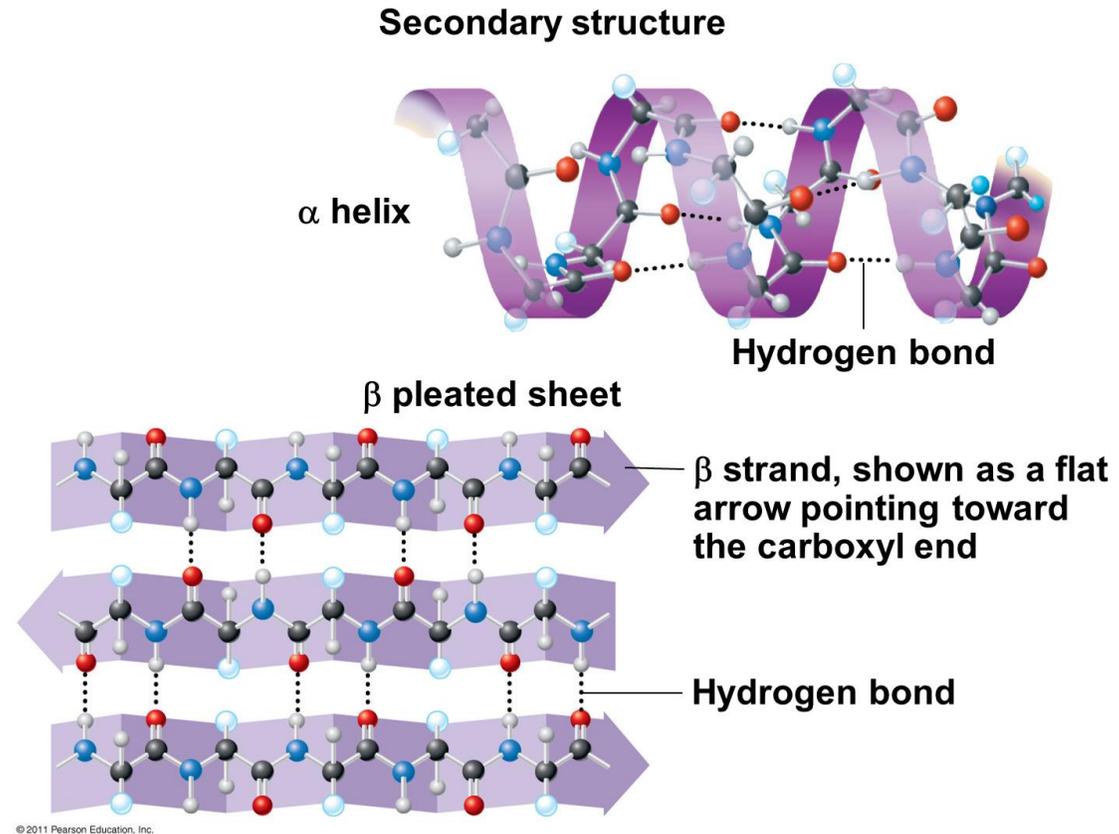


# EECS730: Introduction to Bioinformatics

## Lecture 12: Protein secondary structure prediction



Some slides were adapted from Dr. Dong Xu (University of Missouri Columbia)

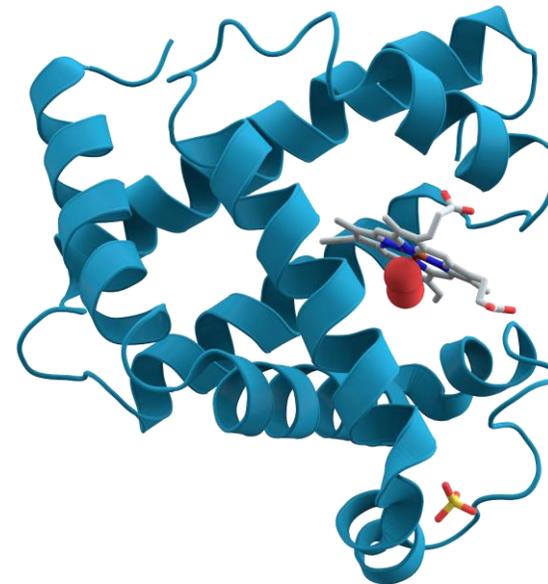
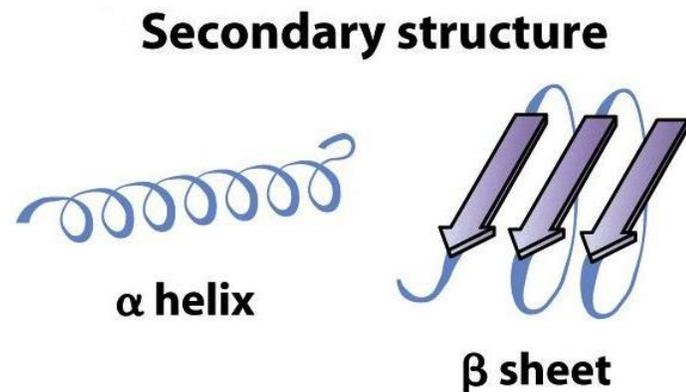
# Structures in Protein

Language:

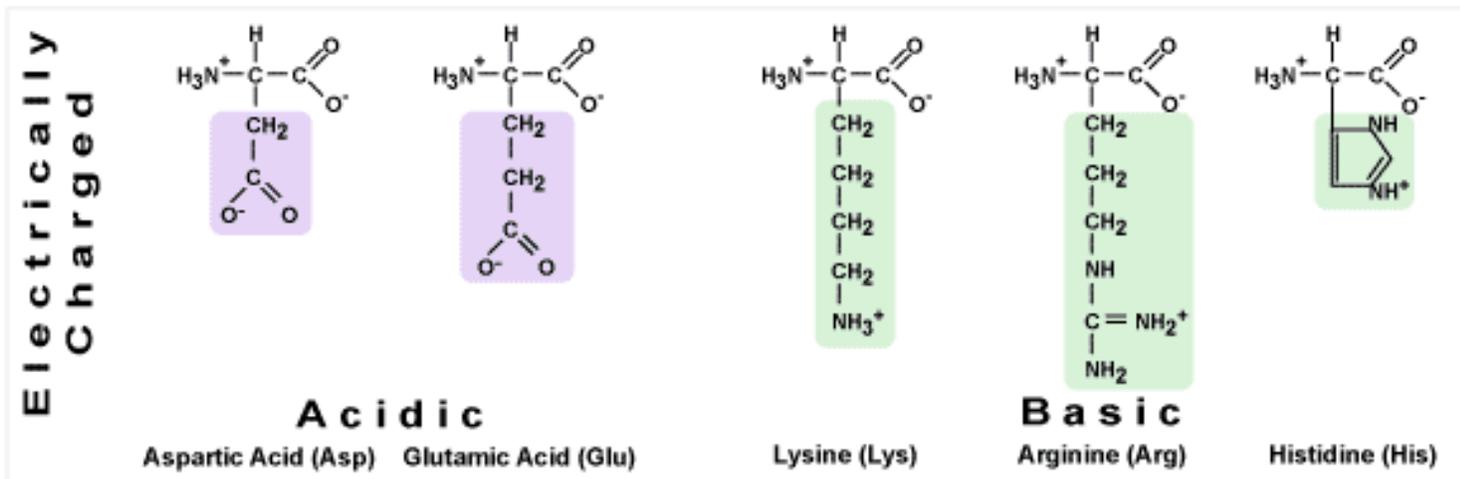
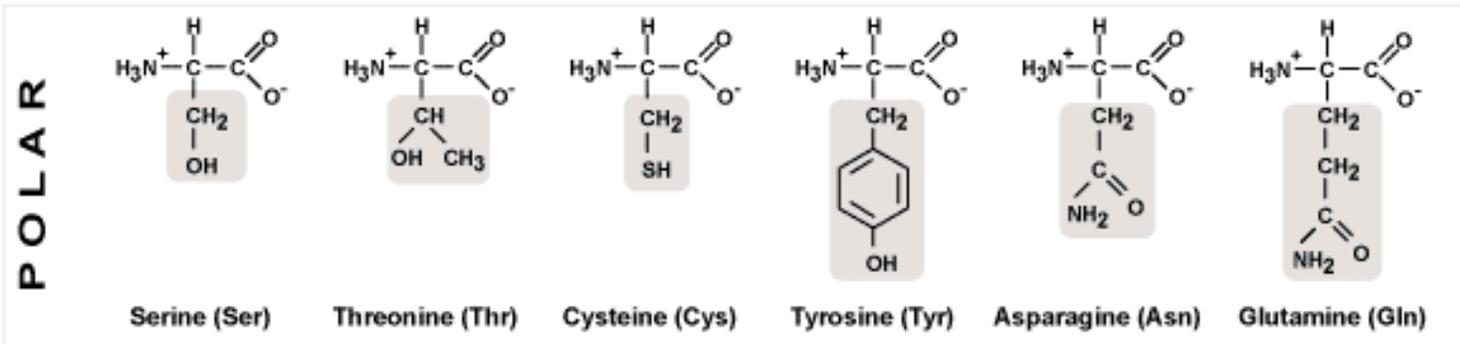
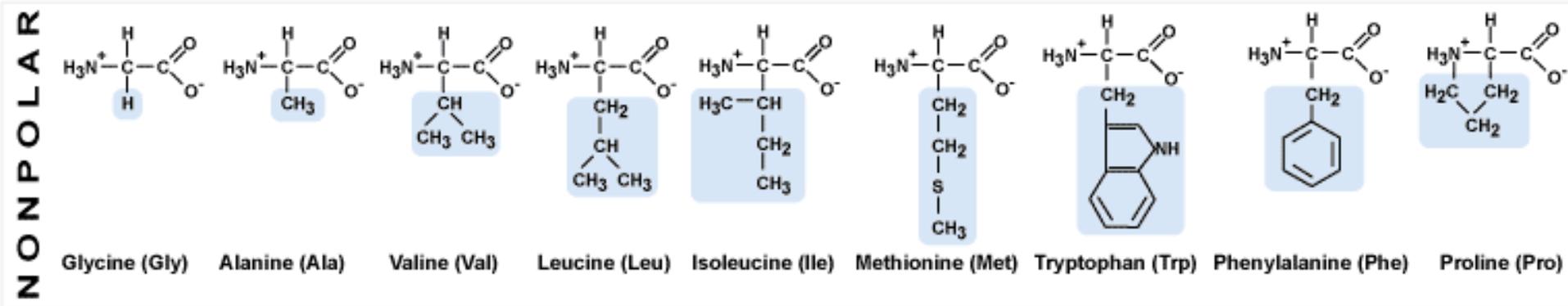
Letters → Words → Sentences

