

# Mathematical and Computational Molecular Biology

## Math/Biol 227 – Brendel – WQ94/95

**Time & Location:** Tu, Th 1:15P – 2:30P (Units: 3); Gilbert 119

**Instructor:** Volker Brendel (380-383A; 723-9256; volker@grendel.stanford.edu)

### Synopsis

Precipitated by an enormous increase in molecular sequence data (both DNA and protein), computational tools have become essential to molecular biology research. This course seeks to provide a state-of-the-art introduction to the subject. Emphasis will be on concepts and principles, combined with hands-on (-keyboard) applications.

### Prerequisites

This interdisciplinary course is directed at graduate and interested undergraduate students of biology, medicine, computer science, statistics, operations research, or mathematics. There are no formal prerequisites as all necessary knowledge will be developed in the course. However, some knowledge of the fundamental concepts of molecular biology and statistical analysis will be helpful. See the instructor for any questions regarding this.

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### Tentative Agenda

- I Tu, Jan. 10 Overview.
- II Th, Jan. 12 Pairwise sequence comparisons I; algorithms of Needleman & Wunsch and Smith & Waterman.
- III Tu, Jan. 17 Pairwise sequence comparisons II; gap penalties; suboptimal alignments.
- IV Th, Jan. 19 Score-based sequence analysis; single sequence features.
- V Tu, Jan. 24 Score-based sequence analysis; pairwise sequence comparisons (SSPA).
- VI Th, Jan. 26 Amino acid substitution scoring matrices.
- VII Tu, Jan. 31 Query search methods; FASTA, BLAST.
- VIII Th, Feb. 2, S. Karlin instructor Sequence comparisons not requiring alignments.
- IX Tu, Feb. 7 Phylogenetic trees from sequence data I.
- X Th, Feb. 9 Phylogenetic trees from sequence data II.
- XI Tu, Feb. 14 Runs, patterns, clusters of particular letter types.
- XII Th, Feb. 16, J. Kleffe instructor Word counts.
- XIII Tu, Feb. 21 Spacings between sequence markers.
- XIV Th, Feb. 23 Profile methods.
- XV Tu, Feb. 28 Optimal signal search profiles (EM algorithm).
- XVI Th, March 2 Hidden Markov chain Models.
- XVII Tu, March 7, D. Brutlag instructor Belief systems and neural networks for secondary structure prediction.
- XVIII Th, March 9 Gene and intron prediction.
- XIX Tu, March 14 Dead week lecture I.
- XX Th, March 16 Dead week lecture II.

# Math & Computer Molecular Biology - Intro

## I) Intro

a) Sequences: DNA, protein

## b) Databases

- Genbank, Genpept

- EMBL, Swiss-prot

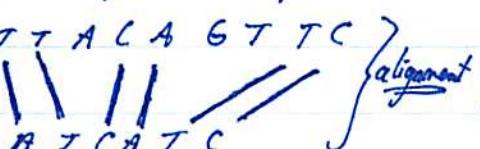
Nature 349:99 . Gilbert

## II) Data-based

Package-based

Technique-based

## III) Pairwise-Sequence Comparisons

a)  TTACAGTTC  
ATCATATC

b) how score --- scoring matrix

## IV) Non-alignment based scores

## V) Database

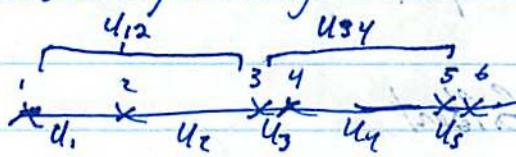
- w/ lots of sequences in the database  
 more likely getting a similarity by chance

## VI) Profile

- e.g. REST. ENZYMES

- expectation maximization - finds motifs

## VII) Distribution / Counting words



Order  $u_1, \dots, u_s$

Can also order  $u_{12}, u_{34}$

7 T T A G A T T  
 7 T A A G A T A T A

uniquely mapped - normal (I)

{ 7 T T A G A T T  
 7 T A A G A T A T A

intergenic - mixed

non local homologous (II)

Volker Agrendel  
3-9256

## Math & Comp. Biology

### SEQUENCE COMPARISON I - PAIRWISE

DNA  
↓  
 $\{A, C, T, G\}_4$

PROTEIN  
↓

$\{A, C, D, E, F, G, H, I, K, L, M, N, P, Q, R, S, T, V, W, Y\}_{20}$

#### EXAMPLE

$A = \overset{?}{A} G C C T A G$       }  
 $B = \overset{?}{C} A G C T G A$       }  
                                   C A G C T A G

#### ALIGNMENT PARAMETERS

- ① mismatches
- ② matches
- ③ gaps
- ④ overhangs

PROBLEM - too many possibilities

### SOLUTION I - NEEDLEMAN & WUNSCH (1970) JMB 48: 443-453

- ① represent all possible alignments on a matrix - as a path

- can't have directionality  
(e.g. 5' vs. 3')  
N is C  
∴ usually interested in diagonal

	C	A	G	C	T	G	A
A		1					1
G			1				
C	1			1			
T				1	1		
A					1		
G						1	

- score for matches/mismatches  
- alignments become diagonals  
- gaps become vertical or horizontal lines

gap in sequence

## NEEDLEMAN-WUNSCH II

- given two sequences

$$A^N = \{a_1, a_2, \dots, a_N\} \quad B^M = \{b_1, b_2, \dots, b_M\}$$

(A) an alignment is given by a set of paired indexes

$$(a_{j_1}, b_{k_1}) (a_{j_2}, b_{k_2}) \dots (a_{j_L}, b_{k_L})$$

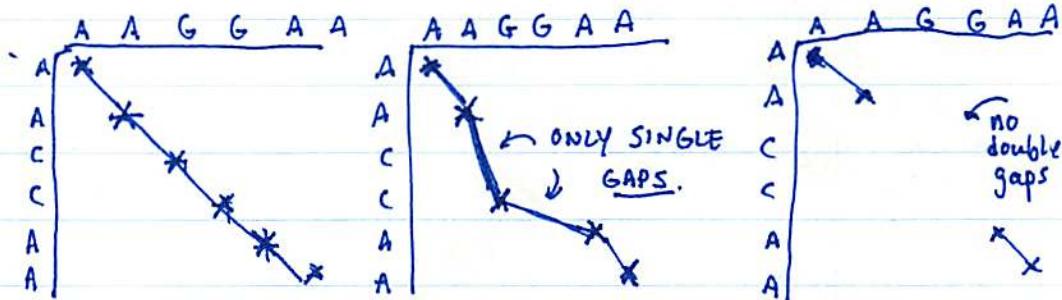
- with the restrictions

$$\begin{array}{l} \textcircled{1} \quad \left. \begin{array}{l} 1 \leq j_1 < j_2 < \dots < j_L \leq N \\ 1 \leq k_1 < k_2 < \dots < k_L \leq M \end{array} \right\} \text{always increasing} \end{array}$$

$$\textcircled{2} \quad \left. \begin{array}{l} \text{if } j_L > j_{L-1} + 1 \text{ then } k_L = k_{L-1} + 1 \\ k_L > k_{L-1} + 1 \text{ then } j_L = j_{L-1} + 1 \end{array} \right\} \text{no double gaps}$$

- that is in matrix the next match has to be in either next column or row.

e.g. AACCAA or AACG-AA but not AACC--AA  
AA-GGAA AA-GGAA



### ⑧ SCORING

$$\begin{aligned} \text{Score for a path} &= S_p = S_p(A, B) \\ &= \sum_k \sigma(a_{j_k}, b_{k_L}) + \sum_L w(j_L - j_{L-1} - 1) + \sum_L w(k_L - k_{L-1} - 1) \end{aligned}$$

substitution scores  
 weight for gaps  $w(L) \leq 0 = \text{cost}$   
 # of gaps in each gap  $w_A$   
 gaps in each gap  $w_B$

- substitution scores

#### Ⓐ SIMPLE

$$\sigma(a_i, b_j) = 1 \cdot i \cdot p \quad a = b \quad w(k) = -K$$

$$\sigma(a_i, b_j) = 0 \quad a \neq b$$

### ④ OPTIMIZATION

① FIND MAX  $S_p$  FOR ALL PATHS

②

ALGORITHM FOR FINDING MAX.

- depends on "no double gap"  
requirement

③ SET  $S_{0j} = w_j$  for all  $j=1, 2, \dots, M$

$S_{i0} = w_i$  for all  $i=1, 2, \dots, M$

} sets gap penalties

$$\text{optimal score for aligning } A_a^i = a_1, \dots, a_i \quad S_{ij} = \max \left\{ \begin{array}{l} S_{i-1, j-1} + \sigma(a_i, b_j) \\ S_{i, j-k} + w_k \text{ for all } k=1, 2, \dots, j \\ S_{i-k, j} + w_k \text{ for all } k=1, 2, \dots, i \end{array} \right\}$$

A      B      C

then  $S = S_{NM}$

### PROOF

- optimal score for aligning  $\underline{\underline{a}}_{i,j} \underline{\underline{b}}_{i,j}$  is

④ optimal score for aligning everything before  $\underline{\underline{a}}_{i,j} \underline{\underline{b}}_{i,j}$  plus score of aligning  $\underline{\underline{a}}_{i,j} \underline{\underline{b}}_{i,j}$

$$= S_{i-1, j-1} + \sigma(a_i, b_j)$$

~~if  $\underline{\underline{a}}_{i,j} \underline{\underline{b}}_{i,j}$  is aligned~~  
these are the only  
three poss. abilities  
to align  $i+j$   
if assume  
no double gaps

