STA 414/2104, Spring 2014, Assignment #2 — Derivation of M step

The assignment handout says the M step update for $\theta_{k,j}$ should be

$$\hat{\theta}_{k,j} = \frac{\alpha + \sum_{i=1}^{n} r_{i,k} x_{i,j}}{2\alpha + \sum_{i=1}^{n} r_{i,k}}$$

where $r_{i,k}$ is the probability that case *i* came from component *k*, estimated in the E step.

The general form of the M step is to maximize $E_Q[\log P(x, z|\theta) + G(\theta)]$, where $G(\theta)$ is the "penalty". (We can ignore the π parameters here, since they don't interact with θ , given that the distribution Q found in the E step is fixed during the M step.) All we really need to know about Q is the responsibilities, $r_{i,k}$, found in the E step as the expectations of the $z_{i,k}$, which indicate which mixture component each data item came from (as in the week 7 lecture slides).

We can write the terms of $E_Q[\log P(x, z|\theta) + G(\theta)]$ that involve $\theta_{k,j}$ as

$$E_{Q} \Big[\log \Big(\prod_{i=1}^{n} \Big(\theta_{k,j}^{x_{i,j}} (1 - \theta_{k,j})^{1 - x_{i,j}} \Big)^{z_{i,k}} \Big) + \alpha (\log(\theta_{k,j}) + \log(1 - \theta_{k,j})) \Big]$$

where note that each $z_{i,k}$ will be either zero one. This can be rewritten as

$$E_Q \Big[\sum_{i=1}^n z_{i,k} \log \left(\theta_{k,j}^{x_{i,j}} (1 - \theta_{k,j})^{1 - x_{i,j}} \right) + \alpha (\log(\theta_{k,j}) + \log(1 - \theta_{k,j})) \Big]$$

$$= \sum_{i=1}^n r_{i,k} \log \left(\theta_{k,j}^{x_{i,j}} (1 - \theta_{k,j})^{1 - x_{i,j}} \right) + \alpha (\log(\theta_{k,j}) + \log(1 - \theta_{k,j}))$$

$$= \sum_{i=1}^n \left(r_{i,k} x_{i,j} \log(\theta_{k,j}) \right) + \sum_{i=1}^n \left(r_{i,k} (1 - x_{i,j}) \log(1 - \theta_{k,j}) \right) + \alpha (\log(\theta_{k,j}) + \log(1 - \theta_{k,j}))$$

$$= \left(\alpha + \sum_{i=1}^n r_{i,k} x_{i,j} \right) \log(\theta_{k,j}) + \left(\alpha + \sum_{i=1}^n r_{i,k} (1 - x_{i,j}) \right) \log(1 - \theta_{k,j}) \Big]$$

To find the maximum with respect to $\theta_{k,j}$, we take the derivative and set it equal to zero:

$$\left(\alpha + \sum_{i=1}^{n} r_{i,k} x_{i,j}\right) / \theta_{k,j} - \left(\alpha + \sum_{i=1}^{n} r_{i,k} (1 - x_{i,j})\right) / (1 - \theta_{k,j}) = 0$$

Multiply this equation by $\theta_{k,j}(1-\theta_{k,j})$, we get

$$\left(\alpha + \sum_{i=1}^{n} r_{i,k} x_{i,j}\right) (1 - \theta_{k,j}) - \left(\alpha + \sum_{i=1}^{n} r_{i,k} (1 - x_{i,j})\right) \theta_{k,j} = 0$$

which gives

$$\alpha + \sum_{i=1}^{n} r_{i,k} x_{i,j} = \left(\alpha + \sum_{i=1}^{n} r_{i,k} x_{i,j} \right) \theta_{k,j} + \left(\alpha + \sum_{i=1}^{n} r_{i,k} (1 - x_{i,j}) \right) \theta_{k,j}$$

One can now easily see that the solution to this is the update above.