A Data-Driven Approach Towards NIF Neutron Time-of-Flight Diagnostics Using Machine Learning and Bayesian Inference

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Summer Internship Final Wrap-up
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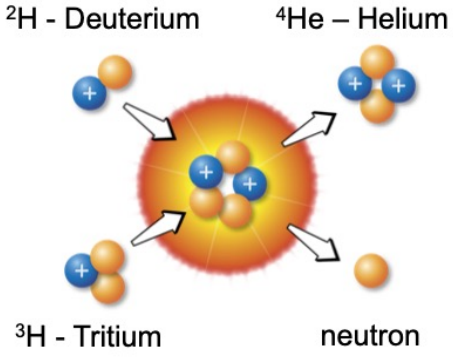
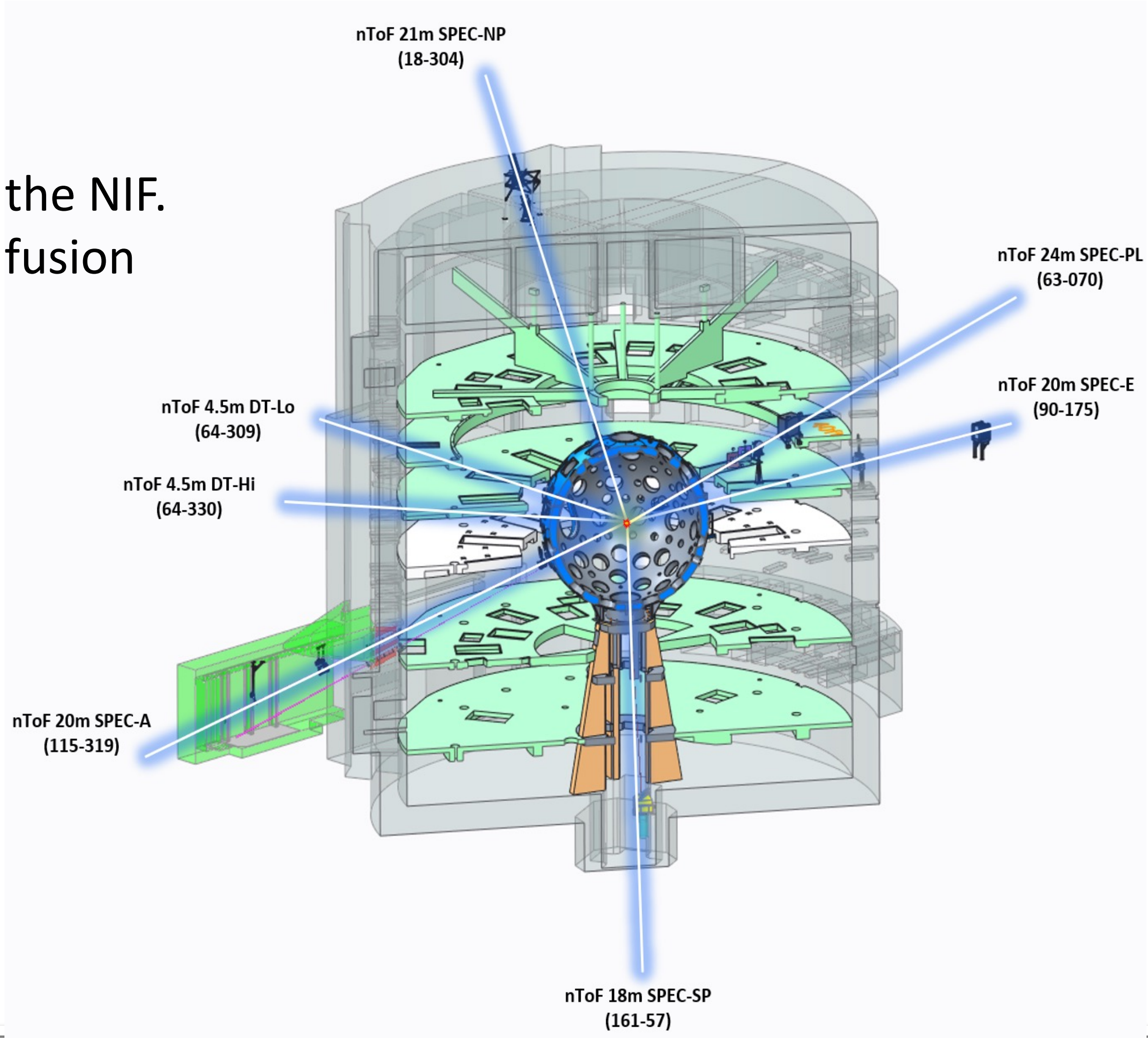
Background: Neutron Time-of-Flight (nToF) Diagnostics

