What, Why and How of Computational Protein Structure Prediction

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Outline

- short and (hopefully) painless introduction to proteins and protein structures
- motivation for computational prediction methods
- overview of computational work in protein structure prediction
- · protein structural class prediction

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Introduction to Proteins

Brief history

- from the Greek protas meaning "of primary importance"
- first proteins were discovered in early 19th century (in 1838) by a Swedish chemist Jöns Jakob Berzelius
 - they were called albuminoids
- for about 100 years chemists argued about their internal structure and finally in 1935 the list of 20 amino acids that compose the proteins was compiled
- nowadays, there are well over 2 millions of known proteins and the detailed structure is known for over 30 thousand of them

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Introduction to Proteins

Basic facts

- a protein is a complex, high-molecular-weight organic molecule that consists of amino acids joined by peptide bonds
 - other bio-macromolecules include polysaccharides, lipids, and nucleic acids
- they are among the most actively-studied molecules in biochemistry

Introduction to Proteins

Basic facts

- proteins are essential to the structure and function of all living cells (including humans) and viruses
 - examples functions include catalysis in chemical reactions (enzymes), forming the cytoskeleton (tubulin), serving various signaling and transporting functions (hemoglobin), implementing immune responses (antibodies), regulation of cell processes (hormones), and the list goes on and on...
 - aside from the fat, human body consists of about 20% of proteins by weight
- why are the proteins so "popular"?
 - they can adopt a huge number of three-dimensional shapes and thus constitute a perfect candidate to become a versatile "agent"

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Introduction to Proteins

Who makes the proteins?

- they are assembled from amino acids using information present in genes
 - genes (located in the cell's nucleus) are transcribed into RNA
 RNA is then subject to post-transcriptional modification and
 - control, resulting in a mRNA (messanger-RNA) that undergoes translation into a protein
 - mRNA is translated inside a cell by ribosomes that match the three-base codons of the mRNA to the three-base anti-codons of the appropriate tRNA (transfer-RNA)
 - the enzyme aminoacyl tRNA synthetase (aaRs) catalyzes the formation of covalent peptide bonds between amino acids effectively forming a protein chain



Bet Introduction to Proteins How are they made? • the translation process produces a linear sequence that is build from amino acids joined by covalent peptide bonds • nobody really knows (at least for larger proteins) how does it happens that a sequence is transformed into a molecule • the sequence folds to form a three dimensional molecule • the mechanics of this folding are largely unknown, although we know a lot in terms of the final product of the folding: • the molecule can be described on four distinct structural levels • it is build from only 20 amino acids • and researchers agree that a unique sequence folds always into the same molecule (based on minimum energy principle)



Amino Acids										
AA	Abbr.	Side chain	Hydro- phobic	Polar	Electric Charge	Size		Aromatic/	DNA codon	Occurre
						Small	Tiny	Aliphatic		nce (%)
Alanine	Ala, A	-CH3	X			X	×		GCU, GCC, GCA, GCG	7.8
Cysteine	Cys, C	-CHISH	x	- -	-	X		-	UGU, UGC	1.9
Aspartate	Asp, D	-CH2COOH		×	negative	×		-	GAU, GAC	5.3
Glutamate	Glu, E	-CH2CH2COOH		X	negative	-			GAA, GAG	6.3
Phenylalanine	Phe, F	-CH2CeHs	X			-	-	Aromatic	000,000	3.9
Glycine	GIY, G	-H	×	-	-	×	×	-	UUU, UUU, GGA, GGG	7.2
Histidine	His, H	-CH2-C3H3N2	-	x	positive	-		Aromatic	CAU, CAC	2.3
Isoleucine	lle, I	-CH(CH3)CH2CH3	X	-	-	-		Aliphatic	AUU, AUC, AUA	5.3
Lysine	Lys, K	-(CH2)+NH2		X	positive	-		-	AAA, AAG	5.9
Leucine	Leu, L	-CH2CH(CH3)2	X					Aliphatic	UUA, DUG, CUU, CUC, CUA, CUG	9.1
Methionine	Met, M	-CH2CH2SCH2	X	-	•	-		-	AUG	
Asparagine	Asn, N	-CH2CONH2	-	x		X		-	AAU, AAC	4.3
Proline	Pro, P	-CH2CH2CH2-	X	-		x		-	CCU, CCC, CCA, CCG	5.2
Glutamine	Gin, Q	-CH2CH2CONH2		X	-	-	•	-	L'AA, CAG	4.2
Arginine	Arg, R	-(CH2):NH-C(NH)NH2		X	positive	-		-	CUU, CUC, CUA, CGG, AGA, AGG	5.1
Serine	Ser, S	-CH2OH	-	L X		X	X	-	UCU, UCC, UCA, UCG, AGU, AGC	6.8
Inreonine	Inf, I	-CH(UH)CH3	× ×	×		×		-	ALU, ALU, ACA, ACG	5.9
valine	val, V	-CH(CH3)2	X			~		Auphatic	GUU, GUC, GUA, GUG	6.6
ryptophan	Trp, W	-CH2CiHiN	X	- -		-		Aromatic	UdG	1.4
Tyrosine	L Lyr, Y	-CH2-C4H4OH	X	X		-		Aromatic	UAU, UAC	3.2









