

### Question 1.

For the mixture model the joint distribution can be written

$$p(x_a, x_b) = \sum_{k=1}^K \pi_k p(x_a, x_b | k)$$

We can find the conditional density  $p(x_b | x_a)$  by making use of the relation

$$p(x_b | x_a) = \frac{p(x_a, x_b)}{p(x_a)}$$

The mixture model the marginal density of  $x_a$  is given by

$$p(x_a) = \sum_{k=1}^K \pi_k p(x_a | k)$$

where

$$p(x_a | k) = \int p(x_a, x_b | k) dx_b$$

Thus we can write the conditional density in the form

$$p(x_b | x_a) = \frac{\sum_{k=1}^K \pi_k p(x_a, x_b | k)}{\sum_{j=1}^K \pi_j p(x_a | j)}$$

Decompose the numerator using  $p(x_a, x_b | k) = p(x_b | x_a, k) p(x_a | k)$

which allows us finally to write the conditional density as a mixture model of the form

$$p(x_b | x_a) = \sum_{k=1}^K \lambda_k p(x_b | x_a, k)$$

where the mixture coefficients are given by

$$\lambda_k = p(x_a | k) = \frac{\pi_k p(x_a | k)}{\sum_{j=1}^K \pi_j p(x_a | j)}$$

and  $p(x_b | x_a, k)$  is the conditional for component  $k$ .

### Question 2

$$(a) \hat{a} = \frac{\frac{1}{2} + \mu}{\frac{1}{2} + \mu} h \quad \hat{b} = \frac{M}{\frac{1}{2} + \mu} h$$

$$(b) \hat{m} = \frac{h - a + c}{6(h - a + c) + 1}$$

### Question 3

$$(a) P(Z=1 | X=1) \propto P(X=1 | Z=1)P(Z=1) = \pi_1 e^{-1}$$

$$P(Z=2 | X=1) \propto P(X=1 | Z=2)P(Z=2) = \pi_2 4e^{-2}$$

$$P(Z=3 | X=1) \propto P(X=1 | Z=3)P(Z=3) = \pi_3 16e^{-3}$$

$$P(Z=1 | X=1) = \frac{\pi_1 e^{-1}}{(2e^{-1} + 8e^{-2} + 16e^{-3})}$$

$$(b) \text{ For each } X=x \quad P(Z=k | X=x) = \frac{P(X=x | Z=k)P(Z=k)}{\sum_k P(X=x | Z=k)P(Z=k)} = \frac{\beta_k^x x e^{-\beta_k x} \pi_k}{\sum_k \beta_k^x x e^{-\beta_k x} \pi_k}$$

### Question 4

$$\sum_{k=1}^K \pi_k = 1 \quad \tilde{Q} = \sum_{k=1}^K r(2_{ik}) \ln \pi_k + \lambda \left( \sum_{k=1}^K \pi_k - 1 \right) \quad \text{Setting the derivative with respect to } \pi_k \text{ equal to zero}$$

$$0 = r(2_{ik}) \frac{1}{\pi_k} + \lambda \quad \lambda = - \frac{\sum_{k=1}^K r(2_{ik})}{\sum_{j=1}^K r(2_{ij})}$$

Maximization with respect to  $A$   $\sum_{k=1}^K A_{jk} = 1 \quad \text{for } j=1, \dots, K$

$$\tilde{Q} = \sum_{n=2}^N \sum_{j=1}^K \sum_{k=1}^K \varepsilon(z_{n-1,j}, z_{nk}) \ln A_{jk} + \sum_{j=1}^K \lambda_j \left( \sum_{k=1}^K A_{jk} - 1 \right)$$

Set the derivative of  $\tilde{Q}$  with respect to  $A_{jk}$  to zero

$$0 = \sum_{n=2}^N \varepsilon(z_{n-1,j}, z_{nk}) \frac{1}{A_{jk}} + \lambda_j$$

Multiply through by  $A_{jk}$  and then sum over  $k$ , make use of summation constraint  $\lambda_j = - \sum_{n=2}^N \sum_{k=1}^K \varepsilon(z_{n-1,j}, z_{nk})$

$$\text{Substituting for } \lambda_j \text{ and solving for } A_{jk} \Rightarrow A_{jk} = \frac{\sum_{n=2}^N \varepsilon(z_{n-1,j}, z_{nk})}{\sum_{k=1}^K A_{jk}}$$

Question 5

$$\sum_{n=1}^N \sum_{k=1}^K r(2_{nk}) \ln p(x_n | \phi_k) = \sum_{n=1}^N \sum_{k=1}^K r(2_{nk}) \sum_{i=1}^D x_{ni} \ln \mu_{ki}$$

Introduce Lagrange multipliers  $\lambda_{nk}$  and maximize the function given by

$$\sum_{n=1}^N \sum_{k=1}^K r(2_{nk}) \sum_{i=1}^D x_{ni} \ln \mu_{ki} + \sum_{k=1}^K \lambda_k \left( \sum_{i=1}^D \mu_{ki} - 1 \right)$$

