Dissertation Defense:

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"Optimization and Control for Scalable Modeling and Inference in Dynamical Systems"

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ABSTRACT

In this thesis, we investigate methodologies for discovery, assimilation, and control of (stochastic) dynamical systems, and introduce algorithms that exploit structural properties for efficiency. Data-driven modeling problems in physics and engineering are governed by high-dimensional dynamical systems, where direct simulation and control can become prohibitively expensive.

Chapter 2 begins with the discovery of mathematical descriptors directly from data, focusing on nonautonomous and translation-invariant systems. By combining the Lagrangian frame of reference with locally time-invariant Koopman approximations, we obtain low-rank linear time-varying surrogate models with a priori predictive error estimators. We validate the approach on canonical flow and 2D advective transport problems. In Chapter 3, we shift focus to stochastic systems, and address uncertainty quantification in multiscale models where stiffness impedes statistical convergence. We propose reduced-order probability density equations, which employ closure terms defined as state-space conditional expectations and learned directly through data assimilation strategies, such as nudging. Chapter 4 generalizes this methodology to high-dimensional observables. The methodology is then applied to stochastic power system models to design estimators for extreme-event probabilities, such as cascading line failures. Numerical results demonstrate both stability and efficiency, outperforming naive Monte Carlo simulation and kernel density estimations.

In Chapter 5, we address the problem of control, which is a central problem in the characterization of extreme events. We present an optimize-then-discretize framework for linear-quadratic control governed by time-inhomogeneous dynamics. Our method employs a modified overlapping Schwarz decomposition in continuous-time, which ensures convergence through the exponential decay of sensitivity property in Hamiltonian systems. Unlike discretize-then-optimize approaches, the framework allows flexible numerical integration schemes while preserving stability. This contribution paves way for distributed nonlinear control as well as deep learning applications, whose analysis is left for future work.