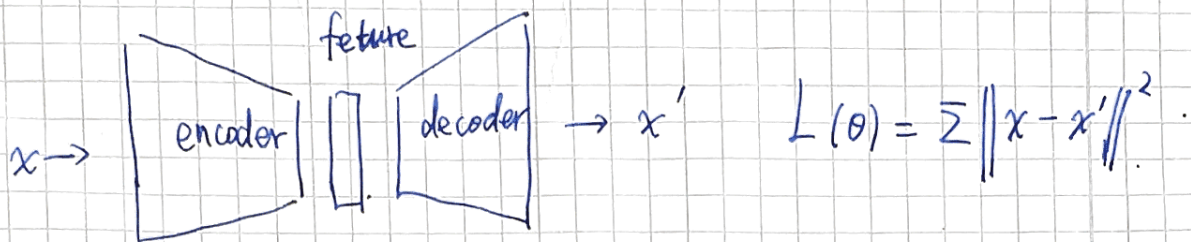


Ex 5-1

a) Autoencoder ~~tries~~ ^{aims} to learn an inverse function (feature map) $h = g_e(x, \theta_e)$, an encoder.

But we cannot measure h directly,

- ① learn feature map.
- ② Reduce dimensionality



b) - ~~Reduce~~ dimensionality Reduction

- Pretraining Restricted Boltzmann Machine.

- outlier detection

- generative model (GAN).

c) Directly copy the input

Ex 5-2

$$a) \quad k(x,y) = \langle x,y \rangle^2 = (x_1 y_1 + x_2 y_2)^2$$

$$= x_1^2 y_1^2 + 2 x_1 x_2 y_1 y_2 + x_2^2 y_2^2$$

$$= \left\langle \begin{pmatrix} x_1^2 \\ \sqrt{2} x_1 x_2 \\ x_2^2 \end{pmatrix}, \begin{pmatrix} y_1^2 \\ \sqrt{2} y_1 y_2 \\ y_2^2 \end{pmatrix} \right\rangle$$

$$= \langle \phi(x), \phi(y) \rangle$$

$$2) \quad k(x,y) = \exp\{-\gamma \|x-y\|^2\} \text{ for } x,y \in \mathbb{R} \text{ and } \gamma > 0$$

$$= \exp\{-\gamma (x-y)^2\}$$

$$= \exp\{-\gamma x^2 + 2xy\gamma - \gamma y^2\}$$

$$= \exp\{-\gamma (x^2 + y^2)\} \cdot \exp\{2xy\gamma\}$$

$$= \exp\{-\gamma (x^2 + y^2)\} \cdot \sum_{k=0}^{\infty} \frac{(2xy\gamma)^k}{k!}$$

$$= \underbrace{\exp\{-\gamma x^2\}} \cdot \underbrace{\exp\{-\gamma y^2\}} \cdot \left[\sum_{k=0}^{\infty} \left(\frac{(2\gamma)^k}{k!} \cdot x^k \cdot \frac{(2\gamma)^k}{k!} \cdot y^k \right) \right]$$

$$= \left\langle \exp\{-\gamma x^2\} \begin{pmatrix} \sqrt{\frac{2\gamma}{0!}} x^0 \\ \vdots \\ \sqrt{\frac{2\gamma^k}{k!}} x^k \\ \vdots \end{pmatrix}, \exp\{-\gamma y^2\} \begin{pmatrix} \vdots \\ \vdots \\ \vdots \\ \vdots \end{pmatrix} \right\rangle$$

$$= \langle \phi(x), \phi(y) \rangle$$

Ex 5-3 Mercer Theorem (Sufficient & unnecessary condition)

To prove a kernel is a valid kernel:

Method 1. first: $k(x,y) = \phi(x)^T \cdot \phi(y)$

Method 2. check $k(x,y) = k_1(x,y) \circ k_2(x,y)$

where k_1, k_2 are valid kernels.

\circ is an operation operator.

if Mercer holds then valid

if valid the Mercer may not hold

a) $a k_1(x_i, x_j) = a \phi_\bullet(x_i)^T \phi_\bullet(x_j) = \sqrt{a} \phi_\bullet(x_i)^T \cdot \sqrt{a} \phi_\bullet(x_j)$
 (Mercer kernel) $= \phi'_\bullet(x_i)^T \cdot \phi'_\bullet(x_j)$

where $\phi'_\bullet(x) = \sqrt{a} \phi_\bullet(x)$.

b) $k(x_i, x_j) = k_1(x_i, x_j) + k_2(x_i, x_j)$
 $= \phi_1(x_i)^T \phi_1(x_j) + \phi_2(x_i)^T \phi_2(x_j)$
 $= (\phi_1(x_i), \phi_2(x_i))^T \cdot (\phi_1(x_j), \phi_2(x_j))$
 $= \phi'(x_i)^T \phi'(x_j)$ where $\phi'(x) = (\phi_1(x), \phi_2(x))$

c) $k(x_i, x_j) = \sum_{l=1}^d w_l k_l(x_i, x_j) \stackrel{(a)}{=} \sum_{l=1}^d \phi_l(x_i)^T \cdot \phi_l(x_j)$

where $\phi'(x) = \begin{pmatrix} \sqrt{w_1} \phi_1(x) \\ \vdots \\ \sqrt{w_d} \phi_d(x) \end{pmatrix} \stackrel{(b)}{=} \phi'(x_i)^T \cdot \phi'(x_j)$

