TOWARD A SCIENCE OF EXPERT SYSTEMS
Erik Horvitz, Stanford University

ABSTRACT

Over the last several years, teams working on expert systems have been exploring formal approaches for better revision and information acquisition. The formalization of major components of expert system operation is useful for understanding and characterizing system behavior and for predicting changes with modification. Formalization also facilitates the involvement of investigators in more well-developed disciplines such as statistics. While the use of formal methodologies for diagnostic problem solving is attractive because of the generality, power, and axiomatic basis of inference, the methodologies have been criticized for making inferences that are difficult to understand and explain. I shall focus on the problem of explaining formal reasoning methodologies. The PATHFINDER system for pathology diagnosis is presented as an example of current research on aspects of the use of formal methodologies in expert systems. I will demonstrate that a formal system is amenable to controlled degradation to enhance its explanatory capability.

1. INTRODUCTION

It is fitting that there be a focus of discussion of expert systems in a session on computers and medical decision-making. Original ground-breaking research on expert systems was the result of attempts to build systems to reason about complex medical problems [1]. Expert systems research developed within the field of artificial intelligence over a decade ago and is now an established engineering sub-discipline of artificial intelligence. It is the intent of expert system research to develop methodologies for the representation and manipulation of the knowledge of experts in a variety of disciplines.

Artificial intelligence research is still in its youth. As in other new disciplines in which unifying theories have not been developed, much work has focused on non-axiomatic, descriptive, and empirical approaches. I would like to briefly introduce the descriptive and formal approaches to research in artificial intelligence in general. I will stress the usefulness of reasoning methodologies that follow from a set of well-characterized axioms. I will then introduce current problems with the use of formal systems. One frequent criticism of formal reasoning strategies is that they are difficult to understand and explain. I will focus on the problem of understanding and explaining in expert systems that use formal methods for reasoning under uncertainty. In this regard, I will present research on the PATHFINDER expert system for pathologic diagnosis [2] and other research on aspects of the use of formal methodologies in expert systems. In answer to complaints about the rigidity and unnatural nature of formal systems, I shall describe how a formal system is amenable to controlled degradation so that it can perform more descriptively.

2. AXIOMATIC AND DESCRIPTIVE APPROACHES

Science has been marked by an ongoing attempt to explain observed patterns and relationships with models that provide reasonable explanations and predictions. Useful theories tend to simplify phenomena through explaining complexity with a relatively small number of ethically or intuitively justifiable properties or axioms.

Unfortunately, theories based on a set of justifiable axioms often do not exist; when they fail to emerge, it is often not obvious why, unique, or desirable. Throughout the history of science, when useful axiomatic theories have not been available, scientists have resorted to descriptive models. Such models summarize complex behavior by describing phenomenology without resorting to fundamental structures. It captures the behavior of systems, often through the postulation of relations that may be inconsistent with one another or with other acquired knowledge. As an example, before Newton constructed the theory of universal gravitation and Kepler developed the equations describing the motion of objects orbiting in gravitational fields, astronomers often depended on epicyclic machines. These machines could approximately describe the movements of heavenly bodies as viewed from the earth, with a complex tangle of gears and chains. They did not explain the physical nature of heavenly bodies with a consistent theory of fundamental relationships.

2.1 Descriptive Expert Systems Research

Much of expert systems research can be characterized either as axiomatic or descriptive. The descriptive expert systems approach centers on the design and empirical evaluation of algorithms that mimic aspects of human behavior. Descriptive expert systems research is not hindered by the lack of a formal axiomatic basis; it is the intent of the research to discover useful strategies for representing and manipulating expert knowledge regardless of the availability or acceptability of a set of self-consistent axioms. Investigations in the descriptive school of research view exploration of the sufficiency of informal models of human problem solving as a more direct approach to difficult problems. That is, given poor understanding, many expert systems researchers attempt to capture expertise through building and experimenting with descriptive models in the spirit of the epicycle machines of long ago.

