Prospects for the application of data-driven methods for computational physics modeling

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With the proliferation of high-resolution datasets and advances in computing and algorithms over the past decade, data science has risen as a discipline in its own right. Machine learning-driven models have attained spectacular success in commercial applications such as language translation, speech and face recognition, bioinformatics, and advertising. The natural question to ask then is: Can we bypass the traditional ways of intuition/hypothesis-driven model creation and instead use data to generate predictions of physical problems? The first part of this talk will review recent work in which inference and machine learning have been used to extract operator matrices, discover dynamical systems, and derive the solution of differential equations. The second part of the talk will discuss the challenges of extending these methods and data-driven modeling in general in the prediction of complex real-world problems. For instance, regardless of the quantity of interest, there may exist several latent variables that might not be identifiable without a knowledge of the physics; we may not have enough data in all regimes of interest; and the data may be noisy and of variable quality. A pragmatic solution, then, is to blend data with existing physical knowledge and enforcing known physical constraints. Thus, one can improve model robustness and consistency with physical laws and address gaps in data. This would constitute a *data-augmented physics-based* modeling paradigm. Examples of this hybrid paradigm will be highlighted in fluid flow and materials applications.