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**Machine Learning I**  
Exercise Sheet 5  
Due on Mon, December 5, 12:15

If you turn in your solutions via email, please send to:

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Include [ML1-1617] in the subject line, turn in a single PDF file and include your name in the file name.

**Exercise 1.** *Starting from the sum-of-squares error function*

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

*derive the maximum likelihood solution for the parameters*

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

where

$$\Phi = \begin{pmatrix} \phi_0(\mathbf{x}_1) & \phi_1(\mathbf{x}_1) & \cdots & \phi_{M-1}(\mathbf{x}_1) \\ \phi_0(\mathbf{x}_2) & \phi_1(\mathbf{x}_2) & \cdots & \phi_{M-1}(\mathbf{x}_2) \\ \vdots & \vdots & \ddots & \vdots \\ \phi_0(\mathbf{x}_N) & \phi_1(\mathbf{x}_N) & \cdots & \phi_{M-1}(\mathbf{x}_N) \end{pmatrix},$$

is the design matrix with basis functions  $\phi_j(\mathbf{x}_i)$ ,  $\mathbf{X} = \{\mathbf{x}_1, \dots, \mathbf{x}_N\}$  the vectors of input training data and  $\mathbf{t} = \{t_1, \dots, t_N\}$  corresponding output training values.

**3 points**

**Exercise 2.** *Consider a data set in which each data point  $(\mathbf{x}_n, t_n)$  is associated with a weighting factor  $r_n > 0$ , so that the sum-of-squares error function becomes*

$$E_D(\mathbf{w}) = \frac{1}{2} \sum_n r_n (t_n - \mathbf{w}^T \phi(\mathbf{x}_n))^2$$

*Find an expression for the solution  $\mathbf{w}^*$  that minimizes this error function. Give two alternative interpretations of the weighted sum-of-squares error function in terms of (i) data dependent noise variance and (ii) replicated data points.*

**2 points**

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**Exercise 3.** *Generate own data sets, e.g. using  $t = f(x) + 0.2\epsilon$  with  $f(x) = \sin(2\pi x)$  and  $\epsilon \sim \mathcal{N}(0, 1)$ , and illustrate the bias-variance decomposition by fitting a polynomial model  $y(x; w) = \sum_{i=0}^r w_i x^i$  to many different data sets  $D_1, \dots, D_L$ , each of length  $N$ . Let  $w^{*,D}$  denote the parameters minimizing the mean squared error on data set  $D$ . Then,*

$$\begin{aligned} \mathbf{bias}^2 &\approx \frac{1}{L} \sum_l \frac{1}{N} \sum_n (\bar{y}(x) - f(x))^2 \\ \mathbf{variance} &\approx \frac{1}{L} \sum_l \frac{1}{N} \sum_n (y(x; w^{*,D_l}) - \bar{y}(x))^2 \end{aligned}$$

where  $\bar{y}(x) = \frac{1}{L} \sum_l y(x; w^{*,D_l})$ .

**5 points**