AI for respiratory diagnosis

CHIST-ERA MUCCA WP5

MedLea

www.medlea-tech.com

MUCCA General Meeting - Liverpool 21/09/2023

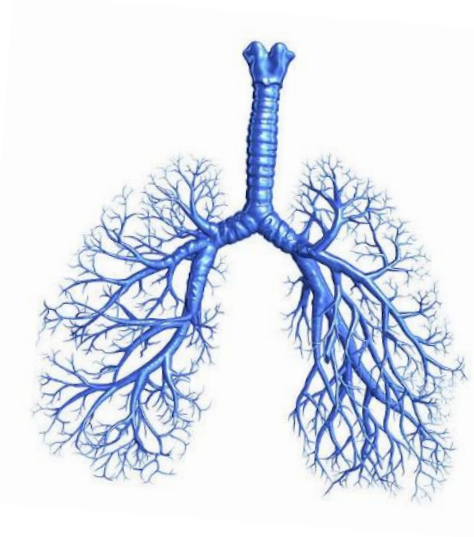
Context

Lungs diseases:

Respiratory diseases hit 10% of population

They are degenerative, largely misdiagnosed or undiagnosed (~30%)

Early diagnosis and prognosis case save lives



Anatomy:

Airways (trachea, bronchi, bronchioles) with 22 generations of bifurcations (2^{22} branches)

Airways are embedded in a tissue (parenchyma) that is filled with alveoli

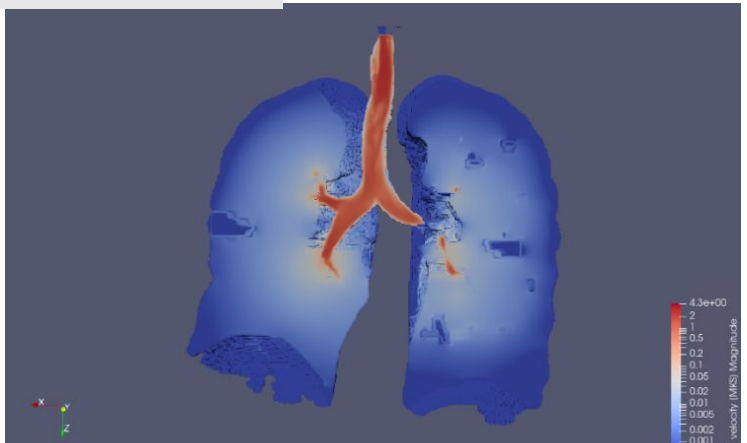
Made of compartments/regions (lobes)

Lungs function like a oscillatory pump and internal resistances make the whole difference

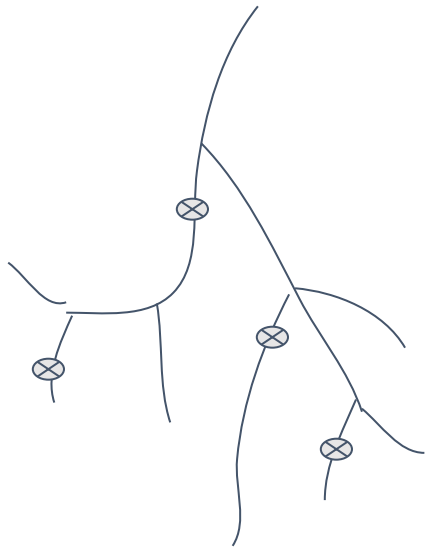
Diagnostic tools:

Morphological: Imaging (CT scans and Rx)

Functional: Spirometry



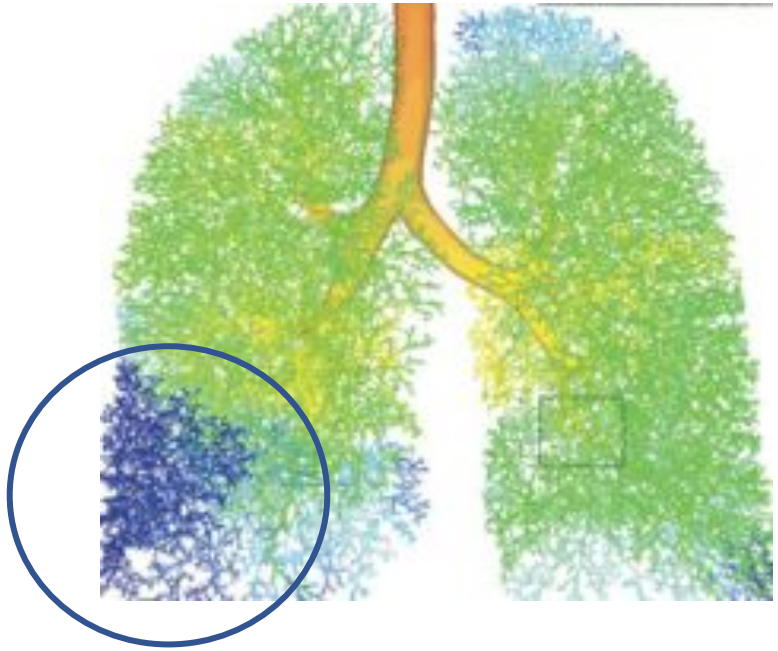
Systemic failures

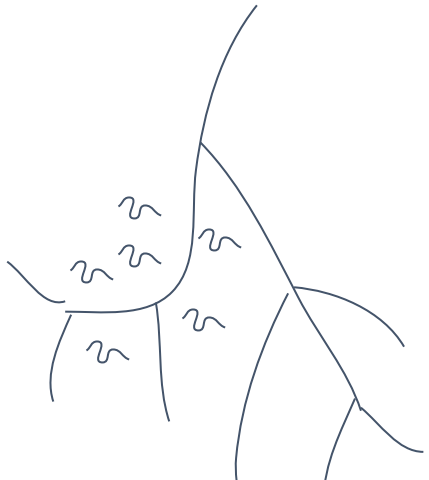


Airways:

- *Focal or multifocal blockages*
- *Effusions / edema / mucus*
- *Inflammations*

Asthma, COPD, BOS, etc.





Fibrosis:

- *Low compliance*
- *Gas diffusion / air trapping*
- *Inflammations back to airways*

pneumonia, covid, IPF, RAS, etc.

From dyspnea to death

Goals

- *Develop an integrated approach for 3D reconstruction from medical images to perform simulation & experiments on respiratory tracts (airways)*
- *Assess airflow and air+mucus dynamics in respiratory tracts: Newtonian and non-Newtonian rheology*
- *Validate simulation results versus idealized and real data from patients geometries*

Compare with experimental data from Bucharest

- *Reach a high level of automation to handle several geometries (patients)*
- *Feed large dataset to AI to reproduce flow patterns automatically and assess causal relations*

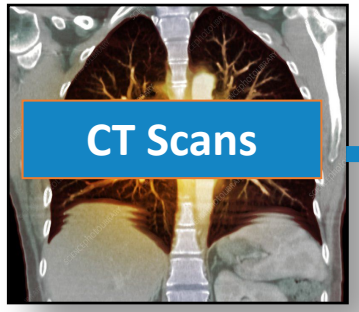
MedLea contribution:

- ***WeResp**: medical images reconstruction*
- ***Moebius**: multiphysics simulator in complex geometries*
- ***AI** for functional analysis*

Description	Year 1				Year2				Year3			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
WP5 MED-2												
T 5.1 Reconstruction on tomographic scans												
T5.2 Experiments and validation on air-mucus in idealized geometries												
T5.3 Experiments and validation on air-mucus in respiratory geometries												
T5.4 Test of xAI on simulation results												

Roadmap

Purpose: xAI + high-performance simulation + experiments to diagnose the impact of mucus excess in patient-specific respiratory health with anatomies acquired from tomographic scans.



Physiological Model

Functional Biomechanics Benchmarks

Non-Linear Response

Idealized Geometries

Viscoelastic Rheology Model & Simulations

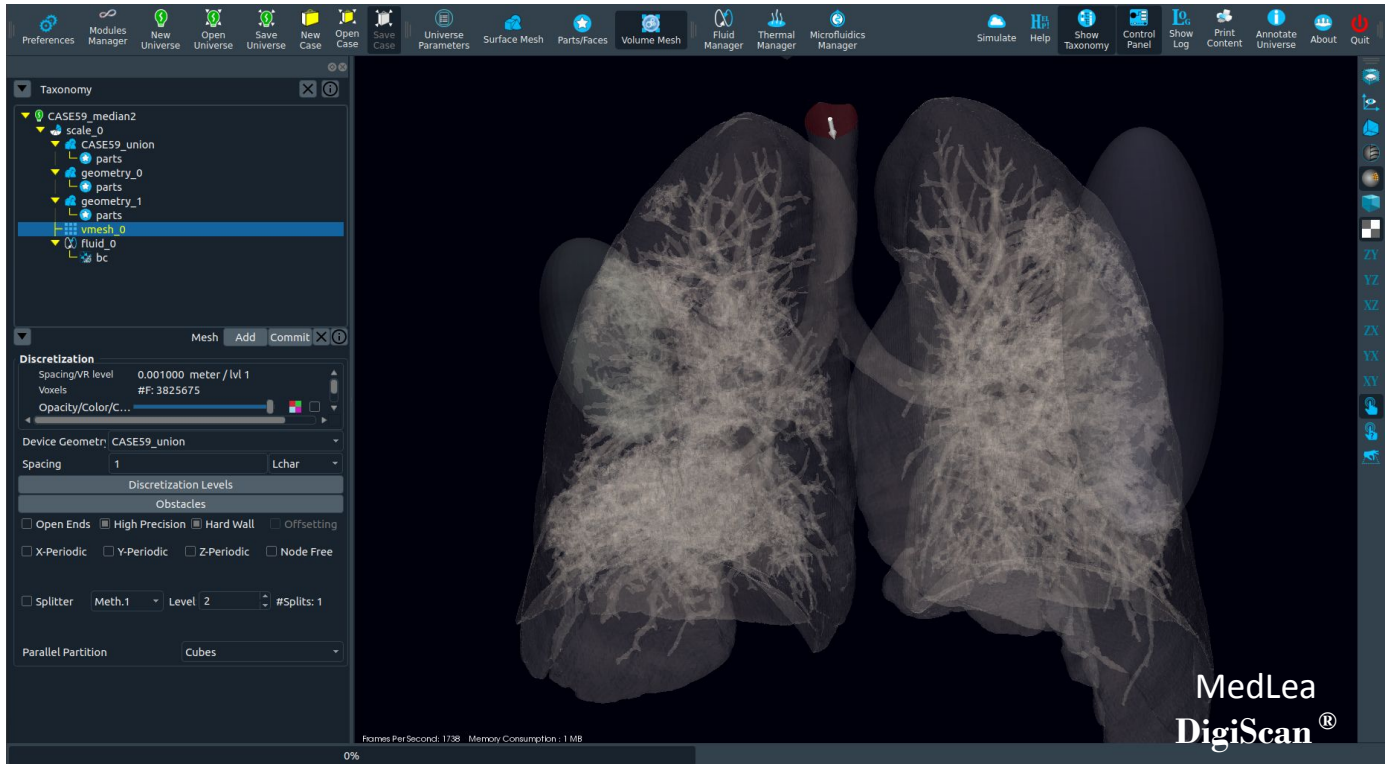
Reparametrization

xAI

Experiments from Bucharest

Yr1 ---------- Yr2 ---------- Yr3 ---------->

Reconstruction of radiological images

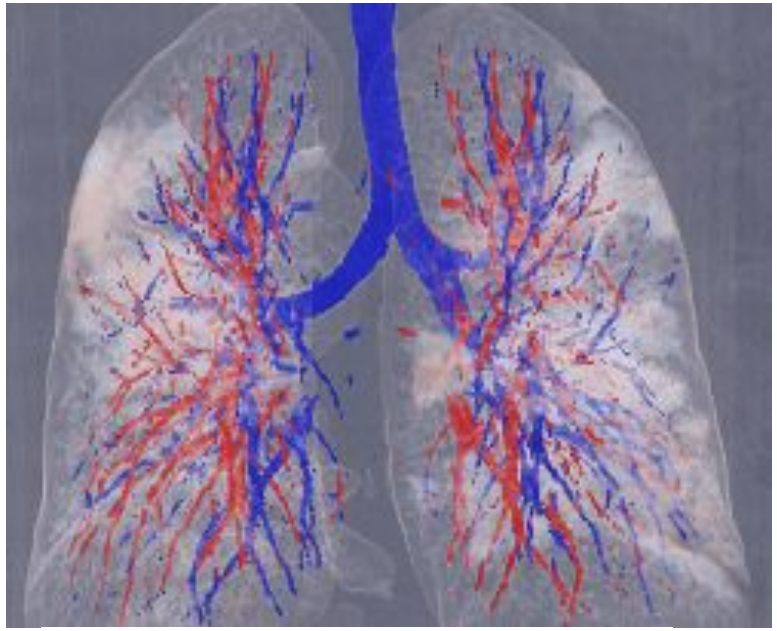


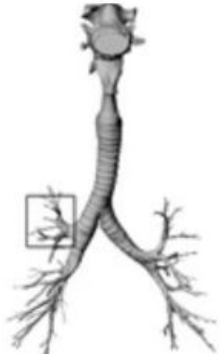
Reconstruct lung tracts automatically

Annotations and metrology

Optimized workflow

1. CT-derived airways. Focus on airways, not parenchyma
2. Reconstruct airways explicitly up to CT resolution (~1 mm)
3. Complement with synthetic airways obeying Murray's law over generations (self-similarity)





