Imperial College London

TOTAL

GANs for Earth Modelling and Inversion

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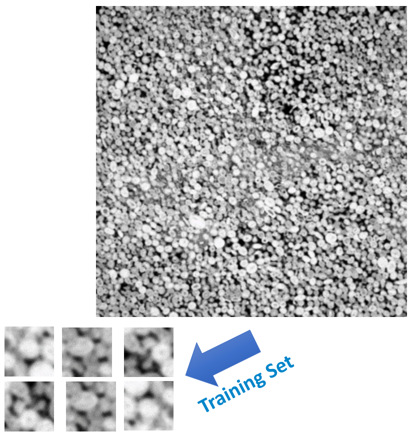
Ketton Limestone Dataset and Preprocessing

- **Oolitic Limestone**
- **Intergranular pores**
- **Intragranular Micro-Porosity**
- **Ellipsoidal grains**
- **99% Calcite**
- **Image Size:**
  - 900^3 voxels @ 26.7 μm

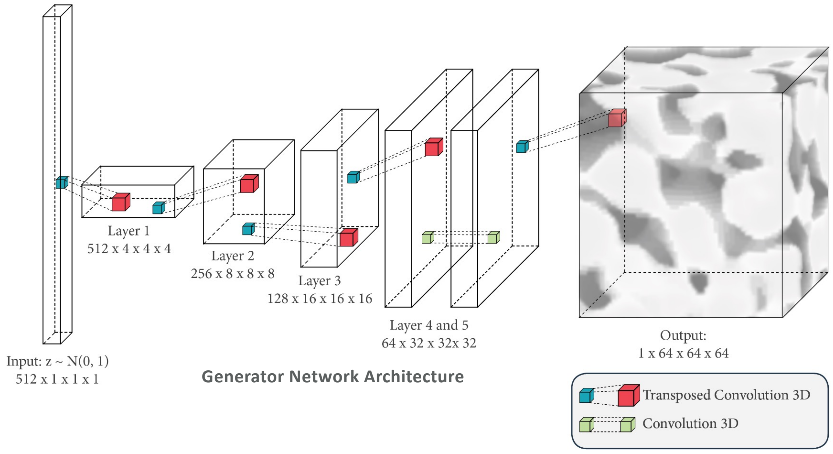
Extract Non-Overlapping Training Images (64^3 $voxels$)



2

Network Architecture - 3D Convolutional Network

Represent $G(z)$ and $D(x)$ as deep neural networks:



Discriminator: Binary Classification Network -> Real / Fake

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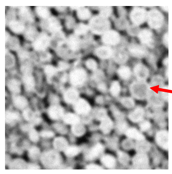
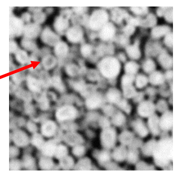
Reconstruction Quality

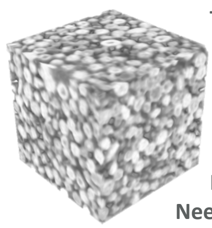
Ketton Training Image

GAN Generated Sample

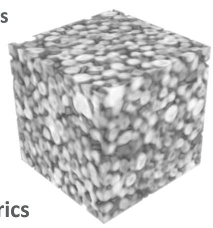


Intergranular Porosity
Moldic Features
Micro-Porosity





Training Time: 8 hours
Generation: 5 sec.



High visual quality
Needs evaluation metrics

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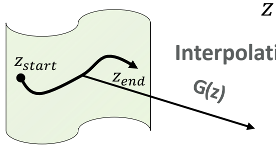
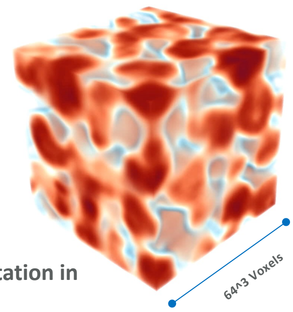
Latent Space Interpolation

Latent space **z**

$$z^* = \beta\, z_{start} + (1-\beta)\, z_{end}, \beta \in [0,1]$$

Interpolation path visualization





Interpolation in latent space:

Shows that generator $G(z)$ has learned a meaningful representation in a lower dimensional space!

