

**6.27** From 6.89, we have:

$$p(\mathbf{t}_N|\boldsymbol{\theta}) = \int p(\mathbf{t}_N|\mathbf{a}_N) p(\mathbf{a}_N|\boldsymbol{\theta}) d\mathbf{a}_N$$

From 6.79, we have:

$$p(\mathbf{t}_N|\mathbf{a}_N) = \prod_{n=1}^N \sigma(a_n)^{t_n} (1 - \sigma(a_n))^{1-t_n}$$

and we know that:

$$p(\mathbf{a}_N|\boldsymbol{\theta}) = \mathcal{N}(\mathbf{a}_N|\mathbf{0}, \mathbf{C}_N) = \frac{1}{(2\pi)^{N/2} |\mathbf{C}_N|^{1/2}} \exp \left\{ -\frac{1}{2} \mathbf{a}_N^T \mathbf{C}_N^{-1} \mathbf{a}_N \right\}$$

$$\Rightarrow p(\mathbf{t}_N|\boldsymbol{\theta}) = \int \left( \prod_{n=1}^N \sigma(a_n)^{t_n} (1 - \sigma(a_n))^{1-t_n} \right) \left( \frac{1}{(2\pi)^{N/2} |\mathbf{C}_N|^{1/2}} \exp \left\{ -\frac{1}{2} \mathbf{a}_N^T \mathbf{C}_N^{-1} \mathbf{a}_N \right\} \right) d\mathbf{a}_N$$

Using 4.135, we have the Laplace approximation of the posterior:

$$p(\mathbf{t}_N|\boldsymbol{\theta}) \approx (p(\mathbf{t}_N|\mathbf{a}_N^*) p(\mathbf{a}_N^*|\boldsymbol{\theta})) \frac{(2\pi)^{N/2}}{|\mathbf{A}|^{1/2}}$$

where from 4.132 :

$$\mathbf{A} = -\nabla \nabla \ln (p(\mathbf{t}_N|\mathbf{a}_N) p(\mathbf{a}_N|\boldsymbol{\theta})) |_{\mathbf{a}_N=\mathbf{a}_N^*}$$

We can get this result directly from 6.82,

$$\mathbf{A} = (\mathbf{W}_N + \mathbf{C}_N^{-1})$$

$$\Rightarrow p(\mathbf{t}_N|\boldsymbol{\theta}) \approx (p(\mathbf{t}_N|\mathbf{a}_N^*) p(\mathbf{a}_N^*|\boldsymbol{\theta})) \frac{(2\pi)^{N/2}}{|(\mathbf{W}_N + \mathbf{C}_N^{-1})|^{1/2}}$$

$$\begin{aligned}
\implies \ln p(\mathbf{t}_N | \boldsymbol{\theta}) &\approx \ln p(\mathbf{t}_N | \mathbf{a}_N^*) + \ln p(\mathbf{a}_N^* | \boldsymbol{\theta}) + \frac{N}{2} \ln(2\pi) - \frac{1}{2} \ln |(\mathbf{W}_N + \mathbf{C}_N^{-1})| \\
&= \Psi(\mathbf{a}_N^*) + \frac{N}{2} \ln(2\pi) - \frac{1}{2} \ln |(\mathbf{W}_N + \mathbf{C}_N^{-1})|
\end{aligned}$$

which is the same as the result in 6.90.

Taking partial derivative of this log-likelihood w.r.t  $\theta_j$ ,

$$\frac{\partial \ln p(\mathbf{t}_N | \boldsymbol{\theta})}{\partial \theta_j} = \frac{\partial}{\partial \theta_j} \left( \ln p(\mathbf{t}_N | \mathbf{a}_N^*) + \ln p(\mathbf{a}_N^* | \boldsymbol{\theta}) + \frac{N}{2} \ln(2\pi) - \frac{1}{2} \ln |(\mathbf{W}_N + \mathbf{C}_N^{-1})| \right)$$

Let's consider the derivative of  $(\ln p(\mathbf{t}_N | \mathbf{a}_N^*) + \ln p(\mathbf{a}_N^* | \boldsymbol{\theta}))$ .

