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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

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

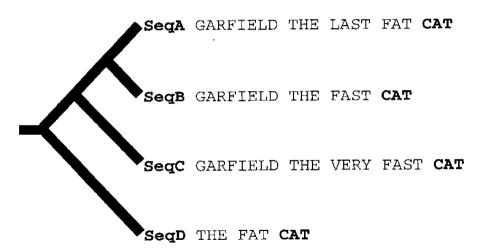


Orthology Detection

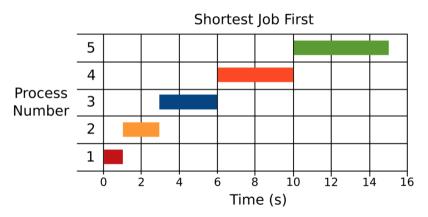
$$egin{pmatrix} S_1 & L & A & S & T & F & A & - & T & C & A & T \ S_2 & L & A & S & T & - & - & - & - & C & A & T \ S_3 & V & E & R & Y & F & A & S & T & C & A & T \ S_4 & - & - & - & - & F & A & - & T & C & A & T \end{pmatrix}$$



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



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

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

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

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



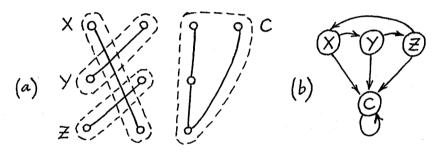


Fig. 1. (a) An alignment graph on three sequences. We use the convention of drawing the characters in a sequence horizontally left to right. (b) Relation \prec^* on its connected components.



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.

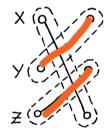
$$\mathcal{A}_{1} = \begin{pmatrix} S_{1} & A & B & - & C & - & D \\ S_{2} & - & B & A & C & - & - \\ S_{3} & - & - & A & - & A & D \end{pmatrix}$$

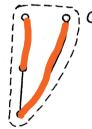


Definition (Trace)

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.

$$\mathcal{A}_{2} = \begin{pmatrix} S_{1} & - & - & A & B & C & D \\ S_{2} & B & A & - & - & C & - \\ S_{3} & - & A & A & - & - & D \end{pmatrix} \qquad \mathbf{Z} \stackrel{\bullet}{\mathcal{C}}$$







Definition (Trace)

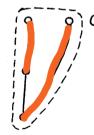
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$$\mathcal{A}_{1} = \begin{pmatrix} S_{1} & A & B & - & C & - & D \\ S_{2} & - & B & A & C & - & - \\ S_{3} & - & - & A & - & A & D \end{pmatrix}$$

$$\mathcal{A}_{2} = \begin{pmatrix} S_{1} & - & - & A & B & C & D \\ S_{2} & B & A & - & - & C & - \end{pmatrix}$$

$$\mathcal{A}_{2} = \begin{pmatrix} S_{1} & - & - & A & B & C & D \\ S_{2} & B & A & - & - & C & - \\ S_{3} & - & A & A & - & - & D \end{pmatrix}$$







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

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4. Check if MWT is at least 2k.



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4. Check if MWT is at least 2k.



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
 THE FAST THE SeqB
 THE FAST THE SeqB
 THE FAST THE SeqB

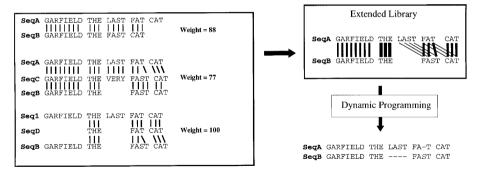
Prim. Weight =100

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

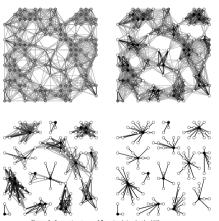


Figure 3. Successive stages of flow simulation by the MCL process.

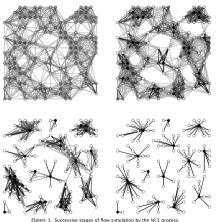
Clusters have high edge connectivity. A random walk is likely to stay within the cluster.

Markov Clustering Algorithm

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



MAGUS

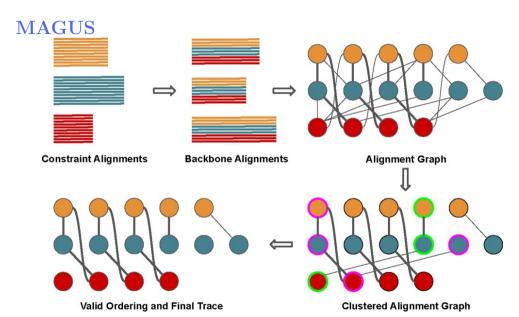


Clusters have high edge connectivity. A random walk is *likely* to stay within the cluster.

Markov Clustering Algorithm

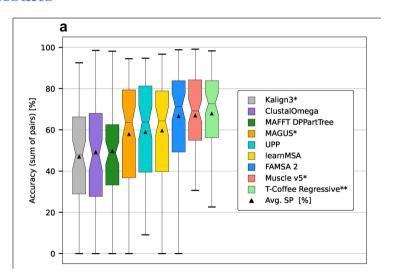
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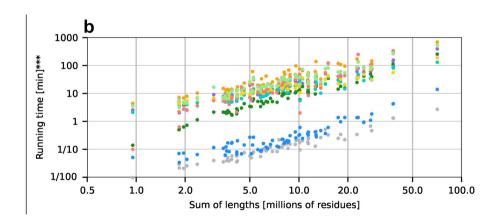


Results





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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