# Protein Evolution Lecture 2

Lucy Colwell

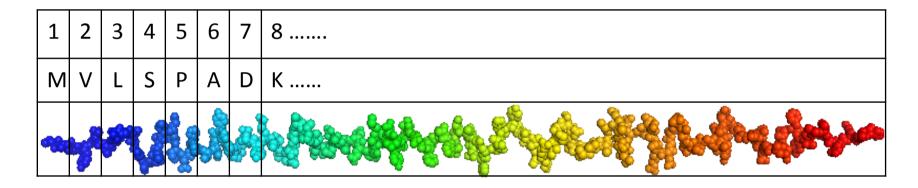
ICTS Winter School on Quantitative Systems Biology

Dec 13 2017

#### How to extract useful information from protein sequences?

Each protein is constructed as a specific chain or string of amino acids. There are 20 different amino acids which are used with roughly equal frequencies across all proteins.

In a specific protein of interest, such as hemoglobin, the order of amino acids is highly important and contains all the information necessary to produce the folded, functional molecule.



We would like to find a probability model for the sequence of amino acids that corresponds to each protein of interest.

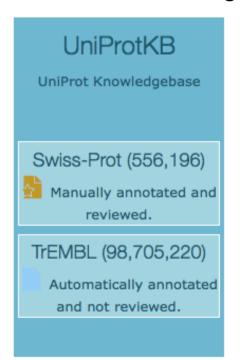
 $P(A_1,...,A_L)$  = Probability that a sequence produces a folded, functional hemoglobin molecule.

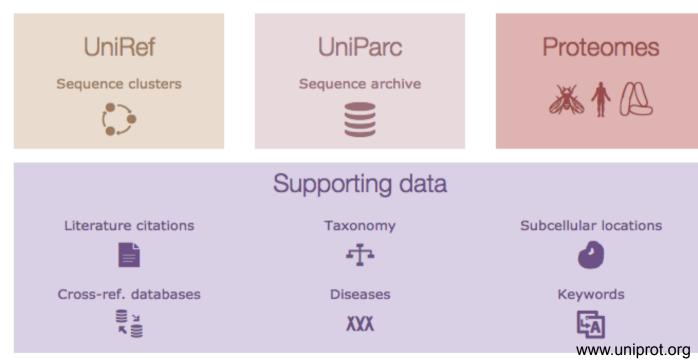
#### **Sequence Similarity**

 $P(A_1,...,A_L)$  = Probability that a sequence produces a folded, functional hemoglobin molecule.

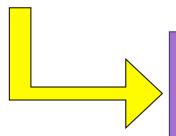
To proceed, we need data – if we can find lots of examples of hemoglobin sequences, then we can treat this as an inverse problem, and look for a model that reproduces the statistics of our observed data.

How can we find this data? Over the last 50 years there has been an explosion of technological innovation, which has enabled us to determine the sequences of huge numbers of biological organisms, and thus of numerous proteins.





### Protein evolution



### Families of homologous proteins

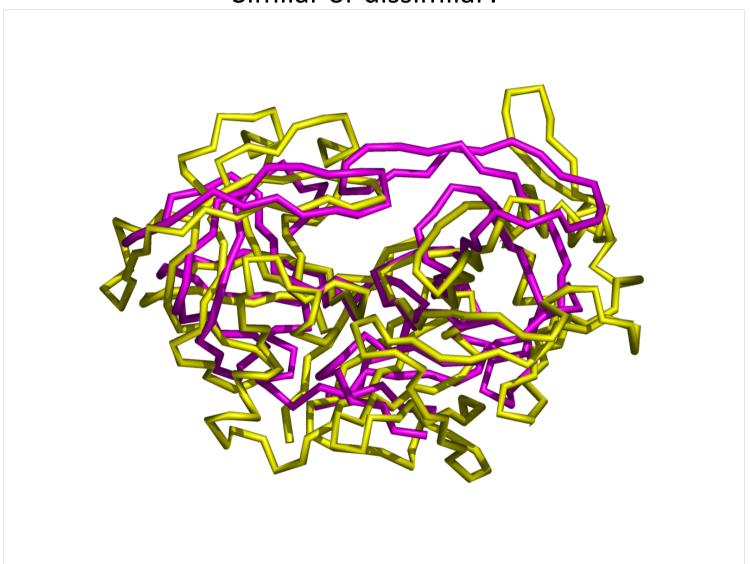
- Similar/dissimilar sequence
- Common 3D structure
- Common function



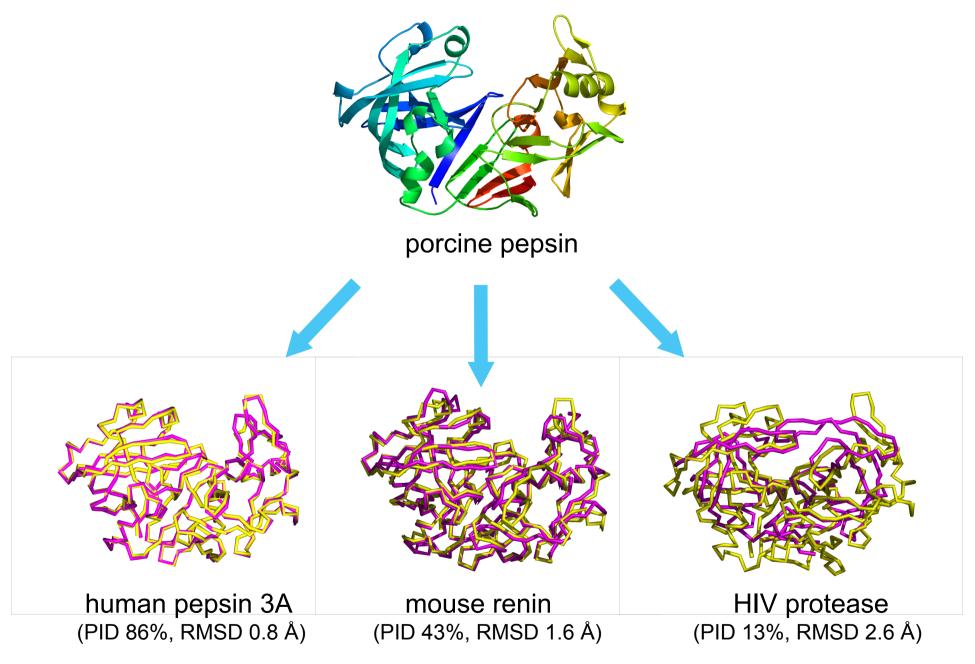


3D structure, function

#### Similar or dissimilar?



To compare proteins, we need to be able to measure similarity between their sequence and their 3D structures.



PID = percentage sequence identity, RMSD = root mean squared deviation

To group sequences into families, we need to be able to answer the question: are two sequences related? This is the most basic sequence analysis task that we will come across. We approach this by first aligning the sequences, and then asking whether the alignment suggests that the sequences are related, or could have occurred by chance.

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Consider this alignment between parts of the human haemoglobin alpha and beta chains:

HBA\_HUMAN GSAQVKGHGKKVADALTNAVAHVDDMPNALSALSDLHAHKL
G+ +VK+HGKKV A++++AH+D++ ++++LS+LH KL
HBB HUMAN GNPKVKAHGKKVLGAFSDGLAHLDNLKGTFATLSELHCDKL

Here identical positions are shown in the middle with letters, while similar positions are shown with plus signs. To define 'similar' we use a substitution matrix – more on this soon.

Note there are many positions at which the two residues are identical, and many others that we call 'functionally conservative' – for example the D-E pair towards the end (both are negatively charged amino acids).

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```
HBA_HUMAN GSAQVKGHGKKVADALTNAVAHV---D--DMPNALSALSDLHAHKL
++ ++++H+ KV + +A ++ +L+ L+++H+ K