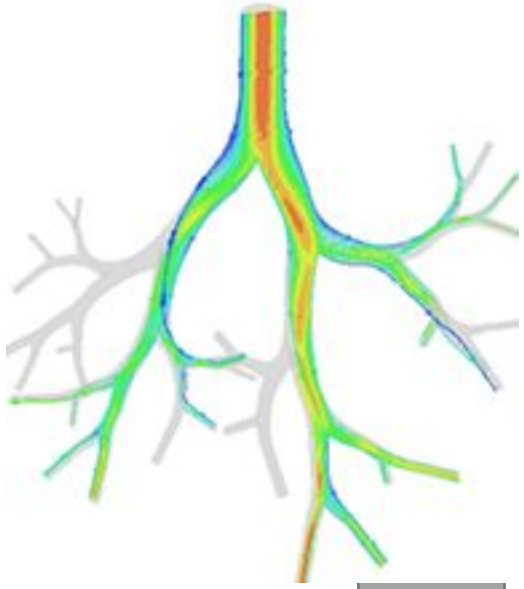
Predicting flows

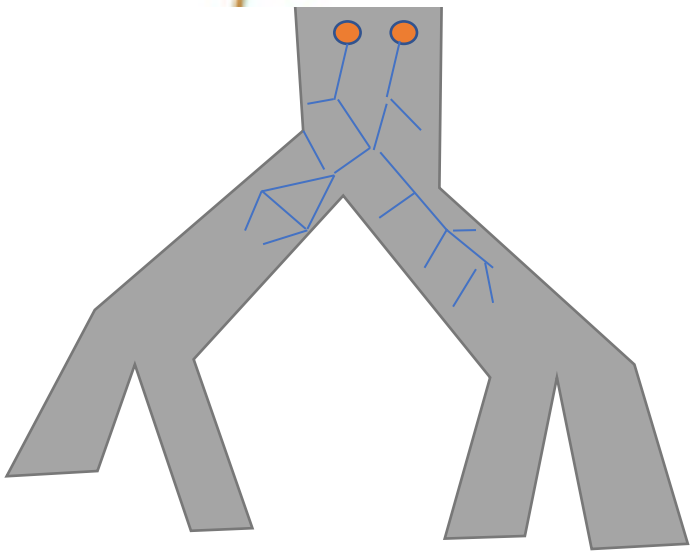
Goals

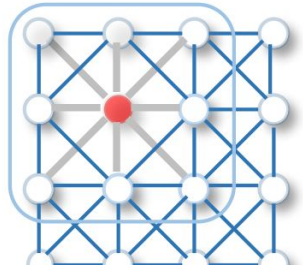
- predict flow distribution at variable Reynolds
- breakdown of 22 generations in bifurcating bricks (1 parent, 2 daughters)
- geometry: from dense to downsampled graphs
- the problem of equivariance (roto-translational symmetries SE3-group)
- Ensure vectors/tensors invariance (eg spherical harmonics basis set)
- Conservations (via Voronoi volumes)

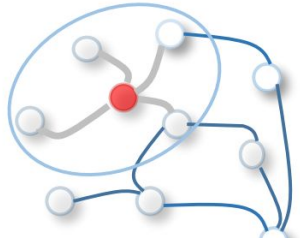
Features

- Flow velocity, pressure, stress tensor
- Minimum distance from walls (to highlight near-wall velocity gradients)
- Maximum inscribed sphere (compress geometrical information and Reynolds proxy)

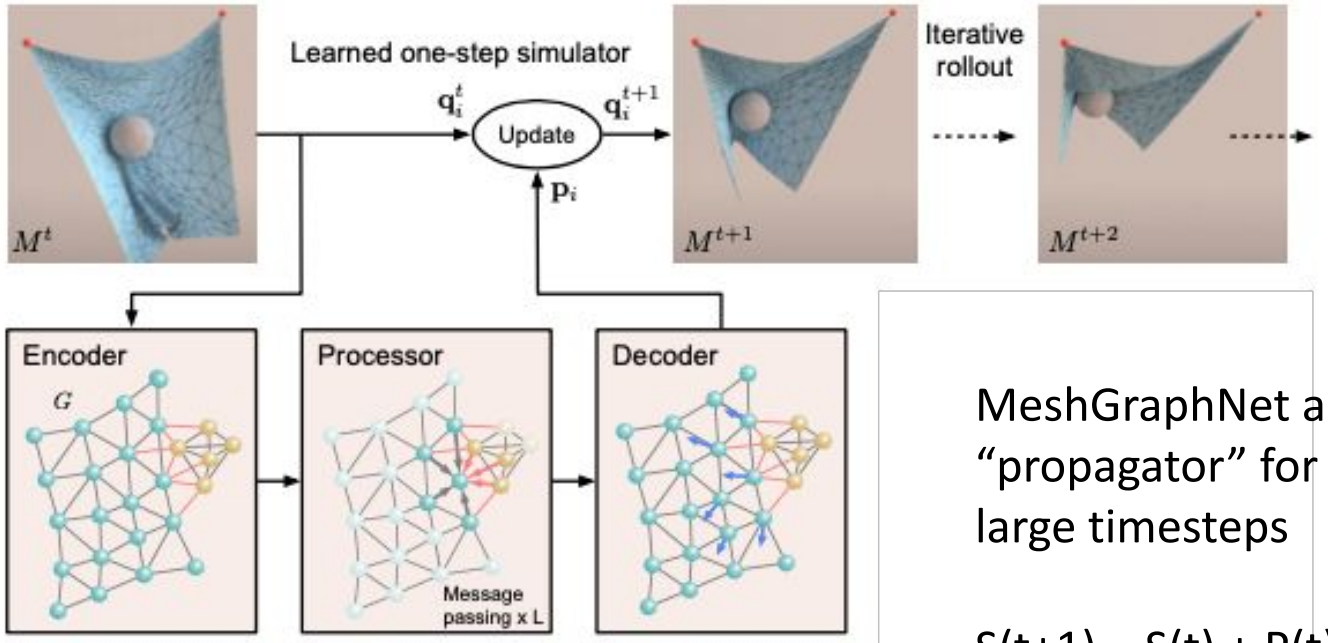








Propagative approach



MeshGraphNet as a "propagator" for large timesteps

S(t+1) = S(t) + P(t)

Pfaff et al. arXiv 2022

Generated a system of 3D synthetic pipes obeying Murray's self-similarity for lengths/calibers

Randomly chosen angles

Geometrical defects

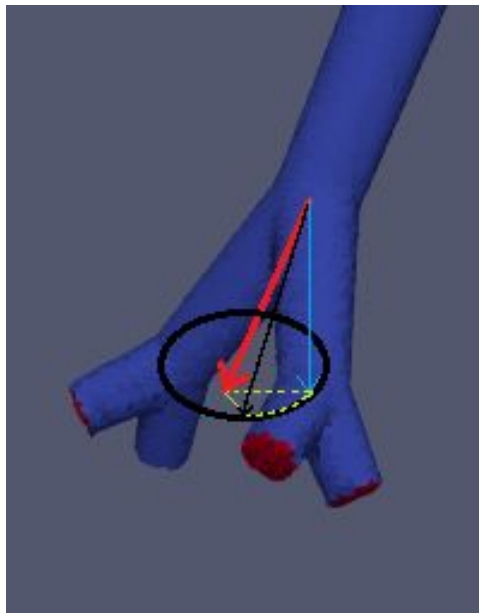
Model geometries

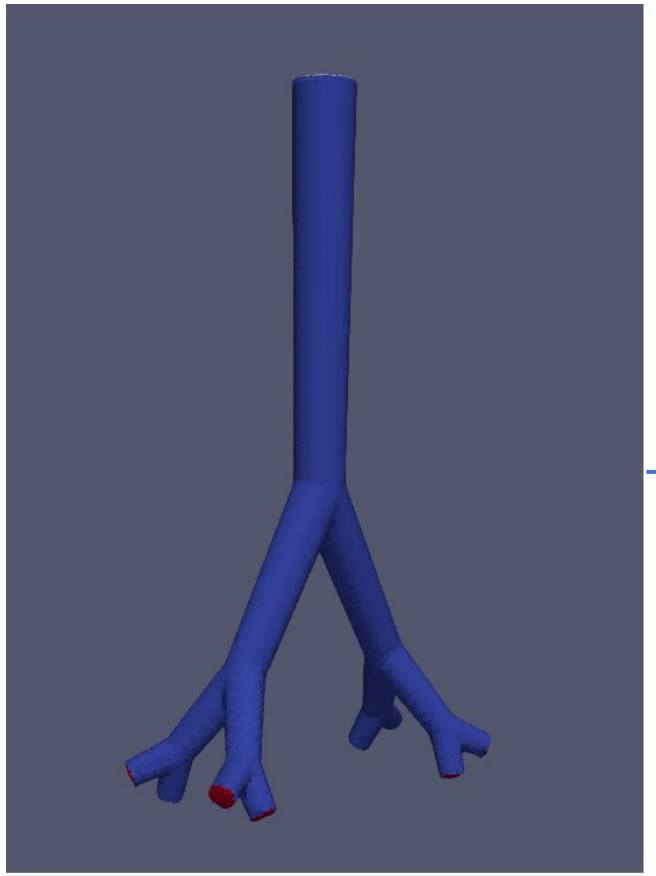
Different approach: develop an AI model able to describe air propagation, starting from simple geometries.

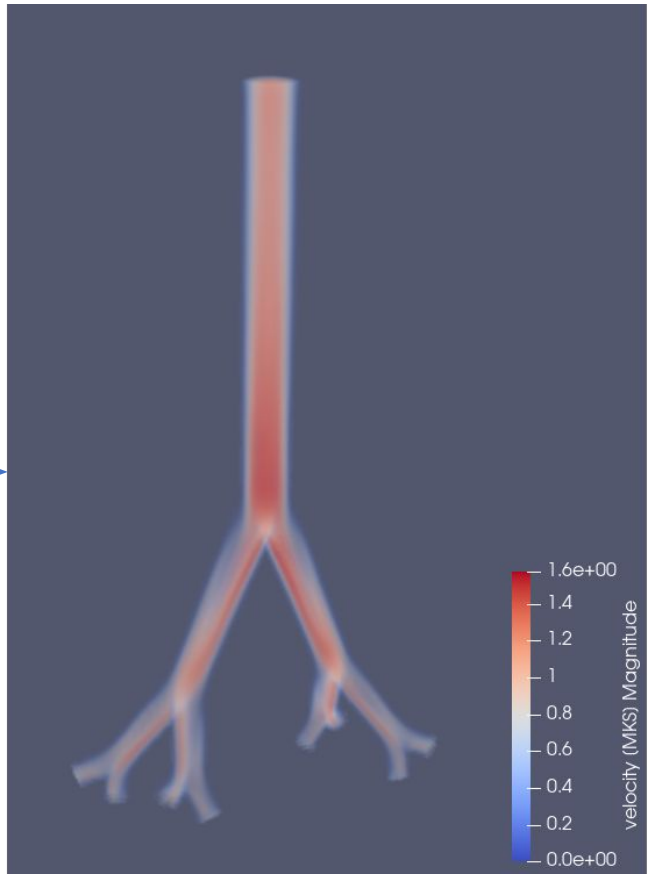
Then we can use a CFD solver on the idealized domain, producing large amounts of data

~100k voxel grids, delta_t ~10e-5 s

CFD simulation







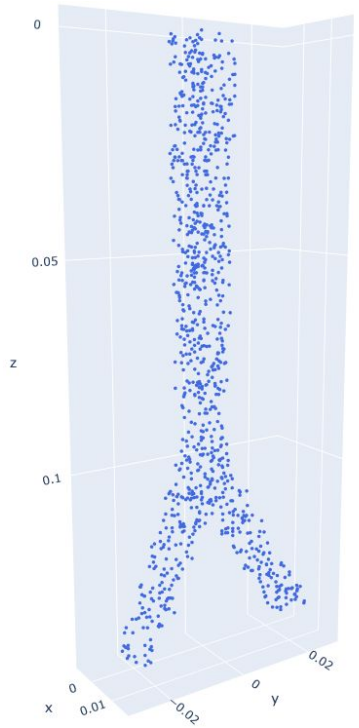
Data production

Several simulations are needed to train our model: **Coarse graining** both in space and time.

