Seeing Permeability with Images

Fast Prediction of Permeability with Convolutional Neural Network

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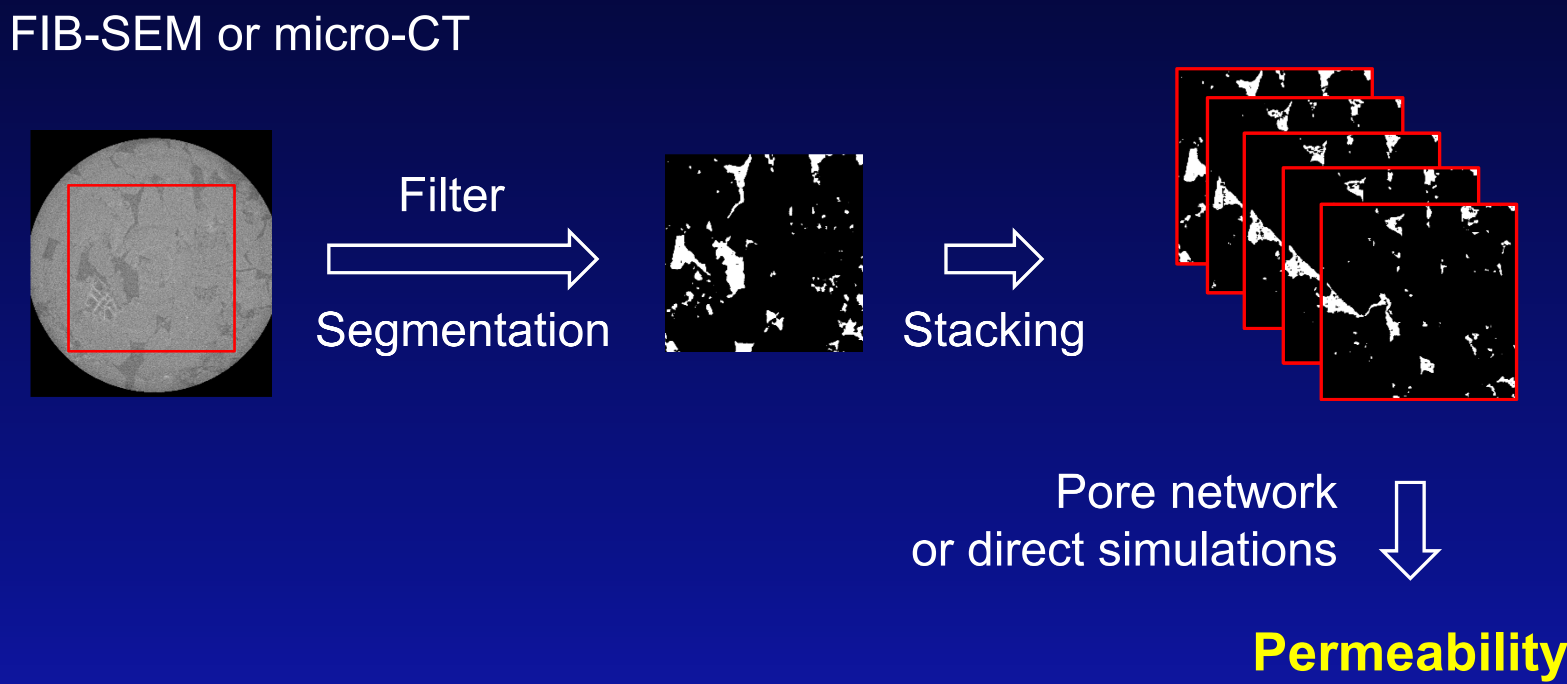
Predicting permeability from images

