

1) one-way ANOVA model

$$\epsilon_{ij} \sim \mathcal{N}(0, \sigma^2_{\epsilon})$$

$$\tilde{y}_{ij} = \mu + \alpha_i + \epsilon_{ij}$$

Priors

$$\pi(\mu) \sim \mathcal{U}(0, 1)$$

$$\pi(\alpha_i) \sim \mathcal{N}(0, \sigma^2_{\alpha})$$

$$\pi(\sigma^2_{\alpha}) \sim \text{IG}(a, b)$$

a, b, σ^2_{α} known.

Constraints

$$\mu | \vec{\tilde{y}}, \alpha, \epsilon \sim \mathcal{N}(\mu_n,$$

Full Conditional Distributions

we can also say,

$$\tilde{y} | \mu, \alpha, \sigma^2 \sim \mathcal{N}(\mu + \alpha_i, \sigma^2)$$

we want posteriors for the following.
 $\left\{ \vec{\tilde{y}} | \mu, \alpha, \sigma^2 \right\}$ Likelihood

$$\left(\begin{array}{l} \mu | \vec{\tilde{y}}, \alpha, \sigma^2 \\ \alpha_i | \vec{\tilde{y}}, \mu, \sigma^2 \\ \sigma^2_{\epsilon} | \vec{\tilde{y}}, \mu, \alpha \end{array} \right) \cdot \mu | \vec{\tilde{y}}, \alpha, \sigma^2 \sim \mathcal{N}(\mu_n + \alpha_i, \frac{\sigma^2}{n})$$

have note for our Gibbs sampler

given the flat prior and the normal conjugate prior.

end up with

$$\phi^{(s)} = \{ \mu^{(s)}, \alpha^{(s)}, \sigma^{2(s)} \}$$

①

• $\alpha_i | \vec{y}, \mu, \sigma^2 \sim \mathcal{N}(\alpha, \sigma^2)$, again
given the normal prior and evidence.

• $\sigma^2 | \vec{y}, \mu, \alpha_i \sim \text{Inv. Gamma}()$
given, $\sigma^2 \sim \text{IG}(a, b)$

we can say,
 $\sigma^2 | \vec{y}, \mu, \alpha_i \sim \text{Inv. Gamma}\left(a + \frac{n}{2}, b + \frac{\sum (y_i - \mu)^2}{2}\right)$
given the normality of the evidence again.

b) Done in lecture

c) What conditions lead to slow convergence for μ and α_i ?

d) $\eta_i = \mu + \alpha_i$ ~ centering
comparing two parameter cases

$\phi = \{\mu, \alpha\}$ } Run Gibbs for each,
 $\eta = \{\mu, \eta\}$ } and compare

(2)

$$p(\mu | \alpha, \vec{y}) \sim \mathcal{N}(\mu + \alpha_i, \frac{\sigma^2}{n})$$

$$p(\alpha | \mu, \vec{y}) \sim \mathcal{N}(\alpha, \sigma_\alpha^2)$$

$$y_{ij} = \mu + \alpha_i + \epsilon_{ij} \quad \begin{matrix} i = 1, \dots, 5 \\ j = 1 \end{matrix}$$

$$\sigma_\epsilon^2 = \sigma_\alpha^2 = 1.$$

$$y | \mu, \alpha, \sigma^2 \sim \mathcal{N}(\mu + \mathbb{1}, \sigma_\epsilon^2)$$

$$\text{Say we let } \mu = 0, \sigma^2 = 1.$$

Then,

$$y | \mu, \alpha, \sigma^2 \sim \mathcal{N}(1, 1)$$

2) Hoff - 6.2

a) Done in code

b) Mixture model

$$z = p \cdot \mathcal{N}(\theta_1, \sigma_1^2) + (1-p) \cdot \mathcal{N}(\theta_2, \sigma_2^2)$$

$$p \sim \text{Beta}(a, b) \quad \frac{1}{\sigma_i} \sim \text{Gamma}(\gamma_0/2, \frac{\gamma_0 \sigma_0^2}{2})$$

$$\theta_i \sim \mathcal{N}(\mu_0, \tau_0^2)$$

(3)

Obtain conditional for;

(x_1, \dots, x_n)

ρ

θ_1

θ_2

σ_1^2

σ_2^2

$$p(\vec{x} | \rho, \theta_1, \theta_2, \sigma_1^2, \sigma_2^2)$$

$$= \mathcal{N}(\theta_{1|2}, \sigma_{1|2}^2)$$

$$p(\theta_1 | \rho, \vec{x}, \theta_2, \sigma_1^2, \sigma_2^2)$$

$$= \mathcal{N}(\theta_{1|2}, \frac{\sigma_{1|2}^2}{2})$$

$$p(\theta_2 | \rho, \vec{x}, \theta_1, \sigma_1^2, \sigma_2^2)$$

$$\sim \mathcal{N}(\theta_{1|2}, \frac{\sigma_{1|2}^2}{2})$$

$$p(\sigma_1^2 | \rho, \vec{x}, \theta_1, \theta_2, \sigma_2^2)$$

$$\sim \text{Inv. Gamma} \left(a + \frac{n}{2}, \frac{b + \sum (x_i - \mu)^2}{2} \right)$$

$$p(\sigma_2^2 | \rho, \vec{x}, \theta_1, \theta_2, \sigma_1^2)$$

$$\sim \text{Inv. Gamma} \left(a + \frac{n}{2}, \frac{b + \sum (x_i - \mu)^2}{2} \right)$$

$$p(\rho | \vec{x}, \theta_1, \theta_2, \sigma_1^2, \sigma_2^2)$$

$$\sim \text{Beta} \left(a + \sum x_i, b + n - \sum x_i \right)$$

(4)