Towards Adapting to Learners at Scale: Integrating MOOC and Intelligent Tutoring Frameworks

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ABSTRACT
Instruction that adapts to individual learner characteristics is often more effective than instruction that treats all learners as the same. A practical approach to making MOOCs adapt to learners may be by integrating frameworks for intelligent tutoring systems (ITSs). Using the Learning Tools Interoperability standard (LTI), we integrated two intelligent tutoring frameworks (GIFT and CTAT) into edX. We describe our initial explorations of four adaptive instructional patterns in the PennX MOOC "Big Data and Education." The work illustrates one route to adaptivity at scale.

Keywords
Intelligent tutoring systems; MOOCs; adaptive instruction; adaptive learning.

ACM Classification Keywords
K.3.1 Computer Uses in Education: Distance learning

INTRODUCTION
There is substantial scientific evidence that instruction that adapts to learners' individual characteristics, such as their knowledge growth, affect, personal interest, or strategies and errors in learning activities, can be more effective than instruction that treats all learners as the same [3]. MOOCs are successful and widespread, but tend to have limited capacity to adapt to learners' individual characteristics. There have been attempts to build forms of adaptivity into MOOCs, such as adaptive problem selection and hint generation [7], or knowledge tracing to assess student mastery [6]. Nonetheless, as of this writing, the vast majority of MOOCs remain non-adaptive. On the other hand, ITSs provide adaptive support with problem-solving activities, both in their "inner loop" (i.e., within problems, by following along with different student strategies or providing feedback on specific errors) and in their "outer loop," (i.e., by selecting problems based on an individual student's recent performance, knowledge, or other individual characteristics) [10]. These systems have been shown to enhance student learning [4].

One route towards facilitating the creation of adaptive MOOCs would be to integrate ITS authoring platforms [9] within a MOOC. In the current work, we focus on two such platforms, namely, the Generalized Intelligent Framework for Tutoring (GIFT) [8] and the Cognitive Tutor Authoring Tools (CTAT) [2]. We integrate these tools into the edX platform. In a previous paper [1], we described the technical integration of the three platforms based on the Learning Tools Interoperability (LTI) e-learning standard. This integration makes it possible to launch GIFT or CTAT activities and modules from within edX, albeit with very little information exchanged between the different platforms – a point we return to below. In the current paper, we describe four simple adaptive instructional patterns that we authored with this tool integration. (Other patterns seem possible; we view our work as an initial step.) We present data regarding the initial use of these patterns within the PennX MOOC "Big Data and Education," and reflect on benefits, limitations, and further possibilities.

ITS FRAMEWORKS
The two ITS frameworks, GIFT and CTAT, support non-programmer authoring of adaptive tutor functionality that is not natively present in many MOOC platforms. GIFT supports authoring of outer-loop adaptivity [10] across a range of activity types, meaning that authors can craft task selection policies that adapt to individual student variables. CTAT supports tutored problem solving with both inner-loop and outer-loop adaptivity, meaning it adapts to student variables in selecting problems and in providing guidance within problems. We briefly describe each framework.

Adaptivity in GIFT

GIFT's engine for Management of Adaptive Pedagogy (eMAP) [8] is based on Merrill's Component Display Theory [5]. It distinguishes four quadrants of instruction: In the ***rules*** and ***examples*** quadrants, the learner is presented with information either on general concepts and procedures, or on specific instances (facts, concepts, procedures, or principles). In the ***recall*** and ***practice*** quadrants, the learner is asked to remember information presented in the rule and example quadrants, or to apply it to solve a problem or make a decision. Based on the learner's performance in the recall and practice quadrants, and (if an author so chooses) also on other states that influence learning (e.g., emotion, engagement), eMAP first provides a broad recommendation (e.g., move learner to other concepts, remediate on current concept, ask a question, prompt for more information, or engage in reflective dialogue), and then selects a targeted concept and specific pedagogic tactic. The author has some control over the pedagogy in eMAP (e.g., which of the quadrants to include and on what student variables to base decisions for traversing the quadrants).

Adaptivity in CTAT

CTAT-built tutors [2] support tutored problem solving with adaptive guidance at the level of problem steps. This guidance consists of hints, error messages, and correctness feedback, all with respect to the steps of problems. The tutor guidance can adapt to student strategies and errors. That is, the tutor can follow the student along multiple solution paths, whichever one the student chooses to go down. It can also recognize specific errors an author has anticipated. In addition, in its outer loop (i.e., its task selection algorithm), CTAT tutors can adaptively select problems for the student to work on, based on its assessment of each individual student's knowledge growth. Towards this end, in its inner loop, any CTAT tutor can infer the probability that a given student masters each knowledge component targeted in the instruction, based on her performance on the tutored problems. (This capability, however, was not used the current study.) Using CTAT, an author can create a tutor without programming. The author creates a problem-solving interface by drag-and-drop and captures problem-solving knowledge in the form of a "behavior graph" through programming-by-demonstration.

