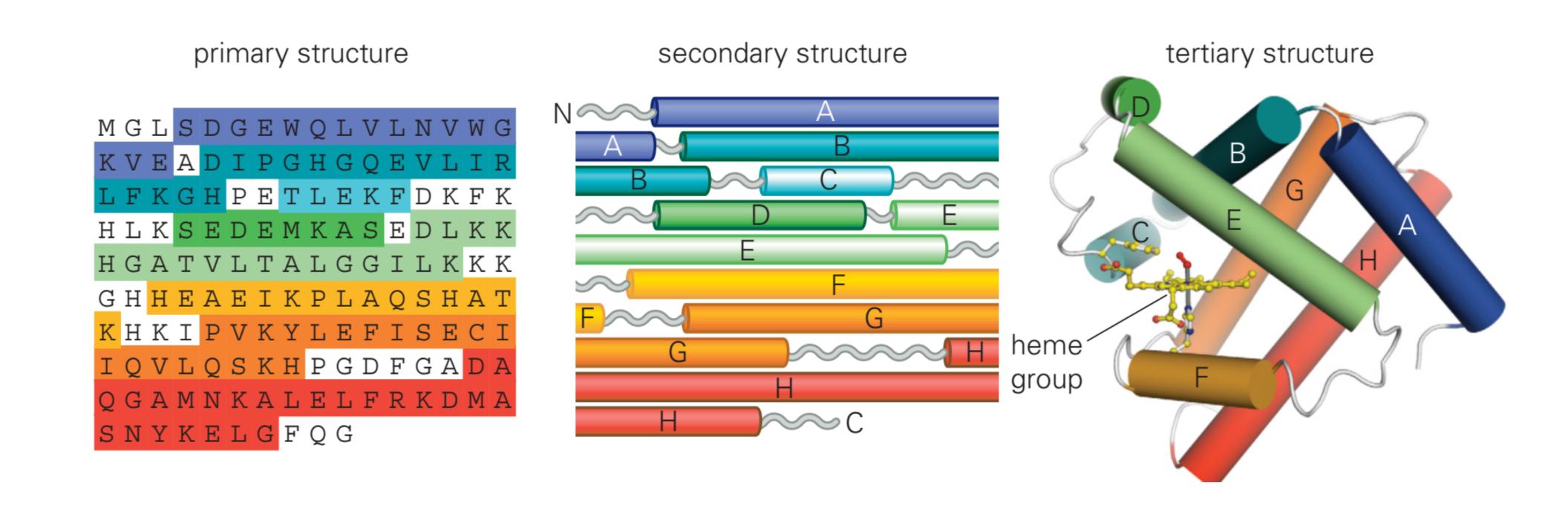
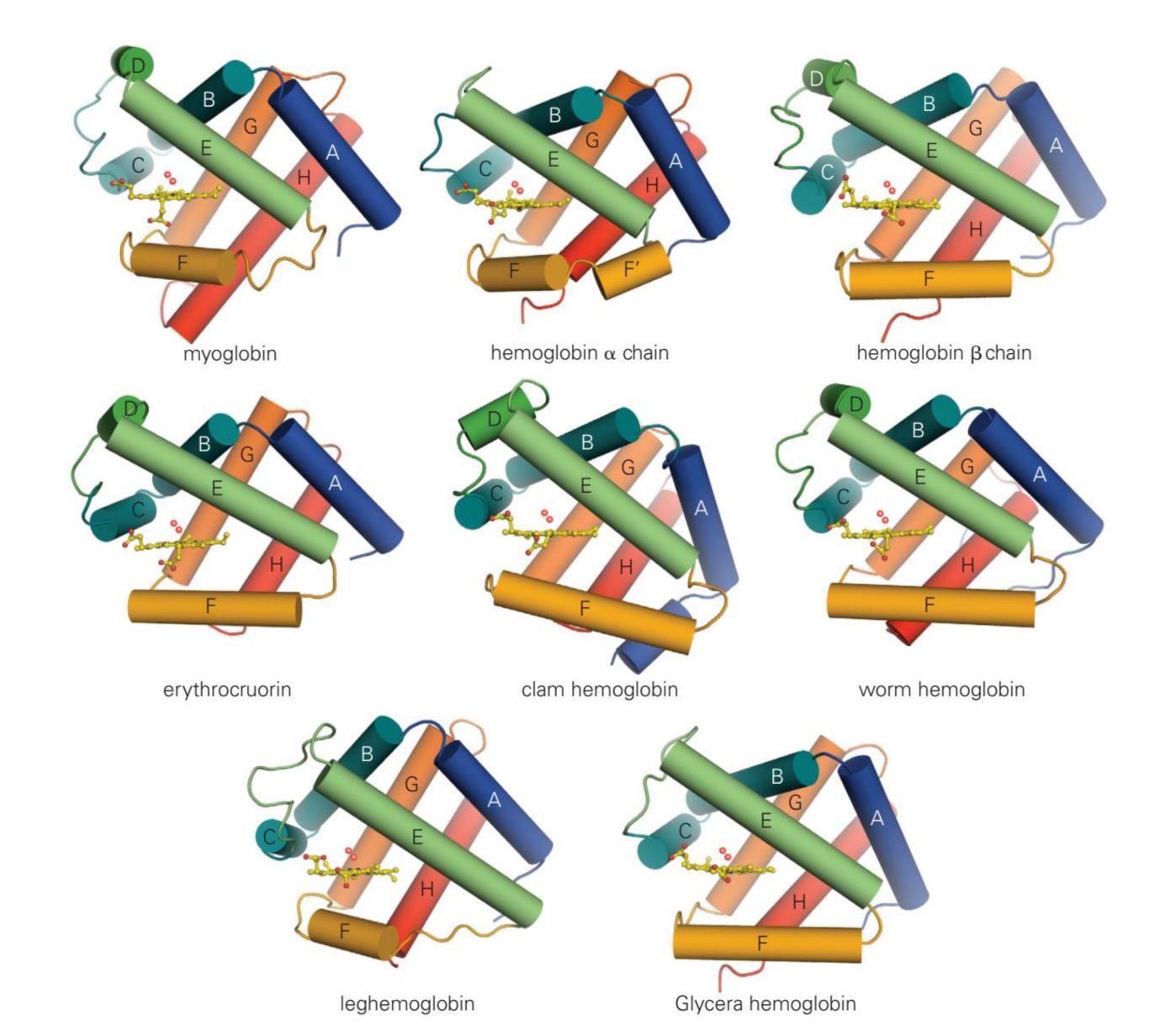
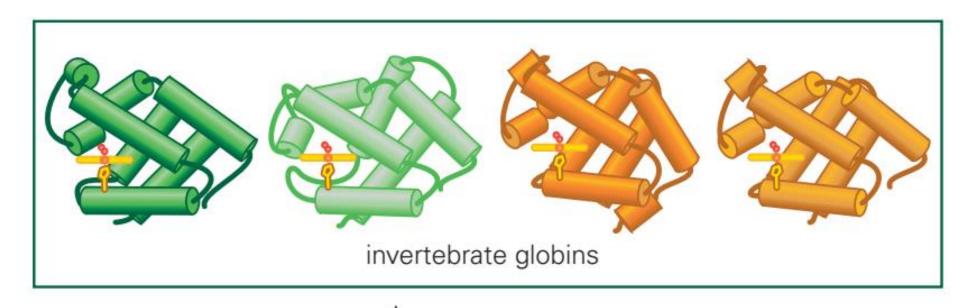
# The amino-acid sequence defines the 3D-structure of proteins



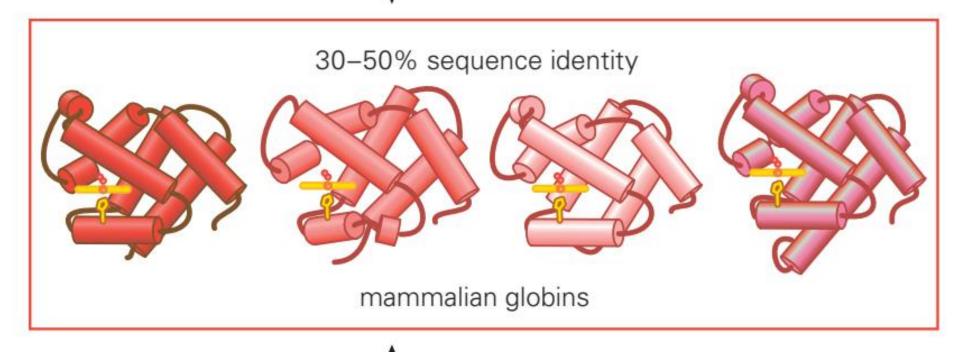
#### Similar sequences have similar folds



