FUNDAMENTALS OF EXPERT SYSTEMS

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1. INTRODUCTION

Expert systems are one of the most exciting applications of computers to emerge in the last decade. They allow a computer program to use expertise to assist in a variety of problems, such as diagnosing equipment failures and designing new equipment. They have built on many years of work in artificial intelligence (AI) on problem solving, and have become a commercially successful demonstration of the power of AI. Correspondingly, by testing current AI methods in applied contexts, expert systems provide important feedback to the science on the strengths and limitations of those methods. In this review, we present the fundamental considerations in constructing an expert system and assess the state of the art. Our discussion focuses on the computer science issues, as opposed to the management or applications issues.

1.1. Characterization and Desiderata

Expert systems are distinguished from conventional programs in several important respects. While no single one of the following characteristics is missing entirely from other well-designed software, all of them together provide a characterization of a distinct class of programs. Suffice it to say that there is not uniform agreement in the literature about any characterization and that few expert systems exhibit all of these characteristics to the same degree. However, the following five characteristics provide a set of desiderata within which we can cluster expert systems.

An expert system is a computer program that:

a) reasons with knowledge that is symbolic as well as mathematical,

b) uses methods that are heuristic (plausible) as well as algorithmic (certain) ,

c) performs as well as specialists in its problem area,

d) makes understandable what it knows and the reasons for its answers,

e) retains flexibility.

An example of an expert system that meets these conditions very well is the Dipmeter Advisor System [Smith & Young 84, Smith 84]. Its task is to assist petroleum engineers determine the "map" of geological strata through which an oil well is being drilled -- e.g., the depth and the dip, or "tilt," of individual layers of sandstone, shale, and other rocks. It meets the above five desiderata in the following respects. (a) The knowledge needed to do this is partly mathematical (e.g., trigonometry), but is largely non-numeric geological knowledge (e.g., knowledge about how sand is deposited around river beds). (b) Its reasoning is based on the same kinds of heuristics that well-logging experts use to interpret data from bore holes. (c) It is an aid to specialists, providing interpretations that are better than those of novices. (d) It uses a variety of graphical and textual displays to make its knowledge understandable and to justify its interpretations. (e) And it is flexible enough to be modified and extended frequently, without rewriting the programs that interpret the knowledge. An example of what the computer screen looks like is shown in Figure 1 below.

<Figure 1 here>

Conditions (a) and (b) above -- symbolic reasoning and heuristic methods -- define expert systems to be artificial intelligence programs, i.e., they use symbolic information and they reason heuristically. Expert systems became an identifiable part of AI in the late 1960's and early 1970's with the realization that applications of AI to science, engineering, and medicine could provide assistance in those disciplines and could, at the same time, uncover additional research problems for AI. In the context of the DENDRAL [Lindsay et al 80] and MACSYMA [Moses 71] programs, computer scientists began to recognize that high performance in a subject area, such as organic chemistry, was more readily achieved by giving a program substantial amounts of subject-specific knowledge than by giving it some general axioms of the subject area plus a very powerful, but general, deductive apparatus. The DENDRAL program represented many specific facts about organic chemistry in a variety of ways and used those facts in rather simple inferences. It represented mass and valence of chemical atoms as values of attributes; it represented classes of unstable chemical compounds as partial graph structures in a table; and it represented some major patterns of fragmentations of molecules in a mass spectrometer as predictive rules. From this work

emerged the first principle of building expert systems, as enunciated by Feigenbaum [Feigenbaum et al 71]:

"In the knowledge lies the power."

Because of this, the concept of a knowledge base has become central in expert systems.

In contrast, most other AI work of the day was concerned with reasoning by general methods such as theorem proving. Researchers were looking for power in a program in its general planning heuristics, for example, as exhibited in problem areas in which knowledge about the objects of the domain was almost irrelevant. A favorite problem area was the so-called "Blocks World" of children's blocks on a table. General knowledge of stability and support, plus general knowledge about planning and constraint satisfaction, was sufficient to allow programs to reason, say, about the sequence of operations needed to stack blocks in a specified order.

Condition (c) separates high performance programs from others. By bringing in human specialists as a standard of comparison, this condition also suggests using the knowledge of specialists to achieve high performance. Pre-defining the scope of problem solving to a narrow "slice" through a domain has become a pragmatically necessary principle of design. As discussed below, bounding the scope of the problem in advance avoids many difficulties associated with building a generally intelligent robot that would behave appropriately in all situations.

Conditions (d) and (e) -- explaining the reasoning and flexibility -- are less frequently cited and are less frequently achieved than (a) - (c). They may be seen as means to the end of achieving high performance but are included here to highlight their importance in designing and implementing any expert system.

Understandability and flexibility are important both while expert systems are being designed and while they are used. During design and implementation, not all the requisite knowledge is in hand, because not even specialists can say precisely what a program needs to know. Thus expert systems are constructed incrementally. An important part of understandability is to use the same terminology that specialists and practitioners use. Understanding the static knowledge base allows one to decide what needs to be added to improve performance. Understanding the dynamics of the reasoning is also important in deciding what to change. Flexibility is thus needed to allow the changes to be made easily. Explanations help designers as well as end-users

understand the reasons for a program's conclusions. This capability is especially important when end-users accept legal, moral, or financial responsibility for actions taken on the program's recommendations.

1.2. Some Examples

There are many expert systems in routine use (see [Rauch-Hindin 86], [Buchanan 86], [Walker and Miller 86], [Harmon & King 85] for lists of examples). Some of the best known, such as XCON and the DIPMETER ADVISOR System, have been used commercially for many years (by Digital and Schlumberger, respectively). The following programs are chosen because they illustrate a variety of problem types and contexts of use. There are roughly two classes of problems addressed in these several systems: (I) problems of interpreting data to analyze a situation, and (II) problems of constructing a solution within specified constraints. Within each category are listed several different examples under general task names that are somewhat descriptive but not necessarily distinct.

Class I: Problems of Interpretation

DATA INTERPRETATION

Schlumberger [DIPMETER ADVISOR] -- interpret down-hole data from oil well bore holes to assist in prospecting [Smith & Young 84]

St.Vincents Hospital (Sydney) -- aid in interpreting diagnostic tests on thyroid function [Horn et al 85]

NL Baroid [MUDMAN] -- determine causes of problems in drilling oil wells and recommend additives to the drilling fluid that will correct them. [Kahn and McDermott 86]

EQUIPMENT DIAGNOSIS

General Motors [VIBRATION]-- determine causes of vibration noises and recommend repairs [Teknowledge 87]

Kodak [BLOW MOLDING INJECTION ADVISOR] -- diagnose faults & suggest repairs for plastic injection molding machines [Teknowledge 87]

AT&T [ACE] -- provide troubleshooting & diagnostic reports on telephone cable problems [Miller et al 84]

General Electric [CATS] -- diagnose problems in diesel-electric locomotives [Sweet 85]

TROUBLESHOOTING PROCESSES

Hewlett Packard -- diagnose causes of problems in photolithography steps of wafer fabrication [Cline et al 85]

Elf Aquitaine Oil Company [DRILLING ADVISOR] -- demonstrate reasoning in finding cause of drill bit sticking in oil well and to correct the problem (used for training) [Rauch-Hindin 86]

MONITORING

IBM [YES/MVS] -- monitor and adjust operation of MVS operating system [Rauch-Hindin 86]

National Aeronautics And Space Administration [LOX] -- monitor data during liquid oxygen tanking process [Kolcum 86]

PREVENTIVE MAINTENANCE

NCR [ESPm] -- monitor computers in the field, analyze error logs, and suggest preventive maintenance procedures before a computer fails [Teknowledge 87]

SCREENING

U.S. Environmental Protection Agency [EDDAS] -- determine which requests for information fall under the exceptions to the Freedom of Information Act [Feinstein & Siems 85]

CREDIT AUTHORIZATION

American Express [AA] -- assist in authorizing charges from card members or in determining that a request is suspect or fraudulent [Klahr et al. 87]

FINANCIAL AUDITING

Arthur Young [ASQ] -- assist auditors with planning and developing approaches to field audits [Hernandez 87]

SOFTWARE CONSULTANT

AT&T [REX] -- advise persons on which subroutines in large statistical package to use for their problems and how to use them [Rauch-Hindin 86]

EQUIPMENT TUNING

Lawrence Livermore National Laboratory [TQMSTUNE] -- specify parameter settings to bring a sensitive instrument into alignment [Rauch-Hindin 86]

INVENTORY CONTROL

Federal Express [INVENTORY SETUP ADVISOR] -- help decide whether or not to stock spares in inventory of 40,000 parts [Teknowledge 87]

Class II: Problems of Construction

CONFIGURATION

Digital Equipment Corp. [XCON] -- translate customers' orders for computer systems into shipping orders [Rauch-Hindin 86]

DESIGN

Xerox [PRIDE] -- design paper handling systems inside copiers and duplicators [Mittal et al 85]

GM Delco Products [MOTOR EXPERT] -- generate information necessary to make production drawings for low voltage DC motor brushes by interacting with designers [Rauch-Hindin 86]

LOADING

U.S. Army [AALPS] -- design loading plan of cargo and equipment into aircraft of different types [AALPS 85]

PLANNING

Hazeltine [OPGEN] -- plan and prepare "operations sheets" of assembly instructions for printed circuit boards [Rauch-Hindin 86]

Hughes Aircraft [HI-CLASS] -- set up sequence of hand-assembly steps for printed circuit boards [Hi-Class 85]

SCHEDULING

Westinghouse [ISIS] -- plan manufacturing steps in Turbine Component Plant to avoid bottlenecks and delays [Fox and Smith 84]

Babcock & Wilcox -- automate generation of weld schedule information (e.g., weld procedure, pre-heat, post-heat, and non-destructive examination requirements.) [Rauch-Hindin 86]

THERAPY MANAGEMENT

Stanford Medical Center [ONCOCIN] -- assist in managing multi-step chemotherapy for cancer patients [Hickam et al 85]

1.3. Historical Note

Early work in AI (1950's - 1960's) focused on (a) psychological modeling, and (b) search techniques. Expert systems synthesize some of that work, but shift the focus to representing and using knowledge of specific task areas. Early work used game playing, and reasoning about children's blocks, as simple task domains in which to test methods of reasoning. Work on expert systems emphasizes problems of commercial or scientific importance, as defined by persons outside of AI. Newell calls MYCIN "the original expert system" (Foreword to [Buchanan & Shortliffe 84]) because it crystallized the design considerations and emphasized the application. Expert systems continue to build on -- and contribute to -- AI research by testing the strengths of existing methods and helping to define their limitations [Buchanan 88]. The process is a continuing one. In the 1970's, expert systems work developed the use of production systems, based on the early work in psychological modeling. In the 1980's, fundamental work on knowledge representation has evolved into useful object-oriented substrates [Stefik & Bobrow 86].

