Lithofacies recognition supporting tools

Inhaúma Neves Ferraz
Universidade Federal Fluminense
ferraz@dcc.ic.uff.br

Ana Cristina Bicharra Garcia
Universidade Federal Fluminense
bicharra@dcc.ic.uff.br

Abstract

The interpretation of well logs is an important issue to find oil in offshore reservoir. Traditional statistical methods have been used to assist this task. Neural networks have also been successfully used. As an alternative fuzzy logic based systems have an extra appeal of intuitive comprehension of some uncertainties. This paper presents an application combining neural networks, fuzzy logic and neuro-fuzzy logic to improve human intuition when analyzing the potential of oil fields.

Keywords: Supervised Learning, Neural Networks, Fuzzy Logic, Neuro- Fuzzy Systems

1. Introduction

A common problem in statistics applications is to estimate a mapping function extracted from input-output sample pairs. The function must be *learned* from the examples supplied by users. The set of examples (known as *training set)* contains elements which consist of paired values of the independent (input) variable and the dependent (output) variable.
In the domain of oil exploration, determining facies from well log data is crucial to determine the oil potential of any given reservoir. Artificial Intelligence techniques are presented here as alternative approaches to statistical methods. We claim the quality of the results can be enhanced and, consequently, the decision on exploring the field improved..

2. Facies

The continuous register of physical properties of rocks in depth constitutes the “well logs”. The physical log properties commonly used are Gamma Ray, Spontaneous Potential, Resistivity, Sonic, Density, Neutron, Nuclear magnetic resonance and Dipmeter logs. Well logs are used to describe rock types in the subsurface, amount of porosity, permeability and types of fluids present in pore spaces of the rocks.
In general, rocks from the core samples are described and classified into categorical models named “facies”, or “lithofacies”. Such facies represent rock types with well-defined geological characteristics. An important task in core-log calibration is training statistical or

neural network models to recognize these facies from log responses, and then extrapolate the models to all the wells [1].
Reservoir properties mainly porosity and permeability are used to predict potential of oil production. Usually the assignment of facies from well data (originated from well cores and well logs) is an intermediate step in the determination of petrophysical properties (porosity and permeability) [2]. Obtaining well logs are cheaper, faster and easier than well cores. It is natural to explore well log data to predict oil potential in a given reservoir.
In order to map in 3D a hydrocarbon reservoir, so that volumes and production capacity can be estimated, the most commonly used workflow includes a first stage of facies simulation and a second stage of infilling of facies with petrophysical properties. Before facies are estimated in space, they must be recognized in the wells drilled. Two main procedures can be used to identify facies in the wells: (1) recognize facies in core samples and correlate facies with well log responses, (2) subdivide log data based on similarities observed, without correlating with rock samples a priori.
Extracting facies from well log curves is a very subjective task. Based on previous experience and expertise each geologist has his/hers methods. Frequently those methods are derived from the available tools present in the expert technical environment.
This kind of extraction usually is not standardized. In fact different degree of expertise from the technical staff will produce different technologic solutions for similar problems.
This environment is a natural candidate to apply systematic methods or semi systematic methods for supporting the task and to direct solutions to similar trails.

3. Supervised learning

A statistics frequent problem common in many areas is to estimate a mapping function from a set of input (independent variable) and output (dependent variable) examples with little or no knowledge of the derived function. Therefore, the quality of the function depends upon the quality of these examples called the training set.
Instead of explicitly programming these mapping functions, systems can be created using different techniques to generate a multivariable function from sparse data, such as:

- Statistical linear regression technique
- Logic induction
- Decision trees
- Association rules
- Belief networks
- Supervised neural nets

All the above techniques depend upon the existence of the training set. We use the statistical method results to be the baseline for comparison because it was widely spread in the Brazilian oil company.

4. Neural Networks

Supervised learning can be made using multivariate statistics, particularly discriminant analysis [3]. This is the classical solution and has been used in the Brazilian oil company for decades. However, the company needed better (more reliable) solutions and the use of supervised neural networks was a low cost alternative solution to study.

