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Evaluating a Simulated Student using Real Students Data for Training and Testing*

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Abstract: SimStudent is a machine-learning agent that learns cognitive skills by demonstration. It was originally developed as a building block of the Cognitive Tutor Authoring Tools (CTAT), so that the authors do not have to build a cognitive model by hand, but instead simply demonstrate solutions for SimStudent to automatically generate a cognitive model. The SimStudent technology could then be used to model human students' performance as well. To evaluate the applicability of SimStudent as a tool for modeling real students, we applied SimStudent to a genuine learning log gathered from classroom experiments with the Algebra I Cognitive Tutor. Such data can be seen as the human students' "demonstrations" of how to solve problems. The results from an empirical study show that SimStudent can indeed model human students' performance. After training on 20 problems solved by a group of human students, a cognitive model generated by SimStudent explained 82% of the problem-solving steps performed correctly by another group of human students.

1 Introduction

Modeling students' cognitive skills is one of the most important research issues for Cognitive Tutors, a.k.a. Intelligent Tutoring Systems [1]. Such a model, often called a *cognitive model*, is used to assess students' performance and to provide feedback (model-tracing), to monitor progress in students' learning over the course of problem-solving, to plan instructional strategies adaptively (knowledge tracing), or simply to give a hint on what to do next [2]. Yet, developing a cognitive model is a labor-intensive task that forces even a skilled expert to work for hundreds of hours.

We have developed a machine learning agent – called *SimStudent* – that learns cognitive skills from demonstration. SimStudent is designed to be used as an intelligent building block of a suite of authoring tools for Cognitive Tutors, called the Cognitive Tutor Authoring Tools, or CTAT [3]. Using the SimStudent technology, an author can simply demonstrate a few solutions. SimStudent generalizes those solutions and generates a cognitive model that is sufficient to explain the solutions. This

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cognitive model is then plugged into a Cognitive Tutor as the knowledge base for model-tracing. This way, the authors are relieved from the burden of building a cognitive model by hand.

The goal of the SimStudent project is twofold: on the engineering side, we investigate whether SimStudent facilitates the authoring of Cognitive Tutors. On the user modeling side, we explore whether the SimStudent helps us advance studies in human and machine learning.

As a step towards the first goal, we have tested SimStudent on several domains including algebra equation solving, long division, multi-column multiplication, fraction addition, Stoichiometry (chemistry), and Tic-Tac-Toe. So far, SimStudent showed a reasonable and stable performance on those test domains [4].

The goal of this paper, as an attempt to address the second goal mentioned above, is to see whether SimStudent actually models cognitive skills acquired by human students during learning by solving problems. To address this issue, we apply SimStudent to the student-tutor interaction log data (i.e., the record of activities collected while human students were learning with a computer tutor) to see whether SimStudent is able to learn the same cognitive skills that the human students learn. In other words, we consider the human students' learning log as the "demonstrations" performed by individual human students. We then train SimStudent with these demonstrations and have it learn cognitive skills. If SimStudent indeed learns cognitive skills in this way, then we would further be able to use SimStudent to investigate human students' learning by analyzing cognitive models generated by SimStudent as well as their learning processes.

The fundamental technology that supports SimStudent is inductive logic programming [5] and programming by demonstration [6]. There are studies on using a machine-learning technique for cognitive modeling and educational tools. Some studies use a machine-learning agent to learn domain principles, e.g., [7]. Some applied a machine-learning technique to model human students' behavior [8, 9], or to assess instructions [10]. Probably the most distinctive aspect of SimStudent developed for the current study is that it generates human-readable (hence editable) production rules that model cognitive skills performed by humans.

The outline of the paper is as follows. We first introduce the Cognitive Tutor that the human students used in the classroom. This gives a flavor of how human students "demonstrated" their skills to the Cognitive Tutor. We then explain how SimStudent learns cognitive skills from such demonstrations. Finally, we show results from an evaluation study on the applicability of SimStudent to the genuine student-tutor interaction log data.

