

Geological Modeling from Legacy Seismic Data with Consideration of Uncertainties

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Geological modeling is a fundamental component of reservoir characterization in geothermal exploration. A structural geological model, usually referred to as a geological model or geomodel, aims to represent the spatial relation between geological features such as rock unit boundaries, horizons, discontinuities (unconformities, faults) and intrusions at various scales [5]. In this contribution, we show how surrogate models can be employed to consider spatially correlated uncertainties in reprocessed legacy seismic data. Due to limited information in depth, geological models can contain significant uncertainties. In the KarboEx2-project, legacy seismic data from former coal exploration in the region of North Rhine Westphalia are digitized and reprocessed with modern seismic processing workflows. We investigate how uncertainties in the interpretation of this legacy data can be considered in subsequent geological modeling workflows.

In the context of model construction, this type of uncertainty relates to the real position of the input points, commonly associated with data uncertainties (seismic processing, picking and interpretation, etc.) [5]. Several position points result from the picking of the horizons on legacy seismic data. A simple way to address this type of uncertainty is to perform sampling from the data treating it as fully correlated (i.e., moving all points simultaneously) or fully uncorrelated (i.e., moving all points independently). However, geological errors are commonly correlated with distance.

One possibility to consider spatial correlations is to generate a geological surrogate model with a lower-dimensional representation of the modelled interface. In addition to accounting for different uncertainties in space, such a low-dimensional representation allows to perform inference, sensitivity analysis, etc. We explore here a workflow based on the application of a Variational Gaussian Process (VGP) model from inducing points using an open-source Python package (GeoML) [1], [2], [3], [4]. The Gaussian process model can provide uncertainty estimates and be trained on small datasets. However, it presents a major difficulty modeling complex data sets (as seismic interpretation) using stationary covariances [4]. Therefore, a way to address this limitation is the application of deep Gaussian process through non-stationary covariances, which better captures complex, spatially varying structural patterns.

Our results show that it is possible to create surrogate models efficiently for a range of geological settings – with a balance between the dimension (input points) of the surrogate model and the level of complexity of the original interface. In addition, due to a variational approach, uncertainties in the input data are naturally propagated into the surrogate model and thus into derived geological realizations. We outline how this AI driven, uncertainty aware modelling approach can be integrated into geothermal exploration workflows, including the uncertainties in the legacy seismic data.

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