

HW2

Q1-

$$\mu = \frac{\begin{bmatrix} 3 \\ 3 \end{bmatrix} + \begin{bmatrix} -3 \\ -3 \end{bmatrix}}{2} = 0$$

Part A)

$$\Sigma_B = \sum_{c=1}^2 (\mu_c - \mu)(\mu_c - \mu)^T = \begin{bmatrix} 3 \\ 3 \end{bmatrix} \begin{bmatrix} 3 & 3 \end{bmatrix} + \begin{bmatrix} -3 \\ -3 \end{bmatrix} \begin{bmatrix} -3 & -3 \end{bmatrix} = 18 \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$$

Part B)

$$\Sigma = \Sigma_B + \Sigma_W = 18 \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} + \begin{bmatrix} 4 & 4 \\ 4 & 9 \end{bmatrix} = \begin{bmatrix} 22 & 22 \\ 22 & 27 \end{bmatrix}$$

$$\Sigma^{-1} \Sigma_B = \frac{18}{22 \times 5} \begin{bmatrix} 27 & -22 \\ -22 & 22 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} = \frac{9}{55} \begin{bmatrix} 5 & 5 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} \frac{9}{11} & \frac{9}{11} \\ 0 & 0 \end{bmatrix} \quad \Lambda = \begin{bmatrix} \frac{9}{11} & 0 \\ 0 & 0 \end{bmatrix} \quad \Phi = \begin{bmatrix} 1 & \frac{1}{\sqrt{2}} \\ 0 & \frac{-1}{\sqrt{2}} \end{bmatrix}$$

Part C)

$$\Phi^T \Sigma_B \Phi = 18 \begin{bmatrix} \frac{1}{\sqrt{2}} & 0 \\ \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & \frac{1}{\sqrt{2}} \\ 0 & \frac{-1}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & \frac{1}{\sqrt{2}} \\ 0 & \frac{-1}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} 18 & 0 \\ 0 & 0 \end{bmatrix}$$

$$\Phi^T \Sigma \Phi = \begin{bmatrix} \frac{1}{\sqrt{2}} & 0 \\ \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 22 & 22 \\ 22 & 27 \end{bmatrix} \begin{bmatrix} 1 & \frac{1}{\sqrt{2}} \\ 0 & \frac{-1}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} 22 & 22 \\ 0 & \frac{-5}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 1 & \frac{1}{\sqrt{2}} \\ 0 & \frac{-1}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} 22 & 0 \\ 0 & 2.5 \end{bmatrix}$$

Part D)

How we arrange the eigenvector matrix affects the output. Considering $\Phi = \begin{bmatrix} 1 & \frac{1}{\sqrt{2}} \\ 0 & \frac{-1}{\sqrt{2}} \end{bmatrix}$ leads to image 2 and $\Phi = \begin{bmatrix} \frac{1}{\sqrt{2}} & 1 \\ \frac{-1}{\sqrt{2}} & 0 \end{bmatrix}$ leads to image 3.

Q2-

Both eigenvalues are 1 and eigenvectors are $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$ and $\begin{bmatrix} 0 \\ -1 \end{bmatrix}$. So, the matrix $\begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}$ does not have two linearly independent eigenvectors and this is why it is not diagonalizable. This is not symmetric and we do not get a unique value for ρ .

Q5-

$$S = m_1 m_1^T + m_2 m_2^T$$

$$\sum \lambda_i = \text{tr}(S) = \text{tr}(m_1 m_1^T) + \text{tr}(m_2 m_2^T) = \text{tr}(m_1^T m_1) + \text{tr}(m_2^T m_2) = \|m_1\|^2 + \|m_2\|^2 = 5$$

Rank of S is 2. Therefore, we have 2 eigenvalues: $\lambda_1 + \lambda_2 = 5$.

