Multiple Whole Genome Alignment

BMI/CS 776
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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

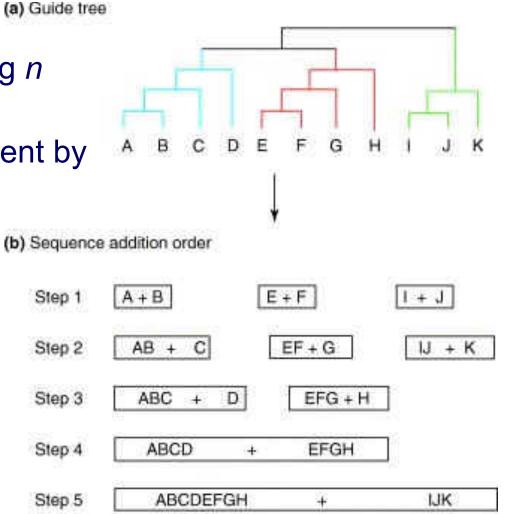
[Brudno et al., Genome Research, 2003]

```
Given: k genomes X^{l}, ..., 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, anchors)
        align_right = progressive_alignment(T.right, anchors)
        align = LAGAN(align_left, align_right, anchors)
        return align
```

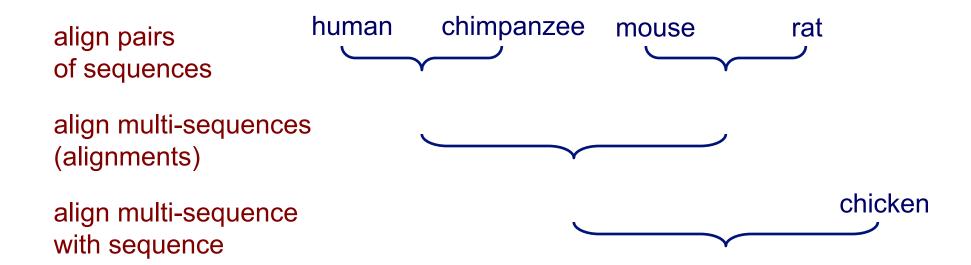
Progressive Alignment

given a guide tree relating n genomes

 construct multiple alignment by performing n-1 pairwise alignments



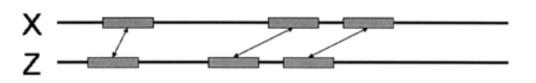
Progressive Alignment: MLAGAN Example

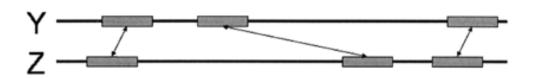


Progressive Alignment: MLAGAN Example

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
- overlapping anchors are reweighted
- 3. LIS algorithm is used to chain anchors