Since  $\mathbf{a}_N^*$  depends on  $\theta_j$ , we apply the chain rule :

$$= \frac{\partial \ln p(\mathbf{t}_N | \mathbf{a}_N^*)}{\partial \mathbf{a}_N^*} \cdot \frac{\partial \mathbf{a}_N^*}{\partial \theta_j} + \frac{\partial \ln p(\mathbf{t}_N | \mathbf{a}_N^*)}{\partial \theta_j} + \frac{\partial \ln p(\mathbf{a}_N^* | \boldsymbol{\theta})}{\partial \mathbf{a}_N^*} \cdot \frac{\partial \mathbf{a}_N^*}{\partial \theta_j} + \frac{\partial \ln p(\mathbf{a}_N^* | \boldsymbol{\theta})}{\partial \theta_j}$$

$$\frac{\partial \ln p(\mathbf{t}_N | \mathbf{a}_N^*)}{\partial \theta_j} = 0 \text{ since } \ln p(\mathbf{t}_N | \mathbf{a}_N^*) \text{ has no direct dependence on } \boldsymbol{\theta}.$$

$$= \left( \frac{\partial \ln p(\mathbf{t}_N | \mathbf{a}_N^*)}{\partial \mathbf{a}_N^*} + \frac{\partial \ln p(\mathbf{a}_N^* | \boldsymbol{\theta})}{\partial \mathbf{a}_N^*} \right) \cdot \frac{\partial \mathbf{a}_N^*}{\partial \theta_j} + \frac{\partial \ln p(\mathbf{a}_N^* | \boldsymbol{\theta})}{\partial \theta_j}$$

By definition of  $\mathbf{a}_N^*$ , it is the mode of the posterior:

$$\mathbf{a}_N^* = \arg \max_{\mathbf{a}_N} (\ln p(\mathbf{t}_N | \mathbf{a}_N) + \ln p(\mathbf{a}_N | \boldsymbol{\theta}))$$

So the gradient of the log-posterior with respect to  $\mathbf{a}_N$  vanishes at the mode as the gradient is 0:

$$\left. \frac{\partial}{\partial \mathbf{a}_N} (\ln p(\mathbf{t}_N | \mathbf{a}_N) + \ln p(\mathbf{a}_N | \boldsymbol{\theta})) \right|_{\mathbf{a}_N = \mathbf{a}_N^*} = 0$$

Hence, the derivative of the log-posterior simplifies to:

$$\frac{\partial}{\partial \theta_j} (\ln p(\mathbf{t}_N | \mathbf{a}_N^*) + \ln p(\mathbf{a}_N^* | \boldsymbol{\theta})) = \frac{\partial \ln p(\mathbf{a}_N^* | \boldsymbol{\theta})}{\partial \theta_j}$$

Finding the derivative of  $\ln p(\mathbf{a}_N^* | \boldsymbol{\theta})$ , and only focusing on direct dependence on  $\boldsymbol{\theta}$ , and ignoring any derivatives dependent on  $\boldsymbol{\theta}$  through  $\mathbf{a}_N^*$ :

