

CSE 312

Autumn 2011

More Algorithms:
Dynamic Programming for
Sequence Alignment

An Important Algorithm Design Technique

Dynamic Programming

Give a solution to a problem using smaller sub-problems, e.g. a recursive solution

Useful when the same sub-problems show up again and again in the solution

“Dynamic Programming”

Program –

A plan or procedure for dealing with some matter

– Webster’s New World Dictionary

Pioneered by Richard Bellman in the 1950s.

Dynamic programming = “planning over time”

Secretary of Defense was hostile to mathematical research.

Bellman sought an impressive name to avoid confrontation.

“it's impossible to use dynamic in a pejorative sense”

“something not even a Congressman could object to”

Sequence Similarity: What

G G A C C A

T A C T A A G

T C C A A T

Sequence Similarity: What

G G A C C A

T A C T A A G

| : | : | | :

T C C - A A T

Sequence Similarity: Why

Most widely used comp. tools in biology
New sequence always compared to
sequence data bases

**Similar sequences often have similar
origin or function**

Recognizable similarity after $10^8 - 10^9$ yr

not to mention:

- Unix “diff”,
- module histories in version control systems,
- programming assignment pairs with sadly questionable evolutionary history,
- etc., etc., ...

Bio Example

<http://www.ncbi.nlm.nih.gov/blast/>

Starting with a protein sequence from:

I easily found related ones in:

Taxonomy Report		
root	64 hits	16 orgs
. Eukaryota	62 hits	14 orgs
. . Fungi/Metazoa group	57 hits	11 orgs
. . . Bilateria	38 hits	7 orgs
. . . . Coelomata	36 hits	6 orgs
. Tetrapoda	26 hits	5 orgs
. Eutheria	24 hits	4 orgs
. Homo sapiens	20 hits	1 orgs
. Murinae	3 hits	2 orgs
. Rattus norvegicus ...	2 hits	1 orgs
. Mus musculus	1 hits	1 orgs
. Sus scrofa	1 hits	1 orgs
. Xenopus laevis	2 hits	1 orgs
. Drosophila melanogaster ...	10 hits	1 orgs
. Caenorhabditis elegans	2 hits	1 orgs
. Ascomycota	19 hits	4 orgs
. Schizosaccharomyces pombe ...	10 hits	1 orgs
. Saccharomycetales	9 hits	3 orgs
. Saccharomyces	8 hits	2 orgs
. Saccharomyces cerevisiae .	7 hits	1 orgs
. Saccharomyces kluyveri ...	1 hits	1 orgs
. Candida albicans	1 hits	1 orgs
. Arabidopsis thaliana	2 hits	1 orgs
. Apicomplexa	3 hits	2 orgs
. Plasmodium falciparum	2 hits	1 orgs
. Toxoplasma gondii	1 hits	1 orgs
. synthetic construct	1 hits	1 orgs
. lymphocystis disease virus	1 hits	1 orgs

us

rat
mouse
pig
frog
fly
a worm
fungus
plants
...

Try it!

pick any protein, e.g. hemoglobin, insulin, exportin,... BLAST to find distant relatives.

Terminology

String: ordered list of letters TATAAG

Prefix: consecutive letters from front
empty, T, TA, TAT, ...

Suffix: ... from end
empty, G, AG, AAG, ...

Substring: ... from ends or middle
empty, TAT, AA, ...

Subsequence: ordered, nonconsecutive
TT, AAA, TAG, ...

Sequence Alignment

a c b c d b
/ \ |
c a d b d

a c - - b c d b
| | |
- c a d b - d -

Defn: An *alignment* of strings S , T is a pair of strings S' , T' (with spaces or '-') s.t.

(1) $|S'| = |T'|$, and $(|S| = \text{"length of } S\text{"})$

(2) removing all spaces leaves S , T

Alignment Scoring

E.g.:
Mismatch = -1
Match = 2

a c b c d b
c a d b d d

a c - - b c d b
- c a d b - d d
-1 2 -1 -1 2 -1 2 -1

Value = 3*2 + 5*(-1) = +1

The *score* of aligning (characters or spaces) x & y is $\sigma(x,y)$.

