

Kernel:

let \mathcal{X} be an non-empty set. A function $K: \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ is a kernel if

\exists \mathbb{R} -Hilbert space \mathcal{H} and $\phi: \mathcal{X} \rightarrow \mathcal{H}$ st. $K(x,y) = \langle \phi(x), \phi(y) \rangle_{\mathcal{H}}$ $\forall x, y \in \mathcal{X}$

Remark: $K(\cdot, \cdot)$ is symmetric since $\langle \cdot, \cdot \rangle_{\mathcal{H}}$ is

construct kernel:

let $K \in \mathbb{R}^{n \times n}$ $k_{ij} = K(x_i, x_j)$

$$[K] = \underbrace{\begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix}}_{U} \underbrace{\begin{bmatrix} | & | & | \\ | & | & | \\ \hline & & \end{bmatrix}}_{\Lambda} \underbrace{\begin{bmatrix} | & | & | \\ | & | & | \\ \hline & & \end{bmatrix}}_{U^T}$$

Since K is symmetric,
it has real eigenvalues

consider feature $\phi(x_i) = [f_1(x_i) \ f_2(x_i) \ \dots \ f_m(x_i)]$

then $\langle \phi(x_i), \phi(x_j) \rangle = K(x_i, x_j)$

PSD Functions

A symmetric function $K: \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ is PSD

if $K \in \mathbb{R}^{n \times n}$ where $k_{ij} = K(x_i, x_j)$ is PSD

Lemma.

let \mathcal{H} be any Hilbert space, \mathcal{X} be an nonempty set

$\phi: \mathcal{X} \rightarrow \mathcal{H}$, then

1° $K(x,y) = \langle \phi(x), \phi(y) \rangle_{\mathcal{H}}$ is a PSD function

2° if K is a PSD function, $\exists \phi: \mathcal{X} \rightarrow \mathcal{H}$ st. $K(x,y) = \langle \phi(x), \phi(y) \rangle_{\mathcal{H}}$

1° take $k_{ij} = K(x_i, x_j)$ $K = U \Lambda U^T$

if $\Lambda \not\succeq 0$, let $z = \sum_{i=1}^n u_i k_{ii} \phi(x_i)$

then $\|z\|_{\mathcal{H}}^2 = \left(\sum_{i=1}^n u_i k_{ii} \phi(x_i) \right)^T \left(\sum_{i=1}^n u_i k_{ii} \phi(x_i) \right)$

$$= \sum_{i,j} u_i k_{ii} u_j k_{jj} \langle \phi(x_i), \phi(x_j) \rangle$$

$$= \sum_i u_i^2 k_{ii}$$

$$= \lambda \|u\|_{\mathbb{R}^n}^2 < 0 \quad \text{impossible}$$

$$\begin{bmatrix} | & | & | \\ | & | & | \\ \hline & & \end{bmatrix} \quad \begin{bmatrix} z \\ \hline u \end{bmatrix}$$

Eg. polynomial kernel

$$k(x,y) = (x^T y)^p = \sum_i x_i y_i \sum_j y_j y_j = \sum_{i,j} (x_i y_i)(y_j y_j)$$

$$\phi(x) = [x_1 x_2 x_3 x_4 \dots x_n]$$

$$k(x,y) = (x^T y + c)^p \quad \phi(x) = [x_1 x_2 x_3 x_4 \dots x_n \quad b \quad c]$$

$$k(x,y) = (\bar{x}^T \bar{y} + c)^d \quad \phi(x) = [\text{all polynomial term up to degree } d]$$

Eg. Gaussian kernel

$$k(x,z) = \exp\left(-\frac{\|x-z\|^2}{2\sigma^2}\right)$$

$$= \exp\left(-\frac{\|x\|^2}{2\sigma^2}\right) \cdot \exp\left(-\frac{\|z\|^2}{2\sigma^2}\right) \exp\left(\frac{x^T z}{\sigma^2}\right)$$

$$= \exp\left(-\frac{\|x\|^2}{2\sigma^2}\right) \cdot \exp\left(-\frac{\|z\|^2}{2\sigma^2}\right) \left[1 + \frac{1}{0!} (x^T z) + \frac{1}{2!} \frac{1}{0!} (x^T z)^2 + \dots + \frac{1}{n!} \frac{1}{0!} (x^T z)^n \dots \right]$$

$$= \left\langle \exp\left(-\frac{\|x\|^2}{2\sigma^2}\right) \begin{bmatrix} 1 \\ \frac{1}{0!} [x] \\ \frac{1}{2!} \begin{bmatrix} x & x \\ x & x \end{bmatrix} \\ \vdots \\ \frac{1}{n!} \begin{bmatrix} x \\ \vdots \\ x \end{bmatrix} \end{bmatrix}, \dots \right\rangle$$