

Question 1

$$y_i^* \sim N(x_i' \beta, 1)$$

$$y_i = \mathbb{I}(y_i^* > 0)$$

$$P(y_i = 1 | x_i) = P(y_i^* > 0 | x_i)$$

$$= P\left(\frac{y_i^* - x_i' \beta}{1} > \frac{0 - x_i' \beta}{1} \mid x_i\right)$$

$$= P(Z > -x_i' \beta \mid x_i) \quad \rightarrow \text{standard normal}$$

$$= 1 - \Phi(-x_i' \beta)$$

$$= \Phi(x_i' \beta) \quad \left. \begin{array}{l} \text{by symmetry of the normal distribution} \end{array} \right\}$$

$$y_i^* = x_i' \beta + \varepsilon_i, \quad \varepsilon_i \sim \text{Logistic}(0, 1)$$

$$y_i = \mathbb{I}(y_i^* > 0)$$

$$P(y_i = 1 | x_i) = P(y_i^* > 0 | x_i)$$

$$= P(y_i^* - x_i' \beta > 0 - x_i' \beta \mid x_i)$$

$$= P(\varepsilon_i > -x_i' \beta \mid x_i) \quad \rightarrow \text{standard logistic}$$

$$= 1 - \text{logit}^{-1}(-x_i' \beta)$$

$$= \text{logit}^{-1}(x_i' \beta) \quad \left. \begin{array}{l} \text{by symmetry of the logistic distribution} \end{array} \right\}$$

Question 2

$$y_i^* | x_i, \beta \sim N(x_i' \beta, 1)$$

$$y_i = \mathbb{I}(y_i^* > 0)$$

$$\beta \sim N(b_0, B_0)$$

$$\pi(y^*, \beta | y, x) \propto L(y | y^*, \beta, x) \pi(y^*) \pi(\beta)$$

$$\propto \prod_{i=1}^n [\mathbb{I}(y_i^* > 0) y_i + \mathbb{I}(y_i^* < 0) (1 - y_i)] \prod_{i=1}^n [\exp(-\frac{1}{2}(y_i^* - x_i' \beta)^2)] |B_0|^{-\frac{1}{2}} \exp[-\frac{1}{2}(\beta - b_0)' B_0^{-1} (\beta - b_0)]$$

$$\pi(y_i^* | \beta, y_i = 1, x) \propto \exp[-\frac{1}{2}(y_i^* - x_i' \beta)^2] \mathbb{I}(y_i^* > 0)$$

$$\pi(y_i^* | \beta, y_i = 0, x) \propto \exp[-\frac{1}{2}(y_i^* - x_i' \beta)^2] \mathbb{I}(y_i^* < 0)$$

$$y_i^* | \beta, y_i = 1, x \sim N_+(x_i' \beta, 1)$$

$$y_i^* | \beta, y_i = 0, x \sim N_-(x_i' \beta, 1)$$

$$\begin{aligned} \pi(\beta | y^*, y, x) &\propto \exp[-\frac{1}{2} \sum_{i=1}^n (-2 \beta' x_i y_i^* + \beta' x_i x_i' \beta)] \exp[-\frac{1}{2} (\beta' B_0^{-1} \beta - 2 \beta' B_0^{-1} b_0)] \\ &\propto \exp[-\frac{1}{2} [\beta' (\sum_{i=1}^n x_i x_i' + B_0^{-1}) \beta - 2 \beta' (\sum_{i=1}^n x_i y_i^* + B_0^{-1} b_0)]] \end{aligned}$$

