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EXPERT SYSTEMS: ARTIFICIAL INTELLIGENCE APPLIED*

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Abstract—This article provides an overview of expert systems, the topic of greatest current interest in Artificial Intelligence (AI). The article describes what an expert system is and sketches the mechanisms by which several of the better known systems operate. The prerequisites for constructing an expert system are given and the state of the art of current expert systems is indicated, with an extensive listing of these systems being provided. The article concludes with a forecast of the nature and applications of future expert systems.

1. INTRODUCTION

1984,

The most popular topic in Artificial Intelligence (AI) today is Expert Systems. Prior to the last decade, in trying to find solutions to problems, AI researchers tended to rely on non-knowledge-guided search techniques or computational logic. These techniques were successfully used to solve elementary problems or very well structured problems such as games. However, real complex problems are prone to have the characteristics that their search space tends to expand exponentially with the number of parameters involved. For such problems, these older techniques have generally proved to be too weak and a new approach was needed. This new approach emphasized knowledge rather than search and has led to the field of Knowledge Engineering and Expert Systems. The resultant expert systems technology, limited to academic laboratories in the 70's, is now becoming cost-effective and is beginning to appear in commercial applications.

2. WHAT IS AN EXPERT SYSTEM?

Feigenbaum, a pioneer in expert systems, states:1

An "expert system" is an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution. The knowledge necessary to perform at such a level, plus the inference procedures used, can be thought of as a model of the expertise of the best practitioners of the field.

The knowledge of an expert system consists of facts and heuristics. The "facts" constitute a body of information that is widely shared, publicly available, and generally agreed upon by experts in a field. The "heuristics" are mostly private, little-discussed rules of good judgement (rules of plausible reasoning, rules of good guessing) that characterize

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expert-level decision making in the field. The performance level of an expert system is primarily a function of the size and quality of the knowledge base that it possesses.

These days, it is common to characterize any large, complex AI system that uses large bodies of domain knowledge as an expert system. Thus, nearly all AI applications to real-world problems can be considered in this category, though the designation "knowledge-based systems" is more appropriate.

3. THE BASIC STRUCTURE OF AN EXPERT SYSTEM

An expert system consists of:

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- (1) a knowledge base (or knowledge source) of domain facts and heuristics associated with the problem;
- (2) an inference procedure (or control structure) for utilizing the knowledge base in the solution of the problem;
- (3) a working memory—"global data base"—for keeping track of the problem status, the input data for the particular problem, and the relevant history of what has thus far been done. ⇒ Explanation module

A human "domain expert" usually collaborates to help develop the knowledge base. Once the system has been developed, in addition to solving problems, it can also be used to help instruct others in developing their own expertise.

— Education at Usage

It is desirable, though still far from common, to have a user-friendly natural language interface to facilitate the use of the system in all three modes: development, problem solving, instruction. In some sophisticated systems, an explanation module is also included, allowing the user to challenge and examine the reasoning process underlying the system's answers. Figure 1 is a diagram of an idealized expert system. When the domain knowledge is stored as production rules, the knowledge base is often referred to as the "rule base," and the inference engine as the "rule interpreter."

An expert system differs from more conventional computer programs in several important respects. Duda² observes that, in an expert system "... there is a clear separation of general knowledge about the problem (the rules forming a knowledge base)

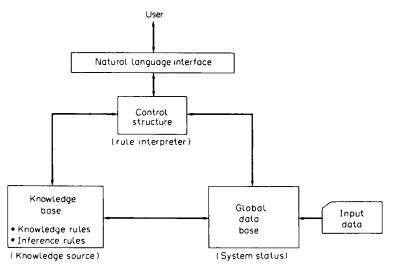


Figure 1. Basic structure of an expert system.

Direction of Inference

from information about the current problem (the input data) and the methods for applying the general knowledge to the problem (the rule interpreter)." In a conventional computer program, knowledge pertinent to the problem and methods for utilizing this knowledge are all intermixed, so that it is difficult to change the program. In an expert system, "... the program itself is only an interpreter (or general reasoning mechanism) and (ideally) the system can be changed by simply adding or subtracting rules in the knowledge base."

