

Predictions of Performance Variations in Inertial Confinement Fusion Experiments at the National Ignition Facility

IAEA FEC 2023

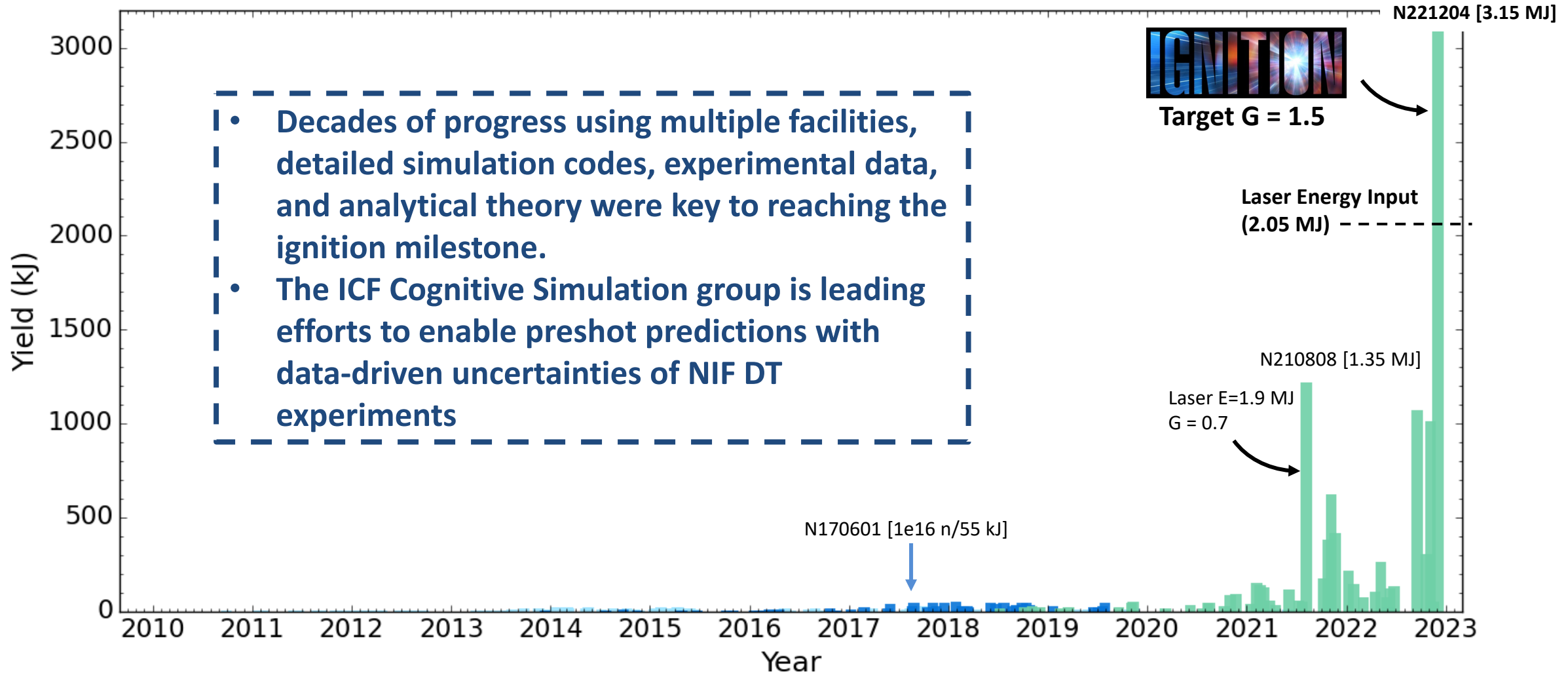
October 18, 2023

Kelli Humbird

Jim Gaffney, Veronika Kruse, Eugene Kur, Bogdan Kustowski, Ryan
Nora, Brian Spears, The ICF Team

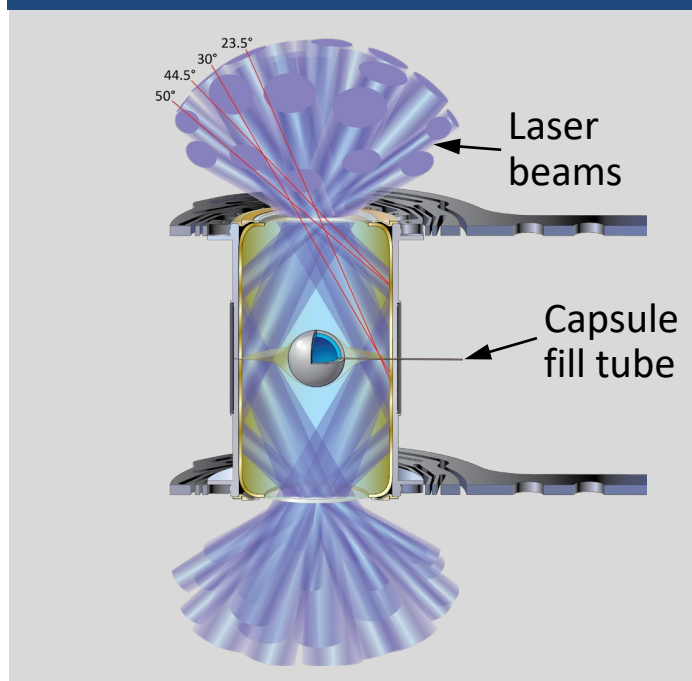


On December 5, 2022, fusion ignition was achieved at the National Ignition Facility

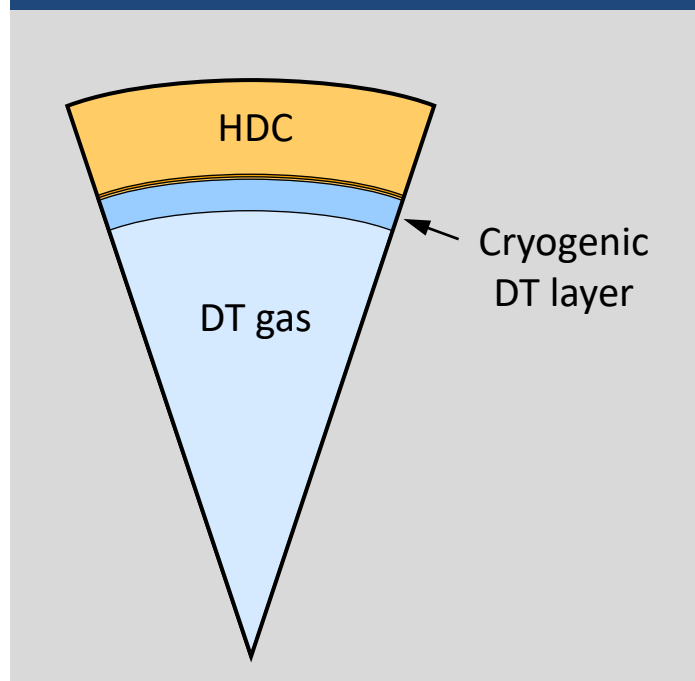


NIF uses a laser-driven hohlraum to compress a fuel pellet to achieve the conditions for ignition

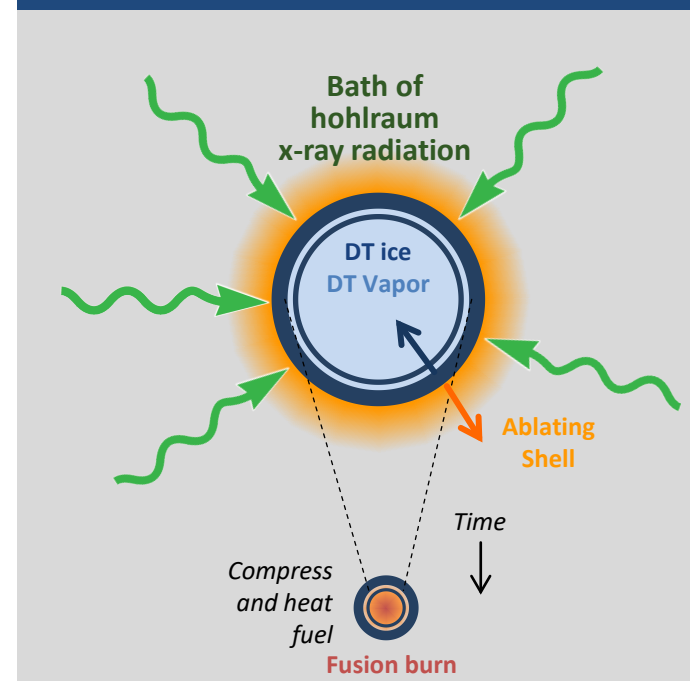
The Hohlraum is a Cylindrical Cavity that Serves as an X-ray Oven