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Protein Structure

Secondary structure examples

- immunoglobulin 12E8 (antibody)
 - different colors denote multiple (4) immunoglobulin molecules two dimers are shown

primary sequence

primary sourcement DIVNTOSOKEPMSTSVGDRVSITCKASONVGTAVAMYQOKEGOSEKLMIYSASNRYTGVE DLADYFCQVSSYELTEGAGYKLELKRADAAPTVSIEPSSGLTSGGASVVCELNNFY: ATDQDSKDSTYSMSSTLTLTKDEYERHNSYTCEATHKTSTSPIVKSFNRNEC FTLTISNMOS VCFLNNFYPKDINVKWKIDGSE

Alquando I fonda I funda Endida I Softa Saginmento Secondary sequence (n. 8-state SDSP assignment) COCERCOGSERECTTCOEREBERES SOCTOEREBERECTSOCERCEPTIBECTITIEEREETTEREBERES COCECTTCOEREBERES SOCTOEREBERECONTICATION INTERFERENCES ECOCOTTCOEREBERESENHINTCOEREBERESTCOSCEREBETTIT

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Detection Structures Detection and Quaternary structures e. the overall shape of a single (or a multi) protein molecule e. a spatial arrangement of the secondary structural motifs b. organd by hydrophobic interactions, hydrogen bonds, ionic interactions and disulfide bonds mean hemoglobin immunoglobulin mean hemoglobin immunoglobulin

Protein Structure

Why is it important to know the structure?

- in short: knowing the structure allows us to modify, e.g. enhance or block, certain protein functions
 example: if a protein is involved in cell division and we block
 - this function, we effectively stop the cell from dividing – when would that be useful?

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Protein Structure

Why is it important to know the structure?

- various molecules/ions can bind to specific protein sites
- the sites are called binding sites and exhibit chemical specificity
- the particle that binds is called a ligand
- the strength of ligand-protein binding is a property of the binding site known as affinity
- since proteins are involved in practically every function performed by a cell, the mechanisms for controlling these functions therefore depend on controlling protein activity
 - regulation can involve a changing protein's shape or
 - concentration, e.g.:
 - allosteric modulation: binding of a ligand at one site on a protein affects the binding of a ligand at another site
 - covalent modulation: covalent modification of a protein affects the
 - binding of a ligand or some other aspect of the protein's function

Protein Structure

How do we learn the sequence?

