An Algorithm to reduce evaluation time of Interpolated Deep Material Network during Hyper parameter tuning

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I. Overview

The availability of high performance computers (HPC) and high resolution μ-CT imaging tools has allowed for digital characterization of materials [1]. The state of the art algorithms [1] are time expensive. Deep Material Network (DMN) [1] is a hybrid ML paradigm used as an alternative to these methods. The DMN involves training in the linear elastic domain called offline training and physics based extrapolation in the nonlinear elastic domain called the online evaluation [2]. The computational advantage that DMN gives over traditional multiscale simulations can be seen in table I.

parameter	Standard solver	DMN
component elements	1 million	1 million
homogenization time per element	0.5-4 hours	60-90 seconds
Total compute time	57-457 years	2-3 years

TABLE I
Comparision of compute time for multiscale simulation of plasticity

In the offline training, machine learning is used to fit the responses of a complex microstructure to an equivalent set of laminates. In essence the response is reproduced by tuning the volume fractions and laminate directions. For the case of fiber reinforced composites, all possible microstructure geometries can be represented by the Fiber Orientation Triangle (FOT). In an interpolated version of DMN, the direction of laminates are parameterized by the fiber orientation on the FOT. Figure 1 shows the simplified training procedure.

In the online evaluation stage, the laminate set is solved using a nonlinear solution method with their respective material laws and boundary conditions. But not all models identified in the offline training lead to good results in the online evaluation [3]. So an identified model parameter set has to be evaluated on a large number of different microstructures to evaluate success of hyper parameter tuning, see Figure 2.

In this work an algorithm is proposed called selective distillation which gives a robust way to choose the best among the obtained models. The effectiveness of the algorithm is proved for a plasticity case study and future scope is discussed.

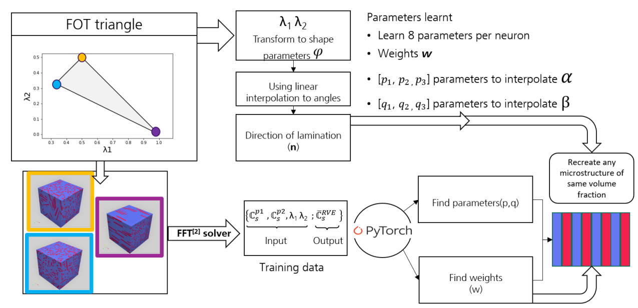

Fig. 1. The figure shows the simplified offline training procedure of an interpolated Deep Material Network

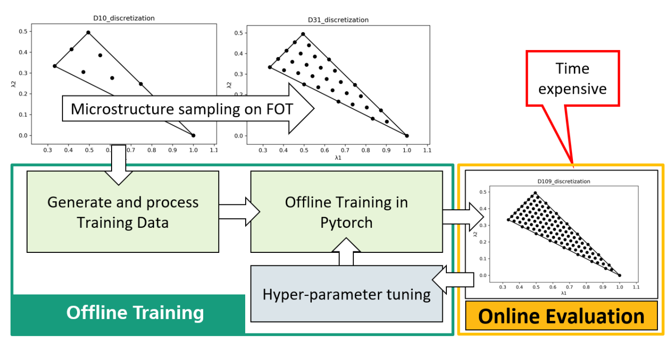

Fig. 2. The figure shows the global steps of hyper parameter tuning in Deep Material Network. Note that retuning is required in the offline training if errors in online predictions are high. The large online evaluations are a bottle neck

References

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[3] A. P. Dey, F. Welschinger, M. Schneider, S. Gajek, and T. Böhlke, Training deep material networks to reproduce creep loading of short fiber-reinforced thermoplastics with an inelastically-informed strategy, Archive of Applied Mechanics, vol. 92, no. 9, pp. 27332755, Sep. 2022.