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Estimating Porosity and Lithofacies from Log Data Using Abductive Networks Machine Learning

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Abstract

Computational intelligence techniques, e.g. neural networks, have been used for modeling and predicting physical rock properties and lithofacies types from wireline logs. This provides the essential data needed for reservoir characterization, without requiring extensive and costly coring or well testing data. We propose using abductive networks machine learning as an alternative approach to the problem. In contrast to neural networks, abductive networks offer simplified and more automated model synthesis, require less user intervention, and select only significant model input parameters. Analytical input-output relationships can be easily derived to give better insight into the modeled phenomena and allow comparison with other models. We used a dataset of well logs and corresponding core data to train and evaluate models for porosity and lithofacies. Results for porosity were compared with a neural network model developed on the same dataset. Simplified analytical relationships for porosity in terms of relevant input logs are generated, and we verify that such relationships adequately explain the dataset. A porosity model was trained on 293 samples selected randomly from one well dataset. Porosity was predicted for the remaining 100 samples of the same well with a root-mean-square-error of 3.8%. The model predicted porosity for the full 327 samples of another well in the same field with comparable accuracy. A 5-class lithofacies model trained on 227 samples predicted the facies for remaining 100 samples of the same well with an overall accuracy of 93%.

1. Introduction

Determination of rock physical properties (e.g. porosity and permeability) and identification of lithofacies types (e.g. sandstone and mudstone) are important aspects of characterizing complex geological formations, estimating reserves, forecasting production, and planning enhanced recovery operations for oil reservoirs. Laboratory measurement of such parameters is possible using core samples extracted at the required depths. However, well bore conditions are not always favorable and the process is tedious and expensive, making it practical only at selected wells and depth intervals. An easier approach is to log the well using electronic equipment to measure and digitally record parameters such as rock density, sonic travel time, neutron backscatter, and natural gamma-ray emission. Rock parameters of interest at uncored locations can then be estimated by extrapolating the relationship between the log data and the corresponding core measurements to other intervals of a cored well or even to adjacent uncored wells. However, difficulties facing this task include: complex, non-linear and often unknown relationships, inherent variability and incompleteness of the log data, effects of data acquisition, and statistical fluctuations in radiation log measurements.

Traditionally, both theoretical [1] and empirical [2] models, and statistical multiple linear regression (MLR) analysis [3] have been used to estimate rock properties in uncored intervals of oil wells. Theoretical approaches tend to oversimplify the behavior of the very complex porous media [4]. In addition to the difficulty in deriving a representative empirical relationship, results apply only to limited regions [5], and suffer from poor generalization [6]. With MLR, the fundamental assumption of a linear relationship between the modeled parameter and the well logs limits the usefulness of the technique [7]. Statistical classifiers such as discriminant analysis have been used to classify lithofacies types [8]. However, the technique suffers from limitations due to the assumption of a statistical normal distribution for the variables, particularly when the training set is small [9].

A recent trend in handling such difficulties has been to resort to artificial intelligence and machine learning techniques, such as neural networks, fuzzy logic, and genetic algorithms. With this approach, a model for the phenomenon considered is developed through training on an adequate number of solved examples. Once synthesized, the model can be used to perform fast predictions of outputs corresponding to new cases previously unseen during training. The method offers a number of advantages over conventional approaches, including increased tolerance to data errors and uncertainties and reduced need for knowledge on the modeled relationships or assumptions on the statistical properties of the data.

Various forms of neural networks have been used to estimate permeability and porosity and identify lithofacies and from wireline logs [10-14]. However, the technique suffers from considerable user intervention during model development, non-transparent nature of the resulting models, the local minima problem, and the need for external stopping criteria to ensure adequate generalization. In some geophysical applications, performance of conventional neural networks alone was not adequate, and the method had to be supplemented by other techniques such as fuzzy logic [15] and genetic algorithms [16]. Neural network paradigms employing the gradient descent approach have been known to produce averaged, smoothed estimates that do not produce local variability of the reservoir permeability [5]. Extreme values were being underestimated or overestimated, rendering results unsatisfactory since fluid flow performance is more sensitive to extreme values rather than averages.