The Fuel Capsule Consists of an Ablator Surrounding DT Ice and Gas

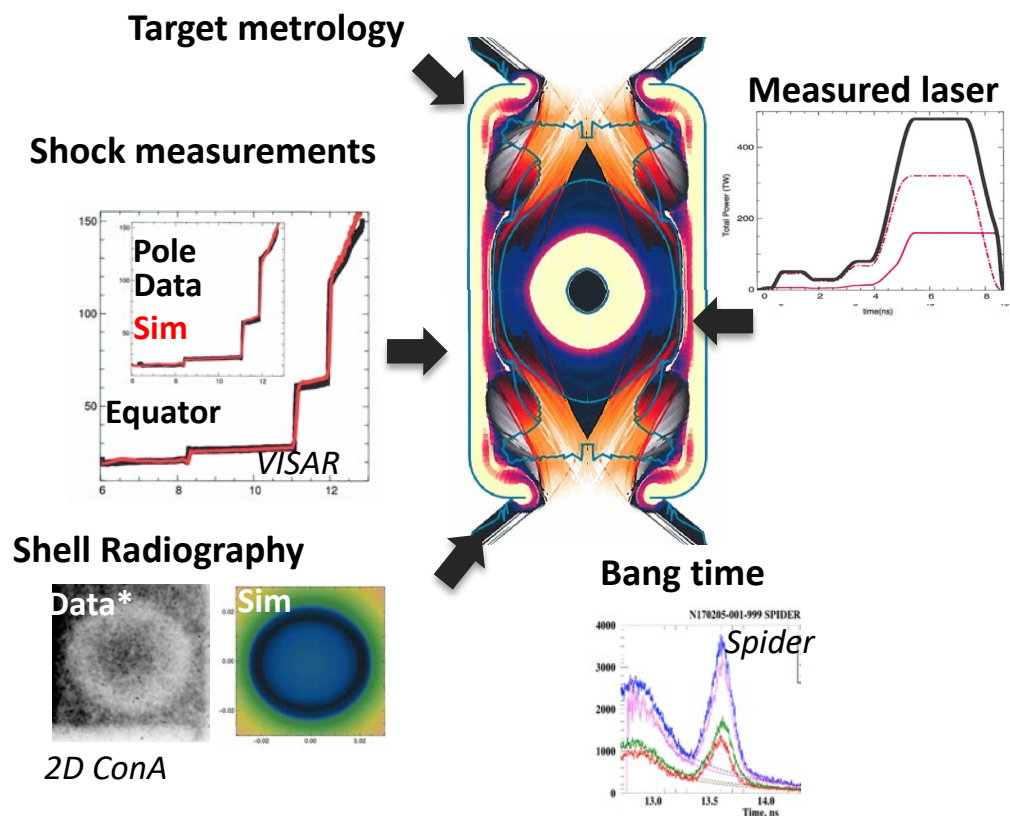


Turn 100 Million Atmospheres of Pressure into 300 Billion



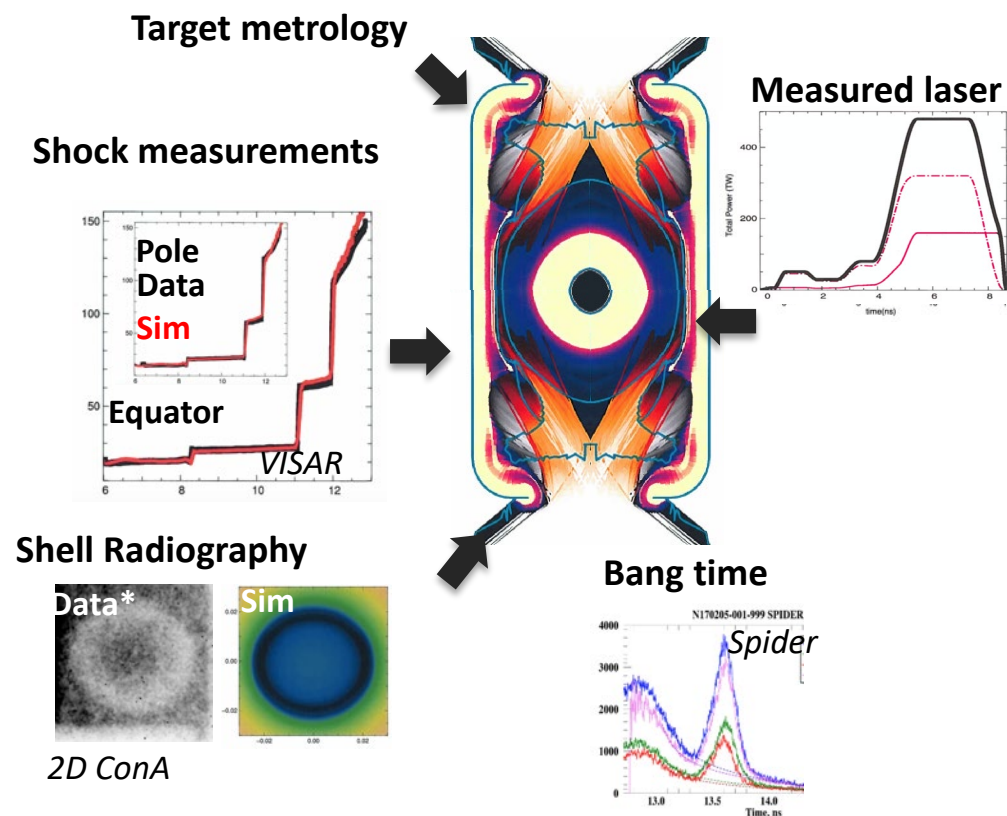
Achieving the conditions for ignition demands precise control of laser and target parameters for a high convergence implosion with low ablator fuel mix

We use simulations that are adjusted to match data in a two-step process to design new experiments



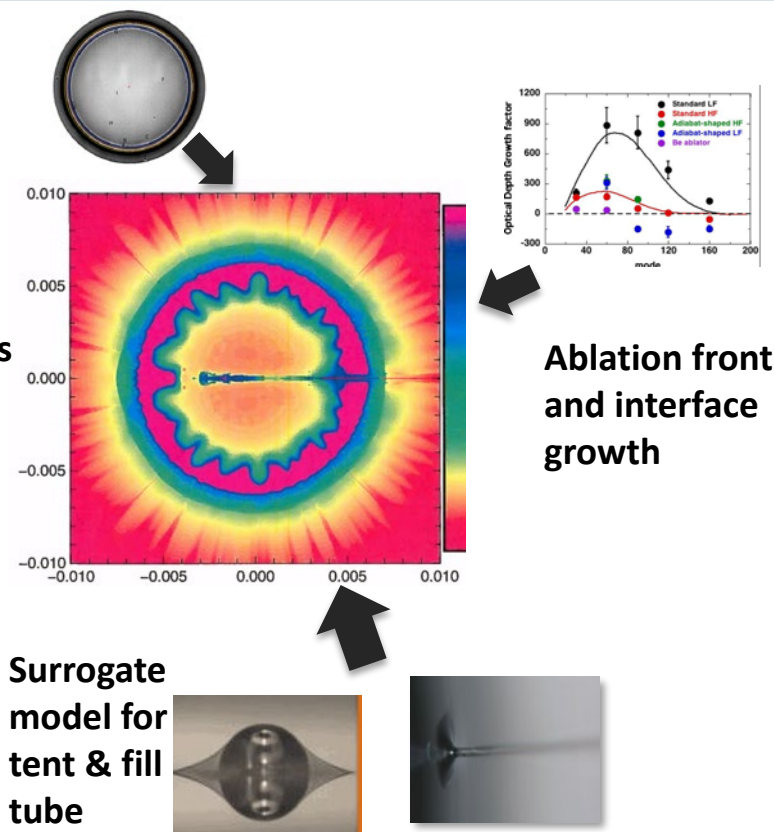
1. Integrated HYDRA hohlraum simulations tuned to match experimental energetics, shock timing, and time-dependent low mode symmetry

We use simulations that are adjusted to match data in a two-step process to design new experiments



$$T_r(r, \theta, t)$$

Surface
roughness

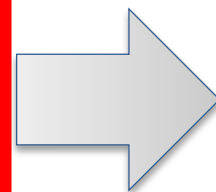


1. Integrated HYDRA hohlraum simulations tuned to match experimental energetics, shock timing, and time-dependent low mode symmetry

2. Higher resolution capsule-only simulations to study hydrodynamic instabilities, engineering features, impacts of capsule defects on performance

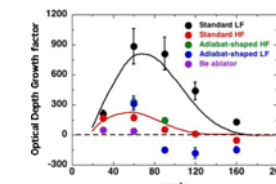
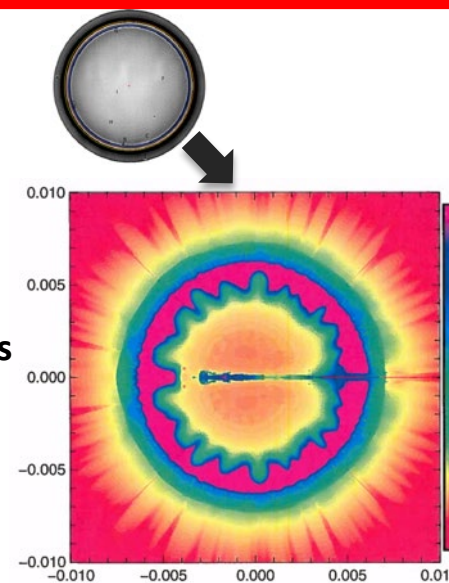
We use simulations that are adjusted to match data in a two-step process to design new experiments

This talk will focus on a statistical approach to capsule-only post shots analysis, and how we use this information to make preshot predictions of new designs



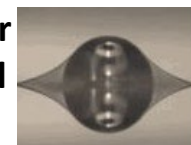
$$T_r(r, \theta, t)$$

Surface roughness



Ablation front and interface growth

Surrogate model for tent & fill tube



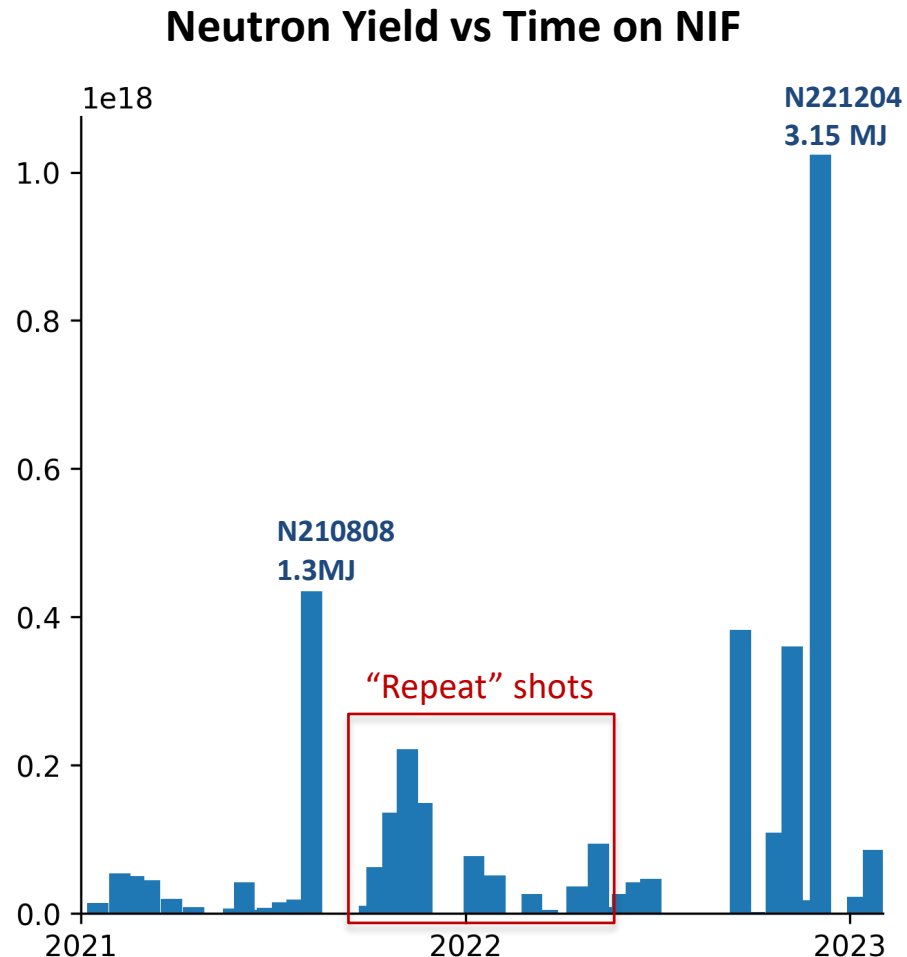
1. Integrated HYDRA hohlraum simulations tuned to match experimental energetics, shock timing, and time dependent low mode symmetry

2. Higher resolution capsule-only simulations to study hydrodynamic instabilities, engineering features, impacts of capsule defects on performance

Bayesian analysis of NIF experiments



ML + statistical analysis of N210808 repeats is enabling preshot predictions, with data-driven uncertainties, of NIF DT experiments



- In early 2022, **multiple near-repeats of N210808** showed large variations in performance
- We've been analyzing this dataset to answer some key questions in ICF physics
 - What drives observed variations?
 - What can these results tell us about expected performance of *future* shots?