Protein:

Primary Structure → Secondary Structure → Tertiary Structure



# Protein side chains

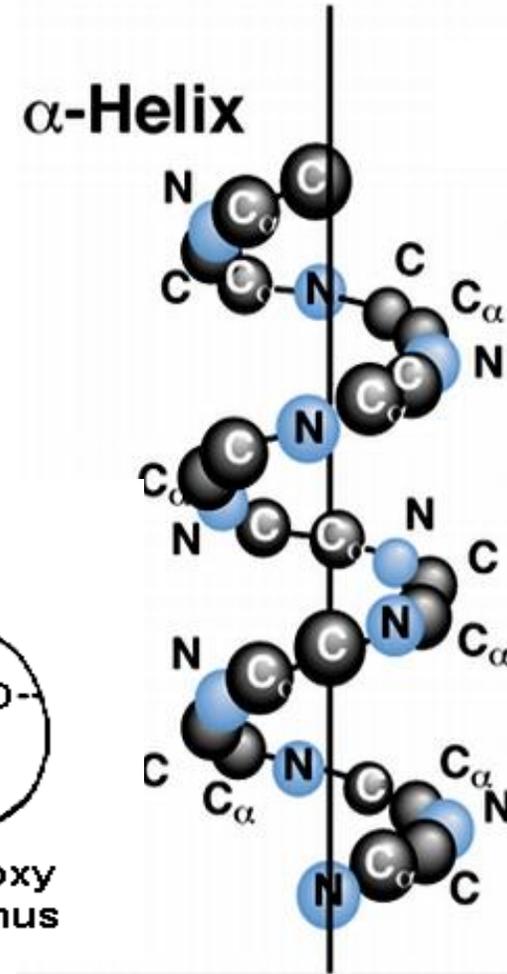
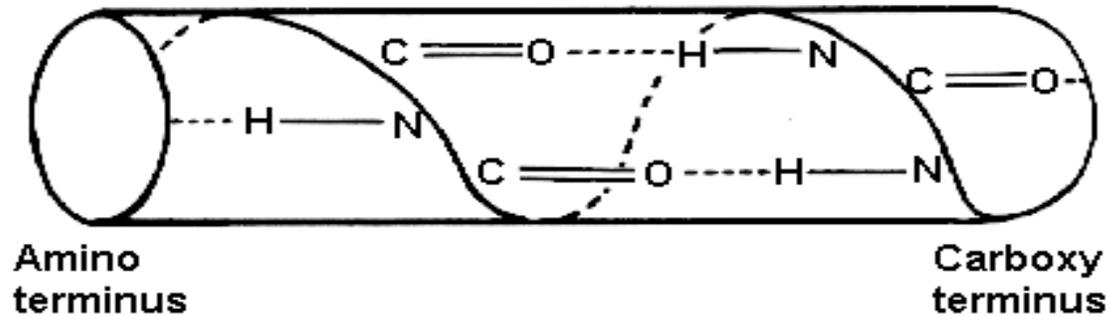


<https://s-media-cache-ak0.pinimg.com/originals/ed/c0/ca/edc0ca6e8323df7bce06fd72ab5eca80.gif>

# $\alpha$ helix

- Single protein chain (local)
- Shape maintained by intramolecular H bonding between -C=O and H-N-

Toilet roll representation of the main chain hydrogen bonding in an alpha-helix.

