

1. Since Σ is positive definite, there exists a matrix A such that $\Sigma = A A^T$

$$\text{Let } y = A^{-1}(x - \mu)$$

$$\text{Then } (x - \mu)^T \Sigma^{-1} (x - \mu) = (A y)^T (A A^T)^{-1} (A y) = y^T y = \|y\|^2$$

$$dx = |\det A| dy$$

$$\text{Thus } \int_{\mathbb{R}^k} f(x) dx = \frac{1}{\sqrt{(2\pi)^k |\Sigma|}} \int_{\mathbb{R}^k} e^{-\frac{1}{2} \|y\|^2} |\det A| dy$$

$$\text{By Gaussian integral, } \int_{\mathbb{R}^k} e^{-\frac{1}{2} \|y\|^2} dy = \sqrt{(2\pi)^k}$$

$$\Rightarrow \int_{\mathbb{R}^k} f(x) dx = \frac{1}{\sqrt{(2\pi)^k |\Sigma|}} \times \sqrt{(2\pi)^k} \times |\Sigma|^{-\frac{1}{2}} = 1$$

$$2. (a) \operatorname{tr}(AB) = \sum_{i=1}^n (AB)_{ii} = \sum_{i=1}^n \sum_{j=1}^m A_{ij} B_{ji}$$

$$\frac{\partial}{\partial A_{xy}} \operatorname{tr}(AB) = \frac{\partial}{\partial A_{xy}} \sum_{i,j} A_{ij} B_{ji} = \frac{\partial}{\partial A_{xy}} A_{xy} B_{yx} = B_{yx}$$

$$\text{So } \frac{\partial}{\partial A} \operatorname{tr}(AB) = B^T$$

$$(b) x^T A x \in \mathbb{R}$$

$$= \operatorname{tr}(x^T A x)$$

$$\text{Since } \operatorname{tr}(AB) = \operatorname{tr}(BA), \text{ for all } A \in \mathbb{R}^{n \times n} \text{ } B \in \mathbb{R}^{n \times m}$$

$$\operatorname{tr}(x^T A x) = \operatorname{tr}(x x^T A)$$

(c) Let
$$L(\mu, \Sigma) = \prod_{i=1}^N \frac{1}{\sqrt{(2\pi)^K |\Sigma|}} e^{-\frac{1}{2}(\mathbf{x}_i - \mu)^T \Sigma^{-1} (\mathbf{x}_i - \mu)}$$

$$\theta = (\mu, \Sigma)$$

$$\theta^* = \underset{\theta}{\operatorname{argmax}} L(\theta) = \underset{\theta}{\operatorname{argmax}} \ln L(\theta)$$

$$\ln L(\theta) = -\frac{N}{2} \ln((2\pi)^K |\Sigma|) - \frac{1}{2} \sum_{i=1}^N (\mathbf{x}_i - \mu)^T \Sigma^{-1} (\mathbf{x}_i - \mu) = \ln(\mu, \Sigma)$$

By (a)-(b)

$$\begin{aligned} \frac{\partial \ln L}{\partial \mu} &= \frac{\partial}{\partial \mu} \left(-\frac{1}{2} \sum_i (\mathbf{x}_i - \mu)^T \Sigma^{-1} (\mathbf{x}_i - \mu) \right) = \frac{\partial}{\partial \mu} \operatorname{tr}((\mathbf{x}_i - \mu)(\mathbf{x}_i - \mu)^T \Sigma^{-1}) \\ &= \frac{1}{2} \Sigma^{-1} \sum_{i=1}^N (\mathbf{x}_i - \mu) = 0 \end{aligned}$$

$$\Rightarrow \mu^* = \frac{1}{N} \sum_{i=1}^N \mathbf{x}_i$$

$$\frac{\partial \ln L}{\partial \Sigma} = -\frac{N}{2} \Sigma^{-1} + \frac{1}{2} \Sigma^{-1} \sum_{i=1}^N (\mathbf{x}_i - \mu)(\mathbf{x}_i - \mu)^T \Sigma^{-1} = 0$$

$$\Rightarrow \Sigma^* = \frac{1}{N} \sum_{i=1}^N (\mathbf{x}_i - \mu)(\mathbf{x}_i - \mu)^T$$

3. What's the use of cross entropy loss, compare with MSE.