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DIMENSION-INDEPENDENT, LIKELIHOOD INFORMED MCMC SAMPLERS FOR BAYESIAN INVERSE PROBLEMS

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When cast in a Bayesian setting, the solution to an inverse problem is given as a distribution over the space where the quantity of interest lives. When the quantity of interest is in principle a field then the discretization is very high-dimensional. Formulating algorithms which are defined in function space yields dimension-independent algorithms, which overcome the so-called curse of dimensionality. These algorithms are still often too expensive to implement in practice but can be effectively used offline and on toy-models in order to benchmark the ability of inexpensive approximate alternatives to quantify uncertainty in very high-dimensional problems. Inspired by the recent development of pCN and other function-space samplers [1], and also the recent independent development of Riemann manifold methods [2] and stochastic Newton methods [3], we propose a class of algorithms [4, 5] which combine the benefits of both, yielding various dimension-independent and likelihood-informed (DILI) MCMC sampling algorithms. These algorithms can be effective at sampling from very high-dimensional posterior distributions.

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