PHYSICS INFORMED MACHINE LEARNING OF SPH: MACHINE LEARNING LAGRANGIAN TURBULENCE

Anonymous authors
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ABSTRACT

Smoothed particle hydrodynamics (SPH) is a mesh-free Lagrangian method for obtaining approximate numerical solutions of the equations of fluid dynamics, which has been widely applied to weakly- and strongly compressible turbulence in astrophysics and engineering applications. We present a learn-able hierarchy of parameterized and "physics-explainable" SPH informed fluid simulators using both physics based parameters and Neural Networks as universal function approximators. Our learning algorithm develops a mixed mode approach, mixing forward and reverse mode automatic differentiation with forward and adjoint based sensitivity analyses to efficiently perform gradient based optimization. We show that our physics informed learning method is capable of: (a) solving inverse problems over the physically interpretable parameter space, as well as over the space of Neural Network parameters; (b) learning Lagrangian statistics of turbulence; (c) combining trajectory based, probabilistic, and field based loss functions; and (d) extrapolating beyond training sets into more complex regimes of interest. Furthermore, our hierarchy of models gradually introduces more physical structure, which we show improves interpretability, generalizability (over larger time scales and Reynolds numbers), and requires less training data.