Qualitative, Quantitative, and Data Mining Methods for Analyzing Log Data to Characterize Students' Learning Strategies and Behaviors

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Abstract: This symposium addresses how different classes of research methods, all based upon the use of log data from educational software, can facilitate the analysis of students' learning strategies and behaviors. To this end, four multi-method programs of research are discussed, including the use of qualitative, quantitative-statistical, quantitative-modeling, and educational data mining methods. The symposium presents evidence regarding the applicability of each type of method to research questions of different grain sizes, and provides several examples of how these methods can be used in concert to facilitate our understanding of learning processes, learning strategies, and behaviors related to motivation, meta-cognition, and engagement.

Symposium Topic

Increasingly, students' educational experiences occur in the context of educational technology. A trend with importance for the Learning Sciences is that this usage is increasingly being logged in very fine-grained fashions, providing a trace of students' conceptual and strategic learning processes and behaviors. As these data become increasingly available to the broad Learning Sciences research community, in some cases through large public data repositories such as the Pittsburgh Science of Learning Center (cf. Koedinger et al, 2008), researchers are increasingly asking the questions: What can we learn from log data (in particular, what can we learn from log data, that is difficult to learn from other types of log data)? And how can we best learn from log data?

The emergence of the Educational Data Mining conference and journal (cf. Baker & Yacef, 2009) have provided one perspective about how to use log data to study education research questions. In Educational Data Mining, automated methods are used to explore and model educational data. However, researchers have also utilized analytical quantitative methods, such as cognitive modeling (Anderson, 1993) – the production of quantitative models within a cognitive architecture to represent student cognition – and human-driven statistical analysis, to explore log data. Similarly, case study and qualitative analysis methods have been used to explore log data.

In this symposium, we bring researchers experienced in the use of these methods to discuss the relative benefits of each of these categories of method for analyzing log data. We focus the discussion on the methods' use to study students' learning processes, learning strategies, and behaviors related to motivation, meta-cognition, and engagement. The progress in methods for analyzing log files has enabled more sophisticated analysis of how students choose to interact with learning software, in turn allowing fine-grained investigation of which students choose which learning strategies, in what situations these strategies manifest themselves, and how the behaviors impact learning. The set of talks demonstrates how each of these methods can help elucidate learner strategies and processes, and how these impact learning, and then discussion illuminates the relative benefits and drawbacks of each of these methods.

Structure of Symposium and Potential Significance of the Contributions

The symposium, chaired by Ryan Baker and Janice Gobert (Worcester Polytechnic Institute), has four presentations: one by Janice Gobert (using quantitative/statistical and qualitative methods to study the relationship between learner characteristics and inquiry skills), one by Ryan Baker (using educational data mining methods and quantitative/statistical methods to study why students game the system), one by Roger

Azevedo (using qualitative and quantitative/modeling methods to study self-regulated learning processes), and one by Ido Roll (using quantitative/modeling and qualitative methods to study student thinking during invention tasks). The four presentations are followed by commentary from our discussant, Wouter van Joolingen, and in turn by vigorous group discussion as to what research questions each methodology is most appropriate for, and what conditions are necessary for each research method to succeed. For example, educational data mining methods often require significant amounts of data to be utilized, whereas qualitative methods are difficult to scale to massive amounts of data. Similarly, Quantitative/modeling methods enable closer understanding of the constructs being studied, whereas educational data mining methods can support higher construct validity, in terms of supporting closer matches between models and "common sense" notions of the constructs, and can integrate model validation explicitly into the model creation process.

The discussion of the issues are brought into context by the multi-methodological experience of each of the presenters, enabling the presenters to speak with insight on the relative merits of different approaches. Given the mixed-method approaches represented, the symposium contains several examples of how these methods can be used in concert to promote valid and innovative research that is only possible through the analysis of log data.

Each of the presentations concerns work that contributes to a deeper understanding of why specific students choose specific learning strategies or behaviors, and how a student's learning strategies and behaviors impact their learning and/or the depth of their learning. These features make the presentations relevant to attendees for whom the methodological issues are of lesser import.

