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Chapter 16

EXTENDING THE USE OF LINGUISTIC PETROGRAPHICAL DESCRIPTIONS TO CHARACTERISE CORE POROSITY

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ABSTRACT

There are many classification problems in petroleum reservoir characterisation, an example being the recognition of lithofacies from well log data. Data classification is not an easy task when the data are not of numerical origin. This paper compares three approaches to classify porosity into groups (very poor, poor, fair, good) using petrographical characteristics described in linguistic terms. The three techniques used are an expert system approach, a supervised clustering approach, and a neural network approach. From the results applied to a core data set in Australia, we found that the techniques performed best in decreasing order of their requirement for significant user effort, for a low degree of benefit achieved.

1. INTRODUCTION

Many forms of heterogeneity in sedimentary rock properties, such as porosity, are present in clastic reservoirs. Understanding the form and spatial distribution of these heterogeneities is fundamental to the successful characterisation of petroleum reservoirs. From a geological viewpoint, the anatomy of reservoir heterogeneity requires two major pieces of information: component lithofacies (and their hydraulic properties) and their internal architecture. Poor understanding of lithofacies distribution results in inaccurate definitions of reserves and improper management schemes. Mapping the continuity of major lithofacies is, therefore, of great importance in reservoir characterisation studies. It is, however, impossible to start this mapping exercise until the major types of lithofacies have been recognised and identified.

Lithofacies recognition is often done in drilled wells where suitable well logs and core samples are available. Pattern recognition techniques, such as k-means cluster analysis (Wolff and Pelissier-Combescure, 1982), discriminant analysis (Jian et al., 1994; Wong et al., 1995), artificial neural networks (Rogers et al., 1992), and fuzzy logic methods (Wong et al., 1997) can be used for classifying well log data into discrete classes. Some hybrid

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techniques (Chang et al., 2000; Wong et al., 2000) are also available. These methods, however, cannot be applied without a prior understanding of the lithological descriptions of the core samples typically available in routine core analysis.

The recognition of major lithofacies is not an easy task in heterogeneous reservoirs. Rock characteristics such as petrophysical, depositional (or sedimentary), and diagenetic (or textural) features are common parameters that are used to define lithofacies. However, geologists with different field experiences often create different lithofacies sets based on the same observational information. These diverse definition occur because no quantitative measurements, but only a series of qualitative or linguistic statements, are provided in lithological descriptions. Thus a subjective decision must be made about how many dominant lithofacies are present and what these lithofacies are.

The objective of this paper is to introduce a systematic approach for the handling of linguistic descriptions of core samples, by contrasting a number of approaches to classify porosity into groups using petrographical characteristics. The three techniques used are an expert system approach, a supervised clustering approach, and a neural network approach. We will briefly describe each technique and provide results. We first review the basics of lithological descriptions and describe each technique. We then demonstrate the value of these techniques using a data set available for an oil well in a reservoir located in the North West Shelf, offshore Australia. We then apply the methods to porosity classification based on core descriptions, and validate the model using unseen cases with known porosity classes.

2. LITHOLOGICAL DESCRIPTIONS

Classifying geological data is a complicated process because linguistic descriptions dominate the results of core analysis studies. The problem is worse for lithological descriptions. Each core sample is usually described by a number of petrographic characters (e.g. grain size, sorting and roundness) in linguistic terms. A typical statement for a core sample could be:

"Sst: med dk gry f-med gr sbrndd mod srt arg Mat abd Tr Pyr Cl Lam + bioturb abd"

which means, 'Sandstone: medium, dark gray, fine-medium grain, sub-rounded, moderate sorting, abundant argillaceous matrix, trace of pyrite, calcareous laminae, and abundant bioturbation.'

Although these statements are subjective, they do provide important indications about the relative magnitudes of various lithohydraulic properties such as porosity and permeability. It is, however, difficult to establish an objective relationship between, say, porosity levels (e.g. poor, fair or high) and the petrographic characters.

