Bayesian Analysis (2016) **11**, Number 3, pp. 945–955

Rejoinder*

Matthew T. Pratola†

1 Introduction

We would first like to sincerely thank the Editors of Bayesian Analysis for inviting this work to be discussed, and for the many discussants who provided interesting and insightful feedback on this work: Bobby Gramacy, Christopher Hans, Luca Martino, Rafael B. Stern, Francisco Louzada, Scotland C. Leman, Andrew Hoegh, Reihaneh Entezari, Radu V. Craiu, Jeffrey S. Rosenthal, A. Mohammadi, M. C. Kaptein and O. Chkrebtii. Thank you! As there were many shared themes amongst the discussants, our rejoinder is organized along the following topics: Alternatives to Metropolis–Hastings, Data Subsetting, Reversible-Jump MCMC (RJMCMC), Priors and Adaptation.

2 Alternatives to Metropolis–Hastings

Many discussants proposed alternatives to the Metropolis–Hastings approach to sampling the posterior, including Multiple Try Metropolis and Combinatorial Sequential Monte Carlo (Martino et al., 2016), the Multiset Sampler (Leman and Hoegh, 2016), Birth–Death MCMC (Mohammadi and Kaptein, 2016) and Parallel Tempering (Chkrebtii, 2016). Generally, these algorithms are "blind" in the sense that they do not exploit the structure of tree-space explicitly to try and move efficiently amongst good trees. However, since they are designed to improve the sampling of general MCMC algorithms they are more widely applicable, albeit possibly with increased computational cost. In combination with the moves proposed in this work one might reasonably expect to see further improvements, or at least faster convergence of the sampler.

2.1 Multiple Try Metropolis

We agree with the suggestions of Martino et al. (2016) to also consider introducing more general sampling algorithms designed to improve mixing, such as Multiple Try Metropolis (MTM) or Combinatorial Sequential Monte Carlo (C-SMC), or combining some of these algorithms with ideas introduced in the paper. The tradeoff of using these general algorithms to improve mixing is usually computational cost which we would prefer to avoid, but good combinations of methods could likely improve things further. In particular, the MTM method seems likely to be a good candidate, and we thank the discussant for this suggestion.

In the MTM method (Martino and Read, 2013; Liu et al., 2000), instead of a single proposal being drawn at each Metropolis–Hastings step, a sample of k states are pro-

*Main article DOI: 10.1214/16-BA999.

†Department of Statistics, The Ohio State University, mpratola@stat.osu.edu

 DOI: 10.1214/16-BA999REJ