Reconstruction of 3D Porous Media From 2D Slices

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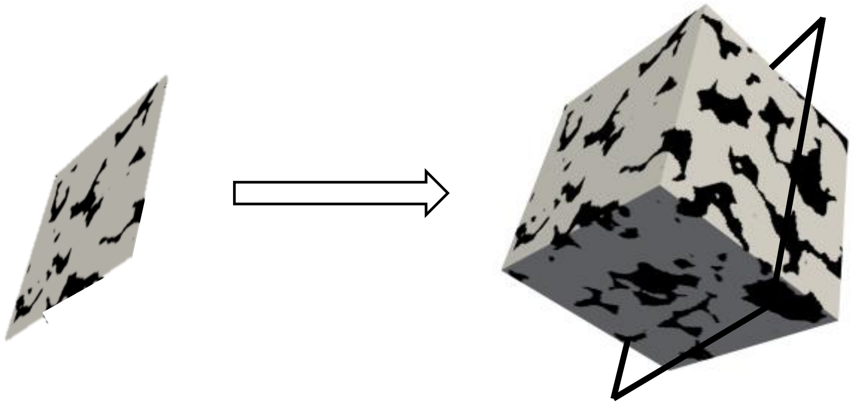
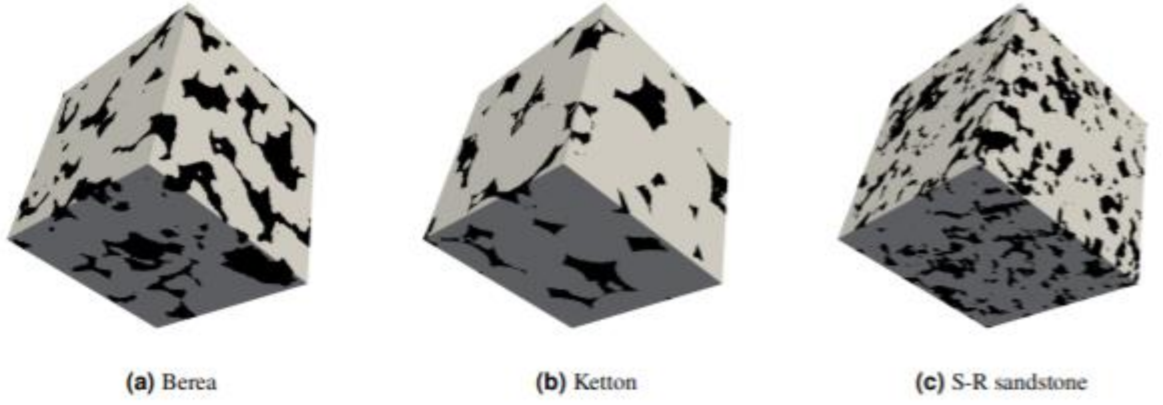
Introduction

Slice to Pores Generative Adversarial Networks(SPGAN):
Use a 2D slice as an input to generate a 3D image



