

Data-assisted reduced-order modeling of climate dynamics

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The response of realistic climate models is characterized by high intrinsic dimensionality with strongly transient features that are often away from the mean. Such systems are not amenable to classical order-reduction methods through projection of the governing equations due to the large intrinsic dimensionality of the underlying attractor as well as the complexity of the transient events. Alternatively, data-driven techniques aim to quantify the dynamics of specific, critical modes by utilizing data-streams and by expanding the dimensionality of the reduced-order model using delayed coordinates. In turn, these methods have major limitations in regions of the phase space with sparse data, which is the case for extreme events. In this work, we develop a novel hybrid framework that complements an imperfect reduced order model, with data-streams that are integrated through a recurrent neural network (RNN) architecture. The reduced order model has the form of projected equations into a low-dimensional subspace that still contains important dynamical information about the system and it is expanded by a long short-term memory (LSTM) regularization. The LSTM-RNN is trained by analyzing the mismatch between the imperfect model and the data-streams, projected to the reduced-order space. The data-driven model assists the imperfect model in regions where data is available, while for locations where data is sparse the imperfect model still provides a baseline for the prediction of the system state. We assess the developed framework on a T21 truncation of the barotropic climate model.