

# 1 Test

- $S_t$ : the  $t$ -th sample.
- $S_T^{in} = \bigcup_{t=1}^T S_t$ : set of sampled individuals up to and including  $T$ -th sample.
- $S_T^{out}$ : set of individuals that has not been sampled after  $T$  sample draws. ( $S_T^{out} \cap S_T^{in} = \emptyset$ ).
- $\mathcal{P} = S_T^{in} \cup S_T^{out}$ : the entire population.
- $d_{i(T)}$ : number of samples that contained individual  $i$ :

$$d_{i(T)} = \sum_{t=1}^T \mathbb{1}\{i \in S_t\}$$

Assuming that samples are drawn independently:

$$\mathbb{E}[d_{i(T)}] = \sum_{t=1}^T \pi_i = T\pi_i$$

where  $\pi_i$  denotes inclusion probability of  $i$ . This suggests estimating  $\pi_i$  by

$$\hat{\pi}_i = \frac{d_{i(T)}}{T} \quad \text{or} \quad \hat{\pi}_i = \frac{1 + d_{i(T)}}{1 + T} \quad (1)$$

where the latter comes from enforcing that probabilities be non-zero. Note that in this case  $\hat{\pi}_i = \frac{1}{1+T} \forall i \in S_T^{out}$ .

Consider the problem from the Bayesian perspective. Assume Beta prior for inclusion probabilities:

$$\pi_i \sim Be(\alpha, \beta)$$

Then

$$\mathbb{E}\left[\sum_{i \in \mathcal{P}} \pi_i\right] = \sum_{i \in \mathcal{P}} \frac{\alpha}{\alpha + \beta} = |\mathcal{P}| \frac{\alpha}{\alpha + \beta} = (|S_T^{out}| + |S_T^{in}|) \frac{\alpha}{\alpha + \beta}$$

Let  $n_t := |S_t|$  be the sample size. While we assume independent replications of the same sampling scheme, depending on the chosen scheme, it is possible for  $n_t$  to be random.

$$\mathbb{E}\left[\sum_{i \in \mathcal{P}} \pi_i\right] = \mathbb{E}[n_t] \Leftrightarrow (|S_T^{out}| + |S_T^{in}|) \frac{\alpha}{\alpha + \beta} = \mathbb{E}[n_t] \quad (2)$$

Estimating  $\mathbb{E}[n_t]$  by  $T^{-1} \sum_{t=1}^T n_t$ , if  $\alpha$  and  $\beta$  were known,  $|S_T^{out}|$  could be inferred from (2).

The likelihood would be

$$d_{i(T)} | \pi_i \sim Bin(T, \pi_i)$$

Then the posterior distribution is

$$\begin{aligned} f(\pi_i | d_{i(T)} = k) &= \frac{\mathbb{P}(d_{i(T)} = k | \pi_i) f(\pi_i)}{\mathbb{P}(d_{i(T)} = k)} \\ &\propto \pi_i^k (1 - \pi_i)^{T-k} \pi_i^{\alpha-1} (1 - \pi_i)^{\beta-1} \\ &= \pi_i^{\alpha+k-1} (1 - \pi_i)^{\beta+T-k-1} \\ &\Rightarrow \pi_i | d_{i(T)} = k \sim Be(\alpha + k, \beta + T - k) \\ &\Rightarrow \mathbb{E}[\pi_i | d_{i(T)} = k] = \frac{\alpha + k}{\alpha + \beta + T} \end{aligned}$$

The marginal likelihood is:

$$\begin{aligned}\mathbb{P}(d_{i(T)} = k) &= \int_0^1 f(\pi_i, d_{i(T)}) d\pi_i = \int_0^1 \mathbb{P}(d_{i(T)} = k | \pi_i) f(\pi_i) d\pi_i \\ &= \binom{T}{k} \frac{B(\alpha + k, \beta + T - k)}{B(\alpha, \beta)}\end{aligned}$$

Note that we never observe  $d_{i(T)} = 0$ . The observed frequencies  $d_{i(T)} > 0$  for  $i \in S_T^{in}$  follow a truncated distribution:

$$\begin{aligned}\mathbb{P}(d_{i(T)} = k | d_{i(T)} > 0) &= \begin{cases} \frac{\mathbb{P}(d_{i(T)}=k)}{1-\mathbb{P}(d_{i(T)}=0)}, & \text{if } k > 0 \\ 0, & \text{otherwise} \end{cases} \\ &= \begin{cases} \binom{T}{k} \frac{B(\alpha+k, \beta+T-k)}{B(\alpha, \beta) - B(\alpha, \beta+T)}, & \text{if } k > 0 \\ 0, & \text{otherwise} \end{cases}\end{aligned}$$

