Bayesian Analysis (2007) **2**, Number 3, pp. 483–494

Comment on Article by Jain and Neal

Steven N. MacEachern*

1 Introduction

It was with great interest that I read Jain and Neal's paper. In the paper, they address a tough problem, namely how to improve the mixing/convergence of Markov chain Monte Carlo (MCMC) algorithms for an important class of models. The models are those involving mixtures of Dirichlet processes, ranging from a fairly straightforward mixture of Dirichlet processes model to the more complex models that are springing up in a wide variety of applications. The algorithms are in the split-merge vein, allowing a different kind of step than incremental Gibbs samplers. The extension of the split-merge technology with targeted proposals to conditionally conjugate models is a welcome addition to the collection of transitions available for fitting models that include the Dirichlet process as a component.

Jain and Neal's algorithms (see also Dahl, 2005) have refined the technology of split-merge samplers so that proposals are no longer "blind", but, through intermediate Gibbs scans, move toward a region of higher posterior probability. The ability to target better proposals results in algorithms that naturally make better proposals, and this improves mixing of the Markov chain. An important element of these intermediate Gibbs scans is their ability to move toward a more appropriate launch state.

This discussion focuses on two features that are hidden in the innards of the algorithm. The first is the notion of identifiability and the second is that of a random scan. Jain and Neal's algorithms make nice use of a non-identifiable model for the intermediate Gibbs scans (section 4.2, step 3 and following) to produce what are presumably better proposals. They also implicitly use a random scan for split and merge proposals in the sense that cases i and j are selected at random (section 4.2, step 1). The remainder of this discussion looks at these issues in the context of a simple, artificial example where one can explicitly calculate rates of convergence for a variety of incremental Gibbs algorithms. The hope is that the example, in spite of its simplicity, provides insight into the effectiveness of the algorithms and suggests potential directions for their further refinement.

2 Identifiability

While details of various algorithms are left for the next section, one recurring issue in proposals for novel algorithms for Dirichlet based models is identifiability. This issue is not limited to mixture models, but arises in many other contexts. There is

*Department of Statistics, The Ohio State University, Columbus, OH, mailto:snm@stat.ohio-state.edu

 ba0007