Why/AutoTutor: A Test of Learning Gains from a Physics Tutor with Natural Language Dialog

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Abstract

Why/AutoTutor is a tutoring system that helps students construct answers to qualitative physics problems by holding a conversation in natural language. Why/AutoTutor provides feedback to the student on what the student types in (positive, neutral, negative feedback), pumps the student for more information, prompts the student to fill in missing words, gives hints, fills in missing information with assertions, identifies and corrects bad answers and misconceptions, answers students' questions, and summarizes answers. In essence, constructivist learning is implemented in a mixed-initiative dialog. Why/AutoTutor delivers its dialog moves with an animated conversational agent whereas students type in their answers via keyboard. We conducted an experiment that compared Why/AutoTutor with two control conditions (Read textbook, nothing) in assessments of learning gains. The tutoring system performed significantly better than the two control conditions on a test similar to the Force Concept Inventory.

AutoTutor and Why/AutoTutor

Why/AutoTutor is the most recent tutoring system in the AutoTutor series developed by the Tutoring Research Group at the University of Memphis. Why/AutoTutor was specifically designed to help college students learn Newtonian qualitative physics (Graesser, VanLehn, Rose, Jordan, & Harter, 2001), whereas the previous AutoTutor systems were on topics of introductory computer literacy (Graesser, Person, Harter, & TRG, 2001; Graesser, P. Wiemer-Hastings, K. Wiemer-Hastings, & Kreuz, 1999) and military tactical reasoning (Ryder, Graesser, McNamara, Karnavat, & Pop, 2002).

The design of AutoTutor was inspired by three bodies of theoretical, empirical, and applied research. These include explanation-based constructivist theories of learning (Aleven & Koedinger, 2002; Chi, deLeeuw, Chiu, LaVancher, 1994; VanLehn, Jones, & Chi, 1992), intelligent tutoring systems that adaptively respond to student knowledge (Anderson, Corbett, Koedinger, & Pelletier, 1995; VanLehn, Lynch, et al.,2002), and empirical research that has documented the collaborative constructive activities that routinely occur during human tutoring (Chi, Siler, Jeong, Yamauchi, & Hausmann, 2001; Fox, 1993; Graesser,

Person, & Magliano, 1995; Moore, 1995; Shah, Evens, Michael, & Rovick, 2002). The process of actively constructing explanations and elaborations of the learning material allegedly produces better learning than merely presenting information to students. This is where human tutors excel in scaffolding learning, because they guide the students in productive constructive processes and simultaneously respond to the student's information needs.

Surprisingly, the dialog moves of most human tutors are not particularly sophisticated from the standpoint of today's pedagogical theories and those theories implemented in intelligent tutoring systems (Graesser et al., 1995). Human tutors normally coach the student in filling in missing pieces of information in an expected answer and they fix bugs and misconceptions that are manifested by the student during the tutorial dialog. Human tutors rarely implement *bona fide* Socratic tutoring strategies, modeling-scaffolding-fading, and other intelligent pedagogical techniques (Collins, Brown, & Newman, 1989). The argument has been made that it is the conversational properties of human tutorial dialog, not sophisticated tutoring tactics, that explain why normal human tutors facilitate learning (Graesser et al., 1995). More sophisticated pedagogical techniques will no doubt increase learning even further. Why/AutoTutor was designed to simulate the dialog moves of normal human tutors who coach students in constructing explanations.

Why/AutoTutor helps students learn by presenting challenging problems (or questions) from a curriculum script and then engaging in mixed initiative dialog that guides the student in constructing an answer. An example question is "Suppose a boy is in a free-falling elevator and he holds his keys motionless right in front of his face and then lets go. What will happen to the keys? Explain why." Another example question is "When a car without headrests on the seats is struck from behind, the passengers often suffer neck injuries. Why do passengers get neck injuries in this situation?" Such questions are designed to require about a paragraph of information (3-7 sentences) to answer. However, initial answers to these questions are typically only 1 or 2 sentences in length, even though students have more knowledge that is relevant to an answer. This is where tutorial dialog may be particularly helpful. AutoTutor engages the student in a mixed initiative dialog that assists

in the evolution of an improved answer and that draws out more of what the students know. AutoTutor provides feedback to the student on what the student types in (positive, neutral, negative feedback), pumps the student for more information ("What else?"), prompts the student to fill in missing words, gives hints, fills in missing information with assertions, identifies and corrects erroneous ideas and misconceptions, answers the student's questions, and summarizes answers. A full answer to the question is eventually constructed during this dialog.