2 Algebra I Cognitive Tutor

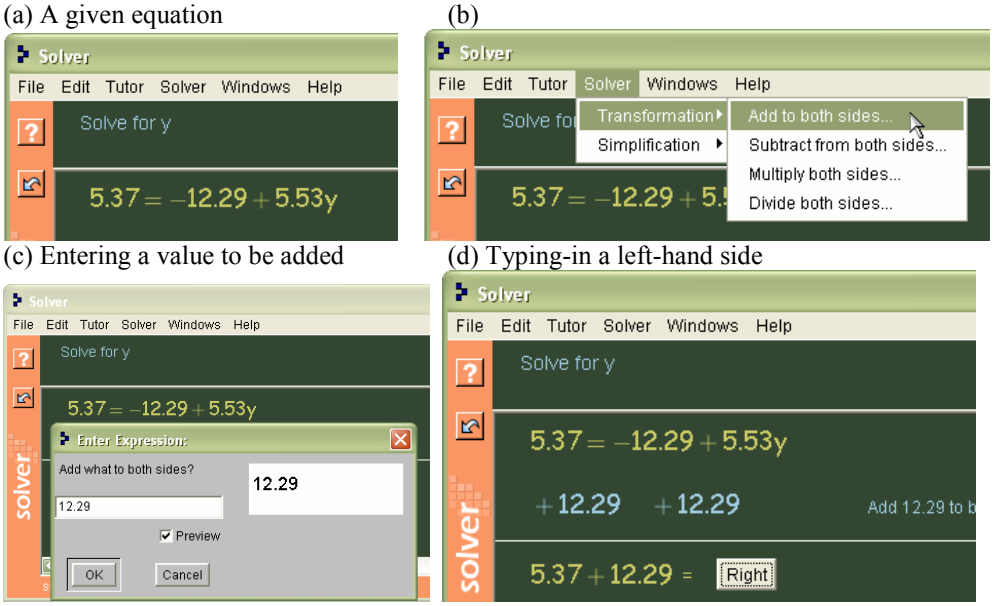
The Algebra I Tutor is a Cognitive Tutor developed by Carnegie Learning Inc. This tutor is used in real classroom situations for high school algebra at about 2000 schools nationwide in the United States [11]. For the current study, we use human students' log data collected from a study conducted in a high school in an urban area of Pittsburgh. There were 81 students involved in the study. The students used the Cognitive Tutor individually to learn algebra equation solving. There were 15 sections taught by the tutor, which covered most of the skills necessary to solve linear

equations. In this paper, we only use the log data collected through the first four sections. The equations in these introductory sections only contain one unknown and the form of equation is A+B=C+D where A, B, C, and D are monomial terms (e.g., a constant R or R*x* where R is a rational number).

The tutor logged the students' activities in great detail. For the current study, however, we only focus on the *problem-solving steps*, which are slightly different from *equation-transformation steps*. Explanations follow.

There are two types of problem-solving steps: (1) an *action step* is to select an algebraic operation to transform an equation into another (e.g., "to declare to add 3*x* to the both sides of the equation"), and (2) a *type-in step* is to do a real arithmetic calculation (e.g., "to enter –4 as a result of adding 3*x* to –4–3*x*"). By performing these problem-solving steps, a given equation is transformed as follows: a student first selects an action and then applies it to both sides of the equation. For example, for an equation shown in **Fig. 1** (a), the student first selected "Add to both sides" from the pull down menu (b), which in turn prompts the student to specify a value to add (c). This completes the first problem-solving step, which by definition is an action step. The student then enters the left- and right-hand sides separately. The **Fig. 1** (d) shows a moment at which the student had just typed-in the left-hand side. Thus, entering a new equation is completed in two problem-solving steps, which are both type-in steps. In sum, three problem-solving steps correspond to a single equation-transformation step that transforms an equation into another. Sometimes, however, the tutor carries out the type-in steps for the student, especially when new skills have just been introduced.

(a) A given equation (b)



(c) Entering a value to be added (d) Typing-in a left-hand side

Fig. 1. Screen shot from the Algebra I tutor

As mentioned above, when a student performs a problem-solving step, the tutor provides immediate feedback on it. This is possible because the tutor has a *cognitive*

model of the target cognitive skills, represented as a set of production rules. Since a cognitive model usually contains production rules not only for correct steps, but also for incorrect steps, the tutor can provide situated feedback on typical errors. The student can also ask for a hint (by pressing the [?] button on the left side of the tutor window) when he/she gets stuck.