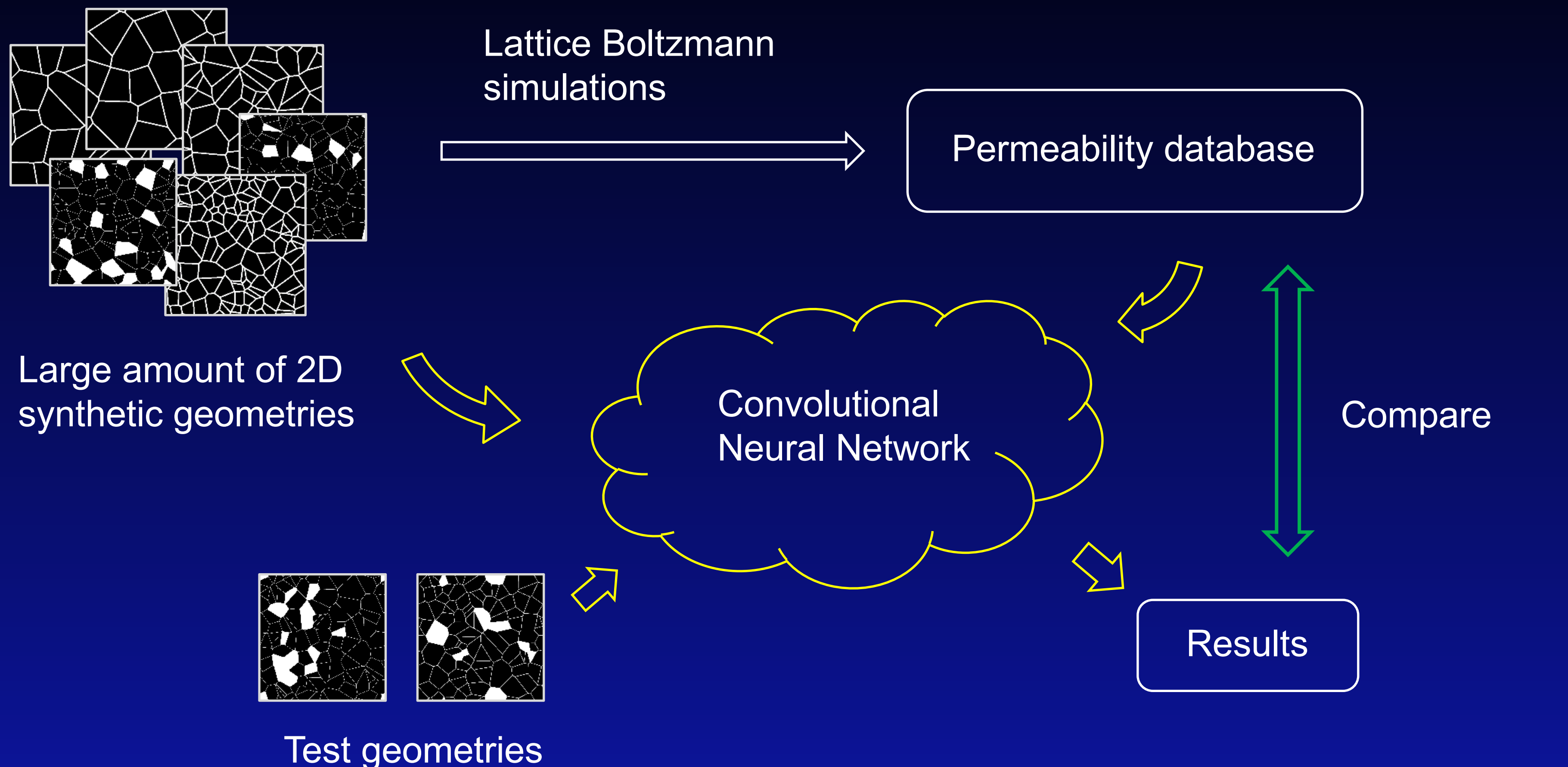
With pore-scale modeling, it is possible to calculate the permeability of a rock if its three-dimensional image is available



Seeing permeability using image recognition

- Image recognition is an active area of **machine learning** using **convolutional neural network**
- https://www.youtube.com/watch?v=LEtc7PCwCRM
- Permeability of porous media is a function of geometry
- Can we ask a computer to **memorize** enough geometries and their permeabilities so that they can **predict permeability upon seeing an image**?

