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Machine Learning of Reduced Lagrangian Models of Turbulence

MICHAEL WOODWARD, Program in Applied Mathematics Department of Mathematics, University of Arizona, Tucson, AZ 85721, YIFENG TIAN, Computer, Computational and Statistical Sciences Division, Los Alamos National Laboratory, Los Alamos, NM 87544, MICHAEL CHERTKOV, MIKHAIL STEPANOV, Program in Applied Mathematics Department of Mathematics, University of Arizona, Tucson, AZ 85721, DANIEL LIVESCU, CHRIS FRYER, Computer, Computational and Statistical Sciences Division, Los Alamos National Laboratory, Los Alamos, NM 87544 — While it has been demonstrated that scientific machine learning can be successfully applied to many fluid dynamics applications, it still remains a great challenge to encode physical constraints. In this work, we develop physics informed machine learning techniques to discover reduced Lagrangian models from turbulence simulation data. Specifically, we utilize symplectic integrators consistent with back propagation over the parameter space while embedding physical constraints within artificial neural networks. We explore parameterized families of molecular dynamics (MD) and smoothed particle hydrodynamics (SPH) models for simulating coarse-grained Lagrangian turbulence and for validating our learning algorithms. From this, we show that our method is capable of extracting relevant physics and can be used for data-driven discovery of parameters (e.g. smoothing kernels in SPH) while retaining a high level of interpretability and explainability. We train and evaluate our method on high fidelity Lagrangian DNS data and show it is capable of capturing turbulent dynamics within the resolved coarse-grained scales.

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