Adaptive Online Learning for Online Nonlinear Control, Faster Machine Learning Optimizer, and Better Finetuning of Large AI Models

Heng Yang
School of Engineering and Applied Sciences
Harvard University

Online learning, an emerging field at the intersection of machine learning and theoretical computer science, studies the problem of making online decisions --subject to per-step feedback from the (potentially adversarial environment)-- to minimize a certain metric called regret, i.e., how suboptimal is the online policy compared to the best offline policy had the player observed the environment's feedback in hindsight. While primarily being a theoretical field, it has found interesting applications such as online control of linear systems.
Adaptive online learning, a branch of online learning, tries to make the online algorithm adaptive to the underlying difficult of the problem, i.e., even though the algorithm does not know the difficulty of the problem before, it behaves as if it knows. Adaptive online learning algorithms are thus more robust to parameter tuning by design.
We are interested in exploring the impact of adaptive online learning algorithms in at least three different directions:

- **Online nonlinear control**. Given a stochastic nonlinear dynamical system with unknown uncertainty, the goal here is to design an online controller that converges to the optimal controller in hindsight. This work aims to generalize the earlier work in online control for linear systems.
- **Faster Machine Learning Optimizer**. A recent result from our group shows that the well-known ADAM algorithm for training deep neural networks can be interpreted as an adaptive online learning algorithm. This leads to an exciting avenue: can we, in turn, leverage more advanced online learning algorithms to design a deep learning optimizer that is faster and better than ADAM?
- **Finetuning Large AI Models**. The pretraining-fintuning pipeline is becoming more prevalent given the success of foundation models. The key question we want to study here is, given a small amount of data, what is the best way to finetune the large models? For example, is SGD or ADAM the best algorithm to finetune them? How can we finetune while avoiding catastrophic forgetting? Can we use finetuning as a way to tackle distribution shifts?

Note that these three directions will be separate efforts, though we do expect the lessons and results learned from each direction could cross fertilize other directions.

Desired background: upper-level undergraduates and master students who are familiar with control theory or machine learning. These projects can vary from being very theoretical to very practical, and we can customize the projects to fit the students' interests. Students with background in control theory, machine learning, and practical deep learning practices are preferred.