A Neural Network-Based Framework for Data-Driven Inelasticity in Two Dimensions

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Abstract

Ongoing research in computational mechanics has led to the development of numerous data-driven methods. Within this class of methods, Kirchdoerfer and Ortiz (1) introduced data-driven mechanics, which substitutes traditional material models with data sets containing discrete pairs of stress and strain. The solution to boundary value problems is then derived by minimizing a distance between these pairs, referred to as material states, and mechanical states, which satisfy equilibrium and kinematic compatibility conditions.

While originally formulated for elastic materials, extending this framework to inelastic material responses is necessary but non-trivial due to the path-dependent behavior of such materials. In our extension (2) we utilize a history surrogate, a quantity designed to store essential information of stress and strain paths. This surrogate works in conjunction with a propagator, which updates the history surrogate at the end of each time step. The path-dependent behavior is embedded into the framework by introducing the history surrogate to both the material and mechanical states as an additional quantity. By doing so, our framework preserves the key characteristics of the original method.

For truss structures, as demonstrated in (3), finding an appropriate history surrogate can be achieved intuitively. However, for two-dimensional problems, the increased complexity of stress and strain paths also makes this task substantially more challenging. To address this, we use a neural network as propagator. The neural network autonomously handles the task of defining and updating the history surrogate based solely on discrete stress and strain data, thereby eliminating the need for explicit update rules or user intervention.

In this contribution, we provide a detailed analysis of our framework's capabilities, beginning with truss structures, which include inelastic material behavior, and results are presented for both an intuitive and neural network propagator. We further extend the discussion to two-dimensional problems, presenting results for the framework using the neural network propagator. Additionally, we examine the challenges associated with a higher-dimensional setting and offer insights into potential strategies for overcoming related issues.

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