

Exercise 01

1.

(a)

Let $g_A(\mathbf{x}) = g_B(\mathbf{x})$, we have:

$$\log(p(\mathbf{x}|y = A)) + \log \pi_A = \log(p(\mathbf{x}|y = B)) + \log \pi_B.$$

Thus,

$$(\mathbf{x} - \mu_A)^T \Sigma_A^{-1} (\mathbf{x} - \mu_A) + \log \pi_A = (\mathbf{x} - \mu_B)^T \Sigma_B^{-1} (\mathbf{x} - \mu_B) + \log \pi_B.$$

Expanding both sides gives,

$$\begin{aligned} & \mathbf{x}^T (\Sigma_A^{-1} - \Sigma_B^{-1}) \mathbf{x} - 2\mathbf{x}^T \Sigma_A^{-1} \mu_A + 2\mathbf{x}^T \Sigma_B^{-1} \mu_B \\ & + (\mu_A^T \Sigma_A^{-1} \mu_A - \mu_B^T \Sigma_B^{-1} \mu_B) \\ & + \log |\Sigma_0| - \log |\Sigma_1| + \log \pi_A - \log \pi_B = 0. \end{aligned}$$

Comparing the equation above with what is given in (a) gives:

$$\begin{aligned} \Lambda &= (\Sigma_A^{-1} - \Sigma_B^{-1}), \\ \omega^T &= -2(\mu_A^T \Sigma_A^{-1} - \mu_B^T \Sigma_B^{-1}), \\ b &= \mu_A^T \Sigma_A^{-1} \mu_A - \mu_B^T \Sigma_B^{-1} \mu_B + \log |\Sigma_0| - \log |\Sigma_1| + \log \frac{\pi_A}{\pi_B}. \end{aligned}$$

(b)

If $\Sigma_A = \Sigma_B$, two terms in Λ cancel out, which results in $\omega^T x + b = 0$. Also, if we denote $\Sigma = \Sigma_A = \Sigma_B$, the weight ω and bias b becomes

$$\begin{aligned} \omega^T &= -2(\mu_A^T - \mu_B^T) \Sigma^{-1}, \\ b &= (\mu_A^T \Sigma^{-1} \mu_A - \mu_B^T \Sigma^{-1} \mu_B) + \log \frac{\pi_A}{\pi_B}, \end{aligned}$$

respectively.

2.

(a) Decision Boundaries for QDA and LDA by Python

```
Q_qda:
[[ 0.42016807 -0.42016807]
 [-0.42016807  0.42016807]]
w_qda:
[[3.07692308 3.07692308]]
b_qda:
[[0.8873032]]
w_lda:
[[1.53846154 1.53846154]]
b_lda:
[[0.]]
```

(b) Plot

See the results in jupyter-notebook.

(c) Result Analysis

Bigger diagonal elements in Σ_B indicates class B is more widespread than A , whilst the negative off-diagonal element furthermore implies a more diverged tendency of class B , which makes the QDA area of class B much bigger.