← in general

Value of an alignment $\sum_{i=1}^{|S'|} \sigma(S'[i], T'[i])$

An *optimal alignment*: one of max value

Optimal Alignment: A Simple Algorithm

(For simplicity, assume $|S| = |T| = n$)

for all choices of n positions from $S \& T$ combined **do**

align the k chosen letters of S with the k *unchosen* letters of T

align all other chars to spaces

compute its value

retain the max

end

output the retained alignment

```
S = abcde
T = vwxyz
--abc-de      ab--c-de
vw--xyz-      --vwxyz-
(two alignments, but same value)
```

Analysis

Assume $|S| = |T| = n$

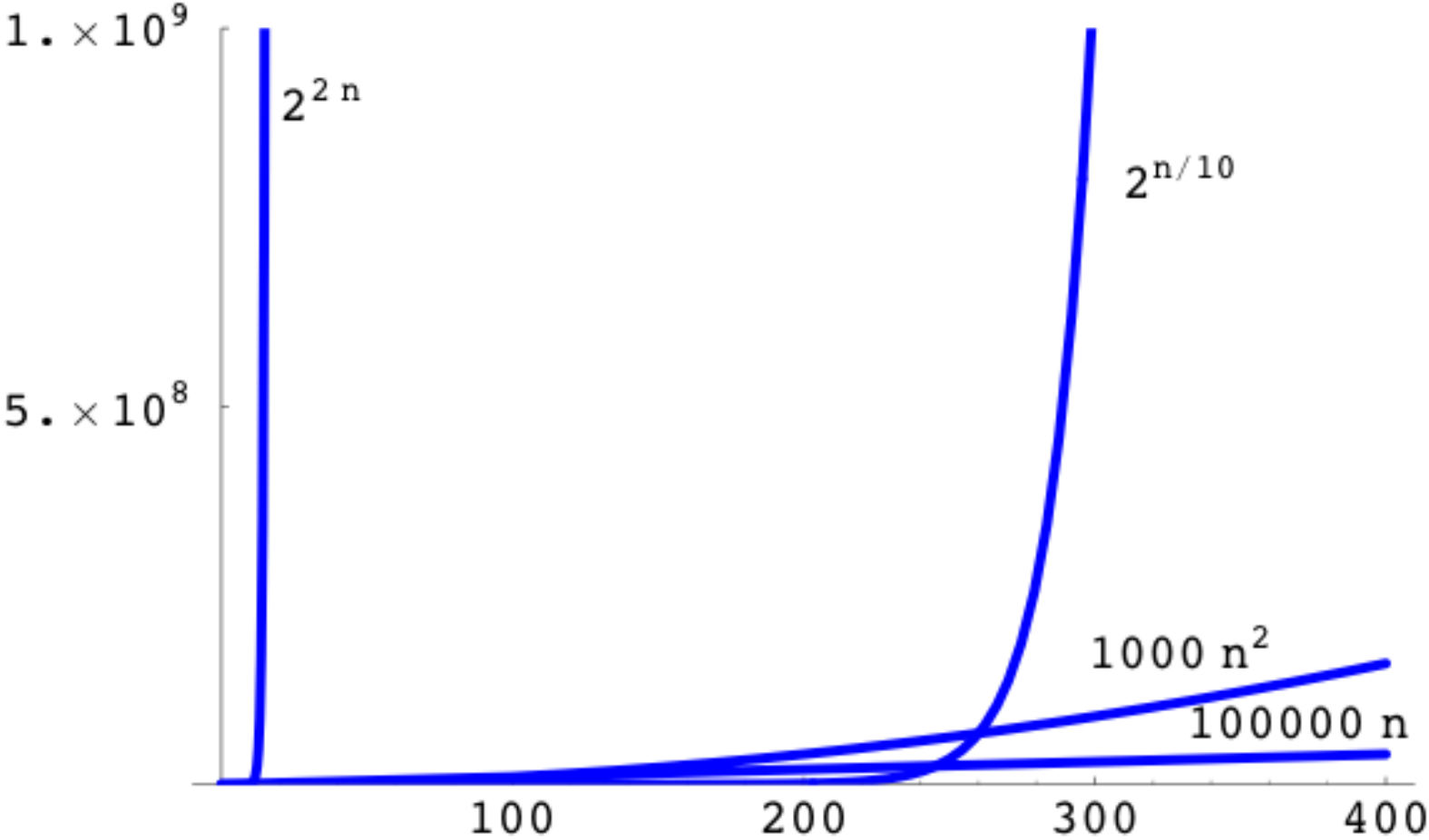
Time to evaluate one alignment: n

How many alignments are there: $\binom{2n}{n}$

Total time: $n \binom{2n}{n} > 2^{2n}$, for $n > 3$

E.g., for $n = 20$, time is $> 2^{40} > 10^{12}$ operations

Polynomial vs Exponential Growth



Dynamic Programming Alg: The Key Idea

Optimal alignment *ends* in 1 of 3 ways:

last chars of S & T aligned with each other

last char of S aligned with space in T

last char of T aligned with space in S

(never align space with space; $\sigma(-, -) < 0$)

In each case, the *rest* of S & T should be

optimally aligned to each other

(else you could improve by doing so)

Optimal Alignment in $O(n^2)$ 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
 $S[1], \dots, S[i]$ with $T[1], \dots, T[j]$
for **all** $0 \leq i \leq n, 0 \leq j \leq m$.

