

CAREER: Towards a Theory of Machine Learning in Feedback Systems

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Overview

Machine learning (ML)-enabled algorithms have found success in domains ranging from recommendation systems to autonomous flight, human-robot interaction to medicine. Once ML is deployed in such settings, decisions interact with the environment, and begin to shape it. For example, users' tastes shift in response to personalized recommendations, while creators strategize to reach a large audience. The resulting *feedback dynamics* can lead to positive effects or unintended negative consequences, with implications for safety, equity, and performance. Ensuring desirable outcomes is one of the most important challenges for the modern practice and theory of machine learning.

Key challenges stem from two facts: the underlying state of the environment (e.g. user preference) is often only partially observed, and dynamics describing its evolution are not easily modelled from first principles. Recent breakthroughs show that modern machine learning practice can grapple with these challenges, at least from a predictive standpoint: large autoregressive models, trained internet scale data, are able to capture the complexities of human language. However, the empirical advances rely on large amounts of data and lack fundamental theoretical understanding. More crucially, they fail to grapple with the challenges of *feedback and impact*—algorithmic decisions must consider how they affect the state of the world and the ability to sense it. This proposal introduces a research program to tackle the challenges of efficiently learning models of feedback systems and designing impact-aware ML algorithms for decision-making.

Intellectual Merit

The proposed work will develop theory and algorithms along three key thrusts, leveraging ideas of state-space models, state estimation and sensor design, and model-based reinforcement learning.

1. Learning models of feedback systems: the proposed work will develop theoretically justified algorithms for identifying models of dynamical systems with partially observed state, with guaranteed *sample complexity*, i.e. bounds on the estimation error in terms of the finite data.
2. Optimizing decisions for performance and estimation: the project will develop model-based algorithms for synthesizing optimal policies for partially observed systems. To deal with non-convexity the project will leverage approximation strategies like receding horizon control, and will justify them by characterizing sub-optimality and computational hardness.
3. Joint learning and decision-making: the proposed work will develop algorithms for learning feedback policies from finite data with performance, equity, and safety guarantees. Extending bandit algorithms to the dynamical/stateful setting will enable targeted data collection.

The algorithmic and theoretical frameworks will be developed in tandem with applications in recommendation systems, human-robot interaction, and autonomous atmospheric navigation.

Broader Impacts

The algorithms and theory developed in this proposal have direct impact on applications like human-robot collaboration and recommendation systems. Through the organization of interdisciplinary workshops and conferences, the proposed work will also impact the broader research communities in ML, EconCS, and Systems & Control. In addition to an integrated education plan at the undergraduate and graduate levels, this proposal includes an initiative for high school outreach through partnership with residential summer programs at Cornell Engineering. The project will develop a hands-on project and interactive education modules about weather forecasting & balloon control. The initiative will seek to broaden participation in and understanding of computing, with a particular focus on predictive technologies, feedback, dynamics, and bias.