This paper proposes using abductive (or polynomial) networks based on the Group Method of Data Handling (GMDH) as an alternative approach that overcomes many of the neural network limitations. The technique has been used in a number of disciplines, including: weather forecasting [17], medical diagnostics [18], electrical load forecasting [19], credit evaluation [20], marketing [21], vibration monitoring [22], soil and agriculture [23], and nuclear spectroscopy [24]. However, the technique appears to be virtually unknown in the petroleum and gas industry, with only a few applications reported, e.g. estimating the useful life of drilling bits [25] and predicting oil Pressure-Volume-Temperature (PVT) properties [26]. Following a brief account of neural network limitations, the GMDH-based technique is introduced. Abductive network models for estimating porosity and lithofacies are described, and data on prediction performance are presented. Results on porosity are compared with a neural network model developed on the same dataset. Simplified analytical relationships are developed and used to explain the dataset.

2. Limitations of Neural Networks

Experience with neural networks has revealed a number of limitations with the technique, including the complexity of the design space [27]. With no analytical guidance on the choice of many design parameters, the developer often follows an ad-hoc, trial-and-error approach of manual exploration that naturally focuses on just a small region of the potential search space. Architectural parameters that have to be guessed *a priori* include the number and size of hidden layers and the type of transfer function(s) for neurons in the various layers. Learning parameters to be determined include initial weights, learning rate, and momentum. Although acceptable results may be obtained, it is obvious that potentially superior models can be overlooked. The considerable amount of user intervention not only slows down model development, but also works against the principle of 'letting the data speak'. To automate the design process, external optimization criteria, e.g. in the form of genetic algorithms, have been proposed [28]. Over-fitting or poor network generalization with new data during actual use is another problem [29]. As training continues, fitting of the training data improves, but performance of the network with new data previously unseen during training may deteriorate due to over-learning. A separate portion of the training data is often reserved for monitoring such performance in order to determine when to stop training. This reduces the amount of data used for actual training, which would be disadvantageous in many situations where training data are scarce. Network pruning algorithms [30] have been proposed to automate stopping of neural network training. Gradient descent employed by the back-propagation algorithm to minimize training error suffers from the local minima problem, which may prevent reaching an optimal model [31]. Another limitation is the opacity or black-box nature of neural network models. The associated lack of explanation capabilities is a handicap in many decision support applications such as medical diagnosis. Additional analysis is required to derive explanation facilities from neural network models, e.g. through rule extraction [32]. Model parameters are buried in large weight matrices, making it difficult to gain insight into the modeled phenomenon or compare the model with available empirical or theoretical models. Information on the relative importance of the various inputs to the model is not readily available, which hampers model reduction through discarding less significant inputs. Additional processing using techniques such as principal component analysis may be required for this purpose [33].

3. GMDH-based Abductive Networks

An alternative modeling approach that helps overcome many of the above limitations is that based on the self-organizing group method of data handling [34]. GMDH-type algorithms can automatically synthesize adequate models that embody the inherent structure of complex and highly nonlinear systems. The automation of model synthesis not only lessens the burden on the analyst but also safeguards the model generated from being influenced by human biases and misjudgements. The GMDH approach is a formalized paradigm for iterated (multi-phase) polynomial regression capable of producing a high-degree polynomial model in effective predictors. The process is 'evolutionary' in nature, using initially simple (myopic) regression relationships to derive more accurate representations in the next iteration. The algorithm selects polynomial relationships and input combinations that minimize the prediction error in each phase. Iteration is stopped automatically at a point in time that strikes a balance between model complexity for accurate fitting of the training data, and model simplicity that enables it to generalize well with new data. It is seen that the algorithm has three main elements: estimation, selection, and stopping. The algorithm applies abduction heuristics for making decisions concerning some or all of the three elements [34]

