BSC 4934: Q'BIC Capstone Workshop

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http://www.cs.fiu.edu/~giri/teach/BSC4934_Su11.html

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Global Alignment: An example

```
V: G A A T T C A G T T A
W: G G A T C G A
```

		G	A	A	T	T	C	A	G	T	T	A
	0	0	0	0	0	0	0	0	0	0	0	0
G	0											
G	0											
A	0											
T	0											
C	0											
G	0											
A	0											

Given

$\delta[I, J]$ = Score of Matching
the I^{th} character of sequence V &
the J^{th} character of sequence W

Compute

$S[I, J]$ = Score of Matching
First I characters of sequence V &
First J characters of sequence W

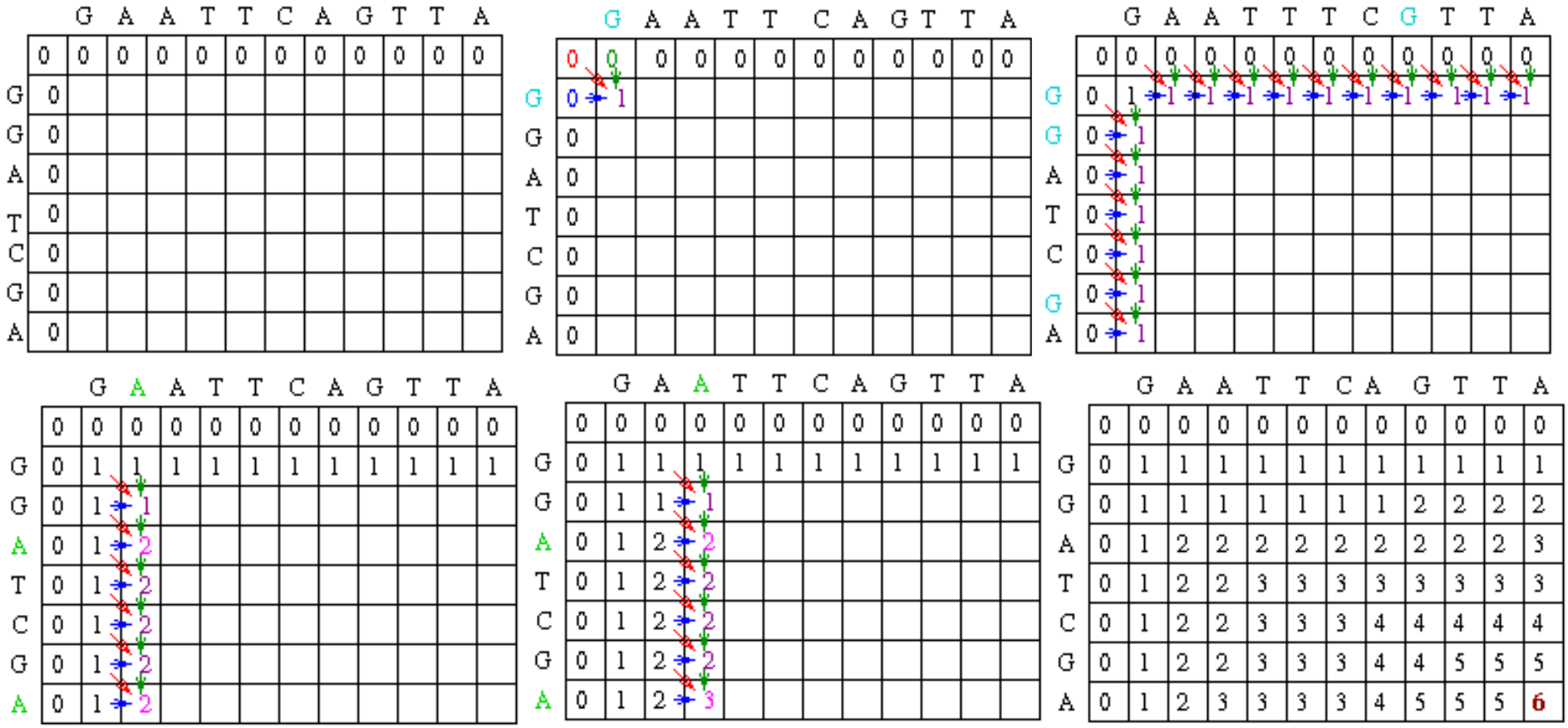
Recurrence Relation

$S[I, J] = MAXIMUM \{$
$S[I-1, J-1] + \delta(V[I], W[J])$,
$S[I-1, J] + \delta(V[I], —)$,
$S[I, J-1] + \delta(— , W[J]) \}$

Global Alignment: An example

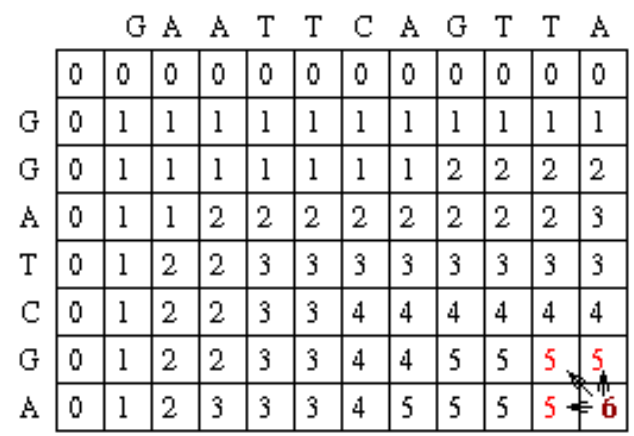
S[I, J] = MAXIMUM {
S[I-1, J-1] + δ(V[I], W[J]),
S[I-1, J] + δ(V[I], —),
S[I, J-1] + δ(— , W[J]) }

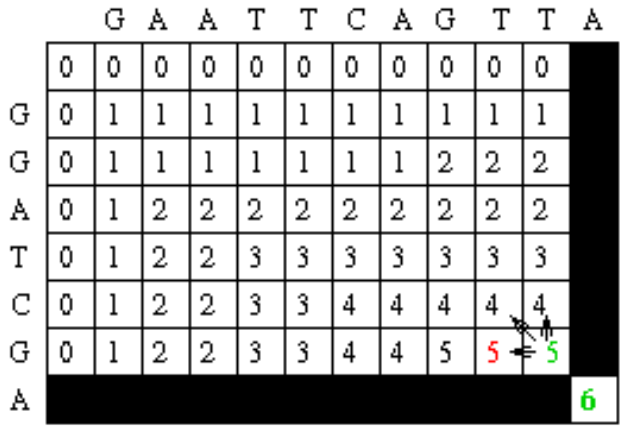
V: G A A T T C A G T T A
W: G G A T C G A

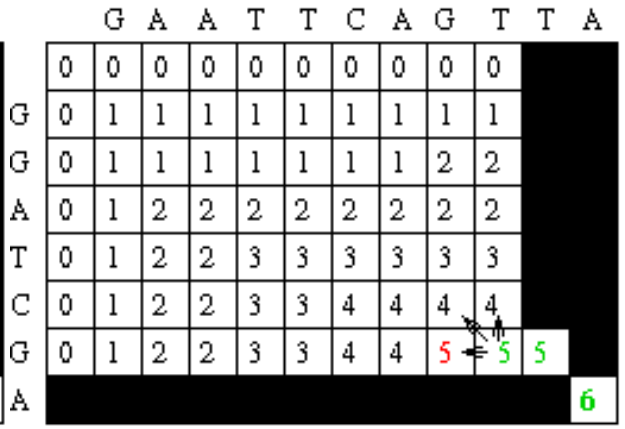


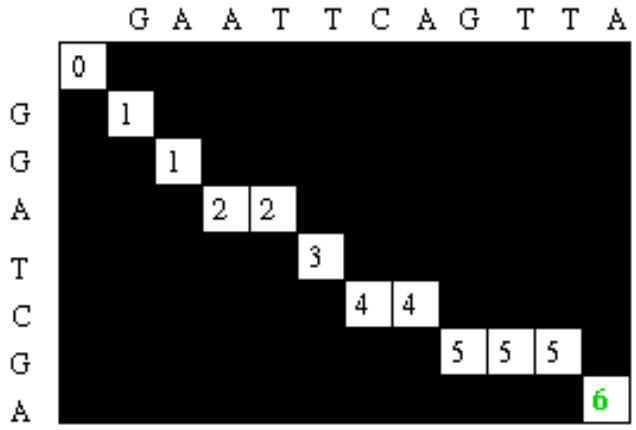
Match score = 1; Mismatch = Gap = -1

Traceback










```
V: G A A T T C A G T T A
   |   |   |  |   |     |
W: G G A - T C - G - - A
```

Improved Traceback

		G	A	A	T	T	C	A	G	T	T	A
	0	0	0	0	0	0	0	0	0	0	0	0
G	0	×1	←1	← 1	← 1	← 1	← 1	← 1	×1	← 1	← 1	← 1
G	0	×1	↑1	↑1	↑1	↑1	↑1	↑1	×2	← 2	← 2	← 2
A	0	↑1	↑1	×2	← 2	← 2	← 2	×2	↑2	↑2	↑2	×3
T	0	↑1	← 2	↑2	×3	×3	← 3	← 3	← 3	×3	×3	↑3
C	0	↑1	↑2	↑2	↑3	↑3	×4	← 4	← 4	← 4	← 4	← 4
G	0	↑1	↑2	↑2	↑3	↑3	↑4	↑4	×5	← 5	← 5	← 5
A	0	↑1	↑2	×3	↑3	↑3	↑4	×5	↑5	↑5	↑5	×6

Improved Traceback

		G	A	A	T	T	C	A	G	T	T	A
	0	0	0	0	0	0	0	0	0	0	0	0
G	0	×1	←1	← 1	← 1	← 1	← 1	← 1	×1	← 1	← 1	← 1
G	0	×1	↑1	↑1	↑1	↑1	↑1	↑1	×2	← 2	← 2	← 2
A	0	↑1	↑1	×2	← 2	← 2	← 2	×2	↑2	↑2	↑2	×3
T	0	↑1	← 2	↑2	×3	×3	← 3	← 3	← 3	×3	×3	↑3
C	0	↑1	↑2	↑2	↑3	↑3	×4	← 4	← 4	← 4	← 4	← 4
G	0	↑1	↑2	↑2	↑3	↑3	↑4	↑4	×5	← 5	← 5	← 5
A	0	↑1	↑2	×3	↑3	↑3	↑4	×5	↑5	↑5	↑5	×6

Improved Traceback

		G	A	A	T	T	C	A	G	T	T	A
	0	0	0	0	0	0	0	0	0	0	0	0
G	0	×1	←1	← 1	← 1	← 1	← 1	← 1	×1	← 1	← 1	← 1
G	0	×1	↑1	↑1	↑1	↑1	↑1	↑1	×2	← 2	← 2	← 2
A	0	↑1	↑1	×2	← 2	← 2	← 2	×2	↑2	↑2	↑2	×3
T	0	↑1	← 2	↑2	×3	×3	← 3	← 3	← 3	×3	×3	↑3
C	0	↑1	↑2	↑2	↑3	↑3	×4	← 4	← 4	← 4	← 4	← 4
G	0	↑1	↑2	↑2	↑3	↑3	↑4	↑4	×5	← 5	← 5	← 5
A	0	↑1	↑2	×3	↑3	↑3	↑4	×5	↑5	↑5	↑5	×6

```
V: G A - A T T C A G T T A
   |   |   | |   |     |
W: G - G A - T C - G - - A
```

Generalizations of Similarity Function

- Mismatch Penalty = α
- Spaces (Insertions/Deletions, InDels) = β
- Affine Gap Penalties:

  (Gap open, Gap extension) = (γ,δ)
- Weighted Mismatch = $\Phi(a,b)$
- Weighted Matches = $\Omega(a)$

Alternative Scoring Schemes

		G	A	A	T	T	C	A	G	T	T	A
	0	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12
G	-2	× 1	← -1	← -2	← -3	← -4	← -5	← -6	← -7	← -8	← -9	← -10
G	-3	↑-1	× -1	← -3	← -4	← -5	← -6	← -7	× -5	← -7	← -8	← -9
A	-4	↑-2	× 0	× 0	← -2	← -3	← -4	← -5	← -6	← -7	← -8	× -7
T	-5	↑-3	↑ -2	↑-2	× 1	← -1	← -2	← -3	← -4	← -5	← -6	← -7
C	-6	↑-4	↑ -3	↑-3	↑-1	× -1	× 0	← -2	← -3	← -4	← -5	← -6
G	-7	↑-5	↑-4	↑-4	↑-2	↑-3	↑-2	× -2	× -1	← -3	← -4	← -5
A	-8	↑-6	↑-5	↑-5	↑-3	↑-4	↑-3	× -1	↑-3	× -3	× -5	× -3

