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Adaptive Practicing Design for Self-paced Online Learning

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Abstract: Self-paced online learning (SPOL) provides great flexibility of learning anytime, anywhere and at any pace, yet it brings some inherent learning barriers because of the distance between students and instructors. This study recognizes two major learning barriers: challenges for instructors to provide proactive support and the need for higher self-directed learning skills in students. Such learning barriers can lead to students' academic struggle and failure. This study suggests three key learning strategies to alleviate learning barriers: a) increasing students' self-awareness of learning, b) identifying struggling students, and c) facilitating students' mastery learning. Focusing on the domain of Data Structures and Algorithms in the computer science discipline, this study proposes systematically designing and embedding adaptive formative assessment in SPOL courses to implement these strategies. Formative assessment is a fundamental process within the learning process. With an adaptive mechanism embedded, it can detect a student's knowledge state more accurately and efficiently. Furthermore, adaptive formative assessment can facilitate students' mastery learning if adaptive formative assessment is designed for practicing. During this mastery learning process with adaptive practicing, it is possible to identify one kind of struggling student – wheel-spinning students, who persistently work on problems or exercises without progressing towards mastery. Different from the research on adaptive assessment that mainly focuses on Intelligent Tutoring Systems, this study investigates an effective adaptive practicing mechanism in the context of self-paced online learning. A prototype of an adaptive practicing system is being created to test the effectiveness of this mechanism in implementing those suggested learning strategies.

Keywords: Adaptive practicing, Adaptive formative assessment, Reinforcement learning, Self-paced online learning, Wheel-spinning, Mastery learning

1. Introduction

Self-paced online learning (SPOL) provides great flexibility of learning, where students can learn anytime, anywhere and at any learning pace (Yan & Lin, 2020). Such flexibility makes SPOL a vital self-directed educational paradigm, often adopted in adult learning, MOOC, and life-long learning. However, because of the distance between students and the instructor as well as the different learning schedules followed by students, some inherent learning barriers exist with this educational model. For example, immediate guidance, feedback and proactive support from human instructors are often absent in SPOL (Yan & Lin, 2020). Consequently, SPOL usually demands higher self-directed learning skills in students, such as time management, self-awareness of learning, help-seeking, and so on. But not every student has an adequate level of such skills (Kinshuk, 2016). Thus, these learning barriers often lead to students' academic failure or struggle. According to a report from Athabasca University (Athabascau.ca, 2020), while most SPOL courses at Athabasca University have relatively high pass rates, some courses still have pass rates as low as 50-60%.

Therefore, to improve learning success, educators should consider designing a more supportive online self-paced learning environment. To facilitate students' self-directed learning and enhance instructors' proactive support to struggling students, this study recognizes three key learning strategies: a) increasing student's self-awareness of learning, b) identifying struggling students, and c) facilitating students' mastery learning. Thus, this study will explore a learning design approach that can effectively implement such strategies.

2. Related Work

As a low stake evaluation approach, formative assessment is recognized as a fundamental process within the learning process (Menéndez, Napa, Moreira, & Zambrano, 2019). It offers self-testing opportunities for students to check their knowledge states, such as the proficiency level of each knowledge component (KC) as well as their learning strengths and weaknesses. Therefore, students' self-awareness of learning can be increased by formative assessment. The increased learning awareness should, in turn, improve students' help-seeking behaviour and time management skills.

However, fixed formative assessment delivers pre-determined questions indiscriminately to every student. As a result, it may not pinpoint or quantify individual students' mastery level given a limited number of questions. Adaptive assessment (or Computerized Adaptive Testing) (Weiss & Kingsbury, 1984), to the contrary, tailors questions to an individual student's knowledge or skill level by choosing a next question based on the student's responses to previous questions. So, if an adaptive mechanism is embedded into formative assessment, the adaptive formative assessment (AFA) can trigger more questions on a KC until the student masters the knowledge or skill (Yan H. , 2020). Therefore, AFA could be more accurate and efficient in detecting a student's proficiency level.

Depending on the adaptive mechanisms and the assessment design, AFA is primarily adopted in a course for two purposes: knowledge diagnosis and learning practice. In the case of learning practice, AFA is often used to promote mastery learning (Beck & Gong, 2013), where a student is provided with hints, feedback or recommended learning materials during the assessment. In this case, AFA can be referred to as adaptive practicing.

Closely related to mastery learning, wheel-spinning (or unproductive persistence) is a critical issue in self-directed learning. According to Beck and Gong (2013), wheel-spinning means students continuously make efforts or invest time to learn a skill without any success (Beck & Gong, 2013). Theoretically, during the mastery learning process with adaptive practicing, wheel-spinning can be flagged if a student has worked on a maximum number of questions for a skill but still not mastered it (Beck & Gong, 2013). Owing to such students' desperation for learning success and need for academic help, it is imperative to identify wheel-spinning students through adaptive practicing.

