

ALMA MATER STUDIORUM UNIVERSITÀ DI BOLOGNA



The multidimensional problem of protein-protein interactions

Rita Casadio

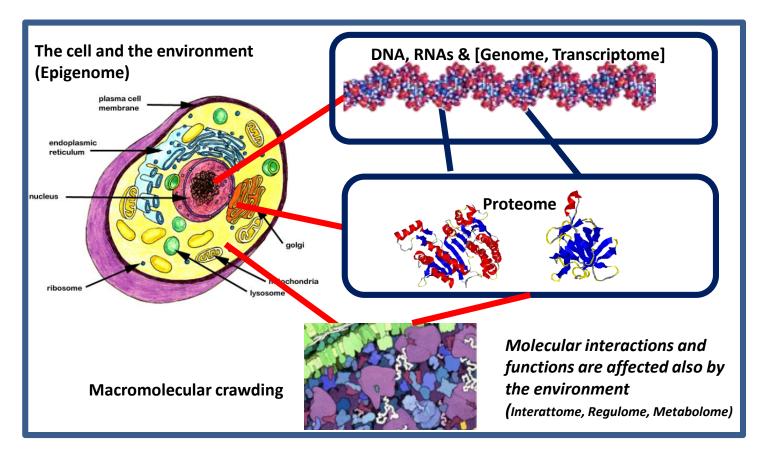
BIOCOMPUTING GROUP University of Bologna, Italy





The ingredients of biological complexity at the cell level

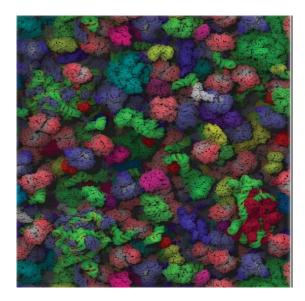
From genes to proteins, their interaction and the interplay with the environment





LIFE IS CROWDED: Macromolecular crowding is under-appreciated, including

protein phase separation



The Crowded Cell: An atomically detailed model of the crowded E. coli cytoplasm, including the 50 most abundant macromolecules. RNA is shown as green and yellow. Reprinted from: McGuffee SR, Elcock AH (2010) Diffusion, Crowding & Protein Stability in a Dynamic Molecular Model of the Bacterial Cytoplasm. *PLoS Comput Biol 6(3): e1000694*.

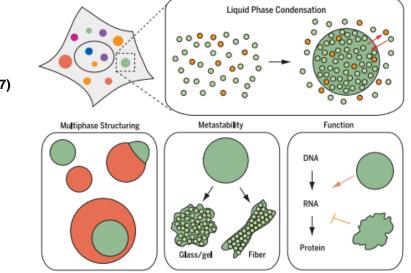
REVIEW SUMMARY

CELLULAR BIOPHYSICS

Liquid phase condensation in cell physiology and disease

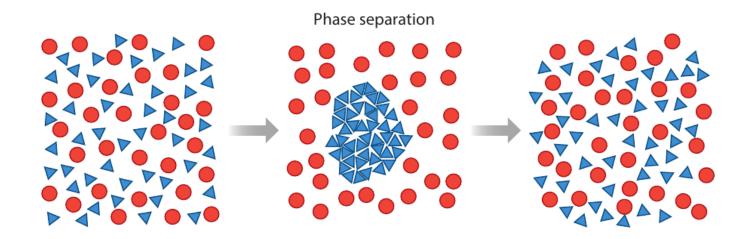
Yongdae Shin and Clifford P. Brangwynne*

Science 357, 1253 (2017)





PROTEIN PHASE SEPARATION



Simplified representation of the dynamics of protein phase separation

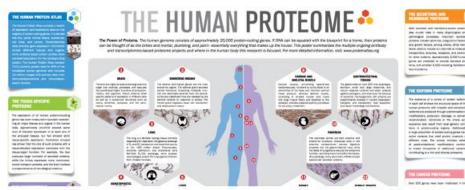
Membraneless organelles are common to several types of cells working under physiological conditions

Savojardo, C., Martelli, P.L., Casadio, R. Ann Rev Biom Data Science 2020, 3.



Two important initiatives for deciphering the human proteomes:

The Protein Atlas:



The protein data covers 15313 genes (78%) for which there are available antibodies. The mRNA expression data is derived from deep sequencing of RNA (RNA-seq) from 37 different normal tissue types



The Human Proteom Project:

HUMAN PROTEOME PROJECT (HPP)



HUMAN PROTEOME PROJECT (HPP)

The Human Proteome Project (HPP) is an international project organized by the Human Proteome Organization (HUPO) that aims to revolutionize our understanding of the human proteome via a coordinated effort by many research laboratories around the workl. It is designed to map the entire human proteome in a systematic effort using currently available and emerging techniques. Completion of this project will enhance understanding of human biology at the cellular level and lay a foundation for development of diagnostic, prognostic, therapeutic, and preventive medical applications.

> More on the HPP



19,823 PREDICTED GENOME-CODING PROTEINS (neXtProt PE1+ PE2 + PE3 + PE4)

17,694

FOUND PROTEINS

2,129

MISSING PROTEINS (neXtProt PE2 + PE3 + PE4)

(neXtProt PE1)



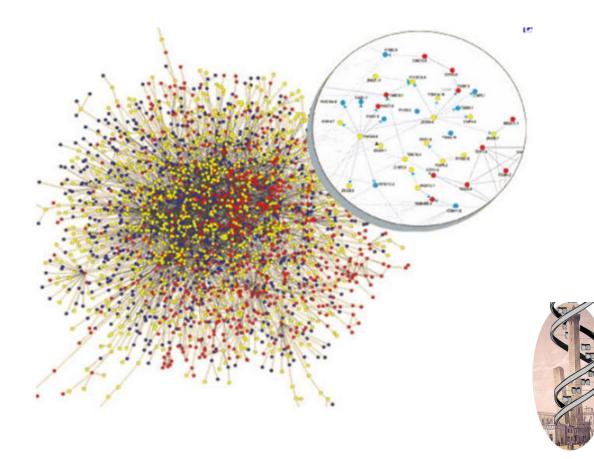


https://www.hupo.org/human-proteome-project

From the proteome to the interactome.... Protein-protein interaction networks

- Play a major role in generating the complexity of cellular processes
- If perturbed can lead to impairment of biological functions and to disease
- Crucial in host-pathogen communication

Yeast two-hybrid Affinity purification + mass spec



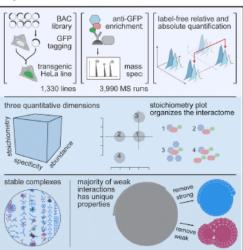


Article

Cell

A Human Interactome in Three Quantitative **Dimensions Organized by Stoichiometries and** Abundances

Graphical Abstract



Authors

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In Brief

Weak interactions shape the cellular protein interaction network as determined from proteomic measures of cellular interaction specificities, the strength of those interactions, and the cellular copy numbers of the proteins involved.

Hiahliahts

- Human interactome dataset connecting 5,400 proteins with 28,500 interactions
- Three quantitative dimensions measure specificities, stoichiometries, and abundances
- Stable complexes are rare but stand out by a signature of balanced stoichiometries
- Weak interactions dominate the network and have critical topological properties







NIH Public Access **Author Manuscript**

> Published in final edited form as: Nat Biotechnol. ; 30(2): 159-164. doi:10.1038/nbt.2106.

