Data-driven stochastic model reduction

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There are many high-dimensional dynamical systems in science and engineering that are too complex or computationally expensive to solve in full, and where only a relatively small subset of the degrees of freedom are observable and of direct interest. Therefore it is useful to derive low-dimensional models that can predict the evolution of the observable variables of interest, and reproduce their statistics at an acceptable cost. The challenges come from the nonlinear interactions between the observed variables and the unobserved variables, the memory effect due to the reduction, and the difficulties in quantifying uncertainties from discrete data.
We address these challenges by developing discrete-time non-Markov stochastic reduced systems for the observed variables, by using data and statistical methods to account for the impact of the unobserved variables. A key ingredient in the construction of the stochastic reduced systems is a discrete-time stochastic parametrization based on inference of nonlinear time series. We demonstrate our approach on the two-layer Lorenz 96 system and the Kuramoto-Sivashinsky equation.