

Gibbs sampler to estimate population size using mark-recapture data

Posterior distribution

The parameters that we primarily interested in are δ and π . However, to allow for conjugacy, we will also be estimating the status of each individual (z_i) as well. Here is what we are after:

$$p(\delta, \pi, \{z_i\} | \{D_{it}\}) \propto p(\{D_{it}\} | \delta, \pi, \{z_i\}) p(\{z_i\} | \delta, \pi) p(\delta, \pi)$$

Notice that detection $\{D_{it}\}$ does not depend on π and therefore

$$p(\{D_{it}\} | \delta, \pi, \{z_i\}) = p(\{D_{it}\} | \delta, \{z_i\})$$

Similarly, if an individual exists or not z_i does not depend on δ . This implies that

$$p(\{z_i\} | \delta, \pi) = p(\{z_i\} | \pi)$$

Putting all this together and assuming that δ and π are a priori independent, we get:

$$\begin{aligned} & \propto p(\{D_{it}\} | \delta, \{z_i\}) p(\{z_i\} | \pi) p(\delta) p(\pi) \\ & \propto \left\{ \prod_{i=1}^{\tilde{N}} \prod_{t=1}^T \text{Bernoulli}(D_{it} | \delta \times z_i) \right\} \left\{ \prod_{i=1}^{\tilde{N}} \text{Bernoulli}(z_i | \pi) \right\} \text{Beta}(\delta | a_\delta, b_\delta) \text{Beta}(\pi | a_\pi, b_\pi) \end{aligned}$$

Full conditional distributions

To create our own Gibbs sampler in R, we have to write the full conditionals, one parameter at a time.

1) FCD for detection parameter δ :

$$\begin{aligned} p(\delta | \dots) & \propto \left\{ \prod_{i=1}^{\tilde{N}} \prod_{t=1}^T \text{Bernoulli}(D_{it} | \delta \times z_i) \right\} \text{Beta}(\delta | a_\delta, b_\delta) \\ & \propto \left\{ \prod_{i \in \Omega} \prod_{t=1}^T \delta^{D_{it}} (1 - \delta)^{1-D_{it}} \right\} \delta^{a_\delta-1} (1 - \delta)^{b_\delta-1} \end{aligned}$$

where Ω is the set of all individuals for which $z_i = 1$.

$$\begin{aligned} & \propto \left\{ \delta^{\sum_{i \in \Omega} \sum_{t=1}^T D_{it}} (1 - \delta)^{\sum_{i \in \Omega} \sum_{t=1}^T [1-D_{it}]} \right\} \delta^{a_\delta-1} (1 - \delta)^{b_\delta-1} \\ & \propto \delta^{[\sum_{i \in \Omega} \sum_{t=1}^T D_{it}] + a_\delta - 1} (1 - \delta)^{[\sum_{i \in \Omega} \sum_{t=1}^T [1-D_{it}]] + b_\delta - 1} \\ p(\delta | \dots) & = \text{Beta} \left(\left[\sum_{i \in \Omega} \sum_{t=1}^T D_{it} \right] + a_\delta, \left[\sum_{i \in \Omega} \sum_{t=1}^T [1 - D_{it}] \right] + b_\delta \right) \end{aligned}$$

2) FCD for proportion of potential individuals that truly exist π :

$$\begin{aligned}
p(\pi | \dots) &\propto \left\{ \prod_{i=1}^{\tilde{N}} \text{Bernoulli}(z_i | \pi) \right\} \text{Beta}(\pi | a_\pi, b_\pi) \\
&\propto \left\{ \prod_{i=1}^{\tilde{N}} \pi^{z_i} (1 - \pi)^{1-z_i} \right\} \pi^{a_\pi-1} (1 - \pi)^{b_\pi-1} \\
&\propto \left\{ \pi^{\sum_{i=1}^{\tilde{N}} z_i} (1 - \pi)^{\sum_{i=1}^{\tilde{N}} 1-z_i} \right\} \pi^{a_\pi-1} (1 - \pi)^{b_\pi-1} \\
&\propto \pi^{\left[\sum_{i=1}^{\tilde{N}} z_i \right] + a_\pi - 1} (1 - \pi)^{\left[\sum_{i=1}^{\tilde{N}} 1 - z_i \right] + b_\pi - 1} \\
p(\pi | \dots) &= \text{Beta} \left(\left[\sum_{i=1}^{\tilde{N}} z_i \right] + a_\pi, \left[\sum_{i=1}^{\tilde{N}} 1 - z_i \right] + b_\pi \right)
\end{aligned}$$

