# Improving Image-Based Characterization of Porous Media with Deep Generative Models

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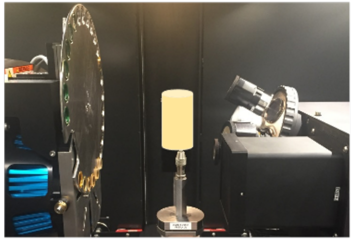
# Introduction

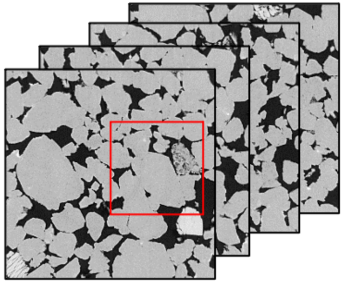
- Fuel switching, $CO_2$ and $H_2$ storage critical for long-term sustainable energy systems (Zoback & Kohli 2019, EIA, Hassanpouryouzband et al. 2021)
- Image-based characterization, digital rock physics critical for study of candidate reservoirs (Ketcham & Carlson 2001, Vega et al. 2013, Blunt 2017)
- **Central problems:**
  - Acquisition expensive, time-consuming, and/or sample destructive
  - Nanoscale shale images acquired in 2D but need 3D for characterization
  - Data too scarce to estimate petrophysical properties
- **Address by applying deep generative models**
  - Central theme: 3D volumes when only 2D training data available

# Characterization Workflow

**Image acquisition**
(SEM, CT, TEM, etc.)



**Curation, Preprocessing, Sampling**



**Model training**

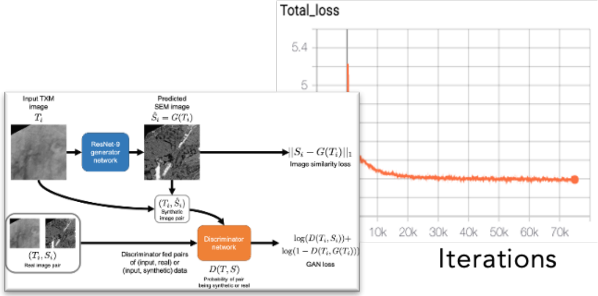
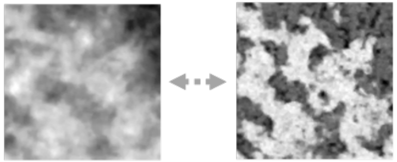
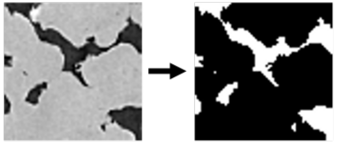


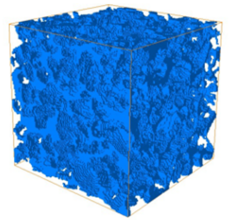

**Image Generation or Prediction**



**Postprocessing**
Filtering, segmentation



**Morphological + Petrophysical Analysis**



$k,\ \phi$

# 3D Image Translation

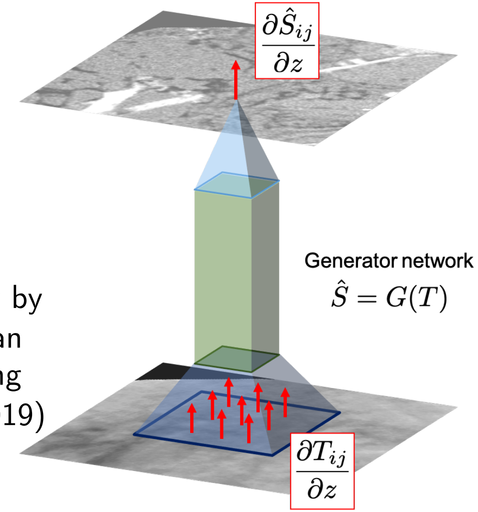
- Multimodal, multiscale imaging emerging characterization approach: acquire images in 2+ modalities to have best of both (Aljamaan et al. 2017)
- Challenges in acquisition, dataset curation, model development
- In this work, acquire:
  - Transmission X-ray microscopy (TXM): sample-preserving, low contrast
  - Focused ion beam-scanning electron microscopy (FIB-SEM): high contrast/resolution, sample-destroying
- Task: predict FIB-SEM from TXM
  - FIB-SEM images are planar, TXM volumetric: predict 3D volumes from 2D training data

