Technical Report TIRM 89-934, Turing Institute, UK, (Jan 1989),
http://www.cs.utexas.edu/users/pclark/papers

Exemplar-Based Reasoning in Geological Prospect Appraisal

Peter Clark
The Turing Institute
36 N.Hanover St
Glasgow, UK

Jan 1989

Abstract

This paper describes a prototype system for the prediction of parameters associated with a geological prospect, required for assessing the likelihood of hydrocarbons at the prospect. A principle characteristic of expert reasoning in this domain involves the recall and use of previous examples ('exemplars') of similar, already-drilled wells in addition to the use of general rules concerning known parameters of the prospect. Such reasoning is a common feature of human problem-solving, and involves generation and use of generalisations at *run-time* when a performance task is known, in contrast to an exhaustive enumeration of generalisations from examples before the performance task is known as performed by many rule induction systems. In this paper we describe the mechanisms for such exemplar-based reasoning in the prototype system, and discuss the characteristics of the problem domain which suggest the appropriateness of this approach.

1 Introduction

In the search for hydrocarbons such as oil and gas, the sites of potential prospects need to be appraised to assess if there are likely to be hydrocarbons present, and if so in what quantities. This task of prospect appraisal is large and complex. This paper describes the application of exemplar-based reasoning methods to one of the sub-problems of this larger task, namely that of determining various numerical parameters of the prospect such as the thickness or porosity of the oil reservoir there, required for making the full appraisal. The system has been developed as a simple prototype to investigate the application of expert systems in this area, and identify potential directions and potential problems for further development.

Rather than storing general rules for inferring porosity (say) from a prospect's attributes, we store specific examples ('exemplars') plus a mechanism for generalising from those examples to the new prospect. It is this which characterises the exemplar-based approach. In our case, the specific exemplars are the (already drilled) nearby wells. Given a prospect to assess, a general explanation of exemplars most related to the prospect is formed using a simple theory formation module, and then applied to the new prospect. Note that the system does not permanently store the general rules for inferring porosity (say) directly from a prospect's attributes – instead the appropriate generalisations are generated at run-time when a particular prospect is to be assessed, and discarded after use.

The principle motivation for this approach follows from interviews with geological experts, as it is a method of reasoning which they were found to use for this particular task. Additionally, in order to offer explanations it is not sufficient simply to present the general theories but also the justifications for the formation of those theories, also requiring a modelling of this theory formation process. Finally, as new wells are drilled, predictions at a prospect may change – for the system to be adaptable to such changing circumstances a model of the theory formation process itself is required. We discuss these motivations in more detail later.

2 Problem Description

For the appraisal of a geological prospect (ie. an *undrilled* site), there are three principle sources of information:

- Seismic information
- well logs, ie. information about drilled sites
- Geological theory

Seismic data provides, amongst other things, information about cross-sectional slices of rock strata in a region, helping experts to form a 3-dimensional model of how the different rock layers lie. This information is noisy and approximate, and some information (eg. what type of rock forms each layer) cannot in general be deduced solely from seismics. Well logs are produced from well drillings, and provide detailed information about the rock strata at different depths. They act as detailed but (often) sparse data points on a map of a region. From this information, the experts are to produce an estimate of the likelihood of there being hydrocarbons present at the prospect, and if so in what quantities.

The task of appraising a geological prospect for hydrocarbons is formidable. Typically it takes a small team of highly trained experts several weeks of work, involving the sifting of a large amount of data, to produce a final estimate of the likelihood of there being hydrocarbons present in the prospect. The appraisal process involves much reasoning about spatial relationships, models of geophysical processes, and the ability to reason with rich but sparsely placed reference points of well data plus large quantities of seismic data. A large amount of experience is required to produce an accurate appraisal, and even then experts themselves frequently disagree, resolutions occurring only after much discussion. In addition, there is limited feedback from the results of actual drilling; as experts predict probabilities of finding oil (typically < 0.4), the correctness of these probability measures can only be judged for sets of wells rather than for individual wells.

