

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

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

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

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

because

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

(3.14)

According to the fixed version of (3.13), this equation should be

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

(3.15)

By defining a design matrix Φ in the form of (3.16), the fixed version of (3.14) 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

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

(3.23)

$$\begin{aligned} \nabla_{\mathbf{w}} E_n(\mathbf{w}) &= -(t_n - \mathbf{w}^T \phi(\mathbf{x}_n)) \phi(\mathbf{x}_n) \\ &= -(t_n - \mathbf{w}^T \phi_n) \phi_n, \end{aligned}$$

where $\phi_n = \phi(\mathbf{x}_n)$. Plug it into (3.22), we obtain (3.23).

(3.28)

Recall the regularized error function

$$\begin{aligned} E(\mathbf{w}) &= \frac{1}{2} \sum_{n=1}^N \{t_n - \mathbf{w}^T \phi(\mathbf{x}_n)\}^2 + \frac{\lambda}{2} \mathbf{w}^T \mathbf{w} \\ &= \frac{1}{2} (\mathbf{t} - \Phi \mathbf{w})^T (\mathbf{t} - \Phi \mathbf{w}) + \frac{\lambda}{2} \mathbf{w}^T \mathbf{w}. \end{aligned}$$

Setting the gradient with respect to \mathbf{w} to $\mathbf{0}$, we have

$$\begin{aligned} \nabla_{\mathbf{w}} E(\mathbf{w}) &= \frac{1}{2} \nabla_{\mathbf{w}} (\mathbf{t}^T \mathbf{t} - 2\mathbf{t}^T \Phi \mathbf{w} + \mathbf{w}^T \Phi^T \Phi \mathbf{w} + \lambda \mathbf{w}^T \mathbf{w}) \\ &= (\Phi^T \Phi + \lambda \mathbf{I}) \mathbf{w} - \Phi^T \mathbf{t} \\ &= \mathbf{0}. \end{aligned}$$

Solving for \mathbf{w} , we obtain

$$\mathbf{w} = (\lambda \mathbf{I} + \Phi^T \Phi)^{-1} \Phi^T \mathbf{t}.$$

3.2 The Bias-Variance Decomposition

(3.40)

$$\begin{aligned} &\mathbb{E}_{\mathcal{D}} [\{y(\mathbf{x}; \mathcal{D}) - h(\mathbf{x})\}^2] \\ &= \mathbb{E}_{\mathcal{D}} [\{y(\mathbf{x}; \mathcal{D}) - \mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})] + \mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})] - h(\mathbf{x})\}^2] \\ &= \mathbb{E}_{\mathcal{D}} [\{y(\mathbf{x}; \mathcal{D}) - \mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})]\}^2 + \{\mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})] - h(\mathbf{x})\}^2 + 2\{y(\mathbf{x}; \mathcal{D}) - \mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})]\} \{\mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})] - h(\mathbf{x})\}] \\ &= \mathbb{E}_{\mathcal{D}} [\{\mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})] - h(\mathbf{x})\}^2] + \mathbb{E}_{\mathcal{D}} [\{y(\mathbf{x}; \mathcal{D}) - \mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})]\}^2] + 2\mathbb{E}_{\mathcal{D}} [y(\mathbf{x}; \mathcal{D}) \mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})] - y(\mathbf{x}; \mathcal{D}) h(\mathbf{x}) - \mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})]^2 + \mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})] h(\mathbf{x})] \\ &= \{\mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})] - h(\mathbf{x})\}^2 + \mathbb{E}_{\mathcal{D}} [\{y(\mathbf{x}; \mathcal{D}) - \mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})]\}^2] + 2\{\mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})]^2 - \mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})] h(\mathbf{x}) - \mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})]^2 + \mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})] h(\mathbf{x})\} \\ &= \{\mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})] - h(\mathbf{x})\}^2 + \mathbb{E}_{\mathcal{D}} [\{y(\mathbf{x}; \mathcal{D}) - \mathbb{E}_{\mathcal{D}}[y(\mathbf{x}; \mathcal{D})]\}^2]. \end{aligned}$$

3.3 Bayesian Linear Regression

(3.50) and (3.51)

$$\begin{aligned}
\mathcal{N}(\mathbf{w}|\mathbf{m}_N, \mathbf{S}_N) &= p(\mathbf{w}|\mathbf{t}) \\
&\propto p(\mathbf{t}|\mathbf{w})p(\mathbf{w}) \\
&= \mathcal{N}(\mathbf{t}|\mathbf{X}, \mathbf{w}, \beta)\mathcal{N}(\mathbf{w}|\mathbf{m}_0, \mathbf{S}_0) \\
&= \left(\prod_{n=1}^N \mathcal{N}(t_n|\mathbf{w}^T\boldsymbol{\phi}(\mathbf{x}_n), \beta^{-1}) \right) \mathcal{N}(\mathbf{w}|\mathbf{m}_0, \mathbf{S}_0).
\end{aligned} \tag{*}$$