Three-dimensional reconstruction of protein networks provides insight into human genetic disease

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¹Department of Biological Statistics and Computational Biology, Cornell University, Ithaca, NY 14853, USA ²Weill Institute for Cell and Molecular Biology, Cornell University, Ithaca, NY 14853, USA ³Department of Medicine, Weill Cornell College of Medicine, New York, NY 10021, USA ⁴Department of Bioinformatics, Maastricht University, 6200 MD Maastricht, The Netherlands

Abstract

In an effort to understand molecular mechanisms of human disease and to determine genes responsible, we systematically examine relationships between 3,949 genes, 62,663 mutations and 3,453 associated disorders within the framework of a three-dimensional structurally resolved human interactome, consisting of 4,222 high-quality binary protein-protein interactions with their

Cell

Cell 159, 1212-1226, November 20, 2014

Resource

A Proteome-Scale Map of the Human Interactome Network

Thomas Rolland, 1,2,19 Murat Taşan, 1,3,4,5,19 Benoit Charloteaux, 1,2,19 Samuel J. Pevzner, 1,2,6,7,19 Quan Zhong, 1,2,8,19 Nidhi Sahni,^{1,2,19} Song Yi,^{1,2,19} Irma Lemmens,⁹ Celia Fontanillo,¹⁰ Roberto Mosca,¹¹ Atanas Kamburov,^{1,4} Susan D. Ghiassian,^{1,12} Xinping Yang,^{1,2} Lila Ghamsari,^{1,2} Dawit Balcha,^{1,2} Bridget E. Begg,^{1,2} Pascal Braun,^{1,2} Marc Brehme,^{1,2} Martin P. Broly,^{1,2} Anne-Ruxandra Carvunis,^{1,2} Dan Convery-Zupan,^{1,2} Roser Corominas,¹ Jasmin Coulombe-Huntington,^{1,14} Elizabeth Dann,^{1,2} Matija Dreze,^{1,2} Amélie Dricot,^{1,2} Changyu Fan,^{1,2} Eric Franzosa,^{1,14} Fana Gebreab,^{1,2} Bryan J. Gutierrez,^{1,2} Madeleine F. Hardy,^{1,2} Mike Jin,^{1,2} Shuli Kang,¹³ Ruth Kiros,^{1,2} Guan Ning Lin,¹³ Katja Luck,^{1,2} Andrew MacWilliams,^{1,2} Jörg Menche,^{1,12} Ryan R. Murray,^{1,2} Alexandre Palagi,^{1,2} Matthew M. Poulin,^{1,2} Xavier Rambout,^{1,2,15} John Rasla,^{1,2} Patrick Reichert,^{1,2} Viviana Romero,^{1,2} Elien Ruyssinck,⁹ Julie M. Sahalie,^{1,2} Annemarie Scholz,^{1,2} Akash A. Shah,^{1,2} Amitabh Sharma,^{1,12} Yun Shen,^{1,2} Kerstin Spirohn,^{1,2} Stanley Tam,^{1,2} Alexander O. Tejeda,^{1,2} Shelly A. Trigg,^{1,2} Jean-Claude Twizere,^{1,2,15} Kerwin Vega,^{1,2} Jennifer Walsh,^{1,2} Michael E. Cusick, ^{1,2} Yu Xia, ^{1,14} Albert-László Barabási, ^{1,12,16} Lilia M. lakoucheva, ¹³ Patrick Aloy, ^{11,1} Javier De Las Rivas,¹⁰ Jan Tavernier,⁹ Michael A. Calderwood,^{1,2,20} David E. Hill,^{1,2,20} Tong Hao,^{1,2,20} Frederick P. Roth, 1,3,4,5,18,* and Marc Vidal^{1,2,*}

Comparing two recently released human interactomes....

Size of two experimental human interactomes recently released

	HuRI ¹	BioPlex2.0 ²
Number of proteins*	8,470	10,844
Number of interactions	51,907	55,498
¹ Database downloaded from http://www.interacton	ne-atlas.org on July 27, 20	019

Reference: 23,423 coding genes of GRCh38.p12

² Database downloaded from <u>https://bioplex.hms.harvard.edu</u> on July 27, 2019
 * Splicing isoforms are collapsed

Overlap between HuRi and BioPlex

	HuRI	BioPlex2.0
Number of shared proteins	4,827 (56.9%)	4,827 (44.5%)
Number of interactions among shared proteins	16,133 (31.1%)	12,610 (22.7%)
Number of shared interactions	829 (5.1%)	829 (6.6%)



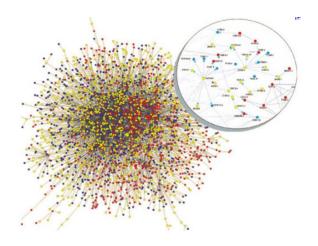
Savojardo, C., Martelli, P.L., Casadio, R. Ann Rev Biom Data Science 2020, 3.

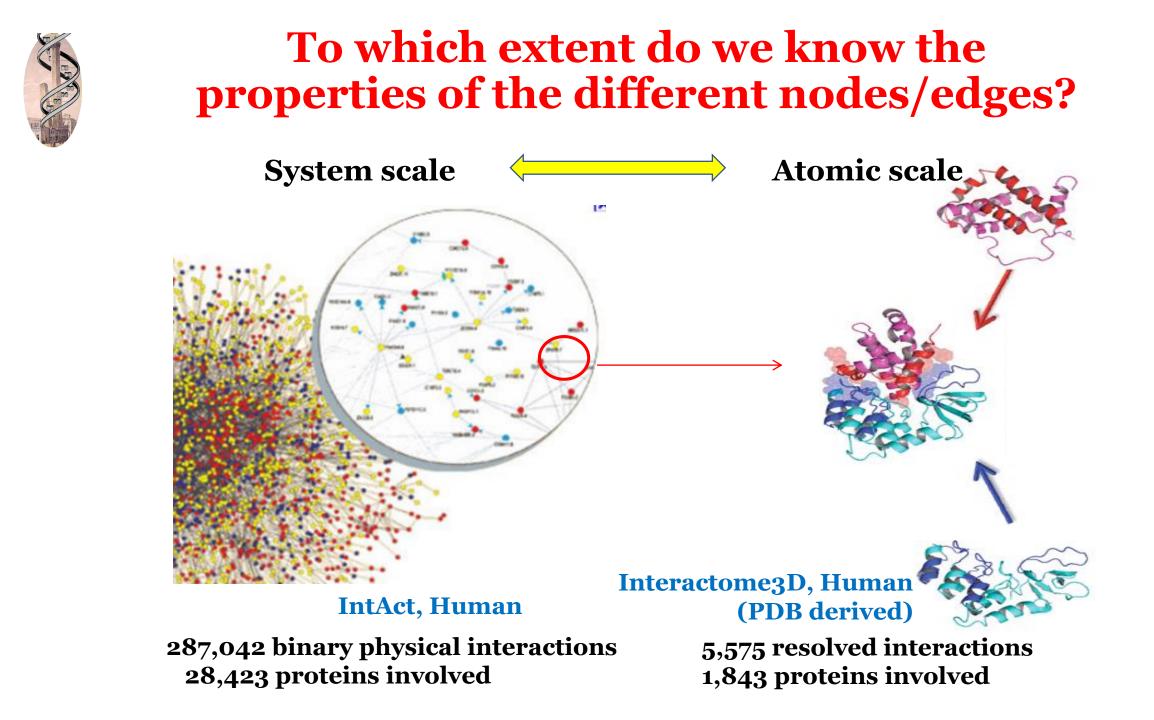




Open issues of the interactomic space:

- Data quality and reproducibility
 Coverage of the proteome
- •Tissue specificity
- Subcellular localisation
- Co-expression





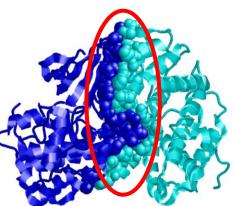


Leveraging available structural information

Prediction of protein interaction sites

Identifying residues in interaction patches in a protein, without knowing the interaction partner

starting from monomer structure



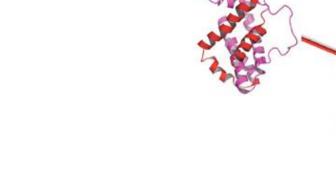
starting from monomer sequence

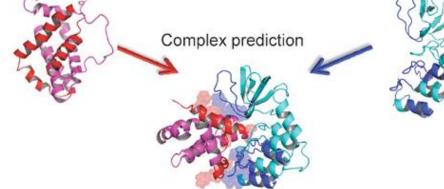
>sp|Q196Z6 MDAVKHPVSSLAPHRLGKGFYFMVNSKQI**IKK**FYNKS**FLEC**SATQETSTTP**H**DRDNMDQA KLCSLVFEIF**KKQT**RLLAH**LVLEE**AIDLNND**LLF**AVIYFNDEAILNSLVRHLYKYKPYYC DFTVRAQELDLVVHLDLGHCIDRLKSFIDPDTACFVLCSNLSQLT**GLNC**LKRVLKHKIIQ KSYHLYLLLKTSHKVQQQWPDPVHVVEKYVTKRMVSYALTDNNPLLLAIVLDRLLVKLPT DDFAPLIVGIIESNRFKVECLPTLLQYHNRVKTTTKPIRI

Why interaction sites are important?

