Contribution to discussion of paper by Brooks, Giudici and Roberts RSS Ordinary meeting, 30 July 2002

Peter Green (University of Bristol)

I welcome this attempt to provide guidelines for proposal construction in reversible jump MCMC. Being simply the adaptation (I would not even say 'extension') of the Metropolis-Hastings method to variable dimension spaces, it seems safe to expect that this will remain an important approach to 'across-model' MCMC simulation, and while there are now numerous successful implementations of the idea, clearly researchers need more help in proposal construction. This seems to be curiously difficult to provide.

I wonder if the authors are tackling the wrong part of the question. The proposal mechanism in equation (5) involves both structural aspects (the choice of the functions $f_{i,j}$ and $v_{i,j,\theta}$) and quantitative ones (the distribution of the random numbers u). In my experience it is the first of these issues that is both more crucial and challenging, while the second, that addressed by the authors, is relatively amenable to tuning based on pilot runs.

In understanding the structural aspects of a proposal, it does not necessarily pay to decompose the target into its prior and likelihood terms. Indeed, for many purposes the origin of the variable dimension distribution under study is or should be irrelevant. The situations where it might be relevant are rather special: the rival models need a strong degree of mutual consistency. Suppose that while different models have quite different parameterisations, there are well-defined functions of parameters with consistent meanings across models - perhaps predictive quantities, or 'fitted values'. Further suppose that prior assumptions about such functions are compatible across models. Then these functions are natural candidates for establishing mappings between models that can be used to construct proposals. This, I believe, is the basis for the utility of 'split & merge' and other 'moment-matching' methods (for more on the latter, see Green and Richardson, 2001); these work where priors are only weakly informative, and where the matching of moments is sufficient to ensure that likelihoods are close. Incidentally, 'split & merge' is a lot more flexible (and less myopic) than is commonly realised, as the values of other variables can be freely used in proposals.

Most of the authors' methods are locally formulated, and this is inevitable for analytic methods in all realistic MCMC contexts. Empirical methods, such as the quite naive but surprisingly effective idea in Section 6 of Green (2002), offer the opportunity of a more global mapping between targets in different models; it could be fruitful to develop both classes further and make comparisons. I would conjecture that local methods will lose out in multimodal situations.

Additional reference

Green, P. J. and Richardson, S. (2001). Modelling heterogeneity with and without the Dirichlet process, *Scandinavian Journal of Statistics*, **28**, 355–375.

Professor P. J. Green, School of Mathematics, University of Bristol, Bristol, BS8 1TW.
P.J.Green@bristol.ac.uk