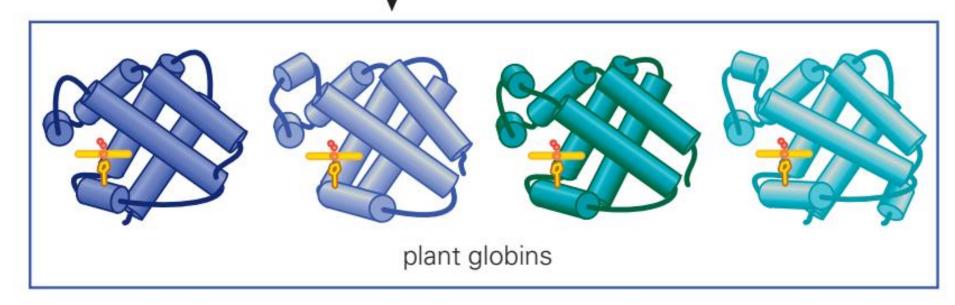
# Importance of sequence similarity

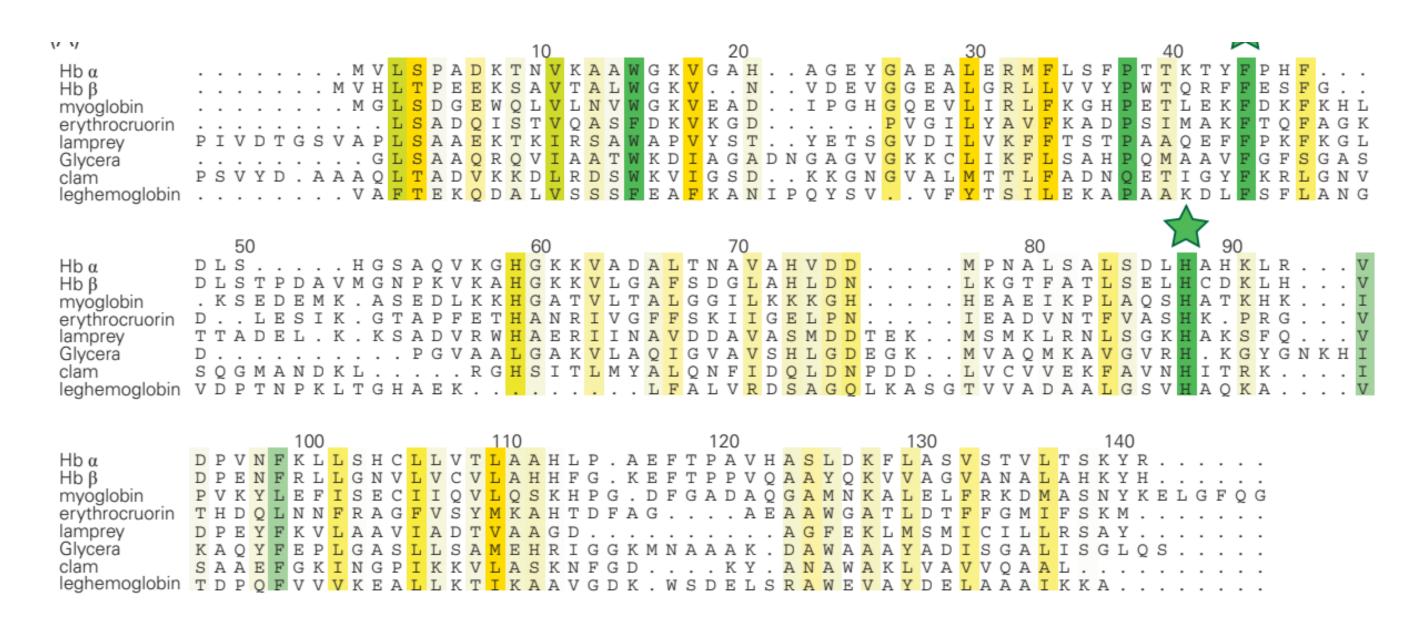


10-20% sequence identity

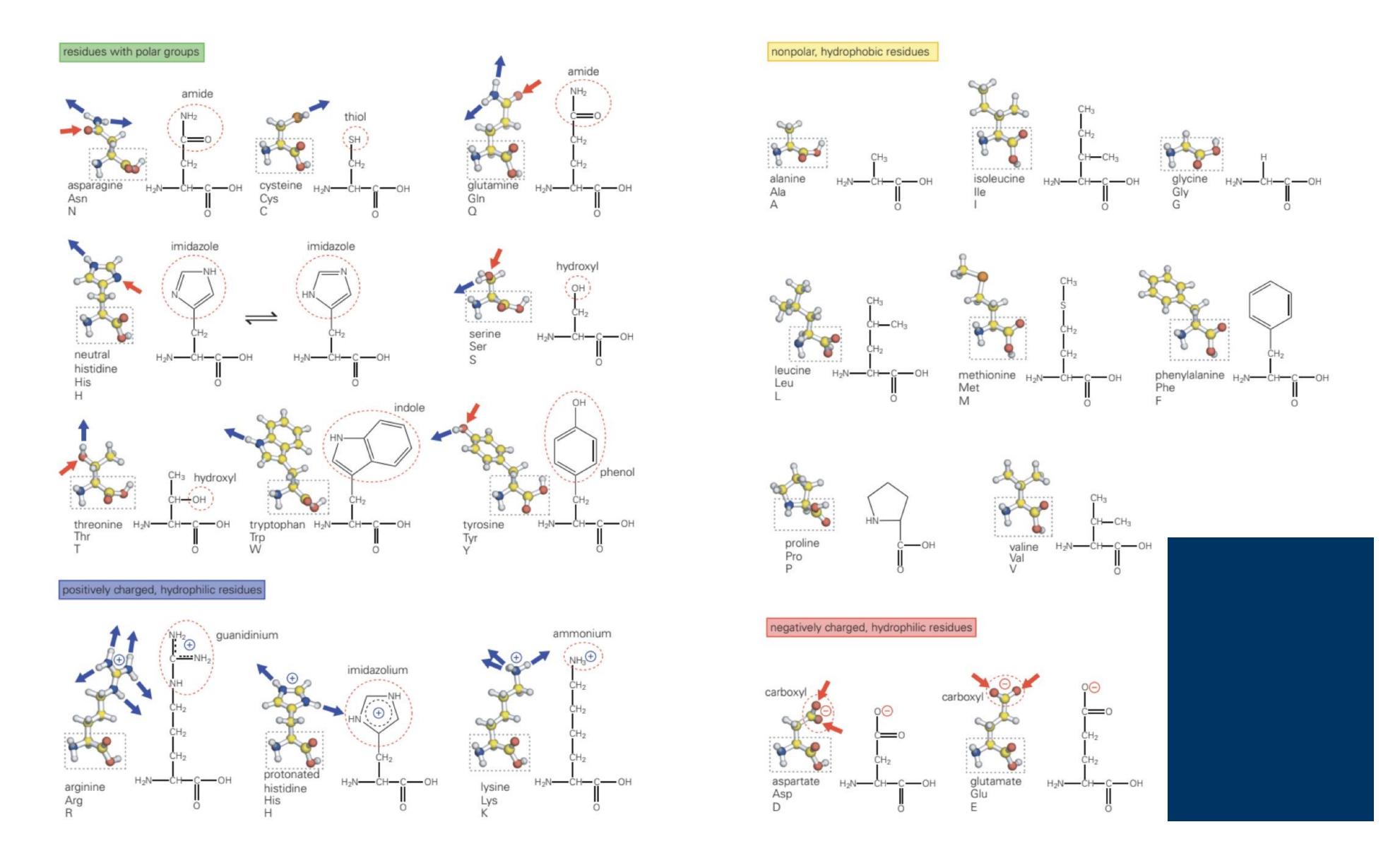


10-20% sequence identity





# How do we "define" similarity?



### Amino acid substitution matrix

- A matrix in which each row and column corresponds to one of the 20 amino acids. Each entry in the matrix is related to the probability that one amino acid is replaced by the other in proteins that are related evolutionarily
- Each entry in the matrix is called a substitution score, Sij, and the value of Sij is related to the frequency with which the ith type of amino acid is replaced by the jth type of amino acid in the alignments of related proteins, relative to the probability that this substitution could occur by random chance, given the abundance of each of the amino acids.

## PAM (Dayhoff) matrices

- "Point Accepted Mutation" is an amino acid substitution model derived from empirical observation of mutations among closely related proteins.
- Counts of mutations from one amino acid to the other nineteen amino acids should be proportional to the rates of transition from that one amino acid to the other nineteen

