CSE 417 Algorithms

Sequence Alignment

Sequence Alignment

What

Why

A Dynamic Programming Algorithm

Sequence Alignment

Goal: position characters in two strings to "best" line up identical/similar ones with one another

i.e. think back to finding similarities in RNA / DNA structure across different proteins in different organisms: similar sequences often have similar structures and helps us understand functionality of

We can do this via Dynamic Programming

What is an alignment?

Compare two strings to see how "similar" they are E.g., maximize the # of identical chars that line up

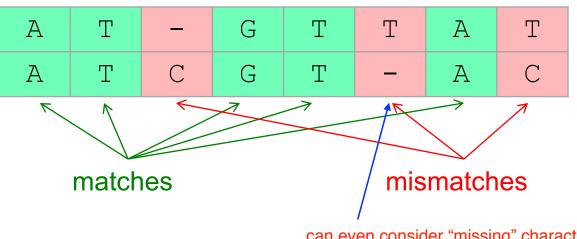
ATGTTAT vs ATCGTAC

A	Т	_	G	Т	Т	A	T
A	Т	С	G	Т	_	A	С

What is an alignment?

Compare two strings to see how "similar" they are E.g., maximize the # of identical chars that line up





Sequence Alignment: Why

Biology

Among most widely used comp. tools in biology

DNA sequencing & assembly

New sequence always compared to data bases

Similar sequences often have similar origin and/or function

Recognizable similarity after 10⁸ –10⁹ yr

Other

keep track of differences rather than storing each copy of the new file.. i.e. version tree

spell check/correct, diff, svn/git/..., plagiarism, ...

Accession	Entry name	Status	Protein names	Organism	Length	
Q7T109	Q7T109_XENTR	亩	MyoD protein	Xenopus tropicalis (Western clawed frog) Silurana tropicalis)	288	

Alignment 1 against Q7T109

964

320

64.0%

9	Some Details from #25					
	E-value	1.0 ×10 -102				
	Positives	74.0%				
	Match length	288				

Position Q7T109 matches from 1 to 288 (288AA), in the query sequence from 1 to 320 (320AA)

