

Chapter 3 Linear Models For Regression

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3.1 Linear Basis Function Models

(3.8)

Recall $t = y(\mathbf{x}, \mathbf{w}) + \epsilon$, where $\epsilon \sim \mathcal{N}(0, \beta^{-1})$. This is equivalent to

$$\begin{aligned} p(\epsilon; \beta) &= \frac{\beta}{\sqrt{2\pi}} \exp \left\{ -\frac{\beta}{2} \epsilon^2 \right\} \\ &= \frac{\beta}{\sqrt{2\pi}} \exp \left\{ -\frac{\beta}{2} (t - y(\mathbf{x}, \mathbf{w}))^2 \right\}, \end{aligned}$$

which implies that

$$p(t|\mathbf{x}, \mathbf{w}, \beta) = \mathcal{N}(t|y(\mathbf{x}, \mathbf{w}), \beta^{-1}).$$

(3.13)

This equation should be

$$\nabla_{\mathbf{w}} \ln p(\mathbf{t}|\mathbf{w}, \beta) = \beta \sum_{n=1}^N \{t_n - \mathbf{w}^T \phi(\mathbf{x}_n)\} \phi(\mathbf{x}_n), \quad (*)$$

because

$$\nabla_{\mathbf{w}} (\mathbf{w}^T \phi(\mathbf{x}_n)) = \phi(\mathbf{x}_n).$$

(3.14)

According to (*), this equation should be

$$\mathbf{0} = \sum_{n=1}^N t_n \phi(\mathbf{x}_n) - \left(\sum_{n=1}^N \phi(\mathbf{x}_n) \phi(\mathbf{x}_n)^T \right) \mathbf{w}. \quad (**)$$

(3.15)

By defining a design matrix Φ in the form of (3.16), (**) can be reduced to

$$\mathbf{0} = \Phi \mathbf{t} - \Phi^T \Phi \mathbf{w}.$$

Solving for \mathbf{w} , we obtain

$$\mathbf{w}_{\text{ML}} = (\Phi^T \Phi)^{-1} \Phi \mathbf{t}.$$

(3.19)

$$\begin{aligned} \frac{\partial}{\partial w_0} E_D(\mathbf{w}) &= - \sum_{n=1}^N \left\{ t_n - w_0 - \sum_{j=1}^{M-1} w_j \phi_j(\mathbf{x}_n) \right\} \\ &= 0. \end{aligned}$$

Solving for w_0 , we obtain

$$\begin{aligned} w_0 &= \frac{1}{N} \sum_{n=1}^N t_n - \frac{1}{N} \sum_{j=1}^{M-1} w_j \sum_{n=1}^N \phi_j(\mathbf{x}_n) \\ &= \bar{t} - \sum_{j=1}^{M-1} w_j \bar{\phi}_j, \end{aligned}$$

where

$$\bar{t} = \frac{1}{N} \sum_{n=1}^N t_n, \quad \bar{\phi}_j = \frac{1}{N} \sum_{n=1}^N \phi_j(\mathbf{x}_n).$$