CAREER: Learning to Optimize Partially Observed Dynamical Systems

Sarah Dean

Overview

Machine learning (ML)-enabled algorithms have found success in domains ranging from robotics to power distribution to recommendation systems. Many of these settings are best characterized as *dynamical systems* and thus machine learning algorithms are best understood as part of a broader *feedback control* loop. Ensuring good performance in such settings—and ruling out unintended consequences—poses an important challenge. Grappling with it requires developing methods drawing on tools from control theory, optimization, machine learning, and statistics.

Key challenges stem from two facts: the state of the dynamical system is often only partially observed, and the equations governing its dynamics are often unknown or uncertain. Recent breakthroughs show that modern machine learning can readily grapple with these challenges: large autoregressive models, trained internet scale data, are able to capture the complexities of human language. However, the empirical advances lack fundamental understanding, and crucially fail to grapple with the challenges of *feedback and impact*—how algorithmic decisions affect the state of the world, or the ability to sense it. This proposal introduces a research program focused on fundamental questions of optimal sensing and control for unknown and partially observed dynamical systems.

Intellectual Merit

The proposed work will develop theory and algorithms along three key themes: First, developing algorithms for the joint design of optimal sensing and control actions. Second, characterizing the sample complexity of identifying unknown dynamics from partial observations. Third, quantifying the sub-optimality of learning to sense and control from finite data. This foundational work will be inspired by and applied to problems in human behavior modelling for robotics and recommender system as well as path planning in dynamic wind fields for atmospheric navigation.

The goal of the first theme is to understand algorithm design when decisions affect both sensing and actuation. The research will draw on established lines of work, which consider these problems separately, to pose the non-convex joint optimization problem. Using the lens of dynamic programming and strategies like receding horizon control, the proposed work will develop efficient (but potentially sub-optimal) algorithms and characterize the computational hardness of the joint sensor and actuation optimization. The second thrust will consider the problem of learning unknown dynamics from partial observations of the state. Drawing on a recent line of work on linear system identification, the proposed work will focus on nonlinear dynamics, including bilinear and control affine systems. The key challenge will be bounding the sample complexity: the number of samples necessary to guarantee small error. For this, the proposed work will advance statistical techniques and random matrix analysis. Finally, the third thrust will combine the previous two and develop algorithms for both learning and controlling unknown and partially observed dynamical systems. The key challenge will be to bound the sub-optimality of data-driven policies and to develop techniques for targetted data collection.

Broader Impacts

The algorithms and theory developed in this proposal have direct impact on applications like human-robot collaboration and recommendation systems. In addition to an integrated education plan at the undergraduate and graduate levels, and research community development through organizing interdisciplinary workshops and conferences, this proposal includes an initiative for K-12 outreach via weather forecasting & balloon control projects and interactive education modules. The initiative will seek to broaden participation in and understanding of computing, with a particular focus on predictive technologies, feedback, and dynamics.