Automatically Learning to Teach to the Learning Objectives

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Abstract

We seek to automatically identify which items to include in a set of curriculum, and how to adaptively select these items, in order to maximize student performance on some specified set of learning objectives. Our experimental results with a histogram tutoring system suggest that Bayesian Optimization can quickly (with only a small amount of student data) find good parameters, and may help instructors identify misalignment between their course, and their desired learning objectives.

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Introduction

Educators want to provide the best learning experience for their students, but there are many ways to create pedagogical content (videos, quizzes, etc), sequence content, and provide personalized support and feedback. Instructors frequently have learning objectives for a course: a list of capabilities the student should have after taking the course. Therefore, a natural way to measure the course effectiveness is to evaluate how well students reach a specified input set of learning objectives, and to adjust the course to improve how well students achieve these objectives. It is well known that changing the content and the way in which material is taught can make an enormous difference to the effectiveness and efficiency in which students learn. For example, creating a blended statistics learning class led to the same final scores in half the time as a traditional statistics in person class [5].

However, which content to change and how to sequence or select content to improve learning is still a challenge. Existing approaches to addressing this often involve researchers performing extensive data analysis to identify places where the existing models or curriculum can be revised in order to improve student learning (see e.g. [2]). Another common approach is to use standard experimental design to compare multiple ways to teach the material, but such work typically requires a very large number of subjects to explore many conditions.

Fortunately in trying to find the best way to teach some material, we may not need to fully quantify the effectiveness of all possible approaches (as is typical in experimental design). This motivates recent machine learning approaches such as using multi-armed bandits optimization to identify the best of a finite set of teaching conditions, or treating the problem as function optimization using Bayesian optimization (BO) to find the maxima of a latent function that describes how adjusting the (continuous) parameters that prescribe how to teach impacts student outcomes in cognitive task learning [4].

Our work builds on this second line of work, but makes several important additional contributions. First, prior work has considered optimizing only fixed instructional policies that are independent of student performance [4] (e.g. optimizing fixed sequence of practicing vocabulary words which does not depend on how students are performing). However, it is well known that it is often beneficial to select the pedagogical material based on how the student is doing. Given this, in our work we consider optimizing over adaptive instructional policies. A second key contribution is to automatically identify when the current curriculum and/or method of teaching is inadequate for obtaining the desired input learning objectives. Our experimental results with a histogram teaching tutoring system demonstrate this, and highlight the opportunity for systems that can proactively assist instructors to focus their attention on which parts of the course (material or ordering) should be revised. This has the potential of greatly accelerating the rate at which classes can be improved, without requiring substantially more (instructional or experimental) resources.

Bayesian Optimization for Instruction

In our work we seek to automatically identify which items to include in a set of curriculum, and how to adaptively select these items, in order to maximize student performance on some specified set of learning objectives. In many situations instructors desire not just effective, but efficient pedagogical approaches. Therefore, the evaluation criteria for a particular way of teaching may combine multiple measures.

We can view this general challenge as an instance of finding the parameter values (indicating a set of items to chose, how to teach) that maximize a function value (student performance on learning objectives when taught using an automated policy with the specified parameters). Of course, in general there are a huge number of possible parameter values to try. Bayesian optimization is a popular machine learning approach for finding the optimal value of a function when evaluating the function at a particular set of parameters is costly, and we wish to minimize the number of parameters tried to find the optimal function value. This is certainly true in education, where each function evaluation corresponds to providing one (or more) real students with a particular instructional curriculum or approach to selecting that curriculum, and measuring the resulting outcome value (effectiveness/efficiency).

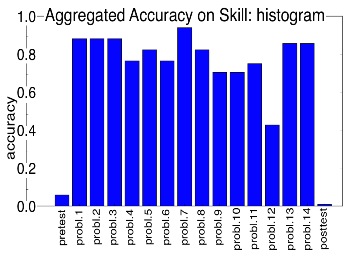

Figure 1: This figure displays the pretest performance and then student performance on each of the sequence of 14 problems, followed by their post test performance. Performance is measured by average accuracy. Note that there seems to be no steady increase in performance, and the pre and post test performance are both less than 10%. This potentially indicates instructional material not suitable for the learning objective.

Histogram Tutor & Preliminary Experiment

As a first step towards this general aim, we used Bayesian Optimization to optimize how to adaptively select activities in an online histogram tutor. Histograms are frequently used to convey information but there is good evidence that many students find understanding histograms challenging. Indeed even after instruction students may lack basic concepts such as what the axes of a histogram represent [3].

