Modified neural ordinary differential equations for stable learning of chaotic dynamics.

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ABSTRACT. In recent times, several deep learning techniques have been used for learning dynamical systems from data. One state-of-the-art technique is the method of neural ordinary differential equations (NODEs) which learns the right hand side of a system of differential equations using a neural network. However, we observe that a basic implementation of NODEs for learning chaotic dynamics is shown to lead to unstable surrogate models. To remedy this, we introduce a novel decomposition of the NODE into a linear and nonlinear term that promotes long-term stability and robustness into the surrogate. The linear term may be specified by utilizing a dictionary or through a multipoint stencil prescribe through a convolutional layer. We observe that our novel NODE is able to learn the chaotic dynamics of the Kuramoto-Sivashinsky equations and provide models that are stable and robust to noise for long durations. Moreover, the prescription of a linear term also allows for the identification of an approximate inertial manifold directly from the data which can be used for further model-order reduction of the surrogate.