Mosser et al, 2017

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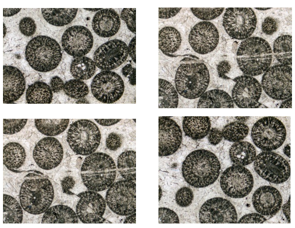
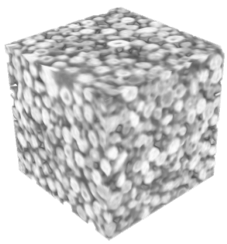
Why condition your generative model to data?

Condition 3D model to 2D sections





Thin sections are more abundant / cheaper -> can help infer 3D structure

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Conditioning to Data: Image Inpainting (Yeh et al. 2016)

Task: Restore missing details given a corrupted / masked image $M \cdot \tilde{x}$

Use a generative model $G(z)$ to find missing details, conditional to given information.

Contextual Loss: $L_{content} = \lambda \left\| M \cdot G(z) - M \cdot \tilde{x} \right\|_2$

Perceptual Loss: $L_{perc} = log(1 - D(G(z)))$

Optimize loss by modifying latent vector z

$M \cdot \tilde{x}$ | Human Artist | $L_2\ Loss$ | $L_{content}$ + L_{perc}

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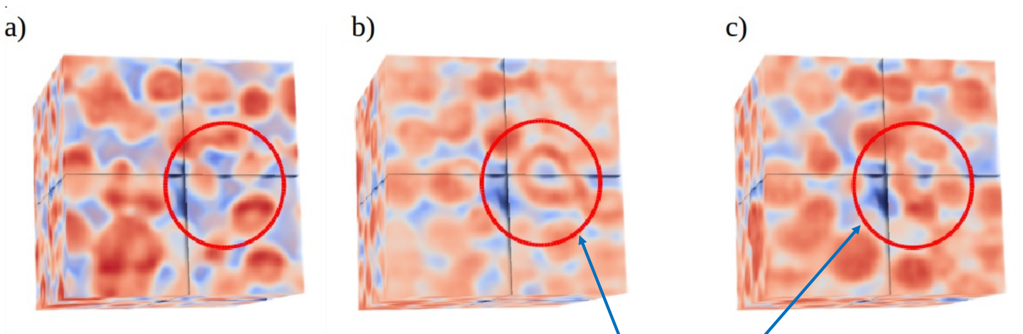
Conditioning – Pore Scale Example



Conditioning Data Ground Truth Volume

Stochastic Sample 1 Conditioned to Data

Stochastic Sample 2 Conditioned to Data

Same 2D conditioning data leads to varied realizations in 3D

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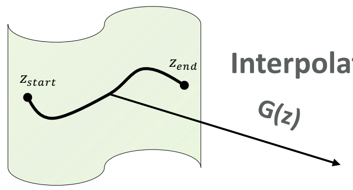
Latent Space Interpolation

Latent space **z**

$$z^* = \beta\, z_{start} + (1 - \beta)\, z_{end}, \beta \in [0, 1]$$



Interpolation path visualization

G(z)

Interpolation in latent space:

Shows that generator has learned a meaningful representation in a lower dimensional space!

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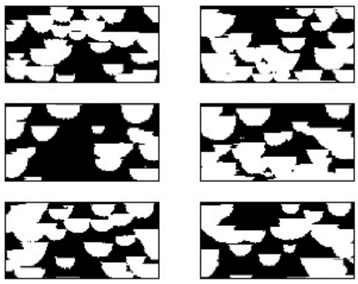
Conditioning – Reservoir Scale Example

