3 M.Sc. Thesis Projects

at the Interface of *Computational Physical Modeling* and *Machine Learning*

in collaboration with Carl Zeiss AG

1) Neural operator for parametric PDEs

What: Partial Differential Equations (PDEs) are ubiquitous in the modeling of physical phenomena (solids, fluids etc). Very often they depend on several parameters that describe e.g. material properties, boundary/initial conditions etc.

Why: In *many-query applications* (e.g. sensitivity analysis, uncertainty quantification, inverse problems, optimization) these PDEs must be solved repeatedly under different parametric values which poses a significant computational burden.

How: Neural Operators are a fairly recent development that attempt to approximate the solution of the PDE as a function of the parametric input with the help of data. Once trained, one need not solve the PDE anymore but can efficiently obtain (approximate) solutions for various parameter values.

Objective: The objective of the project would be to investigate the performance of pertinent Neural-Operator-based architectures and identify advantages and disadvantages in the context of some benchmark problems.

2) Data-driven Reduced order modeling across discretizations and geometry changes

What: Full-order models (FOMs) offer unparalleled resolution for several physical phenomena but generally imply a significant computational burden, especially if these need to be solved under different values of the input parameters or boundary/initial conditions.

Why: Reduced-order Models (ROMs) are lower-dimensional versions which can provide accurate predictions at a much lower cost.

How: ROMs are generally constructed from simulation data obtained from the FOM which is run over a small set of parameters or over a small time-range.

Objective: **The objective of the project would be to investigate the utility of machine-learning tools in the construction of ROMs, particularly in cases where variations in the geometry of the problem domain are considered. Of particular interest are blood flow simulations.**

3) Inverse problems in solid and fluid mechanics

What: Model-based inverse problems arise in several applications and entail identifying model parameters with the help of measurements. As such, they can guide model calibration and validation.

Why: The solution of inverse problems is hampered by the exorbitant number of times the forward model needs to be solved which frequently scales exponentially with the number of model parameters to be identified.

How: Modern formulations account for the uncertainty that arise due to noisy or scarc data while attempting to overcome the significant computational cost associated with their solution.

Objective: The objective of the project would be to investigate machine-learning tools in combination with physics-based models that can lead to efficient solutions of inverse problems in solids and fluids mechanics.