## CSE 397-497: Computational Issues in Molecular Biology

## Lecture 5

# Spring 2004



CSE 397-497: Computational Issues in Molecular Biology Lopresti · Spring 2004 · Lecture 5 Title: "Speech Processing for Multimedia Communications" Speaker: Professor Joseph Olive (University of Nebraska) Date: Thursday, February 5 Time: 4:15 pm

Place: PL 466

(Speech can be viewed as sequence data, too!)



Remember – check schedule for your lecture on Blackboard. Roughly one third of your grade in course is determined by this!

ence comparison & alignment – Dan Lopresti	AT 1
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ence comparison & alignment – Dan Lopresti	JW1
) – Dan Lopresti	AL2, LN1
) – Dan Lopresti	JW2, UM1
	AL3
ence comparison & alignment – Arthur Loder	LN2, ST1
	JW3
ence comparison & alignment – Jesse Wolfgang	UM2, SC1
	LN3
	) – Dan Lopresti ) – Dan Lopresti ence comparison & alignment – Arthur Loder ence comparison & alignment – Jesse Wolfgang

Those taking CSE 497 must send me a ranked list of top 3 student lectures you wish to scribe for by 5:00 pm on Friday.



#### A cartoon you'll learn to appreciate all too soon ...



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## Recall: basic approaches to sequence comparison



So far, the sequence comparison measures we've been discussing can go by any of a variety of names:

- edit or evolutionary distance,
- Levenshtein distance,
- Needleman-Wunsch (biologists),
- Wagner-Fischer (computer scientists),
- Viterbi (EE's),
- Smith-Waterman (in the case of local alignments),
- word-spotting (in the case of semi-global alignments).

There is another special case worth discussing because you'll see the terminology: *longest common subsequence* (*LCS*).



*subsequence* sequence *u* that can be obtained from *s* by removing some symbols.

**TACG** is a subsequence of **TATCTG** 

A sequence *u* is a *common subsequence* of *s* and *t* if it is a subsequence of both.

ACG is a common subsequence of TATCTG and ACTGA

A sequence *u* is a *longest common subsequence (LCS)* of *s* and *t* if it is at least as long as any subsequence of *s* and *t*.

ACTG is an LCS of TATCTG and ACTGA

How does longest common subsequence relate to the notion of an alignment and the optimal dynamic programming algorithm?



We only care about total number of matches. So set  $c_{sub} = 1$  when symbols match, and set all other costs to 0.

... ignore non-match pairings ...

Then same recurrence computes LCS:

$$a[i, j] = \max \begin{cases} a[i-1, j] \\ a[i, j-1] \\ a[i-1, j-1] + c_{sub}(s[i], t[j]) \end{cases}$$

 $1 \le i \le m$ ,  $1 \le j \le n$ 



"The String-to-String Correction Problem with Block Moves," W. F. Tichy, *ACM Transactions on Computer Systems*, 2(4):309-321, November 1984.

Title is bit of misnomer. Really, Tichy is concerned with a simplified editing model that involves a single operation.

For two strings s[1]s[2]...s[m] and t[1]t[2]...t[n], a block move is a triple (p,q,l) such that s[p]...s[p+l-1] = t[q]...t[q+l-1].

In other words, a substring of length l starting at index p in s that corresponds exactly to a substring starting at index q in t.

For example, (0,2,2) is a block move from **TACG** to **CCTATC**.

#### **Covering sets**

For two strings s and t, a *covering set* (of t with respect to s) is a set of block moves such that every symbol t[i] that also appears in s is the target of exactly one block move.



covering set = {(1,0,1), (3,1,3), (1,4,1)}

Note how this differs significantly from the notion of an alignment.

A trivial covering set consists of block moves of length 1, one for each symbol in *t* that appears in *s*.

The goal is to find a *minimal covering set*, i.e., a covering set that is no larger than any covering set for the two strings.

## Covering sets vs. LCS

Tichy notes that traditional alignments (and LCS) don't allow:

(1) crossings:



LCS

re-use of (2)substrings:

Repeated application of LCS doesn't help, either:

$$S = a \underbrace{b c d e a}_{T = c d a b}$$

$$S = a \underbrace{b c d e a}_{T = c d a b}$$

$$T = c d a \underbrace{b}_{c d a b}_{covering set}$$



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Tichy's algorithm for computing a minmal covering set:

(1) Set j = 0.

(2) Find longest substring beginning at *t*[*j*] that appears in *s*.

(3) If no such substring exists (i.e., if t[j] is not in s), then j++.

- (4) If such a substring of length *I* does exist, record it as a block move, set j = j + 1, and return to step 2.
- (5) Repeat until all of *t* is consumed.

