Data-driven flow modeling using Machine Learning and Data Assimilation

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In this talk, we present *intrusive* and *nonintrusive* data-driven approaches of reduced-order modeling for the dynamical prediction of fluid flows.

For the intrusive approach, Proper Orthogonal Decomposition based ROM (POD-ROM) is considered. First, we consider sparse regression methods issued from *statistical learning* to identify the linear unknowns of the ROM. A *bootstrap method* is then proposed to quantify in a probabilistic framework the uncertainties associated with the regression methods. Then, the POD-ROM is augmented with a nonlinear eddy viscosity model that provides an interpretable *physics-based* closed-form representation of the flow dynamics. Finally, the closure term parameters are estimated with a *Dual Ensemble Kalman filter* approach (Dual EnKF) which integrates the model outputs and measurements while taking into account the respective uncertainties.

For the nonintrusive approach, regression models based on Neural Networks (NN-ROM) are considered as an alternative to the POD-ROM. This method addresses the limitations of POD-ROM – the lack of an *a priori* guarantee of stability, and requirement of closure to account for the unresolved modes – at the cost of interpretability of the resulting surrogate model. The derived NN-ROM serves as a time-stepping method for the POD projection coefficients. A novel multistep, residual-based, parametrized neural network is then proposed. This framework is augmented with *Data Assimilation* (DA) to provide accurate long-term dynamical predictions.