

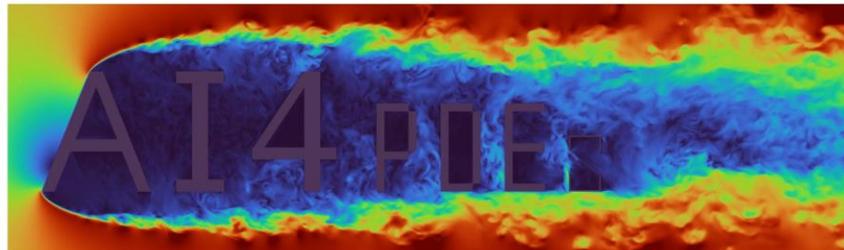
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AI for Scientific Discovery and Multiscale Modelling: - Demonstrating AI4PDEs and AI4Particles

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Edinburgh, UK



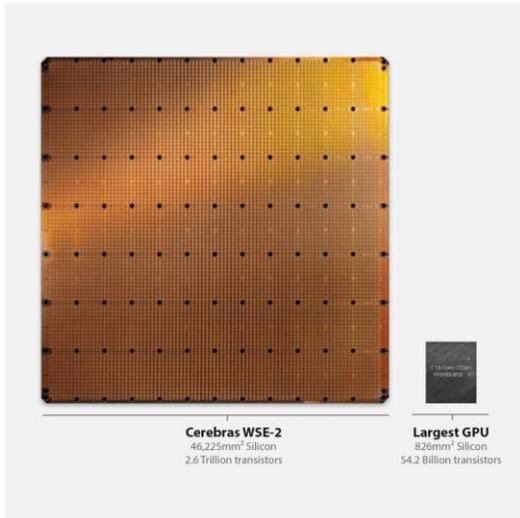
Background and Motivation

- AI & ML technology provide novel solution of complex problem
- Large-scale CFD simulation (exascale computing)
- Numerical modelers intend to develop GPU-based solver

Relax the limitation of computational cost

- New AI computers
- Summary speed - total $10^6 \sim 10^9$ faster

AI models $10^3 \sim 10^6$ faster; AI computer 10^3 faster

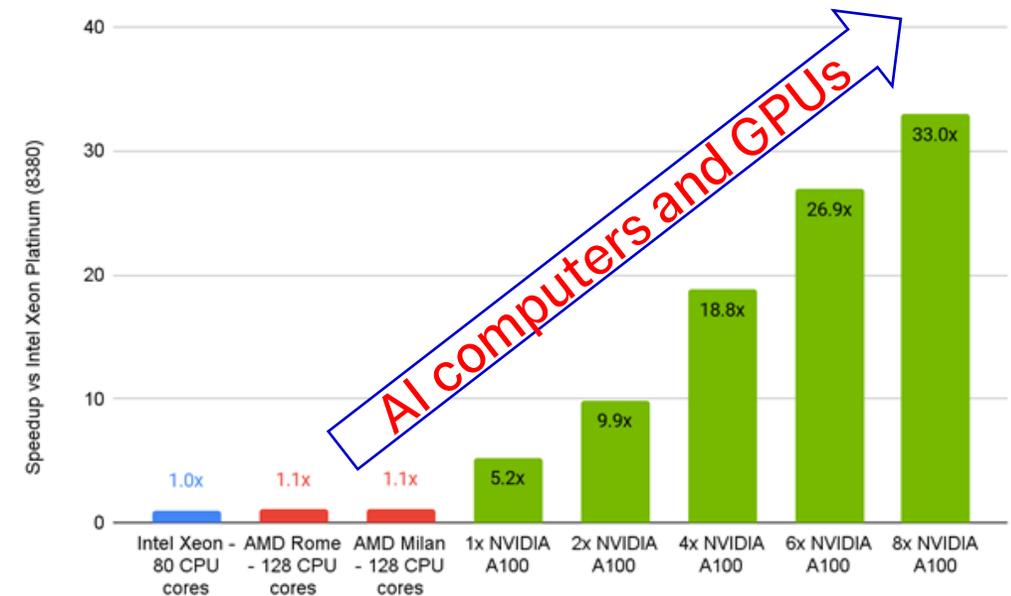
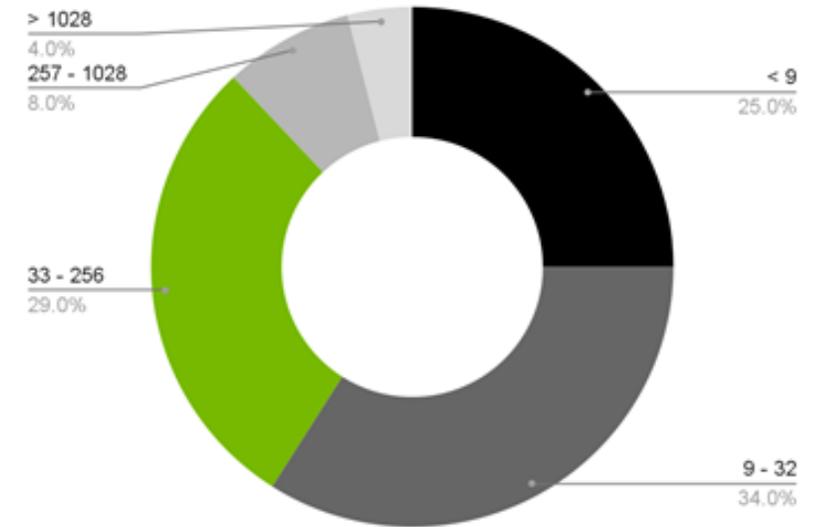


Cerebras 1M node chip



GRAPHCORE IPU

Number of Processors Used by CFD Users



Methodology – AI4PDEs

Artificial Intelligence for Partial Differential Equations
(AI4PDEs)

- Design the values of kernels in ANNs **without data training**
- Represent the discretization of PDEs on **structured mesh**
- Produce **identical** solution to classical approaches

Neural Networks for Partial Differential Equations
(NN4PDEs)

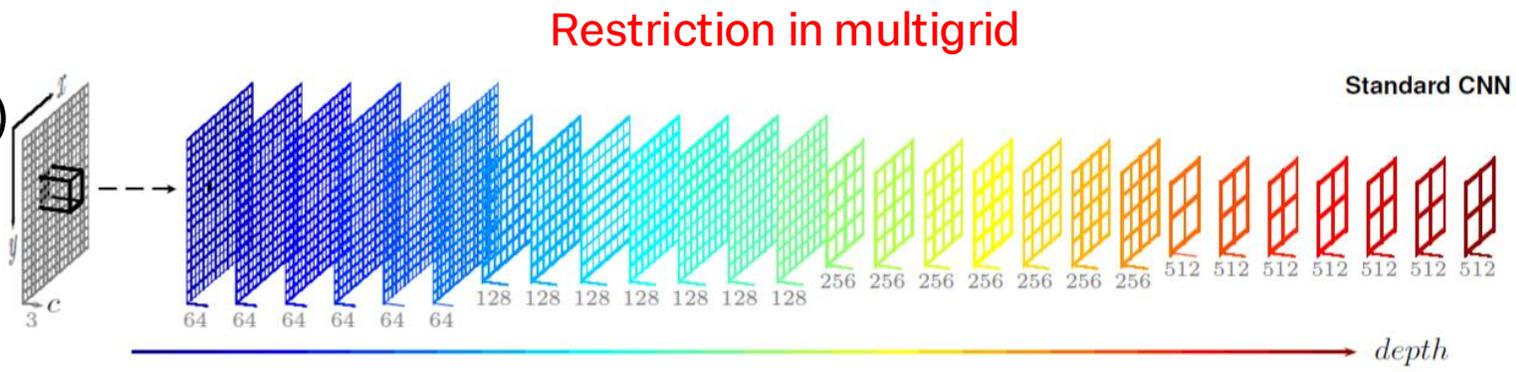
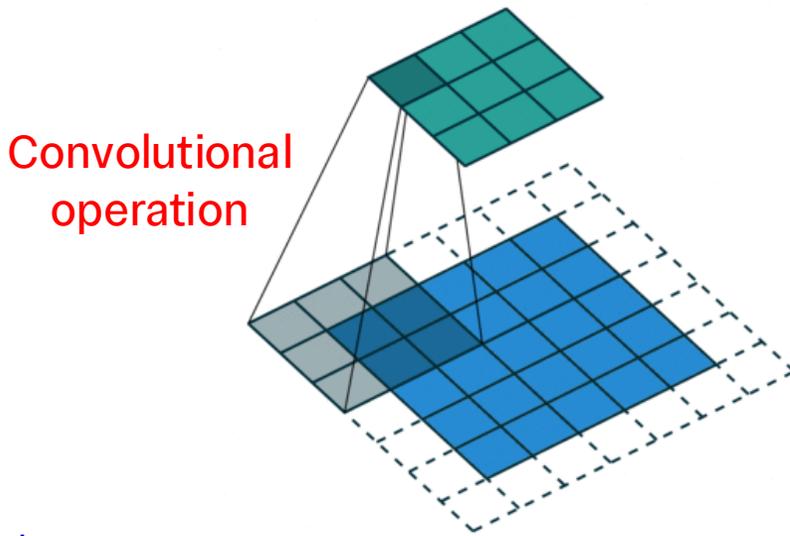