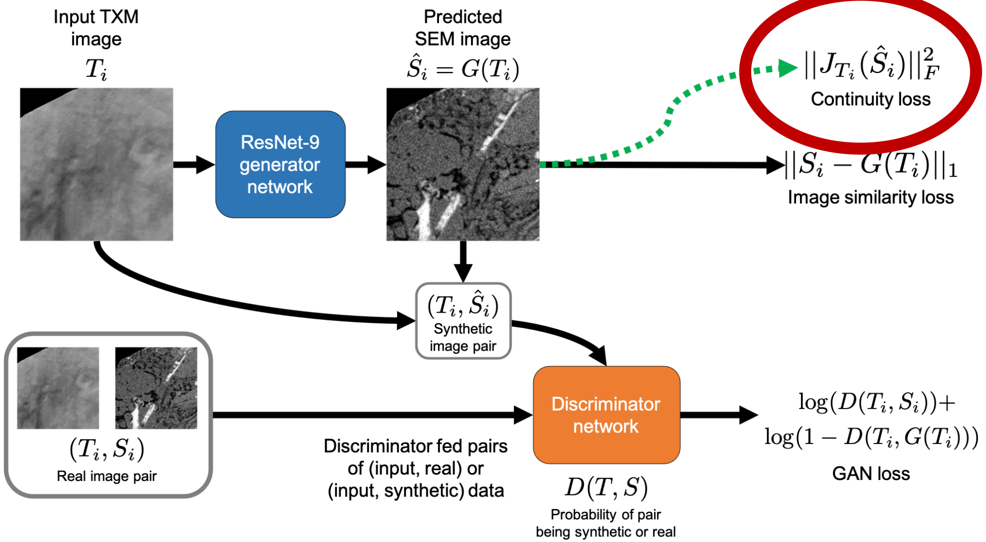
# 3D Image Translation Models

## Use modified style transfer, super-resolution models (Isola et al. 2017, Zhu et al. 2017, Ledig et al. 2016)

Shale image volumes have sparse z-gradients

Enforce continuity by including Jacobian penalty in training (Hoffman et al. 2019)

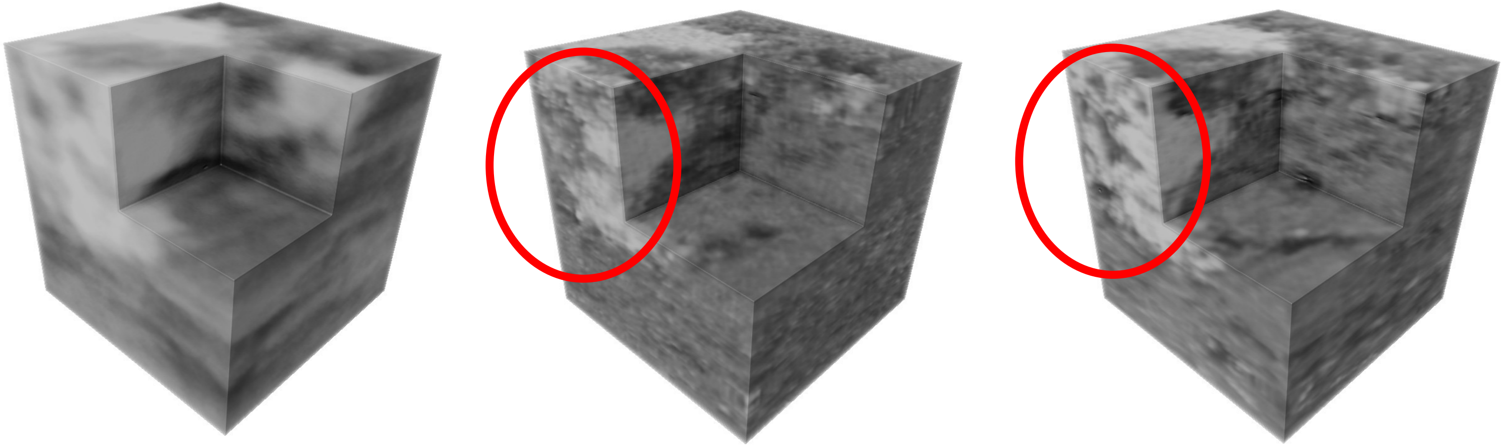



pix2pix model

# 3D Image Translation Results

- Training: 2D image patches w/ regularization
- Evaluation: x-y image slices through 2D-to-2D network



