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This thesis describes a rule-based problem-solving system, termed MYCIN, which is designed to assist physicians with the selection of appropriate therapy for patients with bacterial infections. After a brief survey of medical computing, with an emphasis on computer-based medical decision making, the report describes the clinical problem and the design considerations necessary for a consultation program to gain acceptance by the physicians for whom it is intended. The three system components are then described in detail: 1) a Consultation System which interacts with the (conti

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physician and gives therapeutic advice, 2) an Explanation System which seeks to justify the program's advice, and 3) a Rule-Acquisition System which accepts rules from experts and codes them for use during future consultation sessions. MYCIN's quantitative model of inexact reasoning in medicine is also described in detail, and the results of an evaluation study comparing MYCIN's advice to that of experts are presented. The report closes with speculations regarding future extensions and applications of a system such as MYCIN and with a discussion of the program's contributions to medical decision making and artificial intelligence.

STANFORD ARTIFICIAL INTELLIGENCE LABORATORY
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MYCIN:
A Rule-Based Computer Program For Advising Physicians Regarding Antimicrobial Therapy Selection

Edward Hance Shortliffe

Abstract:

This thesis describes a rule-based problem-solving system, termed MYCIN, which is designed to assist physicians with the selection of appropriate therapy for patients with bacterial infections. After a brief survey of medical computing, with an emphasis on computer-based medical decision making, the report describes the clinical problem and the design considerations necessary for a consultation program to gain acceptance by the physicians for whom it is intended. The three system components are then described in detail: 1) a Consultation System which interacts with the physician and gives therapeutic advice, 2) an Explanation System which seeks to justify the program's advice, and 3) a Rule-Acquisition System which accepts rules from experts and codes them for use during future consultation sessions. MYCIN's advice to that of experts are presented. The report closes with speculations regarding future extensions and applications of a system such as MYCIN and with a discussion of the pogram's contributions to medical decision making and artificial intelligence.

A dissertation submitted to the Committee on Graduate Studies of Stanford University in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Medical Information Sciences.

This research was supported in part by the Advanced Research Projects Agency of the Office of the Secretary of Defense under contract [DAHC04-72-C-0008].

FOREWORD

Portions of this work have already been presented in papers in Computers And Biomedical Research <Shortliffe - 1973,1974b>, Mathematical Biosciences <Shortliffe - 1974c>, and the Proceedings Of The Thirteenth San Diego Biomedical Symposium <Shortliffe - 1974a>.

This work was supported in part by the Medical Scientist Training Program under NIH Grant No. GM-01922. The computer time was provided by Stanford Research Institute under Advanced Research Projects Agency (ARPA) contract DAHC04-72-C-0008, and by the Stanford University Artificial Intelligence Project. Secretarial and copying services were provided at Stanford University School Of Medicine under BHSRE Grant No. HS-00739.

ACKNOWLEDGMENTS

The work described in these pages would still be in its infancy if it were not for the active participation and advice of several individuals. Particularly important has been a close association with the physicians and computer scientists who have met with me once a week throughout the last two years.

Stanley Cohen has regularly provided invaluable contributions at these collaborative sessions, and he also was the first person at Stanford to encourage me to extend my time in medical school in order to undertake the present research. In addition he has served as my principal thesis adviser. I am grateful for the time he has contributed and for his help and guidance.

Another active participant at the weekly sessions, Bruce Buchanan, has provided computer science expertise, a philosopher's outlook, and insightful observations without which the project might well have floundered. The analysis in Chapter 5 is largely a product of readings he suggested and several meetings during which he and I discussed the philosophical issues involved.

I am also grateful to Stanton Axline for his participation in the evolution of MYCIN. He has provided the infectious disease expertise needed for the development of the program's knowledge base and has also suggested several design characteristics that have been implemented to heighten the system's acceptability to physicians.

Within the last year an additional researcher, Randy Davis, has joined the project. Our many conversations have proved invaluable, particularly because he

encouraged me to search for ways to generalize MYCIN's problem-solving approach. I am grateful to Randy for his assistance and for his many new ideas that have helped us improve MYCIN's design and performance.

Several other physicians have assisted us during the two year development period. The project was conceived during early idea sessions at which Thomas Merigan was an active participant, and Gilbert Hunn met regularly with us during the first year. I am also grateful to Michael Podlone and Robert Illa for their assistance testing the program on sample patient cases and for their suggestions regarding its performance. In addition I would like to thank Frank Rhame, Patrick Goodall, Richard Greenman, and Michael Charney for joining with Dr. Merigan to assist with the evaluation study described in Chapter 7.

Most of the computer time used for the development of MYCIN was generously contributed by Stanford Research Institute. I am grateful for the advice and assistance of Bertram Raphael, Peter Hart, Richard Waldinger, Nils Nilsson, and Richard Fikes, all of whom are associated with SRI.

In addition to Dr. Cohen, I would like to thank the members of my doctoral committee who have suggested both academic and research directions appropriate for my interdisciplinary interest: Prof. George Forsythe (Computer Science - deceased), Prof. Byron Brown (Biostatistics), Prof. Patrick Suppes (Philosophy), Dr. Howard Sussman (Pathology), and Prof. Cordell Green (Computer Science).

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I want to close with three special acknowledgements: to Bob Greenes for his friendship and for his encouragement regarding a career combining computers

and medicine, to G. Octo Barnett for his similar encouragement and for suggesting Stanford as an appropriate medical school for someone desiring to combine the two fields, and to my wife Linda, who somehow managed to adjust to our strange and often incompatible schedules, even when I and my computer terminal tied up the home phone lines for hours at a time.

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I. A GUIDE TO THE READER

The subject of this report is a computer-based system, termed MYCIN, which has been designed to assist physicians with clinical decision making. The program utilizes computer techniques derived principally from the subfield of computer science known as Artificial Intelligence (AI). MYCIN's task is to assist with analysis of the decisions involved in the selection of appropriate therapy for patients with infections.

Since the program contains considerable medical expertise and is also a novel application of computing technology, this thesis must necessarily be addressed both to the medical community, where individuals may have limited computer science backgrounds, and to computer scientists, whose knowledge of medical computing and clinical medicine may be similarly abridged. Several sections of this communication may be of interest more to one community than to the other. In this section I therefore present a guide so that the reader may select those portions of the thesis most pertinent to his interests and background.

The thesis is divided into nine chapters, each named with an arabic numeral and divided into sections, specified by Roman numeral designations. Subsections are named by the section numeral followed by one or more arabic designations (e.g., II.1, I.3, IV.2.1, etc., where II.2.1 is the first subdivision of subsection II.2). Chapter, section, or subsection designations that are followed by a single asterisk (*) may be skipped without sacrificing an

understanding of the MYCIN System. These parts of the thesis are detailed explanations of system components at a level that may not appeal to the reader who has more general interests. Sections followed by double asterisks (**) are summaries of subject matter that may be skipped by a reader who feels well-acquainted with the topic of that subdivision.

Figures in the thesis are numbered consecutively within chapters and their names are preceded with the chapter number. Thus Figure 4-8 is the eighth Figure in Chapter 4. Footnotes are used only in Chapter 5. They are specified with consecutively numbered titles of the form FN#. The footnote itself is generally placed immediately after the paragraph in which it is referenced rather than at the bottom of the page.

Reference citations are enclosed in angle brackets (e.g., '<author - 1974>') and include the name of the first author plus the year of publication. When the author published more than one referenced article in a single year, a lower-case letter is appended to the date. This letter corresponds to the way in which the reference is listed in the alphabetized bibliography at the end of the thesis. Use of the first author's name, even in cases where a reference has only two authors, is for brevity and simplicity. No reflection on the contributions of co-authors is intended.

A final point should be made regarding the use of the male pronoun to refer to physicians and patients throughout this thesis. I have decided to follow convention rather than inject awkwardness in an effort to recognize both sexes. It therefore seems wise to stress from the outset that, although such a convention is less than ideal, 'he', 'him', and 'his' are meant to be interpreted without any gender association.

The remainder of this chapter provides an introduction to the fields of medical computing, artificial intelligence, and the clinical problem area for which the MYCIN program has been designed. It concludes with an introductory overview of MYCIN and a sample interactive session which should prepare the reader for the more detailed discussions in subsequent chapters.

Chapter 2 discusses prior work involving computer applications to medical decision making. It begins with descriptions of the more traditional statistical approaches and concludes by concentrating upon some recent programs that have begun to use artificial intelligence techniques.

Chapter 3 presents the design criteria that were considered during MYCIN's development. Acceptability to physicians is emphasized here, and the chapter closes with a brief discussion of how MYCIN attempts to satisfy the criteria.

Chapter 4 describes in detail how the MYCIN program makes decisions. The data structures and control structures are discussed in the context of prior work regarding rule-based problem-solving. Certain subsections of this chapter have been isolated and marked with an asterisk so that non-computer scientists can read the more descriptive information without becoming overly immersed in the details of implementation.

Chapter 5 is a somewhat separate topic from the rest of the thesis and has therefore been written to be self-contained. A reader whose primary interest is in MYCIN's truth model may concentrate on Chapter 5 without needing to refer to other parts of the thesis for clarification of details.

The subject of Chapter 6 is MYCIN's ability to answer questions regarding both its knowledge base and the details of a specific consultation. The nature of the program's dictionary and MYCIN's strategies for understanding natural language are described in detail.

Chapter 7 describes the results of a study undertaken in order to evaluate the program's decision making performance. The methodology and control procedures

used are discussed in conjunction with the study's results.

Chapter 8 introduces the several plans for future extensions of the MYCIN program. These include immediate plans for working on knowledge acquisition procedures, and eventual implementation of the program as one module in a total Hospital Information System.

Finally Chapter 9 summarizes the program's accomplishments to date and discusses MYCIN's contributions to the fields of computer-based medical decision making and artificial intelligence.

II. COMPUTER APPLICATIONS IN MEDICINE

II.1 An Overview Of The Problems And Promise

In the late 1960's David Rutstein wrote a monograph entitled The Coming Revolution In Medicine <Rutstein - 1967>. His analysis was based on the observation of several serious problems for the health professions:

1) modern medicine's skyrocketing costs;

2) the chaos of an information explosion involving both paperwork proliferation and large amounts of new knowledge that no single physician could hope to digest;

3) a geographic maldistribution of MD's;

4) increasing demands on the physician's time as increasing numbers of individuals began to demand quality medical care.

Rutstein concluded that technology provided a reasonable partial solution to several of these problem areas.

In subsequent years technology has indeed increased its influence in the medical sphere, but the problems listed above are still highly visible. Their ultimate solutions will undoubtedly involve a long process, only portions of which can be accomplished by technological innovation alone. Equally important are appropriate supportive legislation, at both state and federal levels, plus a gradual change in the attitudes of health personnel towards their training, their professional duties, and the technological environment that will increasingly

surround them.

The attitudes of health personnel towards computers provide some of the greatest barriers to successful implementation of computer-based systems. A recent study <Startsman - 1972> used an open-ended questionnaire and factor analysis to provide information concerning the optimal interfacing of a computer-based information system with a medical staff. Results indicated that interns, nurses, and ancillary personnel expressed the least willingness to use data processing systems, while medical faculty, pre-clinical medical students, and medical record librarian students were most receptive. Although acknowledging that house staff attitudes may reflect the fast-paced environment in which preoccupation with the immediate physical needs of the patient is the norm, the authors point out that interns and residents comprise precisely the group for which many clinical computing systems should be oriented. Thus, since the study showed that familiarity with computers tends to dispel fears and breed interest, the authors suggest that health personnel should be exposed to data processing techniques during their educational years when they are apt to be most receptive to these kinds of innovation.

The most commonly expressed fears regarding computer applications in medicine involve loss of job (or job stature) due to 'replacement' by a computer, and presumed depersonalization of patient care due to machine intervention. In addition, some physicians are concerned about the legal ramifications in the use of, or failure to use, a computer-based facility <Hall - 1972>. Computers appear remarkably cold and sterile, particularly to individuals unfamiliar with their capabilities and limitations. One commonly finds references to a computer's lack of humanity:

> No one has yet programmed a computer to be of two minds about a hard problem, or to burst out laughing, ... but that may come. <Thomas - 1973>

'Scare' articles in professional journals also help reinforce attitudes of distrust <Eisenberg - 1974>.

A group at Duke University Medical School has suggested that the key to physician acceptance of computer technology lies in a "practical demonstration that physicians or groups of physicians using (computers) have a clear advantage in practice over physicians who maintain the status quo" <Rosati - 1973>. Applications that can make such a demonstration convincingly, however, are difficult to imagine. Norms of practice already vary considerably, even within close geographic proximity, and mechanisms for measuring one clinician's 'advantage' over another's have so far tended to emphasize economic considerations (e.g., length-of-stay and utilization review as a primary method for medical audit and quality assessment).

The subject of economics also raises important questions regarding the cost of medical computing, another major impediment to acceptance of the technological innovation. Difficulty in quantifying the dollar-value of improved patient care quality has understandably frustrated economists who have tried to apply conventional theory to the unique medical marketplace. As a result, there are now specialists in medical economics who have proposed new conventions and analytical tools for considering questions of cost effectiveness and resource allocation within health care environments <Klarman - 1965>. The basic problem remains unsolved despite these efforts. One of the first questions a hospital administrator asks when a computer system is proposed is how much it will cost. It is seldom easy to justify such systems as cost effective because the savings are buried in reduced length-of-stay data, in lowered lab or pharmacy charges for the patient, in 'improved patient care', or in similar real but imprecise monetary measurements.

Finally, many computer innovations are proposed as time saving techniques for the physician. In an age when a doctor shortage and maldistribution is well recognized <Fein - 1967>, such arguments can be highly compelling. By inference, however, any computer program that saves physician time must be doing a task that previously was done by the physician himself. The complex psychological and ethical issues involved here, both for the physician and the patient, will be discussed in greater detail when we describe computer-based clinical decision making in Chapter 2.

II.2 (**) An Overview Of Medical Computing Application Areas

The discussion in Section II.1 does not specify which computer applications are relevant to each point because almost all medical computing systems entail similar philosophical, ethical, and economic considerations. In this subsection I briefly describe the major areas of medical computing service and research. The categories are my own, and may therefore be non-exhaustive, but they should serve to give the reader a general feeling for the ways in which the so-called 'computer revolution' is affecting the administration and the practice of medicine. Notable general references on the subject of computer applications in medicine are Lindberg's volume from the University of Missouri <Lindberg - 1968>, a comprehensive survey of medical computing in England <Abrams - 1970>, a four-volume continuing series that summarizes some of the work underway in the United States <Stacy - 1963,1965,1969,1974>, and a survey article from the New England Journal Of Medicine <Barnett - 1968>.

II.2.1 Business Applications

The most widely used and accepted computer-based applications involve hospital accounting systems. Business computing is perhaps the best developed of all computer applications, both because accounting uses have been a major concern of many computer firms since the industry was in its infancy, and because accounting problems are in general well-defined and thereby more straightforward to develop and implement. Automated accounting developments from the business world have required very little adaptation for application within the hospital. It is hardly surprising, then, that medical accounting functions have been the first to be automated. Not only is this priority logical in light of the success and experience which general industry has acquired by using the computer for financial activities, but the application also demonstrates easily recognizable monetary benefits. A variety of hospital consulting firms are sufficiently aware of the commercial potential of medical financial systems that they now offer expertise for assistance in the selection of accounting machinery <Benson - 1968>.

The need for computing systems to handle financial data and to print out forms has been heightened in recent years by the explosive rise in hospital rates and the concomitant need for increased and improved communication between the hospitals and third party payers or the government. The private physician has been faced with the same paperwork proliferation on a smaller scale. As a result, several service computing firms offer individual office-based financial packages to practitioners who find it difficult to maintain their patient care schedules, particularly with welfare cases, because processing all the paperwork by hand has become exceedingly tedious and time consuming.

It should be noted that much of the public opinion regarding computers is derived from direct contact at the financial level between the consumer and the computers that send him his bills. Thus a patient who is directed to sit at a console for an automated medical history may well think back to his last erroneous

bank statement or computer-generated billing error and rebel at the thought that a similarly error-prone machine is about to take charge of his physical well-being. Physicians asked to read computer-generated summaries may also question the reliability of the information. Thus improved performance levels for business computers, both through increased machine reliability and utilization of well-trained and responsible systems personnel, may be a necessary first step towards improving the public image of computers and thus lowering the barriers of resistance to computing innovation in medicine. This trend is already underway and is aided by an increasing number of young adults who have grown up in an age when computers have been highly visible and accepted. The novelty and mysteriousness of computers have made them especially threatening to individuals who remember, for example, the hand-posted billing statements they received in the pre-computer era.

A final important point regarding the gradual introduction of financial computing into the doctor's office is related to the hardware and communications equipment that will become increasingly familiar and accessible. The same computer terminal that he purchases for sending daily billing and insurance data from his office to a central financial computing service could presumably be used for connecting with a network of computer-based clinical resources such as those described below. Thus little or no additional capital outlay may be necessary for the physician of the future to interact with computer programs designed to help him with the day-to-day practice of medicine. The challenge, then, is to develop such good computer-based clinical tools that the physician will take the time to use them as part of his daily routine (and to pay for the associated computing charges) because he has found that they genuinely help him in his practice without providing a threat to his professional self-esteem.

II.2.2 Biomedical Engineering

It is convenient to divide medical computing applications into those identifiable as biomedical engineering tasks and those more appropriately termed information processing or data handling. Biomedical engineering applications are those in which a primary component is the analysis of analog signals or the construction of sophisticated technologies for man-machine interaction. This is a vast field that includes such applications as medical computer graphics <Newton - 1973, Cox - 1967, Alderman - 1973>, computer assisted pattern recognition from visual signals <Bahr - 1973, Neurath - 1966>, computer analysis of real-time data <Computers and Medicine - 1973a, Harrison - 1971, Henry - 1968>, and various kinds of patient monitoring.

Patient monitoring includes all those applications in which computers are used to process or monitor signals relayed by machines that measure physiological parameters of the patient. By far the largest subfield in this category is the development of programs that aid in the analysis of electrocardiograms (EKG's). In recent years literally hundreds of articles on this subject have been published annually in the medical computing journals, conference proceedings, and books. The vastness of the field reflects the well-recognized need for computer programs that can assist the physician with EKG analysis, particularly in medically underserved areas where the expertise of highly trained cardiologists may not be readily available. However, the size of the field also suggests that the ultimate program for this purpose has not yet been created. Indeed, although several programs do very well at EKG analysis <Wartak - 1971, Caceres - 1964, Pryor - 1969, Wolk - 1972>, none has yet achieved the accuracy of a good and experienced cardiologist. Similar work has also been done on the even more complex problem of electroencephalogram (EEG) analysis. Results in this field have so far been rather rudimentary and have tended to concentrate on the identification of abnormal spikes in the tracings from the various leads <Walter - 1968, Cox - 1972,

Kellaway - 1973>.

The phrase 'patient monitoring', however, generally implies more than signal sampling and analysis <Warner - 1968, American Medical News - 1970, Felsenthal - 1973>. Also involved is the concept of a warning system, wherein a computer is programmed to sample a patient's physiologic parameters at specified intervals and to warn the nursing or medical staff if an abnormal or dangerous reading is noted. The ethical and legal implications of such systems are only gradually being worked out. Even more revolutionary will be systems in which the computer not only notes the abnormalities but takes corrective action by injecting a drug, altering a pacemaker setting, etc. Although such systems are often discussed, none has yet been implemented for ongoing service.

II.2.3 Multi-Phasic Health Testing

As health care critics have increasingly pointed out the tendency for American medicine to concentrate on crisis care, largely ignoring the need for improved preventive medicine, the health care and industrial communities have begun to respond with innovations for screening large populations and identifying individuals with early or latent disease. 'Multi-phasic health testing' (MPHT) is the common term for procedures whereby apparently healthy individuals are given a battery of screening tests to determine who may need further medical attention <Oszustowicz - 1972, Collen - 1964,1965,1966,1969,1971>. The various MPHT installations use computer technology to varying extents, in most cases primarily to collect the data and print them in an organized fashion that facilitates review by staff physicians.

Many MPHT centers also use computers to obtain the patient's medical history. Automated history-taking has been developed primarily within the last decade <Grossman - 1968, Slack - 1966> and generally involves easy-to-use push-button display terminals. The patient sits at the scope for varying lengths

of time, usually from thirty to sixty minutes (depending upon the complexity of his complaints), and answers multiple choice questions by pushing the button beside the correct answer. The programs utilize branching logic so that more specific questions may be asked of patients for whom the detailed information seems relevant (because of answers to previous questions).

Such programs have also been used in hospital outpatient clinics. Summaries of the history are legibly printed by the computer for review by the physician when he sees the patient. He may then pursue in detail topics about which the computer has indicated an extensive history may be necessary. Another benefit of the automated history is the capability to ask questions in one language and to print the summary for the physician in another. Thus the computer may serve as a useful intermediary in cases where, for example, the patient speaks only Spanish or French and the physician only English. Studies to evaluate such systems generally indicate that patients accept the automated history more readily than the physician does <Grossman - 1969,1971>. The summary for the physician is gradually being improved, however, as designers gain experience with this application and insights into the reasons for physician resistance.

II.2.4 Automated Medical Records

One of the great differences between modern medicine and the clinical practice of a century ago is the current tendency for patient care duties to be shared, particularly in teaching institutions. Thus the medical record, which once served primarily as a worksheet where the individual physician could jot down reminders to himself, is now an important means of communication among the physicians caring for the patient. Furthermore, the medical record now serves as an important legal document.

Unfortunately the medical record has not yet evolved to meet the demands of these new requirements. Charts are usually not standardized, are often poorly

organized, and tend to be illegible. Redundancy of data is to be expected since health professionals using the record tend to duplicate the same information; they do not have the time nor patience to search the chart to see if the data have been entered by someone else.

Recognizing the chaos that arises from the conventional medical record system, several researchers have suggested new organization techniques and potential mechanisms for automation. Most notable, perhaps, is the Problem Oriented Medical Record (POMR) proposed by Weed <Weed - 1968,1969a>. He developed the approach at Case Western Reserve, and in recent years has used computer technology to automate the system both there <Weed - 1969b> and at the University of Vermont. The POMR approach has also been advocated as an aid to medical audit <Weed - 1971>, although recently questions have been raised regarding its usefulness for this purpose <Fletcher - 1974>. Nonetheless, the system has received wide attention <Bjorn - 1970, Collins - 1973, Esley - 1972, Feinstein - 1973, Goldfinger - 1973, Hurst - 1971a,1971b,1972,1973, Mittler - 1972> and is now used routinely at several hospitals, particularly in the eastern United States. Only Weed's group has automated the POMR, although similar work has been undertaken at the Massachusetts General Hospital <Greenes - 1969,1970a> where a computer-based clinical data management system has been utilized in the outpatient hypertension clinic, the coronary care unit, and for systemized input of radiology reports <Pendergrass - 1969, Bauman - 1972>. The important point to note regarding the computer systems of Weed and Greenes is that each is designed for use by the physician himself, both for data input and data retrieval. Thus, in accordance with our comments above, physician acceptance of such systems must remain a primary consideration during program development and implementation.

An alternative to both the traditional source-oriented record and the POMR is the time-oriented databank (TOD) introduced at Stanford Hospital <Fries - 1972>. The TOD System, like the POMR, is primarily a revision in the organization

of the hard-copy record. Automation has been introduced only for off-line data entry and analysis. The TDD System emphasizes chronological organization of patient data so that flow-charted trends can be observed over time. Physician interaction with the computer is not yet a part of the TDD approach.

Several other groups have worked with automated records, most of which only peripherally involve the physician. The Kaiser Hospital System is particularly notable in the field <Davis - 1968, Collen - 1964>, but excellent work with both inpatient and outpatient records has also been done elsewhere in the United States <Grossman - 1973, Slack - 1967, Kiely - 1968> and abroad <Buckley - 1973>. Some investigators have looked for ways to automate records without sacrificing the conventional text format <Korein - 1963, Levy - 1964, Bross - 1969> while others have attempted to introduce structure to the records by using checklists or self-encoding forms <Yoder - 1966,1969, Collen - 1971, Hall - 1967>. Finally, some observers have argued that it is premature to study the structure and optimization of patient data-handling without first assessing and improving the quality of the data themselves <Feinstein - 1970>.

II.2.5 Laboratory And Pharmacy Systems

Unlike clinical parameters best known to the physician himself, patient data related to lab tests and administered drugs can be acquired from sources other than the doctor. Thus several systems have been developed to aid in the acquisition and control of laboratory and pharmacy data.

Chemistry laboratory systems are perhaps the most common clinical application of computers. Several excellent systems have been designed <Hamilton - 1973a,1973b, Raymond - 1973, Katona - 1969> to accomplish one or more of the following tasks:

1) accept test orders, in some cases on-line from the wards;

2) generate schedules for the technicians who collect the appropriate samples from the patients;

3) generate worksheets for the technicians running the tests in the laboratory;

4) provide automatic accessioning for control and identification of samples;

5) accept test results on-line from various kinds of equipment;

6) accept other results from terminals in the laboratory;

7) provide rapid access to test results on any patient;

8) generate hard-copy reports, in a variety of formats, for inclusion in the patient chart or for individual use by physicians.

Also suitable for inclusion in the category of laboratory systems are programs for reporting pathology lab diagnoses <Beckett - 1972>, for analyzing antimicrobial sensitivity test results <Hulbert - 1973, Groves - 1974> or identification data <Mullin - 1970>, for organizing and controlling large collections of laboratory specimens <Bachman - 1973>, or for quality control in a microbiology laboratory <Petralli - 1970>.

Pharmacy systems generally assist with label printing, inventory control, and the maintenance of up-to-date patient drug profiles <Evans - 1971, Almquist - 1972>. One hospital has used such profiles to identify outpatients who are drug abusers <Maronde - 1972>. A novel pharmacy control system has been introduced at Stanford Hospital <Cohen - 1972,1974> where new drug prescriptions are compared with the patient's drug profile and warnings for the physician are generated if a potential drug interaction is noted. Finally, the Kaiser Hospital System has reported a computer-based mechanism for monitoring the incidence of adverse drug reactions <Friedman - 1971>.

II.2.6 Hospital Information Systems

A centralized computer that performs or oversees several of the automated functions described above is called a Hospital Information System (HIS). Since such systems tend to require massive computing facilities, commercial firms are particularly interested in such installations. An HIS usually involves an automated mechanism for patient admission and bed census <Hofmann - 1969> so that a computer-based record for each patient exists from the moment he enters the hospital. The patient record then serves as a focus for information flow. Laboratory and pharmacy data are centrally stored and the system transfers orders directly from the ward, where they are ordered, to the appropriate hospital service. Nursing personnel often use the system to post orders and to indicate when drugs have been administered or other patient care services have been performed. Physicians interact with ward terminals to varying extents, depending both upon the system design and the doctor's willingness to participate. A variety of additional services may also be performed by the central machine. Thus an HIS offers a variety of benefits to the various individuals who may use its data base:

> ....To the physician, [HIS is] a system that will provide rapid, accurate, and legible communication of reports, better scheduling procedures and timely and precise implementation of activities ordered for patient care. To the nurse, HIS implies an operation to lighten the clerical load of communication functions, preparing requisitions and transcribing and charting. To the administrator, HIS is a means for using resources more effectively, for gathering the data necessary for appropriate management decisions and for ensuring that information necessary for the patient billing process is readily available and accurate. To the medical research investigator, HIS offers the potential for a data base of patient-care activities that is not only accurate but also organized and easily retrieved and analyzed. <Barnett - 1968>

Unfortunately this ideal picture of universal benefit and acceptance of an HIS has yet to be realized. The HIS at El Camino Hospital in Mountain View, California has served as a model for other institutions considering such ventures.

Initiated by Lockheed Aircraft but currently operated by the Technicon Corporation, this large system has surprised observers with its demonstrated cost effectiveness <Batelle Labs - 1973> but has been plagued by low user acceptance, particularly among physicians <Computerworld - 1973, Computers and Medicine - 1973b, Yasaki - 1973>. Suggested reasons for the problems encountered have been numerous. A 1971 article suggested several mechanisms for meeting resistance to hospital automation <Hofmann - 1971>, some of which appear to have been overlooked by the El Camino planners. The need for eventual users of the system to participate in the planning process is particularly crucial, as is an effective feedback mechanism so that points of discontent can be overcome before they have a chance to grow. The need for thorough pre-implementation planning of the patient data base for an HIS has also been recognized <Sauter - 1973>. Finally there are those who believe that any attempt to introduce a total hospital information system in a single step is doomed to failure from the outset. The alternate approach is to design the various computer services as modules, perhaps on several small machines, and gradually to integrate them into a total system <Greenes - 1970b, Barnett - 1969, Hofmann - 1968>.

II.2.7 Decision Support Systems

Computer programs to assist in clinical decision making are the subject of Chapter 2. That chapter discusses in detail some of the work that has preceded the MYCIN System. At this time it is simply noted that there are two kinds of clinical decisions which may be involved in such systems - determination of the patient's diagnosis or the appropriate way to treat him. In some cases, treatment selection is straightforward once the proper diagnosis has been made. In others, treatment planning may be the most complex step in the decision making process.

II.2.8 Computer-Aided Instruction In Medicine

Computer-Aided Instruction (CAI) has become an accepted part of the educational process for many of today's younger students <Suppes - 1966b,1969>. As the field has developed, students of the health professions have also begun to benefit from techniques developed by CAI researchers <Stolurow - 1970>. In medical education, a number of successful programs are available nationwide through a network supported by the National Library of Medicine <Wooster - 1973>. Several useful programs, most of which avoid problems of natural language understanding, have been developed at Massachusetts General Hospital <Hoffer - 1973>. Ohio State University also has an extensive medical CAI facility <Weinberg - 1973>. Programs that play the role of a patient or otherwise enter into natural language discourse with the student include Cornell's ATS <Hagamen - 1973, Weber - 1972>, and the CASE system at the University of Illinois <Harless - 1973a,1973b>. A program that simulates the patient-physician encounter, with realistic simulation of the time required for the return of lab results, has also been reported <Friedman - 1973>. Little work has been done to evaluate the cost effectiveness of such systems, but a group at the University of California (San Francisco) has been sufficiently concerned with cost factors that they have developed a dedicated CAI system for use on inexpensive minicomputers <Kamp - 1973>.

III. ARTIFICIAL INTELLIGENCE

Although Artificial Intelligence (AI) has been defined in numerous ways, this observer's preference is to acknowledge the intelligence of any machine that performs a task which individuals a century ago would have said was a uniquely human intellectual capability. This is a broad definition that encompasses a much wider range of machines and tasks than is usually ascribed to AI. Its appeal, however, is its tendency to avoid arguments as to whether a specific machine should be called a product of the AI field. Furthermore, it points out that intelligence is a term that perhaps need not apply only to humans. It can be argued that machine intelligence is not 'artificial' at all but is simply a different variety of intelligence that is not hindered by the human interplay of intellect with emotions, fatigue, and those additional characteristics that we currently claim are 'uniquely human'.

In practice, artificial intelligence usually describes a subset of the above definition in which (1) the machine is a digital computer or is controlled by a digital computer, and (2) the task involves symbolic reasoning ('thinking') rather than arithmetic calculations or information storage and retrieval. AI is therefore generally regarded as a subfield of computer science. The foundations of the field are often attributed to an article written by the late A. M. Turing <Turing - 1950>, an English mathematician and logician who proposed an operational test of intelligence, the so-called Turing Indistinguishability Test. In addressing the question "Can machines think?", he suggests that, for all practical

purposes, a machine is intelligent if an individual communicating with the machine (say by means of a teletype) is unable to decide whether he is interacting with a computer or with another human who is also using a teletype.

I shall not attempt to survey the field of artificial intelligence. Several excellent general texts are available that devote considerably more space and energy to such surveys than are available here <Feigenbaum - 1963, Minsky - 1968, Slagle - 1971, Nilsson - 1971>. Critics of the field have also been moved to write entire volumes arguing against the potential of AI <Dreyfus - 1972>. The reader is therefore encouraged to consult a recent survey paper <Nilsson - 1974> for a more thorough discussion of AI and for a comprehensive bibliography of the field. An earlier survey of the field also is available <Minsky - 1961>. In the rest of this section I shall describe Nilsson's categories for organization of the field in an effort to give a brief overview of the kinds of problems with which AI is presently involved. I am indebted to Dr. Nils Nilsson for permission to borrow his thoughts regarding categorization of the field.

There are four basic AI methodologies that have been addressed by almost all workers regardless of their area of application. In addition there are approximately eight application areas which encompass most of the work in AI. In the discussion below I shall list and briefly describe the eight application areas. The four core topics common to most AI work are then introduced.

III.1 (**) Areas Of Application

III.1.1 Game-Playing <Slagle - 1971>

Some of the best known work in artificial intelligence involves the development of computer programs that can play highly complex games. Programs have been written to play checkers <Samuel - 1959,1967>, chess <Greenblatt -

1967>, poker <Waterman - 1970>, bridge <Berlekamp - 1963> and several other games that require complex strategies regarding a large number of alternative actions (moves). Such games must be contrasted with a contest such as Tic-Tac-Toe in which the entire range of alternatives can be exhaustively analyzed by a computer and the machine can thereby be programmed never to lose a game.

III.1.2 Math, Science, And Engineering Aids

There are fewer examples of applications in this category (the one into which MYCIN most appropriately falls). Such programs are perhaps best characterized as decision-support systems and in general are designed for non-computer scientists. Some examples of these programs are discussed in Chapters 2 and 4.

III.1.3 Automatic Theorem Proving <Nilsson - 1971, Chang - 1973>

We are all familiar with high school geometry problems in which the task is to use certain given information in order to prove something else about a geometrical figure. The proving of theorems from known axioms is a general problem area common to various other kinds of deductive logic. Some of the earliest AI programs dealt with this kind of theorem proving and today the field involves some of the most sophisticated applications that have been developed. This application area is thus closely related to several others (e.g., robot planning, automatic programming) in which theorem proving techniques are often used as the basic problem-solving methodology.

III.1.4 Automatic Programming <Balzer - 1972>

Any computer science student who has slaved into the morning hours, trying to find mistakes in one of his programs, can testify to the 'intelligence' required in order to write and debug computer programs that perform specified

tasks. The idea of a computer that 'figures out' how to program itself may seem absurd at first consideration, but considerable progress has been made in this area in recent years. For example, one approach to the problem is to give the computer some sample program inputs and the corresponding output data. The machine is then asked to create a program that will perform the required transformation.

III.1.5 Robots <Rosen - 1972, Fikes - 1972, Coles - 1974>

Science fiction films and modern television notwithstanding, a general purpose robot that walks, talks, and does what you ask it to do has yet to be developed. Work on robotics has involved AI researchers for over a decade, however, and several machines with limited capabilities have been developed. In general this field involves more engineering technology than the other AI application areas because the electrical and mechanical problems in design of the robot itself are substantial. Some projects have limited themselves to computer-controlled arms with associated cameras for scene analysis <Feldman - 1971, Winston - 1972>. These 'hand-eye' machines perform tasks in a fixed table-top environment. Radio-controlled robots on wheels have also been developed <Hart - 1972> and are able to analyze their environment (by means of 'on-board' television cameras) and to perform certain limited tasks. Industry is particularly interested in progress in robotics, as is NASA because of the potential for the use of robots in space exploration. It should be emphasized, however, that the computer program that determines how the robot's task is to be accomplished and then sends appropriate signals to the robot's mechanical devices is an essential part of robot technology and underscores this field's association with the other AI application areas.

III.1.6 Machine Vision <Minsky - 1972, Duda - 1973>

Intimately related to robotics is the development of techniques for analyzing and understanding pictures, usually television pictures. For example, a robot arm that attempts to assemble an engine from parts placed in random locations on a table must be able to locate and recognize the pieces, regardless of their orientation. This problem of scene analysis also involves 3-dimensional perception, edge detection, and disambiguation of lines caused by shadows. Clearly a computer program that makes such judgments on the basis of electrical signals from a television camera is solving a complex intellectual problem.

III.1.7 Natural Language Systems <Schank - 1973, Simmons - 1970, Rustin - 1973>

Computer understanding of natural language, either spoken or written, has fascinated computer scientists ever since attempts were first made, in the 1950's, to write programs for translation of text from one human language to another (e.g., English to Russian). Closely involved with the field of linguistics, workers in this AI application area have been forced to try to understand the nature of language itself. Problems include analysis of syntax, disambiguation of words with multiple meanings, and analysis of the semantics of language, especially during a lengthy discourse when the overall context determines the meaning of individual words. Understanding language typed into a machine by teletype has been taken one step further in recent efforts to develop programs that understand spoken words. The latter problem is similar to machine vision in that the program must first analyze electrical signals (in this case from a microphone rather than a television camera) in order to determine what is said. Only then can an attempt be made to understand the meaning of those words and to respond appropriately.

III.1.8 Information Processing Psychology <Newell - 1970, Schank - 1973, Lindsay - 1972>

Many AI researchers, in accordance with Turing's Indistinguishability Test, are concerned primarily with how well their programs perform the tasks for which they were designed; i.e., they do not necessarily care whether the program solves the problem in the same way that a human does. There are those who believe, however, that by attempting to create programs that solve problems in a manner similar to the workings of the mind, new insights into the psychology of human problem-solving can be discovered. Such work has taken several different forms that interface with all seven of the other AI application areas I have discussed. Nilsson's review article <Nilsson - 1974> is an appropriate first resource for readers interested in learning more about this area of application.

III.2 (**) Basic AI Methodologies And Techniques

The four core topics in artificial intelligence pervade all eight of the application areas discussed above. In Chapters 2 and 4 I shall clarify how the MYCIN System has drawn upon prior work in each of these areas.

III.2.1 Modeling And Representation Of Knowledge

AI authors are fond of citing examples of problems that seem exceedingly difficult until a simplified way of expressing the task is discovered. Consider a favorite such example - a 64-square checkerboard, 8 squares on each side, and a box of dominos. Each domino exactly covers two squares. Thus 32 dominos can be used to cover the entire checkerboard. You are asked to arrange 31 dominos on the board so that all squares are covered except the two squares in diagonally

opposite corners.

Many people given this task would immediately begin trying to arrange dominos as requested. However, an individual who thinks about the problem in the right way will quickly announce that the task is impossible. The key here is to notice that the diagonally opposite squares on a square checkerboard are always the same color. Thus performing the task would require covering 30 squares of one color and 32 squares of the other color. Since every domino must cover one square of each color, dominos arranged on the board must always cover as many squares of one color as the other. Hence the desired final state cannot be achieved (unless some dominos are cut in half).

A variety of modeling and representation schemes have been developed because it has been recognized that the representation of knowledge in the machine may be crucially important to the efficiency with which an AI program is able to perform. These approaches include use of the predicate calculus to represent facts and goals in problem-solving, semantic networks, production systems similar to the grammars that were first proposed by linguists, and procedural representations. The approaches that are most relevant to MYCIN are discussed in Chapter 4.

III.2.2 Reasoning, Deduction, And Problem Solving

Since several AI applications involve the writing of programs that solve problems, the development of computer-based problem-solving techniques has been a central concern for many researchers in the field. The most common example used to describe the reasoning tasks involved is the so-called 'monkey and bananas' problem. Consider a room containing a monkey, a box, and a bunch of bananas that is hanging from the ceiling. Distances are arranged in such a way that the monkey is unable to get the bananas unless he is standing on the box. The problem, then, is to write a program that derives a plan so that the monkey can get the bananas.

Although the problem may at first seem absurdly simple, it must be remembered that computers have no 'common sense' knowledge regarding boxes, monkeys, bananas or distances. The program must therefore be told that boxes may be pushed, that pushing has certain effects on a box and on the individual doing the pushing, that boxes may be climbed upon, etc. An intelligent program then deduces, from this basic world knowledge, that the best plan is for the monkey to push the box under the bananas, to climb on the box, and finally to grasp the bananas.

This apparently trivial problem has served as the focus for innovative problem-solving techniques during the past decade. Numerous methodologies and representations of the problem have been suggested. Of course, many problems that are more difficult have been solved, but the puzzle of the 'monkey and bananas' remains a convenient common ground for explaining a suggested new approach to computer-based reasoning.

III.2.3 Heuristic Search

In many human problem solving situations there are a large number of possible decisions or actions that may be taken. Imagine, for example, the large number of possible moves at most points during a game of chess or checkers. Since each action may in turn lead to several additional potential actions or responses, the number of possible decisions two or more steps into the future often becomes unmanageable. Humans therefore develop strategies for quickly discounting or eliminating possible actions that they can easily see are less desirable than the two or three best potential decisions. They can thus concentrate on the smaller number of actions, comparing their possible outcomes, and making a reasoned decision on the basis of the most rational alternatives. Programs for solving problems must be given similar strategies so that the machine's computational power can be efficiently spent concentrating on a small number of possible actions. Despite the computer's speed and computational powers, many human

problems (such as selecting the best move in a game of chess) are so complex that thorough evaluation of each possible move can be shown to require a near-infinite amount of time! Any trick or strategy that can be used by a program in order to limit the number of alternative actions that it must investigate is known as a heuristic. Hence 'heuristic search' is the name for the AI problem area in which researchers attempt to identify good strategies that adequately limit the number of alternatives that must be considered (but do not eliminate the alternative that would prove to be the best if all possibilities were thoroughly considered).

III.2.4 AI System And Languages <Bobrow - 1973>

A somewhat separate core topic is the development of computing systems and high-level languages for use by AI researchers. Since AI applications typically require powerful capabilities for symbol manipulation, the several common computer languages that emphasize numerical calculations are usually not adequate. Early AI languages emphasized list-processing <Newell - 1957, McCarthy - 1960>, but in recent years newer languages have taken on some of the capabilities that originally were left to the applications programmer <Hewitt - 1969, Teitelman - 1974, Rulifson - 1972, Feldman - 1972>. These include search, pattern matching, and backtracking. MYCIN is written in one of these more recent programming languages, a descendant of LISP <McCarthy - 1962> called INTERLISP <Teitelman - 1974>.

The brief overview included here has been intended to give the reader a sense of the kinds of problems and methodologies with which artificial intelligence is centrally concerned. It may now be clear why the AI field holds intuitive appeal for medical researchers who are examining the reasoning processes involved in clinical judgment, medical diagnosis, and the rational selection of

appropriate therapy. In Section IV I introduce the medical problem area for which the MYCIN system has been designed. Finally, Section V introduces the program itself and gives an example of MYCIN's interactive decision making capabilities.

IV. ANTIMICROBIAL SELECTION

IV.1 (**) Nature Of The Decision Problem

An antimicrobial agent is any drug designed to kill bacteria or to arrest their growth. Thus the selection of antimicrobial therapy refers to the problem of choosing an agent (or combination of agents) for use in treating a patient with a bacterial infection. The terms 'antimicrobial' and 'antibiotic' are often used interchangeably, although the latter actually refers to any one of a number of drugs that are isolated as naturally occurring products of bacteria or fungi. Thus the well-known penicillin mold is the source of an antibiotic, penicillin, that is used as an antimicrobial. Some antibiotics are too toxic for use in treating infectious diseases but are still used in research laboratories (e.g., dactinomycin) or in cancer chemotherapy (e.g., daunomycin). Furthermore, some antimicrobials (such as the sulfonamides) are synthetic drugs and are therefore not antibiotics. There are also semi-synthetic antibiotics (e.g., methicillin) that are produced in chemical laboratories by manipulating a naturally occurring antibiotic molecule. Throughout this thesis I shall not rely upon this formal distinction between 'antimicrobial' and 'antibiotic' but will, rather, use the terms as though they were synonymous. The following list of commonly used antimicrobial agents will introduce the reader to the names of several of these agents. The list includes most of the generic drugs (i.e., non-brand names) with which the MYCIN System is familiar:

ampicillin
bacitracin
carbenicillin
cephalothin
chloramphenicol
clindamycin
colistin
erythromycin
ethambutal
gentamicin
INH
kanamycin
methicillin
nalidixic-acid
nitrofurantoin
PAS
penicillin
polymyxin
rifampin
streptomycin
sulfisoxazole
tetracycline
vancomycin

This list does not include the several non-brand name antimicrobials that are chemically related to the generic drugs above but that have some distinctive feature such as a different preferred route of administration.

The name MYCIN is taken from the common suffix shared by several of the antimicrobial agents. It reflects the central concern of the program, namely the selection of an appropriate therapeutic regimen for a patient with a bacterial infection. MYCIN does not yet consider infections caused by viruses or pathogenic fungi, although these other kinds of organisms cause significant diseases which may be difficult to distinguish clinically from disorders with bacterial etiology.

Antimicrobial selection would be a trivial problem if there were a single non-toxic agent effective against all bacteria capable of causing human disease. However, drugs that are highly useful against certain bacteria are often not the least effective against others. The identity (genus) of the organism causing an infection is therefore an important clue for deciding what drugs are apt to be beneficial for the patient. The following list summarizes the organisms with which MYCIN is familiar. Subtypes are specified only in those cases where the subdivisions have important therapeutic implications:

arizona
bacteroides
borrelia
brucella
citrobacter
clostridium-botulinum
clostridium-species
clostridium-tetani
corynebacteria-diphtheriae
corynebacteria-species
diplococcus-pneumoniae
e.coli
edwardsiella
enterobacter
fusobacterium
hafnia
hemophilus-influenzae
hemophilus-non-influenzae
herellea
klebsiella
listeria
mima
moraxella
mycobacterium-atypical
mycobacterium-balnei
mycobacterium-leprae
mycobacterium-tb
neisseria-gonorrhea
neisseria-meningitidis
neisseria-species
pasteurella
peptococcus
proteus-mirabilis
proteus-non-mirabilis
providence
pseudomonas
salmonella
serratia
shigella
staphylococcus-coag+
staphylococcus-coag-
streptobacillus
streptococcus-alpha
streptococcus-anaerobic
streptococcus-beta(group-A)
streptococcus-beta(non-group-A)
streptococcus-gamma
streptococcus-group-D
streptococcus-microaerophilic
treponema
vibrio

Selection of therapy is a four-part decision process. First the physician must decide whether the patient has a significant bacterial infection requiring treatment. If there is significant disease, the organism must be identified or the range of possible identities must be inferred. The third step is to select a set of drugs which may be appropriate. Finally, the most appropriate drug or combination of drugs must be selected from the list of possibilities. Each step in this decision process is described below.

IV.1.1 Is The Infection Significant?

The human body is normally populated by a wide variety of bacteria. Organisms can invariably be cultured from samples taken from a patient's skin, throat, or stool. These normal flora are not associated with disease in most patients and are, in fact, often important to the body's homeostatic balance. The isolation of bacteria from a patient is therefore not presumptive evidence of

significant infectious disease.

Another complication is the possibility that samples obtained from normally sterile sites (such as the blood, cerebrospinal fluid, or urinary tract) will become contaminated with external organisms either during the collection process itself or in the microbiology laboratory where the cultures are grown. It is therefore often wise to obtain several samples and to see how many contain organisms that may be associated with significant disease.

Because the patient does have a normal bacterial flora and contamination of cultures may occur, determination of the significance of an infection is usually based upon clinical criteria. Does the patient have a fever? Is he coughing up sputum filled with bacteria? Does he have skin or blood findings suggestive of serious infection? Is his chest x-ray normal? Does he have pain or inflammation? These and similar questions allow the physician to judge the seriousness of the patient's condition and often explain why the possibility of infection was considered in the first place.

IV.1.2 What Is The Organism's Identity?

There are a variety of laboratory tests which allow an organism to be identified. The physician obtains a sample from the site of suspected infection (e.g., a blood sample, an aspirate from an abscess, a throat swabbing, or a urine collection) and sends it to the microbiology laboratory for culture. There the technicians first attempt to grow organisms from the sample on an appropriate nutritional medium. Early evidence of growth may allow them to report the morphological and staining characteristics of the organism. However, complete testing of the organism so that a definite identity is determined usually requires 24-48 hours or more.

The problem with this identification process is that the patient may be sufficiently ill at the time when the culture is first obtained that the physician

cannot wait two days before he begins antimicrobial therapy. Early data regarding the organism's staining characteristics, morphology, growth conformation, and ability to grow with or without oxygen may therefore become crucially important for narrowing down the range of possible identities. Furthermore, historical information about the patient and details regarding his clinical status may provide additional useful clues as to the organism's identity.

IV.1.3 What Are The Potentially Useful Drugs?

Even once the identity of an organism is known with certainty, its range of antimicrobial sensitivities may be unknown. For example, although a pseudomonas is usually sensitive to gentamicin, an increasing number of gentamicin-resistant pseudomonae are being isolated. For this reason the laboratory will often run _in vitro_ sensitivity tests on an organism they are growing, exposing the bacterium to several commonly used antimicrobial agents. This sensitivity information is reported to the physician so that he will know those drugs that are likely to be effective _in vivo_.

Sensitivity data do not become available until one or two days after the culture is obtained, however. The physician must therefore often select a drug on the basis of his list of possible identities plus the antimicrobial agents that are statistically likely to be effective against each of the identities. These statistical data are available from many hospital laboratories (e.g., 82% of E.coli isolated at Stanford Hospital are sensitive _in vitro_ to kanamycin) although, in practice, physicians seldom use the probabilistic information except in a rather intuitive sense (e.g., "Most of the E.coli infections I have treated recently have responded to kanamycin").

IV.1.4 Which Drug Is Best For This Patient?

Once a list of drugs that may be useful has been considered, the best regimen is selected on the basis of a variety of factors. These include not only the likelihood that the drug will be effective against the organism, but a number of clinical considerations. For example, it is important to know whether the patient has any drug allergies or whether the drug is contraindicated because of his or her age, sex, or kidney status <Kovnat - 1973>. If the patient has meningitis or brain involvement, does the drug cross the blood-brain barrier? Since some drugs can be given only orally, intravenously (IV), or intramuscularly (IM), the desired route of administration may become an important consideration. The severity of the patient's disease may also be important, particularly for those drugs whose use is restricted on ecological grounds <Finland - 1970, Rose - 1968> or which are particularly likely to cause toxic complications. Furthermore, as the patient's clinical status varies over time and more definitive information becomes available from the microbiology laboratory, it may be wise to change the drug of choice or to modify the recommended dosage regimen.

IV. Evidence That Assistance Is Needed

The 'antimicrobial revolution' began with the introduction of the sulfonamides in the 1930's and penicillin in 1943. The beneficial effects that these and subsequent drugs have had upon mankind cannot be overstated. However, as early as the 1950's it became clear that antibiotics were being misused. A study of office practice involving 87 general practitioners <Peterson - 1956> revealed that antibiotics were given indiscriminately to all patients with upper respiratory infections by 67% of the physicians, while only 33% ever tried to separate viral from bacterial etiologies. Despite attempts to educate physicians

regarding this kind of inappropriate therapy, similar data are reported even today <Kunin - 1973>.

Antibiotic misuse has recently received wide attention <Scheckler - 1970, Roberts - 1972, Kunin - 1973, Simmons - 1974, Carden - 1974>. The studies have shown that very few physicians go through the methodical decision process that I described in Section IV.1. In the outpatient environment antibiotics are often prescribed without the physician having identified or even cultured the offending organism <Kunin - 1973>. In 1972 the FDA certified enough of the commonly used antibiotics (2,400,00 kg) to treat two illnesses of average duration for every man, woman, and child in the country. Yet it has been estimated that the average person has an illness requiring antibiotic treatment no more often than once every 5 to 10 years <Kunin - 1973>. Part of the reason for such overprescribing is the patient's demand for some kind of prescription with every office visit <Muller - 1972>. It is difficult for many physicians to resist such demands, so improved public education is one step toward lessening the problem.

However, antibiotic use is widespread among hospitalized patients as well. Studies have shown that, on any given day, one third of the patients in a general hospital are receiving at least one systemic antimicrobial agent <Roberts - 1972, Scheckler - 1970, Resztak - 1972>. The monetary cost to both patients and hospitals is enormous <Reimann - 1966, Kunin - 1973>. Simmons and Stolley have summarized the issues as follows <Simmons - 1974>:

1) Has the wide use of antibiotics led to the emergence of new resistant bacterial strains?

2) Has the ecology of 'natural' or 'hospital' bacterial flora been shifted because of antibiotic use?

3) Have nosocomial [i.e., hospital-acquired] infections changed in incidence or severity due to antibiotic use?

4) What are the trends of antibiotic use?

5) Are antibiotics properly used in practice?
   - Is there evidence that prophylactic use of antibiotics is harmful, and how common is it?
   - Are antibiotics often prescribed without prior bacterial culture?
   - When cultures are taken, is the appropriate antibiotic usually prescribed and correctly used?

6) Is the increasingly more frequent use of antibiotics presenting the medical community and the public with a new set of hazards that should be approached by some new administrative or educational measures?

Having stated the issues, the authors proceed to cite evidence which indicates that each of these questions has frightening answers - that the effects of antibiotic misuse are so far-reaching that the consequences may often be worse than the disease (real or imagined) being treated!

Our principal concern is with the fifth question, i.e., whether or not physicians are rational in their prescribing habits and, if not, why not? Roberts and Visconti examined these issues in 1,035 patients consecutively admitted to a 500-bed community hospital <Roberts - 1972>. Of 340 patients receiving systemic antimicrobials, only 36% were treated for infection. The rest received either prophylactic therapy (56%) or treatment for symptoms without verified infection (10%). A panel of expert physicians and pharmacists evaluated these therapeutic decisions and only 13% were judged to be rational whereas 66% were assessed as clearly irrational. The remainder were said to be questionable.

Of particular interest were the reasons that therapy was judged to be irrational in those patients for whom some kind of antimicrobial therapy was warranted. This group consisted of 112 patients - 50.2% of the 223 patients who were treated irrationally. It is instructive to list the reasons that were cited, along with the corresponding percentages indicating how many of the 112 patients were involved:

Antimicrobial contraindicated in patient	7.1
Patient allergic	2.7
Inappropriate sequence of antimicrobials	26.8
Inappropriate combination of antimicrobials	24.1
Inappropriate antimicrobial used to treat condition	62.5
Inappropriate dose	18.7
Inappropriate duration of therapy	9.8
Inappropriate route	3.6
Culture and sensitivity needed	17.0
Culture and sensitivity indicate wrong antibiotic being used	16.1

The percentages sum to more than 100% because each therapy may have been judged inappropriate for more than one reason. Thus 62.5% of the 112 patients who required antimicrobial therapy but were treated irrationally were given a drug that was inappropriate for the patient's clinical condition. This observation reflects the need for improved therapy selection in patients requiring therapy - precisely the decision task with which MYCIN is designed to assist.

The hospital at which Roberts and Visconti conducted their study is certainly not the only institution at which physicians tend to prescribe antimicrobials inappropriately. Macaraeg et. al. have also reported serious disagreement between some of the practices and opinions of hospital physicians and those of infectious disease experts practicing at the same institution <Macaraeg - 1971>. Recent review articles <Kunin - 1973, Simmons - 1974> have cited additional studies that have shown similar data.

Now that a need for improved continuing medical education in antimicrobial selection is recognized, there are a variety of valid ways to respond. One is to offer appropriate post-graduate courses for physicians. Another is to introduce surveillance systems for the monitoring and approval of antibiotic prescriptions within hospitals <L. Edwards - 1972, Kunin - 1973>. In addition, physicians should be encouraged to seek consultations from infectious disease experts when they are uncertain how best to proceed with the treatment of a bacterial infection. Finally, an automated consultation system that can substitute for

infectious disease experts when they are unavailable or inaccessible could provide a valuable component of the solution to the therapy selection problem. The computer program described in the remainder of this report is an attempt to fill that need.

V. AN OVERVIEW OF THE MYCIN SYSTEM

V.1 An Introduction To The System's Organization

MYCIN is an evolving computer program that has been developed to assist nonexpert physicians with the decision task discussed in Section IV.1. Work on the system began early in 1972 when it was recognized that the Stanford community could provide the professional and computing resources necessary for attempting a partial solution to the problem of antibiotic misuse that was discussed in Section IV.2. The project has involved both physicians, with expertise in the clinical pharmacology of bacterial infections, and computer scientists, with interests in artificial intelligence and medical computing.

The computing techniques used in the development of MYCIN were formulated over several months as the collaborators met in weekly meetings and discussed representative case histories of patients with infections. It was decided to concentrate initially on the process of selecting therapy for patients with bacteremia (i.e., bacteria in the blood). This remains our primary focus to date. As patients with bacteremia were discussed by the clinicians, the project members tried to identify the semi-formal decision criteria that were being used. It gradually became clear that these criteria, once defined, can be expressed as rules that reflect the knowledge of the experts. Thus MYCIN was developed as a program that could efficiently utilize such rules in an attempt to model the decision processes of the experts from whom they were obtained.

The discussion in Section IV.1 pointed out that there are four parts to the process of selecting antimicrobial therapy. MYCIN must accordingly follow each of these steps when giving advice to a physician. To reiterate, we have sought decision rules that allow the program to do the following:

(a) decide whether the patient has a significant infection;

(b) determine the likely identity of the offending organism;

(c) decide what drugs are apt to be effective against this organism;

(d) choose the drug that is most appropriate given the patient's clinical condition;

Approximately 200 such decision rules have been identified to date. This corpus of rules is termed the 'knowledge-base' of the MYCIN System.

System knowledge must be contrasted with MYCIN's 'data-base'. MYCIN uses two kinds of data when it gives advice. Information about the patient under consideration is termed 'patient data'. These data are entered by the physician in response to computer-generated questions during the consultation. 'Dynamic data', on the other hand, are the data structures created by MYCIN during the consultation - deductions it has made and an ongoing record of how it has arrived at these conclusions. This distinction between MYCIN's knowledge-base and data-base should be understood because the terms are used in their specialized senses throughout this thesis.

The program itself consists of three subcomponents, each of which performs a specialized task. Subprogram 1 is the Consultation System, i.e., that portion of MYCIN which asks questions, makes conclusions, and gives advice. Subprogram 1 is the subject of Chapter 4.

Subprogram 2 is the Explanation System, i.e., the component of MYCIN which answers questions from the user and attempts to justify its advice. The need for such a capability is discussed in Chapter 3, and Chapter 6 explains the

implementation details of the explanation capability.

Subprogram 3, the most recent addition to MYCIN, is the Rule-Acquisition System. This module permits experts to teach MYCIN new decision rules or to alter pre-existing rules that are judged to be inadequate or incorrect. Chapter 3 also discusses the need for this kind of capability. Since this subprogram presently exists only in preliminary form, its current capabilities and plans for future extensions are discussed in Section III of the chapter describing future work (Chapter 8).

Figure 1-1 provides an overview of the three subprograms and the way in which they access MYCIN's knowledge and data. The heavy arrows indicate the system's flow of control between the subprograms, while the light arrows represent information flow between program components and MYCIN's knowledge and data.

The physician begins an interactive session by starting the Consultation System (Subprogram 1). When MYCIN asks questions, the physician enters patient data as indicated in Figure 1-1. MYCIN uses its knowledge-base to process this information and to decide what question to ask next. Whenever a conclusion is made, MYCIN saves the information in its dynamic data structure. If the physician wants to interrupt the consultation in order to ask questions, he may enter the Explanation System (Subprogram 2). After the question-answering session, he returns to Subprogram 1 and the consultation proceeds from the point of digression.

When MYCIN is through asking questions, it gives its therapeutic recommendation, and control then automatically passes to Subprogram 2. At this point the physician may ask questions regarding the consultation and how MYCIN reached its decisions. This feature forces MYCIN to justify its conclusions and permits the physician to reject the program's advice if he feels that some step in the reasoning process has been unsound.

Subprogram 3 is an option available to experts with whom the system is

MYCIN OVERVIEW

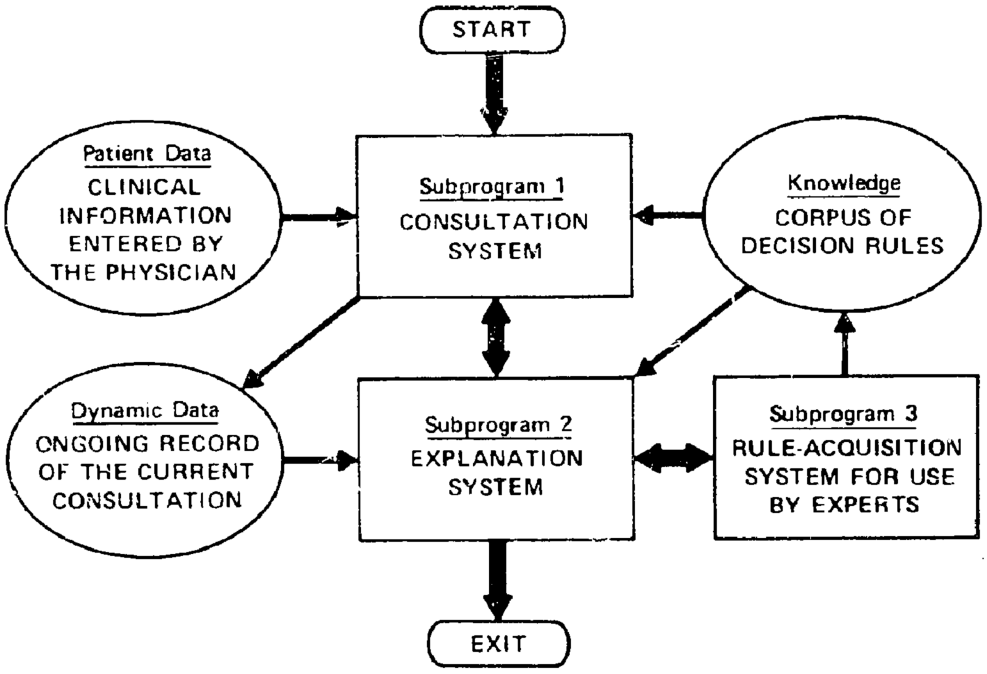


Figure 1-1

familiar. If an expert (when using Subprogram 2) notes an invalid, incomplete, or missing rule, he may enter the Rule-Acquisition System in order to teach MYCIN the new information. This new knowledge is then incorporated into the corpus of rules so that it will be available to Subprogram 1 during future consultation sessions. As noted above, this feature currently exists only in rudimentary form.

Throughout all three subprograms there are a variety of features designed to heighten MYCIN's acceptability to physicians. For example, the system is quite tolerant of spelling or typographical errors, and Subprograms 2 and 3 permit the physician to communicate with MYCIN in the language of clinical medicine rather than some specialized computer language. The need for these kinds of human-engineering considerations is discussed in Chapter 3, and the details are described in the chapters that explain each of the subprograms.

V.2 A Sample Consultation Session

This chapter concludes with a sample consultation session that illustrates MYCIN's consultation and explanation capabilities. The following comments may help the reader understand this sample interactive session more easily:

1) MYCIN asks questions and makes comments in mixed upper- and lower-case letters;

2) MYCIN answers questions and displays decision rules using upper-case letters only;

3) Words typed by the physician are in upper-case letters and always follow MYCIN's prompt character, the double asterisk (**); the asterisks therefore permit words typed by the physician to be distinguished from upper-case phrases printed by MYCIN;

4) Explanatory comments have occasionally been inserted in square brackets at the extreme right margin of the page.

The entire sample consultation session, including the question-answering

interaction, required approximately 20 minutes at a computer terminal.

*****Welcome from MYCIN*****

Teacher's code name: (Enter ? if you do not have one)
**?
Instructions? (Y or N)
**YES

I am a computer program named MYCIN that has been designed to advise you regarding an appropriate choice of infectious disease therapy. I understand that you have a patient from whom a possibly positive culture (called CULTURE-1) has been obtained. Please answer the following questions, terminating each response with RETURN.

If you are not certain of your answer, you may modify the response by inserting a certainty factor (a number from 1 to 10) in parentheses after your response. Absolute certainty (10) is assumed for every unmodified answer.

If you wish to change an answer to a previous question, enter CHANGE followed by the number(s) of the question(s) to be altered. Try to avoid going back, however, because the process requires reconsidering the patient from the beginning and the process may therefore be slow.

Note that you may also enter UNK (for UNKnown) if you do not know the answer to a question, ? if you would like to see some examples of recognized responses, ?? if you want to see all recognized responses, the word RULE if you would like to see the decision rule which has generated the question being asked, the word WHY if you would like to see a more detailed explanation of the question, or the letters QA if you would like to interrupt the consultation in order to ask questions regarding the current status of the program's reasoning. If you are ever puzzled about what options are available to you during a consultation, enter the word HELP and a list of options will be listed for you.