As an example of the descriptive approach to expert system design, the Present Illness Program (PIP) [21], developed ten years ago at M.I.T., was an attempt to simulate the cognition of a physician's reasoning about patients presenting with edema (swelling). A central aspect of the design of the system involved an analysis of the behavior of each of a number of experts. Descriptive cognitive structures called the supervisory program, the diagnostic program, and the memory program were constructed.

A taxonomic category of descriptive systems is based on the rule-based methodology [4]. The rule-based expert systems methodology is the result of attempts to adopt the use of an explicitly enumerative methodology, called production systems [22, 23], to capture aspects of human expertise. Production systems are comprised of sets of logically interacting inference rules of the form IF E THEN H, where E is a hypothesis and H is evidence having relevance to the hypothesis. In practice, rules of logical inference are used in an automated reduction. For descriptive, modular rule sets of inference can be placed on a set of knowledge base of rules to do proofs that content of the forward or backward "viewing" of rules.

One of the most prolific early expert systems was MYCIN [21], a rule-based expert system for the diagnosis of bacterial infection. The MYCIN reasoning framework remains one of the most modular expert system methodologies. MYCIN's knowledge is stored as rules that capture the relationships among relevant medical evidence and hypotheses. For example, a rule in MYCIN might be: "If an organism infecting a patient is gram-positive and grows in clumps then support is the hypothesis that the organism is staphylococcus." It was recognized early on in the M/C/C research that straightforward application of the production rule methodology would be insufficient because of the uncertainty in the relationships between evidence and
hypotheses in medicine.

In order to accommodate these non-deterministic relationships, MYCIN uses certainty factors [4]. To each rule, a certainty factor is attached which represents the change in belief about a hypothesis given some evidence. Certain factors range between 1 and 1. Positive numbers correspond to an increase in belief in a hypothesis while negative numbers correspond to a decrease in belief. An ad hoc calculation for evidence combination was presented in the original research [7, 8].

12. The Axiomatic Approach

In contrast to the descriptive approach, investigators pursuing the formal, axiomatic approach are interested in exploring the adequacy of systems that satisfy desired properties. That is, they design expert systems that are necessarily consistent with desired properties. When such a set is deemed optimal for reasoning in the context of particular tasks it is termed a normative theory for reasoning.

Investigators interested in the formal approach attempt to design expert systems that behave consistently with established theories for reasoning under uncertainty, in exploring the automation of reasoning under uncertainty, investigators have focused, on the vast of theories for the consistent revision of beliefs in the context of previous belief and for controlling information acquisition. Examples of axiomatic theories that have been used in expert systems research for belief revision include probability [24], fuzzy logic [35], Dempster-Shafer theory [2], certainty factors [30], and multi-valued logic [11]. Theories used for controlling information acquisition include information theory [29] and decision theory [23, 25].

Alternative formalisms are often based on class of sets of properties. An expert system engineer can base an expert system on a set of properties that it viewed to be a particularly intuitive or desirable. For example, a set of simple properties about continuous measures of belief can be shown to be consistent with the properties defined by maintaining the consistent extension of belief [3, 6, 20]. Agreement with the properties exacerbates the use of probability theory. A small set of inviolate properties allows an objective of decision theory [27]. (Of course, there are other definitions of logic among the formalisms that allow the optimality or necessity of particular axioms of axioms. For example, there has been ongoing debate in the artificial intelligence community regarding the alternative methodologies for the revision of belief [4, 35].

To date, there have been several attempts to base expert reasoning systems on well-defined formalisms. These efforts have been reported in the Failure [35] system, MEDAS [7] system for emergency medicine, and the PATHFINDER [17] system for orthopaedic diagnosis. These systems were designed to be consistent with well-understood formalisms for reasoning.

