From GUIDON to NEOMYCIN and HERACLES in Twenty Short Lessons

by

William J. Clancey

Department of Computer Science
Stanford University
Stanford, CA 94305
I review the research leading from the GUIDON rule-based tutoring system, including the reconfiguration of MYCIN into NEOMYCIN and NEOMYCIN's generalization in the heuristic classification shell, HERACLES. The presentation is organized chronologically around pictures and dialogues that represent conceptual turning points and crystallize the basic ideas. My purpose is to collect the important results in one place, so they can be easily grasped. In the conclusion, I make some observations about our research methodology.
From GUIDON to NEOMYCIN and HERACLES in Twenty Short Lessons

by

William J. Clancey

Stanford Knowledge Systems Laboratory
Department of Computer Science
701 Welch Road, Building C
Palo Alto, CA 9430

The studies reported here were supported (in part) by:

The Office of Naval Research
Personnel and Training Research Programs
Psychological Sciences Division
Contract No. N00014-85K-0305

The Josiah Macy, Jr. Foundation
Grant No. B852005
New York City

The views and conclusions contained in this document are the authors' and should not be interpreted as necessarily representing the official policies, either expressed or implied, of the Office of Naval Research or the U.S. Government.

Approved for public release; distribution unlimited. Reproduction in whole or in part is permitted for any purpose of the United States Government.
From GUIDON to NEOMYCIN and HERACLES in Twenty Short Lessons

William J. Clancey

Origins

The idea of developing a tutoring program from the MYCIN knowledge base was first described by Ted Shortliffe (1974). In fact, it was the mixed-initiative dialogue of the SCHOLAR teaching program (Carbonell, 1970) that inspired Shortliffe to produce the consultation dialogue of MYCIN. He conceived of it as a question-answer program in SCHOLAR's style, using a semantic network of disease knowledge. Shortly after I joined the MYCIN project in early 1975, Bruce Buchanan and I decided that developing a tutoring program would be my thesis project.

The GUIDON program was operational in early 1979. This review describes the key ideas in GUIDON and the important developments of the following six years as research continued under funding from the Office of Naval Research (ONR), the Defense Advanced Research Projects Agency (DARPA), and the Army Research Institute. The first three years were covered briefly in an earlier report (Clancey & Buchanan 1982). In general, only publications from this project are cited; many other references appear in the cited publications.

Overview: Introduction to the Programs

Figure 1 shows the relationship between programs we have constructed in the past six years, including MYCIN and EMYCIN, which served as the foundation.

The medical consultation system, MYCIN, was generalized to EMYCIN (van Melle, 1979). The tutoring system, GUIDON, was designed to work with any EMYCIN knowledge base (Clancey 1979a, Clancey & Letsinger 1984, Clancey 1982a).

NEOMYCIN, another medical diagnosis program, expands MYCIN's disease knowledge to include competing alternatives, for example, diseases that might be confused with meningitis. This provides an opportunity for teaching diagnostic strategy. MYCIN's strategy of exhaustive, top-down refinement is sufficient for the small set of diseases it knows about, but it is unrealistic for medical diagnosis in general. Using NEOMYCIN, we can convey the more complex processes of forming hypotheses, grouping competitors discriminating among competitors and reasoning causally. A second important idea in NEOMYCIN, distinguishing it from other expert systems, is that the inference procedure for diagnosis is represented in a well-structured language, separate from the medical knowledge. This facilitates explanation and student modeling.

HERACLES is the generalization of NEOMYCIN, standing for Heuristic Classification Shell (Clancey 1985a). By analogy with EMYCIN, we might say that HERACLES is "NEOMYCIN without the knowledge," but there is a big difference. We retain NEOMYCIN's diagnostic procedure; it is reused and adapted in new applications.

GUIDON2 is a set of tutoring systems that work for any HERACLES knowledge base; it is currently being developed with NEOMYCIN. In the GUIDON2 family of programs, we are exploring different forms of student and teacher initiative (Clancey 1984a).

Guidon: "Transfer of Expertise"

In GUIDON (See Figure 2), we held the MYCIN knowledge base constant and considered the additional knowledge about teaching that would provide a good tutoring system. We were especially interested in teaching from different knowledge bases using one program. This exciting...
Figure 1. A Map Showing the Evolution of Research. NEOMYCIN, a reconfiguration of MYCIN, is also a medical consultation program. Research from both programs follows a parallel path: generalizing the system into a knowledge system shell, applying the shell to develop knowledge systems in other domains (PUFF, SACON, CASTER), and developing an instructional system compatible with any knowledge system developed from the shell. This paper describes the key ideas in GUIDON and the upper path of research.

idea was motivated by the EMYCIN design that allows putting in a different knowledge base and carrying on a consultation in a different domain. GUIDON's teaching knowledge is separate from the medical knowledge; so, it is reusable and adaptable to new applications. This is a significant advance over traditional computer-assisted instruction methodology that requires writing a new program for each case to be discussed. We now have two kinds of generality: First, this tutor can discuss any case that MYCIN can solve. Second, we can swap in a different knowledge base and discuss cases in another domain. The separation of the knowledge base from the procedures that interpret it is the important idea.

Discourse Procedures: Alternative Dialogues and Transitions.

Another successful aspect of GUIDON's design is the representation of the tutoring knowledge. This knowledge can be shown as a transition diagram, where each node represents a situation within a tutoring dialogue (See Figure 3). The program has a list of rules for reasoning about what to do at each step. For example, when GUIDON detects that a goal under consideration has been determined (from MYCIN's point of view), it selects from three alternative transitions: presenting a conclusion, presenting a summary, and asking the student to make a hypothesis (Clancey 1979b).

Each of these transitions is encoded by rules called tutoring or t-rules, numbering about 200. We built the system very much like a traditional expert system, running cases and incrementally modifying the t-rules. When the program said something inappropriate, we modified t-rule conditions to change when that kind of remark would occur. Similarly, GUIDON sometimes missed an opportunity to say something interesting. For example, if a fact can be inferred by definition, there is no need to go through a long dialogue, gathering data and forming hypotheses and so on; so we added t-rules to deal with this case, leading the program to give MYCIN's conclusion or to ask for the student's conclusion, depending on the model of what the student knows and the goals for the dialogue.

This works rather well, though it lacks a theoretical foundation. Arbitrary strategies are encoded in the tutoring rules. Building on the t-rule idea, Beverly Woolf has added a hierarchical structure to the alternative dialogues, couched in the terminology of discourse analysis. This represents in a more principled way the choices the program is making. (See Woolf & McDonald 1984.)

THE AI MAGAZINE August, 1986 41
Figure 3. Dialogue Transition Diagram. Each node stands for a situation in a case-method dialogue, represented in GUIDON as a stylized procedure of ordered rules or a rule set, totalling 200 rules in 40 situations. For example, in pursuing a goal explicitly agreed upon by student and program, the student can request more case data. GUIDON can recognize the data as relevant to a subgoal, provide it as a set of related information (block), or determine that there is no need to ask (perhaps because the requested data can be inferred from known information). Arrows that loop back indicate that a situation may occur iteratively or recursively. For example, several related rules might be presented after a given rule is discussed. The italicized labels indicate the basis for a transition: Economy, Domain logic, and Tutoring goals.

Overlay Model: Evaluating a Student Hypothesis

Perhaps the most interesting reasoning in GUIDON involves evaluating a student's partial solution (See Figure 4) (Clancey 1979c). In this example, the student says that the organisms causing the infection could be Diplococcus, Psuedomonas, or Neisseria. The program looks at MYCIN's rules and sets up a consistent mapping. It uses double evidence, a history of interaction with the student, and a measure of rule difficulty to construct a consistent model.

For example, suppose the student mentions Neisseria.

If MYCIN's rules argue for and against this hypothesis, then the student might know the positive evidence, but not the negative evidence. GUIDON concludes in a similar way that Pseudomonas is believed by the student because the patient is burned—but not because of the white blood count (WBC) or because the infection occurred in the hospital (nosocomial)—given that the student didn't mention the two other diagnoses associated with this evidence (E.coli and Klebsiella). It's a straightforward, logical analysis, demonstrating the value of production rules for indexing how facts are concluded and used in a program.

The Sacon Tutorial: Experimenting with other Knowledge Bases

Figure 5 shows an excerpt from a dialogue with GUIDON.
using the SACON knowledge base. It graphically demonstrates the value of keeping GUIDON’s tutoring knowledge general: The same tutoring program can interpret SACON’s rules and discuss a structural analysis problem with a student.

We must now determine whether the shape of the floor section (SUB-STRUCTURE-1) is one of: the surface shapes.

Here is some relevant data you could have asked for: the geometry of the floor section is planar, the modelling dimensionality of the floor section is 2, and continuum is one of the constructions of the floor section.

What does this tell you about the shape of the floor section?

** HELP
Can you conclude that the shape of the floor section is (select from the following):

1. beam—suggestive evidence (.62)
2. semimonococque—suggestive evidence (.62)
3. not shell—strongly suggestive evidence (-.95)
4. plate—with certainty (1.0)

** 4
Yes, that’s right (see RULE100).

Figure 5: Excerpt of GUIDON Tutorial Using SACON Knowledge Base. GUIDON encounters an incomplete subgoal in a rule that it's trying to discuss with the student. A t-rule in the procedure for discussing an incomplete subgoal finds that the subgoal can be inferred by a definitional rule and then invokes the procedure for discussing definitional rules. GUIDON gives the student new information (the geometry, dimensionality, and construction of the floor section), and then asks him if he can now infer the shape of the floor section. The student asks for help, and GUIDON converts the question into a multiple choice. Reasoning about the current problem state, text generation, and quiz construction and evaluation are all accomplished by general t-rules that were originally developed in the context of a medical diagnosis dialogue.

