CONTEXT-DEPENDENT TRANSITIONS IN TUTORING DISCOURSE

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ABSTRACT

Successful machine tutoring, like other forms of human-machine discourse, requires sophisticated communication skills and a deep understanding of the student's knowledge. A system must have the ability to reason about a student's knowledge and to assess the effect of the discourse on him. In this paper we describe Meno-tutor, a LISP program that deliberately plans the rhetorical structure of its output and customizes its responses to the level of understanding of the individual student.

The Nature of Tutoring

The goal of this research has been to identify the kinds of machinery and knowledge that are necessary to carry on an acceptable tutoring discourse. We have studied human tutoring protocols and have identified some of the rules and structures that govern this kind of behavior [Woolf & McDonald, 1983; Woolf, 1984]. In this paper we describe how we used this information to build a preliminary version of a machine tutor.

Tutoring suffers from the same problems that afflict other forms of communication: the system cannot know with certainty whether a student understands the topics being discussed or what meanings can be attributed to his answers. Because students are not aware of what they *do not know*, tutors, even more than typical speakers, must take care to define for both participants the topics and portions of the student's knowledge that are missing or ambiguous.

Tutor: Do you know what the climate is like in Washington and Oregon?

Student: Is it cold?

Tutor: No, it is rather mild. Can you guesss about the rainfall there?

Student: Normal, I guess.

Tutor: Well, the Japan current, which starts in south eastern Pacific, goes along the coast of Japan and across the North Pacific ending up off the coast of Washington and Oregon. How do you think that current affects the climate there?

Student: It's probably rainy.

Tutor: It is indeed very wet, there are rain forests in both Washington and Oregon. What does that tell you about the temperature of the Japan current?

Student: It's warm.

Figure 1: An Example Meno-tutor discourse.

A machine tutor should have the ability to adapt its discourse to the context of student and discourse history; it should, for instance, engage the knowledgeable student in a way that is fundamentally different from the way it engages the confused one. We call this kind of system "context-dependent" and contrast it with what we call "retrieval-oriented" systems, such as the original WEST system [Brown & Burton, 1975] or the BIP project [Barr et al., 1976]. While we have placed our emphasis on choosing among alternative discourses that respond best to what the tutor knows about the student's knowledge and the discourse history, the retrieval-oriented system has been directed at retrieving the correct answer, which is stored in the expert knowledge base. In the latter system the input-output routines act as a front end to the knowledge retrieval system.

In contrast, the context-dependent response considers the sensitive response more effective than the correct response. For instance, correcting a wrong answer may be appropriate at times. However, it may not be appropriate if the student's wrong answer follows a series of wrong answers in which the student has shown a lack of knowledge of the domain and if related topics exist that might help focus the student's attention onto the correct answer. In such a case, the better approach might be to briefly acknowledge the wrong answer and move on to provide more supplemental data.

Examples from Meno-tutor

As an example of a discourse produced by Meno-tutor we present Figure 1. This discourse is modeled directly on a human tutoring dialogue recorded by Stevens et al. [1982, pg 18].[1] That is, we analyzed the common transitions and speech patterns used in this and twelve other human dialogues and defined the structures and knowledge necessary for a machine tutor to behave the same way. In the example, the student's first two answers were wrong[2] and the system marked the student as having limited knowledge about the topic. The question-answer approach was then changed because it was not working and the system chose, instead, to tell the student about the "Japan Current," which is a dominant influence behind the region's climate.

Moving beyond this "reverse engineering," we have begun to explore the "tutoring space" our apparatus defines by varying the domain and the particulars of the rules. The discourse in Figure 2, for example, is based on the same domain as the first, but is done in an alternative tutoring style, brought about by modifying the "meta-rules" that govern whether the tutor explores the student's frontier of knowledge (Figure 1) or probes the student's misconceptions about the current topic as soon as the first mistake is made (Figure 2).

