Hidden Markov Models (HMMs) and Profiles

Swiss Institute of Bioinformatics (SIB)

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Markov Chain Models

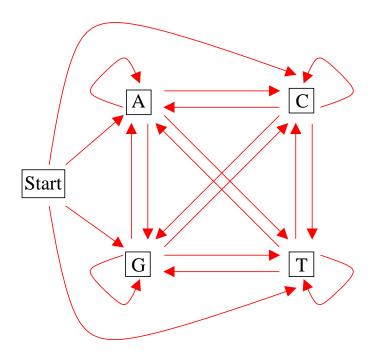
A Markov Chain Model is a succession of states S_i (i = 0, 1, ...) connected by **transitions**. Transitions from state S_i to state S_j has a probability of P_{ij} .

An example of Markov Chain Model:

Transition probabilities:

$$P(A|G) = 0.18, P(C|G) = 0.38, P(G|G) = 0.32, P(T|G) = 0.12$$

$$P(A|C) = 0.15, P(C|C) = 0.35, P(G|C) = 0.34, P(T|C) = 0.15$$



Markov Chain Models

Given a sequence x of length L, we can ask how probable the sequence is given a Markov Chain Model:

$$P(x) = (P(x_L), P(x_{L-1}), ..., P(x_1)) =$$

$$P(x_L|x_{L-1}, ..., x_1)P(x_{L-1}|x_{L-2}, ..., x_1)...P(x_1)$$

Key property of a Markov Chain (of order 1):

$$P(x_i|x_{i-1}, x_{i-2}, ..., x_1) = P(x_i|x_{i-1}).$$

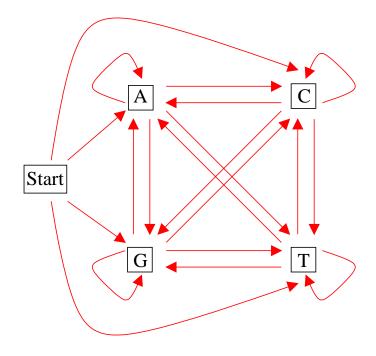
Therefore:

$$P(x) = P(x_L|x_{L-1})P(x_{L-1}|x_{L-2})...P(x_1) =$$

$$P(x_1) \prod_{i=2}^{L} P(x_i|x_{i-1})$$

What all this stuff means?

Given a Markov Chain Model ${\cal M}$ where all transition probabilities are known:



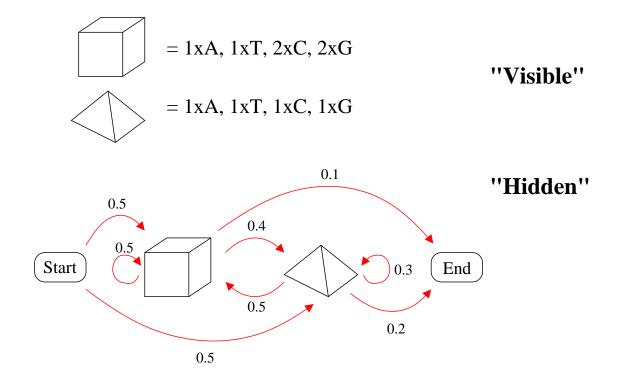
The probability of sequence x = GCCT is:

$$P(GCCT) = P(T|C)P(C|C)P(C|G)P(G)$$

Hidden Markov Models

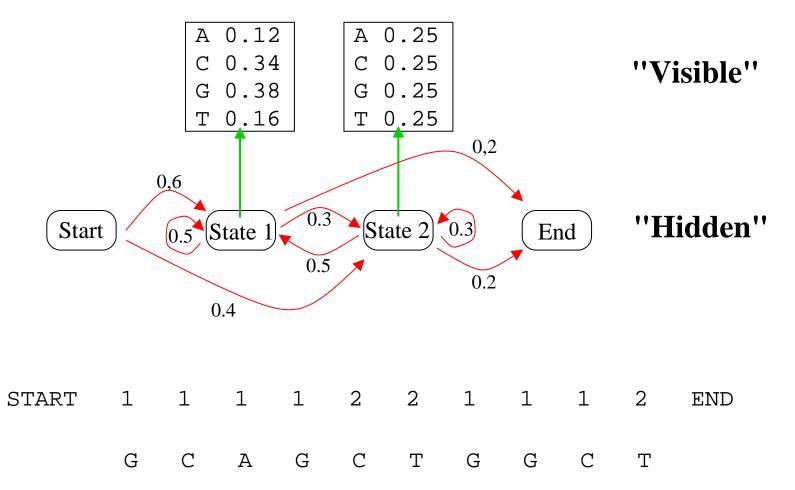
Hidden Markov Models (HMMs) are like Markov Chain Models: a finite number of **states** connected between them by **transitions**.

