Opportunities and Challenges in AI-driven High Repetition Rate HED Experiments

HEDS Seminar
Nov. 10, 2022

Work performed under the auspices of of the U.S. Department of Energy (DOE) by Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344 and funded by the LLNL LDRD program under tracking codes 20-ERD-048 and 21-ERD-015.

Derek Mariscal

Laboratory Directed Research and Development

LLNL-PRES-842360
This work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under contract DE-AC52-07NA27344. Lawrence Livermore National Security, LLC

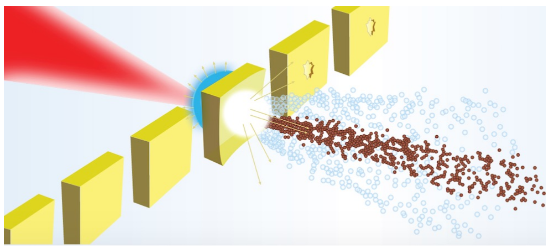
Lawrence Livermore National Laboratory

Acknowledgements

- *Sims:*
  - ***B. Djordjević,** J. Kim, J. Ludwig, A. Kemp, C. Meyers, A. Antoine , S.C. Wilks*
- *Hardware/Diagnostics/Experiments*
  - *G.G. Scott, K. Swanson, G. Zeraouli, R.A. Simpson, E.S. Grace, P. Campbell, M. Hill, Abhik Sarkar, S. Feister, K. Valdez-Sereno, E. Ito, R. Nedbailo, R. Hollinger, S. Wang, J.J. Rocca, G. J. Williams, T. Galvin, S. Herriot , **T. Ma***
- *ML:*
  - ***T. Bremer**, J. Thiagarajan, R. Anirudh, B. Kailkhura, E. Kur, A. Shukla, M. Olson, S. Liu, **B. Spears***

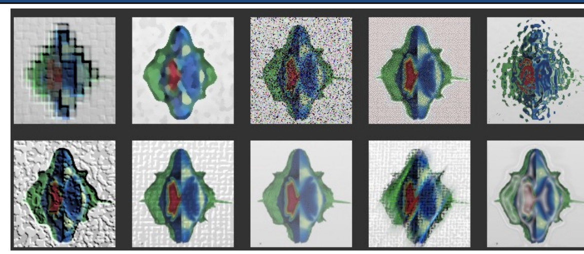
HRR experimentation provides a path to massively accelerate the rate of learning from laser-driven HED plasma experiments

HRR Experiments



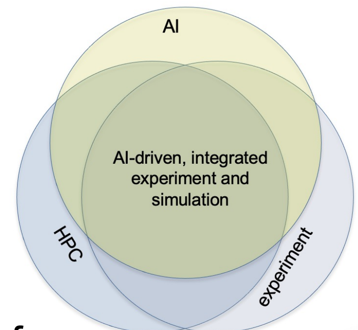
- Opportunity to accelerate data throughput by $>10^4$
- Massive multi-D parameter scans
- Meaningful uncertainties from statistics
- True data-driven science in laser plasma experiments

"Ensemble" Modeling



- Requires many 1k's of low- to mid-fidelity simulations
- Massive multi-D parameter scans
- Surrogate model creation to guide experiments
- Synthetic diagnostics for comparison to expts.

Machine Learning/AI



- ML for:
  - fast/safe laser operation
  - diagnostic analysis
  - Sim-based surrogates
  - "integrated analysis"
- An AI-like system will have to replace human intuition at HRR

ML/AI in Science

Machine Learning & Artificial Intelligence are already making large impacts in scientific discovery & fusion

Perspective

The data-driven future of high-energy-density physics

https://doi.org/10.1038/s41586-021-03382-w
Received: 24 June 2020
Accepted: 22 February 2021
Published online: 19 May 2021

Peter W. Hatfield[1], Jim A. Gaffney[2], Gemma J. Anderson[2], Suzanne Ali[2], Luca Antonelli[3], Suzan Başeğmez du Pree[4], Jonathan Citrin[5], Marta Fajardo[6], Patrick Knapp[7], Brendan Kettle[8], Bogdan Kustowski[2], Michael J. MacDonald[2], Derek Mariscal[2], Madison E. Martin[2], Taisuke Nagayama[7], Charlotte A. J. Palmer[9], J. Luc Peterson[2], Steven Rose[1,8], J J Ruby[10], Carl Shneider[11], Matt J. V. Streeter[8], Will Trickey[3] & Ben Williams[12]

Article

Magnetic control of tokamak plasmas through deep reinforcement learning

https://doi.org/10.1038/s41586-021-04301-9
Received: 14 July 2021
Accepted: 1 December 2021
Published online: 16 February 2022
Open access

Jonas Degrave[1,3], Federico Felici[2,3], Jonas Buchli[1,3], Michael Neunert[1,3], Brendan Tracey[1,3], Francesco Carpanese[1,2,3], Timo Ewalds[1,3], Roland Hafner[1,3], Abbas Abdolmaleki[1], Diego de las Casas[1], Craig Donner[1], Leslie Fritz[1], Cristian Galperti[2], Andrea Huber[1], James Keeling[1], Maria Tsimpoukelli[1], Jackie Kay[1], Antoine Merle[2], Jean-Marc Moret[2], Seb Noury[1], Federico Pesamosca[2], David Pfau[1], Olivier Sauter[2], Cristian Sommariva[2], Stefano Coda[2], Basil Duval[2], Ambrogio Fasoli[2], Pushmeet Kohli[1], Koray Kavukcuoglu[1], Demis Hassabis[1] & Martin Riedmiller[1,3]

Application of machine learning techniques at the CERN Large Hadron Collider

F.F. Van der Veke…
M. Giovannozzi[a]…
M. Schenk[a,c], R. …

Deep learning: A guide for practitioners in the physical sciences

Cite as: Phys. Plasmas 25, 080901 (2018); https://doi.org/10.1063/1.5020791
Submitted: 27 December 2017 . Accepted: 26 June 2018 . Published Online: 15 August 2018

Brian K. Spears, James Brase, Peer-Timo Bremer, Barry Chen, John Field, Jim Gaffney, Michael Kruse, …
Langer, Katie Lewis, Ryan Nora, Jayson Luc Peterson, Jayaraman Jayaraman Thiagarajan, Brian Van …
and Kelli Humbird

The blind implosion-maker: Automated inertial confinement fusion experiment design

Cite as: Phys. Plasmas 26, 062706 (2019); https://doi.org/10.1063/1.5091985
Submitted: 07 February 2019 • Accepted: 16 May 2019 • Published Online: 07 June 2019

P. W. Hatfield, S. J. Rose and R. H. H. Scott

Automated repair of laser damage on National Ignition Facility optics using machine learning

D. …

erm…

IEEE TRANSACTIONS ON PLASMA SCIENCE, VOL. 48, NO. 1, JANUARY 2020

Transfer Learning to Model Inertial Confinement Fusion Experiments

K. D. Humbird, J. L. Peterson, B. K. Spears, and R. G. McClarren

Cognitive simulation models for inertial confinement fusion: Combining simulation and experimental data

Cite as: Phys. Plasmas 28, 042709 (2021); https://doi.org/10.1063/5.0041907
Submitted: 04 January 2021 • Accepted: 26 March 2021 • Published Online: 27 April 2021

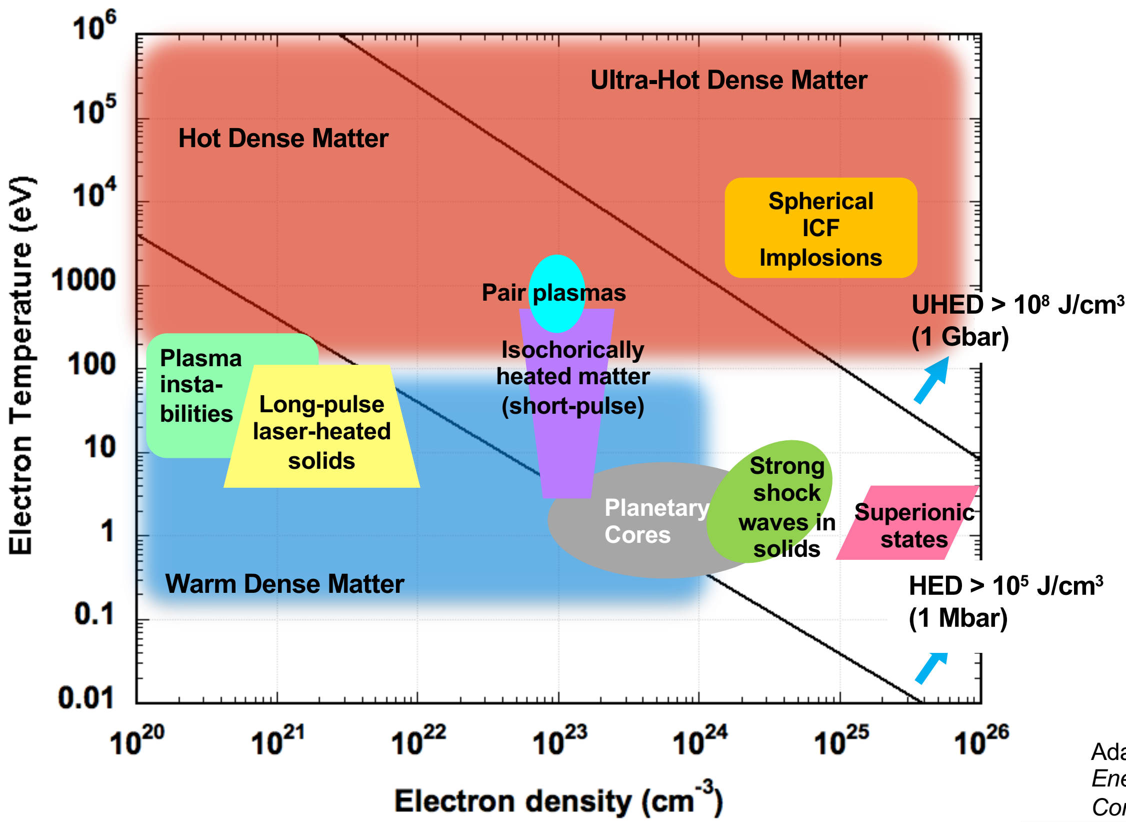
K. D. Humbird, J. L. Peterson, J. Salmonson, et al.

Deep learning: A guide for practitioners in the physical sciences

ite as: Phys. Plasmas 25, 080901 (2018); https://doi.org/10.1063/1.5020791
ubmitted: 27 December 2017 . Accepted: 26 June 2018 . Published Online: 15 August 2018

Brian K. Spears, James Brase, Peer-Timo Bremer, Barry Chen, John Field, Jim Gaffney, Michael Kruse, Steve Langer, Katie Lewis, Ryan Nora, Jayson Luc Peterson, Jayaraman Jayaraman Thiagarajan, Brian Van Essen, and Kelli Humbird

High-Energy-Density (HED) Physics spans a large realm of ρ-T space

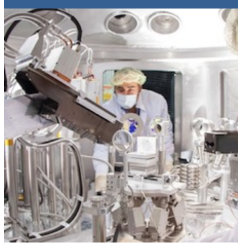


Adapted from NRC, 2003, *Frontiers in High Energy Density Physics: The X-Games of Contemporary Science.*

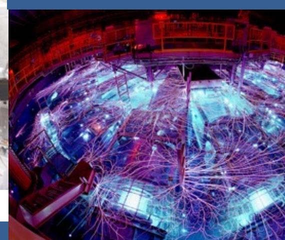
Current HED Facilities

Currently we make use of a number of premier facilities around the US & the world to conduct forefront HED science

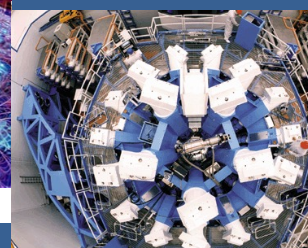
MEC SLAC



Z Machine

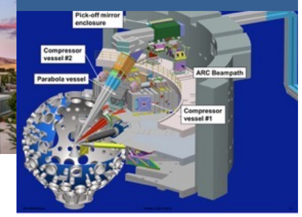


OMEGA-60



NIF

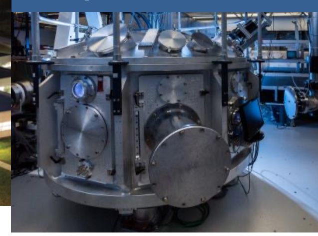
NIF-ARC



TUNL

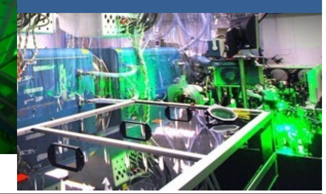
DCS

Jupiter Laser Facility



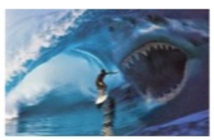
OMEGA EP

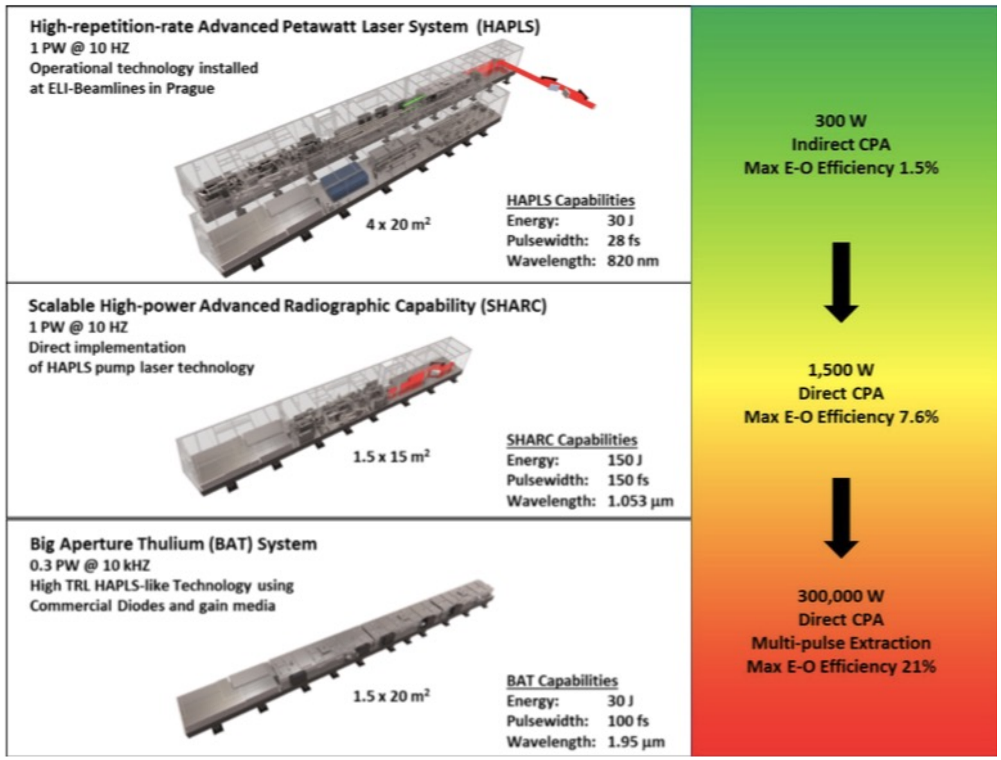
Texas PW



HED science has focused on large, energetic drivers that are mostly single-shot (>shot/30 min)

Numerous rep-rate-capable laser facilities have recently come online, and more are on the way*





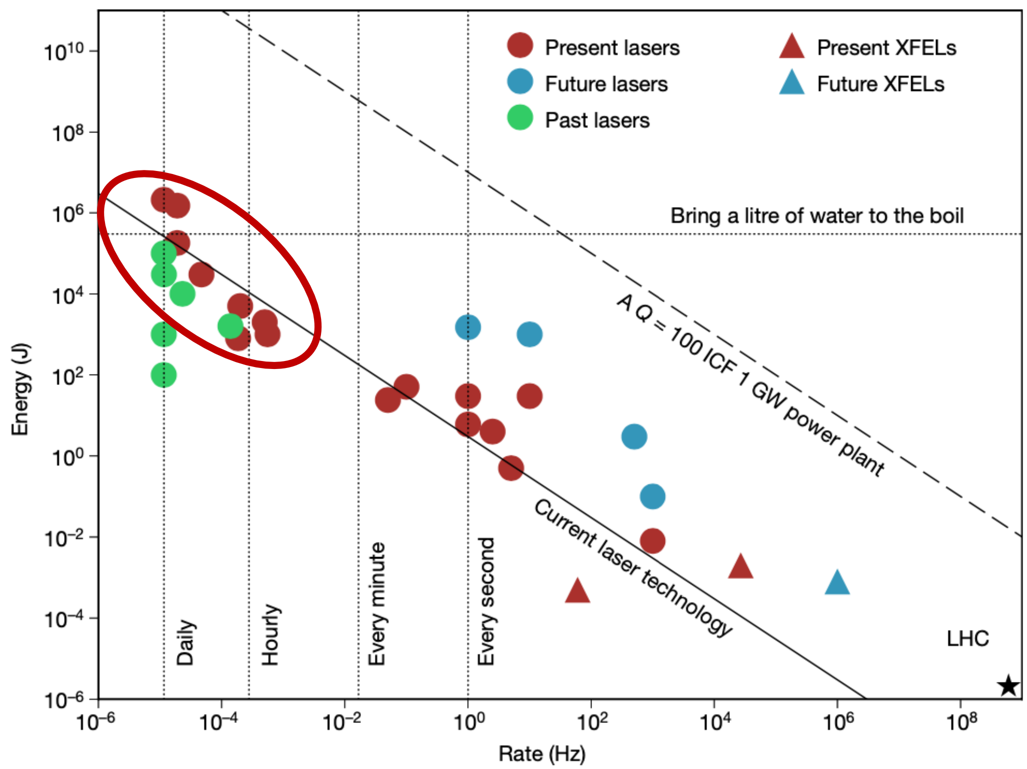
Numerous rep-rate-capable (>1 Hz) laser facilities have recently come online

Developed by NIF APT

Drivers Overview

While there is a lot of value in experiments at high-energy, low shot-rate facilities, the rate of progress is fundamentally limited

"Deep data" at rare conditions (NIF, Omega 60, etc.)

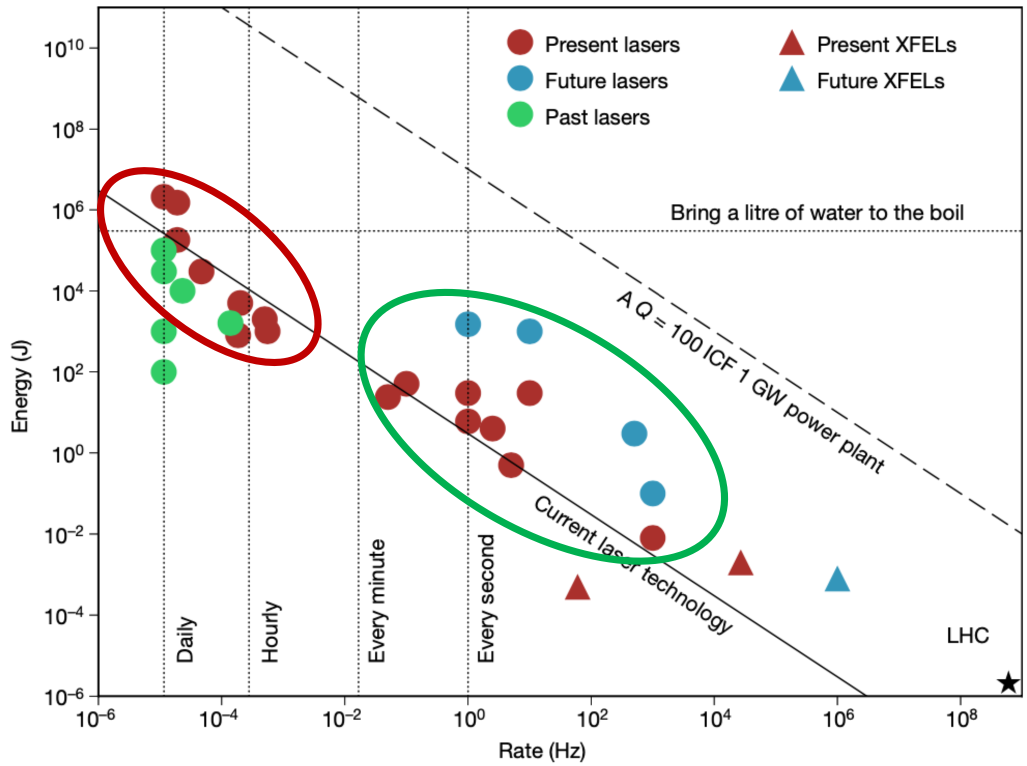


P. Hatfield, et al., "The data-driven future of high-energy-density physics", Nat. Persp. (2021)

In the near-term, laser drivers are moving toward HRR and this provides a tangible opportunity to accelerate HED science

"Deep data" at rare conditions

"Big data" at HED & IFE-relevant conditions

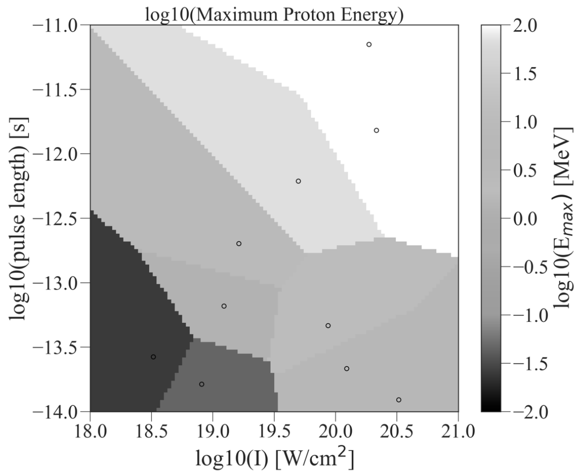


P. Hatfield, et al., "The data-driven future of high-energy-density physics", Nat. Persp. (2021)

More Data

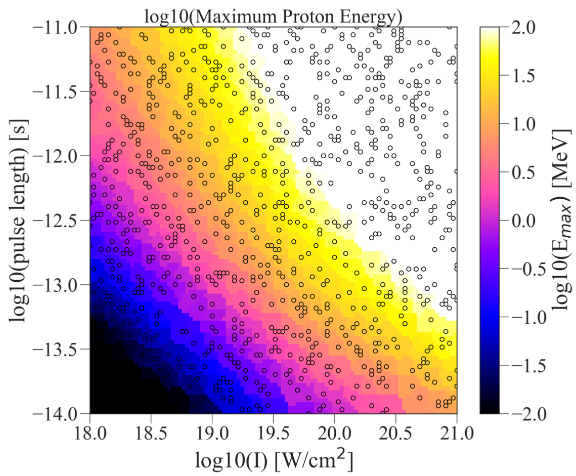
High repetition rate will revolutionize the way HED experiments are done and dramatically increase our rate of learning

Current Paradigm



10 shots in 10 hours

New Paradigm



36,000 shots in 1 hour

High repetition rate lasers present an opportunity to map vast parameter spaces with dramatically increased precision

While conducting many more experiments is useful, it may not be possible (or prudent) to perform “brute force” scans

Six common parameters in ICF designs

10 changes to laser pulse

10 changes to hohlraum size

10 different capsule sizes

10 different capsule thicknesses

10 different ice thicknesses

10 different capsule dopants

Number of samples required scales quickly with number of parameters

$N_{samples/dimension}^{N\_dimensions}$

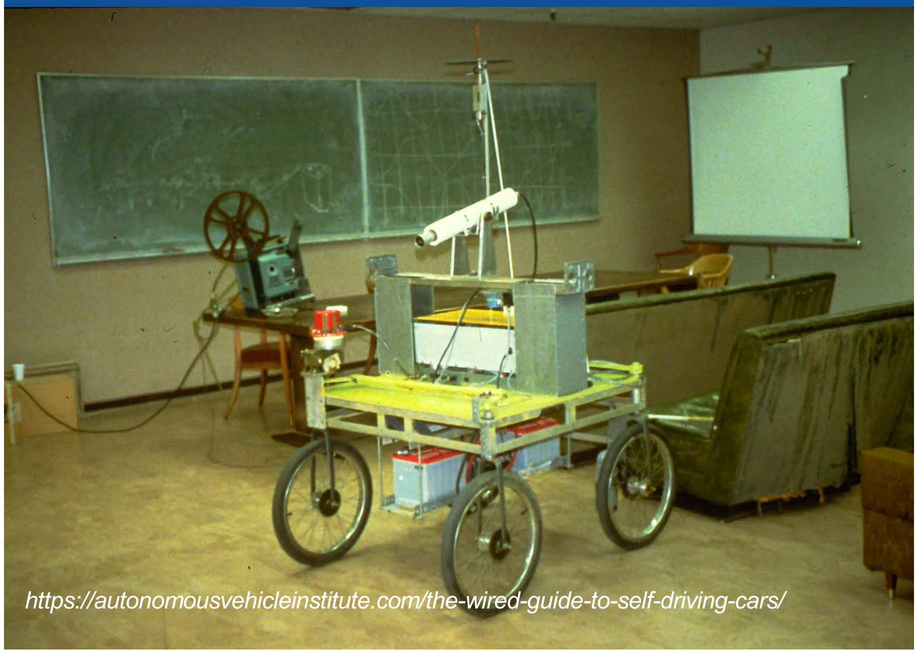
$= 10^6$ samples

→AI-driven systems can make the most of our experiments

AI Operation

We will need AI & ML to operate intelligently at HRR

“Stanford Cart” – circa 1970



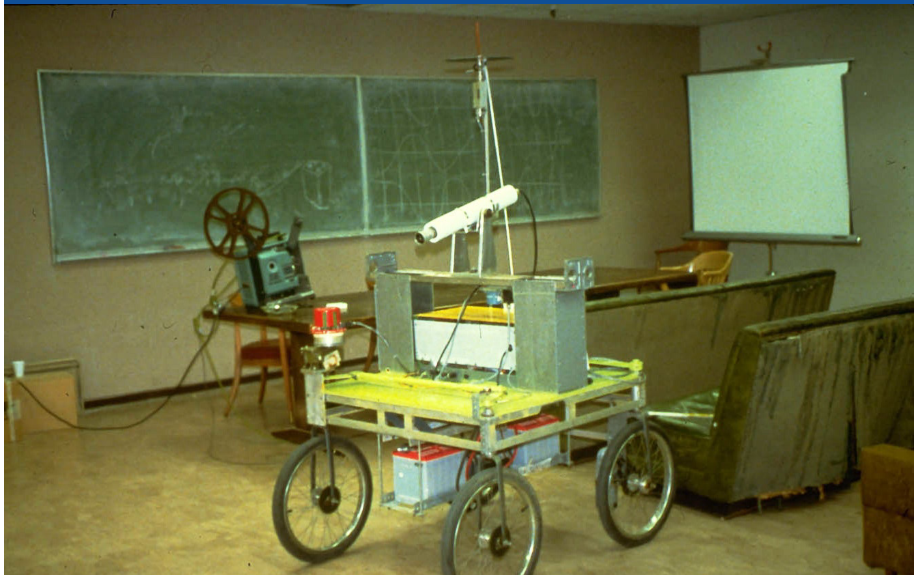
https://autonomousvehicleinstitute.com/the-wired-guide-to-self-driving-cars/

- Early autonomous vehicles took ~20 minutes to plan 1 meter of travel → **0.002 mph**

AI Operation

We will need AI & ML to operate intelligently at HRR!

