CSE 549: Computational Biology

Multiple Sequence Alignment



slides not marked with * by Carl Kingsford



Multiple Sequence Alignment (MSA)

F0034		G
F0020		_
F0021		
F0014		G
F0030		G
F0005		G
F0007	CAATATACACCCTCTCACTATCGGGGAATGCCCCAAATATGTGAAATCAAACAGATTAGTCCTTGCGACTGGGCTCAGAAATAGCCCTCAAAGAGAGAAGAAGAAAAAGAGAGAGGATTATTTGGAGCTATAGCAG	G
F0010	CAATATACACCCTCTCACTATCGGGGGAATGCCCCAAATATGTGAAATCAAACAGATTAGTCCTTGCGACTGGGCTCAGAAATAGCCCTCAAAGAGAGAGAAGAAAAAGAGAGGATTATTTGGAGCTATAGCA	G
F0032	CAATATACACCCTCTCACTATCGGGGGAATGCCCCAAATATGTGAAATCAAACAGATTAGTCCTTGCGACTGGGCTCAGAAATAGCCCTCAAAGAGAGAG	G
F0024		5G
F0012		5G
F0009	CAACATCCACCTCTCACCATTGGGGGAATGCCCCAAATATGTGAAATGTCAAACAGATTAGTCCTTGCTACTGGGCTCAGAAATAGCCCTCAAGGAGAGAGA	6G
F0006		5G
F0008		5G
F0013		5G
F0004		6G
F0027		6G
F0019		G
F0033		G
F0029	CAACATCCACCCTCTCACCATCGGGGAATGCCCCAAATATGTGAAATCAAACAGATTAGTCCTTGCGACTGGGCTCAGAAATAGCCCTCAAGGAGAGAGA	
F0017	CAACATCCACCCTCTCACCATCGGGGAATGCCCCAAATATGTGAAATCAAACAGATTAGTCCTTGCGACTGGGCTCAGAAATAGCCCTCAAGGAGAGAGA	G
F0018	CAACATCCACCCTCTCACCATCGGGGAATGCCCCAAATATGTGAAATCAAACAGATTAGTCCTTGCGACTGGGCTCAGAAATAGCCCTCAAGGAGAGAGA	G
F0015	CAACATCCACCCTCTCACCATCGGGGAATGCCCCAAATATGTGAAATCAAACAGATTAGTCCTTGCGACTGGGCTCAGAAATAGCCCTCAAGGAGAGAAGAAGAAGAAGAAGAAGAAGAAGAAGAAGA	
F0022	CAACATCCACCCTCTCACCATCGGGGAATGCCCCAAATATGTGAAATCAAACAGATTAGTCCTTGCGACTGGGCTCAGAAATAGCCCTCAAGGAGAGAAGAAGAAGAAGAAGAAGAAGAAGAAGAAGA	
F0016		
F0011	CAACATCCACCCTCTCACCATCGGGGAATGCCCCAAATATGTGAAATCAAACAGATTAGTCCTTGCGACTGGGCTCAGAAATAGCCCTCAAGGAGAGAAGAAGAAGAAGAAGAAGAAGAAGAAGAAGA	
F0025	CAACATCCACCCTCTCACCATCGGGGAATGCCCCAAATATGTGAAATCAAACAGATTAGTCCTTGCGACTGGGCTCAGAAATAGCCCTCAAGGAGAGAAGAAGAAGAAGAAGAAGAAGAAGAAGAAGA	-
F0001 F0002	CAACATCCACCCTCTCACCATCGGGGAATGCCCCAAATATGTGAAATCAAACAGATTAGTCCTTGCGACTGGGCTCAGAAATAGTCCTCAAGGAGAGAGA	
F0002		
F0026		
F0020		~
F0023		20
F0035	CAACATACACCCTCTCACCATCGGGGGAATGTCCCAAATATGTGAAATCAAACAAA	~
F0003		~
10005		~

Multiple sequence alignment: find more subtle patterns & find common patterns between all sequence.