ADAPTIVE PATTERNS

The four adaptive patterns implemented for this study using GIFT and CTAT interleave problem solving with declarative instruction, such as lecture videos, in a manner that adapts to some aspect of prior student performance. These patterns would be more difficult to author natively in edX, which has only limited capabilities to adapt instruction and does not support an adaptive inner loop or outer loop.

Tutored Problem Solving

First, we embedded simple CTAT-built tutors within the edX MOOC, to support tutored problem-solving exercises. Although these tutors were simple, they illustrate a form of adaptivity that is often absent from MOOCs, namely, inner loop adaptivity. The tutors present multi-step problem scenarios with hints and feedback that adapt to students' current problem-solving state and errors; also, the tutors reveal the next problem step only when the previous has been correctly completed, as an adaptive way to help manage cognitive load. Although CTAT tutors also support a more advanced form of inner-loop adaptivity (namely, adapting to student strategies within any given problem), that capability was not needed in the given problem set. The CTAT/edX tool integration, however, does support its use.

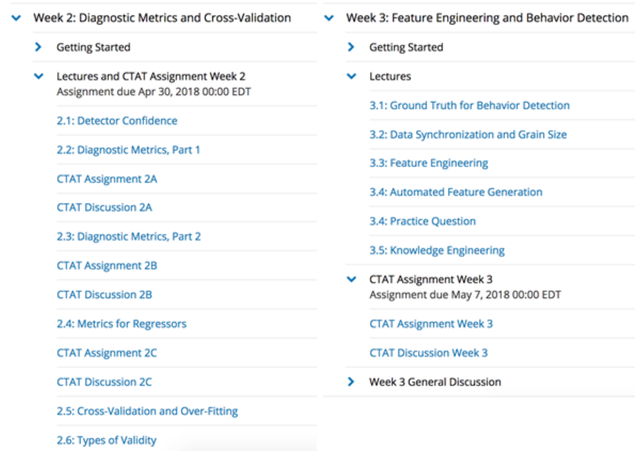

Figure 1. Interleaving module (left), where brief video lectures are interspersed with tutored problem solving supported by CTAT, vs. typical module (right), where video lecture content and tutored problem solving are in separate sections

Fine-grained Interleaving of Videos and Problem Steps

Many MOOCs separate lecture videos from exercises and problem solving (e.g., quizzes). In a typical MOOC module, a student watches several videos and then completes a quiz afterwards. However, this pattern separates learning content from opportunities to use that content. To avoid this less-than-optimal way to learn, we implemented a second adaptive pattern, in which the learner can work on problem steps immediately after viewing the relevant lecture video. In this pattern, lecture videos in edX were interleaved with steps of an elaborate problem-solving scenario in CTAT at arguably a smaller grain size than is typically done in MOOCs. Figure 1 shows how this adaptive pattern looks compared to a typical MOOC module. The pattern is minimally adaptive in that a student is nudged to move on to new content only when he or she has successfully applied previous content in a problem-solving scenario. The students, however, maintain control over the sequencing. They are free to follow the recommended interleaved order of lecture videos and problem-solving steps, but they may also elect to do the activities in their own preferred order. (We note that this pattern is often feasible natively within current MOOCs.)

Hint Message References to Video Lectures

In many MOOCs, students often refer back to videos while completing quizzes, but they do not often have support in knowing where to find relevant content in the video when they need help. We addressed this problem by extending the hints in one of the CTAT-authored problem-solving activities, so they include pointers to specific video segments (illustrated in Figure 2). The design of the step-by-step problem-solving activities gives the system awareness of exactly where a student made a mistake and what knowledge the student may be missing, so it can point the student back to the relevant video instruction or give hints that help in solving the problem.

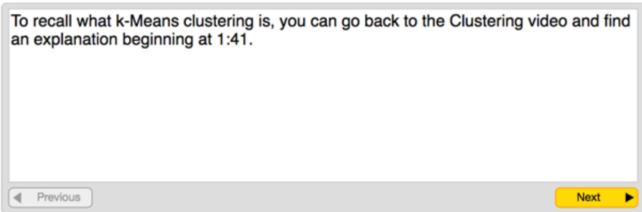

Figure 2. An example hint message that points the student to a specific lecture video and timestamp.

Students can decide to watch the recommended video segment and then return to the problem-solving activity to supply an answer. Alternatively, they can ignore the hint message, and request more hint levels or find other ways to generate a correct answer to the problem step.

