

### 4.2.3 How to derive Forward Algorithm?

We consider forward algorithm as sum of variable from  $S_1$  to  $S_T$ .

$$\begin{aligned}
P(O_1, O_2, \dots, O_T) &= \sum_{S_1, \dots, S_T} P(O_1, O_2, \dots, O_T, S_1, \dots, S_T) \\
&= \sum_{S_1, \dots, S_T} P(S_1)P(S_2|S_1) \prod_{t=3}^T P(S_t|S_{t-1}) \prod_{t=1}^T P(O_t|S_t) \text{(Markov Assumption)} \\
&= \sum_{S_T} \dots \sum_{S_2} \sum_{S_1} \underbrace{P(S_1)P(O_1|S_1)P(S_2|S_1)P(O_2|S_2)}_{\alpha_1^k, k \text{ is the choice of } S_1} \prod_{t=3}^T P(S_t|S_{t-1})P(O_t|S_t) \\
&= \sum_{S_T} \dots \sum_{S_2} \underbrace{\left( \sum_{S_1} \alpha_1^k P(S_2|S_1)P(O_2|S_2) \right)}_{\alpha_2^k} \prod_{t=3}^T P(S_t|S_{t-1})P(O_t|S_t) \text{(Recurrence Rela.)}
\end{aligned}$$

So we know what  $\alpha$  is, and can derive the below algorithm:

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#### Algorithm 1 Forward Algorithm For Evaluation Problem

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- 1: Initialise  $\alpha_1^k = P(S_1 = k)P(O_1|S_1 = k)$  for all  $k$
  - 2: **for**  $t = 2$  to  $T$  **do**
  - 3:    $\alpha_t^k = \sum_i \alpha_{t-1}^i P(S_t = k|S_{t-1} = i)P(O_t|S_t = k)$  for all  $k$
  - 4: **end for**
  - 5:  $P(\{O_t\}_{t=1}^T) = \sum_k \alpha_T^k$
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**Note**: we can get the general form of  $\alpha$  by

$$\begin{aligned}
\alpha_t^k &= \sum_{S_{t-1}} \dots \sum_{S_1} P(S_1)P(O_1|S_1)P(S_2|S_1)P(O_2|S_2) \dots P(S_t = k|S_{t-1})P(O_t|S_t = k) \\
&= \sum_{S_{t-1}} \dots \sum_{S_1} P(S_1, \dots, S_{t-1}, S_t = k, O_1, \dots, O_t) \\
&= P(O_1, \dots, O_t, S_t = k)
\end{aligned}$$

#### 4.2.4 Backward Algorithm

Similar to Forward Algorithm, but we can eliminate the variable from  $S_T$  to  $S_1$

$$\begin{aligned}
P(O_1, O_2, \dots, O_T) &= \sum_{S_1, \dots, S_T} P(O_1, O_2, \dots, O_T, S_1, \dots, S_T) \\
&= \sum_{S_1, \dots, S_T} P(S_1)P(S_2|S_1) \prod_{t=3}^T P(S_t|S_{t-1}) \prod_{t=1}^T P(O_t|S_t) \text{(Markov Assumption)} \\
&= \sum_{S_1} \dots \sum_{S_{T-1}} \underbrace{\sum_{S_T} \beta_T^k P(S_T|S_{T-1})P(O_T|S_T)}_{\beta_{T-1}^k} \prod_{t=2}^{T-1} P(S_t|S_{t-1})P(O_t|S_t) \cdot P(S_1)
\end{aligned}$$

Can we define  $\beta_T^k = P(O_T|S_T)$ ? You can think it yourself.

So we know what  $\beta$  is, and can derive the below algorithm:

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#### Algorithm 2 Backward Algorithm For Evaluation Problem

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- 1: Initialise  $\beta_T^k = 1$  for all  $k$
  - 2: **for**  $t = T - 1$  to 1 **do**
  - 3:    $\beta_t^k = \sum_i \beta_{t+1}^i p(S_{t+1} = i | S_t = k) p(O_{t+1} | S_{t+1} = i)$  for all  $k$
  - 4: **end for**
  - 5:  $P(\{O_t\}_{t=1}^T) = \sum_k \beta_1^k p(O_1 | S_1 = k) p(S_1 = k)$
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**Note**: we can get the general form of  $\beta$  by

$$\begin{aligned}
\beta_t^k &= \sum_{S_{t+1}} \dots \sum_{S_T} P(S_T|S_{T-1})P(O_T|S_T) \dots P(S_{t+1}|S_t = k)P(O_{t+1}|S_{t+1}) \\
&= \sum_{S_{t+1}} \dots \sum_{S_T} P(O_{t+1}, \dots, O_T, S_{t+1}, \dots, S_T | S_t = k) \\
&= P(O_{t+1}, \dots, O_T | S_t = k)
\end{aligned}$$

### 4.3 Problem 3: Decoding Problem

#### 4.3.1 Forward-Backward Algorithm

Similarly, we show how to derive the formula from the perspective of sum over variable.

