High Energy Laser Amplification Waveform Prediction Using a Convolutional Neural Network

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Background & Motivation

Overview:

At the Matter in Extreme Conditions Lab (MEC), high-energy, pulsed, optical lasers, such as the long pulse laser (LPL), are used to create exotic states of matter. To reach these high energies, a system of glass laser amplifiers is utilized. Taking an input pulse of 100mJ, the back end of the LPL can amplify the pulse upwards of 100J. The temporal shape of the amplified pulses is an important performance diagnostic for MEC scientists so that they know, through time, what power is hitting their target. It is also important in Inertial Confinement Fusion facilities where maintaining uniform and predictable pressure on the target is required.

Problem:

The temporal shape of the laser pulses after amplification are not predictable. The Frantz-Nodvik Equation (see below) which describes how the temporal shape of a laser pulse is altered by amplification makes many assumptions—spatially uniform beam profile, no loss, no self-focusing effects, etc—which are not true for the LPL. Thus, if we want to accurately predict the temporal shape of the amplified output pulse based off of the input pulse, we require a new model.

Solution:

Instead of using a simulation based on untrue assumptions, we propose a data-driven model, utilizing a convolutional neural network with a dynamic filter to characterize the laser gain. With this model, we increase the parameter space from 2 parameters to 449 parameters.

Frantz-Nodvik Equation

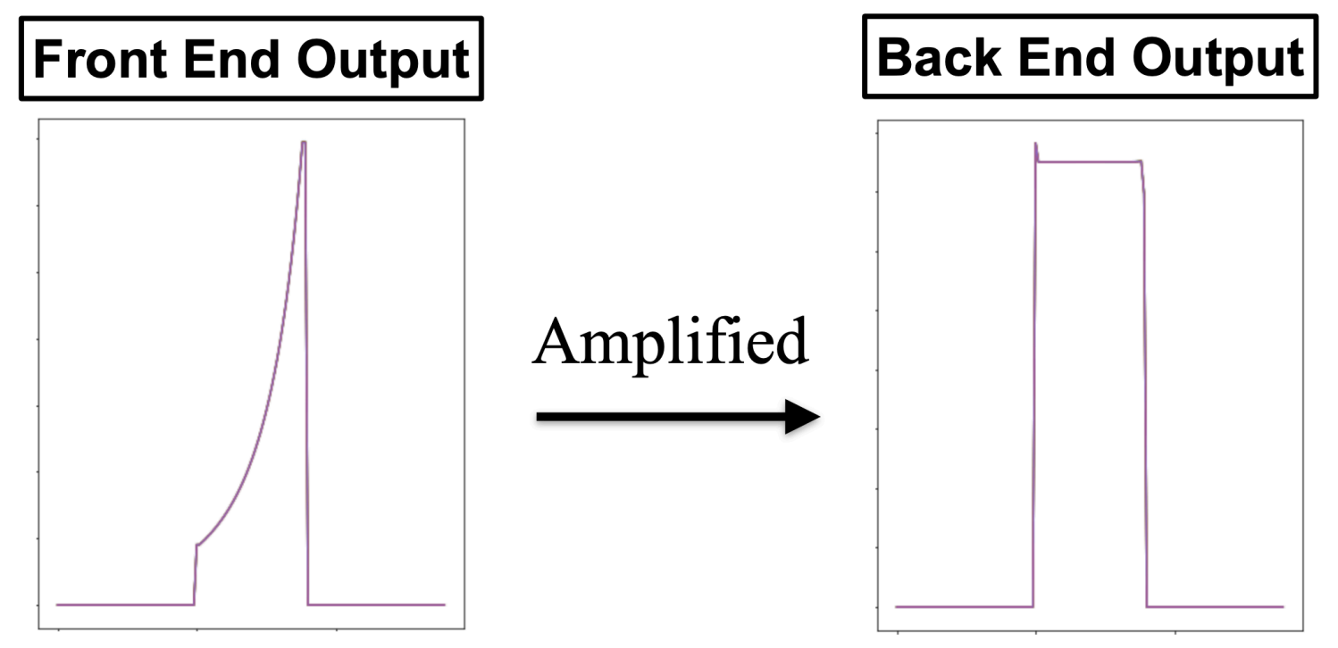
Overview:

Because laser amplifiers cannot maintain a constant gain for arbitrarily high input power (conservation of energy!), the gain is reduced in time — dictated by the Frantz-Nodvik Equation:

