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LATENT VARIABLE NETWORKS FOR MULTIFIDELITY UNCERTAINTY QUANTIFICATION AND DATA FUSION

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We consider the problem of propagating uncertainty through computational simulation models of varying fidelities. Our goal is to estimate, or predict, certain quantities of interest from a specified high-fidelity model when only a limited number of simulations are available. To aid in this task, lower fidelity models can be used to reduce the uncertainty of the high-fidelity predictions. We propose to frame this problem as learning a latent variable network structure for the statistical independence relationships between the models from available simulation data. First a latent variable model is posed for each simulation model under consideration, then a network structure between the models is learned, and finally predictions are made for the output of the highest fidelity model. We demonstrate how existing techniques, such as control variate Monte Carlo and recursive co-kriging [2], can be interpreted as particular realizations of this framework. We compare our approach with variance reduction sampling methods such as Multilevel Monte Carlo [1] and Multifidelity Monte Carlo [3] and demonstrate faster convergence of statistics by exploiting problem structure such as smoothness. Furthermore, we consider both the tasks of learning both the network structure and the parameters of the conditional probability distributions. We demonstrate that structure learning can improve robustness to account for incorrect ordering assumptions on model fidelities. Finally, we describe an experimental design procedure targeted towards reducing the uncertainty of our predictions. Examples are provided for both synthetic and physics-based simulations.

REFERENCES

[1] Giles, M. B. Multi-level Monte Carlo path simulation. *Oper. Res.* (2008) **56**, pp. 607–617.

[2] Le Gratiet, L. and Garnier, J., Recursive co-kriging model for design of computer experiments with multiple levels of fidelity. *International Journal for Uncertainty Quantification*, (2014) **4:5**, pp. 365–386,

[3] Peherstorfer, B. and Willcox, K. and Gunzburger, M., Optimal model management for multifidelity Monte Carlo estimation. *SIAM Journal on Scientific Computing*, (2016) **38:5** pp. A3163–A3194.