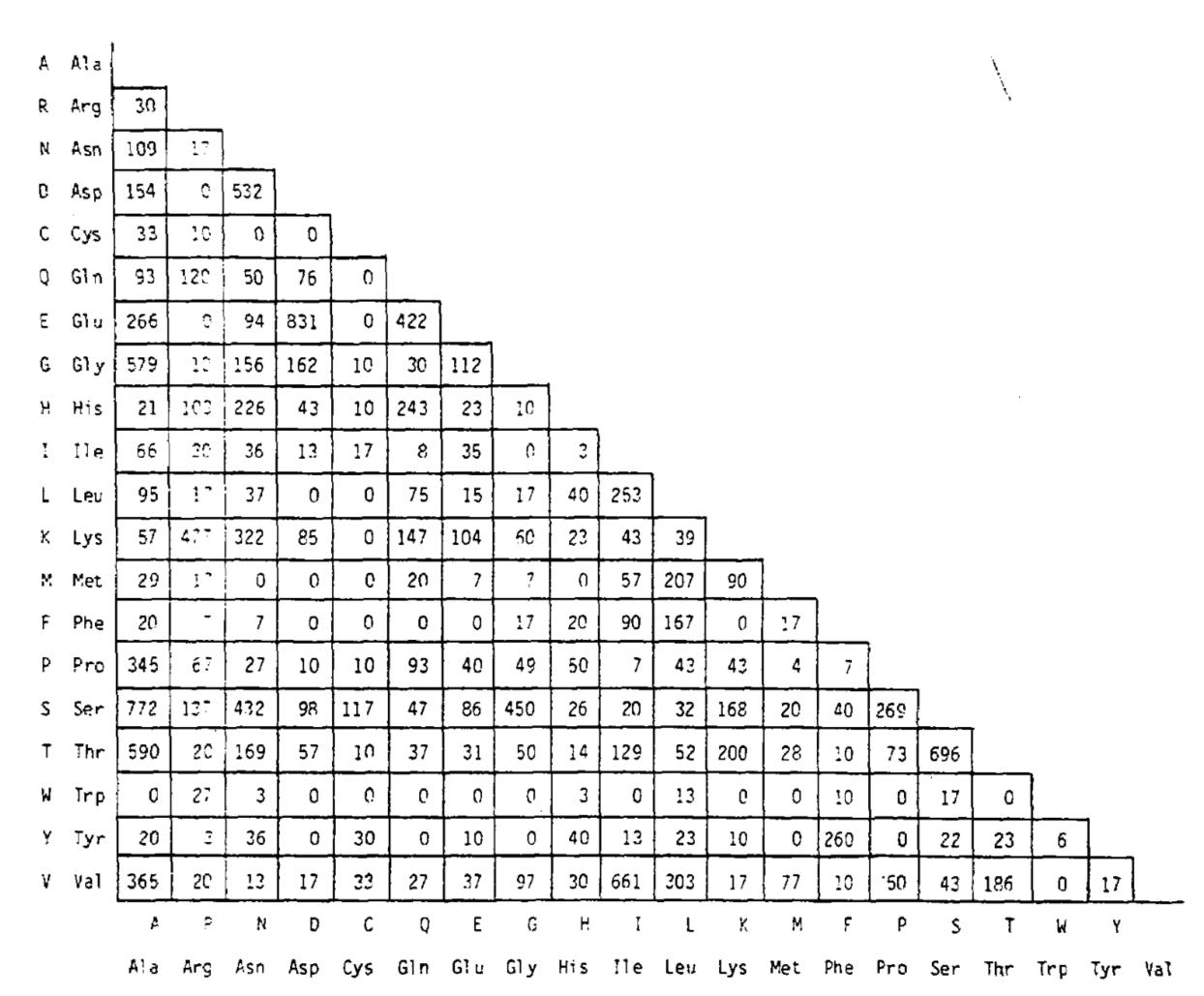


Figure 80. Numbers of accepted point mutations (X10) accumulated from closely related sequences. Fifteen hundred and seventy-

two exchanges are shown. Fractional exchanges result when ancestral sequences are ambiguous.

# PAM (Dayhoff) matrices

- This matrix was then transformed to a transition probability matrix
- The unconditional mutation probability, that is P(i ≠ j), was set to equal 1 mutation for every 100 sites
- 1 PAM unit is thus defined as the unit of time in which we expect 0.01 mutations to occur per site

#### ORIGINAL AMINO ACID

ſ			A	R	N	D	С	Q	E	G	Н	I	L	K	М	F	Р	S	T	W	Υ	٧
}			Ala	Arg	Asn	Asp	Cys	Gln	G] u	Gly	His	Ile	Leu	Lys	Met	Phe	Pro	Ser	Thr	Trp	Tyr	Val
	A	Ala	9867	2	9	10	3	8	17	21	2	6	4	2	6	2	22	35	32	0	2	18
	R	Arg	1	9913	1	0	1	10	0	0	10	3	1	19	4	1	4	6	ı	8	٥	1
	N	Asn	4	1	9822	36	o	4	6	6	21	3	1	13	0	1	2	20	9	1	4	1
Ì	D	Asp	6	0	42	9859	0	6	53	6	4	1	0	3	0	0	1	5	3	o	o	1
١	С	Cys	1	1	0	0	9973	0	0	0	1	1	0	0	0	0	1	5	1	0	3	2
	Q	Gin	3	9	4	5	0	9876	27	1	23	1	3	6	4	0	6	2	2	0	0	1
	Ε	G1 u	10	0	7	56	0	35	9865	4	2	3	1	4	1	0	3	4	2	0	1	2
93	G	Gly	21	1	12	11	1	3	7	9935	1	٥	1	2	1	1	3	21	3	0	0	5
AMINO ACID	Н	His	1	8	18	3	1	20	1	0	9912	0	1	1.	0	2	3	1	1	1	4	1
AMI	I	I le	2	2	3	1	2	1	2	0	0	9872	9	2	12	7	0	1	7	0	1	33
MENT	L	Leu	3	1	3	0	0	6	1	1	4	22	9947	2	45	13	3	1	3	4	2	15
REPLACEMENT	K	Lys	2	37	25	6	0	12	7	2	2	4	1	9926	20	0	3	8	11	O	1	1
REP	M	Met	1	1	0	0	0	2	0	0	0	5	8	4	9874	1	O	1	2	0	0	4
Ì	F	Phe	1	1	1	0	0	0	0	1	2	8	6	0	4	9946	0	2	1	3	28	0
	P	Pro	13	5	2	1	1	8	3	2	5	1	2	2	1	1	9926	12	4	0	٥	2
	S	Ser	28	11.	34	7	11	4	6	16	2	2	1	7	4	3	17	9840	38	5	2	2
	Ţ	Thr	22	2	13	4	1	3	2	2	1	11	2	8	6	1	5	· 32	9871	0	2	9
	W	Trp	0	2	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	9976	1	0
	Υ	Ţyr	1	0	3	0	3	0	1	0	4	1	1	0	0	21	0	1	1	2	9945	1
	٧	Val	13	2	1	1	3	2	2	3	3	57	11	1	17	1	3	2	10	0	2	9901

Figure 82. Mutation probability matrix for the evolutionary distance of 1 PAM. An element of this matrix,  $M_{ij}$ , gives the probability that the amino acid in column j will be replaced by the amino acid in row i after a given evolutionary interval, in this case

1 accepted point mutation per 100 amino acids. Thus, there is a 0.56% probability that Asp will be replaced by Glu. To simplify the appearance, the elements are shown multiplied by 10,000.

# PAM (Dayhoff) matrices

- Different matrices were needed for different expected phylogenetic distances
- Matrices for different PAM can be derived assuming a discretetime Markov chain
- The PAM250 is used most often.
- Transition probabilities get "flatter" the more time has passed

			OK 10.10/L APINO ACID																			
ſ			A	R	K	D	С	Q	Ε	G	Ä	I	L	К	М	F	Р	\$	T	W	Y	٧
		]	Al a	Arg	Asn	Asp	Cys	G) n	G1 u	Gly	His	lle.	Leu	Lys	Met	Phe	Pro	Ser	Thr	Trp	Tyr	Val
	A	Ala	13	6	9	à	5	8	9	12	5	8	6	7	7	4	11	11	11	2	4	9
	R	Arg	3	17	4	3	2	5	3	2	6	3	2	9	4	1	4	4	3	7	2	2
	N	Asn	4	4	6	7	2	5	5	4	6	3	2	5	3	2	4	5	4	2	3	3
ĺ	D	Asp	5	4	8	11	1	7	10	5	6	3	2	5	3	1	4	5	5	1	2	3
ļ	С	Cys	2	1	1	1	52	1	1	2	2	2	1	1	1	1	2	3	2	1	4	2
	Q	Gln	3.	5	5	6	1	10	7	3	7	2	3	5	3	1	4	3	3	1	2	3
- [	Ε	G1 u	5	4	7	11	1	ð	12	5	6	3	2	5	3	1	4	5	5	1	2	3
REPLACEMENT AMINO ACTU	G	Gly	12	5	10	10	4	7	9	27	5	5	4	6	5	3	8	11	à	2	3	7
	Н	His	2	5	5	4	2	7	4	2	15	2	2	3	2	2	3	3	2	2	3	2
	I	He.	3	2	2	2	2	2	2	2	2	10	6	2	6	5	2	3	4	1	3	9
	L	Leu	6	4	4	3	2	6	4	3	5	15	34	4	20	13	5	4	6	6	7	13
	K	Lys	6	18	10	8	2	10	3	5	8	5	4	24	9	2	6	8	8	4	3	5
₩ ₩	M	Met	1	1	1	1	0	1	1	1	1	2	3	2	6	2	1	1	1	1	1	2
	F	Phe	2	1	2	1	1	1	1	1	3	5	6	1	4	32	1	2	2	4	20	3
	p	Pro	7	5	5	4	3	5	4	5	5	3	3	4	3	2	20	6	5	1	2	4
	Š	Ser	9	6	8	7	7	6	7	9	6	5	4	7	5	3	9	10	9	4	4	6
i	Т	Thr	8	5	6	6	4	5	5	6	4	6	4	6	5	3	6	8	11	2	3	6
	W	Trp	0	2	0	0	0	0	0	С	1	0	1	0	0	1	0	1	0	55	I	0
	γ	Tyr	1	1	2	1	3	1	1	1	3	2	2	1	2	15	1	2	2	3	31	2
	٧	Val	7	4	4	4	4	4	4	5	4	15	10	4	10	5	5	5	7	2	4	17