Hardware developments in the last decade have made a significant difference in the commercialization of expert systems. Stand-alone workstations provide special hardware to run AI programming languages efficiently, high resolution interactive graphics, and large address spaces in small boxes at affordable prices [Wah 87]. These have simplified development since it is no longer necessary to depend on large, time-shared central mainframes for development and debugging. They also provide an acceptable answer to questions of portability to field personnel. Development of expert systems -- and the languages and environments (called "shells") for building them -- in standard languages such as Common Lisp and C have essentially eliminated the last barriers to portability.

2. FUNDAMENTAL PRINCIPLES

All AI programs, including expert systems, represent and use knowledge. The conceptual paradigm of problem solving that underlies all of AI is one of search (i.e., a program, or person, can solve a problem by searching among alternative solutions). Although immediately clear and simple, this formulation of the paradigm does little to tell us how to search a solution space efficiently and accurately. The number of possible solutions may be astronomical, as illustrated in Table 1 below. Thus

exhaustive consideration of alternatives is out of the question. Most expert systems, however, use heuristics to avoid exhaustive search, much as experts do. For problem areas in which experts are acknowledged to be more efficient and accurate than non-specialists, it is reasonable to assume that what the experts know can be codified for use by a program. This is one of the fundamental assumptions of knowledge engineering, or the art of building expert systems [Hayes-Roth et al 83].

TABLE 1. The Size Of The Solution Spaces For Several Expert Systems.

MYCIN: combinations of 1-6 organisms from list of 120 organisms (many of which are equivalent)	$> 6 \times 10^6$
INTERNIST: combinations of 1-3 diseases from list of 571	$> 31 \times 10^6$
DIPMETER ADVISOR: combinations of 650 geological categories for an arbitrary number of depth intervals, e.g., 500 ten-foot intervals	$> (500)^{650}$
XCON: arbitrary number of computer system components selected from 20,000 catalog items 50-150 at a time	$> 10^{200}$

In this section, we discuss several dimensions of current architectures: representation of knowledge, reasoning, knowledge acquisition, explanation, system-building tools, and validation. In each of these subsections, we try to elucidate the fundamental principles that underlie the architectural choices. Several criticisms of expert systems are restated in the text, with brief comments, as a way of clearly separating current practice from future promise. We end the section with three advantages of knowledge-based systems over traditional software.

2.1. Representation

One of the hallmarks of an expert system is the use of specific knowledge of its domain of application, applied by a relatively simple inference engine. The phrase "knowledge programming" has been used to denote the relative emphasis of the effort of building an expert system. The single most important representational principle is the principle of declarative knowledge enunciated by McCarthy in the formative years of AI [McCarthy 58]. (Also Winograd's discussion of this principle in [Winograd 75].) Simply put, this principle states that knowledge must be encoded in an intelligent program explicitly, in a manner that allows other programs to reason about it. Arbitrary Fortran or Lisp procedures, for example, cannot be explained or edited by other programs (although they can be compiled and executed), while stylized attribute-value pairs, record structures, or other, more complex, stylized data structures can be.

To a certain extent, a knowledge base is a database. The essential differences between knowledge bases and databases are flexibility and complexity of the relations. Current research on AI and Databases (sometimes called Expert Database Systems) [Kerschberg 86] is reducing these differences. It requires an organizational paradigm plus data structures for implementation. These two parts together constitute the representation of knowledge in an AI program.

Elements of knowledge needed for problem solving may be organized around either the primary objects (or concepts) of a problem area or around the actions (including inferential relations) among those objects. For example, in medicine one may think primarily about the evidential links among manifestations and diseases, and the links among diseases and therapeutic actions, and secondarily around the concepts so linked. In this paradigm, one concentrates on the knowledge that allows inferences to be drawn and actions to be taken -- the "how to" knowledge. Alternatively, one might organize medical knowledge primarily around the taxonomy of diseases and the taxonomy of their manifestations and secondarily about the inference rules that relate manifestations to diseases. In this second paradigm, one concentrates on what might be called the "what is" knowledge. These two conceptual views are known as "action-centered" or "object-centered" paradigms for representing knowledge. They have counterparts at the implementation level in program organization.

For each type of representation, one may identify the primitive unit and the primitive action. The primitive unit, in the case of action-centered representations, is

the fact (e.g., the freezing temperature of water is 0 degrees C). Primitive facts are linked in conditional sentences by rules ("If ... then ..." statements). Note that these links may reflect causal associations, based on theory, or empirical associations, based on experience. An example from the Dipmeter Advisor, which is an abbreviated causal description as found in geology texts, is shown in Figure 2 below.

<FIGURE 2 HERE>

Conversely, the primitive unit of an object-centered representation is the object or "frame", with a number of attributes (called "slots") and values (e.g., a spur gear with number-of-teeth = 24, material = cast-steel, and diameter = 5 cm). Objects typically also encapsulate procedures (called "methods"). In addition, they may contain defaults, uncertainty, relations to other objects (e.g., generalizations, parts), and a variety of other information. An object can be viewed as a structured collection of facts. Minsky [Minsky 75] popularized the use of objects (then called "frames") for AI. An example of an object definition from the Dipmeter Advisor is shown in Figure 3.

<FIGURE 3 HERE>

Smalltalk [Goldberg & Robson 83] was one of the early languages that showed both the power of objects as programming constructs and the power of an integrated graphical programming environment. Many commercial expert system shells contain an object-oriented component [Stefik & Bobrow 86].

The primitive action in action-centered representations is often referred to as "firing a rule:" If the premise conditions of a conditional rule are true in a situation, then take the actions specified in the consequent part of the rule. For example, in a medical system, conclude that an organism may be streptococcus, if its gram stain is positive. This style of programming began as production systems, made popular by Newell's work in the 1960's (see Ch. 2 of [Buchanan & Shortliffe 84]).

Given that rule-oriented programming often involves making deductions, it has been

argued that various forms of logic are well-suited for use in expert systems. Simple systems have used propositional logic, more complex systems have used first order predicate logic, and there is ongoing research in use of higher order logics to express relations among beliefs, temporal relations, necessity, and uncertain information -- both the uncertainty with which data must be regarded in many real systems and uncertainty in the strength of heuristic rules which reflects a lack of detailed understanding of a domain.

> **Criticism: The domain models are not "deep" models.** [Davis 87] Expert systems rely more on special case formulations of relations than on "first principles." Although a set of general principles such as Maxwell's equations govern the behavior of a large class of devices, designers of expert systems prefer to codify special cases, exceptions, and empirical associations, as well as some causal associations, in order to put the general principles in forms that are more quickly applied.

The search for new logical formalisms that are more powerful than predicate calculus reflects the tension between simple, well-understood formalisms and expressive power. In brief, logic indicates an approach but does not provide a complete solution. Numerous extensions must be made to express some of the concepts that are frequently used in applications: uncertainty, strategy knowledge, and temporal relations.

> **Criticism: The reasoning is not formal.** [Nilsson 82] Some logicians are uncomfortable with reasoning that is not theorem proving and knowledge bases that are not axiomatic systems which allow proofs of consistency. It is not clear that formal reasoning, per se, is desirable in expert systems, but it would be desirable to validate knowledge bases analytically.

In object-centered representations, the primitive action is called "sending a message": If an action needs to be taken (e.g., a value of an attribute is needed), send a request to the object that can take the action (e.g., compute, or conclude, the value). For example, in a geology system, send the *Analyze-Sedimentary-Environment* message to an instance of the *Borehole-Interval* object. The effect is to perform an arbitrary action which could include drawing inferences; in our example, the action performed is to draw conclusions about the geological "story" of sedimentation at a specific depth interval penetrated by the oil rig's drill. This style of object-oriented programming owes its definition to Hewitt [Hewitt 77].

In terms of data structures, objects are much like record structures. Each object has a number of fixed fields. Unlike record structures, however, new fields can be added to objects during a computation. Objects divide into two types: instances and classes.

Instances are individuals in a domain (e.g., a specific depth interval from 1200 to 1225 feet in a specific borehole). Classes represent sets of individuals (e.g., any depth interval). They define the characteristics of the individuals which are their instances. Classes are usually organized into hierarchies according to different relations. The most common relations are the specialization, subclass, or "is-a" relation (e.g., a reverse geological fault is a kind of geological fault) and the "part-of" relation (e.g., a fault plane is part of a geological fault). Object-oriented systems allow arbitrary relations to be encoded, but often provide efficient support for one or two specific relations.

In order to support the characteristics of expert systems listed in the Introduction, representation mechanisms must have sufficient expressive power to state, clearly and succinctly, both "what is" knowledge and "how to" knowledge. (This is sometimes called the "epistemological adequacy" of a representation [McCarthy & Hayes 69].) Expressive power has both design-time and run-time implications. One of the key problems for designers of expert systems is management of complexity. Impoverished representation mechanisms force designers to encode information in obscure ways -- which leads to difficulty in extending and explaining the behavior of expert systems. Representation mechanisms that permit efficient compilation and structuring of knowledge reduce run-time requirements of both time and memory.

As an example, an object-oriented language allows some information to be stated once, in an abstract class, and accessed (by inheritance) in a large number of subclasses. A representational mechanism that does not allow this forces designers to confront the complexity of stating essentially the same information many times. This may lead to inconsistency and difficulty in updating the information. It also has an obvious memory cost. At run time, each of the separate encodings of the information may have to be considered individually, resulting in an obvious performance penalty. An example of a taxonomic hierarchy is shown in Figure 4.

<FIGURE 4 HERE>

Action-centered and object-centered paradigms are in fact two ends of a spectrum of representational possibilities. The two emphasize different aspects of modeling. Contemporary AI programs often use heterogeneous representational paradigms (e.g.,

coupling the simplicity of rules with the expressive power of objects).

Extensible representation schemes facilitate the incremental development of expert systems, which is necessary when there is no complete specification of either the problem or of the knowledge required to solve it. When new concepts, attributes, and relations are added incrementally, a designer must not be forced to recode substantial portions of the knowledge already encoded.

> **Criticism: Knowledge bases are not reusable.** [Lenat 86] Since the cost of building a knowledge base is substantial, it would be desirable to amortize it over several related expert systems, with unique extensions to cover unique circumstances. For example, many medical systems use facts about anatomy and physiology, yet often each encodes those facts specifically for use in a unique way.

