A comprehensive deep learning-based approach for reduced order modeling of nonlinear time-dependent parametrized PDEs

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Traditional reduced order modeling techniques such as the reduced basis (RB) method (relying, e.g., on proper orthogonal decomposition (POD)) show severe limitations when dealing with nonlinear time-dependent parametrized PDEs because of the basic assumption of linear superimposition of modes they rely on. For this reason, in the case of problems featuring coherent structures that propagate over time such as transport and wave-type phenomena, or convection-dominated flows, the RB method usually yields inefficient reduced order models (ROMs) if one aims at obtaining reduced order approximations sufficiently accurate compared to the high-fidelity, full order model (FOM) solution. To overcome these limitations, in this talk we show a nonlinear approach to set reduced order models exploiting deep learning techniques. In the resulting nonlinear ROM, to which we refer to as DL-ROM, both the nonlinear trial manifold (corresponding to the set of basis functions in a linear ROM) as well as the nonlinear reduced dynamics (corresponding to the projection stage in a linear ROM) are learned in a non-intrusive way, by relying on deep learning models, trained on a set of FOM solutions obtained for different parameter values. Numerical results show that DL-ROMs are capable of approximating the solution of parametrized PDEs by employing reduced order models whose dimension is equal to the intrinsic dimensionality of the PDE solutions manifold in situations where a huge number of POD modes would be necessary to achieve the same degree of accuracy.