Fundamentals of Artificial Intelligence
Exercise 9: Hidden Markov Models

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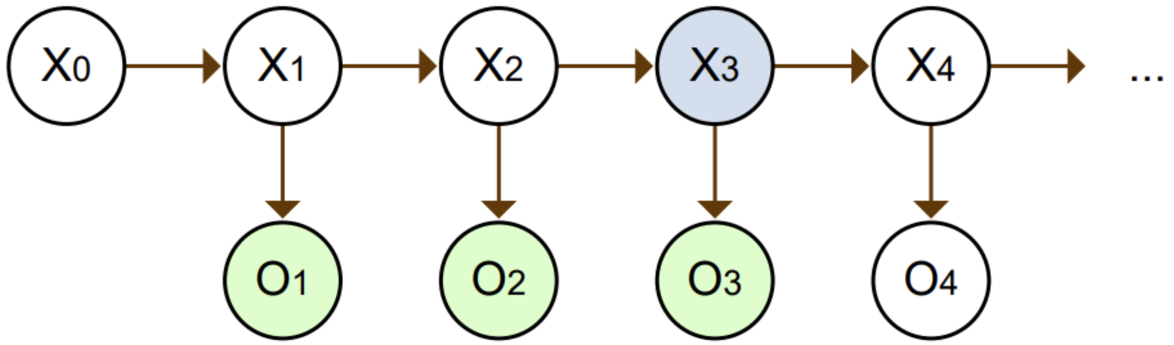
Recap Hidden Markov Models

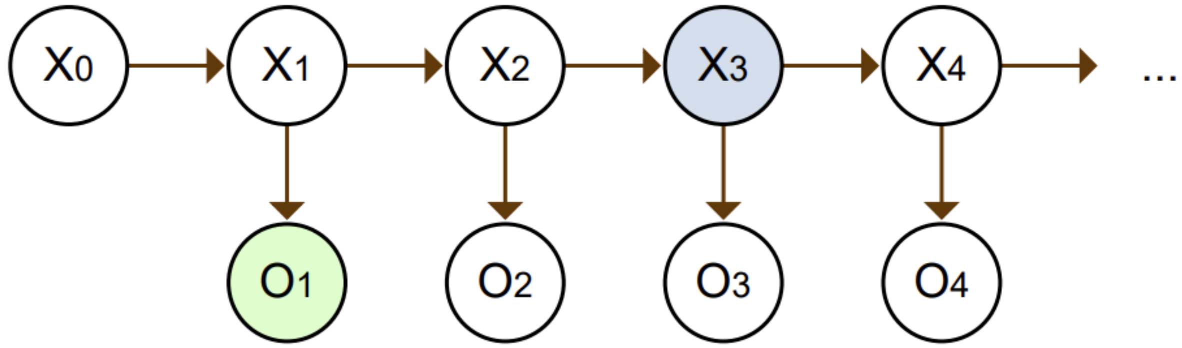
- Discrete underlying real-world states X_t that changes over time t
- Observations E_t at each timestep that can be used to guess at the state with some level of confidence
- Idea is to use the observation E at time t to guess at the state X_t, but then refine our guess using the observations before and after t

