

$$a) \quad r_{ik} = \Pr(h_i = k | x_i, \theta^{(k)}) = \Pr(x_i | h_i = k, \theta^{(k)}) \Pr(h_i = k | \theta^{(k)})$$

$$= \frac{\sum_{j=1}^K \lambda_j \Pr(x_i | h_i = j, \theta^{(k)}) \Pr(h_i = j | \theta^{(k)})}{\sum_{j=1}^K \lambda_j \Pr(x_i | h_i = j, \theta^{(k)}) \Pr(h_i = j | \theta^{(k)})} \quad \text{--- (1)}$$

$$\text{Norm}_x[p, \Sigma] = \frac{1}{(2\pi)^{D/2} |\Sigma|^{1/2}} e^{-1/2 (x-p)^T \Sigma^{-1} (x-p)}$$

So Given $\Sigma = I$

$$\text{Norm}_x[p, \Sigma] = \frac{1}{(2\pi)^{D/2}} e^{-1/2 (x-p)^T (x-p)}$$

Substituting in (1)

$$= \frac{\lambda_k \frac{1}{\sqrt{2\pi}} e^{-1/2 (x_i - p_k)^2}}{\sum_{j=1}^K \lambda_j \frac{1}{\sqrt{2\pi}} e^{-1/2 (x_i - p_j)^2}}$$

$$= \frac{\lambda_k e^{-1/2 (x_i - p_k)^2}}{\sum_{j=1}^K \lambda_j e^{-1/2 (x_i - p_j)^2}}$$

1(c) Defn = $r_{ik} = \begin{cases} 1 & \text{if } k = k_i \\ 0 & \text{otherwise} \end{cases}$

$$v_k^{[t+1]} = \frac{\sum_{i=1}^I r_{ik} x_i}{\sum_{i=1}^I r_{ik}}$$

if $k = k_i$ $p_{k_i}^{[t+1]} = x_i$

else $v_k^{[t+1]}$ doesn't exist

So from mean shift now.

1(b)