

Bioinformatics III

Structural Bioinformatics and Genome Analysis

Part Protein Secondary Structure Prediction

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Chapter 4

Protein Secondary Structure Prediction

Protein Secondary Structure Prediction



4 SS Prediction

4.1 Introduction

Traditional field in bioinformatics

4.2 Assigning SS

First applications of neural networks (Sejnowski, NETalk)

4.2.1 DSSP

4.2.2 STRIDE

4.2.3 DEFINE/P-Curve

4.3 Prediction

4.3.1 Chou-Fasman

4.3.2 GOR

4.3.3 Lim

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4.3.5 PHD, PSIPRED,

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protein folding: first secondary structures are formed then 3D

secondary structure: most local information in primary sequence

prediction of secondary structure is important for

- design of de novo proteins
- homology detection
- model building methods (e.g. “Modeller”)
- determining structures with 2D NMR
- first step of ab initio structure prediction

However secondary structure: influenced by 3D interactions

Example:

amino acid subsequences forming a β -sheet
inserted at another place $\rightarrow$ α -helix

exchange of single amino acids can change the secondary structure

Assigning Secondary Structure to Measured Structures



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training examples: from known structures

How to extract secondary structure?

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“Dictionary of Secondary Structure of Proteins” (DSSP)
Kabsch and Sander 1983 <http://swift.cmbi.ru.nl/gv/dssp/>

assigns sheet and helical structures based on
backbone-backbone hydrogen bonds

hydrogen bond: if bond energy is below -0.5 kcal/mol
from a Coulomb approximation

$$E = f \delta^+ \delta^- \left(\frac{1}{r_{\text{NO}}} + \frac{1}{r_{\text{HC}'}} + \frac{1}{r_{\text{HO}}} + \frac{1}{r_{\text{NC}'}} \right)$$

$f = 332 \text{ Å kcal}/e^2$: normalizing constant
 δ^+ and δ^- : polar charges in electron charges e
distances: next slide

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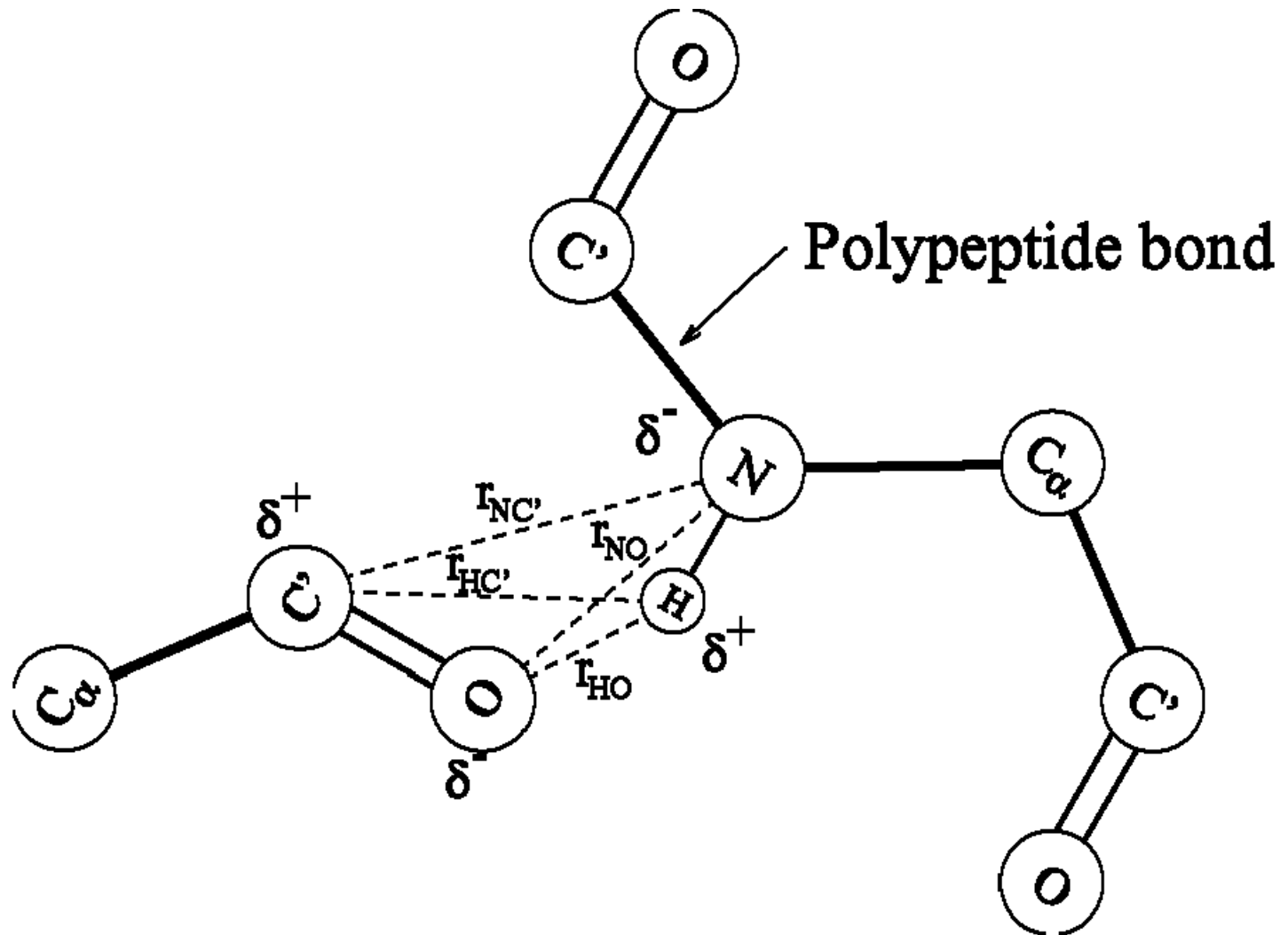
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unbroken structures

overlap: α -helix priority

α -helix: "H" $\rightarrow$ consecutive amino acids $i \rightarrow (i+4)$ hydrogen bonds
ends with two consecutive $i \rightarrow (i+4)$ hydrogen bonds

3_{10} -helix: "G" $\rightarrow$ amino acids $i \rightarrow (i+3)$ hydrogen bonds

π -helix: "I" $\rightarrow$ amino acids $i \rightarrow (i+5)$ hydrogen bonds

Turns: "T" $\rightarrow$ single helix hydrogen bonds

β -sheets: "E" $\rightarrow$ 2 hydrogen bonds or surrounded by hydrogen bonds

β -bridge: "B" $\rightarrow$ single amino acids with hydrogen bonds

bend: "S"

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Symbol	Meaning
H	α -helix
G	3_{10} -helix
I	π -helix
T	turn
E	β -sheet
B	β -bridge
S	bend
-	unassigned

Table 1: The secondary structure symbols assigned by DSSP.

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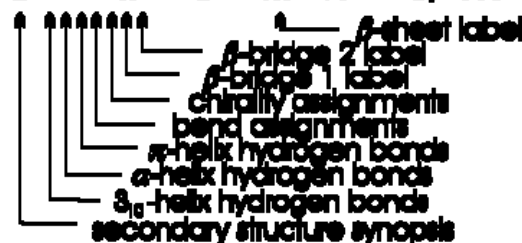
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PDB:1orn

