

For example, in the Cauchy example in Section 3.1, we set the proposal covariance to be the inverse Hessian at the posterior mode, scaled by a factor of 200. We needed such a large scale factor because the normal approximation at the mode shows no correlation, even though there is obvious correlation in the tails. If one knew upfront the extent of the tail dependence, one might have chosen a proposal density that is more highly correlated, and that might give a higher acceptance rate. But of course one seldom, if ever, knows the shape of any target posterior density up front. So even though an acceptance percentage of 1.3% may appear to be low, we should consider the amount of time it would take to improve the proposal density, and especially the number of MCMC iterations it would take to get enough draws that are equivalent to the same number of independent GDS draws.

### 5.3 Cases requiring further research

This paper demonstrated that GDS is a viable alternative to MCMC for a large class of Bayesian non-Gaussian and Gaussian hierarchical models. Of course it would be myopic to claim that GDS is appropriate for all models. By the same token, we cannot assert that GDS would not work for any of the models described below. These models are topics requiring additional research.

**Models with discrete or combinatorial optimization elements** In models that include both discrete and continuous parameters, finding the posterior mode becomes a mixed-integer nonlinear program (MINLP). An example is the Bayesian variable selection problem (George and McCulloch 1997). The difficulty lies in the fact that MINLPs are known to be NP-complete, and thus may not scale well for large problems. Hidden Markov models with multiple discrete states might be similarly difficult to estimate using GDS. Also, it is not immediately clear how one might select a proposal density when some