G	ra	p	h	ic	al

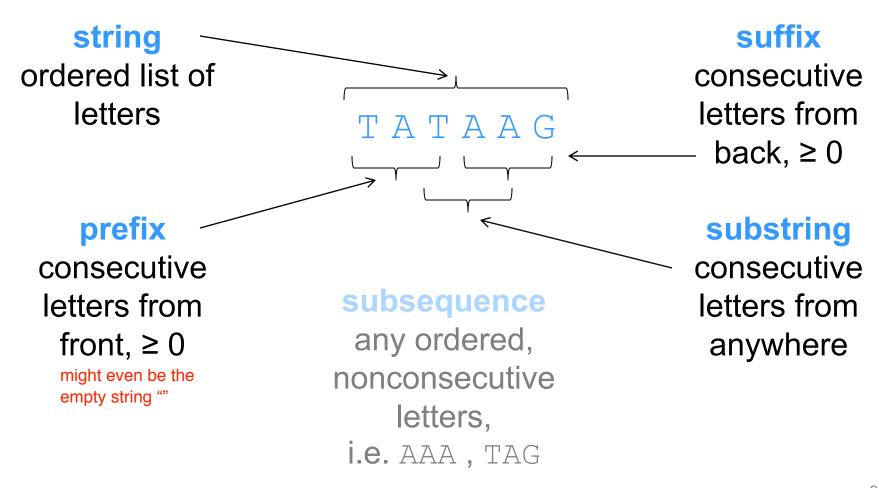
Query length

Score

Identity

1	MELLSPPLRDVDLTAPDGSLCSFATTDDFYDDPCFDSPDLRFFEDLDPRLMHVGALLKPE MELL PPLRD+++T +GSLCSF T DDFYDDPCF++ D+ FFEDLDPRL+HV ALLKPE MELLPPPLRDMEVTEGSLCSFPTPDDFYDDPCFNTSDMSFFEDLDPRLVHV-ALLKPE	60 P15172 57 Q7T109
61 58	EHSHFPAAVHPAPGAREDEHVRAPSGHHQAGRCLLWACKACKRKTTNADRRKAATMRERR + H EDEHVRAPSGHHQAGRCLLWACKACKRKTTNADRRKAATMRERR DPHHNEDEHVRAPSGHHQAGRCLLWACKACKRKTTNADRRKAATMRERR	120 P15172 106 Q7T109
121 107	RLSKVNEAFETLKRCTSSNPNQRLPKVEILRNAIRYIEGLQALLRDQDAAPPGAAAAFYA RLSKVNEAFETLKRCTS+NPNQRLPKVEILRNAIRYIE LQ+LLR Q+ +FY RLSKVNEAFETLKRCTSTNPNQRLPKVEILRNAIRYIESLQSLLRGQEESFY-	180 P15172 158 Q7T109
181 159	PGPLPPGRGGEHYSGDSDASSPRSNCSDGMMDYSGPPSGARRRNCYEGAYYNEAPSEPRP P+ EHYSGDSDASSPRSNCSDGM DYS PP G+RRN Y+ ++Y+++P+ RPVLEHYSGDSDASSPRSNCSDGMTDYS-PPCGSRRNSYDSSFYSDSPNGLRL	240 P15172 210 Q7T109
241 211	GKSAAVSSLDCLSSIVERISTESPAAPALLLADVPSESPPRRQEAAAPSEGESSGDP GKS+ +SSLDCLSSIVERISTESP P + AD SE P +P +GE+ SG GKSSVISSLDCLSSIVERISTESPVCPVIPAADSGSEGSPCSPLQGETLSESGII	297 P15172 7 265 Q7T109

Terminology



Formal definition of an alignment

An alignment of strings S, T is a pair of strings S', T' with dash characters "-" inserted, so that

- 1. |S'| = |T'|, and strings are same length (|S| ="length of S")
- 2. Removing dashes leaves S, T dont delete any letters from strings nor change the order of any characters

Consecutive dashes are called "a gap."

(Note that this is a definition for a general alignment, not optimal.)

Scoring an arbitrary alignment

Define a score for *pairs* of aligned chars, e.g.

scoring system can be more complicated than this. Does not influence algorithm as long as we are only comparing single columns

$$\sigma(x, y) = \begin{cases} match & 2\\ mismatch & -1 \end{cases}$$
 (Toy scores for examples in slides)

Apply that per column, then add.

$$-1$$
 +2 -1 -1 +2 -1 -1

NB: my slides: maximize similarity; KT minimizes diffs

Can we use Dynamic Programming?

1. Can we decompose into subproblems?

E.g., can we align smaller substrings (say, prefix/suffix in this case), then combine them somehow?

2. Do we have optimal substructure?

I.e., is optimal solution to a subproblem independent of context? E.g., is appending two optimal alignments also be optimal? Perhaps, but some changes at the interface might be needed?

Optimal Substructure (In More Detail)

Optimal alignment *ends* in 1 of 3 ways: last chars of S & T aligned with each other last char of S aligned with dash in T last char of T aligned with dash in S (assume $\sigma(-, -) < 0$, so never align dash with dash)

In each case, the rest of S & T should be optimally aligned to each other

O(nm)

Optimal Alignment in O(n²) via "Dynamic Programming"

Input: S, T, |S| = n, |T| = m

Output: value of optimal alignment

Easier to solve a "harder" problem:

V(i,j) = value of optimal alignment of S[1], ..., S[i] with T[1], ..., T[j] for all $0 \le i \le n$, $0 \le j \le m$.

Base Cases

V(i,0): first i chars of S all match dashes

$$V(i,0) = \sum_{k=1}^{i} \sigma(S[k],-)$$

V(0,j): first j chars of T all match dashes

$$V(0,j) = \sum_{k=1}^{j} \sigma(-,T[k])$$

General Case

Opt align of S[1], ..., S[i] vs T[1], ..., T[j]:

$$\begin{bmatrix} \sim \sim \sim S[i] \\ \sim \sim \sim T[j] \end{bmatrix}, \quad \begin{bmatrix} \sim \sim \sim S[i] \\ \sim \sim \sim - \end{bmatrix}, \text{ or } \begin{bmatrix} \sim \sim \sim - \\ \sim \sim \sim T[j] \end{bmatrix}$$

