

Exercise SHEET 4

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Problem 1

- a) Let's consider the case where x_1 and x_2 are jointly Gaussian with

$$E[(x_1, x_2)] = (\bar{x}_1, \bar{x}_2) \quad \text{and}$$

$$\text{Var}[(x_1, x_2)] = \begin{pmatrix} \sigma_1^2 & c \\ c & \sigma_2^2 \end{pmatrix} \quad \text{where } c = \text{covariance}$$

$$\therefore c = \text{Cov}[x_1, x_2] = E[x_1 x_2] - E[x_1]E[x_2]$$

Now, considering the square of the L^2 -Wasserstein distance for the sake of simplicity:

$$(W_2(\pi x_1, \pi x_2))^2 = \inf_c E[(x_1 - x_2)^2]$$

$$= \inf_c E[x_1^2 - 2x_1 x_2 + x_2^2] \quad \text{--- ①}$$

$$\text{We know, } \text{Var}(x) = E[x^2] - (E[x])^2$$

$$\therefore E[x^2] = (E[x])^2 + \text{Var}(x) = \bar{x}_1^2 + \sigma_1^2$$

$$\therefore E[x_1^2] = \bar{x}_1^2 + \sigma_1^2 \quad \left| \begin{array}{l} c = E[x_1 x_2] - E[x_1]E[x_2] \\ \therefore E[x_1 x_2] = c + \bar{x}_1 \bar{x}_2 \end{array} \right.$$

$$\text{and } E[x_2^2] = \bar{x}_2^2 + \sigma_2^2$$

$$\text{From ①} \Rightarrow (W_2(\pi x_1, \pi x_2))^2 = \inf_c (\bar{x}_1^2 + \sigma_1^2 - \cancel{2c} + (\bar{x}_2^2 + \sigma_2^2) - \cancel{2(c + \bar{x}_1 \bar{x}_2)})$$

$$= \inf_c (\bar{x}_1 - \bar{x}_2)^2 + \sigma_1^2 + \sigma_2^2 - 2c$$

The maximum eligible value of c is given by the Cauchy-Schwarz inequality:

$$(\text{Cov}[x_1, x_2])^2 \leq \text{Var}[x_1] \text{Var}[x_2] \Rightarrow c \leq \sigma_1 \sigma_2$$

Therefore,

$$\begin{aligned} (W_2(\pi x_1, \pi x_2))^2 &= (\bar{x}_1 - \bar{x}_2)^2 + \sigma_1^2 + \sigma_2^2 - 2\sigma_1 \sigma_2 \\ &= (\bar{x}_1 - \bar{x}_2)^2 + (\sigma_1 - \sigma_2)^2 \end{aligned}$$

(b) The Kullback-Leibler (KL) divergence of πx_1 from πx_2 is given by:

$$D_{KL}(\pi x_1 \parallel \pi x_2) := \int_{\mathcal{R}} \log \left(\frac{\pi x_1(x)}{\pi x_2(x)} \right) \pi x_1(x) dx$$

$$= \int_{\mathcal{R}} [\log \pi x_1(x) - \log \pi x_2(x)] \pi x_1(x) dx \quad \text{--- (1)}$$

For Gaussian distribution, PDF

$$\pi X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left(-\frac{(x-\bar{x})^2}{2\sigma^2} \right)$$

Substituting the formula for the KL divergence gives:

$$D_{KL}(\pi x_1 \parallel \pi x_2) = \int_{\mathcal{R}}$$

Taking logarithm on both sides, we get,

$$\begin{aligned} \log \pi X(x) &= \log \left(\frac{1}{\sqrt{2\pi\sigma^2}} \exp \left(-\frac{(x-\bar{x})^2}{2\sigma^2} \right) \right) \\ &= \log \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right) + \log \left(\exp \left(-\frac{(x-\bar{x})^2}{2\sigma^2} \right) \right) \\ &= -\frac{1}{2} \log(2\pi\sigma^2) - \frac{(x-\bar{x})^2}{2\sigma^2} \end{aligned}$$

$$\begin{aligned} \text{So, (1)} \Rightarrow \int_{\mathcal{R}} \left[-\frac{1}{2} \log(2\pi\sigma_1^2) - \frac{(x_1 - \bar{x}_1)^2}{2\sigma_1^2} + \frac{1}{2} \log(2\pi\sigma_2^2) + \frac{(x_1 - \bar{x}_2)^2}{2\sigma_2^2} \right] \pi x_1(x) dx \\ = \mathbb{E} \left[\frac{1}{2} \log \frac{\sigma_2^2}{\sigma_1^2} - \frac{1}{2\sigma_1^2} (x_1 - \bar{x}_1)^2 + \frac{1}{2\sigma_2^2} (x_1 - \bar{x}_2)^2 \right] \end{aligned}$$

Here, the first term is constant, and the second term is the variance of X_1 , that is,

$$\frac{1}{2\sigma_1^2} \mathbb{E}[(X_1 - \bar{x}_1)^2] = \frac{1}{2\sigma_1^2} \cdot \sigma_1^2 = \frac{1}{2}$$

For the third term,

$$\begin{aligned} \mathbb{E}[(X_1 - \bar{x}_2)^2] &= \mathbb{E}[X_1^2 - 2\bar{x}_2 X_1 + \bar{x}_2^2] \\ &= (\sigma_1^2 + \bar{x}_1^2) - 2\bar{x}_1 \bar{x}_2 + \bar{x}_2^2 \\ &= \sigma_1^2 + (\bar{x}_1 - \bar{x}_2)^2 \end{aligned}$$

Collecting all three terms, we conclude that,

$$\begin{aligned} D_{KL}(\pi x_1 \parallel \pi x_2) &= \frac{1}{2} \left[\log \frac{\sigma_2^2}{\sigma_1^2} + \frac{\sigma_1^2 + (\bar{x}_1 - \bar{x}_2)^2}{\sigma_2^2} - 1 \right] \\ &= \frac{1}{2} \left[\log \frac{\sigma_2^2}{\sigma_1^2} + \frac{\sigma_1^2}{\sigma_2^2} + \frac{(\bar{x}_1 - \bar{x}_2)^2}{\sigma_2^2} - 1 \right] \end{aligned}$$

Note that this value becomes zero,

$$\text{if } \bar{x}_1 = \bar{x}_2 \text{ and } \sigma_1^2 = \sigma_2^2$$