At the same time, the presentations provide insight as to what types of research questions each type of method can best be used to address, including which ways of using educational data mining methods are optimal, what types of research questions are better addressed through non-automated methods such as cognitive modeling, and when qualitative analysis enables richer understanding than other methods support.

Presentations

Studying the interaction between learner characteristics and inquiry skills in microworlds

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It is broadly recognized that science literacy means that learners have content knowledge, have process skills for conducting inquiry, and have an epistemological understanding of the nature of science (Perkins, 1986). Although this definition prescribes the knowledge ontologies learners need, it is not clear that these forms of knowledge are sufficient to characterize the variance observed in students' scores on conceptual post-test scores. More recently, there has been interest within the intelligent tutoring community in obtaining data on important student characteristics in order to better explain the variance observed in conceptual learning scores.

In this presentation we describe research conducted to study the relationship between learner characteristics and inquiry skills in the Science Assistments project, a free, online, intelligent tutoring system that "assists students while assessing them". The Assistments approach was previously used only in mathematical content domains. The Math Assistments project has been successful at modeling student learning and tutoring students on math skills. Some key findings are: 1) Students' responses to scaffolding are helpful in tracking students' knowledge, and 2) By taking into account the scaffolds requested by students, state scores can be more reliably predicted when compared to using correctness information only. As an extension to this system, the Science Assistments system tutors students on their inquiry skills with the goal of supporting both skill development as well as content knowledge. We have shown that the system can be successfully used to tutor students' understanding of the control for variables strategy (CVS), a key strategy under the larger skill named "design and conduct experiments" (Sao Pedro et al, 2009). In the Science Assistments project, we are also using data on learner characteristics to design individualized instruction and adaptive scaffolding.

In the talk, we discuss qualitative and quantitative-statistical analyses conducted to investigate the relationship between learner characteristics and inquiry skills. Baseline learner characteristic data were gathered from large cohorts of 5th through 8th grade students (n=1000) from three different public middle schools in central Massachusetts. Schools vary in their performance on the state standardized science test (MCAS) from 50% to

90% of students scoring in the "below proficient" category. Our measures for learner characteristics included GRIT, i.e., perseverance (Duckworth & Seligman, 2005), learning orientation, i.e., mastery/performance orientation (Midgley et al, 2000), self-efficacy (Kettelhut, 2007) for science, and epistemologies of models in science (Treagust et al. 2002). Our measures for inquiry learning included students' skills at formulating hypotheses (IV, DV, and a relationship between them), planning and conducting experiments within the learning environment, interpreting data from these trials, and linking data back to their hypotheses. Our results indicate statistically significant relationships between both conceptual post-test knowledge (time1) and conceptual post-test knowledge (time 2) with inquiry skills, adaptive learning (PALS scales 1 & 4), and self-efficacy (for science inquiry and computer use). Results are discussed with regard to the interaction between learner characteristics and inquiry skills.

Educational Data Mining Methods For Studying Student Behaviors Minute by Minute Across an Entire School Year

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In this talk, we discuss how educational data mining methods (cf. Baker & Yacef, 2009), conducted using log files of student use of Cognitive Tutor software for mathematics (Koedinger & Corbett, 2006), have significantly increased our scientific understanding of two behaviors that students engage in. The two behaviors studied are gaming the system and off-task behavior. Gaming the system is defined as attempting to succeed in an interactive learning environment by exploiting properties of the system rather than by learning the material (cf. Baker, Corbett, Koedinger, & Wagner, 2004). Examples of gaming within Cognitive Tutors include systematically guessing or abusing hints. Beyond Cognitive Tutors, gaming the system has been observed in assessment software (Walonoski & Heffernan, 2006), graded-participation newsgroups (Cheng & Vassileva, 2005), and educational games (Miller, Lehman, & Koedinger, 1999; Rodrigo et al, 2007). Off-task behavior (engaging in behavior that does not involve the system or the learning task) has been shown to occur with comparable frequency in Cognitive Tutors and traditional classrooms (cf. Baker et al, 2004). Both off-task behavior and gaming the system have been shown to be associated with poorer learning in Cognitive Tutors (Baker et al, 2004; Baker, 2007).