But the major difference between the two is that the states of the Hidden Markov Models are not a symbol but a **distribution** of symbols. Each state can **emit** a symbol with a probability given by the distribution.



Hidden Markov Model

Example of a simple Hidden Markov Model:



Hidden Markov Models

The parameters of the HMMs:

• **Emission probabilities**. This is the probability of emitting a symbol x from an alphabet α being in state q.

• Transition probabilities. This is the probability of a transition from to a state r being in state q.

Parameter estimation

How we can determine the parameters (emission and transition probabilities) of our model?

To estimate the parameters we use Maximum Likelihood Estimation.

Estimation of the probability of observing one symbol from an alphabet α (in our case $\alpha = \{A, C, G, T\}$):

• Given a set of sequences:

gccgcgcttg gcttggtggc tggccgttgc

• the maximum likelihood estimates are:

$$P(A) = \frac{0}{30} = 0$$
 $P(G) = \frac{13}{30} = 0.433$

$$P(C) = \frac{9}{30} = 0.3$$
 $P(T) = \frac{8}{30} = 0.267$

Parameters estimation

To avoid to set probabilities to 0 we can use different methods:

• For example add pseudo-counts:

$$P(A) = \frac{0+1}{34} = 0,029$$
 $P(G) = \frac{13+1}{34} = 0.412$

$$P(C) = \frac{9+1}{34} = 0.294$$
 $P(T) = \frac{8+1}{34} = 0.265$

A general form for priors estimation:

$$P(A) = \frac{n_a + p_A m}{\left(\sum_i n_i\right) + m}$$

where m is the number of virtual instances (pseudo-counts) and p_A is the prior probability of A.

Parameters estimation

Transition probabilities estimation between the symbols of the alphabet α (for example $\alpha = \{A, C, G, T\}$):

Transition probabilities are estimated for each observed couple of symbols:

$$p_{ij} = \frac{n_{ij}}{\sum_{j'} n_{ij'}}$$

- where p_{ij} is the probability of transition from symbol i to symbol j, and n_{ij} is the number of transition from symbol i to symbol j observed.
- Is possible to add pseudo-counts as described previously.

For example for transition $A \rightarrow G$:

- Count all transitions A \rightarrow A, A \rightarrow C, A \rightarrow G, A \rightarrow T in CpG sequences and non-CpG sequences.
- Transition probability is then calculated:

$$p_{AG} = \frac{n_{AG}}{n_{AA} + n_{AC} + n_{AG} + n_{AT}}$$

An example

Distinguish CpG islands from other sequences regions.

- Two models are required:
 - ▶ a model to represent CpG islands
 - ▶ a null model to represent the other regions

A sequences x is scored for being a CpG island:

$$score(x) = log \frac{P(x|CpGmodel)}{P(x|nullmodel)}$$

Parameters for the CpG island and null models:

CpG	Α	C	G	Т	Null	Α	C	G	Т
Α	0.18	0.27	0.43	0.12	Α	0.18	0.27	0.43	0.12
C	0.17	0.37	0.27	0.19	C	0.17	0.37	0.27	0.19
G	0.16	0.34	0.38	0.12	G	0.16	0.34	0.38	0.12
Т	80.0	0.36	0.38	0.18	Т	80.0	0.36	0.38	0.18

HMMs algorithms

Three important questions can be answered by three algorithms.

How likely is a given sequences under a given model? This is the scoring problem and it can be solved using the Forward algorithm.

What is the most probable path between states of a model given a sequence? This is the alignment problem and it is solved by the Viterbi algorithm.