Match +1
Mismatch –2
Gap (-2, -1)

```
V: G A A T T C A G T T A
   |   | |   |   |     |
W: G G A T - C - G - - A
```

Local Sequence Alignment

- Example: comparing long stretches of anonymous DNA; aligning proteins that share only some motifs or domains.
- Smith-Waterman Algorithm

Recurrence Relations (Global vs Local Alignments)

- S[I, J] = MAXIMUM {
  S[I-1, J-1] + δ(V[I], W[J]),
  S[I-1, J] + δ(V[I], —),
  S[I, J-1] + δ(— , W[J]) }

Global Alignment

- S[I, J] = MAXIMUM { 0,
  S[I-1, J-1] + δ(V[I], W[J]),
  S[I-1, J] + δ(V[I], —),
  S[I, J-1] + δ(— , W[J]) }

Local Alignment

Local Alignment: Example

		G	A	A	T	T	C	A	G	T	T	A
	0	0	0	0	0	0	0	0	0	0	0	0
G	0	× 1	0	0	0	0	0	0	0	0	0	0
G	0	× 1	← 0	0	0	0	0	0	× 1	0	0	0
A	0	0	× 2	× 1	0	0	0	× 1	0	0	0	× 1
T	0	0	↑ 0	× 1	× 2	← 1	0	0	0	× 1	× 1	0
C	0	0	0	0	↑ 0	× 0	× 2	0	0	0	0	0
G	0	0	0	0	0	0	0	0	× 1	0	0	0
A	0	0	× 1	× 1	0	0	0	× 1	0	0	0	× 1

Match +1
Mismatch –1
Gap (-1, -1)

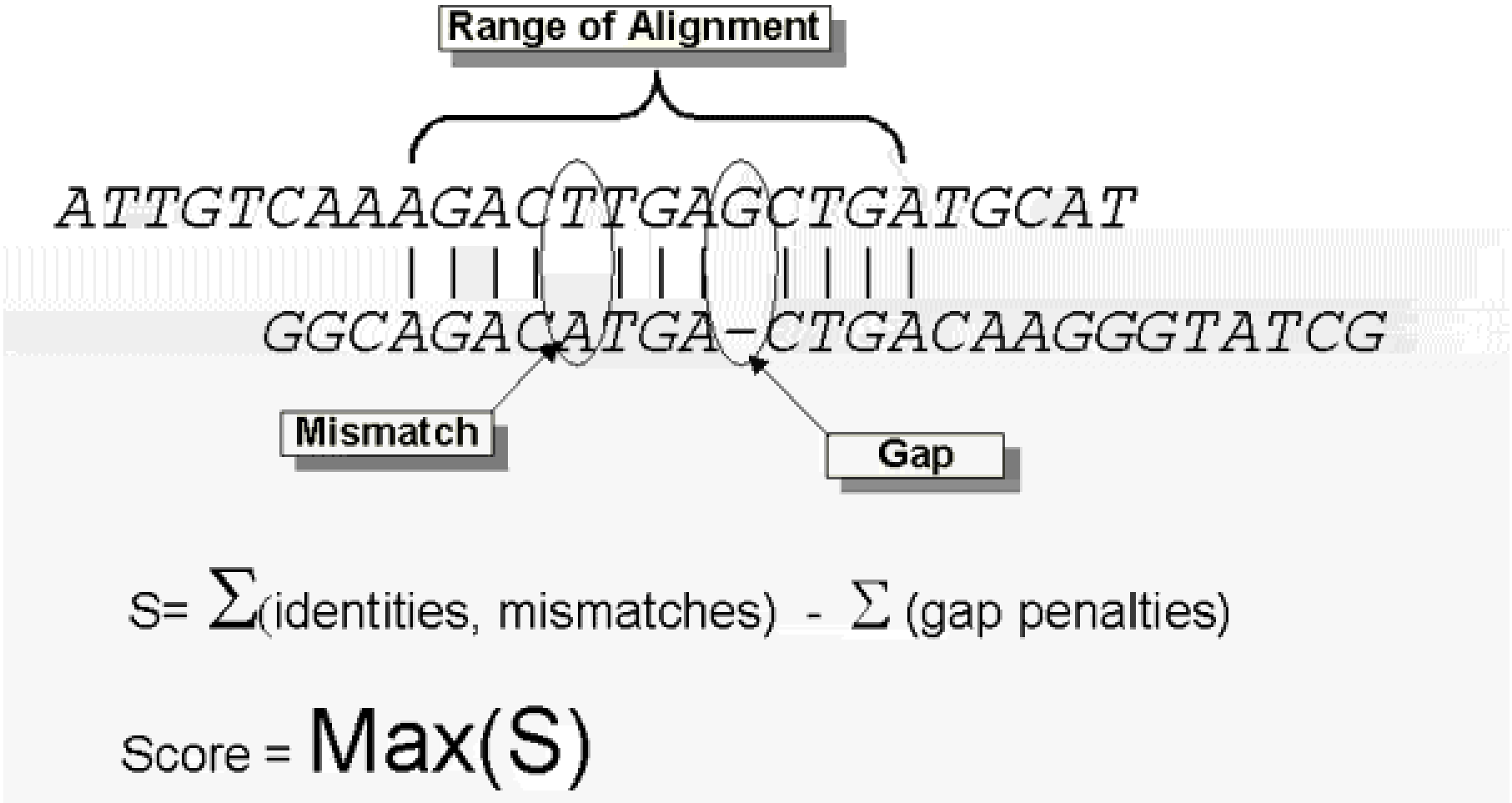
```
V: - G A A T T C A G T T A
     |   | |   |
W: G G - A T - C - G - - A
```

Properties of Smith-Waterman Algorithm

- How to find all regions of "high similarity"?
  - Find all entries above a threshold score and traceback.
- What if: Matches = 1 & Mismatches/spaces = 0?
  - Longest Common Subsequence Problem
- What if: Matches = 1 & Mismatches/spaces = $-\infty$?
  - Longest Common Substring Problem
- What if the average entry is positive?
  - Global Alignment

Slide: Courtesy J. Pevsner

Calculation of an alignment score



$S = \sum(\text{identities, mismatches}) - \sum(\text{gap penalties})$

$\text{Score} = \text{Max}(S)$

Source: http://www.ncbi.nlm.nih.gov/Education/BLASTinfo/Alignment_Scores2.html

How to score mismatches?

Blosum62 scoring matrix

A	**4**																		
R	**-1**	**5**																	
N	**-2**	**0**	**6**																
D	**-2**	**-2**	**1**	**6**															
C	**0**	**-3**	**-3**	**-3**	**9**														
Q	**-1**	**1**	**0**	**0**	**-3**	**5**													
E	**-1**	**0**	**0**	**2**	**-4**	**2**	**5**												
G	**0**	**-2**	**0**	**-1**	**-3**	**-2**	**-2**	**6**											
H	**-2**	**0**	**1**	**-1**	**-3**	**0**	**0**	**-2**	**8**										
I	**-1**	**-3**	**-3**	**-3**	**-1**	**-3**	**-3**	**-4**	**-3**	**4**									
L	**-1**	**-2**	**-3**	**-4**	**-1**	**-2**	**-3**	**-4**	**-3**	**2**	**4**								
K	**-1**	**2**	**0**	**-1**	**-1**	**1**	**1**	**-2**	**-1**	**-3**	**-2**	**5**							
M	**-1**	**-2**	**-2**	**-3**	**-1**	**0**	**-2**	**-3**	**-2**	**1**	**2**	**-1**	**5**						
F	**-2**	**-3**	**-3**	**-3**	**-2**	**-3**	**-3**	**-3**	**-1**	**0**	**0**	**-3**	**0**	**6**					
P	**-1**	**-2**	**-2**	**-1**	**-3**	**-1**	**-1**	**-2**	**-2**	**-3**	**-3**	**-1**	**-2**	**-4**	**7**				
S	**1**	**-1**	**1**	**0**	**-1**	**0**	**0**	**0**	**-1**	**-2**	**-2**	**0**	**-1**	**-2**	**-1**	**4**			
T	**0**	**-1**	**0**	**-1**	**-1**	**-1**	**-1**	**-2**	**-2**	**-1**	**-1**	**-1**	**-1**	**-2**	**-1**	**1**	**5**		
W	**-3**	**-3**	**-4**	**-4**	**-2**	**-2**	**-3**	**-2**	**-2**	**-3**	**-2**	**-3**	**-1**	**1**	**-4**	**-3**	**-2**	**11**	
Y	**-2**	**-2**	**-2**	**-3**	**-2**	**-1**	**-2**	**-3**	**2**	**-1**	**-1**	**-2**	**-1**	**3**	**-3**	**-2**	**-2**	**2**	**7**
V	**0**	**-3**	**-3**	**-3**	**-1**	**-2**	**-2**	**-3**	**-3**	**3**	**1**	**-2**	**1**	**-1**	**-2**	**-2**	**0**	**-3**	**-1**	**4**
	A	**R**	**N**	**D**	**C**	**Q**	**E**	**G**	**H**	**I**	**L**	**K**	**M**	**F**	**P**	**S**	**T**	**W**	**Y**	**V**

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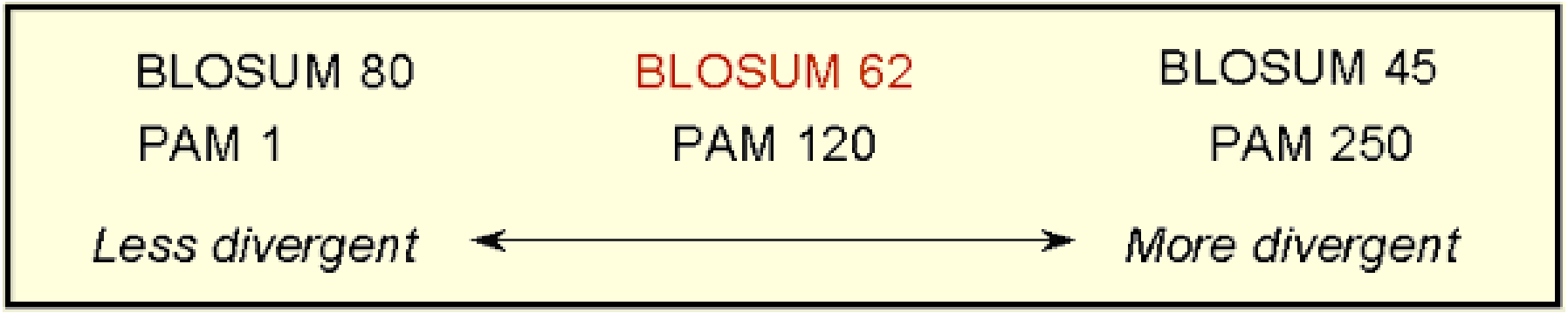
BLOSUM n Substitution Matrices

- For each amino acid pair a, b
  - For each BLOCK
    - Align all proteins in the BLOCK
    - Eliminate proteins that are more than n% identical
    - Count F(a), F(b), F(a,b)
    - Compute Log-odds Ratio

$$\log\left(\frac{F(a,b)}{F(a)F(b)}\right)$$

Scoring Matrix to Use

PAM 40	Short alignments with high similarity (70-90%)
PAM 160	Members of a protein family (50-60%)
PAM 250	Longer alignments (divergent sequences) (~30%)
BLOSUM90	Short alignments with high similarity (70-90%)
BLOSUM80	Members of a protein family (50-60%)
BLOSUM62	Finding all potential hits (30-40%)
BLOSUM30	Longer alignments (divergent sequences) (<30%)



