EGU22-7774
https://doi.org/10.5194/egusphere-egu22-7774
EGU General Assembly 2022


# Efficient inversion with complex geostatistical priors using normalizing flows and variational inference

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We propose an approach for solving geophysical inverse problems which significantly reduces computational costs as compared to Markov chain Monte Carlo (MCMC) methods while providing enhanced uncertainty quantification as compared to efficient gradient-based deterministic methods. The proposed approach relies on variational inference (VI), which seeks to approximate the unnormalized posterior distribution parametrically for a given family of distributions by solving an optimization problem. Although prone to bias if the family of distributions is too limited, VI provides a computationally-efficient approach that scales well to high-dimensional problems. To enhance the expressiveness of the parameterized posterior in the context of geophysical inverse problems, we use a combination of VI and inverse autoregressive flows (IAF), a type of normalizing flows that has been shown to be efficient for machine learning tasks. The IAF consists of invertible neural transport maps transforming an initial density of random variables into a target density, in which the mapping of each instance is conditioned on previous ones. In the combined VI-IAF routine, the approximate distribution is parameterized by the IAF, therefore, the potential expressiveness of the unnormalized posterior is determined by the architecture of the network. The parameters of the IAF are learned by minimizing the Kullback-Leibler divergence between the approximated posterior, which is obtained from samples drawn from a standard normal distribution that are pushed forward through the IAF, and the target posterior distribution. We test this approach on problems in which complex geostatistical priors are described by latent variables within a deep generative model (DGM) of the adversarial type. Previous results have concluded that inversion based on gradient-based optimization techniques perform poorly in this setting because of the high nonlinearity of the generator. Preliminary results involving linear physics suggest that the VI-IAF routine can recover the true model and provides high-quality uncertainty quantification at a low computational cost. As a next step, we will consider cases where the forward model is nonlinear and include comparison against standard MCMC sampling. As most of the inverse problem nonlinearity arises from the DGM generator, we do not expect significant differences in the quality of the approximations with respect to the linear physics case.