How can we learn the HMM parameters given a set of sequences? This is the training problem and is solved using the Forward-backward algorithm and the Baum-Welch expectation maximization.

For details about these algorithms see:

Durbin, Eddy, Mitchison, Krog.

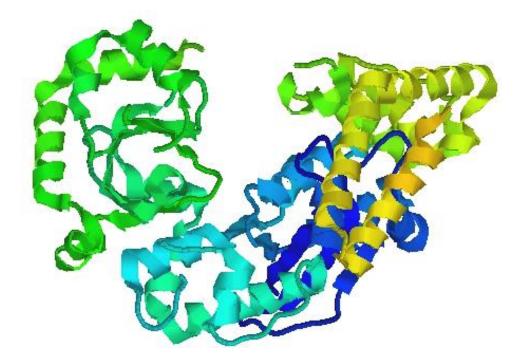
Biological Sequence Analysis: Probabilistic Models of Proteins and Nucleic Acids. $Cambridge\ University\ Press,\ 1998.$

HMMs and protein domains

HMMs are very appropriate for modelization of protein domains.

What are protein domains:

- Domains are discrete structural units.
- Defined by structure.
- Domains are functional units.

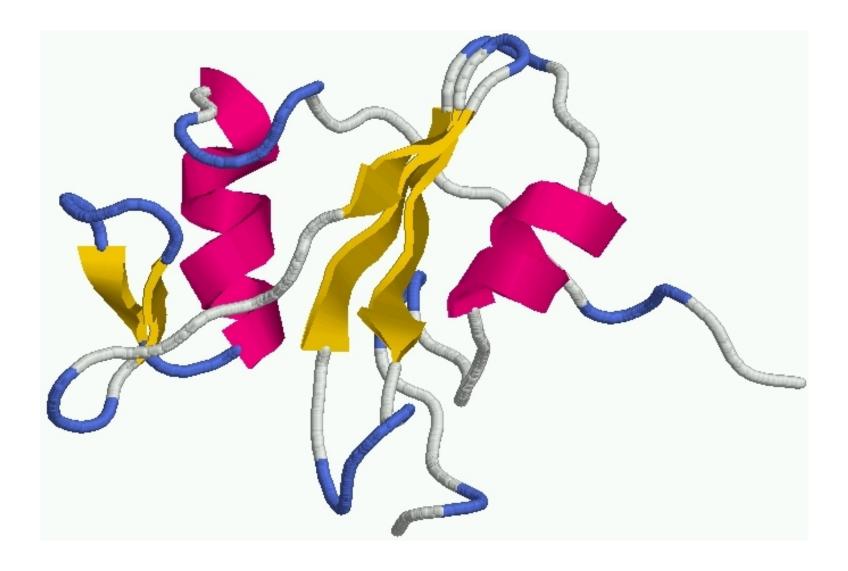


HMMs and protein domains

Multiple alignments are used as training set for the building of HMMs.

