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

Overview

Machine learning (ML)-enabled algorithms play an important role in social and economic life. They are applied in settings ranging from social media and online shopping to hiring and industrial logistics. Such algorithms push ML beyond the paradigm of static prediction to dynamical and interactive decision-making problems. This proposal aims to develop algorithms and theory for interactive and online ML problems, with a special focus on feedback effects and emergent dynamics.

Rich theory and design principles exist for the control, and more recently learning, for systems whose dynamics are governed by physical phenomena. However, many algorithms have non-physical effects on the environments in which they operate; for example, music recommendations may influence a listener's tastes. The timescales on which these effects occur are much longer than the decision-making timescales of many algorithms, which respond to user requests on the scale of minutes to seconds. On the short timescale, dynamics are largely driven by stochasticity in user populations, and decisions are high-dimensional: thousands of features are recorded about users, platforms must select between millions of songs. On the longer timescale, feedback effects are more prevalent. Here, platforms play a role similar to markets leading to strategic behaviors and competition. In both cases, there are patterns in data that can lead to more effective algorithms: for example personalized playlists. Leveraging these patterns to steer longer term dynamics, e.g. towards platform health, remains an elusive question. The proposed work will grapple with these challenges along two fronts:

1. Low-level control algorithms for high dimensional feature and decision spaces (e.g. ranking). Leverage the approximate stationarity, but incorporating long term objectives. Paradigm of online optimization and bandit algorithms.
2. Detecting and steering long term dynamics and feedback effects. Leverage longer timescales and lower dimensional abstractions for system identification and causal inference, to learn dynamics, and simple planning algorithms, to achieve overall platform goals.

The final thrust of this work is to combine the two levels of control towards full stack principled algorithms for platform design and operation. This last thrust will be enabled by relationships with industry and nonprofit organizations in application like recommendation, e-commerce, and search.

Intellectual Merit

Developing low level control algorithms will require intellectual contributions on bandit and online optimization algorithms in realistic settings; on developing a general constraints/optimization framework for fairness and bias; on advancing and applying bandit and other online algorithms to real problems and datasets; drawing connections between feedback control like PID and the systems that we study. Especially robust, uncertain, and adaptive control.

For the high level, system identification with finite sample guarantees and nonlinear systems is an active area of research; most works are focused on physical systems where there is considerable controllability and few constraints on choosing inputs to excite the system; in contrast many online platforms make small only perturbations and perform binary A/B tests. Consequently is is likely that it will not be possible to identify full parameters of models; on a spectrum with the other end being estimating a causal effect and effect size.

Broader Impacts

Many real platforms in different domains from music to news to social media. Also electricity, mobility. Currently many algorithms operate out of control. Better serve long term needs of users and other stakeholders. Ethics and bias. Coupled with a broadening participation initative designed to make algorithmic decisions, in appications like personalized recommendation, more broadly accessible to community members and groups. K-12 education and undergraduate research.