Recap Inference Tasks

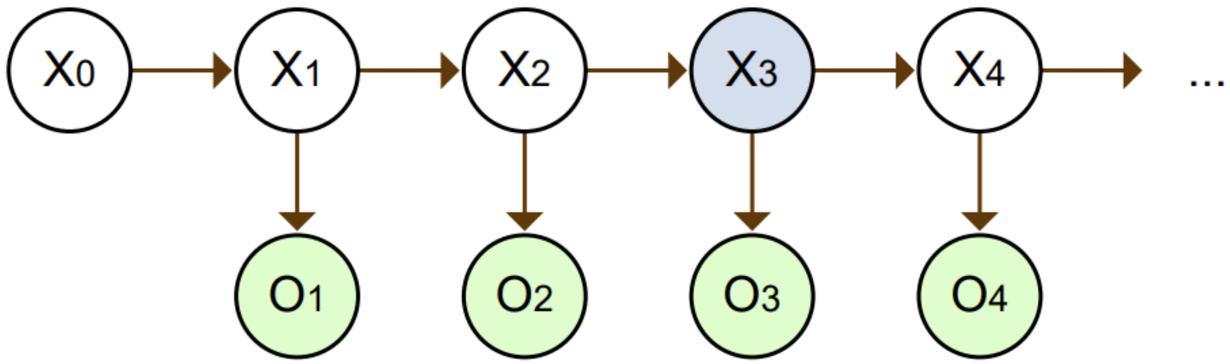
Filtering $P(X_t|o_{1:t})$



Prediction $P(X_k|o_{1:t}), k > t$



Smoothing $P(X_k|o_{1:t}), 0 \leq k < t$



Problem 9.1

ES $\{es, \neg es\}$

A professor wants to know if students are getting enough sleep. Each day, the professor observes whether the students sleep in class, and whether they have red eyes. The professor has the following domain theory:

observations: SC $\{sc, \neg sc\}$ RE $\{re, \neg re\}$

- The prior probability of getting enough sleep, with no observations, is 0.7.

  $P(es) = 0.7$

- The probability of getting enough sleep on night t is 0.8 given that the student got enough sleep the previous night, and 0.3 if not.

  $P(es_t \mid es_{t-1}) = 0.8$ $P(es_t \mid \neg es_{t-1}) = 0.3$

- The probability of having red eyes is 0.2 if the student got enough sleep, and 0.7 if not.

  $P(re \mid es) = 0.2$ $P(re \mid \neg es) = 0.7$

- The probability of sleeping in class is 0.1 if the student got enough sleep, and 0.3 if not.

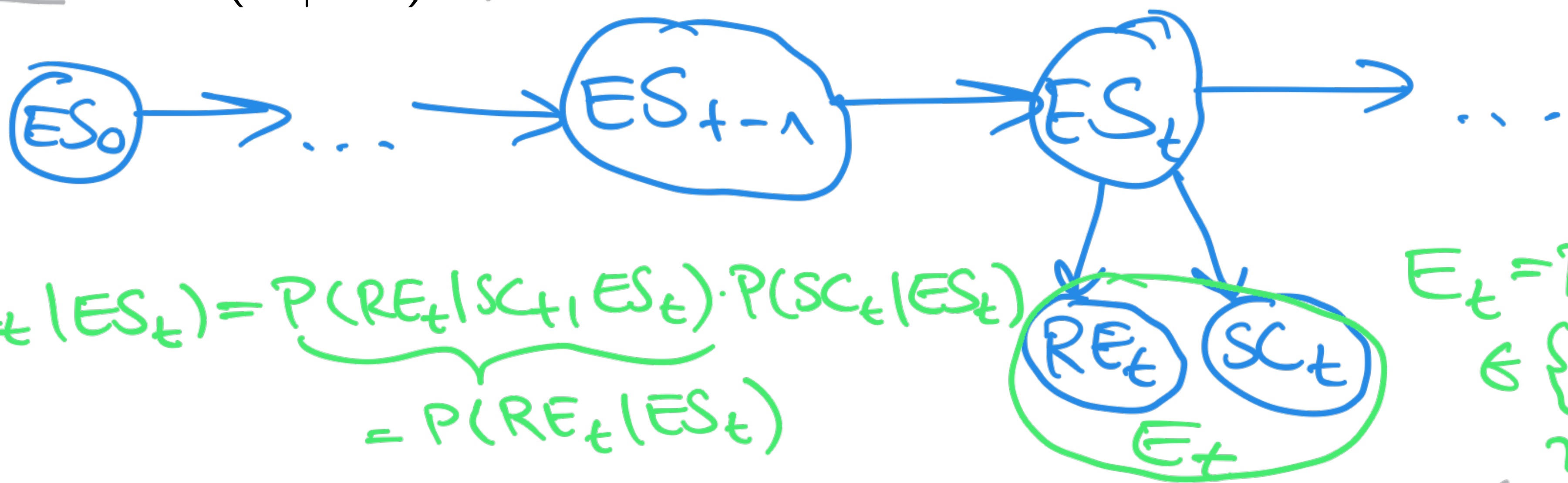
  $P(sc \mid es) = 0.1$ $P(sc \mid \neg es) = 0.3$

a. Formulate this information as an Hidden Markov Model that has only one observation variable. Give the complete probability tables for the model.