Advantage

- ✓ Easy **implementation**
- ✓ Less **quantities** of code
- ✓ More **computational efficient** than conventional CFD solver (~100 times)
- ✓ More **accessible** to optimize by GPU and AI computer
- ✓ Digital twins **assimilating data** and performing **uncertainty quantification**
- ✓ Long term model/code supported by community and AI software

Methodology - Convolutional neural networks

- Convolution neural networks (CNN)
 - ✓ Matrix-free discretization of PDEs
 - ✓ No training of the network
 - ✓ Known weights in the filters
- Convolutional FEM (ConvFEM)
 - ✓ Linear, quadratic and cubic finite element
- Rapid multigrid algorithms
 - ✓ U-net structure of F-cycle and V-cycle



Weights in CNN filters

Solution field on a grid
Central difference stencil
Diffusion operator

C_{06}	C_{16}	C_{26}	C_{36}	C_{46}	C_{56}	C_{66}
C_{05}	C_{15}	C_{25}	C_{35}	C_{45}	C_{55}	C_{65}
C_{04}	C_{14}	C_{24}	C_{34}	C_{44}	C_{54}	C_{64}
C_{03}	C_{13}	C_{23}	C_{33}	C_{43}	C_{53}	C_{63}
C_{02}	C_{12}	C_{22}	C_{32}	C_{42}	C_{52}	C_{62}
C_{01}	C_{11}	C_{21}	C_{31}	C_{41}	C_{51}	C_{61}
C_{00}	C_{10}	C_{20}	C_{30}	C_{40}	C_{50}	C_{60}

*

0	-1	0
-1	4	-1
0	-1	0

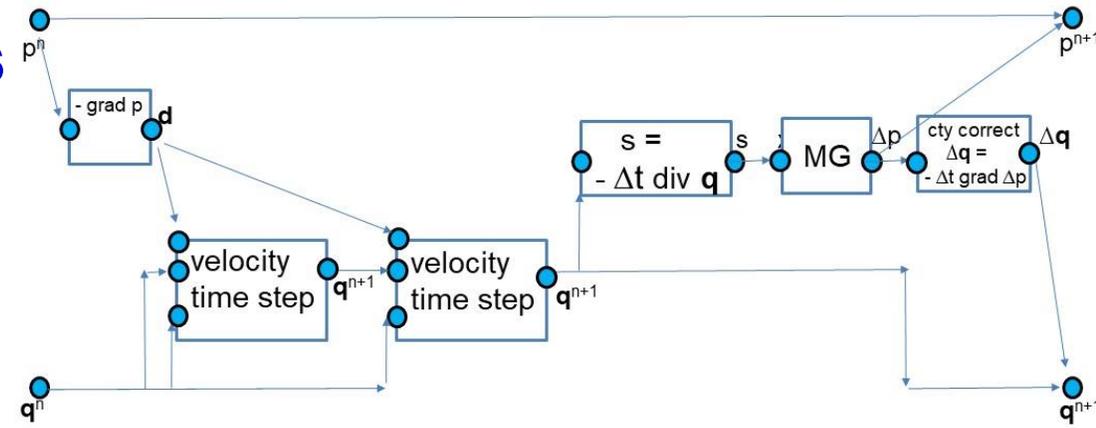
	Y_{33}		

$$Y_{33} = 4C_{33} - (C_{32} + C_{34} + C_{23} + C_{43})$$

Pixel values of a 2D image
Filter
Feature map

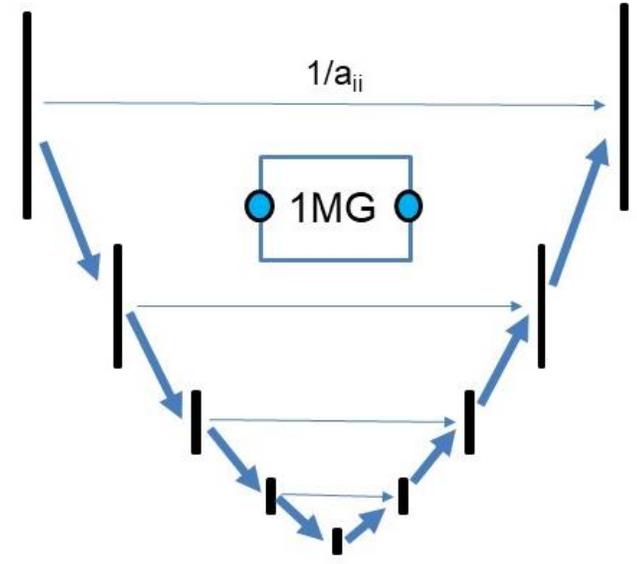
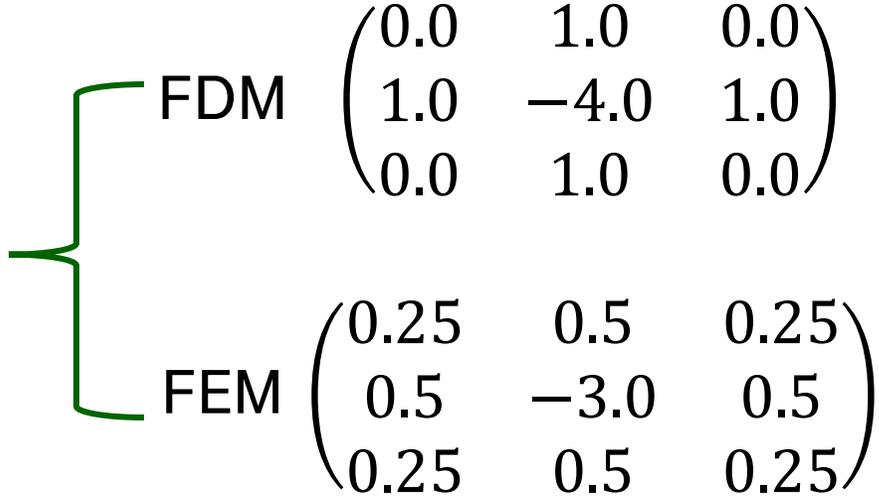
Methodology - Solving CFD with AI Libraries

- Two-step time scheme
- Finite differencing method (FDM)
- Finite element method (FEM)
- F-cycle multi-grid for solving pressure
- Projection method
- Petrov-Galerkin stabilisation



Pressure-velocity coupling

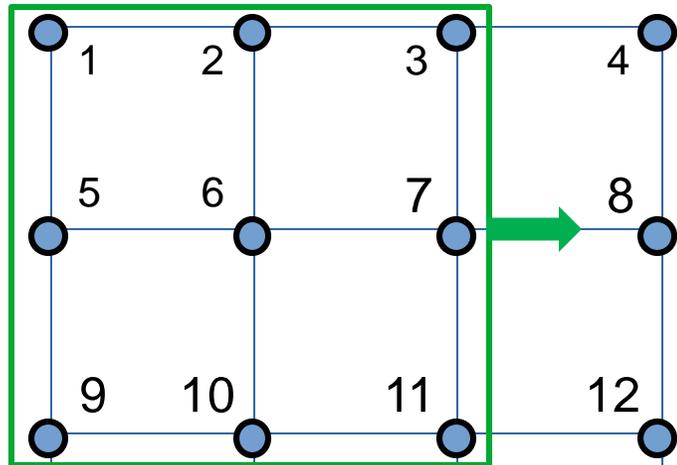
$\nabla^2 \phi$ → Central differencing



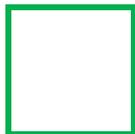
Multigrid with U-net structure

Methodology - example of solving PDEs using AI libraries

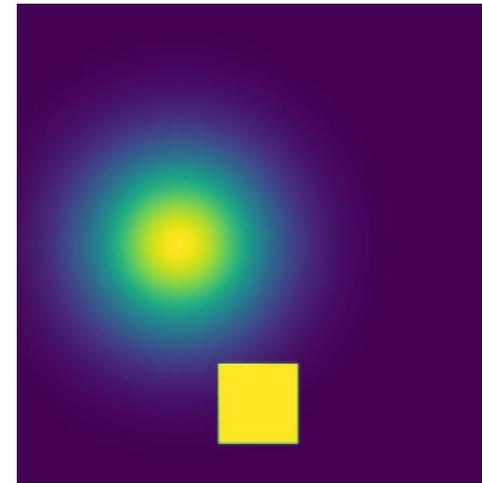
$$\frac{\partial T}{\partial t} + u \frac{\partial T}{\partial x} + v \frac{\partial T}{\partial y} - \nu \nabla^2 T = s$$