- can be deduced from known DNA sequence
- can be learned based on Edman degradation and mass spectrometry methods
- relatively cheap and easy to perform for virtually all proteins

8-11-2-2





Protein Databases

Databases

- PDB
 - the single worldwide repository for the processing and distribution of 3-D structure of proteins
 - manually curated and annotated (by experts) database of known tertiary protein structures
 - URL: http://www.rcsb.org/pdb

Protein Databases

Databases

- SWISS-PROT
 - protein knowledgebase established in 1986 and maintained since 2003 by the UniProt Consortium
 - a collaboration between the Swiss Institute of Bioinformatics and the Department of Bioinformatics and Structural Biology of the Geneva University, the European Bioinformatics Institute (EBI) and the Georgetown University Medical Center's Protein Information Resource (PIR)
 - manually annotated and curated (by experts) database of known protein sequences and relevant information
 - protein function, domain structure (if known), variants, posttranslational modifications, similarities to other proteins
 - URL: http://ca.expasy.org/sprot/sprot_details.html

Protein Databases

Databases

- NCBI
 - integrated access to a variety of sources, including SwissProt, PIR, PRF, PDB, and translations from annotated coding regions in GenBank and RefSeq
 - proteins are submitted and managed by individual researchers
 - they are not curated by experts
 contains mainly protein sequences and relatively little
 additional information
 - URL: http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?CMD=search&DB=protein

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Protein Structure Prediction

Main computational prediction tasks

- contact maps
 - · tertiary structure of a protein can be captured to a large extent by its distance map
 - the distance map is a two-dimensional symmetric matrix that shows which tuples of protein elements are close to each other in the overall molecule
 - » elements range between atoms, through AAs, to segments of
 - secondary structure
 - » in case of amino-acids distances are usually calculated between $\alpha\text{-}C$ atoms

Protein Structure Prediction

Main computational prediction tasks



Protein Structure Prediction

Main computational prediction tasks

- overall secondary structure
 - · comparative methods (dominant)
 - they use previously solved structures (or templates) as starting
 - point
 - for the predicted sequence a search for known homologous sequence is used and the structure is inferred based on the structure of these sequences

Protein Structure Prediction Main computational prediction tasks secondary structure content INPUT: primary sequence (narbonin 1NAR) KPIFREYLGVKPNSTTLHDFPTEIINTETLEFHYILGFAIESYYESGKGTGTFEESNDVELFGPEKVKNLKRR AEENVWVSNAKESLKLIIQKYSDDSGNLIDGIDHYEHTSDEFFATLMGQLITELKKDDLNIMVVSIAFPE TRANSFORMED INPUT: feature space representation of the sequence AA COMPOSITION RESIDUE PROPERTIES 0.3207 0.1103 0.2793 0.1414 0.1483 0.2793 0.2379 0.2276 0.4931 0.2172 0.2414 0.2241 0.169 0.1897 0.1724 0.2544 0.1154 0.2196 0.2893 0.1343 -0.02268 138.1 0.4788 139.6 0.05426 -0.05693 0.01952 0.0342 0.0345 0.0034 0.0759 0.0724 0.0586 0.0586 0.031 0.0828 0.0793 0.0759 0.0034 OUTPUT: secondary structure content helix 0.359, strand 0.217, coil 0.424

Protein Structure Prediction Main computational prediction tasks - secondary structure content · classical prediction uses a feature-based representation of a sequence as the input · percentage amount of each of the three main secondary structures (helices, strands and coils is predicted) either neural networks or multiple-regression methods are used