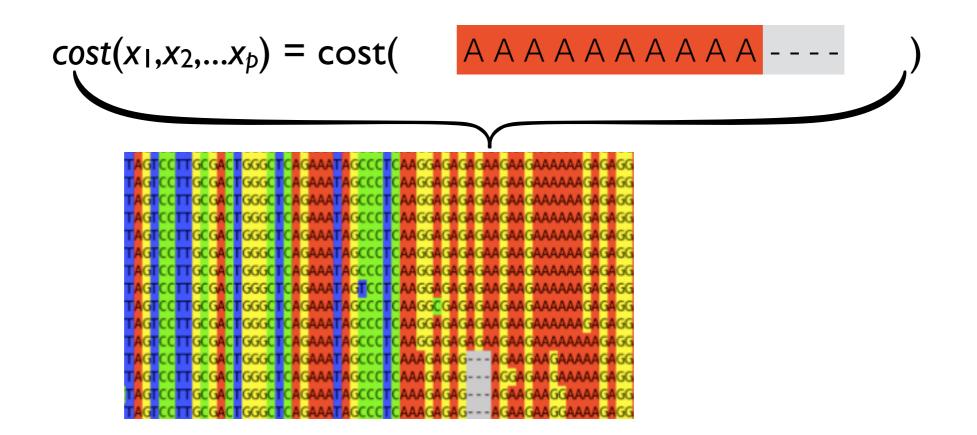
Patterns that seem insignificant in a pair may become significant if shared by many sequences.

Generalizing Alignment to > 2 Strings

Input: Sequences S₁, S₂, ..., S_p

Let $cost(x_1, x_2, ..., x_p)$ be a user-supplied function that computes the quality of a column: an alignment between characters $x_1, x_2, ..., x_p$.

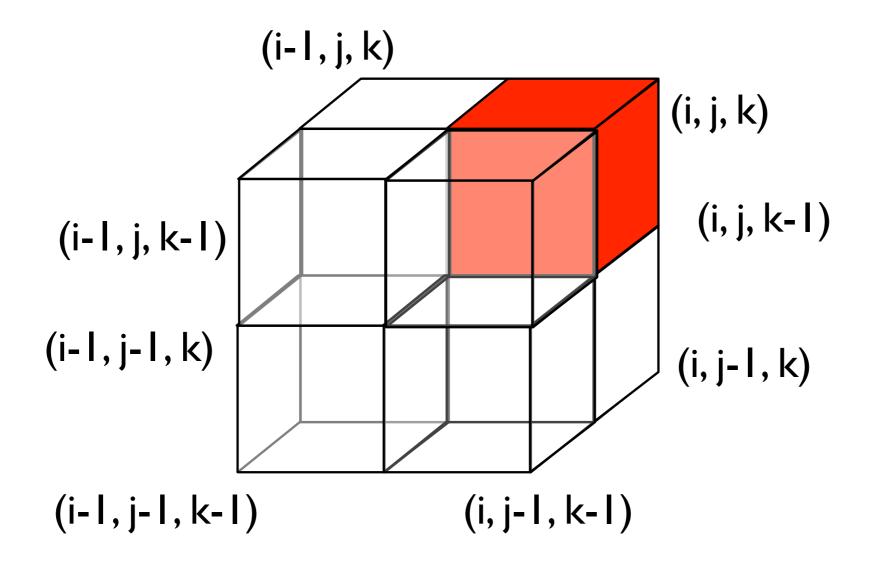
• **Goal**: find alignment M to minimize \sum cost of the columns:



Slow Dynamic Programming

Suppose you had just 3 sequences.

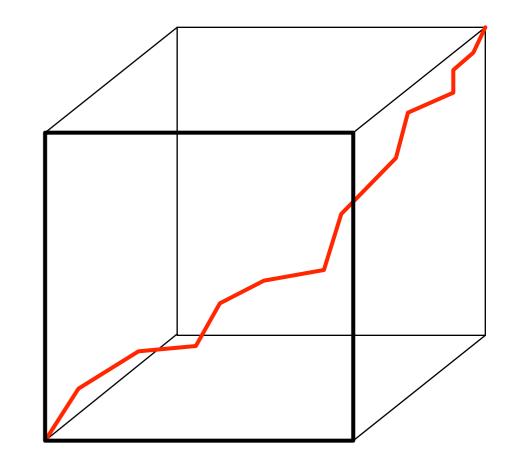
Apply the same DP idea as sequence alignment for 2 sequences, but now with a 3-dimensional matrix



$$DP \text{ Recurrence for 3 sequences} \\ A[i, j, k] = \min \begin{cases} \cos(x_i, y_j, z_k) + A[i - 1, j - 1, k - 1] \\ \cos(x_i, -, -) + A[i - 1, j, k] \\ \cos(x_i, y_j, -) + A[i - 1, j - 1, k] \\ \cos(x_i, -, y_j, -) + A[i, j - 1, k] \\ \cos(x_i, -, z_k) + A[i - 1, j, k - 1] \\ \cos(x_i, -, z_k) + A[i, j, k - 1] \\ \cos(x_i, -, z_k) + A[i, j, k - 1] \end{cases}$$