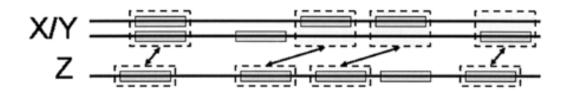
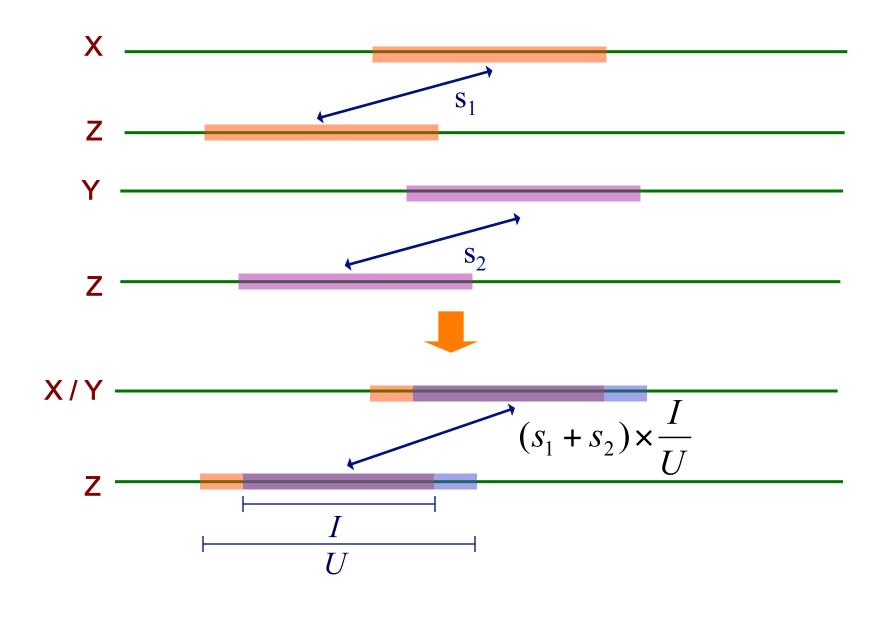
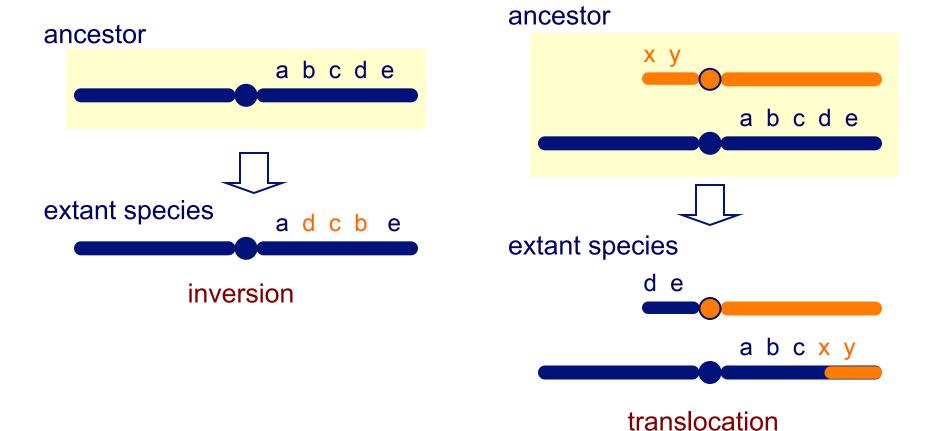


Figure from: Brudno et al. Genome Research, 2003

Reweighting Anchors in MLAGAN

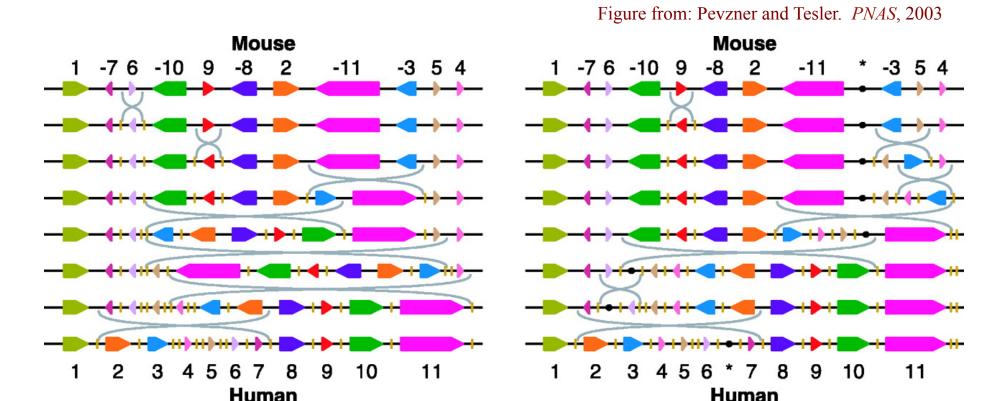


Genome Rearrangements



- can occur within a chromosome or across chromosomes
- can have combinations of these events

Genome Rearrangement Example: Mouse vs. Human X Chromsome



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

The Mauve Method

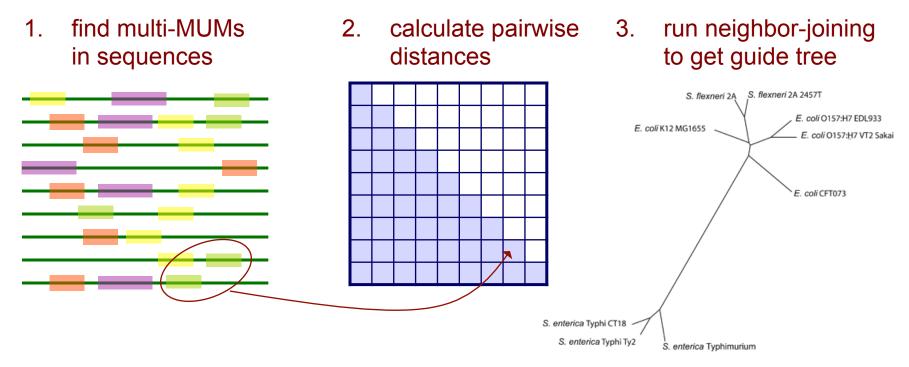
[Darling et al., Genome Research, 2004]

