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Abstract
The purpose of this panel is to discuss current directions in research and design of adaptive tutoring, and the need for a method to uniformly describe tutors within this growing field. Discussions will focus on the increasing complexity of individual tutors, as well as how tutors could be categorized through identification of relevant, constituent parts. A standardized taxonomy would provide the foundation for establishing a quantifiable metric of complexity, which could then be used to compare vastly distinct tutors to one another. Applications of such a metric also include evaluating tutor effectiveness with respect to learning outcomes, comparing capabilities / usability of different adaptive tutor authoring tools, and providing more accurate estimates of the time required to develop an hour of tutoring. Individual elements of tutoring to be discussed within the context of this framework include team tutoring, psychomotor tutoring, multi-platform architectures, personalized tutoring, and authoring complexity.

Disciplines
Ergonomics | Human Factors Psychology

Comments

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The purpose of this panel is to discuss current directions in research and design of adaptive tutoring, and the need for a method to uniformly describe tutors within this growing field. Discussions will focus on the increasing complexity of individual tutors, as well as how tutors could be categorized through identification of relevant, constituent parts. A standardized taxonomy would provide the foundation for establishing a quantifiable metric of complexity, which could then be used to compare vastly distinct tutors to one another. Applications of such a metric also include evaluating tutor effectiveness with respect to learning outcomes, comparing capabilities / usability of different adaptive tutor authoring tools, and providing more accurate estimates of the time required to develop an hour of tutoring. Individual elements of tutoring to be discussed within the context of this framework include team tutoring, psychomotor tutoring, multi-platform architectures, personalized tutoring, and authoring complexity.

INTRODUCTION

Adaptive tutors, or intelligent tutoring systems (ITS), are learning platforms that collect data about a learner(s) through assessments, reports, and sensors, in order to deliver instructional content that is tailored to match the capabilities, states, and traits of each learner (Sottilare, 2014). From a theoretical perspective, tutoring systems are powered by four components: a domain model, a learner model, a tutoring / pedagogical model, and a communication model / tutor-user interface (Woolf, 2009, pp. 44-45). That modularity provides for a wide variety of tutors, each with their own unique characteristics. However, beyond those four components, the adaptive training community lacks a standardized language to describe the composition of an individual tutor, though prior work has sought to broadly classify genres of tutors (Bell, 2015; Nye, Goldberg & Hu, 2015).

A standardized description of an adaptive tutor is something of a moving target. Intelligent tutoring systems are rapidly evolving. Tutors are typically built either as custom solutions, or built upon a particular ITS platform, using a set of authoring tools. In theory, tutors could be developed for any domain of instruction, but in practice adaptive tutors are typically found within well-defined domains such as math and physics. Tutors typically adapt to the learner based on performance characteristics of the learner (but could also include preferences and affective states), and learners typically consume tutors via a traditional computer interface.

RESEARCH CHALLENGE

One goal of the current discussion panel is to examine how adaptive tutoring is evolving beyond the aforementioned configurations to include: tutoring for teams (or teams of teams), tutoring in ill-defined domains, highly-personalized learning, tutoring beyond the desktop using novel input devices, and tutoring outside primarily-cognitive domains (e.g., tutoring for psychomotor tasks). Each of those examples, as well as others, will present new technical challenges for tutoring, which will impact pedagogical methods for adaptive instruction, exchanging data between various simulation and learning systems, and developing authoring tools that afford users of all skill levels the opportunity to leverage the potential of ITS.

In light of the expanding field of adaptive tutoring, it is proposed that a standardized language is needed in order to uniformly describe different types of individual tutors at the sub-system level. That topic serves as the secondary goal of this discussion panel. Further, standardized language would make up classification taxonomy for tutors, which could then be quantified to provide a relative estimate of a tutor’s complexity. That estimate of tutor complexity can yield many useful applications, related to research, design, and evaluation of adaptive tutoring systems. Some of these applications are described below.
Tutor Effectiveness

Suppose that an investigator wanted to compare the relative effectiveness of two vastly different tutors designed to teach the same set of learning objectives. At a high level, the researcher could design a study which may yield some results regarding the performance of the two tutors for a given population, but conclusions made resulting from the study might only generalize to the two specific tutors. With a formal language to classify the complexity of the tutors, it would be possible to examine specific characteristics of the two tutors and look for trends in the research across other studies with the same classification system in order to determine if specific elements of the tutor influence the result. Similarly, it may be possible to make better recommendations regarding the appropriate balance of complexity that optimizes learning outcomes with the cost of developing, deploying, and managing a tutor.

