

CSE 494/598: ALGORITHMS IN COMPUTATIONAL BIOLOGY - ASSIGNMENT 4

Fall 2022

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Due Date: 11/28/2022 11:59pm

Hidden Markov Models

Note: that any program you implement should run within **5 mins (wall time)** to produce an output to be satisfactory.

Hidden Markov Models

Note: Assume initial probabilities are equally likely. Remember to compute probabilities in log space to prevent any underflow errors resulting in probabilities of zero.

1. **[Viterbi Algorithm - 60pt]** Implement the Viterbi Algorithm for finding the most likely sequence of hidden states π , where $Pr(x, \pi)$ is maximized.

Input: An observed sequence of symbols x , followed by alphabet Σ , followed by a list of states $states$, followed by transition matrix T , followed by emission matrix E of an HMM $(\Sigma, states, T, E)$.

Output: The sequence of hidden states that maximizes $Pr(x, \pi)$.

Sample input file content:

xyxzzxyxyy

x y z

A B

	A	B
A	0.641	0.359
B	0.729	0.271

	x	y	z
A	0.117	0.691	0.192
B	0.097	0.42	0.483

Sample output:

AAABBAAAAA

2. **[Parameter Estimation via Viterbi Learning - 60pt]** Implement Viterbi Learning algorithm to estimate the unknown parameters of HMM to maximize $Pr(x, \pi)$ over all possible parameter sets.

Input: A number of iterations i , followed by an observed sequence of symbols x , followed by alphabet Σ , followed by a list of states $states$, followed by initial transition matrix T , followed by emissions matrix E .

Output: Transition matrix followed by emission matrix that maximizes $Pr(x, \Pi)$ over all Π and parameters (transition and emission matrices).

Sample input file content:

100

xxxzyzzxxzyzzxzyxxzyzyzyyyyzzxxxxzzxyzzzxyzzzxyzzxxxxzzxyyzzzzzyzzxxzzxxxyx
yzzyxzzxxyxzyxxyzyxz

x y z

A B

	A	B
A	0.582	0.418
B	0.272	0.728

	x	y	z
A	0.129	0.35	0.52
B	0.422	0.151	0.426

Sample output:

	A	B
A	0.875	0.125
B	0.011	0.989

	x	y	z
A	0.0	0.75	0.25
B	0.402	0.174	0.424

3. **[Soft Decoding Problem - 60pt]** Instead of finding the most likely hidden path, we want to find the conditional probability $Pr(\Pi_i = k \mid x)$ that the HMM was in hidden state k when emitting i th symbol (at step i).

Input: An observed sequence of symbols $x = x_1 \dots x_n$, followed by alphabet Σ , followed by a list of states *states*, followed by transition matrix T , followed by emission matrix E of an HMM $(\Sigma, \text{states}, T, E)$.

Output: All conditional probabilities $Pr(\Pi_i = k \mid x)$ for each state k and each step i (1 to n)

Sample input file content:

yzzzyxzzxx

x y z

BBABABABAB

A B C

Sample output:

	A	B	C
A	0.0	1.0	0.0
B	0.8	0.2	0.0
C	0.333	0.333	0.333

	x	y	z
A	0.25	0.25	0.5
B	0.5	0.167	0.333
C	0.333	0.333	0.333

4. **[Baum-Welch Learning for HMM - 60pt] (OPTIONAL for CSE494)** Implement Baum-Welch algorithm to learn the unknown parameters of HMM. You will need soft decoding of both nodes and edges in Viterbi graph (node soft decoding done in the previous problem).

Input: A number of iterations i , followed by an observed sequence of symbols x , followed by alphabet Σ , followed by a list of states $states$, followed by initial transition matrix T , followed by emissions matrix E .

Output: Transition matrix followed by emission matrix that maximize $Pr(x, \Pi)$ over all possible Π and parameters (transition and emission matrices).

Sample input file content:

```
10
-----
xzyyzyzyxy
-----
x y z
-----
A B
-----
      A      B
A  0.019  0.981
B  0.668  0.332
-----
      x      y      z
A  0.175  0.003  0.821
B  0.196  0.512  0.293
```

Sample output:

```
      A      B
A  0.000  1.0
B  0.786  0.214
-----
      x      y      z
A  0.242  0.0   0.758
B  0.172  0.828  0.0
```