Machine Learning for Missing Dynamics

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In this work, we present a general framework for recovering missing dynamical systems using available data and machine learning techniques. The proposed framework reformulates the prediction problem as a supervised learning problem to approximate a map that takes the memories of the resolved and identifiable unresolved variables to the missing components in the resolved dynamics. The map for this non-Markovian transition kernel is represented by a conditional distribution which is estimated from appropriate RKHS formulation or the long short term memory (LSTM). In the case of short memory terms or Gaussian variables, the success of the RKHS formulation suggests that various parametric modeling approaches that were proposed in various domain of applications can be understood through our RKHS representations. In the case of long-memory non-Markovian terms with non-Gaussian distribution, the LSTM method is an effective tool for recovering the missing dynamics that involves approximation of high-dimensional functions. Supporting numerical results on instructive nonlinear dynamics, including the two-layer Lorenz system, the truncated Burger-Hopf equation, the 57-mode barotropic stress model, and the Kuramoto-Sivashinsky (KS) equation.

Joint work with John Harlim (Penn State University), Haizhao Yang (Purdue University) and Senwei Liang (UC Berkeley).