Bayesian inference + HPC simulations provide *distributions* of simulation inputs that are consistent with experimental data

Simulation ensemble mapping tuning and degradation parameters to synthetic data

- Applied P_1 (constant in time)
- Time dependent applied P_2 (2 parameters)
- Fall-line mix model
- Drive (4 parameters)



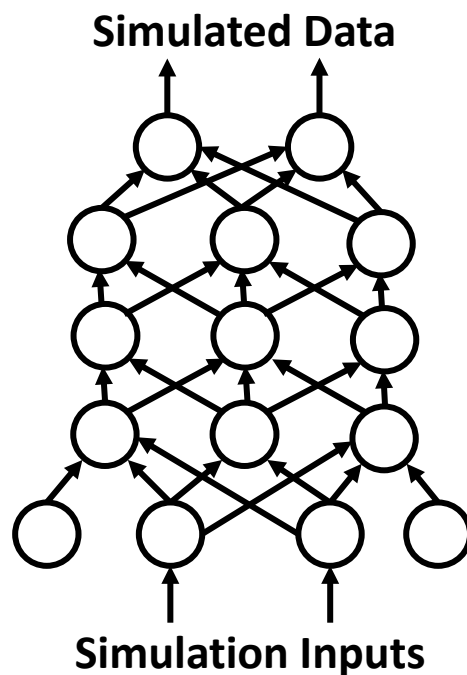
Bayesian inference + HPC simulations provide *distributions* of simulation inputs that are consistent with experimental data

Simulation ensemble mapping tuning and degradation parameters to synthetic data

- Applied P_1 (constant in time)
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Deep neural network (DNN) trained on **ensembles** interpolate simulations in milliseconds



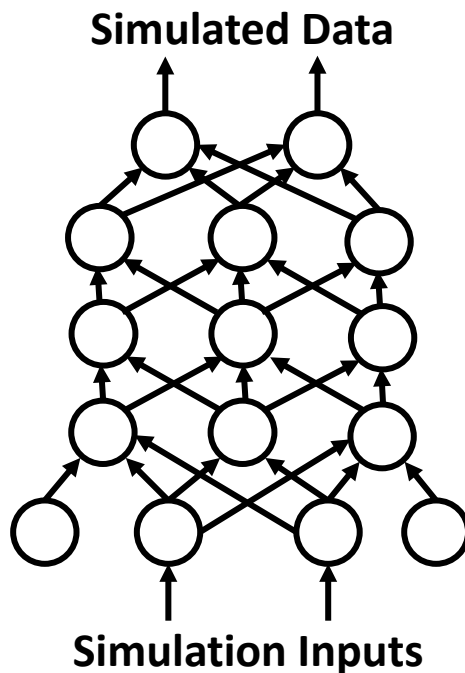
Bayesian inference + HPC simulations provide *distributions* of simulation inputs that are consistent with experimental data

Simulation ensemble mapping tuning and degradation parameters to synthetic data

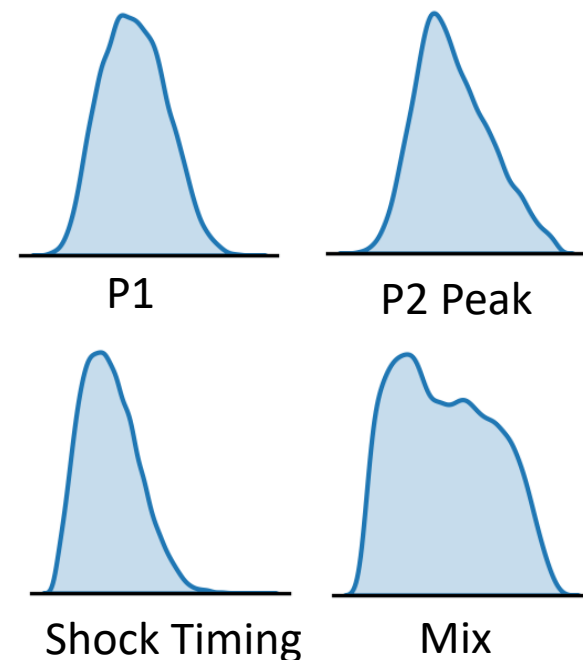
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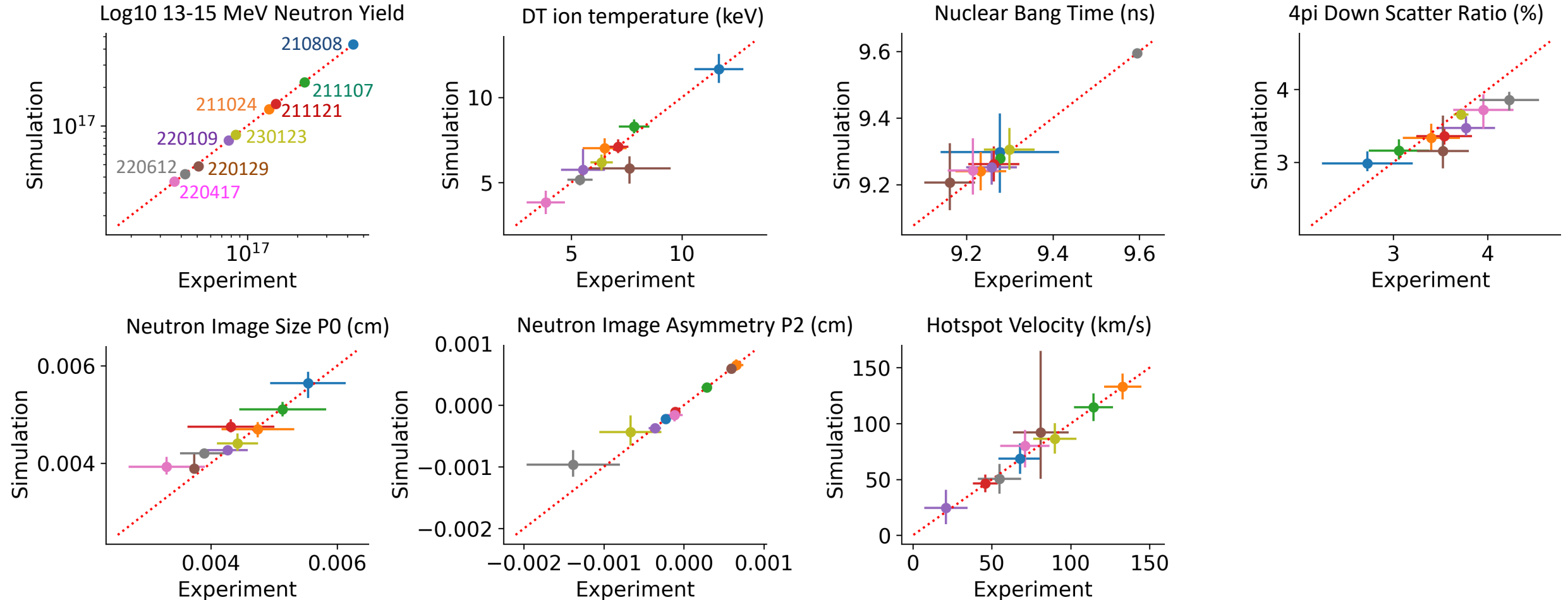
Deep neural network (DNN) trained on **ensembles** interpolate simulations in milliseconds



Markov chain Monte Carlo generates probability distribution of simulation inputs consistent with experiment



We match several experimental observables within measurement uncertainties

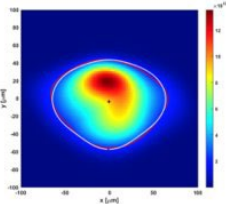


We link single-shot analyses together into a global model to quantify shot to shot variability

