Maximizing Number of Protons in Fusion Process Using Machine Learning

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ABSTRACT

Today, many of us worry about finding alternative energy to reduce our carbon footprint on Earth. Researchers at the National Ignition Facility (NIF) hope that the answer may lie in fusion energy. In December of 2022, NIF achieved the first fusion ignition where a net positive energy was achieved. In this process, 2.05MJ of energy was supplied and 3.15MJ was produced resulting in a net positive of 1.1MJ of energy. With this breakthrough, the future of fusion energy became a lot closer. Ignition requires a beam of energetic protons within a certain energy range (3-15 MeV) produced by ultra-intense short laser pulses incident on a thin solid target. In pursuit of finding optimal conditions for the maximal proton flux, our group at Lawrence Berkeley National Lab (LBNL) proposed running both experimental and simulation campaigns to create sample data that will be used to train machine learning (ML) models. With well-trained ML models, they can be used to determine the combination of operating parameters that will result in the largest output of protons with the optimum energy range. The operating parameters that were varied to find the best output were z target, a variable denoting how far the laser focus is from an aluminum target that generates protons, and third-order dispersion (TOD), a variable reflecting the profile of the laser. The experimental data that the ML models were trained on came from the iP2 beam line at Berkeley Lab Laser Accelerator (BELLA) laser facility. A neural network was trained with all of its hyperparameters optimized to best fit the experimental data. Since experiments are expensive, there was limited data to train. Because of this, plasma simulations were run to sample the parameter space better thereby making the training space more dense. However, simulation's inability to perfectly replicate physical experiments necessitates a neural network that can "learn" the correlation between simulation and experimental data in order to generate accurate predictions of the number of protons from the combination of experimental conditions, namely, z target and TOD. In the future, it is our plan to develop such a network and use it to find optimal combinations that produce the highest number of protons.

I. INTRODUCTION

Today, the main pursuit of many researchers is finding reliable alternative energy sources. Fortunately, there has been tremendous progress towards fusion energy in the past three years. At NIF, in August of 2021, near net zero energy loss with laser fusion was achieved. The relative inefficiency of this process, at the moment, leaves us searching for other ways to obtain maximum gain with minimal input. The field regained momentum in December of 2022 with the first fusion ignition**[1]**. In this experiment the researchers, for the first time, observed a net positive energy gain with 3.15 MJ being the result when only 2.05 MJ was supplied. It was found that a proton source of 10-15 MeV is required to efficiently heat and initiate the fusion target. Following these findings, our team at Lawrence Berkeley National Lab (LBNL) intends to further the research in the field of internal fusion energy (IFE), by determining optimum operating conditions to maximize the number of protons between 3-15MeV**[2]**. Experiments have been performed at the BELLA iP2 facility at LBNL**[3]**, where a laser beam impinges on an aluminum foil target to generate a proton**[4]** beam with a certain energy range. This paper specifically details the research that aims to maximize the number of protons that result from these laser-based experiments that were conducted, varying two experimental parameters, namely, z target and third-order dispersion (TOD). Z target represents the distance between the laser focus and the aluminum foil target that generated protons from the laser interaction, and TOD is a parameter reflecting the laser profile.

II. METHODS AND MATERIALS

We trained surrogate machine learning models, specifically, neural networks using multi-input, single-task functions. The experimental data used to train the neural net were obtained from the iP2 beam line run at the BELLA Center**[3]**. The Pytorch Python library was used in this work to train the neural net. This library includes the base class for the neural network, the loss functions used to evaluate, and the optimizers that change hyperparameters. We built on the workflows that were developed for plasma accelerators**[5]**.

III. RESULTS

With very sparse experimental data (nearly 300 data points), it was difficult for the NN to pick up trends and patterns, as NN typically require thousands of data points. Nevertheless, to test the NN's ability to learn the trend of experimental data, it was trained on data that shows an increase in the number of protons with decreasing z target values. However, the training data also included a slight downslope *(see Figure 1)* to see if the NN would be able to catch the peak and begin to slope downward. The overall NN performance was assumed to perform poorly due to sparsity of data, but we wanted to, at least, capture the peak and downward sloping trend.

