BRIDGING TISSUE-SCALE MULTI-PHYSICS TO ORGAN-SCALE BIOMECHANICS THROUGH MULTI-FIDELITY MACHINE LEARNING

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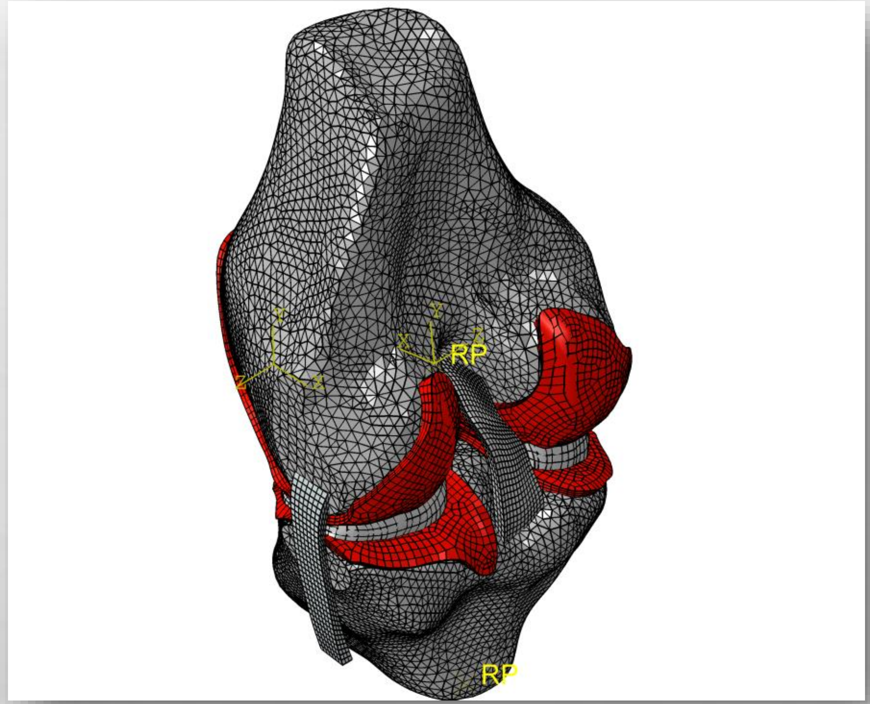
CMBBE 2023 SYMPOSIUM
18TH INTERNATIONAL SYMPOSIUM ON COMPUTER METHODS IN BIOMECHANICS AND BIOMEDICAL ENGINEERING

INTRODUCTION



Preliminaries:

- Knee biomechanics
- Articular cartilage
- Finite element modeling
- Machine learning surrogates
- Multi-fidelity machine learning
- Graph-based inductive learning

INTRODUCTION

$$\underbrace{\boldsymbol{\sigma}}_{\text{total stress}} = \underbrace{\boldsymbol{\sigma}^{COL}}_{\text{fibrillar stress}} - \overbrace{\boldsymbol{\sigma}^{MAT}}^{\text{non-fibrillar stress}} + \overbrace{\boldsymbol{\sigma}^{GAG}}^{\text{osmotic pressure}} - \underbrace{p\mathrm{I}}_{\text{fluid pressure}}$$

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S. S. Sajjadinia, B. Carpentieri, and G. A. Holzapfel, “A backward pre-stressing algorithm for efficient finite element implementation of in vivo material and geometrical parameters into fibril-reinforced mixture models of articular cartilage,” Journal of the Mechanical Behavior of Biomedical Materials, vol. 114, p. 104203, 2021.