Consequently, existing applications of expert systems to prospect appraisal only tackle small parts of the problem, as to perform the entire appraisal task working from basic well logs and seismic sections is beyond the scope of current technology. In figure 1 we present a general description of the different levels of the appraisal task, to set a framework for describing the roles of this and other systems applied to prospect appraisal.

Several existing expert system applications in prospect appraisal (and related fields) address the higher level of this problem structure, requiring that high level information (eg. fault sealing quality) has already been assessed. Examples of such systems are SPII-2 [8], Prospector [6] (in the related field of assessing mineral deposits) and Explorationist [12] (for assessing the amount of oil at a prospect). Prospector, for instance, takes as input

Figure 1: Tasks in prospect appraisal

```
              Overall Risk Appraisal of Prospect
                          ↑   ↑   ↑
      Appraisal of Hydrocarbon Trap, Reservoir and Source
                          ↑   ↑   ↑
        Higher level information for prospect appraisal
        (fault sealing quality, porosity, rock ages etc.)
                          ↑   ↑   ↑
             Low level interpretation of input data
              (contours, faults, stratigraphy etc.)
                          ↑   ↑   ↑
             Input data (seismic sections, well logs)
```

the answers to questions such as “is there evidence for the local absence of sulphur-bearing iron formation?”, or SPII-2 “what is the thickness of the source rock?”. In answering these questions, a large amount of work is required of the expert to interpret seismic data and well logs.

Other systems have addressed the intermediate level of the prospect appraisal task shown in figure 1, namely that of calculating basic parameters required to assess a prospect, but assume that the low level interpretation of well logs and seismic sections has already been performed. For example, the system Mendel [15] assesses the probability of different rock formations being present, and the system Denvad [16] assesses the paeleo-depositional environment of a given rock formation, both taking as input interpreted well log data.

This intermediate level is the level which the prototype system described here addresses. As input, the system takes interpreted well logs and seismic information, and as output produces predictions of various parameter values associated with the hydrocarbon reservoir at the prospect. The particular parameter values we have focused on have been the reservoir thickness and porosity at the prospect site.

Finally, expert systems have also been applied to the lowest level of interpretation, working directly with the well logs and seismic sections. Examples are the systems Litho [2] and Dipmeter Advisor [5]. These systems include pattern recognition modules which interpret the well log plots directly, and produce output about the stratigraphic features at the wells. In the case of Litho, its output was directly used as input to Denvad (above) for further interpretation.

3 The Exemplar-Based Approach

3.1 Concept Representation

Any system which is to reason about concepts needs to have some representation of those concepts within them. Two complementary theories of concept representation, arising in part from work in philosophy, have been particularly studied in artificial intelligence research. *Intentional* theories advocate that concepts be represented by general statements, identifying the important characteristics of concept members. Such statements might be expressed as production rules (eg. in the system R1 [10]) or statements in logic (eg. in Marvin [13]). This form of representation forms the basis of many expert systems. Extensional theories, however, advocate that a concept be represented by the set (or a subset) of *examples* ('exemplars') of it plus a mechanism for generalising from those specific cases to new cases as they arise.

In many expert system applications such as medical diagnosis [14], conclusions about a patient (say) are reached by using general rules to reason about the known symptoms of the patient, without reference to other previously diagnosed patients who may have had similar symptoms (though whether medical experts themselves reason solely in this general way is a question for debate). This reasoning method is in contrast to that which our geology experts used for assessing prospect parameters, where the comparison with nearby, already drilled wells played a crucial role. It is this very process of comparison with and generalisation from particular nearby wells to the new prospect's site which constituted the main problem to be solved to allow predictions to be made.

Thus, rather than solely modelling the use of generalisations for assessing prospect parameters, we are modelling the *formation* of those generalisations from specific similar cases. This was the task which we found most occupied the experts; having formed a coherent theory explaining the nearby wells' parameter values, its application by the experts to the new prospect site was straightforward. We use the word 'theory' in this context to refer to a geologically plausible explanation for known exemplar well parameters which can then be applied to a new prospect to determine parameter values there.