Running time

- n^3 subproblems, each takes 2^3 time \Rightarrow O(n^3) time.
- For p sequences: n^p subproblems, each takes 2^p time for the min and p^2 to compute cost(., ., ...) $\Rightarrow O(p^2 n^p 2^p)$
- Even O(n³) is often too slow for the length of sequences encountered in practice.
- One solution: approximation algorithm.



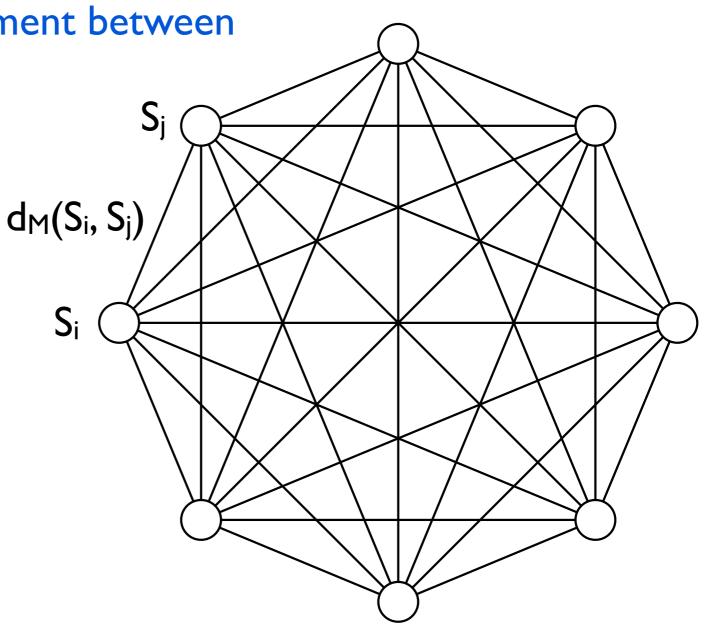
SP-Cost

A particular cost() function, the SP-Cost, is commonly used and allows us to design an approximation algorithm for the MSA problem.

 $d_M(S_i, S_j)$ = the cost of the alignment between S_i and S_j as implied by MSA M.

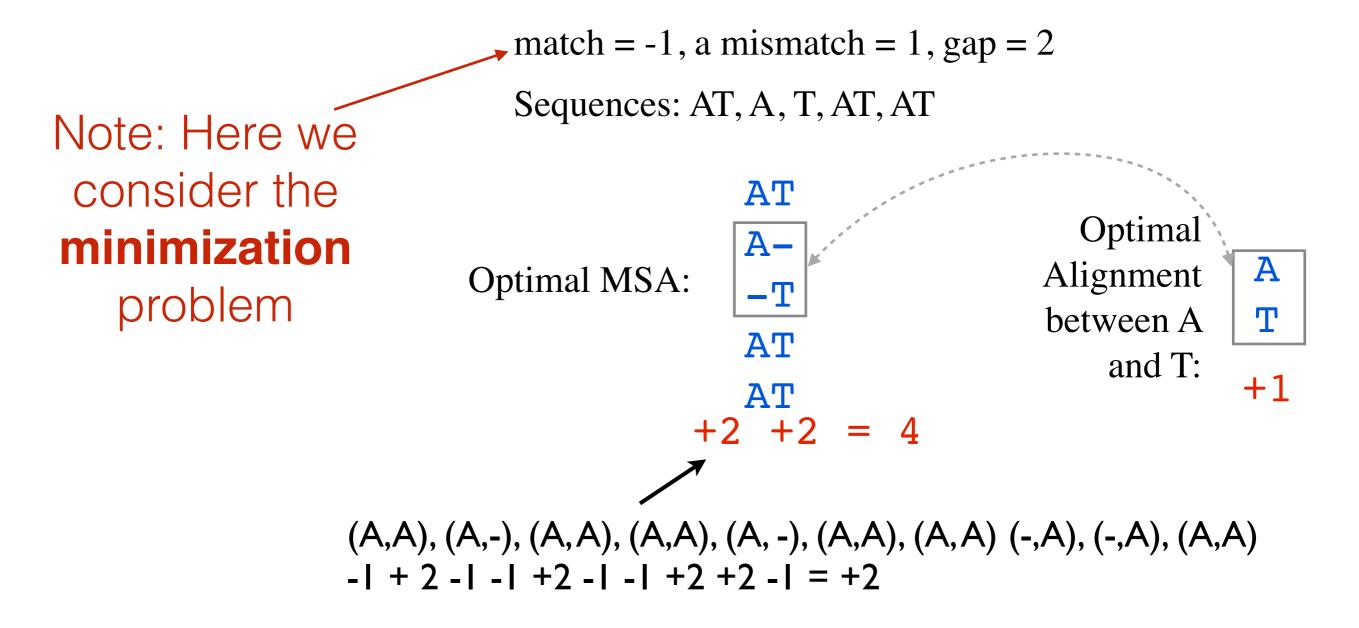
$$SP-Cost(M) = \sum_{i \le j} d_M(S_i, S_j)$$