The angle between m_1 and m_2 is 60 degrees and a plane passes through these vectors. Considering $S\Phi = \lambda\Phi$, Φ in this plane can be written in terms of these vectors: $\Phi = m_1 + \alpha m_2$

$$S\Phi = \lambda\Phi \rightarrow (m_1 m_1^T + m_2 m_2^T)(m_1 + \alpha m_2) = \lambda(m_1 + \alpha m_2) \rightarrow m_1 m_1^T m_1 + m_2 m_2^T m_1 + \alpha m_1 m_1^T m_2 + \alpha m_2 m_2^T m_2 = \lambda m_1 + \lambda \alpha m_2$$

$$m_1^T m_1 = \|m_1\|^2 = 1 \quad m_2^T m_2 = \|m_2\|^2 = 4 \quad m_1^T m_2 = m_2^T m_1 = \|m_1\| \|m_2\| \cos(60) = 1 \times 2 \times \frac{1}{2} = 1$$

$$S\Phi = \lambda\Phi \rightarrow m_1 + m_2 + \alpha m_1 + 4\alpha m_2 = (1 + \alpha)m_1 + (1 + 4\alpha)m_2 = \lambda m_1 + \lambda \alpha m_2$$

$$1 + \alpha = \lambda \quad \text{and} \quad 1 + 4\alpha = \lambda \alpha \quad \rightarrow \quad 2 \text{ equations, 2 unknowns} \quad \rightarrow \quad \lambda_1, \lambda_2 = \frac{5 \pm \sqrt{13}}{2}$$

Q7-

$$\text{Part A)} \quad \frac{\partial}{\partial m} \sum_{i=1}^N (x_i - m)^T (x_i - m) = 0 \quad \rightarrow \quad m = \frac{1}{N} \sum_{i=1}^N x_i$$

$$\text{Part B)} \quad \frac{\partial}{\partial \alpha_i} \sum_{i=1}^N (x_i - m - \alpha_i e)^T (x_i - m - \alpha_i e) = 0 \quad \rightarrow \quad e^T (x_i - m - \alpha_i e) = 0 \quad \rightarrow \quad \alpha_i = e^T (x_i - m)$$

$$\text{Part C)} \quad \frac{\partial}{\partial e} \sum_{i=1}^N (x_i - m - \alpha_i e)^T (x_i - m - \alpha_i e) = 0 \quad \rightarrow \quad \sum_{i=1}^N \alpha_i (x_i - m) = \sum_{i=1}^N \alpha_i^2 e$$

$$\sum_{i=1}^N (x_i - m)(x_i - m)^T e = \sum_{i=1}^N \alpha_i^2 e \quad \rightarrow \quad \frac{1}{N} \sum_{i=1}^N (x_i - m)(x_i - m)^T e = \frac{1}{N} \sum_{i=1}^N \alpha_i^2 e \quad \rightarrow \quad Se = \lambda e$$

e is the eigenvector of S and it is the eigenvector corresponding to greater eigenvalue as we want to minimize the Euclidean distance above.

Q8-

$$\text{From the question: } p(\omega_1)\Sigma_1 + p(\omega_1)m_1m_1^T + p(\omega_2)\Sigma_2 + p(\omega_2)m_2m_2^T = I \quad p(\omega_1)m_1 + p(\omega_2)m_2 = 0$$

$$\text{Part A) } p(\omega_1)\Sigma_1 + p(\omega_2)\Sigma_2 = I - p(\omega_1)m_1m_1^T - p(\omega_2)m_2m_2^T = I - p(\omega_1)m_1m_1^T - p(\omega_2)\left(\frac{-p(\omega_1)}{p(\omega_2)}\right)m_1\left(\frac{-p(\omega_1)}{p(\omega_2)}\right)m_1^T$$

$$[p(\omega_1)\Sigma_1 + p(\omega_2)\Sigma_2]^{-1} = [I - p(\omega_1)m_1m_1^T - \frac{p(\omega_1)^2}{p(\omega_2)}m_1m_1^T]^{-1} = [I - \frac{p(\omega_1)p(\omega_2)+p(\omega_1)^2}{p(\omega_2)}m_1m_1^T]^{-1}$$

