Reconstructing Pore Networks Using Generative Adversarial Networks

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Introduction

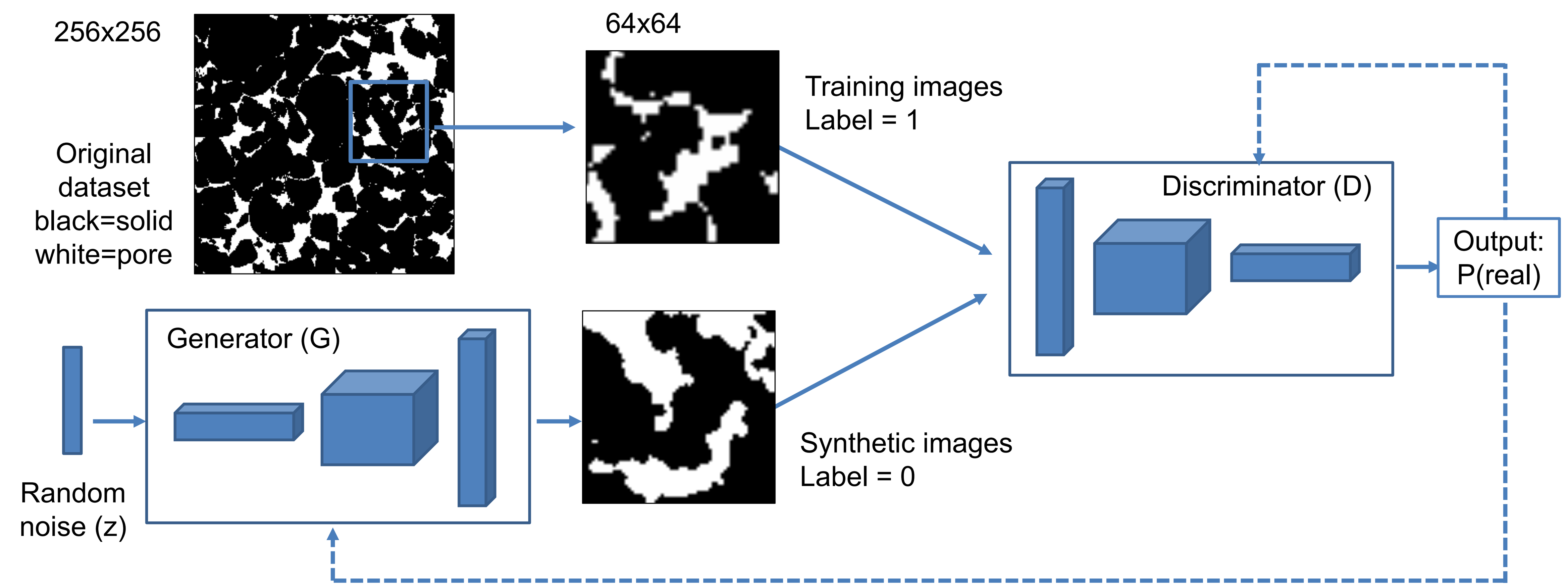
Motivation

- Flow properties (porosity and permeability) of porous media can vary due to rock heterogeneity
- Recreating variations of the pore network can be time-consuming (both in the lab and computationally)
- Recent advances in deep learning have shown promising use of generative adversarial networks (GANs) for rapid generation of 3D images with no a priori model [1]

Objective

- Investigate feasibility of generating 2D sandstone images by training a deep convolutional GAN model (DCGAN) [2]
- Try different architectures to determine optimal parameters
- Evaluate model performance against real images using morphological properties

Model Architecture and Training



DCGAN-1 (Log loss)

$$\min_G \max_D \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z))]$$

DCGAN-2 (Wasserstein)

$$\min_G \max_D \mathbb{E}_{x\sim p_{\text{data}}(x)}[D(x)] - \mathbb{E}_{z\sim p_z(z)}[D(G(z))] + \lambda \mathbb{E}_x[(||\nabla_x D(x)||_2 - 1)^2]$$

DCGAN model: Based on [3]

Layer	Type	Filters	Kernel	Stride	Padding	Batch Norm	Activation
Generator							
1	ConvTransp2D	512	4 x 4	1	0	Yes	ReLU
2	ConvTransp2D	256	4 x 4	2	1	Yes	ReLU
3	ConvTransp2D	128	4 x 4	2	1	Yes	ReLU
4	ConvTransp2D	64	4 x 4	2	1	No	Tanh
Discriminator							
1	Conv2D	64	4 x 4	2	1	No	LeakyReLU
2	Conv2D	128	4 x 4	2	1	Yes	LeakyReLU
3	Conv2D	256	4 x 4	2	1	Yes	LeakyReLU
4	Conv2D	512	4 x 4	1	0	No	Sigmoid

