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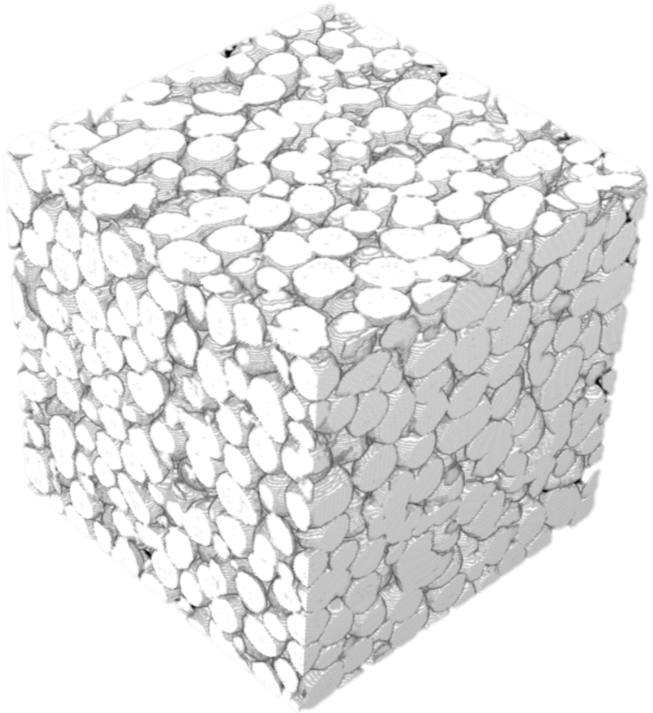
3D Reconstruction of Porous Media using Generative Adversarial Networks



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Overview

- **Motivation**
- **Generative Adversarial Networks (GAN)**
- **Reconstruction Metrics**
- **Application to CT Images of Porous Media**
- **Discussion**
- **Conclusions - Outlook**

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Motivation – Digital Rock and Core Analysis

Scale

- **Physical Representation:**
  - Core
  - Core Plugs
  - (Micro) CT Scans
    - »Multi-Phase Flow
  - FIB-SEM

Physical Experiments:

- RCAL – SCAL

Numerical Experiments

- Pore-Network Models
- Direct Simulation

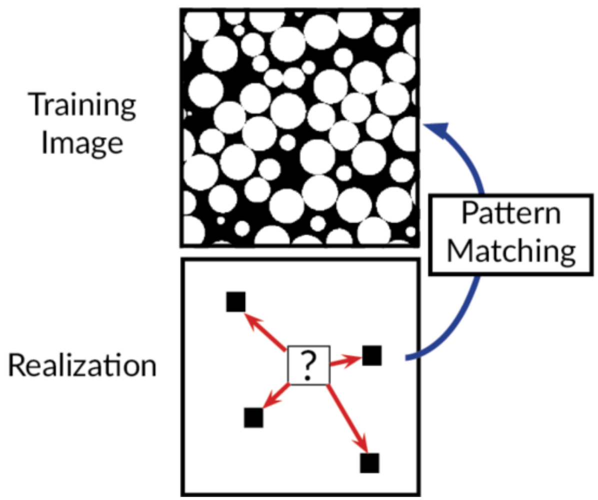
Digital Representation:

- Create 3D synthetic realizations based on Micro-CT Images as input to numerical experiments
- Perform ensemble numerical experiments

