Integration And Selection Of Geological Scenarios Through Multiple Kernel Learning To Improve The Prediction Of Reservoir Properties

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Abstract Due to the sparsity of knowledge available, there exists a variety of possible geological scenarios to describe a petroleum reservoir. A single scenario encapsulates a specific geological concept but is limited to represent the full range of geological variability. In order to reflect the geological uncertainty it is necessary to integrate a diverse range of these scenarios. Two challenges arise from integrating multiple geological scenarios into a prediction model. Firstly, a subset of scenarios has to be determined that explain and account for the geological variability. Secondly, these geological scenarios are most likely heterogeneous, scale dependant and represent a specific spatial region. Mathematically these scenarios are complex to integrate. In this paper we apply Multiple Kernel Learning to integrate multiple possible scenarios and show how it applies feature selection within the multiple inputs.

Introduction

Reservoir simulation aims to predict the flow of fluids through a porous media. It does this by creating a mathematical model that incorporates both the geological model (including the petro physical properties of porosity and permeability) as well as the dynamic fluid flow model. Reservoir Simulation is conducted for a number of reasons. It is applied when determining the extent and spatial location of infill drilling. It is used to predict production rates that are inputs into

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investment decisions and future planning for the life of a reservoir. Thus it is important that models created are realistic and physically possible. Furthermore models should encompass the entire realm of realistic models in order to quantify the uncertainty surrounding prediction.

Therefore from the realm of all possible geological models that apply to a reservoir, we seek models that are geologically realistic. That is, models that are geologically possible and, combined with the dynamic fluid flow model, capture the future values of production rate. Geologically realistic models are bounded and constrained, predicting outputs such as porosity and permeability within a range known to be physically possible. Numerous works have been done on modelling geological realism in petroleum reservoirs [1,2].

Geologically realistic models however encompass a wide range of possible models. Due to the sparsity of accurate information for petro physical properties (porosity and permeability) as well as the heterogeneous nature of the reservoir, it is possible to derive multiple models that honour the data (generally information available from either well logs or well cores). Different modelling techniques will further result in different outcomes. It is probable that these multiple models each account for unique aspects within the geological model. Thus the true geological model is most likely an integration of these models.

Prediction of the geological model and petro physical properties has traditionally been modelled using either Geostatistics [3], Objects Based modelling and more recently Multi Point Statistics [4]. These techniques are still applied today and are being further enhanced. However, these methodologies have two disadvantages. The first, being an inability to integrate multiple possible models and secondly the inability to model nonlinear relationships.

Recent research has focused on addressing these two issues. Kernel learning techniques [5] have been developed to model non-linear relationships. Data Fusion and Data Assimilation techniques such as Ensemble Kalman Filter [6] and Statistical Learning Theory [7,8] have been developed to model environments with sparse data yet an abundance of input variables.

Kernel Learning Methods have been developed to model the non-linear relationships by mapping inputs into a higher dimensional space wherein they are then linearly related to the output variable. Within a reservoir simulation scenario, an abundance of data exists for modelling including downhole logs, output crop data and seismic data. These geological scenarios are heterogeneous, scale dependant and represent a variety of spatial scales. The relationships between these and the petro physical properties of porosity and permeability are non-linear. Mapping these inputs into a higher dimension through the use of kernels allows one to apply linear regression techniques in this higher dimension. Current methodologies employing kernels include Kernel Ensemble Kalman Filters [9], Kernel PCA [10] and Machine Learning techniques including Support Vector Regression [11], Relevance Vector Machines [12] and Multiple Kernel Learning [13].

The non-linear relationship between output and input is quite possibly unique for each input variable. Support Vector Regression (SVR) applies a single kernel to all inputs. Multiple Kernel Learning (MKL) has the advantage in that it applies a unique kernel to each input thus enabling the integration of heterogeneous data by accounting for unique non-linear relationships.

Integration of multiple possible models is closely tied to feature selection. From a range of multiple models, it is important to determine which models are relevant. This is important for both computational efficiency as well as interpretability. Models that are highly correlated in some dimension are superfluous and add noise to a model. Multiple Kernel Learning applies feature selection by constraining the weights of prior model and forcing some to be zero by applying Lasso regularization [14].

In this paper we apply Multiple Kernel Learning to predict permeability and porosity by integrating an ensemble of geological scenarios with additional available information. This generates a further ensemble of models which more accurately represents the true geological model. From this updated ensemble it is possible to quantify the uncertainty of the geological model.