“Stanford Cart” – circa 1970



https://autonomousvehicleinstitute.com/the-wired-guide-to-self-driving-cars/

- Early autonomous vehicles took ~20 minutes to plan 1 meter of travel → **0.002 mph**

Self-driving Race Car - 2022

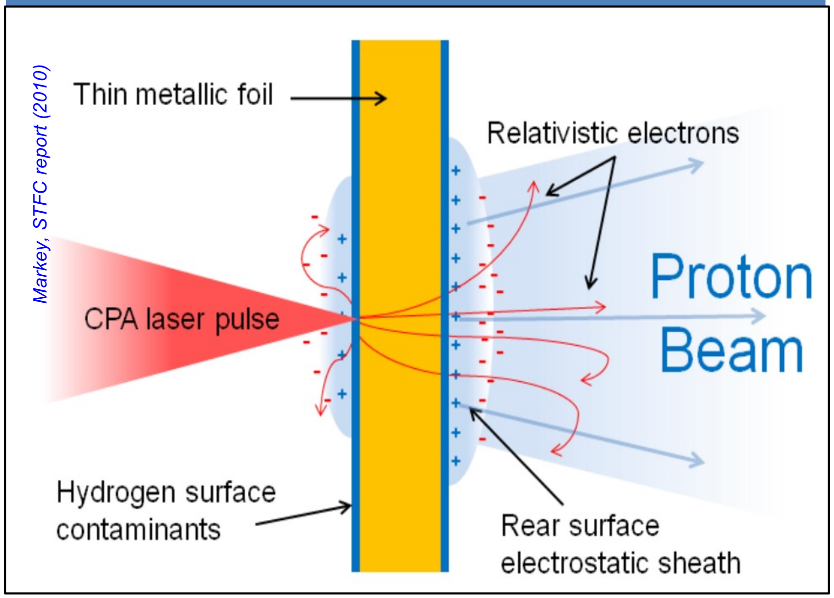
https://newatlas.com/automotive/autonomous-land-speed-record/#gallery:2

- May 2022, w/modern ML & modern hardware, reached **>192 mph**

Ex:Proton Acceleration

It has long been known that 10's of MeV protons can be accelerated from intense (>10^{19} W/cm^2), sub-ps laser interactions with solid targets

Target Normal Sheath Acceleration*

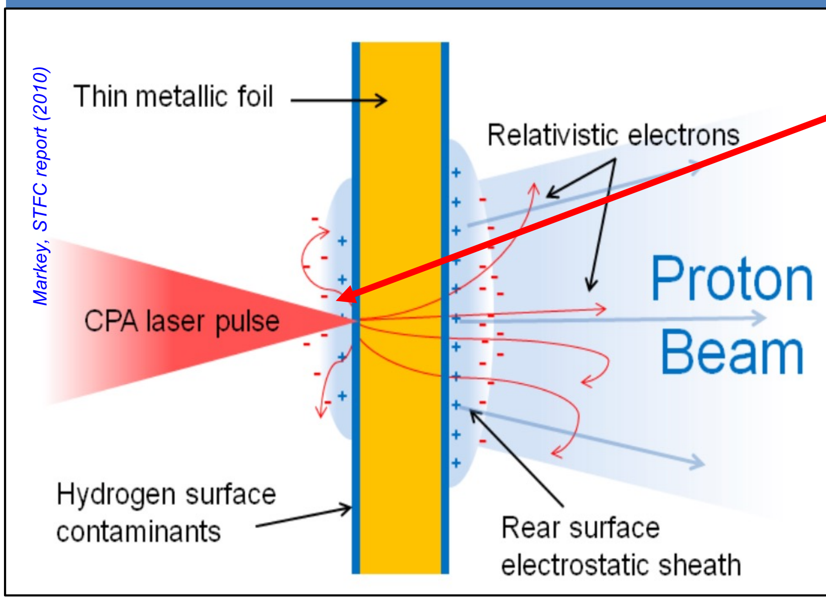


*S. C. Wilks, et al, PoP, (2001)

Ex:Proton Acceleration

It has long been known that 10's of MeV protons can be accelerated from intense (>10^{19} W/cm^2), sub-ps laser interactions with solid targets

Target Normal Sheath Acceleration*



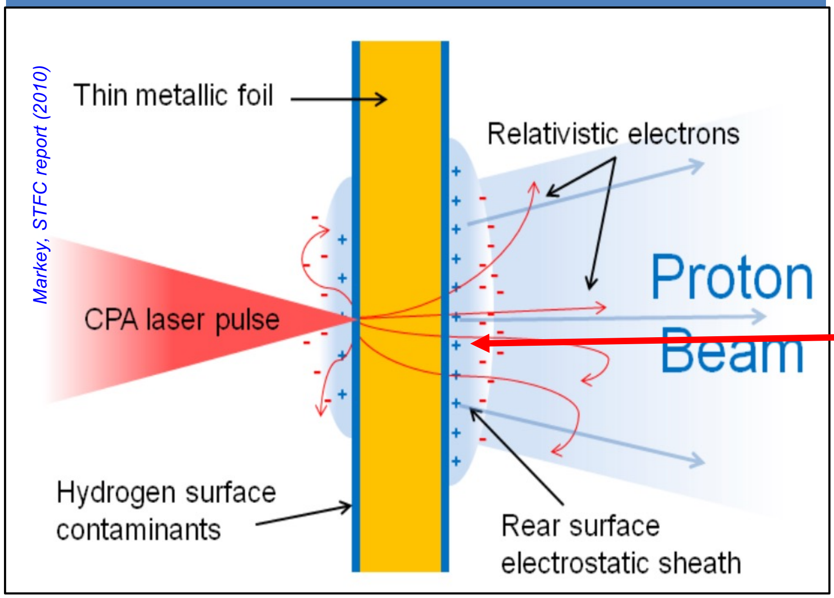
*S. C. Wilks, et al, PoP, (2001)

Fast electrons generated at front surface

Ex:Proton Acceleration

It has long been known that 10's of MeV protons can be accelerated from intense (>10^{19} W/cm^2), sub-ps laser interactions with solid targets

Target Normal Sheath Acceleration*



*S. C. Wilks, et al, PoP, (2001)

Fast electrons generated at front surface

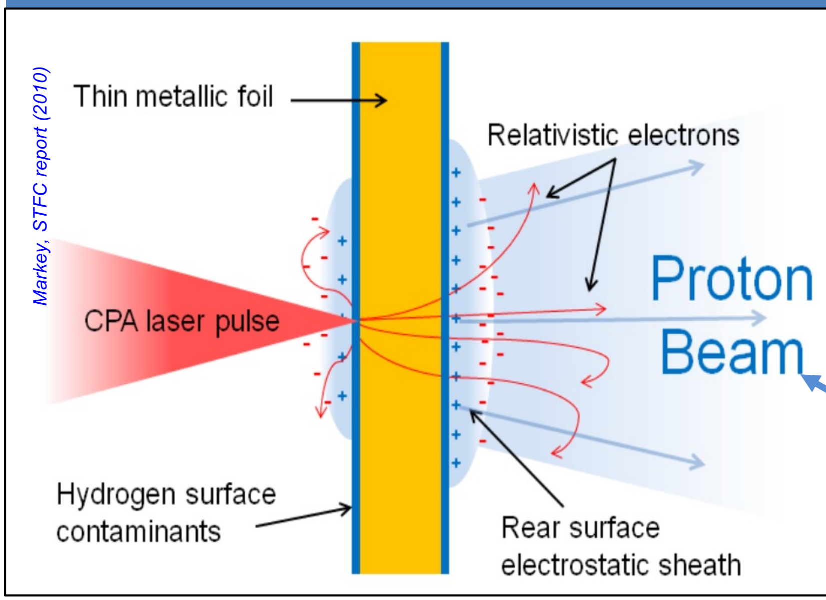
Charge separation induces electric (sheath) field

$$E = \frac{T_{e-hot}}{eL_n}$$

Ex:Proton Acceleration

It has long been known that 10’s of MeV protons can be accelerated from intense (>10^{19} W/cm^2), sub-ps laser interactions with solid targets

Target Normal Sheath Acceleration*



*S. C. Wilks, et al, PoP, (2001)

Fast electrons generated at front surface

Charge separation induces electric (sheath) field

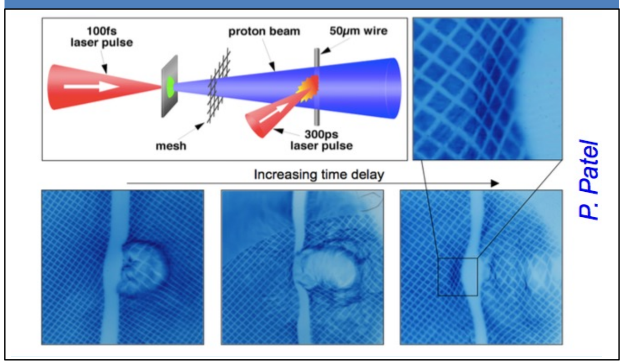
$$E = \frac{T_{e-hot}}{eL_n}$$

Proton energy is proportional to hot electron temperature

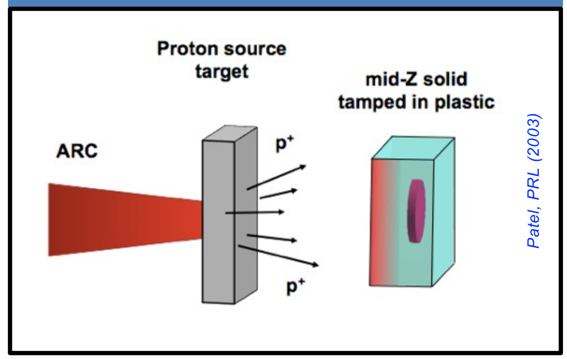
Even our understanding of “simple” problems like ion acceleration can benefit greatly from AI-driven HRR experiments

We are interested in controlling the properties of these beams for various applications in HED science

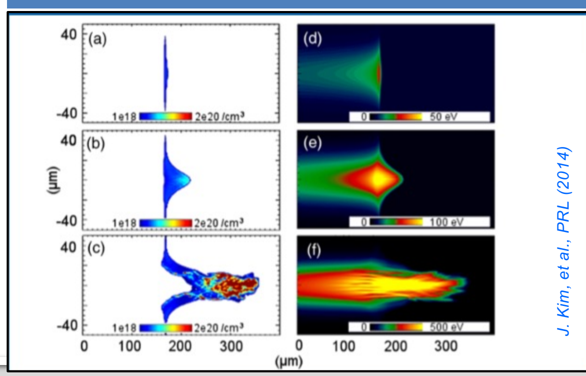
Proton radiography



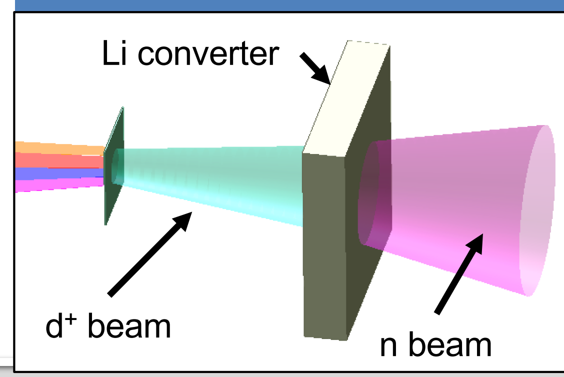
Isochoric heating/WDM



Stopping power



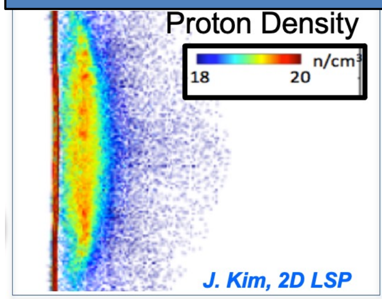
Deuteron/Neutron Sources

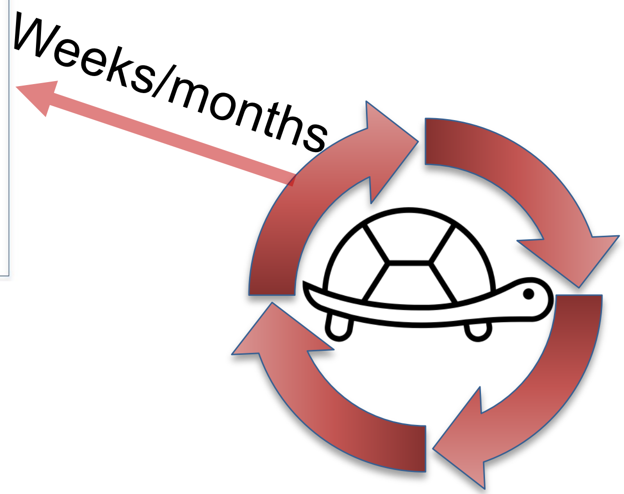


Shot/hr

The process of validating and refining models that are crucial for understanding HED plasmas is a tedious/slow process

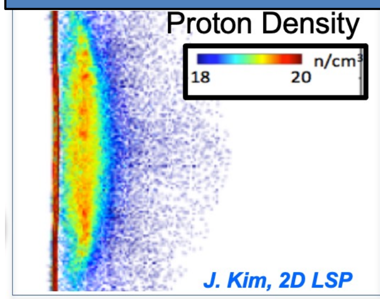
2D PIC Sims (~1k CPU hrs)

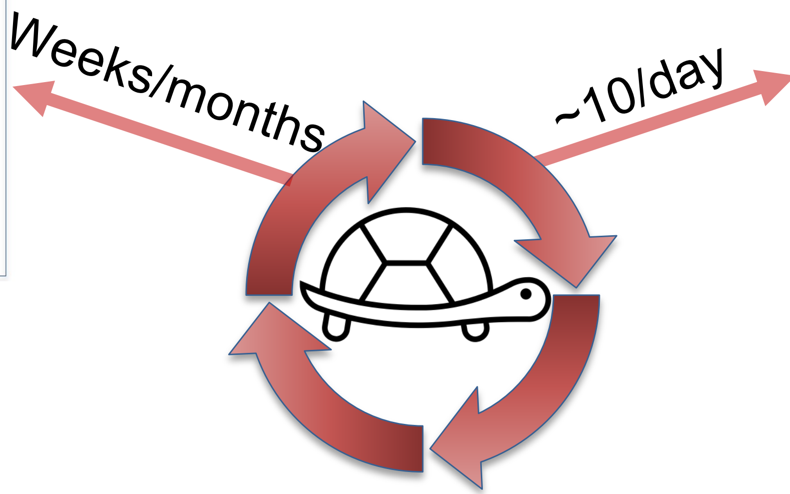




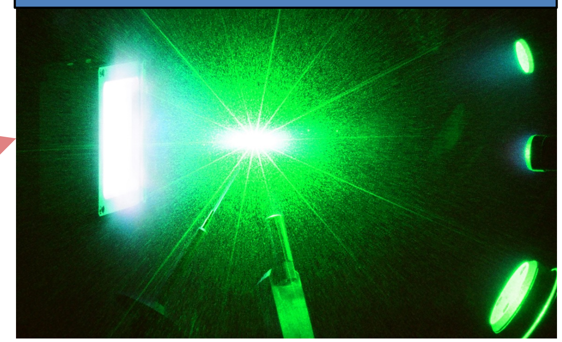
The process of validating and refining models that are crucial for understanding HED plasmas is a tedious/slow process

2D PIC Sims (~1k CPU hrs)



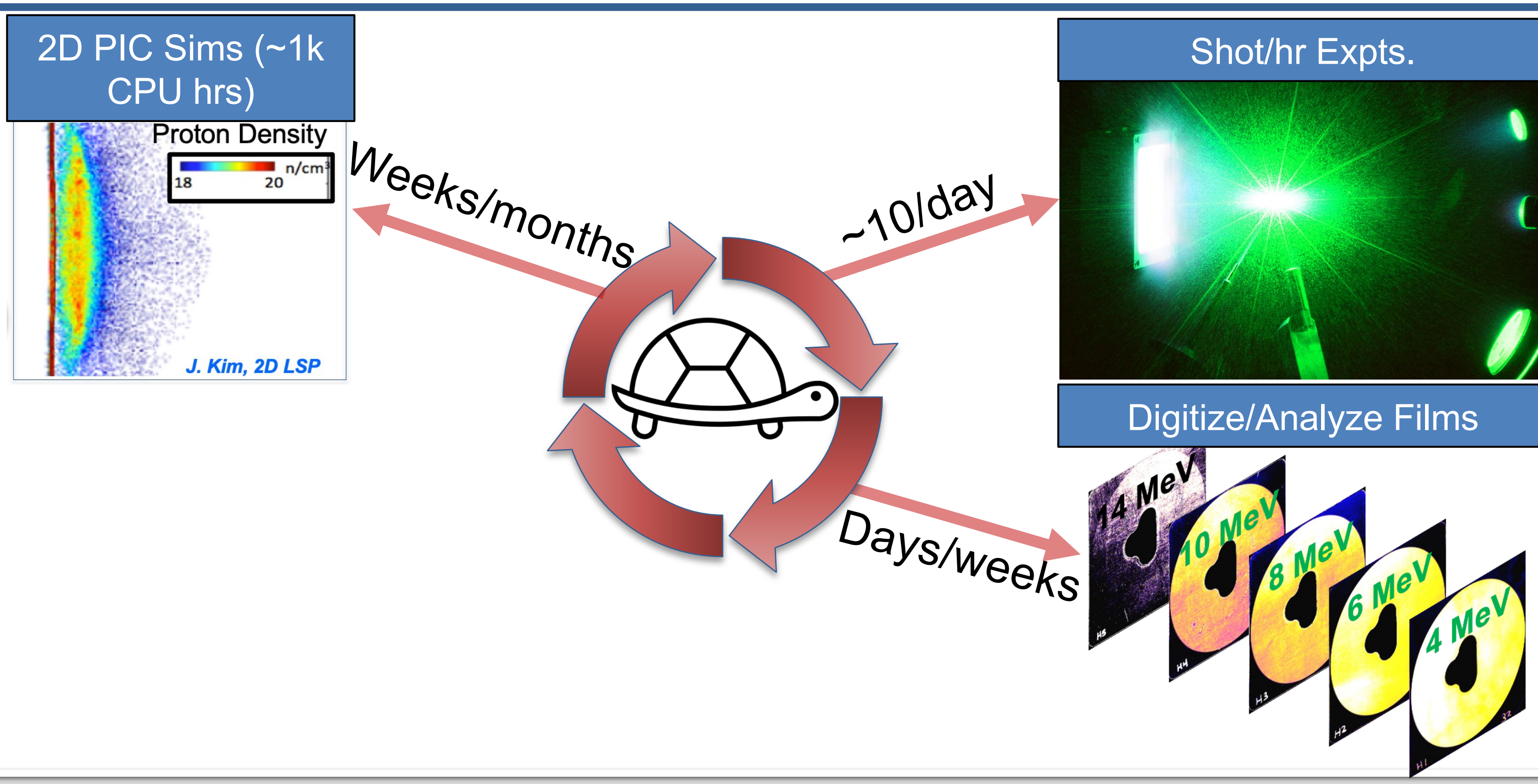


Shot/hr Expts.



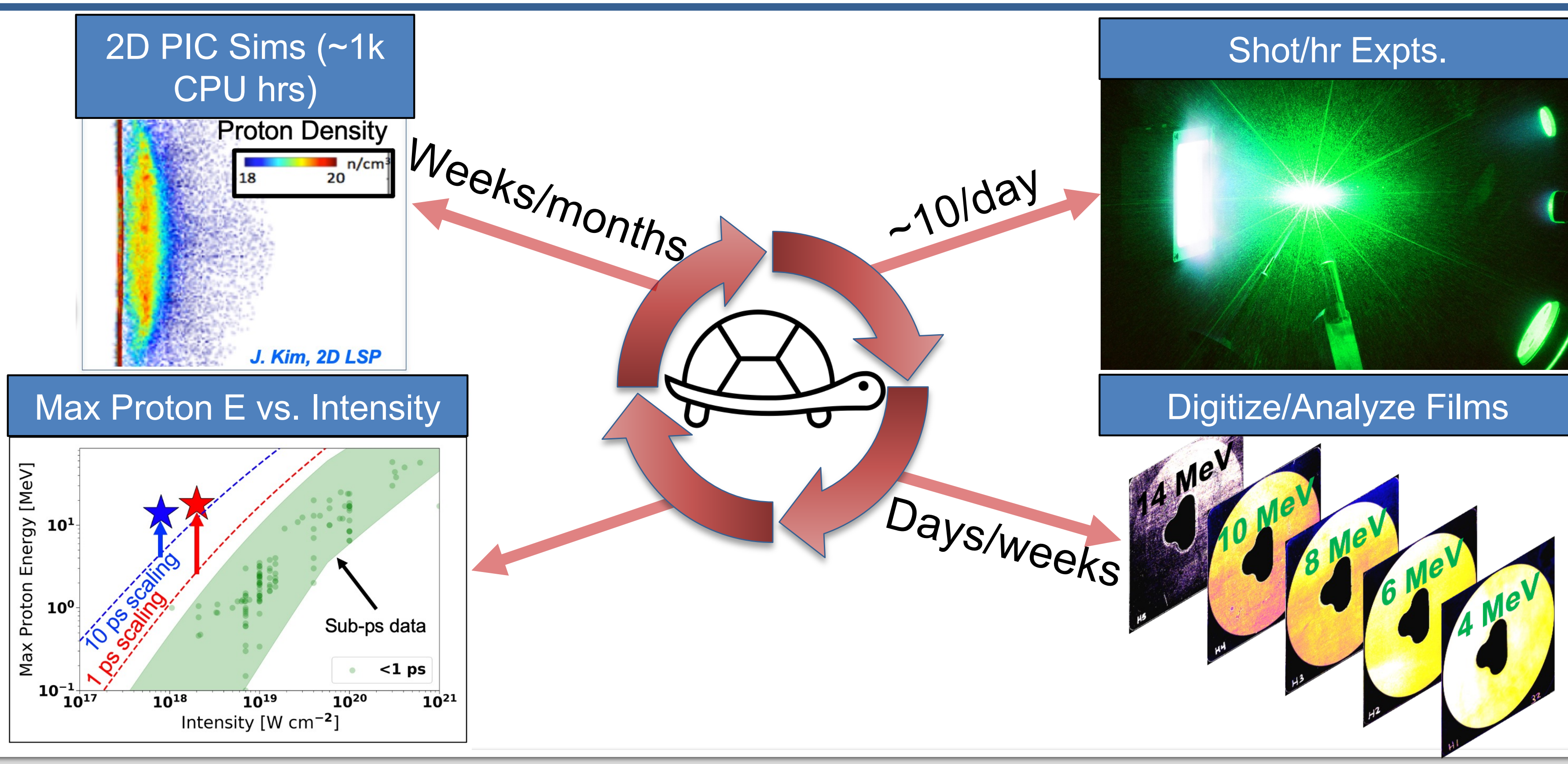
Shot/hr

The process of validating and refining models that are crucial for understanding HED plasmas is a tedious/slow process



Shot/hr

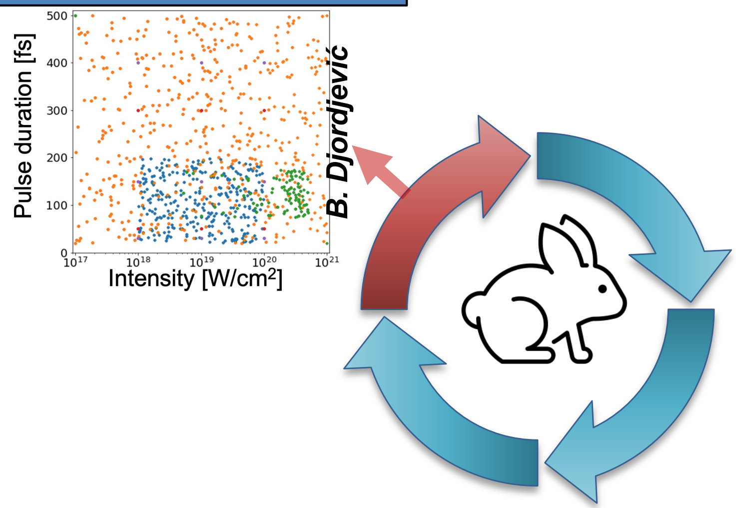
The process of validating and refining models that are crucial for understanding HED plasmas is a tedious/slow process



HRR

By utilizing high data throughput methods in modeling and experiments we can speed up this process by >10,000X

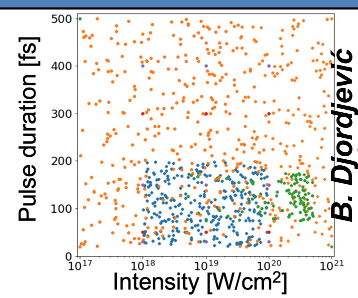
Ensemble 1D PIC Sims
(~10k CPU hrs)

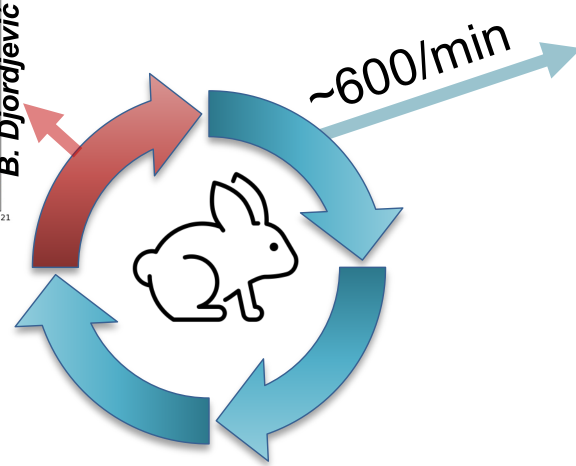


HRR

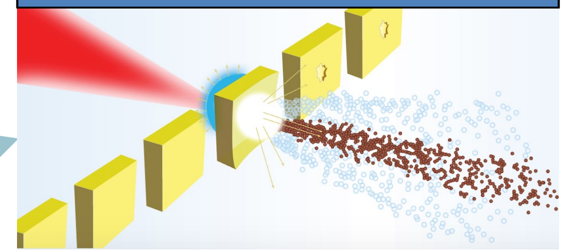
By utilizing high data throughput methods in modeling and experiments we can speed up this process by >10,000X

Ensemble 1D PIC Sims
(~10k CPU hrs)





