

Note:

1. The problems are from the textbook by G. H. Givens and J. A. Hoeting
2. There are total 2 questions: 8.1 and 8.3.
3. The full grade is 10 in this HW with point distributed as

8.1	3
8.3(a)	1
(b)	1
(c)	1
(d)	1
(e)	1
(f)i	1
(f)ii	1

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- 8.1.** One approach to Bayesian variable selection for linear regression models is described in Section 8.2.1 and further examined in Example 8.3. For a Bayesian analysis for the model in Equation (8.20), we might adopt the normal–gamma conjugate class of priors  $\boldsymbol{\beta}|m_k \sim N(\boldsymbol{\alpha}_{m_k}, \sigma^2 \mathbf{V}_{m_k})$  and  $\nu\lambda/\sigma^2 \sim \chi_\nu^2$ . Show that the marginal density of  $\mathbf{Y}|m_k$  is given by

$$\frac{\Gamma((\nu + n)/2) (\nu\lambda)^{\nu/2}}{\pi^{n/2} \Gamma(\nu/2) |\mathbf{I} + \mathbf{X}_{m_k} \mathbf{V}_{m_k} \mathbf{X}_{m_k}^T|^{1/2}} \times \left[ \lambda\nu + (\mathbf{Y} - \mathbf{X}_{m_k} \boldsymbol{\alpha}_{m_k})^T (\mathbf{I} + \mathbf{X}_{m_k} \mathbf{V}_{m_k} \mathbf{X}_{m_k}^T)^{-1} (\mathbf{Y} - \mathbf{X}_{m_k} \boldsymbol{\alpha}_{m_k}) \right]^{-(\nu+n)/2},$$

where  $\mathbf{X}_{m_k}$  is the design matrix,  $\boldsymbol{\alpha}_{m_k}$  is the mean vector, and  $\mathbf{V}_{m_k}$  is the covariance matrix for  $\boldsymbol{\beta}_{m_k}$  for the model  $m_k$ .

**8.3.** Suppose we desire a draw from the marginal distribution of  $X$  that is determined by the assumptions that  $\theta \sim \text{Beta}(\alpha, \beta)$  and  $X|\theta \sim \text{Bin}(n, \theta)$  [96].

- a. Show that  $\theta|x \sim \text{Beta}(\alpha + x, \beta + n - x)$ .
- b. What is the marginal expected value of  $X$ ?
- c. Implement a Gibbs sampler to obtain a joint sample of  $(\theta, X)$ , using  $x^{(0)} = 0, \alpha = 10, \beta = 5$ , and  $n = 10$ .
- d. Let  $U^{(t+1)}$  and  $V^{(t+1)}$  be independent  $\text{Unif}(0,1)$  random variables. Then the transition rule from  $X^{(t)} = x^{(t)}$  to  $X^{(t+1)}$  can be written as

$$\begin{aligned} X^{(t+1)} &= q(x^{(t)}, U^{(t+1)}, V^{(t+1)}) \\ &= F_{\text{Bin}}^{-1}(V^{(t+1)}; n, F_{\text{Beta}}^{-1}(U^{(t+1)}; \alpha + x^{(t)}, \beta + n - x^{(t)})), \end{aligned}$$

where  $F_d^{-1}(p; \mu_1, \mu_2)$  is the inverse cumulative distribution function of the distribution  $d$  with parameters  $\mu_1$  and  $\mu_2$ , evaluated at  $p$ . Implement the CFTP algorithm from Section 8.5.1, using the transition rule given in (8.50), to draw a perfect sample for this problem. Decrement  $\tau$  by one unit each time the sample paths do not coalesce by time 0. Run the function 100 times to produce 100 draws from the stationary distribution for  $\alpha = 10, \beta = 5$ , and  $n = 10$ . Make a histogram of the 100 starting times (the finishing times are all  $t = 0$ , by construction). Make a histogram of the 100 realizations of  $X^{(0)}$ . Discuss your results.

- e. Run the function from part (d) several times for  $\alpha = 1.001, \beta = 1$ , and  $n = 10$ . Pick a run where the chains were required to start at  $\tau = -15$  or earlier. Graph the sample paths (from each of the 11 starting values) from their starting time to  $t = 0$ , connecting sequential states with lines. The goal is to observe the coalescence as in the right panel in Figure 8.5. Comment on any interesting features of your graph.
- f. Run the algorithm from part (d) several times. For each run, collect a perfect chain of length 20 (i.e., once you have achieved coalescence, don't stop the algorithm at  $t = 0$ , but continue the chain from  $t = 0$  through  $t = 19$ ). Pick one such chain having  $x^{(0)} = 0$ , and graph its sample path for  $t = 0, \dots, 19$ . Next, run the Gibbs sampler from part (c) through  $t = 19$  starting with  $x^{(0)} = 0$ . Superimpose the sample path of this chain on your existing graph, using a dashed line.
  - i. Is  $t = 2$  sufficient burn-in for the Gibbs sampler? Why or why not?
  - ii. Of the two chains (CFTP conditional on  $x^{(0)} = 0$  and Gibbs starting from  $x^{(0)} = 0$ ), which should produce subsequent variates  $X^{(t)}$  for  $t = 1, 2, \dots$  whose distribution more closely resembles the target? Why does this conditional CFTP chain fail to produce a perfect sample?