Update on the Pathfinder Project

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ABSTRACT

We review highlights of our research on Pathfinder, a decision-theoretic expert system for hematopathology diagnosis. We have developed techniques for efficiently acquiring, representing, and reasoning with uncertain biomedical knowledge. Specifically, we have developed a methodology for coping with complex dependencies among findings and disease in pathology. The methodology includes an extension of the belief-network representation called similarity networks. Using this methodology, we have constructed a large probabilistic knowledge base for the domain of lymph-node pathology. We have also developed techniques for improving the clarity of explanations through the use of human-oriented abstractions. Finally, we have conducted a formal evaluation of Pathfinder's diagnostic accuracy.

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Introduction

For over 5 years, investigators on the Pathfinder research team have worked to develop decision-theoretic techniques for reasoning under uncertainty when making diagnoses in tissue pathology. Our initial goal was to produce an expert system that reasons efficiently and accurately about lymph-node diseases [6]. In our pursuit, we encountered challenging problems with acquiring, representing, and reasoning with knowledge about the dependencies among the histologic features. We also discovered problems with the explanation of decision-theoretic inference. Our research evolved to its current focus on the development of techniques for the construction of an effective expert system based on the principles of probability and utility theory.

The construction of expressive probability-based expert systems is an important problem for medical informatics research. Experience with several probabilistic reasoning systems that were constructed over 2 decades ago led to diminished interest in such a normative approach to computational decision support [2]. Chief problems cited with the probabilistic and decision-theoretic approaches were the complexities of building, representing, and manipulating normative knowledge bases. In addition to intractability, critics of the normative reasoning in expert systems have cited limited expressiveness of normative representations, dwelling on the apparent chasm between the quantitative approach of probabilistic inference and the informal, qualitative nature of human reasoning[1]. Problems with the tractability of applying probability and utility theory have been a primary motivation for the development of ad hoc and quasiprobabilistic schemes.

We have worked to make normative expert systems tractable and expressive. In addition to our research involving refinement of a large probability-based knowledge base and the development of tractable reasoning strategies, the Pathfinder team has developed and tested capabilities for question justification, user customization, efficient knowledge base modification, and system evaluation.

Pathfinder Problem Area

Our work is motivated by problems identified with the diagnosis of lymph-node diseases from morphologic features and from clinical, immunonology, molecular biology, and cell-kinetics information. A computer-based expert system could diffuse useful expert knowledge and experience to the practicing pathologist, and could help to narrow the wide gap in quality between diagnosis performed at community hospitals and that done by experts. The diagnosis of lymph-node biopsies is one of the most difficult areas of surgical pathology. For epidemiologic, therapeutic, and prognostic reasons, it is important that a precise classification be established so that the patient receives the most appropriate treatment. Most malignant lymphomas have a distinctive natural history and characteristic responses to therapy. The malignant diseases of the lymph nodes have to be distinguished from approximately 30 different benign diseases, many of which closely simulate malignant lymphomas. The complexity in the hematopathology field has caused major problems in the diagnosis of lymph-node diseases.

Reasoning Architecture

The computational architecture of the Pathfinder system is based on the method of *sequential diagnosis* [2]. After a user enters salient features, a list of plausible disease hypotheses, or a differential diagnosis is formulated based on these manifestations. Next, questions are selected that, if answered, can help to reduce the number of diseases under consideration. After the user answers these questions, a new set of hypotheses is formulated and the process is repeated until the user is satisfied that diagnosis is reached. The method of sequential diagnosis is *hypothesis-directed* in that the next best actions—the recommendations made by the system—are selected by strategies, or *modes*, that consider the current list of hypotheses. The method of sequential diagnosis is an advancement on older probability-based programs that require that all relevant findings be available before they make a diagnosis. The current system reasons about approximately 60 malignant and benign diseases of lymph nodes, constructing plausible differential diagnoses through the consideration of evidence about the status of about 100 morphologic and nonmorphologic features presenting in lymph-node tissue. In Pathfinder, *features* are each structured into a set of 2 to 10 mutually exclusive and exhaustive *values*. These values typically represent the degree of severity of a particular feature (e.g., necrosis may be absent, present, or prominent).

