Enhanced Diagnostic Analysis through Deep Learning

LPA Workshop: Control Systems and Machine Learning
Tue. Jan. 25, 2021

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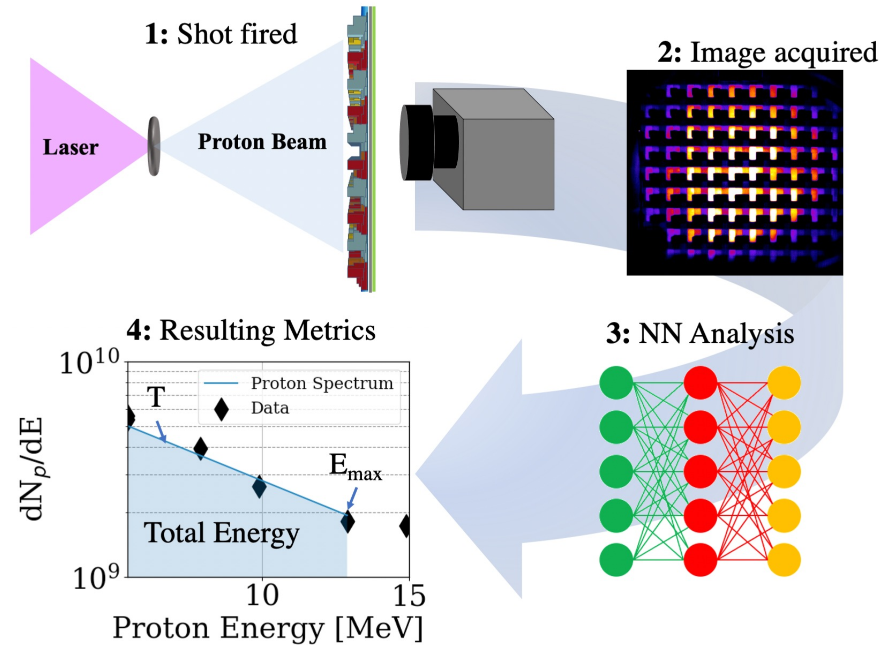
Summary

Neural Networks are an important technology for enabling on-the-fly high-repetition-rate experimental platforms

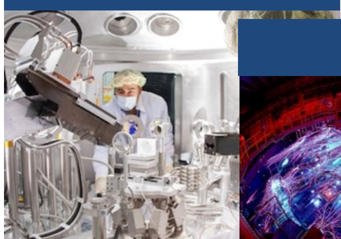
- *Neural networks (NN's) can be used to replace time-consuming "brute force" analysis*
  - *High accuracy results*
  - *High speed (ms depending on # of features)*
- *Accurate models for diagnostics should be used to prepare the best possible NN models*
  - *Process is to generate many examples of synthetic data to train network*
- *Visualizing NN results is important for both assessing model performance and potentially improving diagnostic designs*



Coupling high repetition rate lasers with AI will enable a new regime of HED physics

Currently we make use of some of the premier laser scientific facilities around the US and the world to conduct forefront HED science

MEC SLAC

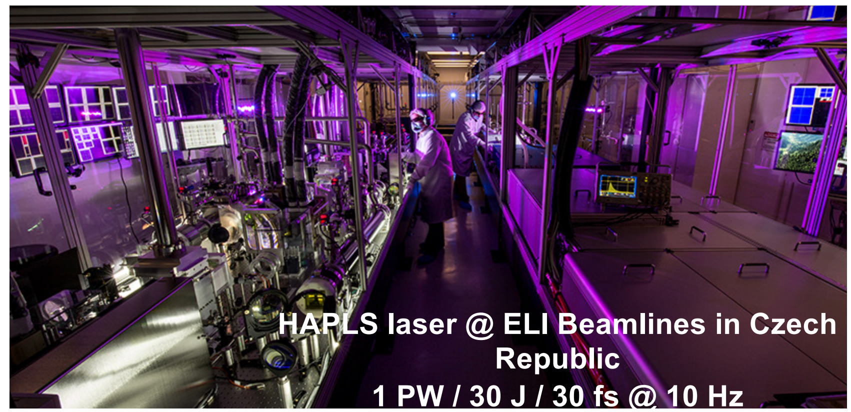


Z Machine

NIF

Until recently, much of HED has focused on large, energetic drivers that are mostly single-shot (~shot per hour)

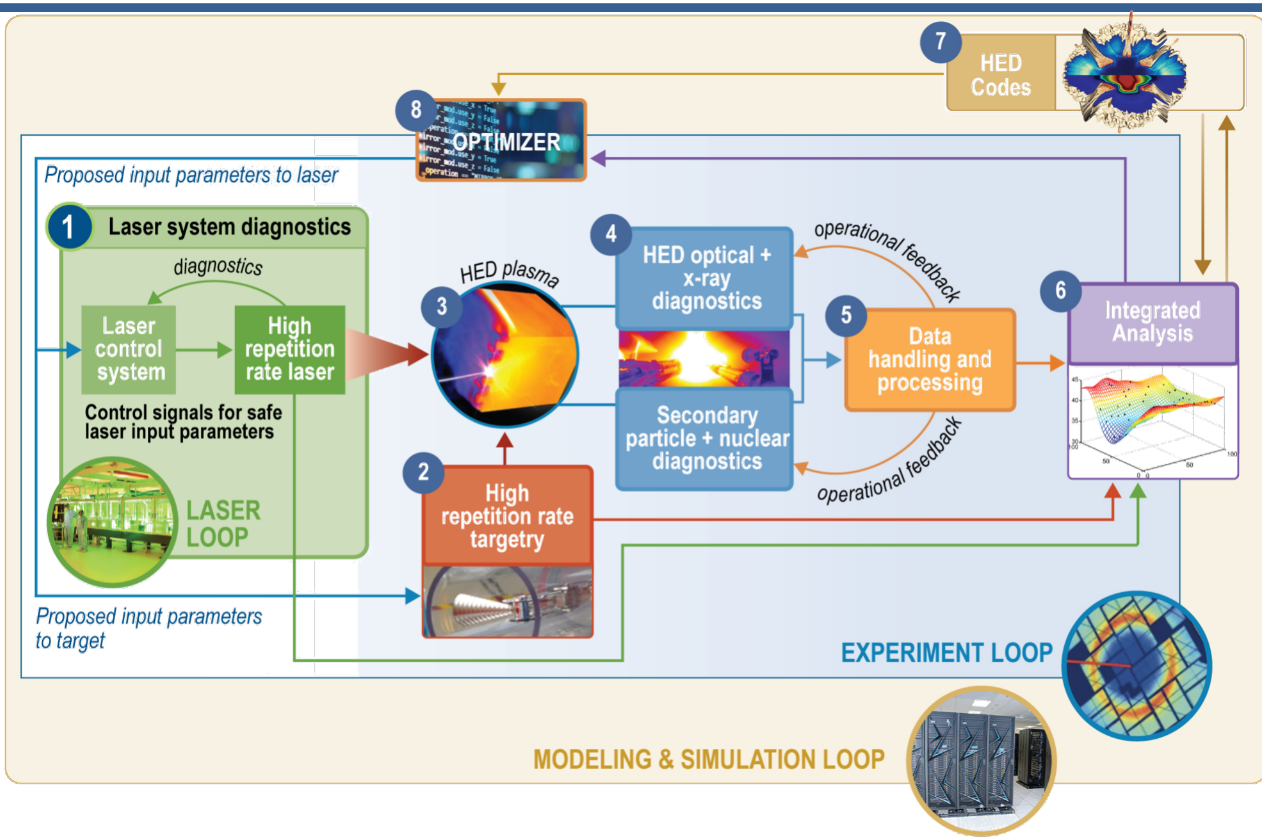
However, next-generation lasers coming online are already rep-rated (>10 Hz)



HAPLS laser @ ELI Beamlines in Czech Republic
1 PW / 30 J / 30 fs @ 10 Hz

We now have to shift paradigms, combining multiple emerging technologies with cognitive simulation to harness the possibilities of autonomous discovery

A self-driving laser system means a fully integrated system that leverages technological capabilities in many domains



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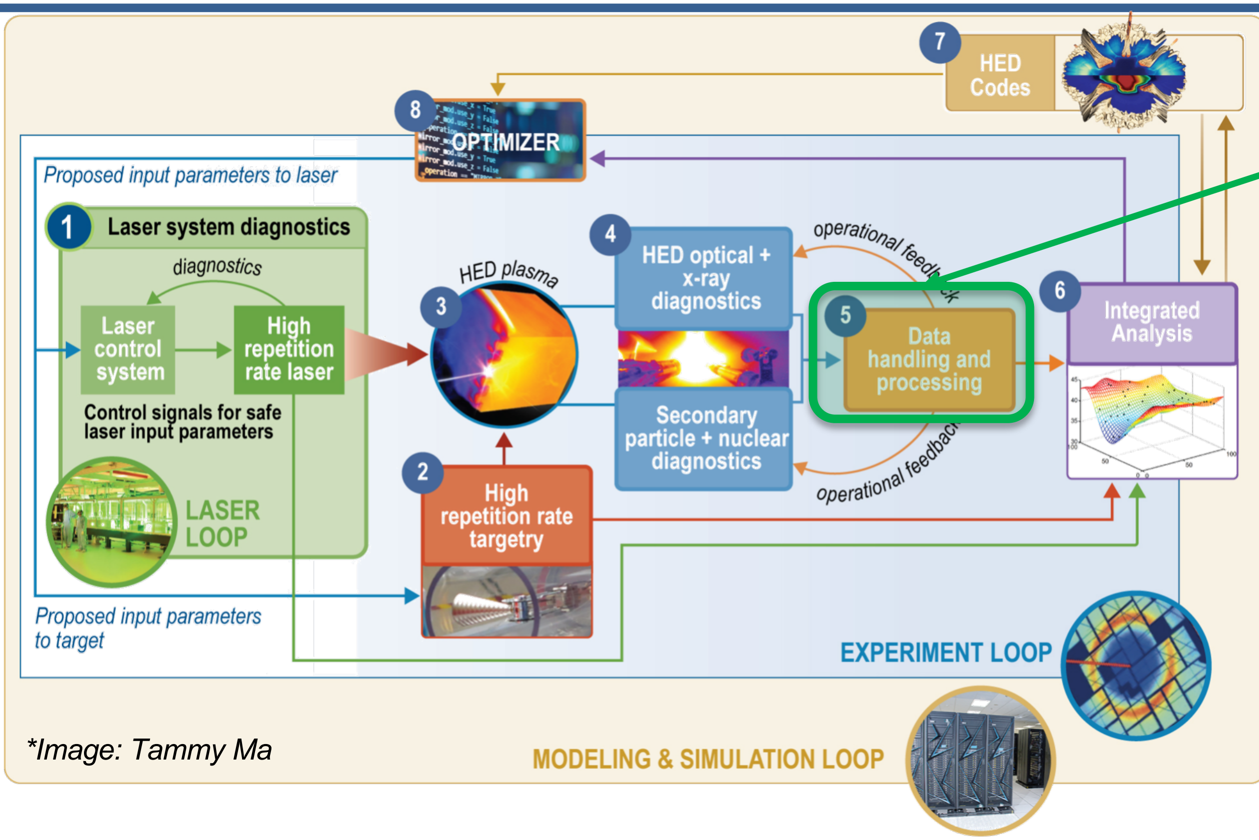
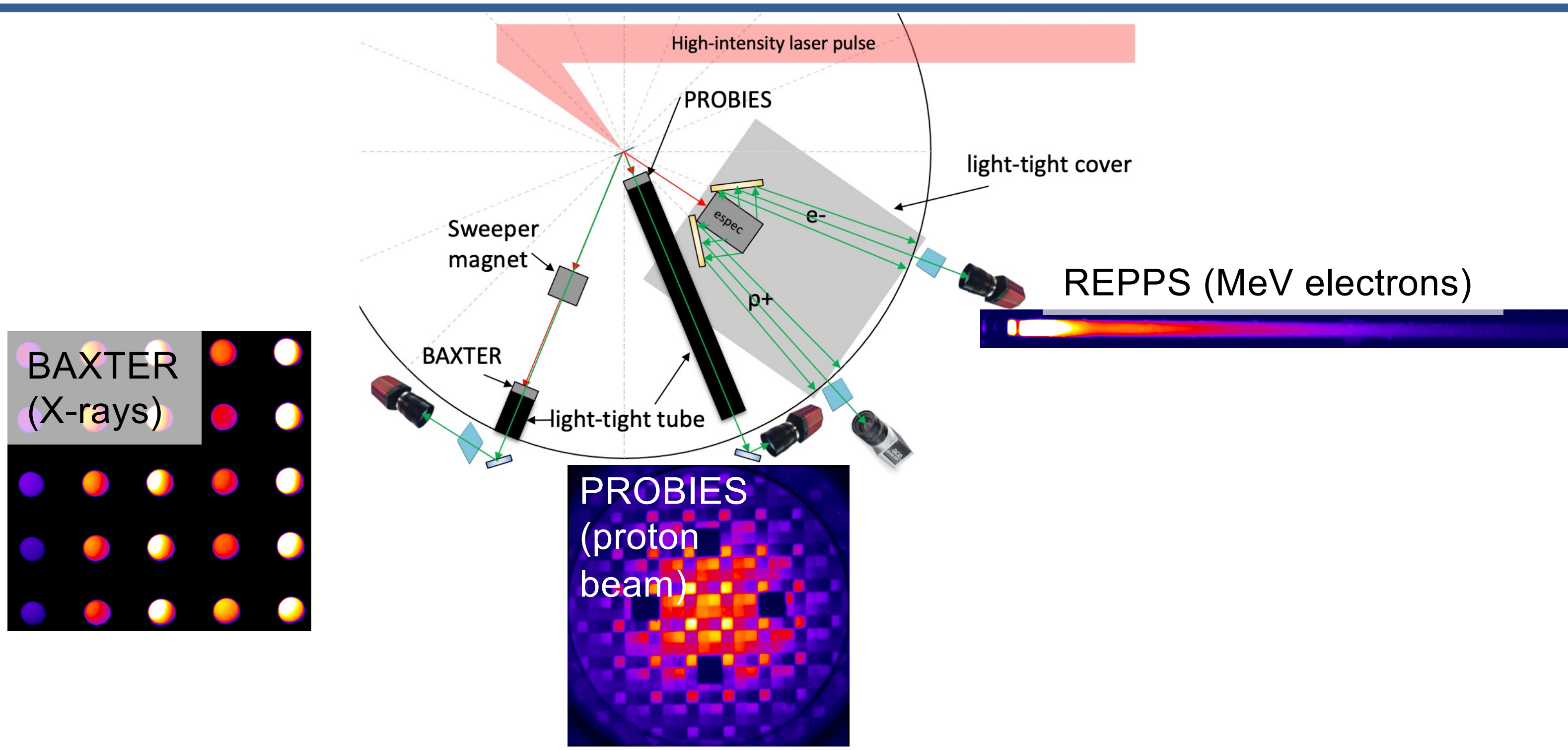