Authoring Effort

The effort associated with creating a tutor has previously been described as requiring anywhere from 50-100 or up to 300 of hours of effort to produce one hour of tutoring content (Aleven, V., McLaren, B. M., Sewall, J., & Koedinger, K. R. 2009; Murray, 1999). Given the vast differences with which each of the four ITS models can be designed and implemented (learner, pedagogical, domain, communication), that metric alone is somewhat nebulous in operationalizing it across tutors that are even similar to a target system. Knowing the type, composition, and/or complexity of the tutoring content would allow for the comparison of effort in producing similar tutors, as well as dissimilar tutors from different domains.

The proposed complexity model can be further extended from the authoring effort node. Authoring effort is not only a function of the complexity of the tutor itself, but the skill of the author and the quality of the authoring tool (or ITS platform) with which the tutor is built. The modeling of authoring skill should be delayed until the other dimensions of the complexity model are better understood.

Authoring Tools for ITS Platforms

Authoring tools are a key application of the proposed tutor complexity model because they are influenced by the complexity of the tutors themselves, and influence the amount of authoring effort required to build those tutors. Authoring tools continue to evolve with the realized potential of individual tutors. As tutors become more complex and varied, more robust authoring tools are needed to allow authors to build, manage, and deploy adaptive training content. However, more powerful authoring tools place the burden on the author to be able to learn and use them. Developers and designers could leverage tutor complexity to attend to the efficiency, usability, depth, and flexibility of authoring tools (Murray, 1999), with respect to end-user authors of various skill and experience levels.

Estimating Tutoring Content

Finally, the estimation of tutoring content is another useful application of a proposed tutor complexity model. Suppose that an instructor has been provided with an adaptive tutor as part of their lesson materials. The instructor would need some reasonable estimate of the time that learners would be engaged with the tutor as part of the instructor’s lesson-planning tasks. A tutor complexity model may be able to provide an estimate of time based on a number of factors including; the number of concepts taught by the tutor, the number of adaptive permutations for each concept, context personalization, the learner model used and the media content assigned to each permutation. An estimation of tutoring content also ties back into other applications of the model including authoring effort, and authoring tool efficiency.

Other Discussion Points

The prior sections have identified potential applications of a tutor complexity model, which considers a number of relevant factors to provide a more accurate, generalizable description of an adaptive tutor. As those factors are identified, there are other issues that should be considered.

First, it will be necessary to determine if tutor characteristics belong in the tutor complexity model at all. Media content, for instance, may be useful in generating an estimate of the learner’s time with the tutor, but media content is generally created outside of an ITS platform, or is linked from some other online resource (e.g., YouTube). An argument can be made that media source content (i.e., content creation) does not belong in the tutor complexity model however, the editing, slicing, or repurposing of existing media content into adaptive tutoring branches may be a more accurate characteristic for consideration in the model (i.e., content curation).

Next, once a suitable factor for the tutor complexity model has been identified, it will be necessary to describe its relationship to other model factors, and its relative weighting to overall tutor complexity. For instance, assume that the number of concepts to be taught by the tutor is a relevant factor in determining a tutor’s relative complexity. What does this relationship look like; is it linear? Or perhaps there is a point at which the addition of additional concepts has little influence on the complexity of the tutor due to economies of scale found in other factors within the composition of the tutor. There will likely be interactions between factors; determining a sufficient level of interaction detail is also relevant to the present discussion.

Finally, panel members will provide their own thoughts on the future directions of adaptive and intelligent tutoring systems. They will provide input to which factors should be considered for tutor complexity, and how those factors influence other components within the model. Guided discussion with the audience (and readers) is encouraged to yield additional insights into the structure and applications of this proposed adaptive tutor complexity model, as well as the future of intelligent tutoring systems.
POSITION STATEMENTS

The Complexity of Team Tutors
Michael Dorneich, Ph.D., Industrial & Manufacturing Systems Engineering, Iowa State University

While there has been much progress in the development of ITSs targeted at the improved the performance of individuals, comparatively less work has been done on the development of ITSs designed for educating or training teams (Sottilare, Holden, Brawner, & Goldberg, 2011). Meanwhile, successful human-led team training has been ongoing, and would benefit greatly from ITSs (Bonner et al., 2015b).

However, progress in team ITSs has been slow for several factors related to complexity. Despite much research on teaming since the 1970s, team performance is widely variable and difficult to predict (Sims & Salas, 2007). The interactions among team members have been studied for decades, and the combinatorial explosion of these interactions, along with the difficulty of quantifying them with a sensor, has made the creation of ITSs for teams difficult (Sottilare, Holden, Brawner, & Goldberg, 2011). When moving beyond individual, task-based tutoring, the success of team tutors depend an additional layer of team skills. These team skills may greatly affect the successes of a team tutor, but team skills may or may not be an explicit part of the pedagogy of the team ITS. Finally, the characteristics of team tasks are also more complex, with potentially different (and changing) roles, timing constants, and interdependencies (Bonner et al., 2015a).