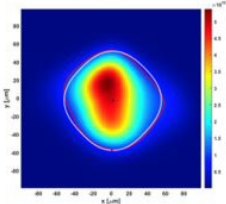
Experimental Data

HYDRA Input Parameters

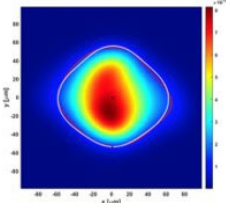
N210808



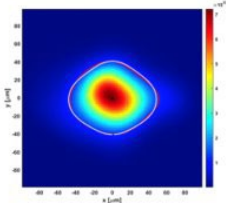
N211024



N211107

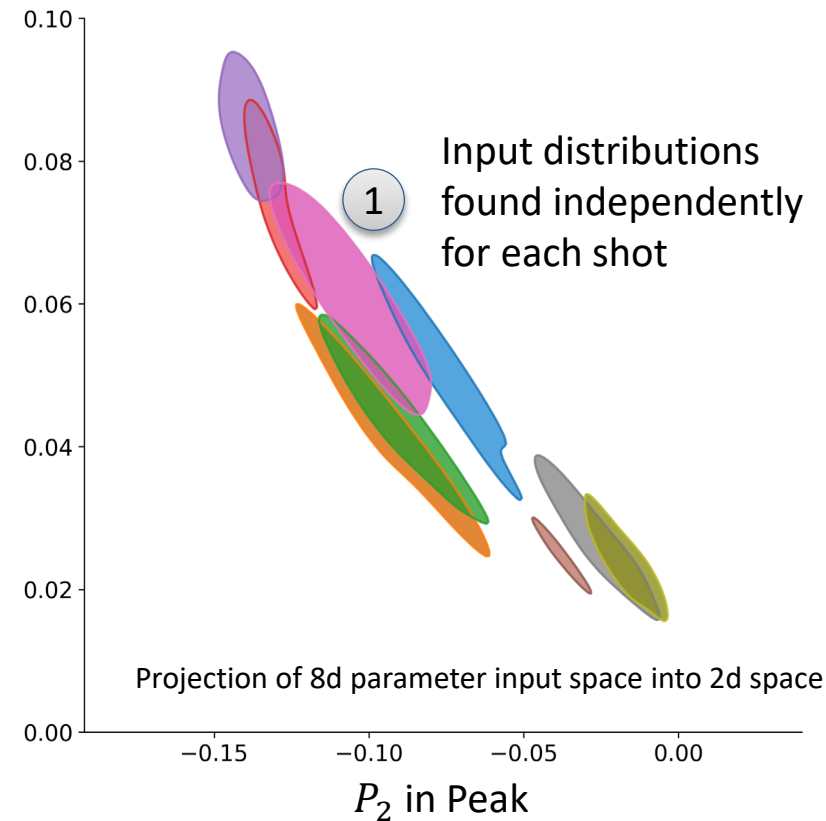


N211121



Bayesian Inference

P_2 at end of drive



Primary Neutron Image
+ yield, Tion, DSR,...

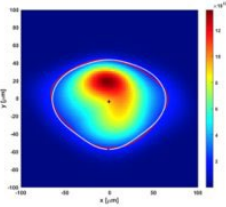


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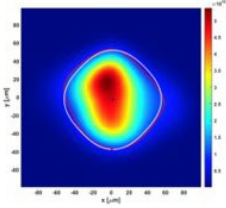
Experimental Data

HYDRA Input Parameters

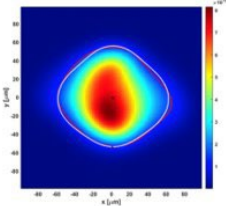
N210808



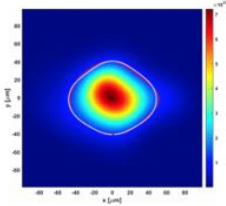
N211024



N211107

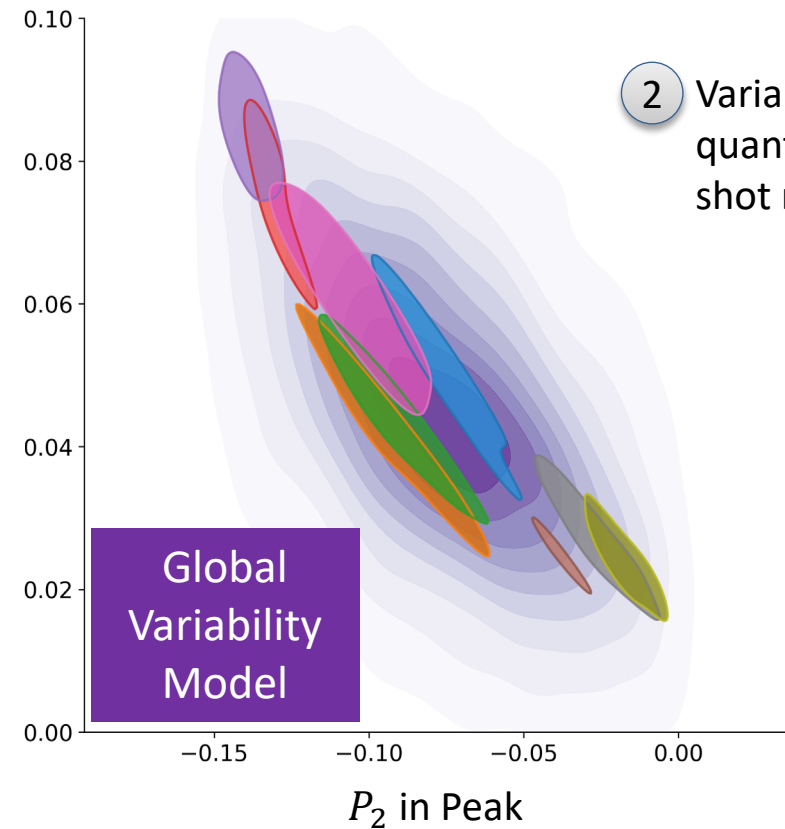


N211121



Bayesian
Inference

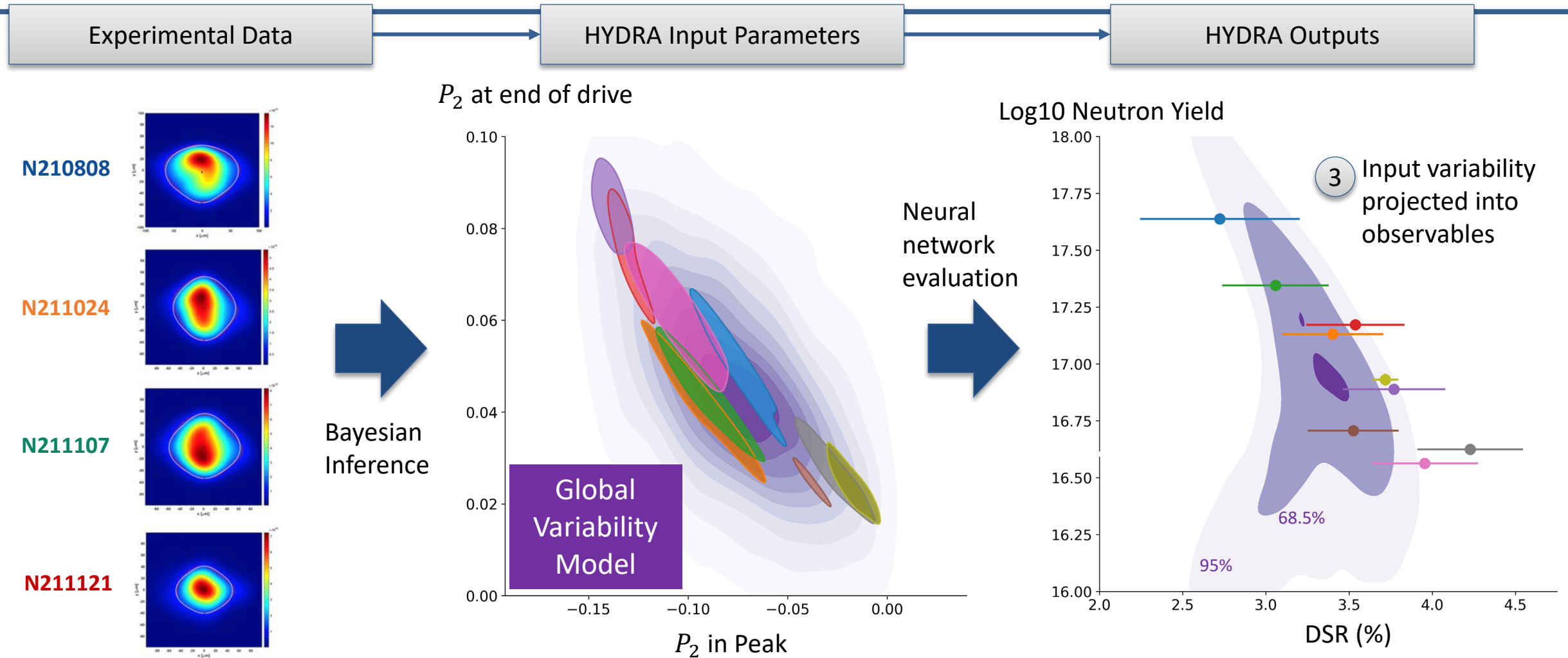
P_2 at end of drive



Primary Neutron Image
+ yield, Tion, DSR,...



We link single-shot analyses together into a global model to quantify shot to shot variability