#	RESIDUE	AA	STRUCTURE	BP1	BP2	ACC	N-H-->O	O-->H-N	N-H-->O	O-->H-N
....										
15	15	V	H X G+	0	0	99	-4,-1.7	3,-1.3	2,-0.2	-2,-0.2
16	16	G	H X G+	0	0	18	-4,-2.5	5,-0.8	1,-0.3	-2,-0.2
17	17	R	H X G+	0	0	94	-4,-2.0	3,-1.5	1,-0.2	-1,-0.3
18	18	L	T < G+	0	0	144	-3,-1.3	-1,-0.2	-4,-0.6	-2,-0.2
19	19	P	T S G-	0	0	107	0, 0.0	-1,-0.3	0, 0.0	-2,-0.1
20	20	G	T < G+	0	0	53	-3,-1.6	-3,-0.2	1,-0.2	-2,-0.1
21	21	T	^ -	0	0	37	-5,-0.8	-1,-0.2	1,-0.1	5,-0.1
22	22	P	> V -	0	0	81	0, 0.0	4,-2.2	0, 0.0	3,-0.7
23	23	H	H S G+	0	0	70	1,-0.2	4,-2.5	2,-0.2	5,-0.1
24	24	A	H S G+	0	0	63	1,-0.2	4,-1.7	2,-0.2	-1,-0.2
25	25	I	H < G+	0	0	99	-3,-0.7	4,-1.8	2,-0.2	-1,-0.2
26	26	G	H X G+	0	0	0	-4,-2.2	4,-1.9	2,-0.2	6,-0.4
27	27	A	H X G+	0	0	12	-4,-2.5	4,-2.7	-5,-0.2	5,-0.5
28	28	T	H < G+	0	0	120	-4,-1.7	-1,-0.2	1,-0.2	-2,-0.2
29	29	Y	H < G+	0	0	176	-4,-1.8	-1,-0.2	-5,-0.2	-2,-0.2
30	30	T	H < G-	0	0	24	-4,-1.9	-2,-0.2	-3,-0.2	-3,-0.2
31	31	G	S < G+	0	0	35	-4,-2.7	-3,-0.2	1,-0.4	-4,-0.1
32	32	D	-	0	0	5	-5,-0.5	-1,-0.4	-6,-0.4	2,-0.3
33	33	I	H -A	3	0A	51	-30,-2.8	-30,-2.4	-3,-0.1	2,-0.5
34	34	I	H -A	2	0A	78	-2,-0.3	-32,-0.2	-32,-0.2	3, 0.0
....										



Output example for DSSP

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3 classes:

Symbol	conventional	newer
H	H	H
G	H	C
I	H	C
T	C	C
E	E	E
B	E	C
S	C	C
–	C	C

Table 1: The 8 secondary classes mapped to 3 classes.

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```

HEADER      HYDROLASE      (SERINE PROTEINASE)      17-MAY-76      1EST
...
240  1  4  4  0 TOTAL NUMBER OF RESIDUES, NUMBER OF CHAINS,
NUMBER OF SS-BRIDGES(TOTAL,INTRACHAIN,INTERCHAIN)      .
10891.0  ACCESSIBLE SURFACE OF PROTEIN (ANGSTROM**2)
162 67.5  TOTAL NUMBER OF HYDROGEN BONDS OF TYPE O(I)-->H-N(J) ;
0  0.0  TOTAL NUMBER OF HYDROGEN BONDS IN      PARALLEL BRIDGES
84 35.0  TOTAL NUMBER OF HYDROGEN BONDS IN ANTIPARALLEL BRIDGES;
...
26 10.8  TOTAL NUMBER OF HYDROGEN BONDS OF TYPE O(I)-->H-N(I+2)
30 12.5  TOTAL NUMBER OF HYDROGEN BONDS OF TYPE O(I)-->H-N(I+3)
10  4.2  TOTAL NUMBER OF HYDROGEN BONDS OF TYPE O(I)-->H-N(I+4)
...
# RESIDUE AA STRUCTURE BP1 BP2 ACC  N-H-->O  O-->H-N  N-H-->O  O-->H-N
2  17  V  B 3  +A 182  OA  8 180,-2.5 180,-1.9  1,-0.2 134,-0.1

TCO  KAPPA ALPHA  PHI  PSI  X-CA  Y-CA  Z-CA
-0.776 360.0  8.1 -84.5 125.5  -14.7  34.4  34.8

.....1.....;.....2.....;.....3.....;.....4.....;.....5.....;.....6.....;.....7...
.-- sequential resnumber, including chain breaks as extra residues
|      .-- original PDB resname, not nec. sequential, may contain letters
|      |      .-- amino acid sequence in one letter code
|      |      |      .-- secondary structure summary based on columns 19-38
|      |      |      |      xxxxxxxxxxxxxxxxxxxxxx recommend columns for secstruc details
|      |      |      |      .-- 3-turns/helix
|      |      |      |      |      .-- 4-turns/helix
|      |      |      |      |      |      .-- 5-turns/helix
|      |      |      |      |      |      |      .-- geometrical bend
|      |      |      |      |      |      |      |      .-- chirality
|      |      |      |      |      |      |      |      |      .-- beta bridge label
|      |      |      |      |      |      |      |      |      |      .-- beta bridge label
|      |      |      |      |      |      |      |      |      |      |      .-- beta bridge partner resnum
|      |      |      |      |      |      |      |      |      |      |      |      .-- beta bridge partner resnum
|      |      |      |      |      |      |      |      |      |      |      |      |      .-- beta sheet label
|      |      |      |      |      |      |      |      |      |      |      |      |      |      .-- solvent accessibility
|      |      |      |      |      |      |      |      |      |      |      |      |      |      |
# RESIDUE AA STRUCTURE BP1 BP2 ACC
|      |      |      |      |      |      |      |      |
35  47  I  E  +  0  0  2
36  48  R  E  >  S- K  0 39C 97
37  49  Q  T 3  S+  0  0  86      (example from 1EST)
38  50  N  T 3  S+  0  0  34
39  51  W  E  <  -KL 36 98C  6
    