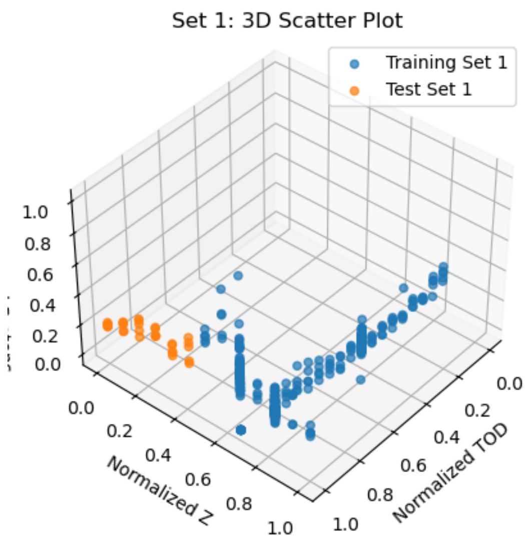

Figure 1: Visualization of normalized data split

We implemented a two input, one output fully connected NN structure with five hidden layers each containing 20 neurons (see *Figure 2)*, as well as a ReLU activation function after each layer. We also consistently trained over 1500 iterations.

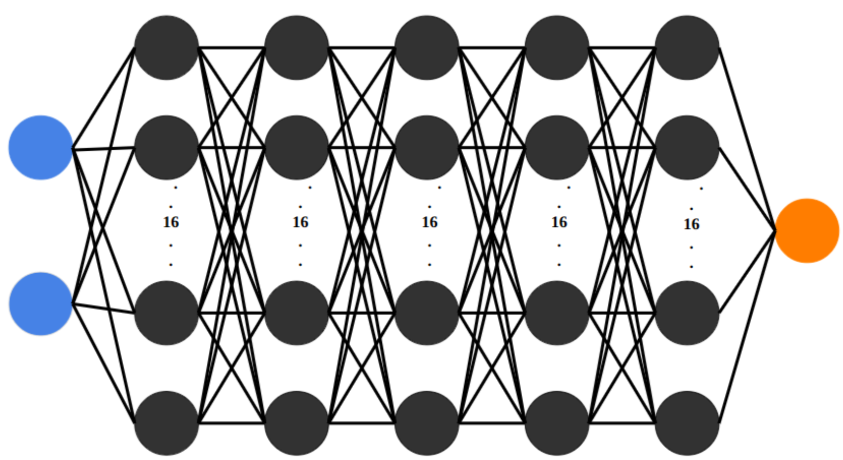

Figure 2: Representation of neural network

The rest of the hyperparameters for this NN were manually chosen one-by-one by testing each feature to see which improved the NN's ability to capture the peak. First, the optimizer was chosen to adjust the weights and biases during training. The optimizers that were tested included stochastic gradient descent (SGD), RMSprop, and Adam. Adam consistently showed the best results. Each optimizer allows for the learning rate to be altered. Learning rate controls how much the optimizer adjusts the weights and biases after an incorrect guess. Due to small values after normalization, a starting rate of 0.001 was chosen. The mean squared error (MSE) loss function was used to determine the level of the NN's success at each iteration. With these parameters the NN was able to nicely capture the peak. To ensure the efficiency of the NN's ability to minimize the loss, a scheduler was added to adjust the learning rate. When the NN detects a plateau or is incapable of decreasing the loss further, the learning rate is reduced in order to make finer adjustments. "ReduceLROnPlateau" was used with the following hyperparameters: patience = 100 (number of trials before it considers the loss unchanging), factor = 0.5 (level of adjustment of the learning rate), and threshold = 1e-4 (level of precision used in detection of change). These chosen values demonstrated a significantly faster reduction in loss compared to a fixed learning rate *(see Figure 4)*.