ORIGINAL AMINO ACID

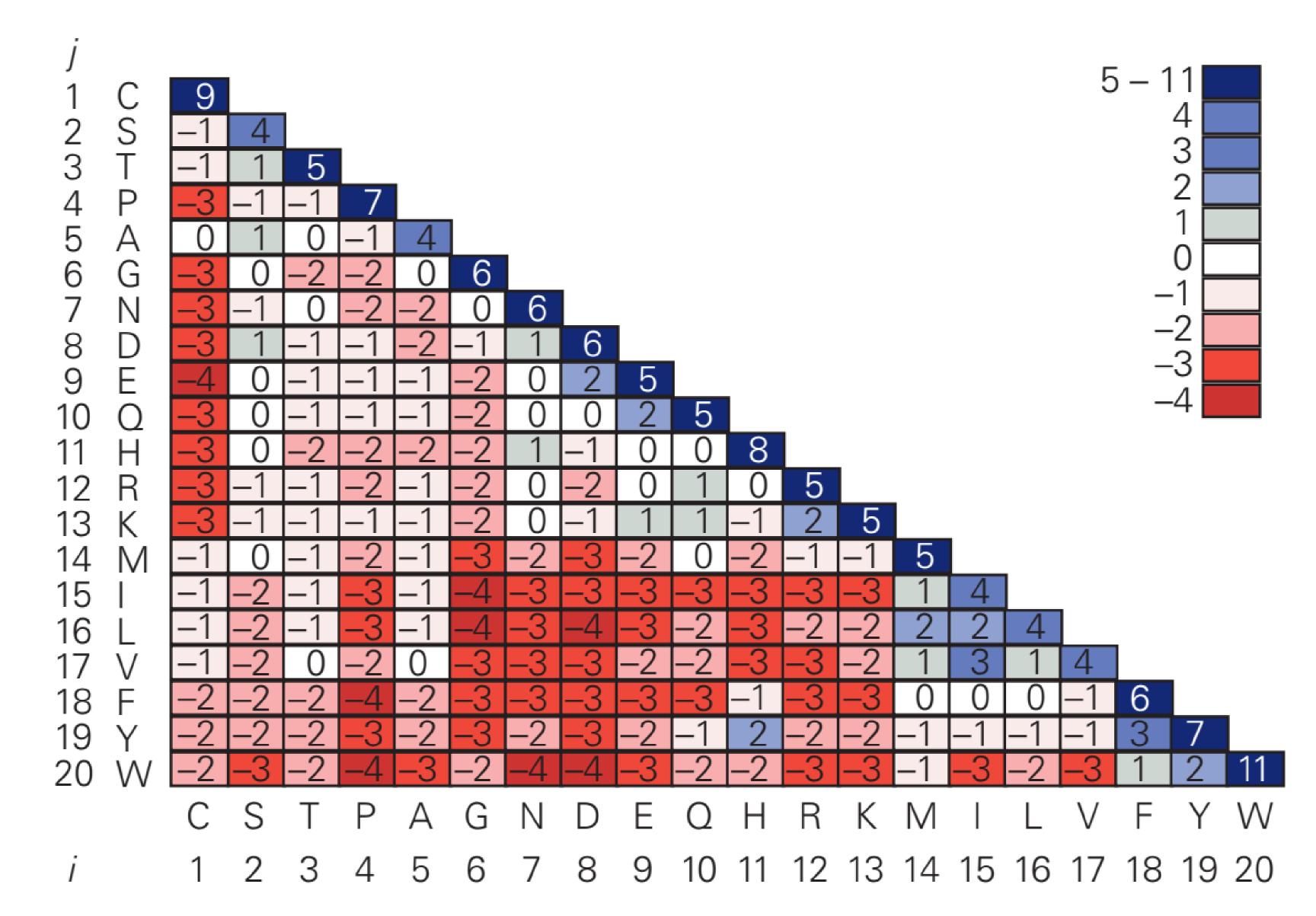
Figure 83. Mutation probability matrix for the evolutionary distance of 250 PAMs. To simplify the appearance, the elements are shown multiplied by 100. In comparing two sequences of average amino acid frequency at this evolutionary distance, there is a 13% probability that a position containing Ala in the first

sequence will contain Ala in the second. There is a 3% chance that it will contain Arg, and so forth. The relationship of two sequences at a distance of 250 PAMs can be demonstrated by statistical methods.

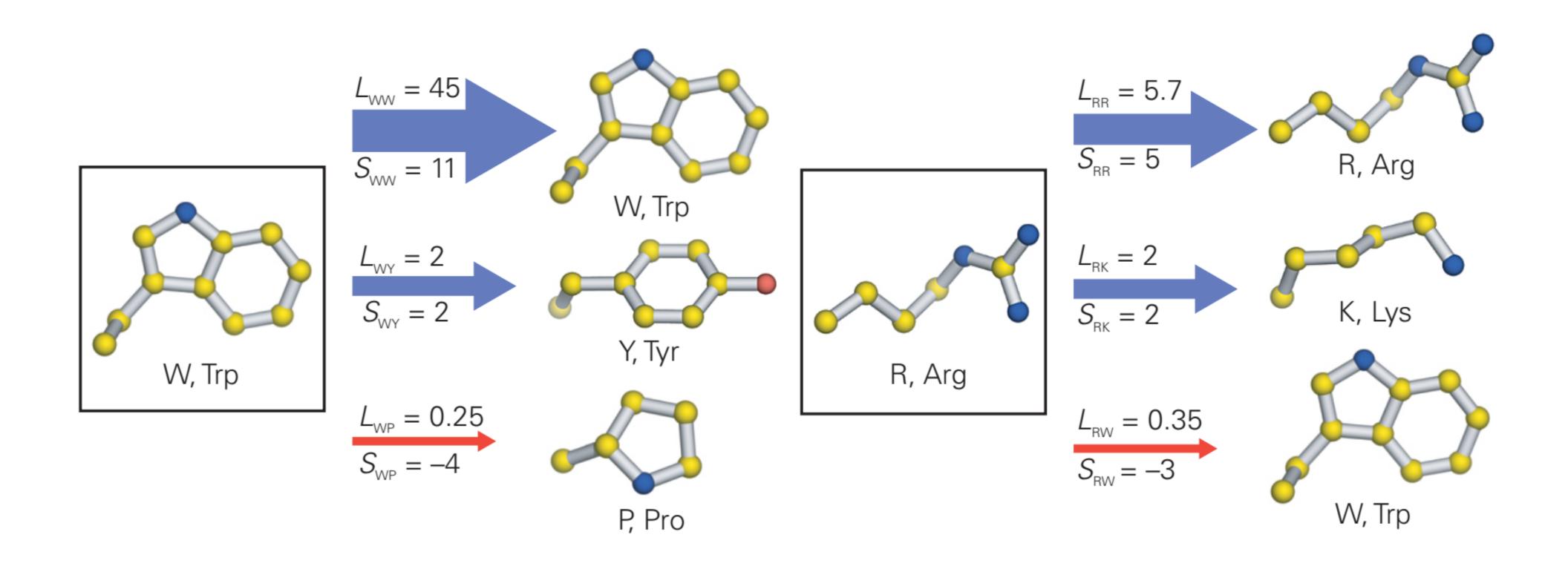
### BLOSUM matrices

- BLOcks SUbstitution Matrix
- BLOSUM looks directly at mutations in motifs of related sequences while PAM's extrapolate evolutionary information based on closely related sequences.
- BLOSUM matrices were built based on pre-existing local alignments and optimised iteratively.
- The BLOSUM substitution score for a pairing is defined in terms of the base-2 logarithm of the substitution likelihood
- High BLOSUM numbers denote high expected similarity
  - BLOSUM 62 is a matrix calculated from comparisons of sequences with a pairwise identity of no more than 62%.
  - Remember PAMs do the opposte, the notation denotes time
- Most programs these days use BLOSUM matrices

