Can we teach neural networks to model porous media?

Session MS 2.12: 3D Reconstruction of Porous Media using Generative Adversarial Networks

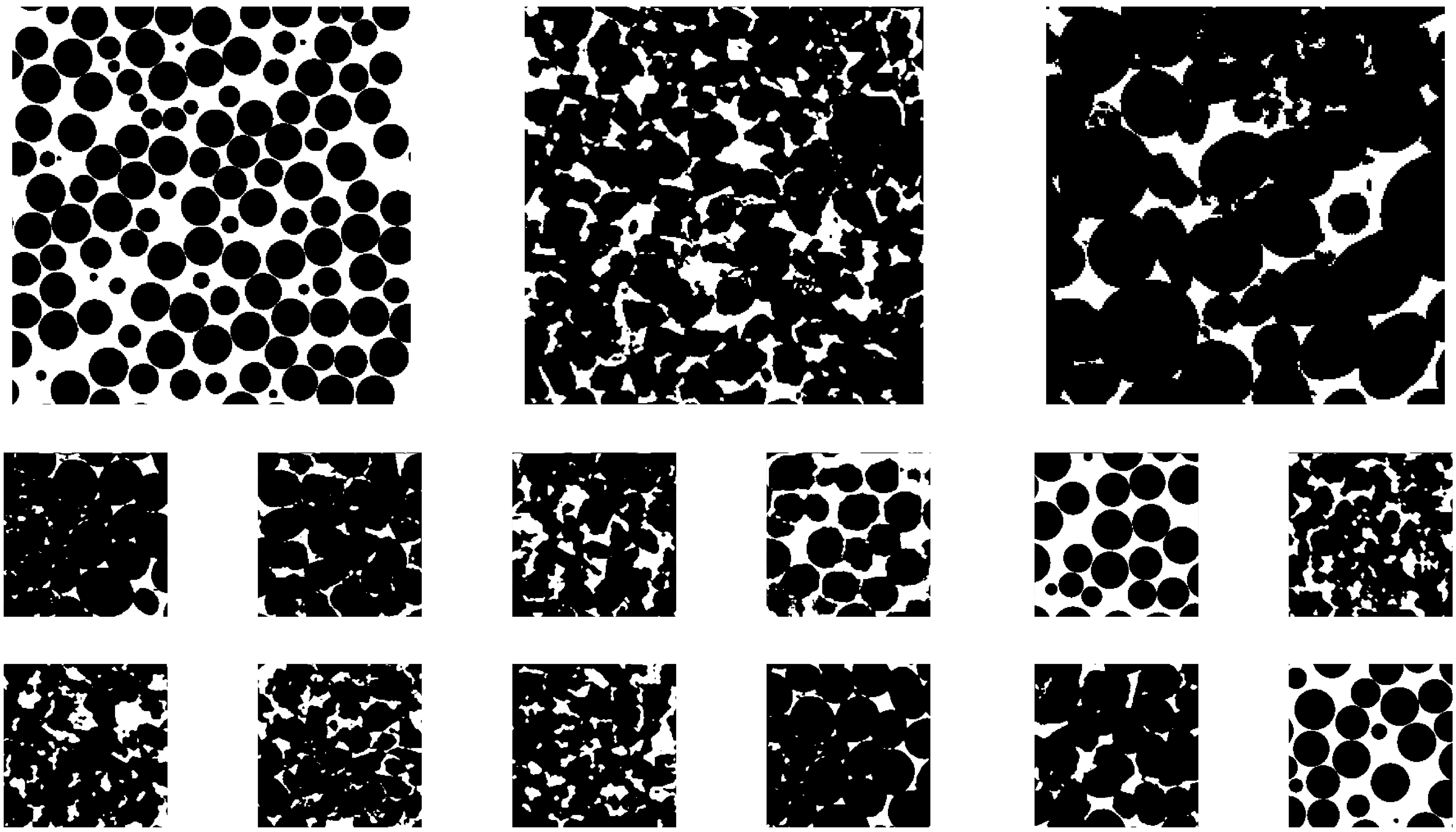
Lukas Mosser, Prof. Olivier Dubrule, Prof. Martin J. Blunt
Department of Earth Science and Engineering, Imperial College London

