Unsupervised learning of constitutive models with neural networks

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In recent years, significant efforts have been made to model material behavior laws using neural networks (NN) [1, 2]. One of the key challenges in this field is ensuring thermodynamic consistency, which can be done by relying on the Generalized Standard Material (GSM) framework [3]. In the GSM framework, the constitutive model is described by two positive convex scalar functions, the Helmholtz free-energy and the dissipation potential. A recent trend involves leveraging input-convex neural networks to represent these two thermodynamic potentials, thereby inherently satisfying thermodynamic principles [4, 5].

These networks can be trained using measurable data within unsupervised frameworks, such as NN-EUCLID (see [2] for the original article and [6] for experimental validation) or NN-mCRE [4, 7]. The aim of this talk is to present recent advances in unsupervised learning applied to the modeling of mechanical constitutive laws. In particular, the two previously mentioned unsupervised approaches will be compared with respect to criteria such as computational efficiency, noise robustness, type of data required, and sensitivity to initialization.

References

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