RECITATION 8 HIDDEN MARKOV MODEL

10-601: Introduction to Machine Learning 11/13/2020

1 HMMs

You are given the following training data:

win_C league_C Liverpool_D

win_C Liverpool_D league_C

Liverpool_D win_C

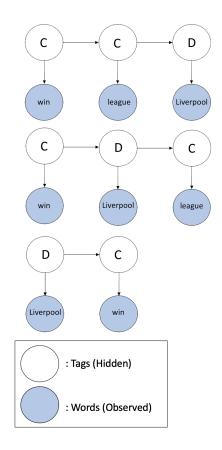


Figure 1: Visualization of Sequences

You are also given the following observed (validation) data:

Liverpool win league

In this question, let each observed state $x_t \in \{1, 2, 3\}$, where 1 corresponds to win, 2 corresponds to league, and 3 corresponds to Liverpool. Let each hidden state $Y_t \in \{C, D\}$, where $s_1 = C$ and $s_2 = D$.

- 1. First, we need to train our HMM by generating the initial probabilities: π , the transition probability matrix: \mathbf{A} , the emission probability matrix: \mathbf{B} .
 - (a) Find π . Recall that $\pi_i = P(Y_1 = s_i)$.
 - Find count matrix

$$\begin{array}{ccc}
Count & & Count \\
C & \begin{bmatrix} 2 \\ 1 \end{bmatrix} & \xrightarrow{\text{Pseudocount}} & C & \begin{bmatrix} 3 \\ 2 \end{bmatrix}
\end{array}$$

• Get probability matrix π :

$$\pi = \begin{array}{cc} C & \begin{bmatrix} 3/5 \\ D & \begin{bmatrix} 2/5 \end{bmatrix} \end{array}$$

- (b) Find Transition Matrix: **A**. Recall that $A_{jk} = P(Y_t = s_k \mid Y_{t-1} = s_j)$
 - Find count matrix

$$\begin{array}{c|ccc} & C & D & & & C & D \\ C & \begin{bmatrix} 1 & 2 \\ 2 & 0 \end{bmatrix} & \xrightarrow{\text{Pseudocount}} & C & \begin{bmatrix} 2 & 3 \\ 3 & 1 \end{bmatrix}$$

• Get Transition Probability matrix **A**:

$$A = \begin{array}{cc} & C & D \\ C & \begin{bmatrix} 2/5 & 3/5 \\ 3/4 & 1/4 \end{bmatrix}$$

- (c) Find Emission Matrix: **B**. Recall that $B_{jk} = P(X_t = k \mid Y_t = s_j)$.
 - ullet Find count matrix

• Get Emission Probability matrix B:

$$B = \begin{array}{ccc} & \text{win league Liverpool} \\ C & \begin{bmatrix} 1/2 & 3/8 & 1/8 \\ 1/6 & 1/6 & 2/3 \end{bmatrix} \end{array}$$

2. What is the likelihood of observing this output? Recall that:

$$\alpha_t(k) = P(x_{1:t}, Y_t = s_k)$$

$$\beta_t(k) = P(x_{t+1:T}|Y_t = s_k)$$

We also have the recursive procedure:

(a)
$$\alpha_1(j) = \pi_j B_{jx_1}$$
.

(b) For
$$t > 1$$
, $\alpha_t(j) = B_{jx_t} \sum_{k=1}^{J} \alpha_{t-1}(k) A_{kj}$

We want to find:

$$\begin{split} &P(X_1 = \texttt{Liverpool}, X_2 = \texttt{win}, X_3 = \texttt{league}) \\ &= \sum_{y_t \in C, D} P(x_1 = \texttt{Liverpool}, x_2 = \texttt{win}, x_3 = \texttt{league}, Y_t = y_t) \\ &= \sum_{y_t \in C, D} \alpha_T(y_t) \end{split}$$

$$\alpha_1 = P(x_1|y_1) \cdot P(y_1)$$
$$= B_{,3} \circ \pi$$

$$= \begin{bmatrix} 1/8 \\ 2/3 \end{bmatrix} \circ \begin{bmatrix} 3/5 \\ 2/5 \end{bmatrix}$$
$$= \begin{bmatrix} 0.075 \\ 0.26667 \end{bmatrix}$$

$$\alpha_2 = P(x_1, x_2, y_2)$$

$$= P(x_2|y_2) \cdot (P(y_2|y_1) \cdot \alpha_1)$$

$$= B_{,1} \circ (A^T \alpha_1)$$

$$= \begin{bmatrix} 1/2 \\ 1/6 \end{bmatrix} \circ \begin{bmatrix} 0.2300025 \\ 0.1116675 \end{bmatrix}$$

$$= \begin{bmatrix} 0.11500125 \\ 0.01861125 \end{bmatrix}$$

$$\alpha_3 = B_{,2} \circ (A^T \alpha_2) = \begin{bmatrix} 0.02248460156 \\ 0.01227559375 \end{bmatrix}$$

