A Deep Learning Approach to Designing Inertial Confinement Fusion Experiments

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Summary

We are developing a transfer learning model that can directly predict experimental observables using experimental inputs, i.e., laser pulse shape and target specifications

- Following the transfer learning approach of Humbird *et al.*,* we are developing a neural network (NN) predicting capability for the fusion yield and areal densities of OMEGA cryogenic implosions
- This approach integrates simulations with experiments by first developing a model that emulates simulations, which is subsequently calibrated/retrained using limited experimental data
- The model requires only experimental inputs (laser pulse and target specifications) to accurately predict experimental observables
- This enables making changes directly in input space and assess effects on implosion performance
- This NN model can be used for rapid exploration of a high-dimensional input parameter space

*K. D. Humbird *et al.*, IEEE Trans. Plasma Sci. 48, 61 (2020).

Motivation

Currently a statistical approach that combines 1-D simulated parameters with experimental results to correct code output and predict implosion performance is utilized

- OMEGA implosions are currently designed using a statistical model that maps experimental results into a simulation database

$$Y_{exp} \rightarrow F_{SM}\left[V_{i1\text{-}D}^{sim}, \alpha_{1\text{-}D}^{sim}, Y_{1\text{-}D}^{sim}, \rho R_{1\text{-}D}^{sim}, T_{1\text{-}D}^{sim} \ldots \text{ output 1-D simulation}\right]$$

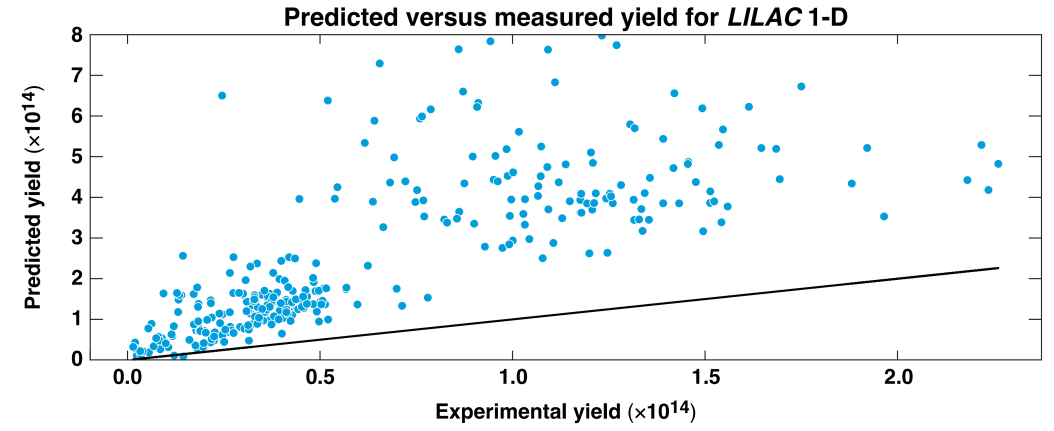
- The new prediction model will use the same inputs as the experiments: the laser pulse shape and target specifications

$$Y_{exp} \rightarrow F^{NN}\,[\text{laser pulse shape + target specs}]$$

- This new prediction model will facilitate rapid exploration of a high-dimensional input parameter space

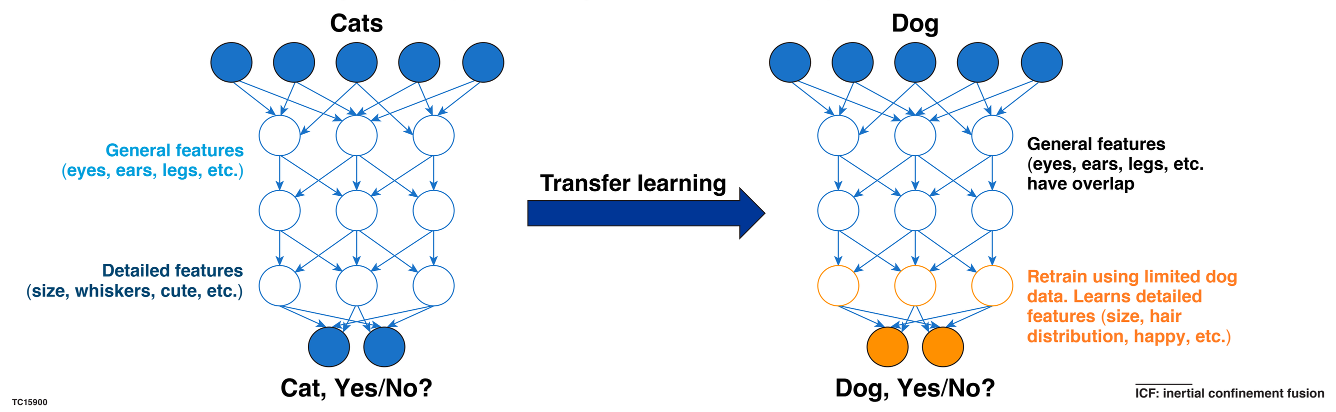
V. Gopalaswamy *et al.*, Nature 565, 581 (2019).

