



Applying Machine Learning at the National Ignition Facility

Matthew Signorotti
Intern, Computing Directorate



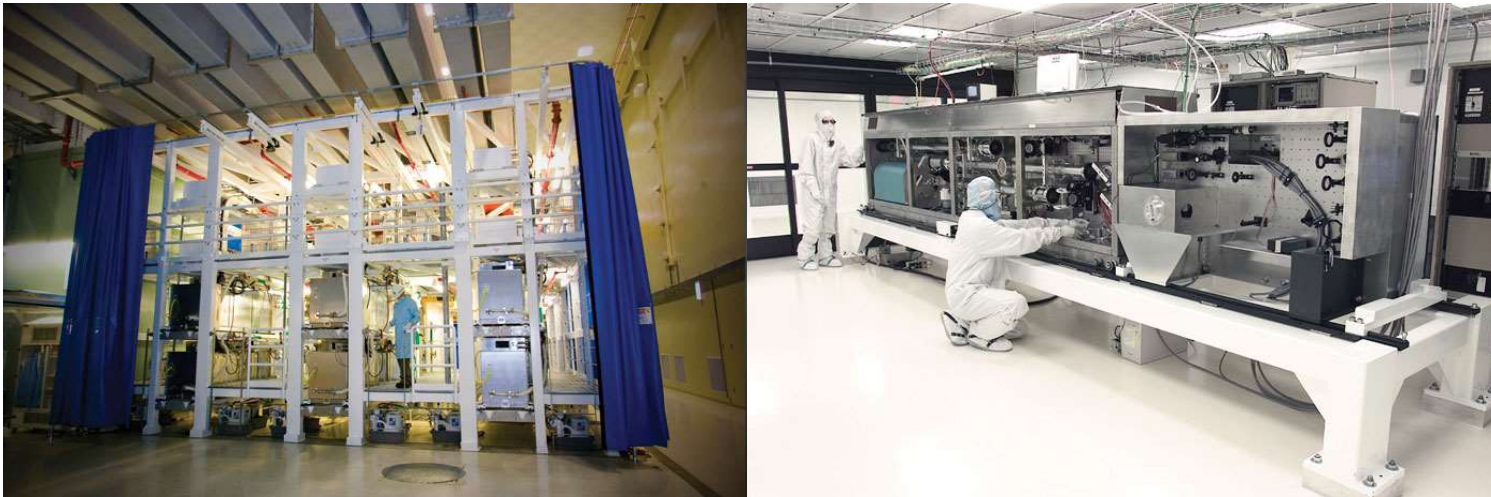
LLNL-PRES-813093

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

Background and Problem Motivation



- Machine learning (ML): a class of algorithms that work with data
- A preliminary machine learning model trained for the Preamplifier Module (PAM) at the National Ignition Facility (NIF) predicts the initial transmission value fed into a closed-loop algorithm
 - Algorithm refines the transmission necessary to reach a goal energy
 - A single iteration takes ~30 seconds; **the goal is to save time by predicting initial transmission values closer to the final value**



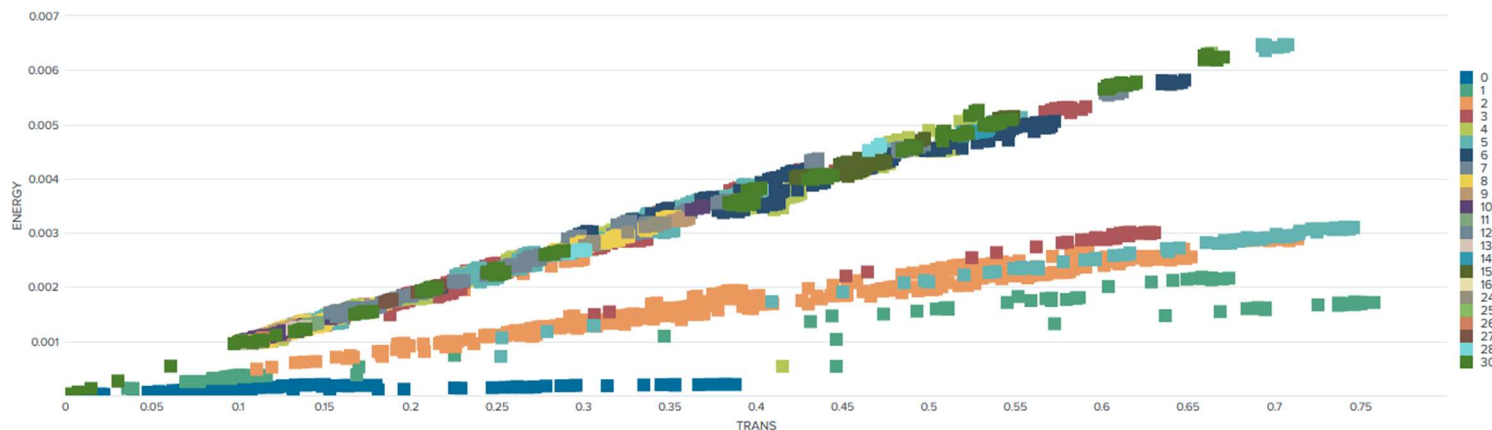
The components of PAM amplify laser energies by a factor greater than 1 billion.

