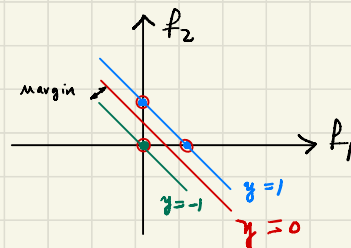


### Tutorial 3

Q1. All data points will be SV.  
Hence:  $a_1, a_2, a_3 > 0$



Q1.2 Pri. 1 Lagrangian:

$$\begin{aligned} \mathcal{L} &= \frac{1}{2} \mathbf{w}^T \mathbf{w} + \frac{1}{2} \sum_{n=1}^3 a_n (1 - b_n (\mathbf{w}^T \mathbf{x}_n + b))^2 \\ &= \frac{1}{2} \mathbf{w}^T \mathbf{w} - \mathbf{w}^T \sum_{n=1}^3 a_n t_n \mathbf{x}_n - b \sum_{n=1}^3 a_n t_n + \frac{1}{2} \sum_{n=1}^3 a_n \end{aligned}$$

Optimality:

$$\nabla_{\mathbf{w}} \mathcal{L} = \mathbf{w} - \sum_{n=1}^3 a_n t_n \mathbf{x}_n = 0 \Rightarrow \mathbf{w} = \sum_{n=1}^3 a_n t_n \mathbf{x}_n$$

$$\mathbf{w} = -a_1 \begin{pmatrix} 0 \\ 1 \end{pmatrix} + a_2 \begin{pmatrix} 1 \\ 0 \end{pmatrix} + a_3 \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

Replacing  $\mathbf{w}$  in  $y(\mathbf{x})$ :

$$y(\mathbf{x}) = \left( \sum_{m=1}^3 a_m t_m \mathbf{x}_m \right)^T \mathbf{x} + b$$

$$= \sum_{m=1}^3 a_m t_m \mathbf{x}_m^T \mathbf{x} + b$$

$$= \sum_{m=1}^3 a_m t_m \underbrace{K(\mathbf{x}_m, \mathbf{x})}_{\text{kernel of } \mathbf{x}_m \text{ and } \mathbf{x}} + b$$

kernel of  $\mathbf{x}_m$  and  $\mathbf{x}$

In reality most of  $a_n = 0$ , which means the prediction is sparse.

Q2.1

$$k_1(x, y) = \phi(x)^T \phi(y) \leftarrow \text{definition of valid kernel}$$

$$k_2(x, y) = \psi(x)^T \psi(y) \leftarrow$$

$$\begin{aligned} k_1(x, y) + k_2(x, y) &= \phi(x)^T \phi(y) + \psi(x)^T \psi(y) \\ &= \underbrace{(\phi(x) \parallel \psi(x))}_{\lambda(x)}^T \underbrace{\begin{pmatrix} \phi(y) \\ \psi(y) \end{pmatrix}}_{\lambda(y)} \\ &= \lambda(x)^T \lambda(y) \checkmark \end{aligned}$$

Q2.2

$$x^T (\lambda_i e_i \ e_i^T) y = (\sqrt{\lambda_i} \ x^T e_i) \cdot (\sqrt{\lambda_i} \ e_i^T y)$$

\*imp  $\lambda_i \gg 0$

$$= \underbrace{(\sqrt{\lambda_i} \ x^T e_i)}_{\phi_i(x)} \underbrace{(\sqrt{\lambda_i} \ e_i^T y)}_{\psi_i(y)} \checkmark$$

Q2.3 This can be derived using above results.

Q2.4  $(x^T y)^n = (x_1 y_1 + x_2 y_2)^n$

$$\begin{aligned} &= (x_1 y_1 + x_2 y_2) \times \dots \times (x_1 y_1 + x_2 y_2) \leftarrow n\text{-factors} \\ &= \sum_{i=1}^n c_i (x_1 y_1)^i (x_2 y_2)^{n-i}, \quad c > 0 \\ &= \sum_{i=1}^n \underbrace{(\sqrt{c_i} x_1^i x_2^{n-i})}_{\phi_i(x)} \underbrace{(\sqrt{c_i} y_1^i y_2^{n-i})}_{\psi_i(y)} \\ &= \phi(x)^T \psi(y) \checkmark \end{aligned}$$

Q2.5 this can be derived using Q2.1 and Q2.4

Q2.6

$$\text{Recall: } e^x = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots$$

$$\text{Hence: } e^{x^T y} = 1 + x^T y + \frac{(x^T y)^2}{2!} + \dots$$

Each of terms above is a valid kernel (Q2.4)

Their summation is also valid. ✓

Q3.

SOLUTION:

$$H(S) = -4/8 \log_2(4/8) - 4/8 \log_2(4/8) = 1$$

$$H_{f_2} = -5/8[4/5 \log_2(4/5) + 1/5 \log_2(1/5)] - 3/8[3/3 \log_2(3/3) + 0 \log_2(0/3)] = 0.4512$$

$$H_{f_1} = -4/8[2/4 \log_2(2/4) + 2/4 \log_2(2/4)] - 4/8[2/4 \log_2(2/4) + 2/4 \log_2(2/4)] = 1$$

$$H(S) - H_{f_2} = 0.5488$$

$$H(S) - H_{f_1} = 0$$

Hence, ID3 will split on the second feature first.