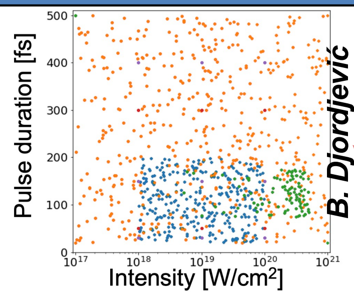
Batch Expts @ Hz

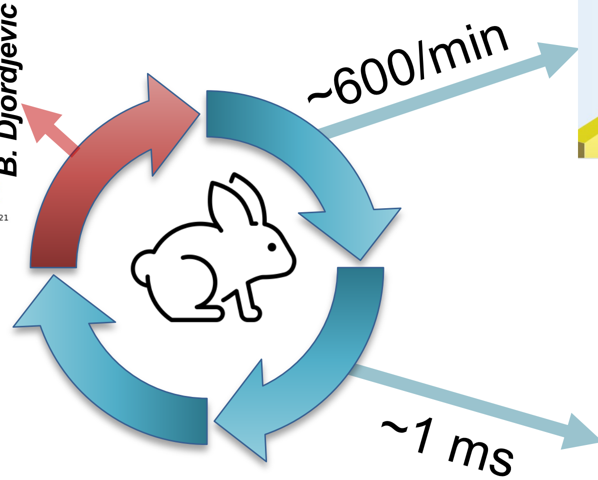


HRR

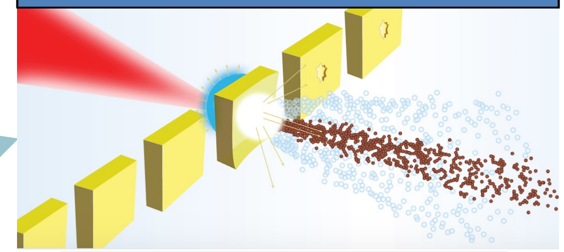
By utilizing high data throughput methods in modeling and experiments we can speed up this process by >10,000X

Ensemble 1D PIC Sims (~10k CPU hrs)

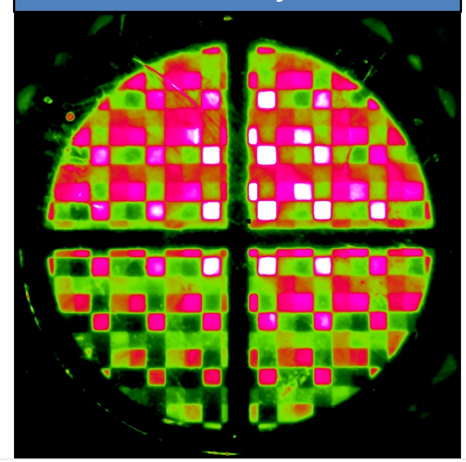




Batch Expts @ Hz



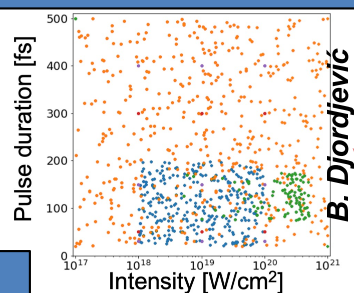
ML Analysis



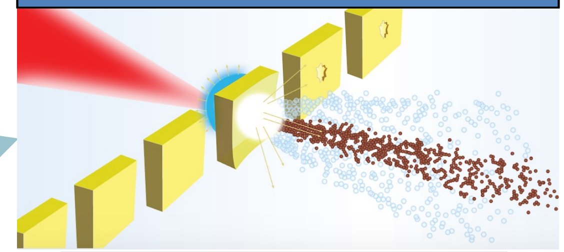
HRR

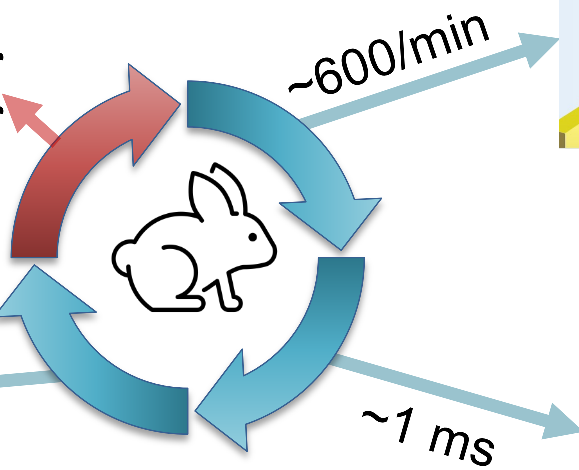
By utilizing high data throughput methods in modeling and experiments we can speed up this process by >10,000X

Ensemble 1D PIC Sims (~10k CPU hrs)

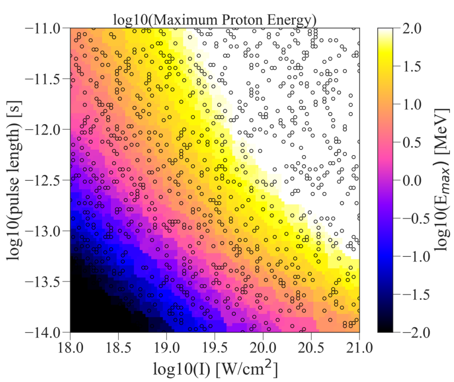


Batch Expts @ Hz

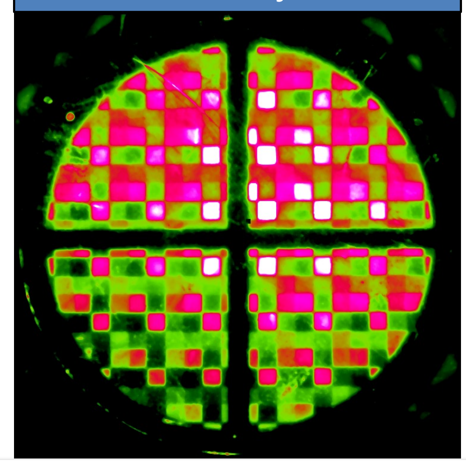




Map Parameter Space

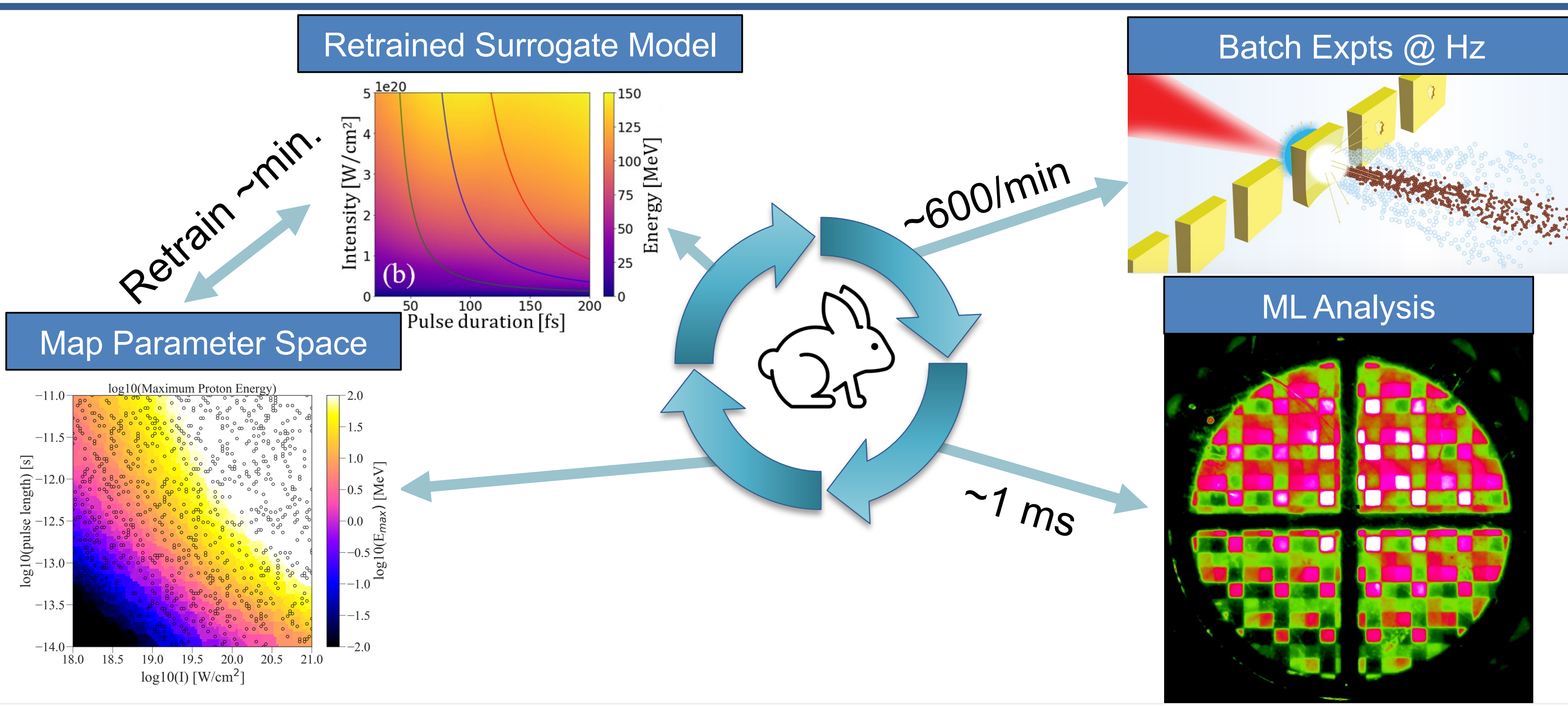


ML Analysis



HRR

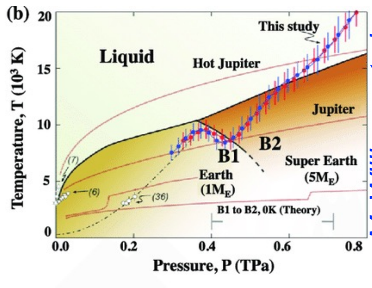
By utilizing high data throughput methods in modeling and experiments we can speed up this process by >10,000X



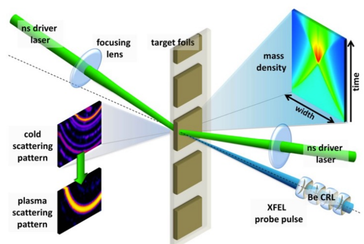
HRR

Many other classes of HED experiments will benefit from the different features of high-throughput experiments

High Pressure Material Properties



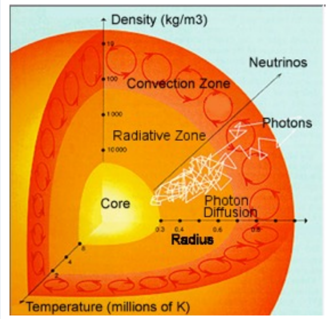
McWilliams et al., Science 2012

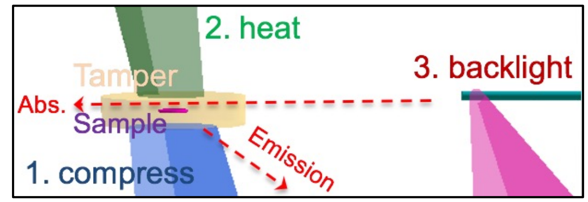


Milathianaki et al., Science (2013)

More shots across phase space

Opacities and Radiative Properties

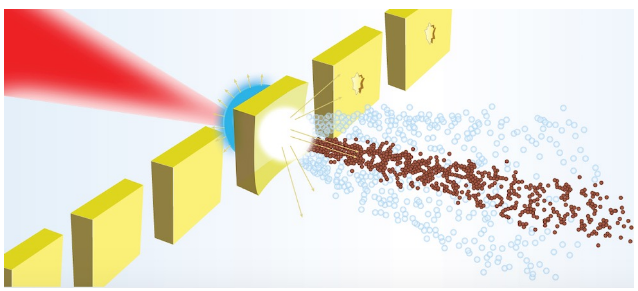




R. Heeter, LLNL

High statistics to reduce error bars and constrain complex models

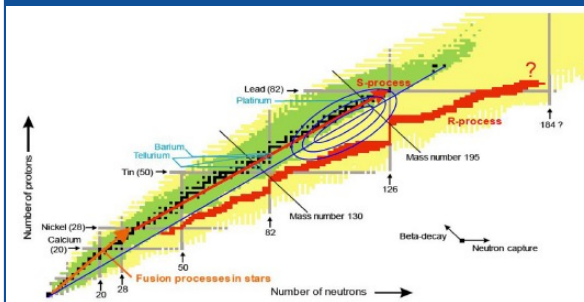
Secondary Source Particle + Radiation Beams



High brightness, high flux, reproducible beams for probing, heating, radiography

T. Ma, G.G. Scott, G.J. Williams, R. Simpson & Team LLNL

Cross Sections for Nuclear Processes

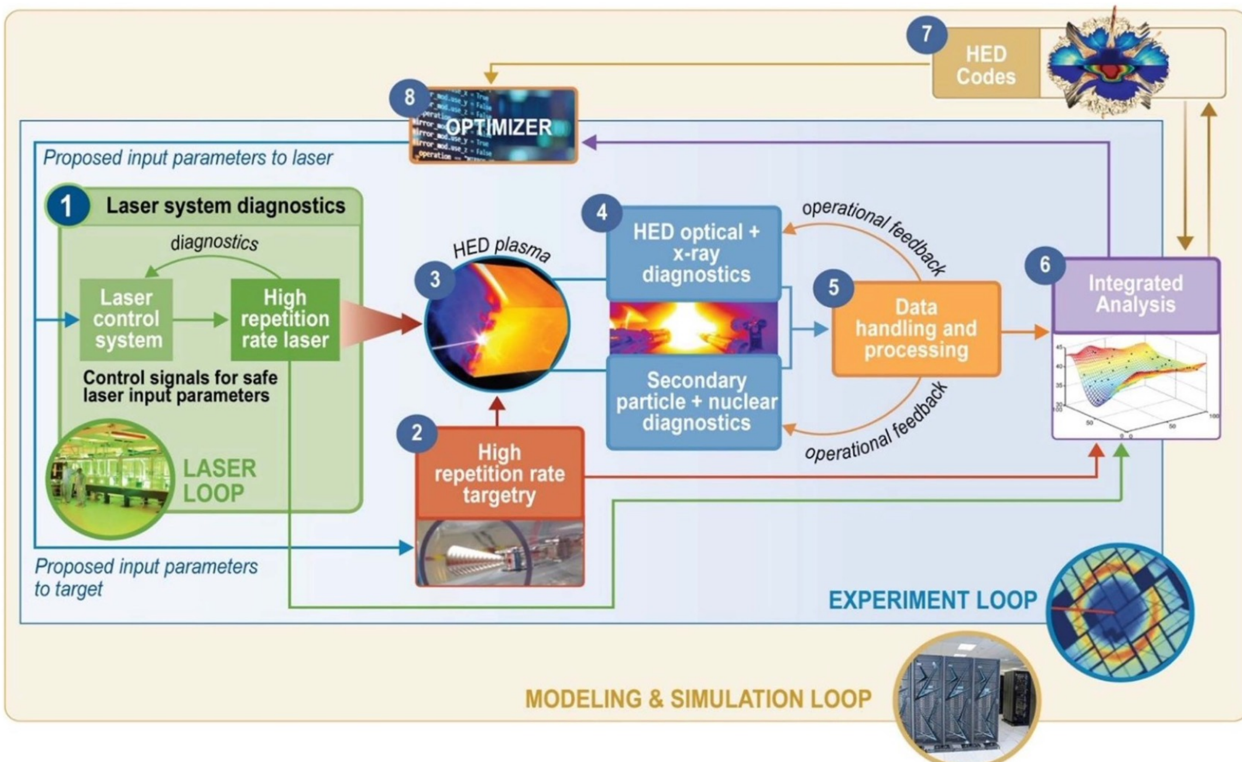


High flux and rapid sources to probe rare or subtle nuclear reactions

D. Habs et al., Appl Phys B 103: 471 (2011)

AI-driven Expts.

High-rep-rate laser science means a full integrated system that integrates technological capabilities across disciplines

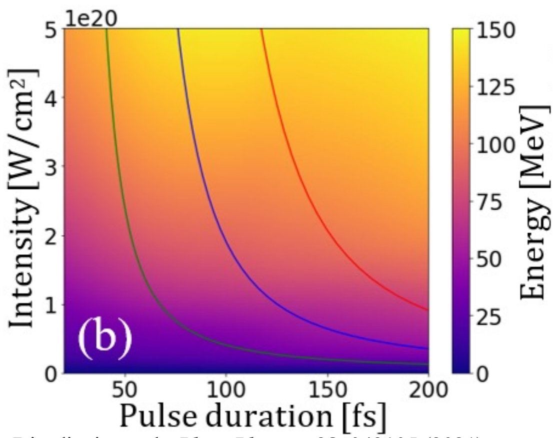


T. Ma, et al., "Accelerating the rate of discovery: toward high-repetition-rate HED science". PPCF, (2021)

There are many challenges that stem from autonomous high-rep-rate experiments that are starting to be addressed

The revolution in computational power and machine learning techniques paves the way for new approaches in prediction, data analysis, and comparing simulation and experiment

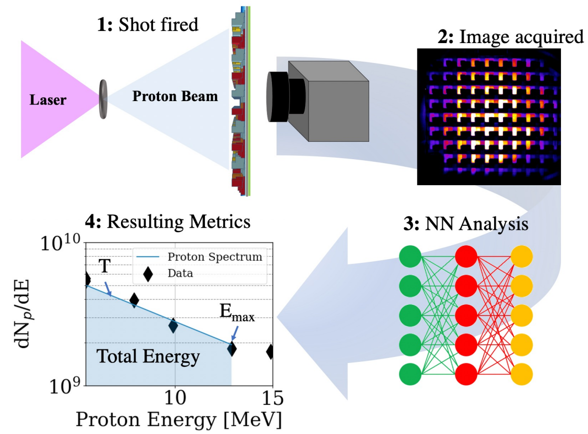
Surrogate Models



B. Djordjevic, et al., *Phys. Plasmas* **28**, 043105 (2021)

- Up to 10^6 times faster than sims
- Re-trainable
- Form exp. basis

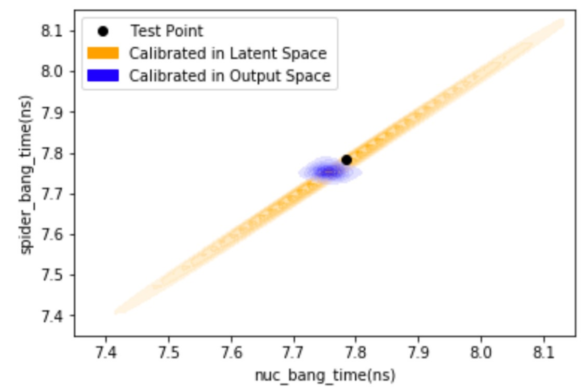
Diagnostic Analysis



D.A. Mariscal, *et al*, "Design of Flexible Proton Beam Imaging Energy Spectrometers (PROBIES)", *PPCF* (2021)

- $>10^3$ times faster than "brute force" analysis
- Accuracy >95%
- Re-trainable
- Edge compute compatible

Guide & Optimize

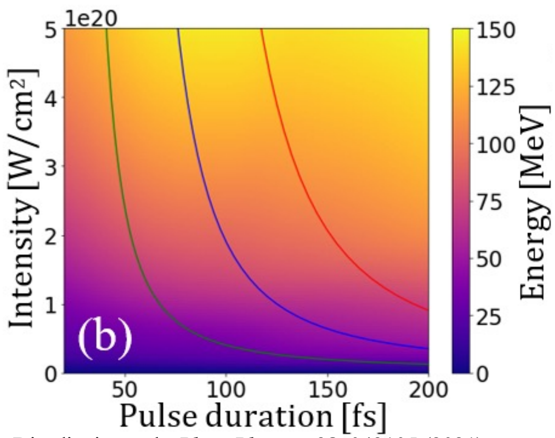


G. Anderson, et al., "Meaningful uncertainties from deep neural network surrogates of large-scale numerical simulations" (2020)

- Model-guided *or* data-driven
- Smart sampling
- Optima in fewer expts.
- Stabilized sources
- Meaningful uncertainties

The revolution in computational power and machine learning techniques paves the way for new approaches in prediction, data analysis, and comparing simulation and experiment

Surrogate Models



B. Djordjevic, et al., *Phys. Plasmas* **28**, 043105 (2021)

- Up to 10^6 times faster than sims
- Re-trainable
- Form exp. basis

Diagnostic Analysis

D.A. Mariscal, *et al*, "Design of Flexible Proton Beam Imaging Energy Spectrometers (PROBIES)", *PPCF* (2021)

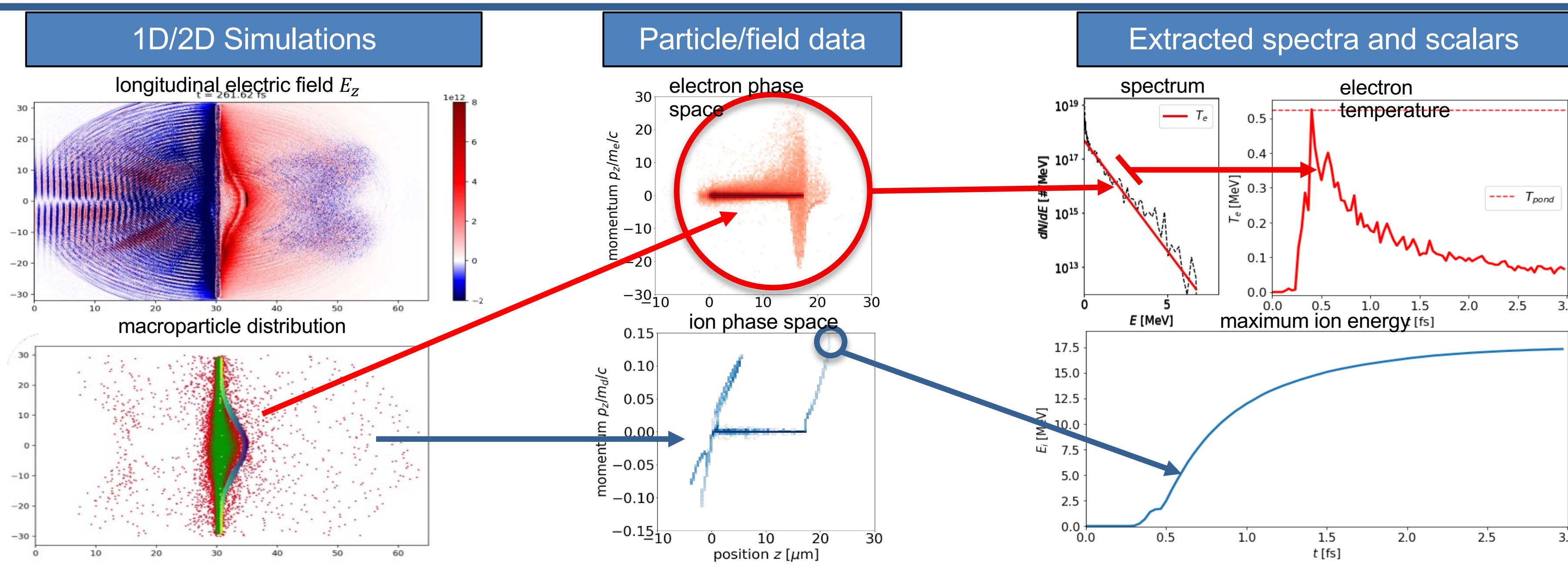
- $>10^3$ times faster than "brute force" analysis
- Accuracy >95%
- Re-trainable
- Edge compute compatible

Guide & Optimize

G. Anderson, et al., "Meaningful uncertainties from deep neural network surrogates of large-scale numerical simulations" (2020)

- Model-guided *or* data-driven
- Smart sampling
- Optima in fewer expts.
- Stabilized sources
- Meaningful uncertainties

Particle-in-cell (PIC) is the primary means of modeling high-intensity laser-plasma interactions



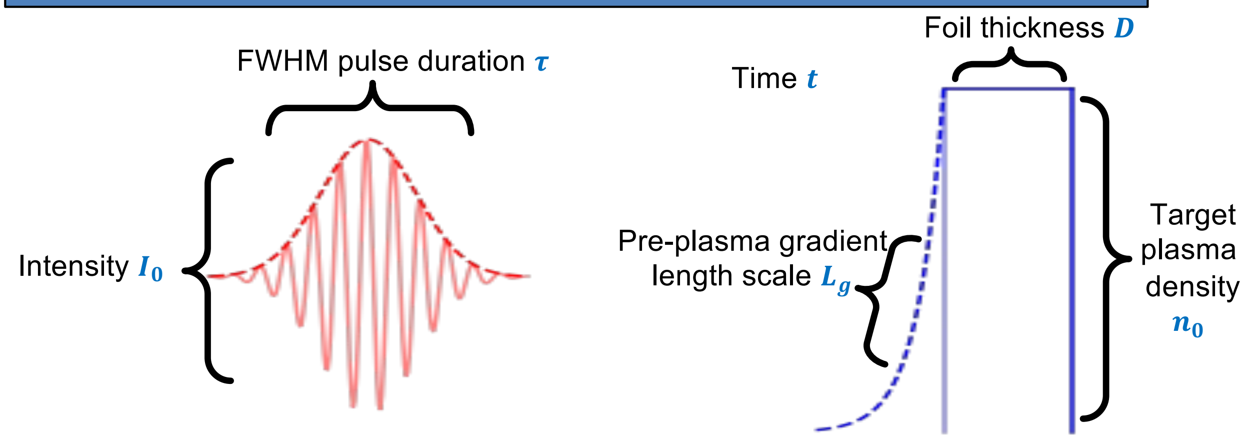
- Primary HPC code is EPOCH (Arber *et al*. PPCF 2015)
- Workhorse is 1D ensembles, but those are missing 2D/3D physics such as magnetic fields, filamentation, collisions, etc.