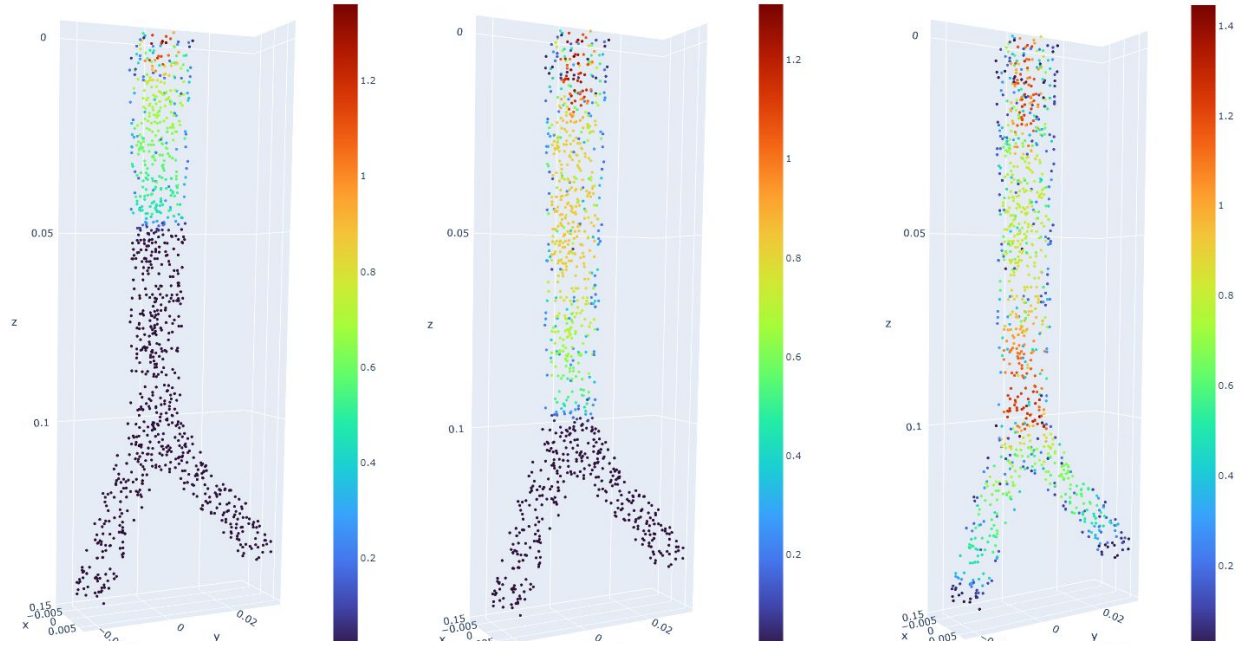
- Uniform random sampling of 1% of nodes
- We retained only one every 20 simulator steps

Information stored on nodes: spatial coordinates (fixed), pressure and velocity components

Extracted probes (point cloud)



Velocity field vs time

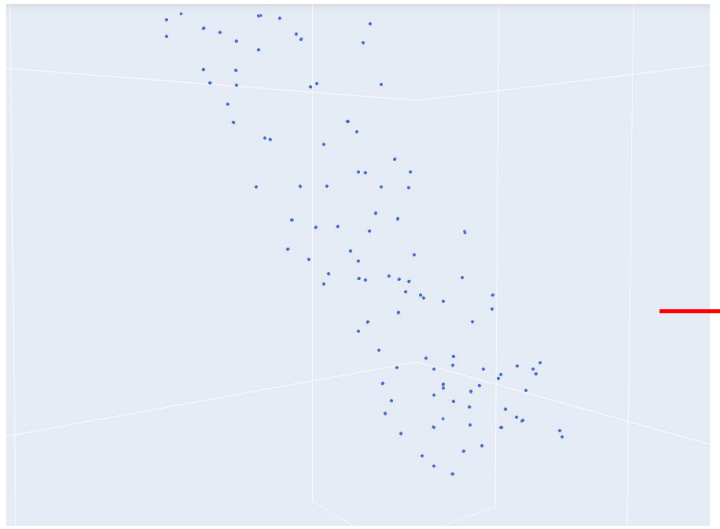


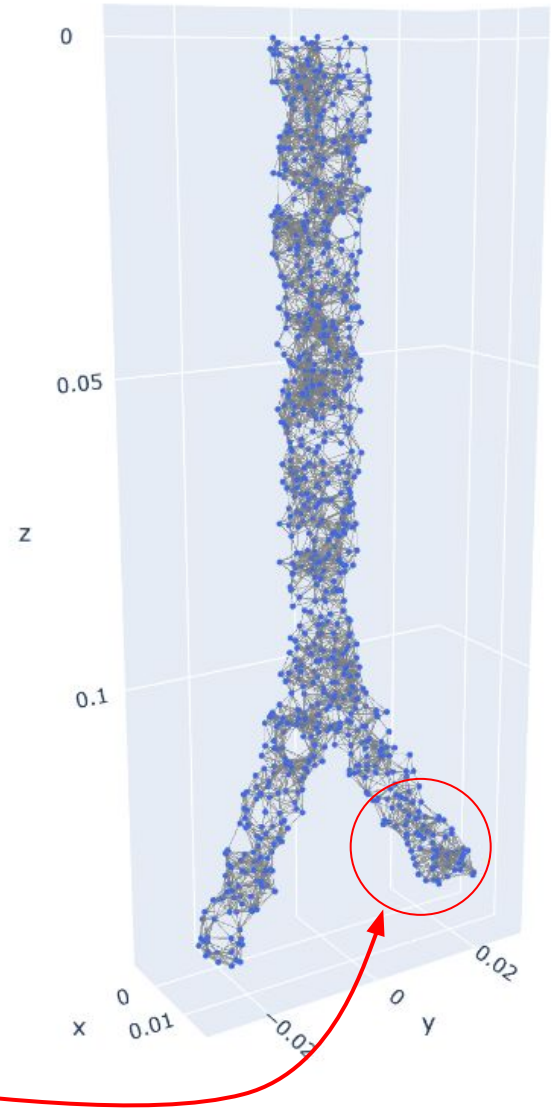
Data production

- Interaction among points modeled as a graph
- Connectivity is produced using a radius nearest neighbours (RNN) algorithm

Dataset production

- We produced 1000 simulations of 500 steps each.
- Every simulation has it own slightly different geometry and unique point cloud. All geometries have one bifurcation
- Every 100 simulations, the inlet velocity changes (+- 20%)





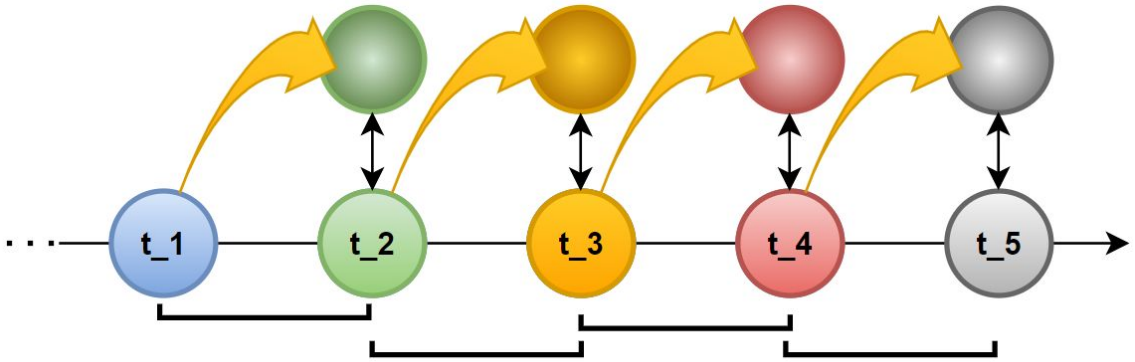
Task identification

One step propagator:

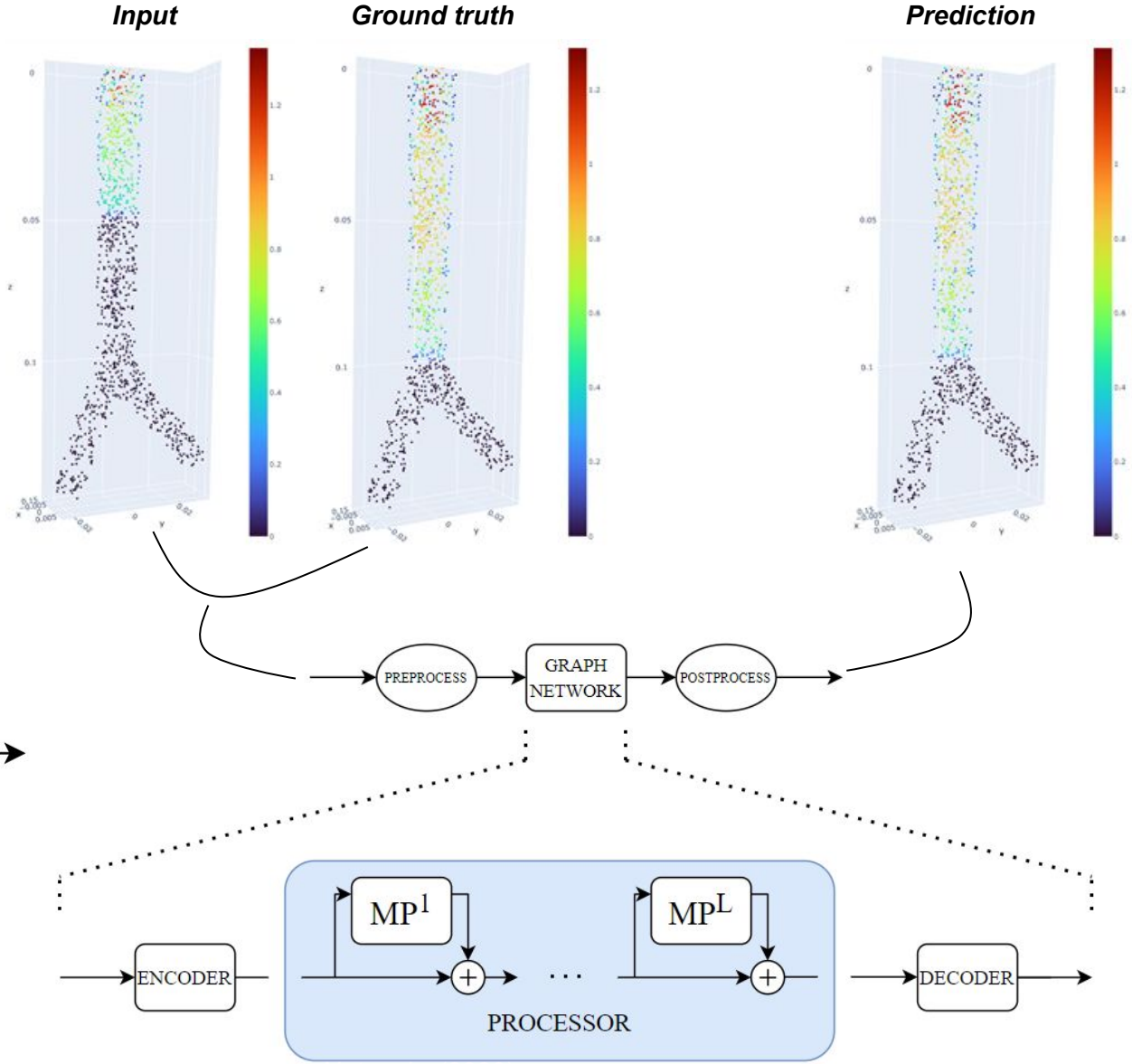
1. *Input state*: P, V at time t
2. *Output state: P, V at time* t+Δt

With window W=1, a simulation of N time frames becomes a set of N-1 pairs

$$\{(t_1, t_2); (t_2, t_3); \ldots; (t_{n-1}, t_n)\}$$



Model design[1]



1, Pfaff et al. ICLR 2021

Multiphase Case

Multiphase Color-LBM scheme

Viscoelastic and multiphase stress tensor are additive components

Stable simulations over complex geometries

Resulting in one set of populations per specie, therefore

Workload for air-mucus is **x100** than for pure air

$$f_p^{*k} = (1 - \omega^k) f_p^k + \omega^k f_p^{eq,k}$$

A lattice Boltzmann method for simulating viscoelastic drops

Cite as: Phys. Fluids 31, 073101 (2019); https://doi.org/10.1063/1.5100327
Submitted: 17 April 2019 • Accepted: 11 June 2019 • Published Online: 02 July 2019

Di Wang, Danielle Tan and Nhan Phan-Thien

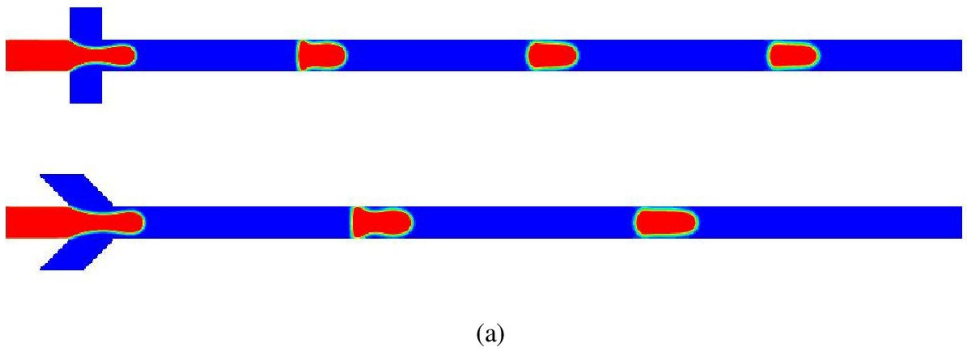
Multiphase non-elastic response validated under microfluidics settings

Dripping/slug regimes correctly identified

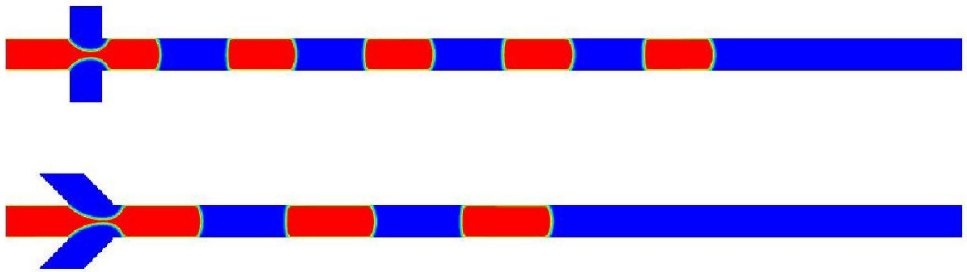
Addition of non-disjoining pressure effects available

