Andrea Manzoni

Predictive Data-Driven Model Reduction and Discovery for Dynamical Systems

Abstract

Reduced order modeling (ROM) techniques, such as the reduced basis method, provide nowadays an essential toolbox in numerical analysis for the efficient approximation of parametrized differential problems, whenever they must be solved either in real-time, or in several different scenarios. These tasks arise in several contexts like, e.g., uncertainty quantification, control and monitoring, as well as data assimilation, ultimately representing key aspects in view of designing predictive digital twins in engineering or medicine. On the other hand, in the last decade deep learning algorithms have witnessed dramatic blossoming in several fields, ranging from image and signal processing to predictive data-driven models. More recently, deep neural networks have also been exploited for the numerical approximation of differential problems yielding powerful physics-informed surrogate models.

In this talk we will explore different contexts in which deep neural networks can enhance the efficiency of ROM techniques, ultimately allowing the real-time simulation of large-scale nonlinear time-dependent problems, and the discovery of dynamical systems. We show how to exploit deep neural networks (like, e.g., convolutional autoencoders) to build ROMs for parametrized PDEs in a fully non-intrusive way. Moreover, we will show how the data-driven discovery paradigm relying on sparse identification of nonlinear dynamics, combined with autoencoders, can be used to identify the system dynamics at the latent level in the case of parametrized dynamical systems. Furthermore, we will also show how to improve a low-fidelity ROM through a multi-fidelity neural network regression technique that allows to merge low- and high-fidelity data, when dealing with both input/output evaluations and solution field approximations.

Through a set of applications from engineering including, e.g., structural mechanics and fluid dynamics problems, we will highlight the opportunities provided by deep learning in the context of ROMs for parametrized PDEs, as well as those challenges that are still open.

This is a joint work with Stefania Fresca, Paolo Conti, Attilio Frangi (Politecnico di Milano), Mengwu Guo (University of Twente), J. Nathan Kutz and Steven Brunton (University of Washington).