

This handout includes space for every question that requires a written response. Please feel free to use it to handwrite your solutions (legibly, please). If you choose to typeset your solutions, the `README.md` for this assignment includes instructions to regenerate this handout with your typeset L^AT_EX solutions.

1.

2.a

$$\begin{aligned}
\ell(\theta^{(t+1)}) &= \alpha \ell_{\text{sup}}(\theta^{(t+1)}) + \ell_{\text{unsup}}(\theta^{(t+1)}) \\
&\geq \alpha \ell_{\text{sup}}(\theta^{(t+1)}) + \sum_{i=1}^n \sum_{z^{(i)}} Q_i^{(t)}(z^{(i)}) \log \frac{p(x^{(i)}, z^{(i)}; \theta^{(t+1)})}{Q_i^{(t)}(z^{(i)})} \\
&\geq
\end{aligned}$$

Definition

Jensen's inequality

2.b

2.c

List the parameters which need to be re-estimated in the M-step:

In order to simplify derivation, it is useful to denote

$$w_j^{(i)} = Q_i^{(t)}(z^{(i)} = j),$$

and

$$\tilde{w}_j^{(i)} = \begin{cases} \alpha & \tilde{z}^{(i)} = j \\ 0 & \text{otherwise.} \end{cases}$$

We further denote $S = \Sigma^{-1}$, and note that because of chain rule of calculus, $\nabla_S \ell = 0 \Rightarrow \nabla_\Sigma \ell = 0$. So we choose to rewrite the M-step in terms of S and maximize it w.r.t S , and re-express the resulting solution back in terms of Σ .

Based on this, the M-step becomes:

$$\begin{aligned} \phi^{(t+1)}, \mu^{(t+1)}, S^{(t+1)} &= \arg \max_{\phi, \mu, S} \sum_{i=1}^n \sum_{j=1}^k Q_i^{(t)}(z^{(i)}) \log \frac{p(x^{(i)}, z^{(i)}; \phi, \mu, S)}{Q_i^{(t)}(z^{(i)})} + \alpha \sum_{i=1}^{\tilde{n}} \log p(x^{(i)}, z^{(i)}; \phi, \mu, S) \\ &= \end{aligned}$$

Now, calculate the update steps by maximizing the expression within the argmax for each parameter (We will do the first for you).

ϕ_j : We construct the Lagrangian including the constraint that $\sum_{j=1}^k \phi_j = 1$, and absorbing all irrelevant terms into constant C :

$$\begin{aligned} \mathcal{L}(\phi, \beta) &= C + \sum_{i=1}^n \sum_{j=1}^k w_j^{(i)} \log \phi_j + \sum_{i=1}^{\tilde{n}} \sum_{j=1}^k \tilde{w}_j^{(i)} \log \phi_j + \beta \left(\sum_{j=1}^k \phi_j - 1 \right) \\ \nabla_{\phi_j} \mathcal{L}(\phi, \beta) &= \sum_{i=1}^n w_j^{(i)} \frac{1}{\phi_j} + \sum_{i=1}^{\tilde{n}} \tilde{w}_j^{(i)} \frac{1}{\phi_j} + \beta = 0 \\ \Rightarrow \phi_j &= \frac{\sum_{i=1}^n w_j^{(i)} + \sum_{i=1}^{\tilde{n}} \tilde{w}_j^{(i)}}{-\beta} \\ \nabla_\beta \mathcal{L}(\phi, \beta) &= \sum_{j=1}^k \phi_j - 1 = 0 \\ \Rightarrow \sum_{j=1}^k \frac{\sum_{i=1}^n w_j^{(i)} + \sum_{i=1}^{\tilde{n}} \tilde{w}_j^{(i)}}{-\beta} &= 1 \\ \Rightarrow -\beta &= \sum_{j=1}^k \left(\sum_{i=1}^n w_j^{(i)} + \sum_{i=1}^{\tilde{n}} \tilde{w}_j^{(i)} \right) \\ \Rightarrow \phi_j^{(t+1)} &= \frac{\sum_{i=1}^n w_j^{(i)} + \sum_{i=1}^{\tilde{n}} \tilde{w}_j^{(i)}}{\sum_{j=1}^k \left(\sum_{i=1}^n w_j^{(i)} + \sum_{i=1}^{\tilde{n}} \tilde{w}_j^{(i)} \right)} \\ &= \frac{\sum_{i=1}^n w_j^{(i)} + \sum_{i=1}^{\tilde{n}} \tilde{w}_j^{(i)}}{n + \alpha \tilde{n}} \end{aligned}$$

μ_j : Next, derive the update for μ_j . Do this by maximizing the expression with the argmax above with respect to μ_j .

First, calculate the gradient with respect to μ_j :

$$\nabla_{\mu_j} =$$

Next, set the gradient to zero and solve for μ_j :

$$0 =$$

Σ_j : Finally, derive the update for Σ_j via S_j . Again, Do this by maximizing the expression with the argmax above with respect to S_j .

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First, calculate the gradient with respect to S_j :

$$\nabla_{S_j} =$$

Next, set the gradient to zero and solve for S_j :

$$0 =$$

This results in the final set of update expressions:

$$\phi_j :=$$

$$\mu_j :=$$

$$\Sigma_j :=$$

2.f

3.a

3.b

4.a

4.b

4.d

4.e

4.g

4.i