

- ①(a) For the Bayesian analysis of the mixed linear model, derive the marginal posterior of the unknowns in the covariance matrices  $R$  and  $G$ , i.e.,  $\phi_R$  and  $\Phi_G$ , for a general prior on them,  $\Pi(\phi_R, \phi_G)$ . Assume the prior on  $\beta$  is  $\Pi(\beta) \propto 1$ , i.e., flat.
- Hint: If it seems hard, you're taking the wrong approach.
- (b) Use the foregoing to derive the marginal posterior (also the restricted likelihood) for  $\phi_R, \phi_G$  for the balanced, one-way random-effect model (BOWREM):

$$y_{ij} = \beta_0 + u_i + \varepsilon_{ij} \quad \text{for } i=1, \dots, N, j=1, \dots, m, \quad u_i \sim N(0, \sigma_u^2), \quad \varepsilon_{ij} \sim N(0, \sigma_e^2)$$

(The restricted likelihood is equation 15.11 on p. 324 of Hodges 2014.)

- ② For the general model in item ①(a) above, assume  $R = \sigma_e^2 I_n$  and assume  $\sigma_e^2$  has an inverse-gamma prior distribution. Re-parameterize from  $(\sigma_e^2, G)$  to  $(\sigma_e^2, G^*)$  for  $G^* = \frac{1}{\sigma_e^2} G$ . Assume  $\sigma_e^2$  and  $G^*$  (!) are independent a priori, so that  $\Pi(\sigma_e^2, G^*) = \Pi(\sigma_e^2) \Pi(G^*)$ . Starting from the marginal posterior for  $\Pi(\phi_R, \phi_G)$  in ①(a), derive the marginal posterior distribution of  $G^*$ .

Hint: (i) Same as above.

(ii) This is not quite a trick question.

Due Tue 30 Jan 2018