### The Rlacimh? matrix

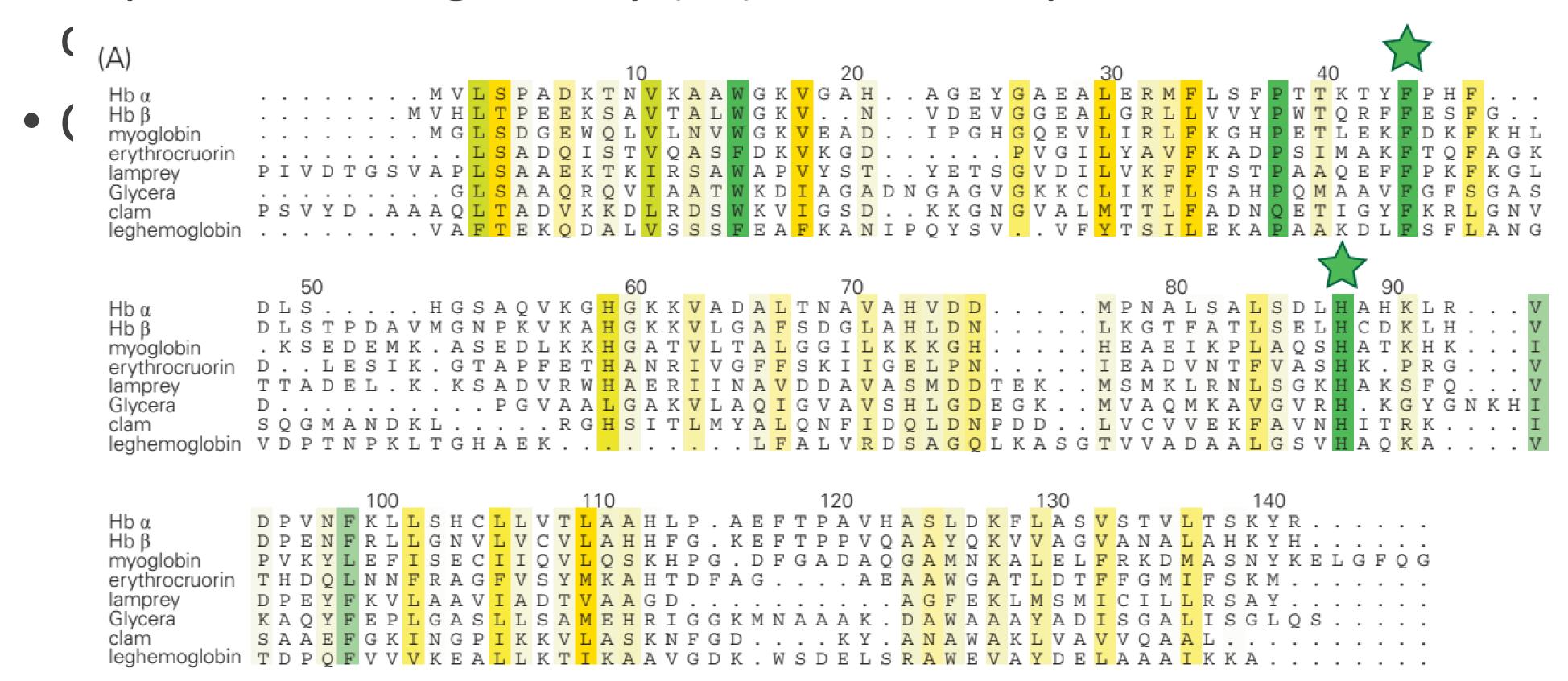


# Substitution scores reflect the chemical properties of the amino acids

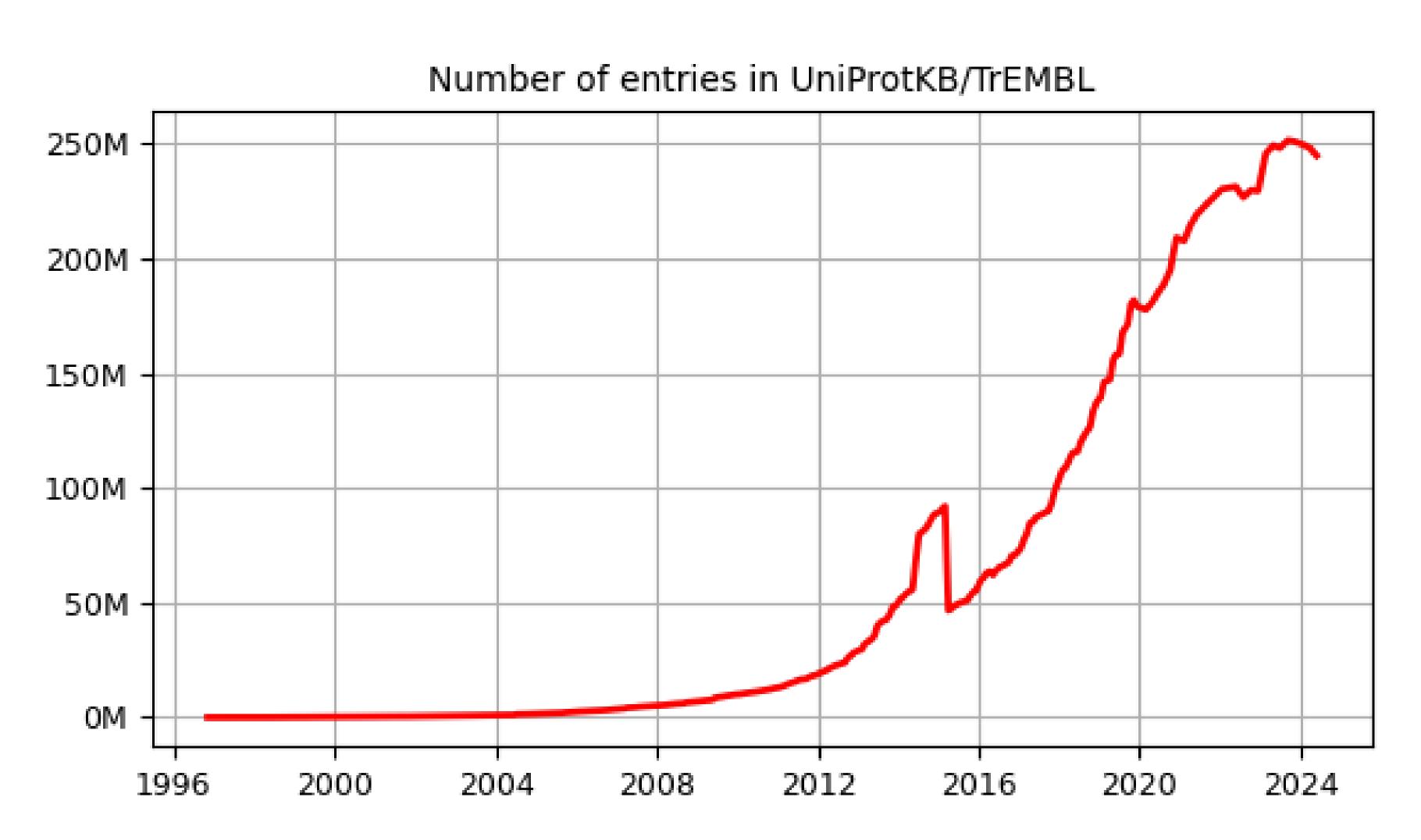


## Multiple Sequence Alignments

- One of the most important tools to understand structure function and structure
- Important to align many (all) avilable sequences to understand

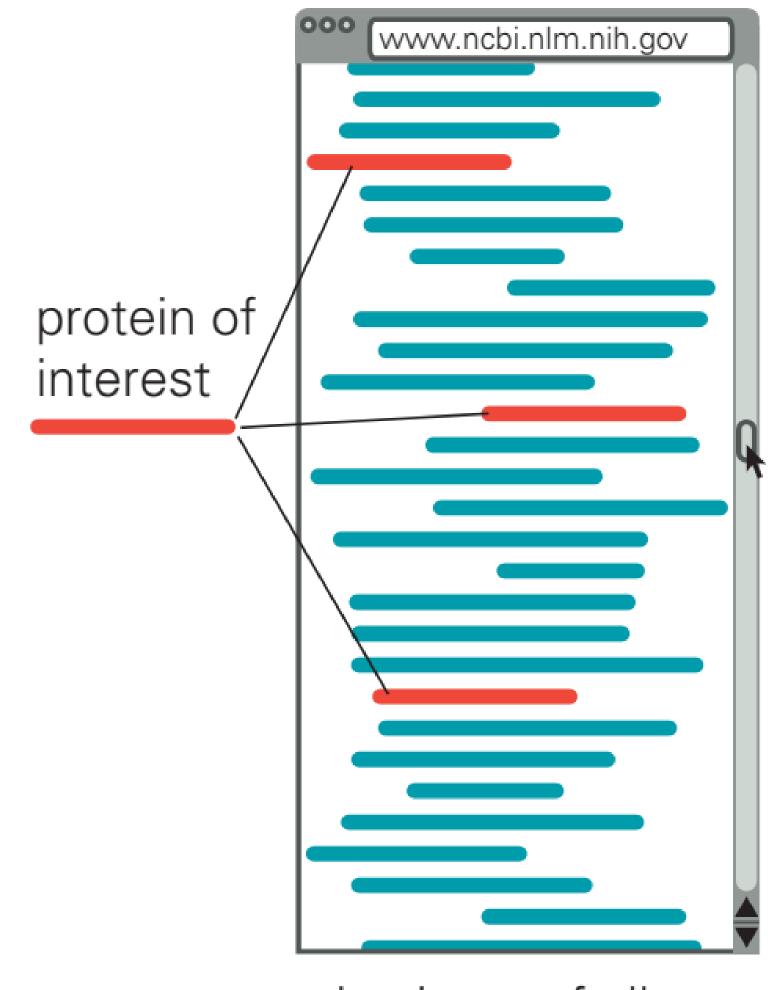


# Number of known protein sequences



# Structure variation is related to sequence variation

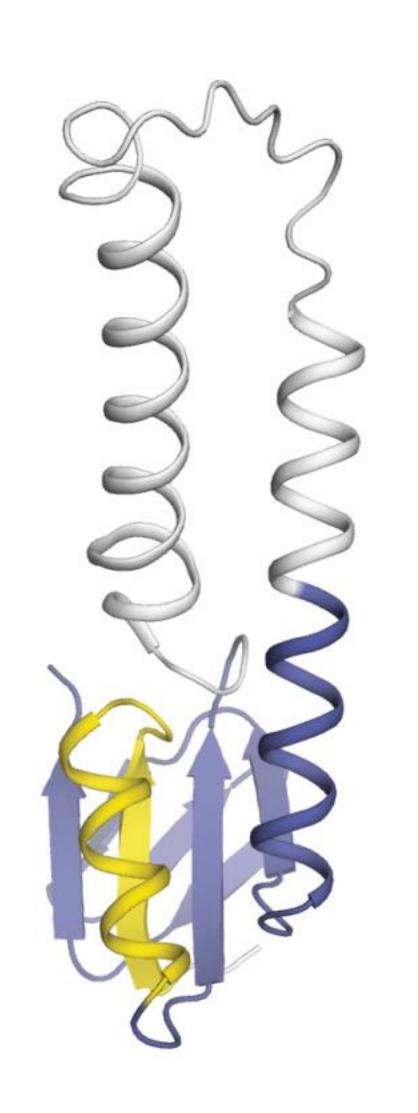
- The protein of interest (is aligned against all known proteins.
- The probability of each alignment being due to related proteins is evaluated using substitution matrices.
- Such searcher are typically performed in "fragments"
- Score are typically returned as the probability for an alignment course to not be due to random chance
  - E-scores
- Popular software
  - Basic Local Alignment Search Tool (BLASTP)
  - Hidden Markov Model (HMMER)

