AI Tutoring: Group 1 Topic Paper

Research questions

What changes take place in the human brain while learning, and how can we create a virtual model of this process in enough fidelity to apply to real-world scenarios? In order to iterate on processes and approaches, as well as on possible presentations of information on any realistic timeframe with today's popular machine learning or AI approaches, a simulated student would be necessary. However, even with this capability, the amount of time needed to derive a workable virtual model of a student strictly from student-computer interactions is likely to be significant – though assists and shortcuts could be derived from some of the approaches described later in our presentation. If a student simulation is untenable for any reason, either due to lack of computing power or if human cognition turns out not to be Turing-complete, this process would then become one where it is essential to create a model that can improve even on very limited or even incomplete data, unlike current trends in machine learning and AI, which require extreme amounts of data to function. Regardless, the student-model concept would require greater capabilities than exist today and may even be an AI-complete problem.

Why do some students understand a concept after the first explanation while others require many repetitions - what drives the differences in learning? Even after hundreds of years of asking the question of what it means to "know" something, we still are unsure. Searle's Chinese Room thought experiment highlights some of this confusion, but we are still a distance away from being able to answer why some people understand something while others do not. All humans start with the same base cognitive architecture, but small differences result in big effects – sometimes there is a missing key piece of information or connection that is only discovered after several attempts are made, and correcting for this type of disconnect is a time consuming process today, though being able to determine a solution quickly would be a valuable feature of any tutor.

How can the content in an educational interface be customized for an individual so that they can most efficiently reach an understanding of the concept? We know that different people learn in different ways – some are physical learners, some visual, some verbal – and there exist several approaches that are used today to determine which type of learning best fits an individual, though these approaches typically require a self-assessment. Ideally, any cognitive tutor would be able to determine the learning style that best fits the student after only a few exchanges, even if the tutor is just walking the student through one of the surveys. Any program or technique that translates information from one learning style to another would likely require at least near-human level natural language processing and translation capabilities, so as to not lose the main concepts described in the original format.

How can we measure the success of a tutoring system - how can we quantify how an AI tutor facilitates "better" learning? In order to measure how well a tutoring system has done, we must look at the subject of the tutoring – the student. Both in a simulated student and a real one, we have a beginning state, before learning, and a desired end state, after learning. However, it can be difficult to determine whether the selected approach is the ideal one – it will be difficult to say whether the student 'might have done better if we had taken a different approach' or not. Perhaps by grouping a larger body of students by similarity and skill level, it may become possible to experiment with different approaches by means of A-B testing. With this data and existing methods of determining mastery of information, it may be possible to evaluate differences in approaches, allowing an AI tutor to improve over time.

Current state-of-the-art:

Open learner model:

One approach to AI tutoring is providing feedback in the form of an open learner model. The idea of an open learner model can be understood by thinking about the general model of an intelligent educational interface as described in *Intelligence Unleashed*[1]. That model describes a tutoring system as algorithmically combining its domain model (knowledge of the subject matter), pedagogy model (knowledge of teaching) and finally its learner model (knowledge about the person seeking to learn from the system) in order to determine the best information to present to the learner. An AI tutoring system which uses an open learner model makes some parts of the system's evaluation of the learner's current knowledge and preferences available to be inspected by the learner. This can take the form of progress bars showing mastery of a particular topic, or comments about how the learner has been using the system. Open learner feedback is important because learners "self-regulate". The intelligent interface can do its best to guide the learner, but ultimately the learner decides what goals to set for themself, what learning strategies to try, and how much effort to put into learning.

In order to understand how open learner feedback can be most effective, it is useful to first attempt to understand how learners utilize feedback in general. In *Feedback and self-regulated learning*[2], a model is presented which describes the process by which learners manage their own learning behaviors. This model is called self-regulated learning. The model includes a sequence of cognitive processes which contribute to the learner's decisions about how to approach a learning task. The sequence of processes is as follows. First the learner interprets the task according to their knowledge and beliefs which can include what the learner thinks the purpose of the task is, and how much effort will be needed to achieve certain outcomes. After interpreting the task, the learner sets goals which can include the quality of the learning products they produce as well as the rate at which progress is made towards creating those products. Next the learner decides on a set of strategies to use in order to achieve the goals they set and produce learning products. The learning products can be external such as answers to test questions, but they can also be internal such as improvements to the learner's internal representation of the subject matter or improvements to their learning strategies.

