PennState College of Earth and Mineral Sciences

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Upscaling relative permeability from pore scale to field scale using conditional deep convolutional Generative Adversarial Networks (GANs)

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Introduction

1. Definition

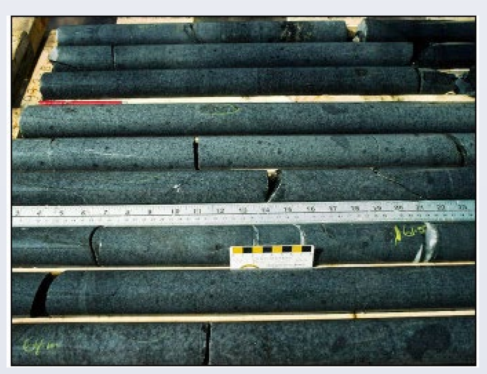
- Relative permeability (k_r) is defined as the ratio of effective permeability of a particular fluid at a particular saturation to absolute permeability of that fluid at total saturation.

$$Q_s = \frac{kk_r A}{\mu L}\delta P, k_r = \frac{k_{eff}}{k}$$

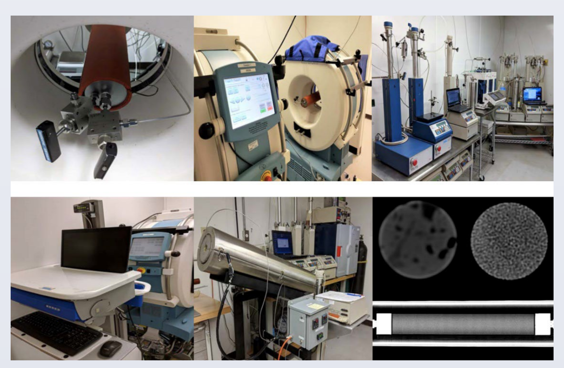
- k_r is an important parameter for controlling CO2 injection volume and plume distribution during the process of CCS.

2. Laboratory measurements of k_r

- Special core analysis (SCAL) is time consuming and expensive
- Core samples are only limited representation of subsurface

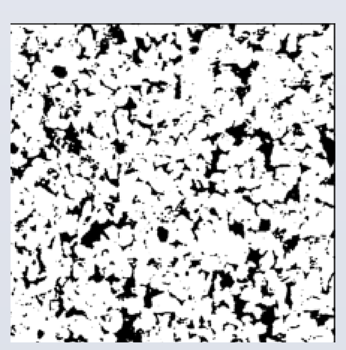


Core logging

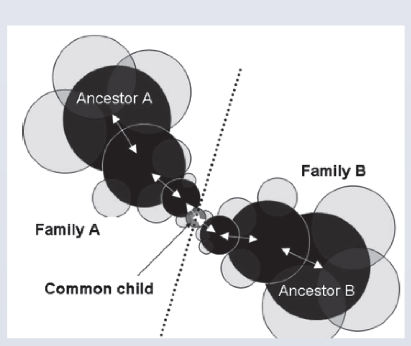


Laboratory measurement of relative permeability

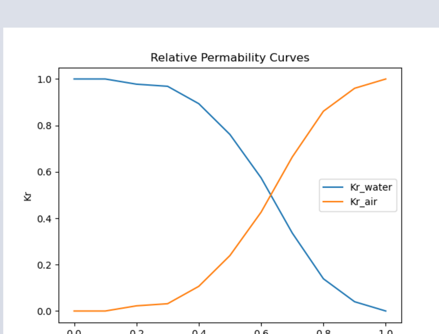
3. Numerical Simulation of k_r



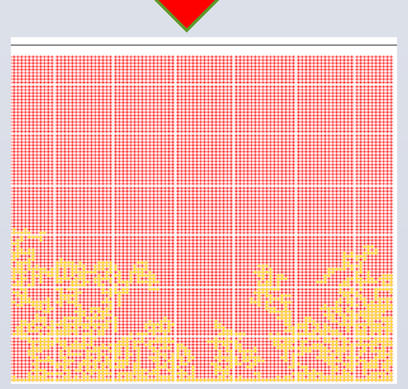
Micro CT image



Pore network model - Dong and Blunt, 2009



Simulated Relative permeability curve (k_r vs S_{nw}) through stokes flow simulation