We discuss two analyses where educational data mining shed light on the nature, causes, and impacts of these behaviors. Each analysis can be considered an example of "discovery with models", where a model developed using educational data mining methods is then applied to a more extensive data set, and utilized to make inferences about how data from factors available in the larger set (additional measures or contextual factors) associate with the predictions from the model (cf. Baker & Yacef, 2009).

In the first analysis, log file data was obtained for 58 students using a Cognitive Tutor for Algebra in 22 topics, across the course of an entire school year. The 58 students solved 73,880 problem steps within the tutoring software, and data on the timing and semantic meaning (wrong, wrong-indicating-misconception, correct, and help; also, the relevant cognitive skill) of their actions was collected. A model validated to accurately infer off-task behavior (cf. Baker, 2007) was applied to each action in the data set. Gaming the system was assessed by "text replays", rapid hand-coding of distilled log files (cf. Baker, Corbett, & Wagner, 2006). An enumeration of the ways intelligent tutor lessons vary from each other was developed via a collaborative design process involving both researchers and practitioners, and was applied to each of the 22 tutor units. The assessments of student behavior and the information on the design of each tutor lesson were combined to discover factors in the design of Cognitive Tutors that predicted the incidence of the behaviors. The resultant models predicted over

50% of the variance in each behavior. One example finding is that problems with many seductive details (cf. Harp & Mayer, 1998) are gamed less, and problems with no cover story at all are gamed less, but problems with sparse ("hokey") cover stories are heavily gamed.

In the second analysis, log file data was obtained for 296 students using a Cognitive Tutor for middle school mathematics in three topics, Geometry, Percents, and Scatterplots. The 296 students solved 72,845 problem steps within the tutoring software, and data on the timing and semantic meaning of their actions (as described above) was collected. Models validated to accurately infer off-task behavior and gaming the system (cf. Baker, Corbett, Roll, & Koedinger, 2008; Baker, 2007) were applied to each action in the data set. Next, we developed logistic regression models to investigate two hypotheses about the mechanisms that led to reduced learning: (a) the behaviors lead to less learning within individual problem steps (immediate harmful impact) and (b) the behaviors lead to overall learning loss due to fewer opportunities to practice (aggregate harmful impact). Our findings suggest that gaming has immediate harmful impact on learning, whereas off-task behavior has aggregate harmful impact on learning.

Deciphering the complex nature of log-file data collected during self-regulated learning with MetaTutor

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MetaTutor is a multi-agent, adaptive hypermedia learning environment that trains and fosters high school and college students' use of self-regulatory processes in the context of learning about science topics such as human body systems. The purpose of the MetaTutor environment is to examine the effectiveness of pedagogical agents (PAs) as external regulatory agents used to detect, trace, model, and foster students' self-regulatory processes during science learning with multiple representations of information. The multi-agent system provides adaptive tutoring based on students' evolving conceptual understanding of the topic and their strategic use of cognitive and metacognitive processes. Each of the four agents is responsible for specific aspects of SRL, including task definition, planning, metacognitive processes, and learning strategies. Based on their specialized roles, each PA has been designed to detect a specific set of SRL processes. For example, Mary the Monitor is in charge of detecting when students deploy metacognitive processes and make metacognitive judgments such as expressing a judgment of learning (JOL; e.g., used in relation to judging one's understanding of the current content) and also in determining the valence (e.g., JOL - or JOL +) associated with the metacognitive judgment. The presupposition of an accurate detection method (by each agent) leads the agent to model the temporal dynamics associated with each SRL process, across all SRL processes, and how they relate to several learning outcomes such as declarative, procedural, and inferential knowledge and mental models of the science topic. This evolving model is then used to foster SRL and content understanding by providing several levels of scaffolding. Instructional scaffolding involves the coordination of other architectural modules of MetaTutor that coordinate and manage the dialogue system between agents and the learner. Instructional scaffolding is provided based on current research on human and computerized tutoring research (Chi et al., 2004; Graesser, D'Mello & Person, in press; VanLehn et al., 2007; Wolff, 2009) and recent studies comparing SRL with ERL (externally-regulated learning; Azevedo et al., 2007, 2008). The types of scaffolding range from having the learner vicariously watch as the agent models the SRL process to having the student use a specific SRL process while being provided with elaborate feedback regarding the effective use of the process (based on Zimmerman & Moylan, in press).