```

- ★ “# RESIDUE”: two columns of residue numbers.
- ★ “AA”: one letter amino acid code, lower case for SS-bridge CYS.
- ★ “S” (first column in STRUCTURE block): compromise summary of secondary structure,
- ★ “BP1 BP2”: residue number of first and second bridge partner followed by one letter sheet label
- ★ “ACC”: number of water molecules in contact with this residue *10. or residue water exposed surface in Angstrom².
- ★ “N-H-_iO” etc.: hydrogen bonds; e.g. -3,-1.4 means: if this residue is residue i then N-H of I is h-bonded to C=O of I-3 with an electrostatic H-bond energy of -1.4 kcal/mol. There are two columns for each type of H-bond, to allow for bifurcated H-bonds
- ★ “TCO”: cosine of angle between C=O of residue I and C=O of residue I-1. For alpha-helices, TCO is near +1, for beta-sheets TCO is near -1. Not used for structure definition.
- ★ “KAPPA”: virtual bond angle (bend angle) defined by the three C-alpha atoms of residues I-2,I,I+2. Used to define bend (structure code ‘S’).
- ★ “ALPHA”: virtual torsion angle (dihedral angle) defined by the four C-alpha atoms of residues I-1,I,I+1,I+2. Used to define chirality (structure code ‘+’ or ‘-’).
- ★ “PHI PSI”: IUPAC peptide backbone torsion angles
- ★ “X-CA Y-CA Z-CA”: echo of C-alpha atom coordinates

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STRuctural IDentification method (STRIDE)

http://www.embl-heidelberg.de/argos/stride/stride_info.html

empirical hydrogen bond energy:

$$E = E_r E_t E_p$$

$$E_r = -2.8 \text{ kcal/mol} \left(\frac{43^6}{r_{\text{NO}}^6} - \frac{33^8}{r_{\text{NO}}^8} \right)$$

$$E_p = \cos^2 \theta$$

$$E_t = \begin{cases} (0.9 + 0.1 \sin(2 t_i)) \cos t_o & \text{for } 0^\circ < t_i \leq 90^\circ \\ K_1 (K_2 - \cos^2(t_i)) \cos t_o & \text{for } 90^\circ < t_i \leq 110^\circ \\ 0 & \text{for } 110^\circ < t_i \end{cases}$$

energy E_r is similar to the Lennard-Jones potential
(optimal distances of 3 Å for the backbone hydrogen bond)

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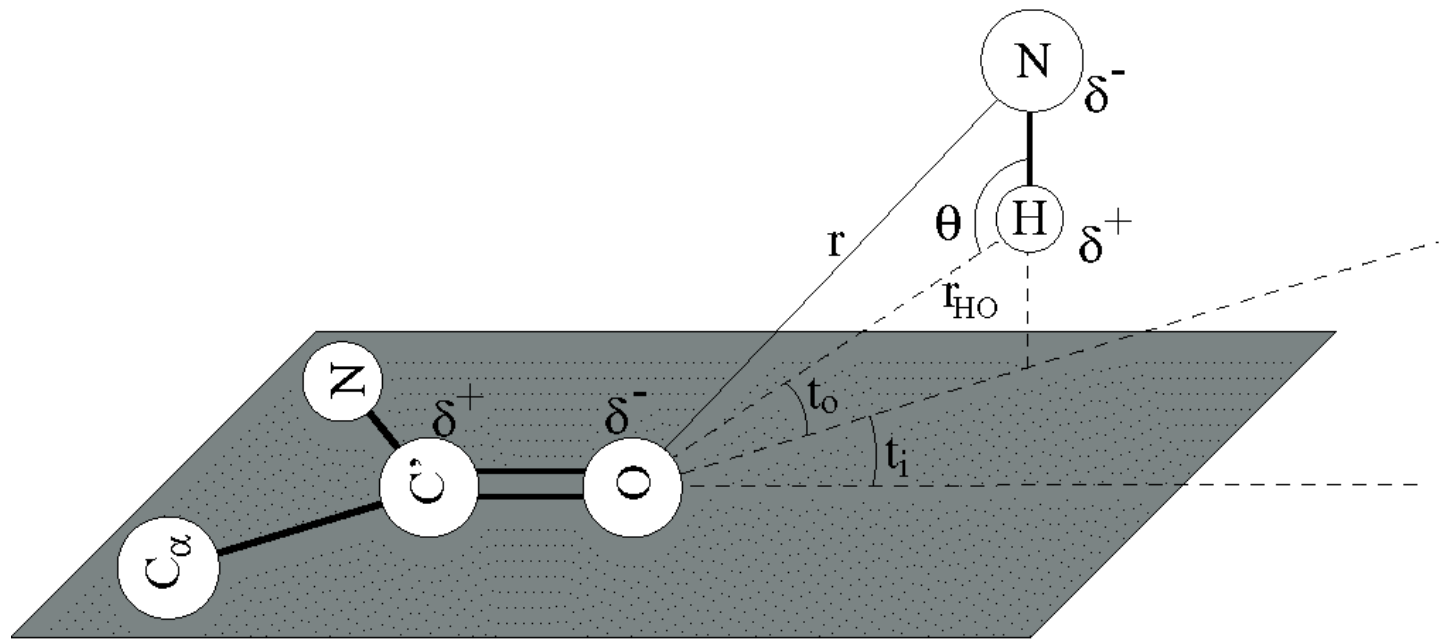
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STRIDE uses additionally to the energy the phi-psi torsion angles

→ Ramachandran plots

STRIDE agree better with experts than DSSP

Symbol	Meaning
H	α -helix
G	3_{10} -helix
I	π -helix
T	turn
E	β -sheet
B	β -bridge
C	unassigned

Table 1: The secondary structure symbols assigned by STRIDE.

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example for the STRIDE output

