Manifold MCMC for Mixture Models

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Abstract

Bayesian inference for Mixture Models is a long standing problem in the statistical literature. While the Gibbs sampler is the most prominent approach for mixture models, it can exhibit strong random walk behaviour which in effect reduces the effective sample size. Efficient Monte Carlo algorithms, such as the Riemann manifold Metropolis Adjusted Langevin Algorithm (MMALA) and Hamiltonian Monte Carlo (RMHMC)(Girolami & Calderhead 2011), overcome the problem of random walks in the expense of calculating higher order derivatives of the joint log likelihood function. Although first order derivatives for mixture models are usually easily computed analytically, there is no closed form solution for the Fisher Information matrix and it's partial derivatives required by RMHMC and MMALA.

In this talk I will present how manifold MCMC samplers can be applied for mixture models using approximations of the expected Fisher Information matrix. A finite sample estimate and an L2 metric between densities will be considered. Examples on synthetic datasets and comparisons in terms of effective sample size and computational cost will be presented.

References

Girolami, A. M. & Calderhead, B. (2011), 'Riemann manifold Langevin and Hamiltonian Monte Carlo methods', *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, **(73)**, 2 123-214.