This interaction plausibly captures some of the behavior we'd like to see in a teaching program. It was produced entirely by t-rules that were written for medical examples and then just plugged into SACON. It took about an hour to make it all work, with a few modifications to cope with syntactic variations in SACON's rules. For further discussion and an example from PUFF, see (Clancey 1979a, Clancey 1982a).

Inadequacy of Mycin: Implicit, Nonpsychological Strategy

We now consider the analysis that led to NEOMYCIN. What problems arise in using MYCIN for teaching?

Figure 6 shows an excerpt from an experiment with GUIDON; this was a pivotal example for me. GUIDON indicates that the the age of the patient, 34, is not evidence for Neisseria. Yet, a rule in the knowledge base says, "If the age of the patient is between 15 and 55, then Neisseria is one of the organisms." I was rather surprised. This rule is consistent with the student’s hypothesis and justification.

The problem is that some of the information in the premise of this rule is still unknown, so MYCIN can't apply the rule. Specifically, there is no indication that the age of the patient is causally related to Neisseria and that the age would be sufficient in itself to suggest this conclusion. GUIDON has no way of knowing that one of the clauses is more directly associated with the conclusion than any other clause. To make this clear, consider another rule: "If the age of the patient is greater than 17 and the patient is an alcoholic, then Diplococcus might be causing the infection." Considering this rule and knowing only that the patient is 34 would not make you think of Diplococcus. Here the age clause controls the application of the rule, preventing the program from asking whether a child is an alcoholic. The causal relation is between alcoholism and Diplococcus.

The student’s knowledge and the procedure being used are very different from MYCIN. The student has probably formed a hypothesis just hearing the age of the patient and some tentative information (not shown in the excerpt) that suggests meningitis. MYCIN will only conclude Neisseria when, from its point of view, it has exhaustively considered the evidence for meningitis and considered whether it is bacterial and so on. MYCIN does a top-down search through the set of diseases, but the student has “triggered” meningitis from just partial information, with no direct evidence for an infection or bacterial infection at all.

To properly respond to the student, we would have to represent the association between age and Neisseria explicitly and separate out the search procedure. However, to recognize what strategy the student is following, we’d have to encode a different strategy, expressing why it makes sense to think about Neisseria just knowing the age and some tentative evidence for meningitis. The very idea of a hypothesis is foreign to MYCIN.

The Idea of Strategy: From “tracing a parameter” to “focusing on a hypothesis”

Figure 7 and Figure 8 illustrate that at a certain level MYCIN's reasoning is arbitrary, lacking the focus on hypotheses we find in people. People group their questions logically; they don't jump around without reason. However, MYCIN does not focus on a particular hypothesis as it goes down through its (implicit) tree of diseases. When it considers types of meningitis or organisms, the types are considered arbitrarily, based on the order in which rules were entered into the program. The program proceeds systematically from infection to meningitis to bacte-
What are the organisms which might be causing the infection?

>> NEISSERIA-MENINGITIDIS
What facts about this case tell you that Neisseria-meningitidis is one of the organisms which might be causing the infection?

>> AGE

- > The fact that the age of Pt538 is 34 years is not evidence for the conclusion that Neisseria-meningitidis is one of the organisms which might be causing the infection.

Do you have a question?

**

---

**Figure 6: Problematic Excerpt of GUIDON Tutorial Using MYCIN Knowledge Base.** The student offers to state a partial solution (student input follows ">>"). The program responds by rephrasing the current topic as a question, "What are the organisms which might be causing the infection?" When the student says Neisseria, GUIDON checks and finds that MYCIN has made no conclusion at all up to this point. A t-rule prompts the student to justify his hypothesis. The student says that he is considering the age of the patient.

It's a lost cause for the student, however; whatever he finds that MYCIN has made no conclusion at all up to this point. At the final prompt, the student can review the available data and MYCIN's reasoning, if desired. In fact, the student's hypothesis is reasonable, but GUIDON would need to know how MYCIN's rules are constructed and a different model of reasoning to understand why the student did something different.

---

What are the organisms which might be causing the infection?

>> NEISSERIA-MENINGITIDIS
What facts about this case tell you that Neisseria-meningitidis is one of the organisms which might be causing the infection?

>> AGE

- > The fact that the age of Pt538 is 34 years is not evidence for the conclusion that Neisseria-meningitidis is one of the organisms which might be causing the infection.

Do you have a question?

**

---

**Figure 6: Problematic Excerpt of GUIDON Tutorial Using MYCIN Knowledge Base.** The student offers to state a partial solution (student input follows ">>"). The program responds by rephrasing the current topic as a question, "What are the organisms which might be causing the infection?" When the student says Neisseria, GUIDON checks and finds that MYCIN has made no conclusion at all up to this point. A t-rule prompts the student to justify his hypothesis. The student says that he is considering the age of the patient.

It's a lost cause for the student, however; whatever he finds that MYCIN has made no conclusion at all up to this point. At the final prompt, the student can review the available data and MYCIN's reasoning, if desired. In fact, the student's hypothesis is reasonable, but GUIDON would need to know how MYCIN's rules are constructed and a different model of reasoning to understand why the student did something different.

---

The Tetracycline Rule:

**Structure, Strategy, and Support**

This brings us to about 1980 when I studied MYCIN's 400 rules to determine how they might be reconfigured for use in teaching. Up to this point, in constructing GUIDON, only limited annotations had been added to the original rule set. Now any change at all would be allowed.

Early on, I developed a framework that turned out to be very useful in protocol analysis. In this framework, explanations are analyzed according to knowledge roles, how knowledge is used in relation to other knowledge (Clancey 1983a) (See Figure 9):

- **The heuristic rule:** A relation between data and diagnoses or therapies
- **Structure:** Subsumption relations among data, diagnoses, and therapies
- **Strategy:** The procedure for applying rules
- **Support:** The justification for rules

As an example of structural knowledge, you might think of "SSS" when trying to remember this framework.

To understand the different kinds of knowledge here, suppose that you have a patient who is four years old. You would probably say, "Well, I'm not going to prescribe tetracycline." However, that's not a very good model of how a physician reasons; this would be a strange conclusion to make right at the beginning. Just as there is a logic for requesting data and for focusing on hypotheses, there is a logic for making assertions given available information. All together, we call this logic the inference procedure. (In the literature, it is also called control knowledge or, more specifically, diagnostic strategy. To emphasize the reasoning about control alternatives, the term managerial strategy or metastrategy is also used, particularly in the education literature [Schoenfeld 1981]).

By strategy, I mean the general goal that leads the physician to remember a heuristic rule. For example, when
32) Does J. Smith have a history of NEUROSURGERY? ** NO
33) Does J. Smith live in a crowded environment? ** NO
34) Do you suspect recent alcoholic history in J. Smith? ** NO
35) Is the meningitis a hospital-acquired infection? ** YES
36) Is J. Smith’s clinical history consistent with EPIGLOTTITIS? ** NO
37) Is J. Smith’s clinical history consistent with OTITIS-MEDIA? ** NO
38) Has J. Smith ever undergone splenectomy? ** NO
39) Is J. Smith a burn patient? ** YES

Figure 7: Sequence of Data Requests from MYCIN Consultation.

Figure 8. Relating MYCIN’s Data Requests to Organism Hypotheses. MYCIN’s questions, shown in Figure 7, have been reordered according to the hypotheses that motivate them. For example, question 33 about living in a crowded environment is asked in order to apply rule 533, which concludes Neisseria. All of the questions pertain to the same goal—determining what organisms therapy should cover—but the rules conclude about different organisms. Neither the sequence of rule applications nor the questions are sorted by organism. Questions 34 and 38 pertain to Diplococcus-pneumoniae, with three intervening questions pertaining to Hemophilus-influenzae. Thus, in pursuing a goal, MYCIN’s reasoning is unfocused at the level of possible values for the goal, in this case organisms that might be causing the infection.

Figure 9. Analysis of Knowledge Relating to MYCIN’s Tetracycline Rule. The rule states, “If the patient is less than seven years old, then remove tetracycline from the list of drugs under consideration.” Relation of age to other contraindication factors (such as whether the patient is pregnant), justification for the rule, and time when it would be considered are relevant to explaining this rule, but are not represented in MYCIN. Making explicit this structural, support, and strategic knowledge enhances our ability to understand and modify MYCIN.

is it important to remember not to prescribe Tetracycline?

Obviously the physician must take this into account when prescribing therapy.

By structural knowledge, I mean the relations by which heuristic rules are indexed and subsequently controlled. In general, this involves categorizing the facts the rules use (for example, patient factors) and the facts they conclude about (for example, therapies).

By support knowledge, I mean the justification for the rule. Why wouldn’t you prescribe tetracycline to someone who is less than seven years old? Here we have a chemical process, a chelation mechanism, that results in the molecule binding to the growing teeth and bones, and a social consideration that attests people don’t want to have discolored teeth. This is a very interesting justification because it shows that giving tetracycline might save
the patient's life, even though it might have an undesirable side effect. That's important to know if tetracycline is the only drug available. It's a nice example of why it's useful to know the justification of a rule—so you can violate the rule and know what the consequences will be.

Generally, this figure suggests a framework for understanding an expert's explanations. When I ask a physician who is solving a problem, "Why did you ask that question?" I classify the answer into one of these categories. If the physician tells me, "Well I'm not going to prescribe tetracycline because the age is less than seven," I am being told what assertions were made from given information (that is, a heuristic rule). If I ask the physician why and I get an explanation having to do with chelation, then I'm being given the justification for the assertion (that is, support). If the physician says "This is just one of the contraindications I'm going to consider," then I'm being told about the organization of his knowledge, the categories used for focusing (that is, structure). Finally, if the physician tells me when contraindications are considered and how each type is considered, then I'm getting the inference procedure (that is, strategy). I tried to consistently apply this analysis when working with physicians, particularly to focus their explanations on strategy and avoid the bottomless pit of support explanations.