Practical implementations of the GMDH paradigm take the form of polynomial [19] or abductive networks [35]. The Abductory Induction Mechanism (AIM) tool [36] automatically synthesises mathematical models from relationships discovered in the training data. It does so by trying out all potential relationships of linear, multiple and polynomial regressions on various combinations of existing variables. Like a neural network, the abductive model can be represented as a multi-layered network with inputs and outputs separated by processing layers. However, while the processing elements in neural networks are identical and restricted by the neuron analogy, AIM builds a network of various types of more powerful numerical functional elements based on prediction performance, see Fig. 1. While the neural network user needs to pre-specify the network structure, with AIM the network size, element types, connectivity, and coefficients for the optimum model are automatically determined, thus reducing user intervention. The algorithm automatically selects only the input variables that contribute significantly to the model. Discarding unnecessary inputs simplifies the resulting model and avoids degradation of model performance due to measurement errors or noise in discarded inputs. It also simplifies and economizes on data collection efforts required for model implementation. AIM adopts a well-defined automatic stopping criteria that does not require a dedicated subset of the training data for model validation during training. This is achieved by minimizing the predicted squared error (PSE) criterion [37] that penalizes model complexity to keep the model as simple as possible for best generalization. The criteria selects the most accurate model that does not overfit the training data, and therefore strikes a balance between the accuracy of the model in representing the training data and its generality which allows fitting previously unseen future data. In this way the model is optimized for the actual use for which it is developed, rather than only at the training phase. The user may optionally control this trade-off between accuracy and generality using the complexity penalty multiplier (CPM) parameter [36]. Values greater than the default value of 1 lead to simpler models that are less accurate but are more likely to generalize well with previously unseen data, while lower values produce more complex networks that may overfit the training data and degrade prediction performance with noise. The CPM is usually the only parameter that the user may need to experiment with during AIM model development, and adequate models are often obtained with the default CPM value. GMDH-based training achieves very fast convergence and does not suffer from the local minima problem [19]. Substitution of the equations of the various functional elements produces a mathematical expression for the overall model relationship, which makes it less of a black box compared to the neural network model. It is often instructive to compare resulting relationships with empirical or first-principles models that may exist for the modeled phenomenon. Such relationships can also show directly relative importance of various inputs to the modeled output.

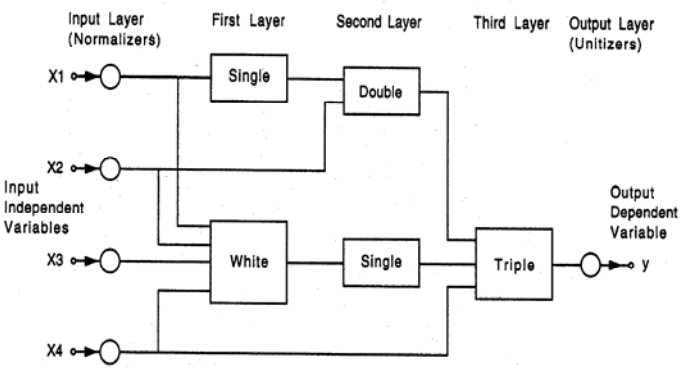

Fig. 1. A typical AIM abductive network model showing various types of functional elements.

AIM models take the form of layered feed-forward abductive networks of functional elements (nodes) [36], see Fig. 1. Elements in the first layer operate on various combinations of the independent input variables (X's) and the single element in the final layer produces the predicted output for the dependent variable y. In addition to the functional elements in the main layers of the network, an input layer of normalizers converts the input variables into an internal representation as Z scores with zero mean and unity variance, and an output layer of unitizers restores the results to the original problem space. The used version of AIM supports the following main functional elements:

(i) A white element that consists of a constant plus a linear weighted sum of all outputs of the previous layer, i.e.:

$$WhiteOutput = W_0 + W_1X_1 + W_2X_2 + ... + W_nX_n \quad (1)$$

Where: X_1, X_2, …….X_n are the inputs to the element and W_0, W_1, W_2, ….W_n are the element weights.

(ii) Single, double, and triple elements which implement a third-degree polynomial expression, with possible cross-terms, for one, two, and three inputs respectively; for example,

$$DoubleOutput = W_0 + W_1X_1 + W_2X_2 + W_3X_1^2 + W_4X_2^2 + W_5X_1X_2 + W_6X_1^3 + W_7X_2^3 \quad (2)$$

The first step in solving a problem with AIM is acquiring a database of input-output solved examples for training and evaluating the model. The database is often randomly split into a training set and an evaluation set, typically with 70% for training and 30% for evaluation. AIM uses the training set to synthesize the model network layer by layer until no further reduction in predicted squared error is possible. Performance of the derived model is then evaluated using the evaluation set. Often the default model obtained with CPM = 1 gives adequate performance, but simpler or more complex models can be tried by setting the appropriate CPM value prior to training. To obtain good AIM models, both the training and evaluation sets should be a good representation of the problem space. AIM's learning task is also simplified by judicious selection of input variables in the training database.

