Efficient deterministic inversion of geophysical data constrained by Deep Generative Models to estimate subsurface parameters with defined spatial patterns

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Inversion constrained by Deep Generative Models

Background

Classical imaging algorithms sometimes fail in reproducing realistic structures. This may in turn result in wrong predictions.

Solution: constrain the inversion to display the expected patterns (e.g. multiple-point statistics).

Difficulty: high-dimensional parameters usually require large number of samples (simulations) for inference.
Inversion constrained by Deep Generative Models

Deep Generative Models (DGM)

1. Train the DGM with many realizations (images) of expected patterns.

2. A latent space with lower number of dimensions is created.

3. Samples with the patterns are obtained by sampling in the latent space and passing through a deep neural network.
Deep Generative Models (DGM)

Implicit generative modeling

\[ m = f(z) \]

Two big contenders: VAE and GAN

**Variational Autoencoder (VAE)**

Training: KL-divergence and reconstruction loss.
Advantages: easy training and high diversity.
Issues: oversmooth samples.

**Generative Adversarial Network (GAN)**

Training: Adversarial loss (generator vs discriminator).
Advantages: sharp samples.
Issues: difficult training and mode collapse (lack of diversity).
Inversion constrained by Deep Generative Models

Optimization of the objective function

Global optimization - computationally expensive

Gradient-based optimization

With a Deep Generative Model:

Instead of optimizing w.r.t. (gridded) parameters, do it w.r.t. latent space of DGM

\[
\begin{align*}
\frac{dS}{dm} & = \frac{dS}{dz} \\
\end{align*}
\]

Chain rule:

\[
\begin{align*}
\frac{dS}{dm} & = \frac{dS}{dz} \\
\end{align*}
\]
Generative Adversarial Network (GAN)

Global optimization - MCMC is working fine.

Gradient-based inversion - issues with convergence to local minima.

Laloy et al. 2018, Water Resources Research

Laloy et al. 2019, Computers and Geosciences
Variational Autoencoder (VAE)

A less strict latent space allows easier optimization?

The ability to break up channels

A tradeoff between the fidelity of samples and the easier optimization.
Comparison of DGMs

Inversion constrained by Deep Generative Models

Inference (gradient-based inversion)

VAE induces a latent space which appears to allow for easier optimization.
Inversion constrained by Deep Generative Models

Comparison of DGMs

WRMSE comparison for gradient-based inversion with GAN and VAE (100 different initial models)

models corresponding to the lowest WRMSE (among the 100 tries):
Concluding remarks and future work

VAE latent space is easier to handle with gradient-based optimization compared to GAN latent space.

There is a tradeoff between pattern fidelity and easier optimization.

Is the method still useful for nonlinear forward operators (e.g. shortest path method)?

What is the impact of the VAE model error on the final inversion result?
Concluding remarks and future work

VAE latent space is easier to handle with gradient-based optimization compared to GAN latent space.

There is a tradeoff between pattern fidelity and easier optimization.

Is the method still useful for nonlinear forward operators (e.g. shortest path method)?

What is the impact of the VAE model error on the final inversion result?

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Variational Autoencoder (VAE)

$p(z)$ chosen Gaussian

$p(m|z)$ obtained from passing $p(z)$ through a DNN

Since $p(z|m)$ is intractable, a variational $q(z|m)$ is used whose mean is a DNN too

\[
p(z) \equiv \mathcal{N}(0, I)
\]

\[
p(x|z) \equiv \mathcal{N}(f(z), cI)
\]

\[
q_x(z) \equiv \mathcal{N}(g(x), h(x))
\]

Maximize:

\[
\mathcal{L}(\theta, \phi; x^{(i)}) = -DKL(q_\phi(z|x^{(i)})||p_\theta(z)) + \mathbb{E}_{q_\phi(z|x^{(i)})} \left[ \log p_\theta(x^{(i)}|z) \right]
\]
VAE jumps

It. 939

It. 940

It. 935
It. 936
It. 937
It. 938
It. 939
It. 940
It. 941
It. 942
It. 943
It. 944
Nonlinear forward traveltime

Does this work with a nonlinear forward model?
Linear vs nonlinear forward traveltime

source #
receiver #

\[ d \]
\[ d + N(0, 1.4 \text{ ns}) \]
\[ d + N(0, 3.0 \text{ ns}) \]