Base Cases

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

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

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

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

General Case

Opt align of $S[1], \dots, S[i]$ vs $T[1], \dots, T[j]$:

$$\left[\begin{array}{c} \sim\sim\sim\sim T[j] \\ \sim\sim\sim\sim S[i] \end{array} \right], \quad \left[\begin{array}{c} \sim\sim\sim\sim T[j] \\ \sim\sim\sim\sim - \end{array} \right], \quad \text{or} \quad \left[\begin{array}{c} \sim\sim\sim\sim - \\ \sim\sim\sim\sim S[i] \end{array} \right]$$

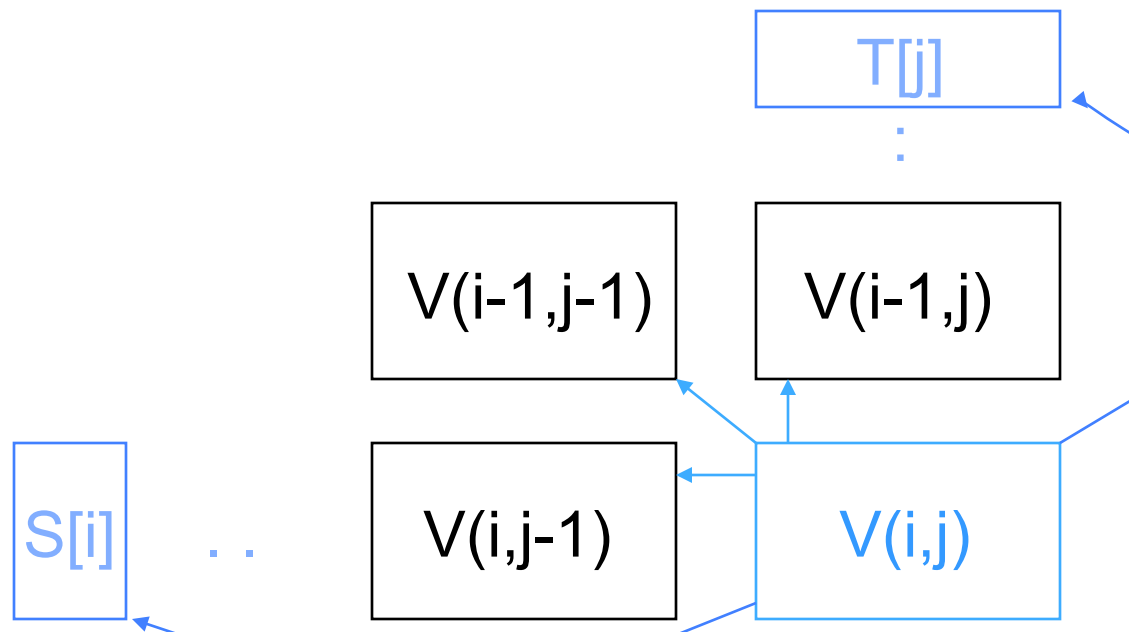
Opt align of
 $S_1 \dots S_{i-1}$ &
 $T_1 \dots T_{j-1}$

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

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

Calculating One Entry

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



Mismatch = -1
Match = 2

Example

i \ j	0	1	2	3	4	5
0	0	-1	-2	-3	-4	-5
1	-1					
2	-2					
3	-3					
4	-4					
5	-5					
6	-6					

← T

↑ S

c
-

 Score(c,-) = -1

Mismatch = -1
Match = 2

Example

i \ j	0	1	2	3	4	5
0	0	-1	-2	-3	-4	-5
1	a	-1				
2	c	-2				
3	b	-3				
4	c	-4				
5	d	-5				
6	b	-6				

← T

↑ S

-
a Score(-,a) = -1

Mismatch = -1
Match = 2

Example

	j	0	1	2	3	4	5
i			c	a	d	b	d
0		0	-1	-2	-3	-4	-5
1	a	-1					
2	c	-2					
3	b	-3					
4	c	-4					
5	d	-5					
6	b	-6					