Reconstruction Methods

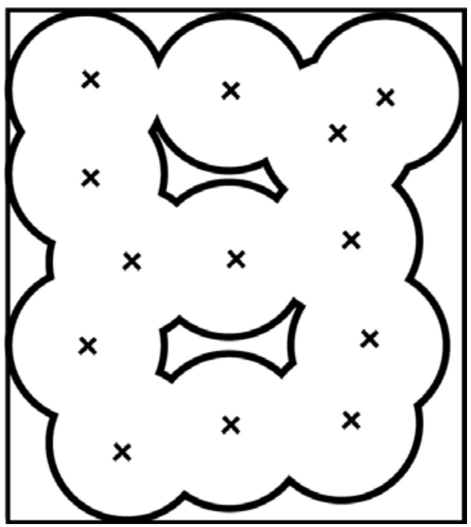
Stochastic Methods

MPS

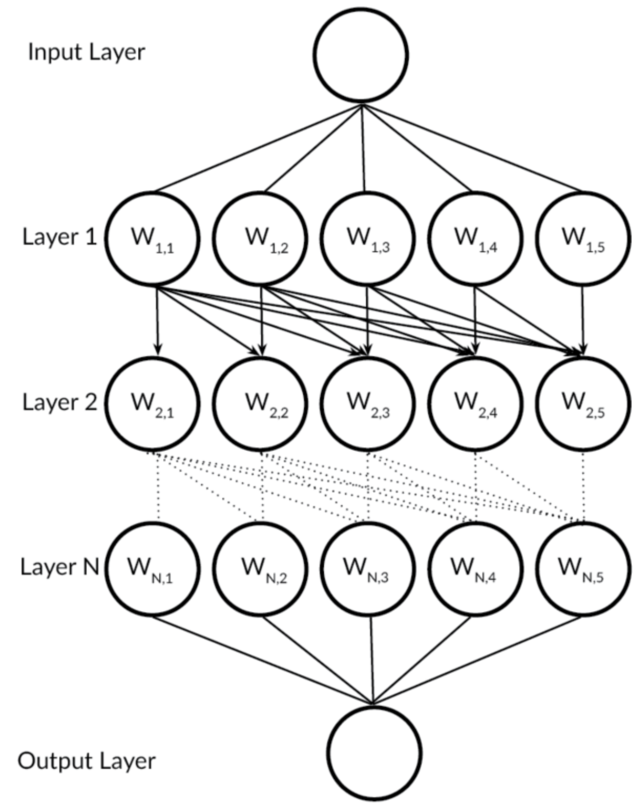


3D - Orthoslices: Okabe 2005

Boolean Models



Neural Networks



Other Methods: Simulated Annealing, SIS, PGS, Image Quilting

Generative Adversarial Networks

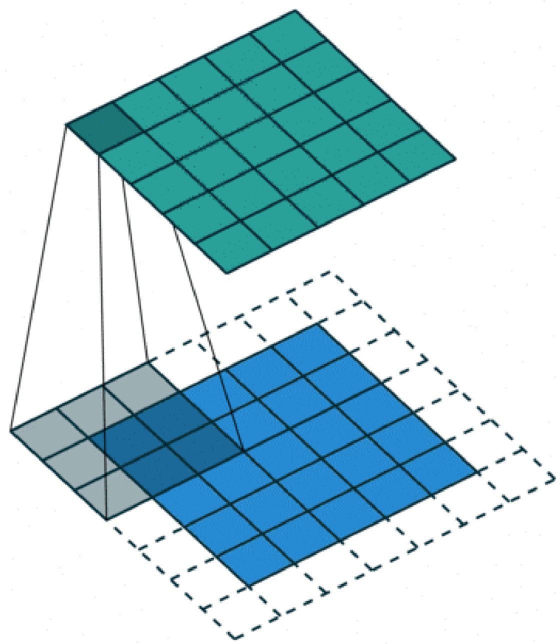
- Consist of two differentiable functions:
  - Generator (G) and Discriminator (D)
    - » Convolutional neural networks
  - Discriminator's goal:
    - » Distinguish real and generated samples
  - Generator's goal:
    - » Samples from latent space
      - ▪ Generates stochastic reconstructions
    - » "Fool" discriminator with generated samples
  - Discriminator tries to approximate:

$$\frac{p_{data}(x)}{p_{data}(x) + p_{generated}(x)}$$

  - Continuously update weights of G and D
  - Convergence:

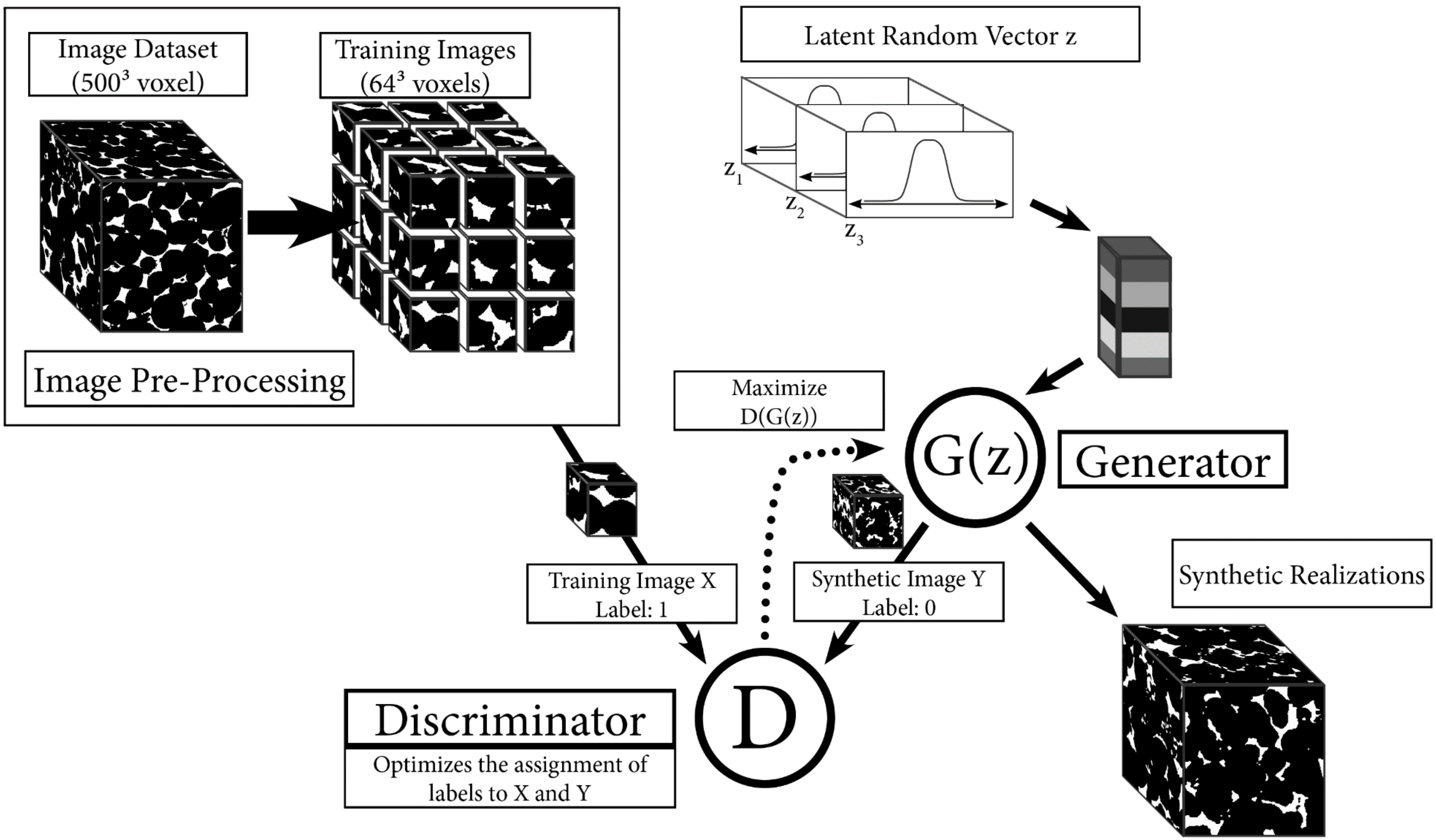
$$p_{data}(x) = p_{generated}(x)$$

(Goodfellow et. al. 2015)