Full dynamic response to be validated vs experiments:

- Open flow (1:4 contraction)
- Confinement (branched tubes)



(a)



(b)

ViscoElasticity (effective single-phase)

Tensorial model: 9 components for polymeric specie + solvent

Oldroyd-B model / Other visco-elastic models (FENE)

Fully parallelized with CUDA for GPUs

$$h_{p,ab}(x + hc_p, t + h) = \frac{1}{\tau_D} h^{eq}_{p,ab} + \left(1 - \frac{1}{\tau_D}\right) h_{p,ab} + \frac{G_{ab}}{A_{ab}} h^{eq}_{p,ab}$$

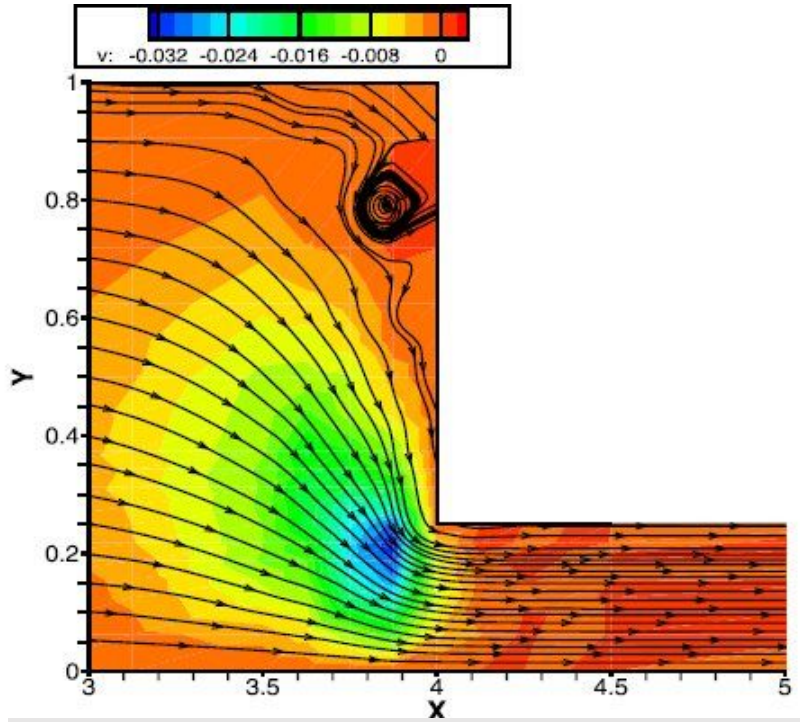
Workload is **x10** than for pure air

The goal is to use GNN to predict viscoelastic dynamics

Journal of Non-Newtonian Fluid Mechanics
Volume 165, Issues 23–24, December 2010, Pages 1637-1653

Lattice Boltzmann method for the simulation of viscoelastic fluid flows

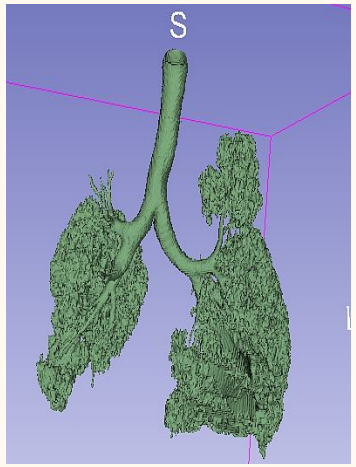
O. Malaspinas [a, b], N. Fiétier [a], M. Deville [a]

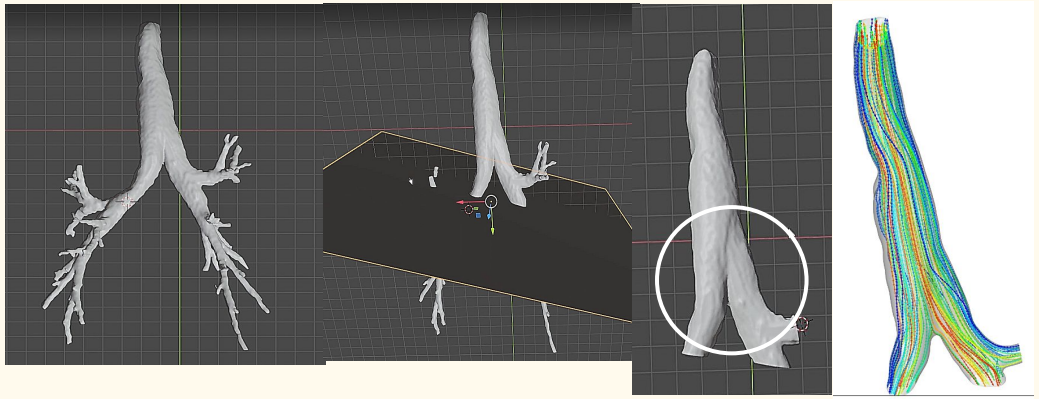


Currently under scrutiny for 1:4 contraction

UPB REOROM
Laboratory
Bucharest
Corneliu Balan

Air-Mucus transport in tracheal model

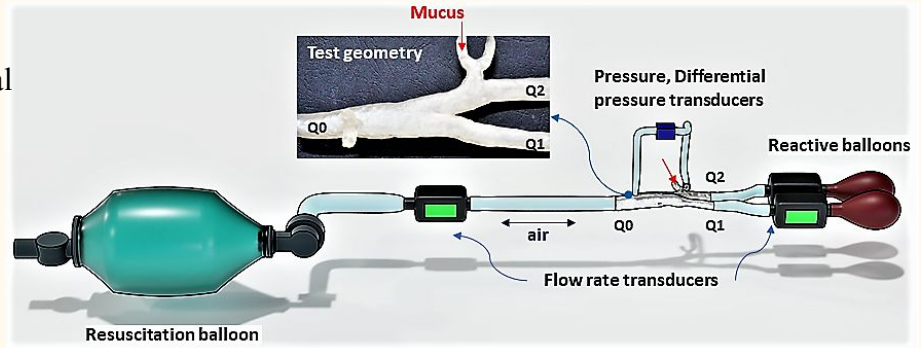


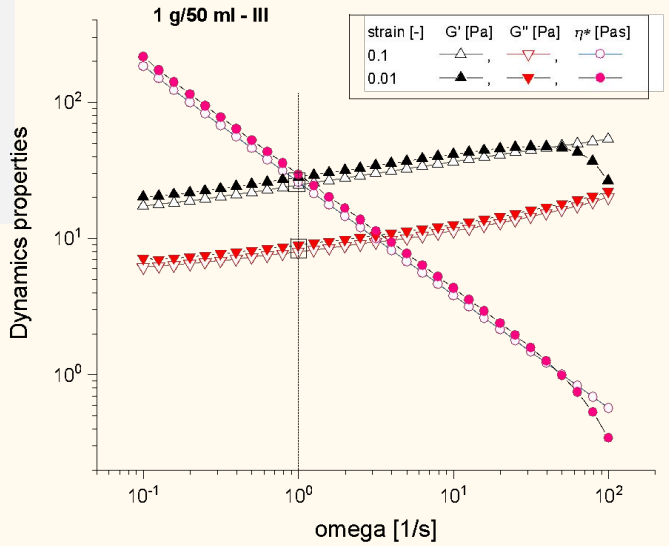


From CT scan to 3D model: step-by-step

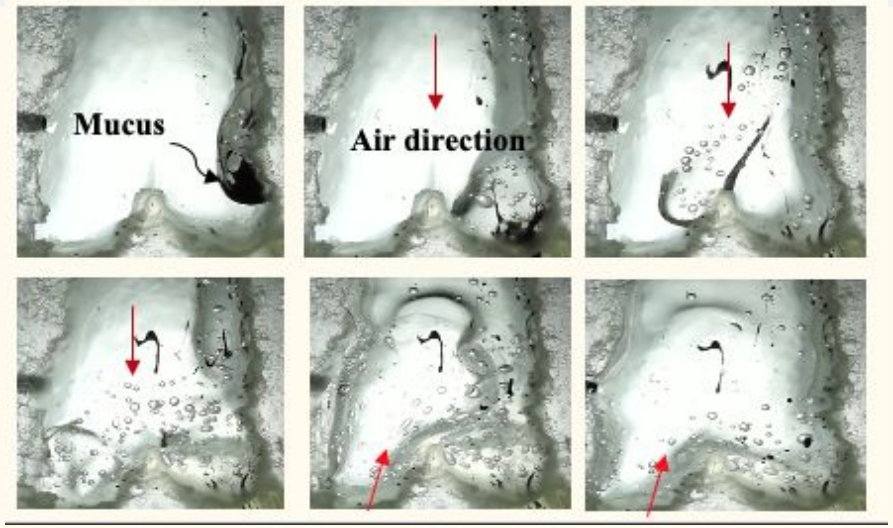
1. Final model from 3DSlicer; **2**. The trachea model in Blender interface;
3. Removed unwanted segments; **4.** Final solid 3D architecture of the trachea and main bronchi (3D printing); **6.** 3D geometry imported in ANSYS Fluent & Moebius; **7.** Steady/unsteady simulations; **8**. Steady/unsteady path-lines

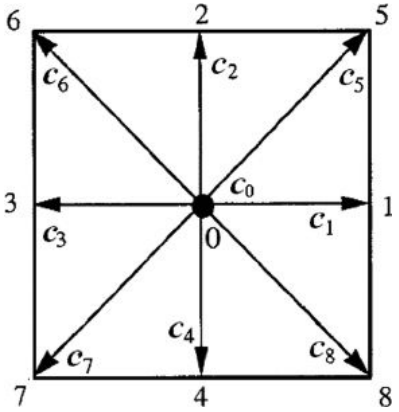
Experimental setup



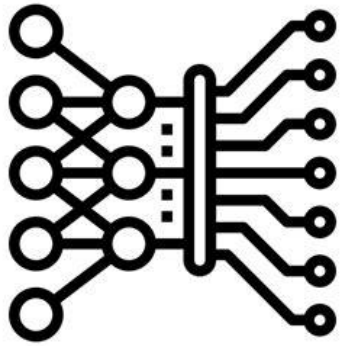


Direct visualization of air-mucus flow in the tracheal bifurcation





Pruning the simulation graph



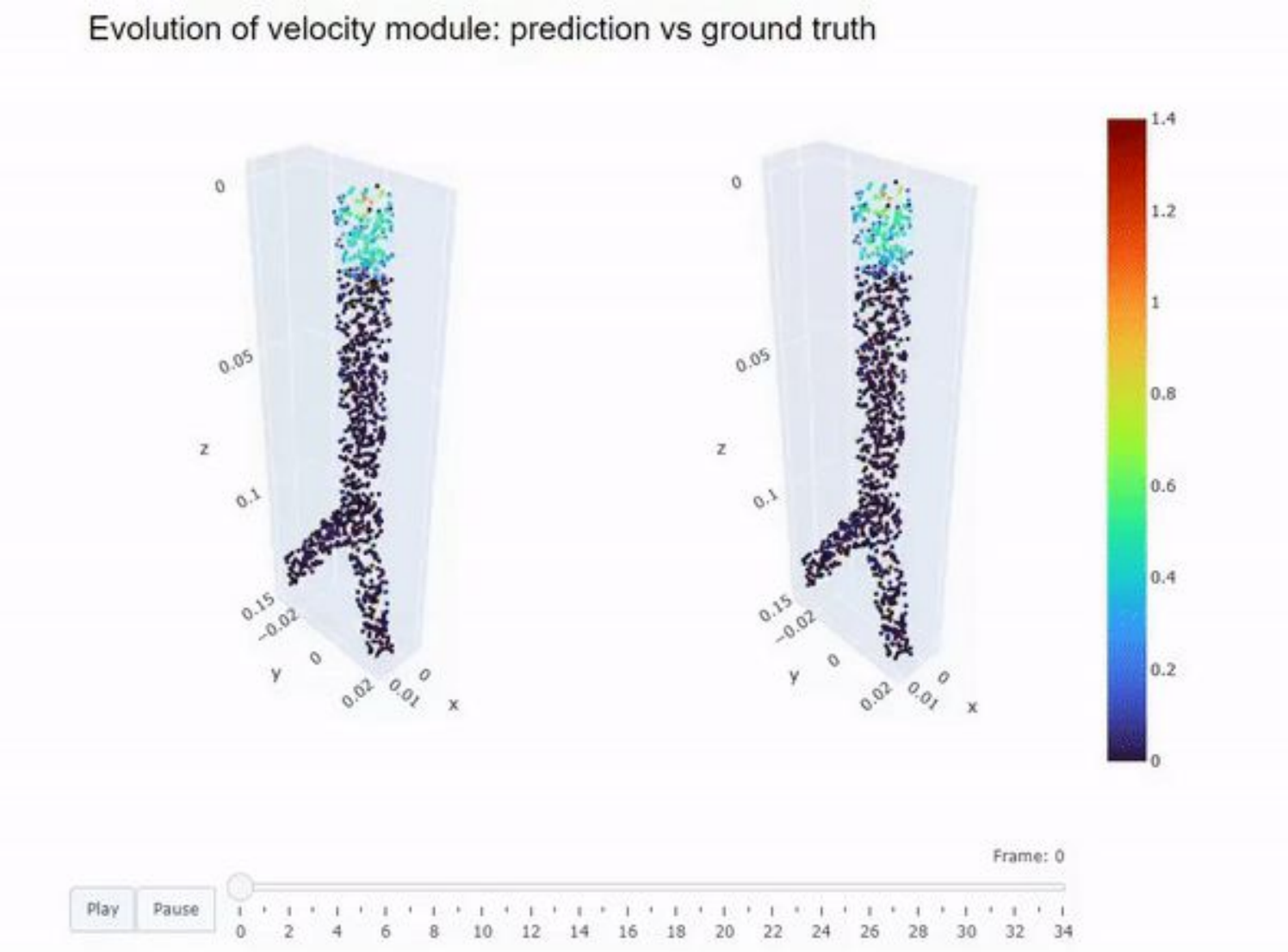
Requests:

- Isotropy ⇒ adjacency must be dense enough
- Steady-state solution ⇒ sufficient for the purpose
  or
- Propagator ⇒ general method for time dependence
- Causality: flow from inlet ⟶ outlet + irreversibility
- Material properties (relative concentrations) + injection rate as controllable parameters

MeshGraphNet suffers from low resolution as “sensing” confinement requires too many nodes

Propagator mode from the original paper is unneeded (at least for pure-air flow)

One step prediction visualized



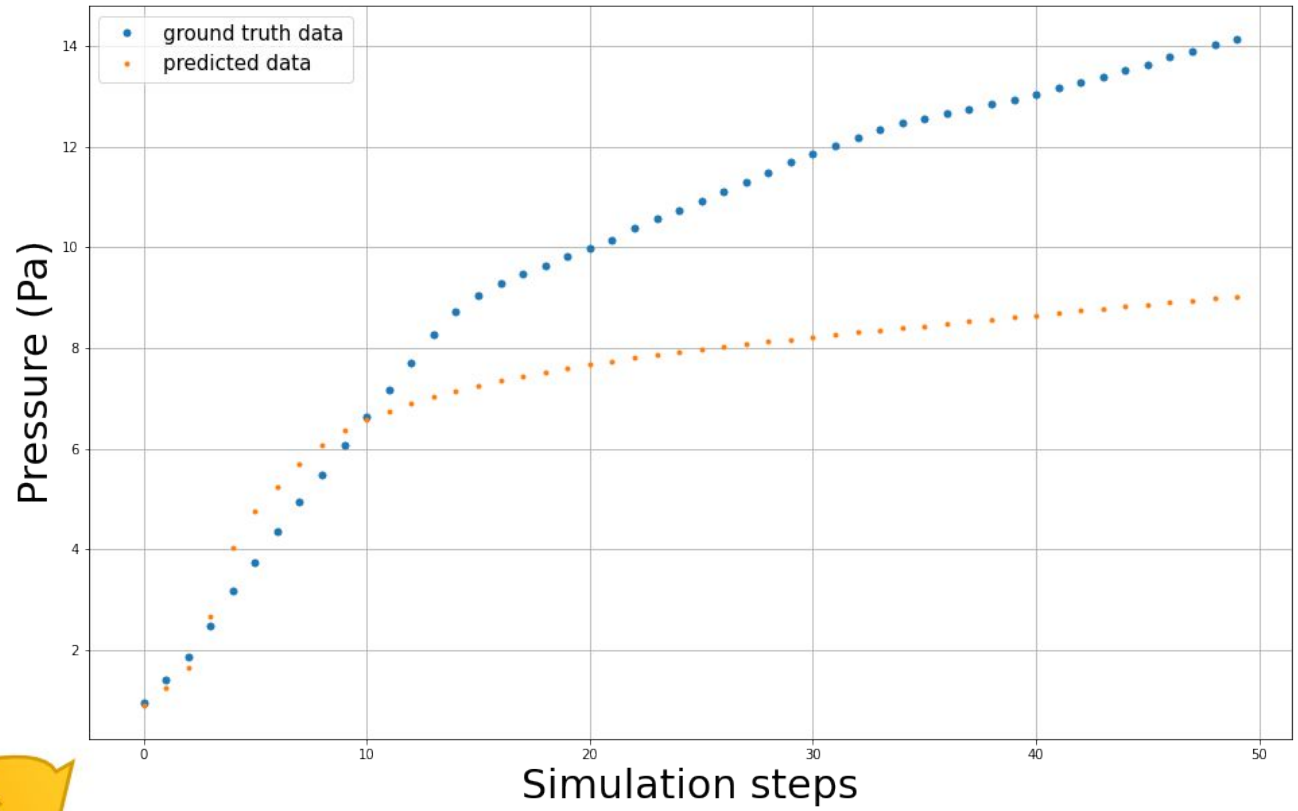
Autoregressive test

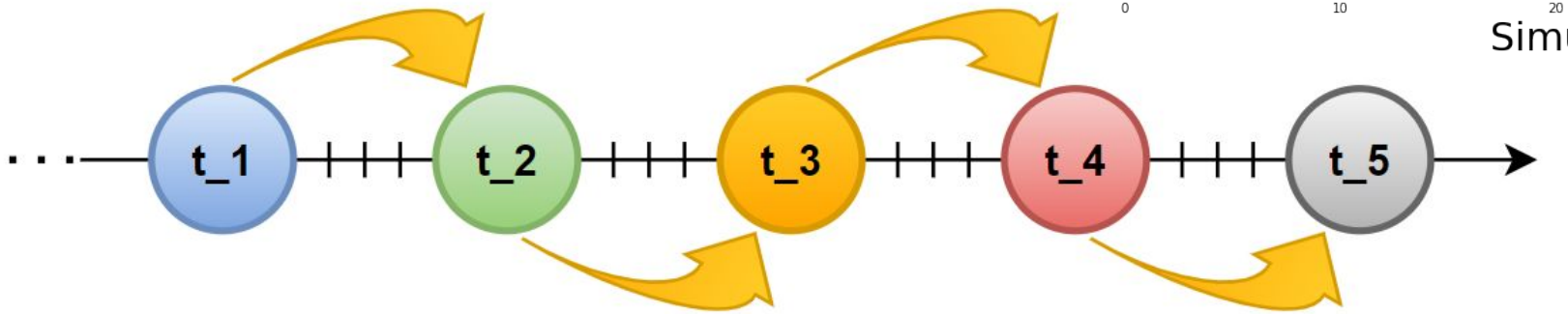
The model fails in autoregressive mode

It accumulates errors and the prediction diverges! Reasons:

- mass/momentum leakage
- non equivariant (SE3 group)

Mean (across nodes) pressure (Pa) for one trajectory





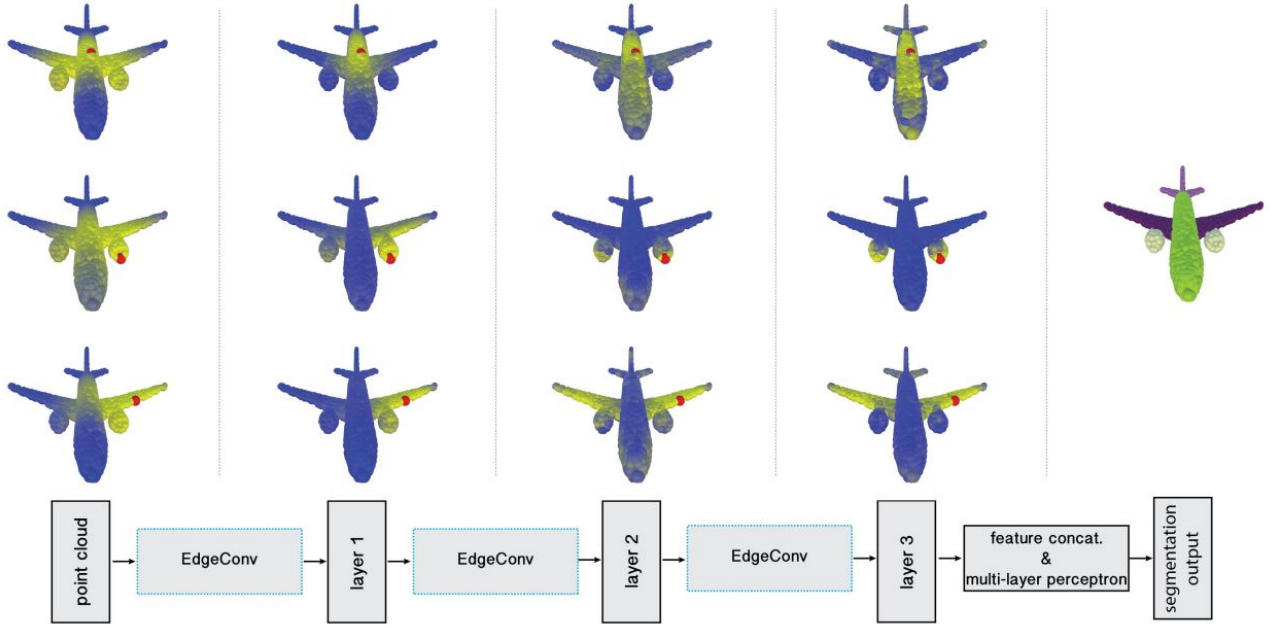
Steady state prediction

Goal: direct prediction of steady-state flow fields given the geometry

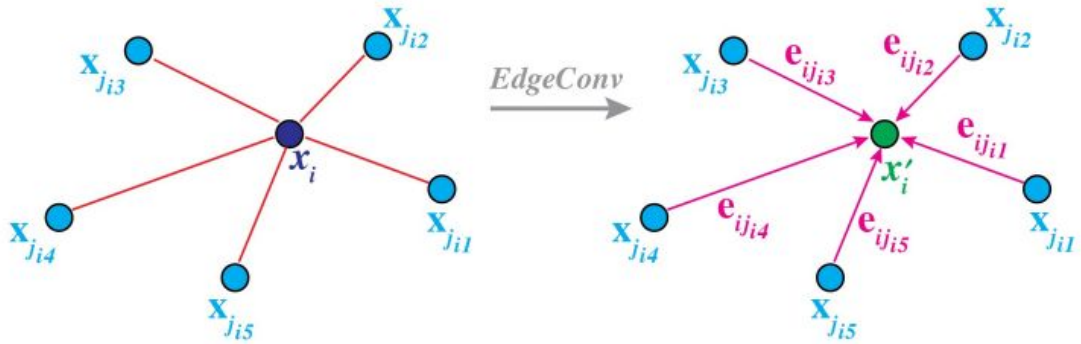
How: develop a model which extracts geometrical features (e.g. spatial coordinates) and uses them to predict physical features (e.g. P,V)

A **different** architecture is needed: DGCNN (Dynamic-Graph CNN)