*Image: Tammy Ma

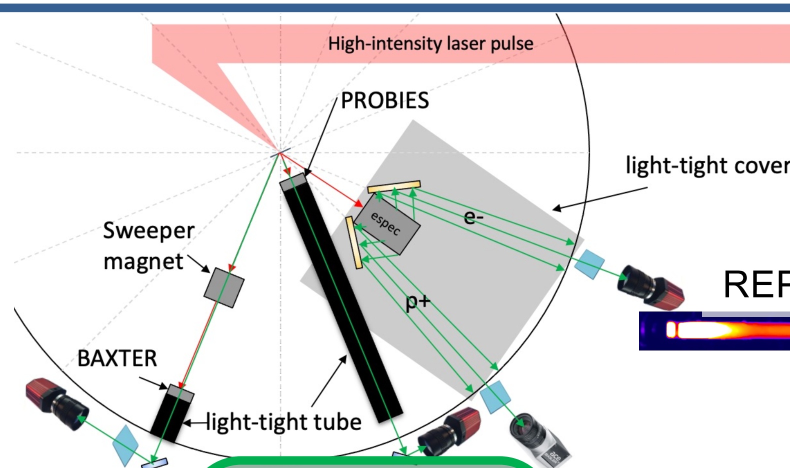
Focus of this talk

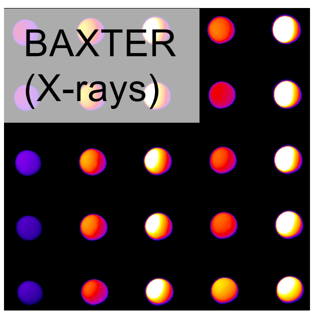
For this to work, diagnostic analysis needs to occur in between shots <<100 ms for 10 Hz

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

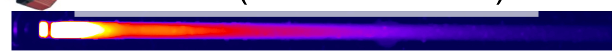


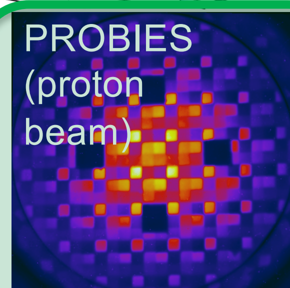
Prototype diagnostics developed at LLNL can record data from high-energy high-intensity laser experiments electronically





REPPS (MeV electrons)

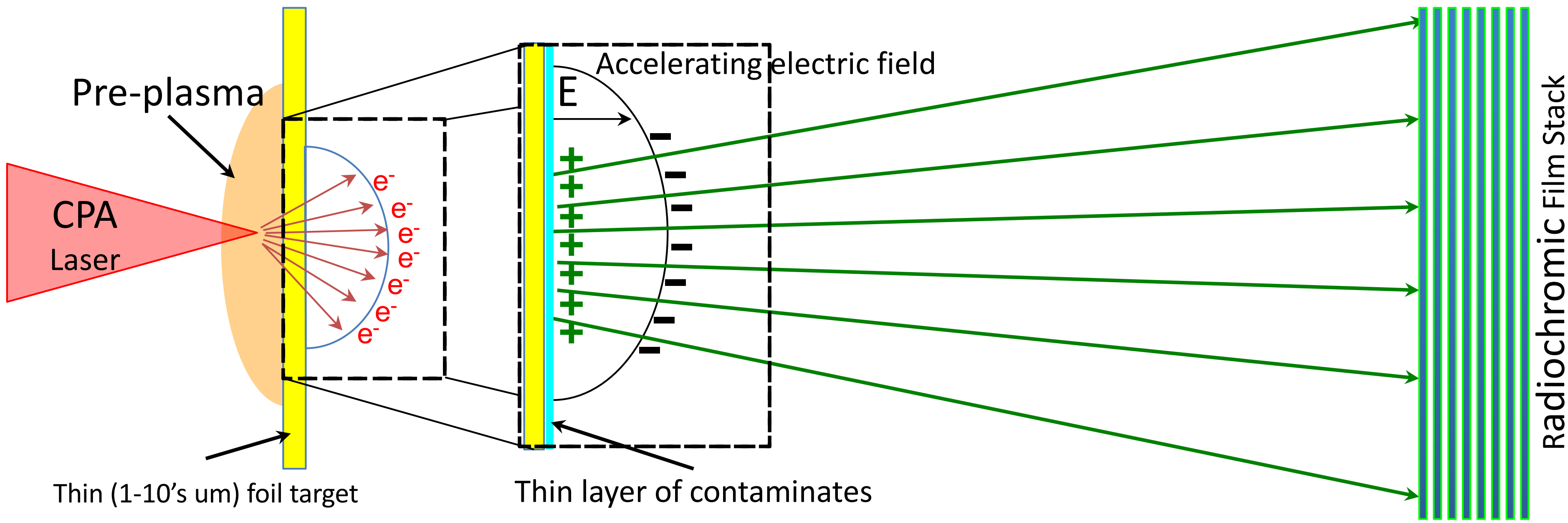




Example for this talk

The PROBIES (proton beam imaging energy spectrometer) has been designed to measure the properties of laser-driven MeV proton beams

MeV energy protons can be accelerated by shooting short-pulse high-intensity lasers at thin (μm’s) targets



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

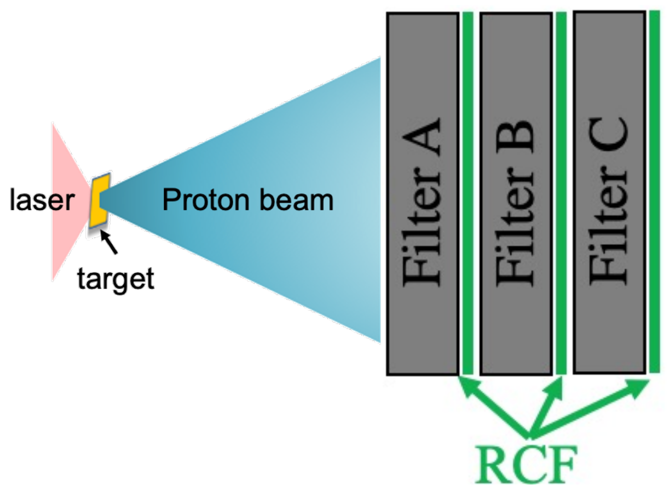
$$T_{e-hot} \approx mc^2 \left(1 + \frac{2U_p}{mc^2}\right)^{1/2}$$

- Protons accelerated from rear surface of foil[1]
  - Large electric field ~TV/m
  - Proton energies proportional to hot electron temperature (relativistic Maxwellian)

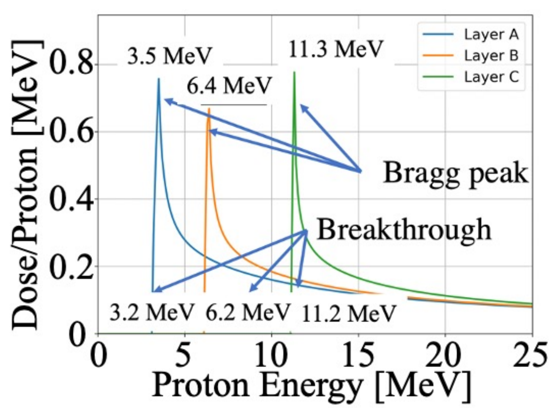
[1]S. C. Wilks, et al, PoP, (2001)

Commonly, stacks of films and filters are used to obtain energy and spatial distribution of proton beams

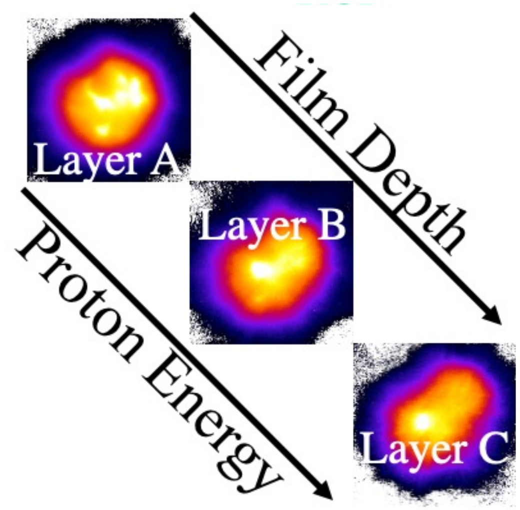
Beam/Detector Setup



Calculated Response of Films

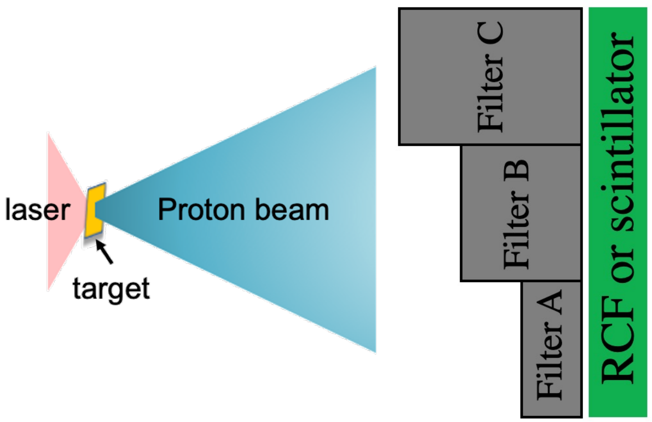


Example Data



Equivalently, we can arrange filters to sample different proton energies at different spatial locations on a single detector

