- Functional biological sequences typically come in families, such as Kinases, Globulins, Histons, Motorproteins,
- Many of the most powerful sequence analysis methods are based on identifying the relationship of an individual sequence to a sequence family.
- Sequences in a family usually diverged from each other in their primary sequence during evolution, while maintaining the same or a related function.
- As a consequence, identifying that a sequence belongs to the family, often allows inference about its function.
- Capturing all signals common to the members of a sequence family is best done by a statistical approach based on a multiple alignment (see later section of this course) of the sequences in the family.

Example 1

Consider an example of a family of 5 sequences GTAT, GGCG, TTCG, GTCA, and GTTA which can be represented by the following multiple alignment:

For each of the four positions in the sequences we want to capture the conservation of specific symbols by determining their probability of occurrence. This leads to a PSSM:

Now each DNA-sequence of length 4 can be scored by summing up the scores of the bases at the corresponding positions, e.g. GTGA gets score 0.8 + 0.8 + 0.0 + 0.4 = 2.0.

- Position specific scoring matrices (PSSMs) have a long history in sequence analysis.
- A high PSSM-score in some region of a sequence often indicates a
 possible biological relationship of this sequence to the family or motif
 characterized by the PSSM.
- There are several databases incorporating PSSMs, e.g. PROSITE, PRINTS, BLOCKS, or TRANSFAC.
- In this section we describe what PSSMs are and we develop methods to search PSSMs.

- A PSSM is a representation of a multiple alignment of related sequences.
- We define it as a function $M: \mathcal{A} \times \{1, \dots, m\} \to \mathbb{R}$, where \mathcal{A} is a finite alphabet and m is the length of M.
- Usually M is represented by an $|\mathcal{A}| \times \textit{m}\text{-matrix}$, see Table 1 for an example.
- Each column of the matrix reflects the frequency of occurrence of an amino acid or nucleotide at the corresponding position of the alignment.
- From now on, let M be a PSSM of length m.
- We define $score(w, M) = \sum_{h=1}^{m} M(w[h], h)$ for a sequence $w \in \mathcal{A}^{m}$ of length m.
- Given a sequence S of length n over alphabet \mathcal{A} and a threshold value th, the PSSM searching problem is to find all positions j, $1 \le j \le n-m+1$ in S such that $score(S[j ... j+m-1], M) \ge th$.

Example 2

Reconsider the PSSM of Example 1:

Now let $S=\mathtt{AGATCCTAACG}$ and th=1.2. Then we obtain two solutions to the PSSM-searching problems:

position	substring	score
3	ATCC	0.0 + 0.8 + 0.6 + 0.0 = 1.4
6	CTAA	0.0 + 0.8 + 0.2 + 0.4 = 1.4

- A simple algorithm for the PSSM searching problem slides along the sequence and computes score(w, M) for each w = S[j ... j + m 1], $j, 1 \le j \le n m + 1$.
- The running time of this algorithm is O(mn).
- This algorithm is used e.g. in the programs FingerPrintScan
 [Scordis et al., 1999], BLIMPS [Henikoff et al., 2000], MatInspector
 [Quandt et al., 1995], and MATCH [Kel et al., 2003].
- The technique of lookahead scoring, introduced in [Wu et al., 2000], gives an improvement over the simple algorithm.
- Lookahead scoring allows to stop the calculation of score(w, M) when it is clear that the given overall score threshold th cannot be achieved.
- A similar technique was used when computing the k-environment for Blast.

Example 3

Reconsider the PSSM of Example 1:

Α	0.0	0.0	0.2	0.4
C	0.0	0.0	0.6	0.0
G	8.0	0.2	0.0	0.4
Т	0.2	8.0	0.2	0.2

- Let S = AGATCCTAACG, th = 1.2 and consider the substrings CCTA and AACG at positions 5 and 8, respectively.
- For the first two characters in these substrings we obtain the score 0.
- The maximum score we can achieve for the last two characters is 0.6 + 0.4.
- So once we have read the first two characters CC of CCTA or AA of AACG, we know that we can achieve a score of at most 1 for the entire string.
- This is below the threshold.
- So we can stop after the first two characters of these substrings.

To explain the lookahead scoring method, define

$$pfxscore_d(w, M) = \sum_{h=1}^d M(w[h], h),$$
 $\max_h = \max\{M(a, h) \mid a \in A\},$
 $\sigma_d = \sum_{h=d+1}^m \max_h$

for any d, $1 \le d \le m$.

- That is, $pfxscore_d(w, M)$ is the score for the prefix w[1...d] of length d.
- Moreover, σ_d is the maximal score that can be achieved in the last m-d positions of the PSSM.
- Let $th_d = th \sigma_d$ be the *intermediate threshold* at position d, for $1 \le d \le m$.

