Error bounds on Koopman-based techniques in learning dynamical systems

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Extended Dynamic Mode Decomposition (EDMD) is a widely used machine learning technique for identifying highly nonlinear dynamical systems directly from data. At its core, EDMD offers a data-driven framework for approximating the Koopman operator, which governs the evolution of a finite set of observable functions along the system's flow. This results in an interpretable surrogate model for analysis, prediction, and control.

A recent variant, kernel EDMD (kEDMD), has gained traction for its ability to bypass the difficult task of selecting a dictionary of observables. Instead, it leverages the canonical feature space of kernels to define data-informed observables automatically.

In this talk, we present our recent results on error bounds for both EDMD and kEDMD in the context of deterministic and stochastic dynamical systems. For kEDMD, we show that a key requirement for deriving approximation error bounds is the invariance of the reproducing kernel Hilbert space (RKHS) under the Koopman operator. By using Wendland or Matérn kernels, we demonstrate that Sobolev spaces satisfy this invariance, enabling us to establish error bounds on the kEDMD approximant in the uniform norm.