

Algorithmic Approaches for Biological Data, Lecture #20

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- Aligning with Gaps and Substitution Matrices



- Aligning with Gaps and Substitution Matrices
- Global versus Local Alignment



- Aligning with Gaps and Substitution Matrices
- Global versus Local Alignment
- Searching Graphs: Breadth First & Depth First

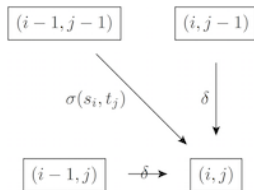
Pairwise Sequence Alignment

		A	G	A	G
	0	-1	-2	-3	-4
A	-1	1			
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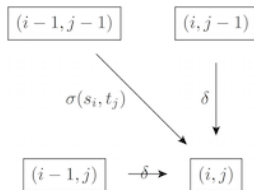
- Pictorially:



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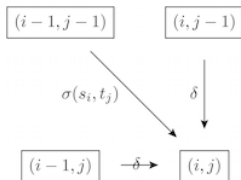
- As equations:

$$S(s_{0..i}, t_{0..j}) = \max \begin{cases} \sigma(s_i, t_j) + S(s_{0..i-1}, t_{0..j-1}) \\ -\delta + S(s_{0..i-1}, t_{0..j}) \\ -\delta + S(s_{0..i}, t_{0..j-1}) \end{cases}$$

where:

$$\delta = 1 \text{ and } \sigma(s, t) = \begin{cases} 1 & \text{if } s = t \\ -1 & \text{otherwise} \end{cases}$$

Aligning with Gaps and Substitution Matrices



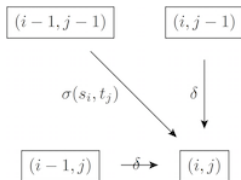
- The basic dynamic programming format can be adjusted for different gaps and substitutions models.

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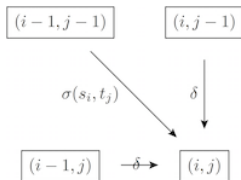
- The basic dynamic programming format can be adjusted for different gaps and substitutions models.
- δ : the gap penalty

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Aligning with Gaps and Substitution Matrices



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- The basic dynamic programming format can be adjusted for different gaps and substitutions models.
- δ : the gap penalty
- σ : scores matches/mismatches.

Gaps Are Treated Equally

- Commonly use **affine** gap penalty function:

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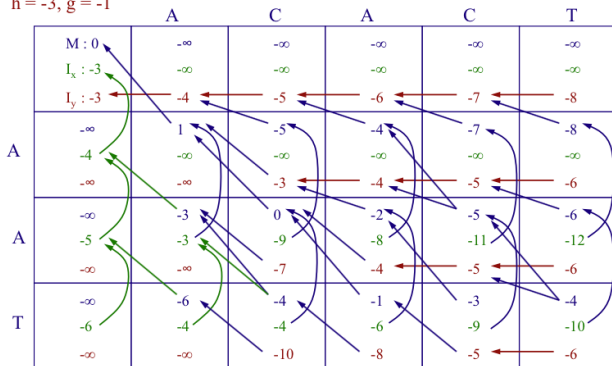
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 - ▶ h : penalty associated with opening a gap
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- Commonly use **affine** gap penalty function:
 - ▶ h : penalty associated with opening a gap
 - ▶ g : (smaller) penalty associated with extending the gap.
- To implement this efficiently, use 2 additional matrices that keeps track of the gaps (one for each sequence).

Global Alignment Example (Affine Gap Penalty)

 $h = -3, g = -1$


Burr Settles, U Wisconsin, 2008

Using Substitution Matrices

- Can view $\sigma(i, j)$ as a substitution matrix.

	A	C	G	T
A	1	-1	-1	-1
C	-1	1	-1	-1
G	-1	-1	1	-1
T	-1	-1	-1	1

Using Substitution Matrices

- Can view $\sigma(i, j)$ as a substitution matrix.
- Substitution matrices commonly used for protein sequences.