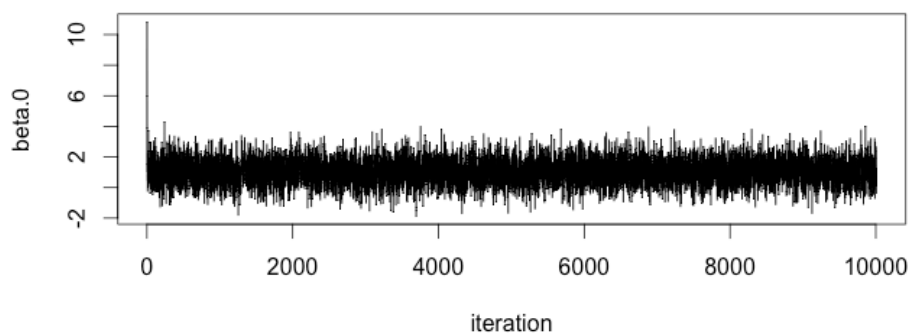
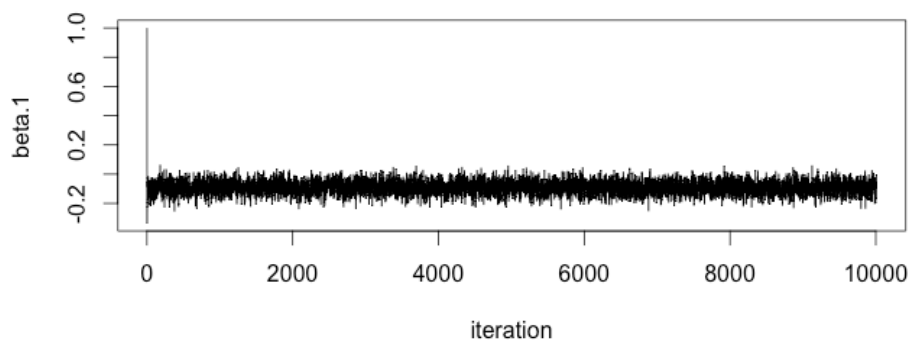
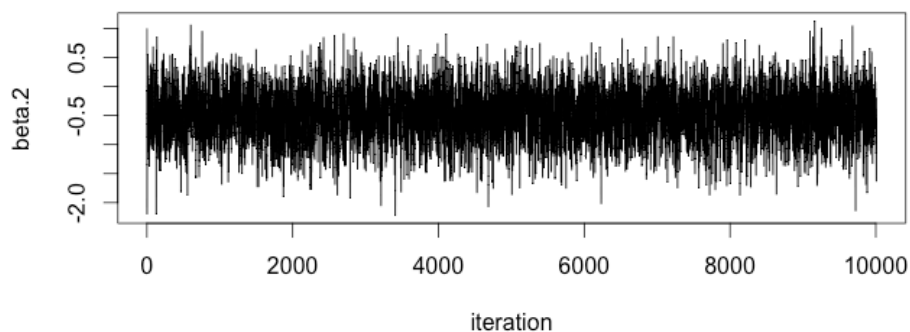
$$\beta | y^*, y, x \sim N_4 \left(\left(\sum_{i=1}^n x_i x_i' + B_0^{-1} \right)^{-1} \left(\sum_{i=1}^n x_i y_i^* + B_0^{-1} b_0 \right), \left(\sum_{i=1}^n x_i x_i' + B_0^{-1} \right)^{-1} \right)$$

Logistic regression case

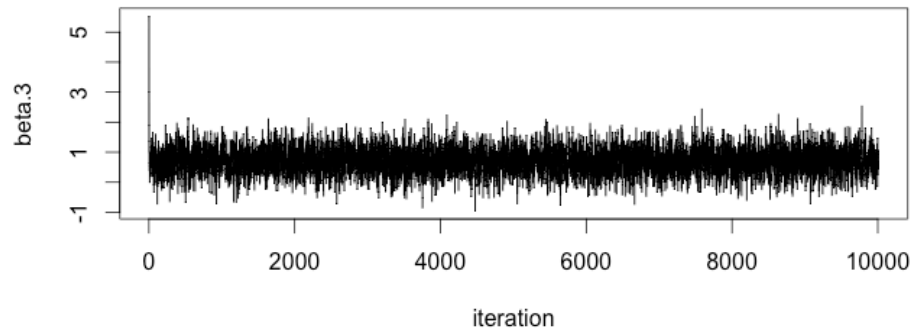
Gibbs sampling in the logistic regression case is more difficult because the normal distribution on β is not a conjugate prior for the logistic regression likelihood.