Sample Response
Did ORGANISM-1 grow in clumps, chains, or pairs?
**CHAINS (7) PAIRS (3)

SUMMARY OF USER OPTIONS:
UNK - answer not known
? - request for examples of recognized responses
?? - request for list of all recognized responses
RULE - request for current decision rule
QA - request to enter question-answering mode
WHY - request for detailed explanation of the question being

```
        asked
      CHANGE XXX - go back and re-request answer to question
                   number XXX
      STOP - Halts the program without completing the consultation
      HELP - Prints this list

                                                [At this point the Consultation
                                                 System (Subprogram 1) begins.]
 7-JUN-74 16:27:27
   --------PATIENT-1--------
   1) Patient's name: (first-last)
   **JEREMIAH SAMPLE
   2) Sex:
   **MALE
   3) Age:
   **60
   I will refer to the most recent positive culture for which you
   desire therapeutic advice as:

      --------CULTURE-1--------
      4) From what site was the specimen for CULTURE-1 taken?
      **BLOOD
-BLOOD
      5) How many days ago was this blood culture (CULTURE-1)
         obtained?
      **2
      I will refer to the first offending organism from this blood
      culture (CULTURE-1) as:

         --------ORGANISM-1--------
         6) Enter the identity (genus) of ORGANISM-1:
         **UNKNOWN
         7) Staining characteristics of ORGANISM-1 (gram):
         **?
         WHAT IS THE STAIN OF ORGANISM-1?
         Expected responses are: ACIDFAST GRAMPOS GRAMNEG
         Enter HELP for list of user options.
         **GRAMNEG
         8) Is ORGANISM-1 a rod or coccus (etc.):
         **ROD
         9) Were any organisms that were significant (but no longer
            require therapeutic attention) isolated within the last
            approximately 30 days?
         **YES

            --------CULTURE-2--------
            10) From what site was the specimen for CULTURE-2 taken?
            **SPUTUM
            11) How many days ago was this upper-resp culture
                (CULTURE-2) obtained?
            **4 1/2 DAYS
            PLEASE USE DECIMAL NUMBERS FOR FRACTIONS
            4 1/2 DAYS NOT A RECOGNIZED RESPONSE
            WHAT IS THE NUMBER OF DAYS SINCE THE SPECIMEN FOR THIS
            UPPER-RESP CULTURE WAS ACQUIRED?
```

```
            Expected responses are: NUMBER OF DAYS
            Enter HELP for list of user options.
            **4.5
            I will refer to the prior organism from this upper-resp
            culture (CULTURE-2) as:

               --------ORGANISM-2--------
               12) Enter the identity (genus) of ORGANISM-2:
               **PSEUDOMONAS
            13) Any other significant organisms isolated from this
                upper-resp culture (CULTURE-2)?
            **YES

               --------ORGANISM-3--------
               14) Enter the identity (genus) of ORGANISM-3:
               **KLEBSIELA
=KLEBSIELLA
            15) Any other significant organisms isolated from this
                upper-resp culture (CULTURE-2)?
            **YES

               --------ORGANISM-4--------
               16) Enter the identity (genus) of ORGANISM-4:
               **ENTERO
=ENTEROBACTER
            17) Any other significant organisms isolated from this
                upper-resp culture (CULTURE-2)?
            **NO
         18) Any other significant earlier cultures from which
             pathogens were isolated?
         **NO
         19) What is the suspected non-sterile portal of entry of
             ORGANISM-1 into this sterile site?
         **RULE

RULE121
-------
      IF:  1)  THE SITE OF THE CULTURE IS ONE OF: THOSE SITES THAT
               ARE NORMALLY STERILE,  AND
           2)  THE PORTAL OF ENTRY OF THE ORGANISM IS THE SAME AS
               THE SITE OF A PRIOR ORGANISM WITH THE SAME IDENTITY
               AS THIS CURRENT ORGANISM
      THEN:  THERE IS FURTHER SUGGESTIVE EVIDENCE (.3)  THAT EACH OF
                THEM IS A PRIOR ORGANISM WITH THE SAME IDENTITY AS
                THIS CURRENT ORGANISM

        **GU
        20) Did ORGANISM-1 grow aerobically?
        **YES
        21) Did ORGANISM-1 grow anaerobically?
        **NO
        22) Was any chemotherapy recently begun specifically to
            combat ORGANISM-1?
```

```
**QA
```

[The physician indicates that he wants to enter the Explanation System (Subprogram 2) for a question-answering (QA) session.]

```
Type HELP for the list of question options.

** IQ WHAT DO YOU THINK THE IDENTITY OF ORGANISM-1 IS AT THIS POINT?
THE IDENTITY OF ORGANISM-1 IS PSEUDOMONAS (.333) KLEBSIELLA (.333)
            ENTEROBACTER (.333)

** RETURN
```

[Having asked the question of interest, the physician returns to the Consultation System (Subprogram 1).]

```
        22) Was any chemotherapy recently begun specifically to
            combat ORGANISM-1?
        **NO
        23) Is Jeremiah Sample (PATIENT-1) a burn patient?
        **RULE

RULE047
-------
      IF:  1)  THE SITE OF THE CULTURE IS BLOOD,  AND
           2)  THE IDENTITY OF THE ORGANISM IS NOT KNOWN WITH
               CERTAINTY,  AND
           3)  THE STAIN OF THE ORGANISM IS GRAMNEG,  AND
           4)  THE MORPHOLOGY OF THE ORGANISM IS ROD,  AND
           5)  THE PATIENT HAS BEEN SERIOUSLY BURNED
      THEN:  THERE IS WEAKLY SUGGESTIVE EVIDENCE (.4)  THAT THE
                 IDENTITY OF THE ORGANISM IS PSEUDOMONAS

        **NO
        24) Is the patient's illness with ORGANISM-1 a
            hospital-acquired infection?
        **YES
        25) Do you consider Jeremiah Sample (PATIENT-1) to be a
            compromised host? (alcoholic, immunosuppressed, etc.):
        **NO
        26) Has Jeremiah Sample (PATIENT-1) had any gu surgery or
            manipulation of the urinary tract?
            (e.g., indwelling catheter, cystoscopy, etc.)
        **WHY


I AM TRYING TO FIND OUT ABOUT THE IDENTITY OF THE ORGANISM.
I ALREADY KNOW THAT:
THE PORTAL OF ENTRY OF THE ORGANISM IS UPPER-GU
THE MORPHOLOGY OF THE ORGANISM IS ROD
THE STAIN OF THE ORGANISM IS GRAMNEG
THE SITE OF THE CULTURE IS BLOOD
THEREFORE, IF:
1)  THE PATIENT HAS NOT HAD A GENITO-URINARY MANIPULATIVE PROCEDURE,
```

```
     AND
2)   URINARY-TRACT-INFECTION IS NOT A PROBLEM FOR WHICH THE PATIENT
     HAS BEEN TREATED
THEN:
THERE IS SUGGESTIVE EVIDENCE (.6)  THAT THE IDENTITY OF THE ORGANISM
     IS E.COLI
(RULE156)
```

[The WHY option demonstrated here is briefly mentioned in Chapter 3. The feature was developed by R. Davis. Its implementation details are therefore not described in this thesis.]

```
**YES
27) Does the patient have 'pseudomonas-type' hemorrhagic
    skin lesions (ecthyma gangrenosum)?
**YES
28) Was the patient treated for the infection with the
    enterobacter (ORGANISM-4)?
**NO
29) Do you feel that the finding of the enterobacter
    (ORGANISM-4) at this normally non-sterile site is
    suggestive of disease in this patient?
**NO
30) Do you believe that the enterobacter (ORGANISM-4) is a
    contaminant (or normal flora in the case of non-sterile
    sites)?
**NO
31) Was the patient treated for the infection with the
    klebsiella (ORGANISM-3)?
**NO
32) Do you feel that the finding of the klebsiella
    (ORGANISM-3) at this normally non-sterile site is
    suggestive of disease in this patient?
**NO
33) Do you believe that the klebsiella (ORGANISM-3) is a
    contaminant (or normal flora in the case of non-sterile
    sites)?
**UNKNOWN
34) Was the patient treated for the infection with the
    pseudomonas (ORGANISM-2)?
**NO
35) Do you feel that the finding of the pseudomonas
    (ORGANISM-2) at this normally non-sterile site is
    suggestive of disease in this patient?
**YES (8)
36) Has the lab reported the in-vitro antibiotic
    sensitivities of the pseudomonas (ORGANISM-2)?
**NO
37) Has Jeremiah Sample (PATIENT-1) had any operations that
    you feel may be relevant to the current infection?
**YES
```

```
            --------OPERATION-1--------
            38) How long ago was OPERATION-1 performed?
            **11 DAYS
            39) Were any antibiotics given during OPERATION-1?
            **YES

               --------DRUG-1--------
               40) What drug?
               **CEFALOTHIN
=CEPHALOTHIN
            41) Were any other antibiotics given at the time of
                OPERATION-1?
            **NO
         42) Any other significant operative procedures?
         **NO
         43) Including this blood culture (CULTURE-1), how many
             cultures were obtained from this normally sterile site
             on the same day?
         **RULE

RULE044
-------
      IF:  1)  THE SITE OF THE CULTURE IS ONE OF: THOSE SITES THAT
               ARE NORMALLY STERILE, AND
           2)  THE NUMBER OF CULTURES IN THE SERIES INCLUDING THE
               CULTURE IS GREATER THAN 1, AND
           3)  THE NUMBER OF CULTURES CONTAINING THE ORGANISM IS
               GREATER THAN 1
      THEN:  THERE IS EVIDENCE (CF= THE QUOTIENT OF THE NUMBER OF
                 CULTURES CONTAINING THE ORGANISM DIVIDED BY THE
                 NUMBER OF CULTURES IN THE SERIES INCLUDING THE
                 CULTURE)  THAT THERE IS SIGNIFICANT DISEASE
                 ASSOCIATED WITH THIS OCCURRENCE OF THE ORGANISM

         **4
         44) How many of the cultures were positive for ORGANISM-1?
         **2
                                              [Note that the certainty factor
                                              (CF) for RULE044 is calculated from
                                              the answers to questions 43 and 44.
                                              CF's are explained in Chapter 5.]
      45) Any other organisms isolated from this blood culture
          (CULTURE-1) for which you would like a therapeutic
          recommendation?
      **NO
      46) Does Jeremiah Sample (PATIENT-1) show any evidence of
          infection at a site inaccessible to culture (e.g., brain,
          bone, liver, etc.)?
      **NO
   47) Were any additional positive specimens recently drawn from
       Jeremiah Sample (PATIENT-1) which revealed one or more
       organisms for which you wish therapeutic advice?
   **NO

     I am ready to print my conclusions.  Press the key marked
```

RETURN when you are ready to see them.

[MYCIN has now asked all questions it feels are necessary in order to decide (a) whether ORGANISM-1 is significant, and (b) the likely identities of ORGANISM-1.]

My therapy recommendation will be based on the following possible identities of the organism(s) that seem to be significant:
<Item 1> The identity of ORGANISM-1 may be PSEUDOMONAS
<Item 2> The identity of ORGANISM-1 may be KLEBSIELLA
<Item 3> The identity of ORGANISM-1 may be ENTEROBACTER
<Item 4> The identity of ORGANISM-1 may be E.COLI
<Item 5> The identity of ORGANISM-1 may be PROTEUS (Subtype unknown)

[MYCIN now begins asking questions to assist with drug selection.]

48) On a scale of 0 to 4, where higher numbers indicate increasing severity, how would you rate Jeremiah Sample (PATIENT-1)'s degree of sickness?
**4
49) Does Jeremiah Sample (PATIENT-1) have a clinically significant allergic reaction to any antimicrobial agent?
**NO
[Considering GENTAMICIN for use against ORGANISM-1 ...]

[Rec 1] My preferred therapy recommendation is as follows:
In order to cover for Items <1> <2> <3> <4> <5>:
Give the following in combination:
1 GENTAMICIN
Dose: 1.7 MG/KG Q8H - IV OR IM
Comments: MODIFY DOSE IN RENAL FAILURE
2 CARBENICILLIN
Dose: 25 MG/KG Q2H - IV
Comments: MODIFY DOSE IN RENAL FAILURE

Do you wish to see the next choice?
**YES
[Considering COLISTIN for use against ORGANISM-1 ...]
[Rejecting SULFISOXAZOLE for use against ORGANISM-1 ...]

[Rec 2] Next best therapy recommendation:
In order to cover for Items <1> <2> <3> <4>:
Give: COLISTIN
Dose: 1.25 MG/KG Q6H - IM
Comments: MODIFY DOSE IN RENAL FAILURE

Do you wish to see the next choice?
**NO

[The Consultation System (Subprogram 1) is now finished. Control therefore automatically passes to the Explanation System (Subprogram 2).]

Please ask any simple-English questions regarding the above consultation session or the overall knowledge of the consultation system. When discussing the consultation above, please refer to organisms, cultures, etc. by their numeric names (e.g., ORGANISM-1). The names of rules need not be printed in full when using the PR option ('PR 37' is okay), but use the whole name in other contexts (e.g., RULE037). Questions may be specified by the numbers that preceded them above. Enter the word STOP when you have no further questions. Certain standard question types may also be preceded by special codes that will speed up the answers to your questions.

Type HELP for the list of question options.

** HELP

QUESTION-ANSWERING (QA) OPTIONS:

HELP	- PRINTS THIS LIST
EQ	- REQUESTS AN EXPLANATION OF THE SPECIFIED QUESTION(S) FROM THE CONSULTATION
IQ	- PREFIX TO A QUESTION WHICH ASKS ABOUT INFORMATION ACQUIRED BY THE PROGRAM DURING THE CONSULTATION
NO PREFIX	- THIS QUESTION QUERIES CONTENTS OF DECISION RULES IN THE SYSTEM
PR	- REQUESTS THAT SPECIFIED RULE(S) BE PRINTED
STOP	- ESCAPE FROM EXPLANATION SYSTEM
RA	- ENTRY TO RULE-ACQUISITION MODULE FOR RECOGNIZED EXPERTS

** IQ WHAT IS THE FINAL DECISION REGARDING THE IDENTITY OF ORGANISM-1?
THE IDENTITY OF ORGANISM-1 IS PSEUDOMONAS (.357) KLEBSIELLA (.177) ENTEROBACTER (.166) E.COLI (.137) PROTEUS (.118) SERRATIA (.042)

** WHAT MADE YOU THINK ORGANISM-1 MIGHT BE A PROTEUS?

I USED RULE163 TO CONCLUDE THAT THE IDENTITY OF ORGANISM-1 IS PROTEUS. THIS GAVE A CUMULATIVE C.F. OF .277. THE LAST QUESTION ASKED BEFORE THE CONCLUSION WAS MADE WAS 26.
I USED RULE084 TO CONCLUDE THAT THE IDENTITY OF ORGANISM-1 IS PROTEUS. THIS GAVE A CUMULATIVE C.F. OF .119. THE LAST QUESTION ASKED BEFORE THE CONCLUSION WAS MADE WAS 24.

** PR 84 163

RULE084

IF: 1) THE SITE OF THE CULTURE IS ONE OF: THOSE SITES THAT ARE NORMALLY STERILE, AND
2) THE LIST OF LIKELY PATHOGENS ASSOCIATED WITH THE

```
                PORTAL OF ENTRY OF THE ORGANISM IS KNOWN,  AND
            3)  THIS ORGANISM AND THE MEMBERS THAT YOU ARE
                CONSIDERING AGREE WITH RESPECT TO THE FOLLOWING
                PROPERTIES: GRAM MORPH AIR
       THEN:  THERE IS STRONGLY SUGGESTIVE EVIDENCE (.8)  THAT EACH
                OF THEM IS THE IDENTITY OF THE ORGANISM
RULE163
-------
       IF:  1)  THE MORPHOLOGY OF THE ORGANISM IS ROD,  AND
            2)  THE STAIN OF THE ORGANISM IS GRAMNEG,  AND
            3)  THE IDENTITY OF THE ORGANISM IS NOT KNOWN WITH
                CERTAINTY,  AND
            4)  THE PATIENT HAS HAD A GENITO-URINARY MANIPULATIVE
                PROCEDURE
       THEN:  1)  THERE IS WEAKLY SUGGESTIVE EVIDENCE (.36)  THAT THE
                  IDENTITY OF THE ORGANISM IS PSEUDOMONAS,  AND
              2)  THERE IS WEAKLY SUGGESTIVE EVIDENCE (.18)  THAT THE
                  IDENTITY OF THE ORGANISM IS PROTEUS,  AND
              3)  THERE IS WEAKLY SUGGESTIVE EVIDENCE (.1)  THAT THE
                  IDENTITY OF THE ORGANISM IS SERRATIA,  AND
              4)  THERE IS WEAKLY SUGGESTIVE EVIDENCE (.18)  THAT THE
                  IDENTITY OF THE ORGANISM IS ENTEROBACTER,  AND
              5)  THERE IS WEAKLY SUGGESTIVE EVIDENCE (.18)  THAT THE
                  IDENTITY OF THE ORGANISM IS KLEBSIELLA

** HOW DID YOU DECIDE THAT PSEUDOMONAS WAS THE MOST LIKELY IDENTITY OF ORGANISM-1?

     I USED RULE163 TO CONCLUDE THAT THE IDENTITY OF ORGANISM-1 IS
       PSEUDOMONAS.  THIS GAVE A CUMULATIVE C.F. OF .651.  THE
       LAST QUESTION ASKED BEFORE THE CONCLUSION WAS MADE WAS 26.
     I USED RULE084 TO CONCLUDE THAT THE IDENTITY OF ORGANISM-1 IS
       PSEUDOMONAS.  THIS GAVE A CUMULATIVE C.F. OF .455.  THE
       LAST QUESTION ASKED BEFORE THE CONCLUSION WAS MADE WAS 24.
     I USED RULE050 TO CONCLUDE THAT THE IDENTITY OF ORGANISM-1 IS
       PSEUDOMONAS.  THIS GAVE A CUMULATIVE C.F. OF .352.  THE
       LAST QUESTION ASKED BEFORE THE CONCLUSION WAS MADE WAS 24.
     I USED RULE040 TO CONCLUDE THAT THE IDENTITY OF ORGANISM-1 IS
       PSEUDOMONAS.  THIS GAVE A CUMULATIVE C.F. OF .833.  THE
       LAST QUESTION ASKED BEFORE THE CONCLUSION WAS MADE WAS 27.
     I USED RULE021 TO CONCLUDE THAT THE IDENTITY OF ORGANISM-1 IS
       PSEUDOMONAS.  THIS GAVE A CUMULATIVE C.F. OF .19.  THE
       LAST QUESTION ASKED BEFORE THE CONCLUSION WAS MADE WAS 21.

** PR 21

RULE021
-------
       IF:  THERE IS A PRIOR ORGANISM WHICH MAY BE THE SAME
              AS THE CURRENT ORGANISM
       THEN:  IT IS DEFINITE (1)  THAT THESE PROPERTIES - IDENTITY -
                SHOULD BE TRANSFERRED FROM A PRIOR ORGANISM WHICH
                MAY BE THE SAME AS THE ORGANISM TO THIS CURRENT
                ORGANISM
```

```
** IQ DID YOU DECIDE ORGANISM-2 WAS THE SAME AS ORGANISM-1?
ORGANISM-4 (.19) ORGANISM-3 (.19) ORGANISM-2 (.19) IS A PRIOR ORGANISM
           WITH THE SAME IDENTITY AS ORGANISM-1

** HOW DID YOU DECIDE THAT ORGANISM-2 WAS THE SAME AS ORGANISM-1?

     I USED RULE005 TO CONCLUDE THAT THE PSEUDOMONAS IS A PRIOR
        ORGANISM WITH THE SAME IDENTITY AS ORGANISM-1.  THIS GAVE
        A CUMULATIVE C.F. OF .19.  THE LAST QUESTION ASKED BEFORE
        THE CONCLUSION WAS MADE WAS 21.
     I USED RULE004 TO CONCLUDE THAT THE PSEUDOMONAS IS A PRIOR
        ORGANISM WITH THE SAME IDENTITY AS ORGANISM-1.  THIS GAVE
        A CUMULATIVE C.F. OF .133.  THE LAST QUESTION ASKED BEFORE
        THE CONCLUSION WAS MADE WAS 18.

** PR 4 S

RULE004
-------
      IF:  1)  THE IDENTITY OF THE ORGANISM IS NOT KNOWN WITH
               CERTAINTY,  AND
           2)  THIS CURRENT ORGANISM AND PRIOR ORGANISMS OF THE
               PATIENT AGREE WITH RESPECT TO THE FOLLOWING
               PROPERTIES: MORPH GRAM
      THEN:  THERE IS WEAKLY SUGGESTIVE EVIDENCE (.4)  THAT EACH OF
                THEM IS A PRIOR ORGANISM WITH THE SAME IDENTITY AS
                THE ORGANISM
RULE005
-------
      IF:  THIS CURRENT ORGANISM AND A PRIOR ORGANISM WITH THE SAME
              IDENTITY AS THE ORGANISM AGREE WITH RESPECT TO THE
              FOLLOWING PROPERTIES: AIR
      THEN:  THERE IS WEAKLY SUGGESTIVE EVIDENCE (.2)  THAT EACH OF
                THEM IS A PRIOR ORGANISM WITH THE SAME IDENTITY AS
                THE ORGANISM

** EQ 48
48     QUESTION 48 WAS ASKED IN ORDER TO FIND OUT JEREMIAH SAMPLE'S
          DEGREE OF SICKNESS (ON A SCALE OF 4) IN AN EFFORT TO
          EXECUTE RULE068.

** PR 68

RULE068
-------
      IF:  1)  THE THERAPY UNDER CONSIDERATION IS GENTAMICIN,  AND
           2)  THE IDENTITY OF THE ORGANISM MAY BE PSEUDOMONAS,  AND
           3)  THE PATIENT'S  DEGREE OF SICKNESS (ON A SCALE OF 4)
               IS GREATER THAN 3,  AND
           4)  [A - THE PATIENT IS NOT ALLERGIC TO ANTIBIOTICS,  OR
               B - CARBENICILLIN IS NOT A DRUG TO WHICH THE PATIENT
               IS ALLERGIC]
```

THEN: RECORD THE FOLLOWING AS A MORE APPROPRIATE THERAPY THAN GENTAMICIN: THE COMBINATION OF GENTAMICIN WITH CARBENICILLIN

** RA
Sorry, but the rule-acquisition module is available only to recognized experts.

[The physician has attempted to enter the Rule-Acquisition System (Subprogram 3). The option is only available to recognized experts, however. That is the reason for the initial question at the beginning of the consultation when the user is asked to give his code name.]

** STOP
50) Do you wish advice on another patient?
**NO

THANK-YOU

Chapter 2

CONTENTS

I. INTRODUCTION

This chapter concentrates on an area of medical computing that was mentioned only briefly in Chapter 1 (Section II.2.7). Computer-assisted medical decision making fascinates numerous researchers, partly because analysis of human reasoning is itself challenging, but more importantly because modern medicine has become so complex that no individual can incorporate all medical knowledge into his decision making powers. The field has developed along a number of dimensions. It is therefore somewhat difficult to devise an organizational structure for examining the work in this area. Three reasonable dimensions for classifying a computer-based system are:

(1) the program's mode of interaction;

(2) the program's purpose;

(3) the program's methodology.

In Section II the field is summarized in terms of dimension (3), i.e., the various methodologies that have been utilized. The other two dimensions merit brief mention, however.

The decision making program's mode of interaction, like that of any computer program, is either on-line with the user (usually under some time-sharing monitor) or remote in a batch-processing or other off-line mode. The majority of such programs now operate on-line, interacting either directly with the decision maker or with someone who will transmit the computer's information to him. There is clearly more opportunity for discourse and explanation in such programs.

An interactive system that gives advice in this fashion is termed a 'consultation program'.

The 'purpose' of a decision making program would provide a useful basis for classification of the field if there were not so much overlap among the categories. There are at least four kinds of program along this dimension:

(1) diagnostic programs

(2) prognostic programs

(3) treatment planning programs

(4) educational programs

Programs specifically designed for educational purposes were mentioned in Section II.2.8 of Chapter 1. Any decision program has potential educational side-effects, however, particularly if it is able to explain the basis for its decisions. Similarly, programs for prognosis and treatment planning must in general make a partial diagnosis of the patient's problem (unless that information is provided by the user at the outset). As was pointed out in Section IV.1 of Chapter 1, MYCIN explicitly considers both diagnosis and treatment planning, and also has rules based upon patient prognosis that aid in therapy selection. Furthermore, as is explained in Chapter 3, educational capabilities have been an important design consideration during the current research. The MYCIN System is therefore an example of a system that encompasses all four of the 'purpose' categories I have named. Classification of decision making programs on the basis of these subcategories is hence not particularly useful.

The reader may well ask why I am so intent upon devising a classification scheme for the programs to be discussed in this chapter. One answer is that classification leads to structure and, in turn, to understanding. It is therefore the very basis of diagnosis itself <Jelliffe - 1973>. Although they often function well, the reasoning processes used by a skilled diagnostician are usually poorly understood, even by the expert (see Chapter 5). Researchers attempting to

devise computer-based approaches that parallel human decision making must therefore assign structure to their problem area in whatever fashion seems most natural. It is helpful to begin by analyzing the diagnostic process itself <Feinstein - 1967, Card - 1970a, Taylor - 1971> and then to seek a reasonable basis for its automation <Lusted - 1968, Gorry - 1970>. The methodology selected undoubtedly reflects both the specific clinical problem area and the researcher's own peculiar biases based upon his past experience. Approaches selected are so numerous that national conferences have been held so that individuals may share the new diagnostic techniques or applications that they have developed <Jacquez - 1972>. Yet two basic concepts underlying all the methodologies are the use of some classification mechanism and, with very few exceptions <Ledley - 1973>, the recognized need for numerical techniques.

If the success of medical decision support programs is measured by user acceptance, however, the field has not produced more than a handful of truly useful programs. Croft has examined this question in detail <Croft - 1972> and suggests that attempts to develop new diagnostic models will be largely unsuccessful until three basic problems are solved:

(1) lack of standard medical definitions;

(2) lack of large, reliable medical data bases;

(3) lack of acceptance of computer-aided diagnosis by the medical profession.

Croft examined the field extensively in reaching these conclusions. He explains the significance of the first two obstacles by observing that the more diseases a model is assigned to diagnose, the more difficult is the diagnostic task and, in turn, the less successful a program is apt to be in reaching correct decisions. Lack of acceptance, as discussed in Section II.1 of Chapter 1, is an even more fundamental problem that cannot be avoided simply by narrowing the diagnostic

range of a computer-based system. Despite Croft's claim that model development should be set aside while the three listed obstacles are being overcome, it could be argued that new diagnostic methodologies which pay more attention to the demands of the user are the only reasonable way to expect that professional attitudes towards computers will improve. MYCIN has been designed with this goal in mind (see Chapter 3).

Several attempts have been made to standardize medical definitions. These include the Standard Nomenclature of Diseases and Operations (SNDO), the International Classification of Diseases - Adapted (ICDA), and the Systemized Nomenclature of Pathology (SNOP). Few of these are used extensively in daily medical practice other than for certain reporting purposes. Brunjes has proposed an 'anamnestic matrix' concept that would permit computer programs to handle non-standardized input in a standardized fashion <Brunjes - 1971>. In addition, a British group which evaluated observer variation in history taking and examination found significant degrees of disagreement that were largely reduced when a system of agreed definitions was developed and utilized by the participating physicians <Gill - 1973>. MYCIN has avoided some of these problems by using a large synonym dictionary and by phrasing questions in a manner designed to maximize uniformity of user response (see Section III.2.2 - Chapter 4).

II. COMPUTER-BASED METHODOLOGIES FOR DECISION SUPPORT

II.1 Data Retrieval As A Decision Aid

The simplest kind of decision support system merely provides the data so that others can make the complicated decisions which depend upon the retrieved information. Such systems generally rely upon a computer-based information storage system that accumulates large amounts of data on several patients. Coded information may include physical parameters, diagnosis, treatment plan, and responses to therapy. Physicians may then request information on previous patients who match a new patient on the basis of one or more parameters. Detailed information on how other individuals with similar disease have responded to therapy may help the physician select the best treatment plan for his patient or better estimate the prognosis for an individual with the particular constellation of symptoms <Feinstein - 1972>. Supporting statistical programs also may provide correlation information that is difficult to deduce merely by looking at retrieved data <Fries - 1972>. A number of medical record systems have been designed with data retrieval requirements as an important consideration <Greenes - 1970a, Shortliffe - 1970, Karpinski - 1971, Feinstein - 1971>.

II.2 Decisions Based Upon Numerical Computations

A limited number of medical problem areas are so well understood that they have been characterized by mathematical formulae. When the computations are complex, physicians are often tempted to take short cuts, making approximations on the assumption that this will compensate for the tendency to forget the formulae or their proper application. Computer programs to assist with the calculations and their interpretation may therefore be highly useful.

One such clinical problem area is the classification and management of electrolyte and acid-base disorders. The relationship of blood pH to variables such as kidney function and electrolyte levels is well characterized by formulae that utilize the numerical values of blood gas and other laboratory tests. Bleich has written a program that assists the physician with evaluation of such problems <Bleich - 1969,1971,1972>, and a similar program has been reported by Schwartz <Schwartz - 1970>. These systems were designed primarily to assist physician users. Their developers therefore faced many of the same problems of user acceptance and human engineering which have been encountered during the design of MYCIN. Both programs take advantage of time-shared systems with flexible storage mechanisms that permit not only the calculation of patient parameters but also the presentation of useful information regarding the patient's status. Possible etiologies are listed and literature references are given so that the physician may pursue the topic if necessary. A similar program which evaluates the respiratory status of patients in a respiratory care unit, and makes therapeutic recommendations, has also been described <Menn - 1973>.

Another problem area in which numerical calculations using well-defined formulae are the primary concern is the customization of drug doses once the agent to be used has been selected. Several examples of programs in this field involve the selection of a digoxin regimen for a patient with heart disease <Sheiner -

1972, Jelliffe - 1972, Peck - 1973>. There is also a program that helps physicians decide on insulin doses for diabetics <Bolinger - 1973>. These systems depend upon a pharmacokinetic model of the body's absorption, metabolism, distribution, and excretion of the drug in question. Inputs to the programs are various clinical parameters for the patient which are then used to calculate the dosage regimen needed to achieve optimal blood levels of the therapeutic agent.

II.3 Probabilistic Approaches To Decision Making

Most computer-based decision making tools for medical practitioners are based upon statistical decision theory. The methods used range from simple binary decision trees to conditional probability, discriminant analysis, and clustering techniques.

Explicit decision trees offer advantages in that they clearly represent, when diagrammed, an algorithmic approach to diagnosis. Such diagrams, if memorized or easily accessible, may be useful in visualizing a particular patient's status and the clinical parameters that should be checked in order to further define his diagnostic (or prognostic) category. The trees are non-dynamic, however, and can therefore not adjust easily to unexpected findings or to unavailable test results. Furthermore, modification of the trees when they are found to be incomplete or inaccurate may be highly complex due to the subtle interrelationships within such reasoning networks. There are several examples of programs that are at least partially dependent upon tree-structured decision pathways <Warner - 1972a, Sletten - 1973, Brodman - 1966, Button - 1973, Koss - 1971, Meyer - 1973>.

By far the most commonly used statistical technique employed for computer-based medical decision making is Bayes' Theorem in its various forms. It

is generally utilized as a first-order approximation to conditional probability under the assumption that the patient's signs and symptoms are jointly independent. In Chapter 5 I discuss the theory in some detail and explain why we chose to reject Bayesian analysis as the basis for MYCIN's decision model. When comprehensive patient data are available, however, Bayes' Theorem offers both excellent results and a methodology that lends itself to automation.

In 1964 Warner et. al. introduced a computer program that aided in the diagnosis of congenital heart disease <Warner - 1964>. Data had been gathered for several hundred patients with congenital cardiac malformations. As a result, all the conditional probabilities needed for the use of Bayes' Theorem could be computed. The program accordingly classified new patients with an accuracy similar to that of cardiologists.

Four years later Gorry and Barnett presented a program that used the same patient data to give results of similar accuracy <Gorry - 1968a>. However, their program used a modification of Bayes' Theorem (see Section II - Chapter 5) which permitted diagnoses to be reached in a sequential fashion. The system was therefore able to suggest the laboratory or physical tests that were most valuable at each step in the decision process. Using a selection function which considered both the current degree of certainty regarding a diagnosis and the cost of additional testing (in terms of money, time delay, and physical pain or inconvenience), the program attempted to minimize the number of tests while maximizing its diagnostic accuracy.

Bayesian programs continue to pervade the literature on computer-based diagnosis. Recent reports from several countries in addition to the United States have presented computer programs using Bayesian analysis both for diagnosis <Gledhill - 1972, Knill-Jones - 1973> and for screening patients who have given automated medical histories <Warner - 1972b>. The technique has been shown to be highly useful in cases where adequate data are available.

Nordyke et. al. presented an interesting study using Bayes' Theorem and two other mathematical techniques for the diagnosis of thyroid disease <Nordyke - 1971>. Having previously reported a pattern recognition approach to the problem <Kulikowski - 1970>, the authors compared both Bayes' Theorem and pattern recognition to a linear discriminant model. 'Pattern recognition' is a general term, the interpretation of which depends upon the application area being discussed. In medical diagnosis the term usually describes a method that "attempts to extract the most characteristic features of each diagnostic category, rather than trying to discriminate directly between categories. A patient is then classified into the category with which his data shares the most features" <Nordyke - 1971>. One variation of this technique may be characterized mathematically using a feature extraction procedure which specifies data vectors that may be subjected to cluster analysis. The linear discriminant model, on the other hand, is an attempt to consider the effects of correlation (or second-order interdependence) between characteristics. The discriminant used in the thyroid study is described in detail in the Nordyke paper.

The data used by Nordyke et. al. were extracted from the records of 2405 patients who had been seen over a six year period for evaluation of thyroid disease. Their results showed that although the pattern recognition technique performed best in identifying ill patients on the basis of history data alone, it produced an inordinate number of false positives. Bayes' Theorem, on the other hand, gave comparatively better diagnostic accuracy as more physical findings and laboratory test results became available. Their report therefore concludes:

> Because each of the methods uses the characteristics of a patient differently, some taking advantage of discriminating information at a given stage better than others, it would seem that a combination of these would be best for a sequential diagnostic procedure. ... However, since the simpler Bayes method provides comparable results at the pre-laboratory stage of diagnosis, it might prove the most effective clinical aid.

Another technique used for sequential decision making is the Shannon entropy formula <Shannon - 1949>:

$$\text{entropy} = -\sum_{\text{all } i} p(Xi) \log p(Xi)$$

Here p(Xi) is the probability that Xi is true (e.g., that the patient has disease Di). Steps in the sequential process are selected so as to maximize the entropy of the set of possible diagnoses. Several programs have successfully used this selection function <Mullin - 1970, Gleser - 1972>, but it should be noted that entropy too is dependent upon good probabilistic information.

All the methodologies discussed so far are examples of techniques utilized in the field of decision analysis <Raiffa - 1968>. The last programs for discussion in this subsection are those that encompass several of the techniques - conditional probabilities, decision trees, utility measures, and selection functions for sequential decision making. Ginsberg's program for diagnosis and management of patients with pleural effusions is an excellent example of this kind of eclectic approach <Ginsberg - 1968,1970>. In addition, one of the early workers with Bayesian diagnostic programs <Gorry - 1968a,1968b>, has gradually broadened his approach to include several additional facets of decision theory. In joint papers published in the American Journal of Medicine, he and his co-workers presented a comprehensive look at decision theory as applied to medical diagnosis <Schwartz - 1973>, and reported a program that uses the techniques to evaluate the etiology of acute renal failure <Gorry - 1973b>. Although neither their techniques nor their results are unique, their presentation is lucid and complete. It has generated positive commentary <Jelliffe - 1973> at a time when, as I have remarked before, the acceptance of computers by physicians is in need of reasoned support.

II.3 Artificial Intelligence And Medical Decisions

There are relatively few examples of artificial intelligence programs used for medical decision making. Since 1970, however, a small number of researchers, most of whom have had experience rooted in the traditional approaches described in Section II.2, have begun to consider AI techniques. Notable among these is G.A. Gorry from MIT. He became aware that the purely statistical programs have had three failings that are major impediments to physician acceptance of the systems. First, the programs have no real 'understanding' of their problem area. Gorry explains this point as follows <Gorry - 1973a>:

> There are several approaches to inferring renal function and assessing whether it is stable or changing. This determination is very important in diagnosis and in choosing management strategies. From the experts, it is possible to obtain the procedure by which they infer a value for renal function. Further, many statements about the interpretation of changes in renal function can be made. To capture the knowledge embodied in these statements, some computer realization of the concept of renal function must be developed.

Artificial intelligence, with its emphasis upon representation of knowledge, offered a natural environment for examining the kind of 'concept formation' that Gorry feels is needed.

The second problem is that, even if the traditional programs have been given an understanding of their problem area, they have no mechanism for discussing their knowledge with the user. Physicians are often uninspired by programs that produce a diagnosis and a four-decimal-place probability estimate without being able to answer questions about how the conclusion was reached. Furthermore, physicians attempting to give the programs new information have shared no common language with the computer. Gorry therefore calls for the development of natural language interfaces to permit discourse between physicians and diagnostic programs. Once again artificial intelligence provides a natural

environment for examining this requirement.

The third problem, closely related to the first two, is the need for programs that can explain (i.e., justify) their advice. This capability requires that a program both understand its reasoning processes and be able to generate explanations in a language that is easily understood by the physician. Gorry's group is therefore currently working on developing knowledge representations and language capabilities that will heighten the acceptability of a system such as their acute renal failure program <Gorry - 1973b>. In Chapter 3, where the design criteria for the MYCIN System are discussed, the similarities between our desiderata and those of Gorry are readily apparent.

The system requirements discussed by Gorry entail more than a natural language 'front end' in combination with a statistically-based program. As discussed in Chapter 6, efficient knowledge representation is generally the foundation for man-machine discourse in natural language. Isner's medical knowledge system, for example, has demonstrated the need for an efficient representation scheme, plus a program with problem-solving skills, if a computer system is to communicate with minimally trained users <Isner - 1972>. I do not mean to suggest, however, that statistical theory has no place in AI research. Several AI programs have used traditional numerical techniques <Good - 1970> but have also utilized data structures which facilitate utilization of knowledge in ways that are not possible if system information is stored solely in probability tables. Our own mathematical decision model is introduced in Chapter 4 and discussed in detail in Chapter 5.

Problem-solving techniques from artificial intelligence also hold a natural appeal for certain researchers in computer-based medical decision making. The various AI methodologies will not be surveyed here because those most pertinent to MYCIN are discussed in Chapter 4. Four medical projects warrant comment in this context however.

The first is the theory formation system of Pople and Werner <Pople - 1972> which does not attempt diagnosis as such, but does make inferences on the basis of model behavior. The program uses an alternative to deduction and induction - abductive logic <Pople - 1973>. A convincing argument can be made that abduction is the basis for medical diagnosis. Consider, for example, the three statements:

(1) If a person has pneumonia, then he has a fever

(2) John has pneumonia

(3) John has a fever

Deductive logic allows us to derive (3) from (1) and (2); i.e., since people with pneumonia have fever, and since John has pneumonia, John must have a fever. Induction, on the other hand, uses one or more observations of people for whom (2) and (3) hold in order to infer that (1) is true; i.e., since I have observed several people with pneumonia, all of whom have fever, it is perhaps generally true that people with pneumonia have a fever. Abduction is the remaining combination, namely using (1) and (3) to infer (2); i.e., since people with pneumonia have fever, and since John has fever, 'perhaps' it is true that John has pneumonia. Clearly the last example parallels a clinical diagnosis on the basis of a patient's symptomology.

Pople and Werner use the abductive model as the basis of a program for inferring neuroanatomical explanations of the behavior of human neurons in response to central stimulation. The system also includes a simulator that tests hypotheses by modeling them and seeing whether the observed responses are duplicated. The problem, of course, is that the word 'perhaps' is not quantified in our explanation of abduction above. It is therefore unclear how to select between two competing hypotheses that are both abductively supported by the same observation(s). In fact, Bayes' Theorem and the other numerical methods we discussed in Section II.2 are attempts to solve precisely this problem, although

the term 'abduction' does not generally appear in the formulation of those techniques.

An Italian group has recently proposed a more quantitative problem-solving approach that uses AI techniques and addresses itself specifically to medical diagnosis <Gini - 1973>. Their central concern, as has been true for several other researchers, is sequential test selection for effective diagnosis, but they propose a model based upon state-transition networks. Having defined operators for transition from one state in the network to another, they present an algorithm for creating a dynamic ordering of the operators on the basis of their 'promise'. The algorithm interfaces with a heuristic mechanism for obtaining a diagnosis, i.e., for finding a set of tested symptoms which match a particular disease definition. It is probably wise to reserve judgment about the approach until this model has been automated in a computer program, but it initially appears to offer little advantage over other programs (cf. pattern recognition) that have attempted to define diseases as sets of symptoms.

As I have described (Section III.1.8 - Chapter 1), there is a large subfield of artificial intelligence in which investigators are motivated by an interest in psychology. A psychologist from Duke University has reported a fascinating program based upon this approach to medical diagnosis <Wortman - 1972>. He views diagnosis as "a search through a hierarchically organized memory composed of diseases, disease categories, categories of categories, etc. ... along with a parallel hierarchy containing the heuristic decision rules for evaluating these categories". After asking a neurologist to 'think aloud' while solving clinical problems, Wortman analyzed the resulting protocols and wrote a program which attempted to mimic the neurologist's approach to cerebellar disease diagnosis. Not only did the program perform as well as the expert in subsequent tests (correctly diagnosing the disease in 19 of 20 sample cases), but it also generated protocols that closely resembled those of the neurologist himself. It

is important to note, however, that the program's performance was also based upon the expert's subjective probabilities relating cerebellar symptomology to each of the 16 selected diseases that were the subject of the experiment. As a result, Wortman's information processing approach still relies upon the availability of data which reflect the preferences of the expert being modeled. MYCIN also needs such information. AI does not necessarily offer a means for avoiding numerical representation of data relationships, but does suggest new and potentially powerful methods for analyzing the problem domain and selecting relevant knowledge. It will be fascinating to observe Wortman's future work to see if his success continues as the range of possible diagnoses increases and the clinical problem areas are expanded.

Noteworthy work combining AI techniques and mathematical models of disease has been progressing at Rutgers University for the last several years. Like some of the investigators discussed in Section II.2, the Rutgers researchers have sought clinical problem areas that could be well-characterized by mathematical models. Envisioning tiered levels of modeling addressed to various degrees of detail, they assert that an appropriate representation scheme will provide an important basis for the design of diagnostic strategies <Amarel - 1972>. Their concern reflects a basic agreement with Gorry in his claim that a diagnostic program needs to 'understand' the decisions that it reaches <Gorry - 1973a>.

The problem area they have selected for testing their approach is the diagnosis and management of glaucoma. This is an ocular disease that may be characterized both by causal relationships over time and mathematical formulae reflecting fluid resistance and flow <Kulikowski - 1971>. They represent disease states in a network based on causal links reflecting various weights (e.g., 'always', 'almost always', 'sometimes', 'never', etc.). The network provides the basis of a consultation program for ophthalmologists who need help in evaluating a patient's status <Kulikowski - 1972a>. Working in close collaboration with an

ophthalmologist, the group has also written programs that permit an expert interactively to modify nodes in the causal network or to add new information to the inferential structure <Kulikowski - 1972b>. The result is a dynamic program that has created considerable interest among clinical professionals to whom it has been presented at a national meeting of ophthalmologists <Kulikowski - 1973>. The causal network and mathematical model lend themselves well to the development of novel strategies for test selection during the consultation process <Kulikowski - 1972c>. Furthermore, the group's agreement with Gorry's call for programs that can explain their decisions <Gorry - 1973a> is reflected in the program's ability to present a 'parse' of those portions of the network which explain the patient's current clinical state <Kulikowski - 1974>. Although certain of the program's human engineering features currently leave much to be desired (the organization of questions during a consultation and the motivation for individual queries appear somewhat confusing to this observer), the glaucoma system represents a pleasing blend of mathematical and AI techniques which hold great promise for those medical problem areas that can be adapted to this kind of causal modeling.

It is unfortunately the case that most human disease states are not sufficiently well understood to be characterized by well-defined mathematical formulae. Even causal relationships are seldom understood. MYCIN is a program that attempts to use AI techniques to model decision making in ill-defined areas such as these. Afterall, experts do reach decision when such medical problems arise, and they can usually offer theoretical arguments for making the judgments that they do. Our goal has been to capture such judgmental knowledge and to create a program that uses the information effectively and in a way that is acceptable to the physicians for whom it is designed. These considerations are described in detail in Chapter 3.

III. SOME PHILOSOPHICAL OBSERVATIONS

Although medical professionals often demonstrate great resistance to computing innovation, obstacles to acceptance are greatest when the application demands 'hands-on' use at a computer terminal or when the program appears to take over intellectual functions, transcending housekeeping or simple 'number crunching' chores. Decision making systems must therefore overcome huge barriers, not only because they usually demand interaction with the professional and are attacking a problem that demands intelligence, but also because the user of the program is in most cases the physician himself. Of all health professionals, the physician is perhaps most pressed for time and most wedded to a self-image that has been ingrained since medical school. Schwartz has discussed this last point <Schwartz - 1970>:

> Physicians as a group have traditionally cherished their ability to learn and retain large numbers of facts, to formulate a differential diagnosis and to carry on decision making activities. Introduction of the computer into these processes could well be viewed by the doctor as devaluating his hard-won medical education and as undermining his intellectual contribution to medical care. This loss of self-esteem would, of course, be exacerbated if the patient were to find in the transfer of many intellectual functions from man to machine a basis for viewing the doctor with diminished admiration and respect. Such loss of status could have serious social, economic, and political consequences for a profession that has historically enjoyed eminence in the public mind.

Concern regarding the attitudes of patients is not without foundation. This observer has recently heard a group of individuals agree that, all other things being equal, if they had to choose between a doctor who used computer-based

consultation programs and one who did not, they would select the physician who was "intelligent enough" to make decisions for himself.

And what of today's medical consultants? How will they react if they are made to feel that their professional expertise is no longer in demand because some computer program has intruded into their clinical problem area? The potential economic implications for both the consultant and the practicing physicians are enormous. Not only may the programs infringe directly on the physician's duties, but, by providing decision support for individuals less highly trained than physicians, may contribute to a reorganization of responsibilities among allied health personnel.

Concerns are also often voiced regarding the effect of such programs on medical education <Schwartz - 1970>. It is not uncommon to hear the suggestion that such programs will remove the motivation for both doctors and medical students to think or read since they will always know that there is a computer program to help them out if there is something they do not know. Schwartz even suggests that the kind of student attending medical school could change because the primary focus of medical training might become the management of a patient's emotional needs.

Partially because the public image of computers has grown to encompass visions of massive data banks monitoring the daily lives of the public, physicians often express concern that computers capable of making decisions will be used to monitor their medical practice. In an age when federal legislation is already threatening the sacred privacy of the individual physician entrepreneur, technical innovations that could potentially automate the peer review process are especially threatening (see, for example, the discussion of MYCIN's possible extension into the monitoring arena, Section V - Chapter 8).

Finally there are enormous legal questions that remain essentially unanswered at present. Who is culpable if a physician follows a computer's advice

and the patient's condition worsens, especially under circumstances when a panel of experts agree that an alternate therapy would have been preferable? Must program designers assume legal responsibilities for their system's mistakes, or does the physician assume ultimate responsibility when he follows a program's advice?

I have proposed a sufficient number of potentially serious questions that the reader may have begun to wonder whether research in computer-based medical decision making should be encouraged to continue at all! Let us step back for a moment, however, to ask how many of the itemized concerns are valid and how many are the result, rather, of misunderstanding on the part of physicians and the public or of poor public relations efforts on the part of system designers.

Perhaps the most important point to note initially is that many of the programs have been developed in response to a well-demonstrated need. Despite the availability of expert consultants in university environments, the expertise of specialists is either unavailable or over-taxed in many parts of the country. As a result local physicians are often forced to make decisions that are less than optimal. Furthermore, even experts may find it difficult adequately to incorporate their experience with several thousand patients into coherent diagnostic strategies. In this sense programs with access to large data bases are potentially useful for physicians at all levels of experience.

Secondly, developers of decision support programs must make it clear, both from their system design and from the tone and content with which they present their work to the medical community, that computer programs for medical decision making are meant to be <u>tools</u> for the physician, not crutches to replace his own clinical reasoning. There is no reason that a computer-based consultation need be any more threatening than a chest x-ray or a battery of tests from the clinical chemistry laboratory. If a consultation program prods the physician to consider a diagnosis or treatment which might otherwise have slipped his mind, it has done a

service both to him and to the patient. Patient education on this point is therefore similarly important. An effort must be made to inform the public that, since certain clinical problems are highly complex, the medical care they receive may be better if their physician seeks the unique capabilities of a computer rather than forging headlong into a diagnostic or therapeutic decision that is based solely upon his current knowledge. Afterall, few patients object to their physician seeking the advice of a human consultant.

The concern regarding the effect of such programs on medical education may be answered by pointing out that consultation systems, if properly designed, have considerable educational side-effects (see Chapter 3). The physician can therefore become more familiar with the problem area and its important considerations after each consultation session. The result is a growing body of knowledge which may gradually decrease the physician's need for the program's advice. A consultation program's success could in fact be measured in part by the tendency for physicians to be decreasingly reliant upon the system.

What of the specialist's concern that consultation programs will take over his role? There is some basis for this worry because computer-based consultations are likely to be less expensive than consultations with human experts. However, it is likely that most physicians will prefer the advice of fellow doctors when the experts are readily available. The greatest contribution of computer programs is therefore apt to arise at odd hours when consultants are not accessible (even the specialists may welcome programs that can assume their roles at 4AM!) or in rural or other non-university environments where the expertise simply does not exist. Furthermore, in an era when the shortage of doctors and their maldistribution is reaching crisis proportions <Fein - 1967, Schwartz - 1970>, computer innovation that encourages reallocation of health care responsibilities among medical personnel may perhaps be viewed more as a social boon than an economic threat to physicians.

Even the concerns regarding automated monitoring of physicians' habits may be largely overinflated. In Section V of Chapter 8 a model is proposed for prospective peer review monitoring that could avoid the threats of retrospective punitive actions on the part of utilization review and medical audit committees. The latter practices are abhorrent to many physicians and partially account for organized medicine's opposition to recent legislation which sets up mandatory peer review mechanisms.

Finally, the questions of legal responsibility are difficult ones to answer since the judicial precedents are not yet well established <Hall - 1972>. However, it seems likely that if the consultation programs are designed to serve as decision tools rather than replacements for the physician's own reasoning processes, the responsibility for accepting or rejecting the computer's advice will probably rest with the physician himself. A more complicated problem arises if a physician diagnoses or treats incorrectly after failing to use a computer program that was readily available to him. Despite the legal questions raised, the potential benefits of decision making programs seem sufficiently large that unanswered judicial concerns should not be allowed to interfere with progress in the field.

Design Considerations For The MYCIN System

Chapter 3

CONTENTS

[This chapter is based on a paper presented by the author at the 13th Annual San Diego Biomedical Symposium <Shortliffe - 1974a>]

I. INTRODUCTION

As discussed in Chapter 2, several computer programs that attempt to model the physician's decision-making processes have been written. Some of these have stressed the diagnostic process itself <Gorry - 1968a, Warner - 1972b, Wortman - 1972>, others have been designed principally for use as educational tools <Hoffer - 1973, Weinberg - 1973, Harless - 1973>, while still others have emphasized their role in providing medical consultations <Bleich - 1972, Peck - 1973, Kulikowski - 1973>. Actually, these applications are inherently interrelated since any program that is aimed at diagnosing disease has potential use for educating and counselling those who lack the expertise or statistical data which have been incorporated into the program. Consultation programs often include diagnosis as a major component although their principal focus involves interactive use by the physician and/or the determination of therapeutic advice.

In general, the educational programs designed for instruction of medical students and other health professionals have met with more long-term success <Wooster - 1973> than has been the case for the diagnostic and consultation programs. The relative success in implementing instructional programs may result because they deal only with hypothetical patients as part of an effort to teach diagnostic and therapeutic concepts, whereas the consultation programs attempt to assist the physician in the management of real patients in the clinical setting. A program making decisions which can directly affect patient well-being must fulfill certain responsibilities to the physician if he is to accept the computer

and make use of its knowledge. This chapter discusses those clinical responsibilities and specifies the way in which they should be reflected in system design. In addition, the ways in which MYCIN seeks to satisfy the design considerations are described. Developmental concerns that relate to nonclinical acceptability criteria (such as economic, administrative, or legal requirements) are not included in this discussion.

II. DESIGN CONSIDERATIONS FOR CONSULTATION PROGRAMS

Physicians will, in general, reject a computer program designed for their use in decision making unless it is accessible, easy to use, forgiving of noncrucial errors from nonexpert typists, reliable, and fast enough to facilitate the physician's task without significantly prolonging the time required to accomplish it. They also require that the program function as a tool to the physician, not as an 'all-knowing' machine that analyzes data and then states its inferences as dogma without justifying them.

Those who design computer programs to give advice to physicians should devise solutions to these requirements in an effort to combat the current lack of acceptance of computer-aided diagnosis by the medical profession <Croft - 1972>. The physician is most apt to need advice from such a program when an unusual diagnostic or therapeutic problem has arisen, precisely the circumstances under which the patient is likely to be acutely ill. Time will therefore often be an important consideration in such cases, and the physician may be unwilling to experiment with a program that does not meet the general requirements mentioned above.

With these considerations in mind, we developed the following list of prerequisites for the acceptance of a clinical consultation program. The list is idealistic, and its components are perhaps currently unattainable, but they do serve as useful guides as long-range goals for workers in the field. Each item is discussed in detail below, but a preliminary summary is presented here. In

general, a therapeutic or diagnostic consultation program:

1) should be useful;

2) should be educational when appropriate;

3) should be able to explain its advice;

4) should be able to understand and respond to simple questions stated in natural language;

5) should be able to acquire new knowledge, either through experience or by being told;

6) should be easily modified.

These design considerations are related to one another, and the need for each tends to follow from those above it on the list. Furthermore, the order of development of capabilities occurs naturally from the bottom to the top of the list; for example, a program may not be able to explain its advice fully until it can respond to simple questions, and a program will not be useful until it can explain its advice. All six considerations, however, are aimed at satisfying those principles which reflect the system's responsibility to the physician and, through him, to the patient.

II.1 The Program Should Be Useful

Clearly the ultimate goal of any program is that it be 'useful', and in the case of consultation systems for use by physicians this word has several important implications. Usefulness is measured along three scales:

a) the need for the assistance which the program provides;

b) the reliability of the advice;

c) the mechanics for accessing the machine and retrieving the desired information.

The validity of advice is of crucial importance. The system must give good advice most of the time and must be able to explain itself when it cannot reach a decision. Otherwise physicians will soon learn that the system is of little practical value and will stop experimenting with it. Evaluative tests should demonstrate that the advice given by the program corresponds to that given by an expert who is provided with the same clinical information, or that the advice is retrospectively shown to be valid at least as often as is the advice of the expert. This requirement means that the program must be given a large amount of knowledge before it is implemented on the hospital wards. In order to insure an accurate data base of clinical knowledge, cooperation and guidance from several experts in the field with which the program is involved is of great importance, and ongoing collaboration with physicians at all levels of system development is even more desirable. Practicing physicians tend to lose interest quickly in an experimental tool that is not clinically useful, even if they are warned that the program is still undergoing developmental work. It is therefore wise to defer implementation until the collaborating experts feel that minimal additional system improvement can be achieved prior to the ultimate test of ongoing clinical use.

The importance of 'human-engineering' aspects of program design is often overlooked. Yet ignoring such issues can prevent acceptance of a system which otherwise gives good advice and fulfills the design criteria I have mentioned. In this sense a consultation program is not 'useful' unless it is 'useable.' Doctors seek mechanisms for saving time without jeopardizing excellence of patient care, so a program which is slow, difficult to access, or frustrating to use will quickly be rejected. Once implemented, the system should be readily available to clinicians who may need its advice on short notice. Care should therefore be taken to provide a sufficient number of terminals so that there need not be lines of physicians waiting for their chance at the program. Furthermore, the user

should require minimal training in order to get advice from the system. It is also desirable that system response time be fast and that the time from sign-on to sign-off be kept as short as possible commensurate with the difficulty of the therapeutic or diagnostic problem for which advice is being sought. If the program is not a multiple-choice or light-pen system and therefore requires typing by the physician, the amount of user input should be minimized and misspellings should be tolerated as much as possible. Users without computer experience tend to think that a machine is unintelligent if it cannot realize that 'tetracyline' was intended to be 'tetracycline', and a physician will not take kindly to a system that requires that he experiment with two or three spellings until he finds the one with which the program is familiar. Relatively minor issues such as these can make the difference between a successful consultation program, acceptable to clinicians, and one that is not. They should certainly not be ignored until clinical implementation is attempted because the problems can often be solved more easily if they are considered during program development.

II.2 The Program Should Be Educational When Appropriate

A physician who seeks advice from a therapeutic consultation program presumably recognizes that he may not have the necessary expertise or data to make the decision on his own. The program will therefore be interacting with an individual who is likely to welcome instructive comments regarding the patient and the way in which the specific therapeutic problem should be approached. However, the physician may not have time for a learning session with the machine. It is therefore not only important that the system be able to explain the knowledge required in order to make an appropriate clinical decision; it should also be sufficiently flexible so that it does not attempt to instruct the user

unless requested to do so.

An additional benefit that accompanies the machine's ability to teach the user about its decision making is the possibility that, when similar clinical circumstances arise in the future, the physician will no longer need to turn to the consultation program. This can help avoid an over-dependence on the machine's capabilities.

II.3 The Program Should Be Able To Explain Its Advice

In most cases, the educational process I referred to above will be accomplished by having the machine explain the advice it has given. However, explanation serves more than an educational purpose. It also provides the program with a mechanism for justification of decisions; a physician will be more willing to accept a program's advice if he is able to understand the decision steps that the system has taken. This gives him a basis on which to reject the system's advice if he finds that the program is not able to justify its decisions sufficiently. It thereby helps the program conform to the physician's requirement that a consultation system be a tool and not a dogmatic replacement for the doctor's own decisions. Gorry has also discussed the need for explanation capabilities in diagnostic consultation systems <Gorry - 1973a> and suggests that the lack of such features in Bayesian decision programs <Gorry - 1968a> partially accounts for their limited success when ward implementation has been attempted. Bleich attributes much of the success of his acid-base consultation program <Bleich - 1972> to its ability to discuss both the electrolyte status of the patient and its method for calculating the characteristics of the patient's acid-base disorder.

II.4 The Program Should Be Able To Understand Questions

A nonrestrictive mechanism by which the physician can communicate with the program is an important feature of a system designed to explain its decisions and educate the user. This is particularly true if an attempt is made to minimize specialized training for users of the program. Thus the program should be able to understand queries from the physician and it must be able to respond to requests for justification of decisions or machine-generated queries which may be puzzling. Yet few problems have given computer scientists more difficulty than the development of programs that can understand and act upon questions that are presented in natural language. As discussed in Section III.1.7 of Chapter 1, the field of computational linguistics has produced researchers who have approached natural language understanding from several different points of view <Schank - 1972, Winograd - 1972, Woods - 1970>, and some investigators have dealt specifically with programs for understanding and answering questions <Simmons - 1970>. These programs have achieved results that are only of limited applicability. It is therefore unlikely that a consultation program developed for use in the clinical setting in the near future will have sophisticated natural language capabilities. Some attempt to solve the problem in a limited sense is appropriate at this time, however, since question-answering is a logical prerequisite for the kinds of explanatory and educational capabilities that I have been proposing.

II.5 The Program Should Be Able To Acquire New Knowledge

A program needs to be able to learn new information in any area of medical therapeutics where changes in decision criteria occur with some regularity. A

facility for teaching new knowledge to the system is therefore desirable since expert clinicians are generally the only ones who can determine when the knowledge of the program is outdated or otherwise inadequate. The need for this kind of program reliability was discussed above. There is perhaps no better way to insure the reliability of the program's knowledge than to permit collaborating experts to experiment with the program during both developmental and implementation stages, to identify weaknesses in the system's decision criteria, and to make corrections or additions to the program's knowledge base. After the program has been implemented in the clinical setting, a knowledge acquisition capability permits the system to continue to improve whenever errors in its decisions are found by an expert familiar with the methods for teaching it the necessary new information.

Realistically, however, few experts in medical therapeutics will have an extensive knowledge of computer programming and the inner workings of the consultation system. It is therefore important to enable the expert to teach the program new decision criteria or information by entering statements in English and letting the program interpret the language and determine how the new data should be incorporated into the knowledge base. Although the computational problems involved are at least as difficult as those encountered during the question-answering task discussed above, this is a powerful capability which will greatly facilitate growth of the program's knowledge to a point at which the collaborating experts agree that the time for ward implementation has arrived.

A second kind of self-improvement by the program, and a feature that is more appropriate in some applications (such as therapy advisors) than in others, is the development of mechanisms for monitoring the effects of the system's advice upon patient welfare and for modifying its decision criteria dynamically in response to such observations. This kind of learning can take place only after implementation in the clinical environment has occurred and only if mechanisms

exist for letting the machine know whether the physician has followed its advice and whether the patient has responded as desired to the medication that was administered. The issue should not be ignored during program development, however, because design of data structures and input/output mechanisms may be modified if the future need for such a facility is recognized.

II.6 The Program's Knowledge Base Should Be Easily Modified

The need for straightforward system modification follows directly from the desire to permit the program to learn new information and decision criteria directly from the expert. If the teaching process requires intimate knowledge of the system's data base and how it is used, few clinical experts will have the time or inclination to acquire the necessary sophisticated insights into the program. For example, an inference model that depends upon a complex decision tree is apt to be difficult to augment without a complete diagram of the tree so that all implications of additions can be observed. A modular system, on the other hand, permits knowledge to be acquired as isolated facts and allows the consultation program itself to decide under what conditions the new information is relevant. This requirement implies a great deal of intelligence in the consultation monitor but avoids the problems that result if the expert is asked to indicate exactly the circumstances under which the information he is offering may be useful.

Modularity of decision criteria also facilitates searches for inconsistencies or contradictions when new information is acquired during the learning process. If all system knowledge is stored in 'packets', comparisons of a new 'packet' with those that already exist can be straightforward. Such checks for contradictions are important if the system is to maintain its validity through many teaching sessions, particularly when several experts with different

views of the consultation program's problem area are simultaneously influencing the system's knowledge base.

It is possible that a consultation system can succeed to a certain extent without addressing itself to all of the design criteria just discussed or, on the other hand, that additional criteria need to be added to the list. However, the design considerations outlined in this chapter provide long-range goals which demand attention even for short-range program development since it is likely that the success of consultation programs will be impeded until each of these problems has been solved. MYCIN has been developed with all six design considerations in mind and, although it is not yet implemented for ongoing use in the clinical setting, it attempts to solve some of the serious design problems discussed above.

III. MYCIN AND THE ACCEPTABILITY CRITERIA

Several of MYCIN's interactive capabilities were demonstrated in the sample consultation included in Section V.2 of Chapter 1. In the remainder of this chapter we shall therefore present extracts of an interactive session, rather than an entire consultation, in an effort to point out how MYCIN reflects the six design considerations discussed above. Since the logical order of explanation of the six capabilities is from last to first, MYCIN's approach to each will be discussed in that order here. The programming details, however, will not be presented until Chapters 4, 6, and 8.

III.1 Modularity To Insure Straightforward Modification

We accomplished modularity of system knowledge by storing all information in decision rules. These rules are coded in LISP internally, but can be translated into an English language version for communication with the user. For example, a rule that is presented to the physician as:

```
IF: 1) THE STAIN OF THE ORGANISM IS GRAMPOS, AND
    2) THE MORPHOLOGY OF THE ORGANISM IS COCCUS, AND
    3) THE GROWTH CONFORMATION OF THE ORGANISM IS CLUMPS
THEN: THERE IS SUGGESTIVE EVIDENCE (.7) THAT THE IDENTITY
      OF THE ORGANISM IS STAPHYLOCOCCUS
```

is actually coded internally as:

```
PREMISE: ($AND (SAME CNTXT GRAM GRAMPOS)
               (SAME CNTXT MORPH COCCUS)
               (SAME CNTXT CONFORM CLUMPS))
 ACTION: (CONCLUDE CNTXT IDENT STAPHYLOCOCCUS TALLY .7)
```

Since all system knowledge is stored in rules of this sort, and since there is no explicit reference to the way in which one rule relates to the others in the system, the decision rules maintain the modularity that is desirable. The way in which the program monitor (Subprogram 1 - Figure 1-1) decides which rules to use during an interactive session is explained in Chapter 4.