Note: step 2 is only non-trivial step. Going beyond naïve implementation, there are several smart ways to do this.



## Computing minimal covering sets

## Example:

Step 1: S = v w v w x y $T =  z v w x w$	longest block move starting with $T[0]$ : none
Step 2: S = v w v w x y T = z   v w x w	longest block move starting with $T[1]$ : (2, 1, 3)
Step 3: S = v w v w x y T = z v w x   w	longest block move starting with $T[4]$ : (1, 4, 1)

Time complexity is O(mn), space complexity is O(m + n).

Time complexity can be reduced to linear using suffix trees (Arthur will cover suffix trees as part of his lecture on Feb. 17).



Informal proof of correctness (for real proof, see paper):

```
Look at resulting string t:

...X(...)X(...)(...)X(...)(...)X...

X = unmatched symbols

(...) = symbols matched in single block move
```

The only way this can fail to be a minimal covering set is if there's a way to coalesce some region of k > 1 blocks into (k - 1) or fewer blocks.



## How do we know this is yields optimal solution?

What properties do we know about blocks in such a region?

- (1) each block consists of consecutive symbols,
- (2) each block is maximal,
- (3) blocks themselves are consecutive.

How could three blocks become two blocks, for example?



Both of these would violate condition (2). QED.

What are the advantages of Tichy's model?

- Allows for a different kind of operation that seems like it might be biologically relevant.
- An efficient algorithm exists.

What are the limitations of Tichy's model?

- Not really full editing all of *t* may not be accounted for.
- Blocks themselves must match exactly no differences allowed between corresponding blocks.



"Block Edit Models for Approximate String Matching," D. Lopresti and A. Tomkins, *Theoretical Computer Science*, vol. 181, no. 1, 1997, pp. 159-179.

Introduces concept of *block edit distance*:

two strings are compared by optimally extracting sets of substrings and placing them into correspondence.

E.g., these could represent biological "motifs" shared between two genetic sequences but appearing in an unknown order.



What are we looking for? An optimal way to solve this problem:



- Don't know block boundaries in advance (to be determined as part of optimization).
- Blocks don't have to be matched in sequential order.
- Allow lower-level editing between blocks (don't depend on finding extact matches).

#### File comparison (copy-and-paste with editing)





#### Hand-drawn sketch matching





"Global dynamic programming alignments of such rearranged sequences yield unpredictable, evolutionarily confusing results ...

Global alignment methods are generally incapable of dealing with intrasequence rearrangements, yet this phenomenon is quite common ...

Dot matrix analysis is the only currently available tool that deals sensibly with this phenomenon."



Dot Plot of B.taurus DNA sequence 2 x B.taurus BoIFN-alpha A mRNA

B.taurus BoIF N-alpha A mRNA (351 to 677)

M. Gribskov and J. Devereux, Sequence Analysis Primer, 1991, pg. 96.

#### Tichy '84

Extends LCS to determine minimal covering set for one of the strings using block moves (i.e., requires exact matches between blocks).

"The String-to-String Correction Problem with Block Moves," W. F. Tichy, *ACM Transactions on Computer Systems*, vol. 2, 1984, pp. 309-321.

## Waterman & Eggert '87

Locates best local alignment, then iterates process to determine next-best alignment that doesn't share any pairings with previous one ("greedy" algorithm).

"A new algorithm for best subsequence alignments with application to tRNA-rRNA comparisons," M. S. Waterman and M. Eggert, *Journal of Molecular Biology*, vol. 197, 1987, pp. 723-728.



Let  $A = a_1 a_2 \dots a_m$  be a string over a finite alphabet.

 $A \mid_{t} \equiv t$ -block substring family of A (multiset of t substrings).

String A: The quick brown fox jumps over the lazy dog.

Some substring families:

quick brown fox	jumps ov	jumps over the		og.	
The quick quick brown		jumps	s over	the la	azy dog.
The quick brown	over	the lazy	y dog.		



 $Cover \equiv$  each symbol appears in some substring  $Disjoint \equiv$  substrings in family do not overlap

Variations:

- C substring family must be a cover **\_\_\_\_\_** more restrictive
- C' substring family need not be a cover less restrictive
- D substring family must be disjoint <---- more restrictive
- D' substring family need not be disjoint less restrictive

A block edit problem is specified by a tuple:  ${C,C'} \times {D,D'} - {C,C'} \times {D,D'}$  So, for example,



represents a specific <u>C'D-CD</u> matching.



CSE 397-497: Computational Issues in Molecular Biology Lopresti · Spring 2004 · Lecture 5 Let *dist* be an underlying distance function between two substrings  $A_{i,i}$  and  $B_{k,l}$ :

dist:  $\{i, j \mid 1 \leq i \leq j \leq m\} \times \{k, l \mid 1 \leq k \leq l \leq n\} \rightarrow \mathbb{R}$ 

dist could be standard string edit distance, for example.