Given: k genomes X^1, \ldots, 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

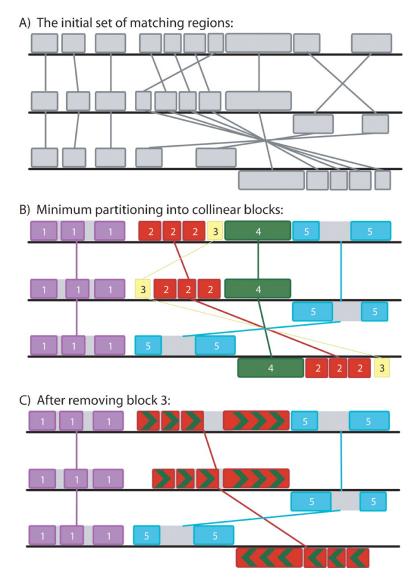


 distance between two sequences is based on fraction of sequences shared in multi-MUMs

3. Selecting Anchors: Finding Local Collinear Blocks

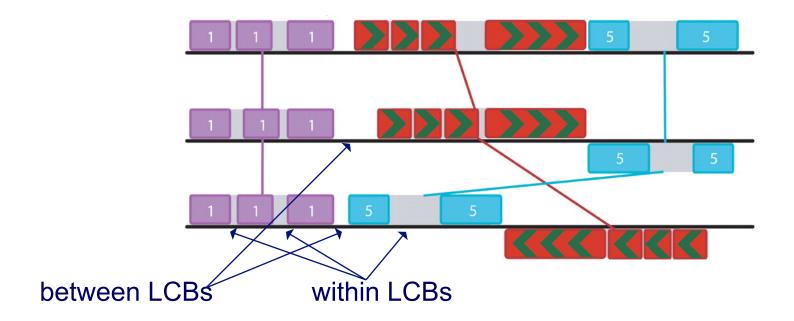
repeat

- 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

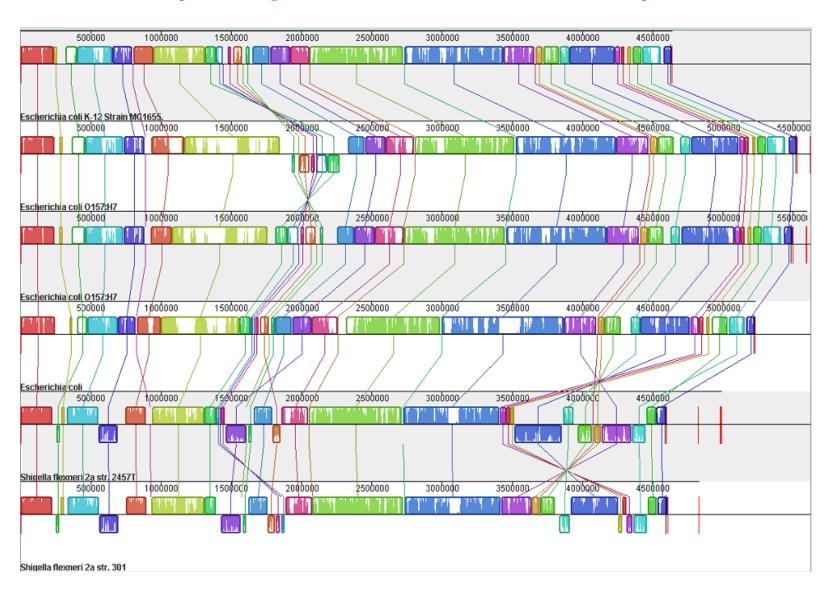


