Thermostatic Controls for Noisy Gradient Systems and Applications to Machine Learning

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A large class of problems in machine learning rely on Bayesian estimation of complex parameter dependencies which can be derived from invariant distributions of associated stochastic differential equations. These methods are closely related to techniques used for sampling molecular systems. Stochastic gradient methods, in which the gradient evaluation depends on a subsampling of the available data, can significantly reduce the computational cost, but the subsampling corrupts the gradient structure and introduces substantial errors in the associated probability distributions for parameters. I will describe the design of ``thermostatic'' controls and effective numerical methods for accurate recovery of the parameter distribution in the presence of severe subsampling error.