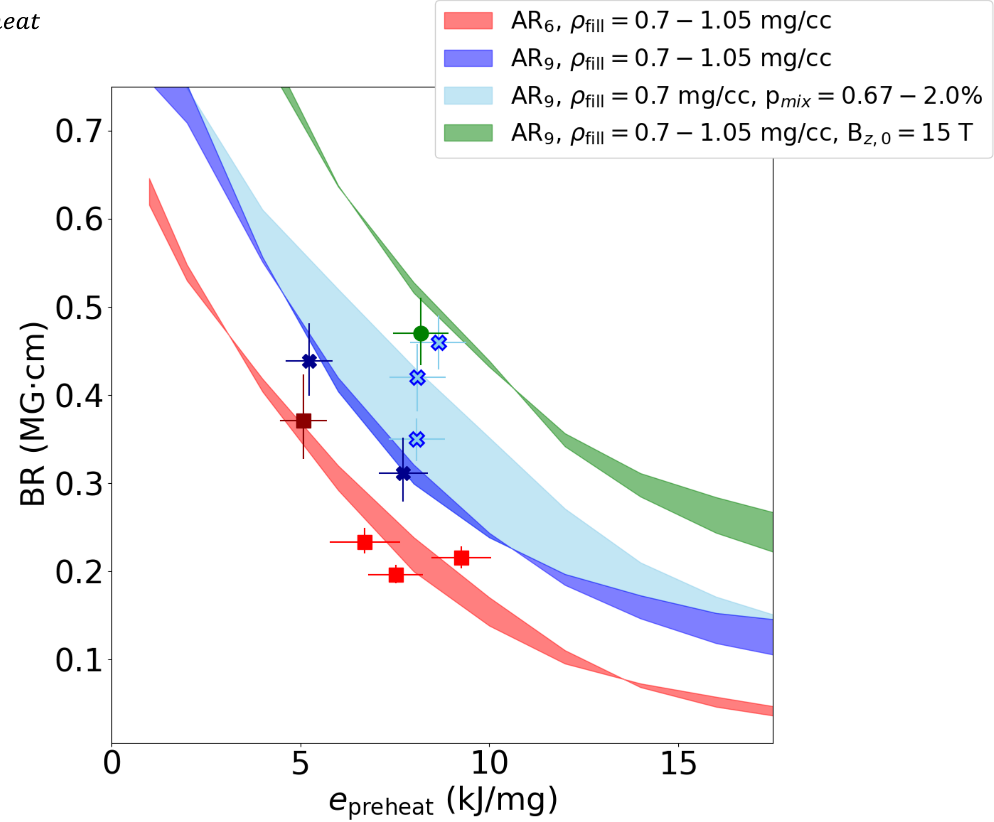
- Higher aspect ratio
  - reduces mass increasing v_{imp} and convergence

$$CR = \frac{R_{in,0}}{R_{in,f}}$$

$$(BR)_f = CR \frac{\phi_f}{\phi_0} (BR)_0$$

- Mix enhanced radiative losses reduces $\nabla_\perp T$
  - Reduces Nernst advection enhances $(BR)_f$
  - Reduces performance

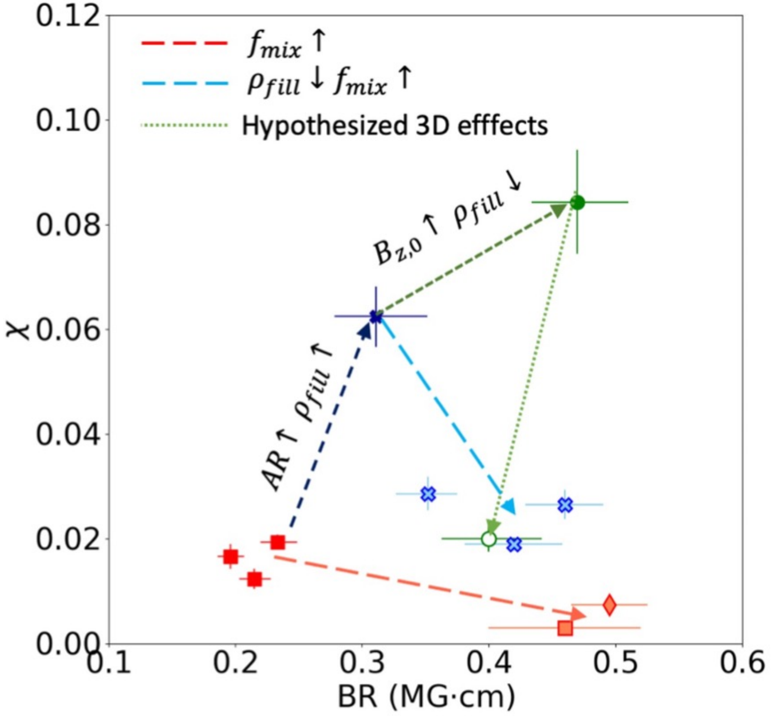
- Increased B_z results increases initial $(BR)_0$
  - Enhances $(BR)_f$ and improves thermal insulation

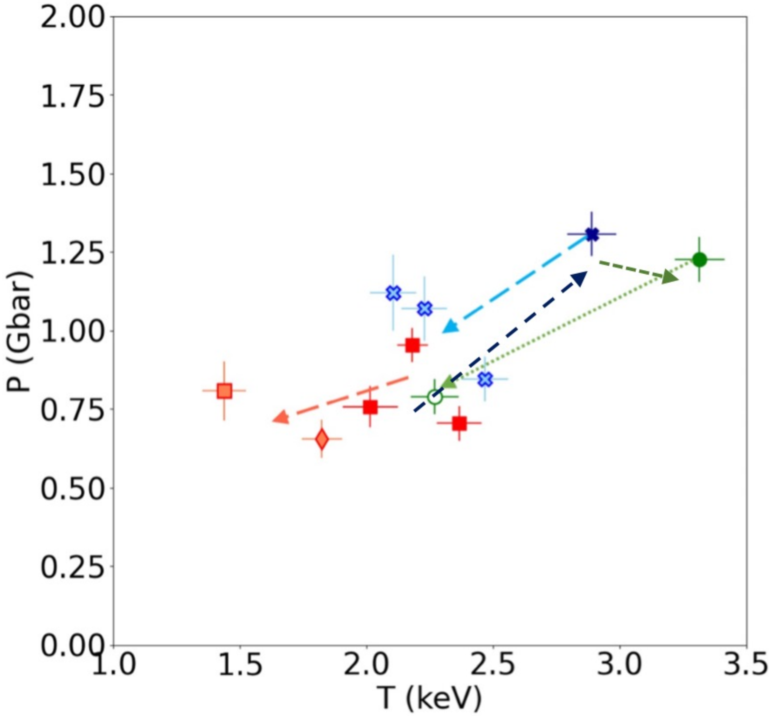


W.E. Lewis *et al.*, Phys. Plasmas (Submitted).

Pairing data driven methods with physics insight, we find that Nernst advection and mix are indeed integral to performance scaling in MagLIF.

