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Utilizing data and physical constraints in machine learning-enabled computational solid mechanics and multiphysics

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Machine learning techniques are gearing up to play a significant role in the field of computational solid mechanics and multiphysics, enabling the integration of experimental data and physical constraints towards data-driven constitutive laws, acceleration of computational techniques for multi-scale modeling, and new paradigms for the solution of forward and inverse problems, to name a few. This talk will cover recent advancements in the aforementioned areas: I) A physics-informed data-driven constitutive modeling approach for isotropic and anisotropic hyperelastic materials is developed. This generalized approach is based on rewriting the stress output as a linear combination of an irreducible integrity basis. The trained laGPR surrogates are able to respect physical principles such as material frame indifference, material symmetry, thermodynamic consistency, stress-free undeformed configuration, and the local balance of angular momentum. Overall, the presented approach is tested on synthetic data from isotropic and anisotropic constitutive laws and shows surprising accuracy even far beyond the limits of the training domain, indicating that the resulting surrogates can efficiently generalize as they incorporate knowledge about the underlying physics. ii) We utilize physics-informed neural networks (PINNs) to solve interval and fuzzy partial differential equations. The resulting network structures termed interval physics-informed neural networks (iPINNs) and fuzzy physics-informed neural networks (fPINNs) show promising results for obtaining bounded solutions of equations involving spatially and/or temporally uncertain parameter fields. In contrast to finite element approaches, no correlation length specification of the input fields as well as no Monte-Carlo simulations are necessary. In fact, information about the input interval fields is obtained directly as a byproduct of the presented solution scheme. Furthermore, all major advantages of PINNs are retained. iii) Finally, a data-driven framework is presented based on the usual offline-online paradigm for solving PDEs, focusing on complex microstructures in the context of both forward and inverse problems. The framework is developed based on conditional and patch-based generative adversarial networks (GAN), typically used in image/video analysis. Here we will focus on an extension to time-dependent problems in the context of poroelasticity.