OPEN ONLINE PLATFORMS ADVANCING DSP EDUCATION

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ABSTRACT

Two open, online educational platforms, OpenStax Exercises and OpenStax Tutor, are working to revolutionize the way in which students learn concepts in diverse subject areas. Born and tested in the area of signal processing education, these tools bring to bear cutting-edge ideas in cognitive science and machine learning to automatically build personalized learning pathways for today's students and to advance the field of learning science. These platforms are introduced and initial results discussed.

***Index Terms*—** OER, machine learning, education, personalized learning

1. INTRODUCTION

There is a crisis throughout science, technology, engineering, and mathematics (STEM) education in the United States: K-12 students perform below their peers from other industrialized countries, enrollments are decreasing while a lower percentage of students are completing degrees, and many graduates are ill-prepared for the workforce because they retain only a fraction of what they learned. Furthermore, faculty are pressured to teach an expanding number of students of varying levels of skill and need, while also covering an increasing volume of material. Significant efforts are underway to address these critical challenges.

OpenStax Exercises (OSE) [1] and OpenStax Tutor (OST) [2] represent ambitious efforts to revitalize STEM education on multiple fronts. On one front, OSE, an initiative spearheaded by the NSF-funded Signal Processing Educational Network (SPEN), provides a framework for educators, students, and practitioners to collaboratively create and share educational activities and assessments. This open homework and test exercise bank combines hundreds of signal processing assessments with a number of tools designed to facilitate community engagement and collaboration. Building on the resources in OSE, OST, an innovative educational tool fusing the latest advances in machine learning, cognitive science, and open educational resources (OER), aims to transition education from a one-size-fits-all approach towards a truly personalized model.

This work was generously supported by grants NSF OCI-1041396 and IIS-1124535. web: rdls.rice.edu — email: {jps, kjd}@kindlinglabs.com, richb@rice.edu, andrew.butler@duke.edu, emarsh@psych.duke.edu

This paper is organized as follows. In Section 2 we describe OSE's main features and discuss content development efforts within SPEN and partner schools. In Section 3, we overview the components of OST, including its underlying machine learning algorithms, cognitive science learning principles, and end-user interfaces. In Section 4, we present results from two rounds of OSE and OST pilot testing. We conclude in Section 5 with directions for future work.

2. OPENSTAX EXERCISES

Online educational systems depend on repositories of online educational content to present to their students. The Internet is home to several big textual and video resource sites that house popular study materials, including Wikipedia, Youtube, and Connexions [3], one of the world's first and largest open-access educational repositories. While practice exercise banks also exist, to build the new kind of personalized learning system discussed in this article, we needed to create an open, customizable homework and test exercise bank. This result is OpenStax Exercises (OSE).

2.1. Developing exercises in OSE

While anyone can use OSE, the site is strongly instructor-focused. OSE is not a site where students come to work through practice problems, but rather a community where instructors come to author, reuse, and share educational activities and exercises across a variety of disciplines.

OSE Exercises come in three different formats: simple, matching, and multipart. Simple exercises have free-form questions that can be open-ended or have multiple-choice answer options. Matching exercises prompt learners to pair items from two lists. Multipart exercises are a set of simple exercises that refer to a common introduction.

Authors write exercises with an easy-to-use, wiki-like markup language, with math expressions encoded in LaTeX. OSE also supports the creation of *dynamic* exercises. Dynamic exercises contain small chunks of logic that determine the values of variables embedded within the question stem and answer choices. When a dynamic exercise is viewed by two different users, those users are being asked the same underlying question but the details and values are different.

When an OSE author is ready to share an exercise with the world, she proactively publishes it. This act of publication permanently saves the current state of the exercise and provides a permalink to access it. As the author changes and republishes the exercise over time, OSE's built-in version control system creates new permalinks to access these later versions of the exercise. This versioning system allows anyone to use, enhance, or embed specific versions of exercises even as new versions become available.

