Dynamic User Modeling within a Game-Based ITS

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ABSTRACT

Intelligent tutoring systems are adaptive learning environments designed to support individualized instruction. The adaptation embedded within these systems is often guided by user models that represent one or more aspects of students' domain knowledge, actions, or performance. The proposed project focuses on the development and testing of user models within the iSTART-2 intelligent tutoring system, which will be informed by dynamic methodologies and data mining techniques. My previous work has used post hoc dynamic methodologies to quantify optimal and in-optimal learning behaviors within the game-based system, iSTART-2. I plan to build upon this work by conducting dynamical analyses in real-time to inform the user models embedded within iSTART-2. I am seeking advice and feedback on the statistical methods and feature selection that should included within the new dynamic user model. The implications of this approach for both iSTART-2 and the EDM field are discussed.

Keywords

Intelligent Tutoring Systems, Dynamic Analysis, Adaptation, Log Data, User Models

1. INTRODUCTION

Intelligent tutoring systems (ITSs) are adaptive learning environments that provide customized instruction based on students' individual needs and abilities [1]. ITSs are typically more advanced than traditional computer-assisted training in that they *adapt* to the users' performance and skill levels [2]. The customizable nature of ITSs has resulted in the successful integration of these systems into a variety of settings [3-5].

One hypothesized explanation for the widespread success of these systems is that ITSs provide individualized feedback and adjust content based on the unique characteristics of each student or user. This pedagogical customization allows students to progress through learning tasks at a pace that is appropriate to their individual learning model [6]. It also ensures that students are not only learning at a shallow procedural level, but they are gaining deeper knowledge at an appropriate pace.

One way in which ITSs store and represent information about learners is via *user models*. User models embedded within ITSs incorporate detailed representations of learners' knowledge, affect, and cognitive processes [7]. It is important to note that these models are often continuously updating throughout the students' interaction within the system. Thus, potentially, every student action or decision made within the system contributes to more accurate and holistic user models. Although this concept seems to be intuitive, researchers often struggle to determine what information belongs within the models and how to optimally quantify the dynamic nature of that information.

In prior work, my colleagues and I have proposed that dynamical systems theory and associated analysis techniques are useful tools for examining behavioral patterns and variations within ITSs [8,9]. Indeed, dynamic systems theory affords researchers a unique means of quantifying patterns that emerge from students' interactions and learning behaviors within an ITS. This approach treats time as a critical variable by focusing on the complex and fluid interactions that occur within a given environment rather than treating behavior as static (i.e., set or unchanging), as is customary in many statistical approaches. In the proposed work, I hypothesize that dynamical methodologies have strong potential to inform user models by quantifying changes in students' interactions and learning behaviors across time. This quantification and modeling of behavior can inform decisions about how content and feedback should be presented to each student based on their current learning trajectory. The overall goal of the proposed work is to test the utility of real-time dynamic analyses as a way to inform user models about optimal (and non-optimal) learning behaviors within a game-based ITS.

1.1 iSTART-2

Interactive Strategy Training for Active Reading and Thinking-2 (iSTART-2) is a game-based ITS designed to improve high school students' reading comprehension via self-explanation strategies [10]. In previous studies, iSTART-2, and its predecessors, have been shown to be effective at improving students' self-explanation quality and reading comprehension ability [11, 12].

iSTART-2 consists of two phases: self-explanation training and game-based practice. During training, students watch a series of videos that introduce them to and provide examples of self-explanations strategies. After students view these videos, they transition to practice (see Figure 1 for a screenshot of the game-based practice interface). During practice, students are able to interact with a suite of mini-games, personalizable features, and achievement screens [13]. The game-based practice embedded within iSTART-2 is designed to promote the generation and identification of self-explanation strategies. Within these practice games students are exposed to game mechanics that serve as a form of feedback on their understanding of the self-explanation strategies (see [11] for more details).

The interface of iSTART-2 uniquely affords students substantial agency and control over their learning path by allowing them to choose how they engage with the practice environment [9]. Such freedom also affords researchers with the opportunity to explore and *model* how and when students engage with these features and activities, and to explore the implications of such choices (i.e., how they affect performance and learning).

