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# Transfer Learning for the calibration of the ICF simulations

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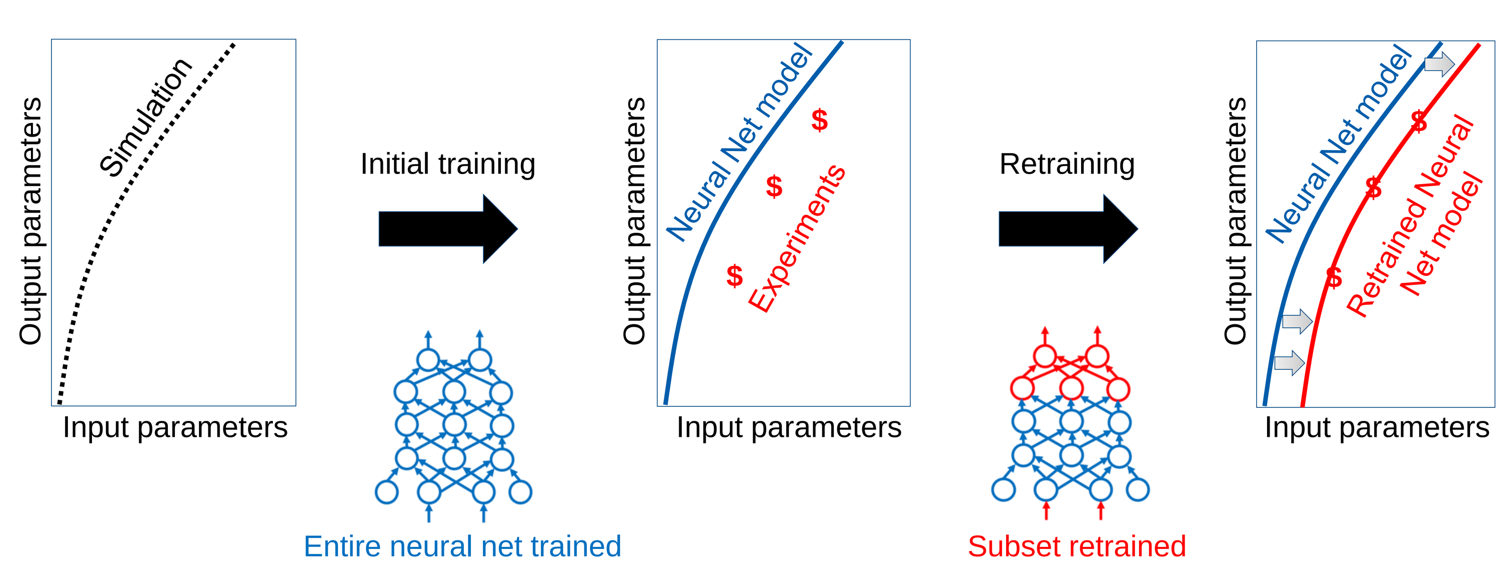
## Abstract