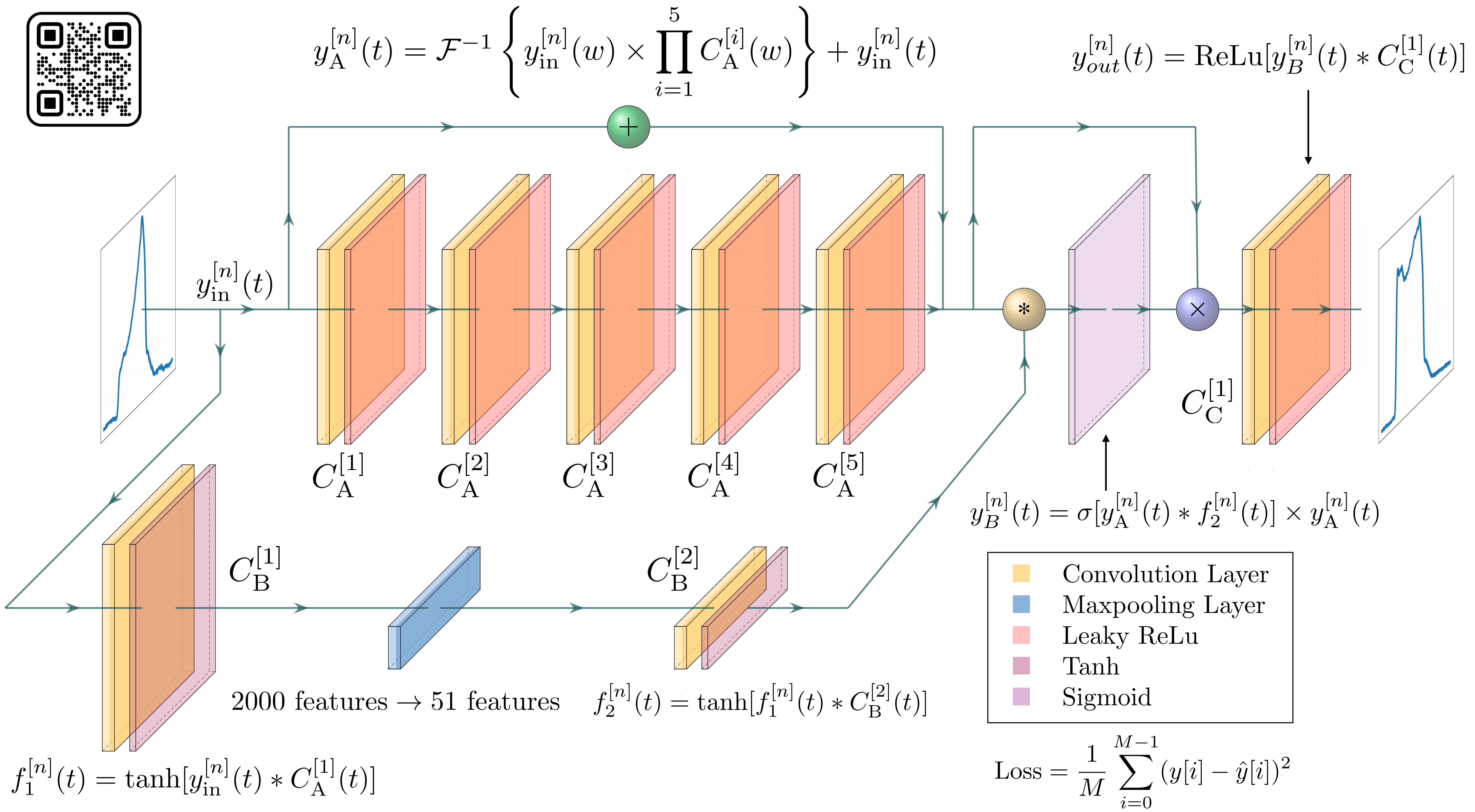
$$E_{\text{out}} = E_{\text{sat}} \ln[1 + e^{g_0} \cdot (e^{E_{\text{in}}/E_{\text{sat}}} - 1)]$$

Exponential Fit:

In order to compensate for gain saturation, the laser scientists in MEC aim for a temporally shaped exponential in the front-end, so a square wave is emitted from the back end (most common temporal shape).



