A Method for Promoting Vicarious Learning in an Online Conversation-Based Intelligent Tutoring System

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Introduction

Conversation-based intelligent tutoring systems (ITSs), like AutoTutor, are highly effective at promoting learning across a wide variety of domains. However, not all students benefit equally from these ITSs. Some evidence suggests vicarious learning and learning alongside a peer agent (i.e., trialogues) are most appropriate for learners with lower levels of domain knowledge. Other studies suggest that high domain knowledge learners benefit more by teaching other student agents. There is a need for careful observations of interactions between learner aptitude and various conversation frameworks. In an ongoing online study, participants are assigned to either an interactive condition where they hold a conversation with a tutor agent, or a yoked-vicarious condition where participants observe the interaction. The results of this experiment will shed light on the varying effectiveness of vicarious learning on students with different levels of domain knowledge.

Background

ITS developers often assume that the system's effectiveness is driven by its interactivity, and for good reason; research regularly shows that interactivity is a critical component for learning. However, some evidence suggests that students with low prior knowledge learn best in vicarious settings, or settings where they can model a peer agent's positive learning behaviors (Craig, Gholson, Brittingham, Williams, & Shubeck, 2012). Additionally, the expertise reversal effect suggests that high prior knowledge students may not always benefit from the increased granularity and interactivity a conversation-based ITS can provide. For example, students with higher levels of knowledge require less instructional support than low knowledge students, and can perform worse with increased support (Kalyuga, 2007). The current study aims to directly compare the effectiveness of different conversational frameworks and determine how they interact with learner domain knowledge in AutoTutor (Graesser, Chipman, Haynes, & Olney, 2005; Nye, Graesser, & Hu, 2014). AutoTutor is a conversation-based ITS that utilizes an Expectation-Misconception Tailored (EMT) dialogue (Graesser et al., 2012).

Relevant Theories

Zone of Proximal Development

Vygotsky describes the "Zone of Proximal Development" (ZPD) as the distance between an individual's level or capacity to currently solve a problem and the potential level to solve a problem with "adult guidance" or peer help (Vygotsky, 1987). In other words, a student is in the ZPD if they are learning content that is not too simple that they could solve it without guidance but is not too difficult that they could not solve it with guidance. The concept of ZPD is routinely applied in problem-based educational settings. However, striking a balance between the promotion of deep-level learning while also remaining in a student's ZPD can be difficult but is thought to be more easily achieved in learning environments that can personally adapt to the individual such as tutoring. A key goal of ITSs is to automatically and intelligently adapt to students to keep them within their ZPD (Graesser et al., 2001).

Aptitude Treatment Interactions & Domain Knowledge

The adaptability of ITSs has improved over time but remains a challenge and a major focus for ITS research. There is a large history of research that explores aptitude treatment interactions in different learning systems (Aleven, Mclaughlin, Glenn, & Koedinger, 2016; Cronbach & Snow, 1977). Consider the following examples that explore just one of many relevant student characteristics that affect learning outcomes. Students with higher levels of knowledge require less instructional support than low knowledge students (Kalyuga, 2007). Low prior knowledge students learn more from static images than just text, whereas high prior knowledge students show no differences in learning between the two formats (ChanLin, 2001). Observing deep level reasoning questions in tutoring improves learning for low prior knowledge students more than high prior knowledge students (Craig, Gholson, Brittingham, Williams, & Shubeck, 2012)

Your Research Methods And Work

Previous studies that had students observe a peer interact with an ITS typically had students watch a recording of the interaction in person (Craig, Driscoll, & Gholson, 2004). In the current study, the "replays", or recordings, are generated automatically which requires no additional steps for interactive students; they simply interact with AutoTutor like they normally would. This approach ensures that only relevant content is recorded, namely each question, hint, or prompt spoken by the tutor agent, and each student response and reaction time.

To adequately assess the effect a system feature has on learning, the experiment must be carefully controlled. To this end, in the current study both the vicarious and interactive lessons look the same. The vicarious lesson replays are nearly identical to their interactive lesson counterparts. However, in the vicarious lessons, there is an indication that the student is "thinking" during the delay between the tutor's question and tutee's response. The interactive student's input is then visibly typed into the input box and remains there until a new question is asked.

