

DEPARTMENT OF THE INTERIOR
U.S. GEOLOGICAL SURVEY

An Expert System for the Identification of Foreshore
Depositional Environments

by

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This report is preliminary and has not been reviewed for conformity with U.S. Geological Survey editorial standards (and stratigraphic nomenclature).

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ILLUSTRATIONS

Figure 1.--

2.--

system for an interactive log analysis package, are described by (Crane, 1985). Other expert systems are currently under development (see for ex., West, 1985).

KNOWLEDGE REPRESENTATION AND INFERENCE ENGINE

The foreshore expert system was constructed using the Knowledge Acquisition System (KAS) and the Prospector inference engine, both developed by SRI International (Reboh, 1981). These tools were chosen primarily because they were available within the U.S. Geological Survey. In this expert system representation, knowledge is represented as an inference network (fig. 1). In the inference network, pieces of evidence (nodes) combine via arcs to form other pieces of evidence and, subsequently, to form hypotheses. For example, in the foreshore system one piece of evidence would be information on the presence of climbing ripples. The top level space, the hypothesis, is that the core or outcrop indicates a beach deposit.

The inference engine, the mechanism that determines which questions are asked when, used in this work uses a backward chaining control strategy. This means that once an hypothesis is chosen to consider, the system works backward from this goal hypothesis to one or more sub-goals needed to support the hypothesis. The evidence needed to support the sub-goals is determined, and this backward chaining continues until the evidence is no longer a combination of lower level information.

The system interacts with the user and asks for certainty factors or the strength of belief in a particular piece of evidence. The certainty factors vary from -5 to 5. A certainty factor of -5 indicates absolute certainty that the characteristic is not present, 5 indicates absolute certainty that it is

present, and 0 indicates no knowledge about the characteristic. Intermediate values indicate some certainty between the extremes (positive or negative). The certainties given by the user are translated by the system to probabilities and the internal system calculations are done in terms of probabilities. The final probability, the probability for the particular hypothesis under consideration, is translated back into a certainty factor before it is given to the user.

Prior probabilities are associated with the nodes in the inference network. These probabilities are intended to represent the likelihood that a particular statement (associated with the particular node) is true. For the foreshore system, for example, there would be a prior probability of burrows being present. The difficulty in assigning prior probabilities is then what "universe" to consider when determining prior probabilities. For example, the universe could be all sedimentary outcrops in the United States, all sedimentary outcrops with which the expert is familiar or any one of many other options. The prior probability would correspondingly represent the probability of burrows being present when considering all sedimentary outcrops in the United States, all outcrops familiar to the expert, etc.

COMBINING EVIDENCE

Evidence in the inference network can be directly acquired from the user (askable) or it can be assembled through logical combinations, plausible inference, or contexts from other evidence. Types of logical combinations are and, or, and not. For example, in figure 1, E_4 is connected to E_5 by not. E_5 is the negation of E_4 . E_4 might be the fact that a certain type of macrofossil is present in the sequence. Then E_5 would be the fact that the macrofossil is not present.

Plausible inference (rules) is of the type:

a piece of evidence E suggests an hypothesis H with strength S.

A piece of evidence E may be highly or only slightly suggestive of the hypothesis H. Two types of strengths S are incorporated: the effect of evidence on the hypothesis when the evidence is present and the effect of evidence on the hypothesis when the evidence is absent. Having these two types of strengths is useful since a piece of evidence may be very suggestive of the hypothesis when present but not reduce the likelihood of the hypothesis when absent. For example, if E is "the internal characteristics of the section are indicative of a marine foreshore deposit," then E is suggestive of the hypothesis that the deposit is a foreshore deposit when E is present and reduces the hypothesis when E is absent.

An example of a context is given by the dashed line between E_2 and E_4 in figure 1. E_2 is a context for E_4 . The user will be asked the question about evidence E_4 only if the certainty associated with E_2 is in the appropriate range. For example, if E_2 represents the presence of burrows in a sedimentary sequence and E_4 indicates that the amount of burrowing decreases upward in the sequence, E_2 is a context for E_4 . It is logical to ask whether burrowing decreases upward only if burrowing has been confirmed in the sequence. Contexts eliminate unnecessary questions and enable the expert system to ask appropriate questions and thus help the system make more efficient use of the user's time.

