RESEARCH GAPS FOR ADAPTIVE AND PREDICTIVE COMPUTER-BASED TUTORING SYSTEMS

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ABSTRACT

Researchers continue to enhance individual computer-based training capabilities to support self-directed learning and account for individual differences (e.g., personality or domain competence). Student-centric tutoring approaches recognize that each student's unique affect, motivation, skills, knowledge, preferences and experiences should influence the content, flow and challenge level of computer-based instruction. In other words, these individual differences should be the basis for adapting instruction to promote learning and predicting the future learning states of the student. This article explores current trends in adaptive and predictive computer-based tutoring methods, identifies gaps and discusses opportunities for future research. The intent of this paper is to introduce concepts discussed in the "adaptive and predictive computer-based tutoring" track of the the Defense and Homeland Security Simulation (DHSS) Workshop 2011.

Keywords: adaptive training, predictive modeling, intelligent tutoring systems, computer-based tutoring

1. INTRODUCTION

In March of 2011, a group of U.S. military scientists met to discuss the research and development of adaptive methodologies for computer-based military training. The Adaptive Training Workshop brought together representatives from each of the military services, the Defense Research Projects Agency (DARPA), the Advanced Distributed Learning (ADL) Co-Lab, and the Department of Education. In part, this workshop influenced the scope and content of this article which has been focused to specifically identify research gaps for adaptive/predictive computer-based tutoring systems that were identified during this March 2011 workshop.

For purposes of the workshop, adaptive training was defined as any training that was adjusted to meet the specific learning needs of individuals or teams. Particular attention was paid to research programs involving intelligent tutor technology which uses artificial intelligence techniques to adapt instructional information to match the student's cognitive and affective needs. Intelligent tutors produce instruction that is the product of an interaction between a student model, representing the state of knowledge, motivation, personality, and other student variables, an expert model representing the material to be trained and a pedagogical model representing the training methods to be employed in presenting the knowledge and skills.

1.1. Adaptive Tutoring Model

By way of example, the **Figure 1** illustrates a functional model of an adaptive tutoring system (Sottilare, 2010) which was adapted from Beck, Stern and Haugsjaa (1996) tutoring model. The major components include a student model (also known as a user, trainee or learner model) which generally contains information about the student's performance, and their overall competency in the domain being trained. It may contain information about their physiological state and their behaviors where this information is used to ascertain their cognitive (e.g., level of engagement) and affective state (e.g., emotions).

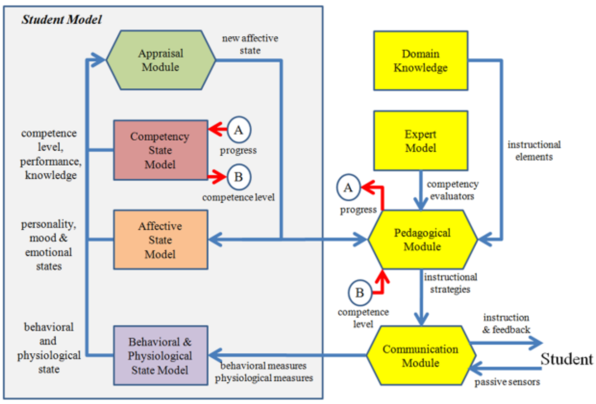

Figure 1: Adaptive Tutoring Model (Sottilare, 2010)

The pedagogical module assesses student progress based on the student's interactions and data in the student model. It uses this information to determine which instructional strategies (e.g., direction, support or questioning) to employ during the training session.

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The expert model is used to measure the progress of the student in the learning domain defined by the domain knowledge. The domain knowledge also defines challenge levels, options for feedback and content presentation.

The communication module is the student interface and includes mechanisms (e.g., visual displays, speakers or haptic devices for touch) to present instruction and feedback to the student. It may also include sensor input for physiological and behavioral measures to assess the cognitive and affective state of the student.

1.2. Tutor Adaptability

Similar to adaptive training, we defined adaptive tutoring "the ability of any computer-based tutor to adjust to meet the specific learning needs of individuals or teams." Student model data allows for the assessment of the student's cognitive (e.g., motivation, comprehension, level of engagement) and affective states (e.g., mood, emotions) by the tutor and is a basis for the tutor to adapt to the student by choosing appropriate instructional strategies. The effectiveness of the tutor's instructional decisions (or strategies) is limited by the tutoring system's ability to accurately classify the student's state. While human tutors generally perform this function with some difficulty, computer-based tutors can use machine learning classifiers and other techniques to evaluate real-time and historical data to interpret the student's current state and adapt the training content, flow and feedback to match. The student data might include, but is not limited to performance, behavioral and physiological sensor data, demographic data, personality profiles, mood surveys and student-system interaction (e.g., graphical user interface selections like check-boxes).