III.2 The Ability To Acquire New Knowledge From Experts

When the consultation program learns from the expert, the process is simply one of acquiring a new rule that conveys the information that the expert believes is lacking in the system. MYCIN's first 150 rules were determined over several months of meetings during which the collaborators discussed representative case histories. These rules were coded into LISP by hand and provided the core knowledge base upon which the early version of the consultation program has operated. Most future rules will be acquired interactively from infectious disease experts. Once an expert has determined what information is needed by the program, he indicates to the Rule-Acquisition System (Subprogram 3 - Figure 1-1) that he wishes to enter a new rule ('NR'). He is then asked to enter the rule in English, following the format of the other rules in the system. MYCIN attempts to translate the rule into a LISP representation and then uses its LISP-to-English routines to print out a version of the rule as it has understood the meaning. The expert is next asked to approve the new rule or to make modifications as necessary. The following session demonstrates this learning

process (user input follows the double asterisk):

```
** NR
The new rule will be called RULE200.
   If:    1 ** THE ORGANISM IS A GRAM NEGATIVE ROD
      and 2 ** IT IS ANAEROBIC
      and 3 ** IT WAS ISOLATED FROM THE BLOOD
      and 4 ** YOU THINK THE PORTAL WAS THE GI TRACT
      and 5 **
 Then:    1 ** IT IS PROBABLY A BACTEROIDES
               On a scale of 1 to 10, how much certainty would
               you affix to this conclusion?
               ** 9
      and 2 **

This is my understanding of your rule:
RULE200
-------
    IF: 1) THE SITE OF THE CULTURE IS BLOOD, AND
        2) THE STAIN OF THE ORGANISM IS GRAMNEG, AND
        3) THE MORPHOLOGY OF THE ORGANISM IS ROD, AND
        4) THE AEROBICITY OF THE ORGANISM IS ANAEROBIC, AND
        5) THE PORTAL OF ENTRY OF THE ORGANISM IS GI
  THEN: THERE IS STRONGLY SUGGESTIVE EVIDENCE (.9) THAT
        THE IDENTITY OF THE ORGANISM IS BACTEROIDES

Okay? (YES or NO)
** YES
```

A similar procedure is used to alter previously existing rules that the expert finds incomplete or otherwise inadequate. Only after expert clinicians have used these features to teach MYCIN additional knowledge will the validity of the program's advice reach an adequate level so that implementation in the hospital can be considered.

The mechanism that MYCIN uses for understanding the natural language input of experts avoids syntactic or semantic analysis; it is, rather, a modified key-word approach in which accumulated clues are combined in order to deduce which attributes of organisms, cultures, patients, etc., are being discussed. The technique is described in detail in Chapter 6.

Once new rules are acquired from the expert, they immediately become available for use by the Consultation System (Subprogram 1). Appropriate checks

must be made to insure that the rule does not contradict any previously existing rule, but the expert need not worry about how the rule interrelates with other rules or when the system should use the new knowledge. At present, only a limited number of rules have been acquired using the scenario demonstrated above (see Section III - Chapter 8). Future work will concentrate on the problem of letting MYCIN learn rules that discuss attributes with which the system is not already familiar. In such instances, the program's 800-word dictionary is of small value in deducing the meaning of the English-language input and new techniques must be developed so that MYCIN can not only learn new rules of this variety but can also learn about the clinical attributes that are being discussed.

III.3 The Ability To Understand Questions

MYCIN answers questions about its decisions by retrieving and printing out the relevant rules (Subprogram 2 - Figure 1-1). Much of the intelligence of the program thus lies in the portion of the program which finds these 'relevant' rules. Questions are answered within 5-20 seconds, considerably faster than is the case with more complex natural language question-answering systems in which both syntactic and semantic content must be analyzed. A physician may ask either (a) informational questions (prefaced with the letters "IQ") which query the status of current knowledge about the patient, (b) questions about the deductions of the current consultation, or (c) general questions about any of MYCIN's judgmental rules, whether used in the current consultation or not. The following question-answering examples demonstrate these capabilities:

```
(a) Informational question:
** IQ WHAT IS THE IDENTITY OF ORGANISM-1?
        THE IDENTITY OF ORGANISM-1 IS E.COLI (.43) PROTEUS (.22)
        PSEUDOMONAS (.22) KLEBSIELLA (.13)

(b) Questions about the current consultation:
** HOW DID YOU DECIDE THAT ORGANISM-1 MIGHT BE A PSEUDOMONAS?
        I USED RULE085 TO CONCLUDE THAT THE IDENTITY OF
        ORGANISM-1 IS PSEUDOMONAS.  THIS GAVE A CUMULATIVE
        CERTAINTY FACTOR OF .6

(c) General questions:
** PR RULE085
RULE085
-------
    IF: 1) THE STAIN OF THE ORGANISM IS GRAMNEG, AND
        2) THE MORPHOLOGY OF THE ORGANISM IS ROD, AND
        3) THE PATIENT IS A COMPROMISED HOST
  THEN: THERE IS SUGGESTIVE EVIDENCE (.6) THAT THE
        IDENTITY OF THE ORGANISM IS PSEUDOMONAS

** DO YOU EVER PRESCRIBE CARBENICILLIN FOR PSEUDOMONAS INFECTIONS?
        Relevant rules: RULE024 RULE068 RULE137 RULE138
        Which ones do you wish to see?
        ** RULE024
RULE024
-------
    IF: 1) THE THERAPY UNDER CONSIDERATION IS GENTAMICIN, AND
        2) THE IDENTITY OF THE ORGANISM IS DEFINITELY PSEUDOMONAS
  THEN: RECORD THE FOLLOWING AS A MORE APPROPRIATE THERAPY THAN
        GENTAMICIN ALONE:  THE COMBINATION OF GENTAMICIN AND
        CARBENICILLIN
```

It is also possible to ask the system (d) to explain questions in retrospect (e.g., "Why did you ask question 17?") and (e) to ask for confirmation of one's own decision rules (e.g., "Is chloramphenicol okay for Salmonella infections?"). The implementation details for these capabilities are the subject of Chapter 6.

III.4 The Ability To Explain Decisions

It should be clear from the above explanation session that the ability to answer questions and remember the details of a consultation provide the mechanism for explaining decisions which may puzzle the user. Questions of type (b) require

that the machine refer to the specific details of the consultation it has just undertaken in order to justify its final decisions. This explanation technique allows the physician to choose those points which he feels need clarification and permits him to avoid questions altogether if he finds the system's advice consistent with his own opinions regarding therapy for the patient.

The question-answering session usually follows a consultation session. However, questions may occur to the physician during the consultation itself and we have therefore implemented two additional explanatory capabilities. One of these allows the user to enter 'QA' in response to any question that is asked by MYCIN. This tells the system to digress temporarily from the consultation and to permit the user to ask questions of the type demonstrated in Section III.3. In this way, the user can query partial results of the program's reasoning and then return control to MYCIN (by entering the word STOP) so that the consultation may proceed from the point of digression.

The second capability permits the user to demand that MYCIN justify any question that is asked. Whenever a question generated by MYCIN puzzles the physician, he simply enters the word RULE and the program responds by printing out the translation of the decision rule which has generated the current question. After printing out the relevant decision rule, MYCIN repeats its question and the consultation continues unhampered. For example:

```
17) Are there any factors in this patient which may
    cause inadequate gastro-intestinal absorption of
    the penicillin (DRUG-1)?
** RULE
RULE049
-------
    IF: 1) THE ROUTE OF ADMINISTRATION OF THE PENICILLIN
           IS ORAL, AND
        2) THERE IS A GI FACTOR WHICH MAY INTERFERE WITH
           THE ABSORPTION OF THE PENICILLIN
```

```
     THEN: THERE IS SUGGESTIVE EVIDENCE (.6) THAT THE ROUTE
           OF ADMINISTRATION OF THE PENICILLIN IS NOT
           ADEQUATE

17) Are there any factors in this patient which may
    cause inadequate gastro-intestinal absorption of
    the penicillin (DRUG-1)?
** NO
```

A similar capability, the WHY option, provides a more detailed and conversational explanation of the program's reasoning. A discussion of the complexities of implementation of this and related capabilities, plus a description of their use, may be found elsewhere <Shortliffe - 1974b, Davis - 1975>.

III.5 Educational Capabilities

As was pointed out in the discussion of the six design considerations, the ability of a consultation program to explain its decisions, and to answer questions about the area of expertise that it is modeling, automatically provides an educational capability. The sample question-answering session and the RULE option demonstrate the variety of ways in which MYCIN educates the user as well as justifies its decisions.

III.6 MYCIN's Usefulness

As has already been stated, the ultimate test of MYCIN's usefulness and acceptability will come when we finally feel it is ready to install in the ward setting. In an effort to prepare for that day, we have tried to develop interactive characteristics which will overcome the standard complaints voiced by

physicians who try to use terminal-based systems.

Whenever MYCIN asks a question, it knows the range of possible answers. It therefore compares the physician's response against the list of recognized responses. If the user's response is not on the list, it determines whether a simple typographical or spelling error will account for the unrecognized response. If spelling correction is unsuccessful, the system lexicon is checked to see if the user's answer is a synonym for one of the recognized responses. If this attempt fails, MYCIN prints out a list of recognized responses and asks the question again.

Both spelling-correction and the listing of recognized responses help reduce the level of frustration which can easily alienate novice users of computer systems. Additional features have also been implemented to assist the physician when he is puzzled by a question that MYCIN is asking. If he enters a question-mark ('?'), MYCIN assumes that he would like to see some sample responses. In addition, any question can be answered with the letters UNK (for UNKnown) if the user is uncertain of the answer but wishes MYCIN's opinion in spite of the incomplete information. Finally, the RULE and WHY options that have already been mentioned help the user feel comfortable with the system and more inclined to accept MYCIN as the clinical tool it is designed to be.

This chapter has concentrated on explaining <u>why</u> the MYCIN System operates the way that it does. The next three chapters will deal with a description of <u>how</u> these goals have been accomplished. In Chapter 4 the subject is the core consultation program itself (Subprogram 1). Chapter 5 explains the mechanism we have devised for quantification of the program's decision processes. Then Chapter 6 summarizes MYCIN's question-answering capabilities (Subprogram 2). The program's limited ability to learn from experts (Subprogram 3) is included as

Section III of Chapter 8 where I discuss future efforts contemplated for improving MYCIN's acceptability and for extending its range of uses.

Chapter 4

CONTENTS

1. INTRODUCTION

In this and the succeeding two chapters MYCIN's implementation is presented in considerable detail. My goal is both to explain the data and control structures used by the program and to describe some of the complex and often unexpected problems that arose during system implementation. Less detailed discussions, which provide a general overview of the material in Chapters 4 and 6, may be found elsewhere <Shortliffe - 1973,1974b>. In Chapter 3 the motivation behind many of MYCIN's capabilities was explained. The reader is encouraged to bear those design criteria in mind throughout the remainder of this communication.

This chapter specifically describes the Consultation System (Subprogram 1). As indicated in Figure 1-1, the subprogram uses both system knowledge from the corpus of rules, plus patient data entered by the physician, in order to generate advice for the user. Furthermore, the program maintains a dynamic data base which provides an ongoing record of the current consultation. As a result, this chapter must discuss both the nature of the various data structures and how they are used or maintained by the Consultation System.

Section II describes the corpus of rules and the associated data structures. It begins by looking at other rule-based systems and proceeds to a formal description of the rules used by MYCIN. Our quantitative truth model is briefly introduced and the mechanism for rule evaluation is explained. This section also describes the clinical parameters with which MYCIN is familiar and

which form the basis for the conditional expressions in the PREMISE of a rule.

In Section III MYCIN's goal-oriented control structure is described. Mechanisms for rule invocation and question selection are explained at that time. The section also discusses the creation of the dynamic data base which is the foundation for both the system's advice and its explanation capabilities as described in Chapter 6.

Section IV is devoted to an explanation of the program's context tree, i.e., the network of interrelated organisms, drugs, and cultures which characterize the patient and his current clinical condition. The need for such a data structure is clarified and the method for propagation (growth) of the tree is described.

As discussed in Section IV.1 of Chapter 1, the final tasks in MYCIN's clinical problem area are the identification of potentially useful drugs and the selection of the best drug or drugs from that list. MYCIN's mechanism for making these decisions is discussed in Section V of this chapter.

Section VI discusses MYCIN's mechanisms for storing patient data and for permitting a user to change the answer to a question. As will be described, these two capabilities are closely interrelated.

In Section VII we briefly mention some contemplated future extensions to the system. The concluding section then summarizes the advantages of the MYCIN approach, making comparisons, when appropriate, with previous work in both artificial intelligence and medical decision making.

II. SYSTEM KNOWLEDGE

II.1 Decision Rules

Automated problem-solving systems use criteria for drawing conclusions which often support a direct analogy to the rule-based knowledge representation used by MYCIN. Consider, for example, the conditional probabilities which underlie the Bayesian diagnosis programs discussed in Chapter 2. Each probability provides information that may be stated in an explicit rule format:

P(h/e) = X means:
IF: e is known to be true
THEN: conclude that h is true with probability X

The advantages of an explicit rule format are discussed in Section III of Chapter 5. It is important to note, however, that the concept of rule-based knowledge is not unique, even for medical decision making programs. As will be explained, MYCIN's innovation rests with its novel application of representation techniques and goal-oriented control structures which have been developed by AI researchers. The contributions of the program to AI and medical decision making are summarized in Chapter 9.

II.1.1 Previous Rule-Based Systems

The need for representation of knowledge in IF-THEN format so pervades problem-solving in artificial intelligence that many AI programs can be interpreted as rule-based systems once one recognizes that all deductive or inferential statements are, in effect, decision rules. In fact, several of the new AI languages have provided data structures and control structures based upon rules (theorems) <Bobrow - 1973>. For example, PLANNER <Hewitt - 1969,1971,1972> provides a formalism for the statement of theorems such as:

```
(CONSEQUENT
        (PART $?X $?Z)
        (GOAL (PART $?X $?Y))
        (GOAL (PART $?Y $?Z)))
```

This theorem simply states, in rule form, that:

```
IF:   YOU CAN FIND AN X THAT IS PART OF A Y, AND
      YOU CAN FIND A Z SUCH THAT THE Y IS PART OF THE Z
THEN: YOU CAN CONCLUDE THAT THE X IS PART OF THE Z
```

Although there are several examples of AI programs that use some variety of rule-based knowledge, only four representative cases will be introduced here. The control structures used for processing the 'rules' in these systems are not discussed until Section III.1.

The first example is the theorem-proving question-answering program named QA3 <Green - 1969>. As was pointed out in the example from PLANNER above, a theorem may be considered a rule. Green states his rules in the predicate calculus. For example:

```
[1]     (FA (X) (IF (IN X FIREMEN) (OWNS X RED-SUSPENDERS)))
[2]     (FA (X) (IF (IN X FIRECHIEF) (IN X FIREMEN)))
```

are universally quantified expressions of the following rules:

[1] IF: X IS A FIREMAN
THEN: X OWNS RED SUSPENDERS

[2] IF: X IS A FIRECHIEF
THEN: X IS A FIREMAN

Green's program uses such 'rules' to answer questions regarding system knowledge. The questions themselves may be stated as rules:

[3] Question: (FA (X) (IF (IN X FIRECHIEF)(OWNS X RED-SUSPENDERS)))

i.e.:

[3] Is the following rule valid?
IF: X IS A FIRECHIEF
THEN: X OWNS RED SUSPENDERS

QA3 uses [1] and [2], plus the 'resolution principle' for theorem proving <Robinson - 1965>, to show that [3] is a valid rule and thereby to answer the question affirmatively. Resolution is mentioned again during the discussion of control structures in Section III.1.

The second example of a rule-based system is the program designed by Colby et. al. for modeling human belief structures <Colby - 1969>. They acquired statements of belief from a human subject and coded them as either facts or rules of inference. Facts had associated numerical weights representing their degree of credibility to the human subject, but the rules reflected simple implication without any weighting of the strength of the relationship. For example:

(F 80 SELF NOTLIKE (CHILD1 HAS AGGRESSIVENESS))

is their system's representation for the fact (F) that the subject (SELF) found it strongly credible (80) that she did not like the aggressiveness of one of her children (CHILD1). A sample rule from their data base is:

(R THEPARENT SLAP HISCHILD IMPLIES THEPARENT DISTRESS HISCHILD)

'Implies' in their rules does not necessarily correspond to logical implication. Instead it may represent relationships that are logical, causal, temporal, or

conceptual. Furthermore, the rules are similar to those of MYCIN in that they represent judgments of a human subject (cf. expert) rather than natural laws.

The main task for Colby and his co-workers involved estimating the credibility of a given proposition describing some actual or hypothetical situation. They tested their model by writing a program that used the belief structures obtained from their human subject in order to assess the credibility of a new hypothesis not already in the data base. They then compared the judgment of the program with the credibility estimate of the subject herself. System rules and facts were linked in a graph structure that was searched by a variety of algorithms in an attempt to assess the credibility of a new proposition. Unfortunately, the human subject left the study before a formal evaluation of the program's credibility estimates could be undertaken.

In the late 1960's Waterman developed a rule-based system for playing poker <Waterman - 1970>. He selected this game because, unlike chess or other games commonly modeled by computer programs, poker is characterized by imperfect knowledge regarding the opponent's position. Close attention was paid to the optimal representation of heuristics needed by a poker playing machine. He decided that a good representation should:

(1) permit separation of the heuristics from the main body of the program;

(2) provide identification of individual heuristics and an indication of how they are interrelated;

(3) be compatible with generalization schemes.

Clearly these desiderata correspond closely to the criterion of knowledge modularity I discussed in Chapter 3. Waterman's concern with these factors stemmed from his desire to create a program that would not only play poker but also learn new heuristics that could be incorporated in a straightforward fashion and would permit improvement of the system's game over time.

Waterman pictured poker as a succession of states, with each play causing a transition from one state to another. The situation at any given time could therefore be characterized by a state vector, and game heuristics would involve decisions based upon the current status of the state vector. Thus heuristics could be represented as production rules or so-called situation-action (SA) rules, i.e., if S is true, then take action A. I shall not present Waterman's formal representation here since that would necessitate a description of his rather complex state vector, but the following excerpt from his paper <Waterman - 1970> should give an adequate description of the kind of heuristic rules which he was able to code:

> If your hand is excellent then bet low if the opponent tends to be a conservative player and has just bet low. Bet high if the opponent is not conservative, is not easily bluffed, and has just made a sizable bet. Call if the pot is extremely large, and the opponent has just made a sizable bet.

The program could be taught such heuristics explicitly and was also able to generalize new rules from its experience when playing the game. The result was a system that eventually played an admirable game of poker.

The last rule-based system for discussion in this section is one of the foremost examples of AI techniques effectively applied to a real-world problem domain. Heuristic DENDRAL is a large set of programs designed to aid in the identification of chemical structures from mass spectral data <Feigenbaum - 1968, Buchanan - 1969>. The input to the system is the data derived for an unknown organic molecule that has been subjected to mass spectral analysis. Heuristic DENDRAL uses this input, plus a complex theory of mass spectroscopy embodied in SA rules, to suggest one or more topological structural formulas for the unknown molecule. The program has a heuristic hypothesis generator which first compiles a set of all reasonable structures on the basis of primary spectral observations. It then uses SA rules acquired from experts in mass spectroscopy to predict

spectra for each of the structural hypotheses. A final evaluation stage selects the one or more hypotheses for which the predicted mass spectrum most closely resembles the spectrum that was empirically observed.

Acquiring the mass spectral rules from experts in organic chemistry, who may have limited knowledge of computers or of the DENDRAL program, has proven to be a task of considerable difficulty <Buchanan - 1970>. One is immediately reminded of the challenge in getting well-formed decision rules for MYCIN by discussing patients with infectious disease experts. An example of one of DENDRAL'S SA rules is the following:

$$\text{SA Rule:}\quad \overset{1}{(C,H)} - \overset{2}{CH2} - \overset{3}{NH} - \overset{4}{CH2} - \overset{5}{CH2} - \overset{6}{CH2} - \overset{7}{(C,H)} \;\text{--->}\; \text{Breakbond}(4\ 5)$$

This rule states that a seven membered chain with the characteristics shown in the Situation part of the rule is apt to undergo a bond break between atoms 4 and 5 when subjected to mass spectral bombardment. It is therefore useful in predicting the spectrum of a molecule which satisfies the situation part of the rule (since peaks in a mass spectrum correspond to molecular fragments of a specific identifiable mass).

The SA rules used by Heuristic DENDRAL have many similarities to those used in Waterman's program <Waterman - 1970>. Just as Waterman chose a production rule system in part so that new heuristics could be learned and integrated with ease, DENDRAL has broadened its scope to consider mechanisms for inferring new SA rules. This adjunct to Heuristic DENDRAL is known as Meta-DENDRAL <Buchanan - 1971,1972>. The idea is to analyze the spectra of known molecules in an effort to infer the theoretical basis for the data that are observed. Because system knowledge is maintained in modular SA rules and is not embedded within the programs themselves, this kind of system enhancement is greatly facilitated. The result is a program that often performs at the level of a post-doctoral chemist

and is able to analyze and draw inferences on such complex cyclic structures as estrogenic steroids <Buchanan - 1973>.

The decision criteria stored in MYCIN's rules are in many ways similar to the 'rules' or 'theorems' that form the knowledge base of the programs I have discussed. All the systems keep their rules separate from their programs so that the functions are domain independent and attempts at generalization are facilitated. As discussed in Section III.1, the rules are actually used in a variety of fashions. Regardless of control structures, however, the advantages of identifiable packets of knowledge should now be clear. A final point to note is that, unlike the rules in the other systems described, MYCIN's decision criteria contain explicit weighting factors which reflect the strength of the indicated inference.

II.1.2 Representation Of The Rules

The 200 rules currently in the MYCIN System consist of a PREMISE, an ACTION, and sometimes an ELSE clause. Every rule has a name of the form 'RULE###' where '###' is a three digit number. When discussing rules in their most general form, it will often be useful to adopt a shortened form of notation. I shall use upper-case letters for conditions and conclusions, inserting a right arrow to indicate implication. Thus

A & B --> C

signifies the rule for which the PREMISE is the conjunction of conditions A and B and the ACTION is C.

The details of rules and how they are used are discussed throughout the remainder of this chapter. I therefore offer a formal definition of rules which will serve in part as a guide for what is to follow. The rules are stored as LISP data structures in accordance with the following Backus Normal Form (BNF) description:

```
        <rule> ::= <premise> <action> | <premise> <action> <else>
     <premise> ::= ($AND <condition> ... <condition>)
   <condition> ::= ( <func1> <context> <parameter> ) |
                   ( <func2> <context> <parameter> <value> ) |
                   ( <special-func> <arguments> ) |
                   ($OR <condition> ... <condition> )
      <action> ::= <concpart>
        <else> ::= <concpart>
    <concpart> ::= <conclusion> | <actfunc> |
                   (DO-ALL <conclusion> ... <conclusion> ) |
                   (DO-ALL <actfunc> ... <actfunc> )
     <context> ::= See Section II.2
   <parameter> ::= See Section II.3
       <value> ::= See Section II.3
       <func1> ::= See Section II.5
       <func2> ::= See Section II.5
<special-func> ::= See Section II.6.2
   <arguments> ::= See Section II.6.2
  <conclusion> ::= See Section III.3.2
     <actfunc> ::= See Section V
```

Thus the PREMISE of a rule consists of a conjunction of conditions, each of which must hold for the indicated ACTION to be taken. Negations of conditions are handled by the individual predicates (<func1> and <func2>) and therefore do not require a $NOT function to complement the Boolean functions $AND and $OR. If the PREMISE of a rule is known to be false, the conclusion or action indicated by the ELSE clause is taken. If the truth of the PREMISE cannot be ascertained, or the PREMISE is false but no ELSE condition exists, the rule is simply ignored.

The PREMISE of a rule is always a conjunction of one or more conditions.

Disjunctions of conditions may be represented as multiple rules with identical ACTION clauses. A condition, however, may itself be a disjunction of conditions. These conventions are somewhat arbitrary but do provide sufficient flexibility so that any Boolean expression may be represented by one or more rules. As is discussed in Section III, multiple rules are effectively OR'ed together by MYCIN's control structure.

For example, 2-leveled Boolean nestings of conditions are acceptable as follows:

Legal:

[1] A & B & C --> D

[2] A & (B OR C) --> D

[3] (A or B or C) & (D or E) --> F

Illegal:

[4] A or B or C --> D

[5] A & (B or (C & D)) --> E

Rule [4] is correctly represented by the following three rules:

[6] A --> D

[7] B --> D

[8] C --> D

whereas [5] must be written as:

[9] A & C & D --> E

[10] A & B --> E

Unlike rules that involve strict implication, the strength of an inference in MYCIN's rules may be modified by a certainty factor (CF). A CF is a number from -1 to +1, the nature of which is described in Section II.4 and in Chapter 5. The notation for indicating the strength of an implication will be as follows:

A & B & C --a--> D

Here the rule states that the conjunction of conditions A, B, and C imply D with

certainty factor a.

The following three examples are rules from MYCIN that have been translated into English from their internal LISP representation (Section II.7). They represent the range of rule types available to the system. The details of their internal representation will be explained as I proceed.

```
RULE037
-------
          IF: 1) THE IDENTITY OF THE ORGANISM IS NOT KNOWN WITH
              CERTAINTY, AND
              2) THE STAIN OF THE ORGANISM IS GRAMNEG, AND
              3) THE MORPHOLOGY OF THE ORGANISM IS ROD, AND
              4) THE AEROBICITY OF THE ORGANISM IS AEROBIC
        THEN: THERE IS STRONGLY SUGGESTIVE EVIDENCE (.8) THAT THE
              CLASS OF THE ORGANISM IS ENTEROBACTERIACEAE

RULE145
-------
          IF: 1) THE THERAPY UNDER CONSIDERATION IS ONE
              OF: CEPHALOTHIN CLINDAMYCIN ERYTHROMYCIN
              LINCOMYCIN VANCOMYCIN, AND
              2) MENINGITIS IS AN INFECTIOUS DISEASE DIAGNOSIS
              FOR THE PATIENT
        THEN: IT IS DEFINITE (1) THE THE THERAPY UNDER CONSIDERATION
              IS NOT A POTENTIAL THERAPY FOR USE AGAINST THE
              ORGANISM

RULE060
-------
          IF: THE IDENTITY OF THE ORGANISM IS BACTEROIDES
        THEN: I RECOMMEND THERAPY CHOSEN FROM AMONG THE FOLLOWING DRUGS:
                    1 - CLINDAMYCIN          (.99)
                    2 - CHLORAMPHENICOL      (.99)
                    3 - ERYTHROMYCIN         (.57)
                    4 - TETRACYCLINE         (.28)
                    5 - CARBENICILLIN        (.27)
```

Before I can explain how rules such as these are invoked and evaluated, it is necessary further to describe MYCIN's internal organization. I shall therefore temporarily digress in order to lay some groundwork for the description of the evaluation functions in Section II.5.

II.2 Categorization Of Rules By Context

II.2.1 The Context Tree

Although it is common to describe diagnosis as inference based upon attributes of the patient, MYCIN's decisions must necessarily involve not only the patient but also the cultures which have been grown, organisms isolated, and drugs that have been administered. Each of these is termed a 'context' of the program's reasoning (see <context> in the BNF description of rules, Section II.1.2). [This use of the word 'context' should not be confused with its meaning in high level languages that permit temporary saving of all information regarding a program's current status - a common mechanism for backtracking and parallel processing implementations].

MYCIN currently knows about ten different context-types:

CURCULS - a current culture from which organisms were isolated

CURDRUGS - an antimicrobial agent currently being administered to a patient

CURORGS - an organism isolated from a current culture

OPDRGS - an antimicrobial agent administered to the patient during a recent operative procedure

OPERS - an operative procedure which the patient has undergone

PERSON - the patient himself

POSSTHER - a therapy being considered for recommendation

PRIORCULS - a culture obtained in the past

PRIORDRGS - an antimicrobial agent administered to the patient in the past

PRIORORGS - an organism isolated from a prior culture

Except for PERSON, each of these context-types may be instantiated more than once during any given run of the consultation program. Some may not be created at all if they do not apply to the given patient. However, each time a context-type is

instantiated it is given a unique name. For example, CULTURE-1 is the first CURCUL and ORGANISM-1 is the first CURORG. Subsequent CURCULS or PRIORCULS are called CULTURE-2, CULTURE-3, etc.

The context-types instantiated during a run of the consultation program are arranged hierarchically in a data structure termed the 'context tree'. One such tree is shown in Figure 4-1. The context-type for each instantiated context is shown in parentheses beside its name. Thus, to clarify terminology, we note that a node in the context tree is called a context and is created as an instantiation of a context-type. This sample context tree corresponds to a patient from whom two current cultures and one prior culture were obtained. One organism was isolated from each of the current cultures, but the patient is being treated (with two drugs) for only one of the current organisms. Furthermore, two organisms were grown from the prior culture but therapy was instituted to combat only one of these. Finally, the patient has had a recent operative procedure during which he was treated with an antimicrobial agent.

The context tree is useful not only because it gives structure to the clinical problem (Figure 4-1 already tells us a good deal about PATIENT-1), but also because we often need to be able to relate one context to another. For example, in considering the significance of ORGANISM-2, MYCIN may well want to be able to reference the site of the culture from which ORGANISM-2 was obtained. Since the patient has had three different cultures, we need an explicit mechanism for recognizing that ORGANISM-2 came from CULTURE-2, not CULTURE-1 or CULTURE-3. The technique for dynamic propagation (i.e., growth) of the context tree during a consultation is described in Section IV.

SAMPLE CONTEXT TREE

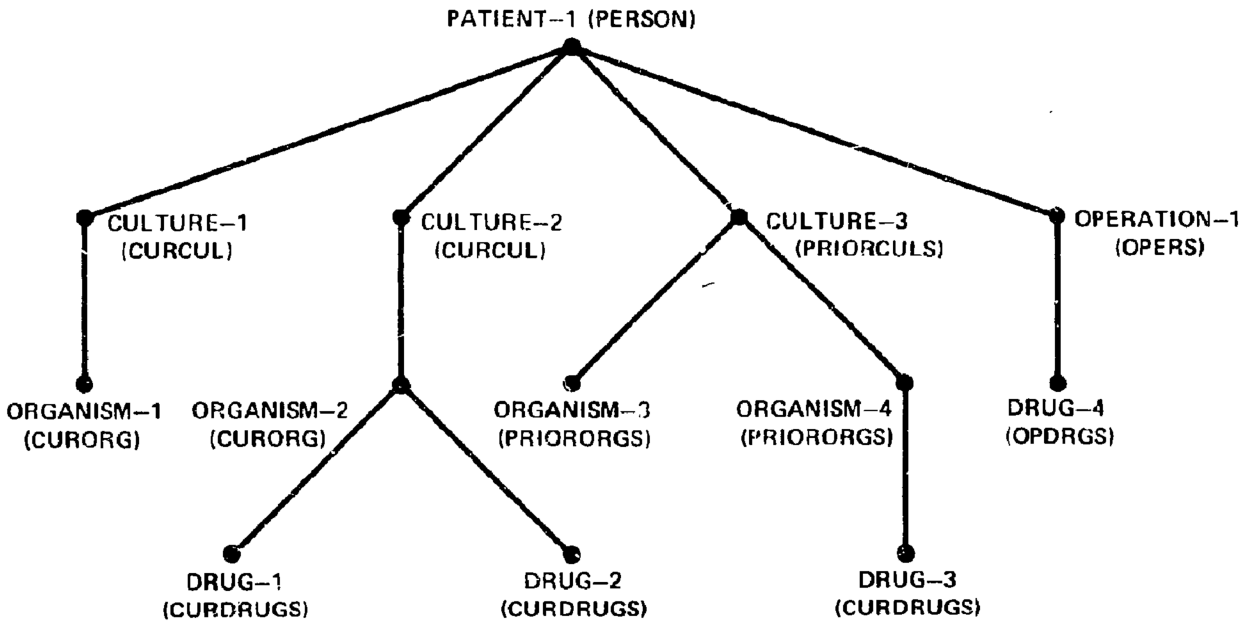


Figure 4–1

II.2.2 Interrelationship Of Rules And The Tree

The 200 rules currently used by MYCIN are not explicitly linked in a decision tree or reasoning network. This feature is in keeping with our desire to keep system knowledge modular and manipulable. However, rules are subject to categorization in accordance with the context-types for which they are most appropriately invoked. For example, some rules deal with organisms, some with cultures, and still others deal solely with the patient himself. MYCIN's current rule categories are as follows (context-types to which they may be applied are enclosed in parentheses):

CULRULES - rules that may be applied to any culture (CURCULS or PRIORCULS)

CURCULRULES - rules that may be applied only to current cultures (CURCULS)

CURORGRULES - rules that may be applied only to current organisms (CURORGS)

ORGRULES - rules that may be applied to any antimicrobial agent that has been administered to combat a specific organism (CURDRUGS PRIORDRGS)

OPRULES - rules that may be applied to operative procedures (OPERS)

ORDERRULES - rules that are used to order the list of possible therapeutic recommendations (POSSTHER)

ORGRULES - rules that may be applied to any organism (CURORGS or PRIORORGS)

PATRULES - rules that may be applied to the patient (PERSON)

PDRGRULES - rules that may be applied only to drugs given to combat prior organisms (PRIORDRUGS)

PRCULRULES - rules that may be applied only to prior cultures (PRIORCULS)

PRORGRULES - rules that may be applied only to organism isolated from prior cultures (PRIORORGS)

THERULES - rules that store information regarding drugs of choice (Section V)

Every rule in the MYCIN system belongs to one, and only one, of these categories. Furthermore, selecting the proper category for a newly acquired rule does not present a problem. In fact, as is discussed in Section III of Chapter 8, category selection can be automated to a large extent.

Consider now a rule such as:

```
RULE124
-------
    IF: 1) THE SITE OF THE CULTURE IS THROAT, AND
        2) THE IDENTITY OF THE ORGANISM IS STREPTOCOCCUS
  THEN: THERE IS STRONGLY SUGGESTIVE EVIDENCE (.8) THAT
        THE SUBTYPE OF THE ORGANISM IS NOT GROUP-D
```

This is one of MYCIN's ORGRULES and may thus be applied either to a CURORGS context or a PRIORORGS context. Referring back to Figure 4-1, suppose RULE124 above were applied to ORGANISM-2. The first condition in the PREMISE refers to the site of the culture from which ORGANISM-2 was isolated (i.e., CULTURE-2) and not to the organism itself (i.e., organisms do not have SITES, but cultures do). The context tree is therefore important, as I mentioned above, for determining the proper context when a rule refers to an attribute of a node in the tree other than the context to which the rule is being explicitly applied. Note that this means that a single rule may refer to nodes at several levels in the context tree. The rule is categorized simply on the basis of the lowest context-type (in the tree) that it may reference. Thus RULE124 is an ORGRULE rather than a CULRULE.

II.3 Clinical Parameters

This subsection describes the data types indicated by <parameter> and <value> in the BNF description of rules (Section II.1.2). Although I have previously asserted that all MYCIN's knowledge is stored in its corpus of rules, the clinical parameters and their associated properties comprise an important class of second level knowledge. I shall first explain the kind of parameters used by the system, and will then describe their representation.

A clinical parameter is a characteristic of one of the contexts in the

context tree, i.e., the name of the patient, the site of a culture, the morphology of an organism, the dose of a drug, etc. All such attributes will be termed 'clinical parameters'. A patient's status would be completely specified by a context tree in which values were known for all the clinical parameters characterizing each node in the tree (assuming the parameters known to MYCIN encompass all those that are clinically relevant - a dubious assumption at present). In general this is more information than is needed, however, so one of MYCIN's tasks is to identify those clinical parameters that need to be considered for the patient about whom advice is being sought. This task is similar to the problem of sequential test selection which was relevant to many of the programs discussed in Chapter 2.

The concept of an attribute-object-value triple is common to much of the AI field. This associative relationship is a basic data type for the SAIL language <Feldman - 1972> and is the foundation for the property-list formalism in LISP <McCarthy - 1962>. Relational predicates in the predicate calculus also represent associative triples. The point is that many facts may be expressed as triples which state that some object has an attribute with some specified value. Stated in the order <attribute object value>, examples include:

(COLOR BALL RED)

(OWNS FIREMAN RED-SUSPENDERS)

(AGE BOB 22)

(FATHER CHILD 'DADDY')

(GRAMSTAIN ORGANISM GRAM-POSITIVE)

(DOSE DRUG 1.5-GRAMS)

(MAN BOB TRUE)

(WOMAN BOB FALSE)

Note that the last two examples are different from the others since they represent a rather different kind of relationship. In fact, several authors would classify

the first six as 'relations' and the last two as 'predicates', using the simpler notation:

MAN(BOB)

-WOMAN(BOB)

Regardless of whether it is written as MAN(BOB) or (MAN BOB TRUE), this binary predicate statement has rather different characteristics from the relations that form natural triples. This distinction will become more clear later (see 'yes-no' parameters below).

MYCIN stores inferences and data using the attribute-object-value concept I have just described. The object is always some context in the context tree, and the attribute is a clinical parameter appropriate for that context. Information stored using this mechanism may be retrieved and updated in accordance with a variety of conventions described throughout this chapter.

III.3.1 The Three Kinds Of Clinical Parameters

There are three fundamentally different kinds of clinical parameter. The simplest variety are the ones we call 'single-valued' parameters. These are attributes such as the name of the patient or the identity of the organism. In general they have a large number of possible values which are mutually exclusive. As a result, only one can be the true value, although several may seem likely at any point during the consultation.

'Multi-valued' parameters also generally have a large number of possible values. The difference is that the possible values need not be mutually exclusive. Thus such attributes as a patient's drug allergies or a locus of infection may have multiple values, each of which is known to be correct.

The third kind of clinical parameter corresponds to the binary predicate discussed above. These are attributes which are either true or false for the given context. For example, the significance of an organism is either true or

false (yes or no), as is the parameter indicating whether the dose of a drug is adequate. Attributes of this variety are called 'yes-no' parameters. They are, in effect, a special kind of 'single-valued' parameter for which there are only two possible values.

II.3.2 Classification And Representation Of The Parameters

The clinical parameters known to MYCIN are categorized in accordance with the context to which they apply. These categories include:

PROP-CUL - those clinical parameters which are attributes of cultures (e.g., site of the culture, method of collection)

PROP-DRG - those clinical parameters which are attributes of administered drugs (e.g., name of the drug, duration of administration)

PROP-OP - those clinical parameters which are attributes of operative procedures (e.g., the cavity, if any, opened during the procedure)

PROP-ORG - those clinical parameters which are attributes of organisms (e.g., identity, gram stain, morphology)

PROP-PT - those clinical parameters which are attributes of the patient (e.g., name, sex, age, allergies, diagnoses)

PROP-THER - those clinical parameters which are attributes of therapies being considered for recommendation (e.g., recommended dosage, prescribing name)

These categories encompass all clinical parameters used by the system. Note that any of the nodes (contexts) in the context tree for the patient may be fully characterized by the values of the set of clinical parameters in one of these categories.

Each of the 65 clinical parameters currently known to MYCIN has an associated set of properties that is used during consideration of the parameter for a given context. Figure 4-2 presents three clinical parameters which together demonstrate several of these properties:

Sample Clinical Parameters

Yes-No Parameter

```
FEBRILE:        <FEBRILE is an attribute of a patient and is therefore a
                 member of the list PROP-PT>

          EXPECT: (YN)
      LOOKAHEAD: (RULE149 RULE109 RULE045)
         PROMPT: (Was * febrile when the culture was drawn?)
          TRANS: (* IS FEBRILE)
```

Single-Valued Parameter

```
IDENT:          <IDENT is an attribute of an organism and is therefore a
                 member of the list PROP-ORG>

  CONTAINED-IN: (RULE030)
        EXPECT: (ONEOF (ORGANISMS))
       LABDATA: T
     LOOKAHEAD: (RULE004 RULE054 ... RULE168)
        PROMPT: (Enter the identity (genus) of * :)
         TRANS: (THE IDENTITY OF *)
    UPDATED-BY: (RULE021 RULE003 ... RULE166)
```

Multi-Valued Parameter

```
INFECT:         <INFECT is an attribute of a patient and is therefore a
                 member of the list PROP-PT>

        EXPECT: (ONEOF PERITONITIS BRAIN-ABSCESS MENINGITIS
                  BACTEREMIA UPPER-URINARY-TRACT-INFECTION
                  ... ENDOCARDITIS)
     LOOKAHEAD: (RULE115 RULE149 ... RULE045)
       PROMPT1: (Is there evidence that the patient has a (VALU) ?)
         TRANS: (AN INFECTIOUS DISEASE DIAGNOSIS FOR *)
    UPDATED-BY: (RULE157 RULE022 ... RULE105)
```

Figure 4-2

EXPECT - this property indicates the range of expected values that the parame .. may have.
if = (YN) then the parameter is a 'yes-no' parameter
if = (NUMB) then the expected value of the parameter is a number
if = (ONEOF <list>) then the value of the parameter must be a member of <list>
if = (ANY) then there is no restriction on the range of values that the parameter may have

PROMPT - this property is a sentence used by MYCIN when it requests the value of the clinical parameter from the user; if there is an asterisk in the phrase (see Figure 4-2), it is replaced by the name of the context about which the question is being asked; this property is used only for 'yes-no' or 'single-valued' parameters.

PROMPT1 - this property is similar to PROMPT except it is used if the clinical parameter is a 'multi-valued' parameter; in these cases MYCIN only asks the question about a single one of the possible parameter values; the value of interest is substituted for (VALU) in the question.

LABDATA - this property is a flag which is either T or NIL; if T it indicates that the clinical parameter is a piece of primitive data, the value of which may be known with certainty to the user (see Section III.2.1).

LOOKAHEAD - this property is a list of all rules in the system which reference the clinical parameter in their PREMISE.

UPDATED-BY - this property is a list of all rules in the system in which the ACTION or ELSE clause permits a conclusion to be made regarding the value of the clinical parameter.

CONTAINED-IN - this property is a list of all rules in the system in which the ACTION or ELSE clause references the clinical parameter but does not cause its value to be updated.

TRANS - this property is used for translating the clinical parameter into its English representation (see Section II.7); the context of the parameter is substituted for the asterisk during translation.

DEFAULT - this property is used only with clinical parameters for which EXPECT = (NUMB); it gives the expected units for numerical answers (e.g., days, years, grams, etc.)

CONDITION - this property, when utilized, is an executable LISP expression which is evaluated before MYCIN requests the value of the parameter; if the CONDITION is true, the question is not asked (e.g., "Don't ask for an organism's subtype if its genus is not known by the user").

The uses of these properties will be discussed throughout the remainder of this chapter and in Chapter 6. However, a few additional points are relevant here.

First, it should be noted that the order of rules on the properties LOOKAHEAD, UPDATED-IN, and CONTAINED-IN is arbitrary and does not affect the program's advice. Second, EXPECT and TRANS are the only properties which must exist for every clinical parameter. Thus, for example, if there is no PROMPT or PROMPT1 stored for a parameter, the system assumes that it simply cannot ask the user for the value of the parameter. Finally, note in Figure 4-2 the difference in the TRANS property for 'yes-no' and non-'yes-no' parameters. In general a parameter and its value may be translated as:

THE <attribute> OF <object> IS <value>

However, for a 'yes-no' parameter such a FEBRILE, it is clearly necessary to translate the parameter in a fashion other than:

THE FEBRILE OF PATIENT-1 IS YES

Our solution has been to suppress the YES altogether and simply to say:

PATIENT-1 IS FEBRILE

11.4 Certainty Factors

Chapter 5 presents a detailed description of certainty factors and their theoretical foundation. This section therefore provides only a brief overview of the subject. A familiarity with the characteristics of certainty factors (CF's) is necessary, however, for the discussion of MYCIN during the remainder of this chapter.

The value of every clinical parameter is stored by MYCIN along with an associated certainty factor that reflects the system's 'belief' that the value is correct. This formalism is necessary because, unlike domains in which objects either have or do not have some attribute, in medical diagnosis and treatment there is often uncertainty regarding attributes such as the significance of the

disease, the efficacy of a treatment, or the diagnosis itself. As discussed in Chapter 2, most medical decision making programs use probability to reflect the uncertainties. CF's are an alternative to conditional probability which offer several advantages in MYCIN's domain (as described in Chapter 5).

A certainty factor is a number between -1 and +1 which reflects the degree of belief in a hypothesis. Positive CF's indicate there is evidence that the hypothesis is valid. The larger the CF, the greater the belief in the hypothesis. When CF=1, the hypothesis is known to be correct. On the other hand, negative CF's indicate that the weight of evidence suggests that the hypothesis is false. The smaller the CF, the greater the belief that the hypothesis is invalid. CF=-1 means that the hypothesis has been effectively disproven. When CF=0, there is either no evidence regarding the hypothesis, or the supporting evidence is equally balanced by evidence suggesting that the hypothesis is not true.

MYCIN's hypotheses are statements regarding values of clinical parameters for the various nodes in the context tree. For example, sample hypotheses are:

h1 = The identity of ORGANISM-1 is streptococcus
h2 = PATIENT-1 is febrile
h3 = The name of PATIENT-1 is John Jones

We use the notation CF[h,E]=X to represent the certainty factor for the hypothesis h based upon evidence E. Thus if CF[h1,E]=.8, CF[h2,E]=-.3, and CF[h3,E]=+1, the three sample hypotheses above may be qualified as follows:

CF[h1,E]=.8 : There is strongly suggestive evidence (.8) that the identity of ORGANISM-1 is streptococcus

CF[h2,E]=-.3 : There is weakly suggestive evidence (.3) that PATIENT-1 is not febrile

CF[h3,E]=+1 : It is definite (1) that the name of PATIENT-1 is John Jones

Certainty factors are used in two ways. First, as noted, the value of

every clinical parameter is stored with its associated certainty factor. In this case the evidence E stands for all information currently available to MYCIN. Thus if the program needs the identity of ORGANISM-1, it may look in its dynamic data base and find:

IDENT of ORGANISM-1 = ((STREPTOCOCCUS .8))

The second use of CF's is in the statement of decision rules themselves. In this case the evidence E corresponds to the conditions in the PREMISE of the rule. Thus

A & B & C --x--> D

is a representation of the statement CF[D,(A&B&C)]=x. For example, consider the following rule:

IF: 1) THE STAIN OF THE ORGANISM IS GRAMPOS, AND
    2) THE MORPHOLOGY OF THE ORGANISM IS COCCUS, AND
    3) THE GROWTH CONFORMATION OF THE ORGANISM IS CHAINS
THEN: THERE IS SUGGESTIVE EVIDENCE (.7) THAT THE
    IDENTITY OF THE ORGANISM IS STREPTOCOCCUS

This rule may also be represented as CF[h1,e]=.7 where h1 is the hypothesis that the organism (context of the rule) is a streptococcus and e is the evidence that it is a gram positive coccus growing in chains.

Since diagnosis is, in effect, the problem of selecting a disease from a list of competing hypotheses, it should be clear that MYCIN may simultaneously be considering several hypotheses regarding the value of a clinical parameter. These hypotheses are stored together, along with their CF's, for each node in the context tree. We use the notation Val[C,P] to signify the set of all hypotheses regarding the value of the clinical parameter P for the context C. Thus if MYCIN has reason to believe that ORGANISM-1 may be either a streptococcus or staphylococcus, although pneumococcus has been ruled out, its dynamic data base might well show:

Val[ORGANISM-1,IDENT] = ((STREPTOCOCCUS .6)(STAPHYLOCOCCUS .4)
(DIPLOCOCCUS-PNEUMONIAE -1))

Note that Chapter 5 shows that the sum of the CF's for supported hypotheses regarding a 'single-valued' parameter (i.e., those parameters for which the hypotheses are mutually exclusive) cannot exceed 1. 'Multi-valued' parameters, on the other hand, may have several hypotheses that are all known to be true. For example:

Val[PATIENT-1,ALLERGY] = ((PENICILLIN 1)(AMPICILLIN 1)
(CARBENICILLIN 1)(METHICILLIN 1))

As soon as a hypothesis regarding a 'single-valued' parameter is proved to be true, all competing hypotheses are effectively disproved:

Val[ORGANISM-1,IDENT] = ((STREPTOCOCCUS 1)(STAPHYLOCOCCUS -1)
(DIPLOCOCCUS-PNEUMONIAE -1))

In Chapter 5 it is demonstrated that CF[h,E] = -CF[not.h,E]. This observation has important implications for the way MYCIN handles the binary-valued attributes we call 'yes-no' parameters. Since 'yes' is 'not.no', it is not necessary to consider 'yes' and 'no' as competing hypotheses for the value of a 'yes-no' parameter (as we do for 'single-valued' parameters). Instead we can always express 'no' as 'yes' with a reversal in the sign of the CF. This means that Val[C,P] is always equal to the single value 'yes', along with its associated CF, when P is a 'yes-no' parameter.

In Section III.3.2 I discuss MYCIN's mechanism for adding to the list of hypotheses in Val[C,P] as new rules are invoked and executed. The following points should be emphasized here, however:

1) the strength of the conclusion associated with the execution of a rule reflects not only the CF assigned to the rule, but also the program's degree of belief regarding the validity of the PREMISE;

2) the support of several rules favoring a single hypothesis may be assimilated incrementally on the list Val[C,P] by using special combining functions described in Section VI of Chapter 5.

II.5 Functions For The Evaluation Of PREMISE Conditions

This section describes the evaluation of the individual conditions (see <condition>, Section II.1.2) in the PREMISE of rules. Conditions in general evaluate to 'true' or 'false' (T or NIL). Thus they may at first glance be considered simple predicates on the values of clinical parameters. However, since there may be several competing hypotheses on the list Val[C,P], each associated with its own degree of belief as reflected by the CF, conditional statements regarding the value of parameters can be quite complex. All predicates are implemented as LISP functions. The functions that undertake the required analysis are of three varieties, specified by the designations <func1>, <func2>, and <special-func> in the BNF rule description (Section II.1.2). This section explains the <func1> and <func2> predicates. The <special-func> category is deferred until Section II.6.2, however, so that I may first introduce our specialized knowledge structures (Section II.6.1).

There are four predicates in the category <func1>. These functions do not form conditionals on specific values of a clinical parameter, but are concerned with the more general status of knowledge regarding the attributes in question. For example, KNOWN[ORGANISM-1, IDENT] is an invocation of the <func1> predicate KNOWN; it would return true if the identity of ORGANISM-1 were known, regardless of the value of the clinical parameter IDENT. KNOWN and the other <func1>

predicates may be formally defined as follows:

Predicates Of The Class <funcl>

Let V=Val[C,P] be the set of all hypotheses regarding the value of the clinical parameter P for the context C.

Let Mv=Max[V] be the most strongly supported hypothesis in V (i.e., the hypothesis with the largest CF)

Let CFmv=CF[Mv,E] where E is the total available evidence

Then, if P is either a 'single-valued' or 'multi-valued' parameter, the four predicates (functions) may be specified as follows:

FUNCTION	IF	THEN	ELSE
KNOWN[C,P]	CFmv>.2	T	NIL
NOTKNOWN[C,P]	CFmv≤.2	T	NIL
DEFINITE[C,P]	CFmv=1	T	NIL
NOTDEFINITE[C,P]	CFmv<1	T	NIL

In words, these definitions reflect MYCIN's convention that the value of a parameter is KNOWN if the CF of the most highly supported hypothesis exceeds .2. The .2 threshold was selected empirically. The implication is that a positive CF less than .2 reflects so little evidence supporting the hypothesis that there is virtually no reasonable hypothesis currently known. The interrelationships among these functions are diagrammed on a CF number line in Figure 4-3. Regions specified are the range of values for CFmv over which the function returns T.

As was pointed out in the previous section, however, 'yes-no' parameters are special cases because we know CF[YES,E] = -CF[NO,E]. Since the values of 'yes-no' parameters are always stored in terms of YES, MYCIN must recognize that a YES with CF=-.9 is equivalent to a NO with CF=.9. The definitions of our four <funcl> predicates above do not reflect this distinction. Therefore, when P is a 'yes-no' parameter, the four functions are specified as follows:

Truth Range For <funcl> Predicates

Case 1: For Attributes Other Than YES-NO Parameters

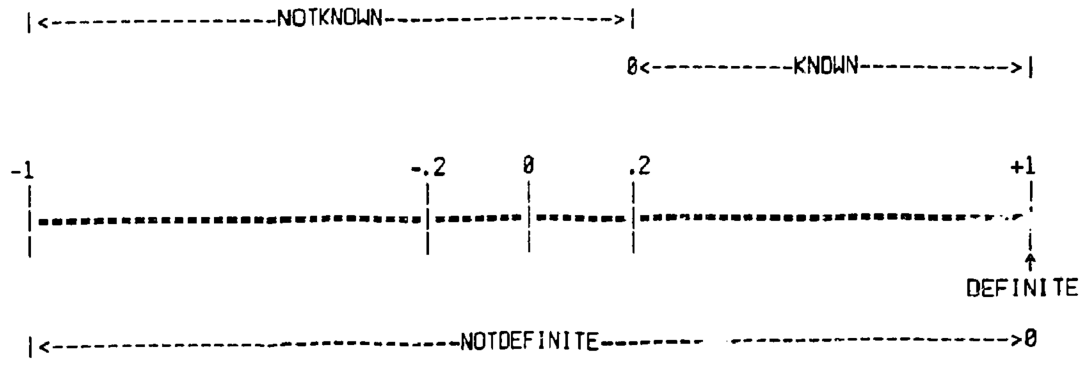


Figure 4-3

FUNCTION	IF	THEN	ELSE
KNOWN[C,P]	|CFmv|>.2	T	NIL
NOTKNOWN[C,P]	|CFmv|≤.2	T	NIL
DEFINITE[C,P]	|CFmv|=1	T	NIL
NOTDEFINITE[C,P]	|CFmv|<1	T	NIL

Figure 4-4 shows the relationship among these functions for 'yes-no' parameters.

There are nine predicates in the category <func2>. Unlike the <func1> predicates, these functions control conditional statements regarding specific values of the clinical parameter in question. For example, SAME[ORGANISM-1, IDENT, E.COLI] is an invocation of the <func2> predicate SAME; it would return true if the identity of ORGANISM-1 were known to be E.coli. SAME and the other <func2> predicates may be formally defined as follows:

Predicates Of The Class <func2>

Let V=Val[C,P] be the set of all hypotheses regarding the value of the clinical parameter P for the context C.

Let I=Intersection[V,LST] be the set of all hypotheses in V which also occur in the set LST; LST contains the possible values of P for comparison by the predicate-function; it usually contains only a single element; if no element in LST is also in V, I is simply the empty set.

Let Mi=Max[I] be the most strongly confirmed hypothesis in I; thus Mi is NIL if I is the empty set;

Let CFmi=CF[Mi,E] where CFmi=0 if Mi is NIL

Then the <func2> predicates are defined as follows:

FUNCTION	IF	THEN	ELSE
SAME[C,P,LST]	CFmi>.2	CFmi	NIL
THOUGHTNOT[C,P,LST]	CFmi<-.2	-CFmi	NIL
NOTSAME[C,P,LST]	CFmi≤.2	T	NIL
MIGHTBE[C,P,LST]	CFmi≥-.2	T	NIL
VNOTKNOWN[C,P,LST]	|CFmi|≤.2	T	NIL
DEFIS[C,P,LST]	CFmi=+1	T	NIL
DEFNOT[C,P,LST]	CFmi=-1	T	NIL
NOTDEFIS[C,P,LST]	.2<CFmi<1	T	NIL
NOTDEFNOT[C,P,LST]	-1<CFmi<-.2	T	NIL

The names of the functions have been selected to reflect their semantics. Figure 4-5 shows a graphic representation of each function and also explicitly states the

Truth Range For <func1> Predicates

Case 2: For YES-NO Parameters

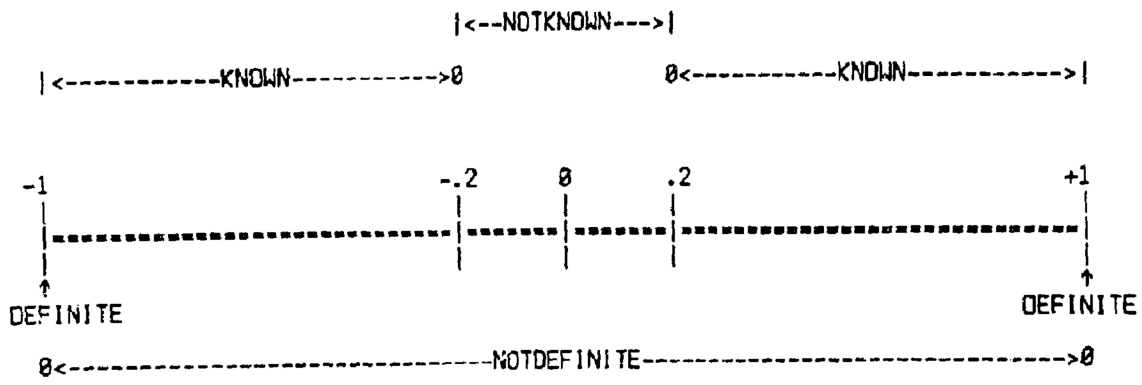
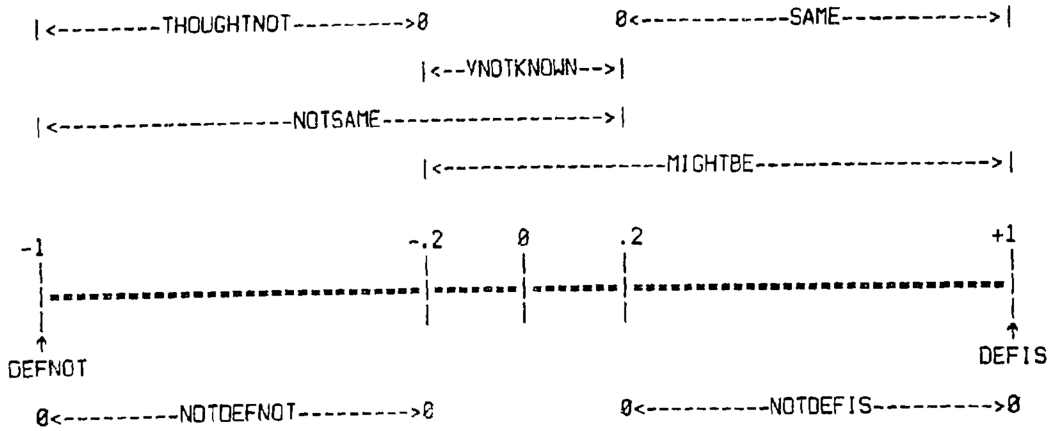


Figure 4-4

Truth Range For <func2> Predicates



SAME or NOTSAME = THOUGHTNOT or MIGHTBE = T

NOTSAME = VNOTKNOWN or THOUGHTNOT

THOUGHTNOT = NOTDEFNOT or DEFNOT

MIGHTBE = VNOTKNOWN or SAME

SAME = NOTDEFIS or DEFIS

Figure 4-5

interrelationships among them.

Note that SAME and THOUGHTNOT are different from all the other functions that I have discussed in that they return a number (CF) rather than T if the defining condition holds. This feature permits MYCIN to record the degree to which PREMISE conditions are satisfied. In order to explain this point, I must discuss the $AND function that oversees the evaluation of the PREMISE of a rule. The reader will recall the BNF description from Section II.1.2:

<premise> ::= ($AND <condition> ... <condition>)

$AND is similar to the standard LISP 'AND' function in that it evaluates its conditional arguments one at a time, returning false (NIL) as soon as a condition is found to be false, and otherwise returning true (T). The difference is that $AND expects some of its conditions to return numerical values rather than simply T or NIL. If an argument cordition returns NIL (or a number equal to .2 or less) it is considered false and $AND stops considering subsequent arguments. On the other hand, non-numeric values of conditions are interpreted as indicating truth with CF=1. Thus each true condition either returns a number or a non-NIL value which is interpreted as 1. $AND then maintains a record of the lowest value returned by any of its arguments. This number, termed TALLY, is a certainty tally which indicates MYCIN's degree of belief in the PREMISE (see Combining Function 2 in Section VI of Chapter 5). Thus .2<TALLY≤1, where TALLY=1 indicates that MYCIN believes the PREMISE to be true with certainty.

Most of the predicates which evaluate conditions in the PREMISE of a rule return either T or NIL as we have shown. Consider, however, the semantics of the most commonly used function, SAME, and its analogous function, THOUGHTNOT. Suppose MYCIN knows:

Val[ORGANISM-1,IDENT] = ((STREPTOCOCCUS .7)(STAPHYLOCOCCUS .3))

Then it seems clear that SAME[ORGANISM-1,IDENT,STREPTOCOCCUS] is in some sense 'more true' than SAME[ORGANISM-1,IDENT,STAPHYLOCOCCUS], even though both

hypotheses exceed the threshold CF=.2. If SAME merely returned T, this distinction would be lost. Thus, for this example:

SAME[ORGANISM-1,IDENT,STREPTOCOCCUS] = .7

SAME[ORGANISM-1,IDENT,STAPHYLOCOCCUS] = .3

whereas KNOWN[ORGANISM-1,IDENT] = T

and NOTDEFIS[ORGANISM-1,IDENT,STREPTOCOCCUS] = T

A similar argument explains why THOUGHTNOT returns a CF rather than T. It is unclear whether any of the other <func2> predicates should return a CF rather than T; my present conviction is that the semantics of those functions do not require relative weightings in the way that SAME and THOUGHTNOT do.

Let me give a brief example, then, of the way in which the PREMISE of a rule is evaluated by $AND. Consider, for example, the following ORGRULE:

```
     IF: 1) THE STAIN OF THE ORGANISM IS GRAMNEG, AND
         2) THE MORPHOLOGY OF THE ORGANISM IS ROD, AND
         3) THE AEROBICITY OF THE ORGANISM IS AEROBIC
   THEN: THERE IS STRONGLY SUGGESTIVE EVIDENCE (.8) THAT
         THE CLASS OF THE ORGANISM IS ENTEROBACTERIACEAE
```

which is internally coded in LISP as:

```
PREMISE: ($AND (SAME CNTXT GRAM GRAMNEG)
               (SAME CNTXT MORPH ROD)
               (SAME CNTXT AIR AEROBIC))
ACTION:  (CONCLUDE CNTXT CLASS ENTEROBACTERIACEAE TALLY .8)
```

Suppose this rule has been invoked for consideration of ORGANISM-1, i.e., the context of the rule (CNTXT) is the node in the context tree termed ORGANISM-1. Now suppose that MYCIN has the following information in its data base (how it gets there is the subject of Section III.3):

VAL[ORGANISM-1,GRAM] = ((GRAMNEG 1.0))

VAL[ORGANISM-1,MORPH] = ((ROD .8)(COCCUS .2))

VAL[ORGANISM-1,AIR] = ((AEROBIC .6)(FACUL .4))

$AND begins by evaluating SAME[ORGANISM-1,GRAM,GRAMNEG]. The function returns CF=1.0, so TALLY is set to 1.0 (see definition of TALLY in the description of $AND above). Next $AND evaluates the second PREMISE condition, SAME[ORGANISM-1,MORPH,ROD], which returns 0.8. Since the first two conditions both were found to hold, $AND evaluates SAME[ORGANISM-1,AIR,AEROBIC] which returns 0.6. Thus TALLY is set to 0.6 and $AND returns T. Since the PREMISE is true, MYCIN may now draw the conclusion indicated in the ACTION portion of the rule. Note, however, that CONCLUDE has as arguments both .8 (i.e., the CF for the rule as provided by the expert) and TALLY (i.e., the certainty tally for the PREMISE). CONCLUDE and the other functions that control inferences are described in Section III.3.2.

II.6 (*) Static Knowledge Structures

Although all MYCIN's inferential knowledge is stored in rules, there are various kinds of static definitional information which are stored differently even though they are accessible from rules.

II.6.1 Tabular and List-Based Knowledge

There are three categories of knowledge structures that could be discussed in this section. However, one of them, MYCIN's 800-word dictionary, is used principally for natural language understanding and is therefore described in Chapter 6. The other two data structures are simple linear lists and knowledge tables.

Simple Lists:

Simple lists provide a mechanism for simplifying references to variables and optimizing knowledge storage by avoiding unnecessary duplication. Two examples should be sufficient to explain this point.

