

3.4 Given the error function :

$$E_D(\mathbf{w}) = \frac{1}{2} \sum_{n=1}^N \{y(\mathbf{x}_n, \mathbf{w}) - t_n\}^2$$

$$= \frac{1}{2} \sum_{n=1}^N \left\{ \left(w_0 + \sum_{i=1}^D w_i(x_{ni} + \epsilon_i) \right) - t_n \right\}^2$$

Expanding the square, we get:

$$= \frac{1}{2} \sum_{n=1}^N \left\{ \left(w_0 + \sum_{i=1}^D w_i(x_{ni} + \epsilon_i) \right)^2 + t_n^2 - 2 \left(w_0 + \sum_{i=1}^D w_i(x_{ni} + \epsilon_i) \right) t_n \right\}$$

If we take expectation w.r.t ϵ , we get:

$$\mathbb{E}_\epsilon[E_D] = \frac{1}{2} \sum_{n=1}^N \left\{ \mathbb{E}_\epsilon \left[\left(w_0 + \sum_{i=1}^D w_i(x_{ni} + \epsilon_i) \right)^2 \right] + t_n^2 - 2 \left(w_0 + \sum_{i=1}^D w_i x_{ni} \right) t_n \right\}$$

$$= \frac{1}{2} \sum_{n=1}^N \left\{ \mathbb{E}_\epsilon \left[\left(w_0 + \sum_{i=1}^D w_i x_{ni} + \sum_{i=1}^D w_i \epsilon_i \right)^2 \right] + t_n^2 - 2 \left(w_0 + \sum_{i=1}^D w_i x_{ni} \right) t_n \right\}$$

$$\left(w_0 + \sum_{i=1}^D w_i x_{ni} + \sum_{i=1}^D w_i \epsilon_i \right)^2$$

$$= \left(w_0 + \sum_{i=1}^D w_i x_{ni} \right)^2 + \left(\sum_{i=1}^D w_i \epsilon_i \right)^2 + 2 \left(w_0 + \sum_{i=1}^D w_i x_{ni} \right) \left(\sum_{i=1}^D w_i \epsilon_i \right)$$

Taking expectation w.r.t ϵ , the third term vanishes, giving us:

$$= \left(w_0 + \sum_{i=1}^D w_i x_{ni} \right)^2 + \mathbb{E}_\epsilon \left[\left(\sum_{i=1}^D w_i \epsilon_i \right)^2 \right]$$

$$\begin{aligned}
&= \left(w_0 + \sum_{i=1}^D w_i x_{ni} \right)^2 + \mathbb{E}_\epsilon \left[\left(\sum_{i,j} w_i w_j \epsilon_i \epsilon_j \right) \right] \\
&= \left(w_0 + \sum_{i=1}^D w_i x_{ni} \right)^2 + \left(\sum_{i,j} w_i w_j \mathbb{E}_\epsilon [\epsilon_i \epsilon_j] \right) \\
&= \left(w_0 + \sum_{i=1}^D w_i x_{ni} \right)^2 + \left(\sum_{i,j} w_i w_j \delta_{ij} \sigma^2 \right)
\end{aligned}$$

Substituting this result in the expression for $\mathbb{E}_\epsilon[E_D]$, we get:

$$\begin{aligned}
\mathbb{E}_\epsilon[E_D] &= \frac{1}{2} \sum_{n=1}^N \left\{ \left(w_0 + \sum_{i=1}^D w_i x_{ni} \right)^2 + \left(\sum_{i,j} w_i w_j \delta_{ij} \sigma^2 \right) + t_n^2 - 2 \left(w_0 + \sum_{i=1}^D w_i x_{ni} \right) t_n \right\} \\
&= \frac{1}{2} \sum_{n=1}^N \left\{ \left(w_0 + \sum_{i=1}^D w_i x_{ni} \right)^2 + t_n^2 - 2 \left(w_0 + \sum_{i=1}^D w_i x_{ni} \right) t_n \right\} \\
&\quad + \frac{N\sigma^2}{2} \left(\sum_{i,j} w_i w_j \delta_{ij} \right) \\
&= \frac{1}{2} \sum_{n=1}^N \left\{ \left(w_0 + \left(\sum_{i=1}^D w_i x_{ni} \right) - t_n \right)^2 \right\} + \frac{N\sigma^2}{2} \left(\sum_{i,j} w_i w_j \delta_{ij} \right)
\end{aligned}$$

The first term minimizes the sum-of-squares error for noise-free input variables, and the second term is the weight-decay regularization term, in which the bias parameter w_0 is omitted from the regularizer.