To ensure that the resulting models are realistic the hyper-parameters of the MKL model are tuned using stochastic optimization algorithm in the history matching framework. This allows one to integrate dynamic production data and constrain the ensemble of models to ensure realism. For this paper we have applied Flexi Particle Swarm optimization [15] to tune the parameters of the model.

Methodology

The procedure applied was as follows: We create a model using Multiple Kernel Learning that integrates multiple possible models with the spatial location of each datum to predict a vector of outputs Y. This model is applied to the grid and the resulting geological model is fed through a flow simulator. The simulated production results are compared to the true production rates and a goodness of fit measure derived. Based on the size of this fit, the hyper-parameters of the MKL model are tuned using a stochastic optimization technique known as flexi Particle Swarm Optimization. Multiple models are run concurrently until the fit converges to a minimum and an ensemble of models is generated. From these models the uncertainty can be quantified.

In this paper the primary focus is on the machine learning algorithm Multiple Kernel Learning and its application to predicting the petro physical properties of a petroleum reservoir from prior geological models. A brief overview of MKL is given below, followed by a case study.

Multiple Kernel Learning is a predictive technique falling within the realm of Machine Learning and more specifically Statistical Learning Theory. It was developed in 2004 by Lanckriet and Bach [13] as an extension of Support Vector Regression.

In contrast to Support Vector Regression, MKL applies a unique kernel to each input scenario / variable (eq()). Hence for observation i, a unique kernel is determine for each variable $j = 1 \ldots l$. This accounts for the heterogeneous nature of scenarios and input variables. Each kernel is then weighted and the weights constrained to sum to one. This is the lasso regularization [] and forces some of the features to have a weight of zero, thereby inducing sparsity in the number of relevant features. An additional advantage of MKL is thus the interpretability of the model. The exact impact of each input is determined from the weighting.

$$K(x_i, x) = \sum_{j=1}^{l} d_j K_j(x_i, x) \tag{1}$$

$$subject\ to \sum_{j=1}^{l} d_j = 1$$

Support Vector Regression and Multiple Kernel Learning have been applied successfully in reservoir simulation [16,17,18].

Multiple Kernel Learning (MKL) maps scenarios and input variables into a higher dimension through the use of kernels. In this dimension a linear relationship exists between predictor and input variables and linear regression can be applied. However, in order to account for sparsity of data and thus ensure generalization MKL modifies the linear regression approach.

Multiple Kernel Learning (MKL) ensures generalization of the model in two ways. Firstly by fitting a soft margin ε around the prediction line. That is, MKL honours the data to within a predefined margin. The width of the margin is a hyper-parameter that is tuned during the history matching process. Secondly MKL adds a regularization term, minimizing the sum of the weights squared (the $l_2$norm) of each input. A complexity factor C controls the balance between the regularization term and minimizing the fit between data and model. This complexity factor is a hyper-parameter of MKL and is tuned during the history matching procedure.

Hence MKL has at least three hyper-parameters that require tuning via history matching. The width of the soft margin ε, the complexity factor C and the parameters of each kernel that are unique to individual inputs and scenarios.

The function derived by Multiple Kernel Learning is given by equation (2).

$$\hat{Y} = f(x) = \sum_{i=1}^{n} (\alpha_i^* - \alpha_i) d_j \sum_{j=1}^{l} d_j K_j(x_i, x) + b_o \tag{2}$$

$$subject\ to \sum_{j=1}^{l} d_j = 1$$

The results of MKL are interpretable in that a weighting is given for each feature as well as for each observation. In eq (2), the α_i represent the weight given to each well. The observations that are used in the model are known as support vectors. Their weight is bounded by the value of the complexity function which avoids large variations occurring in complex models. The advantages of weighting the observations, in reservoir simulation, is the ability to determine which wells are influential and represent areas of spatial diversity where additional drilling may be required.

Case Study

We apply this methodology to the Brugge Case Study that was developed by TNO in the Netherlands. The Brugge Case study is a synthetic oil reservoir based on a North Sea reservoir. It is a complex reservoir comprising 4 depositional environments. The case study is supplied with 104 possible geological models. The true geological model is not supplied and part of the exercise is to create a geological model that integrates these multiple possible models in order to enhance the prediction of production rates in the future.

Thus the case study is an ideal situation to apply Multiple Kernel Learning. The 104 prior models are integrated with additional information and an ensemble of models generated.

Discussion

In this paper we aim to show how Multiple Kernel Learning (MKL) can be applied in the prediction of petro physical properties (porosity and permeability).

