A new Confidence Bound estimation method for neural networks, an application example.

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Abstract

This paper describes recent experiences with the estimation of confidence bounds for supervised neural networks using the method and theories developed by Yang *et al*. (2000). Estimation of confidence bounds is essential for neural network predictions to be successful. The method is applied to an inverted porosity volume that is predicted using a supervised neural network trained on 300 simulated pseudo-wells. The reliability of the neural network prediction is estimated and confidence bounds are placed on the output of the supervised neural network. The method is considered a significant improvement in the application of neural network technology for the oil industry.

Introduction

Artificial Neural Networks are a class of non-linear models, which have been successfully applied in many areas for prediction, pattern recognition, classification and process control. They are commonly used in problems where the underlying physical models are either unknown or very complex. The predictive power and reliability were normally evaluated by comparison of the predicted values and the measured values at control points (i.e. wells in the oil industry). To estimate the reliability more accurate we suggest setting confidence bounds around the predicted values. A new method to estimate the confidence bounds was designed based on evaluation of earlier methods and experiments on simulated seismic data (Yang *et al.*, 2000). The significance of this development is clearly illustrated by the results of the evaluated experiment.

A new method to estimate confidence bounds

Yang *et al. (2000)* compared the existing confidence bound estimation methods and investigated their behaviours when their assumptions are violated. A correction method was launched to estimate the confidence bounds more reliable. The existing methods are asymptotically valid when the number of training points goes to infinite. It is also assumed that the model errors are independent and normally distributed with zero means and the neural network is trained to convergence, and there is no observation error. In reality, these assumptions are rarely satisfied. To evaluate the performance of the confidence bound estimation methods, the coverage of the confidence interval was used as a quantitative measure of the size of the confidence interval. Here, the coverage is the percent of targets that falls within the confidence interval.
The experimental results of Yang *et al.* (2000) showed that the estimated confidence intervals are not always correct. It was observed that the estimated confidence intervals were normally larger than the desired coverage when there was no observation error. Increasing the number of training points reduces the size of the estimated confidence intervals. The existence of irrelevant inputs

and observation error reduces the coverage of the confidence intervals. In such cases, the variance of the estimated confidence intervals could be very large when the number of training points is small. Irrelevant inputs reduce the size of confidence intervals in extrapolation areas, especially when the number of the training points is small. In the presence of observation error, stopping training early increases the coverage of the confidence intervals. With a large number of training points, however, the confidence interval will normally reflect the distribution of the training data. The size of the estimated confidence intervals depends on various conditions such as the level of observation noise and the training process.

Yang et al. (2000) developed a method to estimate the confidence bounds more reliable. The method estimates the bias of the coverage and corrects the confidence bounds. The correction method is performed as follows: a neural network is trained using a training set and is subsequently applied to a test set. This procedure is repeated several times and the average coverage ($1-\alpha_1$) is computed. When the neural network is applied to the application set, the new confidence bounds are corrected by:

$$C_{corrected} = \frac{p\,(\alpha_0\,/\,2)}{p\,(\alpha_1\,/\,2)}\,c$$

where c is the size of the confidence interval computed by the standard algorithm, function *p*(.) is the inverse of the normal cumulative distribution function, and ($1-\alpha_0$) is the desired coverage.

Results

The method is applied to a realistic multi-dimensional prediction case. A supervised neural network was trained to predict the porosity from the combination of seismic waveform, acoustic impedance and the reference depth (fig. 1). The input training data is acquired from the synthetic traces of 300 simulated wells. The data is extracted within a moving window that slides along the well traces. These simulated pseudo-wells were created using a geologically constrained Monte Carlo simulation technique (de Groot *et al.* 1996). Six real wells, located within the 3D seismic survey, act as blind tests to avoid overfitting of the neural network while training. We used a Multi-Layer-Perceptron (MLP) neural network that has one hidden layer with five nodes (fig. 1, left).