Characterization of protein function

- Interaction site <-> functional site
- Disease-related variations often occur at interaction sites
- Discovery of novel interaction patches
- Improvement of docking methods
 - By reducing the number of possible conformations

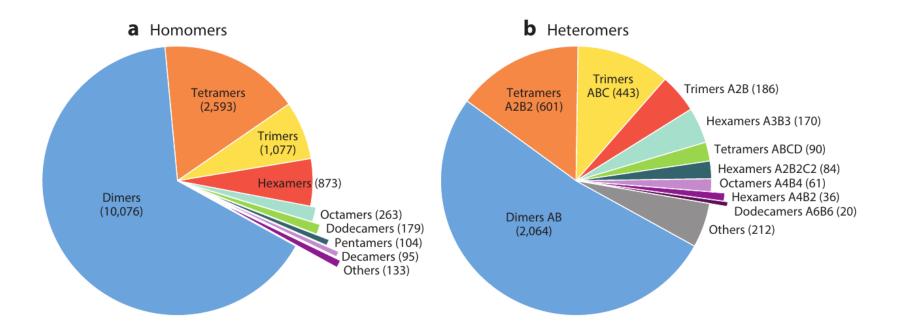




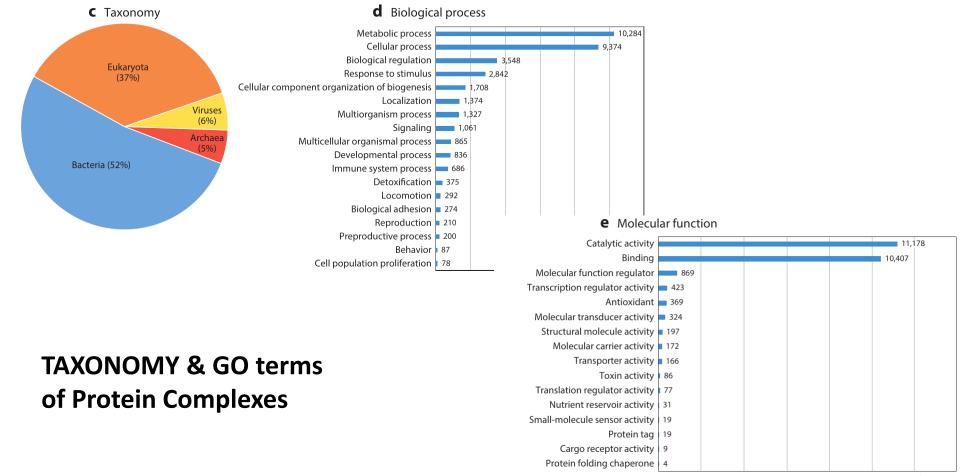


Some Statistics.....from the PDB

WHICH PROTEIN COMPLEXES ? (about 67.000 in the PDB as to July 2019) *About 1/3 of the PDB*

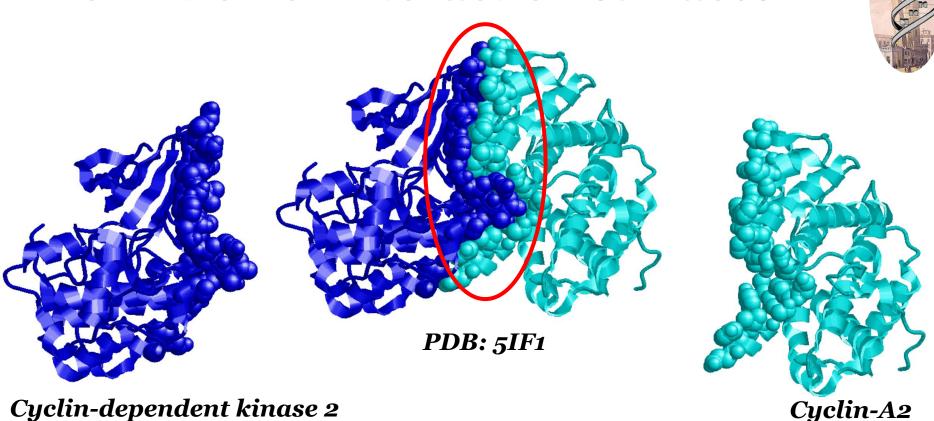


Some Statistics.....from the PDB



(Caption apt.

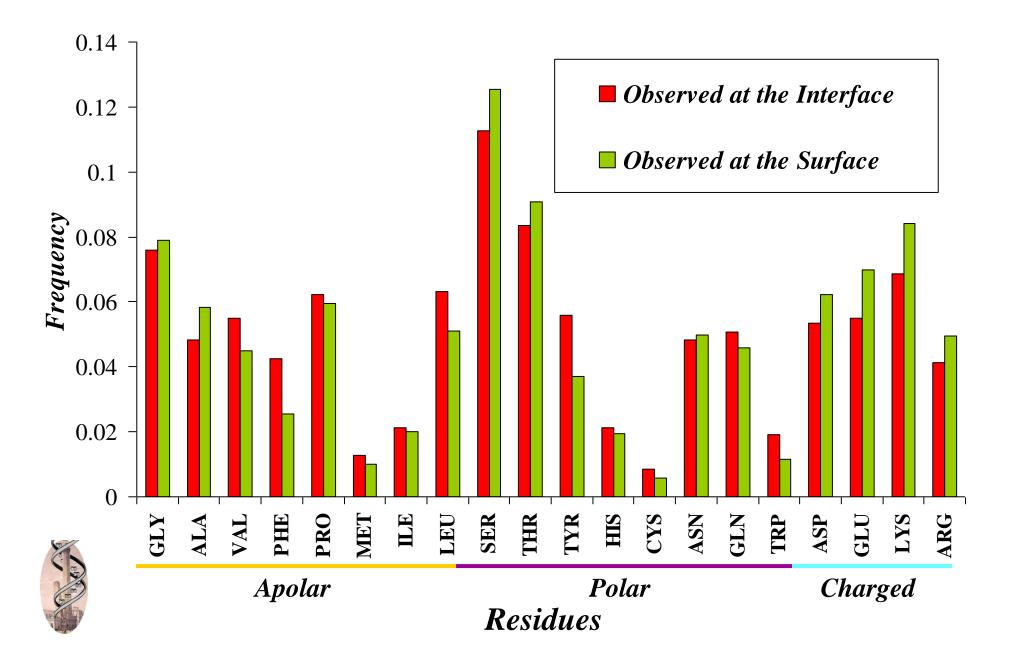
Definition of interaction surfaces



Definition:

The set of any residue showing a Difference in Accessible Surface Area (DASA ≥ 1 Å²) between the monomer and the complex

Distributions of apolar, polar and charged residues



Protein-protein interaction is a biophysical complex phenomenon governed by:

- 1) Shape
- 2) Chemical complementarity
- 3) Flexibility
- 4) Residue specific composition (less charged, more hydrophobic than in the solvent accessible surface of the protein)



Hydrophobic interactions, weak electrostatic interactions, Van der Waals interactions...