Two meta-rules were modified to achieve this second discourse. The first makes the tutor change discourse tactic after a set of topics has been completely discussed and the tutor has some confidence in its assessment of what the student knows. In the first discourse, it was set at a more conservative value. In the second discourse, it caused the shift in strategy after a single wrong answer. The second modified meta-rule shifts the discourse to focus on the student's misconception. Typically, this rule is triggered only after all topics have been covered and a misconception has been observed. In the second discourse this rule was modified to eliminate the first precondition, resulting in the rule being triggered after a single wrong answer occurs which is linked to a common misconception.

Tutor: Do you think it rains much in Oregon?

Student: No.

Tutor: Why do you think it doesn't rain much in Oregon?

Student: Because the neighboring states are dry.

Tutor: The neighboring states are dry, but, you can not generalize from that. In fact, it does rain a lot in Oregon. Can you guess what causes the rain there?

Student: Well, there are high mountains in the region and the states border the Pacific Ocean.

Tutor: Yes. The Pacific borders Oregon. How do you think it is involved in the heavy rainfall there?

Student: Ocean air rises and cools upon reaching the land

Tutor: That is right.

Figure 2: A Second Meno-tutor Discourse.

Our second exploration of the tutoring space was to substitute a new knowledge base for the facts about rainfall, namely elementary PASCAL looping concepts. The focus of this PASCAL tutor is on the misconceptions behind a student's explicit programming errors. The model for the misconceptions drew on the results of of extensive cognitive studies about how novices learn PASCAL constructs [Bonar, 1984; Soloway et al., 1981].

The Meno-tutor defines a general framework within which tutoring rules can be defined and tested. It is not an exhaustive tutor for any one subject but rather a vehicle for experimenting with tutoring in several domains. Though the number of discourses produced is still small (i.e., 5), the fact that our architecture has been adapted to two quite different domains and that we can produce varied but still quite reasonable discourses in short order by changing the particulars of the rules, is evidence of its potential.

[1] The input text from the student is straight from Stevens et al. We feed the conceptual equivalent of the student's input to the system by hand (i.e., what would have been the output of a natural language comprehension system). The output is presently produced by standard incremental replacement techniques but in a way that should permit us to easily move over to a more capable generator (we expect to use MUMBLE [1983]) at the point when we invest in a larger knowledge base and a richer representation.

[2] It's not that those answers were simply "wrong," but that they reflect reasonable default assumptions about what happens in "northern states." An attempt to probe such assumptions is made in the next discourse, in Figure 2.

The Architecture of the Meno-tutor

Meno-tutor separates the planning and the generation of a tutorial discourse into two distinct components: the tutoring component and the surface language generator. The tutoring component makes decisions about what discourse transitions to make and what information to convey or query, and the surface language generator takes conceptual specifications from the tutoring component and produces the natural language output. These two components interface at the third level of the tutoring component as described below. The knowledge base for the tutor is a KL-ONE network annotated with pedagogical information about the relative importance of each topic in the domain.

The tutoring component is best described as a set of decision-units organized into three planning levels that successively refine the actions of the tutor, (see Figure 3). We refer to the network that structures these decisions, defining the default and meta-level transitions between them, as a Discourse Management Network or DMN. The refinement at each level maintains the constraints dictated by the previous level and further elaborates the possibilities for the system's response. At the highest level, the discourse is constrained to a specific tutoring approach that determines, for instance, how often the system will interrupt the student or how often it will probe him about misconceptions. At this level a choice is made between approaches which would diagnose the student's knowledge (*tutor*), or introduce a new topic (*introduce.*) At the second level, the pedagogy is refined into a strategy, specifying the approach to be used. The choice here might be between exploring the student's competence by questioning him, or describing the facts of the topic without any interaction. At the lowest level, a tactic is selected to implement the strategy. For instance, if the strategy involves questioning the student, the system can choose from half a dozen alternatives, e.g., it can question the student about a specific topic, the dependency between topics, or the role of a subtopic. Again, after the student has given his answers, the system can choose from among eight ways to respond, e.g., it can correct the student, elaborate on his answer, or, alternatively, barely acknowledge his answer.