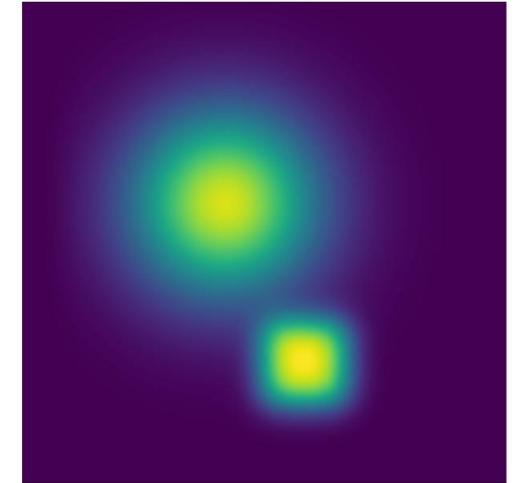
Element node



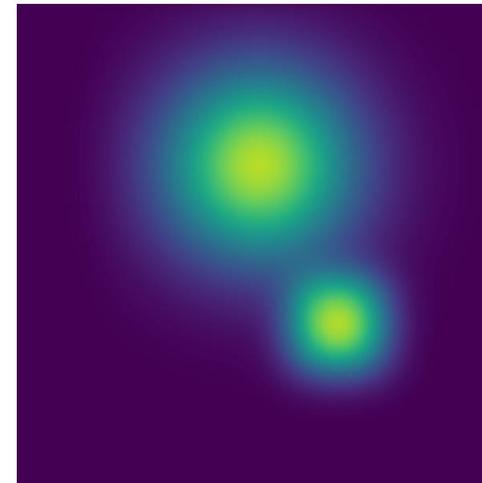
3 x 3 convolutional filter



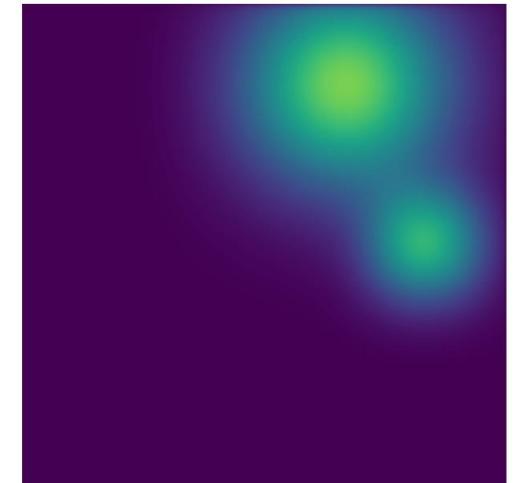
Initial condition



200 timesteps



400 timesteps



600 timesteps

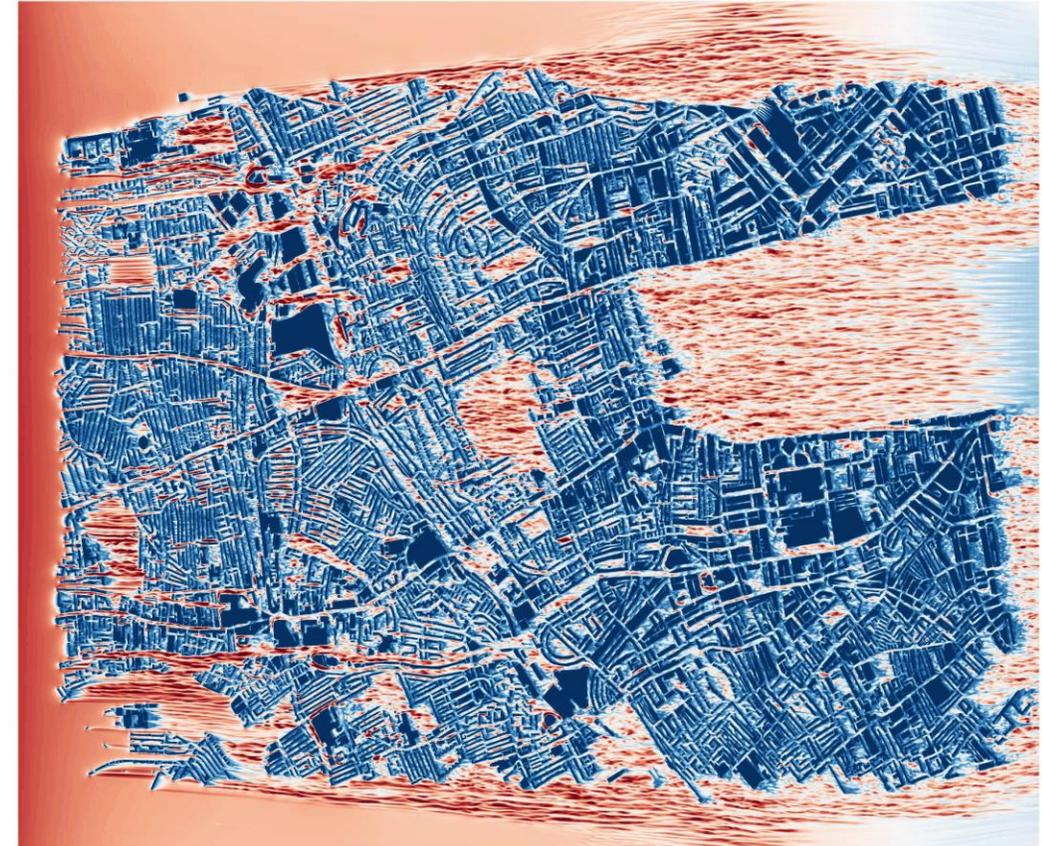
Airflow modelling using AI4PDEs: South Kensington area

$$\frac{\partial q}{\partial t} + u \frac{\partial q}{\partial x} + v \frac{\partial q}{\partial y} + \sigma q - \nu \nabla \cdot \nabla q = -\nabla p \quad \nabla \cdot q = 0$$

- 3D South Kensington area (5km x 4km)
- One-hour computational time \rightarrow 5 hours
- Uniform inflow speed (from left to right) – 1 m/s
- 2 Billion nodes – 4 A100 GPUs



Schematic diagram of the area



Airflow speed (m/s)

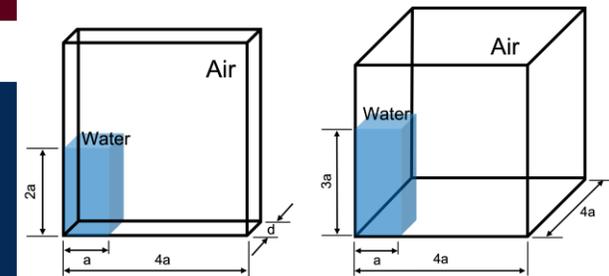
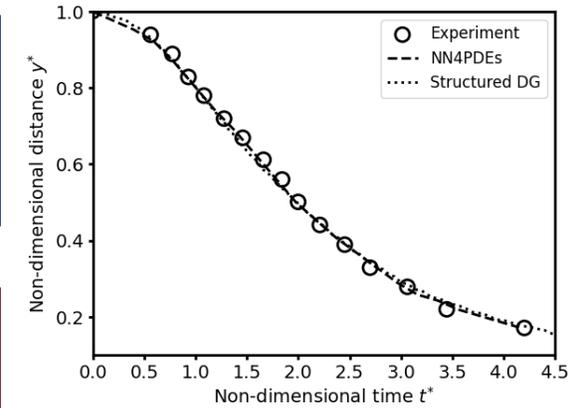
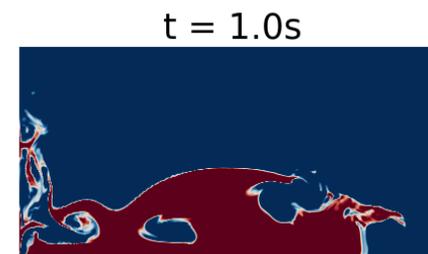
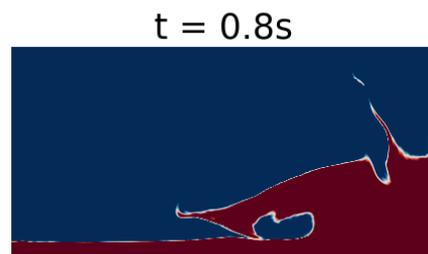
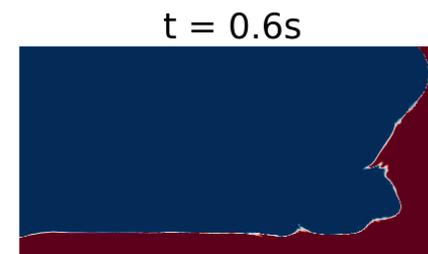
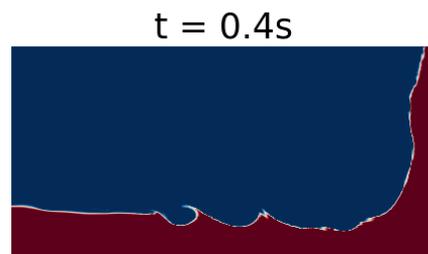
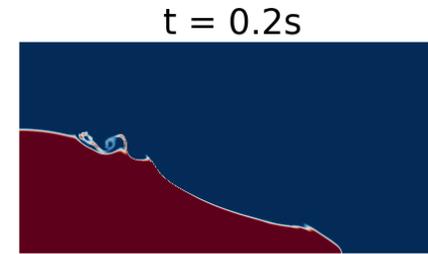
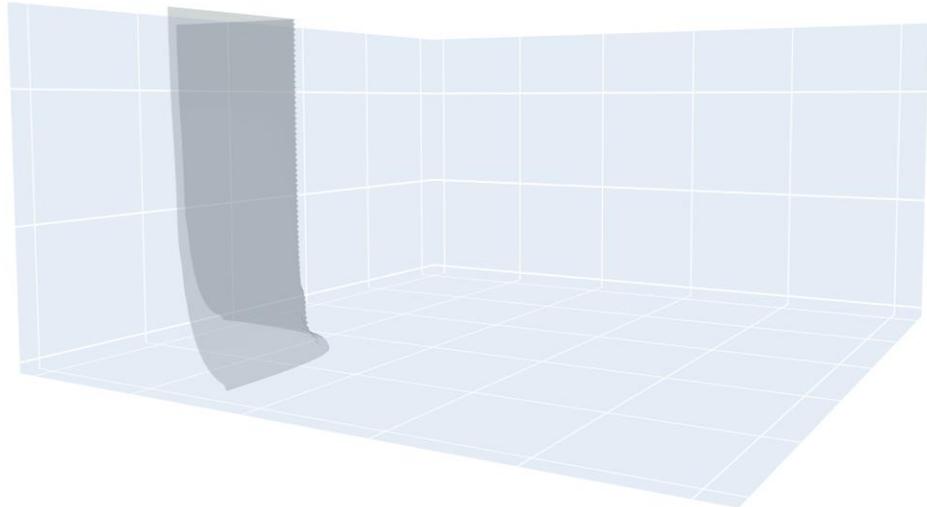
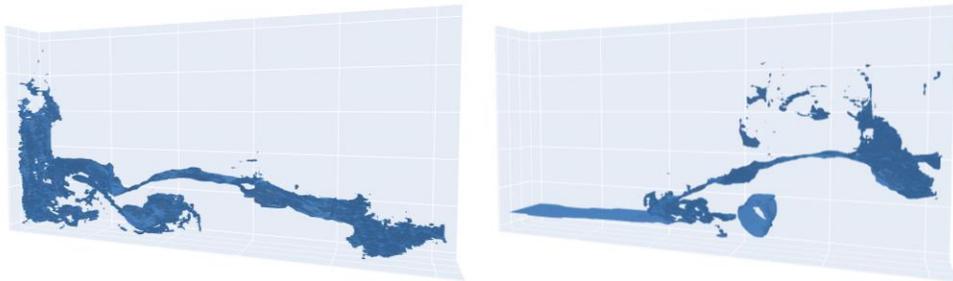
Multiphase flow using AI4PDEs : Collapsing water column

