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50.007 Machine Learning
Homework 3

Q1

A HMM is defined by a tuple $\langle \mathcal{T}, \sigma, \theta \rangle$, where:

- \mathcal{T} is the set of states including the *START* state and *STOP* state: $0, 1, \dots, |\mathcal{T}| - 1$. By convention, we always assume 0 is the start state *START*, and $|\mathcal{T}| - 1$ is the stop state *STOP*.
 - o $\mathcal{T} = \{START, X, Y, Z, STOP\}$
- σ is the set of observation symbols
 - o $\sigma = \{ "a", "b", "c", "d" \}$
- $\theta = \langle a, b \rangle$ consists of two sets of parameters:
 - o Parameter $a_{u,v} \equiv p(y_{next} = v | y_{curr} = u)$ for $u = 0, 1, \dots, |\mathcal{T}| - 2$ and $v = 1, \dots, |\mathcal{T}| - 1$ is the probability of transitioning from state u to state v :
 $\sum_{v=1}^{|\mathcal{T}|-1} a_{u,v} = 1$ for any u .
 - o Parameter $b_u(o) \equiv p(x = o | y = u)$ for $u = 0, 1, \dots, |\mathcal{T}| - 2$ and $o \in \sigma$ is the probability of emitting symbol o from state u : $\sum_{o \in \sigma} b_u(o) = 1$ for any u .

Parameters are transition probability $a_{u,v}$ and emission probability $b_u(o)$

$$\begin{aligned} count(X) &= 6 \\ count(Y) &= 4 \\ count(Z) &= 8 \end{aligned}$$

$$a_{u,v} = \frac{count(u, v)}{count(u)}$$

$u \backslash v$	X	Y	Z	$STOP$
$START$	$\frac{1}{2}$	0	$\frac{1}{2}$	0
X	$\frac{1}{6}$	0	$\frac{2}{3}$	$\frac{1}{6}$
Y	$\frac{1}{4}$	0	0	$\frac{3}{4}$
Z	$\frac{1}{8}$	$\frac{1}{2}$	$\frac{1}{8}$	$\frac{1}{4}$

$$b_u(o) = \frac{count(u \rightarrow o)}{count(u)}$$

$u \backslash o$	a	b	c	d
X	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{6}$	$\frac{1}{6}$
Y	$\frac{1}{2}$	0	$\frac{1}{4}$	$\frac{1}{4}$
Z	$\frac{1}{8}$	$\frac{5}{8}$	$\frac{1}{8}$	$\frac{1}{8}$

Q2

Base case

$$\pi(0, v) = \begin{cases} 1, & \text{if } v = \text{START} \\ 0, & \text{otherwise} \end{cases}$$

Moving forward recursively, for any $k \in 1, \dots, n$

Given $n = 2$,

$k = 1$

$$\begin{aligned} \pi(1, X) &= \pi(0, \text{START}) \cdot a_{\text{START}, X} \cdot b_X(a) \\ &= 1 \cdot \frac{1}{2} \cdot \frac{1}{3} \\ &= \frac{1}{6} \end{aligned}$$

$$\begin{aligned} \pi(1, Y) &= \pi(0, \text{START}) \cdot a_{\text{START}, Y} \cdot b_Y(a) \\ &= 1 \cdot 0 \cdot \frac{1}{2} \\ &= 0 \end{aligned}$$

$$\begin{aligned} \pi(1, Z) &= \pi(0, \text{START}) \cdot a_{\text{START}, Z} \cdot b_Z(a) \\ &= 1 \cdot \frac{1}{2} \cdot \frac{1}{8} \\ &= \frac{1}{16} \end{aligned}$$