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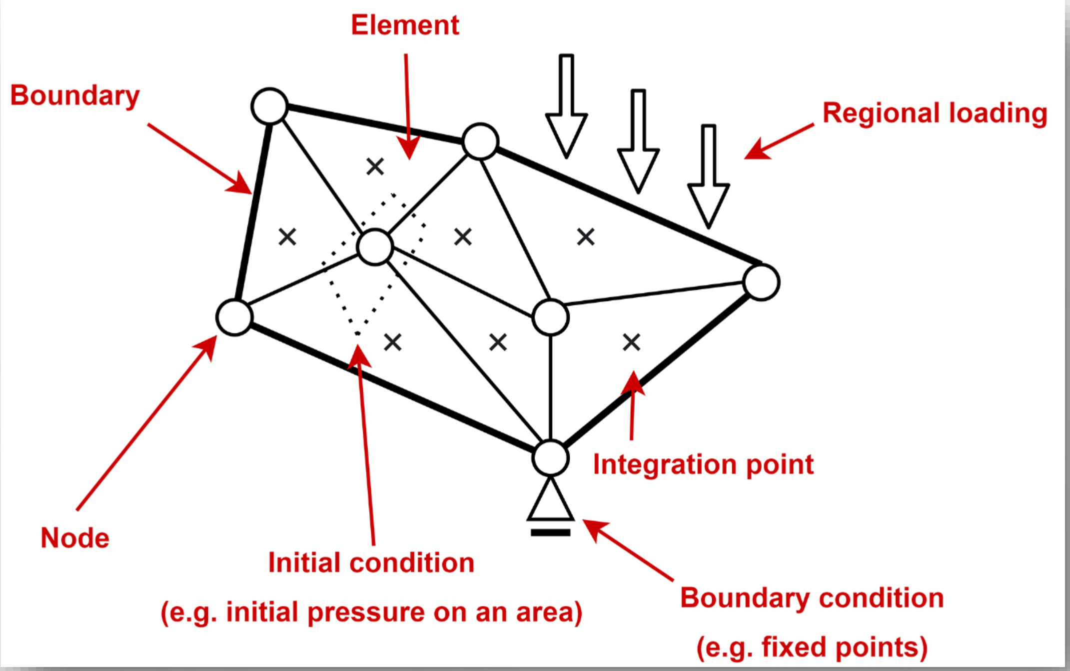

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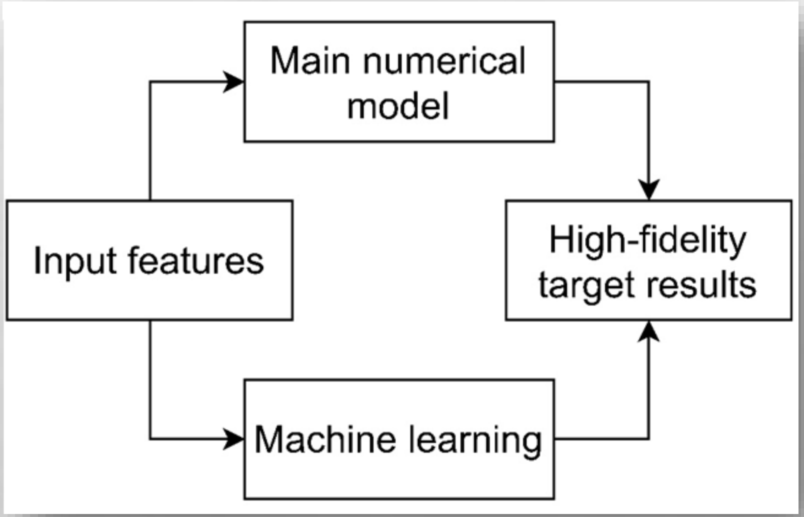

