APPLICATION OF CONVOLUTIONAL NEURAL NETWORK ON RADIATIVE OPACITY COMPUTATIONS

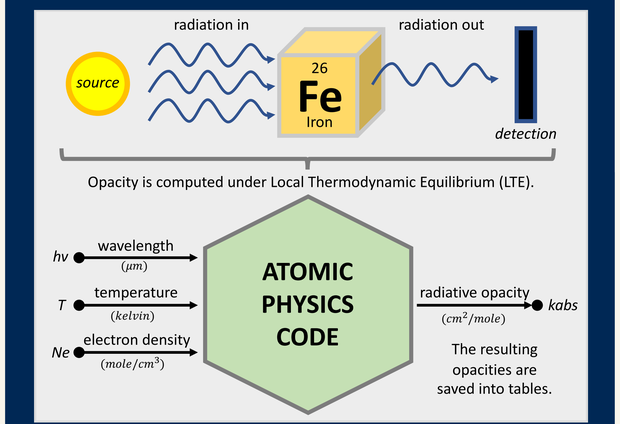
Alex John Quijano*, Robert Clayton Blake+, and Ben C. Yee+

*Applied Mathematics at University of California Merced
+Center for Applied Scientific Computing at Lawrence Livermore National Laboratory

INTRODUCTION

- **Radiative Opacity** is a property describing the penetrability of a given material of varying electron density (*Ne*) and temperature (*T*) by a certain wavelength of photon energy (*hv*).
- **Convolutional Neural Network (CNN)** is a class of machine learning method designed to adaptively learn complex features through backpropagation.

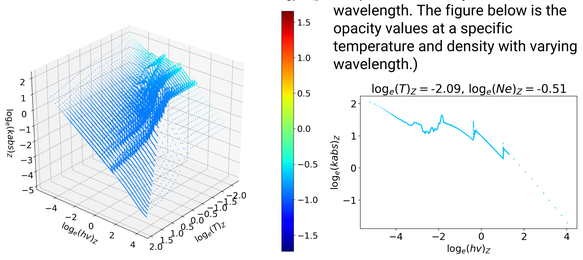
PROBLEMS AND OBJECTIVES



- **Problems:** Opacity tables requires (1) intense memory and have (2) low interpolation accuracy for practical use.
- **Objective:** Use CNN to encode opacity information with (a) less memory and (b) better interpolation accuracy.

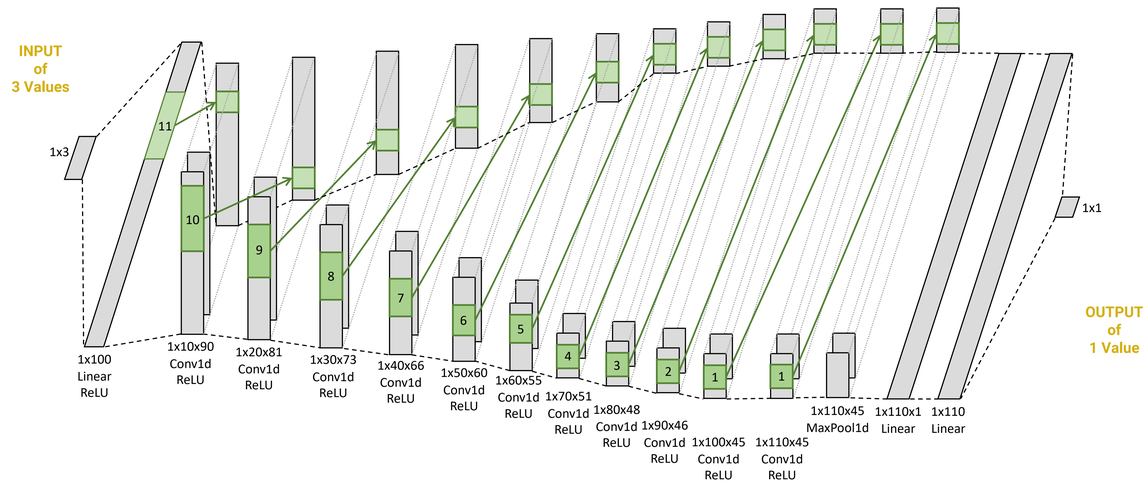
DATA OVERVIEW

- **4D:** The dataset is composed of discrete points in *(Ne,hv,T)* → *kabs* structure.
- **Centered:** Normalized via standard score.
- **Target Element:** Iron.