In Section II.3.2 I showed that the EXPECT property for the clinical parameter IDENT is:

(ONEOF (ORGANISMS))

ORGANISMS is the name of a linear list containing the names of all bacteria known to MYCIN (see Section V.1 of Chapter 1). There is also a clinical parameter named COVERFOR for which the EXPECT property is:

(ONEOF ENTEROBACTERIACEAE (ORGANISMS) G+COCCI G-COCCI)

Thus, by storing the organisms separately on a list named ORGANISMS, we avoid having to duplicate the list of names in the EXPECT property of both IDENT and COVERFOR. Furthermore, using the variable name rather than internal pointers to the list structure facilitates references to the list of organisms whenever it is needed.

A second example involves the several rules in the system which make conclusions based on whether an organism was isolated from a site that is normally sterile or non-sterile. STERILESITES is the name of a simple list containing the names of all normally sterile sites known to the system. There is a similar list named NONSTERILESITES. Thus many rules can have the condition (SAME CNTXT SITE STERILESITES) and the sites need not be listed explicitly in each rule.

Knowledge Tables:

In conjunction with the special functions discussed in the next subsection, MYCIN's knowledge tables permit a single rule to accomplish a task that would otherwise require several rules. A knowledge table contains a comprehensive record of certain clinical parameters plus the values they take on

under various circumstances. For example, one of MYCIN's knowledge tables itemizes the gramstain, morphology, and aerobicity for every bacterial genus known to the system. Consider, then, the task of inferring an organism's gram stain, morphology, and aerobicity if its identity is known with certainty. Without the knowledge table, MYCIN would require several rules of the form:

```
  IF: THE IDENTITY OF THE ORGANISM IS DEFINITELY W
THEN: 1) IT IS DEFINITE (1) THAT THE GRAMSTAIN OF THE
         ORGANISM IS X, AND
      2) IT IS DEFINITE (1) THAT THE MORPHOLOGY OF THE
         ORGANISM IS Y, AND
      3) IT IS DEFINITE (1) THAT THE AEROBICITY OF THE
         ORGANISM IS Z
```

Instead MYCIN contains a single rule of the following form:

```
RULE030
-------
    IF: THE IDENTITY OF THE ORGANISM IS KNOWN WITH CERTAINTY
  THEN: IT IS DEFINITE (1) THAT THESE PARAMETERS - GRAM
        MORPH AIR - SHOULD BE TRANSFERRED FROM THE IDENTITY
        OF THE ORGANISM TO THIS ORGANISM
```

Thus if ORGANISM-1 is known to be a streptococcus, MYCIN can use RULE030 to access the knowledge table to look up the organism's gramstain, morphology, and aerobicity.

II.6.2 Specialized Functions

The efficient use of knowledge tables requires the existence of four specialized functions (the category <special-func> from Section II.1.2). As explained below, each function attempts to add members to a list named GRIDVAL and returns T if at least one element has been found to be placed in GRIDVAL.

under various circumstances. For example, one of MYCIN's knowledge tables itemizes the gramstain, morphology, and aerobicity for every bacterial genus known to the system. Consider, then, the task of inferring an organism's gram stain, morphology, and aerobicity if its identity is known with certainty. Without the knowledge table, MYCIN would require several rules of the form:

```
  IF: THE IDENTITY OF THE ORGANISM IS DEFINITELY W
THEN: 1) IT IS DEFINITE (1) THAT THE GRAMSTAIN OF THE
         ORGANISM IS X, AND
      2) IT IS DEFINITE (1) THAT THE MORPHOLOGY OF THE
         ORGANISM IS Y, AND
      3) IT IS DEFINITE (1) THAT THE AEROBICITY OF THE
         ORGANISM IS Z
```

Instead MYCIN contains a single rule of the following form:

```
RULE030
-------
    IF: THE IDENTITY OF THE ORGANISM IS KNOWN WITH CERTAINTY
  THEN: IT IS DEFINITE (1) THAT THESE PARAMETERS - GRAM
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        OF THE ORGANISM TO THIS ORGANISM
```

Thus if ORGANISM-1 is known to be a streptococcus, MYCIN can use RULE030 to access the knowledge table to look up the organism's gramstain, morphology, and aerobicity.

II.6.2 Specialized Functions

The efficient use of knowledge tables requires the existence of four specialized functions (the category <special-func> from Section II.1.2). As explained below, each function attempts to add members to a list named GRIDVAL and returns T if at least one element has been found to be placed in GRIDVAL.

Functions Of The Class <special-func>

Let V=Val[C,P] be the set of all hypotheses regarding the value of the clinical parameter P for the context C.

Let CLST be a list of objects which may be characterized by clinical parameters.

Let PLST be a list of clinical parameters.

Then:

FUNCTION	Value Of GRIDVAL
SAME2[C,CLST,PLST]	{X | X ∈ CLST & (for all P in PLST) SAME [C,P,Val[X,P]]}
NOTSAME2[C,CLST,PLST]	{X | X ∈ CLST & (for at least one P in PLST) NOTSAME[C,P,Val[X,P]]}
SAME3[C,P,CLST,P*]	{X | X ∈ CLST & SAME[C,P,Val[X,P*]]}
NOTSAME3[C,P,CLST,P*]	{X | X ∈ CLST & NOTSAME[C,P,Val[X,P*]]}
GRID[<object>,<attribute>]	{X | X is a value of the <attribute> of <object>}

GRID is merely a function for looking up information in the specialized knowledge table.

The use of these functions is best explained by example. Consider the following verbalization of a rule given us by one of our collaborating experts:

> If you know the portal of entry of the current organism and also know the pathogenic bacteria normally associated with that site, you have evidence that the current organism is one of those pathogens so long as there is no disagreement on the basis of gramstain, morphology, or aerobicity .

This horrendous sounding rule is coded quite easily using SAME2[C,CLST,PLST], where C is the current organism, CLST is the list of pathogenic bacteria normally associated with the portal of entry of C, and PLST is the set of properties (GRAM MORPH AIR). GRID is used to set up CLST. The LISP version of the rule is:

```
RULE084
-------
     PREMISE: [$AND (GRID (VAL CNTXT PORTAL) PATH-FLORA)
                    (SAME2 CNTXT GRIDVAL (QUOTE (GRAM MORPH AIR))))
     ACTION: (CONCLIST CNTXT IDENT GRIDVAL .8)
```

Note that GRID sets up the initial value of GRIDVAL for use by SAME2, which then

redefines GRIDVAL for use in the ACTION clause. This rule is translated (in somewhat stilted English) as follows:

```
RULE084
-------
    IF: 1) THE LIST OF LIKELY PATHOGENS ASSOCIATED WITH THE
           PORTAL OF ENTRY OF THE ORGANISM IS KNOWN, AND
        2) THIS CURRENT ORGANISM AND THE MEMBERS YOU ARE
           CONSIDERING AGREE WITH RESPECT TO THE FOLLOWING
           PROPERTIES: GRAM MORPH AIR
  THEN: THERE IS STRONGLY SUGGESTIVE EVIDENCE (.8) THAT
        EACH OF THEM IS THE IDENTITY OF THIS CURRENT
        ORGANISM
```

SAME2 and NOTSAME2 can also be used for comparing the values of the same clinical parameters for two or more different contexts in the context tree. For example:

SAME2 [ORGANISM-1 (ORGANISM-2 ORGANISM-3) (GRAM MORPH)]

On the other hand, SAME3 and NOTSAME3 are useful for comparing different parameters of two or more contexts. Suppose you need a predicate that returns T if the site of a prior organism (ORGANISM-2) is the same as the portal of entry of the current organism (ORGANISM-1). This is accomplished by:

SAME3 [ORGANISM-1 PORTAL (ORGANISM-2) SITE]

II.7 (*) Translation Of Rules Into English

Rules are translated into a subset of English using a set of recursive functions which piece together bits of text. I shall demonstrate the process using the PREMISE condition (GRID (VAL CNTXT PORTAL) PATH-FLORA) which is taken from RULE084 as discussed in Section II.6.2.

The reader will recall that every clinical parameter has a property named TRANS that is used for translation (Section II.3.2). In addition, every function, simple list, or knowledge table that is used by MYCIN's rules also has a TRANS

property. For our example the following TRANS properties are relevant:

GRID: (THE (2) ASSOCIATED WITH (1) IS KNOWN)

VAL: (((2 1)))

PORTAL: (THE PORTAL OF ENTRY OF *)

PATH-FLORA: (LIST OF LIKELY PATHOGENS)

The numbers in the translations of functions indicate where the translation of the corresponding argument should be inserted. Thus the translation of GRID's second argument is inserted for the '(2)' in GRID's TRANS property. The extra parentheses in the TRANS for VAL indicate that the translation of VAL's first argument should be substituted for the asterisk in the translation of VAL's second argument. Since PORTAL is a PROP-ORG, CNTXT translates as THE ORGANISM and the translation of (VAL CNTXT PORTAL) becomes:

THE PORTAL OF ENTRY OF THE ORGANISM

Substituting VAL's translation for the (1) in GRID's TRANS, and PATH-FLORA's translation for the (2), the final translation of the conditional clause becomes:

THE LIST OF LIKELY PATHOGENS ASSOCIATED WITH THE PORTAL
OF ENTRY OF THE ORGANISM IS KNOWN

Similarly,

(GRID (VAL CNTXT CLASS) CLASSMEMBERS)

translates as:

THE LIST OF MEMBERS ASSOCIATED WITH THE CLASS OF THE ORGANISM IS KNOWN

All other portions of rules use essentially this same procedure for translation. An additional complexity arises, however, if it is necessary to negate the verbs in ACTION or ELSE clauses when the associated CF is negative. The translator program must therefore recognize verbs and know how to negate them when evidence in a PREMISE supports the negation of the hypothesis that is referenced in the ACTION of the rule.

III. USE OF THE RULES TO GIVE ADVICE

The discussion in Section II was limited to the various data structures used to represent MYCIN's knowledge. The present section proceeds to an explanation of how MYCIN uses that knowledge in order to give advice.

The discussion begins with a summary of previous goal-oriented or rule-based problem-solving systems. I then describe MYCIN's control structure for selecting rules and deciding when to ask questions of the user. Subsequent sections explain the mechanisms for creation of the program's record of the consultation. They also describe a variety of non-trivial complexities which arose during implementation of the system's control structure.

III.1 Previous Goal-Oriented Problem-Solving Systems

Early AI research on machine reasoning concentrated on programs that could solve simple puzzles. From this work a number of problem-solving techniques were developed, many of which continue to pervade artificial intelligence investigation. These have been summarized as follows <Nilsson - 1974>:

(1) heuristic search

(2) problem spaces and states

(3) operators for state transformations

(4) goal and subgoal states

(5) means-ends analysis

(6) reasoning backwards

I will not attempt to discuss all of these here, but will concentrate instead on the techniques used by the four 'rule-based' systems that were selected for discussion in Section II.1.1 and on the various methodologies for goal-oriented problem-solving.

Although MYCIN shares its rule-based knowledge representation with several other AI programs, none of the systems described in Section II.1.1 uses its rules in the way that MYCIN does. Waterman's system, for example, makes decisions by comparing the current state vector with the 'situation' portion of the SA rules <Waterman - 1970>. The rules are maintained in an ordered list and the matching-search begins with the first rule in the list. Searching stops as soon as a match is found; thus the first matched rule defines the program's 'move' in the poker game. Subsequent rules in the list which might also match the current state vector are ignored. As a result, the order of rules in the rule-list is of crucial importance. In general, the most specific rules are placed early in the list so that they effectively filter out state vectors that are well-characterized and for which well-defined heuristics exist.

Although system knowledge is kept modular by the SA rule approach, the rules are implicitly interrelated by their ordering in the list. Furthermore, in Heuristic DENDRAL <Buchanan - 1969>, the interrelationships may be explicit in that the action portion of one rule may include a pointer to one or more other rules. As a result, integration of new rules and modifications to old knowledge may be complicated. Waterman's program attempts to learn new heuristics for incorporation into the ordered list of rules, and Meta-DENDRAL also tackles the problem of generalization (theory formation). Both programs must therefore select the appropriate location or mechanism for incorporating a new rule and, in some cases, must modify other rules so that the new SA heuristic will be invoked under

appropriate circumstances.

Colby's system <Colby - 1969> interrelates its rules in a directed graph <Tesler - 1968>. In judging the credibility of a proposition P, the program looks for relevant beliefs in the graph structure. A directly relevant belief is one that can be derived from P in a single step. These beliefs then serve as the the 'heads' of paths in the graph to be searched. Therefore, Colby's system clearly depends upon explicit interrelationships of both inferential rules and 'facts' (see Section II.1.1). Furthermore, the program uses the rules primarily as a kind of pattern matching mechanism during the evaluation of the proposition in question. Despite its use of rules, the program is not really a problem-solving system and its similarity to MYCIN is therefore largely superficial.

Green's QA3, on the other hand, is a problem-solving system with a theoretical foundation firmly linked to the puzzle-solving programs that I mentioned above <Nilsson - 1974>. As explained in Section II.1.1, QA3's task is to use axioms and theorems (expressed in the first-order predicate calculus) to answer questions <Green - 1969>. Questions are themselves expressed as theorems (rules) and the program attempts to derive the theorem from its knowledge base. The steps in the proof are remembered and then form the basis of the answer to the question. Thus the question (expressed as a theorem) is a 'goal-statement' and the program must have mechanisms for selecting relevant pieces of knowledge which can be combined to accomplish the goal.

QA3's technique for combining knowledge is a modified form of the resolution principle <Robinson - 1965>. The principle explains how to derive a new logical statement, when possible, from a specified pair of clauses. However, a variety of additional strategies is needed for deciding which pieces of knowledge to attempt to resolve. Green's technique is to try to show that the negation of the question is inconsistent with the rest of the system's knowledge. Aided by heuristic search strategies including the set-of-support <Wos - 1965>,

unit preference <Wos - 1964>, and subsumption <Robinson - 1965>, QA3 works backwards from the negation of the question, attempting to derive a contradiction. Thus this theorem-proving approach may be considered goal-oriented in that it works backwards from its goal rather than resolving knowledge clauses at random in hopes of eventually deriving the answer to the question under consideration.

Another intuitively pleasing technique which has found application within the realm of problem-solving <Fikes - 1971, Newell - 1961> is known as means-ends analysis. Often explained in terms of state transition, the technique is based upon the recognition of differences between the current state of the system and the desired state (goal). As a result, useful intermediate states (subgoals) can be defined so that the problem may be reduced to a number of subproblems, each much easier than the total task. Plans for accomplishing each subgoal may then be combined to create a total strategy for achieving the goal.

It is not always natural to express knowledge in terms of operators for state transition, however. As early as 1957 a system was introduced to solve logical problems by working backwards from the goal without means-ends analysis <Newell - 1957>. More recent systems have also utilized the goal-oriented approach <Hewitt - 1969, Rulifson - 1972>. In fact, the consequent theorems of PLANNER <Hewitt - 1972> (implemented in Micro-PLANNER - see also Section II.1.1), provide a control mechanism for knowledge use which seems strikingly similar to those that should ideally be used for medical decision making. I will attempt to justify this claim after a brief description of PLANNER's deductive mechanisms. The examples used here are taken from a recent discussion of AI languages <Bobrow - 1973>.

PLANNER's data types include assertions, goals, and theorems. Consider, for example, a program which knew the following facts:

(PART ARM PERSON)

(PART HAND ARM)

(PART FINGER HAND)

where these stand for attribute-object-value triples such as those I discussed in Section II.3.1. Suppose the program were now asked to decide whether a finger is part of a person, i.e.:

(GOAL (PART FINGER PERSON))

The PLANNER 'GOAL' formalism first looks to see if the fact appears in the program's knowledge base. Since it does not, it looks instead for a 'consequent theorem' with a pattern that matches the GOAL statement (PART FINGER PERSON). Variable positions in patterns are characters preceded by '$?'. Thus the following consequent theorem matches the GOAL:

```
(CONSEQUENT
        (PART $?X $?Z)          <--(pattern)
        (GOAL (PART $?X $?Y))
        (GOAL (PART $?Y $?Z)))
```

When instantiated for the current GOAL, the theorem becomes:

```
(CONSEQUENT
        (PART FINGER PERSON)
        (GOAL (PART FINGER $?Y))
        (GOAL (PART $?Y PERSON)))
```

or, in words, to show that a finger is part of a person, find something ($?Y) of which a finger is a part and which itself is a part of a person. Thus the program has two new instantiated GOAL statements:

(GOAL (PART FINGER $?Y))

(GOAL (PART $?Y PERSON))

The first GOAL statement immediately finds from its knowledge base that (PART FINGER $?Y) holds for $?Y = HAND. Thus the second GOAL becomes (GOAL (PART HAND PERSON)) which can, in turn, be derived by recursive use of the consequent theorem given above. Figure 4-6 diagrams the reasoning network which develops below the initial GOAL. Note that the terminal nodes in this little tree correspond to

GOAL TREE FOR THE *PLANNER* EXAMPLE

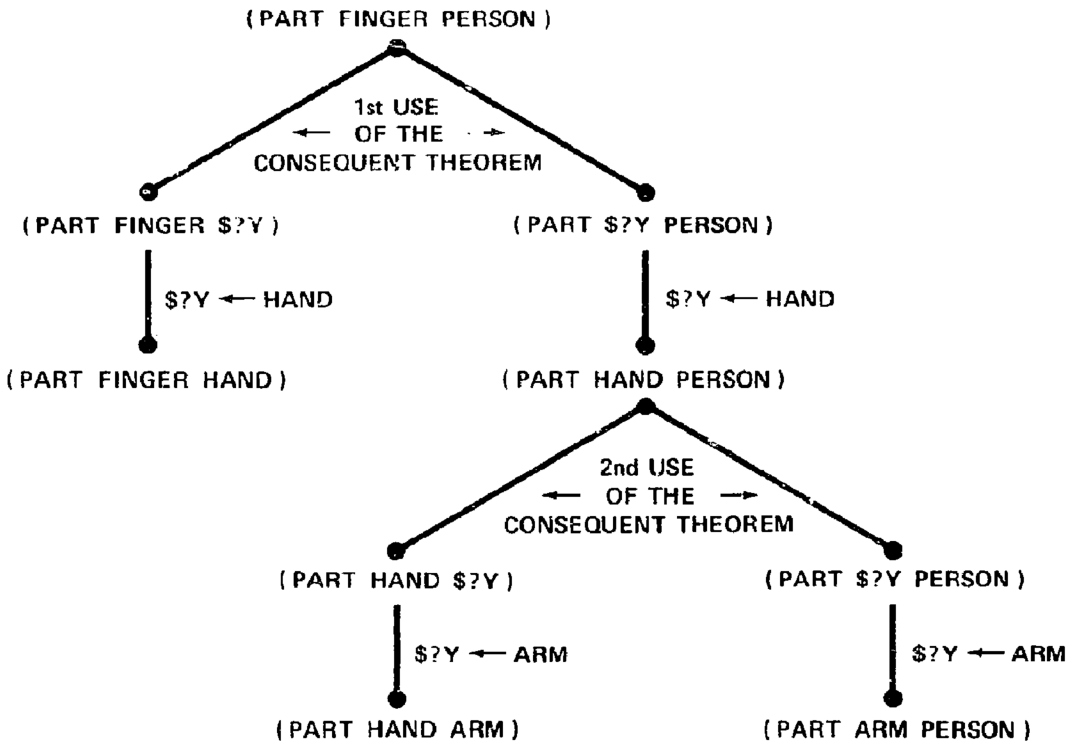

Figure 4-6

facts already in the data base. As is later shown, MYCIN's decision process may also be diagrammed as a reasoning network with a goal at the top and known data as terminal nodes.

Another PLANNER construct is the 'antecedent theorem'. Whenever anything is asserted in a PLANNER program, i.e., added to the data base, the system compares the new knowledge with the pattern portion of all antecedent theorems in the system. Continuing the example from above, consider the following theorem:

```
(ANTECEDENT
        (PART $?X $?Y)          <--(pattern)
        (GOAL (PART $?Y $?Z))
        (ASSERT (PART $?X $?Z)))
```

Suppose the assertion (PART FINGER HAND) were now added to a program that already knew (PART HAND ARM) and (PART ARM PERSON). The new assertion would match the pattern in the theorem above (note I have not yet mentioned any GOAL's) and would therefore invoke the following instantiation:

```
(ANTECEDENT
        (PART FINGER HAND)
        (GOAL (PART HAND $?Z))
        (ASSERT (PART FINGER $?Z)))
```

which says, in words, that since a finger is part of a hand, if you can find something ($?Z) which a hand is part of then you can assert that a finger is part of it too. (GOAL (PART HAND $?Z)) is in this case easily proven from the data base by setting $?Z to ARM. Thus the antecedent theorem succeeds and asserts (PART FINGER ARM). However this new assertion also matches the pattern portion of the antecedent theorem, so the theorem is once again invoked. This time the observation (PART ARM PERSON) leads to the conclusion (PART FINGER PERSON).

A potential problem with antecedent theorems, as should be clear from this example, is that they have a capability to clutter up the system's knowledge base with facts (assertions) that will never be used in achieving goals. When used

judiciously they are powerful mechanisms for simplifying future goals that are likely to need the generated assertions, but the consequent theorems suggest a sense of purpose which is highly appealing for problem-solving applications.

The distinction between consequent and antecedent theorems provides a useful basis for considering some of the different approaches to the medical diagnosis problem. Antecedent theorems may in one sense be compared with a comprehensive process for medical data collection. Clinical screening exams of course have their place (Section II.2.3 - Chapter 1), but medical education tends to stress the rational selection of tests based upon indications in the patient. The alternate approach is to order every test imaginable (including a lengthy history and physical exam) and then to sift through the data in hopes of recognizing unusual patterns or clusters of symptoms which may lead to a diagnosis. The second alternative is not only expensive and time-consuming, but it also requires remarkably little analytical skill on the part of the clinician. The approach does occur, however, particularly among medical students before their clinical skills are well-developed.

The selection of tests on the basis of specific indications, on the other hand, indicates an organized approach to problem-solving which parallels that found in consequent theorems. The good clinician tends to work backwards from his goal (i.e., to diagnose and treat his patient appropriately), making hypotheses and selecting tests in accordance with his desire to minimize unnecessary time-delays or monetary expenditures. This comparison to PLANNER-type consequent theorems may at first seem rather vague, but I shall show in subsequent sections that MYCIN indeed does reason backwards, avoiding the 'shotgun approach' of a diagnostic system based solely upon mechanisms analagous to antecedent theorems.

III.2 MYCIN's Control Structure

MYCIN's rules are directly analogous to the PLANNER consequent theorems discussed in Section III.1. They permit a reasoning chain (see Figure 4-6) to grow dynamically on the basis of the user's answers to questions regarding the patient. In this subsection I describe that reasoning network, explaining how it grows and how MYCIN manages to ask questions only when there is a reason for doing so.

III.2.1 Consequent Rules And Recursion

As was discussed in Section IV.1 of Chapter 1, MYCIN's task involves a four-stage decision problem:

(1) Decide which organisms, if any, are causing significant disease

(2) Determine the likely identity of the significant organisms

(3) Decide which drugs are potentially useful

(4) Select the best drug or drugs

Steps 1 and 2 are closely interrelated since determination of an organism's significance may well depend upon its presumed identity. Furthermore, MYCIN must consider the possibility that the patient has an infection with an organism not specifically mentioned by the user (e.g., an occult abscess suggested by historical information or subtle physical findings). Finally, if MYCIN decides that there is no significant infection requiring antimicrobial therapy, it should skip steps 3 and 4, advising the user that no treatment is thought to be necessary. MYCIN's task area therefore can be defined by the following rule:

```
RULE092
-------
    IF: 1) THERE IS AN ORGANISM WHICH REQUIRES THERAPY, AND
        2) CONSIDERATION HAS BEEN GIVEN TO THE POSSIBLE
           EXISTENCE OF ADDITIONAL ORGANISMS REQUIRING THERAPY,
           EVEN THOUGH THEY HAVE NOT ACTUALLY BEEN RECOVERED
```

```
        FROM ANY CURRENT CULTURES
THEN: DO THE FOLLOWING:
      1) COMPILE THE LIST OF POSSIBLE THERAPIES WHICH, BASED
         UPON SENSITIVITY DATA, MAY BE EFFECTIVE AGAINST
         THE ORGANISMS REQUIRING TREATMENT, AND
      2) DETERMINE THE BEST THERAPY RECOMMENDATIONS FROM THE
         COMPILED LIST
OTHERWISE: INDICATE THAT THE PATIENT DOES NOT REQUIRE THERAPY
```

This rule is one of MYCIN's PATRULES (i.e., its context is the patient - see Section II.2.2) and is known as the 'goal rule' for the system. A consultation session with MYCIN results from a simple two-step procedure (Subprogram 1, Figure 1-1):

(1) Create the patient context as the top node in the context tree (see Section IV for an explanation of how nodes are added to the tree)

(2) Attempt to apply the goal-rule to the newly created patient context

After the second step, the consultation is over and Subprogram 1 relinquishes control to the Explanation System (Subprogram 2 , Figure 1-1). My purpose here, then, is to explain how the simple attempt to apply the goal rule to the patient causes a lengthy consultation with an individualized reasoning chain.

When MYCIN first tries to evaluate the PREMISE of the goal rule, the first condition requires that it know whether there is an organism that requires therapy. MYCIN then reasons backwards in a manner that may be informally paraphrased as follows:

> How do I decide whether there is an organism requiring therapy? Well, RULE090 tells me that organisms associated with significant disease require therapy. But I don't even have any organisms in the context tree yet, so I'd better ask first if there are any organisms and if there are I'll try to apply RULE090 to each of them. However, the PREMISE of RULE090 requires that I know whether the organism is significant. I have a bunch of rules for making this decision (RULE038 RULE042 RULE044 RULE108 RULE122). For example, RULE038 tells me that if the organism came from a sterile site it is probably significant. Unfortunately I don't have any rules for inferring the site of a culture, however, so I guess I'll have to ask the user for this information when I need it ...

This goal-oriented approach to rule invocation and question selection is automated via two interrelated procedures, a MONITOR that analyzes rules and a FINDOUT mechanism that searches for data needed by the MONITOR.

The MONITOR analyzes the PREMISE of a rule, condition by condition, as shown in Figure 4-7. [As discussed in Section II.5, the MONITOR uses the $AND function to oversee the PREMISE evaluation]. When the value of the clinical parameter referenced in a condition is not yet known to MYCIN, the FINDOUT mechanism is invoked in an attempt to obtain the missing information. FINDOUT then either derives the necessary information (from other rules) or asks the user for the data.

FINDOUT has a dual strategy depending upon the kind of information required by the MONITOR. This distinction is demonstrated in Figure 4-8. In general, a piece of data is immediately requested from the user (an ASK! question) if it is considered in some sense 'primitive', as are, for example, most laboratory data. Thus, if the physician knows the identity of an organism (e.g., from a lab report), we would prefer that the system request that information directly rather than try to deduce it via decision rules. However, if the user does not know the identity of the organism, MYCIN uses its knowledge base in an effort to deduce the range of likely organisms.

'Non-laboratory data' are those kinds of information which require inference even by the clinician: e.g., whether an organism is a contaminant or a previously administered drug was effective. FINDOUT always attempts to deduce such information first, asking the physician only when MYCIN's knowledge base of rules is inadequate for making the inference from the information at hand (an ASK2 question).

In Section II.3.2 I described the representation of clinical parameters and their associated properties. The need for two of these properties, LABDATA and UPDATED-BY, should now be clear. The LABDATA flag for a parameter allows

THE *MONITOR* FOR RULES

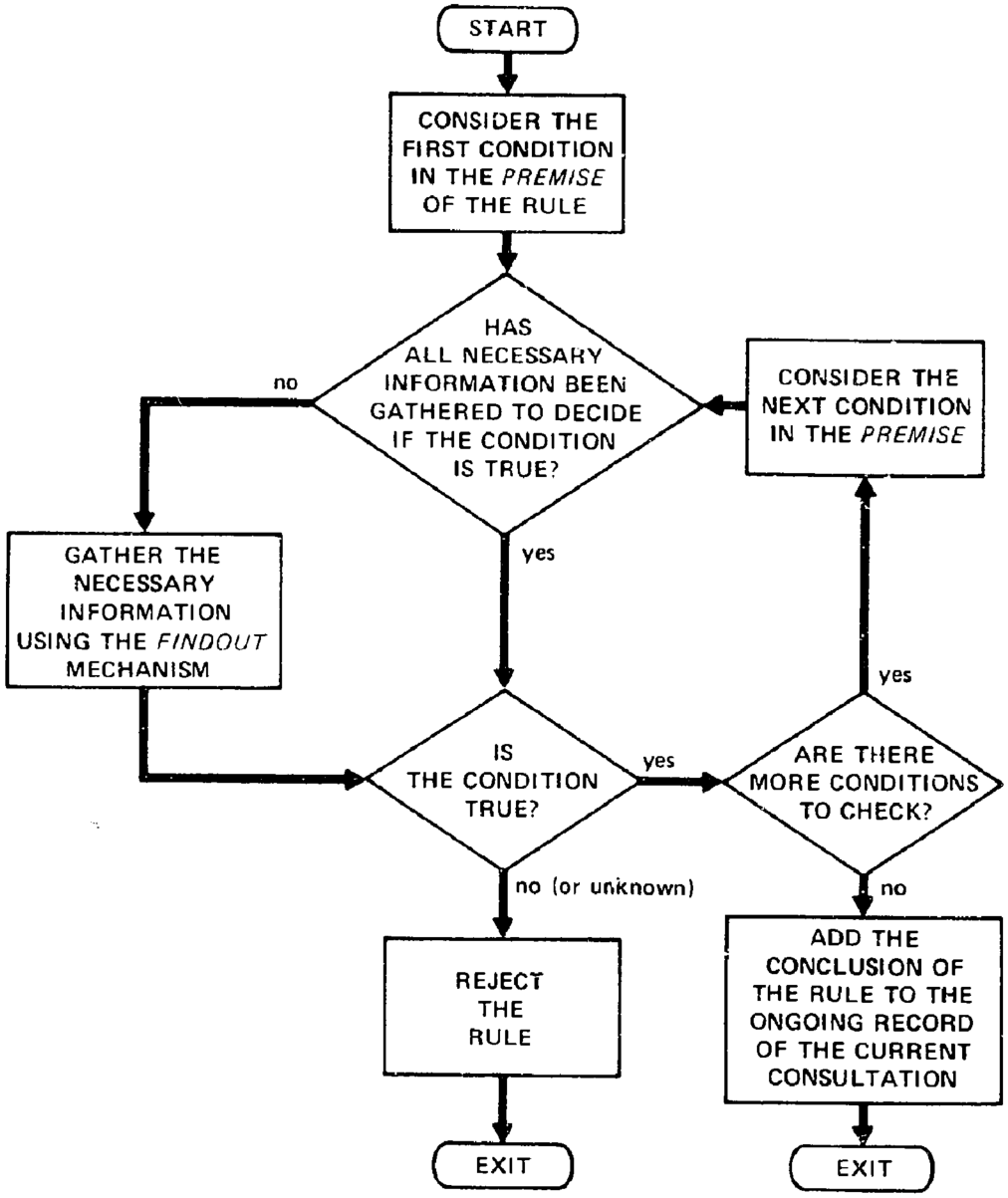

Figure 4-7

THE *FINDOUT* MECHANISM

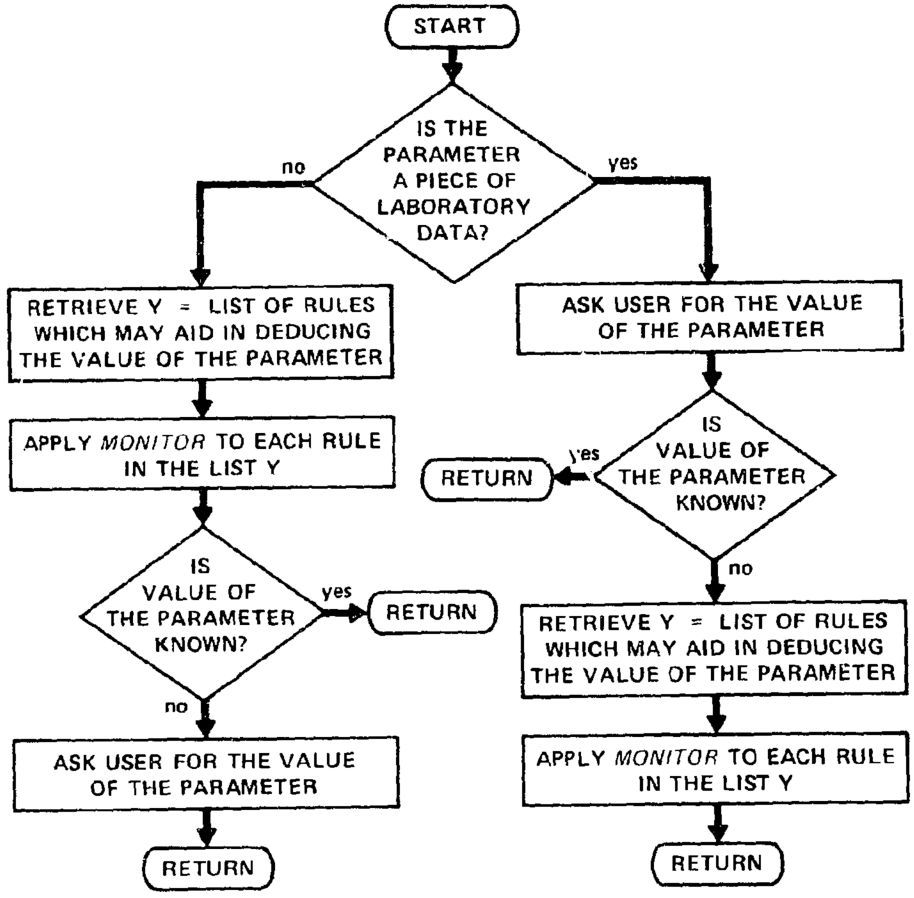

Figure 4-8

FINDOUT to decide which branch to take through its decision process (Figure 4-8). Thus IDENT is marked as being LABDATA in Figure 4-2.

Recall that the UPDATED-BY property is a list of all rules in the system which permit an inference to be made regarding the value of the indicated parameter. Thus UPDATED-BY is precisely the list I have called Y in Figure 4-8. Every time a new rule is added to MYCIN's knowledge base, the name of the rule is added to the UPDATED-BY property of the clinical parameter referenced in its ACTION or ELSE clause. Thus the new rule immediately becomes available to FINDOUT at times when it may be useful. It is not necessary explicitly to specify its interrelationships with other rules in the system.

Note that FINDOUT is accessed from the MONITOR, but the MONITOR may also be accessed from FINDOUT. This recursion allows self-propagation of a reasoning network appropriate for the patient under consideration and selects only the necessary questions and rules. The first rule passed to the MONITOR is always the goal rule. Since the first condition in the PREMISE of this rule references a clinical parameter of the patient named TREATFOR, and since the value of TREATFOR is of course unknown before any data have been gathered, the MONITOR asks FINDOUT to trace the value of TREATFOR. This clinical parameter is not a LABDATA so FINDOUT takes the left-hand pathway in Figure 4-8 and sets Y to the UPDATED-BY property of TREATFOR, the two-element list (RULE090 RULE149). The MONITOR is then called again with RULE090 as the rule for consideration, and FINDOUT is utilized to trace the values of clinical parameters referenced in the PREMISE of RULE090. Note that this process parallels the verbal description of MYCIN's reasoning that was given above. [The reference to tree propagation, however, will not be explained until Section IV].

It is important to recognize that FINDOUT does not check to see whether the PREMISE condition is true. Instead the FINDOUT mechanism traces the clinical parameter exhaustively and returns its value to the MONITOR where the conditional

expression may then be evaluated. [The process is slightly different for 'multi-valued' parameters; see Section III.2.2.1. Hence FINDOUT is called at most one time for a clinical parameter (in a given context - see Section IV). When FINDOUT returns a value to the MONITOR it marks the clinical parameter as having been traced. Thus when the MONITOR reaches the question "HAS ALL NECESSARY INFORMATION BEEN GATHERED TO DECIDE IF THE CONDITION IS TRUE?" (Figure 4-7), the parameter is immediately passed to FINDOUT unless it has been previously marked as traced.

Figure 4-9 is a portion of MYCIN's initial reasoning chain. A comparison with Figure 4-6 will reemphasize the similarities between MYCIN's control structure and the goal-oriented consequent theorems used by PLANNER. In Figure 4-9 the clinical parameters being traced are underlined. Thus REGIMEN is the top goal of the system (i.e., it is the clinical parameter in the ACTION clause of the goal rule). Below each parameter are the rules (from the UPDATED-BY property) which may be used for inferring the parameter's value. Clinical parameters referenced in the PREMISE of these rules are then listed at the next level in the reasoning network. Rules with multiple PREMISE conditions have their links numbered in accordance with the order in which the parameters are traced (by FINDOUT). ASK1 indicates that a parameter is LABDATA so its value is automatically asked of the user when it is needed. ASK2 refers to parameters which are not LABDATA but for which no inference rules currently exist, e.g., whether the dose of a drug is adequate. One of the goals in the future development of MYCIN's knowledge base is to acquire enough rules allowing the values of non-LABDATA parameters to be inferred so that ASK2 questions need no longer occur.

Note that the reasoning network in Figure 4-9 is drawn to reflect maximum size. In reality many portions of such a network need not be considered. For example, RULE042 (one of the UPDATED-BY rules under SIGNIFICANCE) is rejected if

SAMPLE REASONING NETWORK

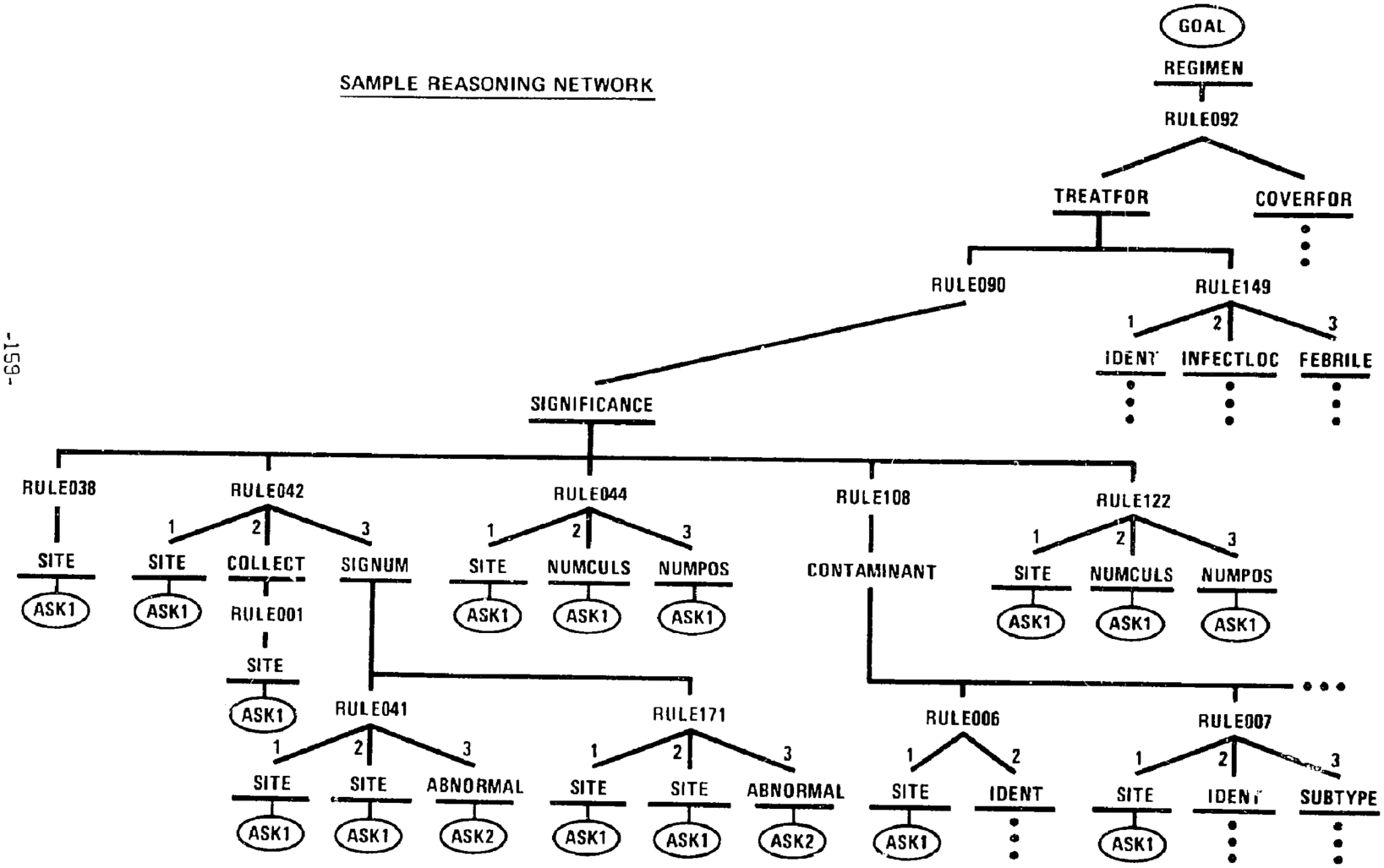

Figure 4-9

the SITE condition is found to be false by the MONITOR. When that happens, neither COLLECT nor SIGNUM need to be traced by FINDOUT and those portions of the reasoning network are not created. Thus the order of conditions within a PREMISE is highly important. In general, conditions referencing the parameters which are most common (i.e., which appear in the PREMISE of the most rules) are put first in the PREMISE of new rules to act as an effective screening mechanism.

A final comment is necessary regarding the box labelled "REJECT THE RULE" in Figure 4-7. This step in the MONITOR actually must check to see if the rule has an ELSE clause. If so, and if the PREMISE is known to be false, the conclusion indicated by the ELSE clause is drawn. If there is no ELSE clause, or if the truth status of the PREMISE is uncertain (e.g., the user has entered UNKNOWN when asked the value of one of the relevant parameters - see Section III.2.2), the rule is simply ignored.

III.2.2 Asking Questions Of The User

As was emphasized in Chapter 3, the conventions for communication between a program and the physician are a primary factor determining the system's acceptability. We have therefore designed a number of features intended to simplify the interactive process that occurs when FINDOUT reaches one of the boxes entitled "ASK THE USER FOR THE VALUE OF THE PARAMETER" (Figure 4-8).

When MYCIN requests the value of a 'single-valued' or 'yes-no' parameter, it uses the PROMPT property as described in Section II.3.2. The user's response is then compared with the EXPECT property of the parameter. If his answer is one of the expected responses, the program simply continues through the reasoning network. Otherwise, MYCIN checks the system dictionary to see if the user's response is a synonym for one of the recognized answers. If this attempt also fails, MYCIN uses INTERLISP spelling-correction routines <Teitelman - 1974> to see

if a simple spelling or typographical error will account for the unrecognized response. If so, the program makes the correction, prints its assumption, and proceeds as though the user had made no error. If none of these mechanisms succeeds, MYCIN tells the user that his response is not recognized, displays a list of sample responses, and asks the question again. Examples of these features are included in the sample consultation session at the end of Chapter 1.

'Multi-valued' parameters are handled somewhat differently. FINDOUT recursively traces such parameters in the normal fashion, but when forced to ask a question of the user it customizes its question to the condition being evaluated in the MONITOR. Suppose, for example, the MONITOR were evaluating the condition (SAME CNTXT INFECT MENINGITIS), i.e., "Meningitis is an infectious disease diagnosis for the patient". If FINDOUT were to ask the question using the regular PROMPT strategy, it would request:

"What is the infectious disease diagnosis for PATIENT-1?"

The problem is that the patient may have several diagnoses, each of which can be expressed in a variety of ways. If the physician were to respond:

"A meningeal inflammation that is probably of infectious origin"

MYCIN would be forced to try to recognize that this answer implies meningitis. Our solution has been to customize questions for 'multi-valued' parameters to reflect the value being checked in the current PREMISE condition. The PROMPT1 property is used, and questions always expect a yes-or-no response:

"Is there evidence that the patient has a meningitis?"

The advantages of this approach are the resulting ability to avoid natural language processing during the consultation itself, and the posing of questions that are specific to the patient under consideration.

In addition to the automatic spelling-correction capability described above, the user is given a number of options that may be utilized whenever MYCIN asks him a question:

UNKNOWN - (may be abbreviated U or UNK) - used to indicate that the physician does not know the answer to the question, usually because the data are unavailable.

? - used to request a list of sample recognized responses.

?? - used to request a list of all recognized responses.

RULE - used to request that MYCIN display the translation of the current decision rule. FINDOUT simply translates the rule being considered by the MONITOR. This feature provides a simple capability for explaining why the program is asking the question. However, it cannot explain motivation beyond the current decision rule.

QA - used to digress temporarily in order to use the Explanation System (Subprogram 2). The features of this system are explained in Chapter 6.

WHY - used to request a detailed explanation of the question being asked. This feature is much more conversational that the RULE option above and permits investigation of the current state of the entire reasoning chain. This explanation capability was designed by R. Davis and is described elsewhere <Shortliffe - 1974b, Davis - 1975>.

CHANGE XXX - used to change the answer to a previous question. Whenever MYCIN asks a question it prints a number in front of the prompt. Thus CHANGE 4 means "Go back and let me re-answer question #4". The complexities involved in this process are discussed in Section VI.1.

STOP - halts the program without completing the consultation.

HELP - prints this list.

III.3 Creation Of The Dynamic Data Base

Figure 1-1 showed that the Consultation System maintains an ongoing record of the consultation. These dynamic data include information entered by the user, inferencee drawn using decision rules, and record-keeping data structures that facilitate question answering by the Explanation System (see Chapter 6).

II.3.1 Data Acquired From The User

Except for questions related to propagation of the context tree, all queries from MYCIN to the physician request the value of a specific clinical parameter for a specific node in the context tree. The FINDOUT mechanism screens the user's response, as described in Section III.2.2, stores it in MYCIN's dynamic data base, and returns the value to the MONITOR for evaluation of the conditional statement which generated the question in the first place (Section III.2.1). The physician's response is stored, of course, so that future rules containing conditions referencing the same clinical parameter will not force the question to be asked a second time.

As we noted in Section II.4, however, the values of clinical parameters are always stored along with their associated certainty factor. A physician's response must therefore have a CF associated with it. MYCIN's convention is to assume CF=1 for the response unless the physician explicitly states otherwise. Thus the following exchange:

```
7) Staining characteristics of ORGANISM-1 (gram):
** GRAMNEG
```

results in:

```
Val[ORGANISM-1,GRAM] = ((GRAMNEG 1.0))
```

If, on the other hand, the user thinks he knows the answer to a question but wants to indicate his uncertainty, he may enter a certainty factor in parentheses after his response. MYCIN expects the number to be an integer between -10 and +10; the program divides the number by 10 to obtain a CF. Using integers simplifies the user's response and also discourages comparisons between the number and a probability measure. Thus the following exchange:

```
8) Enter the identity (genus) of ORGANISM-1:
** ENTEROCOCCUS (8)
```

results in:

```
Val[ORGANISM-1,IDENT] = ((STREPTOCOCCUS-GROUP-D .8))
```

This example also shows how the dictionary is used to put synonyms into standardized form for the patient's data base (i.e., enterococcus is another name for a group-D streptococcus).

A variant of this last example is the user's option to enter multiple responses to a question so long as each is modified by a CF. For example:

```
13) Did ORGANISM-2 grow in clumps, chains, or pairs?
** CLUMPS (6) CHAINS (3) PAIRS (-8)
```

results in:

```
Val[ORGANISM-2,CONFORM] = ((CLUMPS .6)(CHAINS .3)(PAIRS -.8))
```

The CF's associated with the parameter values are then used for evaluation of PREMISE conditions as described in Section II.5. Note that the user's freedom to modify his answers increases the flexibility of MYCIN's reasoning. Without the CF option, the user might well have responded UNKNOWN to question 13 above. The demonstrated answer, although uncertain, gives MYCIN much more information than would have been provided by an UNKNOWN.

III.3.2 Data Inferred By The System

This subsection explains the <conclusion> item from the BNF rule description (Section II.1.2), i.e., the functions that are used in ACTION or ELSE clauses when a PREMISE has shown that an indicated conclusion may be drawn. There are only three such functions, two of which (CONCLIST and TRANSLIST) reference knowledge tables (Section II.6) but are otherwise dependent upon the third, a function called CONCLUDE. CONCLUDE takes five arguments:

CNTXT - the node in the context tree about which the conclusion is being made

PARAM - the clinical parameter whose value is being added to the dynamic data base

VALUE - the inferred value of the clinical parameter

TALLY - the certainty tally for the PREMISE of the rule (see Section II.4)

CF - the certainty factor for the rule as judged by the expert from whom the rule was obtained

The translation of CONCLUDE depends upon the size of CF:

CF≥.8	"There is strongly suggestive evidence that ..."
.4≤CF<.8	"There is suggestive evidence that ..."
CF<.4	"There is weakly suggestive evidence that ..."
Computed CF	"There is evidence that ... "

Thus the following conclusion:

(CONCLUDE CNTXT IDENT STREPTOCOCCUS TALLY .7)

translates as:

THERE IS SUGGESTIVE EVIDENCE (.7) THAT THE IDENTITY
OF THE ORGANISM IS STREPTOCOCCUS

If, for example, the rule with this ACTION clause were successfully applied to ORGANISM-1, an organism for which no previous inferences had been made regarding identity, the result would be:

Val[ORGANISM-1,IDENT] = ((STREPTOCOCCUS X))

where X is the product of .7 and TALLY (see Combining Function 4, Section VI - Chapter 5). Thus the strength of the conclusion reflects both the CF for the rule and the extent to which the PREMISE of the rule is believed to be true for ORGANISM-1.

Suppose a second rule were now found which contained a PREMISE true for ORGANISM-1 and which added additional evidence to the assertion that the organism is a streptococcus. This new evidence somehow has to be combined with the CF (=X) that is already stored for the hypothesis that ORGANISM-1 is a streptococcus. If Y is the CF calculated for the second rule (i.e., the product of the TALLY for that rule and the CF assigned to the rule by the expert), the CF for the hypothesis is updated to Z so that:

Val[ORGANISM-1,IDENT] = ((STREPTOCOCCUS Z))

where Combining Function 1 gives Z = X + Y(1-X). This function is justified and discussed in detail in Section VI of Chapter 5.

Similarly, additional rules leading to alternate hypotheses regarding the identity of ORGANISM-1 may be successfully invoked. The new hypotheses, along with their associated CF's, are simply appended to the list of hypotheses in Val[ORGANISM-1,IDENT]. Note, of course, that the CF's of some hypotheses may be negative, indicating there is evidence suggesting that the hypothesis is not true. When there is both positive and negative evidence for a hypothesis, Combining Function 1 must be used in a modified form. See Chapter 5 for these details, especially Section VII where MYCIN's use of the CF model is discussed with an example.

A final point to note is that values of parameters are stored identically regardless of whether the information has been inferred or acquired from the user (Section III.3.1). The source of a piece of information is maintained in a separate record (Section III.3.3). It is therefore easy to incorporate new rules that infer values of parameters for which ASK2 questions to the user once were necessary.

III.3.3 Creating An Ongoing Consultation Record

In addition to information provided or inferred regarding nodes in the context tree, MYCIN's dynamic data base contains a record of the consultation session. This record provides the basis for answering questions about the consultation (Chapter 6).

There are two general types of records kept. One is information about how values of clinical parameters were obtained. If the value was inferred using rules, a record of those inferences is stored with the rules themselves. Thus whenever an ACTION or ELSE clause is executed, MYCIN keeps a record of the details.

The second record provides a mechanism for explaining why questions were asked. MYCIN maintains a list of questions, their identifying number, the clinical parameter and context involved, plus the rule which led to generation of the question. The program then uses this list in responding to the EQ option (see Chapter 6) during interactive sessions between the physician and Subprogram 2.

III.4 (*) Self-Referencing Rules

As new rules were acquired from the collaborating experts, it became apparent that MYCIN would need a small number of rules which departed from the strict modularity to which we had otherwise been able to adhere. For example, one expert indicated that he would tend to ask about the typical pseudomonas-type skin lesions only if he already had reason to believe that the organism was a pseudomonas. If the lesions were then said to be evident, however, his belief that the organism was a pseudomonas would be increased even more. A rule reflecting this fact must somehow imply an orderedness of rule invocation, i.e., "Don't try this rule until you have already traced the identity of the organism by

using other rules in the system". Our solution has been to reference the clinical parameter early in the PREMISE of the rule as well as in the ACTION. For example:

```
RULE040
-------
    IF: 1) THE SITE OF THE CULTURE IS BLOOD, AND
        2) THE IDENTITY OF THE ORGANISM MAY BE PSEUDOMONAS, AND
        3) THE PATIENT HAS ECTHYMA GANGRENOSUM SKIN LESIONS
  THEN: THERE IS STRONGLY SUGGESTIVE EVIDENCE (.8) THAT THE
        IDENTITY OF THE ORGANISM IS PSEUDOMONAS
```

Note that RULE040 is thus a member of both the LOOKAHEAD property and the UPDATED-BY property for the clinical parameter IDENT. Rules with the same parameter in both PREMISE and ACTION are termed 'self-referencing' rules. The ordered invocation of such rules is accomplished by a generalized procedure described below.

As discussed in Section III.2.1, a rule such as RULE040 is originally invoked because MYCIN is trying to infer the identity of an organism, i.e., FINDOUT is asked to trace the parameter IDENT and recursively sends the UPDATED-BY list for that parameter to the MONITOR. When the MONITOR reaches RULE040, however, the second PREMISE condition references the same clinical parameter currently being traced by FINDOUT. If the MONITOR merely passed IDENT to FINDOUT again (as called for by the simplified flow chart in Figure 4-7), FINDOUT would begin tracing IDENT for a second time, RULE040 would be passed to the MONITOR yet again, and an infinite loop would occur.

The solution to this problem is to let FINDOUT screen the list I call Y in Figure 4-8, i.e., the UPDATED-BY property for the parameter it is about to trace. Y is partitioned by FINDOUT into regular rules and self-referencing rules (where the latter category is defined as those rules which also occur on the LOOKAHEAD list for the clinical parameter). FINDOUT passes the first group of rules to the MONITOR in the normal fashion. After all theses rules have been tried, FINDOUT marks the parameter as having been traced and then passes the

self-referencing rules to the MONITOR. In this way, when the MONITOR considers the second condition in the PREMISE of RULE040, the conditional is evaluated without a call to FINDOUT because the parameter has already been marked as traced. Thus the truth of the PREMISE of a self-referencing rule is determined on the basis of the set of non-self-referencing rules which were evaluated first. If one of the regular rules permitted MYCIN to conclude that an organism might be a pseudomonas, RULE040 might well succeed when passed to the MONITOR. Clearly this mechanism for handling self-referencing rules satisfies the intention of an expert when he gives us decision criteria in self-referencing form.

It should be noted that this approach minimizes the potential for self-referencing rules to destroy certainty factor commutativity. By holding these rules to the last we insure that the certainty tally for their PREMISE (see TALLY, Section II.5) is the same regardless of the order in which the non-self-referencing rules were executed. If there is more than one self-referencing rule that is successfully executed for a given context and parameter, however, the order of their invocation may affect the final CF. The approach we have implemented thus seeks merely to minimize the potential bad effects of self-referencing rules.

III.5 (*) Preventing Reasoning Loops

Self-referencing rules are actually a special case of a more general problem. Reasoning loops involving multiple rules cannot be handled by the mechanism described in Section III.4. The difference is that self-referencing rules are intentional parts of MYCIN's knowledge base whereas reasoning loops are artifacts that must somehow be avoided.

For the following discussion I introduce the following notation:

[q] X ::> Y

means that decision rule 'q' uses clinical parameter X to reach a conclusion regarding the value of clinical parameter Y. Thus a self-referencing rule may be represented by:

[a] E ::> E

where E is the clinical parameter that is referenced in both the PREMISE and the ACTION of the rule. Consider now the following set of rules:

[1] A ::> B
[2] B ::> C
[3] C ::> D
[4] D ::> A

Statement [1], for example, says that under certain unspecified conditions, the value of A can be used to infer the value of B. Now suppose that the MONITOR asks FINDOUT to trace the clinical parameter D. Then MYCIN's recursive mechanism would create the following reasoning chain:

```
                [4]    [1]    [2]    [3]
... D ::> A ::> B ::> C ::> D
```

The difference between this looped reasoning chain and a self-referencing rule is that rule [4] was provided as a mechanism for deducing the value of A, not for reinforcing the system's belief in the value of D. In cases where the value of A is of primary interest, the use of rule [4] would be appropriate. MYCIN solves this problem by keeping track of all parameters currently being traced by the FINDOUT mechanism. The MONITOR then simply ignores a rule if one of the parameters checked in its PREMISE is already being traced. The result, with the value of D as the goal, is a three-membered reasoning chain in the case above:

```
   [1]    [2]    [3]
A ::> B ::> C ::> D
```

Rule [4] is rejected because parameter D is already being traced elsewhere in the current reasoning chain. If the value of A were the main goal, however, the chain would be:

```
   [2]    [3]    [4]
B ::> C ::> D ::> A
```

Note that this simple mechanism allows us to have potential reasoning loops in the knowledge base but to select only the relevant non-looping portions for consideration of a given patient.

A similar problem can occur when a rule permits two conclusions to be made, each about a different clinical parameter. MYCIN prevents loops in such circumstances by refusing to permit the same rule to occur twice in the current reasoning chain.

IV. PROPAGATION OF THE CONTEXT TREE

The mechanism by which the context tree is customized for a given patient has not yet been discussed. As described in Section III.2.1, the consultation program begins simply by creating the patient context and then attempting to execute the goal rule. All additional nodes in the context tree are thus added automatically during the unwinding of MYCIN's reasoning regarding the PREMISE of the goal rule. This section explains first the data structures used for creating new nodes. Mechanisms for deciding when new nodes should be added are then discussed.

IV.1 Data Structures Used For Sprouting Branches

Section II.2.1 was devoted to an explanation of the context tree. At that time I described the different kinds of context and explained that each node in the tree is an instantiation of the appropriate context-type. Each context-type is characterized by the following properties:

PROMPT1 - a sentence used to ask the user whether the first node of this type should be added to the context tree; expects a yes-no answer.

PROMPT2 - a sentence used to ask the user whether subsequent nodes of this type should be added to the context tree.

PROMPT3 - replaces PROMPT1 when it is used; this is a message to be printed out if MYCIN assumes that there is at least one node of this type in the

tree.

PROPTYPE - indicates the category of clinical parameters (see Section II.3.2) which may be used to characterize a context of this type.

SUBJECT - indicates the categories of rules which may be applied to a context of this type.

SYN - indicates a conversational synonym for referring to a context of this type; MYCIN uses SYN when filling in the asterisk of PROMPT properties for clinical parameters.

TRANS - used for English translations of rules referencing this type of context.

TYPE - indicates what kind of internal name to give a context of this type.

MAINPROPS - lists the clinical parameters, if any, that are to be automatically traced (by FINDOUT) whenever a context of this type is created.

ASSOCWITH - gives the context-type of nodes in the tree immediately above contexts of this type.

Two sample context-types are shown in Figure 4-10. The following observations may help clarify the information given in that figure:

(1) PRIORCULS: Whenever a prior culture is created, it is given the name CULTURE-# (see TYPE), where # is the next unassigned culture number. The values of SITE and WHENCUL are immediately traced using the FINDOUT mechanism (see MAINPROPS). The culture node is put in the context tree below a node of type PERSON (see ASSOCWITH) and the new context may be characterized by clinical parameters of the type PRIOR-CUL (see PROPTYPE). The prior culture may be the context for either PRCULRULES or CULRULES (see SUBJECT) and is translated, in questions to the user, as "this (site) culture" (see SYN) where "(site)" is replaced by the site of the culture if it is known. The use of PROMPT1 and PROMPT2 is demonstrated in the sample consultation at the end of Chapter 1.

(2) CURORG: Since there is a PROMPT3 rather than a PROMPT1, MYCIN prints out the PROMPT3 message and assumes (without asking) that there is at least one CURORG for each CURCUL (see ASSOCWITH); the other CURORG properties correspond to those described above for PRIORCULS.

Whenever MYCIN creates a new context using these models, it prints out the name of the new node in the tree, e.g.:

------ORGANISM-1------

Thus the user is familiar with MYCIN's internal names for the cultures, organisms,

Context-Types Used For Propagation Of The Context Tree

PRIORCULS

```
ASSOCWITH:   PERSON
MAINPROPS:   (SITE WHENCUL)
  PROMPT1:   (Were any organisms that were significant
               (but no longer require therapeutic attention)
               isolated within the last approximately 30 days?)
  PROMPT2:   (Any other significant earlier cultures from
               which pathogens were isolated?)
PROPTYPE:    PROP-CUL
  SUBJECT:   (PRCULRULES CULRULES)
     SYN:    (SITE (this * culture))
   TRANS:    (PRIOR CULTURES OF *)
    TYPE:    CULTURE-
```

CURORG

```
ASSOCWITH:   CURCUL
MAINPROPS:   (IDENT GRAM MORPH SENSITIVS)
  PROMPT2:   (Any other organisms isolated from * for which
               you would like a therapeutic recommendation?)
  PROMPT3:   (I will refer to the first offending organism
               from * as:)
PROPTYPE:    PROP-ORG
  SUBJECT:   (ORGRULES CURORGRULES)
     SYN:    (IDENT (the *))
   TRANS:    (CURRENT ORGANISMS OF *)
    TYPE:    ORGANISM-
```

Figure 4-10

and drugs under discussion. The node names may then be used in MYCIN's questions at times when there may be ambiguity regarding which node is the current context, e.g.:

> Is the patient's illness with the staphylococcus (ORGANISM-2) a hospital-acquired infection?

It should also be noted that when PROMPT1 or PROMPT2 is used to ask the physician a question, he need not be aware that the situation is different from that occurring when FINDOUT asks questions. All the user options described in Section III.2.2 operate in the normal fashion.

Finally, the MAINPROPS property requires brief explanation. The claim was previously made that clinical parameters are traced and their values requested by FINDOUT only when they are needed for evaluation of a rule that has been invoked. Yet we must now acknowledge that certain LABDATA parameters are automatically traced whenever a node for the context tree is created. The reason for this departure is our attempt to keep the program acceptable to physicians. Since the order of rules on UPDATED-BY lists is arbitrary, the order in which questions are asked is somewhat arbitrary as well. We have found that physicians are annoyed if the 'basic' questions are not asked first, as soon as the context is created. The MAINPROPS convention forces certain standard questions early in the characterization of a node in the context tree. Parameters not on the MAINPROPS list are then traced in an arbitrary order that depends upon the order in which rules are invoked.

The MAINPROPS convention may be compared to the antecedent theorems of PLANNER that were discussed in Section III.1. Although I argued then against a system based solely upon antecedent theorems, I did acknowledge that they were powerful for certain purposes when they did not clutter memory with unnecessary information. Since the parameters on MAINPROPS lists are important pieces of

information that would uniformly be traced by FINDOUT anyway, the convention we have implemented forces a standardized ordering of the 'basic' questions without generating useless information.

IV.2 Explicit Mechanisms For Branching

There are two situations under which MYCIN attempts to add new nodes to the context tree. The simpler case occurs when rules explicitly reference contexts that have not yet been created. Suppose, for example, MYCIN is trying to determine the identity of a current organism and therefore invokes the following CURORGRULE:

```
RULE004
-------
    IF: 1) THE IDENTITY OF THE ORGANISM IS NOT KNOWN
           WITH CERTAINTY  AND
        2) THIS CURRENT ORGANISM AND PRIOR ORGANISMS OF
           THE PATIENT AGREE WITH RESPECT TO THE FOLLOWING
           PROPERTIES: GRAM MORPH
  THEN: THERE IS WEAKLY SUGGESTIVE EVIDENCE THAT EACH OF
        THEM IS A PRIOR ORGANISM WITH THE SAME IDENTITY
        AS THIS CURRENT ORGANISM
```

The second condition in the PREMISE of this rule references other nodes in the tree, namely nodes of the type PRIORORGS. If no such nodes exist, the MONITOR asks FINDOUT to trace PRIORORGS in the normal fashion. The difference is that PRIORORGS is not a clinical parameter but a context-type. FINDOUT therefore uses PROMPT1 of PRIORORGS to ask the user if there is at least one organism. If so, an instantiation of PRIORORGS is added to the context tree and its MAINPROPS are traced. PROMPT2 is then used to see if there are any additional prior organisms and the procedure continues until the user indicates there are no more PRIORORGS that merit discussion. Finally FINDOUT returns the list of prior organisms to the

MONITOR so that the second condition in RULE004 can be evaluated.

