

8.5. Hierarchical Model and MCMC

Example 8.5.1 Baseball example

Let Y_i be the batting average at the first 45 at bats.

$$Y_i \sim \text{Bin}(45, p_i)$$

$$Y_i \sim N(\theta_i, \sigma^2)$$

$$\theta_i \sim N(\mu, \tau^2) \quad i = 1, 2, \dots, 18$$

$$\mu \sim N(0, 1000)$$

$$(\sigma^2 \tau^2)^{-1} \sim \text{Gamma}(0.001, 0.001)$$

$$\hat{\theta}_i = \bar{z}(\theta_i | \tilde{Y})$$

MCMC . Gibbs Sampler :

$$\theta_i | Y, \mu, \tau^2, \sigma^2$$

$$\mu | Y, \theta_i, \tau^2, \sigma^2$$

$$\tau^2 | Y, \theta_i, \mu, \sigma^2$$

$$\sigma^2 | Y, \theta_i, \mu, \tau^2$$

$$\theta_i | \text{Rest} \sim N(M y_i + (1-M)\mu, M\sigma^2) \quad M = \frac{\tau^2}{\tau^2 + \sigma^2}$$

$$\mu | \text{Rest} \sim$$

$$\theta_i \stackrel{\text{ind.}}{\sim} N(\mu, \tau^2) \Rightarrow \bar{\theta} \sim N(\mu, \frac{\tau^2}{n})$$

$$\mu \sim N(0, 1000)$$

$$\mu | \text{Rest} \sim N\left(M_1 \bar{\theta} + (1-M_1) \cdot 0, M_1 \frac{\tau^2}{n}\right) \quad \text{where } M_1 = \frac{1000}{1000 + \frac{\tau^2}{n}}$$

$$\sigma^2 | \text{Rest}$$

$$Y_i \sim N(\theta_i, \sigma^2)$$

$$l(y) \propto \left(\frac{1}{\sigma^2}\right)^{\frac{n}{2}} \exp\left\{-\frac{\sum (y_i - \theta_i)^2}{2\sigma^2}\right\}$$

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$$\text{since } \sigma^2 \sim \text{INGamma}(\alpha, \beta)$$

$$\Rightarrow l(\sigma^2) \propto \left(\frac{1}{\sigma^2}\right)^{\alpha+1} \exp\left\{-\frac{\beta}{\sigma^2}\right\}$$

$$\sigma^2 | \text{Rest} \propto \left(\frac{1}{\sigma^2}\right)^{\frac{n}{2}} \exp\left\{-\frac{\sum (y_i - \theta_i)^2}{2\sigma^2}\right\} \left(\frac{1}{\sigma^2}\right)^{\alpha+1} \exp\left\{-\frac{\beta}{\sigma^2}\right\}$$

$$\propto \left(\frac{1}{\sigma^2}\right)^{\alpha + \frac{n}{2} + 1} \exp\left\{-\frac{1}{\sigma^2} \left(\frac{\sum (y_i - \theta_i)^2}{2} + \beta\right)\right\}$$

$$\sigma^2 | \text{Rest} \sim \text{INGamma}\left(\alpha + \frac{n}{2}, \frac{\sum (y_i - \theta_i)^2}{2} + \beta\right)$$

$$\tau^2 | \text{Rest} \sim \text{INGamma}\left(\alpha + \frac{n}{2}, \frac{\sum (\theta_i - \mu)^2}{2} + \beta\right)$$

BUGS Bayesian Inference Using Gibbs Sampling

$$\begin{cases} Y_i | \theta_i \stackrel{\text{ind}}{\sim} N(\theta_i, \sigma^2) \\ \theta_i \sim N(\mu, \tau^2) \end{cases}$$

$$E \theta_i | Y_i = M Y_i + (1-M) \mu$$

① Shrinkage effect.

② Borrowing the strength.