OSE is a general-purpose exercise bank, but it was born in a signal processing world. Signal processing students and instructors at several universities [4] have run several content creation sprints. These sprints, along with the use of OSE in several signals classes around the USA, have resulted in a wealth of signal processing exercises being added to OSE.

2.2. Collaborative, community-focused features in OSE

All content in OSE lives under the open Creative Commons Attribution license (CC-BY), meaning that content in the repository can be used, shared, and reused legally in any way as long as the original authors are given credit. While only an author can create a new version of an existing exercise, any OSE user can take advantage of the CC-BY licensing to make a new exercise that builds off an existing exercise; these new exercises are called *derived copies*. Built-in author attribution mechanisms in OSE encourage community members to build on and adapt each other's work by giving credit to both the original and new authors in a derived copy.

OSE empowers its users to enhance existing exercises by adding solutions. In addition to solutions showing the details of how to solve the problem, high-level, prose-only solutions can be written to show an approach on how to solve the problem without giving away everything. Solutions generated by the community are visible to all, including community members, course educators, and even students. In particular, students working OSE exercises via the OST learning platform discussed later can view available solutions once they complete exercises. For these learners, the immediate availability of solutions significantly enhances the learning experience. Each exercise can house multiple solutions, which may take different approaches to solving the exercise.

Users can also curate OSE content in other ways, such as by adding tags to categorize content, by initiating conversations in the comments section, and by using the voting feature. *Upvoting* a question will attract attention to well-written, factually sound questions, thereby leading users to the best, most relevant content as curated by the community. Similarly, *downvoting* a question will bury factually incorrect or nonsense questions. In addition, OSE promotes communication between community members by providing shared work areas called *lists*. A list functions as a private or semi-public folder where multiple members can view, develop and edit content collaboratively.

3. OPENSTAX TUTOR

Research efforts in educational technology have led to a burst of activity in recent years, from applications like the Intelligent Tutoring System (ITS), an interactive web-based system that provides computer-based instruction to students [5] [6], to interactive learning websites offering individualized instruction and feedback. In the same spirit, OpenStax Tutor (OST), a student-focused online learning platform, strives to transition away from today's "one size fits all" approach to education, towards an approach that is truly personalized, i.e., responsive to the needs, skills, and characteristics of individual students. While OST marshals content from OSE, Connexions, and the greater Internet to deliver an online learning experience in modern classrooms, it is becoming much more than just a learning management system. A collaboration between engineers and cognitive scientists at Rice University and Duke University, OST is improving education by uniquely fusing OER, cognitive science learning principles, and data-driven machine learning algorithms.

3.1. Machine learning automates personalization

There are too many topics to teach and too many individual differences among students to approach personalized learning in a non-automated way. We are building machine learning algorithms that collect and analyze a huge universe of learning data from a large number of student interactions in order to build personalized learning pathways that will optimize each student's progress. Housed in a *learning engine*, these algorithms use information about a student's performance and interactions with OST, along with the same information collected from the student's peers, to automatically guide each student to learning materials that maximize the likelihood of meeting their learning goals. Automated analysis of this data can reveal proven learning pathways, ineffective learning pathways, and other hidden relationships between students and problems.

To build these pathways, the learning engine also needs to understand the relationships between the corpus of available learning materials, including exercises, texts, videos, and interactive apps. Our graphical model oriented algorithms are used to create a concept graph that identifies the relationships between different concepts in a subject area, as depicted in Figure 1. A deep understanding of how learning materials interrelate will enable the system to make valuable, timely recommendations to students struggling with a particular concept. For example, a student struggling with a concept can be guided to additional practice problems that test that concept, to study resources that reinforce that concept, or to learning content that reinforces their understanding of prerequisite concepts.

