Data-driven Koopman theory revisited

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Starting with the seminal works of Clancy Rowley (*J. Fluid Mech.*, 2009) and Peter Schmid (*J. Fluid Mech.*, 2010), approximating the Koopman and Perron-Frobenius operators from data has attracted a lot of attention in the past decade. These data-driven formalisms suggest new ways of obtaining low-order models from experimentally accessible measurements, most notably for control purposes. Loiseau & Brunton (in preparation) have recently realized that *Dynamic Mode Decomposition* (DMD), the most widespread algorithm for data-driven approximation of the Koopman operator, is a special instance of a more general optimization problem, paving the way for a better understanding of the properties of these data-driven models.

After having introduced this general optimization problem and its closed-form solution, I will show the equivalence between DMD and classical linear system identification techniques (e.g. ERA, N4SID, etc). I will then illustrate how to combine these data-driven models with *Kalman filtering* and *Model Predictive Control* to manipulate increasingly complex nonlinear dynamical systems. If time permits, some elements pertaining to near-optimal sensor selection will also be discussed.

Figure 1: Data-driven approximation of the leading Koopman singular function for the choatic Lorenz 1963 model. The observable considered consists in time-delayed measurements of the state variable $x(t)$. Blue and orange regions nicely approximate the almost-invariant sets of the dynamics.