4. Modeling of Porosity

Log and core data available for one well (well # 1) were used to construct abductive network models for porosity. Log data consisted of the following seven parameters:

- Depth in feet
- Sonic slowness (DT)
- Gamma ray (GR)
- Neutron porosity (NPHI)
- Normal pressure gradient (PORE)
- Bulk density (ROHB)
- Bulk density, calculated (ROHG)

The core data consisted of depth in feet and measured porosity. Tolerating a mismatch in the region of ± 0.2 ft between the log and core depth measurements allowed 393 data records to be used for model development. This dataset was randomly split into a training set of 293 records and an evaluation set of 100 records. All seven logs were declared as model inputs and the measured core porosity identified as the model output. The abductive network model obtained through training using the default CPM value of 1 is shown in the top row of Table 1. The 2-layer, 2-element model selects all input variables except ROHB. As ROHG and ROHB should be highly correlated, only one of them is selected. The linear White element in the first layer generates a weighted sum of DT, NPHI, PORE, and ROHG. A third degree polynomial represented by the Triple element in the second layer operates on the weighted sum together with the remaining two input parameters (Depth and GR). The model was evaluated on the remaining set of 100 records belonging to the same well used to train the model, and a scatter plot of predicted versus actual values for porosity is shown in Fig. 2(a). The root mean square error (RMSE) is 3.77 and the Pearson correlation coefficient (R) between the two sets of values is 0.92. Fig. 2(b) shows the results of model evaluation on the full dataset of 327 records belonging to another well (well # 2) in the same field. Values for RMSE and R are 3.90 and 0.90, respectively, which indicates acceptable accuracy for estimating porosity in uncored wells using models developed on cored adjacent wells.

The effect of varying the complexity of the abductive model was investigated, and the simpler models obtained with CPM = 2 and 5 are shown in Table 1. The increase in the CPM value from 1 to 2 reduces the number of model inputs selected from 6 to 3, and simplifies the model to a 1-element 1-layer model. At CPM = 5, the model is reduced to a simple wire element that makes a direct connection between the PORE input and the Porosity output, indicating that at this level of model simplicity the porosity is determined only by the normal pressure gradient. It is noted that among all seven input parameters, PORE has the largest correlation coefficient with core porosity (R = 0.88). Table 1 also gives data on relative training time and the RMSE error and the R value

Table 1. Effect of the CPM parameter on the complexity and performance of porosity models.

CPM	Model Structure	Relative Training Time	Porosity RMSE	Actual-Predicted Correlation, R
1	DT, NPHI, PORE, RHOG, Depth, GR → White → Triple → Porosity	1.00	3.77	0.92
2	DT, GR, NPHI → Triple → Porosity	0.56	3.88	0.92
5	PORE → Porosity	0.17	4.04	0.92