```

PDB:1crn
REM  |---Residue---|  |--Structure--|  |-Phi-|  |-Psi-|  |-Area-|  1CRN
....
ASG VAL - 15 15 H AlphaHelix -69.24 -41.22 93.0 1CRN
ASG CYS - 16 16 H AlphaHelix -56.67 -36.00 10.4 1CRN
ASG ARG - 17 17 H AlphaHelix -77.07 -16.13 94.1 1CRN
ASG LEU - 18 18 H AlphaHelix -53.21 -46.17 143.0 1CRN
ASG PRO - 19 19 C Coil -77.19 -7.60 108.9 1CRN
ASG GLY - 20 20 C Coil 106.26 7.31 52.1 1CRN
ASG THR - 21 21 C Coil -52.67 136.34 30.4 1CRN
ASG PRO - 22 22 C Coil -56.98 146.62 81.9 1CRN
ASG GLU - 23 23 H AlphaHelix -56.41 -36.19 60.9 1CRN
ASG ALA - 24 24 H AlphaHelix -63.43 -34.66 61.3 1CRN
ASG ILE - 25 25 H AlphaHelix -74.77 -37.89 90.2 1CRN
ASG CYS - 26 26 H AlphaHelix -64.95 -31.69 0.0 1CRN
ASG ALA - 27 27 H AlphaHelix -62.04 -54.03 11.6 1CRN
ASG THR - 28 28 H AlphaHelix -60.70 -25.49 121.1 1CRN
ASG TYR - 29 29 H AlphaHelix -67.59 -36.30 174.0 1CRN
ASG THR - 30 30 H AlphaHelix -100.96 -18.47 23.4 1CRN
ASG GLY - 31 31 C Coil 91.82 -3.07 36.1 1CRN
ASG CYS - 32 32 C Coil -69.52 164.38 4.6 1CRN
ASG ILE - 33 33 E Strand -129.76 157.03 51.0 1CRN
ASG ILE - 34 34 E Strand -111.56 129.59 70.0 1CRN
....

```


DEFINE and P-Curve



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DEFINE: C_{α} -coordinate match with the optimal secondary structure

first perfect matches are found and then elongated (BLAST)

Problems appear with sheets: bend, curvature

P-Curve: differential geometry to calculate a helicoidal axis

Assignments: pattern matching

Prediction of Secondary Structure



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3 generations according to Burkhard Rost:

1. **Generation:** single residue statistics (70's)
best performance: 60 %
Examples: Chou-Fasman, GORI, Lim's approach
2. **Generation:** window over the current position (80's)
best performance: 65 %
Examples: GORIII, ALB, Schneider's approach
3. **Generation:** profile or position specific scoring matrix (PSSM) 90's
best performance: 78 %
Examples: PHD, Jpred2, SSPro and Porter, PSIPRED, PROF

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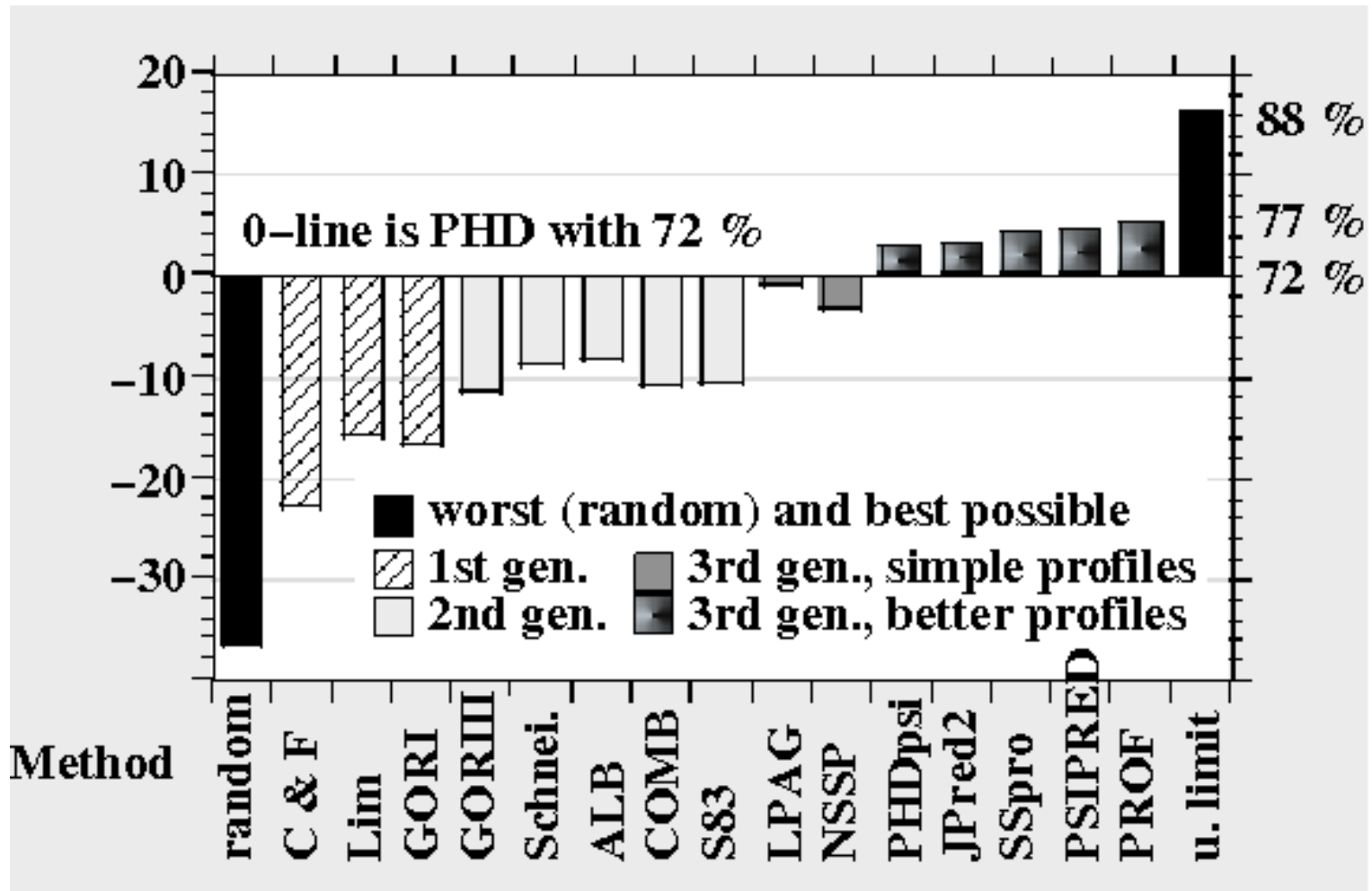
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Chou-Fasman method 1978:

Propensity: likelihood ratio of amino acid a and structure s

$$P_s(a) \quad s = \alpha, \beta, t$$

$$P_s(a) = \frac{p(a, s)}{p(a) p(s)}$$

$p(a, s)$ estimated by the number of amino acid a in structure s divided by the number of all amino acids in the data base

$p(a)$ estimated by the number of amino acid a divided by the number of all amino acids in the data base

$p(s)$ estimated by the number of all amino acids in structure s divided by the number of all amino acids in the data base

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secondary structure: start a nucleation

- α -helices if four out of six residues have $P_{\alpha} > 1.03$
- β -strands if three out of five residues have $P_{\beta} > 1.00$

nucleation elongated until mean of 4 AA propensity is below threshold

Higher average propensity wins

Turns: four residues $\rightarrow$ probability $p(a | t, i)$ amino acid at i in turn
probabilities multiplied (independence) $\rightarrow$ joint probability

first probability must be larger than α -helix and β -strand
second probability larger than $7.5 \cdot 10^{-5}$

Performance: 50-60% of accuracy

random guessing 33%

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GOR (Garnier-Osguthorpe-Robson): statistical principles

probability a in special SS depends on neighbors

frequency matrix F^s of 17 residue window for SS s

$F_{a,j}^s$ frequency of amino acid a at the j th position for SS s

$$P_s(a_l) = \sum_{j=l-8}^{l+8} F_{a_j,j}$$

maximal value $\rightarrow$ SS