LGB2_LUPLU NNPELQAHAGKVFKLVYEAAIQLQVTGVVVTDATLKNLGSVHVSKG
```

In contrast the alignment with leghemoglobin from yellow lupin is much weaker, although these two proteins are evolutionarily related, and have the same 3D structures.

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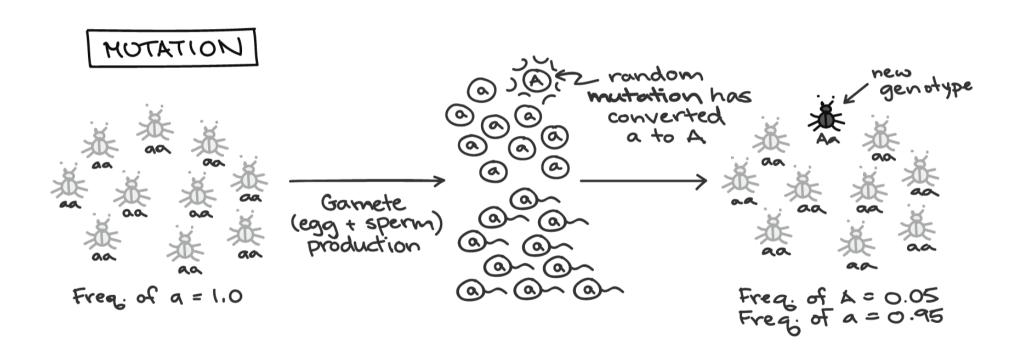
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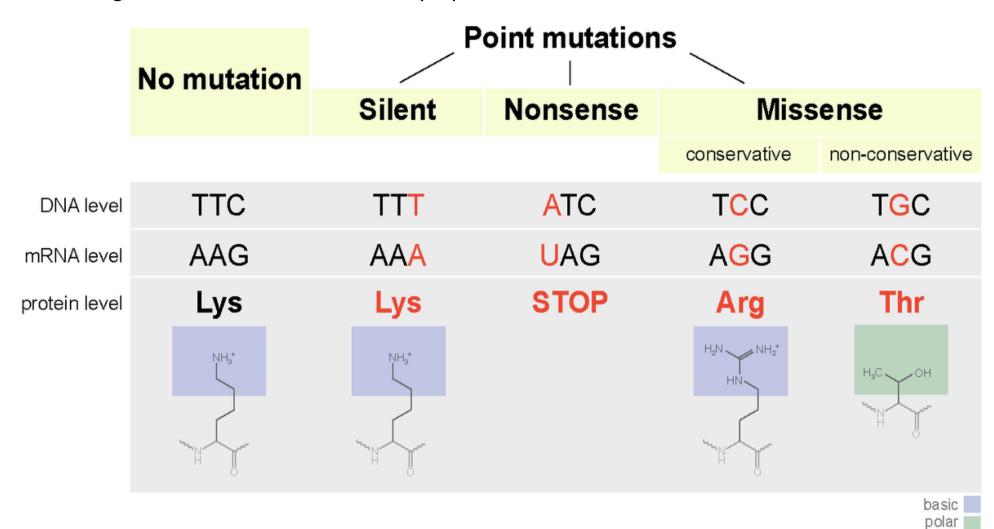
```
HBA_HUMAN GSAQVKGHGKKVADALTNAVAHVDDMPNALSALSD----LHAHKL GS+ + G + +D L ++ H+ D+ A +AL D ++AH+ F11G11.2 GSGYLVGDSLTFVDLL--VAQHTADLLAANAALLDEFPQFKAHQE
```

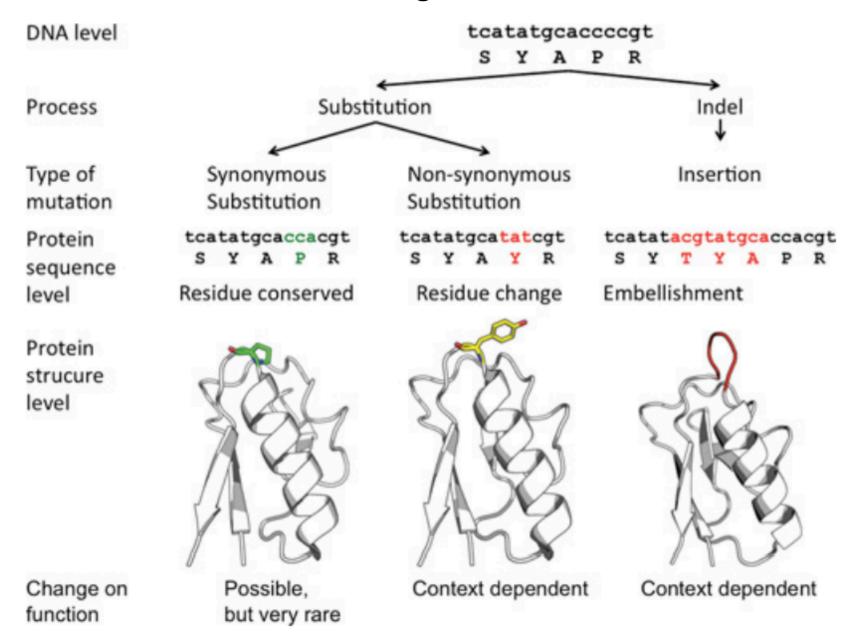
Finally this alignment with a nematode glutathione S-transferase homologue has a similar number of identities and similarities, but the structure and function are completely different.

The purpose of a scoring algorithm is to assess the evidence that two sequences have diverged from a common ancestor by a process of mutation and selection.



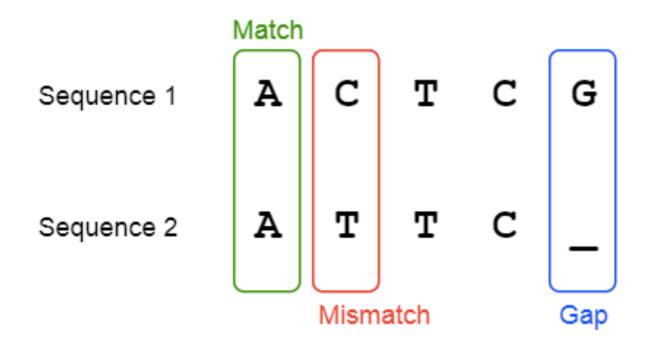
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Total score of an alignment will contain a term for each aligned pair of residues, plus terms for each gap introduced. This will correspond to the logarithm of the relative likelihood that the sequences are related, compared to being unrelated.

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For example, 
$$S(A, A) = S(T, T) = S(C, C) = +5$$
  
 $S(C, T) = -3$   
 $S(gap) = ? -8?$ 

#### **Substitution Matrices**

We need score terms for each aligned residue pair. The intuition for proteins alluded to in these slides could yield 210 scoring terms for all possible pairs of amino acids, but it is useful to have a guiding theory for what the scores mean.

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Consider two protein sequences x and y, we want to compare the random model:

$$x_1, x_2, x_3, x_4, x_5$$
  
 $y_1, y_2, y_3, y_4, y_5$ 

$$P(x,y|R) = \prod_i q_{x_i} \prod_j q_{y_j}$$

$$P(x,y|M) = \prod_i p_{x_i y_i}$$

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with the match model:

$$P(x,y|M) = \prod_{i} p_{x_i y_i}$$

So we want

$$\frac{P(x,y|M)}{P(x,y|R)} = \frac{\prod_{i} p_{x_{i}y_{i}}}{\prod_{i} q_{x_{i}} \prod_{i} q_{y_{i}}} = \prod_{i} \frac{p_{x_{i}y_{i}}}{q_{x_{i}}q_{y_{i}}}$$

This leads to the score  $S = \sum_i s(x_i, y_i)$ , where  $s(a, b) = \log\left(\frac{p_{ab}}{q_a q_b}\right)$  is the log

likelihood ratio that (a,b) is an aligned or match pair, vs occurred at random.

#### **Substitution Matrices – BLOSUM 50**

	A	R	N	D	С	Q	E	G	Н	I	L	K	M	F	P	S	T	W	Y	V
Α	5 -	-2	-1	-2	-1	-1	-1	0	-2	-1	-2	-1	-1	-3	-1	1	0	-3	-2	0
R	-2	7	-1	-2	-4	1	0	-3	0	<b>-4</b>	-3	3	-2	-3	-3	-1	-1	-3	-1	-3
N	-1	-1	7	2	-2	0	0	0	1	-3	<b>-4</b>	0	-2	<b>-4</b>	-2	1	0	<b>-4</b>	-2	-3
D	-2	-2	2	8	-4	0	2	-1	-1	<b>-4</b>	<b>-4</b>	-1	-4	-5	-1	0	-1	<b>-5</b>	-3	-4
С	-1	-4	-2	-4	<b>13</b>	-3	-3	-3	-3	-2	-2	-3	-2	-2	-4	-1	-1	<b>-5</b>	-3	-1
Q	-1	1	0	0	-3	7	2	-2	1	-3	-2	2	0	<b>-4</b>	-1	0	-1	-1	-1	-3
E	-1	0	0	2	-3	2	6	-3	0	<b>-4</b>	-3	1	-2	-3	-1	-1	-1	-3	-2	-3
G	0 :	-3	0	-1	-3	-2	-3	8	-2	<b>-4</b>	<b>-4</b>	-2	-3	<b>-4</b>	-2	0	-2	-3	-3	-4
H	-2	0	1	-1	-3	1	0	-2	10	<b>-4</b>	-3	0	-1	-1	-2	-1	-2	-3	2	<b>-4</b>
I	-1	-4	-3	-4	-2	-3	<b>-4</b>	-4	-4	5	2	-3	2	0	-3	-3	-1	-3	-1	4
L	-2	-3	-4	-4	-2	-2	-3	-4	-3	2	5	-3	3	1	<b>-4</b>	-3	-1	-2	-1	1
K	-1	3	0	-1	-3	2	1	-2	0	-3	-3	6	-2	<b>-4</b>	-1	0	-1	-3	-2	-3
M	-1	-2	-2	-4	-2	0	-2	-3	-1	2	3	-2	7	0	-3	-2	-1	-1	0	1
F	-3	-3	-4	<b>-5</b>	-2	<b>-4</b>	-3	-4	-1	0	1	<b>-4</b>	0	8	<b>-4</b>	-3	-2	1	4	-1
Ρ	-1	-3	-2	<u>-1</u>	-4	-1	-1	-2	-2	-3	-4	-1	-3	<b>-4</b>	<b>10</b>	-1	-1	-4	-3	-3
S	1 -	-1	1	0	-1	0	-1	0	-1	-3	-3	0	-2	-3	-1	5	2	-4	-2	-2
T	0 -	-1	0	-1	-1	-1	-1	-2	-2	-1	-1	-1	-1	-2	-1	2	5	-3	-2	0
W	-3	-3	-4	<b>-5</b>	-5	-1	-3	-3	-3	-3	-2	-3	-1	1	-4	-4	-3	<b>15</b>	2	-3
Y	-2	-1	-2	<b>-3</b>	-3	-1	-2	-3	2	-1	-1	-2	0	4	-3	-2	-2	2	8	-1
V	0 -	-3	-3	-4	-1	-3	-3	<b>-4</b>	-4	4	1	-3	1	-1	-3	-2	0	-3	-1	5

Henikoff, Steven, and Jorja G. Henikoff. "Amino acid substitution matrices from protein blocks." PNAS 1992.

#### **Alignment algorithms**

To construct the BLOSUM matrix a set of aligned, ungapped regions from protein families were assembled and clustered such that two sequences go in the same cluster if their percentage of identical residues exceeds 50%.

