Nonlinear model reduction: Using machine learning to enable rapid simulation of extreme-scale physics models

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Abstract

Physics-based modeling and simulation has become indispensable across myriad applications in science and engineering, ranging from aircraft design to monitoring national critical infrastructure. However, achieving high predictive fidelity necessitates modeling fine spatiotemporal resolution, which can lead to extreme-scale computational models whose simulations consume months on thousands of computing cores. This constitutes a formidable computational barrier: the cost of truly high-fidelity simulations renders them impractical for essential time-critical applications in engineering and science such as rapid design, health monitoring, and control.

In this talk, I will present several recent advances in the field of nonlinear model reduction that exploit concepts from machine learning to overcome this barrier. In particular, I will focus on recently developed manifold-projection techniques, which generate reduced-order models by projecting the equations governing the high-fidelity model onto nonlinear manifolds learned by deep convolutional autoencoders; this approach yields near-optimal performance on transport-dominated problems. I will also describe machine-learning error models, which employ regression techniques to construct statistically validated models of the error incurred by model reduction; this enables reduced-order models to be integrated rigorously into decision-making scenarios.