

## DATA-DRIVEN APPROACHES FOR SOLID MECHANICS

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### MINISYMPOSIUM

This mini-symposium continues the effort of bringing together researchers that work on advancing the data-driven, reduced-order modeling, and machine learning approaches within the realm of solid mechanics. In recent years, advancements in machine learning and data-driven approaches provide new research directions for the modeling and simulation of complex problems in solid mechanics. Several promising directions emerge in the field, ranging from directly exploiting data for computational mechanics without constitutive laws, applying deep learning including manifold learning and autoencoders for reduced-order modeling of nonlinear high-dimensional mechanics problems, to integrating data-driven machine learning techniques with physics-based models for various forward and inverse problems such as the discovery of the underlying governing equations of complex material and physical systems. This mini-symposium focuses on recent research developments and applications in data-driven approaches for computational solid mechanics, with topics that include but are not limited to: 1) Model-free data-driven computational mechanics; 2) Physics-informed machine learning for linear and nonlinear solid mechanics; 3) Data-assisted modeling of heterogeneous materials; 4) Data-driven discovery of constitutive laws and governing equations; 5) Interpretable discovery enabled by machine learning; 6) Causal discovery for explainable modeling; 7) Supervised/Unsupervised data/physics-driven learning of surrogate models; 8) Reduced-order real-time simulation of solid; 9) Inverse design problems with machine learning.