

## EM Extra exercises

(2)

$$\begin{aligned} a.) \quad r_{jk} &= P(k|x^j, \theta) \\ &= \frac{\pi_k U(x^j | a_k, \sigma_k^2)}{\sum_{k'} \pi_{k'} U(x^j | a_{k'}, \sigma_{k'}^2)} \end{aligned}$$

$$\begin{aligned} b.) \quad Q(\theta, q^*) &= \sum_{j,k} r_{jk} (\log(\pi_k) + \log(U(x^j | a_k, \sigma_k^2))) \\ &= \sum_{j,k} r_{jk} (\log(\pi_k) - \log(\sqrt{2\pi}) - \log(\sigma_k) - \frac{1}{2\sigma_k^2} (x^j - a_k)^2) \end{aligned}$$

c.) For the next steps we will have to use the partial derivatives of the above expression.

$$*) \quad \frac{\partial Q}{\partial a_k} = \sum_{j,k} r_{jk} \frac{1}{\sigma_k^2} (x^j - a_k) \stackrel{!}{=} 0 \quad (1)$$

$$*) \quad \frac{\partial Q}{\partial \sigma_k} = \sum_{j,k} r_{jk} \left( -\frac{1}{\sigma_k} + \frac{2(x^j - a_k)^2}{\sigma_k^3} \right) \stackrel{!}{=} 0 \quad (2)$$

For the last ~~one~~ we note that we have a condition that needs to be specified, namely:

$\sum_k \pi_k = 1$ , thus we add this, together with a Lagrange multiplier to ~~the~~ the expression that we are maximizing. Thus we get:

$$\frac{\partial Q}{\partial \pi_k} = \sum_j r_{jk} \frac{1}{\pi_k} \Rightarrow \frac{\sum_j r_{jk}}{\pi_k} + \lambda = 0 \quad (3)$$

Now we are going to solve these equations:

①: given that  $\sigma_k^2 \neq 0$  we find:

$$a_k = \frac{\sum_{\mu} r_{\mu k} x^{\mu}}{\sum_{\mu} r_{\mu k}}$$

$$\textcircled{2} \sum_{\mu} r_{\mu k} \left( \frac{-1}{\sigma_k} + \frac{(x^{\mu} - a_k)^2}{\sigma_k^3} \right) = 0$$

$$\sum_{\mu} r_{\mu k} \frac{(x^{\mu} - a_k)^2}{\sigma_k^2} = \sum_{\mu} r_{\mu k}$$

$$\rightarrow \sigma_k^2 = \frac{\sum_{\mu} r_{\mu k} (x^{\mu} - a_k)^2}{\sum_{\mu} r_{\mu k}}$$

$$\textcircled{3} \text{ we find: } \pi_k = -\lambda \sum_{\mu} r_{\mu k}$$

But we know:

$$\sum_k \pi_k \stackrel{!}{=} 1 \rightarrow \sum_k (-\lambda \sum_{\mu} r_{\mu k}) = -\lambda \sum_{\mu k} r_{\mu k}$$

Now we know:

$\sum_k r_{\mu k} = \sum_k p(k|x^{\mu}, \theta)$ , which since it is a probability must equal 1

$$\rightarrow \sum_{\mu, k} r_{\mu k} = \sum_{\mu} 1 = N$$

$$\Rightarrow -\lambda N = 1 \rightarrow \lambda = \frac{-1}{N}$$

And thus we have:  $\pi_k = \frac{\sum_{\mu} r_{\mu k}}{N}$

If we check these expressions with those found on slide 204, we see that they are (very) equivalent, where we do note that for  $\sigma_k^2$  the expr. between  $(\dots)^2$  is the expression filled into the expectation value for the def. of  $\sigma_k$ , as is the same for  $(\Sigma^i k)_j$  on slide 204!