- Neutron time-of-flight (nToF) diagnostics
  - is an essential tool for diagnosing implosions at the NIF.
  - analyzes the nToF spectrum produced from the fusion reactions to provide important details of the performance of the implosion:
    - neutron yield (DT reaction, DD reaction)
    - ion temperature
    - down-scatter ratio (DSR)





Background: nTOF Physics-Driven Approach

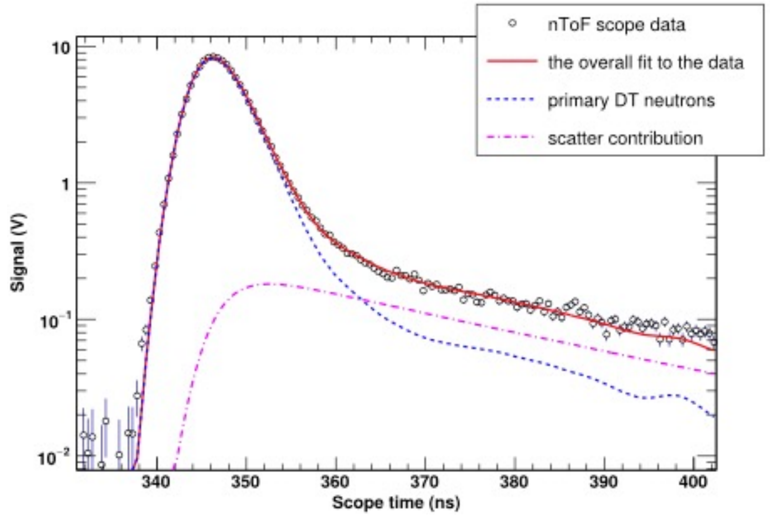
- The neutron time-of flight spectrum:
  - From target chamber to nToF detector
  - With a known distance and time-of-flight, neutron energy can be calculated.

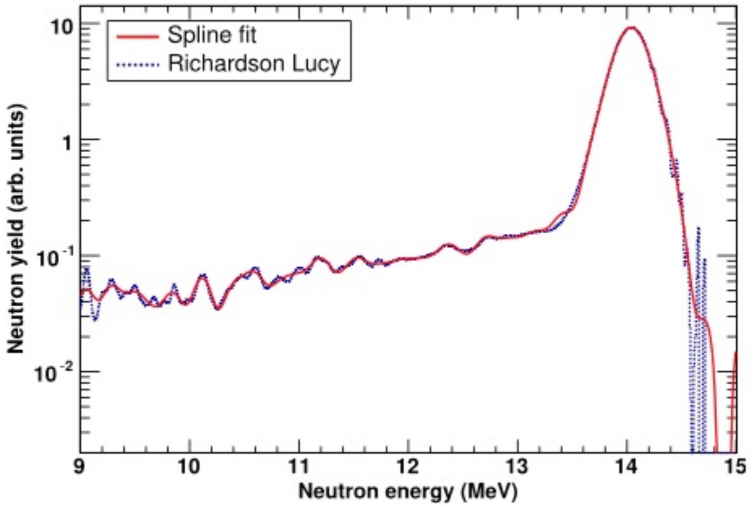
- The fit function[1]:

$$f(t) = I(E(t-t_0))s(E(t-t_0))a(E(t-t_0))\frac{dE}{dt} \otimes R(t).$$

- The Ballabio distribution[2]:

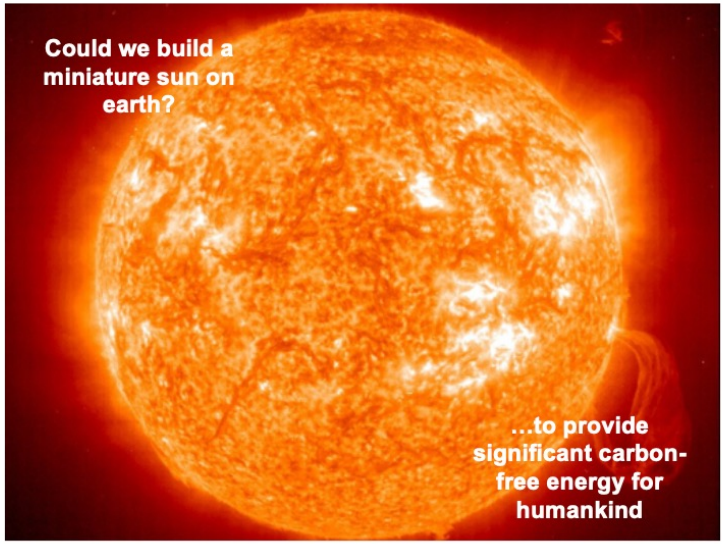
$$I(E) = I_0 \exp\left(-\frac{2\bar{E}}{\sigma^2}(\sqrt{E}-\sqrt{\bar{E}})^2\right)$$





