## Profile Method

**Profile Method, [M. Gribskov et al., '90]**

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### Frequency Table

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Profile Method

Frequency Table

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Weight Matrix

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\[ Weight[i,AA] = \log \left( \frac{Profile[i, AA]}{Profile[N, AA]} \right) \cdot 100 \]
Profile Method

**WEIGHT MATRIX**

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Given the following protein sequence:

MTEDLFGLQDDTLIALHLDN
PAEDTSPFPAALLAELNDLRL
GELSRGLVDPAHSLEIVVAI
CKHLGGGQVVYIPRGQALDSL
IRDLRWINDFNGRNVSZELTT
RYGVTFNTVYKAIRRRRRLK
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 scoring sums-of-pairs multiple alignment.

## Software for MSA

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<th>Type</th>
<th>Website</th>
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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

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How to distinguish?

- Compute

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

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Score($GCAC$)  
= $0.461 - 0.913 + 0.419$  
< 0.  
$GCAC$ not from CpG island.

Score($GCTC$)  
= $0.461 - 0.685 + 0.573$  
> 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

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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 \( \Theta \), emitted sequence \( S \)

**Output**: Most Probable Path \( \Pi \)

**How**: Viterbi’s Algorithm (Dynamic Programming)

Define \( \Pi[i,j] = \) MPP for first \( j \) characters of \( S \) ending in state \( i \)

Define \( P[i,j] = \) Probability of \( \Pi[i,j] \)

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

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

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

LEAPVE
LAPVIE
How to model Pairwise Local Alignments?

START → Skip Module → Align Module → Skip Module → END

How to model Pairwise Local Alignments with gaps?

START → Skip Module → Align Module → Skip Module → END
Standard HMM architectures

Linear Architecture
Standard HMM architectures

Loop Architecture
Standard HMM architectures

Wheel Architecture
Profile HMMs from Multiple Alignments

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<tr>
<th>Gene</th>
<th>Multiple Alignment</th>
</tr>
</thead>
<tbody>
<tr>
<td>HBA_HUMAN</td>
<td>VGA--HAGEY</td>
</tr>
<tr>
<td>HBB_HUMAN</td>
<td>V-----NVDEV</td>
</tr>
<tr>
<td>MYG_PHYCA</td>
<td>VEA--DVAGH</td>
</tr>
<tr>
<td>GLB3_CHITP</td>
<td>VKG------D</td>
</tr>
<tr>
<td>GLB5_PETMA</td>
<td>VYS--TYETS</td>
</tr>
<tr>
<td>LGB2_LUPLU</td>
<td>FNA--NIPKH</td>
</tr>
<tr>
<td>GLB1_GLYDI</td>
<td>IAGADNGAGV</td>
</tr>
</tbody>
</table>

Construct Profile HMM from above multiple alignment.
HMM for Sequence Alignment

A. Sequence alignment

\[
\begin{array}{cccc}
N & F & L & S \\
N & F & L & S \\
N & K & Y & L \\
Q & W & T \\
\end{array}
\]

RED POSITION REPRESENTS ALIGNMENT IN COLUMN
GREEN POSITION REPRESENTS INSERT IN COLUMN
PURPLE POSITION REPRESENTS DELETE IN COLUMN

B. Hidden Markov model for sequence alignment

![Diagram of a Hidden Markov Model](image)

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
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 $\Theta$
- **Criteria:** ML criterion
  - maximize $P(S | M, \Theta)$  HOW???

Problem 6: DESIGN QUESTION

- **Input:** Training Sequence $S$
- **Output:** Choose model structure $M$, and compute the parameters $\Theta$
  - No reasonable solution
  - Standard models to pick from
Iterative Solution to the LEARNING QUESTION (Problem 5)

• Pick initial values for parameters $\Theta_0$

• **Repeat**
  
  Run training set $S$ on model $M$
  
  Count # of times transition $i \Rightarrow j$ is made
  
  Count # of times letter $x$ is emitted from state $i$
  
  Update parameters $\Theta$

• **Until** (some stopping condition)
Entropy

- Entropy measures the variability observed in given data.
- Entropy is useful in multiple alignments & profiles.
- Entropy is max when uncertainty is max.

\[ E = -\sum_c p_c \log p_c \]
G-Protein Couple Receptors

- Transmembrane proteins with 7 $\alpha$-helices and 6 loops; many subfamilies.
- Highly variable: 200-1200 aa in length, some have only 20% identity.
- [Baldi & Chauvin, '94] HMM for GPCRs.
- HMM constructed with 430 match states (avg length of sequences); Training: with 142 sequences, 12 iterations.
GPCR - Analysis

- Compute main state entropy values

- For every sequence from test set (142) & random set (1600) & all SWISS-PROT proteins
  - Compute the negative log of probability of the most probable path $\pi$

\[
H = \sum_a e \log e
\]

\[
Score(S) = -\log(P(\pi \mid S, M))
\]
GPCR Analysis
Figure 8.1: Entropy Profile of the Emission Probability Distributions Associated with the Main States of the HMM After 12 Cycles of Training.
Figure 8.2: Scores (Negative Log-likelihoods of Optimal Viterbi Paths). Represented sequences consist of 142 GPCR training sequences, all sequences from the SWISS-PROT database of length less than or equal to 2000, and 220 randomly generated sequences with same average composition as the GPCRs of length 300, 350, 400, 450, 500, 550, 600, 650, 700, 750, 800 (20 at each length). The regression line was obtained from the 220 random sequences. The horizontal distances in the histogram correspond to the malized scores (6).
Applications of HMM for GPCR

• Bacteriorhodopsin
  - Transmembrane protein with 7 domains
  - But it is not a GPCR
  - Compute score and discover that it is close to the regression line. Hence not a GPCR.

• Thyrotropin receptor precursors
  - All have long initial loop on INSERT STATE 20.
  - Also clustering possible based on distance to regression line.
HMMs – Advantages

• Sound statistical foundations
• Efficient learning algorithms
• Consistent treatment for insert/delete penalties for alignments in the form of locally learnable probabilities
• Capable of handling inputs of variable length
• Can be built in a modular & hierarchical fashion; can be combined into libraries.
• Wide variety of applications: Multiple Alignment, Data mining & classification, Structural Analysis, Pattern discovery, Gene prediction.
HMMs – Disadvantages

- Large # of parameters.
- Cannot express dependencies & correlations between hidden states.