Consider the exponential term

$$\begin{aligned}
& -\frac{\beta}{2} \sum_{n=1}^N (t_n - \mathbf{w}^T\boldsymbol{\phi}(\mathbf{x}_n))^2 - \frac{1}{2}(\mathbf{w} - \mathbf{m}_0)^T \mathbf{S}_0^{-1}(\mathbf{w} - \mathbf{m}_0) \\
&= -\frac{\beta}{2} (\mathbf{t} - \boldsymbol{\Phi}\mathbf{w})^T (\mathbf{t} - \boldsymbol{\Phi}\mathbf{w}) - \frac{1}{2}(\mathbf{w} - \mathbf{m}_0)^T \mathbf{S}_0^{-1}(\mathbf{w} - \mathbf{m}_0),
\end{aligned}$$

by matching the coefficients of the quadratic terms on both sides of (*), we have

$$\mathbf{S}_N^{-1} = \mathbf{S}_0^{-1} + \beta \boldsymbol{\Phi}^T \boldsymbol{\Phi}.$$

Similarly, matching the coefficients of the linear terms on both sides of (*), we have

$$\mathbf{m}_N^T \mathbf{S}_N^{-1} = \beta \mathbf{t}^T \boldsymbol{\Phi} + \mathbf{m}_0^T \mathbf{S}_0^{-1},$$

solving for \mathbf{m}_N , we obtain

$$\mathbf{m}_N = \mathbf{S}_N (\mathbf{S}_0^{-1} \mathbf{m}_0 + \beta \boldsymbol{\Phi}^T \mathbf{t}).$$

(3.57)

To be consistent with (3.58), this equation should be

$$p(t|\mathbf{x}, \mathbf{t}, \alpha, \beta) = \int p(t|\mathbf{x}, \mathbf{w}, \beta) p(\mathbf{w}|\mathbf{t}, \alpha, \beta) d\mathbf{w}.$$

(3.58) and (3.59)

Recall (2.113) and (2.114), mapping $p(t|\mathbf{x}, \mathbf{w}, \beta)$ to $p(\mathbf{y}|\mathbf{x})$, and $p(\mathbf{w}|\mathbf{t}, \alpha, \beta)$ to $p(\mathbf{x})$, we have

$$\begin{aligned}
p(t|\mathbf{x}, \mathbf{w}, \beta) &= \mathcal{N}(t|\mathbf{w}^T \mathbf{x}, \beta^{-1}) \\
&= \mathcal{N}(t|\mathbf{A}\mathbf{w} + \mathbf{b}, \mathbf{L}^{-1}) \\
p(\mathbf{w}|\mathbf{t}, \alpha, \beta) &= \mathcal{N}(\mathbf{w}|\mathbf{m}_N, \mathbf{S}_N) \\
&= \mathcal{N}(\mathbf{w}|\boldsymbol{\mu}, \boldsymbol{\Lambda}^{-1}),
\end{aligned}$$

which implies that

$$\begin{aligned}
\mathbf{A} &= \boldsymbol{\phi}(\mathbf{x})^T \\
\mathbf{b} &= \mathbf{0} \\
\mathbf{L} &= \beta \\
\boldsymbol{\mu} &= \mathbf{m}_N \\
\boldsymbol{\Lambda} &= \mathbf{S}_N^{-1}.
\end{aligned}$$

Substituting them back into (2.115), we obtain (3.58) and (3.59).

(3.63)