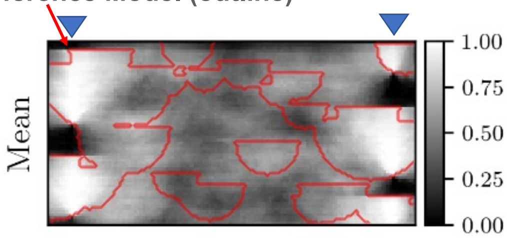
Conditioned Models



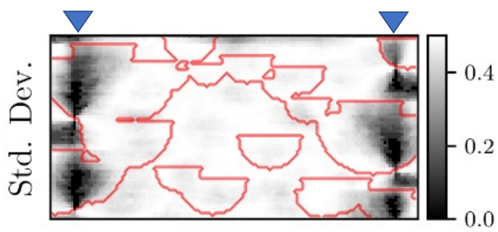
- **Pre-trained 2D-Generative Adversarial Network**
- **Conditioned to two wells (1D conditioning):**

Reference Model (outline)

Position of Wells



Mean (N=100)



Standard Deviation (N=100)

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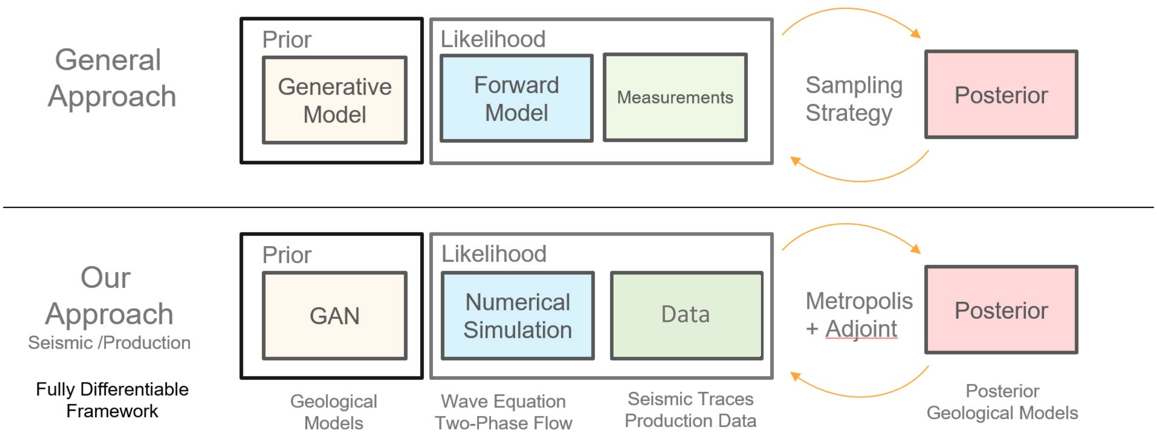
Deep Generative Models for Inversion

Represent Prior with Deep Generative Models

Bayes' Rule

$$p(\mathbf{z}|\mathbf{d}) = \frac{p(\mathbf{d}|\mathbf{z})p(\mathbf{z})}{p(\mathbf{d})} \propto p(\mathbf{d}|\mathbf{z})p(\mathbf{z})$$



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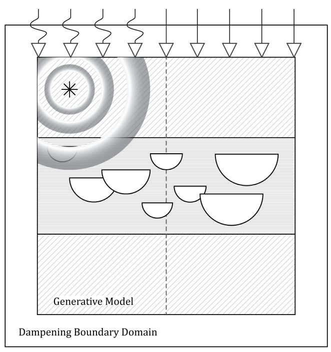
Deep Generative Models for Seismic Inversion

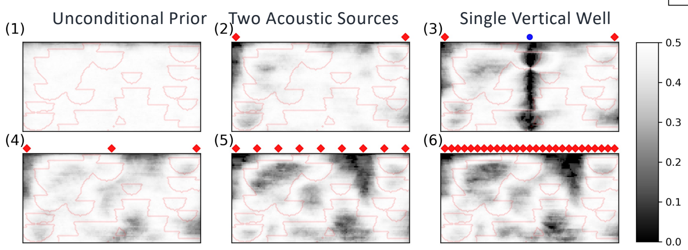
- Generative Model: GAN trained on channel bodies
- Forward Model: Acoustic Wave-Equation and Adjoint
- Sampling Strategy: Approximate McMC – MALA (uses gradient)