$$\text{Part B) } (m_2 - m_1) = \frac{-p(\omega_1)}{p(\omega_2)}m_1 - m_1 = -m_1\left(\frac{p(\omega_1)+p(\omega_2)}{p(\omega_2)}\right) = -m_1\left(\frac{1}{p(\omega_2)}\right) = \frac{-m_1}{p(\omega_2)}$$

$$(m_2 - m_1)^T[p(\omega_1)\Sigma_1 + p(\omega_2)\Sigma_2]^{-1}(m_2 - m_1) = \frac{-m_1^T}{p(\omega_2)}[I - \frac{p(\omega_1)p(\omega_2)+p(\omega_1)^2}{p(\omega_2)}m_1m_1^T]^{-1}\frac{-m_1}{p(\omega_2)} \quad m_1 = \begin{bmatrix} m_{11} \\ m_{12} \end{bmatrix}$$

$$\text{Part C) } |p(\omega_1)\Sigma_1 + p(\omega_2)\Sigma_2| = \left|I - \frac{p(\omega_1)p(\omega_2)+p(\omega_1)^2}{p(\omega_2)}m_1m_1^T\right| = \left|I - Am_1m_1^T\right| = \begin{vmatrix} 1 - Am_{11}^2 & Am_{11}m_{12} \\ Am_{11}m_{12} & 1 - Am_{12}^2 \end{vmatrix} = 1 -$$

$$A(m_{11}^2 + m_{12}^2) + A^2m_{11}^2m_{12}^2 - A^2m_{11}^2m_{12}^2 = 1 - A(m_{11}^2 + m_{12}^2) = 1 - A\|m_1\|^2$$

Q10-

In order to simultaneously diagonalization of Σ_1 and Σ_2 , the simplest way (in my opinion!) is finding the eigenvector matrix of $\Sigma_1^{-1}\Sigma_2$:

$$\begin{aligned}\Sigma_1^{-1}\Sigma_2 &= \frac{1}{1-\frac{1}{4}} \begin{bmatrix} 1 & -0.5 \\ -0.5 & 1 \end{bmatrix} \begin{bmatrix} 1+\frac{\sqrt{3}}{4} & 0.5 \\ 0.5 & 1-\frac{\sqrt{3}}{4} \end{bmatrix} = \frac{4}{3} \begin{bmatrix} 1 & -0.5 \\ -0.5 & 1 \end{bmatrix} \begin{bmatrix} 1+\frac{\sqrt{3}}{4} & 0.5 \\ 0.5 & 1-\frac{\sqrt{3}}{4} \end{bmatrix} = \begin{bmatrix} \frac{4}{3} & -\frac{2}{3} \\ -\frac{2}{3} & \frac{4}{3} \end{bmatrix} \begin{bmatrix} 1+\frac{\sqrt{3}}{4} & 0.5 \\ 0.5 & 1-\frac{\sqrt{3}}{4} \end{bmatrix} = \\ &= \begin{bmatrix} \frac{4}{3} + \frac{\sqrt{3}}{3} - \frac{1}{3} & \frac{2}{3} - \frac{2}{3} + \frac{\sqrt{3}}{6} \\ -\frac{2}{3} - \frac{\sqrt{3}}{6} + \frac{2}{3} & -\frac{1}{3} + \frac{4}{3} - \frac{\sqrt{3}}{3} \end{bmatrix} = \begin{bmatrix} 1 + \frac{\sqrt{3}}{3} & \frac{\sqrt{3}}{6} \\ -\frac{\sqrt{3}}{6} & 1 - \frac{\sqrt{3}}{3} \end{bmatrix}\end{aligned}$$

Calculating eigenvalue and eigenvector matrices from $\Phi(\Sigma - \Lambda) = 0$. We will have:

$$\Lambda = \begin{bmatrix} 1.5 & 0 \\ 0 & 0.5 \end{bmatrix} \quad \text{and} \quad \Phi = \begin{bmatrix} 0.9659 & -0.2588 \\ -0.2588 & 0.9659 \end{bmatrix}$$