- Nernst advection enhanced flux loss limits the gains by increasing preheat alone
  - ρ_{fill}, B_z, I_{max} *etc.* must be improved while mitigating mix to enable performance (χ) gains



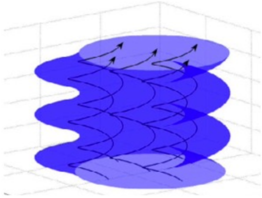


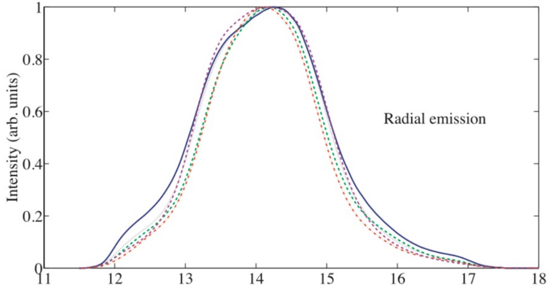
W.E. Lewis *et al.*, Phys. Plasmas (Submitted).

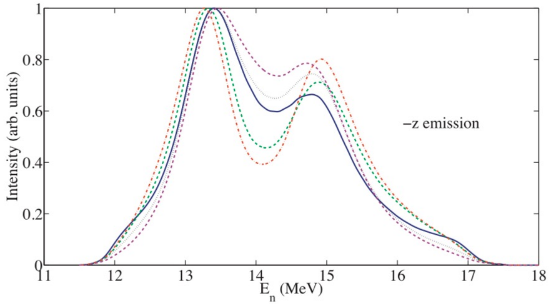
Future directions and potential for collaboration

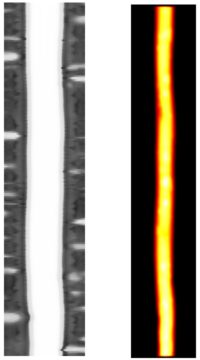
- Relaxed model assumptions
  - nToF shape features
  - 2 ns Gaussian burn history
  - $T_e = T_i$
  - uniform mix assumption
  - 1D power law profile model with
    - $B_z \propto \rho$
    - Axially uniform B-field
  - **Unknown impact of 3D effects**

Magnetic field topology alters secondary neutron spectra

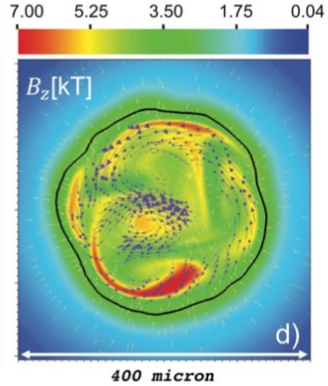








C.A. Jennings



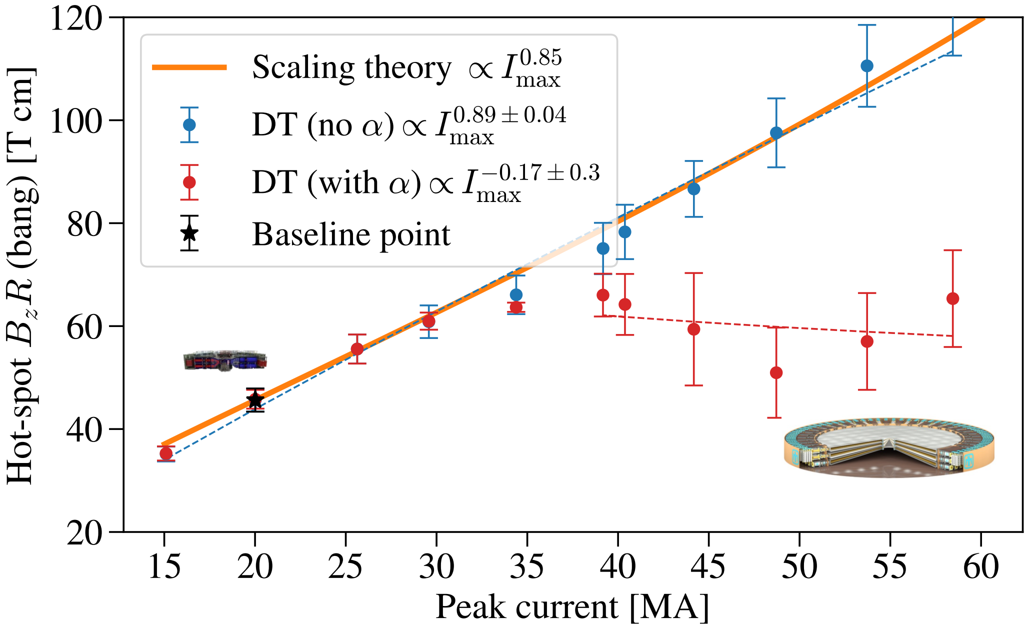
M.R. Weis *et. al.*, Phys. Plasmas **28**, 012705 (2021).

B. Appelbe *et al.*, HEDP **22**, 27 (2017).

Future directions and potential for collaboration

- Scaling to Next Generation Pulsed Power

Magnetization of α's improves when scaling up in current. Simulation with α heating show a "plateau" due to reduced CR_{in} near stagnation.

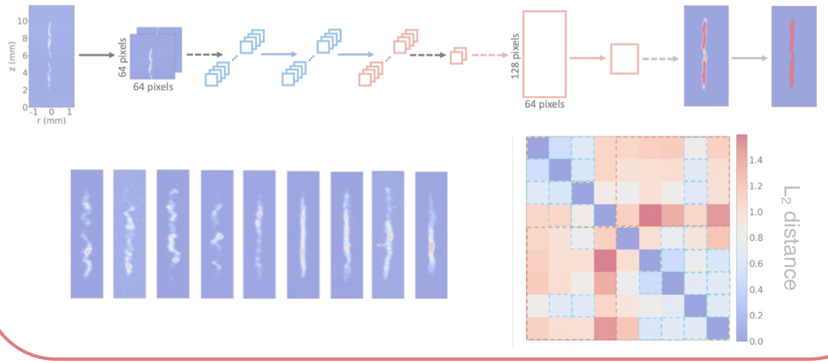


D.E. Ruiz *et. al.*, (Submitted) Phys. Plasmas.