Convolutional filter applied to image

Generative Adversarial Neural Networks



Reconstruction Metrics

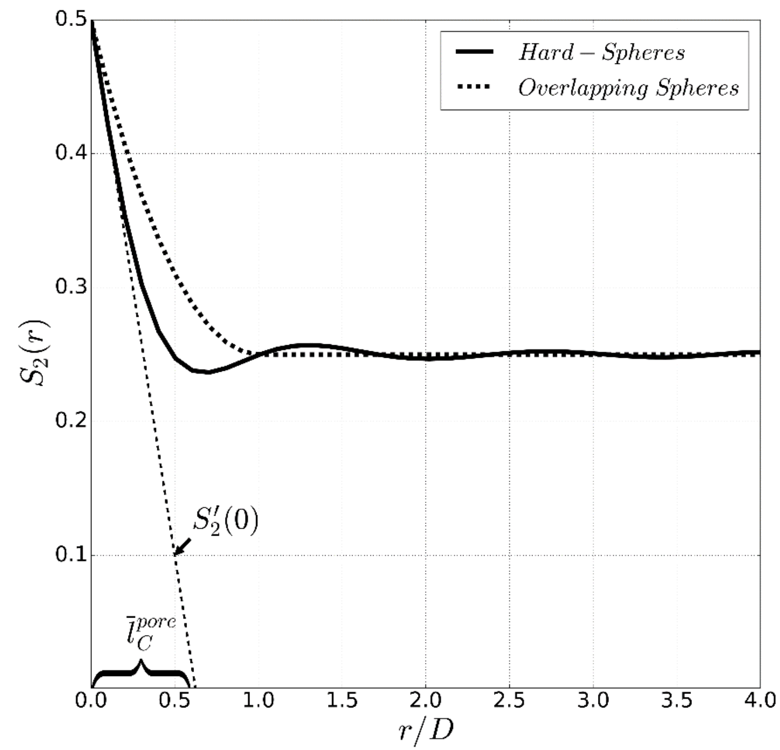
- Statistical Properties
  - Two-Point Probability Function $S_2(r)$
    - » Radial Average / Directional

$$S_2(\mathbf{r}) = \mathbf{P}(\mathbf{x} \in P, \mathbf{x}+\mathbf{r} \in P) \;\; for \;\; \mathbf{x}, \mathbf{r} \in \mathbb{R}^d$$

  - Chord length l_c

- Minkowski Functionals
  - Porosity ϕ
  - Specific Surface Area S_v
  - Specific Euler Characteristic χ_v

- Single Phase Permeability
  - Stokes Equations



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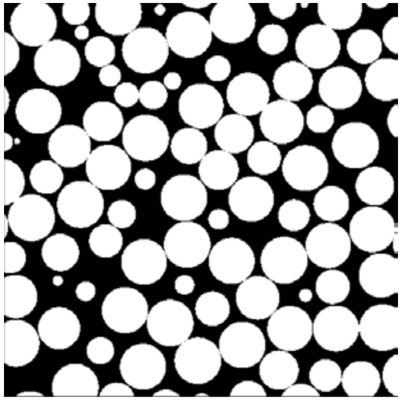
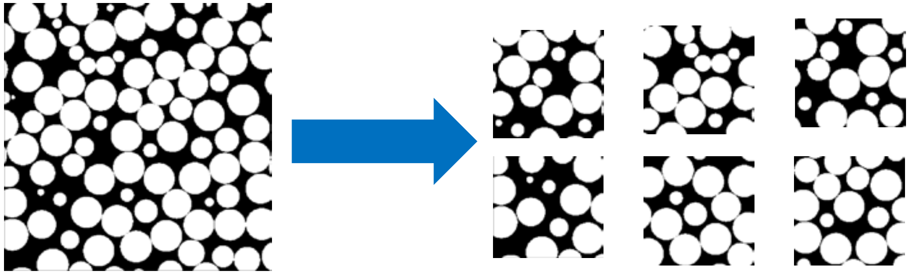
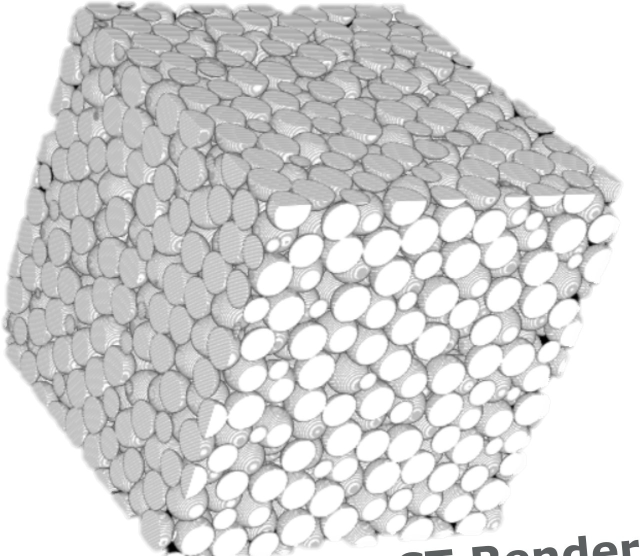
Spherical Beadpack

- Spherical Particles
- Equal Diameters
- Random Packing
- Segmented Training Image
- Image Size:
  - 500^3 voxels
- Training Images:
  - Extract Subdomains (128^3):