3. DATA DESCRIPTIONS

An oil well located in the North West Shelf, offshore Australia, provided a routine core analysis report for this field study. There were 226 core plug samples taken from a total of 54 metres of cores obtained from three intervals. The reservoir is composed of sandstones, mudstones, and carbonate cemented facies. The porosity and permeability values ranged from 2 to 22 percent and from 0.01 millidarcy to 5.9 darcies, respectively.

The report includes porosity measurements from helium injection as well as detailed lithological descriptions on each core sample. The lithological descriptions were summarised into six porosity-related characters: grain size, sorting, matrix, roundness, bioturbation, and laminae. Each character was described by a number of attributes. A total of 56 attributes were used. Table 1 tabulates the character-attributes relationships used in this study.

The objective of this study is to demonstrate how intelligent techniques can be applied in classifying linguistic descriptions of core samples into various porosity classes. We will first develop the knowledge base, implemented for the three methods as expert system, clustering diagram and neural networks, respectively. The knowledge base is

TABLE 1

Character and attributes used for porosity classification

Character (No. of attributes)	Descriptions	Attributes
Grain size (12)	The general dimensions (e.g. average diameter or volume) of the particles in a sediment or rock, or of the grains of a particular mineral that made up a sediment or rock.	Very Fine, Very-Fine to Fine, Fine, Fine to Medium, Medium, Fine to Coarse, Medium to Fine, Medium to Coarse, Fine to Very Coarse, Coarse to Very Coarse, Very Fine with Coarse Quartz, Fine with Coarse Quartz.
Sorting (6)	The dynamic process by which sedimentary particles having some particular characteristic (e.g. similarity of size, shape, or specific gravity).	Well, Moderate to Well, Moderate to Poor, Moderate, Poor to Moderate, Poor.
Matrix (14)	The smaller or finer-grained, continuous material enclosing, or filling the interstices between, the larger grains or particles of a sediment or sedimentary rock.	Argillaceous (Arg), Sideritic (Sid), Siliceous (Sil), Sid with Arg, Sid with Sil, Arg with Sil, Sil with Arg, Carbonaceous, Calcareous, Pyritic with Arg, etc.
Roundness (8)	The degree of abrasion of a clastic particle as shown by the sharpness of its edges and corners as the ratio of the average radius of curvature of the maximum inscribed sphere.	Sub-angular (subang), Angular (Ang) to Subang, Subang to Sub-rounded (subrndd), Subrndd to Ang, Subang, Subrndd, etc.
Bioturbation (6)	The churning and stirring of a sediment by organisms.	Abundant bioturbation (bioturb), Increase bioturb, Bioturb, Decrease bioturb, Minor bioturb, Trace of bioturb.
Lamina (10)	The thinnest or smallest recognisable unit layer of original deposition in a sediment or sedimentary rock	Irregular argular, Irregular Calcareous, Trace of Calcareous, Less Traces, Argillaceous, Calcareous, Irregular Silt, Thick, Irregular.

developed using a number of known porosity cases (training data). The knowledge base will then be tested using an unseen set of core descriptions (test data). The performance can be evaluated by comparing the predicted porosity classes with the actual classes using the correct-recognition rate (i.e. number of correct classifications divided by total number of samples).

4. EXPERIMENTS

In the first phase of the experiment, the porosity values were discretised into four classes: 'Very Poor' (<5%); 'Poor' (5–10%); 'Fair' (10–15%); and 'Good' (>15%). Each sample was characterised by the six characters (with the corresponding attributes) and paired with a porosity class.

For the expert system, we chose a total of 140 samples out of the original 226 samples as the training and test data. This was done because the remaining samples lacked descriptions of some of the characters and were not able to be processed by the initial setup of the expert system, and could perhaps be considered as unrepresentative cases. The 140 cases were randomly divided into two data sets: Set #1 and Set #2. Each data set contained 70 cases. We first used the Set #1 data as the training data to develop the knowledge base. The training stage established new rules and updated old rules until the system gave a 100% correct-recognition for the Set #1 data. Then, the Set #2 data was used as the unseen test data, and the corresponding correct-recognition rate was calculated. Note that the existing rules were not updated at the testing stage and hence some results were 'no conclusion.'