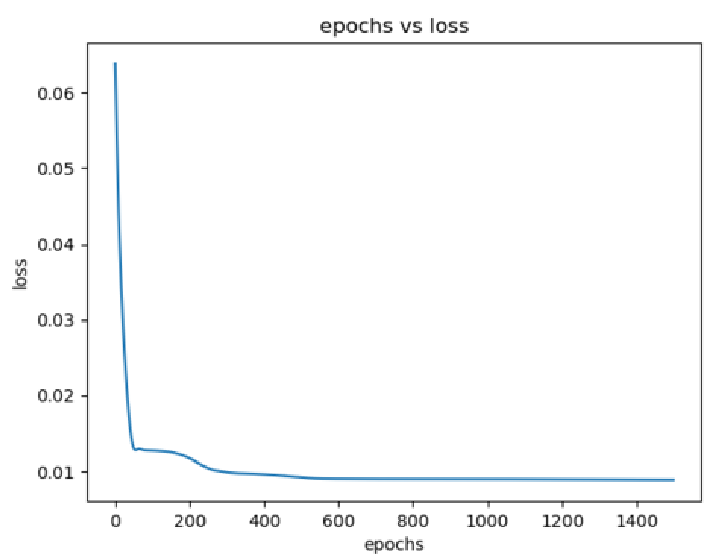

Figure 3: loss over iterations with a fixed learning rate

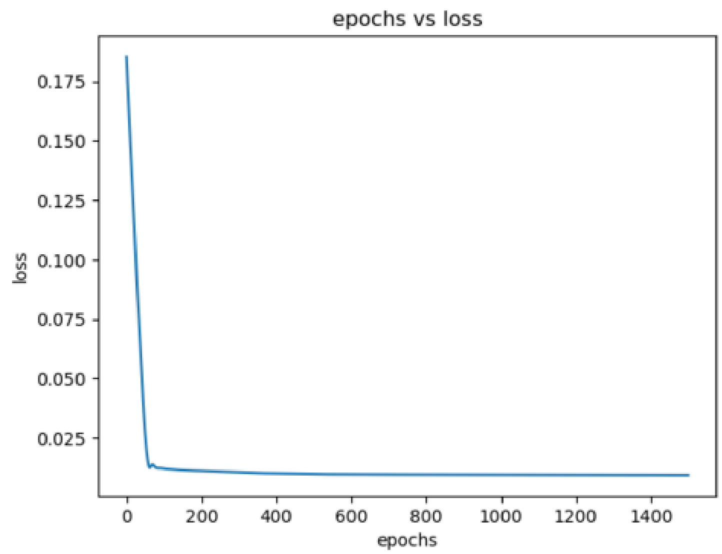

Figure 4: loss over iterations with scheduler

Optuna was used to verify our choices for these hyperparameters. Optuna is a python library that automates the optimal choice of hyperparameters including number of layers, number of neurons, learning rate, patience, factor, and threshold. With the hand-chosen values, our minimal loss was approximately 0.0087 for a given trial. With values suggested by Optuna, there was no significant difference in loss. For simplicity, we kept the hand-chosen hyperparameters where the NN clearly captures the peak of the data and slopes downward matching the experimental trend *(see Figures 5 and 6)*.