$$\mathbf{z}_{t+1} = \mathbf{z}_t - \gamma_t \underbrace{\frac{\partial \|S(G_\theta(\mathbf{z}_t)) - d_{seis}\|_2^2}{\partial G_\theta(\mathbf{z}_t)}}_{\text{Adjoint-Method}} \overbrace{\frac{\partial G_\theta(\mathbf{z}_t)}{\partial \mathbf{z}_t}}^{\text{NN-Backpropagation}} + \underbrace{\gamma_t \nabla \log p(\mathbf{z}_t)}_{\text{Latent-Variable Prior}} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, 2\gamma_t \mathbf{I})$$

- GAN maps from latent-space **z** to image space of geological models



Computational Domain



Standard deviation of samples from the posterior

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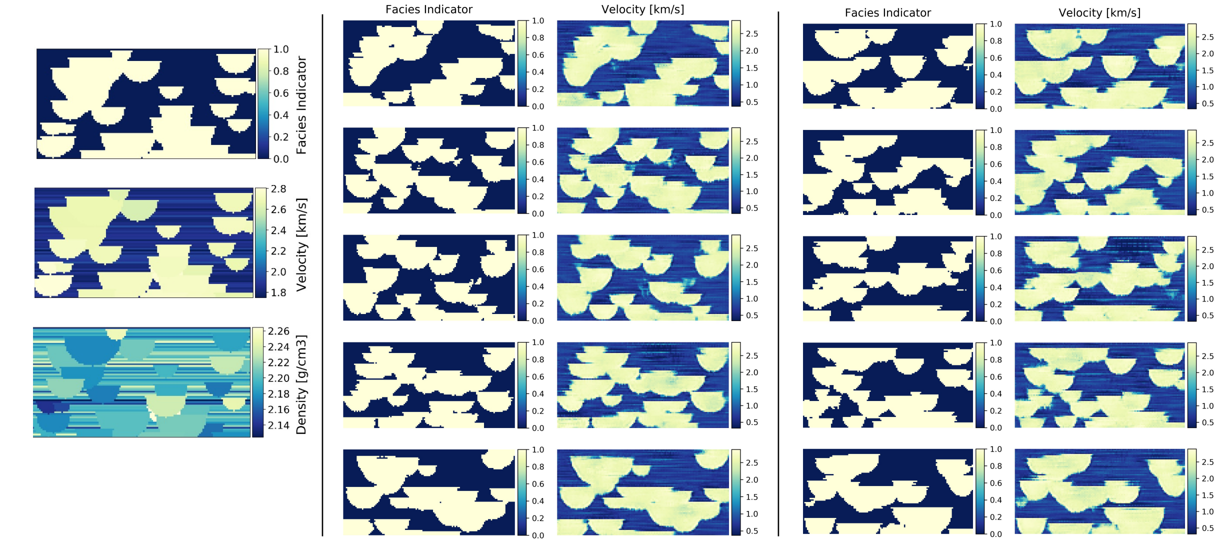
Samples – (Seismic) Inversion

