# Machine Learning 1

## Homework Week 8 - Kernel Method

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# 1 Problem 1: Dual Representation

L2 Loss regularization

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

where $\lambda > 0$

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

$$\leftrightarrow \lambda w = -\sum_{n=1}^{N} (w^T \phi(x_n) - t_n)\phi(x_n)$$

$$\leftrightarrow w = -\frac{1}{\lambda} \sum_{n=1}^{N} (w^T \phi(x_n) - t_n)\phi(x_n)$$

$$w = -\frac{1}{2} \sum_{i=1}^{N} \left(w^\top \phi\left(x_n\right) - t_n\right) \cdot \phi\left(x_n\right)$$

$$= \sum_{n=1}^{N} a_n \phi\left(x_n\right) = \phi^\top \cdot a$$

$$\phi = \begin{bmatrix} \phi\left(x_1\right) \\ \phi\left(x_2\right) \\ \vdots \\ \phi\left(x_n\right) \end{bmatrix}$$

$$a = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$$

$$a_n = \frac{-1}{\lambda} \left(w^\top \phi\left(x_n\right) - t_n\right)$$

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

$$
\begin{aligned}
L &= \frac{1}{2}\sum_{l=1}^{n}\left(w^\top \phi\left(x_n\right) t_n\right)^2 + \frac{\lambda}{2}\|w\|_2^2 \\
=&\frac{1}{2}\left(w^\top \phi - t\right)^\top \cdot \left(w^\top \phi - t\right) + \frac{\lambda}{2} w^\top w \\
=&\frac{1}{2}\left(\phi^\top \cdot w - t^\top\right)\left(w^\top \phi - t\right) + \frac{\lambda}{2} w^\top w & Let Kernel matrix \mathrm{K} \\
=&\frac{1}{2}\left(\phi^\top w \cdot w^\top \phi - \phi^\top w \cdot t - t^\top \cdot w^\top \cdot \phi + t^\top \cdot t\right) + \frac{\lambda}{2} w^\top w \\
=&\frac{1}{2}\left(w^\top \cdot \phi^\top \cdot \phi \cdot w - 2w^\top \cdot \phi^\top \cdot t + t^\top \cdot t\right) + \frac{\lambda}{2} w^\top w \\
=&\frac{1}{2} a^\top \cdot \phi \cdot \phi^\top \cdot \phi \cdot \phi^\top \cdot a - a^\top \cdot \phi \cdot \phi^\top \cdot t + \frac{1}{2} t^\top \cdot t + \frac{\lambda}{2} a^\top \phi \cdot \phi^\top a
\end{aligned}
$$

$= \phi\phi^T$. 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:
  $(Kx, x) = x^T K x = x^T \phi\phi^T x = (\phi^T x)^T(\phi^T x) = \|\phi^T x\|_2^2 \geq 0$

$$
\begin{aligned}
\rightarrow J(a) &= \frac{1}{2} a^T K K a - a^T K t + \frac{1}{2} t^T t + \frac{\lambda}{2} a^T K a \\
\frac{\partial J}{\partial a} &= K K a - K t + \lambda K a = 0 \\
K(Ka &- t + \lambda a) = 0
\end{aligned}
$$

Since K is PSD:

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

# 2 Problem 2: Valid Kernels

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

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 $u$

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

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 $v(x) = f(x)\phi(x) \rightarrow f(x)k_1(x, x')f(x') = v(x)^T v(x')$.

$\rightarrow$f(x)k$_1(x, x')f(x')$ is a valid kernel corresponds to feature map $v$

# 3 Problem 3:Find Kernel Matrix

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

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