Abstract Submitted
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Learning minimal representations for chaotic dynamics of partial differential equations[1] ALEC J. LINOT, MICHAEL D. GRAHAM, University of Wisconsin - Madison — We describe a method of reduced order modeling for systems with high-dimensional chaotic dynamics in which we map data to an "exact" minimal representation called an inertial manifold and evolve trajectories forward in time with this representation. The mapping is learned by training an undercomplete autoencoder where we vary the dimension of the minimal representation. Once we reach the dimension of the inertial manifold there is a drastic drop in recreation error. For the Kuramoto-Sivashinsky equation (KSE), we validate this conclusion against known estimates of the dimension and make predictions for larger domain sizes. Next, we show that time evolution can be predicted in the inertial manifold coordinates either in a data-driven manner by learning a neural network representation for the differential equation on the inertial manifold, or in a hybrid data/equation-based method using knowledge of the governing equations and a nonlinear Galerkin method. For the KSE, both methods show excellent short- and long-time predictive capabilities when using the correct number of dimensions and a significant drop in performance with too few dimensions. Finally, we apply this method to direct numerical simulations of chaotic 2D Kolmogorov flow.

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