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Garnier 1996: information theory

likelihood ratio:
$$P_s(a) = \frac{p(s | a)}{p(s)} \approx \frac{f_{s,a}}{f_s}$$

mutual information between residue a and structure s

$$I(s, a) = H(s) + H(a) - H(s, a)$$

$$H(x) = - \sum_x p(x) \log p(x)$$

$$I(s, a) = \sum_{s,a} p(s, a) \log \frac{p(s, a)}{p(s) p(a)} = \mathbf{E}_{(s,a)} \log \frac{p(s, a)}{p(s) p(a)}$$

local information

$$\log \frac{p(s, a)}{p(s) p(a)} = \log \frac{p(s | a)}{p(s)}$$

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difference of the local information

$$I_{\text{loc}}(\Delta s; a) = \log \frac{p(s | a)}{p(s)} - \log \frac{p(\neg s | a)}{p(\neg s)} =$$

$$\log \frac{p(s | a)}{p(s)} - \log \frac{1 - p(s | a)}{1 - p(s)} =$$

$$\log \frac{p(s | a)}{1 - p(s | a)} + \log \frac{1 - p(s)}{p(s)}$$

$$I_{\text{loc}}(\Delta s; a) = \log \frac{f_{s,a}}{1 - f_{s,a}} + \log \frac{1 - f_s}{f_s}$$

Exponentiating:

$$\frac{p(s | a)}{1 - p(s | a)} = \frac{p(s)}{1 - p(s)} \exp(-I_{\text{loc}}(\Delta s; a))$$

$I_{\text{loc}}(\Delta s; a)$ for 17 positions and probability ratios multiplied together

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single position specific influence of amino acids on SS

GORIII 1987: probability of SS conditioned on amino acid pairs
→ assuming less independence

conditioned on n amino acids requires to estimate
 20^n variables $p(s \mid a_1, \dots, a_n)$

BUT: data sets are not large enough to estimate these values

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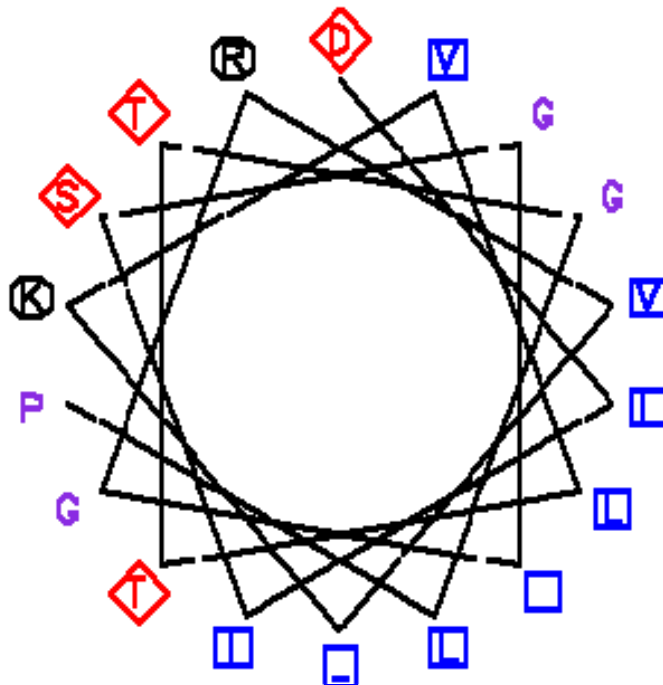
4.4.4 Problems

stereochemical rules for prediction the secondary structure

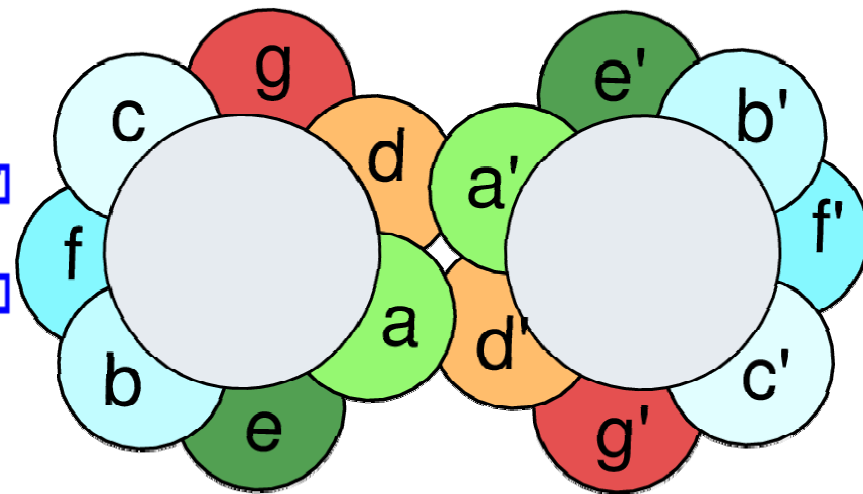
α -helix: hydrophobic side (faces internally of the protein)

biochemical insights $\rightarrow$ high explanatory

Helical wheel



Coiled-coil



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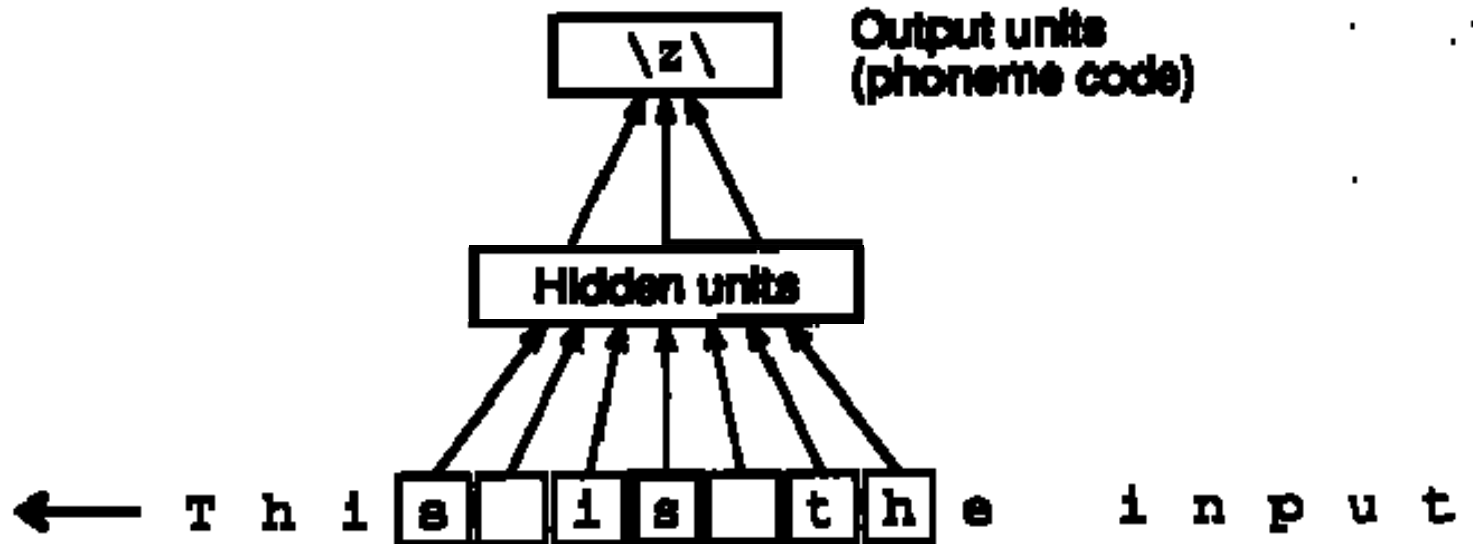
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1988 Qian and Sejnowski with NETTalk architecture

64.3% accuracy



Neural Networks

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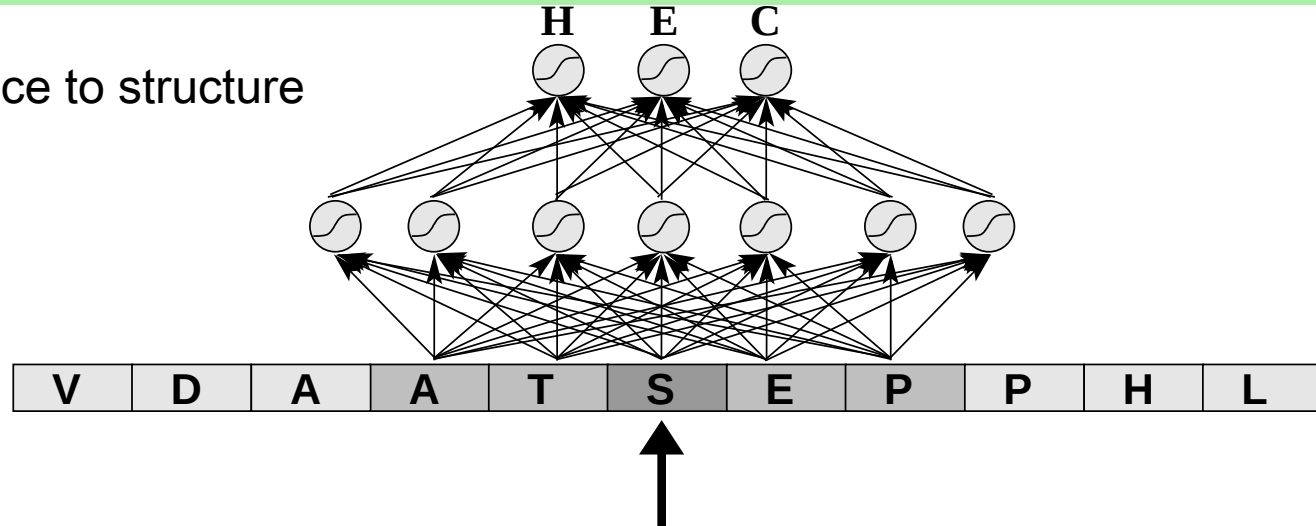
4.4.1 Non-Homologous

4.4.2 SS Classes

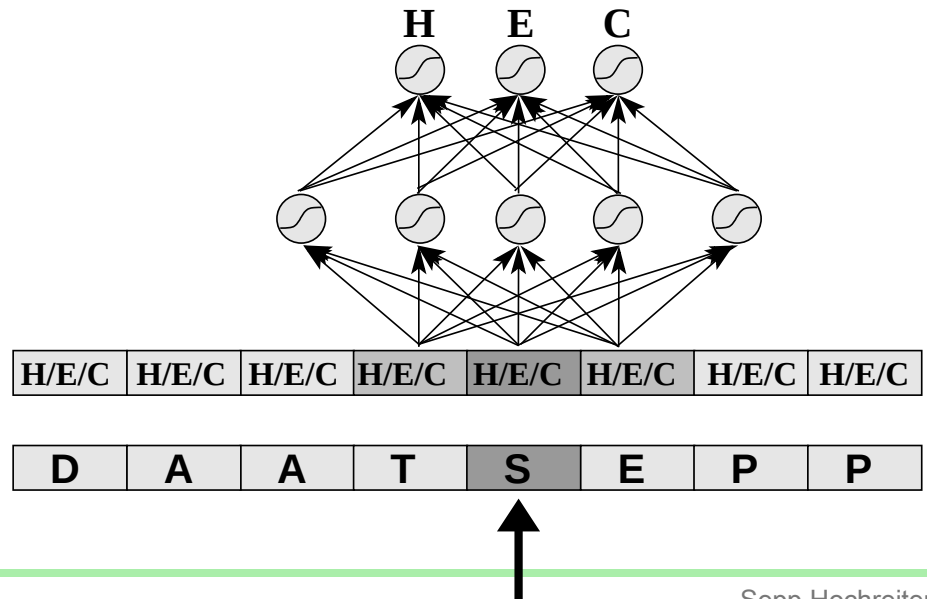
4.4.3 Quality Measures

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Sequence to structure



Structure to structure



PHD, PSIPRED, PREDATOR, JNet, JPred2, NSSP, SSPro



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1993 “Profile network from HeiDelberg” (PHD) introduced by Burkart Rost was a breakthrough: accuracy 70.2 %

important novelty:

profiles (multiple alignments) and position specific scoring matrices (PSSMs) instead of the primary sequence

→ averaged over many sequences which are very similar to the query sequence

→ averaged over the same structure

Helix and or β -sheet regions: better recognized because average gives hydrophobic or hydrophilic regions

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Another important fact: long range information is included

similar local PSSM → similar sequences are used for alignment
→ similar global structure → long range interactions fit

E.g.: strand needs partner → global structure ensures partner

3 levels: sequence-to-structure network

structure-to-structure network

HHHHHCHHHH → HHHHHHHHHH

voting procedure

correct for biases like underestimating β -sheets

PHD, PSIPRED, PREDATOR, JNet, JPred2, NSSP, SSPro



4 SS Prediction	DSSP	E	L	L	L	L	L	E	E	E	E	E	E	E	E	E	E	E	E	E	E	H	H	H
4.1 Introduction	SB	N	S	T	N	K	D	W	W	K	V	E	V	N	D	R	Q	G	F	V	P	A	A	Y
4.2 Assigning SS	a1	N	K	S	N	P	D	W	W	E	G	E	L	N	G	Q	R	G	V	F	P	A	S	Y
4.2.1 DSSP	a2	E	E	H	.	G	E	W	W	K	A	K	s	s	K	R	E	G	F	I	P	S	N	Y
	a3	R	S	T	.	G	D	W	W	L	A	r	v	T	G	R	E	G	Y	V	P	S	N	F