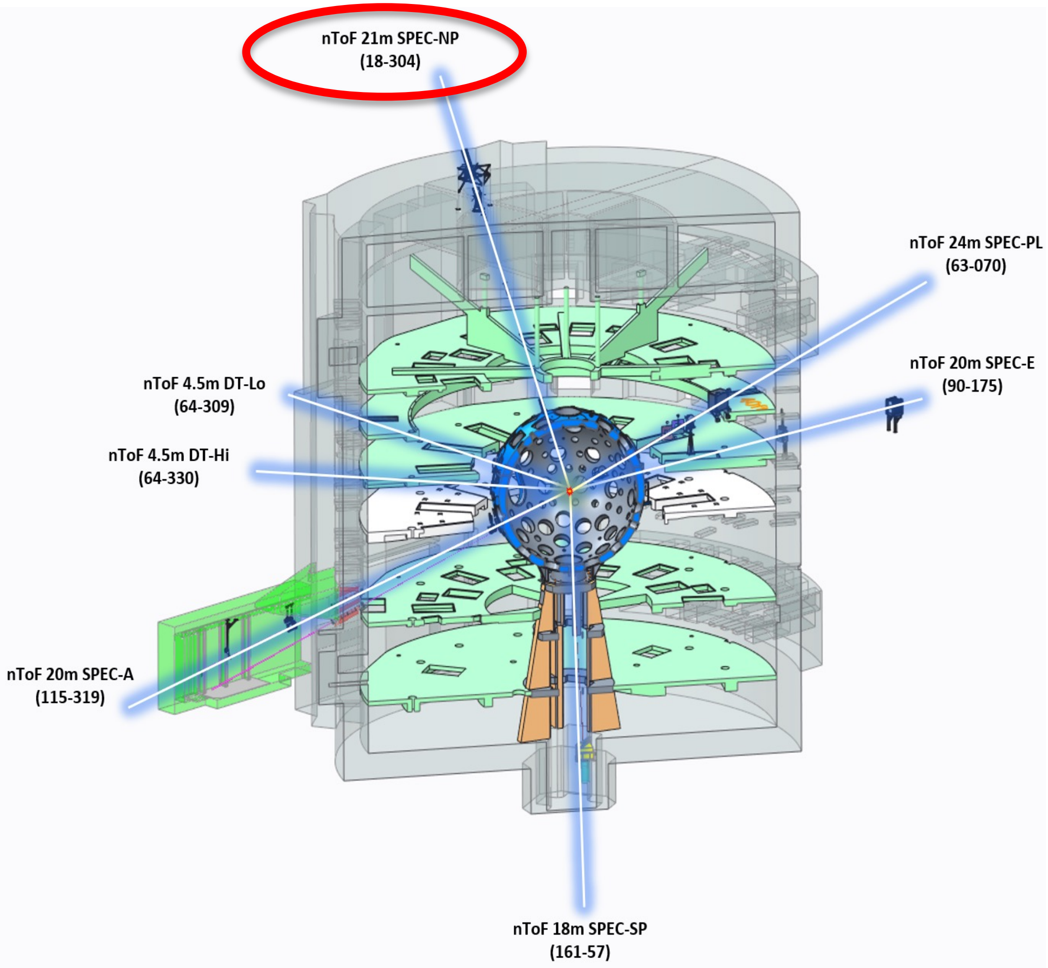
Background: Problem Statement

- Motivation behind using data-driven approaches:
  - To complement the power of physics modeling and simulations
  - To provide more insights about the underlying physics in complex systems
- Goal:
  - To approximate the probability distributions of fusion quantities
  - To quantify correlation between fusion quantities
- Big picture:
  - Provide more information for nToF diagnostics to help ICF experiments to achieve higher performing implosions



Approaches: Project Scope

- Due to the complexity of the problem, we are narrowing down our problem to start out:
  - DT reactions (DD reaction excluded)
  - North pole detector (NTOF-21M-SPEC-NP)
  - Detector #4
  - Shots from 2017 – 2021
- Data generation routine
  - 31 DT shots that have nToF analysis from 2017 – 2021
  - Took the fitted Ballabio model to generate scope traces by specifying model parameters and initial conditions
  - Validated the model with experimental measurements.



Approaches: RoadMap

Bayesian inference (MCMC) (#3)

Prior probability of fusion quantities

Form a Likelihood function

Compare to observations

Accept/reject algorithm

Running simulation models can be computationally expensive

Data generation using ML model (#2)

Generated by a surrogate ML model (DJINN) [1]

--------- OR ----------

Generated by modeling [2,3]

Data generation using physics model (#1)

[1] K. Humbird, *et al* 2019. *IEEE Transactions on Neural Networks and Learning Systems*, *30*(5), 1286–1295.

[2] R. Hatarik *et al* J. Appl. Phys. 118, 184502 (2015)

[3] L. Ballabio *et al* 1998 *Nucl. Fusion* **38** 1723

Approaches: Data Generation

- Using the Ballabio fit model routine, 10,000 data points are generated using a single shot --- N210605-001-999.

  — instrument response function (IRF)
  — detector sensitivity
  — beam attenuation factors

Different shots (taken at different time) may have different IRFs, detector sensitivities and beam attenuation factors due to instrument modifications or performance degradation over time.

  — model parameters:
    - Random sampling using Latin hypercube sampling

	Lower bound	Upper bound
Neutron yield, y_n	$1\ x\ 10^{15}$	$1\ x\ 10^{17}$
Ion temperature , $T_{ion}\ (keV)$	3.5	6.5
Down-scattered ratio, dsr	0.02	0.06

