

Constructing hierarchical models

- Identifying the J experiments/groups that the data come from
- How many repeated observations n_i from each group i , $i=1, \dots, J$
- Find an appropriate sampling distribution for $y_{i:}$, the i 'th observation from the i 'th group, parametrised by a group-specific parameter (vector) θ_i

$$y_{i:} \sim p(y_{i:} | \theta_i), \quad i=1, \dots, n_i, \quad i=1, \dots, J$$

For example $y_{i:} \sim N(\mu_i, \sigma^2)$

If we have covariate information $x_{i:}$ for the individual observations

$$y_{i:} \sim p(y_{i:} | \theta_i, x_{i:})$$

i.e. $(y_{i:}, \theta_i, x_{i:})$ are exchangeable

Example Rats: $y_{i:} \sim \text{Bin}(\theta_i, n_i)$, i.e. $(y_{i:}, \theta_i, n_i)$ are exchangeable

- If no other information is available to distinguish the experiments/groups, then it is appropriate to assume that $p(\theta_1, \dots, \theta_J)$ is invariant to permutation of the indexes $1, \dots, J$

The simplest form: Assume the θ_i 's to be iid from a prior distribution parametrised by a hyperparameter (vector) ϕ , i.e.

$$p(\theta_1, \dots, \theta_J | \phi) = \prod_{i=1}^J p(\theta_i | \phi)$$

okt 27-12:13

- More advanced, if we have covariate information z_i on each group $i=1, \dots, J$, then it is appropriate to model the θ_i 's as conditionally independent given covariate information, i.e.

$$p(\theta_1, \dots, \theta_J | \phi, z_1, \dots, z_J) = \prod_{i=1}^J p(\theta_i | \phi, z_i)$$

Hence, the pairs (θ_i, z_i) are exchangeable

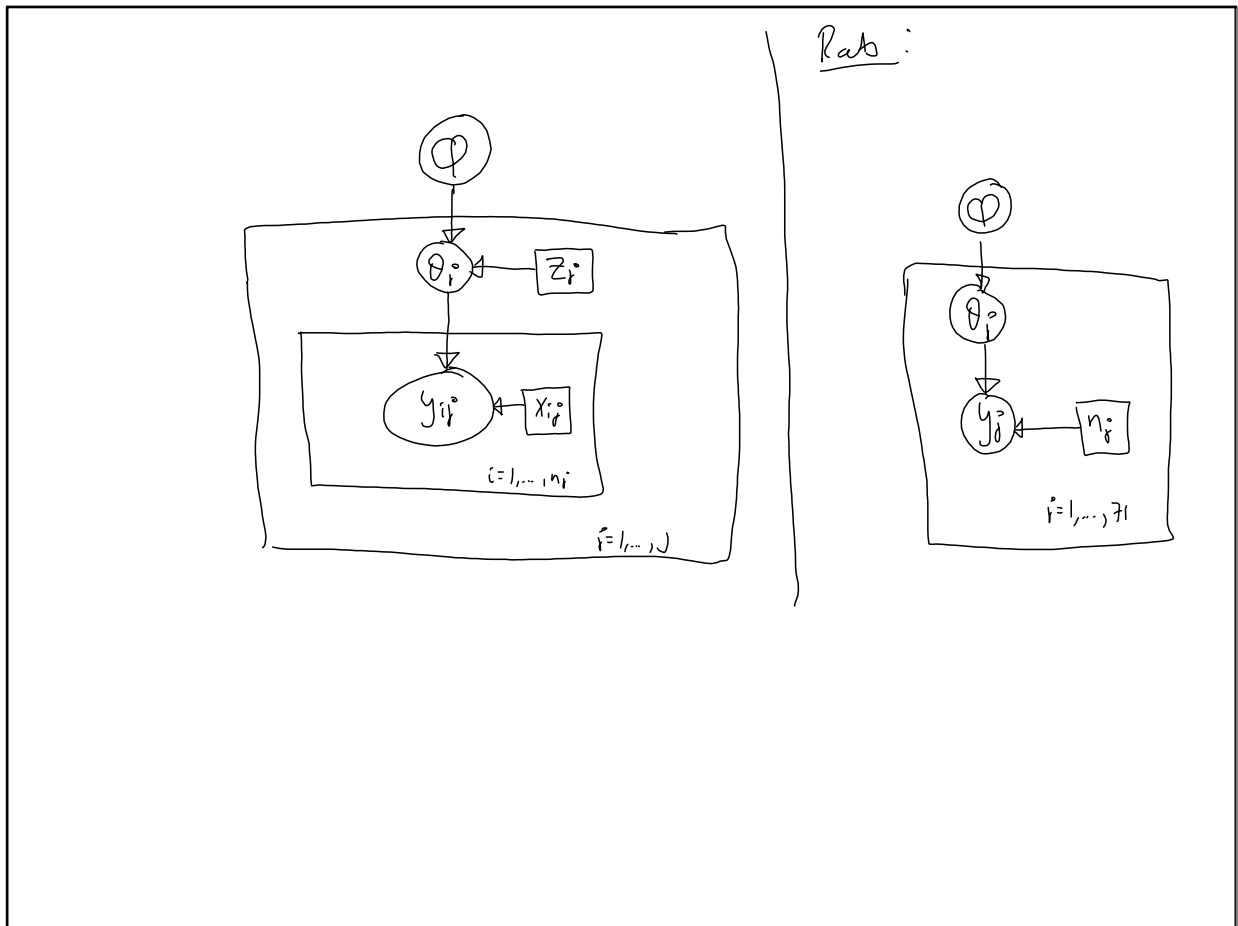
As long as all information available to distinguish the groups is incorporated into z_i , $i=1, \dots, J$, then such a model is appropriate.

- Could also be appropriate to add another layer, e.g. in the Rats example we knew that specific groups of experiments were done in 5 different labs.
- Hyperprior distribution for ϕ
 - If little prior knowledge available, use a diffuse prior

- BUT be careful with improper prior distributions, can result in improper posterior distributions

↳ The more layers and parameters, the more difficult it gets to that the posterior distribution is proper (can be hidden)

okt 27-12:30



okt 27-12:43

Posterior predictive inference

Two different kinds of posterior predictive quantities:

- (1) Predict \tilde{y}_i for some \tilde{i} in $\{1, \dots, J\}$
 - Draw \tilde{y}_i based on posterior draws θ_i
- (2) Predict \tilde{y}_i for a new group $\tilde{i} \notin \{1, \dots, J\}$
 - Draw $\bar{\theta}_i$ based on posterior draws of ϕ
 - Draw $\tilde{y}_i \mid \bar{\theta}_i$

okt 27-12:49