

# Speech Recognition (DSAI 456)

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## Lecture 7

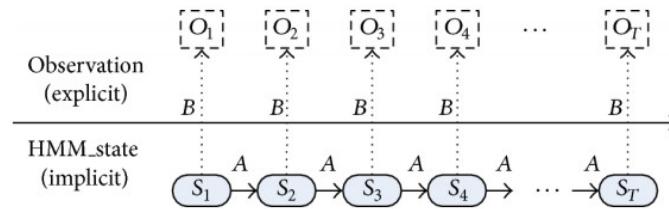
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# Recording is NOT allowed

# Lecture 5 Recap

- HMM : sequence of observed and hidden states
- HMM model  $\lambda = (A, B, \pi)$
- Problems
  - **Evaluation:**  $p(O | \lambda)$ 
    - Direct Computation  $O(TN^T)$
    - Forward Algorithm  $O(TN^2)$
  - **Decoder:**  $p(Q|O, \lambda)$
  - **Learning:**  $\arg \max_{\lambda} p(O|\lambda)$



# The Decoding Problem $p(Q|O, \lambda)$

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Find the most likely sequence of hidden states that produced a given sequence of observations

# The HMM Decoding Problem

Given an observation sequence  $O = (o_1, o_2, \dots, o_T)$  and model  $\lambda$ , find the most likely state sequence  $Q = (q_1, q_2, \dots, q_T)$

# The HMM Decoding Problem

Given an observation sequence  $O = (o_1, o_2, \dots, o_T)$  and model  $\lambda$ , find the most likely state sequence  $Q = (q_1, q_2, \dots, q_T)$

Define the highest probability of a state sequence ending in state  $i$  at time  $t$  generating observations  $o_1, \dots, o_t$  as:

$$\delta_t(i) = \max_{q_1, \dots, q_{t-1}} P(q_1, q_2, \dots, q_{t-1}, q_t = i, o_1, o_2, \dots, o_t \mid \lambda)$$

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You got it right!  use Induction

# Viterbi Algorithm

# Viterbi Algorithm

- Initialization: the highest probability along a single path, at time 1, which accounts for the first observation  $o_1$  and ends in state  $i$

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

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

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Where is the state sequence? 😭

We need to keep track of selected states along the path

# Viterbi Algorithm

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- Initialization

$$\begin{aligned}\delta_1(i) &= \pi_i b_i(o_1), \quad 1 \leq i \leq N \\ \psi_1(i) &= 0\end{aligned}$$

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$$\begin{aligned}P^* &= \max_{1 \leq i \leq N} \delta_T(i) \\ q_T^* &= \arg \max_{1 \leq i \leq N} \delta_T(i)\end{aligned}$$

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- Termination

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

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

Backtrack from  $q_T^*$  to  $q_1^*$  using  $\psi_t(i)$  to get the most probable state sequence

The Viterbi algorithm efficiently solves the decoding problem with complexity  $O(N^2T)$

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