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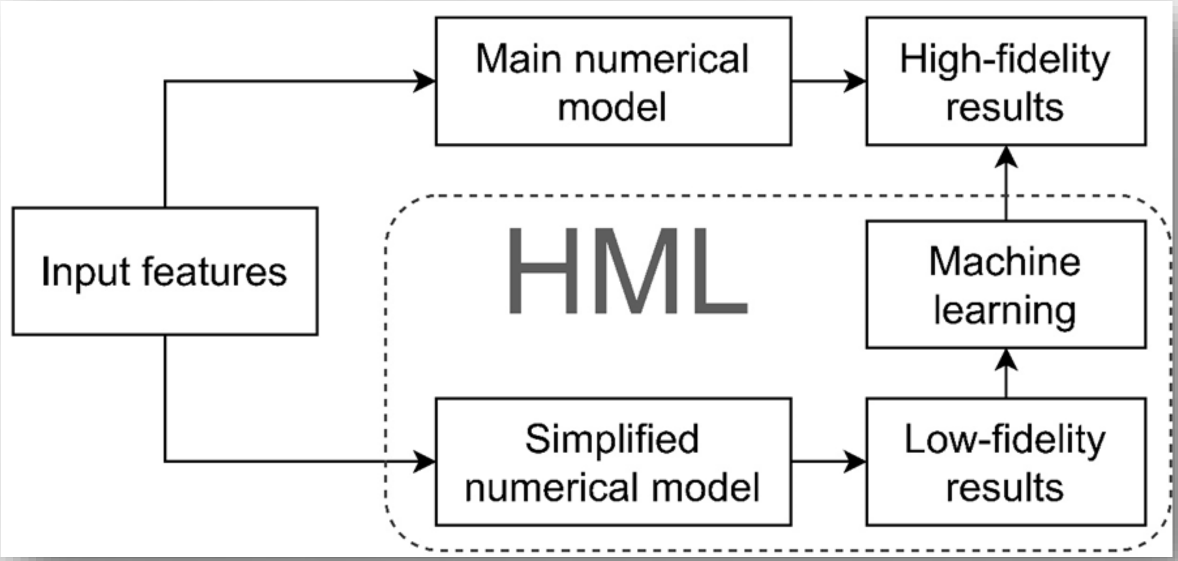

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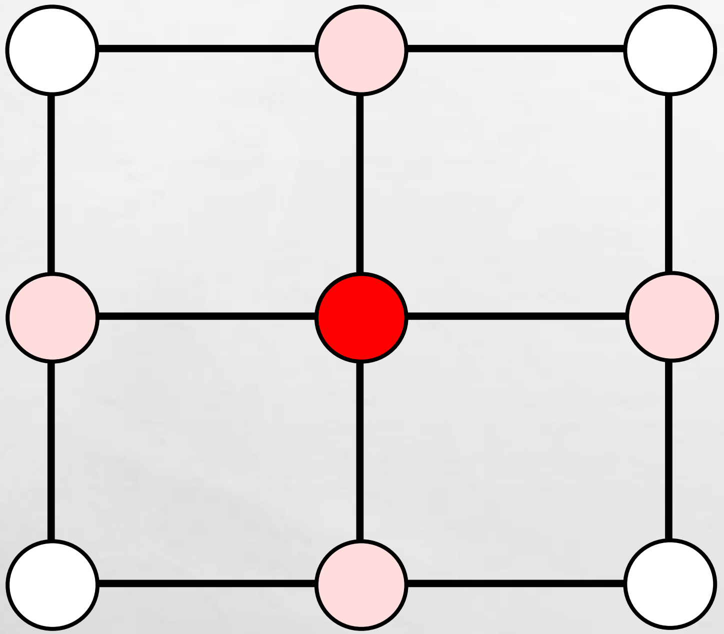