Beam/Detector Setup



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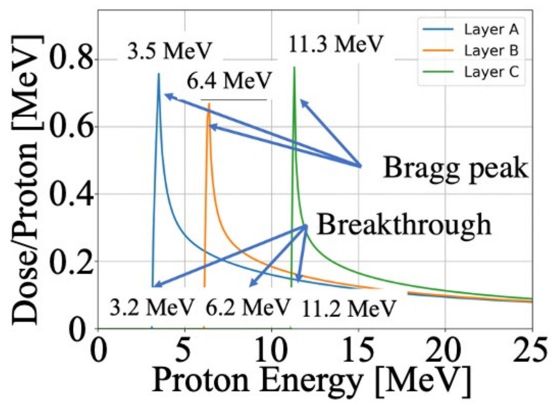
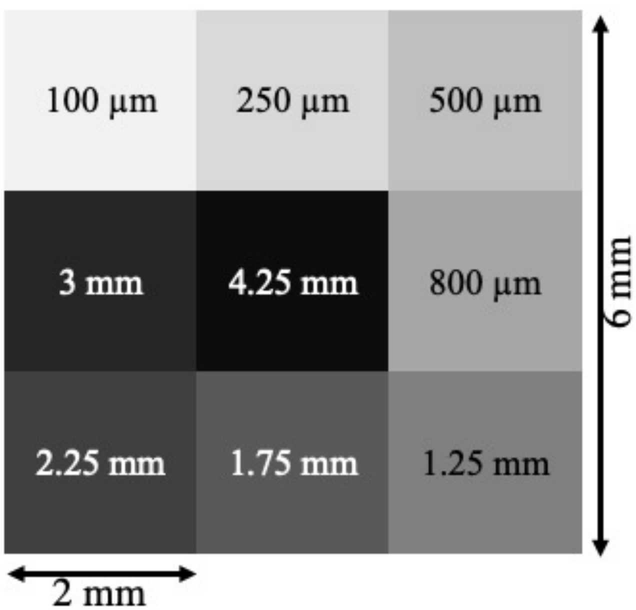


Diagnostic concept: Metzkes J, et al., RSI. 87 083310 (2016); Dover N et al, RSI 88 073304 (2017)

We can extend this concept further by deceasing the transverse size of the filters and arranging them in a pattern

Filter Thicknesses



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Filter Thicknesses

100 µm	250 µm	500 µm
3 mm	4.25 mm	800 µm
2.25 mm	1.75 mm	1.25 mm

2 mm

6 mm

Proton Breakthrough Energies

>2.5 MeV	>4 MeV	>6 MeV
>16 MeV	> 18 MeV	>8 MeV
>14 MeV	>12 MeV	>10 MeV

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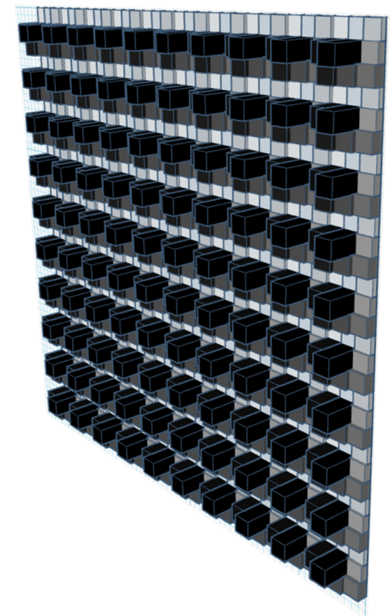
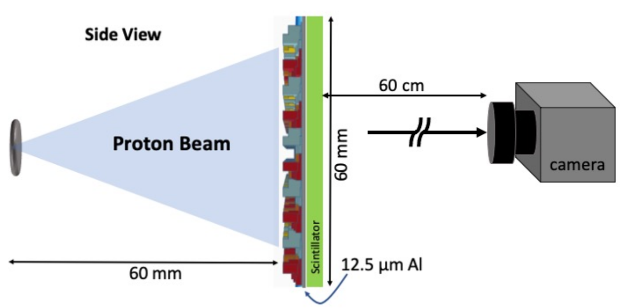
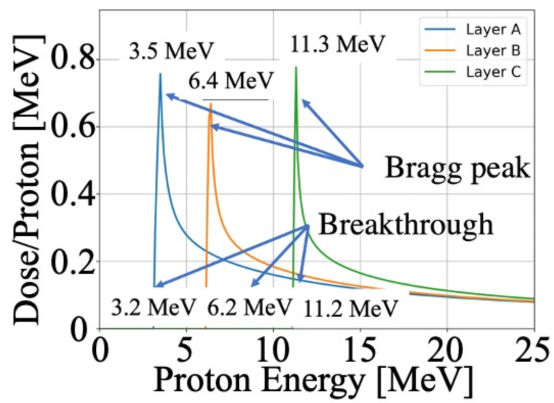
Full Arrangement

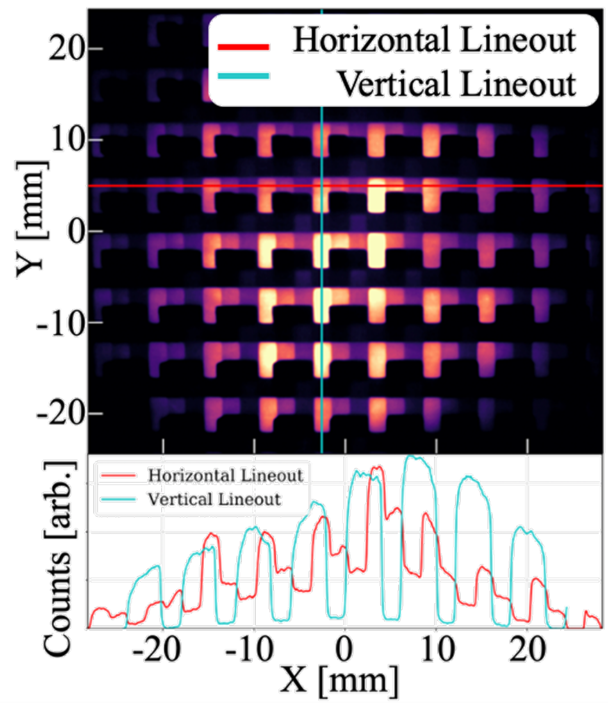


Coupled with a scintillator and a sCMOS detector, PROBIES can replace RCF to detect proton beams at HRR

Beam/Detector Setup	Calculated Response	Example Data



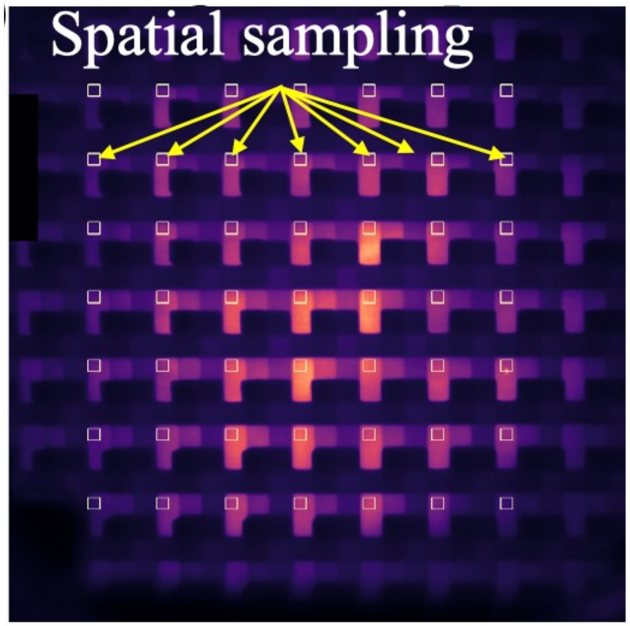




D.A. Mariscal, *et al*, "Design of Flexible Proton Beam Imaging Energy Spectrometers (PROBIES)", *Plasma Plasmas and Controlled Fusion* (2021)

“Brute force” analysis is straight-forward, but time-consuming

1) Sample the data



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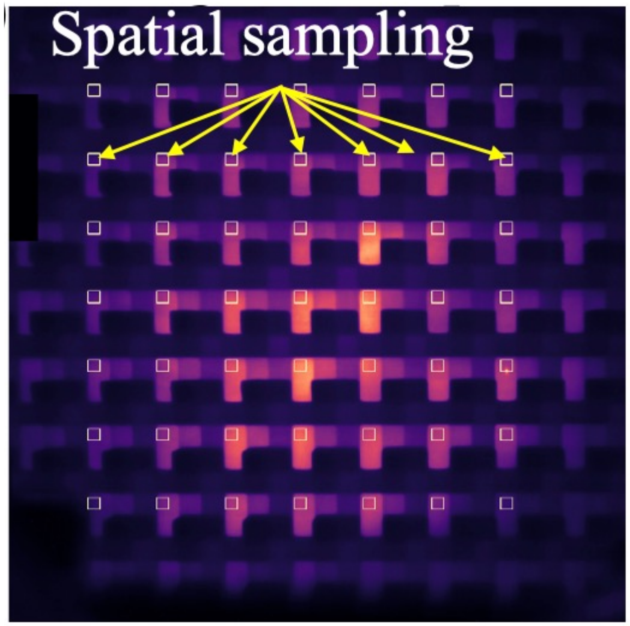
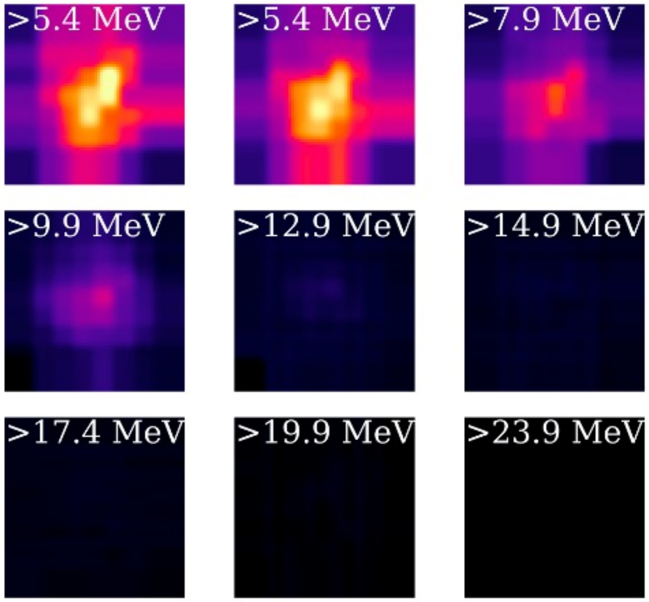
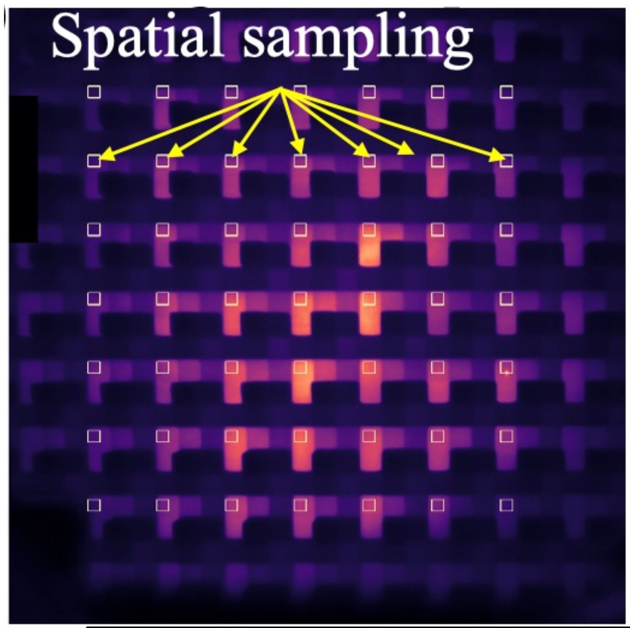