Opt align of
$$S_1...S_{i-1}$$
 & $T_1...T_{j-1}$

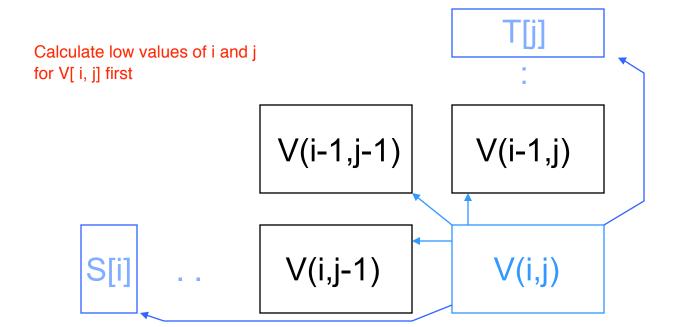
$$V(i,j) = \max$$

Opt align of
$$S_{1}...S_{i-1} & \\ V(i,j) = \max \begin{cases} V(i-1,j-1) + \sigma(S[i],T[j]) \\ V(i-1,j) + \sigma(S[i],-) \\ V(i,j-1) + \sigma(-,T[j]) \end{cases},$$

for all $1 \le i \le n$, $1 \le j \le m$.

Calculating One Entry

$$V(i,j) = \max \begin{cases} V(i-1,j-1) + \sigma(S[i],T[j]) \\ V(i-1,j) + \sigma(S[i],-) \\ V(i,j-1) + \sigma(-,T[j]) \end{cases}$$



scoring function

Mismatch = -1

Match = 2

	j	0	1	2	3	4	5	
<u>i</u>			С	a	t	g	t	← T
0		0	-1	-2	-3	-4	-5	
1	a	-1						
2	С	-2		C -	Sc			
3	g	-3						
4	С	-4						
5	t	-5						
6	g	-6						

	j	0	1	2	3	4	5	
<u>i</u>			С	a	t	g	t	← T
0		0	-1	-2	-3	-4	-5	
1	a	-1	ı					
2	O	-2						
3	g	-3		Sc	ore(-,a			
4	С	-4						
5	t	-5						
6	g	-6						

	j	0	1	2	3	4	5	
i			С	a	t	g	t	←T
0		0	-1	-2	-3	-4	-5	
1	a	-1						
2	С	-2						
3	g	-3						
4	О	-4	_	Sc	ore(-,c	(c) = -1		
5	t	-5	-1					
6	g	-6						



	j	0	1	2	3	4	5	
<u>i</u>			С	a	t	g	t	←T
0		0	-1	-2	-3	-4	-5	
1	а	-1	-1	1				
2	С	-2						
3	g	-3						-2
4	С	-4				σ(a,	a)=+2	σ(-,a)=-1
5	t	-5				5 (2)	-)=-1	1 -3 ca-
6	g	-6			_1			-2 1 ca
	↑ S						ć	aa 20

	j	0	1	2	3	4	5	
i			С	a	t	g	t	←T
0		0	-1	-2	-3	-4	-5	
1	а	-1	-1	1				
2	С	-2	1					Time =
3	g	-3						O(mn)
4	С	-4						
5	t	-5						
6	g	-6						



	j	0	1	2	3	4	5	
<u>i</u>			С	a	t	g	t	←T
0		0	-1	-2	-3	-4	-5	
1	a	-1	-1	1	0	-1	-2	
2	С	-2	1	0	0	-1	-2	
3	g	-3	0	0	-1	2	1	
4	С	-4	-1	-1	-1	1	1	
5	t	-5	-2	-2	1	0	3	
6	g	-6	-3	-3	0	3	2	



