Multiple Whole Genome Alignment

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Goals for Lecture

the key concepts to understand are the following

- the large-scale multiple-alignment task
- progressive alignment
- breakpoint identification
- undirected graphical models
- minimal spanning trees/forests

Multiple Whole Genome Alignment: Task Definition

Given

- a set of n > 2 genomes (or other large-scale sequences)
- a method for scoring the similarity of a pair of characters

Do

 – construct global alignment: identify matches between genomes as well as various non-match features

The MLAGAN Method

[Brudno et al., Genome Research, 2003]

```
Given: k genomes X^{i}, ..., X^{k}, guide tree T
for each pair of genomes X^{i}, X^{j}
anchors(i, j) = find_anchors(X^{i}, X^{j})
align = progressive_alignment(T, anchors)
for each genome X^{i} // iterative refinement
anchors = segments of X^{i} with high scores in align
align = LAGAN(align - X^{i}, X^{i}, anchors) // realign X^{i}
progressive_alignment(T, anchors)
if T is not a leaf node
align_left = progressive_alignment(T.left)
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align_left = progressive_alignment(T.left)
align_right = progressive_alignment(T.right)
align = LAGAN(align_left, align_right, anchors)
return align



Progressive Alignment: MLAGAN Example



Progressive Alignment: MLAGAN Example

suppose we're aligning the multi-sequence X/Y with Z

- 1. anchors from X-Z and Y-Z become anchors for X/Y-Z
- 2. overlapping anchors are reweighted
- 3. LIS algorithm is used to chain anchors



Figure from: Brudno et al. Genome Research, 2003

Reweighting Anchors in MLAGAN





- each colored block represents a syntenic region of the two chromosomes
 the two panels show the two most parsimonious sets of rearrangements to
- the two panels show the two most parsimonious sets of rearrangements to map one chromosome to the other

The Mauve Method

[Darling et al., Genome Research, 2004]

Given: k genomes X^{1} , ..., X^{k}

- 1. find multi-MUMs (MUMs present in 2 or more genomes)
- 2. calculate a guide tree based on multi-MUMs
- 3. find LCBs (sequences of multi-MUMs) to use as anchors
- 4. do recursive anchoring within and outside of LCBs
- 5. calculate a progressive alignment of each LCB using guide tree

* note: no LIS step!

2. Calculating the Guide Tree in Mauve

• unlike MLAGAN, Mauve calculates the guide tree instead of taking it as an input



 distance between two sequences is based on fraction of sequences shared in multi-MUMs

3. Selecting Anchors: Finding Local Collinear Blocks

repeat

- partition set of multi-MUMs, M into collinear blocks
- find minimum-weight collinear block(s)
- remove minimum weight block(s) if they're sufficiently small
 until minimum-weight block is not small enough



4. and 5. Recursive Anchoring and Gapped Alignment

 recursive anchoring (finding finer multi-MUMs and LCBs) and standard alignment (CLUSTALW) are used to extend LCBs



Mauve Alignment of 9 Enterobacteria (Salmonella and E. coli)



Mauve vs. MLAGAN: Accuracy on Simulated Genome Data



Mauve vs. LAGAN: Accuracy on Simulated Genome Data with Inversions



Figure courtesy of Aaron Darling

Evolution with Horizontal Transfer



Mauve Accuracy on Simulated Enterobacteria-like Data



 data here include horizontal transfers



- small HT events have little effect compared to large HT events
- when scored on regions conserved in all 9 taxa, accuracy is always > 98%

Figures courtesy of Aaron Darling



- orthologous segment identification: graph-based method
- breakpoint identification: refine segment endpoints with a graphical model

Establishing Anchors Representing Orthologous Segments

- anchors can correspond to genes, exons or MUMS
- e.g., may do all-vs-all pairwise comparison of genes
- construct graph with anchors as vertices and high-similarity hits as edges (weighted by alignment score)



Rough Orthology Map

k-partite graph with edge weights

vertices = anchors, edges = sequence similarity



Greedy Segment Identification

- for *i* = k to 2 do
 - identify repetitive anchors (depends on number of high-scoring edges incident to each anchor)
 - find "best-hit" anchor cliques of size $\geq i$
 - join colinear cliques into segments
 - filter edges not consistent with significant segments

Mercator Example



repetitive elements (black anchors) are identified; 3-cliques (red and blue anchors) are found

segments are formed by red and blue anchors; inconsistent edges are filtered

2-cliques are found and incorporated into segments

Refining the Map: Finding Breakpoints

• *breakpoints*: the positions at which genomic rearrangements disrupt colinearity of segments



• Mercator finds breakpoints by using inference in an undirected graphical model

Undirected Graphical Models

 an undirected graphical model represents a probability distribution over a set of variables using a factored representation

$$p(\mathbf{b}) = \frac{1}{Z} \prod_{C \in cliques} \psi_C(\mathbf{b}_C) \qquad B_3 \qquad B_4 \qquad B_5 \qquad B_6 \qquad B_7$$

 B_i random variable

b assignment of values to all variables

- \mathbf{b}_{C} assignment of values subset of variables in C
- ψ_{c} function (called a potential) representing the "compatibility" of a given set of values
- Z normalization term



Breakpoint Undirected Graphical Model

• Mercator frames the task of finding breakpoints as an inference task in an undirected graphical model

$$p(\mathbf{b}) = \frac{1}{Z} \prod_{C \in cliques} \psi_C(\mathbf{b}_C)$$

configuration of breakpoints

potential function representing score of multiple alignment of sequences in clique *C* for breakpoints in *b*

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Breakpoint Undirected Graphical Model

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- the possible values for a variable indicate the possible coordinates for a breakpoint
- the potential for a clique is a function of the alignment score for the breakpoint regions split at the breakpoints b_C

Breakpoint Undirected Graphical Model

- inference task: find most probable configuration b of breakpoints
- not tractable in this case
 - graph has a high degree of connectivity
 - multiple alignment is difficult
- so Mercator uses several heuristics

$$p(\mathbf{b}) = \frac{1}{Z} \prod_{C \in cliques} \psi_C(\mathbf{b}_C) \qquad (1) \qquad (9)$$

• assign potentials, based on pairwise alignments, to edges only

$$p(\mathbf{b}) = \frac{1}{Z} \prod_{(i,j) \in edges} \psi_{i,j}(b_i, b_j)$$

• eliminate edges by finding a *minimum spanning forest*, where edges are weighted by phylogenetic distance

Minimal Spanning Forest



Breakpoint Finding Algorithm

- 1. construct breakpoint segment graph
- 2. weight edges with phylogenetic distances
- 3. find minimum spanning tree/forest
- 4. perform pairwise alignment for each edge in MST
- 5. use alignments to estimate $\psi_{i,j}(b_i,b_j)$
- 6. perform max-product inference (similar to Viterbi) to find maximizing b_i

Comments on Whole-Genome Alignment Methods

- employ common strategy
 - find seed matches
 - identify (sequences of) matches to anchor alignment
 - fill in the rest with standard methods (e.g. DP)
- vary in what they (implicitly) assume about
 - the distance of sequences being compared
 - the prevalence or rearrangements
- involve a lot of heuristics
 - for efficiency
 - because we don't know enough to specify a precise objective function (e.g. how should costs should be assigned to various rearrangements)