

3. Recognising the generating model - computing the emission probability for a feature sequence

Let a, b index two HMMs on $F^n \times K^n$

$$a: p_a(s_1), p_a(s_i | s_{i-1}), p_a(x_i | s_i)$$

$$b: p_b(s_1), p_b(s_i | s_{i-1}), p_b(x_i | s_i)$$

Given: observed sequence $x \in F^n$, $x = (x_1, \dots, x_n)$

Question: which model has generated x ?

Any reasonable answer is based on $p_a(x), p_b(x) \Rightarrow$

Task: Compute

$$\begin{aligned} p(x) &= \sum_{s \in K^n} p(x, s) \\ &= \sum_{s_1 \in K} \dots \sum_{s_n \in K} p(s_1) p(x_1 | s_1) \prod_{i=2}^n p(s_i | s_{i-1}) p(x_i | s_i) \end{aligned}$$

Denote: $P_i(s_{i-1}, s_i) = p(s_i | s_{i-1}) p(x_i | s_i)$

$$\Psi_1(s_1) = p(s_1) p(x_1 | s_1)$$

$$\Psi_n(s_n) \equiv 1$$

Expression in the sum reads

$$\Psi_1(s_1) \cdot P_2(s_1, s_2) \cdot \dots \cdot P_n(s_{n-1}, s_n) \cdot \Psi_n(s_n)$$

Summation can be performed iteratively from right to left

$$\Psi_{i-1}(s_{i-1}) = \sum_{s_i \in K} P_i(s_{i-1}, s_i) \Psi_i(s_i)$$

$$p(x) = \sum_{s_1 \in K} \Psi_1(s_1) \Psi_1(s_1)$$

or from left to right

$$\varphi_i(s_i) = \sum_{s_{i-1} \in K} \varphi_{i-1}(s_{i-1}) P_i(s_{i-1}, s_i)$$

$$p(x) = \sum_{s_n \in K} \varphi_n(s_n) \psi_n(s_n)$$

In matrix-vector form we have

$$p(x) = \vec{\varphi}_1 \cdot P_2 \cdot P_3 \cdot \dots \cdot P_n \cdot \vec{\psi}_n$$

Complexity: $\mathcal{O}(n|K|^2)$

Remark: The intermediate results have the following statistical meaning

$$\psi_i(s_i) = p(x_{i+1}, \dots, x_n | s_i)$$

$$\varphi_i(s_i) = p(x_1, \dots, x_i, s_i)$$

4. Recognising the most probable sequence of hidden states

We observe $x = (x_1, \dots, x_n)$ for a known HMM

Question: Which sequence $s = (s_1, \dots, s_n)$ has generated x ?

If the answer is $s^* \in \operatorname{argmax}_{s \in K^n} p(x, s)$, we have to solve

$$s^* \in \operatorname{argmax}_{s \in K^n} \log p(x, s)$$

$$= \operatorname{argmax}_{s \in K^n} \left\{ \log [p(s_1) p(x_1 | s_1)] + \sum_{i=2}^n \log [p(s_i | s_{i-1}) p(x_i | s_i)] \right\}$$

Denote: $M_i(s_{i-1}, s_i) = \log[p(s_i | s_{i-1}) p(x_i | s_i)]$

$$\Psi_1(s_1) = \log[p(s_1) p(x_1 | s_1)]$$

$$\Psi_n(s_n) \equiv 0$$

Now, translate the algorithm from Sec. 3 by replacing operators $x \mapsto +$, $+ \mapsto \max$. E.g. maximising dynamically from right to left

$$\Psi_{i-1}^-(s_{i-1}) = \max_{s_i \in K} [M_i(s_{i-1}, s_i) + \Psi_i^-(s_i)]$$

$$\max_{s \in K^n} \log p(x, s) = \max_{s_1} [\Psi_1(s_1) + \Psi_1^-(s_1)]$$

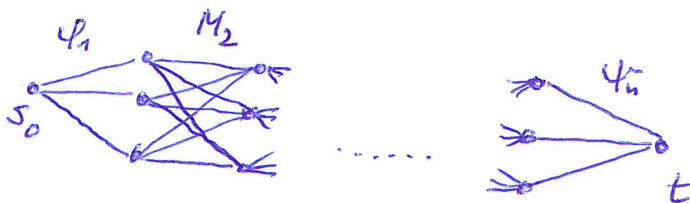
Since we are looking for $s^* \in \operatorname{argmax}_{s \in K^n} p(x, s) \Rightarrow$ introduce pointers $pt_i: K \rightarrow K$ for $i=1, \dots, n-1$

$$pt_{i-1}(s_{i-1}) \in \operatorname{argmax}_{s_i \in K} [M_i(s_{i-1}, s_i) + \Psi_i^-(s_i)]$$

and backtrack an optimiser s^* starting from

$$s_1^* \in \operatorname{argmax}_{s_1 \in K} [\Psi_1(s_1) + \Psi_1^-(s_1)]$$

Similarly, we can maximise from left to right. Both variants search the best path in the graph



Complexity: $O(n|K|^2)$

5. Recognising the sequence of most probable hidden states

Is $s^* \in \underset{s \in K^n}{\operatorname{argmax}} p(x, s)$ always the best answer to the question posed in Sec. 4?

The answer depends on $p(x, s)$ and the loss $\ell(s, s')$

(a) If $\ell(s', s) = \mathbb{1}\{s' \neq s\}$ then $s^* \in \underset{s \in K^n}{\operatorname{argmax}} p(x, s)$

(b) If $\ell(s', s) = \sum_{i=1}^n \mathbb{1}\{s'_i \neq s_i\}$, i.e. Hamming distance

$$s^* \in \underset{s \in K^n}{\operatorname{argmin}} \sum_{s' \in K^n} p(x, s) \sum_{i=1}^n [1 - \delta(s'_i, s_i)]$$

$$\rightarrow s_i^* \in \underset{s_i \in K}{\operatorname{argmax}} p(x, s_i) \quad i=1, \dots, n$$

Problem: Compute prob's $p(x, s_i = k) \quad \forall i=1, \dots, n, \forall k \in K$

Remember quantities φ, ψ from Sec. 3

$$\varphi_i(s_i) = p(x_1, \dots, x_i, s_i)$$

$$\psi_i(s_i) = p(x_{i+1}, \dots, x_n | s_i)$$

Since $p(x | s_i) \stackrel{!}{=} p(x_1, \dots, x_i | s_i) p(x_{i+1}, \dots, x_n | s_i)$ holds for HMMs, we have

$$p(x, s_i) = \varphi_i(s_i) \psi_i(s_i)$$

Complexity: $\mathcal{O}(2n |K|^2)$