

Hidden Markov Models

x_0, x_1, x_2, \dots (random variables) is a Markov chain if

$$\Pr(x_{t+1} | x_0, \dots, x_t) = \underbrace{\Pr(x_{t+1} | x_t)}.$$

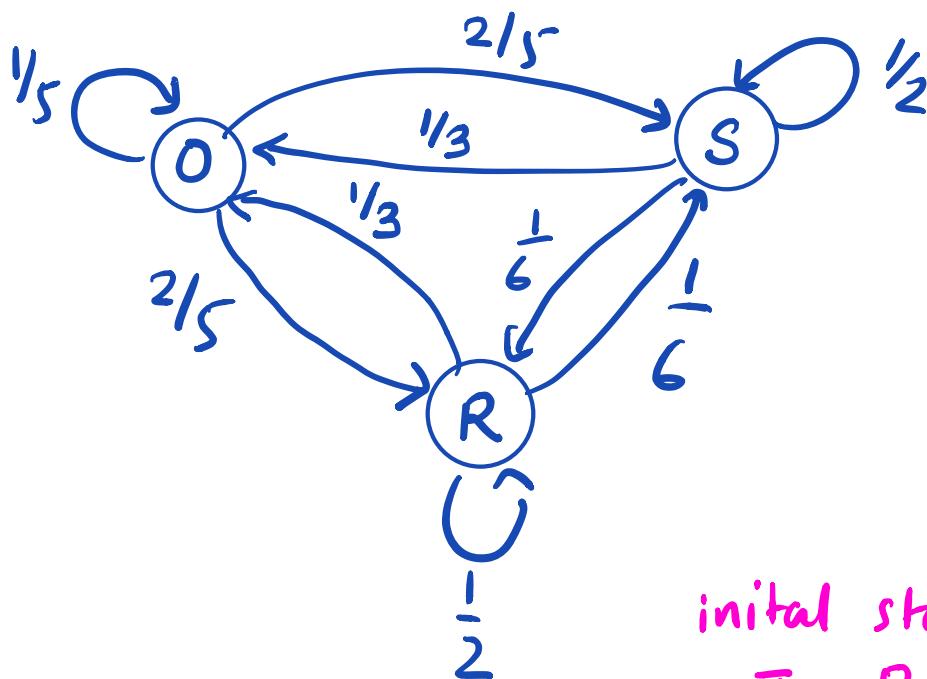
Future independent of past, given the present.

Finite State MC :- N :- # states.

$$x_t \in \{s_1, \dots, s_N\}, p_t(j) = \Pr(x_t = s_j) - ①$$

$$a_{ij} = \Pr(x_{t+1} = s_j | x_t = s_i) - ②$$

EX :-



$$N = 3, \{O, S, R\}, \{s_1, s_2, s_3\}$$

$$\Pr(S|R) = \frac{1}{6}$$

initial state distribution

$$\pi_j = \Pr(x_0 = s_j).$$

1. GOAL :- Given a_{ij} , and π , what is $\Pr(x_{t+1} = s_j)$?

$$\begin{aligned}
 \Pr(X_{t+1} = s_j) &= \sum_{l=1}^N \Pr(X_{t+1} = s_j, X_t = s_l) \\
 &= \sum_{l=1}^N \Pr(X_t = s_l) \cdot \Pr(X_{t+1} = s_j | X_t = s_l) \\
 &= \sum_{l=1}^N (\Pr(X_t = s_l) \cdot a_{lj})
 \end{aligned}$$