MKL has the ability to integrate multiple possible geological scenarios. Prior models may well represent a specific spatial region be or scale. An integration of these models results in a model that better captures the future fluid production rate.

MKL has the ability to select relevant scenarios / models from an ensemble of possible geological models. MKL selects features which are unique and represent spatially independent areas.

MKL provides interpretable results through the use of weighting. The relevant features are weighted between zero and one allowing one to determine the impact of each feature relative to the other features. Furthermore, MKL provides a weighting for each well indicating which wells are unique and contribute the most towards the modelling of the properties.

Using a history matching approach we ensure that the MKL models are realistic. This is done by tuning the hyper-parameters of the MKL model with a stochastic optimization technique that minimizes the fit between simulated and true production data.

Uncertainty within the MKL model is due to the selection of input scenarios and variables available as well as the range of each hyper-parameter. These hyper-parameters include the parameters for individually unique kernels, the complexity factor that balances the complexity of the model and the width of the soft margin which ensures over-fitting of the data does not occur.

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Bibliography

[1] Rojas, T. Demyanov, V., Christie, M. “Use of Geological Prior Information in Reservoir Facies Modelling”. Proceedings of the International Association of Mathematical Geosciences Conference, 5-9 Sep, Salzburg, Austria, 2011.
[2] Alpak, F., Barton, M., Castineira, D. “Retaining geological realism in dynamic modelling: a channelized Turbidite reservoir example from West Africa.” Petroleum Geoscience, v.17, p.35-52, 2011.
[3] Deutsch, C. “Geostatistics Reservoir Modelling” Oxford University Press. 2002

[4] Caers, J. “Petroleum Geostatistics” Society of Petroleum Engineers. 2005.

[5] Scholkopf, A., Smola, A. “Learning with Kernels” MIT Press, 2002

[6] Evensen, G. “Data Assimilation: The Ensemble Kalman Filter.” Springer, Berlin. 2007.

[7] Vapnik, V. “An Overview of Statistical Learning Theory”. IEEE Transactions on Neural Networks, vol. 10, no. 5, September 1999.

[8] Hastie, T., Tibshirani, R., Friedman, J. “The Elements of Statistical Learning” Springer. 2011.

[9] Sarma, P., Chen, W. “Generalization of the Ensemble Kalman Filter Using Kernels for Nongaussian Random Fields” SPE Reservoir Simulation Symposium, The Woodlands, Texas, 2-4 February 2009.

[10] Scholkopf, B., Smola, A., Muller, K. “Kernel Principal Component Analysis”. http://pca.narod.ru/scholkopf_kernel.pdf,

[11] Smola, A., Scholkopf, B. A “Tutorial on Support Vector Regression”. http://alex.smola.org/papers/2003/SmoSch03b.pdf. September, 2003.

[12] Fletcher, T. “Relevance Vector Machines Explained” http://www.tristanfletcher.co.uk/RVM%20Explained.pdf. October 19, 2010

[13] Lanckriet, G., Bach, F. “Multiple Kernel Learning, Conic Duality and the SMO Algorithm”. Proceedings of the 21st Conference on Machine Learning, Banff, Canada, 2004

[14] Ng, A. “Feature selection, L_1 vs. L_2 regularization and rotational invariance”. Proceedings of the 21st International Conference on Machine Learning, Banff, Canada, 2004.

[15] Kathrada, M., “Uncertainty Evaluation of Reservoir Simulation Models using Particle Swarms and Hierarchical Clustering” PhD Thesis, Heriot Watt University, June 2009.

[16] Backhouse, L., Demyanov, V., Christie, M. “Integrating Prior Knowledge through Multiple Kernel Learning for the Prediction of Petroleum Reservoir Properties”, presented at International Association of Mathematical Geology conference (IAMG). 2011.

[17] Demyanov, V., Foresti, L., Kanevski, M., Christie, M. (2010): Multiple Kernel Learning Approach for Reservoir Modelling. ECMOR XII – 12th European conference on the Mathematics of Oil Recovery, 6-9 Sep, Oxford, UK

[18] Demyanov, V., Poznoukhoz, L., Kanevski, M., Christie, M. “Semi-supervised *Support Vector Regression* Reservoir Model”, Proceedings of the VII International *Geostatistics* Congress, Gecainin, Chile, 2008.

WETTER, M. WRIGHT, J. A Comparison of Deterministic and Probabilistic Optimization algorithms for Non-Smooth Simulation-Based Optimization, Building and Environment, 39, 989-999 (2004)