Experience has shown that declarative, modular representations are useful for expert systems. Some information is more difficult to encode in the action-centered paradigm, other information more difficult in the object-centered paradigm. For example, sequencing of actions is difficult to encode in an action-centered paradigm. The same is true of information that is essentially static, such as causal or structural descriptions. On the other hand, object-centered representations have no built-in inference mechanism beyond inheritance (although they support them, and many commercial shells have an integrated rule-oriented component). In addition, in some domains, subclasses are "soft" and it may be inappropriate to wire in hard distinctions between classes (e.g., in geology, classification of rocks according to lithology [sandstone, shale, carbonate] is not firm because the end-members are mixed to varying degrees). Consequently, there is no single answer to the question "Which representation method is best?" Contemporary expert systems use a variety of methods, but attempt to integrate them into a uniform framework. As systems become more complex, it will be more and more difficult to maintain a uniform view.

> **Criticism: Expert systems are "brittle".** [Davis 87, Lenat 86] Without knowledge of first principles or common sense, current expert systems may fail precipitously on a new case that is at the boundary of the system's competence. The performance of humans is more robust: as we reach the extent of what we know about a problem area, we often can give appropriate answers that are approximately correct, although not very precise -- and we know the difference. The standard solution today is to codify rules that screen out cases that are outside the intended scope in order to further ensure that the system is being used in an appropriate way.

2.2. Reasoning

Inference methods are required to make appropriate and efficient use of the items in a knowledge base to achieve some purpose, such as diagnosing a disease. Logically speaking, the two rules of inference most used in problem solving are *modus ponens* -- "If A implies B and you know A, then infer B" -- and *modus tollens* -- "If A implies B and you know not-B, then infer not-A". The former is sometimes called the "chain rule" because inferences can be chained together in a sequence of deductions:

A
A --> B
B --> C
C --> D
Therefore, D

In addition to these two simple rules, rules of quantification are sometimes used -- e.g., "If all A's are B's and x is an A, then x is a B". With a few simple rules of inference such as these driving the problem solving, a knowledge base full of many special facts and relations about the problem area provides the expertise on which high performance is based.

> **Criticism: Expert systems have little common sense.** [McCarthy 83] While it is true that there is no general "common sense reasoning" component in expert systems, it is not at all clear what is required that would be general enough to avoid errors that "any fool" would avoid and specific enough to reason reliably. Designers of current expert systems resolve this by (a) assuming that users can exercise some common sense, and (b) specifying common facts explicitly when needed. The INTERNIST system, for example, contains about 100,000 common sense medical facts such as "males do not get pregnant" and "aspirin obscures the results of thyroid tests" (personal communication from R. Miller).

Some expert systems use a theorem prover to determine the truth or falsity of propositions and to bind variables so as to make propositions true. Others use their own interpreters in order to incorporate more than a theorem prover provides -- most importantly, capabilities for controlling the order of inferences, strategic reasoning, and reasoning under uncertainty. Most fielded rule-based expert systems have used specialized rule interpreters, not based directly on logic. To some extent this reflects timing -- efficient Prolog interpreters and compilers have only recently come available

[Clocksin and Mellish 81]. However, it also reflects a need for more flexible styles of inference (in addition to depth-first backtracking) and control over the strategies guiding the order of inferences.

2.2.1. CONTROLLING THE ORDER OF INFERENCES AND QUESTIONS

From a logical point of view, the order in which new facts are derived is irrelevant, if all logical consequences of the initial facts are to be considered. For pragmatic reasons, expert systems often need to be selective about which facts to consider and which consequences to pursue. Space and time are often limited, for example, and it may also be important to develop a line of reasoning that a user can follow. Thus, expert systems are organized around three different reasoning paradigms: forward, backward, and opportunistic reasoning.

Forward reasoning from data to conclusions is used when the cost or inconvenience of gathering data is low and there are relatively few hypotheses to explore. A forward chaining system starts with a collection of facts and draws allowable conclusions, adding those to the collection and cycling through the rules. The stopping conditions vary from stopping with the first plausible hypothesis to stopping only when no more new conclusions can be drawn. The XCON computer configuration system is a classic example of a forward chaining system.

Expert systems may be faced with inconsistent or time-varying data. As a result, the reasoning employed is often non-monotonic; i.e., conclusions may be altered or withdrawn as problem solving proceeds. This too necessitates a departure from a traditional logical view [Bobrow 80].

Matching the premise clauses of all rules in a knowledge base against each new situation can be prohibitively expensive when there are many rules and many new situations created by inferring new facts. Rules often contain variables that can be bound in many different ways, thus creating additional ways that their premises can match a situation. Rule interpreters commonly provide mechanisms for compilation of rules and rule-matching procedures [Brownston 85]. In addition, all but the simplest rule-based systems organize and index rules in groups in order to control the expense of matching and invocation. Rule groups (called "rule sets", "tasks", or "control blocks") are also used to control the expert system's focus of attention in order to make interactions with users more comprehensible. For example, in a medical system, it

helps users understand the reasoning if data requests are clustered by grouping rules that perform disease diagnosis and those that focus on the patient's history or on the laboratory tests, and those that recommend therapy. (This also facilitates the acquisition of knowledge and the maintenance of knowledge bases.)

Backward reasoning is goal-directed and does not require all relevant data to be available at the time inferences are begun. It is more appropriate when a user supplies many of the data, and when the user cares about the order in which data are requested. MYCIN is a classic example. A backward chaining system starts with a hypothesis (goal) to establish, and asks in effect, "what facts (premise clauses of rules) would need to be true in order to know that the hypothesis is true?". Some of these facts may be known because they were given as initial data, others may be known after asking the user about them, and still others may be known only after starting with them as new subgoals, and doing backward chaining. The stopping conditions vary from stopping with the first hypothesis to be found true (or "true enough") to stopping only after all possibly relevant hypotheses have been explored.

Opportunistic reasoning combines some elements of both data-directed (forward) and goal-directed (backward) reasoning. It is useful when: the number of possible inferences is very large, no single line of reasoning is likely to succeed, and the reasoning system must be responsive to new data becoming known. As new data are observed, or become known, new inferences can be drawn; and as new conclusions are drawn, new questions about specific data become relevant. An opportunistic reasoning system can thus set up expectations, which help focus the discrimination of a few data elements from among an otherwise confusing mass of data. The key element of such a system is an agenda of actions with an associated scheduler, that enables explicit decisions to be made about which actions are to be taken (e.g., which rules to apply and whether to apply them in a forward or backward chaining manner, and which object is to be the focus of attention). By contrast, these decisions are hard-wired into forward and backward chaining systems. An example of one successful prototype based on this paradigm is the HASP system [Nii et al 82]. Acoustic data from sensors in the ocean provide information about the types and locations of vessels. As data are received over time, hypotheses are revised. With each revision, new ambiguities arise, which can be resolved by reprocessing old data or looking for new signals.

2.2.2. USING EXPLICIT STRATEGIES

The three major reasoning paradigms of forward, backward, and opportunistic reasoning are primitive strategies that may need refinement and coordination in order to reflect a complex decision strategy such as medical diagnosis. Representing strategic knowledge explicitly, an important trend in expert systems, becomes important whenever strategic issues are subject to change or explanation. MYCIN's meta-rules, a solution to this problem in the late 1970's, represent knowledge of reasoning strategy as rules [Buchanan & Shortliffe 84]. They differ from the other "domain knowledge" rules in the system in that they refer to those rules in some of their premise or conclusion clauses:

> IF <medical context> AND there are rules that mention fact A and that mention fact B,
>
> THEN reason with the rules mentioning A before the others.

Strategies can also be represented as an organization of steps to perform, in a stylized definition of a procedure [Clancey 86, Hickam et al 85].

2.2.3. REASONING UNDER UNCERTAINTY

Reasoning under uncertainty is essential in problem areas outside of logic and mathematics, in which information is incomplete or erroneous. In medicine, for example, there is rarely complete certainty about having all the data or about the accuracy of the data. Several methods are used in expert systems to deal with uncertainty arising from (a) uncertainty of the data, (b) less than certain associations between data and conclusions, and (c) combinations of these. The major methods for addressing these issues are listed below.

1. Abstraction -- assume that the uncertainty is small and can be safely ignored.

2. Bayes' Theorem -- use prior and posterior probabilities to represent less than certain data and associations; then compute new probabilities with some variation of Bayes' Theorem [Gorry 70].

3. Fuzzy Logic -- represent the uncertainty of propositions such as "John is tall" with a distribution of values; then reason about combinations of distributions [Zadeh 79].

4. Criterion Tables -- assign categories or weights to clauses in rules based on their relative importance in drawing conclusions (e.g., major and minor findings associated with a disease); then allow a conclusion to be drawn if sufficient numbers of clauses in each category are true [Kulikowski & Weiss 82].

5. Certainty Factors (CF's) -- assign single numbers to propositions, and to associations among propositions, representing either probabilities or a combination of probabilities and utilities; then use MYCIN's formulas to determine CF's for inferred beliefs [Buchanan & Shortliffe 84].

2.2.4. SUMMARY

There is no single answer to the question, "Which inference method is best?". Each expert system, or system-building shell, provides a nearly unique set of choices for controlling the inferences, using strategies, and reasoning under uncertainty. Some feature still other issues, such as methods for backtracking (recovering from local failures), critiquing (making no recommendations unless the user needs them), reasoning about shapes or positions, and reasoning about temporal dependencies. Most present-day systems allow no modification of the inference methods they use. This is a shortcoming that has not received widespread attention, but that causes system builders to make inappropriate or unhappy choices because they must work with an inference procedure within a shell, in which someone else made those choices.

2.3. Knowledge Base Development

For the last decade, everyone involved has referred to the process of putting knowledge into a knowledge base as a "bottleneck" in building expert systems [Hayes-Roth et al 83]. Usually this process involves two persons (or teams): an expert whose knowledge is to be partially mirrored in the knowledge base, and a knowledge engineer who interviews the expert to map his/her knowledge into the program's data structures holding the knowledge base. The process is time-consuming and difficult, yet the performance of the resulting expert system depends on it being done well. A survey conducted by SRI International indicates that the average cost of developing an application (knowledge engineering plus end-user interface alone) is about $260,000. For small systems, these costs are about $5000; for large systems, more than $1.5

million [Fried 87]. Note that these estimates do not include the cost of constructing an expert system shell.