⑤  $\underline{\underline{a}}_{i,j} \dots \underline{\underline{b}}_{i,j}$

$$= S_{i,j-k} + w_k$$

⑥  $\underline{\underline{a}}_{i,j} \dots \underline{\underline{b}}_{i,j}$

$$= S_{i-k, j} + w_k$$

RUNNING NW

	A	C	T	G	C	A	
A	-1	0	-2	-3	-4	-5	-6
G	-2						
C	-3						
T	-4						
A	-5						
G	-6						

Score for each cell = Max  
of all 3 adjacent cells

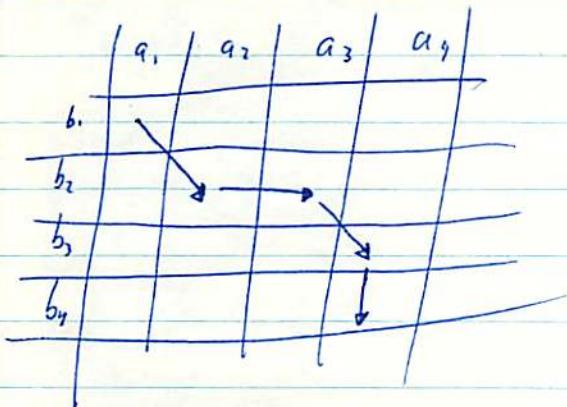
A  
C  
A

# Mathematic & Computation Molecular Biology Pairwise Alignments

$$A = \{a_1, a_2, \dots, a_m\}$$

$$B = \{b_1, b_2, \dots, b_n\}$$

alignment = association of each  $a_1, \dots, a_m$  w/ each  $b_1, \dots, b_n$  (+ gaps)



$\searrow$  = assoc. of  $a_i, b_j$   
 $\downarrow$  = gap in  $b$   
 $\rightarrow$  = gap in  $a$

## Needleman-Wunsch - corrected

- no right angles \*

- no double gaps

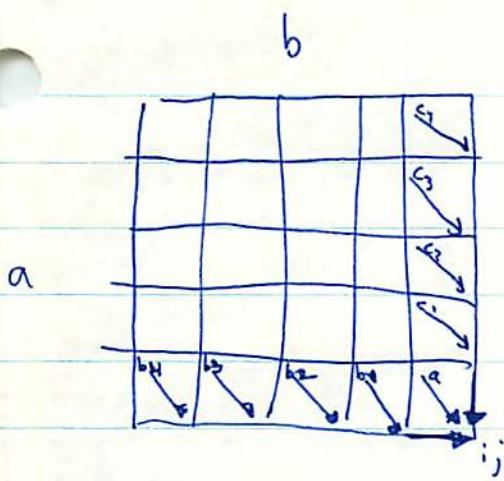
$$P_{path} = \{a_{i_0}, b_{j_0}, \dots, a_{i_l}, b_{j_l}\}$$

$$0 = i_0 < i_1 < \dots < i_l < i_{l+1} = m+1$$

$l = \# \text{ of diagonals} = \text{alignment of positions}$

$$Sp_{for\_path} = \sum_{k=1}^l \sigma \{a_{i_k}, b_{j_k}\} + \sum_{k=1}^l \text{gap}(k)$$

$$S = \max \text{ score} = \max Sp(A, B)$$



$$S_{ij} = \max \{$$

for last position, multiple paths

$$\text{if } a_i \leq s_{i-1, j-1} + \sigma(a_i, b_j)$$

$$\text{if } b_k \leq s_{i-1, j-k} + \sigma(a_i, b_j) + w_k$$

$$\text{if } c_k \leq s_{i-1-k, j-1} + \sigma(a_i, b_j) + w_k$$

$$s_{i-1-k, j-1}$$

$$-2 + 10 = 8$$

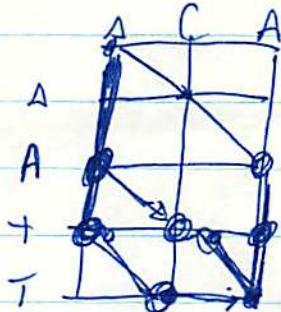
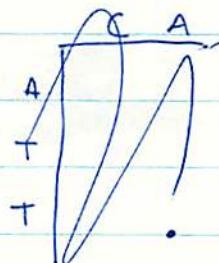
Example match=10

$$\text{mismatch} = -10$$

$$w_1 = -2$$

$$w_2 = -5$$

$$w_3 = -8$$



$$\begin{aligned} & 5 - 10 = -15 - 2 \\ & = -17 \end{aligned}$$

NW

OLO	A	C	A
NW	0	-2	-5
A	-2	-4	0
T	-5	-6	6
T	-8	-8	4

A C A

▲

A

T

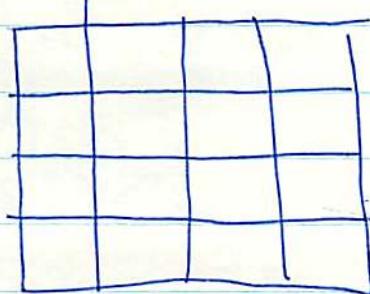
T

- can only work if  $R_w \leq w_k$
- that is gap cannot jump too much

- this # is wrong - can never get 4

GOTO H Let  $w_k = -\alpha - \beta k$   $-K=1, 2, \dots, \alpha, \beta > 0$  AFFINE GAP  
 $\therefore$  for all  $k, \alpha, \beta$   $k w_k \leq w_K$  PENALTIES

This allows speeding up of algorithm



Proof

$$H_{ij} = \max \left\{ \begin{array}{l} S_{i,j-k+1} + w_k \\ S_{i,j-k+2} + w_k \\ \vdots \\ S_{i,j-n} + w_k \end{array} \right\}$$

$$V_{ij} = \max \left\{ \begin{array}{l} S_{j-k+1,i} + w_k \\ S_{j-k+2,i} + w_k \\ \vdots \\ S_{j-n,i} + w_k \end{array} \right\}$$

$$H_{ij} = \max \left\{ S_{i,j-k+1} + w_k \right\}_{k=1 \dots n} = \max \left\{ H_{i,j-k+1} - \beta \right\}$$

$$V_{ij} = \max \left\{ S_{j-k+1,i} + w_k \right\}_{k=1 \dots n}$$

$$S_{ij} = \max \left\{ \begin{array}{l} S_{i-1,j-1} + \sigma(a_i, b_j) \\ H_{ij} \\ V_{ij} \end{array} \right\}$$

These assume that everything ends in corner

Thus end gap penalties are assessed

A A T T A C  
 - A T T - -

But what about if you didn't want to assess these penalties

### I) MODIFICATION J

- start w/ all 0's in ~~all~~ columns  $S_{I,0} = S_{0,J} = 0$

- find max score in last row or column

$$S = \max \{ S_{mj}, S_{In} \}$$

## MODIFICATION II - LOCAL ALIGNMENT

A A A A T T A C A A A  
A T T G C G G G

$S_{i0} = S_{0j} = 0$  a) MAKE ~~the~~ a column/row all 0

b) AS SOON AS YOU GET A NEGATIVE # ... MAKE IT  $\emptyset$ .

$$S_{ij} = \max \left\{ \begin{array}{l} S_{i-1, j-1} + \sigma(a_i, b_j) \\ H_{i,j} \\ V_{i,j} \\ \emptyset \end{array} \right.$$

# Mathematical & Computational Molecular Biology

## FUNDAMENTALS

Alignment  $\leftrightarrow$  lattice path

③ scoring

- substitutions

DNA = 10 scores

$4 \times 4$  matrix =  $4+3+2+1$

protein = 210 scores

$21 \times 20$  matrix =  $20+19+\dots+2+1$

- gap penalties

most use affine gap penalties

$$\alpha + \beta k = w_k ; \alpha, \beta \leq 0$$

④ algorithm - how find high scoring alignments

⑤ interpretations

- how meaningful are alignments (statistics)

## Local-Smith-Waterman

- C A T T G C vs A T G

- mismatch = -1

- match = +3

$w_k = -1 - k$

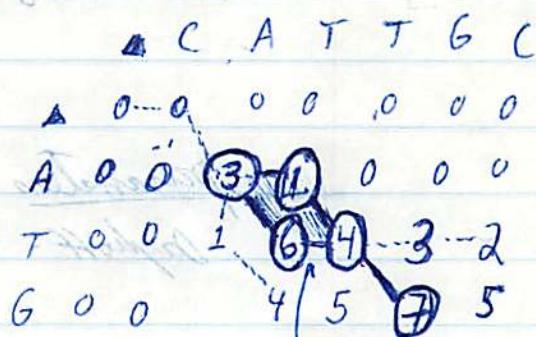
① take max { all poss. scores }

② 0's in first row

③ All H's

④ pick highest score

⑤ trace path

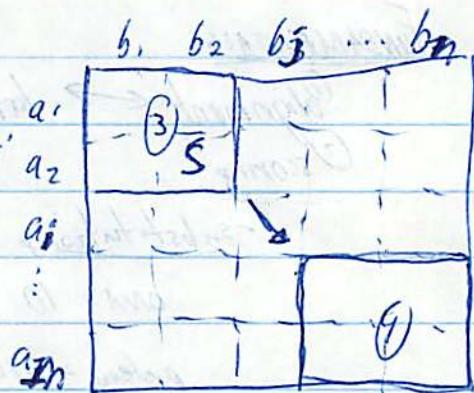


So - what do you do with multiple paths?

### Zuker - Suboptimal Alignments

○ constrain alignments such that they must go through certain points  $a_i, b_j$

② find all  $(a_i, b_j)$  such that there is at least one alignment containing  $(a_i, b_j)$  with score  $S \geq S_{\min} - \delta$



two separate subproblems  
for each point

③ i want to find  $S_{i-1, j-1}$  : optimal score

### Near & Brutlag - Near optimal alignment

- motivation ... are structural & optimal alignment the same  
- Vinkoh & Argos ... reliably aligned regions

Very parameters

Payoff = PAM matrix

why not PAM  
why 3D  
what's  
axis

1/24/95

## Math/Comp

username@grendel      /USER2/username

## SEQF

ZUKER - allows double gaps

~~aaa~~ ~~bbb~~  $w_{KL}$  not  $w_K + w_L$

## STATISTICS

for full NW alignment w/ gaps --- no good theory for getting statistics

- so ① shuffle the segs 100x .. 1000x ..