The tutoring component presently contains forty states, each organized as a LISP structure with slots for functions that are run when the state is evaluated. The slots define such things as the specifications of the text to be uttered, the next state to go to, or how to

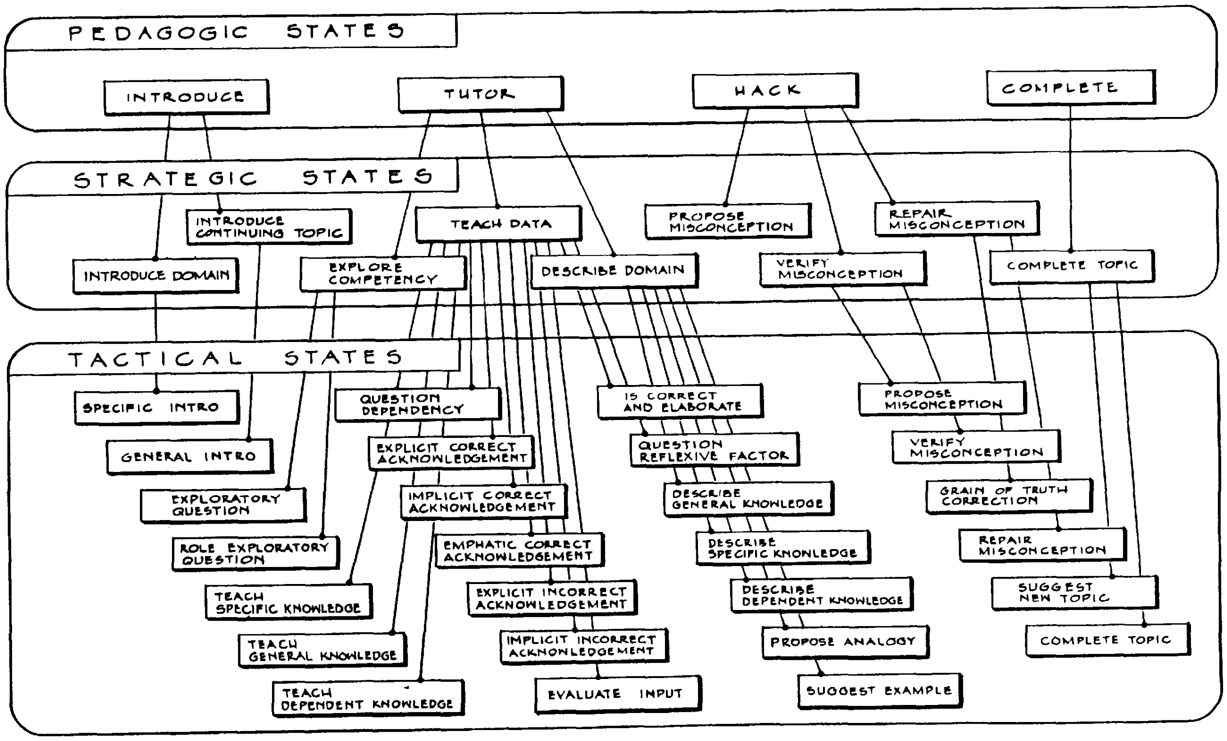


Figure 3: The Discourse Management Network (DMN).

update the student and discourse models. The DMN is structured like an augmented transition network (ATN); it is traversed by an iterative routine that stays within a predetermined space of paths from node to node. Paths, however, are not statically defined; the default path can be preempted at any time by meta-rules that move Meno-tutor onto a new path, the action of the meta-rule corresponding functionally to the high-level transitions observed in human tutoring. These preemptions move the discourse to paths which ostensibly are more in keeping with student history or discourse history than the default path. The ubiquity of the meta-rules—the fact that virtually any transition between tutoring states (nodes) may potentially be preempted—represents an important deviation from the standard control mechanism of an ATN. Formally, the behavior of Meno-tutor could be represented within the definition of an ATN; however the need to include arcs for *every* meta-rule as part of the arc set of every state would miss the point of our design.