Used for classification/part segmentation on point clouds



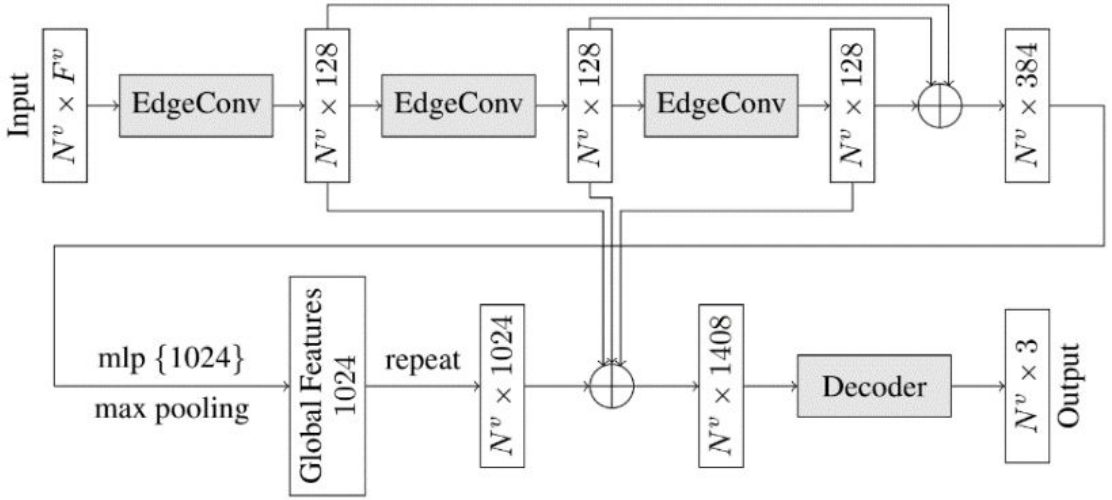
DGCNN layer is called EdgeConv

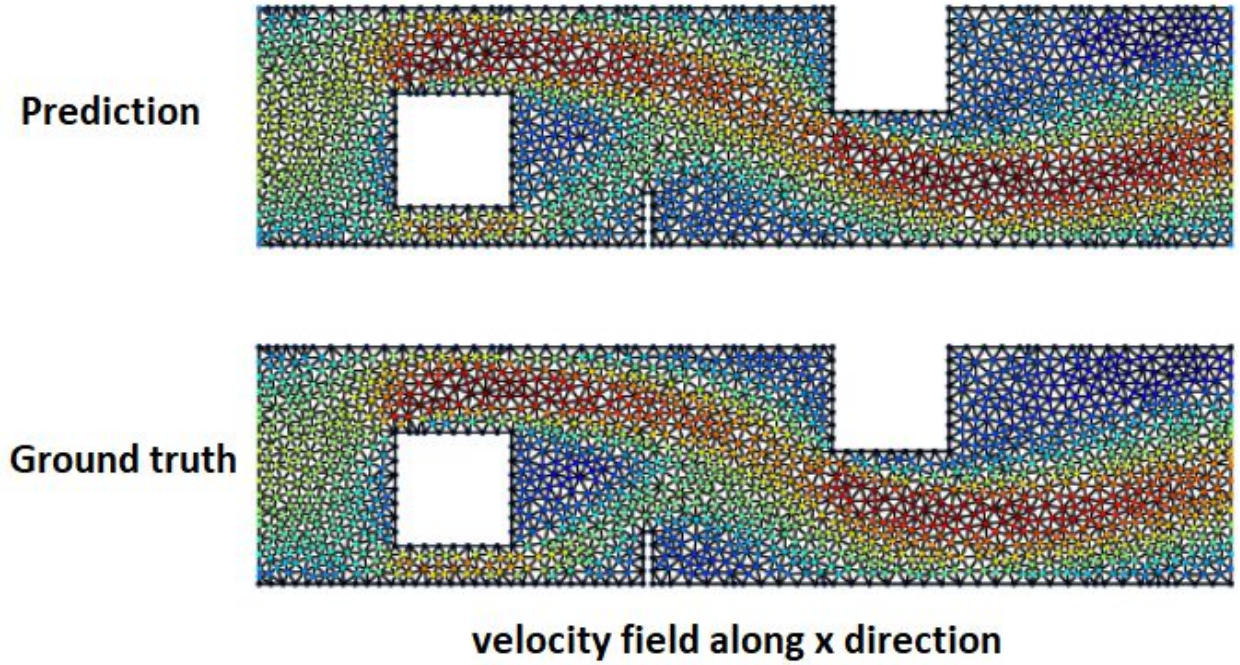


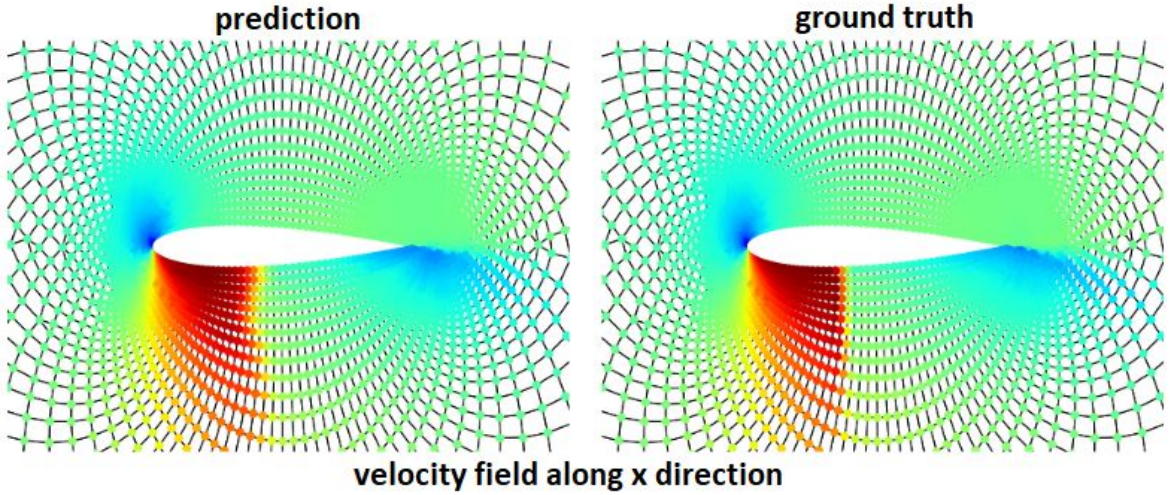
Wang et al. arXiv 2018

Regression task on 2D domains already attempted:

E.g. Harsch et al. ICLR 2021, used **DGCNN** on a dataset composed of 2D channel flows with random objects in them, and one dataset of airfols embedded in a mesh







xAI to diagnose

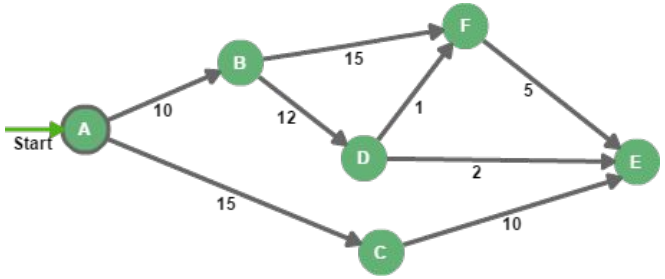
How a doctor decides:

- Direct Diagnosis
  - observe and detect the important blockages
- Diagnosis by Exclusion
  - exclude any other diseases and formulate a diagnosis

The bottom-up approach:

- Why flow distributes unequally? Why a certain region is un-ventilated ?
- Regional plugs along paths: map out the complex landscape for ventilation
- Given the regional fluxes, is air path quantifiable on end-points and in tissues ?
- Provide the analogue of Dijkstra's method, backtrack effective and/or failing ventilatory paths

Which xAI best fits (saliency, TRACIN, occlusion, topological, …) ?



Dealing with large graphs

Data production:

1. 3D simulations for small bricks
2. skeletonization to compress information: velocity, pressure, MIS
3. exploit self-similarity
4. all relevant quantities become scalars (equivariance is built-in)

AI prediction

xAI diagnosis

1. de-skeletonize for local details
2. calibrate / validate
3. re-model

Thank you

… and …

we are hiring!

MedLea

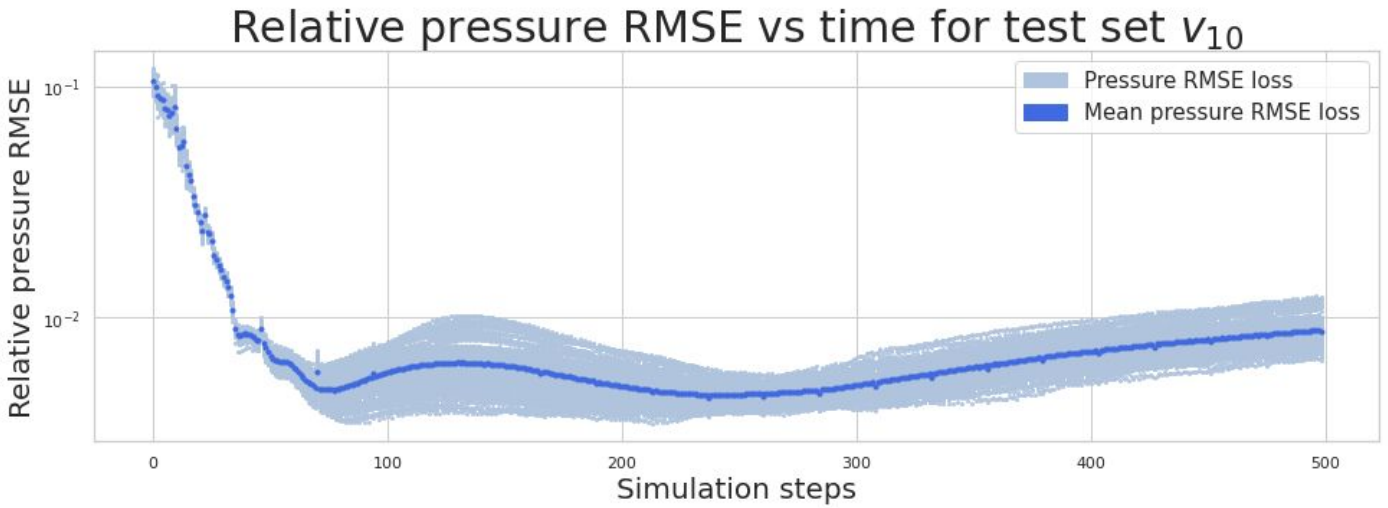
www.medlea-tech.com

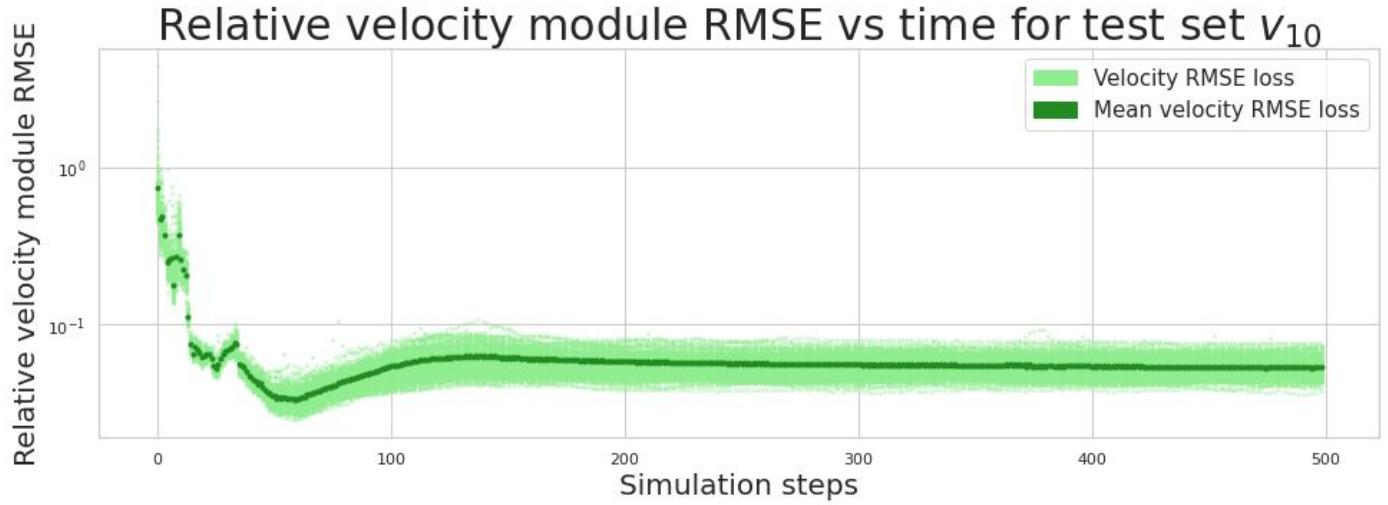
Generalization test

Generalization test on different inlet velocities

- Held out test velocities: **v_1, v_10**
- Model is trained on simulations in groups from **v_2** to **v_9**

On the right: plots of the mean (across nodes) relative root mean-squared error (**RMSE**) for pressure and velocity module, for the 100 trajectories of one test set. Darker color represent the mean across the 100 trajectories.





We are interested in 3D domains

Task identification

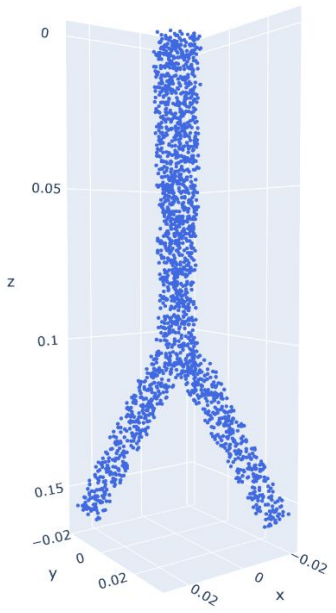
Steady state predictor

1. *Input state*: sampled point cloud resembling the underlying geometry
2. *Output state:* pressure and velocity fields and stress tensor components measured in the steady state

Dataset production

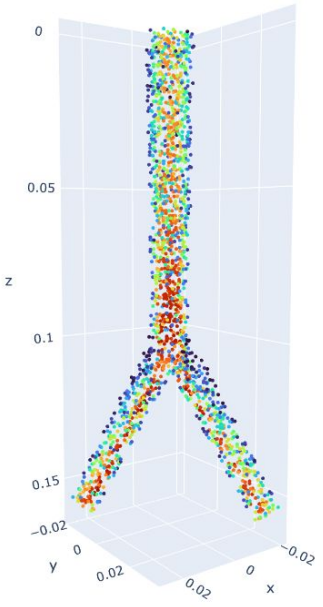
1. 2000 simulations with fixed inlet velocity
2. Uniform sampling of n=2000 points
3. Physical features are extracted only once, when the system has reached the steady state: **1 simulation = 1 data point, time is no longer relevant**