② order the scores

③ how many is score above !

## Problem

④ computer intensive

⑤ changes w/ gap penalties ... must redo for each

## Solutions -

① Disallow gaps (or w/ high penalty)

② all alignments on diagonals

③ take a particular diagonal

$b_1 \dots b_n$

$a_1 \dots a_{n-i}$



④ replace alignment w/ sequence of scores

⑤ find segment pairs w/ highest aggregate score

## Statistical Theory

- Scores :  $s_1, s_2, \dots, s_r$   $\rightarrow$  different scores  
 w/ probabilities:  $p_1, p_2, \dots, p_r$

random variable  $x_1, x_2, \dots, x_N$

prob  $\{x_k = s_k\} \approx p_k$

$$\$_k = \sum_{i=1}^k x_i$$

$$M = \max \{\$_k - \$_j\} \quad 0 \leq j < k \leq N$$

### EXAMPLE

$p_k$

$$s_1 = -5 \quad 0.2$$

$$+3, -1, 5, 1, 5, 5, -3$$

$$s_2 = -3 \quad 0.2$$

16

$$s_3 = -1 \quad 0.2$$

$$\$_1 = -3$$

$$\$_4 = 2$$

$$S_7 = 9$$

$$s_4 = 1 \quad 0.2$$

$$\$_2 = -4$$

$$\$_5 = 7$$

$$s_5 = 5 \quad 0.2$$

$$\$_3 = 1$$

$$\$_6 = 12$$

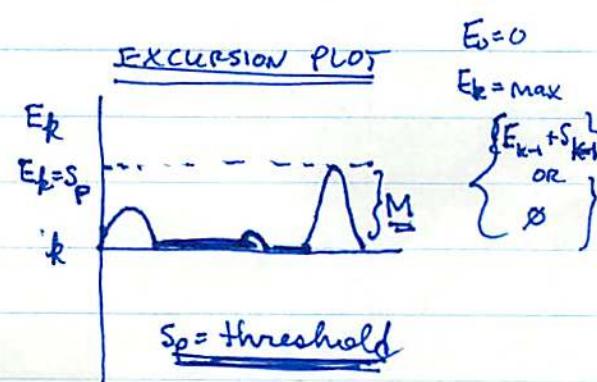
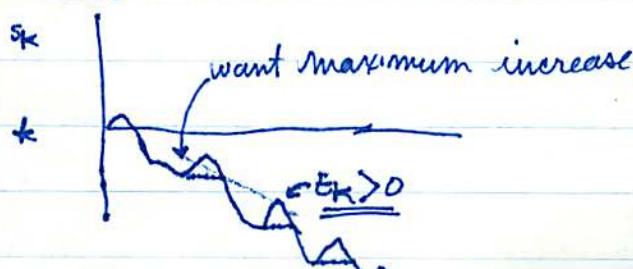
$$\max = S_6 - S_2 = 16$$

### 2 Assumptions

$$- E[X] = \sum_{k=1}^r p_k s_k < 0$$

$$\text{Prob}(X_i > 0) > 0$$

### Results



So... how calculate  $S_p$ ?

$$\text{Prob}\{M > \frac{\ln N}{\lambda} + \chi\} \approx 1 - e^{-\lambda e^{-\lambda x}}$$

$N$  = length  
 $x$  = pos variable  
 $\lambda$  } positive parameters

$$\text{Prob}\{M > S_p\} \approx 1 - e^{-\lambda N e^{-\lambda S_p}}$$

①

$\lambda$  is unique positive root fn

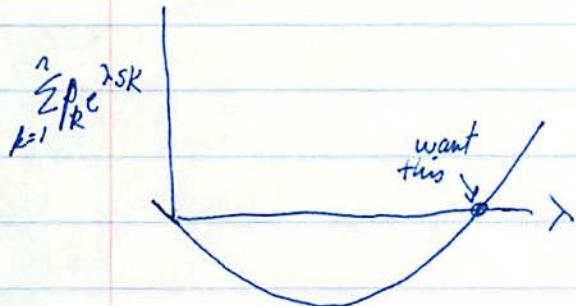
$$\sum_{k=1}^N p_k e^{\lambda s_k} = 1$$

$\lambda$  is scale parameter

if have scores  $s_1, s_2, \dots, s_r$   
 $w/\lambda, S_p$

if have other scores  $s_{r+1}, s_{r+2}, \dots, s_{r+s} = \alpha s_k$

$$\begin{aligned} \textcircled{2} \quad \lambda' \alpha = \lambda & \quad S_p' = \alpha S_p \\ \lambda' = \lambda / \alpha & \end{aligned}$$



$$\textcircled{2} R = \frac{F e^{-2(A+B)}}{\lambda C}$$

$$A = \sum_{k=1}^{\infty} \frac{1}{k} E[e^{\lambda \#_k}; \#_k > 0]$$

$$B = \sum_{k=1}^{\infty} \frac{1}{k} \text{prob}\{\#_k > 0\}$$

$$C = E[\#_1 e^{\lambda \#_1}]$$

F = correction factor for non-addit.

# Mathematical Molecular Biology

multiple alignment ... grand

SEQUENCE OF SCORES

$$x_1, x_2, \dots, x_n$$

$$\text{prob. } \{x_i = s_k\} = p_k$$

i

i=1...N k=1...r

$$s_k = \begin{cases} 0 \\ \dots \end{cases}$$

$$M_{\max} = \max \{ s_e - s_k \}$$

$s_k$  = frequency over  
all the sequences

$$\text{prob. } \{M = s\} = 1 - e^{-k N e^{-\lambda s}}$$

## APPLICATIONS

- for given scheme & significance level  $\rho$   
want  $s_p$  where  $\text{prob. } \{M > s_p\} = \rho$

$$s_p = \frac{1}{\lambda} (\ln N + \ln k - \ln(\ln(1-\rho)))$$

## SAPS

- anonymous FTP
- genomic

- Karlinc  
calculates  $\lambda, k$

## Composition Bias

- in high scoring segments the occurrence frequencies of scores are biased

$$g_k = p_k e^{\lambda s_k}$$

$$\sum g_k = 1$$

if  $s_k > 0 \Rightarrow g_k > p_k$

if  $s_k < 0 \Rightarrow g_k < p_k$

$$s_k \propto \ln \frac{g_k}{p_k}$$

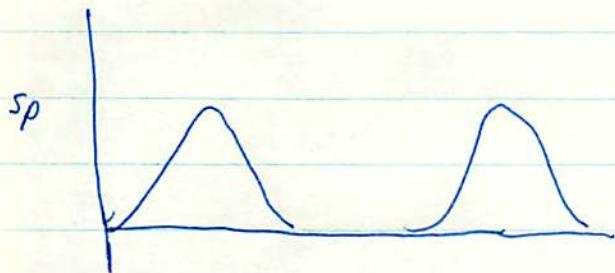
↓

- this can be reversed to calculate  $s_k$  for different biases in alignments

$$\text{EXPECTED LENGTH } E[L] = \frac{s_p}{\sum g_k s_k}$$

## APPLICATIONS - TRANSMEMBRANE Domains

- ① identify regions
- ② make graph
- ③ evaluate w/ max/min plot



but might miss segments containing two distinct domains

## APPLICATION - CHARGE ClUSTERS

STORY		
R, R	+2	+2
D, E	-2	-8
others	-1	-5
cluster		sum of + charges

## HYDROPHOBICITY

## ZARY STRUCTURE

doesn't work well because no positional information

## Application to Sequence Comparisons for a given alignment

$M = \text{length}$        $b_1 b_2 \dots b_{N-i+2}$        $\leftarrow p_k' \quad k=1 \dots n$   
 $N = \text{length}$        $a_2 a_3 \dots a_n$        $\leftarrow p_k \quad k=1 \dots n$   
 $\emptyset \quad N'$   
 - sequence of scores  $\delta \quad \delta \quad \delta$

- get scores for all possible diagonals (no gaps)

- $M$  = maximal segment pair (aggregate score)

  $\text{Prob } \{M > s\} = 1 - e^{-kMN} e^{-\lambda s}$ 

- $k, \lambda$  analogous to before
- $\lambda = \text{unique positive root}$

Target frequencies = freq. of substitutions

$$g_{ij} = p_i \cdot p_j e^{\lambda s_{ij}}$$

$$s_{ij} \propto \frac{g_{ij}}{p_i \cdot p_j}$$

$p_k$  must be somewhat similar to  $p_k'$

## Mathematical & Computational Molecular Biology

### Amino Acid Substitution Scores

④  $20 \times 20$  matrix

- almost always symmetrical

⑤ given these scores ... high scoring segment pairs have a ~~biased~~ composition,

$$q_{ij} = \frac{P_{ij}}{P_{ji}} \xrightarrow{\text{Seq}} \text{scale factor}$$

prob. of generating sequences  $i, j$

$$S_{ij} = \rho \ln \frac{q_{ij}}{P_i P_j}$$

$\xrightarrow{\text{log-odds score}}$   
 $\xrightarrow{\text{proportionality constant}}$

= These scores w/ U target those regions w/  $q_{ij}$

### Assumptions

⑥ at least one score  $> 0$

⑦  $E(S_{ij}) < 0$

### Derivation of Substitution Scores

⑧ A C L L M A G

A C V I M G A

⑨ count substitutions  $k_{ij}, k_{ji}$

$C_{11}, C_{12}, \dots, C_{120}$

⑩ symmetrize  $C_{ij} = k_{ij} + k_{ji}$

$C_{21}, C_{22}, \dots$

⑪ take row, column sums

$C_{i.}$

rows =  $C_{1.}, C_{2.}, C_{3.}, \dots, C_{20.}$

:

columns =  $C_{.1}, C_{.2}, C_{.3}, \dots, C_{.20}$

$C_{20.}, C_{12.}$

$C_{ij} = \# \text{ of subs. } I \leftrightarrow J$

$C_{ii} = 2 \times \# \text{ of } I \leftrightarrow I \text{ matches}$

$C_{i.} = C_{.i} = \# \text{ of } i \text{ residues}$

$C_{..} = \text{total # res.}$

$$f_i = \frac{c_{ii}}{c_{..}} = \text{freq of residue } i$$

④ Getting log-odds scores

⑤ Contingency Table Approach

$$S_{ij} = \ln\left(\frac{c_{ij}}{(c_{i.})(c_{.j})}/c_{..}\right) = \frac{\text{obs}}{\text{expected}}$$

$$= \ln \frac{f_{ij}}{f_{i.} f_{.j}}$$

⑥ How get counts?

