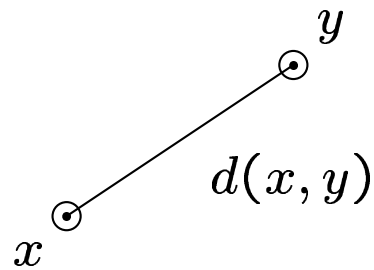


Today's program

1/2h

Sequence comparison



Jyrki Katajainen

Department of Computing
University of Copenhagen

My main sources

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Mike Paterson and Vlado Dančák, Longest common subsequences, *Proceeding of the 19th International Symposium on Mathematical Foundations of Computer Science, Lecture Notes in Computer Science 841*, Springer-Verlag (1994), 127–142

James J. Hunt, Kiem-Phong Vo, and Walter F. Tichy, Delta algorithms: an empirical analysis, *ACM Transactions on Software Engineering and Methodology* **7** (1998)

Symbols and sequences

In biological applications the symbols can be

- amino acids;

a **protein** is a sequence of amino acids;

- bases in DNA molecules;

each cell of an organism has a few very long DNA molecules; such a molecule is called a **chromosome**.

In a computer these symbols are often represented using one-letter codes.

Similarity of molecular sequences

Definitions: Let U and V be two sequences, and let $-$ denote a space (not in U or V).

An **alignment** between U and V is defined as the insertion of spaces in arbitrary locations so that they end up with the same size. No space in U should be aligned with a space in V .

Let $\sigma \begin{pmatrix} x \\ y \end{pmatrix}$ denote the **score** between two symbols x and y . Given an alignment, its *score* is the sum of the scores of the corresponding symbols.

Problem: Compute the **similarity** between U and V , i.e., the score of the best alignment (maximum score).

Example: Assume that $\sigma \begin{pmatrix} x \\ x \end{pmatrix} = +1$, $\sigma \begin{pmatrix} x \\ y \end{pmatrix} = -1$, and $\sigma \begin{pmatrix} - \\ x \end{pmatrix} = -2$. Then the optimal alignment between A B D D E F G H I and A B D E G K H I has score 2.

```
A B D D E F G H I
A B D - E G K H I
```

Dynamic programming

Let $s[i, j]$ denote the similarity between the prefixes of $X[1:i]$ and $Y[1:j]$. That is, we are trying to compute $s[m, n]$.

A recursive definition for matrix s , exploiting an obvious optimal subproblem property, is given as follows.

$$s[i, j] = \max \left\{ \begin{array}{l} s[i-1, j-1] + \sigma \left(\begin{array}{l} X[i] \\ Y[j] \end{array} \right), \\ s[i-1, j] + \sigma \left(\begin{array}{l} X[i] \\ - \end{array} \right), \\ s[i, j-1] + \sigma \left(\begin{array}{l} - \\ Y[j] \end{array} \right) \end{array} \right\}$$

Computing the similarity

The following algorithm fills the similarity matrix row by row.

Global-similarity(X, Y) \triangleright Runtime: $O(mn)$

1 $m \leftarrow \text{length}(X)$

2 $n \leftarrow \text{length}(Y)$

3 $s[0, 0] \leftarrow 0$

4 **for** $j \leftarrow 1$ **to** n

5 $s[0, j] \leftarrow s[0, j-1] + \sigma \left(\begin{array}{c} - \\ Y[j] \end{array} \right)$

6 **for** $i \leftarrow 1$ **to** m

7 $s[i, 0] \leftarrow s[i-1, 0] + \sigma \left(\begin{array}{c} X[i] \\ - \end{array} \right)$

8 **for** $j \leftarrow 1$ **to** n

9 $s[i, j] \leftarrow \max \left\{ \begin{array}{l} s[i-1, j-1] + \sigma \left(\begin{array}{c} X[i] \\ Y[j] \end{array} \right), \\ s[i-1, j] + \sigma \left(\begin{array}{c} X[i] \\ - \end{array} \right), \\ s[i, j-1] + \sigma \left(\begin{array}{c} - \\ Y[j] \end{array} \right) \end{array} \right\}$

10 **return** $s[m, n]$

Example: global alignment

<i>j</i>	0	1	2	3	4	5	6	7	8	9	
<i>i</i>	Y	A	B	D	D	E	F	G	H	I	
0	X	0	←-2	←-4	←-6	←-8	←-10	←-12	←-14	←-16	←-18
1	A	↑-2	↖1	←-1	←-3	←-5	←-7	←-9	←-11	←-13	←-15
2	B	↑-4	↑-1	↖2	←0	←-2	←-4	←-6	←-8	←-10	←-12
3	D	↑-6	↑-3	↑0	↖3	←1	←-1	←-3	←-5	←-7	←-9
4	E	↑-8	↑-5	↑-2	↑1	↖2	↖2	←0	←-2	←-4	←-6
5	G	↑-10	↑-7	↑-4	↑-1	↖0	↖1	↖1	↖1	←-1	←-3
6	K	↑-12	↑-9	↑-6	↑-3	↖2	↖1	↖0	↖0	↖0	←-2
7	H	↑-14	↑-11	↑-8	↑-5	↑-4	↑-3	↑-2	↖1	↖1	↖1
8	I	↑-16	↑-13	↑-10	↑-7	↑-6	↑-5	↑-4	↑-3	↑-1	↖2

Local similarity scores

A **local alignment** between X and Y is an alignment between a substring of X and a substring of Y .