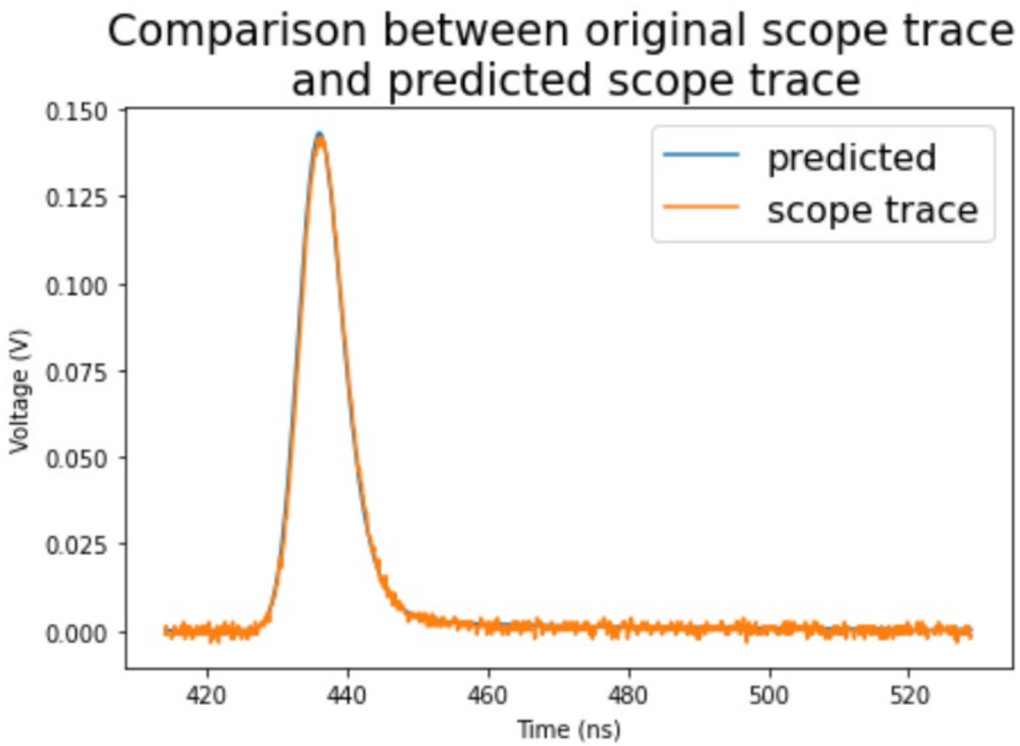
Approaches: Surrogate Model Data Generation Using DJINN

- Deep Jointly Informed Neural Network (DJINN)
- Network architecture

Hyperparameters	Values
Number of tree	1
Depth of tree	6

- Evaluation

Metric	Value
Mean square error	3.2841×10^{-8}
Mean absolute error	4.9561×10^{-5}
Explained variance score	0.9999



Speedup achieve: **x1000**
Surrogate model: ~1ms Ballabio fit model: ~1s

Approaches: Approximate Posterior Probability Using MCMC

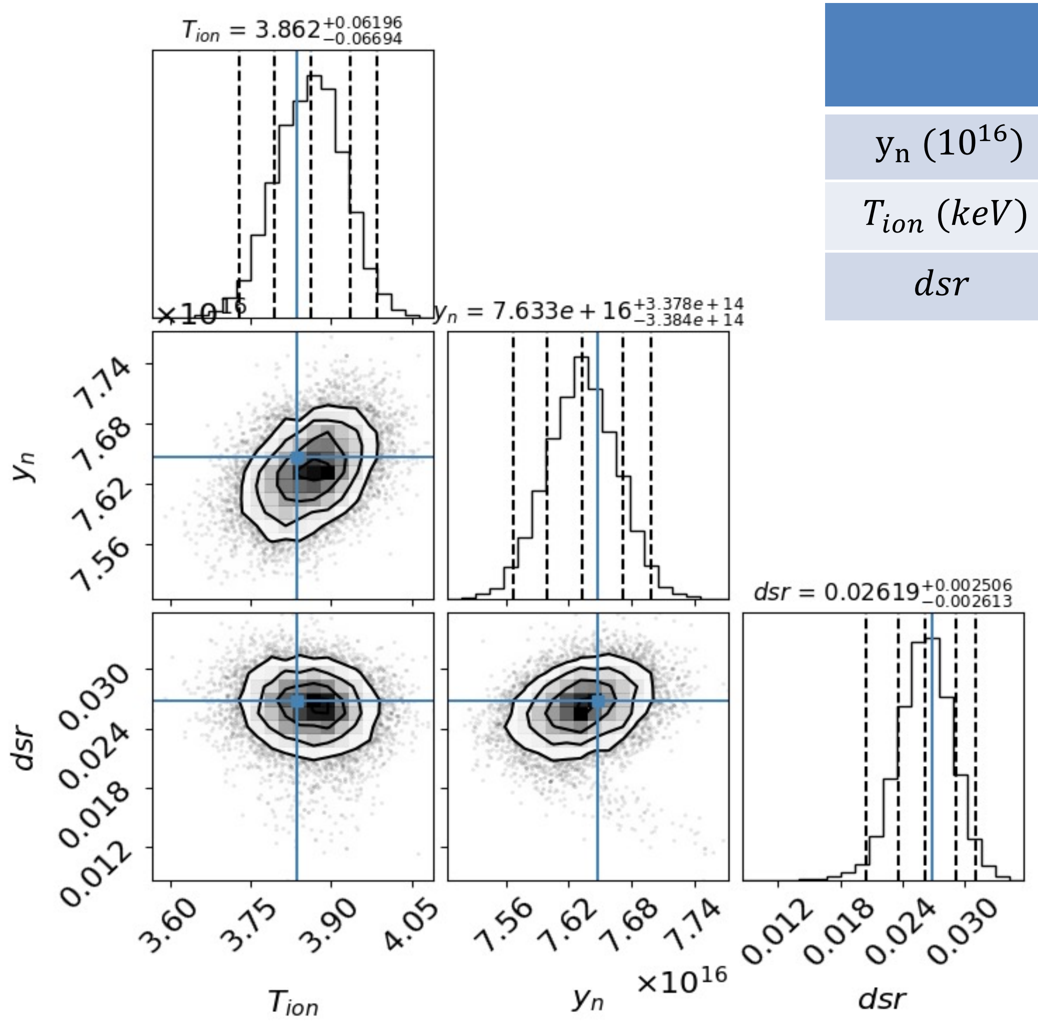
- Markov Chain Monte Carlo
  - Based on Bayes theorem