- Cubic domain size: 0.5 (m) x 0.5 (m) x 0.5 (m)
- Grid point: 512 x 512 x 512 (0.256 billion nodes)
- One single GPU

$$\rho \left(\frac{\partial q}{\partial t} + q \cdot \nabla q \right) + \sigma q - \nabla \cdot (\mu \nabla q) = -\nabla p + s_q + s_t$$

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho q) = 0$$

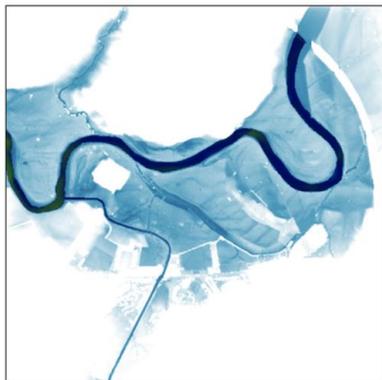
$$\frac{\partial C}{\partial t} + q \cdot \nabla C = 0$$



Multiphase flow using AI4PDEs : Carlisle 2005 flooding

3D flooding using AI4Multiphase and comparison with 2D flooding model

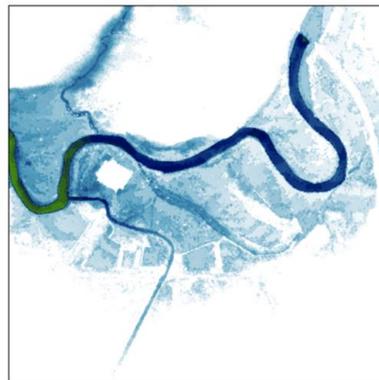
Water depth from 0 to 10 hours



AI4SWE - 951×611

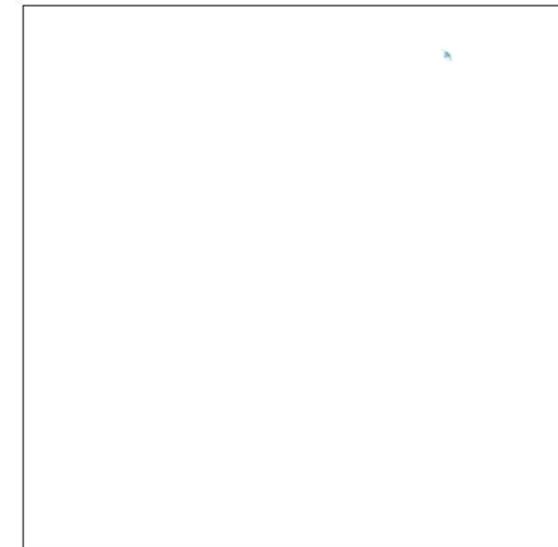


AI4Multi - $512 \times 512 \times 128$



AI4Multi - $512 \times 512 \times 256$

Spatial variation of water depth in the flooded area after 10 hours as predict

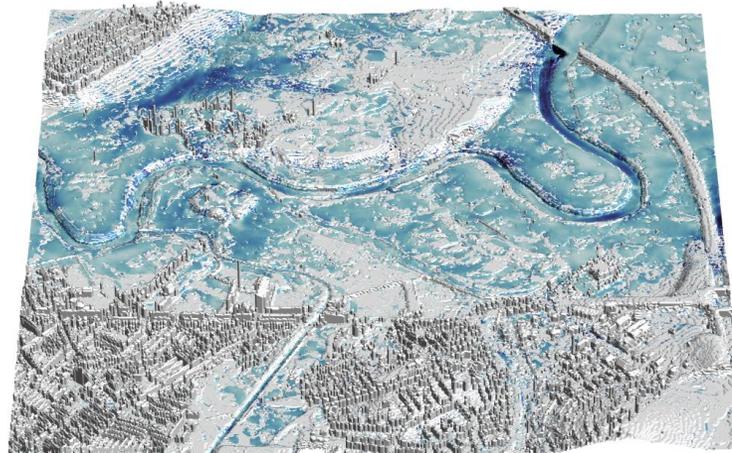


Google Map

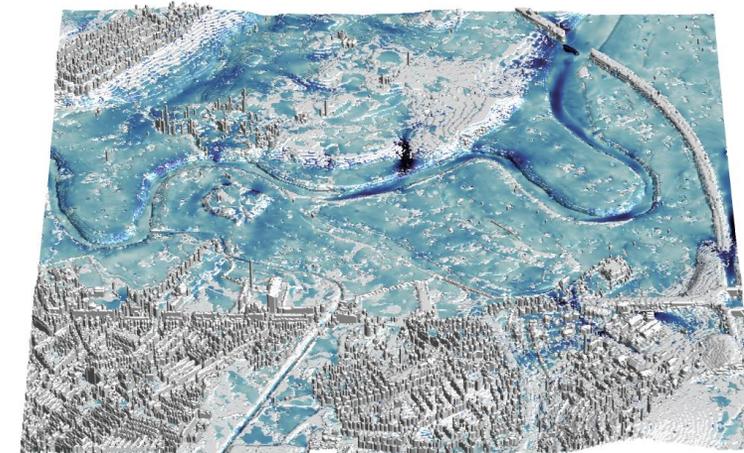


Iso-surface colored by water speed (m/s) at two different time levels

T1



T2

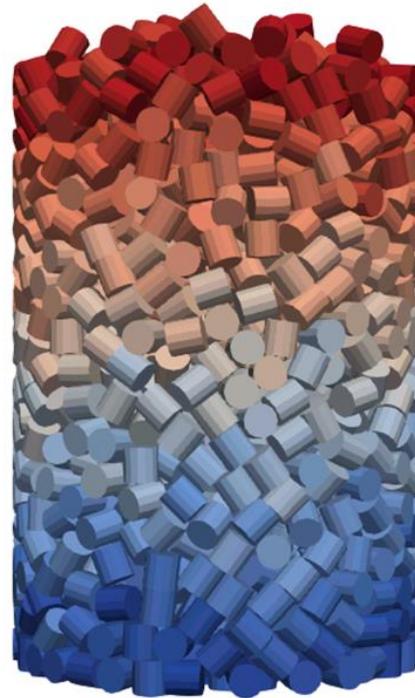


Multiphase flow using AI4PDEs : porous media flow

- Domain size: 0.05 (m) x 0.05 (m) x 0.05 (m)
- Grid spacing: 0.1mm x 0.1mm x 0.1mm
- Number of pellets: ~2000
- Application: CO2 storage
- Surface tension model
- Pressure drop comparing with Ergun equations