1.3. Tutor Predictive Accuracy

Adaptive tutoring indicates that the tutor assesses and reacts as needed. It would be useful for the tutor to be able to assess and predict future states so the tutor could be proactive and head off any negative aspects of the training. For example, the flow of training could be adapted to include interruptions to refocus engagement and reduce training time.

The inclusion of real-time data over the course of a training scenario allows for the prediction of future states and thereby makes the tutor predictive rather than reactive. Ideally, computer-based tutors would be able to fully perceive student behaviors and interpret physiological measures through unobtrusive sensing methods to predict the student's cognitive and affective states. Predicting the student's state is a necessary first step in selecting optimal instructional strategies (e.g., scaffolding for developing students).

Figure 2 illustrates a generic state transition model that might be utilized to examine localized trends and "dead reckon" future states. In the figure, the slope of the predictive vector (shown as an arrow) represents the strength of the trend from State A to State B. A state transition zone can vary in width from a single line (immediate transition shown by blue arrow) to an established position in the new state as shown by the red arrow.

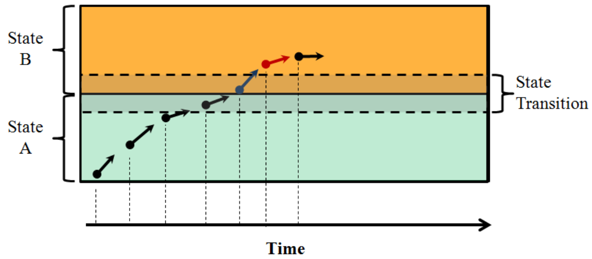

Figure 2: State Transition Model

Research thrusts needed to realize a fully adaptive and predictive tutoring system are reviewed below with particular focus on student modeling, authoring and expert modeling, and instructional strategy selection.

2. CHALLENGES IN ADAPTIVE/PREDICTIVE TUTORING

2.1. Student Modeling

Student models are often referred to interchangeably as student models, user models or trainee models. In order to make appropriate decisions about instructional content, flow, challenge level and feedback to the student, the tutor must first construct a sufficient student model. Ideally, this model would include everything the tutor needs to know about the student to guide the student through the learning experience, but some "tutoring systems" do not explicitly contain a student model. Those tutors that do have student models generally focus on student knowledge and performance to support instructional decisions.

It seems intuitive that having a student model would result in better instructional decisions than not having one, but having a student model isn't sufficient to ensure superior learning since you still must have an effective instructional strategy, intervention or pedagogical technique. In a truly "intelligent" tutoring system (ITS), the student model has to accurately reflect the state of the student and the instructional strategy (e.g., feedback, reflection, pumping, questioning, supporting) must be appropriate to the situation and the student's state to optimize learning.

There are two major challenges (and many questions) in deciding what needs to be in the student model: identifying what information is relevant to instructional decisions; and collecting that information unobtrusively so as not to interfere with the learning process (Sottilare and Proctor, 2011). Outstanding questions include: What inputs, processes and outputs are critical for student models to support adaptive/predictive training applications? Do student models adequately address individual differences?

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So what types of data are included in student models today? Currently, data models include both unprocessed and processed (or derived) data sets. Unprocessed data could include self-reported data like demographics, opinions and survey information, but could also include raw physiological or behavioral data from sensors (e.g., cameras, recording devices). Derived data sets include student states (e.g., competence-level, cognitive state, affective state).

Student models may not be necessary for training simple, drill and practice type tasks, but as the type of task becomes more complex or ill-defined then the value of the student model should take on more importance.

Another consideration in student modeling is the notion of static and dynamic data types. For our purposes, we define "static" data as student data that remains unchanged for the life of the training event and includes, but is not limited to personality data (e.g., openness). "Dynamic" data changes during training and includes, but is not limited to performance measures.

Other factors are referred to as macro/micro or global/local parameters. For example, local adaptation includes actions that are based on recent student events (e.g., selected response "B" and the correct answer is "C") and an intervention might be chosen based on this small sample of performance. A more global approach focused on static personality data leaves little room for prediction or adaptation during training. Hybrid models take global variables into account when initializing strategies and adapt/change through local variables. We need both.

