

Biostat 250 C HW8

Elvis Cui

Han Cui

Dept. of Biostat

UCLA



Q1: Suppose that

$$x_i | x_{\text{fix}} \sim \mathcal{N}\left(\rho \sum_{j=1}^n \frac{w_{ij} x_j}{w_{it}}, \frac{\sigma^2}{w_{it}}\right)$$

where $\sum_{j=1}^n w_{ij} = m_i = w_{it}$ &

$$w_{ii} = 0$$

$$w_{ij} = \begin{cases} 1 & \text{if } (i,j) \in \mathcal{E} \\ 0 & \text{if } (i,j) \notin \mathcal{E} \end{cases}$$

Show that (Brook's Lemma)

$$P(x_1, \dots, x_n) \propto e^{-\frac{1}{2\sigma^2} x^T (D - P W) x}$$

where $x = (x_1, \dots, x_n)^T$, $D = \text{Diag}(w_{1t}, \dots, w_{nt})$

& W is the binary adjacency matrix.

Sol.

Recall Brook's lemma,

$$P(x_1, x_2, \dots, x_n) =$$

$$\frac{P(x_1 | x_2, \dots, x_n) P(x_2 | x_1, x_3, \dots, x_n) \dots P(x_n | x_1, \dots, x_{n-1})}{P(x_1 | x_2, \dots, x_n) P(x_2 | x_1, x_3, \dots, x_n) \dots P(x_n | x_1, \dots, x_{n-1})}$$

$$x \cdot P(x_1, x_2, \dots, x_n)$$

Let $x_{10} = x_{20} = \dots = x_{n0} = 0$, then

$$\frac{P(x_1, \dots, x_n)}{P(0)} = \frac{\prod_{i=1}^n P(x_i | \cdot)}{\prod_{i=1}^n P(0 | \cdot)}$$

I will prove the statement
for special to general.

Step 1: Let $n=2$ & $\begin{cases} w_{1t}=w_{12} \\ w_{2t}=w_{21} \end{cases}$, then

$$\frac{P(x_1, x_2)}{P(0, 0)} = \frac{P(x_1 | x_2) P(x_2 | 0)}{P(0 | x_2) P(0 | 0)} \propto$$

$$\exp \left\{ -\frac{w_{1t}}{2\sigma^2} \left(x_1 - \rho \frac{w_{12} x_2 + w_{11} 0}{w_{1t}} \right)^2 \right\} \times$$

$$\exp \left\{ -\frac{w_{2t}}{2\sigma^2} \left(x_2 - \frac{w_{21} x_1 + w_{22} 0}{w_{2t}} \right)^2 \right\} \times$$

$$\exp \left\{ \frac{w_{1t}}{2\sigma^2} (0 - \rho \frac{w_{12} x_2 + w_{11} 0}{w_{1t}})^2 \right\} \propto$$

$$\exp \left\{ -\frac{1}{2\sigma^2} (w_{1t} x_1^2 + w_{2t} x_2^2 - 2\rho x_1 w_{12} x_2) \right\} =$$

$$\exp \left\{ -\frac{1}{2\sigma^2} (x_1, x_2) \begin{pmatrix} w_{1t} & 0 \\ 0 & w_{2t} \end{pmatrix} - \rho \begin{pmatrix} 0 & w_{12} \\ w_{21} & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \right\}$$

Step 2: General case.

For $i = 1, 2, \dots, n$, we have

$$P(x_i | x_{-i}) \propto e^{-\frac{w_{it}}{2\sigma^2} (x_i - \rho \sum_{j=1}^n \frac{w_{ij} x_j}{w_{it}})^2}$$

$$= e^{-\frac{1}{2\sigma^2} (w_{it} x_i^2 - 2\rho w_i^T x x_i + \frac{\rho^2 (w_i^T x)^2}{w_{it}})}$$

Where

$$\begin{cases} w_i^T = \{w_{i1}, \dots, w_{in}\} \\ x = \{x_1, \dots, x_n\} \\ w_{ii} = 0 \end{cases}$$

Hence, we have

$$\frac{P(X_i | X_0, \dots, X_{(i-1)0}, X_{i+1}, \dots, X_n)}{P(X_{i0} | X_0, \dots, X_{(i-1)0}, X_{i+1}, \dots, X_n)}$$

$$\propto \frac{e^{-\frac{1}{2\sigma^2}(w_{i+}x_i^2 - 2\rho \tilde{w}_i^T \tilde{x} + \frac{\rho^2(\tilde{w}_i^T \tilde{x})^2}{w_{i+}})}}{e^{-\frac{1}{2\sigma^2}(\frac{\rho^2(\tilde{w}_i^T \tilde{x})^2}{w_{i+}})}}$$

$$\propto e^{-\frac{1}{2\sigma^2}(w_{i+}x_i^2 - 2\rho \tilde{w}_i^T \tilde{x})}$$

where $\begin{cases} \tilde{w}_i^T = (w_{i(i)}, w_{i(i+2)}, \dots, w_{i(n)}) \\ \tilde{x} = (x_{i+1}, \dots, x_n) \end{cases}$

are the truncated versions.

Next, interestingly, note that

$$2\rho \sum_{i=1}^n \tilde{w}_i^T \tilde{x}$$

$$= x^T (\rho W) x$$

where $W = [w_1 \ w_2 \ \dots \ w_n]$

and $W = W^T$
(that's why we get factor 2),

We have

$$\frac{P(X_1, \dots, X_n)}{P(0, \dots, 0)} \propto e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (w_{i+}x_i^2 - 2\rho \tilde{w}_i^T \tilde{x})}$$

$$\propto e^{-\frac{1}{2\sigma^2} [\textcircled{1} + \textcircled{2}]}$$

where

$$\textcircled{1} = \sum_{i=1}^n w_{i+} x_i^2 = x^T D x$$

$$D = \text{Diag}(w_{i+})$$

$$\textcircled{2} = -x^T (\rho W) x$$

and

$\textcircled{1} + \textcircled{2}$ is indeed

$$x^T (D - \rho W) x$$

□