= sum of all the costs of the pairwise alignments implied by M.

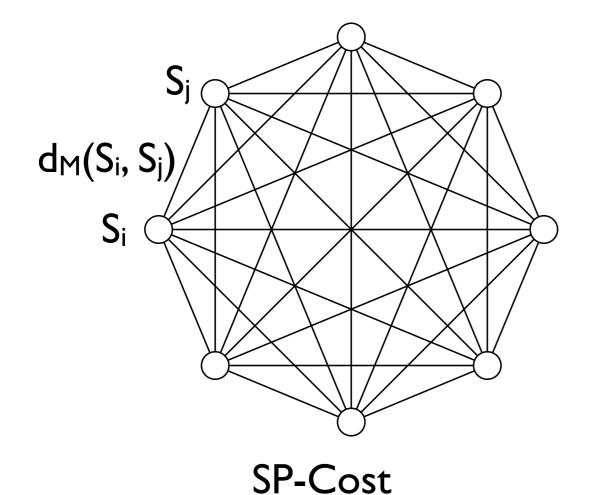


MSA

- A multiple sequence alignment (MSA) implies a pairwise alignment between every pair of sequences.
- This implied alignment need not be optimal, however:



STAR Alignment Approximation



 $\int_{S_c} d_M(S_i, S_c)$ Star-Cost = $\sum_i d_M(S_i, S_c)$

 S_i

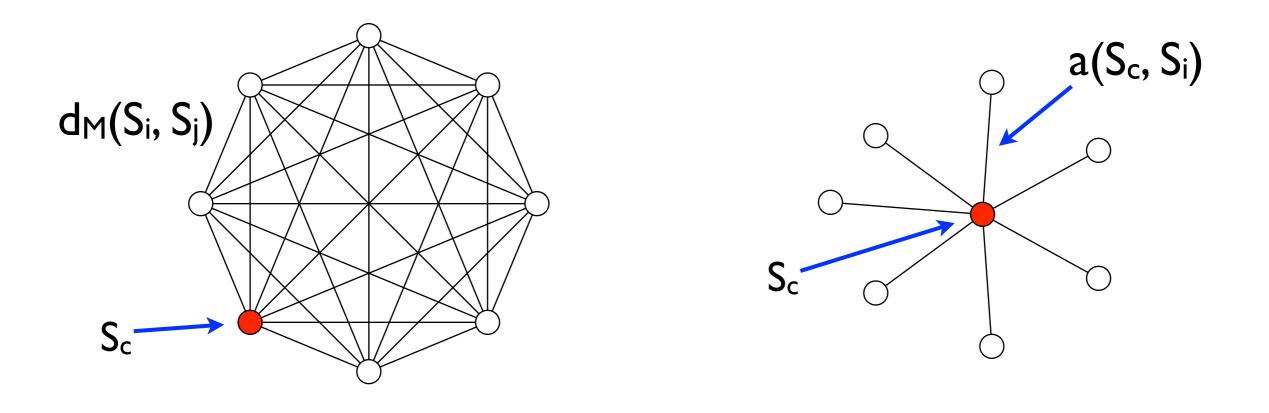
STAR Alignment Algorithm

Input: sequences $S_1, S_2, ..., S_p$

- Build all $O(p^2)$ pairwise alignments.
- Let S_c = the sequence in S_1 , S_2 , ..., S_p that is closest to the others. That is, choose S_c to minimize:

 $\sum_{i\neq c} a(S_c, S_i)$

• Progressively align all other sequences to S_c.



