

Problem Ex.1

$$\begin{aligned}
\hat{y}(x) &= \underset{k}{\operatorname{argmax}} P(Y = k|x) \\
&= \underset{k}{\operatorname{argmax}} f_k(x)\pi_k \\
&= \underset{k}{\operatorname{argmax}} \log f_k(x) + \log \pi_k \\
\log f_k(x) &= -\frac{1}{2}(x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) - \frac{p}{2} \log 2\pi - \frac{1}{2} \log |\Sigma_k| \\
&= x^T \Sigma_k^{-1} \mu_k - \frac{1}{2} \mu_k^T \Sigma_k^{-1} \mu_k - \frac{1}{2} (\log |\Sigma_k| + p \log 2\pi + x^T \Sigma_k^{-1} x)
\end{aligned}$$

Noticed that Σ_k is constant for each k in LDA, so

$$\hat{y}(x) = \underset{k}{\operatorname{argmax}} (\log \pi_k + x^T \Sigma_k^{-1} \mu_k - \frac{1}{2} \mu_k^T \Sigma_k^{-1} \mu_k)$$

Problem Ex.2

(1).LDA classifies to class 2 if and only if $\log \frac{f_2(x)\pi_2}{f_1(x)\pi_1} > 0$.

$$\begin{aligned}
\log \frac{f_2(x)\pi_2}{f_1(x)\pi_1} &= \log \frac{N_2}{N_1} + x^T \Sigma^{-1} (\hat{\mu}_2 - \hat{\mu}_1) - \frac{1}{2} (\hat{\mu}_2^T \Sigma^{-1} \hat{\mu}_2 - \hat{\mu}_1^T \Sigma^{-1} \hat{\mu}_1) \\
&= \log \frac{N_2}{N_1} + x^T \Sigma^{-1} (\hat{\mu}_2 - \hat{\mu}_1) - \frac{1}{2} (\hat{\mu}_2 + \hat{\mu}_1)^T \Sigma^{-1} (\hat{\mu}_2 - \hat{\mu}_1)
\end{aligned}$$

So the LDA rules classifies x to class 2 when

$$x^T \Sigma^{-1} (\hat{\mu}_2 - \hat{\mu}_1) > \frac{1}{2} (\hat{\mu}_2 + \hat{\mu}_1)^T \Sigma^{-1} (\hat{\mu}_2 - \hat{\mu}_1) - \log N_2/N_1$$

(2).In this particular case,

$$\begin{aligned}
\nabla_{\beta_0} &= -2 \sum_{i=1}^N (y_i - \beta_0 - x_i^T \beta) = 0 \\
\beta_0 &= \frac{1}{N} \sum_{i=1}^N (y_i - x_i^T \beta) \\
\nabla_{\beta} &= -2 \sum_{i=1}^N (y_i - \beta_0 - x_i^T \beta) x_i = 0 \\
\beta_0 \sum_{i=1}^N x_i + \beta^T \sum_{i=1}^N x_i x_i^T &= \sum_{i=1}^N y_i x_i
\end{aligned}$$

Noticed that,

$$\sum_{i=1}^N y_i = -N_1 \frac{N}{N_1} + N_2 \frac{N}{N_2} = 0$$

$$\left(\sum_{i=1}^N x_i^T \right) \beta = \beta^T (N_1 \hat{\mu}_1 + N_2 \hat{\mu}_2)$$

So $\beta_0 = -\frac{1}{N} \beta^T (N_1 \hat{\mu}_1 + N_2 \hat{\mu}_2)$. At one hand,

$$\begin{aligned} \sum_{i=1}^N y_i x_i &= -\frac{N}{N_1} N_1 \hat{\mu}_1 + \frac{N}{N_2} N_2 \hat{\mu}_2 = N(\hat{\mu}_2 - \hat{\mu}_1) \\ \sum_{i=1}^N \beta_0 x_i &= -\frac{1}{N} \beta^T (N_1 \hat{\mu}_1 + N_2 \hat{\mu}_2) (N_1 \hat{\mu}_1 + N_2 \hat{\mu}_2)^T \\ &= -\frac{1}{N} \beta^T (N_1^2 \hat{\mu}_1 \hat{\mu}_1^T + N_2^2 \hat{\mu}_2 \hat{\mu}_2^T + N_1 N_2 \hat{\mu}_1 \hat{\mu}_2^T + N_1 N_2 \hat{\mu}_2 \hat{\mu}_1^T) \end{aligned}$$