Since

$$P(x_1 = \text{Liverpool}, x_2 = \text{win}, x_3 = \text{league})$$

= $\sum_{y_t \in C, D} \alpha_T(y_t)$, where we set $T = 3$

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P(x_1 = \text{Liverpool}, x_2 = \text{win}, x_3 = \text{league})
= 0.02248460156 + 0.01227559375
= 0.03476019531
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You are now told that the observed data has the following tags:

3. Given the observed sequence of words (denote $\vec{x} = [\text{Liverpool}, \text{win}, \text{league}]^T)$, what is the probability of these assigned tags $P(Y_1 = D|\vec{x}), P(Y_2 = C|\vec{x}), P(Y_3 = D|\vec{x})$?

Recall that:

$$P(Y_t = s_k | \vec{x}) = \frac{\alpha_t(s_k)\beta_t(s_k)}{P(\vec{x})}$$

So, we need to find β_T

We also have a similar recursive procedure

- (a) $\beta_T(j) = 1$ (All states could be ending states)
- (b) For $1 \le t \le T 1$, $\beta_t(j) = \sum_{k=1}^{J} B_{kx_{t+1}} \beta_{t+1}(k) A_{jk}$ (Generate x_{t+1} from any state)

Remember that: $\beta_t(s_k) = P(x_{t+1:T}|Y_T = s_k)$ and $\beta_T(s_k) = 1$

Using matrix notation:

$$\beta_2 = A(B_{,x_3} \circ \beta_3) = A(B_{,2} \circ \beta_3)$$

Recall that:

$$B_{,2} = \begin{bmatrix} 3/8 \\ 1/6 \end{bmatrix} \text{ and } \beta_3 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \text{ , since } T = 3$$
$$\therefore \beta_2 = \begin{bmatrix} 0.25 \\ 0.3229 \end{bmatrix}$$

Now, we go on to solve β_1

$$\beta_1 = A(B_{,x_2} \circ \beta_2) = A(B_{,1} \circ \beta_2)$$

Again, recall that:

$$B_{,1} = \begin{bmatrix} 1/2 \\ 1/6 \end{bmatrix} \text{ and } \beta_2 = \begin{bmatrix} 0.25 \\ 0.3229 \end{bmatrix}$$
$$\therefore \beta_1 = \begin{bmatrix} 0.08229 \\ 0.1072 \end{bmatrix}$$

Now, we have our α and β matrix:

$$\alpha = \begin{bmatrix} & & C & D \\ 1 & & \begin{bmatrix} 0.0750 & 0.26667 \\ 0.1150 & 0.0186 \\ 0.0225 & 0.0123 \end{bmatrix}$$

$$\beta = \begin{bmatrix} & & C & D \\ 1 & & \begin{bmatrix} 0.0823 & 0.1072 \\ 0.2500 & 0.3229 \\ 1.0000 & 1.0000 \end{bmatrix}$$

$$P(Y_1 = D|\vec{x}) = \frac{\alpha_1(D)\beta_1(D)}{P(\vec{x})}$$
$$= \frac{0.26667 \times 0.1072}{0.03476019531}$$
$$= 0.8224068865$$

$$P(Y_2 = C|\vec{x}) = \frac{\alpha_2(C)\beta_2(C)}{P(\vec{x})}$$
$$= \frac{0.1150 \times 0.2500}{0.03476019531}$$
$$= 0.8270954678$$

$$P(Y_3 = C|\vec{x}) = \frac{\alpha_3(C)\beta_3(C)}{P(\vec{x})}$$
$$= \frac{0.0225 \times 1}{0.03476019531}$$
$$= 0.6472921052$$

4. The sequence of words you observe is again the same:

Liverpool win league

However, you are only given the tag of the last word:

Using the Viterbi Algorithm, what is the most likely sequence of hidden states?