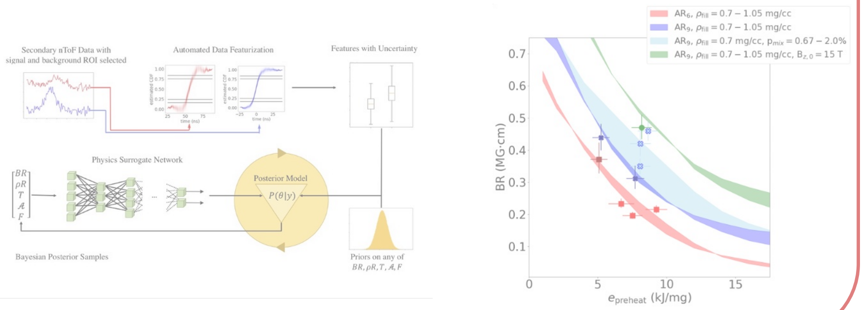
Talk overview

- Introduction
  - Sandia's Z Pulsed Power Facility
  - Magnetized Liner Inertial Fusion
- Exemplars of applied data science for MagLIF
  - stagnation image analysis
  - fuel magnetization parameter analysis
  - future directions and collaboration opportunities!
- Overview of other efforts and concluding remarks

Image analysis



Fuel magnetization



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Optimizing the configuration of plasma radiation detectors in the presence of uncertain instrument response and inadequate physics

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[1]Sandia National Laboratories, Albuquerque, NM 87185, USA
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(Received 31 May 2022; revised 29 November 2022; accepted 30 November 2022)

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Submitted: 01 February 2022 • Accepted: 01 May 2022 • Published Online: 18 May 2022

P. F. Knapp, M. E. Glinsky, M. A. Schaeuble, et al.

COLLECTIONS

Paper published as part of the special topic on Papers from the 63rd Annual Meeting of the APS Division of Plasma Physics

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COLLECTIONS

This paper was selected as an Editor's Pick

Journal of Applied Physics

Simultaneous inference of the compressibility and inelastic response of tantalum under extreme loading

Cite as: J. Appl. Phys. 130, 055901 (2021); https://doi.org/10.1063/5.0056437
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W. J. Schill, R. A. Austin, K. L. Schmidt, et al.

PHYSICAL REVIEW LETTERS 125, 155002 (2020)

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[3]University of New Mexico, Albuquerque, New Mexico 87131, USA

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Michael E. Glinsky, Thomas W. Moore, William E. Lewis, et al.

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ROYAL STATISTICAL SOCIETY
Journal of the Royal Statistical Society
Applied Statistics
Series C
Appl. Statist. (2018)
67, Part 4, pp. 1023–1045

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[Received February 2017. Final revision January 2018]

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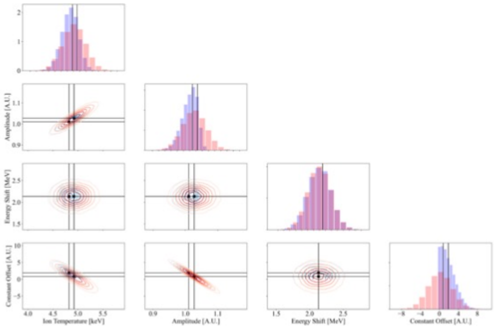
Publica

Advanced Data Analysis in Inertial Confinement Fusion and High Energy Density Physics

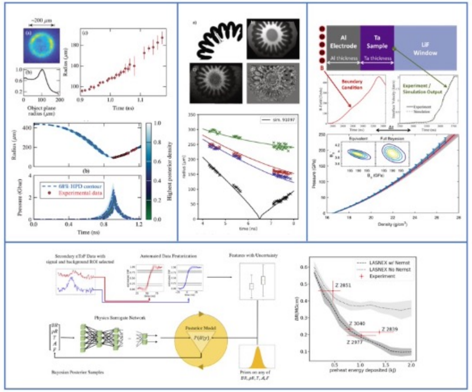
P. F. Knapp[1] and W. E. Lewis[1]
Sandia National Laboratories, Albuquerque, New Mexico 87185, USA

Tutorial on Bayesian inference with code

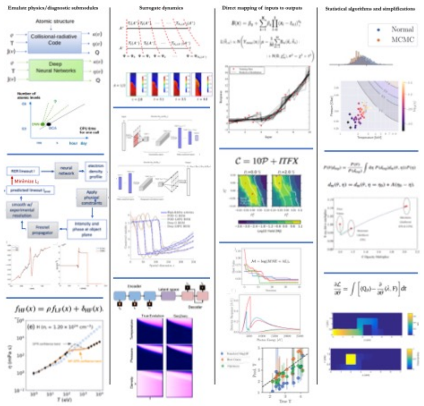


Extensive ICF/HEDP literature review of:

Bayesian inference



Applied ML methods



Submitted to special issue of Rev. Sci. Instrum.

Sandia National Laboratories, Albuquerque, New Mexico 87185 USA

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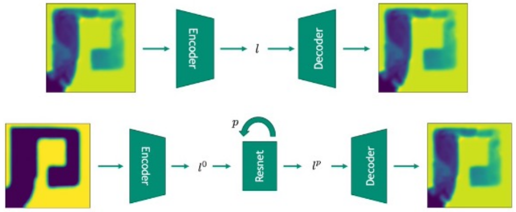
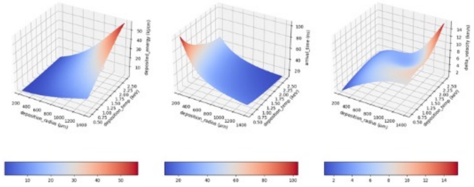
- Simulations:
  - May be **prohibitively costly** for all but the smallest of scoping studies or uncertainty quantification

Surrogate modeling efforts

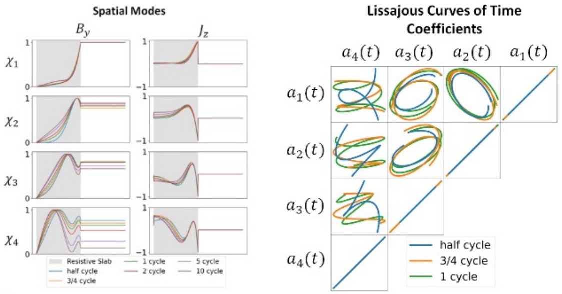
R. Patel *et al.*



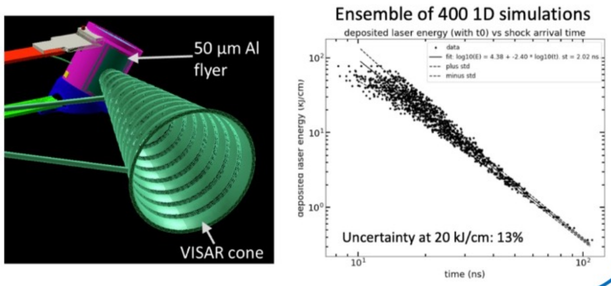
K. Maupin *et al.*



G. Vasey *et al.*



M. Glinsky *et al.*



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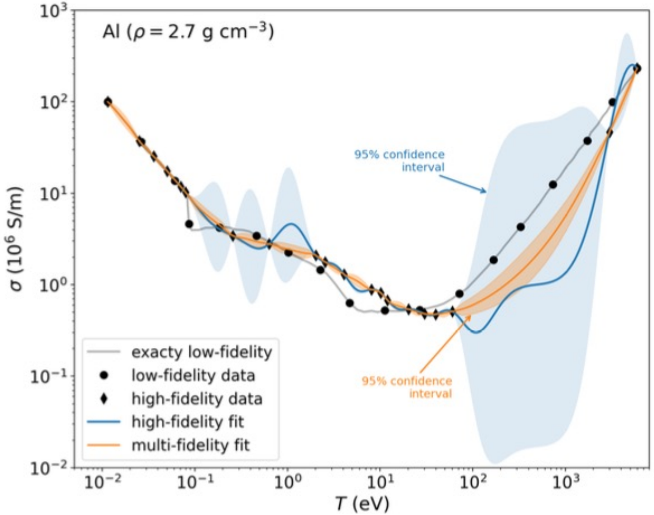
- Simulations/Experiment:
  - **Missing, uncertain, or "aliased" contributions** from known and unknown physics

