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HW3 Machine Learning CS 542

1. Written problems.

(a) Bishop 5.3.

$$P(T|X, w, \Sigma) = \prod_{n=1}^N \mathcal{N}(t_n | y(x_n, w), \Sigma)$$

$$\ln P(T|X, w, \Sigma)$$

$$= -\frac{N}{2}(\ln|\Sigma| + k \ln(2\pi)) - \frac{1}{2} \sum_{n=1}^N (t_n - y_n)^T \Sigma^{-1} (t_n - y_n)$$

where $y_n = y(x_n, w)$.

$$E(w) = \frac{1}{2} \sum_{n=1}^N (t_n - y_n)^T \Sigma^{-1} (t_n - y_n)$$

$$- \frac{N}{2} \ln|\Sigma| - \frac{1}{2} \sum_{n=1}^N (t_n - y_n)^T \Sigma^{-1} (t_n - y_n)$$

$$\Rightarrow -\frac{N}{2} \ln|\Sigma| - \frac{1}{2} \text{Tr} \left[\Sigma^{-1} \sum_{n=1}^N (t_n - y_n) (t_n - y_n)^T \right]$$

We can maximize this by setting the derivative w.r.t Σ^{-1} to zero $\Rightarrow \Sigma = \frac{1}{N} \sum_{n=1}^N (t_n - y_n) (t_n - y_n)^T$

(2)

Thus the optimal value for Σ depends on w through y_n .

To address the dependence between w and Σ , we could try an iterative scheme, alternating between updates of w and Σ until some convergence criterion is reached.

(b) Bishop 5.4.

$t \in \{0, 1\}$ data set label

$k \in \{0, 1\}$ true class label ; $y(x, w) = P(k=1|x)$

$$P(t=1|x) = \sum_{k=0}^1 P(t=1|k) P(k|x) = (1-\epsilon) y(x, w) + \epsilon (1-y(x, w)).$$

$$P(t|x) = P(t=1|x)^t (1-P(t=1|x))^{1-t}.$$

$$E(w) = - \sum_{n=1}^N \{ t_n \ln [(1-\epsilon) y(x_n, w) + \epsilon (1-y(x_n, w))] + (1-t_n) \ln [1 - ((1-\epsilon) y(x_n, w) + \epsilon (1-y(x_n, w)))] \}$$

(3)

5.26.

$$5.201 \quad \Omega_n = \frac{1}{2} \sum_k (G y_k)^2 \Big|_{x_n}$$

5.201 \rightarrow 5.201 and 5.70
~~5.201~~

$$\Rightarrow \Omega_n = \frac{1}{2} \sum_k \left(\sum_{\tilde{n}} r_{ni} \frac{\partial y_{nk}}{\partial x_{ni}} \right)^2 \quad (188)$$

$$= \frac{1}{2} \sum_k \left(\sum_{\tilde{n}} T_{ni} J_{nk} \right) \quad (189)$$

5.202, 5.203, 5.205

$$\begin{aligned} \beta_{nj} &= \sum_{\tilde{n}} w_{ji} \alpha_{ni} \\ &= \sum_{\tilde{n}} w_{ji} G x_{ni} \\ &= \sum_{\tilde{n}} w_{ji} \sum_{\tilde{n}'} T_{ni'} \frac{\alpha_{ni'}}{\partial x_{ni'}} \\ &= \sum_{\tilde{n}} w_{ji} T_{ni}. \end{aligned}$$

$$\Omega_n = \frac{1}{2} \sum_k (G y_{nk})^2 = \frac{1}{2} \sum_k \alpha_{nk}^2$$

$$\begin{aligned} \frac{\partial \Omega_n}{\partial w_{rs}} &= \sum_k (G y_{nk}) G (\delta_{nkr} z_{ns}) \\ &= \sum_k \alpha_{nk} (\phi_{nkr} z_{ns} + \delta_{nkr} \alpha_{ns}) \end{aligned}$$

(4)

(5.74)

$$\delta_{nkr} = h'(a_{nr}) \sum_l w_{lr} \delta_{nkl}$$

5.205 and 5.207.

$$\phi_{nkr} = G \delta_{nkr}$$

$$= G \left(h'(a_{nr}) \sum_l w_{lr} \delta_{nkl} \right)$$

$$= h''(a_{nr}) \beta_{nr} \sum_l w_{lr} \delta_{nkl} + h'(a_{nr}) \sum_l w_{lr} \phi_{nkl}$$