4. and 5. Recursive Anchoring and Gapped Alignment

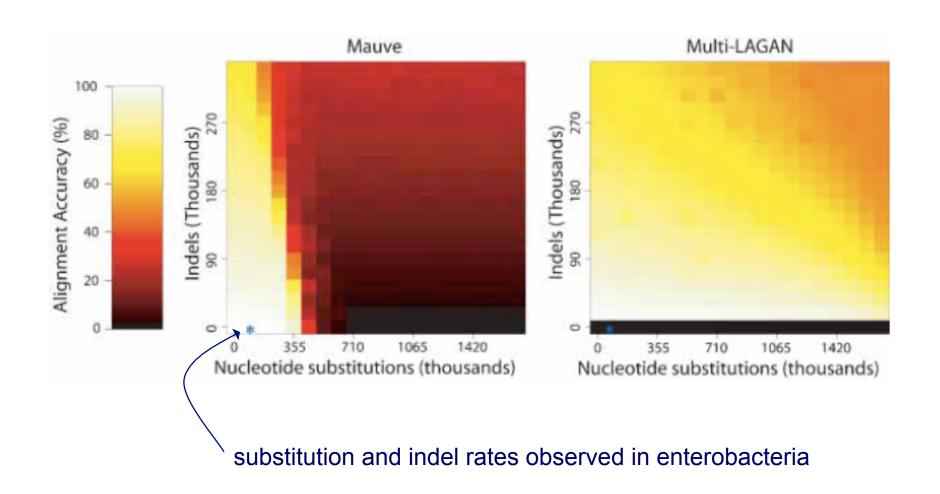
 recursive anchoring (finding finer multi-MUMs and LCBs) and standard alignment (CLUSTALW) are used to extend LCBs



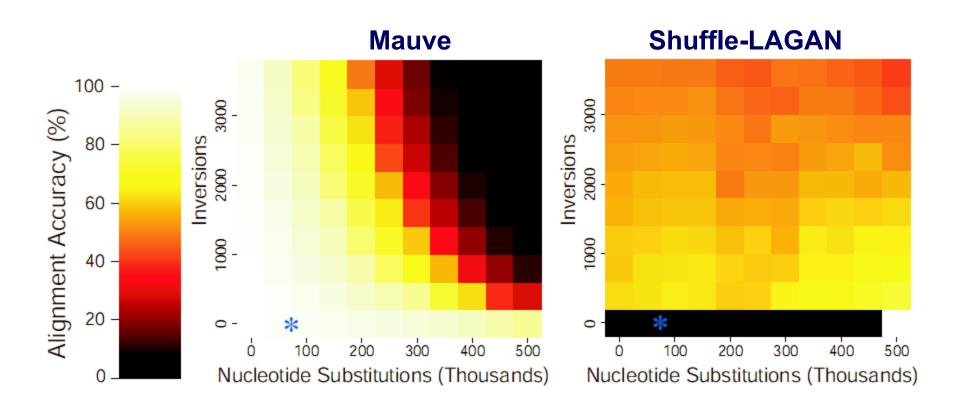
Mauve Alignment of 9 Enterobacteria (Shigella and E. coli)



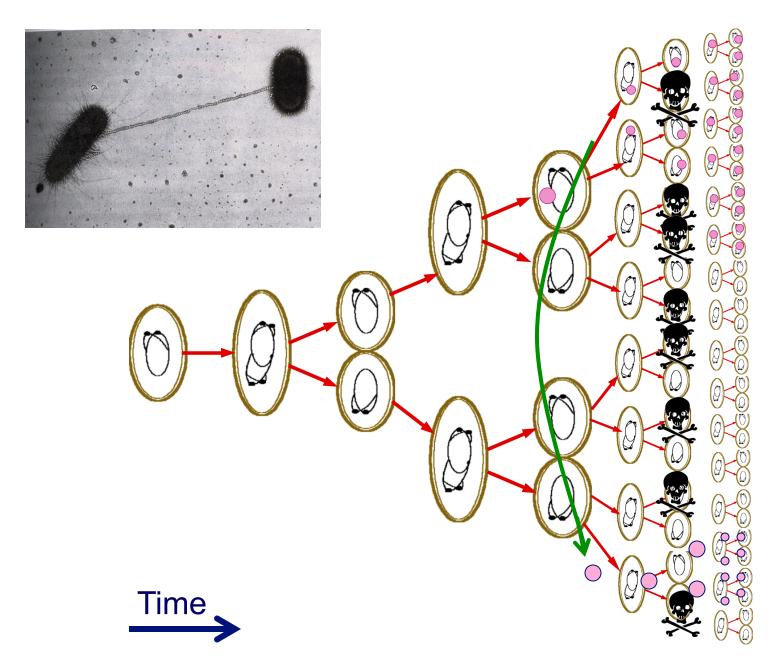
Mauve vs. MLAGAN: Accuracy on Simulated Genome Data