tural class	bonin 1NAR)								
ctural class primary sequence (nar	bonin 1NAR)								
: primary sequence (nar	DONIN TNAK)								
CONVENCED UNDERFORT INTERTIPEUN	INPUT: primary sequence (narbonin 1NAR)								
AEENWWVSNAKESLKLIIQKYSDDSCNLIDGIDIHYEHIRSDEPFAIDGUITELKODDLINUVSIAFSENNARFYAYIDIUGUV YQFSNQQKPVSTDDAFVEIFKSLEKDYHPHKVLPGFSTDPLDYKHNKITRDIFIGCTRLVQTFSLPGVFFWNANDSVIPKRDGDKPFI									
TRANSFORMED INPUT: feature space representation of the sequence									
AA COMPOSITION	RESIDUE PROPERTIES (electric charge, chemical group, etc.)	HYDROPHOBICITY based residue properties							
0.0345 0.0034 0.0759 0.0724 0.0586 0.0586 0.0586 0.0586	0.3207 0.1103 0.2793 0.1414 0.1483 0.2793 0.2379 0.2276 0.4931 0.2172 0.2414 0.2241 0.169 0.1897	0.2544 0.1154 0.2198 0.2893 0.1343 -0.02268 138.8 0.4788 139.6 0.05428 -0.05693 0.01952 0.03342							
101 IR 15	QURPUSTIDARVEI FKSLEKDYHPHKVL IR SFORMED INPUT: featur iar AA COMPOSITION Lassis a. 2015 9. 0.0734 0.0556 a. 0.0564 a. 0.0759 0.0759 0.0759 0.0056 a	(AP V DECEMBENT VERSION V							

Protein Structure Prediction

Main computational prediction tasks

reference	structural class	helix (a) amount	strand (B) amount	additional constrains and comments				
Nakashima	a proteins	> 15%	< 10%	contains dominantly antiparallel 8-sheets				
et al., 1986	B proteins	< 15%	> 10%	contains dominantly parallel B -sheets				
	α+β proteins	> 15%	> 10%	otherwise				
	μ/β proteins irregular	> 15%	> 10%					
Chou, 1995	a proteins	≥ 40%	≤ 5%	more than 60% antiparallel 8-sheets				
	6 proteins	≤ 5%	≥ 40%	more than 60% parallel B sheets				
	α+β proteins	≥ 15%	≥ 15%					
	a/B proteins	≥ 15%	≥ 15%					
	E proteins	≤ 10%	≤ 10%					
Eisenhaber	a proteins	> 15%	< 10%	otherwise				
et al., 1996	B proteins	< 15%	> 10%					
	mixed proteins irregular	> 15%	> 10%					
SCOP	a proteins	N/A	N/A	manual classification				
Murzin	β proteins							
et al., 1995	α+β proteins							
	a/B proteins							
	+ 7 other classes			© Lukasz Kurgan, 2				



Structural Class Prediction

- · over a dozen prediction methods, which were never comprehensively compared, were proposed
- · very basic protein representation
- composition vector + polypeptide composition
- · no established test beds
 - each method tested on a different datasets

 - test types: resubstitution and jackknife

53/61	Str	uctura		lass	: Pr	edic	tio	n	
	sequence		ize and est data	homology o sets		ouro	cheating and test	j in design ing]
classification	represen-	classes	1	c	lataset		classification acc		uracy
algorithm	tation		size	homology	domains	reference	resub	jackknife	reference
Vector decomposition	AA compos. vector	3 classes Eisenhaber et al., 1996	260	unknown unknown	no	Eisenhaber et al., 1996	60.8	57.7 57.3	Eisenhaber et al., 1996
Geometric classification	AA comp vector	4 classes SCOP	359	unkn, but homologous	yes		94.3	84.1	Chou & Maggiora, 1998
Component coupled geometric classification	AA comp vector	4 classes SCOP	359	unkn, but homologous	yes	Chou &	94.4	84.7	Bu at al., 1999
	energy auto- correlation functions	4 classes SCOP	359	unkn, but homologous	yes	Maggiora, 1998	96.7	90.5	
Bayes classification	AA comp vector	4 classes Nakashima et al., 1986	131	unknown	no	Nakashima et al., 1986	99.2	42.7	
		4 classes Chou, 1995	120	unknown	no	Chou, 1995	100	53.3	Wang & Yuan.
		3 classes Eigenhohor et el., 1008	260	unknown	no	Eisenhaber	86.5	62.7	2000
			4 classes SCOP	1189	40% 30%	yes ves	Wang & Yuan, 2000	63.8	53.8
Discriminant analysis	AA&polypeptide	4 classes SCOP	1054	40%	yes	Lun et al. 2002	91.7	<u>76.2</u>	Luo et al., 2002
	AA comp vector	4 classes SCOP	1054	40%	ves		66.2	55.8	
Information discrepancy based classification	polypeptides	4 classes SCOP	359	unkn, but homologous	yes	Chou & Maggiora, 1998		95.8	Jin et al., 2003
		4 classes SCOP	1401	30%	ves	Jin et al., 2003		75.0	
Support Vector Machines	AA comp vector	4 classes SCOP	359	unkn, but homologous	yes	Chou &	93.0	95.2	
	AA comp vector	7 classes SCOP	1601	unkn, but homologous	yes	Maggiora, 1998	87.0	84.1	Cai et al., 2003
Intimate sorting classification	AA comp vector functional	7 classes SCOP	2230	20%	yes	Chou & Cai, 200	4	98.8	Chou & Cai, 2004
	composition		<u> </u>					© Lukas:	Kurgan, 2006