PROPAGATING PROBABILITIES

Prior probabilities are assigned by the expert and the knowledge engineer. The knowledge engineer translates the experts knowledge into a form that can be used by the system. The prior probabilities are updated and

posterior probabilities are derived as the user volunteers certainties for evidence about a specific outcrop or core. When evidence is combined through plausible inference, a Bayesian method is used to update the probabilities (Reboh, 1981). The updating is summarized by the graph in figure 2. The analytic expression for this graph is:

$$P(H|E') = \frac{P(H|\sim E) + \frac{P(H) - P(H|\sim E)}{P(E)} P(E|E')}{P(H) + \frac{P(H|E) - P(H)}{1-P(E)} [P(E|E') - P(E)]}$$

$0 \leq P(E|E') < P(E)$
 $P(E) \leq P(E|E') \leq 1$

The graph and equation show $P(H|E')$, the consequent probability, as a function of $P(E|E')$, the antecedent probability. E' denotes the observations that have led the user to think evidence E is present. $P(E|E')$ denotes the probability of the evidence E being present given these other observations. Similarly, $P(H|E')$ denotes the probability of the hypothesis given these other observations. When $P(E|E') = 0$, when the probability of E given the observations is zero, then $P(H|E') = P(H|\sim E)$, the probability of the hypothesis given that E is not present ($\sim E$ represents "not E "). The other two juncture points on the graph can be interpreted similarly. When the observations E' tell us nothing about E , $P(E|E')$ remains at the prior probability for E , $P(E)$. Then $P(H|E')$ will remain at $P(H)$, the prior probability for H . When $P(E|E') = 1$, we are certain E is present given the observations and $P(H|E') = P(H|E)$.

When each of N pieces of evidence ($E_i; i=1, \dots, N$) has some effect on H through a rules combination, the posterior odds $O(H|E')$ is obtained as:

$$O(H|E') = \prod_{i=1}^N L_i' \quad O(H)$$

$$\text{where } L_i' = \frac{O(H|E_i')}{O(H)}$$

$$\text{and } O(H) = \frac{P(H)}{1-P(H)}$$

See (Reboh, 1981) for further details.

For logical combinations, formulas from fuzzy set theory (Zadeh, 1965) are used to update probabilities. For a conjunction, $E = E_1 \text{ and } E_2 \text{ and...and } E_n$,

$$P(E|E') = \text{minimum}_i P(E_i|E')$$

For a disjunction, $E = E_1 \text{ or } E_2 \text{ or ...or } E_n$,

$$P(E|E') = \text{maximum}_i P(E_i|E')$$

and for a negation, $E = \sim E_1$

$$P(E|E') = 1 - P(E_1|E').$$

(Reboh, 1981). One main difference between logical and plausible relations is that, in logical combinations, the posterior probability is determined by the probability of only one of the components, for example, the maximum component for a conjunction. In contrast, in rules combinations, the probabilities of all the components are used to determine the posterior probabilities.

The set of questions asked by the system varies with each interaction. Answers to earlier questions determine the character of later questions in the interaction. One reason why interactions vary is the use of contexts as described earlier.

At any request for a certainty for a piece of evidence, the user can respond with "why" or a "?". The system responds to a "why" with the reason why that piece of information is needed in determining the overall likelihood of the hypothesis. The response to a "?" is a more detailed explanation or rephrasing, usually at a more basic level, of the question.

APPLICATION

The foreshore expert system described here determines if a particular outcrop or core indicates a foreshore depositional environment. The model of the beach foreshore is, more specifically, a storm dominated marine foreshore in a prograding shoreline. It is a composite based on H. E. Clifton's work on modern beaches of the Pacific, Atlantic, and Gulf Coasts of the United States and the Mediterranean coast of Spain and ancient beach deposits. The ancient deposits include Pleistocene terrace deposits from the west coast of the United States and the Spanish Mediterranean coast, Tertiary deposits from California, Texas, New Jersey, and Hungary, and Cretaceous deposits from Utah and Colorado.

Various types of evidence are requested from the user. Initially, questions are asked which will screen out outcrops or cores which are very unlikely to be foreshore deposits. For example, one question asked early in the interaction is:

To what degree do you believe that marine deposits are present within the succession that includes the deposit in question?

If the certainty volunteered by the user for this question is too low, the system will not ask any further questions and will summarize by stating that it is very unlikely that this particular outcrop or core represents a foreshore deposit. On the other hand, if the response to the question above

and to each of the other screening questions has a high enough certainty, further evidence is requested to determine the likelihood of the deposit representing a foreshore environment.

The evidence falls into several categories: the internal characteristics of the deposit, information on the unit above the one under consideration, information on the unit below the one under consideration, and information common to the unit under consideration and the underlying unit.