Proposed Application: Preamplifier Module

ML can predict an initial transmission value...but how well?



- Current method: linear interpolation ($transmission = goal\ energy / energy\ reading$)
- One year of data (below) consisting of transmissions, pulse shapes, energies, etc.



For this laser beam, there is a clear linear relationship between goal energy and the transmission chosen, when grouped into bins by pulse width (the different colors in this plot).

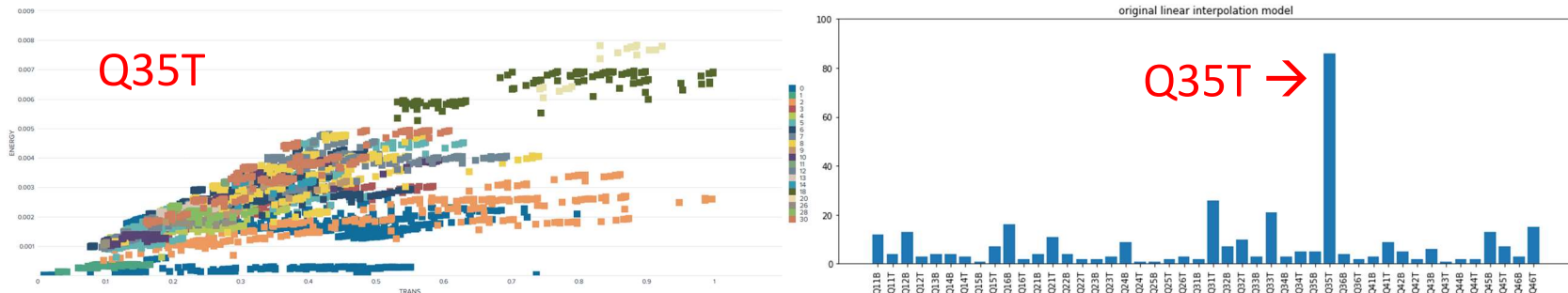
- Preliminary random forest model suffered from methodological issues (“overfitting”, inaccurate performance estimates), addressed as follows:
 - Developed two methods to divide data into training and testing sets, in order to prevent/identify overfitting and better simulate real-world model deployment
 - To better evaluate model performance, trained nearest-neighbors model to estimate number of closed-loop iterations under a model (more relevant than the default metric, R^2)

Results and Future Work

A framework for future machine learning projects at NIF



1. Trained various ML models (linear/polynomial, nearest-neighbor, decision tree, random forest, neural network, ensemble)
 - Linear interpolation model may be slightly preferable for minimizing time
 - However, ML models are comparable and, paradoxically, yield a greater R^2 score despite inferior time performance estimates
2. ML/statistical analysis can also help assess current state of beams
 - ANOVA hypothesis test found energy-transmission relationship is not the same for all beams, with p -value $\sim 5.4e-93$
 - Identified possible hardware issue with certain beams, especially Q35T (plotted below)



Beam Q35T was discovered to be significantly less predictable by linear interpolation (left). The beam plotted to the left, Q35T, is most frequently on the critical path of the closed-loop algorithm (right).

- For future projects, can easily create new sub-directories alongside PAM
- All work done in Python; will need interface with Java to deploy models