In the current study, participants are asked to complete a brief demographics survey, followed by a pretest of 10 shallow-level multiple-choice questions. Participants then receive didactic training on the material, which consists of 70 slides of text and images covering the domain of critical thinking and scientific reasoning. Participants then receive a post-training assessment consisting of 20 shallow-level multiple-choice items. Participants are then randomly assigned into either the vicarious condition or interactive condition. Vicarious participants are randomly assigned one recording of a previous participant's interactions with AutoTutor. Participants either actively work through, or observe, 7 "case studies" which contain a brief description (e.g., news column) of a fictional study. Interactive participants are asked to find and describe the flaws in each study (e.g., premature generalization of the results; confusing correlation with causation). Finally, participants receive an assessment consisting of 20 multiple-choice deep-level reasoning questions.

Real World Applications

The design and results of this study will have several real world applications. First, the method used in this study to promote online vicarious learning with AutoTutor avoids some logistical challenges alternative of other approaches. For example, one alternative method might be to request participants to take a video capture of their screens before they interact with AutoTutor. This approach has several issues, including human error associated with downloading, installing, and using third-party software. Participants would then have to take the extra step of uploading their videos so they can be accessed by the researcher. The current approach automatically records all interaction data in a learning record store (LRS). The "replay" AutoTutor modules access the LRS and use the recorded input from previous interactions as the input for the vicarious modules.

This approach has helped expand AutoTutor vicarious research online and maintains content equivalency across conditions.

The results of the ongoing study will help future ITS developers interested in creating systems that intelligently adjust to student domain knowledge. The results will help determine if high-domain knowledge students learn critical thinking and scientific reasoning best when they are interacting directly with the system, or when they observe other high-domain knowledge students interact with AutoTutor. Likewise, the results will help future ITS developers determine when low-domain knowledge should either interact with the system directly, or when they should learn vicariously. If these students learn best vicariously, the results will help determine if they should observe students with similar levels of domain knowledge, or students with a better understanding of the content.

The scientific reasoning and critical thinking content of this study is borrowed from a previous iteration of AutoTutor, Operation ARA (Millis, Forsyth, Wallace, Graesser, & Timmins, 2017). This domain is of increasing relevance given the ongoing trend of inaccurate and misleading information found in social media and some news outlets. There is broad value in developing a system that teaches students how to be skeptical and scrutinize information they find online.

Future Directions

Looking ahead, this method for capturing interactive data and generating vicarious lessons can be applied to research on trialogues. Trialogues in AutoTutor can occur between a human learner, an on-screen peer agent, and a tutor agent. The peer agent can be programed to agree or disagree with a student's response, to provide their own correct or incorrect responses, or function as a competitor in a serious-game scenario. This approach has been used in other applications of AutoTutor, like Operation ARA (Acquiring Research Acumen; Halpern et al., 2012) and AutoTutor CSAL (Center for the Study of Adult Literacy; Graesser et al., 2016). Recorded interaction data located in the LRS can also be used as spoken text for peer agents.

A major bottleneck for ITS development is content creation. In the interaction data, each response is assessed by its overlap with an ideal answer by using both latent semantic analysis (LSA) and regular expressions. For the trialogue example, this means that the peer agent can operate as a high prior knowledge student, a low prior knowledge student, or a student that shares a knowledge level with the learner. Using this approach, high prior knowledge students could teach low prior knowledge peer agents, whose script is drawn from a previous student's interaction with AutoTutor.

Over time, the interaction data used to populate a peer agent's script could be determined at a question-by-question level. For example, human students who enter a lesson with a misconception could have that misconception addressed by a specific peer agent's statement. That statement could then be used in future lessons. Ultimately, the ideal peer agent for any given student could be an amalgam of statements drawn from multiple students who previously interacted with AutoTutor.

Summary

This study will contribute to the growing literature of ITS research that seeks to determine how ITSs can best adapt to students. The experiment will help determine if there is an aptitude-treatment interaction between vicarious or interactive learning in AutoTutor. The results should inform future ITS developers interested in creating systems that intelligently adjust to student domain knowledge. The method developed to conduct streamlined, content-equivalent, online research with AutoTutor opens up new avenues of research. Specifically, research that focuses on the effect of each pedagogical feature in an ITS on learning.

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