

DEEP LEARNING AND REDUCED ORDER MODELING FOR DIFFERENTIAL EQUATIONS

1800 - SCIENTIFIC COMPUTING

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ABSTRACT

The solution of differential equations using full-order models (FOMs) incurs significant computational costs, especially in real-time simulations and multi-query routines. To address this challenge, reduced order models (ROMs) have emerged as a crucial framework for generating efficient and reliable approximations essential for simulations in basic sciences and industrial applications. The increasing demand for efficient non-intrusive methods, coupled with the availability of large amounts of data from measurements or simulations, has spurred the development of new techniques for complexity reductions based on deep learning in computational science. These approaches leverage state-of-the-art machine learning algorithms capable of extracting previously unseen patterns inherent in the data.

Integrating data-driven techniques with physics-based approaches enhances the modeling capabilities and interpretability of the models, enabling consistent and accurate predictions even for complex systems. This integration has given rise to several research lines that combine traditional ROMs with scientific machine learning.

This mini-symposium aims to bring together researchers actively involved in the theories, methods, and applications of deep learning-based techniques for complexity reduction. The areas of interest include, but are not limited to, deep-learning-based reduced order modeling, approximations using neural operators, physics-informed deep learning, multi-fidelity methods, as well as the approximation and mathematical properties of neural networks.

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