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LEVERAGING ACTIVE DIRECTIONS FOR EFFICIENT MULTIFIDELITY UQ

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Uncertainty Quantification (UQ) is critical in order to enable predictive numerical simulations for scientific discoveries and advanced engineering design. However, in the presence of complex high-fidelity simulations and a large number of uncertainty parameters the computational cost becomes prohibitive.

In recent years, multifidelity (MF) UQ has been introduced in order to alleviate this issue and it is based on the aggregation of several lower accuracy models with an handful of higher fidelity computations. In this talk we focus on sampling based approaches. The first method introduced in this class has been the multilevel Monte Carlo method (MLMC) [1] where the convergence of the deterministic scheme is exploited to decrease the need for realizations at the higher (more expensive) resolution levels. In the presence of different fidelities, i.e. lack of formal convergence between levels, the control variate (CV) approach has been introduced with the idea to take advantage of the correlation between models [2, 3, 4]. A combination of MLMC and CV can also be designed to exploit both discretization and model fidelities [5].

In this talk we introduce the idea of exploiting important directions, as for instance Active Subspaces (AS) [6], in order to further accelerate multilevel and multifidelity sampling strategies. The key idea is to use the important directions as a shared space between models on which the correlation is maximized. This approach does not requires the AS to be identical between models and it also suited for problems in which the models have dissimilar input parameterization. The combination of ML/MF sampling approaches and AS will be described and the advantage of the proposed method will be discussed and demonstrated for several test cases and applications.

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