An effective adaptive practicing system (APS) can implement the three learning strategies for a more supportive, self-paced online learning environment. The core of the adaptive practicing system is the adaptive mechanism. Adaptive mechanism design may consist of two primary tasks: a) choosing an adaptive policy and b) creating the knowledge modelling algorithm (KM) (Pelánek, 2017). KM is used to trace and estimate a student's knowledge level or cognitive skills. Many KM models have been explored and tested, such as Bayesian Knowledge Tracing (BKT) (Corbett & Anderson, 1995), Item Response Theory (IRT) (Hambleton, Swaminathan, & Rogers, 1991), Performance Factor Analysis (PFA) (Gong, Beck, & Heffernan, 2010), etc. Most of these KM models have been studied in the context of Intelligent Tutoring Systems (ITSs). Another promising technique for the adaptive mechanism is reinforcement learning (RL). RL uses a rewarding mechanism to sequence actions to optimize the outcomes in an uncertain and changing environment without firstly fitting a model with historical data (Kaelbling, Littman, & Moore, 1996). In the context of adaptive learning, RL can be used to sequence practicing items or learning activities to maximize learning effectiveness. As one reinforcement learning (RL) family, Multi-armed Bandit algorithms (MAB) (Berry & Fristedt, 1985)are starting to attract researchers' attention in the educational world (Lin, 2020). MAB includes different algorithms, such as Thompson Sampling, UBC, Contextual-Bandit, etc.

In the context of SPOL, this study identifies seven features that the adaptive mechanism should provide: i) promoting mastery learning through adaptive practicing; ii) accommodating knowledge change during the adaptive practicing. As students are using hints and feedback or refer to learning materials during the assessment, students' knowledge will keep changing; iii) considering the prerequisite dependency among knowledge components; iv) allowing one question to test on multiple KCs; v) using other students' historical data to improve the KM model but not to fit a KM model. Students in the SPOL are following different learning paces and learning approaches. Thus, it could be challenging to use other students' historical data to fit a model; vi) utilizing students' profiles and learning data available from the whole learning environment. Such data can include motivation, time availability, learning goal, learning approaches, and prior knowledge; vii) analyzing such data as answer correctness, item difficulty, answer time, attempts, forgetting, interval time between attempts.

3. Research Question

Based on the educational needs identified as the seven features and the potential of an APS to meet such needs, this study is investigating an effective adaptive mechanism for APS in the context of self-paced online learning. Different disciplines and domains usually have different pedagogies. The STEM (Science, Technology, Engineering, and Mathematics) disciplines share certain common pedagogical needs such as STEM-related conceptual development, scientific inquiry, engineering design and problem-solving (Kennedy & Odell, 2014). Focusing on the domain of Data Structures and Algorithms in the computer science discipline, this study proposes systematically designing and embedding adaptive practicing in SPOL courses to foster a more supportive learning environment. Thus, the research question of this study is –

For self-paced online computing courses in Data structures and Algorithms, what adaptive mechanism can be designed in the adaptive practicing system to detect a student's knowledge state effectively, identify wheel-spinning students, and promote the mastery of learning?

4. Research Plan and Method

As one member of an AIED research group in my institute, I have been working with my colleagues on this study. This study is planned to go through the following stages. For my Ph.D. research, I am mainly focusing on the first two stages.

a. Adaptive mechanism design for the APS (current stage)
b. Simulation of the adaptive mechanism
c. Adaptive practicing system building
d. Experiment with a case study
e. Evaluation of the effectiveness of adaptive mechanism design

I am currently working on the first stage -- designing the adaptive mechanism based on the identified seven features. Once the adaptive policy and the knowledge modelling algorithm are determined, a simulation will be used to test the adaptive mechanism.

Then, the adaptive practicing system will be built by the team. The APS should be LTI compliant so that it can work with different LMSs and still retain the system's quality from a research perspective.

To validate the effectiveness of the APS, an experiment with a real STEM SPOL course will be conducted. At this point, a course (COMP272) in the domain of Data Structures and Algorithms offered at Athabasca University is chosen for the case study. Also, the course professor is creating a question bank for the APS at this stage.

After the APS runs a certain period in COMP272, a comparison study will be conducted from the three perspectives: self-awareness of learning, wheel-spinning detection, and mastery learning promotion. As students in the SPOL are following different learning paces and learning approaches, it could be more appropriate if we use a same cohort of students instead of different groups of students to evaluate the effectiveness of the APS. Therefore, an A-B-A-B design is considered to measure a baseline (the first A), a treatment measurement (the first B), the withdrawal of treatment (the second A), and the re-introduction of treatment (the second B) (Kirk, 2017). We will compare students who have used the APS and those who did not have the chance to use the APS in the past. A survey with students and an interview with the course instructor will be conducted. Students' performance data will also be examined.

5. Anticipated Contribution

This study aims to design an effective adaptive mechanism for the adaptive practicing system in self-paced online learning in a domain of the computer science. The objectives of the APS are to detect students' knowledge state accurately and efficiently, promote mastery learning and identify wheel-spinning students. The ultimate goal of the APS is to facilitate students' self-directed learning and enhance instructors' proactive support to a group of struggling students. Thus, a more supportive learning environment can be created for students.

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