Generative Adversarial Networks as Priors for Inverse Problems

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Abstract

Direct observations of properties of porous media within the earth's interior are sparse and therefore solving inverse problems is a common task in geoscience. Setting inverse problems in a Bayesian framework allows the aim to find the posterior distribution of rock properties given observed data. This work aims to introduce a representation of the prior distribution given by a generative adversarial network (GAN). We show that GANs can be used to address many difficult problems in the geosciences, including seismic inversion (Mosser et al. 2018), generation of pore-space images (Mosser et al. 2017), and history matching in reservoir simulation.

GANs allow sampling from probability distributions that are implicitly defined by a large set of training images. Two differentiable functions, a generator and discriminator, are trained in a competitive two-player setting. We show that a Metropolis-adjusted Langevin algorithm (MALA) can be used as a geological prior. Our future work aims to expand this methodology to history matching of hydraulic reservoir production.

Generative Adversarial Networks (GANs)

GANs represent a flexible methodology to create functions that allow stochastic solutions of the ill-posed seismic inversion problem at reservoir scale, constrained by the acoustic wave equation to be obtained. We perform stochastic inversion using the MALA-sampling approach for a reservoir scale acoustic wave propagation problem (right). The reflected wave-field is sparsely sampled by a number of recording devices at the surface. This represents an ill-posed inverse problem. The generative network acts as a prior on subsurface structures and allows samples from the posterior to be obtained that match the observed data.

Stochastic inversion seeks to obtain samples of the posterior distribution of rock properties e.g. the spatial distribution of rock p-wave velocity or permeability, given observed data, combined with a prior representing our belief of what possible distributions of these quantities of interest may look like. This is summarized by Bayes' rule:

\[
p(y|x) = \frac{p(x|y) \cdot p(y)}{\int p(x|y) \cdot p(y) \, dy}
\]

To obtain samples from the posterior, we apply a Metropolis-adjusted Langevin algorithm (MALA). The prior is given by a GAN pre-trained on synthetic river channel systems and dependent only on the set of latent variables. The observed data is given by a forward simulation on an unseen geological cross-section.

Stochastic inversion - GANs + PDEs

The generator maps any point in the latent space to the space of images. Interpolation between points in latent space results in interpolation in the image domain where each intermediate step is a sample of the implicit probability distribution defined by the training set.

Optimization is performed by sampling and modifying a random latent vector by computing gradients with respect to the contextual loss and the perceptual loss by backpropagating through the differentiable discriminator function.

MALA - Posterior Sampling

The spatial distribution of permeability is sampled from a GAN trained on river channel systems. Using the adjoint-state equation, latent variables are modified to optimize the mismatch between the observed pressure field and the generated data by solving Darcy flow using a numerical finite-element solution on the GAN generated permeability field. The resulting channel systems closely match the ground truth permeability data.

References


History Matching in Latent Space

Our future work aims to use generative models as geological priors for reservoir-scale inverse problems such as history matching of hydroporocion production data. As a first step we solve a well-posed inverse problem of Darcy flow at the reservoir scale with Dirichlet boundary conditions: We perform stochastic inversion and generate samples from the posterior to be obtained that match the observed data.

Conclusions

- The differentiable nature of generative adversarial networks and their latent vector representations allows challenging problems in the geosciences to be addressed such as seismic inversion or pore-space image generation.
- GANs represent a flexible methodology to create functions that allow sampling from probability distributions defined by a set of training images.
- Using a Metropolis-adjusted Langevin algorithm allows stochastic inversion with deep generative models to be a prior on spatial property distributions.
- Future work will expand the presented methodology to ill-posed inverse problems for flow and transport such as history matching of hydrocarbon reservoir production data.