

DeepTutor: An Effective, Online Intelligent Tutoring System that Promotes Deep Learning

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Abstract

We present in this paper an innovative solution to the challenge of building effective educational technologies that offer tailored instruction to each individual learner. The proposed solution in the form of a conversational intelligent tutoring system, called DeepTutor, has been developed as a web application that is accessible 24/7 through a browser from any device connected to the Internet. The success of several large scale experiments with high-school students using DeepTutor is a solid proof that conversational intelligent tutoring at scale over the web is possible.

Introduction

We describe the intelligent tutoring system DeepTutor (www.deeptutor.org) that aims at fortifying students' knowledge by scaffolding their learning process while engaging in problem-solving activities. That is, the proposed system assists learners while applying concepts through problem solving. A problem solving tutoring service fits well with after-school activities in which students typically reinforce their understanding of concepts (first presented in the classroom) through problem solving after school, e.g. by accessing our intelligent tutor.

Fully-online, 24/7 tutoring is possible because we developed our system as a web service which makes it possible for learners to access the system from anywhere, anytime using Web-enabled devices. In two large scale experiments with DeepTutor involving close to 1,000 high school students, students accessed the system through a browser from a device of their choice including smartphones and tablets (we have an HTML5 interface). The success of these experiments is a solid proof that

conversational intelligent tutoring is possible 24/7 at this moment in time (Rus et al, 2014).

Our DeepTutor system is a dialogue-based system that targets conceptual, as opposed to quantitative, problem solving and reasoning (Rus et al., 2013). An important reason for targeting conceptual aspects of science topics is the fact that they are more challenging. We integrate self-explanation learning strategies, advanced scaffolding methods through dialogue, feedback, and the framework of learning progressions (LPs) proposed by the science education research community. For instance, learning progressions are used to build advanced domain models that organize the domain knowledge from the learner perspective. Deep dialogue management and natural language understanding components are needed in order to manage the dialogue between students and the system and understand students' natural language utterances. Understanding students' natural language utterances is crucial for assessing their knowledge level with respect to the target domain which in turn guides the type and frequency of feedback the system gives students.

DeepTutor offers both macro-adaptivity (instructional tasks are selected appropriately for each student based on her level of mastery) and micro-adaptivity (once working on a task, students are offered help as needed based on their individual performance on that task). Intelligent tutoring systems that emphasize micro-adaptivity only have been shown to induce very good learning gains in students. These systems do offer a one-size-fits-all type of macro-adaptivity in the sense that researchers through a careful cognitive analysis select tasks for the target population as a whole. That is, all students will be assigned the same set of tasks regardless of their knowledge state. Furthermore, results reported by these systems are from experiments conducted in the lab while in