Input TXM Volume

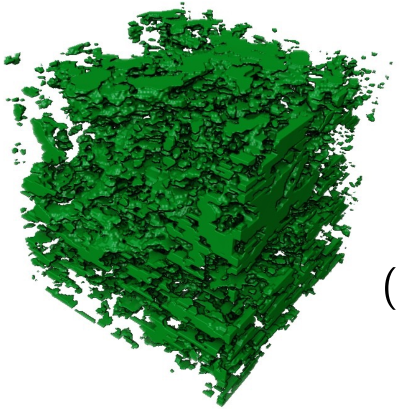
Predicted FIB-SEM (baseline model)

Predicted FIB-SEM (with regularization)

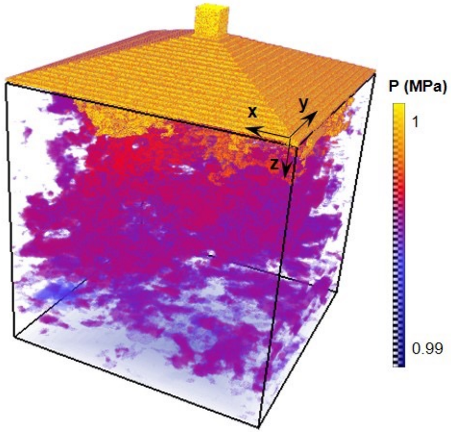
# Simulation in Translated Volumes

- Simulate flow through lower-density regions
- Permeability: accurate for core scale, too large for matrix-scale

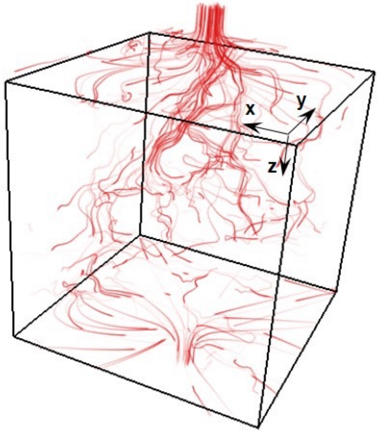
| SRGAN Model | k (d) | $\varphi$ | $\varphi_{connected}$ |
|---|---|---|---|
| Original | $2.37 \times 10^{-5}$ | 20.7% | 18.7% |
| Regularized | $3.01 \times 10^{-5}$ | 18.9% | 17.4% |



Segmented low-density regions (kerogen+minerals)