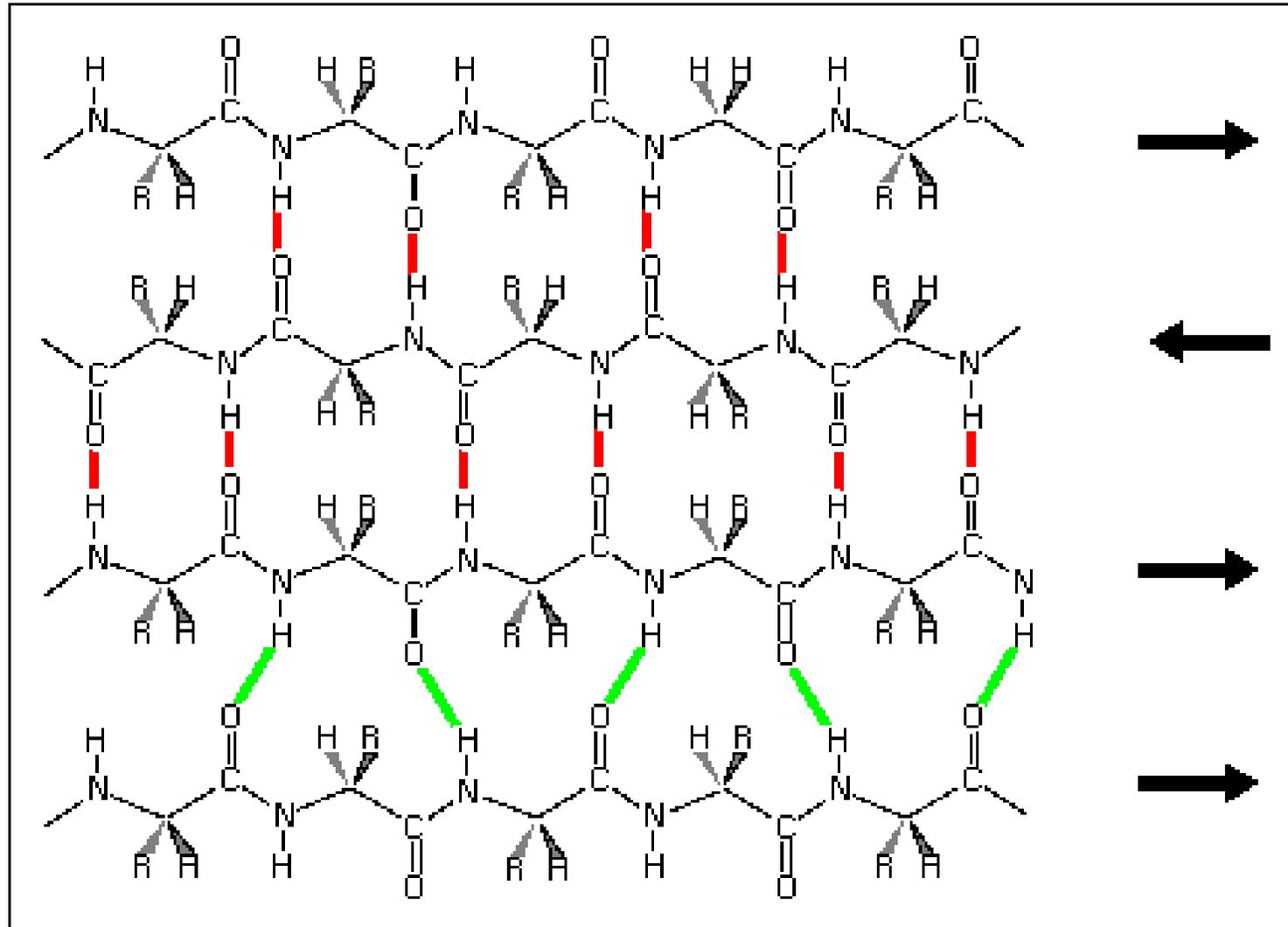


# $\beta$ sheet

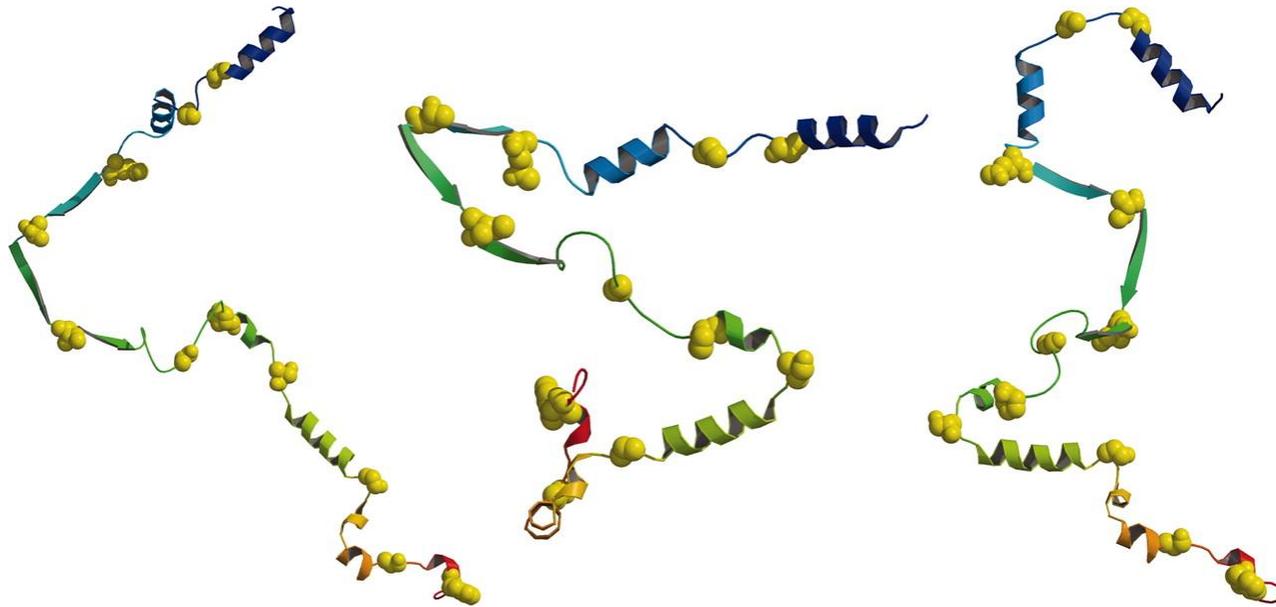
- Several protein chains
- Shape maintained by intramolecular H bonding between chains
- Non-local on protein sequence



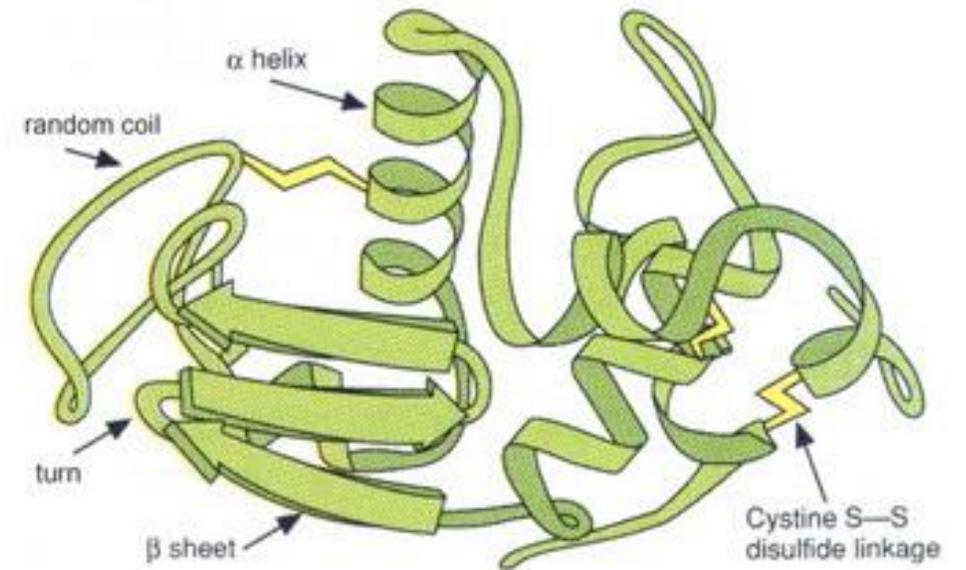
# $\beta$ -sheet (parallel, anti-parallel)



# Random coil



<http://www.pnas.org/content/101/34/12497/F3.large.jpg>



[https://getrevising.co.uk/revision-cards/biology\\_asf212ocr\\_specification\\_and\\_answers](https://getrevising.co.uk/revision-cards/biology_asf212ocr_specification_and_answers)

“A **random coil** is a polymer conformation where the monomer subunits are oriented **randomly** while still being bonded to adjacent units.” - Wikipedia

# Classification of secondary structure

- Defining features
  - Dihedral angles
  - Hydrogen bonds
  - Geometry
- Assigned manually by experimentalists
- Automatic
  - [DSSP \(Kabsch & Sander, 1983\)](#)
  - STRIDE (Frishman & Argos, 1995)
  - Continuum (Andersen et al.)

# Classification

- Eight states from DSSP

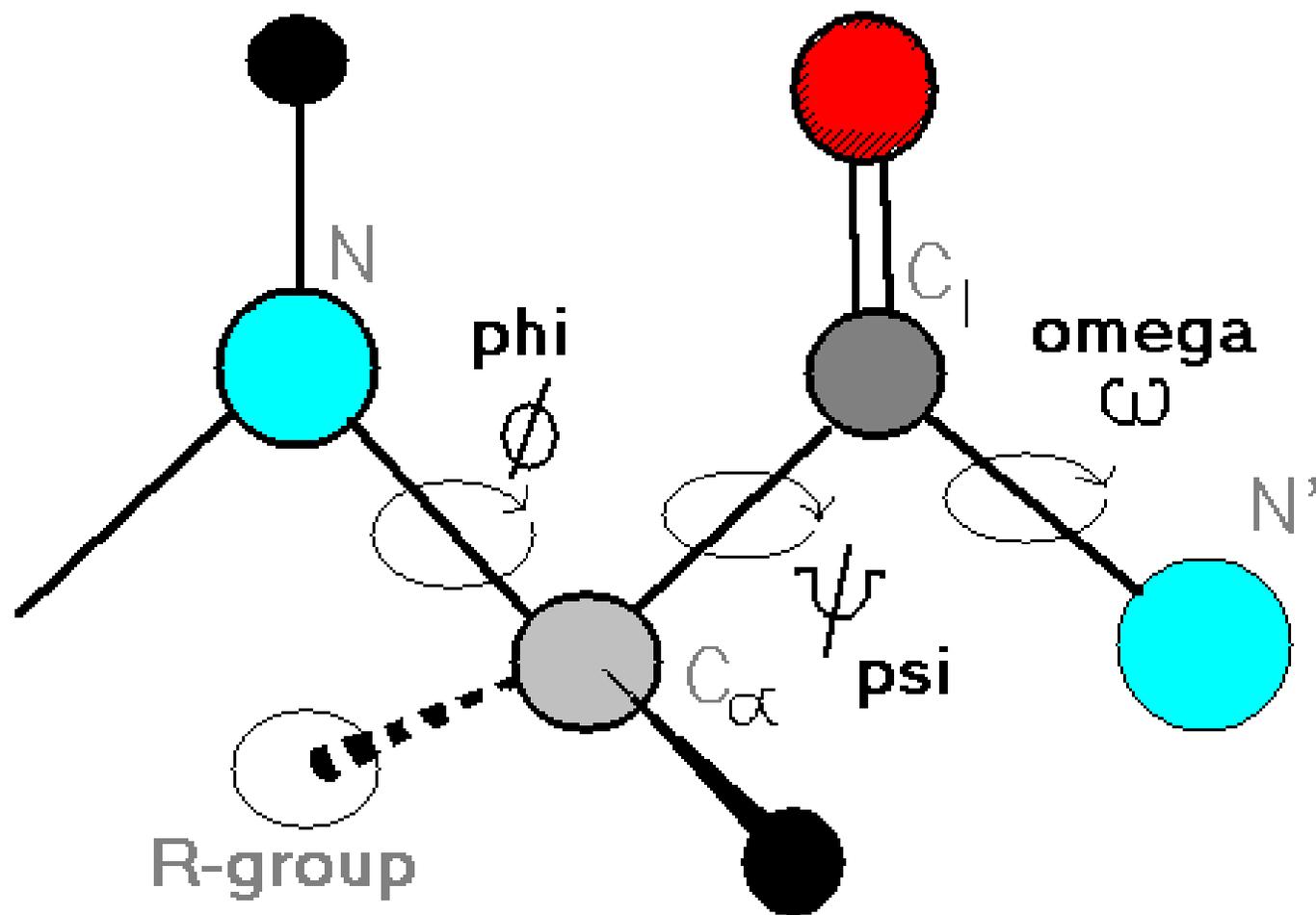
- H:  $\alpha$ -helix
- G:  $3_{10}$  helix
- I:  $\pi$ -helix
- E:  $\beta$ -strand
- B: bridge
- T:  $\beta$ -turn
- S: bend
- C: coil