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Once we have a scoring model, we then need a way to find the optimal alignment between two sequences. If we allow gaps, then there are

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Luckily, dynamic programming algorithms provide a way of efficiently finding the optimal alignment. The idea is to start from an existing smaller alignment, and evaluate all possible next moves.

Global alignment: Needleman-Wunsch algorithm – align whole sequences.

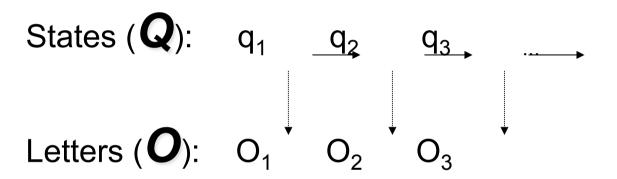
Local alignment: Smith-Waterman algorithm – align subsequences.

### Next – multiple sequence alignment

Helix				1	AAZ	AAA	AA.	AA.	AA	AA	AA	Α		вв	BB	BBI	вві	3B	вв	BB	ВВ	CC	:CC	CC	CCC	CC	3
HBA HUMAN				VL	SPA	ADK	TN	VK.	AA	WG	KV	GA		ΗA	GE	YG	AE	AL:	ER	MF.	LS	FF	ľТ	'KТ	YF	PHI	ť
HBB HUMAN			V	HL'	ГPІ	EEK	SA	VT.	AL	WG	KV			NV	DE	VG	GE/	\L	GR	LL	VV	YF	נשי	'QR	FFI	ESI	ť
MYG PHYCA				VL	SEC	SEW	QL.	VL:	ΗV	WA	KV	EΑ		DV	AG	HG(	QD:	Ľ	IR	LF	KS	HF	EI	'LE	KFI	DRI	ť
GLB3 CHITP				-LS	SAI	QI	ST	VQ.	AS	FD	KV	KG				DP	VG:	[L	YΑ	VF:	KA	DF	SI	MA	KF	TQI	ť
GLB5 PETMA	PIV	DTGS	SVA	PLS	SAZ	λEK	ΤK	IR	SA	WA	PV	YS		ΤY	ΕT	SG	VD:	ĽĽ	VK	FF	TS	TF	Α	١QE	FF	PKI	ť
LGB2 LUPLU			G	AL:	TE S	SQA	AL	VK	SS	WE	EF	NΑ		NI	PK	HTI	HRI	F	IL	VL	ΕI	AF	ΑP	KD	LF	S-I	ť
GLB1 GLYDI				GL	SAZ	AQR	QV	IΑ	ΑТ	WK	DI	AG	ΑD	NG	AG	VGI	KDO	CL	ΙK	FL	SA	HF	QN	IAA	VF	G-1	ť
Consensus				Ls	s			v	a	W	kv					g		L		f		F	٠Ĩ.	,	F	1	ť
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Helix		DDI	DDD	DDI	EEI	CEE	EE.	EE	ЕE	ЕF	EE	ЕE	ЕE	ЕE							FF	'FF	'F'F	FF	FFI	FF	
HBA HUMAN	-DL	S		HG	SAÇ	)VK	GH	GK	KV	AD	AL	TN	ΑV	AΗ	V-	1	D	-Di	MP	NA.	LS	ΑI	SI	)LH	AH!	KL-	-
HBB HUMAN	GDL	STPI	DAV.	MG1	NPI	KVK	AΗ	GK	ΚV	LG	AF	SD	GL	AΗ	L-	1	D	-N	LK	GT:	FΑ	TI	SF	LH	CDI	KL-	-
MYG PHYCA	KHL	KTE	<b>AEM</b>	KAS	SEI	OLK	KH	GV	TV	LT	'AL	GA	ΙL	KK		1	K-(	3H	HE.	AE:	LK	PI	ıΑÇ	)SH	AT:	KH-	_
GLB3 CHITP	AG-	KDLE	SI	KG:	ΓAΙ	PFE	TH.	AN.	RI	VG	FF	SK	ΙI	GΕ	L-	-P·		-N	IE.	AD'	VN	TF	'VI	SH	KP	RG-	-
GLB5 PETMA	KGL	TTAI	QL	KKS	SAI	OVR	WH.	AE:	RI	ΙN	ΙΑV	ND	ΑV	AS	M-	–DI	DTI	ΞK	MS.	MK.	LR	DI	SC	KH	AK:	SF-	-
LGB2 LUPLU	LK-	GTSE	EVP	QNI	NPI	ELQ	AH.	AG	ΚV	FK	ĽV	ΥE	AA	ΙQ	LQ	VT(	GΨ	JV	TD.	AT:	LK	NI	ıG۶	SVH	VSI	KG-	_
GLB1 GLYDI	SG-	<i>I</i>	AS-	I	DP(	AVE	AL	GA:	ΚV	LA	QI	GV	ΑV	SH	L-	-GI	DEC	3K	MV.	AQ	ΜK	ΑV	/GV	/RH	KG	YGI	V
Consensus		t				v.	. H	g :	kv		a		a.		1	(	d			a	ı.	1		H			
Helix	FF	GGGG	GG	GG	GG	GG	GG	GG	GG			Η	ΗН	ΗН	HH	нні	НН	H	нн	ΗН	ΗН	HE	HF	НН	Η		
HBA_HUMAN	-RV	DPVN	1FK	LLS	SHO	CLL	VT.	LA	AΗ	LP	ΆE	FT	PΑ	VH	AS:	LDI	KFI	A	sv	ST	VΙ	TS	KY	'R–			-
HBB_HUMAN	-HV	DPEN	IFR	LL(	GNV	/LV	CV.	LA	ΗН	FG	KE	FT	PP	VQ	AA	YQI	ΚV	/A	GV.	AN.	AL	ΑF	ΙKΥ	/H-			-
MYG_PHYCA	-KI	PIKY	LE	FI	SE	ΙΙ	HV.	LH	SR	ΗP	GD	FG	ΑD	ΑQ	GA	MNI	KAI	Æ	LF.	RK	DΙ	ΑA	KY	(KE	LG:	YQ(	3
GLB3_CHITP	V	THDÇ	)LN	NFI	RA(	FV	SY	MK.	AΗ	T-	-D	FΑ	-G	ΑE	AA	WG	ATI	'D	TF.	FG	ΜI	FS	KM	1			-
GLB5_PETMA	-QV	DPQY	/FK	VL	AA۱	/IA	DΤ	VA.	AG					-D	AG	FE	KLI	1S	ΜI	CI	LL	RS	AY	<b>/</b>			-
LGB2_LUPLU	V	ADAF	IFP	VVI	KE/	AIL	KΤ	IK	ΕV	VG	AK	WS	ΕE	LN	SA	WT:	IA:	ZD:	$\mathbf{EL}$	AI'	VI	KK	(EN	IND	AA.		-
GLB1_GLYDI																						IS	GI	JQS			-
Consensus	v		f	1	•			• •	• •			f		•	aa	. ]	k.	•			1	. 2	sky	7			

#### **Hidden Markov Models**

A **Hidden Markov Model** (HMM) is a discrete-time finite-state Markov chain coupled with a sequence of letters emitted when the Markov chain visits its states.



The sequence  $\mathbf{O}$  of emitted letters is called "the observed sequence" because we often know it while <u>not</u> knowing the state sequence  $\mathbf{Q}$ , which we call "hidden".

Used extensively throughout computational biology for 'labeling' data – and in particular for classifying and aligning protein sequence data.

#### Sean R Eddy

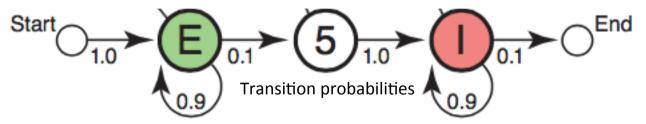
NATURE BIOTECHNOLOGY VOLUME 22 NUMBER 10 OCTOBER 2004

As a simple example, imagine the following 5' splice-site recognition problem. Assume we are given a DNA sequence that begins in an exon, contains one 5' splice site and ends in an intron. The problem is to identify where the switch from exon to intron occurred—where the 5' splice site (5'SS) is.

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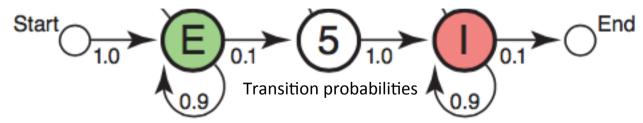


HMM with three states – exon, 5'SS and intron, and the probabilities of moving between these states.

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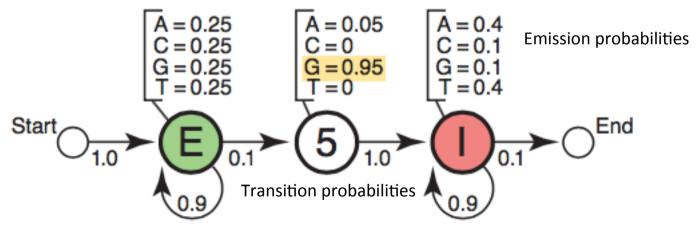


