

2. (a)

$$\text{Let } A = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ \vdots & \ddots & & \vdots \\ a_{n1} & & & a_{nn} \end{pmatrix} \quad B = \begin{pmatrix} b_{11} & b_{12} & \dots & b_{1n} \\ \vdots & \ddots & & \vdots \\ b_{n1} & & & b_{nn} \end{pmatrix}$$

$$\Rightarrow \text{tr}(AB) = \text{tr} \begin{pmatrix} \sum_{j=1}^n a_{1j} b_{j1} & & & \\ & \sum_{j=1}^n a_{2j} b_{j2} & & \\ & & \ddots & \\ \vdots & & & \sum_{j=1}^n a_{nj} b_{jn} \end{pmatrix}$$

$$= \sum_{k=1}^n \left(\sum_{j=1}^n a_{kj} b_{jk} \right)$$

$$\therefore \frac{\partial}{\partial A} \text{tr}(AB) = \frac{\partial}{\partial A} \left(\sum_{k=1}^n \sum_{j=1}^n a_{kj} b_{jk} \right)$$

$$= \begin{pmatrix} \frac{\partial s}{\partial a_{11}} & \frac{\partial s}{\partial a_{12}} & \dots & \frac{\partial s}{\partial a_{1n}} \\ \vdots & & & \\ \frac{\partial s}{\partial a_{n1}} & & & \frac{\partial s}{\partial a_{nn}} \end{pmatrix}$$

$$\text{where } s := \sum_{k=1}^n \sum_{j=1}^n a_{kj} b_{jk}$$

$$= \begin{pmatrix} b_{11} & b_{21} & b_{31} & \dots & b_{n1} \\ \vdots & & & & \\ \vdots & & & & \\ b_{1n} & & & & b_{nn} \end{pmatrix}$$

$$= B^T$$

2. (b)

Let $x = (x_1, x_2, \dots, x_n)^t$ A is similar to (a)

$$\Rightarrow x^T A x = x^T (A x)$$

$$= x^T \begin{pmatrix} \sum_{j=1}^n a_{1j} x_j \\ \sum_{j=1}^n a_{2j} x_j \\ \vdots \\ \sum_{j=1}^n a_{nj} x_j \end{pmatrix}$$

$$= (x_1, x_2, \dots, x_n) \begin{pmatrix} \sum_{j=1}^n a_{1j} x_j \\ \sum_{j=1}^n a_{2j} x_j \\ \vdots \\ \sum_{j=1}^n a_{nj} x_j \end{pmatrix}$$

$$= x_1 \cdot \sum_{j=1}^n a_{1j} x_j + x_2 \cdot \sum_{j=1}^n a_{2j} x_j + \dots + x_n \sum_{j=1}^n a_{nj} x_j$$

$$= \sum_{k=1}^n \sum_{j=1}^n x_k a_{kj} x_j$$

$$\text{and } \text{tr}(x x^T A) = \text{tr} \left(\begin{pmatrix} x_1 x_1 & x_1 x_2 & \dots & x_1 x_n \\ \vdots & & \ddots & \\ x_n x_1 & & & x_n x_n \end{pmatrix} A \right)$$

$$= \text{tr} \begin{pmatrix} x_1 \cdot \sum_{k=1}^n x_k a_{k1} & \dots \\ \vdots & \ddots & \\ x_n \sum_{k=1}^n x_k a_{kn} \end{pmatrix}$$

$$= \sum_{j=1}^n x_j \sum_{k=1}^n a_{kj} x_k = \sum_{j=1}^n \sum_{k=1}^n x_j a_{kj} x_k$$

$$= \sum_{j=1}^n \sum_{k=1}^n x_k a_{kj} x_j = \sum_{k=1}^n \sum_{j=1}^n x_k a_{kj} x_j$$

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

2(c)

Let $x_1, x_2, \dots, x_m \in \mathbb{R}^k$ be i.i.d. sample from $x_i \sim \mathcal{N}(\mu, \Sigma)$

where $\mu \in \mathbb{R}^k$ is mean $\Sigma \in \mathbb{R}^{k \times k}$ is covariance matrix

and the p.d.f is $f(x) = \frac{1}{\sqrt{(2\pi)^k |\Sigma|}} \exp\left\{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)\right\}$

