#### Motif finding: Lecture 2

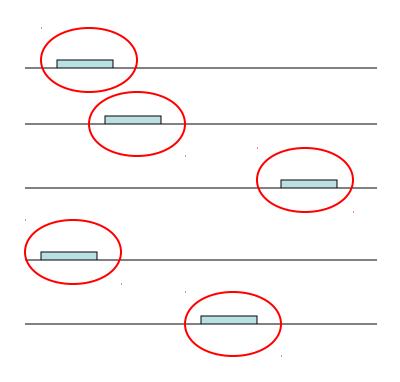
**CS 498 CXZ** 

#### Recap

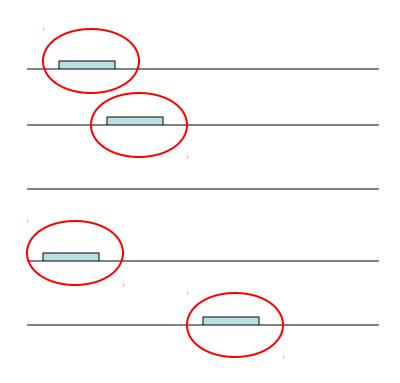
- Problem 1: Given a motif, finding its instances
- Problem 2: Finding motif ab initio.
  - Paradigm: look for over-represented motifs
  - Gibbs sampling

# Ab initio motif finding: Gibbs sampling

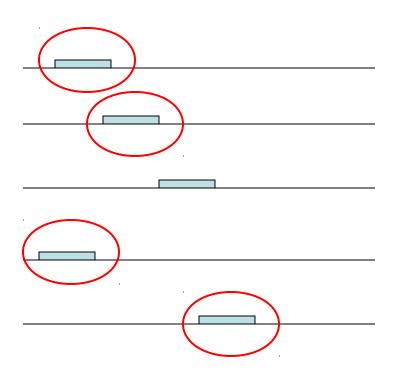
- Popular algorithm for motif discovery
- Motif model: Position Weight Matrix
- Local search algorithm



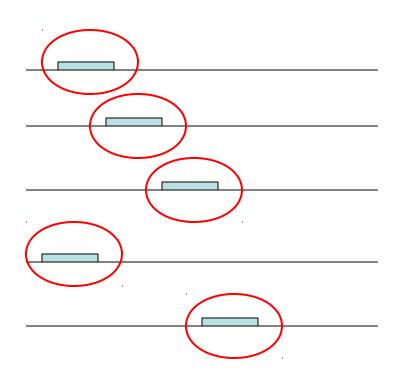
Current motif = PWM formed by circled substrings



Delete one substring



Try a replacement:
Compute its score,
Accept the replacement
depending on the score.



New motif

# Ab initio motif finding: Expectation Maximization

- Popular algorithm for motif discovery
- Motif model: Position Weight Matrix
- Local search algorithm
  - Move from current choice of motif to a new similar motif, so as to improve the score
  - Keep doing this until no more improvement is obtained : Convergence to local optima

#### How is a motif evaluated?

- Let W be a PWM. Let S be the input sequence.
- Imagine a process that randomly picks different strings matching W, and threads them together, interspersed with random sequence
- Let Pr(S|W) be the probability of such a process ending up generating S.

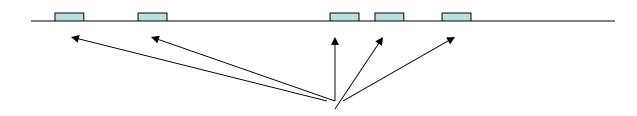
#### How is a motif evaluated?

