Modeling the Interplay Between Knowledge and Affective Engagement in Students

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ABSTRACT

Two major goals in Educational Data Mining are determining students’ state of knowledge and determining their affective state as students progress through the learning session. While many models and solutions have been explored for each of these problems, relatively little work has been done on examining these states in parallel, even though the psychology literature suggests that it is an interplay of both of these states that influences how a student performs and behaves. This work proposes a model that takes into account the performance and behavior of students when working with an Intelligent Tutoring System in order to track both knowledge and engagement and tests it on data from two different systems and explores the usefulness of such models.

Keywords: Affect Detection, Behavior, Engagement, Knowledge Tracing, Performance

INTRODUCTION

Intelligent Tutoring Systems (Cognitive Tutors, or adaptive interactive learning environments) are meant to personalize learning by simulating the behaviors of a human tutor, adapting to students’ needs in order to better teach the student. In order to do this, they must have an estimation of each student’s knowledge as they progress through the tutoring session. Such systems might use these estimations of a student’s mastery of the subject to decide whether to adjust the difficulty of problems given (the level of challenge) or progress to a new unit (move on, as the previous unit is mastered). These models may also be used by teachers and researchers, instead of the software itself, to estimate students’ mastery of individual skills or whole knowledge units.

In the field of Educational Data Mining, the standard way to model and trace student knowledge is via knowledge tracing (Corbett & Anderson, 1995). However, students often become disengaged as they use the software, confounding models that rely solely on performance data on individual questions to estimate students’ changing knowledge. To these models that estimate
students’ state of knowledge depending solely on correct/incorrect student answers, it might appear as though a student is forgetting or unlearning when she/he is simply no longer engaged in using the system. For example, Figure 1 is the result of mastery estimation using a traditional Bayesian model, which assumes that forgetting is possible. The estimations here suggest that this student was un-learning, while after looking at the database logs in detail it was clear that, after the 7th problem the student was just clicking through all the available multiple-choice answers without attempting to answer correctly (not taking the task “seriously”). This type of behavior is defined by Baker et al (2004) as “gaming the system” and is considered to be an indicator of disengagement or a negative valence affective state.

In this context, affect is defined as the current feeling or emotional state of the student, such as frustration, confusion, or engaged concentration. The ability to detect affect is useful for Intelligent Tutors as it allows for the possibility for the tutor to intervene when a negative affective state is detected and help the student become engaged and motivated to learn. Some systems make use of sensor data to determine affect (Arroyo et al, 2009), but this is often impractical in a real-life learning scenario. If a student is assigned homework using a tutoring system, for example, researchers cannot expect that all students will have webcams, pressure mice, or posture sensors in their homes. Even in the classroom, except when researchers provide sensors for a specific study, it is unreasonable to expect to collect sensor data on every student. Some researchers have created sensor-less affect detectors using human coders who observe students’ apparent affective state during a session and then match these observations to behaviors that occur within the system at the same time in order to create a model, such as BROMP (Ocumpaugh et al, 2014). While this has led to good results, it is time-intensive, requiring a certain number of observations and highly trained coders.

While research has been done in tracing engagement without sensors or coders (Beck, 2005), little work has been done in modeling both knowledge and affect in parallel, attempting to account for these biases in knowledge estimation. In particular, a student’s performance cannot be assumed to depend solely upon his or her knowledge of a skill, as how he or she is feeling will

Figure 1. Bayesian knowledge estimation of disengaged student on one skill (bottom line)
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