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- Can view $\sigma(i, j)$ as a substitution matrix.
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- PAM = Percent Accepted Mutation

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 - ▶ Dayhoff *et al.*, 1978
 - ▶ Used for closely related protein sequences
 - ▶ Based on global alignment

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- BLOSUM = Blocks Substitution Matrix

	A	C	G	T
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G	-1	-1	1	-1
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Using Substitution Matrices

- Can view $\sigma(i, j)$ as a substitution matrix.
- Substitution matrices commonly used for protein sequences.
- PAM = Percent Accepted Mutation
 - ▶ Dayhoff *et al.*, 1978
 - ▶ Used for closely related protein sequences
 - ▶ Based on global alignment
- BLOSUM = Blocks Substitution Matrix
 - ▶ Henikoff & Henikoff, 1992
 - ▶ Used for more divergent sequences
 - ▶ Based on local alignment

	A	C	G	T
A	1	-1	-1	-1
C	-1	1	-1	-1
G	-1	-1	1	-1
T	-1	-1	-1	1

Global versus Local Alignment

		G	C	C	C	T	A	G	C	G
	0	0	0	0	0	0	0	0	0	0
G	0	1	0	0	0	0	0	1	0	1
C	0	0	2	1	1	0	0	0	2	0
G	0	1	0	1	0	0	0	1	0	3
C	0	0	2	1	2	0	0	0	2	1
A	0	0	0	1	0	1	1	0	0	1
A	0	0	0	0	0	0	2	0	0	0
T	0	0	0	0	0	1	0	1	0	0
G	0	1	0	0	0	0	0	1	0	1

Paul Reiners, IBM, 2008

- Global: Needleman & Wunsch, 1970.
- Local: Smith & Waterman, 1981.
- Instead of looking for the global best score, look for the best score for subsequences of the initial sequences.

Global versus Local Alignment

		G	C	C	C	T	A	G	C	G
	0	0	0	0	0	0	0	0	0	0
G	0	1	0	0	0	0	0	1	0	1
C	0	0	2	1	1	0	0	0	2	0
G	0	1	0	1	0	0	0	1	0	3
C	0	0	2	1	2	0	0	0	2	1
A	0	0	0	1	0	1	1	0	0	1
A	0	0	0	0	0	0	2	0	0	0
T	0	0	0	0	0	1	0	1	0	0
G	0	1	0	0	0	0	0	1	0	1

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- Global: Needleman & Wunsch, 1970.
- Local: Smith & Waterman, 1981.
- Instead of looking for the global best score, look for the best score for subsequences of the initial sequences.
- Examples:
 - ▶ finding motifs (conserved patterns) across sequences,
 - ▶ comparing sequences against longer sequences (e.g. blast search).

Smith-Waterman Algorithm

	G	C	C	C	T	A	G	C	G
	0	0	0	0	0	0	0	0	0
G	0	1	0	0	0	0	0	1	0
C	0	0	2	1	1	0	0	0	2
G	0	1	0	1	0	0	0	1	0
C	0	0	2	1	2	0	0	2	1
A	0	0	0	1	0	1	1	0	0
A	0	0	0	0	0	0	2	0	0
T	0	0	0	0	0	1	0	1	0
G	0	1	0	0	0	0	1	0	1

Paul Reiners, IBM, 2008

- The equation is slightly different:

Smith-Waterman Algorithm

		G	C	C	C	T	A	G	C	G
G	0	0	0	0	0	0	0	0	0	0
G	0	1	0	0	0	0	0	1	0	1
C	0	0	2	1	1	0	0	0	2	0
G	0	1	0	1	0	0	0	1	0	3
C	0	0	2	1	2	0	0	0	2	1
A	0	0	0	1	0	1	1	0	0	1
A	0	0	0	0	0	0	2	0	0	0
T	0	0	0	0	0	1	0	1	0	0
G	0	1	0	0	0	0	0	1	0	1

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- The equation is slightly different:

$$s(i,j) = \max \begin{cases} \sigma(i,j) + s(i-1,j-1) \\ -\delta + s(i,j-1) \\ -\delta + s(i-1,j) \\ 0 \end{cases}$$

- Initialize: first row and first column set to 0's
- Traceback: find maximum value of $s(i,j)$ anywhere in the the matrix, stop when we get to a cell with 0.

Smith-Waterman Algorithm

		G	C	C	C	T	A	G	C	G
	0	0	0	0	0	0	0	0	0	0
G	0	1	0	0	0	0	0	1	0	1
C	0	0	2	1	1	0	0	0	2	0
G	0	1	0	1	0	0	0	1	0	3
C	0	0	2	1	2	0	0	0	2	1
A	0	0	0	1	0	1	1	0	0	1
A	0	0	0	0	0	0	2	0	0	0
T	0	0	0	0	0	1	0	1	0	0
G	0	1	0	0	0	0	0	1	0	1

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In Pairs: Local Alignment

		A	A	G	A
T					
T					
A					
A					
G					

- Use σ from Monday, but $\delta = 2$.