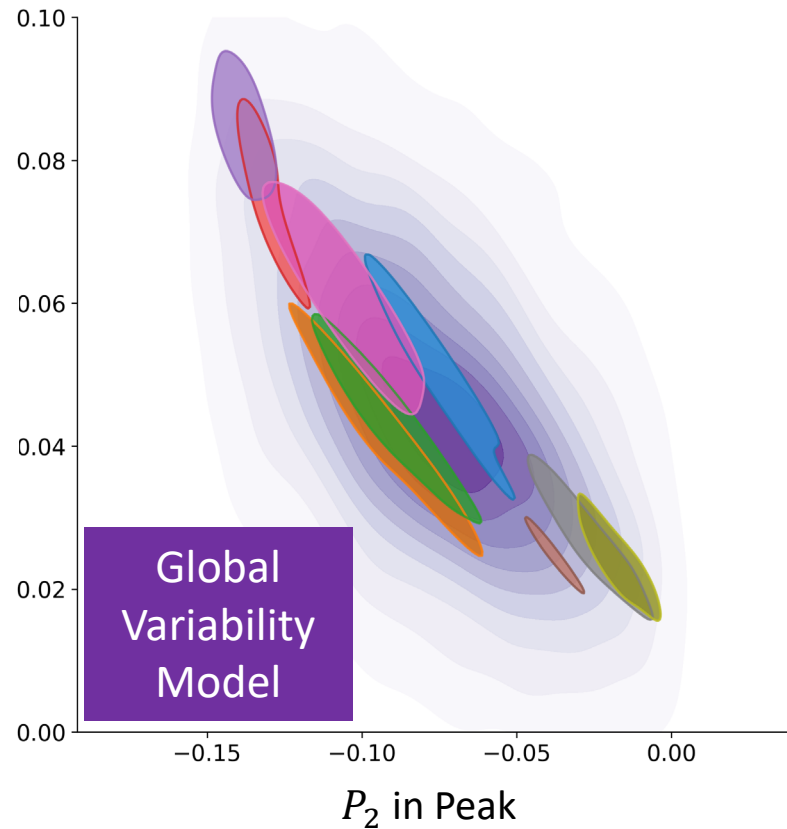


Preshot predictions of performance variability



The global variability model acts as a “prior” for predictions of new designs

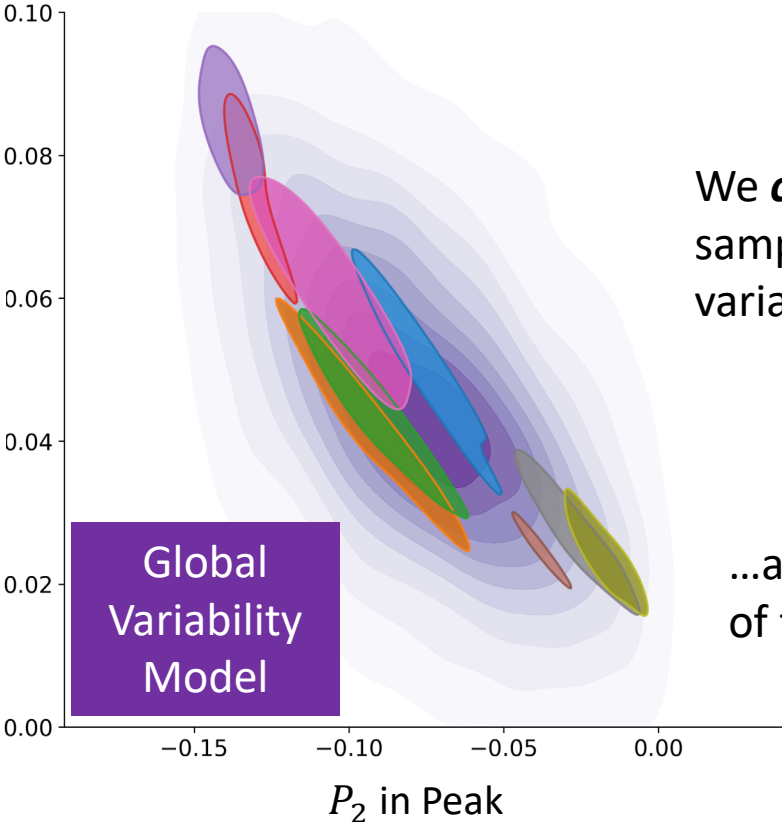
P_2 at end of drive



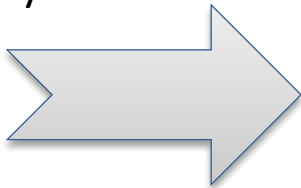
- Describes all shot-to-shot variations
- Statistical model that can be sliced, transformed, perturbed, and ***applied to new designs***

To predict performance variability, we need to propagate the input distribution through a model for the new design

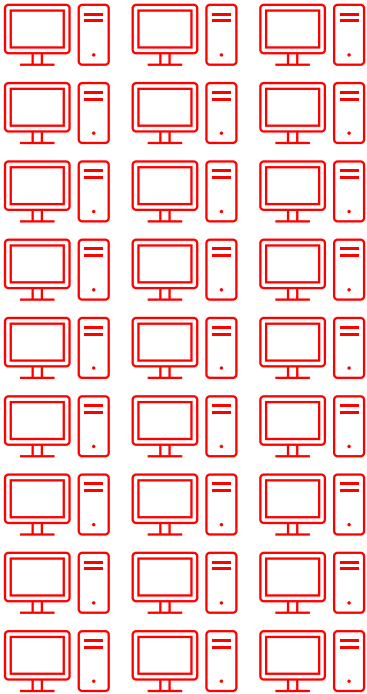
P_2 at end of drive



We *could* draw thousands of samples from the global variability model...



...and run HYDRA simulations of the new design



HYDRA output

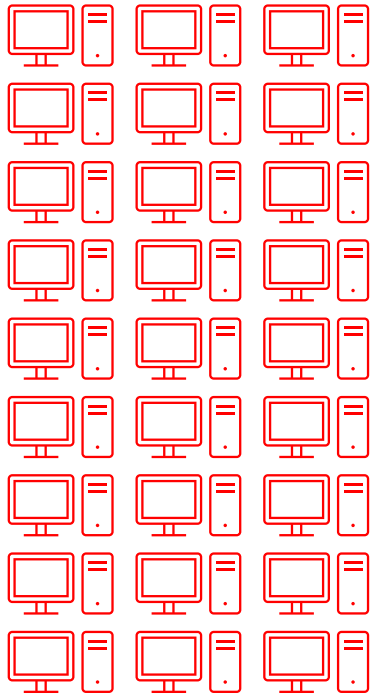
Sim #	Yield (x10 ¹⁷)	DSR (%)
1	1.0	3.0
2	2.2	2.5
3	5.0	3.1
4	8.6	2.9
...	-	-
99,999	0.9	3.3
100,000	3.4	3.6

But this would take several months to do!

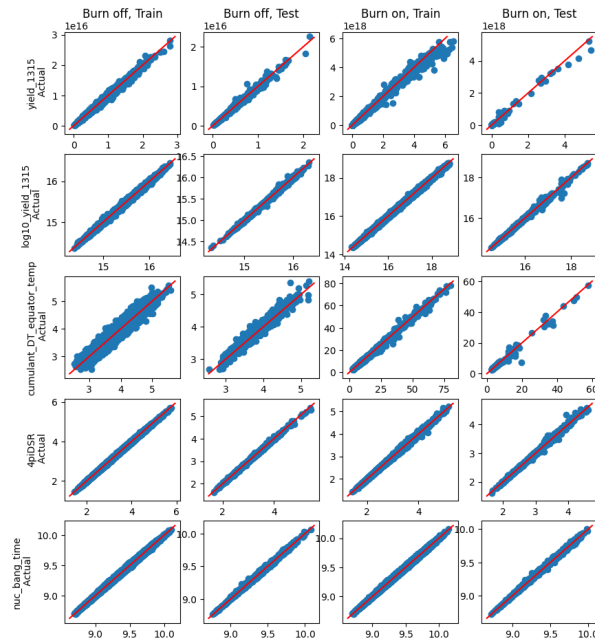


Transfer learning retrains an existing neural network to predict new designs with only tens of new simulations

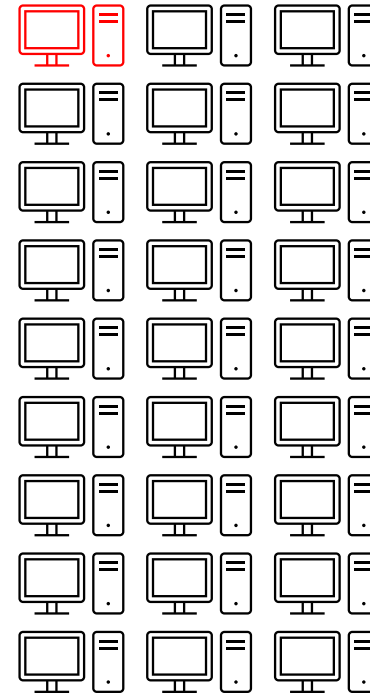
Tens of
Thousands of
HPC Simulations



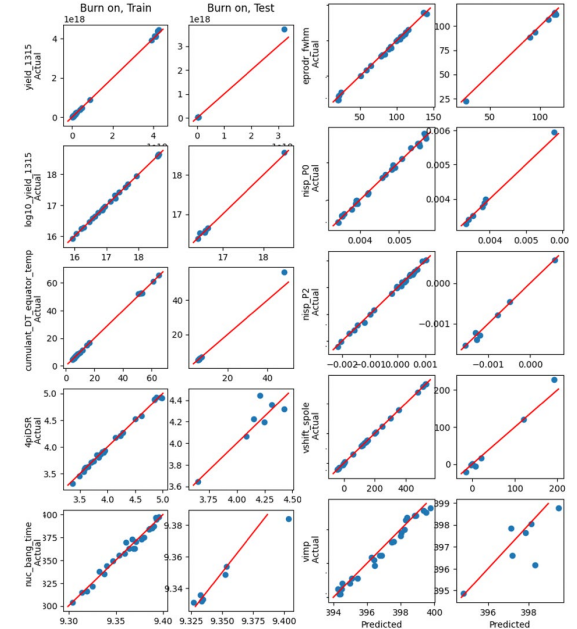
Neural Network Based
on N210808 Shot Series



Tens of HPC
Simulations

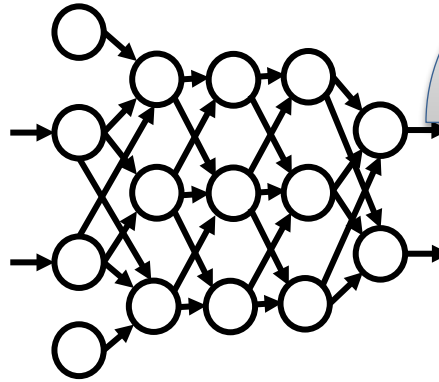


Retrained Neural Network
Good for New Shot



We expected N221204 to get 2x the yield of N210808* with a high probability of reaching ignition