NEOMYCIN research focuses on representing strategy and structure because this is the deficiency of GUIDON we most want to improve. We also sense that structure and strategy are at the top of a pyramid of knowledge and are more limited in nature. A research effort focused on them is attractive because this knowledge conceivably might be carefully and exhaustively explored.

The Beckett Tapes: An Articulate Teacher

In 1980, Reed Letsinger and I worked with Tim Beckett, M.D., who was recommended by Ted Shortliffe and who turned out to be a rather fortunate choice. Beckett was known at Stanford for being a good teacher. He could articulate general principles for reasoning very well. He didn't just say what it is you should ask about or what your conclusions should be—he was able to speak in general terms about how you should think.

We taped interviews and classroom interactions, and transcribed and studied them (Clancey 1984b). In one interaction, Beckett interrupts a student who is examining a patient played by another student:

When you ask these questions about whether gargling makes it better or worse, or whether it's better certain times of the day, are you thinking about how that's going to help you move down different diagnoses? ... ask a couple of general questions maybe that could lead you into other areas to follow up on, rather than zeroing in.

Note the absence of medical terms in his strategic advice. Again:

We're talking at the top of infections, but before we go down infections, are there any other things you can think of? The mistake you don't want to make is leaving out the important things on top.

We repeatedly heard these general statements—move down different diagnoses, ask general questions, don't leave out important things on top. These were the strategic gems—better than I could have expected—that would allow us to construct NEOMYCIN. Essentially, I saw the opportunity here for a program that would talk procedurally about these operations: Moving down different diagnoses, asking general questions, not leaving out important things at the top. This procedure is separate from the medical knowledge, describing how the medical knowledge is searched. That is, the statement of strategy does not directly mention domain terms; it is abstract.

In Beckett's explanations, we see regular switching back and forth between the concrete situation and a generalization:

Ask it very generally, like "Have you had any major medical problems, or are you on any medication?" Those types of general questions are important to ask early on because they really tell you how soon you can focus down.

You have to think of some of the common things, but at the same time you have to think of some of the serious things that may not be common. What is a serious infection that can get in your throat?

This last example shows most clearly my model of inference in NEOMYCIN.

Refining the diagnosis and thinking of some of the common things, the physician looks into the domain model and asks, "What is a serious infection that can get in the throat?" and "What are some of the common things that could cause it?" This is how the metarules in NEOMYCIN work.

As confirmation of the potential effectiveness of Beckett's approach, we analyzed his best student's reasoning. The student obviously followed the procedure Beckett articulated in class. Of course, not all students would necessarily find Beckett's teaching approach to be useful, but we had an existence proof and clear statements of at least one diagnostic procedure, so we wrote the approach down.

About this time, we also had the first glimmer of how an explicit procedure could help a student learn relevant medical knowledge. When I had Beckett present problems to me, I often lacked the medical knowledge to carry out the procedure. However, knowing the procedure, I found that I could ask reasonably intelligent questions: "I know I should be thinking about some of the serious and common causes of this disease, but I don't know what they are." This has evolved into our version of explanation-based learning (see The Situation-Specific Model: From
Neomycin: Separating the Medical Knowledge from the Diagnostic Procedure

Figure 10 shows the architecture of NEOMYCIN, illustrating the idea of separating the diagnostic inference procedure (control knowledge) from the medical knowledge. Crucially, both are represented in well-structured languages so that they can be reasoned about by the explanation, knowledge-acquisition, and student-modeling programs (Clancey 1983b).

![Figure 10. Architecture of NEOMYCIN. An inference procedure queries the knowledge base, relating findings and hypotheses to one another in order to make a diagnosis. For example, given that the patient has diplopia (double vision), the program asks the knowledge base what could cause it. One or more hypotheses might be returned, which the inference procedure will proceed to discriminate, test, and refine, making further inquiries about disease and symptom relations.](image)

Davis’s conception of metarules for expressing strategy inspired this design. However, TEIRESIAS’s metarules compose domain facts with procedure, just like MYCIN’s rules (Clancey 1983a). NEOMYCIN’s metarules mention no domain terms. Moreover, they constitute a coherent procedure that completely controls every data request and every inference; so there is no back chaining of rules at all.

As is apparent in Beckett’s generalizations, we can think of this procedure as “asking questions of the domain model.” The language of relations used in metarules corresponds to the propositions in the knowledge base. These relations impose a classification on domain terms. This is what I called structural knowledge in the tetracycline analysis.

Given a hypothesis, the program asks, “What is a common cause of this disorder?” The program then looks up this relation in the knowledge base. In this sense, the inference procedure is interpreting the domain model. If we compiled the procedure—instantiating and composing it with respect to a particular knowledge base—we would get something very similar to MYCIN’s rules. In making this abstraction, stating these general rules, I’m not claiming that people reason through general statements every time or even realize that these patterns exist. In particular, reasoning categorically probably involves automatic processes of memory. Some distinctions, such as considering causal prerequisites of diseases before effects, might be regularities that the physician does not consciously realize (Clancey 1984c).

I now believe that these domain relations are in large part what we want to teach students, as generalizations, to help them learn about new diseases. In describing how to focus reasoning, we are indirectly saying how knowledge should be practically organized. For example, we say, “You should think in terms of common causes and serious causes.” That is much more informative than saying, “You should form a hypothesis” or “You should reason forward.” We hypothesize that the procedure is automatic once you have the knowledge. A medical student might not have to be told to refine hypotheses, but he has to be taught the subtypes of fungal meningitis.

The Disease Taxonomy: Searching an Abnormal Process Classification

There are several dimensions for describing NEOMYCIN’s reasoning: psychological aspects of memory and attention, AI representation and control techniques, and aspects of medical causal reasoning. Figure 11 provides one perspective in which these dimensions come together.

The main part of the knowledge base is a taxonomy of diseases or, more generally, a classification of abnormal processes. Each disease describes a process, something that has happened to the patient in the past, accounting for the set of observed manifestations. In general, there can be many different taxonomies, orthogonal and tangled.

How do we know that a given taxonomy is complete? This important question did not explicitly arise in MYCIN research because we didn’t isolate the disease taxonomy as a separate object of study. We now hypothesize that the physician’s diagnostic classification, particularly its level of specificity, depends on how it will be used. The physician is not involved in scientific research here; what goes into the taxonomy is based on distinctions useful for selecting therapy. For example, NEOMYCIN makes no attempt to determine precisely which type of viral meningitis the patient has. The reason is that they’re all treated the same—with a lot of aspirin and orange juice—and it is irrelevant to resolve the cause any further. Thus, NEOMYCIN’s

---

1Masculine expressions in this article are used as generic terms. No bias is intended.
a program that can understand arbitrary LISP code. Too much of the design is implicit and not available for explanation. Therefore, we devised a highly structured representation, organized around the idea of rule sets, with every "loop" encoded as a separate task (subprocedure) and the control of rules stated declaratively (simple vs. iterative, try-all versus stop-on-success). Each task has a typed focus (argument), local variables, and an explicit "end condition" (equivalent to the "while" or "until" condition of a loop). Making every program statement a rule facilitates interpreted control, annotation, and record keeping.

The overall design is similar to LOOPS, which evolved at the same time as NEOMYCIN. However, NEOMYCIN's metarules use variables, rather than domain terms. Also, the end condition, inherited by task invocation, enables a procedure anywhere on the current stack to regain control, either because its goal is completed or there is reason to reconsider how its subgoals are being accomplished. Figure 13 shows the flow of control in terms of focus changes.

In writing down the diagnostic procedure as rules, we are following the same methodology used in developing MYCIN and GUIDON. With the knowledge expressed in a disciplined way, it now becomes possible to study patterns and to consider how the knowledge could be derived. Such implications are too numerous to recapitulate here. The interested reader will find the metarules listed in (Clancey 1984c), with a discussion of the procedure in terms of operators and the cognitive, social, mathematical, and case population constraints implicit in the rules. The next section considers the procedure as a grammar.

Image and Odysseus:
Parsing the diagnostic process

Given the abstract nature of the tasks and metarules, they can be viewed as a kind of grammar for parsing a problem solver's sequence of requests for data. Such an analysis is shown in Figure 14, the picture I had in the back of my mind in about 1980 when I wanted some way for GUIDON to reason about what a student was doing. An interpretation of a student's partial solution provides a good basis for assisting him when he doesn't know what to do next. Such an interpretation is also a source of information for relating a student's explicitly stated diagnosis to a model of his domain knowledge. As a contextual analysis, it potentially shortens the interactive dialogue that might be necessary to confirm the student's understanding.

Bob London, David Wilkins, and I have been developing student-modeling programs with the common goal of using NEOMYCIN's diagnostic procedure to interpret a sequence of student requests for data. London has followed a top-down approach in the IMAGE program (London & Clancey, 1982); Wilkins's ODYSSEUS program uses exhaustive, bottom-up reasoning (Wilkins, Buchanan, &
Figure 12. Invocation of Diagnostic Tasks, Shown as a Lattice. Each task is represented in NEOMYCIN as a stylized procedure, shown here as a node, with the subprocedures it calls below it. For example, pursuing a hypothesis involves testing and refining the hypothesis. To relate new findings and hypotheses, all tasks eventually call FORWARD-REASON, which invokes additional tasks not shown here. GENERATE-QUESTIONS is invoked when there is insufficient information to proceed; it chases down leads in different ways, thus explaining its central position. Note also that FINDOUT calls TEST-HYPOTHESIS so that domain rules will be selected deliberately, replacing the back chaining of EMYCIN. Using this representation for explanation and student modeling requires additional knowledge about task preconditions and postconditions and how metarules controlling task invocation are ordered.

Clancey 1984). Evaluation of these alternative approaches is in progress.