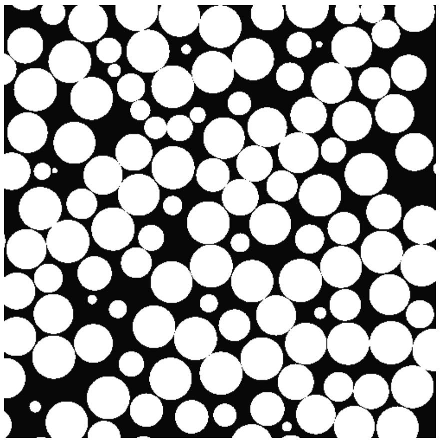
Original Image   Training Images

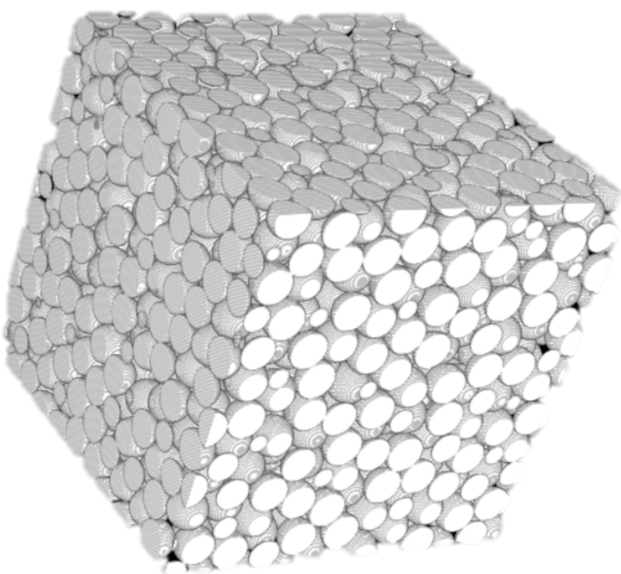


3D Micro-CT Render
500 voxels

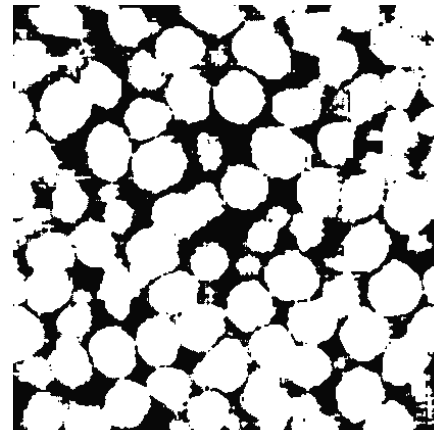
Beadpack Dataset

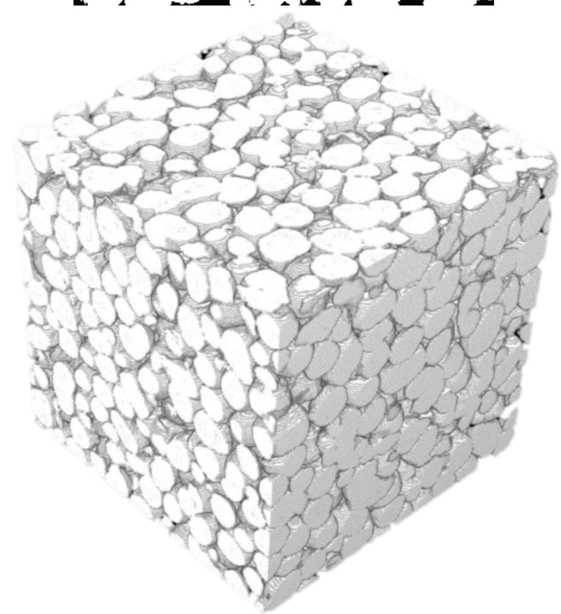
Training Image





Synthetic Image





Training: 20 hours

Generation: 5 seconds

Training Images: 128^3**voxels**