sh2.stk ABL1 CAEEL WYHGKISRSDSEAILGS..GITGSFLVRESET.SIGO...YTISVRHDG......RVFHYRINVDNTE.....KMFITQEVK..FRTLGELVHHH P85A HUMAN 624 WNVGSSNRNKAENLLRG..KRDGTFLVRESS..KOGC...YACSVVVDG.....EVKHCVINKTATG......YGFAEPYNLYSSLKELVLHY WYYGRITRADAEKLLSN..KHEGAFLIRISES.SPGD...FSLSVKCPD......GVOHFKVLRDAOS......KFFLWVVK..FNSLNELVEYH 134 DRK DROME WYYGKVTRHQAEMALNE.RGHEGDFLIRDSES.SPND...FSVSLKAQG......KNKHFKVQLKET......VYCIGQRK..FSTMEELVEHY 356 NCK HUMAN WFFRTISRKDAERQLLAPMNKAGSFLIRESES.NKGA...FSLSVKDITTQG...EVVKHYKIRSLDNG......GYYISPRIT..FPTLQALVQHY BLK_MOUSE WYFCKLSRKDTERLILLPGNERGTFLIRESET.TKGA...YSLSLRDWDETK..GDNCKHYKIRKLDNG.....GYYITTRTO..FMSLOMLVKHY YES XIPHE WYFGDVKRAEAEKRLMVRGLPSGTFLIRKAET.AVGN...FSLSVRDGD......SVKHYRVRKLDTG......GYFITTRAP..FNSLYELVOHY STK HYDAT WFLGKIKRVEAEKMLNQSFNQVGSFLIRDSET.TPGD...FSLSVKDQD......RVRHYRVRRLEDG.....SLFVTRRST..FQILHELVDHY SRK1 SPOLA 162 WFFENVLRKEADKLLLÄEENPRGTFLVRPSEH.NPNG...YSLSVKDWEDGR..GYHVKHYRIKPLDNG.....GYYIATNOT..FPSLOALVMAY SRC1 DROME 14 WYMGPVSROEAOTRLOG..ORHGMFLVRDSST.CPGD...YVLSVSENS......RVSHYIINSLPNR......RFKIGDOE..FDHLPALLEFY CRKL HUMAN WFHCKITREOAERLLYP..PETCLFLVRESTN.YPCD...YTLCVSCEG......KVEHYRIIYSSSK......LSIDEEVY..FENLMOLVEHY 156 CSK CHICK WFHGKISGOEAVOOLOP..PEDGLFLVRESAR.HPGD...YVLCVSFGR......DVIHYRVLHRDG......HLTIDEAVF..FCNLMDMVEHY 196 MATK HUMAN WFHPTISGIEAEKLLQE.QGFDGSFLARLSSS.NPGA...FTLSVRRGN.....EVTHIKIQNNGDF......FDLYGGEK..FATLPELVOYY CSW DROME WFHCNLSGKEAEKLILE.RGKNGSFLVRESQS.KPGD...FVLSVRTDD......KVTHVMIRWQDKK......YDVGGGES..FGTLSELIDHY 186 CSW DROME WYHCKLDRTIAEERLRQ.AGKSGSYLIRESDR.RPGS...FVLSFLSQMN.....VVNHFRIIAMCGD......YYIGG.RR..FSSLSDLIGYY GTPA HUMAN WYHASLTRAQAEHMLMR.VPRDGAFLVRKRNE..PNS...YAISFRAEG......KIKHCRVQQEGQT......VMLGNSE...FDSLVDLISYY PIP4 RAT WFHCKISRDESEQIVLIGSKTNCKFLIRARDN...GS...YALGLLHEG......KVLHYRIDKDKTG.....KLSIPGCKN..FDTLWOLVEHY KSYK PIG 163 WYHSSLTREEAERKLYSGAOTDGKFLLRPRKE..QGT...YALSLIYGK.....TVYHYLISODKAG.....KYCIPEGTK..FDTLWQLVEYL 239 ZA70 HUMAN 671 WYAGPMERAGAEGILTN. RSDGTYLVRORVK.DTAE...FAISIKYNV.....EVKHIKIMTSEG......LYRITEKKA.FRGLLELVEFY 745 VAV MOUSE 15 FFFGNITREEAEDYLVQGGMSDGLYLLRQSRN.YLGG...FALSVAHGR......KAHHYTIERELNG.....TYAIAGGRT..HASPADLCHYH 92 KSYK HUMAN EAWREIQRWEAEKSLMKIGLQKGTYIIRPSR..KENS...YALSVRDFDEKKK.ICIVKHFQIKTLQDEK.....GISYSVNIRN.FPNILTLIQFY 184 SPK1 DUGTI BTK_HUMAN WYSKHMTRSQAEQLLKQ.EGKEGGFIVRDSS..KAGK...YTVSVFAKSTGDP.QGVIRHYVVCSTPQS.....QYYLAEKHL..FSTIPELINYH 362 WYCRNTNRSKAEQLLRT.EDKEGGFMVRDSS..QPGL...YTVSLYTKFGGEG.SSGFRHYHIKETATSP....KKYYLAEKHA..FGSIPEIIEYH 329 TEC_MOUSE WYNKSISRDKAEKLLLD.TGKEGAFMVRDSR..TAGT...YTVSVFTKAVVSENNPCIKHYHIKETNDNP....KRYYVAEKYV..FDSIPLLINYH ITK HUMAN 150 WYHRNITRNOAEHLLRO.ESKEGAFIVRDSR..HLGS...YTISVFMGARRST.EAAIKHYOIKKNDSG.....OWYVAERHA..FOSIPELIWYH 231 TXK HUMAN 214 WYVCYMSRORAESLLKO.GDKEGCFVVRKSS..TKGL...YTLSLHTKVPO....SHVKHYHIKONARC.....EYYLSEKHC..CETIPDLINYH SRC2 DROME WYHGAIPRIEAGELLK....KOGDFLVRESHG.KPGE...YVLSVYSDG......ORRHFIIOYVDNM......YRFEGTG..FSNIPOLIDHH 531 FER HUMAN WFHGVLPREEVVRLLNN....DGDFLVRETIRNEESQ...IVLSVCWNGH......KHFIVQTTGEG.....NFRFEGPP..FASIQELIMHQ 510 FPS DROME WFHGKISKQEAYNLLMT.VGQVCSFLVRPSDN.TPGD...YSLYFRTNE.....NIQRFKICPTPN.....NQFMMGGRY..YNSIGDIIDHY 426 GTPA HUMAN YFHGLIQREDVFQLLDN....NGDYVVRLSDP.KPGEPRSYILSVMFNNKLDE.NSSVKHFVINSVENK......YFVNNNMS..FNTIQOMLSHY 101 YKF1 CAEEL YYFPFNGR.OAEDYLRS..KERGEFVIROSSR.GDDH...LVITWKLDKD.....LFOHIDIOELEKENPLALGKVLIVDNOK..YNDLDOIIVEY 1339 SPT6 YEAST

