



MASTER IN TECNOLOGIE BIOINFORMATICHE APPLICATE ALLA
MEDICINA PERSONALIZZATA

Protein Sequence Analysis

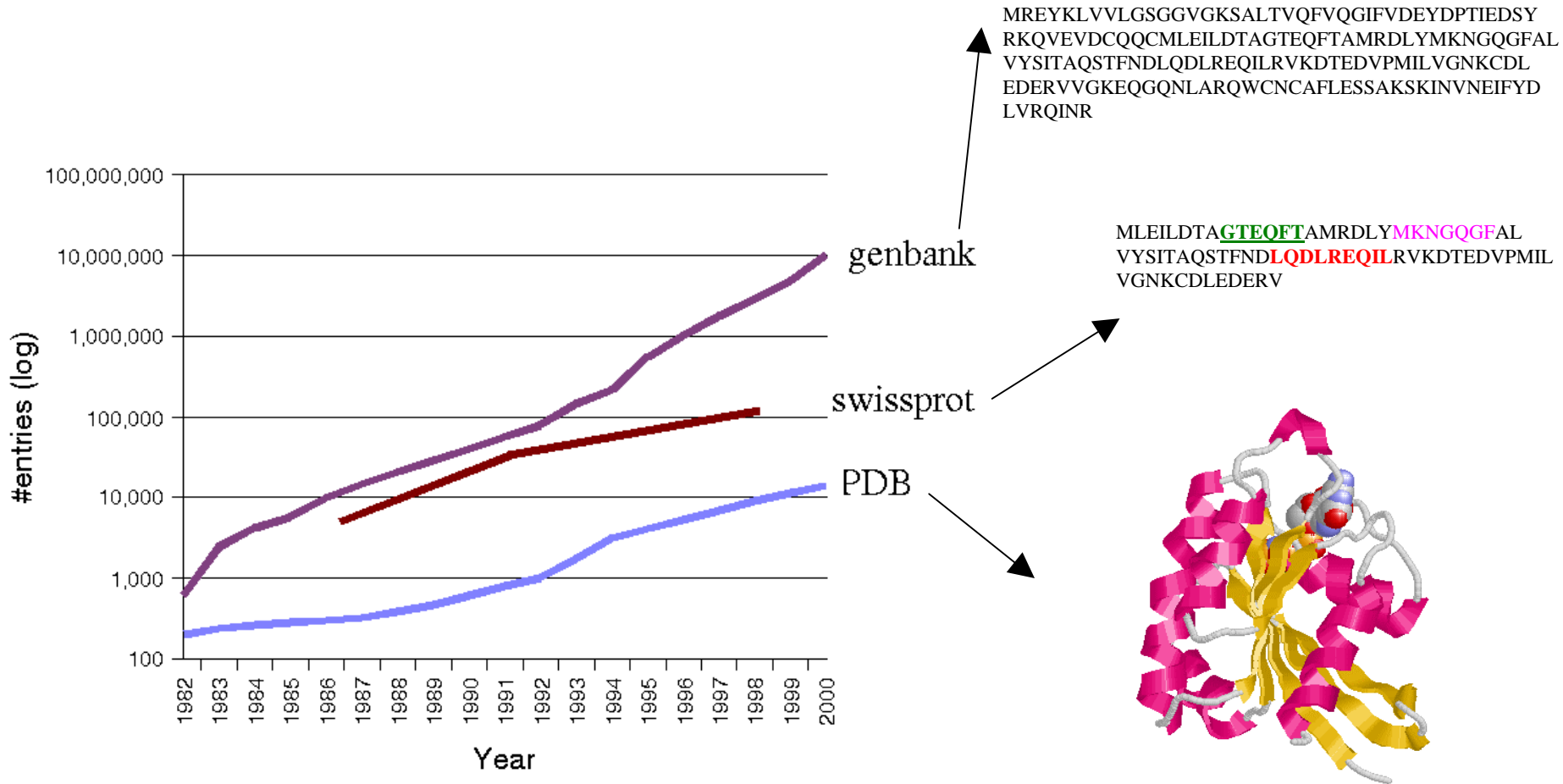
Extraction of Structural (1D) Features from Sequence Alignments

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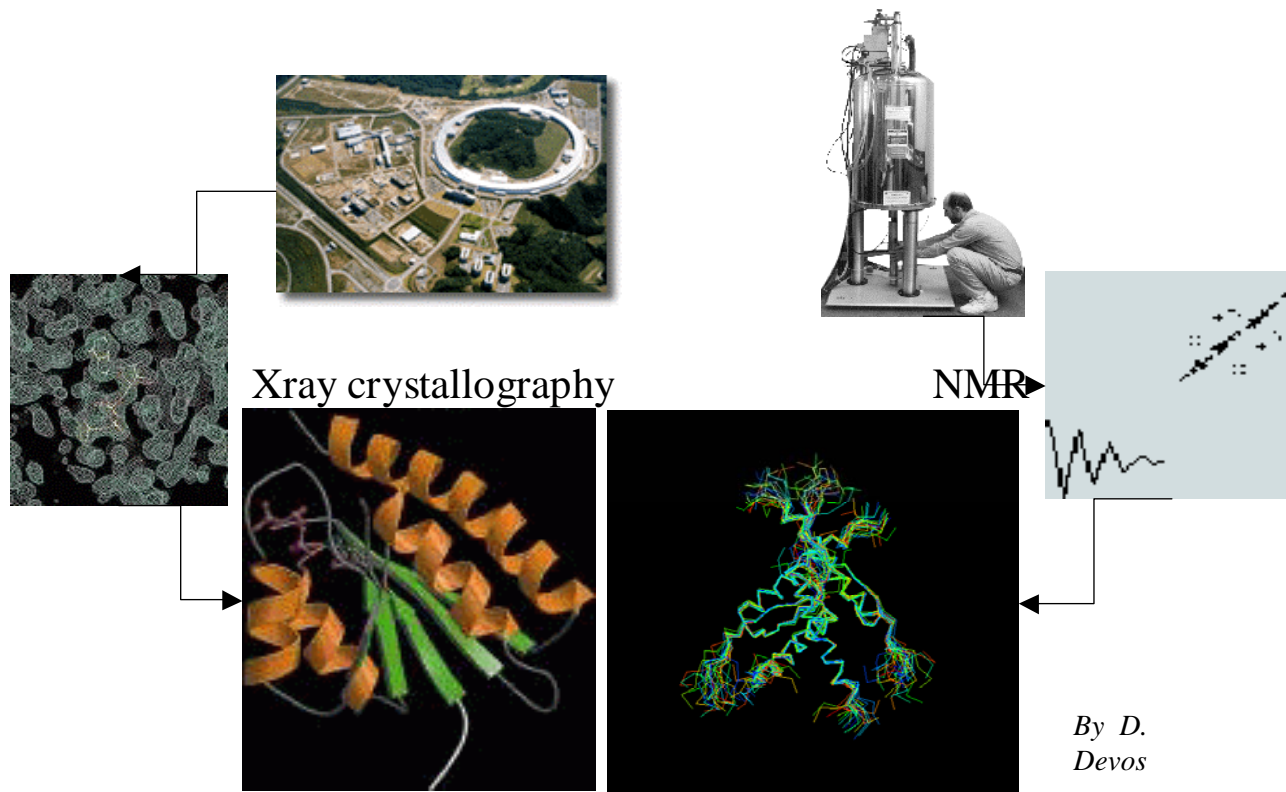


Protein Structure



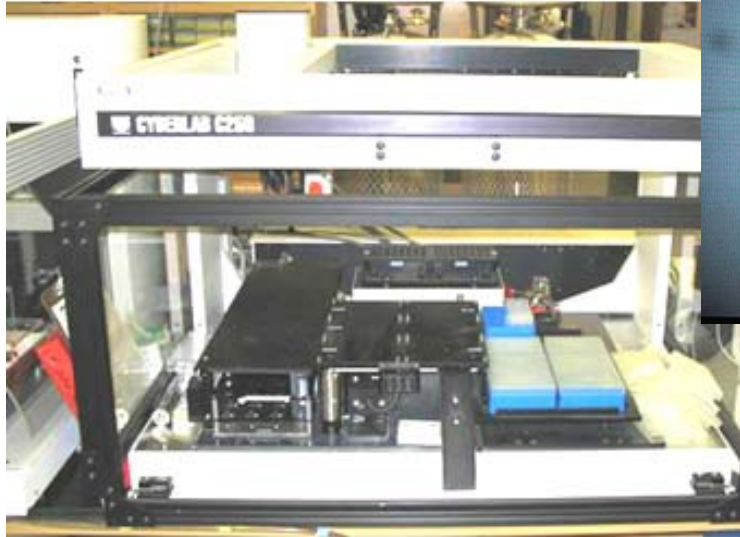
Determining protein structures

Low-throughput (“traditional”) approach



Determining protein structures

High-throughput approach – Structural Genomics



determination by X-ray crystallography.

- [The Northeast Structural Genomics Consortium \(NEGS\)](#)

The NEGS is focused on human proteins and proteins from eukaryotic and prokaryotic organisms. The project also includes the study of proteins that are interesting from a functional genomics perspective using spectroscopy.

- [The Southeast Collaboratory for Structural Genomics \(SECSG\)](#)

The objective of the SECSG is to develop and test experimental and computational methods for X-ray crystallography and NMR methods and to apply these strategies to scan the genomes of *Homo sapiens* and an ancestrally-related prokaryotic microorganism having a similar genome size.

- [Structural Genomics of Pathogenic Protozoa Consortium \(SGPP\)](#)

The SGPP consortium aims to determine and analyze the structures of a large number of proteins from *Trypanosoma brucei*, *Trypanosoma cruzi* and *Plasmodium falciparum*, the causative agents of African trypanosomiasis, Chagas disease, and malaria. X-ray crystallography is being used for structural determination of these proteins.

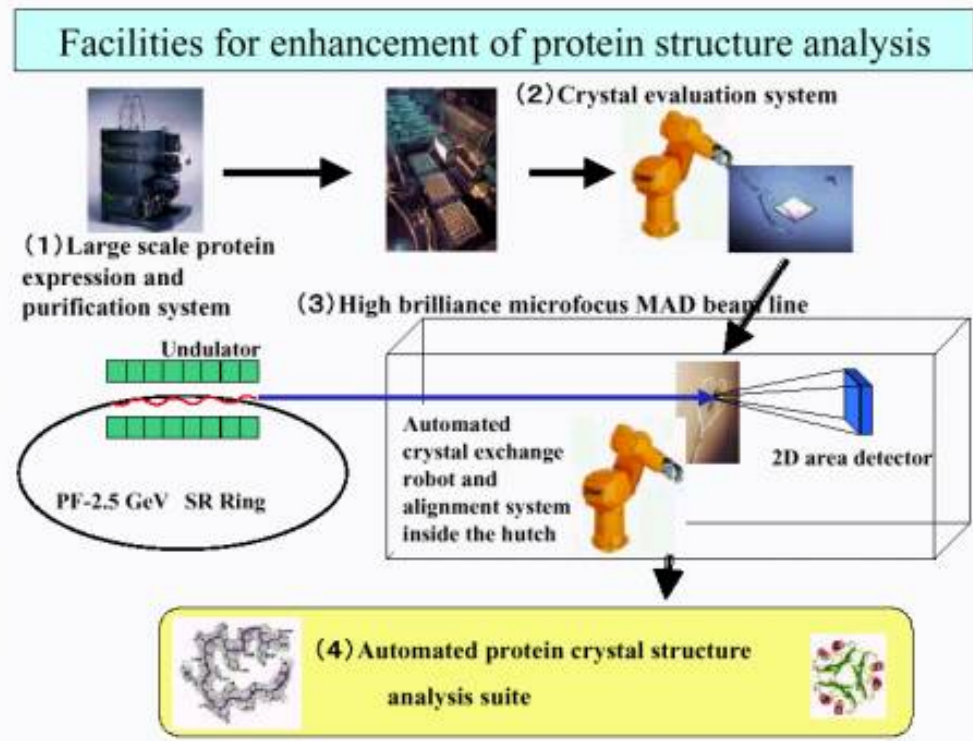
- [The TB Structural Genomics Consortium \(TB\)](#)

The goal of the TB consortium is to determine the structures of over 400 proteins from *Thermotoga maritima*. The information that currently exists and that is generated by the project. The protein structures are being determined using X-ray crystallography.

