Learning from data through the lens of models: Large-scale Bayesian inversion and applications to the flow of the Antarctic ice sheet

Omar Ghattas
Professor, University of Texas at Austin

Abstract: Many physical systems are characterized by complex nonlinear behavior coupling multiple physical processes over a wide range of length and time scales. Mathematical and computational models of these systems often contain numerous uncertain parameters, making high-reliability predictive modeling a challenge. Rapidly expanding volumes of observational data--along with tremendous increases in HPC capability--present opportunities to reduce these uncertainties via solution of large-scale inverse problems. Bayesian inference provides a systematic framework for inferring model parameters with associated uncertainties from (possibly noisy) data and any prior information. However, solution of Bayesian inverse problems via conventional Markov chain Monte Carlo (MCMC) methods remains prohibitive for expensive models and high-dimensional parameterizations, as result from discretization of infinite dimensional uncertain fields. However, despite the large size of observational datasets, typically they inform only low dimensional manifolds in parameter space, due to ill-posedness of the inverse problem. Based on this property we design scalable Bayesian inversion algorithms that adapt to the structure and geometry of the posterior probability, thereby exploiting an effectively-reduced parameter dimension and making Bayesian inference tractable for some large-scale, high-dimensional inverse problems. We discuss an inverse problem for the flow of the Antarctic ice sheet, which has been solved for as many as one million uncertain parameters at a cost (measured in forward ice sheet flow solves) that is independent of both the parameter and data dimensions. This work is joint with Tobin Isaac (Georgia Tech), Noemi Petra (UC Merced), and Georg Stadler (NYU).

Bio: Dr. Omar Ghattas is a Professor of Geological Sciences and Mechanical Engineering at the University of Texas at Austin. He is also the Director of the Center for Computational Geosciences and Optimization in the Oden Institute for Computational Engineering and Sciences and holds the John A. and Katherine G. Jackson Chair in Computational Geosciences. He is a member of the faculty in the Computational Science, Engineering, and Mathematics (CSEM) interdisciplinary PhD program in the Oden Institute, and holds courtesy appointments in Computer Science and Biomedical Engineering. He has general research interests in forward and inverse modeling, optimization, and uncertainty quantification of large-scale complex mechanical, geological, and biological systems. With collaborators, he received the ACM Gordon Bell Prize in 2003 (for Special Achievement) and again in 2015 (for Scalability), and was a finalist for the 2008, 2010, and 2012 Bell Prizes. He received the 2019 SIAM Computational Science & Engineering Best Paper Prize, and the 2019 SIAM Geosciences Career Prize. He is a Fellow of the Society for Industrial and Applied Mathematics (SIAM).

Monday, April 29th, 4:00-5:00pm
1310 Yeh Student Center