Figure 14 shows a parse of reasoning produced by the ODYSSEUS program. We’re testing this program with “synthetic” students, systematically varying NEOMYCIN and comparing ODYSSEUS’s interpretation to the known variations in the knowledge base. Another application is to give ODYSSEUS a sequence of data requests and to have it determine what knowledge base changes would be required to produce this sequence, consistent with the inference procedure. We believe that the simple classification nature of the inference procedure makes this approach plausible. We’re developing this capability for a tutoring program called GUIDON-DEBUG (Clancey, et al. 1986). The same program could be used for knowledge acquisition.

Neoxpl: Strategic Explanation

Using NEOMYCIN’s well-structured representation, Diane Hasling, Glenn Rennels, and I (1983) reformulated MYCIN’s WHY/HOW explanations in terms of metarules and tasks. Figure 15 shows how procedural information is available prosaically (by asking WHY) or through the task stack.

Although our WHY/HOW system goes up the goal stack in a way similar to MYCIN’s explanation program, this new program takes advantage of the structured representation to be more selective about what it says. In particular, it looks at the focus of a task to determine whether to mention the task as it goes up the stack. A focus can be one of three basic terms—a finding, a hypothesis, or a domain rule—or a list of these. If the focus is a rule or list of rules, the explanation program skips over the task (for example, APPLYRULES). The task is mentioned if its metarule establishes a new focus, such as going from a list of hypotheses to a single hypothesis (GROUP-AND-DIFFERENTIATE) or from a hypothesis to a rule (TEST-HYPOTHESIS). This turns out to be a good explanation heuristic. A new explanation system under development uses the propositional encoding of the metarules (described later) to select particular rule-premise clauses to mention.
Figure 13. Predominant Focus Shifts in Diagnosis. This diagram simplifies the dynamic flow of control between tasks, revealing how findings and hypotheses are related. New findings suggest new hypotheses and support existing hypotheses (FORWARD-REASON); a decision is made to focus on a particular HYPOTHESIS (ESTABLISH-HYPOTHESIS-SPACE); a decision is made to focus on a particular finding (TEST-HYPOTHESIS); the implications of the new information are considered, and so on. In contrast, MYCIN does not change its goals on the basis of new data or deliberately order the goals and data it will pursue. Accomplishing this by abstract metarules (not specifying domain terms) requires explicitly representing relations between findings and hypotheses, on the basis of which they will be selectively considered.

Tasks (appearing in bold italics) can be related to Figure 12, which shows the subtasks they invoke. In practice, ESTABLISH-HYPOTHESIS-SPACE is only invoked if there is reason to stop pursuing the current HYPOTHESIS. Criteria for applying domain rules in FORWARD-REASON are complex. For example, new findings are related to hypotheses "in focus"; if a new HYPOTHESIS "explains" the known findings at least as well as existing hypotheses, it is considered; new hypotheses are related to previously known findings, etc. The program stops when its differential, the list of most-specific hypotheses under consideration, has been discriminated, tested, and refined.

MRS/Neomycin: From Findings and Hypotheses to Relations

Student modeling, debugging, and explanation require that our programs reason about the premises of metarules, particularly to determine which domain facts matched and why rules failed. Originally, metarule premises were encoded in LISP. In a hybrid system called MRS/NEOMYCIN, Conrad Bock and I rerepresented metarule premises in MRS, a logic-programming language that provides a framework for multiple representations of knowledge and control of reasoning (Genesereth & Smith 1982). Bock also recoded the interpreter in MRS rules, and placed a simple deliberation-action loop at the top (Clancey & Bock 1982). Unfortunately, recoding the interpreter slowed down the program by an order of magnitude and made the procedure too obscure to read or maintain. In the current version of the program, we retain the original interpreter and use a variant of MRS as a specification language for metarule premises, which are compiled into Lisp. This provides the well-structured, uniform language our modeling and explanation programs require without sacrificing runtime efficiency. Figure 16 illustrates how MRS is used in the metarules and definitional rules for relations.

Primitive relations are compiled as direct LISP operations, using explicit declarations about how propositions are represented in the LISP-encoded knowledge base. For example, a TYPE proposition is represented as a property list structure, so the compiler substitutes a GETPROP, an ASSOC, or more complex loop construction, depending on what terms are known when the proposition is encountered in the metarule. In encoding propositions in standardized LISP structures, distinguishing between the language for expressing knowledge and how it is stored in the computer, we are exploiting the multiple representation aspect of MRS, which is one interpretation of its name. A number of elegant patterns in the metarules made the compiler easy to write (Clancey, forthcoming). Figure 17 summarizes how rules, tasks, and relations are encoded as EMYCIN rules and parameters and how these entities are related. Our success in building HERACLES on top of EMYCIN demonstrates the generality of the original parameter-rule representation language. It is closer to a typical frame language than is commonly realized.

The most exciting result of this reformulation is what it reveals about the relational nature of the knowledge base. It is now evident that the metarules are selecting foci (findings, hypotheses, domain rules) on the basis of how they are related to one another. These relations can be either static (for example, red-flag finding, one that needs to be explained) or dynamic (for example, hypothesis in focus). The knowledge base can be viewed as a database, defined in terms of these three primitive terms and relations among them. Writing a new metarule tends to require defining a new preference relation for discriminating among findings, hypotheses, and domain rules. That is, each new relation further classifies the primitive terms in a way useful for controlling reasoning. For example, the metarule shown in Figure 16 required the new relation, "a finding that needs to be explained." As this example shows, the meaning of a relation is tied to how the relation is used. This is particularly clear for relations such as follow-up question and trigger rule.

A detailed analysis shows that the metarules are collecting, sorting, and filtering domain terms and rules on the basis of their applicability as operands (foci) for the operators (subtasks) that will accomplish the current task.
Figure 14. ODYSSEUS’s Parse of a Student’s Data Requests. Given a sequence of requests for patient data, listed on the right side of the figure (Q5, Q6, Q7), the program indicates all of the alternative justifications for why a question might have been asked. For example, the student’s query about seizures (FINDOUT/Seizures, Q6) might have been asked to determine whether the disease is caused by an Intracranial Mass Lesion, Subarachnoid Hemorrhage, and so on. The program indicates in inverse video, combining its bottom-up analysis with a top-down parse, that this question relates to meningitis (TEST-HYPOTHESIS/Meningitis), as part of the process of discriminating hypotheses (GROUP-AND-DIFFERENTIATE). Thus, the problem state (hypotheses under consideration) and the tasks interact to explain finding requests in terms of a logic for focusing on hypotheses and findings. Note that by the same analysis the question about a fever (Febrile, Q5) has three consistent interpretations. This kind of analysis is not possible using MYCIN because, first, its reasoning did not involve “looking up” from “triggered hypotheses” and, second, its inference procedure is represented behaviorally as specific productions. A functional representation, as diagnostic tasks, relates surface behavior to abstract goals, which can be accomplished in multiple ways.

For example, metarules for TEST-HYPOTHESIS collect, sort, and filter potential findings to support a hypothesis.

Refining a hypothesis means collecting, sorting, and filtering its causes and subtypes (for example, distinguishing between common and serious causes). Generally, the domain relations classify NEOMYCIN’s experiential knowledge of predefined disease models (see Heracles: From Diseases to Stereotypes) according to how they are triggered, tested, discriminated, and refined by operators (tasks) for constructing a problem-specific, historical accounting of the disease process (see The Situation Specific Model: From a Diagnosis to an Explanation).

NEOMYCIN has about 170 relations in its control vocabulary. They appear in the 75 metarules, grouped into 29 tasks. In HERACLES, the generalization of NEOMYCIN, the knowledge engineer can modify these metarules, defining new relations for describing his domain.

Guidon-Watch: Reifying the Process

The availability of graphics has changed how we can illustrate reasoning and is shaping our ideas of what we’d like to show. As a first step toward implementing a new instructional program on top of NEOMYCIN, Mark Richer and I (1985) used the Interlisp-D window and menu features to construct a complex interactive system for browsing the knowledge base and watching reasoning. This includes the dynamic task tree (similar to Figure 14) and the task stack (see Figure 15). Our work has been directly inspired by Brown’s emphasis on reifying or making concrete the reasoning process (Brown 1983).

Figure 18 shows how the disease taxonomy is overprinted to reveal the pattern of NEOMYCIN’s reasoning. In GUIDON-DEBUG, now under development, it is possible to roll back the consultation display to show any window at the time any given question was asked. This is a debugging facility we could hardly have imagined even five years ago.
7) What is Susanne's temperature (in Fahrenheit)?
** 185.8 Fahrenheit

8) Has Susanne experienced seizures recently?

**i.e. why are we asking whether Susanne has experienced seizures recently?

We are trying to decide whether Susanne has meningitis.

Recent seizures is strongly associated with meningitis.