IV.3 Implicit Mechanisms For Branching

There are two kinds of implicit branching mechanisms. One of these is closely associated with the example of the previous section. As shown in Figure 4-1 (Section II.2.1), a prior organism is associated with a prior culture. But the explicit reference to prior organisms in RULE004 made no mention of prior cultures. Thus if FINDOUT tries to create a PRIORORGS in response to an explicit reference but finds there are no PRIORCULS, the program knows there is an implied need to ask the user about prior cultures before asking about prior organisms. Since PRIORCULS are associated with the patient himself, and since the patient node already exists in the context tree, only one level of implicit branching is required in the evaluation of RULE004.

The other kind of implicit branching occurs when the MONITOR attempts to evaluate a rule for which no appropriate context exists. For example, the first rule invoked in an effort to execute the goal rule is a CURORGRULE (see RULE090, Figure 4-9). Since no current organism has been created at the time the MONITOR is passed this CURORGRULE, MYCIN automatically attempts to create the appropriate nodes and then to apply the invoked rule to each.

V. SELECTION OF THERAPY

The discussion in Sections III and IV concentrated on the PREMISE of MYCIN's principal goal rule (RULE092 - Section III.2.1). This section explains what happens when the PREMISE is found to be true and the two-step ACTION clause is executed.

Unlike other rules in the system, the goal rule does not lead to a conclusion (Section III.3.2) but instead instigates actions. The functions in the ACTION of the goal rule thus correspond to the <actfunc> class that was introduced in the BNF description of Section II.1.2. The first of these functions causes a list of potential therapies to be created. The second allows the best drug or drugs to be selected from the list of possibilities.

V.1 Creation Of The Potential Therapy List

There is a class of decision rules, the THERULES (Section II.2.2), that are never invoked by MYCIN's regular control structure because they do not occur on the UPDATED-BY list of any clinical parameters. These rules contain sensitivity information for the various organisms known to the system. For example:

```
RULE088
-------
    IF: THE IDENTITY OF THE ORGANISM IS PSEUDOMONAS
  THEN: I RECOMMEND THERAPY CHOSEN FROM AMONG THE FOLLOWING DRUGS:
              1 - COLISTIN            (.98)
              2 - POLYMYXIN           (.96)
              3 - GENTAMICIN          (.96)
              4 - CARBENICILLIN       (.65)
              5 - SULFISOXAZOLE       (.64)
```

The numbers associated with each drug are the probabilities that a pseudomonas isolated at Stanford Hospital will be sensitive (in vitro) to the indicated drug. The sensitivity data were acquired from Stanford's microbiology laboratory (and could easily be adjusted to reflect changing resistance patterns at Stanford or the data for some other hospital desiring a version of MYCIN with local sensitivity information). Rules such as the one shown here provide the basis for creating a list of potential therapies. There is one such rule for every kind of organism known to the system.

MYCIN selects drugs only on the basis of the identity of offending organisms. Thus the program's first task is to decide, for each current organism deemed to be significant, which hypotheses regarding the organism's identity (IDENT) are sufficiently likely so that they must be considered in choosing therapy. MYCIN uses the CF's of the various hypotheses in order to select the most likely identities (see Section VII, Chapter 5). Each identity is then given an 'Item number' (see below) and the process is repeated for each significant current organism. The 'Set of Indications' for therapy is then printed out, e.g.:

```
My therapy recommendation will be based on the following possible
identities of the organism(s) that seem to be significant:
 <Item 1> The identity of ORGANISM-1 may be
          STREPTOCOCCUS-GROUP-D
 <Item 2> The identity of ORGANISM-1 may be
          STREPTOCOCCUS-ALPHA
 <Item 3> The identity of ORGANISM-2 is PSEUDOMONAS
```

Each Item in this list of therapy indications corresponds to one of the THERULES.

For example, Item 3 corresponds to RULE088 above. Thus MYCIN retrieves the list of potential therapies for each indication from the associated THERULE. The default (in vitro) statistical data are also retrieved. MYCIN then replaces the default sensitivity data with real data about those of the patient's organisms, if any, for which actual sensitivity information is available from the laboratory. Furthermore, if MYCIN has inferred sensitivity information from the in vivo performance of a drug that has already been administered to the patient, this information also replaces the default sensitivity data. Thus the 'compiled list of potential therapies' is actually several lists, one for each Item in the Set of Indications. Each list contains the names of drugs and, in addition, the associated number representing MYCIN's judgment regarding the organism's sensitivity to each of the drugs.

V.2 Selecting The Preferred Drug From The List

When MYCIN recommends therapy it tries to suggest a drug for each of the Items in the Set of Indications. Thus the problem reduces to selecting the best drug from the therapy list associated with each Item. Clearly the probability that an organism will be sensitive to a drug is an important factor in this selection process. However, there are several other considerations. MYCIN's strategy is to select the best drug on the basis of sensitivity information but then to consider contraindications for that drug. Only if a drug survives this second screening step is it actually recommended. Furthermore, MYCIN also looks for ways to minimize the number of drugs recommended and thus seeks therapies that cover for more than one of the Items in the Set of Indications. The selection/screening process is described in the following two subsections.

V.2.1 Choosing The Apparent First Choice Drug

The procedure used for selecting the apparent first choice drug is a complex algorithm which is somewhat arbitrary and is thus currently under revision. In this section I shall therefore describe the procedure in somewhat general terms since the actual LISP functions and data structures are not particularly enlightening.

There are three initial considerations used in selecting the best therapy for a given item:

(1) the probability that the organism is sensitive to the drug;

(2) whether the drug is already being administered;

(3) the relative efficacy of drugs that are otherwise equally supported by the criteria in (1) and (2).

As is the case with human consultants, MYCIN does not insist on a change in therapy if the physician has already begun a drug which may work, even if that drug would not otherwise be MYCIN's first choice.

Drugs with sensitivity numbers within .05 of one another are considered to be almost identical on the basis of criterion (1). Thus RULE088 above, for example, indicates no clear preference among colistin, polymyxin, and gentamicin for pseudomonas infections (if default sensitivity information from the rule is used). However, our collaborating experts have ranked the relative efficacy of antimicrobials on a scale from 1 to 10. The number reflects such factors as whether the drug is bacteriostatic or bacteriocidal, or its tendency to cause allergic sensitization. Since gentamicin has a higher relative efficacy than either colistin or polymyxin, it is the first drug considered for pseudomonas infections (unless known sensitivity information or previous drug experience indicates that an alternate choice is preferable).

Once MYCIN has selected the apparent best drug for each item in the Set of

Indications, it checks to see if one of the drugs is also useful for one or more of the other indications. For example, if the first choice drug for Item 1 is the second choice drug for Item 2, and if the second choice drug for Item 2 is almost as strongly supported as the first choice drug, Item 1's first choice drug also becomes Item 2's first choice drug. This strategy permits MYCIN to attempt to minimize the number of drugs to be recommended.

A similar strategy is used to avoid giving two drugs of the same drug class. For example, MYCIN knows that if the first choice for one Item is penicillin and the first choice for another is ampicillin, then the ampicillin may be given for both indications.

In the ideal case MYCIN will find a single drug that effectively covers for all the Items in the Set of Indications. But even if each Item remains associated with a different drug, a screening stage to look for contraindications is required. This rule-based process is described in the next subsection. It should be stressed, however, that the manipulation of drug lists described above is algorithmic, i.e., it is coded in LISP functions that are called from the ACTION clause of the goal rule. There is considerable 'knowledge' in this process. Since rule-based knowledge provides the foundation of MYCIN's ability to explain its decisions, it would be desirable eventually to remove this therapy selection method from functions and place it in decision rules. I will return to this point in Section VII.

V.2.1 Rule-Based Screening For Contraindications

Unlike the complex list manipulations described in the previous subsection, criteria for ruling out drugs under consideration may be effectively placed in rules. The rules in MYCIN for this purpose are termed ORDERRULES. The advantages to placing this knowledge in rules are the ones I discussed in Chapter 3, i.e., modularity, ease of modification, and facilitation of explanation and

other question-answering. A sample rule of this type is:

RULE055

IF: 1) THE THERAPY UNDER CONSIDERATION IS TETRACYCLINE, AND
2) THE AGE (IN YEARS) OF THE PATIENT IS LESS THAN 13
THEN: THERE IS STRONGLY SUGGESTIVE EVIDENCE (.8) THAT
TETRACYCLINE IS NOT A POTENTIAL THERAPY FOR USE
AGAINST THE ORGANISM

In order to use MONITOR and FINDOUT with such rules, we must construct appropriate nodes in the context tree and must be able to characterize them with clinical parameters. The context-type used for this purpose is termed POSSTHER (Section II.2.1) and the parameters are classified as PROP-THER (Section II.3.2). Thus when MYCIN has selected the apparent best drugs for the Items in the Set of Indications, it creates a context corresponding to each of these drugs. POSSTHER contexts occur below CURORGS in the context tree. FINDOUT is then called to trace the relevant clinical parameter which collects contraindication information (i.e., this becomes a new goal statement) and the normal recursive mechanism through the MONITOR insures that the proper ORDERRULES are invoked.

ORDERRULES allow a great deal of drug-specific knowledge to be stored. For example, RULE055 above insures that tetracycline is ruled out in youngsters who still have developing bone and teeth. Similar rules tell MYCIN never to given streptomycin or carbenicillin alone, not to give sulfonamides except in urinary tract infections, and not to give cephalothin, clindamycin, lincomycin, vancomycin, cefazolin, or erythromycin if the patient has meningitis. Other ORDERRULES allow MYCIN to consider the patient's drug allergies, dosage modifications, or ecological considerations (e.g., save gentamicin for pseudomonas, serratia, and hafnia unless the patient is so sick that you cannot risk using a different aminoglycoside while awaiting lab sensitivity data). Finally, there are rules that suggest appropriate combination therapies (e.g., add carbenicillin to gentamicin for known pseudomonas infections). In considering

such rules MYCIN often is forced to ask questions which never arose during the initial portion of the consultation. Thus the physician is asked additional questions during the period after MYCIN has displayed the Items in the Set of Indications but before any therapy is actually recommended.

After the presumed first-choice drugs have been exposed to the ORDERRULE screening process, MYCIN checks to see whether any of the drugs is now contraindicated. If so, the process described in Section V.2.1 is repeated. New first-choice drugs are then subjected to the ORDERRULES as I have described above. The process continues until all the first-choice drugs are found to have been instantiated already as POSSTHERS. These then become the system's recommendations. Note that this strategy may result in the recommendation of drugs that are only mildly contraindicated so long as they are otherwise strongly favored. The therapy recommendation itself takes the following form:

```
My preferred therapy recommendation is as follows:
   In order to cover for Items <1> <2> <3>:
      Give the following in combination:
           1. PENICILLIN
              Dose: 285,000 UNITS/KG/DAY - IV
           2. GENTAMICIN
              Dose: 1.7 MG/KG Q8H - IV OR IM
              Comments: MODIFY DOSE IN RENAL FAILURE
```

The user may also ask for second, third, and subsequent therapy recommendations until MYCIN is able to suggest no reasonable alternatives. The mechanism for these iterations is merely a repeat of the processes described above but with recommended drugs removed from consideration.

VI. MECHANISMS FOR STORAGE OF PATIENT DATA

VI.1 Changing Answers To Questions

If a physician decides he wants to change his response to a question that he has already answered, MYCIN must do more than merely redisplay the prompt, accept the user's new answer, and make the appropriate change to the value of the clinical parameter in question. The question was originally asked because the PREMISE of a decision rule referenced the clinical parameter. Thus his original response affected the evaluation of at least one rule, and subsequent pathways in the reasoning network may have been affected as well. It is therefore necessary for MYCIN somehow to return to the state it was in at the time the question was originally asked. Its subsequent actions can then be determined by the corrected user response.

Reversing all decisions made since a question was asked is a complex problem, however. The most difficult task is to determine what portions of a parameter's cumulative CF preceded or followed the question requiring alteration. In fact, the extra data structures needed to permit this kind of backing-up are so large and complicated, and would be used so seldom, that it seems preferable simply to restart the consultation from the beginning when the user wants to change one of his answers.

Restarting is of course also less than optimal, particularly if it requires that the physician reenter the answers to questions that were correct the

first time around. Our desire to make the program acceptable to physicians required that we devise some mechanism for changing answers, but restarting from scratch also had obvious drawbacks regarding user acceptance of the system. We therefore needed a mechanism for restarting MYCIN's reasoning process but avoiding questions that had already been answered correctly. When FINDOUT asks questions it therefore uses the following algorithm:

[1] - before asking the question, check to see if the answer is already stored (in the Patient Data Table - see [3]); if the answer is there, use that value rather than asking the user; otherwise go to [2].

[2] - ask the question using PROMPT or PROMPT1 as usual.

[3] - store the user's response in the Patient Data Table under the appropriate clinical parameter and context.

The Patient Data Table, then, is a growing record of the user's responses to questions from MYCIN (see Patient Data, Figure 1-1). It is entirely separate from the dynamic data record (Section III.3.1) that is explicitly associated with the nodes in the context tree. Note that the Patient Data Table contains only the text responses of the user - there is no CF information (unless included in the user's response), nor are there data derived from MYCIN's rule-based inferences.

The Patient Data Table and the FINDOUT algorithm above make the task of changing answers much simpler. The technique MYCIN uses is the following:

[a] - Whenever the user wants to change the answer to a previous question, he enters CHANGE <numbers>, where <numbers> is a list of the questions whose answers need correction (see Section III.2.2);

[b] - MYCIN looks up the indicated question numbers in its question record (see Section III.3.3);

[c] - The user's responses to the indicated questions are removed from the current Patient Data Table;

[d] - MYCIN reinitializes the system, erasing the entire context tree, including all associated parameters; however it leaves the Patient Data Table intact except for the responses deleted in [c];

[e] - MYCIN restarts the consultation from the beginning.

This simple mechanism results in a restarting of the Consultation System (Subprogram 1) but does not require that the user enter correct answers a second time. Since the Patient Data Table is saved, step [1] of the FINDOUT algorithm above will find all the user's responses until the first question requiring alteration is reached. Thus the first question asked the user after he gives the CHANGE command is, in fact, the earliest of the questions he wants to change. There may be a substantial pause after the CHANGE command while MYCIN reasons through the network to the first question requiring alteration, but a pause is to be preferred over a mechanism requiring reentry of all question answers. The implemented technique is entirely general because answers to questions regarding tree propagation (Section IV.1) are also stored in the Patient Data Table.

IV.2 Remembering Patients For Future Reference

When a consultation is complete, the Patient Data Table contains all responses necessary for generating a complete consultation for that patient. It is therefore straightforward to store the Patient Data Table (on disk or tape) so that it may be reloaded in the future. FINDOUT will automatically read responses from the Table, rather than ask the user, so a consultation may be run several times on the basis of only a single interactive session.

There are two reasons for storing Patient Data Tables for future reference. One is their usefulness in evaluating changes to MYCIN's knowledge base. The other is the resulting ability to re-evaluate patients once new

clinical information becomes available.

VI.2.1 Evaluating New Rules

New rules may have a large effect on the way a given patient case is handled by MYCIN. For example, a single rule may reference a clinical parameter not previously sought or may lead to an entirely new chain in the reasoning network. It is therefore useful to reload Patient Data Tables and run a new version of MYCIN on old patient cases. A few new questions may be asked (because their responses are not stored in the Patient Data Table). Conclusions regarding organism identities may then be observed, as may the program's therapeutic recommendations. Any changes from the decisions reached during the original run (i.e., when the Patient Data Table was created) must be explained. When a new version of MYCIN evaluates several old Patient Data Tables in this manner, aberrant side effects of new rules may be found. Thus stored patient cases provide a useful mechanism for screening new rules before they become an integral part of MYCIN's knowledge base.

VI.2.2 Re-evaluating Patient Cases

The second use for stored Patient Data Tables is the re-evaluation of a patient once additional laboratory or clinical information becomes available. If a user answers several questions with UNKNOWN during the initial consultation session, MYCIN's advice will of course be based upon less than complete information. After storing the Patient Data Table, however, the physician may return for another consultation in a day or so once he has more specific information. MYCIN can use the previous Patient Data Table for responses to questions whose answers are still up-to-date. The user therefore needs to answer only those questions that reference new information. A mechanism for the physician to indicate directly what new data are available has not yet been

automated, however.

A related capability to be implemented before MYCIN becomes available in the clinical setting is a SAVE command. If a physician must leave the computer terminal midway through a consultation, this option will save the current Patient Data Table on the disk. When he returns to complete the consultation he will reload the patient record and the session will continue from the point at which he entered the SAVE command.

It should be understood that saving the current Patient Data Table is not the same as saving the current state of MYCIN's reasoning. Thus, as we have stated above, changes to MYCIN's rule corpus may result in different advice from an identical Patient Data Table. Finally, I wish to emphasize our awareness that disk storage of patient information immediately raises questions of data confidentiality. We will attempt to insure appropriate data protection once MYCIN is available in the clinical setting.

VII. FUTURE EXTENSIONS

In this section I summarize some current ideas for improvement of the consultation program described in this chapter. Each of the topics mentioned is the subject of current efforts by one or more of the researchers currently associated with the MYCIN project.

VII.1 Dynamic Ordering Of Rules

The order in which rules are invoked by the MONITOR is currently controlled solely by their order on the UPDATED-BY property of the clinical parameter being traced. (An exception to this point is the self-referencing rules - see Section III.4.1). The order of rules on the UPDATED-BY property is also arbitrary, tending to reflect nothing more than the order in which rules were acquired. Since FINDOUT sends all rules on such lists to the MONITOR, and since our certainty factor combining function is commutative (Section VI - Chapter 5), the order of rules is unimportant.

Some rules are much more useful than others in tracing the value of a clinical parameter. For example, a rule with a six-condition PREMISE that infers the value of a parameter with a low CF requires a great deal of work (as many as six calls to FINDOUT) with very little gain. On the other hand, a rule with a large CF and only one or two PREMISE conditions may easily provide strong evidence

regarding the value of the parameter in question. It may therefore be wise for FINDOUT to order the rules in the UPDATED-BY list on the basis of both information content (CF) and the work necessary to evaluate the PREMISE. Then if the first few rules are successfully executed by the MONITOR, the CF associated with one of the values of the clinical parameter may be so large that invocation of subsequent rules will require more computational effort than they are worth. If FINDOUT therefore ignores such rules (i.e., does not bother to pass them to the MONITOR), considerable time savings may result. Furthermore, entire reasoning chains will in some cases be avoided and the number of questions asked the user could accordingly be decreased.

VII.2 Dynamic Ordering Of Conditions Within Rules

The MONITOR diagram in Figure 4-7 reveals that conditions are evaluated strictly in the order that they occur within the PREMISE of the rule. In fact, I have stressed that the order of conditions is therefore important and that the most commonly referenced clinical parameters should be placed earliest in the PREMISE.

Suppose, however, that in a given consultation the clinical parameter referenced in the fourth condition of a rule has already been traced by FINDOUT because it was referenced in some other rule that the MONITOR has already evaluated. As currently designed, MYCIN checks the first three conditions first, even if the fourth condition is already known to be false. Since the first three conditions may well require calls to FINDOUT, the rule may generate unnecessary questions and expand useless reasoning chains.

The solution to this problem would be to redesign the MONITOR so that it reorders the PREMISE conditions, first evaluating those that reference clinical

parameters which have already been traced by FINDOUT. In this way a rule will not cause new questions nor additions to the reasoning network if any of its conditions are known to be false at the outset.

VII.3 Pre-screening Of Rules

An alternate approach to the problem described in the preceding section would be for FINDOUT to judge the implications of every parameter it traces. Once the value has been determined by the normal mechanism, FINDOUT could use the LOOKAHEAD list for the clinical parameter in order to identify all rules referencing the parameter in their PREMISE conditions. FINDOUT could then evaluate the relevant conditions and mark the rule as failing if the condition turns out to be false. Then, whenever the MONITOR begins to evaluate rules that are invoked by the normal recursive mechanism, it will check to see if the rule has previously been marked as false by FINDOUT. If so, the rule could be quickly ruled out without needing to consider the problem of re-ordering the PREMISE conditions.

At first glance, the dynamic re-ordering of PREMISE conditions appears to be a better solution than the one I have just described. The problem with rule pre-screening is that it requires consideration of all rules on the parameter's LOOKAHEAD list, some of which may never actually be invoked during the consultation. Thus the disadvantages are similar to those that can accompany the PLANNER antecedent theorems that were previously described (Section III.1).

VII.4 Placing All Knowledge In Rules

Although most of MYCIN's knowledge is placed in decision rules, I have pointed out several examples of knowledge that is not rule-based. The simple lists and knowledge tables of Section II.6 may perhaps be justified on the basis of efficiency arguments, especially since those knowledge structures may be directly accessed and utilized by rules.

However, the algorithmic mechanisms for therapy selection that were described in Section V are somewhat more bothersome. Although we have managed to put many drug-related decision criteria in the ORDERRULES, the mechanisms for creating the potential therapy lists and for choosing the apparent first choice drug are programmed explicitly in a series of relatively complex LISP functions. Since MYCIN's ability to explain itself is based upon rule-retrieval (Chapter 6), the system cannot give good descriptions of these drug selection procedures. It is therefore desirable to place more of the drug selection knowledge in rules.

Such efforts should provide a useful basis for evaluating the power of our rule-based formalism. If the goal-oriented control structure we have developed is truly general, one would hope that algorithmic approaches to the construction and ordering of lists could also be placed in decision rule format. We therefore intend to experiment with ways for incorporating the remainder of MYCIN's knowledge into decision rules that are invoked by the standard MONITOR/FINDOUT process.

VII.5 The Need For A Context Graph

The context tree used by MYCIN is the source of one of the system's primary problems in attempting to simulate the consultation process. As was

pointed out in Section II.2.1, every node in the context tree leads to the uppermost patient node by a single pathway. In reality, however, drugs, patients, organisms, and cultures are not interrelated in this highly structured fashion. For example, drugs are often given to cover for more than one organism. The context tree does not permit a single CURDRUG or PRIORDRUG to be associated with more than a single organism. What we need, therefore, is a network of contexts in the form of a graph rather than a pure tree. The current reasons why MYCIN needs a tree structured context network are explained in Section II.2. We have come to recognize that a context graph capability is an important extension of the current system, however, and this will be the subject of future design modifications. When implemented, for example, it will permit a physician to discuss a prior drug only once even though it may have been given to cover for several prior organisms.

VIII. ADVANTAGES OF THE MYCIN APPROACH

There are four principle advantages of the MYCIN approach that have contributed to the system's current level of success. Each of these distinguishes MYCIN from the medical decision making programs described in Chapter 2. They also reflect MYCIN's debt to previous work in the AI field.

VIII.1 Modularity Of Knowledge

As discussed in Chapter 3, one of the major design considerations during the development of MYCIN has been the isolation of pieces of knowledge as discrete facts. MYCIN's decision rules achieve this goal. Since each rule represents a discrete packet of knowledge, the integration of new information into the system is simplified. Furthermore, the rules can serve as the basis for MYCIN's explanation and question-answering capabilities (Chapter 6).

Modularity of knowledge is seldom found in diagnostic programs. Some statisticians would argue, in fact, that the interrelationships of observations are so complex that a formal Bayesian approach is the only reasonable way to guarantee good predictions. As I argue in Chapter 5, however, the statistician's stance is greatly weakened when the knowledge is primarily judgmental and it defies statistical formulation. By accepting the inexact nature of many medical decisions, and by acknowledging that the quantification scheme accompanying our

rules is only an approximation technique, we are left free to isolate our knowledge statements and to reap the associated benefits provided by that representation scheme. In fact, almost all of those capabilities which make MYCIN truly innovative may be directly attributed to the program's rule-based representation of knowledge.

VIII.2 Dynamic Reasoning Chain

It is reasonable to ask why MYCIN does not create an explicit decision tree from its rules, code them for maximal efficiency, and then rely upon conventional techniques for decision analysis based upon progression through a branching tree. It must be remembered, however, that the reasoning network for MYCIN is goal-oriented (Figure 4-9). Conventional decision trees start at the top node and follow a path through the tree based upon decisions reached at each subsequent node. When a terminal node in the tree is finally reached, that is the diagnosis. MYCIN's terminal nodes, on the other hand, correspond to starting points in the accumulation of data (i.e., ASK1 or ASK2 nodes - Figure 4-9). MYCIN's task is to determine which of these terminal nodes to use in an effort to reach the top of the tree. Thus the form of MYCIN's reasoning network is distinctive from a conventional decision tree in that the top node represents the goal for MYCIN rather than the starting point.

Although MYCIN's rules do not naturally form a conventional decision tree, it is possible that a researcher with experience constructing decision trees could, in time, convert MYCIN's knowledge base into a traditional tree-shaped format. This has not seemed to be a particularly natural approach, however. There are three principal factors that would complicate any such attempt:

(1) Although decision theory has provided mechanisms for incorporating probabilistic knowledge into decision trees, there is no obvious mechanism for combining MYCIN's certainty factors with a branching network;

(2) MYCIN's current control structure depends upon a dynamic set of contexts and the ability to use rules more than once; this suggests that a decision tree using MYCIN's knowledge would need to have mechanisms for reusing certain portions, perhaps by defining decision tree 'macros';

(3) MYCIN's reasoning network is actually not tree-shaped; this complexity was not shown in the sample network of Figure 4-9, but since MYCIN's rules often form reasoning loops (Section III.5) and since a single observation often affects several of the ascending branches in the network, a graph structure would actually provide a more accurate representation of MYCIN's reasoning network.

It has also been suggested that, even if we do not convert MYCIN's reasoning network to a conventional decision tree, we could at least explicitly 'compile' it. It should be noted, however, that since MYCIN works backwards from the goal-rule, there is no disadvantage to creating a dynamic reasoning chain as it proceeds. The total network that could be created from MYCIN's rules is so vast that it appears preferable simply to create the portion of the network that is appropriate for the patient under consideration. An explicit network would not avoid the need for MYCIN to work backwards from the topmost goal node. Furthermore, it would introduce the obvious disadvantage that newly acquired rules could not be automatically incorporated into MYCIN's reasoning as they are by the current dynamic control structure.

VIII.3 Domain-Independent Control Structure

Except for the functions described in Section V, most of MYCIN's functions are domain-independent. In particular, the entire MONITOR/FINDOUT mechanism contains no explicit knowledge of the problem domain for which it has been designed. It is therefore tempting to consider writing new rules for additional

medical (or non-medical) problem areas and to see whether the MYCIN formalism will allow valid consultations in those areas as well. Of course, new clinical parameters and their associated properties would also have to be created, but the resulting knowledge structures are designed to be capable of forming the basis both for consultation sessions using Subprogram 1 and for question-answering sessions using Subprogram 2 (Chapter 6).

Use of the MYCIN approach for another problem area has not yet been attempted, however, and it would therefore be premature to claim that MYCIN's approach can indeed be generalized for other domains. One reason that we have not attempted to apply the approach elsewhere is our recognition, based on experience to date, that the formulation of new decision rules is no straightforward matter, at least for medical applications. Physicians have not in general structured their own decision processes, and a clinical expert who consistently makes excellent recommendations may have great difficulty describing the steps in reasoning that he uses to make his decisions. Thus, although we are hopeful that the MYCIN formalism can be adapted to another problem area with minimal modification, such efforts would be distracting at a time when our principal concern is the expansion of MYCIN's clinical expertise regarding antimicrobial therapy.

VIII.4 Reasoning With Judgmental Knowledge

The primary advantage to the MYCIN approach, however, is its ability to model medical reasoning that is based upon neither diagnostic algorithms, physiological models, nor statistical analysis. In fact, MYCIN's principal contribution to the field of computer-based medical decision making may well be its reasoning model which uses the informal judgmental knowledge of experts.

Other programs have attempted to use 'estimates' provided by expert physicians <Leaper - 1972> but have been limited by efforts to couch these estimates in probabilistic terms. MYCIN not only provides an intuitively pleasing mechanism for recording (decision rules) and interpreting (certainty factors) these numbers, but it provides a flexible control structure and interactive capabilities which encourage the physician to accept the program as the useful and cooperative clinical tool that it is designed to be.

A Model Of Inexact Reasoning In Medicine (*)

Chapter 5

CONTENTS

[A condensation of this material will soon appear in Mathematical Biosciences <Shortliffe - 1974c>]

I. INTRODUCTION

Efforts to develop techniques for modeling clinical decision making have had a dual motivation. Not only has their potential clinical significance been apparent, but the design of such programs has required an analytical approach to medical reasoning which has in turn led to a distillation of decision criteria that in some cases had never been explicitly stated before. It is a fascinating and educational process for experts to reflect on the reasoning steps that they have always used when providing clinical consultations.

As discussed in Chapter 2, several programs have successfully modeled the diagnostic process <Gorry - 1968a,1973, Warner - 1964>. Each of these examples has relied upon statistical decision theory as reflected in the use of Bayes' Theorem for manipulation of conditional probabilities. Use of the theorem, however, requires either large amounts of valid background data or numerous approximations and assumptions. The success of Gorry and Barnett's early work <Gorry - 1968a>, and a similar study by Warner et. al. using the same data <Warner - 1964>, depended to a large extent upon the availability of good data regarding several individuals with congenital heart disease. Gorry et. al. <Gorry - 1973b> have had similar access to data relating the symptoms and signs of acute renal failure to the various potential etiologies.

Although conditional probability provides useful results in areas of medical decision making such as those I have mentioned, vast portions of medical experience suffer from so little data and so much imperfect knowledge that a

rigorous probabilistic analysis, the ideal standard by which to judge the rationality of a physician's decisions, is not possible. It is nevertheless instructive to examine models for the less formal aspects of decision making. Physicians seem to use an ill-defined mechanism for reaching decisions despite a lack of formal knowledge regarding the interrelationships of all the variables that they are considering. This mechanism is often adequate, in well-trained or experienced individuals, to lead to sound conclusions on the basis of a limited set of observations /FN1/.

FN1. Intuition may also lead to unsound conclusions, as noted by Schwartz et. al. <Schwartz - 1973>.

These intuitive and inexact aspects of medical reasoning are reflected in an argument expounded by Helmer and Rescher <Helmer - 1960>. They assert that the traditional concept of 'exact' versus 'inexact' science, with the social sciences accounting for the second class, has relied upon a false distinction usually reflecting the presence or absence of mathematical notation. They point out that only a small portion of natural science can be termed exact - areas such as pure mathematics and subfields of physics in which some of the exactness "has even been put to the ultimate test of formal axiomatization". In several areas of applied natural science, on the other hand, decisions, predictions, and explanations are only made after exact procedures are mingled with unformalized expertise. Society's general awareness regarding these observations is reflected in the common references to the 'artistic' components in the 'science of medicine'.

This chapter examines the nature of such nonprobabilistic and unformalized reasoning processes, considers their relationship to formal probability theory, and proposes a model whereby such incomplete 'artistic' knowledge might be quantified. We have developed this model of inexact reasoning in response to

MYCIN's needs; i.e., the goal has been to permit the opinion of experts to become more generally available to nonexperts. The model is, in effect, an approximation to conditional probability. Although conceived with MYCIN's problem area in mind, it is potentially applicable to any domain in which real world knowledge must be combined with expertise before an informed opinion can be obtained to explain observations or to suggest a course of action.

The presentation begins with a brief discussion of Bayes' Theorem as it has been utilized by other workers in this field. The theorem will serve as a focus for discussion of the clinical problems that we would like to solve by using computer models. The potential applicability of the proposed decision model is then introduced in light of MYCIN's rule-based design. Once the problem has been defined in this fashion, I shall discuss some of the philosophy of science literature that relates to the decision making problem under consideration. The criteria and numerical characteristics of our quantification scheme will then be proposed, and the chapter will conclude with a discussion of how the model is being used by MYCIN when it offers opinions to physicians regarding antimicrobial therapy selection.

II. FORMULATION OF THE PROBLEM

The medical diagnostic problem can be viewed as the assignment of probabilities to specific diagnoses after analyzing all relevant data. If the sum of the relevant data (or evidence) is represented by E, and Di is the ith diagnosis (or 'disease') under consideration, then P(Di/E) is the conditional probability that the patient has disease i in light of the evidence E. Diagnostic programs have traditionally sought to find a set of evidence that allows P(Di/E) to exceed some threshold, say .95, for one of the possible diagnoses. Under these circumstances the second ranked diagnosis is sufficiently less likely (<.05) that the user is content to accept disease i as the diagnosis requiring therapeutic attention /FN2/.

FN2. Several programs have also included utility considerations in their analyses. For example, an unlikely but lethal disease that responds well to treatment may merit therapeutic attention because P(Di/E) is non-zero (although very small).

Bayes' Theorem is useful in these applications because it allows P(Di/E) to be calculated from the component conditional probabilities:

$$P(Di/E) = \frac{P(Di)\ P(E/Di)}{\sum_{j=1}^{n} P(Dj)\ P(E/Dj)}$$

In this representation of the theorem, Di is one of n disjoint diagnoses. P(Di)

is simply the a priori probability that the patient has disease i before any evidence has been gathered. P(E/Di) is the probability that a patient will have the complex of symptoms and signs represented by E, given that he has disease Di.

I have so far ignored the complex problem of identifying the 'relevant' data that should be gathered in order to diagnose the patient's disease. Evidence is actually acquired piece-by-piece, the necessary additional data being identified on the basis of the likely diagnoses at any given time. Diagnostic programs that mimic the process of analyzing evidence incrementally often use a modified version of Bayes' Theorem that is appropriate for sequential diagnosis <Gorry - 1968a>:

> Let E1 be the set of all observations to date, and S1 be some new piece of data. Furthermore, let E be the new set of observations once S1 has been added to E1. Then:
>
> $$P(Di/E) = \frac{P(S1/Di\&E1)\ P(Di/E1)}{\sum_{j=1}^{n} P(S1/Dj\&E1)\ P(Dj/E1)}$$

The successful programs that use Bayes' Theorem in this form require huge amounts of statistical data, not merely P(Di/Sk) for each of the pieces of data, Sk, in E, but also the interrelationships of the Sk within each disease Dj /FN3/. The congenital heart disease programs <Gorry - 1968a, Warner - 1964> were able to acquire all the necessary conditional probabilities from a survey of several hundred patients with confirmed diagnoses and thus had non-judgmental data upon which to base their Bayesian analyses.

FN3. For example, although S1 and S3 are independent over all diseases, it may be true that S1 and S2 are closely linked for patients with disease Di. Thus relationships must be known within each Dj; overall relationships are not sufficient.

Edwards has summarized the kinds of problems that can arise when an

attempt is made to gather the kinds of data needed for rigorous analysis:

> ...My friends who are expert about medical records tell me that to attempt to dig out from even the most sophisticated hospital's records the frequency of association between any particular symptom and any particular diagnosis is next to impossible - and when I raise the question of complexes of symptoms, they stop speaking to me. For another thing, doctors keep telling me that diseases change, that this year's flu is different from last year's flu, so that symptom-disease records extending far back in time are of very limited usefulness. Moreover, the observation of symptoms is well-supplied with error, and the diagnosis of diseases is even more so; both kinds of errors will ordinarily be frozen permanently into symptom-disease statistics. Finally, even if diseases didn't change, doctors would. The usefulness of disease categories is so much a function of available treatments that these categories themselves change as treatments change - a fact hard to incorporate into symptom-disease statistics.
>
> All these arguments against symptom-disease statistics are perhaps somewhat overstated. Where such statistics can be obtained and believed, obviously they should be used. But I argue that usually they cannot be obtained, and even in those instances where they have been obtained, they may not deserve belief. <W. Edwards - 1972>

An alternative to exhaustive data collection is to use the knowledge that an expert has about the disease - partly based upon experience and partly on general principles - to reason about diagnoses. In the case of this judgmental knowledge acquired from experts, the conditional probabilities and their complex interrelationships cannot be acquired in an exhaustive manner. Opinions can be sought and attempts made to quantify them, but the extent to which the resulting numbers can be manipulated as probabilities is not clear. We shall explain this last point more fully as we proceed. First let us examine some of the reasons that it might be desirable to construct a model that allows us to avoid the inherent problems of explicitly relating the conditional probabilities to one another.

As was pointed out in Section II of Chapter 4, a conditional probability statement is, in effect, a statement of a decision criterion or rule. For example, the expression P(Di/Sk)=X can be read as a statement that there is a 100X% chance that a patient observed to have symptom Sk has disease Di. Stated in

rule form:

IF: THE PATIENT HAS SIGN OR SYMPTOM Sk
THEN: CONCLUDE THAT HE HAS DISEASE Di WITH PROBABILITY X

I shall often refer to statements of conditional probability as decision rules or decision criteria in the diagnostic context. The value of X for such rules may not be obvious (e.g., "y strongly suggests that z is true" is difficult to quantify), but an expert may be able to offer an estimate of this number based upon clinical experience and general knowledge, even when such numbers are not readily available otherwise.

A large set of such rules obtained from textbooks and experts would clearly contain a large amount of medical knowledge. It is conceivable that a computer program could be designed to consider all such general rules and to generate a final probability of each Di based upon data regarding a specific patient. Bayes' Theorem would only be appropriate for such a program, however, if values for P(S1/Di) and P(S1/Di&S2) could be obtained. As has been noted, these requirements become unworkable, even if the subjective probabilities of experts are used, in cases where a large number of diagnoses (hypotheses) must be considered. The first would require acquiring the inverse of every rule, and the second requires obtaining explicit statements regarding the interrelationships of all rules in the system.

In short, we would like to devise an approximate method that allows us to compute a value for P(Di/E) solely in terms of P(Di/Sk), where E is the composite of all the observed Sk (see Sections V and VI). Such a technique will not be exact, but since the conditional probabilities reflect judgmental (and thus highly subjective) knowledge, a rigorous application of Bayes' Theorem will not necessarily produce accurate cumulative probabilities either. Instead we look for ways to handle decision rules as discrete packets of knowledge and for a

quantification scheme that permits accumulation of evidence in a manner that adequately reflects the reasoning process of an expert using the same or similar rules.

III. MYCIN'S RULE-BASED APPROACH

As has been discussed, MYCIN's principle task is to determine the likely identity of pathogens in patients with infections and to assist in the selection of a therapeutic regimen appropriate for opposing the organisms under consideration. In Chapter 4 we explained how MYCIN models the consultation process, utilizing judgmental knowledge acquired from experts in conjunction with certain statistical data that are available from the clinical microbiology laboratory and from patient records. MYCIN's decision rules are similar in form to those just introduced in Section II.

It is useful to consider the advantages provided by a rule-based system for computer use of judgmental knowledge. It should be emphasized that we see these advantages as being sufficiently strong in certain environments that we have devised an alternative and approximate approach that parallels the results available from using Bayes' Theorem. I do not argue against the use of Bayes' theory in those medical environments in which sufficient data are available to permit adequate use of the theorem.

The advantages of rule-based systems for diagnostic consultations include:

1) the use of general knowledge (from textbooks or experts) for consideration of a specific patient; even well-indexed books may be difficult for a nonexpert to use when considering a patient whose problem is not quite the same as those of patients discussed in the text;

2) the use of judgmental knowledge for consideration of very small classes of patients with rare diseases about which good statistical data are not available;

3) ease of modification; since the rules are not explicitly related to one another and there need be no pre-structured decision tree for such a system, rule modifications and the addition of new rules need not require complex considerations regarding interactions with the remainder of the system's knowledge;

4) facilitated search for potential inconsistencies and contradictions in the knowledge base; criteria stored explicitly in packets such as rules can be searched and compared without major difficulty;

5) straightforward mechanisms for explaining decisions to a user by identifying and communicating the relevant rules;

6) an augmented instructional capability; a system user may be educated regarding system knowledge in a selective fashion, i.e., only those portions of the decision process that puzzle him need be examined.

One of MYCIN's rules, which I shall use for illustrative purposes throughout this chapter, is the following:

```
IF: 1) THE STAIN OF THE ORGANISM IS GRAM POSITIVE, AND
    2) THE MORPHOLOGY OF THE ORGANISM IS COCCUS, AND
    3) THE GROWTH CONFORMATION OF THE ORGANISM IS CHAINS
THEN: THERE IS SUGGESTIVE EVIDENCE (.7) THAT THE IDENTITY
    OF THE ORGANISM IS STREPTOCOCCUS
```

This rule was acquired from an expert in infectious disease therapy and reflects his belief that gram positive cocci growing in chains are apt to be streptococci. When asked to weight his belief in this conclusion /FN4/, he indicated a 70% belief that the conclusion was valid. Translating to the notation of conditional probability, this rule at first seems to say P(H1/S1&S2&S3)=.7 where H1 is the hypothesis that the organism is a streptococcus, S1 is the observation that the organism is gram positive, S2 that it is a coccus, and S3 that it grows in chains. Questioning of the expert gradually reveals, however, that despite the apparent similarity to a statement regarding a conditional probability, the number .7

differs significantly from a probability. The expert may well agree that P(H1/S1&S2&S3)=.7, but he becomes uneasy when he attempts to follow the logical conclusion that therefore P(not.H1/S1&S2&S3)=.3. The three observations are evidence (to degree .7) in favor of the conclusion that the organism is a streptococcus and should not be construed as evidence (to degree .3) against streptococcus. I shall refer to this problem as Paradox 1 and return to it later in the exposition after the interpretation of the .7 in the rule above has been introduced.

FN4. In the English language version of the rules, the program uses phrases such as 'suggestive evidence' as in the above example. However, the numbers following these terms, indicating degrees of certainty, are all that is used in the model. The English phrases are not given by the expert and then quantified; they are, in effect, 'canned-phrases' used only for translating rules into English representations. The prompt used for acquiring the certainty measure from the expert is: "On a scale of 1 to 10, how much certainty do you affix to this conclusion?".

It may at first seem tempting to conclude that the expert is irrational if he is unwilling to follow the implications of his probabilistic statements to their logical conclusions. Another interpretation, however, is that the numbers he has given should not be construed as probabilities at all, that they are judgmental measures that reflect a level of belief. The nature of such numbers, and the very existence of such concepts, have interested philosophers of science for the last half century. I shall therefore digress temporarily to examine some of these philosophical issues and to demonstrate that they provide insights which prove applicable to the analysis of the medical decision making problem under consideration. In the last section of this chapter I shall show how the model described here has been implemented for ongoing use by the MYCIN program.

IV. PHILOSOPHICAL BACKGROUND

The familiar P-function /FN5/ of traditional probability theory is a straightforward concept from elementary statistics. However, due to imperfect knowledge and the dependence of decisions upon individual judgments, the P-function no longer seems entirely appropriate for modeling some of the decision processes in medical diagnosis. This problem with the P-function has been well-recognized and has generated several philosophical treatises during the last thirty years. One difficulty with these analyses is that they are, in general, more theoretical than practical in orientation. They have characterized the problem well but have offered few quantitative or theoretical techniques that lend themselves to computer simulation of related reasoning processes. It is useful to examine these writings, however, in order to avoid recognized pitfalls.

FN5. The P-function may be defined in a variety of ways. Emanuel Parzen <Parzen - 1960> suggests a set-theoretical definition:

> Given a random situation, which is described by a sample description space S, probability is a function P[.] that to every event E assigns a non-negative real number, denoted by P[E] and called the probability of the event E. The probability function must satisfy three axioms:
>
> Axiom 1: $P[E] \geq 0$ for every event E
>
> Axiom 2: $P[S] = 1$ for the certain element S
>
> Axiom 3: $P[E \cup F] = P[E] + P[F]$ if $EF = \emptyset$ or, in words, the probability of the union of two mutually exclusive events is the sum of their probabilities.

This section therefore summarizes some of the theory that should be

considered when analyzing the decision problem that we have described. Section IV.1 discusses several interpretations of probability itself, the theory upon which Bayes' Theorem relies. The difficulties met when trying to use the P-function during the modeling of medical decision making are reiterated. Section IV.2 discusses the theory of confirmation, an approach to the interpretation of evidence. I shall point out that confirmation provides a natural environment in which to model certain aspects of medical reasoning. Section IV.3 then briefly summarizes some other approaches to the problem, each of which has arisen in response to the inadequacies of applied probability. Although each of these alternate approaches is potentially useful in the problem area that concerns us, we have chosen to develop a quantification scheme based upon the concept of confirmation.

IV.1 Probability

Swinburne provides a useful classification of the theories of probability proposed over the last two hundred years <Swinburne - 1973>. The first of these, the Classical Theory of probability, asserts that, if the probability of an event is said to be p, then "there are integers m and n such that p=m/n ... such that n exclusive and exhaustive alternatives must occur, m of which constitute the occurrence of S". This theory, like the second and third to be described, is called 'statistical probability' by Swinburne. These interpretations are typified by statements of the form "the probability of an A being a B is p".

The second probability theory cited by Swinburne, Propensity Theory, asserts that probability propositions "make claims about a propensity or 'would-be' or tendency in things. If an atom is said to have a probability of 0.9 of disintegrating within the next minute, a statement has been made about its

'propensity' to do so.

The Frequency Theory is based upon the familiar claim that propositions about probability are propositions about proportions or relative frequencies as observed in the past. This interpretation provides the basis for statistical data collection as used by most of the Bayesian diagnostic programs.

Harré observes that statistical probability seems to differ syntactically from the sense of probability used in inference problems such as medical diagnosis <Harré - 1970>. He points out that the traditional concept of probability refers to what is likely to turn out to be true (in the future) whereas the other variety of probability examines what has already turned out to be true but which cannot be determined directly. Although these two kinds of problems may be approached on the basis of identical observations, the occurrence or non-occurrence of future events is subject to the probabilistic analysis of statistics whereas the verification of a belief, hypothesis, or conjecture concerning a truth in the present requires a 'process' of analysis which is commonly referred to as 'confirmation'. This distinction on the basis of tense may seem somewhat artificial at first, but does serve a useful purpose as we attempt to develop a framework for analysis of the diagnosis problem.

Swinburne also discusses two more theories of probability, each of which bears more direct relation to the problem at hand. One is the Subjective Theory originally put forward by Ramsey <Ramsey - 1931> and developed in particular by Savage <Savage - 1954> and de Finetti <de Finetti - 1972>. In their view, statements of probability regarding an event are propositions regarding people's actual belief in the occurrence (present or future) of the event in question. Although this approach fails as an explanation of statistical probability (where beliefs that may be irrational have no bearing upon the calculated probability of, say, a 6 being rolled on the next toss of a die), it is alluring for our purposes because it attempts to recognize the dependence of decisions, in certain problem

areas, upon both the weight of evidence and its interpretation as based upon the expertise (beliefs) of the individual making the decision. In fact, de Finetti has stated part of our problem explicitly <de Finetti - 1972>:

> On many occasions decision-makers make use of expert opinion. Such opinions cannot possibly take the form of advice bearing directly on the decision; ... Occasionally, [the expert] is required to state a probability, but it is not easy to find a convenient form in which he can express it.

Furthermore, the goals of the subjective probabilists seem very similar to those which I have also delineated:

> We hold it to be chimerical for anyone to arrive at beliefs, opinions, or determinations without the intervention of his personal judgment. We strive to make such judgments as dispassionate, reflective, and wise as possible by a doctrine which shows where and how they intervene and lays bare possible inconsistencies among judgments.

One way to acquire the subjective probabilities of experts is suggested by Savage and described by a geological analyst as follows <Grayson - 1960>:

> The simplest [way] is to ask the geologist. ... The geologist looks at the evidence, thinks, and then gives a figure such as 1 in 5 or 50-50. Admittedly this is difficult. ... Thus, several ways have been proposed to help the geologist make his probability estimate explicit. ... The leading proponent of personal [i.e., subjective] probabilities, Savage, proposes what seems to be the most workable method. One can, namely, ask the person not how he feels but what he would do in such and such a situation. Accordingly, a geologist would be confronted with a choice-making situation.

There is one principal problem to be faced, however, in attempting to adopt the subjectivist model for our computer program, namely the subjectivists' criticism of those who avoid a Bayesian approach. Subjectivists assert that the conditional and initial probabilities needed for use of the theorem may simply be acquired by asking the opinion of an expert. We must reject this approach when the number of decision criteria becomes large, however, because it would require that experts be asked to quantify an unmanageably large number of

interrelationships /FN6/.

FN6. It would also complicate the addition of new decision criteria since they would no longer be modular and would thus require itemization of all possible interactions with pre-existing criteria.

A final point to be made regarding subjectivist theory is that the probabilities so obtained are meant to be utilized by the P-function of statistical probability so that inconsistencies among the judgments offered by the experts may be discovered. Despite apparently irrational beliefs that may be revealed in this way (where 'irrational' here means that the subjective probabilities are inconsistent with the axioms of the P-function), the expert opinions provide useful criteria which may lead to sound decisions if it is accepted that the numbers offered are not necessarily probabilities in the traditional sense of the word. It is our assertion that a new quantitative system should therefore be devised in order to utilize the experts' criteria effectively.

Let us return now to the fifth and final category in Swinburne's list of probability theories <Swinburne - 1973>. This is the Logical Theory which gained its classical exposition in J.M.Keynes' "A Treatise On Probability" <Keynes - 1921>. Since that time, its most notable proponent has been Rudolf Carnap. In the Logical Theory, probability is said to be a logical relation between statements of evidence and hypotheses. Carnap describes this and the frequency interpretation of probability as follows <Carnap - 1950>:

> (i) Probability(1) is the degree of confirmation of a hypothesis h with respect to an evidence statement e; e.g., an observational report. This is a logical semantical concept. A sentence about this concept is based, not on observation of facts, but on logical analysis. ...
>
> (ii) Probability(2) is the relative frequency (in the long run) of one property of events or things with respect to another. A sentence about this concept is factual, empirical.

In order to avoid confusion regarding which concept of probability is being discussed, the term 'probability' will hereafter be reserved for probability(2), i.e., the P-function of statistical probability. Probability(1), or epistemic probability (as Swinburne describes it <Swinburne - 1973>), will be called 'degree of confirmation' in keeping with Carnap's terminology.

IV.2 Confirmation

Carnap's interpretation of confirmation rests upon strict logical entailment. Several authors, however, have viewed the subject in a broader context such as our application requires. For example, just as the observation of a black raven would logically 'confirm' the hypothesis that "All ravens are black" (where 'confirm' here means 'lends credence to'), we also want the fact that an organism is gram positive to 'confirm' the hypothesis that it is a streptococcus, even though the conclusion is based upon world knowledge and not logical analysis.

Carnap makes a useful distinction among three forms of confirmation which we should consider when trying to characterize the needs of our decision model <Carnap - 1950>. He calls these classificatory, comparative, and quantitative uses of the concept of confirmation. These are easily understood by example:

a) classificatory: "the evidence e confirms the hypothesis h"

b) comparative: "e1 confirms h more strongly than e2 confirms h" or "e confirms h1 more strongly than e confirms h2"

c) quantitative: "e confirms h with strength x"

In the medical problem, our desire is to use a semi-quantitative approach in order to reach a comparative goal. Thus, although our individual decision criteria

might be quantitative (e.g., "Gram positive suggests streptococcus with strength 0.1"), the effort is merely aimed at singling out two or three identities of organisms that are approximately equally likely and which are 'comparatively' much more likely than any others. There is no need to quote a number that reflects the consulting expert's degree of certainty regarding his decisions.

When quantitative uses of confirmation are discussed, the degree of confirmation of hypothesis h on the basis of evidence e is written as C[h,e]. This form roughly parallels the familiar P-function notation for conditional probability, P(h/e). Carnap has addressed the question of whether it is reasonable to quantify degree of confirmation <Carnap - 1973>. He notes that, although the concept is familiar to us all, we attempt to use it for comparisons of relative likelihood rather than in a strict numerical sense. In this classic work on the subject, however, he suggested that we all know how to use confirmation as a quantitative concept in contexts such as "with predictions of results of games of chance [where] we can determine which numerical value [others] implicitly attribute to probability(1), even if they do not state it explicitly, by observing their reactions to betting proposals. The reason for our reliance on the opinions of experts is reflected in his observation that individuals with experience are inclined to offer theoretical arguments to defend their viewpoint regarding an hypothesis; "this shows that they regard probability(1) as an objective concept". However, he was willing to admit the subjective nature of such concepts some years later when, in discussing the nature of inductive reasoning, he wrote <Carnap - 1962>:

> I would think that inductive reasoning should lead, not to acceptance or rejection [of a proposition], but to the assignment of a number to the proposition, viz. its value (credibility value) ... This rational subjective probability ... is sufficient for determining first the rational subjective value of any act, and then a rational decision.

As mentioned above, quantifying confirmation and then manipulating the

numbers as though they were probabilities quickly leads to apparent inconsistencies or paradoxes. Carl Hempel presented an early analysis of confirmation <Hempel - 1965>, pointing out as we have that C[h,e] is a very different concept from P[h/e]. His famous Paradox of the Ravens was presented early in his discussion of the logic of confirmation. Let h1 be the statement that "All ravens are black" and h2 the statement that "All non-black things are non-ravens." Clearly h1 is logically equivalent to h2. If one were to draw an analogy with conditional probability, it might at first seem valid, therefore, to assert that C[h1,e]=C[h2,e] for all e. However, it appears counter-intuitive to state that the observation of a green vase supports h1 even though the observation does seem to support h2. C[h,e] is therefore different from P[h/e] for it seems somehow wrong that the observation of a vase could logically support an assertion about ravens. A re-examination of this paradox in light of our proposed quantification scheme is included as Appendix 1 (Section VIII.1).

Another characteristic of a quantitative approach to confirmation which distinguishes the concept from probability was well recognized by Carnap <Carnap - 1950> and discussed in Barker <Barker - 1957> and Harré <Harré - 1970>. They note that it is counter-intuitive to suggest that the confirmation of the negation of an hypothesis is equal to one minus the confirmation of the hypothesis, i.e., C[h,e] is not 1-C[not.h,e]. The streptococcal decision rule asserted that a gram positive coccus growing in chains is a streptococcus with a measure of support specified as 7 out of 10. This translates to C[h,e]=.7 where h is "The organism is a streptococcus" and e is the information that "The organism is a gram positive coccus growing in chains." As discussed above (Paradox 1 - Section III), an expert does not necessarily believe that C[not.h,e]=.3. The evidence is said to be supportive of the contention that the organism is a streptococcus and can therefore hardly also support the contention that the organism is not a streptococcus.

Since we believe that C[h,e] does not equal 1-C[not.h,e], we recognize that disconfirmation is in some sense separate from confirmation and must be dealt with separately. As Harré puts it <Harré - 1970>, "we need an independently introduced D-function, for disconfirmation, because, as we have already noticed, to confirm something to ever so slight a degree is not to disconfirm it at all, since the favourable evidence for some hypothesis gives no support whatever to the contrary supposition in many cases". Our decision model must therefore reflect this distinction between confirmation and disconfirmation (i.e., confirmatory and disconfirmatory evidence).

The logic of confirmation has several other curious properties that have puzzled philosophers of science. Wesley Salmon recently discussed many confirmation characteristics in a Scientific American article <Salmon - 1973>. His earlier analysis on the confirmation of scientific hypotheses <Salmon - 1966> led to the conclusion that the structure of such procedures is best expressed by Bayes' Theorem and a frequency interpretation of probability. Such an assertion is appealing because, as Salmon expresses the point, "it is through this interpretation, I believe that we can keep our natural sciences empirical and objective". However, our model is not offered as a solution to the theoretical issues with which Salmon is centrally concerned. We have had to abandon Bayes' Theorem and the P-function simply because there are large areas of expert knowledge and intuition which, although amenable in theory to the frequency analysis of statistical probability, defy rigorous analysis because of insufficient data, and, in a practical sense, because experts resist expressing their reasoning processes in coherent probabilistic terms.

IV.3 Alternate Approaches

There are additional approaches to this problem area that bear mentioning, even though they are peripheral to confirmation and probability as we have described them. One is the theory of 'Fuzzy Sets' first proposed by Zadeh <Zadeh - 1965> and further developed by Goguen <Goguen - 1968>. The theory attempts to analyze and explain an ancient paradox paraphrased by Goguen as follows:

> If you add one stone to a small heap, it remains small. A heap containing one stone is small. Therefore (by induction) every heap is small.

The term 'fuzzy set' refers to the analogy with set theory whereby, for example, the set of tall people contains all 7-foot individuals but may or may not contain a man who is 5 feet 10 inches tall. The 'tallness' of a man in that height range is subject to interpretation, i.e., the edge of the set is 'fuzzy'. Thus, membership in a set is not binary-valued ('true' or 'false') but is expressed along a continuum from 0 to 1 where 0 means "not in the set," 1 means "in the set", and 0.5 means "equally likely to be in or out of the set". These numbers hint of statistical probability in much the same way that degrees of confirmation do. However, like confirmation, the theory of fuzzy sets leads to results that defy numerical manipulation in accordance with the axioms of the P-function. Although an analogy between our diagnostic problem and fuzzy set theory can be made, the statement of diagnostic decision criteria in terms of set membership does not appear to be a natural concept for the experts who must formulate our rules. Furthermore, the quantification of Zadeh's 'linguistic variables', and the mechanisms for combining them, are as yet poorly defined. Fuzzy sets have therefore been mentioned here primarily as an example of another semi-statistical field in which classical probability theory fails.

There is also a large body of literature discussing the 'Theory of

Choice', an approach to decision making that has been reviewed by Luce and Suppes <Luce - 1965>. The theory deals with the way in which personal preferences and the possible outcomes of an action are considered by an individual who must select among several alternatives. Tversky describes an approach based upon 'elimination by aspects' <Tversky - 1972>, a method by which alternatives are ruled out on the basis of either their undesirable characteristics (aspects) or the desirable characteristics which they lack. The theory thus combines preference (utility) with a probabilistic approach. Shackle suggests a similar approach <Shackle - 1952,1955>, but utilizes different terminology and focuses on the field of economics. He describes 'expectation' as the act of "creating imaginary situations, of associating them with named future dates, and of assigning to each of the hypotheses thus formed a place on a scale measuring the degree of belief that a specified course of action on our own part will make this hypothesis come true" <Shackle - 1952>. Selections among alternatives are made not only on the basis of likely outcomes, but also on uncertainty regarding expected outcomes (hence his term the 'Logic of Surprise').

Note that the theory of choice differs significantly from confirmation theory in that the former considers selection among mutually exclusive actions on the basis of their potential (future) outcomes, and personal preferences regarding those outcomes, whereas confirmation considers selection among mutually exclusive hypotheses on the basis of evidence observed and interpreted in the present. Confirmation does not involve personal utilities, although, as I have noted, interpretation of evidence may differ widely on the basis of personal experience and knowledge. Thus I would argue that the theory of choice might be appropriately applied to the selection of therapy once a diagnosis is known, a problem area in which personal preferences regarding possible outcomes clearly play an important role, but that the formation of the diagnosis itself more closely parallels the kind of decision task that engendered the theory of

confirmation.

I return, then, to confirmation theory as the most useful way to think about the medical decision making problem that I have described. Swinburne suggests several criteria for choosing among the various confirmation theories that have been proposed <Swinburne - 1970>, but his reasons are based more upon theoretical considerations than the pragmatics of our real world application. I will therefore propose a technique which, although it closely draws upon the theory of confirmation that was described above, is based upon desiderata derived intuitively from the problem at hand and not from a formal list of acceptability criteria /FN7/.

FN7. Acceptability criteria are proposed by several authors such as Carnap <Carnap - 1950>, Swinburne <Swinburne - 1970>, Salmon <Salmon - 1966>, and Törnebohm <Törnebohm - 1966>. Although our model was not developed with any such list of criteria as guidance, we shall show in Sections V and VI that the technique we propose satisfies Tornebohm's criteria in light of the approximation mechanisms that were introduced for the combination of incrementally acquired evidence.

V. THE PROPOSED MODEL OF EVIDENTIAL STRENGTH

This section introduces our quantification scheme for modeling inexact medical reasoning. It begins by defining the notation that we use and by describing the terminology. A formal definition of the quantification function will then be presented. The remainder of the section discusses the characteristics of the defined functions. It closes with consideration of the model when it is compared to Törnebohm's criteria for acceptability of a quantification technique regarding evidential strength <Törnebohm - 1966>.

Although the proposed model has several similarities to a confirmation function such as those mentioned above, I shall introduce new terms for the measurement of evidential strength. This convention will allow me to clarify from the outset that we seek only to devise a system that captures enough of the flavor of confirmation theory that it can be used for accomplishing our computer-based task. We have chosen 'Belief' and 'Disbelief' as our units of measurement, but these terms should not be confused with their formalisms from epistemology. The need for two measures was introduced above in our discussion of a disconfirmation measure as an adjunct to a measure for degree of confirmation. The notation will be as follows:

a) MB[h,e]=X means "The measure of increased Belief in the hypothesis h, based on the evidence e, is X"

b) MD[h,e]=Y means "The measure of increased Disbelief in the hypothesis h, based on the evidence e, is Y"

The evidence e need not be an observed event, but may be a hypothesis (itself subject to confirmation). Thus I may write MB[h1,h2] to indicate the measure of increased Belief in the hypothesis h1 given that the hypothesis h2 is true. Similarly MD[h1,h2] is the measure of increased Disbelief in hypothesis h1 if hypothesis h2 is true.

To illustrate in the context of the sample rule from MYCIN, consider e = "The organism is a gram positive coccus growing in chains" and h = "The organism is a streptococcus". Then MB[h,e]=.7 according to the sample rule given us by the expert. The relationship of the number .7 to probability will be explained as I proceed. For now let me simply state that the number .7 reflects the extent to which the expert's Belief that h is true is increased by the knowledge that e is true. On the other hand, MD[h,e]=0 for this example, i.e., the expert has no reason to increase his Disbelief in h on the basis of e.

In accordance with subjective probability theory, it may be argued that the expert's personal probability P(h) reflects his belief in h at any given time. Thus 1-P(h) can be viewed as an estimate of the expert's Disbelief regarding the truth of h. If P(h/e) is greater than P(h), the observation of e increases the expert's Belief in h while decreasing his Disbelief regarding the truth of h. In fact, the proportionate decrease in Disbelief is given by the ratio:

$$\frac{P(h/e) - P(h)}{1 - P(h)}$$

This ratio is called the measure of increased Belief in h resulting from the observation of e, i.e., MB[h,e].

Suppose, on the other hand, that P(h/e) were less than P(h). Then the

observation of e would decrease the expert's Belief in h while increasing his Disbelief regarding the truth of h. The proportionate decrease in Belief is in this case given by the ratio:

$$\frac{P(h) - P(h/e)}{P(h)}$$

We call this ratio the measure of increased Disbelief in h resulting from the observation of e, i.e., MD[h,e] /FN8/.

FN8. Tornebohm suggests a similar measure of evidential strength <Tornebohm - 1966>, but uses C(H) instead of P(H), where C(H) is the amount of information contained in H.

To summarize these results in words, we consider the measure of increased Belief, MB[h,e], to be the proportionate decrease in Disbelief regarding the hypothesis h that results from the observation e. Similarly, the measure of increased Disbelief, MD[h,e], is the proportionate decrease in Belief regarding the hypothesis h that results from the observation e, where Belief is estimated by P(h) at any given time and Disbelief is estimated by 1-P(h). These definitions correspond closely to the intuitive concepts of confirmation and disconfirmation that we have discussed above. Note that since one piece of evidence cannot both favor and disfavor a single hypothesis, when MB[h,e]>0, MD[h,e]=0 and when MD[h,e]>0, MB[h,e]=0. Furthermore, when P(h/e)=P(h) the evidence is independent of the hypothesis (neither confirms nor disconfirms) and MB[h,e]=MD[h,e]=0.

The above definitions may now be specified formally in terms of conditional and <u>a priori</u> probabilities: /FN9/

$$MB[h,e] = \begin{cases} 1 & \text{if } P(h)=1 \\ \dfrac{\max[P(h/e),P(h)] - P(h)}{\max[1,0] - P(h)} & \text{otherwise} \end{cases}$$

$$MD[h,e] = \begin{cases} 1 & \text{if } P(h)=0 \\ \dfrac{\min[P(h/e),P(h)] - P(h)}{\min[1,0] - P(h)} & \text{otherwise} \end{cases}$$

FN9. P(h) is used to denote <u>a priori</u> probabilities. More correctly they might be written as P(h/0), i.e., the probability of h on no evidence.