In Pairs: Local Alignment

		A	A	G	A
T					
T					
A					
A					
G					

- Use σ from Monday, but $\delta = 2$.
- What are the best local alignments?

In Pairs: Local Alignment

		A	A	G	A
	0	0	0	0	0
T	0				
T	0				
A	0				
A	0				
G	0				

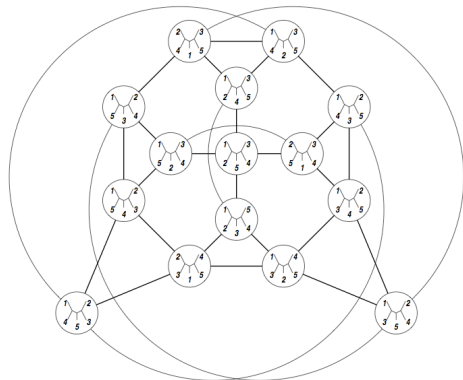
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In Pairs: Local Alignment

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		0	0	0	0	
T		0	0	0	0	
T		0	0	0	0	
A		0	1	1	0	1
A		0	1	2	0	1
G		0	0	0	3	1

- Use σ from Monday, but $\delta = 2$.
- What are the best local alignments?

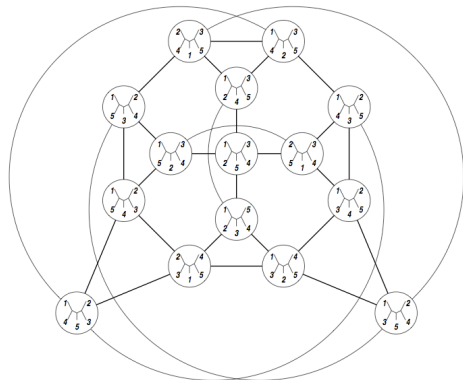
In Pairs: Searching Graphs



Bastert *et al.*, 2002

- Develop a strategy to visit every node of the graph (i.e. what data structures are needed?)

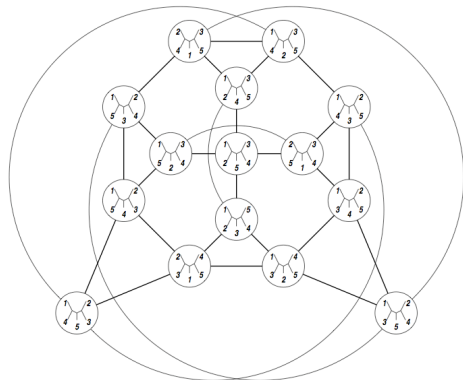
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- Develop a strategy to visit every node of the graph (i.e. what data structures are needed?)
- The bookkeeping is important.

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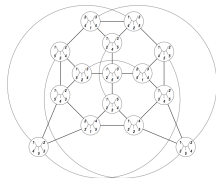


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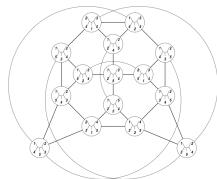
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- Two common strategies:



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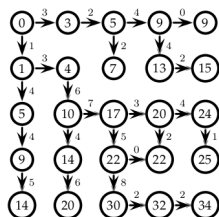
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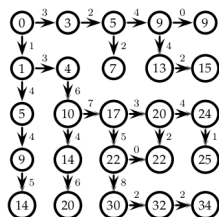
- Two common strategies:
 - ▶ **Breadth First Search (BFS):** visit all the neighbors, then visit all the neighbors' neighbors, etc.
 - ▶ **Depth First Search (DFS):** for each neighbor, visit its' neighbors, and continue as far down as possible.
- Bookkeeping is important:
 - ▶ Keep a "To Do" list (priority queue) of nodes still to visit.
 - ▶ Mark nodes as you visit them, so, you know not to visit again.

Recap



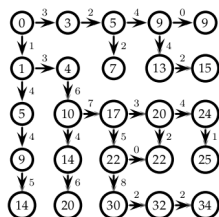
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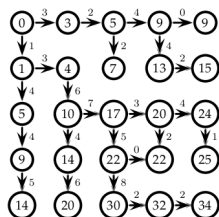
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- Dynamic Programming: will do local & global alignments in lab today.
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- Challenges available at rosalind.info.