The following dialog excerpt from a tutoring session on conceptual physics illustrates some of AutoTutor's dialog features.

AutoTutor (SEED QUESTION): When a car without headrests on the seats is struck from behind, the passengers often suffer neck injuries. Why do passengers get neck injuries in this situation?

Student: The passenger experiences a backward acceleration, while the car moves forward.

AutoTutor (PUMP): And can you add to that?

Student: This is because the passenger experiences a force opposite in direction to the force on the car.

AutoTutor (POSITIVE FEEDBACK): Um, yes, correct!

AutoTutor (HINT): When the neck provides a large force, what within the neck would get damaged?

Student: the spine

AutoTutor (NEUTRAL NEGATIVE FEEDBACK): umm

AutoTutor (PROMPT): I think you can get this. Damage within the neck will occur in the ligaments and the . . . . . ? [*spoken with rising intonation and accompanied with a prompting hand gesture*]

Student: muscles

AutoTutor (POSITIVE FEEDBACK): Brilliant!

AutoTutor (PROMPT RESPONSE): ligaments and the muscles.

AutoTutor (DIALOG ADVANCER): Let's keep going.

AutoTutor (HINT): Additionally, when there is no headrest present in the car, what accelerates the head of the passenger?

Student: the impact from behind

AutoTutor (PROMPT): I am sure you can get this. The head of the passenger will be accelerated by the passenger's . . . . .? [*spoken with rising intonation and accompanied with a prompting hand gesture*]

Student: car

AutoTutor (NEGATIVE FEEDBACK): Wrong!

AutoTutor (PROMPT RESPONSE): by the passenger's neck.

[*moving ahead 22 turns in the dialog*]

AutoTutor (QUESTION PROMPT): Do you perhaps have any general conceptual physics questions?

Student: no

AutoTutor (FINAL ANSWER PROMPT): How would you answer my first question, having gone over what we've just talked about?

Student: The passengers get neck injuries because the neck needs to exert a large force on the head equal to the force on the body. When struck, the body will continue to move in the direction of motion of the car, while the car exerts a force on the passenger's body in the opposite direction. The force of the neck on the head must equal the force of the head on the neck, and the force on the neck's smaller mass often results in torn muscles and ligaments.

AutoTutor (POSITIVE FEEDBACK): Great!

AutoTutor (SUMMARY): To recap, when a car is struck from behind, the force of impact will cause the car to experience a large forward acceleration. The car seat is attached to the car and will also have the same large acceleration. When the car is hit from behind, the seat will exert the same acceleration to the torso of the body. In order for the head to go along with the torso, it will need to be accelerated at the same rate as the torso. Since the head has no acceleration being applied to it by a headrest, the neck gets stretched damaging its muscles and ligaments in an attempt to produce the required large acceleration.

Figure 1 shows the interface of Why/AutoTutor. The major question is selected and presented in the top-right window. This major question (e.g., involving a boy dropping keys in a falling elevator) remains at the top of the web page until it is finished being answered by a multi-turn dialog between the learner and Why/AutoTutor. The students use the bottom-right window to type in their contributions for each turn, with the content of both tutor and student turns being reflected in the bottom-left window. The animated conversational agent resides in the upper-left area. The agent uses either an AT&T or a Microsoft Agent speech engine to speak the content of AutoTutor's turns during the process of answering the presented question.

The computational architectures of Why/AutoTutor and earlier versions of AutoTutor have been discussed extensively in previous publications (Graesser, Person et al., 2001; Graesser, VanLehn, et al., 2001; Graesser, Wiemer-Hastings et al., 2001), so this paper will provide only a brief sketch of the components. Why/AutoTutor was written in Java and resides on a Pentium-based server platform to be delivered across the web. The software residing on the server has a set of permanent databases that do not get updated throughout the course of tutoring. These include (a) the curriculum script repository consisting of questions, answers, and associated dialog moves, (b) lexicons, syntactic parsers, and other computational linguistics modules, (c) a question answering facility, (d) a corpus of documents, including a text book on conceptual physics, and (e) latent semantic analysis (LSA) vectors for words, curriculum content, and the document corpus.

