

### Problem 1: The Evaluation problem

input: HMM defined by  $\lambda = [A, B, \pi]$  and an observation sequence  $O = o_1, o_2, o_3, \dots, o_T$

output: the probability of observing the sequence  $O$  given the HMM  $\lambda$ :  $P(O|\lambda)$

ex)  $O = a \ a \ b \ c \ c \ c \Rightarrow |O| = 6$

\* if we have  $N$  states, there are  $N^6$  possible sequences of states underlying the observation sequence  $O$

Let's define a few fundamental probabilities:

$\triangleright P[\text{observing } O \text{ given a sequence of states } Q] = P(O|Q) = P(o_1|q_1) P(o_2|q_2) \dots P(o_T|q_T)$   
 $= b_{q_1}(o_1) b_{q_2}(o_2) \dots b_{q_T}(o_T)$

$\triangleright P[\text{having a particular sequence of states } Q] = P(Q) = \pi_{q_1} a_{q_1, q_2} a_{q_2, q_3} \dots a_{q_{T-1}, q_T}$

$\triangleright$  Joint probability of  $O$  and  $Q$ :  $P(O, Q) = P(O|Q) \cdot P(Q)$

$\Rightarrow P(O|\lambda) = \sum_{\text{all seq. of states } Q} P(O|Q) P(Q) = \sum_{q_1, q_2, \dots, q_T} \pi_{q_1} b_{q_1}(o_1) a_{q_1, q_2} b_{q_2}(o_2) \dots a_{q_{T-1}, q_T} b_{q_T}(o_T)$

$O(N^T) \rightarrow$  impractical

### The Forward Algorithm (dynamic programming)

a defn  $\alpha_t$ : forward variable

$\alpha_t(i) = P(o_1, o_2, \dots, o_t, q_t = s_i)$ : probability of observing the first  $t$  observations and being in state  $s_i$  @ time  $t$

#### 1) initialization

$\alpha_1(i) = \pi_i b_i(o_1), \quad 1 \leq i \leq N$  ← compute for each state  $i$

#### 2) recurrence

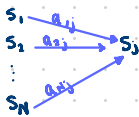
$\alpha_{t+1}(j) = \left[ \sum_{i=1}^N \alpha_t(i) a_{ij} \right] b_j(o_{t+1}), \quad 1 \leq t \leq T-1, \quad 1 \leq j \leq N$

#### 3) termination

$P(O|\lambda) = \sum_{i=1}^N \alpha_T(i)$

$O(N^2T)$

because the  $\alpha$  calculation iterates through all  $i$ 's ( $1 \leq i \leq N$ ), and we do the calculation for all states  $j$  ( $1 \leq j \leq N$ ) for each time  $t$  ( $1 \leq t \leq T-1$ ).



\* can arrive at state  $s_j$  @ time  $t+1$  from any state  $s_i$  ( $1 \leq i \leq N$ )

### Problem 2: The decoding problem

input: HMM defined by  $\lambda = [A, B, \pi]$  and an observation sequence  $O = o_1, o_2, o_3, \dots, o_T$

output: the most likely sequence of states  $Q = q_1, q_2, \dots, q_T$  given the observation sequence  $O$

### The Viterbi Algorithm

$\delta_t(i) = \max_{q_1, \dots, q_{t-1}} P[q_1, \dots, q_{t-1}, q_t = s_i | o_1, o_2, \dots, o_t]$ : the most probable sequence of states  $q_1, \dots, q_{t-1}$ ?

#### 1) initialization:

$\delta_1(i) = \pi_i b_i(o_1), \quad 1 \leq i \leq N$

$\psi_1(i) = 0, \quad 1 \leq i \leq N$  #backtracking

#### 2) recurrence:

$\delta_t(j) = \max_{1 \leq i \leq N} [\delta_{t-1}(i) a_{ij}] b_j(o_t), \quad 1 \leq j \leq N, \quad 2 \leq t \leq T$

$\psi_t(j) = \arg \max_{1 \leq i \leq N} [\delta_{t-1}(i) a_{ij}], \quad 1 \leq j \leq N, \quad 2 \leq t \leq T$

#### 3) Termination:

$P^* = \max_{1 \leq i \leq N} [\delta_T(i)]$

$q_T^* = \arg \max_{1 \leq i \leq N} [\delta_T(i)]$

$q^*$ : state index

#### 4) Backtracking:

$q_t^* = \psi_{t+1}(q_{t+1}^*), \quad t = T-1, T-2, \dots, 2, 1$

$Q_{opt} = q_1^* q_2^* \dots q_T^*$

also  $O(N^2T)$