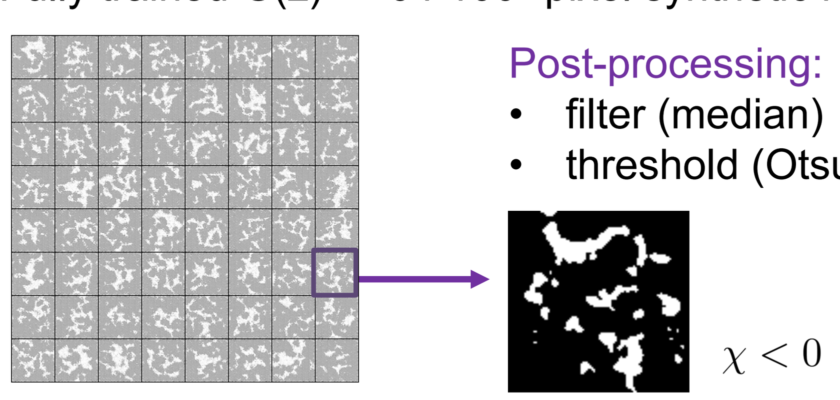
Strategies:

- Modified generator loss function – prevent vanishing gradients
$$\log D(G(z))$$
- One-sided label smoothing
- Wasserstein distance with gradient penalty – shown to improve convergence [4]

Data Acquisition & Evaluation

Image size (voxels)	256 x 256 x 256
Voxel size	6.12 um
Subvolume spacing	16 pixels
Training image size	64 x 64
# of training images	36,869

Fully trained G(z) → 64 100^2 pixel synthetic realizations



Post-processing:
- filter (median)
- threshold (Otsu)

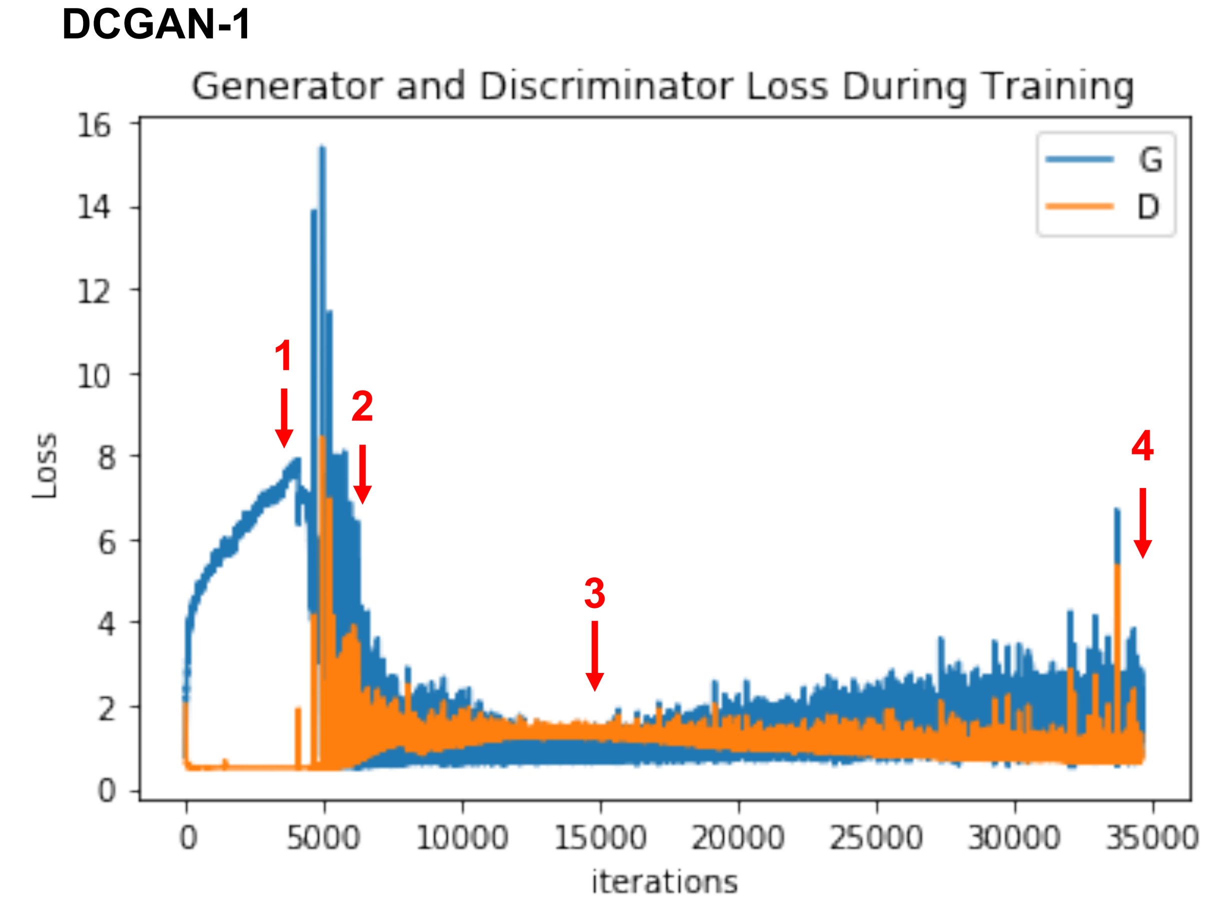
Evaluation metrics (2D Minkowski functionals)