$P(es) = 0.7$, and $P(\neg es) = 0.3$;
$P(es_t | es_{t-1}) = 0.8$, and $P(es_t | \neg es_{t-1}) = 0.3$;
$P(re | es) = 0.2$, and $P(re | \neg es) = 0.7$;
$P(sc | es) = 0.1$, and $P(sc | \neg es) = 0.3$.

ES_{t-1}	$P(es_t \mid ES_{t-1})$
t	0.8
f	0.3

$P(es_0)$
0.7



$$P(RE_t \wedge SC_t | ES_t) = \underbrace{P(RE_t | SC_t, ES_t)}_{= P(RE_t | ES_t)} \cdot P(SC_t | ES_t)$$

$E_t = RE_t \wedge SC_t$
$\in \{ re_t \wedge sc_t,\ \neg re_t \wedge sc_t,\ re_t \wedge \neg sc_t,\ \neg re_t \wedge \neg sc_t \}$

ES_t	$P(E_t = re \wedge sc \mid ES_t)$	$P(\neg re \wedge sc \mid ES)$	$P(re \wedge \neg sc \mid ES)$	$P(\neg re \wedge \neg sc \mid ES)$
t	$P(re \mid es) P(sc \mid es) = 0.2 \cdot 0.1 = 0.02$	0.08	0.18	0.72
f	$P(re \mid \neg es) P(sc \mid \neg es) = 0.7 \cdot 0.3 = 0.21$	0.09	0.49	0.21

$P(es) = 0.7$, and $P(\neg es) = 0.3$;
$P(es_t | es_{t-1}) = 0.8$, and $P(es_t | \neg es_{t-1}) = 0.3$;
$P(re | es) = 0.2$, and $P(re | \neg es) = 0.7$;
$P(sc | es) = 0.1$, and $P(sc | \neg es) = 0.3$.

Problem 9.1 b

Consider the following evidence values:

- $\mathbf{e}_1$ = not red eyes, not sleeping in class; $e_1 = \neg re \wedge \neg sc$
- $\mathbf{e}_2$ = red eyes, not sleeping in class; $e_2 = re \wedge \neg sc$
- $\mathbf{e}_3$ = red eyes, sleeping in class. $e_3 = re \wedge sc$

↗ slide 20-22

b. State estimation: Compute $P\left(EnoughSleep_t | \mathbf{e}_{1:t}\right)$ for each $t = 1, 2, 3$.

$$\underbrace{P(ES_t | e_{1:t})}_{f_{1:t}} = P(ES_t | e_{1:t-1}, e_t)$$

$$= \alpha\, P(e_t | ES_t, \cancel{e_{1:t-1}})\, P(ES_t | e_{1:t-1})$$ Sensor Markov assumption

$$= \alpha\, \underbrace{P(e_t | ES_t)}_{O_t} \sum_{es_{t-1}} \underbrace{P(ES_t, es_{t-1} | e_{1:t-1})}_{\underbrace{P(ES_t | es_{t-1}, \cancel{e_{1:t-1}})}_{T}\, \underbrace{P(es_{t-1} | e_{1:t-1})}_{f_{1:t-1}}}$$ Markov assumption

$$f_{1:t} = \alpha\, O_t\, T\, f_{1:t-1}$$

$\mathbf{e}_1 = \neg re \wedge \neg sc$,
$\mathbf{e}_2 = re \wedge \neg sc$,
$\mathbf{e}_3 = re \wedge sc$