Given the model just described, there are many kinds of feedback that the learner can receive. The kinds of feedback can be classified according to which parts of the learner's cognitive processes the feedback is based on. Perhaps the most commonly thought of kind of feedback is outcome feedback such as graded test answers. Outcome feedback is based on external learning products and does not assess the individual cognitive processes that make up the learning process. In contrast, the learner constantly provides internal feedback for themself by monitoring every step in the self-regulated learning model. The learner is aware of their knowledge, beliefs, goals, strategies, and the decisions they have made while learning. The learner can also monitor incremental progress towards their goals. Internal feedback can be more effective than outcome feedback because it is based on more information than just external products. Since monitoring assesses progress relative to goals in real time, it can trigger the learner to select new strategies or goals while performing the task. A final kind of feedback is cognitive feedback which encourages the learner to reflect on their learning approach and can include telling learners about strategies they can use, or asking them to explicitly write down decisions they make during the self-regulation process. Cognitive feedback helps learners see the relationships between their approach to learning and their performance on tasks. An open learner model can directly supply outcome and cognitive feedback, and can also make information available that improves the internal feedback that the learner is self-generating.

Here are a couple of examples of AI tutoring systems which utilize an open learner model to provide feedback. The first example comes from *Supporting students' self-regulated learning with an open* *learner model in a linear equation tutor*[3] which presents an intelligent tutoring system that goes through the steps to solving equations. Its learner model keeps track of learner progress on different types of problems, and how well the learner applies various techniques. A study was conducted that compared the learning process of learners who used a basic version of the system to learners who were given a version with additional feedback mechanisms. The additional feedback was in the form of asking learners to self-assess their learning progress after each question and then showing the learner how their mastery progress bars were updated as a result of their performance. This feedback encouraged learners to think about mistakes or challenges that they experienced while completing the problem and to evaluate how effective their methods were. The study results show that the learners using the improved system made fewer incorrect attempts and requested fewer hints.

The second example comes from *Exploring the impact of a learning dashboard on student affect*[4] which added a learning dashboard to an intelligent tutoring system. They intended for the dashboard to help learners self-regulate and therefore feel less "lost" while using the system. The dashboard helps them set goals, and reflect on progress towards those goals. The system calculates how much effort the learner has put in based on how much time has been spent, and the amount of additional information and hints requested. The system calculates mastery progress bars based on a Bayesian analysis of past answers. Both the effort and mastery levels are displayed to the learner and this open learner model feedback makes it easy for the learner to see their progress and also encourages them to self-monitor. This study was focused on learner affect and asked learners to periodically report their emotional state while using the system. The results were less conclusive than the first study and showed that having access to the dashboard seemed to make learners both more likely to be excited and more likely to be unexcited than learners without access to the dashboard. The best method of presenting the dashboard seemed to differ for males and females. In general, the results highlight the utility of having a learning dashboard available but leave questions for how its use should be encouraged. While this study and the linear equation intelligent tutoring system suggest that open learner models are helpful, more work seems to be needed to optimize the feedback for individual learners.

<u>Dialogue based tutor:</u>

Another approach to tutoring using an artificially intelligent agent is through a dialogue-based tutor. This form of tutoring through artificial intelligence is unsurprisingly mostly a natural language processing problem, as the agent needs to be able to understand the answer supplied by the user through language, and then be able to determine if the answer is correct. Largely, this comes down to the agent being able to process two forms of knowledge presented through dialogue: information and intention. There are many solutions to these independently, such as machines being able to determine whether a statement is a question or an assertion, or connecting different information expressed at different point in the dialogue. Once you attempt to put the ability to determine information and intention into a single agent, however, the list becomes vastly smaller, as this is a very complicated task.