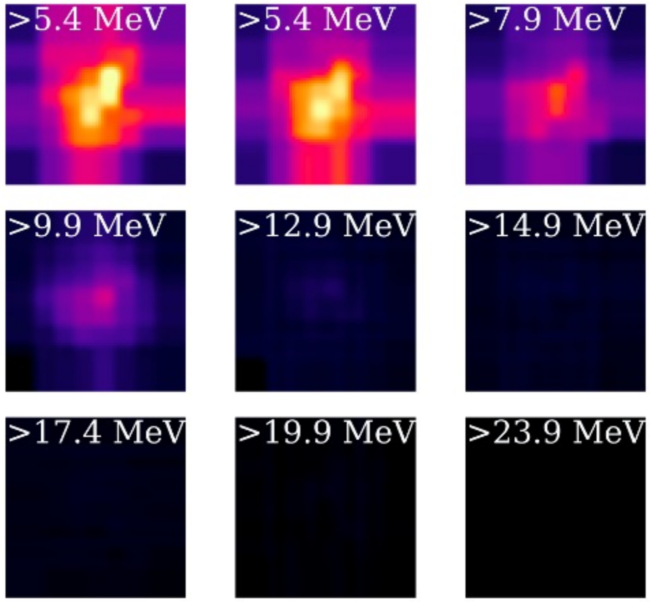
2) Interpolate new images

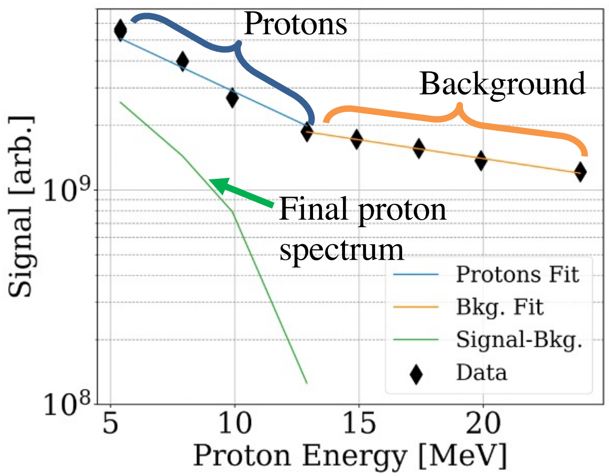


"Brute force" analysis is straight-forward, but time-consuming

1) Sample the data	2) Interpolate new images	3) Reconstruct proton spectrum

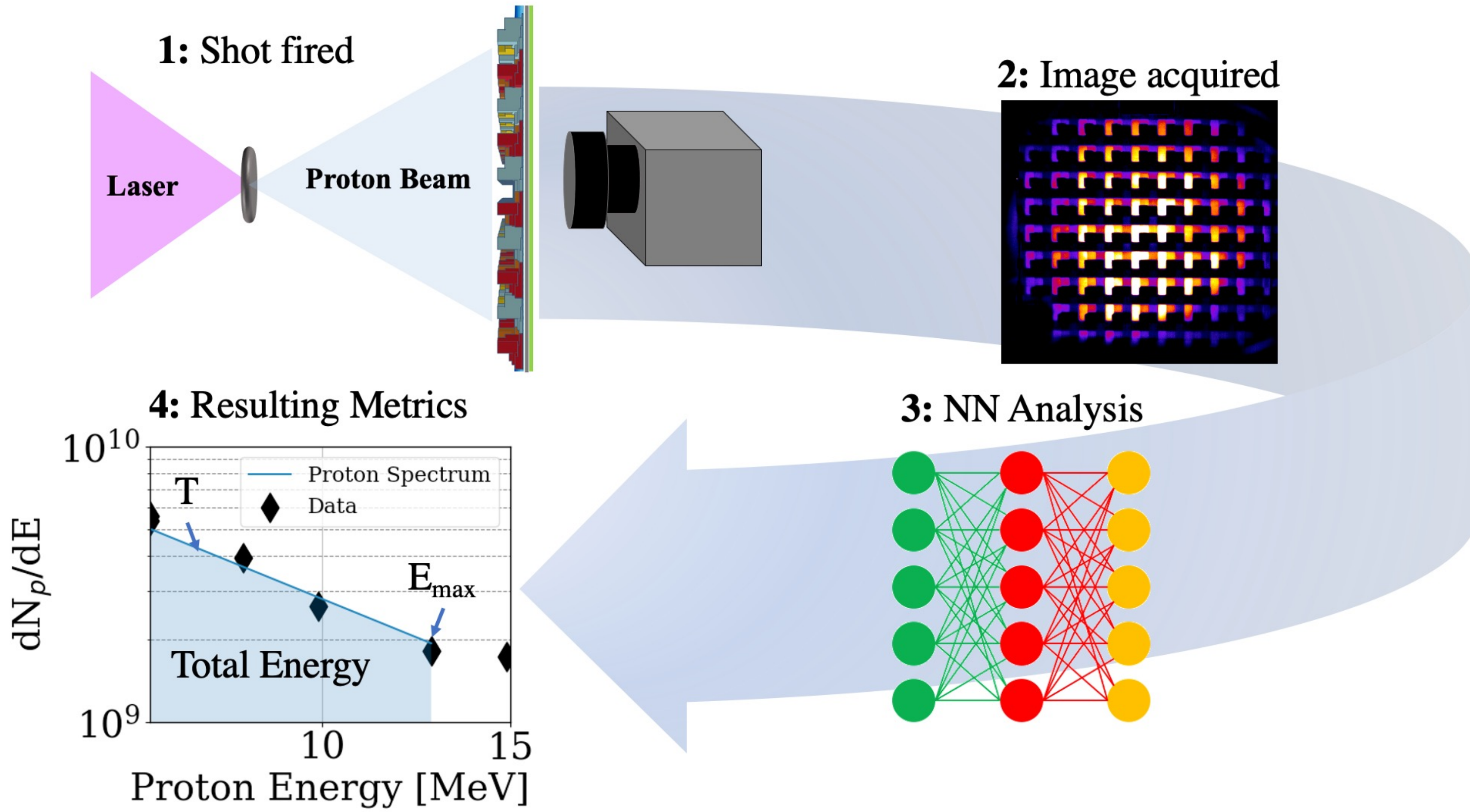






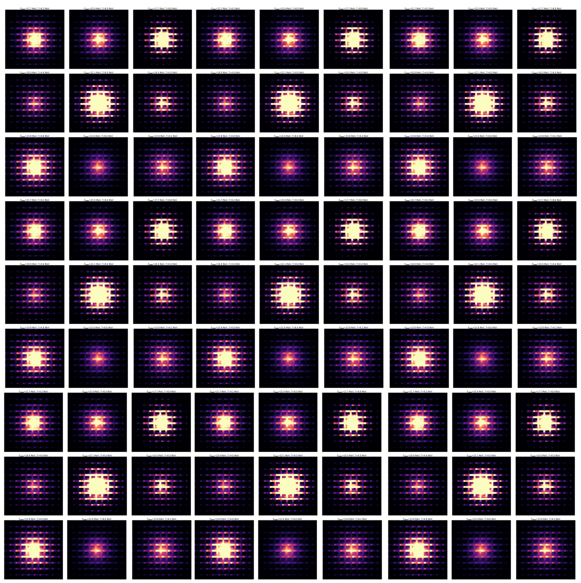
On a modern laptop, this takes 10's of seconds to produce the spectrum and metrics of interest

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



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

1) Generate LOTS of data



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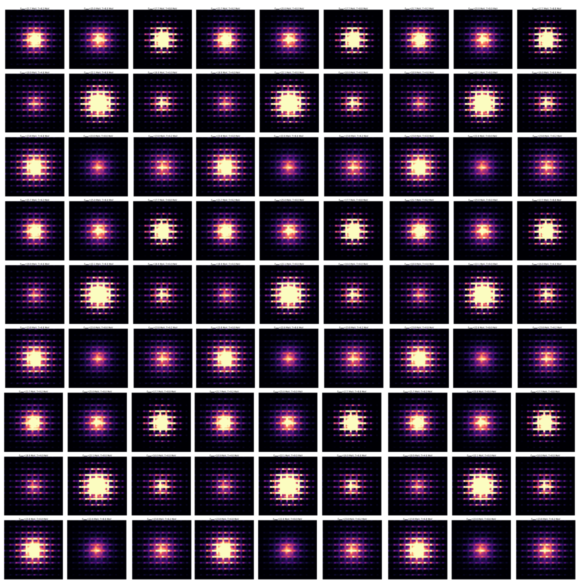
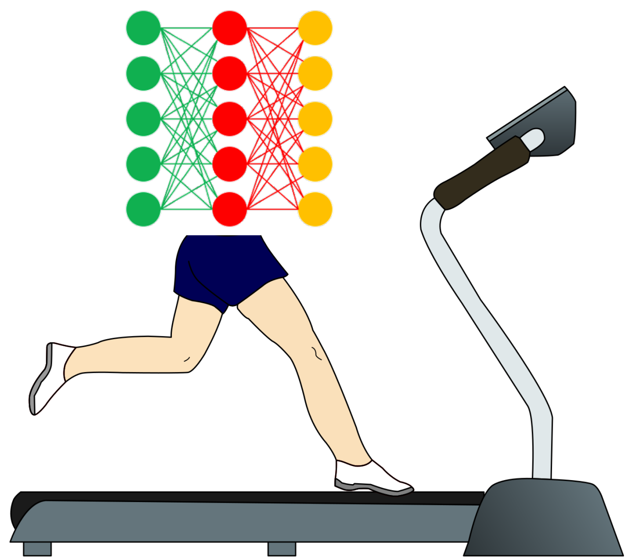
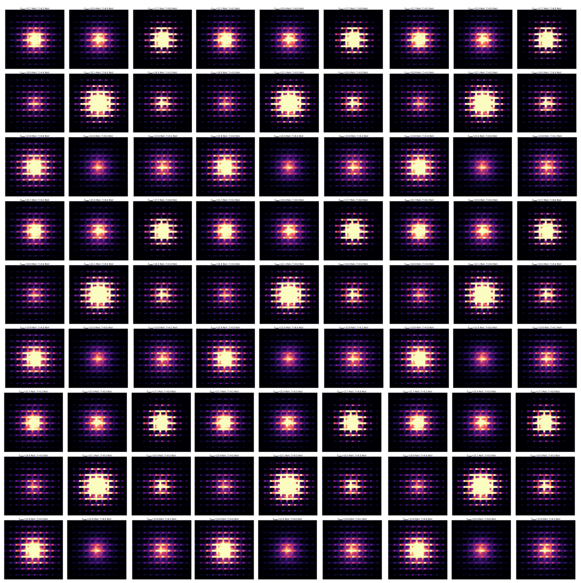