3.1. The knowledge base

The most popular approach to representing the domain knowledge (both facts and heuristics) needed for an expert system is by production rules (also referred to as "SITUATION-ACTION rules" or "IF-THEN rules").* Thus, often a knowledge base is made up mostly of rules which are invoked by pattern matching with features of the task environment as they currently appear in the global data base.

3.2. The control structure

In an expert system a problem-solving paradigm must be chosen to organize and control the steps taken to solve the problem. A common, but powerful approach involves the chaining of IF-THEN rules to form a line of reasoning. The rules are actuated by patterns (which, depending on the strategy, match either the IF or the THEN side of the rules) in the global data base. The application of the rule changes the system status and therefore the data base, enabling some rules and disabling others. The rule interpreter uses a control strategy for finding the enabled rules and for deciding which of the enabled rules to apply. The basic control strategies used may be top-down (goal driven), bottom-up (data driven), or a combination of the two using a relaxation-like convergence process to join these opposite lines of reasoning together at some intermediate point to yield a problem

4. ARCHITECTURE OF EXPERT SYSTEMS

solution. However, virtually all the heuristic search and problem solving techniques that

the AI community has devised have appeared in the various expert systems.

One way to classify expert systems is by function (e.g. diagnosis, planning, etc). However, examination of existing expert systems indicates that there is little commonality in detailed system architecture that can be detected from this classification. A more fruitful approach appears to be to look at problem complexity and problem structure and deduce what data and control structures might be appropriate to handle these factors.

The Knowledge Engineering community has evolved a number of techniques (presented in the excellent tutorial by Stefik et al.³ and summarized in Gevarter⁴) which can be utilized in devising suitable expert system architectures.

The use of these techniques in four existing expert systems is illustrated in Table 1 (a-d). Table 1 (a-d) outlines the basic approach taken by each of these expert systems and shows how the approach translates into key elements of the Knowledge Base, Global Data Base

^{*} Not all expert systems are rule-based. The network-based expert systems MACSYMA, INTERNIST/CADUCEUS, Digitalis Therapy Advisor, HARPY and PROSPECTOR are examples which are not. Buchanan and Duda⁸ (1982) state that the basic requirements in the choice of an expert system knowledge representation scheme are extendibility, simplicity and explicitness. Thus, rule-based systems are particularly attractive.

Table 1. Characteristics of example expert systems

Table 1 (a).

1. Derive constraints from the data constraints on molecular candidate structures structure from candidates are cardidate structure from candidates are cardidates structure from candidates are candidates. 4. Compare with data candidate structures structures to satisfy constraints and proach the most interesting spectrographs from structures. Start with elementary ideas in Elementary ideas in finite set space of possible conjectures that can be generated conjectures and pursue that line for discarding bad ideas of reasoning conjectures and pursue that line for discarding bad ideas of consequences and pursue that line for discarding bad ideas.	Purpose	Approach	Knowledge base	Key elements of Global data base	Control structure
Start with elementary ideas in these elementary ideas conjectures that can be see elementary ideas conjectures and pursue that line set most interesting of reasoning of reasoning interesting resting the stitution interesting resting interesting resting resting interesting resting resti	Generate plausible structural representations of organic molecules from mass spectrogram data	Derive constraints from the data Generate candidate structures Fredict mass spectrographs for candidates Compare with data	Rules for deriving constraints on molecular structure from experimental data Procedure for generating candidate structures to satisfy constraints Rules for predicting spectrographs from structures	Mass spectrogram data Constraints Candidate structures	Forward chaining Plan, generate and test
Approach Knowledge base Global data base Start with elementary ideas in Elementary ideas in finite set theory Search a space of possible conjectures that can be generated from these elementary ideas conjectures and pursue that line Choose the most interesting conjectures and pursue that line for discarding bad ideas Choose the most interesting elementary ideas for discarding bad ideas Choose the most interesting elementary ideas for discarding bad ideas	System: DENDRAL; Institution	n: Stanford University; Authors: Feigenbaum	& Lederberg; Function: Data interprete Table 1(b).	tion.	
Start with elementary ideas in Elementary ideas in finite set recording the set theory set theory search a space of possible conjectures that can be generated conjectures that can be generated mathematical concepts by from these elementary ideas conjectures and pursue that line heuristics of "interestingness" for discarding bad ideas for conjectures and pursue that line heuristics of reasoning for discarding bad ideas	Purpose	Approach	Knowledge base	Key elements of Global data base	Control structure
	Discovery of mathematical concepts	Start with elementary ideas in set theory Search a space of possible conjectures that can be generated from these elementary ideas Choose the most interesting conjectures and pursue that line of reasoning	Elementary ideas in finite set theory Heuristics for generating new mathematical concepts by modifying and combining elementary ideas Heuristics of "interestingness" for discarding bad ideas	Plausible candidate concepts	Plan, generate, and test