$k = 2$

$$\begin{aligned} \pi(2, X) &= \max_u \{ \pi(1, u) \cdot a_{u, X} \cdot b_X(d) \} \\ &= \max \{ \pi(1, X) \cdot a_{X, X} \cdot b_X(d), \pi(1, Y) \cdot a_{Y, X} \cdot b_X(d), \pi(1, Z) \cdot a_{Z, X} \cdot b_X(d) \} \\ &= \max \left\{ \frac{1}{6} \cdot \frac{1}{6} \cdot \frac{1}{6}, 0 \cdot \frac{1}{4} \cdot \frac{1}{6}, \frac{1}{16} \cdot \frac{1}{8} \cdot \frac{1}{6} \right\} \\ &= \frac{1}{216} \end{aligned}$$

$$\begin{aligned} \pi(2, Y) &= \max_u \{ \pi(1, u) \cdot a_{u, Y} \cdot b_Y(d) \} \\ &= \max \{ \pi(1, X) \cdot a_{X, Y} \cdot b_Y(d), \pi(1, Y) \cdot a_{Y, Y} \cdot b_Y(d), \pi(1, Z) \cdot a_{Z, Y} \cdot b_Y(d) \} \\ &= \max \left\{ \frac{1}{6} \cdot 0 \cdot \frac{1}{4}, 0 \cdot 0 \cdot \frac{1}{4}, \frac{1}{16} \cdot \frac{1}{2} \cdot \frac{1}{4} \right\} \\ &= \frac{1}{128} \end{aligned}$$

$$\begin{aligned}
\pi(2, Z) &= \max_u \{\pi(1, u) \cdot a_{u,Z} \cdot b_Z(d)\} \\
&= \max \{\pi(1, X) \cdot a_{X,Z} \cdot b_Z(d), \pi(1, Y) \cdot a_{Y,Z} \cdot b_Z(d), \pi(1, Z) \cdot a_{Z,Z} \cdot b_Z(d)\} \\
&= \max \left\{ \frac{1}{6} \cdot \frac{2}{3} \cdot \frac{1}{8}, 0 \cdot 0 \cdot \frac{1}{8}, \frac{1}{16} \cdot \frac{1}{8} \cdot \frac{1}{6} \right\} \\
&= \frac{1}{72}
\end{aligned}$$

Transition from y_n to $STOP$

$$\begin{aligned}
\pi(3, STOP) &= \max_v \{\pi(2, v) \cdot a_{v,STOP}\} \\
&= \max \{\pi(2, X) \cdot a_{X,STOP}, \pi(2, Y) \cdot a_{Y,STOP}, \pi(2, Z) \cdot a_{Z,STOP}\} \\
&= \max \left\{ \frac{1}{216} \cdot \frac{1}{6}, \frac{1}{128} \cdot \frac{3}{4}, \frac{1}{72} \cdot \frac{1}{4} \right\} \\
&= \frac{3}{512}
\end{aligned}$$

Backtracking

$$\begin{aligned}
y_2^* &= \arg \max_v \{\pi(2, v) \cdot a_{v,STOP}\} \\
&= \arg \max_v \{\pi(2, X) \cdot a_{X,STOP}, \pi(2, Y) \cdot a_{Y,STOP}, \pi(2, Z) \cdot a_{Z,STOP}\} \\
&= \arg \max_v \left\{ \frac{1}{216} \cdot \frac{1}{6}, \frac{1}{128} \cdot \frac{3}{4}, \frac{1}{72} \cdot \frac{1}{4} \right\} \\
&= \arg \max_v \left\{ \frac{1}{1296}, \frac{3}{512}, \frac{1}{288} \right\} \\
&= Y
\end{aligned}$$

$$\begin{aligned}
y_1^* &= \arg \max_u \{\pi(1, u) \cdot a_{u,Y}\} \\
&= \arg \max_u \{\pi(1, X) \cdot a_{X,Y}, \pi(1, Y) \cdot a_{Y,Y}, \pi(1, Z) \cdot a_{Z,Y}\} \\
&= \arg \max_u \left\{ \frac{1}{6} \cdot 0, 0 \cdot 0, \frac{1}{16} \cdot \frac{1}{2} \right\} \\
&= \arg \max_u \left\{ 0, 0, \frac{1}{32} \right\} \\
&= Z
\end{aligned}$$