Recall that:

$$\omega_t(s_k) = \max_{y_{1:t-1}} P(x_{1:t}, y_{1:t-1}, y_t = s_k)$$

$$b_t(s_k) = \arg\max_{y_{1:t-1}} P(x_{1:t}, y_{1:t-1}, y_t = s_k)$$

- (a) What is the most likely sequence of tags given the observed data? (Select C if there is a tie)
 - i. Set up the matrices ω and b

$$\omega = \begin{bmatrix} \omega_0 & C & D & START \\ \omega_0 & \begin{bmatrix} 0 & 0 & 1 \\ - & - & - \\ \omega_2 & & - & - \end{bmatrix}$$

and

$$b = \begin{array}{c} b_1 \\ b_2 \\ b_3 \end{array} \begin{bmatrix} C & D \\ - & - \\ - & - \\ - & - \end{bmatrix}$$

Initialize $w_0(START) = 1$

ii. Solve for matrix entries using Dynamic Programming:

$$\begin{split} \omega_1(C) &= \max_{s_j \in \mathtt{C}, \mathtt{D}, \mathtt{START}} P(x_1 = \mathtt{Liverpool} | Y_1 = \mathtt{C}) \omega_0(s_j) P(Y_1 = \mathtt{C}) \\ &= \frac{1}{8} \cdot 1 \cdot \frac{3}{5} \\ &= \frac{3}{40} \end{split}$$

$$b_1(\mathbf{C}) = \mathtt{START}$$

$$\begin{split} \omega_1(D) &= \max_{s_j \in \mathtt{C},\mathtt{D},\mathtt{START}} P(x_1 = \mathtt{Liverpool}|Y_1 = \mathtt{D}) w_0(s_j) P(Y_1 = \mathtt{D}) \\ &= \frac{2}{3} \cdot 1 \cdot \frac{2}{5} \\ &= \frac{4}{15} \end{split}$$

$$b_1(D) = START$$

$$\begin{split} \omega_2(C) &= \max_{s_j \in \mathtt{C}, \mathtt{D}} P(x_2 = \mathtt{win} | Y_2 = \mathtt{C}) \omega_1(s_j) P(Y_2 = \mathtt{C} | Y_1 = s_j) \\ &= \max \left(\frac{1}{2} \cdot \frac{3}{40} \cdot \frac{2}{5}, \frac{1}{2} \cdot \frac{4}{15} \cdot \frac{3}{4} \right) \\ &= \frac{1}{10} \end{split}$$

$$b_2(\mathbf{C}) = \mathbf{D}$$

$$\begin{split} \omega_2(D) &= \max_{s_j \in \mathtt{C}, \mathtt{D}} P(x_2 = \mathtt{win} | Y_2 = \mathtt{D}) \omega_1(s_j) P(Y_2 = \mathtt{D} | Y_1 = s_j) \\ &= \max \left(\frac{1}{6} \cdot \frac{3}{40} \cdot \frac{3}{5}, \frac{1}{6} \cdot \frac{4}{15} \cdot \frac{1}{4} \right) \\ &= \frac{1}{90} \end{split}$$

$$b_2(D) = D$$

$$\begin{split} \omega_3(C) &= \max_{s_j \in \mathtt{C},\mathtt{D}} P(x_3 = \mathtt{league}|Y_3 = \mathtt{C}) \omega_2(s_j) P(Y_3 = \mathtt{C}|Y_2 = s_j) \\ &= \max\left(\frac{3}{8} \cdot \frac{1}{10} \cdot \frac{2}{5}, \frac{3}{8} \cdot \frac{1}{90} \cdot \frac{3}{4}\right) \\ &= \frac{3}{200} \end{split}$$

$$b_3(\mathbf{C}) = \mathbf{C}$$

$$\begin{split} \omega_3(D) &= \max_{s_j \in \mathtt{C},\mathtt{D}} P(x_3 = \mathtt{league}|Y_3 = \mathtt{D}) \omega_2(s_j) P(Y_3 = \mathtt{D}|Y_2 = s_j) \\ &= \max\left(\frac{1}{6} \cdot \frac{1}{10} \cdot \frac{3}{5}, \frac{1}{6} \cdot \frac{1}{90} \cdot \frac{1}{4}\right) \\ &= \frac{1}{100} \end{split}$$

$$b_3(D) = C$$

Now, to figure out the order, we set $\hat{y}_t = b_{t+1}(\hat{y}_{t+1})$

$$\begin{split} y_{T+1} &= \mathtt{END} \\ y_3 &= \mathtt{C} \\ \hat{y}_2 &= b_3(\mathtt{C}) \\ &= \mathtt{C} \\ \hat{y}_1 &= b_2(\mathtt{C}) \\ &= \mathtt{D} \\ \hat{y}_0 &= b_1(\mathtt{D}) \\ &= \mathtt{START} \end{split}$$

So, the most likely sequence is START-D-C-C-END