**if:** 1) The patient has experienced seizures recently, and 2) The patient's fontanelle is abnormally tense or bulging

**then:** There is strongly suggestive evidence (8) that the patient has meningitis

**TRIGGER:** True

<table>
<thead>
<tr>
<th>FINDING</th>
<th>RULE</th>
<th>MAXCF</th>
<th>SIMCF</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEIZURES</td>
<td>RULE063</td>
<td>900</td>
<td></td>
</tr>
<tr>
<td>PEPFANL-FONTANEL</td>
<td>RULE047</td>
<td>600</td>
<td></td>
</tr>
<tr>
<td>HEADACHE</td>
<td>RULE029</td>
<td>600</td>
<td></td>
</tr>
<tr>
<td>MENINGITIS</td>
<td>RULE034</td>
<td>600</td>
<td></td>
</tr>
<tr>
<td>STIFF-NECK-ON-FLY</td>
<td>RULE048</td>
<td>600</td>
<td></td>
</tr>
<tr>
<td>CsfCellCount</td>
<td>RULE131</td>
<td>700</td>
<td></td>
</tr>
<tr>
<td>VBC</td>
<td>RULE131</td>
<td>700</td>
<td></td>
</tr>
<tr>
<td>CsfProtein</td>
<td>RULE137</td>
<td>900</td>
<td></td>
</tr>
</tbody>
</table>

**Figure 15.** Multiple Views of the Diagnostic Process: Question, Evidence Relation, Task Stack, Metarules, and Prosaic Condensation. When NEOMYCIN asked about seizures (question 8), the user selected a subitem in the KB WINDOWS menu, which caused the task stack—the current line of reasoning—to be displayed. The rule above a task is the metarule that invoked it; thus, rule 400 selected meningitis as a focus, invoking TEST-HYPOTHESIS with it as an argument. Selecting meningitis in this window caused the table in the lower left to be displayed. Here, boldface type indicates positive findings and successfully applied rules. Greyed areas correspond to negative findings and failed rules. Thus, the patient is not a neonate; rule 424 succeeded. Arrows preceding a finding indicate that the finding is in a triggering relation with the hypothesis. For example, the headache volunteered in the chief complaint caused the program to try to apply rule 424. When the user selected EXPLAIN in the menu adjacent to the consultation typescript, the program summarized the line of reasoning, skipping over “uninteresting” tasks.

**Heracles: From Diseases to Stereotypes**

In late 1983 I began to consider how NEOMYCIN might be generalized. What kinds of problems can be conveniently solved by an architecture consisting of a classification network and a separate, abstract control strategy? In particular, to what problems can the same diagnostic strategy be applied? It was obvious from the start that the procedure had nothing specifically to do with medicine; was it more general than diagnosis? In attempting to teach the NEOMYCIN approach to AI students, I found that it was possible to redescribe other knowledge bases in its terms. For example, in terms of the mapping between models of situation descriptions and selected solutions, “people are to diseases” as “meals are to wines.” I had also recently reread Rich’s work on user modeling (Rich 1979), intending to apply this to our explanation program. I recognized that it fit the same pattern—models of people related to a taxonomy of books. Finally, I recalled that Rubin (1975) and Aikins (1983) emphasized that diseases are described
Figure 16: Propositional Representation of a Metarule. This is one of six metarules for accomplishing the task PROCESS-FINDING, which is invoked whenever a new finding becomes known. The metarule detects that this finding is serious and has to be explained (a red-flag finding), or it's something that's not currently explained by the set of possibilities under consideration. The program gathers up the trigger rules—automatic inferences—and tries to apply them. The idea is that if the finding doesn't always have to be explained and it's explained by hypotheses that were already triggered, you shouldn't trigger a new hypothesis. For example, if the patient has a headache, and other evidence suggests meningitis, which would explain the headache, there's no need to consider other explanations of the headache. Intermediate relations, such as EXPLAINEDBY, are defined by other rules (simplified here). All pattern variables in these rules are instantiated as domain rules or terms. All expressions are implicitly universally quantified.

TASK: PROCESS-FINDING
FOCUS: $FINDING

Metarule

IF:  
(AND (OR (FINDINGTYPE $FINDING REDFLAG)  
           (NOT (DIFF.EXPLAINED $FINDING)))  
        (MAKESET (TRIGGERS? $FINDING $RULE)  
             RULELST))

THEN:(TASK APPLYRULES RULELST)

If the finding must always be explained or it is not currently explained by the differential, then trigger hypotheses that explain it.

Definitional relation rules

IF:  
(AND (DIFFERENTIAL $HYP)  
       (EXPLAINEDBY $FINDING $HYP))

THEN:(DIFF.EXPLAINED $FINDING)

A finding is explained by the differential if it's explained by some hypothesis in the differential.

IF:  
(OR (CAUSED-BY $F $SH)  
       (AND (TYPE $SH $PARENT)  
            (EXPLAINEDBY $F $PARENT)))

THEN:(EXPLAINEDBY $F $SH)

A finding is explained by a hypothesis if it is caused by the hypothesis or by some more general category.

Figure 17. How Control Knowledge is Encoded in HERACLES. HERACLES is implemented as a specialization of EMYCIN. Above is shown the original conception of domain parameters and rules. In HERACLES parameters are specialized as domain relations, control tasks, and domain terms, conditionally inferred and invoked by rules. We use "relation" in the mathematical sense to refer to both predicates and functions. "Finding" and "hypothesis" formally classify the domain terms (for example, meningitis), and informally are used to refer to propositions in a situation-specific model; so, we say that "the patient has meningitis" is a hypothesis.

Tasks are accomplished by an interpreter that applies metarules. Propositions used by metarule premises (such as (EXPLAINED-BY $F $SH) appearing in Figure 16), can be inferred definitionally by rules or can be inferred by procedural attachment (for example, accessing Lisp structures). These propositions are both static and dynamic. They classify domain propositions and domain rules, as well as characterizing the problem-solving state (such as whether a hypothesis is in the differential or whether a task has been done yet). Additional relations that classify tasks are used by the task interpreter (not shown here). Metarule actions apply domain rules, request (from the user) or conclude domain propositions, or invoke other tasks. In particular, the task FINDOUT uses all of these methods to infer domain propositions. In HERACLES all domain rules are applied directly by metarules rather than by back chaining. Only domain rules mention domain terms directly; other rules use variables.

THE AI MAGAZINE August, 1986 53
Figure 18. Overprinting a Classification Network to Show How it is Searched. Nodes blink and are boxed to make visible the "looking up" and "looking down" process of diagnosis. Numbers indicate the relative certainty of conclusions; the cumulative certainty factor (CUMCF) includes hierarchical propagation. Heavy-bordered boxes indicate the program's differential—the most specific cut through the taxonomy and causal network. The differential is printed in the lower right window with indenting to show specialization by process subtype and cause. When a hypothesis is selected, the evidence window can be displayed, indicating which findings and rules have been considered and the outcome of each consideration. Dozens of other windows are available, including different views of causal networks and the history of task invocation.

(in knowledge bases) as stereotypes. The general model of heuristic classification fell into place: Some problems can be solved by selection, heuristically relating a classification of problem data to a classification of known solutions (Clancey 1985a).

To my chagrin, this new model required a reconceptualization of parts of NEOMYCIN. We began to consider the diseases as stereotypes, we introduced qualitative abstraction of numeric data where it had been omitted in MYCIN, and we realized that our representation of diseases as classes is inadequate given what is required in general and what is evident in other programs (for example, allowing for multiple inheritance). We call the reconceptualized framework HERACLES. It is not a completed tool but an idea that continues to evolve.

Figure 19 illustrates the heuristic classification analysis of SACON, a program that many of us knew about and talked about for five or six years, but that few understood until its knowledge base was portrayed in this way. The purpose of SACON is to select a configuration of programs
in a structural analysis software package developed by the Marc Corporation. These programs can analyze an object for structural failure in many ways, some of which are unnecessarily accurate and time consuming. An expert can tell you which of the programs should be run to analyze a particular structure, and that is SACON's task. Imposing a type classification on SACON's concepts, and labeling inferences as abstractions, heuristics, and refinements, we find a previously hidden secondary structure which helps us to understand what SACON does.

Studying and generalizing knowledge-based programs, we can go quite a bit further. First, we can realize that as stereotypes the classifications are models of systems: specifications or descriptions of systems and plans for assembly or modification of systems. Second, the classification sequences, relating one model to another, are regular and limited in nature, constituting tasks. A model of system being monitored is related to a plan for controlling its behavior. A diagnostic model of a faulty system is related to a repair plan. A specification is related to a design and then to an assembly plan. Finally, the idea of systems, tasks, and common sequences is independent of how the solutions are computed each step along the way. Either heuristic classification or some constructive method (perhaps involving nonmonotonic reasoning, hypothetical worlds, and so on) might be used. It is important to remember that this inference structure shows the pattern of inferences that map given information to final solutions, and makes no claims about the process or order in which the inferences are made. Further examples and extensive discussion appear in (Clancey 1985a, 1986).

Caster: From Diseases to Abnormal Substances and Processes

In addition to the disorder taxonomy (Figure 11), a knowledge base for diagnostic problems constructed in HERACLES might include a causal-associational network. Disorders in this network are descriptions of internal states in the system being diagnosed. Figure 20 shows such a network for CASTER, a knowledge system for sand-casting diagnosis.

Tim Thompson and I (1986) developed this program in order to better understand the distinction between the pathophysiological states of the causal net and the etiologies, or final causes, of the disorder taxonomy. This distinction was emphasized in the CASNET program (Weiss et al. 1978); our interest was to apply the ideas to a nonmedical problem.

What did we learn from the CASTER experiment? First, for diagnosing malfunctions in some manufacturing process, it is useful to organize the disorder taxonomy according to each stage in the overall process (pattern design, melting, and so on). In contrast, the top level of NEOMYCIN's taxonomy corresponds to defects in the neurological system, viewing it as an object, not a process: assembly flaw (congenital), environmental influence (infection, toxicity, trauma, psychological load), or degeneration (vascular disorder, immunoresponse, muscular disorder). In both of these physical systems, externally observable manifestations are explained in terms of internal system behavior, tracked back to faulty structures and malfunctions of subsystems. These are in turn explained by the etiologies, processes in which the system interacted with its environment, bringing it to its current state. In medicine, these etiologies include congenital problems (caused by the mother's lifestyle or her environment), psychogenic problems (emotional overload), trauma (structurally damaging the body), toxic environment, and so on. In the human body, internal systems generate new subsystem structures, so developmental and degenerative processes are also important etiologies. We believe that this analysis can be generalized to cover all physical systems.

