

CSE 5525 Artificial Intelligence II

Quiz #6: Hidden Markov Models

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At time t , Peter is in some state X_t . The two states Peter alternates between are saving the world (denoted as S) and being a CSE student (denoted as C). Let the evidence E_t be whether or not Peter is seen in the CSE labs at time t .

The transition probabilities are provided in the following table (left), where the row corresponds to X_{t-1} and the column to X_t . For example, $P(X_t = S | X_{t-1} = C) = 0.4$.

X_{t-1}	X_t	$P(X_t X_{t-1})$
C	C	0.6
C	S	0.4
S	C	0.2
S	S	0.8

X_t	E_t	$P(E_t X_t)$
C	true	0.7
C	false	0.3
S	true	0.1
S	false	0.9

The model for evidence E_t is provided in the following table, where the row corresponds to X_t and the column to E_t . For example, $P(E_t = \text{false} | X_t = S) = 0.9$.

Questions:

- 1) Assume we have current belief $B(X_t) = P(X_t | e_{1:t})$, how to compute for passage of time?

$$B'(X_{t+1}) = P(X_{t+1} | e_{1:t}) = \sum_{X_t \in \{S, C\}} \underbrace{P(X_{t+1} | X_t)}_{\text{transition}} \underbrace{P(X_t | e_{1:t})}_{B(X_t)}$$

How to update the belief with the observation of evidence (forward algorithm)?

$$B(X_{t+1}) = P(X_{t+1} | e_{1:t+1}) \propto_{X_{t+1}} B'(X_{t+1}) P(e_{t+1} | X_{t+1})$$

2) Let the initial beliefs be $P(X_0 = S) = P(X_0 = C) = 0.5$. Fill in the following table for $t = 1$, first computing for passage of time, and then for observation of evidence $E_1 = \text{true}$. Finally, normalize the values from the observation column to get the beliefs. Round to three decimal places.

$P(X_1|X_0=S)P(X_0=S|e_0) + P(X_1|X_0=C)P(X_0=C|e_0) \quad B'(X_1)P(E_1=\text{true}|X_1)$

X_1	passage of time $B'(X_1)$	update with evidence $E_1 = \text{true}$	$B(X_1)$
S	$0.8 \times 0.5 + 0.4 \times 0.5 = 0.6$	$0.6 \times 0.1 = 0.06$	$\frac{0.06}{0.06 + 0.28} = 0.176$
C	$0.2 \times 0.5 + 0.6 \times 0.5 = 0.4$	$0.4 \times 0.7 = 0.28$	$\frac{0.28}{0.06 + 0.28} = 0.824$

3) Repeat for $t = 2$, with the observation of evidence $E_2 = \text{false}$. When using any previous value for computations, use their rounded value. Round to three decimal places.

$P(X_2|X_1=S)B(X_1=S) + P(X_2|X_1=C)B(X_1=C)$

X_2	passage of time $B'(X_2)$	update with evidence $E_2 = \text{false}$	$B(X_2)$
S	$0.8 \times 0.176 + 0.4 \times 0.824 = 0.470$	$0.470 \times 0.9 = 0.423$	$\frac{0.423}{0.423 + 0.159} = 0.727$
C	$0.2 \times 0.176 + 0.6 \times 0.824 = 0.530$	$0.530 \times 0.3 = 0.159$	$\frac{0.159}{0.423 + 0.159} = 0.273$

4) Assume now we are using a particle filter with 3 particles to approximate our belief instead of using exact inference as in 1 – 3). Imagine we have just applied transition model sampling (passage of time) from state X_0 to X_1 , and now have the set of particles S, S, C . What is our belief about X_1 before considering noisy evidence?

X_1	passage of time $B'(X_1)$
S	$\frac{2}{3}$
C	$\frac{1}{3}$

5) Now assume we receive evidence $E_1 = \text{true}$. What is the weight for each particle, and what is our belief now about X_1 (before weighted re-sampling)?

particle	weight
S	0.1
S	0.1
C	0.7

X_1	after observation $B(X_1)$
S	$\frac{0.1 + 0.1}{0.1 + 0.1 + 0.7} = 0.222$
C	$\frac{0.7}{0.1 + 0.1 + 0.7} = 0.778$

6) Will performing weighted re-sampling on these weighted particles to obtain our three new particle representation for X_1 cause our belief to change?

Yes, sampling is an approximation and three unweighted particles will not be able to represent 0.222, 0.778 (i.e. only can do 0, 1, 0.333, 0.667)

7) Recall from the lecture that $m_t[x_t] = \max_{x_{1:t-1}} P(x_{1:t-1}, x_t, e_{1:t})$, which is the probability of the most likely path that ends at x_t , considering the path up to t and the evidence up to t . Use **Viterbi algorithm** to compute $m_1[S_1]$, $m_1[C_1]$, $m_2[S_2]$, $m_2[C_2]$ for the sequence of evidence $E_1 = \text{true}$, $E_2 = \text{false}$. Define $m_0[S] = m_0[C] = 0.5$. Use exact numbers in your calculations and answers. What was Peter most likely doing at time $t = 1$ and at time $t = 2$?

$$\begin{aligned} m_t[X_t] &= \max_{X_{1:t-1}} P(X_{1:t-1}, X_t, e_{1:t}) \\ &= P(e_t | X_t) \cdot \max_{X_{t-1}} P(X_t | X_{t-1}) m_{t-1}[X_{t-1}] \end{aligned}$$

$$\begin{aligned} m_1[S_1] &= P(E_1 = \text{true} | X_1 = S) \cdot \max_{X_0} \begin{cases} P(X_1 = S | X_0 = S) m_0[X_0 = S] \\ P(X_1 = S | X_0 = C) m_0[X_0 = C] \end{cases} \\ &= 0.1 \times \max(0.8 \times 0.5, 0.4 \times 0.5) \\ &= 0.04 \end{aligned}$$

$$\begin{aligned} m_1[C_1] &= P(E_1 = \text{true} | X_1 = C) \cdot \max_{X_0} \begin{cases} P(X_1 = C | X_0 = S) m_0[S] \\ P(X_1 = C | X_0 = C) m_0[C] \end{cases} \\ &= 0.7 \times \max(0.2 \times 0.5, 0.6 \times 0.5) \\ &= 0.21 \end{aligned}$$