Implementation History

Several implementations of Pathfinder have been developed. The earliest version of the system was written in the Maclisp language on the SUMEX-AIM National Resource DEC-2060. Later, the program was translated into the Portable Standard Lisp (PSL) language, and was moved to the Hewlett-Packard 9836 LISP workstation. Last year, we reimplemented the program in MPW Object Pascal on the Macintosh II. Much of the recent testing and refinement of the knowledge base has been carried out within the Macintosh II environment. A knowledge-acquisition program, called SimNet, was implemented in the same system. SimNet was designed to operate as a parallel application, enabling an engineer to cycle easily between knowledge-base tuning and expert-system testing.

Development of the Knowledge Base

Work in the representation of knowledge was undertaken in several areas: (1) the identification of a set of consensus features and diseases, (2) the acquisition of probabilistic dependencies among features and diseases, and (3) the development of a new representation called similarity networks.

Construction of a Consensus Diagnostic Model

A crucial step in the construction of the current system was developing a consensus about the structure of the knowledge base—that is, about the diseases, features, and feature values that Pathfinder should consider as the fundamental dimensions of the uncertain reasoning problem. We held several meetings where four experts in the field of lymph-node pathology

(Drs. Bharat Nathwani, Jerome Burke, Costan Berard, and Ronald Dorfman) communicated and agreed on the basic attributes of the knowledge base.

Representation of Probabilistic Dependencies

The phrase "knowledge-acquisition bottleneck" has been used frequently among researchers in medical informatics and in artificial intelligence to express frustration about the difficult process of encoding knowledge. Indeed, the acquisition of knowledge has been considered the limiting reagent in the construction of genuinely useful computer aids. This has been especially true in the case of probability-based reasoning systems.

Two difficulties have provided major challenges to the construction of normative expert systems in medicine: (1) more than one disease may be present at one time, and (2) features are probabilistically dependent on one another, even when the diseases affecting a patient are known with certainty. To date, almost all probability-based knowledge bases have assumed that diseases are mutually exclusive and that all features are independent, given disease. In Pathfinder, the assumption that diseases are mutually exclusive is appropriate, because co-occurring diseases almost always appear in different lymph nodes or in different regions of the same lymph node. Also, the large scope of Pathfinder makes reasonable the assumption that the set of diseases is exhaustive. The assumption of global conditional independence, however, is highly inaccurate. Given certain diseases, for example, finding that follicles are abundant in the tissue section increases greatly the chances that sinuses in the interfollicular areas will be partially or completely destroyed. Thus, Pathfinder has provided an excellent testbed to study, in isolation, one of the central difficulties in knowledge acquisition for normative systems.

We have addressed the problem of probabilistic dependencies with a promising representation, developed in the decision science community, called *belief networks* [9]. Although belief networks have been used as an alternative to decision trees for doing single analyses, their use in expert systems has been relatively rare. We have used belief networks because of the representation's soundness and expressiveness.

Belief Networks for Building Large Knowledge Bases. A belief network is a graphical knowledge-representation language that represents probabilistic dependencies among propositions and events. The representation rigorously describes probabilistic relationships, yet has a human-oriented qualitative structure that facilitates knowledge acquisition and communication. The representation is an acyclic directed graph containing nodes representing uncertain variables, and arcs representing dependencies among the variables. Missing arcs in a belief network express assertions of conditional independence.

Figure 1 shows a portion of the belief network for Pathfinder that models the task of distinguishing among the subtypes of Hodgkin's diseases and several diseases that resemble Hodgkin's disease. The disease node represents the mutually exclusive set of possible diseases. Arcs from the disease node to nodes representing features reflect the expert's belief that the probability of observing a particular value for each feature depends on the disease that is present. The arcs among feature nodes represent dependencies among the features. For example, the arcs from Non-sin non-foll (nonsinus, nonfollicular areas) and F number (number of follicles) to Sinuses reflects the expert's belief that the probability of seeing intact or obliterated sinuses depends on the status of the nonsinus, nonfollicular areas and on the

