Machine learning for nonlinear model order reduction

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Abstract

In many engineering domains, numerical simulations have become essential for the design of industrial products. With the development of high-performance computing, advanced numerical models can now be applied to real-world problems involving complex physical phenomena. However, as numerical predictions become more and more accurate, it is crucial to quantify uncertainties induced by the lack of information about the environment of the physical system. In the aeronautical industry, the thermo-mechanical behavior of materials working at high temperatures in aircraft engines is predicted by elasto-viscoplastic constitutive laws. Although accurate, predictions made by these models highly depend on the thermal loading which is not exactly known because of modeling and experimental uncertainties. Reducing the computational cost of these numerical simulations is a critical challenge towards a more reliable design, as it would become possible to run a large number of simulations for uncertainty quantification.

The complexity of numerical simulations can be mitigated by projection-based model order reduction, which consists in computing an approximate solution in a low-dimensional approximation space that is adapted to the physics problem. Nonetheless, when uncertainties on some parameters highly affect the response of the physical system, the solution manifold can no longer be embedded in a low-dimensional subspace of the solution space. In this case, one can build a dictionary of local reduced-order models that are associated to different regions of the solution manifold, as suggested in [1]. This dictionary of models can be obtained by partitioning the solution space by means of a physics-informed cluster analysis with a suitable dissimilarity measure involving simulation data. In the exploitation phase, the selection of the most suitable model in the dictionary for a given configuration of the environment of the physical system is sometimes too time-consuming for uncertainty propagation purposes. To address this issue, a classification algorithm can be trained for automatic model recommendation. In this way, the choice of the reduced-order model can be adapted to the environment and the state of the physical system to get fast and accurate predictions about its behavior. This methodology combining physics-based modeling and machine learning algorithms is presented in [2].

Keywords: model order reduction, clustering, classification, computational physics.

References

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