Characterizing effective flow units in a multiscale porous medium

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Abstract

Recent advances in imaging techniques and related modeling have made it possible to study micron and sub-micron scales in unprecedented detail. Currently, performing direct simulations at a representative scale has proven computationally prohibitive, hence, the ability to simulate flow cannot keep up with the size of images available (e.g. x-ray micro-tomography or large area scanning electron microscopy). To overcome this issue, we propose to train a neural network architecture to understand relationships between pore-scale morphology and the simulation outputs. With this, we improve our portability and prediction time. Convolutional neural networks are attractive for this task because they support flexible input size, they are able to capture local interactions, and they can find places that present similar patterns. Generally, deeper networks have better prediction performance, but they are very difficult to train due to the vanishing gradient problem. Also, information from different scales is commonly lost along the network.

Characterizing effective flow units in a multiscale porous medium
A deep learning study

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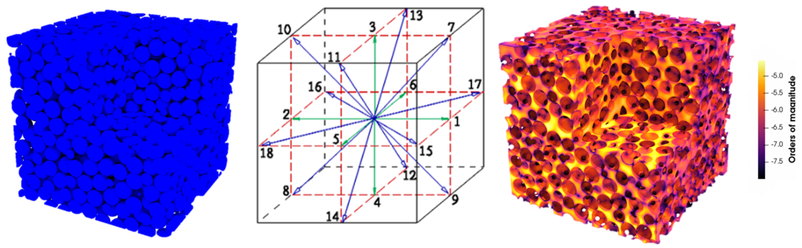
Introduction and background

Recent advances in imaging techniques and related modeling have made it possible to study micron and sub-micron scales in unprecedented detail. Currently, performing direct simulations at a representative scale has proven computationally prohibitive, hence, the ability to simulate flow cannot keep up with the size of images available (e.g. x-ray micro-tomography or large area scanning electron microscopy).

The multi-relaxation-time scheme of the lattice-Boltzmann method [4] is able to describe flow through complicated geometries with the help of high performance computing (many thanks to Texas Advanced Computing Center). By discretizing:

$$f_\alpha(x + e_\alpha\delta_t, t + \delta_t) - f_\alpha(x,t) = -S_{\alpha i}(f_i(x,t) - f_i^{eq}(x,t)), \qquad (1)$$

for a 3D domain, we are able to accurately simulate single-phase flow through a sphere-pack[3]. The advantage of this method is that we can obtain the velocity tensor and pressure field in a natural geometry. On the other hand, a supercomputer cluster is needed.



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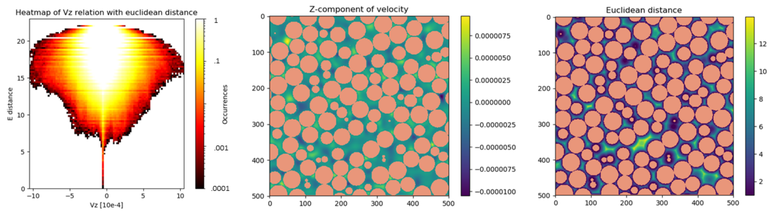
Objectives

Pore-space velocities span several orders of magnitude (positive and negative range), and describing the fluid pathways with simple relationships is not feasible; so using analytical solutions is not viable. Hence, the objectives of this work are:

- To test the practicality of using advanced statistical learning tools (deep learning) for flow prediction at the pore-scale.
- Provide guidelines on hyperparameter selection and data transforms for obtaining the best performance.

Data analysis and preparation

The velocity component parallel to the pressure gradient and the distance away from the solid grain (the latter is a proxy for pore space topology description) show no correlation:



During training, the neural network will presumably find spatial correlations at different scales between the two.

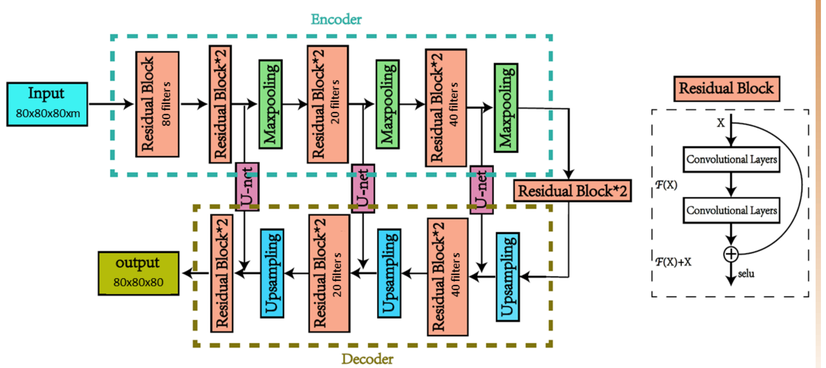
We tried the following data transformations to help network perform better:

Data transforms and average prediction error: training with 1 sample		
Method	**Advantage**	e_r
Original data	Predictions with original units	$>>$ 100 %
Modified log $(sign(y)log10(\|y\|))$	Well defined boundaries between o.m.	$>$ 100 %
MinMax	Range [0-1]	$\sim$ 30 %
MinMaxPreserving0s	Accurate predictions for solid	$\sim$ 16 %

The training was carried out on 80^3 subsets of the 500^3 sphere-pack.

Network architecture

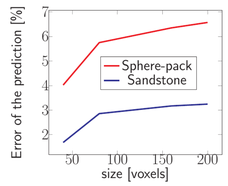
The network [1] is composed by residual blocks that capture the relations at different scales. The input is a 3D image with m features, the output is the desired property (pressure or velocity).



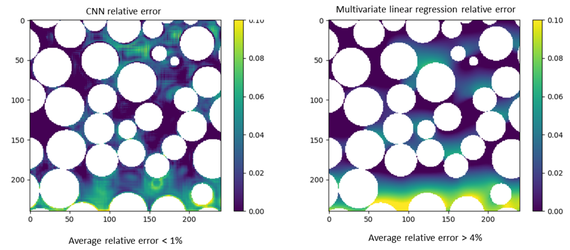
Results

Using 6 sphere-pack datasets, we trained our network varying the filter size. After training we got the following prediction results:

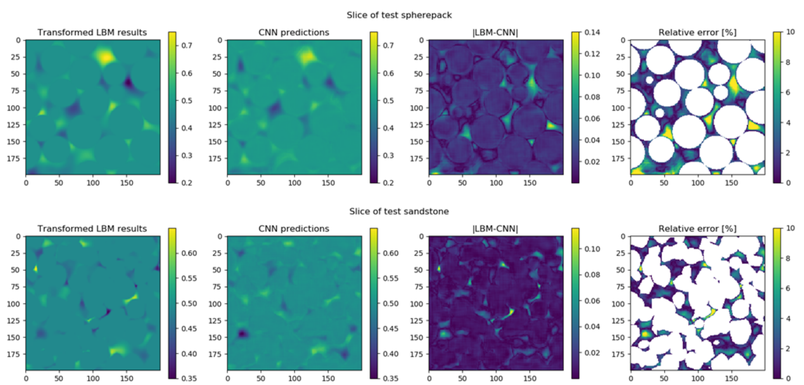
Kernel sizes and average prediction error		
Sizes	$e_r(80^3)_{max}$	$\overline{e}_r(80^3)$
$3^3-3^3-1^3$	40.75 %	6.73 %
$5^3-3^3-3^3$	29.24 %	6.93 %
$5^3-3^3-1^3$	30.42 %	5.74 %



Using the Euclidean metric and the distance to the source, our method was able to outperform simpler ones in pressure predictions.



For velocity predictions, we tested our model with other sphere-pack subsections and with a sandstone[2] ($\phi = 0.2$):



The lbm simulation on the sandstone took twice as long compared to the sphere-pack due a more constrained medium. Nevertheless, the NN predictions are much more accurate.

Conclusions and future work

- Basic geometry information is sufficient to predict flow properties for a homogeneous sample.
- Future work: For this work we explored laminar flow of a low viscosity fluid. We are currently working on expanding the capabilities of our network to handle multiscale domains and multiphase flow.

References and reproducibility

[1] https://github.com/je-santos. 2019.
[2] C. F. Berg. *Fontainebleau 3D models*. http://www.digitalrocksportal.org/projects/57. 2016. DOI: 10.17612/P75P4P.
[3] J. Finney. *Finney Packing of Spheres*. http://www.digitalrocksportal.org/projects/47. 2016. DOI: 10.17612/P78G69.
[4] J. E. Santos, C. J. Landry, and M. Prodanovic. In: 2018. DOI: 10.15530/urtec-2018-2902946.