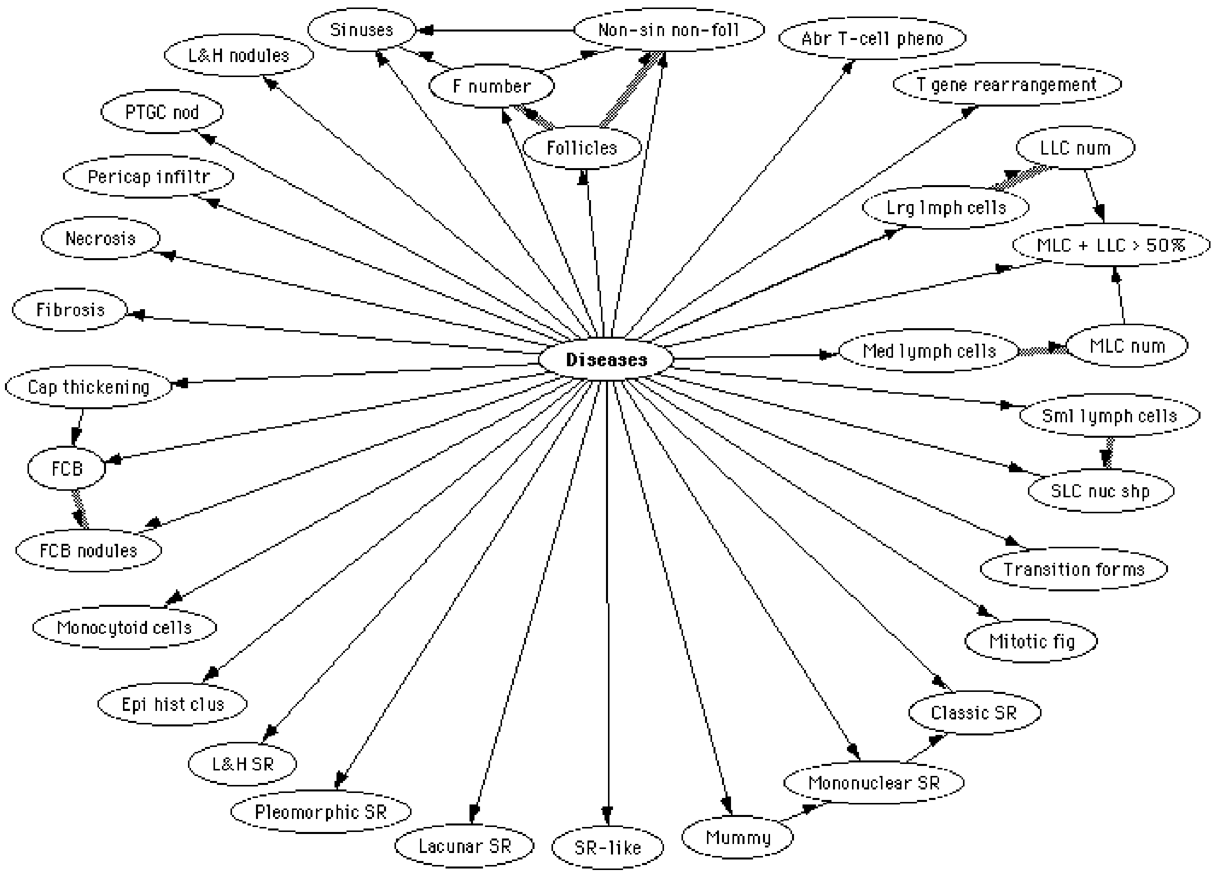

Figure 1: A portion of the Pathfinder belief network. The arcs from the disease node (center) to the features represents the influence of the disease state on the appearance of the features. The arcs among the features indicates probabilistic dependency among features. The wider arcs capture the concept of irrelevancy.

number of follicles, in addition being influenced by the disease that is present. The lack of arcs pointing to Necrosis, for example, expresses the expert's assertion that the probability of seeing necrosis is independent of all other features, given disease.

Enriching the Belief-Network Language. Although the use of belief networks has aided somewhat the knowledge-acquisition task, the lymph-node expert could not construct a complete belief network for Pathfinder directly. Several steps were taken to increase the expressiveness of the belief-network representation so that a belief network for the domain could be constructed. First, several *prototypical classes* or commonly occurring classes of dependence among features and diagnostic hypotheses were identified. For example, pathologists often wish to express their knowledge that a value of one feature can render one or more features irrelevant to diagnosis. A new *irrelevancy arc* was developed for the representation of this dependency [3]. Several of these arcs (thick lines) are pictured in Figure 1. The arc from the node Sml lymph cells to SLC nuclear shape, for example, tells us that the nuclear shape of small lymph cells is irrelevant, or is "not applicable," when small lymph cells are absent.