One system that attempts to answer this problem is that described in *Is a Dialogue-Based Tutoring System that Emulates Helpful Co-constructed Relations during Human Tutoring Effective* [5]. In this paper, the author explore an alternative approach to the Rimac tutoring system. It retains some of the characteristics of traditional Rimac, such as it's basis in rhetorical structure theory, a form of organizing dialogue in order to extract information and intention in a dialogue. Where the author's approach differed from the traditional approach of Rimac was in their exploration of how lines of dialogue were connected.

In the traditional approach to Rimac, a form of dialogue organization called "directed line of reasoning" (DLR) is utilized to form a hierarchical structure of dialogue. This is done by having a list of questions that the system will be asking the student, which is sequentially progresses down. If the student answers the question correctly, then the system will move onto the next question in the list, until the end of the list is reached. If the student answers the question incorrectly, however, the traditional version of Rimac enters a sort of correctional state, in which it attempts to correct the students knowledge through additional dialogue. After the system has concluded the correctional flow, it returns to the main list of questions once again, progressing ever sequentially down it until it is complete.

The authors propose an alternative approach to organizing their dialogue, called discourse relations. Discourse relations work by assigning various relationships between pieces of dialogue. The authors were primarily concerned with a physics tutor, and as such one example of this can be seen in the relationship between an equation and when that equation holds true, a relationship known as "situation:condition". If the student were to answer a question with only the correct equation (situation) portion of the answer, the tutor will then prompt the student to supply the condition that describes why the condition holds true in the presented scenario.

It was then decided that an experiment may be of help to the authors, in order to determine the impact that their approach to Rimac may have in a real life environment. So the authors put together an experiment consisting of an experimental and a control group, where the number of males and females in each group was taken note of. Each group underwent the same process; at the start of class each student would take a pretest for some set duration, then they would be exposed to their assigned version of Rimac (directed line of reasoning versus discourse relations), and then finally they would take a posttest at the beginning of their next class. Through this process, the authors were able to measure how each group gained knowledge through their versions of Rimac, and how it impacted their scores going from pretest to posttest. The tests consisted of two types of questions: multiple choice and open response.

The results of this experiment were stunning, as they showed that not only did the experimental group perform better than the control group on average, but they were also able to determine a pronounced effect on open response as well as by female students. They then attempted to determine whether or not their findings of more gain for female students was caused by some uncontrolled bias in their experiment, but they were unable to determine any cause of this, and so they determined that their findings were reliable. They came to understand the increased gain on open response problems through the concept that their experimental version of Rimac provided a better understanding of the concepts. As such, the author's goals prior to this paper were to determine whether they could more generally create discourse relations, rather than be specific per subject, and to create a more general experiment to determine the widespread use of their experimental version of Rimac.

Learning by Teaching**:**

The traditional way for an individual to learn is to study the material themselves or perhaps through lessons from their teacher. An alternative method is to have the person teach the material to someone else. Such an approach is effective because to teach another, the tutor will need to maintain a proper understanding of the concepts and invoke this knowledge in the teaching process. One example of learning by teaching is the rubber-duck debugging, where the user talks to an inanimate duck, explaining how the code works in detail. In doing so, the user will better understand how their program works and is able to figure out the source of the error.

Learning by teaching works due to two major activities involved: explaining and questioning [6]. In explaining, the tutor actively engages in the knowledge-building process as they elaborate on the deeper principles and applications of a concept. Simultaneously, the tutor can monitor their own comprehension and generate more helpful explanations to further their own learning. Questioning is also crucial, as it allows the tutor to extrapolate beyond the basic learning material and reason about deeper concepts and relationships. Asking a tutee such questions will allow for both the teacher and student to expand their knowledge. These activities are only beneficial only if the user is not affected by the knowledge-telling bias. Essentially, this reduces the effectiveness of teaching and learning since the tutor will simply give statements that revealed answers with no additional detail. Knowledge-telling is not entirely harmful since it can help with rehearsing the material but overall, this is not beneficial for either the tutor or tutee to actually learn the content.