All these factors influence the other measures of complexity proposed by the panel. The complexity in authoring increases with the need of a learner module for each team member, as well as learner modules at the team level if team skills are taught in addition to task skills. Furthermore, beyond individual performance, the interactions between team members are a rich source of information from which to base tutoring. The design of the learning experience itself can also become more complex, as everyone is interacting not only with the ITS but with other teammates, which are more variable and less controllable.

This talk will focus on the interaction of tutoring and team theory to suggest a taxonomy of characteristics that could be used to describe team tutors in terms of the type of team members, the type of team tasks, and the type of tutoring used. Furthermore, this talk will extend this taxonomy using the disciplinary vocabulary of human-machine systems (Parasuraman, Sheridan, & Wickens, 2000) and automation etiquette (Miller, Wu, & Funk, 2008; Yang & Dorneich, 2016) to describe not only the team tutor itself, but the complex interplay between a team tutor and multiple team members.

Cognitive Complexity of Authoring vs. Experiencing ITSs
Stephen B. Gilbert, Ph.D., Associate Director, Virtual Reality Applications Center, Iowa State University

In pursuit of the panel’s goal of common language to compare intelligent tutoring systems’ complexity, it is worth focusing especially on two components of ITSs: the authoring and the learning experience. To facilitate comparing ITS authoring, Green & Petre’s framework of cognitive dimensions (Green & Petre, 1996) will be described. This framework of 13 dimensions arose from usability analysis and has been used to compare visual programming languages with non-visual languages as well as to compare the two ITS authoring tools CTAT and xPST (Devasani, Gilbert, & Blessing, 2012).

Secondly, the complexity of learning experience will be explored using a framework integrating the ideas of touchpoints from customer experience design (Patrício, Fisk, Falcão e Cunha, & Constantine, 2011) and Streveler et al.’s elegant overview of conceptual learning within engineering (Streveler, Litzinger, Miller, & Steif, 2008).

These measures might well be more useful for the ITS domain than traditional computational complexity measures such as cyclomatic complexity (i.e., a software metric used to indicate complexity of a system) and computational time required per big O notation (i.e., used to describe the performance or complexity of an algorithm).

ITS Methods in a Psychomotor Task Environment
Benjamin S. Goldberg, Ph.D., Adaptive Tutoring Scientist, Learning in Intelligent Tutoring Environments Laboratory, U.S. Army Research Laboratory

A current theme in ITS research is extending the application of ITS beyond cognitive problem spaces and into psychomotor skill domains. While this can be considered a novel extension of traditional ITS methods, its implementation doesn’t vary significantly from traditional applications. It utilizes models built on domain and learner information to inform a pedagogical decision (Goldberg, 2016). In this instance, the domain isn’t informed solely by performance and procedural information captured within a desktop learning environment; rather, it involves tasks that link cognition with physical interaction incorporating combinations of hand-eye coordination, muscle memory, and behavioral techniques to meet task objectives (e.g., striking a target on a marksmanship range).

With the intent of ITSs to provide effective instruction in the absence of human intervention, a psychomotor ITS has two overarching complexities: (1) configuring a sequence of interactions that adhere to skill acquisition and psychomotor skill development theory, and (2) building assessments within the various interactions that drive coaching (e.g., provide corrective feedback) and manage adaptations within the practice environment (e.g., increase the task complexity to maintain desirable difficulties). The first complexity highlights the requirement for a system to be structured in a fashion that adheres to instructional theory as it associates with the taxonomy of psychomotor domains (Bloom, 1956). Lessons should be structured in a way that supports deliberate practice with content to support interactive remediation and coaching methods. Ongoing work will be discussed that addresses this complexity, with an agent-based authoring approach serving as use case to frame the common language approach.
The second complexity in the psychomotor ITS space is real-time assessment support. For instructional purposes, models must be in place for assessing an individual’s skill across physical task components for the purpose of driving focused coaching and remediation practices. The goal is to identify a performance deficiency or misconception through modeling techniques that can drive pedagogical interventions. A challenge is collecting task relevant data from the training environment that associates with specific components of skill application. We will discuss current methods applied within an ARL project, the limitations surrounding the approach, and how those techniques serve as a basis for modeling any psychomotor task domain to enable assessment practice.

**Adaptive Tutoring for Lifelong Learning**  
Cheryl I. Johnson, Senior Research Psychologist, Naval Air Warfare Center Training Systems Division

Recognizing the need for more on-demand, personalized training to make the acquisition and maintenance of skills more efficient and effective, the Navy has undertaken several new initiatives targeting the application of technology-based solutions to training and education across the Navy training pipeline. These initiatives are guiding requirements for a more integrated, interoperable Navy learning experience driven by adaptive training, intelligent tutoring and automated performance measurement.