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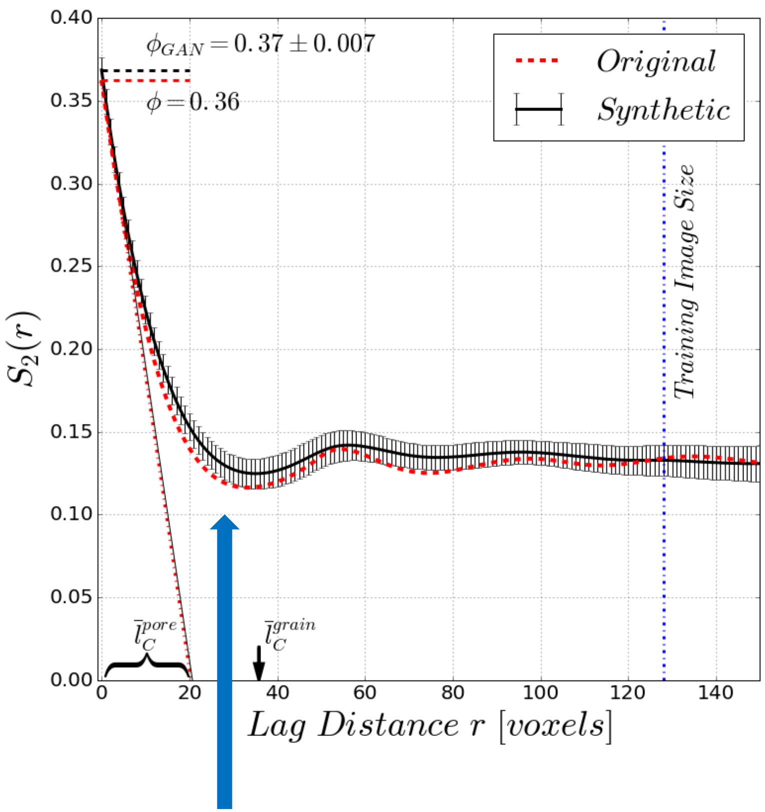
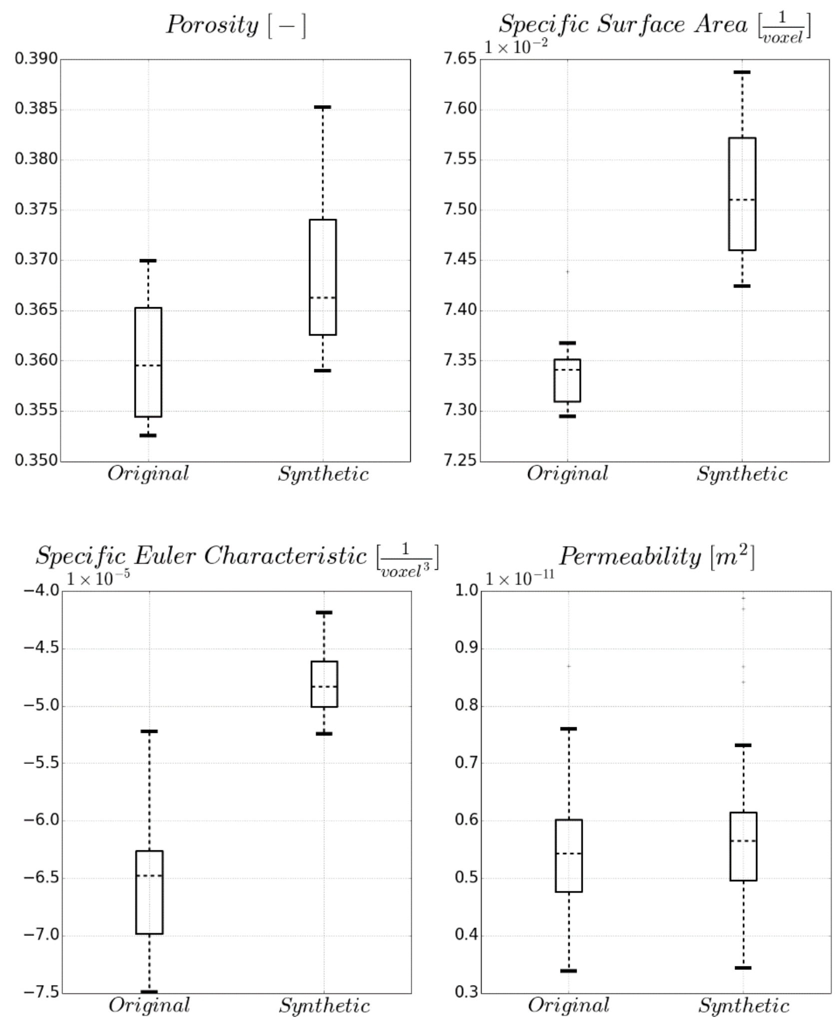
Beadpack – $S_2(r)$ and Morphological Analysis





- **Captures "Hole-Effect"**
- **Spherical shapes complex to learn from data only**

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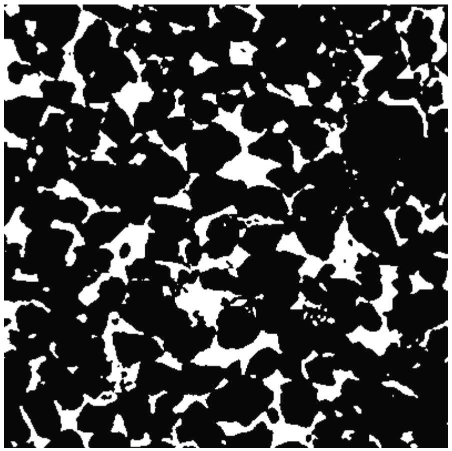
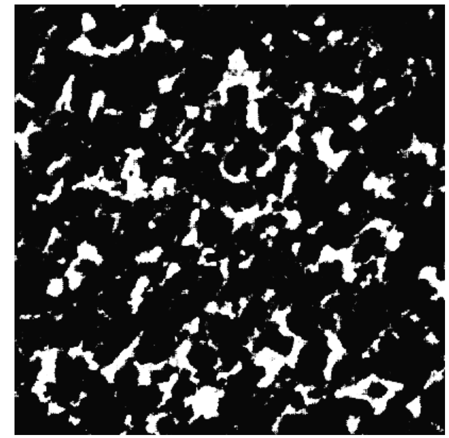
Berea Sandstone Dataset

