

These notes summarise selected lecture concepts and are not a substitute for working through the lecture slides, tutorials, and self-study exercises. Feel free to personalise and develop them into your own summary sheet.

Learning problem — Model: Stationary HMM with visibles $v_i \in \{1, \dots, M\}$, latents $h_i \in \{1, \dots, K\}$ and parametrisation

$$p(h_1 = k; \mathbf{a}) = a_k \quad p(h_i = k | h_{i-1} = k'; \mathbf{A}) = A_{k,k'} \quad p(v_i = m | h_i = k; \mathbf{B}) = B_{m,k}$$

Data: $\mathcal{D} = \{\mathcal{D}_1, \dots, \mathcal{D}_n\}$, where each $\mathcal{D}_j$ is a sequence of visibles of length d_j . Task: Determine MLE for $\theta = (\mathbf{a}, \mathbf{A}, \mathbf{B})$. Constraints: parameters are all non-negative; $\mathbf{a}$ and the values of each column of $\mathbf{A}$ and $\mathbf{B}$ sum to one.

Objective for EM — The objective for M-step of the EM algorithm is

$$\begin{aligned} J(\theta, \theta_{\text{old}}) = & \sum_{j=1}^n \sum_k p(h_1 = k | \mathcal{D}_j; \theta_{\text{old}}) \log a_k + \\ & \sum_{j=1}^n \sum_{i=2}^{d_j} \sum_{k,k'} p(h_i = k, h_{i-1} = k' | \mathcal{D}_j; \theta_{\text{old}}) \log A_{k,k'} + \\ & \sum_{j=1}^n \sum_{i=1}^{d_j} \sum_{m,k} \mathbb{1}(v_i^{(j)} = m) p(h_i = k | \mathcal{D}_j; \theta_{\text{old}}) \log B_{m,k} \end{aligned}$$

subject to the constraints on the parameters.

EM (Baum-Welch) algorithm — Given parameters θ_{old} :

1. For each sequence $\mathcal{D}_j$ compute the posteriors

$$p(h_i, h_{i-1} | \mathcal{D}_j; \theta_{\text{old}}) \quad p(h_i | \mathcal{D}_j; \theta_{\text{old}})$$

using the alpha-beta recursion.

2. Update the parameters

$$\begin{aligned} a_k &= \frac{1}{n} \sum_{j=1}^n p(h_1 = k | \mathcal{D}_j; \theta_{\text{old}}) \\ A_{k,k'} &= \frac{\sum_{j=1}^n \sum_{i=2}^{d_j} p(h_i = k, h_{i-1} = k' | \mathcal{D}_j; \theta_{\text{old}})}{\sum_{k=1}^K \sum_{j=1}^n \sum_{i=2}^{d_j} p(h_i = k, h_{i-1} = k' | \mathcal{D}_j; \theta_{\text{old}})} \\ B_{m,k} &= \frac{\sum_{j=1}^n \sum_{i=1}^{d_j} \mathbb{1}(v_i^{(j)} = m) p(h_i = k | \mathcal{D}_j; \theta_{\text{old}})}{\sum_{j=1}^n \sum_{i=1}^{d_j} p(h_i = k | \mathcal{D}_j; \theta_{\text{old}})} \end{aligned}$$

Repeat step 1 and 2 using the new parameters for θ_{old} . Stop if change in likelihood or parameters is less than a threshold.