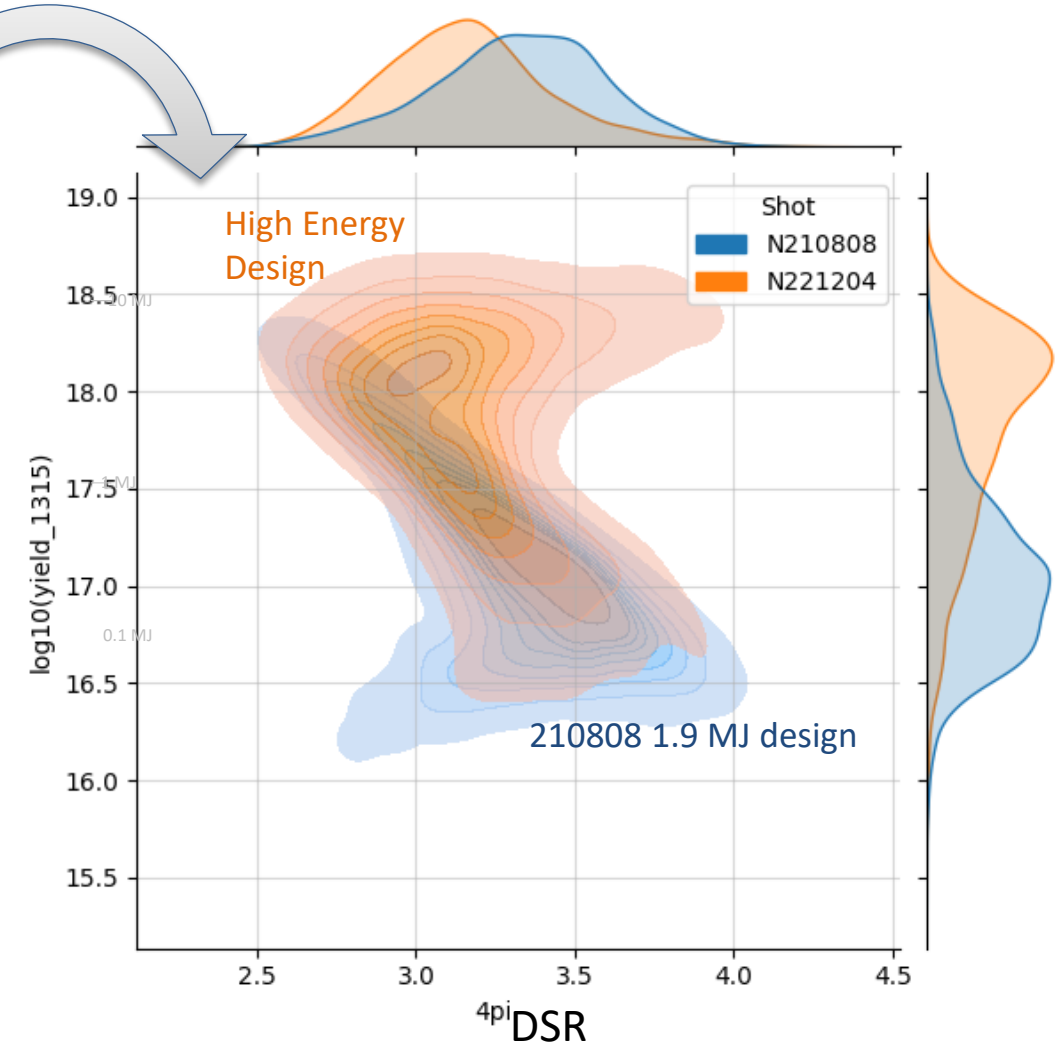
Global variability model is evaluated by N221204 (re)trained network



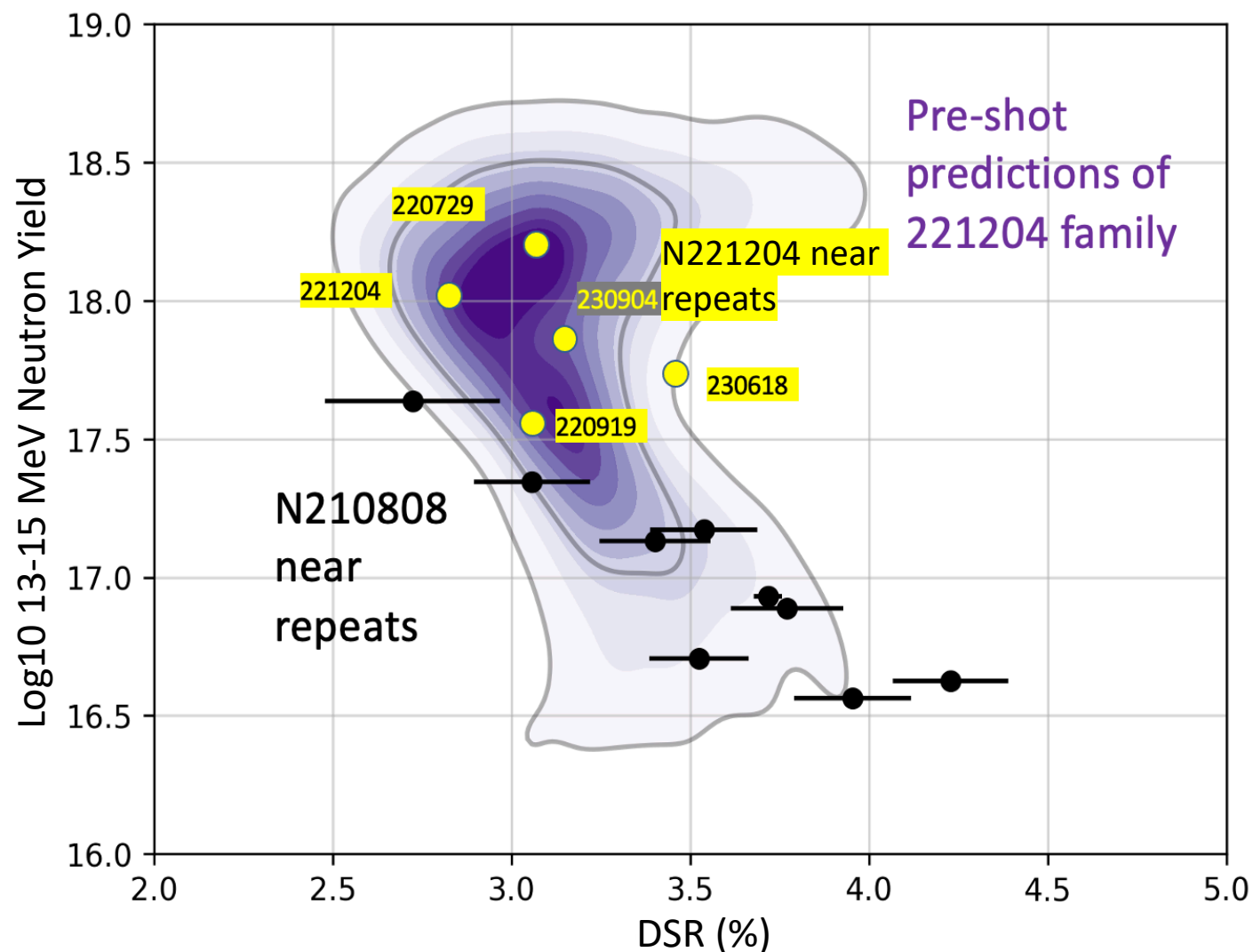
Shot	Expected Yield [MJ] Median, (50% CI)	$P(\text{Yield} > E_{\text{laser}})^{**}$	$P(\text{Yield} < 1\text{MJ})$
N210808	0.3 MJ (0.2 – 0.6)	7%	85%
N221204	2.6 MJ (0.9 – 5.0)	59 %	43%

**Laser energy = 2.05MJ for 12/5; 1.9MJ for N210808

*N210808 yield was 1.35MJ

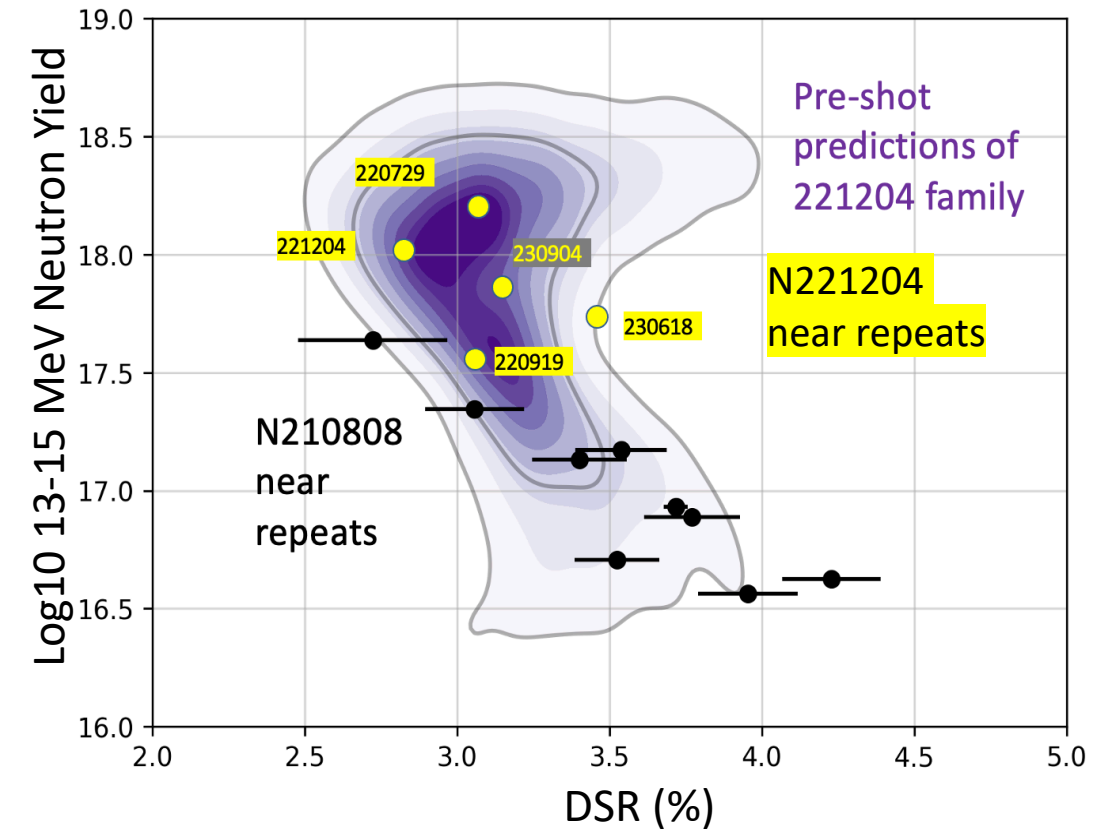


Repeat experiments of the 2.05MJ design continue to populate the distribution of predicted performance variability



Using a combination of simulations, prior experiments, Bayesian statistics, and machine learning, we *predicted* that N221204 had a greater than 50% chance of reaching ignition

- Our recent predictions provide an exciting glimpse of how ICF studies could be done in the future
- Ensemble-based Bayesian post-shot analysis of ICF data informs us of which degradation mechanisms were important *and* how they are correlated with each other
- Method for routine preshot predictions *with uncertainties* for NIF DT experiments improves our predictive capability and enables us to explicitly optimize designs under realistic uncertainties
- This approach presents a general framework that can readily be adapted to other application areas



This work is built upon decades of research by an incredible team across the Lab and the wider community!



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Materials**
Advanced Diamond Technologies

**UR
LLE** 

AWE 

IIIT | **PSFC** Plasma Science and Fusion Center

 **GENERAL ATOMICS**

NNSA
National Nuclear Security Administration



Huge specific thanks to the ICF CogSim and the Hybrid E teams!