We can run ~100 1D simulations for the cost of just one 2D simulation, enables wide parameter space investigation

PIC Modeling

Ensembles of simulations are generated to act as training data for ML models for rapid interpolation and investigation of parameter space

6D Parameter Scan: Simulation Inputs



t [ps]	I_0 [W/cm^2]	τ [fs]	D [μm]	n_0 [n_c]	L_g [μm]
[0,5]	$[10^{17}, 10^{21}]$	[20,500]	[5,25]	[80,120]	[0,10]

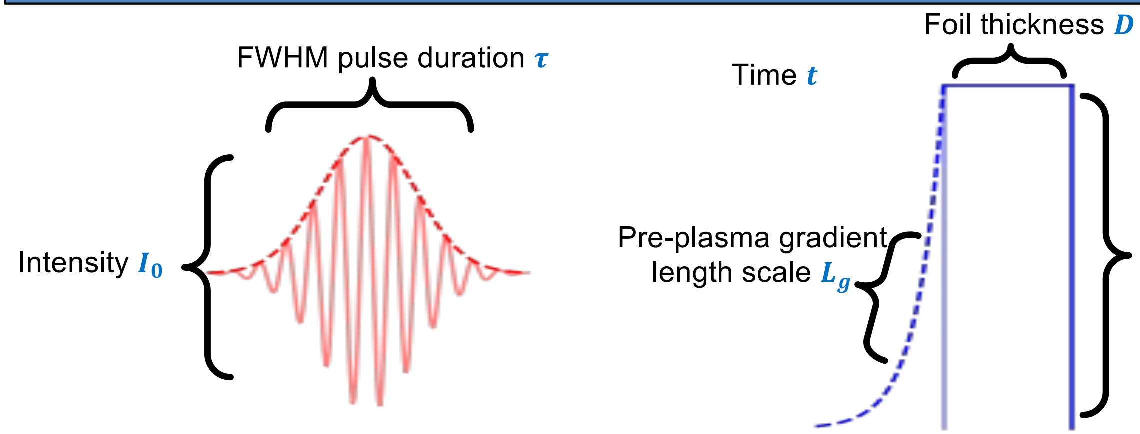
B.Z. Djordjević, et al. "Modeling laser-driven ion acceleration with deep learning."

*All modeling + ML, B. Z. Djordjević

PIC Modeling

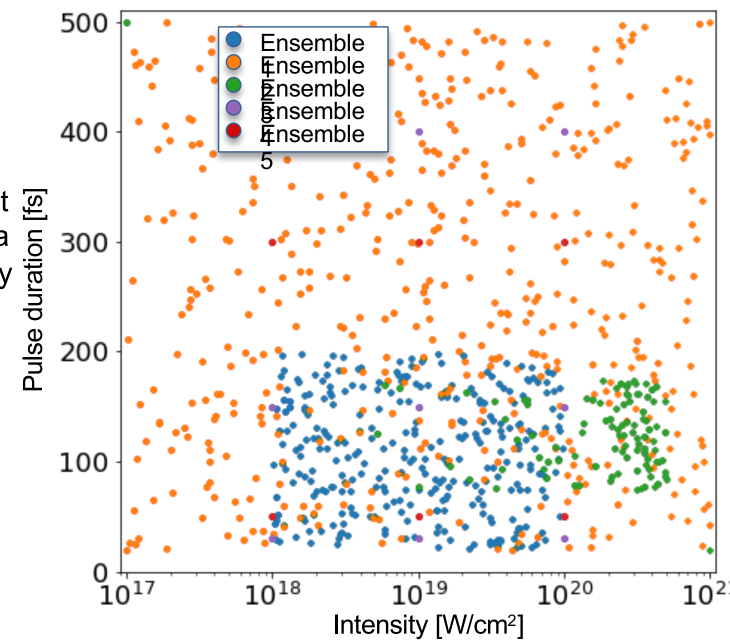
Ensembles of simulations are generated to act as training data for ML models for rapid interpolation and investigation of parameter space

6D Parameter Scan: Simulation Inputs



t [ps]	I_0 [W/cm^2]	τ [fs]	D [μm]	n_0 [n_c]	L_g [μm]
[0,5]	$[10^{17}, 10^{21}]$	[20,500]	[5,25]	[80,120]	[0,10]

1,000+ 1D Simulations

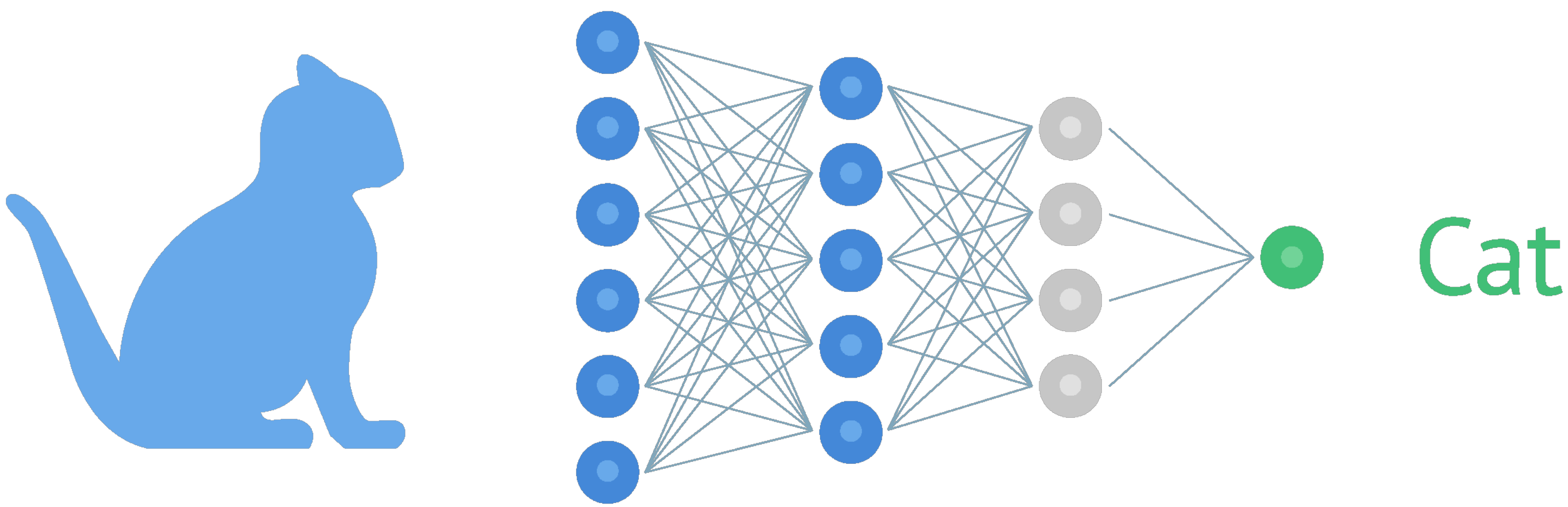


- Simulation distribution selected using Latin hypercube sampling

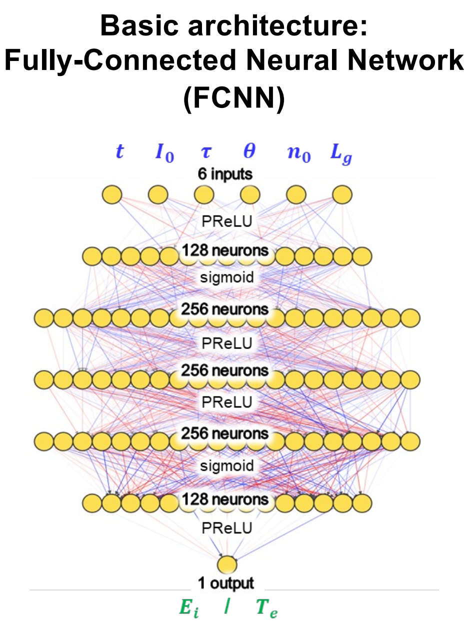
We can run ~10-100 1D simulations (10-100 CPU hrs) for the cost of just one 2D simulation, enables wide parameter space investigation

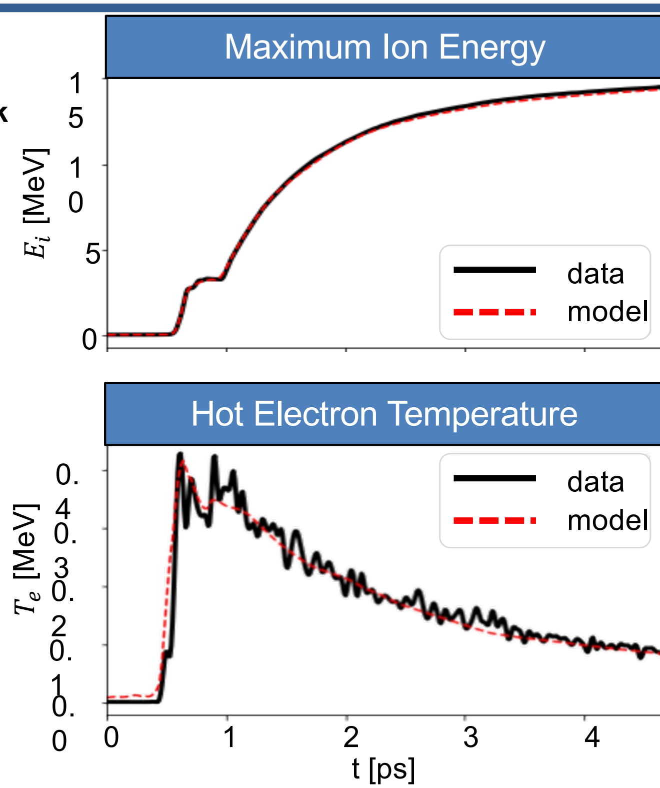
Transfer Learning

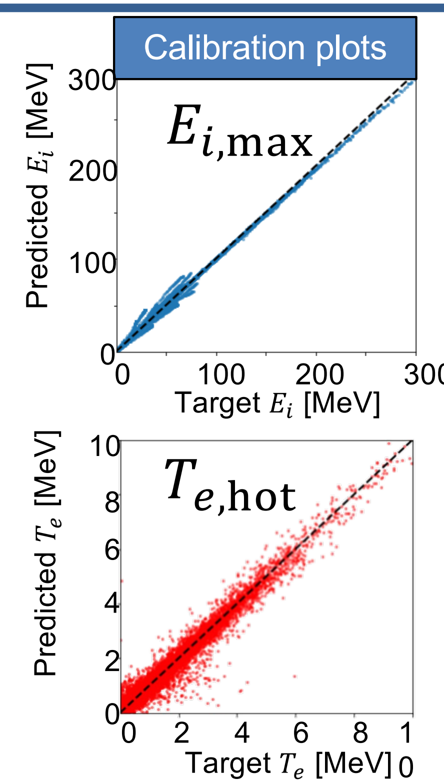
Machine Learning can identify objects in images (or interpolate across parameter space when posed as a "regression" problem)



We can create surrogate models to learn trends within the dataspace using deep neural networks





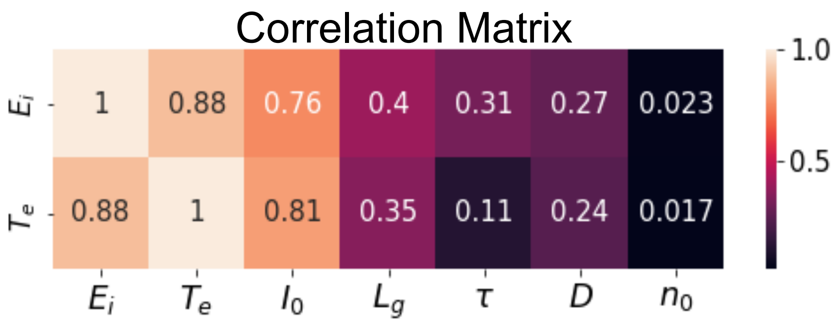


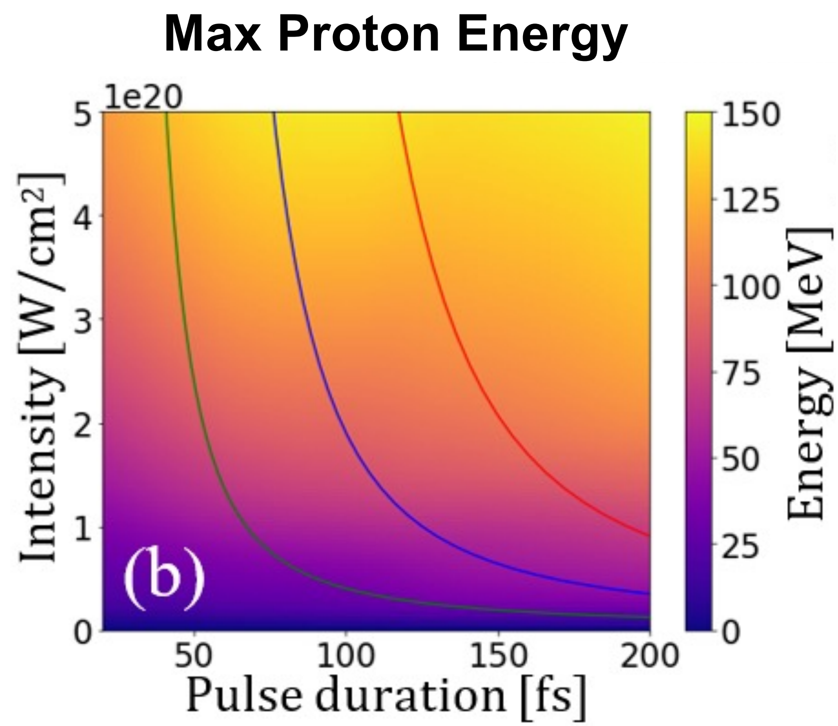
Djordjević POP, 2021

The surrogate is able to reproduce data and interpolate within the parameter space

**All modeling + ML, B. Z. Djordjević*

Large datasets can be mined for correlations between physics inputs and outputs

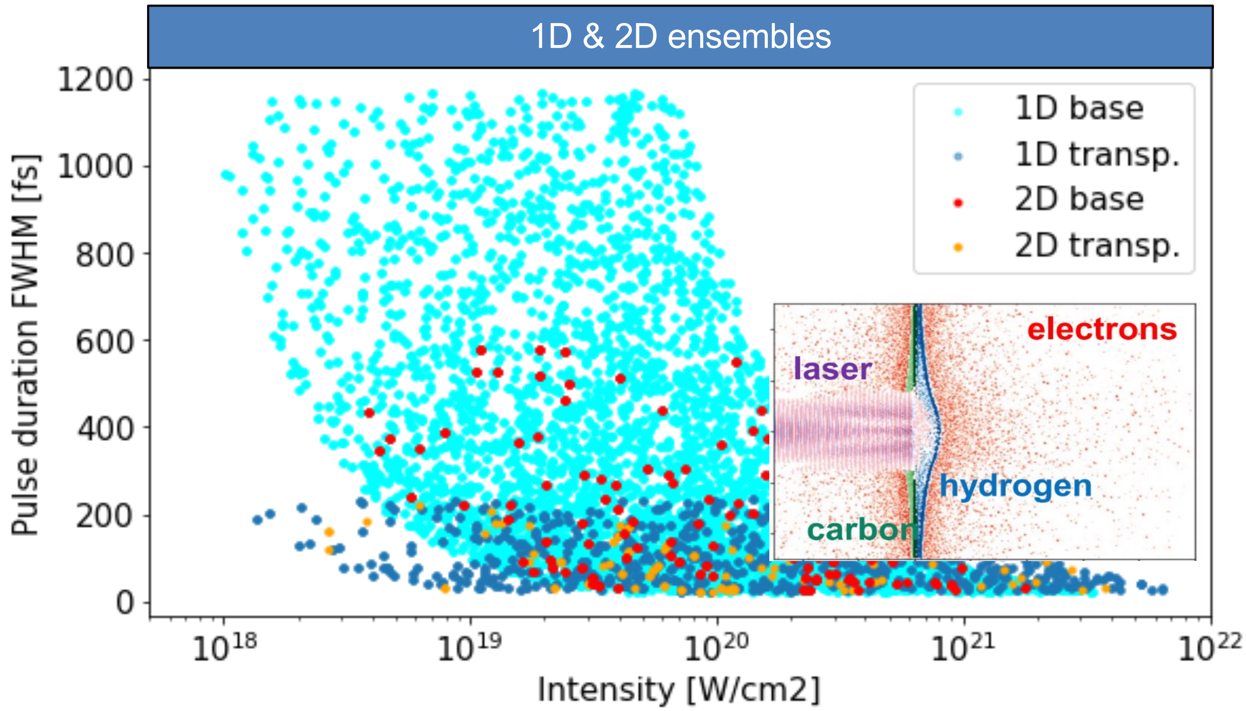




Djordjević POP, 2021

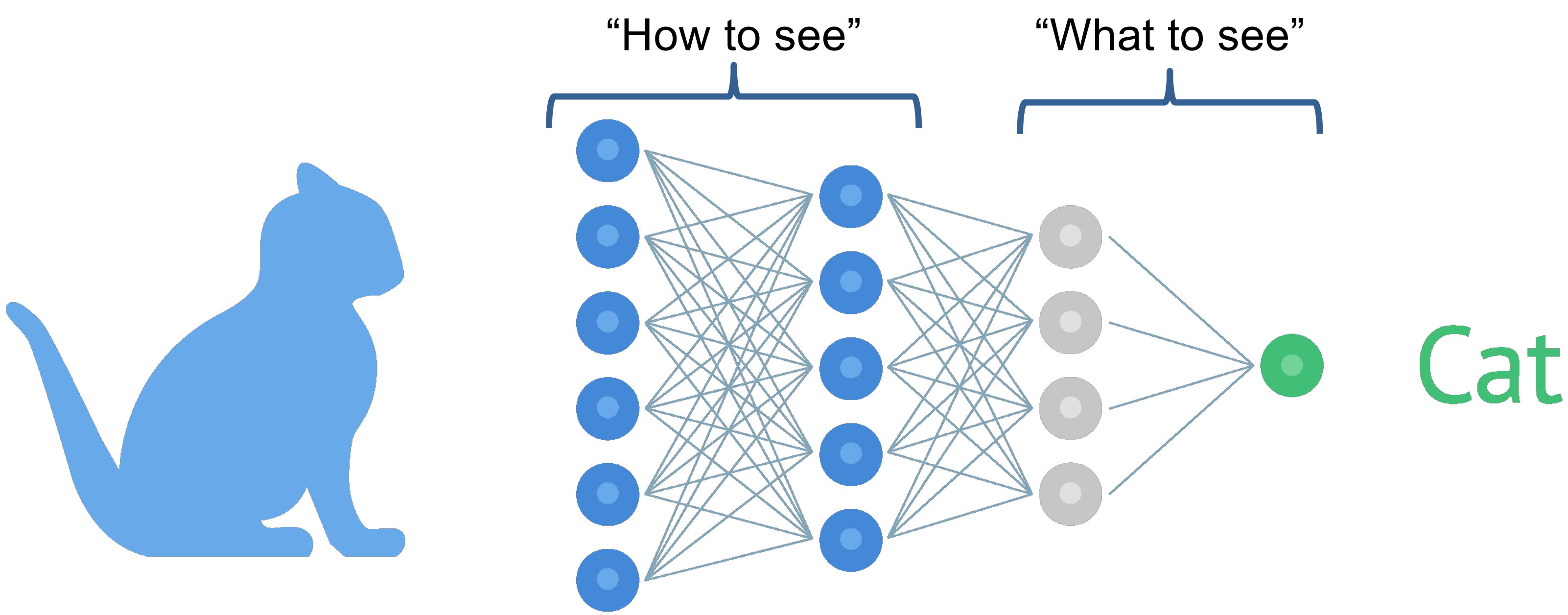
NN-based parameter scans can rapidly explore parameter space over several orders of magnitude in 6 dimensions

An ensemble of 2D simulations is too costly on its own but contains critical physics and is closer to the experimental reality

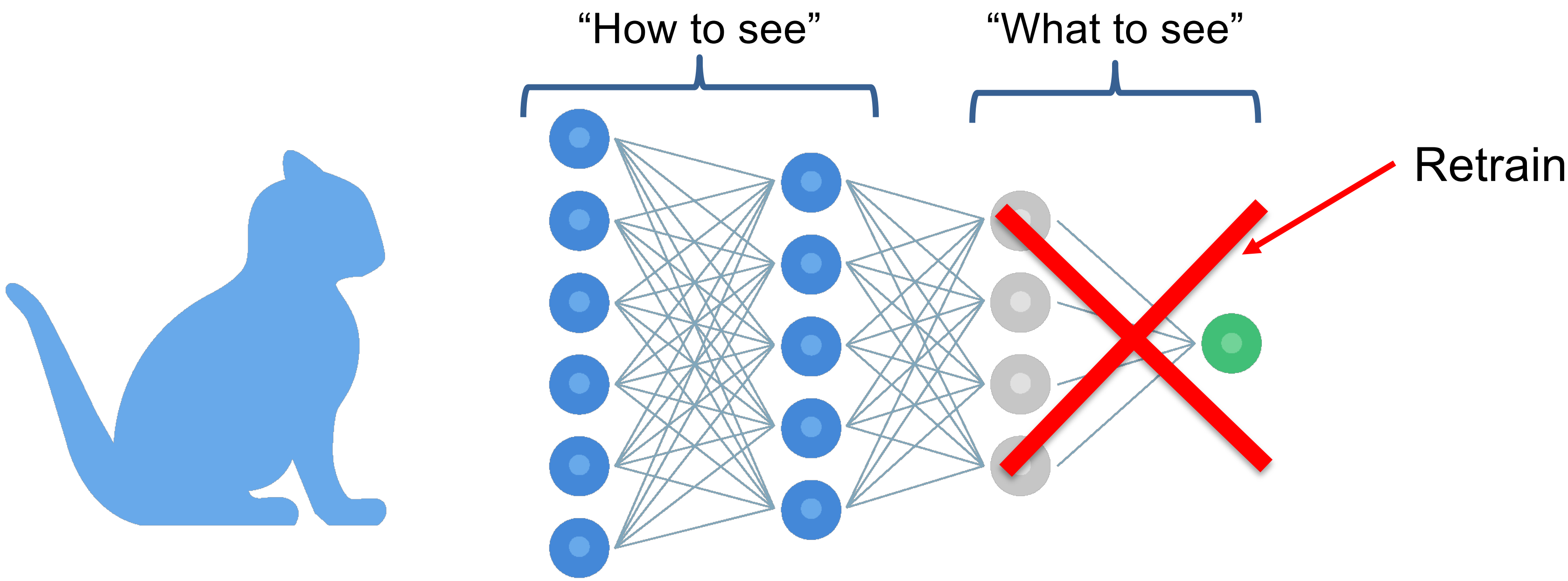


1D ensemble serves as basis for transfer learning on several sub-ensembles

Different parts of a deep convolutional network have different roles



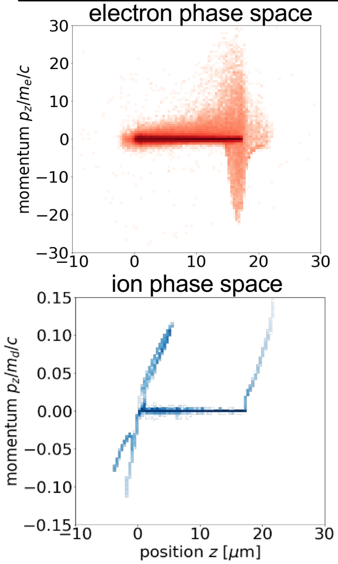
We can "transfer" the knowledge contained in our model to different but similar data

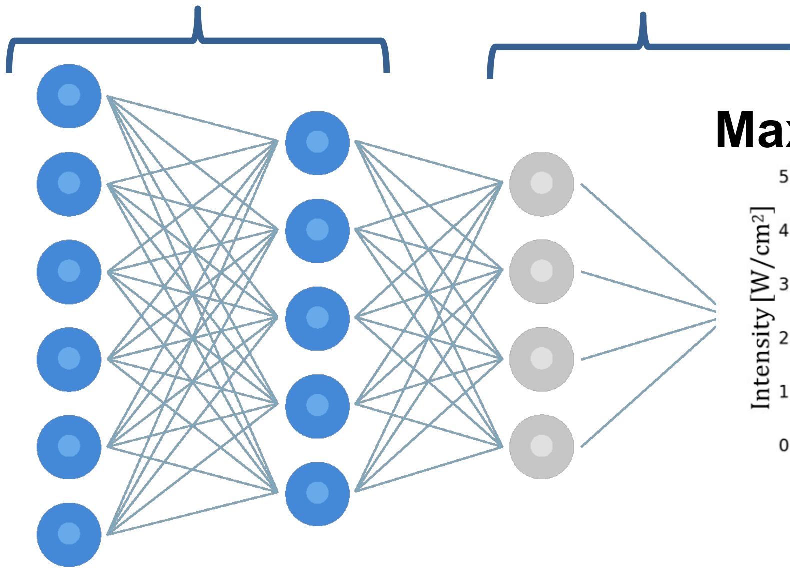


We retain the early layers in the NN, and only need to retrain the last several layers on new data

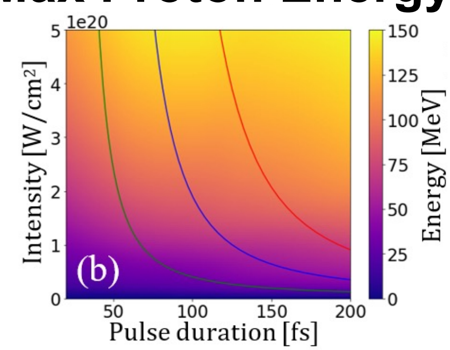
In this case, we have a model that knows how to predict physics quantities from 1D simulations

Input:
1D Simulation Data



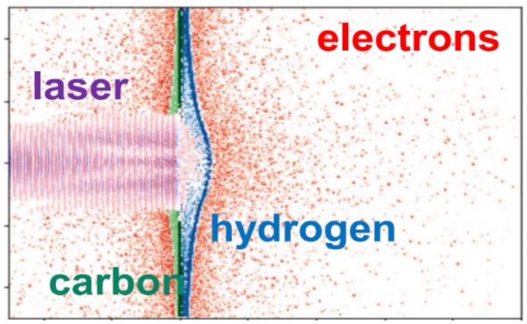


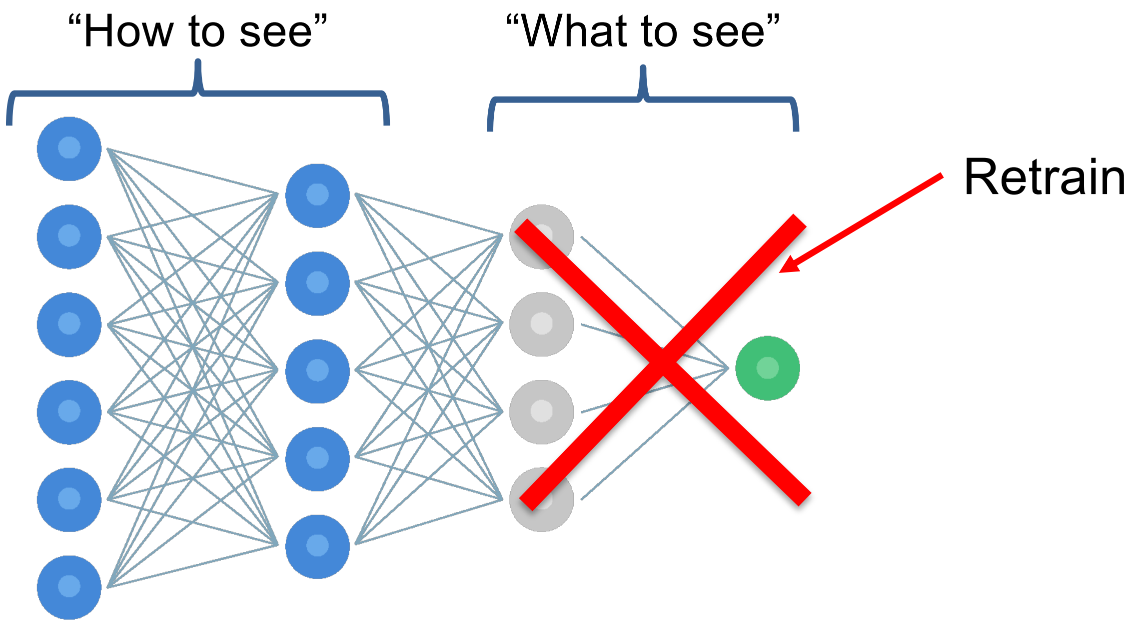
Max Proton Energy



We then use sparse/limited data (2D simulations) to retrain some of our network and obtain a model that predicts 2D quantities