\therefore The likelihood function is

$$\begin{aligned} L(\mu, \Sigma) &= \prod_{i=1}^m \frac{1}{\sqrt{(2\pi)^k |\Sigma|}} \exp\left\{-\frac{1}{2}(x_i - \mu)^T \Sigma^{-1}(x_i - \mu)\right\} \\ &= \left[(2\pi)^k |\Sigma|\right]^{-\frac{m}{2}} \cdot \exp\left\{\sum_{i=1}^m \left[-\frac{1}{2}(x_i - \mu)^T \Sigma^{-1}(x_i - \mu)\right]\right\} \end{aligned}$$

$$\begin{aligned} \Rightarrow \ln(L) &= -\frac{m}{2} (\log(2\pi)^k + \log|\Sigma|) + \sum_{i=1}^m \left[-\frac{1}{2}(x_i - \mu)^T \Sigma^{-1}(x_i - \mu)\right] \\ &= -\frac{mk}{2} \log 2\pi - \frac{m}{2} \log |\Sigma| - \frac{1}{2} \sum_{i=1}^m (x_i - \mu)^T \Sigma^{-1}(x_i - \mu) \end{aligned}$$

Find $\hat{\mu}$

$$\text{Let } \frac{\partial}{\partial \mu} (\ln(L)) = 0$$

$$\Rightarrow -\sum_{i=1}^m \Sigma^{-1}(x_i - \mu) = 0$$

$$\Rightarrow \sum_{i=1}^m (x_i - \mu) = 0$$

$$\Rightarrow \hat{\mu} = \frac{1}{m} \sum_{i=1}^m x_i$$

Find $\hat{\Sigma}$

$$\ln(L) = -\frac{mk}{2} \log 2\pi - \frac{m}{2} \log |\Sigma| - \frac{1}{2} \sum_{i=1}^m (x_i - \mu)^T \Sigma^{-1}(x_i - \mu)$$

$$\stackrel{\text{by (b)}}{=} C - \frac{m}{2} \log |\Sigma| - \frac{1}{2} \text{tr}\left(\sum_{i=1}^m (x_i - \mu)(x_i - \mu)^T \Sigma^{-1}\right), \quad C \in \mathbb{R}$$

$$\begin{aligned}
 \therefore \frac{\partial}{\partial \Sigma} (\ln(L)) &= \frac{\partial}{\partial \Sigma} \left(-\frac{m}{2} \log |\Sigma| \right) - \frac{1}{2} \frac{\partial}{\partial \Sigma} \left(\text{tr} \left(\sum_{i=1}^m (x - \mu)(x - \mu)^T \Sigma^{-1} \right) \right) \\
 &\stackrel{\text{by (a)}}{=} -\frac{m}{2} (\Sigma^{-1})^T + \frac{1}{2} \Sigma^{-1} \sum_{i=1}^m (x - \mu)(x - \mu)^T \Sigma^{-1} \\
 &= -\frac{m}{2} \Sigma^{-1} + \frac{1}{2} \Sigma^{-1} \sum_{i=1}^m (x - \mu)(x - \mu)^T \Sigma^{-1}
 \end{aligned}$$

$$\text{Let } \frac{\partial}{\partial \Sigma} (\ln(L)) = 0$$

$$\Rightarrow -\frac{m}{2} \Sigma^{-1} + \frac{1}{2} \Sigma^{-1} \sum_{i=1}^m (x - \mu)(x - \mu)^T \Sigma^{-1} = 0$$

$$\Rightarrow \sum_{i=1}^m (x - \mu)(x - \mu)^T = m \cdot \Sigma$$

$$\therefore \hat{\Sigma} = \frac{1}{m} \sum_{i=1}^m (x - \mu)(x - \mu)^T$$

3,

GDA 假設條件為高斯分布，但若資料不屬於高斯分布的話，模型會如何變化？