Inertial confinement fusion radiation-hydrodynamic simulations do not consistently predict OMEGA cryogenic implosion experiments



Transfer learning is a useful technique for building the deep learning model because it alleviates the challenge of having small datasets, as is the case with ICF experiments

- Transfer learning takes a pre-existing neural net and adapts it for a different related task

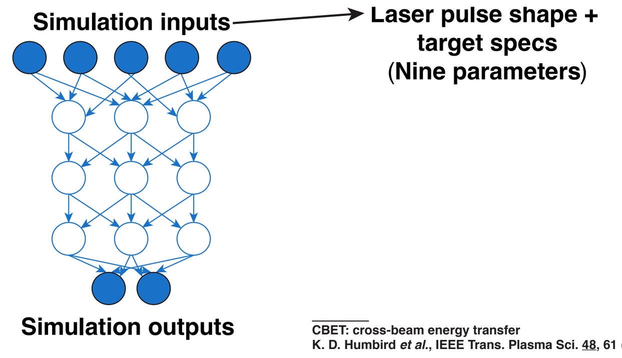


ICF: inertial confinement fusion

A low-fidelity neural net model is trained from a simulation database of parametrized laser and target specifications

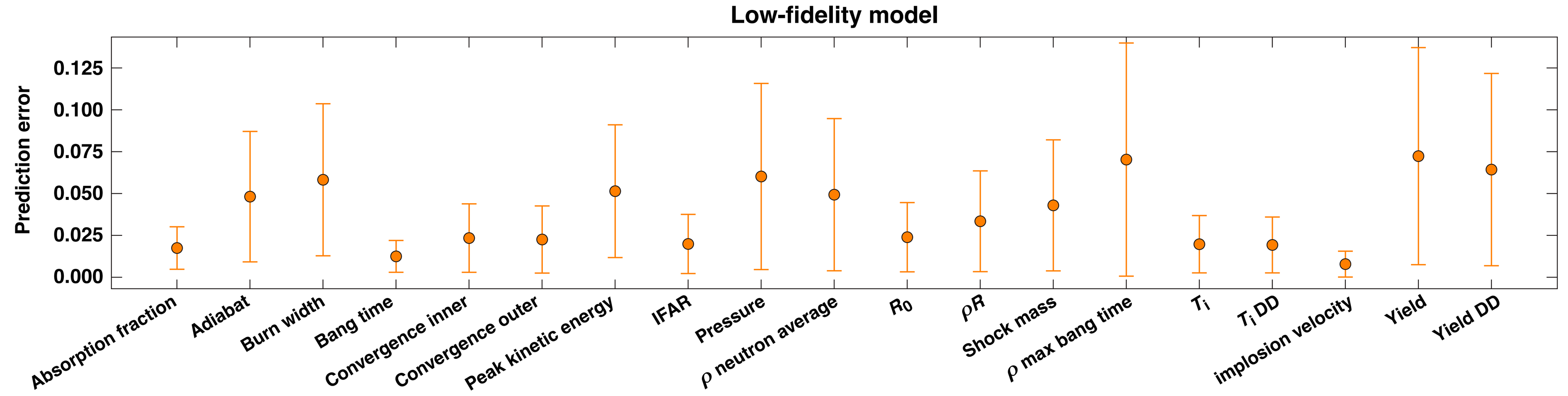
- Model developed in TensorFlow
- 22k simulations used for training
- Low-fidelity means *LILAC* (1-D ICF simulation code) with no CBET, without nonlocal thermal transport
- 7500 used for validation

Low-fidelity model	
Hidden layers	4
Hidden layer units	11-13-22-16
Learning rate	0.004
Batch size	1500
Epochs	1000



CBET: cross-beam energy transfer
K. D. Humbird *et al.*, IEEE Trans. Plasma Sci. 48, 61 (2020).