Input:
2D Simulation Data



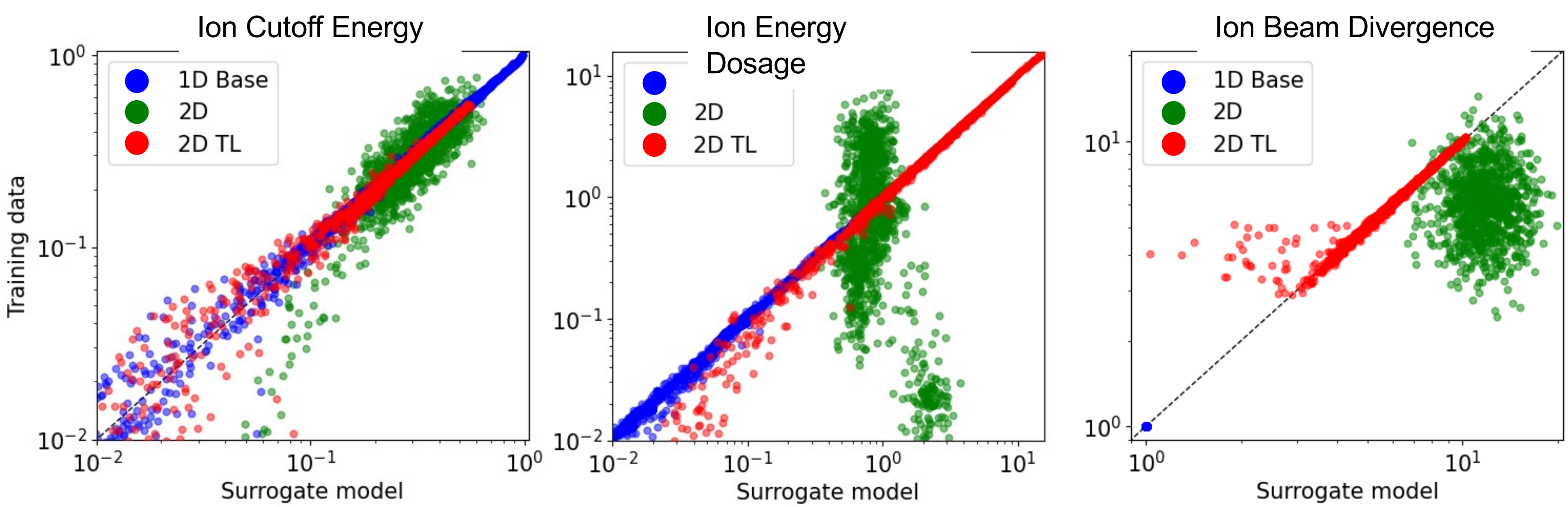


While we have thousands of 1D simulations, we have just a couple hundred 2D simulations

2D Transfer Learning

Transfer learning is being used to elevate 1D ensembles and teach surrogate models 2D physics it otherwise could not

Transfer learning makes sparse 2D predictions viable



Transfer learning allows for higher performing neural network surrogates on small, complex datasets

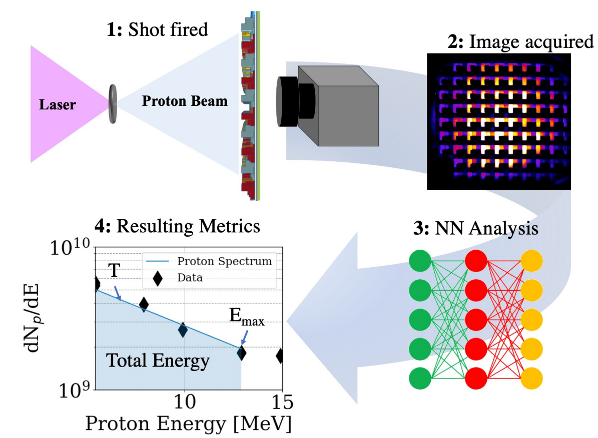
The revolution in computational power and machine learning techniques paves the way for new approaches in prediction, data analysis, and comparing simulation and experiment

Surrogate Models

B. Djordjevic, et al., *Phys. Plasmas* 28, 043105 (2021)

- Up to 10^6 times faster than sims
- Re-trainable
- Form exp. basis

Diagnostic Analysis



D.A. Mariscal, *et al*, "Design of Flexible Proton Beam Imaging Energy Spectrometers (PROBIES)", *PPCF* (2021)

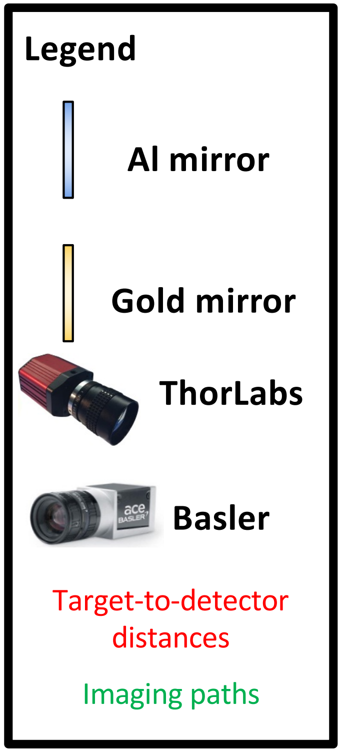
- $>10^3$ times faster than "brute force" analysis
- Accuracy >95%
- Re-trainable
- Edge compute compatible

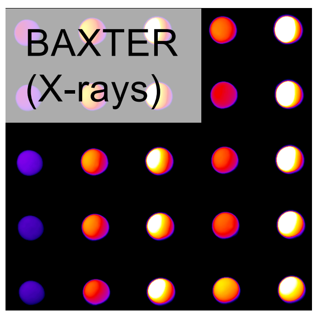
Guide & Optimize

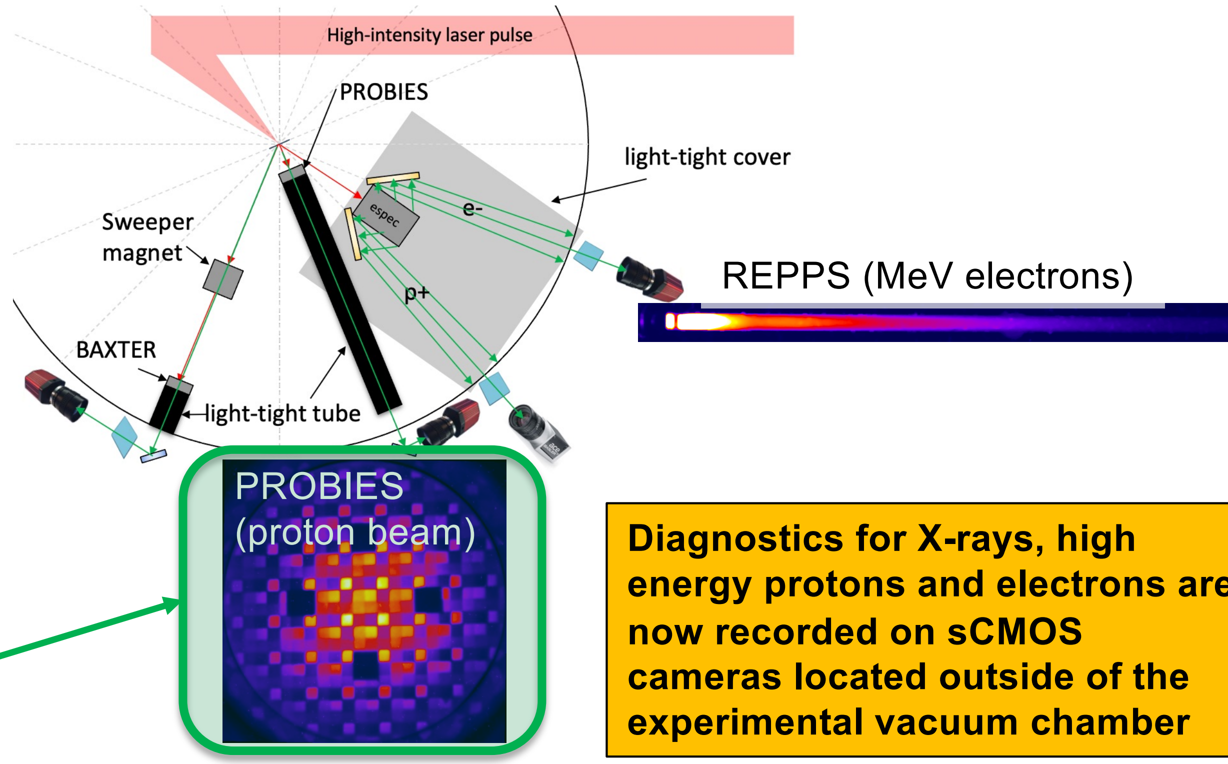
G. Anderson, et al., "Meaningful uncertainties from deep neural network surrogates of large-scale numerical simulations" (2020)

- Model-guided *or* data-driven
- Smart sampling
- Optima in fewer expts.
- Stabilized sources
- Meaningful uncertainties

Prototype diagnostics developed by LLNL can record data from high-energy high-intensity laser experiments electronically







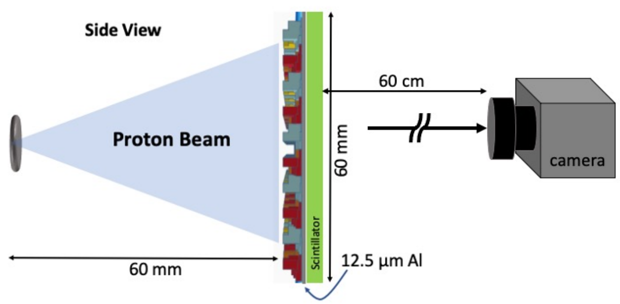
Example here

Diagnostics for X-rays, high energy protons and electrons are now recorded on sCMOS cameras located outside of the experimental vacuum chamber

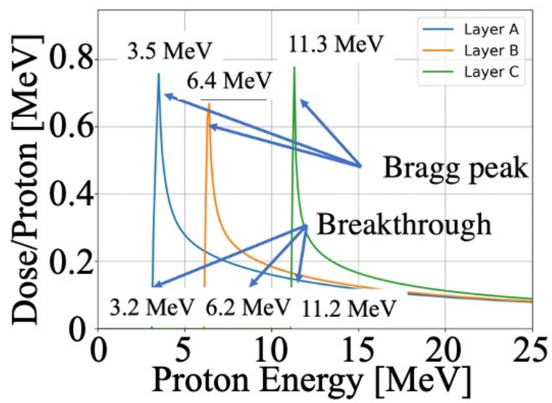
PROBIES

We have developed a differentially filtered proton diagnostic that can measure proton beam spectra and spatial profile at HRR

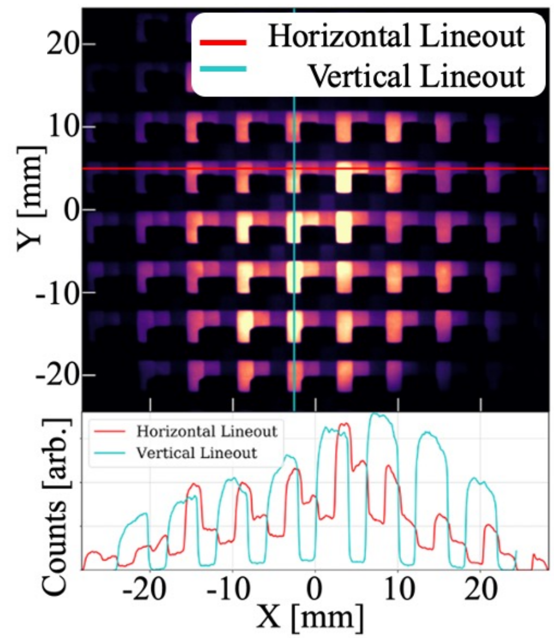
Beam/Detector Setup



Calculated Response



Example Data



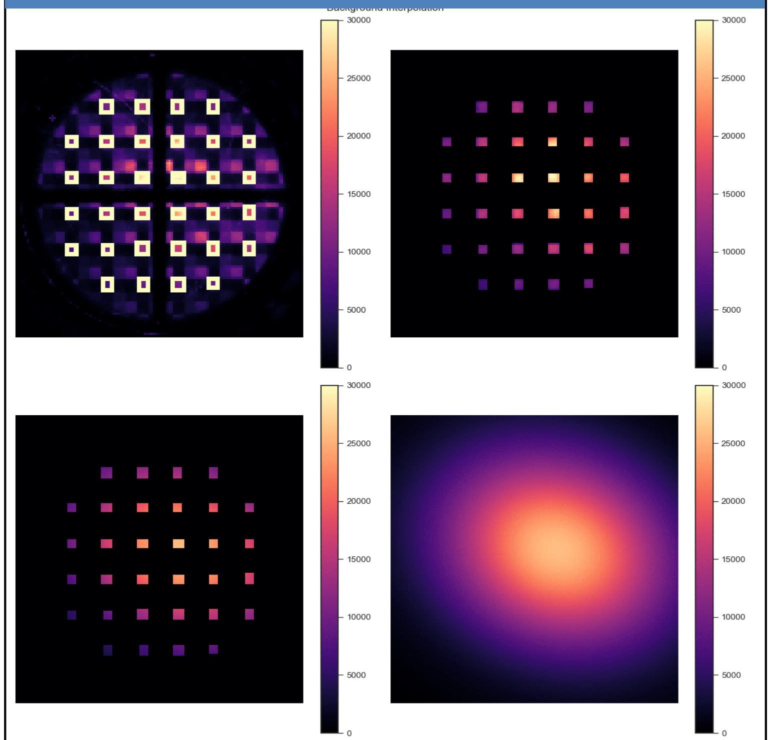
By spatially arranging different thickness filters, we can detect different energies of protons at different spatial locations

D.A. Mariscal, *et al*, "Design of Flexible Proton Beam Imaging Energy Spectrometers (PROBIES)", *Plasma Plasmas and Controlled Fusion* (2021)

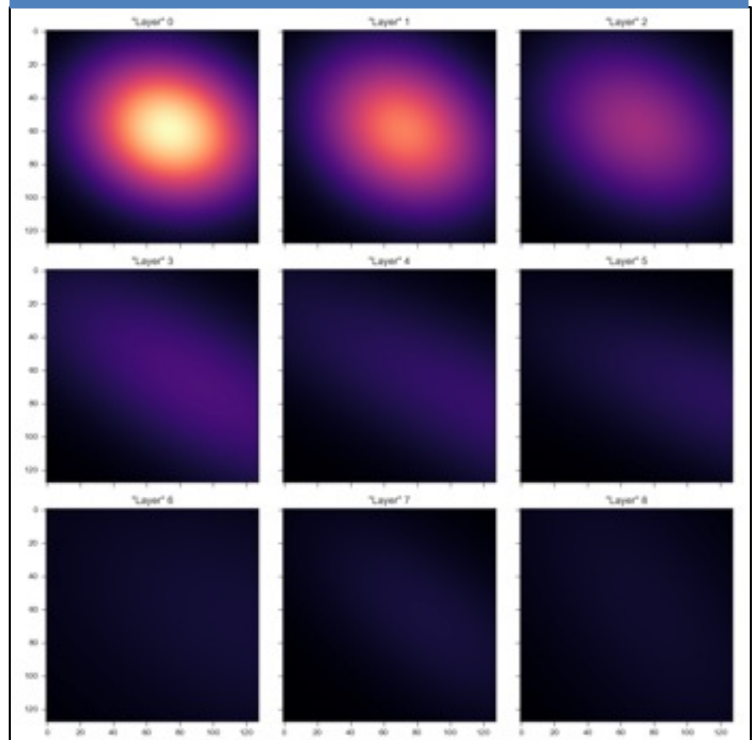
Traditional Analysis

Analysis follows a similar procedure to RCF analysis

Sampling & Interpolation



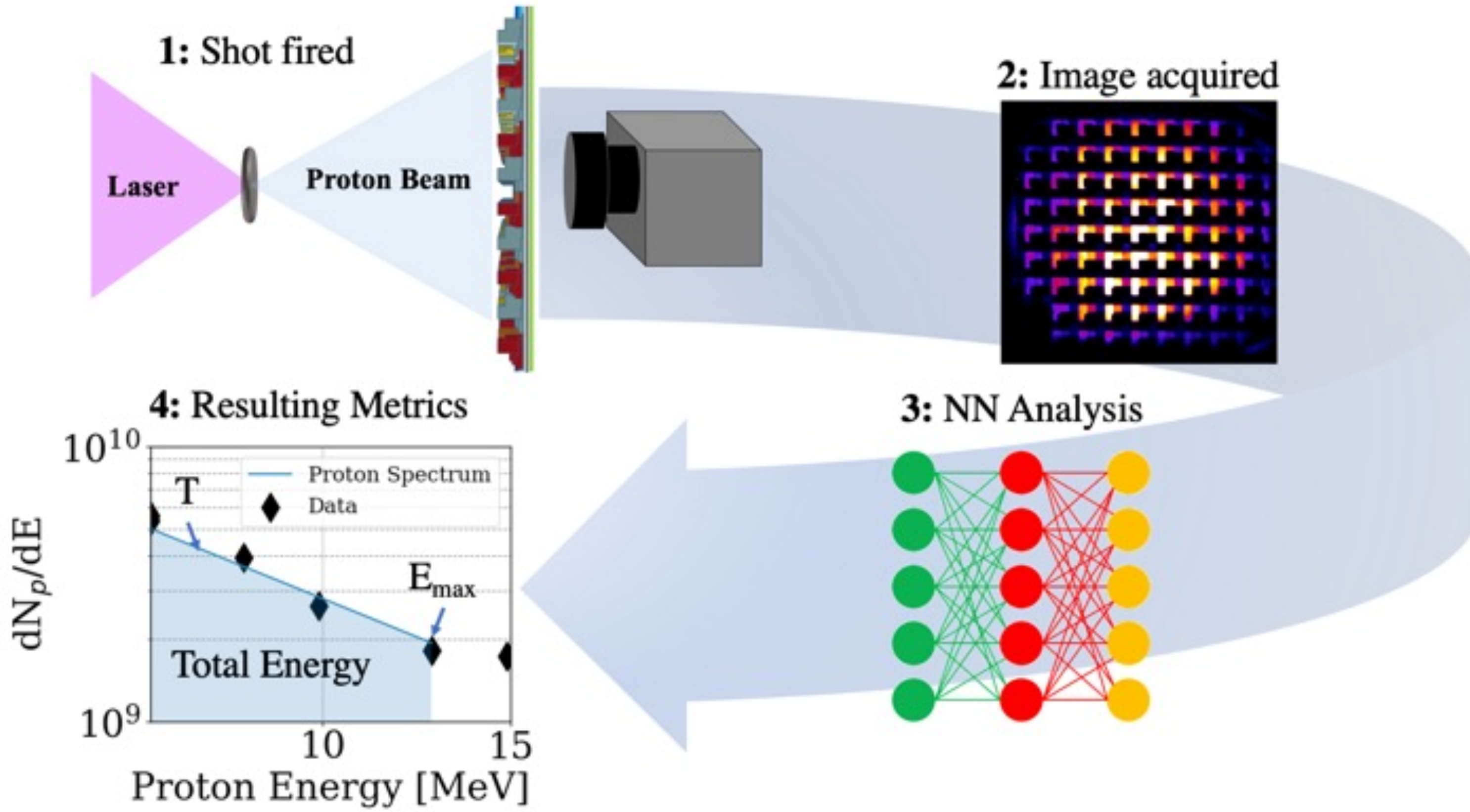
Interpolated Layers (Energy Resolved)



On a modern laptop, this takes 10's of seconds to produce the spectrum and metrics of interest

ML Analysis

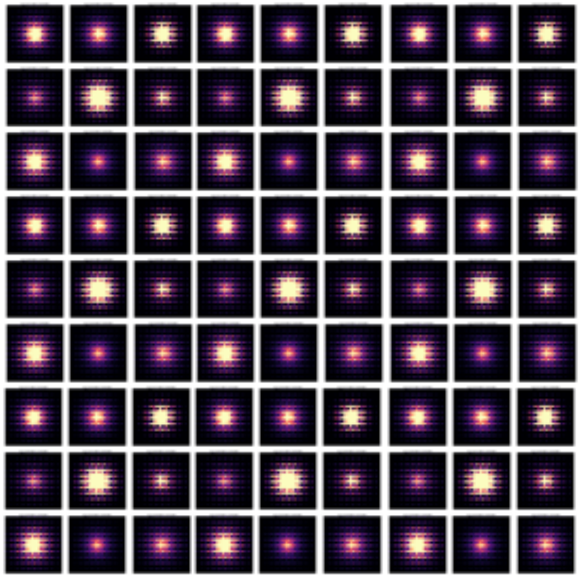
We are aiming to use neural networks to shortcut this process for our diagnostics



ML Analysis

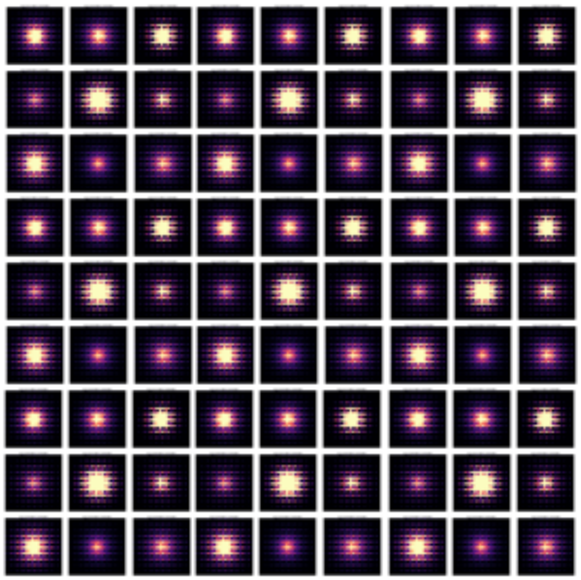
The process for developing neural networks for data analysis is straight-forward

1) Generate LOTS of data



The process for developing neural networks for data analysis is straight-forward

1) Generate LOTS of data



2) Train a NN

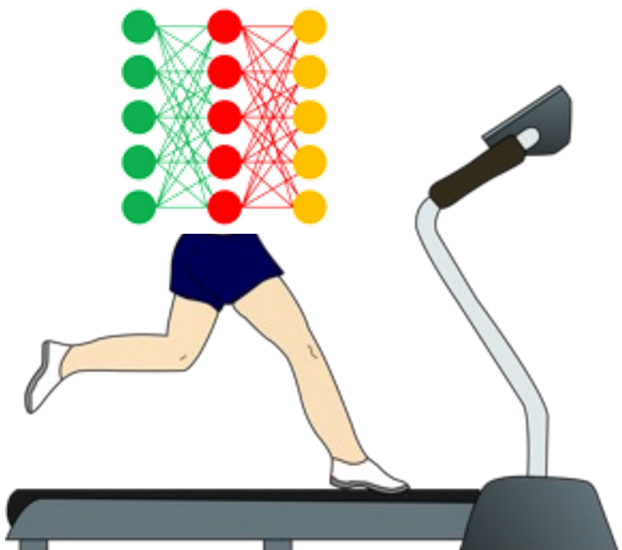
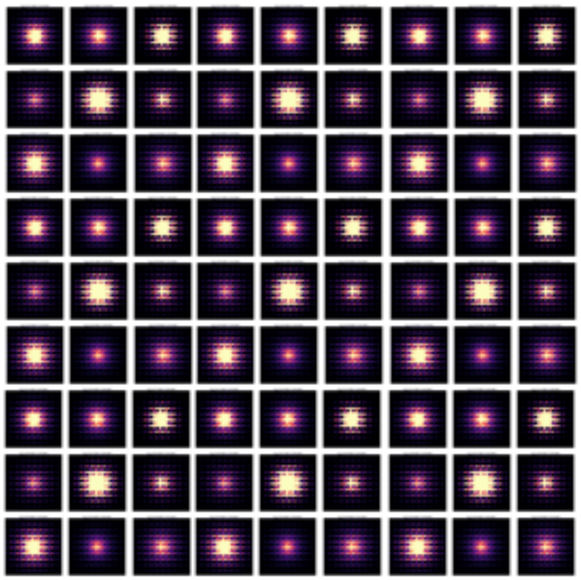


Image: clipground.com

ML Analysis

The process for developing neural networks for data analysis is straight-forward

1) Generate LOTS of data	2) Train a NN	3) Rapid & Accurate Analysis



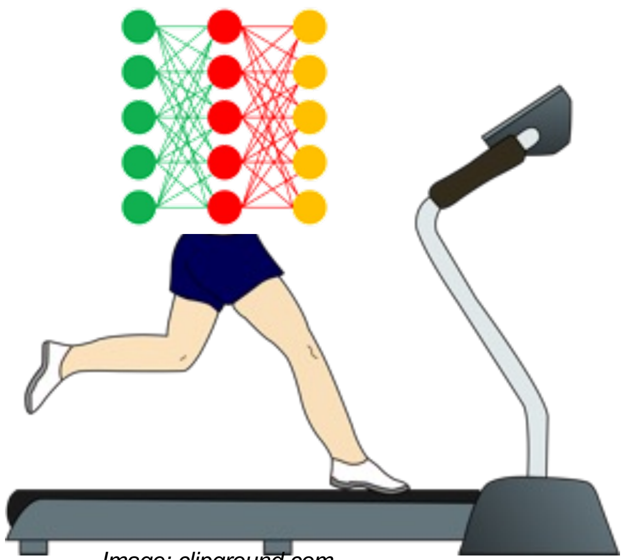
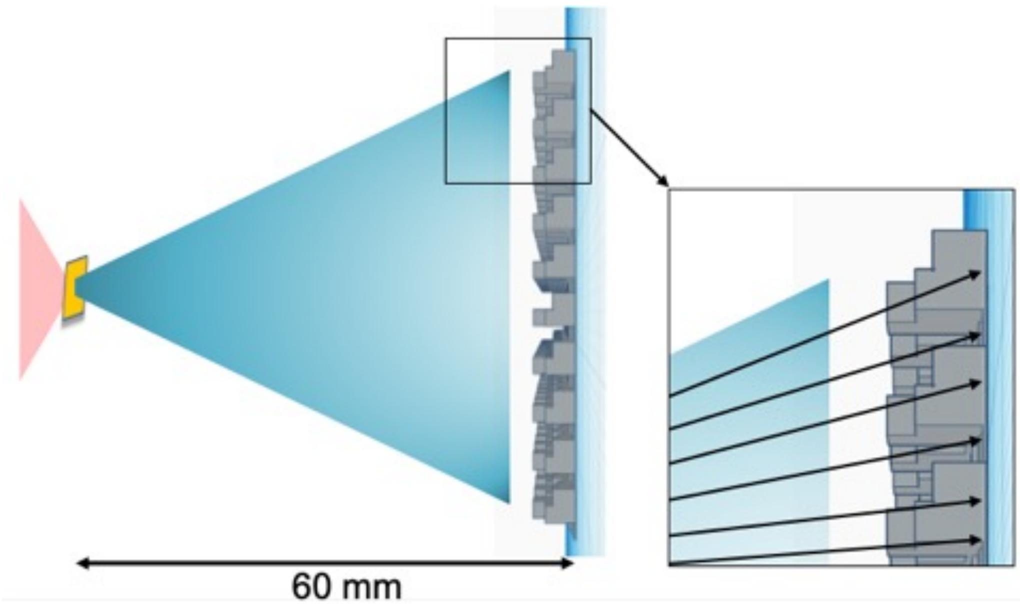