ES_{t-1}	$P(es_t \mid ES_{t-1})$
true	0.8
false	0.3

ES_t	$P(re \wedge sc \mid ES_t)$	$P(\neg re \wedge sc \mid ES_t)$	$P(re \wedge \neg sc \mid ES_t)$	$P(\neg re \wedge \neg sc \mid ES_t)$
true	0.02	0.08	0.18	0.72
false	0.21	0.09	0.49	0.21

$$T_{ij} = P(X_t = x_i \mid X_{t-1} = x_j) \rightarrow T = \begin{bmatrix} P(es_t \mid es_{t-1}) & P(es_t \mid \neg es_{t-1}) \\ P(\neg es_t \mid es_{t-1}) & P(\neg es_t \mid \neg es_{t-1}) \end{bmatrix} = \begin{bmatrix} 0.8 & 0.3 \\ 0.2 & 0.7 \end{bmatrix}$$

$$(O_{ij})_t = \begin{cases} P(e_t \mid X_t = x_i), & \text{if } j = i \\ 0 & \text{otherwise} \end{cases} \rightarrow O_1 = \begin{bmatrix} P(\neg re \wedge \neg sc \mid es_t) & 0 \\ 0 & P(\neg re \wedge \neg sc \mid es_t) \end{bmatrix} = \begin{bmatrix} 0.72 & 0 \\ 0 & 0.21 \end{bmatrix}$$

$$O_2 = \begin{bmatrix} 0.18 & 0 \\ 0 & 0.49 \end{bmatrix}$$

$$O_3 = \begin{bmatrix} 0.02 & 0 \\ 0 & 0.21 \end{bmatrix}$$

$\mathbf{f}_{1:t} = \alpha \mathbf{O}_t \mathbf{T} \mathbf{f}_{1:t-1}$, $\mathbf{T} = \begin{bmatrix} 0.8 & 0.3 \\ 0.2 & 0.7 \end{bmatrix}$, $\mathbf{O}_1 = \begin{bmatrix} 0.72 & 0 \\ 0 & 0.21 \end{bmatrix}$, $\mathbf{O}_2 = \begin{bmatrix} 0.18 & 0 \\ 0 & 0.49 \end{bmatrix}$, $\mathbf{O}_3 = \begin{bmatrix} 0.02 & 0 \\ 0 & 0.21 \end{bmatrix}$

$$f_0 = \begin{bmatrix} P(es_0) \\ P(\neg es_0) \end{bmatrix} = \begin{bmatrix} 0.7 \\ 0.3 \end{bmatrix}$$

$$f_{1:1} = \alpha O_1 T f_0 = \alpha \begin{bmatrix} 0.72 & 0 \\ 0 & 0.21 \end{bmatrix} \begin{bmatrix} 0.8 & 0.3 \\ 0.2 & 0.7 \end{bmatrix} \begin{bmatrix} 0.7 \\ 0.3 \end{bmatrix} = \alpha \begin{bmatrix} 0.4680 \\ 0.0735 \end{bmatrix}$$

$$\alpha = \frac{1}{0.4680 + 0.0735}$$

$$= \begin{bmatrix} 0.8643 \\ 0.1357 \end{bmatrix}$$

$$f_{1:2} = \alpha O_2 T f_{1:1} = \ldots = \begin{bmatrix} 0.5010 \\ 0.4990 \end{bmatrix}$$

$$f_{1:3} = \alpha O_3 T f_{1:2} = \ldots = \begin{bmatrix} 0.1045 \\ 0.8955 \end{bmatrix}$$

Problem 9.1 c

c. Smoothing: Compute $P(EnoughSleep_t|\mathbf{e}_{1:3})$ for each $t = 1, 2, 3$.

$$P(ES_t|e_{1:r}) = P(ES_t|e_{1:t}, e_{t+1:r})$$

$r=3$

$\vdots$ ↗ slide 43

$$= \alpha \underbrace{P(ES_t|e_{1:t})}_{f_{1:t}} \underbrace{P(e_{t+1:r}|ES_t)}_{:= b_{t+1:r}}$$

$$= \alpha f_{1:t} \times b_{t+1:r}$$

$$b_{t:r} = P(e_{t:r}|ES_{t-1})$$

$\vdots$ ↗ slide 44

$$= \sum_{es_t} P(e_t|es_t) \underbrace{P(e_{t+1:r}|es_t)}_{b_{t+1:r}} P(es_t|ES_{t-1})$$