System: AM; Institution: Stanford University; Author: Lenat; Function: Concept formation.

Table 1 (c).

Purpose	Approach	Knowledge base	Global data base	Control structure
Configure VAX computer systems (from a customer's order of components).	Break problem up into the following ordered subtasks: 1. Correct mistakes in order 2. Put components into CPU cabinets 3. Put boxes into unibus cabinets and put components in boxes 4. Put panels in unibus cabinets 5. Lay out system on floor 6. Do the cabling Solve each subtask and move on to the next one in the fixed order	Properties of (roughly 500) VAX components Rules for determining when to move to next subtask based on system state Rules for carrying out subtasks (to extend partial configuration) (Approximately 1200 rules total)	Customer order Current task Partial configuration (System state)	"MATCH" (data driven) (no backtracking)
; Institution: CMU; A	System: R1; Institution: CMU; Author: McDermott; Function: Design.	Table 1 (d).		
Purpose	Approach	K nowledge base	Key elements of Global data base	Control structure
Diagnosis of bacterial infections and recommendations for antibiotic therapy	Represent expert judgmental reasoning as condition-conclusion rules together with the expert's "certainty" estimate for each rule Chain backwards from hypothesized diagnoses to see if the evidence supports it Exhaustively evaluate all hypotheses Match treatments to all diagnoses which have high certainty values	Rules linking patient data to infection hypotheses Rules for combining certainty factors Rules for treatment	Patient history and diagnostic tests Current hypothesis Status Conclusions reached thus far, and rule numbers justifying them	Backward chaining thru the rules Exhaustive search

System: MYCIN; Institution: Stanford University; Author: Shortliffe; Function: Diagnosis.

Table 2. Control structures of some well known expert systems

	Search space transformations	ierarchical refinement notivices resolution sea rules	Н											×		×		×		
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			Domain	Medicine	Chemistry	Elec. circuits	Medicine	Geology	Chemistry	Math	Medicine	Chemistry	Computers	Robots	Robots	Genetics	Elec. circuits	Speech unders.	Speech unders.	
			Function	Diagnosis	Data interpr.	Analysis	C.A.I.	Knowl. acquis.	Learning	Concept formation	Monitoring	Data interpr.	Design	Planning	Planning	Design	Design	Signal interpr.	Signal interpr.	
			System	MYCIN	DENDRAL	EL	GUIDON	KAS	META-DENDRAL	WA	νM	GAI	RI	ABSTRIPS	NOAH	MOLGEN	SYN	HEARSAY 11	HARPY	

and Control Structure. An indication of the basic control structures of the systems in Table 1 (a-d) and some of the other well known expert systems, are given in Table 2.

Table 2 represents expert system control structures in terms of the search direction, the control techniques utilized, and the search space transformations employed. The approaches used in the various expert systems are different implementations of two basic ideas for overcoming the combinatorial explosion associated with search in real complex problems. These two ideas are:

- (1) Find ways to efficiently search a space.
- (2) Find ways to transform a large search space into smaller manageable chunks that can be searched efficiently. -> Main Problem of RETE algorithm.

It will be observed from Table 2 that there is little architectural commonality based either on function or domain of expertise. Instead, expert system design may best be considered as an art form, like custom home architecture, in which the chosen design can be implemented from the collection of available AI techniques in heuristic search and problem solving.

