

HW10

04/07/2024

Q1

- (a) The kernel of posterior density for $\beta | \mathbf{y}, \mathbf{X}$ is not easily recognisable as any known distribution, so an analytic solution may not be easily obtained and MH algorithm is then suitable for sampling from the posterior.

Let $q(\beta_{new} | \beta_{old})$ be the density of given proposal distribution $N_p(\beta_{old}, \widehat{Cov}(\hat{\beta}_{ML}))$. The algorithm in pseudo code is as follows:

- (i) Set the starting value of $\beta^{(0)}$, e.g. using prior mean \mathbf{b}_0 .
 - (ii) For $t = 1, \dots, 1000$:
 1. Draw β^* from $q(\beta^* | \beta^{(t-1)})$.
 2. Compute the acceptance probability: $\alpha(\beta^* | \beta^{(t-1)}) = \min \left(1, \frac{p(\beta^* | \mathbf{y}, \mathbf{X}) q(\beta^{(t-1)} | \beta^*)}{p(\beta^{(t-1)} | \mathbf{y}, \mathbf{X}) q(\beta^* | \beta^{(t-1)})} \right)$
 3. With probability $\alpha(\beta^* | \beta^{(t-1)})$ set $\beta^{(t)} = \beta^*$. Else, set $\beta^{(t)} = \beta^{(t-1)}$.
 - (iii) Optionally, discard first B iterations as burn-in.
 - (iv) Output samples $\beta^{(B+1)}, \dots, \beta^{(1000)}$.
- (b) Point estimates of individual parameters can be approximated from the generated random draws. The posterior mean is approximated by the sample average:

$$\mathbb{E}(\beta | \mathbf{y}, \mathbf{X}) \approx \frac{1}{1000 - B} \sum_{t=B+1}^{1000} \beta^{(t)}$$

- (c) The credible interval can be defined via empirical quantiles of the respective random draws, e.g. 90% credible interval:

$$\hat{Q}_{0.05}(\beta | \mathbf{y}, \mathbf{X}) \approx q_{0.05}(\beta^{(B+1)}, \dots, \beta^{(1000)})$$

$$\hat{Q}_{0.95}(\beta | \mathbf{y}, \mathbf{X}) \approx q_{0.95}(\beta^{(B+1)}, \dots, \beta^{(1000)})$$