Much of the process of knowledge engineering is engineering. Yet there are several difficult issues of a fundamental nature wrapped up in the steps of the process. (1) During the first step, problem assessment, the knowledge engineer must match characteristics of the proposed problem against characteristics of known solution methods. Unfortunately there are no good taxonomies of either problems or solution methods, and no good criteria for deciding that there is a match.

> **Criticism: The expert's conceptual framework may not be the same as the user's.** [Winograd & Flores 86] Knowledge engineers work under the assumption that the experts they work with know the context of intended use and the intended users' terminology and point of view. There are no safeguards built into today's systems to test this assumption.

(2) The second major step is exploratory programming, in which a series of experimental prototypes are constructed quickly, first as a proof-of-concept, then with successively larger fractions of an expert's knowledge showing that a part of the problem can be (partially) solved with that knowledge encoded in a specific environment. Two substantial issues here are formulating an accurate conceptual framework, including terminology, to allow knowledge to be added incrementally; and interacting with -- not just passively listening to -- the expert efficiently to elicit what he/she knows about the problem that is relevant for the expert system.

(3) Developing the knowledge base, to increase both the breadth and depth of the system's competence, is the third major step. This step takes the most time (several person-years) but is relatively straightforward if steps (1) and (2) have been done well. One difficult issue here is anticipating characteristics of end-users and their context of use. Another is deciding what new facts and relations are and are not relevant for the system's performance -- and understandability -- in context. The competing paradigms for making this decision -- and for knowledge engineering generally -- May be called "model-directed" and "case-directed" knowledge base development. In the former, the knowledge base is largely developed along the lines of a model, or theory, of the problem area. In the latter, it is largely developed in response to errors exhibited in solving test cases. Neither is entirely adequate by itself; knowledge engineers must use both. Whatever combination of development paradigms is used, it is important to understand that there is no clear stopping criterion for development. This presents

problems in providing for continual additions and modifications to a knowledge base, as mentioned above in discussing extensibility.

(4) The last step of the process is software engineering, to ensure that the system fits into the end-users' environment, is responsive to their needs, etc. The difficult issues at this step are not unique to expert systems. It is included as a reminder that a successful application requires more than developing a knowledge base.

> **Criticism: Expert systems do not learn from experience.** Research on machine learning is maturing to the point where expert systems will be able to learn from their mistakes and successes. Learning by induction from a large library of solved cases is already well enough understood to allow induction systems to learn classification rules that an expert system then uses [Michie et al 84, Michalski et al 86]. There is increasing emphasis on learning in context, sometimes called explanation-based learning or apprentice learning, that appears to hold promise for expert systems [Mitchell et al. 86].

2.4. Explanation

One of the defining criteria of expert systems is their ability to "explain" their operation. Early forms of explanation focussed on showing the line of reasoning, typically a sequence of rule firings, that led to a particular conclusion. This was normally done in stylized natural language (Part Six of [Buchanan & Shortliffe 84]). The user could ask the system questions of the form "How did you conclude ..." In a sense it is an extension to the kind of dialog that was originally shown in the SHRDLU system [Winograd 72]. That system answered questions by actually looking in its environment and on its own goal stack (i.e., agenda of goals and subgoals).

Although natural language interfaces were used almost exclusively in early expert systems, powerful, low cost graphics workstations have fueled a trend towards graphical interfaces (e.g., the Steamer system, used to train naval personnel to operate steam power plants onboard ships [Hollan et al. 84]). Contemporary systems often provide mixed natural language and graphical interfaces (e.g., the Drilling Advisor [Rauch-Hindin 86]).

Lines of reasoning (e.g., the GUIDON-WATCH System [Richer 85]) may be shown as graphs that permit user interaction to explore alternative possible lines of reasoning. Perhaps this makes clear the fact that current explanation facilities are much like sophisticated program debugging facilities and are often used as such. As all good debugging systems, they permit the programmer/user to examine system operation in

high-level terms, rather than in terms of the low-level machine instructions actually executed. There is a trend today towards recording justifications that underlie the items in the knowledge base [Smith et al 85]. These can be used to augment explanations. Research is ongoing to enable expert systems themselves to use this information.

The term "explanation" can also be used to cover examination of the static knowledge base. Object-oriented representations and sophisticated graphics facilities enhance the ability of a domain specialist to understand what has been encoded [Smith et al 87]. As found in the GUIDON system [Clancey 86], however, such facilities do not in and of themselves constitute a tutoring system.

> **Criticism: Expert systems have little self-knowledge.** [Lenat et al 83] While expert systems can often give explanations of what they know, they do not have a general "awareness" of what the scope and limitations of their own knowledge are. Meta-level knowledge, such as rules of strategy, can also offset this shortcoming in special situations but does not constitute a general capability.

One could argue that the user of a conventional Fortran program can also examine the "knowledge base" of the program. Depending on how the program is written, this is true to a certain extent. It would typically be done with a text editor. One thing that sets expert systems apart, however, is their ability to be queried in the runtime context. Whereas a conventional program can be examined only statically, an expert system can be examined dynamically. It is true that a programmer can examine the stack of a conventional program with a debugger, but such programs do not maintain an explicit goal stack or line of reasoning. This is not a statement about implementation language, but rather about system design style.

2.5. System-Building Tools/Shells

When the first commercial expert systems were being developed, the developers were faced with two major problems: eliciting and encoding the domain knowledge necessary to solve the problem at hand, and building programming systems with which to encode/apply the knowledge. There were almost no generally applicable rule interpreters or object-oriented programming languages. Most of the early "shells" had been constructed in universities as part of specific applications. They typically made too many assumptions about either the domain of application or the problem-solving methods to be used. Furthermore, they were typically only usable by highly trained specialists. Finally, their run time, space, and implementation language requirements

precluded their use in a wide variety of environments. Nevertheless, these shells represented generalizations -- in code -- of principles learned from experience with prior expert systems.

One of the most practical effects of the recent commercial application of expert systems is the development of many dozens of robust shells and tool sets [Bundy 86, Gevarter 87, Harmon 87, Richer 86]. These shells range in capability from those that can support little more than experimentation with rule-based techniques, to those that can support efficient development and operation of substantial systems. A few of the more powerful shells are used to support current research in expert systems. The shells are implemented in a number of programming languages (e.g., Lisp, C, Prolog) and run on a variety of hardware, including inexpensive PC's, workstations, and mainframe computers.

Today, users can expect a high-end shell to offer support for a number of programming paradigms. The two most common are rule-oriented programming and object-oriented programming. Both forward and backward chaining are standard, as is support for structuring rules into collections (or rule sets) according to task. Rules are typically efficiently compiled into code in the underlying implementation language. Not all rule languages are extensible. The OPS5 rule language, for example, allows new action functions to be defined, but does not allow new matching predicates [Brownston 85].

When support for object-oriented programming is provided, it includes multiple inheritance, message-passing, and active values. A common way to combine rules and objects is to construct a method that responds to a message by applying a set of rules, with either forward or backward chaining. Such a method may also be invoked in response to a change in an active value. The Reactors system, for example, uses active values to respond to changes in the operating conditions of a nuclear power plant to invoke rules that suggest new responses [Rauch-Hindin 86].

Some shells provide support for uncertainty in rules and in facts. The certainty factor calculus originally developed for the MYCIN system is widely used. Complete integration of inexact reasoning and objects has not yet been achieved. It is currently limited to support of uncertainty for slot values. Support for uncertainty in inter-object relations is less common.

Criticism: Expert systems are not well integrated with database management systems, large numerical packages, or other existing software & systems. This was a shortcoming in the early years of commercial systems in which expert systems were designed as stand-alone tools. Today's commercial systems are considerably better integrated with other uses of computers. It is now common to see support for mixed language environments (e.g., with some code in Lisp and some in C).

Over the past few years increasing attention has been focussed on tools to support interaction between humans and expert systems. There are two major reasons for this: (i) in many fielded systems the end-user interface accounts for a substantial portion of the overall system and success depends heavily on the quality of user interaction [Smith 84]; and, (ii) the knowledge acquisition process is simplified and enhanced when the expert can readily examine the evolving knowledge base and directly interact with the system to refine its understanding of the domain (e.g., [Davis & Lenat 82]). It has also been found that the tools used to represent domain knowledge and strategy knowledge (e.g., objects and rules) can be applied to structuring user interfaces. Extensible systems and tools have been developed to support interaction requirements for knowledge engineers, experts, and end-users [Smith et al 87].

2.6. Validation

There are many dimensions along which we might wish to judge an expert system. The three most important of these are computational, psychological "look and feel", and performance. Computational issues include speed, memory required, extensibility, and portability. Psychological issues include ease of use, understandability and "naturalness," and online help. Performance issues -- the sine qua non -- include the scope of competence, percentage of false positive and negative solutions (false hits and misses), and time or money saved. Some involve evaluations of the static knowledge base (e.g., its scope) while others involve looking at the program in use (e.g., its ease of use or statistics on correctness).

Formal validations of expert systems are rarely published, if done at all. The formal validation of MYCIN's performance (Part 10 of [Buchanan & Shortliffe 84]) stands out as an exception. In that study, outside evaluators reviewed therapy recommendations, for several randomly selected patients, as made by MYCIN and nine persons whose expertise ranged from acknowledged specialist to medical student. The evaluators (in a blinded study) judged MYCIN's recommendations to be indistinguishable from those of the specialists. In practice, expert systems are validated in the same way as

conventional software. Developers mostly demonstrate that a new system solves a variety of difficult problems before it is turned over to end-users [O'Keefe et al 87]. A few of the end-users then try the new system in context on a large number of cases -- often in parallel with the old method for solving these problems. Any errors that are detected are fixed. When the end-users and their managers are convinced of the program's effectiveness, the program is put into routine use -- often at a single site first.

With conventional programs, we often test each branch of each subroutine with boundary values of variables, to assure ourselves that the program's parts behave as specified. In an expert system, each element of the knowledge base is examinable in the same fashion as a single, small subroutine. As with subroutines, the places where unforeseen errors occur are in the interactions among the elements. These have to be uncovered by empirical tests -- running the program on a large, random sample of problems (within the specified scope) and determining which cases are solved correctly and which not. In the absence of a complete logical analysis that proves the correctness of both the knowledge base and the inference engine, we must analyze performance empirically. The criteria for "acceptable" levels of errors of any type, however, must be determined by weighing costs of errors of each type against the benefits of correct solutions.

2.7. Advantages Over Traditional Software

In general, the main issues in building expert systems revolve around complexity, interpretability, and explicit, modular forms of knowledge. In this section we summarize some of the advantages of using expert systems instead of writing conventional software.