Workflow

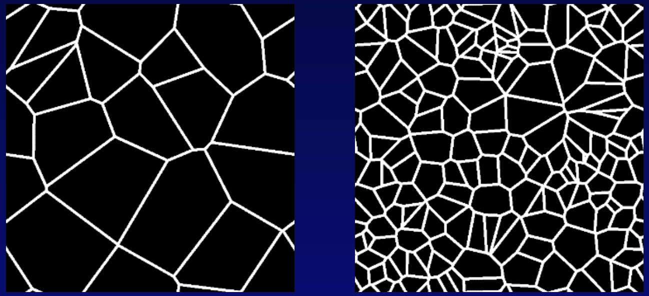


Lattice Boltzmann
simulations
Permeability database
Large amount of 2D
synthetic geometries
Convolutional
Neural Network
Compare
Results
Test geometries

Generation of training data

In this preliminary study, we use 2D synthetic geometries

- They can be generated in large quantities
- Permeability calculations are relatively quick



Homogeneous geometries

- 600 x 600 pixels
- Channels are 6 pixels wide
- Porosity: 8-26%
- Permeability in good agreement with Kozeny-Carman equation

$$k = \frac{0.14\phi^3}{s^2\left(1-\phi\right)^3}$$

s: surface area (length) per solid volume (area)

ϕ: porosity

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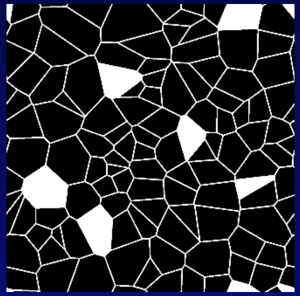

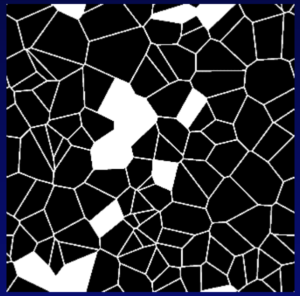

Heterogeneous geometries

- Simulate porous media with dilated pores (more realistic)
- Porosity: 10-36%
- Permeability cannot be predicted by Kozeny-Carman equation

Total samples in the training set

- 980 homogeneous geometries
- 2450 heterogeneous geometries

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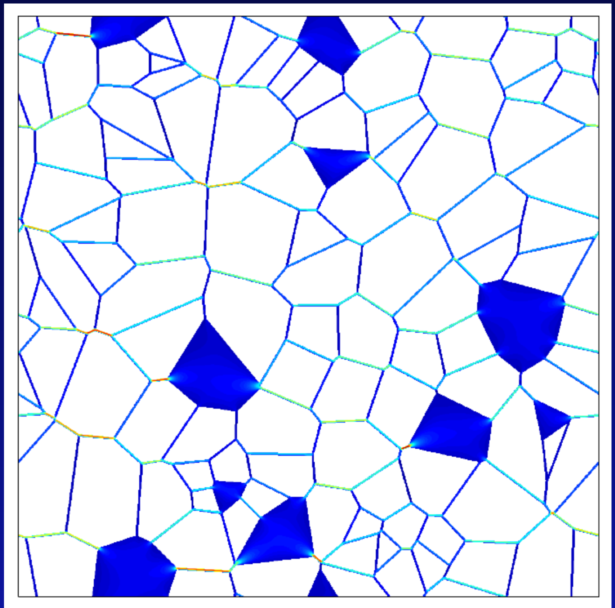


Flow field from LB

Permeability database

- Flow in every geometry is solved by the lattice Boltzmann (LB) method
- Permeability of geometry is obtained from Darcy's law

$$k = -\mu u L / \Delta p$$

- Permeabilities from LB simulations form the ground truth to teach to the image recognition program

Convolutional neural network

Neural network is a class of machine learning methods that uses optimization to find transformations between input(s) and output(s)

$$\overset{\substack{\text{Output}\\ \downarrow}}{\mathbf{y}} = \underbrace{\mathbf{W}^{(2)}\boldsymbol{\sigma}\Big(\underbrace{\mathbf{W}^{(1)}\overset{\substack{\text{Input}\\ \downarrow}}{\mathbf{q}}+\mathbf{b}^{(1)}}_{\text{Layer 1}}\Big)+\mathbf{b}^{(2)}}_{\text{Layer 2}}$$