$P(e_t|es_t) \downarrow O_t$, $P(es_t|ES_{t-1}) \downarrow T$

$$b_{t:r} = T^T O_t b_{t+1:r}$$

$\mathbf{b}_{t:r} = \mathbf{T}^\top \mathbf{O}_t \mathbf{b}_{t+1:r}$, $\quad \mathbf{T} = \begin{bmatrix} 0.8 & 0.3 \\ 0.2 & 0.7 \end{bmatrix}$, $\mathbf{O}_1 = \begin{bmatrix} 0.72 & 0 \\ 0 & 0.21 \end{bmatrix}$, $\mathbf{O}_2 = \begin{bmatrix} 0.18 & 0 \\ 0 & 0.49 \end{bmatrix}$, $\mathbf{O}_3 = \begin{bmatrix} 0.02 & 0 \\ 0 & 0.21 \end{bmatrix}$

initialize: $b_{4:3} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

$$b_{3:3} = T^T O_3 b_{4:3} = \begin{bmatrix} 0.8 & 0.2 \\ 0.3 & 0.7 \end{bmatrix} \begin{bmatrix} 0.02 & 0 \\ 0 & 0.21 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.0580 \\ 0.1530 \end{bmatrix}$$

$$b_{2:3} = T^T O_2 b_{3:3} = \dots = \begin{bmatrix} 0.0233 \\ 0.0556 \end{bmatrix}$$

$$P(ES_t | e_{1:3}) = \alpha f_{1:t} \times b_{t+1:3}$$

$$P(ES_1 | e_{1:3}) = \alpha f_{1:1} \times b_{2:3} = \alpha \begin{bmatrix} 0.8643 \\ 0.1557 \end{bmatrix} \times \begin{bmatrix} 0.0233 \\ 0.0556 \end{bmatrix} = \alpha \begin{bmatrix} 0.0201 \\ 0.0075 \end{bmatrix} = \begin{bmatrix} 0.7277 \\ 0.2723 \end{bmatrix}$$

$$\frac{1}{0.0201 + 0.0075}$$

$$P(ES_2 | e_{1:3}) = \alpha f_{1:2} \times b_{3:3} = \dots = \begin{bmatrix} 0.2757 \\ 0.7243 \end{bmatrix}$$