Pressure Field

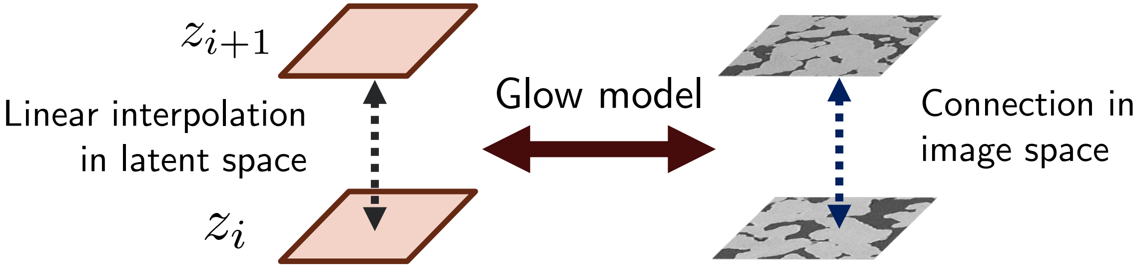



Streamlines

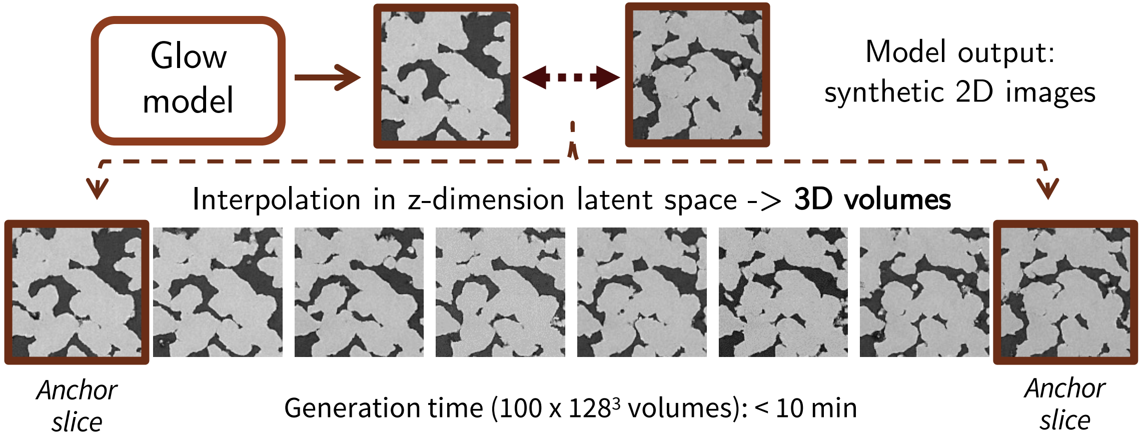
# Porous Media Image Synthesis

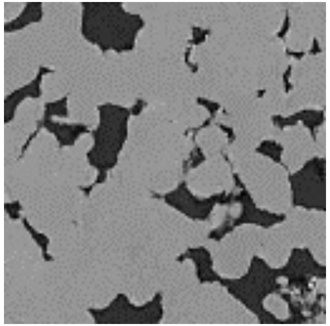
- Nanoscale imaging data often suffers from data scarcity
  - Unable to estimate properties from limited data
- **Main idea:** train generative model to synthesize images of sample
  - Computed rock properties from synthetic images (Adler et al. 1990)
- Methods for porous media image synthesis divided between:
  - Statistical methods (Roberts et al. 1997, Manwart et al. 2000)
  - Deep-learning based methods (Mosser et al. 2017)
- Current methods limitations for application to shales:
  - 3D generation from 2D images: limited to binary images (Okabe & Blunt 2004)
  - 3D grayscale generation: requires 3D training data (Mosser et al. 2017)
  - Multimodal/multiscale image generation unexplored

# Image Synthesis Approach




- Generative flow model (Glow) from Kingma et al. 2018
- 3D grayscale generation from 2D training data
- 3D volume generation equivalent to evaluating batch of 2D images, can be done in parallel

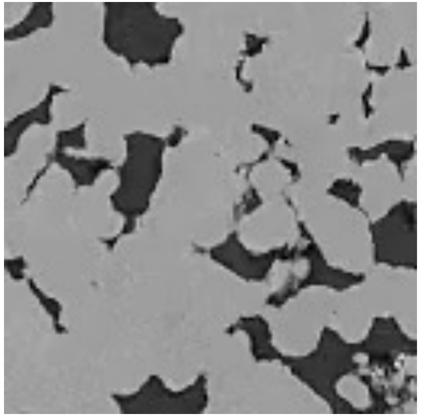


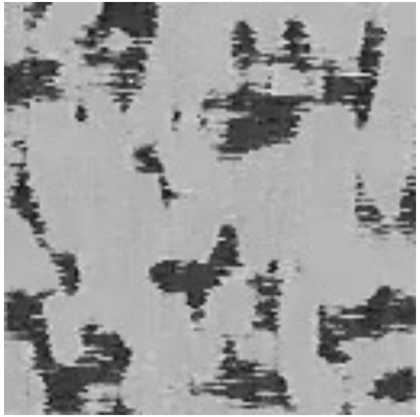
$128^3$ voxel sandstone
6.12 μm/voxel
12 interpolated images

# Image Generation Results

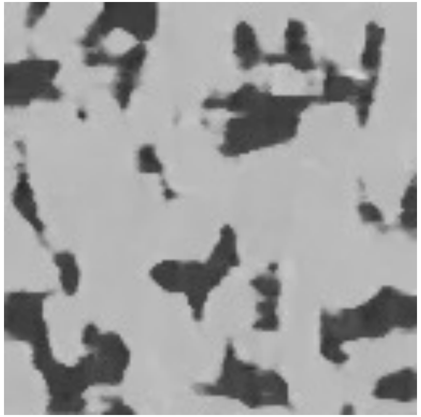
- Bentheimer sandstone μ-CT image (6.12 μm/voxel)
- x-y images closely resemble training images
- Post-processing improves appearance, reduces artifacts