Progressive Alignment

• Build a multiple sequence alignment up from pairwise alignments.

Start with an alignment between S_c and some other sequence:

SC YFPHF-DLS----HGSAQVKAHGKKVGDALTLAVGHL---DDLPGAL S1 FFPKFKGLTTADQLKKSADVRWHAERII---NAVNDAVASMDDTEKMS

Add 3rd sequence, say S2, and use the SC \leftrightarrow S1 alignment as a guide, adding spaces into the MSA as needed.

$SC \leftrightarrow S2$ alignment:

- SC YFPHFDLSHGSAQVKAHGKKVGDALTLAVGHLDDLPGAL
- S2 YFPHFDLSHG-AQVKG--KKVADALTNAVAHVDDMPNAL

New {SC, SI, S2} alignment (red gaps added in S2):

- SC YFPHF-DLS----HGSAQVKAHGKKVGDALTLAVGHL----DDLPGAL
- S1 FFPKFKGLTTADQLKKSADVRWHAERII-NAVNDAVASMDDTEKMS
- S2 YFPHF-DLS----HG-AQVKG--KKVADALTNAVAHV----DDMPNAL

Continue with S3, S4, ...

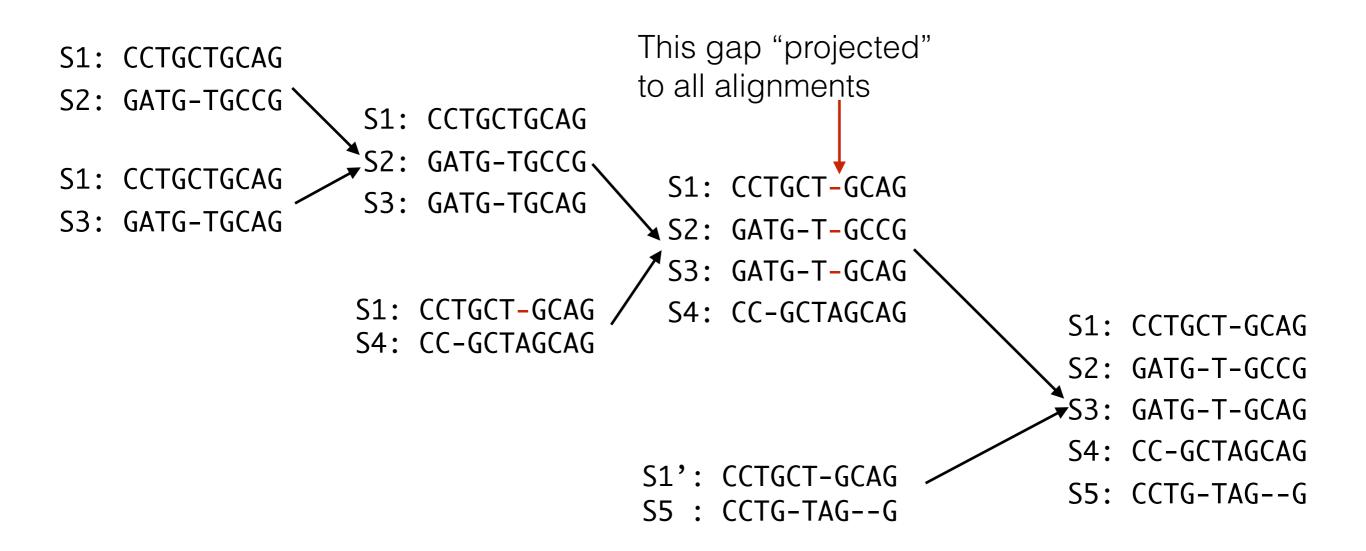
The STAR algorithm

Algorithm Star-Alignment

Input: Γ = set of k strings S_1, S_k . **Output**: Compute the global multiple alignment with minimum score 1 Find the string S' (center) that minimizes $\sum_{S \in \Gamma - S'} \delta(S, S')$ 2 Denote $S_1 = S'$ and the rest of the strings as S_2, S_k 3 Iteratively add S_2, S_k to the alignment as follows:

- 4 Suppose S_1, \dots, S_{i-1} are already aligned as S'_1, \dots, S'_{i-1}
- 5 Align S_i to S'_1 to produce S'_i and S''_1 aligned
- 6 Adjust S'_2, \dots, S'_{i-1} by adding spaces where spaces were added to S''_1 7 Replace S' by S''
- 7 Replace S'_1 by S''_1

Merging pairwise alignments



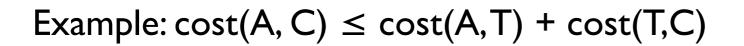
The "once a gap, always a gap" rule is applied — the MSA will tend to get *longer* with more sequences

* example from http://www.comp.nus.edu.sg/~ksung/algo_in_bioinfo/slides/Ch6_MSA.pdf

Performance

Assume the cost function satisfies the triangle inequality:

 $cost(x,y) \le cost(x,z) + cost(z,y)$



cost of a mutation from $A \rightarrow C$

cost of a mutation from $A \rightarrow T$ and then from $T \rightarrow C$

STAR = cost of result of star algorithm under SP-cost

OPT = cost of optimal multiple sequence alignment (under SP-cost)

Theorem. If cost satisfies the triangle inequality, then STAR $\leq 2 \times OPT$.

Example: if optimal alignment has cost 10, the star alignment will have $cost \le 20$.

Proof (1)

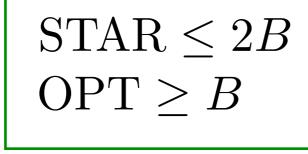
Theorem. If cost satisfies the triangle inequality, then STAR \leq 2OPT.

 $\frac{\text{STAR}}{\text{OPT}} \le 2$

For some *B* we will prove the 2 statements:

This will imply:

$$\implies \frac{\text{STAR}}{\text{OPT}} \le \frac{2B}{B} = 2$$



Proof (2)

Theorem. If cost satisfies the triangle inequality, then STAR \leq 2OPT.