Examination of these expressions will reveal that they are identical to the definitions introduced above. The formal definition is introduced, however, to demonstrate the symmetry between the two measures. In addition, we define a third measure, termed a certainty factor (CF) that combines the MB and MD in accordance with the following definition:

$$CF[h,e] = MB[h,e] - MD[h,e]$$

The certainty factor thus is an artifact for combining degrees of Belief and Disbelief into a single number. Such a number is needed in order to facilitate comparisons of the evidential strength of competing hypotheses. The use of this composite number will be described below in greater detail. The following observations help to clarify the characteristics of the three measures that I have defined (MB, MD, CF):

<u>Characteristics Of The Belief Measures</u>

A) Range of degrees:

a) $0 \leq MB[h,e] \leq 1$

b) $0 \leq MD[h,e] \leq 1$

c) $-1 \leq CF[h,e] \leq +1$

B) Evidential strength and mutually exclusive hypotheses:

If h is shown to be certain [P(h/e)=1]:

a) $MB[h,e] = \frac{1-P(h)}{1-P(h)} = 1$

b) $MD[h,e] = 0$

c) $CF[h,e] = 1$

If the negation of h is shown to be certain [P(not.h/e)=1]:

a) $MB[h,e] = 0$

b) $MD[h,e] = \frac{0-P(h)}{0-P(h)} = 1$

c) $CF[h,e] = -1$

Note that this gives MB[not.h,e]=1 if and only if MD[h,e]=1 in accordance with the definitions of MB and MD above. Furthermore, the number 1 represents absolute Belief(or Disbelief) for MB(or MD). Thus if MB[h1,e]=1 and h1 and h2 are mutually exclusive, MD[h2,e]=1 /FN10/.

FN10. There is a special case of Characteristic B that should be mentioned. This is the case of logical truth or falsity where P(h/e)=1 or P(h/e)=0, regardless of e. Popper has also suggested a quantification scheme for confirmation <Popper - 1959> in which he uses $-1 \leq C[h,e] \leq +1$, defining his limits as:

$$-1 = C[not.h,h] \leq C[h,e] \leq C[h,h] = +1$$

This proposal led one observer <Harré - 1970> to assert that Popper's numbering scheme "obliges one to identify the truth of a self-contradiction with the falsity of a disconfirmed general hypothesis and the truth of a tautology with the confirmation of a confirmed existential hypothesis, both of which are not only question begging but absurd". As I shall demonstrate in Section VI, we avoid Popper's problem by introducing mechanisms for approaching certainty asymptotically as items of confirmatory evidence are discovered.

C) Lack of evidence:

a) MB[h,e]=0 if h is not confirmed by e (i.e., e and h are independent or e disconfirms h)

b) MD[h,e]=0 if h is not disconfirmed by e (i.e., e and h are independent or e confirms h)

c) CF[h,e]=0 if e neither confirms nor disconfirms h (i.e., e and h are independent)

We are now in a position to examine Paradox 1 (Section III), the expert's concern that although evidence may support a hypothesis with degree X, it does not support the negation of the hypothesis with degree 1-X. In terms of our proposed model, this reduces to the assertion that, when e confirms h:

$$CF[h,e] + CF[not.h,e] = 1$$

This intuitive impression is verified by the following analysis:

$$CF[not.h,e] = MB[not.h,e] - MD[not.h,e]$$

$$= 0 - \frac{P(not.h/e) - P(not.h)}{-P(not.h)}$$

$$= \frac{[1-P(h/e)] - [1-P(h)]}{1 - P(h)} = \frac{P(h) - P(h/e)}{1 - P(h)}$$

$$CF[h,e] = MB[h,e] - MD[h,e]$$

$$= \frac{P(h/e) - P(h)}{1 - P(h)} - 0$$

Thus:

$$CF[h,e] + CF[not.h,e] = \frac{P(h/e) - P(h)}{1 - P(h)} + \frac{P(h) - P(h/e)}{1 - P(h)}$$

$$= 0$$

Clearly this result occurs because (for any h and any e) MB[h,e]=MD[not.h,e]. This conclusion is intuitively appealing since it states that evidence which supports a hypothesis disfavors the negation of the hypothesis to an equal extent.

We noted earlier that experts are often willing to state degrees of belief

in terms of conditional probabilities but they refuse to follow the assertions to their logical conclusions (e.g., Paradox 1 above). It is perhaps revealing to note, therefore, that when the a priori belief in a hypothesis is small (i.e., P(h) is close to zero), the CF of a hypothesis confirmed by evidence is approximately equal to its conditional probability on that evidence:

$$CF[h,e] = MB[h,e] - MD[h,e] = \frac{P(h/e) - P(h)}{1 - P(h)} - 0 \approx P(h/e)$$

whereas, as shown above, CF[not.h,e] $\approx$ -P(h/e) in this case. This observation suggests that confirmation, to the extent that it is adequately represented by CF's, is close to conditional probability (in certain cases) although it still defies analysis as a probability measure.

We believe, then, that the proposed model is a plausible representation of the numbers an expert gives when asked to quantify the strength of his judgmental rules. He gives a positive number (CF>0) if the hypothesis is confirmed by observed evidence, suggests a negative number (CF<0) if the evidence lends credence to the negation of the hypothesis, and says there is no evidence at all (CF=0) if the observation is independent of the hypothesis under consideration. The CF combines knowledge of both P(h) and P(h/e). Since the expert often has trouble stating P(h) and P(h/e) in quantitative terms, there is reason to believe that a CF that weights both the numbers into a single measure is actually a more natural intuitive concept (e.g., "I don't know what the probability is that all ravens are black, but I do know that every time you show me an additional black raven my belief is increased by X that all ravens are black.")

If we therefore accept CF's rather than probabilities from experts, it is natural to ask under what conditions the physician's behavior based upon CF's is irrational /FN11/. We know from probability theory, for example, that if there are n mutually exclusive hypotheses hi, at least one of which must be true, then

..P(hi/e)=1 for all e. In the case of certainty factors, we can also show that there are limits on the sums of CF's of mutually exclusive hypotheses. Judgmental rules acquired from experts must respect these limits or else the rules will reflect irrational quantitative assignments.

FN11. We assert that behavior is irrational if actions taken or decisions made contradict the result that would be obtained under a probabilistic analysis of the behavior.

Sums of CF's of mutually exclusive hypotheses have two limits - a lower limit for disconfirmed hypotheses and an upper limit for confirmed hypotheses. The lower limit is the obvious value that results because CF[h,e]≥-1 and because more than one hypothesis may have CF=-1. Note first that a single piece of evidence may absolutely disconfirm several of the competing hypotheses. For example, if there are n colors in the universe and Ci is the ith color, then ARCi may be used as an informal notation to denote the hypothesis that all ravens have color Ci. If we add the hypothesis ARC0 that some ravens have different colors from others, we know $\sum_{0}^{n} P[ARCi]=1$. Consider now the observation e that there is a raven of color Cn. This single observation allows us to conclude that CF[ARCi,e]=-1 for 1≤i≤n-1. Thus, since these n-1 hypotheses are absolutely disconfirmed by the observation e, $\sum_{1}^{n-1} CF[ARCi,e]=-(n-1)$. This analysis leads to the general statement that, if k mutually exclusive hypotheses hi are disconfirmed by an observation e:

$$\sum^{k} CF[hi,e] \geq -k \qquad \text{[for hi disconfirmed by e]}$$

In the colored raven example, the observation of a raven with color Cn still left two hypotheses in contention, namely ARCn and ARC0. What, then, is CF[ARCn,e], CF[ARC0,e], and the sum of CF[ARCn,e] and CF[ARC0,e]? The values of CF[ARCn,e] and CF[ARC0,e] are intimately related with the Paradox of the Ravens as discussed in Appendix 1. The limit on their sum, however, is important here as we attempt to characterize the rational use of CF's. In fact, it can be shown that,

if k mutually exclusive hypotheses hi are confirmed by an observation e, the sum of their CF's does not have an upper limit of k but rather:

$$\sum^{k} CF[hi,e] \leq 1 \qquad \text{[for hi confirmed by e]}$$

In fact, $\sum^{k} CF[hi,e]$ is <u>equal</u> to 1 if and only if k=1 <u>and</u> e implies h1 with certainty, but the sum can get arbitrarily close to 1 for small k and large n. The analyses that lead to these conclusions are included as Appendix 2 (Section VIII.2).

The last result allows us critically to analyze new decision rules given by experts. Suppose, for example, we are given the following rules: CF[h1,e]=.7 and CF[h2,e]=.4 where h1 is "The organism is a streptococcus", h2 is "The organism is a staphylococcus", and e is "The organism is a gram positive coccus growing in chains". Since h1 and h2 are mutually exclusive, the observation that $\sum_{i}^{2} CF[hi,e] > 1$ tells us that the suggested certainty factors are inappropriate. The expert must either adjust the weightings or we must normalize them so that their sum does not exceed 1. In other words, because behavior based on these rules would be irrational, we must change the rules.

In concluding this section, I shall briefly examine Törnebohm's criteria for acceptability of a theory of confirmation <Törnebohm - 1966>. He states that:

> It would be desirable to have a measure of evidential strength or degree of confirmation Dc satisfying the following conditions:
>
> Dc1. If E L-implies H, then Dc(H/E)=max.
> Dc2. If E L-implies not.h, the Dc(H/E)=min.
> Dc3. Dc(HE/E) = Dc(H/E)
> Dc4. If E and H are independent of each other, then Dc(H/E)=0.
>
> Unfortunately it does not seem possible to construct a reasonable measure satisfying all these conditions...

Note that CF[H,E] satisfies Dc1, Dc2, and Dc4 for max=1 and min=-1. However, it can be shown /FN12/ that CF[HE,E]=CF[H,E] if and only if P(E/H)=1. Thus, despite its intuitive appeal, the CF we have defined fails to satisfy all four

acceptability criteria suggested by Törnebohm. I shall point out later, however, that the conventions we have adopted for combining CF's allow us to satisfy Dc3.

FN12. I shall demonstrate the result for E confirming H. The proof for E disconfirming H is similar.

$$CF[HE,E] = MB[HE,E] - MD[HE,E]$$

$$= MB[HE,E] - 0$$

$$= \frac{P(HE/E) - P(HE)}{1 - P(HE)} = \frac{P(H/E) - P(HE)}{1 - P(HE)}$$

But: $$CF[H,E] = MB[H,E] - MD[H,E]$$

$$= MB[H,E] - 0$$

$$= \frac{P(H/E) - P(H)}{1 - P(H)}$$

Thus $CF[HE,E] = CF[H,E]$ if and only if:

$$P(H) = P(HE) = P(E/H)\ P(H)$$

i.e., $P(E/H) = 1$

VI. THE MODEL AS AN APPROXIMATION TECHNIQUE

Certainty factors provide a useful way to think about confirmation and the quantification of degrees of belief. However, I have not yet described how the CF model can be usefully applied to the medical diagnosis problem. The remainder of this chapter will explain conventions that we have introduced in order to utilize the certainty factor model. Our starting assumption is that the numbers given us by experts who are asked to quantify their degree of Belief in decision criteria are adequate representations of the numbers that would be calculated in accordance with the definitions of MB and MD if the requisite probabilities were known.

In Section II, when discussing Bayes' Theorem, I explained that I would like to devise a method that allows us to approximate the value for P(Di/E) solely from the P(Di/Sk), where Di is the ith possible diagnosis, Sk is the kth clinical observation, and E is the composite of all the observed Sk. I have explained why probabilities are inadequate representations of the decision rules with which we wish to deal. Thus our goal should be rephrased in terms of certainty factors as follows:

> Suppose that MB[Di,Sk] is known for each Sk, MD[Di,Sk] is known for each Sk, and E represents the conjunction of all the Sk. Then our goal is to calculate CF[Di,E] from the MB's and MD's known for the individual Sk's.

Suppose that E = S1&S2, and that E confirms Di. Then:

$$CF[Di,E] = MB[Di,E] - 0 = \frac{P(Di/E) - P(Di)}{1 - P(Di)}$$

$$= \frac{P(Di/S1\&S2) - P(Di)}{1 - P(Di)}$$

Clearly there is no exact representation of CF[Di,S1&S2] purely in terms of CF[Di,S1] and CF[Di,S2]. As was true for the discussion of Bayes' Theorem in Section II, the relationship of S1 to S2, within Di and all other diagnoses, needs to be known in order to calculate P(Di/S1&S2). Furthermore, the CF scheme adds one complexity not present with Bayes' Theorem because we are forced to keep MB's and MD's isolated from one another /FN13/. I shall therefore introduce an approximation technique for handling the net evidential strength of incrementally acquired observations. The combining convention must satisfy the following criteria (where E+ represents all confirming evidence acquired to date, and E- represents all disconfirming evidence acquired to date):

Defining Criteria

1) Limits:

a) MB[h,E+] increases towards 1 as confirming evidence is found, equalling 1 only if a piece of evidence logically implies h with absolute certainty

b) MD[h,E-] increases towards 1 as disconfirming evidence is found, equalling 1 only if a piece of evidence logically implies not.h with certainty

c) $CF[h,E-] \leq CF[h,E-\&E+] \leq CF[h,E+]$

These criteria reflect our desire to have the measure of Belief approach certainty asymptotically as partially confirming evidence is acquired, and to have the measure of Disbelief approach certainty asymptotically as

partially disconfirming evidence is acquired.

2) Absolute confirmation or disconfirmation:

a) If MB[h,E+]=1, then MD[h,E-]=0 regardless of the disconfirming evidence in E-; i.e., CF[h,E+]=1

b) If MD[h,E-]=1, then MB[h,E+]=0 regardless of the confirming evidence in E+; i.e., CF[h,E-]=-1

c) The case where MB[h,E+]=MD[h,E-]=1 is contradictory and hence the CF is undefined

3) Commutativity:

If S1&S2 indicates an ordered observation of evidence, first S1 and then S2:

a) MB[h,S1&S2] = MB[h,S2&S1]

b) MD[h,S1&S2] = MD[h,S2&S1]

c) CF[h,S1&S2] = CF[h,S2&S1]

The order in which pieces of evidence are discovered should not affect the level of Belief or Disbelief in a hypothesis. This criterion assures that the order of discovery will not matter.

4) Missing information:

If S? denotes a piece of potential evidence, the truth or falsity of which is unknown:

a) MB[h,S1&S?] = MB[h,S1]

b) MD[h,S1&S?] = MD[h,S1]

c) CF[h,S1&S?] = CF[h,S1]

The decision model should function by simply disregarding rules of the form CF[h,S2]=X if the truth or falsity of S2 cannot be determined.

FN13. Suppose S1 confirms Di (MB>0) but S2 disconfirms Di (MD>0). Then consider CF[Di,S1&S2]. In this case, CF[Di,S1&S2] must reflect both the disconfirming nature of S2 and the confirming nature of S1. Although these measures are reflected in the component CF's (it is intuitive in this case, for example, that CF[Di,S2] $\leq$ CF[Di,S1&S2] $\leq$ CF[Di,S1]), we shall demonstrate that it is important to handle component MB's and MD's separately in order to preserve commutativity

(see Item 3 of the Defining Criteria).

There are a number of observations to be made on the basis of these criteria. For example, Items 1 and 2 indicate that the MB of a hypothesis never decreases unless its MD goes to 1. Similarly the MD never decreases unless the MB goes to 1. In Section V, where it was always true that MB=0 or MD=0, it was always the case that either CF=MB-0 or CF=0-MD. As evidence is acquired sequentially, however, both the MB and MD may become non-zero. Thus CF=MB-MD is an important indicator of the net Belief in a hypothesis in light of current evidence. Furthermore, a certainty factor of zero may indicate either absence of both confirming and disconfirming evidence (as discussed in Section V), or the observation of pieces of evidence that are equally confirming and disconfirming. In effect CF[h,e]=0 is the "don't know more than I did before" value (i.e., equally confirmed and disconfirmed). Negative CF's indicate that there is more reason to disbelieve the hypothesis than to believe it. Positive CF's indicate that the hypothesis is more strongly confirmed than disconfirmed.

It is important also to note that, if E=E+&E-, then CF[h,E] represents the certainty factor for a complex new rule that could be given us by an expert. CF[h,E], however, would be a highly specific rule customized for the few patients satisfying all the conditions specified in E+ and E-. Since the expert gives us only the component rules, we seek to devise a mechanism whereby a calculated cumulative CF[h,E], based upon MB[h,E+] and MD[h,E-], gives a number close to the CF[h,E] that would be calculated if all the necessary conditional probabilities were known.

With these comments in mind, I therefore present the following four combining functions, the first of which satisfies the criteria that I have outlined. The other three functions are necessary conventions for implementation of the model.

Combining Functions

1) Incrementally acquired evidence /FN14/:

a) $$MB[h,S1\&S2] = \begin{cases} 0 & \text{if } MD[h,S1\&S2] = 1 \\ MB[h,S1] + MB[h,S2](1-MB[h,S1]) & \text{otherwise} \end{cases}$$

b) $$MD[h,S1\&S2] = \begin{cases} 0 & \text{if } MB[h,S1\&S2] = 1 \\ MD[h,S1] + MD[h,S2](1-MD[h,S1]) & \text{otherwise} \end{cases}$$

2) Conjunctions of hypotheses:

a) $MB[h1\&h2,E] = \min(MB[h1,E], MB[h2,E])$

b) $MD[h1\&h2,E] = \max(MD[h1,E], MD[h2,E])$

3) Disjunctions of hypotheses:

a) $MB[h1 \text{ or } h2,E] = \max(MB[h1,E], MB[h2,E])$

b) $MD[h1 \text{ or } h2,E] = \min(MD[h1,E], MD[h2,E])$

4) Strength of evidence:

If the truth or falsity of a piece of evidence S1 is not known with certainty, but a CF (based upon prior evidence E) is known reflecting the degree of Belief in S1, then if MB'[h,S1] and MD'[h,S1] are the degrees of Belief and Disbelief in h when S1 is known to be true with certainty (i.e., these are the decision rules acquired from the expert) then the actual degrees of Belief and Disbelief are given by:

a) $MB[h,S1] = MB'[h,S1] \cdot \max(0, CF[S1,E])$

b) $MD[h,S1] = MD'[h,S1] \cdot \max(0, CF[S1,E])$

This criterion relates to our statement early in Section V that evidence in favor of a hypothesis may itself be an hypothesis subject to confirmation. Suppose, for instance, you are in a darkened room when testing the generalization that all ravens are black. Then the observation of a raven that you think is black, but that may be navy blue or purple, is less strong evidence in favor of the hypothesis that all ravens are black than if the sampled raven were known with certainty to be black. Here the hypothesis being tested is "All ravens are black" and the evidence is itself an hypothesis, namely the uncertain observation

that "This raven is black".

FN14. It was pointed out to us by Professor E. Sondik (Stanford University) that the first of these functions is equivalent to:

$$MB[h,S2] = \frac{MB[h,S1\&S2] - MB[h,S1]}{1 - MB[h,S1]}$$

Thus this Combining Function parallels our original definition of an MB, but with MB's substituted for the probability measures that we lack. Note also that this formula bears the same relationship to our MB definition as the sequential diagnosis form of Bayes' Theorem does to the simple Bayes formula (Section II).

Function 1 simply states that, since an MB(or MD) represents a proportionate decrease in Disbelief(or Belief), the MB(or MD) of a newly acquired piece of evidence should be applied proportionately to the Disbelief(or Belief) still remaining. Function 2a indicates that the measure of Belief in the conjunction of two hypotheses is only as good as the Belief in the hypothesis that is believed less strongly, whereas Function 2b indicates that the measure of Disbelief in such a conjunction is as strong as the Disbelief in the most strongly disconfirmed. Function 3 yields complementary results for disjunctions of hypotheses. The corresponding CF's are merely calculated using the definition CF=MB-MD. The reader is left to satisfy himself that Function 1 satisfies the Defining Criteria /FN15/.

FN15. Note that MB[h,S?]=MD[h,S?]=0 when examining Criterion 4.

Functions 2 and 3 are needed in the use of Function 4. Consider, for example, a rule such as:

CF'[h,S1&S2&(S3 or S4)] = X /FN16/

FN16. For example:

IF: 1) THE STAIN OF THE ORGANISM IS GRAM NEGATIVE, AND
2) THE MORPHOLOGY OF THE ORGANISM IS ROD, AND
3) [A - THE AEROBICITY OF THE ORGANISM IS AEROBIC,
OR B - THE AEROBICITY OF THE ORGANISM IS UNKNOWN

THEN: THERE IS SUGGESTIVE EVIDENCE (.6) THAT THE CLASS OF THE ORGANISM IS ENTEROBACTERIACEAE

Then, by Function 4:

$$CF[h,S1\&S2\&(S3 \text{ or } S4)] = X \cdot \max(0, CF[S1\&S2\&(S3 \text{ or } S4),E])$$

$$= X \cdot \max(0, MB[S1\&S2\&(S3 \text{ or } S4),E] - MD[S1\&S2\&(S3 \text{ or } S4),E])$$

Thus we use Functions 2 and 3 to calculate:

$$MB[S1\&S2\&(S3 \text{ or } S4),E]$$

$$= \min(MB[S1,E], MB[S2,E], MB[S3 \text{ or } S4,E])$$

$$= \min(MB[S1,E], MB[S2,E], \max(MB[S3,E], MB[S4,E]))$$

$MD[S1\&S2\&(S3 \text{ or } S4),E]$ is calculated similarly.

It is also worth noting that Function 2 gives, for H confirmed by E:

$$CF[HE,E] = MB[HE,E] - MD[HE,E]$$

$$= \min(MB[H,E],MB[E,E]) - \max(MD[H,E],MD[E,E])$$

$$= \min(MB[H,E],1) - \max(MD[H,E],0)$$

$$= MB[H,E] - MD[H,E]$$

$$= CF[H,E]$$

Thus the use of an approximation via Function 2 allows us to satisfy Dc3 of Tornebohm's criteria (see end of Section V) and hence to satisfy all his requirements for a quantitative approach to confirmation.

An analysis of Function 1 in light of the probabilistic definitions of MB and MD does not prove to be particularly enlightening. The assumptions implicit in this function include more than an acceptance of the independence of S1 and S2. The function was conceived purely on intuitive grounds in that it satisfied the four Defining Criteria I have listed. However, some obvious problems are

present. For example, the function always causes the MB or MD to increase, regardless of the relationship between new and prior evidence. Yet Salmon has discussed an example from subparticle physics <Salmon - 1973> in which either of two observations taken alone confirm a given hypothesis, but their conjunction disproves the hypothesis absolutely! Our model assumes the absence of such aberrant situations in the field of application for which it is designed. The problem of formulating a more general quantitative system for measuring confirmation is well recognized and referred to by Harré (11): "The syntax of confirmation has nothing to do with the logic of probability in the numerical sense, and it seems very doubtful if any single, general notion of confirmation can be found which can be used in all or even most scientific contexts". Although we have suggested that perhaps there <u>is</u> a numerical relationship between confirmation and probability, we agree that the challenge for a confirmation quantification scheme is to demonstrate its usefulness within a given context, preferably without sacrificing human intuition regarding what the quantitative nature of confirmation should be.

Our challenge with Function 1, then, is to demonstrate that it is a close enough approximation for our purposes. We have attempted to do so in two ways. First we have implemented the function as part of the MYCIN System (Section VII) and have demonstrated that the technique models the conclusions of the expert from whom the rules were acquired. Second, we have written a program that allows us to compare CF's computed both from simulated real data and by using Function 1. Our notation for the following discussion will be as follows:

CF*[h,E] = the computed CF using the definition of CF from Section V (i.e. 'perfect knowledge' since P(h/E) and P(h) are known)

CF[h,E] = the computed CF using Function 1 and the known MB's and MD's for each Sk where E is the composite of the Sk's (i.e., P(h/E) not known but P(h/Sk) and P(h) known for calculation of MB[h,Sk] and MD[h,Sk])

The program was run on sample data simulating several hundred 'patients'. Clearly the question to be asked was whether CF[h,E] is a good approximation to CF*[h,E]. Figure 5-1 shows a graph summarizing our results. For the vast majority of cases, the approximation does not produce a CF[h,E] radically different from the true CF*[h,e]. In general, the discrepancy is greatest when Function 1 has been applied several times (i.e., several pieces of evidence have been combined /FN17/). The most aberrant points, however, are those that represent cases in which pieces of evidence were strongly interrelated for the hypothesis under consideration (termed 'conditional non-independence'). This result is expected because it reflects precisely the issue which makes it difficult to use Bayes' Theorem for our purposes.

FN17. This result is in keeping with Zadeh's observation from fuzzy logic that "the more steps there are in the proof, the fuzzier the result" <Zadeh - 1974>.

Thus I should make it clear that we have not avoided many of the problems inherent with the use of Bayes' Theorem in its exact form. We have introduced a new quantification scheme which, although it makes many assumptions similar to those made by subjective Bayesian analysis, permits us to utilize criteria as rules and to manipulate them to the advantages described in Section III. In particular, the quantification scheme also allows us to consider confirmation separately from probability and thus to overcome some of the inherent problems that accompany an attempt to put judgmental knowledge into a probabilistic format. Just as Bayesians who use their theory wisely must insist that events be chosen so that they are independent (unless the requisite conditional probabilities are

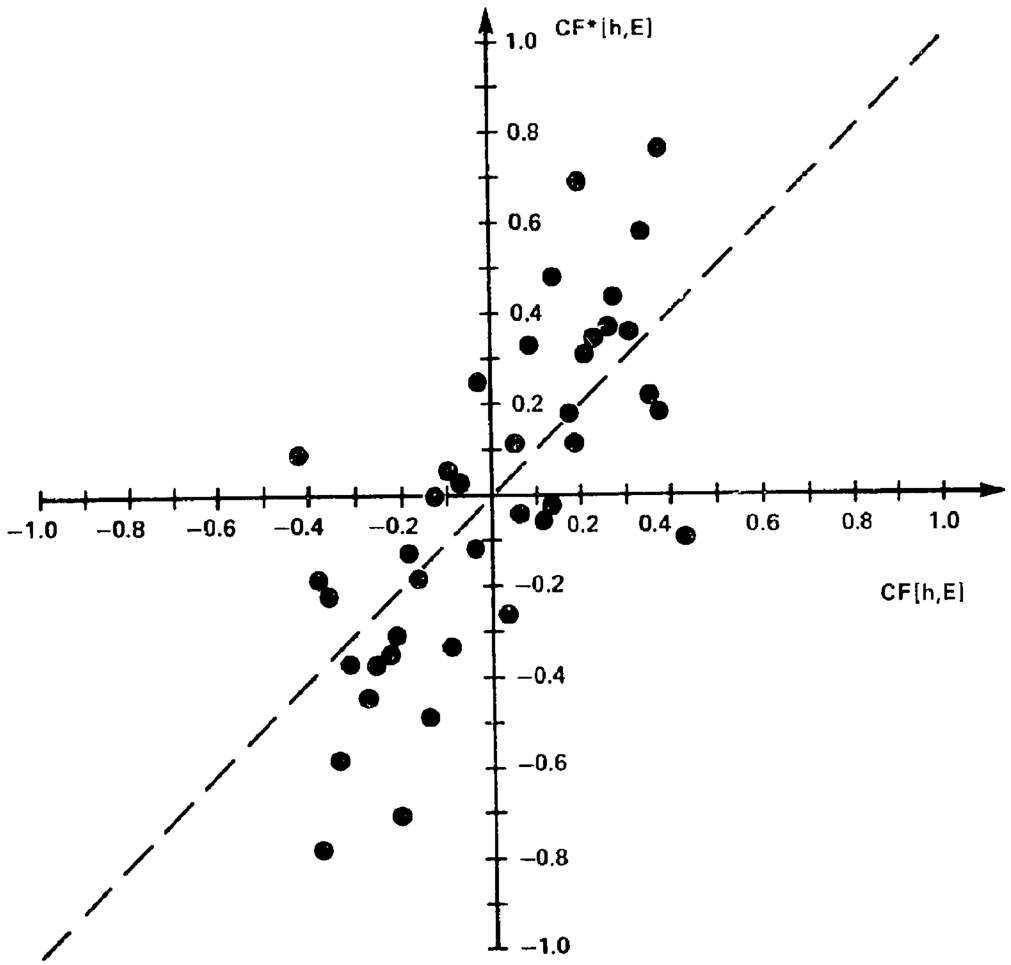

Figure 5-1

known), we must insist that dependent pieces of evidence be grouped into single rather than multiple rules. As Edwards has pointed out <W. Edwards - 1972>, a similar strategy must be used by Bayesians who are unable to acquire all the necessary data:

> [An approximation] technique is the one now most commonly used. It is simply to combine conditionally non-independent symptoms into one grand symptom, and obtain [quantitative] estimates for that larger more complex symptom.

The system therefore becomes unworkable for applications in which large numbers of observations must be grouped in the PREMISE of a single rule in order to insure independence of the decision criteria. In addition, we must recognize logical subsumption when examining or acquiring rules and thus avoid counting evidence more than once /FN18/. The justification for our approach therefore rests not with a claim of improving upon Bayes' Theorem but rather with the development of a mechanism whereby judgmental knowledge can be efficiently represented and utilized for the modeling of medical decision making, especially in contexts where (a) statistical data are lacking, (b) inverse probabilities are not known, and (c) conditional independence can be assumed in most cases.

FN18. For example, if S1 implies S2, then CF[h,S1&S2]=CF[h,S1] regardless of the value of CF[h,S2]. Function 1 does not 'know' this. Rules must therefore be acquired and utilized with care (see Section III - Chapter 8).

VII. MYCIN'S USE OF THE MODEL

Formal quantification of the probabilities associated with medical decision making can become so frustrating that some investigators have looked for ways to dispense with probabilistic information altogether <Ledley - 1973>. Diagnosis is not a deterministic process, however, and we believe that it should be possible to develop a quantification technique that approximates probability and Bayesian analysis and that is appropriate for use in those cases where formal analysis is difficult to achieve. The certainty factor model that we have introduced is such a scheme. It has been implemented as a central component of the MYCIN System. The program uses certainty factors to accumulate evidence and to decide upon likely identities for organisms causing disease in patients with bacterial infections. A therapeutic regimen is then determined - one that is appropriate to cover for the organisms requiring therapy.

All of the program's knowledge is stored in decision rules such as those described in Sections II and III. Each rule has an associated certainty factor that reflects the measure of increased Belief or Disbelief of the expert who suggested the rule. The capturing of such quantitative medical intuitions has been the subject of recent investigations by others <Card - 1970b> but, as we have noted, our approach has been simply to ask the expert to rate the strength of the inference on a scale from 1 to 10 (see FN4, Section III).

MYCIN remembers the alternate hypotheses that are confirmed or disconfirmed by the rules for inferring an organism's identity. With each

hypothesis is stored its MB and MD, both of which are initially zero. When an rule for inferring identity is found to be true for the patient under consideration, the ACTION portion of the rule allows either the MB or the MD of the relevant hypothesis to be updated using the first Combining Function (Section VI). When all applicable rules have been executed, the final CF may be calculated, for each hypothesis, using the definition CF=MB-MD. These alternate hypotheses may then be compared on the basis of their cumulative certainty factors. Hypotheses that are most highly confirmed thus become the basis of the program's therapeutic recommendation.

Suppose, for example, that the hypothesis H1 that the organism is a streptococcus has been confirmed by a single rule with a CF=.3. Then, if E represents all evidence to date, MB[H1,E]=.3 and MD[H1,E]=0. If a new rule is now encountered which has CF=.2 in support of H1, and if E is updated to include the evidence in the PREMISE of the rule, we now have MB[H1,E]=.44 and MD[H1,E]=0. Suppose a final rule is encountered for which CF=-.1. Then if E is once again updated to include all current evidence, we use Function 1 to obtain MB[H1,E]=.44 and MD[H1,E]=.1. If no further system knowledge allows conclusions to be made regarding the possibility that the organism is a streptococcus, we calculate a final result that CF[H1,E]=.44-.1=.34. This number becomes the basis for comparison between H1 and all the other possible hypotheses regarding the identity of the organism.

It should be emphasized that this same mechanism is used for evaluating <u>all</u> knowledge about the patient, not just the identity of pathogens. When the user answers a system-generated question, the associated certainty factor is assumed to be +1 unless he explicitly modifies his response with a CF (multiplied by ten) enclosed in parentheses. Thus, for example, the following interaction might occur (MYCIN's prompt is in lower-case letters):

```
14) Did the organism grow in clumps, chains, or pairs?
** CHAINS (6) PAIRS (3) CLUMPS (-8)
```

This capability allows the system automatically to incorporate the user's uncertainties into its decision processes. A rule that referenced the growth conformation of the organism would in this case find:

```
MB[chains,E] = .6        MD[chains,E] = 0
MB[pairs,E]  = .3        MD[pairs,E]  = 0
MB[clumps,E] = 0         MD[clumps,E] = .8
```

Consider, then, the sample rule we introduced in Section II:

$$CF[H1,S1\&S2\&S3] = .7$$

where H1 is the hypothesis that the organism is a streptococcus, S1 is the observation that the organism is gram positive, S2 that it is a coccus, and S3 that it grows in chains. Suppose gram stain and morphology were known to the user with certainty so that MYCIN has recorded:

$$CF[S1,E] = 1 \qquad CF[S2,E] = 1$$

In the case above, however, MYCIN would find that:

$$CF[S3,E] = .6 - 0 = .6$$

Thus it is no longer appropriate to use the rule in question with its full confirmatory strength of .7. That CF was assigned by the expert on the assumption that all three conditions in the PREMISE would be true with certainty. The modified CF is calculated using the fourth Combining Function (Section VI):

$$CF[H1,S1\&S2\&S3] = MB[H1,S1\&S2\&S3] - MD[H1,S1\&S2\&S3]$$
$$= .7 * \max(0, CF[S1\&S2\&S3,E]) - 0$$

Calculating CF[S1&S2&S3,E] using the second Combining Function, this gives:

$$CF[H1,S1\&S2\&S3] = .7 * .6 - 0$$
$$= .42 - 0$$

i.e., $MB[H1,S1\&S2\&S3] = .42$

and $MD[H1,S1\&S2\&S3] = 0$

Thus the strength of the rule is reduced to reflect the uncertainty regarding S3. Function 1 is now used to combine .42 (i.e., MB(H1,S1&S2&S3)) with the previous MB for the hypothesis that the organism is a streptococcus.

I have shown that the numbers thus calculated are approximations at best. Hence it does not seem justifiable simply to accept as correct the hypothesis with the highest CF after all relevant rules have been tried. Therapy is therefore chosen to cover for all identities of organisms that account for a sufficiently high proportion of the possible hypotheses on the basis of their CF's. This is accomplished by ordering them from highest to lowest and selecting all those on the list until the sum of their CF's exceeds z (where z is equal to .9 times the sum of the CF's for all confirmed hypotheses). This technique explains the comment in Section IV where (during the discussion of Carnap's comparison of quantitative, comparative, and classificatory uses of the concept of confirmation) I expressed our desire to use a semi-quantitative approach in order to attain a comparative goal.

Finally, it should be noted that our definition of CF's allows us to validate those of our rules for which frequency data become available. This will become increasingly important as the program becomes a working tool in the clinical setting where it can actually be used to gather the statistical data needed for its own validation. In the meantime, validation will necessarily involve the comments of recognized infectious disease experts who will be asked to evaluate the program's decisions and advice. Early experience with a limited set of rules has provided suggestive evidence that MYCIN will someday give advice similar to that suggested by infectious disease experts (see Chapter 7). We are therefore gaining confidence that the certainty factor approach will continue to prove itself as the number of decision rules increases and we acquire rules from additional infectious disease experts.

VIII. APPENDICES

VIII.1 Appendix 1 - The Paradox Of The Ravens

In order to examine the Paradox of the Ravens (Section IV.2), I introduce the following informal notation:

iRB represents the hypothesis that exactly i ravens are black

ARB represents the hypothesis that all ravens are black (i.e., yRB where y = the number of ravens)

iNBNR represents the hypothesis that exactly i non-black objects are non-ravens

ANBNR represents the hypothesis that all non-black objects are non-ravens (i.e., zNBNR where z = the number of non-black objects)

BR represents the observation of a raven that is found to be black

NBNR represents the observation of a non-black object that is found to be a non-raven

The Paradox, then, is based on the observation that it is counter-intuitive to assert that CF[ARB,NBNR]=CF[ANBNR,NBNR]. Yet our definition of a CF quickly leads to the conclusion that the equality does hold since ARB is logically equivalent to ANBNR and thus P(ARB/NBNR)=P(ANBNR/NBNR). It may therefore be tempting to assert that the certainty factor model of confirmation has failed to provide insight into the Paradox.

However, as Suppes has pointed out <Suppes - 1966a>, the reason the Paradox occurs is because we are convinced that "we are right in our intuitive

assumption that we should look at randomly selected ravens and not randomly selected non-black things in testing the generalization that all ravens are black". Expressed in terms of certainty factors, our intuition is that CF[ARB,BR] >> CF[ARB,NBNR] and, in fact, that CF[ARB,NBNR]=0. Thus we prefer to sample ravens rather than non-black objects in testing the hypothesis ARB, i.e., we feel that a black raven is significantly greater evidence in favor of the hypothesis than is a green vase.

Let us use our definition of CF, then, to calculate both CF[ARB,BR] and CF[ARB,NBNR]. We define:

y = the number of ravens in the universe

z = the number of non-black objects in the universe

We then make the following two assumptions:

(1) $z \geq y$

This assumption, although clearly true for the example at hand, may seem bothersome as a requirement for the analysis. However, it will be shown that, in fact, the Paradox is reversed for $z<y$. Consider, for example, a universe of 100 ravens and 5 non-black objects that may or may not be ravens. In this case observation of a green vase is clearly <u>better</u> evidence in favor of the hypothesis that all ravens (in this limited universe) are black than is the observation of a black raven.

Suppes uses another example to make this point <Suppes - 1966a>. Suppose we want to test the generalization that all voters in a specific district are literate. We can either sample voters and see whether they are literate or else sample illiterate individuals and check to be sure they are non-voters. The preferable strategy seems intuitively to depend upon whether there are more voters than illiterate individuals, i.e., upon the relationship between z and y from our example.

(2) We initially have no knowledge regarding either colors of ravens nor distributions of colors in the universe.

This assumption allows us to state that, before observing any ravens, we believe all the hypotheses iRB to be equally likely /FN19/. Thus:

$$P(iRB) = \frac{1}{y+1} = 1/(y+1) \quad \text{for } 0 \leq i \leq y$$

which leads to the conclusion that P(ARB)=P(yRB)=1/(y+1).

FN19. This amounts to the assumption of a uniform distribution of the P(iRB) before sampling begins. The analysis proceeds more easily with this assumption, but it should be clear that another prior distribution will not alter the qualitative nature of our final result.

Using assumptions (1) and (2) we can also show that:

$$P(i|NBNR) = \begin{cases} 0 & \text{for } 0 \leq i < z-y \\ 1/(y+1) & \text{for } z-y \leq i \leq z \end{cases}$$

The reader is left to satisfy himself that this statement is valid /FN20/. It leads to the conclusion that P(ANBNR)=P(zNBNR)=1/(y+1). This is an important result since ARB and ANBNR are logically equivalent and we therefore must require that P(ARB)=P(ANBNR).

FN20. Note that there can be no fewer than z-y non-ravens among the z non-black objects.

From our definitions of certainty factors, we now note that:

$$CF[ARB,BR] = MB[ARB,BR] - MD[ARB,BR]$$

$$= MB[ARB,BR] - 0$$

$$= \frac{P(ARB/BR) - P(ARB)}{1 - P(ARB)} = \frac{P(ARB/BR) - 1/(y+1)}{1 - 1/(y+1)}$$

and:

$$CF[ARB,\overline{NBNR}] = MB[ARB,\overline{NBNR}] - MD[ARB,\overline{NBNR}]$$

$$= MB[ARB,\overline{NBNR}] - 0$$

$$= \frac{P(ARB/\overline{NBNR}) - P(ARB)}{1 - P(ARB)}$$

$$= \frac{P(ANBNR/NBNR) - P(ANBNR)}{1 - P(ANBNR)}$$

$$= \frac{P(ANBNR/NBNR) - 1/(y+1)}{1 - 1/(y+1)}$$

Thus we can calculate CF[ARB,BR] if we can derive P(ARB/BR) and can calculate CF[ARB,NBNR] if we can derive P(ANBNR/NBNR). Both of the requisite conditional probabilities can be found using Bayes' Theorem:

$$P(ARB/BR) = \frac{P(BR/ARB)\ P(ARB)}{\sum^{y} P(BR/iRB)\ P(iRB)} = \frac{1 \quad 1/(y+1)}{\sum^{y} i/y \quad 1/(y+1)} = \frac{y}{\sum^{y} i}$$

$$= 2/(y+1) \quad \text{since } \sum^{y} i = y(y+1)/2$$

$$P(ANBNR/NBNR) = \frac{P(NBNR/ANBNR)\ P(ANBNR)}{\sum^{z} P(NBNR/iNBNR)\ P(iNBNR)}$$

$$= \frac{1 \quad 1/(y+1)}{\sum_{z-y}^{z} i/z \quad 1/(y+1)}$$

$$= \frac{z}{\sum_{1}^{z} i - \sum_{1}^{z-y-1} i} = \frac{2z}{z(z+1) - (z-y-1)(z-y)}$$

$$= \frac{2z}{2z + 2zy - y - y\uparrow 2} = \frac{2z}{(y+1)\ (2z-y)}$$

$$= \frac{2}{y+1} \cdot \frac{z}{2z-y} = (2z)/[(y+1)(2z-y)] \quad /FN21/$$

Thus: $$CF[ARB,BR] = \frac{2/(y+1) - 1/(y+1)}{1 - 1/(y+1)} = 1/y$$

and: $$CF[ARB,NBNR] = \frac{(2z)/[(y+1)(2z-y)] - 1/(y+1)}{1 - 1/(y+1)} = 1/(2z-y)$$

Note that $CF[ARB,BR] \geq CF[ARB,NBNR]$ and that the equality only holds when $z=y$. Thus if there are fewer ravens than non-black objects, observing a black raven confirms the hypothesis ARB more strongly than a green vase confirms that all ravens are black.

FN21. Note that P(ARB/BR) = P(ARB/NBNR) if z=y!

But we wished to show that our intuitions are correct in suggesting that CF[ARB,BR] >> CF[ARB,NBNR] and that CF[ARB,NBNR]=0. As mentioned in the discussion of assumption (1) above, our intuition is tainted by our knowledge of the real world. For instance, we may be willing to accept estimates of y and z such that y=10↑7 and z=10↑15 /FN22/. Then:

CF[ARB,BR] = 1/(10↑7) = .0000001

CF[ARB,NBNR] = 1/[(2)(10↑15)-(10↑7)] ≈ 1/[(2)(10↑15)]

≈ .0000000000000005

Clearly CF[ARB,NBNR] is essentially zero, and CF[ARB,BR] is significantly greater than CF[ARB,NBNR]. Note, however, that these results are obtained only because we are willing to accept the original estimates for x and y.

FN22. Actually z is undoubtedly larger, but these numbers will suffice for current purposes.

VIII.2 Appendix 2 - Proof Of The Upper Limit

I include here a proof of the assertion that the sum of the CF's of confirmed but mutually exclusive hypotheses cannot exceed 1. Since MD[h,e]=0 for a hypothesis that is confirmed by e, CF[h,e]=MB[h,e] when e confirms h. Suppose there are n mutually exclusive hypotheses hi confirmed by evidence e. Then we wish to identify the upper limit on $\sum^{n}$CF[hi,e], i.e., on $\sum^{n}$MB[hi,e]. To simplify the manipulation of symbols:

Let: $a_i = P(h_i/e)$ such that $\sum^{n} a_i \leq 1$

$b_i = P(h_i)$ such that $\sum^{n} b_i < 1$ and $0 < b_i < 1$ for all i

Then: $a_i > b_i$ for all i since the h_i are confirmed by e.

We wish to find the upper limit, if any, on:

$$\sum^{n} MB[h_i,e] = \sum^{n} \frac{a_i - b_i}{1 - b_i}$$

PROOF:

We first note that, for n=1:

$$\sum_{i}^{n} \frac{a_i - b_i}{1 - b_i} = \frac{a_i - b_i}{1 - b_i} \leq 1 \text{ since } a_i \leq 1$$

For n>1, however:

$$\sum_{i}^{n} \frac{a_i - b_i}{1 - b_i} < \sum^{n} \frac{a_i - b_i}{(1-b_i)\prod_{j\neq i}(1-b_j)} \quad \text{since } \prod_{j=1}^{n}(1-b_j) < 1$$

$$< \frac{\sum^{n}(a_i - b_i)}{\prod^{n}(1 - b_j)} = \frac{\sum^{n} a_i - \sum^{n} b_i}{\prod^{n}(1 - b_j)}$$

But: $$\pi(1 - b_j) = 1 - \sum_{i=1}^{n} b_i + \sum_{i=1}^{n}\sum_{j\neq i}^{n} b_i b_j - \sum_{i=1}^{n}\sum_{j\neq i}^{n}\sum_{k\neq j\neq i}^{n} b_i b_j b_k + \ldots.$$

$$= 1 - \sum_{i=1}^{n} b_i + \sum_{i=1}^{n}\sum_{j\neq i}^{n} b_i b_j \left(1 - \sum_{k\neq j\neq i}^{n} b_k\right) +$$

$$\sum_{i=1}^{n}\sum_{j\neq i}^{n}\sum_{k\neq j\neq i}^{n}\sum_{l\neq k\neq j\neq i}^{n} b_i b_j b_k b_l \left(1 - \sum_{m\neq l\neq k\neq j\neq i}^{n} b_m\right) + \ldots.$$

And since $\sum^{n} b_i < 1$, $1 - \sum^{n} b_i > 0$ in all terms above.

Thus: $\prod^{n}(1-b_j) > 1 - \sum^{n} b_i$

Therefore:

$$\sum^{n} \frac{a_i - b_i}{1 - b_i} < \frac{\sum^{n} a_i - \sum^{n} b_i}{\prod^{n}(1 - b_j)}$$

$$< \frac{\sum^{n} ai - \sum^{n} bi}{1 - \sum^{n} bi} < \frac{1 - \sum^{n} bi}{1 - \sum^{n} bi} \quad \text{since } \sum^{n} ai < 1$$

$$< 1$$

Thus we have demonstrated that 1 is the upper limit for the sum of the CF's of confirmed mutually exclusive hypotheses.

The rather weak inequality we have shown is better understood, however, if we examine a special case. Suppose there are m mutually exclusive hypotheses such that $\sum^{n} P(hi)=1$. We assume that each is initially equally likely, i.e., $P(hi)=1/m$. Suppose now that first n of the m hypotheses are confirmed by the evidence e. Then:

$$\sum^{n} CF[hi,e] = \sum^{n} MB[hi,e] - \sum^{n} MD[hi,e]$$

$$= \sum^{n} \frac{P(hi/e) - P(hi)}{1 - P(hi)} - 0 = \sum^{n} \frac{P(hi/e) - 1/m}{1 - 1/m}$$

$$= \sum^{n} \frac{m\,P(hi/e) - 1}{m - 1} = \frac{1}{m-1}\left[m \sum^{n} P(hi/e) - n\right]$$

$$= \frac{m \sum^{n} P(hi/e) - n}{m - 1} \leq 1$$

This interesting result shows that the sum is equal to 1 only if h1 is taken to be certain on the basis of e and when n=1. If only two hypotheses remain possible after e has been observed and all the others have been ruled out with certainty, $\sum^{n} P(hi/e)=1$ but $\sum^{n} CF[hi,e]=(m-2)/(m-1)$ and is therefore less than one.

The Explanation System

Chapter 6

CONTENTS

1. INTRODUCTION

As was emphasized in Chapter 3, one of the primary requirements for user acceptance of a consultation program is an ability to explain decisions. Rule-based knowledge has greatly simplified the implementation of such a capability in the MYCIN System. The portion of the system used for explanation is termed Subprogram 2 (Figure 1-1). It is automatically invoked at the end of each consultation session, and may also be accessed optionally during the consultation itself (see the QA option, Section III.2.2 - Chapter 4).

Since MYCIN explains decisions only in response to queries from the user, the Explanation System is also a question-answering (QA) system. Subprogram 2 is therefore often called the QA-module, a term that reflects MYCIN's debt to other AI programs for answering questions <Simmons - 1970, Fox - 1970>.

The ability to answer questions obviously requires that the queries be understood. Since we have been anxious to minimize special training needed for use of the MYCIN System, we have been eager to let the physician ask questions using simple English. As discussed in Section III.1.7 of Chapter 1, however, writing programs to understand natural language is complex because of the myriad ways that individuals may choose to express themselves. Although several powerful techniques have been developed <Winograd - 1972, Woods - 1970, Schank - 1972>, they all suffer from being either somewhat slow computationally or difficult to generalize in domains other than those for which they were designed. Since physicians will quickly reject a system that takes two or three minutes to

answer a question, we sought an approach that would emphasize speed of response rather than human-style discourse. Yet we did want to make the system powerful enough to answer most questions that a physician might want to ask. Since the goals of rapid response and powerful capabilities tend to work at cross purposes, we have been forced to try to strike a balance between the two. The approach described in this chapter is thus neither as fast as desirable (it requires 5-20 seconds to answer a question) nor as powerful (it has no sense of discourse, anaphora, or complex syntax). However, its performance is usually adequate, and an experienced user who becomes aware of its limitations is able to retrieve most of the information he desires. Furthermore, it should be emphasized that the consultation itself, which is afterall the primary focus of the MYCIN System, requires no natural language processing. Use of the QA module is optional, and a physician who is in a hurry therefore need not take the time to seek explanations if he is satisfied with the advice the program has given.

As demonstrated in the sample consultation at the end of Chapter 1, the Explanation System offers several options to the user:

QUESTION-ANSWERING (QA) OPTIONS

HELP	- PRINTS THIS LIST
EQ	- REQUESTS AN EXPLANATION OF THE SPECIFIED QUESTION(S) FROM THE CONSULTATION
IQ	- PREFIX TO A QUESTION WHICH ASKS ABOUT INFORMATION ACQUIRED BY THE PROGRAM DURING THE CONSULTATION
NO PREFIX	- THIS QUESTION QUERIES CONTENTS OF DECISION RULES IN THE SYSTEM
PR	- REQUESTS THAT SPECIFIED RULE BE PRINTED
STOP	- ESCAPE FROM EXPLANATION SYSTEM
RA	- ENTRY TO RULE-ACQUISITION MODULE FOR RECOGNIZED EXPERTS

In this chapter I describe each of these options, explaining both how they are

used and how they are implemented. Only the IQ and NO PREFIX options require natural language processing.

Section II describes how each option is used, giving examples of each. Those who are interested primarily in MYCIN's capabilities, rather than details of implementation, may wish to read only this section.

In Section III the system dictionary is described. The dictionary is one of MYCIN's static knowledge structures, which we first mentioned in Section II.6 of Chapter 4. Section IV explains how this dictionary serves as a mechanism for understanding simple English phrases.

Section V concentrates on MYCIN's technique for answering rule-retrieval questions (i.e., the NO PREFIX option in the list above). It begins with an overview of the problem and then presents a step-by-step description of the question-answering mechanism. The understanding process described in Section IV is, of course, integral to this rule-retrieval problem.

Section IV's understanding process is also used in answering 'IQ questions', i.e., questions preceded by the letters IQ (see Section II.2.1). These questions differ from those described in Section V because they require analysis of the dynamic data base rather than rule-retrieval (Figure 1-1). Section VI explains the mechanism for answering such questions.

The chapter concludes with a brief discussion, in Section VII, of the Explanation System's limitations and of how we intend to improve the program's capabilities in the future.

II. USING THE QUESTION-ANSWERING SYSTEM

Unlike the Consultation System (Subprogram 1) in which MYCIN takes the initiative, asking questions and waiting for the physician to respond, the Explanation System expects the user to guide the interaction. This approach allows the system to instruct the physician or explain its advice only with regard to specific topics that may be puzzling to the user. Thus MYCIN prints its prompt characters (the double asterisk - '**'), waits for a question, performs the requested procedure, redisplays the prompt characters, and then waits for the next user input. This process continues until the user enters the word STOP.

In this section I describe the capabilities of the Explanation System, i.e., the various QA-options listed in Section I. MYCIN checks every input sentence to see if it begins with one of the special prefixes (HELP, EQ, IQ, PR, STOP, or RA). If not, it assumes that the user has asked a rule-retrieval question. Examples of rule-retrieval questions are discussed in Section II.1. The EQ and IQ options are explained in Section II.2.

Option prefixes serve one of two purposes. Most allow MYCIN to perform certain repetitive tasks without invoking time-consuming natural language routines (e.g., HELP, EQ, PR, STOP, and RA). The IQ option, on the other hand, is required at present so that MYCIN can distinguish between the two principal kinds of questions that <u>do</u> involve English language understanding. Without the IQ prefix MYCIN would need to deduce the distinction on semantic or syntactic grounds, a complex problem that we have temporarily avoided by using the prefix

mechanism. The distinction between IQ and rule-retrieval questions will be clarified as we proceed.

III.1 Rule-Retrieval Questions

Since most of MYCIN's knowledge is contained in its corpus of 200 rules, many questions can be effectively answered by retrieving and displaying the relevant rule(s). Thus the challenge for MYCIN's QA routines is to 'understand' a question well enough to decide which rules should be retrieved.

II.1.1 General Questions

MYCIN can answer rule-retrieval questions that are either specific to a given consultation (Section II.1.2) or general in nature. General questions reference the corpus of rules without considering the status of the dynamic data base (Figure 1-1), i.e., they ask questions about MYCIN's knowledge rather than about how that knowledge has been applied to the patient under consideration. The following examples demonstrate how MYCIN uses both rule-retrieval and its LISP-to-English translation capability in order to answer general questions from the user:

```
** WHAT DO YOU PRESCRIBE FOR ACTINOMYCETES INFECTIONS?

        RULE002
        -------
            IF: THE IDENTITY OF THE ORGANISM IS ACTINOMYCETES
          THEN: I RECOMMEND THERAPY CHOSEN FROM AMONG THE FOLLOWING DRUGS:
                    1 - PENICILLIN              (.99)
                    2 - TETRACYCLINE            (.99)
                    3 - ERYTHROMYCIN            (.99)
```

```
** UNDER WHAT CONDITIONS IS AN ORGANISM APT TO BE A CONTAMINANT?

Relevant rules: Several rules including: RULE042 RULE106 RULE109 RULE123 RULE155
Which do you wish to see?
** 155
        RULE155
        -------
            IF: 1) THE SITE OF THE CULTURE IS ONE OF THOSE SITES THAT ARE
                   NORMALLY STERILE, AND
                2) THE STAIN OF THE ORGANISM IS GRAMNEG
          THEN: THERE IS STRONGLY SUGGESTIVE EVIDENCE (.8) THAT THE
                ORGANISM IS NOT A CONTAMINANT

** WHY DO YOU ASK THE AGE OF THE PATIENT?

Relevant rules: Several rules including RULE118 RULE135 RULE137 RULE138 RULE150
Which do you wish to see?
** 150
        RULE150
        -------
            IF: 1) THE THERAPY UNDER CONSIDERATION IS SULFISOXAZOLE, AND
                2) THE AGE (IN YEARS) OF THE PATIENT IS LESS THEN .58, AND
                3) THE PATIENT IS JAUNDICED
          THEN: IT IS DEFINITE (1) THAT SULFISOXAZOLE IS NOT A POTENTIAL
                THERAPY FOR USE AGAINST THE ORGANISM

** WHAT DOES IT MEAN IF PENICILLINASE IS ADDED TO THE CULTURE BOTTLE?

        RULE039
        -------
            IF: 1) THE SITE OF THE CULTURE IS BLOOD, AND
                2) THE STAIN OF THE ORGANISM IS GRAMPOS, AND
                3) PENICILLINASE WAS ADDED TO THE CULTURE
          THEN: THERE IS WEAKLY SUGGESTIVE EVIDENCE (.4) THAT THE
                ORGANISM IS A CONTAMINANT

** WHAT IS RULE030?

        RULE030
        -------
            IF: THE IDENTITY OF THE ORGANISM IS KNOWN WITH CERTAINTY
          THEN: IT IS DEFINITE (1) THAT THESE PROPERTIES - GRAM MORPH
                AIR - SHOULD BE TRANSFERRED FROM THE IDENTITY OF THE
                ORGANISM TO THIS ORGANISM

** IS THERE A RULE THAT DISCUSSES STREPTOCOCCAL MORPHOLOGY?

No.  I have no such rules at present.

** DO YOU EVER CONCLUDE THAT GRAM POSITIVE COCCI ARE CONTAMINANTS?

THE FOLLOWING RULE MAY BE RELEVANT:
        RULE039
        -------
                (see translation above)
```

II.1.2 Questions Regarding The Current Consultation

As discussed in Section III.3.3 of Chapter 4, MYCIN maintains a record of how it makes decisions during every consultation. This record is then used by the QA system in order to answer rule-retrieval questions that are specific to the current consultation. MYCIN answers these questions differently from the way it responds to general rule-retrieval questions. Instead of displaying all the relevant rules, the program mentions what rules were used, when they were invoked during the consultation (i.e., after which question number), and what certainty factor (CF) was associated with the specified conclusion. The following examples from the sample consultation in Chapter 1 demonstrate this capability:

```
** WHAT MADE YOU THINK ORGANISM-1 MIGHT BE A PROTEUS?

        I USED RULE163 TO CONCLUDE THAT THE IDENTITY OF ORGANISM-1
                IS PROTEUS.  THIS GAVE A CUMULATIVE C.F. OF .277.  THE
                LAST QUESTION ASKED BEFORE THE CONCLUSION WAS MADE WAS 26.
        I USED RULE084 TO CONCLUDE THAT THE IDENTITY OF ORGANISM-1
                IS PROTEUS.  THIS GAVE A CUMULATIVE C.F. OF .119.  THE
                LAST QUESTION ASKED BEFORE THE CONCLUSION WAS MADE WAS 24.

** HOW DID YOU DECIDE THAT ORGANISM-2 WAS THE SAME AS ORGANISM-1?

        I USED RULE005 TO CONCLUDE THAT THE PSEUDOMONAS (ORGANISM-2) IS A PRIOR
                ORGANISM WITH THE SAME IDENTITY AS ORGANISM-1.  THIS GAVE
                A CUMULATIVE C.F. OF .19.  THE LAST QUESTION ASKED BEFORE
                THE CONCLUSION WAS MADE WAS 21.
        I USED RULE004 TO CONCLUDE THAT THE PSEUDOMONAS (ORGANISM-2) IS A PRIOR
                ORGANISM WITH THE SAME IDENTITY AS ORGANISM-1.  THIS GAVE
                A CUMULATIVE C.F. OF .133.  THE LAST QUESTION ASKED BEFORE
                THE CONCLUSION WAS MADE WAS 18.
```

II.2 Questions Regarding The Dynamic Data Base

The questions described in Section II.1.2 involve both rule-retrieval and access to the consultation record which is part of the dynamic data base (Figure 1-1). There are two additional kinds of question, however, which reference dynamic data but do not access the program's knowledge base of rules. These are described in the following two subsections.

II.2.1 IQ Questions

IQ questions require natural language processing in much the same way that rule-retrieval questions do. The IQ prefix is simply a flag for MYCIN so that it knows that the following question does not require rule-retrieval. IQ stands for 'Informational Question', an attempt to help the user recognize when the prefix is necessary. The distinction unfortunately is often unclear to the novice user, so we are currently looking for ways to dispense with the need for the prefix (Section VII).

An IQ question merely requests the current value of some clinical parameter from the dynamic data base (see Section III.3 - Chapter 4). It does not ask how the value was acquired (i.e., whether supplied by the physician or inferred using rules). Thus "How did you decide ORGANISM-1 is a pseudomonas?" is a rule-retrieval question, but "Is ORGANISM-1 a pseudomonas?" requires the IQ prefix. The following examples from the sample consultation in Chapter 1 demonstrate the IQ capability:

```
** IQ WHAT IS THE FINAL DECISION REGARDING THE IDENTITY OF ORGANISM-1?
        THE IDENTITY OF ORGANISM-1 IS PSEUDOMONAS (.357) KLEBSIELLA (.177)
                ENTEROBACTER (.166) E.COLI (.137) PROTEUS (.118) SERRATIA (.042)
```

```
** IQ DID YOU DECIDE ORGANISM-2 WAS THE SAME AS ORGANISM-1?
        ORGANISM-4 (.19) ORGANISM-3 (.19) ORGANISM-2 (.19) IS A PRIOR ORGANISM
                WITH THE SAME IDENTITY AS ORGANISM-1
```

II.2.2 The EQ Command

During a consultation the user may request an explanation of any question that he is asked (see the RULE and WHY options, Section III.2.2 - Chapter 4). We also wanted to permit the physician to request such explanations after the consultation is complete. Therefore MYCIN maintains a record of every question asked. (This same record is used for changing the answers to questions, as described in Section VI.1 - Chapter 4). The EQ option allows the physician to ask MYCIN for explanations of consultation questions (EQ = Explain Question). MYCIN answers by specifying the clinical parameter and context that were being considered when the question was asked. It also gives the rule that caused the question to be generated. Thus:

```
** EQ 48
48      QUESTION 48 WAS ASKED IN ORDER TO FIND OUT THE PATIENT'S DEGREE
                OF SICKNESS (ON A SCALE OF 4) IN AN EFFORT TO EXECUTE RULE068.
```

The EQ command accepts a list of question numbers as arguments and explains each in the manner demonstrated. The user may then display any rules with which he is not familiar by using the PR command (Section II.3). Note that the EQ command requires no language processing. If anything following the command is not a legal question number, it is simply ignored.

II.3 Additional Options

In addition to the options already described, the user of the Explanation

System may give the HELP, STOP, RA, and PR commands. The first three take no arguments. HELP simply displays the list of user options and thus parallels the HELP command available during the consultation itself (Section III.2.2 - Chapter 4). STOP provides a mechanism for escaping from Subprogram 2 once the user is through asking questions. RA is available only to experts who are known to the system. It permits the user to enter the Rule-Acquisition System (Subprogram 3 - Figure 1-1) which is described in Chapter 8.

The PR command provides a quick way to ask the rule-retrieval question "What is RULE030?" (see Section II.1.1). It accepts one or more numbers as arguments and assumes that they correspond to the numbers of rules which the user wishes to see. Thus "PR 30" causes RULE030 to be printed. Several examples of the PR option are included in the sample consultation at the end of Chapter 1.

III. (*) THE SYSTEM DICTIONARY

Although MYCIN's dictionary is a central component of the program's ability to understand English questions, the 800-word lexicon is also used by the consultation program when the physician enters a synonym for an expected response (Section III.2.2 - Chapter 4). The dictionary is more than a table of synonyms, however. This section describes its format and explains MYCIN's automated mechanism for generating dictionary entries.

III.1 Format Of The Dictionary

Every word in MYCIN's dictionary is accompanied by a word pointer. If a word points at itself, it is called a 'terminal' word. Every word that is not a terminal word has a pointer to a word that is terminal. Thus all words in the dictionary are either terminal or are associated with a terminal word by means of a pointer.

Terminal words are the basic words used by MYCIN, e.g., names of clinical parameters or expected values of clinical parameters. Thus both SITE and BLOOD are terminal, as is PENICILLIN, STREPTOCOCCUS, BRAIN-ABSCESS, ALLERGY, etc. Words that are non-terminal are closely related to the terminal words to which they point. The most common type of association is between synonyms. For example, all brand name drugs point to their generic equivalents, ENTEROCOCCUS points to

STREPTOCOCCUS-GROUP-D, and PNEUMOCOCCUS points to DIPLOCOCCUS-PNEUMONIAE. When two or more words are so closely related that MYCIN does not currently need to distinguish among them, one is usually terminal and the others point to it. For example, MOUTH and PHARYNX both point to the terminal word THROAT even though the three words are not strictly synonymous.

In addition to their pointers, all terminal words are characterized by one or more of the following properties:

EXPECTED - this is a list of all clinical parameters, if any, for which the terminal word is an expected value (see EXPECT, Section II.3.2 - Chapter 4).

INPROPS - this is a list of all the clinical parameters, if any, for which the terminal word is used in the PROMPT, PROMPT1, or TRANS (see the explanation of these properties of clinical parameters in Section II.3.2 - Chapter 4).

INFUNCS - this is a list of all the functions which are used in rules and for which the terminal word is used in their TRANS property (see Section II.7 - Chapter 4).

Only terminal words may be characterized by these three properties. If a non-terminal word is used in the PROMPT or TRANS of a parameter, the parameter is added to the INPROPS list of the associated terminal word.