The "internal characteristics" category includes information on the thickness of the deposit in question; whether it fines or coarsens upward; whether heavy minerals increase or decrease upward; the abundance of mica; the inclination of and the grading within the planar parallel laminae; the presence of trace fossils; the presence of ripples and climbing ripples, and the direction of the ripples; and the presence and inclination of pebble imbrication. Questions about the underlying unit are asked only if the user believes there is continuous deposition below the deposit in question; if so, the information on the unit below will aid in determining the likelihood of the deposit in question being a foreshore. Questions asked about the underlying unit include whether or not there is evidence of subaerial exposure, whether the underlying beds are cross-bedded, and whether or not there are high angle foresets, marine fauna, and bioturbation. Similarly, questions are asked about the overlying unit if there is continuous deposition above the deposit under consideration. A few questions about the presence of shallow water fauna and the presence and position of macrofossils in the planar laminated and/or cross-bedded section make up the fourth category of information.

DISCUSSION

Expert systems differ from conventional programs and are appropriate for depositional environment interpretation because they incorporate heuristic knowledge as well as the factual knowledge which is included in conventional programs. The heuristic knowledge, or experience-based intuitive understanding, is an important part of the identification of depositional environments from outcrop or core characteristics. Moreover, in an expert system, the knowledge base is separate from the inference engine, or procedure for operating on the knowledge base or data. In conventional programs the procedure and the data are intertwined. The separation of the knowledge base and inference engine makes it easier to update the knowledge base or change the knowledge base as beliefs about a particular environment change.

This system, as well as others in development and planned are useful tools in geologic work. The system should be viewed as another tool, in somewhat the same vein as database, mapping, and statistical software. These systems are not intended to replace the expert, but rather to make his knowledge more readily available to the worker in his field.

Depositional environment expert systems may be consulted, used in teaching, and in comparing knowledge about one depositional environment with knowledge about another environment. The consulting function encompasses a range of uses. A high level user who is fairly certain what the cores or outcrops indicate can consult the system for or check to see if he has considered all the characteristics included in the system. At the other extreme, a user with limited experience can use the system in a consulting mode that is quite close to a teaching mode.

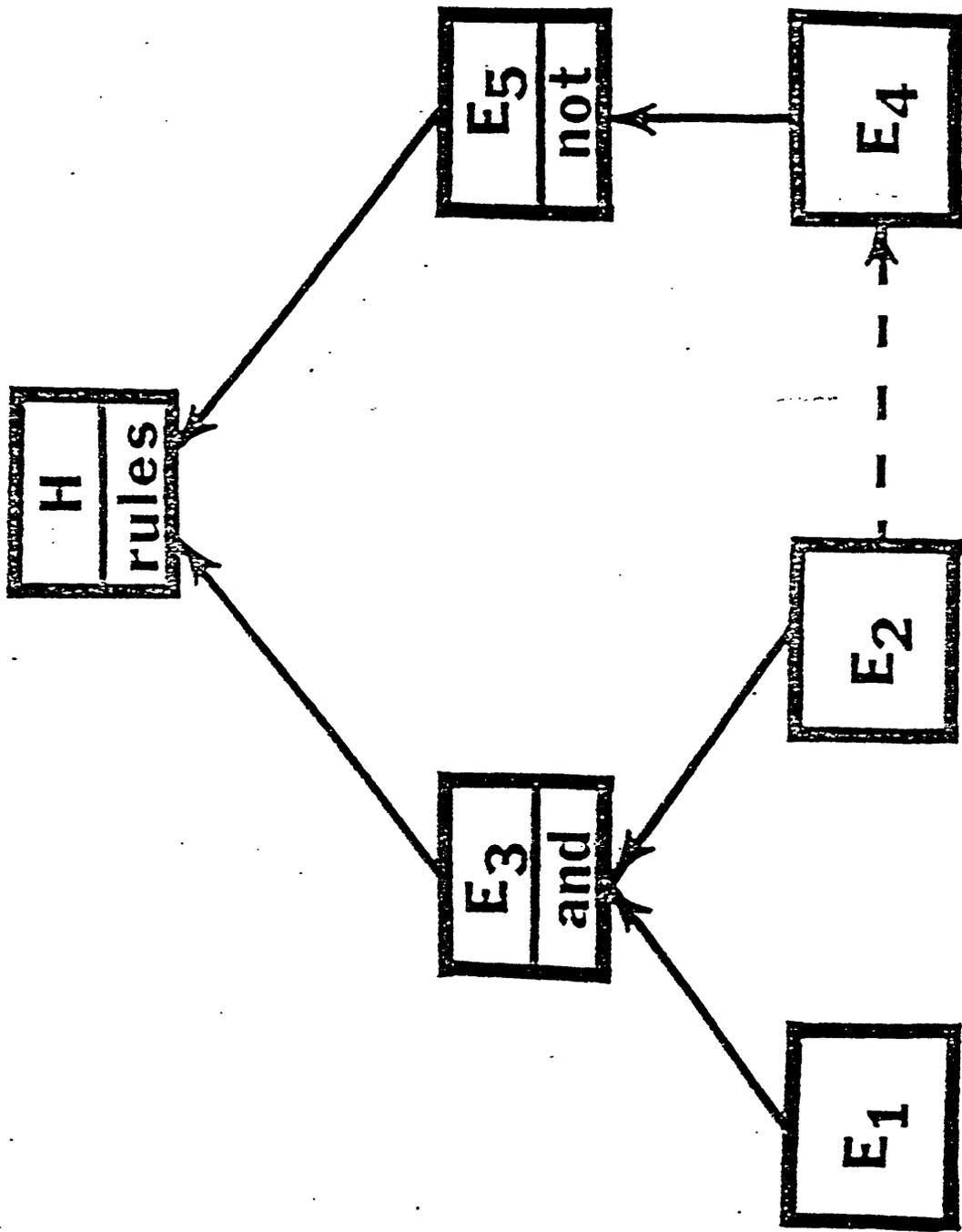
The system is useful as a teaching tool. During an interaction, when the system has accumulated enough information, it provides the overall certainty that the outcrop or core under consideration represents a foreshore deposit. The system also provides information on which pieces of evidence were important in reaching the conclusion and provides the reasoning used in deriving the certainty. This information enables the user to gain an understanding of the various outcrop or core characteristics that are considered and of the logic used to determine the overall likelihood of the environment. The "why" facility can be used to clarify the system's logic and a "?" can be used if terminology or questions are not clear. Because references can be added easily, this and other expert systems can provide rapid and easy access to reference material.