me

Finding Alignments: Trace Back

Arrows = (ties for) max in V(i,j); 3 LR-to-UL paths = 3 optimal alignments

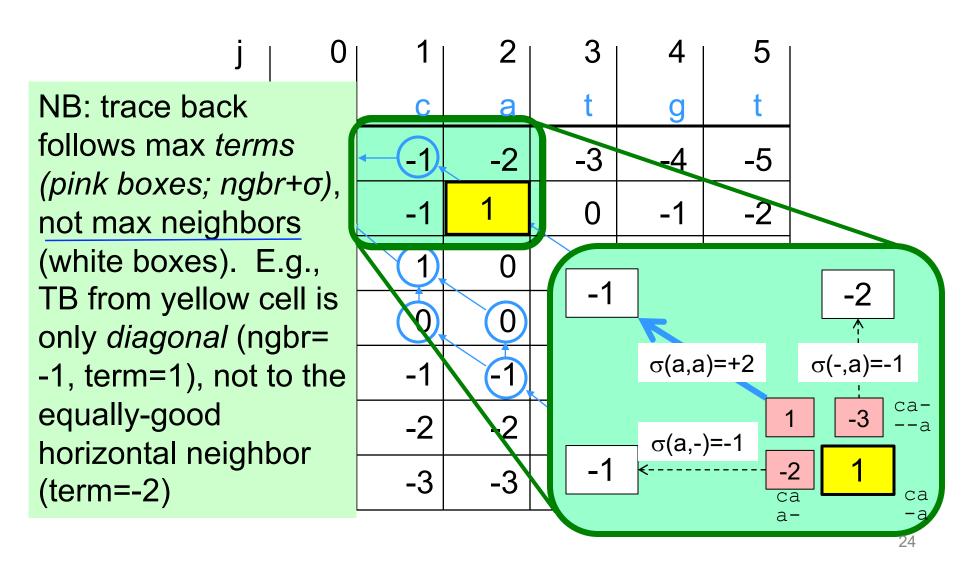
	j	0	1	2	3	4	5	
<u>i</u>			С	a	t	g	t	←
0		0	-1	-2	-3	-4	-5	
1	a	-1	-1	1	0	-1	-2	
2	С	-2	1	0	0	-1	-2	
3	9	-3	0	0	-1	2	1	
4	С	-4	-1	-1	-1	1,	1	
5	t	-5	-2	-2	1,	0	3	
6	g	-6	-3	-3	0	3	2	

3 alignments? C.f. slide 12.

Ex: what are the

Finding Alignments: Trace Back

Arrows = (ties for) max in V(i,j); 3 LR-to-UL paths = 3 optimal alignments



Complexity Notes

```
Time = O(mn), (value and alignment)
```

Space =
$$O(mn)$$

NOT alignment though

Easy to get <u>value</u> in Time = O(mn) and Space = O(min(m,n))

Only need to store the previous row... but makes traceback harder.

Possible to get value and alignment in Time = O(mn) and Space = O(min(m,n)), but tricky. (KT section 6.7)

Variations

Local Alignment best substring of S and substrings of T, find the ones with the highest similarity

- Preceding gives *global* alignment, i.e. full length of both strings;
- Might well miss strong similarity of part of strings amidst dissimilar flanks

Gap Penalties

10 adjacent dashes cost 10 x one dash?

Many others

Similarly fast DP algs often possible

Significance of Alignments

Is "42" a good score?

Compared to what?

Usual approach: compared to a specific "null model", such as "random sequences"

Interesting stats problem; much is known

Summary: Alignment

- Functionally similar proteins/DNA often have recognizably similar sequences even after eons of divergent evolution
- Ability to find/compare/experiment with "same" sequence in other organisms is a huge win
- Surprisingly simple scoring works well in practice: score positions separately & add, usually w/ fancier affine gap model
- Simple dynamic programming algorithms can find *optimal* alignments under these assumptions in poly time (product of sequence lengths)
- This, and heuristic approximations to it like BLAST, are workhorse tools in molecular biology, and elsewhere.

Summary: Dynamic Programming

Keys to D.P. are to

- a) Identify the subproblems (usually repeated/overlapping)
- b) Solve them in a careful order so all small ones solved before they are needed by the bigger ones, and
- c) Build table with solutions to the smaller ones so bigger ones just need to do table lookups (*no* recursion, despite recursive formulation implicit in (a))
- d) Implicitly, optimal solution to whole problem devolves to optimal solutions to subproblems

A really important algorithm design paradigm