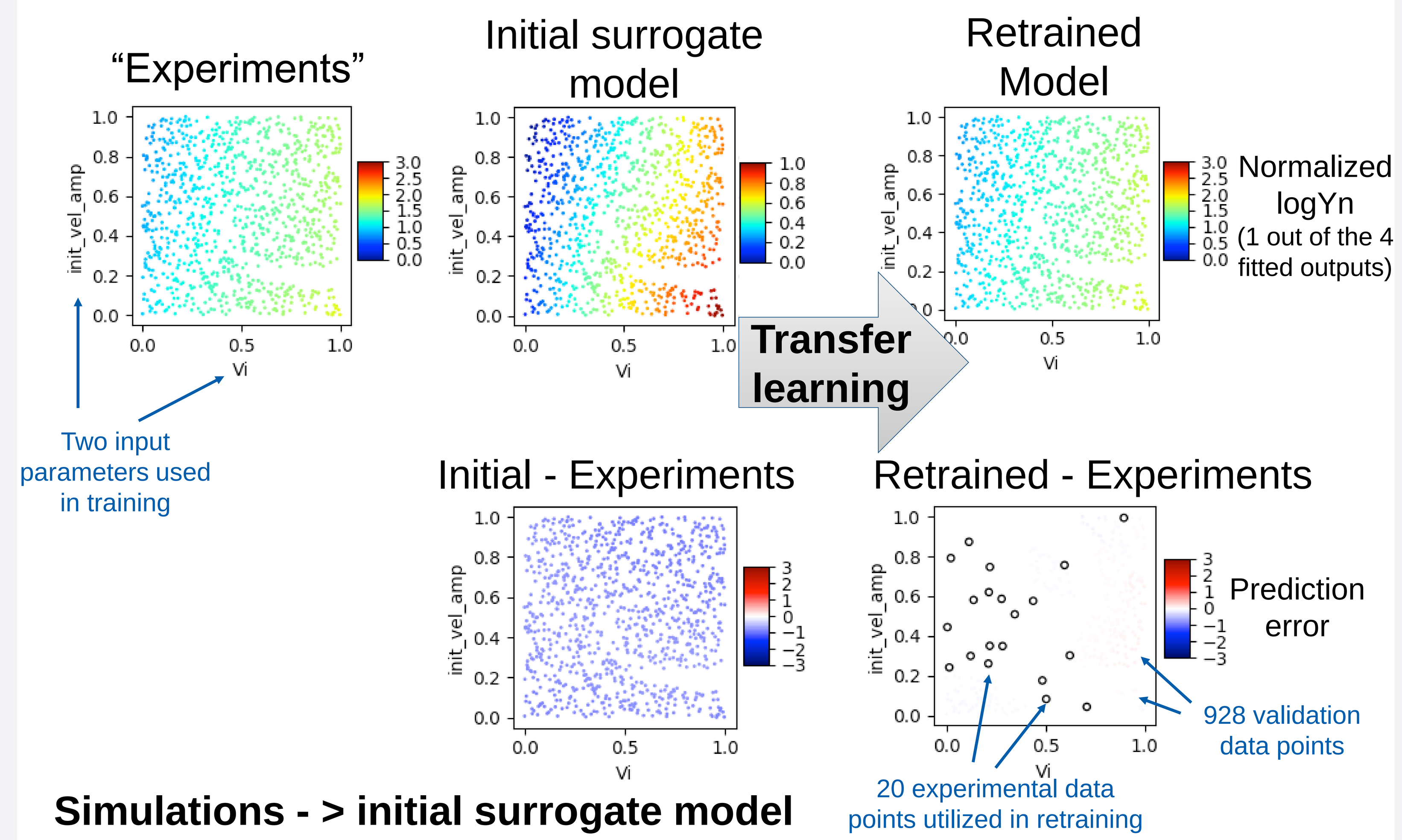
Transfer learning refers to exploiting the knowledge gained from solving one problem and applying it to solve a different but related problem. A well-known example is reusing publicly available neural network models that have been trained on very large sets of images, and partially retraining them to solve a new classification task, for which fewer data are available. In this presentation, we discuss numerical tests that have been carried out to investigate the applicability of transfer learning to calibrate the Inertial Confinement Fusion (ICF) computer simulations against sparse experimental data, which will be obtained at the National Ignition Facility (NIF).

## Calibration of the computer simulations against sparse experimental data




- A number of computer simulations is run for a set of input parameters.
- For simplicity, only one input and one output parameter are shown in the figure.
- A neural network is initially trained to predict selected outputs of the simulations. This neural network is the initial surrogate model and it needs to accurately predict the simulation outputs.
- The presumption is that the simulation physics is captured in the first layers of the network. The last layer(s) are retrained to better match the expensive, sparse experimental data.