2.7.1. COMPLEXITY

Complexity of Problem. Often when one begins designing an expert system, the problem is not precisely specified, nor is the knowledge required to solve it. Initial descriptions of the problem are oversimplified, so the complexity becomes known only as early versions of the system solve simple versions of the problem. Expert systems are said to approach competence incrementally. A declarative, modular representation of knowledge, applied in a uniform manner, is the key to managing this kind of complexity.

Complexity of Project Management. The traditional life-cycle model of software construction and maintenance presumes that problems are well specified. An alternative model, used in constructing expert systems, is exploratory programming in which problem definition and problem solution are mutually reinforcing. A key element in exploratory programming is a powerful, integrated development environment [Sheil 84].

Complexity of System. Conventional software can in principle be written by good programmers to solve any problem that an expert system solves. Frequently a system that is initially constructed in a shell system is rewritten in Fortran, PL1, C, or some other well-known language. Constructing the system in the first place, however, requires considerably more flexibility than is provided in a non-interpreted language, unless the designer has considerably more ability than most, or unless the shell system (itself in C or some other language) provides an interpreter for elements in its knowledge base.

2.7.2. INTERPRETATION

One of the facilities that is commonly used to advantage in expert systems is evaluation -- *EVAL* to the Lisp programmer. This facility allows the user (or the system itself) to specify a query or arbitrary computation to the running system and evaluate it in the runtime context. It lays open to examination the entire state of the system and its environment -- including the knowledge base, the line of reasoning, agenda, etc. This is the sense in which programs written in interpretive languages like Lisp are said to themselves constitute data. It is one of the most important facilities upon which an expert system depends. It allows a system to reason about not only incoming data but also about past inferences and even the way in which it makes inferences. To a certain extent, operating systems also perform this kind of introspection. However, these systems can usually only be tuned in a number of pre-defined ways, according to a fixed set of parameters -- operating systems typically cannot look at their own procedures. By contrast, expert systems in principle can do this kind of detailed introspection, examining their procedures as well as their data.

In order for this capability to be effectively used, it is important that the knowledge be represented explicitly (declaratively) and uniformly, and that it be applied in a relatively uniform manner. While it may be possible in principle to reason about primary Lisp code, in practice it is extremely difficult -- for humans as well as programs.

2.7.3. KNOWLEDGE

Specialized knowledge of a problem area is the key to high performance. And the key insight from AI has been that representing a program's knowledge declaratively provides considerable advantages over hard-wiring what a program knows in coded subroutines. There is a continuum, of course, from parameterized procedures to completely stylized, understandable, high-level procedure descriptions and today's expert systems have room to improve. As discussed extensively above, the central knowledge issues in building expert systems are: representation, reasoning, acquisition, and explanation. Today's expert systems demonstrate the adequacy of current AI methods in these four areas, for some well-chosen problems. Shells, or system-building environments, codify many of the present methods. Yet there remain limitations on what can be easily represented, used, acquired, or explained, which are presently stumbling blocks.

3. STATE OF THE ART

Several recent books and publications provide extensive overviews and details about the state of the art. See, for example, [Waterman 86], [Rauch-Hindin 86], [Mishkoff 85], [Scown 85] plus numerous current journals and newsletters such as *Expert Systems, IEEE Expert, The AI Magazine, Expert System Strategies,* and *The Applied Artificial Intelligence Reporter.* In this section we encapsulate our own understanding of the state of the art.

3.1. Size of System

The numbers of expert systems and persons working on them have grown to the point that building expert systems has become routine. While there are definitely limits to their size and scope, it is difficult to characterize them -- either numerically or symbolically. For example, MYCIN contained about 1000 rules and 20 class names, and XCON contains about 6000 rules and 100 class names. The INTERNIST system contains about 2600 rules, with another 50,000 links among roughly 600 diseases (objects), and 80 manifestations (slots) per disease (chosen from approximately 4500 manifestations in all). The reasons why numbers such as these are difficult to compare are: (a) there May be substantial differences in the level of conceptual detail covered in a rule in different shells (e.g., EMYCIN vs OPS5); (b) there is more in a knowledge base than rules and object names; (c) complex procedures contain considerable

knowledge, even though not represented declaratively; (d) a single concept, or a single clause in a rule, may stand for something very complex (e.g., "state of the patient") of for something quite straightforward (e.g., "patient's age"). It is also the case that as developers attempt to encode more information in objects (attempting to make fewer assumptions about how the knowledge will be used), the number of rules tends to be reduced in a faster than linear fashion. This occurs because the rules are written to be applied to members of hierarchically organized classes of objects, and not just to single individuals.

A few expert system shells have small upper limits on the size of knowledge base that can be accommodated, mostly for reasons of memory size of the underlying personal computer. Even systems that today are counted as modestly large or complex, mention only a few thousand objects (or classes of objects) and relations among them (e.g., rules). These limits may be due to experts' and knowledge engineers' limitations in keeping track of larger numbers of items (and their interactions) -- and to managers' unwillingness to spend more than 12-24 months in developing a system -- and not to hardware or software limits. New technology will be required, however, when we try to build knowledge bases that contain millions of items. An approximate characterization of the complexity of present-day knowledge bases is shown in Table 2 below. Assuming that facts are represented as object-attribute-value triples (e.g., "the identity of Organism-2 is E. coli"), it makes some sense to ask how many there are. There are complications, however, because (a) classes may be defined for arbitrarily many instances; and (b) values may take on continuous values (e.g., any real number). So instead of showing the number of facts, Table 2 shows the number of components of facts. Also, instead of showing only the number of rules, this table indicates the depth and breadth of inference networks. It also suggests that knowledge bases are more complex when they must deal with uncertain facts and relations.

Table 2: Approximate Measures of Complexity of Expert Systems Built Routinely in the Late 1980's

Vocabulary

# Objects	10's to 10,000's of objects or classes of objects
# Attributes per object	10 - 250 named attributes

# Legal values per attribute	3 - 100 discrete values, plus arbitrarily many discrete ranges of values of continuous attributes.
Inferential Relations (Rules)	
# Rules	100's to 1000's
Depth of Longest Chains	2 - 10 steps from primary data to final conclusion
Breadth of Inferences	2 - 10 ways of inferring values of any single attribute
Degrees of Uncertainty	yes, facts and relations may be expressed with degrees of uncertainty

The time it takes to build a system varies greatly depending on the scope of the problem and the expectations about the end product. A prototype that is expected to demonstrate feasibility on a small troubleshooting problem, for example, may be built by a single person in one to ten weeks. A fully developed system ready for field use on a complex problem, on the other hand, may take a team of several persons one to three years or more. One measure of our increased understanding of knowledge programming is that students are now routinely assigned one-term class projects which would have been two-year doctoral research projects a decade ago.

3.2. Type of Problem

Several types of problems for which systems can be built were listed above in two categories: interpretation and construction. We lack a robust taxonomy of problem types (among the best so far is the one proposed in [Chandrasekaran 86]), so the individual examples still provide a better characterization of the types of problems than general descriptions. The majority of expert systems described in the open literature address problems of data interpretation -- mostly for purposes of troubleshooting or equipment diagnosis. They are mainly organized around the method of evidence gathering, in which evidence is gathered for and against a fixed set of hypotheses (or solutions), and the answer(s) with the best evidence is selected [Buchanan & Shortliffe

84]. This is also known as catalog selection or heuristic classification [Clancey 85]. Most of the commercial shells address problems of this type. However, more and more systems are being built for problems of the second category, and shell systems are emerging to handle the myriad constraints that shape a design, assembly, configuration, schedule, or plan.

> **Criticism: Expert systems do not reason exactly as human experts do, e.g., they have no intuition.** [Dreyfus and Dreyfus 86] So far, the problems that have been most successfully solved with expert systems have been those in which inferential knowledge is easily formulated as rules and the organization of objects and concepts is easily formulated as taxonomic (class-subclass-instance) hierarchies and part-whole hierarchies. Reasoning by analogy or by intuition are still too unpredictable (and ill-understood) to use in high performance systems.

3.3. Some Limitations and Research Topics

Expert systems are designed to solve specific problems in well circumscribed task domains in which specialists can articulate the knowledge needed for high performance. Current methods for designing and building them have limitations, briefly discussed as criticisms above. These limitations intersect somewhat with the research issues listed here. The difference between them is one of emphasizing performance (pragmatics) or issues (theory). In each of these areas some work has been done. To date, however, proposed methods have not been well integrated with shell systems, often because proposed methods have not been convincingly generalized or demonstrated. These constitute a partial list of doctoral dissertation topics brought into focus by work on expert systems. General solutions to any of these problems would constitute valuable contributions to AI.

3.3.1. RESEARCH TOPICS IN REPRESENTATION

1. CAUSALITY -- how to represent causal relations and causal models

2. STRUCTURE & FUNCTION -- how to represent structural and functional models, and their interdependencies

3. CONTINUOUS SPACE & TIME -- how to represent (and reason efficiently about) arbitrary spatial regions and intervals of time

4. PROCESSES -- how to represent explicitly knowledge about processes and

procedures

5. PROBLEM-SOLVING METHODS -- how to represent knowledge solving specific classes of problems.

6. REUSABILITY -- how to represent domain knowledge or strategy knowledge so that it can be reused in different applications and extended by different users.

3.3.2. RESEARCH TOPICS IN REASONING

1. SCALE -- how to reason efficiently with knowledge bases that are orders of magnitude larger than today's (millions of items instead of thousands).

2. INTERACTIONS -- how to reason effectively about multiple, interacting problems (e.g., faults in a device whose effects reinforce or mask each other or that otherwise provide test results that are different from the union of results for individual faults).

3. INTEGRATION -- how to exploit the special-purpose reasoning methods in existing software packages (e.g., spread sheets) with knowledge-based reasoning.

4. DISTRIBUTED KNOWLEDGE -- how to pass information (data, problems, and solutions) and coordinate activity in a network of distributed problem solvers (machine and human) reliably and efficiently.

5. PARALLEL PROBLEM SOLVING -- how to solve parts of a problem simultaneously on different computers and synthesize a solution.

6. FIRST PRINCIPLES -- how to represent and use theoretical laws of prediction for other purposes such as design or failure diagnosis, and how to effectively combine this type of reasoning with the use of simple associations.

7. CONSTRAINT-BASED REASONING -- how to apply constraints efficiently to define solutions to arbitrary constraint satisfaction problems, e.g., to avoid backtracking as much as possible.

