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Thermodynamics-informed Graph Neural Networks for anatomically accurate digital human twins

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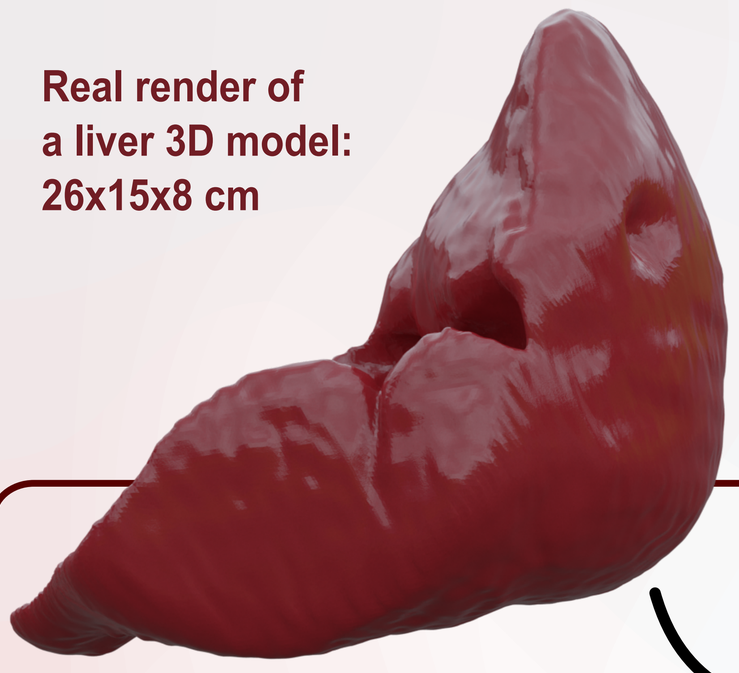
Real render of a liver 3D model: 26x15x8 cm



Problem:

We want to describe the **dynamic system**:

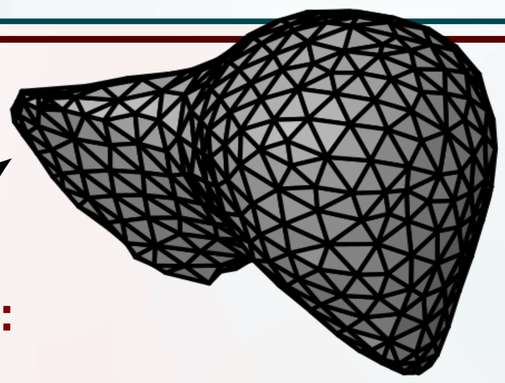
$$\dot{\mathbf{z}} = F(\mathbf{z}, t), \quad t \in I = (0, T], \quad z(0) = z_0,$$

$$\dot{\mathbf{z}}_{t+1} = \dot{\mathbf{z}}_t + \Delta t \dot{\mathbf{z}} = \dot{\mathbf{z}}_t + \boxed{F(t)}_{?}$$

Keypoints:

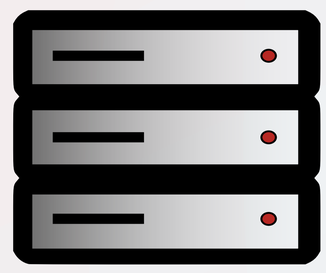
- **Real Time** Simulation
- **Mesh Independent** Solution
- Inductive Biases
- **Hybrid Artificial** Intelligence

Methods and architecture:



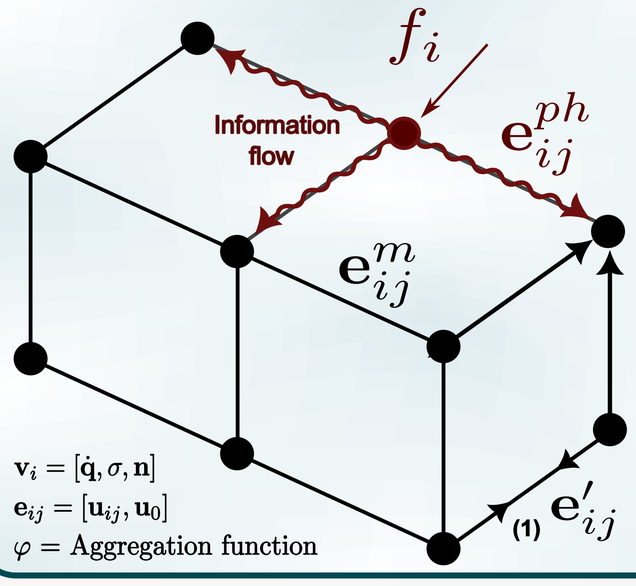
Mesh Preprocessing:
Low poly 3D model with volumetric meshing