Ground Truth Example | 2 Acoustic Sources | 27 Acoustic Sources



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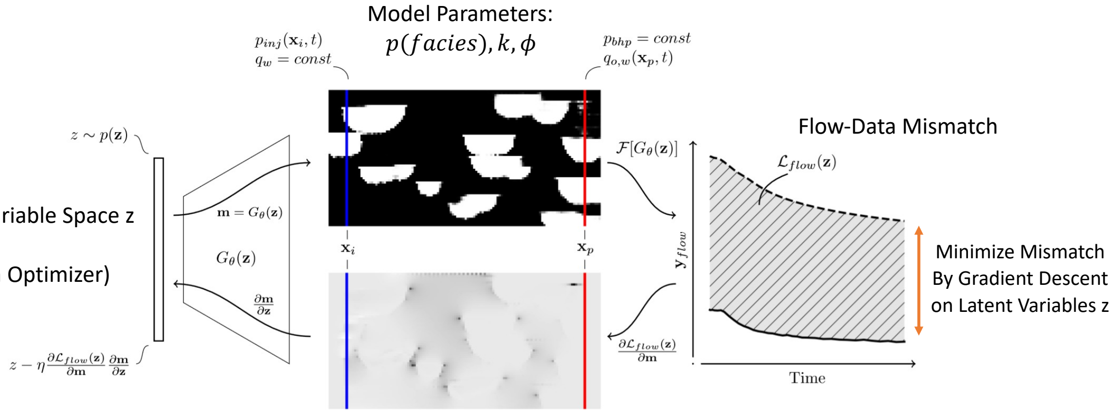
Deep Flow: History-Matching in Generative Model Space

Water-Injection into an Undersaturated Oil Reservoir



Gradients of Data Mismatch
with Respect to Model Parameters
$p(facies), k, \phi$

PyTorch + MRST

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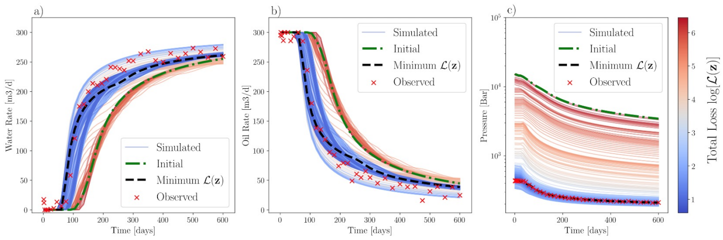
Deep Flow - Results

Evolution of Inversion in Flow-Data Space



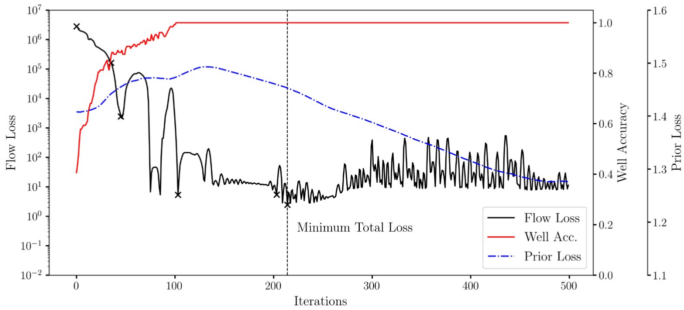
Evolution of Inversion in Model Space

Uses Adam Optimizer on **z**

Many Local Minima in Loss

Quickly finds “good” minima

Well Accuracy Stays High



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Publications and Code

References

DeepFlow: History Matching in the Space of Deep Generative Models. ***arXiv:1905.05749***, Mosser, L., Dubrule, O. and Blunt, M.J., (2019)

Stochastic seismic waveform inversion using generative adversarial networks as a geological prior. ***Math Geosci* 52, 53–79,** Mosser, L., Dubrule, O., & Blunt, M. J. (2020).

Reconstruction of three-dimensional porous media using generative adversarial neural networks. ***Physical Review E*, *96*(4), 043309,** Mosser, L., Dubrule, O., & Blunt, M. J. (2017).

Stochastic reconstruction of an oolitic limestone by generative adversarial networks. ***Transport in Porous Media*, 1-23,** Mosser, L., Dubrule, O., & Blunt, M. J. (2017).

Conditioning of Generative Adversarial Networks for Pore and Reservoir Scale Models, **80th EAGE Conference**, Mosser L., Dubrule, O., & Blunt, M. J. (2018).

Code

Unconditional Prior Generation: github.com/LukasMosser/PorousMediaGan
Conditioning to Data: github.com/LukasMosser/GeoGAN
Stochastic Seismic Waveform Inversion: github.com/LukasMosser/stochastic_seismic_waveform_inversion
Deep Stochastic Inversion (History Matching): github.com/LukasMosser/DeepFlow

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