It should be noted that the exemplar-based approach *does* still involve the formation and use of theories. However, the approach is characterised by the formation of such theories at run-time rather than beforehand, and the discarding of such theories after their use.

3.2 Motivation for the Exemplar-based Approach

Why is it that in domains such as medical diagnosis comparison of new patients (say) with previously encountered similar patients is rare, whereas in assessing prospect parameters such as porosity the comparison with similar nearby wells plays a central role? As a contrast, consider alternative strategies which do *not* use nearby exemplar wells directly in calculating porosity – for example we could (but did not) find experts using a general mathematical function of a reservoir's depth, x & y co-ordinates to find porosity, or applying a set of rules to these known parameters to conclude porosity. We briefly examine two characteristics of our problem domain which lead to the exemplar-based approach being adopted, which we term 'concept variability' and 'concept volatility'.

1. **Concept Variability:** Of principle difficulty to the formation of overall generalisations is the high variability in parameters such as reservoir porosity with respect to changes of other parameters. For example, a tiny change in the location of a prospect site may cause a large change in porosity, and there are many discontinuities caused by geological faulting and other phenomena.

   As a consequence, when experts form a theory explaining the porosity of nearby wells, such theories tend to be confined to highly localised areas. The site of the prospect forms a focus for such theories, and small changes in site location require that predictions and their justifications be reassessed. In other words, the gains to be made by storing particular explanations are limited due to their specificity, and most new sites will require a separate assessment to be made rather than re-using theories formed for other sites.

2. **Concept Volatility:** A second characteristic of the problem domain is the volatility of concepts involved. In medicine a patient whose symptoms defy the general theory is unlikely to cause major changes in that theory and consequent re-diagnoses of patients with similar symptoms. However, in prospect assessment the addition of new data from a newly drilled nearby well may cause a dramatic change in predicted values. This sensitivity in prospect assessment is again due to the concept's complexity, where variations are predictable within only a small area. As a result, geological knowledge about a region comprises of a large number of local theories, rather than a single global theory. Due to these 'local theories' being mainly based on only a relatively small number of exemplar wells, the addition or deletion of a single exemplar can cause a large change in prediction.

   In addition, the state of general geological knowledge (as opposed to detailed knowledge about specific geological sites) is constantly changing, and predictions which would have been made ten years ago would differ from those made today even given exactly the same data. This fact also contributes to the volatility of concepts.

   As a result, experts are constantly reassessing predictions made for various prospects as new data and theories emerge. These factors act against the formation of stable, long-term descriptions of prospect parameter variation in a given area, and instead promote the exemplar-based approach of working directly from examples.

4 System Description

We now proceed to describe the prototype system.

4.1 Representation of Input Information

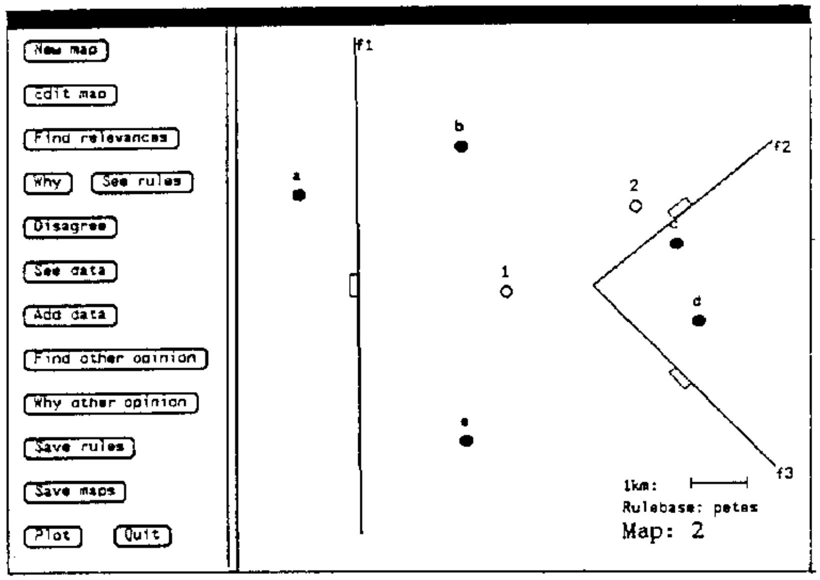
The input to the prototype system consists of interpreted well and seismic information, and in this section we briefly describe how this information has been represented. Interpreted well log information is stored simply as a vector of attribute-value pairs.