Diagonalization:

$$\Phi^T \Sigma_1 \Phi = \begin{bmatrix} 0.9659 & -0.2588 \\ -0.2588 & 0.9659 \end{bmatrix} \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix} \begin{bmatrix} 0.9659 & -0.2588 \\ -0.2588 & 0.9659 \end{bmatrix} = \begin{bmatrix} 0.75 & 0 \\ 0 & 0.75 \end{bmatrix}$$

$$\Phi^T \Sigma_2 \Phi = \begin{bmatrix} 0.9659 & -0.2588 \\ -0.2588 & 0.9659 \end{bmatrix} \begin{bmatrix} 1 + \frac{\sqrt{3}}{4} & 0.5 \\ 0.5 & 1 - \frac{\sqrt{3}}{4} \end{bmatrix} \begin{bmatrix} 0.9659 & -0.2588 \\ -0.2588 & 0.9659 \end{bmatrix} = \begin{bmatrix} 1.125 & 0 \\ 0 & 0.375 \end{bmatrix}$$

Q11-

$$\Sigma = S - mm^T \quad (A - B)^{-1} = A^{-1} - \frac{1}{1 + \text{trace}(BA^{-1})} A^{-1}BA^{-1} \quad \text{trace}(AB) = \text{trace}(BA)$$

$$|X + AB| = |X| |I + BX^{-1}A| \quad |I + AB| = |I + BA|$$

$$|I + cr| = 1 + rc \quad \text{Where } c \text{ is a column matrix and } r \text{ a row matrix.}$$

$$\text{From the useful formulae above:} \quad \Sigma^{-1} = (S - mm^T)^{-1} = S^{-1} - \frac{1}{1 + \text{trace}(mm^T S^{-1})} S^{-1}mm^T S^{-1}$$

$$\Sigma^{-1}m = S^{-1}m - \frac{1}{1 + \text{trace}(mm^T S^{-1})} S^{-1}mm^T S^{-1}m = S^{-1}m \left(1 - \frac{1}{1 + \text{trace}(mm^T S^{-1})} m^T S^{-1}m\right)$$

$$\text{trace}(mm^T S^{-1}) = \text{trace}(m^T S^{-1}m) = m^T S^{-1}m$$

$$\Sigma^{-1}m = S^{-1}m \left(1 - \frac{1}{1 + m^T S^{-1}m} m^T S^{-1}m\right) = S^{-1}m \left(\frac{1}{1 + m^T S^{-1}m}\right)$$

$$\text{On the other hand: } |\Sigma| = |S - mm^T| = |S| |I + m^T S^{-1}m| = |S| |I + S^{-1}mm^T| = |S| (1 + m^T S^{-1}m)$$

$$\text{So, } \Sigma^{-1}m = S^{-1}m \left(\frac{1}{1 + m^T S^{-1}m}\right) = S^{-1}m \frac{|S|}{|\Sigma|} \quad \text{Therefore: } \Sigma^{-1}m = \frac{|S|}{|\Sigma|} S^{-1}m$$

Q12-

$$\Sigma \lambda_i = \lambda = \text{trace}(\Sigma^{-1} m m^T) = \text{trace}(m^T \Sigma^{-1} m) = m^T \Sigma^{-1} m$$

$$\Sigma^{-1} m m^T \phi = \phi \lambda = \phi m^T \Sigma^{-1} m \quad \text{The eigenvector that makes the equation true is } \phi = \Sigma^{-1} m$$

Q13-

Part A. $J(\varphi) = \varphi^T \Sigma \varphi - \lambda(\varphi^T \varphi - 1) \quad \frac{\partial J(\varphi)}{\partial \varphi} = 2\Sigma \varphi - 2\lambda \varphi = 0 \quad \Sigma \varphi = \lambda \varphi$

φ is the eigenvector of matrix Σ and it is corresponding to the maximum eigenvalue since we want to minimize the cost function.