HMM with three states – exon, 5'SS and intron, and the probabilities of moving between these states. To estimate which state each element of the DNA sequence is in, we need information about the statistics of exon, splice site and intron sequences – these are the emission probabilities.

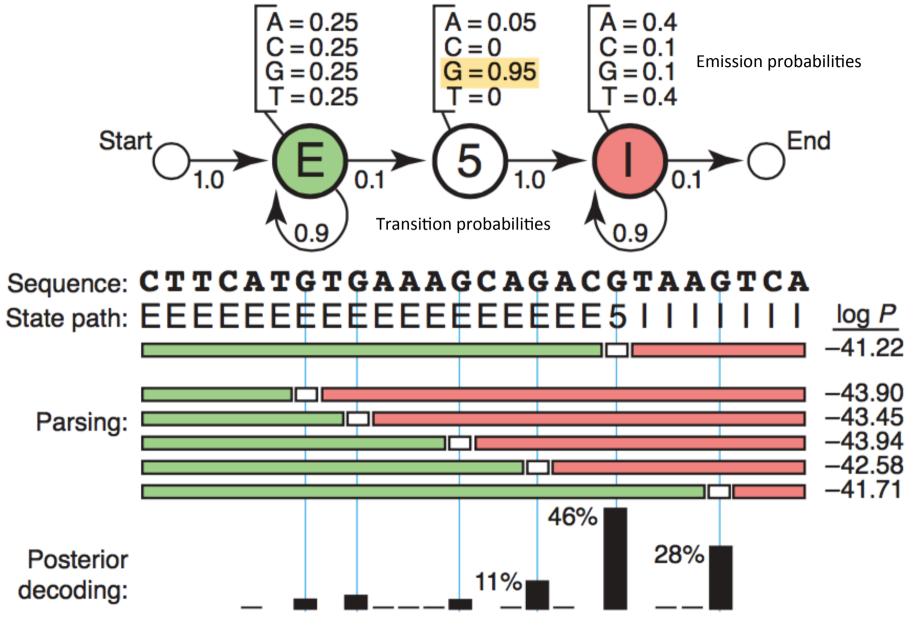
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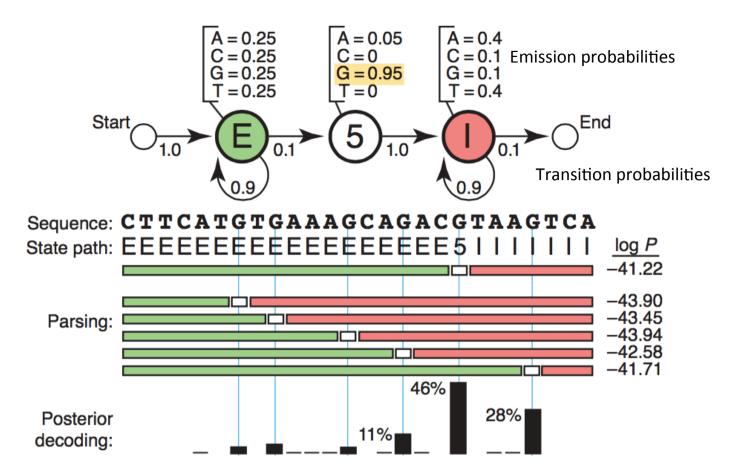


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A toy HMM for 5' splice site recognition.

Eddy, Nature Biotech, 2004



The probability  $P(S,\pi|HMM,\theta)$  that an HMM with parameters  $\theta$  generates a state path  $\pi$  and an observed sequence S is the product of all the emission probabilities and transition probabilities that were used.

Here for the 26 nucleotide sequence, there are 27 transitions and 26 emissions – the log of the product of all 53 probabilities yields log  $P(S,\pi|HMM,\theta) = -41.22$ .



#### Pfam 31.0 (March 2017, 16712 entries)

The Pfam database is a large collection of protein families, each represented by **multiple sequence alignments** and **hidden Markov models (HMMs)**. **More...** 

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GLB1_PARCH/17-123	QKKIVRKTWHQ.LMRNKTSFVTDLFIRIFAYDPAAQNKFPQM.AGMS.ASQLRSSRQMQAHAIRVSSIMSEYIE
HMP_ECOLI/6-103	TIATVKATIPL.LVETGPKLTAHFYDRMFTHNPELKEIFN.MSNQRNGDQREALFNAIAAYAS
HMP_ECOLI/6-103 (SS)	HHHHHHHHHH. HHTTHHHHHHHHHHHHHHHH-GGGGGTSTTSHHHHHHHHHHHHHHH
BAHG_VITST/6-103	TINIIKATVPV.LKEHGVTITTTFYKNLFAKHPEVRPLFD.MGRQESLEQPKALAMTVLAAAQNIEN
BAHG_VITST/6-103 (SS)	HHHHHHHHHHTHHHHHHHHHHHHHHHH-GGGGGGGSS-TTHHHTTHHHHHHHHHHTTTG
GLB1_CALSO/5-105	DIKNVQDTWGK.LYDQWDAVHASKFYNKLFKDSEDISEAFVKAGTGSGIAMKRQALVFGAILQEFVA
GLB2_CALSO/5-108	DIAAVQTSWRR.CYCSWDNEDGLKFYQTLFDSNSKIRHAFESAGATNDTEMEKQANLFGLMMTQFID
A0A0E8VH55_MYCTX/42-136	DALRVLQNAFK.LDDPELVRRFYAHWFALDASVRDLFP.PDMGAQRAAFGQALHWVYGELVA
GLB1B_ANATR/17-122	QKDLLRLSWGV.LSVDMEGTGLMLMANLFKTSSAARTKFARL.GDVSAGKDNSKLRGHSITLMYALQNFID
GLB_BUSCA/6-116	QKTALKESWKV.LGADGPTMMKNGSLLFGLLFKTYPDTKKHFKHFDDATFAAMDTTGVGKAHGVAVFSGLGSMIC
GLB_CERRH/6-116	SKSALASSWKT.LAKDAATIQNN <mark>G</mark> ATLFSLLFKQFPDTRNYFTHF.GNMS.DAEMKTTGVGKAHSMAVFAGIGSMID
HBP2_CASGL/13-122	QEALVVKSWSA.MKPNAGELGLKFFLKIFEIAPSAQKLFS.FLKDSNVPLERNPKLKSHAMSVFLMTCESAV
HBP1_CASGL/7-116	QEALLKQSWEV.LKQNIPAHSLRLFALIIEAAPESKYVFS.FLKDSNEIPENNPKLKAHAAVIFKTICESAT
LGB1_LUPLU/8-116	QVALVKSSFEE.FNANIPKNTHRFFTLVLEIAPGAKDLFS.FLKGSSEVPQNNPDLQAHAGKVFKLTYEAAI
LGB1_MEDSA/7-112	QEALVNSSWEA.FKQNLPRYSVFFYTVVLEKAPAAKGLFS.FLKNSAEVQDSPQLQAHAEKVFGLVRDSAV
GLB1_GLYDI/6-111	QRQVIAATWKD.IAGADNGAGVGKDCLIKFLSAHPQMAAVFG.F.SGASDPGVAALGAKVLAQIGVAVS
GLB1_GLYDI/6-111 (SS)	нинининини. нетттттинининининине-ссининетssтт-инининининининин
GLBP1_GLYDI/7-115	QVAALKASWPE.VSAGDGGAQLGLEMFTKYFHENPQMMFIFG.YSGR.TEALKHSSKLQHHGKVIIDQIGKAVA
GLB_APLJU/6-113	DAGLLAQSWAP.VFANSDANGASFLVALFTQFPESANFFNDF.KG.KSLADIQASPKLRDVSSRIFARLNEFVS
GLB73_CHITH/23-129	EASLVQSSWKA.VSHNEV <mark>D</mark> ILAAVFAAYPDIQAKFPQF.AG.KDLASIKDTGAFATHATRIVSFLSEVIA
GLB6_CHITH/22-128	QADLVKKTWST.VKFNEVDILYAVFKAYPDIMAKFPQF.AG.KDLDSIKDSAAFATHATRIVSFLSEVIS
GLB3_CHITH/20-120	QISTVQASFDK.VK <mark>GDPVGIL</mark> YAVFKAD <mark>P</mark> SIMAKFTQF.A <mark>G</mark> .KDLESIK <mark>G</mark> TA <mark>P</mark> FEIHANRIV <b>G</b> FFSKIIG
GLB3_CHITH/20-120 (SS)	нининнин т. ттт <mark>инининнин - ини тт-тт.тт.s-ини</mark> тт <del></del> ынитининнинниннин
GLB1_CHITH/21-126	QIAAAKASWNT.VKNNQVDILYAVFKAN <mark>P</mark> DIQTAFSQF.AG.KDLDSIKGTPDFSKHAGRVVGLFSEVMD
GLB10_CHITH/11-117	EVEQVQATWKA.VSHDEVEILYTVFKAHPDIMAKFPKF.AG.KDLEAIKDTADFAVHASRIIGFFGEYVT
GLB8_CHITH/9-115	QLALFKSSWNT.VKHNEVDILYAVFKANPDIQAKFPQF.AG.KDLDSIKDSADFAVHSGRIVGFFSEVIG
GLB2_CHITH/22-128	EASLVRGSWAQ.VKHSEVDILYYIFKANPDIMAKFPQF.AG.KDLETLKGTGQFATHAGRIVGFVSEIVA
HBF1_URECA/7-113	QIKAIQDHWFLNIK <mark>GCLQAA</mark> ADSIFFKYLTAY <mark>PG</mark> DLAFFHKF.SS.VPLY <mark>G</mark> LRSNPAYKAQTLTVINYLDKVVD
HBF1_URECA/7-113 (SS)	нининининительнительный транции в second of the second of
GLBT_CHITH/13-116	QVAAVKGDWEK.IKGSGVEILYFFLNKFPGNFPMFKKL.GNDLAAAKGTAEFKDQADKIIAFLQGVIE
MYG_CYPCA/3-108	DAELVLKCWGG.VEADFEGTGGEVLTRLFKQHPETQKLFPKF.VG.IASNELAGNAAVKAHGATVLKKLGELLK
MYG_ALLMI/7-113	EWKHVLDIWTK.VESKLPEHGHEVIIRLLQEHPETQERFEKF.KHMKTADEMKSSEKMKQHGNTVFTALGNILK
MYG_GALGA/3-108	DWDKVNSVWSA.MEANITAVGQNILLRLFEQYPESQSYFPKL.KN.KSLGELKDTADIKAQADTVLKALGNIVK
MYG_HETPO/3-108	EWEHVNKVWAV.VEPDIPAVGLAILLRLFKEHKETKDLFPKF.KE.IPVQQLGNNEDLRKHGVTVLRALGNILK