- Find W so as to maximize Pr(S|W)
- Difficult optimization
- Special technique called "Expectation-Maximization" or E-M.
- Iteratively finds a new motif W that improves Pr(S|W)

#### Basic idea of iteration

PWM L. □ ← Current motif

2. Scan sequence for good matches to the current motif.



3. Build a new PWM out of these matches, and make it the new motif

#### Guarantees

- The basic idea can be formalized in the language of probability
- Provides a formula for updating W, that guarantees an improvement in Pr(S|W)

#### MEME

- Popular motif finding program that uses Expectation-Maximization
- Web site

http://meme.sdsc.edu/meme/website/meme.html

# Ab initio motif finding: CONSENSUS

- Popular algorithm for motif discovery, that uses a greedy approach
- Motif model: Position Weight Matrix
- Motif score: Information Content

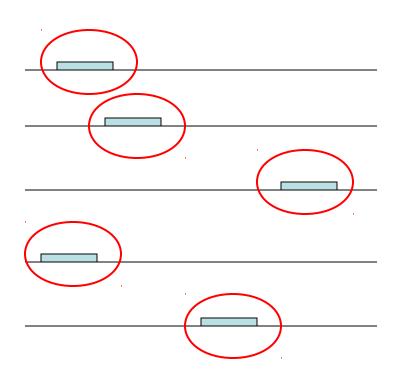
#### Information Content

- PWM W:
- $W_{gk}$  = frequency of base  $\beta$  at position k
- $q_{\beta}$ = frequency of base  $\beta$  by chance
- Information content of W:

#### Information Content

- If  $W_{\beta k}$  is always equal to  $q_{\beta}$ , i.e., if W is similar to random sequence, information content of W is 0.
- If W is different from q, information content is high.

#### CONSENSUS: basic idea

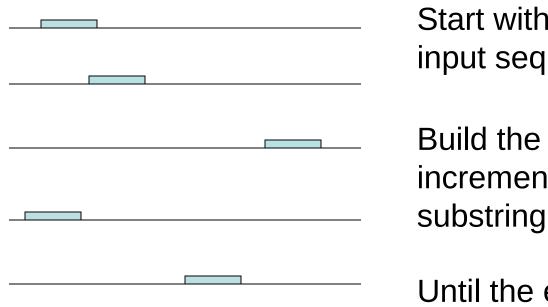


Final goal: Find a set of substrings, one in each input sequence

Set of substrings define a PWM. Goal: This PWM should have high information content.

High information content means that the motif "stands out".

#### CONSENSUS: basic idea



Start with a substring in one input sequence

Build the set of substrings incrementally, adding one substring at a time

Until the entire set is built

# CONSENSUS: the greedy heuristic

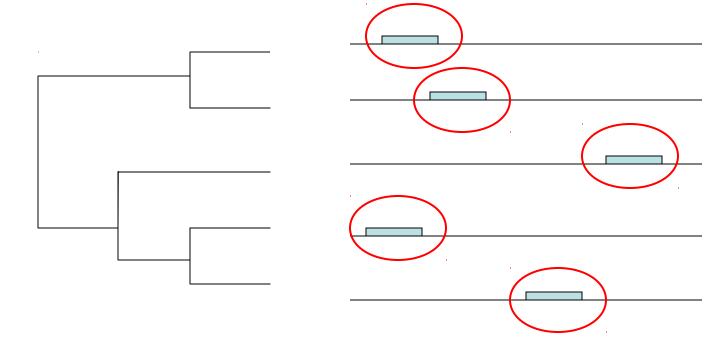
- Suppose we have built a partial set of substrings {s<sub>1</sub>,s<sub>2</sub>,...,s<sub>i</sub>} so far.
- Have to choose a substring  $s_{i+1}$  from the input sequence  $S_{i+1}$
- Consider each substring s of S<sub>i+1</sub>
- Compute the score (information content) of the PWM made from {s<sub>1</sub>,s<sub>2</sub>,...,s<sub>i</sub>,s}
- Choose the s that gives the PWM with highest score, and assign  $s_{i+1} \leftarrow s$

## Phylogenetic footprinting

- So far, the input sequences were the "promoter" regions of genes believed to be "co-regulated"
- A special case: the input sequences are promoter regions of the same gene, but from multiple species.
  - Such sequences are said to be "orthologous" to each other.