Two scenarios:

- ❖ Air is injected from bottom to top (single-phase)
- ❖ Air is injected into water from bottom to top (multi-phase)



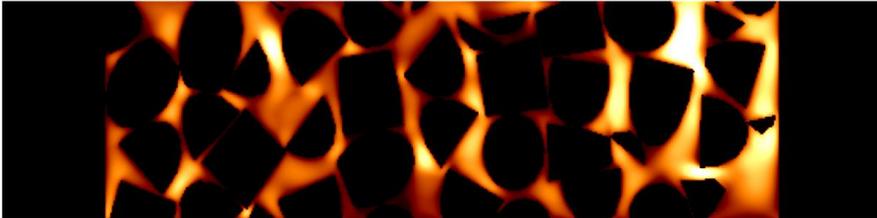
Multiphase flow using AI4PDEs : porous media flow

Flow speed (m/s) in the tank – single phase flows

Cutting plane at $x=1.0R$



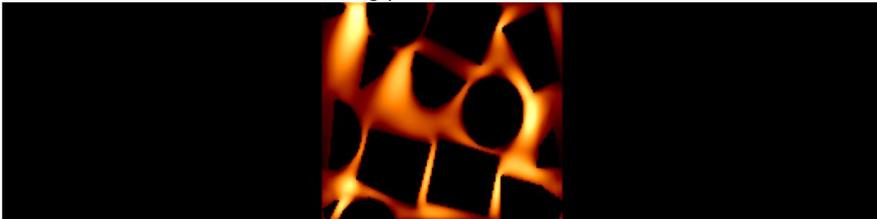
Cutting plane at $x=0.5R$



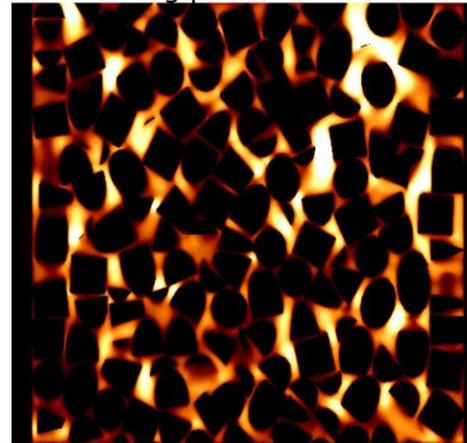
Cutting plane at $x=0.25R$



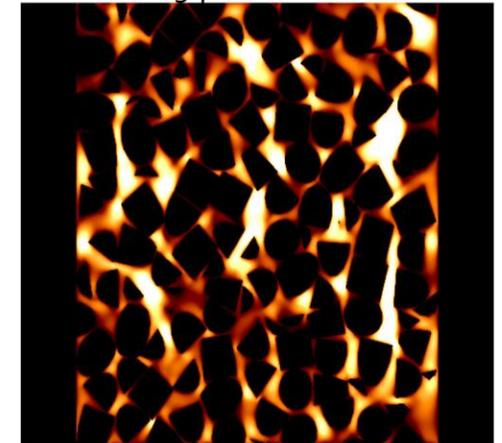
Cutting plane at $x=0.125R$



Cutting plane at $x=1.0R$



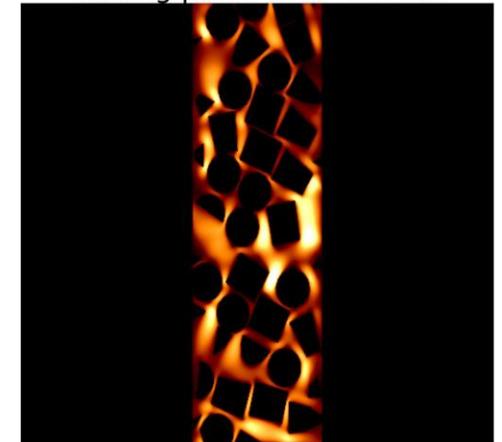
Cutting plane at $x=0.5R$



Cutting plane at $x=0.25R$



Cutting plane at $x=0.125R$



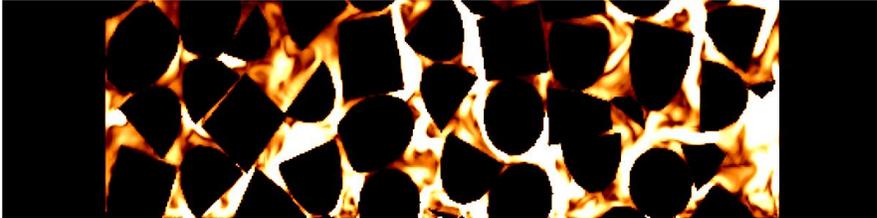
Multiphase flow using AI4PDEs : porous media flow

Flow speed (m/s) in the tank – multi phase flows

Cutting plane at $x=1.0R$



Cutting plane at $x=0.5R$



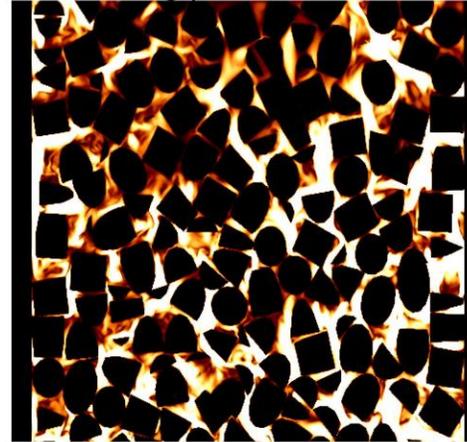
Cutting plane at $x=0.25R$



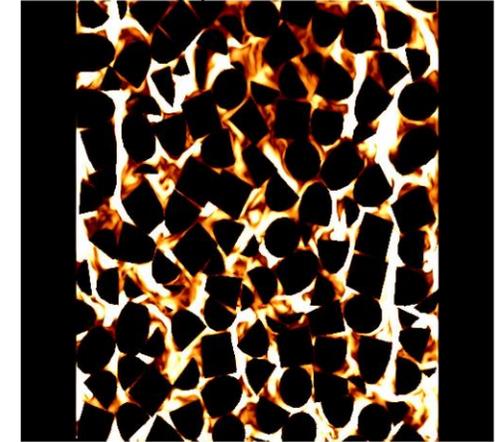
Cutting plane at $x=0.125R$



Cutting plane at $x=1.0R$



Cutting plane at $x=0.5R$



Cutting plane at $x=0.25R$



Cutting plane at $x=0.125R$



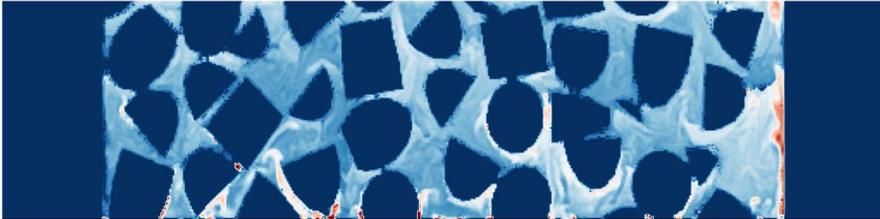
Multiphase flow using AI4PDEs : porous media flow