$$\begin{aligned}
\text{cov}[y(\mathbf{x}), y(\mathbf{x}')] &= \text{cov}[\phi(\mathbf{x})^T \mathbf{w}, \mathbf{w}^T \phi(\mathbf{x}')] \\
&= \mathbb{E}[\phi(\mathbf{x})^T \mathbf{w} \mathbf{w}^T \phi(\mathbf{x}')] - \mathbb{E}[\phi(\mathbf{x})^T \mathbf{w}] \mathbb{E}[\mathbf{w}^T \phi(\mathbf{x}')] \\
&= \phi(\mathbf{x})^T \mathbb{E}[\mathbf{w} \mathbf{w}^T] \phi(\mathbf{x}') - \phi(\mathbf{x})^T \mathbf{m}_N \mathbf{m}_N^T \phi(\mathbf{x}') \\
&= \phi(\mathbf{x})^T (\text{cov}[\mathbf{w}] + \mathbb{E}[\mathbf{w}] \mathbb{E}[\mathbf{w}^T]) \phi(\mathbf{x}') - \phi(\mathbf{x})^T \mathbf{m}_N \mathbf{m}_N^T \phi(\mathbf{x}') \\
&= \phi(\mathbf{x})^T (\text{cov}[\mathbf{w}] + \mathbf{m}_N \mathbf{m}_N^T) \phi(\mathbf{x}') - \phi(\mathbf{x})^T \mathbf{m}_N \mathbf{m}_N^T \phi(\mathbf{x}') \\
&= \phi(\mathbf{x})^T \text{cov}[\mathbf{w}] \phi(\mathbf{x}') \\
&= \phi(\mathbf{x})^T \mathbf{S}_N \phi(\mathbf{x}') \\
&= \beta^{-1} k(\mathbf{x}, \mathbf{x}').
\end{aligned}$$

3.4 Bayesian Model Comparison

(3.67)

$$\begin{aligned}
p(t|\mathbf{x}, \mathcal{D}) &= \sum_{i=1}^L p(t, \mathcal{M}_i | \mathbf{x}, \mathcal{D}) \\
&= \sum_{i=1}^L p(t|\mathbf{x}, \mathcal{M}_i, \mathcal{D}) p(\mathcal{M}_i | \mathcal{D}).
\end{aligned}$$

(3.72)

$$\begin{aligned}
\ln p(\mathcal{D}) &\simeq \ln \left\{ p(\mathcal{D} | \mathbf{w}_{\text{MAP}}) \left(\frac{\Delta w_{\text{posterior}}}{\Delta w_{\text{prior}}} \right)^M \right\} \\
&= \ln p(\mathcal{D} | \mathbf{w}_{\text{MAP}}) + M \ln \left(\frac{\Delta w_{\text{posterior}}}{\Delta w_{\text{prior}}} \right).
\end{aligned}$$

3.5 The Evidence Approximation

(3.78) and (3.79)

$$\begin{aligned}
p(\mathbf{t} | \alpha, \beta) &= \int p(\mathbf{t} | \mathbf{w}, \beta) p(\mathbf{w} | \alpha) d\mathbf{w} \\
&= \int \left[\prod_{n=1}^N \mathcal{N}(t_n | \mathbf{w}^T \phi(\mathbf{x}_n), \beta^{-1}) \right] \mathcal{N}(\mathbf{w} | \mathbf{0}, \alpha^{-1} \mathbf{I}) d\mathbf{w} \\
&= \int \left[\prod_{n=1}^N \sqrt{\frac{\beta}{2\pi}} \exp \left\{ -\frac{\beta}{2} (t_n - \mathbf{w}^T \phi(\mathbf{x}_n))^2 \right\} \right] \frac{1}{(2\pi)^{M/2} |\alpha^{-1} \mathbf{I}|^{1/2}} \exp \left\{ -\frac{1}{2} \mathbf{w}^T (\alpha^{-1} \mathbf{I})^{-1} \mathbf{w} \right\} d\mathbf{w} \\
&= \left(\frac{\beta}{2\pi} \right)^{N/2} \left(\frac{\alpha}{2\pi} \right)^{M/2} \int \exp \left\{ -\frac{\beta}{2} \sum_{n=1}^N (t_n - \mathbf{w}^T \phi(\mathbf{x}_n))^2 - \frac{\alpha}{2} \mathbf{w}^T \mathbf{w} \right\} d\mathbf{w} \\
&= \left(\frac{\beta}{2\pi} \right)^{N/2} \left(\frac{\alpha}{2\pi} \right)^{M/2} \int \exp \left\{ -\frac{\beta}{2} (\mathbf{t} - \Phi \mathbf{w})^2 - \frac{\alpha}{2} \mathbf{w}^T \mathbf{w} \right\} d\mathbf{w} \\
&= \left(\frac{\beta}{2\pi} \right)^{N/2} \left(\frac{\alpha}{2\pi} \right)^{M/2} \int \exp \left\{ -E(\mathbf{w}) \right\} d\mathbf{w},
\end{aligned}$$

where $E(\mathbf{w})$ satisfies (3.79).