Following empirical Bayes approach, maximise the marginal likelihood to obtain hyperparameters  $\alpha$  and  $\beta$ .

$$\begin{aligned}L(\alpha, \beta; T, k_1, \dots, k_i) &\stackrel{indep}{=} \prod_{i \in S_T^{in}} \binom{T}{k_i} \frac{\Gamma(\alpha + k_i) \Gamma(\beta + T - k_i)}{\Gamma(\alpha + \beta + T)} \cdot \frac{1}{\frac{\Gamma(\alpha) \Gamma(\beta)}{\Gamma(\alpha + \beta)} - \frac{\Gamma(\alpha) \Gamma(\beta + T)}{\Gamma(\alpha + \beta + T)}} \\ &= \prod_{i \in S_T^{in}} \binom{T}{k_i} \frac{\Gamma(\alpha + k_i) \Gamma(\beta + T - k_i) \Gamma(\alpha + \beta)}{\Gamma(\alpha) \Gamma(\beta) \Gamma(\alpha + \beta + T) - \Gamma(\alpha) \Gamma(\beta + T) \Gamma(\alpha + \beta)}\end{aligned}$$

Using the recursive formula of gamma function  $\Gamma(x) = (x-1)\Gamma(x-1)$  and the fact that  $T, k_i \in \mathbb{N}_0 := \mathbb{N} \cup \{0\}$  allows to rewrite the marginal likelihood as:

$$\begin{aligned}L(\alpha, \beta; T, d_{i(T)} = k_i \forall i \in S_T^{in}) &= \prod_{i \in S_T^{in}} \binom{T}{k_i} \frac{\Gamma(\alpha) \Gamma(\beta) \Gamma(\alpha + \beta)}{\Gamma(\alpha) \Gamma(\beta) \Gamma(\alpha + \beta)} \\ &\quad \times \frac{\prod_{j=1}^{k_i} (\alpha + k_i - j) \prod_{j=1}^{T-k_i} (\beta + T - k_i - j)}{\prod_{j=1}^T (\alpha + \beta + T - j) - \prod_{j=1}^T (\beta + T - j)} \\ &= \prod_{i \in S_T^{in}} \binom{T}{k_i} \frac{\prod_{j=1}^{k_i} (\alpha + k_i - j) \prod_{j=1}^{T-k_i} (\beta + T - k_i - j)}{\prod_{j=1}^T (\alpha + \beta + T - j) - \prod_{j=1}^T (\beta + T - j)} \\ &\quad \propto \left[ \prod_{j=1}^T (\alpha + \beta + T - j) - \prod_{j=1}^T (\beta + T - j) \right]^{-|S_T^{in}|} \\ &\quad \times \prod_{i \in S_T^{in}} \prod_{j=1}^{k_i} (\alpha + k_i - j) \prod_{j=1}^{T-k_i} (\beta + T - k_i - j)\end{aligned}$$

The corresponding marginal log-likelihood is

$$\begin{aligned}l(\alpha, \beta) &:= \log L(\alpha, \beta; T, d_{i(T)} = k_i \forall i \in S_T^{in}) \\ &= const + \left[ \sum_{i \in S_T^{in}} \sum_{j=1}^{k_i} \log(\alpha + k_i - j) + \sum_{j=1}^{T-k_i} \log(\beta + T - k_i - j) \right] \\ &\quad - |S_T^{in}| \log \left( \prod_{j=1}^T (\alpha + \beta + T - j) - \prod_{j=1}^T (\beta + T - j) \right)\end{aligned} \tag{3}$$

Derivatives:

$$\begin{aligned} \frac{\partial l(\alpha, \beta)}{\partial \alpha} &= \sum_{i \in S_T^{in}} \sum_{j=1}^{k_i} (\alpha + k_i - j)^{-1} \\ &\quad - |S_T^{in}| \frac{\sum_{j=1}^T \prod_{m=1}^{j-1} (\alpha + \beta + T - m) \prod_{m=j+1}^T (\alpha + \beta + T - m)}{\prod_{j=1}^T (\alpha + \beta + T - j) - \prod_{j=1}^T (\beta + T - j)} \end{aligned} \quad (4)$$

$$\begin{aligned} \frac{\partial l(\alpha, \beta)}{\partial \beta} &= \sum_{i \in S_T^{in}} \sum_{j=1}^{T-k_i} (\beta + T + k_i - j)^{-1} \\ &\quad - |S_T^{in}| \frac{\sum_{j=1}^T \prod_{m=1}^{j-1} (\beta + T - m) \prod_{m=j+1}^T (\beta + T - m)}{\prod_{j=1}^T (\alpha + \beta + T - j) - \prod_{j=1}^T (\beta + T - j)} \end{aligned} \quad (5)$$