Abstract

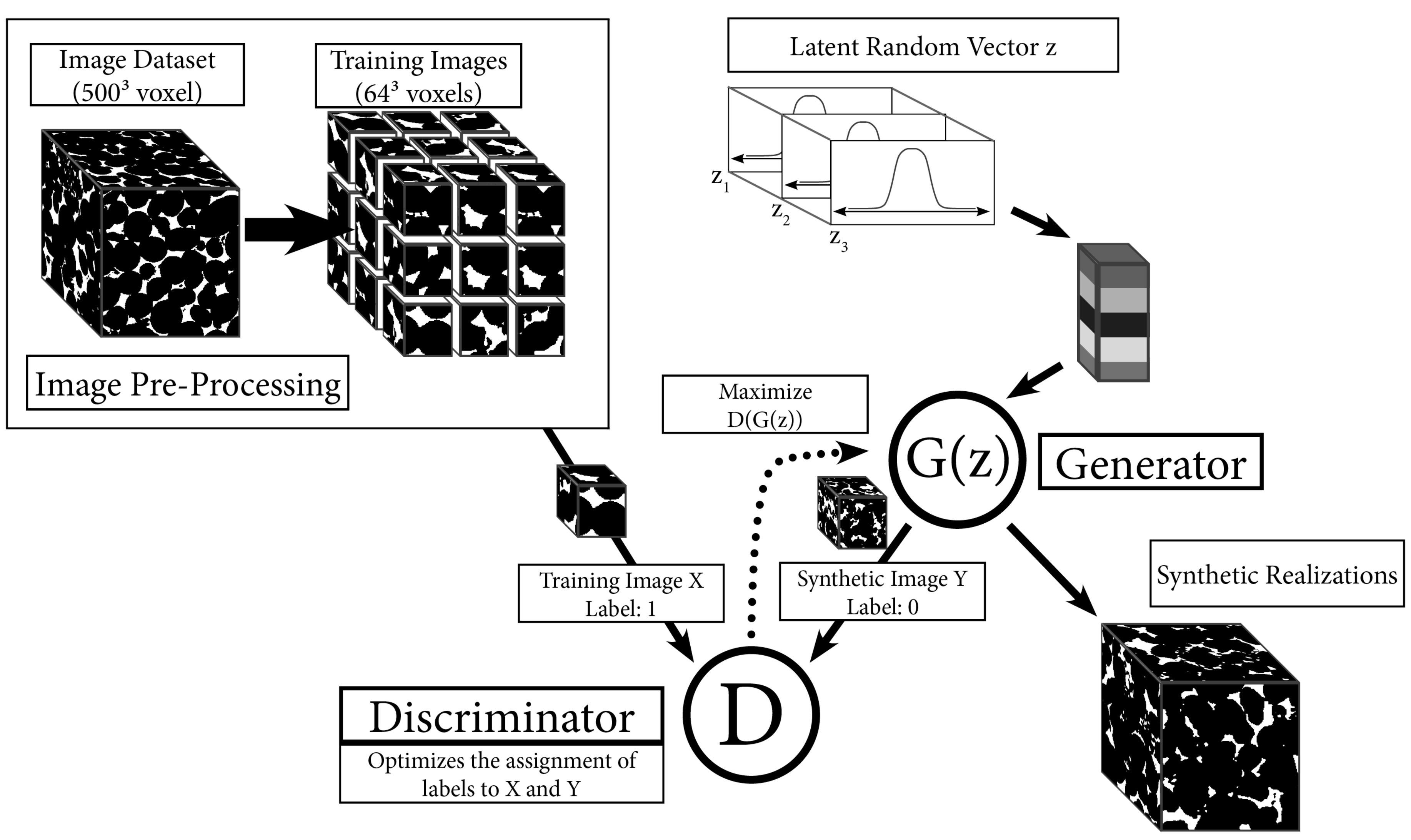
We present a novel method to reconstruct the solid-void structure of porous media by applying a generative neural network (GAN) that allows an implicit description of the probability distribution represented by three-dimensional image datasets. We show that this method of unsupervised learning is able to generate representative samples of porous media and honor their statistics. We successfully compare measures of pore morphology, such as the Euler characteristic, two-point statistics and directional single-phase permeability of synthetic realizations with the calculated properties of a bead pack, Berea sandstone and Ketton limestone. Results show that GANs can be used to reconstruct high-resolution three dimensional images of porous media at different scales that are representative of the morphology of the images used to train the neural network. The fully convolutional nature of the trained neural network allows the generation of large samples while maintaining computational efficiency. Compared to classical stochastic methods of image reconstruction, the implicit representation of the learned data distribution can be stored and reused to generate multiple realizations of the pore structure very rapidly.

Which ones are real and which ones are fake?

Spherical Beadpack | Berea Sandstone | Ketton Limestone



How does it work?



- Segmented volumetric training images are extracted at 64^3 voxels.
- Generator applies convolutional neural network to samples from a normal distributed latent space and generates new stochastic reconstructions.
- The discriminator receives training and generated images G(z) and tries to distinguish between real and "fake" images.
- The misclassification error is used to improve the discriminator's ability to distinguish the two data distributions.
- The generator continuously improves to "fool" the discriminator.
- When convergence is reached the generator can be used to generate new 3-D sampled images.

Preprint: arXiv:1704.03225 [cs.CV]
Code: github.com/LukasMosser/PorousMediaGAN