HBAM_LITCT/6-102	EKSAVASLWEK.IAPQTNKL <mark>G</mark> AESMERLFKNH <mark>P</mark> ETKSFFSRFDISPGSQDLLTH <mark>GG</mark> KIFGALGEAIK
HBAD_ERYML/6-106	DRRLLQASVGK.LGCRLEDIGADALNRLLITFPQSKTYFSHFNLSPGSKDIIHQGEKVGKALDSALK
HBAD_PASMO/6-106	DKKLIQQIWGK.LGGAEEEIGADALWRMFHSYPSTKTYFPHFDLSQGSDQIRGHGKKVVAALSNAIK
HBAT_HORSE/7-107	DRATVRALWKK.MGSNVGVYATEALERMFLGFPSTTTYFLHLDLSLGSTQVKAHGQKVADALTLAVE
HBA1_BOSMU/6-106	DK <mark>G</mark> NVKAAW <mark>G</mark> K.V <mark>GGHAAEYG</mark> AEALERMFLSF <mark>P</mark> TTKTYFPHFDLSQGSAQVK <mark>GHG</mark> AKVAAALTKAVE
HBA1_IGUIG/6-106	DKNHIRAIWGH.VDNNPEAFGVEALTRLFLAYPATKTYFAHFDLNPGSAQIKAHGKKVVDALTQAVN
HBA1_PLEWA/7-107	DKHNVKAIWDH.VKGHEEAIGAEALYRMFCCMPTTRIYFP.A.KDLSERSSYLHSHGKKVVGALTNAVA
HBA1_XENBO/7-107	DKKHIKAIMPS.IAAHGDKFGGEALYRMFLVNPKTKTYFPTFDFHHNSKQISAHGKKVVDALNEASN
HBAZ_CAPHI/7-107	ERTIILSLWSK.ISTQADVI <mark>G</mark> TETLERLFSCY <mark>P</mark> QAKTYFPHFDLHSGSAQLRAHGSKVVAAVGDAVK
HBA3_PLEWA/7-107	EKALVVGLCGK.ISGHCDALGGEALDRLFASFGQTRTYFSHFDLSPGSADVKRHGGKVLSAIGEAAK
HBA_CATCL/6-107	DKADVKIAWAK.ISPRADEI <mark>G</mark> AEAL <mark>G</mark> RMLTVY <mark>P</mark> QTKTYFAHW.ADLSPGSGPVKHGKKVIMGAIGDAVT
HBB_HETPO/7-106	ELHEITTTWKS.IDKHSL <mark>G</mark> AKALARMFIVY <mark>P</mark> WTTRYFGNL.KEFTACSYGVKEHAKKVTGALGVAVT





Pfam

Pfam clan

InterPro

PROSITE

SCOP

**SUPERFAMILY** 

PF00042 ₱

CL0090 ₺

IPR000971 №

PS01033 ₺

cd01067 №

1hba 🚱

1hba 🚱

#### Family: Globin (PF00042) 2557 structures 66 architectures Summary Summary: Globin **Domain organisation** Pfam includes annotations and additional family information from a range of different sources. These sources can be accessed via the tabs below. Clan Wikipedia: Globin Pfam InterPro **Alignments HMM logo** This is the Wikipedia entry entitled "Globind". More... Trees Globin Edit Wikipedia article Curation & model Not to be confused with globulin or globular protein. **Species** The globins are a superfamily of heme-containing globular proteins, involved in binding and/or transporting oxygen. These proteins all incorporate the globin fold, Globin family a series of eight alpha helical segments. Two prominent members include myoglobin and hemoglobin. Both of these proteins reversibly bind oxygen via a heme Interactions prosthetic group. They are widely distributed in many organisms.[2] Structures Contents [hide] Jump to... 🌵 1 Structure 1.1 Helix packing enter ID/acc 2 Evolution 2.1 Sequence conservation 3 Subfamilies 4 Examples 5 See also 6 References the Structure of deoxyhemoglobin Rothschild 37 beta Trp----Arg: a mutation that creates an intersubunit Structure chloride-binding site.[1] Globin superfamily members share a common three-dimensional fold. [3] This 'globin fold' typically consists of eight alpha helices, although some proteins have Identifiers additional helix extensions at their termini. [4] Since the globin fold contains only helices, it is classified as an all-alpha protein fold. Symbol Globin

The globin fold is found in its namesake globin families as well as in phycocyanins. The globin fold was thus the first protein fold discovered (myoglobin was the

The eight helices of the globin fold core share significant nonlocal structure, unlike other structural motifs in which amino acids close to each other in primary sequence are also close in space. The helices pack together at an average angle of about 50 degrees, significantly steeper than other helical packings such as the

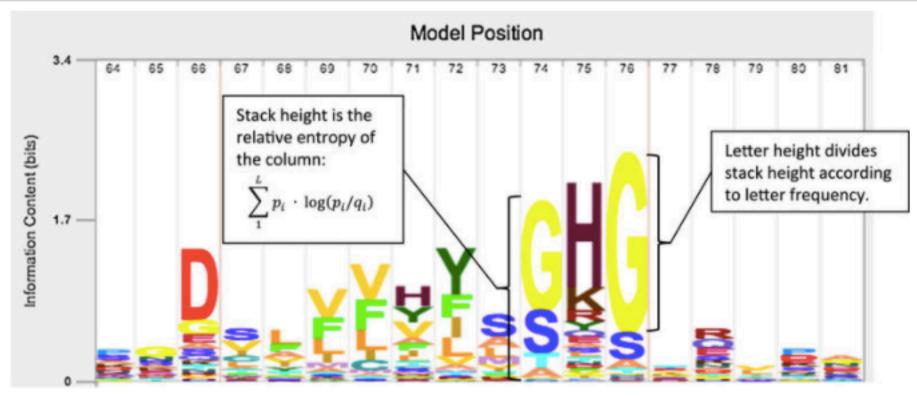
helix bundle. The exact angle of helix packing depends on the sequence of the protein, because packing is mediated by the sterics and hydrophobic interactions of

first protein whose structure was solved).

the amino acid side chains near the helix interfaces.

Helix packing





Example profile logo. This logo shows positions 64 to 81 of the Peptidase\_C14 profile HMM from Pfam (PF00656, Pfam 27.0), produced using Skylign. The profile HMM was constructed using hmmbuild (default parameters) from HMMER 3.1 on the Pfam seed alignment. One of the active sites of this Caspase domain is found at position 75. This site is invariant in active peptidases, but not in this profile HMM. This is the result of two forces: (1) the Pfam alignment includes non-peptidase homologs, which do not contain a Histidine at this position, and (2) HMMER intentionally drives down the information content per position (using an approach called entropy weighting [12]) to increase sensitivity to remote homologs.