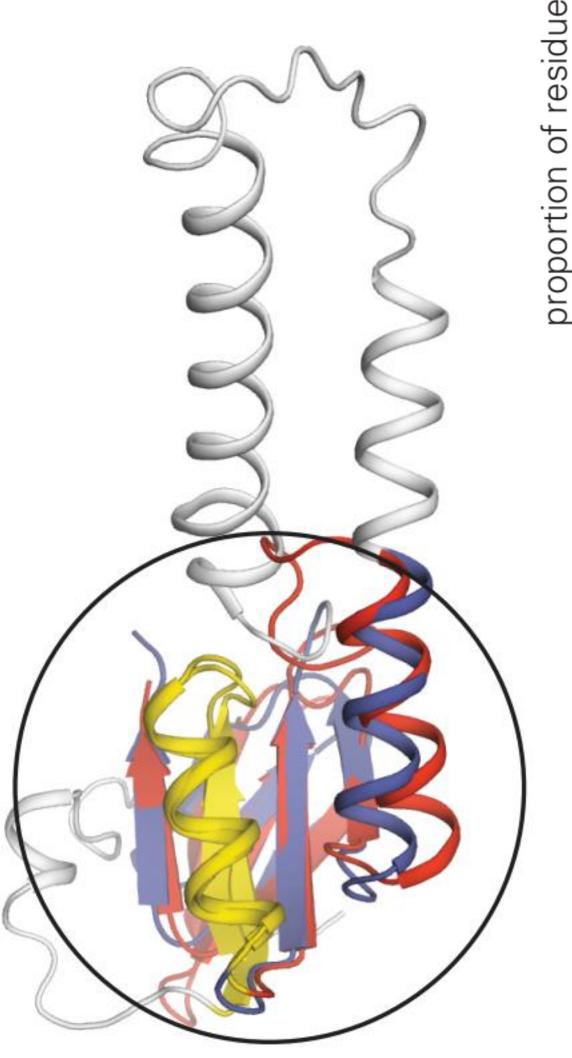


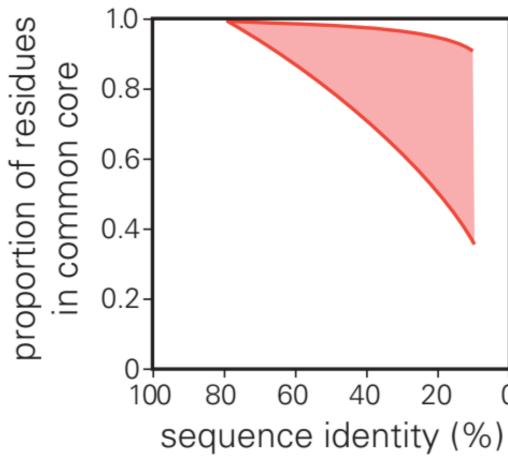
database of all known sequences

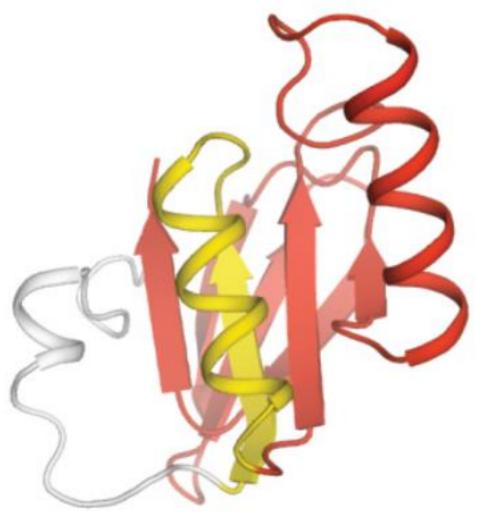
### Common structural core

- What can we say about proteins that are not so similar in their sequences?
- We can partition the structures into multiple regions, with and without similarities.
- Proteins can share a common structural core