## Numerical test: successful calibration using 20 “experiments”



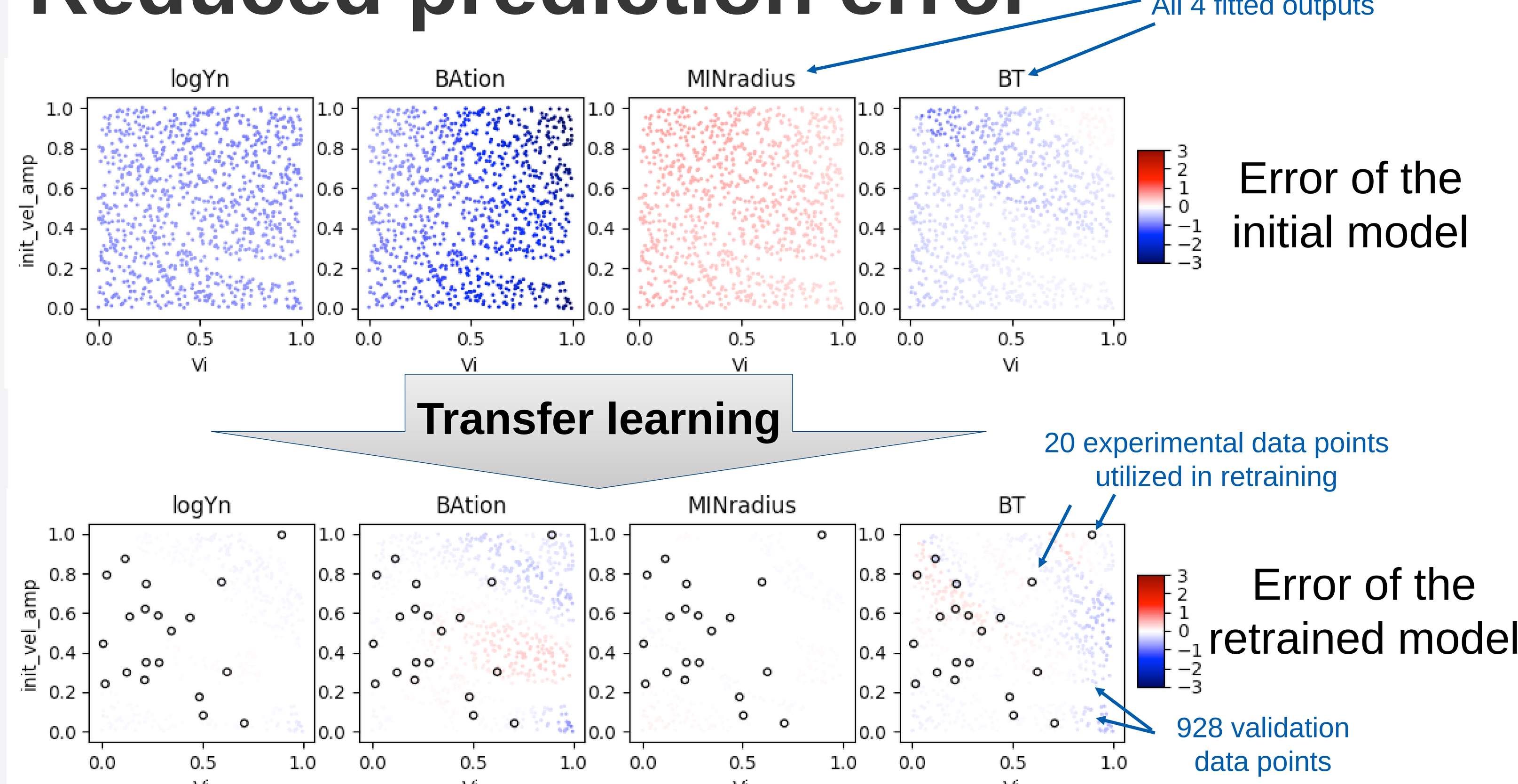

**Simulations - > initial surrogate model**

- Run a set of 1K simulations with the nominal physics.
- A neural network surrogate model is trained using 2 input parameters and 4 outputs. The surrogate model matches the simulations nearly perfectly; the simulations are therefore not shown in the figure.