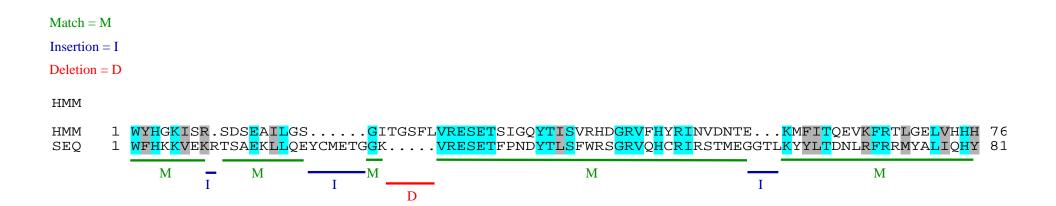
HMMs and protein domains



HMMs and protein domains

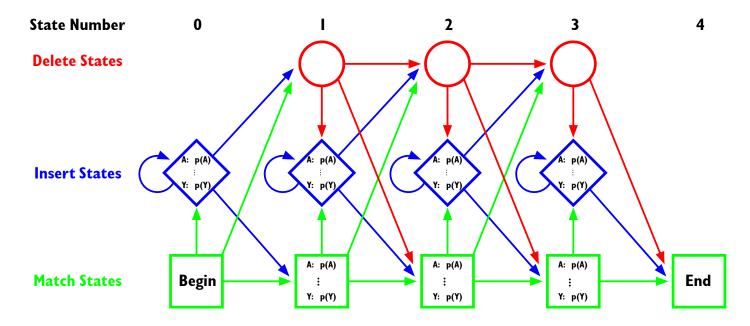
A model based on three types of states is appropriate to modelize biological sequences:

- match state: Emits a symbol corresponding to a match.
- insert state: Emits a symbol between matches.
- **delete state**: Non-emitting silent state.