⑦ Blosum (Hen.Koff & Hen.Koff)

- take blocks

- each position make a column vector of diff residues

- consider all pairwise comparisons

- each row for substitutions

5A

AA = 10

AC = 15

3C

CC = 3

CS = 6

2S

SR = 1

SS = 10

	A	C	S	
A	20	15	10	45
C	15	6	6	27
S	10	6	2	18
	45	27	18	

⑧ STRUCTURE

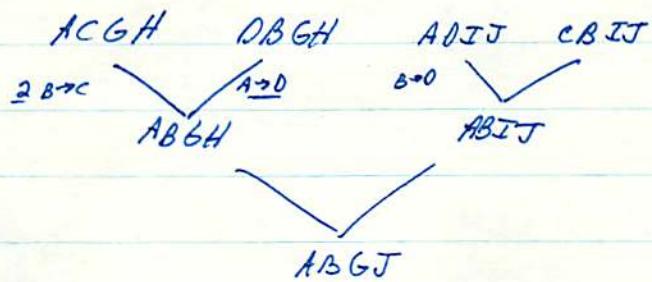
⑨ Pw Al.gments

⑩ PAMs - inferred from evolutionary data

⑥ PAMs - Dayhoff

- ⑥ infer substitutions from a likely evolutionary tree
  - only works for highly conserved proteins

⑥ example - 4 seqs



⑥ use this to get substitution counts  $k_{ij}$

⑥ symmetrize to  $c_{ij}$  - so both directions the same

→ ⑥ Use transition probabilities of change over time

- MARKOV MODEL

- changes are governed by probability transition matrices

$M_{ij} = \text{prob. that } j \text{ changes to } i \text{ in 1 unit of time}$

$$\sum_{i=1}^{20} M_{ij} = 1$$

ASSUMPTIONS

- mutations occur at constant rate
- accepted changes

PAMS

① Define relative mutability ~ how often does a particular aa change?

$$M_{IJ} = \frac{C_{IJ} - C_{JJ}}{C_{IJ}} = \frac{\# \text{ residues involved in substitution}}{\text{all of that residue}}$$

② 1-step transition probability  $\xrightarrow{\text{prob. that}}$

$$\underline{M_{JJ} = 1 - \rho M_{IJ}}$$

$\rho$  is set in way such that  
# changes in 1 unit time = 1%

so  $\sum_{J=1}^w f_J M_{IJ} = 0.99$  : fraction not changing

solve  $\rho = \frac{1}{100 \sum_{J=1}^w f_J M_{IJ}}$

1 accepted point mutation per 100 residues

③  $I \neq J$

$$\underline{M_{IJ} = \rho M_{IJ} \frac{C_{IJ}}{C_J - C_{JJ}}}$$

PROPERTIES

④  $\sum_{I=1}^w M_{IJ} = 1$

⑤  $M_{IJ}^n$  = prob. of  $J \rightarrow I$  in  $n$  units

$$M_{IJ}^{(n)} = (M_{IJ})^n$$

⑥ Stationary distribution

$$\begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_w \end{pmatrix}$$

$$\therefore (M_{IJ}) \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_w \end{pmatrix} = \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_w \end{pmatrix}$$

!! only works for proteins with the same composition

⑦  $f_J M_{IJ} = f_I M_{JI}$   
 $f_J M_{IJ}^n = f_I M_{JI}^n$

$\therefore$  SYMMETRICAL LOG ODDS SCORE

$$\textcircled{c} \quad S_{IJ} = \ln \frac{M_{IJ}}{f_I}^n$$

LOG-ODDS SCORES

as  $n \rightarrow \infty \quad M_{IJ} \rightarrow f_I$   
 $\therefore \text{all scores} \rightarrow \phi$

Which PAM's

$\sigma_n$  small ... for highly conserved

$\sigma_n$  large ... for highly divergent

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## Genomic Signatures

Dinucleotide Relative Abundances -- invariant w/in species

$P_{xy}^*$ < 0.77	$P_{xy}^*$ 0.77 - 0.81	0.81 - 0.88	0.88 -	
--	-	0	+	++

## Distances

$$\text{residual dinuc} = \frac{f_{ij}}{f_i \cdot f_j} - 1$$

$$- P^*(F_{IJ}) = \sum |P_{IJ}^*(F) - P_{IJ}^*(g)| / w_{IJ} = w_{IJ} = 1/16$$

- use

① Ind. Ident Distrb

$$P_{xy}^* \rightarrow 1$$

② betw. species distances generally greater than  
w/in species distances

	1	2	3	4
1	0			
2	0.025	0		
3	0.008	0.017	0	
4	0.032	0.014	0.025	0
5	0.009	0.021	0.008	0.027

ADVANTAGE OF THIS APPROXIMATION  
 USES AVERAGE VALUES OF THIS DISTANCE  
 ANY K THIS APPROXIMATION IS BETTER THAN THESE OTHER APPROXIMATIONS

(135) (24)  
 (513)

## Explanations

(A) why is TpA low?

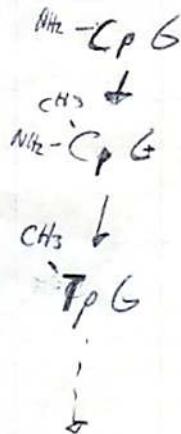
- ① lowest stacking energy of dinucs
- most unstable dinuc.

but doesn't explain non-coding bias ← ② RNase preferentially degrades UtpA

- ③ part of many regulatory sequences

(B) why is CpG low?

- ① methylation → deamination;



- but doesn't explain why CpG low in mitochondria because no methylation

② CTAG low

① kinks easily

② clusters in rRNA

③ dense in replication origins

④ GATC low in almost all bacteriophages in E. coli

If

$\rho_{xy}^* \leq 0.78$  = highly significant underrepresentation

$\rho_{xy}^* \geq 1.22$  = " " overrepresentation

### Examples

- CG is low for all vertebrates

- single mutants from this

CG → CA } overrepresented in animals  
, → TG

### ② Proks

- TA v. low

- ~~CTG~~ v. low .... embedded in this is stop codon

- ATAG v. high .... but other stop codons not low.

$$\frac{f_{xyz}}{f_x f_y f_z} \left( \frac{f_{xy}}{f_x f_y} \right) \left( \frac{f_{yz}}{f_y f_z} \right) \left( \frac{f_{xz}}{f_x f_z} \right)^{xNz}$$

↑ residual dinucleotide effects

factoring  
 out  
 mononuc.  
 freqs

$$\frac{f_{xyz}}{f_{xy} f_{xz} f_{yz}} = \text{TRINUCLEOTIDE FREQS w/  
ALL MONO, DI REMOVED}$$

$$\frac{f_{xyzw}}{f_x f_y f_z f_w} \left( \begin{array}{l} \text{dinucleotides} \\ \text{residues} \end{array} \right) \left( \begin{array}{l} \text{trinucleotides} \\ \text{residues} \end{array} \right) = \text{TETRA w/ ALL MONO, DI TRI. REMOVED}$$

REMOVING STRANOS - SYMMETRIZING

$$f_{xy}^* \quad f_A^* = f_T^* = \frac{1}{2}(f_A + f_T)$$

$$f_{GT}^* = f_{AC}^* = \frac{1}{2}(f_{GT} + f_{AC})$$

TAKE LONG  
ENOUGH SEQUENCE  
THEN THE  
 $f_A = f_T$ ,

$$\therefore P_{xy}^* = \frac{f_{xy}^*}{f_x^* f_y^*}$$

## Dinucleotides

① How measure bias

② longer is better  $\rightarrow$  ignores needed

③ mononucleotide content

- GC varies between 10-80%

- doesn't fit w/ habitat

- must factor out mononucleotides

$$- E(f_{xy}) = f_x \cdot f_y$$

$$\boxed{-0.005 \text{ RATIO} \quad \frac{f_{xy}}{f_x f_y} - 1} = \text{DINUCLEOTIDE BIAS}$$

④ trinucleotides

- Markov model of order 1

~~$f_{ABC}$~~  given

$$f_{ABC} = \Pr \{A|BC\} \cancel{\Pr \{BC\}} \quad \leftarrow \text{since order 1} \\ C \text{ has no effect} \\ \text{on } A$$

$$= \Pr \{A|B\} \Pr \{BC\}$$

$$= \Pr \{AB\} \Pr \{BC\} \\ \overline{\Pr \{B\}}$$

ORDER 2

$$f_{ABCD} = \frac{\Pr \{ABC\} \cancel{\Pr \{BCD\}}}{\Pr \{BC\}}$$

ORDER n=2

$$f_{x_1 \dots x_n} = \frac{f \{x_1 \dots x_{n-1}\} f \{x_2 \dots x_n\}}{f \{x_2 \dots x_{n-1}\}}$$

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2/2/95

Enormous database of sequences

DNA - 200,000,000 bit

PROT ... 60,000 bit

Structures

Lots of opportunities to see patterns in data

① Complete genomes

- which are genes
- repeats
- word patterns

② Short words

- over/under representations & biases
- compare diff. pieces of DNA

③ Mononucleotides

- ④ G+C varies enormously
  - e.g. 130 chores in humans
  - not biased in bacteria, flies