Model Architecture



$$y_{\text{A}}^{[n]}(t) = \mathcal{F}^{-1}\left\{ y_{\text{in}}^{[n]}(w) \times \prod_{i=1}^{5} C_{\text{A}}^{[i]}(w) \right\} + y_{\text{in}}^{[n]}(t)$$

$$y_{out}^{[n]}(t) = \text{ReLu}[y_B^{[n]}(t) * C_{\text{C}}^{[1]}(t)]$$

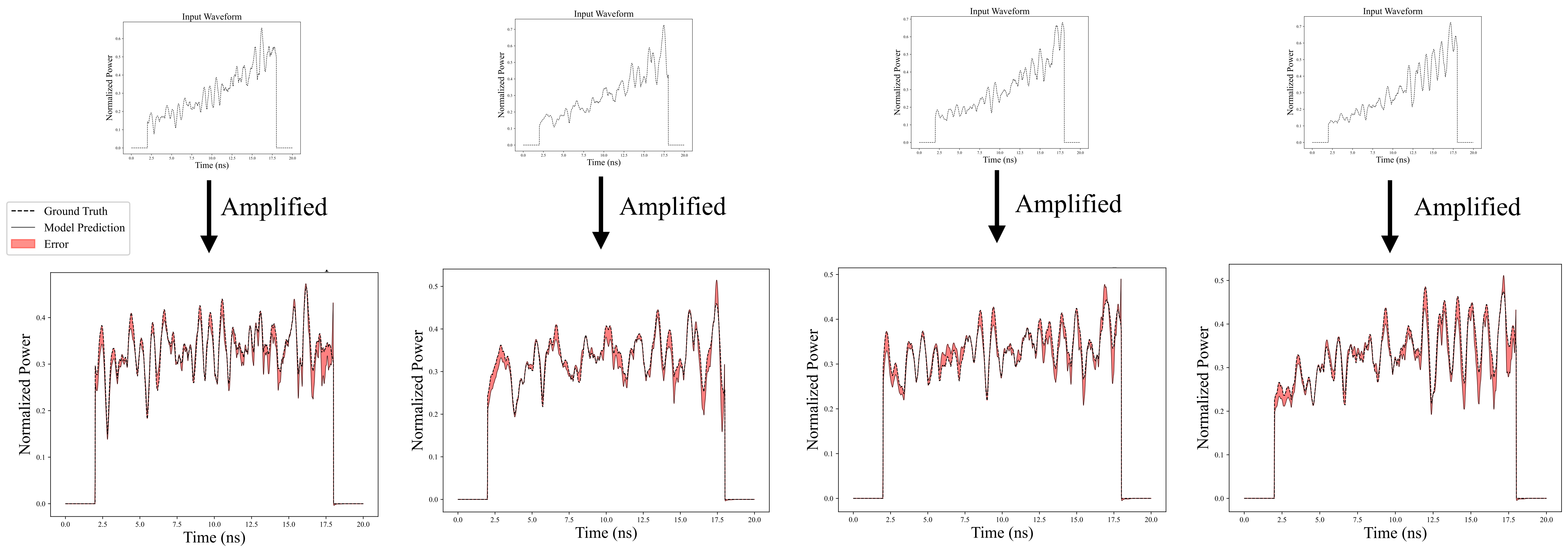
$$y_B^{[n]}(t) = \sigma[y_{\text{A}}^{[n]}(t) * f_2^{[n]}(t)] \times y_{\text{A}}^{[n]}(t)$$

