

STAT 4510J Bayesian Analysis

Fall 2022 – Homework4 Decision Theory

This homework is done by **Wei Linda**



1 Problem 1

$$\begin{aligned}
 & (\mu - \mu_0)^T \Lambda_0^{-1} (\mu - \mu_0) + \sum_{i=1}^n (y_i - \mu)^T \Sigma^{-1} (y_i - \mu) \\
 &= \mu^T \Lambda_0^{-1} \mu - 2\mu^T \Lambda_0^{-1} \mu_0 + n\mu^T \Sigma^{-1} \mu - 2 \sum_{i=1}^n \mu^T \Sigma^{-1} y_i + \text{const} \\
 &= \mu^T (\Lambda_0^{-1} + n\Sigma^{-1}) \mu - 2\mu^T (\Lambda_0^{-1} \mu_0 + n\Sigma^{-1} \bar{y}) + \text{const} \\
 &= \left(\mu - (\Lambda_0^{-1} + n\Sigma^{-1})^{-1} (\Lambda_0^{-1} \mu_0 + n\Sigma^{-1} \bar{y}) \right)^T (\Lambda_0^{-1} + n\Sigma^{-1}) \left(\mu - (\Lambda_0^{-1} + n\Sigma^{-1})^{-1} (\Lambda_0^{-1} \mu_0 + n\Sigma^{-1} \bar{y}) \right) \\
 &= (\mu - \mu_n)^T \Lambda_n^{-1} (\mu - \mu_n)
 \end{aligned}$$

2 Problem 2

$$\begin{aligned}
 P(\theta) &= 0.1 N(-1, 0.5^2) + 0.9 N(1, 0.5^2) \\
 p_1(\theta | y) &\propto p_1(y | \theta) p_1(\theta) \sim N\left(\frac{\frac{1}{10} + \bar{y} \cdot 0.5^2}{0.5^2 + \frac{1}{10}}, \frac{\frac{0.5^2}{10} \times 1}{0.5^2 + \frac{1}{10}}\right) \\
 &= N\left(-\frac{13}{28}, \frac{1}{14}\right) \\
 P_2(\theta | y) &\propto P_2(y | \theta) P_2(\theta) \sim N\left(\frac{u \times \frac{1}{10} + \bar{y} \times 0.5^2}{0.5^2 + 0.1}, \frac{0.5^2 + 1}{0.5^2 + 0.1}\right) \\
 &= N\left(\frac{3}{28}, \frac{1}{14}\right) \\
 w_1 &= \frac{\lambda_1 \cdot p_1(y | \theta)}{\lambda_1 p_1(y | 0) + \lambda_2 p_2(y | \theta)} \\
 &= \frac{0.1 \times N(y = -0.25 | -1, 0.5^2 + \frac{1}{10})}{0.1 \times N(y = -0.25 | -1, 0.5^2 + \frac{1}{10}) + 0.9 N(y = 0.5 | 1, 0.5^2 + \frac{1}{10})} \\
 &= 0.32
 \end{aligned}$$

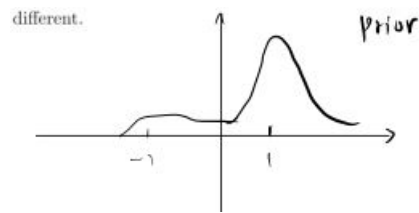


图 1: prior

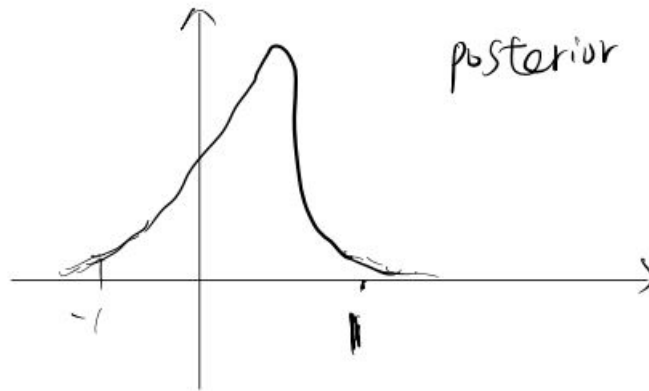


图 2: posterior

$$W_2 = 0.68.$$

$$\therefore P(\theta | y) = 0.32 \times N\left(-\frac{13}{28}, \frac{1}{14}\right) + 0.68 N\left(\frac{3}{28}, \frac{1}{14}\right)$$

posterior

3 Problem 3

$$\begin{aligned} & E[\theta_j | \tau, y] \\ &= E[E[\theta_j | \tau, y, n]] \\ &= E\left[\frac{\frac{1}{\sigma_j^2} y_j + \frac{1}{\tau^2} u}{\frac{1}{\sigma_j^2} + \frac{1}{\tau^2}} \mid \tau, y\right] \\ &= \frac{\frac{1}{\sigma_j^2} y_j + \frac{1}{\tau^2} \hat{u}}{\frac{1}{\sigma_j^2} + \frac{1}{\tau^2}} \quad \hat{u} = \frac{\sum_{j=1}^J \frac{1}{\sigma_j^2 + \tau^2} \bar{y}_j}{\sum_{j=1}^J \frac{1}{\sigma_j^2 + \tau^2}}. \end{aligned}$$

$$\begin{aligned}& \text{Var} [\theta_j \mid \tau, Y] \\&= E [\text{Var} [\theta_j \mid \tau, y, u]] + \text{Var} [E [\theta_j \mid \tau, y, u]] \\&= E \left[\frac{\sigma_j^2 \tau^2}{\sigma_j^2 + \tau^2} \mid \tau, y \right] + \left(\frac{\sigma_j^2}{\tau^2 + \sigma_j^2} \right)^2 Vn. \\&= \frac{\sigma_j^2 \tau^2}{\sigma_j^2 + \tau^2} + \left(\frac{\sigma_j^2}{\tau^2 + \sigma_j^2} \right)^2 Vu. \\&V_n^{-1} = \sum_{j=1}^J \frac{1}{\tau^2 + \sigma_j^2}\end{aligned}$$