Our histogram tutor consists of activities/questions for 8 different skills considered core knowledge about histograms and/or common misconceptions [3]. These skills represent our learning objectives for students. We also created a test based closely on assessment items previously made to evaluate some of these skills [3]. Note that the BO approach can be applied much more broadly to tutors without skill labels on activities.

Bayesian Knowledge Tracing (BKT) is a popular 4-parameter model of student learning [1]. A simple approach for mastery teaching adds a fifth threshold parameter: halt teaching a skill when the BKT estimate of the probability that the student has mastered the skill exceeds the threshold. However, without student data it is unclear how to set the parameters of a BKT mastery teaching policy. Even given data, existing approaches tend to use maximum likelihood methods to fit the BKT parameters and then hand set the threshold parameter. However, BKT only approximately models student learning, and it may be beneficial to directly optimize all 5 mastery parameters.

For each skill, we seek to directly find the 5-parameter BKT policy $\boldsymbol{\pi}$ that maximizes the function value $f(\boldsymbol{\pi})$, where $p_{\boldsymbol{\pi},s}$ is the normalized post test score for this given skill, $p_{\boldsymbol{\pi}}$ is the normalized post test score over all skills (with *0.7* as desired passing score), and $l_{\boldsymbol{\pi},s}$ is the number of practice problems given to the student for this skill (subscript $\boldsymbol{\pi}$ means following policy $\boldsymbol{\pi}$). This objective encourages policies where the student quickly does well broadly and on this skill.

$$f(\boldsymbol{\pi}) = \frac{p_{\boldsymbol{\pi},s} + \mathbb{I}(p_{\boldsymbol{\pi}} \geq 0.7)}{\sqrt{l_{\boldsymbol{\pi},s} + 1}}$$

We use BO to efficiently search over the space of policies for each skill. When a new student starts to use our tutor, we first use BO with the popular expected improvement acquisition function to identify a good next set of policy parameters to try for each skill. These parameters define a mastery policy that is used to teach a student and determine when to halt and present the student with the post test. Given the student's result on the post test, we compute the above $f(\boldsymbol{\pi})$ value that is used by BO to select a (potentially new) set of parameters $\boldsymbol{\pi}$ to try for the next student.

As an initial exploration, we used this approach to teach a sequence of 30 subjects that were recruited through Amazon turk. In between each subject BO was used to automatically identify the next set of parameters to use. Subjects were compensated for their time, and were prescreened such that subjects who already appeared to understand histograms were not included.

We then took the best policy parameters $\boldsymbol{\pi}_{\mathbf{bst}}$ identified after 30 subjects, and tested performance of this policy on 10 new subjects. We were interested in the average performance of $\boldsymbol{\pi}_{\mathbf{bst}}$ for two reasons. First, $\boldsymbol{\pi}_{\mathbf{bst}}$ is expected to yield best performance so far (in contrast to parameters BO chooses at each step/student that could be exploratory). Second, student post test scores can be quite noisy (on a small set of problems), and averaging multiple scores gives us a better estimate of the expected *f*. We compared the average objective values to a simple but reasonable baseline we tried with 19 subjects: provide all available content on each skill. We had the same or better objective value for each skill compared to the baseline policy. This suggests that BO can be a beneficial tool for quickly identifying how best to sequence activities to achieve a desired objective.

Interestingly, the final policies identified as yielding the best expected objective gave zero practice problems for 6 of the 8 skills. One possibility is that our objective function may not represent our true desired intent — for example, it may over penalize an increase in the number of practice opportunities. From this perspective, algorithmic optimization of teaching may be a useful tool for helping reveal potential gaps between instructor's stated learning goals and objectives for the class, and what they may actually hope to achieve. A second possible explanation for our tutor learning not to teach certain skills is that the available curriculum for these skills does not improve post test scores — providing an important indication of misalignment between the teaching materials and the stated goals. To investigate this possibility, we examined if there was a positive trend between the number of practice items provided and student learning. Figure 1 shows one of the skills where there was not: both pretest and post test scores are low, even though student performance is consistently quite high on all tutor practice opportunities, without any significant trend upwards. This suggests that the material available is not well aligned with the desired learning objective as measured in the assessment item. Therefore, this data-driven optimization can also quickly help to identify key limitations of the existing curriculum (or, class of methods for teaching it) in terms of achieving the instructor's goals. The instructor can then source or invent new materials, or identify alternate approaches for teaching, in order to help students better and more efficiently accomplish the desired learning objectives.

Conclusion

We have shared a preliminary investigation into using Bayesian Optimization to automatically find the adaptive instructional policy parameters designed to optimize a given input teaching objective. Our results suggest that BO can quickly (within a small number of students) find good parameters, and can be used as a tool to help instructors identify misalignment between their present curriculum and approaches to sequencing that material, and their desired learning objectives.

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