Adaptive Remediation Following Recall Questions

Finally, our fourth adaptive pattern supports adaptive remediation following "recall questions," implemented with GIFT's eMAP engine. Specifically, we created (within one of the course units) GIFT modules with the following structure: Students first see a video lecture that presents key concepts. They then study a short slide deck of examples meant to augment the material shown in the video. (The video and slide deck cover the rules and examples quadrants in eMAP.) Students are then presented with recall questions, that is, questions that test their knowledge of the content of the videos and examples. GIFT's Structured Review screen (Figure 3) shows students whether their recall answers are correct. If they answer the recall questions correctly, they are returned to edX, where they can then choose to enter the next part of the course. If they answer incorrectly, however, they are directed back to the lecture video or to the example slide deck. Subsequently, if they continue to follow the GIFT sequence, they return to the recall questions to retry them. While the return to the recall questions is primary remedial path in the given unit, students can decide to exit this path before getting all recall questions right.

RESULTS: LEARNERS' EXPERIENCE

We piloted the adaptive patterns in the 2017 run of the PennX MOOC "Big Data and Education." The course started with 2,226 unique registered users, 44 of whom had paid and registered to receive a verified certificate. By the end of the course's 8-week run, there were 3,464 unique registered users, with 85 verified registrants. Of this cohort, 34 passed the course and received a completion certificate.

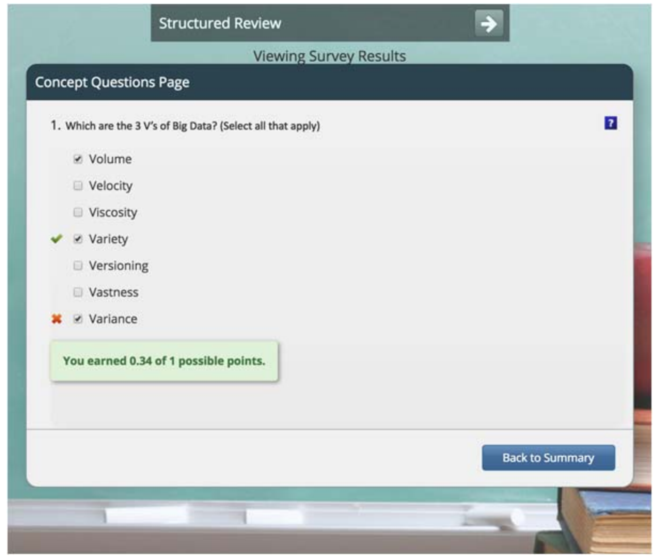

Figure 3. The Structured Review screen allows students to see how they did after answering the recall questions. Clicking the arrow button at the top of the screen automatically directs the student back to the lecture video or example slide deck, or to a screen saying they've completed the module.

As a measure of the utility of the adaptive patterns, we consider, based on course log data, whether students followed the recommended sequence of activities in each of the three adaptive patterns.

First, 34 students completed 80% of the tutored problems, the criterion for course completion. Across these problems, they answered 47-67% of the problem steps correctly at the first try, without taking a hint from the tutor, indicating that the tutors were reasonably challenging for students.

Second, regarding the interleaving pattern, of the 366 students who attempted at least one of the three interleaved CTAT problem-solving activities (the interleaving occurred in only one course unit), 96 learners (26%) followed the recommended order of modules, interleaving at a fine grain size between lectures and problem solving. Of the 96 learners who interleaved, 22 learners went on to pass the course and earn certificates. That is, of the 34 course completers, 22 (65%) interleaved between video lectures and quiz segments. This finding suggests, perhaps, that students who intend to complete the course are more likely to abide by the recommended interleaving pattern.

On the other hand, the hint messages in the tutored CTAT activities that suggested that the student go back to a particular video segment were not generally followed. The 66 learners who started the tutored problem-solving activities that contained these types of hints received a total of 675 hint messages, of which 59 (8.7% of hints) referred to a video segment. Only three learners (4.5% of students who accessed the tutor) re-watched the video segment mentioned in the message. The rest of the students who saw the video references chose to ignore them –relying on other hints or other means to complete the tutored activity.

Finally, adaptive remediation behavior was quite frequent (see Table 1): students followed GIFT's suggestions to review material after answering a recall question incorrectly 85% of the time (321 out of 377 instances of recall questions with errors) and spent, on average, several minutes with these materials. On the other hand, students exited to edX without fixing all errors to recall questions 56% of the time, which is probably more than ideal.