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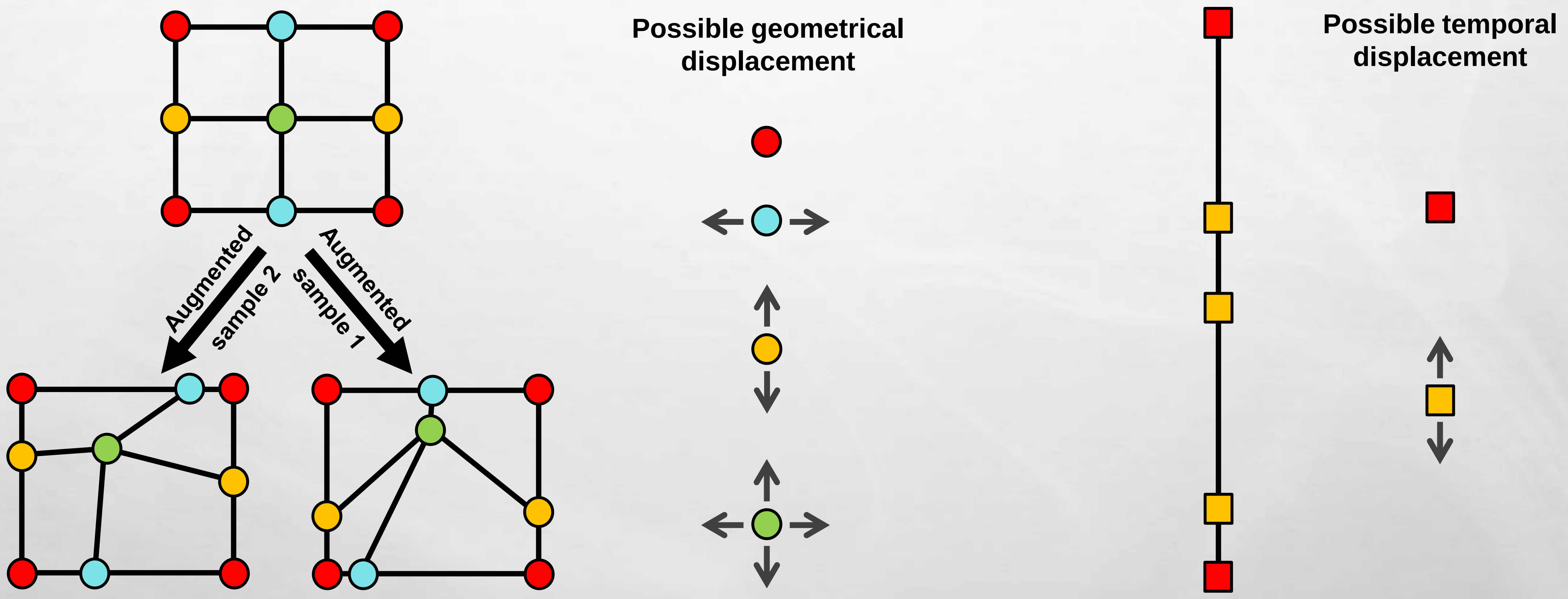
RESEARCH AIMS

- Hybrid machine learning with different frames
- Improving training
- Data augmentation
- Multiscale surrogate modeling