Blaistell

- ⑤ Markov models ... of any order
  - show that DNA's are not dependent on neighboring bases
  - too many local repeats

- ⑥ Chaos models -- not yet applied well

- ⑦ Linguistic models -- doesn't think this is good either
  - freq. of words

- DOESN'T BELIEVE IN FITTING MODELS
- BELIEVES IN BENCHMARKS

# Math / Comp. Molecular Biology

$$\log_{10} \frac{1}{10} = -\log_{10} 10 = -1$$

## Substitution Matrices

- substitution scores  $\{s_{ij}\}_{i=1 \dots 20, j=1 \dots 20}$ ; symmetric
- matrices -- do not have to be square nor symmetrical

EXAMPLE - COMPARE STRUCTURES & SEQUENCES = INVERSE FOLDING  
Odeon counts

		A C D ... Y	f <sub>1</sub> f <sub>2</sub> f <sub>3</sub> ... f <sub>20</sub>	amino acids
		matrix $e_{ij}$ : freq. of each aa. in each class $E_1, E_2, E_3$		
structures	environments	$\alpha$		
$\beta$	$\gamma$			

① form scores  $s_{ij} = \ln \frac{e_{ij}}{E_i f_j} = \ln \frac{\text{observed}}{\text{expected}}$   
 ② use for comparisons

-  $s_{ij}$  occurs w/ prob.  $p_{ij}$

① in HSSP, substitution freqs are  $\sim g_{ij} = \frac{p_{ij}}{p_{ii}} e^{s_{ij}}$

② typical length of HSSP at a given significance  $\rho$  is

$$L_\rho = \frac{s_p}{H/\lambda}$$

as  $H$  incr. the length shrinks  
 as  $H$  decr. the length increases

$$s_p = \text{significant short thresholds} = \frac{1}{\lambda} \{ \ln M + \ln k - \ln [-\ln(\lambda\rho)] \}$$

$$H = \lambda \sum_{i=1}^{20} \sum_{j=1}^{20} g_{ij} s_{ij} = \text{"relative entropy"} (\text{Aitchie})$$

-  $H$  varies among matrices

③  $F_I = \text{expected fraction of identities in HSSP}$

$$F_I = \sum_{i=1}^{l=20} g_{ii}$$

$$F_P = \sum_{i=1}^{l=20} \sum_{j=1}^{l=20} g_{ij} \quad (g > 0) \quad = \text{fraction of conservative substitutions}$$

### CREATING MATRICES

$\text{OPIM}_F = \text{percent identity matrices}$

= target HSSP where  $F_I = F$

④ start w/ subs. counts from learning set  $\Rightarrow c_{ij}$

- derive from segments w/ a lot of identities

- assume ratio of changes will be constant even w/ lower identities

$$\text{Conditionals } g_{ij} = \frac{c_{ij}}{\sum c_{ii}} \quad h_{ij} = \frac{c_{ij}}{c_{..} - \sum c_{ii}}$$

$$s_{ii} = \ln \frac{f_{g,ii}}{f_{\cdot,ii}}$$

$$s_{ij} = \frac{(1-F)h_{ij}}{f_{\cdot,ij}}$$

$$⑤ \sum_{i=1}^{20} \sum_{j=1}^{20} f_{\cdot,ij} e^{\lambda s_{ij}} = 1$$

$$⑥ F_I = \sum_{i=1}^{20} g_{ii} = \sum_{i=1}^{20} f_{\cdot,ii} \cdot c_{ii} = \sum_{i=1}^{20} F_{g,ii}$$

## BLAST

- also includes some correction for multiple sequences in the database
- adjusts  $\epsilon$  so that length is based on length of entire database

## PAIRWISE ALIGNMENTS

SSPA - significant segment pair alignment

- ① determining all HSSPs
- ② order HSSPs optimally
- ③ eliminate overlaps
- ④ score =  $\frac{\sum \text{HSSPs}}{\max. \text{selfscore} \text{ or } \min. \text{settscore}}$   $\int$  GLOBAL SCORE

$$\text{Score} = \frac{\sum \text{HSSPs}}{\text{range Max or min for range of alignment}}$$

$$\text{Score} = \frac{\sum \text{HSSPs}}{\text{aligned region}}$$

2/9/95

## Phylogeny

- taking sequences and ordering a tree
- organizing relationships to reflect evolutionary descent

Assume evolutionary changes are caused by mutations that are substitutions or deletions or inversions

## Complications

Observed now - infer past

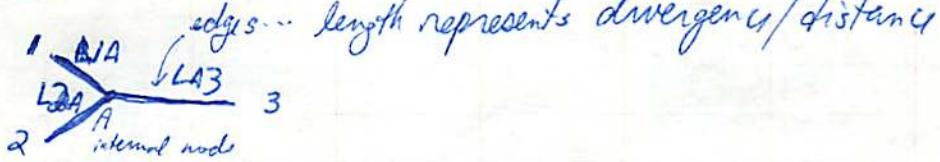
BMCs

## 3 types of similarities

- ancient shared characteristics
- derived shared characteristics
- convergent shared characteristics

## Trees

### 3 species



L1A + L2A  
L1A + LA3  
L2A + LA3

D<sub>12</sub> D<sub>13</sub> D<sub>23</sub>

$$L1A + L2A = D_{12}$$

$$L1A + LA3 = D_{13}$$

$$L2A + LA3 = D_{23}$$

$$L1A = \frac{1}{2} \{ D_{12} + D_{13} - D_{23} \}$$

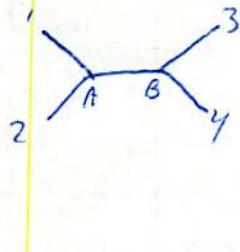
$$L2A = \frac{1}{2} \{ D_{12} + D_{23} - D_{13} \}$$

$$LA3 = \frac{1}{2} \{ D_{13} + D_{23} - D_{12} \}$$

UNIQUE SOLUTION

- but unique solution is meaningless

### 4 species



$$\binom{4}{2} \text{ distances} = 6$$

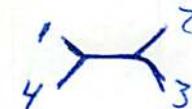
$$\begin{matrix} D_{12} & D_{13} & D_{14} \\ D_{23} & D_{24} \\ D_{34} \end{matrix}$$

5 Branches

LA  
LB  
LAC  
LBC  
LBD

① System is overdetermined

② but ... other trees ... 3 total  $2^{n-2}-1$

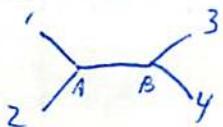


### In general

	1	2	3	4	5	6	n	$n-1$
- n species	$\binom{n}{2}$	1	3	6	10	12	$D_n$	$D_{n-1}$
- $D_n$ pairwise distances	$\binom{n}{2}$	1	3	6	10	12	$D_n$	$D_{n-1}$
- $L_n$ branch lengths	$\binom{2n-3}{2n-3}$	1	<del>3+2=5</del>	<del>2=7</del>			$L_n$	$L_{n-2}$
- $T_n$ topologies	$(1 \cdot 3 \cdot 5 \cdot \dots \cdot (2n-5))$	1	1	3	15		$T_n$	$L_n T_n$

$$\frac{(2n-5)!}{(2^{n-3})(n-3)!}$$

## 4 species



- even w/ unequal rates -- can factor out rates
- because have a shared segment

$$\left. \begin{array}{l} L_{1A} + L_{A2} = D_{12} \\ L_{1A} + L_{AB} + L_{B3} = D_{13} \\ L_{1A} + L_{AB} + L_{B4} = D_{14} \\ L_{2A} + L_{AB} + L_{B3} = D_{23} \\ L_{2A} + L_{AB} + L_{B4} = D_{24} \\ D_{B3} + L_{B4} = D_{34} \end{array} \right\}$$

what is the condition for solution to exist?

$$\textcircled{1}^* \quad D_{12} + D_{34} \leq D_{13} + D_{24} = D_{14} + D_{23}$$

> < ≡ ≈

① If  $D_{13} + D_{24} = D_{14} + D_{23} \Rightarrow$  there is a unique solution with properties \*

② But generally use least-squares estimate to approximate solution  $L_{ij}$

i try to minimize LS

LSQ solution

$$L_{1A} = \frac{1}{4} \{D_{13} + D_{14} + D_{23} - D_{24}\} + \frac{1}{2} D_{12}$$

$$L_{2A} = \frac{1}{4} \{D_{23} + D_{24} - D_{13} - D_{14}\} + \frac{1}{2} D_{12}$$

$$L_{B3} = \frac{1}{4} \{D_{13} + D_{23} - D_{14} - D_{24}\} + \frac{1}{2} D_{34}$$

$$L_{B4} = \frac{1}{4} \{D_{14} + D_{24} - D_{13} - D_{23}\} + \frac{1}{2} D_{34}$$

$$L_{AB} = \frac{1}{4} \{D_{13} + D_{14} + D_{23} + D_{24}\} - \frac{1}{2} (D_{12} + D_{34})$$

$$f D_{13} + D_{24} = D_{14} + D_{23} =$$

For additive tree

$$L_{1A} = \frac{1}{2}(D_{12} - D_{23} + D_{13})$$

⋮  
⋮

When sequences are v. similar most mutations are independent ∴ distances are additive

### Fitch

- assumes relaxed additivity
- take 4 species at a time

### Methods

Find correct tree & estimate branch lengths

cistance

parsimony

likelihood

Distance matrix methods

=  $n$  species : (OTUs operational taxonomic units)

