Data to Decisions via Multifidelity Modeling and Adaptive Reduced Models

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ABSTRACT

The next generation of complex engineered systems will be endowed with sensors and computing capabilities that enable new design concepts and new modes of decision-making. For example, new sensing capabilities on aircraft will be exploited to assimilate data on system state, make inferences about system health, and issue predictions on future vehicle behavior—with quantified uncertainties—to support critical operational decisions. However, data alone is not sufficient to support this kind of decision-making; our approaches must exploit the synergies of physics-based predictive modeling and dynamic data.

Our approaches must also go beyond reliance on a single model, instead exploiting the potential of a rich set of information sources. Multifidelity modeling refers to the situation where we have available several numerical models that describe a system of interest. Different models may arise from a choice to resolve the physics at different scales, from invoking different modeling assumptions, and from deriving surrogates such as projection-based reduced-order models and data-fit models; thus, the different models vary in fidelity and computational costs. A multifidelity approach seeks to exploit optimally all available models and data for a particular task (e.g., optimization, uncertainty quantification). The idea is to use the cheaper models as much as possible but to maintain the quality of higher-fidelity estimates and associated guarantees of convergence.

This talk describes our recent work in adaptive and multifidelity methods for optimization under uncertainty of large-scale problems in engineering design. We combine traditional projection-based model reduction methods with machine learning methods, to create data-driven adaptive reduced models that exploit the synergies of physics-based computational modeling and physical data [1]. We develop multifidelity formulations to combine these reduced models with higher-fidelity "truth" models. For uncertainty propagation, we use a control variate formulation that leads to the multifidelity Monte Carlo method [2]. For failure probability estimation, we formulate a multifidelity importance sampling approach. In both cases, we retain confidence in the estimates of statistics of interest even in the absence of rigorous error bounds on the reduced models themselves [3].

REFERENCES

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