

False positive occupancy model with latent 'false positive' indicator variables

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1 DESCRIPTION

An occupancy model that accommodates false negative and false positive errors. A secondary “negative control” data set is used for estimating the probability of a false positive error.

2 IMPLEMENTATION

The file `occ.fp.sim.R` simulates data according to the model statement below, and `occ.fp.latent.var.mcmc.R` contains the MCMC algorithm for parameter estimation.

3 MODEL STATEMENT

Let y_{ij} be a binary observation representing a detection/non-detection, where $i = 1, \dots, N$ indexes sample units and $j = 1, \dots, J_i$ indexes replicate observations within a sample unit. Also let v be the number of detections out of M trials obtained in the “negative control” dataset. Let z_i denote the latent occupancy state and v_{ij} represent the latent 'false positive' state variable.

$$\begin{aligned} y_{ij} &\sim \begin{cases} \text{Bern}(p_{ij}), & v_{ij} = 0, z_i = 1 \\ 1, & v_{ij} = 1, z_i = 1 \\ 0, & v_{ij} = 0, z_i = 0 \\ 1 & v_{ij} = 1, z_i = 0 \end{cases} \\ v_{ij} &\sim \text{Bern}(\phi) \\ z_i &\sim \text{Bern}(\psi_i) \\ \psi_i &= \text{logit}^{-1}(\mathbf{x}'_i \boldsymbol{\beta}) \\ p_{ij} &= \text{logit}^{-1}(\mathbf{w}'_{ij} \boldsymbol{\alpha}) \\ \boldsymbol{\beta} &\sim \mathcal{N}(\boldsymbol{\mu}_\beta, \sigma_\beta^2 \mathbf{I}) \\ \boldsymbol{\alpha} &\sim \mathcal{N}(\boldsymbol{\mu}_\alpha, \sigma_\alpha^2 \mathbf{I}) \\ v &\sim \text{Binom}(M, \phi) \\ \phi &\sim \text{Beta}(a, b) \end{aligned}$$

4 FULL-CONDITIONAL DISTRIBUTIONS

4.1 Occupancy state (z_i)

$$\begin{aligned}
[z_i \mid \cdot] &\propto \prod_{j=1}^{J_i} [y_{ij} \mid p_{ij}, v_{ij}, z_i] [z_i \mid \psi_i] \\
&\propto \prod_{j=1}^{J_i} \left(\text{Bern}(y_{ij} \mid p_{ij})^{1-v_{ij}} \right)^{z_i} \left(1_{\{y_{ij}=1\}}^{v_{ij}} \right)^{z_i} \left(1_{\{y_{ij}=0\}}^{1-v_{ij}} \right)^{1-z_i} \left(1_{\{y_{ij}=1\}}^{v_{ij}} \right)^{1-z_i} \text{Bern}(z_i \mid \psi_i) \\
&\propto \prod_{j=1}^{J_i} \left(1_{\{y_{ij}=1\}}^{v_{ij}} \left(p_{ij}^{y_{ij}} (1-p_{ij})^{1-y_{ij}} \right)^{1-v_{ij}} \right)^{z_i} \left(1_{\{y_{ij}=0\}}^{1-v_{ij}} 1_{\{y_{ij}=1\}}^{v_{ij}} \right)^{1-z_i} \psi_i^{z_i} (1-\psi_i)^{1-z_i} \\
&\propto \prod_{j=1}^{J_i} \left(\psi_i 1_{\{y_{ij}=1\}}^{v_{ij}} \left(p_{ij}^{y_{ij}} (1-p_{ij})^{1-y_{ij}} \right)^{1-v_{ij}} \right)^{z_i} \left((1-\psi_i) 1_{\{y_{ij}=0\}}^{1-v_{ij}} 1_{\{y_{ij}=1\}}^{v_{ij}} \right)^{1-z_i} \\
&= \text{Bern}(\tilde{\psi}_i),
\end{aligned}$$

where,

$$\tilde{\psi}_i = \frac{\psi_i \prod_{j=1}^{J_i} \left(1_{\{y_{ij}=1\}}^{v_{ij}} \right) \left(p_{ij}^{y_{ij}} (1-p_{ij})^{1-y_{ij}} \right)^{1-v_{ij}}}{\psi_i \prod_{j=1}^{J_i} \left(1_{\{y_{ij}=1\}}^{v_{ij}} \right) \left(p_{ij}^{y_{ij}} (1-p_{ij})^{1-y_{ij}} \right)^{1-v_{ij}} + (1-\psi_i) \prod_{j=1}^{J_i} \left(1_{\{y_{ij}=0\}}^{1-v_{ij}} 1_{\{y_{ij}=1\}}^{v_{ij}} \right)}.$$