-  $\binom{n}{2}$  distances

128

-  $\frac{(2n-5)!}{(2^{n-3}(n-3))!}$  distinct bifurcating trees w/ OTU leafs

$$\left( \frac{128!}{2^{61} \cdot 61!} \right)$$

-  $2n-3$  branches

Task

- ① find correct topology
- ② estimate branch lengths

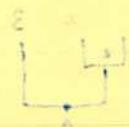
Methods

- ① evaluate all trees -- use LS -- get distances -- pick smallest

2/14/25

UPGMA = unweighted pair group method of arithmetic mean

Observed Distances	1	2	3	4	...
1	$d_{12}$	$d_{13}$	$d_{14}$	...	
2		$d_{23}$	$d_{24}$	...	
3					
4					



Recursion (reduce # of species)

① find smallest distance ...  $D_{12}$

②  $D_{12}/2$  - make branches joined w/ length  $D_{12}/2$

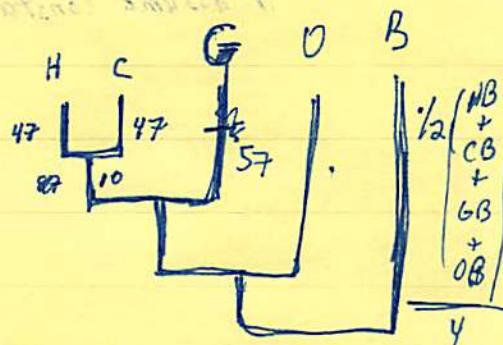
③ replace 1 & 2 by 12

④ convert  $D_{x-12} = \frac{D_{x_1} + D_{x_2}}{2}$

⑤

Example

	H	C	G	O	B
H		0.14	0.180	0.207	
C		0.115	0.194	0.218	
G			0.188	0.218	
O				0.216	
B					0.216



	HC	G	O	B
HC		0.187 0.188 0.189	0.212 0.215	
G			0.218	
O				0.216
B				0.216

	O	B
	0.188	0.218 0.216

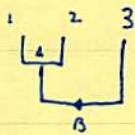
## ADVANTAGES

- v.v. fast

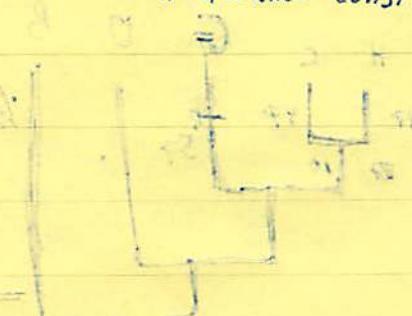
## Properties

- branch lengths always positive
- from any internal node to the leaf you get the same average distance
- $\therefore$  only works w/ constant evolutionary rate

- if get correct topology then the estimates of the branch lengths are least squares if assume constant rate

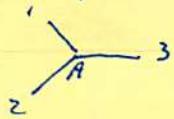


1276  
1370  
2370  
 $AB > 0$



## Fitch & Margoliash

- works on triplets



$$L_{1A} = \frac{1}{2} \{ D_{12} + D_{13} - D_{23} \}$$

$$L_{2A} = \frac{1}{2} \{ D_{12} + D_{23} - D_{13} \}$$

$$L_{3A} = \frac{1}{2} \{ D_{13} + D_{23} - D_{12} \}$$

① start w/ matrix

② find smallest distance  $D_{12}$

③ group remaining distances into 1 → n

$$D_m = \frac{D_{13} + D_{14} + D_{15} \dots + D_{1n}}{n-2}$$

$$D_{2n} = \frac{D_{23} + D_{24} + D_{25} \dots + D_{2n}}{n-2}$$

④ calculate branch lengths from \*

⑤ group 1, 2

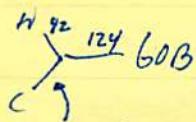
⑥ then convert  $D_m$   $D_{2n}$  like UPGMA ... w/ averages

Example --

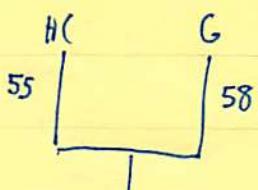
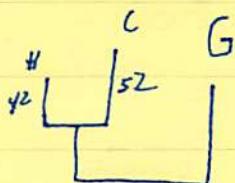
$$D_{HC} = 94$$

$$D_A(6OB) = \frac{1}{3} (111 + 180 + 207) = 166$$

$$D_C(6OB) = 176$$

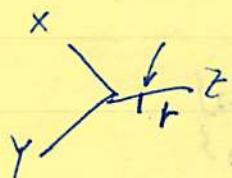


$$\frac{1}{2}(D_{12} + D_{23} - D_{13}) = 52$$



$$8 = 55 - \frac{(42+52)}{2}$$

rooting



assume constant rate

$$2\lambda t = r$$

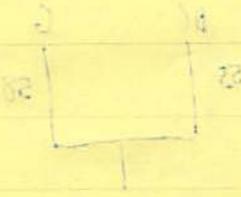
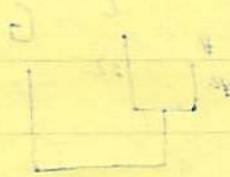
$$= x + z - r$$

$$= y + z - r$$

Least Squares  $\bar{r} = \frac{1}{4}(x+y+2z)$

Then -- do branch swapping

-- try to minimize Least Squares



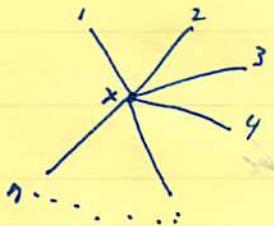
## Neighbor-Joining

Saitou & Nei 1987 JME 4:406-425

① species w/ matrix

② derive topology differently

③ begin w/ star-like topology



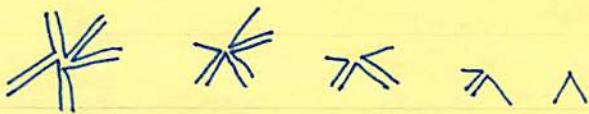
:  $L_{1x}, L_{2x}, L_{3x}, L_{4x} \dots L_{nx}$  = branches

: distances =  $D_{ij}$

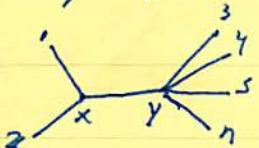
④ want to minimize sum of branch lengths

⑤ assume branch lengths are additive

$$S_0 = \sum_{i=1}^n L_{xi} \stackrel{\text{ASSUME ADDITIVE}}{=} \frac{1}{n-1} \sum_{ij} D_{ij}$$



⑥ consider diff. topologies



length =  $L_{12} + L_{1x} + L_{2x} + L_{xy} + L_{y3} + L_{yy}$

$$\begin{aligned} \text{SUM FOR } S_{12} = S_{12} &= L_{1x} + L_{2x} + L_{xy} + \sum_{i=3}^n L_{yi} \stackrel{\text{ASSUME ADDITIVE}}{=} D_{12} + \frac{1}{n-3} \sum_{3 \leq i \leq j} D_{ij} \\ \text{THIS TOPOLOGY} &\quad \underbrace{D_{12}}_{\approx D_{12}} + \frac{1}{2(n-2)} \sum_{k=3}^n (D_{1k} - L_{1x} - L_{yk} + D_{2k} - L_{2x} \\ &\quad - L_{y2}) \end{aligned}$$

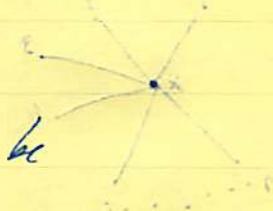
$$= \frac{1}{2(n-2)} \sum_{k=3}^n (D_{1k} + D_{2k}) + \frac{1}{2} D_{12} + \frac{1}{n-2} \sum_{3 \leq i < j} D_{ij}$$

④ calculate all possible  $D_{xy}$   $\binom{n}{2}$

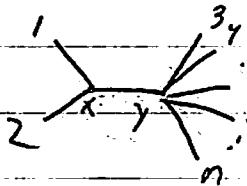
⑤ choose that which gives minimum sum

⑥ reduce distance matrix by taking averages

It turns out - that the distances come out to be  
the least squares estimate.



### Neighbor-Joining



$S_{12}$  = sum of branch lengths

$$= L_{1x} + L_{2x} + L_{xy} + \sum_{k=3}^n L_{yk}$$

$$= \frac{1}{2} D_{1,2} + 2 \left( \frac{1}{n-2} \right) \sum_{i=3}^n (D_{1,i} + D_{2,i}) + \frac{1}{n-2} \sum_{3 < i < j} D_{ij}$$

~~and  $L_{1x} = D_{1,2}$~~

$$\min [(L_{12} - D_{1,2})^2 + (L_{13} - D_{1,3})^2 + (L_{14} - D_{1,4})^2, \dots]$$

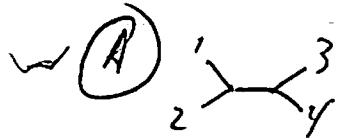
$$\sum L_{1x} = \sum S_i = S_{12}$$

Calculates branch lengths as with Fitch-Margolash

## Claim

~~NJ if tree is additive~~

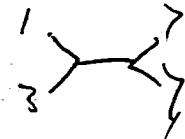
NJ... if distances are additive it will find correct topology.



$$S_{12} = \frac{1}{2}D_{12} + \frac{1}{4}(D_{13} + D_{14} + D_{23} + D_{24}) + \frac{1}{2}D_{34}$$

$$= S_{34}$$

$$S_{13} = S_{24} = \frac{1}{2}D_{13} + \frac{1}{2}D_{24} + \frac{1}{4}(D_{12} + D_{14} + D_{23} + D_{34})$$



$$\boxed{S_{13} - S_{12} = -\frac{1}{4}D_{12} + \frac{1}{4}D_{13} + \frac{1}{4}D_{24} - \frac{1}{4}D_{34}}$$

$$= \frac{1}{4}(D_{13} + D_{24} - D_{12} - D_{34})$$

$S_3 - S_{12} > 0 \Rightarrow$  tree is correct

$$D_{12} + D_{34} < D_{13} + D_{24} \quad \text{similar to } \underline{\text{before}} \text{ for additive tree}$$

$$D_{12} + D_{34} \leq D_{13} + D_{24} = D_{14} + D_{23}$$

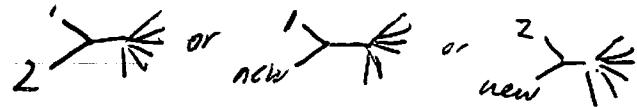
∴ for  $N=4$  NJ gives correct tree

w/ non-additive

$$D_{12} + D_{34} \leq D_{13} + D_{24} \leq D_{14} + D_{23} \quad \left\{ \begin{array}{l} \text{one will be tree} \\ \text{if } \underline{D_{12} + D_{34} \leq D_{14} + D_{23} \leq D_{13} + D_{24}} \end{array} \right.$$