$$\begin{aligned} \frac{\partial \ln p(\mathbf{a}_N^* | \boldsymbol{\theta})}{\partial \theta_j} &= \frac{\partial}{\partial \theta_j} \ln \left( \frac{1}{(2\pi)^{N/2} |\mathbf{C}_N|^{1/2}} \exp \left\{ -\frac{1}{2} \mathbf{a}_N^{*T} \mathbf{C}_N^{-1} \mathbf{a}_N^* \right\} \right) \\ &= \frac{\partial}{\partial \theta_j} \left( -\frac{N}{2} \ln(2\pi) - \frac{1}{2} \ln |\mathbf{C}_N| - \frac{1}{2} \mathbf{a}_N^{*T} \mathbf{C}_N^{-1} \mathbf{a}_N^* \right) \\ &= 0 - \frac{1}{2} \cdot \frac{\partial \ln |\mathbf{C}_N|}{\partial \theta_j} - \frac{1}{2} \cdot \frac{\partial (\mathbf{a}_N^{*T} \mathbf{C}_N^{-1} \mathbf{a}_N^*)}{\partial \theta_j} \\ &= -\frac{1}{2} \cdot \text{Tr} \left( \mathbf{C}_N^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \right) - \frac{1}{2} \cdot \left( \mathbf{a}_N^{*T} \left( \frac{\partial \mathbf{C}_N^{-1}}{\partial \theta_j} \right) \mathbf{a}_N^* \right) \\ &= -\frac{1}{2} \cdot \text{Tr} \left( \mathbf{C}_N^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \right) - \frac{1}{2} \cdot \left( -\mathbf{a}_N^{*T} \mathbf{C}_N^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \mathbf{a}_N^* \right) \\ &= \frac{1}{2} \cdot \left( \mathbf{a}_N^{*T} \mathbf{C}_N^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \mathbf{a}_N^* \right) - \frac{1}{2} \cdot \text{Tr} \left( \mathbf{C}_N^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \right) \end{aligned}$$

Finding the derivative of  $-\frac{1}{2} \ln |(\mathbf{W}_N + \mathbf{C}_N^{-1})|$ :

$$\begin{aligned} -\frac{\partial}{\partial \theta_j} \left( \frac{1}{2} \ln |(\mathbf{W}_N + \mathbf{C}_N^{-1})| \right) &= -\frac{1}{2} \frac{\partial}{\partial \theta_j} \ln |(\mathbf{W}_N + \mathbf{C}_N^{-1})| \\ &= -\frac{1}{2} \text{Tr} \left( (\mathbf{W}_N + \mathbf{C}_N^{-1})^{-1} \frac{\partial (\mathbf{W}_N + \mathbf{C}_N^{-1})}{\partial \theta_j} \right) \end{aligned}$$

$$\begin{aligned}
&= -\frac{1}{2}Tr \left( (\mathbf{W}_N + \mathbf{C}_N^{-1})^{-1} \left( \frac{\partial \mathbf{W}_N}{\partial \theta_j} + \frac{\partial \mathbf{C}_N^{-1}}{\partial \theta_j} \right) \right) \\
&= -\frac{1}{2}Tr \left( (\mathbf{W}_N + \mathbf{C}_N^{-1})^{-1} \left( \left( \sum_{n=1}^N \frac{\partial \mathbf{W}_N}{\partial a_n^*} \cdot \frac{\partial a_n^*}{\partial \theta_j} \right) - \mathbf{C}_N^{-1} \frac{\partial \mathbf{C}_N}{\partial \theta_j} \mathbf{C}_N^{-1} \right) \right) \\
&= -\frac{1}{2}Tr \left( (\mathbf{C}_N^{-1} (\mathbf{C}_N \mathbf{W}_N + \mathbf{I}_N))^{-1} \left( \left( \sum_{n=1}^N \frac{\partial \mathbf{W}_N}{\partial a_n^*} \cdot \frac{\partial a_n^*}{\partial \theta_j} \right) - \mathbf{C}_N^{-1} \frac{\partial \mathbf{C}_N}{\partial \theta_j} \mathbf{C}_N^{-1} \right) \right) \\
&= -\frac{1}{2}Tr \left( (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \mathbf{C}_N \left( \left( \sum_{n=1}^N \frac{\partial \mathbf{W}_N}{\partial a_n^*} \cdot \frac{\partial a_n^*}{\partial \theta_j} \right) - \mathbf{C}_N^{-1} \frac{\partial \mathbf{C}_N}{\partial \theta_j} \mathbf{C}_N^{-1} \right) \right) \\
&= -\frac{1}{2}Tr \left( (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \mathbf{C}_N \left( \sum_{n=1}^N \frac{\partial \mathbf{W}_N}{\partial a_n^*} \cdot \frac{\partial a_n^*}{\partial \theta_j} \right) \right) \\
&\quad + \frac{1}{2}Tr \left( (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \mathbf{C}_N \mathbf{C}_N^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \right) \\
&= -\frac{1}{2}Tr \left( (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \mathbf{C}_N \left( \sum_{n=1}^N \frac{\partial \mathbf{W}_N}{\partial a_n^*} \cdot \frac{\partial a_n^*}{\partial \theta_j} \right) \right) \\
&\quad + \frac{1}{2}Tr \left( (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \right)
\end{aligned}$$

