Project 4

Richard Affolter

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Problem 8: Estimating match emission probabilities

Table 1 shows the number of observations of the symbol a at position i across all sequences in the multiple alignment Ei(a) of our data.

Table 1: $E_i(a)$

	1	2	3
A	4	0	0
\mathbf{C}	0	0	5
G	0	4	0
Τ	0	0	0
			_

With this we can calculate the match emission probabilities $e_i(a)$ by adding a pseudo-count and dividing each column by its column-sum. The resulting table is shown below.

Table 2: $e_i(a)$

	1	2	3
A	5/8	1/8	1/9
\mathbf{C}	1/8	1/8	6/9
G	1/8	5/8	1/9
Τ	1/8	1/8	1/9

Problem 9: Estimating insert emission probabilities

We can repeat the same procedure as above with the insert states. Again we get the observed inserts $E_i(a)$ and can use them to calculate the estimated insert emission probabilities $e_i(a)$

Table 3: $E_i(a)$

	1	2	3
A	0	5	0
\mathbf{C}	0	0	0
G	0	1	0
Τ	0	0	0

Table 4: $e_i(a)$

	1	2	3
A	1/4	6/10	1/4
\mathbf{C}	1/4	1/10	1/4
G	1/4	2/10	1/4
Τ	1/4	1/10	1/4

Problem 10: Estimating transition probabilities

The paths of each sequence trough the profile HMM are:

bat: Begin $\to M_1 \to M_2 \to M_3 \to \text{End}$ rat: Begin $\to M_1 \to D_2 \to I_2 \to I_2 \to M_3 \to \text{End}$ cat: Begin $\to M_1 \to M_2 \to M_3 \to \text{End}$ gnat: Begin $\to D_1 \to M_2 \to I_2 \to I_2 \to I_2 \to M_3 \to \text{End}$ goat: Begin $\to M_1 \to M_2 \to I_2 \to M_3 \to \text{End}$

With this we can draw the following diagram of the paths

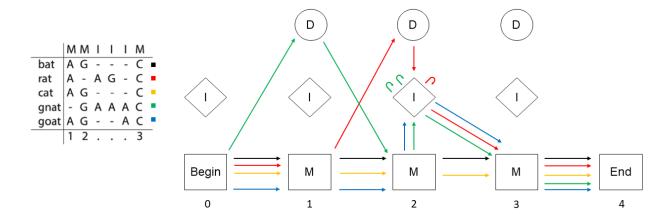


Figure 1: profile JMM for each sequence

We can use these paths to count $T_i(k \to l)$. The count table is the following

Table 5: $T_i(k \to l)$

	0	1	2	3
$\overline{M o M}$	4	3	2	5
$M \to I$	0	0	2	0
$M \to D$	1	1	0	0
$I \to M$	0	0	3	0
$I \to I$	0	0	3	0
$I \to D$	0	0	0	0
$D \to M$	0	1	0	0
$D \to I$	0	0	1	0
$D \to D$	0	0	0	0

With this we can estimate $t_i(k \to l)$ as:

Table 6: $t_i(k \to l)$

	0	1	2	3
$\overline{M o M}$	5/8	4/7	3/7	6/8
$M \to I$	1/8	1/7	3/7	1/8
$M \to D$	2/8	2/7	1/7	1/8
$I \to M$	1/3	1/3	4/9	1/3
$I \to I$	1/3	1/3	4/9	1/3
$I \to D$	1/3	1/3	1/9	1/3
$D \to M$	1/3	2/4	1/4	1/3
$D \to I$	1/3	1/4	2/4	1/3
$D \to D$	1/3	1/4	1/4	1/3

Problem 11: Protein family membership classification

1. Run source("profileHMM.R")

```
source("profileHMM.R")
```

2. Read the two alignments 'GTP_binding_proteins.txt' and 'ATPases.txt' into memory using the function parseAlignment().

```
GTP_data = parseAlignment("GTP_binding_proteins.txt")
ATP_data = parseAlignment("ATPases.txt")
```

3. Use the function learnHMM() to parametrise two profile HMMs: one for each protein family (multiple alignment).

```
GTP_profile = learnHMM(GTP_data)
ATP_profile = learnHMM(ATP_data)
```

4. Identify the position(s) with the highest match and with the highest insert emission frequencies over all symbols. Plot the respective match and insert emission frequencies for the identified positions.

```
library(dplyr)
GTP_profile$mE %>% which.max() %>% arrayInd(dim(GTP_profile$mE)) -> GTP_idx
ATP_profile$mE %>% which.max() %>% arrayInd(dim(ATP_profile$mE)) -> ATP_idx

cat(
    "For GTP binding proteins the pos. with the highest match emission frequency is position",
    colnames(GTP_profile$mE)[GTP_idx[2]], "\n (with highest frequency of ",
    GTP_profile$mE[GTP_idx], ")\n")
```

match frequencies:

For GTP binding proteins the pos. with the highest match emission frequency is position 76 ## (with highest frequency of 0.9370861)

```
cat("For ATPases the pos. with the highest match emission frequency is position",
    colnames(ATP_profile$mE)[ATP_idx[2]], "\n (with highest frequency of ",
    ATP_profile$mE[ATP_idx], ")\n")
```