24	26	E	H	< S+	0	0	132
25	27	R	H	< S+	0	0	125
26	28	N		<	0	0	41
27	29	K			0	0	197
28		!			0	0	0
29	34	C			0	0	73
30	35	I	E	-cd	58	89B	9
31	36	L	E	-cd	59	90B	2
32	37	V	E	-cd	60	91B	0
33	38	G	E	-cd	61	92B	0

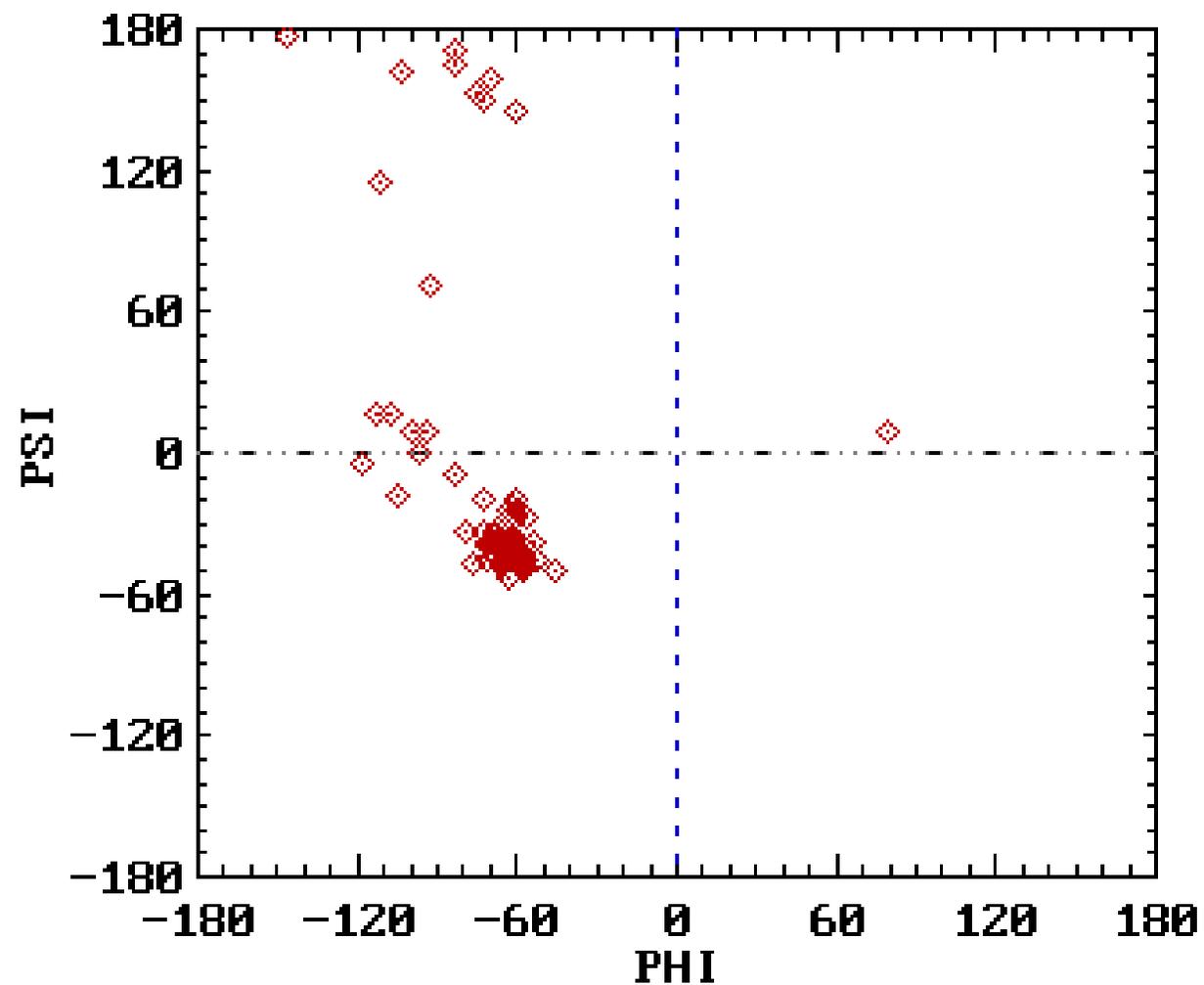
- CASP Standard

- H = (H, G, I), E = (E, B), C = (C, T, S)