Training Image



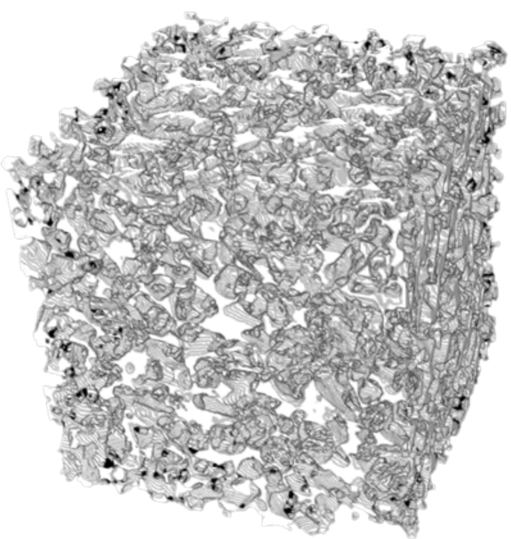
Synthetic Image

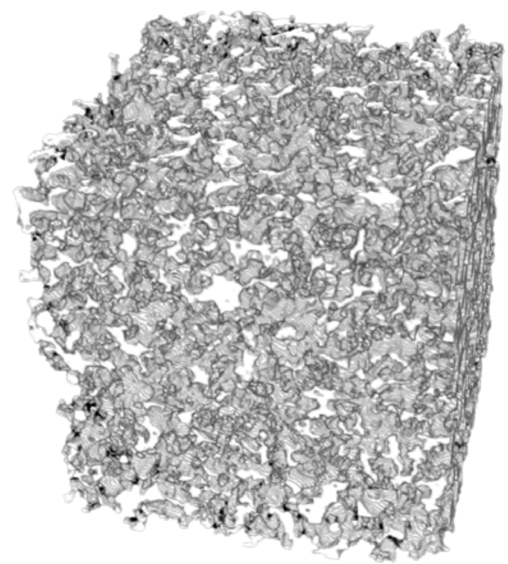


Training: 15 hours

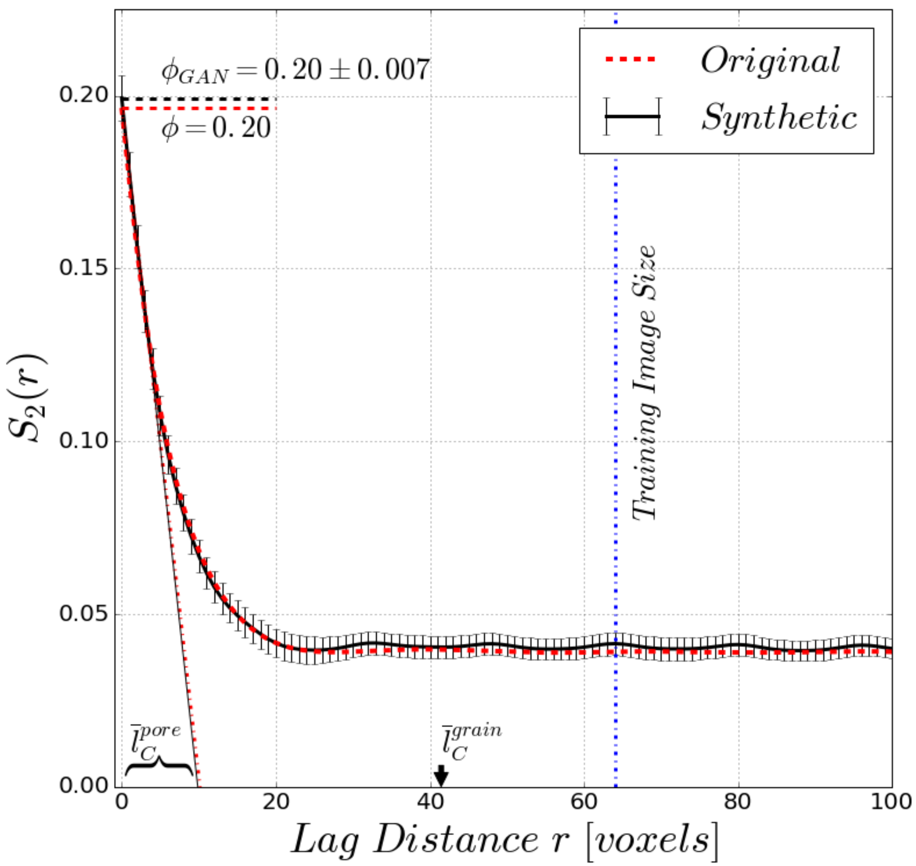
Generation: 2 seconds

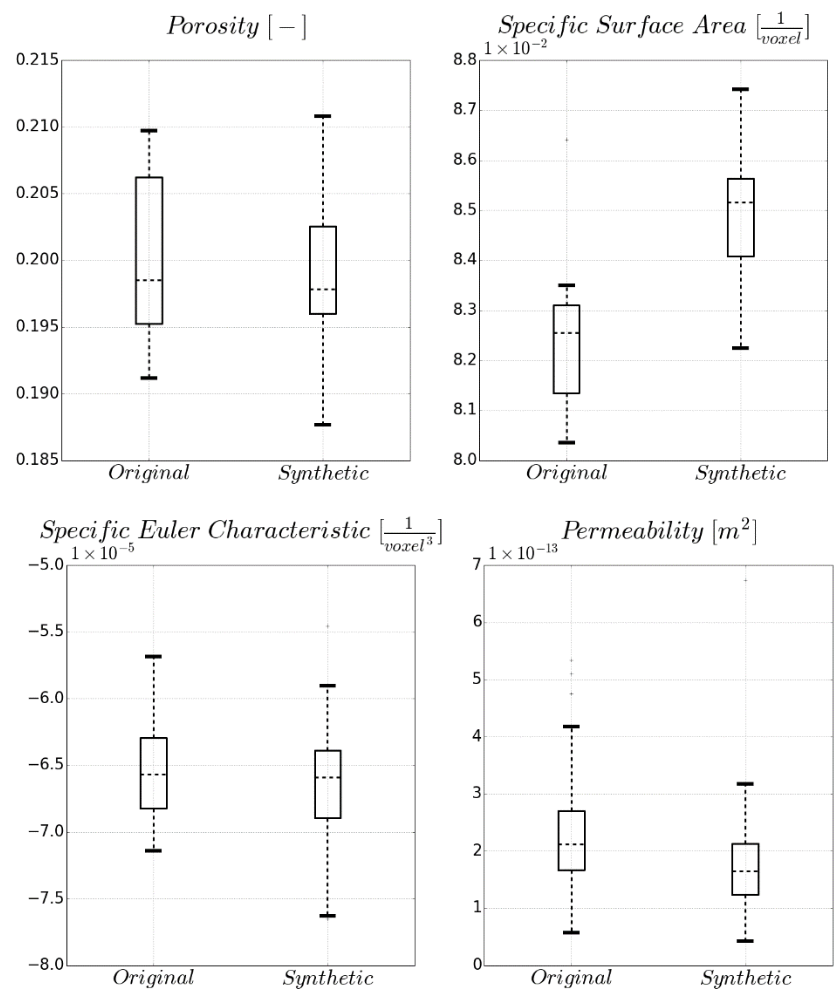
Training Images: 64^3





Berea – $S_2(r)$ and Morphological Analysis





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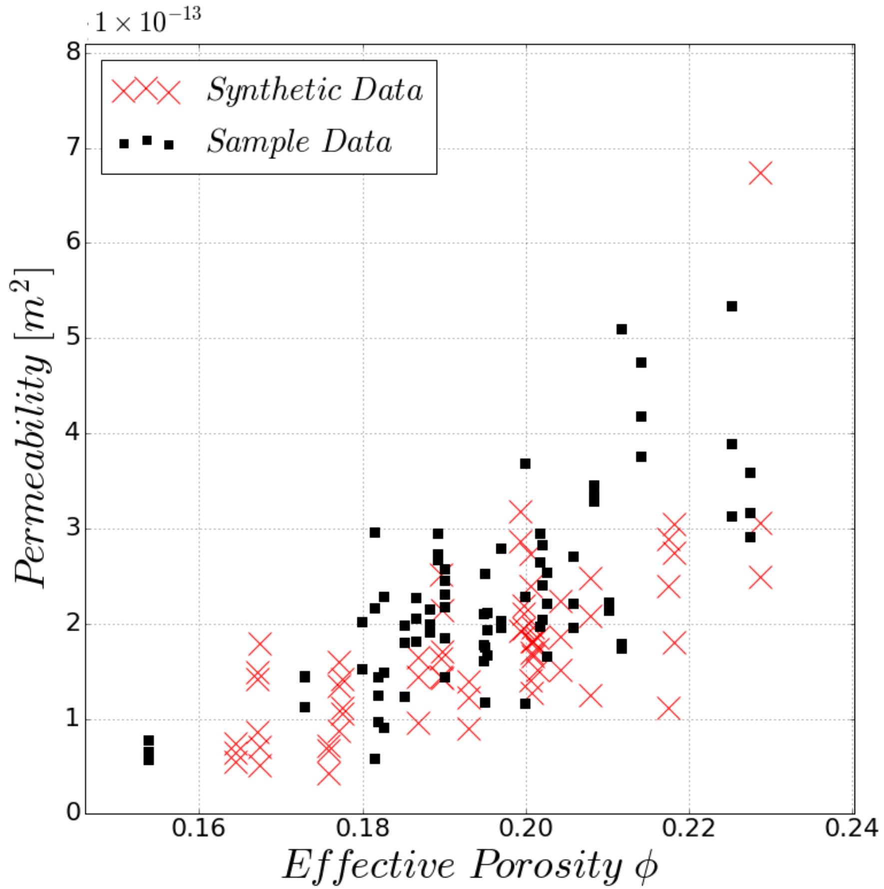
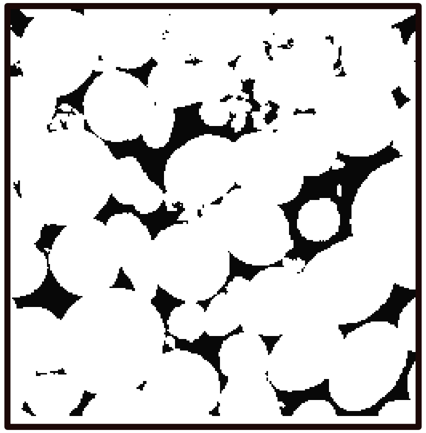
Berea - Permeability Evaluation

- **Computed permeability vs. effective porosity**
- **Domain size (128^3 voxels):**
  - **2x TI size (64^3voxels)**
- **Synthetic reconstructions show k~ϕ_{eff} with:**
  - **Similar trend**
  - **Magnitude**
- **Allows effective property to be estimated for ensemble of stochastic reconstructions**