Indicator field (0 to 1) in the tank - multi phase flow

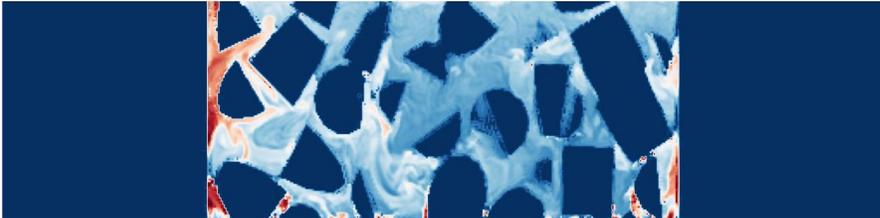
Cutting plane at $x=1.0R$



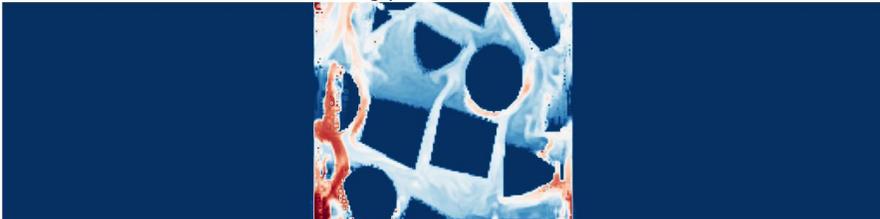
Cutting plane at $x=0.5R$



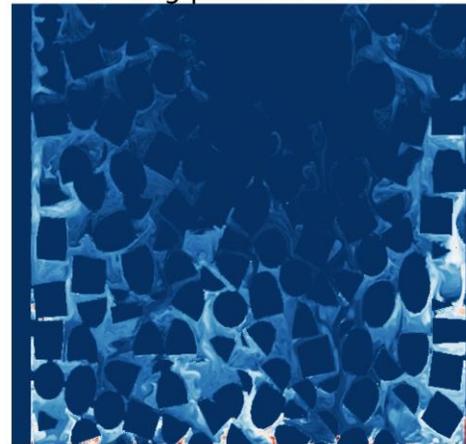
Cutting plane at $x=0.25R$



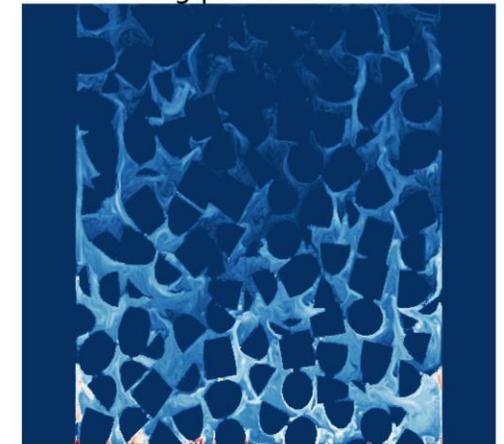
Cutting plane at $x=0.125R$



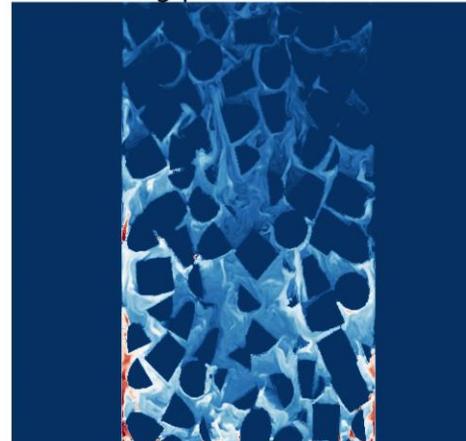
Cutting plane at $x=1.0R$



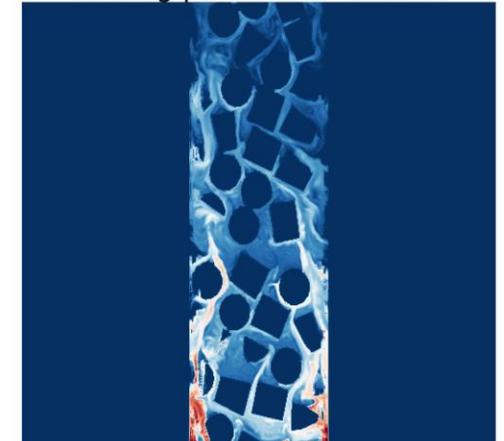
Cutting plane at $x=0.5R$



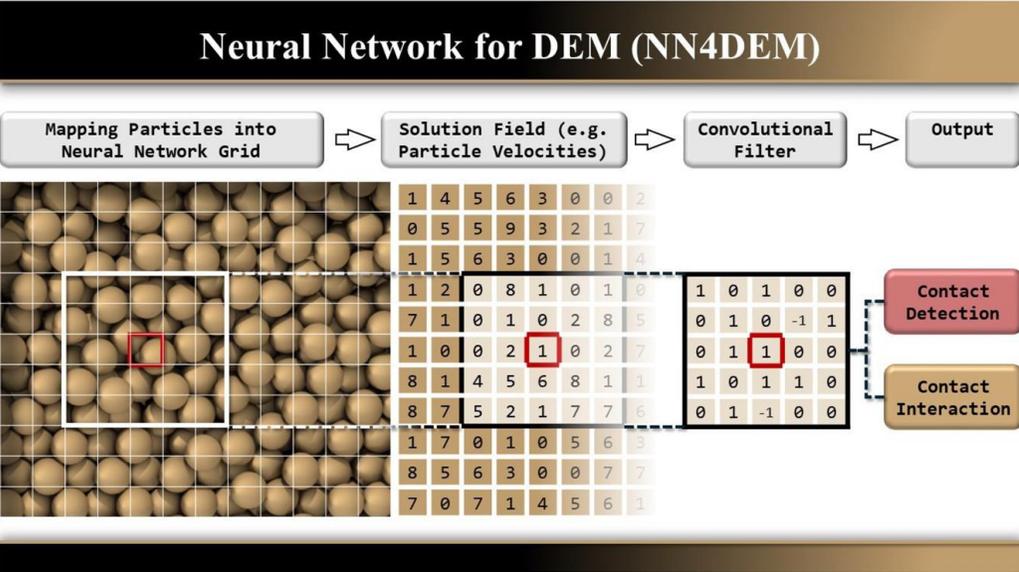
Cutting plane at $x=0.25R$



Cutting plane at $x=0.125R$



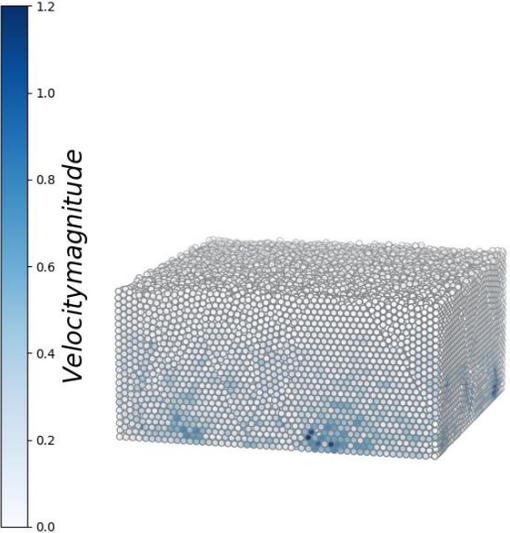
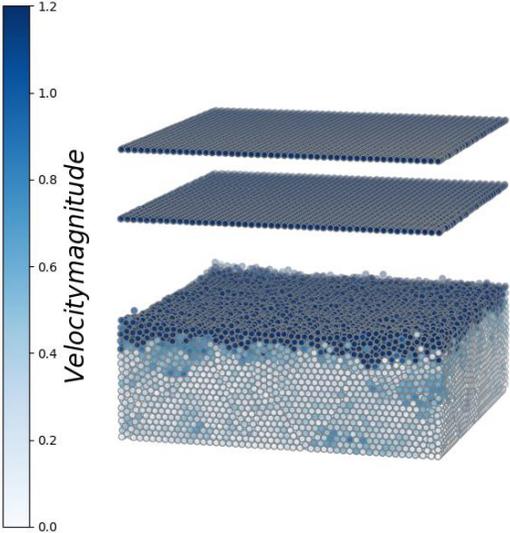
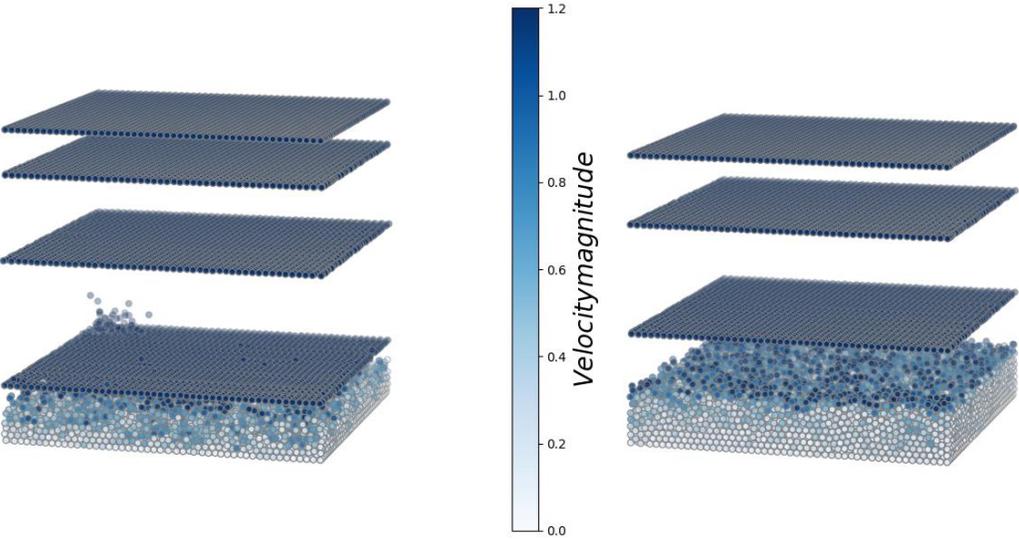
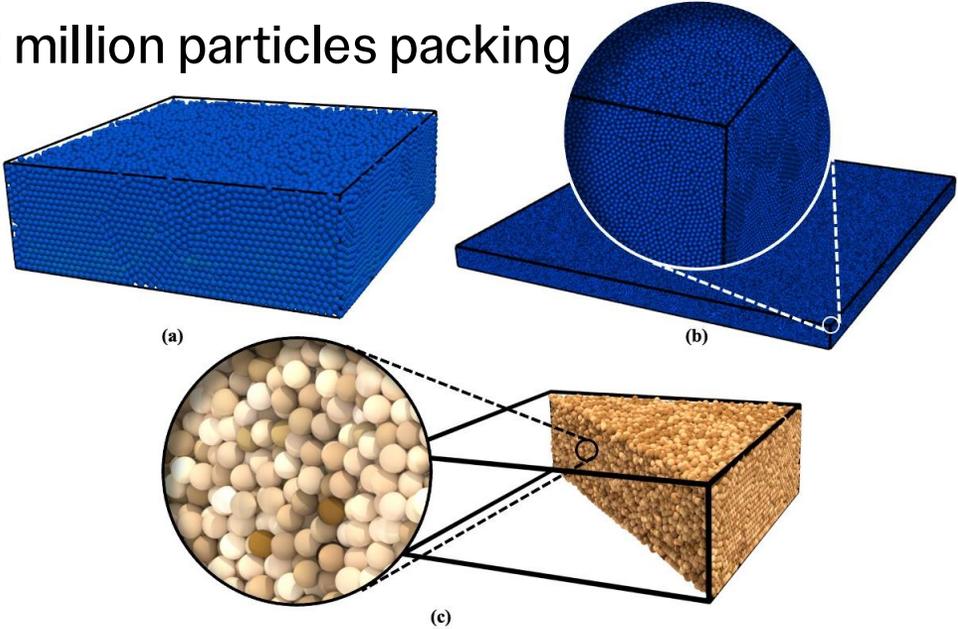
Example of particle packing using AI4particle/systems