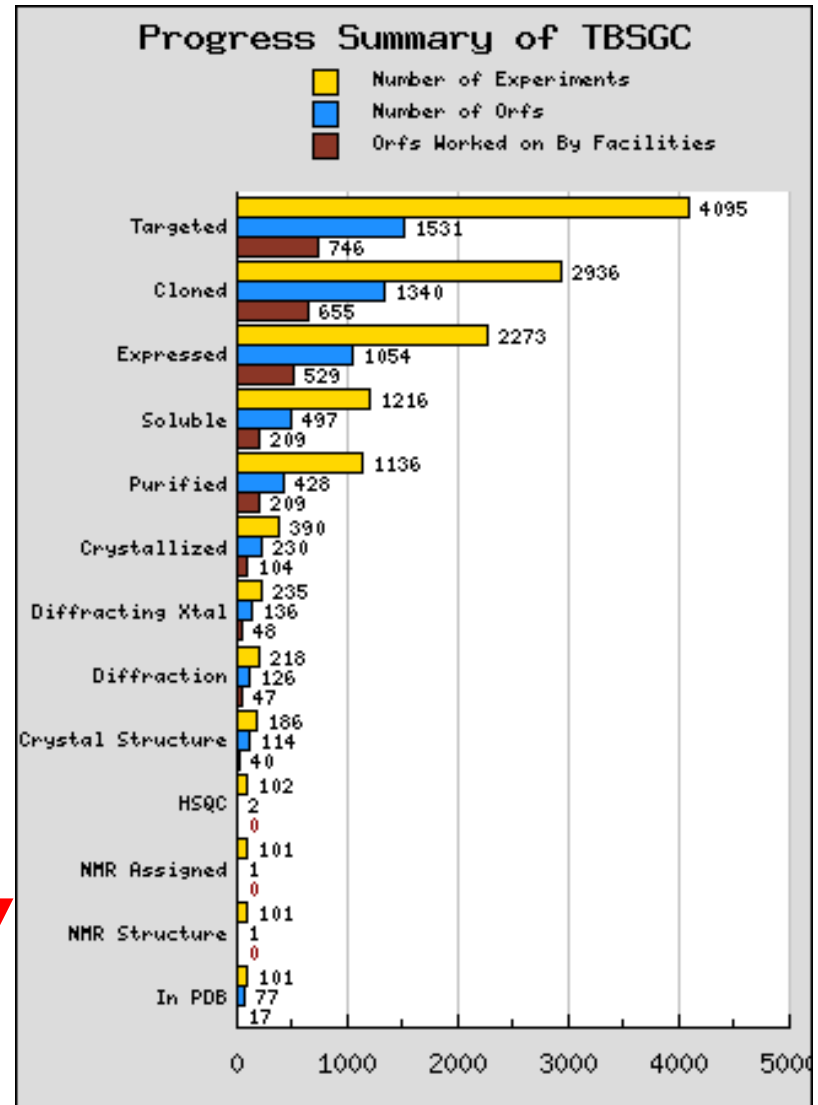
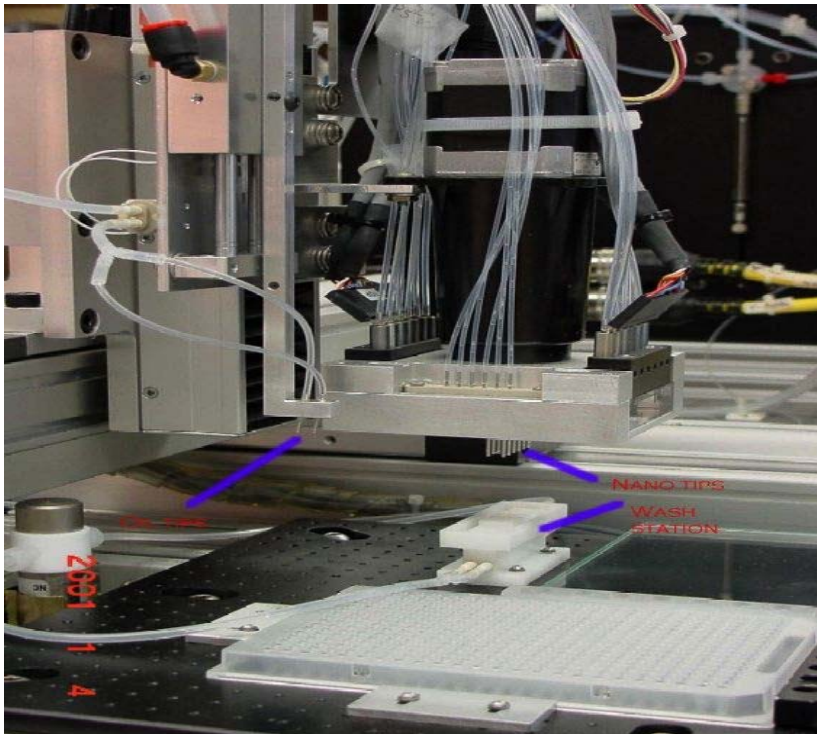
Genomes of two minimal genomes, *Mycoplasma genitalium* and *Mycoplasma pneumoniae* are being used for structural genomics.

The goal of the project is the high-throughput structure determination of biologically important proteins in *Arabidopsis thaliana*. The project is also interested in determining the structure of biologically important proteins in *Arabidopsis thaliana*.

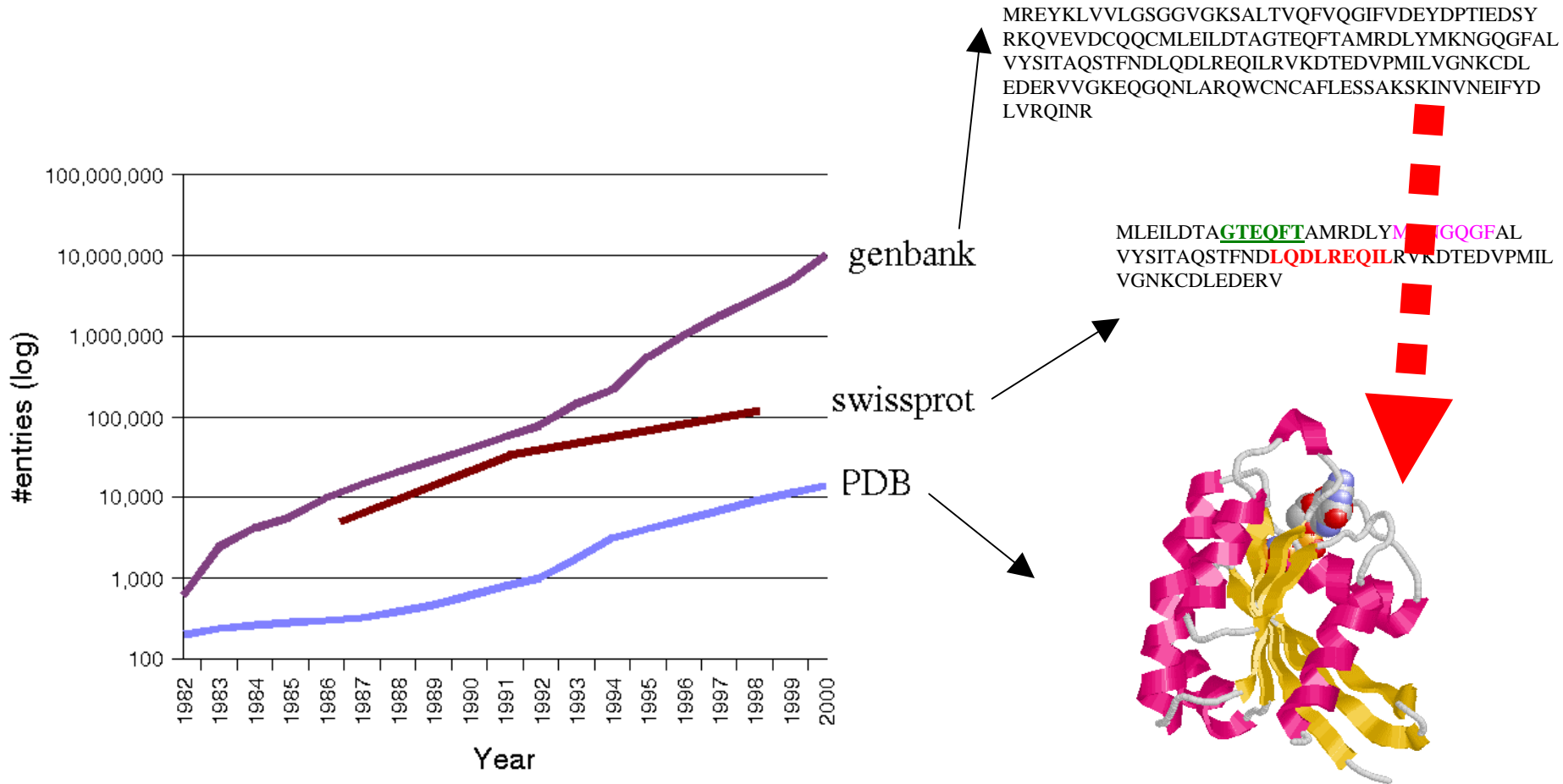
The main proteins of interest are signaling proteins and enzymes. The project is also interested in determining the structure of biologically important proteins in *Thermotoga maritima*, and creating a high-throughput pipeline for structural determination.