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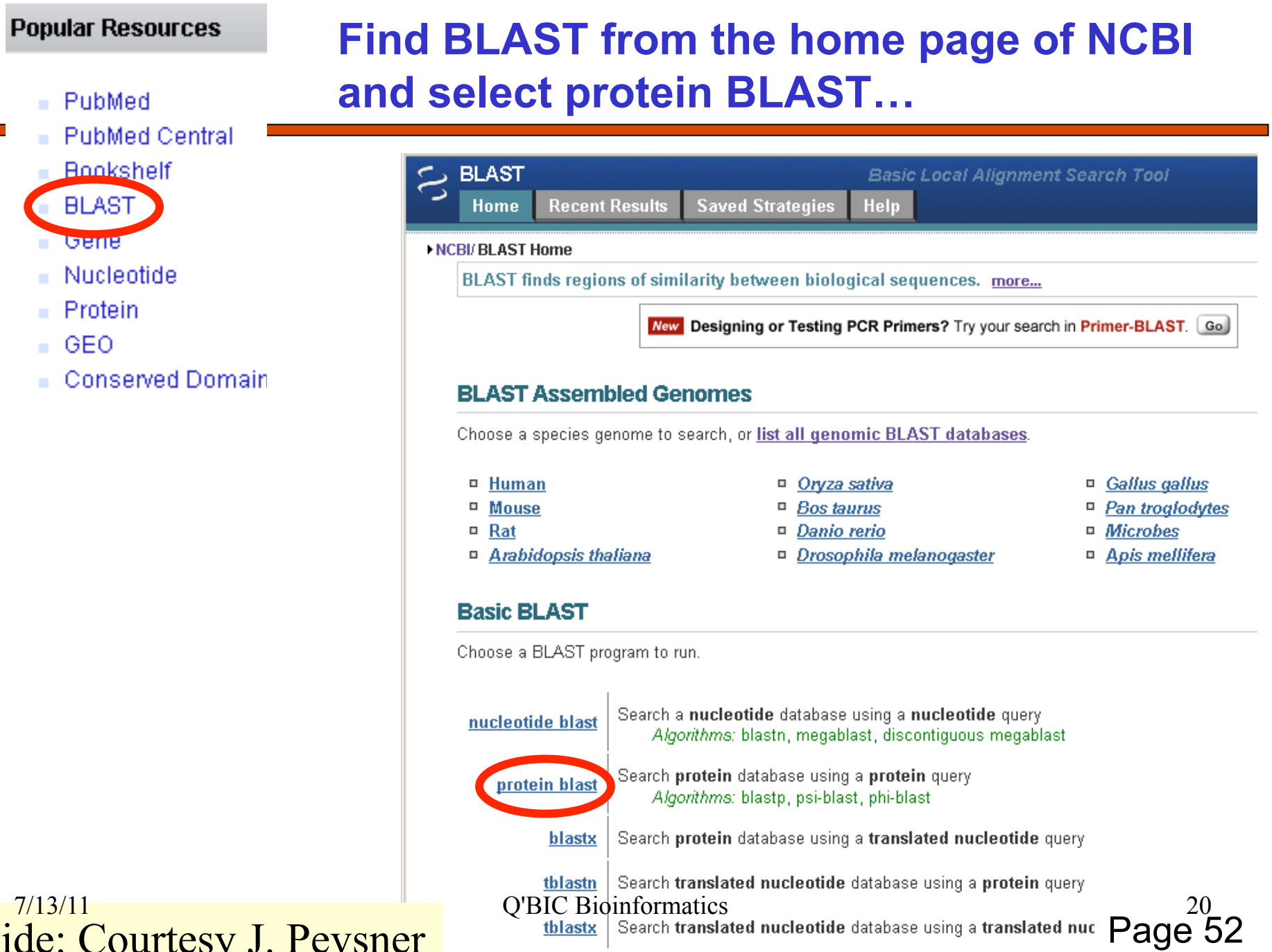
BLAST: Steps

- Choose your sequence
- Choose your tool
- Choose your database
- Select parameters, if needed
- Interpret your results

Find BLAST from the home page of NCBI and select protein BLAST…



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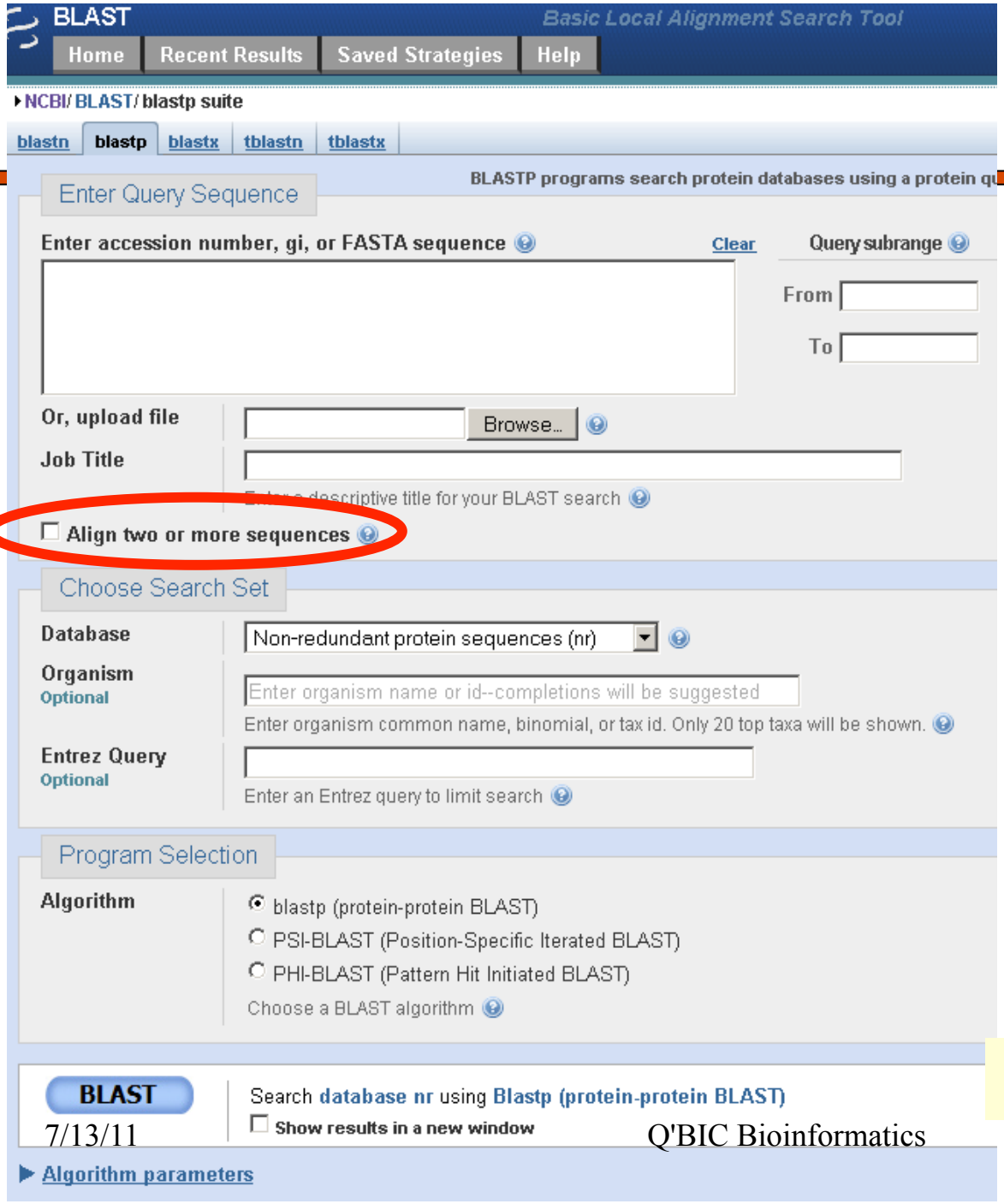

Choose align two or more sequences…

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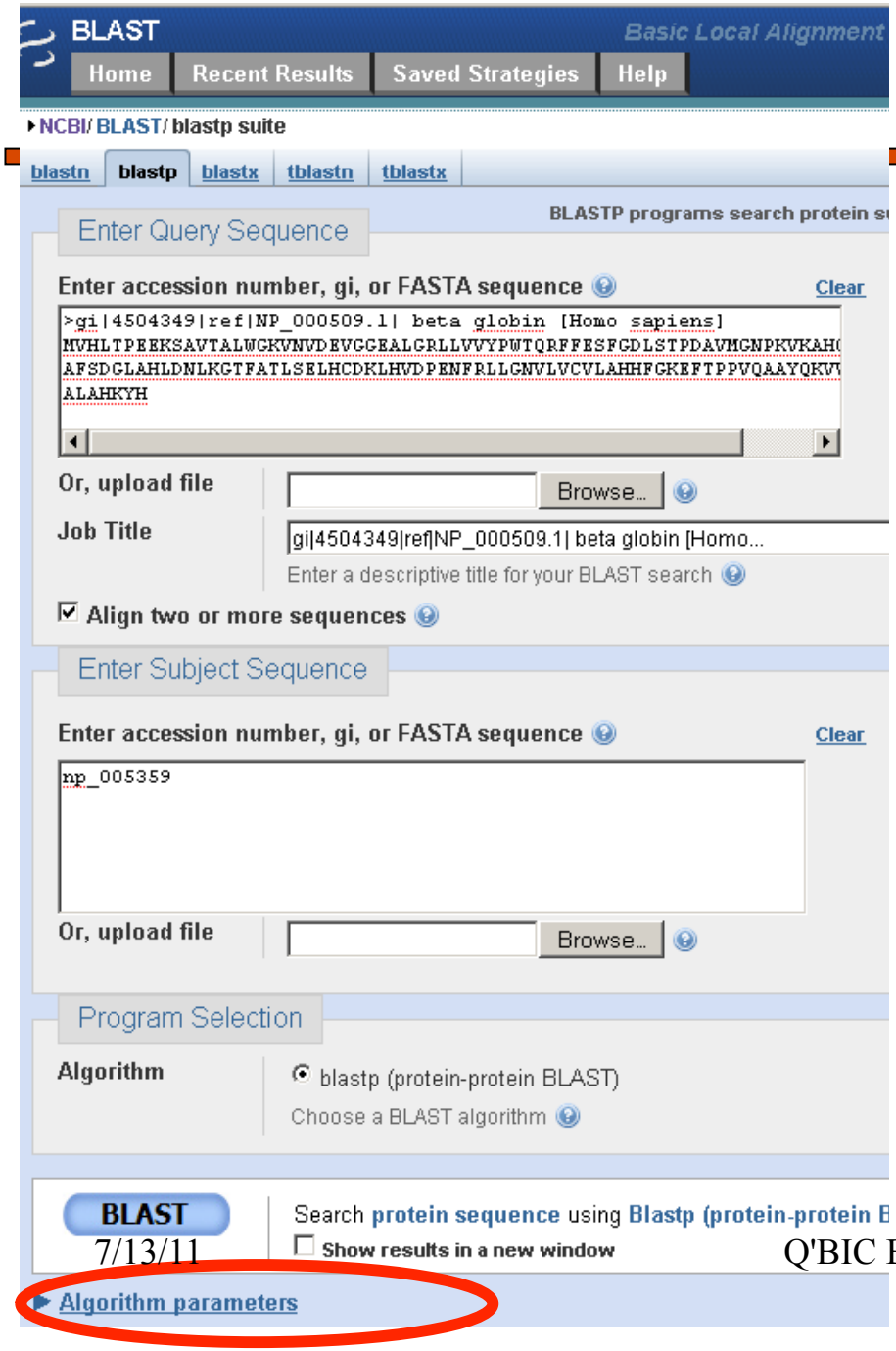
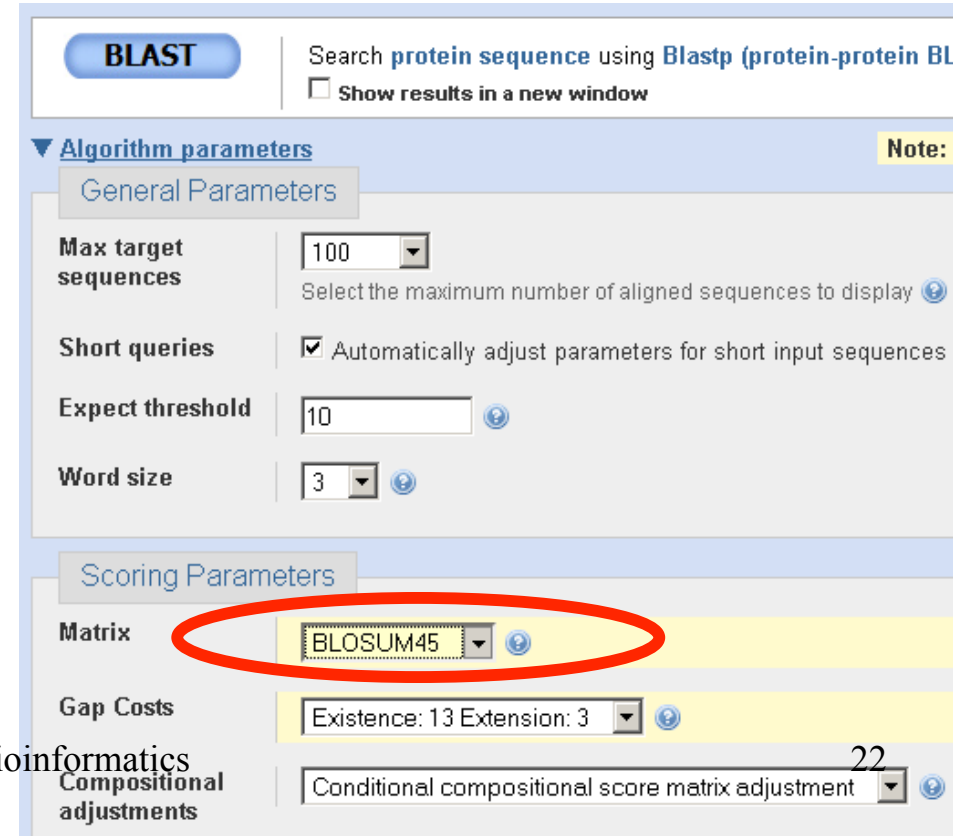
Enter the two sequences (as accession numbers or in the fasta format) and click BLAST.

