Responding to Unexpected Student Utterances in CIRCSIM-Tutor v. 3: Analysis of Transcripts

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Abstract
CIRCSIM-Tutor is a dialogue-based intelligent tutoring system that conducts dialogues with medical students about blood pressure regulation. To obtain models for computer-generated dialogues, we analyzed dialogues involving expert human tutors. In this paper we describe some of the interesting and complex patterns we isolated from the human tutorial dialogues in cases where the student gave erroneous or otherwise unexpected results.

Introduction
CIRCSIM-Tutor is an intelligent tutoring system for cardiovascular physiology designed to help first-year medical students solve problems involving the negative feedback system that controls blood pressure. Students are asked to predict the direction of change of seven core variables, the most important cardiovascular parameters. The tutor analyzes these predictions, finds the errors, and chooses a method to correct each one. The tutor then embarks on a remedial dialogue.

To understand the behavior of human tutors and to produce a detailed knowledge representation for the tutorial planner in the next version of CIRCSIM-Tutor v. 3, we started with human tutoring dialogues. We have approximately fifty transcripts of professors of physiology tutoring medical students, with the tutor and student in different rooms communicating keyboard-to-keyboard. Out of the more than 5000 turns we have collected, we have analyzed over 270 turns of dialogue. Using an SGML-based annotation system, we marked up the tutorial goal structure in the transcripts to use as a basis for plan-based text generation (Freedman and Evens, 1996). Our analysis produces multiple nested annotations showing both global goals for tutoring and local goals for maintaining a coherent conversation and providing appropriate responses to the student.

In this paper we show how this method of analysis can be used to model the complex dialogues generated by expert tutors when faced with unexpected student utterances.

Methods of Tutoring
CIRCSIM-Tutor v. 3 requires a set of tutorial and conversational goal schemata in order to produce coherent conversations. The analysis in this paper is an extension of the one introduced by Freedman (1996). It is based on approximately 350 instances of global tutoring goals and 50 instances of local goals.

Tutorial goals are expanded in a hierarchy. Two sections of dialogue are generated for each variable that the student did not predict correctly. T-introduces-variable introduces the variable as a referent in the conversation and T-tutors-variable does the actual tutoring. For example, a dialogue for correcting RAP might start like this:

<T-corrects-variable var=RAP>
<T-introduces-variable>
  tu: You made some errors here. Let's start with RAP.
</T-introduces-variable>
<T-tutors-variable>
  <T-tutors-via-determinant>
    <T-tutors-relationship from-var=CO to-var=RAP>
      <T-elicits>
        tu: How would a change in CO influence RAP?
      </T-elicits>
    </T-tutors-relationship>
  </T-tutors-via-determinant>
</T-tutors-variable>
</T-corrects-variable>
Tutoring requires at least three levels of goals below the variable level: the method level, the topic level, and the primitive level. The method level shows how to teach about a variable. It can be used to express various types of deductive reasoning, interactive questioning and exploration of anomalies. The topic level represents each item that must be taught. These content items largely involve domain content. The primitive level shows how this information is communicated to the student. In the above example, T-tutors-via-determinants is a method. T-tutors-relationship is a topic, and T-elicits is a primitive level goal.

To refine T-tutors-variable the tutor chooses a method depending on a number of factors, including domain knowledge (e.g., the mechanism of action of a variable), dialogue history (e.g., the student’s previous utterance) and the student model (e.g., how well the student is doing). For example, if the variable is controlled by the nervous system, the tutor often chooses the question and answer style method T-does-neural-DLR. (DLR stands for directed line of reasoning, a form of Socratic dialogue.)

T-does-neural-DLR

tu: … Can you tell me how TPR is controlled?
st: Autonomic nervous system.
tu: [Yes.] And the predictions that you are making are for the period before any neural changes take place.
tu: So what about TPR?
st: No change.

For non-neural variables the most common schema is T-tutors-via-determinants. With this method the tutor corrects the value of a variable by invoking a relationship with another core variable.

T-tutors-via-determinants

tu: What parameter determines the value of RAP?
st: CO.
tu: What relationship do they have?
st: Inverse.
tu: Right, then what is the value of RAP?

Both of these methods are based on the domain reasoning used by the tutor to solve the problem. Our tutors also use other methods which are less directly based on domain reasoning. T-moves-forward is similar to T-tutors-via-determinants but it applies when the determinant has already been mentioned in the conversation.

T-moves-forward

tu: [Since CO goes up early in the response, that will cause RAP to fall.] Now what will happen to SV?

In T-shows-contradiction, the tutor corrects the student’s error by pointing out a physiological inconsistency in the student’s answers.

T-shows-contradiction

tu: You said that RAP goes up but earlier you said that CO went up. How is that possible?