SPGAN



Different sandstones

GAN

3D->3D

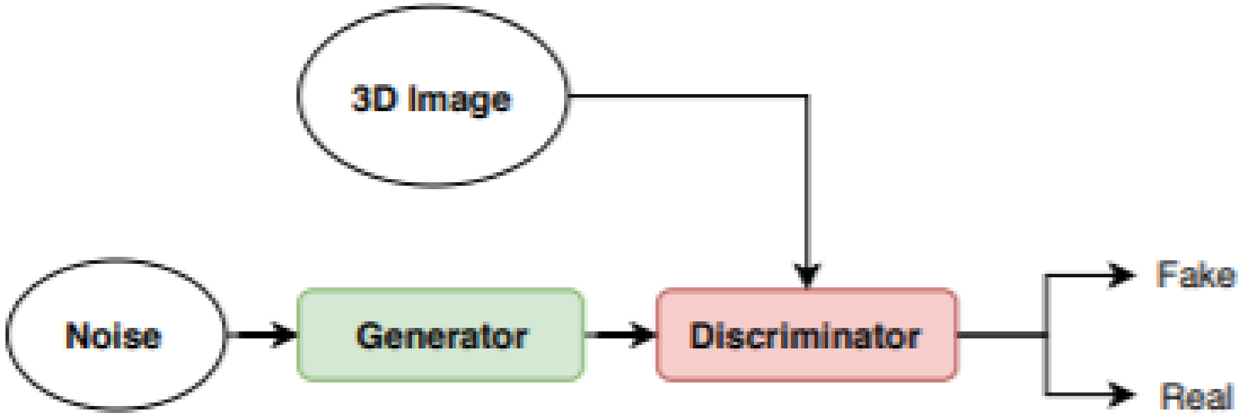


Figure 12. Architecture of Generative Adversarial Networks

Loss:

$$\min_{\theta}\max_{\phi} \mathscr{L}(\theta,\phi) = \mathbb{E}_{x\sim p_{\mathtt{data}}}[\log D_{\phi}(x)] + \mathbb{E}_{z\sim p_z}[\log(1 - D_{\phi}(G_{\theta}(z)))].$$

SPGAN

2D->3D $p_{data}(x|s)$

x : 3D porous media
s : 2D slice
condition: class

Condition GAN

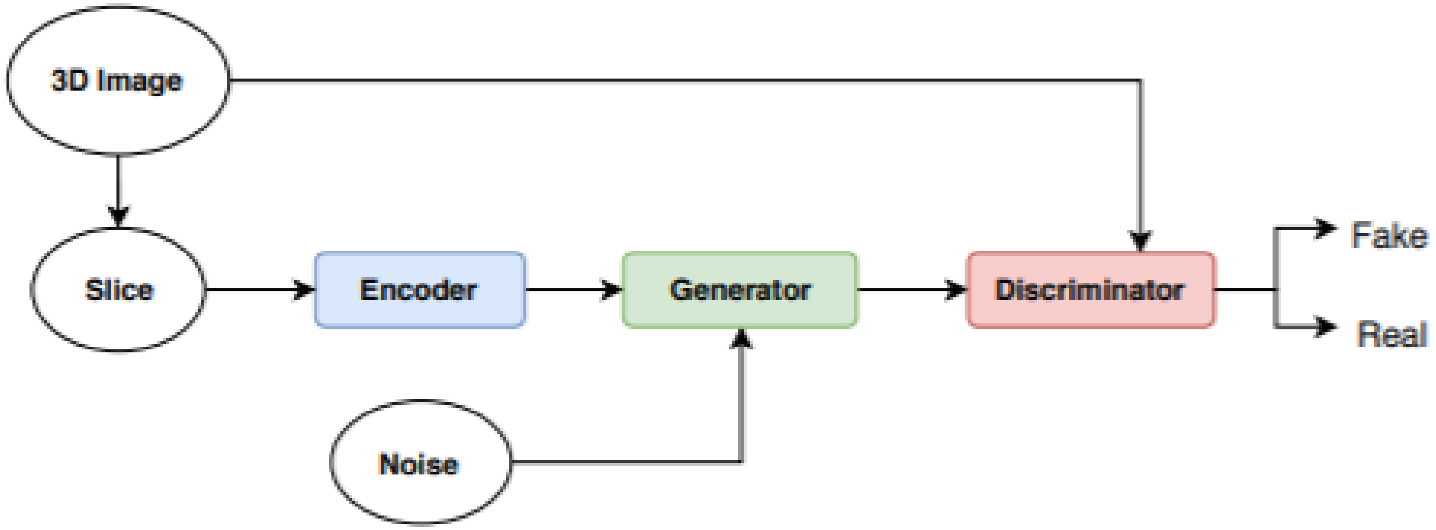


Figure 13. Architecture of Slice to Pores Generative Adversarial Networks

SPGAN

slice compression:

- specific porous structure
- regular shapes

$$L(s) = \| s - \mathbf{M} \odot G_\theta(E_\tau(s), z) \|_2^2 \rightarrow \min_{\tau,\theta}$$