An example of an attribute-value set for a particular well is as follows:

```
Well name: 31/03
Position: 40' lat, 30' long
Reservoir depth: 10000 ft
Reservoir thickness: 100 ft
  Net to Gross Ratio: 13%
Porosity: 15%
Other features: drilled 1972
```

For the prototype, the only seismic information used is that which deals with faults and lithography changes, as these features were particularly influential in the prediction of reservoir thickness and porosity. For a fully developed system we would like to include more seismic information. Fault and lithography boundaries are again represented by vectors of attribute-value pairs in the above manner. This interpreted well and seismic data is provided by the user via an interface allowing both graphical and textual input. An example of a graphical display of a simple configuration of faults, wells (solid circles)

Figure 2: Map of a geological region



and prospect sites (hollow circles) is shown in figure 2. Other data associated with each object is stored in its associated vector.

4.2 The Exemplar Selection and Transformation Model

Given the location of a prospect, the expert is to assess the values of various parameters such as reservoir thickness or porosity at the prospect using the information he or she has available. Following from our interviews, the general method which the experts use can be described loosely as follows:

1. Find a theory (ie. geologically plausible explanation) for the known values of the parameter in question (eg. thickness) at nearby wells

2. Apply this theory to the new prospect to find the desired parameter value there

In order to form the 'best' theory, two principle questions need to be addressed:

1. Which wells are most relevant to consider when assessing the new prospect?

2. How should the information at these wells be transferred to the new prospect?

A measure of 'relevance' of nearby wells is important for two purposes. Most importantly, theories rarely fit the data perfectly and consequently some measure of which data points should have most weight placed on them is necessary. Secondly there is also an efficiency consideration - expending resources explaining irrelevant observations is wasteful.

It should be noted that we do not simply assign to the new prospect the characteristics of the most relevant well. Instead, we search for an appropriate transformation by which these characteristics can be 'deformed' to apply to the new prospect (hence our use of the word 'relevance' rather than 'similarity'). This is an important feature, and distinguishes this system from other exemplar-based systems which simply pass characteristics from the most similar exemplar to a new instance unchanged (eg. [1], [7]). Instead, our approach can be viewed as an application of the 'prototype plus deformation' technique, as used in the Taxman-II system [9].

The appropriate transformation to use is determined by the theory which is selected to explain the data at wells relevant to the new prospect. As a simple example, an expert may form a theory that a stratigraphic layer of sand (serving as an oil reservoir) is gradually getting thinner along a line in a particular direction. This theory will be formed and confirmed by the known sand thicknesses observed at different wells, and defines a simple linear transformation expressing how thickness varies with position. Using this transform, we can use the known position of the new prospect site to form a prediction of the thickness there.

Both these processes – of assessing the relevance of nearby wells and of forming a theory to explain their data and hence predict values at the site of a new prospect – are complex, knowledge-based tasks. We proceed to describe how they have been addressed in the prototype system.

4.2.1 Exemplar Selection and Relevance

Rather than simply select a number of nearby wells to use with equal weight as the basis of our prediction and ignore the others, a sliding scale of importance or 'relevance' of nearby wells to the new prospect's prediction is applied. A high relevance for a well means that the parameter values of that well are particularly important to account for in any theory about the parameter values at the prospect site.

