Neural network applications in geophysics

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Introduction

Neural networks can be thought of multi-channel processing systems which attempt to learn and generalize a set of processing rules given a number of known inputs and, optionally, known outputs. This makes neural networks ideal tools for solving the types of problems we encounter in geophysical data analysis, and especially in exploration seismic applications. In this review paper, I will first discuss the basics of neural networks, and then summarize the ways in which neural networks have been used in exploration seismic analysis. These applications range from the detection of first breaks on seismic records to more recent applications such as the prediction of reservoir properties using seismic attributes. Illustrations will be given from several of these methods.

Neural networks: an overview

We first need to answer the question: what is a neural network? The simplest answer is that a neural network is a mathematical algorithm that can be trained to solve a problem that would normally require human intervention. Although there are many different types of neural networks, there are two ways in which they are categorized: by the type of problem that they can solve and by their type of learning. Neural network applications in seismic data analysis generally fall into one of two categories: the classification problem, or the prediction problem. In the classification problem, we assign an input sample to one of several output classes, such as sand, shale, limestone. In the prediction problem we assign a specific value to the output sample, such as a porosity value.

Neural networks can also be classified by the way they are trained, using either supervised or unsupervised learning. In supervised learning the neural network starts with a training dataset for which we know both the input and output values. The neural network algorithm then "learns" the relationship between the input and output from this training dataset, and then applies the "learned" relationship to a larger dataset for which we do not know the output values. The most common example of the supervised learning neural network is the multi-layer perceptron, or MLP, which has become almost synonymous with the term neural network, and is illustrated in Figure 1.

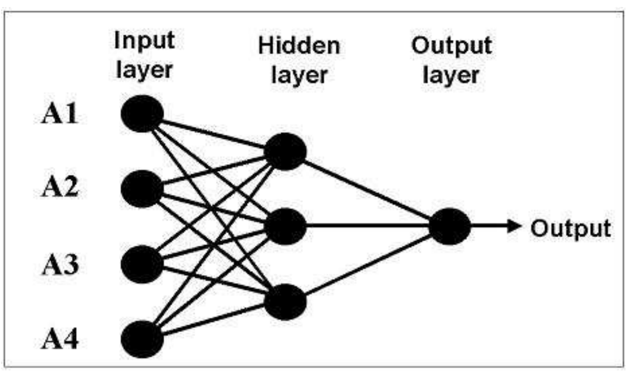

Figure 1. A multi-layer perceptron neural network.

The MLP shown in Figure 1 consists of three layers, and the lines between the layers represent weights that are applied to the outputs of each layer. The circles in the first layer represent the inputs (A1 through A4), but in the other two layers are nonlinear functions which are applied to the weighted outputs. The weights in the MLP are determined by backpropagating the errors between the inputs and the outputs, and this is both time consuming and potentially non-repeatable. More recent supervised neural networks such as the probabilistic neural network (PNN) and generalized regression neural network (Masters, 1995), and the radial basis function neural network (RBFN) (Bishop (1995)) use a single layer of Gaussian functions and do not have the limitations of the MLP.

Unsupervised neural networks do not require a training dataset but instead try to find patterns, or clusters, within the input dataset in multidimensional space. Although this can be done using the statistical technique of K-means clustering (Duda et al., 2001), a more powerful method involves using the Kohonen Self Organizing Map (KSOM) (Kohonen, 2001).

There are many other types of neural networks, such as the Hopfield neural network, which involve recursive processes rather the feed-forward process discussed here, but these will not be considered in this review.

Geophysical applications of neural networks

In two recent review articles, van der Baan and Juten (2000) and Poulton (2002) both discuss the theory of neural networks and the application of neural networks to geophysics. Although neural network theory dates back to the mid-twentieth century, applications to geophysics were relatively late in arriving, and the earliest papers cited in these two reviews date back only to the late 1980's and early 1990's. The authors of these early studies focussed entirely on the MLP approach described in the previous section, and discussed seismic applications such as first break picking and trace editing (McCormack, 1990, Upham and Carey, 1991). Non-seismic applications involved electomagnetic and magnetotelluric prospecting, as well as well log analysis.

More recent applications of neural networks in geophysics have two things in common: they use a wider array of algorithms than just the MLP and they have become almost exclusively associated with the term "seismic attributes". In these methods, a number of seismic attributes are used to predict either some reservoir property of the subsurface using supervised neural network, or a facies distribution using unsupervised methods. A review of seismic attributes and their uses (and abuses) was given recently by Sheline (2005). The use of seismic attributes in neural network applications allows us to build the multidimensionality needed for the successful application of neural network technology. However, as pointed out by Sheline (2005) we must also take care to make sure we understand the geophysical implication of each attribute. The application of supervised attribute analysis for the prediction of reservoir parameters using the PNN, GRNN, and RBFN methods described the first section was shown by Hampson et al. (2001) and Russell et al. (2003). Figure 2, from Hampson et al. (2001) shows the prediction of a P-wave velocity log using multiple seismic attributes and the GRNN method.