Setting the derivative with respect to  $\mu_{ki}$  to zero we obtain

$$0 = \frac{\partial}{\partial \mu_{ki}} r(2_{nk}) \frac{x_{ni}}{\mu_{ki}} + \lambda_k$$

Multiplying through by  $\mu_{ki}$ , summing over  $i$ , and making use of the constraint on  $\mu_{ki}$  together with result  $\sum_i x_{ni} = 1$  we have

$$\lambda_k = - \sum_{n=1}^N r(2_{nk})$$

back-substituting for  $\lambda_k$  and solving for  $\mu_{ki}$

$$\mu_{ki} = \frac{\sum_{n=1}^N r(2_{nk}) x_{ni}}{\sum_{n=1}^N r(2_{nk})}$$

Similarly,

$$\sum_{n=1}^N \sum_{k=1}^K r(2_{nk}) \ln p(x_n | \phi_k) = \sum_{n=1}^N \sum_{k=1}^K r(2_{nk}) \sum_{i=1}^D (x_{ni} \ln \mu_{ki} + (1-x_{ni}) \ln (1-\mu_{ki}))$$

Maximizing with respect to  $\mu_{ki}$  we obtain

$$\mu_{ki} = \frac{\sum_{n=1}^N r(2_{nk}) x_{ni}}{\sum_{n=1}^N r(2_{nk})}$$

Question 6

(a)  $p(X, Z | \theta) = \prod_{r=1}^R p(X^{(r)}, Z^{(r)} | \theta)$

$$\begin{aligned} p(Z | X, \theta) &= \frac{p(X, Z | \theta)}{\sum_r p(X^{(r)}, Z^{(r)} | \theta)} \\ &= \frac{\prod_{r=1}^R p(X^{(r)}, Z^{(r)} | \theta)}{\sum_{z^{(r)}} \sum_{x^{(r)}} \prod_{r=1}^R p(X^{(r)}, Z^{(r)} | \theta)} \\ &= \prod_{r=1}^R \left( \frac{p(X^{(r)}, Z^{(r)} | \theta)}{\sum_{z^{(r)}} p(X^{(r)}, Z^{(r)} | \theta)} \right) y \\ &= \prod_{r=1}^R p(Z^{(r)} | X^{(r)}, \theta) \end{aligned}$$

(b) joint distribution

$$Q(\theta, \theta_{old}) = E_Z [\ln p(X, Z | \theta)] = E_Z \left[ \sum_{r=1}^R \ln p(X^{(r)}, Z^{(r)} | \theta) \right]$$

$$= \sum_{r=1}^R p(Z^{(r)} | X^{(r)}, \theta_{old}) \ln p(X, Z | \theta)$$

$$= \sum_{r=1}^R \sum_{k=1}^K r(2_{rk}^{(r)}) \ln \pi_{rk} + \sum_{r=1}^R \sum_{k=1}^K \sum_{j=1}^N \sum_{k=1}^K \varepsilon(z_{n-1,j}^{(r)}, z_{n,k}^{(r)}) \ln A_{jk} + \sum_{r=1}^R \sum_{k=1}^K r(2_{rk}^{(r)}) \ln p(x_n^{(r)} | \phi_k)$$

maximize the quantity with respect to  $\pi$  and  $A$  with Lagrange multiplier

Then we can get  $\pi_k = \frac{\sum_{r=1}^R r(2_{rk}^{(r)})}{\sum_{r=1}^R \sum_{j=1}^N r(2_{nj}^{(r)})}$

$$A_{jk} = \frac{\sum_{r=1}^R \sum_{n=2}^N \varepsilon(z_{n-1,j}^{(r)}, z_{n,k}^{(r)})}{\sum_{r=1}^R \sum_{n=2}^N \varepsilon(z_{n-1,j}^{(r)}, z_{n,l}^{(r)})}$$

(c) the parameters of the Gaussian emission densities appear only in the last term.

$$\sum_{n=1}^N \sum_{k=1}^K r(2_{nk}) \ln p(x_n | \phi_k) = \sum_{n=1}^N \sum_{k=1}^K r(2_{nk}) \ln N(x_n | \mu_k, \Sigma) = \sum_{n=1}^N \sum_{k=1}^K r(2_{nk}) \left( -\frac{1}{2} \ln (2\pi) - \frac{1}{2} \ln |\Sigma| - \frac{1}{2} (x_n - \mu_k)^T \Sigma^{-1} (x_n - \mu_k) \right)$$

maximize the quantity with respect to  $\mu_k$  and  $\Sigma$ . Setting the derivative with respect to  $\mu_k$  to zero and rearranging

$$\mu_k = \frac{\sum_{n=1}^N r(2_{nk}) x_n}{\sum_{n=1}^N r(2_{nk})}$$

Rewrite the final term in the form  $\frac{NkD\ln(2\pi)}{2} - \frac{Nk\ln|\Sigma_k|}{2} - \frac{1}{2}\text{Tr}(\Sigma_k^{-1}\hat{\Sigma}_k)$

Differentiating w.r.t.  $\Sigma_k$

$$\Sigma_k = \frac{\sum_{n=1}^N r(2nk)(X_n, \mu_k X_n, \Sigma_k X_n)}{\sum_{n=1}^N r(2nk)}$$