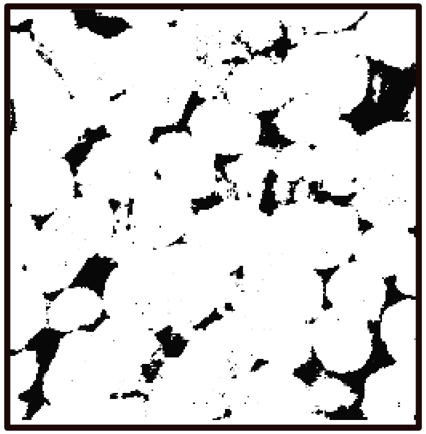


Ketton Dataset

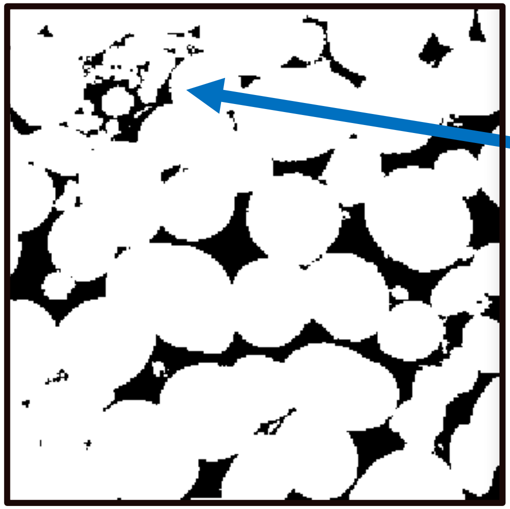
Training Image



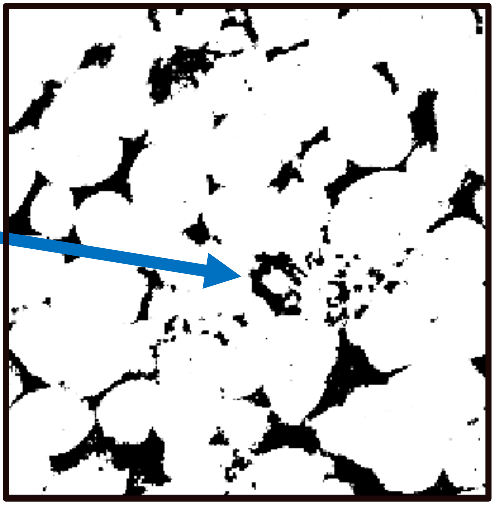
Synthetic Image



Training: 15 hours
Generation: 2 seconds



**Fragments
and
Micro-porosity?**



Discussion

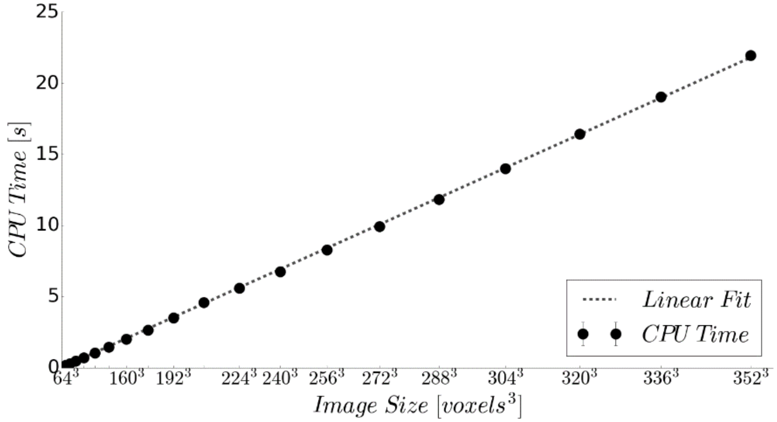
- Method is independent of imaging technique

- Training time is long (10s hours) – reconstruction time fast (seconds)

- Very active research topic in ML community
  - Improved GAN formulations – more stable and quality estimates

- No direct control over reconstruction metric
  - Requires continuous monitoring of derived properties

- Computational Scaling:
  - Linear in number of voxels
  - Very fast on CPU and GPU
  - Main requirement: Memory



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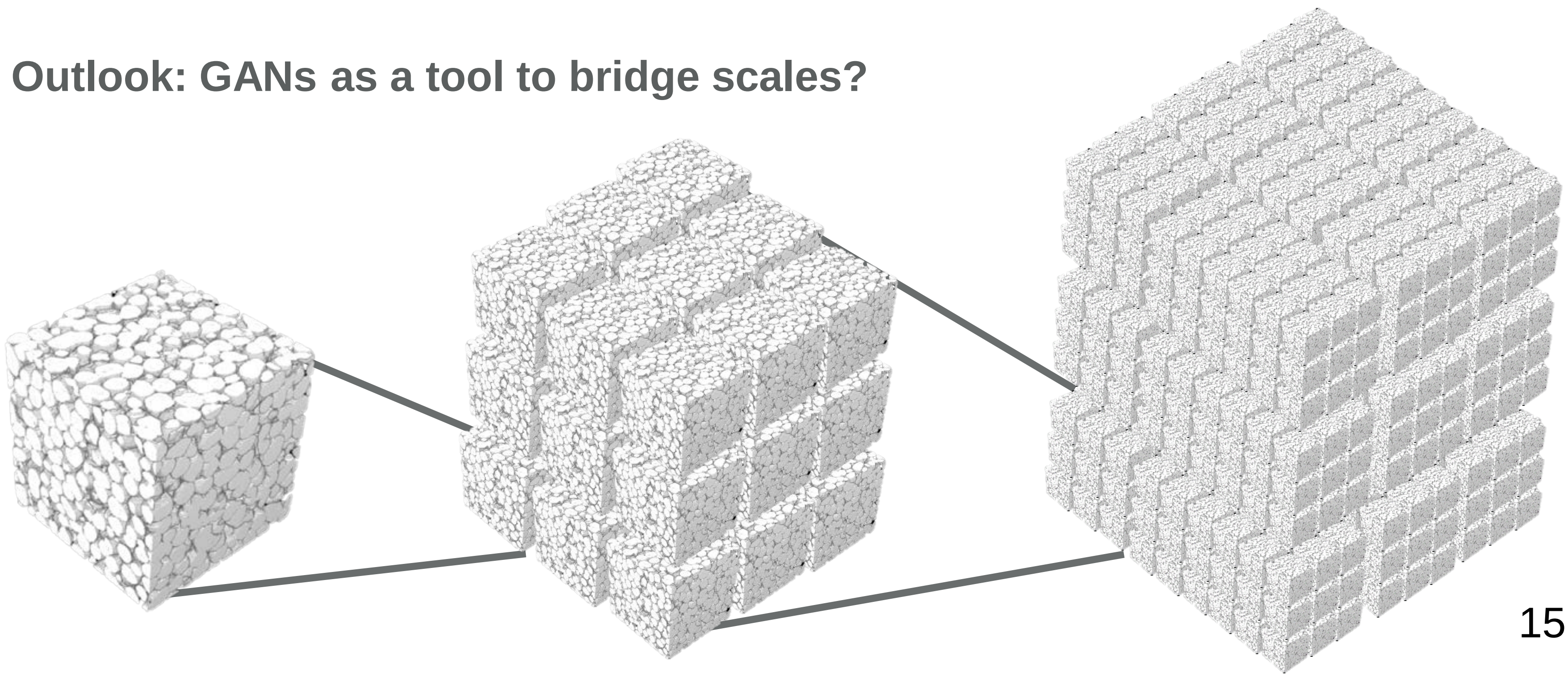
Conclusions and Outlook

- **Presented a new method for stochastic image reconstruction based on generative adversarial neural networks (GAN)**
- **GANs allow computational efficient sampling of large 3D reconstructions**
  - **Capture two-point statistics, image morphology and permeability**
- **Outlook: GANs as a tool to bridge scales?**



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Thank you!

Questions?

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Pre-print: arXiv:1704.03225

Code: github.com / LukasMosser / PorousMediaGAN