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Linear properties of machine-learning-based closure models for collisionless plasmas

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Multiscale plasma processes govern a wide range of energetic phenomena in both laboratory and astrophysical settings, from turbulence and reconnection in Earth's magnetosphere to extreme transport conditions in accretion disks and stellar environments. A complete kinetic description of such plasmas requires solving the Vlasov equation in both configuration and velocity space. While this formalism captures the full richness of the dynamics, the associated phase space makes direct simulations prohibitively expensive for most practical applications. To mitigate this challenge, reduced fluid and moment models with appropriate closure relations are often employed. However, constructing accurate closure models that faithfully represent kinetic effects while being computationally tractable and inexpensive remains a central open problem.

Recent advances in machine learning, particularly operator-learning frameworks such as the Fourier Neural Operator (FNO), have opened new possibilities for deriving closure relations directly from kinetic simulation data. FNOs can approximate high-order closures and have been shown to predict heat flux with significant computational savings (Wei et al. 2023; Huang et al. 2025). However, these studies evaluated performance primarily in terms of data-driven accuracy, without systematic validation against classical kinetic theory. As a result, it remains unclear whether the learned models preserve fundamental physical properties or simply interpolate within the training domain. In particular, the consistency of FNO-based closures with well-established linear theories of Landau damping and heat flux (Hammett and Perkins, 1990; Hammett et al. 1992) has not yet been demonstrated.

In this work, we test whether FNO-based closure models are capable of reproducing the linear response properties captured in classical closures. Our investigation proceeds in two stages. First, we reproduce prior FNO-based results for heat flux prediction using particle density, velocity, and pressure fields as input, thereby verifying the reported performance of recent machine-learning models. Second, we introduce a modified FNO architecture in which nonlinear activation functions are replaced with linear ones, in order to isolate the linear component of the learned operator. The resulting predictions of heat flux are then directly compared against classical linear closure models, providing a clear benchmark for physical fidelity.

Preliminary results indicate that FNO-based closures can successfully reproduce heat flux behaviour when supplied with appropriate fluid moment data. This suggests that the operator-learning framework is sufficiently flexible to capture classical physics when data is appropriately provided. Ongoing work focuses on embedding physical and linear constraints within the operator-learning process and testing the physics of FNO closures across parameter ranges. By systematically benchmarking against both recent machine-learning models and classical linear theory, this study seeks to bridge the gap between data-driven approaches and physics-based plasma modelling. Ultimately, the goal is to develop closure models that are not only efficient and accurate but also interpretable and firmly grounded in first-principles physics.