$\sum_{n=1}^N \frac{\partial \mathbf{W}_N}{\partial a_n^*} \cdot \frac{\partial a_n^*}{\partial \theta_j}$  is a sum of diagonal matrices, each of which is multiplied by a scalar.

The  $n^{th}$  element of  $\frac{\partial \mathbf{W}_N}{\partial a_n^*}$  is given by:

$$\begin{aligned}
\frac{\partial \sigma(a_n^*)(1 - \sigma(a_n^*))}{\partial a_n^*} &= \sigma(a_n^*) \frac{\partial (1 - \sigma(a_n^*))}{\partial a_n^*} + (1 - \sigma(a_n^*)) \frac{\partial \sigma(a_n^*)}{\partial a_n^*} \\
&= \sigma(a_n^*)(-\sigma(a_n^*)(1 - \sigma(a_n^*))) + (1 - \sigma(a_n^*))\sigma(a_n^*)(1 - \sigma(a_n^*))
\end{aligned}$$

$$= \sigma(a_n^*)(1 - \sigma(a_n^*))(1 - 2\sigma(a_n^*))$$

Substituting this back, and expanding the trace of the first term into a sum of diagonal values, we get:

$$\begin{aligned} &= -\frac{1}{2} \sum_{n=1}^N \left[ (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \mathbf{C}_N \right]_{nn} \sigma(a_n^*)(1 - \sigma(a_n^*))(1 - 2\sigma(a_n^*)) \left( \frac{\partial a_n^*}{\partial \theta_j} \right) \\ &\quad + \frac{1}{2} \text{Tr} \left( (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \right) \end{aligned}$$

The terms arising from the explicit dependence on  $\boldsymbol{\theta}$  are :

$$\begin{aligned} &\frac{1}{2} \cdot \left( \mathbf{a}_N^{*T} \mathbf{C}_N^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \mathbf{a}_N^* \right) - \frac{1}{2} \cdot \text{Tr} \left( \mathbf{C}_N^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \right) \\ &\quad + \frac{1}{2} \text{Tr} \left( (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \right) \end{aligned}$$

Combining the trace terms, we get :

$$\frac{1}{2} \text{Tr} \left( (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \right) - \frac{1}{2} \text{Tr} \left( \mathbf{C}_N^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \right)$$

Using cyclic property of Trace, this becomes:

$$\begin{aligned} &= \frac{1}{2} \text{Tr} \left( (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \right) - \frac{1}{2} \text{Tr} \left( \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \right) \\ &= \frac{1}{2} \text{Tr} \left( (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} - \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \right) \\ &= \frac{1}{2} \text{Tr} \left( \left( (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} - \mathbf{I}_N \right) \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \right) \end{aligned}$$

Using Woodbury Identity,

$$\begin{aligned} & (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} - \mathbf{I}_N \\ &= -\mathbf{C}_N (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \mathbf{W}_N \end{aligned}$$

Substituting back the result, we get:

$$-\frac{1}{2} \text{Tr} \left( \mathbf{C}_N (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \mathbf{W}_N \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \right)$$

Using cyclic property of Trace, this becomes:

$$\begin{aligned} &= -\frac{1}{2} \text{Tr} \left( \mathbf{C}_N^{-1} \mathbf{C}_N (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \mathbf{W}_N \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \right) \\ &= -\frac{1}{2} \text{Tr} \left( (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \mathbf{W}_N \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \right) \end{aligned}$$

Finally, the terms arising from the explicit dependence on  $\boldsymbol{\theta}$  are given by:

$$\frac{1}{2} \left( \mathbf{a}_N^{*T} \mathbf{C}_N^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \mathbf{C}_N^{-1} \mathbf{a}_N^* \right) - \frac{1}{2} \text{Tr} \left( (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \mathbf{W}_N \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) \right)$$

which is the same as the result in 6.91.