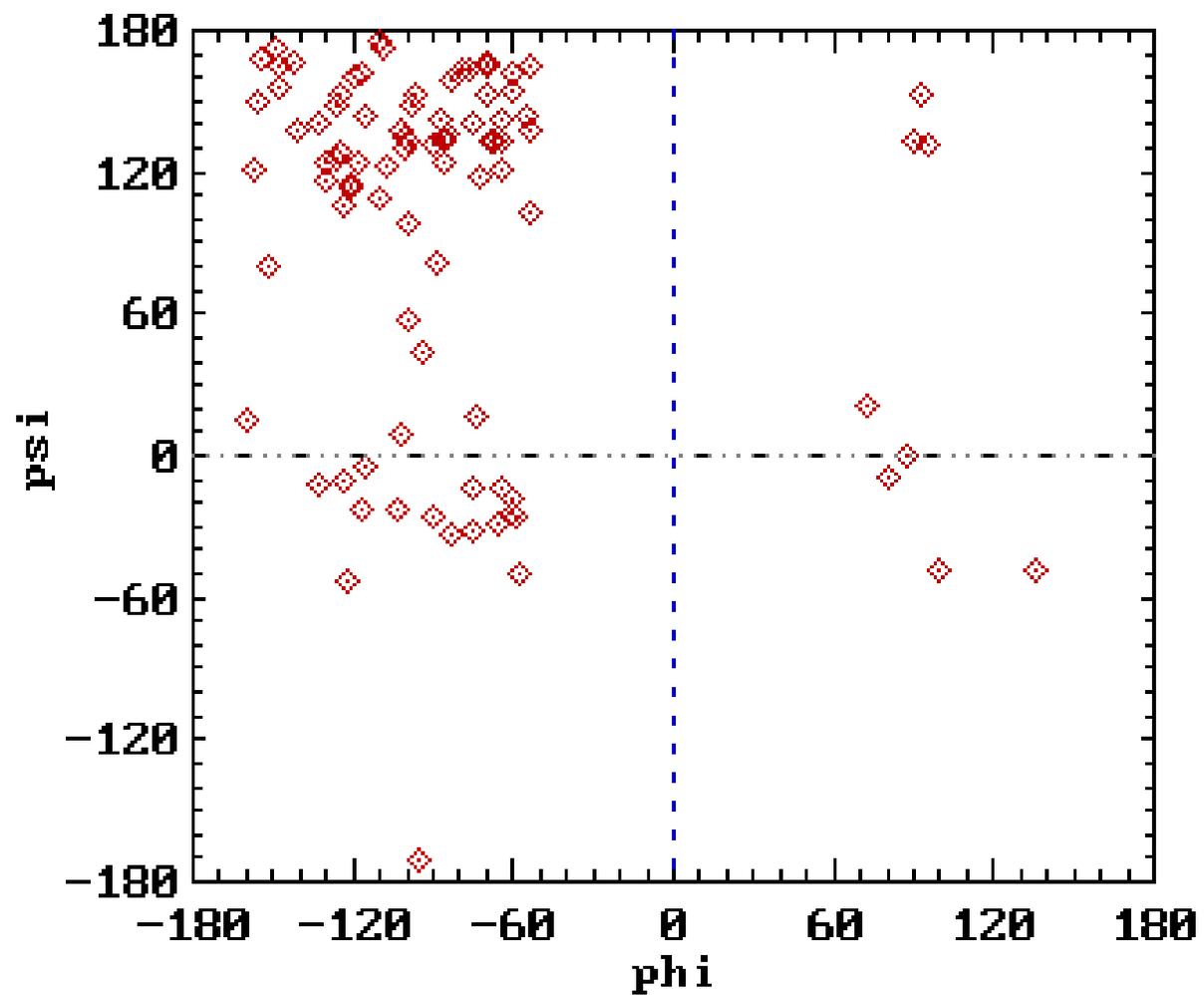
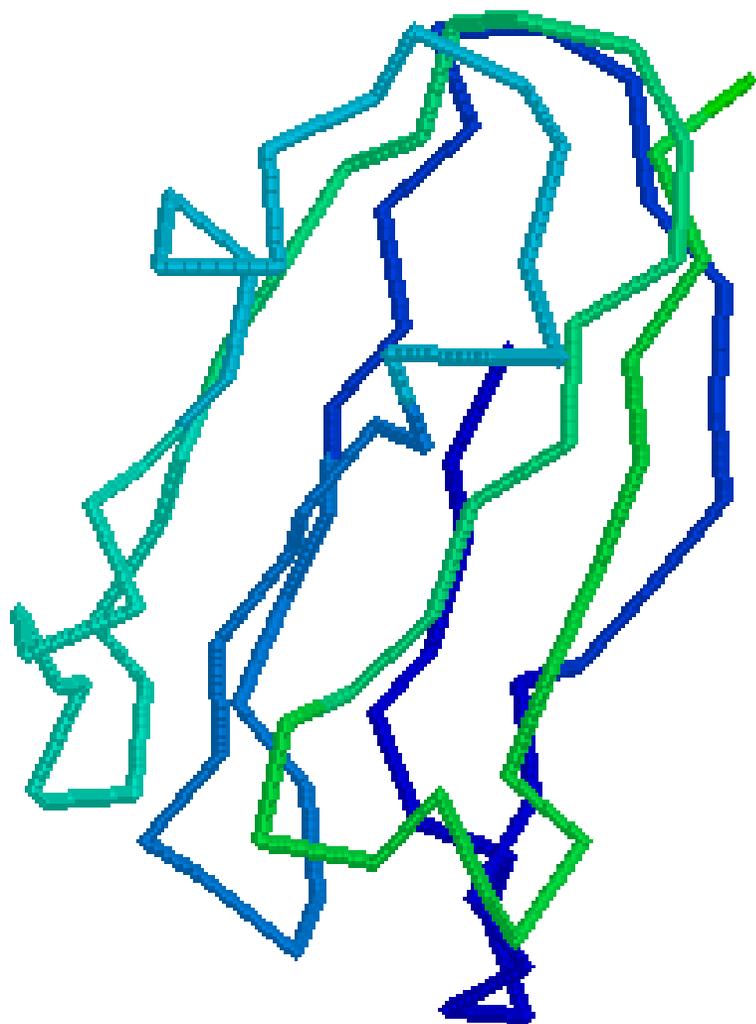
# Dihedral angles



# Ramachandran plot (alpha)



# Ramachandran plot (beta)



# Protein secondary structure prediction

Given a protein sequence (primary structure)

GHWIATRGQLIREAYEDYRHFSSECPFIP

Predict its secondary structure content

(C=Coils H=Alpha Helix E=Beta Strands)

CEEEECHHHHHHHHHHCCHHCCCCC

# Protein secondary structure prediction

- An easier problem than 3D structure prediction (more than 40 years of history).
- Accurate secondary structure prediction can be an important information for the tertiary structure prediction
- Protein function prediction
- Protein classification
- Predicting structural change

# Naïve way

- You can always predict protein secondary structure by pairwise sequence alignment
- Similar to the non-coding RNA sequence-structure alignment
- We are going to focus on scenarios where no homology can be detected (no good alignment can be computed)
- *De novo* prediction

# Summary of methods

## Statistical method

Chou-Fasman method, GOR I-IV

## Nearest neighbors

NNSSP, SSPAL

## Neural network

PHD, Psi-Pred, J-Pred

## Support vector machine (SVM)

## HMM

# Measure

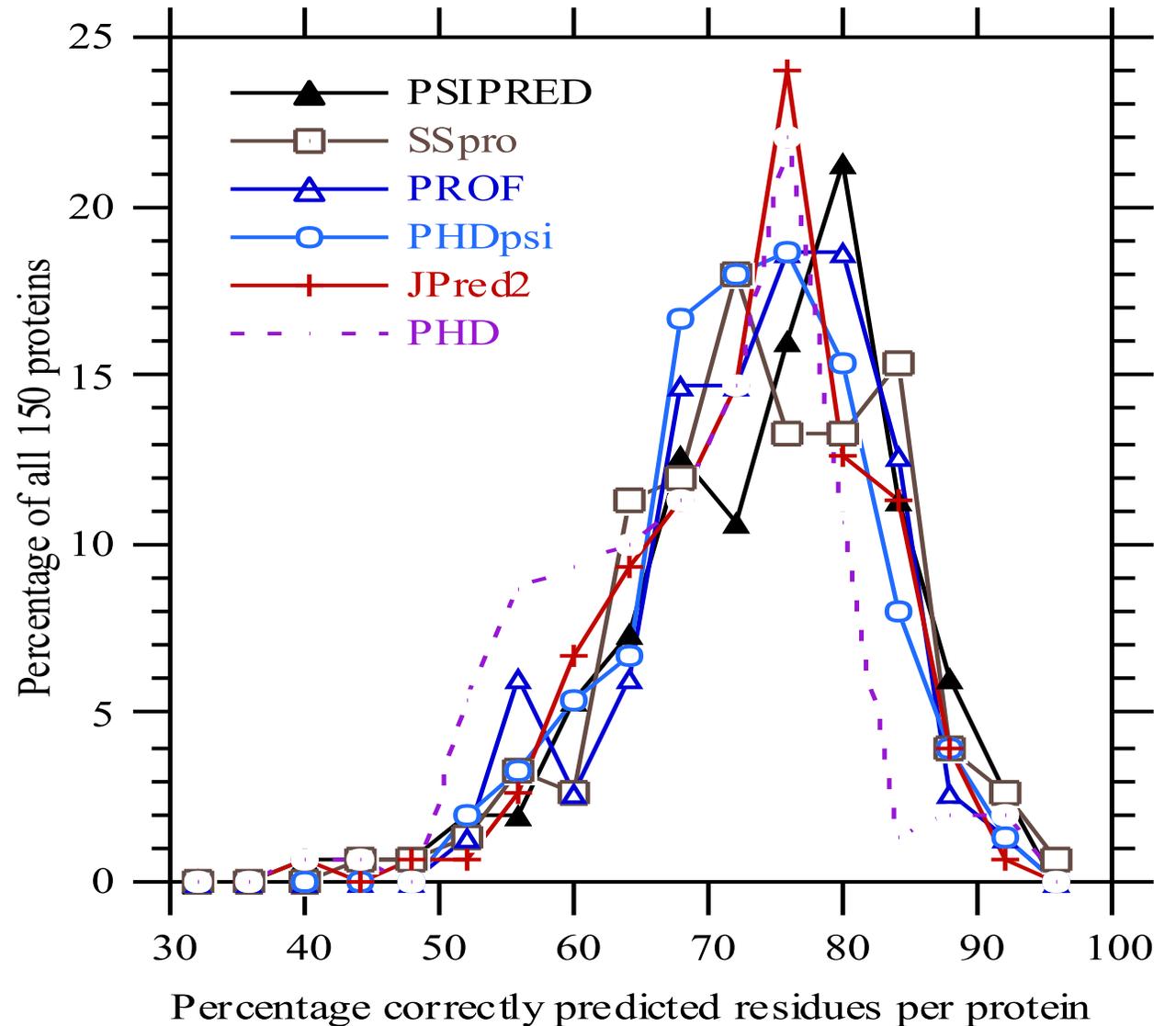
Three-state prediction accuracy:  $Q_3$

$$Q_3 = \frac{\text{correctly predicted residues}}{\text{number of residues}}$$

A prediction of all loop:  $Q_3 \sim 40\%$

# Accuracy

<b>1974</b> Chou & Fasman	~50-53%
<b>1978</b> Garnier	63%
<b>1987</b> Zvelebil	66%
<b>1988</b> Qian & Sejnowski	64.3%
<b>1993</b> Rost & Sander	70.8-72.0%
<b>1997</b> Frishman & Argos	<75%
<b>1999</b> Cuff & Barton	72.9%
<b>1999</b> Jones	76.5%
<b>2000</b> Petersen et al.	77.9%



