Reduced-order modeling and learning of parameterized dynamical systems: state-of-the-art vs. avant-garde methods

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Short Description

Model order reduction (MOR) generally refers to a collection of methodologies that can be employed to replace a large-scale dynamical system having a complex structure (and is characterized by many ordinary/partial differential equations), with a much simpler and smaller dynamical system (characterized by few equations with simplified dynamics). In the last decades, a plethora of methodologies have been proposed to reduce complex dynamical systems, either in the time domain or in the frequency domain, either in the finite-dimensional or infinite-dimensional setup, having linear and/or nonlinear dynamics, or being characterized by ODEs or PDEs (potentially, with algebraic equations as well). Parametric MOR (or pMOR) is specifically tailored to the class of dynamical systems that depend on one or more parameters. Examples include parameterized partial differential equations and large-scale systems of parameterized ordinary differential equations. Parametric MOR aims at generating accurate models of lower complexity that characterize the system response for different values of the parameters. It is relevant for applications in design, control, optimization, and uncertainty quantification-settings that require repeated model evaluations over different parameter values. Data-driven pMOR (DD-pMOR), on the other hand, is of high interest when the high-fidelity dynamical model with parametric dependencies is not (exactly) known. In such scenarios, only certain measurements associated with the full-order and complex system may be available. These data are measured through direct numerical simulations (through numerical integration or differentiation generated by high-fidelity solvers) or measured with high-precision equipment (in the laboratories). Such data sets include snapshots in the time domain (of state variables, or of inputs/outputs associated with the original system), or in the frequency domain data (such as the frequency response, S- and X-parameters, impedance/admittance data, etc.). Using only data, a parameterized dynamical model is learned through different types of strategies and methods, including the reduced-basis method (arguably the most powerful approach for parameterized PDEs), optimization-based and machine learning methods, or moment-matching interpolatory approaches (such as the Loewner framework, or one-sided approaches that use signal generators). This MS brings together a multitude of methodologies, both for traditional (or intrusive pMOR) that require explicit access to the high-fidelity models and also for DD-pMOR that require only data, with an emphasis on the latter type of methods. Contributions will mostly be made for applications to ODEs but also some to PDEs, which use time-domain but also frequency-domain data. The types of MOR methods are mostly based on optimization tools, but some are enforcing moment matching (or interpolation).