We also swapped the usage of both data sets, that is, the Set #2 data were used for training and the Set #1 data for testing, and the whole process was repeated. The objective of the swapping experiment was to determine if there was a simulation bias associated with the random data-splitting procedure.

For the clustering algorithm and neural networks, we will perform the same experiments with the same data arrangement.

In the following sections the three techniques are briefly described, followed by the results sections for each experiment, followed by our conclusions, and suggestions for future work.

5. EXPERT SYSTEM

We have used an expert system knowledge acquisition and maintenance technique, to establish new rules (acquire knowledge) and to update existing rules (maintain knowledge) when suitable observations are obtained. Rules are formulated in the conventional form: IF [conditions] THEN [conclusion]. Knowledge is added to the system only in response to a case where there is an inadequate (i.e. none) or incorrect classification. This technique of 'ripple down rules' has been used in ion chromatography (Mulholland et al., 1993). The notion of basing classification on keystone cases has previously been used in petrography (Griffith, 1987). In cases of an incorrect classification, a human expert needs to provide a justification, in terms of the difference(s) associated with the case that shows the error or prompts the new rules, that explains why his/her interpretation is better than the interpretation given for such cases. Hence, the approach is able to adapt new rules or knowledge without violating previously established rules, and hence, all rules are consistent within the system.

The basic logic is simple and interpretable. There is only one requirement to develop the rule bases: all the cases must be described with a fixed set of descriptive characters. The rules can be viewed as binary decision trees. Each node in the tree is a rule with any desired conjunctive conditions. Each rule makes a classification, the classification is passed down the tree, and the final classification is determined by the last rule that is satisfied. The technique is very simple and has no further complications beyond the description given here. Its benefits derive from its simplicity, and its applicability without the need for an expert system specialist to build the knowledge base. There are some deficiencies, which we describe in the context of our results.

6. SUPERVISED CLUSTERING

A supervised clustering technique was also used. Clustering techniques are generally unsupervised. The benefit of the supervised approach is that the expert can label as acceptable clusters which make suitable distinctions in the data classification. Clusters which are not suitable can be labelled for further clustering. A portion of the data is held out (as for all the three techniques used) from the technique so that the success rate can be validated using this unseen data.

Visual Clustering Classifier (VC+) is a visual system through which users can conduct clustering operations to generate classification models. Clustering as an unsupervised learning mechanism has been widely used for clustering analysis (Jain and Dubes, 1988). Clustering operations divide data entities into homogeneous groups or clusters according to their similarities. As a clustering algorithm, k-means algorithm measures the similarities between data entities according to the distances between them. Lin and Fu (1983) applied a k-means based clustering algorithm for the classification of numerical data entities. To apply clustering algorithm to data mining applications, two important issues need to be resolved: large data set and categorical attribute. Extended from k-means algorithm, k-prototype algorithm (Huang, 1998) has resolved these two issues.

This k-prototype algorithm is based on an assumption that the similar data entities should be located closer than other data entities. Those similar data entity groups are normally called 'clusters'. A classification divides a data set into a few groups that are normally called 'classes'. The classes are determined either by human experts or a few data fields of the data entities, such as the application discussed in this paper. Therefore clusters and classes are not equivalent. To apply k-prototype algorithm for classification, the class distribution of the data entities in the generated clusters must be considered.

Two steps are required for the development of a classification model using VC+: cluster hierarchy construction; and classification model generation. Once the training data set has been loaded into VC+, a root cluster node for the cluster hierarchy is generated. The root contains the entire training data set. The user can apply the

