OUTLINE FOR Independent Metropolis-Hastings Steps for Generalized Linear Models with Latent Gaussian Processes via Global Conditional Laplace Approximations

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Abstract

KEY WORDS:

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1 Outline

(Yes I know the title is long)

1.1 Basic Problem

Want to sample from a difficult posterior density. Suppose it has model parameter θ and latent process gaussian process y, and we observe data z. The target posterior distribution is $[\theta, y|z] \propto [z|y, \theta][y|\theta][\theta]$ where $[y|\theta]$ is a normal density. A common MCMC strategy for this class of models is a data augmentation Gibbs sampler, i.e. draw $\theta \sim [\theta|y, z]$ and $y \sim [y|\theta, z]$ iteratively. Often $[\theta|y, z]$ is a relatively easy to sample from, but $[y|\theta, z]$ is not a density of known form and so requires a Metropolis step.

1.2 Laplace approximations

There are three ways we can employ Laplace approximations here:

1. Global Laplace approximation as a joint Metropolis proposal for $[y, \theta|z]$. But θ is often non-normal in the posterior.

2. Local conditional Laplace approximation as a proposal for $[y|\theta, z]$, i.e. compute the Laplace approximation to $[y|\theta, z]$ every iteration of MCMC. But then we have to do numerical optimization to find y's conditional mode every iteration of the MCMC, which can be expensive.

3. Global conditional Laplace approximation as a proposal for $[y|\theta, z]$, i.e. compute the global Laplace approximation once, then compute the implied conditional distribution for $[y|\theta, z]$ every iteration. Often much cheaper because much of the computation can be pre-computed. (This is the main contribution)

1.3 Basic structure of the paper

1. Introduction
2. Describe the problem for latent Gaussian process models.
3. Describe Laplace approximations and introduce the "Global conditional Laplace approximation" (GCLA)
4. Give some intuition for when the GCLA will be good vs. a GLA or a LCLA (global LA and local conditional LA). Maybe a theorem that explains why GCLA works about as well as LCLA.
5. 2-4 examples illustrating both good and bad, with some simulations. (It doesn't always work. In particular, when the data model is highly non-normal, it can be extremely poor).

1.4 PSO tie in?

It's possible that the best of our PSO algorithms is actually good at finding the posterior mode in some cases. Worth checking, and if so, we have another minor contribution (and a chance to cite the STAT paper we're pushing out).