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Nonlinear dimensionality reduction and prediction of chaotic spatiotemporal dynamics in translation-symmetric systems via deep learning[1] ALEC LINOT, MICHAEL D. GRAHAM, University of Wisconsin-Madison — Many flow geometries, including pipe, channel and boundary layer, have an unbounded or spatially periodic direction in which the governing equations have continuous translation symmetry. As a model for such systems we consider the Kuramoto-Sivashinsky equation (KSE) in a periodic domain for a parameter regime with chaotic dynamics. We describe a method to map the dynamics of the KSE onto a translationally invariant low-dimensional manifold and evolve them forward in time using neural networks (NN). Invariant dimensionality reduction is achieved by first applying the method of slices to phase-align the spatial structures at each time, which are then input into an undercomplete autoencoder that maps the original dynamics onto a lower-dimensional manifold where the long-time dynamics live. The spatial structure on this manifold and also the spatial phase are integrated forward in time using a NN. This approach significantly outperforms linear methods, such as POD, for drastic dimensionality reduction. Furthermore, evolving the nonlinear dynamics on the manifold with this NN architecture allows us to capture statistics of the chaotic attractor, whereas linear methods, like dynamic mode decomposition (DMD), fail to capture nonlinear dynamics.

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