Every time a student performs a step, the tutor logs it. The log contains, among other things, (1) the equation on which the step was made, (2) the action taken (either the name of the algebraic operation selected from the menu for an action step, or the symbol "type-in" for a type-in step), (3) the value entered (e.g., the value specified to be added to the both sides for the "add" action mentioned above, or the left- and right-hand side entered for the type-in steps), and (4) the "correctness" of the step, which is either "correct" (in case the student's steps is correct), "error" (the student's steps is incorrect), or "hint" (when the student asked a hint).

3 Overview of SimStudent

This section is a brief overview of SimStudent. We first explain how SimStudent learns cognitive skills from demonstration. The double meaning of "demonstration" in the current context will then be explained – a demonstration by an author who is building a Cognitive Tutor, and a "demonstration" in a learning log made by human students. We then explain briefly how SimStudent learns a cognitive model. Due to the space limitation, we do not provide details of the learning algorithms. See [12] for more details.

3.1 Cognitive modeling with SimStudent

Fig. 2 shows a sample interface for a Cognitive Tutor to teach algebra equation solving. In this particular tutor, equation-solving steps are represented in a simple table with three columns. The first two columns represent the left-hand side (LHS) and the right-hand side (RHS) of an equation (e.g., 41.72y + 87 = 34.57). The third column represents the name of a *skill* applied to transform an equation into another. In this tutor, an equation is transformed with three *problem-solving steps* that are (1) to specify a skill, e.g., "subtract 87" from both sides, (2) to enter LHS, e.g., "41.72y", and (3) to enter RHS, e.g., "34.57–87."

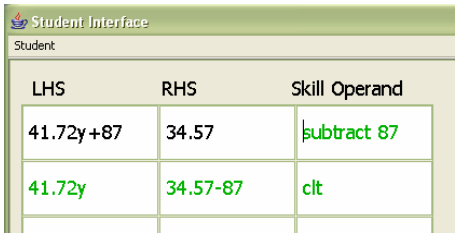


Fig. 2. A tutor interface for algebra equation solving.

A step is modeled with a tuple representing *what* was done *where*. The what-part is further decomposed into an *action* taken and a value *input* by the action. The where part is called *selection* because it is an element of the user interface that the demonstrator selected to do some action on. In summary, a problem-solving step is represented with a tuple <selection, action, input>. For example, when the demonstrator inputs "41.72y" into the LHS on the 2nd row, the tuple reads <C1R2, 41.72y, Fill_in_cell> where C1R2 represents a cell at the 1st column in the 2nd row.

SimStudent learns a single production rule for each of the problem-solving steps demonstrated. The demonstrator must specify two things when demonstrating a problem-solving step; (1) the *focus of attention*, and (2) the *skill name*. The focus of attention is a set of previous selections or the given equation. For example, in **Fig. 2**, the first problem-solving step, which is to enter "subtract 87," requires two elements, "41.72y+87" and "34.57," as the focus of attention. The *skill name* must be unique for unique steps and consistent throughout the demonstration. In the above example, the skill to enter "subtract 87" is called "subtract," and the skill to enter "41.72y" and "34.57-87" is "subtract-typein." The actual value entered (e.g., "subtract 87") is called an "input."

3.2 Learning algorithm

Production rules are represented in the Jess production rules description language [13]. A production rule used in the Cognitive Tutors consists of three major parts: (1) WME-paths, (2) feature conditions, and (3) an operator sequence. The first two components construct the left-hand side of a production rule, which specifies which elements of the interface are involved in the production rule, and what conditions should hold about those elements in order for the production rule to be fired. The operator sequence constitutes the right-hand side actions of the production rule, which specifies what should be done with the interface elements to make the "input" value of the step (see the definition of the tuple in section 3.1).

SimStudent utilizes three different learning algorithms to learn three components (the WME-path, the feature conditions, and the operator sequence) separately. An example would best explain how. Suppose a step is demonstrated and named as N. Also suppose that this is the k-th *instance* of demonstration for the skill N. Let's denote this as I(N,k). Let's assume that the skill N requires two elements as focus of attention, and we denote them as $<F^{N,k}_1, F^{N,k}_2>$, the elements of focus of attention for the k-th instance of the skill N.

