

## Chapter 6 Kernel Methods

Yue Yu

### 6.1 Dual Representations

(6.3)

By setting the gradient of  $J(\mathbf{w})$  with respect to  $\mathbf{w}$  to  $\mathbf{0}$ , it is easy to see that

$$\begin{aligned}\mathbf{w} &= \arg_{\mathbf{w}} \nabla_{\mathbf{w}} J(\mathbf{w}) = \mathbf{0} \\ &= \arg_{\mathbf{w}} \left( \sum_{n=1}^N \{ \mathbf{w}^T \phi(\mathbf{x}_n) - t_n \} + \lambda \mathbf{w} = \mathbf{0} \right) \\ &= -\frac{1}{\lambda} \sum_{n=1}^N \{ \mathbf{w}^T \phi(\mathbf{x}_n) - t_n \} \phi(\mathbf{x}_n) \\ &= \Phi^T \mathbf{a}\end{aligned}$$

where

$$\mathbf{a} = -\frac{1}{\lambda} (\Phi \mathbf{w} - \mathbf{t}).$$

(6.5)

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

(6.8)

From the derivation of (6.3), we have

$$\begin{aligned}\mathbf{a} &= -\frac{1}{\lambda} (\Phi \mathbf{w} - \mathbf{t}) \\ &= -\frac{1}{\lambda} (\Phi \Phi^T \mathbf{a} - \mathbf{t}) \\ &= -\frac{1}{\lambda} (\mathbf{K} \mathbf{a} - \mathbf{t}).\end{aligned}$$

Solving for  $\mathbf{a}$ , we obtain

$$\mathbf{a} = (\mathbf{K} + \lambda \mathbf{I}_N)^{-1} \mathbf{t}.$$

(6.9)

$$y(\mathbf{x}) = \mathbf{w}^T \phi(\mathbf{x}) = \mathbf{a}^T \Phi \phi(\mathbf{x}) = (\Phi \phi(\mathbf{x}))^T \mathbf{a} = \mathbf{k}(\mathbf{x})^T (\mathbf{K} + \lambda \mathbf{I}_N)^{-1} \mathbf{t}.$$

## 6.2 Constructing Kernels

(6.13)

To verify (6.13) is a valid kernel, we see that for any vector  $\mathbf{u} \in \mathbb{R}^N$ ,

$$\mathbf{u}^T \mathbf{K} \mathbf{u} = \mathbf{u}^T (c \mathbf{K}_1) \mathbf{u} = c (\mathbf{u}^T \mathbf{K}_1 \mathbf{u}) \geq 0,$$

which implies that  $\mathbf{K} \succeq 0$ .

(6.14)

To verify (6.14) is a valid kernel, we first notice that  $k(\mathbf{x}, \mathbf{x}')$  is symmetric by

$$k(\mathbf{x}', \mathbf{x}) = ck_1(\mathbf{x}', \mathbf{x}) = ck_1(\mathbf{x}, \mathbf{x}') = k(\mathbf{x}, \mathbf{x}').$$

Also, we see that for any vector  $\mathbf{u} \in \mathbb{R}^N$ ,

$$\begin{aligned} \mathbf{u}^T \mathbf{K} \mathbf{u} &= \sum_{i=1}^N \sum_{j=1}^N k(\mathbf{x}_i, \mathbf{x}_j) u_i u_j \\ &= \sum_{i=1}^N \sum_{j=1}^N k_1(\mathbf{x}_i, \mathbf{x}_j) (f(\mathbf{x}_i) u_i) (f(\mathbf{x}_j) u_j) \\ &= \sum_{i=1}^N \sum_{j=1}^N k_1(\mathbf{x}_i, \mathbf{x}_j) v_i v_j \\ &\geq 0 \end{aligned}$$

where we denote  $v_i = f(\mathbf{x}_i) u_i$ , implying  $\mathbf{K} \succeq 0$ . Therefore, (6.14) is a valid kernel.