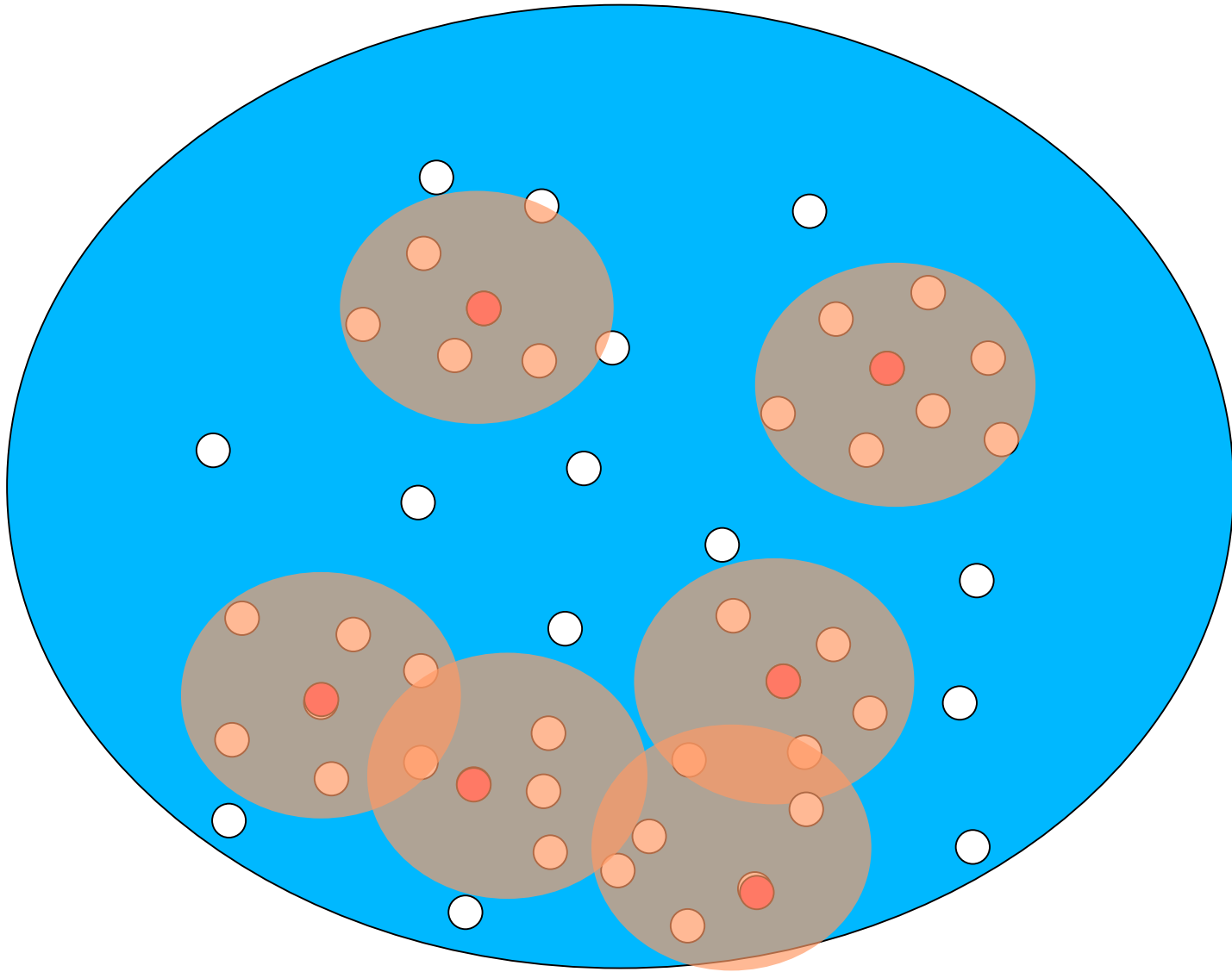
Structural Genomics



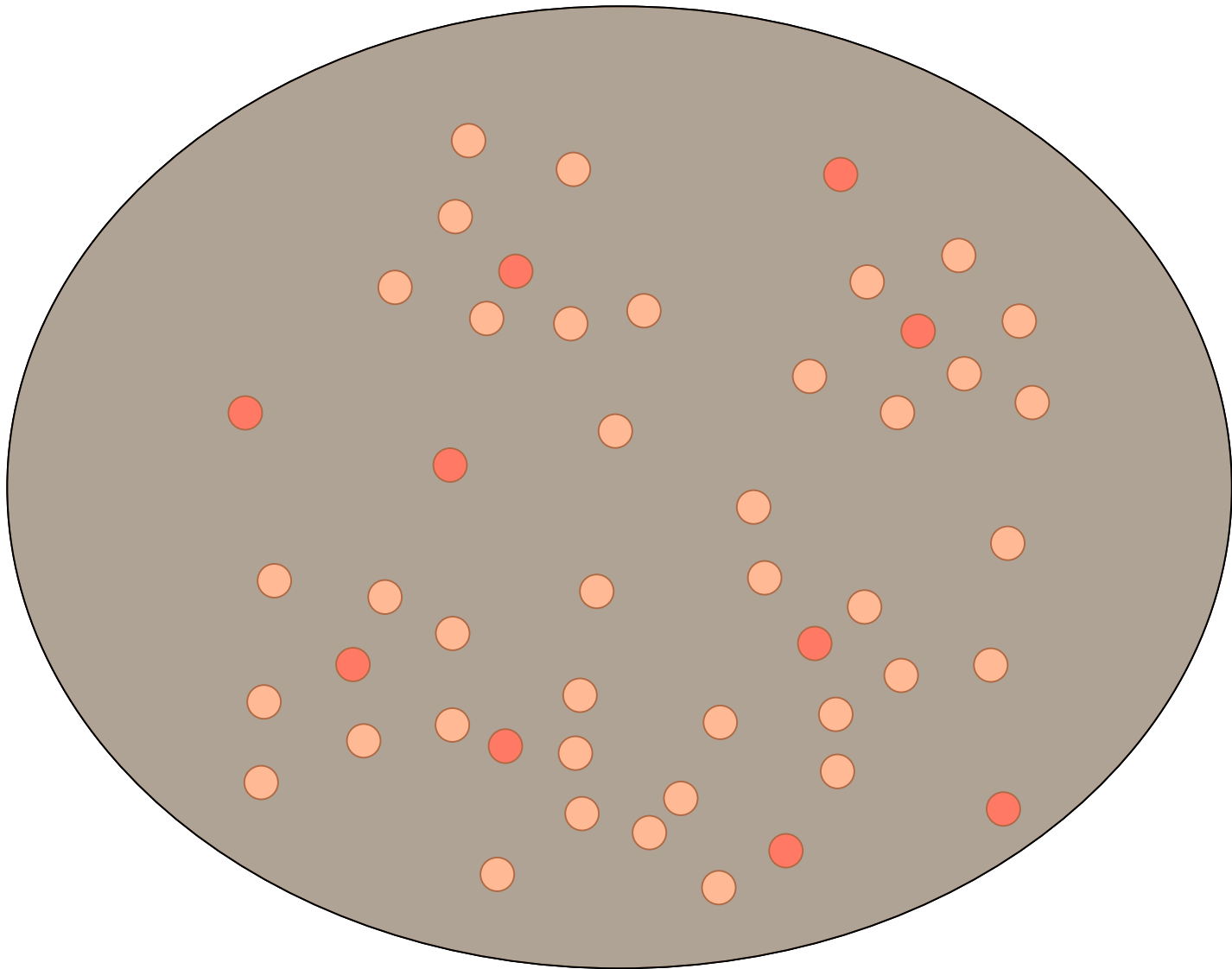
Protein Structure



Structural Genomics and Protein Structure Prediction

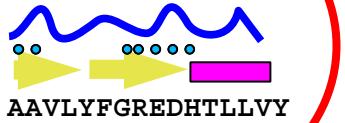


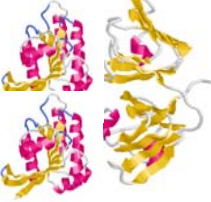


Structural Genomics and Protein Structure Prediction



Protein Structure Prediction

Classification of Prediction Methods

| Nivel estructura proteínas | Secundaria | ----- | terciaria | cuaternaria |
|-------------------------------|--|---|---|--|
| Representación de la proteína | <p>1D</p>  <p>AAVLYFGREDHTLLVY</p> | <p>2D</p>  <p>AAVLYFGREDHTLLVY</p> | <p>3D</p>  | <p>4D</p>  |
| Uso de información extra | | | | |
| <i>Ab Initio</i> | pred. str. secundaria | mutaciones correlacionadas | <ul style="list-style-type: none"> - dinámica molecular - minimización de energía | <i>docking</i> |
| <i>No Ab-Initio</i> | pred. str. secundaria | | <ul style="list-style-type: none"> - modelado por homología - <i>threading</i> | <i>docking con filtros</i> |

Protein Structure Prediction

1D Characteristics

1D Characteristics: Features that can be represented by a single value associated to each residue (B. Rost).

These values can be labels representing “states”, like in secondary structure (H: helix, E: beta, ...). They can also be continuous values (% accesible surface, ...).

Some 1D characteristics:

Secondary structure

Solvent accessibility

Post-transcriptional modifications

signal peptides

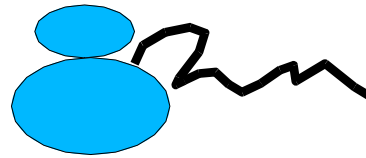
Coiled-coils

Unstructured regions

etc.



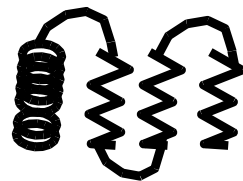
1D Characteristics - Secondary Structure



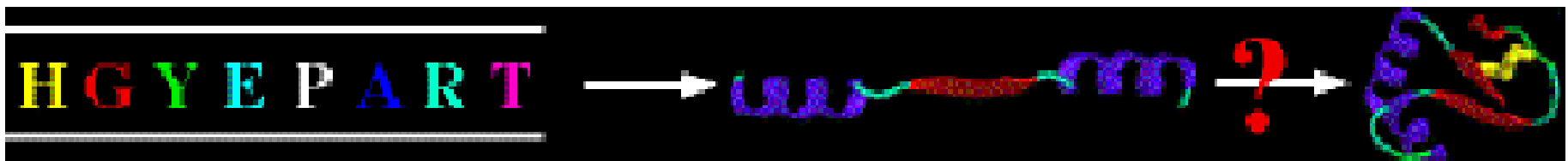
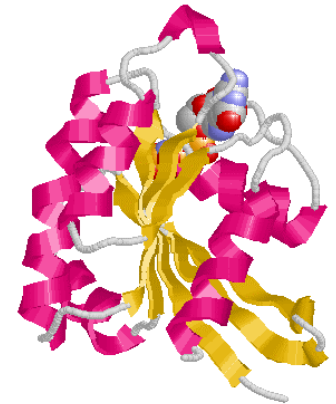
Primary structure