A second interesting result is the set of heuristics we discovered for constructing a well-formed causal network (Clancey 1984d). These heuristics include asking the expert about categories of states; asking about unobservable states that track back to different etiologies; distinguishing clearly between substances and processes, particularly, never causally linking substances directly; and working backward from repairs to causes. This last point emphasizes that the purpose of the causal-associational and etiologic taxonomy is to make choices about repair, a point I emphasized in The Disease Taxonomy: Searching an Abnormal Process Clarification. Uncertainty in diagnostic reasoning need only be resolved to the extent that it makes a difference in distinguishing among repairs.

Our heuristics can be viewed as criteria for critiquing a behavioral causal model. Can we formalize these constraints so that they can be taught to a student? Viewing a diagnosis as a model is the first step.

The Situation-Specific Model:
From a Diagnosis to an Explanation

This lesson might be the most important. It is the idea that a diagnosis is not the name of a disease but an argument which causally relates the manifestations which need to be explained (because they are abnormal) to the processes that brought them about (See Figure 21). A number of ideas come together here:

- Diseases are processes (see The Disease Taxonomy: Searching an Abnormal Process Classification and Caster: From Diseases to Abnormal Substances and Processes.) Thus, a diagnosis is a network causally linking manifestations and states to processes.
- A causal explanation applies the general concepts and links in a knowledge base to construct a case-specific model (Patil, Szolovits, & Schwartz 1981). Thus, the network linking manifestations and diseases is a model of a particular sequence of events in the world (also called a situation-specific model).
A causal explanation has the structure of a geometry proof: It must account for all of the findings and must be coherent and consistent. Thus, the situation-specific model must be a connected graph with one process at the root (assuming a single fault).

The evolution of these ideas is intriguing, revealing how our computational tools and the use of the computer as a modeling medium changes how we think. Sometime in 1985 it occurred to me that we could extend the windows offered by GUIDON-WATCH to include a graph showing how the final diagnosis related to the known findings. When I saw the way Anderson replaced a linear geometry proof by a graph (using the same Interlisp-D graphics package), the analogy between a causal explanation and a proof became concrete (Anderson, Boyle, & Yost 1985). Thus, the example from another domain showed how Patil's idea of a patient-specific model could be useful in teaching, and the availability of the graphics package encouraged us to create the picture to see what it would look like.

It is astounding to realize how many hundreds of expert systems are cranking out diagnoses with neither the programs nor their designers ever explicitly considering a diagnosis as a coherent causal model. They don't even check to see if all of the findings are covered by the final diagnosis. Our language is too loose: The program prints the name of a disorder, and we say, "The program has made a diagnosis." However, where is the explanation argument?

For the purpose of teaching, this graph could perhaps be the best way to reify the process of diagnosis. For several years, inspired by Brown's emphasis on "process versus product" (possibly derived from Dewey [1964]), I've been searching for some written notation that we could use, something analogous to algebra, to make visible what the operators of diagnosis (NEOMYCIN's tasks) are doing. The analogy with geometry turns out to be stronger than the analogy with algebra because each inference itself relies on a proof, analogous to the causal arguments behind each link of the situation-specific model. In algebra the inference rules are all axioms.

Giving this window to the student, we might have him carry out the diagnosis by posting his hypotheses and linking them to the known findings. Each step along the way, there are visible problems to be solved. The student can see that he is trying to construct a logically consistent network. Behind each request for data is an operation for making the network hang together—explaining the findings that need to be explained and refining the hypotheses that need to be made more specific. An instructional program is now being developed based on this idea. Called GUIDON-MANAGE, it has a student "manage" the diagnosis by explicitly applying strategic operators.

---

Diagnostic operators examine and modify the differential (most specific diseases under consideration), linking and refining them. Thus, HERACLES tasks are operators for constructing a situation-specific model (similar to ABEL's diagnostic operators (Patil, Szolovits, & Schwartz 1981)).

---

Figure 19. Inference Structure of SACON. An abstract description of inference chains is shown above a particular sequence of associations. SACON abstracts the given structure and relates this abstraction to half a dozen rules of thumb that make a quantitative prediction of the structure's behavior under stress. Specifically, the fact that the structure is a beam is combined with information about its size, support, and load distribution in order to select a numeric equation, which computes stress and deflection. These predictions are abstracted, and definitionally related to the structural analysis program. Specifically, the characterization of stress, combined with information about loading and error tolerance, is classified as a particular kind of "analysis" for which the program is specialized. The SACON program selects from about 30 different program combinations. This corresponds to the number of organisms in MYCIN, and is probably good to remember when considering whether the heuristic classification method is appropriate for solving a problem.
This is an amazing change. Ten years ago I thought I was trying to teach parameters and rules, and now I'm saying that I want to teach the student to be an efficient model builder. What can we tell the student that will help him critique the model that he's constructing? For example, we'll say, "All the important findings need to be explained." Observing that he has failed to do something that needs to be done, we'll tell him about the operators, so he can step back and say, "Well, what knowledge might I be missing that prevented me from carrying out that task?" So debugging by explanation of failure—proceeding from model constraints to operators to knowledge relations—is the approach we're following. This leads to an interesting model of learning (Clancey et al. 1986).

**Methodological Lessons**

To summarize ongoing projects mentioned or alluded to here, we are currently doing the following:

- Developing instructional programs based on NEOMY-CIN
- Studying learning in the setting of debugging a knowledge base
- Reimplementing the explanation program to use the logic encoding of the metarules (stating this program in the same task-metarule language so that it might reason about its own explanations)
- Generalizing our graphics package using object-oriented techniques
- Applying the student-modeling program, ODYSSEUS, to knowledge acquisition
- Preparing HERACLES for use by other people

I'm going to jump up a level here to consider some methodological lessons we can draw from this research.

Figure 1 provides a simplified summary of how the various programs and research ideas are connected. We observe two examples of a specific expert system being generalized, with the resulting shell used to construct other specific systems and a tutoring shell. Is there any logic in this sequence that might reveal something about learning in general or at least about how we learn by constructing programs?

In the section names in this article, I indicated the sequence of terminological changes ("from ... to . . .") that seem to mark each major change in my understanding.
Figure 21. Partial Diagnostic Model in NEOMYCIN. The process of diagnosis is the construction of a proof tree, relating the findings and disorders that could have caused these findings. At some intermediate state when solving the problem, the network is disconnected and partial. The patient has seizures; what could have caused that? There is some support for Acute Bacterial Meningitis and Increased Intracranial Pressure, but these two hypotheses haven’t been related. Is there some underlying cause (process) that could account for all of the manifestations? Diagnostic operators can be viewed as graph construction operators, focusing on particular nodes and trying to grow the graph down to support possible explanations or refining it upward to more specific explanations. A final situation-specific model is a connected network, with some root process that we say explains the internal states (such as Increased Intracranial Pressure), which, in turn, explain the observed findings. This graph, as an argument having the structure of a proof, is the diagnosis, not the term Acute Bacterial Meningitis.

The renaming that occurred in moving from “clinical parameter” to “model” is dramatic. None of the intermediate concepts (hypothesis, relation, process, and so on) is new, but it is interesting to note how they are retained and how they build upon one another as the knowledge structures are reinterpreted from different perspectives.

Thus, in HERACLES today, we have parameters, terms, hypotheses, diseases, processes, stereotypes, and models. All of these remain true descriptions of what’s in our program. The perspective changes, broadening from language terminology (parameters, terms) to reasoning phenomenology (hypotheses), domain ontology (disease process taxonomy); and, finally, epistemological distinctions (stereotypes, models). With the heuristic classification perspective at the top—couched in terms of systems, tasks, and models (Clancey 1986)—previous terminology is retained for describing the program at different levels.

Looking closely at the sequence of research itself, there are some clear patterns:

- Abstracting or generalizing terminology to incorporate another specific domain (for example, moving from disease to disorder process)
- Separating a domain model (what is “true”) from the inference process (what to do) by identifying and justifying procedural sequences (for example, defining relations for ordering MYCIN’s rule clauses and, later, defining relations for ordering NEOMYCIN’s metarules)
- Justifying domain relations in terms of underlying constraints and patterns (for example, a theory for generating appropriate follow-up questions or trigger rules or a theory for generating a causal network in terms of faulty structures and malfunctions)

Figure 22 summarizes the overall pattern. The point of the analysis phase is to detect patterns that we want to
model explicitly and that have been mapped into the language in an implicit and perhaps undisciplined way. Thus, findings and hypotheses, causality and subtype, and disease knowledge and procedures are not distinguished in MYCIN. Findings and hypotheses are both represented as parameters. Cause and subtype are represented by sequences of clauses in rules, or in the relation between a parameter and its values (for example, parameter—"the kind of Meningitis"; value—"Bacterial"). Focusing procedures are also encoded by rule clause ordering.

There is apparently no end to this criticism; the same game can be played with NEOMYCIN. For example, in attempting to improve the explanation program we find that the use of terms in NEOMYCIN’s original metarules is ludicrously undisciplined; they are used like arbitrary program variables, with no apparent connection between $SHYP and $CURFOCUS. Interpreting this representation for diagnosis causes no difficulties, but the explanation program needs to know that the metarules refer to the same kind of entity, a hypothesis.

This analysis suggests that detecting patterns of statements in some language, articulating a new classification model, and defining a new procedure by which the statements are to be interpreted are intricately related. Recalling the analysis of metarules (MRS/NEOMYCIN: From Findings and Hypotheses to Relations), we observe that each new purpose for interpreting a representation requires new distinctions—new relations—to classify existing domain terms, rules, and relations among them. Thus, the compiler needs to know which domain relations are predicates and which are functions (in the mathematical sense). ODYSSEUS needs to know when metarules can be reordered. The teaching program needs to know why metarules are ordered a certain way. In classifying relations and terms, we are constantly asking, “Which things can be procedurally operated upon in the same way?”