Optionally select "Algorithm parameters" and note the matrix option.





Pairwise alignment result of human beta globin and myoglobin

Myoglobin RefSeq

Information about this alignment: score, expect value, identities, positives, gaps…

```
>ref|NP_005359.1|  G  myoglobin [Homo sapiens]
 ref|NP_976311.1|  UG  myoglobin [Homo sapiens]
 ref|NP_976312.1|  G  myoglobin [Homo sapiens]
 ▶11 more sequence titles
 Length=154

 GENE ID: 4151 MB | myoglobin [Homo sapiens] (Over 10 PubMed links)

 Score = 47.4 bits (144),  Expect = 8e-11, Method: Compositional matrix adjust.
 Identities = 37/145 (25%), Positives = 57/145 (39%), Gaps = 2/145 (1%)

Query  4    LTPEEKSAVTALWGKVNVDEVG--GEALGRLLVVYPWTQRFFESFGDLSTPDAVMGNPKV  61
            L+  E   V  +WGKV  D  G   E L RL   +P T   F+ F  L + D +  +  +
Sbjct  3    LSDGEWQLVLNVWGKVEADIPGHGQEVLIRLFKGHPETLEKFDKFKHLKSEDEMKASEDL  62

Query  62   KAHGKKVLGAFSDGLAHLDNLKGTFATLSELHCDKLHVDPENFRLLGNVLVCVLAHHFGK  121
            K HG  VL A    L    + +     L++ H  K  +  +    +   ++ VL
Sbjct  63   KKHGATVLTALGGILKKKGHHEAEIKPLAQSHATKHKIPVKYLEFISECIIQVLQSKHPG  122

Query  122  EFTPPVQAAYQKVVAGVANALAHKY  146
            +F    Q A  K +      +A  Y
Sbjct  123  DFGADAQGAMNKALELFRKDMASNY  147
```

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Query = HBB
Subject = MB

Middle row displays identities; + sign for similar matches

Pairwise alignment result of human beta globin and myoglobin: the score is a sum of match, mismatch, gap creation, and gap extension scores

```
 Score = 18.1 bits (35),  Expect = 0.015, Method: Composition-based stats.
 Identities = 11/24 (45%), Positives = 12/24 (50%), Gaps = 2/24 (8%)

Query  12  VTALWGKVNVD--EVGGEALGRLL  33
           V  +WGKV  D    G E L RL
Sbjct  11  VLNVWGKVEADIPGHGQEVLIRLF  34
```

match	4 11 5 6 4 6 6 5 4 5 4	sum of matches: +60
mismatch	-1 1 0 -2 -2 -4 0 -2 0 -3 0	sum of mismatches: -13
gap open	-11	sum of gap penalties: -12
gap extend	-1	
		total raw score: 60 - 13 - 12 = 35

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Pairwise alignment result of human beta globin and myoglobin: the score is a sum of match, mismatch, gap creation, and gap extension scores

```
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Query  12  VTALWGKVNVD--EVGGEALGRLL  33
           V  +WGKV  D    G E L RL
Sbjct  11  VLNVWGKVEADIPGHGQEVLIRLF  34
```

match	4 11 5 6 6 5 4 5 / 6 4 / 4	sum of matches: +60
mismatch	-1 1 0 -2 -2 -4 0 / -2 0 -3 0	sum of mismatches: -13
gap open	-11	sum of gap penalties: -12
gap extend	-1	
		total raw score: 60 - 13 - 12 = 35

V matching V earns +4
T matching L earns -1

These scores come from a "scoring matrix"!

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Multiple Alignments

- Global
  - ClustalW, ClustalX
  - MSA
  - T-Coffee
- Local
  - BLOCKS
  - eMOTIF
  - GIBBS
  - HMMER
  - MACAW
  - MEME
- Other
  - Profile Analysis from msa (UCSD)
  - SAM HMM (from msa)

MSA of glyceraldehyde 3-phosphate dehydrogenases: example of high conservation

```
fly        GAKKVIISAP SAD.APM..F VCGVNLDAYK PDMKVVSNAS CTTNCLAPLA
human      GAKRVIISAP SAD.APM..F VMGVNHEKYD NSLKIISNAS CTTNCLAPLA
plant      GAKKVIISAP SAD.APM..F VVGVNEHTYQ PNMDIVSNAS CTTNCLAPLA
bacterium  GAKKVVMTGP SKDNTPM..F VKGANFDKY. AGQDIVSNAS CTTNCLAPLA
yeast      GAKKVVITAP SS.TAPM..F VMGVNEEKYT SDLKIVSNAS CTTNCLAPLA
archaeon   GADKVLISAP PKGDEPVKQL VYGVNHDEYD GE.DVVSNAS CTTNSITPVA

fly        KVINDNFEIV EGLMTTVHAT TATQKTVDGP SGKLWRDGRG AAQNIIPAST
human      KVIHDNFGIV EGLMTTVHAI TATQKTVDGP SGKLWRDGRG ALQNIIPAST
plant      KVVHEEFGIL EGLMTTVHAT TATQKTVDGP SMKDWRGGRG ASQNIIPSST
bacterium  KVINDNFGII EGLMTTVHAT TATQKTVDGP SHKDWRGGRG ASQNIIPSST
yeast      KVINDAFGIE EGLMTTVHSL TATQKTVDGP SHKDWRGGRT ASGNIIPSST
archaeon   KVLDEEFGIN AGQLTTVHAY TGSQNLMDGP NGKP.RRRRA AAENIIPTST

fly        GAAKAVGKVI PALNGKLTGM AFRVPTPNVS VVDLTVRLGK GASYDEIKAK
human      GAAKAVGKVI PELNGKLTGM AFRVPTANVS VVDLTCRLEK PAKYDDIKKV
plant      GAAKAVGKVL PELNGKLTGM AFRVPTSNVS VVDLTCRLEK GASYEDVKAA
bacterium  GAAKAVGKVL PELNGKLTGM AFRVPTPNVS VVDLTVRLEK AATYEQIKAA
yeast      GAAKAVGKVL PELQGKLTGM AFRVPTVDVS VVDLTVKLNK ETTYDEIKKV
archaeon   GAAQAATEVL PELEGKLDGM AIRVPVPNGS ITEFVVDLDD DVTESDVNAA
```


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Multiple Alignments: CLUSTALW

* identical

: conserved substitutions

. semi-conserved substitutions

```
gi|2213819          CDN-ELKSEAIIEHLCASEFALR-------------MKIKEVKKENGDKK 223
gi|12656123         ----ELKSEAIIEHLCASEFALR-------------MKIKEVKKENGD-   31
gi|7512442          CKNKNDDDNDIMETLCKNDFALK-------------IKVKEITYINRDTK 211
gi|1344282          QDECKFDYVEVYETSSSGAFSLLGRFCGAEPPPHLVSSHHELAVLFRTDH 400
                       : .   : *  . . *:*               . :*:
```

Red: AVFPMLW (Small & hydrophobic)

Blue: DE (Acidic)

Magenta: RHK (Basic)

Green: STYHCNGQ (Hydroxyl, Amine, Basic)

Gray: Others

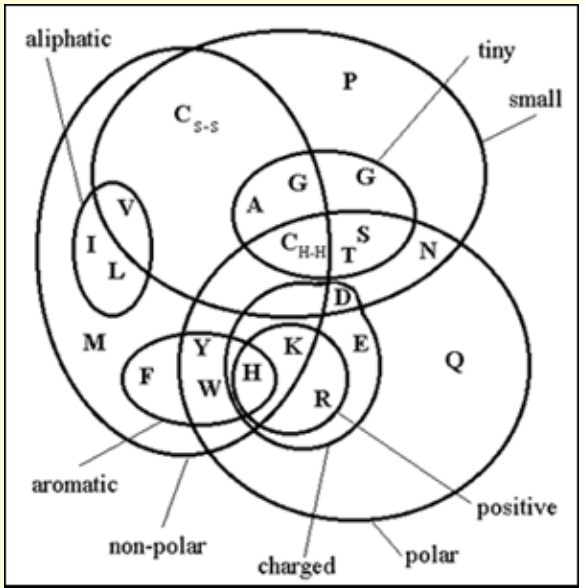


Figure 1. A Venn diagram showing the relationship of the 20 naturally occurring amino acids to a selection of physio-chemical properties thought to be important in the determination of protein structure.

Multiple Alignments

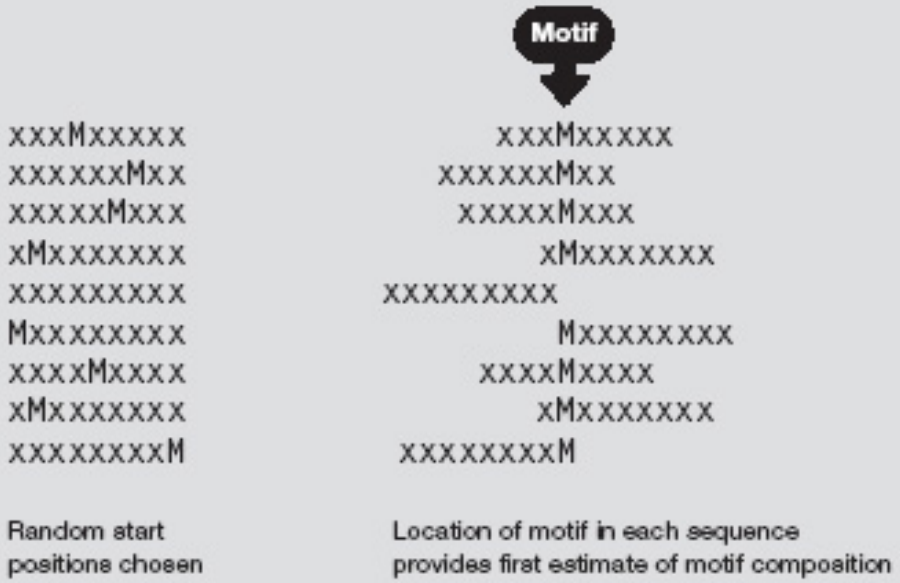
- Family alignment for the ITAM domain (Immunoreceptor tyrosine-based activation motif)

```
CD3D_MOUSE/1-2   EQLYQPLRDR EDTQ-YSRLG GN
Q90768/1-21      DQLYQPLGER NDGQ-YSQLA TA
CD3G_SHEEP/1-2   DQLYQPLKER EDDQ-YSHLR KK
P79951/1-21      NDLYQPLGQR SEDT-YSHLN SR
FCEG_CAVPO/1-2   DGIYTGLSTR NQET-YETLK HE
CD3Z_HUMAN/3-0   DGLYQGLSTA TKDT-YDALH MQ
C79A_BOVIN/1-2   ENLYEGLNLD DCSM-YEDIS RG
C79B_MOUSE/1-2   DHTYEGLNID QTAT-YEDIV TL
CD3H_MOUSE/1-2   NQLYNELNLG RREE-YDVLE KK
CD3Z_SHEEP/1-2   NPVYNELNVG RREE-YAVLD RR
CD3E_HUMAN/1-2   NPDYEPIRKG QRDL-YSGLN QR
CD3H_MOUSE/2-0   EGVYNALQKD KMAEAYSEIG TK
Consensus/60%    -.lYpsLspc pcsp.YspLs pp
```

Simple Modular Architecture Research Tool

Multiple Alignment

A. Estimate the amino acid frequencies in the motif columns of all but one sequence. Also obtain background.



How to Score Multiple Alignments?