Image: clipground.com

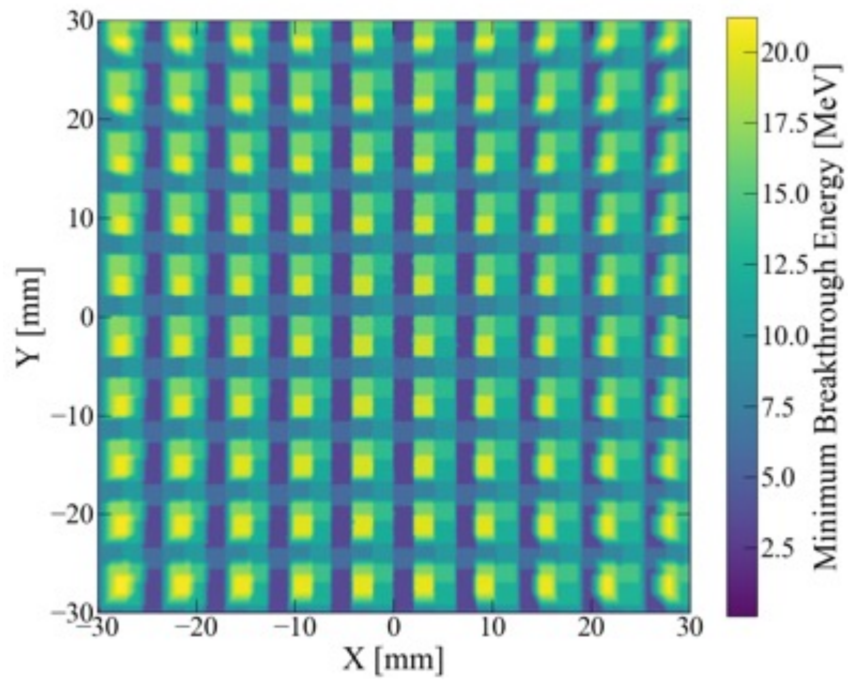
Diagnostic Model

To begin the process, we use a diagnostic model to create a large database of synthetic data

Ray-trace through 3D filter

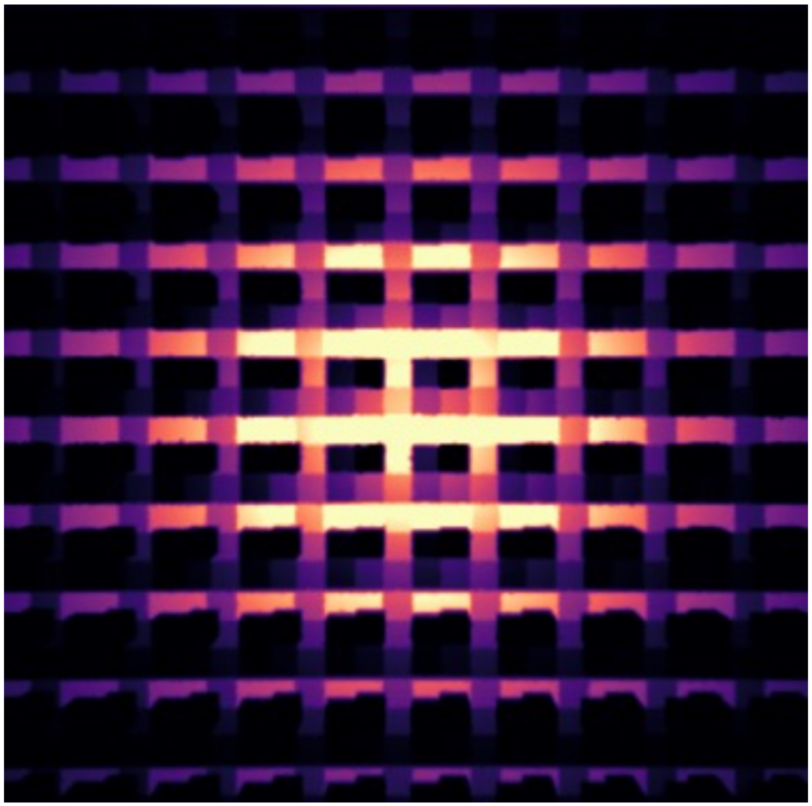


Proton



Synthetic Data

We can then repeat this process to generate a 10's of thousands of synthetic images



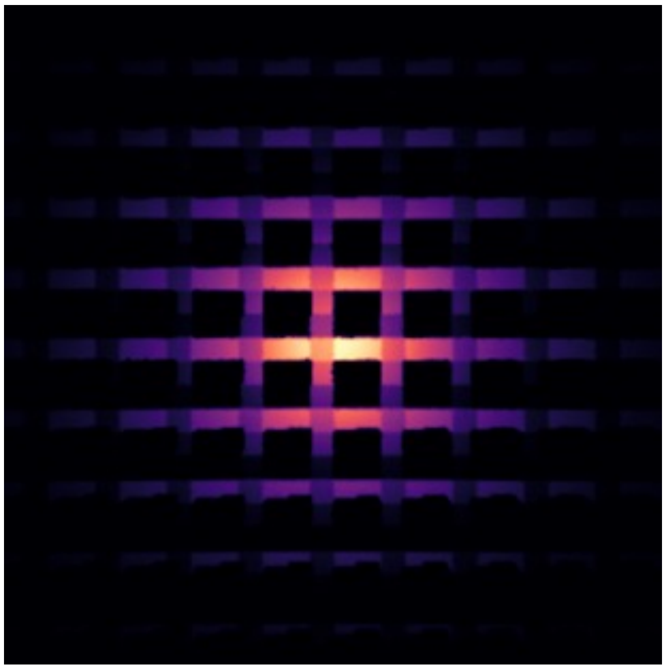
5D parameter scan* for data generation
• N→ 10^9 - 10^{12}
• T→ 1 - 20 MeV
• E_{max} → 5 - 20 MeV
• Divergence_alpha → 25 – 40 deg
• E_{total}→ Calculated from N, T, & E_{max}

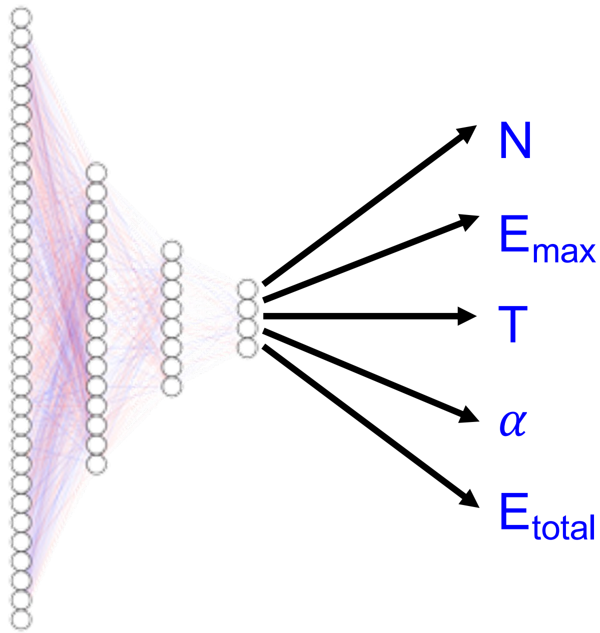
Data Preparation

- Latin hypercube sampling to generate ~10k sample images
- Image augmentation with noise, blurring, etc. to expand to ~40k
- Data (images/labels) normalization before training

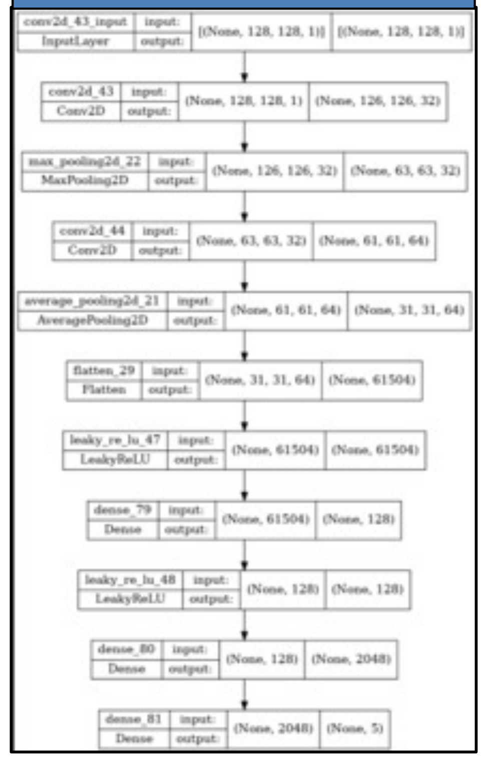
Neural Network

Once we have the data, we train a convolutional neural network to extract our analysis quantities





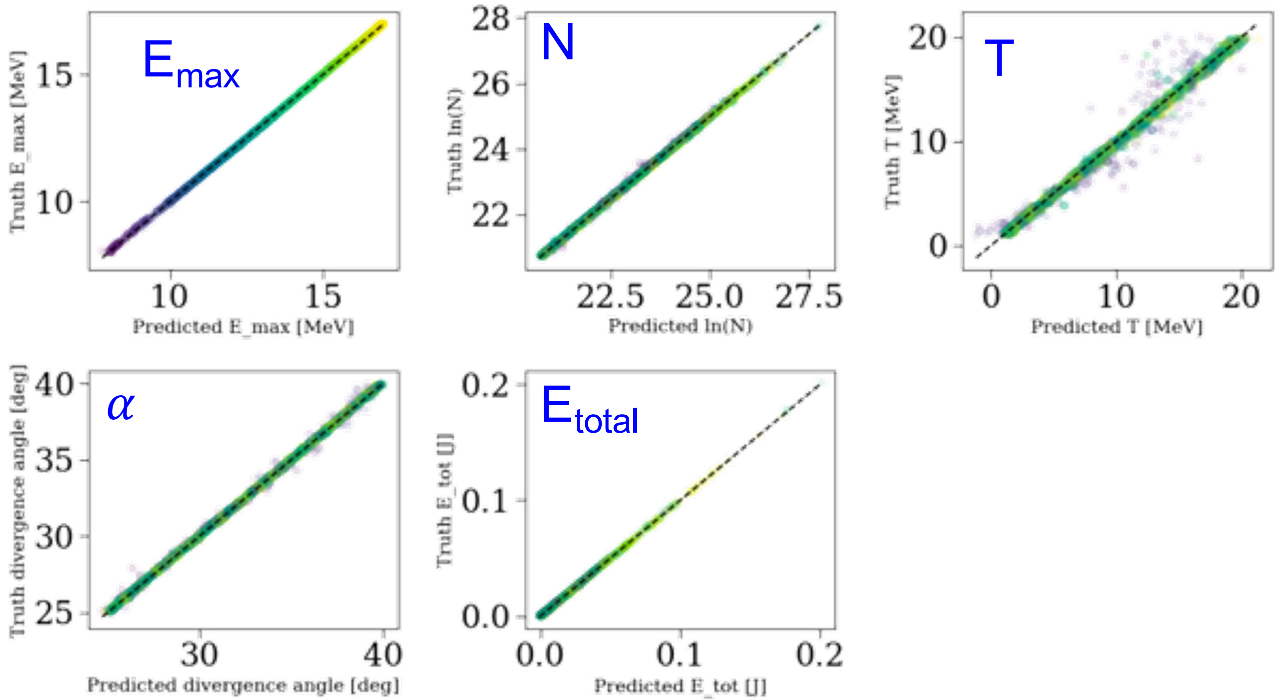
ConvNN Structure*



*TensorFlow

Neural Network

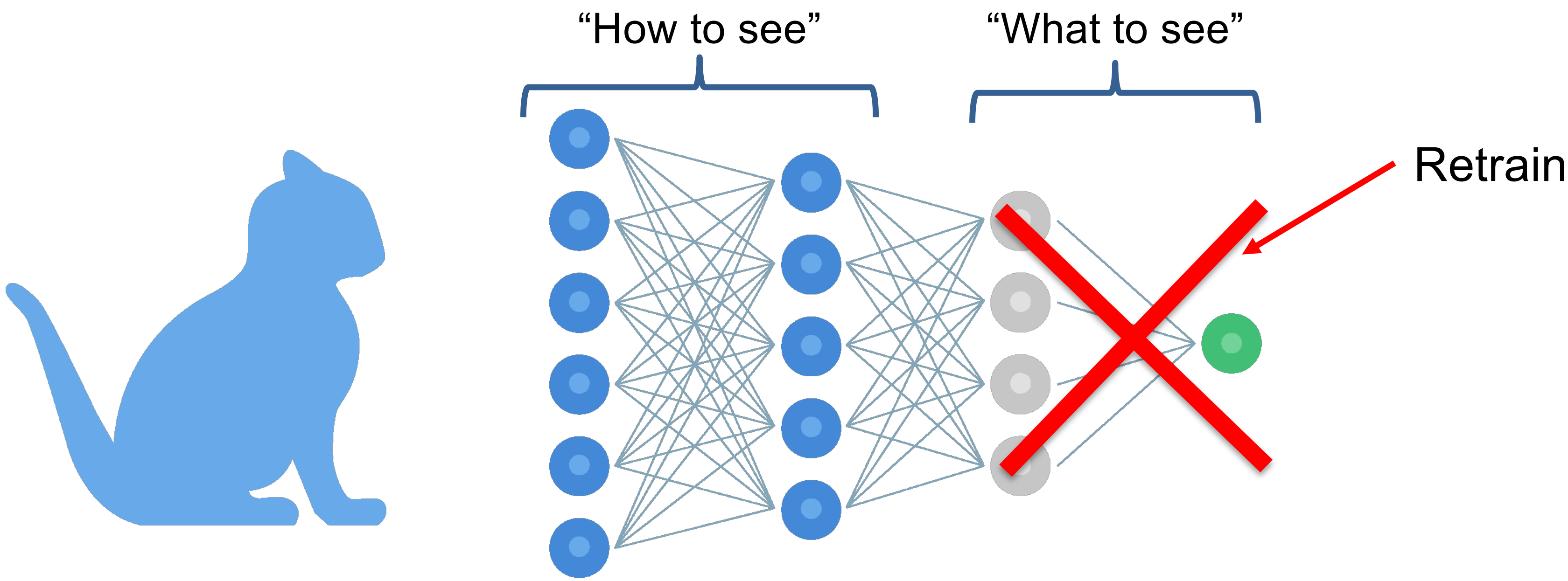
These NN's can be very accurate and are very fast (compared to the brute force analysis approach)



These models can analyze images on the ms time-scale (depending on image size) enabling on-the-fly analysis of diagnostics at HRR

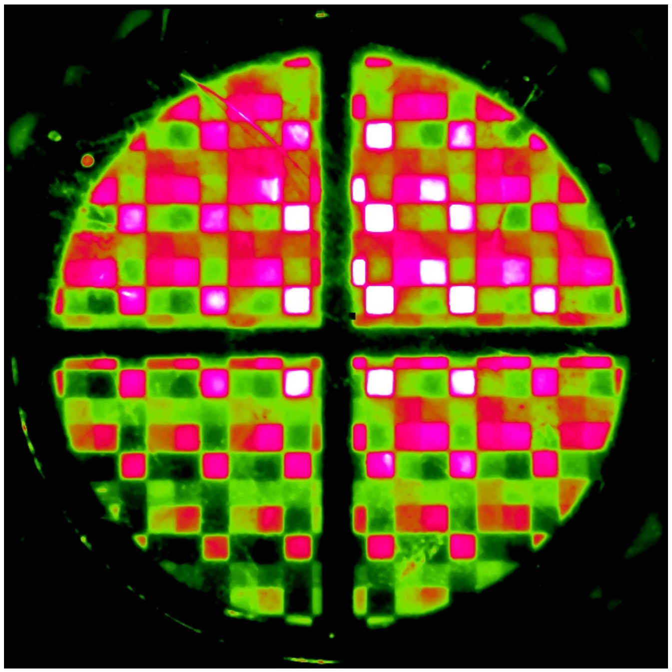
Also: R.A. Simpson, et al., "Development of a deep learning based automated data analysis for step-filter x-ray spectrometers in support of high-repetition rate short-pulse laser-driven acceleration experiments", RSI 92, 075101 (2021)

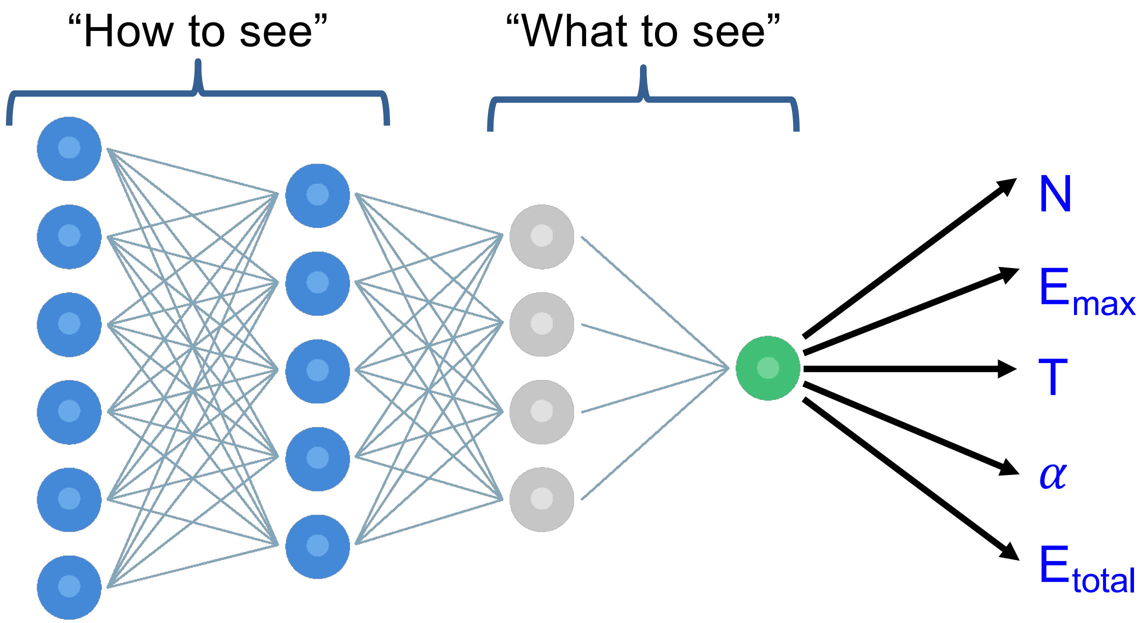
We also utilize the concept of "transfer" learning to teach our models how to analyze real experimental data



We retain the early layers in the NN, and only need to retrain the last several layers on new data

Experimental data is similar to synthetic data, but simulated data does not contain all of the experimental reality

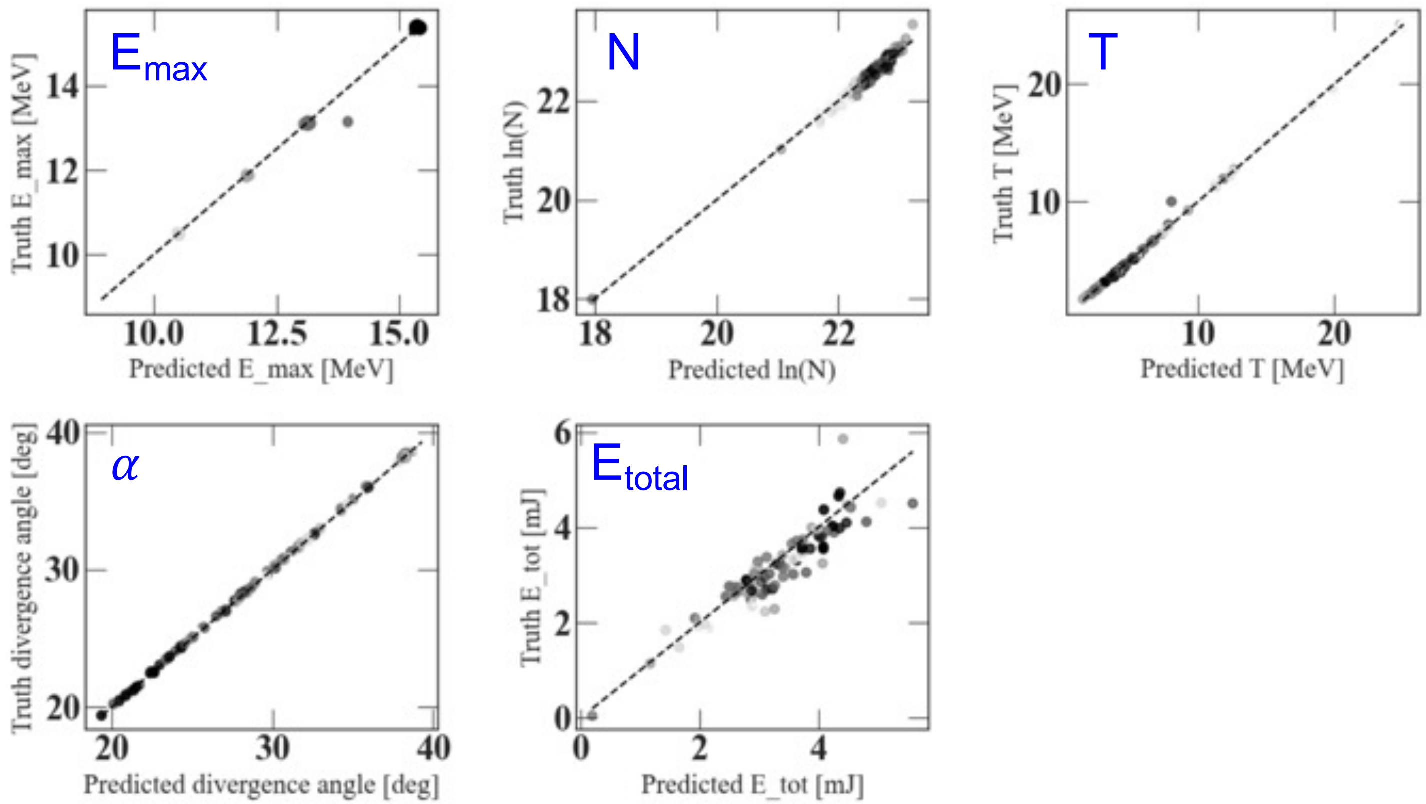




We can re-use the part of a NN that knows how to identify key features in PROBIES data from training on synthetic examples

Transfer Learning

After retraining the network with experimental data, the NN can accurately predict the metrics of interest* on real data

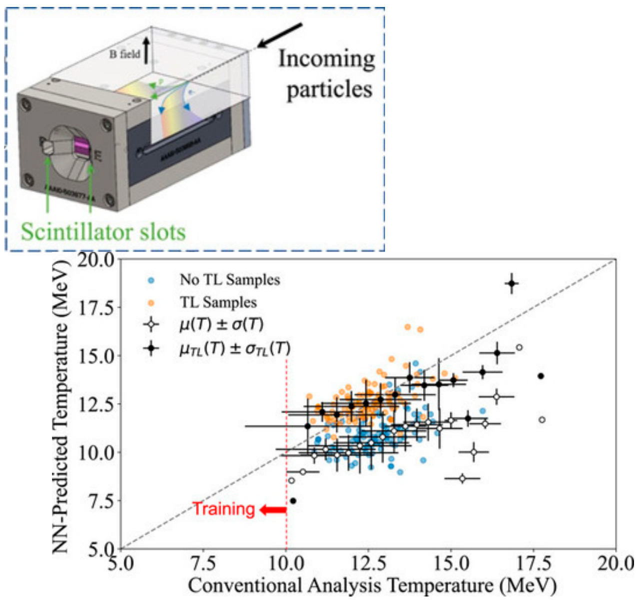


*absolute calibrations for scintillators ongoing

ML-Analyzed Diagnostics

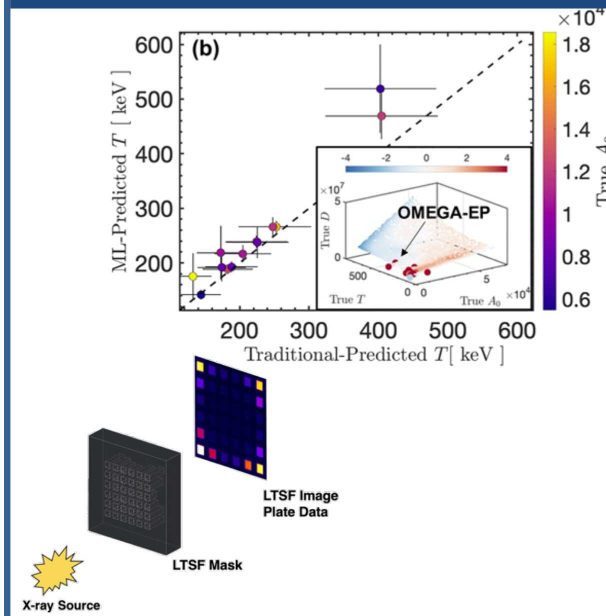
Diagnostics must be HRR-capable while remaining robust to extremely hostile experimental environments (EMP, neutrons, etc.)