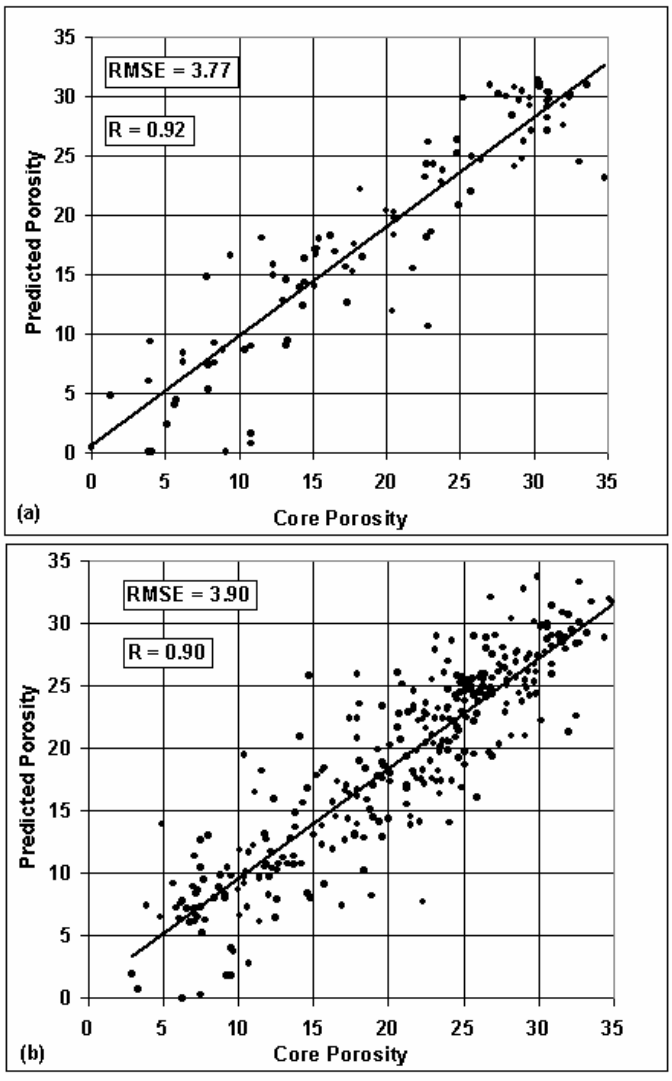

Fig. 2. Scatter plots for core and predicted porosity when the porosity model with CPM = 1 was evaluated: (a) on 100 new records of the same well, and (b) on 327 new records of a different well.

between the actual and predicted porosity values for the evaluation set in the same well. While increasing the CPM parameter significantly reduces model complexity and shortens training time, the simplified models still perform adequately in predicting porosity. The simplified models help derive manageable analytical expressions that can give better insight into the modeled relationship and be compared with other theoretical or empirical models that may be available. For example, equations synthesized for all the functional elements of the simplified model having CPM = 2 are shown in Fig. 3.

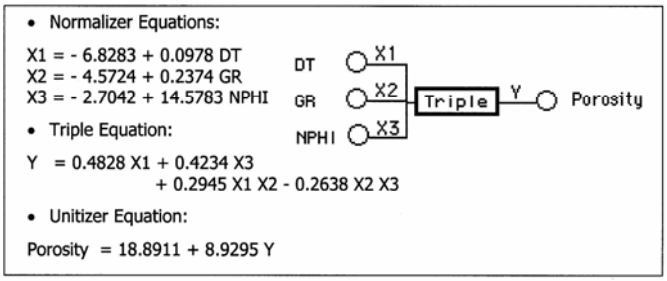

Fig. 3. Details of the porosity model obtained with CPM = 2.

Symbolic substitution for the equations gives the following nonlinear relationship for porosity in terms of the three input log parameters:

$$\text{Porosity} = 32.1 - 0.7516\,\text{DT} + 212.4483\,\text{NPHI} - 2.7412\,\text{GR} + 0.0608\,\text{DT GR} - 8.1575\,\text{NPHI GR} \quad (3)$$

Performing the same operation for the model with CPM = 5 gives the following linear relationship:

$$\text{Porosity} = 117.88\,\text{PORE} - 2.35 \quad (4)$$

To verify that Eqn. (4) is an adequate representation of the dataset, Porosity is plotted versus the PORE log for the full dataset of 393 records for well # 1 in Fig. 4. The best line fit that has its intercept anchored to –2.35 has a slope of 116, which is very close to the slope of 117.88 in Eqn. (4).

Performance of the abductive models described above was compared with that of a neural network model developed on the same data using the NeuroSolutions 4.0 software for Windows. The (7-3-1) model had seven neurons in the input layer, 3 neurons having a hyperbolic tangent transfer function in a single hidden layer, and one neuron with a linear transfer function in the output layer. 20% of the training dataset were used for cross validation during training. Evaluating of the neural model on the 100 evaluation records from the same well gave RMSE = 3.76 and R = 0.92, which are comparable with the corresponding values for the default abductive model at CPM = 1. Other abductive models shown in Table 1 are much simpler than the neural network model, with only a small degradation in prediction performance.