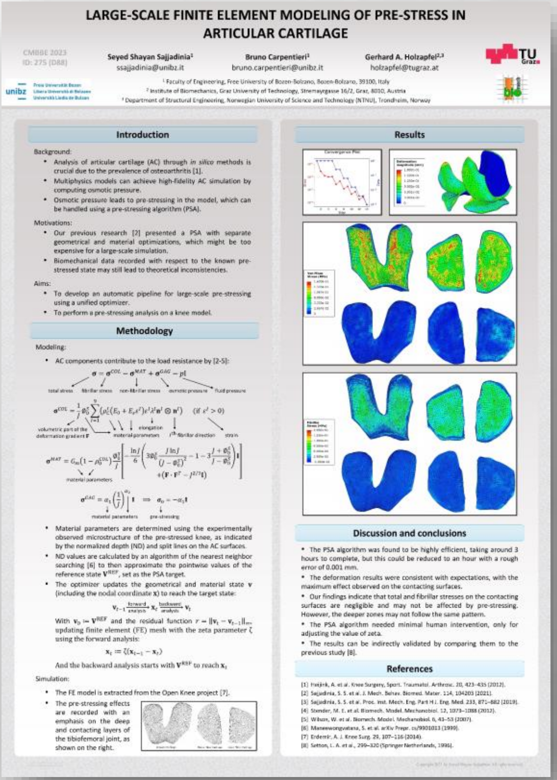
METHODOLOGY: INTERPOLATION



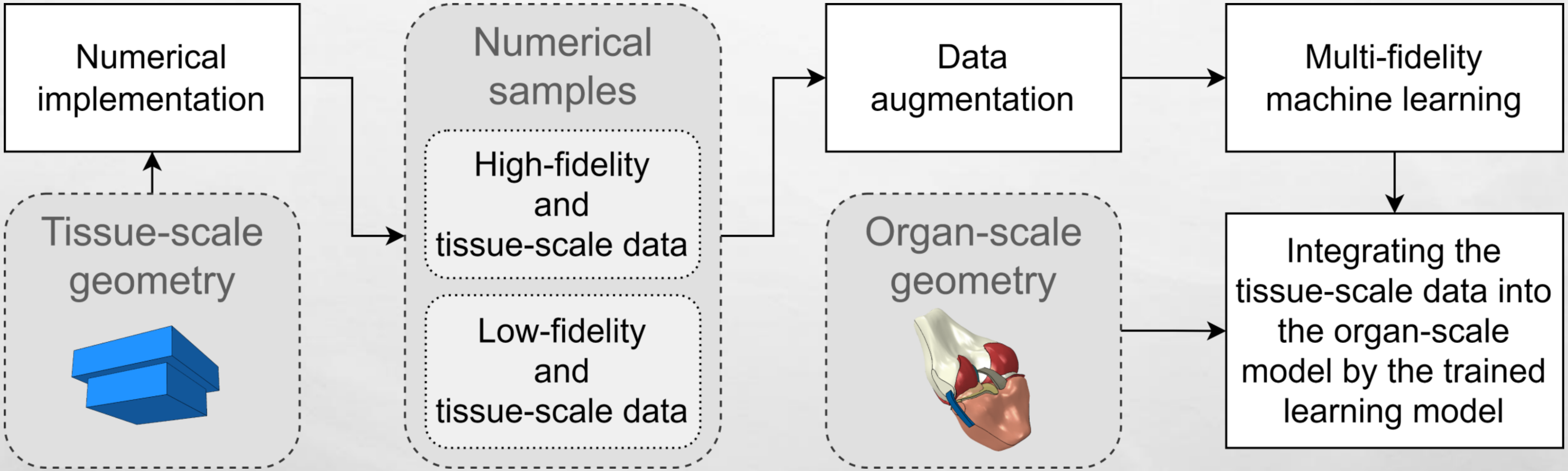
METHODOLOGY: BIOMECHANICS

- **High-fidelity model: multi-physics equations**
- **Low-fidelity model: viscoelastic equations**
- **Small-scale simulation: contacting bodies with a simple mesh**
- **Large-scale simulation: contact in a tibiofemoral joint**