Winograd reached the same conclusion in his analysis of how language arises. The need to take action reorients us to the world, forcing us to make new distinctions. The relevant properties attributed to an object are determined by the role the object plays in an action: “This grounding of description in action pervades all attempts to formalize the world into a linguistic structure of objects, properties, and events” (Winograd & Flores 1986). Indeed, by this analysis the world and its objects exist only in language, mediated by action.

The expert system methodology of writing down knowledge in some structured way so that it can later be studied and better formalized is a remarkable, exciting turning point in epistemological practice. We try to understand why a relation holds by abstracting it and then trying to find similar relations in the knowledge base. If a pattern holds, we restate everything more abstractly. Why is it correct to say that “broken mold” causes “inadequate feeding”? What other causal links in the network connect the same kind of concepts, leaving out the same kind of details? Do all links in the network connect structures to functions? Is there any reason why they should?

Having written a model down, the most powerful tools

THE AI MAGAZINE August, 1986 59
of language come into play:
- It is possible to reflect on what was said, to ask why it is true, to develop a better understanding or theory.
- An incremental critique and transformation process becomes possible—the best way to build anything so that it is reliable and useful (Petroski 1985).

Computational languages provide a way of writing things down so that the model is executable, the very thing we need for modeling processes. AI research is exploring how to model physical, inferential, communicative, motoric, and perceptual processes using qualitative (principally nonnumeric, relational) representations (Clancey 1986). Graphics provide a medium for visualizing processes, so we can understand the complexity of the systems we construct (Hollan, Hutchins, & Weitzman 1984; Clancey 1983c, Richer & Clancey 1985) and even start to ask new questions as icons and graphs become part of our language for stating theories. The marriage of qualitative modeling and graphics in the 1980s, made available on cheaper, more powerful machines, provides a sharp stimulus to AI research and a good reason to be optimistic about the progress to come.

Acknowledgements
This article was prepared as a final ONR technical report for the period 1979-1985. The GUIDON project was first funded jointly by Marshall Farr at ONR and Dexter Fletcher at DARPA. Other tutoring programs in the ONR/ARPA family at that time included WHY, WEST, and SOPHIE. Avron Barr, John Seely Brown, Ira Goldstein, and Keith Wescourt helped us to define the initial proposal, conveying the problems and methods then current in the research community. Bruce Buchanan was principal investigator, shaping the clarity and style of the first proposal and continuing today to serve as advisor on the project.

I sincerely thank the students and programmers who have made so many significant contributions to the NEOMYCIN and HERACLES programs (chronologically): Reed Letsinger, Bob London, Conrad Bock, Diane Warner Hasing, David Wilkins, Glenn Rennels, Mark Richer, Tim Thompson, Steve Barnhouse, Arif Merchant, David Leserman, and Naomi Rodolitz. Victor Yu, M.D. helped me understand MYCIN in the early years. I am especially grateful to the late Tim Beckett, M.D. for showing me what a good physician teacher can do. Curt Kasper, M.D., John Macias, and Bevan Yueh have enthusiastically collaborated in our recent work.

The project was funded jointly by ONR and the Army Research Institute during the period 1981-1985 (ONR contract N00014-79C-0302). Computational resources have been provided by the Sumex-Aim National Resource (NIH grant RR00785). Organization and maintenance of computer resources in the Knowledge Systems Laboratory is managed by Tom Rindfleisch. Continuing research is supported in part by ONR contract N00014-85-K-0035 and by a grant from the Josiah Macy, Jr. Foundation.

This paper is based on a talk I gave at the Computer Science Colloquium at Carnegie-Mellon University on 19 November 1985. I thank David Evans for arranging to have the talk taped and Rene Bornstein for her accurate transcription. Many useful revisions were suggested by Steve Barnhouse, Ted Crowello, Bob Engelmore, and Mark Richer. Special thanks to Susan King for typing the final copy.

References

Continued on Page 187.
Clancey, continued from page 60


THE AI MAGAZINE August, 1986 187
Dr. Robert Carroll
OP 01B
Washington, DC 20370

LCDR Robert Carter
Office of the Chief of Naval Operations
OP-01B
Pentagon
Washington, DC 20350-2000

Dr. Fred Chang
Navy Personnel R&D Center
Code 51
San Diego, CA 92152-6800

Dr. Alphonse Chapin
University of Pittsburgh
Pittsburgh, PA 15213

Dr. Eugene Charniak
Brown University
Computer Science Department
Providence, RI 02912

Dr. Paul R. Chatelier
OUSDRE
Pentagon
Washington, DC 20350-2000

Dr. Micheline Chi
Learning R & D Center
University of Pittsburgh
3919 O’Hara Street
Pittsburgh, PA 15213

Mr. Raymond E. Cristal
AFHRL/HOE
Brooks AFB, TX 78235

Dr. Yee-Yeen Chu
Perceptronics, Inc.
21111 Erwin Street
Woodland Hills, CA 91367-371

Dr. William Clancey
Stanford University
Knowledge Systems Laboratory
101 Welch Road, Bldg. C
Palo Alto, CA 94304

Chief of Naval Education and Training
Liaison Office
Air Force Human Resource Lab
Operations Training Division
Williams AFB, AZ 85224

Assistant Chief of Staff for Research, Development, Test, and Evaluation
Naval Education and Training Command (N-5)
NAS Pensacola, FL 32508

Dr. Allan M. Collins
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

Dr. John J. Collins
Director, Field Research Office
Office, Orlando
NPRDC Liaison Officer
NTSC Orlando, FL 32811

Dr. Stanley Collyer
Office of Naval Technology
Code 222
800 N. Quincy Street
Arlington, VA 22217-5000

Dr. Lynn A. Cooper
Learning R&D Center
University of Pittsburgh
3919 O’Hara Street
Pittsburgh, PA 15213

Dr. Meredith P. Crawford
American Psychological Association
Office of Educational Affairs
1200 17th Street, N.W.
Washington, DC 20036

Dr. Hans Crombag
University of Leyden
Education Research Center
Boerhaavelaan 2
2334 EN Leyden
The NETHERLANDS

LT Judy Crookshanks
Chief of Naval Operations
OP-112G
Washington, DC 20370-2000

Dr. Kenneth B. Cross
Anacapa Sciences, Inc.
P.O. Drawer Q
Santa Barbara, CA 93102

Dr. Mary Cross
Department of Education
Adult Literacy Initiative
Room 4145
400 Maryland Avenue, SW
Washington, DC 20202

CTB/McGraw-Hill Library
2500 Garden Road
Monterey, CA 93940

CAPT P. Michael Curran
Office of Naval Research
800 N. Quincy St.
Code 125
Arlington, VA 22217-5000

Dr. Cary Czichon
Intelligent Instructional Systems
Texas Instruments AI Lab
P.O. Box 660245
Dallas, TX 75266

Bryan Dallman
AFHRL/LRT
Lowry AFB, CO 80230

LT John Deaton
ONR Code 125
800 N. Quincy Street
Arlington, VA 22217-5000

Dr. Natalie Deaton
Department of Computer and Information Sciences
University of Oregon
Eugene, OR 97403

Dr. Gerald F. De Jong
Artificial Intelligence Group
Coordinated Science Laboratory
University of Illinois
Urbana, IL 61801

Goery Delacote
Directeur de L’informatique et Technologie Scientifique et Technique
CNRS
15, Quai Anatole France
75700 Paris FRANCE

Mr. Robert Denton
AFMPC/MCYP
Randolph AFB, TX 78150

Mr. Paul DiRienzo
Commandant of the Marine Corps
Code LBC-4
Washington, DC 20380

Dr. R. K. Dismukes
Associate Director for Life Sciences
AFOSR
Bolling AFB
Washington, DC 20332

Defence Technical Information Center
Cameron Station, Bldg 5
Alexandria, VA 22314
Attn: TC
(12 Copies)

Dr. Thomas M. Duffy
Communications Design Center
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Barbara Eason
Military Educator’s Resource Network
InterAmerican Research Associates
1555 Wilson Blvd
Arlington, VA 22209

Edward E. Eddowes
CNATRA N301
Naval Air Station
Corpus Christi, TX 78419

Dr. John Ellis
Navy Personnel R&D Center
San Diego, CA 92252

Dr. Richard Elster
Deputy Assistant Secretary of the Navy (Manpower)
OASN (M&RA)
Department of the Navy
Washington, DC 20350-1000

Dr. Susan Embretson
University of Kansas
Psychology Department
426 Fraser
Lawrence, KS 66045

Dr. Randy Engel
Department of Psychology
University of South Carolina
Columbia, SC 29208

Lt. Col Rich Entlich
HQ, Department of the Army
OCSA(DACS-DPM)
Washington, DC 20310

Dr. Susan Epstein
Hunter College
144 S. Mountain Avenue
Montclair, NJ 07042
Dr. Mazie Knerr
Program Manager
Training Research Division
HUMRRO
1100 S. Washington
Alexandria, VA 22314

Dr. Janet L. Kolodner
Georgia Institute of Technology
School of Information & Computer Science
Atlanta, GA 30332

Dr. Stephen Kosslyn
Harvard University
1236 William James Hall
33 Kirkland St.
Cambridge, MA 02138

Dr. Kenneth Kotovsky
Department of Psychology
Community College of Allegheny County
800 Allegheny Avenue
Pittsburgh, PA 15233

Dr. David M. Krantz
2 Washington Square Village
Apt. # 15J
New York, NY 10012

Dr. Benjamin Kuipers
University of Texas at Austin
Department of Computer Science
T.S. Painter Hall 3.28
Austin, Texas 78712

Dr. David R. Lambert
Naval Ocean Systems Center
Code 441T
271 Catalina Boulevard
San Diego, CA 92152-6800

Dr. Pat Langley
University of California
Department of Information and Computer Science
Irvine, CA 92717