Lab 11

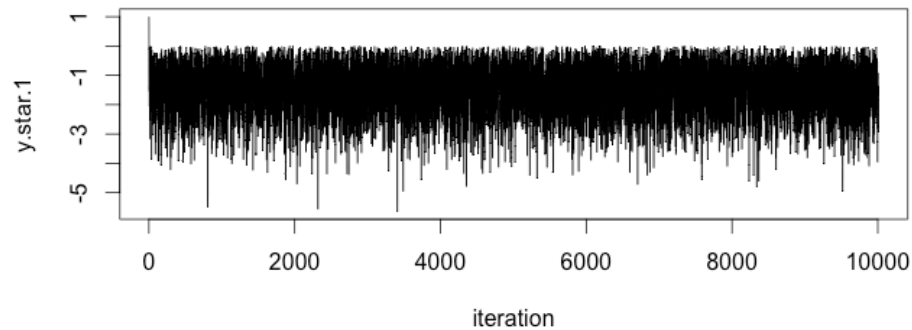
Using the full conditionals above and prior $b_0 = (0, 0, 0, 0)'$ and $B_0 = I$, I performed 10,000 iterations of Gibbs sampling. Below are the trace plots for the elements of β and one y_i^* :

Trace plot for beta.0**Trace plot for beta.1****Trace plot for beta.2**

Trace plot for beta.3



Trace plot for y.star.1

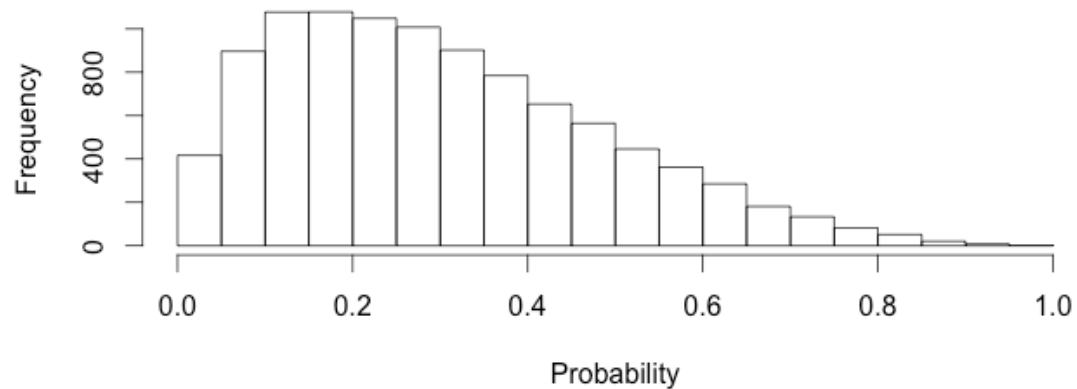


10 burn-ins were thrown out for each parameter for the analysis to follow.

26-year old TA

For each iteration, I calculated the probability of an accident [probability that a draw from $N(x'\beta, 1) > 0$] for the TA $x = (1, 26, 0, 1)'$. Below is a histogram of these probabilities:

Posterior predictive probability of accident for 26-year-old TA



The mean probability that the TA was involved in an accident in the last six months is **0.2950**.

Mercedes parking

For each iteration, I calculated the probability of an accident [probability that a draw from $N(x'_i\beta, 1) > 0$] for $x'_1 = (1, 17, 1, 0)$ and $x'_2 = (1, 18, 1, 1)$. The mean probability for x_1 is 0.1837 and the probability for x_1 is 0.3659. **Thus, I would rather have the 17-year-old who has done a driver's education course and hates statistics park my Mercedes.**