Properties of interaction surfaces (>5000)

Feature	Method/Program/Source
Residue propensity	AA frequency tables
Physico-chemical properties	AAINDEX, hydropathy scales, propensities
Residue conservation	PSI-BLAST, Jackhmmer, HHBlits
Curvature	Coleman method, SurfRace
Depth and protrusion indexes	PSAIA
Solvent exposure	DSSP, PSAIA, NACCESS
Secondary structure	DSSP, STRIDE
B-Factors	Curated from PDB
Electrostatic potentials	APBS, FoldX, DelPhi
Energy of solvation	APBS

No major emerging feature



Information is in complex feature combinations



A sample of implemented methods

Method	Category	Based on	Reference
Gallet et al., 2000	Sequence	AA frequency tables	Gallet et al., 2000
Ofran and Rost, 2003	Sequence	Sequence profile + Neural networks	Ofran and Rost, 2003
Chen and Li, 2010	Sequence	Hydrophobicity and sequence profiles + SVM	Chen and Li, 2010
SPPIDER	Structure	Predicted solvent accessibily fingerprint + SVM	Porollo and Meller, 2007
cons-PPISP	Structure	Structural features + Consensus Neural Networks	Chen et al, 2005
ProMate	Structure	Structural property histograms and patch refinement	Neuvirth et al, 2004
PresCont	Structure	Evolutionary information+structural features+SVM	Zeliner et al, 2012
PredUS	Template + Structure	Structural neighbors transfer+SVM refinement	Zhang et al, 2001
PrISE	Template	Local surface similary based on structural element distributions	Jordan et al, 2012
HomPPI	Template	Homologous sequence-based transfer	Xue et al, 2011

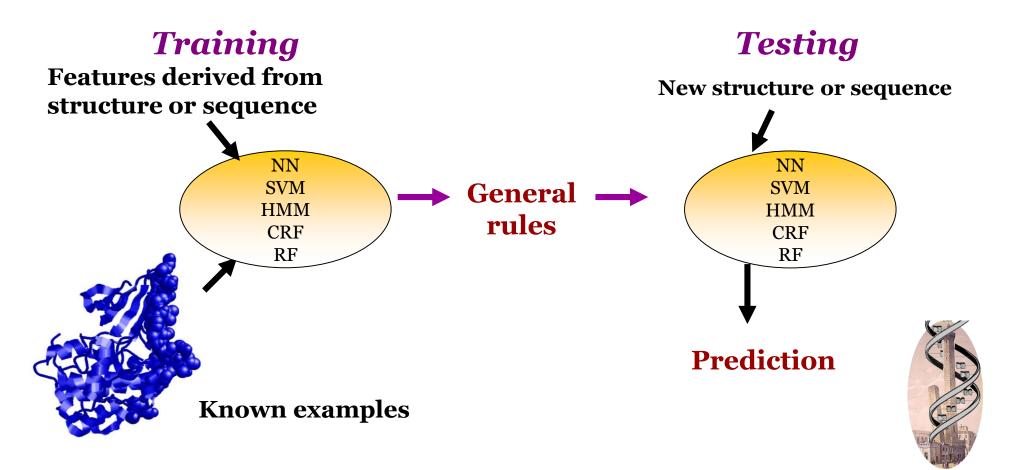
Nowadays: a classification of available computational approaches

- Template-based methods
 - Exploit sequence/structure similarity to transfer interaction sites from known structural templates
 - Good accuracy
 - Requires templates of the interacting complex
- Machine-learning approaches
 - Sequence-based predictors
 - Extract information from monomer sequence
 - Broad applicability
 - Low accuracy
 - Structure-based predictors
 - Extract information from both sequence and structure of the monomer
 - More accurate than sequence-based methods
 - Requires structural model of the monomer

Machine learning methods

Problem: label each residue as interacting or not

• **Methods:** Neural Networks (NN), Support Vector Machines (SVM), Hidden Markov Models (HMMs), Conditional Random Fields (CRF), Random Forests (RF)



Predictors @ Bologna Biocomputing Group www.biocomp.unibo.it/predictors

• ISPRED1 (Fariselli et al., 2001, 2002)

- Structure-derived features
- Method: Artificial Neural Networks (ANNs)
- Input features: sequence profiles computed from multiple sequence alignments

• ISPRED2, ISPRED3 (Savojardo et al., 2011)

- Structure-derived features
- Method: Hidden Markov Support Vector Machines (HM-SVMs)
- Input features: sequence profiles + solvent accessibility

• ISPRED4 (Savojardo et al., 2017)

- Structure-derived features
- Method: SVM+Grammatical-Restrained Hidden CRF (Fariselli et al., 2009)
- Input features: extended feature set to encode each surface residue

ISPRED-SEQ (Savojardo et al., 2020, in preparation)

- Sequence-derived features
- Method: Deep learning
- Input features: extended feature set to encode each residue



Prediction of protein–protein interaction sites in heterocomplexes with neural networks

Piero Fariselli¹, Florencio Pazos², Alfonso Valencia² and Rita Casadio¹

¹CIRB and Department of Biology, University of Bologna via Irnerio, Bologna, Italy; ²Protein Design Group, CNB-CSIC Cantoblanco, Madrid, Spain

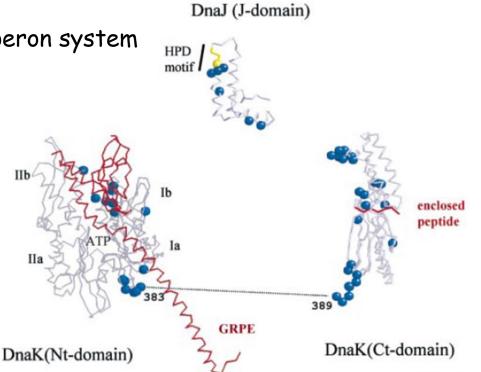
In this paper we address the problem of extracting features relevant for predicting protein-protein interaction sites from the three-dimensional structures of protein complexes. Our approach is based on information about evolutionary conservation and surface disposition. We implement a neural network based system, which uses a cross validation procedure and allows the correct detection of 73% of the residues involved in protein interactions in a selected database comprising 226 heterodimers. Our analysis confirms that the

chemico-physical properties c⁻⁻⁻ difficult to distinguish from the face. However neural networl _ representation of the interacting are sufficient to generalize over the different features of the contact patches and to predict whether a residue in the protein surface is or is not in contact. By using a blind test, we report the prediction of the surface interacting sites of three structural components of the Dnak molecular chaperone system, and find close agreement with previously published experimental results. We propose that the predictor can significantly complement results from structural and functional proteomics.

tworl The Dnak molecular chaperon system

Fig. 4. Prediction of the interacting surface for the three structural components of the DnaK molecular chaperone system. The structures of DnaK N-terminal and C-terminal domains, that has been determined separately (PDB codes 1dkg and Idkx, respectively), are shown at the bottom. The structure of the DnaJ J-domain (PDB code 1xbl) is shown at the top. CA carbons of residues predicted at the putative interfaces by the neural network are shown as spheres depicted in blue. The peptide fragment (enclosed in the DnaK Ct-domain) and the nucleotide exchange factor GrpE protein (co-crystallised with the Dnak Nt-domain) are shown in red colour with thick backbone. The DnaJ conserved HPD motif is shown in yellow.

ISPRED & the role of experimental validation





ISPRED4: features

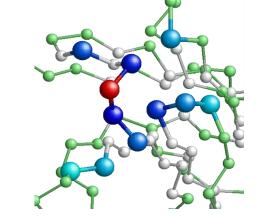
- Surface residues are determined (relative solvent accessibility ≥20%)
- 46 descriptors are used to encode each <u>surface</u> residue
- Descriptors derived from sequence and averaged on structure:
 - Sequence profile from MSA (20)
 - Residue conservation and co-evolution from MSA (3)
 - Residue physico-chemical properties (11)
- Descriptors extracted from structure:
 - Solvent exposure computed by DSSP (1)
 - Depth and protrusion geometrical indexes (7)
 - Secondary structure (3)
 - Average B-factor (1)



Savojardo C, et al., Bioinformatics 2017

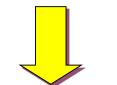
Implementing a ML based method: feature average with respect to the structural environment

For each exposed C_a (in red) the 10 closest exposed C_as are selected within 1.2 nm (in blue)



