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DATA-ENHANCED REDUCED ORDER MODELING

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ABSTRACT

Reduced order methods (ROMs) are crucial for fast and accurate numerical predictions in engineering applications, especially when dealing with many-query scenarios in optimization, uncertainty quantification, and parameter estimation. Many classic model order reduction approaches - such as proper orthogonal decomposition or reduced basis methods - have a solid mathematical foundation that guarantees approximation accuracy and keeps the ROM interpretable to the governing physical laws. However, many practical applications are too complex (e.g., large Kolmogorov n-width) or inaccessible (e.g., private or legacy codes) for classic ROMs to approximate reliably. Therefore, in recent years, many data-driven and non-intrusive techniques have been introduced to enhance ROMs by exploiting additional data from full-order computations. Under the umbrella of scientific machine learning, this combination of domain knowledge, physical principles, and artificial intelligence offers the advantages associated with machine learning techniques while remaining physically interpretable. However, many open problems still need to be solved to reliably merge these techniques and create stable ROMs, especially for large-scale applications with relatively sparse available high-fidelity simulations.

This mini-symposium aims to present recent computational strategies to improve the construction of ROMs with data. We also want to foster discussions about potential future research directions in linear and nonlinear model order reduction, scientific machine learning, and data-driven methods.

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