← T

-	-
a	c
-1	

Score(-,c) = -1

↑ S

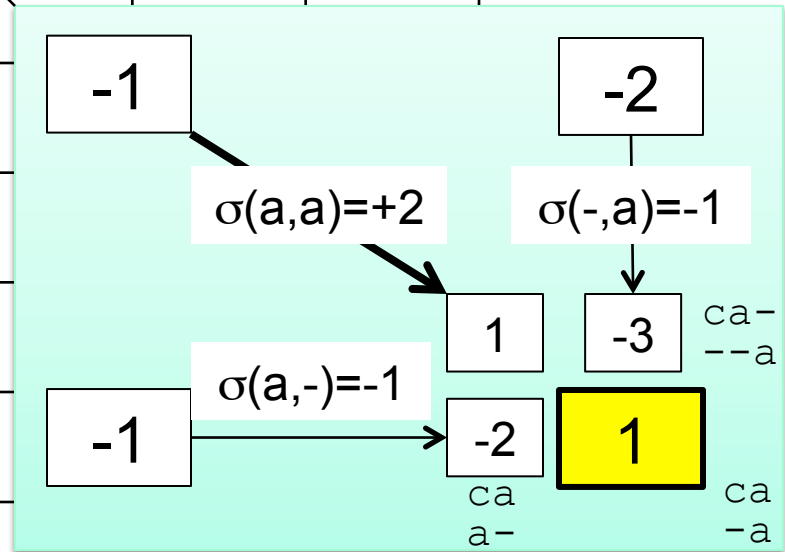
Mismatch = -1
Match = 2

Example

i \ j	0	1	2	3	4	5
		c	a	d	b	d
0	0	-1	-2	-3	-4	-5
1	a	-1	-1	1		
2	c	-2				
3	b	-3				
4	c	-4				
5	d	-5				
6	b	-6				

← T

↑ S



Mismatch = -1
 Match = 2

Example

	j	0	1	2	3	4	5
i			c	a	d	b	d
0		0	-1	-2	-3	-4	-5
1	a	-1	-1	1			
2	c	-2	1				
3	b	-3					
4	c	-4					
5	d	-5					
6	b	-6					

←T

Time =
 $O(mn)$

↑S

Mismatch = -1
 Match = 2

Example

	j	0	1	2	3	4	5	
i			c	a	d	b	d	←T
0		0	-1	-2	-3	-4	-5	
1	a	-1	-1	1	0	-1	-2	
2	c	-2	1	0	0	-1	-2	
3	b	-3	0	0	-1	2	1	
4	c	-4	-1	-1	-1	1	1	
5	d	-5	-2	-2	1	0	3	
6	b	-6	-3	-3	0	3	2	

↑
S

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	
i			c	a	d	b	d	←T
0		0	-1	-2	-3	-4	-5	
1	a	-1	-1	1	0	-1	-2	
2	c	-2	1	0	0	-1	-2	
3	b	-3	0	0	-1	2	1	
4	c	-4	-1	-1	-1	1	1	
5	d	-5	-2	-2	1	0	3	
6	b	-6	-3	-3	0	3	2	

↑S

Complexity Notes

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

Space = $O(mn)$

Easy to get **value** in Time = $O(mn)$ and
Space = $O(\min(m,n))$

Possible to get value *and alignment* in
Time = $O(mn)$ and Space = $O(\min(m,n))$
but tricky.

Significance of Alignments

Is “42” a good score?

Compared to what?

Hypothesis Testing again!

Compared to a specific “null model”,
such as “random sequences,” is the data
more likely under null or alt hypothesis?

Significance of Alignment

Usual context is “I just searched for S in a big database & my best match, T, scored 42”

Idea 1:

Align & score S against many *random* sequences

The fraction of them having better score than alignment of S to T, is the (empirical) probability of a chance alignment as good as observed S:T alignment (e.g., if 1 in 100 are better, then “ $p \approx .01$ ”)

Idea 2:

Just as sums of r.v.’s converge to normal (CLT), *max* of a bunch of r.v.’s also converges to a limit distribution (called EVD), so use tails of that distribution to estimate prob of a chance match

Summary

Sequence similarity has important applications in biology and elsewhere

Surprisingly simple scoring often works well in practice: score positions separately & add

Simple “dynamic programming” algorithms can find *optimal* alignments under these assumptions in polynomial time (product of sequence lengths)

Keys to D.P. are to

- a) identify the subproblems (usually repeated/overlapping)
- b) be sure opt solutions to subproblems are needed for opt solution globally
- c) solve in a careful order; solve all small ones before needed by bigger ones
- d) 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))