# Assumptions

- The entire information for forming secondary structure is contained in the primary sequence.
- Side groups of residues will determine structure.
- Examining windows of 13 - 17 residues is sufficient to predict structure.
- Basis for window size selection:
  - $\alpha$ -helices 5 – 40 residues long
  - $\beta$ -strands 5 – 10 residues long

# Chou-Fasman Method

From PDB database, calculate the **propensity** for a given amino acid to adopt a certain ss-type

$$P_{\alpha}^i = \frac{P(\alpha | aa_i)}{p(\alpha)} = \frac{p(\alpha, aa_i)}{p(\alpha)p(aa_i)}$$

Example:

#Ala=2,000, #residues=20,000, #helix=4,000, #Ala in helix=500

$P(\alpha, aa_i) = 500/20,000$ ,  $p(\alpha) = 4,000/20,000$ ,  $p(aa_i) = 2,000/20,000$

$P = 500 / (4,000/10) = 1.25$

# Chou-Fasman Method

## Chou-Fasman Parameters

<u><math>P_{\alpha}</math></u>		<u><math>P_{\beta}</math></u>		<u><math>P_{\pi}</math></u>	
<b>Glu</b>	<b>1.51</b>	<b>Val</b>	<b>1.70</b>	<b>Asn</b>	<b>1.56</b>
<b>Met</b>	<b>1.45</b>	<b>Ile</b>	<b>1.60</b>	<b>Gly</b>	<b>1.56</b>
<b>Ala</b>	<b>1.42</b>	<b>Tyr</b>	<b>1.47</b>	<b>Pro</b>	<b>1.52</b>
<b>Leu</b>	<b>1.21</b>	<b>Phe</b>	<b>1.38</b>	<b>Asp</b>	<b>1.46</b>
<b>Lys</b>	<b>1.16</b>	<b>Trp</b>	<b>1.37</b>	<b>Ser</b>	<b>1.43</b>
<b>Phe</b>	<b>1.13</b>	<b>Leu</b>	<b>1.30</b>	<b>Cys</b>	<b>1.19</b>
<b>Gln</b>	<b>1.11</b>	<b>Cys</b>	<b>1.19</b>	<b>Tyr</b>	<b>1.14</b>
<b>Trp</b>	<b>1.08</b>	<b>Thr</b>	<b>1.19</b>	<b>Lys</b>	<b>1.01</b>
<b>Ile</b>	<b>1.08</b>	<b>Gln</b>	<b>1.10</b>	<b>Gln</b>	<b>0.98</b>
<b>Val</b>	<b>1.06</b>	<b>Met</b>	<b>1.05</b>	<b>Thr</b>	<b>0.96</b>
<b>Asp</b>	<b>1.01</b>	<b>Arg</b>	<b>0.93</b>	<b>Trp</b>	<b>0.96</b>
<b>His</b>	<b>1.00</b>	<b>Asn</b>	<b>0.89</b>	<b>Arg</b>	<b>0.95</b>
<b>Arg</b>	<b>0.98</b>	<b>His</b>	<b>0.87</b>	<b>His</b>	<b>0.95</b>
<b>Thr</b>	<b>0.83</b>	<b>Ala</b>	<b>0.83</b>	<b>Glu</b>	<b>0.74</b>
<b>Ser</b>	<b>0.77</b>	<b>Ser</b>	<b>0.75</b>	<b>Ala</b>	<b>0.66</b>
<b>Cys</b>	<b>0.70</b>	<b>Gly</b>	<b>0.75</b>	<b>Met</b>	<b>0.60</b>
<b>Tyr</b>	<b>0.69</b>	<b>Lys</b>	<b>0.74</b>	<b>Phe</b>	<b>0.60</b>
<b>Asn</b>	<b>0.67</b>	<b>Pro</b>	<b>0.55</b>	<b>Leu</b>	<b>0.59</b>
<b>Pro</b>	<b>0.57</b>	<b>Asp</b>	<b>0.54</b>	<b>Val</b>	<b>0.50</b>
<b>Gly</b>	<b>0.57</b>	<b>Glu</b>	<b>0.37</b>	<b>Ile</b>	<b>0.47</b>

# Chou-Fasman Method

## Helix, Strand

1. Scan for window of 6 residues where average score  $> 1$  (4 residues for helix and 3 residues for strand)
2. Propagate in both directions until 4 (or 3) residue window with mean propensity  $< 1$
3. Move forward and repeat

## Conflict solution

Any region containing overlapping alpha-helical and beta-strand assignments are taken to be helical if the average  $P(\text{helix}) > P(\text{strand})$ . It is a beta strand if the average  $P(\text{strand}) > P(\text{helix})$ .

Accuracy:  $\sim 50\% \rightarrow \sim 60\%$

GHWIA TRGQLI REAYED YRHFSSECPFIP

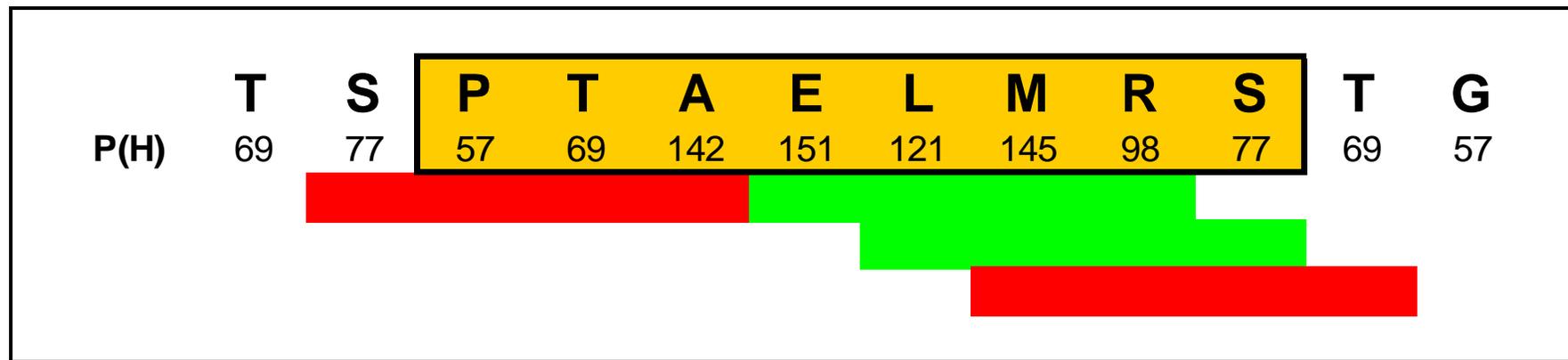
# Initialization

Identify regions where 4/6 have a P(H)  
>1.00 “alpha-helix nucleus”

	<b>T</b>	<b>S</b>	<b>P</b>	<b>T</b>	<b>A</b>	<b>E</b>	<b>L</b>	<b>M</b>	<b>R</b>	<b>S</b>	<b>T</b>	<b>G</b>
P(H)	69	77	57	69	142	151	121	145	98	77	69	57
	<b>T</b>	<b>S</b>	<b>P</b>	<b>T</b>	<b>A</b>	<b>E</b>	<b>L</b>	<b>M</b>	<b>R</b>	<b>S</b>	<b>T</b>	<b>G</b>
P(H)	69	77	57	69	142	151	121	145	98	77	69	57

# Extension

Extend helix in both directions until a set of four residues have an average  $P(H) < 1.00$ .



# Nearest Neighbor Method

- Predict secondary structure of the central residue of a given segment from homologous segments (neighbors)
  - (i) From database, find some number of the closest sequences to a subsequence defined by a window around the central residue
  - (ii) Compute  $K$  best non-intersecting local alignments of a query sequence with each sequence.
- Use  $\max(n_\alpha, n_\beta, n_c)$  for neighbor consensus or  $\max(s_\alpha, s_\beta, s_c)$  for consensus sequence hits

# Environment preference score

Each amino acid has a preference to a specific structural environments.