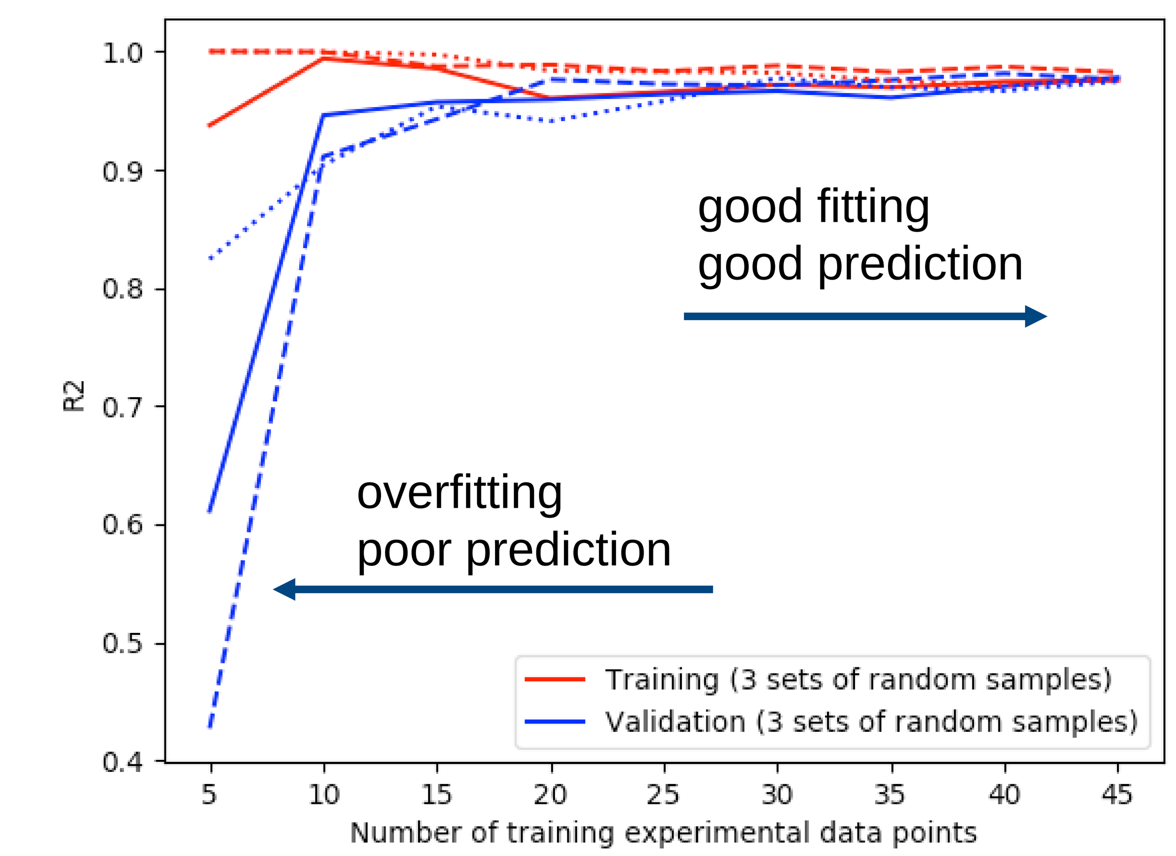
**Experiments - > elevated surrogate model**

- Run another set of 1K simulations with the perturbed physics.
- The last layer of the neural network surrogate model is retrained to match 20 of these new simulations.
- The remaining ~1K new simulations are used as a validation data set.

## Reduced prediction error




## The effect of the available experimental data volume on the calibration quality




- We repeated the calibration experiment while varying the number of available experimental data points between 5 and 45.
- The entire procedure was repeated three times using different location of the experimental data in the parameter space
- The $R^2$ goodness of fit was computed for both the training and validation data.
- The calibration is accurate if 20-30 experiments are available.
- If only 5 experiments are available, the error is higher and strongly depends on the location of the experiments.

## Conclusions

Preliminary results are encouraging and motivate further research of the transfer-learning-based calibration using:

- Larger data volumes
- Not only scalar outputs but also images and time histories
- More complex architectures, such as Generative Adversarial Networks
- Real experiments instead of simulated experiments

**Take-away message: Transfer learning is a promising tool for the calibration of ICF simulations**

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