Prob(t, j)

```

    {
        if t = 0
            return πj;
    }

```

else

$$\text{sum} = \sum_{l=1}^N a_{lj} \cdot \text{Prob}(t-1, l)$$

return sum

fib(n)

```

    {
        if n=0 or n=1
            return 1
        else
    }

```

else

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    return
        fib(n-1) + fib(n-2)
    }

```

$$\Pr(X_{t+1} = s_j) = \sum_{\substack{x_0 \dots x_t}} \underbrace{\Pr(X_{t+1} = s_j, X_t, \dots, x_0)}_{N^t}$$

Dynamic Programming

$$\sum_{l=1}^N$$

Recall,

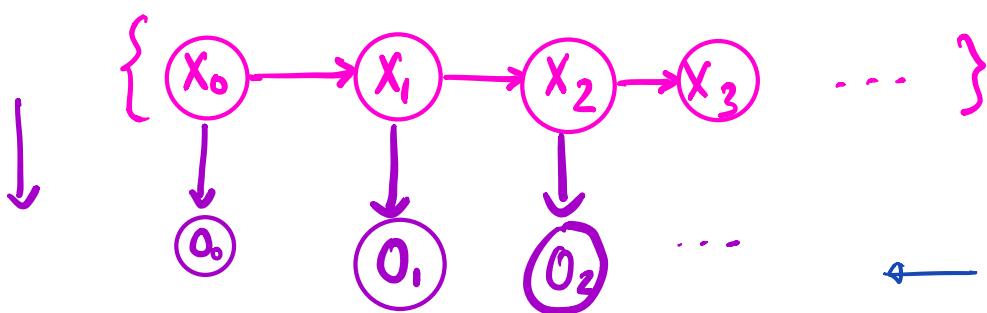
$$p_{t+1}(j) = \sum_{l=1} \alpha_{lj} \cdot \underline{\underline{p_t(l)}}.$$

- Compute distbⁿ @ time t+1, we can remember distbⁿ @ time t.

$$\left\{ \begin{array}{l} p_0(s) = \pi_s \\ \text{for } i=1, \dots, t+1 \\ \quad \text{for } s=1, \dots, N \\ \quad \underline{\underline{p_i(s)}} = \sum_{l=1}^N p_{i-1}(s) \cdot a_{ls} \end{array} \right. \rightarrow \boxed{\frac{N^2 t}{N^t}}$$

Hidden Markov Models.

(Murphy Ch 17), (Rabiner - tutorial)
↓ (summer to read list).



① X_0, X_1, \dots a MC. (hidden, a_{ij}, π)...

O_0, O_1, O_2, \dots ← get to see (observation).

Ex :- • speech • communication ...

$$\textcircled{2} \quad \Pr(O_t | X_t, X_0 \dots X_{t-1}, O_0, \dots, O_{t-1}) = \Pr(O_t | X_t).$$

$N - \# \text{ states}$ $O_1, \dots \in \{O_1, \dots, O_M\}$.

Let $b_i(j) = \Pr(O_t = O_j | X_t = s_i)$

HMM. { $\{S_1 \dots S_N\}, \{O_1 \dots O_M\}, a_{ij}, b_i(j), \pi$ } Model

1. State prob. estimation.

Estimate $\Pr(X_t = s_j | O_1 \dots O_t)$?

2. Most Probable Path (MPP). (Viterbi Algorithm)

Given $O_1 \dots O_T$,

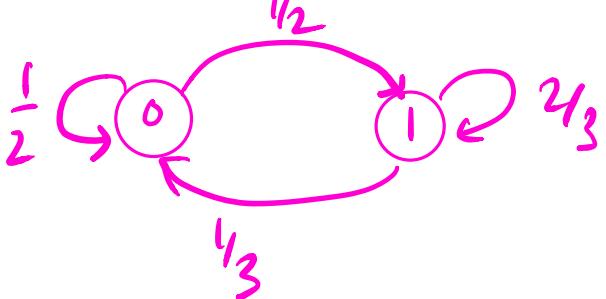
$\max_{S_0, S_1, \dots, S_T} \Pr(X_0 = s_0, X_1 = s_1, \dots, X_T = s_T | O_1 \dots O_T)$.

(CDMA, auto subtitles)

3. Learn the HMM (BW).

$\max_{\text{models}} \Pr(O_1 \dots O_T | \text{model})$.

EXAMPLE :- $N = 2$. $M = 11$



→ easy

$$\{-5, -4, \dots, 5\}.$$

- if $x_t = 0$, observe an even # @ random
 $\{4, -2, 0, 2, 4\} \rightarrow l_5$.
- if $x_t = 1$, observe an odd # @ random
 $\{-5, -3, -1, 1, 3, 5\} \rightarrow l_6$.

1. State prob. estimation.

Estimate $\text{Prob}(x_{t+1} = s_j | o_1, \dots, o_t)$?

$$\{s_1, \dots, s_N\} \quad \{o_1, \dots, o_M\}.$$

→ $a_{ij} = \Pr(x_{t+1} = s_j | x_t = s_i), \quad b_i(o) = \Pr(o_t = o_i | x_t = s_i)$

• $\alpha_t(i) := \text{Prob}(o_1, \dots, o_t, x_t = s_i), \quad \sum_{i=1}^N \alpha_t(i) = \text{Prob}(o_1, \dots, o_t)$

$$\begin{aligned} \alpha_{t+1}(j) &= \text{Prob}(o_1, \dots, o_{t+1}, x_{t+1} = s_j) \\ &= \sum_{i=1}^N \text{Prob}(o_1, \dots, o_t, \underbrace{x_t = s_i}_{\circlearrowleft}, o_{t+1}, x_{t+1} = s_j) \\ &= \sum_{i=1}^N \text{Prob}(o_1, \dots, o_t, \underbrace{x_t = s_i}_{\circlearrowleft}) \cdot \overbrace{\Pr(x_{t+1} = s_j | x_t = s_i)}^{\circlearrowright} \end{aligned}$$

$$\Pr(O_{t+1} | X_{t+1} = s_j)$$

$$= \sum_{i=1}^N \alpha_t(i) \cdot a_{ij} \cdot b_j(O_{t+1})$$

1. Compute $\alpha_t(1), \dots, \alpha_t(N)$ (time = $N^2 t$)

$$2. \Pr(X_{t+1} = s_j | O_0 \dots O_{t+1}) = \frac{\alpha_{t+1}(j)}{\alpha_{t+1}(1) + \dots + \alpha_{t+1}(N)} - \textcircled{1}$$

$$= \frac{\Pr(O_1 \dots O_{t+1}, X_{t+1} = s_j)}{\sum_{i=1}^N \Pr(O_0 \dots O_{t+1}, X_{t+1} = s_i)}$$

2. Most Probable Path (MPP).

Given $O_1 \dots O_T$,

$$\max_{S_0 S_1 \dots S_T} \text{Prob}(x_0 = s_0, x_1 = s_1, \dots, x_T = s_T | O_1 \dots O_T).$$

$$\arg \max_{X_0 \dots X_T} \Pr(x_0 \dots x_T | \overbrace{O_0 \dots O_T}^{O_1 \dots O_T}) \longrightarrow$$

$$= \arg \max_{X_0 \dots X_T} \frac{\text{Prob}(O_0 \dots O_T | X_0 \dots X_T) \cdot \Pr(X_0 \dots X_T)}{\boxed{\Pr(O_0 \dots O_T)} X}$$

$$= \arg \max_{\underline{X_0} \dots \underline{X_T}} \text{Prob}(O_0 \dots O_T | \underline{x_0} \dots \underline{x_T}) \cdot \Pr(\underline{x_0} \dots \underline{x_T})$$

Let $\delta_t(i) = \max_{x_0 \dots x_{t-1}} \Pr(\underbrace{x_0 \dots x_{t-1}}_{N=3}, \underline{\underline{x_t=s_i}}, \underline{\underline{o_1 \dots o_t}})$