The WME-path is a straightforward generalization of the focus of attention. The elements specified in the focus of attention are elements on the tutor interface. They can thus be uniquely identified in terms of their "location" in the interface. Suppose, for example, that the first element of focus of attention in the j-th instance of the skill N, $F^{N,j}_1$ is "a cell in the 1st column on the 2nd row." If the first element of focus of attention in the (j+1)-th instance $F^{N,j+1}_1$ is "a cell in the 1st column on the 3rd row," then the WME-path for the 1st element of focus of attention for the skill N would be "a cell in the 1st column at any row."

SimStudent uses FOIL [14] to learn feature conditions. The target concept is the "applicability" of the skill N given the focus of attention $<F^N_1, F^N_2>$, or in a prolog-like form $N(F^N_1, F^N_2)$. When a step I(N,k) is demonstrated, it serves as a positive example for the skill N, and a negative example for all other skills. Basically, as the demonstration proceeds, the skill N has all $<F^{N,k}_1, F^{N,k}_2>$ as positive examples, and $<F^{X,k}_1, F^{X,k}_2>$ as negative examples, where X is all the other skills demonstrated. We provide FOIL with a set of *feature predicates* as the background knowledge with which to compose hypotheses for the target concept. Some examples of such feature predicates are isPolynomial(A), isNumeratorOf(A,B), isConstant(A). Once a hypothesis is found for the target concept, the body of the hypothesis becomes the feature condition in the left-hand side of the production rule. Suppose, for example,

that FOIL found a hypothesis $N(F^N_1, F^N_2)$:- isPolynomial(F^N_1), isConstant(F^N_2). The left-hand side feature condition for this production rule would then say that "the value of the first focus of attention must be a polynomial and the second value must be a constant."

SimStudent applies iterative-deepening depth-first search to learn an operator sequence for the right-hand side of the production rules. When a new instance of demonstration on skill *N* is provided, SimStudent searches for the shortest operator sequence that derives the "input" from the focus of attention for the all instances demonstrated. Those *operators* are provided prior to learning as background knowledge.

4 Evaluation

To evaluate the applicability of the SimStudent technology to genuine real students' learning log, we conducted an evaluation study to see (1) whether SimStudent can generate cognitive models for the real students' performance, and if so (2) how accurate such models are.

The tutor interface shown in **Fig. 2** is also used in the current study as a tutor interface for SimStudent to be demonstrated. It is a simple but straightforward realization of the human students' performances in a SimStudent-readable form. There is an issue on focus of attention to be mentioned here. When the human students were using the Algebra I Tutor, they did not indicate their focus of attention, and hence no information of focus of attention is stored in the log. We have presumed that both LHS and RHS are used as the focus of attention for the action steps. Likewise, for the type-in steps, we presume that the Skill Operand and the cell immediately above the cell to be typed-in are the focus of attention. So, for example in **Fig. 2**, if "34.57-87" is entered, which is a skill "subtract-typein", the elements "34.57" and "subtract 87" are used as the focus of attention.

4.1 Data

The students' learning log was converted into *problem files* that SimStudent can read. Each problem file contains the sequence of problem-solving steps made by a single student to solve a single problem. There were 13451 problem-solving steps performed by 81 human students. These problem-solving steps were converted into 989 problem files.

4.2 Method

We applied the following validation technique. The 81 students were randomly split into 14 groups. Each of those 14 groups were used exactly once for training and once for testing. More precisely, for the *n*-th validation, the *n*-th group is used for training and the (*n*+1)-th group is used for testing. A total of 14 validation sessions were then run.

During training, SimStudent learned cognitive skills only on those steps that were correctly performed by the human students. In other words, SimStudent learned only the correct skill applications "demonstrated" by the human students.

Because of memory limitations, we could use only as many as 20 training and 30 test problems in each of the validation sessions. To select those problems, a human student was randomly selected in a given group. If the selected human student did not have enough problem files, then more human students were selected randomly. A total of 280 training and the 420 test problems were used across the 14 validation sessions.

