

$$E(x|m, \theta) = \sum_m \log(p(x, m | \theta) \cdot P(m | x, \theta^+))$$

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$$= \sum_m \left[\sum_i \sum_{j \in S_i} \log(p(x_{ij} | m_j = k, \theta) \cdot p(m_j | \theta)) \right] \cdot P(m | x, \theta^+)$$

$$= \sum_i \sum_j \sum_{m_i} \dots \sum_{m_n} \sum_{m_j} \left[\log(p(x_{ij} | m_j = k, \theta) \cdot p(m_j | \theta)) \right] \cdot P(m | x, \theta^+)$$

$$= \sum_i \sum_j \sum_{m_j} \sum_{\substack{mq \\ q \neq j}} \left[\log(p(x_{ij} | m_j = k, \theta) \cdot p(m_j = k | \theta)) \right] \cdot P(m | x, \theta^+)$$

$$E(x|m, \theta) = \sum_i \sum_j \sum_{m_j} \log(p(x_{ij} | m_j = k, \theta) \cdot p(m_j = k | \theta)) \sum_{\substack{mq \\ q \neq j}} P(m | x, \theta^+) \quad (1)$$

Let's expand the term $\sum_{\substack{mq \\ q \neq j}} P(m | x, \theta^+)$

$$\sum_{\substack{mq \\ q \neq j}} P(m | x, \theta^+) = \sum_{\substack{mq \\ q \neq j}} \prod_i \prod_j P(m_j | x_{ij}, \theta^+)$$

$$= \prod_i \prod_j \sum_{\substack{mq \\ q \neq j}} P(m_j | x_{ij}, \theta^+)$$

$$= \prod_i \prod_j \sum_{\substack{mq \\ q \neq j}} P(m_q | x_{iq}, \theta^+) \leftarrow$$

just for clarity, I changed the indices to q to show what will happen when the j th term is extracted

$$\begin{aligned}
 \sum_{\substack{m_q \\ q \neq j}} P(m | x, \theta^+) &= \sum_{\substack{m_q \\ q \neq j}} \dots \\
 &= \prod_i \prod_{q \neq j} \sum_{\substack{m_q \\ q \neq j}} P(m_q | x_{iq}, \theta^+) \\
 &= \prod_i \prod_{q \neq j} \left(\sum_{\substack{m_q \\ q \neq j}} P(m_q | x_{iq}, \theta^+) \right) \cdot P(m_j | x_{ij}, \theta^+)
 \end{aligned}$$

We just extracted the j th term from the product.

$$\sum_{\substack{m_q \\ q \neq j}} P(m_q | x_{iq}, \theta^+) = 1 \quad \text{So replacing in that equation}$$

$$\sum_{\substack{m_q \\ q \neq j}} P(m | x, \theta^+) = \prod_i \prod_{q \neq j} (1) \cdot P(m_j | x_{ij}, \theta^+) = P(m_j | x_{ij}, \theta^+)$$

Replacing in (1) \Rightarrow

$$E(x | \theta, m) = \sum_i \sum_{\substack{j \\ j \in S_i}} \sum_{m_j} \log(P(x_{ij} | m_j = k, \theta) \cdot P(m_j = k, \theta) \cdot P(m_j | x_{ij}, \theta^+))$$

$m_j \in \{0, 1\} \Rightarrow$

$$E(x | m, \theta) = \sum_i \sum_{\substack{j \\ j \in S_i}} \sum_{k=0}^1 \log(P(x_{ij} | m_j = k, \theta) \cdot P(m_j = k, \theta)) \cdot P(m_j = k | x_{ij}, \theta^+)$$

Here $j \in S_i$, Set of Annotators for image j

$$E = \sum_i \sum_j \sum_{m_j} \log \left(P(x_{ij} | m_j = k, \theta) \cdot P(m_j = k | \theta) \right) \cdot \underbrace{P(m_j = k | x_{ij}, \theta^+)}_{\alpha_{jk}}$$

$$E = \sum_i \sum_j \left[\alpha_{j1} \log \left(\frac{1}{\sqrt{2\pi}\sigma} \exp \left(-\frac{(x_{ij} - \mu_i)^2}{2\sigma^2} \right) \right) + \log \left(\frac{1-P}{10} \right) \alpha_{j0} \right]$$