Part B.

$$\varphi_{k+1} = \varphi_k - \mu(2\Sigma \varphi - 2\lambda \varphi) = \varphi_k - \mu(2\Sigma \varphi - 2\varphi^T \Sigma \varphi \varphi) = \varphi_k - \mu(\Sigma \varphi - (\varphi^T \Sigma \varphi) \varphi)$$

What happened to 2? I defined a new variable: 2μ and named it μ again!

Part C.

$$\Sigma_0 = \epsilon I$$

$$\varphi_0 = \alpha [1 \ 1 \ \dots \ 1]^t$$

$$\hat{m}_0 = [0 \ 0 \ \dots \ 0]^t$$

$$\mu = \mu_0$$

for $k=1:N$

$$\hat{m}_k = \frac{(k-1) \hat{m}_{k-1} + x_k}{k}$$

$$\hat{\Sigma}_k = (1 - (k-1)/k)(x_k - \hat{m}_k)(x_k - \hat{m}_k)^t + ((k-1)/k) \hat{\Sigma}_{k-1}$$

$$\varphi_k = \varphi_{k-1} - \mu(\hat{\Sigma}_k \varphi_{k-1} - (\varphi_{k-1}^t \hat{\Sigma}_k \varphi_{k-1}) \varphi_{k-1})$$

end

Q14-

$$\Sigma = \Phi \Lambda \Phi^{-1} \rightarrow \Sigma^{-1} = (\Phi \Lambda \Phi^{-1})^{-1} = ((\Phi \Lambda)(\Phi^{-1}))^{-1} = \Phi(\Phi \Lambda)^{-1} = \Phi \Lambda^{-1} \Phi^{-1}$$

Q15-

$$D_A = P^{-1}AP \rightarrow A = PD_AP^{-1}$$

$$D_B = P^{-1}BP \rightarrow B = PD_BP^{-1}$$

$$AB = PD_AP^{-1}PD_BP^{-1} = PD_AD_BP^{-1} = PD_BD_AP^{-1} = PD_BP^{-1}PD_AP^{-1} = PD_BP^{-1}PD_AP^{-1} = PD_BP^{-1}PD_AP^{-1} = BA$$

Q16-

The covariance matrix Σ has orthonormal basis $\phi_1, \phi_2, \dots, \phi_n$.

A data point can be written as $v = c_1\phi_1 + c_2\phi_2 + \dots + c_n\phi_n$

$$\Sigma^m v = c_1\Sigma^m\phi_1 + c_2\Sigma^m\phi_2 + \dots + c_n\Sigma^m\phi_n$$

Remember $\Sigma\phi_i = \lambda_i\phi_i$, $\Sigma^m\phi_i = \lambda_i^m\phi_i$

$$\Sigma^m v = c_1\lambda_1^m\phi_1 + c_2\lambda_2^m\phi_2 + \dots + c_n\lambda_n^m\phi_n$$

Lets find the angle between $\Sigma^m v$ and ϕ_1 :

$$\begin{aligned} \cos \theta &= \frac{\Sigma^m v \cdot \phi_1}{\|\Sigma^m v\|} = \frac{(\Sigma^m v)^t \phi_1}{\|\Sigma^m v\|} = \frac{(c_1\lambda_1^m\phi_1 + c_2\lambda_2^m\phi_2 + \dots + c_n\lambda_n^m\phi_n)^t \phi_1}{\|\Sigma^m v\|} \\ &= \frac{c_1\lambda_1^m\phi_1^t \phi_1 + c_2\lambda_2^m\phi_2^t \phi_1 + \dots + c_n\lambda_n^m\phi_n^t \phi_1}{\|\Sigma^m v\|} = \frac{c_1\lambda_1^m}{\sqrt{(\Sigma^m v)^t (\Sigma^m v)}} \\ &= \frac{c_1\lambda_1^m}{\sqrt{c_1^2\lambda_1^{2m} + c_2^2\lambda_2^{2m} + \dots + c_n^2\lambda_n^{2m}}} \end{aligned}$$

With increasing m , $c_1\lambda_1^m$ gets larger and we can ignore the other terms. This leads to $\cos \theta = 1 \rightarrow \theta = 0$