Data-Driven Nonlocal Heat Transport Modeling in Plasmas Using Neural Networks

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Accurately modeling nonlocal electron heat transport is critical for advancing simulations of high-energy-density plasmas, including those relevant to inertial confinement fusion and astrophysical systems [1]. Classical models such as Spitzer–Härm [2] and nonlocal formulations like Luciani–Mora–Virmont [3] fail under strongly nonlocal conditions, where the electron mean free path approaches or exceeds the temperature gradient scale length. To overcome these limitations, we propose two neural network approaches, each offering distinct advantages for modeling nonlocal transport.

The first approach employs a Convolutional Neural Network (CNN) trained on kinetic simulation data [4]. Using the initial ratio of electron mean free path to temperature gradient length as input, the CNN predicts the spatiotemporal evolution of heat flux. It is fast to train and delivers accurate predictions, but, like most data-driven models, it functions as a black box with limited interpretability of the underlying transport physics. The second approach employs a Conditional Neural Network (cNN) trained to learn the nonlocal heat flux kernel as a function of key physical parameters. This method enables the construction of a dynamic, physics-informed kernel that can accurately reconstruct the heat flux across space and time. While more computationally expensive to train, the cNN offers greater interpretability and a clear connection to the physical structure of the nonlocal transport process, making it a valuable tool for deeper analysis and model validation.

Our work demonstrates the value of machine learning in capturing complex, nonlocal behaviors beyond the reach of classical models. It highlights the potential for hybrid modeling strategies in future plasma simulation frameworks.

References

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