Both the descriptive and axiomatic approaches have led to the construction of systems that perform at levels rivaling experts in a variety of domains. Given the complexity of problems at hand and the breadth of the field, both approaches have been useful in exploring techniques for automated reasoning. In general, there has been a healthy interplay between the descriptive and the axiomatic research; a dynamic research milieu is encouraged by the coexisting approaches.

3. THE BENEFITS OF FORMALIZATION

A worst fundamental goal of research should be the development of useful theories. As in any science, the study of automated reasoning would benefit greatly from attempts to construct theories for representing and manipulating knowledge. Whether an investigator impulsively chooses to become involved with descriptive or formal research, a fundamental goal should be the construction of a formal science. A clear theoretical basis for components of expert systems would be extremely useful. While there have already been strides in the application of formal theories to expert systems, greater understanding could facilitate the design, control, and characterization of expert systems.

The subscription to axiomatic bases for components of expert reasoning can be useful in a number of ways. It can assist a system engineer in the design of his or her system, it will remain consistent with a set of desired properties, designing a system on an axiomatic theory means that the system will be self-consistent. If an axiomatic theory is not used in building an expert system, it can be quite difficult to maintain self-consistency. The presence of inconsistencies in complex computer systems often leads to unpredictable behavior.

Recent research on the ad hoc certainty factor model used for combining evidence in the MYCIN system introduced above has found the original model to be self-inconsistent [16, 18]. Recent work has focused on removing inconsistencies in the model [16]. The consistent reformulation of certainty factors demonstrates that the belief revision theorem is a specialization of probability in that assumptions of conditional independence are imposed by the methodology. For example, it can be shown that evidence must be conditionally independent given and its negation [16]. The determination of self-consistency and the detection of contraindications were facilitated by the formalization of MYCIN's reasoning strategies.

Formal models can also assist an engineer directly when a system is modified. A formal system allows for the crisp prediction of changes in system behavior in response to system modifications. This may be quite difficult to predict the impact of a modification for which the underlying theoretical structure is available. Having the ability to predict the effect of system modifications is extremely important for the maintenance of systems, for the generalization of specific outcomes, and for the incremental refinement of techniques. Incremental refinement can be particularly crucial in the development of a (theoretical framework) for automated reasoning.

Most relevant for this conference, formalization can also be crucial for expert systems research to benefit from the participation of investigators in other highly-developed disciplines. As more and more complex expert systems research are of special relevance in this respect, it would be useful if it could attract researchers to assist in solving difficult problems. Formal descriptions of systems and methodologies are important as they provide conceptual handles necessary for communication with researchers in other fields.

4. PROBLEMS WITH THE FORMAL APPROACH

Two central issues arise in discussions of the axiomatic approach: problems regarding the propriety of engineering and publication, as well as explanation.

4.1. Tractability of Engineering and Computation

More so than for any other reason, researchers in artificial intelligence have looked beyond acquisition-based techniques for complex domains because of the computational overhead of inference and the requirement for large amounts of knowledge. Formal methodologies are viewed as being unattractive for knowledge processing [3, 34].
4.2 Explanation

Another significant problem cited with respect to formal methodologies is that it is difficult to explain reasoning. An unknown number of factors influence the success of reasoning and the methods of reasoning. The results of reasoning have not been identified as a fundamental feature of formal systems. The development of methods for reasoning in expert systems has made it possible to explain reasoning in an artificial intelligence research field.

It has been said that formal methodologies like probability theory and decision analysis lead to unanswerable problems. The manipulation of the equations of conditional probability or decision trees may indeed be quite difficult to succinctly explain. Such difficulties have spurred some of the ongoing work on techniques for justifying the results of formal reasoning systems. [23, 27, 30]. We shall focus more closely on this problem below.

5. GRACEFUL DEGRADATION OF PERFORMANCE

The concerns about problems with explanation, knowledge acquisition and computational tractability of systems based on formalisms for reasoning under uncertainty are valid. Indeed, the methodologies demand large amounts of data and computation. Concerns about the opacity of explanations of recommendations are also justified.