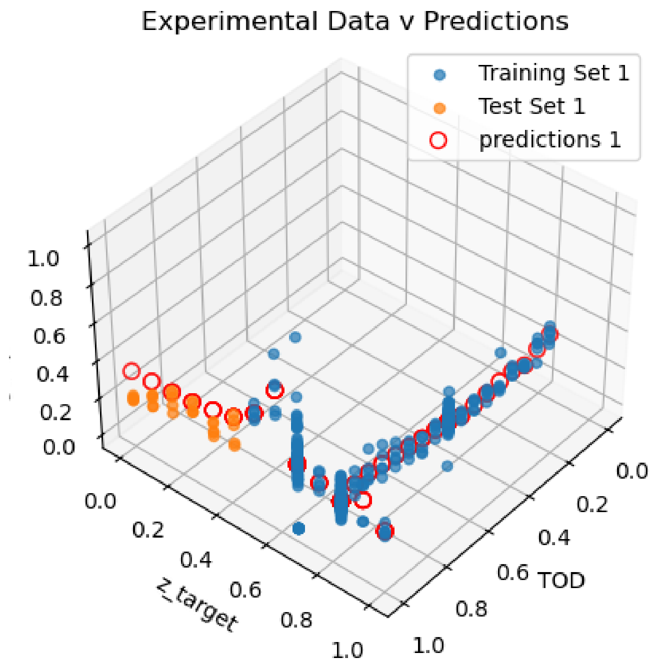

Figure 5: 3D representation of NN predictions

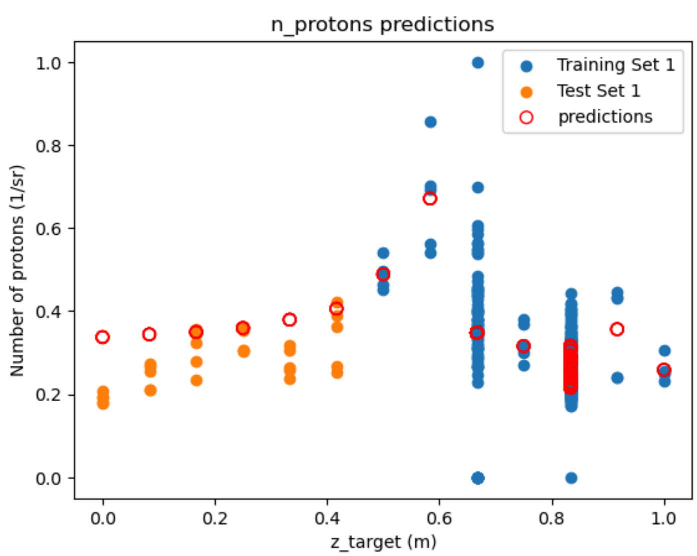

Figure 6: 2D visualization of NN predictions in testing region

IV. DISCUSSION

This NN training on the experimental data is a solid starting point for the overall goal to find experimental conditions that will maximize proton flux. With this foundation, the next steps will involve incorporating simulation data in order to fill in gaps from the experimental data. Since the simulations will not quantitatively agree with the f experiments, the NN will have to determine a correlation between the two in order to make predictions of what the experiments would show in other regions of our sample space. Currently, the plans will be to continue with this NN and introduce multi-fidelity and transfer learning techniques, where the experimental data is designated as high fidelity and the simulation data is low fidelity.

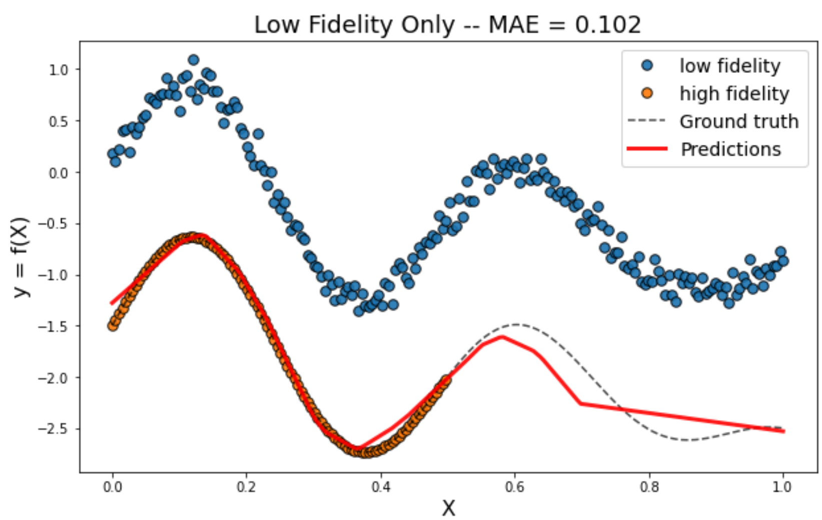

*Figure 7: Example graph of multi-fidelity problems from Adapt Python Package Documentation***[6]**

V. CONCLUSION

Currently, the NN struggles with predictions using only experimental data, mainly because it is being tested in an extrapolated region where the NN was not trained. However, the NN does pick up key trends and is able to capture the peak in the number of protons. With added training data that uniformly samples the parameter space, i.e., more simulation data points, the NN will be able to make better predictions using transfer learning techniques. Thus, by combining experiments and simulations, and leveraging the fact that the respective data are correlated, a transfer-learning enabled NN can be used to determine optimal input combinations for maximal proton production needed in fusion ignition.

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