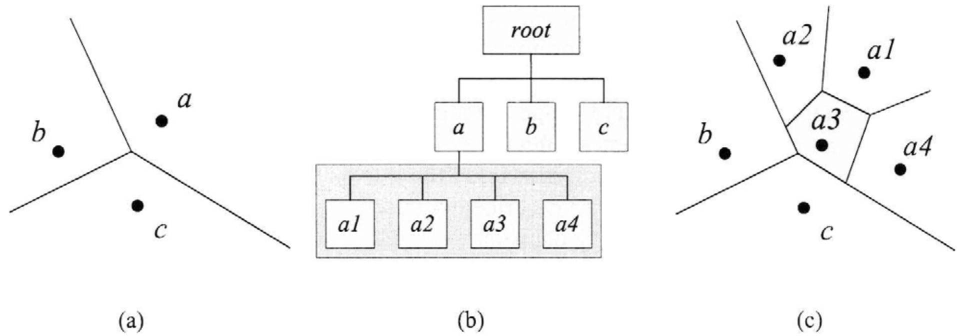

Fig. 1. Cluster hierarchy construction: (a) clustering result on root; (b) cluster hierarchy; and (c) result of the clustering on node a.

clustering operation on the data set to generated clusters that will be the children nodes of the root node. A leave cluster node in the cluster hierarchy will be further partitioned if the shape of distribution is not good or there is no a dominant class in the data entities in this cluster. Fig. 1 illustrates the procedure for generating a classification model. Firstly three clusters that have centers: a, b and c are generated by a clustering operation on root node. The cluster hierarchy will be generated. This cluster hierarchy will be expended after node a is further partitioned.

If there is a dominant class in the data entities in a leave cluster node, the center of this cluster will be marked as this class. The classification model generated by VC+ consists of all the leave nodes that have been marked. The class of the cluster in the classification model which has the shortest distance to a given data entity will determine the class of this data entity. If there is no dominant class for the data entities in a leave node and this leave node cannot be further partitioned due to the number of data entities contained, this leave node will be left unmarked and will not be included in the classification model.

To apply k-prototype clustering for classification, there are many non-deterministic criteria that directly affect the classification result, such as the number of clusters, the start cluster centers, and the chosen features. However it is out of computational power if all of the combination of these criteria were taken considered. VC+ provides various visualisation tools to display data entities, statistical results and also allows users to compare the results of different clustering operations. It also adopts visualisation techniques to incorporate users' expertise in the procedure for the generation of classification models. This approach increases the exploration space of the mining system. This approach has advantages on handling noise and outliers.

7. NEURAL NETWORKS

Neural networks can perform supervised classification. In this study, a standard 12 input $\times$ 7 hidden $\times$ 4 output backpropagation neural network was used. The input data was encoded by means of a linguistic encoding technique into 12 numeric inputs.

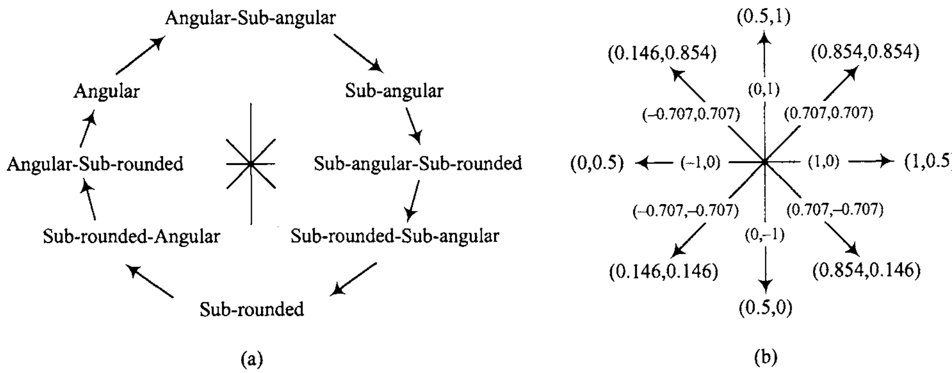

Fig. 2. (a) Circular encoding of roundness (sphericity); (b) normalisation to sine and cosine values.

The simplest case is for 'Sorting', where the characters of 'Poor – Poor-moderate – Moderate-poor – Moderate – Moderate-well – Well-moderate – Well' are easy to place in a sequence, and allocated values evenly distributed from 0 to 1.