In addition to the techniques indicated in Table 2, also emerging are distributed knowledge and problem solver approaches exemplified by the MDX expert system (Chandrasekaran⁵) and the object-oriented programming language, LOOPS (Stefik et al.⁶).

5. EXISTING EXPERT SYSTEMS

The uses of expert systems are virtually limitless. They can be used to help: diagnose, repair, monitor, analyze, interpret, consult, plan, design, instruct, explain, learn, and conceptualize.

Table 3 is a list, classified by function and domain of use, of most of the existing major expert systems. It will be observed that there is a predominance of systems in the Medical and Chemistry domains following from the pioneering efforts at Stanford University. From the list, it is also apparent that Stanford University dominates in number of systems, followed by MIT, CMU, BBN and SRI, with several dozen scattered efforts elsewhere.

The list indicates that thus far the major areas of expert systems development have been in diagnosis, data analysis and interpretation, planning, computer-aided instruction, analysis, and automatic programming. However, the list also indicates that a number of pioneering expert systems already exist in quite a number of other functional areas. In addition, a substantial effort is under way to build expert systems as tools for constructing expert systems.

6. CONSTRUCTING AN EXPERT SYSTEM

Duda² states that to construct a successful expert system, the following prerequisites must be met:

There must be at least one human expert acknowledged to perform the task well.

The primary source of the expert's exceptional performance must be special knowledge, judgment, and experience.

The expert must be able to explain the special knowledge and experience and the methods used to apply them to particular problems.

The task must have a well-bounded domain of application.

Table 3. Existing expert systems by function

	Table 3. Existing expert systems by function	unction	
Function	Domain	System*	Institution
Diagnosis	Medicine Medicine Medicine Medicine Medicine Medicine Computer faults Computer faults Nuclear reactor accidents	PIP CASNET INTERNIST/CADUCEUS MYCIN PUFF MDX DART IDT REACTOR	MIT Rutgers U. U. of Pittsburgh Stanford U. Stanford U. Ohio State U. Stanford U. EG&C Idaho Inc.
Data analysis and interpretation	Geology Chemistry Chemistry Geology Protein crystallography Determination of causal relationships in medicine Determination of causal relationships in medicine Oil well logs	DIPMETER ADVISOR DENDRAL GAI PROSPECTOR CRYSALIS RX ABEL ELAS	M.I.T./Schlumberger Stanford U. Stanford U. Stanford U. Stanford U. Stanford U. MIT AMOCO
Analysis	Electrical circuits Symbolic mathematics Mechanics problems Naval task force threat analysis Earthquake damage assessment for structures Digital circuits	EL MACSYMA MECHO TECH SPERIL CRITTER	MIT MIT Edinburgh Rand/NOSC Purdue U. Rutgers U.
Design	Computer system configurations Circuit synthesis Chemical synthesis	R1/XCON SYN SYNCHEM	CMU/DEC MIT SUNY Stonybrook
Planning	Chemical synthesis Robotics Robotics Planctary flybys Errand planning Molecular genetics Mission planning Job shop scheduling Design of molecular genetics experiments	SECHS NOAH ABSTRIPS DEVISER OP-PLANNER MOLGEN KNOBS ISIS-II SPEX	U. of Cal. Santa Cruz SRI SRI SRI JPL Rand Stanford U. MITRE CMU