8. ANALOGICAL REASONING -- how to find "reasonable" pairs of problems or knowledge bases that make useful analogies, and how to use all and only "relevant" mappings out of the thousands of possible mappings.

3.3.3. RESEARCH TOPICS IN KNOWLEDGE ACQUISITION

1. INTELLIGENT EDITORS & DEBUGGING TOOLS -- how to assist in designing and building an expert system for a specialized task without already knowing about that task area.

2. LEARNING -- how to learn new knowledge from present experience, or from libraries of past problems; how to avoid assuming that those data are necessarily correct.

3. CONSISTENCY -- how to find inconsistencies in a knowledge base, especially when it contains items with degrees of uncertainty; and how to suggest ways of making groups of items consistent.

4. MULTIPLE SOURCES OF KNOWLEDGE -- how to combine the contributions of many different specialists into a coherent knowledge base, especially when their knowledge is seemingly contradictory or is framed in incompatible vocabularies.

3.3.4. RESEARCH TOPICS IN EXPLANATION

1. CUSTOMIZED EXPLANATIONS -- how to tailor an explanation for an individual user and context without pre-specifying answers for each different class of situations.

2. INTELLIGENT SUMMARIZATION -- how to provide intelligible, purposive summaries of complex procedures and situations from a record of all the details.

RESEARCH TOPICS ON SHELLS

- KNOWLEDGE COMPILATION -- how to efficiently compile rules and objects while preserving explanation capabilities.

The limitations mentioned briefly above -- although stated negatively to indicate boundaries of what is common practice -- also indicate directions in which expert systems are growing. While some partial solutions to some of these shortcomings have been elucidated in research laboratories and a few are exhibited in commercial systems, we will see more and more of these capabilities integrated in large systems of the future.

4. CONCLUSIONS AND SUMMARY

4.1. Design Principles

Out of the experimental work with expert systems over the last five to ten years, several "architectural principles" of expert systems have emerged. In 1982, Davis [Davis 82] articulated an early set of principles based on experience with a few rule-based systems. (See also [McDermott 83] for another set of generalizations and Ch. 5 of [Hayes-Roth et al 83] for practical advice for knowledge engineers.) Given additional experience, we can augment and refine these principles.

4.1.1. MODULAR, DECLARATIVE EXPRESSIONS OF KNOWLEDGE ARE NECESSARY

1. Represent all knowledge explicitly. This simplifies explanation of system behavior as well as refinement, both by human designers or by the system itself. The main feature of an expert system is the suite of specific knowledge it has about its domain of application. For reasons of extensibility and flexibility, it is important to separate (a) the abstract concepts and relations of the target domain, from (b) inferences which can be made in the domain, i.e., "what is known" from "how to use it."

2. Keep elements of the knowledge base as independent and modular as possible. When updating rules or links among objects, the fewer the interactions with other parts of the knowledge base the easier the isolation and repair of problems. Although complete independence of rules or objects

is impossible (without complex, lengthy descriptions of the context of relevance), partitioning the knowledge base into small, nearly independent modules facilitates maintenance. Common partitionings include: (a) domain-specific knowledge (e.g., a model of structural geology, which could be used in a variety of applications), (b) task-specific knowledge (e.g., the knowledge of how to use the model of structural geology, together with a model of the data sensed by a dipmeter tool, to interpret the data in terms of geological structures), (c) knowledge about interaction with developers and users, (d) problem solving knowledge (e.g., strategies like top-down refinement and least-commitment constraint propagation), and (e) other domain-independent knowledge (e.g., common sense facts, mathematics, etc.).

3. Separate the knowledge base from the programs that interpret it. (Historically this has been phrased as "separate the knowledge base and the inference engine" [Davis 82].)

4. Consider interaction with users as an integrated component. It is important to avoid dealing with user interaction issues in an "add on" manner, after the expert system has been designed. High quality user interaction frameworks are often essential to end-user utility. They are also important to widen the knowledge acquisition bottleneck.

5. Avoid assumptions about context of use. Extending a knowledge base is made difficult when assumptions about how the individual packets of knowledge will be used are implicitly encoded. For example, important premise conditions of a rule may be omitted because the system developer knows the context in which that rule will be applied (as noted earlier with the sample rule from the Dipmeter Advisor system.) This is also very important if domain-specific knowledge bases are to be reused for a variety of applications.

4.1.2. UNIFORMITY, SIMPLICITY, EFFICIENCY AND EXPRESSIVE POWER ARE INTER-DEPENDENT

1. Use as uniform a representation as possible, although specialized representations are often worth the cost of translating among representations, because they may improve run-time performance and simplify knowledge acquisition.

2. Keep the inference engine simple. A program's ability to reason about its actions depends on its ability to reason about the way it makes inferences and complex inference procedures make this task more difficult. But this may cause problems in expressing knowledge in "appropriate" ways and in run-time efficiency

3. Use a uniform vocabulary throughout, but multiple representations are a must. For example, objects are an appropriate way to encode the abstract concepts of a domain or a problem-solving method, but they offer no built-in inference mechanism. Hence additional machinery (e.g., rules) must be added to encode heuristics for making inferences in the domain.

4. There is a logical equivalence among representational choices, but an object-centered paradigm offers the most flexibility, and thus the most expressive power.

5. Be sure the reasoning is based on sound, conceptually simple strategic knowledge. A knowledge base is more than a bag of facts and relations; it is used for a purpose with a reasoning strategy in mind. The clearer that strategy is, the more coherent the knowledge base will be. However, this may negatively affect run-time performance.

4.1.3. REDUNDANCY IS DESIRABLE

1. Exploit redundancy. One advantage of a modular representation of the domain knowledge is that it allows the system to explore multiple lines of reasoning. By contrast, a conventional program typically has a single procedure with a fixed sequence of steps for achieving a goal. Reasoning

with uncertain or missing data, or with knowledge that is uncertain or incomplete, requires building redundancy into the reasoning to allow correct conclusions to be drawn in spite of these deficiencies.

4.2. Summary

Expert systems use AI methods for representing and using experts' knowledge about specific problem areas. They have been successfully used in many decision-making contexts in which (a) experts can articulate much of what they know (e.g., in training manuals), (b) experts reason qualitatively (e.g., based on what they have learned from experience) to augment the formulas in textbooks, and (c) the amount of knowledge required to solve problems is circumscribed and relatively small.

While there remain many open research problems of great interest and importance, expert systems -- and the shell systems that are generalizations of them -- encapsulate solutions to many problems associated with the representation, use, acquisition, and explanation of knowledge. The engineering solutions used in today's expert systems are not without limits, but they are well-enough understood and robust enough to support commercial applications. Moreover, each application provides more experimental data about the strengths of current AI methods.

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Literature Cited

Figure Legends

Figure 1. Dipmeter Advisor screen: This screen shows a partial explanation for a conclusion drawn by the system. The left hand column shows natural gamma radiation against depth. To its right is shown dip against depth. Individual dip estimates (called "tadpoles") show the magnitude of the dip as horizontal position, and the azimuth as a small direction line. High quality estimates have solid circles, low quality estimates are hollow. A dip pattern, found by the system, is shown as crosshatching over the relevant tadpoles. On the left are three small windows describing the fact that the system has inferred the existence of a Growth Fault, a specialized type of Normal Fault. One window describes the attributes of the fault, another shows a portion of the reasoning trace, and a third describes the rule that made the inference.

Figure 2. Dipmeter Advisor system rule: One of a set used to perform sedimentary environment analysis. This rule is only attempted after the system has determined that the overall sedimentary environment is a deltaic plain.

Figure 3. Dipmeter Advisor system object: Encapsulates information about normal or tensional geologic faults. Individual attribute (slot) names are shown in boldface (e.g, **Hanging-Wall-Block**). Where used, synonyms for attribute names are enclosed in braces (e.g., Downthrown-Block). The "type" of each attribute value is shown in square brackets (e.g., the value of the **Strike** slot is expected to be a datum of type **Azimuth**).

Figure 4. Dipmeter Advisor system Tectonic Feature hierarchy: Subclasses of each object are shown in boldface, to its right, connected to it by lines. Individual instances are shown in lightface.

References

[AALPS 85] AALPS.
SRI: AI and the Military.
The Artificial Intelligence Report 2(1):6-7, January, 1985.

[Bobrow 80] Bobrow, D.G. (ed.).
Artificial Intelligence (Special Issue on Non-Monotonic Logic, 13:1-1-2.
North Holland Publishing Co., , April, 1980.

[Brownston 85] Brownston, L., Farrel, R., Kant, E., and Martin, N.
Programming Expert Systems in OPS5.
Addison-Wesley Publishing Company, Inc., Reading, Mass., 1985.

[Buchanan 86] Buchanan, B.G.
Expert systems: working systems and the research literature.
Expert Systems 3(1):32-51, January, 1986.

[Buchanan 88] Buchanan, B. G.
Artificial intelligence as an experimental science.
In J. H. Fetzer (editor). *Aspects of Artificial Intelligence*, . D. Reidel, Amsterdam, 1988.

[Buchanan & Shortliffe 84]
Buchanan, B.G., and E.H. Shortliffe.
Rule-Based Expert Systems: The MYCIN Experiments of the Stanford Heuristic Programming Project.
Addison-Wesley, Reading, MA, 1984.

[Bundy 86] Bundy, A. (ed.).
Catalogue of Artificial Intelligence Tools.
Springer-Verlag, New York, 1986.
(2nd ed.).

[Chandrasekaran 86]
Chandrasekaran, B.
Generic tasks in knowledge-based reasoning: High-level building blocks for expert system design.
IEEE Expert :23-30, Fall, 1986.

[Clancey 85] Clancey, W.J.
Heuristic Classification.
Artificial Intelligence , December, 1985.

[Clancey 86] Clancey, W. J.
From GUIDON to NEOMYCIN and HERACLES in twenty short lessons: ONR final report 1979-1985.
AI Magazine 7(3):40-60, 187, August, 1986.

[Cline et al 85] Cline, T., Fong, W., Rosenberg, S.
An Expert Advisor for Photolithography.
Technical Report, Hewlett-Packard, 1501 Page Mill Rd., Palo Alto, CA 94304, January, 1985.

[Clocksin and Mellish 81]
Clocksin, W. F. and Mellish, C. S.
Programming in Prolog.
Springer-Verlag, New York, 1981.

[Davis 82] Davis, R.
Expert systems: Where are we? And where do we go from here?
The AI Magazine 3(2):1-22, spring, 1982.

