Neural Closure Model for Dynamic Mode Decomposition Forecasts

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Dynamic Mode Decomposition (DMD) is a data-driven, equation-free dimensionality reduction algorithm [4, 5, 7] that constructs an approximate linear operator for a sequential data set. It has been demonstrated that DMD can serve as a computationally efficient forward model to provide forecasts in a wide variety of applications. However, DMD forecast suffer from three key issues. First, the absence of truncated modes and lack of adaptation may lead to drastically different forecasts [4], especially due to the linear approximation of possibly highly nonlinear dynamics [6]. Second, as the standard DMD formulation is steady in time, it may become irrelevant in evolving systems [9, 3, 6, 1]. Third, uncertainties are not commonly represented and sub-DMD (closure) models not commonly utilized [3, 2, 8]. To address these issues, we investigate augmenting the stochastic DMD model with a closure model parameterized using neural networks. We demonstrate our new results on several test cases in high-dimensional computational multivariate ocean dynamics and modeling.

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