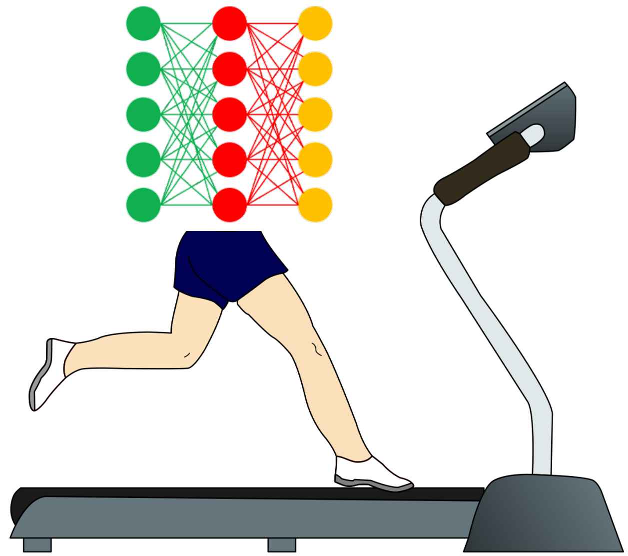
2) Train your NN



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

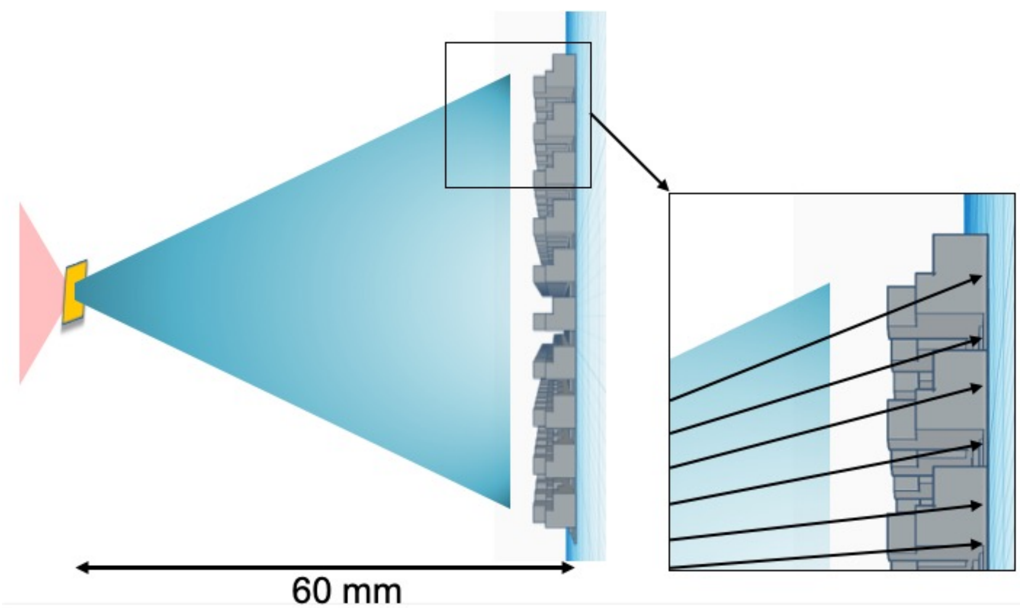
1) Generate LOTS of data	2) Train your NN	3) Never analyze data again



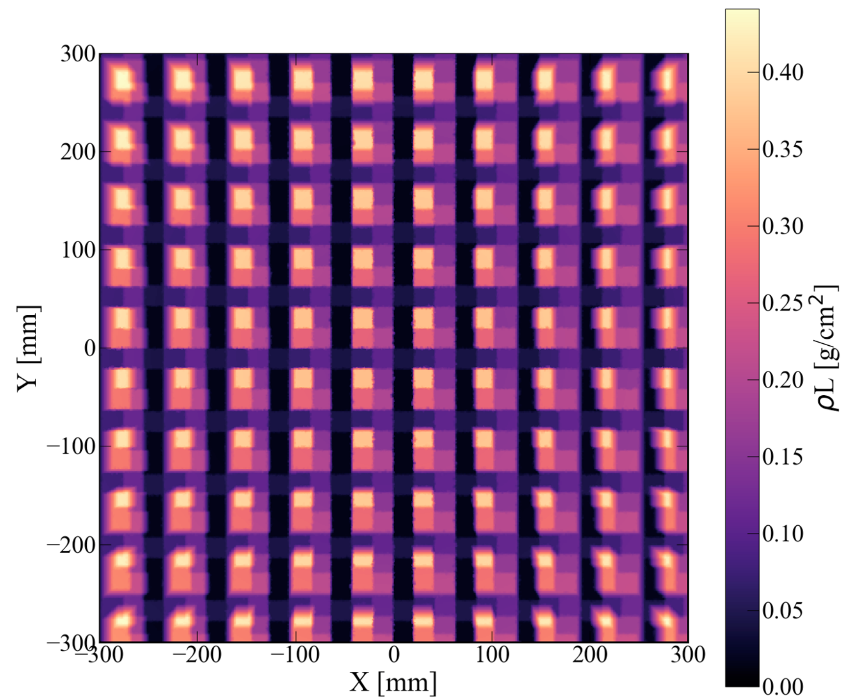


To demonstrate this concept, we use a diagnostic model to create a large database of synthetic data

Ray-trace through 3D filter

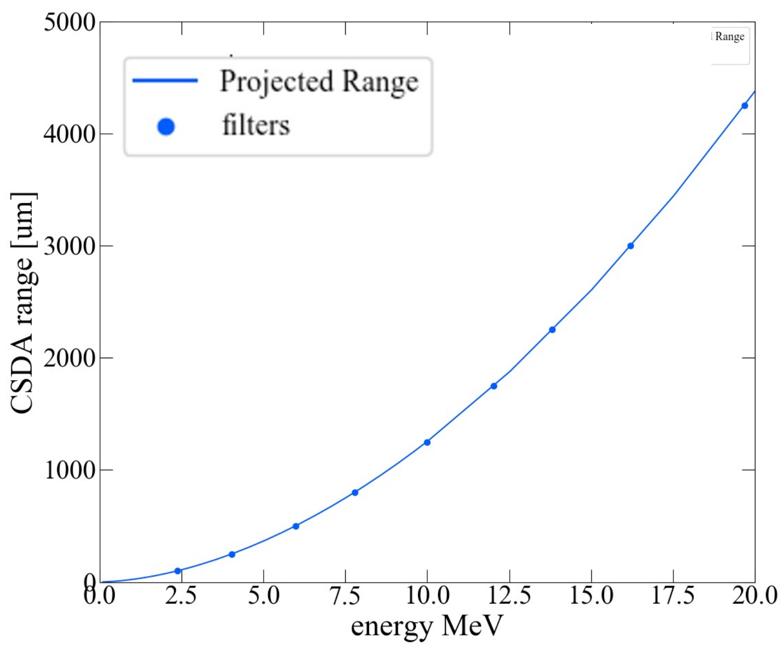


Line-integrated areal density map

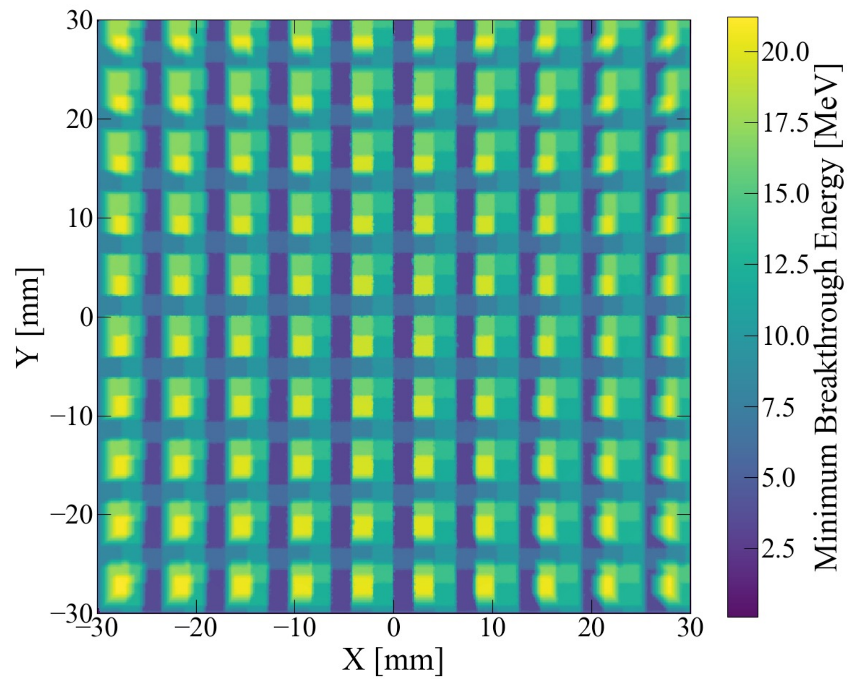


Next step is to determine the minimum proton energy required to "break through" at each point

Breakthrough Energy vs. Filter Thickness*



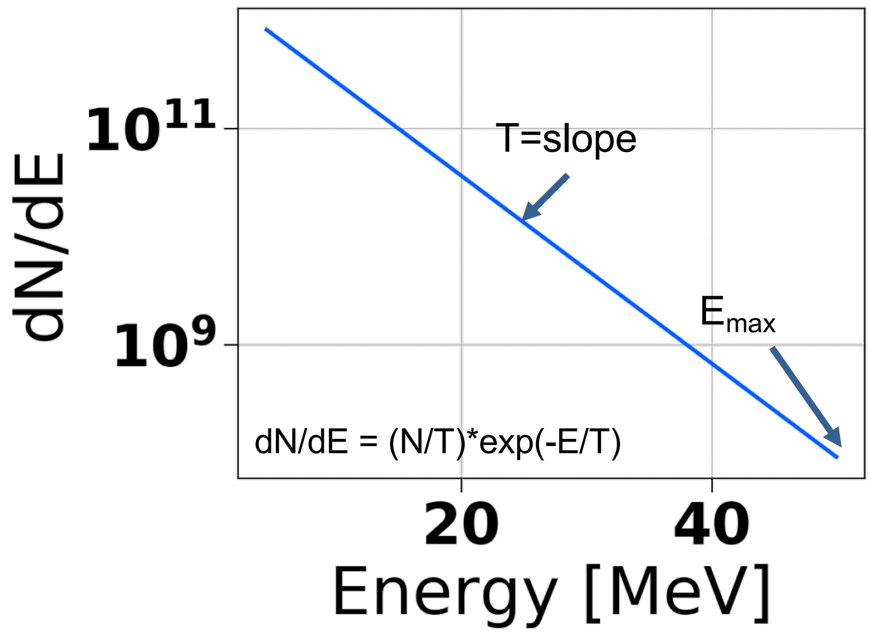
Map of proton breakthrough energies



*NIST PSTAR or stopping range of ions in matter (SRIM)

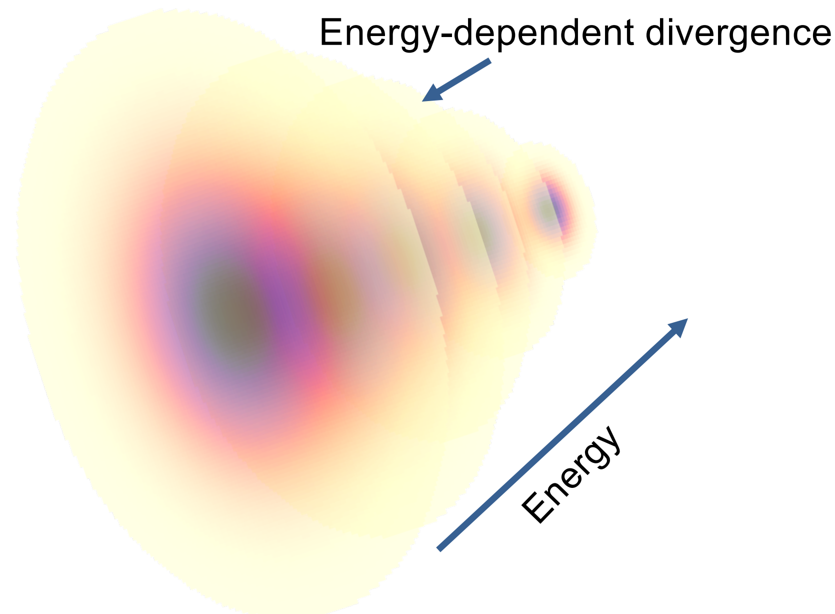
We then assume a proton spectrum and beam profile