Illustration of a two-layer neural network

$\boldsymbol{\sigma}$: activation function

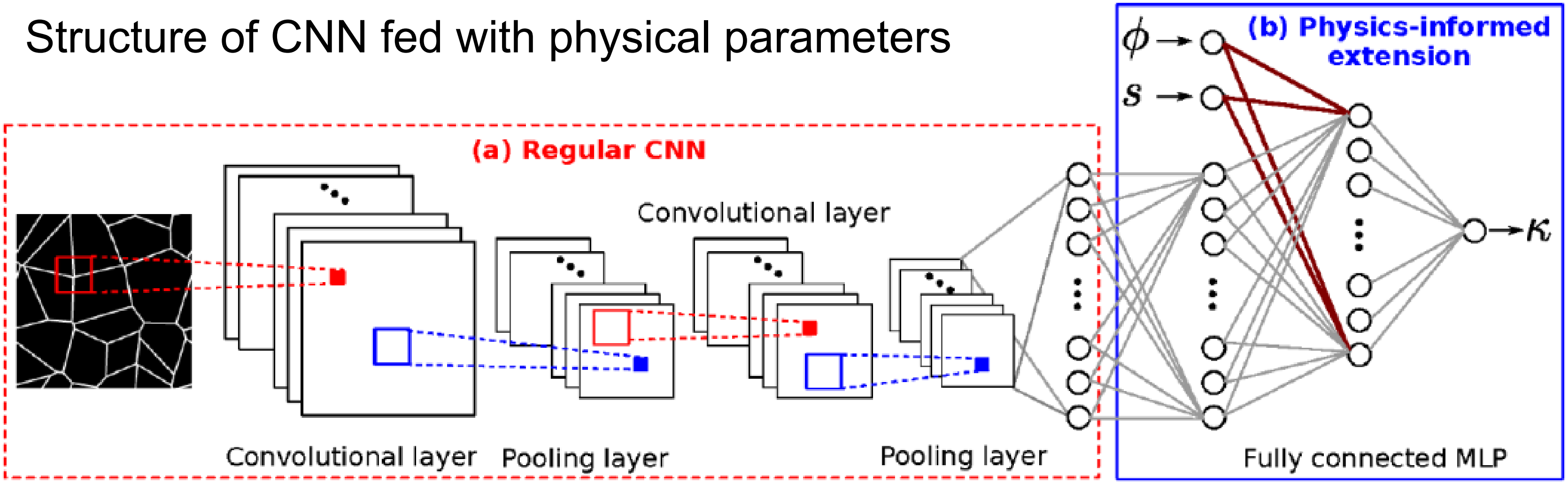
$\mathbf{W}^{(i)}$: weights

$\mathbf{b}^{(i)}$: bias

Convolutional neural network is simplification of neural network taken into consideration of close correlation between nearby pixels in an image and translational invariance of an image