	a4	F	S	.	.	.	.	F	F	G	V	e	v	D	D	L	Q	V	F	V	P	P	A	Y
4.2.2 STRIDE	V	0	0	0	0	0	0	0	0	0	40	0	60	0	0	0	0	20	20	60	0	0	0	0
4.2.3 DEFINE/P-Curve	L	0	0	0	0	0	0	0	0	20	0	0	20	0	0	20	0	0	0	0	0	0	0	0
	I	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0
	M	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4.3 Prediction	F	20	0	0	0	0	0	20	20	0	0	0	0	0	0	0	0	0	60	20	0	0	0	20
4.3.1 Chou-Fasman	W	0	0	0	0	0	0	80	80	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	80
4.3.2 GOR	G	0	0	0	0	50	0	0	0	20	20	0	0	0	0	40	0	0	80	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	40	40	0
4.3.3 Lim	P	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	20	0	0
	S	0	60	25	0	0	0	0	0	0	0	0	0	20	20	0	0	0	0	0	0	40	20	0
4.3.4 Neural Networks	T	0	0	50	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0
	C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4.3.5 PHD, PSIPRED, Jpred	H	0	0	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	R	20	0	0	0	0	0	0	0	0	0	20	0	0	0	60	20	0	0	0	0	0	0	0
4.4 Evaluating	K	0	20	0	0	25	0	0	0	40	0	20	0	0	20	0	0	0	0	0	0	0	0	0
	Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	40	0	0	0	0	0	0	0
4.4.1 Non-Homologous	E	20	20	0	0	0	25	0	0	20	0	60	0	0	0	0	40	0	0	0	0	0	0	0
	N	40	0	0	100	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	40	0
4.4.2 SS Classes	D	0	0	0	0	0	75	0	0	0	0	0	0	20	40	0	0	0	0	0	0	0	0	0
4.4.3 Quality Measures	N _{hel}	0	0	1	3	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	N _{its}	0	0	0	0	0	0	0	0	0	0	2	3	1	0	0	0	0	0	0	0	0	0	0
4.4.4 Problems																								

PHD, PSIPRED, PREDATOR, JNet, JPred2, NSSP, SSPro



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first level:
sequence-to-
structure



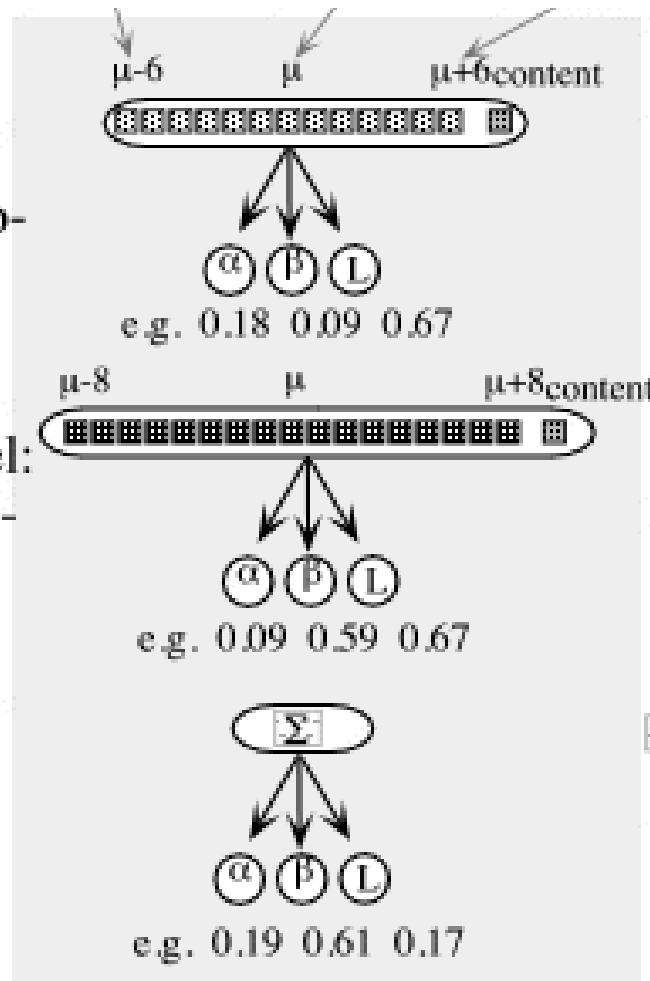
second level:
structure-to-
structure



third level:
jury
decision



winner-take-all:



$\boxtimes$ = 24 units per residue
 20 for amino acids,
 1 for spacer
 1 for conservation weight
 2 for insert/delete
 $\boxtimes$ = 20 units for amino
 acid content in protein

$\boxtimes$ = 35 units per residue
 7*3 for α , β , L
 7*1 for spacer
 7*1 for conservation weight
 $\boxtimes$ = 20 units for amino
 acid content in protein

Σ = 3 units per architecture
 used in jury decision
 for: α , β , L

prediction = β
 (unit with maximal value)

PHD, PSIPRED, PREDATOR, JNet, JPred2, NSSP, SSPro



4 SS Prediction

4.1 Introduction

PHD: accuracy 70.2% for profiles
vs. 63% for primary sequence

4.2 Assigning SS

4.2.1 DSSP

4.2.2 STRIDE

PSIPRED: based on PSI-BLAST PSSM

4.2.3 DEFINE/P-Curve

Other methods:

4.3 Prediction

NSSP

4.3.1 Chou-Fasman

PHDpsi

4.3.2 GOR

JNet

4.3.3 Lim

SSpro

4.3.4 Neural Networks

PROF

4.3.5 PHD, PSIPRED,

JPred2

4.4 Evaluating

SSpro: based on a recurrent neural network

4.4.1 Non-Homologous

4.4.2 SS Classes

Currently the best performing method is an extension of SSPro:

4.4.3 Quality Measures

Porter

4.4.4 Problems

PHD, PSIPRED, PREDATOR, JNet, JPred2, NSSP, SSPro

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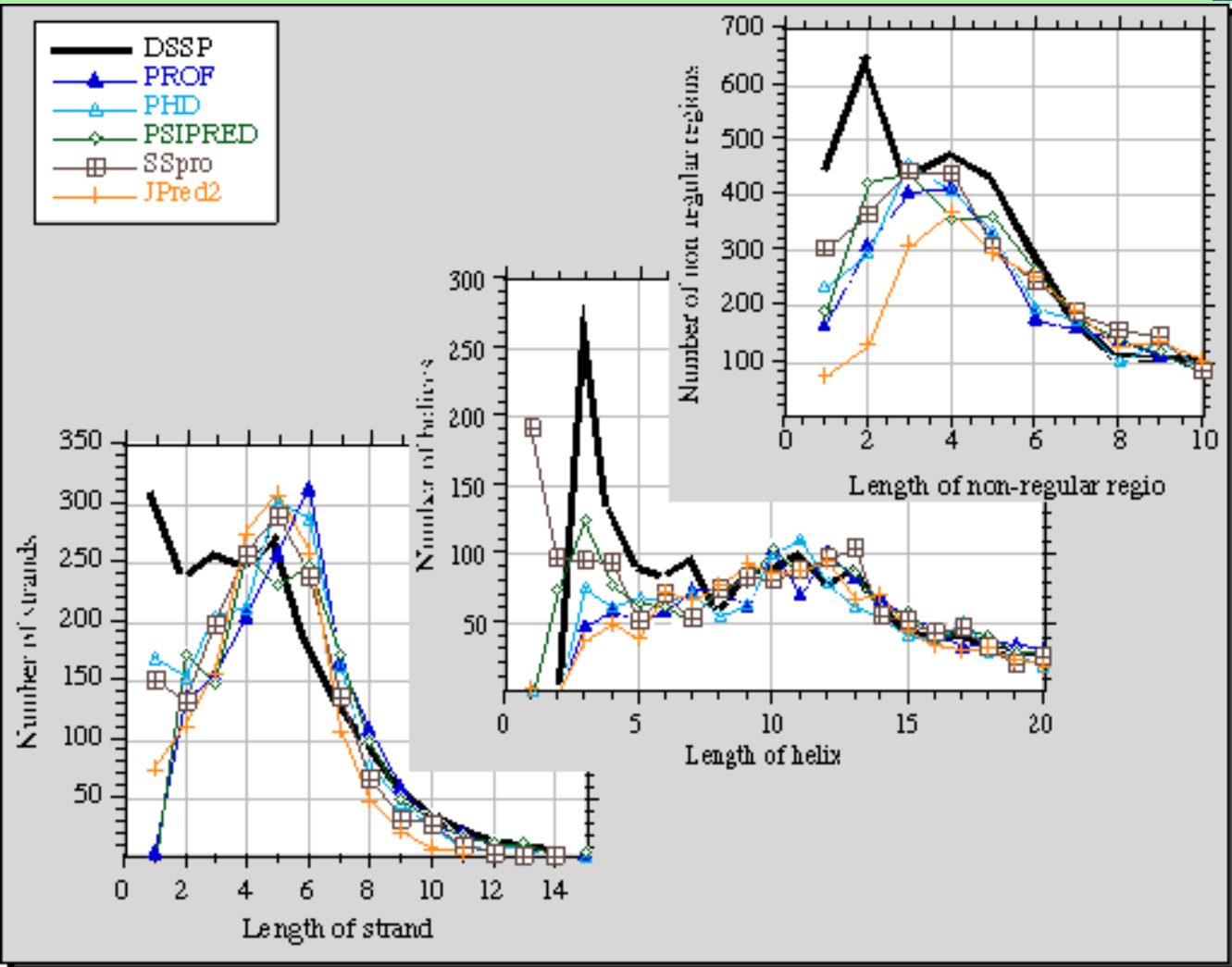
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Distribution of segment length and predicted segment length

PHD, PSIPRED, PREDATOR, JNet, JPred2, NSSP, SSPro



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```

SEQ  MELVLALYDYQEKSPREVTMHKGDILTLNSTNKHNNKVEVNDRQGFVPAAYVKKLD
OBS   EEEE      E--E      EEEEE      EEEEE      EEEEEHHHEEEE
1st C+F  HHHHHHH      HHHHH      EEEEE      HHHHH      EEEEEHHHHHHH
2nd GOR  HHHHHHH      HHH      EEEEE      EEEEHH      HH      HHHHHHH
3rd PHD   EEEEE      EE      EEEEEEE      HHHHH      EEEE HHHEEE
Rel     948999972587775211443884899847697314344045955111321221558
      *  *****  *****      **  ****  *****      ****      ***
  