Local-similarity(X, Y) \triangleright Runtime: $O(mn)$

1 $m \leftarrow \text{length}(X)$

2 $n \leftarrow \text{length}(Y)$

3 $best \leftarrow 0$

4 **for** $j \leftarrow 1$ **to** n

5 $s[0, j] \leftarrow s[0, j-1] + \sigma \left(\begin{array}{c} - \\ Y[j] \end{array} \right)$

6 **for** $i \leftarrow 1$ **to** m

7 $s[i, 0] \leftarrow s[i-1, 0] + \sigma \left(\begin{array}{c} X[i] \\ - \end{array} \right)$

8 **for** $j \leftarrow 1$ **to** n

9 $s[i, j] \leftarrow \max \left\{ \begin{array}{l} 0, \\ s[i-1, j-1] + \sigma \left(\begin{array}{c} X[i] \\ Y[j] \end{array} \right), \\ s[i-1, j] + \sigma \left(\begin{array}{c} X[i] \\ - \end{array} \right), \\ s[i, j-1] + \sigma \left(\begin{array}{c} - \\ Y[j] \end{array} \right) \end{array} \right\}$

10 $best \leftarrow \max\{best, s[i, j]\}$

11 **return** $best$

Example: local alignment

<i>j</i>	0	1	2	3	4	5	6	7	8	9
<i>i</i>	Y	A	B	D	D	E	F	G	H	I
0	X	0	0	0	0	0	0	0	0	0
1	A	0	↖ ₁	0	0	0	0	0	0	0
2	B	0	0	↖ ₂	← ₀	0	0	0	0	0
3	D	0	0	↑ ₀	↖ ₃	← ₁	0	0	0	0
4	E	0	0	0	↑ ₁	↖ ₂	↖ ₂	← ₀	0	0
5	G	0	0	0	0	↖ ₀	↖ ₁	↖ ₁	↖ ₁	0
6	K	0	0	0	0	0	↖ ₀	↖ ₀	↖ ₀	0
7	H	0	0	0	0	0	0	0	↖ ₁	0
8	I	0	0	0	0	0	0	0	0	↖ ₂

Optimal local alignment (score 3):

A B D

A B D

Possible improvements

The amount of space used can be reduced to $O(m+n)$.

This is left as a home exercise. (Hint: Use divide and conquer.)

Also, there exists an algorithm with time complexity $O(dn)$, where d is the difference between the maximum possible score and the optimal score. Thus, the higher the similarity, the faster the answer. Space-saving versions can also be derived.

Basic idea: compute only the similarities around the main diagonal; double the distance from the diagonal until one can be sure that the solution is optimal.

Scoring functions

- identity/non-identity function: $\sigma \begin{pmatrix} x \\ x \end{pmatrix} = M$, $\sigma \begin{pmatrix} x \\ y \end{pmatrix} = m$, and $\sigma \begin{pmatrix} - \\ x \end{pmatrix} = g$ (usually $g < 0$, and naturally $m < M$).

$$\sigma \begin{pmatrix} -A \\ C- \end{pmatrix} < \sigma \begin{pmatrix} A \\ C \end{pmatrix} \Rightarrow 2g < m$$

$$\sigma \begin{pmatrix} -AT \\ TA- \end{pmatrix} < \sigma \begin{pmatrix} AT \\ TA \end{pmatrix} \Rightarrow m \text{ closer to } M \text{ than } 2g$$

The values $M = 1$, $m = -1$, and $g = -2$ fulfil these restrictions.

- subadditive functions: $f(k_1+k_2+\dots+k_n) \leq \sum_{i=1}^k f(k_i)$. The idea is that k spaces are more probable than k isolated spaces.
- For protein sequences, the use of PAM k matrices is commonplace. These take into account the relative replaceability in an evolutionary scenario.

Longest common subsequence

Special case: $\sigma \begin{pmatrix} x \\ y \end{pmatrix} = 0$ and $\sigma \begin{pmatrix} x \\ x \end{pmatrix} = 1$.

Definitions: We say that $U = \langle u_1, u_2, \dots, u_k \rangle$ is a **subsequence** of $X = \langle x_1, x_2, \dots, x_m \rangle$ if there exist indices $1 \leq i_1 < \dots < i_k \leq m$ such that $U = \langle x_{i_1}, x_{i_2}, \dots, x_{i_k} \rangle$. U is a **common subsequence** of X and Y if U is a subsequence of both X and Y . We let $|U|$ denote the length of U .

Problem: Given two sequences X and Y , find their longest common subsequence.

Example: The LCS of the sequences

<u>a</u>	<u>b</u>	r	<u>a</u>	<u>c</u>	<u>a</u>	d	a	<u>b</u>	r	<u>a</u>		
			—	—	—			—	—	—		
a	b	c	a	b	a	b	c	a	b	b	c	a

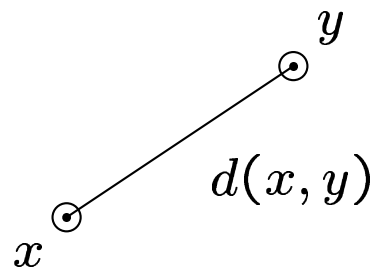
is abcaaba and is of length 7.

Related applications

- compression in revision control systems
- displaying of differences between files
- merging of the changes in two different files relative to a common base
- saving space when taking backups
- taking checkpoints in database systems
- updating terminal display over a slow network
- distributing updates for software and other data over the web
- speech processing
- spell checking
- improving I/O performance when processing data

Conclusion

The distance between our teaching and real world is a bit larger than ε , but not much larger.



Jyrki Katajainen

Department of Computing
University of Copenhagen