A first quality indication of the neural network is its training performance. The normalised root-mean-square (RMS) and the scatter plot (predicted vs. actual porosity value) show the training history and the final result (fig. 1, center and right). Training was stopped when no further improvement was achieved. The trained neural network was applied to the six real wells to invert the seismic data to a predicted porosity. For each prediction the 90% confidence interval was calculated using a simple, commonly used algorithm proposed by Chryssolouris et al. (1996) (see also Yang et al. 2000). The RMS was calculated for the test set and the coverage of the confidence interval was computed. This procedure was repeated 50 times.

The results of the 50 trials are displayed in figure 2. The RMS is around 0.1, except in a few cases where the neural network was badly initialized and the RMS was much larger. Although the number of samples in the test set is only 84 (14 datapoints per well) the coverage was stable, varying between 0.7 and 0.9. However, there is clearly a bias as the coverage is lower than the desired coverage of 0.9, which demonstrates that the simple equation to calculate the confidence intervals is not adequate. Therefore the correction equation from Yang et al. (2000) was applied to correct the size of the confidence interval. A correction factor of 1.3647 was computed and multiplied to the size of the confidence interval given by the standard method. The results for two wells are shown in figure 3. It shows the predicted values with the confidence interval before

and after the correction is applied. The size of the interval was increased to have a higher and more accurate average coverage.
In the past the prediction result could only be validated by making a comparison between the predicted values and the measured porosity in the wells, i.e. based on the input data only. With the newly designed method we are now able to estimate the confidence bounds as well, not only for the training and test sets but also for the application set. The method developed by Yang *et al.* (2000) was used to estimate the confidence bounds in a reliable manner that is considered superior to standard algorithms used to date.

Conclusions

The estimation of confidence bounds has significantly improved the applicability of the prediction of (petrophysical) parameters by supervised neural networks. Besides a comparison between predicted and measured data a confidence interval can now be obtained for each predicted value. This will reduce the uncertainties that are related to the evaluation of prospects and fields in the oil industry.

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References

Yang, L., Kavli, T., Carlin, M., Clausen, S., and de Groot, P. F. M., 2000. An Evaluation of Confidence Bound Estimation Methods for Neural Networks, ESIT 2000: 322 - 329.

De Groot, P. F. M., Bril, A. H., Floris, F. J. T., Campbel, A. E., 1996. Monte Carlo simulation of wells, Geophysics 61(3): 631 - 638.

Chryssolouris, G., Lee, M., Ramsey, A., 1996. Confidence interval prediction for neural network models, IEEE Trans. Neural Networks 7(1): 229 - 232.

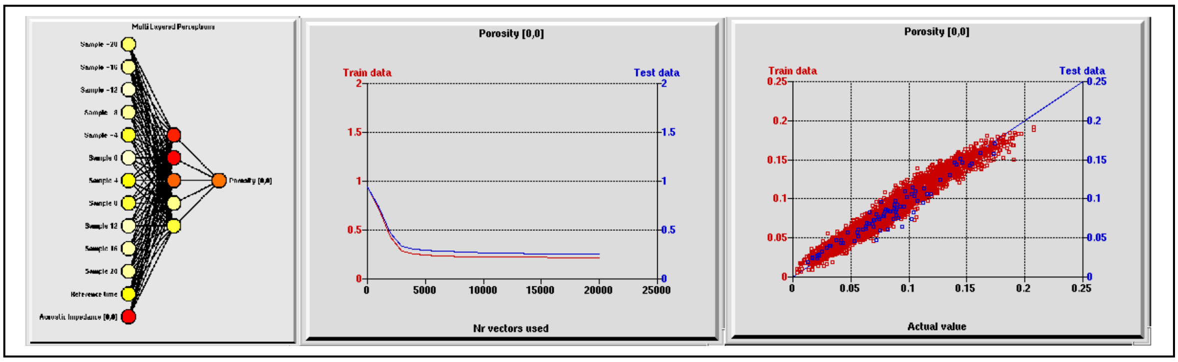

Fig. 1 Trained supervised MLP neural network topology (left), normalised RMS plot (center) and scatter plot of predicted values vs. actual values (right).