x-y plane



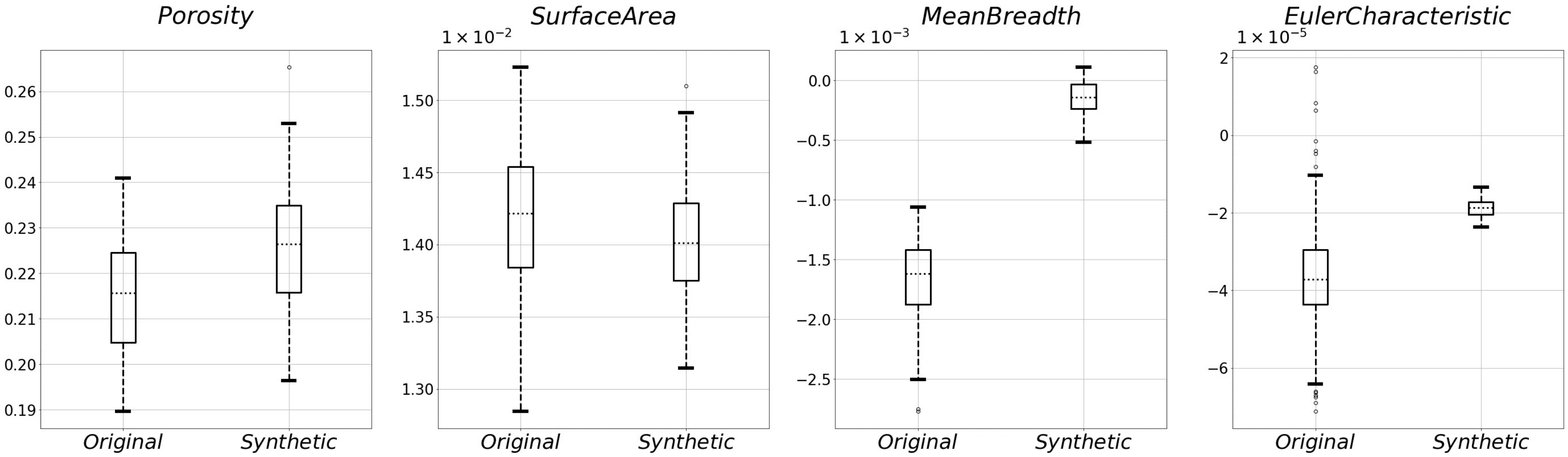
x-z plane



x-z plane
(w/ r=2 spherical median filter)

# Morphological Features of Generated Images

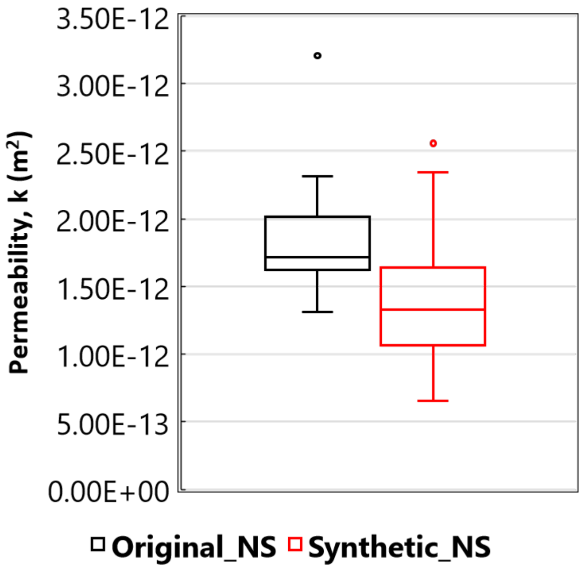
- Image volume is filtered (3D median filter) and binarized (Otsu) first
- Computed in ImageJ: MorphoLibJ (Legland 2007), Analyze Regions 3D
- Normalized with volume of sample to obtain densities