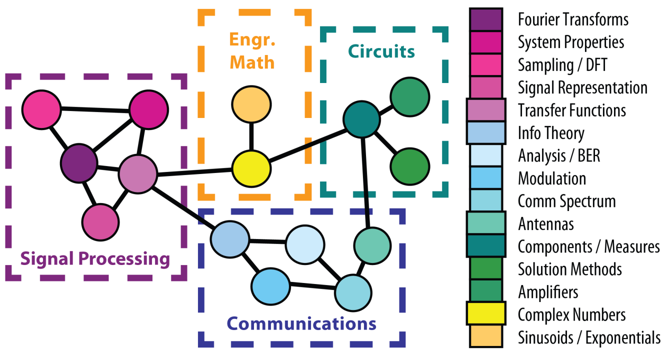

Fig. 1. Concept graph learned from a Connexions textbook (Johnson [7]).

3.2. Cognitive science learning principles

As machine learning researchers continue to develop the above algorithms, our cognitive science researchers are designing and discovering the learning principles that are most effective in helping students reach their learning goals, particularly for higher education STEM classes. The OST platform integrates three robust, replicable, and generalizable learning principles from cognitive science: retrieval practice [8], spaced practice [9], and feedback [10]. Each of these principles has been shown to increase long-term retention and transfer of learning and were recently recommended in a practice guide by The Institute of Education Sciences [11].

3.2.1. Retrieval practice

OST requires students to practice retrieving and reconstructing knowledge. When a student initially views a multiple-choice exercise, OST presents only the question stem and prompts students to enter a free-form response. Only after students have locked in a free-form answer will OST reveal the list of multiple-choice answers. By prompting students to generate their own solutions before showing multiple-choice answers, OST compels students to actively retrieve knowledge from memory, instead of passively recognizing answers.

3.2.2. Spaced practice

OST's use of spaced practice gives students multiple, time-separated opportunities to learn, apply and reinforce concepts. Spaced practice contrasts strongly with a traditional *massed* practice approach, which reinforces concepts during a relatively short interval (e.g. one homework assignment).

3.2.3. Timely, informative feedback

OST presents timely, informative feedback to students after they complete exercises in order to help them correct their errors and maintain correct knowledge. Presentation of feedback consists of showing students their answer choices, the correct answer choice, a brief message confirming if the answer was correct or incorrect, and available solutions from OSE. Although OST cannot compel students to fully process the feedback, instructors can make viewing feedback mandatory for credit.

3.3. The course management side of OST

As the above machine learning and cognitive science research progresses, educators have piloted a beta version of OST in undergraduate electrical engineering courses at the Georgia Institute of Technology, Rice University and the University of Texas at El Paso. The beta version of OST integrates the learning principles discussed above, enables instructors to embed OER content, and includes separate browser-based interfaces for instructors, students, and human subjects researchers. Described in more detail below, Figure 2 overviews the instructor and student interactions in OST.

3.3.1. Instructor interface

While OST offers educators a number of administrative tools, such as ability to create class sections, manage student enrollment in OST, and give administrative permissions to coeducators and assistants, the primary component of the instructor interface is the learning plan editor. Shown in steps (a) and (b) of Figure 2, an OST learning plan consists of the sequence of study resources and exercises that students review and complete via the OST student interface.

To construct a learning plan, an instructor breaks a course into a number of *topics*. A normal course might cover 10-20 high-level topics. The instructor then adds learning content from OSE, Connexions, and other web sites into each topic. The instructor then schedules the topics into assignments, where one assignment may cover more than one topic. Instructors can specify assignment rules, e.g. start and due dates, whether the assignment is open or closed book, whether group work is allowed, etc. When assignments are ready, OST automatically delivers them to students, folding in spaced practice as needed. As students complete assignments, instructors can view student work and grades.

3.3.2. Student interface

When an assignment becomes available, OST sends students an email directing them to the assignment URL. The main page of the assignment includes study resources and exercises, as well as assignment rules: due date, whether the assignment is open or closed book, and if group work is authorized. For each exercise in an assignment, OST presents the question stem and prompts the student to enter a free-form response; once the student locks in free-form work, OST reveals