NJ  
11 species

- induction from n-1 to n
- 3 poss. b. l. ties



- if  $S_{12}$  is the smallest

$$\text{consider } S_{1n} - S_{12} = \frac{1}{2} D_{1A} + \frac{1}{2(n-2)} [D_{12} + D_{13} + \dots + D_{1,n-1}] + [D_{2n} + D_{3n} + \dots + D_{3,n-1}]$$

$$+ \frac{1}{n-2} [(D_{3} + D_{24} \dots + D_{3,n-1}) + (D_{34} + \dots + D_{3,n-1}) + (\dots)]$$

$$- \left[ \frac{1}{2} D_{12} - \frac{1}{2(n-2)} [ (D_{13} + D_{14} \dots + D_{1n}) + (D_{23} \dots + D_{2n}) ] \right]$$

$$+ \frac{1}{n-2} (D_{34} + D_{35} + \dots + D_{3n-1} \\ + D_{45} + \dots + D_{4n})$$

$$S_{1n} - S_{12} = \frac{1}{2n-2} \sum_{k=3}^{n-1} (D_{1n} + D_{2k} - D_{12} - D_{kn})$$



$$D_{1A} + D_{2k} - D_{12} - D_{kn} = a + b + d + e - (a + c + d) - (b + c + e) \\ = -2c$$

$$-\frac{1}{2} \sum_{k=3}^{n-1} -2c \text{ is always } < 0$$

$$\therefore S_{1n} - S_{12} \text{ would be } > 0$$

2/16/95

Fitch, Doolittle & Feng (JME 18:30. 1981)  
Neighboring

- give two neighbors a  $\pm 1$  score for each set of four sequences with that pair in which those two are closest

$$\cancel{\text{off}} \quad \binom{n-2}{2} \quad \# \text{ of choices}$$

- use this matrix of neighborliness for tree making

Parsimony · Stewart + 1993 Nature, 361:603

- ① Given an alignment ... each aligned position is represented by a tree
- ② Reconstruct internal nodes of trees & get fewest substitutions
- ③ Add up over all columns

Predict True Tree = tree w/ minimal substitutions

But ... must look at all trees

### EXAMPLE

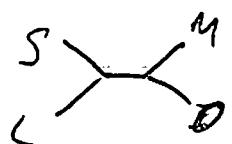
shark

lungfish

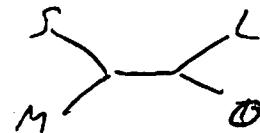
monkey

outgroup

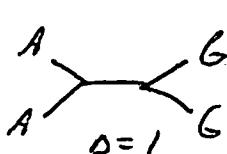
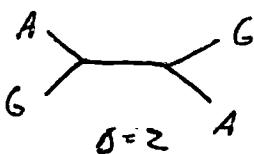
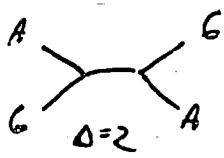
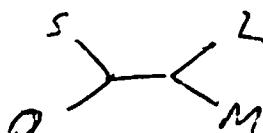
	Non Ref	Non Infra	Non Inter	Non Inter
shark	G A T C	C T A G G C		
lungfish	G G T C	A C A T G T		
monkey	G G T C	A T A T C T		
outgroup	G A T A	C C A G C A		
	1 2 3 4	5 6 7 8 9 10		



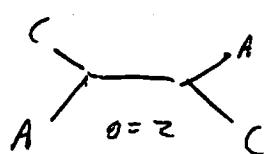
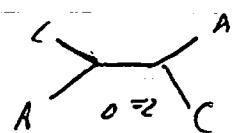
OR



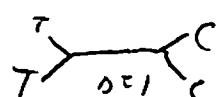
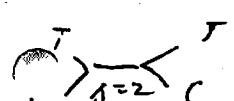
OR



~~Position 2~~



position 5



position 6

$\Sigma = 9$

$\Sigma = 9$

$\Sigma = 7$

Maximum likelihood

Phylogenetic or phonetic trees

Principle ...

Observed data -  $D$

- several alternative probability models (e.g. ... d.P.t. trees)  $M_i$

-  $P(D|M_i)$  = prob. of observing  $D$  under model  $M_i$

-  $P(M_i|D)$  = likelihood of  $M_i$

$$= \frac{P(M_i, D)}{P(D)} = p \frac{P(D|M_i) P(M_i)}{\sum_i P(D|M_i) P(M_i)} = \text{BAYES FORMULA}$$

$P(M_i)$  = a prior probabilities

= assume all  $P(M_i)$  equally likely

$$= \frac{P(D|M_i)}{\sum P(D|M_i)}$$

$\therefore$  Most likely model is the one that maximizes  $P(D|M_i)$

Example

- coin tossing

- if prob(H) =  $p = M_p$

- if  $n$  tosses w/  $k$  heads =  $D$

$$L = \text{Prob}(D|M_p) = \binom{n}{k} p^k (1-p)^{n-k}$$

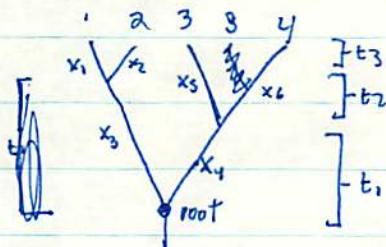
$$\log L = \log \binom{n}{k} + \log p^k + \log (1-p)^{n-k} \quad \text{use } \underline{\log} \text{ Likelihood}$$

$$\frac{N_i}{N_{\text{WEN}}} = \frac{d \log L}{d p} = 0 = \dots$$

$\hat{p} = \frac{k}{n}$

## Max. Likelihood in Phylogeny

① Given Tree ... Estimate Branch Lengths  
 (Langley & Fitch JME 3:161)



-  $x_i$  = # of substitutions

- times = unknown

model = poisson process for substitution events

$$P_t(X=x) = \text{prob. of } x \text{ subs. in time } t \\ = \frac{\lambda^x e^{-\lambda t}}{x!}$$

### ASSUMPTIONS

- events in one time period independent of others
- linearity for small times
- $\lambda$  is constant

### ESTIMATION

- can only calculate  $\lambda^t = v$

$$\text{LIKELIHOOD} = L_1 \cdot L_2 \cdot L_3 \cdot L_4 \quad L_1 = \frac{V_1^{x_4} e^{-V_1}}{x_4!} \quad L_2 = \frac{(V_1 + V_2)^{x_3} e^{-(V_1 + V_2)}}{x_3!}$$

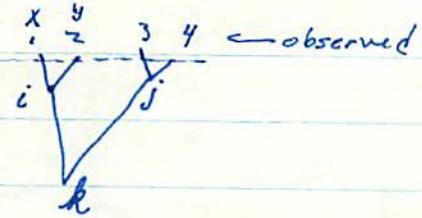
$$L_3 = \frac{V_3^{x_1 + x_2} e^{-2V_3}}{x_1! x_2!} \quad L_4 = \frac{(V_2 + V_3)^{x_5 + x_6} e^{-2(V_2 + V_3)}}{x_5! x_6!}$$

$$\text{MAX LIKELIHOOD} = \text{take derivative } \frac{d}{dx_1} \frac{d}{dx_2} \frac{d}{dx_3} \frac{d}{dx_4} \\ = \text{set to zero}$$

2) GIVEN SEAS -- ESTIMATE TOPOLOGY & BRANCH LENGTHS

- specify ...  $\rho_{ij}^t$  = prob. in time  $t$  that get  $i \rightarrow j$  change

- likelihood can be specified for any topology ... on a per nucleotide basis



$$L = \prod_{k=1}^4 \left( P_k \cdot \left( \sum_{i=1}^4 P_{ki}^{t_i} \rho_{ix}^{t_1} \rho_{iy}^{t_2} \right) \left( \sum_{j=1}^4 P_{kj}^{t_j} \rho_{jz}^{t_3} \rho_{jw}^{t_4} \right) \right)$$

One parameter model  $\rho_{ij}^t = (1 - e^{-\lambda t}) \rho_j$   $i \neq j$   
 $\rho_{ii}^t = e^{-\lambda t} + (1 - e^{-\lambda t}) \rho_i$

$e^{-\lambda t}$  = prob of no event

Algorithm

① sum up log-likelihoods over all sites

② find maximum in terms of  $v = \lambda t$

③ get most likely tree

Consistency checks

④ bootstrapping ... resample columns w/ replacement  
- but ...