Proton Beams



K. Swanson, et al., "Applications of machine learning to a compact magnetic spectrometer for high repetition rate, laser-driven particle acceleration", RSI (2022)

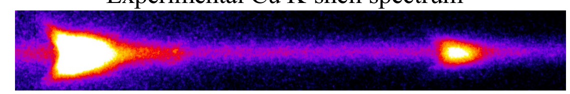
Multi-keV X-rays



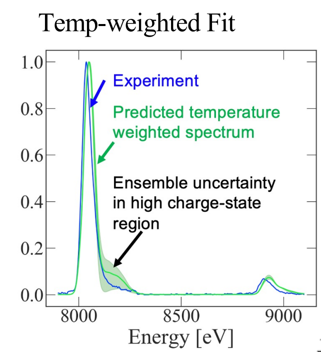
R.A. Simpson, et al., "Development of a deep learning based automated data analysis for step-filter x-ray spectrometers in support of high-repetition rate short-pulse laser-driven acceleration experiments", RSI 92, 075101 (2021)

X-ray Spectra

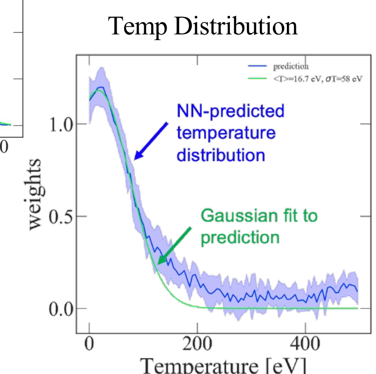
Experimental Cu K-shell spectrum



Temp-weighted Fit



Temp Distribution



D.A. Mariscal, *et al., PoP (2022)*

Incorporating ML into diagnostics ("edge" computing) will be necessary for rapid and accurate analysis that leaves time for on-the-fly decisions**

The revolution in computational power and machine learning techniques paves the way for new approaches in prediction, data analysis, and comparing simulation and experiment

Surrogate Models

B. Djordjevic, et al., *Phys. Plasmas* **28**, 043105 (2021)

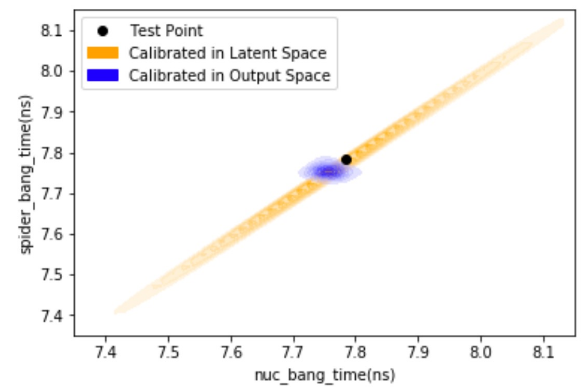
- Up to 10^6 times faster than sims
- Re-trainable
- Form exp. basis

Diagnostic Analysis

D.A. Mariscal, *et al*, "Design of Flexible Proton Beam Imaging Energy Spectrometers (PROBIES)", *PPCF* (2021)

- $>10^3$ times faster than "brute force" analysis
- Accuracy >95%
- Re-trainable
- Edge compute compatible

Guide & Optimize



G. Anderson, et al., "Meaningful uncertainties from deep neural network surrogates of large-scale numerical simulations" (2020)

- Model-guided *or* data-driven
- Smart sampling
- Optima in fewer expts.
- Stabilized sources
- Meaningful uncertainties

Experiments

We utilize a DAZZLER* for spectral phase & amplitude shaping of high-intensity laser pulses

DAZZLER Pulse Shaping

*https://fastlite.com/produits/dazzler-ultrafast-pulse-shaper/

$$\varphi(\omega) = \varphi(\omega_0) + \varphi'(\omega_0)\Delta\omega + \frac{1}{2}\varphi''(\omega_0)\Delta\omega^2 + \frac{1}{6}\varphi'''(\omega_0)\Delta\omega^3 + \frac{1}{24}\varphi^{(4)}(\omega_0) + \cdots$$

ω_0 – center frequency

Where:

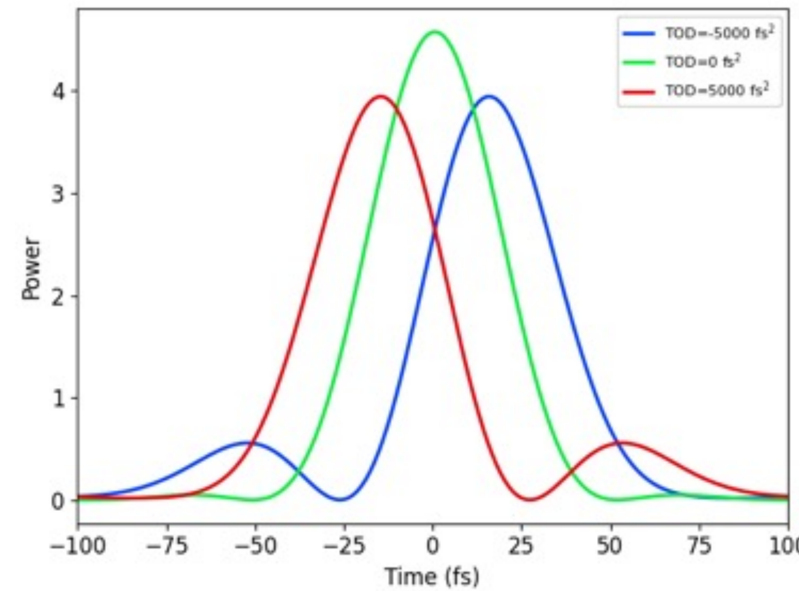
$GDD_0 \equiv \varphi''(\omega_0)$ – Group Delay Dispersion (GDD)

$TOD_0 \equiv \varphi'''(\omega_0)$ – Third Order Dispersion (TOD)

$FOD_0 \equiv \varphi^{(4)}(\omega_0)$ – Fourth order Dispersion (FOD)

T. Galvin

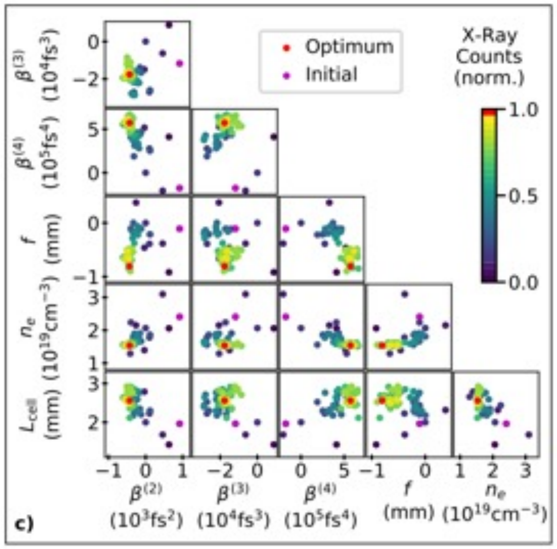
Example Laser Pulse Shapes (TOD)



Pulse shaping via a DAZZLER lends itself readily to autonomous experiments with simple and fast electronic control

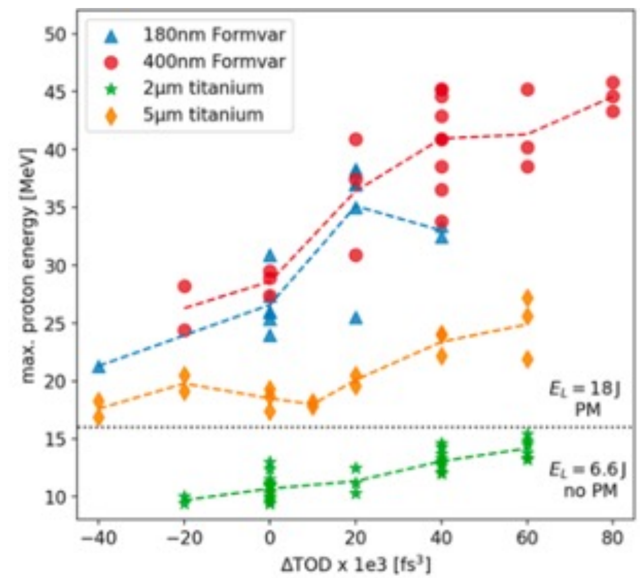
Recent works have shown that pulse shaping is a strong lever for experimental outputs

LWFA: Electron Beam/X-ray Enhancements



R.J. Shalloo, et al., Nat. Coms. 11, 6355 (2020)

Proton Beam Enhancements

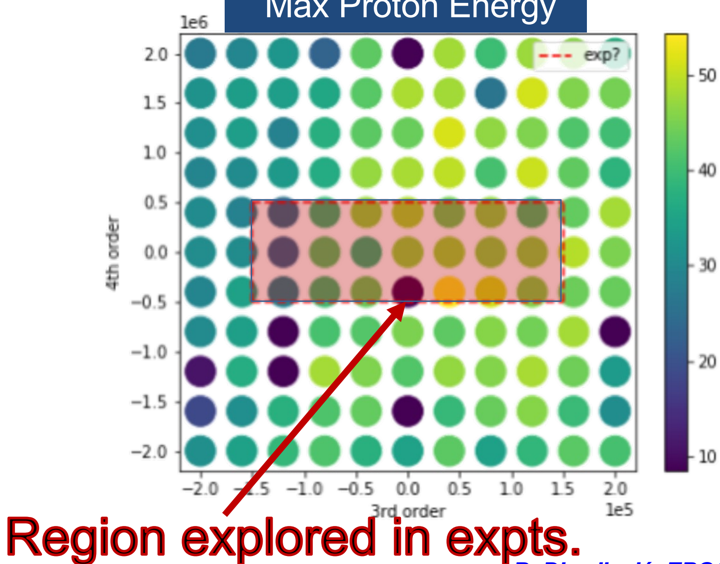


T. Ziegler, et al., Sci. Rep. 11, 7338 (2021)

Using ensemble (thousands) of 1D PIC simulations, we can map the large 3+ dimensional parameter space accessible w/ pulse shaping

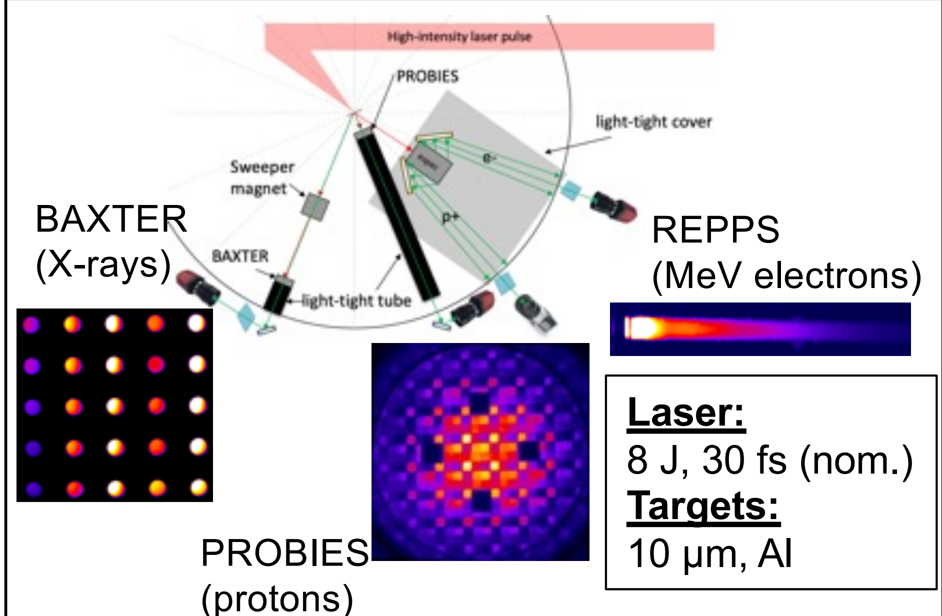
Ensemble Simulations of Pulse Shaping

Max Proton Energy



B. Djordjević, EPOCH, 1D ensemble

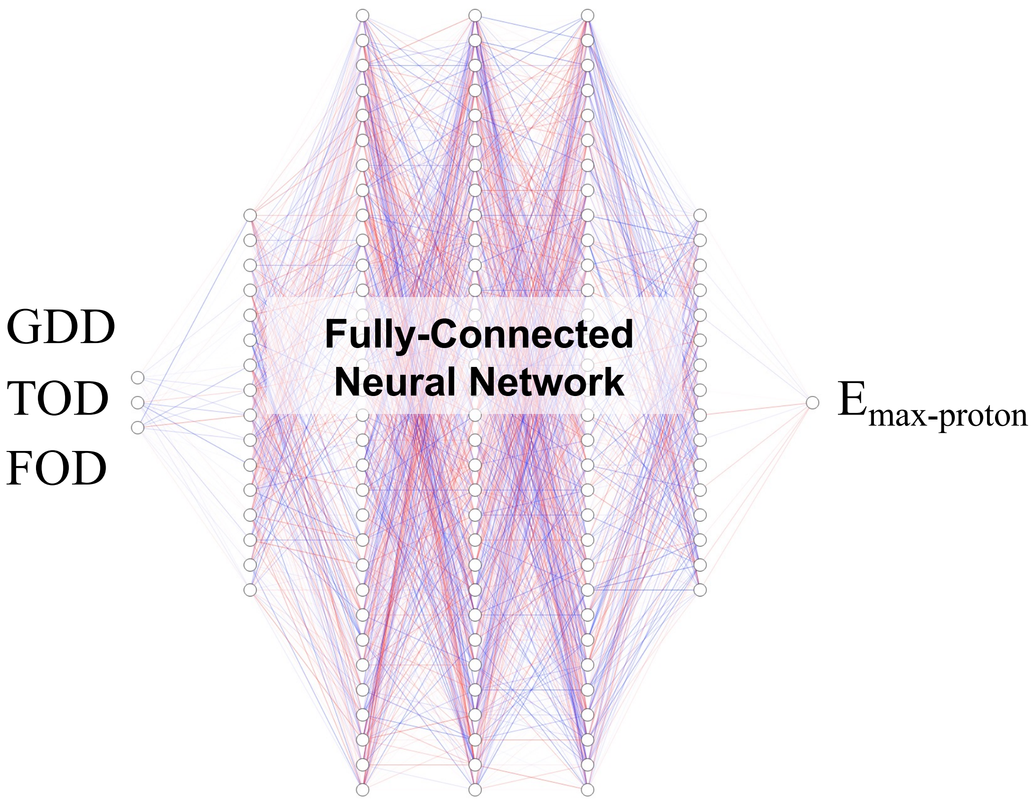
Proton Accel. Experiments @ CSU ALEPH



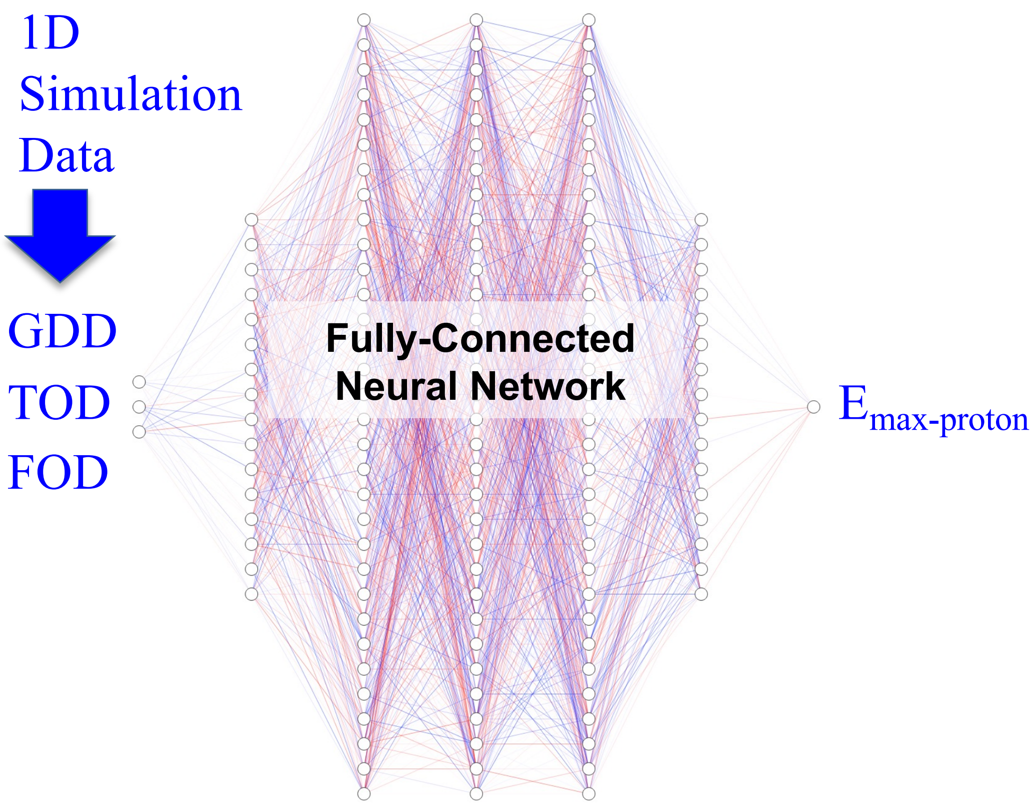
Laser:
8 J, 30 fs (nom.)
Targets:
10 μm, Al

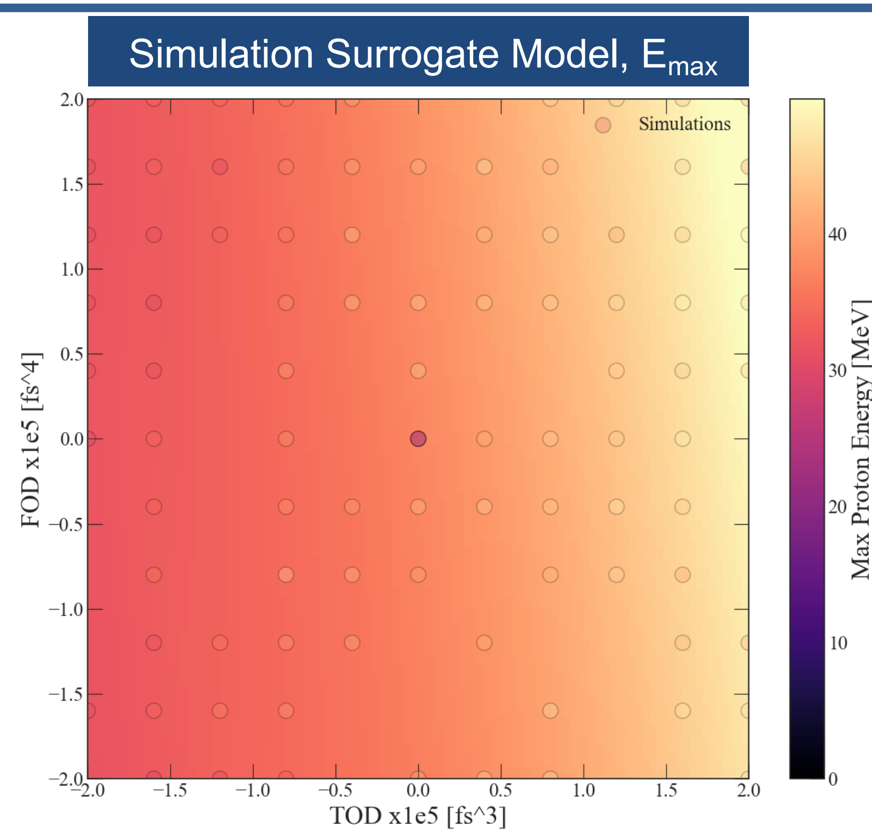
With high-rep-rate compatible diagnostics* we can characterize the outputs from solid target interactions to validate simulations and retrain our surrogate model

We can use existing experimental data to demonstrate the functional form of ML-guided experiments



We first utilize ensemble simulations to train a surrogate model for an experimental output (max proton energy)

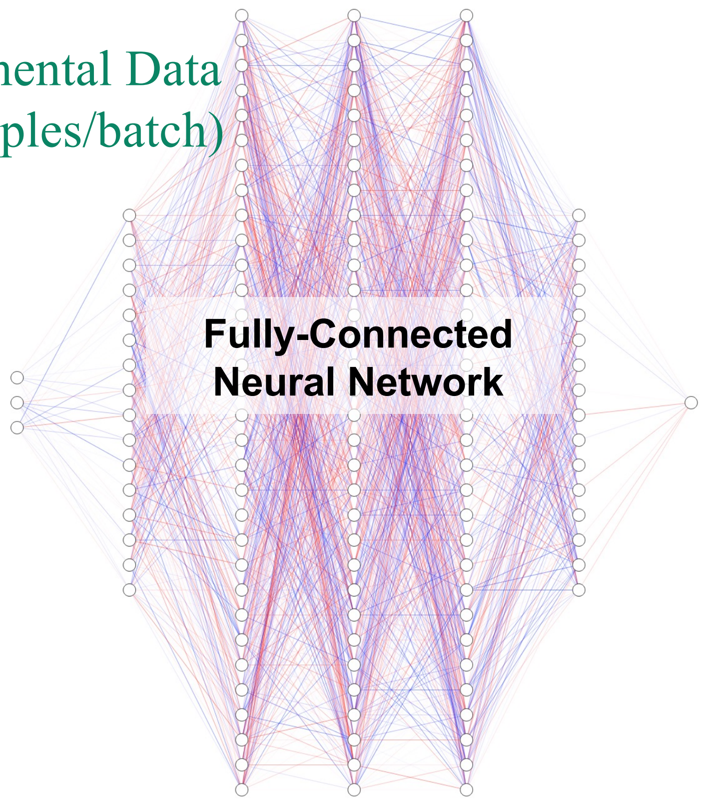




We then "freeze" several layers in the NN and feed in experimental data in small batches to retrain the model using transfer learning

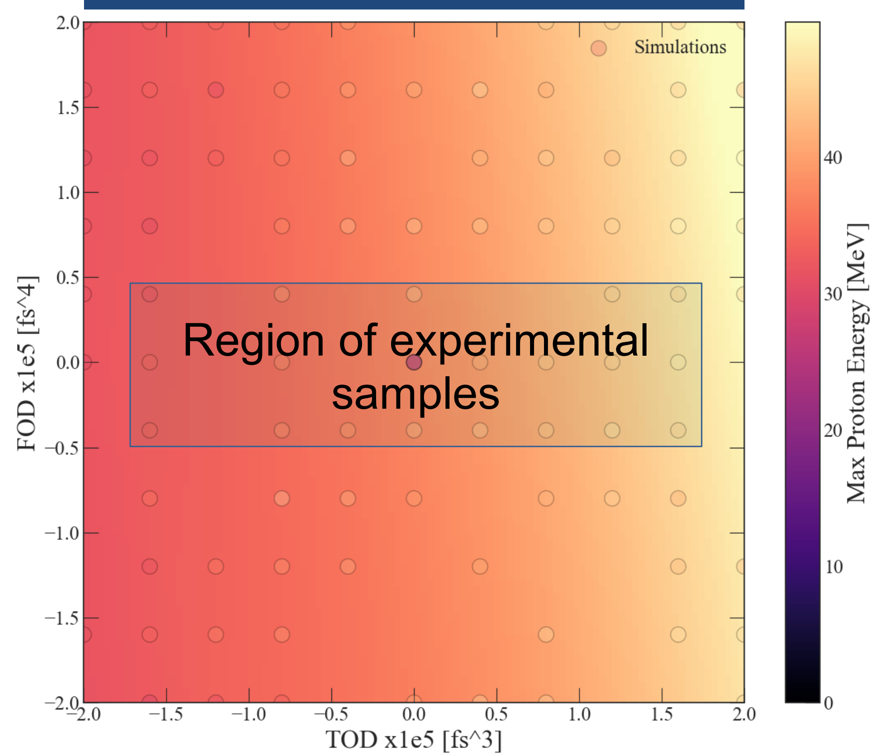
Experimental Data
(10 samples/batch)

GDD
TOD
FOD

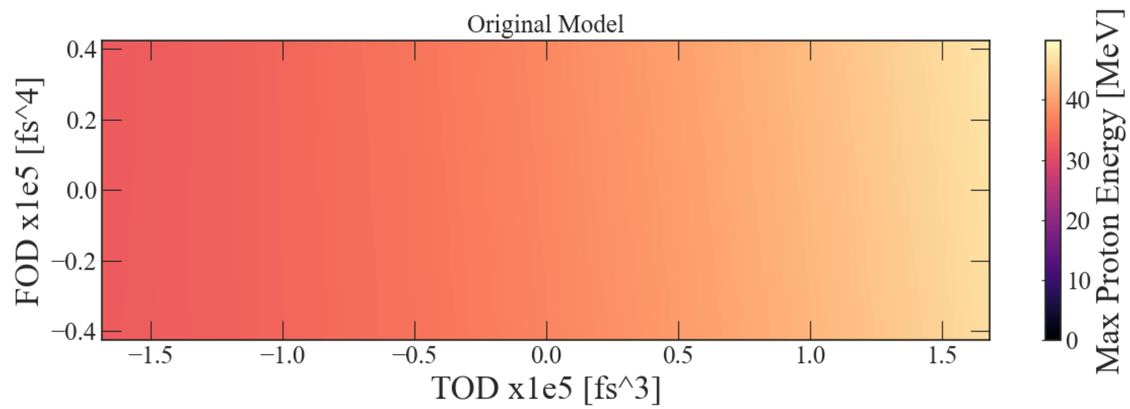


$E_{max\text{-}proton}$

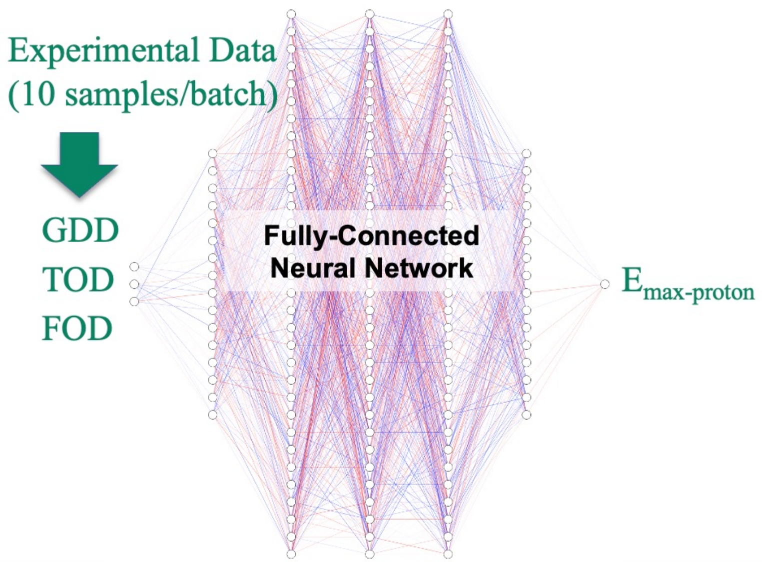
Simulation Surrogate Model, E_{max}

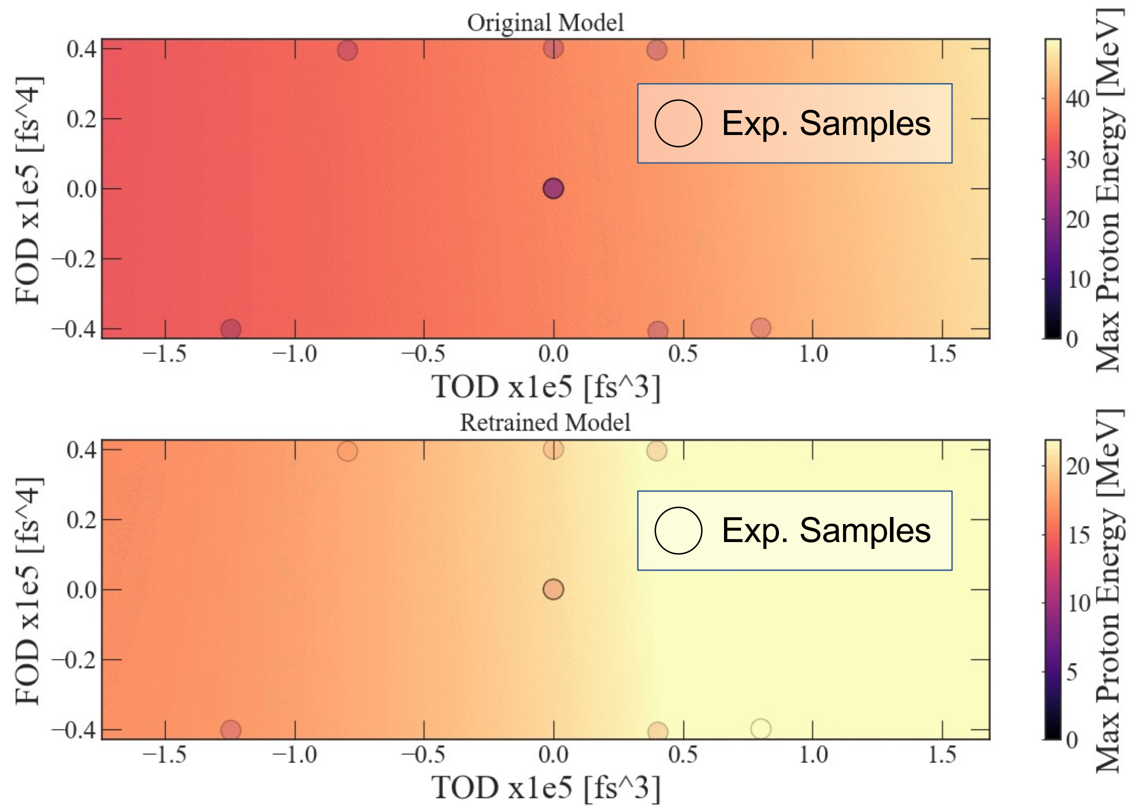


The model then learns the experimental offsets and trends as it receives more data

