

## CS613 \ Assignment #4 Solutions

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1)

Let there be a density model with the mixture distribution  $p(x) = \sum_{k=1}^K \pi_k p(x|k)$ , and  $x$  is partitioned into 2 parts  $x = (x_a, x_b)$ . Following is a proof that the conditional density  $p(x_b|x_a)$  is itself a mixture distribution, with expressions for the mixing coefficients and the component densities.

We need to show that:

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

The marginal density of  $x_a$  is:

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

...

2)

2.1) The unnormalized joint distribution of the factor graph is:

$$\tilde{p}(x) = f_a(x_1, x_2) f_b(x_2, x_3) f_c(x_2, x_4) f_d(x_3, x_5)$$

2.2) The marginal distribution of  $x_3$  by the sum-product algorithm is:

$$\mu_{x_1 \rightarrow f_a}(x_1) = 1$$

$$\mu_{f_a \rightarrow x_2}(x_2) = \sum_{x_1} f_a(x_1, x_2)$$

$$\mu_{x_4 \rightarrow f_c}(x_4) = 1$$

$$\mu_{f_c \rightarrow x_2}(x_2) = \sum_{x_4} f_c(x_2, x_4)$$

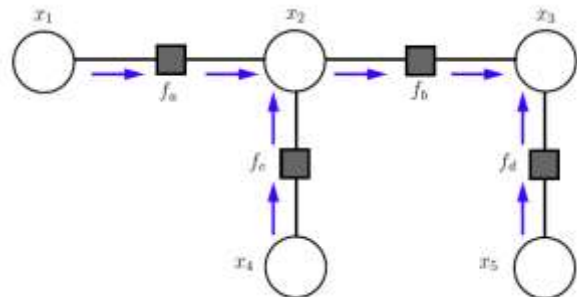
$$\mu_{x_2 \rightarrow f_b}(x_2) = \mu_{f_a \rightarrow x_2}(x_2) \mu_{f_c \rightarrow x_2}(x_2)$$

$$\mu_{f_b \rightarrow x_3}(x_3) = \sum_{x_2} f_b(x_2, x_3) \mu_{x_2 \rightarrow f_b}(x_2)$$

$$\mu_{x_5 \rightarrow f_d}(x_5) = 1$$

$$\mu_{f_d \rightarrow x_3}(x_3) = \sum_{x_5} f_d(x_3, x_5)$$

$$\Rightarrow \text{The marginal distribution of } x_3 \text{ is: } \mu_{f_b \rightarrow x_3}(x_3) \mu_{f_d \rightarrow x_3}(x_3) = \sum_{x_2} f_b(x_2, x_3) \sum_{x_1} f_a(x_1, x_2) \sum_{x_4} f_c(x_2, x_4) \sum_{x_5} f_d(x_3, x_5)$$



**3)**

Following is a proof that if any elements of the parameters  $\pi$  or  $A$  for a hidden Markov model are initially set to zero, then those elements will remain zero in all subsequent updates of the EM algorithm.

We know the update rules for the starting probability  $\pi$  and the transition probability matrix  $A$  are:

$$\pi_k = \frac{\gamma(z_{1k})}{\sum_{j=1}^K \gamma(z_{1j})}, \quad A_{jk} = \frac{\sum_{n=2}^N \xi(z_{n-1,j}, z_{nk})}{\sum_{l=1}^K \sum_{n=2}^N \xi(z_{n-1,j}, z_{nl})}$$

In the  $E$  step there will be no training samples associated with 0-probability states or transitions to 0-probability transitions.

Therefore the updated probabilities in the  $M$  step will remain 0 as well.

Looking at the joint posterior of two successive latent variables,  $\xi(z_{n-1}, z_n)$ :

$$\xi(z_{n-1}, z_n) = p(z_{n-1}, z_n | X) = \frac{p(X | z_{n-1}, z_n) p(z_{n-1}, z_n)}{p(X)} =$$

$$\frac{p(x_1, \dots, x_{n-1} | z_{n-1}) p(x_n | z_n) p(x_{n+1}, \dots, x_N | z_n) p(z_n | z_{n-1}) p(z_{n-1})}{p(X)} \stackrel{A_{jk}=0 \Rightarrow p(z_n | z_{n-1})=0}{=} 0$$

Therefore all future updates are zero.