Another type of prototypical dependency is the *mass effect* [3], which arises from the competition for limited space within a given organ. This effect often is important in describing the probabilistic relationships among populations of cells that present in histologic analysis. For example, in lymph-node pathology, different pathological processes compete for limited volume in the lymph node. The dominance of one proliferating cell assembly (e.g., follicles, sinuses, or nonsinus, nonfollicular areas) or cell type (e.g., small, medium, or large lymphoid cells) within a structure of the lymph node tends to diminish the likelihood that other pathologic cell assemblies or cell types will be seen. The identification of the mass effect and of other common patterns of dependence was useful in developing a vocabulary that enhanced communication among experts and knowledge engineers and alerted both groups to the possible presence of dependencies among different sets of features.

Similarity Networks for Focusing Attention. In addition to creating a richer vocabulary for expressing dependencies, a new representation was developed, called *similarity networks*, that enables an expert to decompose a large belief-network problem into well-defined and manageable belief-network subproblems [3, 5].

A similarity network consists of a similarity graph and a collection of local belief networks. A *similarity graph* is an undirected graph whose nodes represent mutually exclusive diseases, and whose arcs connect diseases that an expert considers to be similar or difficult to discriminate in practice. Figure 2 shows a portion of the similarity graph for Pathfinder that involves the subtypes of Hodgkin's disease and the diseases that closely resemble Hodgkin's disease. The arc between Interfollicular HD (interfollicular Hodgkin's disease) and Mixed cellularity HD (mixed-cellularity Hodgkin's disease), for example, reflects the expert's opinion that these two diseases are often mistaken for each other in practice.

Associated with each arc in a similarity network is a *local belief network*. The local belief network for an arc is a belief network that contains only those features that are relevant to the differential diagnosis of the two diseases that are connected by that arc. The local belief networks are typically small, because the disease pairs for which they are constructed are similar. For example, associated with the arc between Mixed cellularity HD and Interfollicular HD, in Figure 2, is the network shown in Figure 3. The local belief network contains the features F number, Sinuses, and Non-sin Non-foll. Only these features are relevant to the differential diagnosis of mixed-cellularity and interfollicular Hodgkin's disease.

The SimNet program can combine the local belief networks associated in a similarity network program to form a *global belief network*. A portion of the global belief network for Pathfinder, constructed from a similarity network for lymph-node disease, was shown in Figure 1. It has been demonstrated that, provided the similarity network is completely connected and several other technical conditions are met, the global belief network constructed from a similarity network is a valid belief network for the entire domain [5]. Thus, the similarity-network representation greatly facilitates the construction of large belief networks. A similarity network allows an expert to decompose the task of building a large belief network into modular and relatively small subtasks. Using a similarity network, an expert can focus his attention on small dependency problems for actual clinical dilemmas. In the case of lymph-node pathology, the expert could not construct the global belief network without the aid of the similarity-network representation.

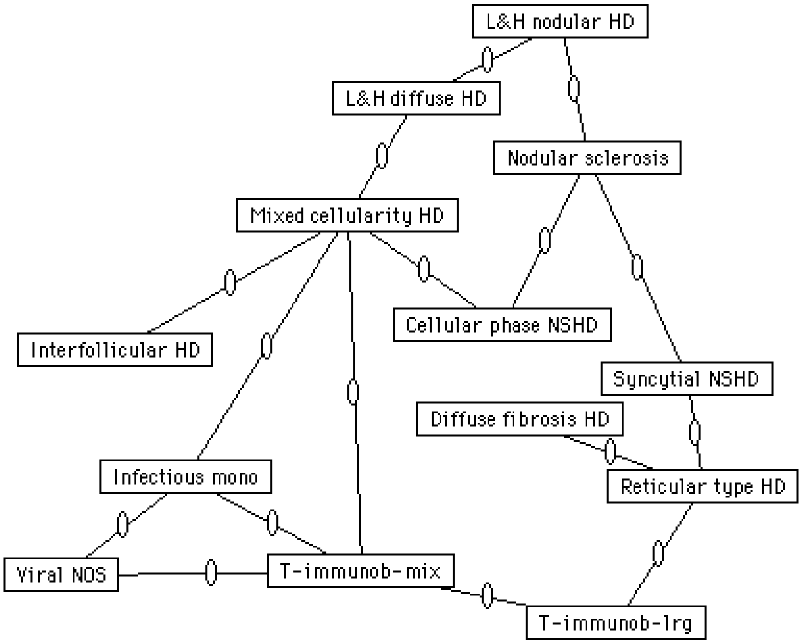

Figure 2: A portion of the similarity graph for Pathfinder. (HD = Hodgkin's disease; NSHD = nodular-sclerosing Hodgkin's disease.)