The relevance of a well's data to a new prospect is not simply dependent on the distance between the two. The data of a nearby well may have little influence on that at a prospect (eg. if there is major faulting between the two), whereas wells a relatively long distance away may be important (eg. if the rock strata between them and the prospect are flat and uninterrupted). Both seismic data and well logs are important in assessing a well's relevance.

We have adopted a simple numerical representation of relevance, namely a number between 0 (completely irrelevant) and 100 (most relevant), and the assessment of a well's relevance to a particular prospect is modelled by a small, backward-chaining rule-based system. The well is initially assigned a relevance of 100, and then rules in the rule-base subsequently 'modify' this by assessing various factors which tend to decrease well relevance.

Two examples of the rule-base are:

```
% Major faults
rule1 ::
if fault(F) is between_prospect_and_well
and fault(F) isnt postdepositional
and type of fault(F) is major
then major_fault(F) modifier = 40.

% Distance rule
rule2 ::
if position of prospect is PPos
and position of well is WPos
and line(PPos to WPos) has_length D
then distance(D) modifier = 100 - D*5.
```

(A modifier is calculated using the equation in the rule's conclusion, unless the equation evalutes to less than zero in which case the modifier is set to zero). Some of the <condition> parts of these rules will have been concluded by other rules. Each modifier which is concluded by the rule-base acts as a (percentage) multiplying factor for the overall relevance. For example, if the distance D between the prospect and well was 5km, and there was also a major fault between them, then the resulting relevance of the well to the prospect would be:

$$\text{Well Relevance} = 100 \times (40/100) \times (75/100) = 30$$

where 100 is the initial relevance, and the modifiers 40 and 75 result from the two rules above firing.

Because the relevance of a well to a prospect is not a simple function of (say) their distance apart, we adopted a rule-based approach for making this assessment. One advantage of this approach is that the system is able to offer an explanation of its conclusions, and it facilitates easy correction and updating of the rule-base should the user disagree. A simple 'learning apprentice' module, modelled loosely on the Teiresias rule acquisition system [4], has been added to allow the user a dialog with the system to examine its reasoning, and correct it should he or she disagree.

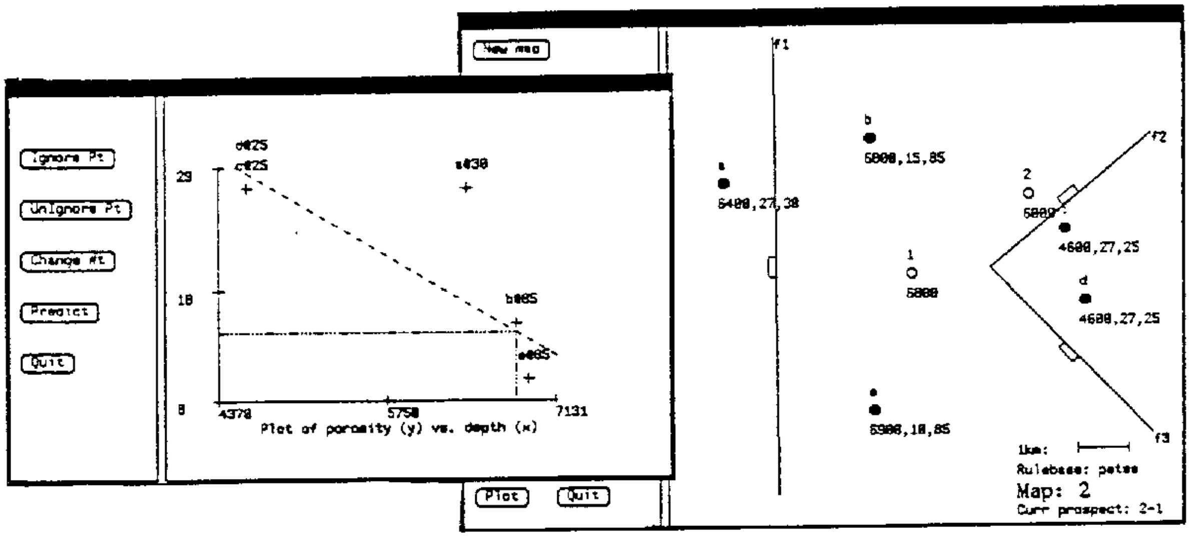
4.2.2 Exemplar Transformation and the Formation of Theories

Forming a geologically plausible theory to explain the data observed at nearby wells is a skilled task, involving the use of detailed but sparse data points (wells), seismic information, spatial reasoning and geological experience gathered over several years.