Optimal state sequence: Z, Y

Q3

$$p(x_1, \dots, x_n, y_1, \dots, y_n) = \prod_{i=1}^{n+1} p(y_i | y_{i-2}, y_{i-1}) \times \prod_{i=1}^n p(x_i | y_i)$$

$$y_{-1} = y_0 = \text{START}$$

$$y_{n+1} = \text{STOP}$$

Looking at a truncated version of the joint probability, focusing on the first k tags for any $k \in \{1, \dots, n\}$:

$$r(y_1, \dots, y_k) = \prod_{i=1}^k a_{y_{i-2}, y_{i-1}, y_i} \times \prod_{i=1}^k b_{y_i}(x_i)$$

where $k \neq n + 1$,

$$a_{t,u,v} = \frac{\text{count}(t, u, v)}{\text{count}(t, u)}$$

$$b_v(o) = \frac{\text{count}(v \rightarrow o)}{\text{count}(v)}$$

$t, u, v \in \mathcal{T}$, where \mathcal{T} is the set of states including the *START* and *STOP* states.
 σ is the set of observation symbols.

$a_{t,u,v}$ is the probability of transitioning from state t to state u to state v
 $b_v(o)$ is the probability of emitting observation symbol o from state v

Hence,

$$\begin{aligned} p(x_1, \dots, x_n, y_0, y_1, \dots, y_{n+1}) \\ &= r(y_1, \dots, y_k) \cdot a_{y_{n-1}, y_n, y_{n+1}} \\ &= r(y_1, \dots, y_n) \cdot a_{y_{n-1}, y_n, \text{STOP}} \end{aligned}$$

For any $k \in \{1, \dots, n\}$, let $S(k, u, v)$ be the set of tag sequences y_1, \dots, y_k such that $y_{k-1} = u$, $y_k = v$. In other words, $S(k, u, v)$ is a set of all sequences of length k whose last two tags are in the order of u, v .

Forward recursive algorithm:

$$\pi(k, u, v) = \max_{(y_1, \dots, y_k) \in S(k, u, v)} r(y_1, \dots, y_k)$$

In other words, $\pi(k, u, v)$ can be thought as solving the maximization problem partially, over all the tags y_1, \dots, y_{k-2} with the constraint that tag u is used for y_{k-1} and tag v for y_k . If we have $\pi(k, u, v)$, then $\max_v \pi(k, u, v)$ evaluates $\max_{y_1, \dots, y_k} r(y_1, \dots, y_k)$. We leave u and v in the definition of $\pi(k, u, v)$ so that we can extend the maximization one step further as we unravel the model in the forward direction.

Base case:

$$\pi(0, u, v) = \begin{cases} 1, & \text{if } u = START \text{ and } v = START \\ 0, & \text{otherwise} \end{cases}$$

Moving forward recursively:

$$\begin{aligned} &\text{For any } k \in \{1, \dots, n\}, \text{ for any } u, v \in \mathcal{T}, \\ &\pi(k, u, v) = \max_{t \in \mathcal{T}} \{\pi(k-1, t, u) \cdot a_{t,u,v} \cdot b_v(x_k)\} \end{aligned}$$

Transition from y_n to $STOP$:

$$\begin{aligned} &\max_{y_1, \dots, y_n} p(x_1, \dots, x_n, y_0 = START, y_1, \dots, y_n, y_{n+1} = STOP) \\ &= \max_{u, v \in \mathcal{T}} \{\pi(n, u, v) \cdot a_{u,v,STOP}\} \end{aligned}$$

Backtracking

$$y_{n-1}^*, y_n^* = \arg \max_{u, v} \{\pi(n, u, v) \cdot a_{u,v,STOP}\}$$

For $k = n-2$ to $k = 1$:

$$\begin{aligned} y_k^* &= \arg \max_t \{\pi(k+1, t, y_{k+1}^*) \cdot a_{t, y_{k+1}^*, y_{k+2}^*} \cdot b_{y_{k+2}^*}(x_{k+2})\} \\ &= \arg \max_t \{\pi(k+1, t, y_{k+1}^*) \cdot a_{t, y_{k+1}^*, y_{k+2}^*}\} \end{aligned}$$

