

## CPSC 535D: Assignment 1

February 16, 2007

### 1. QUESTION 1: BAYESIAN LINEAR MODEL

Consider the following Bayesian linear model

$$Y = X\beta + \sigma\varepsilon$$

where  $Y = (y_1, \dots, y_n)^T$ ,  $X$  is a  $n \times p$  matrix,  $\beta = (\beta_1, \dots, \beta_p)^T$  and  $\varepsilon = (\varepsilon_1, \dots, \varepsilon_p)^T$  is  $p \times 1$ . We observe  $X$  and  $Y$  whereas  $\varepsilon \sim \mathcal{N}(0, I_p)$ .

- Compute the maximum likelihood estimate of  $(\beta, \sigma^2)$ .

We set the following prior distribution on  $(\beta, \sigma^2)$

$$\begin{aligned} p(\beta, \sigma^2) &= p(\beta | \sigma^2) p(\sigma^2) \\ &= \mathcal{N}(\beta; m, \sigma^2 V) \mathcal{IG}\left(\sigma^2; \frac{\mu}{2}, \frac{\nu}{2}\right) \end{aligned}$$

- Establish analytically the expression of the posterior distribution  $p(\beta, \sigma^2 | Y)$ .
  - Establish analytically the expression of the marginal posterior distribution  $p(\beta | Y)$  and  $p(\sigma^2 | Y)$ .
  - Establish analytically the expression of the marginal likelihood (also called evidence)  $p(Y)$ .
  - Establish analytically the expression of the predictive distribution  $p(y | Y, x)$ .
- Consider a collection of potential models for the data

$$\mathcal{M}_i : Y = X_i \beta_i + \sigma_i \varepsilon$$

with prior  $p(\beta_i, \sigma_i^2) = \mathcal{N}(\beta_i; m_i, \sigma_i^2 V_i) \mathcal{IG}(\sigma_i^2; \frac{\mu_i}{2}, \frac{\nu_i}{2})$ .

- Compute the Bayes factor  $\frac{p(Y | \mathcal{M}_i)}{p(Y | \mathcal{M}_j)}$  and simplify the expression when we use a data-dependent prior known as the g-prior where

$$V_i = \delta^2 (X_i X_i^T)^{-1}.$$

### 2. QUESTION 2: GENETIC LINKAGE MODEL

Assume that 197 animals are distributed into four categories as

$$\begin{aligned} Y &= (y_1, y_2, y_3, y_4) \\ &= (125, 18, 20, 34) \end{aligned}$$

with cell probabilities

$$\left( \frac{1}{2} + \frac{\theta}{4}, \frac{1}{4}(1 - \theta), \frac{1}{4}(1 - \theta), \frac{\theta}{4} \right).$$

- Derive and implement an Expectation-Maximization algorithm to estimate the Maximum Likelihood estimate of  $\theta$ .

We assume that  $\theta \sim \mathcal{U}[0, 1]$ , i.e. we set a uniform prior on  $[0, 1]$  for  $\theta$ .

- Design and implement an accept/reject procedure to sample from the posterior  $p(\theta|y)$ .

- Design and implement an importance sampling method to sample from the posterior  $p(\theta|y)$ .

- Compare the efficiency of both algorithms.