Social interaction data (e.g., trust, communication) may be more important for training on tasks that require more than the knowledge and skills of the individual student (e.g., team training). Individual attributes like as cooperation, adaptability, openness/friendliness and situational awareness might have significant value in obtaining objectives and in assessing team performance as part of a collective student model.

Finally, the literature seems to agree on the importance of accounting for knowledge and competence in instructional design and delivery, and so they are important to student modeling. However, the influence of other factors (e.g., ethics/values, technology acceptance) on the learning effectiveness of tutors remains an open question.

2.2. Authoring Tools and Expert Modeling

A grand challenge in the development, usability and efficacy of computer-based tutors is the ease with which tutors can be configured configuring tutors to support different training domains and populations. Today, computer-based tutoring systems are generally handcrafted products with little standardization, interoperability or reusability. Authoring tools are needed to support the development of training content and expert models by domain experts with little programming skills. Interoperability standards would go a long way toward making the modularity and reuse of tutor components (model structures, communication protocols and scenario content) easy to produce, modify and maintain.

The development of expert models remains a key cost in developing tutoring systems. Expert models represent ideal student performance to which actual student performance is compared. Expert models are typically painstakingly developed through observation of subject matter experts performing specific tasks.

Some of the questions driving research in the area of expert modeling include: How does the state of knowledge of expertise in some domains differ from others? How do we describe and formalize expertise in general? How do we articulate learning objectives in such a way that they support development of expert models?

Finally, "expert model" may be a misleading term. It may really be a journeyman model with standards defined so that students complete the training when they obtain sufficient competency to get the job done, but not at an expert level. An expert model is really a model of what is correct. The student's performance is compared to correct performance.

There was a discussion over whether or not an expert model should be computational or not. A position was put forth that for domains that are stable the effort to develop a computational model should be expended. For less stable tasks were there maybe multiple ways to accomplish the task or adaptive behaviors are appropriate it is hard to articulate what expertise is and therefore very difficult to model quantitatively.

2.3. Instructional Strategy Selection

A key research task in developing computer-based tutors that can select appropriate instructional strategies is too observe, assess and model the behaviors of experts. In other words, build an expert model for instructing that is adapted not only for the student, but also for the learning context. This task analysis is complicated by the fact that many teachers broadcast information to many students and it is difficult to sort out what behaviors make a difference in individual learning.

Major functions for the instructor are diagnosis, remediation, prescription, demonstration, feedback, motivational support, attention orienting, and questioning. One of the most difficult tasks for a computer-based tutor is to understand what the student knows, assess options to correct deficiencies and then pick the optimal strategy. For example, feedback has to be at the right level of understanding to be useful to the student.

The instructor model is considered by many to be the long pole in the computer-based tutoring tent. Another challenge is that diagnosis doesn't work well without a good student model. Providing all of the

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pedagogical approaches that are needed is very difficult using the current artificial intelligence techniques. A question is often raised about whether the computer-based tutors should replace teachers or whether we should be developing methods for providing decision support aids to teachers in the near term. The authors view the intended use of tutoring technologies as supportive of training tasks in environments where human tutors are either unavailable or impractical.

3. DISCUSSION

3.1. Assessing Computer-based Team Tutor Performance

What should be the basis for assessing the maturity and effectiveness of computer-based team tutoring technologies? Sottilare and Gilbert (2011) identified several factors that should be considered in this assessment: adaptability, perception, accuracy, instructional strategy selection, interoperability and most importantly, learning effect.

Adaptability of the tutor is the capability to understand the student's learning needs and change the content, flow and interaction (e.g., feedback, questioning) prior to and during instruction to meet those learning needs. Adaptability is the result of perception, accurate assessment of student state and optimized instructional strategies.

Perception, in this context, is the ability of the computer-based tutor to sense and understand the student's physiological and behavioral data to populate the student model. Today, the gold-standard for perception is the human tutor who uses behavioral cues to interpret the student's state. This is more art and less science since cues can be misinterpreted. Good human tutors use multiple cues and the student's performance to assess the "readiness to learn".

"Readiness to learn" is a multidimensional state defined here to be the student's level of engagement, their motivation, their understanding of prerequisite skills and their affective state (e.g., personality factors, mood and emotions). Computer-based tutors have the potential to integrate additional sensor information (e.g., physiological data including heart rate, neurological data and respiration rate) beyond the capabilities of human tutors. The limiting factors in maximizing the perceptive powers of computer-based tutors lies in their abilities to sense student behaviors and physiological data unobtrusively, and then use that data to accurately model the student's state.