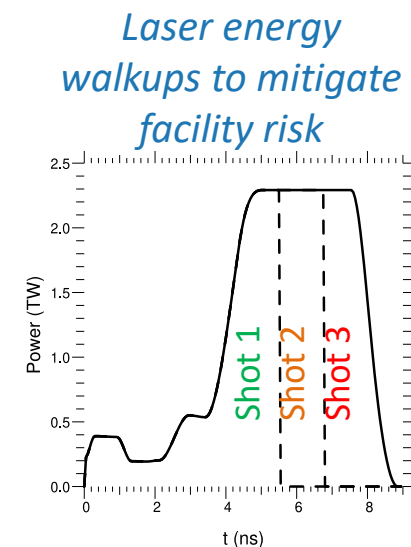
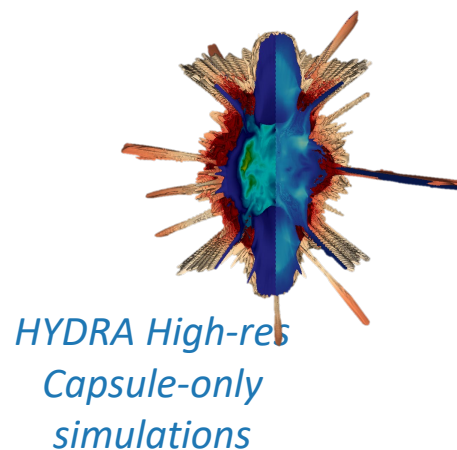
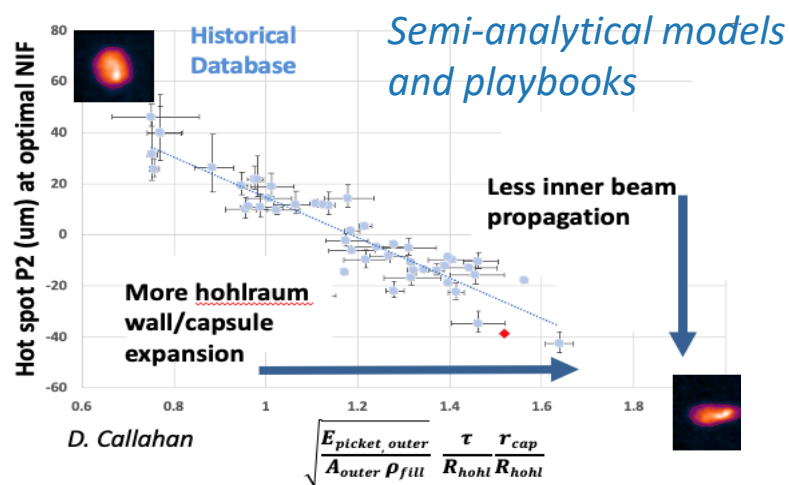
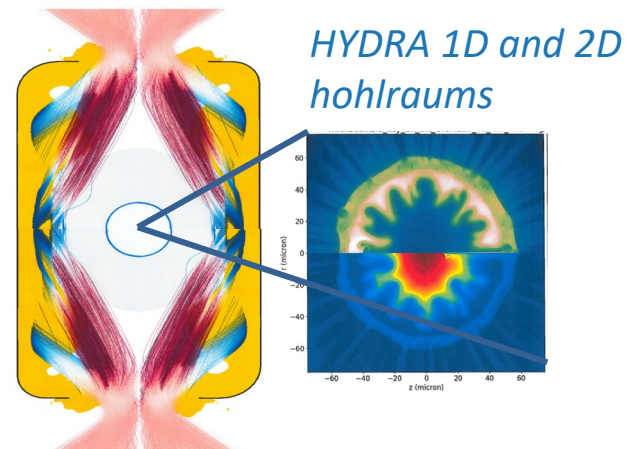


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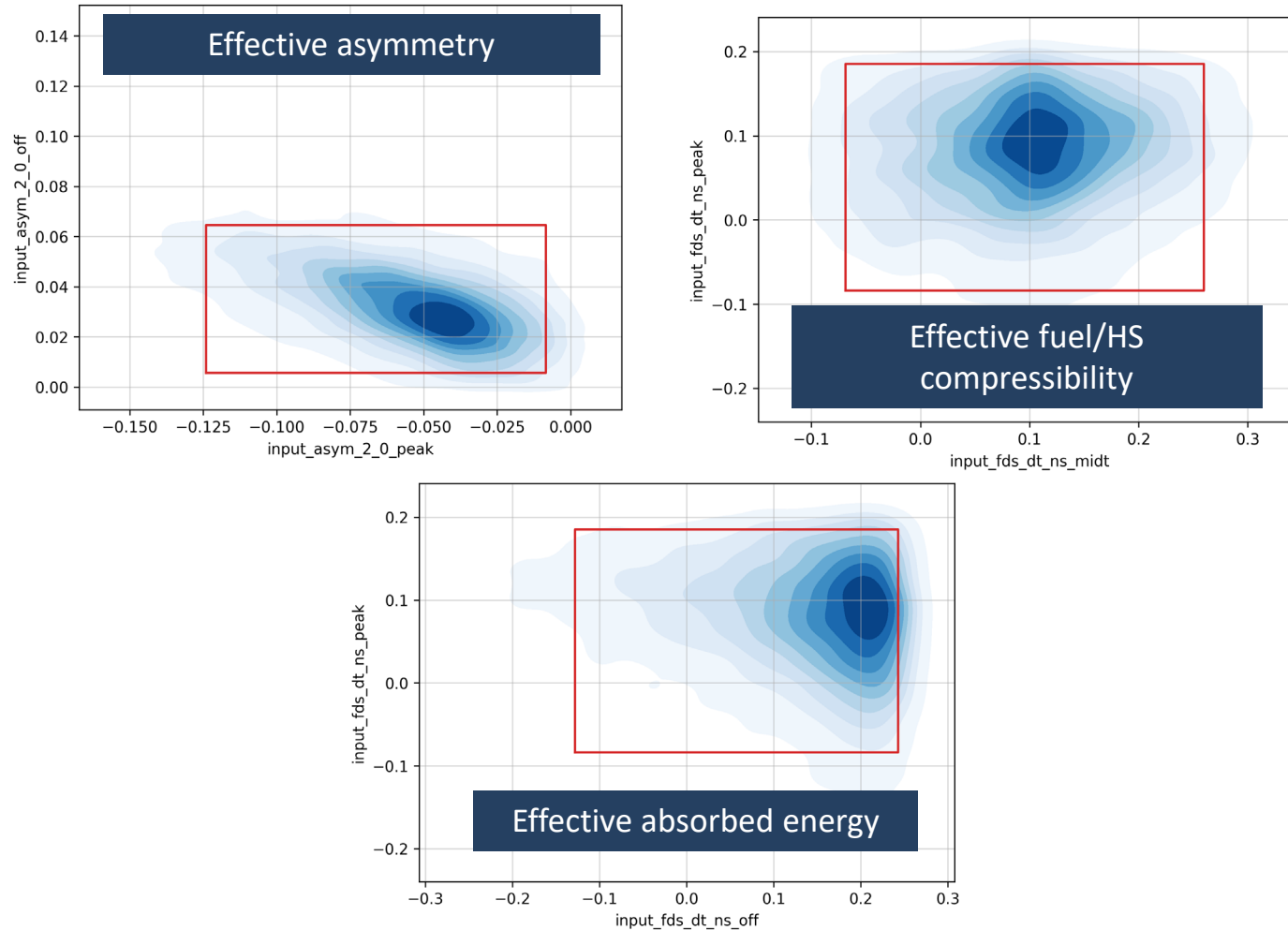
Current practices use a variety of tools and routine experimental validation to design ICF experiments

- We use combination of tools to design ICF experiments at the NIF
 - Radiation hydrodynamic simulations
 - Theory/ Semi-analytical models
 - Experimental playbooks
 - Machine learning models

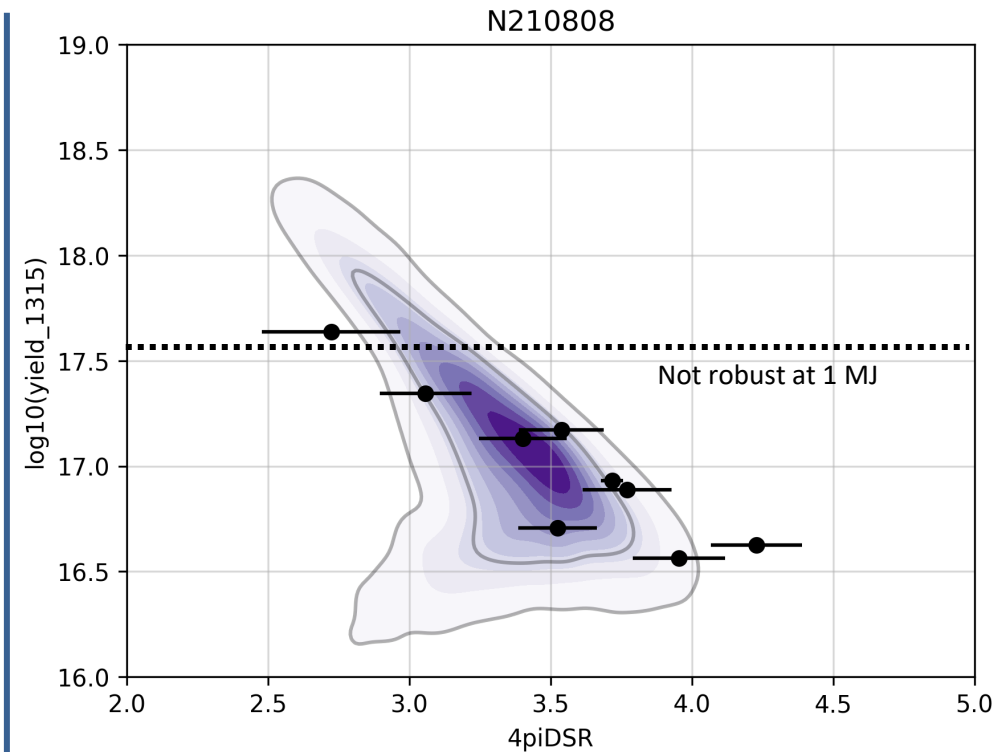


The N210808 repeats constrain the perturbations that are likely to occur and their predicted impact

