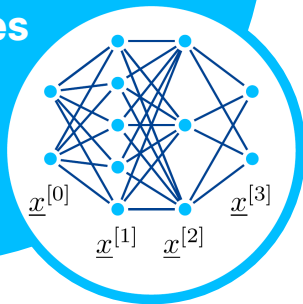


**Symmetry
preserving
data-driven
surrogates**



Symmetry is one of the simplest to incorporate model reduction methods. Symmetry boundary conditions can save substantial amount of cpu time and memory in many practical FE simulations and the investigation of crystal symmetries can lower the number of material parameters considerably.

When replacing material models by machine learned surrogates the incorporation of symmetry is possible through manifold methods. In this work focus will be on crystal symmetries. Starting from invariants defined as a function of the underlying symmetry group, high efficiency can be attained. Other approaches include averaging techniques or minimum domain approaches where the smallest possible part of the full input space is discretized.

In the student research topic different machine learning models for feedforward neural networks and radial basis function networks will be implemented and compared. Evaluation criteria will be formulated and a scoring scheme shall be developed to ease comparison and model selection. Ultimately, the design of toolbox for easy integration into more exhaustive parametric surrogate models should be the result of the project.

Tasks

- literature research
- implement different models using pytorch
- run benchmrks
- develop a quality measure
- draft a simple to use toolbox

Technical requirements

- python programming skills
- basic knowledge in material modeling and in neural networks