The next lemma reveals an important property of prefix scores:

Lemma 1

The following statements are equivalent:

- 1 $pfxscore_d(w, M) \ge th_d$ for all $d, 1 \le d \le m$.
- 2 $score(w, M) \ge th$.

Proof

1⇒2: Suppose that 1 holds. Consider the special case for d=m. Then $\sigma_m = \sum_{h=m+1}^m \max_h = 0$ and

$$score(w, M) = \sum_{h=1}^{m} M(w[h], h)$$

= $pfxscore_m(w, M)$
 $\geq th_m$
= $th - \sigma_m$
= th .

Proof

2⇒1: Suppose that 2 holds. Let d, $1 \le d \le m$ be fixed but arbitrary. Then

$$score(w, M) = \sum_{h=1}^{m} M(w[h], h)$$

= $\sum_{h=1}^{d} M(w[h], h) + \sum_{h=d+1}^{m} M(w[h], h)$
= $pfxscore_{d}(w, M) + \sum_{h=d+1}^{m} M(w[h], h)$

Hence $score(w, M) \ge th$ implies $pfxscore_d(w, M) + \sum_{h=d+1}^m M(w[h], h) \ge th$.

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Proof

Since $M(w[h], h) \leq \max_h$ for all $h, 1 \leq h \leq m$, we conclude

$$\sum_{h=d+1}^m M(w[h],h) \leq \sum_{h=d+1}^m \mathsf{max}_h = \sigma_d$$

and hence

$$pfxscore_d(w, M) \ge th - \sum_{h=d+1}^m M(w[h], h)$$

$$\ge th - \sigma_d$$

$$= th_d.$$

- Lemma 1 gives a necessary condition for a PSSM-match, which can easily be exploited: When computing score(w, M) by scanning w from left to right, one checks for d = 1, 2, ..., if the intermediate threshold th_d is achieved.
- If not, the computation can be stopped.
- See Algorithm 1 for pseudo-code and Table 1 for an example applying the algorithm.
- The lookahead scoring algorithm runs in O(kn) time, where k is the average number of PSSM-positions per sequence start position actually evaluated.
- In the worst case, k is in O(m), which leads to the worst case running time of O(mn), not better than the simple algorithm.
- However, k is expected to be much smaller than m, leading to considerable speedups in practice.

Algorithm 1 (Lookahead scoring)

Input: Sequence S of length n, PSSM M of length m, threshold th **Output**: all positions in S matching M.

```
1: compute th_d for 1 < d < m
2: for all i \leftarrow 1 upto n - m + 1 do
       score \leftarrow 0
3:
       for all d \leftarrow 1 upto m do
4.
           score \leftarrow score + M(S[i+d-1], d)
5:
           if score < th_d then
6:
                break
7:
            end if
8:
       end for
9:
     if score > th then
10:
            print(match at position j with score score)
11:
        end if
12:
13: end for
```

Table 1: PSSM of length m=10 of a zinc-finger motif. Let th=400 be the score threshold. Then only substrings beginning with C or V can match the PSSM, since all other amino acids score below the intermediate threshold $th_1=-7$. That is, lookahead scoring will skip over all substrings beginning with amino acids different from C and V, as $M({\rm V},1)=16\geq th_1=-7$ and $M({\rm C},1)=92\geq th_1=-7$ and $M(x,1)< th_1=-7$ for all other aminoacids x.

A	-19	5	7	-29	-14	-25	7	-34	7	-7
C	92	-17	-8	99	-22	-34	-8	-27	40	43
D	-45	17	-29	-55	14	-25	-25	-44	-16	16
E	-49	22	-28	-61	22	-16	-24	-43	-14	-7
F	-30	-28	2	-42	-28	-37	-19	-60	-9	-27
G	-36	-15	-25	-45	9	-30	-23	-41	-14	-15
H	-38	-7	-10	-47	-8	-15	-22	-8	-6	-9
I	-12	-23	25	-31	-26	-36	4	-16	-17	-24
K	-41	-8	-23	-52	15	45	-15	-38	14	-5
L	-21	-27	-4	-34	-27	-34	-10	-14	-20	-26
M	-22	-21	-5	-36	-20	-26	-8	-17	-15	-18
N	-40	-26	-25	-49	-7	-18	-19	-39	-10	-6
P	-46	18	-32	-56	-26	-35	-29	-51	-24	-25
Q	-44	-7	-26	-55	-3	-9	-21	-40	-11	25
R	-44	-13	-25	-55	31	49	11	-36	12	13
S	-30	-9	-18	-38	-13	-25	-13	-39	15	25
T	-25	9	13	-35	5	-26	31	-35	9	-8
V	16	-19	22	-29	-23	-33	31	-21	-13	-21
W	-35	-33	-11	-44	-30	-39	-31	-1	-16	-30
Y	-34	-25	36	-46	-24	-31	-22	56	20	-24
σ_d	407	385	349	250	219	170	139	83	43	0
th _d	-7	15	51	150	181	230	261	317	357	400

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