

Double Collapsed Gibbs sampler

- Goals: sample $[S|Y]$, $[Y_{n+1}|Y]$
- Idea: use gibbs sampler, conditionally, $[s_i | s_{-i}, Y]$

• Derivation:

$$\text{Note: } [S, Y] = [s, y_i | Y_{-i}] [Y_i]$$

$$\text{so } [s_i | s_{-i}, Y] \stackrel{s_i}{\propto} [s, Y] \stackrel{s_i}{\propto} [s_i, y_i | s_{-i}, Y_{-i}]$$

• Let $Y_{-i,j} = (y_{\ell=1:i}, s_{\ell=j})$

$$\begin{aligned} \text{so } [s_i=j | s_{-i}, Y] &\stackrel{s_i}{\propto} [y_i | s_i=j, s_{-i}, Y_{-i}] [s_i=j | s_{-i}, Y_{-i}] \\ &= [y_i | s_i=j, Y_{-i,j}] [s_i=j | s_{-i}] \end{aligned}$$

Let $k = \# \text{ unique } s_{\ell} : s_{\ell} \in s_{-i}$

$n_{-i,j} = \# \ell \in -i \text{ s.t. } s_{\ell} = j$

$$\text{Then } P(s_i=j | s_{-i}) = \begin{cases} \frac{\alpha}{\alpha+n-1} & j=k+1 \\ \frac{n_{-i,j}}{\alpha+n-1} & j \in \{1, \dots, k\} \end{cases}$$

let θ_j be param of j^{th} cluster

$$\begin{aligned}\text{Then } [y_i | s_i=j, y_{-i,j}] &= \int [y_i | s_i=j, y_{-i,j}, \theta_j] [\theta_j | s_i=j, y_{-i,j}] \\ &= \int N(y_i; \theta_j) [\theta_j | s_i=j, y_{-i,j}] d\theta_j\end{aligned}$$

$$\begin{aligned}[\theta_j | s_i=j, y_{-i,j}] &\propto [y_{-i,j} | s_i=j, \theta_j] [\theta_j | s_i=j] \\ &= [y_{-i,j} | s_i=j, \theta_j] [\theta_j] \\ &= \left(\prod_{\substack{l: s_l=j \\ l \neq i}} N(y_l; \theta_j) \right) g_0(\theta_j)\end{aligned}$$

$$\text{so } [y_i | s_i=j, y_{-i,j}] = \int N(y_i; \theta_j) \left(\prod_{\substack{l: s_l=j \\ l \neq i}} N(y_l; \theta_j) \right) g_0(\theta_j) d\theta_j$$

$$\theta_j = (\mu_j, \tau_j^{-1}) \sim \text{normal gamma } (\mu_0, \kappa, a_\tau, b_\tau)$$

$$\text{so } [y_i | s_i=j, y_{-i,j}] \propto \begin{array}{l} \text{posterior for} \\ \text{normal likelihood} \\ \text{normal-gamma prior} \end{array}$$

$$[Y_{n+1} | Y]$$

Sample $S^{(t)} \sim [S | Y]$ $t=1, \dots, N$ using gibbs sampler.

Let $k^{(t)} = \# \text{ unique } S_l^{(t)} \text{ s.t. } l \in \{1, \dots, n\}$
 $n_j^{(t)} = \# l \in \{1, \dots, n\} \text{ s.t. } S_l^{(t)} = j \text{ (} j \in \{1, \dots, k\} \text{)}$
 $Y_{(j)}^{(t)} = (Y_l : l \in \{1, \dots, n\}, S_l^{(t)} = j) \text{ (} j \in \{1, \dots, k\} \text{)}$

Then from gibbs sampler derivations,

$[Y_{n+1} | S_{n+1}=j, Y_{(j)}^{(t)}] = \text{posterior mg}(Y_l : S_l^{(t)}=j, l \in \{1, \dots, n\})$

$$P(S_{n+1}=j | S^{(t)}) = \begin{cases} \frac{\alpha}{\alpha+n-1} & j=k+1 \\ \frac{n_j^{(t)}}{\alpha+n-1} & j \in \{1, \dots, k\} \end{cases}$$

$$\begin{aligned} E[Y_{n+1} | Y] &= \int \int [Y_{n+1} | S_{n+1}, S, Y] [S_{n+1} | S, Y] [S | Y] dS_{n+1} \\ &\approx \frac{1}{N} \sum_{t=1}^N \int [Y_{n+1} | S_{n+1}, S^{(t)}, Y] [S_{n+1} | S^{(t)}, Y] dS_{n+1} \\ &= \frac{1}{N} \sum_{t=1}^N \sum_{j=1}^{k+1} [Y_{n+1} | S_{n+1}=j, Y_{(j)}^{(t)}] [S_{n+1}=j | S^{(t)}] \end{aligned}$$