Or by deduction. For $d \in \mathbb{N}^+$,

(1) $w_l k_l(x_i, x_j) \circ$ is valid,

$$\begin{aligned}
 d) \quad k(x_i, x_j) &= k_1(x_i, x_j) \cdot k_2(x_i, x_j) \\
 &= \phi_1(x_i)^T \cdot \phi_1(x_j) \cdot \phi_2(x_i)^T \phi_2(x_j) \\
 &= \cancel{\phi_1(x_i)^T \phi_2(x_i)^T \cdot \phi_1(x_j) \phi_2(x_j)} \\
 &= \left[\sum_{m=1}^{M_1} \phi_1(x_i)_m \phi_1(x_j)_m \right] \left[\sum_{n=1}^{M_2} \phi_2(x_i)_n \phi_2(x_j)_n \right] \\
 &= \sum_{m=1}^{M_1} \left[\phi_1(x_i)_m \phi_1(x_j)_m \cdot \sum_{n=1}^{M_2} \phi_2(x_i)_n \cdot \phi_2(x_j)_n \right] \\
 &= \sum_{m=1}^{M_1} \sum_{n=1}^{M_2} \left[\phi_1(x_i)_m \cdot \phi_2(x_j)_m \cdot \phi_2(x_i)_n \cdot \phi_2(x_j)_n \right] \\
 &= \sum_{m=1}^{M_1} \sum_{n=1}^{M_2} \left[(\phi_1(x_i)_m \cdot \phi_2(x_i)_n) \cdot (\phi_1(x_j)_m \cdot \phi_2(x_j)_n) \right] \\
 &= \sum_{m=1}^{M_1} \sum_{n=1}^{M_2} \left[\phi_1(x_i)_m \cdot \phi_2(x_i)_n \right] \cdot \left[\phi_1(x_j)_m \cdot \phi_2(x_j)_n \right] \\
 &= \begin{pmatrix} \phi_1(x_i)_1 \cdot \phi_2(x_i)_1 \\ \phi_1(x_i)_1 \cdot \phi_2(x_i)_2 \\ \vdots \\ \phi_1(x_i)_1 \cdot \phi_2(x_i)_2 \\ \phi_1(x_i)_2 \cdot \phi_2(x_i)_1 \\ \vdots \\ \phi_1(x_i)_m \cdot \phi_2(x_i)_{m_2} \end{pmatrix} \cdot (\phi_1(x_j)_1 \cdot \phi_2(x_j)_1, \dots, \phi_1(x_j)_m \cdot \phi_2(x_j)_{m_2}) \\
 &= \phi(x_i) \phi(x_j)
 \end{aligned}$$

where $\phi(x) = \begin{pmatrix} \phi_1(x)_1 \cdot \phi_2(x)_1 \\ \vdots \\ \phi_1(x)_{M_1} \cdot \phi_2(x)_{M_2} \end{pmatrix}$

$$e) \quad \cancel{k(x_i, x_j)} = \cancel{\phi_1(x_i)^T \phi_1(x_j)} \cdot \cancel{k_1(x_i, x_j)} \stackrel{p(d)}{=} \cancel{(\phi(x_i)^T \cdot \phi(x_j))} \stackrel{p}{=}$$

$$c) \quad k(x_i, x_j) = \sum_{l=1}^d w_l k_l(x_i, x_j)$$

Proof by deduction:

For $d \in \mathbb{N}^+$, (i) $d=1$, $k(x_i, x_j) = w_1 k_1(x_i, x_j)$
is a valid kernel (a)

(ii) Assume $d=n$ gives a valid kernel $\sum_{l=1}^n w_l k_l(x_i, x_j)$

Then $d=n+1$

$$k(x_i, x_j) = \sum_{l=1}^{n+1} w_l k_l(x_i, x_j) = \sum_{l=1}^n w_l k_l(x_i, x_j) + w_{n+1} k_{n+1}(x_i, x_j)$$

is a valid kernel. (b) #

$$e) \quad k(x_i, x_j) = (k_1(x_i, x_j))^p$$

Proof by deduction:

For $p \in \mathbb{N}^+$, $p=1$, $k(x_i, x_j) = k_1(x_i, x_j)$ is valid.

Assume $p=n$ gives a valid kernel $k_1(x_i, x_j)$

then for $p=n+1$ $k(x_i, x_j) = (k_1(x_i, x_j))^{n+1} = (k_1(x_i, x_j))^n \cdot k_1(x_i, x_j)$
is a valid kernel (d)