32 million particles packing

$$\vec{v} = \frac{\vec{F}}{m} + \vec{g},$$

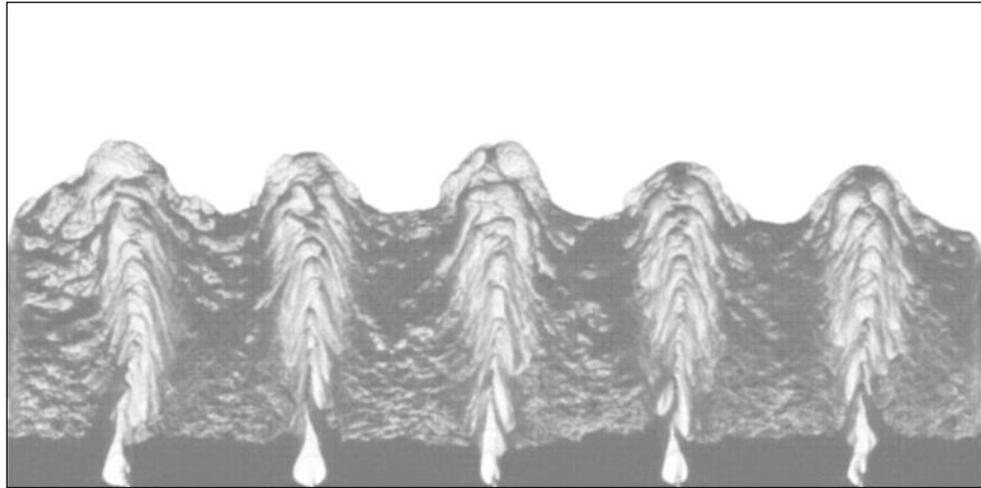
$$\vec{\epsilon} = \frac{\vec{T}}{I}.$$



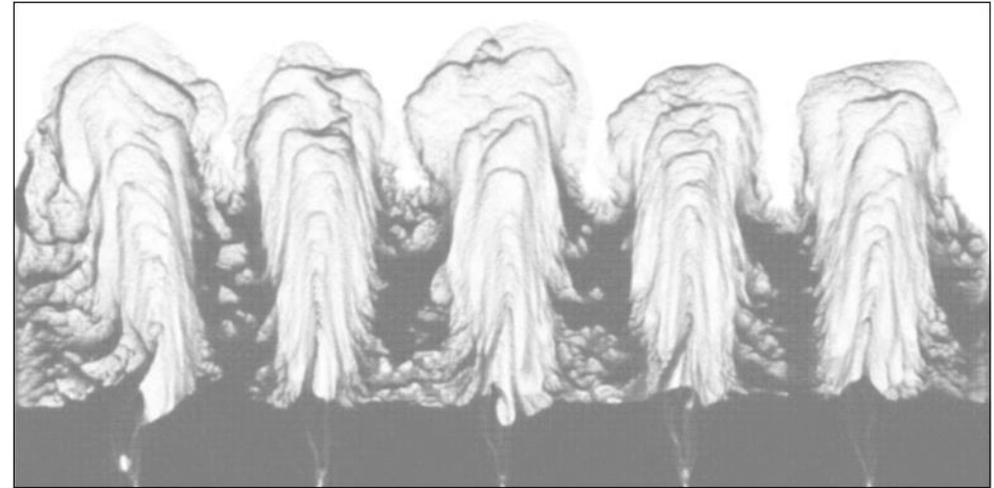
Fluidised bed flow modelling – AI4Systems (AI4PDEs + DEM)

