

Exercice 3: Bayesian analysis of a one-way random effects model

1) En utilisant la formule de Bayes, on a:

$$IP(X, \mu, \sigma^2, \tau^2 | Y) \propto IP(Y | X, \mu, \sigma^2, \tau^2) IP(X | \mu, \sigma^2) \pi(\mu, \sigma^2, \tau^2)$$

(X ne dépend pas de τ^2)

$$IP(Y=y_j | X=x_i, \mu, \sigma^2, \tau^2) = IP(\varepsilon = y_j - x_i | \tau^2, \mu, \sigma^2)$$

Donc on a finalement:

$$IP(X, \mu, \sigma^2, \tau^2 | Y) \propto \tau^{-Nk} \exp\left(-\frac{\sum_{i=1}^N \sum_{j=1}^{k_i} (y_{ij} - x_i)^2}{2\tau^2}\right) \sigma^{-N} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^N (x_i - \mu)^2\right) \\ \times \sigma^{-2(\alpha+1)} \exp(-\beta/\sigma^2) \tau^{-2(\gamma+1)} \exp(-\beta/\tau^2)$$

2) Déterminons les probabilités conditionnelles pour chaque paramètre:

$$IP(\sigma^2 | Y, X, \mu, \tau^2) \propto \sigma^{-(N+2(\alpha+1))} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^N (x_i - \mu)^2 - \frac{\beta}{\sigma^2}\right)$$

$$\Rightarrow \sigma^2 | X, \mu \sim \text{inv}\Gamma\left(\alpha + \frac{N}{2}, \beta + \frac{1}{2} \sum_{i=1}^N (x_i - \mu)^2\right)$$

dans le sens "proportionnel"

$$IP(\tau^2 | Y, X, \mu, \sigma^2) \propto \tau^{-(Nk+2(\gamma+1))} \exp\left(-\frac{1}{2\tau^2} \sum_{i=1}^N \sum_{j=1}^{k_i} (y_{ij} - x_i)^2 - \frac{\beta}{\tau^2}\right)$$

$$\Rightarrow \tau^2 | Y, X, \mu, \sigma^2 \sim \text{inv}\Gamma\left(\gamma + \frac{Nk}{2}, \beta + \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^{k_i} (y_{ij} - x_i)^2\right)$$

$$IP(\mu | X, \sigma^2) \propto \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^N (x_i - \mu)^2\right)$$

$$\propto \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^N (x_i^2 - 2\mu x_i + \mu^2)\right)$$

$$\propto \exp\left(-\frac{N}{2\sigma^2} \left[\left(\sum_{i=1}^N x_i / N\right)^2 - 2\mu \left(\sum_{i=1}^N x_i / N\right) + \mu^2\right]\right)$$

$$IP(\mu | X, \sigma^2) \propto \exp\left(-\frac{N}{2\sigma^2} \left(\sum_{i=1}^N x_i / N - \mu\right)^2\right)$$

$$\Rightarrow \mu | X, \sigma^2 \sim \mathcal{N}\left(\frac{1}{N} \sum_{i=1}^N X_i, \frac{\sigma^2}{N}\right)$$

$$\begin{aligned} \bullet \text{IP}(X | Y, \mu, \sigma^2, \tau^2) &\propto \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^N (X_i - \mu)^2 - \frac{1}{2\tau^2} \sum_{j=1}^{k_1} (X_{i,j} - X_i)^2\right) \\ &\propto \prod_{i=1}^N \exp\left(-\frac{(X_i^2 - 2\mu X_i + \mu^2)}{2\sigma^2} - \frac{\sum_{j=1}^{k_1} (X_{i,j}^2 - 2X_{i,j} X_i + X_i^2)}{2\tau^2}\right) \\ &\propto \prod_{i=1}^N \exp\left(-X_i^2 \left(\frac{1}{2\sigma^2} + \frac{k_1}{2\tau^2}\right) + X_i \left(\frac{\mu}{\sigma^2} + \frac{\sum_{j=1}^{k_1} X_{i,j}}{\tau^2}\right) - \left(\frac{\mu^2}{2\sigma^2} + \frac{\sum_{j=1}^{k_1} X_{i,j}^2}{2\tau^2}\right)\right) \\ &\propto \prod_{i=1}^N \exp\left(-\left(X_i - \frac{\left(\frac{\tau^2 \mu + \sigma^2 \sum_{j=1}^{k_1} X_{i,j}\right)}{\tau^2 + k_1 \sigma^2}\right)^2\right) \end{aligned}$$

$$\Rightarrow X_i | Y, \mu, \sigma^2, \tau^2 \sim \mathcal{N}\left(\frac{\tau^2 \mu + \sigma^2 \sum_{j=1}^{k_1} X_{i,j}}{k_1 \sigma^2 + \tau^2}, \frac{\sigma^2 \tau^2}{k_1 \sigma^2 + \tau^2}\right)$$

car les X_i sont indépendants, donc chaque densité sera proportionnelle à une gaussienne.

3) Calculons la probabilité conditionnelle de X, μ :

$$\begin{aligned} \text{IP}(X, \mu | Y, \sigma^2, \tau^2) &\propto \prod_{i=1}^N \exp\left(-\frac{1}{2\tau^2} \sum_{j=1}^{k_1} (X_i - X_{i,j})^2 - \frac{(X_i - \mu)^2}{2\sigma^2}\right) \\ &\propto \prod_{i=1}^N \exp\left(-\frac{1}{2\tau^2} \sum_{j=1}^{k_1} (X_i^2 - 2X_{i,j} X_i + X_{i,j}^2) - \frac{1}{2\sigma^2} (X_i^2 - 2\mu X_i + \mu^2)\right) \\ &\propto \prod_{i=1}^N \exp\left(-\frac{1}{2} \left(X_i^2 \left(\frac{\sigma^2 k_1 + \tau^2}{\tau^2 \sigma^2}\right) - \frac{2X_i \sum_{j=1}^{k_1} X_{i,j}}{\tau^2} - \frac{2X_i \mu}{\sigma^2} + \frac{\mu^2}{\sigma^2} \right)\right) \end{aligned}$$

$$\Rightarrow X, \mu | Y, \sigma^2, \tau^2 \sim \mathcal{N}(\mu, \Sigma)$$

$$\text{avec } \Sigma = \begin{bmatrix} \frac{\sigma^2 k_1 + \tau^2}{\tau^2 \sigma^2} & 0 & 0 & -1/\sigma^2 \\ 0 & \frac{\sigma^2 k_1 + \tau^2}{\sigma^2 \tau^2} & -1/\sigma^2 & \frac{N}{\sigma^2} \\ -1/\sigma^2 & -1/\sigma^2 & 0 & 0 \end{bmatrix}^{-1}$$

$$\mu = \sum x \left(\frac{\sum_{j=1}^n x_{ij}}{n} \right) \dots \left(\frac{\sum_{j=1}^n y_{ij}}{n} \right)$$