Data Generation:
- Quasi-Static simulations
- Fixed nodes on visceral face
- Imposed displacemet on 1 to 3 nodes
- Viscoelastic and Hyperelastic properties



Database

[2] Geometric Bias



Phantom Graph
Mesh Graph

$$^{(2)}\mathbf{v}_i' \leftarrow f^v[\mathbf{v}_i, \varphi(\mathbf{e}_{ij}')]$$

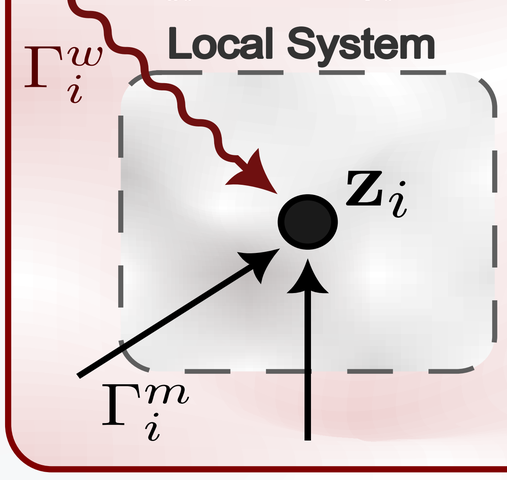
f^v and f^e being residual MLPs

$$^{(1)}\mathbf{e}_{ij}' \leftarrow f^e[\mathbf{v}_i, \mathbf{v}_j, \mathbf{e}_{ij}]$$

$\mathbf{v}_i = [\dot{\mathbf{q}}, \sigma, \mathbf{n}]$
$\mathbf{e}_{ij} = [\mathbf{u}_{ij}, \mathbf{u}_0]$
φ = Aggregation function

[1,3,4] Physic Bias

Boundary operator:
Energy and entropy exchange



Fullfillment 1st and 2nd law of Thermodynamics

Local GENERIC imposition

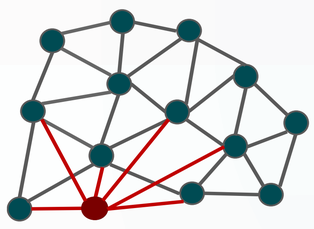
$$\dot{\mathbf{z}} = \mathbf{L}\frac{\partial E}{\partial \mathbf{z}} + \mathbf{M}\frac{\partial S}{\partial \mathbf{z}} - \mathbf{L}_\Gamma \frac{\partial E_\Gamma}{\partial \mathbf{z}} - \mathbf{M}_\Gamma \frac{\partial S_\Gamma}{\partial \mathbf{z}}$$

$$L_i(z_i)\frac{\partial s_i}{\partial z_i} = 0$$
$$M_i(z_i)\frac{\partial e_i}{\partial z_i} = 0$$

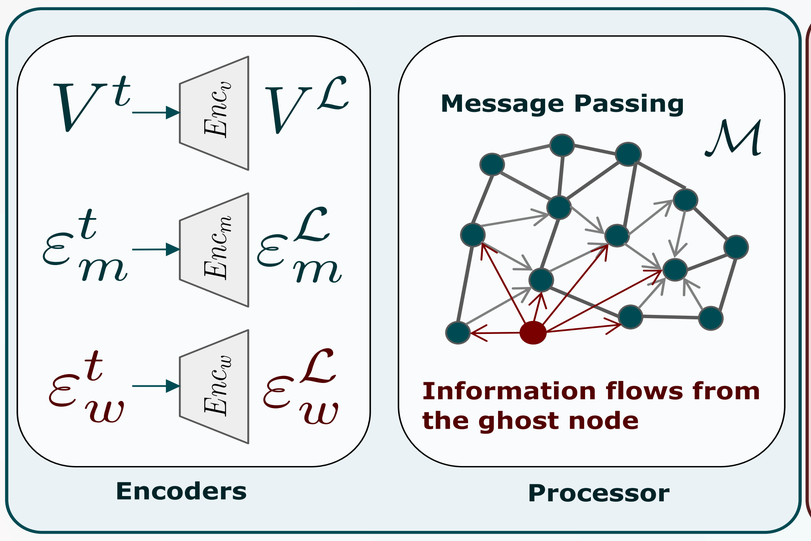
Degeneracy Conditions

Forward pass:

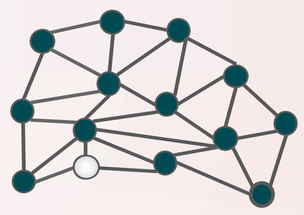
V^t = Nodal Embeddings
ε^t = Edge Embeddings



$\mathbf{z}^t$



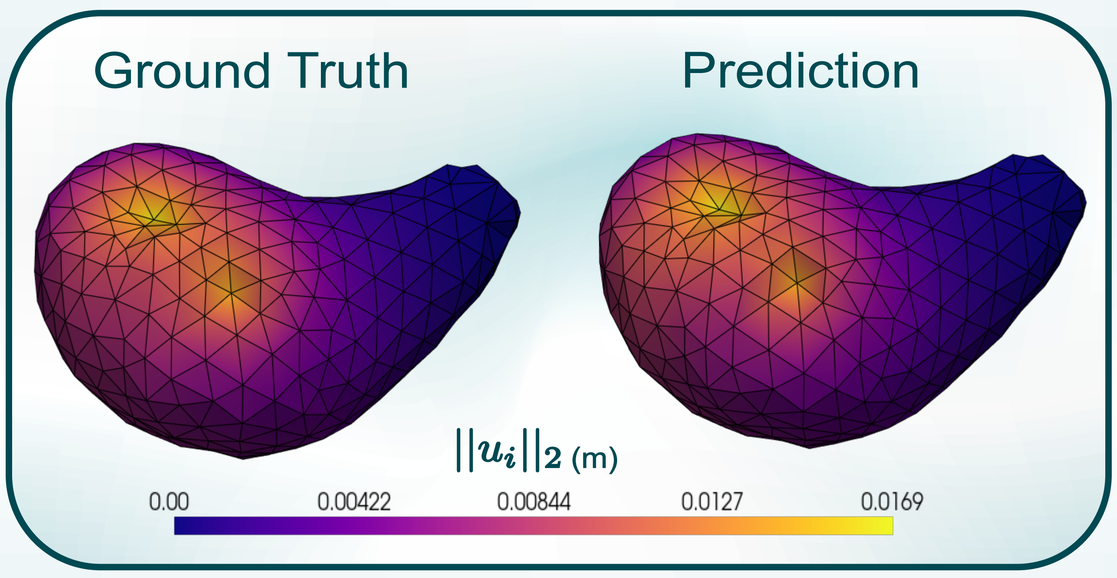
Net prediction



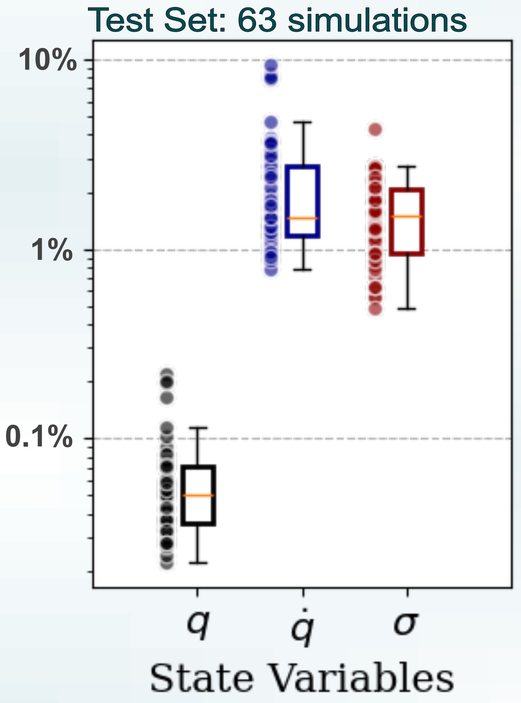
$\mathbf{z}^{t+1}$

Results and discussion:

Highly accurate predictions with high robustness



Unseen load condition at inference!



References

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Contact me!

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