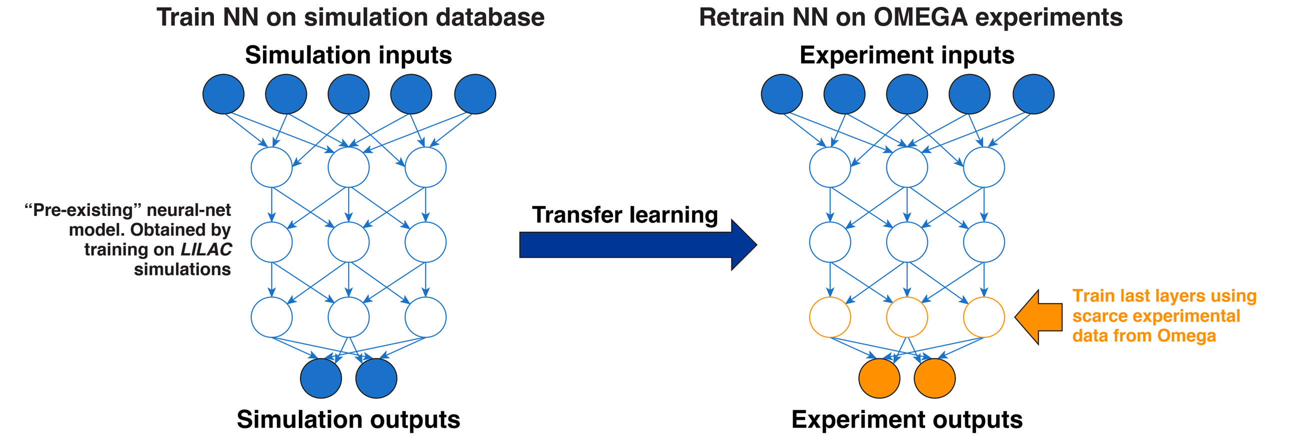
The low-fidelity neural net model is an acceptable emulator of the 1-D low-fidelity simulation code



$$\text{Error} = \frac{(\text{Low-fidelity NN}) - (\text{Low-fidelity } LILAC)}{(\text{Low-fidelity } LILAC)}$$

IFAR: in-flight aspect ratio

Transfer learning is used to make a single model that combines simulations with experiments*



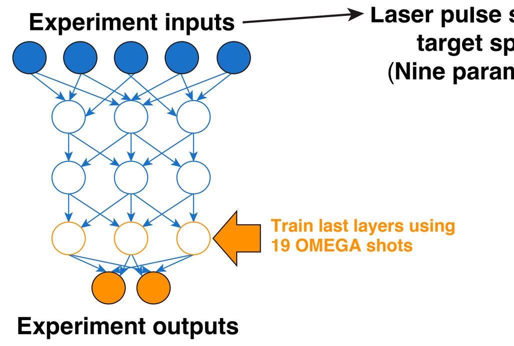
*K. D. Humbird *et al.*, IEEE Trans. Plasma Sci. 48, 61 (2020).

Transfer learning is used to integrate the low-fidelity neural-net model with experiments

- The first two layers are frozen
- The last two layers are retrained
- 19 experiments used for training
- 4 experiments used for validation

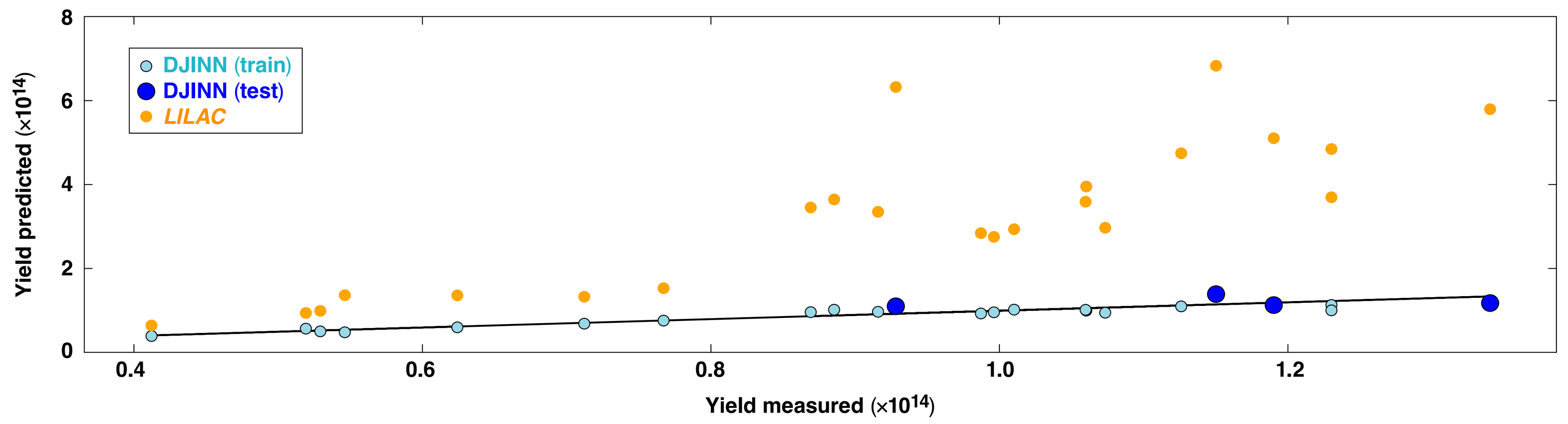
Low-fidelity model	
Hidden layers	4
Hidden layer units	11-13-22-16
Learning rate	0.004
Batch size	1500
Epochs	1000