Encoder: $E_{ae}(x_i, \theta_E)$
Generator $G_\theta(z, h)$
Obtain the central slice from the 3D image **M**

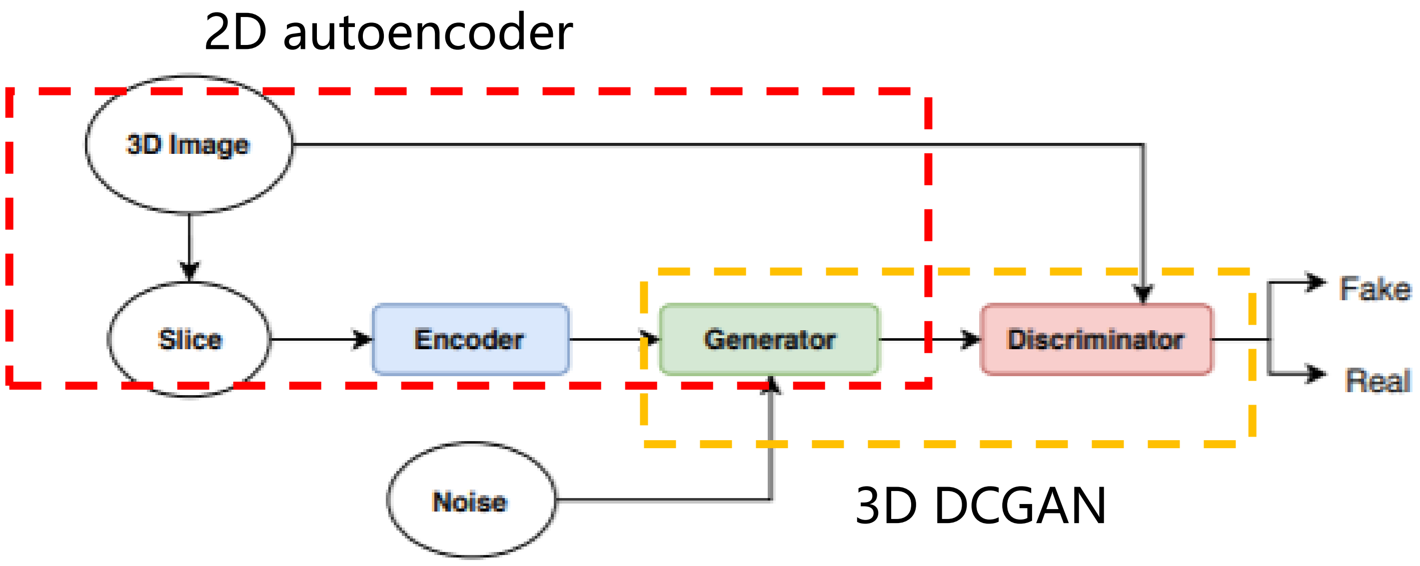


Figure 13. Architecture of Slice to Pores Generative Adversarial Networks

$$L(D_\phi, G_\theta) = \mathbb{E}_{x \sim p_{data}(x)}[\log D_\phi(x)] + \mathbb{E}_{z \sim p_{noise}(z)}[\log(1 - D_\phi(G_\theta(E_\tau(s), z)))] \rightarrow \min_\theta \max_\phi .$$