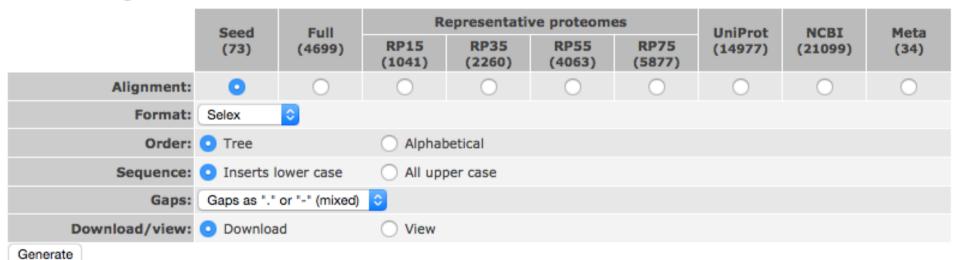




### Family: Globin (PF00042)



#### Format an alignment



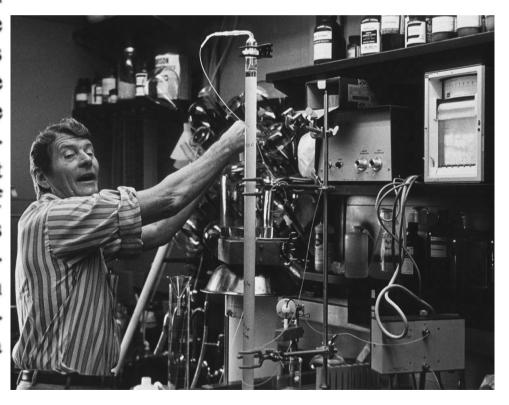
20 July 1973, Volume 181, Number 4096

#### Empirical considerations of the large amount of data now available on correlations between sequence and threedimensional structure (48), together with an increasing sophistication in the theoretical treatment of the energetics of polypeptide chain folding (49) are beginning to make more realistic the idea of the a priori prediction of protein conformation. It is certain that major advances in the understanding of cellular organization, and of the causes and control of abnormalities in such organization, will occur when we can predict, in advance, the three-dimensional phenotypic consequences of a genetic message.

## SCIENCE

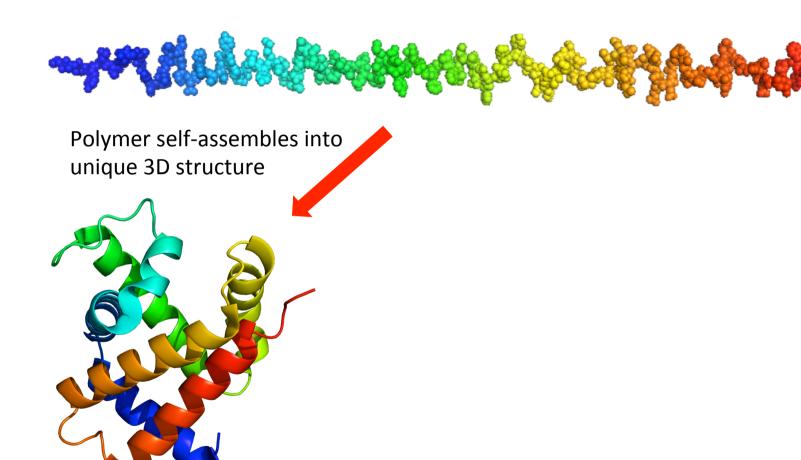
# **Principles that Govern the Folding of Protein Chains**

Christian B. Anfinsen

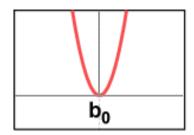


Anfinsen CB (1973). "Principles that govern the folding of protein chains". Science 181 (4096): 223–230.

#### What makes this problem hard?

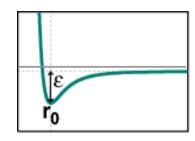


#### Potential function for MD



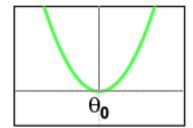
#### Bond

$${\displaystyle\sum_{i}^{\mathit{bonds}}} K_{b,i} (b_i - b_{0,i})^2$$



#### van der Waals

$$\sum_{pairs\cdot i,j} \left[\varepsilon_{ij} \left(\frac{r_{0,ij}}{r_{ij}}\right)^{12} - 2\varepsilon_{ij} \left(\frac{r_{0,ij}}{r_{ij}}\right)^{6}\right]$$



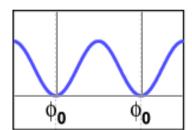
#### Angle

$$\sum_{i}^{bond} K_{\theta,i} (\theta_i - \theta_{0,i})^2$$



#### Electrostatic

$$332 \sum_{pairs \cdot i, j} \left( \frac{q_i q_j}{r_{ij}} \right)$$



#### Dihedral

torsion angles  $\sum K_{\phi,i} \{1 - \cos[n_i (\phi_i - \phi_{0,i})]\}$ 

$$F = -\frac{\partial U}{\partial x}$$

$$F = ma$$

Evaluate forces and perform integration for every atom

$$x_3 - x$$

 $v = \frac{x_3 - x_2}{\partial t}$  Each picosecond of simulation time requires 500 iterations of cycle

$$\partial t = 2 \text{ fs}$$

E.g. w/ 50,000 atoms, each ps (10<sup>-12</sup> s) involves 25,000,000 evaluations

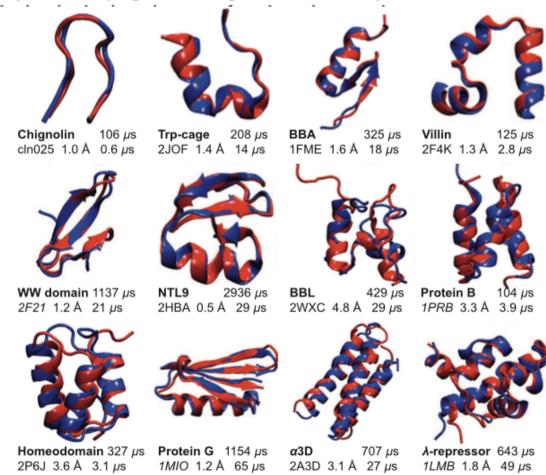
### **How Fast-Folding Proteins Fold**

Kresten Lindorff-Larsen, 1\* + Stefano Piana, 1\* + Ron O. Dror, 1 David E. Shaw 1,2 +

An outstanding challenge in the field of molecular biology has been to understand the process by which proteins fold into their characteristic three-dimensional structures. Here, we report the results of atomic-level molecular dynamics simulations, over periods ranging between 100 µs and 1 ms, that reveal a set of common principles underlying the folding of 12 structurally diverse

Our research group has developed a specialized supercomputer, called Anton, which greatly accelerates the execution of atomistic molecular dynamics (MD) simulations. In addition, we recently modified the CHARMM force field in an effort to make it more easily transferable among different protein classes.

Lindorff-Larsen, Kresten, et al. "How fast-folding proteins fold." Science 334.6055 (2011): 517-520.



Rosetta – an algorithm that introduced assembly of sequence similar fragments was a major step forward in computational approaches to the protein folding problem.

Swiftly followed by 'folding at home' and the

# Crystal structure of a monomeric retroviral protease solved by protein folding game players

Firas Khatib<sup>1</sup>, Frank DiMaio<sup>1</sup>, Foldit Contenders Group, Foldit Void Crushers Group, Seth Cooper<sup>2</sup>, Maciej Kazmierczyk<sup>3</sup>, Miroslaw Gilski<sup>3,4</sup>, Szymon Krzywda<sup>3</sup>, Helena Zabranska<sup>5</sup>, Iva Pichova<sup>5</sup>, James Thompson<sup>1</sup>, Zoran Popović<sup>2</sup>, Mariusz Jaskolski<sup>3,4</sup> & David Baker<sup>1,6</sup>

Following the failure of a wide range of attempts to solve the crystal structure of M-PMV retroviral protease by molecular replacement, we challenged players of the protein folding game Foldit to produce accurate models of the protein. Remarkably, Foldit players were able to generate models of sufficient quality for successful molecular replacement and subsequent structure determination. The refined structure provides new insights for the design of antiretroviral drugs.

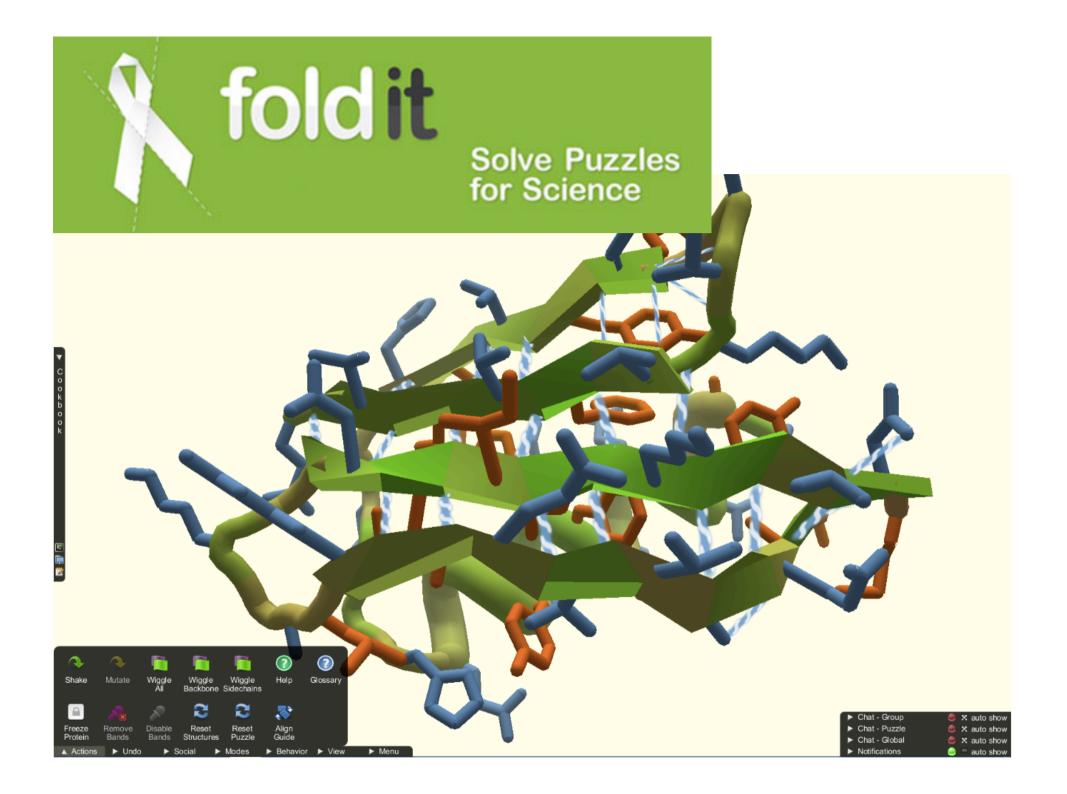
WHAT