To summarize, MYCIN's dictionary is composed of approximately 800 words, each of which points to a dictionary word. If a word points to itself it is known as a terminal word. Non-terminal words all point to terminal words. Every terminal word is characterized by one or more of the properties EXPECTED, INPROPS, INFUNCS. As discussed in Chapter 8, the INFUNCS property is used for acquisition of new rules, whereas INPROPS and EXPECTED provide the basis for dictionary-based understanding of phrases (see Section IV). A sample portion of the dictionary is shown below. Non-terminal words are marked by enclosing their associated terminal words in angle brackets ('<>'). Thus, in the sample below, CHLORAMPHENICOL is the terminal word associated with CHLOROMYCETIN. Note, also, that the terminal word

CHAINS has both an INPROPS property and an EXPECTED property.

```
        .
        .
CEPHALOTHIN
        EXPECTED: (DNAME SENSITIVS THERAPY ALLERGY PNAME TNAME)
CERTAINTY
        INFUNCS: (DEFINITE NOTDEFINITE NOTDEFNOT)
CERVIX
        EXPECTED: (SITE PORTAL)
CHAINS
        INPROPS: (CONFORM)
        EXPECTED: (CONFORM)
CHARACTERISTICS
        INPROPS: (GRAM)
CHEMOTHERAPY
        INPROPS: (CURDRUGS PRIORDRUGS)
CHLORAMPHENICOL
        EXPECTED: (DNAME SENSITIVS THERAPY ALLERGY PNAME TNAME)
CHLOROMYCETIN           <CHLORAMPHENICOL>
CHLORTETRACYCLINE
        EXPECTED: (DNAME SENSITIVS)
        .
        .
```

III.2 Automated Generation Of The Dictionary

Prior to the development of the Explanation System, MYCIN's dictionary simply contained the forty or fifty words that were adequate for handling synonyms and spelling correction during analysis of responses in the Consultation System (Section III.2.2 - Chapter 4). This portion of the dictionary was created by hand because there is no simple way to deduce synonyms. Most of the remainder of the dictionary has been generated automatically by a procedure described below. This technique saved us a laborious job and yet provided a vocabulary which in most cases serves us admirably. The spelling correction program provided by INTERLISP <Teitelman - 1974> has also greatly simplified the task.

The properties which characterize each clinical parameter (Section II.3 -

Chapter 4) serve as the basis for generation of dictionary entries. Our approach has been to identify those words in the prompt or translation of a parameter which have high semantic content. These words are then added to the dictionary, and are marked with their associated parameter using the INPROPS list. When they later appear in a question from a user, MYCIN can use the INPROPS list to infer what clinical parameter is being discussed (see Section IV).

Generating dictionary entries requires a mechanism for finding the 'core word' associated with each new word that MYCIN is considering adding to its vocabulary. The core word, which will be symbolized by the letter C, is a terminal word that may already be in the dictionary. If no current dictionary word is the appropriate core word, the new word is added to the dictionary as a terminal word. If X is a word being considered for addition to MYCIN's dictionary, the core word C is found in accordance with the following procedure:

Technique For Identifying Core Words

[1] - if X is a pronoun, article, preposition, simple verb, or other word known to have minimal semantic content, C is undefined; this requires that MYCIN know many of these common word types.

[2] - if X is in the dictionary, C is the terminal word associated with X (or is X if X is terminal).

[3] - if spelling correction succeeds when X is compared to the dictionary, C is set to the terminal word associated with the dictionary word matched by X; this mechanism generally allows us to ignore problems of misspelling, typographical errors, verb tense, or singular vs. plural nouns.

[4] - if spelling correction fails, Winograd's algorithm for recognizing word roots <Winograd - 1972> is used in an attempt to find a dictionary word that is a root of X; if the root search succeeds, C is the terminal word associated with the dictionary word matched by X.

[5] - if none of the above mechanisms is successful, C is merely X itself.

If the core word C is defined in Step [5], C is added to the dictionary as a new terminal word. Clearly Steps [1] through [4] are screening procedures which

attempt to prevent new entries to the dictionary if a word that is closely related semantically is already in the system's vocabulary.

The word X, which is considered for addition to the system dictionary in accordance with the above procedure, is associated with the clinical parameters and functions used in MYCIN's rules. Whenever a new clinical parameter or function is created, a special utility program is called to generate new dictionary entries in accordance with the following procedure:

Procedure For Creating Dictionary EntriesUQST.

For a clinical parameter P:

(i) Look at the PROMPT (or PROMPT1) word-by-word. For each word X:
  (a) find the core word C; if C is undefined, quit;
  (b) if C is defined, add C to the dictionary if it is not already there; if P is not a member of the INPROPS list for C, add P to INPROPS;

(ii) Look at the TRANS of P word-by-word and repeat as in (i);

(iii) Look at the EXPECT list of P word-by-word and repeat as in (i) except use the property EXPECTED instead of INPROPS;

Similarly, for a function F that is used in rules:

(i) Look at the TRANS of F word-by-word. For each word X:
  (a) find the core word C; if C is NIL, quit;
  (b) if C is defined, add C to the dictionary if it is not already there; if F is not a member of the INFUNCS list for C, add F to INFUNCS.

The sample portion of the dictionary included at the end of Section III.1 demonstrates the results of the procedure above. Note, for example, that the terminal word CHAINS has the clinical parameter CONFORM on both its INPROPS and EXPECTED list. That is because CHAINS is an expected value of the parameter and because the word is also used in the prompt for CONFORM: "Did * grow in clumps, chains, or pairs?". Similarly, three functions are on the INFUNCS list for the terminal word CERTAINTY because all three functions use the word when rules containing them are translated into English (Section II.7 - Chapter 4).

The INPROPS and EXPECTED properties for terminal words in the dictionary are the basis of MYCIN's natural language capabilities. The INFUNCS property, on the other hand, is used by the Rule-Acquisition System (Subprogram 3 - Figure 1-1) as described in Section III of Chapter 8.

IV. (*) USE OF THE DICTIONARY TO UNDERSTAND PHRASES

The key to MYCIN's natural language capabilities is its mechanism for 'understanding' what clinical parameters the user is discussing. This section describes how a phrase may suggest the various clinical parameters known to the system and how, in turn, MYCIN selects those which appear to be most strongly suggested.

IV.1 Finding Vocabulary Clues

The reader will recall that there are three ways in which a word may reference a clinical parameter:

(1) the word may be terminal and have one or more clinical parameters on its INPROPS list;

(2) the word may itself be the name of a clinical parameter;

(3) the word may be terminal and have one or more clinical parameters on its EXPECTED list.

These three possible features associated with each word are listed here in increasing order of significance; i.e., we have found that parameters on the EXPECTED list of a word are more apt to be intended by the user than those on the INPROPS list. Thus for INPROPS parameters to be accepted as part of the user's intention, supportive evidence is required from neighboring words in the phrase

being analyzed. These weighting distinctions will be further described in the next section.

An example may help clarify this discussion. Consider the phrase "gram positive cocci". The first step in understanding this kind of sentence fragment is to replace each word by its core word (Section III.2). For the above example, this gives the expression (GRAM GRAMPOS COCCUS). Looking up each of these terminal words in the dictionary, MYCIN finds:

GRAM	a - the name of a clinical parameter b - INPROPS: GRAM
GRAMPOS	a - INPROPS: NUMPOS b - EXPECTED: GRAM
COCCUS:	a - INPROPS: MORPH b - EXPECTED: MORPH

These observations provide so-called 'vocabulary clues' regarding the meaning of the phrase "gram positive cocci": the core word GRAM implicates the clinical parameter GRAM, the core word GRAMPOS implicates both NUMPOS and GRAM, and the core word COCCUS implicates the parameter MORPH. MYCIN transfers the English phrase into an internal representation which is a list with elements of the form (<parameter>(<value>)). For the example under consideration this gives:

((GRAM (GRAMPOS)) (MORPH (COCCUS)) (NUMPOS (ANY)))

which, roughly translated, means:

> The phrase appears to be discussing one or more of the following:
>
> 1) GRAM, Value GRAMPOS: i.e., the clinical parameter 'gramstain' and its value 'gram positive';
>
> 2) MORPH, Value COCCUS: i.e., the clinical parameter 'morphology' and its value 'coccus';
>
> 3) NUMPOS, Value ANY: i.e., the clinical parameter regarding the number of positive cultures drawn on a given day, without reference to any particular value.

Clearly the first two of these suppositions are correct and the third is not, although confusion due to the presence of the word 'positive' in the translations of both GRAMPOS and NUMPOS is not surprising. The next section explains how MYCIN attempts to choose from among these possible meanings.

IV.2 Selecting The Most Likely Meaning

As mentioned in the previous section, we have found that EXPECTED clues and parameter name clues tend to be more significant than the INPROPS references to clinical parameters. Clues derived from parameter names and EXPECTED values are therefore assigned a strength of 2, while INPROPS vocabulary clues are only given a strength of 1. A second convention requires that a word which is a parameter name may not also receive support for that parameter from its own INPROPS list. These conventions have been derived on purely empirical grounds; i.e., it appears that they serve to optimize system performance.

Let us describe how these conventions are applied in the context of the example from the previous section. The reader will recall that the internal representation of "gram positive cocci" was ((GRAM (GRAMPOS)) (MORPH (COCCUS)) (NUMPOS (ANY))). Actually, each of the items in this list is also assigned an associated weighting factor which reflects the strength of the relevant vocabulary clues. Recall that "gram positive cocci" has (GRAM GRAMPOS COCCUS) as its core word equivalent. Thus the weighting factor for (GRAM (GRAMPOS)) is 4 because (a) the core word GRAM is a parameter name [strength=2], and (b) the core word GRAMPOS has the parameter GRAM on its EXPECTED list [strength=2]. Similarly, the weighting factor for (MORPH (COCCUS)) is 3 because the core word COCCUS has MORPH on both its INPROPS list [strength=1] and its EXPECTED list [strength=2]. The weighting factor for (NUMPOS (ANY)), on the other

hand, is only 1 because NUMPOS is implicated solely by its presence on the INPROPS list of GRAMPOS. The actual internal representation of "gram positive cocci" after the 'understanding' process has occurred is therefore:

((GRAM (GRAMPOS) 4) (MORPH (COCCUS) 3) (NUMPOS (ANY) 1))

Since GRAM and MORPH are more strongly implicated than NUMPOS in this representation, the latter parameter is deleted from the system's understanding of the phrase "gram positive cocci". The threshold used for making this decision is one half of the maximum weighting factor, i.e., 2 in the above example.

Note that the result of this analysis would have been quite different if the input phrase had in fact dealt with the number of positive cultures (i.e., NUMPOS). Consider, for example, the phrase "number of positive cultures" which has the core equivalent (NUMBER GRAMPOS CULTURE). In this case all three core words have NUMPOS on their INPROPS list, whereas GRAM is implicated only by the word GRAMPOS. Thus the weighting factors would in this case be 3 for (NUMPOS (ANY)) and only 2 for (GRAM (GRAMPOS)).

The program which chooses clinical parameters and their values in this fashion was written with full recognition that its design is empirical and that situations may arise when its algorithm will not perform well. However, it does provide a useful internal representation of word phrases which, as is shown in subsequent sections, can be easily adapted for question-answering purposes. Chapter 8 describes how the same mechanism provides a straightforward first-level approach to the problem of rule-acquisition.

Before proceeding to an explanation of how MYCIN uses the above technique to answer rule-retrieval questions, this section concludes with brief mention of how the approach is related to prior work in the field. Although we are not aware of a natural language system using the same method we have described, a dictionary with pointers to various parts of MYCIN's knowledge base holds certain similarities to Quillian's semantic nets <Quillian - 1966>. Words in Quillian's

system are defined solely in terms of other words and associative links so there is no equivalent to our terminal words. However, our approach could be described as a dictionary-based filter for words in an input phrase; we effectively run a sentence through the dictionary and then see what parts of MYCIN's knowledge base 'light up'. Quillian's approach is often described in similar terms.

V. (*) ANSWERING RULE-RETRIEVAL QUESTIONS

V.1 Overview Of The Approach

As demonstrated in Section II.1, much of MYCIN's natural language capability depends upon an ability to identify and retrieve those rules in the knowledge base which appear relevant to the question under consideration. This section describes how MYCIN uses the understanding mechanism of Section IV in order to translate a question into a request for rule-retrieval.

A retrieval request consists of two components, named PREMPART2 and ACTPART2. Each component is derived from a different part of the input question. There is also a variable named RULES which indicates the rules to be considered during the retrieval search. If there is no restriction on the rules to be searched, as is usually the case, RULES is the word ANY or the character '?'. The question-mark indicates that the user has asked for rule names to be retrieved (e.g., "What rule tells you ..."), whereas ANY requests that entire translations of retrieved rules be displayed.

PREMPART2 is a list of those clinical parameters, and their associated values when specified, which should be referenced in the PREMISE of rules to be retrieved. If PREMPART2 is the word ANY, no restriction is placed on the PREMISE of retrieved rules. ACTPART2 is the same as PREMPART2 in format except that it refers to the ACTION or ELSE clauses of retrieved rules rather than to their PREMISE.

Some examples may help clarify the meaning of these components:

1) Question: "If an organism is a gram negative rod, of what class is it a member?"
RULES = ANY
PREMPART2 = ((MORPH ROD) (GRAM GRAMNEG))
ACTPART2 = ((CLASS ANY))
Here the request is for any rules in the system (RULES) that reference a morphology of value 'rod' and a gramstain of value 'gramneg' in their PREMISE (PREMPART2), and which conclude something about a class of 'any' value (ACTPART2). Clearly rules satisfying this request will answer the question.

2) Question: "Is there a rule that discusses streptococcal morphology?"
RULES = ?
PREMPART2 = ((IDENT STREPTOCOCCUS)(MORPH ANY))
ACTPART2 = ANY
This time the request is for the names of any rules (RULES=?) that reference an identity of value 'streptococcus' and a morphology of 'any' value in their PREMISE.

Clearly the major problem is the mapping of an input question into appropriate values of RULES, PREMPART2, and ACTPART2. The procedure by which this is accomplished and rules are retrieved is a four-step process summarized in Figure 6-1. Those sections of this chapter which explain each step are specified in the figure. Note that Step 3 utilizes the understanding mechanism described in Section IV in order to transform core word phrases (PREMPART1 and ACTPART1) into the rule-retrieval components described above (PREMPART2 and ACTPART2).

V.2 Pattern-Directed Question Analysis

The first two steps in the analysis of an incoming question involve a partitioning procedure which attempts to discern what parts of the question refer to the PREMISE of rules to be retrieved and what portions should be assigned to the ACTION. This breakdown process is controlled by a set of patterns which are matched against the input sentence as described below. The patterns used by MYCIN

Overview Of The Rule-Retrieval Procedure

INPUT QUESTION

↓

STEP 1 — CORE WORD EQUIVALENT (Section V.2)

Transform input question into its core word equivalent.

↓

STEP 2 — PATTERN-DIRECTED QUESTION ANALYSIS (Section V.2)

Partition core word equivalent into PREMPART1 and ACTPART1 where:

PREMPART1 = portion of core word equivalent which is judged to refer to PREMISE conditions of rules to be retrieved;

ACTPART1 = portion of core word equivalent which is judged to refer to ACTION or ELSE clauses of rules to be retrieved.

↓

STEP 3 — ANALYSIS OF QUESTION COMPONENTS (Section V.3)

Use the Understanding Procedure (Section IV) to transform PREMPART1 into PREMPART2 and ACTPART1 into ACTPART2 where:

PREMPART2 = clinical parameters and values judged to be referenced in the PREMISE conditions of rules to be retrieved;

ACTPART2 = clinical parameters and values judged to be referenced in the ACTION or ELSE clauses of rules to be retrieved.

↓

STEP 4 — FINDING THE ANSWERS (Section V.4)

Undertake rule-retrieval using PREMPART2, ACTPART2, plus the LOOKAHEAD and UPDATED-BY lists for the implicated clinical parameters.

↓

DISPLAY ANSWER TO QUESTION

Figure 6-1

are based upon several sample questions from users who had queries about the operation of the consultation program. Their questions were studied and patterns were created to insure proper partitioning of questions phrased in a similar manner. This pattern-directed approach to sentence partitioning is similar in motivation and design to the pattern-based language capabilities of Colby's system for simulation of paranoid processes <Colby - 1974>.

The breakdown procedure attempts to assign portions of the input sentence to one of four categories. These four sentence components are as follows:

RULES - the 'focus' of the sentence as described in the previous section; i.e., either the character '?', the word ANY, or a list of specific rule names; default value is ANY;

VERB - the 'verb' of the sentence; all questions involve one of the three verbs USE, CONCLUDE, or RECOMMEND; CONCLUDE is the default value;

PREMPART1 - the words from the question, if any, that are judged to refer to the PREMISE part of the rules to be retrieved;

ACTPART1 - the words from the question, if any, that are judged to refer to the ACTION part of the rules to be retrieved.

For example:

1) Question: "If the gramstain of an organism is negative and it is a rod, do you conclude that it may be a pseudomonas?"
RULES = ANY
VERB = CONCLUDE
PREMPART1 = (IF GRAM ORGANISM GRAMNEG ROD)
ACTPART1 = (THAT MAY PSEUDOMONAS)

2) Question: "Is there a rule that discusses streptococcal morphology?"
RULES = ? [because the question asks for the name of a rule]
VERB = USE
PREMPART1 = (THAT USE STREPTOCOCCUS MORPH)
ACTPART1 = NIL

MYCIN assigns values to these four components using the following algorithm:

[a] - Each word in the question is replaced by its core word (Section IV.1) unless the core word is undefined, in which case the word is left unchanged; note that this approach automatically corrects misspellings;

[b] - A pattern matching procedure is attempted using the thirty patterns currently known to the system. Each pattern has associated actions which are undertaken if a match is found. Action portions of patterns either set flags or assign words to the categories RULES, VERB, PREMPART1, or ACTPART1.

[c] - If any portions of the input question remain unmatched by patterns and unassigned to one of the four partition categories, they are assigned using a default algorithm.

Once a sentence has been partitioned in this way, the sentence components can be analyzed using the procedure described in Section V.3.

The patterns used in [b] are matched in a specific order, i.e., they have been written in such a way that order is important. Pattern-matching occurs as follows:

i) - if the first character of the pattern is '&', the remainder of the pattern must match, word-for-word, the beginning words in the core word equivalent of the input question;

ii) - otherwise the words in the pattern are matched against strings of words occurring anywhere within the input sentence; the character '$' matches an arbitrary number of words.

The following pattern will serve to illustrate this procedure. In the action portion of the pattern, VACANT is a list of those breakdown components to which a value has not yet been assigned. The APAT function assigns values to components if they are still on the vacant list.

```
PAT005
------
   PATTERN:     (& WHAT $ MEAN)
   ACTIONS:     ((APAT RULES ANY)
                 (APAT VERB CONCLUDE)
                 (DREMOVE ACTPART1 VACANT))
```

This pattern will match questions of the following form:

"What does it mean if ... "
"What do you think it would mean if ... "
etc.

Once the pattern has been successfully matched, RULES is set to the word ANY, VERB is set to CONCLUDE, and ACTPART1 is removed from the VACANT list so that it will not be assigned any words from the question. This pattern therefore says that questions beginning with "What ... mean ... " are asking for the retrieval of rules in which unspecified conclusions (ACTPART1=NIL) are reached on the basis of PREMISE conditions that are not specified by the pattern itself.

We have written a program which permits easy addition (i.e., ordered insertion) of new patterns or the editing of old ones. Thus it is straightforward to augment and modify the system's pattern-directed capabilities as new question-types are encountered.

The default algorithm mentioned in [c] above merits some explanation since it is the one part of MYCIN's approach that requires minimal syntactic processing. After [a] and [b], there will in general still be words remaining in the input question that were unmatched by any pattern. Call them QUES. The default algorithm completes the definition of the partitioning components as follows:

[a] - if RULES was not set by a pattern, set it to ANY;

[b] - if VERB was not set by a pattern, set it to the default verb;

[c] - if only one of PREMPART1 and ACTPART1 is unassigned, set it equal to QUES;

[d] - if both PREMPART1 and ACTPART1 are assigned, ignore whatever is left in QUES;

[e] - if neither PREMPART1 nor ACTPART1 is assigned, look for ways internally to divide QUES so that half can be assigned to PREMPART1 and half to ACTPART1. The scheme here is first to look for punctuation, then for verbs, then prepositions, and finally for articles. For example, "Is it true that gram negative rods are Enterobacteriaceae?" gives QUES=(THAT GRAM GRAMNEG ROD IS ENTEROBACTERIACEAE) which is partitioned to (GRAM GRAMNEG ROD $ ENTEROBACTERIACEAE) and gives PREMPART1=(GRAM GRAMNEG ROD) and

ACTPART1=(ENTEROBACTERIACEAE). An example of a question in which partitioning must be accomplished by using an article is "When is a gram negative rod an Enterobacteriaceae?".

V.3 Analysis Of Question Components

The next stage in understanding a question is the mechanism for performing the following transformations:

PREMPART1 -> PREMPART2

ACTPART1 -> ACTPART2

i.e., for transforming the components of a partitioned question (PREMPART1, ACTPART1 - Section V.2) into the components of a formal retrieval request (PREMPART2, ACTPART2 - Section V.1). The retrieval variable RULES has already been defined during the partitioning process, and the component VERB is not needed for rule-retrieval but is useful for reference when MYCIN finally displays the answer to the question (see Section V.4).

PREMPART2 is derived from PREMPART1 using the dictionary-based understanding mechanism described in Section IV. The identical procedure is used to transform ACTPART1 into ACTPART2. Since both ACTPART1 and PREMPART1 are comprised totally of core words (i.e., terminal words - see derivation of core words as described in Section IV.1), the EXPECTED and INPROPS lists provide a mechanism for determining which clinical parameters are under discussion.

In the next section we describe how the three-part rule-retrieval request is used to answer questions. Before proceeding to that explanation, however, we present the following examples to demonstrate how a question is first partitioned (Section V.2) and then transformed into a rule-retrieval request.

**WHAT DOES IT MEAN IF NO IMPROVEMENT IN YOUR PATIENT'S SIGNS IS OBSERVED IN RESPONSE TO YOUR THERAPY?

```
                              RULES = ANY
                             VERB = CONCLUDE
PREMPART1 = (IF NO RESPONSE      PREMPART2 = ((SYMPTOMS ANY)
     YOUR PATIENT SIGNS                       (SIGNS ANY))
     OBSERVED YOUR THERAPY)
ACTPART1 = NIL                   ACTPART2 = ANY
```

Here the final request is to find any rule in the system (RULES = ANY) in which the clinical parameter SYMPTOMS or SIGNS is referenced in the PREMISE (PREMPART2) and in which any conclusion is drawn (ACTPART2).

**ARE EITHER CHLORAMPHENICOL OR GENTAMICIN OKAY FOR TREATMENT OF SALMONELLA INFECTIONS?

```
                              RULES = ANY
                             VERB = RECOMMEND
PREMPART1 = (SALMONELLA          PREMPART2 = ((INFECT ANY)
     INFECTIOUS)                              (IDENT SALMONELLA)
                                              (COVERFOR SALMONELLA))
ACTPART1 = (EITHER               ACTPART2 = ((ALLERGY CHLORAMPHENICOL)
     CHLORAMPHENICOL OR                      (ALLERGY GENTAMICIN)
     GENTAMICIN OKAY)                        (SENSITIVS CHLORAMPHENICOL)
                                             (SENSITIVS GENTAMICIN)
                                             (RECOMMEND CHLORAMPHENICOL)
                                             (RECOMMEND GENTAMICIN))
```

This time the rule-retrieval request appears to be much less specific than in the first example. MYCIN is told to check all rules in the system (RULES = ANY) and to retrieve any rule in which the following two conditions hold: (i) the PREMISE references the clinical parameter INFECT, the identity salmonella, or the clinical parameter indicating that salmonella must be covered for, and (ii) the ACTION mentions either chloramphenicol or gentamicin in conjunction with the clinical parameter ALLERGY or SENSITIVS or as a drug meriting recommendation. As is discussed in the next section, the semantics of this kind of request are such that only one rule in the system is retrieved, i.e., the therapy rule indicating how MYCIN treats for salmonella infections.

V.4 Finding The Answers

Although a retrieval-request, such as the one derived in the last example of the previous section, may indicate that MYCIN has less than a complete 'understanding' of the question that was asked, the intended meaning is usually included in the disjunction of conditions in FREMPART2 and ACTPART2. Furthermore, the extra conditions often are semantically nonsensical so that none of MYCIN's rules satisfy those parts of the request. As a result, MYCIN usually retrieves precisely the one or two rules that answer the question. At worst an extra rule or two is retrieved along with the ones that are actually desired. This technique MYCIN uses for translation of questions into fixed-format retrieval requests is similar to the approach used by Green in his QA system for retrieving information regarding baseball statistics <Green - 1961>.

Rule-retrieval itself is a straightforward process once the request has been generated from the input question. Each of the three request components retrieves its own list of rules. RULES, of course, either retrieves all rules or those which are specifically mentioned in the input question. PREMPART2 merely uses the LOOKAHEAD list for its clinical parameters (see Section II.3.2 - Chapter 4) in order to find all rules which reference at least one of the indicated parameters in their PREMISE. Similarly ACTPART2 retrieves rules on the UPDATED-BY list of its clinical parameters. The list of rules which potentially answer the question (termed GOODRULES) is thus simply the intersection of the three component rule-lists. The final screening step before MYCIN displays its answer depends upon whether the query was a general question or a question regarding the current consultation.

V.4.1 General Questions

The reader will recall that a general rule-retrieval question is one which references MYCIN's knowledge base independently of a specific consultation. The final step in selecting the rules for question-answering is to select those from the intersection list (GOODRULES) which reference the values of clinical parameters that were specified in the retrieval request.

Consider, for example, the question "Are either chloramphenicol or gentamicin okay for treatment of salmonella infections?". As explained in Section V.3, the question gives the following retrieval request:

```
RULES = ANY

PREMPART2 = ((INFECT ANY) (IDENT SALMONELLA) (COVERFOR SALMONELLA))

ACTPART2 = ((ALLERGY CHLORAMPHENICOL) (ALLERGY GENTAMICIN)
            (SENSITIVS CHLORAMPHENICOL) (SENSITIVS GENTAMICIN)
            (RECOMMEND CHLORAMPHENICOL) (RECOMMEND GENTAMICIN))
```

Thus RULES retrieves all rules in the system, PREMPART2 retrieves the union of the LOOKAHEAD lists for INFECT, IDENT, and COVERFOR, and ACTPART2 retrieves the union of the UPDATED-BY lists for ALLERGY, SENSITIVS, and RECOMMEND. Hence GOODRULES is the intersection of these three lists, i.e., all rules that use IDENT, COVERFOR, or INFECT to conclude the value of ALLERGY, SENSITIVS, or RECOMMEND.

MYCIN now screens the GOODRULES to see if the correct parameter values are referenced. For example, a rule is deleted from GOODRULES if neither chloramphenicol nor gentamicin is mentioned in the ACTION. Similarly, rules selected because of the IDENT or COVERFOR parameter are deleted from GOODRULES if salmonella is not mentioned in the PREMISE. Since the value of INFECT is unspecified in the request, however, GOODRULES with INFECT in their PREMISE are not deleted regardless of the INFECT value that they discuss. When this screening process is complete for the sample question, RULE083 is currently the only rule remaining in GOODRULES. MYCIN therefore assumes that RULE083 is the answer to the user's question:

```
** ARE EITHER CHLORAMPHENICOL OR GENTAMICIN OKAY FOR TREATMENT OF
      SALMONELLA INFECTIONS?

YES.
        RULE089
        -------
            IF: THE IDENTITY OF THE ORGANISM IS SALMONELLA
          THEN: I RECOMMEND THERAPY CHOSEN FROM AMONG THE FOLLOWING DRUGS:
                  1 - COLISTIN                    (.99)
                  2 - CHLORAMPHENICOL             (.99)
                  3 - NITROFURANTOIN              (.99)
                  4 - GENTAMICIN                  (.99)
                  5 - KANAMYCIN                   (.62)
                  6 - TETRACYCLINE                (.54)
                  7 - CEPHALOTHIN                 (.54)
                  8 - SULFISOXAZOLE               (.50)
                  9 - AMPICILLIN                  (.46)
```

If GOODRULES contains more than a single rule after the screening process, MYCIN responds by listing the names of the relevant rules rather than their complete translations. The user is then asked to indicate which rules, if any, he would like to see displayed.

If GOODRULES is empty after the screening process, MYCIN assumes that it has no rules adequate for answering the question. For VERB=USE it responds "I do not have a rule which uses that information". Otherwise it simply says "I have no such rules at present".

V.4.2 Questions Regarding The Current Consultation

MYCIN assumes that a rule-retrieval question refers to the current consultation if any of the words in the query is the name of a node in the current context tree. Thus "How do you decide if an organism is a pseudomonas?" is a general question, whereas "How did you decide that ORGANISM-1 was a pseudomonas?" clearly references the current consultation.

Having noted that the question discusses a specific context, MYCIN then analyzes the question for rule-retrieval in the same manner described for general questions. The GOODRULES screening procedure differs somewhat, however. The

reader will recall that one portion of the ongoing record of a consultation (Section III.3.3 - Chapter 4) is rule-related information recording how various decisions were made. Thus MYCIN screens the GOODRULES by checking to see if they were used to make the indicated conclusion for the specified context. Thus, if a rule were used to conclude that ORGANISM-2 was a pseudomonas, but had not been successfully applied to ORGANISM-1, the rule would be deleted from GOODRULES in responding to the above question regarding the identity of ORGANISM-1.

If GOODRULES becomes empty after this screening process, MYCIN responds "I have no record of a deduction which answers your question". Otherwise it responds by explaining what rule(s) it used to make the indicated decision, what certainty factors were involved, and when during the consultation the conclusions were drawn:

** HOW DID YOU DECIDE ORGANISM-1 WAS A PSEUDOMONAS?

I USED RULE084 TO CONCLUDE THAT THE IDENTITY OF ORGANISM-1 IS
PSEUDOMONAS. THIS GAVE A CUMULATIVE C.F. OF .15. THE LAST
QUESTION ASKED BEFORE THE CONCLUSION WAS MADE WAS 17.

The user could now use the PR command to display RULE084 or the EQ command to find out why question 17 was asked.

VI. (*) ANSWERING IQ QUESTIONS

As was explained in Section II.2.1, IQ questions ask for the current values of clinical parameters. Although they require natural language processing, they are preceded by the letters IQ to distinguish them from rule-retrieval questions.

The complex sentence analysis described in Section V is unnecessary for IQ questions. All MYCIN needs to do is figure out what clinical parameter and context is under discussion. The context is identified simply by comparing each word in the question with the names of nodes in the current context tree. If the context cannot be inferred in this fashion, MYCIN immediately asks the user to rephrase his question, specifying the context under discussion.

MYCIN decides which clinical parameter is intended by using the dictionary-based 'understanding' routine described in Section IV. Each word in the question is first converted into its core word. The INPROPS and EXPECTED lists for the terminal words then serve to help MYCIN infer which clinical parameter is the subject of the question. Once it knows the clinical parameter and context, the requested information can easily be retrieved from the dynamic data base and displayed for the physician using the system's LISP-to-English translation routines.

Consider, for example, the following question:

** IQ WHAT IS THE IDENTITY OF ORGANISM-1?

MYCIN immediately observes that the context under discussion is ORGANISM-1.

Passing the remainder of the question to the 'understanding' program (Section IV), it finds that the vocabulary clues lead to ((IDENT ANY)). It therefore concludes that the user has asked for the value of the clinical parameter IDENT for the context ORGANISM-1. This information is retrieved from the data base, and each hypothesis is displayed along with its associated C.F.:

THE IDENTITY OF ORGANISM-1 IS PSEUDOMONAS (.357) KLEBSIELLA (.177)
ENTEROBACTER (.166) E.COLI (.137) PROTEUS (.118) SERRATIA (.042)

VII. FUTURE EXTENSIONS

Improvements to MYCIN's language and explanation capabilities must necessarily bear in mind the important balance between comprehension and speed of execution. By customizing MYCIN's capabilities to the unique characteristics of its rule-based knowledge, we have managed to devise a surprisingly powerful although simplistic approach to question-answering. MYCIN does not 'understand' questions in the sophisticated ways that characterize the most powerful and general of today's natural language systems. Yet it still manages to answer many questions adequately without a large expenditure of computer time during the analysis of each question. Since the language capabilities of MYCIN have been developed in response to a clear need for an explanation system (Chapter 3), rather than because of an inherent interest in the theory of language or computational linguistics, we are content at present to build upon the simple characteristics and limited power of MYCIN's current approach.

We are less than pleased, however, with those aspects of the current approach that will clearly interfere with the program's acceptability to physicians. Although doctors can learn to phrase their questions simply and to expect rules in response, limits on the kind of questions that can be asked or answered commonly lead to user frustration. We have therefore identified the following goals for improvement of the Explanation System's language capabilities:

[1] - develop a mechanism for permitting the physician to ignore the distinction between IQ and rule-retrieval questions; the IQ prefix should be unnecessary and MYCIN should itself deduce when a question is merely asking for the value of a parameter rather than for rule-retrieval.

[2] - develop a mechanism for answering questions regarding those parts of MYCIN's knowledge that are not rule-based (see Section II.6.1 - Chapter 4); the current approach does not permit QA access to simple lists or knowledge tables.

[3] - as discussed in Section VII of Chapter 4, develop methods for moving algorithmic knowledge from functions to rules so that questions regarding therapy selection may be answered using standard rule-retrieval techniques.

Finally, work is currently underway to improve MYCIN's explanation capabilities during the consultation itself. The RULE command we described in Chapter IV (Section III.2.2) is less than satisfactory as an explanation or educational mechanism because it does not explain why the current rule has been invoked by MYCIN's goal-oriented control structure. A series of commands to allow the user to manipulate the entire reasoning chain is currently under development and should greatly enhance MYCIN's ability adequately to explain its questions and reasoning processes <Shortliffe - 1974b, Davis - 1975>.

Chapter 7

CONTENTS

I. INTRODUCTION

In Chapter 3 I pointed out that the primary design consideration for MYCIN was that it be useful. The other five acceptability criteria discussed in that chapter (i.e., an educational capability, explanation, natural language understanding, knowledge acquisition, and modularity of knowledge) were justified in terms of their ability to enhance the system's usefulness. It was also explained that a consultation program's usefulness can be measured along three scales:

a) the need for the assistance which the program provides;

b) the reliability of the advice;

c) useability; i.e., the mechanics for accessing the machine and retrieving the desired information.

Evaluating the MYCIN System thus requires an assessment of the program's performance along all three of these dimensions.

Section IV.2 of Chapter 1 addressed itself to the first of these three usefulness scales. There is ample evidence that antimicrobial agents are misused and that physicians would benefit from a mechanism that could improve the basis for antimicrobial therapy selection. An implied second component to this question is whether MYCIN is actually able to encourage more rational antimicrobial prescribing habits. Clearly this question cannot be answered until the program has been implemented for ongoing use in the clinical setting.

The reliability of MYCIN's advice, on the other hand, can be assessed even before the program becomes generally available. In fact, as has previously been stated, we do not plan to implement MYCIN on the hospital wards until we are convinced that the program does give reliable advice for patients with bacteremia. We have therefore devised an experimental method for judging the system's validity and have undertaken a study using this technique. Section II of this chapter explains this validation procedure. In Section III the results of the first such study are presented.

The third usefulness scale (i.e., the system's useability) has been considered throughout MYCIN's development. The success of attempts to make the program easy-to-use cannot be rigorously evaluated, however, until MYCIN is generally available. At that time we will be able to talk to physicians who have interacted with the system and to compile data indicating whether they consult MYCIN regularly or lose interest after one or two encounters.

Evaluation of MYCIN will therefore be a continuing process occurring in stages. The first phase involves validation of the program's advice and will thus pre-date implementation. Subsequent stages will assess acceptability, clinical impact, and other questions that can be adequately answered only after MYCIN is generally available. In the final section of this chapter I discuss some of these questions and our plans for analyzing them.

II. METHODS

As explained in Section IV.1 of Chapter 1, MYCIN's task involves four subproblems: (i) deciding whether the bacteria are associated with significant disease, (ii) deciding the likely identity of organisms, (iii) deciding which drugs should be considered, and (iv) selecting the best of the potential drugs. An attempt to evaluate the validity of MYCIN's advice thus demands that we examine each of these subproblems individually. If we were to look only at MYCIN's final recommendations, we would be unable to decide which of the four subtasks accounted for any errors in the program's advice. A physician using the program is unaware of the list of drugs compiled during task (iii), however, because the actual interaction only displays the final recommendation (see the sample consultation at the end of Chapter 1). Tasks (iii) and (iv) are thus so closely interrelated that they may be evaluated together. Finally, it is important to judge the adequacy of MYCIN's interactive process with regard to questions asked or omitted. Pre-implementation validation of the program's performance may therefore be based upon analysis of the following five questions:

(1) Is all necessary information requested by MYCIN during the consultation, and does the program avoid extraneous questions?

(2) Assuming 'yes' to (1), does MYCIN correctly decide whether an organism is significant?

(3) Assuming 'yes' to (2), does MYCIN correctly determine the identity of significant organisms?

(4) Assuming 'yes' to (3), does MYCIN recommend appropriate therapy for

the significant organisms?

(5) Is MYCIN's overall performance judged to be adequate?

This section describes the methods used in a study designed to answer these five questions. 'Correct' decisions are assumed to be those that would be made by infectious disease experts, because there is no single objective standard against which we may measure MYCIN's performance. Since experts often have differences of opinion, however, it was necessary to devise a study that would allow us to control for disagreements among them. We therefore asked five infectious disease experts to assist us with the evaluation of MYCIN's advice, requesting that each review fifteen patient cases. Since each expert evaluated the same fifteen patients, we were able to compare their opinions both with one another's recommendations and with MYCIN's. This approach provided us with a total of 75 patient evaluations.

II.1 Selecting Sample Patients

The fifteen patient cases used for this study were selected over a two month period using a method that attempts to be unbiased but was not rigorously randomized. Since MYCIN's knowledge base had been developed primarily for handling patients with bacteremia and since this is the first clinical problem area for which we hope to validate MYCIN's advice, patients for the study were identified by monitoring positive blood cultures reported by the microbiology laboratories at Stanford and the affiliated Veteran's Hospital. During the 60-day period, fellows in Infectious Diseases or Clinical Pharmacology were occasionally asked to meet with the author, bringing with them the chart of some current inpatient whose primary bacteriologic problem was clearly seen to be in the blood

rather than at some other site. MYCIN was then asked to give advice for treating each of the patients, and the resulting Patient Data Table (Section VI - Chapter 4) was saved for future reference. The fifteen patients thus selected were representative of the kinds of complex infectious disease problems encountered at a referral center such as Stanford. In future studies, however, the criteria for patient selection will be rigorously defined in an effort to achieve a truly random patient sample.

Figure 7-1 summarizes the fifteen patients who were selected. The average patient age was 38.3 years with a range from 2 to 79. The patients together provided 21 organisms in the blood (average per patient = 1.4) which were either known to exist or which MYCIN concluded were sufficiently implicated that therapy should cover for them. Of the 21 organisms, the identities of 12 (57%) were unknown and thus had to be inferred by MYCIN before a therapeutic regimen could be recommended. Four of the organisms were gram positive rods (19%), four were gram positive cocci (19%), and the other thirteen were gram negative rods (62%). The absence of gram negative cocci in our sample is not surprising in light of Stanford's patient population and the fact that we selected patients on the basis of primary bacteremia uncomplicated by diagnoses such as meningitis. Of the twelve organisms with unknown identity, three were gram positive rods (25%), eight were gram negative rods (67%), and the twelfth was a gram positive coccus (8%).

II.2 Design Of An Evaluation Procedure

There were a number of possible ways to use the patient cases selected. One was simply to give the charts to the cooperating experts and to ask for their opinions regarding therapy. The problem with this course, other than the simple logistics of getting five busy individuals to review fifteen charts in a short

Summary Of The Fifteen Patients

Pt. #	Pt. Age	Organism's Identity (If Known)	Gramstain	Morphology	Aerobicity
1	23	Staphylococcus-coag-	+	coccus	aerobic
		Corynebacteria-species	+	rod	aerobic
2	31	-	+	rod	facul
		Bacteroides	-	rod	anaerobic
		Streptococcus-anaerobic	+	coccus	anaerobic
3	63	-	+	coccus	aerobic
4	70	-	-	rod	facul
5	79	-	-	rod	facul
6	18	Staphylococcus-coag+	+	coccus	aerobic
7	39	Moraxella	-	rod	facul
8	60	-	-	rod	aerobic
9	40	-	-	rod	facul
10	60	-	+	rod	anaerobic
11	24	-	-	rod	aerobic
		Bacteroides	-	rod	anaerobic
12	22	-	-	rod	facul
13	15	-	-	rod	aerobic
14	29	-	+	rod	aerobic
		-	-	rod	aerobic
		Bacteroides	-	rod	anaerobic
15	2	Hemophilus-influenzae	-	rod	aerobic

Figure 7-1

period of time, was the wealth of information in the chart that is not normally requested by MYCIN. Since one of our goals was to determine the adequacy of MYCIN's questions, we felt it was important to limit the evaluators' information to that requested by MYCIN and then to see how limited or constrained they felt. We also wanted to evaluate some of the patients at a time prior to when full information became available regarding the identity of an organism. The patient charts would have provided subsequent information that we did not want available to the experts since it would not be provided to MYCIN.

A second approach contemplated was to have each expert seek consultations from MYCIN for each of the fifteen patients. Although this could have been attempted, with a MYCIN project member providing answers to questions asked by the program, it was simpler and less time-consuming to have MYCIN evaluate each patient only once. As described in Section II.1, clinical fellows (who were not directly involved in evaluating MYCIN's performance) generated consultation sessions for each of the fifteen patients. A hard-copy terminal was used so that five copies of each session could be created, one for each expert. Thus the experts reviewed runs of the program that were very similar to the sample at the end of Chapter 1.

An evaluation form was then designed to be inserted at appropriate points throughout the copy of the consultation session. The experts were asked to answer the evaluation questions before proceeding to the next part of the consultation. In this way each of the consultation sessions was divided into three parts:

(1) Questions generated by MYCIN and answered by the user;

(2) The statement of MYCIN's conclusions regarding the significance and identity of organisms;

(3) The statement of MYCIN's first-choice therapy recommendation.

Portions of the evaluation form were included after each of these three parts of

the consultation.

Part 1 -

The first part of the evaluation form, inserted after the questions generated by MYCIN and answered by the user, provided the data necessary to assess the adequacy of MYCIN's interaction. The experts were asked to cross out any questions they felt were unnecessary and to list any additional information they would have liked before deciding the significance or likely identity of the offending organisms. In addition, the experts were asked to indicate the significance of each current organism as judged on the basis of questions that MYCIN did ask. They were similarly asked to indicate, on a comprehensive checklist, all possible identities of the offending organisms that were sufficiently likely that they required consideration during formulation of a therapeutic plan. This portion of the evaluation form thus provided us with data regarding the experts opinions before saw MYCIN's assessment of the organism's significance and identity.

Part 2 -

The second part of the evaluation form, inserted after MYCIN's Set of Indications for therapy (Section V.1 - Chapter 4), provided additional data which allowed us to answer the questions regarding MYCIN's ability to determine the significance and identity of offending organisms. The experts were asked to circle those items on the Set of Indications with which they agreed, to cross out those with which they disagreed, and to leave untouched those items which could have been ignored for therapeutic reasons even though they were reasonable or could not be ruled out with certainty. Taken with the questions regarding significance and identity from Part 1 of the evaluation form, these data permit us to assess both agreement among experts and their degree of agreement with MYCIN.

Part 2 of the evaluation form also asked each expert to list the drug regimen that he would recommend for the indications listed by MYCIN. Thus, even if he disagreed with MYCIN's Set of Indications, he was asked to suggest appropriate therapy based upon MYCIN's conclusions.

Part 3 -

The final part of the evaluation form, included at the end of the consultation sessions, provided the data necessary for judging the appropriateness of MYCIN's therapeutic recommendation. If MYCIN's suggested regimen was different from that of the expert, he was asked to indicate whether he felt that the program's recommendation was an acceptable and sufficient alternative. Finally, each expert was asked to judge the overall performance of MYCIN in handling the patient case.

II.3 Organization Of The Study

None of the five experts who agreed to assist with the evaluation of MYCIN had been involved with its design or the specification of the rules in its knowledge base. One participant had been briefly concerned with the project during its first two months but had not been involved for almost two years and was unfamiliar with either the form or content of the rules in the system. The five experts were the Head of the Division of Infectious Diseases at Stanford Medical School, three senior fellows in Infectious Diseases, and one junior fellow from the same division.

The author met with each of the participants separately to explain the evaluation form and to familiarize him with MYCIN and its mode of interaction. At that time each expert actually tried the program and sought advice from MYCIN on

one of the fifteen patients (Patient Number 3), with the author providing answers to questions generated by the program. The first evaluation form was filled out at appropriate times during this introductory consultation session.

Once he was familiar with MYCIN's mode of interaction, each participant was given copies of MYCIN's consultation sessions regarding the fourteen other patients (i.e., all patients other than Number 3). He was asked to study the consultations and to fill out the evaluation forms at his leisure. A follow-up survey revealed that the average time required for this process was about four hours. The forms were then returned to the author for data extraction and analysis. After an expert had reviewed all fifteen patient cases, he was given a brief summary sheet on which he was asked to assess MYCIN's overall strengths and weaknesses plus its potential usefulness in the clinical setting.

III. DATA ANALYSIS

As was pointed out at the beginning of Section II, our evaluation questions for consideration in this study fall into the following five categories:

[1] Adequacy of MYCIN's interaction;

[2] MYCIN's ability to infer the significance of organisms;

[3] MYCIN's ability to infer the identity of organisms;

[4] MYCIN's ability to select therapy;

[5] Overall adequacy of MYCIN's performance.

This section describes the data gathered in an effort to assess each of these five parameters. It includes the results from the 75 evaluation forms, a quantitative analysis of the data, and a discussion of the results. It then concludes with an assessment of those problems which must be solved before MYCIN is ready for ward implementation.

III.1 Summary Of Results Regarding The Five Questions

The five principal evaluation parameters will be discussed individually in this subsection. In each case I have attempted to devise a normalization procedure so that MYCIN's performance can be compared among the fifteen patient cases. We purposely selected an uneven number of experts for the study so that there would always be a clear majority on matters of judgment. Many of the items

of data analyzed thus depend upon agreement among three or more of the experts.

III.1.1 Adequacy Of MYCIN's Interaction

Our efforts to evaluate this parameter depended upon the following five items from each of the fifteen patient consultations:

(1) Number of questions crossed out by at least one expert

(2) Number of questions crossed out by three or more experts

(3) Number of additional questions suggested by at least one expert

(4) Number of additional questions suggested by three or more experts

(5) Total number of questions asked by MYCIN

As shown in Figure 7-2, the data for these five items may be summarized as follows:

ITEM	AVERAGE	STANDARD DEVIATION	RANGE
(1)	1.9	1.5	0-5
(2)	0	0	0
(3)	7.5	4.1	2-17
(4)	0.9	1.4	0-4
(5)	41.9	14.9	16-72

These data provide the basis for an attempt to assess the current adequacy of MYCIN's interaction. We propose that the answers to the following four questions can be represented by the indicated ratios of data items:

(i) Does MYCIN ask too many questions? [#2/#5]

(ii) Does MYCIN neglect important questions? [#4/#5]

(iii) Do experts agree regarding extraneous questions? [#2/#1]

(iv) Do experts agree regarding missing questions? [#4/#3]

These questions are phrased in such a way that the answer will be 'yes' if the ratio is 1 and 'no' if the ratio is zero. As shown in Figure 7-2, the quantitative answers to these four questions may be summarized as follows:

DATA ITEMS	PATIENT NUMBER 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	$\bar{X}$	σ
(1) Number of questions crossed out by at least one expert.	3	1	0	1	5	3	1	4	0	2	3	3	1	1	1	1.9	1.5
(2) Number of questions crossed out by three or more experts.	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(3) Number of additional questions suggested by at least one expert.	5	8	11	5	11	3	11	10	11	17	5	4	5	5	2	7.5	4.1
(4) Number of additional questions suggested by three or more experts.	0	0	0	0	0	1	2	1	4	4	0	0	0	1	0	0.9	1.4
(5) Total number of questions asked by MYCIN.	34	59	57	50	72	40	16	47	23	49	38	38	49	28	29	41.9	14.9
EVALUATION QUESTIONS																	
(i) Does MYCIN ask too many questions?- #2/#5 (YES = 1.0)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(ii) Does MYCIN neglect important questions?- #4/#5 (YES = 1.0)	0	0	0	0	0	.03	.13	.02	.15	.08	0	0	0	.04	0	.03	.05
(iii) Do experts agree regarding extraneous questions?-#2/#1 (YES = 1.0)	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	.07	.26
(iv) Do experts agree regarding missing questions? - #4/#3 (YES = 1.0)	0	0	0	0	0	.33	.18	.1	.35	.24	0	0	0	.2	0	.09	.13

Adequacy Of MYCIN's Interaction

Figure 7-2

QUESTION	AVERAGE	STANDARD DEVIATION	RANGE
(i)	0	0	0
(ii)	.03	.05	0-.15
(iii)	.07	.26	0-1
(iv)	.09	.13	0-.35

These results indicate that there is remarkably little agreement among the experts regarding what questions are unnecessary (iii) or what questions are missing (iv). In fact, as indicated by data item (2), the experts were willing to accept as useful all the questions MYCIN asked for each of the fifteen patients. The small values for (i) and (ii) reveal that the number of extraneous or missing questions is small compared to the total number of questions asked.

However, the ratio used in (ii) is somewhat misleading because all questions are not equal in information content (as any good diagnostician can attest). The verbal comments of the experts make it clear that they do not believe MYCIN asks enough questions to get a good feel for the 'whole patient', although they seldom agree on exactly what additional questions are needed. For example, an evaluator remarked on one form:

> MYCIN fails adequately to assess the status of the patient because cardiovascular status and immunocompromised status are not explored sufficiently, nor are such things as urinalysis, chest films, soft tissue lesions, etc.

It would appear, then, that the principal inadequacies of MYCIN's interaction involve missing rather than extraneous questions. This suggests that more rules are needed so that MYCIN is better aware of just how sick the patient is. Of course, the program's control structure is such that these new rules will not be invoked unless MYCIN is also given rules telling it how to use the information in deducing significance or selecting therapy.

III.1.2 MYCIN's Ability To Infer The Significance Of Organisms

This parameter may be assessed by checking to see whether MYCIN and the experts agree regarding the significance of current organisms. The data items are the following:

(6) Number of current organisms requiring treatment according to three or more experts

(7) Number of current organisms requiring treatment according to MYCIN

As shown in Figure 7-3, the data for these two items may be summarized as follows:

ITEM	AVERAGE	STANDARD DEVIATION	RANGE
(6)	1.0	0.8	0-3
(7)	1.2	0.9	0-3

The question to be answered using these data is represented by their ratio:

(v) Does MYCIN treat only when necessary? [#6/#7]

As shown in Figure 7-3, the quantitative answer to this question may be summarized as follows:

QUESTION	AVERAGE	STANDARD DEVIATION	RANGE
(v)	.88	.28	0-1

Clearly the higher the average for question (v), the closer agreement there has been among the experts and MYCIN regarding the significance of organisms in the fifteen patients. The one case in which three or more experts decided therapy was unnecessary, but in which MYCIN went ahead and treated (Patient 3), involved an organism for which the program modified its recommendation by saying that it was not certain that therapy was needed but that it would suggest a drug since it could not rule out significant infection. The other two cases in which there was less than complete agreement among MYCIN and the experts (Patients 2 and 11) involved organisms that had not been reported by the user but which MYCIN decided had been implicated on the basis of other clinical evidence.

DATA ITEMS	PATIENT NUMBER 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	$\bar{x}$	σ
(6) Number of current organisms requiring therapy, according to 3 or more experts.	0	2	0	1	1	1	1	1	0	1	1	1	1	3	1	1.0	0.8
(7) Number of current organisms requiring therapy, according to MYCIN.	0	3	1	1	1	1	1	1	0	1	2	1	1	3	1	1.2	0.9
EVALUATION QUESTIONS																	
(v) Does MYCIN treat only when necessary? - #6/#7 (YES = 1.0)	1	.67	0	1	1	1	1	1	1	1	.5	1	1	1	1	.88	.28

MYCIN's Ability To Infer The Significance Of Organisms

Figure 7-3

III.1.3 MYCIN's Ability To Infer The Identity Of Organisms

This parameter involves the task upon which the majority of rule-acquisition efforts to date have been centered. We would therefore hope that the program performs well in identifying pathogens. The data items extracted from the evaluation forms are the following:

(8) Number of identities mentioned by three or more experts

(9) Number of identities mentioned by at least one expert

(10) Number of identities mentioned by three or more experts but ignored by MYCIN

(11) Number of items on MYCIN's Set of Indications that were circled by three or more experts

(12) Number of items on MYCIN's Set of Indications that were crossed out by three or more experts

(13) Number of items on MYCIN's Set of Indications that were neither crossed out nor circled by three or more experts

(14) Number of items on MYCIN's Set of Indications

These data were ignored for Patients 1,6,7,9, and 15, i.e., those patients for whom the identities of all organisms were already known with certainty or for whom MYCIN did not attempt to identify pathogens because it decided that they were insignificant. As shown in Figure 7-4(a), the data for these seven items may be summarized as follows:

ITEM	AVERAGE	STANDARD DEVIATION	RANGE
(8)	6.8	2.4	4-12
(9)	9.9	2.2	6-14
(10)	2.0	2.1	0-6
(11)	4.3	1.9	2-7
(12)	0.1	0.3	0-1
(13)	0.1	0.3	0-1
(14)	4.9	1.5	2-7

There are now five questions which may be answered using ratios of the

DATA ITEMS	PATIENT NUMBER 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	$\bar{X}$	σ
(8) Number of identities mentioned by three or more experts.	-	4	10	6	6	-	-	7	-	5	6	6	6	12	-	6.8	2.4
(9) Number of identities mentioned by at least one expert.	-	8	10	10	9	-	-	11	-	6	12	9	10	14	-	9.9	2.2
(10) Number of identities mentioned by three or more experts but ignored by MYCIN.	-	0	6	2	1	-	-	1	-	3	0	1	1	5	-	2.0	2.1
(11) Number of items on MYCIN's Set of Indications that were circled by three or more experts.	-	4	4	3	5	-	-	6	-	2	6	5	5	7	-	4.3	1.9
(12) Number of items on MYCIN's Set of Indications that were crossed out by three or more experts.	-	0	0	0	0	-	-	0	-	0	1	0	0	0	-	0.1	0.3
(13) Number of items that were neither crossed out nor circled by three or more experts.	-	0	0	1	0	-	-	0	-	0	0	0	0	0	-	0.1	0.3
(14) Number of items on MYCIN's Set of Indications	-	4	4	4	5	-	-	6	-	2	7	5	5	7	-	4.9	1.5

MYCIN's Ability To Infer The Identity Of Organisms

Figure 7-4(a)

data items above:

(vi) Do experts agree regarding identities of organisms? [#8/#9]

(vii) Does MYCIN fail to consider important possible identities? [#10/#14]

(viii) Do experts accept MYCIN's conclusions regarding identities of organisms? [#11/(#14-#13)]

(ix) Do experts discount MYCIN's conclusions regarding identities? [#12/(#14-#13)]

(x) Does MYCIN tend to prescribe for unlikely identities? [#13/#14]

As shown in Figure 7-4(b), the quantified answers to these questions may be summarized as follows:

QUESTION	AVERAGE	STANDARD DEVIATION	RANGE
(vi)	.89	.16	.5-1
(vii)	.50	.57	0-1.5
(viii)	.99	.04	.86-1
(ix)	.02	.05	0-.14
(x)	.03	.08	0-.25

Question (vi) shows that experts tend to agree more regarding identities of organisms than they did regarding extraneous or missing questions [(iii) and (iv)]. There are still situations where some experts ignore possibilities that others feel are important, however. Since a value of 1.0 would have represented absolute agreement, the experts tended to agree only about two thirds of the time.

The value of question (vii) is not quite so meaningful since it merely represents the ratio of important identities that were ignored by MYCIN to the total number that were considered. It is the number of organisms in data item (10) which is perhaps most important to assess. There it will be noted (Figure 7-4(a)) that Patients 3 and 14 account for a large number of ignored identities. These are both cases in which MYCIN treated for a specific organism subtype when the experts indicated that the subtype was unknown. For example, for Patient 3 MYCIN decided that the organism was a streptococcus-beta(group-a) whereas the

EVALUATION QUESTIONS	PATIENT NUMBER 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	$\bar{x}$	σ
(vi) Do experts agree regarding the identity of organisms? - #8/#9 (YES = 1.0)	-	.5	1	.6	.67	-	-	.63	-	.85	.5	.67	.6	.86	-	.69	.16
(vii) Does MYCIN fail to consider important possible identities? - #10/#14 (As many as considered = 1)	-	0	1.5	.5	.2	-	-	.15	-	1.5	0	.2	.2	.71	-	.50	.57
(viii) Do experts agree with MYCIN regarding the identity of organisms? - #11/(#14-#13) (YES = 1.0)	-	1	1	1	1	-	-	1	-	1	.86	1	1	1	-	.99	.04
(ix) Do experts discount MYCIN's conclusions regarding the identity? - #12/(#14-#13) (YES = 1.0)	-	0	0	0	0	-	-	0	-	0	.14	0	0	0	-	.02	.05
(x) Does MYCIN tend to prescribe for unlikely identities? - #13/#14 (As many as considered = 1)	-	0	0	.25	0	-	-	0	-	0	0	0	0	0	-	.03	.08

MYCIN's Ability To Infer The Identity Of Organisms

Figure 7-4(b)

experts simply selected streptococcus(subtype-unknown). Since there were seven possible streptococcal subtypes, six of these that were judged likely by the experts were effectively ignored by the program's decision. This accounts for the large number of identities that appear to have been missed and is thus somewhat misleading. In future studies, confusion regarding this point may perhaps be reduced by deleting the '(subtype-unknown)' option from the identity checklist in the evaluation form. That would force the evaluators to select only those subtypes that are reasonably likely. If one were to reduce the value for question (vii) to reflect only those organisms for which MYCIN neglected to name an entire genus of implicated organisms, the new result would be only .19 instead of .50.

Question (viii) shows that experts almost always agree with the identities that MYCIN does decide merit therapeutic attention. Similarly questions (ix) and (x) indicate that they seldom discount identities MYCIN feels are important. Note that for all three of these questions a value of 1.0 represents an affirmative answer.

It appears, then, that MYCIN is overly inclined to narrow down the range of possible identities requiring attention. The identities it treats for are usually important but it should perhaps not be so quick to rule out some of the other possibilities. This suggests that some new rules are needed or that the certainty factors and conclusions of existing rules may require adjustment.

III.1.4 MYCIN's Ability To Select Therapy

There are six data items used to assess this parameter of MYCIN's current performance:

(15) Number of drugs selected by three or more experts

(16) Number of drugs selected by at least one expert

(17) Number of experts selecting the same preferred regimen as MYCIN did

(18) Number of experts approving MYCIN's first choice regimen

(19) Number of drugs recommended by MYCIN

(20) Average number of drugs recommended by the experts

These data were ignored for Patients 1 and 9 since MYCIN did not feel that those two patients required antimicrobial therapy. As shown in Figure 7-5(a), the data for these six items may be summarized as follows:

ITEM	AVERAGE	STANDARD DEVIATION	RANGE
(15)	1.8	0.8	1-3
(16)	3.3	1.4	1-6
(17)	2.4	1.9	0-5
(18)	3.6	1.4	1-5
(19)	1.4	0.7	1-3
(20)	2.0	0.9	1-3.4

There are now four questions which may be answered using ratios involving the data items above:

(xi) Do experts agree with one another regarding first-choice therapy? [#15/#16]

(xii) Do experts select the same first choice therapy as MYCIN does? [#17/5]

(xiii) Do experts find MYCIN's first choice therapy acceptable? [#18/5]

(xiv) Is MYCIN more inclined to prescribe multiple drugs? [#19/#20]

As shown in Figure 7-5(b), the quantified answers to these questions may be summarized as follows:

QUESTION	AVERAGE	STANDARD DEVIATION	RANGE
(xi)	.58	.27	.33-1
(xii)	.48	.39	0-1
(xiii)	.72	.29	.2-1
(xiv)	.77	.27	.3-1.1

Questions (xi), (xii), and (xiii) all have values in the range of 0 to 1.0, where 1.0 represents an affirmative response. Thus the results show that, although the experts agree with one another (.58) slightly more than they agree with MYCIN (.48), in both cases the agreement only occurs about half the time. On

DATA ITEMS	PATIENT NUMBER 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	$\bar{X}$	σ
(15) Number of drugs selected by three or more experts.	-	2	1	1	3	1	1	2	-	1	3	2	2	3	1	1.8	0.8
(16) Number of drugs selected by at least one expert.	-	4	1	2	4	3	3	2	-	3	3	3	6	6	3	3.3	1.4
(17) Number of experts selecting the same first choice drug regimen as MYCIN did.	-	3	5	4	0	3	3	4	-	3	5	1	0	0	0	2.4	1.9
(18) Number of experts approving MYCIN's first-choice regimen.	-	5	5	4	1	4	4	5	-	2	5	5	2	2	3	3.6	1.4
(19) Number of drugs recommended by MYCIN.	-	2	1	1	1	1	1	2	-	1	3	1	2	1	1	1.4	0.7
(20) Average number of drugs recommended by the experts.	-	2.4	1	1	3	1.6	1	1.8	-	1.2	3	2	2.8	3.4	1.4	2.0	0.9

MYCIN's Ability To Select Therapy

Figure 7-5(a)

EVALUATION QUESTIONS	PATIENT NUMBER 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	$\bar{x}$	σ
(xi) Do experts agree with one another regarding first-choice therapy? - #15/#16 (YES = 1.0)	-	.5	1	.5	.75	.33	.33	1	-	.33	1	.67	.33	.5	.33	.58	.27
(xii) Do experts select the same first-choice therapy as MYCIN does? - #17/5 (YES = 1.0)	-	.6	1	.8	0	.6	.6	.8	-	.6	1	.2	0	0	0	.48	.39
(xiii) Do experts find MYCIN's first-choice therapy acceptable? - #18/5 (YES = 1.0)	-	1	1	.8	.2	.8	.8	1	-	.4	1	1	.4	.4	.6	.72	.29
(xiv) Is MYCIN inclined to prescribe more or fewer drugs than experts do? - #19/#20 (Same as experts = 1.0)	-	.83	1	1	.33	.63	1	1.1	-	.85	1	.5	.71	.3	.71	.77	.27

MYCIN's Ability To Select Therapy

Figure 7-5(b)

the other hand, the experts are willing to accept MYCIN's advice as a reasonable alternative about 72 percent of the time and, as shown by data item (18) in Figure 7-5(a), there is always at least one expert who feels that MYCIN's selection was adequate.

Question (xiv) differs from the other three questions because a value of 1.0 indicates equivalence between MYCIN and the experts. A value exceeding 1 occurs if MYCIN recommends more drugs than the experts, and a value less than 1 indicates that MYCIN recommends fewer drugs. Thus the overall data indicate that MYCIN is more conservative about prescribing multiple drugs than the experts are. A glance at Figure 7-5(b), however, reveals that when the ratio for question (xiv) is low, the experts are less inclined to accept MYCIN's therapy (e.g., Patients 5 and 14). This suggests that MYCIN may be too concerned about economizing on drugs and that its therapy selection algorithm (Section V.2 - Chapter 4) should be appropriately adjusted.

III.1.5 Overall Adequacy Of MYCIN's Performance

The final parameter is judged with a single data item (see Figure 7-6):

(21) Number of physicians approving of the total consultation

ITEM	AVERAGE	STANDARD DEVIATION	RANGE
(21)	3.1	1.6	1-5

The corresponding question is:

(xv) Do experts approve the performance of the program? [#21/5]

QUESTION	AVERAGE	STANDARD DEVIATION	RANGE
(xv)	.63	.32	.2-1

The data therefore indicate that for the fifteen patients and five evaluators, the experts approve of MYCIN's overall performance approximately 63 percent of the time.