MIT CMU RAND Stanford U.	CMU	CMU CMU Stanford U. System Controls Inc. NOSC, San Diego/SDC U. of Toronto	Stanford U.	Stanford U.	BBN Stanford U. Stanford U. BBN BBN BBN BBN BBN BBN BBN	Stanford U. Rutgers SRI	Rand Stanford U. USC/ISI Stanford U. CMU IBM U. of MD Rutgers Smart Sys. Tech. Tokyo U.
HODGKINS AIRPLAN TATR METADENDRAL FIRISKO	AM	HEARSAY II HARPY SU/X HASP STAMMER-2 ALVEN ANALYST	ΝΛ	SACON	SOPHIE GUIDON EXCHECK STEAMER BUGGY WHY WEST WUMPUS	TEIRESIAS EXPERT KAS	ROSIE AGE HEARSAY III EMYCIN OPS 5 RAINBOW KMS EXPERT ARBY MECS-AI
Medical diagnosis Naval aircraft ops Tactical targeting Chemistry Henristics	Mathematics	Speech understanding Speech understanding Machine acoustics Ocean surveillance Sensors on board naval vessels Medicine—Left ventrical performance Military situation determination	Patient respiration	Structural analysis computer program	Electronic troubleshooting Medical diagnosis Mathematics Steam propulsion plant operation Diagnostic skills Causes of rainfall Coaching of a game Coaching of a game	Medical diagnosis Medical consultation Geology	Medical diagnosis Medical consultation Electronic systems diagnosis Medical consultation using time-oriented data
Learning from experience	Concept formation	Signal interpretation	Monitoring	Use advisor	Computer aided instruction	Knowledge acquisition	Expert system construction

Table 3. (continued)

Function	Domain	System*	Institution
Consultation/intelligent assistant	Battlefield weapons assignments Medicine Radiology Computer sales Medical treatment Nuclear power plants	BATTLE Digitalis Therapy Advisor RAYDEX XCEL ONCOCIN CSA Model-Based Nuclear Power Plant Consultant	NRL AI Lab MIT Ruigers U. CMU/DEC Stanford U. GA Tech
Management	Diagnostic prompting in Medicine Estate planning Automated factory Project management	RECONSIDER TAX ADVISOR IMS CALLISTO	U. of CA, S.F. U. of IL CMU DEC
Automatic programming	Modelling of oil well logs	ONIX CHI PECOS LIBRA SAFE	Schlumberger-Doll Res. Kestrel Inst. Stanford U. Stanford U. USC/ISI
Image understanding		DEDALUS Programmer's apprentice VISIONS ACRONYM	SRI MIT U. of Mass. Stanford U.

* References to these systems can be found in Duda, 2 Stefik et al., 3 Buchanan, 7 Buchanan and Duda, 8 Barr and Feigenbaum, 9 IJCAI-81, 10 and AAAI-82.11

Using present techniques and programming tools, the effort required to develop an expert system appears to be converging towards five man-years, with most endeavors employing two to five people in the construction.

7. SUMMARY OF THE STATE-OF-THE-ART

Buchanan⁷ indicates that the current state of the art in expert systems is characterized by:

Narrow domain of expertise

Spa h'al Complexity

Because of the difficulty in building and maintaining a large knowledge base, the typical domain of expertise is narrow. The principal exception is INTERNIST, for which the knowledge base covers 500 disease diagnoses. However, this broad coverage is achieved by using a relatively shallow set of relationships between diseases and associated symptoms. (INTERNIST is now being replaced by CADUCEUS, which uses causal relationships to help diagnose simultaneous unrelated diseases.)

Limited knowledge representation languages for facts and relations

Relatively inflexible and stylized input-output languages

Stylized and limited explanations by the systems

Laborious construction

At present, it requires a knowledge engineer to work with a human expert to laboriously extract and structure the information to build the knowledge base. However, once the basic system has been built, in a few cases it has been possible to write knowledge acquisition systems to help extend the knowledge base by direct interaction with a human expert, without the aid of a knowledge engineer.

Single expert as a "knowledge czar"

We are currently limited in our ability to maintain consistency among overlapping items in the knowledge base. Therefore, though it is desirable for several experts to contribute, one expert must maintain control to insure the quality of the data base.

Fragile behavior

In addition, most systems exhibit fragile behavior at the boundaries of their capabilities. Thus, even some of the best systems come up with wrong answers for problems just outside their domain of coverage. Even within their domain, systems can be misled by complex or unusual cases, or for cases for which they do not yet have the needed knowledge or for which even the human experts have difficulty.

Requires knowledge engineer to operate

Another limitation is that for most current systems only their builders or other knowledge engineers can successfully operate them—a friendly interface not having yet been constructed.