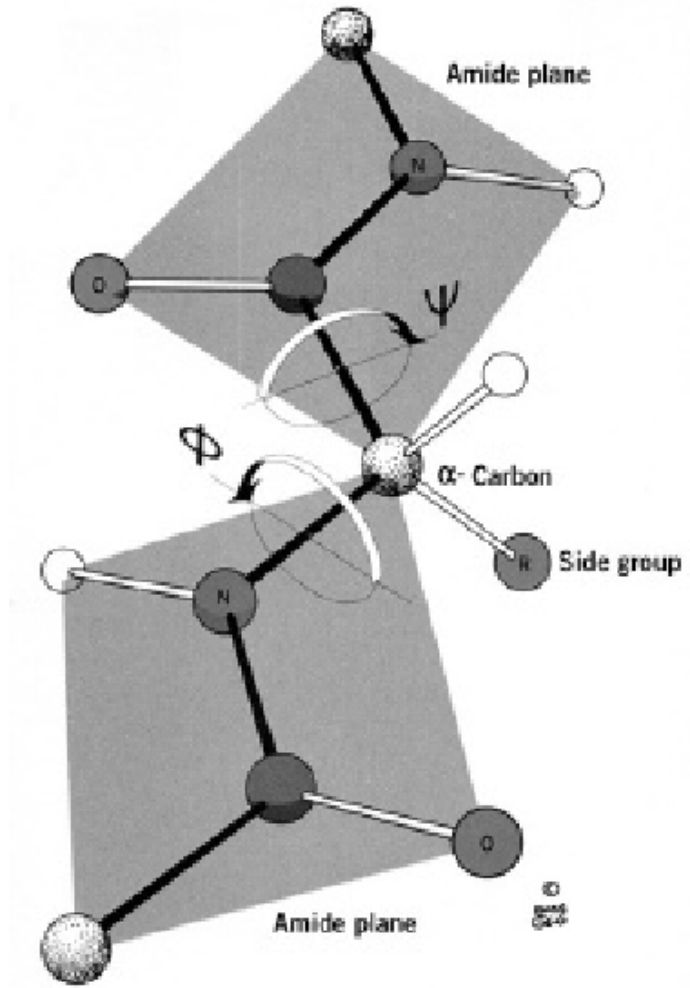
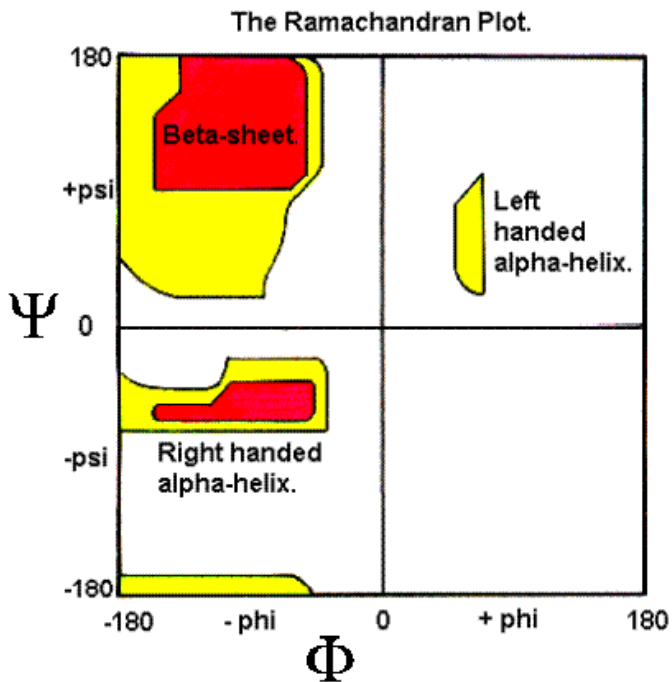
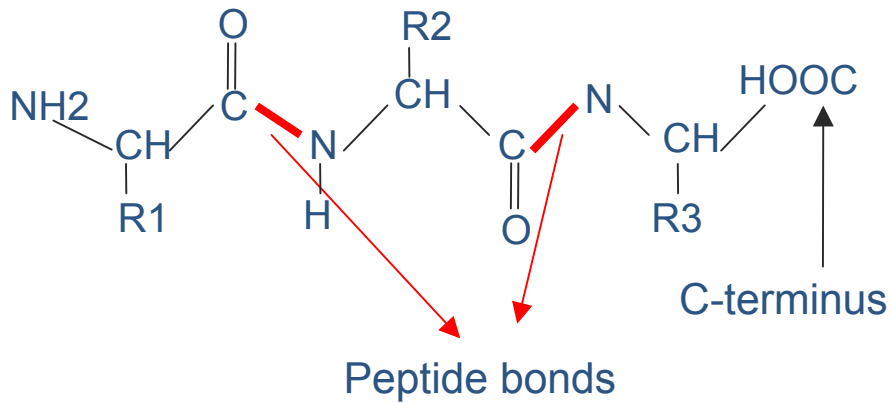
Secondary structure



Tertiary structure



1D Characteristics Secondary Structure



1D Characteristics Secondary Structure

1 ASKGEELFTGVVPILVELDGDVNGHKFSVSGEGEGDATYGKLTLLKFICTT
TTGGGSS EEEEEEEEEEEEEETTEEEEEEEEEEEEEETTT EEEEEEEETT

51 GKLPVPWPTLVTTFSYGVQCFSRYPDHMKRHDFFKSAMPEGYVQERTIFF
SS SS GGGGHHHSSS GGG B GGGGG HHHHTTTT EEEEEEEEE

101 KDDGNYKTRAEVKFEGLTLVNRIELKGIDFKEDGNILGHKLEYNYNSHNV
TTS EEEEEEEEEEEEEETTEEEEEEEEEEEEE TTSTTTTT B S EEE

151 YIMADKQKNGIKVNFKIRHNIEDGSVQLADHYQQNTPIGDGPVLLPDNHY
EEEEEGGTEEEEEEEEEEEEEETTS EEEEEEEEEEESSSS SEE

201 LSTQSALSKDPNEKRDHMLLEFVTAAGIT HGMDELYK
EEEEEEEE TT SSEEEEEEEEEES

Definition: T=hydrogen bond turn, H=helix, G=310 helix, I=phi helix, B=residue in isolated beta bridge, E=strand, and S=bend

Prediction: H/E/T (3 states only)

Secondary Structure

First-generation Methods

Statistical methods simply based on the tendency of each amino acid to form each type of secondary structure.

- Chou & Fasman en 1974, proposed the first method. They calculated the tendencies from the **15 structures** solved. Later, this method showed a reliability of **57% when tested on 62 proteins**. (= > close to random)
- Garnier (1978), calculated these probabilities for pairs of residues, improving the reliability (**~60%**)

Chou, P.Y. and Fasman, G.D. (1974) Prediction of protein conformation. *Biochemistry*, **13**, 222-244/225.

Garnier, J., Osguthorpe, D.J. and Robson, B. (1978) Analysis of the accuracy and implications of simple methods for predicting the secondary structure of globular proteins. *J. Mol. Biol.*, **120**, 97-120.

Secondary Structure First-generation Methods

| Name | P(a) | P(b) | P(turn) | f(i) | f(i+1) | f(i+2) | f(i+3) |
|---------------|------|------|---------|-------|--------|--------|--------|
| Alanine | 142 | 83 | 66 | 0.06 | 0.076 | 0.035 | 0.058 |
| Arginine | 98 | 93 | 95 | 0.070 | 0.106 | 0.099 | 0.085 |
| Aspartic Acid | 101 | 54 | 146 | 0.147 | 0.110 | 0.179 | 0.081 |
| Asparagine | 67 | 89 | 156 | 0.161 | 0.083 | 0.191 | 0.091 |
| Cysteine | 70 | 119 | 119 | 0.149 | 0.050 | 0.117 | 0.128 |
| Glutamic Acid | 151 | 037 | 74 | 0.056 | 0.060 | 0.077 | 0.064 |
| Glutamine | 111 | 110 | 98 | 0.074 | 0.098 | 0.037 | 0.098 |
| Glycine | 57 | 75 | 156 | 0.102 | 0.085 | 0.190 | 0.152 |
| Histidine | 100 | 87 | 95 | 0.140 | 0.047 | 0.093 | 0.054 |
| Isoleucine | 108 | 160 | 47 | 0.043 | 0.034 | 0.013 | 0.056 |
| Leucine | 121 | 130 | 59 | 0.061 | 0.025 | 0.036 | 0.070 |
| Lysine | 114 | 74 | 101 | 0.055 | 0.115 | 0.072 | 0.095 |
| Methionine | 145 | 105 | 60 | 0.068 | 0.082 | 0.014 | 0.055 |
| Phenylalanine | 113 | 138 | 60 | 0.059 | 0.041 | 0.065 | 0.065 |
| Proline | 57 | 55 | 152 | 0.102 | 0.301 | 0.034 | 0.068 |
| Serine | 77 | 75 | 143 | 0.120 | 0.139 | 0.125 | 0.106 |
| Threonine | 83 | 119 | 96 | 0.086 | 0.108 | 0.065 | 0.079 |
| Tryptophan | 108 | 137 | 96 | 0.077 | 0.013 | 0.064 | 0.167 |
| Tyrosine | 69 | 147 | 114 | 0.082 | 0.065 | 0.114 | 0.125 |
| Valine | 106 | 170 | 50 | 0.062 | 0.048 | 0.028 | 0.053 |

Glu, Met Ala y Leu : strong tendency to form **helix**.

Val, Ile y Tyr: strong tendency to form **strand**.

Chou, P.Y. and Fasman, G.D. (1974) Prediction of protein conformation. *Biochemistry*, **13**, 222-244/225.

Garnier, J., Osguthorpe, D.J. and Robson, B. (1978) Analysis of the accuracy and implications of simple methods for predicting the secondary structure of globular proteins. *J. Mol. Biol.*, **120**, 97-120.

Secondary Structure

Second-generation Methods

- Their main characteristic is the usage of a window of adjacent residues, so that context information is used for the prediction.
- Many algorithms (fed with this contextual information) were used (Neural networks, graph theory, rule-based systems, multivariate analysis, ...)
- This innovation improve the accuracy close to 70%.

• Limitations

- Accuracy (< 70% - 3 states -)
- Low accuracies for β -strands.
- Tendency to predict short secondary structure elements (both α and β).
- Due to:
 - The number of known structures (for training) is still low and they do not cover the space of sequences.
 - Long range interactions (residues far apart in the sequence but close in 3D) are not taken into account.

Secondary Structure Third-generation Methods

Initiated by Levin (~69%) and Rost & Sander (PHD 72%)

- The main novelty is the inclusion of evolutionary information in the form of multiple sequence alignments (profiles – Levin, 1993).
- The problem with the bad predictions for β -strands is solved by balancing the training set since 3D structures contain more α than β (Rost y Sander, 1994)
- For methods based on NN, a second network is used to smooth the predictions and avoid short elements.
- This breaks the 70% limit.

Levin JM, Pascarella S, Argos P, Garnier J. (1993). Quantification of secondary structure prediction improvement using multiple alignments. *Protein Eng.* **6(8)**:849-54.

Rost, B. and Sander, C. (1993) Improved prediction of protein secondary structure by use of sequence profiles and neural networks. *Proc Natl Acad Sci U S A*, **90**, 7558-7562.

Rost, B., Sander, C. and Schneider, R. (1994) PHD - A mail server for protein secondary structure prediction. *Comp. Applic. Biosci.*, **10**, 53-60.

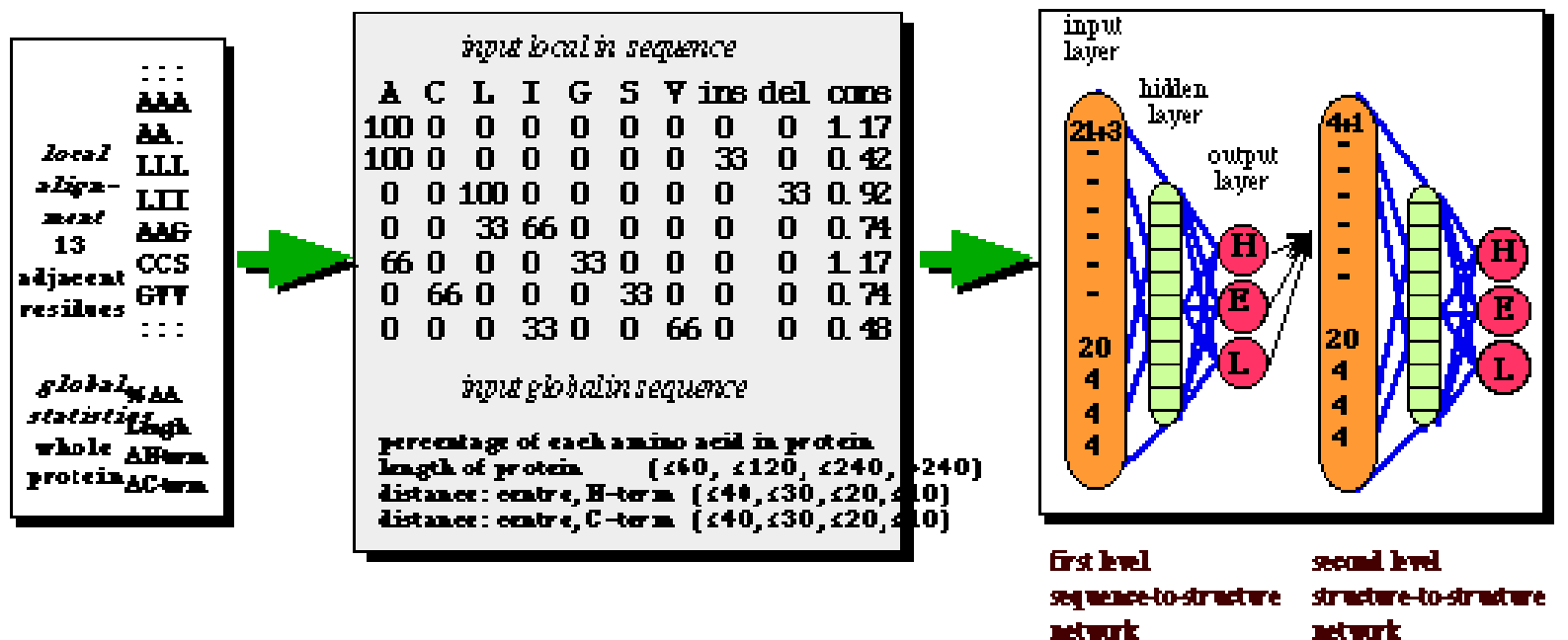
Secondary Structure Third-generation Methods

PHD

sequence information from protein family

profile derived from multiple alignment for a window of adjacent residues

two levels of neural network systems: PHDsec and PHDhtm



Rost, B. and Sander, C. (1993) Improved prediction of protein secondary structure by use of sequence profiles and neural networks.