Distance scale



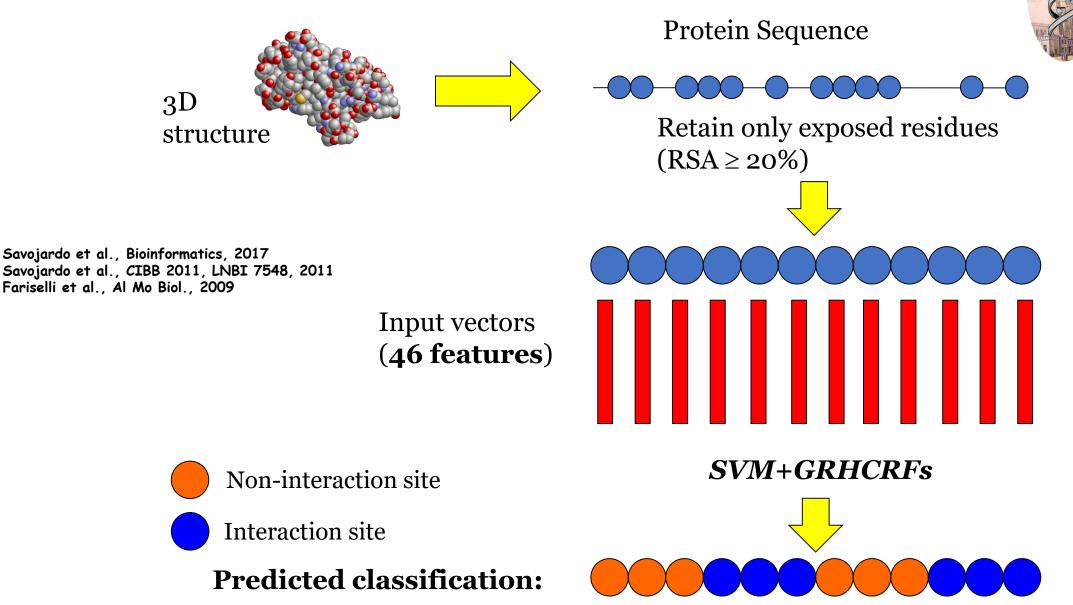


Columns of the feature profile are extracted and averaged

	A	0		0	0	0	0	1	0	0	0	0	0	0	10	0	0	0	0	0	
	С	0		0	0	0	0	H	0	0	0	0	0	0	0	0	0	0	0	0	
	D	0		0	70	0	0	H	0	0	60	0	0	0	0	20	0	0	0	10	
	Ε	0		0	0	0	0	H	0	0	0	0	0	0	0	70	0	0	0	10	
	F	0		0	0	10	0	H	33	0	0	0	0	0	0	0	0	0	0	0	
_	G	10		0	30	0	30	H	0	100	0	0	0	0	50	0	0	0	0	30	
	Н	0		0	0	0	10	H	0	0	10	30	0	0	0	0	0	0	0	0	
;	K	0	4	0	0	0	0	H	0	0	0	10	100	70	0	0	0	0	100	0	
	I	0		0	0	0	0	H	0	0	0	30	0	0	0	0	0	0	0	0	
-	L	0		0	0	0	0	H	0	0	30	0	0	0	0	0	0	0	0	30	
	М	0		0	0	0	0	H	0	0	0	0	0	0	0	0	60	0	0	0	
	Ν	0		0	0	0	10	H	0	0	0	0	0	30	10	0	0	0	0	0	
	P	0		0	0	0	0	H	0	0	0	0	0	0	0	0	0	0	0	0	
_	Q	0		0	0	0	40	H	0	0	0	30	0	0	0	0	0	0	0	0	
	R	0	5	0	0	0	0	H	0	0	0	0	0	0	0	0	0	0	0	0	
	S	0		0	0	0	0	H	33	0	0	0	0	0	0	10	10		0	0	
	Т	20		0	0	0	0	H	33	0	0	0	0	0	30	0	30	100	0	0	
	V	0		0	0	0	10	H	0	0	0	0	0	0	0	0	0	0	0	20	
	W	0	1	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	
	Y	70		0	0	90	0		0	0	0	0	0	0	0	0	0	0	0	0	



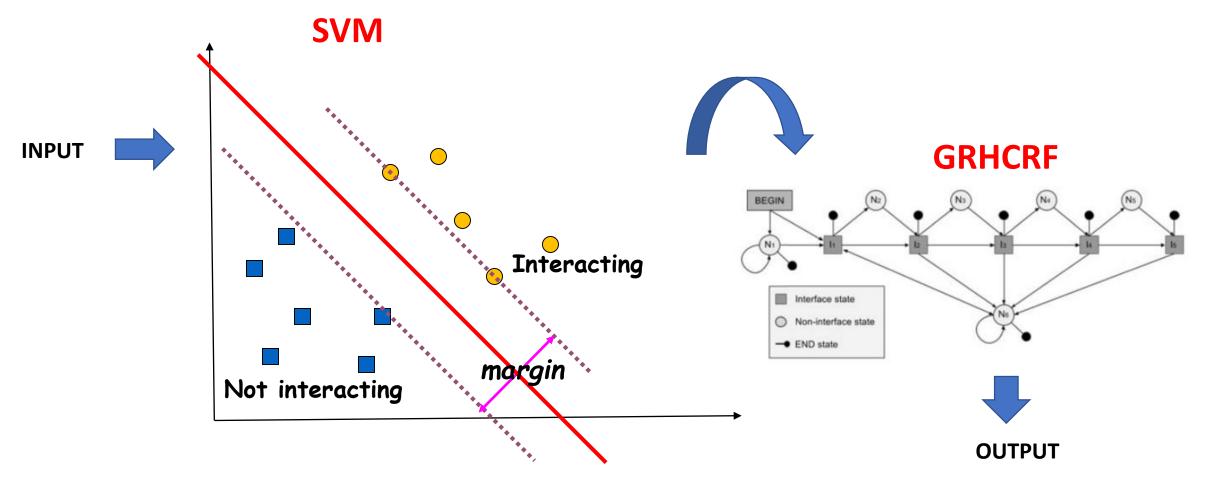
ISPRED4 workflow





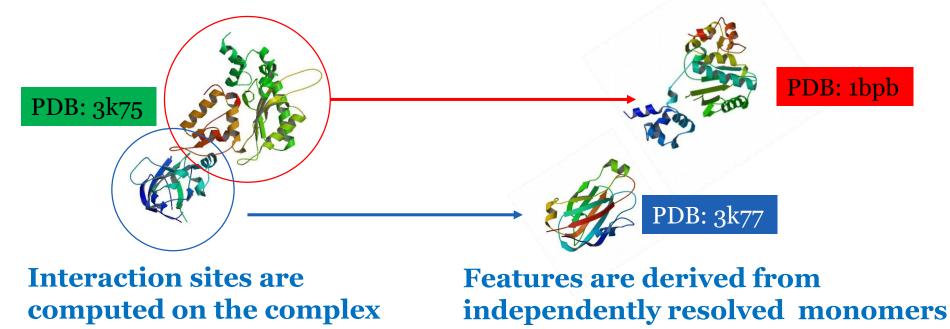
ISPRED4: Support Vector Machines (SVM) + Grammatical Restrained Hidden Conditional Random Fields (GRHCRFs)

Savojardo et al., Bioinformatics, 2017 Savojardo et al., CIBB 2011, LNBI 7548, 2011 Fariselli et al., Al Mo Biol., 2009



Training dataset

To avoid biases due to conformational changes upon binding

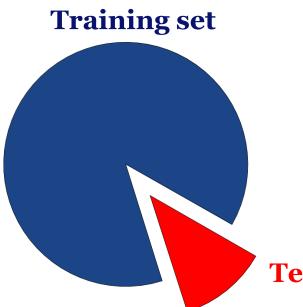


- **TrainStructDB: 151** high-resolution protein complexes derived from the Docking Benchmark v5 => **314** unbound chains
 - 67,235 total residues
 - 39,046 exposed residues
 - 8,649 interaction sites 30,397 non interaction sites



Evaluation procedure

10 Fold cross-validation procedure on TrainStructDB



Performance is evaluated in the testing set

Testing set



Scoring indexes

• Residue-level scoring measures TP: True positives, FN: False negatives FP: False positives, TN: True negative

$$Precision(Specificity) = \frac{TP}{TP + FP}$$
$$Recall(Sensitivity) = \frac{TP}{TP + FN}$$
$$Q2 = \frac{TP + TN}{TP + TN + FP + FN}$$



 $F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}}$$

CAPRI Blind dataset

• CAPRI: Critical Assessment of Predicted Interactions (https://www.ebi.ac.uk/msd-srv/capri/)

- Targets extracted from past CAPRI experiments (rounds 1-29)
- Only targets sharing < 30% sequence identity with any sequence in the training set
- 22 different bound structures including 29 chains
 - 6,369 total residues
 - 3,613 exposed residues
 - 868 interaction sites 2,
 - 2,745 non interaction sites



Performance comparison

Performance on the TrainStructDB dataset (Cross-validation)