Formal methodologies for reasoning under uncertainty have been put forth as general theories. They have not been designed for use in complex reasoning systems that might be dominated by limitations in computational and engineering resources. An interesting and potentially fruitful area for investigation is the development of strategies for modifying formal methodologies to perform under specified constraints. The process of simplifying reasoning resource limitations followed by an attempt to refine the methodology after the initial iteration has demonstrated that the problem world with limited resources perform better constrained environments could be more useful than the outright dismissal of the theories. Such techniques could allow an engineer to gracefully degrade a system's performance to reflect diminishing amounts of available engineering or computational resources.

Theories of belief revision and information acquisition have not traditionally been accompanied by tools that allow a well-defined relaxation of requirements. It would be productive to develop such methodologies to generalize the conditions under which reasoning is possible. Theories of belief revision and the formation of a recommendation and computation time. Useful approaches to graceful degradation of various aspects of reasoning behavior would make the disagreements, which properties of general parameters, etc. The developments of strategies for the controlled degradation of reasoning would allow artificial intelligence researchers in continue to build upon the theoretical achievements of more mature disciplines.

We will now turn to an example of the degradation of expert system performance to justify constraints on the complexity of inference. As we shall see, degrading an optimal reasoning methodology can serve to enhance the explanation capability in an expert system.

6. EXPLAINING COMPLEX REASONING

I would like to demonstrate an example of the decomposition of a complex reasoning methodology. I hope that it may serve as an example of a category of situations that can help investigators successfully apply sophisticated models. First I will present an information-optimizing reasoning strategy that makes inferences that are difficult to explain. I will then describe how a less efficient but more explainable strategy could be generated.

6.1 The Complexity of Reasoning Under Uncertainty

We have proposed [19] that a central aspect of the difficulty that investigators have in explaining expert system recommendations is based on the intrinsic complexity of formal reasoning under uncertainty. As often noted, a fundamental difference between simple deduction and more general reasoning under uncertainty is the inference complexity: within a deductive system, any particular path in a conclusion is considered to be a sufficient proof; in contrast, reasoning under uncertainty usually entails the consideration of all paths [23]. Formal theories of belief revision and information acquisition generally involve the parallel consideration of a greater number of propositions than simple logical deduction problems. For example, probabilistic reasoning systems calculate the values of single conditional probabilities to summarize many steps of inference. This complex normalization process, so central in probabilistic inference, has been seen as a problem in expert system understandability [1].

What is the fundamental basis for problems with complexity? Cognitive psychology results can lend insight to this question. Problems associated with the comprehension of complex problems such as the operation of complex reasoning strategies have been a long-standing research focus within cognitive psychology [2]. Classic research in this field has demonstrated severe limitations in the ability of humans to consider more than a handful of concepts in the short term [21]. In fact, studies [34] have discovered that humans cannot recall and reason about more than two concepts in an environment with distractions. Such results underscore the need for managing the complexity of expert systems inference.

For humans to successfully understand, plan, prove, and design in environments that are informationally complex, they must devise schemes for decomposing large unwieldy problems into smaller, isolated sub-problems. I will present a scheme for decomposing a complex problem through the decomposition of complex formal reasoning. Before presenting the work, I must first describe the hypothesis-driven architecture called PATHFINDER.

7. THE PATHFINDER PROJECT

PATHFINDER [17] is a hypothesis-driven expert system for the diagnosis of lymph node pathology, based upon the appearance of microscopic features. It is a computerized disease classification system. It uses the principle of a cohort system to construct a patient's disease. It is the assignment of a value to a feature constitutes a piece of evidence. The PATHFINDER system reasons about 80 diseases, considering over 500 pieces of evidence.

7.1 The Hypothetico-Deductive Architecture

The PATHFINDER system is based on a hypothetico- deductive architecture. The hypothetico-deductive method (also referred to as the method of sequential diagnosis) [13] has been adopted in several expert systems research projects, including the Acute Renal Failure [15] expert, the INTERNIST-1 [25] expert for diagnosing patients with a variety of internal medicine, and the MEDIC [1] system for emergency medicine.