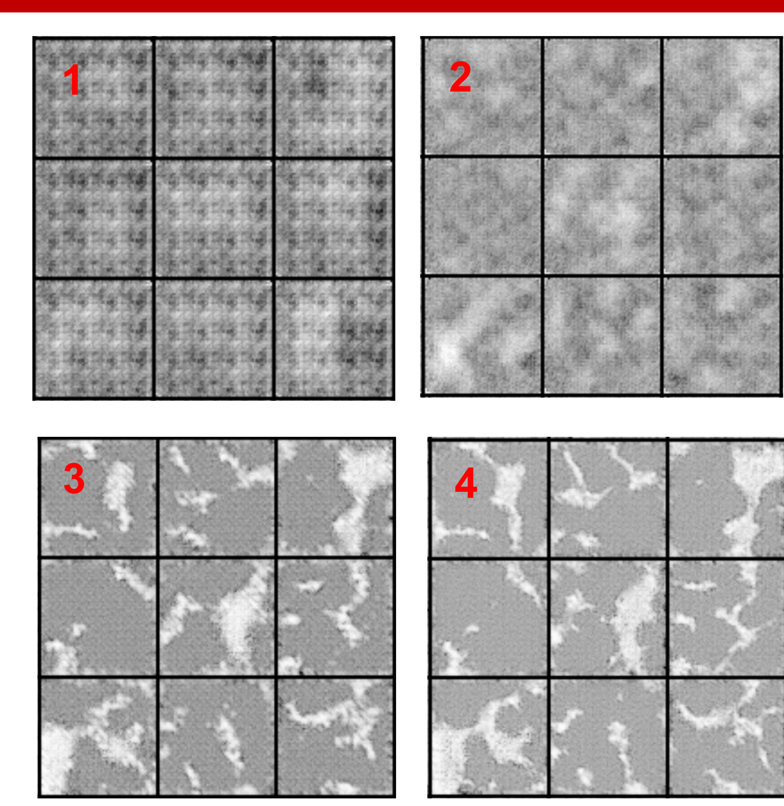
- Area ~ available pore (white) space
- Perimeter ~ pore shape
- Euler characteristic, χ ~ connectivity

$$\chi = n_{connected} - n_{holes}$$

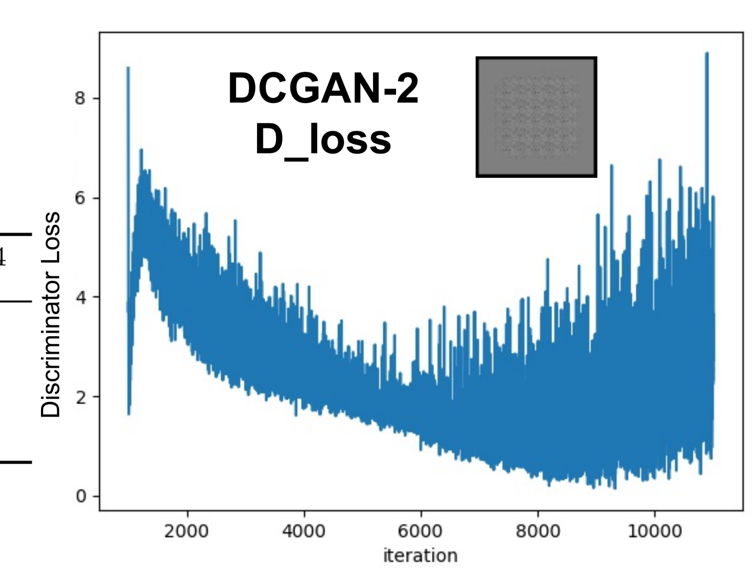
Results

DCGAN-1





Model	Pore area	Perimeter, $\times 10^{-2}$	Euler characteristic, $\chi \times 10^{-4}$
Train set	0.220	6.94	−3.89
DCGAN-1	0.217	6.82	−4.28
DCGAN-2	0.268	42.26	−88



Conclusion

- Label smoothing had a noticeable effect on training stability
- DCGAN model performs well for 2D case using the log loss function
- Wasserstein distance does not work/leads to collapse, possibly due to binary nature of data

Future work

- Modify to train and generate 3D reconstructions of the pore network
- Explore other network architectures and the effect on training stability
- Evaluate performance using other metrics, e.g. single phase permeability

References and Acknowledgements

[1] L . Mosser, O. Dubrule, and M. J. Blunt, "Reconstruction of three-dimensional porous media using generative adversarial neural networks," Physical Review E, vol. 96, no. 4, 2017.
[2] A. Radford, L. Metz, and S. Chintala, "Unsupervised Representation Learning With Deep Convolutional Generative Adversarial Networks," arXiv:1511.06434, 2016.
[3] N. Inkawhich, "DCGAN Tutorial," https://pytorch.org/tutorials/beginner/dcgan_faces_tutorial.html.
[4] I. Gulrajani, F. Ahmed, M. Arjovsky, V. Dumoulin, and A. Courville, "Improved Training of Wasserstein GANs," arXiv:1704.00028, 2017.

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