4.2 False positive state (v_{ij})

$$\begin{aligned}
[v_{ij} \mid \cdot] &\propto [y_{ij} \mid p_{ij}, v_{ij}, z_i] [v_{ij} \mid \phi] \\
&\propto \left(\text{Bern}(y_{ij} \mid p_{ij})^{1-v_{ij}} \right)^{z_i} \left(1_{\{y_{ij}=1\}}^{v_{ij}} \right)^{z_i} \left(1_{\{y_{ij}=0\}}^{1-v_{ij}} \right)^{1-z_i} \left(1_{\{y_{ij}=1\}}^{v_{ij}} \right)^{1-z_i} \text{Bern}(v_{ij} \mid \phi) \\
&\propto \left(\text{Bern}(y_{ij} \mid p_{ij})^{z_i} \right)^{1-v_{ij}} \left(1_{\{y_{ij}=1\}}^{z_i} \right)^{v_{ij}} \left(1_{\{y_{ij}=0\}}^{1-z_i} \right)^{1-v_{ij}} \left(1_{\{y_{ij}=1\}}^{1-z_i} \right)^{v_{ij}} \text{Bern}(v_{ij} \mid \phi) \\
&\propto \left(\left(p_{ij}^{y_{ij}} (1-p_{ij})^{1-y_{ij}} \right)^{z_i} \right)^{1-v_{ij}} \left(1_{\{y_{ij}=1\}}^{z_i} \right)^{v_{ij}} \left(1_{\{y_{ij}=0\}}^{1-z_i} \right)^{1-v_{ij}} \left(1_{\{y_{ij}=1\}}^{1-z_i} \right)^{v_{ij}} \phi^{v_{ij}} (1-\phi)^{1-v_{ij}} \\
&\quad \left(\phi 1_{\{y_{ij}=1\}}^{z_i} 1_{\{y_{ij}=1\}}^{1-z_i} \right)^{v_{ij}} \left((1-\phi) \left(p_{ij}^{y_{ij}} (1-p_{ij})^{1-y_{ij}} \right)^{z_i} 1_{\{y_{ij}=0\}}^{1-z_i} \right)^{1-v_{ij}} \\
&= \text{Bern}(\tilde{\phi}),
\end{aligned}$$

where,

$$\tilde{\psi}_i = \frac{\phi 1_{\{y_{ij}=1\}}^{z_i} 1_{\{y_{ij}=1\}}^{1-z_i}}{\phi 1_{\{y_{ij}=1\}}^{z_i} 1_{\{y_{ij}=1\}}^{1-z_i} + (1-\phi) \left(p_{ij}^{y_{ij}} (1-p_{ij})^{1-y_{ij}} \right)^{z_i} 1_{\{y_{ij}=0\}}^{1-z_i}}.$$

4.3 Occupancy coefficients (β)

$$\begin{aligned}
[\beta \mid \cdot] &\propto \prod_{i=1}^N [z_i \mid \psi_i] [\beta] \\
&\propto \prod_{i=1}^N \text{Bern}(z_i \mid \psi_i) \mathcal{N}(\beta \mid \mu_\beta, \sigma_\beta^2 \mathbf{I}).
\end{aligned}$$

The update for β proceeds using Metropolis-Hastings.

4.4 Detection coefficients (α)

$$\begin{aligned}
[\alpha \mid \cdot] &\propto \prod_{i=1}^N \prod_{j=1}^{J_i} [y_{ij} \mid p_{ij}, v_{ij}, z_i] [\alpha] \\
&\propto \prod_{i=1}^N \prod_{j=1}^{J_i} \left(\text{Bern}(y_{ij} \mid p_{ij})^{1-v_{ij}} \right)^{z_i} \mathcal{N}(\alpha \mid \mu_\alpha, \sigma_\alpha^2 \mathbf{I}).
\end{aligned}$$

The update for α proceeds using Metropolis-Hastings. Note that the product over i and j only includes instances of i and j such that $z_i = 1$ and $v_{ij} = 0$.

4.5 Probability of a false detection (ϕ)

$$\begin{aligned}
[\phi \mid \cdot] &\propto [v \mid M, \phi] [\phi] \\
&\propto \text{Binom}(v \mid M, \phi) \text{Beta}(a, b) \\
&\propto \phi^v (1 - \phi)^{M-v} \phi^{a-1} (1 - \phi)^{b-1} \\
&\propto \phi^{v+a-1} (1 - \phi)^{M-v+b-1} \\
&= \text{Beta}(v + a, M - v + b)
\end{aligned}$$