So we got that:

$$\beta_0 \sum_{i=1}^N x_i + \beta^T \sum_{i=1}^N x_i x_i^T = \left(\sum_{i=1}^N x_i x_i^T - \frac{N_1^2}{N} \hat{\mu}_1 \hat{\mu}_1^T - \frac{N_2^2}{N} \hat{\mu}_2 \hat{\mu}_2^T - \frac{N_1 N_2}{N} \hat{\mu}_1 \hat{\mu}_2^T + \frac{N_1 N_2}{N} \hat{\mu}_2 \hat{\mu}_1^T \right) \beta$$

At the other hand,

$$\begin{aligned} (N-2)\Sigma &= \sum_{x \in C_1} (x - \hat{\mu}_1)(x - \hat{\mu}_1)^T + \sum_{x \in C_2} (x - \hat{\mu}_2)(x - \hat{\mu}_2)^T \\ &= \sum_{i=1}^N x_i x_i^T - N_1 \hat{\mu}_1 \hat{\mu}_1^T - N_2 \hat{\mu}_2 \hat{\mu}_2^T \\ N\Sigma_B &= \frac{N_1 N_2}{N} (\hat{\mu}_1 - \hat{\mu}_2)(\hat{\mu}_1 - \hat{\mu}_2)^T \\ &= \frac{N_1 N_2}{N} (\hat{\mu}_1 \hat{\mu}_1^T + \hat{\mu}_2 \hat{\mu}_2^T - \hat{\mu}_1 \hat{\mu}_2^T - \hat{\mu}_2 \hat{\mu}_1^T) \end{aligned}$$

Noticed that $N = N_1 + N_2$, now we got:

$$\begin{aligned} (N-2)\Sigma + N\Sigma_B &= \sum_{i=1}^N x_i x_i^T - \frac{N_1^2}{N} \hat{\mu}_1 \hat{\mu}_1^T - \frac{N_2^2}{N} \hat{\mu}_2 \hat{\mu}_2^T - \frac{N_1 N_2}{N} \hat{\mu}_1 \hat{\mu}_2^T + \frac{N_1 N_2}{N} \hat{\mu}_2 \hat{\mu}_1^T \\ (N-2)\Sigma + N\Sigma_B &= \beta_0 \sum_{i=1}^N x_i + \beta^T \sum_{i=1}^N x_i x_i^T \end{aligned}$$

So,

$$((N-2)\Sigma + N\Sigma_B)\beta = N(\hat{\mu}_2 - \hat{\mu}_1) \quad (1)$$

(3). Noticed that $(\hat{\mu}_1 - \hat{\mu}_2)^T \beta \in \mathbb{R}$.

$$\Sigma_B \beta = \frac{N_1 N_2}{N^2} (\hat{\mu}_1 - \hat{\mu}_2) [(\hat{\mu}_1 - \hat{\mu}_2)^T \beta]$$

So $\Sigma_B \beta$ is in the direction of $\hat{\mu}_1 - \hat{\mu}_2$. From (1), we conclude that $\Sigma \beta \propto (\hat{\mu}_2 - \hat{\mu}_1)$.

Problem Ex.3

Let A denotes that the patient has flu, B denotes he/she has a fever and C denotes cough. Considering the circumstance, there should be $B \subset A$ and $C \subset A$.

$$\begin{aligned}P(B|A) &= \frac{P(B)}{P(A)} = 0.5 \\P(BC|A) &= \frac{P(BC)}{P(A)} = 0.25 \\P(B) &= P(C) = 0.25, P(BC) = 0.125 \\Corr(B, C) &= \frac{P(BC) - P(B)P(C)}{\sqrt{P(B)P(\bar{B})P(C)P(\bar{C})}} \\&= \frac{1}{3}\end{aligned}$$