In order to find  $P(S_t = k, \{O_t\}_{t=1}^T)$ :

$$\begin{aligned}
P(S_t = k, \{O_t\}_{t=1}^T) &= \sum_{S_1} \cdots \sum_{S_{t-1}} \sum_{S_{t+1}} \cdots \sum_{S_T} P(S_1, \dots, S_{t-1}, S_t = k, S_{t+1}, \dots, S_T, \{O_t\}_{t=1}^T) \\
&= \sum_{S_1} \cdots \sum_{S_{t-1}} \sum_{S_{t+1}} \cdots \sum_{S_T} \prod_{t=1}^{t-1} P(S_t|S_{t-1})P(O_t|S_t) \cdot \\
&\quad P(S_t = k|S_{t-1})P(O_t|S_t = k) \parallel P(S_{t+1}|S_t = k)P(O_{t+1}|S_{t+1}) \prod_{t=2}^T P(S_t|S_{t-1})P(O_t|S_t)
\end{aligned}$$

We can see that the left part of  $\parallel$  is just  $\alpha_t^k$  and right part of is just  $\beta_t^k$

we can easily derive the forward-backward algorithm as below:

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**Algorithm 3** Forward-Backward Algorithm For Decoding Problem

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- 1: Initialise  $\alpha_1^k = P(S_1 = k)P(O_1|S_1 = k)$  for all  $k$
  - 2: Initialise  $\beta_T^k = 1$  for all  $k$
  - 3: **for**  $t = T - 1$  to 1 **do**
  - 4:    $\beta_t^k = \sum_i \beta_{t+1}^i p(S_{t+1} = i|S_t = k)p(O_{t+1}|S_{t+1} = i)$  for all  $k$
  - 5: **end for**
  - 6: **for**  $t = 2$  to  $T$  **do**
  - 7:    $\alpha_t^k = \sum_i \alpha_{t-1}^i P(S_t = k|S_{t-1} = i)P(O_t|S_t = k)$  for all  $k$
  - 8: **end for**
  - 9:  $P(S_t = k, \{O_t\}_{t=1}^T) = \alpha_t^k \beta_t^k$
  - 10:  $P(S_t = k|\{O_t\}_{t=1}^T) = \frac{P(S_t=k, \{O_t\}_{t=1}^T)}{P(\{O_t\}_{t=1}^T)} = \frac{\alpha_t^k \beta_t^k}{\sum_i \alpha_t^i \beta_t^i}$
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### 4.3.2 Backward-Forward Algorithm

Then we take a further step to think how to make it backward-forward by changing the order of sum of variable.

From the above expansion, since  $P(O_t|S_t = k)$  are independent of variable  $S_1, \dots, S_{t-1}, S_{t+1}, S_T$  we can leave it out and then the left part can be re-written as :

$$\begin{aligned}
\text{Left Part} &= \sum_{S_1} \cdots \sum_{S_{t-1}} P(S_1)P(S_2|S_1) \prod_{t=1}^{t-1} P(S_t|S_{t-1})P(O_t|S_t) \cdot P(S_t = k|S_{t-1}) \\
&= \sum_{S_1} \cdots \sum_{S_{t-1}=i} \underbrace{P(S_t = k|S_{t-1})P(O_{t-1}|S_{t-1})}_{\alpha_{t-1}^i} P(S_{t-1}|S_{t-2}) \prod_{t=1}^{t-2} P(S_t|S_{t-1})P(O_t|S_t) \\
&= \sum_{S_1} \cdots \sum_{S_{t-2}=i} \underbrace{\sum_{S_{t-1}=j} \alpha_{t-1}^j P(S_{t-1}|S_{t-2})P(O_{t-2}|S_{t-2})}_{\alpha_{t-2}^i} P(S_{t-2}|S_{t-3}) \prod_{t=1}^{t-3} P(S_t|S_{t-1})P(O_t|S_t)
\end{aligned}$$

