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Computationally efficient methods for Bayesian inversion and uncertainty quantification

Computing solutions to large-scale Bayesian inverse problems can be a challenging task. Recent work on generalized hybrid iterative approaches has enabled the efficient computation of Tikhonov regularized solutions (e.g., computing maximum a posteriori estimates), but the computational costs to obtain uncertainty estimates for these solutions still remain prohibitive. In this talk, we describe efficient methods that are based on the generalized Golub-Kahan bidiagonalization for estimating variances of the posterior distribution and for efficient sampling from the posterior distribution. These methods are ideal for problems where explicit computation of the square root and inverse of the covariance kernel for the prior covariance matrix is not feasible. Such scenarios arise, for example, in problems where covariance kernels are defined on irregular grids, e.g., those from the Matérn class, and the resulting covariance matrices are only available via matrix-vector multiplication. Numerical examples from seismic imaging applications demonstrate the effectiveness of the described approaches.

This is joint work with Arvind Saibaba, North Carolina State University.