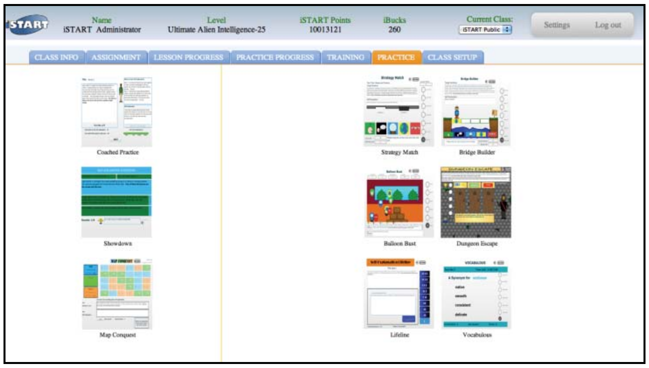

Figure 1. Screen shot of iSTART-2 Selection Menu

1.2 Current Work

My doctoral research will use educational data mining methods to inform and build dynamic student models within game-based ITSs such as iSTART-2 [13]. Specifically, this study will explore how dynamic techniques such as Hurst exponents and Entropy analysis can be used in real-time to quantify students' behaviors, performance, and cognition while they learn within iSTART-2. Analyses of students' logged choices have been shown to be a *blueprint* regarding successful and unsuccessful behaviors for learning [13, 15]. Therefore, the logged information from iSTART-2 will be used in conjunction with dynamical analysis techniques as a means to quantify various types of in-system behaviors and their impact on learning outcomes in real-time. This information will then be used to adapt the pedagogical content students are exposed to.

2. Proposed Contributions of Current Work

The current work has both *local* and *global* implications. Locally, the development of dynamic user models will improve iSTART-2 pedagogy. Currently, iSTART-2 has limited user models (only guides self-explanation feedback) embedded within the system. Thus, the inclusion of a dynamic user model is expected to improve system feedback and guide the content presentation provided to students. For instance, one research question that arises from this work is how to support optimal learning trajectories for every student. Dynamic user models have the potential to recognize non-optimal learning behaviors and provide feedback or navigate students toward more effective learning behaviors within the practice environment. Thus, it is hypothesized that the implementation of dynamic models will improve the design and generalizability of iSTART-2.

Globally, this project will contribute to the AIED and EDM fields. User models are an important and often crucial aspect of ITS development. However, very few systems (if any) use dynamic data mining techniques to inform their student models. This work will be among the first studies to use techniques such as Hurst exponent analysis in real-time to inform user models that will ultimately be used to adapt the content and feedback presented to students. The methods presented here are generalizable and thus can be used in a variety of settings beyond iSTART-2. Although the goal of the current work is to design user models for the iSTART-2 system, this work is driven by the overarching goal of gaining a better understanding of students' learning processes.

3. Previous Work

My previous research has revealed that dynamic methodologies are useful tools for quantifying students' behavioral patterns within iSTART-2 [8,9,13,14,15]. For instance, Entropy is a dynamical methodology used to measure the amount of predictability within a system or time series [16]. My colleagues and I have employed post hoc Entropy analysis to quantify variations in students' behaviors within iSTART-2 and related them to performance differences. Based on students' choices within games, an Entropy score can be calculated that is indicative of the degree to which students' choice patterns are controlled versus random. In [13], students' Entropy scores were included within a regression analysis to examine how students' choices within the system influenced their self-explanation performance. Students who engaged in more controlled interaction patterns (i.e., strategic and planned out) within iSTART-2 also generated higher quality self-explanations compared to students who acted in more random or impulsive manners.

While Entropy provides an overall view of students' choice patterns within a system, it does not capture fine-grained fluctuations that manifest over time. To address this issue, Hurst exponents have been conducted using iSTART-2 log data. Hurst exponents [17] are similar to Entropy analyses in that they quantify tendencies or fluctuations present within a time series. However, Hurst exponents also act as long-term correlations that can characterize the fluctuations that manifest across time. Hurst exponents classify these fluctuations as persistent, random, or antipersistent [18]. Using this approach, we can identify when students choose to perform the same action(s) repetitively [8]. This technique affords a fine-grained look at students' behaviors across time. Although Entropy and Hurst exponent analyses have shed light upon the effects of students' interactions within an ITS on learning, the analyses thus far have all been conducted post hoc (i.e., using data mining techniques). Thus, the current work seeks to build upon these dynamical analyses and apply dynamic data mining techniques in *real-time* as a means to inform student models within iSTART-2.

4. Advice Sought

For this doctoral consortium, advice is sought regarding two core concerns. First, *what features should be included in dynamic user models?* Currently, I have solely focused on students' behaviors and in-system performance within the game-based practice portion of the system. However, iSTART-2 has powerful logging functionality capable of collecting everything from mouse movements to keystrokes. Thus, in this setting I would benefit from expert opinions or discussions concerning what features should (or could) be included within dynamic user models.

Second, *what other dynamic methodologies and tools are available and relevant to user modeling?* Thus far, I have used random walks, Entropy and Hurst analyses. However each of these measures have one or more weaknesses. For instance, to reliably calculate a Hurst exponent, multiple data points are needed (e.g., over 100), therefore calculating Hurst in real-time may not be practical in all situations (i. e., a single session study). Thus, I would benefit from expert opinion and guidance regarding other dynamic measures or methodologies that could be used in real-time as a way to inform user models within iSTART-2.

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