Q4

Assume a predefined set of possible states $\{0, 1, \dots, N-1, N\}$, where $0 = START$ and $N = STOP$.

$$\begin{aligned} & p(x_1, \dots, x_n, y_1, \dots, y_n, z_i = u, x_i, \dots, x_n, y_i, \dots, y_n; \theta) \\ &= p(x_1, \dots, x_{i-1}, y_1, \dots, y_{i-1}, z_i = u; \theta) \cdot p(x_i, \dots, x_n, y_i, \dots, y_n | z_i = u; \theta) \\ &= \alpha_u(i) \cdot \beta_u(i) \end{aligned}$$

$\alpha_u(i) = p(x_1, \dots, x_{i-1}, y_1, \dots, y_{i-1}, z_i = u; \theta)$ is the forward probability

$\beta_u(i) = p(x_i, \dots, x_n, y_i, \dots, y_n | z_i = u; \theta)$ is the backward probability

Forward probability algorithm

Base case:

$$\alpha_u(1) = a_{START,u} \quad \forall u \in \{1, \dots, N-1\}$$

Recursive case:

For $i = 1, \dots, n-1$:

$$\begin{aligned} \alpha_u(i+1) &= p(x_1, \dots, x_i, y_1, \dots, y_i, z_{i+1} = u; \theta) \\ &= \sum_v p(x_1, \dots, x_i, y_1, \dots, y_i, z_i = v, z_{i+1} = u) \\ &= \sum_v p(x_1, \dots, x_{i-1}, y_1, \dots, y_{i-1}, z_i = v, x_i, y_i, z_{i+1} = u) \\ &= \sum_v p(x_1, \dots, x_{i-1}, y_1, \dots, y_{i-1}, z_i = v) \\ &\quad \cdot p(x_i | z_i = v) \cdot p(y_i | z_i = v, x_i) \cdot a_{v,u} \\ &= \sum_v \alpha_v(i) \cdot a_{v,u} \cdot b_v(x_i) \cdot c_{v,x_i}(y_i) \quad \forall u \in \{1, \dots, N-1\} \\ &\quad \text{where } b_v(x_i) = p(x_i | z_i = v), \\ &\quad c_{v,x_i}(y_i) = p(y_i | z_i = v, x_i) \end{aligned}$$

Backward probability algorithm

Base case:

$$\beta_u(n) = a_{u,STOP} \cdot b_u(x_n) \cdot c_{u,x_n}(y_n) \quad \forall u \in \{1, \dots, N-1\}$$

Recursive case:

For $i = n-1, \dots, 1$:

$$\begin{aligned} \beta_u(i) &= p(x_i, \dots, x_n, y_i, \dots, y_n | z_i = u; \theta) \\ &= p(x_i, \dots, x_n, y_i, \dots, y_n, z_{i+1} = v | z_i = u) \\ &= p(x_i, y_i, z_{i+1} = v, \dots, x_{i+1}, \dots, x_n, y_{i+1}, \dots, y_n | z_i = u) \\ &= \sum_v a_{u,v} \cdot b_u(x_i) \cdot c_{u,x_i}(y_i) \cdot \beta_v(i+1) \quad \forall u \in \{1, \dots, N-1\} \end{aligned}$$

Time complexity

- Length of observation pairs = n
- Set of possible states at each position = T
- At each position, there are T forward and T backward probabilities to compute
 - o Time complexity = $O(2T)$
- For each forward and backward probabilities, there are T number of operations
 - o Time complexity = $O(T)$

Hence, given the length of observation pairs = n , the overall time complexity is $O(2nT^2)$, which is then simplified to $O(nT^2)$.