For some of the fields more complicated encoding was necessary. For example, in the case of a circular linguistic term ordering, two variables are required to be able to encode the values. The values of the sine and cosine for an even distribution around a circle are required. This is illustrated for 'Sphericity' and 'Roundness' in Fig. 2.

As there are eight values, the familiar points of 0°, 45°, 90° and so on are used. The (sin, cos) tuples are shown in Fig. 2. The values are in the range from -1 to 1, which are then normalised to the range 0 to 1. The property of this circular encoding is that for all adjacent points the sum of the absolute values of the changes to the values is the same.

8. RESULTS

The data set contains 140 data records. We randomly divided the data set into two sets with equal size (70 each): Set #1 and Set #2. The classification matrixes generated for these two data sets are shown respectively in Tables 2–4. For each table, the first sub-table shows the blind test results using Set #1 for training and Set #2 for testing, and the second sub-table shows the blind test with the sets swapped. Note that for the supervised clustering we could not do this, since the human experimenter was making the supervision choices, it was not possible to do a second proper blind test. For the neural network we can again perform this swapped blind training and testing cycle.

As can be seen from the tables, the three techniques performed fairly similarly, with the supervised clustering algorithm performing the best, followed by the expert system technique and then the neural network.

Note that the results presented here are those achieved after some preliminary experiments, particularly with the neural network model to discover a reasonably successful architecture and an appropriate input encoding, with the expert system and supervised clustering models to discover the degree of cognitive effort required to

TABLE 2

Porosity classification results using expert system

Actual class	Predicted class					Total	% Correct
	VP	PR	FR	GD	NC		
(a) Blind test results on Set #1							
VP	10	0	0	0	1	11	90.9
PR	1	10	0	0	7	18	55.6
FR	1	0	7	5	7	20	35.0
GD	0	0	1	17	3	21	81.0
Overall % Correct = 62.9%							
(b) Blind test results on Set #2							
VP	9	6	1	0	1	17	52.9
PR	0	10	1	1	6	18	55.6
FR	0	0	8	1	1	10	80.0
GD	0	0	4	19	2	25	76.0
Overall % Correct = 65.7%							

VP = Very Poor; PR = Poor; FR = Fair; GD = Good; NC = No Conclusion; and % Correct is the correct-recognition rate.

TABLE 3

Porosity classification results on Set #1 using supervised clustering

Actual class	Predicted class				Total	% Correct
	VP	PR	FR	GD		
VP	8	2	1	0	11	72.7
PR	4	11	2	1	18	61.1
FR	1	4	14	1	20	70.0
GD	1	4	1	15	21	71.4
Overall % Correct = 68.6%						

VP = Very Poor; PR = Poor; FR = Fair; GD = Good; and % Correct is the correct-recognition rate.

achieve good results. While these are hard to quantify, it was clear that the supervised clustering required the most attention, followed by the expert system technique. The neural network preliminary experiments needed to be done initially, subsequently there was no intellectual effort required. This was not the case for the other techniques.

9. EXTENSIONS

In the second phase of the experiment, the expert system setup was modified to allow missing data, so the full data set could be used. Some modifications to the data encoding were tried, and the porosity values were discretised into 5 classes, adding a 'Very Good Porosity' class. This has the effect of reducing the random guess success rate from 25% to 20%.

TABLE 4

Porosity classification results using neural networks

Actual class	Predicted class				Total	% Correct
	VP	PR	FR	GD		
(a) Blind test results on Set #1						
VP	8	1	2	0	11	72.7
PR	4	11	3	0	18	61.1
FR	2	1	10	7	20	50.0
GD	2	3	3	13	21	61.9
Overall % Correct = 60.0%						
(b) Blind test results on Set #2						
VP	8	8	0	1	17	47.1
PR	0	11	5	2	18	61.1
FR	1	1	6	2	10	60.0
GD	0	2	4	19	25	76.0
Overall % Correct = 62.8%						

VP = Very Poor; PR = Poor; FR = Fair; GD = Good; and % Correct is the correct-recognition rate.

The experiments were re-run using the full date set, split 2/3 training, 1/3 testing, using all three techniques. The overall results were very similar. The supervised clustering algorithm produced 64.2% accuracy, the neural network result on the test set was 60%, and the expert system result was 59.7%.

