Genome Informatics mid-term exam, fall 2023.

November 23, 2023

Name \& student ID:

## Problem 1.



Suppose the model starts in $Z_{1}$ or $Z_{2}$ each with $50 \%$ probability, in other words: $\mathrm{P}\left[S_{1}=Z_{1}\right]=\mathrm{P}\left[S_{2}=Z_{2}\right]=0.5$.

Define:

$$
\alpha_{i j} \stackrel{\text { def }}{=} \mathrm{P}\left[X_{1 . . i}, S_{i}=Z_{j} \mid \lambda\right] \beta_{i j} \stackrel{\text { def }}{=} \mathrm{P}\left[X_{i+1 . . n} \mid S_{i}=Z_{j}, \lambda\right]
$$

with $\lambda$ meaning the HMM model and its parameter values described above.

Problem 1a. Formally prove that:

$$
\mathrm{P}\left[X_{1 . . n}, S_{i}=Z_{j} \mid \lambda\right]=\alpha_{i j} \beta_{i j}
$$

Explicitly state any assumptions used, including assumptions that are part of the definition of a Hidden Markov Model. I'm looking for a formal proof based mainly on symbolic manipulation.

Name \& student ID: $\qquad$

## Problem 1b.

Fill in the values missing from this table.

| i | 1 | 2 | 3 | 4 | 5 | 6 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| $X$ | T | H | H | H | T | T |
| $\mathrm{\alpha}_{i 1}$ | 0.1500 | 0.0910 | 0.0464 | 0.0230 | 0.0049 | 0.0015 |
| $\mathrm{\alpha}_{i 2}$ | 0.4000 | 0.0620 | 0.0134 | 0.0045 | 0.0079 | 0.0061 |
| $\mathrm{\alpha}_{i 3}$ | 0.0000 | 0.0550 | 0.0373 | 0.0209 | 0.0111 | 0.0057 |
| $\beta_{i 1}$ | 0.0415 | 0.0792 | 0.1463 | 0.2406 | 0.4400 | 1.0000 |
| $\beta_{i 2}$ | 0.0176 | 0.0387 | 0.1072 | 0.4506 | 0.6900 | 1.0000 |
| $\beta_{i 3}$ | 0.0328 | 0.0663 | 0.1348 | 0.2724 | 0.5100 | 1.0000 |

Question. Given $X=$ THHHTT, what is the expected number of time steps the model spent in state $Z_{2}$ ? In other words:

$$
\sum_{i=1}^{n} \mathrm{P}\left[S_{i}=Z_{2} \mid X, \lambda\right]
$$

## Counting Number of Alignments

Name \& student ID:

## Problem 2.

In the problem we consider the number of ways to align to sequences $X$ and $Y$ of lengths $n$ and $m$ respectively. Let $x$ and $y$ denote some character in $X$ and $Y$ respectively ( $x$ and $y$ could be the same or different).

The basic rule is there are three kinds of columns.

(mis)match: | x | gap in $\mathrm{X}:$ | $-\quad$ gap in $\mathrm{Y}:$ | x |
| ---: | ---: | ---: | ---: |
| y |  | y |  |

Sometimes alignments with alternating gaps are disallowed. By "alternating gaps" I mean a column with a gap in X immediately following a column with a gap in Y. In other words an alignment containing

| $-x$ | or | $x-$ |
| :--- | :--- | :--- |
| $y-$ |  | $-y$ |

Has an alternating gap.

## Problem 2a.

Let $C(n, m)$ denote the number of ways to align sequences of length $n$ and $m$, allowing alternating gaps in the alignment. You can confirm by hand that $C(1,1)=3$.

Stipulate the recursive relations and base cases necessary to use dynamic programming to compute $C(n, m)$ for positive integers $n, m$.

Use this method to compute $C(3,7)$. Make a table to show your work.