Hypothetico-deductive systems are presented with an initial set of evidence. The initial evidence is used to
assign a probabilistic or quasi-probabilistic score to each hypothesis and a list of plausible hypotheses is formulated from the scores. Then, questions are selected which can help decrease the number of hypotheses under consideration. After a user requests to receive new information, a new set of hypotheses is formulated and the entire process is repeated until a single diagnosis is reached.

The question selection strategies are termed hypothesis-directed in that reasoning strategies operate on the current list of hypotheses under consideration to generate recommendations for additional evidence gathering. Investigators in the INTERNIST I and PATHFINDER research groups have explored the usefulness of tailoring different reasoning strategies to the current list of diseases under consideration of differential diagnosis. For example, the strategy selected to narrow the differential diagnosis may depend upon the number of diseases in the differential, the probability distribution over the differential, or both.

The service generated by hypothesis-directed strategies is often difficult to explain because of the complexity of their operation. This is especially true if recommendations are the result of inferences based on a large hypothesis list. Hypothesis-directed strategies may consider the necessity of hundreds of hypotheses in a single inference step.

The scoring scheme employed by PATHFINDER is based upon the theory of subjective probability [9]. The subjective probabilities of experts are used to infer the probability that each disease is responsible for the evidence that has been entered into the system. Depending on the number and the distribution of probabilities among diseases on the differential diagnosis, PATHFINDER chooses one of several alternative diagnostic strategies for selecting questions. As in other hypothesis-directed systems, it is the goal of the question selection strategies to weight the optimal test to be evaluated next in an effort to reduce the uncertainty in the differential diagnosis.

Several PATHFINDER strategies discriminate among large numbers of diseases and features in the generation of scores. I shall not describe all of the hypothesis-directed reasoning strategies used by PATHFINDER. Rather, we will look at issues surrounding the explanation of a particular PATHFINDER hypothesis-directed reasoning strategy—entrapment-discriminate and its descendant, group-discriminate.

7.2 A Strategy to Minimize Uncertainty

The PATHFINDER entrapment-discriminate reasoning strategy is one of several used to refine the differential diagnosis list ranging from two to eighty diseases. The strategy is based on recommendations about information acquisition by searching for tests that maximize a measure of information contained in the differential diagnosis. Similar information-maximizing strategies have been examined in the MEDAIDS and the AnrA reasoning system.

Entrapment-discriminate makes use of a measure of information known as relative-entropy. In this context, relative entropy is a measure of the additional information provided by a piece of evidence E, about a differential diagnosis D. Formally, $H(D, E) = \sum_{D_i} p(D_i|E) \log \left( \frac{p(D_i|E)}{p(D_i)} \right)$, where $p(D_i|E)$ is the probability that disease $D_i$ is present before evidence $E$ is known, the prior probability of the disease, and $p(D_i)$ is the probability that disease $D_i$ is present, known, the posterior probability of the disease. For a justification of relative entropy as a measure of information gain, see [29].

As each feature consists of a set of mutually exclusive and exhaustive values, we can denote the possible evidence associated with a particular feature $F$, as $E_1, E_2, \ldots, E_n$, where $n$ is the number of mutually exclusive values associated with the feature. Entrapment-discriminate selects features which give the highest expected relative entropy

$\Delta(D, F_i) = \sum_{E_j} p(E_j|F_i) H(D|E_j)$,

where the quantity is summed over feature values $E_1, E_2, \ldots, E_n$ and $p(E_j)$ is calculated using the expansion rule

$p(E_j) = \sum_j p(F_i, E_j) p(F_i)$.

In an information-theoretic sense, the questions selected by the entrapment-discriminate strategy are optimal quantifying that the goal of the pathologist is to reduce uncertainty in the differential as much as possible.