- Sum of Pairs Score (SP)
  - Optimal alignment: $O(d^N)$ [Dynamic Prog]
  - Approximate Algorithm: Approx Ratio 2
    - Locate Center: $O(d^2N^2)$
    - Locate Consensus: $O(d^2N^2)$

Consensus char: char with min distance sum

Consensus string: string of consensus char

Center: input string with min distance sum

Multiple Alignment Methods

- Phylogenetic Tree Alignment (NP-Complete)
  - Given tree, task is to label leaves with strings
- Iterative Method(s)
  - Build a MST using the distance function
- Clustering Methods
  - Hierarchical Clustering
  - K-Means Clustering

Multiple Alignment Methods (Cont'd)

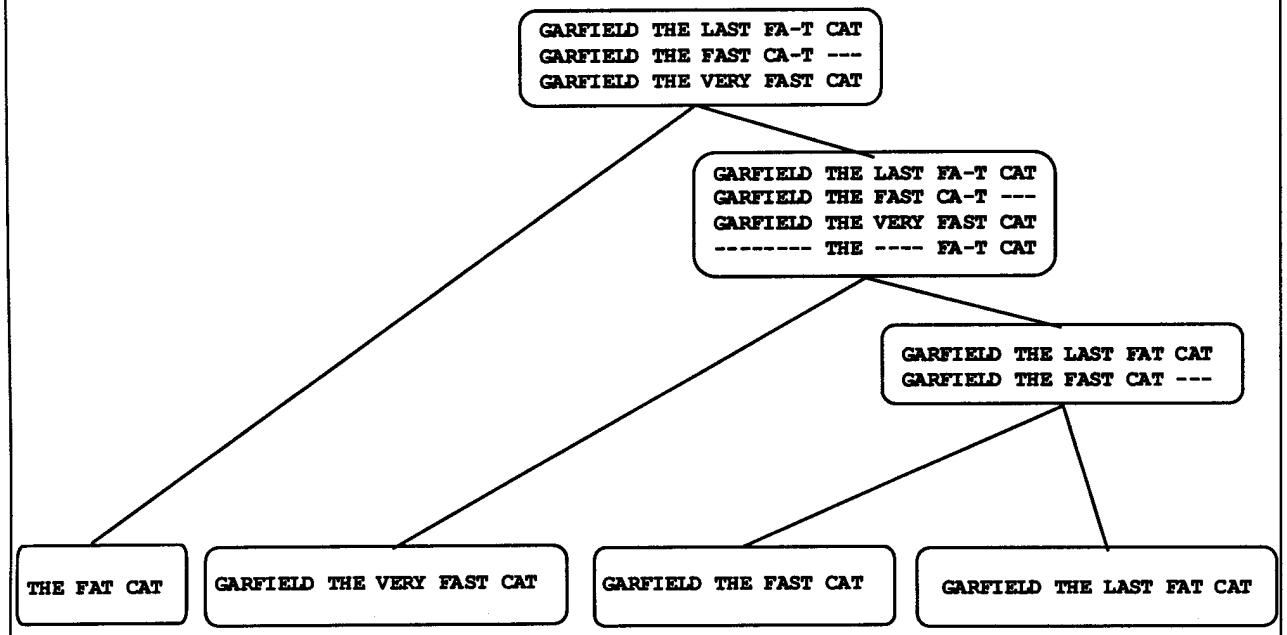
- Gibbs Sampling Method
  - Lawrence, Altschul, Boguski, Liu, Neuwald, Winton, *Science*, 1993
- Hidden Markov Model
  - Krogh, Brown, Mian, Sjolander, Haussler, *JMB*, 1994

Multiple Sequence Alignments (MSA)

- Choice of Scoring Function
  - Global vs local
  - Gap penalties
  - Substitution matrices
  - Incorporating other information
  - Statistical Significance
- Computational Issues
  - Exact/heuristic/approximate algorithms for optimal MSA
  - Progressive/Iterative/DP
  - Iterative: Stochastic/Non-stochastic/Consistency-based
- Evaluating MSAs
  - Choice of good test sets or benchmarks (BAliBASE)
  - How to decide thresholds for good/bad alignments

Progressive MSA: CLUSTALW

Figure 1. Limits of the progressive strategy.



This example shows how a progressive alignment strategy can be misled. In the initial alignment of sequences 1 and 2, ClustalW has a choice between aligning CAT with CAT and making an internal gap or making a mismatch between C and F and having a terminal gap. Since terminal gaps are much cheaper than internals, the ClustalW scoring schemes prefers the former. In the next stage, when the extra sequence is added, it turns out that properly aligning the two CATs in the previous stage would have led to a better scori ng sums-of-pairs multiple alignment.

C. Notredame, *Pharmacogenomics*, **3**(1), 2002.

Software for MSA

Table 1. Some recent and less recent available methods for MSAs.

Name	Algorithm	URL	Ref.
MSA	Exact	http://www.ibc.wustl.edu/ibc/msa.html	[28]
OMA	Iterative DCA	http://bibiserv.techfak.uni-biefield.de/oma	[61]
MultAlin	Progressive	http://www.toulouse.inra.fr/multalin.html	[41]
ComAlign	Consistency-based	http://www.daimi.au.df/~ ocaprani	[75]
Praline	Iterative/progressive	jhering@nimr.mrc.ac.uk	[48]
Prrp	Iterative/Stochastic	ftp://ftp.genome.ad.jp/pub/genome/saitama-cc/	[47]
HMMER	Iterative/Stochastic/HMM	http://hmmer.wustl.edu/	[68]
GA	Iterative/Stochastic/GA	czhang@watnow.uwaterloo.ca	[52]

C. Notredame, *Pharmacogenomics*, **3**(1), 2002.

MSA: Conclusions

- Very important
  - Phylogenetic analyses
  - Identify members of a family
  - Protein structure prediction
- No perfect methods
- Popular
  - Progressive methods: CLUSTALW
  - Recent interesting ones: Prrp, SAGA, DiAlign, T-Coffee
- Review of Methods [C. Notredame, *Pharmacogenomics*, **3**(1), 2002]
  - CLUSTALW works reasonably well, in general
  - DiAlign is better for sequences with long insertions & deletions (indels)
  - T-Coffee is best available method

CpG Islands

- Regions in DNA sequences with increased occurrences of substring "*CG*"
- Rare: typically *C* gets methylated and then mutated into a T.
- Often around promoter or "start" regions of genes
- Few hundred to a few thousand bases long

Problem 1:

- Input: Small sequence S
- Output: Is S from a CpG island?
  - Build Markov models: M+ and M —
  - Then compare

Markov Models

+	A	C	G	T
A	0.180	0.274	0.426	0.120
C	0.171	0.368	0.274	0.188
G	0.161	0.339	0.375	0.125
T	0.079	0.355	0.384	0.182

–	A	C	G	T
A	0.300	0.205	0.285	0.210
C	0.322	0.298	0.078	0.302
G	0.248	0.246	0.298	0.208
T	0.177	0.239	0.292	0.292

How to distinguish?

- Compute

$$S(x) = \log\left(\frac{P(x \mid M+)}{P(x \mid M-)}\right) = \sum_{i=1}^{L} \log\left(\frac{p_{x(i-1)xi}}{m_{x(i-1)xi}}\right) = \sum_{i=1}^{L} r_{x(i-1)xi}$$

r=p/m	A	C	G	T
A	-0.740	0.419	0.580	-0.803
C	-0.913	0.302	1.812	-0.685
G	-0.624	0.461	0.331	-0.730
T	-1.169	0.573	0.393	-0.679

Score(GCAC)
= .461-.913+.419
< 0.
GCAC not from CpG island.

Score(GCTC)
= .461-.685+.573
> 0.
GCTC from CpG island.

Problem 1:

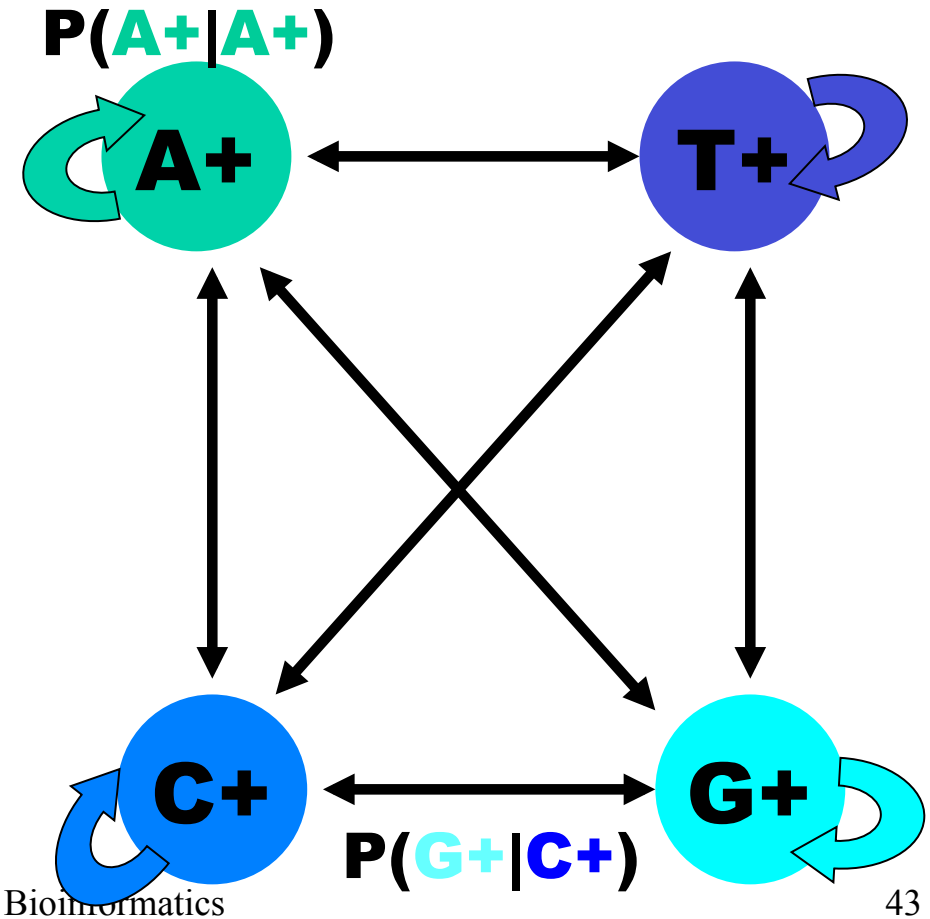
- Input: Small sequence S
- Output: Is S from a CpG island?
  - Build Markov Models: M+ & M-
  - Then compare

Problem 2:

- Input: Long sequence S
- Output: Identify the CpG islands in S.
  - Markov models are inadequate.
  - Need Hidden Markov Models.

