Multi-fidelity information fusion algorithms for high dimensional systems and massive data-sets

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We develop a framework for multi-fidelity information fusion and predictive inference in high dimensional input spaces and in the presence of massive data-sets. Hence, we tackle simultaneously the “big-N” problem for big data and the curse-of-dimensionality in multi-variate parametric problems. The proposed methodology establishes a new paradigm for constructing response surfaces of high dimensional stochastic dynamical systems, simultaneously accounting for multi-fidelity in physical models as well as multi-fidelity in probability space. Scaling to high dimensions is achieved by data-driven dimensionality reduction techniques based on hierarchical functional decompositions and a graph-theoretic approach for encoding custom auto-correlation structure in Gaussian process priors. Multi-fidelity information fusion is facilitated through stochastic auto-regressive schemes and frequency-domain machine learning algorithms that scale linearly with the data. Taking together these new developments lead to linear complexity algorithms as demonstrated in benchmark problems involving deterministic and stochastic fields in up to 100,000 input dimensions and 100,000 training points on a standard desktop computer.