Why/AutoTutor uses LSA as the backbone for representing world knowledge about conceptual physics, or any other subject matter that is tutored (Graesser, P. Wiemer-Hastings, K. Wiemer-Hastings, Harter, Person, & TRG, 2000; Olde, Franceschetti, Karnavat, Graesser, & TRG, 2002).
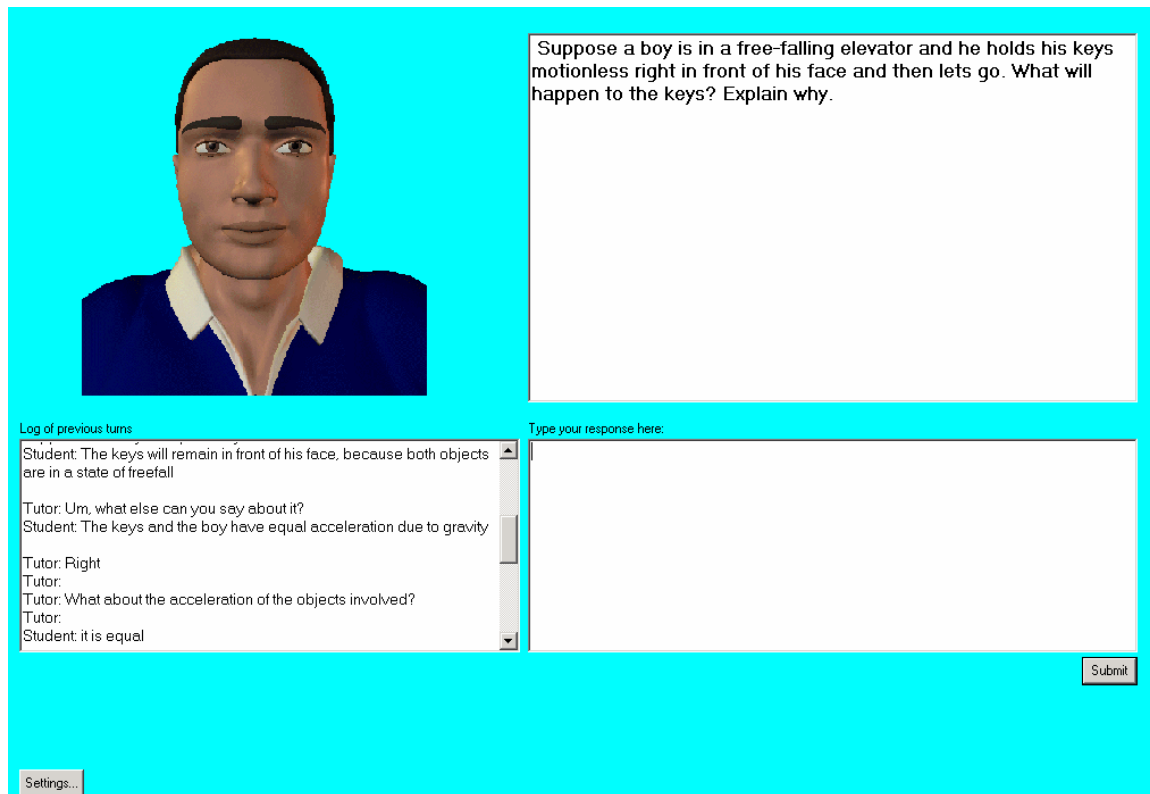
Figure 1: Interface of Why/AutoTutor

LSA is a high-dimensional, statistical technique that, among other things, measures the conceptual similarity of any two pieces of text, such as a word, sentence, paragraph, or lengthier document (Foltz, Gilliam, & Kendall, 2000; Kintsch, 1998; Landauer, Foltz, & Laham, 1998). Why/AutoTutor uses LSA to perform conceptual pattern matching operations when we compare student contributions to expected good answers and to anticipated misconceptions. An expectation is considered covered if the student's contributions end up matching the expectation by some LSA threshold of overlap. Similarly, a misconception is considered present if the student's input matches the misconception by some LSA threshold.

In addition to the static data modules mentioned above, Why/AutoTutor has a set of processing modules and dynamic storage units that maintain qualitative content and quantitative parameters. These storage registers are frequently updated as the tutoring process proceeds. For example, Why/AutoTutor keeps track of student ability (as evaluated by LSA from student Assertions), student initiative (such as the incidence of student questions), student verbosity (number of words per turn), and the progress in having a question answered by virtue of the dialog history. The dialog management module of AutoTutor flexibly adapts to the student by virtue of these parameters, so it is extremely unlikely that two conversations with AutoTutor are ever the same.

The dialog management module is an augmented finite state network. The nodes in the network refer to knowledge goal states (e.g., expectation E is under focus and AutoTutor wants to get the student to articulate it) or dialog states (e.g., the student just expressed an assertion as the first turn in answering the question). The arcs refer to categories of tutor dialog moves (e.g., feedback, pumps, prompts, hints, summaries, etc.) or discourse markers that link dialog moves (*okay, moving on, furthermore*). A particular arc is traversed when particular conditions are met (e.g., it is the student's first turn and the student's assertion is correct).

