

Advancements in Scientific Machine Learning techniques for time-dependent problems and applications

600 - Data Science, Machine Learning and Artificial Intelligence

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ABSTRACT

Time-dependent systems, governed by discrete dynamical models or evolutionary partial differential equations (PDEs), describe various scientific and engineering applications. The combination of handling numerical approximation via time-advancing schemes and, at the same time, discovering differential equations from time series measurements poses significant challenges to scientific machine learning methods (SciML). This minisymposium aims at exploring recent advances in data-driven and hybrid end-to-end SciML approaches for enhancing the modeling and simulation of time-dependent phenomena.

Specifically, our scope is to present recent advances and emerging trends in operator learning approaches designed to model temporal dynamics, including architectures such as recurrent neural networks (RNNs), neural ordinary differential equations (NODEs), attention-based architectures, and other discrete- or continuous-time formulations. Particular attention will be devoted to techniques and applications that integrate machine learning with classical numerical solvers, accelerate time integration, and improve solution strategies for learning stiff or multiscale surrogate models in multi-query regimes. In this context, key challenges to be addressed include balancing computational efficiency with numerical fidelity, enhancing generalization and long-term prediction, tuning high-dimensional models with limited data, and preserving physical consistency.

We especially encourage submissions that apply these methods in computational mechanics and biomedical applications, including areas such as computational cardiology, tissue modeling, and poro-mechanics.

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