

### 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

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

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 under the sum has the form

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

Summation can be performed iteratively from right to left

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

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

or from left to right

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

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

In matrix-vector forms we have

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

complexity:  $n|K|^2$

Remark The intermediate results have the following statistical meaning

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

$$\psi_i(s_i) = P(x_1, \dots, x_i, s_i)$$

#### 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  $s^* = \operatorname{argmax}_{s \in K^n} P(x, s)$ , we have to solve

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

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

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 algorithm from sec. 3 by replacing operators  $x \mapsto +$ ,  $+ \rightarrow \max$ . E.g. maximising dynamically from right to left

$$\psi_{i-1}(s_{i-1}) = \max_{s_i} [M_i(s_{i-1}, s_i) + \psi_i(s_i)]$$

$$\max_{S \in K^n} \log p(x, S) = \max_{s_1} [\psi_1(s_1) + \psi_2(s_2)]$$

We are looking for  $s^* = \operatorname{argmax}_S p(x, S) \Rightarrow$

introduce  $\rho_{t_i} : K \rightarrow K$  for  $i = 1, \dots, n-1$

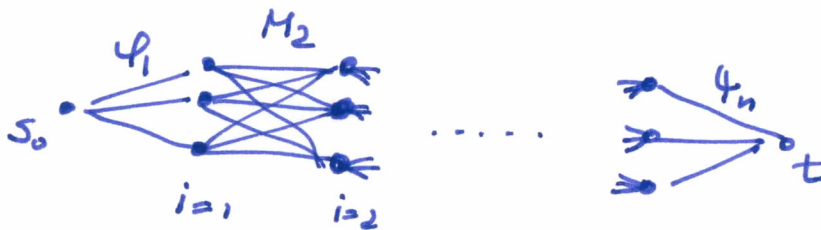
$$\rho_{t_{i-1}}(s_{i-1}) = \operatorname{argmax}_{s_i} [M_i(s_{i-1}, s_i) + \psi_i(s_i)]$$

Backtrack an optimizer  $s^*$  starting from

$$s_1^* = \operatorname{argmax}_{s_1} [\psi_1(s_1) + \psi_2(s_1)]$$

Similarly, we can maximise from left to right

Both variant search the best path in the graph



Complexity:  $n |K|^2$

### 5. Recognising the sequence of most probable hidden states

Is  $s^* = \operatorname{argmax}_{s \in K^u} p(x, s)$  the best answer to the question posed in sec. 4?

Answer depends on  $p(x, s)$  and the loss  $C(s', s)$

$$s^* = \operatorname{argmin}_{s \in K^u} \sum_{s' \in K^u} p(x, s') C(s', s)$$

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

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

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

$$= \operatorname{argmax}_{s \in K^u} \sum_{i=1}^n \sum_{s' \in K^u} p(x, s') \delta(s'_i, s_i)$$

$$= \operatorname{argmax}_{s \in K^u} \sum_{i=1}^n p(x, s_i)$$

$$\hookrightarrow \boxed{s_i^* = \operatorname{argmax}_{s_i} p(x, s_i)} \quad i=1, \dots, u$$

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

Answer: Remember quantities  $\psi, \varphi$  from sec. 3

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

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

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

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

Complexity:  $2n |K|^2$