

# Affect and Inference in Bayesian Knowledge Tracing with a Robot Tutor

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## ABSTRACT

In this paper, we present work to construct a robotic tutoring system that can assess student knowledge in real time during an educational interaction. Like a good human teacher, the robot draws on multimodal data sources to infer whether students have mastered language skills. Specifically, the model extends the standard Bayesian Knowledge Tracing algorithm to incorporate an estimate of the student's affective state (whether he/she is confused, bored, engaged, smiling, etc.) in order to predict future educational performance. We propose research to answer two questions: First, does augmenting the model with affective information improve the computational quality of inference? Second, do humans display more prominent affective signals in an interaction with a robot, compared to a screen-based agent? By answering these questions, this work has the potential to provide both algorithmic and human-centered motivations for further development of robotic systems that tightly integrate affect understanding and complex models of inference with interactive, educational robots.

## Keywords

socially assistive robots, bayesian knowledge tracing, affect, tutoring

## 1. INTRODUCTION

Assessing student knowledge states (i.e. what a student does or doesn't know) is an essential task for any tutor. Bayesian Knowledge Tracing (BKT) is a widely used algorithm that predicts, from past student performance, the probability that a student has mastered a particular skill.

Under the BKT model, different educational skills are encoded as nodes in a Bayesian network. Each "skill node" in the network represents a student's understanding of a specific skill. Each skill is modeled separately, and the models used in BKT are a special case of Hidden Markov Models: at each time step, each skill node is assumed to be in

one of two hidden states ("learned" or "not-learned") and the observables are binary evaluations (Correct/Incorrect) of responses to questions that require a specific skill.

While BKT is one of the most widely used algorithms in research and practice, the model makes some limiting assumptions. In this paper, we describe work to augment the BKT model by incorporating affective sensing into the inference model and implementing the system on a physically embodied robot.

As described above, BKT uses a student's pattern of correct/incorrect responses to update the estimated probability that a student knows a particular skill. Computationally, patterns of correct/incorrect responses are a sparse channel of information from which to infer skill mastery - they don't tell the whole story. Good human teachers use question responses as simply one form of evaluation among many.

Therefore, we propose to extend the model to take into account affective signals like student engagement and facial expression while solving a problem. By drawing on factors such as student boredom, smiles, or other signs of engagement, a more sophisticated model may improve the quality of the inference or shorten the necessary interaction time to achieve an acceptable accuracy.

In addition to this computational extension, we also describe work to determine whether humans display more emphatic and recognizable affective signals in interactions with a physical robot. If confirmed, this finding would provide additional motivation for the use of robots as educational tutors compared to screen-based agents.

## 2. RELATED WORK

BKT models are widely used in ITS research [2]. Most of the work on affect in the ITS literature focuses on trying to *infer* affect. Typically, once affective states are detected, simple behavioral rules are triggered. For example, if confusion is detected, the system might repeat the previous lesson. Notably, the detected affective state is not used to improve or train the knowledge state inference model. One exception is work by Xu et al. that uses EEG input as a component of the knowledge tracing model [4] However, EEG signals are noisy and lack a clear semantics. While models that incorporate EEG data do exhibit slightly improved performance, they do not readily lend themselves construction or interpretation by researchers or educational experts.

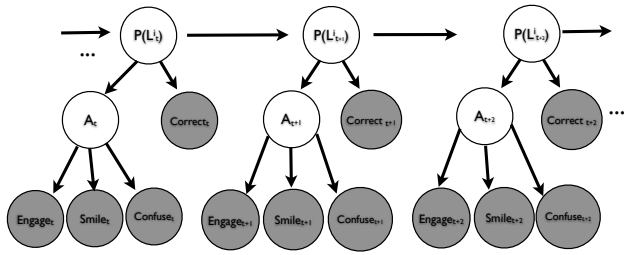
Along with the work by Xu et al., the closest work to this research is that of Szafr and Mutlu [3] and Brown and Howard [1] in which participants interacted with social robot tutor while wearing an EEG reader. The computational ar-

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HRI Pioneers HRI '15 Portland, Oregon USA

ACM 978-1-4503-3318-4/15/03.

<http://dx.doi.org/10.1145/2701973.2702720>



**Figure 1: A BKT model that uses a hierarchical model of affect, based on several features, to drive inference**

chitectures attempted to infer from EEG data when students’ engagement was dropping and used this information to adjust the robot’s behavior in order to re-engage the student.

We consider this work distinct from previous efforts to unite affect, tutoring, and robots in that we are using affect as an input to a *student learning* model. While other work has used affect as an input to behavioral rules, this work is the first in which a robotic tutoring system uses affective data as an input to student models.

### 3. COMPUTATIONAL MODEL

We propose to augment the BKT model by adding additional observable nodes to the HMM, representing affective features such as engagement, smile detection, and confusion. These features might be represented by a hierarchical model, combined into a single affect “score” (Figure 1), or simply as separate observable nodes connected to the hidden state. Because the focus of this research is on how affect can aid inference, all affective sensing will be performed by commercial products such as the Affectiva Affdex SDK or the Microsoft Kinect v2.

### 4. PROPOSED RESEARCH

We plan to conduct an experiment with two conditions: one with a physical robot and one with a video of the robot. Students will take an initial pre-test to assess their baseline level of knowledge; the results will seed both models as prior probabilities. Next, students will interact with the tutor for approximately ten minutes. During the course of the interaction, students will play a game on an Android tablet and the tutor will play along, ask questions, and present educational content. The rules guiding the behavior of the robot will be identical in both conditions.

During the interaction, the system will collect and log all data (actions taken within the game, student’s affective state during interaction, the robot’s actions, audio, video, etc.) in the form of ROSbags which will serve as a training corpus for the affective and standard BKT models. After the interaction, the child will complete a post-test, which will serve as test data to compare the predictions made by the two models.

#### 4.1 Does Incorporating Affect Improve Inference?

One research question we want to answer is “Does augmenting the BKT model with affect sensing provide computational benefits?” To answer this question, we will compare the final models from the affective BKT model (trained

on both affective and question response data) and standard BKT model (a model trained on just the question response data). The models will be evaluated by fit to student response data from after the interaction. More concretely - at the end of the interaction, how well do the final models predict post-test performance? We hypothesize that the predictions of the affective BKT model will fit the data better than the predictions of the standard BKT model.

### 4.2 Do People Display More Readable Affect With Robots?

Another question we wish to address is “Do students display more *readable* affect during interactions with a physical robot?” To answer this question, we will compare the performance of the affective classifier in the robot conditions and the video condition. The ground truth will be obtained by human coding of video footage of the interaction, and classifier performance will be evaluated by fit to the human-labeled data. We hypothesize that the affective classifier will be more accurate in identifying the human-labeled affect in the robot condition compared to the video condition.

### 5. CONCLUSION

Developing socially assistive robots capable of sustaining engaging, educational interactions requires more than just applying ITS algorithms to a new platform. Humans adopt different attitudes and behaviors towards physical robots, which provides an opportunity to design new forms of engaging, educational media, but also suggests additional challenges to overcome. Through this work, we hope to foster new research at the intersection of affect sensing, intelligent tutoring algorithms, and educational HRI.

### 6. ACKNOWLEDGMENTS

This research was supported by the National Science Foundation (NSF) under Grants CCF-1138986 and an NSF GRF under Grant No. 1122374. Any opinions, findings and conclusions, or recommendations expressed in this paper are those of the authors and do not represent the views of the NSF.

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