CAREER: Reliable Machine Learning and Decision-Making in Feedback Systems

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Overview

Machine learning (ML)-enabled algorithms play an important role in social and economic life. In settings ranging from social media to music and video streaming, ML is pushed beyond the paradigm of static prediction towards dynamical and interactive decision-making problems. It is crucial to consider the emergent effects of feedback between ML, decisions, and the broader world; both to mitigate unintended consequences and to achieve better performance.

Social, behavioral, and economic dynamics are not easily described by universally accepted models. To some extent, this challenge can be addressed by the use of data and ML. However, advances are necessary to apply tools from areas like control theory, system identification, and reinforcement learning. At the lowest level, individual decisions must be made on the timescale of seconds despite high dimensional feature and decision spaces (e.g. ranking). Here, the dynamics are largely driven by the stochasticity of user populations. On longer timescales, feedback effects become more prevalent, for example due to strategic behaviors or opinion formation. This proposal introduces a plan for grappling with the challenge of dynamics on both timescales: developing theory and algorithms for ML and decision-making interactive and feedback-laden settings.

Intellectual Merit

The proposed work will grapple with these challenges along two fronts:

1. Fast low-level learning and control algorithms for stochastic environments with high dimensional feature and decision spaces, epitomized by online ranking with long term objectives.
2. Methods for measuring feedback effects and steering long term dynamics, with a special emphasis on the constraints and realities of online platforms.

At both levels, the proposed work will focus on developing algorithms with strong theoretical foundations and reliable empirical performance. In addition, the theoretical characterization of these settings will surface design principles by elucidating fundamental trade-offs.

The development of low-level control and learning algorithms will leverage tools from bandits and online optimization, which have long considered decision-marking in unknown and stochastic environments. Applying these tools to the realistic settings of interest will require advancing the state-of-the-art: long term objectives and impacts, constraints arising from concerns of fairness and bias, and combinatorial action spaces (e.g. ranking). The proposed work will investigate connections between these algorithms and classic low-level control techniques, including proportional-integral-derivative (PID) control, and will also draw on the fields of robust and adaptive control.

Methods for measuring and steering longer term dynamics will draw on tools of nonlinear system identification and control. However, most existing techniques implicitly assume physical dynamics with considerable controllability and and freedom to probe system behaviors. In contrast, many online platforms perform of A/B tests and rely on causal inference to draw limited conclusions. The proposed work will innovate at intermediate points along the spectrum from from full identification to binary effect size estimation, with a focus on designing intervections.

Broader Impacts

The algorithms developed in this proposal have direct impact on many important social and economic domains ranging from social media and news to electricity grids and on-demand mobility. They will enable the design of systems which better serve long term needs of stakeholders. In addition to an integrated education plan at the undergraduate and graduate levels, this proposal includes an initiative for K-12 outreach via interactive education modules. It will seek to broaden participation in and understanding of computing, with a particular focus on the ethics, bias, and mathematics of personalization algorithms, like music recommendation.