7.3 Problems With the Optimal Strategy

Soon after the implementation of entrapment-discriminate mode, we discovered that several expert pathologists, including the expert that provided the system knowledge, often found that selected questions were difficult to understand when the differential contained more than approximately ten diseases. The entrapment-discriminate strategy of selecting questions that have discriminate among all diseases on a differential diagnosis often seemed to be too complex for experts. This is not surprising in light of the limitations of human short term memory discussed above.

We also had problems explaining the recommendations of entrapment-discriminate whenever there were more than two diseases on the differential. Attempts were made to provide textual and graphical explanations for the powerful strategy's recommendations. One such graphical explanation, justified questions by listing, for each disease, the feature value which would favor that disease. Physicians found such complex explanations to be difficult to understand.

7.4 The Graceful Decomposition of Diagnostic Problem Solving

The observed problems with the entrapment-discriminate strategy stimulated our interest in strategies for simplifying and explaining, hypothesis-directed reasoning. We discovered that pathologists often merge the complexity of the diagnostic problem-solving task by reasoning about a very small number of disease categories or groups at any one time. Questions that discriminate among natural groups, rather than between disease categories, may be more easily understood.

Specifically, the clinical expert pathologists on the PATHFINDER team often impose a single group-discriminate strategy for the problem-solving task. As opposed to a strategy of discriminating among all the diseases on the differential, the pathologist's discrimination task at any point in reasoning about a case is confined to only two groups of diseases. As categories of diseases are ruled out, the particular pairs of groups considered become increasingly specific. For example, if there are benign and malignant diseases on a differential diagnosis, the pathologist expert often deems inappropriate the questions that best discriminate between the benign and malignant groups rather than questions that might best discriminate among all of the diseases. If all benign diseases have been ruled out, leaving only primary malignancies and metastatic diseases on the differential diagnosis, the pathologist will attempt to discriminate between the primary malignancy and the metastatic categories.

We found that the expert's diagnostic strategy can be described by the traversal of a hierarchy of disease categories. The problem-solving hierarchy (see Fig. 1) is a binary tree of disease groups. The hierarchy can be used to
group the differential diagnosis at various levels of refinement.

It is interesting to note that several previous studies of medical reasoning have identified similar problem-solving hierarchies [10, 11, 12] for managing the complexity of a wide variety of reasoning tasks.

The discovery of this expert reasoning strategy in lymph node pathology suggested the development of a new question-answering strategy that could discriminate among binary groups of diseases instead of individual diseases. It was hoped that design and application of such a strategy would make explanation clear; at the user would only have to consider the reference of a recommendation to a group.

Our attempt to naturally constrain the discriminatory focus of the entry-group-discrimination strategy led to a new reasoning strategy we named group-discrimination. The group-discrimination strategy selects questions based on their ability to discriminate between the most specific pair of disease categories that accounts for all diagnoses in the differential.

For a given differential diagnosis, group-discrimination identifies the most specific grouping possible and then asks questions that best discriminate among groups of diseases. More formally, suppose the differential is split

\text{Figure 1: Heuristic problem-solving hierarchy}


\text{into two groups, } G_A \text{ and } G_B \text{ of } n_1 \text{ and } n_2 \text{ diseases respectively:}

\begin{align*}
G_A &= \{G_{A1}, G_{A2}, \ldots, G_{Am}\} \\
G_B &= \{G_{B1}, G_{B2}, \ldots, G_{Bn}\}.
\end{align*}

As we assume that only one lymph node disease is present in PATHFINDER, we can consider the diseases in mutually exclusive events. We are interested in the probability that the true diagnosis will be in each group. To calculate this probability we add the probabilities of all the diseases within each group. That is, the probability that a group contains the true diagnosis is

\begin{align*}
P(G_j) &= P(G_{Aj}) + P(G_{Bj}) \quad j = 1, 2.
\end{align*}

We can also calculate \(P(G_j|E_i)\), the probability of the final diagnoses being contained in a group, considering a new piece of evidence \(E_i\). This is

\begin{align*}
P(G_j|E_i) &= \frac{P(G_{Aj}|E_i)P(E_i)}{\sum_{k=1}^{2} P(G_{Ak}|E_i)P(E_i)} \quad j = 1 \text{ or } 2.
\end{align*}