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Neural networks technique is a mature technology to be used. We used a typical back propagation network. Data cleaning and selection were the usual ones such as normalization, pruning and correlation [4]. Each element of the output layer on our neural network model produces the output

$$y_i^O = f\left(\sum_{j=1}^{m} w_{ij}^O . f\left(\sum_{k=1}^{n} w_{jk}^H . I_k\right)\right)$$

where y_i^O represents the output of the i-th processing element, w_{ij}^O *and* w_{ij}^H represent the connection weights between processing elements i and j in output and hidden layers, I_K represents the input of the k_{th} processing element and f represents the transfer function for processing elements. If we denote the overall action of the neural network by φ then $y(t) = \varphi(x(t))$ where **x(t)** is a sample of the data to classify.

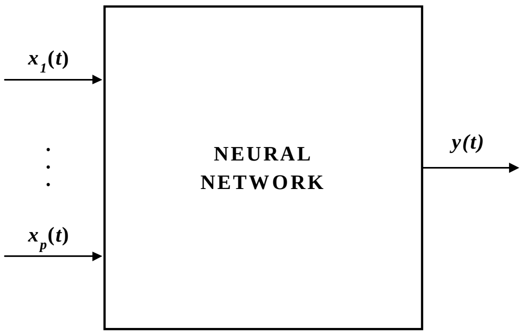

Figure 1 Artificial Neural Systems Architecture

Although the training data was not big, the results improved significantly compared to the statistical approach. Even after the enhancement of the results, the results the needed for better estimating methods remained. It guided the research to further analysis such as the use of fuzzy logic.

5. Fuzzy Logic

There are a large number of different methods to implement Fuzzy logic approach. The convergence relies on the cornerstone that any interpretation of data is possible, but some are more probable than others.

Fuzzy Logic have been applied to lithology with some success sometimes hardcoded [5] and sometimes with supervised learning [6] [7].

A "dassifier" is a procedure that maps a vector $\mathbf{x} = (x_1, \ldots, x_p)$ based on an attribute space X^p in a "dass" ω, $\Gamma : X^p \to \Omega$. Each class can be considered as a fuzzy subset $\omega_j = \{(\mathbf{x}, \mu_{\omega_j}(\mathbf{x})), \mathbf{x} \in X^p\}$ where $\mu_{\omega_j}(\mathbf{x}_0)$ represents the membership of $\mathbf{x}_0$ to class ω_j [8].

Fuzzy discretization is the partition of attribute space in fuzzy subsets assigning a decision (or label) to each subset.

Selecting $\mathbf{n_i}$ fuzzy subsets for each attribute we fuzzify the input value and obtain $\mathbf{u}_i = \left(\mu_{A_{i1}}(x_i), \ldots, \mu_{A_{in_i}}(x_i)\right)$, a vector containing rule activation values. Fuzzification output is inference input $\mathbf{v}_i = \mathbf{u}_i.\Phi_i$ where the $\mathbf{v}_i = \left(\mu_{\omega_1}(x_i), \ldots, \mu_{\omega_m}(x_i)\right)$ contains the partial conclusions. Φ_i is the weight matrix

$$\Phi_i(A_{ik}, \omega_j) = \frac{\sum_{t=1..N} \mu_{A_{ik}}(x_i(t)).v_j(t)}{\sum_{t=1..N} \mu_{A_{ik}}(x_i(t))}$$

The weight matrix is obtained from the training set $T = \{(\mathbf{x}(t), v(t)),\ t = 1..N\}$ where **x(t)** is a sample and **v(t)** is the desired output for that sample.
A T-norm operator, giving as final conclusion a vector **v** of class membership, aggregates partial conclusions. Defuzzification consists of the decision process that converts a conclusion vector into a class $\mathbf{w_0}$.
Figure 2 exhibits a scheme of the process.