(3.80) to (3.84)

According to (3.79),

$$\begin{aligned}
E(\mathbf{w}) &= \beta E_D(\mathbf{w}) + \alpha E_W(\mathbf{w}) \\
&= \frac{\beta}{2} \|\mathbf{t} - \Phi \mathbf{w}\|^2 + \frac{\alpha}{2} \mathbf{w}^T \mathbf{w} \\
&= \frac{1}{2} (\mathbf{w}^T (\alpha \mathbf{I} + \beta \Phi^T \Phi) \mathbf{w} - 2\beta \mathbf{t}^T \Phi \mathbf{w} + \beta \mathbf{t}^T \mathbf{t}).
\end{aligned} \tag{*}$$

Comparing with the quadratic term in (3.80), we have

$$\frac{1}{2} \mathbf{w}^T \mathbf{A} \mathbf{w} = \mathbf{w}^T (\alpha \mathbf{I} + \beta \Phi^T \Phi) \mathbf{w},$$

which implies that

$$\mathbf{A} = \alpha \mathbf{I} + \beta \Phi^T \Phi. \tag{**}$$

Then, by comparing with the linear term in (3.80), we have

$$\mathbf{m}_N^T \mathbf{A} = \beta \mathbf{t}^T \Phi.$$

Noticing that \mathbf{A} is symmetric, solving for \mathbf{m}_N , we obtain

$$\mathbf{m}_N = \beta \mathbf{A}^{-1} \Phi^T \mathbf{t}. \tag{***}$$

Substitute (**) and (***) into (*), we have

$$\begin{aligned}
E(\mathbf{w}) &= \frac{1}{2} (\mathbf{w}^T (\alpha \mathbf{I} + \beta \Phi^T \Phi) \mathbf{w} - 2\beta \mathbf{t}^T \Phi \mathbf{w} + \beta \mathbf{t}^T \mathbf{t}) \\
&= \frac{1}{2} (\mathbf{w}^T \mathbf{A} \mathbf{w} - 2\beta \mathbf{t}^T \Phi \mathbf{w} + \beta \mathbf{t}^T \mathbf{t}) \\
&= \frac{1}{2} \{ (\mathbf{w} - \mathbf{m}_N)^T \mathbf{A} (\mathbf{w} - \mathbf{m}_N) + \mathbf{m}_N^T \mathbf{A} \mathbf{w} - \mathbf{m}_N^T \mathbf{A} \mathbf{m}_N - 2\beta \mathbf{t}^T \Phi \mathbf{w} + \beta \mathbf{t}^T \mathbf{t} \} \\
&= \frac{1}{2} (\mathbf{w} - \mathbf{m}_N)^T \mathbf{A} (\mathbf{w} - \mathbf{m}_N) + \frac{1}{2} (\beta \mathbf{t}^T \mathbf{t} - \mathbf{m}_N^T \mathbf{A} \mathbf{m}_N) \\
&= \frac{1}{2} (\mathbf{w} - \mathbf{m}_N)^T \mathbf{A} (\mathbf{w} - \mathbf{m}_N) + \frac{1}{2} (\beta \mathbf{t}^T \mathbf{t} - 2\mathbf{m}_N^T \mathbf{A} \mathbf{m}_N + \mathbf{m}_N^T \mathbf{A} \mathbf{m}_N) \\
&= \frac{1}{2} (\mathbf{w} - \mathbf{m}_N)^T \mathbf{A} (\mathbf{w} - \mathbf{m}_N) + \frac{1}{2} \{ \beta \mathbf{t}^T \mathbf{t} - 2\mathbf{m}_N^T \mathbf{A} (\beta \mathbf{A}^{-1} \Phi^T \mathbf{t}) + \mathbf{m}_N^T (\alpha \mathbf{I} + \beta \Phi^T \Phi) \mathbf{m}_N \} \\
&= \frac{1}{2} (\mathbf{w} - \mathbf{m}_N)^T \mathbf{A} (\mathbf{w} - \mathbf{m}_N) + \frac{1}{2} \{ \beta \mathbf{t}^T \mathbf{t} - 2\beta (\Phi \mathbf{m}_N)^T \mathbf{t} + \beta \mathbf{m}_N^T \Phi^T \Phi \mathbf{m}_N \} + \frac{\alpha}{2} \mathbf{m}_N^T \mathbf{m}_N \\
&= \frac{1}{2} (\mathbf{w} - \mathbf{m}_N)^T \mathbf{A} (\mathbf{w} - \mathbf{m}_N) + \frac{\beta}{2} \|\mathbf{t} - \Phi \mathbf{m}_N\|^2 + \frac{\alpha}{2} \mathbf{m}_N^T \mathbf{m}_N \\
&= E(\mathbf{m}_N) + \frac{1}{2} (\mathbf{w} - \mathbf{m}_N)^T \mathbf{A} (\mathbf{w} - \mathbf{m}_N),
\end{aligned}$$

where $E(\mathbf{m}_N)$ satisfies (3.82).