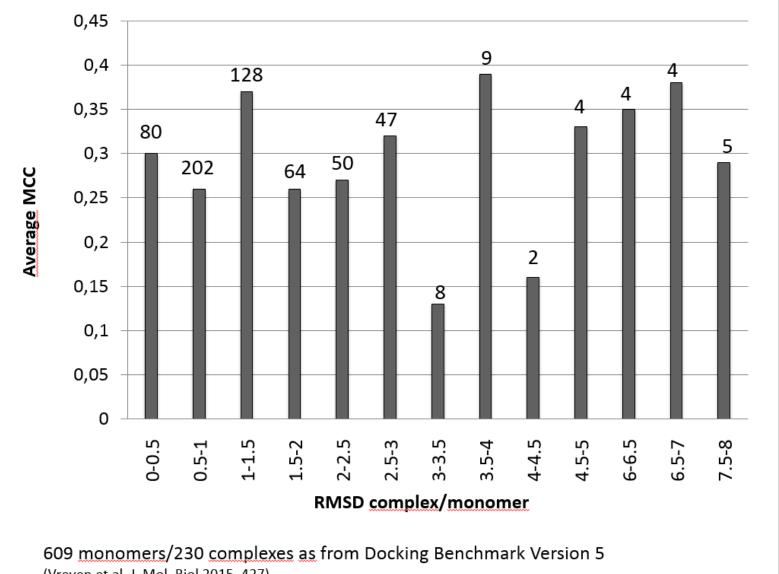
Method	Method type	Precision	Recall	F1	Q2	MCC
ISPRED4	Structure	0.78	0.39	0.52	0.84	0.48
ISPRED3	Structure	0.26	0.80	0.39	0.47	0.16
SPPIDER	Structure	0.39	0.54	0.45	0.72	0.28
cons-PPISP	Structure	0.46	0.27	0.34	0.77	0.23
PredUs	Homology	0.37	0.76	0.50	0.67	0.34
PrISE	Homology	0.42	0.41	0.41	0.83	0.33

Performance on the CAPRI blind dataset

Method	Method type	Precision	Recall	F1	Q2	MCC
ISPRED4	Structure	0.60	0.38	0.47	0.67	0.28
ISPRED3	Structure	0.26	0.68	0.38	0.45	0.05
SPPIDER	Structure	0.36	0.39	0.37	0.68	0.16
cons-PPISP	Structure	0.33	0.17	0.22	0.72	0.08
PredUs	Homology	0.38	0.62	0.47	0.67	0.26
PrISE	Homology	0.41	0.36	0.38	0.72	0.21



ISPRED4 scoring over the Docking Benchmark Version 5





(Vreven et al, J. Mol. Biol 2015, 427)

ISPRED4 website http://ispred4.biocomp.unibo.it



Home SearchJob Software/Datasets References Contact BiocomputingGroup

Welcome to the ISPRED4 prediction server

C A	straucture. In particu by extracting severa Submit a PD To start using ISPR	lar, ISPREDv4 adopts machine-learning methods (features from the protein sequence and structure. 3 file ED4 you simply need to upload a protein 3D structu	r predicting protein-protein interface residue starting from prote SVM+CRF) to predict interaction state of each residue in the prote re in PDB format and specify the protein chain you want to analyze enver accents in input a single protein structure. Download example	e.
В	input data.	Sequence view		
Input PDB file:	Sfoglia Nessun file selezi	Protein id: Protein length:	5HLU [chain A] 152	
PDB chain:		Surface length (RSA>=0.16):	101	
	Submit job	Interface Surface Buried 2 2 8 8 0 1	K V K A D V A O B O O D I I I K F K S I K Z F L K K O I I Z A A X Y K Z O O O I A TX I K I P	K K D R F Z K F K A K K A S K D F

Detailed report

Residue number	Residue type	ASA	RSA	Predicted RSA	Depth	Protrusion	Surface	Interface	Probability
22	Α	19	0.18	0.42	0.53	0.51	yes	no	0.21
23	G	7	0.08	-	-	-	no	-	-
24	Н	4	0.02	-	-	-	no	-	-
25	G	1	0.01	-	-	-	no	-	-
26	Q	29	0.15	-	-	-	no	-	-
27	D	44	0.27	0.14	0.34	0.33	yes	no	0.27
28	I	2	0.01	-	-	-	no	-	-
29	L	3	0.02	-	-	-	no	-	-
30	I	7	0.04	-	-	-	no	-	-
31	R	104	0.42	0.36	0.36	0.58	yes	yes	0.88
32	L	11	0.07	-	-	-	no	-	-
33	F	3	0.02	-	-	-	no	-	-
34	к	102	0.5	0.31	0.17	0.77	yes	no	0.44
35		49	0.38	0.18	0.22	0.79	yes	yes	0.74
36	н	39	0.21	0.16	0.81	0.54	yes	no	0.4
37		78	0.57	0.33	0.43	0.86	yes	yes	0.92
38	E	68	0.35	0.25	0.14	0.85	yes	yes	0.7

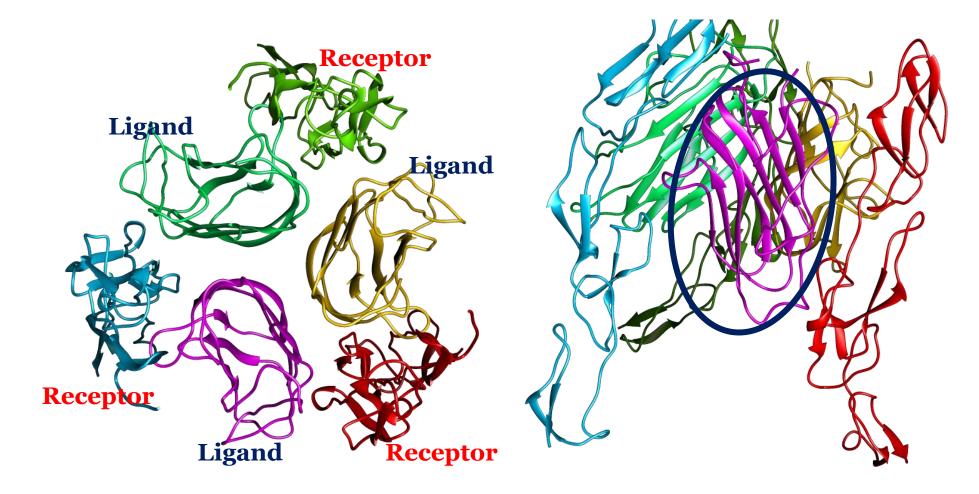


ISPRED4 at work & applications

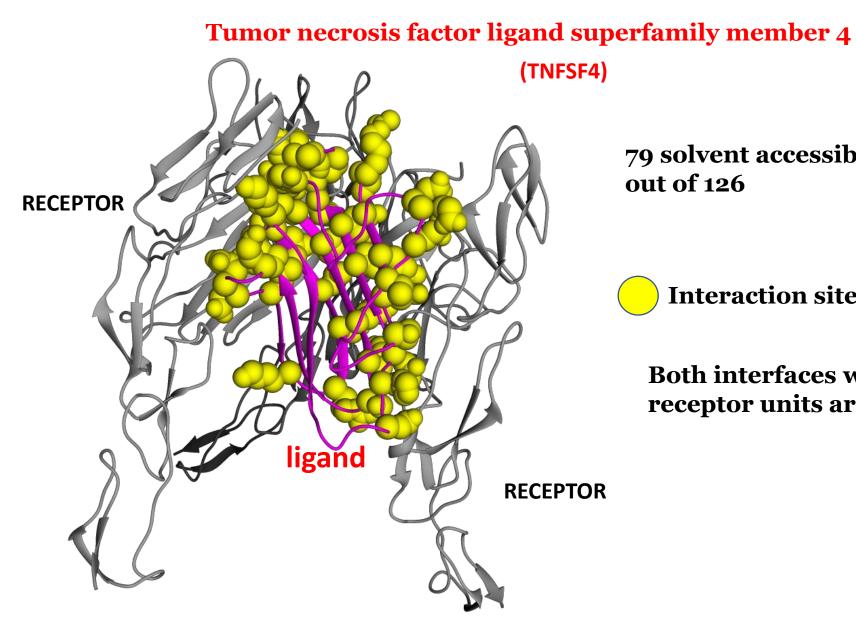
2HEV: complex between OX40L and OX40 extracytoplasmic domains (2.41 Å)