Assumed Proton Energy Spectrum



1. Pick N, T, and Ep-max

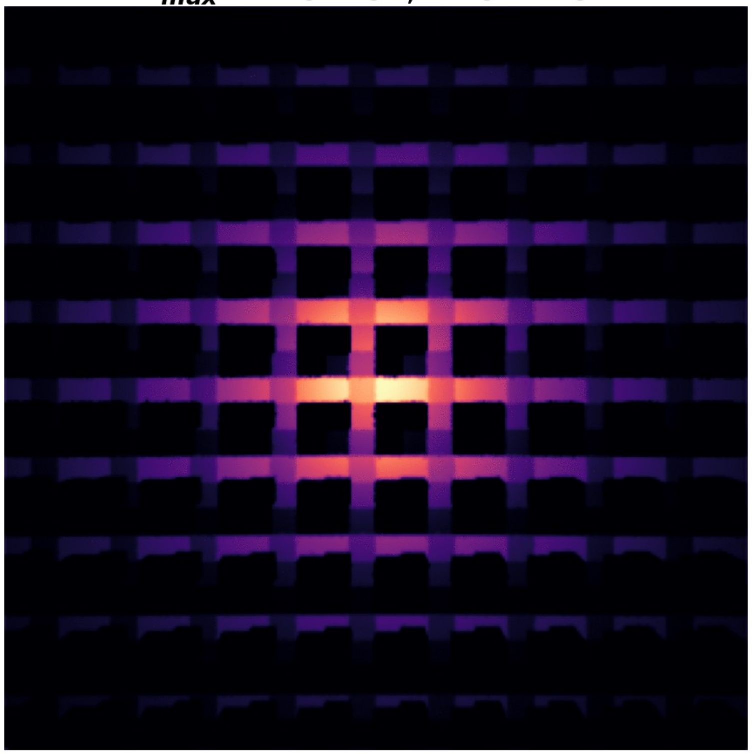
Proton Beam energy vs. Spatial Profile



2. Create “slices” of proton beam and compare/integrate signal from protons

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

E_{max}=11.9 MeV, T=8.2 MeV



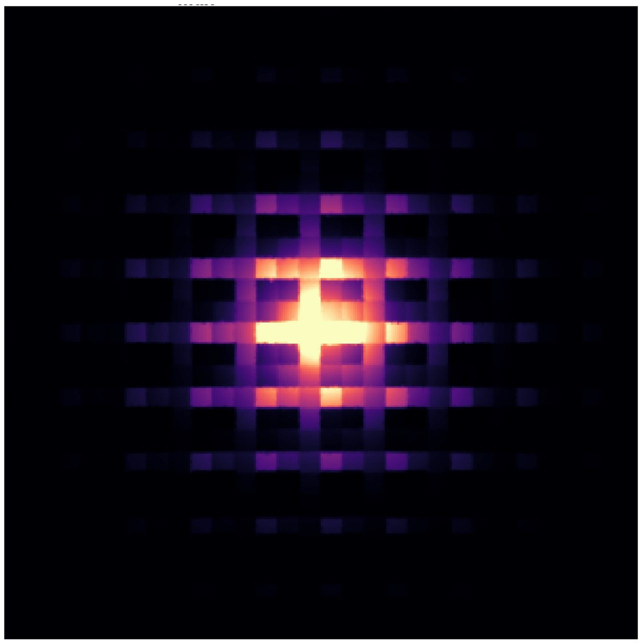
4D parameter scan for data generation

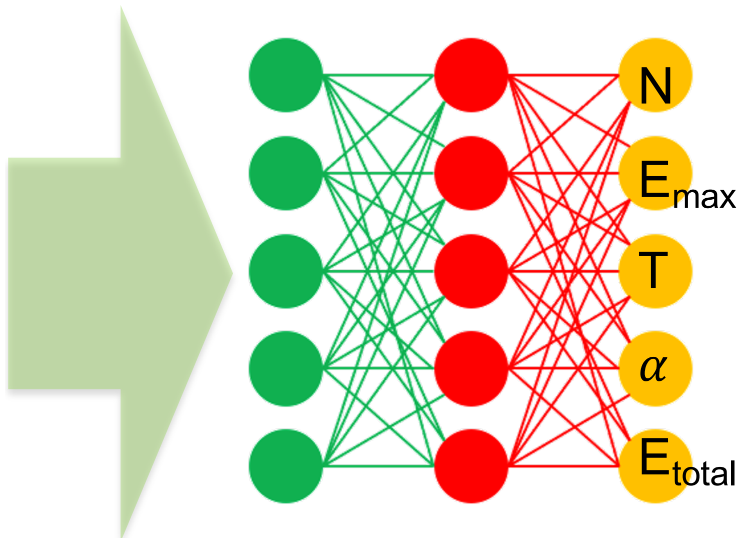
- N→ 10^{10} - 10^{12}
- T→ 0.25 - 5 MeV
- E_{max} → 5 - 35 MeV
- Divergence_alpha → 25 – 40 deg

Use LHS to generate ~20k sample images

These images are also augmented with noise, etc. to expand the total number of examples to ~100k

Once we have the data, it is straight-forward to train a neural network to extract our analysis quantities





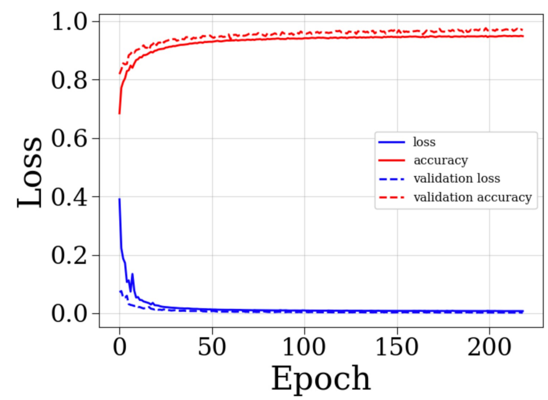
Simple NN (tensorflow)

Input

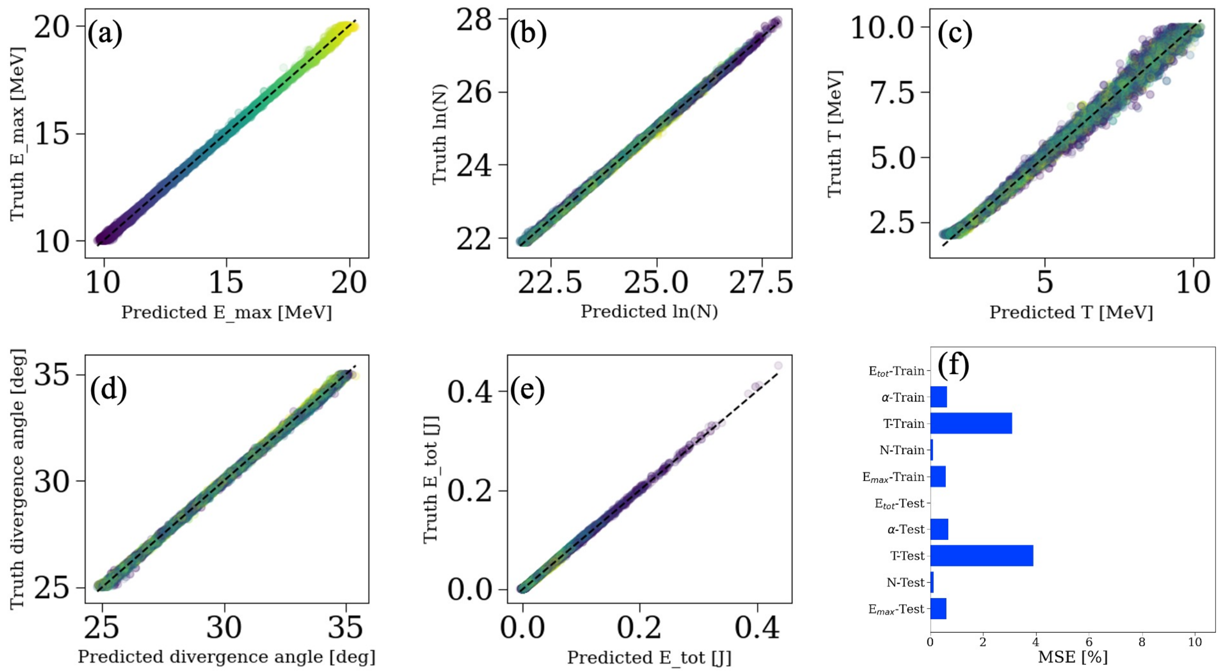
512 neurons (ReLU)

Dropout (20%)

Output: 5 neurons (linear)



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

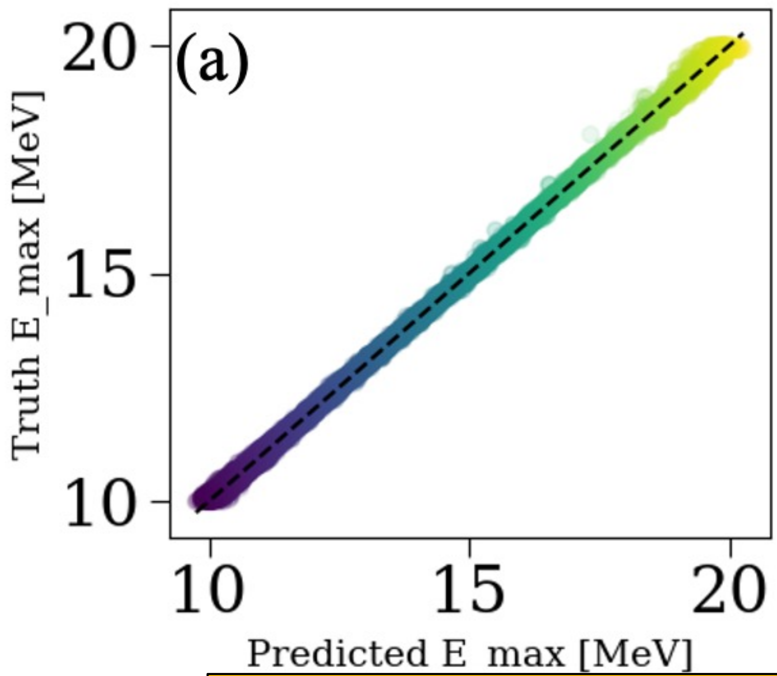


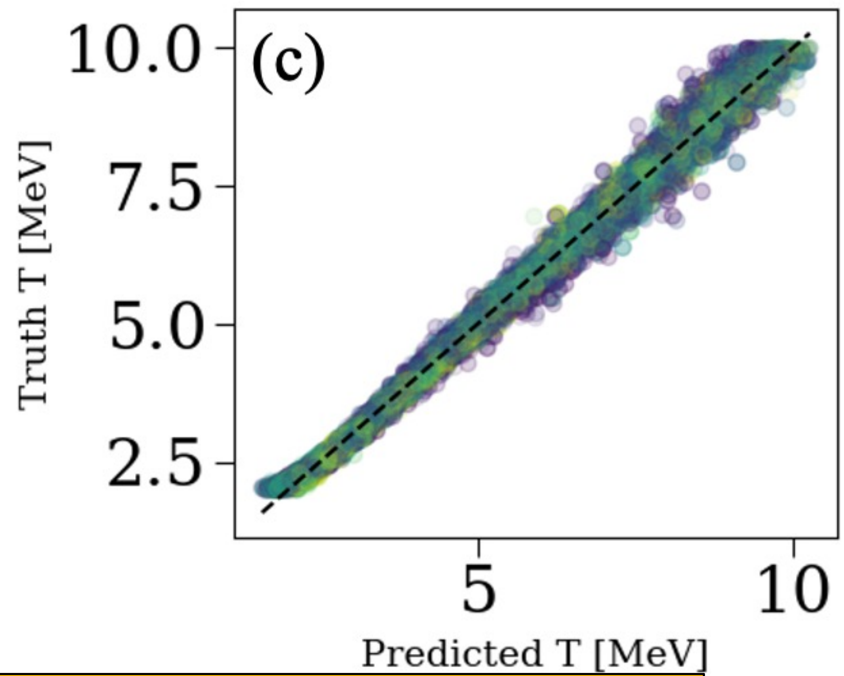
D.A. Mariscal, *et al*, "Design of Flexible Proton Beam Imaging Energy Spectrometers (PROBIES)", *Plasma Plasmas and Controlled Fusion* (2021)

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

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)

It is important to visualize your data to look for potential weaknesses in diagnostic design