Because heuristic, as well as factual, knowledge is explicitly represented by the expert system, the system allows the comparison of the heuristic knowledge used by one expert with that used by another expert for the same environment. The representation of the knowledge facilitates the isolation of areas where the experts differ, and allows the identification of those differences. Similarly, the heuristics used for several different environments can be compared. These comparisons can be important in refining currently-accepted models for the environment in question.

Other system benefits include the fact that the development of an expert system is useful to the expert; the process may reveal inconsistencies or intuitive leaps for which he has no basis. These systems can save the expert's time by elevating the expertise of co-workers. It can also be important in preserving the expertise of experienced workers.

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INFERENCE NETWORK

Figure 1.--Inference network. Pieces of evidence (E_i) are combined to form other pieces of evidence and, subsequently, a hypothesis (H) by using logical relations (and, or, not), contexts (depicted by the dashed arrow), and plausible inference (rules, each with an associated strength S).

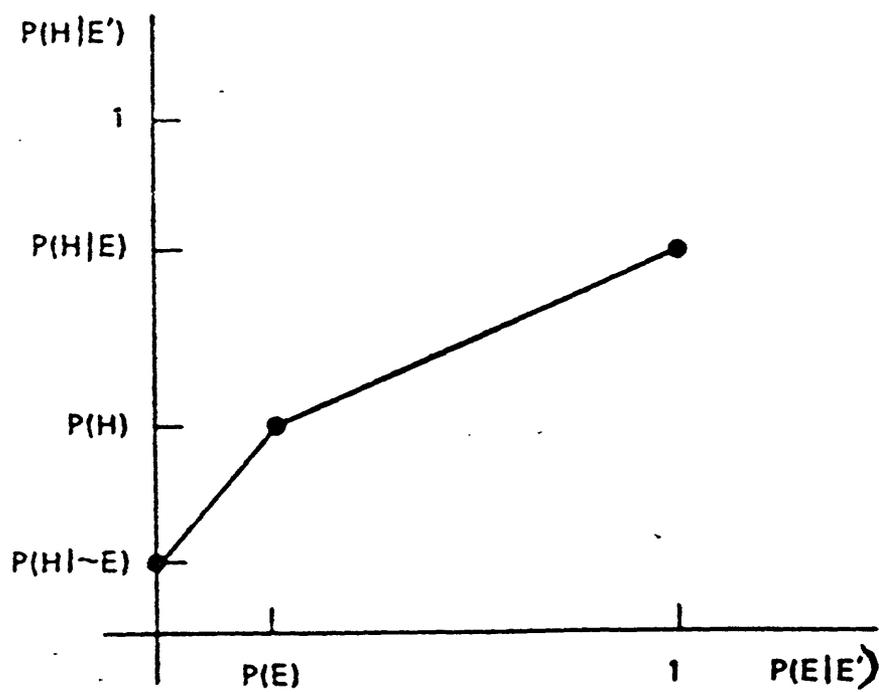


Figure 2. --Consequent probability as a function of the antecedent probability.