Machine Learning 1

Homework Week 8 - Kernel Method

Tran Hai Nam - 11219279 - DSEB

1 Problem 1: Dual Representation

L2 Loss regularization

$$J(W) = \frac{1}{2}\sum_{i=1}^{N}\left(w^T\phi\left(x_n\right)t_n\right)^2 + \frac{\lambda}{2}w^Tw$$

where $\lambda > 0$

$$\begin{aligned}
\frac{\partial J(w)}{\partial w} &= \sum_{n=1}^{N}(w^T\phi(x_n) - t_n)\phi(x_n) + \lambda w = 0 \\
&\leftrightarrow \lambda w = -\sum_{n=1}^{N}(w^T\phi(x_n) - t_n)\phi(x_n) \\
&\leftrightarrow w = -\frac{1}{\lambda}\sum_{n=1}^{N}(w^T\phi(x_n) - t_n)\phi(x_n)
\end{aligned}$$

$$\begin{aligned}
w &= -\frac{1}{2}\sum_{i=1}^{N}\left(w^\top\phi\left(x_n\right) - t_n\right)\cdot\phi\left(x_n\right) \\
&= \sum_{n=1}^{N}a_n\phi\left(x_n\right) = \phi^\top\cdot a \\
\phi &= \begin{bmatrix}\phi\left(x_1\right) \\ \phi\left(x_2\right) \\ \vdots\left(x_n\right)\end{bmatrix} \\
a &= \begin{bmatrix}a_1 \\ a_2 \\ \vdots \\ a_n\end{bmatrix} \\
a_n &= \frac{-1}{\lambda}\left(w^\top\phi\left(x_n\right) - t_n\right)
\end{aligned}$$

$\rightarrow$ Substituse $w = \phi^\top a$

$$L = \frac{1}{2}\sum_{l=1}^{n}\left(w^\top \phi\left(x_n\right) - t_n\right)^2 + \frac{\lambda}{2}\|w\|_2^2$$
$$= \frac{1}{2}\left(w^\top \phi - t\right)^\top \cdot \left(w^\top \phi - t\right) + \frac{\lambda}{2} w^\top w$$
$$= \frac{1}{2}\left(\phi^\top \cdot w - t^\top\right)\left(w^\top \phi - t\right) + \frac{\lambda}{2} w^\top w$$
$$= \frac{1}{2}\left(\phi^\top w \cdot w^\top \phi - \phi^\top w \cdot t - t^\top \cdot w^\top \cdot \phi + t^\top \cdot t\right) + \frac{\lambda}{2} w^\top w$$
$$= \frac{1}{2}\left(w^\top \cdot \phi^\top \cdot \phi \cdot w - 2w^\top \cdot \phi^\top \cdot t + t^\top \cdot t\right) + \frac{\lambda}{2} w^\top w$$
$$= \frac{1}{2} a^\top \cdot \phi \cdot \phi^\top \cdot \phi \cdot \phi^\top \cdot a - a^\top \cdot \phi \cdot \phi^\top \cdot t + \frac{1}{2} t^\top \cdot t + \frac{\lambda}{2} a^\top \phi \cdot \phi^\top a$$

Let Kernel matrix $K = \phi\phi^T$. K is symmetric (a) and positive semi-definite (PSD) (b):

- $K^T = (\phi\phi^T)^T = (\phi^T)^T\phi^T = \phi\phi^T = K$ (a)
- $(Kx, x) \geq 0 \ \forall \ x \in R^n$ since:
  $(Kx, x) = x^T K x = x^T \phi\phi^T x = (\phi^T x)^T(\phi^T x) = \|\phi^T x\|_2^2 \geq 0$

$$\rightarrow J(a) = \frac{1}{2} a^T K K a - a^T K t + \frac{1}{2} t^T t + \frac{\lambda}{2} a^T K a$$
$$\frac{\partial J}{\partial a} = KKa - Kt + \lambda K a = 0$$
$$K(Ka - t + \lambda a) = 0$$

Since K is PSD:

$$Ka - t + \lambda a = 0$$
$$(K + \lambda I)a = t$$
$$a = (K + \lambda I)^{-1} t$$

2 Problem 2: Valid Kernels

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

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

Since $k_1(x, x')$ is a valid kernel $\rightarrow$ exist an feature vector $\phi(x)$ such that $k_1(x, x') = \phi(x)^T\phi(x)$.

Let $u(x) = \sqrt{c}k_1(x, x') \rightarrow ck_1(x, x') = u(x)^T u(x)$

$\rightarrow ck_1(x, x')$ is a valid kernel corresponds to feature map u

Similarity, $k_1(x, x')$ is a valid kernel $\rightarrow$ exist an feature vector $\phi(x)$ such that $k_1(x, x') = \phi(x)^T\phi(x)$.

Let $v(x) = f(x)\phi(x) \to f(x)k_1(x,x')f(x'v(x)^T v(x')$.
$\to f(x)k_1(x,x')f(x')$ is a valid kernel corresponds to feature map v

3 Problem 3:Find Kernel Matrix

- $X = \begin{bmatrix} -3 & 4 \\ 1 & 0 \end{bmatrix} \to \phi(x) = \begin{bmatrix} -3 & 4 & \sqrt{(-3)^2 + 4^2} \\ 1 & 0 & \sqrt{1^2 + 0^2} \end{bmatrix} = \begin{bmatrix} -3 & 4 & 5 \\ 1 & 0 & 1 \end{bmatrix}$

$$\begin{aligned} K &= \phi\phi^T \\ &= \begin{bmatrix} -3 & 4 & 5 \\ 1 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} -3 & 1 \\ 4 & 0 \\ 5 & 1 \end{bmatrix} \\ &= \begin{bmatrix} (-3)\cdot(-3) + 4\cdot 4 + 5\cdot 5 & (-3)\cdot 1 + 4\cdot 0 + 5\cdot 1 \\ 1\cdot(-3) + 0\cdot 4 + 1\cdot 5 & 1\cdot 1 + 0\cdot 0 + 1\cdot 1 \end{bmatrix} \\ &= \begin{bmatrix} 50 & 2 \\ 2 & 2 \end{bmatrix} \end{aligned}$$