The system presently contains 20 meta-rules; most originate from more than one state and move the tutor to a single, new state. The preconditions of the meta-rules determine when it is time to move off the default path: they examine data structures such as the student model (e.g., Does the student know a given topic?), the discourse model (e.g., Have enough questions been asked on a given topic to assess whether the student knows it?), and the domain model (e.g., Do related topics exist?). Two meta-rules are described in an informal notation in Figure 4 and in more detail in the next section.

An Example of Discourse Planning

In this section, we show how the decision-units and meta-rules interact in the tutoring process. We describe the generation of a portion of the discourse in Figure 1. The example discourse begins after the student's second incorrect answer. Snapshots 1-6 show Meno-tutor's passage through a small portion of the Discourse Management Network (DMN) as it plans and generates the sample discourse.

As shown in Snapshot 1, the tutor begins in the state *explicit-incorrect-acknowledgement*, which is a tactical state the principal action of which is to say something, in this case "No." Having said this, the tutor still has "control" of the discourse and can continue to elaborate its response to the student's wrong answer. In the present design there is no default path out of the state at the tactical level.[3] We decided, in designing these rules, that the best thing to do at this point is to move to a higher planning level and to consider reformulating either the strategy or the pedagogy of the utterance. Therefore, the tutor returns to the strategic level and to the parent state, *teach-data*, as indicated by the up arrow in Snapshot 1.

S1-EXPLORE – a Strategic Meta-rule

From:	teach-data
To:	explore-competency

Description: Moves the tutor to begin a series of shallow questions about a variety of topics.

Activation: The present topic is complete and the tutor has little confidence in its assessment of the student's knowledge.

Behavior: Generates an expository shift from detailed examination of a single topic to a shallow examination of a variety of topics on the threshold of the student's knowledge.

T6-A.IMPLICITLY – a Tactical Meta-rule

From:	explicit-incorrect-acknowledgement
To:	implicit-incorrect-acknowledgement

Description: Moves the tutor to utter a brief acknowledgement of an incorrect answer.

Activation: The wrong answer threshold has been reached and the student seems confused.

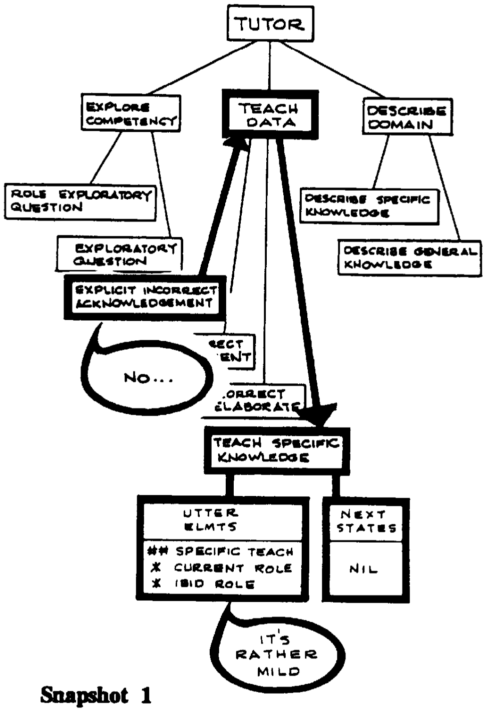
Behavior: Shifts the discourse from a explicit correction of the student's answer to a response that recognizes, but does not dwell on, the incorrect answer.

Figure 4: Informal Notation of the Meta-rules.

Once in *teach-data*, we move along the default path down to the tactical level to *teach-specific-data*. In general, at this point, a meta-rule might have applied to take the tutor to a more particular tactical state. At *teach-specific-data* an utterance is constructed from the specification **specific-value (current-topic)**, where **current-topic** has been carried forward from the previous ply of the discourse and is "the climate in Washington and Oregon." The attribute value of this topic is "rather mild" (a canned phrase), and the surface language generator renders it in this discourse context as "It's rather mild."