[Davis 87] Davis, R.
Robustness and transparency in intelligent systems.
In *Human Factors in Automated and Robotic Space Systems*, pages 211-233. Committee on Human Factors, Natl. Research Council, 2101 Constitution Ave., Washington, D.C., 1987.

[Davis & Lenat 82]
Davis, R. and Lenat, D. B.
Knowledge-Based Systems in Artificial Intelligence.
McGraw Hill, New York, 1982.

[Dreyfus and Dreyfus 86]
Dreyfus, H. and Dreyfus, S.
Why expert systems do not exhibit expertise.
IEEE Expert :86-90, Summer, 1986.

[Feigenbaum et al 71]
Feigenbaum, E.A., Buchanan, B.G., and Lederberg, J.
On Generality and Problem Solving: A Case Study Using the DENDRAL Program.
In B. Meltzer and D. Michie (editors), *Machine Intelligence 6*, pages 165-190. American Elsevier, New York, 1971.

[Feinstein & Siems 85]
Feinstein, J.L. and Siems, F.
EDAAS: An expert system at the US Environmental Protection Agency for avoiding disclosure of confidential business information.
Expert Systems 2(2):72-85, April, 1985.

[Fox and Smith 84]
Fox, M. S. and Smith, S. F.
ISIS-A knowledge-based system for factory scheduling.
Expert Systems 1(1):25-49, 1984.

[Fried 87] Fried, L.
The dangers of dabbling in expert systems.
Computerworld :6 ff., June 29, 1987.

[Gevarter 87] W. B. Gevarter.
The Nature and Evaluation of Commercial Expert System Building Tools.
Computer 20(5):24-41, May, 1987.

[Goldberg & Robson 83]
Goldberg, A. and Robson, D.
Smalltalk-80: The Language and its Implementation.
Addison-Wesley Publishing Company, Menlo Park, 1983.

[Gorry 70] Gorry, G. A.
Modelling the diagnostic process.
J. Med. Educat. 45:293-302, 1970.

[Harmon 87] Harmon, P.
Currently available expert systems-building tools.
Expert Systems Strategies 3(6):11-18, July, 1987.

[Harmon & King 85]
Harmon, P. and King D.
Expert Systems: Artificial Intelligence in Business.
John Wiley & Sons, New York, 1985.

[Hayes-Roth et al 83]
Hayes-Roth, F., D. A. Waterman, Lenat, D. B., eds.
Building Expert Systems.
Addison-Wesley, Reading, MA, 1983.

[Hernandez 87] Hernandez, R.
Big eight firm audits with Mac.
Applied Artificial Intelligence Reporter 4(7):9, July, 1987.

[Hewitt 77] Hewitt, C.
Viewing Control Structures as Patterns of Passing Messages.
Artificial Intelligence 8:323-364, 1977.

[Hi-Class 85] Hi-Class.
AI Brings Smarts to PC-Board Assembly.
Electronics :17-18, July, 1985.

[Hickam et al 85]
Hickam, D.H., Shortliffe, E.H., Bischoff, M.B., and Jacobs, C.D.
The Treatment Advice of a Computer-Based Cancer Chemotherapy Protocol Advisor.
Annals of Internal Medicine , December, 1985.

[Hollan et al. 84]
Hollan, J. D., Hutchins, E. L., Weitzman, L.
STEAMER: An interactive inspectable simulation-based training system.
The AI Magazine 5(2):15-27, 1984.

[Horn et al 85] Horn, K.A., Compton, P., Lazarus, L., Quinlan, J.R.
An expert computer system for the interpretation of thyroid assays in a clinical laboratory.
The Australian Computer Journal 17(1):7-11, February, 1985.

[Kahn and McDermott 86]
Kahn, G. and McDermott, J.
The Mud System.
IEEE Expert 1(1):23-32, Spring, 1986.

[Kerschberg 86] Kerschberg, L. (editor).
Expert Database Systems: Proceedings of the First International Workshop.
Benjamin Cummings, Menlo Park, CA, 1986.

[Klahr et al. 87] Klahr, P. et al.
The authorizer's assistant: a large financial expert system application.
In *Proceedings of the Third Australian Conference on Applications of Expert Systems*, pages 11-32. New South Wales Institute of Technology, Sydney, May, 1987.

[Kolcum 86] Kolcum, E.H.
NASA demonstrates use of AI with expert monitoring system.
Aviation Week & Space Technology :79-85, March, 1986.

[Kulikowski & Weiss 82]
Kulikowski, C., and Weiss, S.
Representation of expert knowledge for consultation: The CASNET and EXPERT projects.
In P. Szolovits (editor), *Artificial Intelligence in Medicine*, pages 21-55. Westview Press, Boulder, CO, 1982.

[Lenat 86] Lenat, D.B., Prakash, M. and Shepherd, M.
CYC: Using common sense knowledge to overcome brittleness and knowledge acquisition bottlenecks.
AI Magazine VI(4):65-85, Winter, 1986.

[Lenat et al 83] Lenat, D. B., Davis, R., Doyle, J., Genesereth, M., Goldstein, I., Schrobe, H.
Reasoning about reasoning.
In Hayes-Roth, F., Waterman, D A., and Lenat, D B. (editor), *Building Expert Systems*, . Reading, Ma.: Addison-Wesley, 1983.

[Lindsay et al 80]
Lindsay, R .K., Buchanan, B. G., Feigenbaum, E. A., Lederberg, J.
Applications of Artificial Intelligence for Organic Chemistry: The DENDRAL Project.
McGraw-Hill, New York, 1980.

[McCarthy 58] McCarthy, J.
Programs with common sense.
In *Proc. Symposium on the Mechanisation of Thought Processes*, pages 77-84. National Physical Laboratory, 1958.
[Reprinted 1968 in 'Semantic information processing', ed. M. L. Minsky, pp. 403-409. Cambridge, MA: MIT Press.].

[McCarthy 83] McCarthy, J.
Some expert systems need common sense.
Annals of the New York Academy of Science , 1983.
Invited presentation for the New York Academy of Sciences Science Week Symposium on Computer Culture, April 5-8, 1983.

[McCarthy & Hayes 69]
McCarthy, J. and Hayes, P.
Some Philosophical Problems from the Standpoint of Artificial Intelligence.
In B. Meltzer and D. Michie (editors), *Machine Intelligence 4*, pages 463-502. Edinburgh University Press, Edinburgh, 1969.

[McDermott 83] McDermott, J.
Extracting knowledge from expert systems.
In *IJCAI-83*, pages 100-107. IJCAI, Karlsruhe, West Germany, August, 1983.
Volume 1.

[Michalski et al 86]
Michalski, R.S., Mozetic, I., Hong, J., Lavrac, N.
The multi-purpose incremental learning system AQ15 and its testing application to three medical domains.
In *Proc. AAAI-86*, pages 1041-1045. AAAI, Philadelphia, PA, August, 1986.

[Michie et al 84]
Michie, D., Muggleton, S., Riese, C., Zubrick, S.
RULEMASTER: A Second-Generation Knowledge-Engineering Facility.
In *The First Conference on Artificial Intelligence Applications*, pages 591-597. IEEE, IEEE Computer Society Press, December, 1984.

[Miller et al 84] Miller, F.D., Copp, D.H., Vesonder, G.T., Zielinksi, J.E.
THE ACE EXPERIMENT: Initial evaluation of an expert system for preventive maintenance.
In (editor), *Artificial Intelligence in Maintenance: Proc. Joint Services Workshop*, pages 421-427. Air Force Systems Command, June, 1984.
Publication #AFHRL-TR-84-25.

[Minsky 75] Minsky, M.
A framework for representing knowledge.
In Patrick H. Winston (editor), *The Psychology of Computer Vision*, pages 211-277. McGraw-Hill, New York, 1975.

[Mishkoff 85] Mishkoff, H. C.
Understanding Artificial Intelligence.
Texas Instruments Information Publishing Center, P.O.Box 225474, Dallas, TX 75265, 1985.

[Mitchell et al. 86]
Mitchell, J. M., Carbonell, J. G., and Michalski, R. S., eds.
Machine Learning: A Guide to Current Research.
Kluwer Academic Publications, Boston, 1986.

[Mittal et al 85] Mittal, S., Dym, C.L., and Morjaria, M.
PRIDE: An expert system for the design of paper handling systems.
In C.L. Dym (editor), *Applications of Knowledge-Based Systems to Engineering Analysis and Design,* . ASME Press, 1985.

[Moses 71] Moses, J.
Symbolic integration: The stormy decade.
Communications ACM 8:548-560, 1971.

[Nii et al 82] Nii, H. P., Feigenbaum, E. A., Anton, J. J., Rockmore, A. J.
Signal-to-symbol transformation: HASP/SIAP case study.
AI Magazine 3(2):23-35, spring, 1982.

[Nilsson 82] Nilsson, N. J.
Symbolic Computation: Principles of Artificial Intelligence.
Springer-Verlag, Berlin, 1982.

[O'Keefe et al 87]
O'Keefe, R.M., Balci, O., and Smith, E.P.
Validating Expert System Performance.
IEEE Expert :81-89, Winter, 1987.

[Rauch-Hindin 86]
Rauch-Hindin, W.B.
Artificial Intelligence In Business, Science, and Industry: Volume I- Fundamentals, Volume II - Applications.
Prentice-Hall, New Jersey, 1986.

[Richer 85] Richer, M.H. and Clancey, W.J.
Guidon-Watch: A Graphic Interface for Viewing a Knowledge-Based System.
IEEE Computer Graphics and Applications :51-64, November, 1985.

[Richer 86] Richer, M. H.
Evaluating the Existing Tools for Developing Knowledge-Based Systems.
Expert Systems 3(3):166-183, 1986.

[Scown 85] Scown, S. J.
The Artificial Intelligence Experience.
Digital Equipment Corp., 1985.

[Sheil 84] Sheil, B.A.
Power Tools For Programmers.
In D. R. Barstow and H. E. Shrobe and E. Sandewall (editors), *Interactive Programming Environments*, pages 19-30. McGraw-Hill, New York, NY, 1984.

[Smith 84] R. G. Smith.
On the Development of Commercial Expert Systems.
AI Magazine 5(3):61-73, Fall, 1984.

[Smith & Young 84]
Smith, R. G. and Young, R. L.
The Design Of The Dipmeter Advisor System.
In *Proceedings of the ACM Annual Conference*, pages 15-23. ACM, New York, October, 1984.