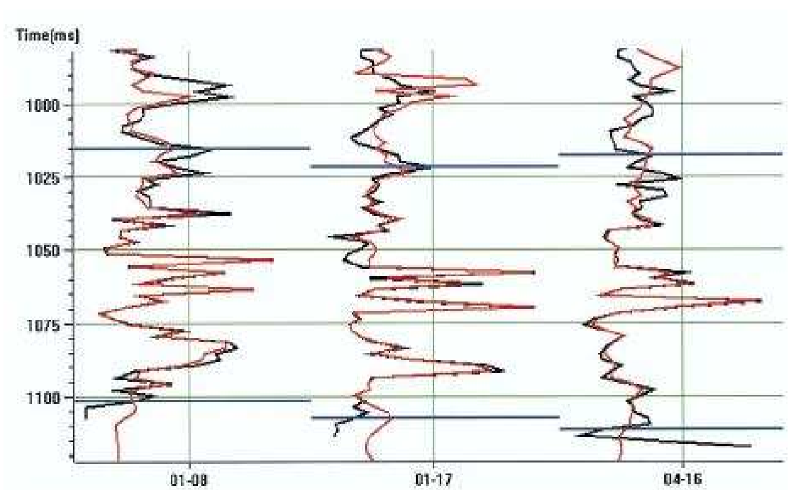

Figure 2. Prediction of P-wave sonic logs using 6 attributes, where the black line shows the original log and the red line shows the predicted log. (Hampson et al., 2001)

An alternate approach to the supervised prediction of reservoir parameters using seismic attributes is given by Russell et al. (2003), in which the RBFN method is used.

Turning our attention to unsupervised neural network methods, Coléou et al. (2003) present a review of unsupervised facies classification methods, in which they compare principal components analysis (PCA), K-means clustering, and the KSOM technique. Figure 3, taken from their paper, shows a comparison of the K-means and KSOM methods for the identification of both 6 and 12 classes. The facies interpretation is virtually identical for the KSOM method, but quite different for the K-means method, which indicates that the KSOM method is more robust in the prediction of geological facies. Note that in Figure 3 the KSOM method is referred to simply as the SOM (self organizing map) method.

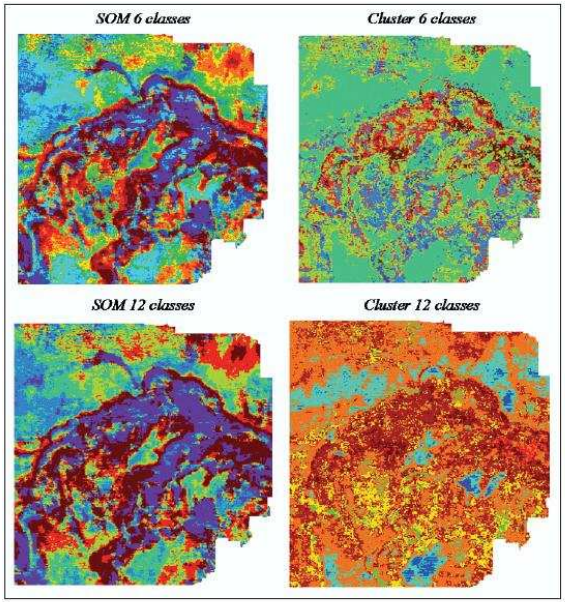

Figure 3. The use of the KSOM method (left) and K-means clustering method (right) for the prediction of 6 classes (top) and 12 classes (bottom) in facies classification. Notice that the KSOM method is consistent in the two cases, whereas the clustering method is not consistent.. (Coléou et al. (2003))

Conclusions

Over the last fifteen years, neural networks have been increasingly applied to geophysical analysis problems. The original applications to seismic data stressed first break picking and trace editing, but more recent applications have focussed on the prediction of reservoir properties and facies analysis using both supervised and unsupervised neural network techniques. Given the increased interest in neural networks by the geophysical community over the last few years, it is easy to predict that this interest will continue to grow. Certainly, the increased power of computers over the coming years will lead to more efficient parameter estimation within the currently used neural networks. We are also likely to see the application of new types of neural networks to new types of problems such as noise attenuation, inversion and imaging.

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