## Counting Number of Alignments

Name \& student ID:

## Problem 2b.

Let $D(n, m)$ denote the count the number of ways to align sequences of length $n$ and $m$, disallowing alternating gaps in the alignment. Consider $D(n, 0)=D(0, m)=1$. You can confirm by hand that $D(1,1)=1$.

Stipulate the recursive relations and base cases necessary to use dynamic programming to compute $D(n, m)$ for positive integers $n, m$. Hint, you can use the same technique as that used for affine gap cost alignment.

Use this method to compute $D(3,7)$. Make a table to show your work.

## Neighbor Joining Phylogenetic Tree Inference

Name \& student ID:

| $\mathbf{B}$ | $\mathbf{C}$ | $\mathbf{D}$ | $\mathbf{E}$ |  |
| ---: | ---: | ---: | ---: | ---: |
| 16 | 16 | 14 | 10 | $\mathbf{A}$ |
|  | 2 | 4 | 8 | $\mathbf{B}$ |
|  |  | 4 | 8 | $\mathbf{C}$ |
|  |  |  | 6 | $\mathbf{D}$ |

## Problem 3.

Use the Saitou \& Nei Neighbor joining algorithm to infer a plausible tree for species A,B,C,D,E (topology \& edge lengths) from the distance matrix shown. Use symbols $\mathbf{F}, \mathbf{G}, \mathbf{H}$ to denote internal nodes.

Name \& student ID:

## Problem 4.

Background A zero order (plain) Markov model for single stranded DNA generates DNA sequences $X=X_{1} \ldots X_{n}$ under the assumption that $\mathrm{P}\left[X_{i+1} \mid X_{1 . .}\right]=\mathrm{P}\left[X_{i+1}\right]$. Since $\mathrm{P}[\mathrm{a}]+$ $\mathrm{P}[\mathrm{c}]+\mathrm{P}[\mathrm{g}]+\mathrm{P}[t] \equiv 1$, the model has 3 degrees of freedom. Given a suitable prior distribution (don't worry about it for this question) and the length $n$ of a training sequence $X$; the frequency of three nucleotides ( $\mathrm{a}, \mathrm{c}$, and g for example) is sufficient (and minimal) information needed to train the model.

## Problem 4a.

A 1st order (plain) Markov model for single stranded DNA generates DNA sequences $X=$ $X_{1} \ldots X_{n}$ under the assumption that $\mathrm{P}\left[X_{i+1} \mid X_{i}\right]=\mathrm{P}\left[X_{i+1} \mid X_{1 . . i}\right]$.

Given a suitable prior distribution and the length $n$ of a training sequence, list a sufficient (and as minimal as possible) set of statistics on from $X$ which can be used to train the model.

## 2-Stranded DNA Dinucleotide Order Markov Model

Name \& student ID:

## Problem 4b.

A 1st order (plain) Markov model for double stranded DNA generates double stranded DNA sequences $D=D_{1} \ldots D_{n}$. Where each element $D_{i}$ represents a pair from the set: $\{\mathrm{a}=\mathrm{t}, \mathrm{c} \equiv \mathrm{g}, \mathrm{g} \equiv \mathrm{c}, \mathrm{t}=\mathrm{a}\}$. The assumption is that $\mathrm{P}\left[D_{i+1} \mid D_{i}\right]=\mathrm{P}\left[D_{i+1} \mid D_{1 . . i}\right]$.

So for example $D$ might be:

```
gataca
```

ctatgt
One strand, gataca, happens to be written on top, but often this is arbitrary. In that case the opposite strand tgtatc should be equivalent for the purpose of training a Markov model.

Let $D$ be double stranded data we want to train on. Assume we train on a sequence $X$ which is one of the two strands of $D$. We constrain our result to be the same no matter which strand is used. So in the example above $X=$ gataca or $X=$ tgtatc should both give the same result.

Given a suitable prior distribution and the length $n$ of the training sequence; list a sufficient (and as minimal as possible) set of statistics on from $X$ which can be used to train the model. Explain as necessary to demonstrate your reasoning.

