

# Homework 6

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## Problem 1

(a)

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```
1 Initialize  $\alpha = \mathbf{0} \in \mathbb{R}^n$  ;
2 while TRUE do
3    $m = 0$  ;
4   for  $(\mathbf{x}_i, y_i) \in D$  do
5     if  $y_i (\sum_j \alpha_j y_j x_j)^\top x_i \leq 0$  then
6        $\alpha_i \leftarrow \alpha_i + 1$ ;
7        $m \leftarrow m + 1$ ;
8     end
9     if  $m = 0$  then
10      break
11     end
12   end
13 end
```

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(b)

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```
1 Initialize  $\tilde{\alpha} = \mathbf{0} \in \mathbb{R}^n$  ;
2 while TRUE do
3    $m = 0$  ;
4   for  $(\mathbf{x}_i, y_i) \in D$  do
5     if  $y_i \sum_j \alpha_j y_j k(x_j, x_i) \leq 0$  then
6        $\alpha_i \leftarrow \alpha_i + 1$ ;
7        $m \leftarrow m + 1$ ;
8     end
9     if  $m = 0$  then
10      break
11     end
12   end
13 end
```

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(c)

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```
1 Initialize  $\tilde{\alpha} = \mathbf{0} \in \mathbb{R}^n$  ;
2 Initialize  $\mathbf{K}$  of size  $n \times n$  ;
3 for  $i \in \{1, \dots, n\}$  do
4   for  $j \in \{1, \dots, n\}$  do
5      $\mathbf{K}_{ij} = k(x_i, x_j)$ 
6   end
7 end
8 while TRUE do
9    $m = 0$  ;
10  for  $(\mathbf{x}_i, y_i) \in D$  do
11    if  $y_i \sum_j \alpha_j y_j \mathbf{K}_{ji} \leq 0$  then
12       $\alpha_i \leftarrow \alpha_i + 1$  ;
13       $m \leftarrow m + 1$  ;
14    end
15    if  $m = 0$  then
16      break
17    end
18  end
19 end
```

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(d)

$$h(x^*) = \text{sgn} \left( \sum_i \alpha_i y_i x_i x^* \right) = \text{sgn} \left( \sum_i \alpha_i y_i k(x_i, x^*) \right)$$

## Problem 2

Since  $k_1, k_2$  are valid kernels, the kernel matrices related to it  $K^{(1)}, K^{(2)}$  satisfies:

1.  $K_{ij}^{(1)} = K_{ji}^{(1)}, K_{ij}^{(2)} = K_{ji}^{(2)}$
2.  $K^{(1)} \geq 0 \Rightarrow v^\top K^{(1)} v \geq 0; K^{(2)} \geq 0 \Rightarrow v^\top K^{(2)} v \geq 0, \forall v \geq \mathbf{0}$ .

(a)

**Symmetric:**  $K_{ij} = k(x_i, x_j) = ck_1(x_i, x_j) = K_{ij}^{(1)} = K_{ji}^{(1)} = ck_1(x_j, x_i) = k(x_j, x_i) = K_{ji}$

**Positive semidefinite:** Since  $k(x_i, x_j) = ck_1(x_i, x_j), \forall i, j$ , it follows that  $K = cK^{(1)}$ , therefore for same  $v$  mentioned above, it follows that  $v^\top K v = v^\top cK^{(1)} v = c \underbrace{v^\top K^{(1)} v}_{\geq 0} \geq 0, \forall c \geq 0 \Rightarrow K \geq 0$

(b)

**Symmetric:**  $K_{ij} = k_1(x_i, x_j) + k_2(x_i, x_j) = K_{ij}^{(1)} + K_{ij}^{(2)} = K_{ji}^{(1)} + K_{ji}^{(2)} = k_1(x_j, x_i) + k_2(x_j, x_i) = k(x_j, x_i) = K_{ji}$

**Positive semidefinite:** Since  $k(x_i, x_j) = k_1(x_i, x_j) + k_2(x_i, x_j), \forall i, j$ , it follows  $K_{ij} = K_{ij}^{(1)} + K_{ij}^{(2)} \Rightarrow K = K^{(1)} + K^{(2)}$ . Therefore  $v^\top K v = v^\top (K^{(1)} + K^{(2)}) v = (v^\top K^{(1)} + v^\top K^{(2)}) v = \underbrace{v^\top K^{(1)} v}_{\geq 0} + \underbrace{v^\top K^{(2)} v}_{\geq 0} \geq 0, \forall v \geq \mathbf{0}$

(c)