In a validation session, the 30 test problems were tested. The validation took place after *each* training problem on which SimStudent was trained. Since there were 20 training problems, a total of 600 tests were carried out for validation. There were 32 operators and 12 feature predicates used as the background knowledge.

4.3 Results

In two out of 14 validation sessions, we identified corrupted data and could not complete runs on these. In one validation session, not all cognitive skills discussed below appeared in the training problems. Hence there are 11 validation sessions (220 training and 330 test problems) used for the analysis discussed in the rest of the section.

Table 1. Frequency of learning for each skill appearing in the training problems. The numbers on the first row are the IDs for the validation sessions. The validation sessions and the skills are sorted by the total number.

Skill	014	010	009	004	008	011	006	003	001	005	007	Total	Ave.
divide	22	21	22	20	22	19	20	21	20	21	20	228	20.73
divide-typein	20	16	18	18	14	12	12	10	10	10	12	152	13.82
subtract	15	18	12	14	13	11	16	9	6	11	7	132	12.00
add	7	4	10	6	10	8	5	12	14	10	13	99	9.00
subtract-typein	14	16	8	12	10	6	10	4	2	4	6	92	8.36
multiply	9	10	9	6	8	11	9	10	8	6	6	92	8.36
add-typein	6	2	10	6	8	6	2	6	8	6	6	66	6.00
multiply-typein	6	8	4	6	2	6	4	4	6	6	2	54	4.91
Total	99	95	93	88	87	79	78	76	74	74	72	915	83.18

4.3.1 Learning opportunities

There were 12 skills involved in the training problems. Eight of them are action skills and another four are type-in skills. Four out of the eight action skills were learned in only a very few training problems and they did not appear in all validation sessions. Therefore, we have excluded those skills from the analysis. In sum, there are four action skills and four type-in skills included in the current analysis. **Table 1** shows the frequency of learning for each of those skills. The skills add, subtract, multiply, and divide are action skills. The skill add, for example, is to add a term to both sides. The skill add-typein is for a type-in step that follows the step "add." Note that those eight skills are the most basic skills used to solve simple equations.

4.3.2 Learning curve analysis

To analyze how SimStudent's learning improved over the time, we measured the "accuracy" of production rules on the test problems. Each time learning was completed on a training problem, each of the steps in the 30 test problems were model-traced using the production rules available at that moment. An attempt at model-tracing is defined to be *successful* when there is a production rule with the LHS conditions that hold and the RHS operator sequence generates an "input" that matches the step.

Fig. 3. Overall performance improvement in terms of the average ratio of successful model-tracing aggregated across all validation sessions and the (eight) skills. The x-axis shows the number of training problems.

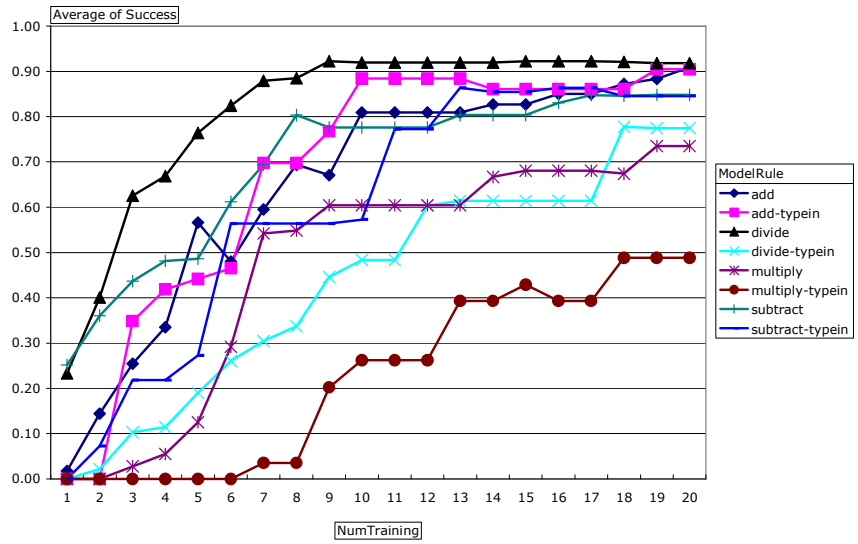


Fig. 4. Learning curve on individual skills. The learning curve shown in **Fig. 3** is decomposed into individual skills.

