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$Sequence\ Similarity$

Which pair of sequences are the closest?

$$S_1 = AAAAA$$
 $S_2 = AGAGA$ $S_3 = GGAAA$



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Orthology Detection

$$egin{pmatrix} S_1 & L & A & S & T & F & A & - & T & C & A & T \ S_2 & L & A & S & T & C & A & - & T & - & - & - \ S_3 & V & E & R & Y & F & A & S & T & C & A & T \ S_4 & - & - & - & - & F & A & - & T & C & A & T \end{pmatrix}$$

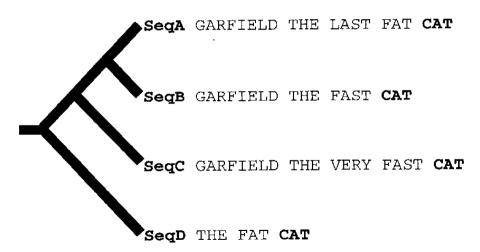


Orthology Detection

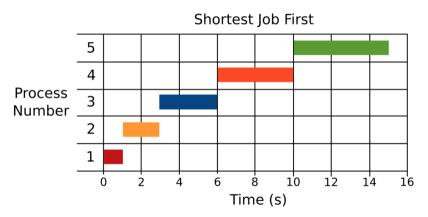
$$egin{pmatrix} S_1 & L & A & S & T & F & A & - & T & C & A & T \ S_1 & L & A & S & T & - & - & - & - & C & A & T \ S_3 & V & E & R & Y & F & A & S & T & C & A & T \ S_4 & - & - & - & - & & F & A & - & T & C & A & T \ \end{pmatrix}$$



Phylogeny Estimation



Scheduling





Outline

Multiple Sequence Alignment

Pairwise Alignments

Alignment Graphs

Maximum Weight Trace

T-COFFEE

MAGUS

Results

Questions



Problem (Multiple Sequence Alignment)

$$\sum_j d(a_{1j},\ldots,a_{nj})$$



Problem (Multiple Sequence Alignment)

$$\sum_{j} d(a_{1j}, \ldots, a_{nj})$$

$$d(\cdot) = \begin{cases} +\infty & \text{if number unique characters is more than 1} \\ 1 & \text{otherwise} \end{cases}$$



Problem (Multiple Sequence Alignment)

$$\sum_{j} d(a_{1j}, \ldots, a_{nj})$$

$$d(\cdot) = \begin{cases} 0 & \text{if number unique characters is more than 1} \\ -1 & \text{otherwise} \end{cases}$$



Problem (Multiple Sequence Alignment)

$$\sum_{j} d(a_{1j}, \ldots, a_{nj})$$

$$d(\cdot) = \# \text{ dashes} + \# \text{ unique} - 1$$



Pariwise Alignments

Edit Distance

/	λ	T	T	A	A	G	$C \setminus$
λ	0	1	2	3	4	5	6
A	1	1	2	2	3	4	5
A	2	2	2	2	2	3	4
T	3	2	2	3	3	3	4
T	4	3	2	2	3	4	4
A	5	4	3	2	2	3	4
$\begin{pmatrix} \lambda \\ A \\ A \\ T \\ T \\ A \\ A \\ G \end{pmatrix}$	6	5	4	3	2	3 3 2	$\frac{4}{3}$
$\backslash G$	7	6	5	4	3	2	3/



Definition (Alignment Graph)

Given a set of sequences S_1, \ldots, S_n , and a scoring function d, and a set of *pairwise* alignments A_1, \ldots, A_k , construct $G = (V, E, \prec)$, where

- 1. For each sequence, for each *site* s_{ij} , create a vertex
- 2. For each alignment A_i , for each homology s_{ij} , s_{kl} , add weight $d(s_{ij}, s_{kl})$ to the edge
- 3. For each pair site s_{ij} and $s_{ij'}$ where j' > j, add $s_{ij}, s_{ij'}$ to \prec



$$S_1 = ABCD \qquad S_2 = BAC \qquad S_3 = AAD$$

$$A_1 = \begin{pmatrix} S_1 & A & B & - & C & D \\ S_2 & - & B & A & C & - \end{pmatrix}$$

$$A_2 = \begin{pmatrix} S_2 & B & A & - & C \\ S_3 & - & A & A & D \end{pmatrix}$$

$$A_3 = \begin{pmatrix} S_1 & - & A & B & C & D \\ S_3 & A & A & - & - & D \end{pmatrix}$$



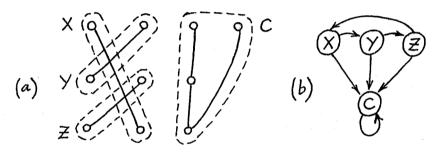


Fig. 1. (a) An alignment graph on three sequences. We use the convention of drawing the characters in a sequence horizontally left to right. (b) Relation \prec^* on its connected components.