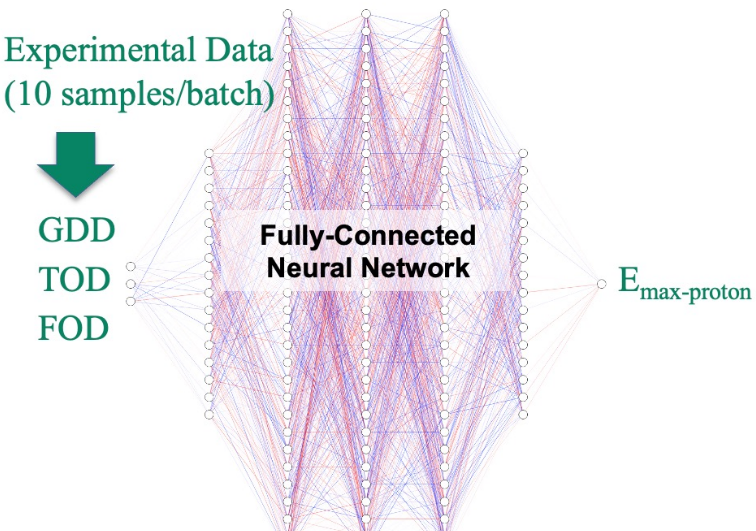


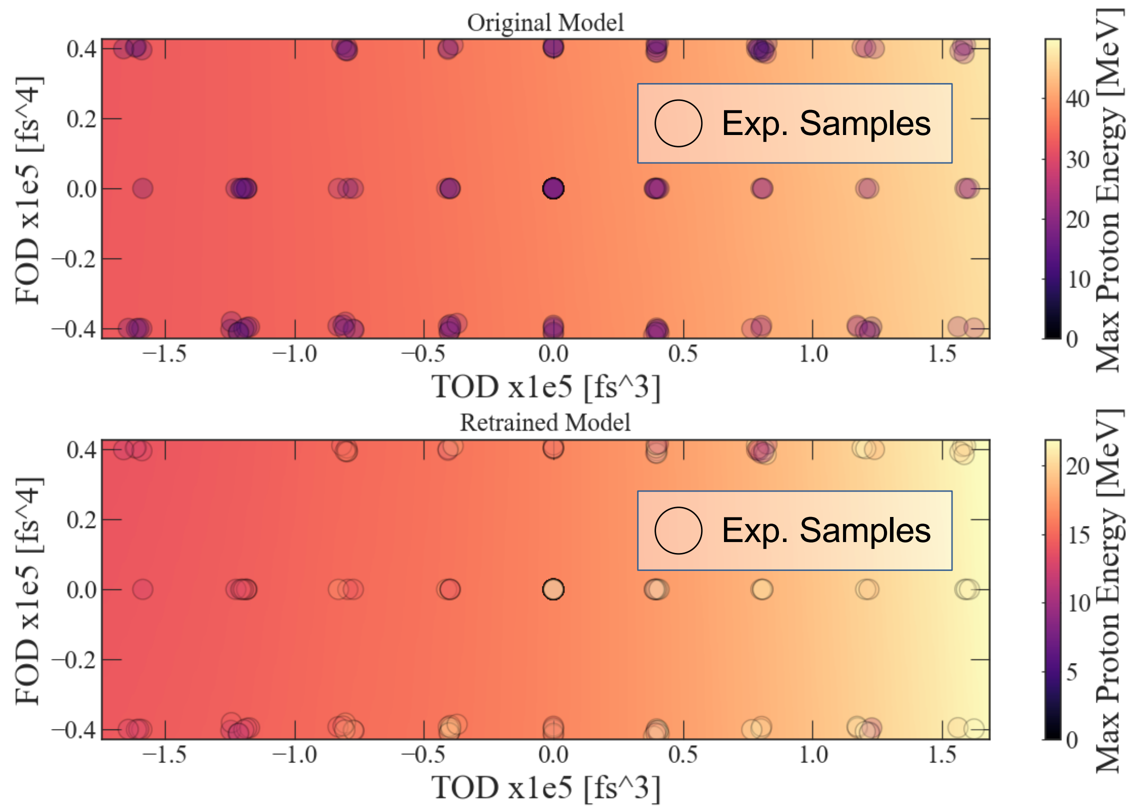
The model then learns the experimental offsets and trends as it receives more data





The model then learns the experimental offsets and trends as it receives more data



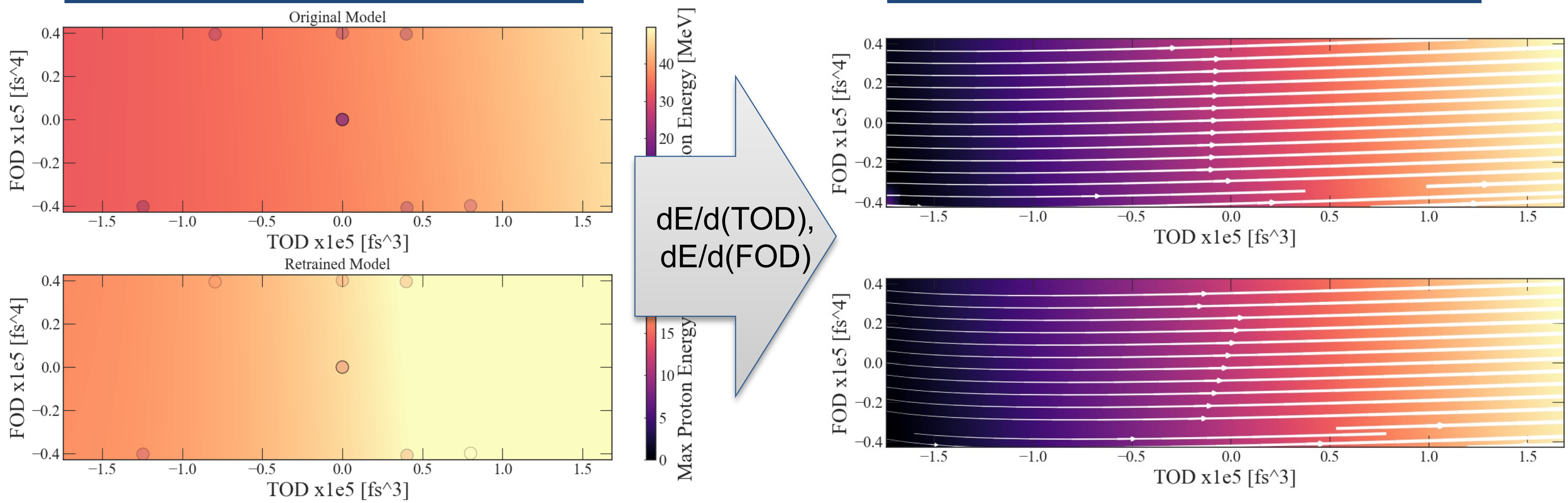


While 1D simulations predicted the general trends, they assumed higher laser energy

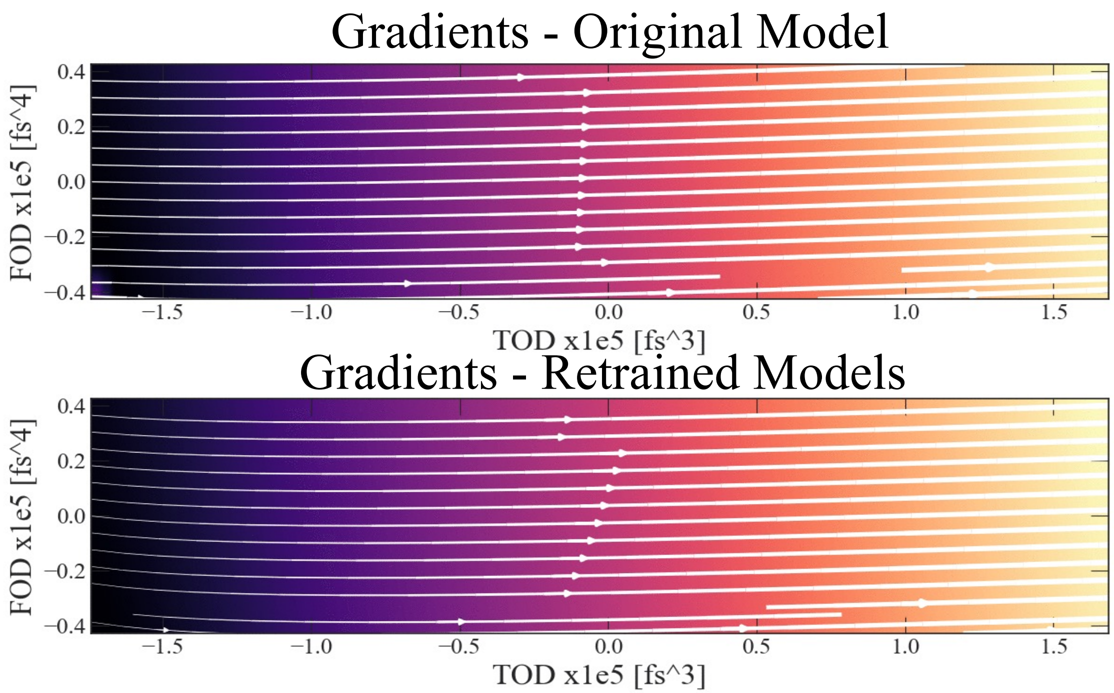
We also obtain gradients in the multi-dimensional parameter space "for free" and can use them to inform adaptive sampling

Simulation Surrogate Model, E_{max}

Gradients in parameter space

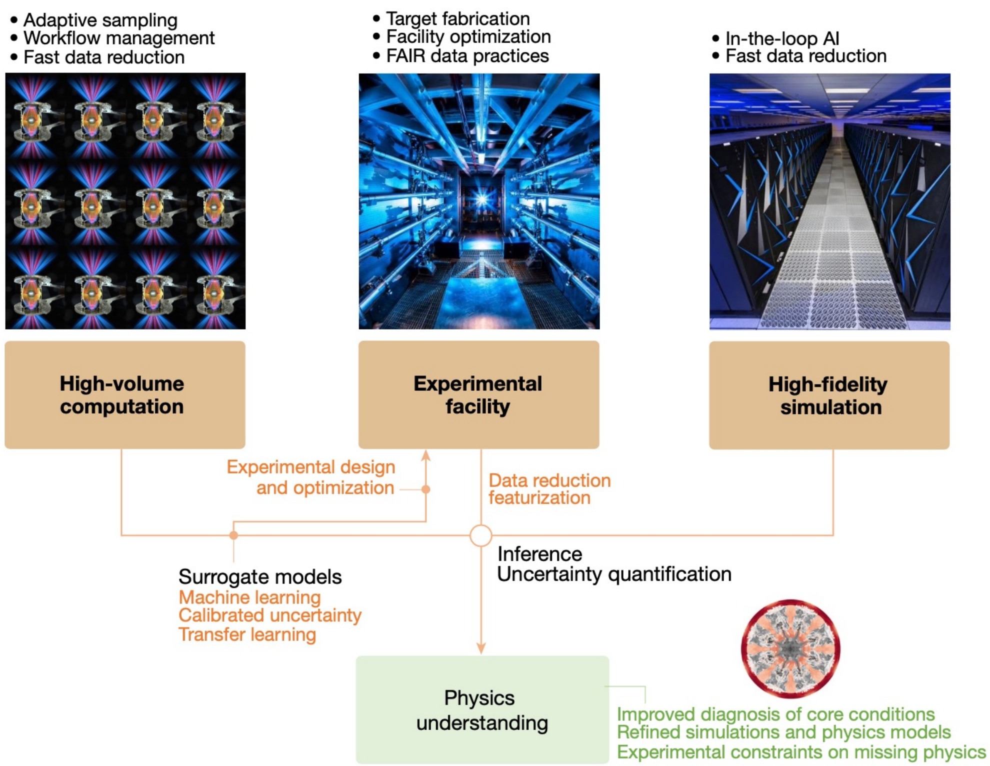


We also obtain gradients in the multi-dimensional parameter space "for free" and can use them to inform adaptive sampling

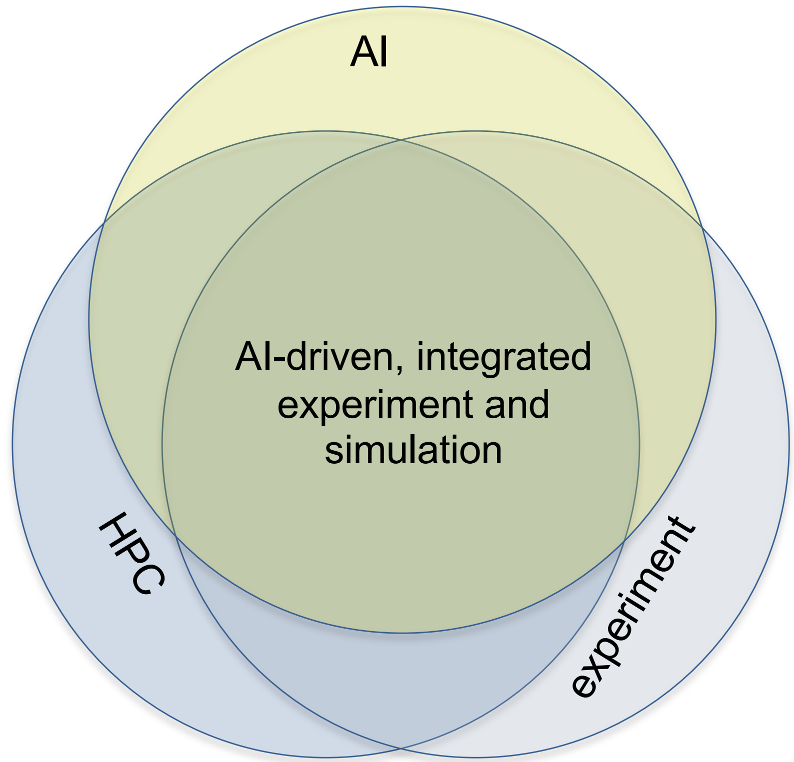


Gradients provide directions to regions that may be under-sampled and potential optima

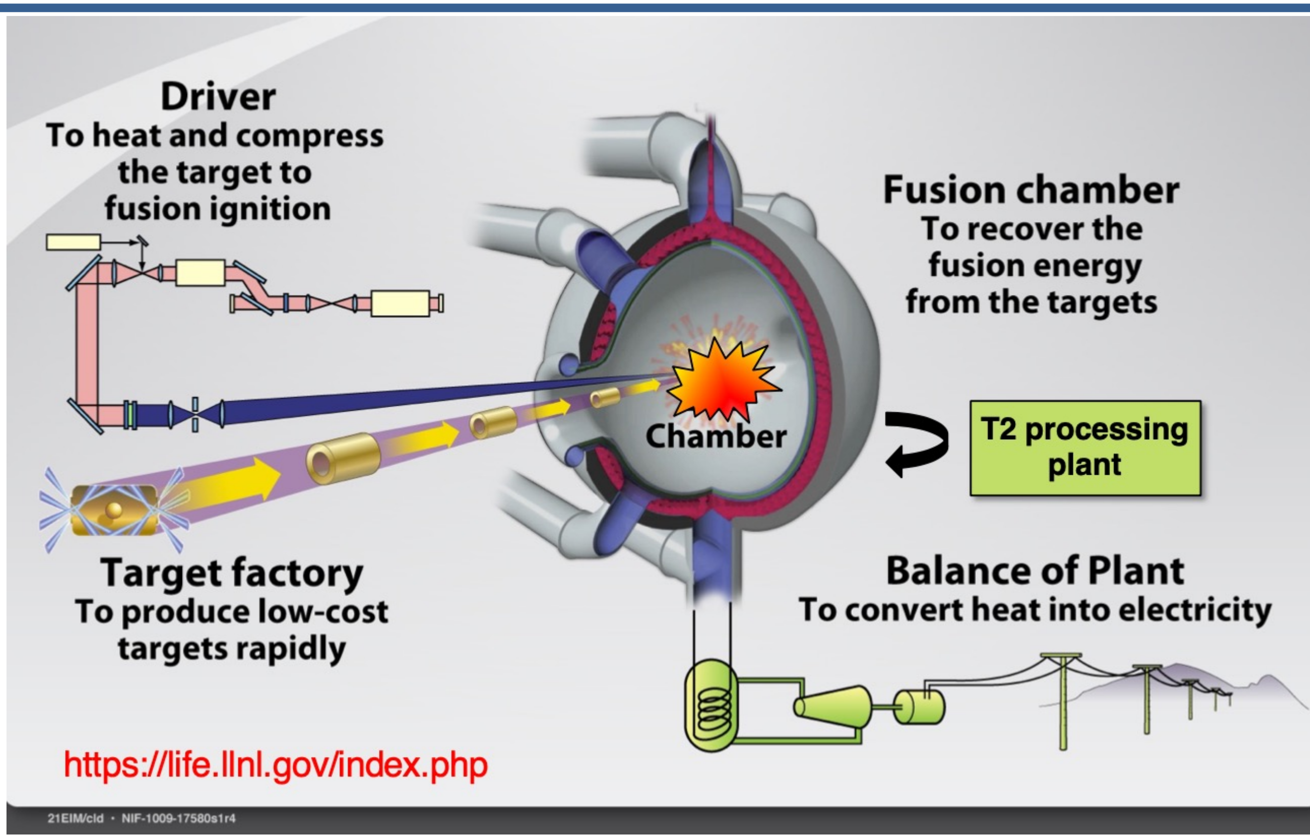
Most of the enabling technology exists, but integration will be the near-term focus



P. Hatfield, et al., Nat. Persp. (2020)



Conceptual IFE plants will need to operate highly complex systems at multi-Hz levels and will rely on S&T from HRR HED experimentation in the near-term



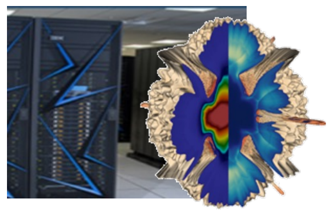
Cross-cuts

Both HRR HED and IFE have common near-term development needs across many areas

Optical Technology

Large optics

HPC & HED Codes

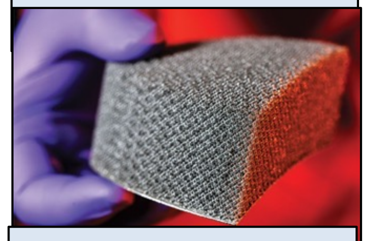


Advanced modeling, codes, ML & AI

Target Fabrication

Complex/rapid

Additive Manufacture



Novel materials, adaptive preparation

Laser Facilities

Large & Mid-scale

Community Ties

Labs, University, Industry

Diagnostics

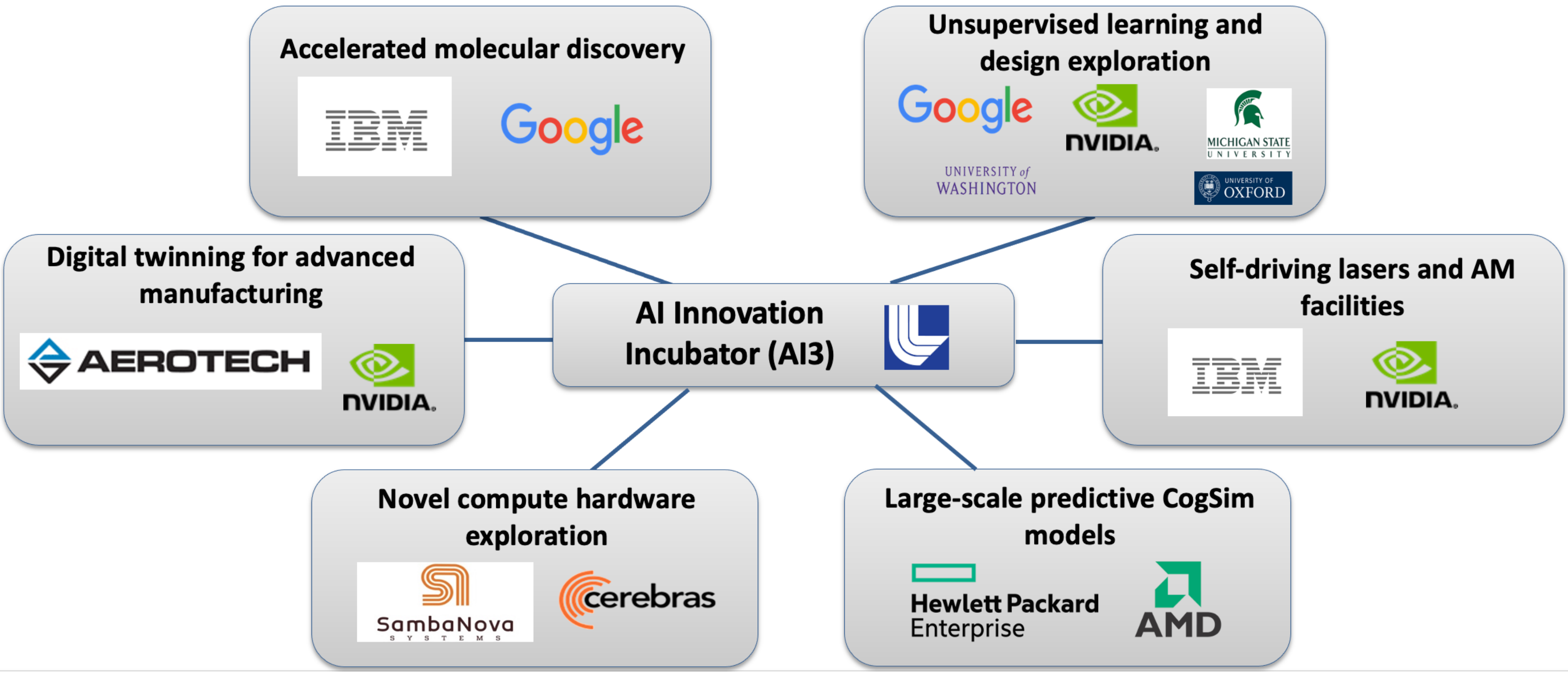
Robust, HRR-capable

Frontier Laser Technology

kW-MW Petawatt Lasers

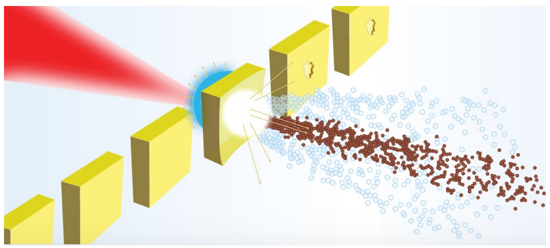
Many component technologies exist, but further development is required to enable them to work in concert with minimal human influence

There is a wealth of expertise in AI/ML to draw from and partnerships will be vital to making rapid progress



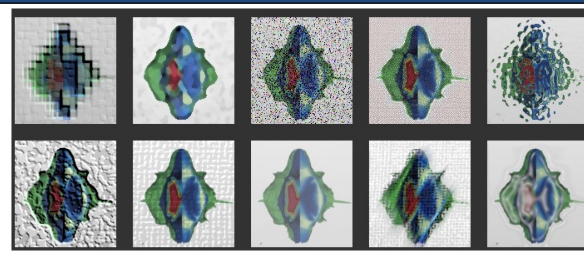
HRR experimentation provides a path to massively accelerate the rate of learning from laser-driven HED plasma experiments and will be key to development of IFE

HRR Experiments



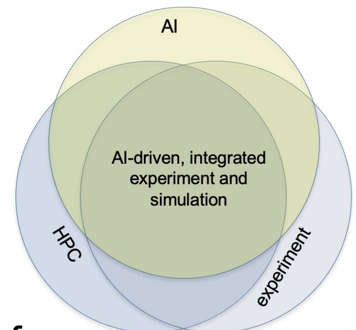
- Opportunity to accelerate data throughput by $>10^4$
- Massive multi-D parameter scans
- Meaningful uncertainties from statistics
- True data-driven science in laser plasma experiments

"Ensemble" Modeling



- Requires many 1k's of low- to mid-fidelity simulations
- Massive multi-D parameter scans
- Surrogate model creation to guide experiments
- Synthetic diagnostics for comparison to expts.

Machine Learning/AI



- ML for:
  - fast/safe laser operation
  - diagnostic analysis
  - Sim-based surrogates
  - "integrated analysis"
- An AI-like system will have to replace human intuition at HRR

Lawrence Livermore
National Laboratory