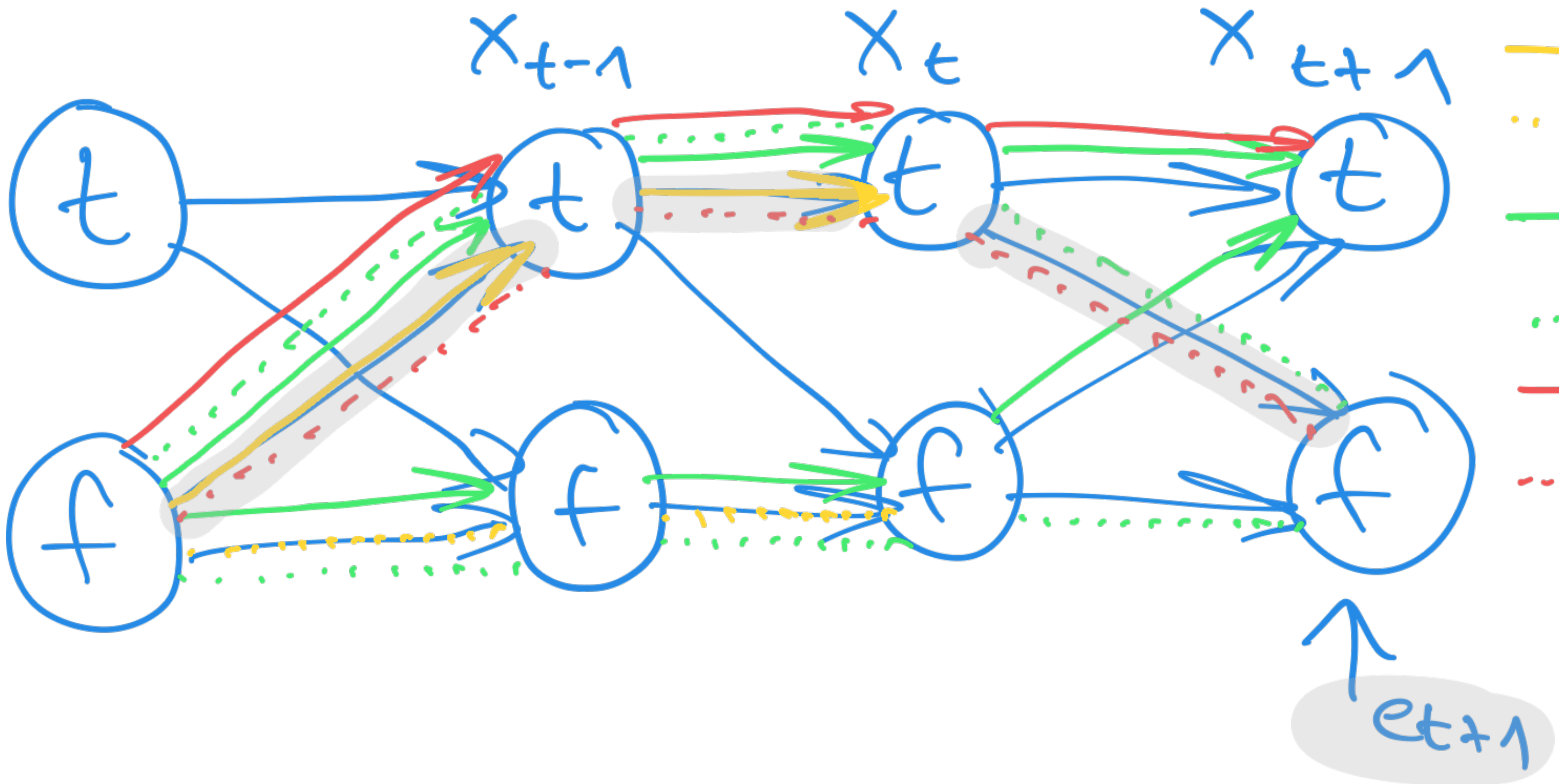
Problem 9.1 c

Problem 9.1 d

d. Find the most likely state sequence.

Viterbi's Algorithm

$$\max_{x_1 \dots x_t} \mathbf{P}\left(x_1, \dots x_t, X_{t+1} | \mathbf{e}_{1:t+1}\right) = \alpha \mathbf{P}\left(e_{t+1} | X_{t+1}\right) \max_{x_t} \left(\mathbf{P}\left(X_{t+1} | x_t\right) \max_{x_1 \dots x_{t-1}} P\left(x_1, \dots x_t | \mathbf{e}_{1:t}\right) \right).$$



— most likely path ending in X_t=true

··· mlp ending in X_t=false

— candidate mlp ending in X_{t+1}=t

··· " " " X_{t+1}=f

— mlp ending in X_{t+1}=t

··· " " X_{t+1}=f

Viterbi's Algorithm

$$\max_{x_1\dots x_t} \mathbf{P}(x_1,\dots x_t, X_{t+1}|\mathbf{e}_{1:t+1}) = \alpha \underbrace{\mathbf{P}(e_{t+1}|X_{t+1}) \max_{x_t}\Big(\mathbf{P}(X_{t+1}|x_t) \underbrace{\max_{x_1\dots x_{t-1}} P(x_1,\dots x_t|\mathbf{e}_{1:t})}_{\mu_1(ES_1)}\Big)}_{\mu_2(ES_2)}.$$

$$\mu_1(ES_1) = p(ES_1|e_{1:1}) = f_{1:1} = \begin{bmatrix} 0.8643 \\ 0.1357 \end{bmatrix}$$

→ prob. of mlp ending in es
→ " " " in $\neg es$

Step 1:

$$\mu_2(ES_2) = \mathbf{P}(e_2|ES_2) \max_{ES_1} \mathbf{P}(ES_2|ES_1)\, \mu_1(ES_1).$$

$$= P(e_2|ES_2) \max\{P(ES_2|es_1)\mu_1(es_1),\ P(ES_2|\neg es_1)\mu_1(\neg es_1)\}$$