Tumor necrosis factor ligand superfamily member 4 (TNFSF4) Tumor necrosis factor receptor superfamily member 4 (TNFRS4)



2HEV: known interaction sites





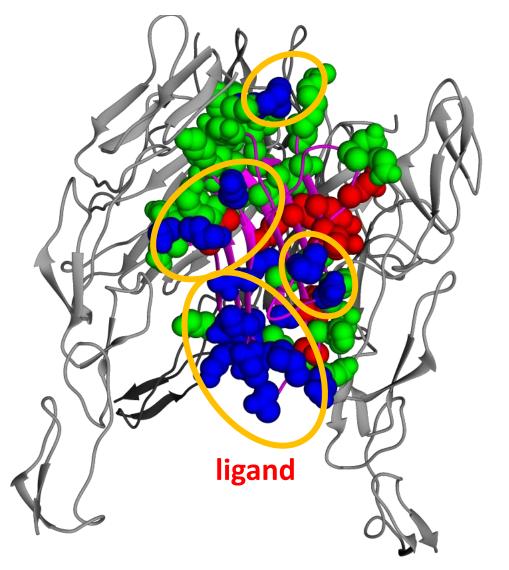
79 solvent accessible residues out of 126



Both interfaces with the receptor units are considered

2HEV: prediction with ISPRED4

Tumor necrosis factor ligand superfamily member 4



Correctly predicted (34/43)

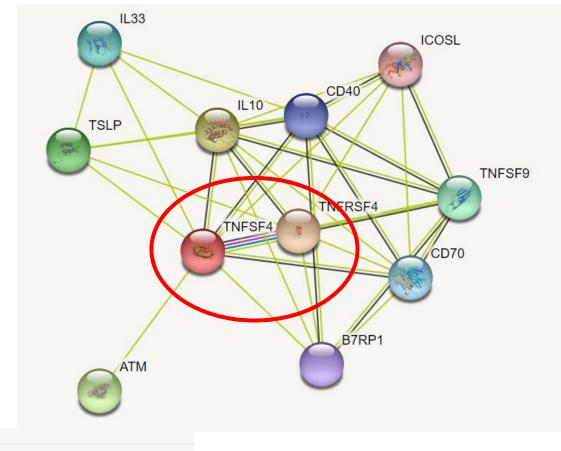
False negatives (9/43)

(TNFSF4)

False positives (19) or new possible interaction patches?

High precision predictor (0.78)

New possible interaction patches for the complex: other interactions reported in PPI networks



Known Interactions

- from curated databases

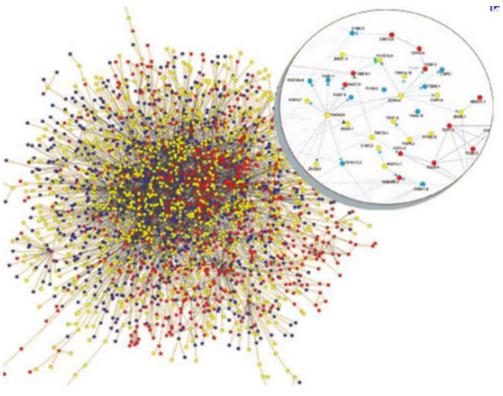
experimentally determined

From STRING, https://string-db.org/

Searching for protein interactions sites that are involved in disease related variations

Materials

- The human protein 3D data base
- Humsavar (ebi16.uniprot.org/docs/humsavar)
- ISPRED4



Interaction sites, variations and diseases

	Disease related	Neutral	Total	No of proteins
Variated sites on OMIM related proteins	14,103	9,127	23,230	3,804
Mapped on PDB	7,204	3,151	10,355	1,363
Solvent exposed	2,774	2,115	4,889	1,324
Predicted in interaction	1,194	703	1,897	654
	Disease related	Neutral		
Interaction/exposed	43%	33%		EXT
Interaction site distribution	63%	37%		

Testing hypothesis:

Are proteins involved in phase transitions endowed with intrinsically disorder regions (IDRs)?

e.g. Boeynaems S, Alberti S, Fawzi NL, Mittag T, Polymenidou M, et al. 2018. Protein Phase Separation: A New Phase in Cell Biology. Trends Cell Biol. 28:420-435

Materials

- A data base of detected protein-protein interactions (IntAct and Bio-Grid)
- A data base of a database of protein disorder and mobility annotations (MobiDB)
- A set of proteins known to form a membrane-less organelle
- ISPRED4 structure and/or sequence based

IntAct: www.ebi.ac.uk/intact/; Bio-Grid:thebiogrid.org/; MobiDB: mobidb.bio.unipd.it/



The membrane-less organelle and its proteins

- Cajal bodies (CBs) are spherical nuclear bodies of 0.3–1.0 µm in diameter found in the nucleus of proliferative cells like embryonic cells and tumor cells, or metabolically active cells like neurons. CBs are membrane-less organelles and largely consist of proteins and RNA.
- 25 proteins were present in UniprotKB (September 2019) with a Cajal body Cellular Component annotation. Most of the proteins have only a known sequence.



1 I Calcung	process p		cordector site			of proteins of t	
<u>UniProt</u>	Gene	Length (#)	PPI (#)	Flexible sites (#)	Flexible PPI (#)	IntAct interactors (#)	BioGRID interactors (#)
P38432	COIL	576	149	244	14	123	110
Q9BUR4	WRAP53	548	166	165	24	41	54
Q16637	SMN1	294	90	145	44	268	213
P55199	ELL	621	64	194	3	36	54
Q06787	FMR1	632	106	243	49	294	84
Q14331	FRG1	258	44	90	13	14	19
Q15020	SART3	963	115	199	4	125	211
Q5JVS0	HABP4	413	112	313	87	25	105
Q5W0Q7	USPL1	1092	136	169	4	24	25
Q6NT76	HMBOX1	420	42	151	12	130	70
Q7LC1 1		1001	170	110	F F	77	CF.

Predicting protein-protein interaction sites and flexible regions of proteins of the Cajal body

RESULTS



Q7ZE Q7ZE Q8W

Correlation between the number of interactors, PPI and flexible sites of the <u>Cajal</u> granule proteins

	PPI (#)	Flexible sites (#)	Elexible PPI (#)
IntAct	0.4 *	0.05	0.59 **
BioGRID	0.41 *	0.12	0.59 **

* Significant at 5%

** Significant at 1%

Savojardo, C., Martelli, P.L., Casadio, R. Ann Rev Biom Data Science 2020, 3.

Conclusions

- The Cajal body human proteins have a much larger number of interactors than the average (13 and 18 per human protein, respectively in IntAct and in BioGRID).
- The number of interactors per protein moderately correlates with the number of residues in IDRs (Flexible sites)
- Correlation increases if the number of PPI is considered
- Correlation reaches a satisfactory value when the number of residues that can be annotated both as PPI and IDR is considered

Suggestion: the inherent flexibility of the residues makes it possible to adjust the interacting surface protein to multiple partners





Our predictors in Bologna

PREDICTORS (NN, SVM, HMM, GRHCRF)

BaCelLo - Balanced subCellular Localization predictor **BAR+** - Bologna Annotation Resource BetAware - Detection of Prokaryotic outer-membrane betabarrel proteins **CCHMM** - Predictor of Coiled-Coils Regions in Proteins **CCHMMPROF** - Predictor of Coiled-Coils Regions in Proteins exploiting evolutionary information **CORNET** - Predictor of Residue Contacts in Proteins **DCON** - Predictor of Disulfide Connectivity in Proteins **DisLocate** - Find Disulfide bonds in Eukaryotes with predicted subcellular Localization FT-COMAR - Fault Tolerance Reconstruction of 3D Structure from Protein Contact Maps **HIPPIE** - Protease Inhibitor engine I-MUTANT - Neural Network based Predictor of Protein stability Changes upon Single Point Mutation I-MUTANT 2.0 - Support Vector Machines based Predictor of Protein stability Changes upon Single Point **Mutation from Protein Sequence and Structure** I-MUTANT Suite - Support Vector Machines based Predictor of Protein stability Changes of protein variants and of human SNPs **ISPRED** - Predictor of Protein Interaction Sites K-Fold - Predictor of the Protein Folding Mechanism and Rate **PhD-SNP** - Support Vector Machines based Predictor of human Deleterious Single Nucleotide Polymorphysms **PredGPI** - Predictor of GPI-Anchored Proteins SNPs&GO - Predictor of Human Disease-related Mutations in Proteins with Functional Annotations SPEPLip - Predictor of Signal Peptide and Lipoprotein Cleavage Sites in Proteins YAP - Yet Another Alignment Program (Pairwise Sequence Alignment Using Secondary Structures) **APPLICATION SERVERS**

