1 Exercise 1

We have N samples (x_i, y_i) $\boldsymbol{\pi} = (\pi_1, ..., \pi_M), \boldsymbol{\theta} = (\theta_{1,1}, ...\theta_{M,K})$
$a_m =\mid \{i \mid z_i = m, \forall i \in [1, N]\} \mid$, $b_{m,k} =\mid \{i \mid z_i = m$ and $x_i = k, \forall i \in [1, N]\} \mid$

$$\begin{aligned}
l(\boldsymbol{\pi}, \boldsymbol{\theta}) &= \sum_{i=0}^{n} log(p(x_i, z_i)) \\
&= \sum_{i=0}^{n} log(p(x_i \mid z_i)p(z_i)) \\
&= \sum_{i=0}^{n} (log(\theta_{z_i,x_i}) + log(\pi_{x_i}))
\end{aligned}$$

$l(\boldsymbol{\pi}, \boldsymbol{\theta})$ is concave. We want to minimize $-l(\boldsymbol{\pi}, \boldsymbol{\theta})$ subjected to $\sum_{k=1}^{K} \pi_k = 1$ and $\sum_{k=1}^{K} \sum_{m=1}^{M} \theta_{m,k} = 1$ Lets introduce the langrangian.

$$L(\boldsymbol{\pi}, \boldsymbol{\theta}, \lambda_1, \lambda_2) = -(\sum_{i=0}^{n}(log(\theta_{z_i,x_i}) + log(\pi_{x_i}))) + \lambda_1(\sum_{k=1}^{K} \pi_k - 1) + \lambda_2(\sum_{k=1}^{K} \sum_{m=1}^{M} \theta_{m,k} - 1)$$

The Slaters constraint qualification are trivialy verified and therefore the problem has strong duality property. Therefore we have

$$\min_{\boldsymbol{\pi}, \boldsymbol{\theta}} -l(\boldsymbol{\pi}, \boldsymbol{\theta}) = \max_{\lambda_1, \lambda_2} L(\boldsymbol{\pi}, \boldsymbol{\theta}, \lambda_1, \lambda_2)$$

Moreover the lagrangian is convex with respect to $\boldsymbol{\pi}$ and $\boldsymbol{\theta}$

$$\frac{\partial L}{\partial \pi_m} = 0 \Rightarrow \tilde{\pi}_m = \frac{a_m}{\lambda_1}$$

$$\frac{\partial L}{\partial \theta_{m,k}} = 0 \Rightarrow \tilde{\theta}_{m,k} = \frac{b_{m,k}}{\lambda_2}$$

Using the constrains we can calculate λ_1, λ_2.

$$\begin{aligned}
\tilde{\pi}_m &= \frac{a_m}{N} \\
\tilde{\theta}_{m,k} &= \frac{b_{m,k}}{N}
\end{aligned}$$

2 Exercicse 2

2.1 Generative model LDA

We have N samples and $n = \mid \{i, y_i = 0, \forall i \in [1, N]\} \mid$

$$
\begin{aligned}
l(\omega, \Sigma, \mu_0, \mu_1) &= \sum_{i=1}^{N} log(p(x_i, y_i)) \\
&= \sum_{i=1}^{N} log(p(x_i \mid y_i)p(y_i)) \\
&= \sum_{\substack{i=1,\\ y_i=0}}^{N} log(p(x_i \mid y_i = 0)) + nlog(\omega) + \sum_{\substack{i=1,\\ y_i=0}}^{N} log(p(x_i \mid y_i = 1)) + (N-n)log(1-\omega) \\
&= -\frac{Nd}{2} log(2\pi) + \frac{N}{2} log(\mid \Sigma^{-1} \mid) - \sum_{\substack{i=1,\\ y_i=0}}^{N} \frac{1}{2}(x_i - \mu_0)^T \Sigma^{-1}(x_i - \mu_0) \\
&- \sum_{\substack{i=1,\\ y_i=1}}^{N} \frac{1}{2}(x_i - \mu_1)^T \Sigma^{-1}(x_i - \mu_1) + nlog(\omega) + (N-n)log(1-\omega)
\end{aligned}
$$

This log likelyhood is not concave in $(\omega, \Sigma, \mu_0, \mu_1)$. It is concave in (ω, μ_0, μ_1) with Σ fixed.

$$\nabla_\omega l = \frac{n}{\omega} - \frac{N-n}{1-\omega}$$

$\nabla_\omega l = 0$ gives us :

$$\tilde{\omega} = \frac{n}{N}$$

Calculating the gradient in μ_0, μ_1 and equalating it to 0 gives us.

$$\tilde{\mu}_0 = \frac{1}{n} \sum_{\substack{i=1,\\ y_i=0}}^{N} x_i$$

$$\tilde{\mu}_1 = \frac{1}{N-n} \sum_{\substack{i=1,\\ y_i=1}}^{N} x_i$$

Let us now differentiate l w.r.t. Σ^{-1}.
Let $A = \Sigma^{-1}$, $\Sigma_0 = \frac{1}{n} \sum_{\substack{i=1,\\ y_i=0}}^{N} (x_i - \mu_0)^T (x_i - \mu_0)$,
$\Sigma_1 = \frac{1}{N-n} \sum_{\substack{i=1,\\ y_i=1}}^{N} (x_i - \mu_1)^T (x_i - \mu_1)$

We have :

$$
\begin{aligned}
l(\omega,\Sigma,\mu_0,\mu_1) =& -\frac{Nd}{2}log(2\pi) + \frac{N}{2}log(\mid \Sigma^{-1} \mid) - \frac{1}{2}\text{Trace}(A(n\Sigma_0 + (N-n)\Sigma_1) \\
&+ nlog(\omega) + (N-n)log(1-\omega) \\
\nabla_A l =& \frac{N}{2}A^{-1} - \frac{1}{2}(n\Sigma_0 + (N-n)\Sigma_1)
\end{aligned}
$$

Which leads to

$$\tilde{\Sigma} = \frac{n}{N}\Sigma_0 + \frac{N-n}{N}\Sigma_1$$

We have found a unique stationnary point for the likelyhood. To be sure it is a maximum we would have to calculate the Hessian.
Now we will calculate the $p(y=1 \mid x)$.

$$p(y=1 \mid x) = \frac{p(x \mid y=1)p(y=1)}{p(x)}$$

$$
\begin{aligned}
log(\frac{p(y=1 \mid x)}{p(y=0 \mid x)}) &= log(\frac{1-\omega}{\omega}) - \frac{1}{2}(x-\mu_1)\Sigma^{-1}(x-\mu_1) + \frac{1}{2}(x-\mu_0)\Sigma^{-1}(x-\mu_0) \\
log(\frac{p(y=1 \mid x)}{p(y=0 \mid x)}) &= log(\frac{1-\omega}{\omega}) + \frac{1}{2}(\mu_0^T\Sigma^{-1}\mu_0 - \mu_1^T\Sigma^{-1}\mu_1) + x^T\Sigma^{-1}(\mu_1-\mu_0) \\
p(y=1 \mid x) &= \frac{1}{1 + \frac{w}{1-w}\exp\left(\frac{1}{2}(\mu_1^T\Sigma^{-1}\mu_1 - \mu_0^T\Sigma^{-1}\mu_0)\right)\exp\left(-x^T\Sigma^{-1}(\mu_1-\mu_0)\right)}
\end{aligned}
$$

It is of the form

$$p(y=1 \mid x) = \frac{1}{1+\alpha\exp x^T a}$$

If $\alpha = 1$ we find the formula of logistic regression

2.2 QDA model