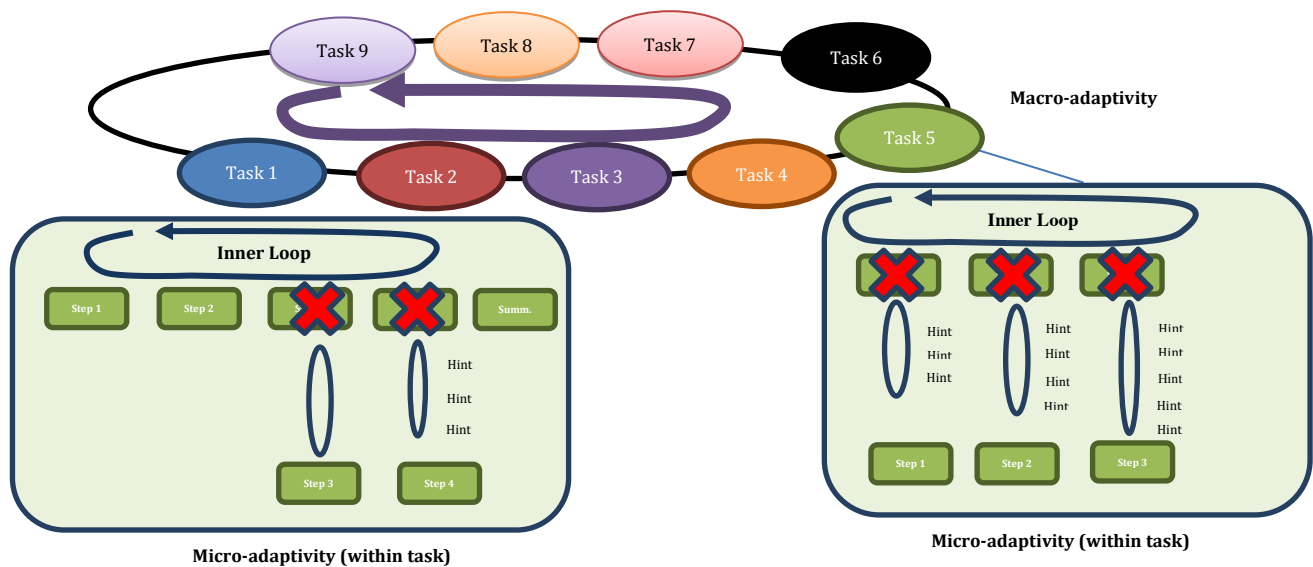


Figure 1. The overall architecture of our intelligent tutoring system showing the three major loops: the outer or tasks loop, the solution or steps loop, and the hints loop.

our case, we have conducted an experiment “in the wild”, outside of a controlled environment.

DeepTutor is the first conversational intelligent tutoring system that offers true macro-adaptivity and which was shown to induce significantly better learning gains in the wild compared to controls such as reading worked-out solutions.

Overview of Our Intelligent Tutoring System

Our system is a dialogue-based intelligent tutoring system (ITS) that tutors students on science topics through problem-solving. When interacting with the system, students are challenged to solve qualitative Physics problems. Physics is our current target domain although the system has been developed with cross-topic, cross-domain scalability in mind. Students read a problem and then start providing an answer in the form of a short essay. Their solutions are automatically evaluated using natural language assessment methods and if necessary, e.g. the student provides an incorrect or incomplete solution, a dialogue follows. The goal of the dialogue is to coach students in finding the solutions by themselves based on constructivist theories of learning and Socratic principles of instruction. That is, the system helps student articulate the missing steps in the solution she provided so far through hints in the form of questions. Furthermore, DeepTutor corrects immediately any misconceptions students articulate. Feedback is provided as well (positive feedback – “Great job.”; negative feedback – “This is incorrect.”; neutral feedback - “Ok.” etc.).

Our ITS implements the following general problem-solving strategy:

- Build an accurate mental model of the problem description
- Identify the known facts and unknown variables based on the problem description
- Develop a plan for solving for the answer starting with the known facts and relying on concepts and principles from the target domain (in our case Newtonian Physics).

We can think of our system as involving three major loops, shown in Figure 1. The outer loop selects tasks for the learner to work on (macro-adaptivity). Once a task is selected, the dialogue within a task follows an inner loop (within-task loop) that selects the steps of the solution to work on. Once a step is selected, there is a hint loop that handles the scaffolding hint sequence of progressively informative hints. This is an enhancement over the two-loop architecture presented by VanLehn (2006). In fact, there are other loops at higher level as implied by the DENDROGRAM model of instruction (Rus, Conley, & Graesser, 2014).

References

- Rus, V., D’Mello, S., Hu, X., & Graesser, A.C. 2013. Recent Advances in Conversational Intelligent Tutoring Systems, *AI Magazine*, 34(3):42-54.
- Rus, V., Conley, M., & Graesser, A. 2014. The DENDROGRAM Model of Instruction: On Instructional Strategies and Their Implementation in DeepTutor, *Design Recommendations for Adaptive Intelligent Tutoring Systems: Adaptive Instructional Strategies (Volume 2)*, (Eds. Sottolare, R.), Army Research Lab.
- VanLehn, K. 2006. The behavior of tutoring systems. *International Journal of Artificial Intelligence in Education*. 16 (3), 227-265.