Then *block edit distance* between *A* and *B* is defined as:

$$bdist(A,B) \equiv \min_{t} \min_{A|_{t},B|_{t}} \min_{\sigma \in S(t)} \left\{ t \cdot c_{block} + \sum_{i=1}^{t} dist(A^{(i)}, B^{\sigma(i)}) \right\}$$

where S(t) is the permutation group on t elements.

How hard is it to compute block edit distance?

		String B				
		C'D'	C'D	CD'	CD	
String A	C'D'	O(m <sup>2</sup> n <sup>2</sup> )	*	*	*	
	C'D	O(m²n)	NP-complete	*	*	
	CD'	O(m <sup>2</sup> n <sup>2</sup> )	NP-complete	NP-complete	*	
	CD	O(m²n)	NP-complete	NP-complete	NP-complete	

\* By symmetry, C'D'-CD is the same problem as CD-C'D', etc.



CD-CD block edit distance is most restrictive form of problem.

Sketch of proof (for full proof, see paper): reduction is from uniprocessor scheduling [GJ79].

Instance: Set T of jobs and, for each  $Job_t \in T$ ,

- a length  $I(t) \in Z+$
- a release time  $r(t) \in Z_0$ +
- a deadline  $d(t) \in Z+$

Question: Is there a uniprocessor schedule for T that satisfies release time constraints and meets all deadlines?

A Guide to the Theory of NP-Completeness, M. R. Garey and D. S. Johnson, W.H. Freeman and Company, 1979.

## **CD-CD** block edit distance is NP-complete

Example:	Job	Lengtl	h Relea	se Deadli	ne
	1	3	0	4	
	2	3	1	10	
	3	2	2	8	
	4	2	5	8	
	0 1 2	2 3 4	56	7 8	9 10
			Time		
	Job	Jo	b <sub>2</sub> Job4	Job	<b>,</b>

Details are intricate because you must construct job substrings so that they can only be matched at appropriate time slots.

With this construction, solution to CD-CD block edit distance problem would imply solution to uniprocessor scheduling. QED.

If at least one of the substring families is unconstrained, we can solve the problem in polynomial time.

We define matrix  $W^1$  for  $1 \le i \le j \le m$  as:

$$W^{1}(i, j) \equiv \min_{k \leq l} \left\{ dist(a_{i} \dots a_{j}, b_{k} \dots b_{l}) \right\}$$

That is,  $W^1$  records the cost of the best possible match between  $a_i \dots a_i$  and any substring of *B*.







#### Poly-time algorithm for CD-C'D' block edit distance

 $M(i) \equiv \text{cost of best block match between } a_1 \dots a_i \text{ and all of } B$ . Once we have computed M(i) for  $i = 1, 2, \dots, m$ , our final answer is bdist(A, B) = M(m).



Can be solved using dynamic programming:

$$M(i) = \min_{j < i} \{ M(j) + W^{1}(j+1,i) \}$$
  
... and takes time  $O(m^{2}) + T(W^{1})$ .

**Recall that** 
$$W^1(i, j) \equiv \min_{k \leq l} \{ dist(a_i \dots a_j, b_k \dots b_l) \}$$

Naively, we must ...

- ... fill in  $O(m^2)$  entries by ...
- ... comparing  $O(n^2)$  values ...
- ... each of which takes time *O*(*mn*) to compute when *dist* is standard edit distance.

Which yields an  $O(m^3n^3)$  algorithm (ugh).



Fortunately, *W* can be computed much more efficiently:

- (1) As we know, local comparison modification of the dynamic programming algorithm allows best match in *B* for a fixed substring in *A* to be found in time O(mn). This saves  $O(n^2)$ .
- (2) Also, table generated for matching  $a_i ... a_n$  to *B* contains information about best substring matches for all prefixes  $a_i ... a_k$  as well, for  $i \le k \le n$ . Hence, only O(m) such tables need be built, saving another O(m).

Thus,  $T(W) = O(m^2n)$ , which is also determines overall time.



Readings for next time:

- Section 3.5 in your textbook.
- "Rapid and Sensitive Protein Similarity Searches,"
   D. J. Lipman and W. R. Pearson, *Science*, vol. 227, no. 4693, 1985, pp. 1435-1441.
- "GenBank," D. A. Benson, I. Karsch-Mizrachi, D. J. Lipman, J. Ostell and D. L. Wheeler, *Nucleic Acids Research*, 2003, Vol. 31, No. 1, pp. 23-27.

Remember:

- Come to class prepared to discuss what you have read.
- Check Blackboard regularly for updates.