## could help find a cure

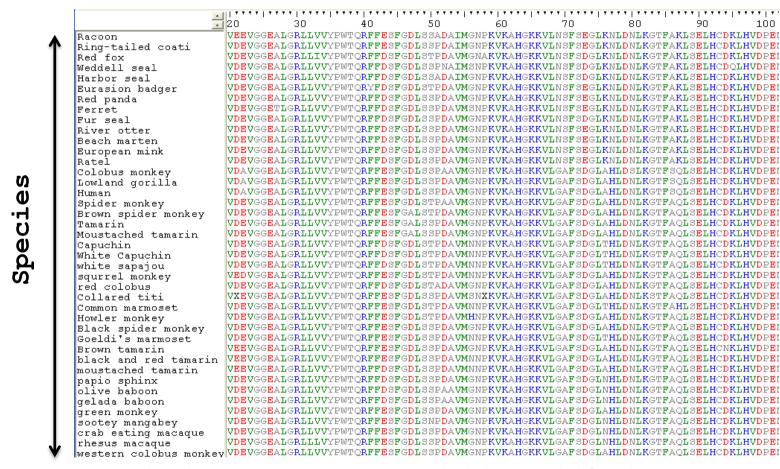


Help Stanford University scientists studying Alzheimer's, Huntington's, Parkinson's, and many cancers by simply running a piece of software on your computer.



#### How to extract useful information from protein sequences?

We can think of protein sequences from different species as samples from a probability distribution....



We want to use this data to parameterize a probability model for the protein sequence.

 $P(A_1,...,A_L)$  = Probability that a sequence produces a folded, functional hemoglobin molecule.

#### First order models

 $P(A_1,...,A_L)$  = Probability that a sequence produces a folded, functional hemoglobin molecule.

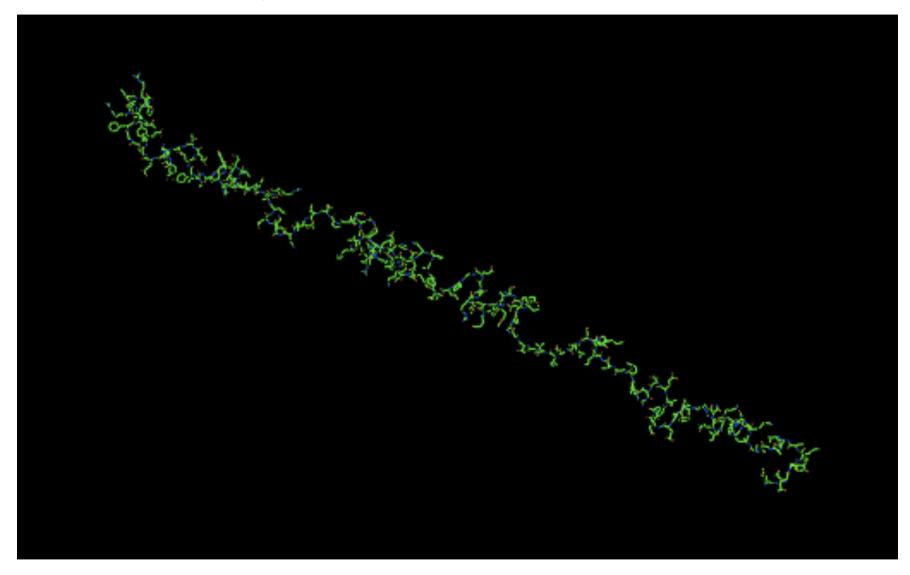
To start, we might ask that the model matches the distribution of amino acids seen at each sequence position in the data (the set of available sequences).

$$P_i(A_i) = \sum_{\{A_k | k \neq i\}} P(A_1, ..., A_L) = f_i(A_i)$$

Hidden Markov Models are often used to model protein sequence evolution. Different sequence positions (variables) are assumed to evolve independently of one another – there are no interactions.

Does this model tell us anything about protein structure and function?

Those residues close in sequence will be close in 3D structure....



but their conservation level doesn't provide much information about the 3D structure.

#### First order models

 $P(A_1,...,A_L)$  = Probability that a sequence produces a folded, functional hemoglobin molecule.

To start, we might ask that the model matches the distribution of amino acids seen at each sequence position in the data (the set of available sequences).

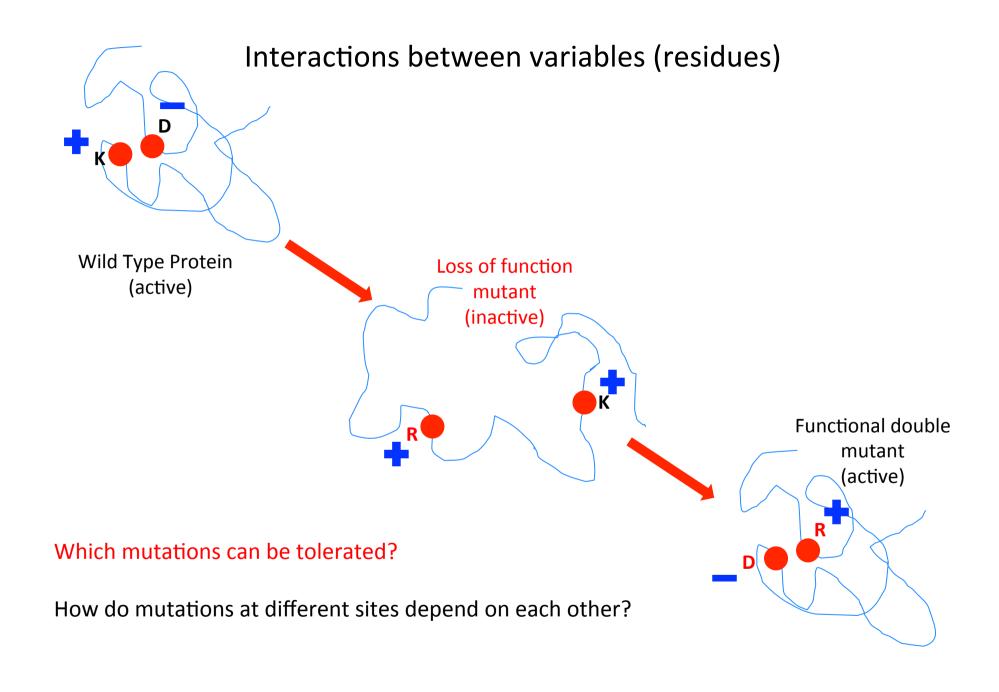
$$P_i(A_i) = \sum_{\{A_k | k \neq i\}} P(A_1, ..., A_L) = f_i(A_i)$$

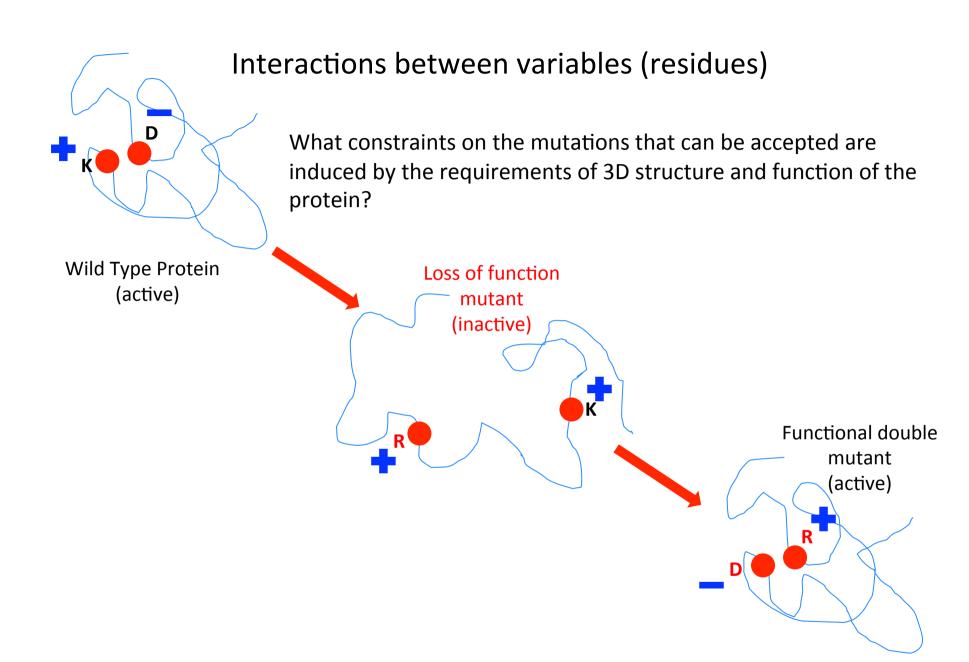
Hidden Markov Models are often used to model protein sequence evolution. Different sequence positions (variables) are assumed to evolve independently of one another – there are no interactions.

Does it tell us anything about the 3D protein structure......NOT MUCH

How can we get to 3D protein structure and/or function?

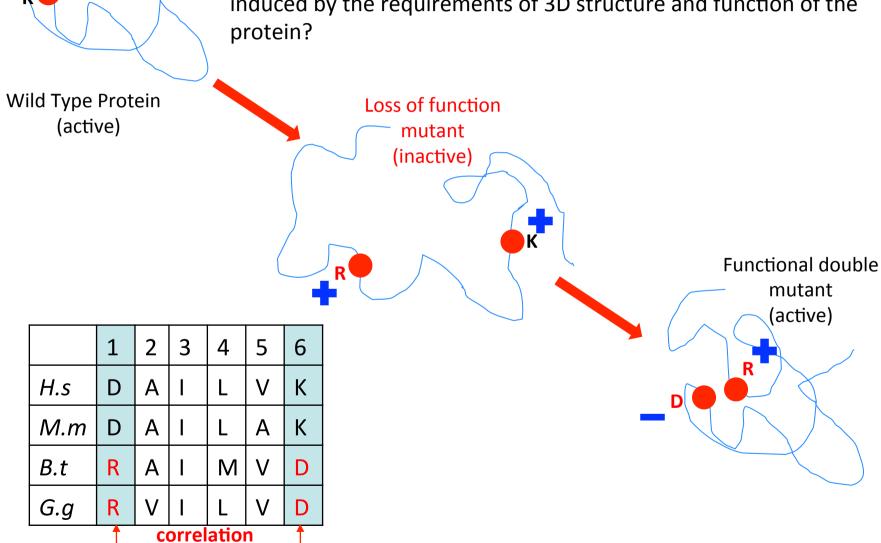




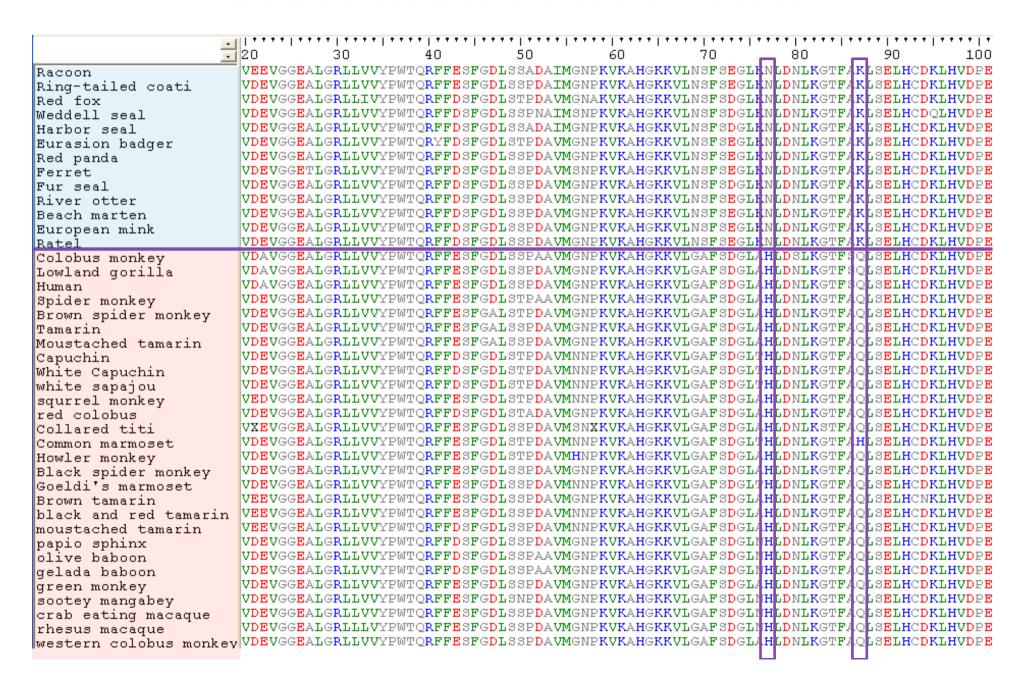


## Interactions between variables (residues)

What constraints on the mutations that can be accepted are induced by the requirements of 3D structure and function of the

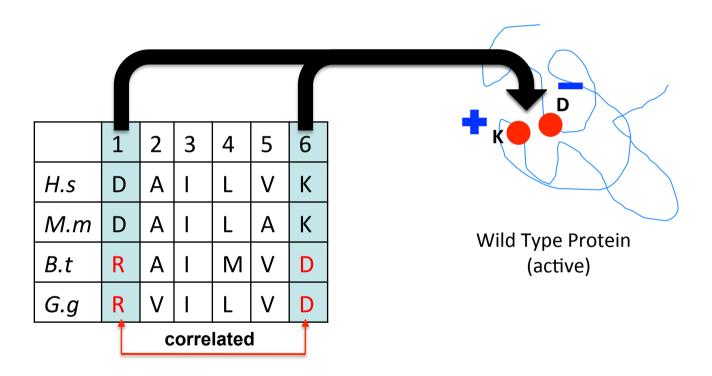


#### Interactions lead to covariance of amino acids



#### Exploit correlation structure of protein sequences

What constraints on the mutations that can be accepted are induced by the requirements of 3D structure and function of the protein?



Can we **invert correlations** in the sequence data to provide information about **the 3D protein structure?** 

Burger, Lukas, and Erik Van Nimwegen. PLoS computational biology 6.1 (2010): e1000633. Marks\*, Debora S., Colwell\*, Lucy J. et al. PloS one 6.12 (2011): e28766,

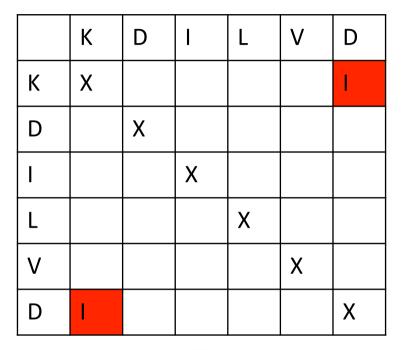
#### Measure pair correlations in the sequence alignment

	1	2	3	4	5	6
H.s	K	D	-	L	>	D
M.m	K	D	I	L	>	D
S.c	D	D	I	K	>	Η
S.p	D	Ε	I	L	V	Н



Compute (for example) the mutual
information for each pair of columns

$$MI_{ij} = \sum_{A_i, A_j=1}^{q} f_{ij}(A_i, A_j) \ln \left( \frac{f_{ij}(A_i, A_j)}{f_i(A_i) f_j(A_j)} \right)$$





Wild Type Protein



#### Measure pair correlations in the sequence alignment

	1	2	3	4	5	6
H.s	K	D	-	L	٧	D
M.m	K	D	I	L	٧	D
S.c	D	D	I	K	٧	Н
S.p	D	Ε	I	L	٧	Н



	K	D	1	L	>	D
K	X					_
D		Х				
1			Х			
L				Х		
V					Х	
D	1					Х

Compute (for example) the mutual information for each pair of columns

$$MI_{ij} = \sum_{A_i, A_j=1}^{q} f_{ij}(A_i, A_j) \ln \left( \frac{f_{ij}(A_i, A_j)}{f_i(A_i) f_j(A_j)} \right)$$

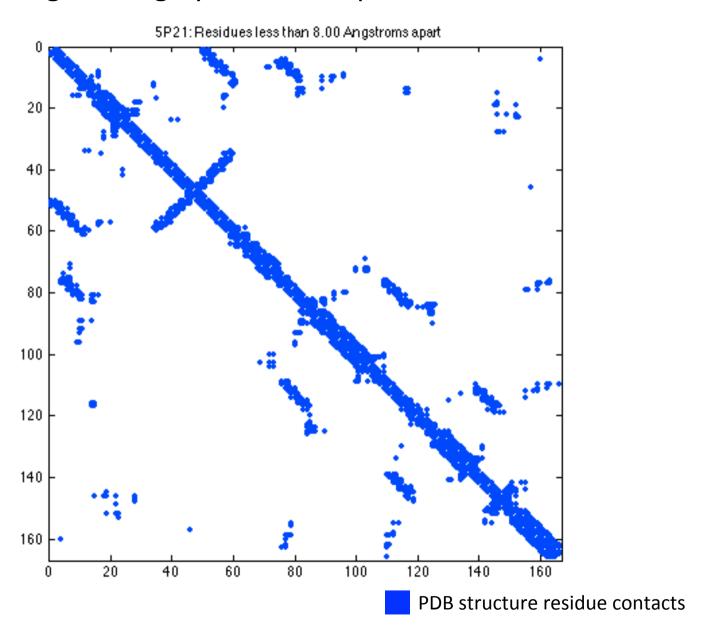
Are the most correlated residue pairs close in tertiary protein structure?



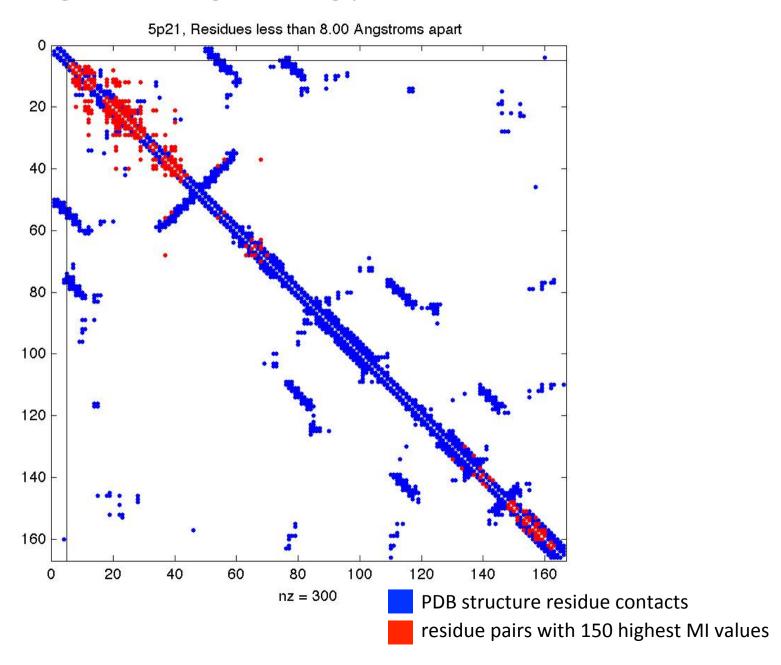
Wild Type Protein



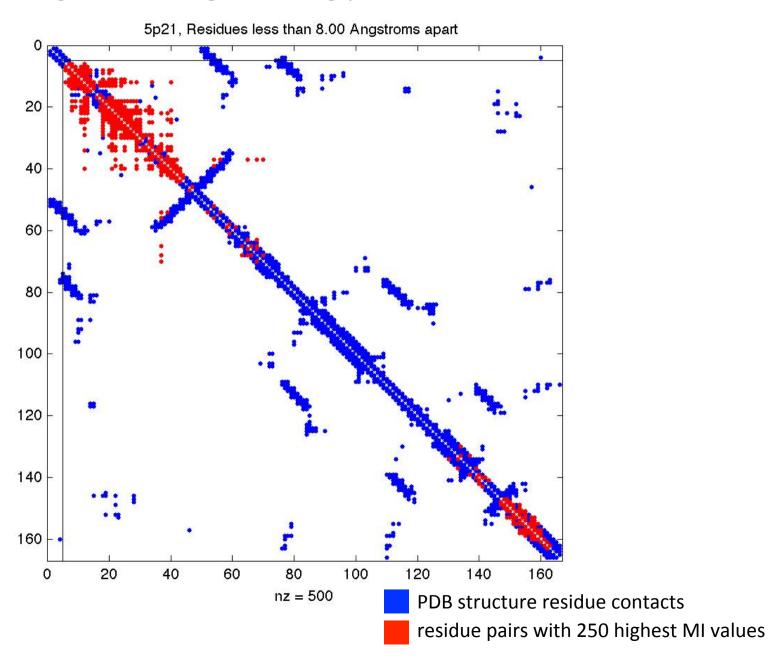
#### Testing: Are highly correlated pairs close in structure?



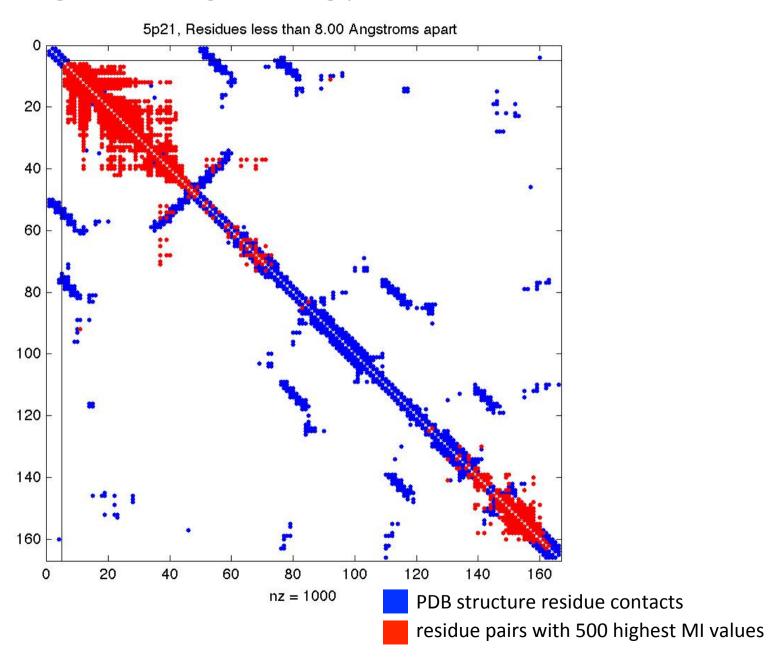
#### Testing MI: Are high-scoring pairs close in structure?



#### Testing MI: Are high-scoring pairs close in structure?

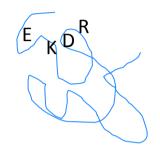


#### Testing MI: Are high-scoring pairs close in structure?

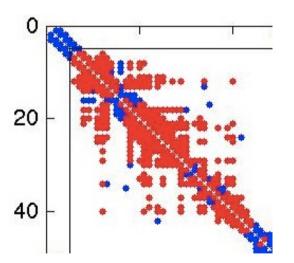