We present quantitative and qualitative analyses of log-file data from a mixed-method study with sixty (N = 60) college students using MetaTutor to learn about the circulatory system. Our analyses focus on the various data analytic techniques used to make inferences from the complex log-file data. The quantitative analyses focus on comparisons between frequency use of SRL processes, duration of SRL processes during learning, amount of time spent on each type of informational source, strategic moves made during each session, navigation patterns, and learning outcomes and their relation to specific type of scaffolding and agent moves during the learning session. We also provide descriptive and qualitative data focusing on the quality and cyclical nature of learners' deployment of SRL processes and the agents' use of ERL processes. Overall, this study stands to contribute to theoretical conceptions of SRL and ERL, examination of the cyclical nature between SRL and ERL, and the role of various scaffolding methods to foster learning. Lastly, we also derive instructional implications for the design of intelligent learning environments.

Analysis of students' actions during online invention activities - seeing the thinking through the numbers.

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Intelligent Tutoring Systems are widely used coached problem-solving environments (Koedinger, Anderson, Hadley & Mark, 1997; VanLehn, Lynch, Schulze, Shapiro & Shelby, 2005). They are successful, in part, due to their ability to give adaptive feedback (Corbett & Anderson, 2001; Koedinger & Aleven, 2007). More specifically, Intelligent Tutoring Systems adapt to students' behavior and knowledge by tracing students' learning trajectories using a cognitive model of the domain (Corbett & Anderson, 1995). A different family of educational technologies supports students during discovery and scientific inquiry tasks (de Jong & van Joolingen, 1998). However, the large solution space in these tasks, among other reasons, make the model tracing approach very hard to design and implement in these environments (van Joolingen, 1999; Veermans, de Jong & van Joolingen, 2000).

In this symposium we discuss data from the Invention Lab, an intelligent tutoring environment for invention tasks in the domain of Variability, built using the Cognitive Tutor Authoring Tools (Aleven, McLaren, Sewall & Koedinger, 2006). Invention tasks are a form of scientific inquiry activities, in which students are asked to invent solutions to novel mathematical problems without prior instruction (Roll, Aleven & Koedinger, 2009; Schwartz & Martin, 2004). In order to tailor the support students receive to their knowledge, the Invention Lab analyzes students' responses and identifies features that are apparent or missing from their solutions. To deal with the unique challenges of inquiry tasks, the lab uses two cognitive models - a metacognitive model of the inquiry process, and a domain-level model of variability. The domain-level model combines two approaches, model tracing (Corbett & Anderson, 1995) and constraint based models (Mitrovic, Koedinger & Martin, 2003), in order to extract the conceptual features of students' solutions. We present qualitative and quantitative results from an in-vivo evaluation of the Invention Lab with 92 students in a public middle school. Specifically, we focus on how the Invention Lab analyzes students' inventions, and how its log files open a window into students thinking, giving us an opportunity to identify a-ha moments at the domain and metacognitive levels as the data unfolds students' learning trajectories.

Discussant

The session discussant is Wouter van Joolingen. Wouter van Joolingen is Professor of Instructional Technology at the University of Twente, The Netherlands. His main research interest is the use of technology to support inquiry learning, which includes the design of cognitive tools to support inquiry processes and modeling with intuitive interfaces, such as freehand drawings. He studies the influence of cognitive tools and/or the interaction with learner characteristics such as motivation and or epistemological beliefs. Currently he is technical coordinator of the European SCY (Science Created by You) project in which science learning is modelled as the creation and exchange of *Emerging Learning Objects*. An important role is seen for pedagogical agents that base their behavior on the real-time analysis of learner interaction data.

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