Encoder $E_t(s)$
Discriminator $D_\phi(x)$

SPGAN

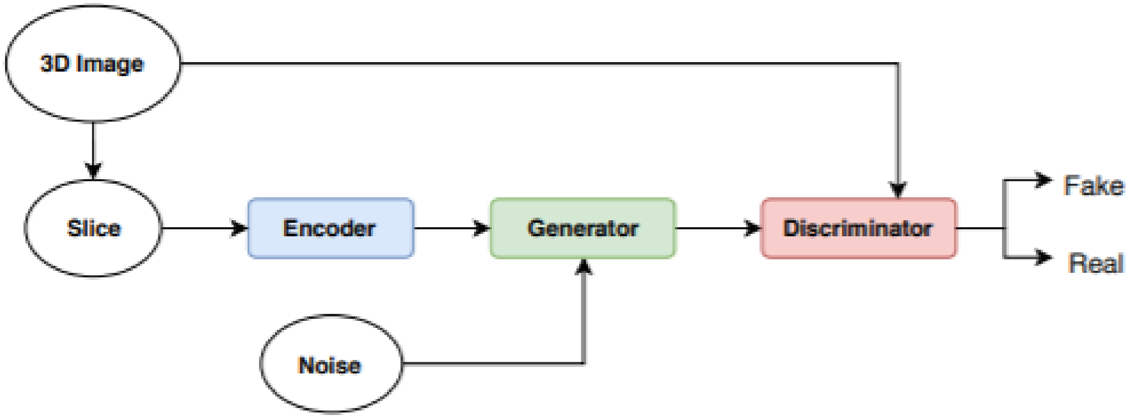


Figure 13. Architecture of Slice to Pores Generative Adversarial Networks

for *number of training iterations* **do**

Sample minibatch of k 3D images $\{x_1, \ldots, x_k\}$ from the dataset;

Obtain the minibatch of slices $\{s_1 = \mathbf{M} \odot x_1, \ldots, s_k = \mathbf{M} \odot x_k\}$, using the mask $\mathbf{M}$;

Sample minibatch of k noise vectors $\{z_1, \ldots, z_k\}$ from the prior distribution $p_z(z)$;

Update the encoder by ascending its stochastic gradient

$$\nabla_\tau \frac{1}{k} \sum_{i=1}^{k} \| s_i - \mathbf{M} \odot G_\theta(E_\tau(s_i), z_i) \|_2^2$$

Update the generator by ascending its stochastic gradient

$$\nabla_\theta \frac{1}{k} \sum_{i=1}^{k} \| s_i - \mathbf{M} \odot G_\theta(E_\tau(s_i), z_i) \|_2^2$$

Obtain the minibatch of latent representations $\{h_1 = E_\tau(s_1), \ldots, h_k = E_\tau(s_k)\}$;

Update the discriminator by ascending its stochastic gradient

$$\nabla_\phi \frac{1}{k} \sum_{i=1}^{k} [\log D_\phi(x_i) + \log(1 - D_\phi(G_\theta(z_i, h_i)))]$$

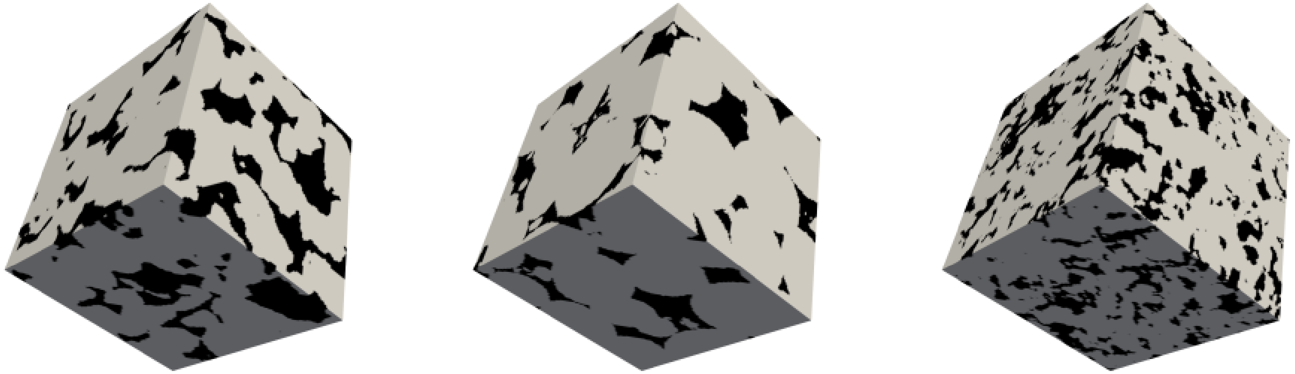
Update the generator by descending its stochastic gradient