Proc Natl Acad Sci U S A, **90**, 7558-7562.

Rost, B., Sander, C. and Schneider, R. (1994) PHD - A mail server for protein secondary structure prediction. *Comp. Applic. Biosci.*, **10**, 53-60.

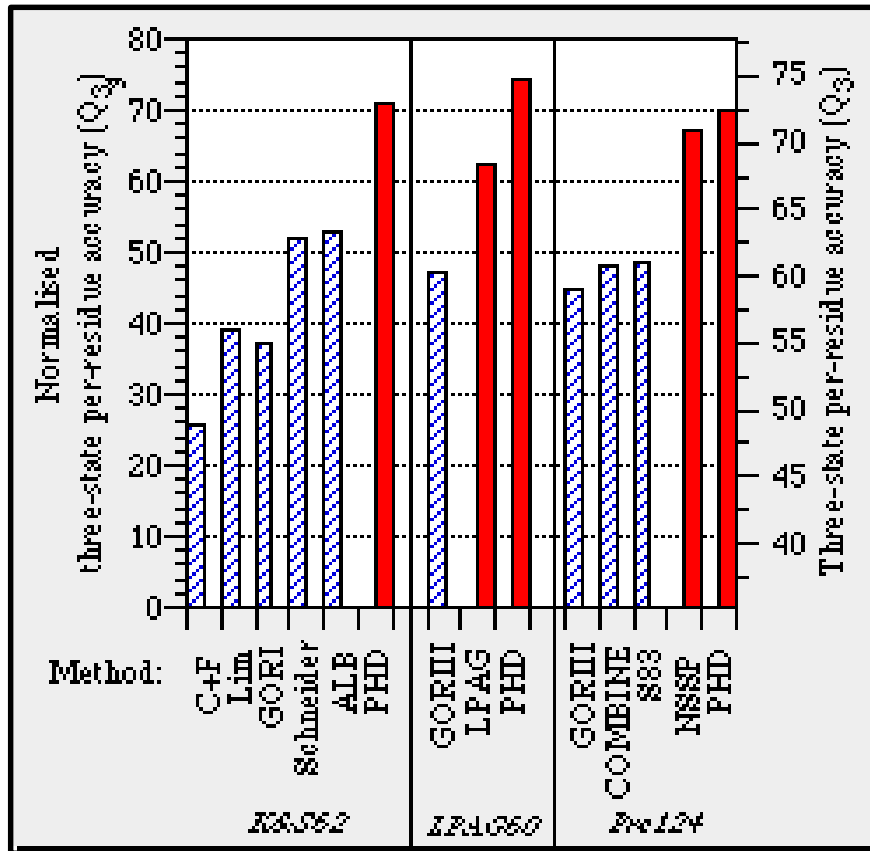
Secondary Structure Third-generation Methods

- Most forthcoming methods followed PHD's strategy, improving the results basically by improving the input multiple sequence alignment (including remote homologues (PSI-BLAST), filtering, ...). *PSIPRED* (1999) ~77%, HMMs used by Kevin Karplus *et al.* in *SAMT99sec* (1999).
- The other main strategy is to combine predictions coming from different methods (consensus methods). *Jpred2* (Cuff y Barton, 2000).

Jones, D.T. (1999) Protein secondary structure prediction based on position-specific scoring matrices. *J Mol Biol*, **292**, 195-202.

Cuff JA, Clamp ME, Siddiqui AS, Finlay M, Barton GJ. (1998). JPred: a consensus secondary structure prediction server. *Bioinformatics*. **14(10)**:892-3.

Secondary Structure Prediction



1st generation methods: Chou & Fasman, Lim, GORI

2nd generation methods : Schneider, ALB, GORIII

3rd generation methods: LPAG, COMBINE, S83, NSSP, PHD

76-78%

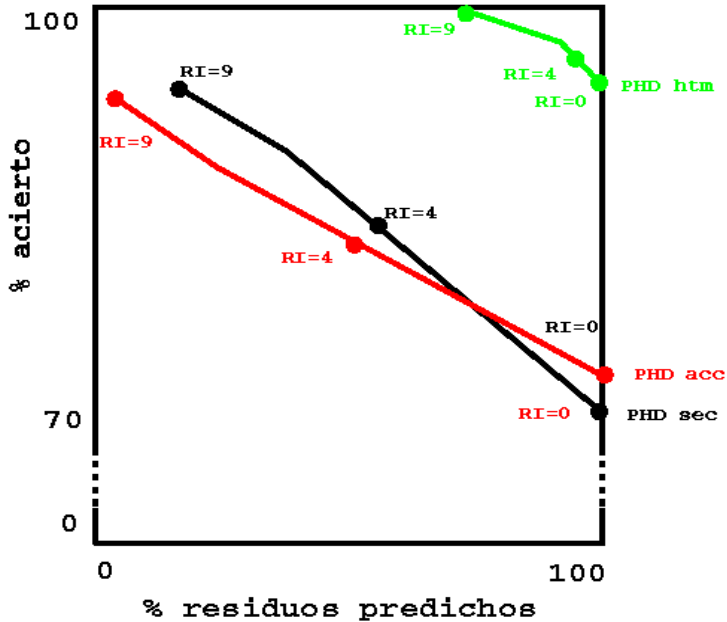
Accuracy limit?

- Limit in the definition of secondary structure (DSSP vs. others)
- Limit in the local information

Secondary Structure Prediction

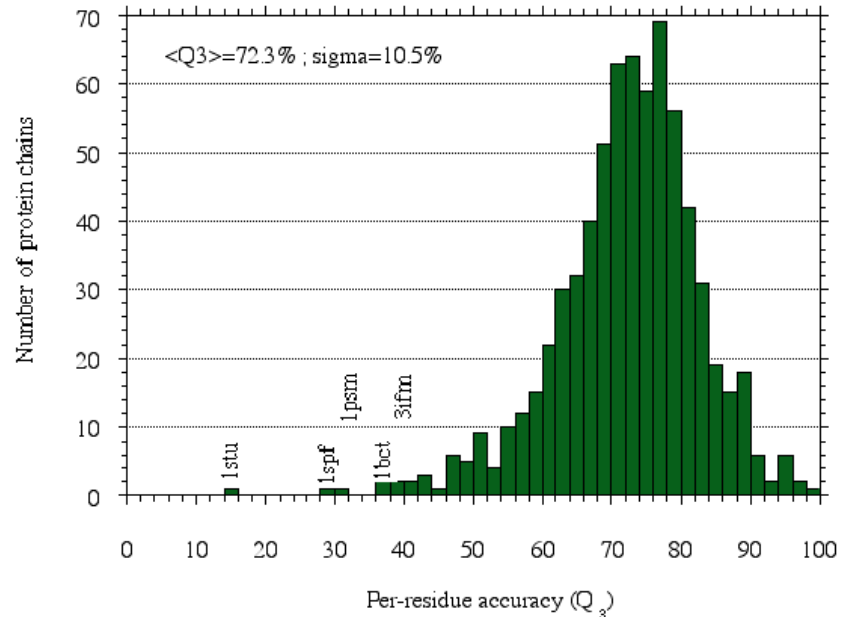
Things to take into account

Balance accuracy/coverage



Results vary from one protein to another

Prediction accuracy varies!



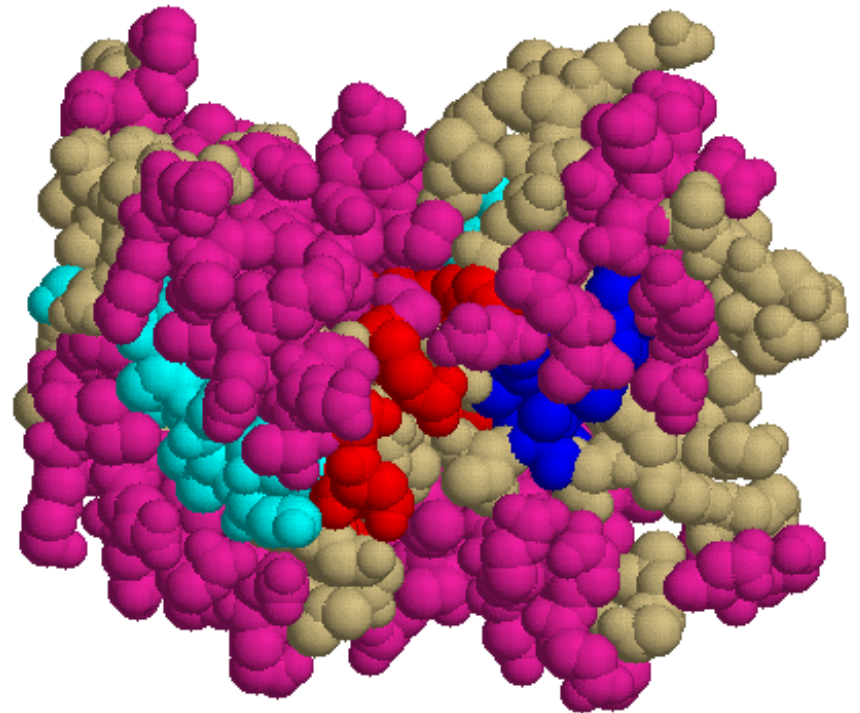
David River (Columbia New York)