$$f_2^{[n]}(t) = \tanh[f_1^{[n]}(t) * C_{\text{B}}^{[2]}(t)]$$

$$f_1^{[n]}(t) = \tanh[y_{\text{in}}^{[n]}(t) * C_{\text{A}}^{[1]}(t)]$$

$$\text{Loss} = \frac{1}{M} \sum_{i=0}^{M-1} (y[i] - \hat{y}[i])^2$$

Training Results



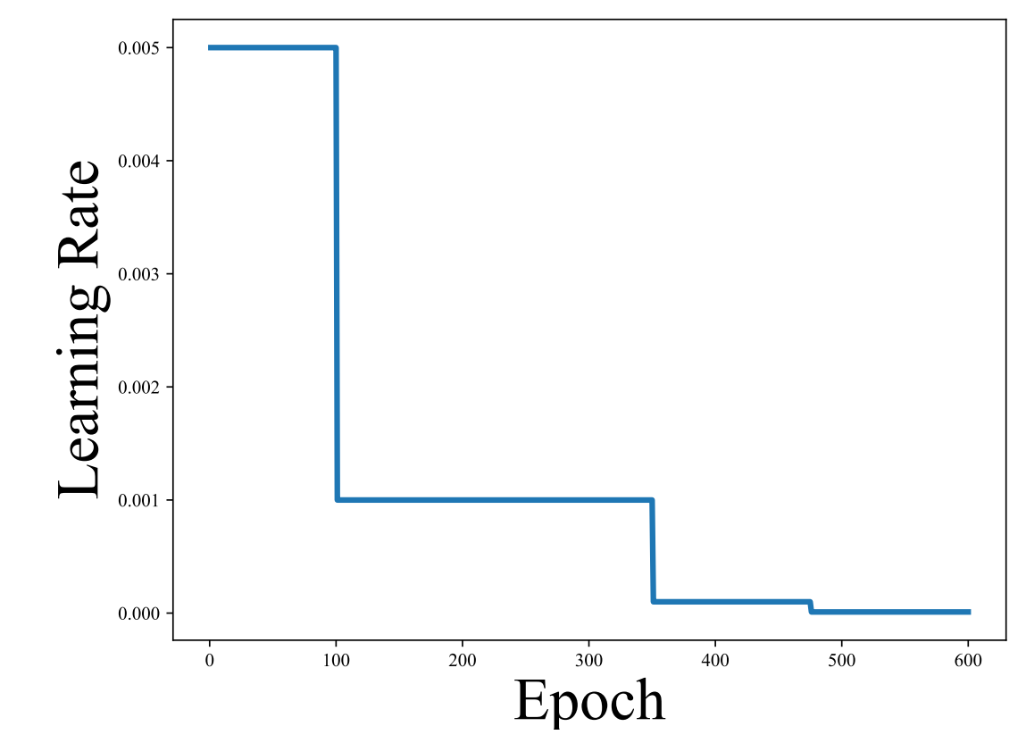
Results:

- Used simulated, but complex data for training to demonstrate that the model is capable of accurate prediction.
- After improvements with the measurement system (see photodetectors and implementation), there is potential for accurate prediction with a larger parameter space.

$$\text{Error} = \frac{1}{N} \sum_{n=0}^{N-1} \frac{1}{M} \sum_{i=0}^{M-1} \frac{y_n[i] - \hat{y}_n[i]}{y_n[i]} = 8.17\%$$

Hyperparameters & Hardware

Hyperparameters:



Epochs = 600,
Batch Size = 1 (for training with dynamic filter)
Samples = 700

Hardware:

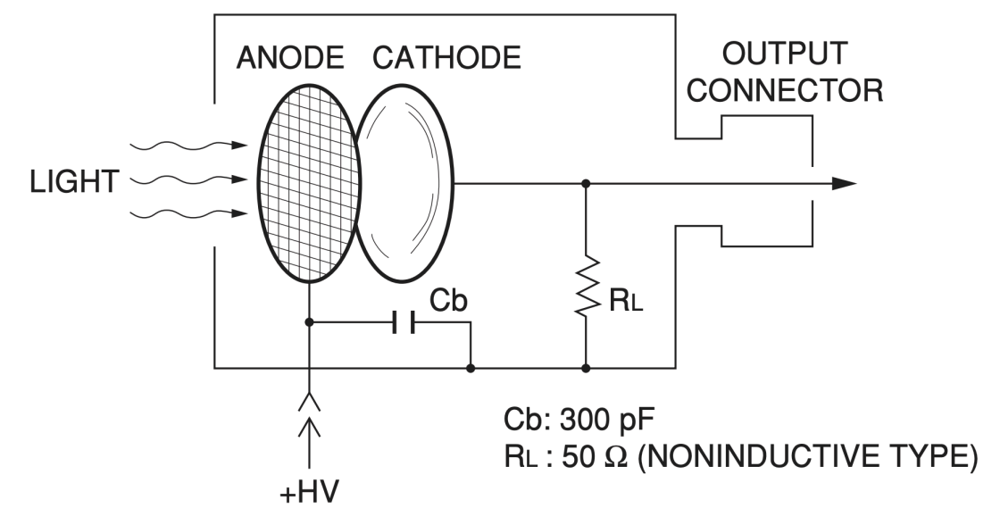
Trained using AMD Epyc 7702, 64 CPU-cores, 2GHz base clock, 512GB RAM on SLAC's S3DF servers

Photodetectors & Implementation

Measurement Devices:

Because the current photodiodes in the LPL system are not returning data that is reliable nor internally consistent, we have purchased two Hamamatsu R1328U Biplanar Phototubes to improve measurement accuracy. The first tests have shown promising results.

Phototube Schematic



Future Implementation:

After the new phototubes are put into place, we will need ~700 samples to train the model, which can take a few months to gather. Additionally, the loss function can be altered such that it has bias towards more recently taken samples. This will allow for the model to remain accurate despite slight changes in the system over time.

Acknowledgements

I would like to thank my mentor Eric Cunningham for his knowledgable guidance and invaluable insights on all things laser related. I would also like to thank the entire MEC team for welcoming me into their lab and to the LCLS internship program for having me back for another summer.