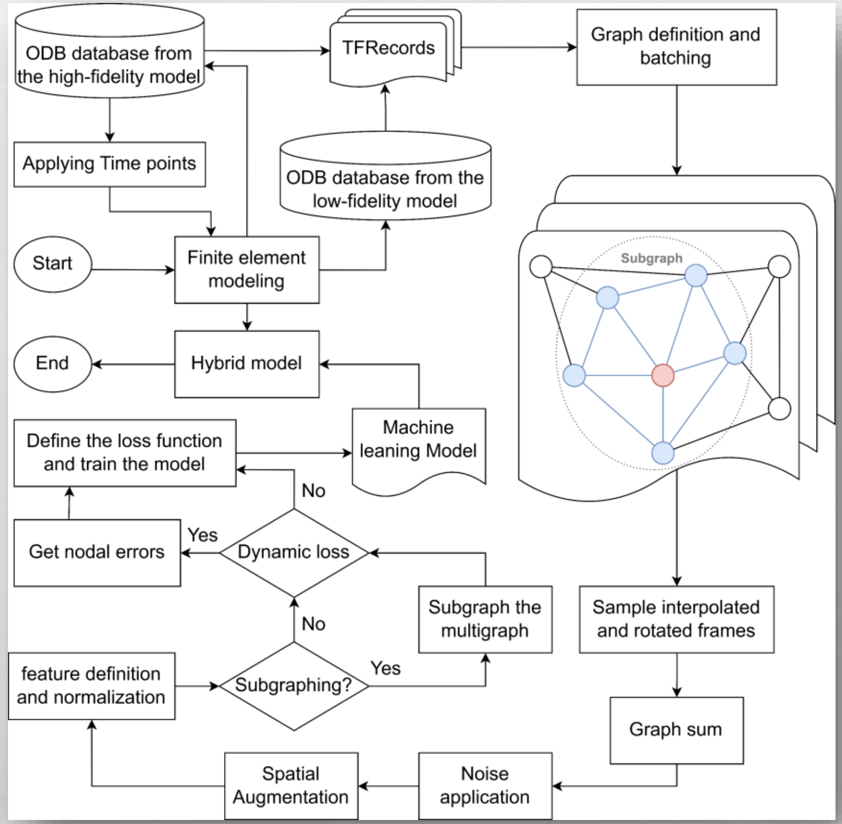
See my poster



METHODOLOGY: DATA AUGMENTATION



METHODOLOGY: WORKFLOW



Training with:

- MAE loss
- MAE loss with static subgraphing
- MAE loss with dynamic subgraphing
- Weighted loss
- Dynamically weighted loss
- Maximal loss (top 100)
- Maximal loss (top 10000)

RESULTS AND DISCUSSION

- **Fluid pressure**

Type	Noise Std	Latent Size	Averaged Valid Error	Averaged Test Error	Max Valid Error	Max Test Error	Max K
MAE loss with dynamic subgraphing	0.2	16	0.57	0.81	3.49	6.39	1
MAE loss with static subgraphing	0.2	64	0.33	1.04	3.77	6.93	1
MAE loss	0.2	64	**0.19**	**0.22**	3.05	3.75	1
Dynamically weighted loss	0.2	64	0.41	0.5	3.99	5.23	1
Weighted loss	0.2	64	0.38	0.57	3.61	5.88	1
Maximal loss (top 100)	0.2	64	0.37	0.48	**2.5**	3.58	1
Maximal loss (top 10000)	0.2	16	0.26	0.29	2.77	**3.53**	1

RESULTS AND DISCUSSION

- **Osmotic pressure**

Type	Noise Std	Latent Size	Averaged Valid Error	Averaged Test Error	Max Valid Error	Max Test Error	Max K
MAE loss with dynamic subgraphing	0.1	64	0.24	0.27	2.3	2.65	0.5
MAE loss with static subgraphing	0.1	64	0.29	0.35	2.45	2.69	0.5
MAE loss	0.1	64	**0.13**	**0.16**	2.54	2.74	0.5
Dynamically weighted loss	0.1	64	0.18	0.24	1.73	**1.96**	0.5
Weighted loss	0.1	64	0.15	0.19	2.07	2.25	0.5
Maximal loss (top 100)	0.1	64	0.21	0.3	**1.55**	1.99	0.5
Maximal loss (top 10000)	0.1	64	0.15	0.22	1.88	2.6	0.5

RESULTS AND DISCUSSION

- **Fibrillar stress**

Type	Noise Std	Latent Size	Averaged Valid Error	Averaged Test Error	Max Valid Error	Max Test Error	Max K
MAE loss with dynamic subgraphing	0.5	16	0.59	0.72	2.93	2.94	0.5
MAE loss with static subgraphing	0.5	64	0.44	0.66	2.45	2.56	0.5
MAE loss	0.5	64	**0.32**	**0.33**	2.69	2.75	0.5
Dynamically weighted loss	0.5	64	0.44	0.68	3.24	3.23	0.5
Weighted loss	0.5	64	0.44	0.78	2.43	2.47	0.5
Maximal loss (top 100)	0.5	64	0.38	0.42	1.93	**1.97**	0.5
Maximal loss (top 10000)	0.5	64	0.35	0.44	**1.91**	1.99	0.5

THANK YOU