Sensitivity analysis, uncertainty quantification, and causal statistics

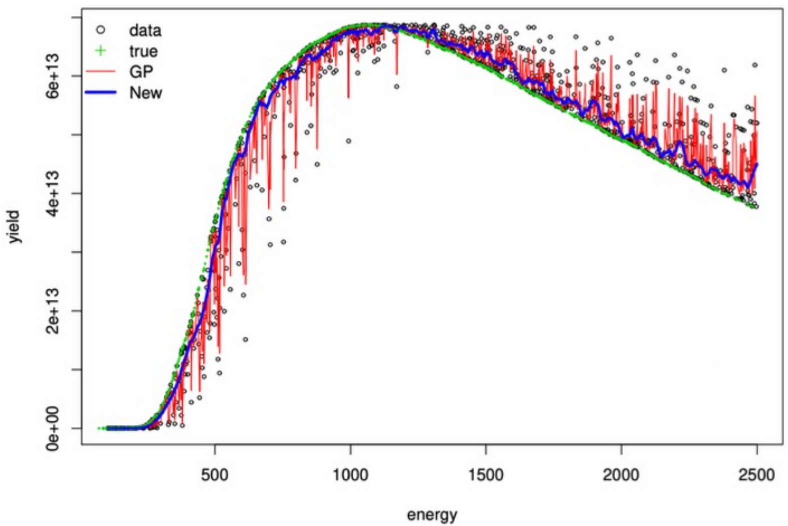
Maxwell Fellowship

L. Stanek *et al.*



LDRD

R. Joseph and K. Maupin *et al.*



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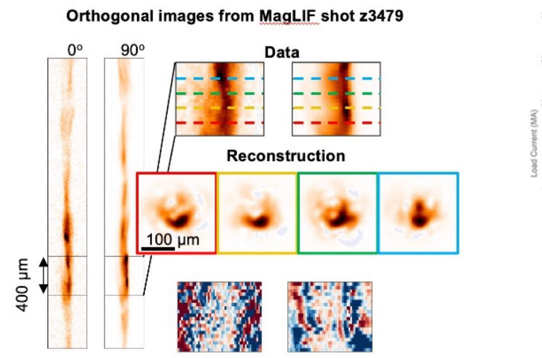
- Experiments:
  - **Sparsity constraints** (e.g. few view angles)
  - Potentially **ill-conditioned diagnostic inversion**

Working with sparse data and ill-posed diagnostic inversion

J. Fein *et al.*



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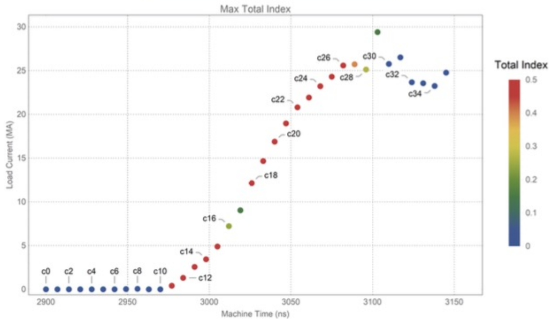
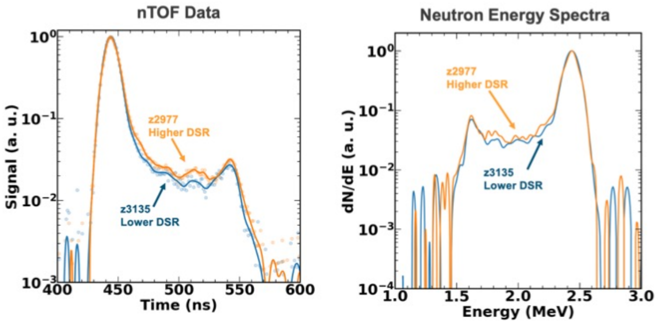
Sandia National Laboratories, Albuquerque, New Mexico 87185 USA

A. Porwitzky *et al.*



O. Mannion *et al.*

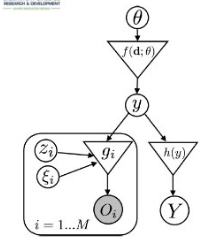


Data-driven methods have found successful application across a range of problems in HEDP at Z and continues to grow!

- Experiments:
  - **Low repetition rates**
  - **Costly to execute**

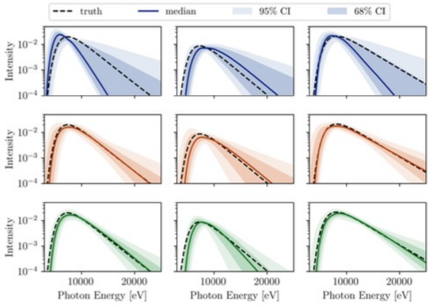
Quantifiable performance, optimization of diagnostics and experiment design

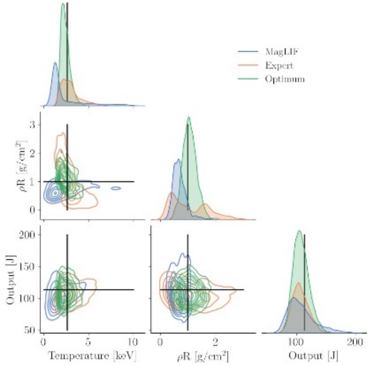
P. Knapp *et al.*



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

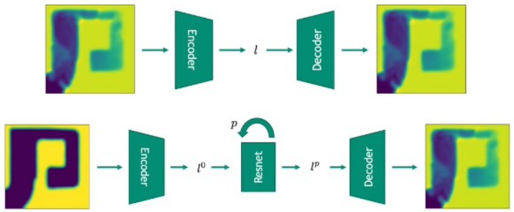
$$Z_{\text{opt}} = \underset{z_i}{\operatorname{argmin}} \sum_{j=1}^{J} \mathcal{M}_j$$





P.F. Knapp *et al.* J. Plasma Phys. (2023).

R. Patel *et al.*



A. Porwitzky and Gabriel Shipley *et al.*

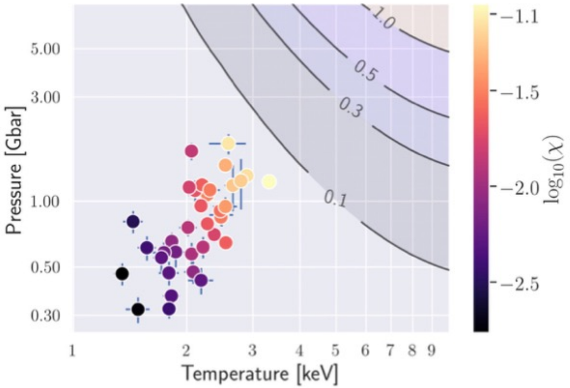
STAY TUNED!