$$\nabla_\theta \frac{1}{k} \sum_{i=1}^{k} [\log(1 - D_\phi(G_\theta(z_i, h_i)))] .$$

end

Algorithm 1: Algorithm of training SPGAN model

Result

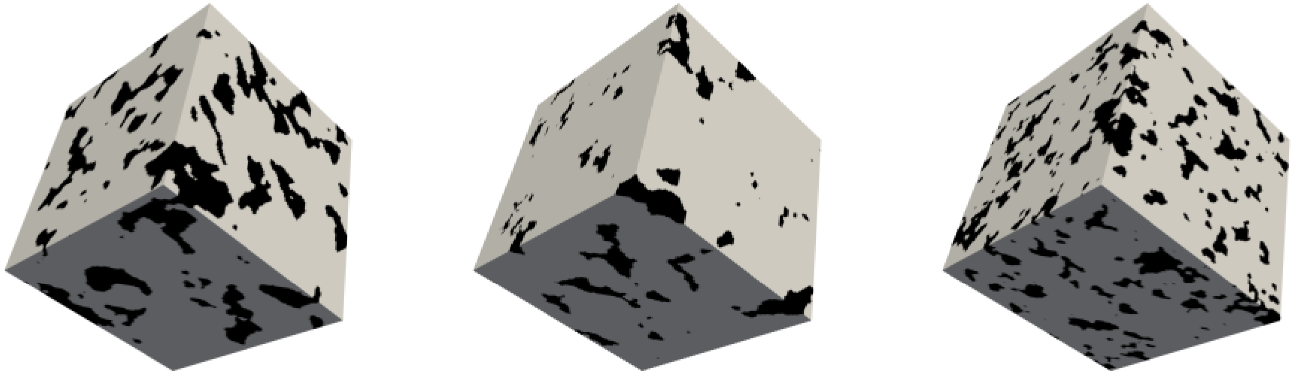


(a) Berea (b) Ketton (c) S-R sandstone

Figure 2. Original 3D samples of three different types: Berea, Ketton, South-Russian sandstone

Feature extract:

- Porosity
- Permeability
- Two-point correlation function



(a) Berea (b) Ketton (c) S-R sandstone

Figure 3. Generated 3D samples of three different types: Berea, Ketton, South-Russian sandstone