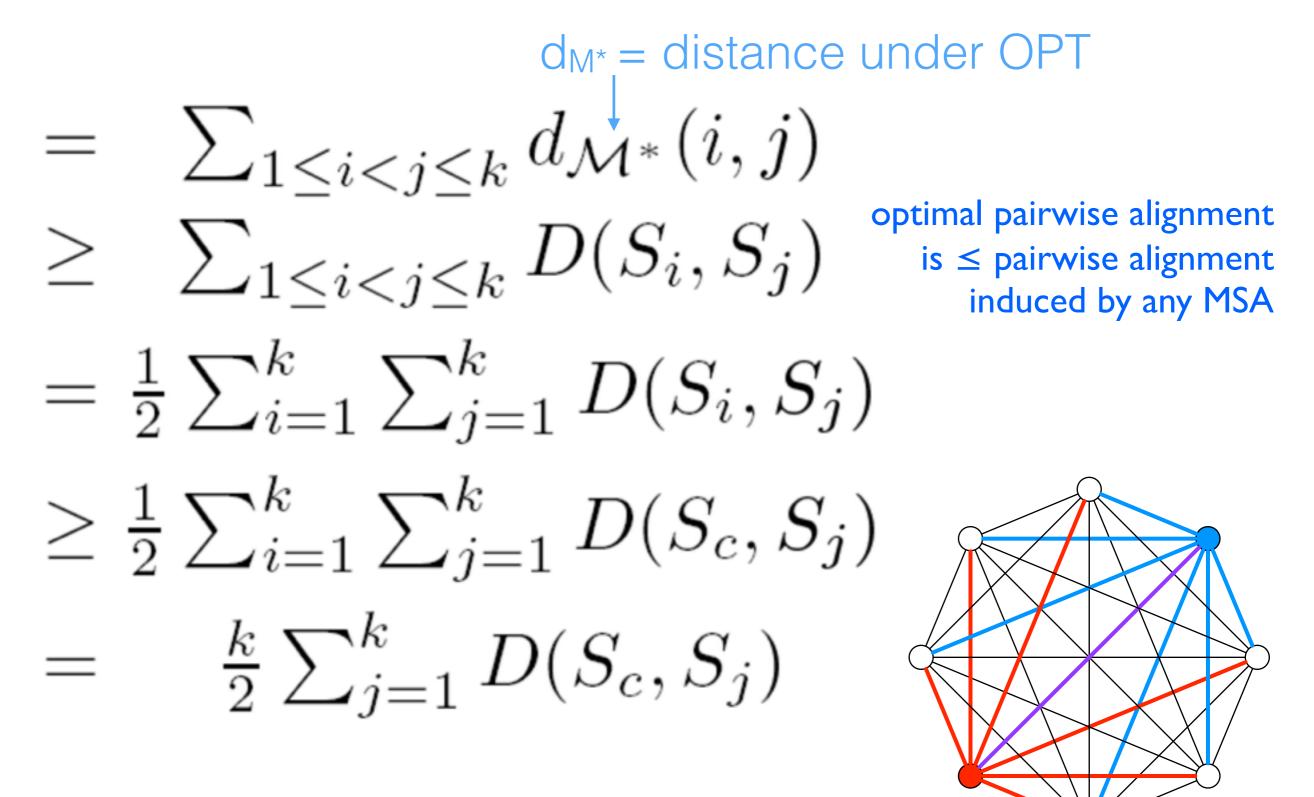
 $d_M = distance under STAR$

 $\sum_{\substack{1 \le i < j \le k \\ \frac{1}{2} \sum_{i=1}^{k} \sum_{j=1}^{k} d_{\mathcal{M}}(i,j)} d_{\mathcal{M}}(i,j)$

 $\leq \frac{1}{2} \sum_{i=1}^{k} \sum_{j=1}^{k} [D(S_c, S_i) + D(S_c, S_j)]$ = $\frac{k}{2} \sum_{i=1}^{k} D(S_c, S_i) + \frac{k}{2} \sum_{j=1}^{k} D(S_c, S_j)$ = $k \sum_j D(S_c, S_j)$

Proof (3)

Theorem. If cost satisfies the triangle inequality, then STAR \leq 2OPT.



End of Proof

For some *B* we will prove the 2 statements:

$$\begin{array}{l} \mathrm{STAR} \leq 2B\\ \mathrm{OPT} \geq B \end{array}$$

This will imply:

$$\implies \frac{\text{STAR}}{\text{OPT}} \le \frac{2B}{B} = 2$$

$$2 \cdot STAR \leq 2k \sum_{i} \mathsf{D}(S_i, S_c)$$
$$2 \cdot OPT \geq k \sum_{i} \mathsf{D}(S_i, S_c)$$

$$\implies \frac{\text{STAR}}{\text{OPT}} \le \frac{2k \sum_{i} \mathsf{D}(S_i, S_c)}{k \sum_{i} \mathsf{D}(S_i, S_c)} = 2$$

Consensus Sequence

For every column j, choose $c \in \sum$ that minimizes $\sum_{i} \text{cost}(c, S_i[j])$

(typically this means the most common letter)

S1 YFPHF-DLS----HGSAQVKAHGKKVG----DALTLAVAHLDDLPGAL

- S2 YFPHF-DLS----HG-AQVKG-GKKVA----DALTNAVAHVDDMPNAL
- S3 FFPKFKGLTTADQLKKSADVRWHAERII----NAVNDAVASMDDTEKMS
- S4 LFSFLKGTSEVP--QNNPELQAHAGKVFKLVYEAAIQLQVTGVVVTDATL

CO YFPHFKDLS----HGSAQVKAHGKKVG----DALTLAVAHVDDTPGAL

- Consensus is a summarization of the whole alignment.
- Consensus sequence is sometimes used as an estimate for the ancestral sequence.
- Sometimes the MSA problem is formulated as: find MSA M that minimizes: $\sum_{i} d_{M}(CS, S_{i})$