From *teach-specific-knowledge* there is again no default path and the tutor moves up again to *teach-data* (Snapshot 2). This time, however, the context has changed and before *teach-data* can move along the

[3] With a different set of rules, the tutor might, for example, continue speaking or it might reinforce the student's answer, perhaps by repeating it or elaborating part of it.

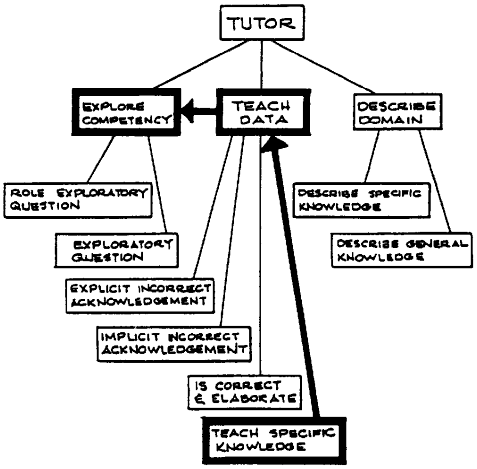


Snapshot 1

default path as before, a meta-rule takes the tutor to a different decision-unit. The context has changed because the topics brought up until this point in the discourse have been answered or resolved. In detail, what happened was that, when the tutor supplied the correct answer to its own question (i.e., "It's rather mild"), the DMN register *question_complete* was set, satisfying one of the preconditions of the meta-rule, S1-EXPLORE (shown in Figure 4). The other precondition for this meta-rule was already satisfied, namely that some topics related to the current topic remain to be discussed (as indicated by another register). When S1-EXPLORE is triggered it moves the tutor to *explore-competency*, in effect establishing that previous topics are complete and that a new topic can be explored. The next most salient topic in the knowledge base is "rainfall in Washington and Oregon" and it becomes the current topic.

Once in *explore-competency*, the tutor takes a default path to the tactical level and to *exploratory-question* (Snapshot 3), where it asks another question on a topic at the threshold of the student's knowledge. The utterance this time is constructed from the specification **question-model (current-topic)** – "Can you quess about the rainfall there?"

At this point Meno-tutor continues along a default path and enters the tactical state *evaluate-input* (not shown) which receives and evaluates the student's answer. This answer is again wrong and the default path moves the tutor, once again to *explicit-incorrect-acknowledgement*, where it would normally correct the student, as before. However, this state is not evaluated because the context is different and a new meta-rule, T6-A.IMPLICITLY (Figure 4) fires first, moving the tutor to another decision-unit (Snapshot 4). The difference in context is two-fold: 1) the student seems confused and 2) the test for wrong answers threshold is met. Recognizing a confused student is admittedly a subjective and imprecise inference for a machine tutor. In this implementation, we have chosen to measure it as a function of the number of questions asked, the number of incorrect responses given, and the extent to which the student's frontier of knowledge has been explored. In the example discourse, two questions have been asked, two answers have been incorrect, and the student's frontier of knowledge is barely explored. Therefore, the student is judged to be confused and the meta-rule T6-A.IMPLICITLY is triggered, forcing the system to move to the tactical state *implicit-incorrect-*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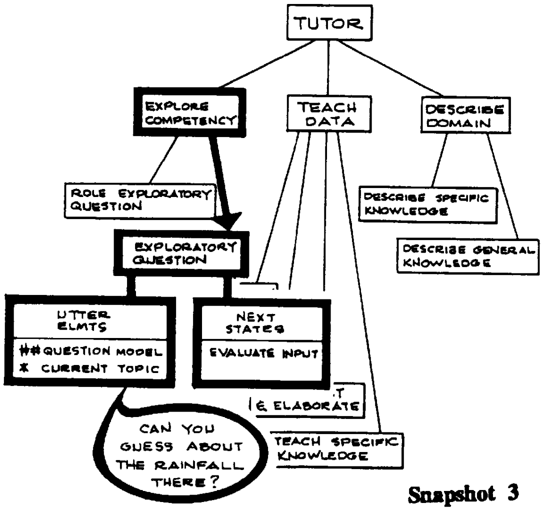
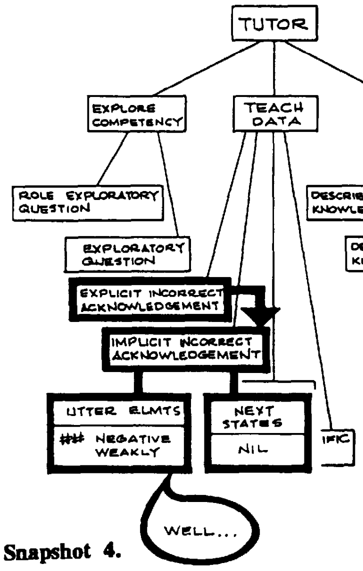