Data-driven methods have found successful application across a range of problems in HEDP at Z and continues to grow!

- Experiments:
  - **Low repetition rates**
  - **Measurements** are performed **in harsh environments** resulting in known and unknown artifacts
  - **Sparsity constraints** (e.g. few view angles)
  - **Multi-modal** and **often highly** spatio-temporally **integrated** data (e.g. x-ray imaging, neutron time of flight, etc.)
  - **Defining accessible and relevant observables**

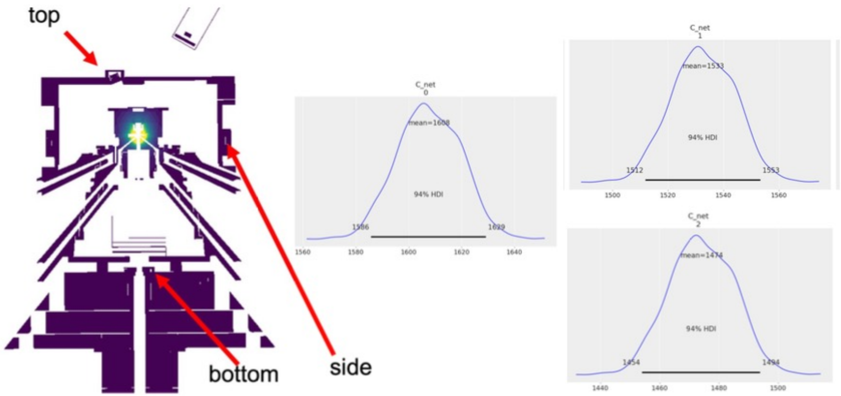
Rigorous uncertainty quantification and Bayesian inference

P. Knapp *et al.*

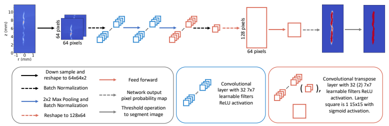


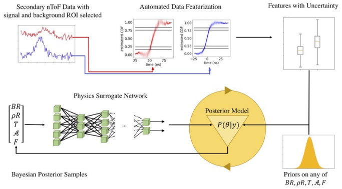
P.F. Knapp *et al.* Phys. Plasmas (2022).

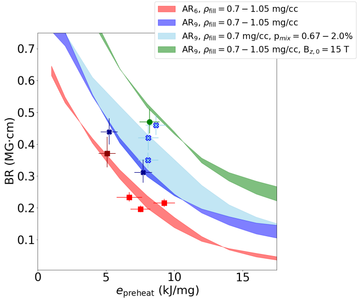
M. Mangan *et al.*



Closing remarks

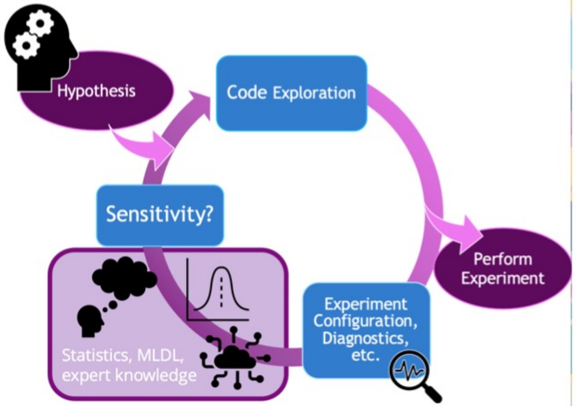




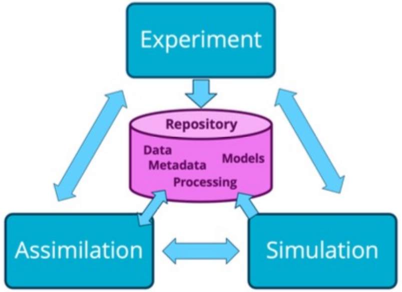


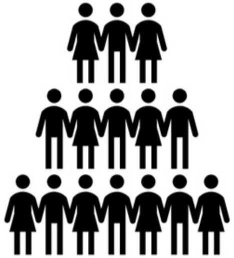
- **Research at the intersection of applied machine-learning and physics**
  - is accelerating the cycle of experiment design and physics discovery.
  - tools and technology that *enable* the physicist to do what they do best
- Looking to explore applications of data science to
  - Next generation pulsed power (e.g. current delivery scaling)
  - 3D effects
  - Experiment design
  - Etc.
- We are interested in collaborations across many areas in HEDP. Please reach out!

Vision for the future*



Needs





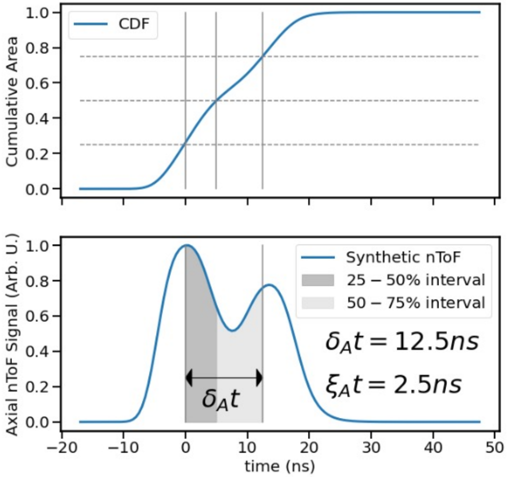
Focused on the right problems

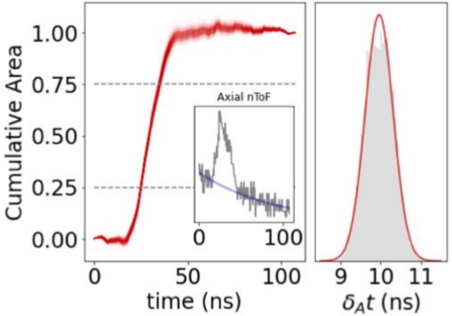
*courtesy P.F. Knapp

Backup Slides

We wish to “featurize” the nToF data collected experimentally to reduce dimensionality while retaining relevant information.