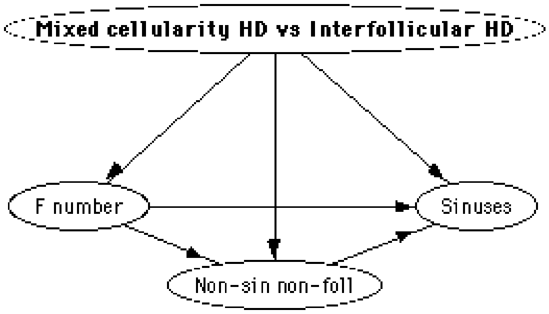

Figure 3: The local belief network that captures the problem of differentiating mixed-cellularity Hodgkin's disease from interfollicular Hodgkin's disease. (F number = follicles number; Non-sin non-foll = nonsinus, nonfollicular areas.)

Several important features of the similarity-network representation are discussed in [5]. For example, similarity networks can be extended to include local belief networks for sets of hypotheses that contain two or more elements. Essentially, we need only to replace the similarity graph with a similarity hypergraph. (A hypergraph consists of nodes and edges among node sets of arbitrary size.) The representation also can be used in situations where diseases are not mutually exclusive. In addition, an expert can use the representation to simplify the assessment of probabilities associated with the global belief network.

A Graphical Knowledge-Acquisition Tool. A crucial step in the development of the completed probabilistic-dependency model for the lymph-node system was the construction of a computer-based knowledge acquisition tool, called SimNet, based on the similarity network representation [3, 5]. All the figures of belief networks and similarity networks shown in this paper were acquired with SimNet. The tool allows similarity networks to be constructed and edited on large bit-mapped displays. In practice, an expert first uses the system to create a similarity graph. The expert then selects an arc of interest, and the program automatically sets up a belief-network template (containing only the disease node) from which the expert can construct the local belief network. As the belief networks are created by the expert, the global belief network is automatically constructed. An expert can then use SimNet to assess the probabilities associated with the global belief network.

The Worth-Numeraire Utility Model

Early versions of Pathfinder used information theory to select the features that are useful for evaluation [6]. That is, only the informational content of alternative unevaluated features was used to generate a recommendation for further observations. In this approach, all diseases are assumed to be equally serious and all questions and tests are considered to be equally expensive to evaluate. In the lymph-node domain, however, this assumption is highly inaccurate. For example, if a patient has a viral infection and is incorrectly diagnosed as having cat-scratch disease—a disease caused by an organism that is killed with antibiotics—the consequences are not severe. In fact, the only nonnegligible consequence is that the patient will take antibiotics unnecessarily for several weeks. If, however, a patient has Hodgkin's disease and is incorrectly diagnosed as having an insignificant benign disease such as a viral infection, the consequences are often lethal. If the diagnosis had been made correctly, the patient would have immediately undergone radio- and chemotherapy, with a 90-percent chance of a cure. If the disease is diagnosed incorrectly, however, and thus is not treated, it will progress. By the time major symptoms of the disease appear and the patient once again seeks help, the cure rate with appropriate treatment may have dropped to less than 20 percent.

To avoid such inappropriate assumptions, we extended Pathfinder by constructing a utility model for the lymph-node domain. We asked the lymph-node expert to assess the significance of each possible misdiagnosis separately. Specificially, for each combination of d_i and d_j, we asked him, "How undesirable is the situation in which you have disease d_i and are diagnosed as having disease d_j?" The expert served as the source of the utilities becuase of his familiarity with the diseases and treatments in the domain.

The most difficult part of creating the utility model was developing a unit of preference that could be used to measure the disutilities associated with both major and minor misdiagnoses. A version of Howard's *worth-numeraire* model [8] provided a solution to this problem. In this model, disutilities associated with major misdiagnoses are measured in terms of life-and-death gambles, whereas disutilities associated with minor diagnoses are measured in terms of dollars. To measure the disutility of a major misdiagnosis, for examnple, we asked the expert to imagine that he had—say—Hodgkin's disease, and was misdiagnosed as having mononucleosis. We then asked him to imagine that there was a magic pill that would rid him of this disease with probability $1 - p$, but would kill him, immediately and painlessly, with probability p. The expert then provided the value of p that made him indifferent between his current situation and taking the pill. To measure the disutility of a minor misdiagnosis—say, cat-scratch disease for viral lymphadenitis—we simply asked the expert how much he would be willing to pay to be cured if he were in such a situation.