#### Why does this fail? Construct and analyze a model

Wild Type Protein





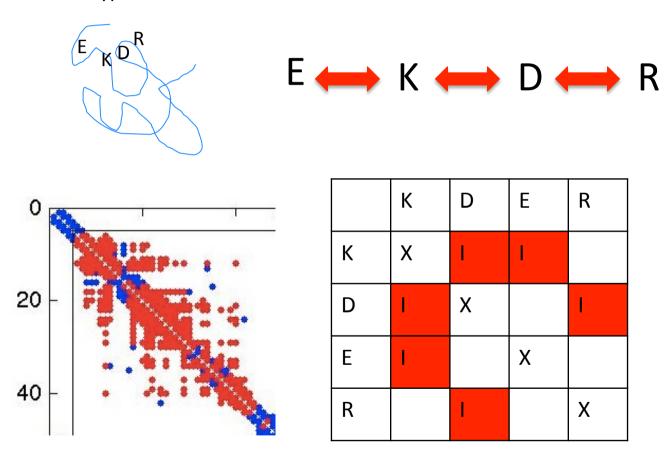


	K	D	E	R
К	Х	I		
D	I	Х		
E			Х	
R				Х

PDB structure residue contacts
residue pairs with 100 highest MI values

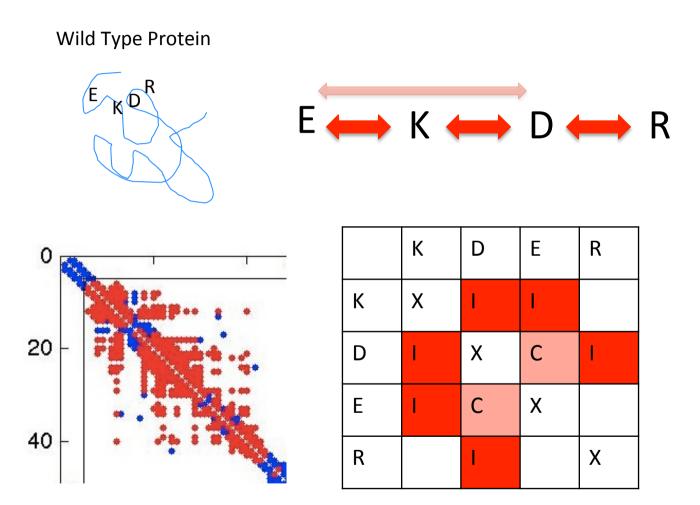
#### Construct and analyze a model

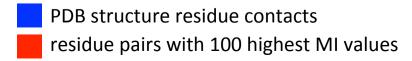




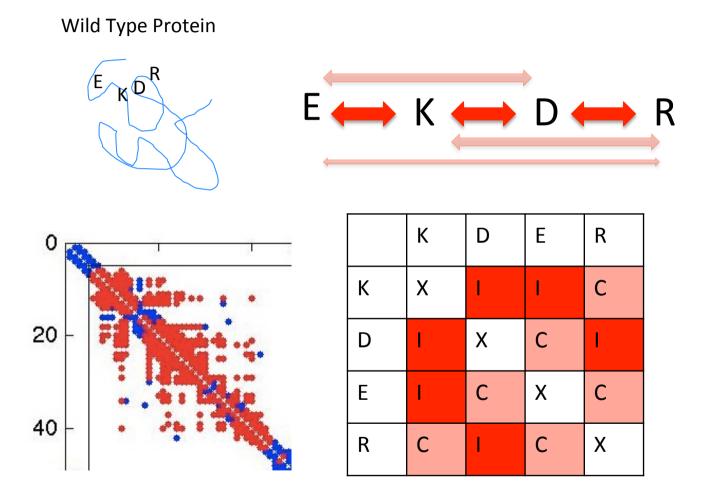
PDB structure residue contacts residue pairs with 100 highest MI values

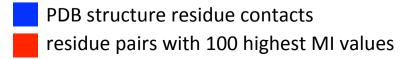
#### Construct and analyze a model





#### Construct and analyze a model





#### Probability model

 $P(A_1,...,A_L)$  = Probability a sequence is part of protein family

$$P_i(A_i) = \sum_{\{A_k | k \neq i\}} P(A_1, ..., A_L) = f_i(A_i)$$

$$P_{ij}(A_i, A_j) = \sum_{\{A_k | k \neq i, j\}} P(A_1, ..., A_L) = f_{ij}(A_i, A_j)$$

Satisfy these constraints and choose the maximum entropy or least constrained model:

$$S = -\sum_{\{A_i | i=1,...,L\}} P(A_1,...,A_L) \ln P(A_1,...,A_L)$$

#### Probability model

 $P(A_1,...,A_L)$  = Probability a sequence is part of protein family

$$= \frac{1}{Z} \exp \left\{ -\sum_{i} h_{i} A_{i} - \sum_{(i,j)} e_{ij} \left( A_{i}, A_{j} \right) \right\}$$

#### Probability model

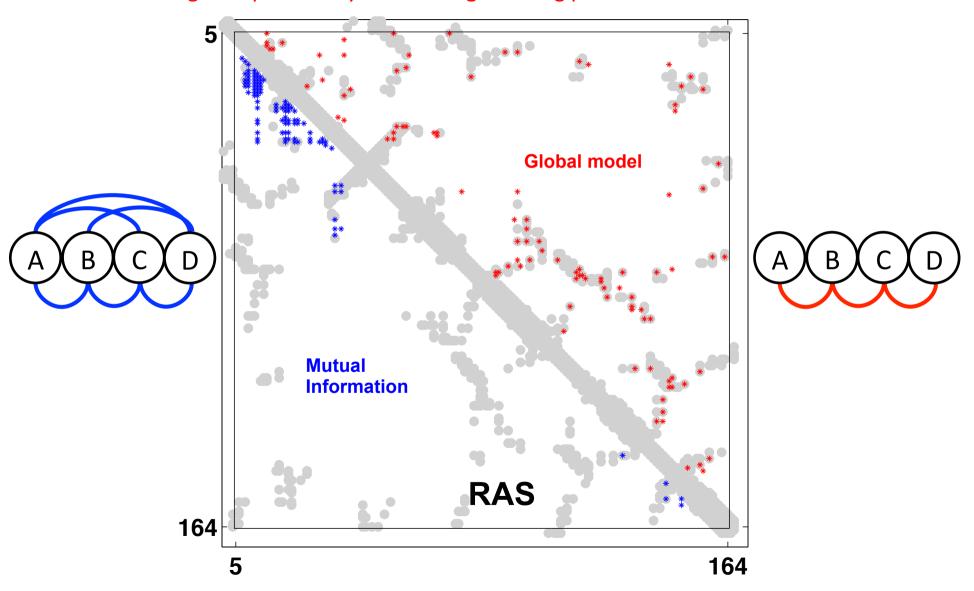
 $P(A_1,...,A_L)$  = Probability a sequence is part of protein family

$$= \frac{1}{Z} \exp \left\{ -\sum_{i} h_{i} A_{i} - \sum_{(i,j)} e_{ij} \left( A_{i}, A_{j} \right) \right\}$$

naïve mean field approximation, assume small couplings

$$e_{ij}\left(A_{i},A_{j}\right) = \left(C^{-1}\right)_{ij}\left(A_{i},A_{j}\right)$$

Solution: A global probability model – high scoring pairs are close in structure!



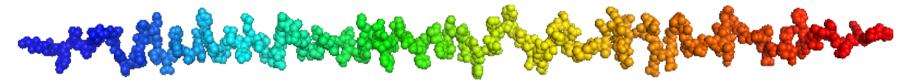
Is this enough information to fold the protein?



Start with an extended polypeptide, add predicted secondary structure

Our hypothesis is the high scoring pairs will be close in the structure – so constrain the distance between the residues in each pair.

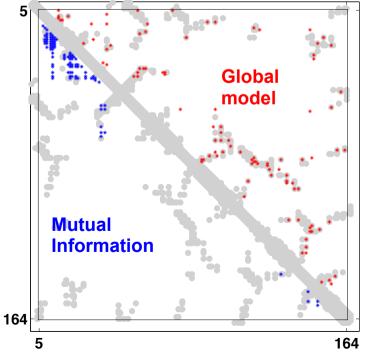
Is this enough information to fold the protein?

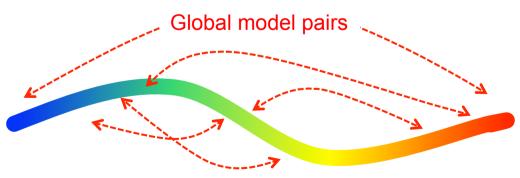


Start with an extended polypeptide, add predicted secondary structure

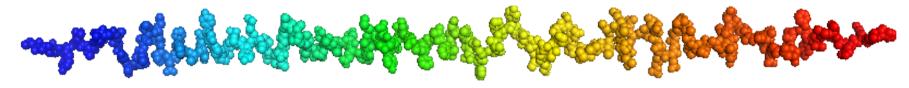
Our hypothesis is the high scoring pairs will be close in the structure – so constrain the distance between the residues in each pair.

This massively reduces the space of possible 3D conformations of the protein



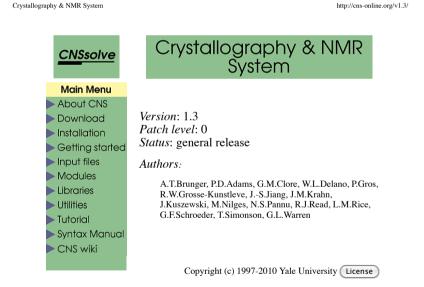


#### Folding the protein



Start with an extended polypeptide

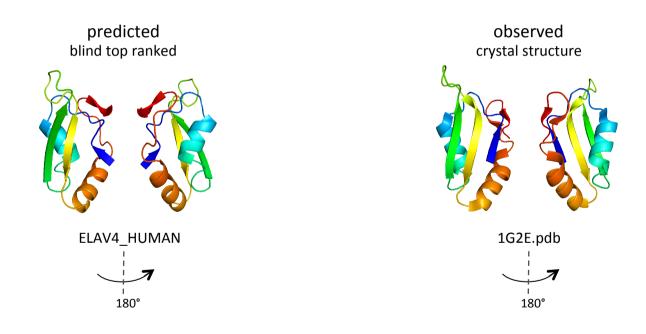
Our hypothesis is the high scoring pairs will be close in the structure – so we constrain the distance between the two residues in each pair.



Use these distance constraints together with predicted secondary structure in the standard distance geometry and simulated annealing protocol from CNS to generate structures

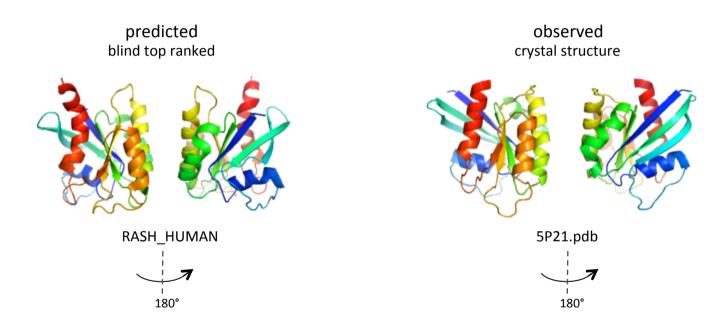
Correlations in the mutation patterns of amino acids within a protein used to predict tertiary structure.

An RNA binding domain: 2.9Å C-alpha rmsd over 67 residues



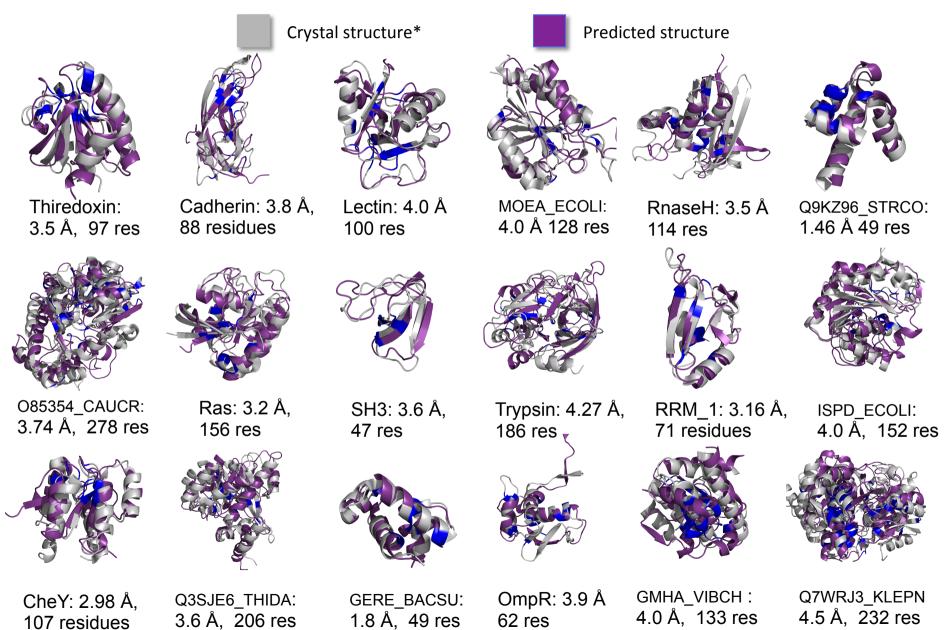
Correlations in the mutation patterns of amino acids within a protein used to predict tertiary structure.

RAS: 3.5Å C-alpha rmsd over 161 residues



Beta strands positioned well enough to predict correct registration with the exception of the beta one strand, which was very recently shown to exist in both the conformations that we find.

#### Comparison of predicted and observed structures

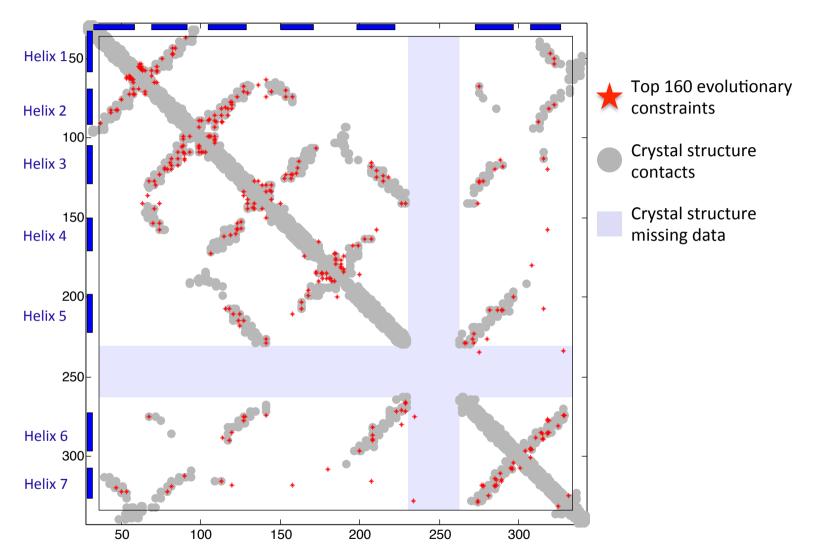


Challenge: transmembrane proteins

Hard experimentally No high throughput Drug targets - > 40%

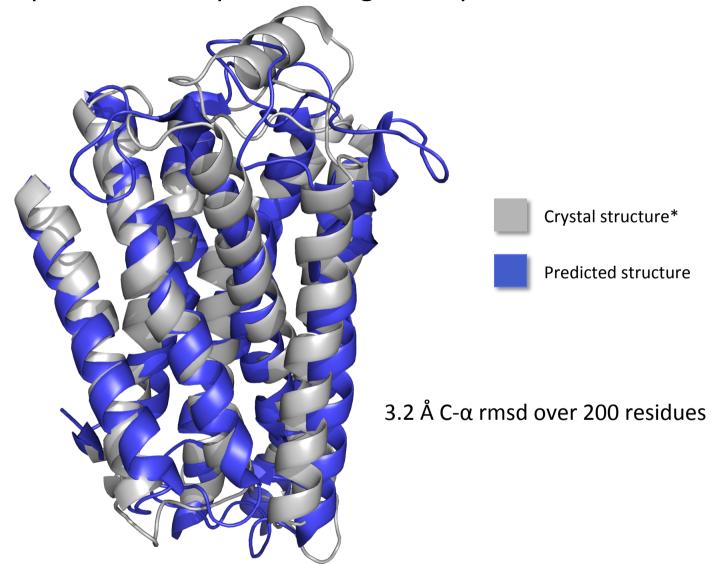
De novo prediction

#### β2 adrenergic receptor : evolutionary constraints



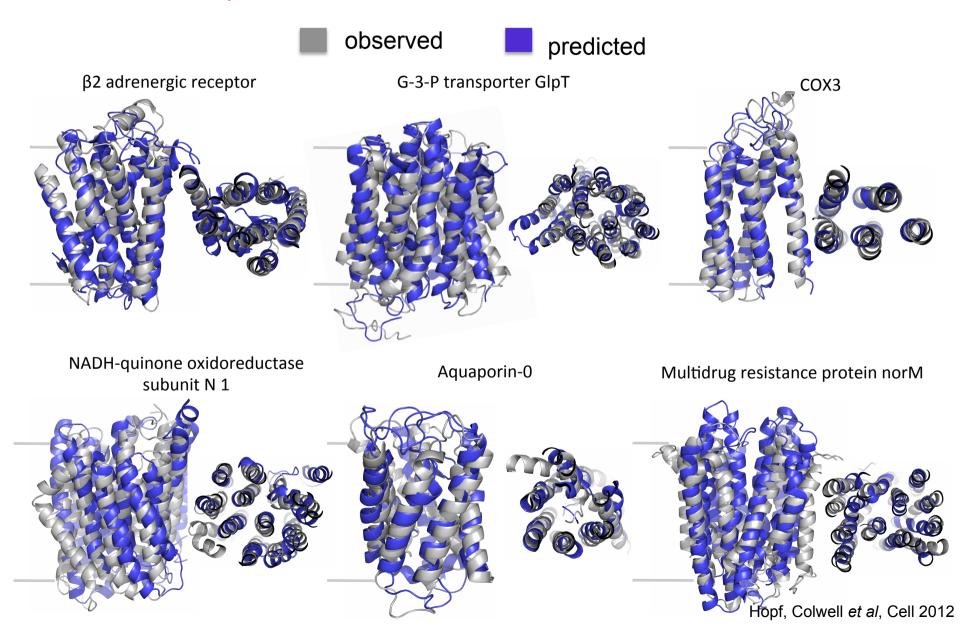
The β2 adrenergic receptor, a seven transmembrane helix GPCR family member.

#### Blind prediction for $\beta 2$ adrenergic receptor



<sup>\*</sup>Crystal Structure: Rasmussen SG, DeVree BT, Zou Y, Kruse AC, Chung KY, Kobilka TS, Thian FS, Chae PS, Pardon E, Calinski D, Mathiesen JM, Shah ST, Lyons JA, Caffrey M, Gellman SH, Steyaert J, Skiniotis G, Weis WI, Sunahara RK, Kobilka BK. Nature. 2011 Jul 19.

#### Blind structure prediction.



## 11 medically important membrane proteins of unknown structure predicted