- Width and asymmetry features with uncertainty
    - percentiles of nToF signals
        - integration smooths noise
        - error from Bayesian fitting
- nToF avoids e.g.
    - unavailable timing fiducial
    - ill-posed instrument response deconvolution

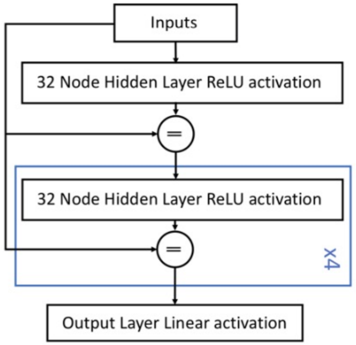


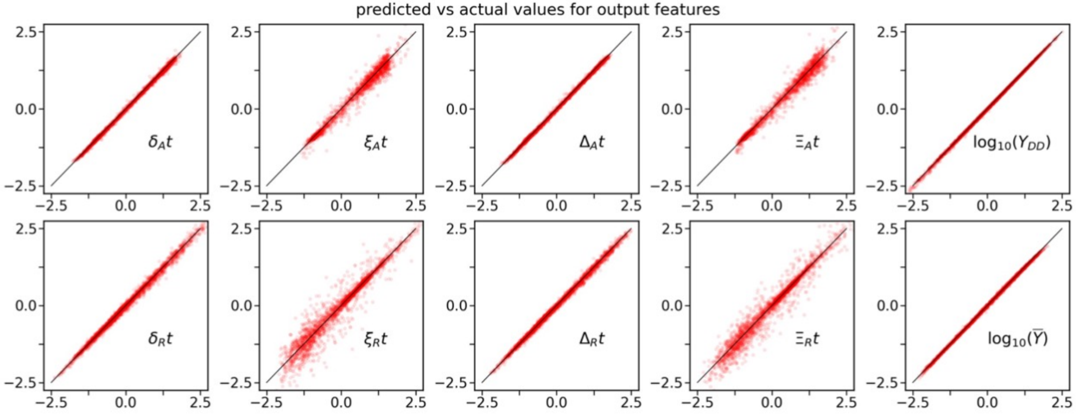


W.E. Lewis *et al.*, Phys. Plasmas **28**, 092701 (2021).

The physics model is used to generate training data for a neural network surrogate, which drastically improves evaluation times.

- ~65k simulation samples
  - 95%-4%-1% train-validation-test split
- neural network with skip connections
  - about 5.5k fit parameters
- Validation data used to estimate error
  - propagate uncertainty of surrogate





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

Bayes theorem allows us to incorporate multiple sources of data and rigorously define statistical data models for UQ.

Bayes theorem

Posterior distribution for parameters (x) given data (y)

Prior information on parameters

$$p(\mathbf{x}|\mathbf{y}) = p(\mathbf{y}|\mathbf{x})p(\mathbf{x})/p(\mathbf{y})$$

Likelihood function describing distribution of data around model

Parameter independent normalization (unimportant)

- Provides a distribution of model parameters most consistent with data
- We incorporate sources of uncertainty from:
  - use of NN surrogate
  - featurizing nToF
  - DD and DT yield measurements

A bit of maths…

Bayes theorem and manipulations:

Posterior distribution for parameters (x) given data (y)

Prior information on parameters

$$p(\mathbf{x}|\mathbf{y}) = p(\mathbf{y}|\mathbf{x})p(\mathbf{x})/p(\mathbf{y})$$

Likelihood function describing distribution of data around model

Parameter independent normalization (unimportant)

Introduce latent variable z to track uncertainty from surrogate

$$p(\mathbf{x}|\mathbf{y}) = \int p(\mathbf{x},\mathbf{z}|\mathbf{y})d\mathbf{z}$$

Bayes theorem for data including surrogate model

$$p(\mathbf{x},\mathbf{z}|\mathbf{y}) \propto p(\mathbf{y}|\mathbf{x},\mathbf{z})p(\mathbf{z}|\mathbf{x})p(\mathbf{x})$$

Our data models:

Physics model value normally distributed about NN prediction with OOS estimate of covariance

$$p(\mathbf{z}|\mathbf{x}) \sim \mathcal{N}(f_{NN}(\mathbf{x}), \Lambda_{NN})$$

Assumed independence of different measured quantities

$$\begin{aligned} p(\mathbf{y}|\mathbf{x},\mathbf{z}) &= p(\mathbf{y}|\mathbf{z}) \\ &= p(\mathbf{y}_{\mathrm{ntoF}}|\mathbf{z}_{\mathrm{ntoF}})p(y_Y|z_Y)p(y_{\overline{Y}}|z_{\overline{Y}}) \end{aligned}$$

Observations normally distributed about “latent model”

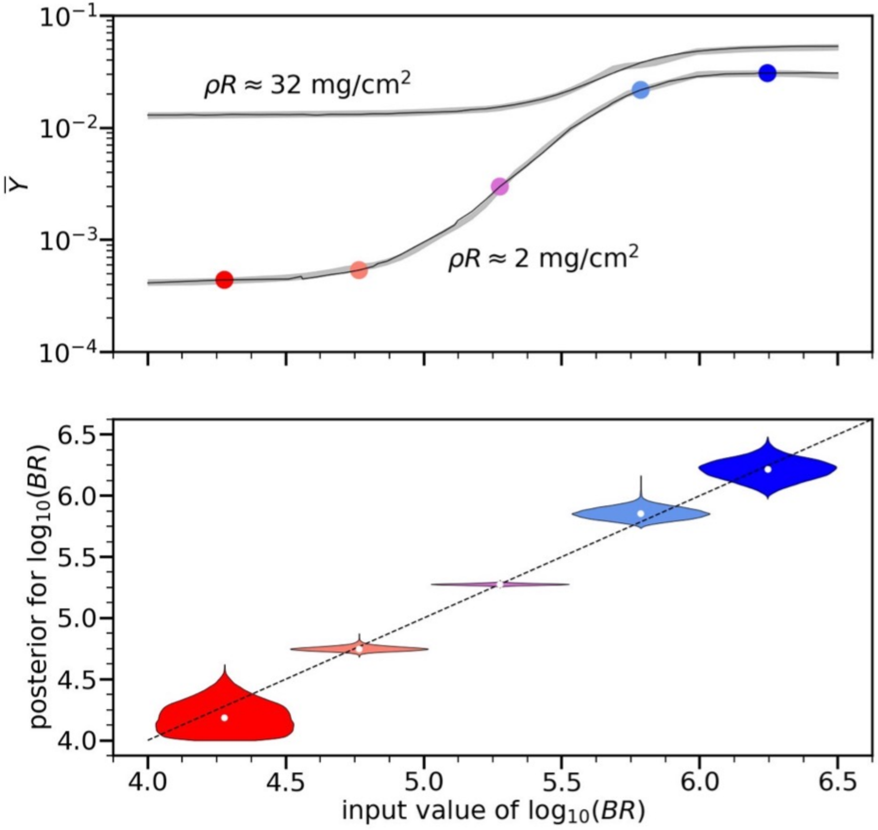
$$p(y_Y|z_Y) \sim \mathcal{N}(z_Y, \Lambda_Y)$$

$$p(y_{\overline{Y}}|z_{\overline{Y}}) \sim \mathcal{N}(z_{\overline{Y}}, \Lambda_{\overline{Y}})$$

$$p(\mathbf{y}_{\mathrm{nToF}}|\mathbf{z}_{\mathrm{nToF}}) \sim \mathcal{N}(\mathbf{z}_{\mathrm{nToF}}, \Lambda_{\mathrm{nToF}})$$

The analysis performed well when benchmarked against synthetic datasets and the only available previously analyzed experiment.

