Exploring Child-Robot Tutoring Interactions with Bayesian Knowledge Tracing

Samuel Spaulding and Cynthia Breazeal
Media Lab
Massachusetts Institute of Technology
Cambridge, MA

Abstract

Computer Science researchers have long sought ways to apply the fruits of their labors to education. From the Logo turtles to the latest Cognitive Tutors, the allure of computers that will understand and help humans learn and grow has been a constant thread in Artificial Intelligence research. Now, advances in robotics and our understanding of Human-Robot Interaction make it feasible to develop physically-present robots that are capable of presenting educational material in an engaging manner, adapting online to sensory information from individual students, and building sophisticated, personalized models of a student's mastery over complex educational domains.

In this paper, we discuss how using physical robots as platforms for artificially intelligent tutors enables an expanded space of possible educational interactions. We also describe a work-in-progress to **(1)** extend previous work in personalized user models for robotic tutoring and **(2)** further explore the differences between interaction with physical robots and on-screen agents. Specifically, we are examining how embedding an tutoring interaction inside a story, game, or activity with an agent may differentially affect learning gains and engagement in interactions with physical robots and screen-based agents.

Introduction

Widespread, robust robotic technology is still in its infancy. As a result, software-based Intelligent Tutoring Systems (ITSs) have had greater success in promoting learning gains in real classroom environments than physical robots, thus far. One of the most promising techniques from the ITS literature is Bayesian Knowledge Tracing (BKT) in which different educational skills or "Knowledge Components" are encoded as nodes in a Bayesian Network (Desmarais and Baker 2012).

However, there is a growing body of evidence that suggests that physically-present robotic tutors can be more effective and engaging than screen-only systems, if certain conditions are met. ITS research provides a core foundation of Artificial Intelligence techniques to build upon, but additional work is required to adapt such techniques to handle the different actions, expectations, and interaction dynamics that come with physical robot tutors.

Physically Present Robot Tutors

Although using a screen-based avatar for educational tutoring provides advantages in cost and scalability, there are still myriad reasons why a physically present robot tutor may ultimately be a more effective platform for Artificial Intelligence tutoring. Much work in HRI has been dedicated to investigating the effects of robotic presence compared to screen-based representations. We summarize a few key works and their results here:

(1) *Physical robots increase task compliance.* In a 2011 study, students were more likely to comply with a physical robot's request than a screen-based representation's request, even if the task was odd or uncomfortable (Bainbridge et al. 2011).

(2) *Physical robots are more able to maintain effective long-term relationships.* In a 6 week study of robots in the home, participants with physical robot partners recorded caloric intake and exercise habits for twice as long as those who used the same software or a paper equivalent (Kidd and Breazeal 2008).

(3) *Physical robots produce greater learning gains.* In a 2012 study, students played several rounds of a puzzle game. and received lessons on techniques for solving the puzzle. Those who got lessons from a physical robot completed the final puzzles significantly faster and improved their solving time significantly more than those who received identical lessons from an on-screen video of the same robot (Leyzberg et al. 2012).

Experimentally, physically present robots have been shown to have several advantages over screen-based agents. But the nature of these effects is not fully understood, nor do we have a good theory of how to leverage such effects to design more effective robot tutors. The next section describes an ongoing project to improve a robot tutor's ability to model more complex domains and to identify specific changes in the dynamics of tutoring interactions with physically present robots.

Framing Educational Interactions with a Physically Present Robot Tutor

We describe here a work in progress to extend the state-of-the-art in adaptive robot tutoring. This work uses BKT to model an educational domain and track a student's progress through the curriculum. In (Leyzberg et al. 2012) and (Leyzberg, Spaulding, and Scassellati 2014), a robot tutor built a model of students' knowledge of strategies for solving a puzzle game, then offered personalized lessons targeted at improving solving performance. These works isolated the effects of personalization and embodiment and showed that both lead to increased learning gains in a tutoring interaction. Our research looks to enhance the scope of that work by **(1)** improving the model to handle hierarchical, inter-dependent domains of knowledge (previous work assumed that skills were independent and could be learned in any order) and **(2)** exploring more subtle differences between physical robots and screen-based agents in tutoring interactions.

Computational Model: Bayesian Knowledge Tracing in a Language Domain

We plan to use Bayesian Knowledge Tracing to model students' understanding of a subset of basic english grammar rules.

Each node in the network represents a random variable, the probability that a student understands the corresponding Knowledge Component (in this case, a specific grammar rule or concept), conditioned on its parent nodes. Knowledge Component nodes are not themselves directly observable, but instead update their conditional probabilities in response to evidence provided by the user in the form of right or wrong answers (represented as *observable* "question" nodes, connected to the Knowledge Components each question depends on). The models used in BKT are therefore a special case of Hidden Markov Models, where each component can be in one of two hidden states, "learned" or "not learned" (Yudelson, Koedinger, and Gordon 2013).