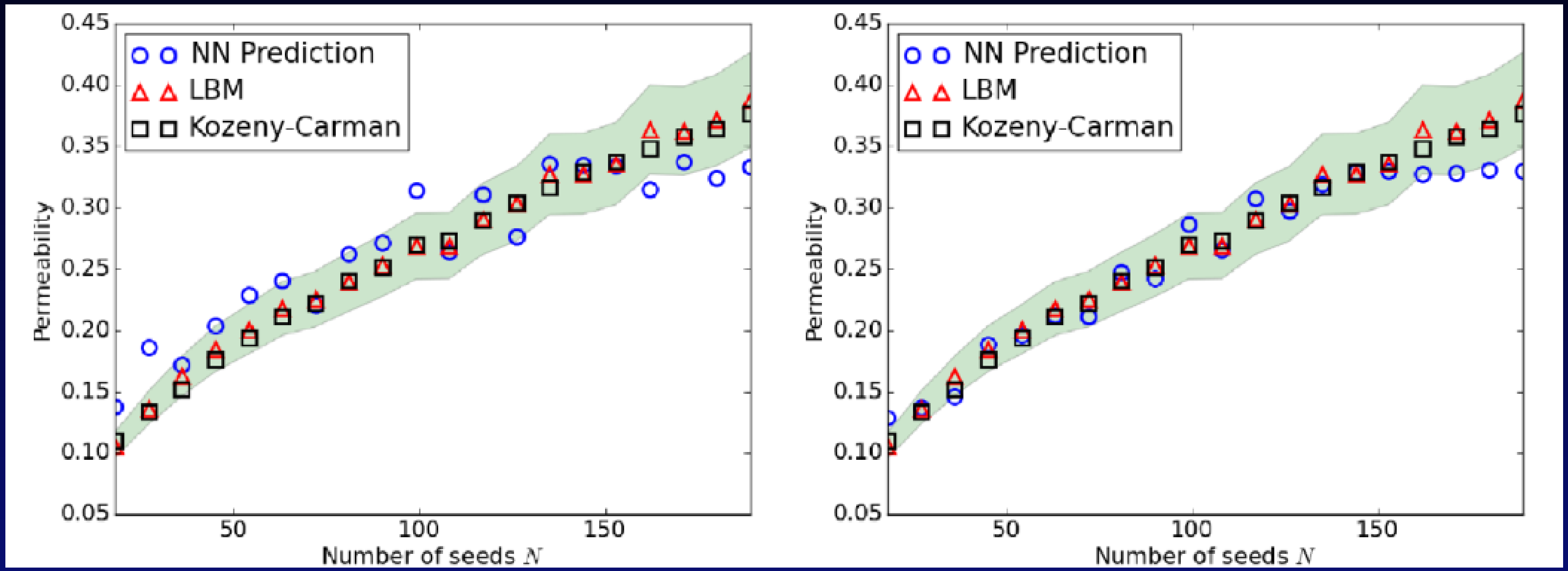
Convolutional neural network

Structure of CNN fed with physical parameters



- Seven layers: Convolution → pooling → convolution → pooling → fully connected (x3)
- Physical parameters (porosity and surface area) are passed into the second fully-connected layer to assist fitting