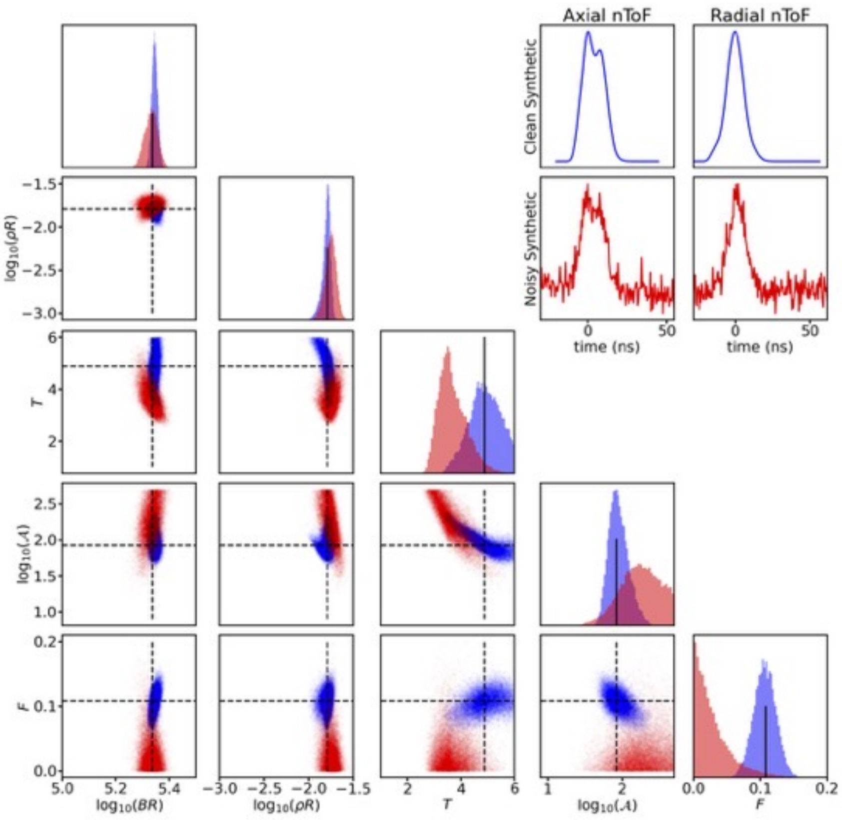
- Surrogate model quantitatively captures features of physics model
- We have demonstrated that BR inference on noisy synthetic data is robust to S/N ratios comparable to experiment
- Results are consistent with the only available previously analyzed experiment.



W.E. Lewis *et al.*, Phys. Plasmas (2021).

The analysis performed well when benchmarked against synthetic datasets and the only available previously analyzed experiment.

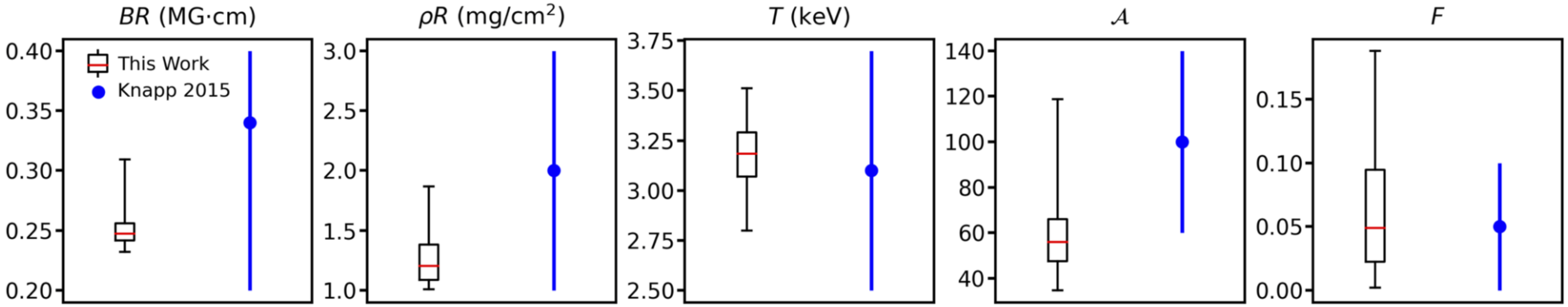
Shape features, DD and DT yields sufficient for BR recovery from noisy synthetic data even when other model parameters obscured.



W.E. Lewis *et al.*, Phys. Plasmas (2021).

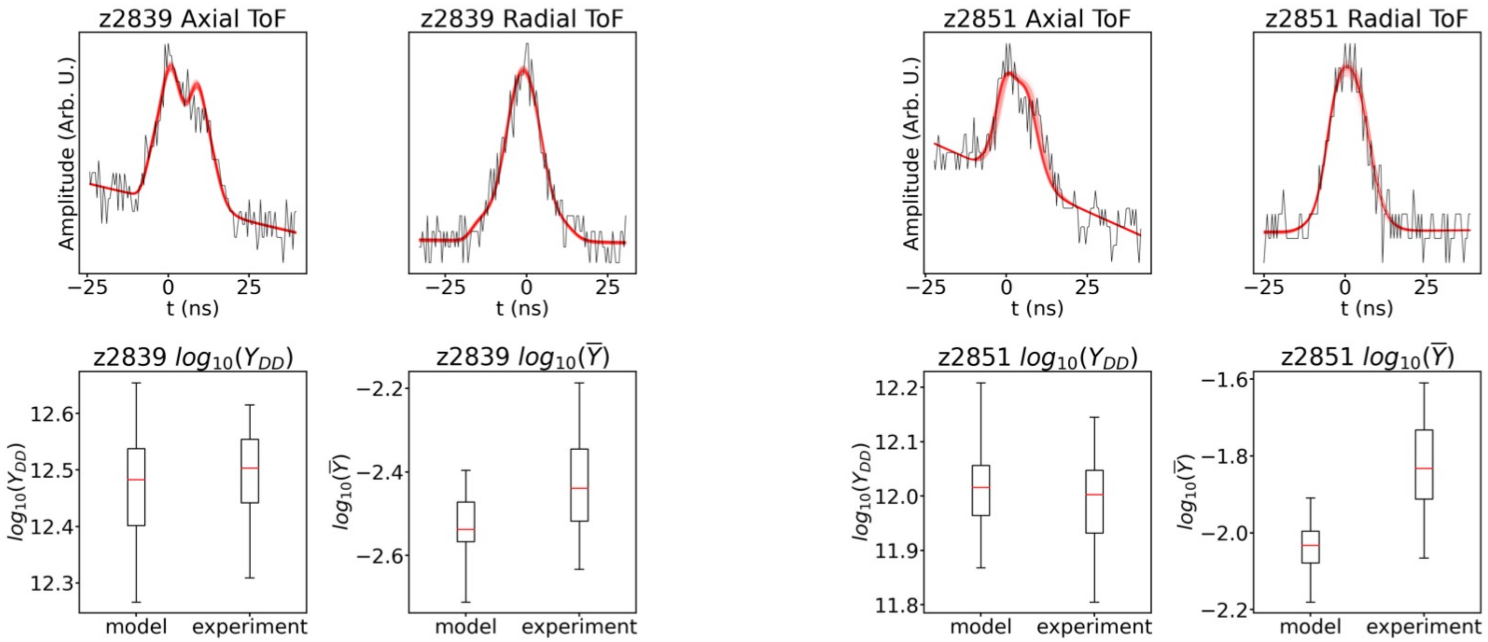
The analysis performed well when benchmarked against synthetic datasets and the only available previously analyzed experiment.