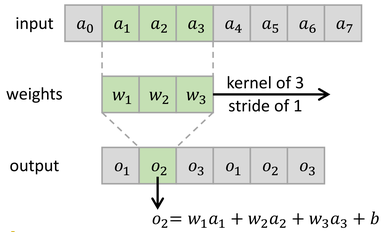
(The left figure shows the opacity values within a local range of temperature, density, and wavelength. The figure below is the opacity values at a specific temperature and density with varying wavelength.)

THE NEURAL NETWORK



1D CONVOLUTIONS (IN-DETAIL)

- **Simple example:**



- **Conv1d** (PyTorch):

Input size → (N, C_{in}, L_{in})
output size → (N, C_{out}, L_{out})

N is the batch size, C is the number of channels, and L is the length

$$\underbrace{o(N_i, C_{out_j})}_{\text{output}} = \underbrace{b(C_{out_j})}_{\text{bias}} + \sum_{k=0}^{C_{in}-1} \underbrace{w(C_{out_j}, k)}_{\text{weight}} * \underbrace{a(N_i, k)}_{\text{Input}}$$

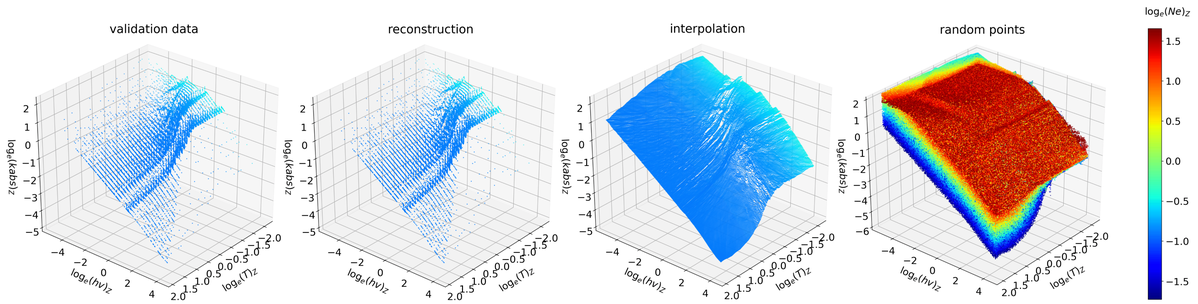
RESULTS

- **Datasets:** The data was separated into training (70%) and validation (30%) sets by randomly selecting points.
- **Training:** The CNN was trained with a Root Mean Squared Error (RMSE) loss function with Adam optimization.
- **MAIN POINT:** The CNN reconstructed the opacity with low residual errors as well as interpolated the entire range of varying temperature, density, and wavelength.

(Opacity reconstruction using CNN of specific temperature and density with varying wavelength.)

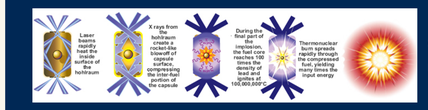
(The evolution of the loss while training.)

(The residual error distribution of the validation set versus the reconstructions.)



(The actual opacity points (left fig.) and the opacity reconstruction using the CNN (left-middle fig) within a local range and the interpolated points (right-middle fig.) and using random points (right fig.) of temperature, density, and wavelength)

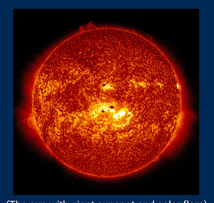
SIGNIFICANCE



(Inertial Confinement Fusion – ICF)

Image: NIF at LLNL.

- Opacities are used for radiation hydrodynamics simulations to **understand how photons propagate through a complex medium**.
- The opacities can be **used for Inertial Confinement Fusion (ICF) simulations at the National Ignition Facility (NIF)**.
- Opacity is an important quantity that largely impacts the structure of a star. Understanding stellar interior radiative transport can lead to **understanding stellar evolution**.



(The sun with giant sunspot and solar flare)

Image: NASA

CONCLUSION AND OUTLOOK

- A CNN is created to rapidly **compute opacity given density, temperature, and wavelength**. Results show that the CNN can reconstruct the existing opacity computations with low error.
- **Parameter pruning** can be done to make the CNN faster and smaller. More analysis on the opacity tables can be done to **improve the model for other elements**.

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UNIVERSITY OF CALIFORNIA MERCED

DSSI DATA SCIENCE SUMMER INSTITUTE

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