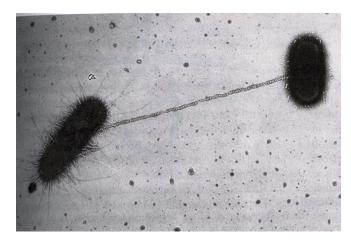
Mauve vs. LAGAN: Accuracy on Simulated Genome Data with Inversions



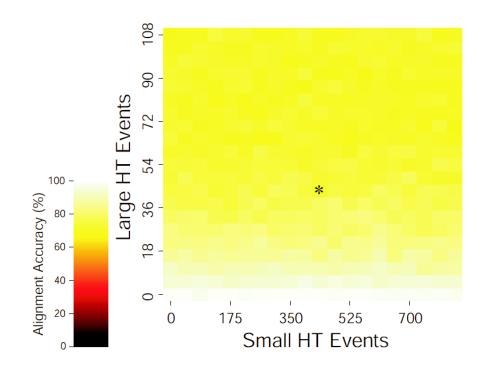
Evolution with Horizontal Transfer



Mauve Accuracy on Simulated Enterobacteria-like Data

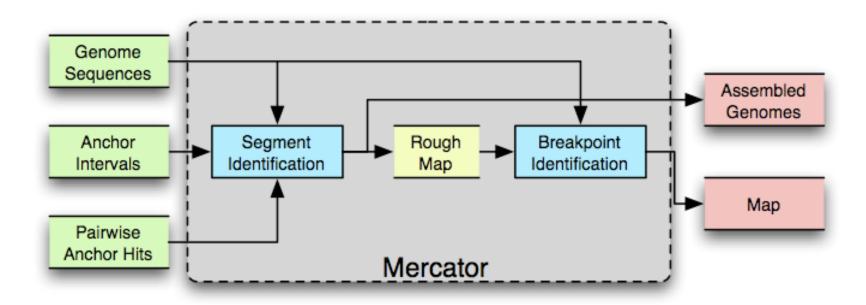


 data here include horizontal transfers



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

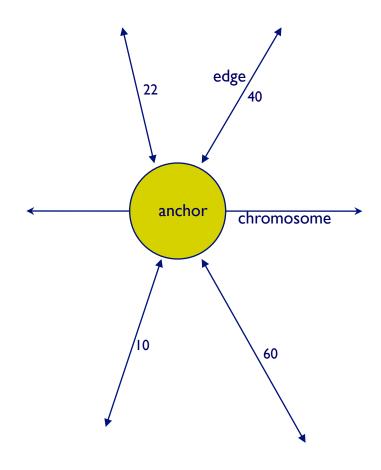
Mercator



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

Establishing Anchors Representing Orthologous Segments

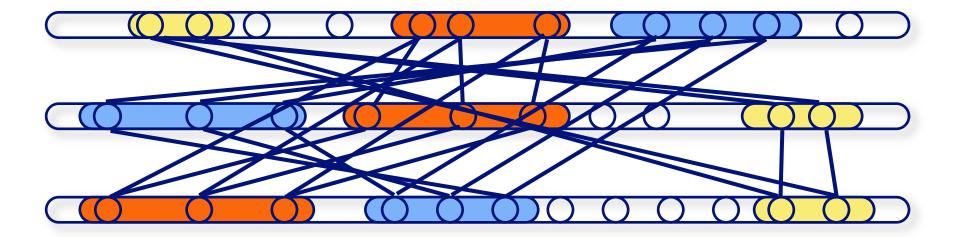
- anchors can correspond to genes, exons or MUMS
- e.g., may do all-vs-all pairwise comparison of genes
- construct graph with anchors as vertices and high-similarity hits as edges (weighted by alignment score)