M. Diane Langston
Communications Design Center
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Dr. Jill Larkin
Carnegie-Mellon University
Department of Psychology
Pittsburgh, PA 15213

Dr. Robert Lavler
Information Sciences, FRL
GTE Laboratories, Inc.
40 Sylvan Road
Waltham, MA 02254

Dr. Paul E. Lehner
PAR Technology Corp.
7926 Jones Branch Drive
Suite 170
McLean, VA 22102

Dr. Alan M. Lesgold
Learning & R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Dr. Alan Lesher
Deputy Division Director
Behavioral and Neural Sciences
National Science Foundation
1800 G Street
Washington, DC 20550

Dr. Jim Levin
University of California
Laboratory for Comparative Human Cognition
D003A
La Jolla, CA 92039

Dr. John Levine
Learning & R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Dr. Michael Levine
Educational Psychology
210 Education Bldg.
University of Illinois
Champaign, IL 61801

Dr. Charles Lewis
Faculteit Sociale Wetenschappen
Rijksuniversiteit Groningen
Oude Boteringestraat 23
9712GC Groningen
The NETHERLANDS

Dr. Clayton Lewis
University of Colorado
Department of Computer Science
Campus Box 430
Boulder, CO 80309

Library
Naval War College
Newport, RI 02840

Library
Naval Training Systems Center
Orlando, FL 32813

Dr. Charlotte Linde
SRI International
333 Ravenswood Avenue
Menlo Park, CA 94025

Dr. Marcia C. Linn
Lawrence Hall of Science
University of California
Berkeley, CA 94720

Dr. Robert Linn
College of Education
University of Illinois
Urbana, IL 61801

Dr. Don Lyon
P. O. Box 44
Higley, AZ 85236

Dr. Jane Malin
Mail Code SR 111
NASA Johnson Space Center
Houston, TX 77058

Dr. William L. Maloy
Chief of Naval Education and Training
Naval Air Station
Pensacola, FL 32508

Dr. Sandra P. Marshall
Dept. of Psychology
San Diego State University
San Diego, CA 92182

Dr. Manton M. Matthews
Department of Computer Science
University of South Carolina
Columbia, SC 29208

Dr. Richard E. Mayer
Department of Psychology
University of California
Santa Barbara, CA 93106

Dr. James McBride
Psychological Corporation
c/o Harcourt, Brace, & Jovanovich Inc.
1250 West 6th Street
San Diego, CA 92101

Dr. David J. McGuinness
Gallaudet College
800 Florida Avenue, N.E.
Washington, DC 20002

Dr. Kathleen McKeown
Columbia University
Department of Computer Science
New York, NY 10027

Dr. Joe McLachlan
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. James McMichael
Assistant for MPT Research, Development, and Studies
OP 0187
Washington, DC 20370

Dr. Barbara Means
Human Resources Research Organization
1100 South Washington
Alexandria, VA 22314

Dr. Douglas L. Medin
Department of Psychology
University of Illinois
603 E. Daniel Street
Champaign, IL 61820

Dr. Arthur Meltzer
U.S. Department of Education
724 15th Street
Washington, DC 20208

Dr. Jose Mestre
Department of Physics
Harbor Lab Government Laboratory
University of Massachusetts
Amherst, MA 01003

Dr. Al Meyrowitz
Office of Naval Research
Code 1133
800 N. Quincy
Arlington, VA 22217-5000

Dr. Ryszard Michalski
University of Illinois
Department of Computer Science
1304 West Springfield Avenue
Urbana, IL 61801

Prof. D. Michie
The Turing Institute
36 North Hanover Street
Glasgow G1 2AD, Scotland
UNITED KINGDOM

Dr. George A. Miller
Department of Psychology
Green Hall
Princeton University
Princeton, NJ 08540
Dr. W. Steve Sellman
OASD(NRI&L)
2B269 The Pentagon
Washington, DC 20301

Dr. Sylvia A. S. Shafto
OEIR
555 New Jersey Ave., NW
Washington, DC 20208

Dr. T. B. Sheridan
Dept. of Mechanical Engineering
MIT
Cambridge, MA 02139

Dr. Ben Shneiderman
Dept. of Computer Science
University of Maryland
College Park, MD 20742

Dr. Ted Shortliffe
Computer Science Department
Stanford University
Stanford, CA 94305

Dr. Lee Shulman
Stanford University
1040 Cathcart Way
Stanford, CA 94305

Dr. Randall Shumaker
Naval Research Laboratory
Code 7510
4555 Overlook Avenue, S.W.
Washington, DC 20375-5000

Dr. Robert S. Siegler
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr. Herbert A. Simon
Department of Psychology
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

LTCOL Robert Simpson
Defense Advanced Research Projects Administration
1400 Wilson Blvd.
Arlington, VA 22209

Dr. Zita M Simutis
Instructional Technology
Systems Area
ARI
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. H. Wallace Sinaiko
Manpower Research and Advisory Services
Smithsonian Institution
801 North Pitt Street
Alexandria, VA 22314

Dr. Derek Sleeman
Stanford University
School of Education
Stanford, CA 94305

Dr. Charles F. Smith
North Carolina State University
Department of Statistics
Raleigh, NC 27695-8703

Dr. Edward E. Smith
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

Dr. Linda B. Smith
Department of Psychology
Indiana University
Bloomington, IN 47405

Dr. Alfred F. Smode
Senior Scientist
Code O7A
Naval Training Systems Center
Orlando, FL 32813

Dr. Richard E. Snow
Department of Psychology
Stanford University
Stanford, CA 94306

Dr. Elliot Soloway
Yale University
Computer Science Department
P.O. Box 2158
New Haven, CT 06520

Dr. Richard Sorensen
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Kathryn T. Sproehr
Brown University
Department of Psychology
Providence, RI 02912

James J. Staszewski
Research Associate
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr. Marian Stearns
SRI International
333 Ravenswood Ave.
Room B-S324
Menlo Park, CA 94025

Dr. Robert Sternberg
Department of Psychology
Yale University
Box 11A, Yale Station
New Haven, CT 06520

Dr. Albert Stevens
Bolt Beranek & Newman, Inc.
10 Moulton St.
Cambridge, MA 02238

Dr. Paul J. Sticha
Senior Staff Scientist
Training Research Division
HumMRRO
1100 S. Washington
Alexandria, VA 22314

Dr. Thomas Sticht
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. David Stone
KAI Software, Inc.
3420 East Shea Blvd.
Suite 161
Phoenix, AZ 85028

Cdr Michael Suman, PD 303
Naval Training Systems Center
Code NS1. Comptroller
Orlando, FL 32813

Dr. Hariharan Swaminathan
Laboratory of Psychometric & Evaluation Research
School of Education
University of Massachusetts
Amherst, MA 01003

Mr. Brad Symson
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. John Tangney
AFOSR/NL
Bolling AFB, DC 20332

Dr. Kikumi Tatsuoka
CERL
252 Engineering Research Laboratory
Urbana, IL 61801

Dr. Martin M. Taylor
DCIM
Box 2000
Downsvi, Ontario CANADA

Dr. Perry W. Thorndyke
FMC Corporation
Central Engineering Labs
1185 Coleman Avenue, Box 580
Santa Clara, CA 95052

Major Jack Thorpe
DARPA
1400 Wilson Blvd.
Arlington, VA 22209

Dr. Douglas Towne
Behavioral Technology Labs
1845 S. Elena Ave.
Redondo Beach, CA 90277

Dr. Amos Tversky
Stanford University
Dept. of Psychology
Stanford, CA 94305

Dr. James Tweeddale
Technical Director
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Paul Twohig
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Headquarters, U. S. Marine Corps
Code MIP-20
Washington, DC 20380

Dr. Kurt Van Lehn
Department of Psychology
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Dr. Beth Warren
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

Dr. David J. Weiss
N660 Elliott Hall
University of Minnesota
75 E. River Road
Minneapolis, MN 55455

Roger Weissinger-Baylon
Department of Administrative Sciences
Naval Postgraduate School
Monterey, CA 93940

Dr. Donald Wattman
MITRE
1820 Dolley Madison Blvd.
MacLean, VA 22102
Dr. Keith T. Wescourt
FMC Corporation
Central Engineering Labs
1185 Coleman Ave., Box 580
Santa Clara, CA 95052

Dr. Joseph L. Young
Memory & Cognitive Processes
National Science Foundation
Washington, DC 20550

Dr. Douglas Wetzel
Code 12
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Steven Zornetzer
Office of Naval Research
Code 1140
800 N. Quincy St.
Arlington, VA 22217-5000

Dr. Barbara White
Bolt Beranek & Newman, Inc.
10 Moulton Street
Cambridge, MA 02238

Dr. Michael J. Zyda
Naval Postgraduate School
Code 52CK
Monterey, CA 93943-5100

Dr. Hilda Wing
Army Research Institute
5001 Eisenhower Ave.
Alexandria, VA 22333

A. E. Winterbauer
Research Associate
Electronics Division
Denver Research Institute
University Park
Denver, CO 80208-0454

Dr. Robert A. Wisher
U.S. Army Institute for the Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Martin F. Wiskoff
Navy Personnel R & D Center
San Diego, CA 92152-6800

Dr. Merlin C. Wittrock
Graduate School of Education
UCLA
Los Angeles, CA 90024

Mr. John H. Wolfe
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Wallace Wulfeck, III
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Joe Yasatuke
AFHRL/LAT
Lowry AFB, CO 80230

Dr. Masoud Yazdani
Dept. of Computer Science
University of Exeter
Exeter EX4 4QL
Devon, ENGLAND

Major Frank Yohannan, USMC
Headquarters, Marine Corps
(Code MPI-20)
Washington, DC 20380

Mr. Carl York
System Development Foundation
101 Lytton Avenue
Suite 210
Palo Alto, CA 94301
END
Feb.
1988
DTIC