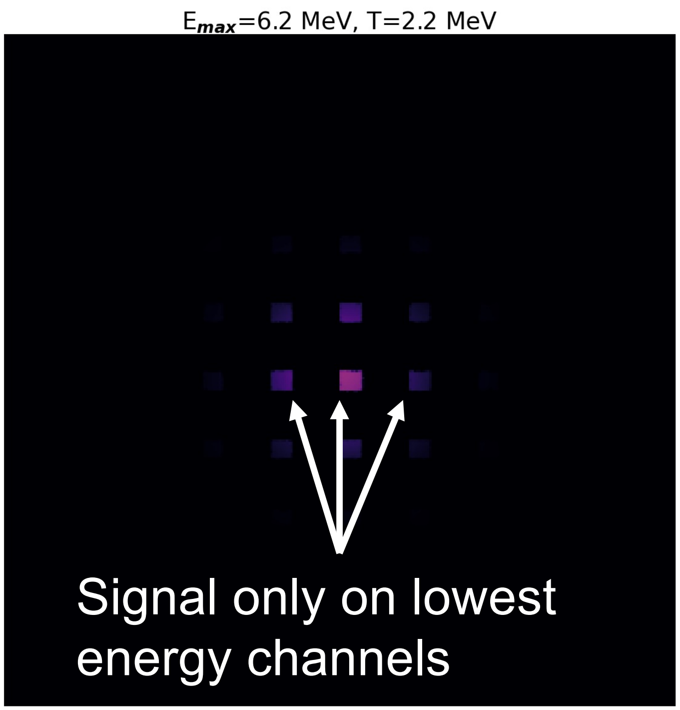
D.A. Mariscal, *et al*, "Design of Flexible Proton Beam Imaging Energy Spectrometers (PROBIES)", *Plasma Plasmas and Controlled Fusion* (2021)

The model struggles to predict the temperature of the spectrum when the maximum proton energy is low

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)

There is a simple reason for poor model inference of T at low max proton energies

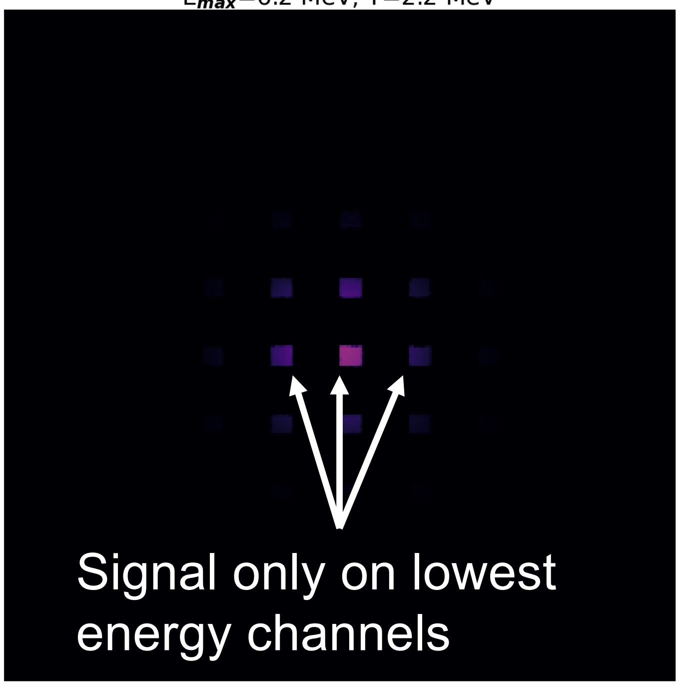
Low E_{max}

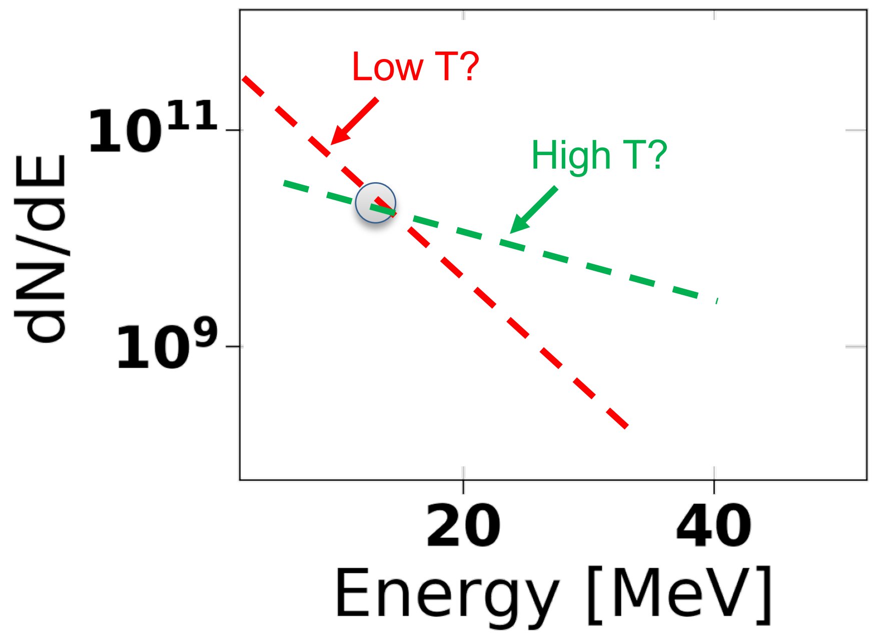


There is a simple reason for poor model inference of T at low max proton energies

Low E_{max}

E_{max}=6.2 MeV, T=2.2 MeV





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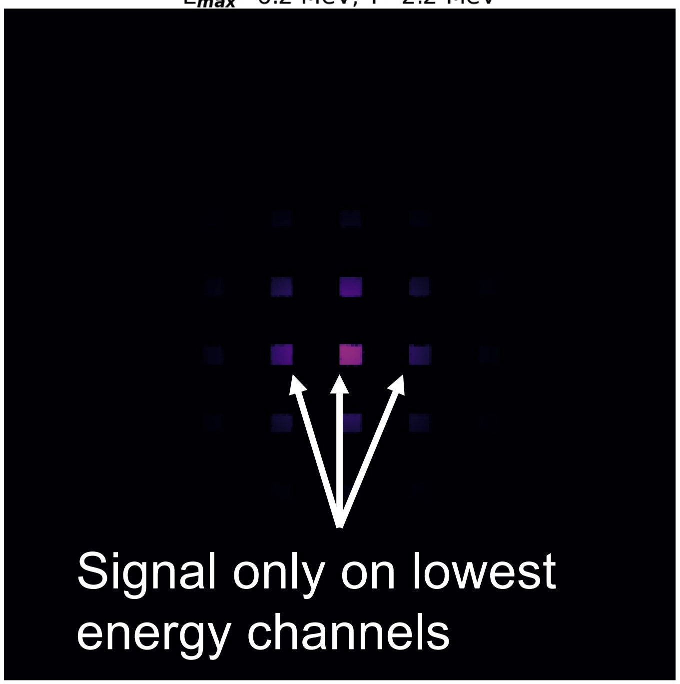
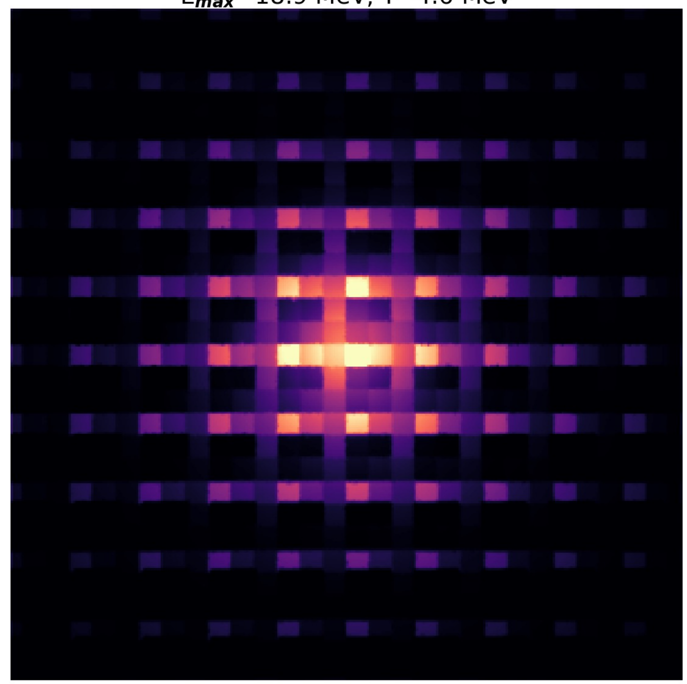
Low E_{max}	High E_{max}

E_{max}=6.2 MeV, T=2.2 MeV



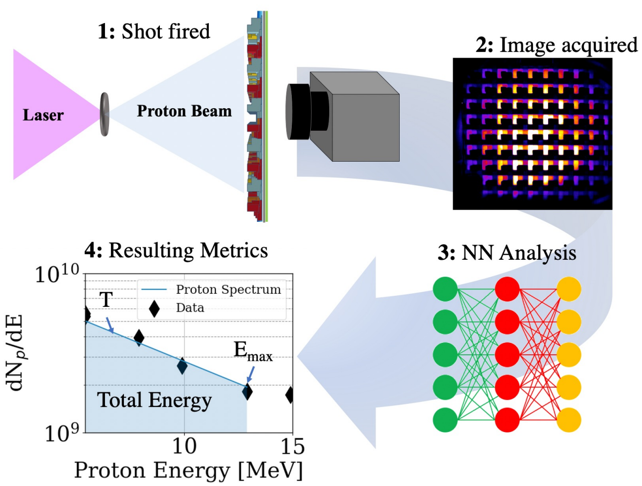
E_{max}=18.9 MeV, T=4.6 MeV



If you struggle to obtain good network performance, you may be exceeding the limits of your diagnostic

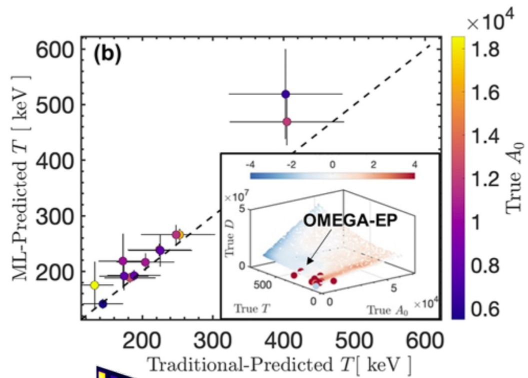
Deep learning will enable rapid, accurate, and rich data analysis

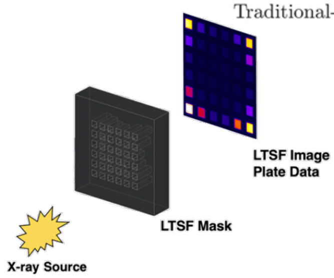
Proton Beams



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

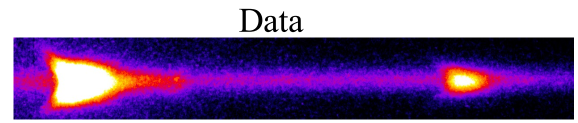
Multi-keV X-rays

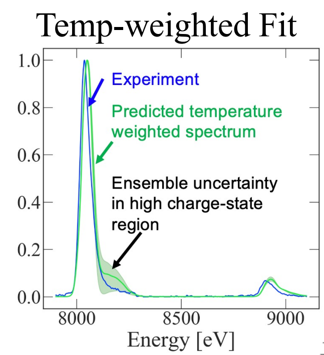


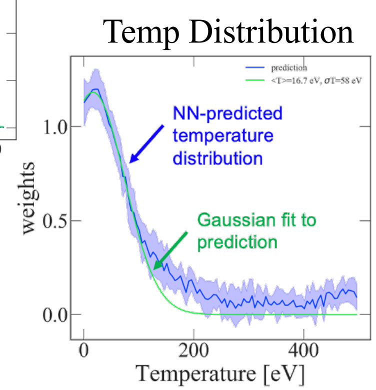


R.A. Simpson, et al., "Development of a deep learning based automated data analysis for step-filter x-ray spectrometers in support of high-repetition rate short-pulse laser-driven acceleration experiments", RSI 92, 075101 (2021)

Enhanced Analysis of X-ray Spectra







D.A. Mariscal, *In Preparation*

Discussion topic: What is the importance of feature reduction?