Definition (Trace)

A *trace* of an alignment graph $G = (V, E, \prec)$ is a subset of the $T \subset E$ where $G^* = (V, T, \prec^*)$ is acyclic.

$$\mathscr{A} = \begin{pmatrix} S_1 & A & B & C & - & D \\ S_2 & - & B & A & C & - \\ S_3 & - & - & A & A & D \end{pmatrix}$$



Problem (Maximum Weight Trace (MWT))

Given an alignment graph $G = (V, E, \prec)$, find the trace T that maximizes

$$\sum_{e \in T} w(e)$$



Theorem (Kececioglu'93)

Maximum Weight Trace is NP-Hard

Proof.

Consider an instance G = (V, E) and integer k of Feedback Set.

- 1. For every vertex v, create sequence $S_v = v$
- 2. For every edge $u \to v$, create sequence $S_{uv} = uv$
- 3. Create pairwise alignments

$$\begin{pmatrix} S_u & u & - \\ S_{uv} & u & v \end{pmatrix} \qquad \begin{pmatrix} S_v & - & v \\ S_{uv} & u & v \end{pmatrix}$$



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Let $D(x_1, \ldots, x_n)$ denote maximum weight trace over *prefixes* $S_i[1:x_i]$. Then,

$$D(\overrightarrow{x}) = \max_{\overrightarrow{b} \in [2]^n} \{ D(\overrightarrow{x} - \overrightarrow{b}) + d(\overrightarrow{S}^{\overrightarrow{b}}) \}$$

Thus, MWT can be solved in $O((2k)^n poly(n))$.

Using the *Branch-and-Bound* paradigm, this can be fast



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From Fa'24 CS 374 homework 14, this can be improved to $O(nk^n poly(n))$.

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- 1. Aggregate pairwise alignments through triples
- 2. Calculate new pairwise distances
- 3. Compute guide trees
- 4. Progressively align using guide tree



b)Primary Library

Seca GARFIELD THE LAST FAT CAT

 SeqA
 GARFIELD THE LAST FAT CAT SeqB
 Frim. Weight = 88
 SeqB
 GARFIELD THE GARFIELD THE SeqB
 THE FAST THE SEqB

 SeqB
 GARFIELD THE SeqB
 GARFIELD THE SeqB
 GARFIELD THE SeqB
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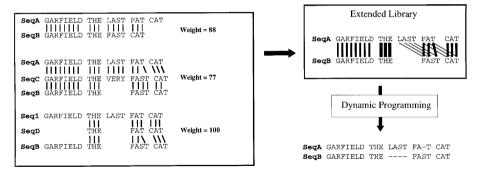
Prim. Weight =100

SeqB GARFIELD THE ---- FAST CAT Prim Weight = 100 SeqC GARFIELD THE VERY FAST CAT

SeqC GARFIELD THE VERY FAST CAT Prim. Weight = 100



c)Extended Library for seq1 and seq2





a)Regular Progressive Alignment Strategy





MAGUS

- 1. Create alignment graph from backbone alignments
- 2. Cluster with Markov Clustering (MCL)
- 3. Break all clusters that violate ordering



MAGUS

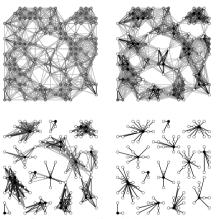


Figure 3. Successive stages of flow simulation by the MCL process.

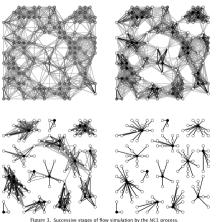
Clusters have high edge connectivity. A random walk is likely to stay within the cluster.

Markov Clustering Algorithm

- 1. Expansion (random walk)
- 2. Inflation (amplify probabilities)
- Repeat



MAGUS

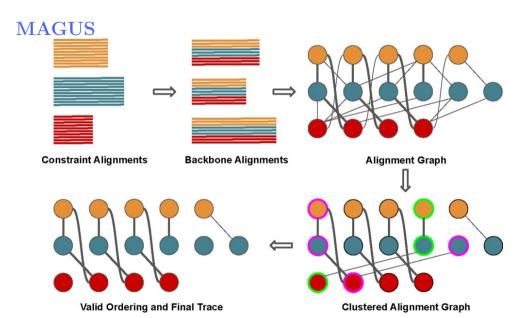


Clusters have high edge connectivity. A random walk is *likely* to stay within the cluster.

Markov Clustering Algorithm

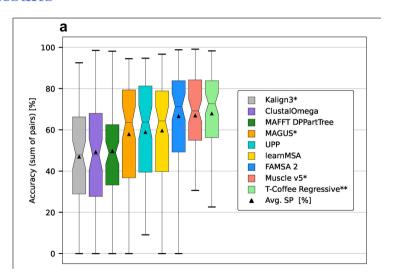
- 1. Expansion (random walk)
- 2. Inflation (amplify probabilities)
- 3. Repeat







Results





Results

- 1. T-Coffee (Regressive) is the best
- 2. Consistency based methods are very good (MAGUS, T-Coffee, Muscle)
- 3. Single-stage aligners are bad (Kalign, ClustalOmega, ...)
- 4. Exception for FAMSA



Questions

- 1. How can we encode genome events into the alignment graph?
- 2. Can T-COFFEE perform better if we give it multiple sequence alignments (instead of pairwise) as input?
- 3. Do other clustering algorithms (beyond MCL) cluster the alignment graph better in MAGUS?



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