**Using dynamical systems ideas to combine in a principled way data-driven models and domain-driven models**

Michael W. Mahoney, ICSI and Department of Statistics, UC Berkeley

While data-driven models such as those common in machine learning tend to be relatively domain-agnostic and thus are widely-applicable across many domains, it is a fundamental challenge how best to combine such data-driven models with fine-scale domain-driven models that are common in physics and other natural sciences and that make strong use of domain-specific insight. Here, we describe recent work on using techniques from dynamical systems theory to combine these two types of models in a principled way. We'll describe how to develop physics-informed autoencoders using Lyapunov stability, and how to use couple forward and backward dynamics for Koopman autoencoders to enable better forecasting of sequential data. We'll also describe how these sorts of techniques feed back to more traditional machine learning and can be used to diagnose and robustify against adversarial data.