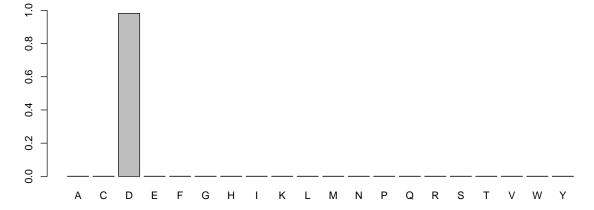
For ATPases the pos. with the highest match emission frequency is position 7 ## (with highest frequency of 0.9823091)

match emission frequencies of GTP binding proteins at position 76



```
barplot(ATP_profile$mE[,ATP_idx[2]], ylim = c(0,1),
    main = "match emission frequencies of ATPases at position 7")
```

match emission frequencies of ATPases at position 7



```
library(dplyr)
GTP_profile$iE %>% which.max() %>% arrayInd(dim(GTP_profile$iE)) -> GTP_idx
ATP_profile$iE %>% which.max() %>% arrayInd(dim(ATP_profile$iE)) -> ATP_idx

cat(
    "For GTP binding proteins the pos. with the highest insert emission frequency is position",
    colnames(GTP_profile$mE)[GTP_idx[2]], "\n (with highest frequency of ",
    GTP_profile$iE[GTP_idx], ")\n")
```

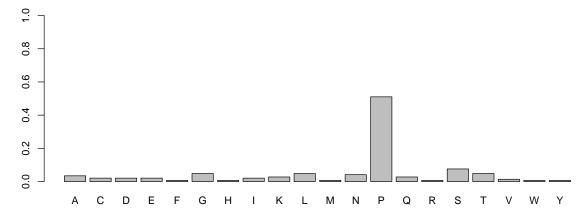
insert frequencies:

For GTP binding proteins the pos. with the highest insert emission frequency is position 49 ## (with highest frequency of 0.5103448)

```
cat("For ATPases the pos. with the highest insert emission frequency is position",
    colnames(ATP_profile$mE)[ATP_idx[2]], "\n (with highest frequency of ",
    ATP_profile$iE[ATP_idx], ")\n")
```

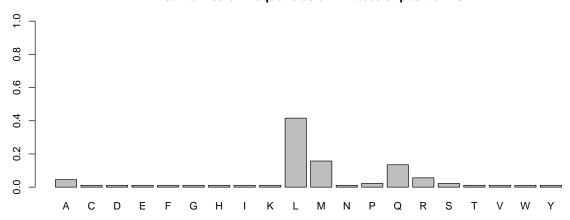
For ATPases the pos. with the highest insert emission frequency is position 70 * (with highest frequency of 0.4157303)

insert emission frequencies of GTP binding proteins at position 49



```
barplot(ATP_profile$iE[,ATP_idx[2]], ylim = c(0,1),
    main = "insert emission frequencies of ATPases at position 70")
```

insert emission frequencies of ATPases at position 70



5. The file Unclassified proteins.txt contains 31 protein sequences from unknown families. Load the protein sequences into a list using the parseProteins() function.

```
Unclassified_data = parseProteins("Unclassified_proteins.txt")
```

6. The function forward() takes as input a profile HMM \mathcal{M} and a sequence x. It returns the log odds ratio

$$\log \frac{P(x \mid \mathcal{M})}{P(x \mid \mathcal{R})}$$

of the probability of observing the sequence x given the model \mathcal{M} versus the probability of observing the sequence x given the random model \mathcal{R} . For each unclassified protein $x^{(i)}$ in the list, apply the forward algorithm for both models M_1 and M_2 to obtain the log odds ratio

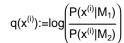
$$q(x^{(i)}) := \log \left(\frac{P(x^{(i)} \mid M_1)}{P(x^{(i)} \mid M_2)} \right)$$

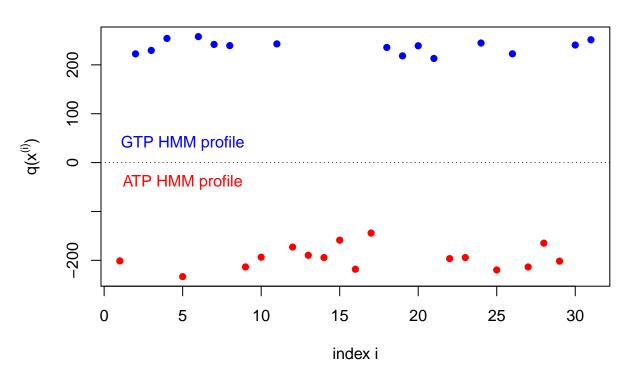
Plot the values $q(x^i)$ and include this in your report. Which proteins in the list belong to which family? Can you clearly decide for each protein?

```
lapply(Unclassified_data, forward, HMM = GTP_profile) %>% unlist() -> GTP_log
lapply(Unclassified_data, forward, HMM = ATP_profile) %>% unlist() -> ATP_log
q = GTP_log - ATP_log
names(q) = 1:length(q)
print(q)
```

```
## 25 26 27 28 29 30 31
## -219.7358 222.5847 -213.5467 -164.8467 -201.6350 240.5883 251.3384
```

```
library(latex2exp)
ylab_string = TeX(r"($q(x^{(i)}))")
q_string =
   TeX(r"($q(x^{(i)}):= \log \left(\frac{P(x^{(i)} | M_1)}{P(x^{(i)} | M_2)} \right)$)")
par(mar = c(4, 5, 5, 1))
plot(q, xlab = "index i",ylab = ylab_string, main = q_string, pch = 16,
        col = ifelse(q < 0,'red','blue'), cex.main = 0.75)
abline(h = 0, lty = 3)
text(5, 40, labels = "GTP HMM profile", col = "blue")
text(5, -40, labels = "ATP HMM profile", col = "red")</pre>
```





We can see in the plot that we have a nice linear separation between the two models. Sequences with a positive q have a higher probability to belong to the GTP binding protein family than to belong to the ATPase family. For sequences with a negative q it is the other way around. Since for no sequence q is close to zero we can clearly decide for each protein.