## Introduction to Bayesian Data Analysis Tutorial 10

- (1) Problem 10.4 (Hoff) Gibbs sampling: Consider the general Gibbs sampler for a vector of parameters  $\phi$ . Suppose  $\phi^{(s)}$  is sampled from the target distribution  $p(\phi)$  and then  $\phi^{(s+1)}$  is generated using the Gibbs sampler by iteratively updating each component of the parameter vector. Show that the marginal probability  $Pr(\phi^{(s+1)} \in A)$  equals the target distribution  $\int_A p(\phi)d\phi$ .
- (2) Problem 10.5 (Hoff) Logistic regression variable selection: Consider a logistic regression model for predicting diabetes as a function of  $x_1$ =number of pregnancies,  $x_2$ =blood pressure,  $x_3$ =body mass index,  $x_4$ =diabetes pedigree and  $x_5$ =age. Using the data in azdiabetes.dat, centre and scale each of the x-variables by subtracting the sample average and dividing by the sample standard deviation for each variable. Consider a logistic regression model of the form  $Pr(Y_i = 1 | \mathbf{x_i}, \gamma, \beta) = \exp(\theta_i)/(1 + \exp(\theta_i))$  where

$$\theta_i = \beta_0 + \beta_1 \gamma_1 x_{i,1} + \beta_2 \gamma_2 x_{i,2} + \beta_3 \gamma_3 x_{i,3} + \beta_4 \gamma_4 x_{i,4} + \beta_5 \gamma_5 x_{i,5}$$

In this model, each  $\gamma_i$  is either 0 or 1, indicating whether or not variable j is a predictor of diabetes. For example, if it were the case that  $\gamma = (1, 1, 0, 0, 0)$ , then  $\theta_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2}$ . Obtain the posterior distributions for  $\beta$  and  $\gamma$ , using independent prior distributions for the parameters, such that  $\gamma_j \sim \text{Bern}(1/2)$ ,  $\beta_0 \sim \text{normal}(0, 16)$  and  $\beta_j \sim \text{normal}(0, 4)$  for each j > 0.

- (a) Implement a Metropolis-Hastings algorithm for approximating the posterior distribution of  $\boldsymbol{\beta}$  and  $\boldsymbol{\gamma}$ . Examine the sequences  $\beta_j^{(s)}$  and  $\beta_j^{(s)} \times \gamma_j^{(s)}$  for each j and discuss the mixing of the chain.
- (b) Obtain  $Pr(\gamma_j = 1 | \mathbf{x}, \mathbf{y})$  for each j. How good do you think the MCMC estimates of these posterior probabilities are?
- (c) For each j, plot posterior densities and obtain posterior means for  $\beta_j \gamma_j$ .