Results – homogeneous geometries

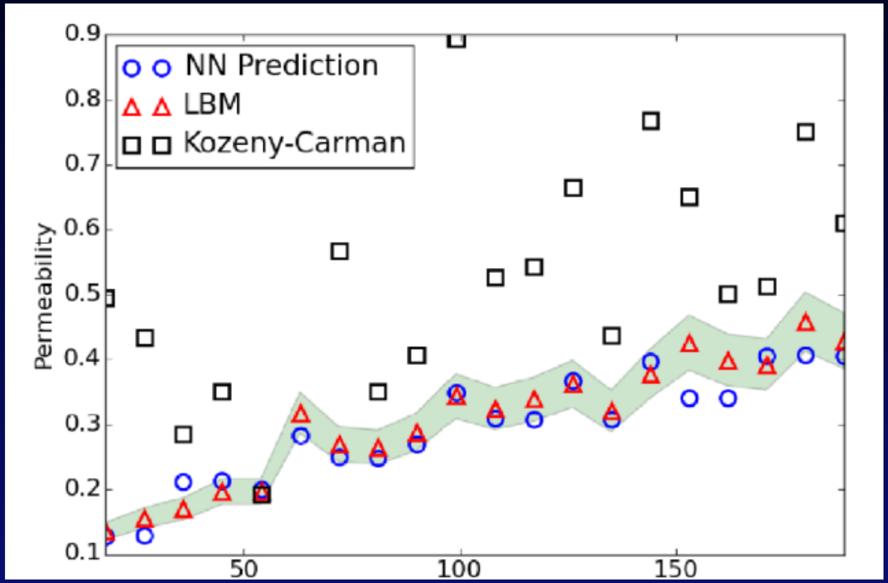


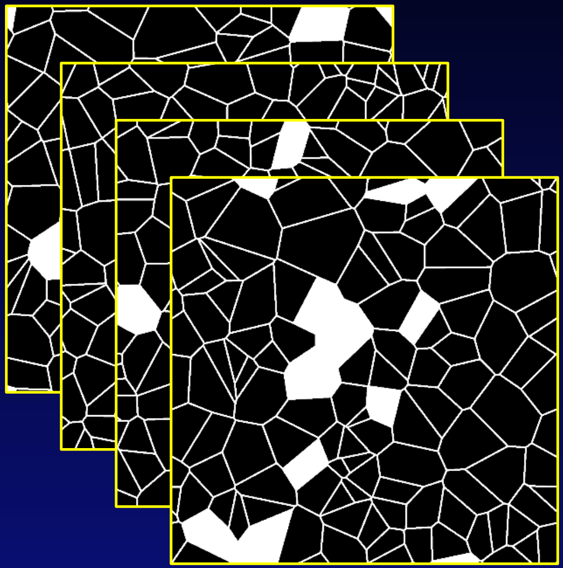
→ direction of increasing porosity →

- Permeability is in the unit of pixel^2
- 1 pixel = 1 µm, 1 pixel^2 = 1 darcy
- 1 pixel = 10 nm, 1 pixel^2 = 0.1 md

CNN with physics-informed extension (right) predicts permeabilities with higher accuracy

Results – heterogeneous geometries

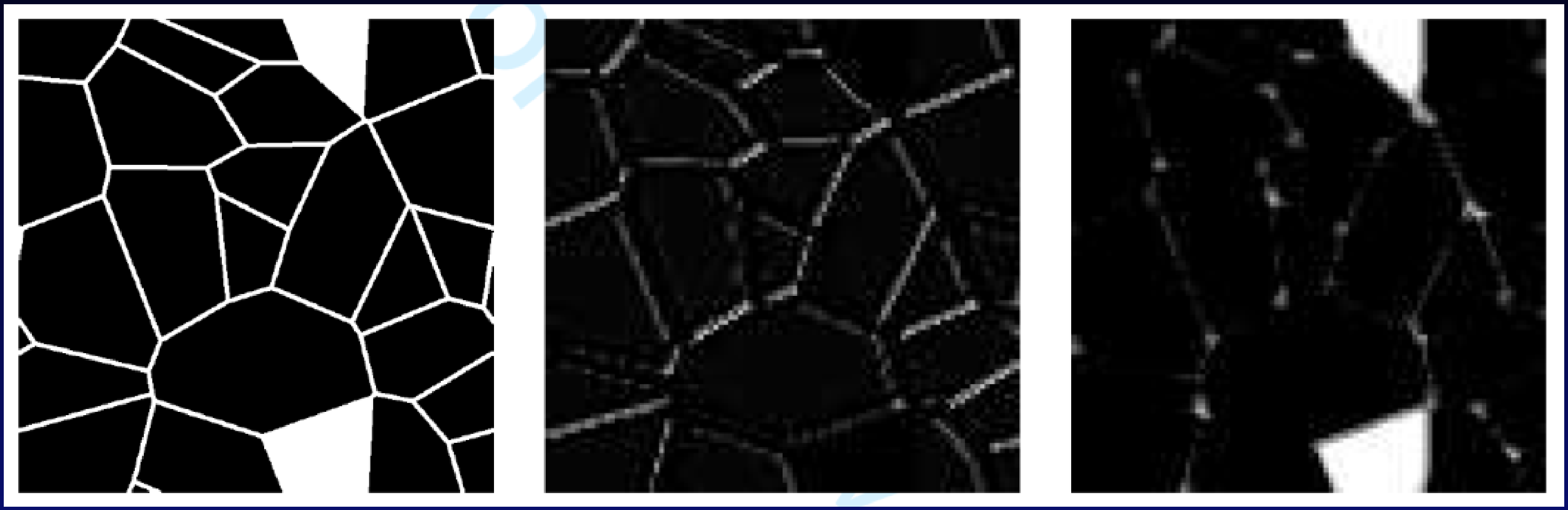




For heterogeneous geometries

- Kozeny-Carman equation failed to predict most permeabilities
- CNN can predict permeabilities to within 10% of “ground truth”
- Computational time is 1000 times faster than simulation

Why it works so well?



Original Feature 1 Feature 2

Looking into the structure of a trained CNN reveals that CNN “learns” to divide the original image into channels and dilated pores and correlate permeability to the channels, as dilated pores are isolated and therefore offer little in promoting the permeability.

Challenges

- 3D geometries
- Real rocks
- Other rock properties

Collaborators

- Heng Xiao, Virginia Tech.
- Jinlong Wu (PhD), Virginia Tech.

AlphaGo (Deepmind) versus Ke Jie, 2017