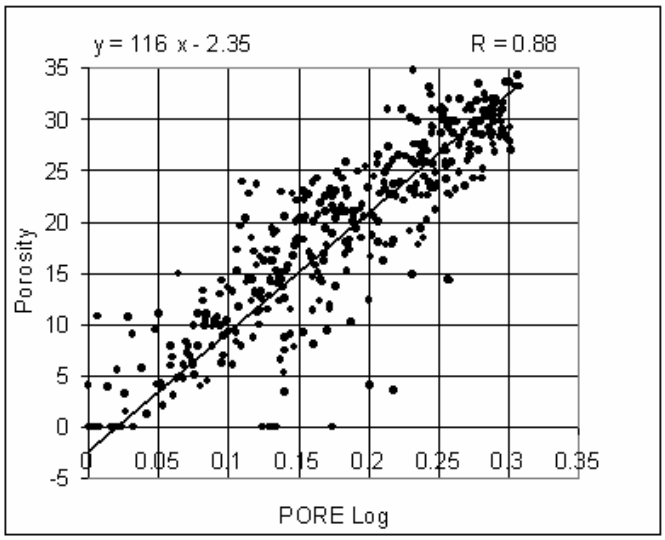

Fig. 4. Scatter plot of the core porosity versus the PORE log for the full dataset of 393 records of well # 1.

5. Modeling of Lithofacies

Data for well # 2 consisted of 327 records similar to those described for well # 1. As shown in Section 4, this full dataset was used to evaluate the porosity models developed using well # 1 on an entirely different well in the same field. In addition to core porosity data, information from well # 2 included lithofacies classification into five different types labeled as 1, 2, 3, 4, and 5. Percentage abundance of these five types in the full dataset of well # 2 are 19, 20, 36, 17, and 8%, respectively. A single-output abductive network model was developed for the lithofacies types where the model output assumed an integer value from 1 to 5 representing the five facies classes. The model was trained on 227 records and evaluated on the remaining 100 records for the same well. Fig. 5 shows the structure of the abductive network model synthesized using CPM = 0.5.

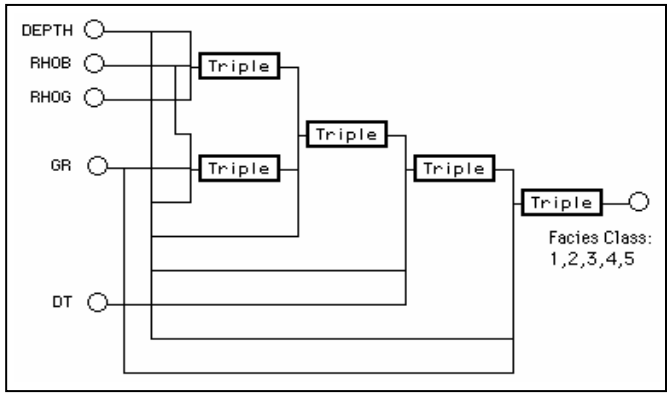

Fig. 5. Lithofacies classification model synthesized with CPM = 0.5.

This is a five-input, four-layer, highly nonlinear model. Only the depth, the two bulk density parameters, the gamma log, and the sonic log contribute to the model. The depth features strongly, and constitutes an input to all five Triple elements of the model. Classification performance of the model is shown in Table 2 in the form of a 5x5 confusion matrix. Classes 1 and 2 are each classified with 100% sensitivity. Class 8 is classified with 100% positive predictive value. Most classification errors occur with classes 4 and 5, which have the smallest population in the dataset. Overall classification accuracy is 93%. Neural network applications reported in the literature classify lithology from logs with approximately 90% accuracy [14].

Table. 2. Confusion matrix for classifying the 100 evaluation records of the same well using the lithofacies model shown in Fig. 5.

		Predicted Classification					Sensitivity for Individual Classes, %
		1 (18)	2 (22)	3 (39)	4 (13)	5 (8)	
Actual Classification	1 (17)	17	0	0	0	0	100
	2 (20)	0	20	0	0	0	100
	3 (37)	0	1	36	0	0	97.3
	4 (16)	0	1	3	12	0	75
	5 (10)	1	0	0	1	8	80

6. Conclusions

We have demonstrated the use of abductive network machine learning as a new tool for estimating rock properties from well logs and core data. While estimation accuracy is comparable with neural networks, the new approach simplifies model development, automatically selects effective inputs, gives better insight into the modeled phenomena, and allows comparison with available analytical models. Future work will consider modeling other formation characteristics, including permeability and fluid saturation. Other areas of interest include seismic attributes analysis and synthesizing Magnetic Resonance Imaging (MRI) well logs from conventional geophysical logs.

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