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Machine Learning Methods for Reservoir Prediction Modelling Under Uncertainty - Tackling Multiples Scales

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SUMMARY

Reservoir prediction modelling conventionally involves complex statistical models that aim to integrate feature on multiple scales. These features are sourced from various types of data and often have a significant impact on flow performance. Conventional geostatistical algorithms provide a framework to integrate data from different scales, such as: geological interpretation of depositional structure based on analogues (e.g. by using conceptual training images); spatial correlation of geological bodies, their variety and geometrical relations (e.g. with imbedded geometrical shapes or elicited relations from analogues); high resolution seismic can be a source of multi-scale model features that can be integrated into stochastic model by means of soft conditioning.
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The way the data are integrated into a model is subject to uncertainty of the data themselves as well as the model relations that bond the data. It is essential to allow enough flexibility in the model to account for possible uncertainties at different scales: geological interpretation, spatial correlation, connectivity and heterogeneity. Geostatistical approach is sometimes not flexible enough to integrate multiple geological interpretations or multi-scale data conditioning.

Machine learning approach offers novel opportunities to integrate uncertain information on multiple scales. The present work includes different examples of how machine learning algorithms can elicit essential relations from data, integrated them into a model and handle relevant uncertainty in an inverse modelling way:

1) Distinguishing between multiple geological conceptual interpretations is achieved by navigating in a classified metric space of multiple training images to generate history-matched models.

2) Informative priors for channel geometry relations elicited from natural river analogues improve the control of the model realism in calibrating to dynamic data.

3) Multi-scale spatial features obtained from a decomposed high-resolution seismic are blended back together to condition the model in a non-linear way using kernel learning. This approach provides model realisations based on different combinations of spatial features at different scales that can match the observed dynamic reservoir response.