Structural variables:

secondary structure, solvent accessibility

Non-redundant protein structure database: FSSP

$$S(i, j) = \log \frac{p(aa_i | E_j)}{p(aa_i)} = \log \frac{p(aa_i, E_j)}{p(aa_i) p(E_j)}$$

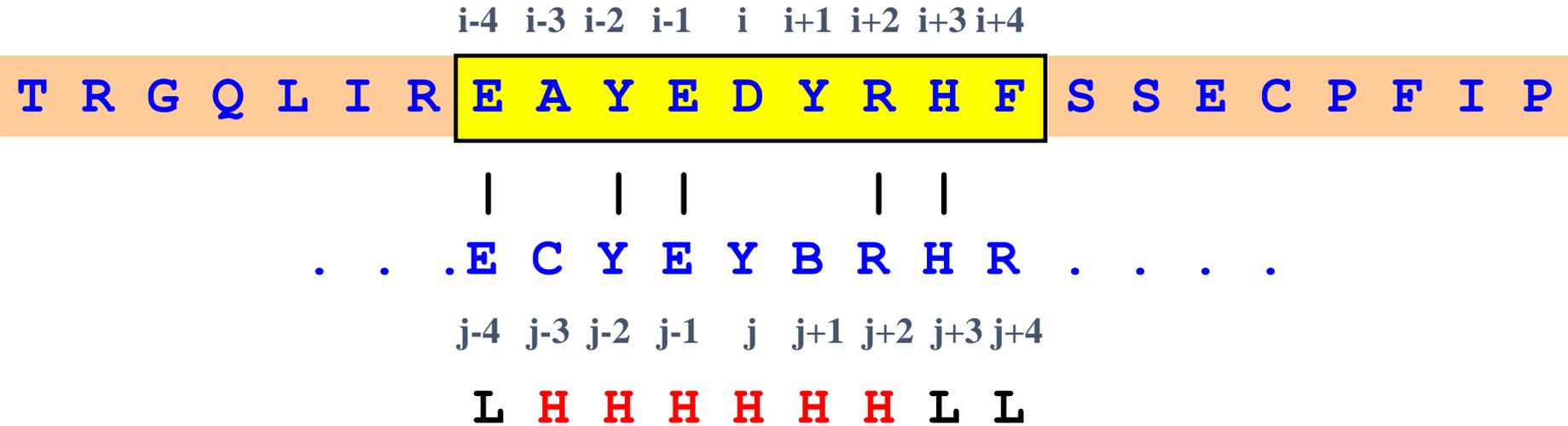
# Scoring matrix

	Helix			Sheet			Loop		
	Buried	Inter	Exposed	Buried	Inter	Exposed	Buried	Inter	Exposed
ALA	-0.578	-0.119	-0.160	0.010	0.583	0.921	0.023	0.218	0.368
ARG	0.997	-0.507	-0.488	1.267	-0.345	-0.580	0.930	-0.005	-0.032
ASN	0.819	0.090	-0.007	0.844	0.221	0.046	0.030	-0.322	-0.487
ASP	1.050	0.172	-0.426	1.145	0.322	0.061	0.308	-0.224	-0.541
CYS	-0.360	0.333	1.831	-0.671	0.003	1.216	-0.690	-0.225	1.216
GLN	1.047	-0.294	-0.939	1.452	0.139	-0.555	1.326	0.486	-0.244
GLU	0.670	-0.313	-0.721	0.999	0.031	-0.494	0.845	0.248	-0.144
GLY	0.414	0.932	0.969	0.177	0.565	0.989	-0.562	-0.299	-0.601
HIS	0.479	-0.223	0.136	0.306	-0.343	-0.014	0.019	-0.285	0.051
ILE	-0.551	0.087	1.248	-0.875	-0.182	0.500	-0.166	0.384	1.336
LEU	-0.744	-0.218	0.940	-0.411	0.179	0.900	-0.205	0.169	1.217
LYS	1.863	-0.045	-0.865	2.109	-0.017	-0.901	1.925	0.474	-0.498
MET	-0.641	-0.183	0.779	-0.269	0.197	0.658	-0.228	0.113	0.714
PHE	-0.491	0.057	1.364	-0.649	-0.200	0.776	-0.375	-0.001	1.251
PRO	1.090	0.705	0.236	1.249	0.695	0.145	-0.412	-0.491	-0.641
SER	0.350	0.260	-0.020	0.303	0.058	-0.075	-0.173	-0.210	-0.228
THR	0.291	0.215	0.304	0.156	-0.382	-0.584	-0.012	-0.103	-0.125
TRP	-0.379	-0.363	1.178	-0.270	-0.477	0.682	-0.220	-0.099	1.267
TYR	-0.111	-0.292	0.942	-0.267	-0.691	0.292	-0.015	-0.176	0.946
VAL	-0.374	0.236	1.144	-0.912	-0.334	0.089	-0.030	0.309	0.998

# Distance between $k$ -mers

Alignment score is the sum of score in a window of length  $l$ :

$$Score(i, j) = \sum_{k=-l/2}^{l/2} [M(i+k, j+k) + cS(i+k, j+k)]$$



# Inference based on neighbors

1	-	L	H	H	H	H	H	H	L	L	-	S <sub>1</sub>	
2	-	L	L	H	H	H	H	H	L	L	-	S <sub>2</sub>	
3	-	L	E	E	E	E	E	E	L	L	-	S <sub>3</sub>	
4	-	L	E	E	E	E	E	E	L	L	-	S <sub>4</sub>	
n	-	L	L	L	L	E	E	E	E	E	-	S <sub>n</sub>	
n+1	-	H	H	H	L	L	L	E	E	E	-	S <sub>n+1</sub>	
													•
													•

- $\max(n_\alpha, n_\beta, n_L)$  or  $\max(\sum s_\alpha, \sum s_\beta, \sum s_L)$

# Incorporating evolutionary information

- ❑ “All naturally evolved proteins with more than **35%** pairwise identical residues over more than **100** aligned residues have similar structures.”
- ❑ Stability of structure w.r.t. sequence divergence (<12% difference in secondary structure).
- ❑ **Position-specific sequence profile**, containing crucial information on evolution of protein family, can help secondary structure prediction (increase information content).
- ❑ Gaps rarely occur in helix and strand.
- ❑ ~1.4%/year increase in Q3 due to database growth at the beginning.

# Evolution information

- ❑ Sequence-profile alignment.
- ❑ Compare a sequence against protein family.
- ❑ More specific.
- ❑ BLAST vs. PSI-BLAST.
- ❑ Look up PSSM instead of PAM or BLOSUM.

$$Score(i, j) = \sum_{k=-l/2}^{l/2} [PSSM(j+k, i+k) + cS(i+k, j+k)]$$

**Achieved accuracy ~75%**

# PSIPRED (Neuron networks)

- ❑ D. Jones, J. Mol. Boil. **292**, 195 (1999).
- ❑ Method : Neural network
- ❑ Input data : PSSM generated by PSI-BLAST
- ❑ Bigger and better sequence database
  - ❑ Combining several database and data filtering
- ❑ Training and test sets preparation
  - ❑ No sequence & structural homologues between training and test sets by PSI-BLAST (mimicking realistic situation).

# PSIPRED

- PSI-BLAST (iterative sequence-profile alignment)
- Searching the target sequencing against protein database and generates profile
- The profile contains evolutionary information
- Use profile of proteins with known secondary structure as training for neuron network

# PSIPRED

- A window of 15 amino acid residues was found to be optimal.
- The first input layer comprises 315 input units, divided into 15 groups of 21 units. The extra unit per amino acid is used to indicate where the window spans either the N or C terminus of the protein chain.
- A large hidden layer of 75 units was used for the first network, with another three units making the output layer where the units represent the three-states of secondary structure (helix, strand or coil).
- A second network has an input layer comprising just 60 input units, divided into 15 groups of four. Again the extra input in each group is used to indicate that the window spans a chain terminus.
- A smaller hidden layer of 60 units was used for the second network.