```

```

SEQ  EGTELNKKIDEEP IAFGLVALNVMVVGDAEGGTEAAEESLSGI EGVSNIEVTDVRLM
OBS   EE      EEE      EEEEEEEEE      GGGGHHHHH      EEEEEEEEE
JPred2   HH      EEEEEEEEE      HHHHHHH      EEEEHHH
PHD      EEEE      EHHHHHHHEEEEE      HHHHHHH      EEEEEHHH
PHDpsi   EEEE      EEEHHHHHEEEEE      HHHHHHH      EEEEHHH
PROF     EEEE      EHHHHHEEEEE      HHHHH      EEEEEEEEE
PSIPRED  HHEEEEEEEEEEEEE      HHHHHHHHH      EEEEEEEEE
SSPro    EEE      HEHHEEEHEEE      HHHHHHHHH      EEEEEHH
EVA-4    EEE      HEHHEEEEEEEEE      HHHHHHHHH      EEEEEHH
  
```

Secondary structure prediction for different methods from
1st generation to 3rd generation

PHD, PSIPRED, PREDATOR, JNet, JPred2, NSSP, SSPro

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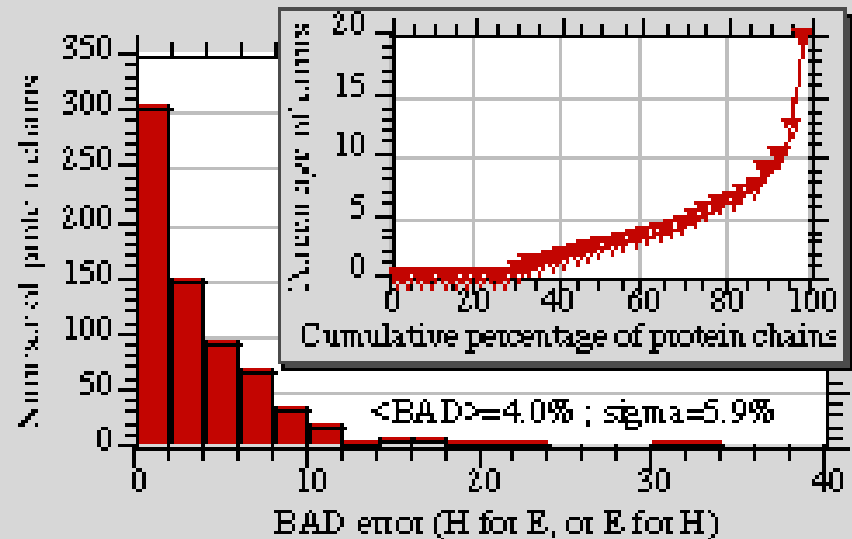
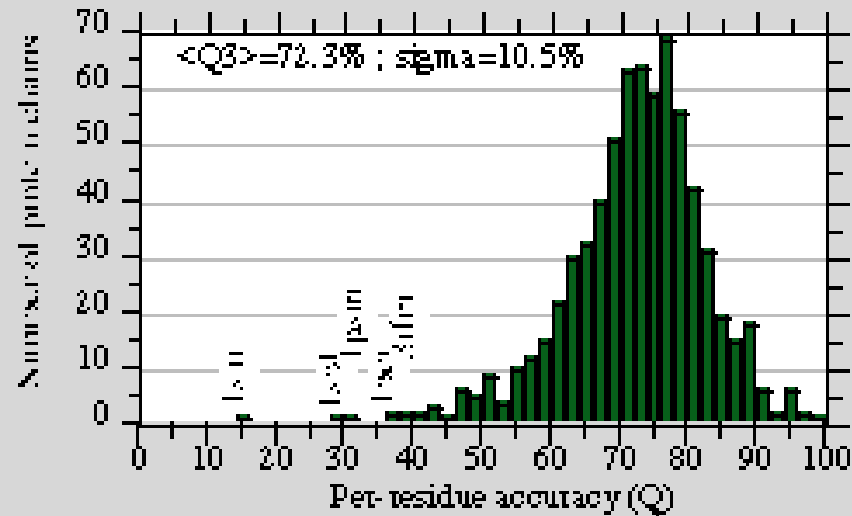
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PHD, PSIPRED, PREDATOR, JNet, JPred2, NSSP, SSPro



