Personalized Education

Tailoring the presentation of information to the needs of individual students leads to massive gains in student outcomes (Bloom 1984). This finding is likely due to the fact that different students learn differently, perhaps as a result of variation in ability, interest or other factors (Schiefele, Krapp, and Winteler 1992). Adapting presentations to the educational needs of an individual has traditionally been the domain of experts, making it expensive and logistically challenging to do at scale, and also leading to inequity in educational outcomes.

Increased course sizes and large MOOC enrollments provide an unprecedented access to student data. We propose that emerging technologies in reinforcement learning (RL), as well as semi-supervised learning, natural language processing, and computer vision are critical to leveraging this data to provide personalized education at scale.

Sources of Difficulty

Personalized instruction is readily cast as a reinforcement-learning problem. The student’s knowledge and interests are a (sometimes unobserved) state, the collection of pedagogical tools (videos, text, activities, games, etc.) are the set of actions with corresponding costs reflecting their demands in terms of time or other resources, and performance on some measure of learning (say a final exam) is the final reward.

The largest barrier to automation is the scale of the problem, which comes into play in three ways. First, a comprehensive student model may contain many features that are extraneous for any particular topic, resulting in increased sample complexity demands for learning. Second, any given topic may have thousands of pedagogical actions associated with it. (A video search for “derivatives tutorial” yields about $10^5$ results.) Third, student state changes are typically unobserved, and there may be a large temporal delay between when an action is taken and when reward (learning demonstrated on a test) is observed. Human instructors frequently use ad-hoc informal tests and affective impressions to gauge the effect of educational content, but replicating this observational adaptability is challenging.

Current Progress

Intelligent tutoring systems have been successfully deployed in a number of problem-rich domains, such as LISP programming, Algebra, and Genetics (Koedinger and Corbett 2006). These systems achieve near human-tutor level gains (Corbett 2001) by inferring student mastery (state) over practice problems, then using an expert-crafted policy to advance students through a linear curriculum. These techniques are currently difficult and expensive to apply to less structured domains, and they do not accommodate much variation in students.

It has been previously proposed that RL could be used to optimize pedagogical approaches (Iglesias et al. 2009). Unfortunately, the RL algorithms previously considered do not scale well to teaching an entire course. For example, Rafferty et al. (2011) explore the possibility of using a POMDP to model student belief over several possible conceptions of a single task. Their empirical study shows the efficacy of adaptation to inferred state, but the technique is not currently amenable to larger-scale problems. Chi et al. (2011) consider introductory physics tutoring as an RL problem, but are limited to modeling only a few actions and state features because of the cost of collecting exploratory trajectories under a uniform random policy. Similar work in computer science education (Iglesias et al. 2009) used simulated students to collect data for an initial policy, but were also highly constrained because of the high sample complexity of Q learning. In the next three sections, we propose problem formulations and the application of emerging techniques that could overcome these barriers to scalability.

A Contextual Bandit Problem

Assume that for each student we have explicitly constructed a feature vector (say by administering personality tests, clustering based on behavior in previous courses, or through some kind of tagging system), and we have a collection of
possible pedagogic actions. If we look at only immediate performance on a topical assessment, we can cast the personalized instruction problem as a contextual bandit. Approaches such as the contextual Gaussian process bandit algorithm (Srinivas et al. 2012) suggest that this kind of personalization may be feasible, although this approach does not solve the longer-term problem of curricular planning. To achieve sufficiently low sample complexity, an efficient task-relevant characterization of contexts and actions is necessary, requiring a compact model of students and a similarity measure between pedagogical resources.

A (Hierarchical) POMDP

In many educational settings, it is impractical to assess students after every pedagogical action due to the expense in creation of validated assessments, administration, and student time. As a result, reward is delayed and state is only partially observable. Additionally, we do not have access to the “true” model of the student. In this setting, relevant hidden features must be invented and inferred by the algorithm. The scale of the curricular problem may be mitigated by decomposing the curriculum into shorter term goals, akin to an instructor’s “units”. There has been some compelling work in the direction of decomposing POMDPs: the work of Wray, Witwicki, and Zilberstein (2017) decomposes a large problem into entity-specific POMDPs whose recommendations are combined, and Sridharan, Wyatt, and Dearden (2010) decomposes observational actions at different levels of granularity. Approaches like these may allow efficient (approximate) solution of otherwise intractably large POMDPs.

An “Active” POMDP with Human-Collaborative Actions

Eventually, we desire a system that can not only personalize instruction autonomously, but can also collaborate with human experts. In particular, we would like such a system to identify pedagogical bottlenecks where new pedagogical actions may have greater efficacy for a specific subset of students, or to identify states of high uncertainty where a targeted assessment might differentiate hidden states. This idea is similar in spirit to the work of Mandel et al. (2017), which considers the problem of finding the optimal states for which to ask a human (expert) to construct new actions.

Integration with Other Techniques

While the underlying problems are defined in reinforcement-learning terms, their solutions will likely integrate some of the cutting-edge techniques from other areas. For example, semantic embeddings developed in the context of Natural Language Processing may provide a way to generalize educational insights across enormous action spaces. Computer vision and emotion detection could play a valuable role in reading students and reducing uncertainty of their state. Techniques from semi-supervised learning might be used to improve the generalization across student states. Recent work in explainable machine learning may improve adoption and use of personalized instruction agents, and also provide insight into effective student–pedagogy combinations.

Call to Action

We have an unprecedented access to student data at scale, exciting new developments in scalable RL, and compelling deployed technologies in natural language processing and computer vision. If the AI research community invests time into researching sample-efficient RL algorithms as outlined above, the impact to education—as well as many other domains that would benefit from interactive personalization—would be profound and far reaching.

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