An involution framework for Metropolis-Hastings algorithms on general state spaces

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We consider a general framework for Metropolis-Hastings algorithms used to sample from a given target distribution on general state spaces. Our framework is based on a fundamental involution structure, and shown to encompass several popular algorithms as special cases, both in the finite- and infinite-dimensional settings. In particular, random walk, preconditioned Crank-Nicolson (pCN), schemes based on a suitable Langevin dynamics such as the Metropolis Adjusted Langevin algorithm (MALA), and also ones based on Hamiltonian dynamics including several variants of the Hamiltonian Monte Carlo (HMC) algorithm. In addition, we provide an abstract framework for algorithms that generate multiple proposals at each iteration, which yield efficient sampling schemes through the use of modern parallel computing resources. Here we derive several generalizations of the aforementioned algorithms following as special cases of this multiproposal framework. To illustrate effectiveness of these sampling procedures, we present applications in the context of some Bayesian inverse problems in fluid dynamics.

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