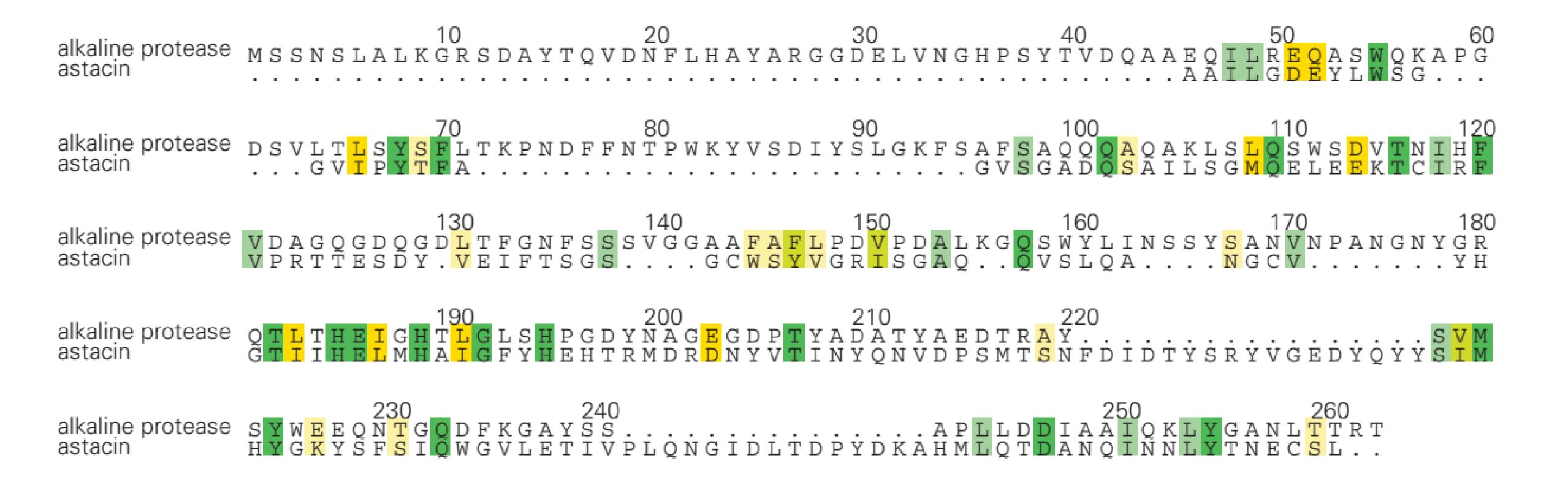




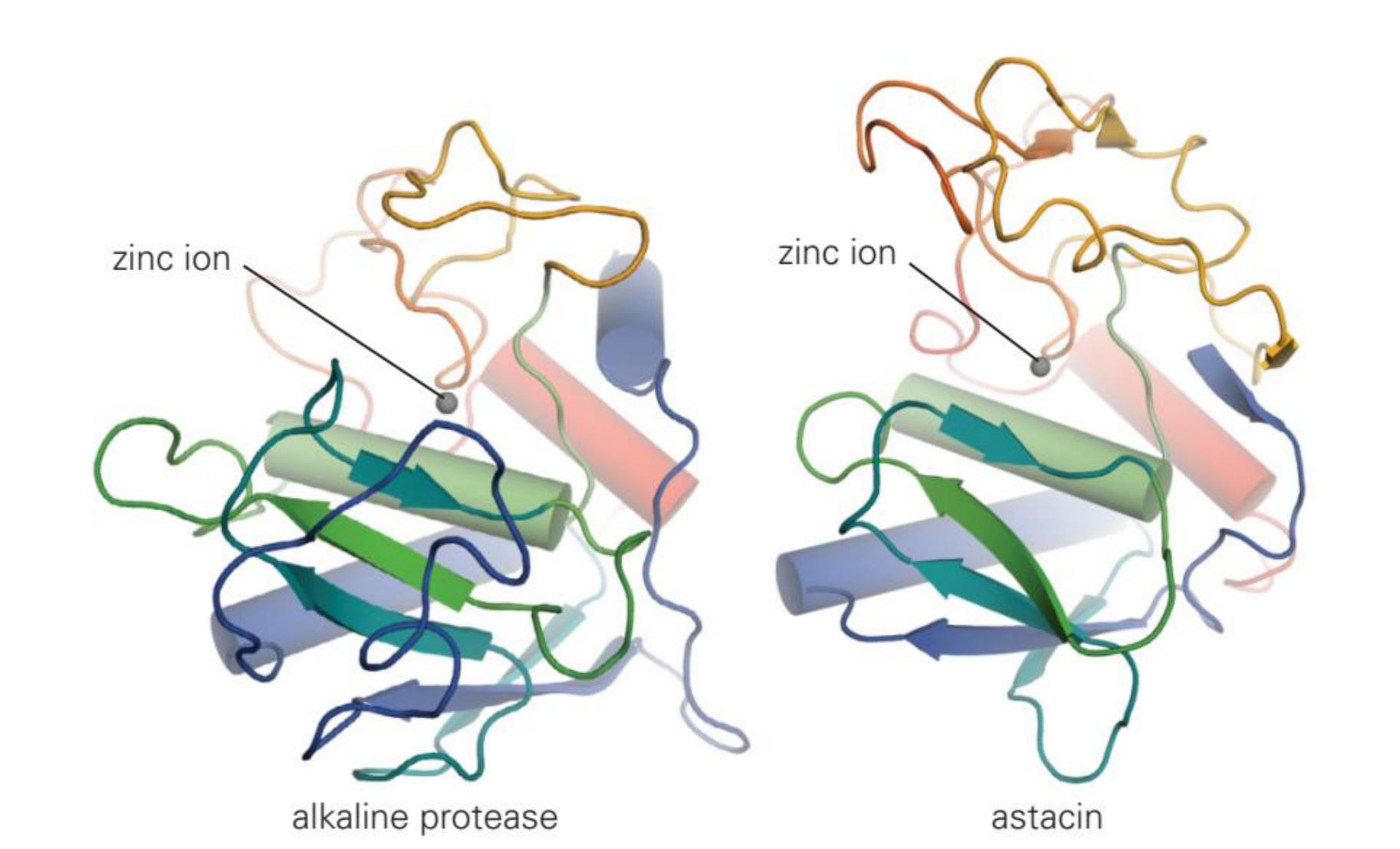


common core

# Conservation along the whole sequence can be missleading

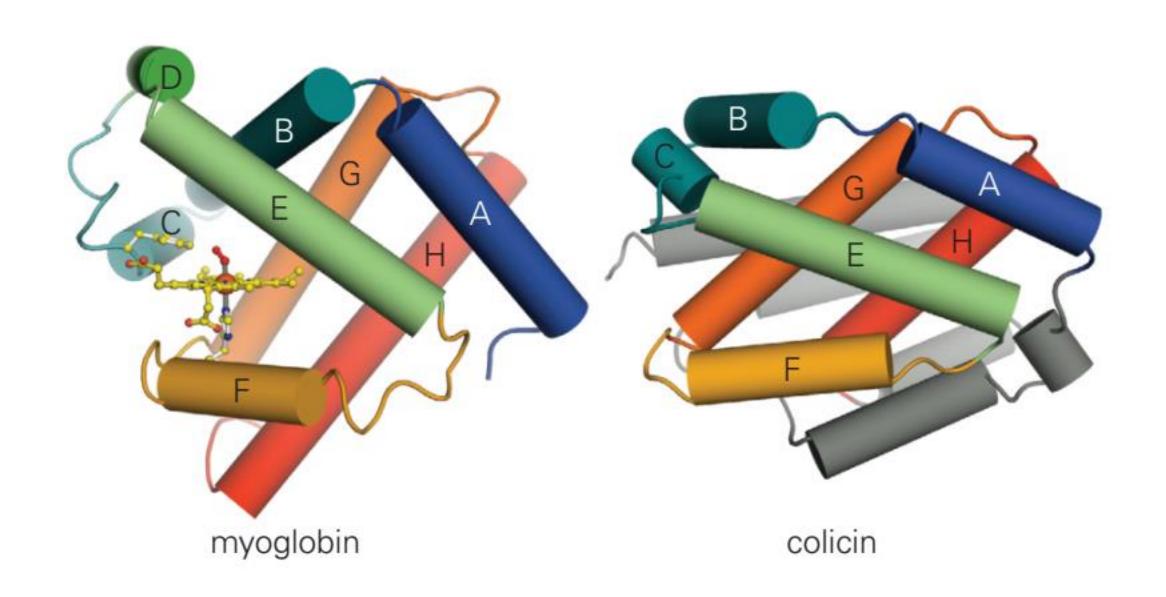


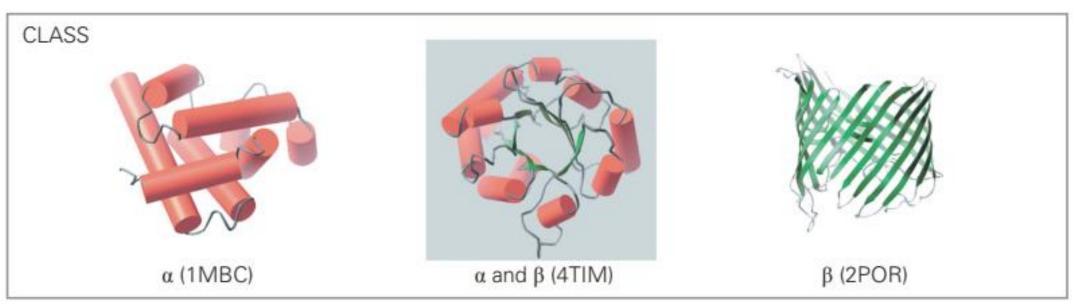
# Conservation within the conserved core is important for e.g. catalysis

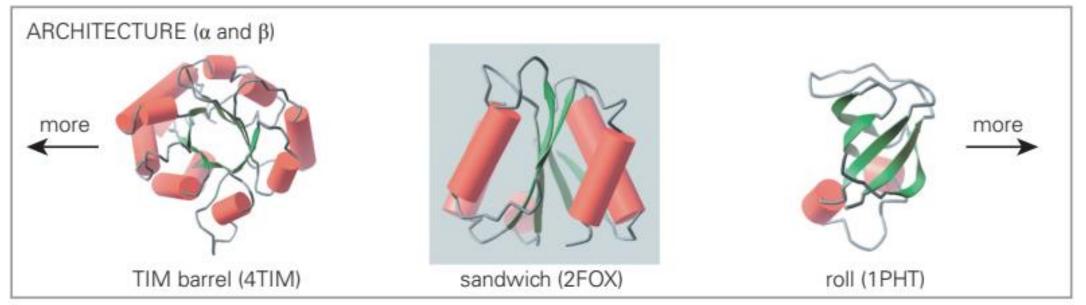


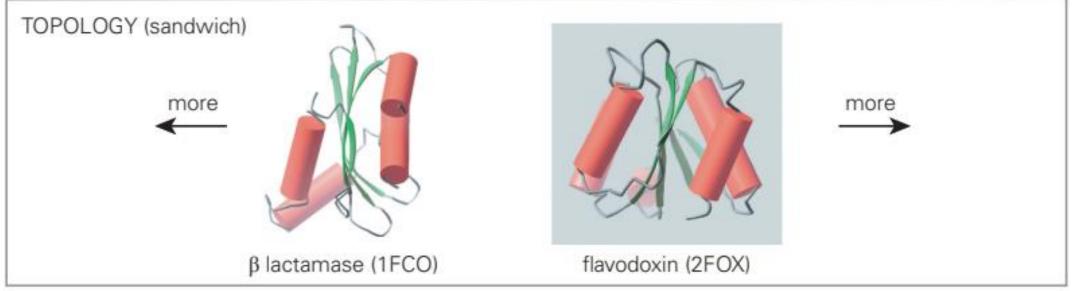
Conserved cores are often reused for different