Profiles

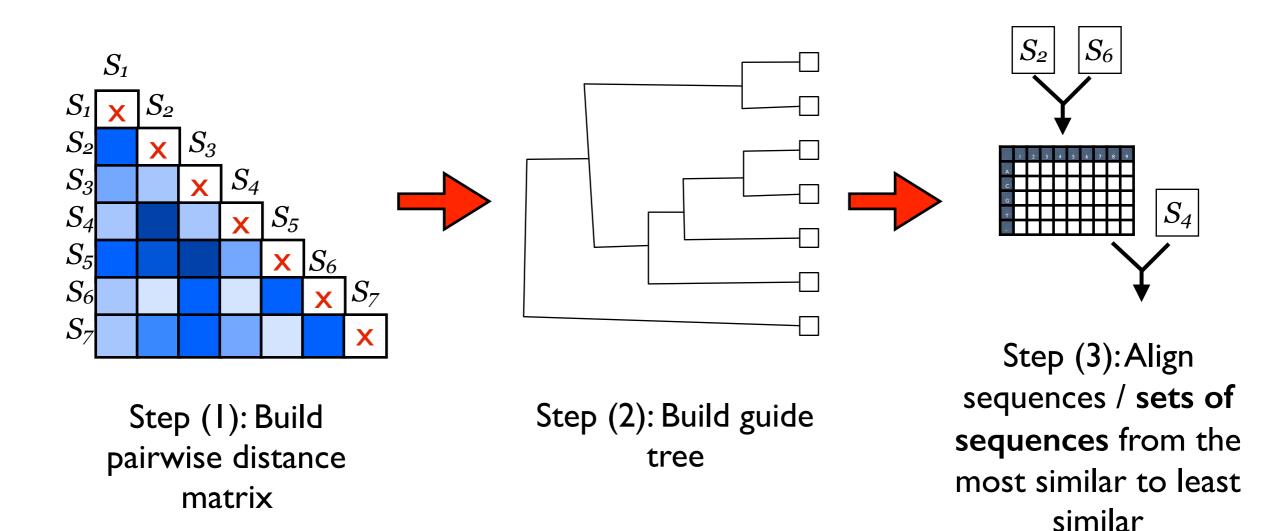
- Another way to summarize an MSA:
 - S1 ACG-TT-GA
 - S2 ATC-GTCGA
 - S3 ACGCGA-CC
 - S4 ACGCGT-TA

Column in the alignment								Call this profile			
		l	2	3	4	5	6	7	8	9	matrix R
	A	Ι	0	0	0	0	0.25	0	0	0.75	
	С	0	0.75	0.25	0.5	0	0	0.25	0.25	0.25	Fraction of time
	G	0	0	0.75	0	0.75	0	0	0.5	0	given column had
	Т	0	0.25	0	0	0.25	0.75	0	0.25	0	the given characte
	-	0	0	0	0.5	0	0	0.75	0	0	

Character

CLUSTLW

- CLUSTLW is a widely used, "classical" heuristic multiple aligner.
- Not the fastest, not the most accurate, but pretty good.
- Large # of heuristic tricks included in the software, but basic idea is straightforward:



Profile-based Alignment

gap in profile introduced to better fit sequence

	I	2	3	4
А	Ι	0	0	0
С	0	0.75	0.25	0.5
G	0	0	0.75	0
Т	0	0.25	0	0
-	0	0	0	0.5

5	6	7	8	9
0	0.25	0	0	0.75
0	0	0.25	0.25	0.25
0.75	0	0	0.5	0
0.25	0.75	0	0.25	0
0	0	0.75	0	0

Score of matching character x with column j of the profile:

$$P(x,j) = \sum_{c \in \Sigma} \sin(x,c) \times R[c,j]$$

ACC - AGACGA

sim(x,c) = how similar character x isto character c (e.g. score(x,c)).

$$A[i,j] = \max \begin{cases} A[i-1,j-1] + P(x_i,j) & \text{ali} \\ A[i-1,j] + \text{gap} & \text{int} \\ A[i,j-1] + P(``_-``,j) & \text{int} \end{cases}$$

align x_i to column jintroduce gap into profile introduce gap into x

Recap

- Multiple sequence alignments (MSAs) are a fundamental tool. They help reveal subtle patterns, compute consistent distances between sequences, etc.
- Quality of MSAs often measured using the SP-score: sum of the scores of the pairwise alignments implied by the MSA.
- Same DP idea as pairwise alignment leads to exponentially slow algorithm for MSA for general *p*.
- 2-approximation obtainable via star alignments.
- MSAs often used to create profiles summarizing a family of sequences.