Fig. 3 shows the learning curves aggregated across all eight skills and averaged across the 11 validation sessions. **Fig. 4** shows the learning curve for the individual skills. Overall, SimStudent learned skills quite well. After training on 20 problems, the ratio of successful model-tracing reached at least 73% on most of the skills. However, some skills were not exactly learned as well as the other skills – it seems to be difficult

to learn the skill "multiply-typein." It turned out that not all skills had the same number of opportunities to be learned. Different training problems have different solution steps, and hence contain a different number of instances for each of the skills to be demonstrated.

Fig. 5 shows how the accuracy of model-tracing grew as SimStudent had more and more opportunities to learn individual skills. The x-axis shows the *frequency of learning* (in contrast to the number of problems demonstrated). The y-axis shows the *overall average of the average ratio* of successful model-tracing aggregated from the beginning when a certain number of instances of learning occurred. That is, this graph shows how quickly (or slowly) the learning occurred. For example, even when two skills ended up with having the same performance rate (e.g., the skills "add" and "add-typein" shown in **Fig. 4**), it can be read from **Fig. 5** that the skill "add-typein" reached its final performance quickly within only 5 instances of demonstration.

The four action skills, add, subtract, multiply, and divide, were learned at the same rate. Different type-in skills had different rates and the quality of the production rules (i.e., the accuracy of model-tracing) varied significantly. We have yet to investigate the reason for the variation in the learning rate of these skills.

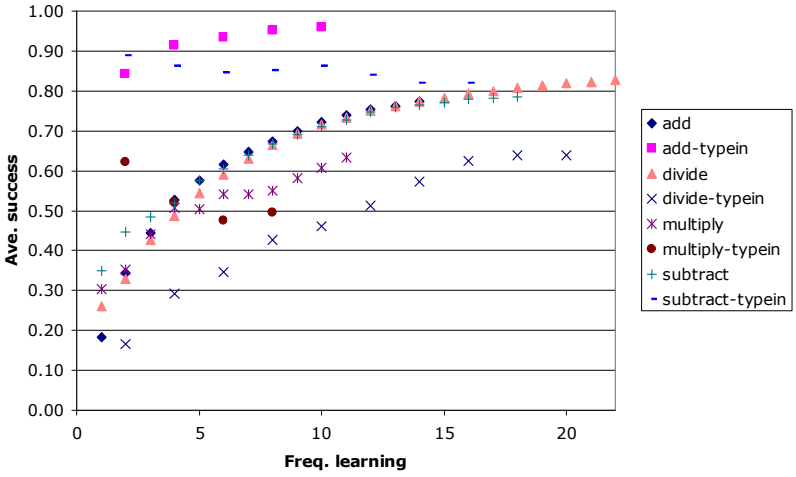


Fig. 5. Average of the average ratio of successful model-tracing in the first *x* opportunities for learning. For example, for the skill "add," the average success ratio for the first 3 learning opportunities were .18, .50, and .64. Therefore, on the above graph, the value for the 3rd plot for add is .44.

5 Conclusion

We have shown that SimStudent can indeed model human students' performances from their learning activity log. The accuracy of model-tracing based on the cognitive model generated by SimStudent reached 83% after training on 20 problems performed by human students.

As long as the human students exhibit correct performances (i.e., the performances are consistent), even when they have variations in strategy and

representations, SimStudent can generate a cognitive model that is consistent with the human students' (correct) performances. We have yet to improve the learning ability of SimStudent so that the human students' incorrect behaviors can be modeled. This is one of the important issues to be addressed in the future.

The above finding on the ability of SimStudent to model real students' performance suggests potential ways to expand the applicability of SimStudent. For example, if we can model human students' erroneous performances as well, then it might be possible to predict human students' performance on novel problems. Technically speaking, modeling "incorrect" performances does not differ greatly from modeling a "correct" performance, as long as the human student makes a systematic error (based on a stable misconception). The real challenge would then be how to deal with the inconsistent behaviors (e.g., guess, slip, or even gaming).

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