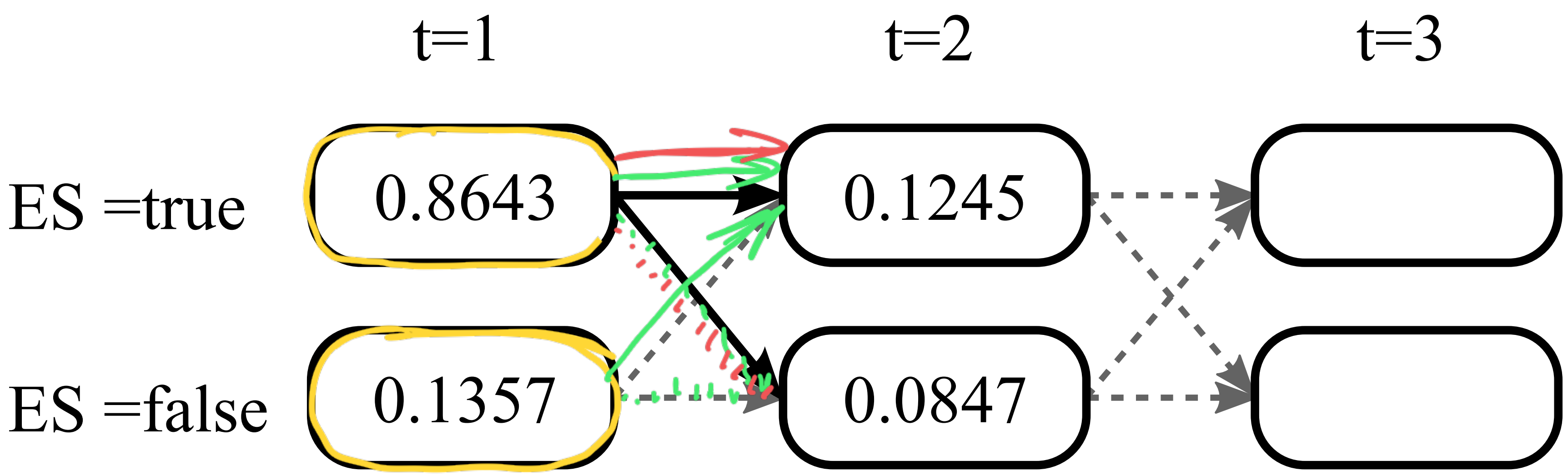
$$= P(e_2|ES_2) \max\left\{\begin{bmatrix} 0.6914 \\ 0.1729 \end{bmatrix}, \begin{bmatrix} 0.0407 \\ 0.0550 \end{bmatrix}\right\}$$

$es_1 \to es_2$ (0.6914); $es_1 \to \neg es_2$ (0.1729); $\neg es_1 \to es_2$ (0.0407); $\neg es_1 \to \neg es_2$ (0.0550)

$$= \begin{bmatrix} \overset{0.18}{\cancel{0.6914}} \\ \underset{0.49}{\cancel{0.1729}} \end{bmatrix} \times \begin{bmatrix} 0.6914 \\ 0.1729 \end{bmatrix}$$

$$= \begin{bmatrix} 0.1245 \\ 0.0847 \end{bmatrix}$$

→ unnormalized prob. for the mlp ending es_2 ($es_1 \to es_2$)
" " " " " " $\neg es_2$ ($es_1 \to \neg es_2$)


t=1
t=2
t=3
ES =true
0.8643
0.1245
ES =false
0.1357
0.0847

Viterbi's Algorithm

$$\max_{x_1\dots x_t} \mathbf{P}\left(x_1,\dots x_t, X_{t+1}|\mathbf{e}_{1:t+1}\right) = \alpha \mathbf{P}\left(e_{t+1}|X_{t+1}\right) \underbrace{\max_{x_t}\left(\mathbf{P}\left(X_{t+1}|x_t\right) \underbrace{\max_{x_1\dots x_{t-1}} P\left(x_1,\dots x_t|\mathbf{e}_{1:t}\right)}_{\mu_2(ES_2)}\right)}.$$

$$\mu_2(ES_2) = \begin{bmatrix} 0.1245 \\ 0.0847 \end{bmatrix}$$

→ unnormalized prob. of the mlp ending in es_2 $(es_1 \to es_2)$
→ " " " $\neg es_2$ $(es_1 \to \neg es_2)$