(6.15)

To verify (6.15) is a valid kernel, let  $q(k_1(\mathbf{x}, \mathbf{x}')) = \sum_m c_m k_1(\mathbf{x}, \mathbf{x}')^m$  where  $c_m \geq 0$ . By repeatedly applying (6.18), we see that  $k_1(\mathbf{x}, \mathbf{x}')^m$  is a valid kernel. Then, according to (6.13),  $c_m k_1(\mathbf{x}, \mathbf{x}')^m$  is also a valid kernel. Finally, using (6.17), we can conclude that  $q(k_1(\mathbf{x}, \mathbf{x}')) = \sum_m c_m k_1(\mathbf{x}, \mathbf{x}')^m$  is a valid kernel.

(6.16)

To verify (6.16) is a valid kernel, we first notice that  $k(\mathbf{x}, \mathbf{x}')$  is symmetric by

$$k(\mathbf{x}', \mathbf{x}) = \exp(k_1(\mathbf{x}', \mathbf{x})) = \exp(k_1(\mathbf{x}, \mathbf{x}')) = k(\mathbf{x}, \mathbf{x}').$$

Also, we see that for any vector  $\mathbf{u} \in \mathbb{R}^N$ ,

$$\begin{aligned} \mathbf{u}^T \mathbf{K} \mathbf{u} &= \sum_{i=1}^N \sum_{j=1}^N k(\mathbf{x}_i, \mathbf{x}_j) u_i u_j \\ &= \sum_{i=1}^N \sum_{j=1}^N \exp(k_1(\mathbf{x}_i, \mathbf{x}_j)) u_i u_j. \end{aligned}$$

Applying the Maclaurin series for the exponential term, we have

$$\mathbf{u}^T \mathbf{K} \mathbf{u} = \sum_{i=1}^N \sum_{j=1}^N \left( \sum_{n=0}^{\infty} \frac{k_1(\mathbf{x}_i, \mathbf{x}_j)^n}{n!} \right) u_i u_j \geq 0$$

where we made use of (6.15), implying  $\mathbf{K} \succeq 0$ . Therefore, (6.16) is a valid kernel.

**(6.17)**

To verify (6.17) is a valid kernel, we first notice that  $k(\mathbf{x}, \mathbf{x}')$  is symmetric by

$$k(\mathbf{x}', \mathbf{x}) = k_1(\mathbf{x}', \mathbf{x}) + k_2(\mathbf{x}', \mathbf{x}) = k_1(\mathbf{x}, \mathbf{x}') + k_2(\mathbf{x}, \mathbf{x}') = k(\mathbf{x}, \mathbf{x}').$$

Also, we see that for any vector  $\mathbf{u} \in \mathbb{R}^N$ ,

$$\begin{aligned} \mathbf{u}^T \mathbf{K} \mathbf{u} &= \sum_{i=1}^N \sum_{j=1}^N k(\mathbf{x}_i, \mathbf{x}_j) u_i u_j \\ &= \sum_{i=1}^N \sum_{j=1}^N (k_1(\mathbf{x}_i, \mathbf{x}_j) + k_2(\mathbf{x}_i, \mathbf{x}_j)) u_i u_j \\ &= \sum_{i=1}^N \sum_{j=1}^N k_1(\mathbf{x}_i, \mathbf{x}_j) u_i u_j + \sum_{i=1}^N \sum_{j=1}^N k_2(\mathbf{x}_i, \mathbf{x}_j) u_i u_j \\ &\geq 0, \end{aligned}$$

which implies that  $\mathbf{K} \succeq 0$ . Therefore, (6.17) is a valid kernel.

**(6.18)**

To verify (6.18) is a valid kernel, we first notice that  $k(\mathbf{x}, \mathbf{x}')$  is symmetric by

$$k(\mathbf{x}', \mathbf{x}) = k_1(\mathbf{x}', \mathbf{x}) k_2(\mathbf{x}', \mathbf{x}) = k_1(\mathbf{x}, \mathbf{x}') k_2(\mathbf{x}, \mathbf{x}') = k(\mathbf{x}, \mathbf{x}').$$