Note that the expert system required some user effort in manual pre-processing to discover plausible rules and sequencing the data appropriately, to compensate for missing parameters. This is due to the system relying on cornerstone cases, which is prone to bias from the sequence of presentation of examples. Qualitatively, this appeared to be a greater cognitive burden than the equivalent task of encoding the inputs for the neural network, as that had to be done once only and did not require perusal of the entire training set and extraction of significant patterns.

Some extra experiments were performed using the expert system technique to discover the significance of such user pre-processing.

In the first of these extra experiments, very specific rules were created for each pattern, choosing all of the available non-null characters. This produced a result of 51.6% on the test set. This indicates that the previous effort in manual pre-processing had some significant effect, and the difficulty of doing this. The next experiment was to include the null fields for each pattern in each rule. Thus, if for a pattern no 'Sorting' character was reported, the rule specified that the value for this field be 'None'. This produced a result of 38.7%, verifying our belief that the system was providing some generalisation, and demonstrating the importance of making sensible rules. At the same time, we discovered the minimum possible error on the test set (with this data split) of 15% as there are some patterns with identical characters and different category.

Some extra experiments were also performed with the neural network, to modify the output encoding. The initial encoding was a standard one, with an output neuron active for each category. This binary encoding is known to be less than ideal where there is some continuity or ordering between output classes. This is clearly the case for our experiment, 'Good porosity' > 'Fair Porosity' and so on. When the values of the outputs close to class boundaries were modified so that the difference from adjacent values of the pairs of adjacent categories was minimised, an average of 7.1% improvement was found. That is, for example two patterns on either side of the 'Good' and 'Fair' porosity which initially would have been 1,0 and 0,1 now become 0.51,0.49 and 0.49,0.51. This reduces the artificiality of our decision as to the location of the class boundaries and hence better classification ensues. Note that the fuzzy encoding means that it is no longer a simple calculation to determine number of correct classifications. We have chosen to defuzzify the network target and actual outputs to category numbers in the appropriate range, and used a category number difference of <0.5 to indicate a category match. If we allow a catgory match <1.0 (we accept the adjacent category as suitable) then the results for the test sets on partitions 1 and 2 rise to 92.2% and 93.9% respectively. While accepting the entire net category as suitable is excessive, use of this technique allows a determination of the degree to which the incorrect results are plausible, particularly for value between 0.5 and 1.0.

The next step is therefore to modify the unsatisfactory expert system technique to allow such 'fuzzy' output encodings. This will require a major rework of the system, and is a limited form of the integration we propose below.

10. CONCLUSIONS

We have contrasted three techniques for using linguistic information from core analysis reports for classification. We have found that the use of pre-processing and clustering, and output encodings improve the results of the neural network. This kind of effort is required to satisfactory results from the expert system and supervised clustering techniques, which both require a major cognitive effort on the part of the user.

We can conclude that at this stage it is clear that the neural network technique is the best choice. The results are marginally worse, but the results are reproducible without a significant burden on the user.

To be fair, the expert system produced results using symbolic inputs essentially the same as the neural network on the numerically encoded inputs. This suggests that with the use of this encoding further improvements may be achieved. The benefit of expert system technique is that a rule trace is possible for every decision, so failures can be accounted for and successes understood by users. This tends to be an issue in the wider use of neural networks, where the 'black box' nature of predictions is unacceptable, mistrusted or merely not preferred.

The next stage in our work will be to properly integrate the three techniques. Thus, a neural network will be used to learn the significant properties of the data, which can then be examined and verified by the use of the clustering technique, and the training file constructed for the expert system technique. Even further down the track, we can envisage an on-line interactive use of the three techniques. Thus, when a new rule is required in the expert system, the neural network can be run on the as yet uncategorised patterns remaining to suggest some rules, and the clusters of patterns correctly or incorrectly classified be visualised on screen.

The use of these techniques systematically will allow the incorporation of such linguistic information with numeric well logs for improved results.

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