Result

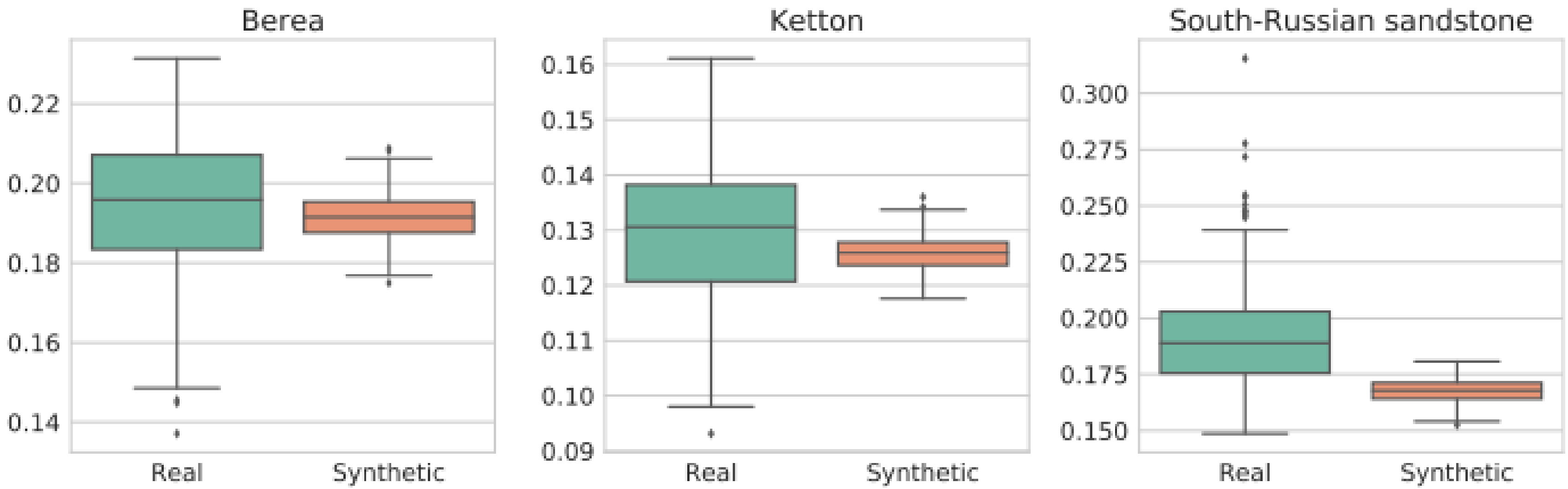


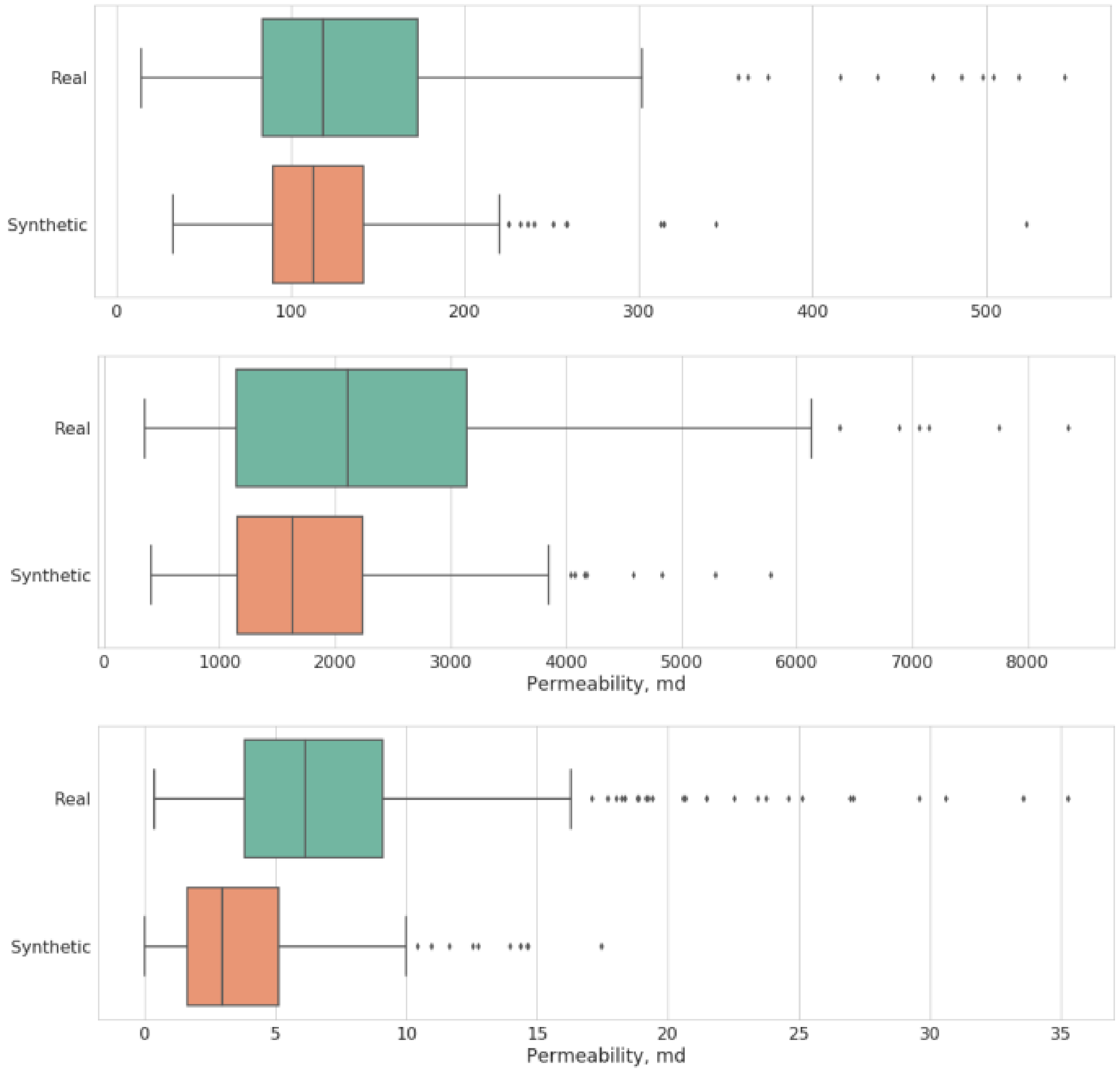
Figure 4. Porosity comparison for three types of porous media. Each type is represented by 300 real and 300 generated samples. For each sample we computed porosity and created box-plot.

