

# Exercise sheet 6

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12:41

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Task 1. Kullback-Leibler divergence of two multivariate normal distributions  
The Kullback-Leibler divergence of two continuous distributions  $P$  and  $Q$  is defined as:

$$KL(P \parallel Q) = \int_{-\infty}^{\infty} p(x) \log \frac{p(x)}{q(x)} dx.$$

Compute it analytically in the case where  $P$  and  $Q$  are two multivariate normal distributions  $P = N(\mu_1, \Sigma_1)$  and  $Q = N(\mu_2, \Sigma_2)$ . Derive the Kullback-Leibler-divergence for two distinct normal distribution.

$$\textcircled{1} p, q(x) = \frac{1}{\sqrt{(2\pi)^M |\Sigma_{1,2}|}} \exp\left[-\frac{1}{2} (x - \mu_{1,2})^T \Sigma_{1,2}^{-1} (x - \mu_{1,2})\right] \quad \text{with } x, \mu_1, \mu_2 \in \mathbb{R}^M, \Sigma_{1,2} \in \mathbb{R}^{M \times M}$$

$$\begin{aligned} KL[P \parallel Q] &= \int p(x) [\log p(x) - \log q(x)] dx \\ &= \int p(x) \left[ -\frac{M}{2} \log 2\pi - \frac{1}{2} \log |\Sigma_1| - \frac{1}{2} (x - \mu_1)^T \Sigma_1^{-1} (x - \mu_1) \right. \\ &\quad \left. + \frac{M}{2} \log 2\pi + \frac{1}{2} \log |\Sigma_2| + \frac{1}{2} (x - \mu_2)^T \Sigma_2^{-1} (x - \mu_2) \right] dx \end{aligned}$$

$$\begin{aligned} x^T A y &= \text{tr}(A y x^T) = \int p(x) \left[ \frac{1}{2} \log \frac{|\Sigma_2|}{|\Sigma_1|} - \frac{1}{2} (x - \mu_1)^T \Sigma_1^{-1} (x - \mu_1) + \frac{1}{2} (x - \mu_2)^T \Sigma_2^{-1} (x - \mu_2) \right] dx \\ &= \frac{1}{2} \log \frac{|\Sigma_2|}{|\Sigma_1|} - \frac{1}{2} \int p(x) (x - \mu_1)^T \Sigma_1^{-1} (x - \mu_1) dx + \frac{1}{2} \int p(x) (x - \mu_2)^T \Sigma_2^{-1} (x - \mu_2) dx \\ &= \frac{1}{2} \log \frac{|\Sigma_2|}{|\Sigma_1|} - \frac{1}{2} \int p(x) \text{tr} \left[ \Sigma_1^{-1} (x - \mu_1) (x - \mu_1)^T \right] dx + \frac{1}{2} \int p(x) (x - \mu_2)^T \Sigma_2^{-1} (x - \mu_2) dx \\ &= \frac{1}{2} \log \frac{|\Sigma_2|}{|\Sigma_1|} - \frac{1}{2} \text{tr} \left( \Sigma_1^{-1} \mathbb{E}_p[(x - \mu_1) (x - \mu_1)^T] \right) + \frac{1}{2} \mathbb{E}_p[(x - \mu_2)^T \Sigma_2^{-1} (x - \mu_2)] \\ &\quad \begin{cases} \bullet \mathbb{E}_p[(x - \mu_1) (x - \mu_1)^T] = \Sigma_1 & \text{Matrix Cookbook} \\ \bullet \mathbb{E}_p[(x - \mu_2)^T \Sigma_2^{-1} (x - \mu_2)] \stackrel{(\text{3.80})}{=} (\mu_1 - \mu_2)^T \Sigma_2^{-1} (\mu_1 - \mu_2) + \text{tr}(\Sigma_2^{-1} \Sigma_1) \end{cases} \\ &= \frac{1}{2} \left[ \log \frac{|\Sigma_2|}{|\Sigma_1|} - \underbrace{\text{tr}(\Sigma_1^{-1} \cdot \Sigma_1)}_{=\text{tr}(1_M) = M} + (\mu_1 - \mu_2)^T \Sigma_2^{-1} (\mu_1 - \mu_2) + \frac{1}{2} \text{tr}(\Sigma_2^{-1} \Sigma_1) \right] \\ &= \frac{1}{2} \left[ \log \frac{|\Sigma_2|}{|\Sigma_1|} - M + (\mu_1 - \mu_2)^T \Sigma_2^{-1} (\mu_1 - \mu_2) + \text{tr}(\Sigma_2^{-1} \Sigma_1) \right] // \end{aligned}$$