1D Methods

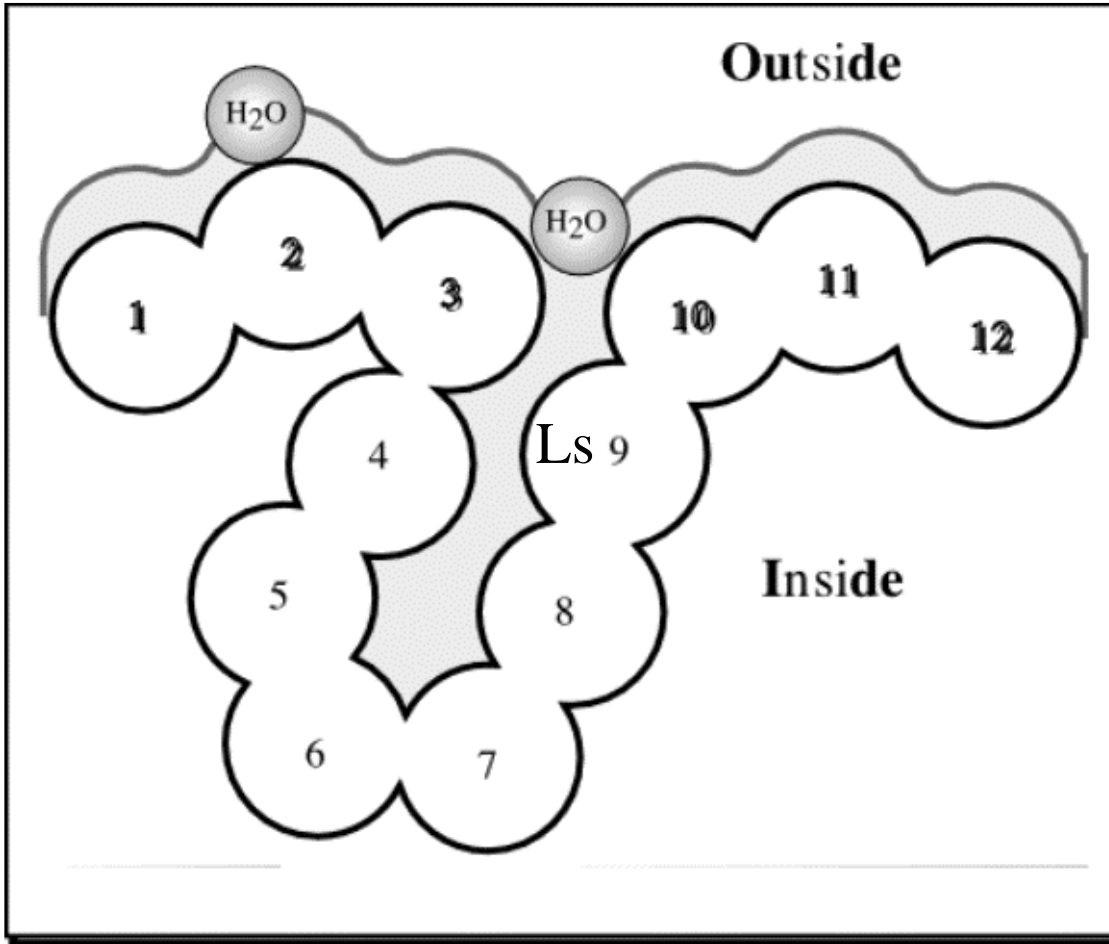
Solvent Accessibility

- Model discrimination
- Functional sites / binding sites
- Mutant design, protein labeling, etc.



1D Methods

Solvent Accessibility



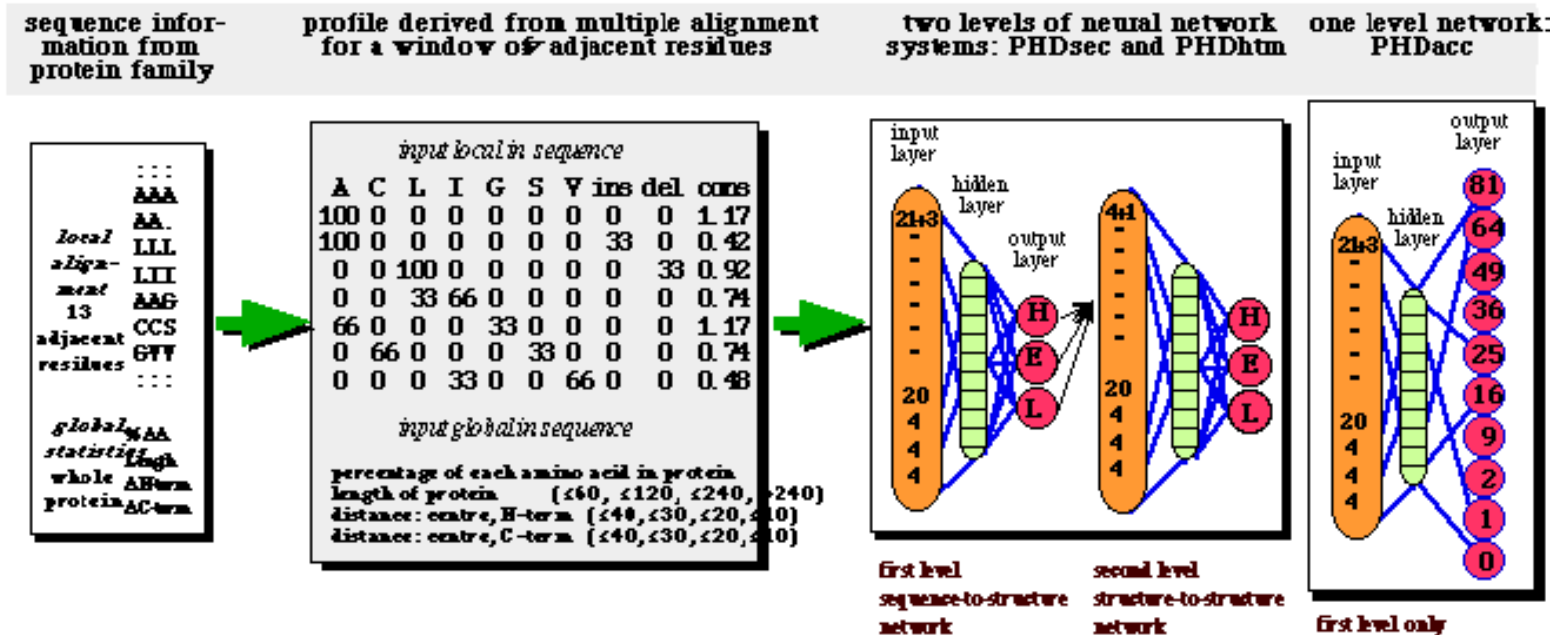
Programs for defining accessibility report (from the 3D structure) the accessible surface of each residue in Å².

Most prediction methods reduce the problem by considering only 2 states: **buried** (rel. accs. <16%, abs <50 Å²) and **exposed** (rel. accs. ≥ 16%, abs ≥50 Å²).

1D Methods

Solvent Accessibility

- Same “history” as secondary structure: frequencies (tendencies) -> windows -> neural networks + evolutionary information (alns.) / consensus.
- Usually the programs are the same, with small adaptations of the NN for the representation of accessibility.



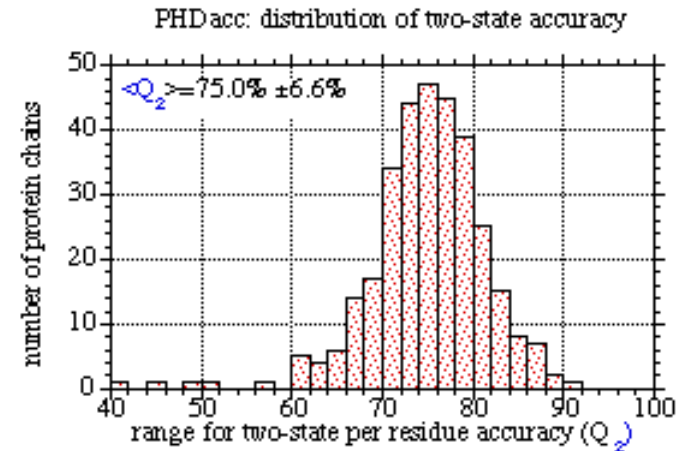
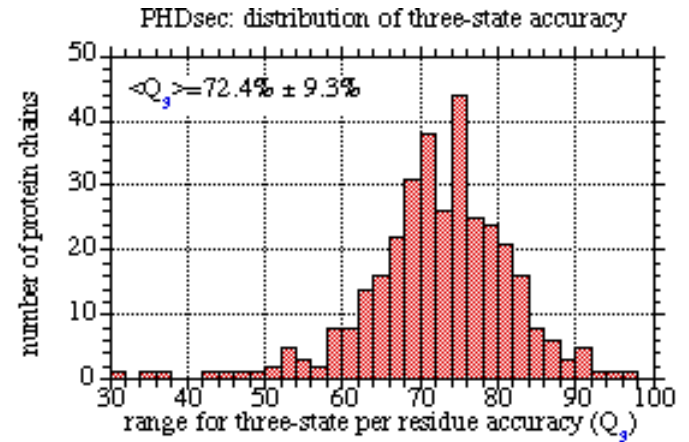
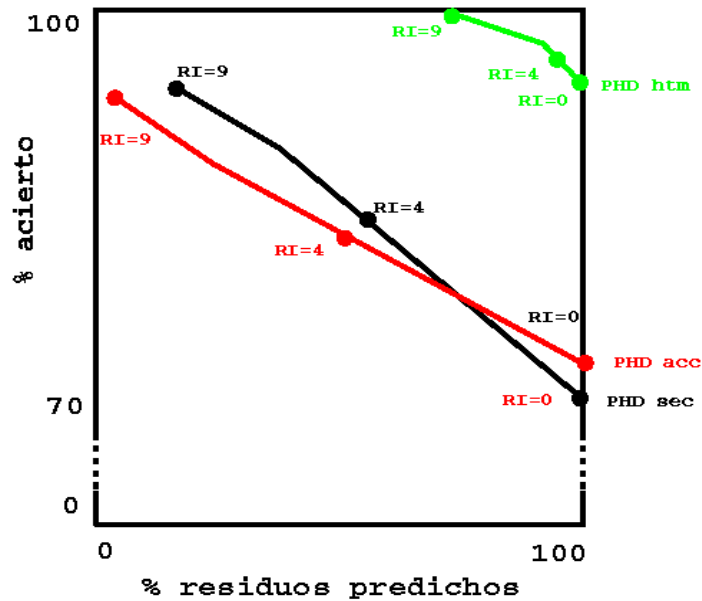
Rost, B. and Sander, C. (1993) Improved prediction of protein secondary structure by use of sequence profiles and neural networks.

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1D Methods

Solvent Accessibility



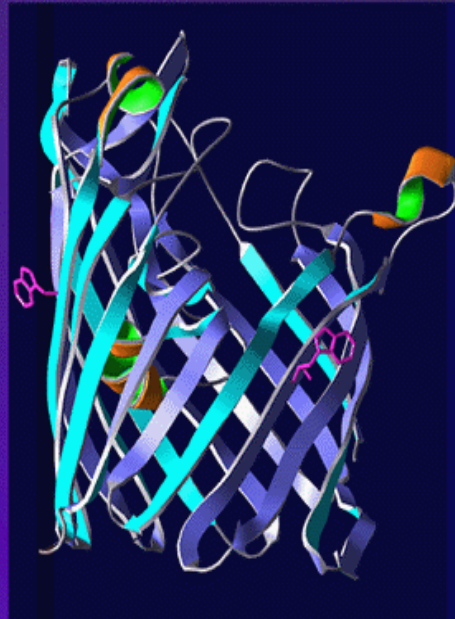
1D Methods

Transmembrane segments

Known Structures of Transmembrane Protein Domains
fall into Two Categories



α -Helical Bundle
(Bacteriorhodopsin, PDB 1AP9)



β -Barrel
(Matrix Porin, PDB 1OPF)

©JHK

-Difficult to crystalize. Few structures

- Preliminary information on domains, functional areas, etc.