Result

Berea

Ketton

South-Russian



Permeability for sandstones

Result

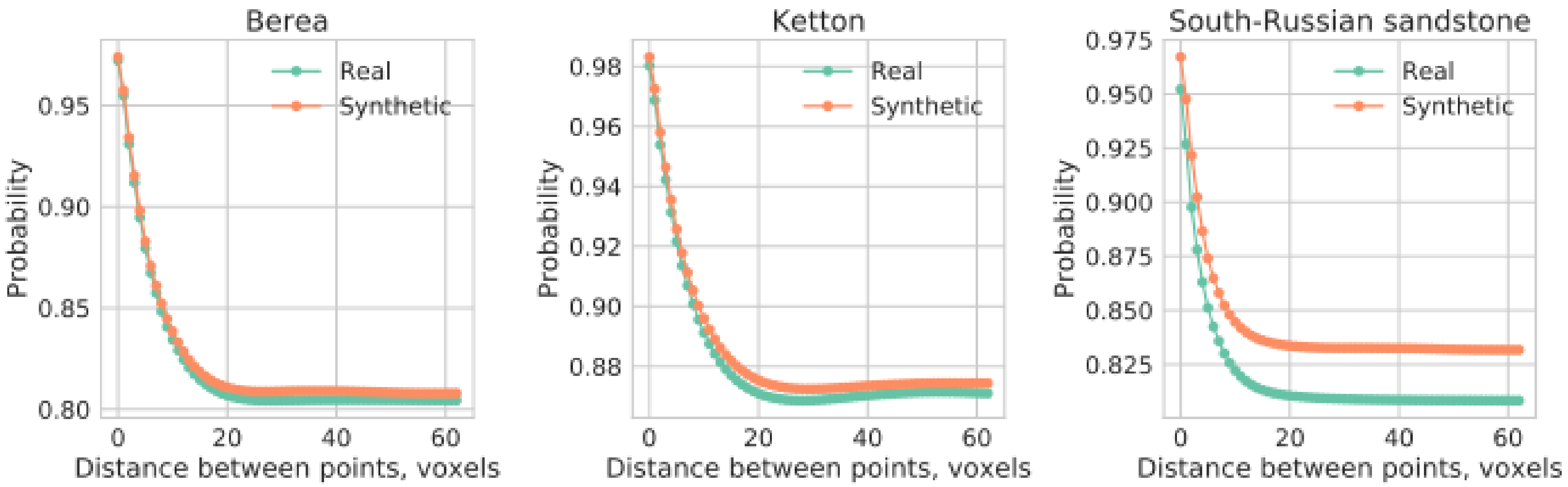


Figure 5. Two-Point Correlation Function. For each type of porous media we for both real and synthetic samples we compute probability, that a distance between two points will lie inside the void space. We used PoresPy library[17] for computations.

Conclusion:

1. Our decoder is a 3D convolutional neural network, thus we should be able to get the central 2D slice from it,
2. Decoder takes as an input not only latent representation but also a noise vector from some prior distribution $pz(z)$.

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