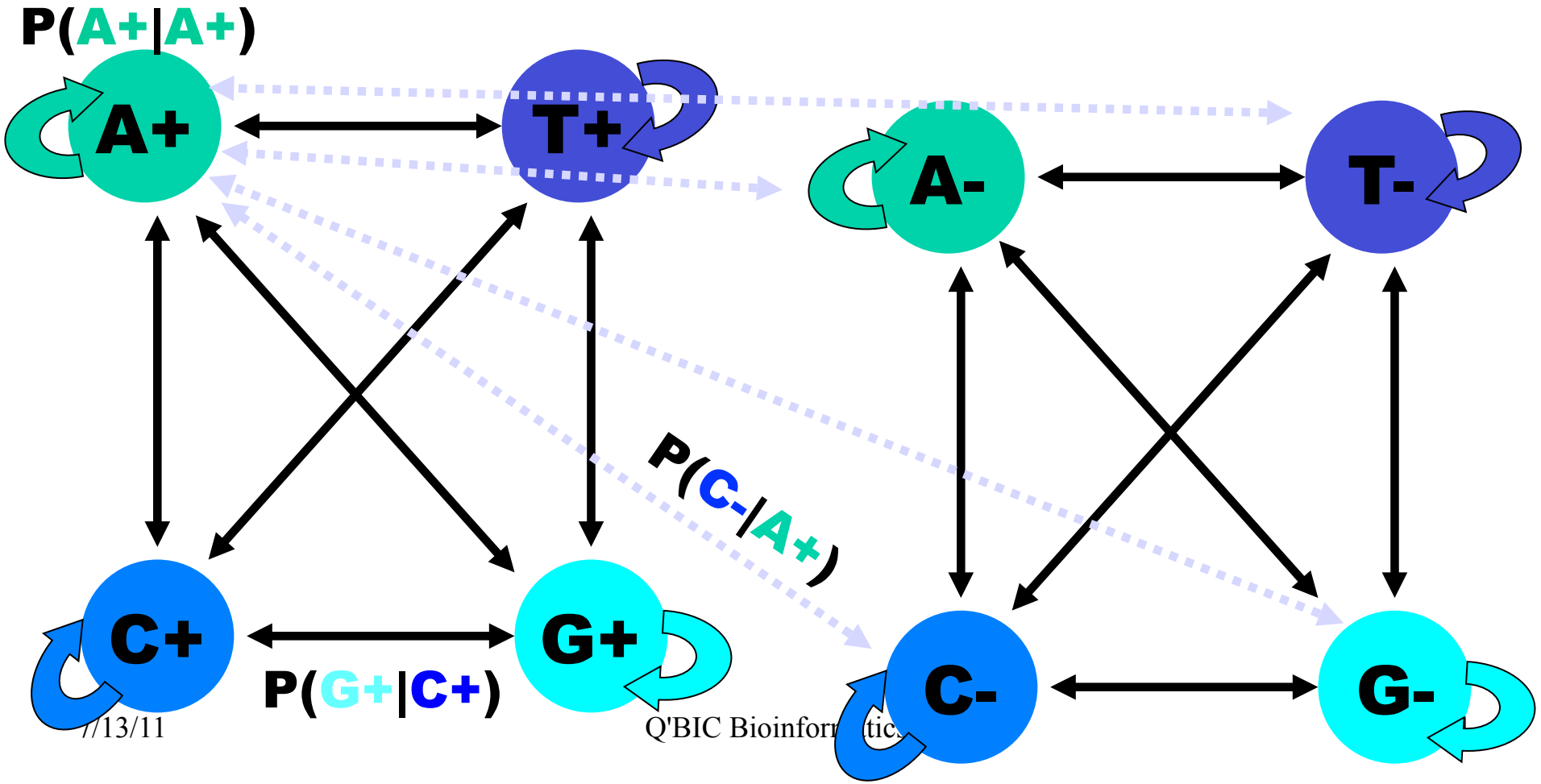
Markov Models

+	A	C	G	T
A	0.180	0.274	0.426	0.120
C	0.171	0.368	0.274	0.188
G	0.161	0.339	0.375	0.125
T	0.079	0.355	0.384	0.182



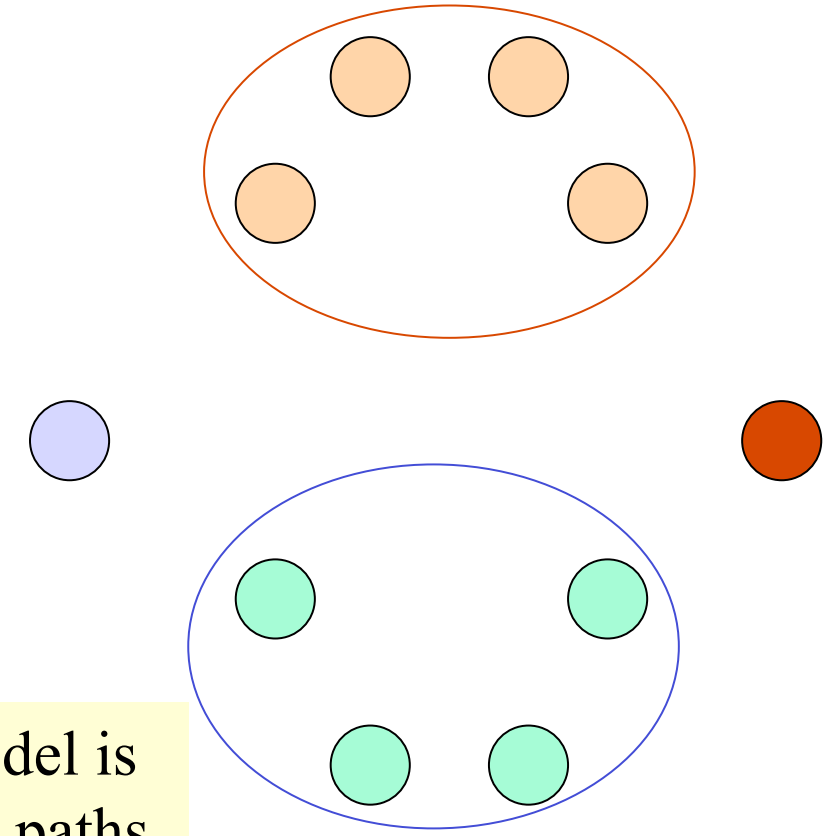
CpG Island + in an ocean of –
First order Hidden Markov Model

MM=16, HMM= 64 transition probabilities (adjacent bp)



Hidden Markov Model (HMM)

- States
- Transitions
- Transition Probabilities
- Emissions
- Emission Probabilities



- What is hidden about HMMs?

Answer: The path through the model is hidden since there are many valid paths.

How to Solve Problem 2?

- Solve the following problem:

Input: Hidden Markov Model M,
parameters Θ, emitted sequence S

Output: Most Probable Path Π

How: Viterbi's Algorithm (Dynamic Programming)

Define Π[i,j] = MPP for first j characters of S ending in state i

Define P[i,j] = Probability of Π[i,j]

- **Compute state i with largest P[i,j].**

Profile Method

PROFILE METHOD, [M. Gribskov et al., '90]

Location in Seq.	Sequence 1	2	3	4	5	6	7	Protein Name
14	G	V	S	A	S	A	V	Ka RbtR
32	G	V	S	E	M	T	I	Ec DeoR
33	G	V	S	P	G	T	I	Ec RpoD
76	G	A	G	I	A	T	I	Ec TrpR
178	G	C	S	R	E	T	V	Ec CAP
205	C	L	S	P	S	R	L	Ec AraC
210	C	L	S	P	S	R	L	St AraC
13	G	V	N	K	E	T	I	Br MerR

FREQUENCY TABLE

	A	C	D	E	F	G	H	I	K	L	M	N	P	Q	R	S	T	V	W	Y
1	0	2	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	4	0	0
3	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	6	0	0	0	0
4	1	0	0	1	0	0	0	1	1	0	0	0	3	0	1	0	0	0	0	0
5	1	0	0	2	0	1	0	0	0	0	1	0	0	0	0	3	0	0	0	0
6	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	5	0	0	0
7	0	0	0	0	0	0	0	4	0	2	0	0	0	0	0	0	0	2	0	0

7

Profile Method

FREQUENCY TABLE

	A	C	D	E	F	G	H	I	K	L	M	N	P	Q	R	S	T	V	W	Y
1	0	2	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	4	0	0
3	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	6	0	0	0	0
4	1	0	0	1	0	0	0	1	1	0	0	0	3	0	1	0	0	0	0	0
5	1	0	0	2	0	1	0	0	0	0	1	0	0	0	0	3	0	0	0	0
6	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	5	0	0	0
7	0	0	0	0	0	0	0	4	0	2	0	0	0	0	0	0	0	2	0	0

WEIGHT MATRIX

	A	C	E	G	I	K	L	M	N	P	R	S
1	0	108	0	101	0	0	0	0	0	0	0	0
2	21	78	0	0	0	0	44	0	0	0	0	0
3	0	0	0	23	0	0	0	0	46	0	0	102
4	21	0	32	0	38	32	0	0	0	86	39	0
5	21	0	62	23	0	0	0	74	0	0	0	72
6	21	0	0	0	0	0	0	0	0	0	69	0
7	0	0	0	0	98	0	44	0	0	0	0	0

$$Weight[i, AA] = \log\left(\frac{Freq[i,AA]}{p[AA] \cdot N}\right) \cdot 100$$

8

Profile Method

WEIGHT MATRIX

	A	C	E	G	I	K	L	M	N	P	R	S
1	0	108	0	101	0	0	0	0	0	0	0	0
2	21	78	0	0	0	0	44	0	0	0	0	0
3	0	0	0	23	0	0	0	0	46	0	0	102
4	21	0	32	0	38	32	0	0	0	86	39	0
5	21	0	62	23	0	0	0	74	0	0	0	72
6	21	0	0	0	0	0	0	0	0	0	69	0
7	0	0	0	0	98	0	44	0	0	0	0	0

Given the following protein sequence:

M T E D L F G D L Q D D T I L A H L D N
P A E D T S R F P A L L A E L N D L L R
G E L S R L G V D P A H S L E I V V A I
C K H L G G G Q V Y I P R G Q A L D S L
I R D L R I W N D F N G R N V S E L T T
R Y G V T F N T V Y K A I R R M R R L K

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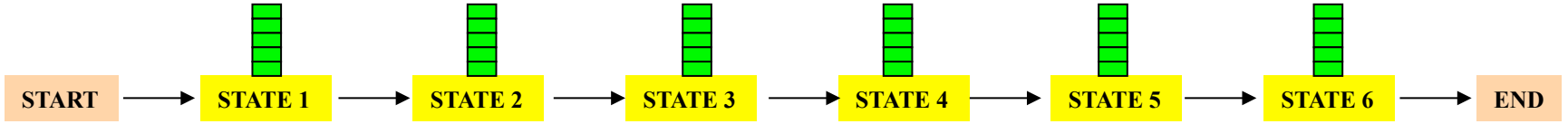
Profile HMMs

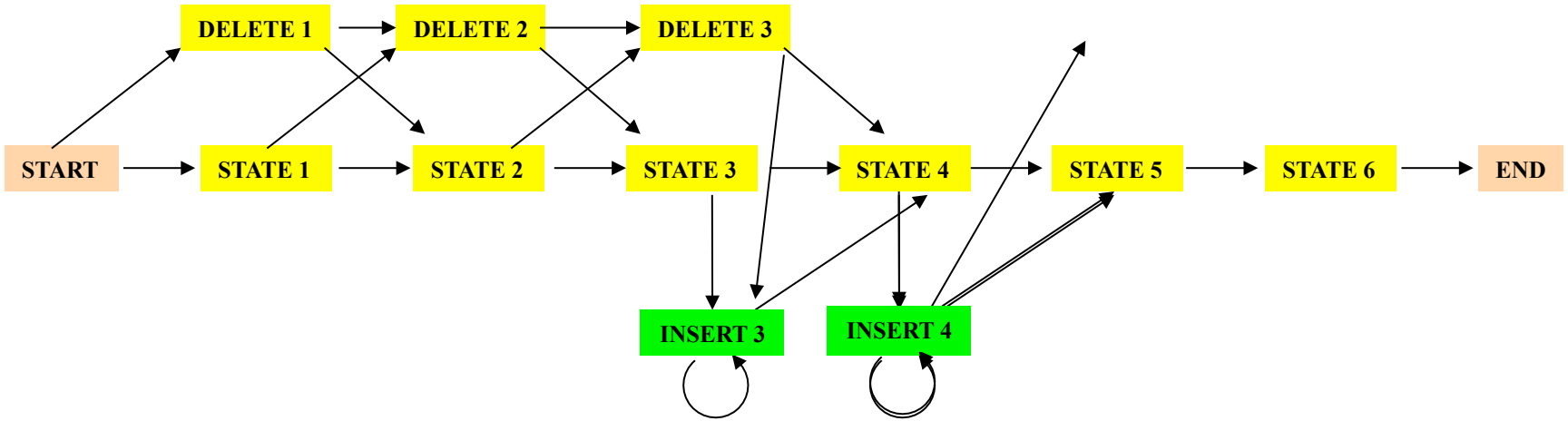
PROFILE METHOD, [M. Gribskov et al., '90]