8.6. Empirical Bayes

X_i be the batting average for the first 45 at-bats

VST.

$$Y_i = 2\sqrt{n} \arcsin \sqrt{X_i} = 2\sqrt{45} \arcsin \sqrt{X_i}$$

$$\begin{cases} Y_i | \theta_i \stackrel{\text{ind}}{\sim} N(\theta_i, 1) \\ \theta_i \stackrel{\text{ind}}{\sim} N(\mu, \tau^2) \end{cases} \quad \theta_i = 2\sqrt{45} \arcsin \sqrt{p_i}$$

$$\theta_i | Y \sim N(M Y_i + (1-M)\mu, M) \quad M = \frac{\tau^2}{1+\tau^2}$$

$$\hat{\theta}_i = E \theta_i | Y = M Y_i + (1-M)\mu$$

$$f(y_i | \mu, \tau^2) = \int f(y_i | \theta_i) f(\theta_i | \mu, \tau^2) d\theta_i$$

$$E Y_i = E(E Y_i | \theta_i) = E \theta_i = \mu$$

$$E Y_i^2 = E(E Y_i^2 | \theta_i) = E(\theta_i^2 + 1) = \mu^2 + \tau^2 + 1$$

$$\text{Set } \begin{cases} \mu = m_1 \\ \mu^2 + \tau^2 + 1 = m_2 \end{cases} \Rightarrow \begin{cases} \hat{\mu} = m_1 \\ \frac{\hat{\tau}^2}{1+\hat{\tau}^2} = (m_2 - 1 - m_1^2)_+ \\ = \max(0, m_2 - 1 - m_1^2) \end{cases}$$

$$\hat{M} = \frac{\hat{\tau}^2}{1+\hat{\tau}^2}$$

$$\begin{aligned} \hat{\theta}_i &= \hat{M} Y_i + (1-\hat{M}) \hat{\mu} \\ &= \hat{M} Y_i + (1-\hat{M}) \bar{Y} \end{aligned}$$

borrowing the strength

Lindley - James - Stein Estimator.

$$Y_i \stackrel{\text{ind}}{\sim} N(\theta_i, \sigma^2) \quad i=1, 2, \dots, p$$

MLE: $\hat{\theta}_i = y_i$

$$\hat{\theta}_{i,JS} = \left(1 - \frac{(p-2)\sigma^2}{\sum Y_i^2}\right) Y_i + \frac{(p-2)\sigma^2}{\sum Y_i^2} 0$$

$$\text{if } p > 2, \quad E \sum (\hat{\theta}_i - \theta_i)^2 < E \sum (Y_i - \theta_i)^2$$

Lindley - Jones - Stein Estimator

$$\hat{\theta}_{1,LS} = \hat{M}_{LS} y_i + (1 - \hat{M}_{LS}) \bar{y}$$

$$\hat{M}_{LS} = 1 - \frac{(p-3)\sigma^2}{\sum (y_i - \bar{y})^2}$$

Nonparametric empirical Bayes approach.

Two-group models

$H_0^i: \theta_i = 0 \rightarrow$ ^{NOT} i -th gene is significant

$H_a^i: \theta_i = 1 \rightarrow$ i is significant

$\underline{t_i} \approx \underline{(z_i)} \rightarrow$ test statistic

$$z_i | H_0^i \sim N(0, 1) = f_0(x)$$

$$z_i | H_a^i \sim f_1(x)$$

$$\left\{ \begin{array}{l} z_i \stackrel{\text{ind}}{\sim} (1 - \theta_i) f_0(z_i) + \theta_i \underline{\underline{f_1(z_i)}} \\ \theta_i \stackrel{\text{ind}}{\sim} \text{Bernoulli}(\pi_1) \end{array} \right.$$

$$\text{local fdr} \quad P(\theta_i = 0 | z) = \frac{\pi_0 f_0(z_i)}{\pi_0 f_0(z_i) + \pi_1 f_1(z_i)} = \frac{\pi_0 f_0(z_i)}{f(z)}$$

$$z_i \stackrel{\text{ind}}{\sim} \pi_0 f_0(z_i) + \pi_1 f_1(z_i)$$

$\hat{f}(z) \approx$ kernel density

$$\text{local fdr} = \frac{\pi_0 f_0(z_i)}{\hat{f}(z_i)} \approx \frac{f_0(z_i)}{\hat{f}(z_i)}$$

Sun and Cai (2007, JASA)