GIFT Exercise	1-1	1-2	1-3	1-4	1-5	1-6
Viewed video at least once	390	322	217	156	146	139
Submitted answers to questions	271	228	160	138	*	118
Answered incorrectly at least once	34	121	124	79	*	19
Viewed video two or more times	29	106	104	70	*	12
Avg (secs) replay duration after incorrect answers**	430	271	195	158	*	147
Exited before correcting all errors	20	64	71	47	*	9
* Exercise 1-5 had no recall questions. ** Capped at 1 hour to limit effect of idle windows.						

Table 1: Adaptive remediation: Students' acceptance of GIFT suggestions to replay video lectures after submitting answers to recall questions, by exercise.

CONCLUSION

Ideally, MOOCs would be more adaptive to learners. They would select or recommend sequences of activities on an individual basis, based on up-to-date assessment of a range of student variables, derived from the student's prior work in the MOOC and possibly other sources of data. The work described in his paper is a small step toward this ideal. It illustrates a novel path towards supporting adaptivity at scale (e.g., in MOOCs), namely, by integrating frameworks for intelligent tutoring systems into a MOOC platform.

We test four adaptive instructional patterns in an edX MOOC, made possible by this integration. Based on course log data, we analyze the frequency with which students followed adaptive paths through the activities, as a low-bar test of the value of the adaptivity. (A high-bar test might focus on enhanced learning gains.) Of the four patterns, tutored problem solving and adaptive remediation based on recall questions (created in GIFT) appeared to be most useful, whereas references to video segments embedded in hint messages of tutored problems were not useful. This merits further investigation. Beyond these patterns, other forms of adaptivity seem feasible and worth exploring within the GIFT/CTAT/edX tool integration, such as selecting or adjusting problem-solving activities based on what is learned about the given individual student in the declarative parts of the instruction (e.g., what videos the student saw). An important – though non-trivial – next step in our work is therefore to share a student model across the three platforms. Currently, GIFT and CTAT each have their own student models, but edX does not have a student model. Sharing a student model would go a long way towards realizing the ideal situation described above. To conclude, tool integration such as that illustrated in the current work may well turn out to be an important and practical approach to bringing into MOOCs the latest that adaptive technologies such as ITSs have to offer.

REFERENCES

1. V. Aleven, R. Baker, R. Long, J. Sewall, J. M. Andres, Y. Wang, O. Popescu, and N. Blomberg, N. 2017. Integrating MOOCs and intelligent tutoring systems: edX, GIFT, and CTAT. In *Proc. 5th Annual GIFT Users Symposium* (GIFTSym5), 11-21.
2. V. Aleven, B. M. McLaren, J. Sewall, M. van Velsen, O. Popescu, S. Demi, M. Ringenberg, and K. R. Koedinger. 2016. Example-tracing tutors: Intelligent tutor development for non-programmers. *Int. Jrnl. of AI in Educ.* 26, 1: 224-269.
3. V. Aleven, E. A. McLaughlin, R. A. Glenn and K. R. Koedinger. 2017. Instruction based on adaptive learning technologies. In *Handbook of Research on Learning and Instruction*, R. E. Mayer and P. A. Alexander (Eds.). Routledge, New York, 522-560.
4. J. A. Kulik and J. D. Fletcher. 2015. Effectiveness of intelligent tutoring systems. *Rev. of Educ. Res.* 86, 1: 42-78.
5. M. D. Merrill. 1983. Component display theory. In *Instructional-design theories and models: An overview of their current status*, C. M. Reigeluth (Ed.). Lawrence Erlbaum, Hillsdale, NJ, 282-333.
6. Z. A. Pardos, Y. Bergner, D. T. Seaton, and D. E. Pritchard. 2013. Adapting Bayesian Knowledge Tracing to a Massive Open Online Course in edX. In *Proc. of the Int. Conf. on Educational Data Mining* (EDM 2013), 137-144.
7. Y. Rosen, I. Rushkin, A. Ang, C. Federicks, D. Tingley, and M. J. Blink. 2017. Designing adaptive assessments in MOOCs. In *Proc. Fourth ACM Conf. on Learning@Scale*, 233-236.
8. R. A. Sottilare, R. S. Baker, A. C. Graesser and J. C. Lester. 2017. Special Issue on the Generalized Intelligent Framework for Tutoring (GIFT): Creating a stable and flexible platform for Innovations in AIED research. *Int. Jrnl. of AI in Educ.* 1–13.
9. R. Sottilare, A. Graesser, X. Hu, and H. Holden (Eds.). 2013. Design recommendations for adaptive intelligent tutoring systems. US Army Research Laboratory, Orlando, FL.
10. VanLehn, K. 2016. Regulative loops, step loops and task loops. *Int. Jrnl. of AI in Educ.* 26, 1: 107-112.