Low-fidelity model	
Retrained layers	Last 2
Learning rate	0.0003
Batch size	1
Epochs	2300



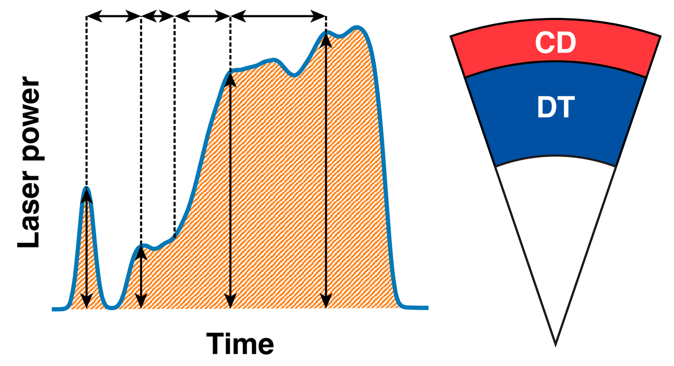
K. D. Humbird *et al.*, IEEE Trans. Plasma Sci. 48, 61 (2020).

Initial results show that the transfer learning model retrained on 19 experiments accurately predicts the validation data



*K. D. Humbird *et al.*, IEEE Trans. Plasma Sci. 48, 61 (2020).

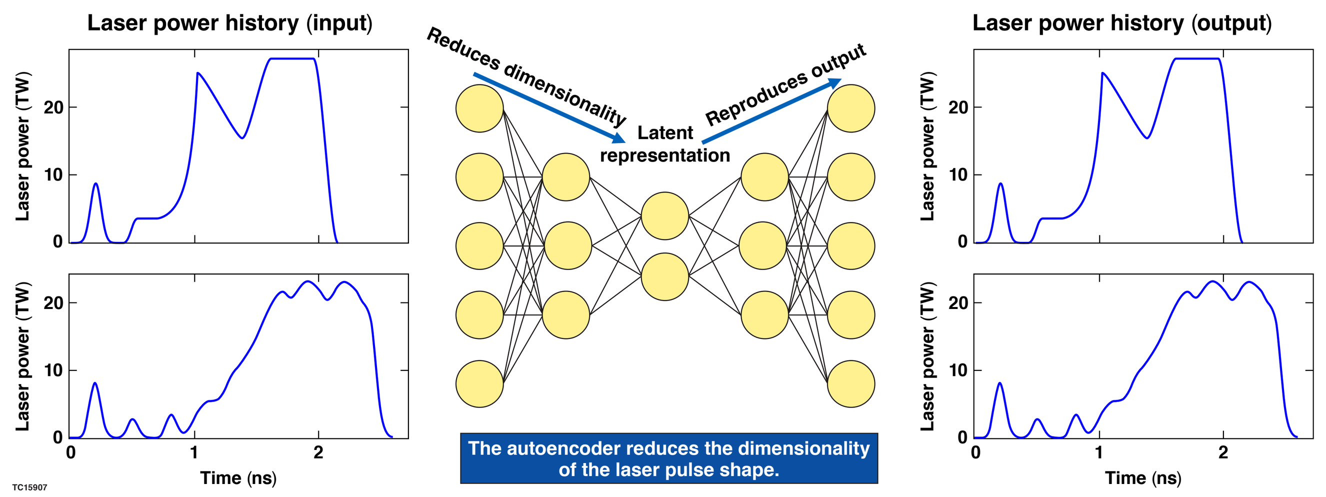
The experimental inputs form a high-dimensional parameter space



- Picket powers
- Foot power
- Foot picket width
- Foot width
- Foot rise time
- Rise time
- Drop power
- Flat top
- Spike power
- Spike start time
- Spike slope
- Energy on target
- Thickness of DT fuel
- Thickness of ablator
- Composition of fuel
- Composition of ablator
- Outer radius
- etc.