Theories express a relationship between parameters describing wells. For example, a theory might include a statement that a stratigraphic layer of sand (acting as an oil reservoir) is gradually getting thinner in a particular direction (expressing a relationship between position and reservoir thickness), or another might include a statement that the deeper the reservoir, the lower its porosity will be (expressing a relationship between depth and porosity). At the simplest level, these theories can be suggested by making plots or cross-sectional sketches using the exemplar wells as data points, and then seeing how well a straight line (say) fits the data. However, experts often go beyond this simple approach, altering and refining their theories, in particular including extra seismic information into the theory. For example faults may introduce discontinuities in a plot or cross-sectional sketch, or the rising and sinking of rock layers over time might explain particular poorly fitting data points.

In the prototype system, due to the complexity of the theory formation task, we have not attempted to automate this process fully but instead provide tools to assist the expert in forming theories. For the purposes of the prototype, only theories involving simple mathematical relationships (eg. linear, exponential) between parameters are representable. The expert is able to investigate these relationships by making plots of the parameters involved, and from the plots predictions at the prospect can be made. Each well provides a point on the graph, weighted by its associated relevance. The user is able to ignore points or change relevances should he or she wish to experiment with details of a particular plot. In this way, the expert can explore basic theories using the tools available, and examine quickly whether they fit well or more sophisticated analysis is needed. For a more fully developed system, this area of theory formation should be extended.

Figure 3: Modelling a linear variation between reservoir porosity and depth



As an example, figure 3 illustrates an example plot of reservoir depth vs. porosity, with well points weighted by their relevances derived by applying the rule-based system. The map on the right shows a plan view of the region, with wells as solid black circles. The three numbers shown next to each well in this map are the depth (feet), porosity (percentage) and relevance to prospect **1** (percentage) respectively. Points for each well are are plotted on the graph on the left, and weighted by their appropriate relevance to prospect **1** (centre of the map). The numbers attached to each point on the plot is the calculated relevance. Note that wells **b** and **e** have high relevance (85), well **a** has lower relevance (30) and wells **c** and **d** have lowest relevance (25 each) although they are all approximately the same distance from prospect **1**. The variation in relevance, concluded from the rule base, is mainly due to the presence of faults between prospect **1** and wells **a**, **c** and **d**, and also due to the differing size of the faults. The relevances determine the weights to place on the points when finding the best fit line.

From this plot, the (unknown) porosity of prospect **1** can be inferred from its (known) depth of 6800 feet, producing a prediction of porosity being 15%. The dash-dotted lines on the plot refer to this interpolation.

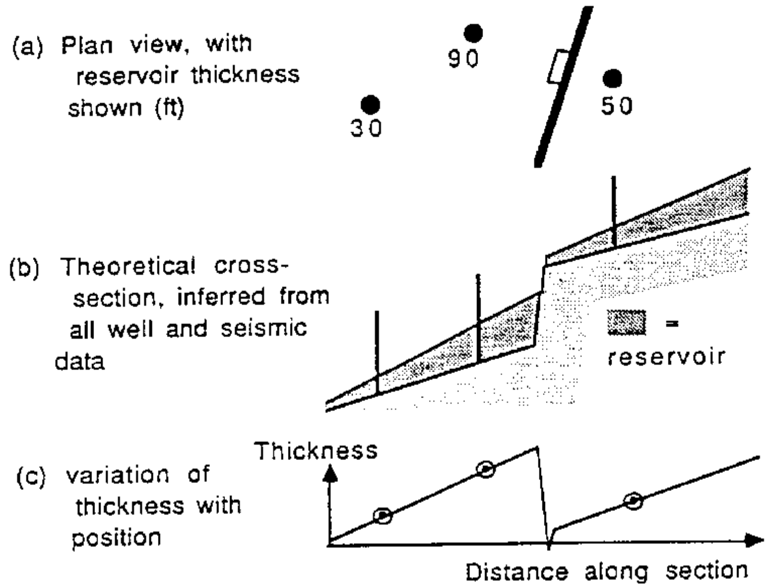
Should the plot not fit well, other plots (eg. log plots) might be tried. Wells which are poorly fitting may suggest to the expert to search for an explanation for the discrepancy, and hence may have their relevances changed.