Therefore, the relative entropy of the grouped differential can be defined. In particular,

\begin{align*}
H_G[\{E_i\}] &= \sum_{j=1}^{2} P(G_j|E_i) \log_2 P(G_j|E_i)/P(G_j).
\end{align*}

This quantity represents the additional information contained in \(E_i\) about the grouped differential diagnosis.

Group-discrimination selects those features which give the highest expected relative entropy.

Notice that the group-discrimination strategy ignores information concerning the probability of diseases within each group. Only the probabilities that the diagnoses fit within a group is considered in the calculations.

\section{Discussion}

We integrated the group-discrimination strategy into the PATHFINDER system so that it continues to refine differential diagnoses until all diseases remaining on the differential diagnoses are in a category at one of the leaves of the binary problem-solving tree. At this point, other hypothesis-directed strategies are applied to quintessence pursuing a diagnosis. As the group-discrimination reasoning strategy has a simple discriminatory focus and most closely follows the decision making process of the expert lymph node pathologist rather than entry-discrimination, it is quite easy to explain.

Instead of trying to present complex summaries explaining how each piece of evidence might impact on belief in the presence of a number of diagnoses, an explanation of questions generated by group-discrimination most simply demonstrates how possible responses effect the two groups under consideration.

The PATHFINDER system justifies the usefulness of questions selected by group-discrimination with a graphical display. Fig. 2 presents a small portion of a PATHFINDER construction. At the top of the figure is the differential diagnosis, grouped into benign and malignant categories (at the current level of refinement). Below, several lymph node features recommended by group-discrimination are listed. The group-discriminative strategy has determined that these features can best discriminate between the benign and malignant diseases. In this case, the user requested explanation for the selected feature recommendation.

The positions of a set of interlinks in the justification graph at the bottom of the display and the degree to which each group of diseases is favored by each possible feature value. Specifically, the position of an interlink is a function of the likelihood ratio \(p(B|C)/p(E|C)\). In the example, the values favored for an apoplytically strong support diagnosis on the differential diagnosis that are in the benign group, while the values hold-to-back and closely packed strongly support the malignant disease hypothesis.

A user can easily ascertain how a question discriminates between two groups of diseases. Evidence that is obtained to support a diagnosis for one group or the other. Even in an environment filled with distinctions, the behavior of the strategy is adequately explained by such simple graphs.

Unfortunately, the more explainable group reasoning strategy has some disadvantages. A predictable problem with the use of group-discrimination is that if the differential diagnoses refinement process does not always proceed as quickly as it does with the application of the optimal entry-discriminative. That is, group-discrimination is not as efficient as the more powerful entry-discriminative. On average, a larger number of test-result-gathering requests will be made by group-discriminative to achieve a similarly refined differential diagnosis. This must be the case is
I believe that continued research on the pragmatics of applying formal models in the face of severe limitations in data and computation, as well as the ability of system users to be beneficial. The development and refinement of methodologies for the controlled degradation of reasoning will allow artificial intelligence researchers to build upon the genuine achievements of other disciplines.

Acknowledgements

I am indebted to David Heckerman for many productive conversations. Mr. Heckerman has been an insightful reader of the PATHFINDER Project. I thank Moshe Ben-Bassat, Lawrence Fagen, Ben Gross, Ted Shortliffe and Peter Sutorovs for interesting discussions. I am grateful to Sharmi Nakwani and Costa Serard for sharing with me their thoughts on problem solving in psychology. This work was supported in part by the John Macy, Jr. Foundation, the Henry J. Kaiser Family Foundation, the Ford Aerospace Corporation, and the SUMEX-ALM Research under NII Grant RR-0073.

References