Input

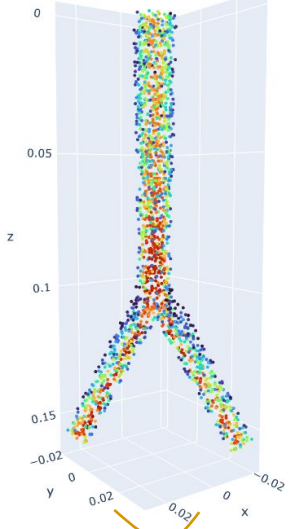


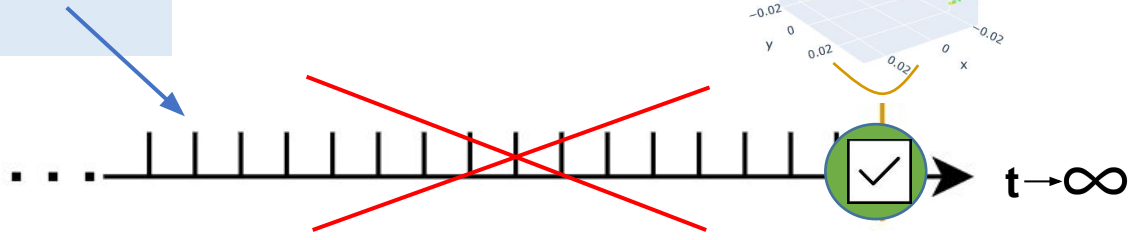
Model

Prediction



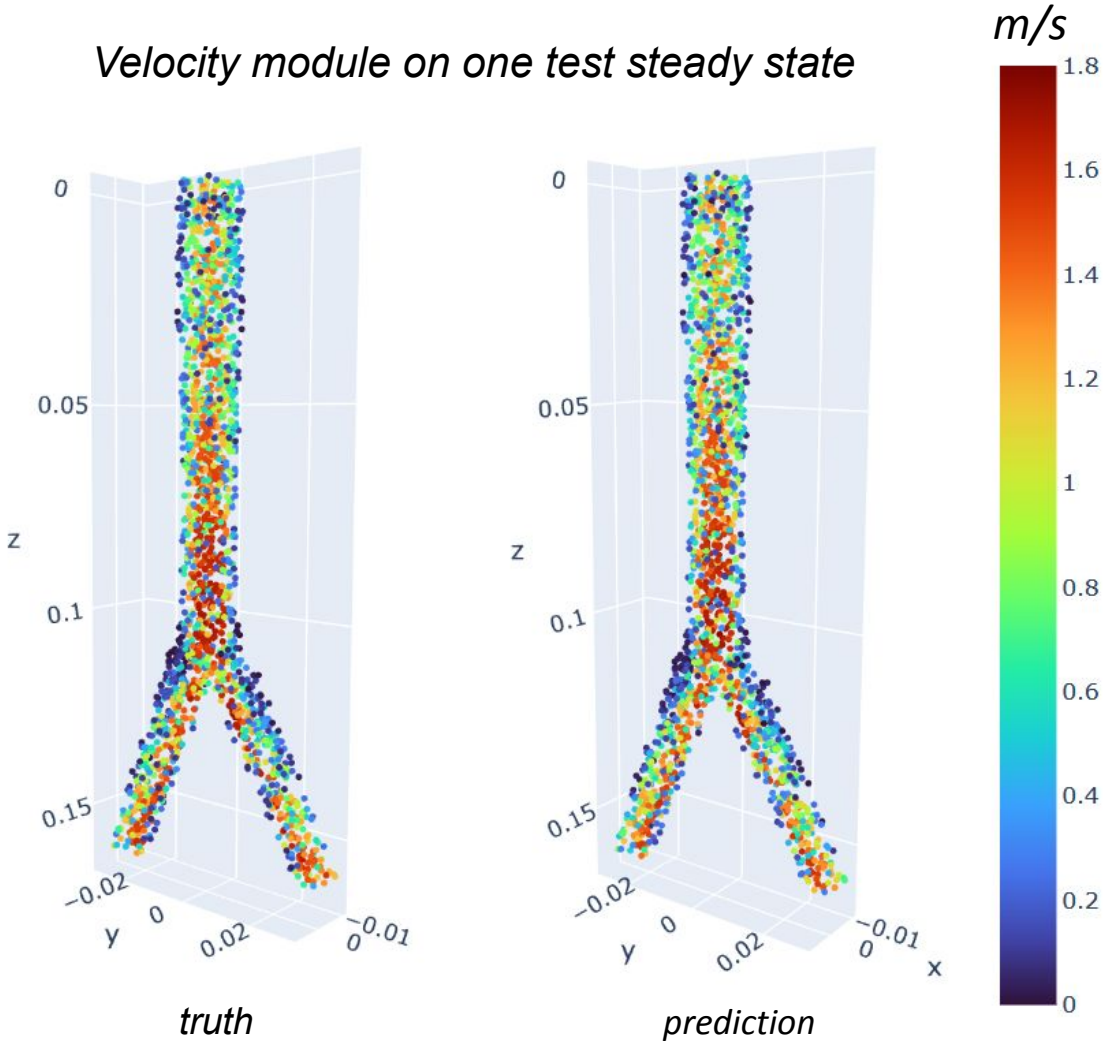
Ground truth

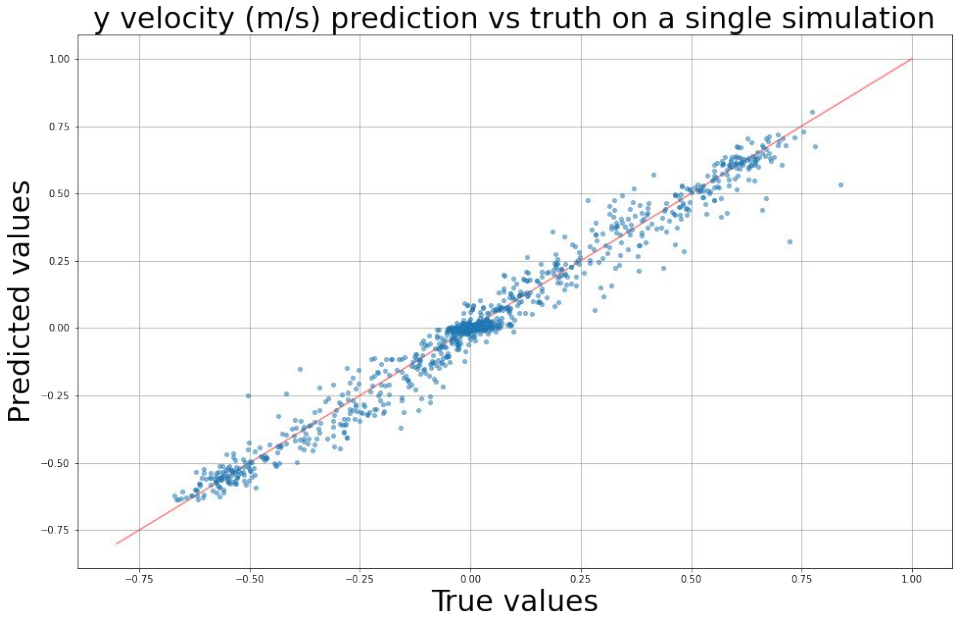


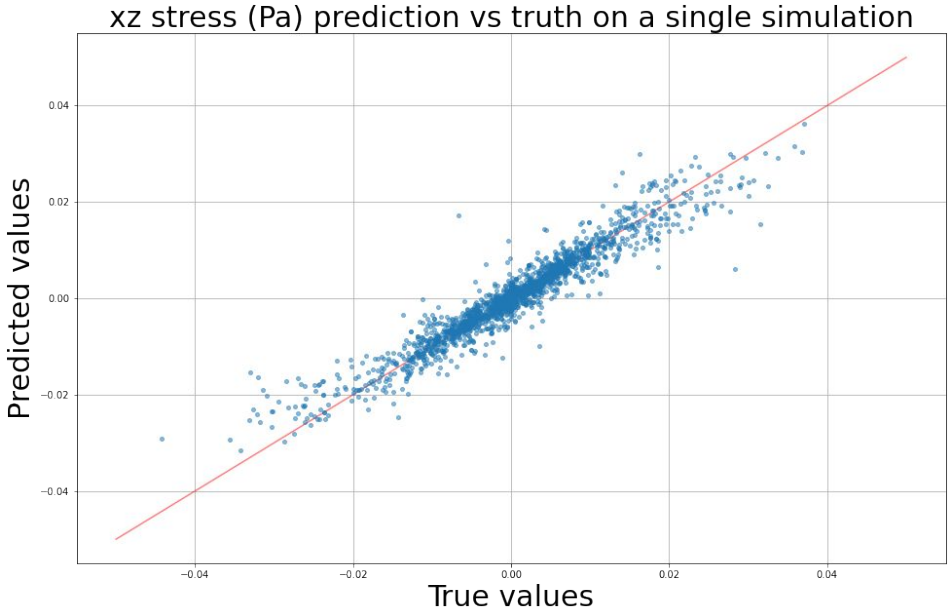


Preliminary results

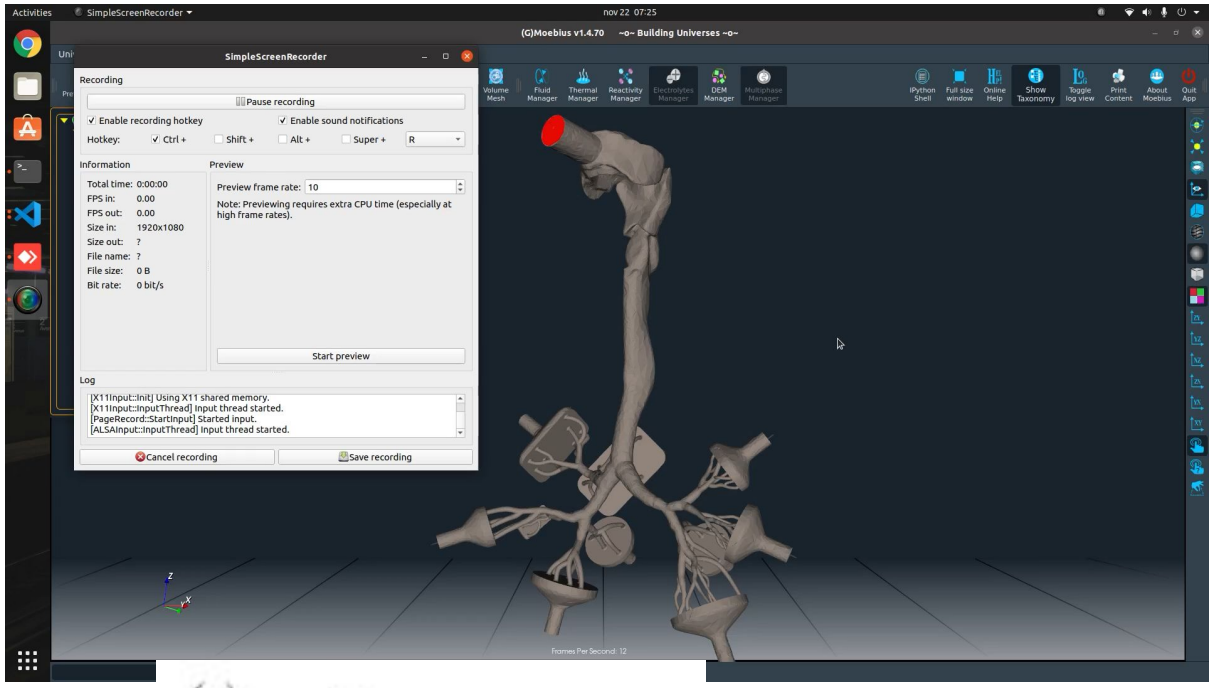
Velocity module on one test steady state

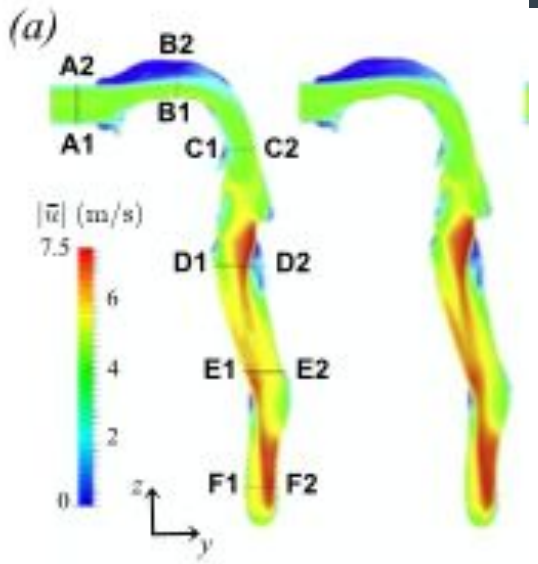






The SimInhale benchmark (from Cost action MP1404)





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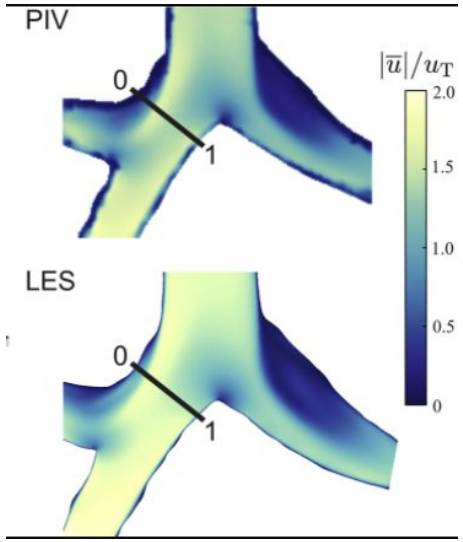
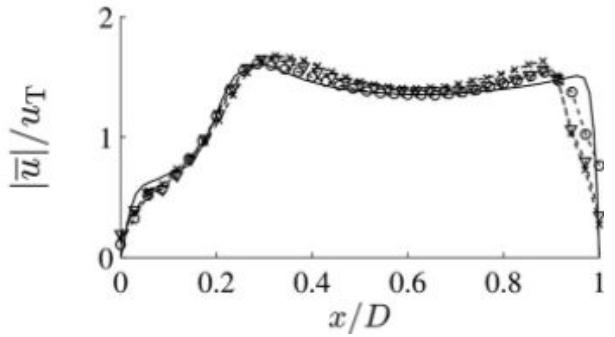
Regional aerosol deposition in the human airways: The SimInhale benchmark case and a critical assessment of *in silico* methods

P. Koullapis[a], S.C. Kassinos[a], J. Muela[b], C. Perez-Segarra[b], J. Rigola[b], O. Lehmkuhl[c], Y. Cui[d], M. Sommerfeld[e], J. Elcner[f], M. Jicha[f], I. Saveljic[g], N. Filipovic[g], F. Lizal[f], L. Nicolaou[h,*]