Step 2:

$$\mu_3\left(ES_3\right) = \mathbf{P}\left(e_3|ES_3\right) \max_{ES_2} \mathbf{P}\left(ES_3|ES_2\right)\mu_2\left(ES_2\right).$$

$$= \begin{bmatrix} 0.02 \\ 0.21 \end{bmatrix} \max\left\{ \underbrace{\begin{bmatrix} 0.0996 \\ 0.0249 \end{bmatrix}}_{es_2}, \underbrace{\begin{bmatrix} 0.0254 \\ 0.0593 \end{bmatrix}}_{\neg es_2} \right\}$$

$es_1 \to es_2 \to es_3$

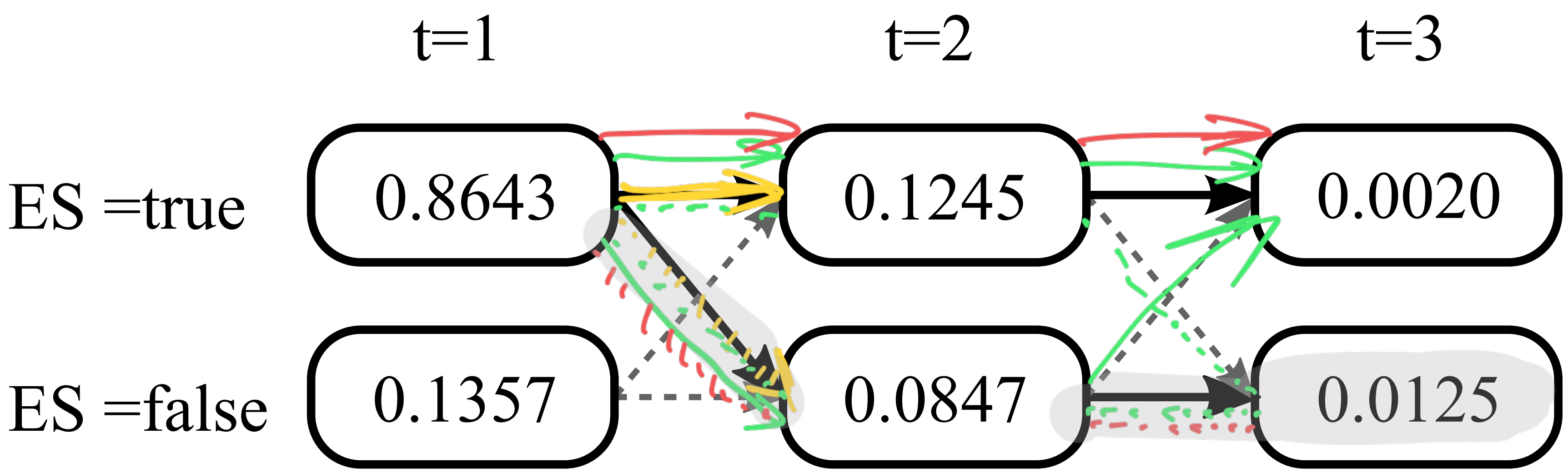
$es_1 \to \neg es_2 \to es_3$

$es_1 \to \neg es \to \neg es_3$

$es_1 \to es_2 \to es_3$

$$= \begin{bmatrix} 0.0020 \\ 0.0125 \end{bmatrix}$$

← unnormalized prob. of mlp ending in es_3 $(es_1 \to es_2 \to es_3)$
← " " " $\neg es_3$ $(es_1 \to \neg es_2 \to \neg es_3)$


t=1
t=2
t=3
ES =true
ES =false
0.8643
0.1245
0.0020
0.1357
0.0847
0.0125