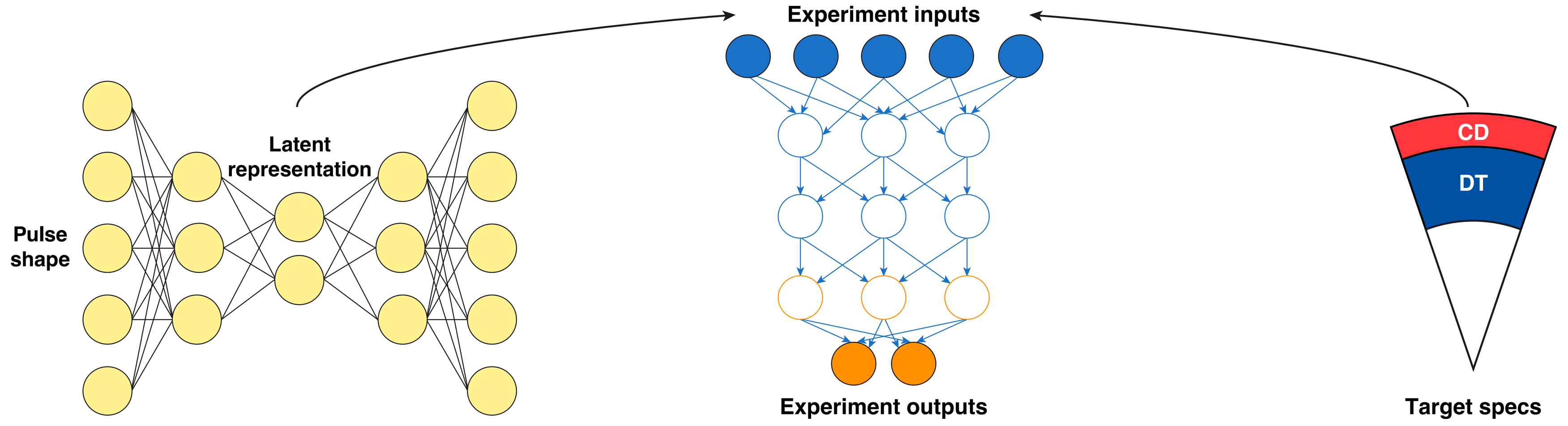
V. Gopalaswamy *et al.*, Nature 565, 581 (2019).
V. Gopalaswamy, Ph.D. thesis, University of Rochester, 2021

To extend the applicability of the model to a broader class of laser pulse shapes, an autoencoder is being developed

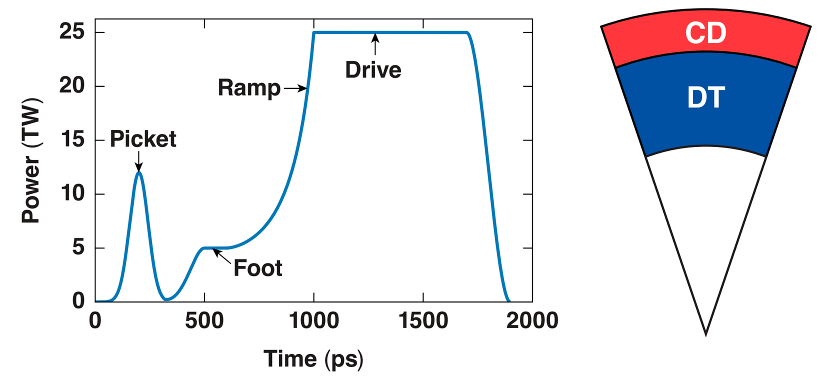


The autoencoder reduces the dimensionality of the laser pulse shape.

We are extending the transfer learning approach to predict experiments in a large parameter space of arbitrary pulse shapes and target dimensions



To test the approach, we first develop the model in a restricted experimental input parameter space



- Picket power
- Foot power
- Foot picket width
- Foot width
- Average drive
- Drive rise time
- Energy on target
- Ice thickness
- Capsule outer radius

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