The worth-numeraire model of Howard provides a means to convert disutilities expressed in monetary terms to small chances of immediate, painless death. The lymph-node expert, for example, had a conversion rate of $20 per micromort. A *micromort* is a one–in–one-million chance of immediate, painless death. The conversion makes possible the direct comparision of disutilities for minor and major misdiagnoses.

Integration of Heuristic Abstraction

Our early work uncovered a set of inference-related issues that we attributed to constraints on human cognitive resource constraints and preferences [6, 7]. In particular, while building and testing the Pathfinder expert system for diagnosis in anatomic pathology, we found that straightforward applications of decision-theoretic inference could lead to computer problem-solving behavior viewed as confusing or counterintuitive by users. Early, less-flexible versions of Pathfinder worked solely on the finest distinctions available in the system's representation. We found that users tended to work at higher levels of abstraction than did our straightforward decision-theoretic approach. Users also preferred to make specific transitions from one subproblem to another.

Knowledge acquisition with several pathologists unearthed alternative problem-solving hierarchies that were often used to segment a single complex diagnostic reasoning task (from the perspective of the decision-theoretic system) into a set of tasks at increasingly detailed levels of abstraction. These human-oriented abstraction strategies allow a pathologist to reason about groups of similar diseases, rather than to consider each disease as a separate entity. We have worked to acquire and apply alternative control strategies from trainees and experts. We enhanced the Pathfinder system so that a user could probe a differential diagnosis from alternative perspectives. The current system allows a user to select dynamically alternative strategies for grouping the current differential diagnosis.

Evaluation of Pathfinder

Recently, the diagnositc accuracy of the current version of Pathfinder, in which probabilistic dependencies are represented, was compared to that of an earlier version of the program, in which all features are assumed to be conditionally independent [5]. In the evaluation study, 53 cases were were selected in sequence from a large library of referrals. For each case, a community pathologist reported salient morphologic features to both versions of Pathfinder. Often, the pathologist reported additional features (to both systems) that were recommended for evaluation by one or both systems. She entered geatures until she was satisfied that at least one of the programs had reached a diagnosis. We guaged the diagnostic accuracy of the probability distributions produced by Pathfinder by assigning it a score based on two metrics: an expert-rating metric, and a formal decision-theoretic metric. The two approaches were complimentary in their ability to identify components of the system that affected diagnostic accuracy [4].

Expert-Rating Approach

In the expert-rating approach, the domain expert was asked to rate directly, on a subjective scale, the quality of probability distributions produced by each version of Pathfinder. For each case, he was shown the list of features reported by the nonexpert and the distributions produced by the two programs. He was then asked, "On a scale from zero to ten—zero being totally unacceptable and ten being perfect—how accurately does each distribution reflect your beliefs?" The 0-to-10 scale provided an informal measure of the difference between the diagnostic accuarcy of the two probabilistic models.

The expert-rating evaluation metric is useful because it is easy to apply and readily exposes differences between probability distributions. Unfortunately, inferring the *importance* of differences with this metric is difficult. It is impossible to deduce from the expert-rating method, for example, whether or not additional effort to improve diagnositic accuarcy would be cost-effective.

Decision-Theoretic Approach

We used the utility model described previously to evaluate the significance of differences in the probability distributions produced by the two versions of Pathfinder. In this approach, the observations of the community pathologist for a particular case are presented to the expert, who provides a probability distribution over the diseases. This distribution is called the *gold-standard* distribution. The expert is not allowed to examine the case microscopically, because his ability to recognize features is superior to that of the community pathologist. Given the gold-standard distribution for a case, a score for the distribution produced by the sophisticated probability model is determined. First, the utility model is used in conjunction with the gold-standard distribution to determine the optimal diagnosis, called the *gold-standard diagnosis*. Similarly, the utility model is used in conjunction with the distribution produced by the sophisticated model to determine the optimal diagnosis under the assumption that this distribution is correct. Next, the expected utility of each of the two diagnoses is computed with respect to the gold-standard distribution. The score for the distribution produced by the sophisticated probability model is just the expected utility of the gold-standard diagnosis minus the expected utility of the diagnosis infered from the probability model. A distribution achieves a perfect score of 0 whenever the optimal diagnosis inferred from the model is the same as the optimal diagnosis inferred by the gold

	Expert-rating scores	
	mean	sd
Independence KB	7.99	2.32
Dependency KB	8.94	1.51

Table 1: Expert-rating scores comparing the diagnostic accuarcy of the conditional-independence knowledge base (Independence KB) with that of the knowledge base containing dependency information (Dependency KB).