Pattern freq distribution

$P(\text{pattern } P \text{ occurs } x \text{ times}) = ?$

Definition: Sequence  $S$  is in state  $(x, i)$  if it contains  $P$   $x$  times  
and ends on  $P_i$ .  
 $i = 0, \dots, m-1$

State  $S$  f(x)

$$S(x, i:j) = \left\{ \begin{array}{l} x_k, t_{ij} \\ x_{j+1}, t_{ij} \end{array} \right\} \begin{array}{l} t_{ij} \neq m \\ t_{ij} = m \end{array}$$

To study words depends on what order of markov model

1 ORDER

- word = AAT

- need A

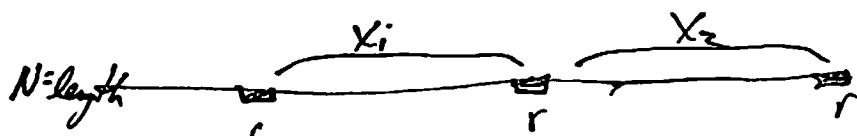
G

T

AA

AAT

Distribution between patterns



$k = \# \text{ of events}$

$$P(N_m < k) = P(X_1 + \dots + X_{k-1} > n)$$

- if  $N$  is large,  $k$  large  $X$  = normally distributed



$x_0 = 1st$  passage

tion get Markov model

## Multiple Alignments

global multiple alignments

- progressive pairwise alignments

- profile methods

- 1) Lawrence & Reilly Proteins. 7:41
- 2) Krug et al JMB 235:1501
- 3) Lawrence et al Science 263:209

local multiple alignments = motifs??

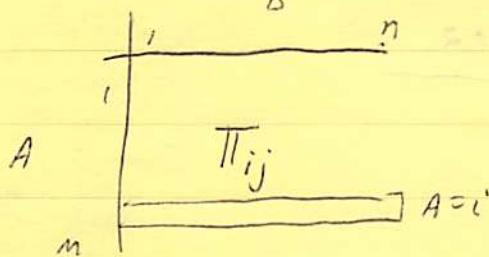
e.g. - Protein-DNA binding sites  
- proteotesters

Cannot do pairwise alignments because each protein will come up w/ diff. regions

## TWO FUNDAMENTAL CONCEPTS

Conditional probability

- two events A + B



- cond. prob = prob {B=j | A=i}

$$= \frac{P(B=j \cap A=i)}{P(A=i)}$$

$$= \frac{\pi_{i,j}}{\sum_{j=1}^n \pi_{i,j}}$$

$$② f(x_1, x_2 \dots x_n) = \sum_{i=1}^{i=n} p_i \log x_i \quad w/ \quad \sum x_i = 1$$

This  $f(x)$  has maximum  $x_i = \frac{p_i}{\sum p_i}$

A) Motif has no gaps

- Some seqs have motif; some don't

$n$  seqs  $\{S_1, \dots, S_n\}$   
length  $\{L_1, \dots, L_n\}$

- Sequence  $P_{Lj}$   $k = \text{start pt.}$   $w = \text{motif length}$   $P_{Rj} = \text{right prob.}$

$P_{Lj}$

or

$k=0$   $\underline{\dots \dots}$   $k=L-w+2$   $\underline{\dots \dots}$

$P_o = \text{prob. that seq has motif}$

likelihood

want to maximize  $\mathcal{L}(\theta | S)$   $\theta = P_{Lj}, P_{Rj}, P_{ij}, P_o$

## EM Algorithm

- start w/  $\theta$
- finds  $\theta'$  such that  $g(\theta')$  is  $\geq g(\theta)$
- the way to find the next  $\theta'$

$$\log g_\theta(s_s) = \log h_\theta(s_s, k) - \log w_\theta(k | s_s)$$

$$\log g_{\theta'}(s_s) - \log g_\theta(s_s) = \frac{\log h_{\theta'}(s_s, k)}{h_\theta(s_s, k)} - \log \frac{w_{\theta'}(k | s)}{w_\theta(k | s)}$$

- multiply by  $w_\theta(k | s_s)$  & sum ( $= 1$  because  $\sum = 1$ )

$$\log g_{\theta'}(s_s) - \log g_\theta(s_s) = \sum_k w_\theta(k | s_s) \log \frac{h_{\theta'}(s_s, k)}{h_\theta(s_s, k)} \quad \text{by } \cancel{w_\theta(k | s)}$$

$$- \sum_k w_\theta(k | s_s) \log \frac{w_{\theta'}(k | s)}{w_\theta(k | s)}$$

$$g_{\theta'}(s_s) \geq g_\theta(s_s)$$

if  $\theta'$  such that  $\max \sum w_\theta(k | s_s) \log h_{\theta'}(s_s, k)$

$$= \sum_j \sum_k w_\theta(k | s_s) n(l_s k_j) \log p'_L$$

$$+ (\text{from right}) + \sum w_\theta(k | s_s) \log (w_{\theta'}(k | s_s))$$

$$\max \text{ when } p'_L = \sum_k w_\theta(k | s_s) n(l_s k_j)$$

$$\sum_j \sum_k w_\theta(k | s_s) n(l_s k_j)$$

Algorithm for searching for max  $\theta$

$\# \text{ of times } J \text{ in left}$   
 $\text{is } J \text{ at pos. } k$

$\Phi(S_S/K) = \prod_j P_{LJ}^{n(LSk_j)} P_{RJ}^{n(RSk_j)} \prod_j P_{ij}^{n(Skj)}$

$$\Phi(S_S, K) = \Phi(S_S/K) \cdot (\text{prob not.f is not } K)$$

$$= \Phi(S_S/K) w_{S\theta}(k)$$

$$w_{S\theta}(k) = P_j \left( \frac{1}{L_S - w_2} \right) : k = 1, 2, \dots$$

$$\frac{1 - P_J}{2} \quad \begin{matrix} \text{---} \\ k=0 \end{matrix} \quad \text{OR} \quad \begin{matrix} \text{---} \\ k=W-L+2 \end{matrix}$$

$$g_\theta(S_J) = \sum_k \Phi(S_J, k) \quad \boxed{\text{--- MAXIMIZE}}$$

$$w_\theta(k/S) = \frac{\Phi(S_S, k)}{g_\theta(S_S)}$$

to do this -- start w/  $\theta$ , search for local maxima

repeat

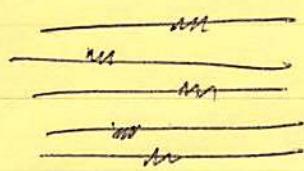
## EM Continued

- for  $S$  sequences replace  $\sum_k$  w/  $\sum_s \sum_k$

### interpretation

- for any parameters ...
  - can calc. prob. that motif is at  $k$  /  $\text{wa}(k|S_s)$
  - can then calc. new parameters from observed frags. of  $L_j R \dots$

## Stochastic Analog = GIBBS Sampling



try to maximize signal vs. background score

$$\text{signal} = p_{ij}$$

$$\text{background} = p_j$$

$$\text{for position } k \quad A_k = \frac{\pi p_{ij}}{\pi p_j} = \frac{\text{signal}}{\text{background}}$$

$$\therefore \text{want to maximize } \sum_s \sum_i \sum_j n_{k_s i j} \log \frac{p_{ij}}{p_j} \text{ over all } k_s$$

① choose random start

② save 1 sequence out

③ scan that sequence for new  $A_k$  using weights from other seqs

④ new parameters

# Dong Brügel Correlations $\rightarrow$ Structure in Biological Sequences

Molecular Biology is a Information Science

① DNA  $\rightarrow$  RNA  $\rightarrow$  PROTEIN  $\rightarrow$  FUNCTION

② Genetic info  $\rightarrow$  molecular structures  $\rightarrow$  biochemical function  $\rightarrow$  Biological Behavior

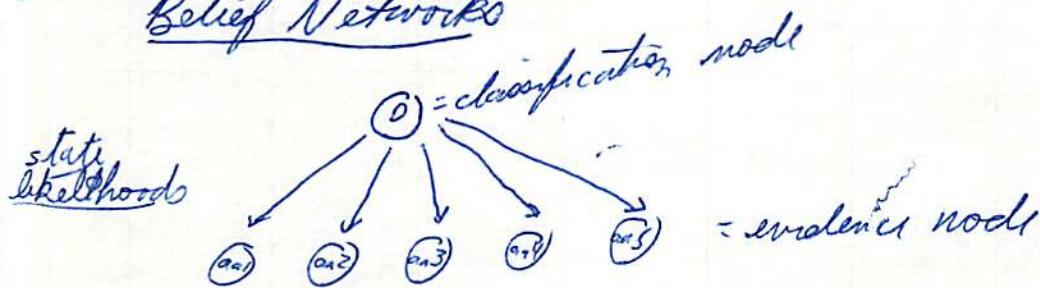
## Problems

- genetic info is redundant
- structural info is redundant
- multiple features encoded by 1 sequence
  - protein sequence
  - folding
  - th. & tx rate

## Representation

- most representations assume that sites are independent

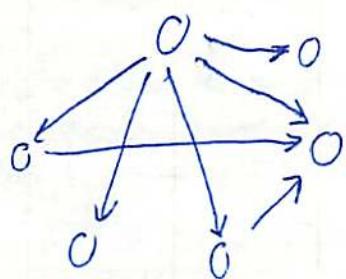
## Belief Networks



see Neapolitan

can add correlations

see Protein Science  
send email  
to bruegel@cmu.edu



## $\alpha$ -helix

- in 3D space residue  $i$  is closest to  $i+3, i+4$
- took a reduced set w/ ~~more~~ no homologs

## Test of correlations

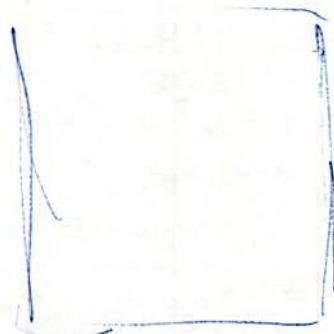
### Ochi-squared

④ mutual information

⑤ monte-carlo simulation

## Example

$i, i+4$	D	not D
K		
not K		



## overrepresented

KD	EK	SA
KE	FM	GA
LL	JL	PF

## underrep

KL

- removed these helices
- appear these aa's interact
- <sup>④</sup>RANDOMIZED BONDS ...

### Generalize

- reduced alphabet size  
by classifying into different alphabets
- convert aa into # (parametric) & look  
for correlation coefficient

④ Do w/  $20 \times 20$  alphabet

- repeat
- pick most similar
  - group them
- (but what about fringe groups?)

