UCLA

Plasma Physics Seminar

Physics & Astronomy Building (PAB) Room 4-330
Via Zoom: https://ucla.zoom.us/j/92785449357?pwd=SVBTSko3bTdEUW03dzQwNks1Q2lKZz09
Friday, February 9, 2024 at 12:30PM
Lunch will be served at 12:00PM

Embedding Lorentz transformation symmetry in data-driven reduced plasma models from fully kinetic simulation

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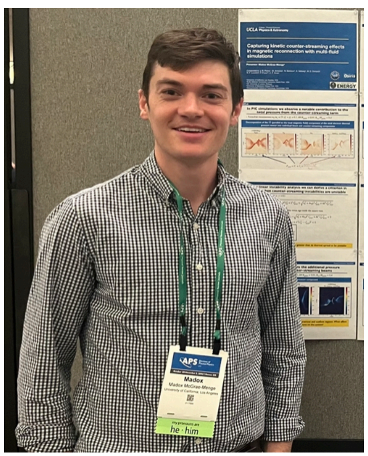

Abstract: Techniques from data science and machine learning are offering new approaches to developing theoretical and computational models of plasma dynamics directly from data. In particular, recent work has demonstrated the possibility of leveraging sparse regression techniques to recover interpretable plasma models [in the form of partial differential equations (PDEs)] from the data of fully-kinetic particle-in-cell (PIC) simulations. However, to robustly apply this methodology to uncover new reduced models of poorly understood plasma dynamics, it is important to embed fundamental physical symmetries in the inference procedure. In this work, we focus on embedding Lorentz transformation symmetry, i.e. the form of the inferred equations is invariant to special relativistic transformations. We present two complementary methods of embedding this fundamental symmetry: 1) data augmentation via Lorentz transformations and 2) strongly enforcing Lorentz symmetry by formulating the equation inference in the language of Lorentz tensors. We demonstrate the advantages of these symmetry-embedding strategies in the inference of the fundamental hierarchy of plasma models, from the kinetic Vlasov equation to the single-fluid plasma equations from *ab initio* PIC simulation data. In particular, we show that these symmetry-embedding strategies lead to 1) more accurate identification of model coefficients, 2) the elimination of spurious unphysical PDE terms that violate Lorentz transformation symmetry, and 3) greatly relaxes the amount of original "lab-frame" data needed from expensive kinetic simulations. These symmetry-embedding strategies open the door to inferring new physically-consistent reduced plasma physics models from high-fidelity data, such as kinetic-fluid closures and anomalous transport models, which are essential for the development of multi-scale plasma models.