Note that inductive tools such as ID3 [11] or CN2 [3] are not appropriate to our problem of forming a general theory from examples because we are predicting a numeric value rather than membership of a class, we are working with few (<10, usually) examples and we wish to give different weights to the examples. In addition, in future we wish to incorporate more domain knowledge into this theory formation process.

5 Discussion and Conclusion

We have been addressing the problem of predicting the values of various parameters, such as reservoir thickness and porosity, at the sites of potential geological prospects. These parameters are characterised by being highly sensitive to variations in other parameters,

Figure 4: Complex theories about reservoir thickness



and the prediction of that variability being often localised to small areas and sensitive to the addition of new data and theories. We found as a consequence that experts, given a prospect to assess, took an approach based on the selection of relevant wells, the formation of a theory to explain their data, and the application of that theory to the new prospect. It is this approach which characterises exemplar-based reasoning, and which we have attempted to model at a simple level in the prototype system developed.

One limitation of the prototype system as it stands is the small range of theories explaining correlations between well parameters which are representable. Currently the system is confined to the representation of linear correlations between pairs of parameter values, and this representational side should be extended in future applications.

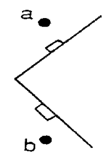
A second constraint is the limited seismic data which is used by the system – contour information, in particular, plays an important role in understanding parameter variations in a region, but it is only represented at present by point depths of reservoir layers at drilled wells.

As a brief illustration of the sort of theories we would like to incorporate, figure 4 provides an example. Given the sketch map shown in (a), plus additional seismic information, an expert may produce a cross-sectional slice (b), giving a plot (c) of thickness vs. position along this section. This plot incorporates seismic knowledge about the top reservoir contour and fault, plus geological knowledge about the effect of faulting on reservoir deposits. Hence, a simple straight line plot through these three points is a poor approximation to this much more complex theory about the reservoir thickness variation in the region.

There are two further characteristics of the reasoning of experts in the field which are difficult to model and would be an difficult problem for future development:

- **Spatial Reasoning:** There is considerable spatial reasoning involved in prospect appraisal, a form of reasoning in which people are particularly able but which is still a source of difficulty in computing. For example, even the seemingly simple concept "on the other side of a fault boundary" is complicated by fault boundaries not being straight and having poorly defined start and end points (eg. in figure

Figure 5: Two wells on the same side of a fault boundary



5, an expert would consider wells **a** and **b** to be on the same side of a fault). In interviews, experts were easily able to form two- and three-dimensional models of the different rock layers in a prospect's vicinity using available well and seismic data, whilst also accounting for the various physical processes which could have given rise to the predicted structures. Thus the experts' theories include not only reasoning about static two and three dimensional structures, but also about the dynamics of physical processes and how they interact with such structures. Such reasoning is important in understanding a potential prospect, but difficult to model.

- **Reasoning with Uncertainty:** A second related difficulty is that often there will be several plausible theories, requiring sophisticated reasoning with uncertainty to select between them – again a well-known area where expert system technology often has difficulty. The important role of reasoning with uncertainty is indicated by the fact that experts themselves will often disagree about predictions relating to a prospect, the disagreement only resolved by considerable debate (and sometimes not even then), symptomatic of the complexity of the task.