Snapshot 3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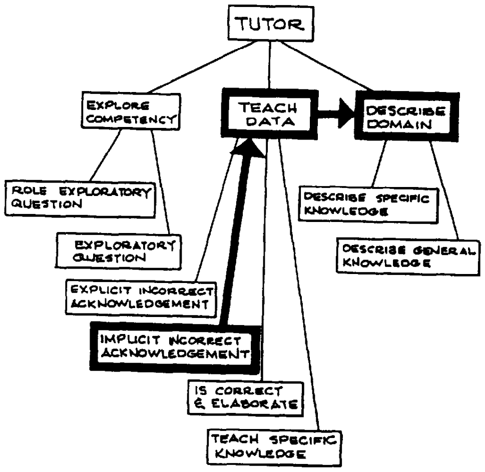
Snapshot 4.

acknowledgement. Instead of correcting the student, this state causes a response which implicitly recognizes, but does not dwell on, the incorrect answer. The tutor responds with "Well, . . ."

There is no default path from *implicit-incorrect-acknowledgement* and the tutor moves up to *teach-data* (Snapshot 5). Once here, a meta-rule, S3-DESCRIBE, moves the tutor to *describe-domain*, terminating the question-answer approach and beginning a lengthy descriptive passage about a single topic. This happened because the threshold of wrong answers has been met (as recorded by a register) and there is a link from the major topic, "climate in Washington and Oregon," to an undiscussed geographical factor on which it is dependent, namely the "Japan Current."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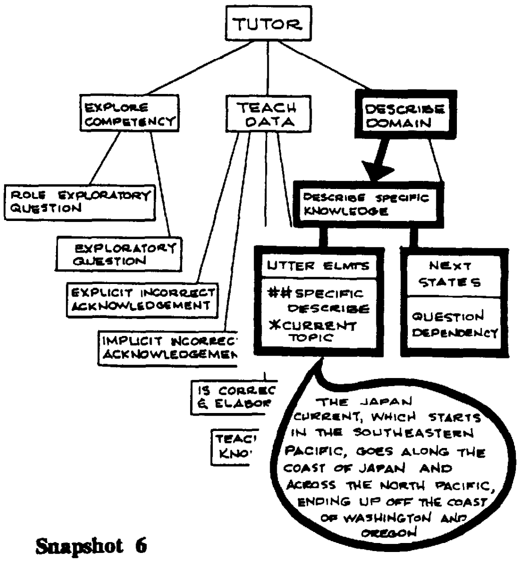
Snapshot 5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Snapshot 6

From *describe-domain*, the tutor takes the default path to *describe-specific-knowledge* at the tactical level (Snapshot 6) and constructs an utterance from the specification **specific-describe (current-topic).** **Specific-describe** enunciates each attribute of its argument and Meno-tutor says "the Japan Current, which starts in the Southeast Pacific, goes along the coast of Japan and across the North Pacific, ending up off the coast of Washington and Oregon."

Current Status

At this point in our research, the tutor´s knowledge of two domains is shallow and, as mentioned above, we have not yet interfaced the tutoring component with the surface language generator. Our intent is to develop a complex knowledge base, in either the domain of rainfall or PASCAL, to extend the surface language generator to deal with the domain, and to build a simple natural language parser to understand the student´s input.

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