Nevertheless, Randy Davis¹² observes that there have been notable successes. A methodology has been developed for explicating informal knowledge. Representing and using empirical associations, five systems have been routinely solving difficult problems— DENDRAL, MACSYMA, MOLGEN, R1 and PUFF—and are in regular use. The first three all have serious users who are only loosely coupled to the system designers.

DENDRAL, which analyzes chemical instrument data to determine the underlying molecular structure, has been the most widely used program (see Lindsay et al.¹³). R1, which is used to configure VAX computer systems, has been reported to be saving DEC twenty million dollars per year, and is now being followed up with XCON. In addition, as indicated in Table 3, hundreds of systems have been constructed and are being experimented with.

8. FUTURE TRENDS

Figure 2 lists some of the expert systems applications currently under development.

It will be observed that there appear to be few domain or functional limitations in the ultimate use of expert systems. However, the nature of expert systems is changing. The limitations of rule-based systems are becoming apparent. Not all knowledge can be readily structured in the form of empirical associations. Empirical associations tend to hide causal relations (present only implicitly in such associations). Empirical associations are also inappropriate for highlighting structure and function.

Thus, the newer expert systems are adding deep knowledge having to do with causality and structure. These systems will be less fragile, thereby holding the promise of yielding correct answers often enough to be considered for use in autonomous systems, not just as intelligent assistants.

The other change is a trend towards an increasing number of non-rule based systems. These systems, utilizing semantic networks, frames and other knowledge representations, are often better suited for causal modeling and representing structure. They also tend to simplify the reasoning required by providing knowledge representations more appropriate for the specific problem domain.

Figure 3 (based largely on Hayes-Roth IJCAI-81 Expert system tutorial¹⁰ and on Feigenbaum¹) indicates some of the future opportunities for expert systems. Again no limitation is apparent.

It thus appears that expert systems will eventually find use in most endeavors which require symbolic reasoning with detailed professional knowledge—which includes much of the world's work. In the process, there will be exposure and refinement of the previously private knowledge in the various fields of applications.

On a more near-term scale, in the next few years we can expect to see expert systems with thousands of rules. In addition to the increasing number of rule-based systems we can also expect to see an increasing number of non-rule based systems. Also anticipated are much improved explanation systems that can explain (make "transparent") why an expert system did what it did and what things are of importance.

Medical diagnosis and prescription
Medical knowledge automation
Chemical data interpretation
Chemical and biological synthesis
Mineral and oil exploration
Planning/scheduling
Signal interpretation
Signal fusion – situation interpretation
from multiple sensors
Military threat assessment
Tactical targeting
Space defense

Air traffic control
Circuit diagnosis
VLSI design
Equipment fault diagnosis
Computer configuration selection
Speech understanding
Intelligent computer-aided instruction
Automatic programming
Intelligent knowledge base access
and management
System management
Tools for building expert systems

Figure 2. Expert system applications now under development.

Building and construction

Design, planning, scheduling, control

Equipment

Design, monitoring, control, diagnosis, maintenance, repair, instruction

Command and control

Intelligence analysis, planning, targeting, communication

Weapon systems

Target identification, adaptive control, electronic warfare

Professions

(Medicine, law, accounting, management, real estate, financial, engineering) Consulting, instruction, analysis Education

Instruction, testing, diagnosis, concept formation and new knowledge development from experience.

Imagery

Photo interpretation, mapping, geographic problem-solving.

Software

Instruction, specification, design, production, verification, maintenance

Home entertainment and advice-giving

Intelligent games, investment and finances, purchasing, shopping, intelligent information retrieval Intelligent agents

To assist in the use of computer-based systems

Office automation

Intelligent systems

Process control

Factory and plant automation

Exploration

Space, prospecting, etc.

Figure 3. Future opportunities for expert systems.

By the late 80's, we can expect to see intelligent, friendly and robust human interfaces and much better system building tools (currently a major need).

Somewhere around the year 2000, we can expect to see the beginnings of systems which semiautonomously develop knowledge bases from text. The result of these developments may very well herald a maturing information society where expert systems put experts at everyone's disposal. In the process, production and information costs should greatly diminish, opening up major new opportunities for societal betterment.

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