Computer-based tutoring systems use a variety of methods to evaluate student data and accurately determine student state (e.g., cognitive and affective). Machine learning classifiers are extensively used to assess state and include, but are not limited to rule-based classifiers, Bayesian networks, decision trees and regression algorithms. It is generally accepted that improvements to state classification will result in higher probability of selecting an appropriate and more effective instructional strategy.

Examples of instructional strategies include scaffolding, modeling, cooperative learning and prior knowledge activation (Cooper, 1993). Scaffolding places heavy emphasis on support early in learning and gradually less support as the student's competence grows (Cooper, 1993). In modeling, the tutor demonstrates specific concepts and skills for the learner (Bandura, 1986). Finally, cooperative learning leverages the experience of peers to engage with learners to improve their knowledge and understanding of instructional content (Wells, 1990).

The accessibility of instructional content is enhanced by the interoperability of the tutor. The easier it is to link computer-based tutors to instructional media, the more useful and accessible that tutor will be. Recently, instructional developers (Thomas and Young, 2009) have adapted tutor interfaces to accept what has traditionally been entertainment content (e.g., computer games) to enhance the engagement level of students resulting in "serious games" or games for training.

The bottom line for any tutor (human or instructional technology) is its positive influence on learning or effect size. Bloom (1984) described a two-sigma (2σ) difference between a learner's achievements in a classroom environment vs. a learner's achievement with a one-on-one tutor. Kulik (1994) analyzed 97 research studies on tutors and found that most tutoring systems have an average difference (or "effect size") of 0.32σ. This low compared to expected larger effect sizes ($> 2.0\sigma$).

3.2. Conclusions

While computer-based tutoring had been around for some time, there is little evidence of their use in military training. This is likely in part due to the absence of authoring tools to make tutors easy to develop and maintain without the need for technical experts.

Tutors for the most part have been developed for structured (well-defined) knowledge domains such as algebra, physics and trouble shooting. Tutors for ill-defined domains that require decision making in the face of complex, and confusing situations are a significant challenge given the maturity of tutoring technology today.

Competence and state of knowledge are the key elements in student models. The student model can also take into account more local time sensitive information like attention. Other potential components of student models need to have their contributions investigated further. The richer the student model the finer grained the tutoring objects can be and the more accurate the assignment of instructional strategies.

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3.3. Recommendations for Future Research

Pedagogy was seen as a major hurdle that needed further research, since there were very few firm guidelines on the relationship between student performance diagnosis and the ensuing instructional method.

It makes sense that the more the tutor knows about the student, the more effective its pedagogical decisions will be. The student model in today's tutors is insufficient to account for individual differences (e.g., personality), which include states (e.g., motivation, engagement) and traits (e.g., preferences). The influence of individual differences is in many cases unknown and requires additional research. An expanded student model needs to be developed based on empirical evidence to define the influence of individual differences.

Another recommended area for research is accelerated learning and retention. While the effect of computer-based tutoring technologies on learning is still not well understood, their ability to accelerate learning is even less clear.

Retention continues to lag behind learning research due to issues with retaining participants over a series of experiments, but "it does little good to attain a higher level of competence quickly if it leads to poorer knowledge and skill retention" (Andrews & Fitzgerald, 2010).

Finally, five instructional strategy research topics that would benefit from additional investment are analysis, diagnosis, prescription, mental model mismatch (misconceptions) and demonstration.

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Dr. Robert A. Sottilare is the Associate Director for Science & Technology within the U.S. Army Research Laboratory - Human Research and Engineering Directorate (ARL-HRED). Dr. Sottilare has over 27 years of experience as both a U.S. Army and Navy training and simulation researcher, engineer and program manager. He leads the international program for ARL's Simulation and Training Technology Center (STTC) and participates in training technology panels within both The Technical Cooperation Program (TTCP) and the North Atlantic Treaty Organization (NATO). He has a patent for a high resolution, head mounted projection display (U.S. Patent 7,525,735) and his recent publications have appeared in the Educational Technology Journal, the Journal for Defense Modeling and Simulation, the NATO Human Factors and Medicine Panel's workshop on Human Dimensions in Embedded Virtual Simulation and the Intelligent Tutoring Systems Conference 2010. Dr. Sottilare is a graduate of the Advanced Program Managers Course at the Defense Systems Management College at Ft. Belvoir, Virginia and his doctorate in modeling & simulation is from the University of Central Florida. The focus of his current research program is in machine learning, student modeling and the application of artificial intelligence tools and methods to adaptive training environments. Dr. Sottilare oversees the

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