Results are consistent with previous analysis of z2591



W.E. Lewis *et al.*, Phys. Plasmas (2021).

When posterior parameter samples are run through the full physics model, good agreement with observations is obtained.



The agreement obtained with observations indicates that our results are consistent with what would be obtained were it feasible to conduct a Bayesian analysis using the full physics model.

W.E. Lewis *et al.*, accepted Phys. Plasmas (2021).

Observations of BR generally consistent with scaling expected from magnetic Reynolds and Nernst dimensionless parameters

$$BR(t) = \mathrm{CR}(t)\ \Psi(t)\ (BR)_0$$

$$\mathrm{Rm} \doteq 0.01 \frac{[BR(\mathrm{T\,cm})] \cdot [\dot{R}(\mathrm{km/s})]}{[T(\mathrm{keV})]}.$$

$$\mathrm{Ne} \doteq 200 \frac{[T(\mathrm{keV})]}{[BR(\mathrm{T\,cm})] \cdot [\dot{R}(\mathrm{km/s})]} \beta_\wedge^{uT}(x_e)$$

$$\beta_\wedge^{uT} \doteq x_e \frac{3.053 + 1.5x_e^2}{3.7703 + 14.79x_e + x_e^4},$$

$$x_e = 6.40 \cdot (10)^{-3} \frac{[T(\mathrm{keV})]^{3/2} \cdot [B_z(\mathrm{T})]}{\ln\Lambda \cdot [\rho(\mathrm{g/cm^3})]};$$

D.E. Ruiz *et. al.*, (Submitted) Phys. Plasmas.

Rm considers thermal conduction losses in Bohm-like regime and combined effects of internal flow in isobaric cores and Nernst advection

Ne is the ratio of characteristic Nernst velocity and characteristic implosion velocity

flux losses will decrease (i.e., Ψ will become larger) when:

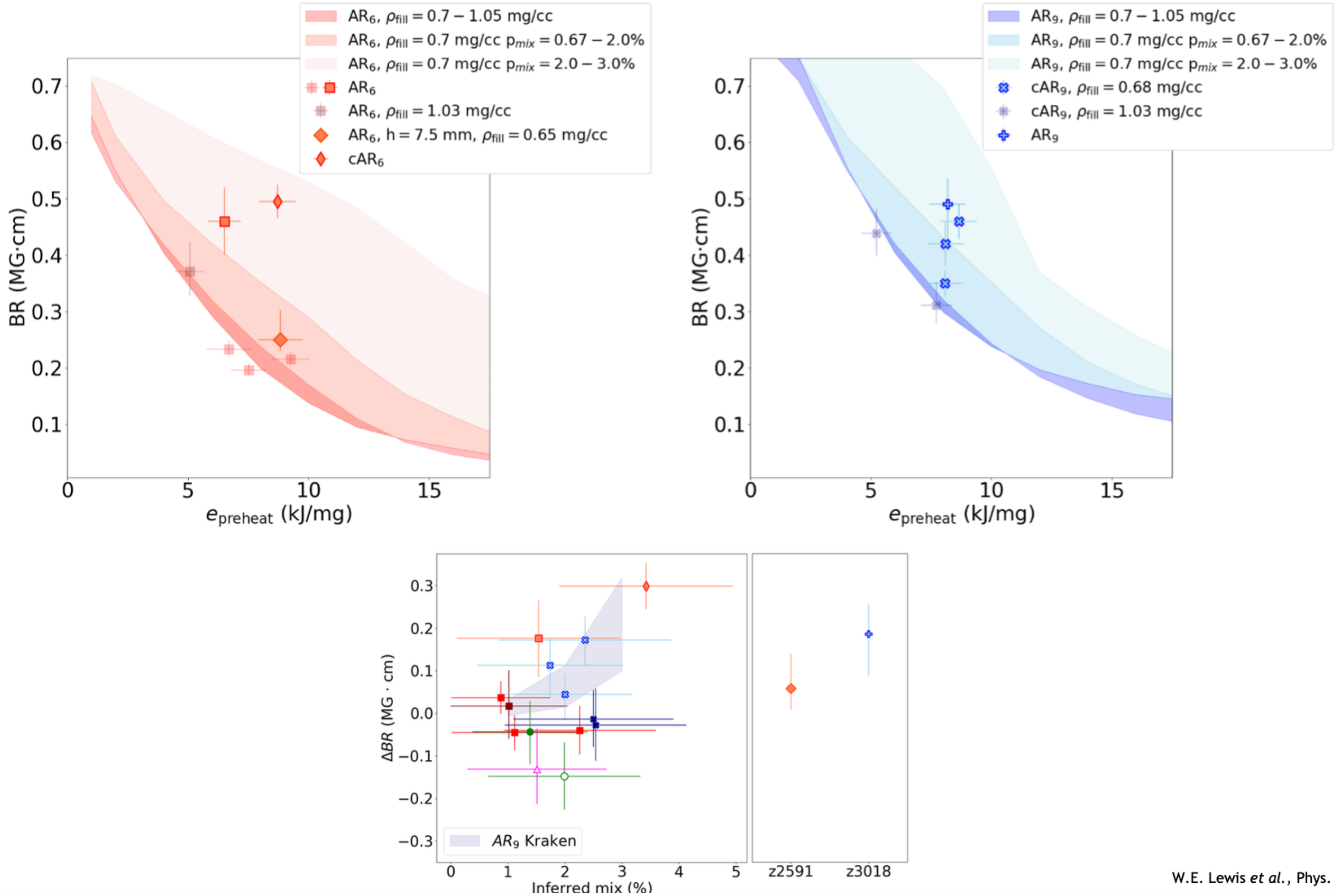
(i) the magnetization of the plasma is greater as measured by the BR product or the electron Hall parameter x_e,

(ii) the implosions are faster resulting in relatively weaker Nernst velocity v_{Ne} and less time for magnetic-flux to escape,

(iii) the fuel temperature is lower, *e.g.* as a result of lower e_{preheat} or enhanced radiative losses from mix less reducing transport of magnetic field due to thermal gradients.

W.E. Lewis *et al.*, Phys. Plasmas (Submitted).

Anomalously large BR appears consistent with enhanced mix to mix inference has large error bars.



W.E. Lewis *et al.*, Phys. Plasmas (Submitted).