- Feature reduction has multiple important benefits
  1. Model training is significantly cheaper with reduced number of features
     1. Reduced RAM requirements for training: fewer features → more training examples → better informed models
     2. Inverse problem (generating diagnostic data from inputs), easier to evaluate training scores (even if MSE is small, can be large as N_features increases)
  2. Increased inference speed (tradeoff between speed/accuracy)
     1. Ex) inference on 60x60 images ~few ms (CPU) or < ms (GPU), → VGA resolution ~30 ms(CPU) or ~few ms (GPU)
     2. Enables lightweight hardware to be used at the edge (ex: NVIDIA Jetson, Coral TPU's, FPGA's)
     3. Extra time for ensemble NN's (uncertainty estimation)

*Possible that some diagnostics may be more accurate with more features

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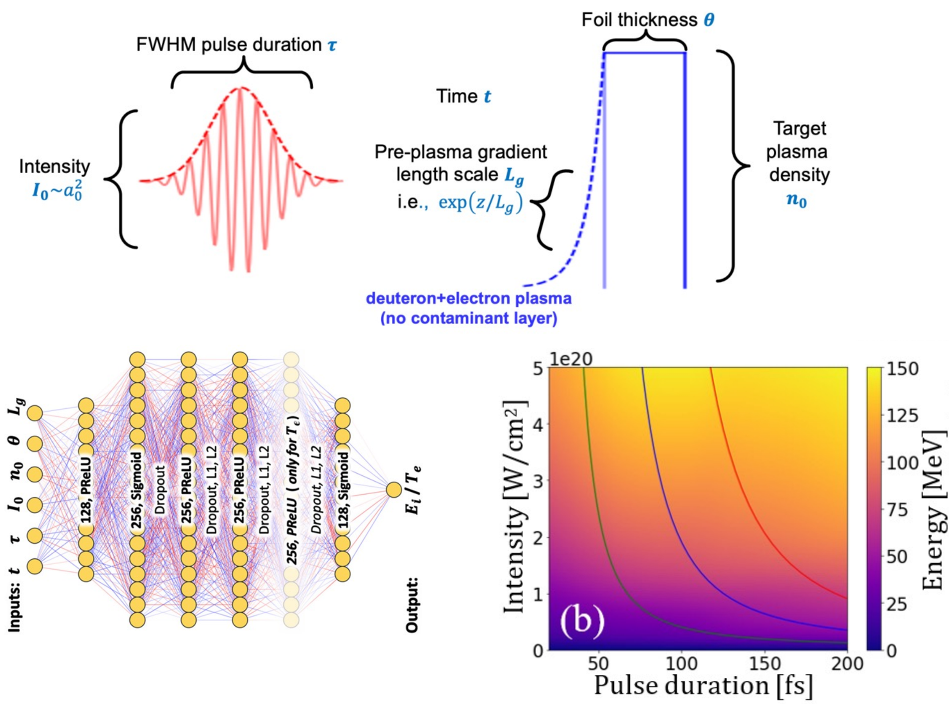
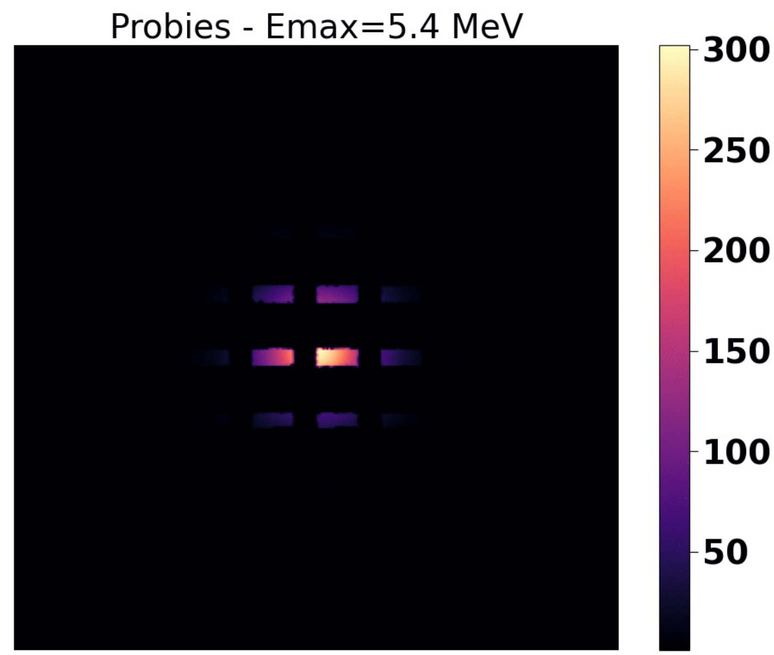
We are working to connect diagnostic analysis with ensemble PIC simulations to enable more detailed inference of exp. parameters

Proton Spectra from Ensemble PIC Sims



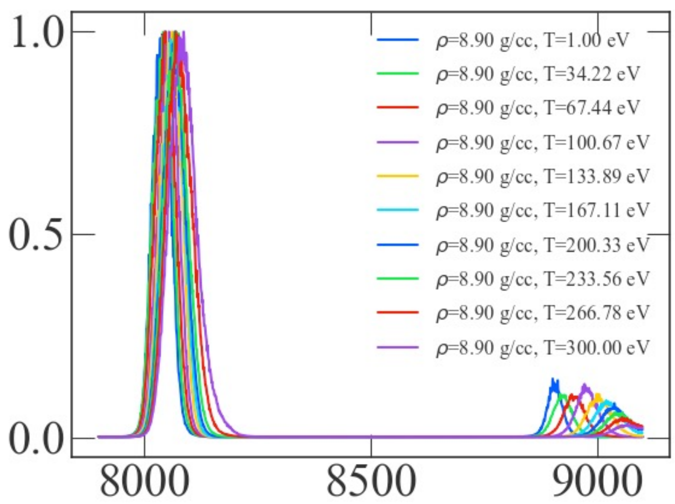
B. Djordjevic, et al., *Phys. Plasmas* **28**, 043105 (2021)

Synthetic PROBIES data from Sims

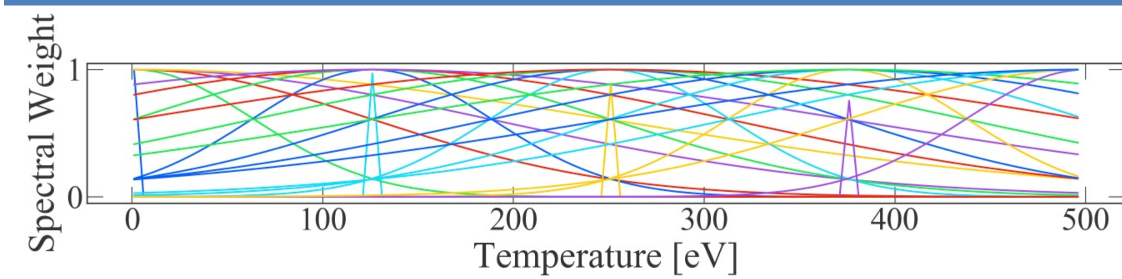


Neural networks can be taught to find temperature/density distributions in experimental data, as opposed to single values

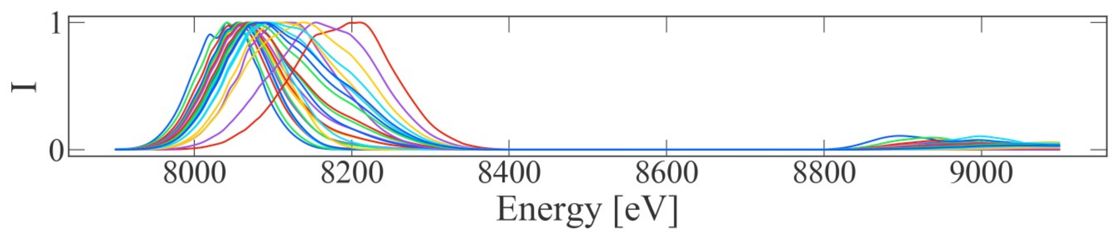
1. Use surrogate to generate several hundred spectra



2. Generate a large number of Gaussian weighting distributions

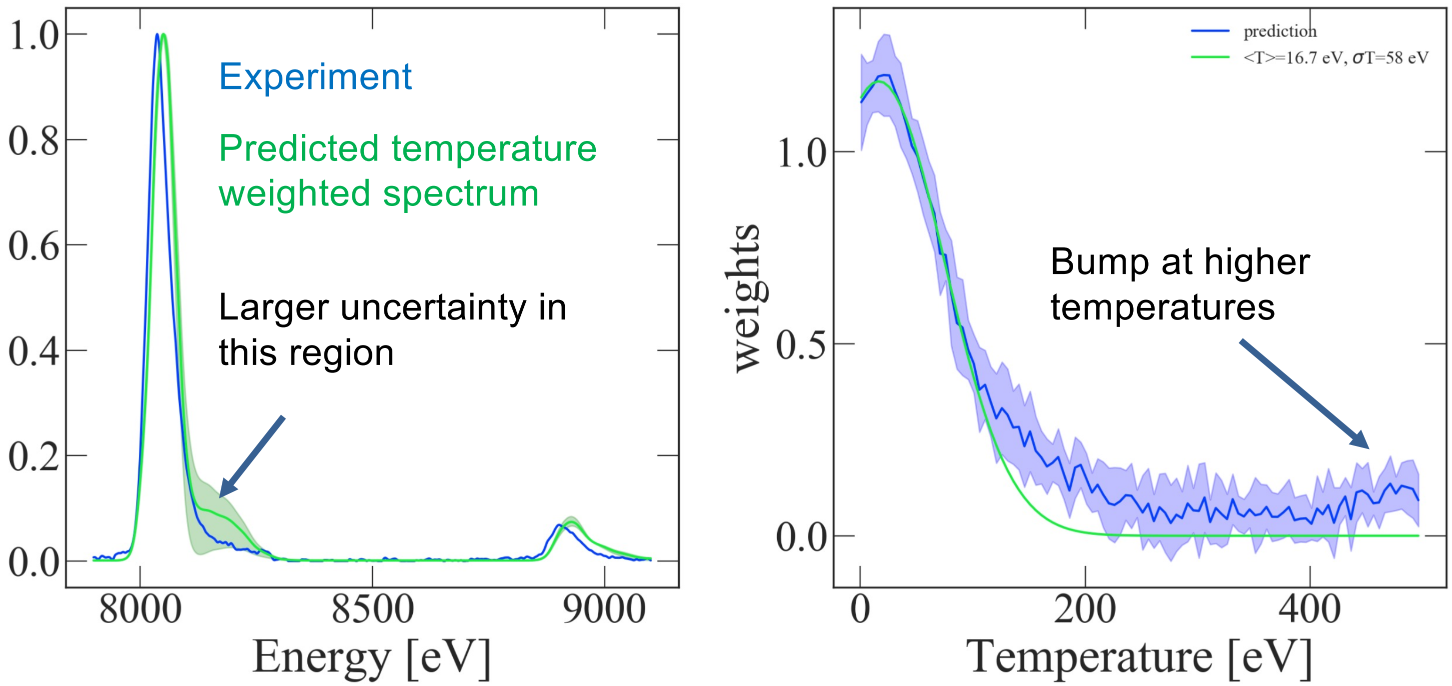


3) Multiply each **set** of spectra (1) by weighting function (2) and then sum



Now, we feed the summed spectra (3) in as training data and <u>ask the NN to predict the shape of the weighting function (2)</u>

As before, we can use the opinion of multiple NN's to estimate uncertainty in predictions of spectra and weighting function



While imperfect, this method appears to capture the more subtle features in the spectra and allows us to see the contribution of both cold and hot components