# PSIPRED

Raw profile from PSI-BLAST Log File

Position-based scoring matrix used

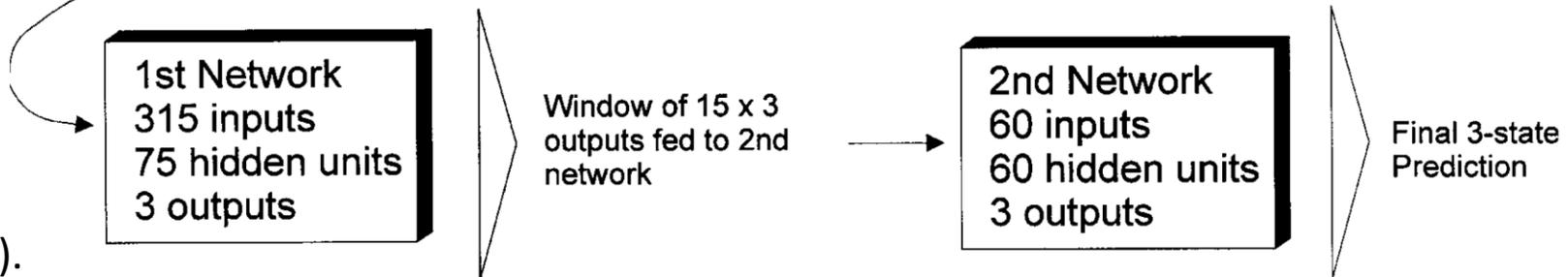
A	R	N	D	C	Q	E	G	H	I	L	K	M	F	P	S	T	W	Y	V
-3	-4	-4	-4	-3	-4	-4	-4	-2	-1	-1	-4	-1	8	-5	-3	-3	0	2	-2
0	-1	-1	3	-4	3	4	1	-1	-4	-4	0	-3	-4	-2	-1	-2	-4	-3	-3
0	-1	2	1	-3	4	0	-1	-2	-4	-3	1	-2	-4	-2	2	0	-4	-3	-3
-2	-3	-4	-5	-2	-3	-4	-6	-4	0	6	0	0	-1	-4	-3	-2	-4	-2	0
0	-3	-1	-2	-3	0	-2	4	-3	-3	0	-2	-2	-4	-3	3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

Window of 15 rows

A	R	N	D	C	Q	E	G	H	I	L	K	M	F	P	S	T	W	Y	V
0.4	0.3	0.3	0.3	0.2	0.9	0.3	0.3	0.4	0.4	0.4	0.3	0.4	0.9	0.1	0.4	0.4	0.5	0.7	0.4
0.3	0.2	0.3	0.8	0.4	0.3	0.7	0.1	0.6	0.2	0.4	0.3	0.5	0.2	0.1	0.4	0.8	0.2	0.3	0.2
0.1	0.1	0.4	0.3	0.5	0.1	0.1	0.3	0.1	0.1	0.4	0.2	0.4	0.9	0.3	0.4	0.4	0.9	0.3	0.6
0.6	0.3	0.3	0.1	0.3	0.5	0.5	0.2	0.1	0.4	0.4	0.3	0.6	0.9	0.1	0.5	0.1	0.5	0.7	0.4
⋮																			
⋮																			
⋮																			

15 x 20 scaled inputs to 1st network

- Window size = 15
- Two networks
- Accuracy ~76%**



# SVM

**Table 1.** The percentage of the training set that form support vectors and accuracy on the test set (the above random column shows the SVM's improvement over the trivial prediction)

Classifier	SVs (at upper bound)	Accuracy	Above random
C/ $\neg$ C	55.0 (48.8)	77.7	20.9
H/ $\neg$ H	40.9 (34.9)	86.4	19.8
E/ $\neg$ E	36.5 (30.4)	85.6	9.8
C/H	46.1 (39.5)	84.2	30.1
C/E	48.5 (40.7)	81.3	20.3
H/E	36.0 (29.6)	88.0	34.3

$$K(\mathbf{x}, \mathbf{z}) = \left( \frac{\mathbf{x} \cdot \mathbf{z} + 1}{50} \right)^2$$

# SVM

- The inputs from each sequence appear in the form of a  $20 \times M$  position-specific scoring matrix from three iterations of a PSI-BLAST search, where  $M$  is the length of the target sequence. The scoring matrix for a window of 15 positions, centered on the target residue, is used as the input to the SVM.
- In cases where the window extends beyond the protein termini, 'empty' attributes are filled with zeros

# SVM cont.

**Table 3.** Results from 3-fold cross-validation of the final SVM prediction method on a data set of 1095 proteins

	H	E	C	
(a)				
obs(helix)	80.40	3.31	16.29	
obs(sheet)	4.76	68.75	26.50	
obs(coil)	10.63	10.15	79.22	
(b)				
pred(helix)	83.93	4.97	11.10	
pred(sheet)	4.03	83.62	12.34	
pred(coil)	13.35	21.71	64.93	
(c) $Q_3$	Sov	$C_H$	$C_E$	$C_C$
$77.07 \pm 0.26\%$	$73.32 \pm 0.39\%$	0.725	0.634	0.585

(a) Shows the SVM's assignment of the observed structural classes with diagonal entries representing the per residue  $Q_X^{\text{obs}}$  scores for each structure type. (b) Shows the true class assignments of the predictions with diagonal entries indicating the  $Q_X^{\text{pred}}$  scores. (c) Shows the mean  $Q_3$  and Sov scores per protein. The confidence interval is given by  $\sigma/\sqrt{n}$ , where  $n$  is the number of protein sequences.  $C_X$  represents Matthew's correlation co-efficients for helix, sheet and coil.

**Performance ~77%**

# Sequence features other than PSSM

Average nonbonded energy per atom  
Percentage of exposed residues  
Average accessible surface area  
Residue accessible surface area in folded protein  
No. of hydrogen bond donors  
Polarity  
Hydrophilicity value  
Polar requirement  
Long range nonbonded energy per atom  
Negative charge  
Positive charge  
Size  
Normalized relative frequency of bend  
Normalized frequency of  $\beta$ -turn  
Molecular weight  
Relative mutability

Normalized frequency of coil  
Average volume of buried residue  
Conformational parameter of  $\beta$ -turn  
Residue volume  
Isoelectric point  
Optimized propensity to form reverse turn  
Chou–Fasman parameter of coil conformation  
Information measure for loop  
Free energy in  $\beta$ -strand region  
Side chain volume  
Amino acid composition of total proteins  
Average relative probability of helix  
 $\alpha$ -Helix indices  
Relative frequency of occurrence  
Helix–coil equilibrium constant  
Amino acid composition  
No. of codon(s)  
Net charge  
Normalized frequency of turn

Relative frequency in  $\alpha$ -helix  
Average nonbonded energy per residue  
Bulkiness  
Normalized relative frequency of coil  
Refractivity  
Normalized frequency of left-handed  $\alpha$ -helix  
Heat capacity  
Free energy in  $\alpha$ -helical region  
Hydrophobicity factor  
Normalized frequency of extended structure  
Normalized frequency of  $\beta$ -sheet, unweighted  
Normalized frequency of  $\beta$ -sheet  
Information measure for pleated-sheet  
Hydropathy index  
Eisenberg hydrophobic index  
Average side chain orientation angle  
Average interactions per side chain atom  
Transfer free energy  
Percentage of buried residues

# Deep learning network

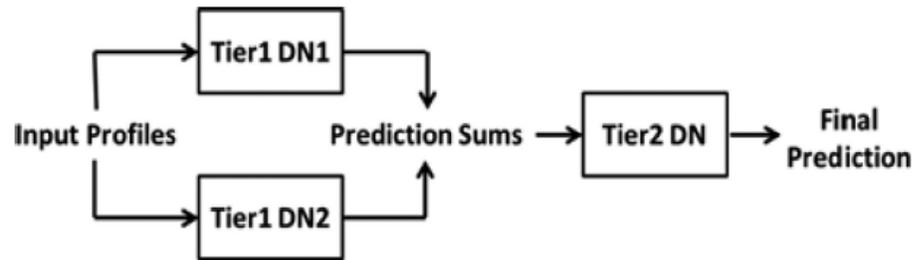


Fig. 2.  
Block diagram showing the DNSS secondary structure prediction workflow.

## Performance of Input Profile Features

Rank	Features	Q <sub>3</sub> (%)	Sov (%)
1	PSSM + FAC	79.1	72.38
2	PSSM	79.07	72.2
3	RES + PSSM	77.15	69.82
4	RES + PSSM + FAC	76.42	64.01
5	RES	63.04	52.36
6	FAC	62.22	54.94
7	RES + FAC	62.21	51.24

# Summary

- “However, secondary structure prediction has failed to appreciably improve upon the state-of-the-art 80% accuracy. As noted, recent methods have improved upon this accuracy by a small margin, but we must question how important it is to tweak secondary structure prediction tools to generate such a small improvement in accuracy. It is looking more and more like secondary structure prediction scores may not significantly improve until the discovery of features that can benefit the prediction process over and above the contribution of the sequence profiles alone.”