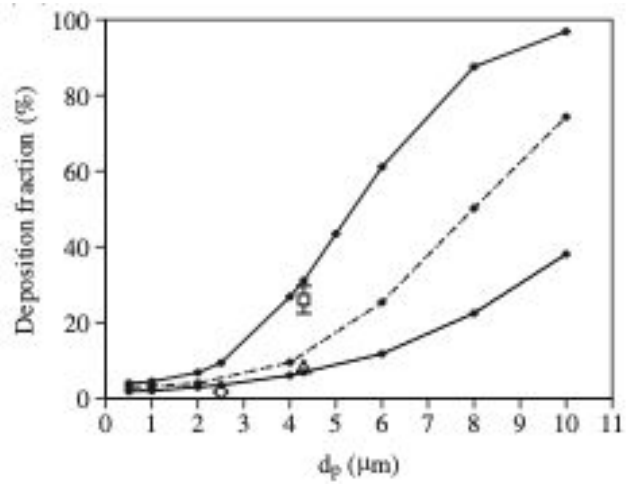




Fully reconstructed airways to 4th generation

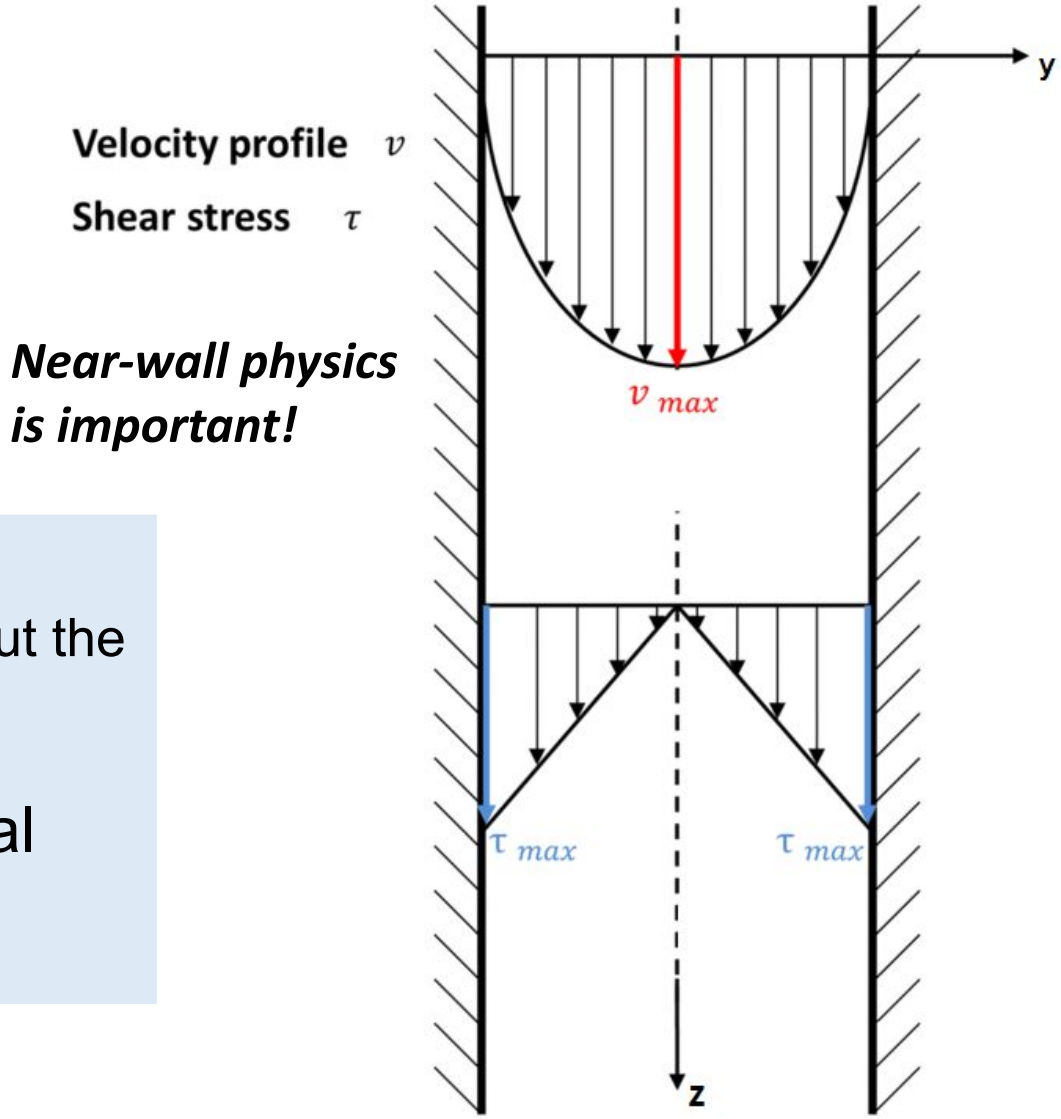
Benchmark for fluid mechanics and PIV data

Focus on particle deposition



Adding new features: stress components

In the last few months, we also added the stress tensor components, to better inform the model about velocity gradients.

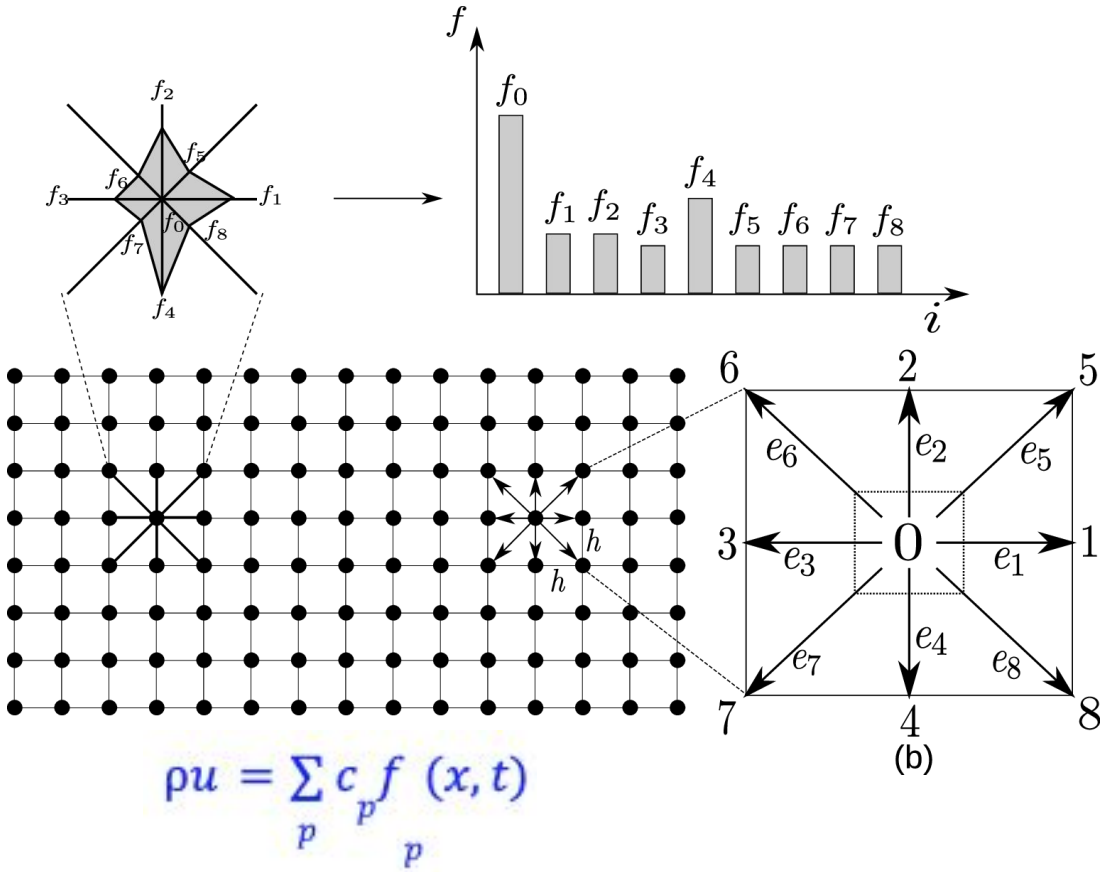


Near-wall physics is important!

The model is capable of managing additional features without degrading pressure and velocities prediction, but the autoregressive goal still requires a lot of work.

We decided to change our task from a physical propagator to a **steady state predictor**

Simulation details



$$\rho u = \sum_p c_p f_p(x,t)$$

$$\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u}\cdot\nabla)\mathbf{u} = -\frac{1}{\rho}\nabla p + \mathbf{F} + \frac{\mu}{\rho}\nabla^2\mathbf{u}$$

One control parameter:
*Reynolds number = diameter*velocity/viscosity*

Lattice Boltzmann Method (kinetic approach)

Nodes on a dense graph with regular adjacency

High-order Isotropy

Collisions + message passing at every micro-step

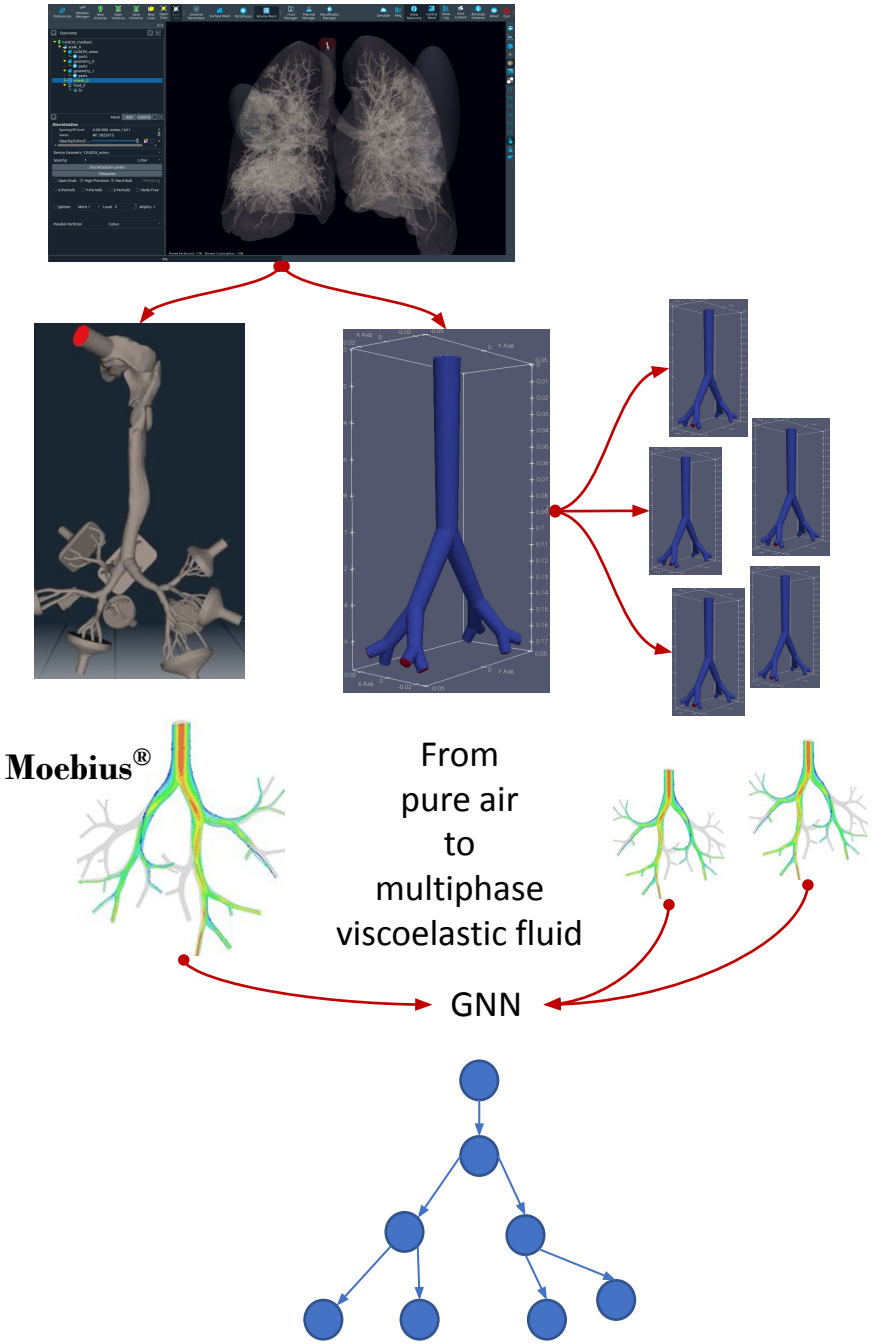
Same approach for hollow airways & porous tissues

$$f_p(x + hc_p, t + h) = \frac{1}{\tau} f_p^{eq} + (1 - \frac{1}{\tau}) f_p + F_p$$

Dissipative and irreversible dynamics (obeying MaxEnt theorem)

Field-particle duality encoded: particle tracking to determine the swarm of pathlines

Airflows



Confined, stationary flow in complex pipes and air-mucus flow

$$\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u}\cdot\nabla)\mathbf{u} = -\frac{1}{\rho}\nabla p + \mathbf{F} + \frac{\mu}{\rho}\nabla^2\mathbf{u}$$

Pulsatile period >> viscous timescale ⇒ final state vs boundary condition

1:1 mapping between injection rate and flow pattern

Air-mucus creeping dynamics has a slow evolution

Pulsatile dynamics as a sequence of stationary states (adiabatic process)

GNN

How do we work on graph data?

Graph neural networks

- Used on unstructured data: molecules, social networks ecc.
- Based on ***message passing,*** a generalization of convolution
- Suitable architecture to leverage physical inductive biases:
  - Local interactions
  - Superposition principle