

Notes on the Derivation

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December 16, 2015

1 Derivation on the EM Algorithm

All notation follows Streeter(2015)'s paper.

The log likelihood function for the observed data is

$$\mathcal{L} = \sum_s \{ \log[\sum_j p_j \prod_t \mathcal{B}(q_t^j, v_t)] \}$$

Also borrow the notation

$$L_{s,j} = p_j \prod_t \mathcal{B}(q_t^j, v_t)$$
$$z_{s,j} = \frac{L_{s,j}}{\sum_{j'} L_{s,j'}}$$

1.1 q_t^j

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial q_t^j} &= \sum_s \frac{\frac{\partial L_{s,j}}{\partial q_t^j}}{\sum_j L_{s,j}} \\ &= \sum_s \left(\frac{\partial L_{s,j}}{\partial q_t^j} \frac{1}{L_{s,j}} \right) \frac{L_{s,j}}{\sum_j L_{s,j}} \\ &= \sum_s \frac{\partial \log(L_{s,j})}{\partial q_t^j} z_{s,j} \\ &= \frac{1}{q_t^j(1-q_t^j)} \sum_s (v_t^s(1-q_t^j) - (1-v_t^s)q_t^j) z_{s,j} \\ &= \frac{1}{q_t^j(1-q_t^j)} \sum_s (v_t^s - q_t^j) z_{s,j} \\ &= 0 \end{aligned}$$

From here it is easy to derive that

$$\hat{q}_{t+1}^j = \frac{\sum_s v_t^s z_{s,j}}{\sum_s z_{s,j}}$$

Streeter then use beta prior to shrink the estimate by

$$q_{t+1}^j = \frac{\alpha - 1 + \sum_s v_t^s z_{s,j}}{\alpha + \beta - 2 + \sum_s z_{s,j}}$$

Note that the original v_s^j is likely a typo.

1.2 p_j

To add the constraint that $\sum_j p_j = 1$, use the lagrange multiplier so that

$$\begin{aligned} \frac{\partial \mathcal{G}}{\partial p^j} &= -\lambda + \sum_s \frac{1}{p^j} \frac{L_{s,j}}{\sum_j L_{s,j}} = -\lambda + \frac{1}{p^j} \sum_s z_{s,j} = 0 \\ \frac{\partial \mathcal{G}}{\partial \lambda} &= 1 - \sum_j p^j = 0 \end{aligned}$$

Some simple algebra yields

$$p_{t+1}^j = \frac{\sum_s z_{s,j}}{\sum_{j'} \sum_s z_{s,j'}}$$

2 Derivation on the Equivalence to BKT

The weight can be derived from the fact that the probability of mastering the knowledge component has to be the same at time t has to be the same.

$$P(M_t = 1) = \sum_j p_j I(q_t^j = 0.8)$$

Let $j = 1, 2, 3$ denotes the solid line, dash line and dot line respectively.

In the first period

$$P(M_1 = 1) = p_1 = 0.5$$

In the second period

$$\begin{aligned} P(M_2 = 1) &= p_1 + p_2 \\ P(M_2 = 1) &= P(M_2 = 1, M_1 = 1) + P(M_2 = 1, M_1 = 0) \\ &= P(M_2 = 1 | M_1 = 1) P(M_1 = 1) + P(M_2 = 1 | M_1 = 0) P(M_1 = 0) \\ &= 1 * 0.5 + 0.5 * 0.5 \\ p_2 &= 0.25 \end{aligned}$$

It can be proved by generalization that

$$p_j = 0.5^j$$