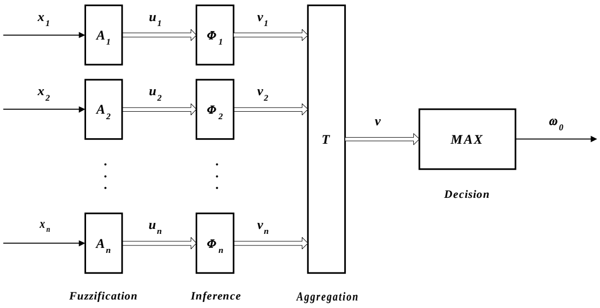

Figure 2 Fuzzy systems decision support approach

6. Neuro-fuzzy Systems

Joining neural networks and fuzzy logic provides an interesting solution whenever possible. In our case study, joining both technology was feasible and worth a try. We used similar fuzzification schemes. For each attribute of the input data, fuzzifying its value generated a vector of rule activation values. In the fuzzy solution the fuzzification generated a set of vectors($\mathbf{u_i}$) and in the neuro-fuzzy solution we used a single concatenated vector **u**.
The **u** vector is the input data to be applied in the radial basis neural network. After the supervised learning, the neuro-fuzzy system output is $\mathbf{y}(t) = \mathbf{f}\left(\mathbf{u}(t).\Theta + \boldsymbol{\beta}\right)$ where **y(t)** is a vector containing each class membership, Θ is the connection parameters matrix, $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_m)$ is the bias vector and $\mathbf{f} : R^M \to [0,1]^m$ is the vector version of activation function. We can by-pass the bias and then $\mathbf{y}(t) = \mathbf{u}(t).\Theta$.
Supervised learning gives $\boldsymbol{\theta}$. We look for a parameter set $\boldsymbol{\theta}^*$ to minimize root mean square error, $\boldsymbol{\theta}^* = \min_{\boldsymbol{\theta}}\left(\left\|\mathbf{W}\boldsymbol{\theta} - \mathbf{V}\right\|\right)$ [9] where $\mathbf{V} = [v(1), \ldots, v(N)]^T$ is the desired output and **W** the regression matrix or interpolation matrix [10]. The solution of $\mathbf{W}\boldsymbol{\Theta} = \mathbf{V}$ is obtained from single value decomposition. Figure 3 exhibits a schema of the process.

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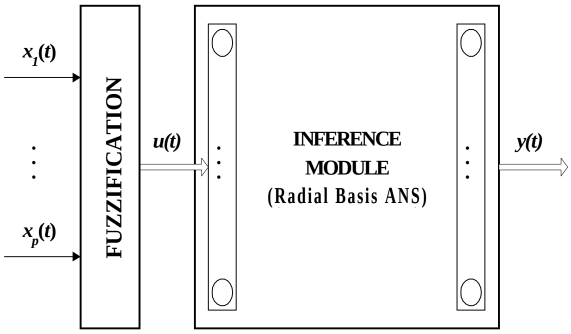

Figure 3: General architecture of neuro-fuzzy systems.

9. Discussion

Our client had available data results from using discriminant analysis technique over a great deal of oil wells. We obtained the results for 20 oil wells and applied the classifiers described in this paper for comparison. The recall computational costs of all our classifiers were negligible, always much less than one second in Pentium III processors. All learning processing time for neural networks were under 30 seconds. Or fuzzy systems this learning processing time vary: with no variable combination these times were negligible and with high level of variable combination the processing time raised quickly just to 97 seconds.

Table 1 presents a comparison behavior using Artificial Intelligence (AI) and non-AI techniques to recognize facies in 20 oil wells based in average results over several runs. As we can see, the best results were obtained with standard neural networks techniques. Fuzzy and neuro-fuzzy solutions presented very similar results and they are not conclusive. It must be emphasized users have used successfully neural networks for years and are not so confident in fuzzy applications. We used the same data attributes for the three approaches and the same fuzzy discretization.

Table 1 Comparison of techniques

Technique	Range of Successful results
Discriminant Analysis	50-60%
Back Propagation Neural Nets	68-80%
Fuzzy Logic	57-70%
Neural Fuzzy	63-69%

New techniques always bring the dream of better results. However, sometimes the fittest technique is already available. As we can see the best results were obtained with standard neural networks techniques.

10.Conclusion

Generating a multi-technique workbench for lithologic studies is a strong impulse of confidence increase in rock estimation. In this paper we have focused on discussing the results of applying different techniques to the same set of facies data, though, we believe the process of pre and post processing are fundamental steps to reach relevant results and to provide excellent insights about the oil field.

In our experiment for the facies classification problem in offshore oil fields, AI techniques outperformed traditional statistical methods. Among the AI techniques, although the performance difference was not significant, the users (geologists) preferred Back Propagation Neural Network and decided to adopted as the standard technique.

We think the results obtained using fuzzy logic can be improved as soon as the geologists become familiar with parameter tuning and variable combination. Fuzzy parameters must be refined using a non-uniform discretization scheme for different variables and using different ranges for distinct values of physical properties of rocks represented by well logs.

The greatest advantage of he proposed techniques is the increment of the success rate in facies recognition (7% in average). This increment save a significant amount of money for the corporation and the authors are very pleased to see the technical work become highly profitable to the customers.

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