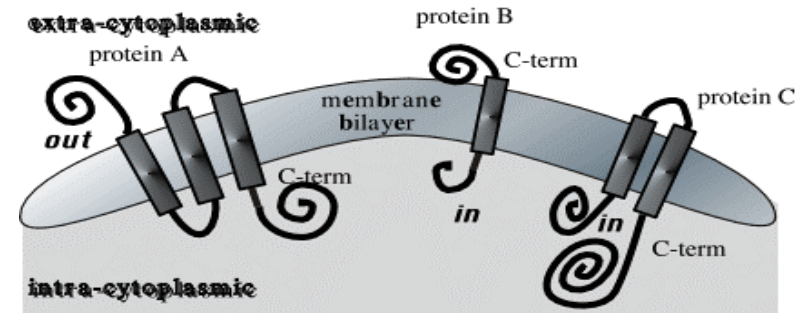
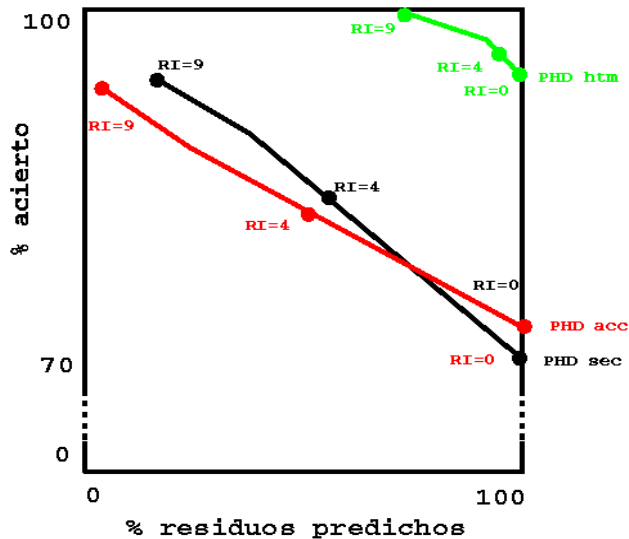
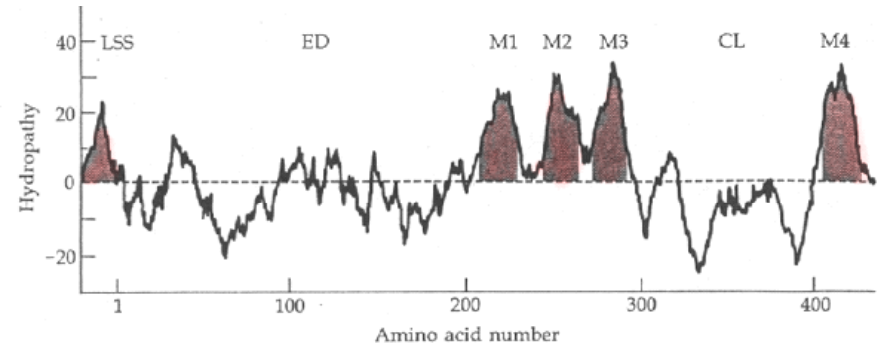
1D Methods

Transmembrane helices

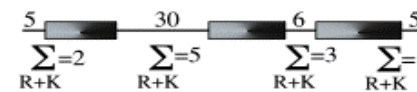
- 20-30 residues.
- hydrophobic.
- charged cytoplasmic loops, ...

Clear characteristics => easy to “learn”

Same NN as for sec. and acc.



Positive-inside-rule



Loop lengths

Charge:
Number of
R+K
in loops 1-4

final prediction:

$$\Delta = (5+1) - (2+3) > 0$$

=> first loop out

1D Methods

Transmembrane helices

MEMSAT - <http://bioinf.cs.ucl.ac.uk/psipred/>

TMAP - <http://www.mbb.ki.se/tmap/index.html>

TopPred2 - <http://bioweb.pasteur.fr/seqanal/interfaces/toppred.html>

HMMTOP - <http://www.enzim.hu/hmmtop/>

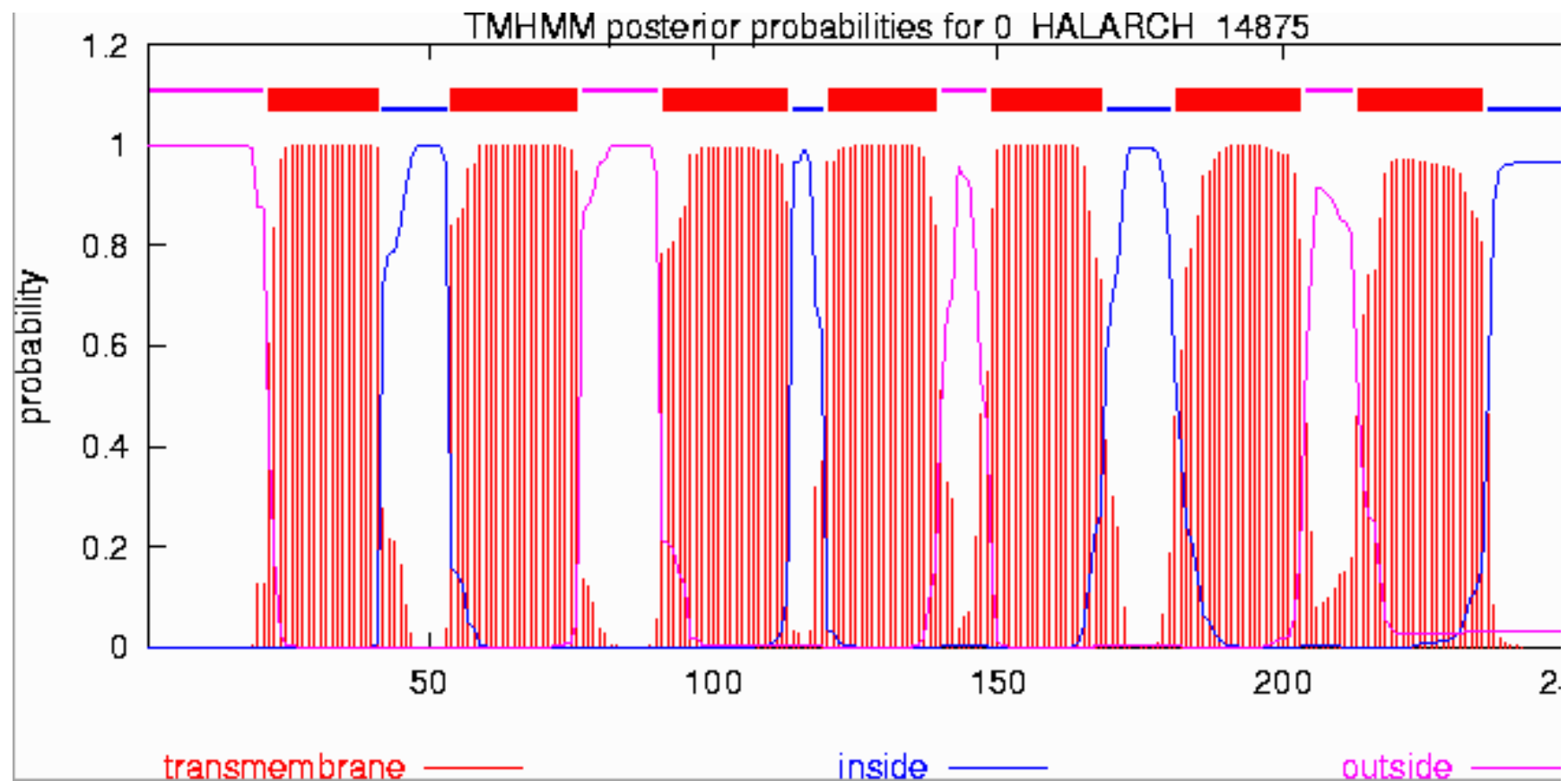
PHDhtm - <http://www.embl-heidelberg.de/predictprotein/>

DAS - <http://www.enzim.hu/DAS/DAS.html>

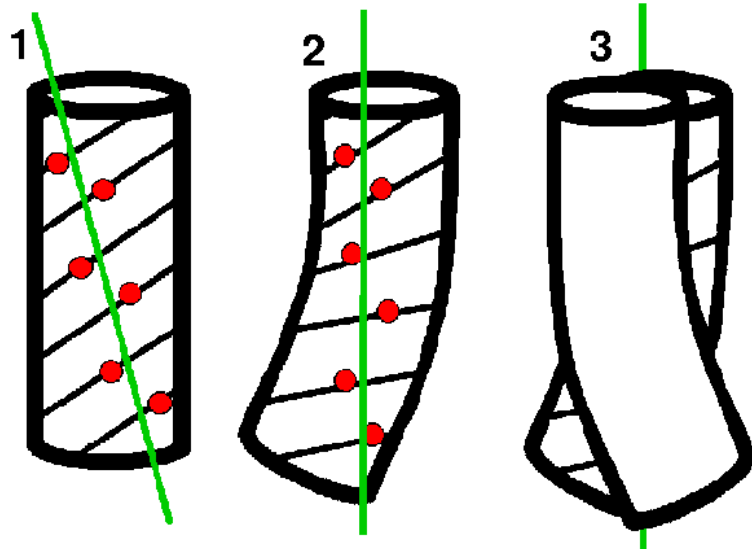
TMHMM - <http://www.cbs.dtu.dk/services/TMHMM/>

1D Methods

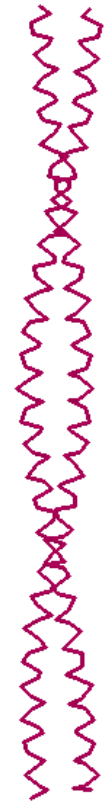
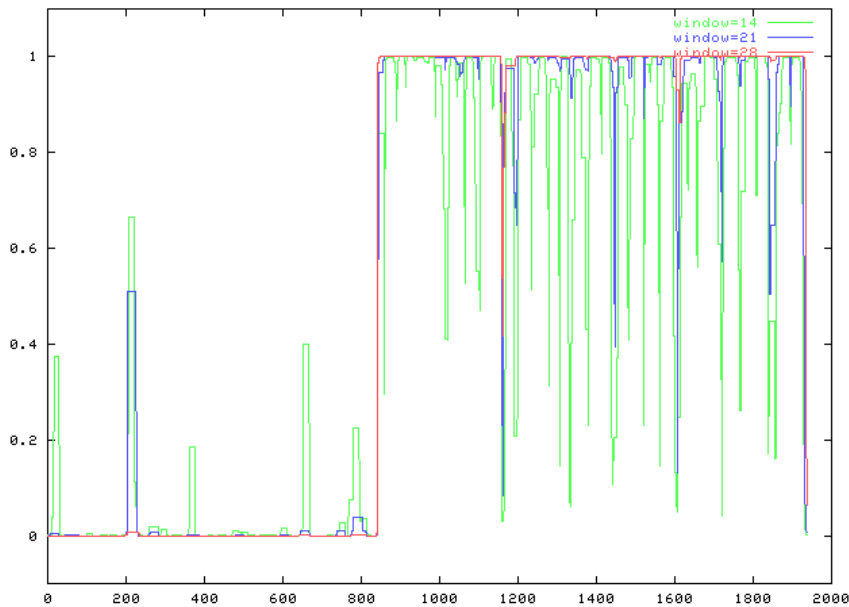
Transmembrane helices