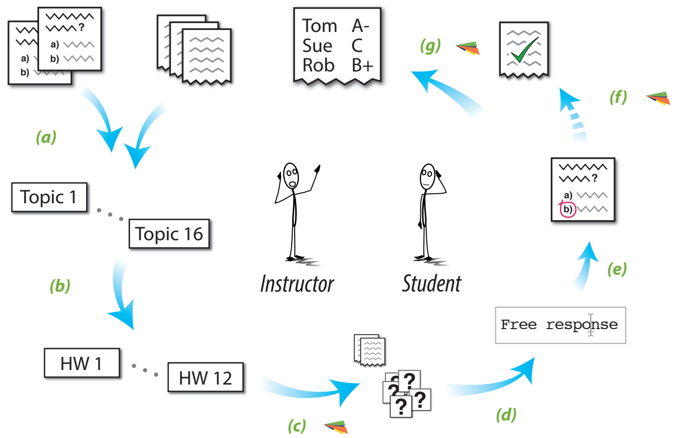

Fig. 2. How instructors and students interact with OST: Instructor creates a learning plan by (a) organizing exercises and learning materials into topics and (b) creating assignment plans. OST uses (a) and (b) to build and deliver assignments (c) to students. OST prompts students to enter (d) free-form response and (e) multiple-choice answer before presenting (f) feedback. OST builds a (g) grade report for instructors.

possible multiple-choice answers and prompts the student to select the answer corresponding to free-form work. For each exercise students complete, OST presents feedback: the correct answer and hints about how to achieve the solution, if available in OSE. Students repeat this process for each exercise in an assignment.

3.4. Human subjects research infrastructure

OST has a deeply-integrated human subjects research infrastructure. Most classes operating in the beta release of OST have a cognitive science research experiment running within them. Inside OST, students can electronically consent to be part of the research study and cognitive science researchers can control and monitor the progress of the experiment. OST contains strong firewall mechanisms to make sure that the interests of educators and researchers are kept separate; educators never see research information (e.g. anonymized research IDs) and researchers never see identifying information (e.g. names, email addresses).

4. EXPERIMENTAL RESULTS

We now describe the results of two experiments comparing the impact of OST on learning outcomes relative to standard educational practice (SEP). To make this comparison, we consider two types of homework assignments: (i) OST assignments and (ii) SEP assignments. As described in sections 3.2.1, 3.2.2, and 3.2.3, OST assignments space practice for a given topic across multiple assignments, thereby providing students with repeated, spaced opportunities to engage in retrieval practice related to that topic, and require students to view feedback. In contrast, SEP assignments follow the typical method in education: students get practice on the topic that was covered that week, but do not receive any follow-up practice, and feedback is provided a week later without any requirements for students to view it. The two experiments were conducted in a core course for upper level engineering majors (ELEC 301: Signals and Systems) at Rice University during Fall of 2011 and 2012. In both experiments, students completed weekly homework assignments that alternated between OST and SEP. All homework assignments contained between 10–20 problems and students were allowed to work on assignments in groups; however, they were required to enter final answers and view feedback individually.

The midterm and final exam in the course were used to assess the relative efficacy of OST and SEP. The exams consisted of new problems related to the core concepts taught each week, where each problem could be linked to a specific week and categorized as either OST or SEP treatment. Students used OST to complete the midterm and final exam; these tests were closed book and students were required to work the problems individually.

In both experiments, students' performance on the homework assignments did not differ as a function of whether they completed the problems through OST or SEP, which indicates that there were no pre-existing differences in the difficulty of the material learned via the two learning methods. However, students performed better on the exams when they had learned the material using OST relative to when they had learned using SEP. Overall, the findings from this set of experiments confirm the efficacy of the beta version of OST. Student use of OST produced superior long-term retention and transfer of learning when compared to SEP. The magnitude of this effect in both experiments was equivalent to an improvement of half a letter grade in the course.

5. FUTURE WORK

In our ongoing efforts, we are working to incorporate more machine learning algorithms into production use on OST, to produce both optimized pathways and learner analytics. OSE's list of question types is continuing to grow, as well as different options for embedding questions in other applications on the Web. We are actively recruiting new courses to be run on OST in conjunction with new learning research experiments. Interested parties should contact OST staff at openstaxtutor.org/contact.

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