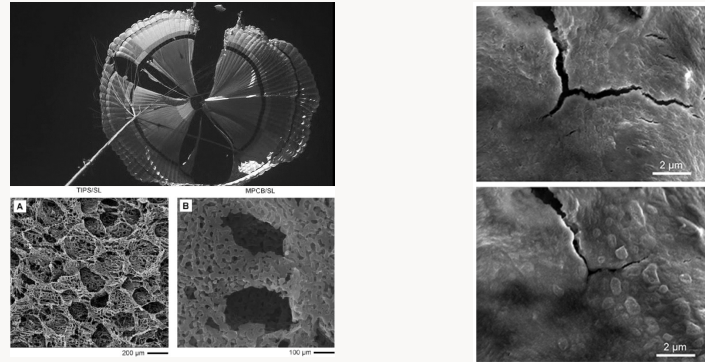


Learning Constitutive Relations using Symmetric Positive Definite Neural Networks

Background



How to model complex constitutive behaviors from observations?

Failure of parachute test; multiscale porous scaffolds; fracture in batteries. Source: NBC News; Luigi Ambrosio; Technologyreview

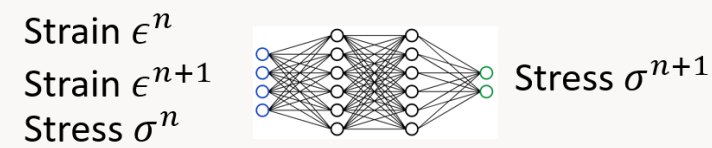
- ▶ It is challenging to model complex material constitutive behavior with conventional mathematical modeling approaches.
- ▶ Deep neural networks emerge as an empirically successful function approximator for complex and high dimensional functions.
- ▶ To leverage the physics to the largest extent, we **couple neural-network-based constitutive relations and partial differential equations**.
- ▶ Training the neural network requires back-propagating through both the numerical partial differential equation solvers and deep neural networks.
- ▶ Most important of all, **what conditions should deep neural networks satisfy to stabilize numerical solvers?**

Software

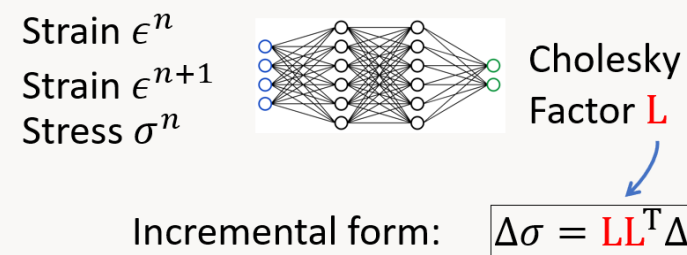
NNFEM.jl <https://github.com/kailaix/NNFEM.jl>

SPD-NN

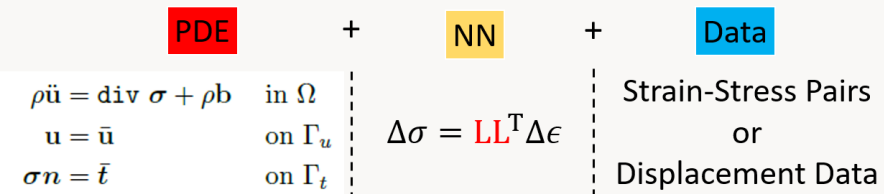
- ▶ Conventional neural-network-based constitutive relations



- ▶ Symmetric positive definite neural networks (SPD-NN)



Residual Learning



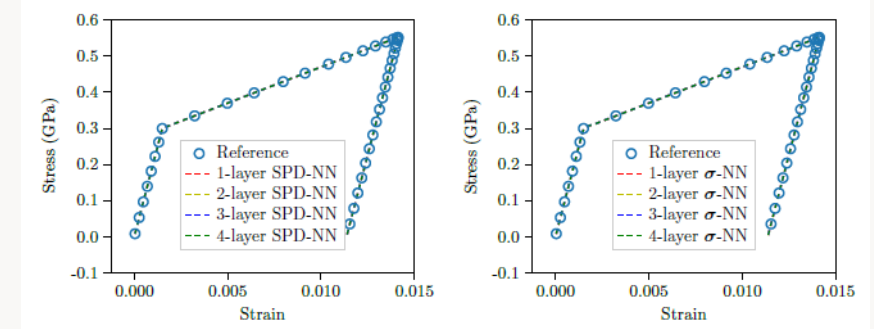
↓
Finite Element Residual

$$\arg \min_{\theta} \mathcal{L}(\theta) := \sum_{j=1}^N \sum_{i=2}^{n-1} (M\ddot{u}_j^i + P(u_j^i, \sigma_j^i(\theta)) - f_j^i)^2$$

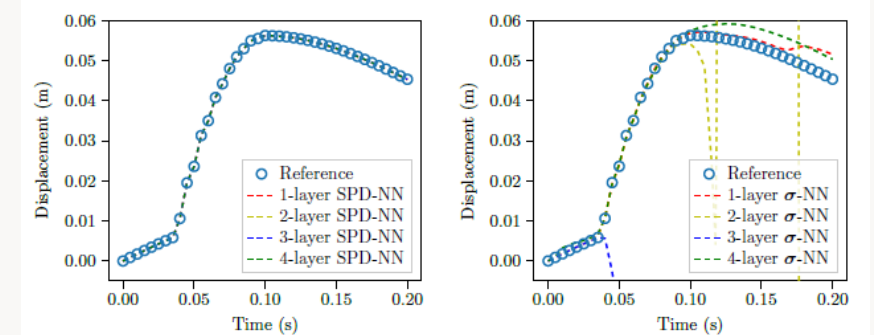
- ▶ The time integrator of the PDE resembles a recurrent neural network.
- ▶ Automatic differentiation through both PDE solvers and neural networks.

Result

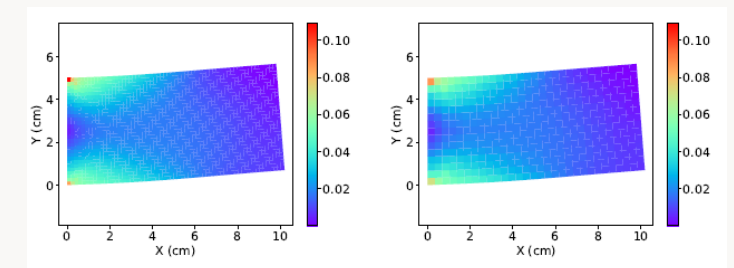
- ▶ Elasto-plasticity
 - Both SPD-NNs and conventional NNs predict strain-stress curves accurately.



- But when they are coupled with a numerical solver, only SPD-NNs are stable.



- ▶ Hyperelasticity



- ▶ Multi-scale

