

Random intercept model, integrated mean:

$$\begin{aligned}\text{judgment}_i &\sim N(\alpha_{j[i]} + \beta_1(\text{issue}_{\text{non-at-}}), \sigma^2) \\ \alpha_j &\sim N(\mu_{\alpha_j}, \sigma_{\alpha_j}^2), \text{ for id } j = 1, \dots, J\end{aligned}$$

Random intercept model, separate mean, treatment coding:

$$\begin{aligned}\text{judgment}_i &\sim N(\mu, \sigma^2) \\ \mu &= \alpha_{j[i]} + \beta_1(\text{issue}_{\text{non-at-}}) \\ \alpha_j &\sim N(\mu_{\alpha_j}, \sigma_{\alpha_j}^2), \text{ for id } j = 1, \dots, J\end{aligned}$$

Random intercept model, separate mean, sum coding:

$$\begin{aligned}\text{judgment}_i &\sim N(\mu, \sigma^2) \\ \mu &= \alpha_{j[i]} + \beta_1(\text{issue}_1) \\ \alpha_j &\sim N(\mu_{\alpha_j}, \sigma_{\alpha_j}^2), \text{ for id } j = 1, \dots, J\end{aligned}$$

By-item and by-participant random intercepts:

$$\begin{aligned}\text{judgment}_i &\sim N(\mu, \sigma^2) \\ \mu &= \alpha_{j[i], k[i]} \\ \alpha_j &\sim N(\gamma_0^\alpha + \gamma_1^\alpha(\text{issue}_1), \sigma_{\alpha_j}^2), \text{ for item } j = 1, \dots, J \\ \alpha_k &\sim N(\mu_{\alpha_k}, \sigma_{\alpha_k}^2), \text{ for id } k = 1, \dots, K\end{aligned}$$

By-participants random intercepts and random slopes (at-issueness):

$$\begin{aligned}\text{judgment}_i &\sim N(\mu, \sigma^2) \\ \mu &= \alpha_{j[i]} + \beta_{1j[i]}(\text{issue}_1) \\ \begin{pmatrix} \alpha_j \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{pmatrix} \mu_{\alpha_j} \\ \mu_{\beta_{1j}} \end{pmatrix}, \begin{pmatrix} \sigma_{\alpha_j}^2 & \rho_{\alpha_j \beta_{1j}} \\ \rho_{\beta_{1j} \alpha_j} & \sigma_{\beta_{1j}}^2 \end{pmatrix}\right), \text{ for id } j = 1, \dots, J\end{aligned}$$

By-participant random intercepts and issue-slopes + by-item random intercepts and issue-slopes:

$$\begin{aligned}\text{judgment}_i &\sim N(\mu, \sigma^2) \\ \mu &= \alpha_{j[i], k[i]} \\ \begin{pmatrix} \alpha_j \\ \gamma_{1j} \end{pmatrix} &\sim N\left(\begin{pmatrix} \gamma_0^\alpha + \gamma_{1k[i]}^\alpha(\text{issue}_1) \\ \mu_{\gamma_{1j}} \end{pmatrix}, \begin{pmatrix} \sigma_{\alpha_j}^2 & \rho_{\alpha_j \gamma_{1j}} \\ \rho_{\gamma_{1j} \alpha_j} & \sigma_{\gamma_{1j}}^2 \end{pmatrix}\right), \text{ for item } j = 1, \dots, J \\ \begin{pmatrix} \alpha_k \\ \gamma_{1k} \end{pmatrix} &\sim N\left(\begin{pmatrix} \mu_{\alpha_k} \\ \mu_{\gamma_{1k}} \end{pmatrix}, \begin{pmatrix} \sigma_{\alpha_k}^2 & \rho_{\alpha_k \gamma_{1k}} \\ \rho_{\gamma_{1k} \alpha_k} & \sigma_{\gamma_{1k}}^2 \end{pmatrix}\right), \text{ for id } k = 1, \dots, K\end{aligned}$$

From fixed effects models to random effects models to mixed effects ones:

Data:
Assume we measure travel time on rails,
6 in total, three times per rail.

Here's the intercept-only model:

$$y_{ij} = \beta + \epsilon_{ij} \quad | i = 1, \dots, M, \quad j = 1, \dots, n_i$$

observed travel time for observation j on rail i mean travel time independent rails number of observations per rail (3 per)

equivalent to: $\text{lm}(\text{travel} \sim 1)$

now let's add a fixed effect: the rails

$$y_{ij} = \beta_i + \epsilon_{ij}, \quad i = 1, \dots, M, \quad j = 1, \dots, n_i$$

effect of each rail removes the intercept

equivalent to: $\text{lm}(\text{travel} \sim \text{rail} - 1)$

Now, a random effects model (treating the rails as samples from a population of rails)

$$y_{ij} = \bar{\beta} + (\beta_i - \bar{\beta}) + \epsilon_{ij}$$

average travel time for the rails in the experiment

Now with the by-rails classification:

$$y_{ij} = \bar{\beta} + b_i + \epsilon_{ij}$$

mean travel time across the sampled rails random variable representing the deviation from the population mean of the mean travel time for the i-th rail

In addition, we need the distribution of the random variables b_i + ϵ_{ij} :

$$b_i \sim N(0, \sigma_b^2), \quad \epsilon_{ij} \sim N(0, \sigma_e^2)$$

between-rail variability within-rail variability

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