Data-driven model order reduction in computational mechanics

Background

In order to simulate a certain material, a constitutive model, relating deformation with stresses, needs to be derived. Finding an accurate phenomenological model for materials with complicated microstructure such as composite materials is usually very complicated and often involves several nonphysical parameters. Therefore, instead of deriving the constitutive model, one can explicitly define a microscopic problem on a representative volume element, which represents the microstructure of the material. By solving this microscopic problem, an effective constitutive model can be obtained. However, the microscopic problem needs to be solved for every point of the macroscopic problem, resulting in a computationally very expensive simulation which is infeasible for multi-query contexts such as optimization, control or design. To make such analyses possible, there is a need for reduced order models that can approximate the microscopic simulation. To accomplish that, we focus on data-driven approaches, utilizing methods of Machine Learning and Data Science.

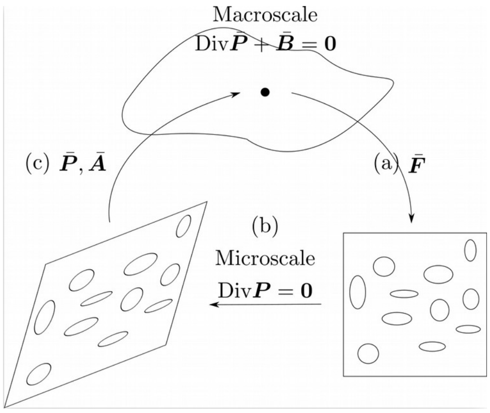

Figure 1: Instead of solving only the macroscale problem, a coupled two-scale problem involving a microscale is solved.

In a previous work, we have already constructed a surrogate model for an elastic microstructure. However, for applications, it is also important to be able to approximate more complicated material phenomena such as plasticity. The main difficulty in plasticity arises from the history-dependency: the stress depends not only on the current deformation but on all previous deformations. A specific type of neural networks, namely recurrent neural networks, have the capability of learning sequential data and therefore have the capability of learning such history-dependent behavior. The goal of this project is thus to extend the previous work to elasto-plastic microstructures by utilizing recurrent neural networks.

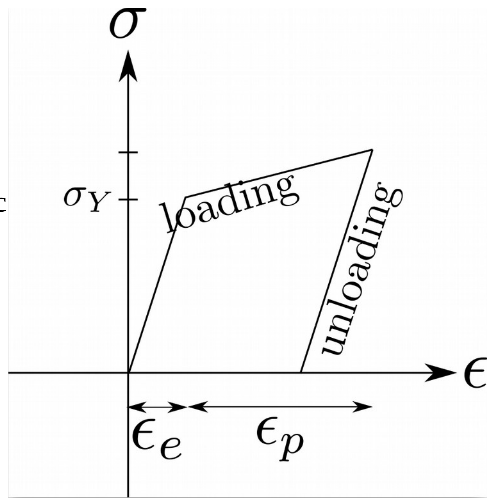

Figure 2: When loading above the yield stress, the material will deform plastically. After unloading, the plastic strains will remain.

Tasks

- Read and understand literature (provided by supervisor)
- Generate datasets by solving the microscopic simulation for different test cases
- Implement and optimize neural network architectures in Python
- Compare the results obtained with different approaches in literature
- [Optional] Embed the reduced order model into a macroscopic problem and compare the results with the solution obtained with the full order model

Requirements

- Basic knowledge of Machine Learning/Deep Learning
- Programming experience with Python in general and in particular the packages NumPy and PyTorch
- Some knowledge of Partial Differential Equations or Continuum Mechanics and Nonlinear Finite Element Method might be beneficial

Supervisor

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