DATA ITEMS	PATIENT NUMBER 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	$\bar{X}$	σ
(21) Number of physicians approving of total consultation.	5	5	5	4	1	4	2	5	1	1	4	4	1	2	3	3.1	1.6

EVALUATION QUESTIONS

(xv) Do experts approve the performance of the program? - #21/5 (YES = 1.0)	1	1	1	.8	.2	.8	.4	.1	.2	.2	.8	.8	.2	.4	.6	.63	.32

Overall Adequacy Of MYCIN's Performance

Figure 7-6

An associated question of some interest is whether some evaluators were much harder to please than others. A review of the evaluation forms has revealed a remarkable similarity among the experts, although there is no uniformity regarding which of the consultation sessions they approved (as Figure 7-6 showed):

Evaluator	Number Of Patients For Whom MYCIN's Therapy Is Approved	Number Of Patients For Whom MYCIN's Overall Performance Is Approved
Head Of Division	10	10
Senior Fellow 1	11	10
Senior Fellow 2	12	11
Senior Fellow 3	9	8
Junior Fellow	11	8
TOTAL	53 = 72%	47 = 63%
AVERAGE	10.6	9.4

III.2 Discussion

The results presented in the previous subsection are perhaps best summarized by a comment from one of the evaluators. When asked to whom he would be willing to recommend the current version of MYCIN if it were available on the wards, he indicated it would be useful for medical students but qualified his response as follows:

> I would recommend that they use it as a 'learning game' and then question appropriate people about some decisions. I would not yet recommend basing patient therapy on MYCIN exclusively though in many cases its recommendations were identical to mine or were what I would consider reasonable alternatives. However, too often I felt the result was inadequate or wrong...

This attitude was also reflected in the comment of one expert who said he would recommend the current version of MYCIN to medical students with the advice "Use it as a stimulus to your thoughts..."

It is hardly surprising that MYCIN is not yet an 'expert' since much of the effort to date has been directed toward system design and programming rather than rule-acquisition. It is therefore encouraging that none of the experts had negative comments when queried about operation of the program itself (although one did express concern that the consultation sessions might be too time-consuming - a point that remains to be tested after MYCIN is implemented for general use). The majority of criticisms and negative performance features that have been identified by the current study are ones which can be tackled simply by creating or revising rules rather than by making major design changes.

Knowledge acquisition will thus be a major thrust for future work on the MYCIN System. The study described here suggests several useful areas for development of needed new rules. Once the system's knowledge and performance have improved to the satisfaction of the collaborating experts, an evaluation study similar to the present experiment will be undertaken. If the experts approve MYCIN's overall performance adequately at that time (e.g., more than, say, 90 percent acceptability), we will be ready to introduce MYCIN on the wards as a bacteremia therapy consultation resource.

With MYCIN's eventual implementation in mind, we asked the evaluators to assess the potential for MYCIN to become a reliable clinical tool. We also asked them to indicate whether they believed physicians would use the program:

Junior Fellow: "Yes, but much work will be required..."

Head Of Division: "Yes, but only if it interacts better with the 'whole patient'..."

Senior Fellow: "Probably yes, particularly since there is sufficient cross-reactivity and low toxicity amongst antibiotics for even second and third choices to work well."

Senior Fellow: "Yes, but needs alot of work to get a feel for what might be the etiology of the bacteremia."

Senior Fellow: "Yes, but order of selection of drugs will have to be modified by disease state as well as bacteriology, e.g., endocarditis vs. urinary tract

infections vs. meningitis, etc."

Thus, although all the experts currently feel that MYCIN is not ready for ongoing use except perhaps as a learning game, they all recognize its promise and can cite specific knowledge that must be added in the form of new rules that will enable MYCIN's advice to become more fully reliable.

IV. QUESTIONS YET TO BE ANSWERED

When the problems described in the previous section have been adequately eliminated (a process expected to require six months to a year), MYCIN will be made available for ongoing use in the clinical setting (see Section II - Chapter 8). At that point the clinicians associated with the project will begin to divide their time between expanding MYCIN's knowledge into infectious disease problems other than bacteremia and evaluating the impact which the program may have upon the physicians with whom it interacts. Thus future studies will not only evaluate the validity of MYCIN's advice based upon its evolving corpus of rules, but will also attempt to answer a series of questions regarding its success as a clinical tool.

IV.1 MYCIN's Acceptability To Physicians

Unless MYCIN is accepted by the physicians who must use it, its ability to give valid advice will be of little value. Chapter 3 emphasized those features of the system that were designed to heighten its acceptability. Once the system is generally available, however, new requirements may become evident. We must therefore implement ongoing mechanisms for identifying those aspects of the program which interfere with the willingness of physicians to use it.

One approach will be to keep a record of physicians who have tried the

system and to interview them in order to assess their reactions. It is inevitable that MYCIN's interactive capabilities will have to be constantly modified and improved as feedback from physician users is obtained. Another feedback mechanism will be to permit the physician to type in comments at any time during a consultation. Such remarks can be stored in the computer and regularly reviewed by MYCIN project members.

A second tactic is to identify those physicians who have never tried the system and to find out why. If they are simply unaware of the program's existence, that failing can be easily rectified by an appropriate publicity campaign. If their failure to consult MYCIN results from a basic aversion to interacting with a computer, on the other hand, or if they have heard negative comments about the program from their colleagues, it is important to determine whether changes in the system or its mode of interaction will help to make it more attractive. Although physicians have been involved in the design of MYCIN from the outset, it is unlikely that all the concerns of potential users will have been taken into account. We must therefore be prepared to modify the program, or even radically to overhaul it, in an effort to maximize MYCIN's use by those physicians who may need it when they prescribe for an infectious disease problem.

IV.2 MYCIN's Impact On Prescribing Habits

A second important set of questions to be answered once the system is implemented involves its effect on physician prescribing habits. This can be adequately assessed only if control data regarding current prescribing practices are obtained before MYCIN becomes available. It will then be possible to judge whether antimicrobials are used more appropriately after MYCIN has begun to exert its influence.

It will also be important to assess whether physicians who use MYCIN actually follow its advice. When they do not, we should find out why since that may help with the specification of missing decision rules. If, on the other hand, they reject MYCIN's advice and prescribe less appropriately, an attempt must be made to understand why MYCIN failed to influence them. For example, there may be problems with the Explanation System that prevent it from convincing the user that the program's reasoning is valid.

The educational impact of MYCIN can also be judged by monitoring prescribing habits before and after the system is available. It is possible that MYCIN will result in a new awareness of antibiotic prescribing habits throughout the hospital staff so that even physicians who have never used the program will prescribe more appropriately. Furthermore, clinicians who use the program extensively at first may grow to depend upon it less as they become more familiar with the important therapeutic considerations.

IV.3 MYCIN's Impact On Patient Care

Influencing physician prescribing habits is not a sufficient goal for MYCIN unless it also has demonstrably beneficial effects upon patient care. It will therefore be necessary to develop mechanisms for measuring MYCIN's effect on the quality of care for patients with bacterial infections.

A number of approaches are possible. One is merely to monitor the response of a patient's disease when he is treated with the regimen suggested by MYCIN. Not only may such monitoring provide evidence that MYCIN is suggesting appropriate therapy but, in cases where the patient does not respond as desired, it may also help identify inadequacies in the decision rules that have been given to MYCIN by experts.

Monitoring individual patients provides information that is more anecdotal than statistically significant, however. It may therefore be wise to gather data reflecting trends in length-of-stay for hospitalized patients, incidence of adverse reactions to antimicrobial agents, or pharmacy costs to the patient. All these parameters may reflect beneficial effects of MYCIN that can be verified statistically.

IV.4 (*) Speed, Efficiency, And Storage Requirements

Descriptions of MYCIN often lead to questions regarding the potential difficulty in implementing a completed system without the program proving too large and slow. The final answers concerning these issues will not be available until we get a better feel for how many new rules and system changes will be necessary before MYCIN can become an effective and acceptable clinical tool. We have devoted considerable thought and discussion, however, to the running time and storage requirements of a high performance consultation program such as the one we hope MYCIN will eventually become. Although economic considerations may eventually require that the program be translated for use on a small computer (see Section IV.5), we are convinced that response time or computer storage limitations are unlikely to present difficulties in implementing a completed version of MYCIN under the present TENEX operating system <Myer - 1971>. Some of the considerations involved in this conclusion are:

Space:

The TENEX system that we currently use allocates up to 256 thousand virtual words of memory (512 pages) to each user. Of the 490 pages that we currently use, approximately 320 pages are used by the INTERLISP system, which

includes such features as the spelling corrector, CLISP (Conversational LISP), and the LISP compiler. Of the remaining 170 pages, approximately 100 pages (50 K) are for the compiled MYCIN program. The other 70 pages contain MYCIN's rules, clinical parameters, knowledge tables, and working space. The current program appears to operate adequately within these space limitations. As noted in Section V.2 of Chapter 1, that lengthy sample consultation required approximately 20 minutes at a computer terminal, including the time devoted to the optional use of the Explanation System. Moreover, the following options are available to accommodate future growth of the system:

(a) Smaller LISP:
Many INTERLISP features are useful for developing a new program but are not essential for running a performance system. For example, the LISP compiler, LISP editor, and CLISP are all unnecessary for MYCIN's purposes. In response to the demand by many INTERLISP users that the language dispense with certain features in return for increased memory availability, the language will soon have an 'overlay' feature that will permit INTERLISP users to customize versions of LISP in accordance with their individual requirements. When implemented, the 'overlay' capability will permit us to create a much smaller version of LISP containing only those features needed by MYCIN.

(b) Modular Programs:
The three major components of the MYCIN System (Subprograms 1,2, and 3 - Figure 1-1) are currently loaded into core for every run of the program. However, this is not necessary. For a consultation session only Subprogram 1 needs to be used. At the end of an advice-giving session (or in response to the QA command, Section III.2.2 - Chapter 4), the Explanation System can be added to the Consultation System. The Rule-Acquisition System will not be used at all during standard consultations. Since Subprogram 3 depends upon the expert being able to run Subprogram 1 and 2 as well, however, space considerations may be most important during rule-acquisition sessions. The 'overlay' feature mentioned above should alleviate some of these space problems by permitting the three subprograms to be loaded when needed and then deleted programmatically.

(c) The Rule Corpus:
By far the fastest growing part of the system is the rule corpus. Although the rest of MYCIN is continually being modified, its size has not increased substantially for several months. Relative to the rest of the program, MYCIN's 200 current rules take up only a small amount of space (16 pages = 8 K). Thus, we believe that the system can easily accommodate the many additional rules which we recognize will be needed.

(d) Recoding For Efficiency:
In the initial stages of this work, less attention was paid to space considerations than to major design considerations. As we proceed further with development of the program, we expect to be able to recode parts to enable them to make more efficient use of working space and to take up less space themselves.

Running Time:

Because MYCIN requires substantial interaction at the terminal, it is, to a large extent, input-output bound. However, at times the system becomes compute bound, such as when it must chain through a large number of rules that do not generate questions, or when it is garbage collecting the working space. Except for a few lapses during these compute bound activities, the program's running time is currently acceptable. We are therefore developing ways to further optimize our rule searching strategy (Section VII - Chapter 4) and to reuse active core locations so that fewer garbage collections will occur.

The number of users in a time sharing environment is also a major consideration. To alleviate this potential problem once MYCIN is implemented on the wards, it is possible to arrange for changes to the scheduling algorithm during periods of peak use, and we can at least alert the physician to a potential slow-down when the number of other users is large. It is also worth noting that the times when consultants in infectious disease therapy are least apt to be available (i.e., late at night and on weekends) are precisely those periods when time-sharing systems are most apt to have a low number of users. Thus, the system becomes a particularly viable alternative to the human consultant when he is unavailable.

Since the efficiency of MYCIN is another important consideration, we have accomplished a substantial improvement in execution time by compiling our code for service use of the program. The INTERLISP block compiler may appropriately be used for portions of the code and will give us extra efficiency not attainable by compiling each function individually.

We believe that the present organization of the knowledge base makes for efficient processing of the set of rules. When the number of rules increases substantially, we expect that the present organization will continue to cope successfully for three reasons. First, the rules are divided by context-type so that potentially useful rules are eliminated from consideration if their classification is inappropriate for the context being examined. Second, the rules are linked together in such a way that determining the truth or falsity of the PREMISE of one rule does not require a search of all other rules. Finally, since we have devised a strategy for recognizing those branches of the reasoning network that have already been searched, new rules that reference clinical parameters with which the system is already familiar will not result in exponential growth of the search space.

IV.5 The Cost Of MYCIN's Consultations

An important topic that has previously been ignored in this thesis is the cost of a system like MYCIN. The present system was developed on a large computer (Digital Equipment Corporation PDP-10) which is seldom found in hospitals. Furthermore, the operating system and the INTERLISP language <Teitelman - 1974> are designed primarily for AI applications and are therefore mostly found in university or government research environments. Before MYCIN can become generally available outside the university environment, therefore, it will probably need to be rewritten for a computing system that is more accessible to those hospitals most in need of the program's services. As a result, any attempt to evaluate the cost of a consultation with MYCIN would be premature at present. Research and development expenses naturally bear little resemblance to the costs that will be incurred once MYCIN is an ongoing service system on an in-hospital computer.

INTERLISP has been a powerful development tool, but it is slow and demands more computing power than most hospitals can afford.

IV.6 Legal Implications Of A System Like MYCIN

As discussed in Section III of Chapter 2, questions regarding the legal implications of computer-based medical decision making are as yet largely unanswered. During MYCIN's implementation and evaluation on the wards, however, legal issues are apt to arise. For example, some physicians may be reluctant to consult the program until they know the legal ramifications of following or ignoring MYCIN's advice. Hospital lawyers may be able to provide assistance with such questions. If there have been any test cases on the subject, however, they have not been nationally prominent, and it is therefore difficult to state with certainty who must accept responsibility. I have stressed, however, that MYCIN is a tool for the physician and not a replacement for his own clinical judgment. It therefore seems likely that the ultimate legal responsibility will rest with the clinician rather than with the computer system or its developers.

Future Directions For The MYCIN System

Chapter 8

CONTENTS

Chapter 8

I. INTRODUCTION

As was discussed in Chapter 7, there are several questions regarding MYCIN's performance that are currently unanswered. Most of these involve issues that cannot be adequately analyzed until the program has been introduced for ongoing use in the clinical setting. This chapter introduces our plans for clinical implementation and evaluation of MYCIN. It also discusses some immediate and long range goals for expansion of MYCIN's capabilities.

Section II discusses the current status of the MYCIN project, the short range goals, and the way in which the research group is currently organized. Section III then briefly describes one of MYCIN's goals which has already received considerable attention, namely the problem of rule-acquisition (Subprogram 3 - Figure 1-1). I first explain the current operation of the Rule-Acquisition System and then proceed to a discussion of what additional capabilities will be needed. I also discuss the way in which MYCIN can automatically identify and correct inconsistencies or contradictions as new knowledge is added to the corpus of system rules, and conclude with an assessment of how a growing rule corpus will affect system performance.

The remainder of the chapter deals with issues that are not immediate concerns but which reveal the potential for eventual wide influence of a program like MYCIN. Section IV deals with how MYCIN could efficiently be implemented as a module in a total Hospital Information System (HIS) or in any environment where computer-based patient data could be shared. Section V takes the HIS example one

step further, pointing out ways in which MYCIN could be instituted as a non-punitive peer review mechanism for prospective monitoring of physician prescribing habits. Section VI then discusses the potential educational applications of MYCIN, and I conclude with brief mention of other task domains in which the MYCIN formalisms could potentially be applied.

II. PLANS FOR THE IMMEDIATE FUTURE

Although the work described in this thesis has involved the combined efforts of several collaborating physicians and computer scientists, all of the programming and much of the system design has been the work of the author. Recent additions to the system that were undertaken by other individuals were therefore deleted from discussion in these pages and are described elsewhere <Shortliffe - 1974b>. After a two year growing period, during which the program gradually took shape and began to reveal its potential, MYCIN began to interest other individuals who were able to devote time to the project. Research funding also became available and, as a result, MYCIN currently involves the full time efforts of at least five individuals. This infusion of people with diverse interests, but united by a common fascination with applications of AI in medicine, has enabled MYCIN to begin to expand in a number of new directions. In this section I shall describe some of these projects.

The primary concern at present is to introduce MYCIN in the clinical setting at Stanford Hospital. As I discussed in Chapter 7, this involves developing the program's knowledge base for bacteremia until we are convinced that MYCIN does indeed give expert advice for patients with that subset of bacterial infections. Clinical fellows in Infectious Diseases and Clinical Pharmacology are currently analyzing MYCIN's rules and exercising the program with actual patient cases in an effort to identify additional rules, both for bacteremia and other infectious disease problems, that will help to improve the program's

performance.

Once the knowledge base is deemed adequate, interactive terminals will be placed on appropriate wards at Stanford Hospital and the affiliated Veterans Administration Hospital in Palo Alto. Since users often need to refer back to parts of a consultation, quiet but fast hard-copy terminals will probably be utilized. After physicians have been educated regarding MYCIN's availability and how it is used, a formal evaluation of the program's clinical impact and acceptability will be undertaken. Current prescribing habits will be monitored prior to introduction of the program so that valid control data will be available.

Chapters 4 and 6 both closed with discussions of some of the recognized improvements needed for Subprograms 1 and 2. Work on some of these problems is already underway. In particular, one project member is studying the problem of transferring function-based knowledge about drug selection to rules. A second investigator is examining the current design of the Explanation System to see whether the IQ prefix can be dropped from informational questions (Section II.2.1 - Chapter 6) without introducing so much syntactic or semantic processing that the QA-module becomes unworkably slow.

Finally, one project member is examining several issues related to computer programs that 'understand' their own operation. MYCIN provides an interesting practical environment for this kind of theoretical study because its goal-oriented control structure and formalized rules provide generalized data structures which do let the program analyze itself. The WHY option to which we have alluded (Section III.2.2 - Chapter 4) is the first result of this work, but attention is also being paid to the semantics of certainty factors, rule-acquisition, and problems resulting from the interaction of new rules with a large corpus of pre-existing rules.

III. KNOWLEDGE ACQUISITION

Although we have already spent much time studying mechanisms for acquisition of new rules and have also undertaken some preliminary programming, so many of the problems in this domain remain unsolved that we have postponed discussing the current status until this chapter. Rule-acquisition is accomplished via Subprogram 3 (Figure 1-1). As indicated in the figure, this subprogram may be entered from Subprogram 2 if the user is an infectious disease expert who is recognized by the system (see the RA option, Section II.3 - Chapter 6). The expert enters a new rule in English, it is translated into LISP, and the rule is then added to the knowledge base so that it will be available for future consultations.

It might seem reasonable to call rule-acquisition either teaching (by the expert) or learning (by the machine). Both terms are potentially misleading, however, because 'teaching' may lead to confusion with Computer-Aided Instruction (CAI) and 'learning' has a rather special meaning in the AI field. When a program 'learns', the term usually means that experience has allowed an intelligent program to infer a truth or strategy and to incorporate the fact or heuristic into its knowledge base. For example, I used the word when describing Waterman's poker program <Waterman - 1970> and its ability to 'learn' heuristics. The classic example of a learning program is Samuel's checker-playing system which modifies its evaluation function in response to experience playing the game and has thereby improved so that it regularly beats its creator <Samuel - 1959,1967>.

Winston described a program that 'learns' how to identify geometric objects from examples and counterexamples <Winston - 1970>.

As currently envisioned, Subprogram 3 differs from these examples of 'learning' programs in that it waits to be told what it needs to know. Thus the expert must deduce exactly what information is missing from the system or what previous rule is incorrect. Although the Explanation System simplifies this task, the expert is the primary problem solver for improving MYCIN's knowledge base. Possible mechanisms for changing this emphasis are discussed in Section IV.

III.1 Current Status Of Rule-Acquisition

The current version of Subprogram 3, although it is limited in usefulness, does serve to demonstrate both the generality of MYCIN's natural language capabilities and a potential methodology for powerful interactive knowledge acquisition. Limited effort has been spent on this capability to date, and the speed with which a mechanism for learning simple rules was developed suggests that more concentrated efforts in this area may well prove fruitful in a relatively short period of time.

III.1.1 Overview Of Subprogram 3

Subprogram 3 allows an expert either to enter a new decision rule or to change a pre-existing rule which is in some way inadequate. Both tasks require similar computer processing, so I shall first discuss acquisition of new rules and then explain the necessary modifications for altering old rules.

Subprogram 3 acquires new rules using the following ten-step procedure:

[1] - Tell the expert the name of the rule he is creating;

[2] - Acquire PREMISE conditions one-by-one, translating each from English into the corresponding LISP representation;

[3] - Acquire ACTION clauses one-by-one, translating each into its LISP representation and requesting an associated certainty factor (CF) when necessary;

[4] - Display an English translation of the rule using the standard LISP-to-English routines (Section II.7 - Chapter 4);

[5] - Ask the user to approve the translated version; if the rule is not correct, allow him to make changes and then go back to Step [4];

[6] - Search for contradictions, inconsistencies, or subsumptions involving the new rule and other rules that are already part of the knowledge base; interact with the user as necessary in order to clarify any problems that are noted;

[7] - Ask for assistance classifying the rule, if necessary (Section II.2.2 - Chapter 4);

[8] - Add the rule to the LOOKAHEAD list for all clinical parameters referenced in the PREMISE (Section II.3.2 - Chapter 4);

[9] - Add the rule to either the CONTAINED-IN list or the UPDATED-BY list for all clinical parameters referenced in the ACTION (Section II.3.2 - Chapter 4);

[10] - Tell the expert that the new rule is part of MYCIN's knowledge base.

Note that Step [9] insures that the rule will automatically be invoked when appropriate because FINDOUT will find the rule on the UPDATED-BY list of the parameter for which the new decision criterion is useful (Section III.2.1 - Chapter 4). Note also that the current procedure ignores ELSE clauses since these are seldom needed; the ability to add an ELSE clause to a rule will of course eventually be added.

Section III.1.2 briefly describes how the above procedure has been implemented, and Section III.1.3 discusses our initial plans regarding the implementation of Step [6]. The impact of a new rule on the pre-existing corpus is an important theoretical problem, particularly in light of the complexities introduced by our certainty factor scheme. In Section III.1.4, I close with a

discussion of the way a growing rule corpus may affect the speed and efficiency of consultation sessions.

This subsection will first conclude, however, with a sample interactive session illustrating the current capabilities of the Rule-Acquisition System. As usual, words entered by the physician follow the double asterisk:

```
** NR
The new rule will be called RULE200

  IF:   1 ** THE ORGANISM IS A GRAM NEGATIVE ROD
    and 2 ** IT IS ANAEROBIC
    and 3 ** IT ENTERED THE BLOOD FROM THE GI TRACT
    and 4 **
THEN:   1 ** IT IS PROBABLY A BACTEROIDES
            On a scale of 1 to 10, how much certainty would you
            affix to this conclusion
            ** 9
    and 2 **

This is my understanding of your rule:
        RULE200
        -------
            IF: 1) THE SITE OF THE CULTURE IS BLOOD, AND
                2) THE SITE OF THE CULTURE IS GI, AND
                3) THE STAIN OF THE ORGANISM IS GRAMNEG, AND
                4) THE MORPHOLOGY OF THE ORGANISM IS ROD, AND
                5) THE AEROBICITY OF THE ORGANISM IS ANAEROBIC
          THEN: THERE IS STRONGLY SUGGESTIVE EVIDENCE (.9) THAT THE
                IDENTITY OF THE ORGANISM IS BACTEROIDES

Okay? (YES or NO)
** NO
```

In this example MYCIN has incorrectly interpreted the expert's statement regarding the gastrointestinal tract (GI). The physician has therefore indicated that the program's understanding of the rule is not yet correct. The session continues:

```
Change PREMISE? (YES or NO)
** YES
Want to see the current version? (YES or NO)
** NO
Change (C), Delete (D), or Add (A) a component:
** C
Which Component? (Enter number)
** 2
```

```
Enter the new component:
    New: ** PORTAL OF ENTRY IS THE GI TRACT
More changes to this PREMISE? (YES or NO)
** NO
Change ACTION? (YES or NO)
** NO

This is my understanding of your rule:
        RULE200
        -------
            IF: 1) THE SITE OF THE CULTURE IS BLOOD, AND
                2) THE STAIN OF THE ORGANISM IS GRAMNEG, AND
                3) THE MORPHOLOGY OF THE ORGANISM IS ROD, AND
                4) THE AEROBICITY OF THE ORGANISM IS ANAEROBIC, AND
                5) THE PORTAL OF ENTRY OF THE ORGANISM IS GI
          THEN: THERE IS STRONGLY SUGGESTIVE EVIDENCE (.9) THAT THE
                IDENTITY OF THE ORGANISM IS BACTEROIDES

Okay? (YES or NO)
** YES
```

This time the rule correctly reflects the intention of the expert. Note that the PREMISE conditions have been re-ordered for efficiency; clauses referencing parameters which are most likely to have been referenced before (and whose values are thus apt to be known) are placed near the beginning of the PREMISE. The algorithm used for re-ordering is described in Section III.1.2.

Steps [1] through [5] of the acquisition procedure have been completed in the sample session above. Of the remaining steps, only Step [7] currently requires further interaction with the user. MYCIN can easily infer that the new rule is some kind of organism rule, but it is not obvious whether it should be classified as an ORGRULE, a CURORGRULE, or a PRORGRULE. Therefore MYCIN concludes with the following question:

```
This rule may best be described as a rule which:
        1 - Applies to all organisms
        2 - Applies to prior organisms only
        3 - Applies to current organisms only
** 1
```

```
Thank you for you assistance.
RULE200 is now part of the Consultation System.
```

RULE200 is thus classified as an ORGRULE and the rule-acquisition procedure is complete. The rule has been added to the LOOKAHEAD list for SITE, GRAM, MORPH, AIR, and PORTAL and to the UPDATED-BY list for IDENT. Thus the rule will be invoked whenever MYCIN is trying to infer the identity of an organism. The internal representation of the rule created by the above interaction is as follows:

```
RULE200
-------
    PREMISE:  ($AND (SAME CNTXT SITE BLOOD)
                    (SAME CNTXT GRAM GRAMNEG)
                    (SAME CNTXT MORPH ROD)
                    (SAME CNTXT AIR ANAEROBIC)
                    (SAME CNTXT PORTAL GI))
    ACTION:   (CONCLUDE CNTXT IDENT BACTEROIDES TALLY .9)
```

MYCIN's mechanism for changing rules parallels the above procedure, starting at the point where the expert was asked if he wanted to change the PREMISE of RULE200. Thus when the physician indicates that he wants to change a rule, he is asked for the name of the rule requiring alteration and is then permitted to modify only that portion of the rule which is faulty. It is not necessary to delete the erroneous rule and to re-enter it from the beginning as though it were new.

Although we are eager to permit experts to teach the system new rules, there are potential dangers in letting anyone have uncontrolled access to MYCIN's knowledge base. This observation is particularly worrisome while the Step [6] consistency check is in rather rudimentary form. We therefore do not yet automatically store new rules as part of the permanent Consultation System. Instead they are stored temporarily in a file assigned specifically to the expert from whom the rules were acquired. Whenever that expert uses the system he may

load his personal rules and they are automatically added to MYCIN's knowledge base. MYCIN project members have an opportunity to examine both the new rules and the English text from which they were derived, however, before the new knowledge is transferred from the expert's personal file to the permanent Consultation System.

III.1.2 (*) Implementation Details

This subsection explains how MYCIN translates English text into an executable LISP expression for inclusion as part of a rule. It also describes how the program orders the PREMISE conditions for efficiency and how it narrows down the number of categories to which the rule could potentially be assigned.

MYCIN uses the same routines for understanding natural language in Subprogram 3 that it utilizes in Subprogram 2 (Section IV - Chapter 6). As is true for question-answering, MYCIN must decide what clinical parameters and values are being discussed. However, it must also decide what predicate (function) is implied by the input phrase. This latter problem explains the need for the INFUNCS list associated with some of the terminal words in MYCIN's dictionary (Section III - Chapter 6).

When the expert enters a phrase, it is transformed into a core word expression and passed to the 'understanding' routines. A flag is first set, however, so that the system will know to check the INFUNCS property as well as EXPECTED and INPROPS. The understanding program thus returns both a list of clinical parameters, with associated values, and a list of functions. The parameters that are implicated help MYCIN choose from among the possible functions.

For example, consider the phrase "the organism is a gram negative rod", i.e., the first condition entered by the physician in the sample interaction from the previous section. This phrase is transformed into the core expression

(ORGANISM GRAM GRAMNEG ROD) which is analyzed by the understanding routines (see Section IV - Chapter 6) and returns ((GRAM GRAMNEG)(MORPH ROD)). None of the core words implicates a function, however, so MYCIN must select from among the default predicates for PREMISE conditions, namely SAME, NOTSAME, KNOWN, and NOTKNOWN (see Section II.5 - Chapter 4). NOTSAME and NOTKNOWN are ruled out because MYCIN found no negations in the input phrase. Thus the choice is narrowed to SAME or KNOWN.

The reader will recall that KNOWN is a <func1> predicate whereas SAME is a <func2> predicate. Since <func1> predicates do not reference specific values of parameters, whereas <func2> parameters do, SAME is clearly more appropriate for the example phrase. The input expression references both parameters and their values. Since KNOWN would not be able to use the specified values, but SAME can, the <func2> predicate is preferred.

Every function that may be used in rules has an associated template that is used for rule-acquisition. For example, the template for KNOWN is (KNOWN CNTXT PARAM) and for SAME is (SAME CNTXT PARAM VALU). Once MYCIN has concluded that SAME is the function implicated by the input phrase, it merely substitutes the implicated parameters and values into the template for SAME. Thus "the organism is a gram negative rod" maps into two PREMISE conditions, (SAME CNTXT GRAM GRAMNEG) and (SAME CNTXT MORPH ROD). As shown in the previous section, these are two of the conditions in the internal representation of RULE200. Note also that this approach permits the expert to specify multiple conditions in a single input phrase.

If the input expression had been "the gramstain and morphology of the organism are not known", on the other hand, the understanding routines would have returned KNOWN and NOTKNOWN as possible functions and the parameter expression ((GRAM ANY)(MORPH ANY)). Since the input expression contained the word 'not', MYCIN would have selected NOTKNOWN as the implicated function and would have used its associated template to create the two PREMISE conditions (NOTKNOWN CNTXT GRAM)

and (NOTKNOWN CNTXT MORPH).

If a template contains the element 'CF', MYCIN knows to request a certainty factor to be inserted in that place. For example, the template for CONCLUDE is (CONCLUDE CNTXT PARAM VALU TALLY CF). Thus when a decision rule using CONCLUDE is acquired, such as in the example shown in the previous section, MYCIN asks "On a scale of 1 to 10, how much certainty would you affix to this conclusion?" The user's response is divided by 10 and inserted for CF in the template. If the conclusion involves a negation, however, the number is negated before the substitution. If the ACTION of RULE200 had been "It is probably not a bacteroides", for example, the substituted number would have been -.9 instead of .9.

Conditions in the PREMISE of a rule are re-ordered during rule-acquisition when necessary. The goal is to place the most commonly referenced clinical parameters earliest in the rule. A rough estimate of a parameter's usefulness is the number of rules on its LOOKAHEAD list, i.e., the longer the LOOKAHEAD list, the more rules reference that parameter in their PREMISE. Thus in the sample new rule from the previous section, the condition referencing the parameter SITE is placed first in the PREMISE because the LOOKAHEAD list for SITE is long. On the other hand, PORTAL is used in just a few rules, has a short LOOKAHEAD list, and is thus placed last in the PREMISE. RULE200 will therefore not force FINDOUT to trace PORTAL unless all four of the previous conditions hold. If the new rule forces a question regarding the SITE, on the other hand, the user is not apt to object because this parameter appears in so many rules that it is almost certain to be traced for every patient.

As was pointed out in Section II.2.2 of Chapter 4, rules are classified in accordance with the lowest node in the context tree that they reference. Thus a rule such as RULE200 that references both a PROP-CUL (SITE) and several PROP-ORGS (GRAM, MORPH, AIR, PORTAL, IDENT) must be some kind of organism rule since

organisms occur below cultures in the context tree. Subprogram 3 is able to reach this conclusion without assistance because it knows the nature of the context tree and knows how the various parameters are classified. Since there are three kinds of organism rules, however, and since there is no obvious clue from the input expression which allows MYCIN to deduce which category is appropriate, the program must request assistance for the final step in the categorization process. The way in which MYCIN requests this help was demonstrated in the sample session from the previous section. Note that the expert need have no detailed understanding of rule categories nor the context tree in order to answer the question.

III.1.3 (*) Interaction Of New And Old Rules

Step [6] of the rule-acquisition procedure (Section III.1.1) requires a screening process to see if the new rule improperly interacts with other rules in the knowledge base. Although we have given considerable thought to this problem, Subprogram 3 does not yet undertake this consistency check. Programs to accomplish the necessary screening will be written in the near future, however, and I present here some preliminary observations.

(1) Subsumption:

I mentioned the problem of subsumption several times in Chapter 5. Of all the aberrant interactions of new rules with the pre-existing corpus, subsumption is perhaps the easiest to handle in an automated fashion. Suppose, for example, there were already a rule in the corpus as follows (see Section II.4 - Chapter 4 for an explanation of the notation):

[a] A & B & C --x--> D

If an expert now entered the following new rule, a problem of subsumption would arise:

[b] A & B & C & E & F --y--> D

Clearly any time rule [b] is satisfied, rule [a] will also be satisfied since the PREMISE of [b] subsumes the PREMISE of [a]. Yet rule [a] adds nothing to [b] and it would be improper to use both rules in the same context. On the other hand, eliminating [a] is not an adequate solution because [a] may apply in contexts where [b] does not and in those cases the knowledge inherent in [a] is needed.

The solution to the problem is to modify [a] so that it is no longer subsumed by [b] but so that it still will hold for all contexts that fail for [b] but would succeed for [a]. Namely, we propose replacing [a] with a new rule [c]:

[c] A & B & C & (not.E or not.F) --z--> D

Now any context that would have satisfied [a] will succeed either for [b] or [c] but not for both. Negation here implies a predicate's complement over the certainty factor range. Thus not.SAME is NOTSAME, not THOUGHTNOT (Section II.5 - Chapter 4). The transition from [a] to [c] may be accomplished automatically except for the possible change in CF (from x to z). We therefore propose displaying [c] for the expert and asking for the CF he would assign.

Finding old rules such as [a] that are subsumed by new rules such as [b] does not require a search through the entire rule corpus. MYCIN merely uses the LOOKAHEAD and UPDATED-BY lists for the clinical parameters in [b] to find rules which use all or some of the same parameters to deduce values of the same parameter. These rules may then be checked for subsumption.

(2) Single-Rule Contradictions

It is also easy to find single rule contradictions using LOOKAHEAD and UPDATED-BY lists. However, the discrepancies cannot be handled in an automated fashion and the inconsistencies must be 'discussed' with the user. Two rules contradict each other if they use the same conditions to reach the same conclusion but with different certainty factors. Clearly the extreme case occurs when one CF is positive and the other is negative; in such instances the experts disagree not

only on the degree of evidence but also on the direction of evidence! Although such contradictions have not yet arisen during the development of MYCIN, Subprogram 3 must be prepared to identify and handle such problems if they do arise. Hopefully the expert will usually suggest a compromise CF which is also acceptable to the expert from whom the old rule was acquired. Expert clinicians often disagree on clinical questions, however, and we must be willing to accept this fact during the design of MYCIN's knowledge acquisition capabilities. If no acceptable compromise can be found, it may be necessary to store both of the rules and later to ask the user whether he wishes advice based upon the rules acquired from Dr. X or those from Dr. Y. This solution does not seem unreasonable since physicians commonly do have to choose among consultants.

(3) Multiple-Rule Contradictions

The most complex interactions between a new rule and the pre-existing corpus occur when the new rule is inconsistent not with a single old rule but with a reasoning chain of old rules. Not only are such inconsistencies difficult to find, but it is also difficult to judge the severity of contradictions because of the interaction of reasoning chains with the CF's of the component rules. In fact, unless the new rule has CF=1 or the reasoning chain is comprised only of rules with CF=1 (a situation for which R. Davis recently coined the descriptive term 'unity path'), it may perhaps be argued that no true contradiction exists. R. Davis is currently examining the nature of such inconsistencies in order to decide both how to find them using an automated mechanism and also under what conditions they may be ignored.

III.1.4 Impact Of Knowledge Growth On System Performance

A question we are often asked is whether rule-acquisition will lead to an exponential growth problem. If each new rule permitted an entire new pathway to sprout in the reasoning network below it, we would have to expect exponential growth of search time as the number of rules increased to, say, 500 from the current 200. Indeed, if each new rule referenced several clinical parameters with which the system was not already familiar, and if each of these attributes in turn required a series of rules for use in inferring its value, both the size of the network and the time required for a consultation would grow unmanageably large. Our experience has so far indicated, however, that most new rules reference only the 65 clinical parameters with which the system is already familiar. Since each of these attributes is traced by the FINDOUT mechanism at most once during a consultation session, a new rule referencing parameters already traced for other reasons will generate no additional search time (except for that required to evaluate the single rule itself). Thus, growth in the size of the reasoning network and in search time is at most linear for a new rule that references only clinical parameters that are already recognized and traced by MYCIN. Furthermore, the new rule will have no effect whatsoever on search time in consultations where it is not invoked by the dynamic FINDOUT mechanism. Since we expect that the number of clinical parameters will not increase in proportion to the number of rules, we do not anticipate exponential growth problems.

III.2 Future Extensions

The current rule-acquisition mechanism is limited in scope and applicability for a variety of reasons. Although the current approach may perhaps be adjusted so that it will accept all well-formed rules referencing

clinical parameters known to the system, its dependence upon MYCIN's dictionary (Section III - Chapter 6) reveals its inability to learn rules that relate to unfamiliar concepts. Suppose, for example, that an expert wishes to enter a rule in which a condition involves a clinical parameter that has not been used by any existing rule. The 'understanding' routines (Section IV - Chapter 6) will of course miss the relevant vocabulary clues since there will be no dictionary entries related to that parameter.

Furthermore, suppose the new parameter refers to a context-type that has never before been created. For example, the length of time a Foley catheter has been in place might be a new parameter (TIME-IN-PLACE) for a new kind of context (CATHETER or PROCEDURE). Learning about new kinds of nodes for the context tree is a problem for which the current approach is clearly ill-equipped.

Finally, the most serious problem arises if the expert references a predicate (function) which has not previously been programmed. There will of course be no INFUNCS clues nor template, and an attempt to automate this kind of rule-acquisition will perhaps be dependent upon the AI field known as automatic programming.

Future extensions to Subprogram 3 will therefore attempt to handle unrecognized parameters, contexts, and functions. We have not yet defined how best to approach these problems. We are currently relying on a variety of specialized 'service' functions for defining new parameters explicitly and for easily entering and editing LISP versions of rules when Subprogram 3 has failed to acquire their English versions correctly.

In closing this section, I should also mention an entirely different approach to knowledge acquisition that was recently suggested by R. Waldinger of Stanford Research Institute. He pointed out that MYCIN could ask an expert how to treat a specific patient and, if the advice differed from that which the program would have recommended, could seek explanations from the expert. For example:

```
MYCIN: What would you prescribe?
EXPERT: I would give X.
     M: Oh?  Why would you give X?
     E: It is the first choice drug for Y.
     M: True.  But how did you know the organism was Y?
     E: Because its PARAM was Z.
     M: I see.  But how did you know its PARAM was Z?
                .
                .
               etc.
```

The natural language problems inherent in this approach appear to be somewhat formidable, but the idea is rather enticing and may appeal to researchers with an interest in the theoretical problems underlying this kind of AI task.

IV. MYCIN AND SHARED DATA BASES

Section II.2.6 of Chapter 1 described Hospital Information Systems (HIS) and their potential for assisting with information handling chores in the clinical environment. Regardless of whether such systems are implemented as a single large installation, or as a set of integrated but independently developed submodules, they are characterized by large amounts of diverse patient data that can be shared among the system components.

Let us consider what MYCIN's role might be in an HIS which contains up-to-date patient information in the following categories:

(1) - chemistry laboratory data (including hematology)

(2) - pharmacy data

(3) - microbiology laboratory data

(4) - clinical data traditionally found in the patient chart

It should be clear that most of the clinical parameters used by MYCIN may be classified in one of these categories. Thus if MYCIN were a component in a comprehensive HIS and could reference the patient's information from the above four data bases, several of the questions currently asked of the physician would no longer be necessary. For example, information regarding current and prior cultures would be available from data base (3) and the patient's recent drug history could be found in data base (2). In fact, any piece of information currently classified as LABDATA (Section II.3.2 - Chapter 4) would presumably be

available from one of the four data bases. The user would therefore be asked to interact with MYCIN only for consideration of those non-LABDATA parameters for which the rule corpus was unable to infer values (Figure 4-8). This corresponds to the observation that ASK1 questions would no longer be necessary and that only ASK2 questions would need to be displayed for the physician (see Figure 4-9).

As was pointed out in Section III.2.1 of Chapter 4, however, one of the goals in the future development of MYCIN's knowledge base is to acquire enough rules allowing the values of non-LABDATA parameters to be inferred so that ASK2 questions need no longer occur. One of the impediments to this goal has been the tendency for such rules to generate large numbers of highly specific questions which make MYCIN appear to be groping for ideas and which are thus annoying for the user. Consider, for example, the non-LABDATA parameter COMPROMISED which is a 'yes-no' parameter indicating whether the patient is a compromised host. There are currently no rules for inferring the value of this parameter, so an ASK2 question is generated whenever FINDOUT tries to find its value (Figure 4-8). If MYCIN were to make the conclusion on its own, rather than to leave the decision up to the judgment of the user, the program would require a series of rules itemizing disease categories which suggest that a patient's immune response system is not functioning normally. Such rules would in turn generate a series of apparently groping questions such as "Does the patient have leukemia?", "Is the patient an alcoholic?", etc. If a series of questions regarding diagnoses could be answered via queries sent to other HIS data bases, however, the more basic rules regarding compromised-host status could be added to MYCIN's knowledge base without generating annoying questions for the physician.

The discussion of the preceding paragraphs indicates the way in which access to shared clinical data bases could reduce the number of questions asked of the physician by MYCIN. Since much of MYCIN's current time requirement is bound by the terminal-based interaction with the physician, an efficient linkage between

MYCIN and other data bases might well decrease the time from sign-on until MYCIN's recommendation becomes available. In the extreme case, one can imagine a user simply giving MYCIN the name of his patient and answering no additional questions. MYCIN would evaluate the patient on the basis of primitive data (LABDATA) obtainable directly from the clinical laboratory, microbiology, pharmacy, and medical record data bases. After a variable length of time (depending upon the complexity of the patient's infectious disease problem), a therapeutic recommendation would be printed by MYCIN and the physician would be able to use the Explanation System (Chapter 6) to query the program regarding the reasoning behind the suggested regimen.

A formally constituted HIS is not a prerequisite for the shared data base application of MYCIN just described. All that is really necessary is the up-to-date data bases plus communication links between the computers in which the information is stored. Stanford Hospital already has all four of the required data bases: pharmacy <Cohen - 1974>, microbiology <Petralli - 1970>, clinical chemistry <Sussman - unpublished>, and medical records <Fries - 1972>. Unfortunately, all four systems were developed independently and currently operate on separate computers. Since all the programs would benefit from from access to one another's patient data, however, communication links between the machines are being contemplated. As soon as these are available, we hope to connect MYCIN to the network and to develop the mechanisms for direct access to patient data in accordance with the model that we described above.

If the four clinical data bases are effectively linked, as is planned, another potential addition to MYCIN would be an ability to monitor a patient's response to the recommended therapy. In this way it could perhaps acquire statistics that would enable it to alter its drug selection strategy or first-choice drugs. If this capability were implemented, it would resemble the kind of machine 'learning' discussed at the beginning of Section III.

V. PROSPECTIVE MONITORING OF PRESCRIBING HABITS

Of all the issues currently involving American organized medicine, there is perhaps none more emotion-laden than the question of peer-review. Known euphemistically as patient care appraisal, quality-of-care assessment, or quality assurance, peer review has entered the political arena since a Social Security amendment was signed into law in 1972. Known as Public Law 92-603, the legislation requires that Professional Standards Review Organizations (PSRO) be set up to monitor medical practice, to identify problems, and to take steps to correct them. PSRO's are to be instituted locally in all parts of the country, and until January of 1976 physician organizations have priority in establishing them.

Although physicians had begun to participate in peer review activities prior to passage of the new legislation, until recently emphasis has been on assessing those parameters of practice which are most easily measured. Thus utilization review committees and tissue review boards have traditionally taken on the primary peer review responsibilities. PL 92-603 has sparked new interest in peer review issues, however, both with regard to how review should be undertaken and whether the government should be able to interfere in an area which had previously been the concern solely of the medical practitioners themselves. Organized medicine has many reservations regarding PSRO <Watts - 1973>, and the strengths and weaknesses of the legislation have been much analyzed <Welch - 1973>.

As mentioned in Section III of Chapter 2, it is the conviction of this observer that the primary reasons for physician opposition to peer review legislation result from the fact that medicine is one of the few professions in which individuals have traditionally been free from close observation and criticism. Legislation to promote government influence on medical care delivery, whether it be MEDICARE or PSRO, is thus met with widespread opposition and, in some cases, fear <Gottesman - 1972>. What is particularly worrisome to physicians is the potential for being punished when they make decisions that are judged by others to be mistakes.

Regardless of whether PSRO deserves opposition, the bill has been signed into law and is not apt to be repealed. It is therefore time to look for ways to insure that the new peer review mechanisms will both accomplish the goals of the legislation and will be at least mildly acceptable to physicians. I therefore cite the following proposed criteria for acceptability of the developing peer review mechanisms:

(1) - They should be able to judge questions of medical care, not merely parameters such as length-of-stay data;

(2) - They should emphasize educational benefits rather than punitive actions when errors are noted;

(3) - They should ideally inform the physician of a possible error before it is too late to rectify matters;

(4) - They should encourage feedback from physicians regarding strengths and weaknesses of the approach.

The importance of the second point cannot be overstated. There has already been experience to indicate that patient care monitoring can be made acceptable to physicians if they are not led to believe that they will be punished when errors are observed <Alper - 1974>.

With criteria such as those above in mind, authors have begun to suggest ways to choose peer review methods <Brook - 1973>. For several years there have

been efforts to assess quality of care by reviewing patient charts <Fessel - 1972>. Medical audit of this variety is difficult, however, because the task is arduous, it requires a time-commitment from the reviewing physicians, and the criteria for judging care are, in general, ill-defined. One innovation has been the institution of departmental medical audit workshops at which physicians attempt to delineate what should be the criteria for quality care at their hospital. These criteria can then be used for assessment of care when medical records are reviewed.

The above discussion has been an attempt to lay the groundwork for justifying the claim that MYCIN provides a useful model for a peer review mechanism satisfying the cited acceptability criteria. I shall explain this model by describing an existing system and discussing how MYCIN could be adapted in a similar way.

The MEDIPHOR System <Cohen - 1974> was briefly mentioned in Section II.2.5 of Chapter 1. This is a large computer program developed at Stanford Medical School for the prospective control and study of drug interactions in hospitalized patients. Using a comprehensive and documented data base of drug interaction information, the system generates warnings to pharmacists, nursing personnel, and physicians when potentially interacting drug combinations have been prescribed. Drug profiles for patients are available to the system because it also serves as a label printing machine in the hospital pharmacy. Whenever a label is printed, the computer records the information in the patient's drug profile. Thus whenever a new drug is prescribed, the machine can use its drug interaction data base to search for interactions between the new prescription and drugs the patient is already receiving. If a potential interaction is found, a warning is printed in the pharmacy and sent to the ward along with the drug. There the physician and nursing staff may consider the interaction information before the interacting drug is administered. If the physician decides to give the drug, he at least knows

about the potential for adverse effects and is therefore careful to monitor the appropriate clinical parameters of the patient.

The MEDIPHOR System offers many of the advantages of the peer review acceptability criteria I described. Clearly it addresses itself to an important clinical practice question that is difficult to assess even by chart review. Furthermore, it points out potential problems before they occur and thus reveals its educational emphasis. Physicians are more apt to be defensive about their decisions if possible errors are not pointed out until two or three months after the incident. By that time, notification is certain to appear like a scolding since it is too late for corrective action to be taken. Finally, a system like MEDIPHOR can also be used to accumulate the data necessary for judging trends in the quality of care, at least for the topic of drug interactions.

Suppose, now, that the various computer-based data banks at Stanford Hospital were joined by communication links as discussed in Section IV. In that section I explained how MYCIN could provide consultations without asking questions of the physician so long as all the pertinent data were available in one of the Stanford data bases. Under those circumstances, the physician seeking advice is needed only to initiate the consultation. Consider, then, the potential for initiating the consultation program not in response to a request from a physician seeking advice but instead whenever an antimicrobial agent is prescribed in the hospital pharmacy. The MEDIPHOR System could notify MYCIN regarding the patient, drug, and dose. MYCIN could then use its knowledge base to decide how it would treat the patient and whether the drug actually prescribed is appropriate. If a prescription were clearly inappropriate, MYCIN could send the relevant information back to MEDIPHOR and a warning could in turn be generated in the pharmacy. This warning would then be returned to the ward with the prescribed drug where the physician could consider MYCIN's recommendations before deciding whether to administer the drug he had originally prescribed. The physician would, in effect,

receive a consultation from MYCIN when he needed it rather than when he asked for it.

This approach to peer review provides an exciting potential for impacting the antimicrobial prescribing habits of physicians, and for monitoring other clinical practice questions as MYCIN-like knowledge bases are developed for additional problem areas. Dr. S. Cohen has observed, during discussions of the above model, that peer review may be considered as 'covert consultation' in much the same sense that human consultations may be looked upon as 'overt peer review'. This model for prospective monitoring of prescribing habits is particularly appealing because it satisfies our proposed acceptability criteria for a peer review mechanism.

This section concludes with an example of a situation in which the monitoring model we have described would be highly useful. During early development of the MYCIN System, we reviewed several patient charts in an effort to identify decision rules needed by the program. In one such chart we found that a patient had been treated with streptomycin as a single agent to combat an organism which was known to be resistant to streptomycin in vitro. Furthermore, the patient who was given the drug (which is toxic to the kidney) had chemistry laboratory values for BUN and creatinine indicating that he was in renal failure. In short, the streptomycin therapy was highly inappropriate. If MYCIN had been monitoring antimicrobial prescriptions in the hospital pharmacy. It would have automatically evaluated the streptomycin prescription. The lab values for BUN and creatinine would have been available from the clinical laboratory data base, and the microbiology data base would have revealed the organism's resistance to the drug. MYCIN would therefore have concluded that the streptomycin was inappropriate and a warning would have been generated. It is possible, in turn, that the warning would have had a beneficial educational impact on the physician who made the improper therapeutic decision. As was discussed in Section IV.2 of

Chapter 1, there is much evidence that this kind of inappropriate prescribing of an antibiotic is not an isolated incident, although the above example is, perhaps, somewhat extreme.

VI. EDUCATIONAL APPLICATIONS

As I have emphasized throughout this thesis, an ability to instruct the user was an important consideration during the design of MYCIN. We believe it is possible to learn a great deal simply by asking MYCIN for consultative advice and taking advantage of the program's explanation capabilities. It is quite likely, in fact, that medical students in their clinical years will comprise a large percentage of MYCIN's regular users once it is available on the wards.

It would be possible, however, to adapt MYCIN so that its emphasis became primarily educational rather than consultative. This could be accomplished in a number of ways. In one scenario, MYCIN would present a sample patient to a student. The program would then judge the student's ability to ask important questions and to reach valid conclusions regarding both the identity of the organism(s) and the most appropriate therapeutic regimen. By comparing the student's questions and decisions to its own, MYCIN could infer inadequacies in the user's knowledge and enter into a tutorial discourse customized for the student. A similar instructional session might be generated even for actual patient cases provided by the student. Although there is great potential for this kind of educational use of MYCIN's knowledge base, we have no plans to pursue this application in the near future.

VII. OTHER APPLICATIONS OF THE MYCIN FORMALISM

In Section VIII.3 of Chapter 4 I noted that one of the principal advantages of the MYCIN approach is its domain independent control structure. Attempts have also been made to preserve generality in Subprograms 2 and 3. We have not yet tested this claim with a second data base, however. As explained in Chapter 4, acquiring rules and defining parameters are such complex and time-consuming tasks that we have so far been unable to experiment with alternate clinical problem areas.

Our current plan is gradually to broaden MYCIN's knowledge base into other infectious disease topics (i.e., in addition to bacteremia). We feel it is important, however, eventually to test the approach in medical decision areas that have nothing to do with antimicrobial therapy. Not only will this assist in determining the generality of the MYCIN formalism, but it will also help us define which clinical problems are best suited for a rule-based system rather than for Bayesian or model-based approaches. As I have stated before, MYCIN's formalism seems to be most appropriate for applications in which informal judgmental knowledge is the basis for decisions. If good statistical information is available or a problem is suited to physiological modeling, an alternate approach may be preferable. Until MYCIN is tested in new arenas, we will be unable to reach justifiable decisions regarding these issues.

It is also interesting to ask whether MYCIN's approach can be usefully applied to non-medical problems. Although we have no current intention to

investigate such questions ourselves, other AI researchers have begun to indicate an interest in pursuing this rule-based approach for non-medical applications. Of particular relevance, of course, are those problems that can benefit from a technique for coding the heuristics of an individual.

Conclusions

Chapter 9

CONTENTS

Chapter 9

I. SUMMARY

MYCIN is a large computer program developed by the author over a two year period. The program's knowledge base, and many aspects of system design, were contributed by collaborating physicians and computer scientists who have met with the author once a week throughout the two years. In recent months the project has expanded to include additional physicians and computer scientists who will be contributing full-time efforts to the future expansion of MYCIN's capabilities.

This chapter summarizes the material that has been presented in this thesis. In this section I reiterate the clinical problem for which MYCIN is designed to offer advice. I then briefly review how the program attempts to solve the problem. Section II discusses MYCIN's contribution to computer-based medical decision making, and I conclude in Section III with consideration of the program's contribution to the field of artificial intelligence.

I.1 The Problem

The principal goal of the MYCIN project has been to devise a computer-based system for assisting and educating physicians who need advice about appropriate antimicrobial therapy. The basis of rational infectious disease therapy is identification of the offending micro-organisms. Accurate identification is important because drugs that are highly effective against

certain bacteria are often useless against others. The patient's clinical status and history, including such information as previous infections and treatment, provide valuable data to assist the physician with the identification task. However, bacteriological cultures that use specimens taken from the site of the patient's infection usually provide the most definitive identifying information.

Initial culture reports from a microbiology laboratory may become available within 12 hours from the time a clinical specimen is obtained from the patient. The information in these early reports often serves to classify the organism in general terms but does not permit precise identification. It may be clinically unwise to postpone therapy until identification of the infecting organism can be made with certainty, however, a process that usually requires 24-48 hours or longer. Thus, it is often necessary for the physician to estimate the range of possible organisms and to start appropriate treatment even before the laboratory is able to identify the offending organism and its antibiotic sensitivities.

As discussed in Section IV.2 of Chapter 1, there is ample evidence that physicians often do not choose antimicrobial therapy wisely. Studies discussed in that chapter have shown that physicians will often reach therapeutic decisions which differ significantly from those that would have been suggested by infectious disease experts. It is not uncommon for physicians to treat patients for whom experts believe no antimicrobial therapy is indicated. Furthermore, nonexperts sometimes choose a drug regimen designed to cover for all possibilities, prescribing either several drugs or one of the so-called 'broad-spectrum' antibiotics, even though appropriate utilization of clinical clues might have led to a more rational (and often less toxic) therapy. Since professional resources are often overburdened in today's hospitals, a computer-based system that could serve effectively in a consultation role to the nonexpert - and gain his respect - would be highly useful. MYCIN has been designed to provide readily accessible

advice and instruction which will help bridge this gap between practicing physicians and experts in infectious disease therapy.

MYCIN has also been developed with an awareness of the current lack of acceptance of computer-assisted decision making by the medical profession. We have attempted to analyze the reasons for the common opposition to such programs and to endow MYCIN with characteristics that will make it more acceptable. These points are discussed in detail in Section III of Chapter 2 and in Chapter 3.

I.2 The Solution

The MYCIN System is offered as a solution to the two problems described in the previous section; i.e., it attempts to give good advice regarding antimicrobial selection and it attempts to do so in a way which will make the system acceptable to physicians. In order to solve both these problems, MYCIN has been designed with three principal capabilities in mind:

(1) an ability to give good advice;

(2) an ability to explain the basis for its advice;

(3) an ability to acquire new knowledge easily so that its advice can improve over time.

Thus MYCIN consists of three subprograms, each of which addresses itself to one of these three goals.

Subprogram 1 is a Consultation System. This component uses information about a patient, plus MYCIN's knowledge of bacterial infections, in order to decide (a) whether the patient needs to be treated, (b) the likely identity of offending organisms, (c) the possible drugs for use against these organisms, and (d) the best drug or drugs for the particular patient in light of his current

clinical condition. Information about the patient is entered by the physician in response to questions asked by MYCIN. Each question asks for the value of some clinical parameter used by the program when it makes decisions. If all such values were known, the patient's clinical status would be fully characterized. MYCIN's task, however, is efficiently to select those of the clinical parameters (currently 65 in number) which are needed for adequate consideration of a given patient. The program's current knowledge is stored in 200 isolated decision rules, each of which is invoked only if the program has reason to believe it may be useful. This efficient use of system knowledge is accomplished by a goal-oriented control structure which dynamically creates a reasoning network appropriate for the clinical problem under consideration. The details of Subprogram 1 are the subject of Chapter 4.

Subprogram 2 is an Explanation System. This component attempts to answer questions from the user both during and after a consultation session. Furthermore, it attempts to do so in terms that will convince the physician that it reaches decisions in much the same way that he does. The user may ask MYCIN to explain the reason for a question during the consultation or may demand explanations of decisions that the program has reached. In an effort to make such explanations easy to obtain, even by a novice user, Subprogram 2 has been given a limited ability to understand simple English. In addition, its responses to questions are expressed in English and require no knowledge of MYCIN's internal representation or control structure in order to be understood. The details of Subprogram 2 are described in Chapter 6.

Subprogram 3 is a Rule-Acquisition System designed for use by experts in infectious disease therapy. The capabilities of this system component are currently incomplete, but it is possible for an expert to teach MYCIN certain simple rules which are then incorporated into the system's knowledge base for use in future consultations. An expert is encouraged to use Subprograms 1 and 2 in an

effort to identify problems with MYCIN's knowledge of infectious disease therapy. Subprogram 3 then permits him to enter new rules or to modify old ones which he has found to be inadequate. The rule-acquisition procedure, like Subprogram 2, attempts to understand knowledge statements expressed in English so that the expert need not learn a computer language nor details of MYCIN's implementation. Subprogram 3 is the subject of Section III in Chapter 8.

II. CONTRIBUTION TO COMPUTER-BASED MEDICAL DECISION MAKING

MYCIN has several novel attributes that distinguish it from other programs for medical decision making. Foremost among these is its ability to reason with informal judgmental knowledge acquired from experts. Although the system makes no attempt explicitly to model the psychological processes of a clinical decision maker, its modular decision rules and the certainty factor quantification scheme permit a physician's intuitions to be coded without major difficulty. Thus MYCIN's decisions need not depend upon the diagnostic algorithms, physiologic models, nor the statistical analyses that pervade much of the field (Chapter 2). The MYCIN formalism is therefore potentially applicable to decision making in the large number of clinical problem areas for which pathophysiology is poorly understood and statistical data are incomplete or nonexistent.

It should be noted that the MYCIN approach does not rule out applications for which reliable data become available. The formal certainty factor definitions and combining functions permit probabilistic information and judgmental knowledge to be used in unison. Furthermore, extensions to MYCIN may permit causal links to be coded in rule form so that the present control structure need not be modified. Although MYCIN may not provide the 'best' solution for decision making in every clinical problem area, it may well serve as a useful adjunct to alternative techniques in most medical decision making applications.

Another important contribution of MYCIN's approach is its ability to reach decisions based upon whatever information is available at the time of the

consultation. As is true for human consultants, MYCIN gives more reliable advice as more comprehensive information becomes available. Explicit decision trees or decisions based upon clinical algorithms tend to require pieces of information in a fixed order; if a datum is unavailable, the physician must wait for the appropriate test result before completing the consultation session. Of course there are times when so little information is available that MYCIN cannot reach a reasonable decision. In general, however, MYCIN makes the best decision it can on the basis of current data and the user is encouraged to return for more definitive advice as further information becomes available. In a problem area such as the treatment of infectious disease, interim decisions while awaiting further data are often in the best interests of the acutely ill patient.

Avoiding explicit decision trees has provided other advantages besides an ability to operate solely on the basis of current information. Most important among these is MYCIN's ability to incorporate new knowledge without explicitly being told how or when it will be useful. The program's control structure for dynamic reasoning (Chapter 4) automatically utilizes any rule-based knowledge that appears to be relevant. Storing knowledge in rules has also facilitated an ability to explain why questions are asked and to justify the basis for the program's therapeutic recommendations.

Finally, MYCIN has been designed to be more than merely an interesting theoretical approach to medical decision making in this therapeutic problem area. From the outset we have stressed the goal of eventually implementing the program for ongoing use by physicians. We have sought to understand why such programs have met resistance in the past, and we have in turn implemented a number of features, including a comprehensive explanation capability, designed to heighten MYCIN's acceptability to physicians. Although the program is not yet sufficiently knowledgeable for ongoing clinical use (Chapter 7), physicians who have used the system have uniformly indicated that they believe the program <u>can</u>

become sufficiently reliable and will hence be used by the clinicians for whom it has been designed.

III. CONTRIBUTION TO ARTIFICIAL INTELLIGENCE

MYCIN's mechanisms for representing and utilizing judgmental knowledge also heighten its interest for computer scientists working in the field of artificial intelligence. Unlike formal problem-solving systems based upon axiomatic knowledge, MYCIN suggests an approach for modeling the kinds of inexact reasoning that typify many real-world problems. AI researchers have recognized the need for some way to combine the attributes of decision theory with those of machine problem-solving <Feldman - 1974>, and MYCIN provides what is perhaps the first general approach to this problem. Certainty factors are potentially applicable to a number of AI application areas. For example, conversations with AI researchers have revealed that tasks such as identifying objects in machine vision or phonemes in speech understanding are typified by the kind of indecision that CF's are designed to handle.

Although neither MYCIN's goal-oriented control structure nor its dependence upon rule-based knowledge is unique (see Chapter 4), no other AI system has used its knowledge in quite the same way. As I have emphasized, MYCIN's formalism is domain independent and thus may prove useful for AI researchers who wish to automate other tasks that are dependent upon the heuristics of individuals. Furthermore, the use of rules with CF=1, or with a certainty factor derived from reliable statistical data, provides a mechanism for coding theorems, real-world data, and definitional information. This formal knowledge may then be used simultaneously with the informal knowledge that is representative of the

intuitive inexact reasoning that typifies much of human problem-solving.

MYCIN has also been developed with more attention to human engineering than is typical of much of the AI field. The goal has been to develop mechanisms for interacting with medical professionals who are not only unfamiliar with AI but have often never used computers before. MYCIN's rules have therefore served as a highly useful representation scheme since they can be individually retrieved in order to explain why questions have been asked or to justify aspects of the program's advice. As AI applications for use by scientists and other individuals become more common, MYCIN may well suggest some useful guidelines for interactions with novice computer users.

Another lesson to be learned from MYCIN is that a single programmer, working full-time for two years with a powerful interactive language such as INTERLISP, can create an AI program that serves a useful purpose. Observers often bemoan the current state of the art in AI, asserting that it will be years before machines can perform problem-solving tasks at a level approximating that of humans. MYCIN has shown, however, that if researchers are willing to accept the current limitations of the AI field, and to select real-world goals that are compatible with those limitations, a useful system can be developed using techniques for representation and control that would not have been available if it were not for prior work in artificial intelligence. MYCIN's question-answering (QA) skills are an example of this point. The techniques used for natural language understanding are dependent upon several simplifying assumptions that ignore syntax, semantics, and the psychology of language. The last two of these are perhaps the principal barriers to further AI progress in the field of linguistics (Chapter 6). The limited QA capabilities that result, however, are in general satisfactory for the application area in which they are to be used. Although it would clearly be preferable if the program could participate in free form discourse, MYCIN has shown that a useful interim solution can be developed

once the current limitations of the field have been accepted.

Finally, MYCIN has contributed to the AI field by providing evidence which suggests that current AI techniques may be adequate for assisting professionals with an important real-world problem. There has been a tendency for theoretical AI work to concentrate on tasks which are often described as 'toy problems'. Although such problems are generally non-trivial and AI researchers can themselves appreciate the challenges involved, the relative paucity of AI programs that deal with real-world tasks has not always benefitted the image of the field. Although MYCIN's effectiveness as a clinical tool has not yet been fully demonstrated, the preliminary evaluations described in Chapter 7 make us optimistic about its future. We are therefore pleased to be able to offer MYCIN as an example of a way in which current AI technology can potentially contribute to the betterment of public health through improved care for patients with infections.

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