T-explores-anomaly is superficially similar, but is used in cases where the reported facts only appear inconsistent. Its goal is to ensure that the student really understands the deeper qualitative relationships among the variables.

T-explores-anomaly

tu: So, we have HR down, SV up and CO down. How is that possible?

Although our main goal in annotating transcripts is to collect data for text generation (Reiter and Dale. 1997), a secondary goal is to learn about the tutoring strategies of human tutors. Thus we occasionally annotate strategies which a computerized tutor may not be able to handle in the same way that human tutors do. For example, we use the term T-diagnoses-error when the tutor wants to identify the student’s problem.

T-diagnoses-error

tu: Why do you think that TPR will decrease?

Methods like T-tutors-via-deeper-concepts are used to give more detailed explanations to the student. After failing to get a correct answer from the student using only the seven core variables. This method gives information to the student (or elicits it from the student) in terms of a more detailed physiological model.

T-tutors-via-deeper-concepts

tu: The central venous compartment is a compliant structure that contains a certain volume of blood …

Topics

A method consists of a series of topic operators. For example, the following topic operators could be used to build the T-tutors-via-determinants form mentioned above.

T-tutors-determinant

tu: What are the determinants of RAP?

T-tutors-relationship

tu: How does the value of CO affect the value of RAP?

T-tutors-value

tu: So, what would happen to RAP?

To build the T-does-neural-DLR form, one would need the following topic operators, followed by T-tutors-value.

T-tutors-mechanism

tu: Can you tell me how TPR is controlled?

T-tutors-DR-info

tu: The predictions that you are making are for the period before any neural changes take place.

Whenever a deeper conceptual model has been introduced, the tutor must eventually return to the core variable which started the discussion. The topic T-tutors-PT-entry can be used for this purpose:
Primitives

The topics share the primitive operators T-elicits and T-informs. The T-elicits operator is used when we want the student to participate actively by answering a question. With T-informs the tutor gives some information to the student. At any level operators can have arguments such as variable name or information desired. Other arguments refer to interpersonal aspects of an utterance (attitude) or textual aspects (narrative mode). Arguments are also inherited from higher level, enclosing goals.

T-elicits info=var-value

tu: What is the value of cardiac output [CO]?

T-informs info=DR-info attitude=remind

tu: Remember, we are dealing with the period before any change in nervous activity occurs.

T-informs narrative-mode=summary

tu: So HR increases and that makes CO go up ...
(cardiac output) and RAP. Boldface forms represent the tutorial hierarchy while italic ones represent responses to the student’s immediately previous utterance. In this example, the tutor replaces the current method with **T-tutors-deeper-concepts**, which will attempt to teach the same information in a different way. The new method goes step-by-step from CO to CBV (central blood volume), CBV to CVP (central venous pressure), and CVP to RAP.

Figure 2 shows an example of the tutor responding to a near miss. The student mentions CVP, which is not a core variable. The tutor responds by attempting to lead the student from CVP, which is a step on the right path, to the desired answer, CO. In this case this procedure must be followed twice in order to get to CO. Once the desired answer is obtained, the **T-tutors-via-determinants** method continues as before, with the topic **T-tutors-value**.

In Figure 1, since CO was mentioned in the first method, the tutor knows at the beginning of the new method that all the steps from CO to RAP will be covered. In Figure 2, the tutor moves backward from RAP to CO, using the student’s responses to determine how many steps must be mentioned. The sequence terminates when the student mentions CO.

Figure 3 shows an example of a response to a “don’t know” answer. In the near miss example of Figure 2, the student gave the tutor something to build on but this is not the case with the “don’t know” answer in Figure 3. Therefore the tutor must teach the knowledge from scratch, as in Figure 1. Figure 3 differs from Figure 1 in two ways. First, the tutor is working backward along the concept map because the desired endpoint, CO, has not been mentioned yet. Second, the new method is subordinate to the current topic, namely **T-tutors-determinant**, because the goal of the new method is only to answer the question “what determines the value of RAP?” Thus the last topic of the original method, i.e. **T-tutors-value**, is still required whereas in Figure 1 it is not.

In all three examples the student’s answer triggers a change in the tutor’s plan, thus personalizing the response in accordance with the student’s knowledge.

**Conclusion**

Transcript analysis has given us new insights into a hierarchical plan-based understanding of the behavior of human tutors. It has enabled us to be more precise about many aspects of operator structure and selection. We illustrated this fact by showing several examples of tutors responding to different student errors.

In addition, by using standard, machine-readable SGML, we can perform computerized analyses of the corpus. Starting from a detailed and rigorous markup which corresponds to the plan operators needed by the system reduces the amount of knowledge engineering required to add the operators to our knowledge base. This is an important step toward enabling CIRCSIM-Tutor v. 3 to generate correct and natural tutoring dialogues.

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Figure 3. Response to “don’t know” student answer