CO_2 Invasion percolation

4. Limitations

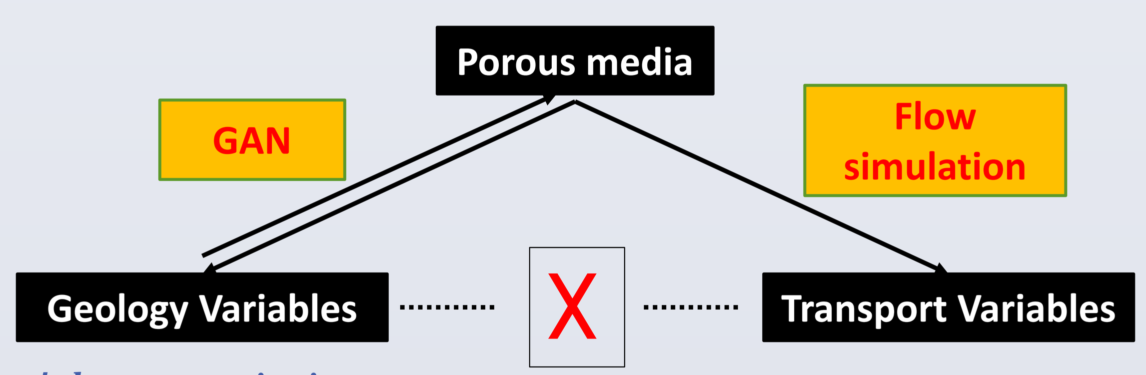
- Both laboratory measurement and numerical simulation of relative permeability require availability of cores plugs or their micro-CT images, which only represent a small portion of subsurface information.
- Reservoir simulation typically considers K_r function as homogeneous for whole field scale whereas assuming heterogeneous distribution of geological properties such as porosity and permeability. Inconsistency between transport properties and static geological properties limit the accuracy of reservoir model.

Objectives

This research aims to develop a tool which can infer and upscale relative permeability function at field scale through integrating both pore scale simulation and field scale static geological properties (porosity, permeability and pore size distribution); add an extra heterogeneity fluid transport model (k_r) besides reservoir characterization model; extrapolate sparse and expensive data (k_r) from large volume of data (ϕ and k_{abs}) at field scale.

Methodology

Physics informed conditional deep convolutional generative adversarial networks (C-DCGAN) can build the bridge between static variables (ϕ *etc.*) and dynamic variables (k_r, χ *etc.*) by reconstructing porous media that combine information from both pore scale (training images) and field scale features (e.g. well logs). Below is the workflow:



Generative adversarial network (fig.1) is consisted by 2 deep convolutional neural networks: Generator (G) and discriminator (D). They are competing to minmax cross entropy loss function:

$$E_x(\log D(x)) + E_z\big(log1 - D(x^*)\big)$$

$$x: training\ images.\ x^*: fake\ images, G(z)$$

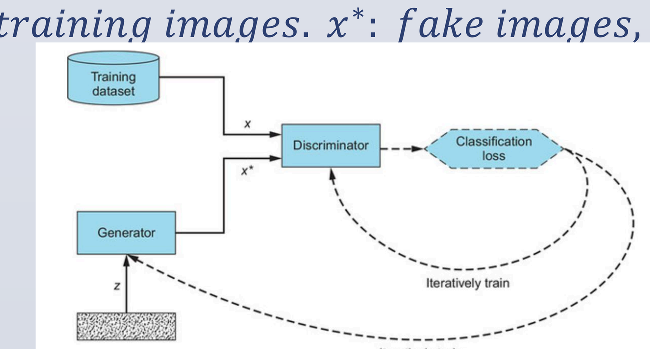


Fig. 1. Architecture of GAN - Jakub and Valdimir, 2020

The generation process of conditional DCGAN (fig.2) is controlled by both physical vector $y: \{\phi, k_{abs}, D \ldots\}$and Gaussian noise z. The minmax cross entropy loss function will be rewritten in below form:

$$E_x(\log D(x|y)) + E_z\big(log1 - D(x^*|y)\big)$$

$$x: training\ images.\ x^*: fake\ images, G(z|y)$$

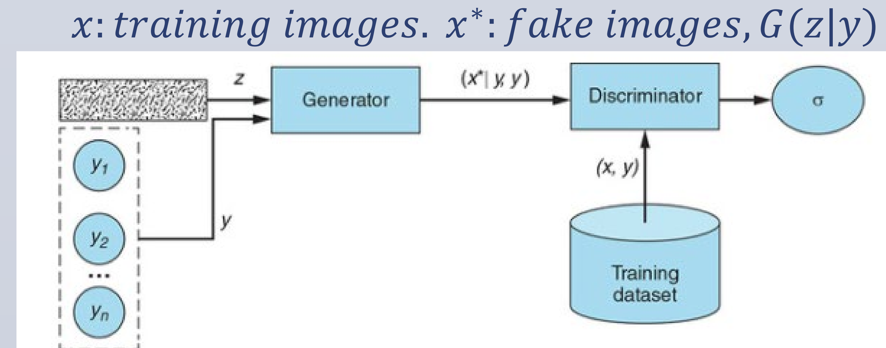


Fig. 2. Architecture of GAN - Jakub and Valdimir, 2020

Results

- Distribution of reconstructed hydraulic properties (ϕ and k_r) using DCGAN has converged with distribution of these parameters in training images.
- Conditional DCGAN has ability to interpolate the structure of porous media given an unseen input distribution of hydraulic properties in training images (Fig.4 & 5).
- Given multiple spatial realizations of porosity, permeability and pore size distribution near wellbore, generator extracted from trained condition DCGAN will be able to generate multiple realizations of k_r curves in each grid block (Fig.6)