In support of the Sailor 2025 and High Velocity Learning initiatives, the Navy is investing in research and development of adaptive tutoring systems to enable more learner-centered training that is effective, engaging, and available at the point of need. One such effort, the Personal Assistant for Lifelong Learning (PAL3), was designed to address the skill decay that occurs when sailors experience long gaps in instruction (e.g., some students may wait 3-6 months between A and C schools) by providing a resource that they can use to help them build and maintain their skills. To provide guidance to students and encourage the utilization of PAL3, the system includes an embodied pedagogical agent that helps students navigate through a library of curated learning resources (including multiple intelligent tutoring systems, tutorial videos, and webpages) by providing recommendations based on the student’s learning record (Swartout et al., 2016). The learning record not only tracks the activities the student has completed and his/her performance on training modules, but also records the student’s goals and future assignments and contains an underlying forgetting model to ensure that skills are revisited periodically to prevent skill decay. This research effort will culminate in a training effectiveness evaluation to determine whether recent A-school graduates who use the PAL3 system will experience less skill decay and be more prepared for C-school than students without PAL3.

The development and implementation of adaptive tutoring systems, such as PAL3, present specific challenges in execution. Among the challenges to be addressed in the current PAL3 system include storing and optimizing a persistent learner model across multiple tutoring systems, mitigating connectivity issues, and protecting against cyber security issues. Regarding the first challenge, as the complexity of tutoring systems increases, the need for managing large amounts of data also increases in order to create a persistent learner model. Another challenge is the practical concern of connectivity with the system. Because PAL3 is intended for use by sailors, there is the issue of limited or sporadic access to the internet, and tutoring systems must therefore be available in an off-line capacity so that learners will be able to use the system regardless of geographical location. Finally, the challenge of protecting such data about performance in tutoring systems and progress toward learning and career goals must also be considered from the perspective of cyber security. Implementing necessary information assurance requirements for cyber security will be imperative for protecting sensitive information.

Looking to the future, we are working on a new effort building off of the successes of PAL3, entitled “Learning Continuum and Performance Aid (LCA)P” with the goal of providing a suite of flexible, interoperable applications that support an individual sailor’s education and training needs throughout his/her Navy career. This effort will result in a proof of concept to demonstrate the utility of tracking an individual’s training record and job performance to support a variety of goals, including individual career management and selection, skill classification, re-engineering of training content, supervisor evaluations, and Fleet readiness tracking to provide solutions to enhance training effectiveness and efficiency across the Navy training pipeline.

**Personalization in Adaptive Instruction**  
Anne M. Sinatra, Ph.D., Adaptive Tutoring Scientist, Learning in Intelligent Tutoring Environments Laboratory, U.S. Army Research Laboratory

Personalizing instruction for an individual learner can take many forms. Materials can be adjusted based on prior knowledge, interest preferences (context personalization), or even individual characteristics such as motivation or personality. However, these adaptations may have different impacts on different learners, as well as in different domains of instruction. One way to examine the impact of these types of personalization is through making comparisons of tutors that adapt based on different personalized criteria. A domain-independent ITS framework such as the Generalized Intelligent Framework for Tutoring (GIFT) addresses one of the challenges related to comparing tutors: the same structure and similar materials can be used to author tutors in different topic areas for comparison based on learner behavior and outcomes (Sottilare, Brawner, Goldberg, & Holden, 2012). However, a second challenge exists: how do you standardize the complexity of the tutor to make sure that you are making equivalent comparisons?

All of these methods of adaptation require additional paths and options to be created by the course author. If motivation level and/or personality are used for adaptation, then materials need to be present for all levels of these variables. If context personalization is utilized, then multiple topic-customized versions of each question and learning material need to be created (Sinatra, 2015). If prior knowledge is a factor in the adaptation, then the tutor may bypass topics...
or have abbreviated versions of the materials for higher prior knowledge individuals. Having a method for standardizing and quantifying the levels and types of available adaptations may help in making comparisons between personalization methods and in different domains. For instance, if an algebra tutor adjusts based on context and there are three different interests that the content can be personalized to (sports, movies, aviation), and a reading tutor has four different options for the customization of the reading passages (cars, manufacturing, comic books, musical instruments) how could one compare their outcomes?

As there are many approaches to context personalization (Sinatra, 2016), knowing the way that the information is being presented and customized is vital, as well as knowing the unique aspects of the domain being taught, knowing the number of different context possibilities, and knowing how the outcomes are being assessed. A unified method for defining complexity should consider all the different types of personalization that can occur in an adaptive tutor and lead to the quantification of relevant outcomes.

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REFERENCES