$$\alpha_{j1} = P(m_j = 1 | x_{ij}, \theta^+) \quad \text{and} \quad \alpha_{j0} = P(m_j = 0 | x_{ij}, \theta^+)$$

$$\frac{\partial E}{\partial \mu_i} = \sum_j \alpha_{j1} \left[\frac{x_{ij} - \mu_i}{\sigma^2} \right] = 0 \quad \left(\sum_i \text{ disappears since we only derive with respect to } \mu_i \text{ only the } i\text{th term is left.} \right)$$

$$\Rightarrow \frac{\partial E}{\partial \mu_i} = \sum_j x_{ij} \alpha_{j1} - \sum_j \alpha_{j1} \mu_i = 0$$

$$\boxed{\mu_i = \left(\sum_{j \in S_i} x_{ij} \alpha_{j1} \right) \cdot \frac{1}{\sum_{j \in S_i} \alpha_{j1}}}$$

$j \in S_i$
 S_i : annotators for image i

$$\frac{\partial E}{\partial \sigma} = \sum_i \sum_j \left[\left(-\frac{1}{\sigma} + \frac{(x_{ij} - \mu_i)^2}{\sigma^3} \right) \cdot \alpha_{j1} \right]$$

$$\sum_i \sigma^2 \sum_j \alpha_{j1} = \sum_i \left(\sum_j \alpha_{j1} (x_{ij} - \mu_i)^2 \right)$$

$$\sum_i \sigma^2 \sum_j \alpha_{j1} = \sum_i \sum_j \alpha_{j1} (x_{ij} - \mu_i)^2$$

$$\sigma^2 = \frac{\sum_i \sum_j (x_{ij} - \mu_i)^2 \alpha_{j1}}{\sum_i \sum_j \alpha_{j1}}$$

$$\Rightarrow \boxed{\sigma = \left[\frac{\sum_i \sum_j (x_{ij} - \mu_i)^2 \alpha_{j1}}{\sum_i \left(\sum_j \alpha_{j1} \right)} \right]^{1/2}}$$

$j \in S_i$:
 S_i : annotators for image i

$$\frac{\partial E}{\partial \beta} = \sum_i \sum_j \left[\frac{\alpha_{j1}}{\beta} - \frac{1}{1-\beta} \alpha_{j0} \right] = 0$$

$$\Rightarrow \sum_i \sum_j \frac{\alpha_{j1}}{\beta} - \sum_i \sum_j \frac{\alpha_{j0}}{1-\beta} = 0$$

$$\sum_i \sum_j (1-\beta) \alpha_{j1} - \sum_i \sum_j \beta \alpha_{j0} = 0$$

$$\sum_i \sum_j (\alpha_{j0} + \alpha_{j1}) \beta = \sum_i \sum_j \alpha_{j1}$$

$$\beta = \frac{\sum_i \sum_j (\alpha_{j1})}{\sum_i \sum_j (\alpha_{j0} + \alpha_{j1})}$$

$j \in S_i$: S_i the set of
annotators for
image i

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$$\alpha_{j0} = P(m_j=0 | x_{ij}, \theta^+) = \frac{P(x_{ij} | m_j=0, \theta^+) \cdot P(m_j=0 | \theta^+)}{P(m_j=0 | \theta^+) \cdot P(x_{ij} | m_j=0, \theta^+) + P(m_j=1 | \theta^+) \cdot P(x_{ij} | m_j=1, \theta^+)}$$

Similarly

$$\alpha_{j1} = P(m_j=1 | x_{ij}, \theta^+) = \frac{P(x_{ij} | m_j=0, \theta^+) \cdot P(m_j=0 | \theta^+)}{P(m_j=0 | \theta^+) \cdot P(x_{ij} | m_j=0, \theta^+) + P(m_j=1 | \theta^+) \cdot P(x_{ij} | m_j=1, \theta^+)}$$

$$P(m_j=0 | x_{ij}, \theta^+) = 1 - P(m_j=1 | x_{ij}, \theta^+)$$

$$P(m_j=1 | x_{ij}, \theta^+) = \frac{\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x_{ij}-\mu_1)^2}{\sigma^2}\right) \cdot \beta}{\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x_{ij}-\mu_1)^2}{\sigma^2}\right) \beta + (1-\beta) \cdot \frac{1}{10}}$$