Introduction to Machine Learning

CSCE 478/878

Programming Assignment 2

Spring 2019

Hidden Markov Model

Part A: 478 (70 pts) & 878 (115 pts)
Part B: 478 & 878 (30 pts)
Extra credit (BONUS) tasks for both 478 & 878: 10 pts

Total: 478 (100 pts) & 878 (145 pts)

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Obtained Score:

1. Forward Algorithm

Time Complexity:

For each timestep (T) we make a calculation for each hidden state (N) each with a consisting of summing over the number of hidden states (N). This yields time complexity of $T \times N \times N$ or $O(T \times N^2)$.

Space Complexity:

We are calculating alpha which is of length N and width T so the space complexity is $N \times T$

2. Backward Algorithm

Time Complexity:

Similar to the the forward algorithm, for each timestep (T) we make a calculation for each hidden state (N) each with a consisting of summing over the number of hidden states (N). This yields time complexity of $T \times N \times N$ or $O(T \times N^2)$.

Space Complexity:

For the backward we are calculating beta which also of length N and width T so the space complexity is $N \times T$ for the backward algorithm as well.

3. Forward-Backward

Time Complexity:

For each timestep we calculate alpha and beta each with time complexity $O(T \times N^2)$. We then perform N^2 multiplications at each time step T. As a result we have a time complexity of $O(3 \times (T \times N^2))$.

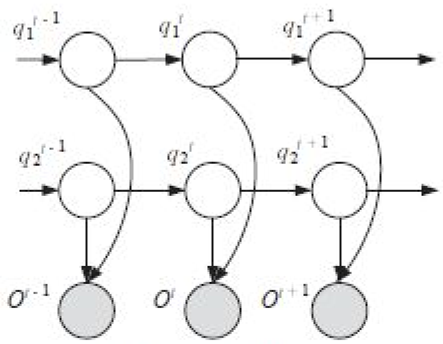
Space Complexity:

For the forward-backward smoothing algorithm we are calculating a posterior probability matrix of N and width T so the space complexity is $N \times T$.

4. The space complexity of the forward-backward algorithm can be a draw back particularly for large numbers of state sequences or for longer observations.

5.

Our single series of observed sequences results from one of two mental states. One could argue that there is not an hourly transition between being healthy or depressed, and instead there are healthy and depressed people. We would then attempt to predict if a person was depressed or health based on a series of observations. For these assumptions, the factorial HMM may prove useful for improving our depression tracking app. A visual representation of a factorial HMM from Alpaydin (2014) is shown below.



(b) Factorial HMM

In our case each of q1 represents the healthy mental state while q2 represents the depressed mental state. For each of the observed states there are probabilities that the observation was the child of each of the hidden states. For the implementation, the probability of each observed state being the result of a hidden state must be known. These are given in the table below:

	Movement	Passive Social Networking	Active Social Networking	Texting	Access Psych Health App /Sites
q1 (Healthy)	0.5	0.1	0.3	0.1	0.0
q2 (Depressed)	0.05	0.35	0.2	0.2	0.2