	Decision-theoretic scores (micromorts)	
	mean	sd
Independence KB	340	1684
Dependency KB	16	104

Table 2: Decision-theoretic scores comparing the diagnostic accuracy of the conditional-independence knowledge base (Independence KB) with that of the knowledge-base containing dependency information (Dependency KB).

standard. Similarly, a score for the simple probability model is determined. To compare the two probability models, we simply compare the avearage score of each model across all cases.

Results of the Evaluation

The expert-rating and decision-theoretic scores for the two versions of Pathfinder are shown in Tables 1 and 2, respectively. Although the standard deviations are wide, both metrics show a significant difference using a bootstrap permutation test (achieved significance level (ASL) = 0.007 for the expert-rating scores, and ASL = 0.07 for the decision-theoretic scores). The difference of 0.95 between the means of the expert-rating scores does not carry much meaning. However, the difference of approximately 300 micromorts between the two approaches as determined by the decision-theoretic metric has a clear interpretation. Assuming that a patient is willing to convert micromorts to dollars at a rate of \$20 per micromort, as our expert was, the results in this metric show that it is worth approximately \$6000 *per case* to the patient to apply the more sophisticated Pathfinder knowledge instead of the earlier knowledge base that assumed global independence among features.

Summary and Conclusions

We have described our research on tractable methods for acquiring, representing, and performing inference with decision-theoretic knowledge. We saw that the belief network is a solid foundation for the representation of uncertain knowledge. We discussed several enhancements to the representation that make it an intuitive and tractable representation for large knowledge bases. We addressed the problem of unnatural behavior and opacity of normative inference by introducing human-oriented abstraction to Pathfinder. Finally, we described an expert-rating and decision-theoretic metric for evaluating the diagnostic accuracy of a probabilistic model, and we used these metrics to compare a sophisticated dependency model with a simple model that embodies the assumption of global conditional independence among features.

We have shown that a decision-theoretic representation is sufficiently tractable and expressive to capture the important knowledge in the domain of lymph-node pathology. We hope that this demonstration will inspire other researchers to develop normative expert systems for medicine.

Acknowledgments

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References

[1] G.A. Gorry. Computer-assisted clinical decision making. *Methods of Information in Medicine*, 12:45–51, 1973.

[2] G.A. Gorry and G.O. Barnett. Experience with a model of sequential diagnosis. *Computers and Biomedical Research*, 1:490–507, 1968.

[3] D.E. Heckerman. Formalizing heuristic methods for reasoning with uncertainty. Technical Report KSL-88-07, Medical Computer Science Group, Section on Medical Informatics, Stanford University, Stanford, CA, May 1987.

[4] D.E. Heckerman. An empirical comparison of three scoring schemes. In *Proceedings of Fourth Workshop on Uncertainty in Artificial Intelligence*, pages 158–169, Minneapolis, Minnesota, July 1988. American Association for Artificial Intelligence.

[5] D.E. Heckerman. *Probabilistic Similarity Networks*. PhD thesis, Medical Computer Science Group, Departments of Computer Science and Medicine, Stanford University, 1989. In preparation.

[6] D.E. Heckerman, E.J. Horvitz, and B.N. Nathwani. Pathfinder research directions. Technical Report KSL-89-64, Medical Computer Science Group, Section on Medical Informatics, Stanford University, Stanford, CA, October 1985.

[7] E.J. Horvitz, D.E. Heckerman, B.N. Nathwani, and L.M. Fagan. The use of a heuristic problem-solving hierarchy to facilitate the explanation of hypothesis-directed reasoning. In *Proceedings of Medinfo*, pages 27–31, Washington, D.C., October 1986. Medinfo.

[8] R.A. Howard. On making life and death decisions. In R.A. Howard and J.E. Matheson, editors, *Readings on the Principles and Applications of Decision Analysis*, volume II, chapter 26, pages 483–506. Strategic Decisions Group, Menlo Park, CA, 1980.

[9] R.A. Howard and J.E. Matheson. Influence diagrams. In R.A. Howard and J.E. Matheson, editors, *Readings on the Principles and Applications of Decision Analysis*, volume II, pages 721–762. Strategic Decisions Group, Menlo Park, CA, 1981.