Also, we see that for any vector  $\mathbf{u} \in \mathbb{R}^N$ ,

$$\begin{aligned} \mathbf{u}^T \mathbf{K} \mathbf{u} &= \sum_{i=1}^N \sum_{j=1}^N k(\mathbf{x}_i, \mathbf{x}_j) u_i u_j \\ &= \sum_{i=1}^N \sum_{j=1}^N k_1(\mathbf{x}_i, \mathbf{x}_j) k_2(\mathbf{x}_i, \mathbf{x}_j) u_i u_j \\ &= \sum_{i=1}^N \sum_{j=1}^N \phi_1(\mathbf{x}_i)^T \phi_1(\mathbf{x}_j) \phi_2(\mathbf{x}_i)^T \phi_2(\mathbf{x}_j) u_i u_j \\ &= \sum_{i=1}^N \sum_{j=1}^N \left( \sum_{l=1}^M \phi_{1l}(\mathbf{x}_i) \phi_{1l}(\mathbf{x}_j) \right) \left( \sum_{m=1}^M \phi_{2m}(\mathbf{x}_i) \phi_{2m}(\mathbf{x}_j) \right) u_i u_j \\ &= \sum_{l=1}^M \sum_{m=1}^M \left( \sum_{i=1}^N \phi_{1l}(\mathbf{x}_i) \phi_{2m}(\mathbf{x}_i) u_i \right)^2 \\ &\geq 0, \end{aligned}$$

which implies that  $\mathbf{K} \succeq 0$ . Therefore, (6.18) is a valid kernel.

(6.20)

To verify (6.20) is a valid kernel, recall that any symmetric matrix  $\mathbf{S}$  can be diagonalized by  $\mathbf{S} = \mathbf{Q}\mathbf{\Lambda}\mathbf{Q}^T$  where the columns of  $\mathbf{Q}$  are orthogonal eigenvectors. Hence,

$$k(\mathbf{x}, \mathbf{x}') = \mathbf{x}^T \mathbf{A} \mathbf{x}' = \mathbf{x}^T \mathbf{Q} \mathbf{\Lambda} \mathbf{Q}^T \mathbf{x}' = (\mathbf{Q}^T \mathbf{x})^T \mathbf{\Lambda} (\mathbf{Q}^T \mathbf{x}').$$

Denoting  $\mathbf{v} = \mathbf{Q}^T \mathbf{x}$  and  $\mathbf{v}' = \mathbf{Q}^T \mathbf{x}'$ ,

$$k(\mathbf{x}, \mathbf{x}') = \mathbf{v}^T \mathbf{\Lambda} \mathbf{v}' = \sum_{i=1}^N \Lambda_{ii} v_i v'_i = \sum_{i=1}^N (\sqrt{\Lambda_{ii}} v_i) (\sqrt{\Lambda_{ii}} v'_i) = \boldsymbol{\phi}(\mathbf{x})^T \boldsymbol{\phi}(\mathbf{x}') = k'(\boldsymbol{\phi}(\mathbf{x}), \boldsymbol{\phi}(\mathbf{x}'))$$

where  $k'$  is the linear kernel, and the square roots exist because the eigenvalues for a positive semidefinite matrix are non-negative. Therefore, according to (6.19),  $k(\mathbf{x}, \mathbf{x}')$  is a valid kernel.

(6.21)

$$\begin{aligned} k(\mathbf{x}, \mathbf{x}') &= k_a(\mathbf{x}_a, \mathbf{x}'_a) + k_b(\mathbf{x}_b, \mathbf{x}'_b) \\ &= \sum_{s=1}^S \phi_{as}(\mathbf{x}_a) \phi_{as}(\mathbf{x}'_a) + \sum_{t=1}^T \phi_{bt}(\mathbf{x}_b) \phi_{bt}(\mathbf{x}'_b) \\ &= \sum_{i=1}^{S+T} \phi_i(\mathbf{x}) \phi_i(\mathbf{x}'), \end{aligned}$$

which is a valid kernel.

(6.22) – To be updated

$$\begin{aligned} k(\mathbf{x}, \mathbf{x}') &= k_a(\mathbf{x}_a, \mathbf{x}'_a) k_b(\mathbf{x}_b, \mathbf{x}'_b) \\ &= \sum_{s=1}^S \phi_{as}(\mathbf{x}_a) \phi_{as}(\mathbf{x}'_a) \sum_{t=1}^T \phi_{bt}(\mathbf{x}_b) \phi_{bt}(\mathbf{x}'_b) \\ &= \sum_{s=1}^S \sum_{t=1}^T \{ \phi_{as}(\mathbf{x}_a) \phi_{bt}(\mathbf{x}_b) \} \{ \phi_{as}(\mathbf{x}'_a) \phi_{bt}(\mathbf{x}'_b) \} \end{aligned}$$