

False positive occupancy model with marginalized likelihood

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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.marginal.lik.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.

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

4 FULL-CONDITIONAL DISTRIBUTIONS

4.1 Occupancy state (z_i)

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

where,

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

4.2 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.

4.3 Detection coefficients (α)

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

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 $z_i = 1$.

4.4 Probability of a false detection (ϕ)

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