**Note** : we then get the general form of  $\alpha$  by

$$\begin{aligned}
\alpha_x^j &= \sum_{S_{x+1}} \cdots \sum_{S_{t-1}} P(S_t = k|S_{t-1})P(O_{t-1}|S_{t-1}) \cdots P(S_{x+1}|S_x = j)P(O_x|S_x = j) \\
&= \sum_{S_{x+1}} \cdots \sum_{S_{t-1}} P(O_x, \dots, O_{t-1}, S_{x+1}, \dots, S_t = k|S_x = j) \\
&= P(O_x, \dots, O_{t-1}, S_t = k|S_x = j)
\end{aligned}$$

Similarly, the right part can be re-written as :

$$\begin{aligned}
\text{Right Part} &= \sum_{S_T} \cdots \sum_{S_{t+1}} P(S_{t+1}|S_t = k)P(O_{t+1}|S_{t+1}) \prod_{t+2}^T P(S_t|S_{t-1})P(O_t|S_t) \\
&= \sum_{S_T} \cdots \sum_{S_{t+1}=i} \underbrace{P(S_{t+1}|S_t = k)P(O_{t+1}|S_{t+1})}_{\beta_{t+1}^i} P(S_{t+2}|S_{t+1})P(O_{t+2}|S_{t+2}) \prod_{t+3}^T P(S_t|S_{t-1})P(O_t|S_t) \\
&= \sum_{S_T} \cdots \sum_{S_{t+2}=i} \underbrace{\sum_{S_{t+1}=j} \beta_{t+1}^j P(S_{t+2}|S_{t+1})P(O_{t+2}|S_{t+2})}_{\beta_{t+2}^i} P(S_{t+3}|S_{t+2})P(O_{t+3}|S_{t+3}) \cdots
\end{aligned}$$

**Note**: we then get the general form of  $\beta$  by

$$\begin{aligned}
\beta_x^j &= \sum_{S_{x-1}} \cdots \sum_{S_{t+1}} P(S_{t+1}|S_t = k)P(O_{t+1}|S_{t+1}) \cdots P(S_x = j|S_{x-1})P(O_x|S_x = j) \\
&= \sum_{S_{x-1}} \cdots \sum_{S_{t+1}} P(O_{t+1}, \dots, O_x, S_{t+1}, \dots, S_x = j|S_t = k) \\
&= P(O_{t+1}, \dots, O_x, S_x = j|S_t = k)
\end{aligned}$$

Based on above two parts, we can summarise the following backward-forward algorithm:

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**Algorithm 4** Backward-Forward Algorithm For Decoding Problem

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- 1: Initialise  $\alpha_{t-1}^i = P(S_t = k|S_{t-1} = i)P(O_{t-1}|S_{t-1} = i)$  for all  $i$
  - 2: Initialise  $\beta_{t+1}^i = P(S_{t+1} = i|S_t = k)P(O_{t+1}|S_{t+1} = i)$  for all  $i$
  - 3: **for**  $x = t + 2$  to  $T$  **do**
  - 4:    $\beta_x^i = \sum_j \beta_{x-1}^j P(S_x = i|S_{x-1} = j)p(O_x|S_x = i)$
  - 5: **end for**
  - 6: **for**  $x = t - 2$  to  $1$  **do**
  - 7:    $\alpha_x^i = \sum_j \alpha_{x+1}^j P(S_{x+1} = j|S_x = i)P(O_x|S_x = i)$
  - 8: **end for**
  - 9: Further Define  $\alpha_0 = \sum_i \alpha_1^i P(S_1 = i)$
  - 10: Further Define  $\beta_{T+1} = \sum_i \beta_T^i$
  - 11:  $P(S_t = k, \{O_t\}_{t=1}^T) = \alpha_0 \beta_{T+1} \cdot P(O_t|S_t = k)$
  - 12:  $P(S_t = k|\{O_t\}_{t=1}^T) = \frac{P(S_t=k, \{O_t\}_{t=1}^T)}{P(\{O_t\}_{t=1}^T)} = \frac{\alpha_0 \beta_{T+1} \cdot P(O_t|S_t=k)}{\sum_k \alpha_0 \beta_{T+1} \cdot P(O_t|S_t=k)}$
  - 13: For special case: if  $t = 1$ : We set  $\alpha_0 = P(S_1 = k)$ .
  - 14: If  $t = T$ : we set  $\beta_{T+1} = 1$ .
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You can check what's the remaining term to the left/right of the  $\parallel$  to see how to derive this special condition.