Arc traversal is sometimes contingent on outputs of computational algorithms and procedures that are sensitive to the dynamic evolution of the dialog. These algorithms and procedures operate on the snapshot of parameters, data content, knowledge goal states, student knowledge, dialog states, LSA measures, and so on, that reflect the current conversation constraints and achievements. For example, there are algorithms that select dialog move categories that attempt to get the student to fill in missing information in expectation E. There are several alternative algorithms to achieve this goal. Consider one of the early algorithms we adopted. If the student has almost finished articulating expectation E, but lacks a critical noun or verb, then a prompt category would be selected because the function of prompts is to extract single words from students. The particular prompt selected from the curriculum script would be tailored to extracting the particular missing word through another module that fills dialog move categories with

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content. If the student is classified as high ability and has failed to articulate most of the words in expectation E, then a hint category might be selected. Fuzzy production rules make these selections.

An alternative algorithm to fleshing out expectation E uses two cycles of hint-prompt-assertion. That is, AutoTutor's selection of dialog movers over successive turns follows an ordering: first hint, then prompt, then assert, then hint, then prompt, then assert. AutoTutor exists the two cycles as soon as the student articulates expectation E to satisfaction (i.e., the LSA threshold is met).

Other processing modules in AutoTutor execute various important functions: speech act classification, linguistic information extraction, evaluation of student assertions, selection of the next expectation to cover, and speech production with the animated conversational agent. It is beyond the scope of this paper to describe these modules.

Previous Empirical Studies of Tutorial Learning

One-to-one tutoring is a powerful method of promoting knowledge construction, as has been shown through available empirical studies (Bloom, 1984; Cohen, Kulik, & Kulik, 1982; Corbett, 2001). The vast majority of the tutors in these studies of human tutoring have had moderate domain knowledge and little or no training in pedagogy or tutoring; the tutors were peer tutors, cross-age tutors, or paraprofessionals, but very rarely accomplished tutors. The unaccomplished human tutors enhanced learning with an effect size of .4 standard deviation units (called sigmas), which translates to approximately an improvement of half a letter grade (Cohen et al., 1982). The accomplished human tutors produced effect sizes of 2 sigmas according to Bloom (1984), although the magnitude of this effect should be questioned due the relative small number of studies that have looked at accomplished tutors.

In the arena of computer tutors, intelligent tutoring systems with sophisticated pedagogical tactics but no natural language dialog produce effect sizes of approximately 1 sigma (Corbett, 2001; VanLehn et al., 2002). Previous versions of AutoTutor have produced gains of .4 to 1.5 sigma (a mean of .7), depending on the learning measure, the comparison condition, the subject matter, and version of AutoTutor (Graesser, Moreno, et al., 2003; Person et al., 2001; VanLehn & Graesser, 2002). This places previous versions of AutoTutor somewhere between an unaccomplished human tutor and an intelligent tutoring system. It might be noted, however, that one recent evaluation of physics tutoring (VanLehn & Graesser, 2002) remarkably reported that the learning gains produced by accomplished human tutors via computer mediate conversation were equivalent to the gains produced in two computer tutors with natural language dialog (Why/AutoTutor and Why/Atlas, a system developed at the University of Pittsburgh). The effectiveness of different tutoring systems clearly requires additional research.

Present Study of Why/AutoTutor

We conducted an experiment that assessed learning gains of Why/AutoTutor, compared with two comparison conditions. Those assigned to the **AutoTutor** Condition learned conceptual physics by participating in a tutorial dialog with Why/AutoTutor for approximately 3-4 hours. Those in the **Read-textbook** condition read textbook chapters on the same Newtonian physics topics covered by Why/AutoTutor, for a comparable amount of study time; the textbook was Hewitt's *Conceptual Physics* (1998). There was also a no-material **Control** condition in which the subjects did not receive any material on conceptual physics. The participants were 67 college students enrolled in a college physics course at Ole Miss, Rhodes College, and the University of Memphis. The participants were randomly assigned to the three conditions, except that twice as many subjects were to be assigned to the AutoTutor condition as in the two comparison conditions. Learning gains were assessed by administering a pretest and a posttest that consisted of multiple choice questions. The questions were extracted from or were similar to those in the Force Concept Inventory (Hestenes, Wells, & Swackhamer, 1992). Another method of assessing learning was the quality of their answers to an additional sample of qualitative physics questions, but these data are not reported in the present study.