3) FCD for the status of each individual:

Say we have 100 potential individuals. One would think that we need to sample 100 z_i parameters, one representing the status of each individual. In reality, however, the z_i 's that correspond to individuals that we saw at least once (i.e., $D_{it} = 1$ for at least one t) are not truly random quantities. In other words, according to the assumptions in our model, we know these individuals truly exist (i.e., $z_i = 1$). The problem is when we never see a particular animal (i.e., when $D_{it} = 0$ for all t). In this case, either:

- the animal exists but we failed to detect them; OR
- the animal does not exist.

In other words, z_i is a random quantity only when $D_{it} = 0$ for all t . For this reason, we just write the full conditional distributions for these animals.

$$p(z_i | D_{i1} = 0, \dots, D_{iT} = 0, \dots) \propto \left\{ \prod_{t=1}^T \text{Bernoulli}(D_{it} | \delta \times z_i) \right\} \text{Bernoulli}(z_i | \pi)$$

To use the equal sign, we can write this using a generic constant K :

$$\begin{aligned}
p(z_i | D_{i1} = 0, \dots, D_{iT} = 0, \dots) &= K \left\{ \prod_{t=1}^T \text{Bernoulli}(D_{it} | \delta \times z_i) \right\} \text{Bernoulli}(z_i | \pi) \\
&= K \times \left\{ \prod_{t=1}^T (\delta \times z_i)^{D_{it}} [1 - (\delta \times z_i)]^{1-D_{it}} \right\} \times \{ \pi^{z_i} (1 - \pi)^{1-z_i} \}
\end{aligned}$$

Because we know that $D_{it} = 0$ for all t , this becomes:

$$= K \times [1 - (\delta \times z_i)]^T \times \{ \pi^{z_i} (1 - \pi)^{1-z_i} \} \text{ [eqn. 1]}$$

Now let's examine what is $p(z_i = 1|D_{i1} = 0, \dots, D_{iT} = 0, \dots)$. If we substitute $z_i = 1$ into eqn. 1, we get $K \times [1 - \delta]^T \times \pi$. One way to interpret this equation is that the animal exists (given by probability π) but we just failed to observe it in every single survey (given by probability $[1 - \delta]^T$). Similarly, what is $p(z_i = 0|D_{i1} = 0, \dots, D_{iT} = 0, \dots)$? If we substitute $z_i = 0$ into eqn. 1, we get $K \times (1 - \pi)$.

It would seem like we are stuck because we do not know what our constant K is. However, we actually have all the information we need to determine K . We know that:

$$p(z_i = 0|D_{i1} = 0, \dots, D_{iT} = 0, \dots) + p(z_i = 1|D_{i1} = 0, \dots, D_{iT} = 0, \dots) = K(1 - \delta)^T \pi + K(1 - \pi) = 1$$

Therefore:

$$K = \frac{1}{(1 - \delta)^T \pi + (1 - \pi)}$$

This implies that:

$$p(z_i = 1|D_{i1} = 0, \dots, D_{iT} = 0, \dots) = K(1 - \delta)^T \pi = \frac{(1 - \delta)^T \pi}{(1 - \delta)^T \pi + (1 - \pi)}$$

If we want to sample z_i from its FCD, we generate a Bernoulli random variable with probability given by $\frac{(1 - \delta)^T \pi}{(1 - \delta)^T \pi + (1 - \pi)}$. In other words:

$$z_i|D_{i1} = 0, \dots, D_{iT} = 0, \dots \sim \text{Bernoulli}\left(\frac{(1 - \delta)^T \pi}{(1 - \delta)^T \pi + (1 - \pi)}\right)$$