Structural Class Prediction

Our study

- multi-goal study, which includes investigation of eight prediction algorithms
 - Naive Bayes (NB), Radial Basis Function neural network (RBF), Instance Based classifier (IB1), C4.5 (C4.5), Radio Basis Function neural network (RBF), Instance Based classifier (IB1), (RIP), Support Vactor Machine (SVM), and Logistic Regression (LR)
- three datasets with different homologies
- two low homology (1189 and 2340 sequences) and one high homology (359 sequences) three protein sequence representations
 - composition vector, 2) energy autocorrelation, 3) newly proposed representation based on composition and composition moment vectors vector, chemical group composition, hydrophobic autocorrelations and molecular weight
- and finally three test procedures
- resubstitution, jackknife, 10-fo





Structural Class Prediction Structural Class Prediction Sequence representation Test procedures high quality of the composition vector with respect to structural class resubstitution test is unreliable and should not be reported prediction was confirmed 10-fold cross-validation is shown to be at least the same good as the . increase of accuracy lift due to using the new representation is 2.0% for support vector machines and 4.3% for logistic regression jackknife test execution of the jackknife test requires substantial computational time, in comparison with less demanding and commonly performed 10-fold cross-validation (evaluation of the logistic regression method using 10-fold cross-validation requires about 50 minutes, and using jackknife test about 8400 minutes) the improvements concern the most accurate classi iers rage accuracy datase 25PDB 1189 359 representation CV AC 66 CV AC 66 V AC 66 10 fold cross validation compared with jackknit

Structural Class Prediction

The study have shown that

- sequence homology is found to significantly affect accuracy
- new to the field logistic regression prediction algorithm generates results that are competitive or better when compared with the past results
- for eight considered prediction algorithms, state-of-the-art sequences representation and low, about 30%, homologous dataset, the best results are in the range of 57% accuracy
- the newly proposed sequence representation is beneficial for high quality prediction algorithms
- the resubstitution tests are shown to significantly overestimate the prediction accuracy, and the commonly performed jackknife test procedure leads to unnecessarily high computational demand
 therefore 10-fold cross-validation should be used for the future studies

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Protein Structure

Where to get started?

· secondary structure

- overall secondary structure
- Hernga J. Computational methods for protein secondary structure prediction using multiple sequence alignments, *Curr Protein* Pept 302, 1(3), pp.273-301, 2000 Prolytish D and Rotts B. Alignment grow, secondary structure prediction improves, *Proteins*, 6(2), pp.197-205, 2002 - structural class
 - Chou KC, Progress in protein structural class prediction and its impact to bioinformatics and proteomics, *Curr Protein Pept Sci*, 65), pp. 2139, 2006 Wang 22, Apa 11 Aan 22, How Good is the Prediction of Protein Structural Class by the Component-Coupled Method?, Proteins, 34, pp. 165-17, 2000

secondary structure content

Lee S, Lee BC and Kim D, Prediction of protein accordary structure content using amino acid composition and evolutionary information. Proteins, 52(4), pp. 1107-14, 2006
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