The experiment included two sessions, approximately 2-3 hours each, one week apart. The first session consisted of a pretest followed by a learning phase, while the second session began with the learning phase and ended with a posttest. Two different test versions (A, B) were counterbalanced across conditions as pre and post tests. Each test has a multiple choice part and a conceptual physics essay part. There were 40 multiple choice items pulled from the Force Concept Inventory (FCI) in each version, A and B. There were 4 conceptual physics questions in each of the two versions of the test.

During the learning phases, participants received either Why/AutoTutor (N=32), Read-textbook (N=16), or Control (N=19). The learning phase of Why/AutoTutor covered 10 conceptual physics questions, such as the example in Figure 1. Each problem took approximately 20 minutes to answer, as the student and AutoTutor collaborative answered the questions. The participants in the Read-textbook condition read the textbook for an approximately equivalent amount of time, as estimated by the tutoring sessions reported in VanLehn and Graesser (2002). VanLehn and Graesser (2002) cover additional details about the tests, learning materials, and methodology.

We computed the proportion of multiple choice questions that were answered correctly on the pretest and posttest. Table 1 presents the means and standard deviations (SD) of the pretests and posttests in the three conditions. The right column in table includes adjusted posttest scores that statistically control for the pretest score; standard errors are in parentheses.

An ANOVA was conducted on the scores, using a 3x2 factorial design, with condition as a between-subject variable and test phase (pre versus post) as a repeated measures variable. There was a statistically significant condition by test phase interaction, $F(2,64) = 12.28$, $p < .01$, $MS_{error} = .005$. The pattern of means clearly showed more learning gains from pretest to posttest in the Why/AutoTutor condition than the other two conditions. An ANCOVA was statistically significant when we analyzed the posttest scores, using the pretest scores as a covariate, $F(2,63)= 14.81$, $p < .01$. The adjusted posttest scores showed the following ordering among means: Why/AutoTutor > Read-textbook = Control. The effect size (sigma) of the learning gains of Why/AutoTutor was .75 when its pretest served as a control, .61 when the posttest Control mean served as the control, and 1.22 when the posttest Read-textbook mean served as the control. These effect sizes are comparable to the intelligent tutoring of systems on physics reported by VanLehn et al. (2002).

Table 1: Proportion Correct on Pretests and Posttests

Condition	Pretest Mean (SD)	Posttest Mean (SD)	Adjusted Posttest (Std. Error)
AutoTutor	0.597 (.170)	0.725 (.153)	0.727 (.016)
Read-textbook	0.566 (.126)	0.586 (.114)	0.610 (.022)
Control	0.633 (.172)	0.632 (.153)	0.608 (.020)

Two alternative measures of learning gains were computed to show differences between conditions. First, the simple learning gains were computed as Posttest-Pretest. A one-way ANOVA performed on the simple learning gains showed significant differences among conditions, $F(2,64)=12.28$, $p < .01$, $MS_{error} = .010$. As shown in Table 2, and confirmed in follow up planned comparisons, there was the following ordering of means: Why/AutoTutor > Read-textbook = Control. Second, we computed the normalized gain score, a standard that often has been used to report learning gain proportions: [(Posttest-Pretest) / (1-Pretest)]. An ANOVA performed on the normalized gain scores showed the same significant effect, $F(2,64)=13.17$, $p < .01$, $MS_{error} = .008$, and ordering of means.

Table 2: Learning Gains Proportions

Condition	Simple Learning Gains (SD)	Normalized Gain Score (SD)
AutoTutor	0.128 (.111)	0.303 (.279)
Read-textbook	0.020 (.068)	0.033 (.168)
Nothing	-0.001 (.100)	-0.109 (.337)

Conclusions

These results of the present study on qualitative physics follow previous trends in AutoTutor research that have continually shown it to be an effective learning tool (Graesser, Moreno, et al., 2003; Person et al., 2001). Why/AutoTutor consistently outperformed its comparison conditions in three alternative comparisons that were considered (pretest for Why/AutoTutor, Read-textbook control, and a no learning material Control). These results are compatible with the claim that there is something about tutorial dialog in natural language that promotes learning in these constructivist learning environments.

We are currently exploring what it is, more precisely, that accounts for the learning gains (VanLehn & Graesser, 2002). Is it the dialog facility, the responsive feedback, the student's active construction of information, the construction of explanations, or some other factor that is responsible for learning gains? Perhaps the same amount of learning might occur if we have them simply study the explanation and answer for each question. Now that we know that learning does occur, we can dissect the potential causes of learning in subsequent research.

Acknowledgments

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