Location in Seq.	Sequence 1 2 3 4 5 6	Protein Name
14	G V S A S A	Ka RbtR
32	G V S E M T	Ec DeoR
33	G V S P G T	Ec RpoD
76	G A G I A T	Ec TrpR
178	G C S R E T	Ec CAP
205	C L S P S R	Ec AraC
210	C L S P S R	St AraC
13	G V N K E T	Br MerR

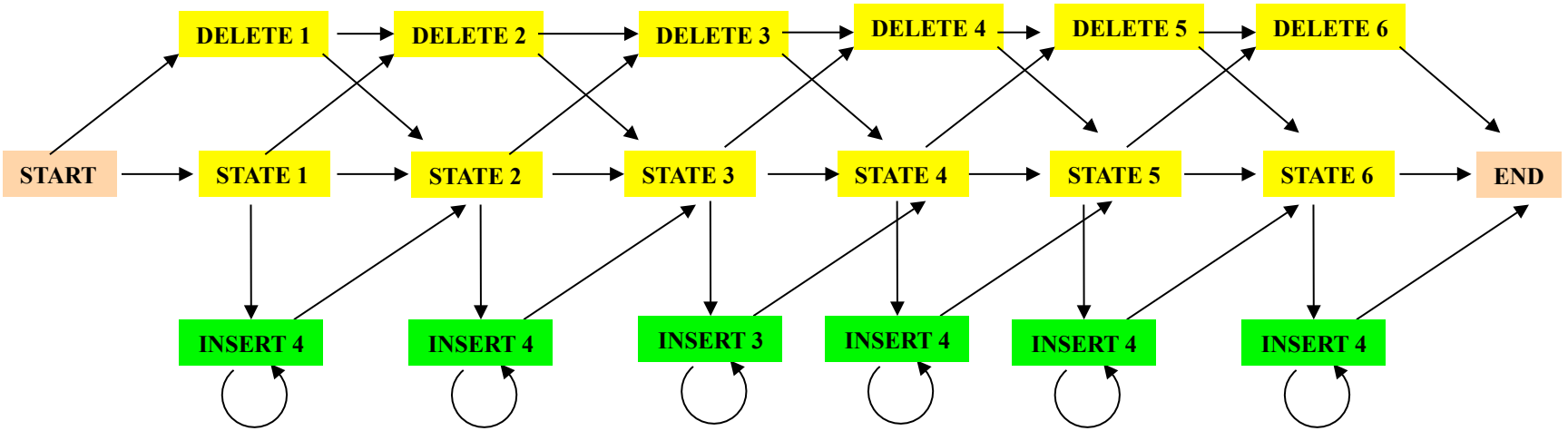


Profile HMMs with InDels

- Insertions
- Deletions
- Insertions & Deletions



Profile HMMs with InDels

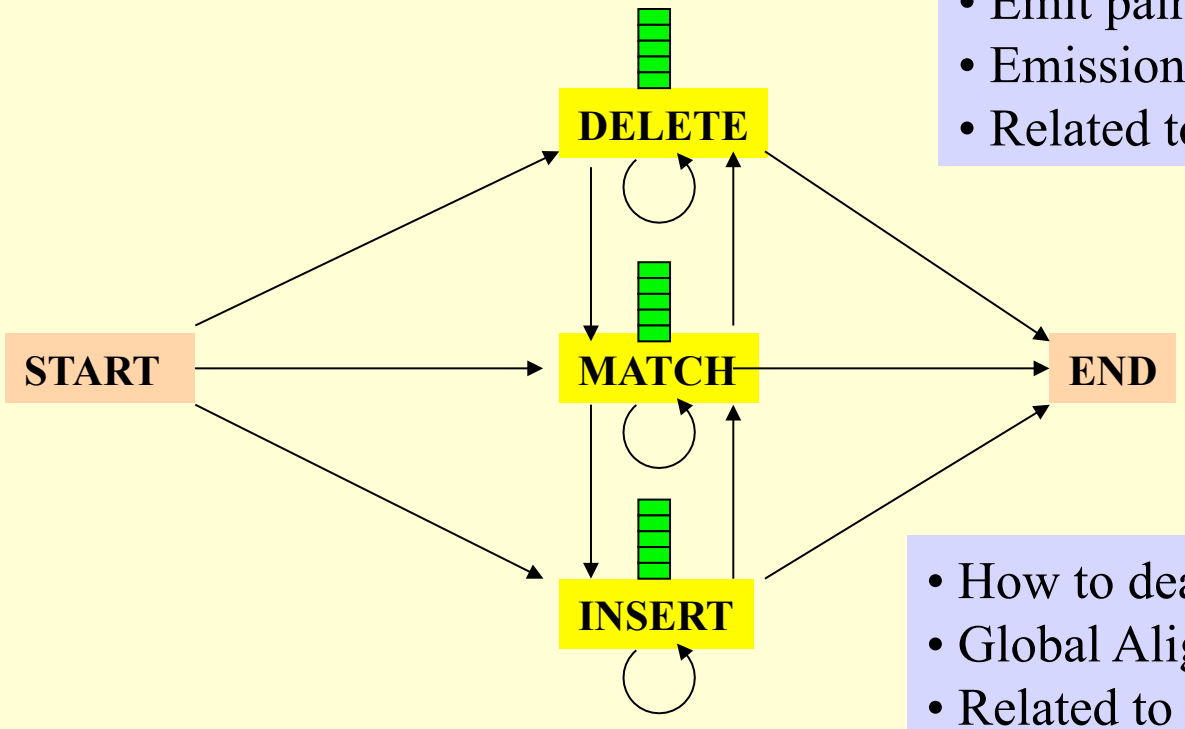


Missing transitions from DELETE j to INSERT j and from INSERT j to DELETE j+1.

How to model Pairwise Sequence Alignment

LEAPVE

LAPVIE

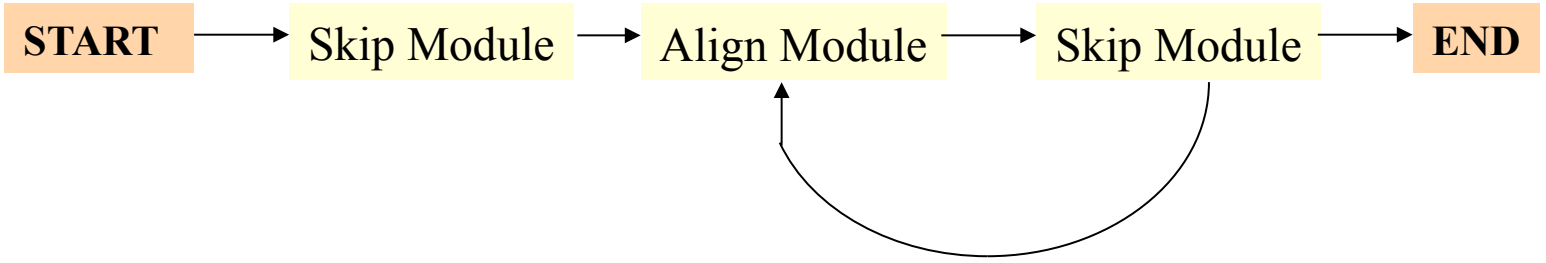


Pair HMMs
- Emit pairs of synbols
- Emission probs?
- Related to Sub. Matrices

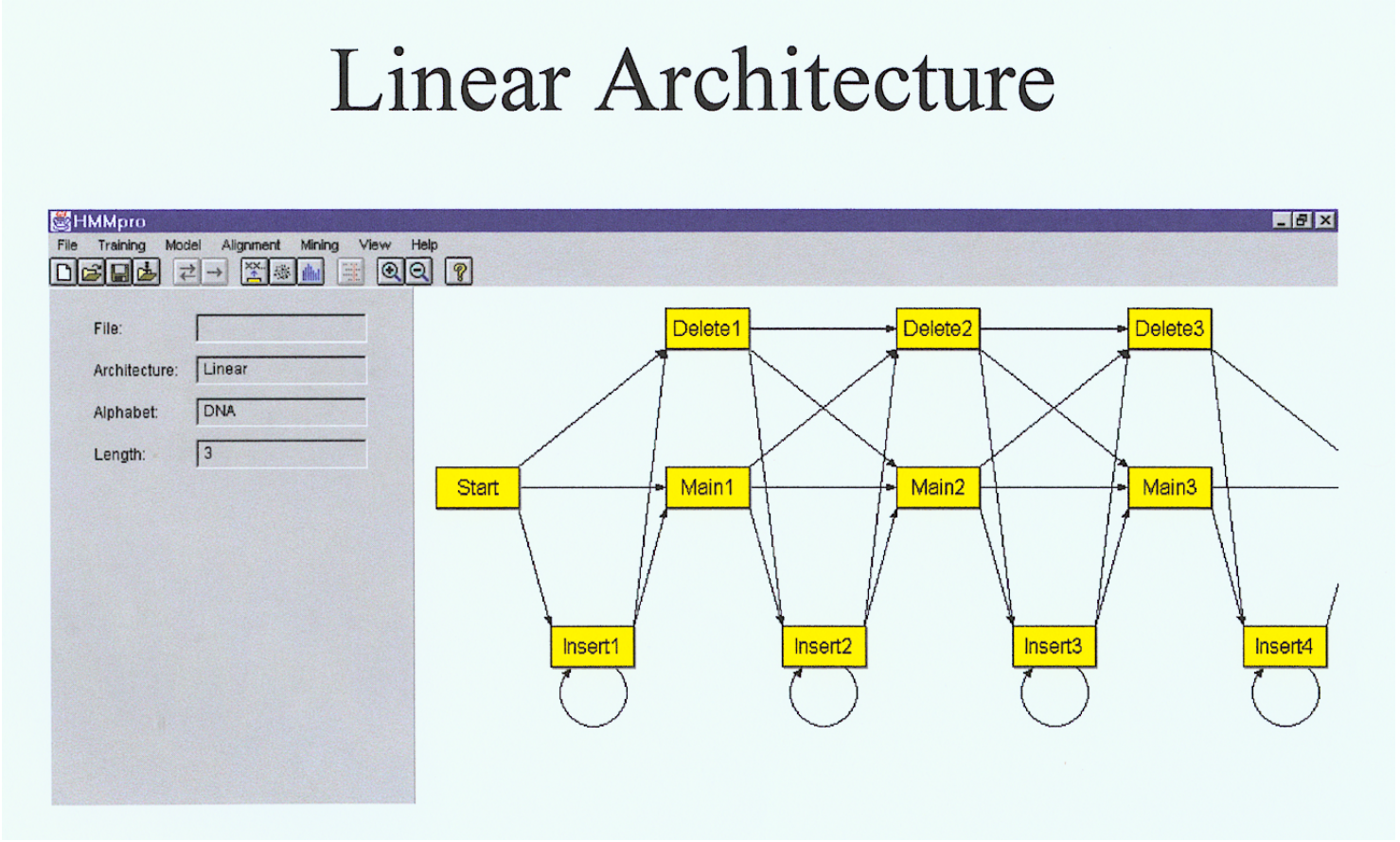
- How to deal with InDels?
- Global Alignment? Local?
- Related to Sub. Matrices

How to model Pairwise Local Alignments?