The actual AI based implementation to achieve learning by teaching involves a teachable agent (TA). The TA is essentially a sentient hybrid of an agent and avatar that is designed for educational applications. An agent is simply a more intelligible program that can actively engage with the environment by itself while an avatar is a character that represents and is controlled by a human. Avatars are beneficial since they encourage a user to take more risks since they do not necessarily suffer the consequences. As an agent, the TA offers new models of thinking and reasoning that the students can learn from. As an avatar, the TA embodies properties that the students can adopt without taking intellectual risks of learning something by one's own. Such a combination of properties of agents and avatars makes the TA an ideal fit in the educational setting.

To inquire more about these unique properties of the TA, a study by Chase et. Al investigated the protégé effect, where students would think of the TA as a protégé and will put in more effort to learn for their TA [7]. In the experiment, two sets of students were exposed to different conditions of agents. In the TA condition, students will interact with an agent to help it learn and in the avatar condition, the agent represents the student and they have to learn for themselves. The students first customize their agents, learn the material and will create a concept map of what they have learned, which the TA uses to answer questions. The agents test their knowledge in a game show and depending on the results, students can review the material or continue playing the game show. After this procedure, the students took a learning posttest where those in the TA condition got higher scores on the posttest than those in the avatar condition. Ultimately, this was because students in the TA condition spent more time on reading and learning activities than others.

To better understand the mechanisms behind the increased learning effort of the TA condition, the researchers conducted a follow-up study on the psychological aspects of the protégé effect. A different set of students interacted with only TAs and were also encouraged to think aloud. The researchers gathered two main observations from these statements. Firstly, the students acted as if the TA was a social being which was partly them and partly an independent reasoning agent. In exhibiting this behavior, the subjects used mental ("The TA knows it" or "I don't understand") and responsibility attributions ("We did it", "I didn't teach her that"). These statements illustrate the role of the TA as a protégé. The social inclinations of how students communicate with the protégé are valuable since they align with a human's innate psychology of a social being. Another crucial factor was how TA students acknowledged failure more often than avatar students. In realizing failure more often, the students realize that they need to learn more to help the TA perform better. Also, from the student's perspective, the TA takes partial responsibility for the failure. This represents the ego-protective buffer, where the TA's failure deflects blame away from the student's lack of knowledge. Therefore, the student will not feel entirely at fault at their intellect and will have more motivation to continue learning.

Another implementation for TAs is the APLUS system [8], where students will be teaching a TA how to solve linear equations. The system also provides metacognitive scaffolding, giving advice like selecting which kind of problems to test the TA and what resources to review to better teach the students how to instruct the TA. Similar to the previous study, two sets of student interacted with a TA and a basic agent. APLUS has a TA and expects students to learn by teaching where APLUSTutor is a traditional agent that simply instructs the students about the concept in a goal-oriented manner (GOP) as a typical teacher would. The results convey a test score improvement in both systems. The prior competency of the student did not matter since low and high performing students saw gains in their test scores in both approaches. The main conjecture is that the improvement in Learning by teaching is just as effective as the improvement from the traditional learning approach.

Future work and insights:

With the teachable agent concept, a student obtains mastery by necessarily thinking in different ways – "learning by teaching" – which takes advantage of how humans can quickly process and translate concepts from one form to another. Investigation further into this topic could cover the human capabilities of translation and problem-solving – we instinctively are capable of re-wording concepts and finding missing information when communicating, though these processes are not yet fully understood, and still further from being replicated by computer systems.

An examination of the biases that contribute to the learning processes are essential, as the Rimac experiment shows us a clear gender bias as well as bias introduced through how information is presented (multiple choice/free response). Further research in this field could result in deeper understanding of the exact methods that result in human learning; some capabilities that would be good to reproduce, as well as some that wouldn't.

The organization of information is essential to understanding how it can be learned optimally. Cognitively, how do humans organize information such that we can understand both the intent of an utterance and the information it presents, and how could a machine imitate this function? A cognitive representation of the connections between pieces of information would benefit almost all human-computer interactions, not just those in education.

Understanding is not memorization, but testing memorization is easy. Testing mastery with free-form text input would be another order of difficult task, considering the number of ways to make the same arguments, or to say the same things. From a technical standpoint, this could be similar to language translation with limited data. This almost certainly requires a more powerful NLP capability than exists today.

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