[Smith et al 85] Smith, R.G., Winston, H.A., Mitchell, T.M., and Buchanan, B.G.
Representation and Use of Explicit Justifications for Knowledge Base Refinement.
In *Proceedings of IJCAI85*, pages 673-680. IJCAI, Morgan Kaufmann Publishers, Los Altos, CA, 1985.

[Smith et al 87] Smith, R.G., Barth, P.S., and Young, R.L.
A Substrate for Object-Oriented Interface Design.
In B. Shriver and P. Wegner (editor), *Research Directions In Object-Oriented Programming*, pages 253-315. MIT Press, Cambridge, MA, 1987.

[Stefik & Bobrow 86]
Stefik, M.J. and Bobrow, D.G.
Object-Oriented Programming: Themes and Variations.
AI Magazine 6(4):40-62, 1986.

[Sweet 85] Sweet, L.
Research in progress at General Electric.
AI Magazine 6(3):220-227, Fall, 1985.

[Teknowledge 87]
Teknowledge.
TEKSolutions: Customer Success Stories.
Teknowledge, 1850 Embarcadero Rd., Palo Alto, CA 94303, 1987.

[Wah 87] Wah, B.W. (ed.).
Computer (Special Issue on Computers for AI Applications).
IEEE, January, 1987.

[Walker and Miller 86]
Walker, T.C. and Miller, R.K.
Expert Systems 1986.
SEAI Technical Publications, P.O.Box 590, Madison, GA 30650, 1986.

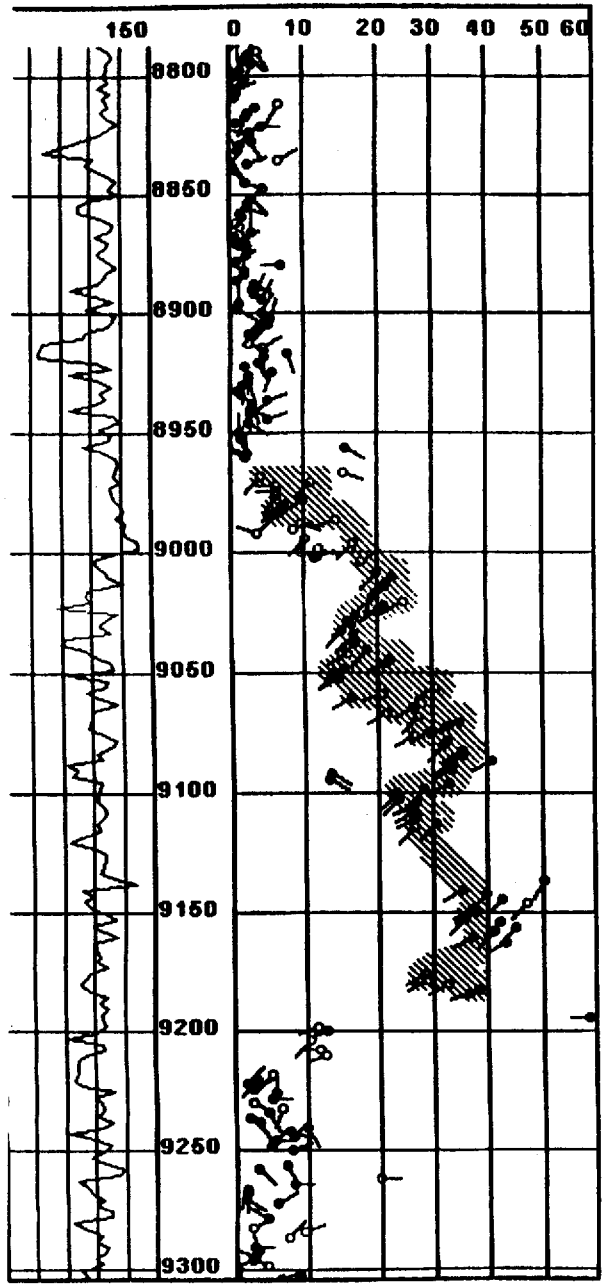
[Waterman 86] Waterman, D. A.
A Guide to Expert Systems.
Addison-Wesley, Reading, MA, 1986.

[Winograd 72] Winograd, T.
Understanding Natural Language.
Academic Press, New York, 1972.
Another version appears as "A Procedural Model of Language Under- standing" in Computer Models of Thought and Language, Roger Schank and Kenneth Colby [eds.], W.H.Freeman, San Francisco, CA, 1973. based on Phd thesis, MIT, 1971.

[Winograd 75] Winograd, T.
Frame representations and the procedural/declarative controversy.
In D. G. Bobrow and A. Collins (editors), *Representation and Understanding: Studies in Cognitive Science*, pages 185-210.
Academic Press, New York, 1975.

[Winograd & Flores 86]
Winograd, T. and Flores, F.F.
Understanding Computers and Cognition.
Ablex, Norwood, N.J., 1986.

[Zadeh 79] Zadeh, L. A.
A theory of approximate reasoning.
In J.E. Hayes, D. Michie, and L.I. Mikulich (editors), *Machine Intelligence 9*, pages 149-195. Ellis Horwood Ltd., Chichester, England, 1979.



Type: GROWTH-FAULT
TOP: 9182.0
BOTTOM: 9262.0
Creator: (NORMAL-FAULT-RULESET-0239 . NFR3A)
Modifier: ((NORMAL-FAULT-RULESET-0239 . NFR9A)
(NORMAL-FAULT-RULESET-0239 . NFR3A))
STRIKE: "SSE-NNW (150 deg)"
DIRECTION-TO-DOWNTHROWN-BLOCK: "ENE (60 deg)"
MIN-FAULT-CUT: 216.0
ILLUSTRATION:

Normal Fault

rollover

NORMAL-FAULT-0240
has been asserted by the rule **NFR3A**
with TOP = 8950.0
with BOTTOM = 9262.0
match variables were :
:UNCONFORMITY = **UNCONFORMITY-0241**
:NORMAL-FAULT = **NORMAL-FAULT-0240**
:RED = **RED-PATTERN-0197**
:MISSING-SECTION = **MISSING-SECTION-0196**

has been modified by the rule **NFR9A**

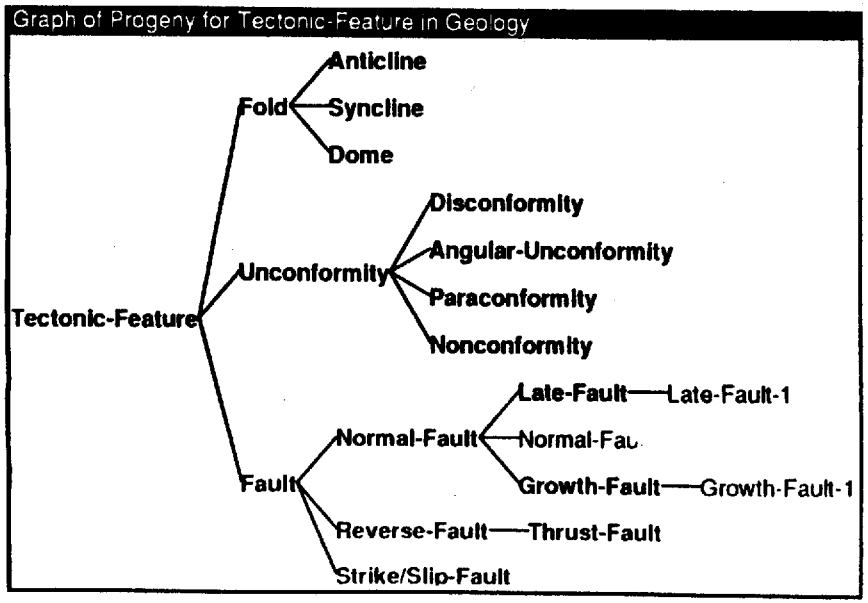
Explanation

NFR9A
Source:
J. A. Gilreath
Author:
P. Pruchnik & R. Smith, altered by D. Hammock 10-25-84

(In a region where the primary type of distortion is rollover, if there is a normal fault with a red pattern greater than 200 ft. in length associated with it then the fault is probably a growth fault; the fault cuts the well somewhere below the bottom of the red pattern, the strike of the fault is perpindicular to the azimuth of the pattern, the direction to the downthrown block is opposite the azimuth of the pattern & the length of the pattern gives a rough number for the mininum cut of the fault.)

Normal Fault

rollover


Graph of Progeny for Tectonic-Feature in Geology
Tectonic-Feature
Fold
Anticline
Syncline
Dome
Unconformity
Disconformity
Angular-Unconformity
Paraconformity
Nonconformity
Fault
Normal-Fault
Late-Fault
Late-Fault-1
Normal-Fau
Growth-Fault
Growth-Fault-1
Reverse-Fault
Thrust-Fault
Strike/Slip-Fault

Crevasse-Fan-Rule

If:

(1) **There exists** an element from Sand-Zones in well *Well* <s>
(2) **There exists** an element from Energy-Zones in well *Well* <e>,
    such that there is an intersection of s and e <i1>, and
    such that the Energy of e is Moderate
(3) **There exists** an element from Texture-Zones in well *Well* <t>,
    such that there is an intersection of i1 and t <i2>, and
    such that the Grain-Size of t is (Fine-Sand Medium-Sand), and
    such that the Sorting of t is Moderately-Well-Sorted

then:

(1) Create a Crevasse-Fan-Zone from the top of i2 to the bottom of i2 in well *Well*

Normal Fault

Object: Normal-Fault
Synonyms:
Generalizations: Fault
Groups:
Type: Class
Edited: 13-Dec-87 14:26:25 PST **By:** Schoen
Picture[Bitmap]:

Hanging-Wall-Block{Downthrown-Block} **[Object]:**
Upper-Distortion-Region[Object]:
Breccia-Region{Crushed-Zone} **[Object]:**
Fault-Plane[Object]:
Lower-Distortion-Region[Object]:
Foot-Wall-Block{Upthrown-Block} **[Object]:**
Time-Of-Faulting[Geologic-Age]:
Strike[Azimuth]:
Slip[Floatingpointnumber]:
Fault-Angle{Hade} **[Dipmagnitude]:**
Direction-To-Downthrown-Block[Azimuth]:
Throw[Distance]:
Draw[Lisp]: Drawfault
Instantiate[Lisp]: Instantiatefault
Detect[Rule]: (Rule-Nfr1 Rule-Nfr3 Rule-Nfr4 Rule-Nfr5 Rule-Nfr7)
Specialize[Rule]: (Rule-Nfr6 Rule-Nfr9 Rule-Nfr11 Rule-Nfr12)

<COALECON>
ANN-REV.MSS
" " .BIB

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Table of Contents