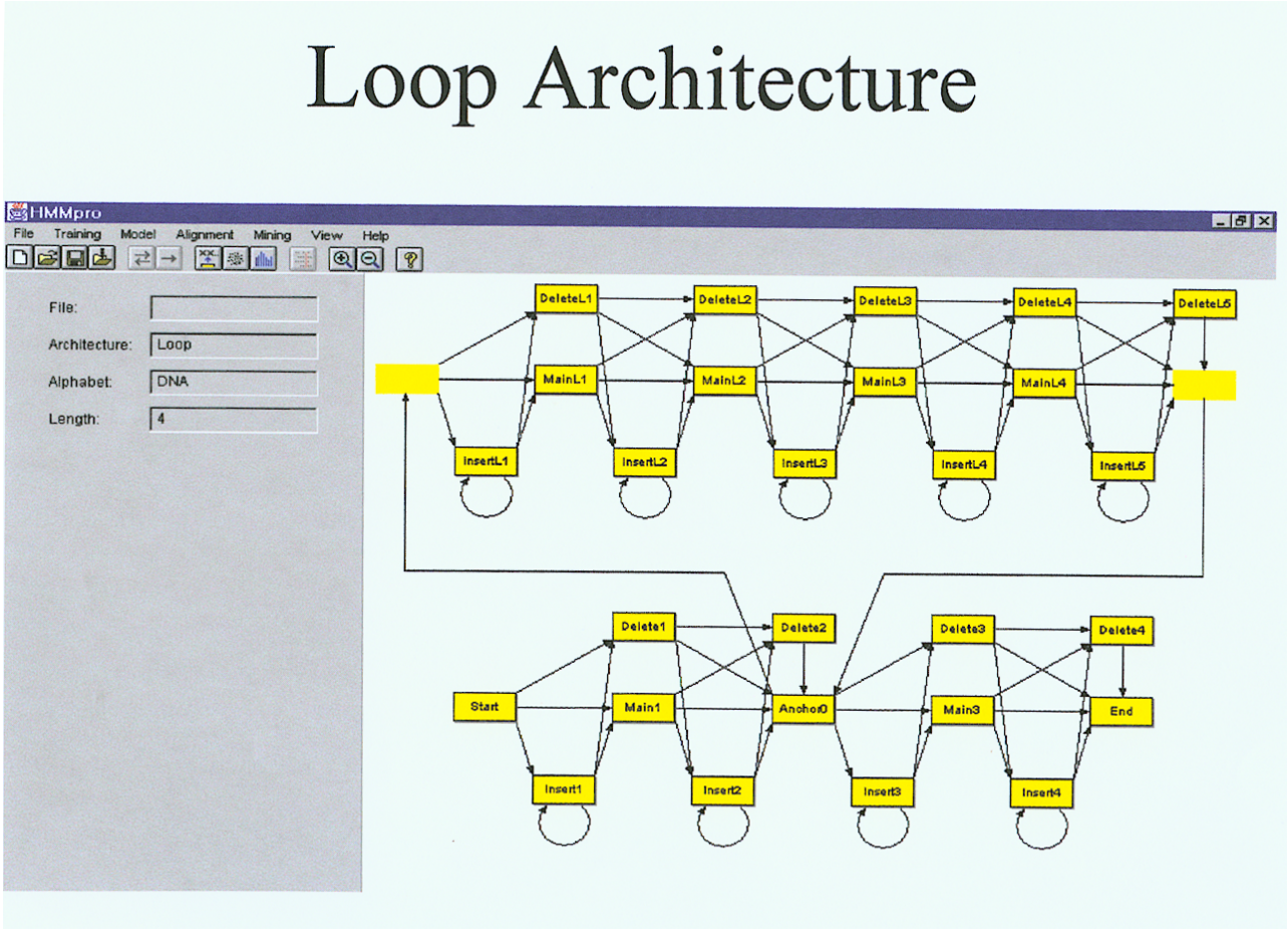
How to model Pairwise Local Alignments with gaps?



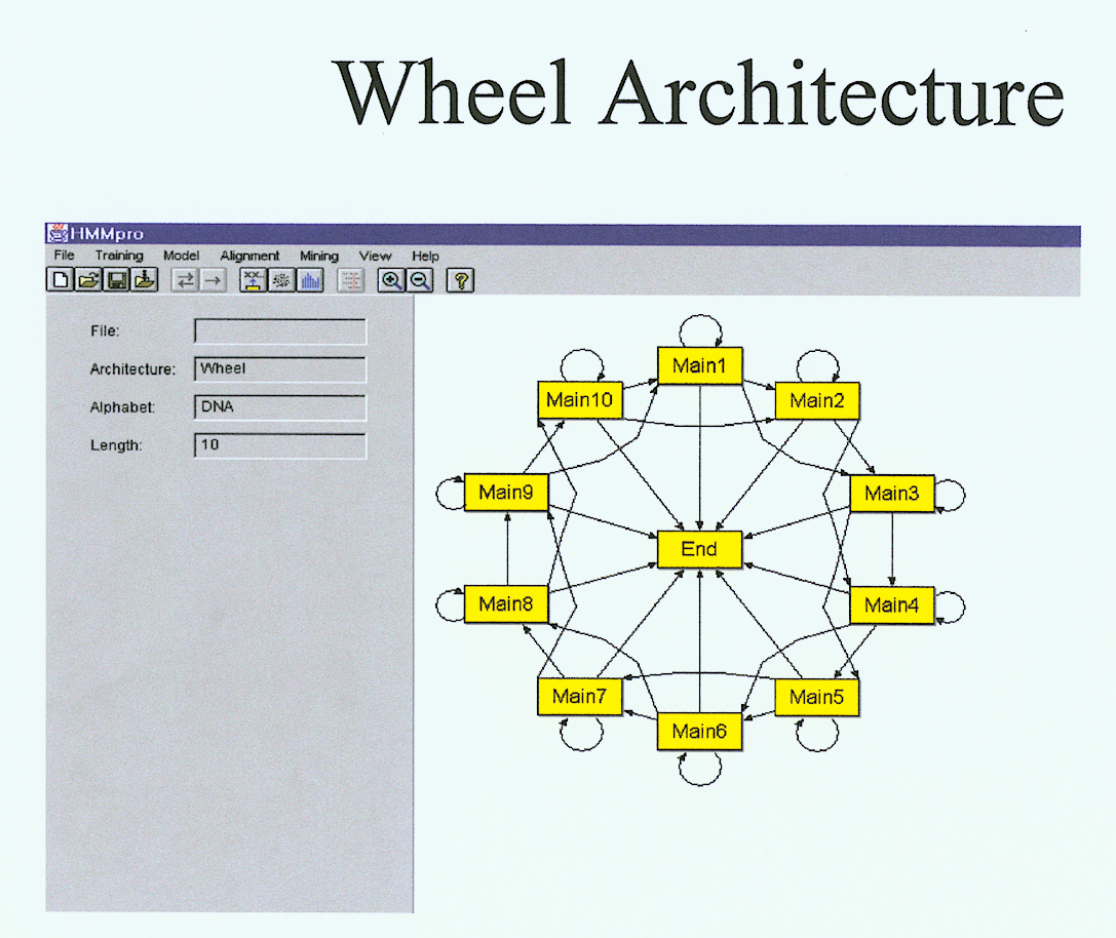
Standard HMM architectures



Standard HMM architectures



Standard HMM architectures



Profile HMMs from Multiple Alignments

```
HBA_HUMAN    VGA--HAGEY
HBB_HUMAN    V----NVDEV
MYG_PHYCA    VEA--DVAGH
GLB3_CHITP   VKG------D
GLB5_PETMA   VYS--TYETS
LGB2_LUPLU   FNA--NIPKH
GLB1_GLYDI   IAGADNGAGV
```

Construct Profile HMM from above multiple alignment.

HMM for Sequence Alignment

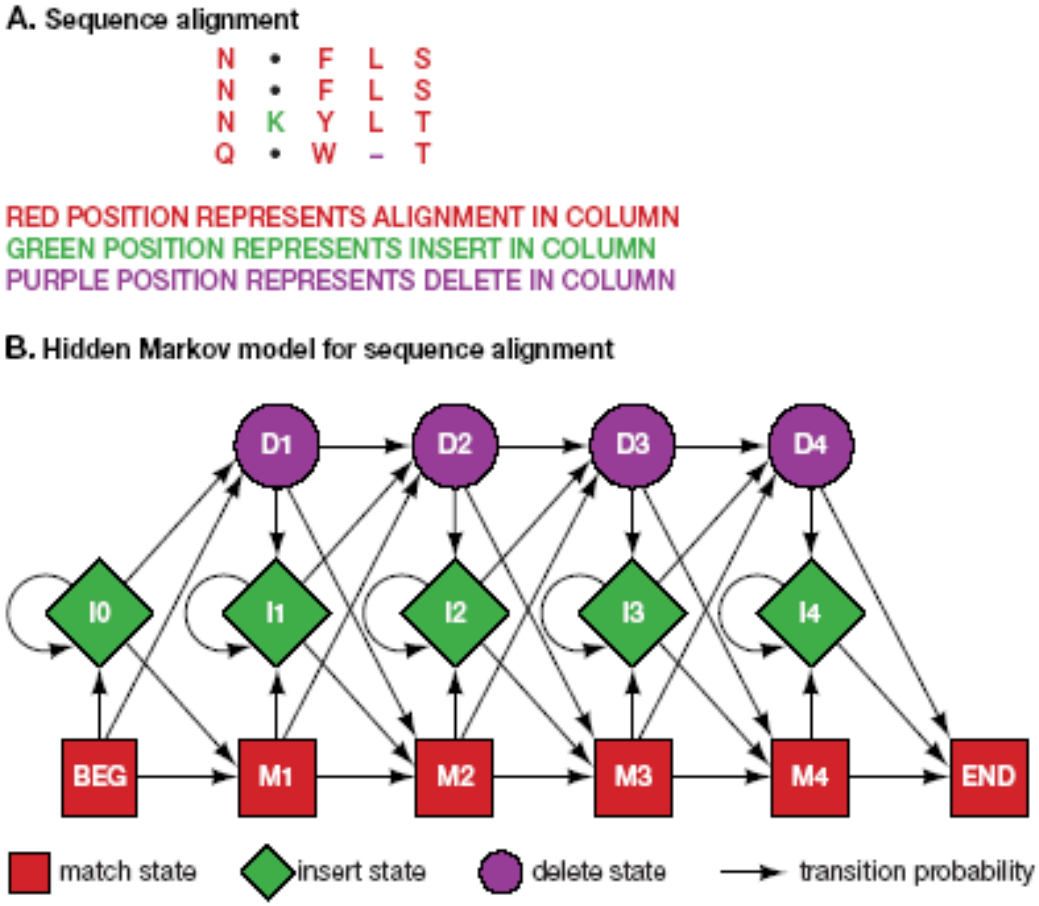


FIGURE 5.16. Relationship between the sequence alignment and the hidden Markov model of the alignment (Krogh et al. 1994). This particular form for the HMM was chosen to represent the sequence, structural, and functional variation expected in proteins. The model accommodates the identities, mismatches, insertions, and deletions expected in a group of related proteins. (*A*) A section of an msa. The illustration shows the columns generated in an msa. Each column may include matches and mismatches (*red* positions), insertions (*green* positions), and deletions (*purple* positions). (*B*) The HMM. Each column in the model represents the possibility of a match, insert, or delete in each column of the alignment in *A*. The HMM is a probabilistic representation of a section of the msa. Sequences can be generated from the HMM by starting at the beginning state labeled BEG and then by following any one of many pathways from one type of sequence variation to another (states) along the state transition arrows and terminating in the ending state labeled END. Any sequence can be generated by the model and each pathway has a probability associated with it. Each square match state stores an amino acid distribution such that the probability of finding an amino acid depends on

Problem 3: LIKELIHOOD QUESTION

- Input: Sequence S, model M, state i
- Output: Compute the probability of reaching state i with sequence S using model M
  - Backward Algorithm (DP)

Problem 4: LIKELIHOOD QUESTION

- Input: Sequence S, model M
- Output: Compute the probability that S was emitted by model M
  - Forward Algorithm (DP)

Problem 5: LEARNING QUESTION

- Input: model structure M, Training Sequence S
- Output: Compute the parameters Θ
- Criteria: ML criterion
    - maximize $P(S \mid M, \Theta)$ HOW???

Problem 6: DESIGN QUESTION

- Input: Training Sequence S
- Output: Choose model structure M, and compute the parameters Θ
    - No reasonable solution
    - Standard models to pick from

Iterative Solution to the LEARNING QUESTION (Problem 5)

- Pick initial values for parameters Θ_0
- Repeat

  Run training set *S* on model M

  Count # of times transition i ⇒ j is made

  Count # of times letter x is emitted from state i

  Update parameters Θ
- Until (some stopping condition)

Entropy

- Entropy measures the variability observed in given data.

$$E = -\sum_{c} p_c \log p_c$$

- Entropy is useful in multiple alignments & profiles.

- Entropy is max when uncertainty is max.