

ASSIGNMENT: 01 (RMJ916)

$$1) P(x|y=i) = N(x|\mu_i, \Sigma)$$

→ Standard Normal distribution

$$N(x|\mu_i, \Sigma) \rightarrow \mu_i \rightarrow \text{mean, Variance} = \Sigma$$

$$= \frac{1}{\sqrt{2\pi\Sigma}} e^{-\frac{(x-\mu_i)^2}{2\Sigma}}$$

$$\therefore N(x|\mu_i, \Sigma) = \frac{1}{\sqrt{2\pi\Sigma}} e^{-\frac{(x-\mu_i)^2}{2\Sigma}}$$

$$\rightarrow a_i = \ln[P(x|y=i)P(y=i)]$$

here we putting value $P(x|y=i) = N(x|\mu_i, \Sigma)$

$$a_i = \ln[N(x|\mu_i, \Sigma)P(y=i)]$$

$$= \ln[(2\pi\Sigma)^{-\frac{1}{2}} \exp\{-\frac{1}{2}(x-\mu_i)^T \Sigma^{-1} (x-\mu_i)\} * P(y=i)]$$

$$= \ln(2\pi\Sigma)^{-\frac{1}{2}} + \ln[\exp\{-\frac{1}{2}(x-\mu_i)^T \Sigma^{-1} (x-\mu_i)\}] + \ln[P(y=i)]$$

$$= \ln(2\pi)^{\frac{d}{2}} (\Sigma)^{-\frac{1}{2}} + \{-\frac{1}{2}(x-\mu_i)^T \Sigma^{-1} (x-\mu_i)\} + \ln[P(y=i)]$$

$$= \ln(2\pi)^{\frac{d}{2}} (\Sigma)^{-\frac{1}{2}} - \frac{1}{2\Sigma} [x^T x - 2x \cdot \mu_i + \mu_i^T \mu_i] + \ln[P(y=i)]$$

($\because (x-y)^2 = x^2 - 2xy + y^2$)

$$= \ln(2\pi)^{\frac{d}{2}} (\Sigma)^{-\frac{1}{2}} - \frac{1}{2\Sigma} x^T x + \frac{2}{2\Sigma} x \mu_i - \frac{1}{2\Sigma} \mu_i^T \mu_i + \ln[P(y=i)]$$

$$= -\frac{1}{2\Sigma} x^T x + \frac{(\mu_i x)}{\Sigma} + \ln(2\pi)^{\frac{d}{2}} (\Sigma)^{-\frac{1}{2}} - \frac{1}{2\Sigma} \mu_i^T \mu_i + \ln[P(y=i)]$$

$$\therefore w^T = \frac{\mu_i}{\Sigma}$$

$$\text{So, } a_i = -\frac{1}{2\Sigma} x^T x + (w^i)^T x + b_i$$

$$\therefore b_i = -\frac{1}{2\Sigma} \mu_i^T \mu_i + \ln[P(y=i)] + \ln((2\pi)^{\frac{d}{2}} \Sigma)^{-\frac{1}{2}}$$

So, now we have as a chapter 8

$$p(y=i|x) = \frac{\exp(a_i)}{\sum_j \exp(a_j)}$$

$$= \frac{\exp\left\{-\frac{1}{2\varepsilon} x^T x + (\omega^i)^T x + b_i\right\}}{\sum_j \exp\left(-\frac{1}{2\varepsilon} x^T x + (\omega^j)^T x + b_j\right)}$$

$$= \frac{\exp\left(-\frac{1}{2\varepsilon} x^T x\right) \cdot \exp\left((\omega^i)^T x + b_i\right)}{\sum_j \exp\left(-\frac{1}{2\varepsilon} x^T x\right) \cdot \exp\left((\omega^j)^T x + b_j\right)}$$

$$= \frac{\exp\left(-\frac{1}{2\varepsilon} x^T x\right) \cdot \exp\left((\omega^i)^T x + b_i\right)}{\exp\left(-\frac{1}{2\varepsilon} x^T x\right) \cdot \sum_j \exp\left((\omega^j)^T x + b_j\right)}$$

(...cancel out
the $-\frac{1}{2\varepsilon} x^T x$)

$$= \frac{\exp\left((\omega^i)^T x + b_i\right)}{\sum_j \exp\left((\omega^j)^T x + b_j\right)}$$

$$\therefore a_i = (\omega^i)^T x + b_i$$

→ Here, in this equation x is linear. So,

$$p(x|y=i) = \mathcal{N}(x|\mu_i, \Sigma)$$

compute
 $a_i = \ln[p(x|y=i)P(y=i)]$

is linear.

→ But, if $p(x|y=i)$ has different covariance

$$\text{as, } p(x|y=i) = \mathcal{N}(x|\mu_i, \Sigma_i)$$

it is not linear

That time Σ_i value is different we can't cancel it
and we can not say that it is constant as
linear so, it is not linear.
See explanation in below,

$$\rightarrow N(x|\mu_i, \Sigma_i) = \frac{1}{\sqrt{2\pi\Sigma_i}} e^{-\frac{(x-\mu_i)^2}{2\Sigma_i}}$$

$$\rightarrow w^T = \frac{\mu_i}{\Sigma_i} \quad \& \quad b_i = -\frac{1}{2\Sigma_i} \mu_i^T \mu_i + \ln(p(y=i)) + \ln \frac{1}{(2\pi)^{d/2} (\Sigma_i)^{1/2}}$$

so, now we have put value

$$\begin{aligned} p(y=i|x) &= \frac{\exp(a_i)}{\sum_j \exp(a_j)} \\ &= \frac{\exp\left(-\frac{1}{2\Sigma_i} x^T x + (w^i)^T x + b^i\right)}{\sum_j \exp\left(-\frac{1}{2\Sigma_j} x^T x + (w^j)^T x + b^j\right)} \end{aligned}$$

we cannot cancel out $-\frac{1}{2\Sigma_i} x^T x$

so, α_i is not linear.