# Phylogenetic footprinting

#### Input sequences



Related by an evolutionary tree

Find motif

# Phylogenetic footprinting: formally speaking

#### Given:

- phylogenetic tree *T*,
- set of orthologous sequences at leaves of T,
- length *k* of motif
- threshold *d*

#### Problem:

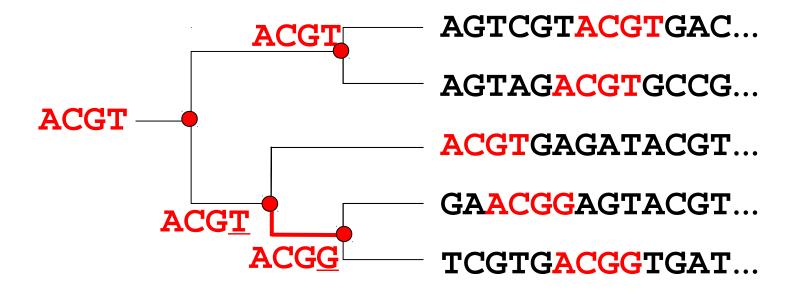
• Find each set *S* of *k*-mers, one *k*-mer from each leaf, such that the "parsimony" score of *S* in *T* is at most *d*.

# Small Example



Size of motif sought: k = 4

#### Solution

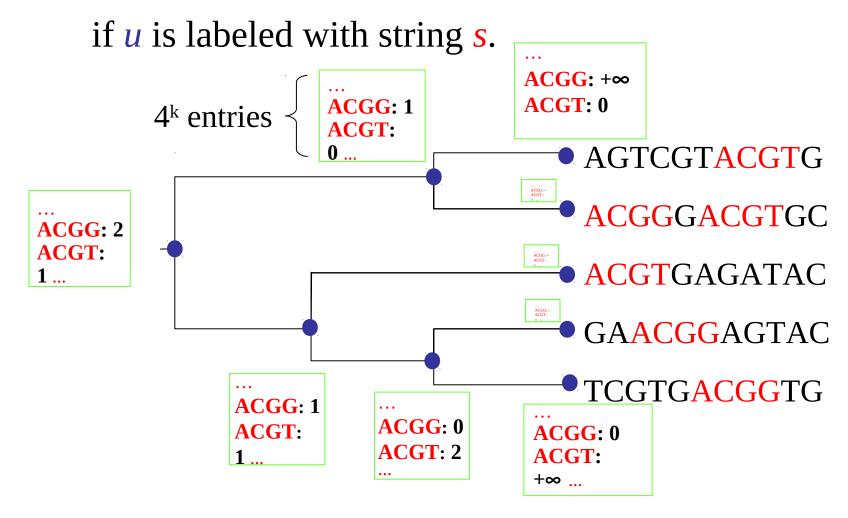


Parsimony score: 1 mutation

# An Exact Algorithm

(Blanchette's algorithm)

 $W_u[s]$  = best parsimony score for subtree rooted at node u,



#### Recurrence

$$W_{u}[s] = \sum_{v: \text{ child }} \min_{t} (W_{v}[t] + d(s, t))$$

of u

# Running Time

$$W_{u}[s] = \sum_{v: \text{ child }} \min_{t} (W_{v}[t] + d(s, t))$$

 $O(k \cdot 4^{2k})$  time per node

of u

#### What after motif finding?

- Experiments to confirm results
- DNasel footprinting & gel-shift assays
- Tells us which substrings are the binding sites

### Before motif finding

- How do we obtain a set of sequences on which to run motif finding?
- In other words, how do we get genes that we believe are regulated by the same transcription factor?
- Two high-throughput experimental methods: ChIP-chip and microarray.

# Before motif finding: ChIP-chip

- Take a particular transcription factor TF
- Take hundreds or thousands of promoter sequences
- Measure how strongly TF binds to each of the promoter sequences
- Collect the set to which TF binds strongly, do motif finding on these

## Before motif finding: Microarray

- Take a large number of genes (mRNA) in the form of a soup
- Make a "chip" with thousands of slots, one for each gene
- Pour the gene (mRNA) soup on the chip
- Slots for genes that are highly expressed in the soup light up!

## Before motif finding: Microarray

- Hence measure activity of thousands of genes in parallel
- Collect set of genes with similar expression (activity) profiles and do motif finding on these.