

Hidden Markov Model

Wei Wang @ CSE, UNSW

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- $P(S_{1:k} \mid O_{1:k}) \stackrel{\text{def}}{=} P(S_1, \dots, S_k \mid O_1, \dots, O_k)$
- What do we need?
 - $\arg \max P(S_{1:k} \mid O_{1:k})$
 - Can we derive even $P(S_1 \mid O_1)$?

k=1的时候



s是state O是observation

- $P(S_{1:k} \mid O_{1:k}) \stackrel{\text{def}}{=} P(S_1, \dots, S_k \mid O_1, \dots, O_k)$
- What do we need? 在给定观测样本序列前提下,得到最大概率的状态序列排序
 - $\arg \max P(S_{1:k} \mid O_{1:k})$
 - Can we derive even $P(S_1 \mid O_1)$?
 - Need to use the Bayes rule:

$$P(S_{1:k} \mid O_{1:k}) = \frac{P(O_{1:k} \mid S_{1:k}) \cdot P(S_{1:k})}{P(O_{1:k})}$$

- Because of the “arg max”, we have

$$\begin{aligned} \arg \max_{S_{1:k}} P(S_{1:k} \mid O_{1:k}) &= \arg \max_{S_{1:k}} P(O_{1:k} \mid S_{1:k}) \cdot P(S_{1:k}) \\ &= \arg \max_{S_{1:k}} P(O_{1:k}, S_{1:k}) \end{aligned}$$

- Since we can compute the probabilities, the naive method is to consider all $O(N^k)$ state sequences, where N is the number of states.

- A common trick (for Markov Chains) is to check if we can use recursion (thanks for the abundant conditional independences given by the Markov assumption).

Note:

$$\begin{aligned}P(O_{1:k+1} \mid S_{1:k+1}) &= P(O_{k+1} \mid O_{1:k}, S_{1:k+1}) \cdot P(O_{1:k} \mid S_{1:k+1}) \\&= P(O_{k+1} \mid S_{k+1}) \cdot P(O_{1:k} \mid S_{1:k})\end{aligned}$$

$$P(S_{1:k+1}) = P(S_{1:k}) \cdot P(S_{k+1} \mid S_k)$$

Then

$$\begin{aligned}&P(O_{1:k+1}, S_{1:k+1}) \\&= P(O_{k+1} \mid S_{k+1}) \cdot P(O_{1:k} \mid S_{1:k}) \cdot P(S_{1:k}) \cdot P(S_{k+1} \mid S_k) \\&= P(O_{k+1} \mid S_{k+1}) \cdot P(S_{k+1} \mid S_k) \cdot P(O_{1:k}, S_{1:k})\end{aligned}$$

$$\begin{aligned}
 P(O_{1:k+1}, S_{1:k+1}) &= P(O_{1:k}, S_{1:k}) \cdot \left(P(O_{k+1} \mid S_{k+1}) \cdot P(S_{k+1} \mid S_k) \right) \\
 &= P(O_{1:k}, S_{1:k}) \cdot f(S_k, S_{k+1})
 \end{aligned}$$

- Note that the value of S_k is important when considering applying “max”.
- Define $\delta(k, v) \stackrel{\text{def}}{=} \max_{S_{1:k-1}} P(O_{1:k}, S_{1:k-1}, v)$, we have the recurrence:

$$\delta(k+1, v) = \max_u (\delta(k, u) \cdot f(u, v))$$

with the boundary condition:

$$\delta(1, v) = P(O_1, v)$$

- Then

$$\max_{S_{1:k+1}} P(O_{1:k+1}, S_{1:k+1}) = \max_v \max_{S_{1:k}} P(O_{1:k+1}, S_{1:k}, v) = \max_v \delta(k+1, v)$$

- The arg max solution can be obtained via backtracking or some additional data structure.