Rough Orthology Map

k-partite graph with edge weights

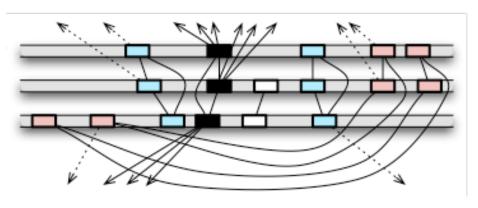
vertices = anchors, edges = sequence similarity



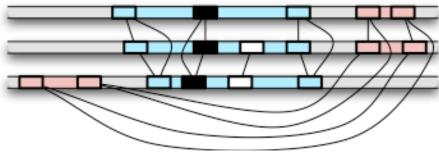
Greedy Segment Identification

- 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 ≥ i
 - join colinear cliques into segments
 - filter edges not consistent with significant segments

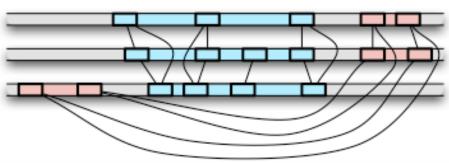
Mercator Example



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



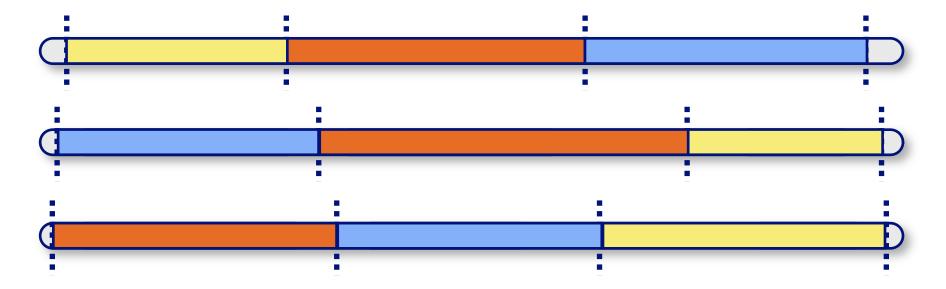
segments are formed by red and blue anchors; inconsistent edges are filtered



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

$$p(\mathbf{b}) = \frac{1}{Z} \prod_{C \in cliques} \psi_C(\mathbf{b}_C) \qquad \begin{array}{c} (B_1) & (B_2) \\ B_3 & (B_4) \\ B_5 & (B_6) \end{array}$$

- 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

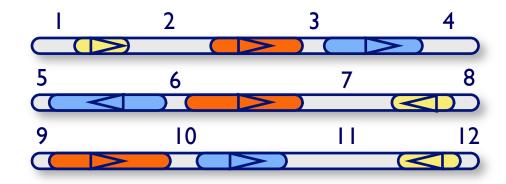
Undirected Graphical Models

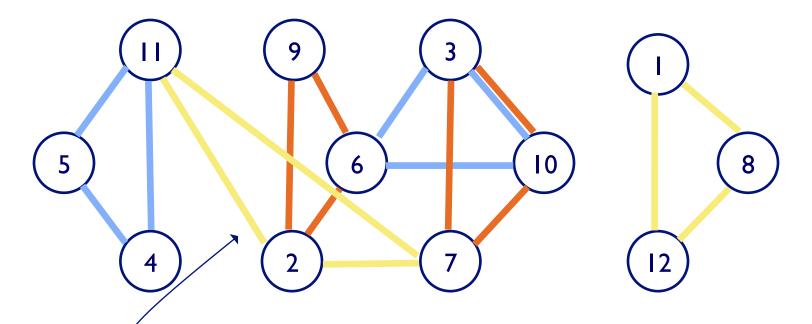
$$p(\mathbf{b}) = \frac{1}{Z} \prod_{C \in cliques} \psi_C(\mathbf{b}_C) \qquad \begin{array}{c} B_1 \\ B_2 \\ B_3 \\ B_5 \\ \end{array} \qquad \begin{array}{c} B_4 \\ B_7 \\ \end{array}$$

for the given graph:

$$p(\mathbf{b}) = \frac{1}{Z} \psi_1(b_1, b_3, b_5) \psi_2(b_1, b_6, b_7) \psi_3(b_2, b_4, b_6)$$