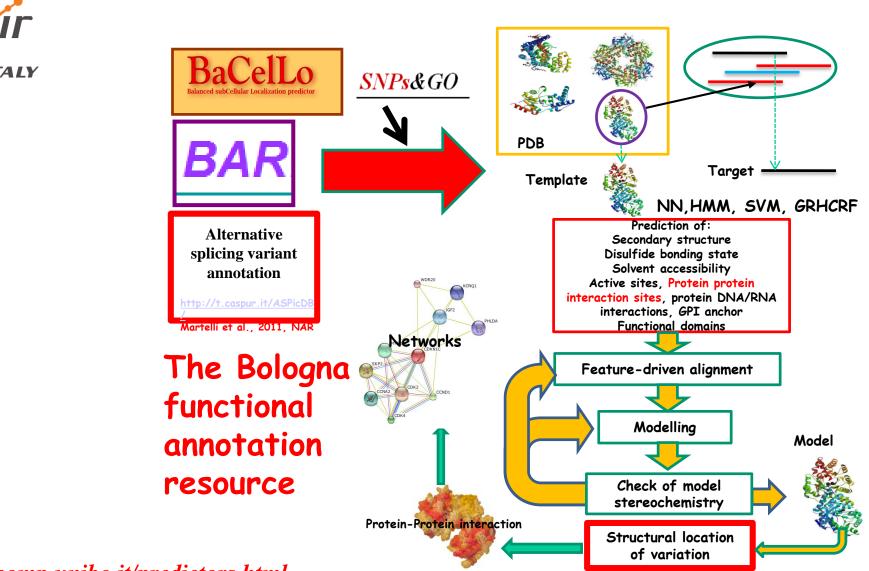
TRAMPLE: the transmembrane protein labelling environment **PONGO:** a web server for multiple predictions of all-alpha transmembrane proteins DATA BASES eSLDB - eukaryotic Subcellular Localization DataBase **ZenPatches** - Database of predicted protein interaction sites

DBMFHS - Data Base of Minimally-Frustrated Helical Segments



http://www.biocomp.unibo.it/predictors.html

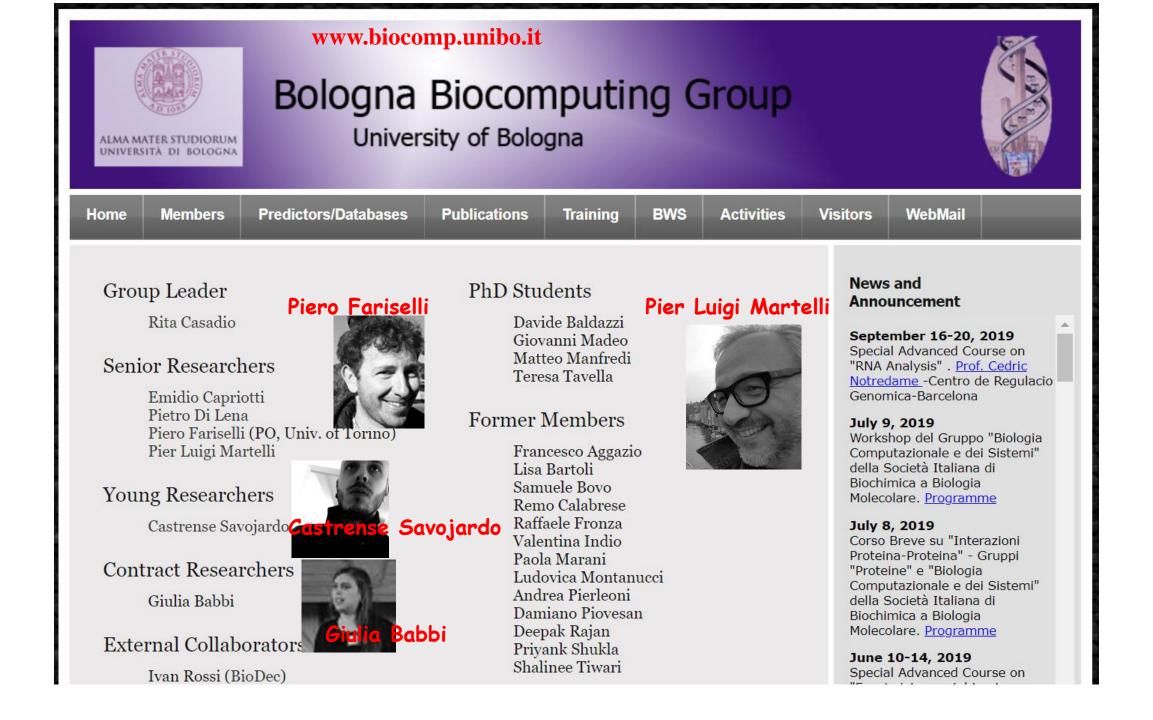




http://biocomp.unibo.it/predictors.html

2

https://bio.tools/t?collectionID="Bologna Biocomputing Group"





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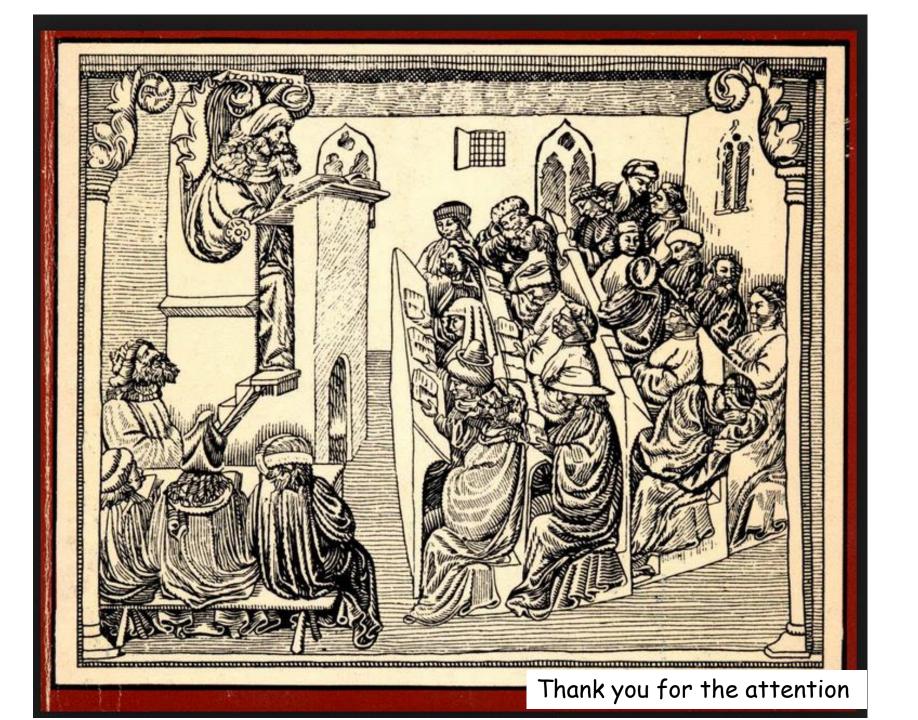
Bologna Winter School 2014 Bioinformatics for Biological Complexity

'RNA Analysis" . Prof. Cedric Notredame -Centro de Regula Genomica-Barcelona

July 9, 2019 Workshop del Gruppo "Biologia Computazionale e dei Sistemi" della Società Italiana di Biochimica a Biologia Molecolare. Programme

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June 10-14, 2019



Bioinformatics, 33(11), 2017, 1656–1663 doi: 10.1093/bioinformatics/btx044 Advance Access Publication Date: 25 January 2017 Original Paper



Structural bioinformatics

ISPRED4: interaction sites PREDiction in protein structures with a refining grammar model

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ANNUAL REVIEWS

Annual Review of Biomedical Data Science Protein–Protein Interaction Methods and Protein Phase Separation

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Ann.Rev.Biomed.Data Sci. 2020 3:89-112