The only term arising from the dependence of  $\mathbf{a}_N^*$  on  $\boldsymbol{\theta}$  is:

$$-\frac{1}{2} \sum_{n=1}^N \left[ (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \mathbf{C}_N \right]_{nn} \sigma(a_n^*) (1 - \sigma(a_n^*)) (1 - 2\sigma(a_n^*)) \left( \frac{\partial a_n^*}{\partial \theta_j} \right)$$

which is the same as the result in 6.92.

From 6.84, we have:

$$\begin{aligned}
\mathbf{a}_N^* &= \mathbf{C}_N(\mathbf{t}_N - \boldsymbol{\sigma}_N) \\
\Rightarrow \frac{\partial \mathbf{a}_n^*}{\partial \theta_j} &= \frac{\partial}{\partial \theta_j}(\mathbf{C}_N(\mathbf{t}_N - \boldsymbol{\sigma}_N)) \\
&= \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) (\mathbf{t}_N - \boldsymbol{\sigma}_N) + \mathbf{C}_N \left( \frac{\partial (\mathbf{t}_N - \boldsymbol{\sigma}_N)}{\partial \theta_j} \right) \\
&= \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) (\mathbf{t}_N - \boldsymbol{\sigma}_N) - \mathbf{C}_N \left( \frac{\partial \boldsymbol{\sigma}_N}{\partial \theta_j} \right) \\
&= \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) (\mathbf{t}_N - \boldsymbol{\sigma}_N) - \mathbf{C}_N \left( \sum_{n=1}^N \frac{\partial \boldsymbol{\sigma}_N}{\partial a_n^*} \cdot \frac{\partial a_n^*}{\partial \theta_j} \right)
\end{aligned}$$

$$\sum_{n=1}^N \frac{\partial \boldsymbol{\sigma}_N}{\partial a_n^*} \cdot \frac{\partial a_n^*}{\partial \theta_j} \text{ is a vector with the } n^{th} \text{ given by : } \sigma(a_n^*)(1 - \sigma(a_n^*)) \left( \frac{\partial a_n^*}{\partial \theta_j} \right)$$

$$\Rightarrow \sum_{n=1}^N \frac{\partial \boldsymbol{\sigma}_N}{\partial a_n^*} \cdot \frac{\partial a_n^*}{\partial \theta_j} = \mathbf{W}_N \left( \frac{\partial \mathbf{a}_N^*}{\partial \theta_j} \right)$$

Substituting this back, we get:

$$\begin{aligned}
\frac{\partial \mathbf{a}_N^*}{\partial \theta_j} &= \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) (\mathbf{t}_N - \boldsymbol{\sigma}_N) - \mathbf{C}_N \mathbf{W}_N \left( \frac{\partial \mathbf{a}_N^*}{\partial \theta_j} \right) \\
\Rightarrow (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N) \frac{\partial \mathbf{a}_N^*}{\partial \theta_j} &= \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) (\mathbf{t}_N - \boldsymbol{\sigma}_N) \\
\Rightarrow \frac{\partial \mathbf{a}_N^*}{\partial \theta_j} &= (\mathbf{I}_N + \mathbf{C}_N \mathbf{W}_N)^{-1} \left( \frac{\partial \mathbf{C}_N}{\partial \theta_j} \right) (\mathbf{t}_N - \boldsymbol{\sigma}_N)
\end{aligned}$$

which is the same as the result in 6.94.