$$\underbrace{P(A|B)}_{\text{Posterior}} = \frac{\overbrace{P(B|A)}^{\text{Likelihood}}.\overbrace{P(A)}^{\text{Prior}}}{\underbrace{P(B)}_{\text{Evidence}}}$$

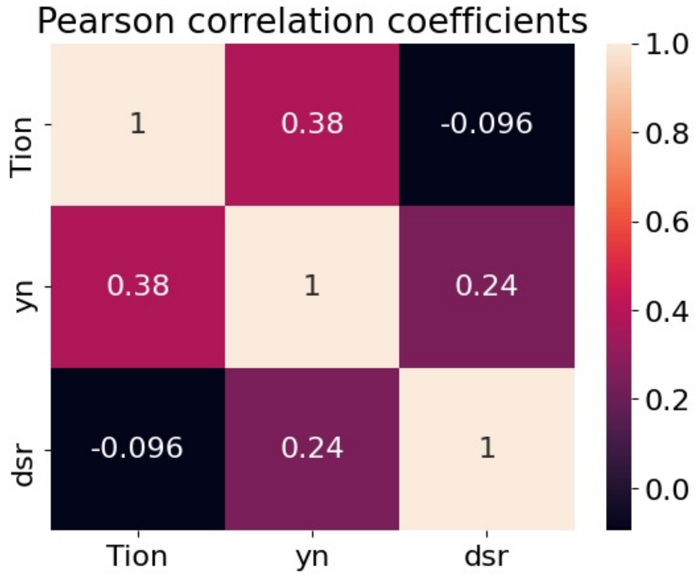
  - Combination of Markov Chain and Monte Carlo
  - Random sampling from distributions such that the current state is probabilistically dependent on the previous state

MCMC Parameters	Values
Framework	PyMC3 + Theano
Prior probability distribution	Normal distribution Uniform distribution
Likelihood function	DJINN surrogate model
Sampling method	No U-Turn Sampler (NUTS)
Multiprocessing	4
Number of iterations	3,000 (x4)
Number of burn samples	1,000 (x4)
Execution time	~ 1.5 mins

Summary: Preliminary Results From MCMC



	Ground truth	2.5% quantile	16% quantile	50% quantile	84% quantile	97.5% quantile
y_n (10^{16})	**7.6468**	7.5684	7.6007	**7.6338**	7.6662	7.6979
T_{ion} (keV)	**3.8364**	3.7320	3.7971	**3.8615**	3.9284	3.9817
dsr	**0.0268**	0.0207	0.0237	**0.0262**	0.0287	0.0312



Currently, result reported are performed on **test data without noise**.

Accurate modeling of signal noise is needed before it can be performed on experimental data

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