In this domain, correct demonstrations depend on mastery of both "higher-level" concepts and specific rules. For instance, understanding how to properly construct the english sentence "The dogs were running" requires **(1)** using the correct number of the noun, **(2)** understanding how to use the past tense and **(3)** understanding how to conjugate verbs to the gerund form. Some observable skills are independent (e.g., 'dog' to 'dogs' requires understanding of number only and the general rule of appending the "-s" suffix) while other observables may map to multiple skills with hierarchical structures or inter-dependencies. For instance, properly conjugating "is" to "were" requires general understanding of both tense *and* number, as well as the specific rule for the past plural form of "is").

In total, we expect to track and model students' proficiency with 16 different base-level skills (specific conjugation/declension rules) and 3 meta-concepts (number, tense, and gerund)

User Study: Framing Educational Interactions with Physical Robots and Screen Agents

In addition to implementing a BKT model on a physical robot tutor, we are also investigating how to design better tutoring interactions with physical robots.

New interaction modalities are made available with a physical robot, thus the space of possible types of interactions correspondingly increases. While the underlying set of skills to teach remains fixed, the different contexts in which the tutoring interaction can take place expands. For instance, a physical robot trying to teach students about colors can point to different colors, physically manipulate objects of different colors, and play games that involve mixing different colors together. A screen-based agent is capable of doing the same kinds of actions, but the context would necessarily also take place on a screen (e.g., virtually mixing colors or highlighting various colors on a tablet screen).

While previous ITS research has often focused on traditional quiz or "workbook" style interactions, the use of agents in tutoring facilitates embedding the educational interaction in a different context (e.g., a story or game). What has not been investigated, however, is whether such an embedding is equally effective with software-based agents or physical robots.

Thus, we are planning a 2x2 experiment to examine the effect that this embedding has on screen-based and physical-robot tutoring interactions with children (embedded tutoring interaction x physical robot). We hypothesize that

(1) Users who experience the tutoring interaction embedded in a story domain will exhibit greater willingness to engage with the system, compared to those who experience the interaction in a traditional "quiz-style" interaction.

(2) Users who experience the tutoring interaction embedded in a story domain will exhibit greater learning gains, compared to those who experience the interaction in a traditional "quiz-style" interaction.

(3) Users who experience the tutoring interaction embedded in a story domain *with a physical robot* will exhibit greater willingness to engage with the system, compared to those who experience the story domain with a screen-based agent.

(4) Users who experience the tutoring interaction embedded in a story domain *with a physical robot* will exhibit greater learning gains, compared to those who experience the story domain with a screen-based agent.

Conclusion

Developing socially assistive robots capable of sustaining engaging, educational interactions requires more than just applying ITS algorithms to a new platform. There is significant evidence that 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. For instance, humans may expect a robot to respond to natural forms of communication, such as deictic gestures and natural language. If the robot cannot perform up to the human's expectations, the allure of the interaction may be lost (Breazeal 2004). By investigating the different strengths and weaknesses of using physical robots alongside, we hope to pair HRI understanding with A.I. techniques to develop more effective artificially intelligent tutors.

Acknowledgement

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.

References

Bainbridge, W. A.; Hart, J. W.; Kim, E. S.; and Scassellati, B. 2011. The benefits of interactions with physically present robots over video-displayed agents. *International Journal of Social Robotics* 3(1):41–52.

Breazeal, C. 2004. Social interactions in hri: the robot view. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on* 34(2):181–186.

Desmarais, M. C., and Baker, R. S. 2012. A review of recent advances in learner and skill modeling in intelligent learning environments. *User Modeling and User-Adapted Interaction* 22(1-2):9–38.

Kidd, C. D., and Breazeal, C. 2008. Robots at home: Understanding long-term human-robot interaction. In *Intelligent Robots and Systems, 2008. IROS 2008. IEEE/RSJ International Conference on*, 3230–3235. IEEE.

Leyzberg, D.; Spaulding, S.; Toneva, M.; and Scassellati, B. 2012. The physical presence of a robot tutor increases cognitive learning gains. In *Proceedings of the 34th Annual Conference of the Cognitive Science Society. Austin, TX: Cognitive Science Society*.

Leyzberg, D.; Spaulding, S.; and Scassellati, B. 2014. Personalizing robot tutors to individuals' learning differences. In *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction*, 423–430. ACM.

Yudelson, M. V.; Koedinger, K. R.; and Gordon, G. J. 2013. Individualized bayesian knowledge tracing models. In *Artificial Intelligence in Education*, 171–180. Springer.