Given the difficulty of some of these problems, we see the role of a further developed system (as indeed for the prototype itself) to be of an expert's assistant, acting as a suggester and recorder of theories about a region, allowing theories to be tested and previous theories to be examined as new information arrives, but essentially acting as an 'intelligent' tool to be used by the expert in the prospect appraisal task.

Acknowledgements

This work was funded by Enterprise Oil plc, and I particularly thank Dave Rhodes, Tony Scurr and John Crowle for their enthusiasm and patience during the development of this prototype. Thanks also to Claude Sammut for valuable discussions and ideas, and to Robin Boswell for comments on an earlier draft of this paper.

References

[1] E. R. Bareiss, B. W. Porter, and C. C. Wier. PROTOS: An exemplar-based learning apprentice. In P. Langley, editor, *Proc. 4th International Workshop on Machine Learning*, pages 12–23, CA, 1987. Kaufmann.

[2] A. Bonnet and C. Dahan. Oil-well interpretation using expert system and pattern recognition technique. In *IJCAI-83*, pages 185–189, 1983.

[3] P. Clark and T. Niblett. Induction in noisy domains. In I. Bratko and N. Lavrač, editors, *Progress in Machine Learning (proceedings of the 2nd European Working Session on Learning)*, pages 11–30. Sigma, Wilmslow, UK, 1987.

[4] R. Davis. Interactive transfer of expertise: Acquisition of new inference rules. In *IJCAI-77*, pages 321–328, 1977.

[5] R. Davis, H. Austin, I. Carlbom, B. Frawley, P. Pruchnik, R. Sneiderman, and J. A. Gilreath. The dipmeter advisor: interpretation of geological signals. In *IJCAI-81*, volume 2, pages 846–849, 1981.

[6] R. Duda, J. Gaschnig, and P. Hart. Model design in the Prospector consultant system for mineral exploration. In B. L. Webber and N. J. Nilsson, editors, *Readings in Artificial Intelligence*, pages 334–348. Tioga, CA, 1981.

[7] D. Kibler and D. W. Aha. Learning representative exemplars of concepts: an initial case study. In P. Langley, editor, *Proc. 4th International Workshop on Machine Learning*, CA, 1987. Kaufmann.

[8] J. Lebailly, R. Martin-Clouaire, and A. Prade. Use of fuzzy logic in a rule-based system in petroleum geology. In E. Sanchez and L. A. Zadah, editors, *Approximate Reasoning In Intelligent Systems*, pages 125–144. Pergamon, 1987.

[9] L. T. McCarty and N. S. Sridharan. A computational theory of legal argument. Technical Report LRP-TR-13, Rutgers Univ., Lab. for C.S. Research, NJ, 1982.

[10] J. McDermott. R1: A rule-based configurer of computer systems. *Artificial Intelligence*, 19(1):39–88, 1982.

[11] J. R. Quinlan. Learning efficient classification procedures and their application to chess endgames. In J. G. Carbonell, R. S. Michalski, and T. M. Mitchell, editors, *Machine Learning, vol. 1.* Tioga, Palo Alto, CA, 1983.

[12] C. A. Reid, R. M. Fung, R. M. Tong, and E. Tse. A knowledge representation for reasoning about petroleum geology. In *Procs. Second Conference on Artificial Intelligence Applications*, pages 125–129, 1985.

[13] C. Sammut and R. Banerji. Learning concepts by asking questions. In J. G. Carbonell, R. S. Michalski, and T. M. Mitchell, editors, *Machine Learning, vol. 2.* Tioga, Palo Alto, CA, 1986.

[14] E. H. Shortliffe. *Computer-Based Medical Consultations: MYCIN.* American Elsevier, NY, 1976.

[15] P. van der Pas and L. J. B. Hoffman. Knowledge engineering research in petrophysics in shell. In *Procs. Second International Expert System Conference*, pages 205–209, 1986.

[16] J. Yan. Identifying depositional environment structure: an expert system approach using object-oriented programming and model-driven verification. In *Procs. Sixth International Workshop on Expert Systems and their Applications*, pages 1081–1092, 1986.