HMMs and protein domains

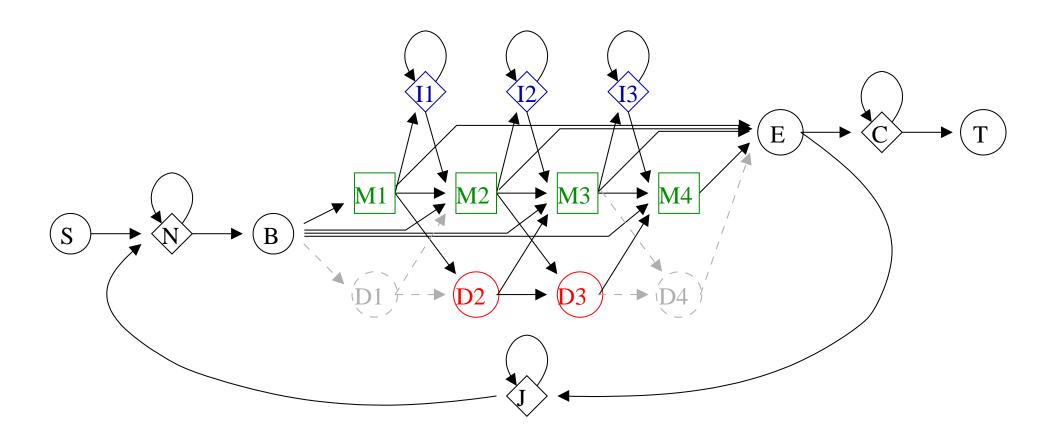
Simple HMM protein sequence model



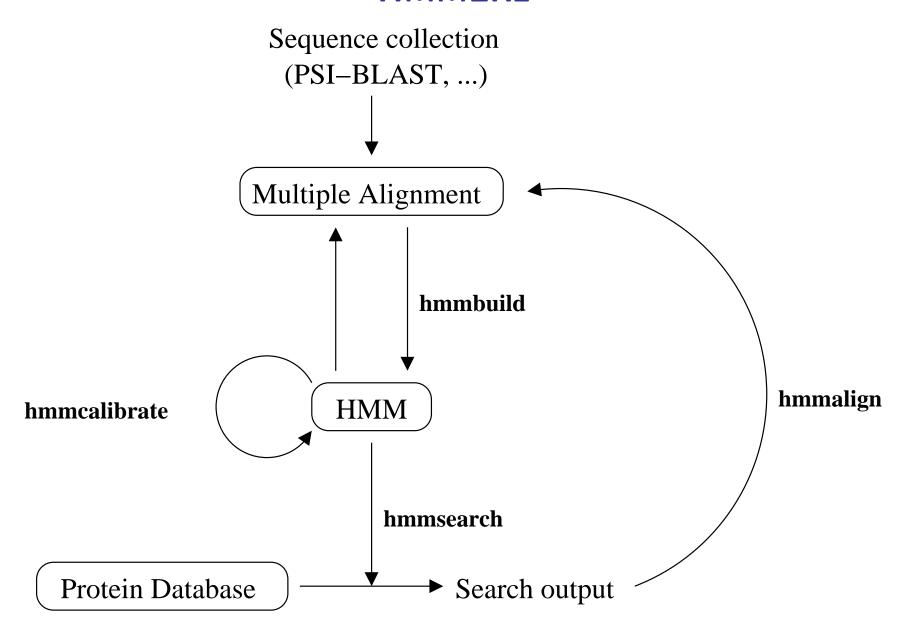
HMMER2

Package developed by Sean Eddy (http://hmmer.wustl.edu/).

HMMER uses the "Plan 7" architecture:



HMMER2



Generalized profiles

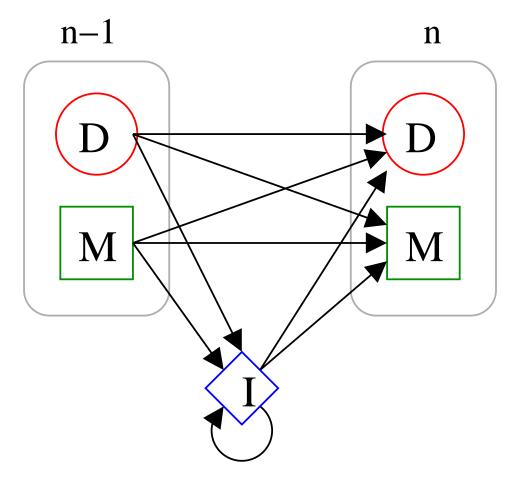
Generalized profiles combine aspects of Position Specific Score Matrices (PSSMs) and Hidden Markov Models (HMMs).

Generalized profiles are composed of alternating match and insert positions. Scores are associated with each position.

- The match position gives a residue specific match extension score and a deletion extension score.
- The insert position gives residue specific insertion scores.
- Scores are also associated to all possible transitions.