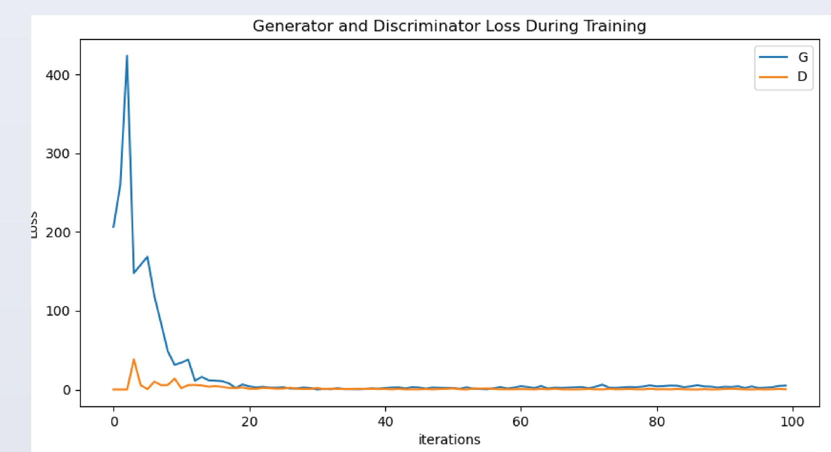


Fig. 3. Training history of conditional DCGAN

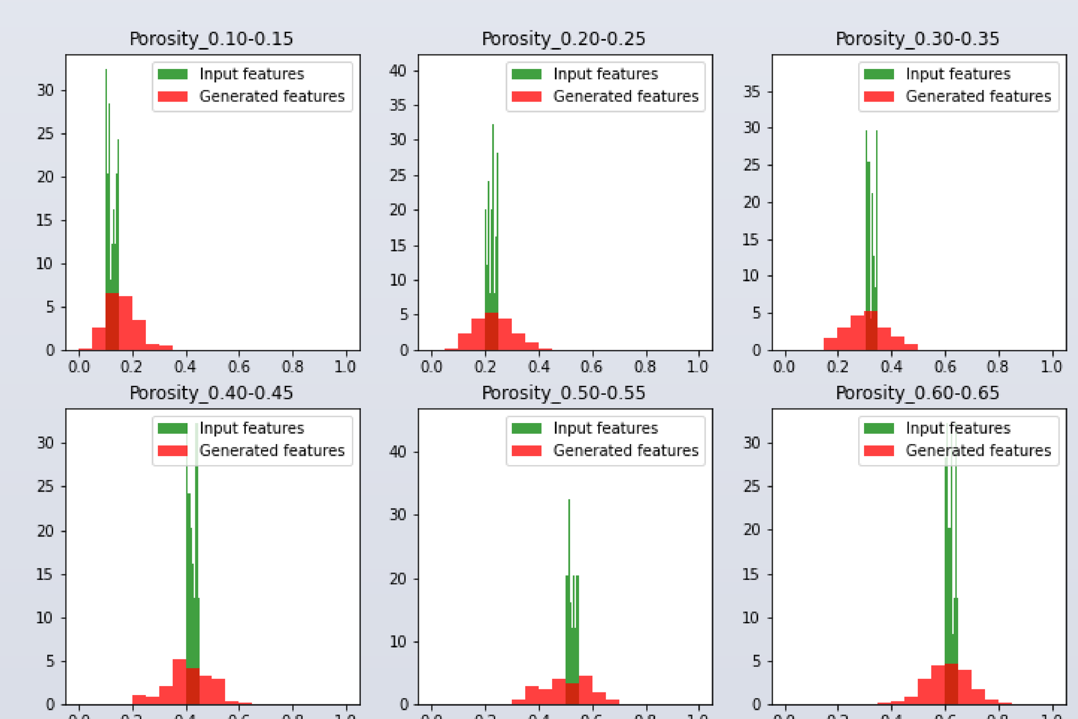


Fig. 4 Reconstructed porous media conditioned to porosity input

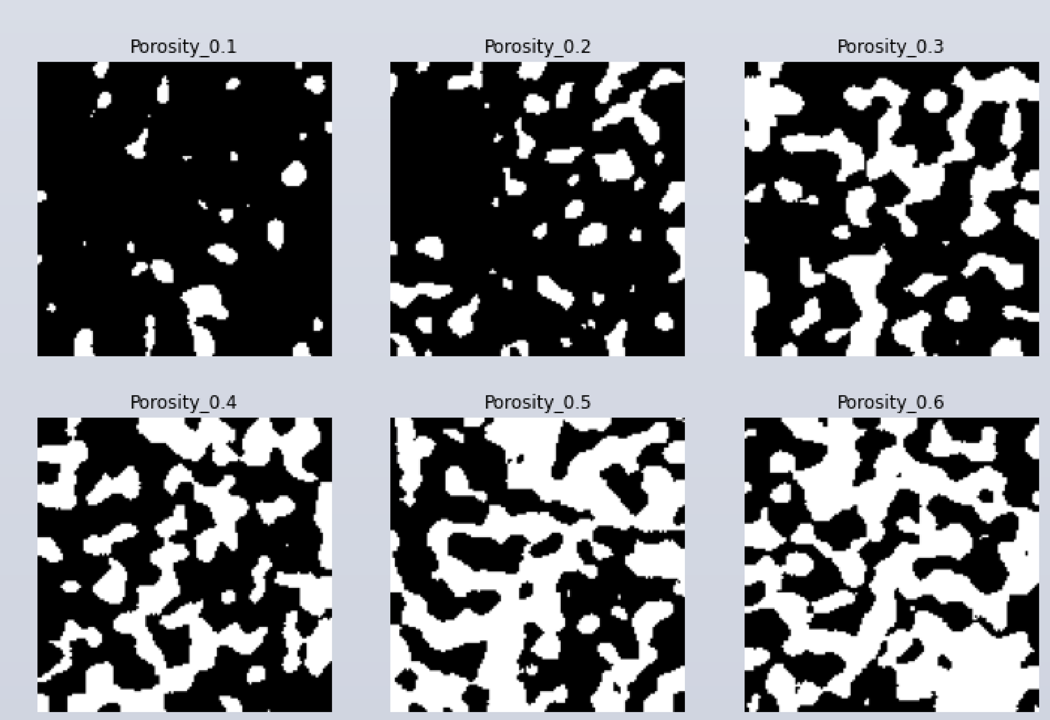
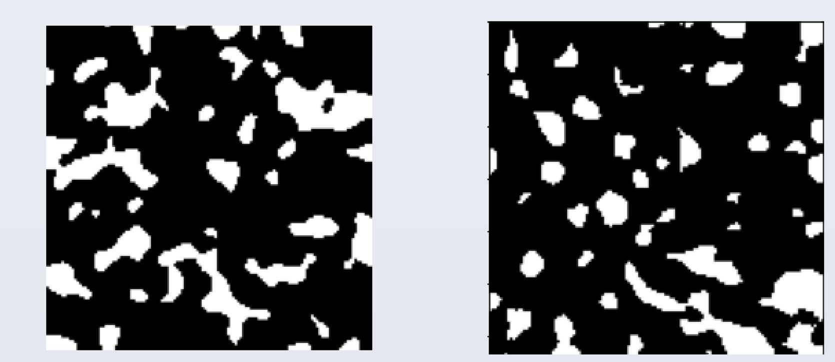


Fig. 5. Reconstructed porous media image conditioned to porosity input

Conclusion

- This study indicates that physics insisted data driven approach (C-DCGAN) can reconstruct porous media while combining both pore scale (training images) and field scale features (reservoir characterization features)
- This study introduces a new workflow to successfully predict relative permeability given only static Geological features such as porosity etc.
- This study introduces a more accurate characterization of phase flowing behavior in reservoir simulation to support future reservoir simulation development



Training image $\phi = 0.2$ Reconstructed image $\phi = 0.18$

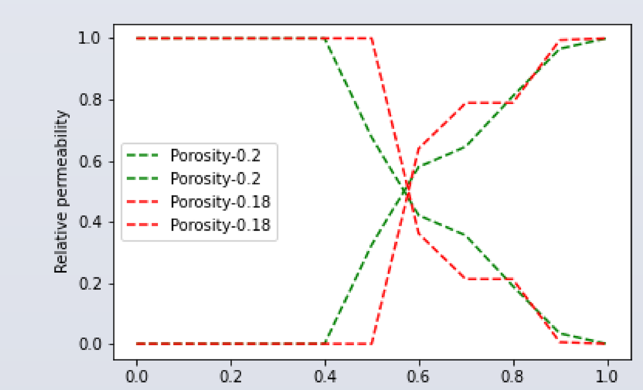


Fig. 6. Relative permeability upscaling according to porosity perturbation to DCGAN

References

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