Coiled-coils



Coils output for HYSA HUMAN



[**a**bc**d**efg]_n

Sorting signals - PSORT

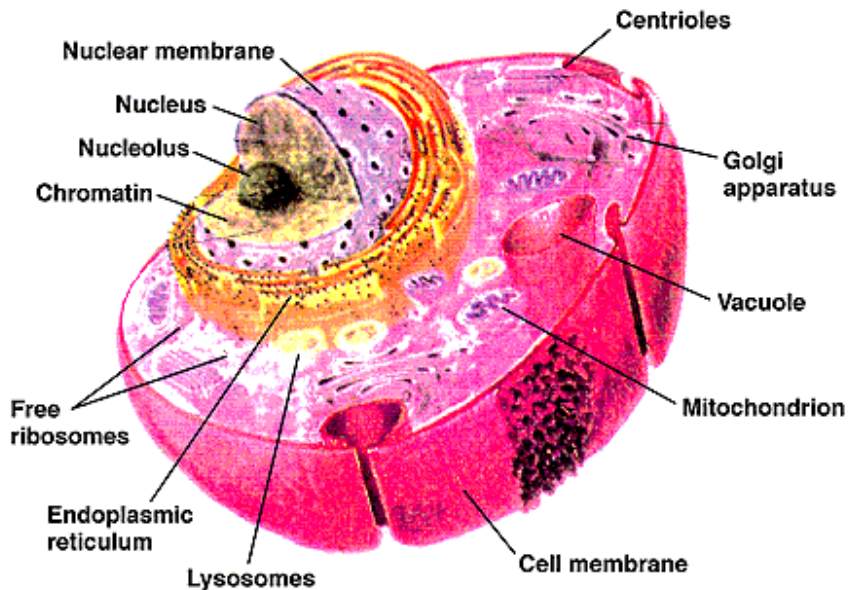
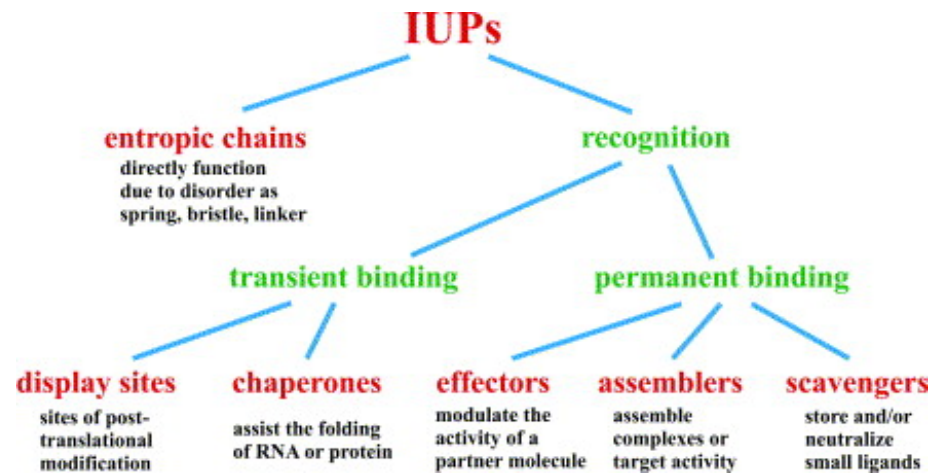
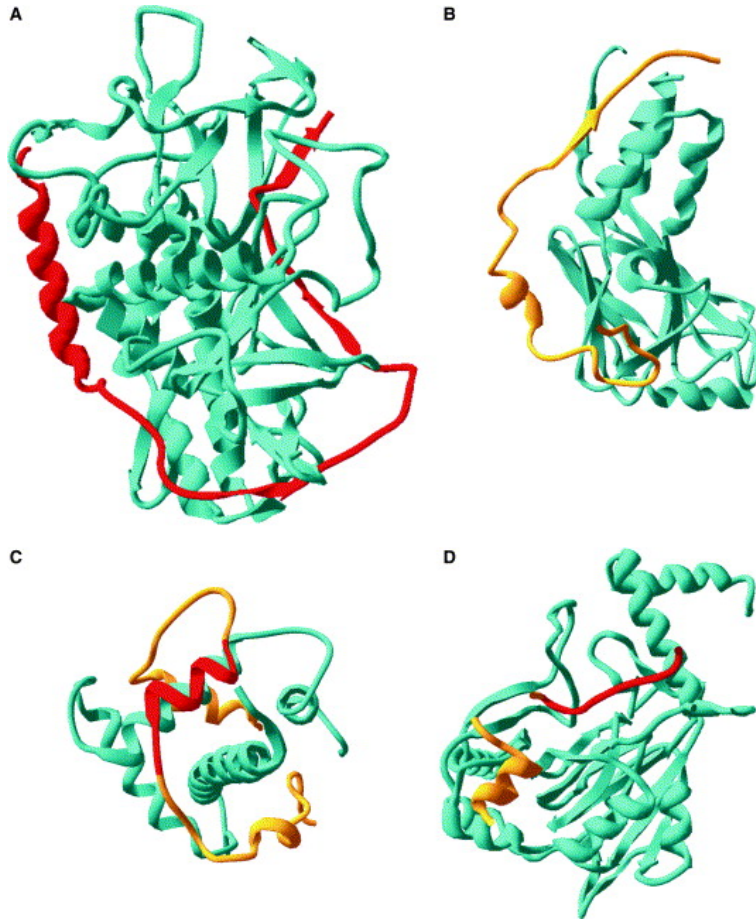


Table 1. Features detected by PSORT II

| Feature | Criteria | Refs |
|-----------------------------------|--|-----------|
| N-terminal signal peptide | Modified McGeoch's method and the cleavage-site consensus | 10, 11 |
| Mitochondrial-targeting signal | Amino acid composition of the N-terminal 20 residues and some weak cleavage-site consensus | 5, 12 |
| Nuclear-localization signals | Combined score for various empirical rules | |
| ER-lumen-retention signal | The KDEL-like motif at the C-terminus | |
| ER-membrane-retention signal | Motifs: XXRR-like (N-terminal) or KKXX-like (C-terminal) | |
| Peroxisomal-targeting signal | PTS1 motif at the C-terminus and the PTS2 motif | |
| Vacuolar-targeting signal | [TIK]LP[NKI] motif | |
| Golgi-transport signal | The YQRL motif (preferentially at the cytoplasmic tail) | |
| Tyrosine-containing motif | Number of tyrosine residues in the cytoplasmic tail | |
| Dileucine motif | At the cytoplasmic tail | |
| Membrane span(s)/topology | Maximum hydrophobicity and the number of predicted spans; charge difference across the most N-terminal transmembrane segment | 5, 13, 14 |
| RNA-binding motif | RNP-1 motif | 15 |
| Actinin-type actin-binding motifs | From PROSITE | 15 |
| Isoprenyl motif | CaaX motif at the C-terminus | |
| GPI-anchor | Type-1a membrane protein with very short tail | |
| N-myristoylation motif | At the N-terminus | |
| DNA-binding motifs | 63 motifs from PROSITE | 15 |
| Ribosomal-protein motifs | 71 motifs from PROSITE | 15 |
| Prokaryotic DNA-binding motifs | 33 motifs from PROSITE | 15 |
| Amino acid composition | Neural network score that discriminates between cytoplasmic and nuclear proteins | 3 |
| Coiled-coil structure | Number of residues in the predicted coiled-coil state | 17 |
| Length | Length of the sequence | |

Unstructured proteins and protein regions



Tompa, P. (2005) The interplay between structure and function in intrinsically unstructured proteins. *FEBS Lett*, **579**, 3346-3354.

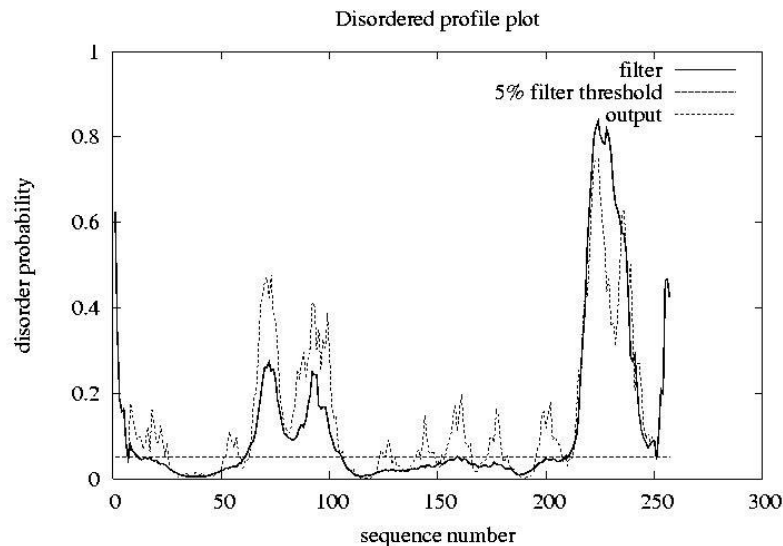
Vucetic, S., Brown, C. J., Dunker, A. K. & Obradovic, Z. Flavors of protein disorder. *Proteins* **52**, 573-84. (2003).

Unstructured regions Prediction Methods

Compositionally biased regions. Wootton et al (*SEG*).

Specific for disorder. 003 Jones UCL (David Jones, University College London) support vector machines (*DISOPRED*)

| Group | N | CASP6 | | | Score |
|-------|----|-------|-------|-------|-------|
| | | Spec. | Sens. | Prod. | |
| 193 | 66 | 0.715 | 0.828 | 0.593 | 6.57 |
| 96 | 65 | 0.507 | 0.955 | 0.485 | 5.07 |
| 3 | 66 | 0.496 | 0.949 | 0.471 | 4.84 |
| 347 | 66 | 0.509 | 0.915 | 0.466 | 4.66 |
| 676 | 58 | 0.450 | 0.952 | 0.428 | 4.31 |
| 18 | 23 | 0.358 | 0.990 | 0.354 | 4.20 |
| 60 | 66 | 0.398 | 0.965 | 0.384 | 3.65 |
| 675 | 59 | 0.584 | 0.715 | 0.418 | 3.43 |
| 461 | 65 | 0.422 | 0.885 | 0.373 | 3.11 |
| 536 | 66 | 0.344 | 0.983 | 0.338 | 3.09 |
| 633 | 64 | 0.549 | 0.713 | 0.391 | 3.00 |
| 686 | 57 | 0.323 | 0.964 | 0.312 | 2.81 |
| 472 | 61 | 0.390 | 0.891 | 0.348 | 2.62 |
| 667 | 59 | 0.326 | 0.903 | 0.295 | 2.20 |
| 673 | 59 | 0.459 | 0.743 | 0.341 | 2.15 |
| 19 | 44 | 0.244 | 0.987 | 0.240 | 1.81 |
| 674 | 59 | 0.178 | 0.980 | 0.175 | 1.15 |
| 679 | 55 | 0.163 | 0.995 | 0.162 | 1.00 |
| 545 | 64 | 0.406 | 0.691 | 0.280 | 0.80 |
| 245 | 60 | 0.060 | 0.942 | 0.057 | -0.55 |



Wootton, J.C. and Federhen, S. (1996) Analysis of compositionally biased regions in sequence databases. *Meth in Enzym*, **266**, 554-571

Ward, J. J., McGuffin, L. J., Bryson K., Buxton, B. F. & Jones, D. T. (2004). The DISOPRED server for the prediction of protein disorder. *Bioinformatics*, **20**:2138-2139.

Other 1D characteristics

ExPASy Proteomics tools <http://www.expasy.ch/tools>

COIL – Coiled-coil regions.

PSORT - prediction of signal proteins and localisation sites

SignalP - prediction of signal peptides

ChloroP - prediction of chloroplast peptides

NetOGlyc - prediction of O-glycosylation sites in mammalian proteins

Big-PI - prediction of glycosyl-phosphatidyl inositol modification sites

DGPI - prediction of anchor and breakage sites for GPI

NetPhos - prediction of phosphorylation sites (Ser, Thr, Tyr) in eukaryotes

NetPicoRNA - prediction of cleavage sites for proteases in the picornavirus

NMT - prediction of N-miristoilation of N-terminals

Sulfinator - predicts sulphattation sites in tyrosines