There is an equivalence between the structure of generalized profiles and a linear HMMs.

Generalized profiles



Pftools

The package has been developed by Philipp Bucher (http://www.isrec.isb-sib.ch/ftp-server/pftools/).

The package contains:

- pfmake for building a profile starting from multiple alignments.
- pfsearch to search a profile against a protein database.
- pfscan to search a protein against a profile database.

Two tools have been created to translate profiles from and into HMMs:

- htop: HMM to profile.
- ptoh: profile to HMM.

HMM-profiles and Generalized profiles

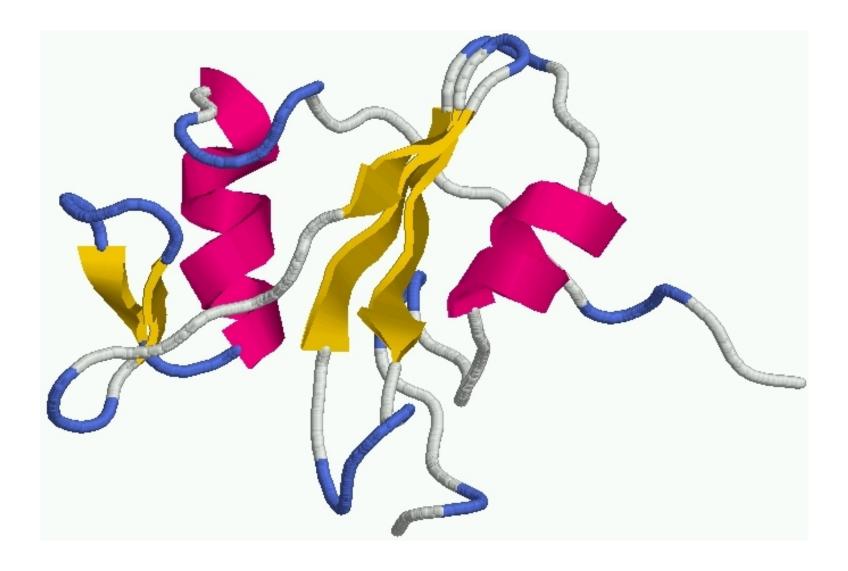
The meaning of the position specific scores in the generalized profiles:



The emission probabilities of HMM-profiles can be translated into a scoring system as for the generalized profiles:



HMMs and protein domains



Protein domain databases

A non-exhaustive list of protein domain databases:

Pfam

- ▶ http://www.sanger.ac.uk/Pfam.
- ▶ Collection of protein domains and families (3071 entries in Pfam release 6.6).
- ▶ Uses HMMs (HMMER2).
- ▶ Good links to structure, taxonomy.

PROSITE

- http://www.expasy.ch/prosite.
- ▶ Collection of motifs, protein domains, and families (1494 entries in Prosite release 16.51).
- ▶ Uses generalized profiles (Pftools) and patterns.
- ▶ High quality documentation.

Protein domain databases

A non-exhaustive list of protein domain databases (continue):

Prints

- http://bioinf.man.ac.uk/dbbrowser/PRINTS.
- Collection of conserved motifs used to characterize a protein.
- ▶ Uses fingerprints (conserved motif group).
- ▶ Very good to describe sub-families.
- ▶ Release 32.0 of PRINTS contains 1600 entries, encoding 9800 individual motifs.

ProDom

- ▶ http://prodes.toulouse.inra.fr/prodom/doc/prodom.html.
- ▶ Collection of protein motifs obtained automatically using PSI-BLAST.
- ▶ Very high throughput ... but no annotation.
- ▶ ProDom release 2001.2 contains 101957 families (at least 2 sequences for family).

• ..

InterPro

InterPro is an attempt to group a number of protein domain databases:

- Pfam
- PROSITE
- PRINTS
- ProDom
- SMART
- TIGRFAMs

InterPro try to have and maintain a high quality annotation.

Very good accession to examples.

InterPro web site: http://www.ebi.ac.uk/interpro.

A stand alone package (iprscan) and the database are available for UNIX platforms to run a complete Interpro analysis: ftp://ftp.ebi.ac.uk/pub/databases/interpro.

Interpro

