

#5.6

logistic sigmoid function

$$y_k = \sigma(a_k)$$

$$\frac{d\sigma}{da} = \sigma(1-\sigma)$$

$$\begin{aligned} \therefore \frac{dE(w)}{da_k} &= -t_k \frac{1}{y_k} [y_k(1-y_k)] + (1-t_k) \frac{1}{1-y_k} [y_k(1-y_k)] \\ &= [y_k(1-y_k)] \left[ -t_k \frac{1}{y_k} + (1-t_k) \frac{1}{1-y_k} \right] \\ &= -t_k(1-y_k) + y_k(1-t_k) \\ &= -t_k + \cancel{t_k y_k} + y_k - \cancel{t_k y_k} = y_k - t_k \quad \# \end{aligned}$$

#5.24 根據 (5.113) (5.115) (5.116) (5.117):

$$\tilde{a}_j = \sum_i \tilde{w}_{ji} \tilde{x}_i + \tilde{w}_{j0}$$

$$= \sum_i \frac{1}{a} w_{ji} (ax_i + \cancel{b}) + w_{j0} - \frac{b}{a} \sum_i w_{ji}$$

$$= \sum_i w_{ji} x_i + w_{j0} = a_j \quad (\text{經過轉換後 hidden unit } a_j \text{ 沒有改變, 若作用在 } a_j \text{ 上的 activation function 也沒變, 則 } \tilde{z}_j = z_j)$$

接著處理第2層 layer:

$$\tilde{y}_k = \sum_j \tilde{w}_{kj} \tilde{z}_j + \tilde{w}_{k0}$$

$$= \sum_j (c w_{kj} \cdot z_j) + c w_{k0} + d = c \left[ \sum_j (w_{kj} \cdot z_j) + w_{k0} \right] + d$$

$$= c y_k + d$$

由此可証,  $\tilde{y}_k$  和  $y_k$  之間的線性轉換可由 (5.119) 與 (5.120) 達到 #

陳俊宇  
电机所  
109061520

#6.1b Based on total derivative of function  $f$

$$f((w+\Delta w)^T \phi_1, (w+\Delta w)^T \phi_2, \dots, (w+\Delta w)^T \phi_N) \\ = \sum_{n=1}^N \frac{\partial f}{\partial (w^T \phi_n)} \cdot \Delta w^T \phi_n = \left[ \sum_{n=1}^N \frac{\partial f}{\partial (w^T \phi_n)} \cdot \phi_n^T \right] \cdot \Delta w$$

$$\therefore \nabla_w f = \sum_{n=1}^N \frac{\partial f}{\partial (w^T \phi_n)} \cdot \phi_n^T$$

$$\nabla_w g = \frac{\partial g}{\partial (w^T w)} \cdot 2w^T$$

為了找到  $w$  可使  $J$  最小，設  $J$  對  $w$  的偏微分為 0

$$\nabla_w J = \nabla_w f + \nabla_w g = \sum_{n=1}^N \frac{\partial f}{\partial (w^T \phi_n)} \cdot \phi_n^T + \frac{\partial g}{\partial (w^T w)} \cdot 2w^T = 0$$

$$\therefore w = - \frac{\frac{\partial (w^T w)}{\partial g}}{2 \cdot \frac{\partial g}{\partial g}} \cdot \sum_{n=1}^N \frac{\partial f}{\partial (w^T \phi_n)} \cdot \phi_n^T \\ = - \frac{1}{2a} \cdot \sum_{n=1}^N \frac{\partial f}{\partial (w^T \phi(x_n))} \phi(x_n)$$

( $a$  為  $\frac{\partial g}{\partial (w^T w)}$ ，因為  $g$  為 monotonically increasing function, 所以  $a > 0$ )

#6.2b  $p(a_{n+1}|t_n) = \int p(a_{n+1}|a_n) p(a_n|t_n) da_n$  (式 6.77)

式 (6.78)  $\leftarrow \int \mathcal{N}(a_{n+1} | k^T C_n^{-1} a_n, c - k^T C_n^{-1} k) \cdot \mathcal{N}(a_n | a_n^*, H^{-1}) da_n$   
式 (6.86)

By  $p(y) = \int p(y|x) p(x) dx$

可得  $p(a_{n+1}|t_n) = \mathcal{N}(A\mu + b, L^{-1} + A\Lambda^{-1}A^T)$

其中  $A = k^T C_n^{-1}$ ,  $b = 0$ ,  $L^{-1} = c - k^T C_n^{-1} k$ ,  $\mu = a_n^*$ ,  $\Lambda = H$ .

因此, mean: (式 6.84)

$$A\mu + b = k^T C_n^{-1} a_n^* = k^T C_n^{-1} C_n (t_n - \tau_n) = k^T (t_n - \tau_n)$$



Covariance matrix : 式(6.85)

$$\begin{aligned} L^{-1} + AA^{-1}A^T &= C - k^T C_N^{-1} k + k^T C_N^{-1} H^{-1} (k^T C_N^{-1})^T \\ &= C - k^T (C_N^{-1} - C_N^{-1} H^{-1} C_N^{-1}) k \\ &= C - k^T (C_N^{-1} - C_N^{-1} (W_N + C_N^{-1})^{-1} C_N^{-1}) k \\ &= C - k^T (C_N^{-1} - \underbrace{(C_N W_N C_N + C_N^{-1})^{-1}}_{\text{symmetric}}) k \end{aligned}$$

接著採用 matrix identity (C.7) 化簡上式, 即可得式(6.88) #