20M particles in 2D – running on one single GPU

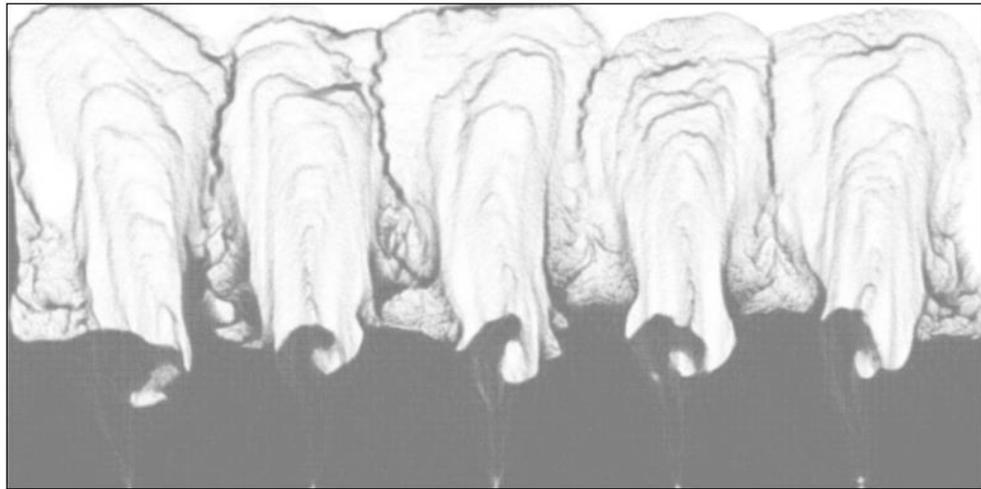
T1



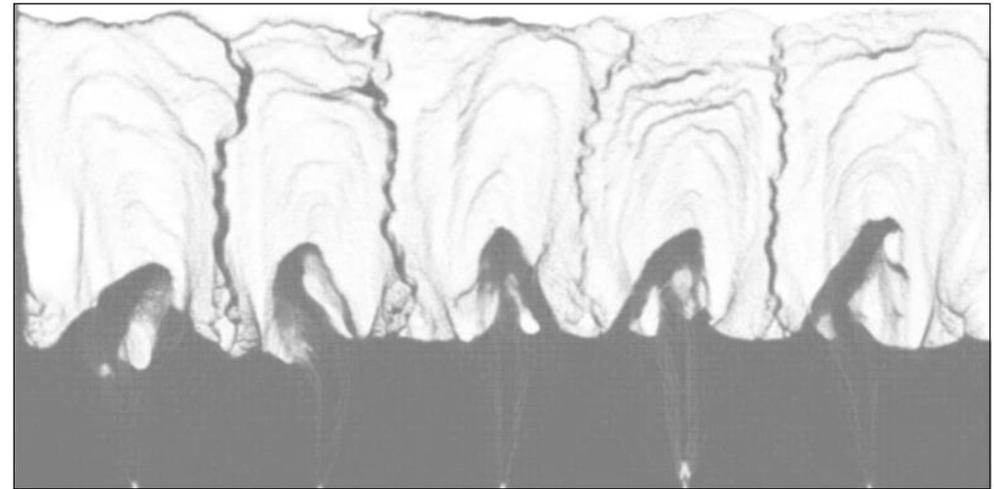
T2



T3



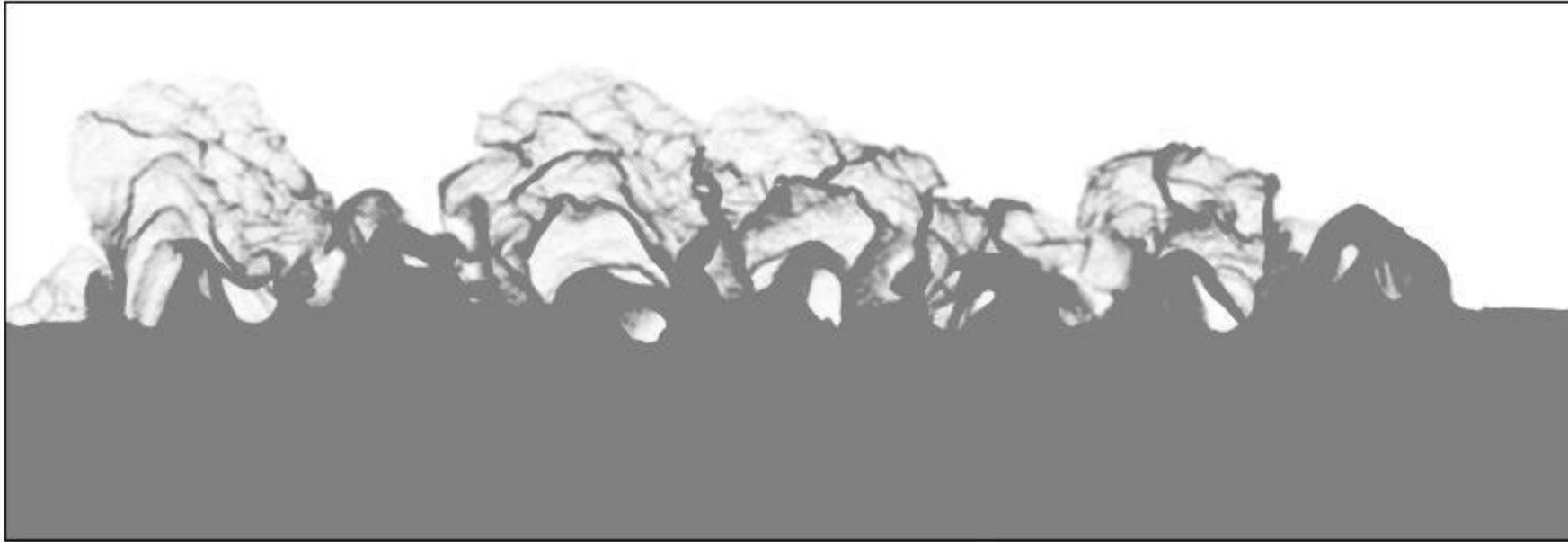
T4



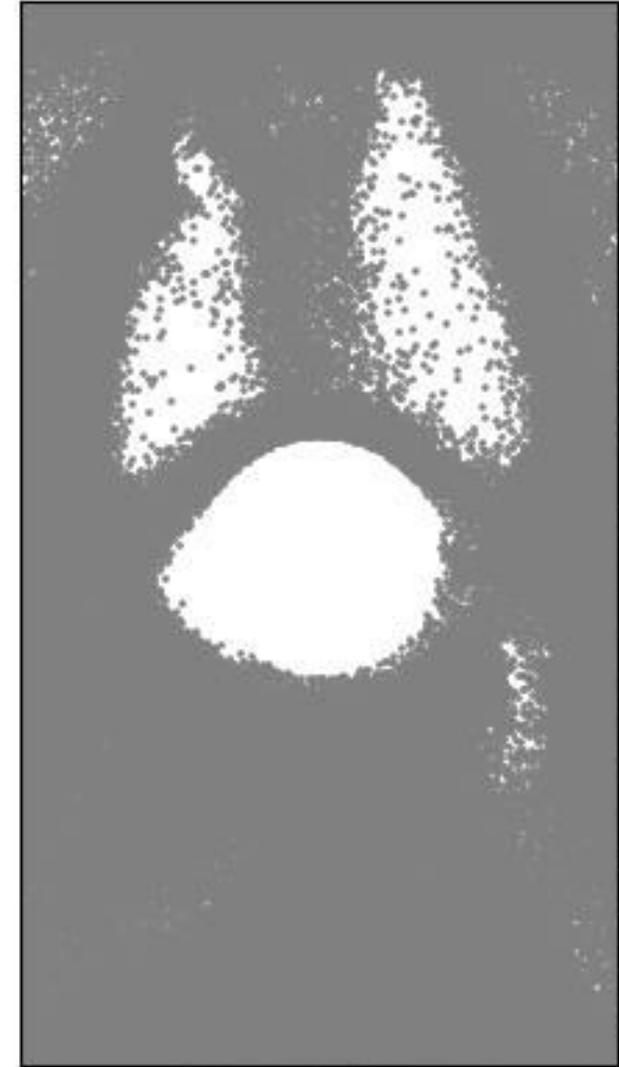
Example of 2D fluidised bed coupling NN4Particle/System with fluid solver

- CFD-DEM simulation (NN4PDEs + NN4Particles)
- Molecular modelling application

Fluidised bed with an obstacle



40M particles in 2D – running on one single GPU



Summary and conclusion (NN4PDEs)

- A new numerical solver using AI libraries is proposed, namely NN4PDEs or AI4PDEs. (NVIDIA Modulus)
- The new approach has been validated to predict physical mechanics.
- This approach has been demonstrated on a number of benchmark and realistic problems.

Single-phase flows, multi-phase flows, solid mechanics

- We found the advantage of this approach.

Flexible → CPUs, GPUs and new AI computers

Rapid Computing → digital twins, sensitivity and optimization

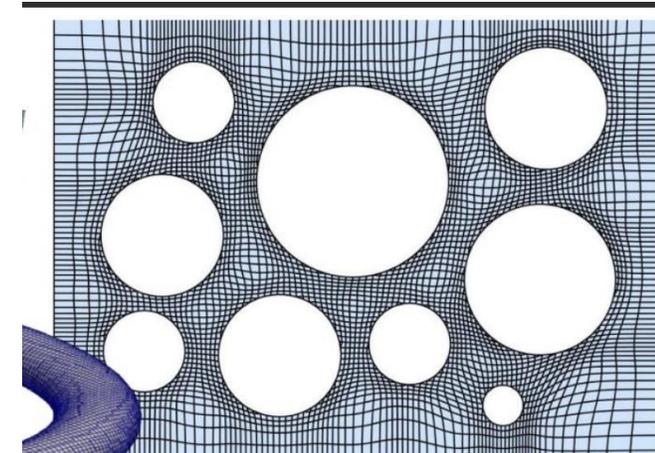
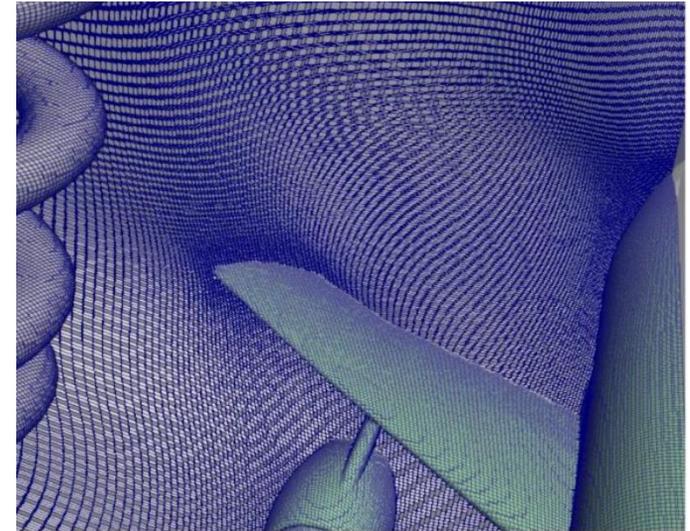
Portable → easy to maintain and develop further

- Further work

Multi-physics solver (molecular dynamics, reservoir system)

Exascale computing (NVIDIA)

Complicated mesh system (distorted and unstructured mesh)



References (NN4PDEs)

- Phillips TRF, Heaney CE, Chen B, Buchan AG, Pain CC. Solving the discretised neutron diffusion equations using neural networks. *International Journal for Numerical Methods in Engineering*. (2023) Nov 15;124(21):4659-86.
- Phillips TRF, Heaney CE, Chen B, Buchan AG, Pain CC. Solving the Discretised Boltzmann Transport Equations using Neural Networks: Applications in Neutron Transport. arXiv preprint arXiv:2301.09991. (2023).
- Chen B, Heaney CE, Pain CC. Using AI libraries for Incompressible Computational Fluid Dynamics. arXiv preprint arXiv:2402.17913. (2024).
- Chen B, Heaney CE, Gomes JL, Matar OK, Pain CC. Solving the Discretised Multiphase Flow Equations with Interface Capturing on Structured Grids Using Machine Learning Libraries. *Computer Methods in Applied Mechanics and Engineering*. (2024) 426:116974.
- Chen B, Nadimy A, Heaney CE, Sharifian MK, Estrem LV, Nicotina L, Hilberts A, Pain CC. Solving the Discretised Shallow Water Equations Using Neural Networks. *Advances in Water Resource*. (2024)
- Naderi S, Chen B, Yang T, Xiang J, Heaney CE, Latham JP, Wang Y, Pain CC. A discrete element solution method embedded within a Neural Network. *Powder Technology*. (2024) 448:120258.
- Li, Lin., Xiang, J., Chen, B., Heaney, C E., Dargaville, S., Christopher C. Pain. Implementing the Discontinuous-Galerkin Finite Element Method using Graph Neural Networks. *Neural Networks*. (2024)
- A. Nadimy, B. Chen, Z. Chen, C. E. Heaney, C. C. Pain Solving the Discretised Shallow Water Equations Using Non-Uniform Grids and Machine-Learning Libraries, SSRN preprint. (2025)

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Thank you