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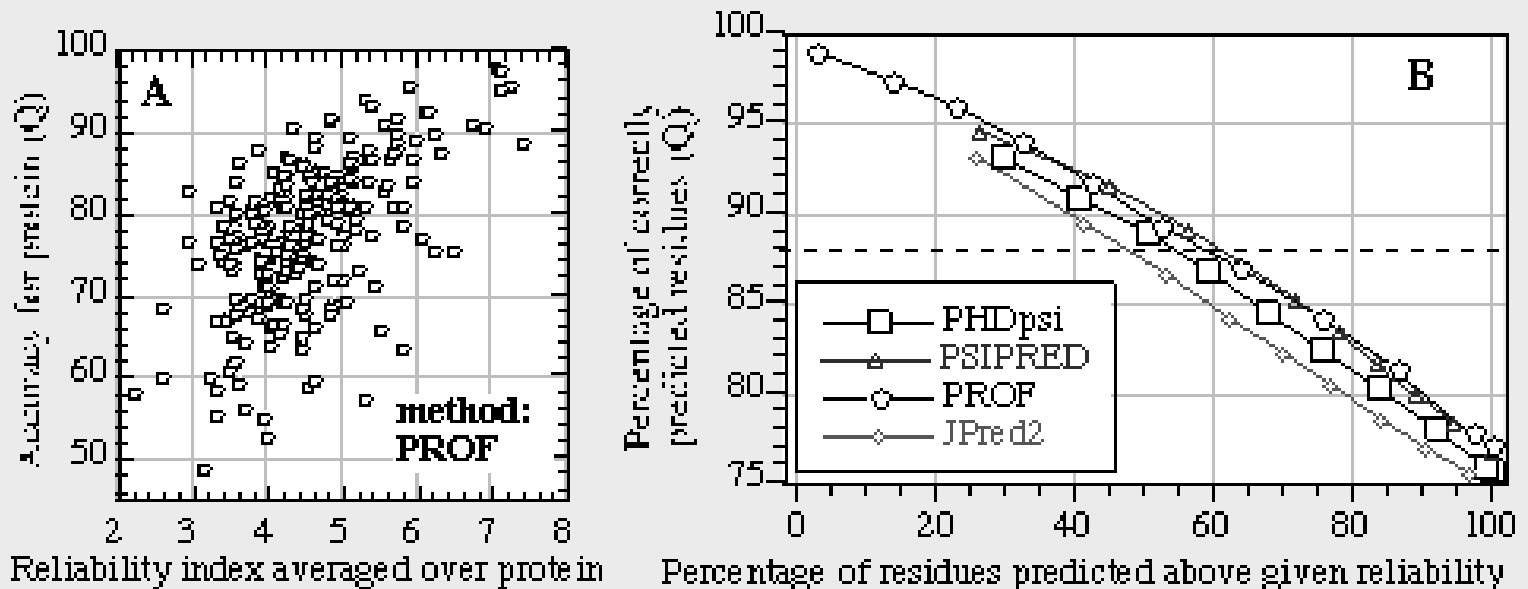
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Reliability and accuracy are plotted against each other.

If residues are predicted with higher reliability then the accuracy is higher.

Evaluating Secondary Structure Prediction



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Models: constructed on training data and tested on test data

data must be based on known structures (PDB)

Non-Homologous Test Sequences



4 SS Prediction

4.1 Introduction

test set: independent identical distributed (iid)

4.2 Assigning SS

nature does not sample proteins iid

4.2.1 DSSP

4.2.2 STRIDE

selection bias stems from the experimenter

4.2.3 DEFINE/P-Curve

correct for the non-iid sampling:

4.3 Prediction

proteins which are similar to the training set are removed
(30% to 40% of mutual identity)

4.3.1 Chou-Fasman

4.3.2 GOR

4.3.3 Lim

identity between pairs of test sequences is below the threshold
(some sequences types are very often in the test)

4.3.4 Neural Networks

4.3.5 PHD, PSIPRED,

4.4 Evaluating

4.4.1 Non-Homologous

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Secondary Structure Classes



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how the secondary structure has been assigned: DSSP or STRIDE ?
(differ only at the end of structural elements)

3 classes H,E, and C : how the mapping is done?

Symbol	conventional	newer	with turn
H	H	H	H
G	H	C	C
I	H	C	C
T	C	C	T
E	E	E	E
B	E	C	C
S	C	C	C
-	C	C	C

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binary classification task with a positive class (+1) and a negative class (-1) with N test examples

1. TP: true positive - positive correctly predicted;
2. FN: false negative - positive incorrectly predicted;
3. FP: false positive - negative incorrectly predicted;
4. TN: true negative - negative correctly predicted.

true	predicted		total
	+1	-1	
+1	TP	FN	TP + FN
-1	FP	TN	FP + TN
total	TP + FP	FN + TN	N

Table 1: Confusion matrix.

4 SS Prediction

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4.4.4 Problems

$$\text{accuracy} = \frac{TP + TN}{N}$$

$$\text{specificity} = \frac{TN}{FP + TN}$$

$$\text{sensitivity} = \frac{TP}{TP + FN}$$

$$\text{balanced error} = 0.5 (\text{specificity} + \text{sensitivity})$$

$$\text{Matthews corr.} = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FN) (TP + FP) (FN + TN) (FP + TN)}}$$

$$\text{weight of evidence} = \log \frac{TP \cdot TN}{FP \cdot FN}$$

Receiver Operating Characteristic curve (ROC):

plots sensitivity vs. (1 - specificity) for a binary classifier system

plot of the fraction of true positives vs. the fraction of false positives

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4.4.2 SS Classes

4.4.3 Quality Measures

4.4.4 Problems

Measures used in secondary structure prediction

Q_3 accuracy – percent correct from all

sub-classifier accuracies: Q_H Q_E Q_C

β -sheets: most problems

quality measure is the segment overlap (SOV for Segment Overlap)

$$\text{SOV}_s = \frac{1}{N_s} \sum_{S_1 \cap S_2 \in s} \frac{\min \text{ov}(S_1, S_2) + \delta(S_1, S_2)}{\max \text{ov}(S_1, S_2)} \text{length}(S_1)$$

- S_1 and S_2 : observed and predicted SS segments of $s=H,E,C$
- $\text{Length}(S_1)$ is the number of residues in the segment S_1
- $\min \text{ov}(S_1, S_2)$: is the length of actual overlap
- $\max \text{ov}(S_1, S_2)$: is the length of total extend of S_1 and S_2
- $\delta(S_1, S_2)$ measure of disagreement

4 SS Prediction

4.1 Introduction

4.2 Assigning SS

4.2.1 DSSP

4.2.2 STRIDE

4.2.3 DEFINE/P-Curve

4.3 Prediction

4.3.1 Chou-Fasman

4.3.2 GOR

4.3.3 Lim

4.3.4 Neural Networks

4.3.5 PHD, PSIPRED,

4.4 Evaluating

4.4.1 Non-Homologous

4.4.2 SS Classes

4.4.3 Quality Measures

4.4.4 Problems

$$\delta(S_1, S_2) = \min \left\{ \begin{array}{l} \max \text{ov}(S_1, S_2) - \min \text{ov}(S_1, S_2) \\ \min \text{ov}(S_1, S_2) \\ \text{length}(S_1)/2 \\ \text{length}(S_2)/2 \end{array} \right\}$$

$S_1 \cap S_2 \in s$ pairs of segments have at least one residue in state s

N_s number of residues from sequence 1 in state s :

$$N_s = \sum_{S_1 \cap S_2 \in s} \text{length}(S_1) + \sum_{S_1 \cap S_2 \notin s, S_1 \in s} \text{length}(S_1)$$

overall segment overlap

$$\text{SOV} = \frac{1}{N} \sum_{s \in \{H, E, C\}} \sum_{S_1 \cap S_2 \in s} \frac{\min \text{ov}(S_1, S_2) + \delta(S_1, S_2)}{\max \text{ov}(S_1, S_2)} \text{length}(S_1)$$

$$N = \sum_{s \in \{H, E, C\}} N_s = N_H + N_E + N_C$$

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support vector machine approaches:
higher SOV value with state of the art values Q_3

tested the support vector approach and obtained
 $Q_3=78.84\%$ and $SOV=77.85\%$

PROFS $Q_3=76.51\%$

PSIPRED $Q_3=77.75\%$ and $SOV=67.36\%$

According to the diploma thesis of Sebastian Drescher

Problems in Quality Comparisons



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new method is compared to the results of previous methods
newer methods use newer versions of

- data bases like the NR
- software like PSI-BLAST

- the original data set

newer methods know

- about the pitfalls other methods
-
- performance threshold to achieve