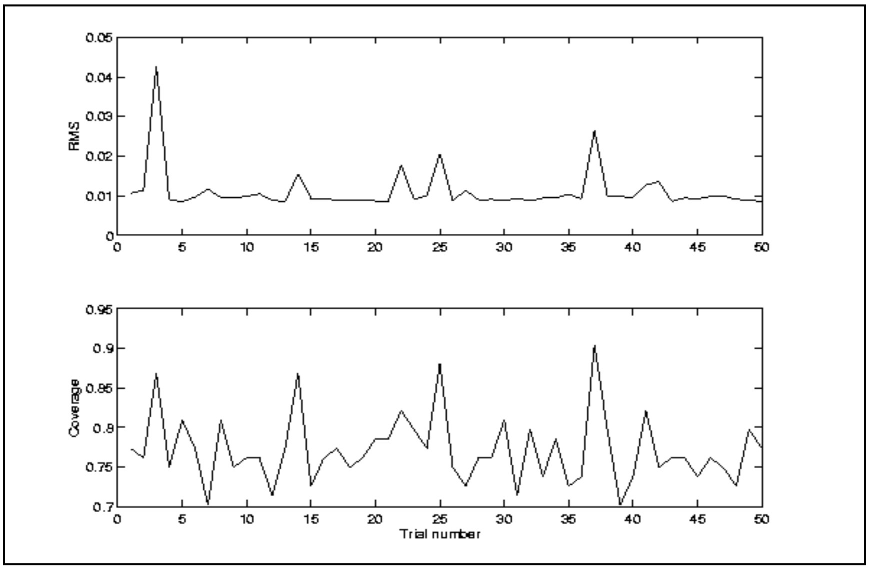

Fig. 2 RMS values (top) and coverage (base) for 50 trials.

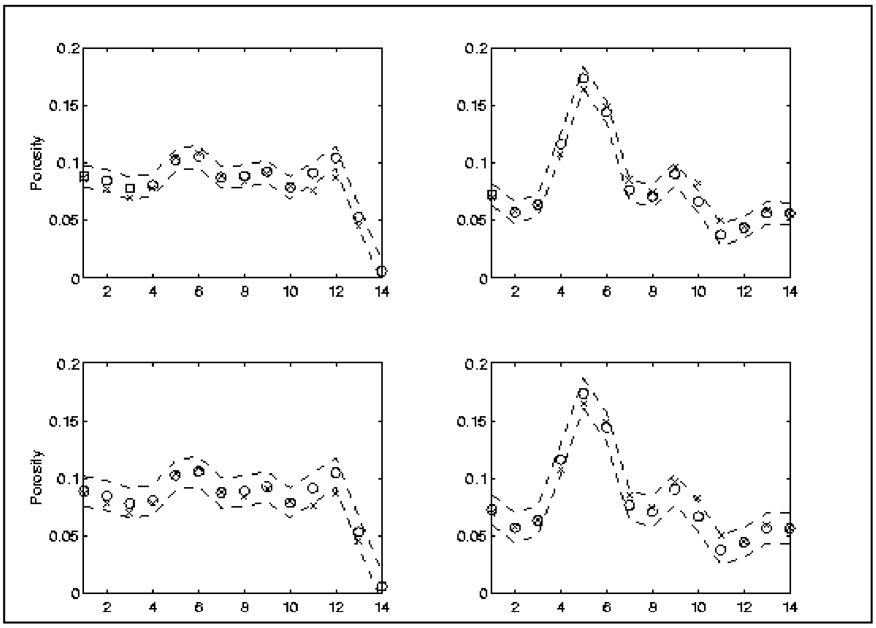

Fig. 3 Prediction results Well 1 and Well 2 with 90% confidence bounds using a standard algorithm (top, dashed lines) and using the corrected confidence interval using formula by Yang et al. (base, dashed lines). Predicted values (x), and measured values (o).