The Breakpoint Graph

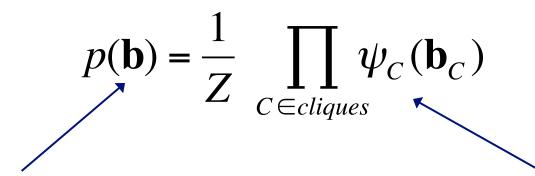




some prefix of region 2 and some prefix of region 11 should be aligned

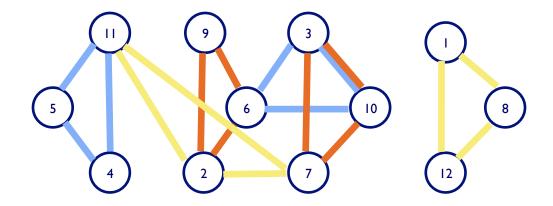
Breakpoint Undirected Graphical Model

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

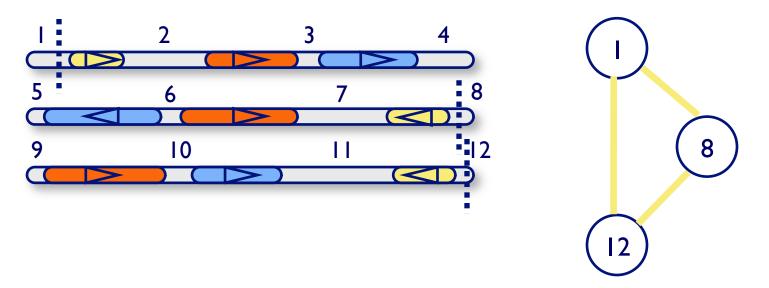


configuration of breakpoints

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

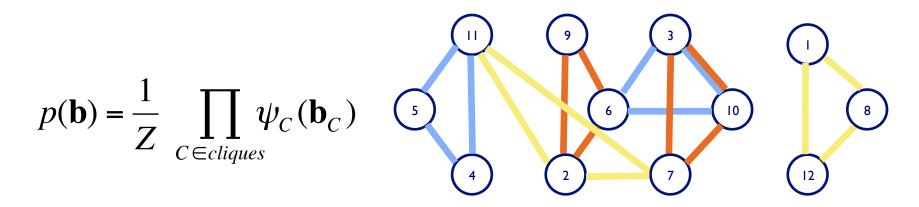


Breakpoint Undirected Graphical Model



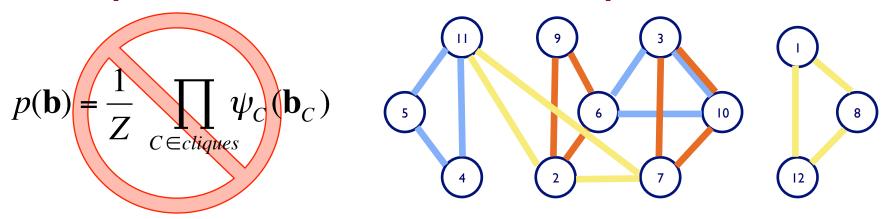
- the possible values for a variable indicate the possible coordinates for a breakpoint
- the potential for a clique is a function of the alignment score for the breakpoint regions split at the breakpoints \mathbf{b}_{C}

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

Making Inference Tractable in Breakpoint Undirected Graphical Model



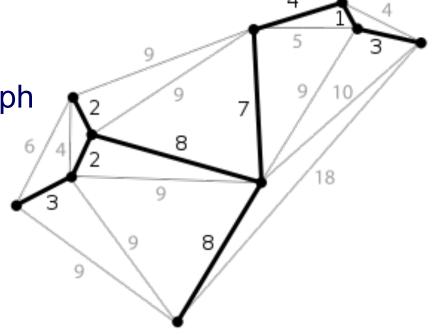
assign potentials, based on pairwise alignments, to edges only

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

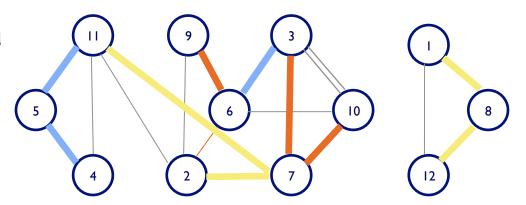
 eliminate edges by finding a minimum spanning forest, where edges are weighted by phylogenetic distance

Minimal Spanning Forest

 minimal spanning tree: a minimal-weight tree that connects all vertices in a graph



 minimal spanning forest: a set of MSTs, one for each connected component



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)