Input perturbations

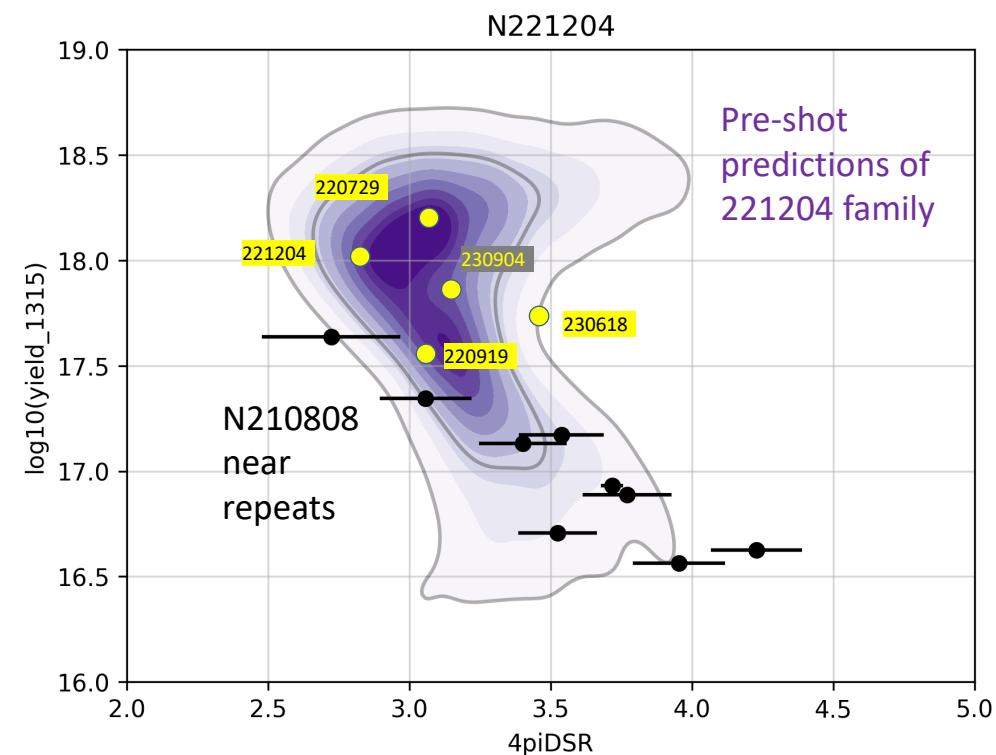
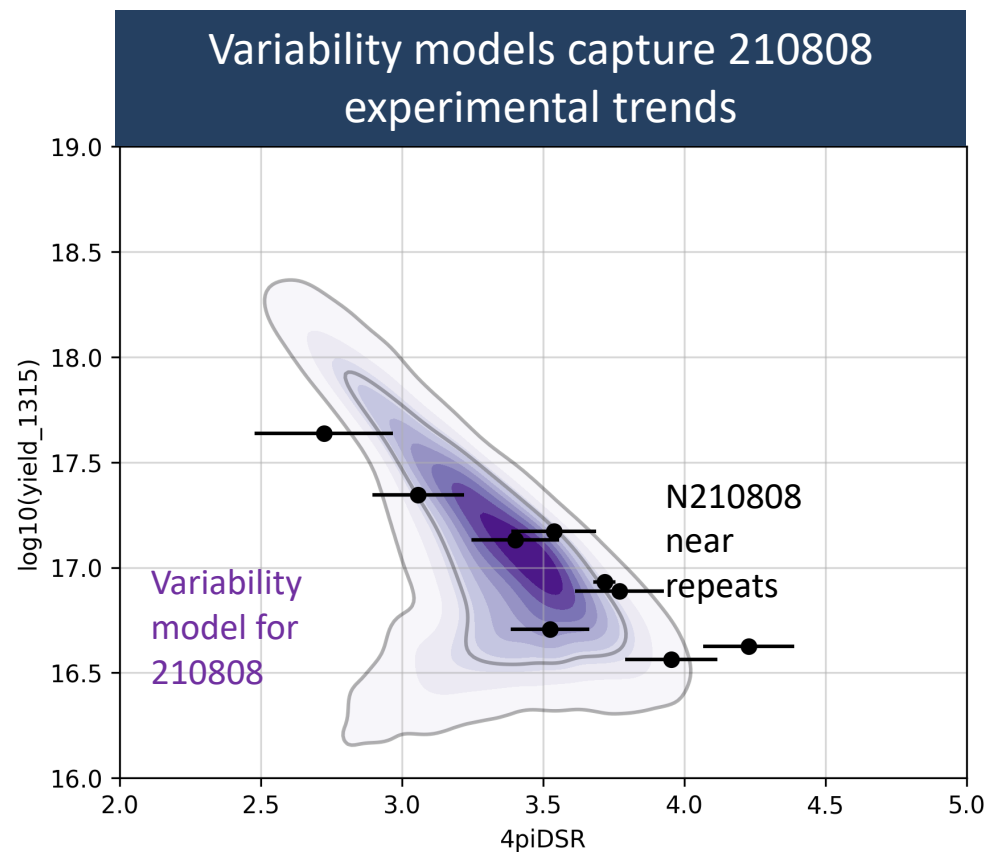


Model predictions and observations



This model works well for N210808 across a wide range of experimental conditions

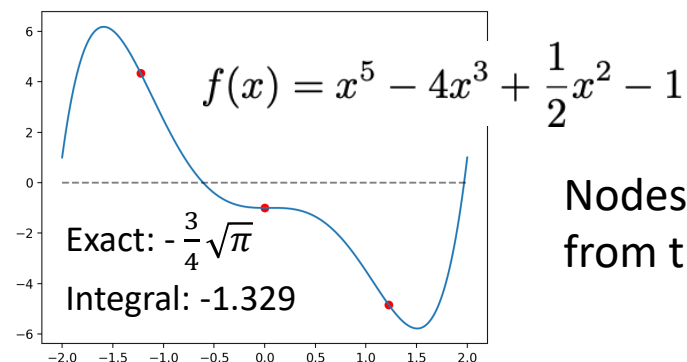
Our predictive capability and our experiments are in agreement about N221204 improvements and variation



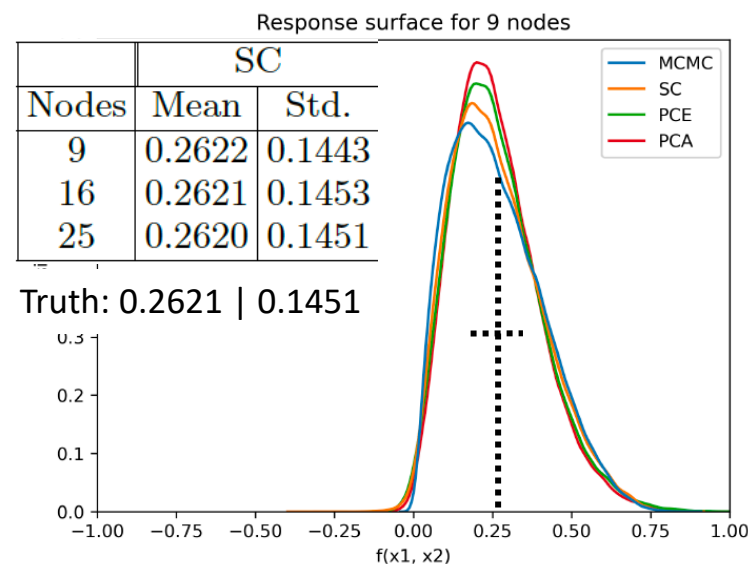
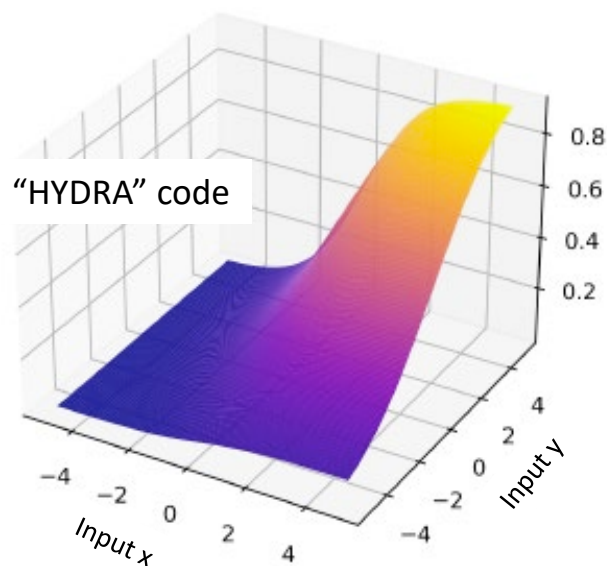
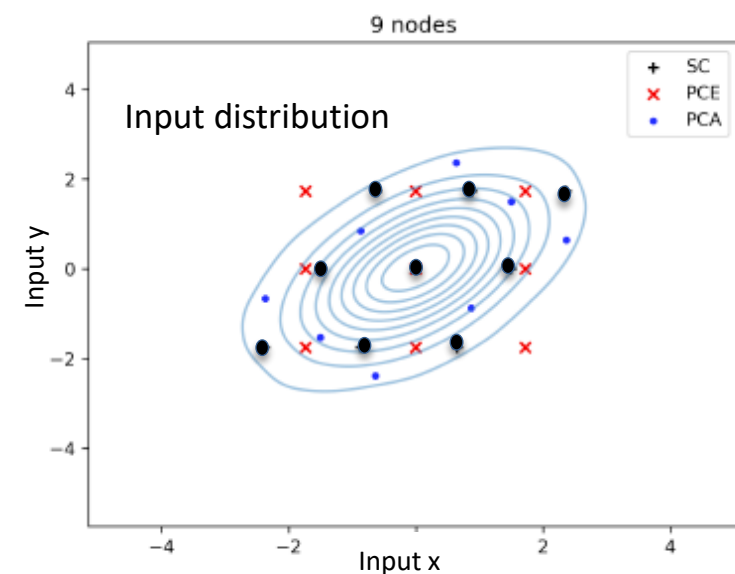
We used Stochastic Collocation to determine which input parameters to use for each of the HYDRA simulations

$$\int_{-\infty}^{\infty} f(x) \exp(-x^2) dx \approx \sum_{i=1}^n w_i f(x_i)$$

n points *exactly* integrate $2n-1$ degree polynomial



Nodes and weights are determined from the Hermite polynomials





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