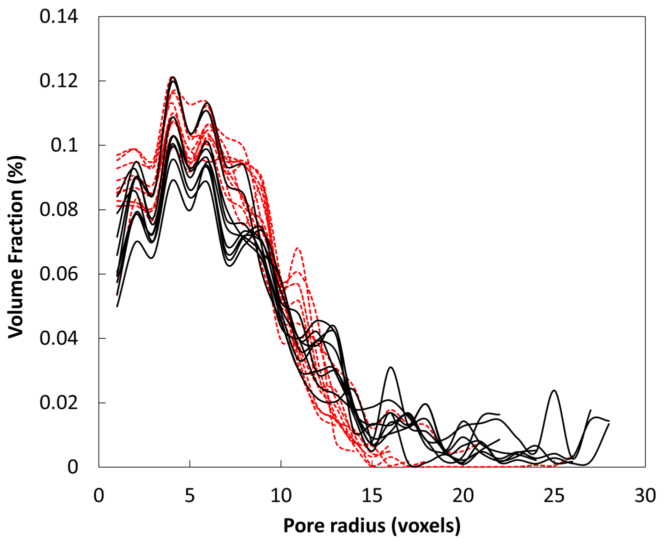



Original: 100 volumes (subsampled from micro-CT), $128^3$ voxel
Synthetic: 100 unique volumes; $128^3$ voxel, interpolation step size = 12

# Petrophysical Properties of Synthetic Volumes

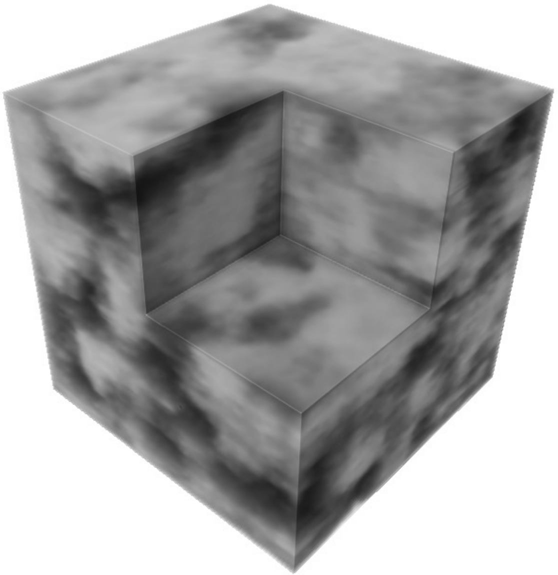
- Single-phase permeability: Navier-Stokes (NS) equations for steady state, incompressible flow (simpleCycFoam), 15-20 volumes synthetic and original
- Differences in mean breadth (curvature) and Euler characteristic parameters may explain distribution differences



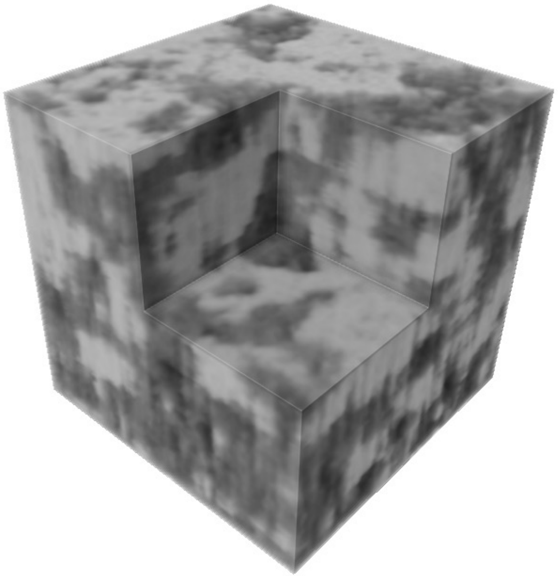



# Multimodal Image Generation

Generate multimodal data by treating modalities as image channels



Synthetic TXM volume



Synthetic FIB-SEM volume

$128^3$ voxel volume,
$62.7^3$ nm/voxel,
Post-processed with
1x1x3 median filter

# Conclusions and Future Steps

- **Deep generative models enable new reservoir rock characterization methods**
  - Overcome limitations of imaging machines to create volumes
  - Address data scarcity by generating realistic new data samples
  - Improved nanoscale characterization → direct production implications for shales
- Data translation: regularization during training creates volumes suitable for flow simulation
- Data synthesis: accurate recreation of 3D volumes, capable of multimodal/grayscale generation from 2D data
- Next steps:
  - Integrate unpaired imaging data into data translation models
  - Quantify uncertainty in properties with synthetic data (Guan et al. 2020)
  - Impose nanoporosity to create multiscale volume (Frouté et al. 2020)

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- Code:
  - Shale image translation: https://github.com/supri-a/TXM2SEM
  - RockFlow: https://github.com/supri-a/RockFlow
  - Isola (2017), Zhu (2017), Kingma (2018), y0ast/Glow-Pytorch repo, Mosser (2017)

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