Since  $k_1$  is a kernel, it follows that  $k_1(x_i, x_j) = \phi_1(x_i)^\top \phi_1(x_j)$ , for some  $\phi$  as a valid transformation. Also since  $f(\cdot)$  is a scalar-valued function, it follows that  $\sqrt{f(\cdot)}$  is also one. Also note that if  $\phi(\cdot)$  is a transformation from  $\mathbb{R}^d$  to  $\mathbb{R}^m$ , so does  $c\phi(\cdot), \forall c \in \mathbb{R}$  as scalar does not affect the dimension of transformation. Therefore since  $\sqrt{f(\cdot)}$  outputs a scalar, by given.  $\sqrt{f(\cdot)}\phi_1(\cdot)$  is also a transformation from  $\mathbb{R}^d$  to  $\mathbb{R}^m$ . Let  $\phi(x) = \sqrt{f(x)}\phi_1(x)$ , therefore  $\phi(x_i)^\top \phi(x_j) := k(x_i, x_j)$  is a **valid kernel**, which by what we conclude above, simplifies to:

$$\begin{aligned} &= \left( \sqrt{f(x_i)}\phi_1(x_i) \right)^\top \left( \sqrt{f(x_j)}\phi_1(x_j) \right) \\ &= \sqrt{f(x_i)}\phi_1(x_i)^\top \sqrt{f(x_j)}\phi_1(x_j) \\ &= \sqrt{f(x_i)}\phi_1(x_i)^\top \phi_1(x_j) \sqrt{f(x_j)} \\ &= \sqrt{f(x_i)}k_1(x_i, x_j) \sqrt{f(x_j)} \end{aligned}$$

Hence we showed a product of 2 scalar-valued functions and another valid kernel, whose name is  $k(x_1, x_2)$  is a **valid kernel**.

### Problem 3

(a)

$$\begin{bmatrix} k(x_1, x_1) & k(x_1, x_2) \\ k(x_2, x_1) & k(x_2, x_2) \end{bmatrix} = \begin{bmatrix} 4 & 0 \\ 0 & 4 \end{bmatrix}$$

(b)

The  $\tau^2$  is like the penalty term work as a regularization term to prevent overfitting. By modifying  $\tau$ , one can control the scale of the Kernel to modify the scale of penalty.  $+\tau^2 I$  increases the diagonal entries by  $\tau^2$  many and help the kernel less susceptible to numeric instability especially when the kernel matrix is nearly singular.

Also, since  $K$  is already positive semi-definite,  $K + \tau^2 I$  will make the new kernel matrix positive definite as  $v^\top K' v = v^\top (K + \tau^2 I) v = v^\top K v + v^\top \tau^2 I v \geq \tau^2 > 0$ . Hence making the kernel matrix symmetric positive-definite can guarantee its invertibility.

(c)

$$\alpha = K^{-1} y = \begin{bmatrix} \frac{1}{4} & 0 \\ 0 & \frac{1}{4} \end{bmatrix} \begin{bmatrix} 0 \\ 2 \end{bmatrix} = \begin{bmatrix} 0 \\ \frac{1}{2} \end{bmatrix}$$

$$\begin{aligned} h(x_1^*) &= \sum_i k(x_1^*, x_i) \alpha_i = k(x_1^*, x_1) \alpha_1 + k(x_1^*, x_2) \alpha_2 = k(0, -1) \times 0 + k(0, 1) \times \frac{1}{2} = \frac{1}{2} \\ h(x_2^*) &= \sum_i k(x_2^*, x_i) \alpha_i = k(x_2^*, x_1) \alpha_1 + k(x_2^*, x_2) \alpha_2 = k(2, -1) \times 0 + k(2, 1) \times \frac{1}{2} = \frac{9}{2} \end{aligned}$$