Linear Gaussian State Space Models

We construct two linear Gaussian state space models (Durbin and Koopman, 2012) each consisting of 100 latent states and observations. State transitions are governed by a first order AR process, and we seek inferences about the transition process, and the system and observation noise. We consider two equivalent parameterizations of the state transition process. First, in terms of the intercept and mean of the AR process, which have largely uncorrelated posteriors (independent parameterization), and second, in terms of the intercept and autocorrelation, which are known to be highly correlated (correlated parameterization). For the correlated parameterization, we consider an informed MCMC algorithm, which blocks the intercept and autocorrelation parameters. We deliberately include this inferior parameterization, to assess MCMC performance in the case of known strong posterior correlation. In practice, an analyst may not know which model parameterization(s) will produce uncorrelated posterior dimensions.

Spatial Model

We consider a spatially dependent hierarchical model. The data consist of 148 measurements of scallop abundance at various locations off the New York and New Jersey coastline, and was collected by the Northeast Fisheries Science Center of the National Marine Fisheries Service in 1993. The data set is publicly available at `http://www.biostat.umn.edu/~brad/data/myscallops.txt`, and is analyzed in Banerjee, Carlin, and Gelfand (2003), pages 44-65. Following Banerjee, Carlin, and Gelfand (2003), we model the mean log-abundance as multivariate normal with covariance that decays exponentially as a function of distance. The covariance is given by $\text{cov}(g_i, g_j) = \sigma^2 \exp(-d_{i,j}/\rho)$, where the observations are modeled as Poisson counts $y_i \sim \text{Poisson}(\exp(g_i))$, and $d_{i,j}$ is the distance between observations y_i and y_j. Since this covariance structure induces a trade-off between σ and ρ, we expect these parameters to be correlated in the posterior distribution.

Generalized Linear Mixed Model

We include a reasonably sized generalized linear mixed model (GLMM; Gelman and Hill, 2006, chapter 6). We make use of the Minnesota Health Plan dataset available in Waller and Zelterman