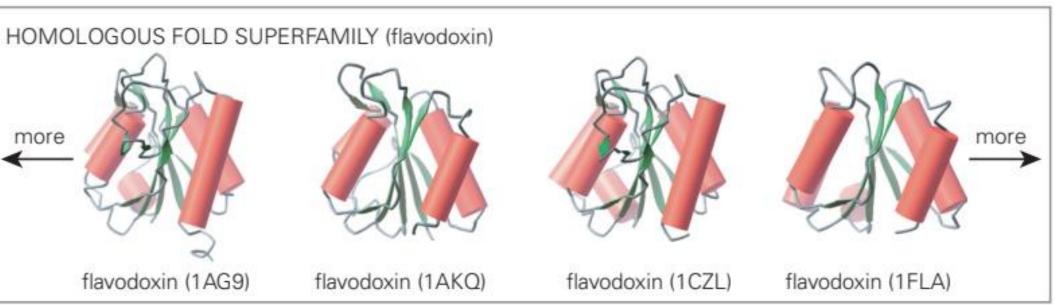




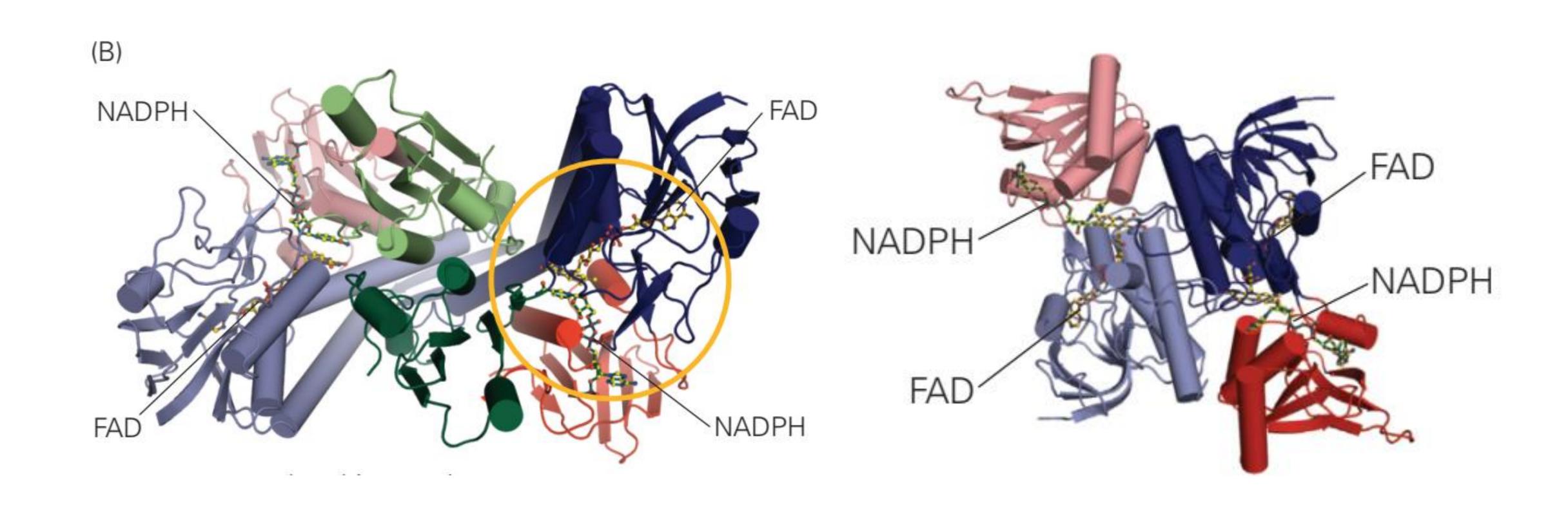




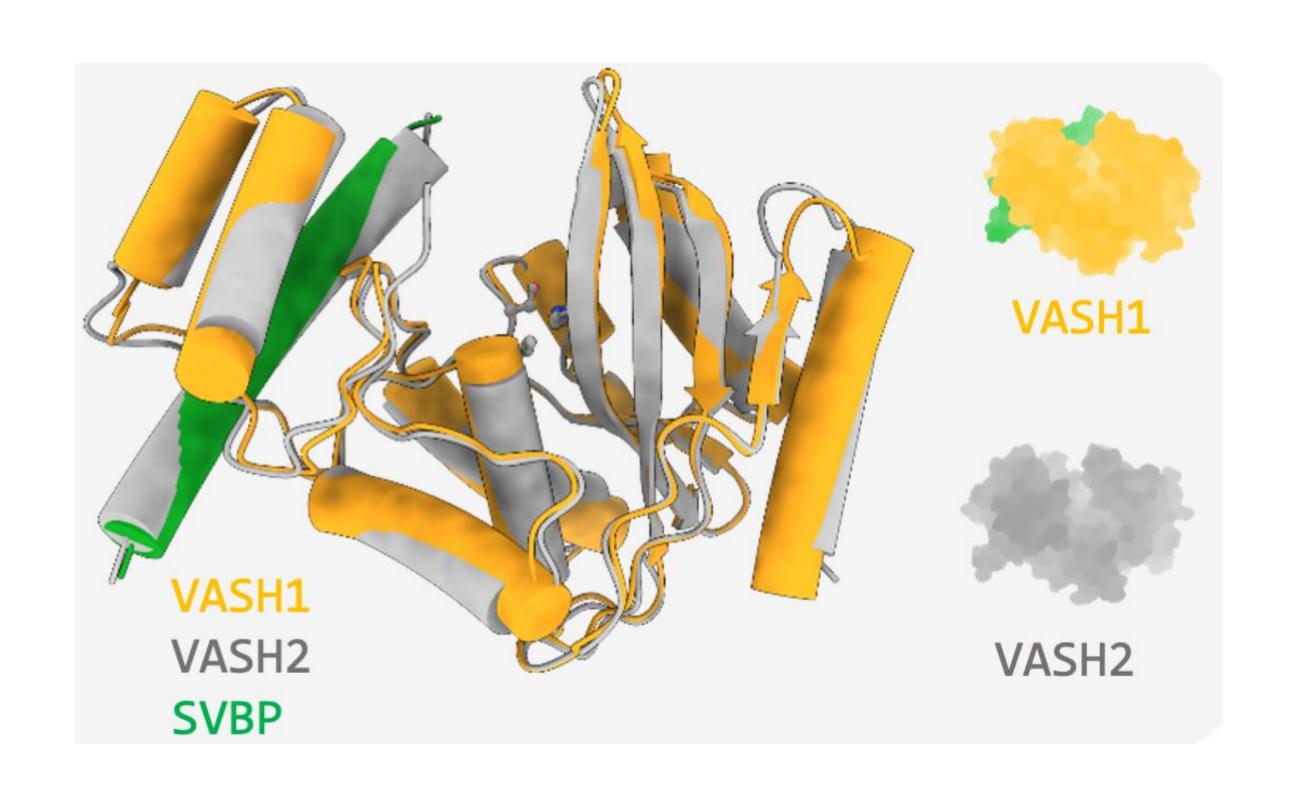


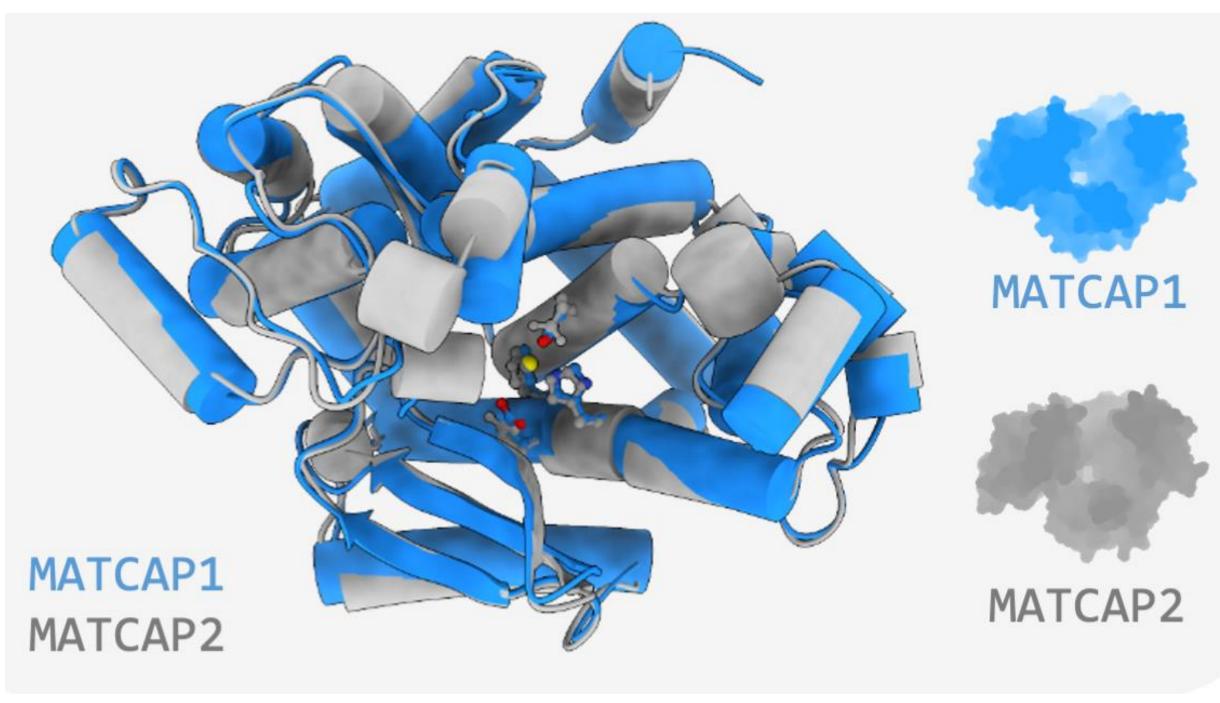


# The same function can be served by different folds: convergent evolution



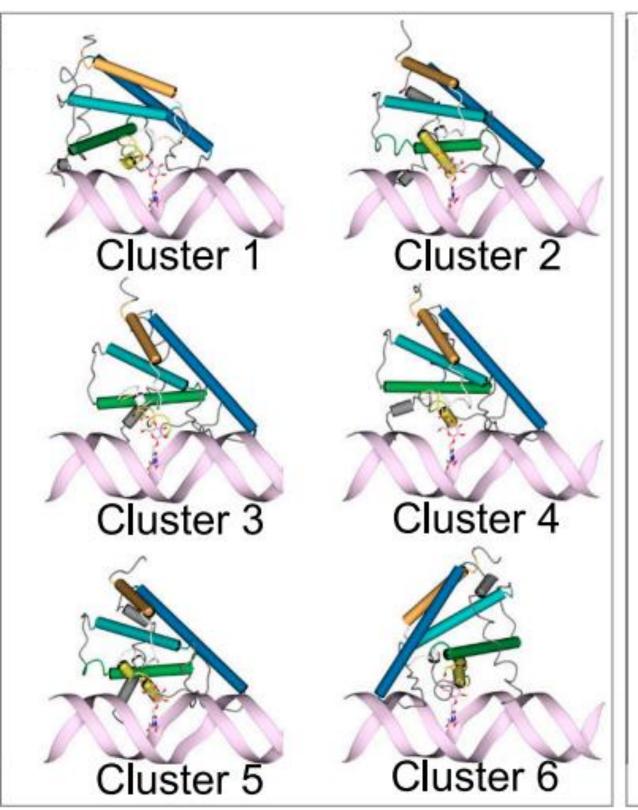
# The same function can be served by different folds: convergent evolution

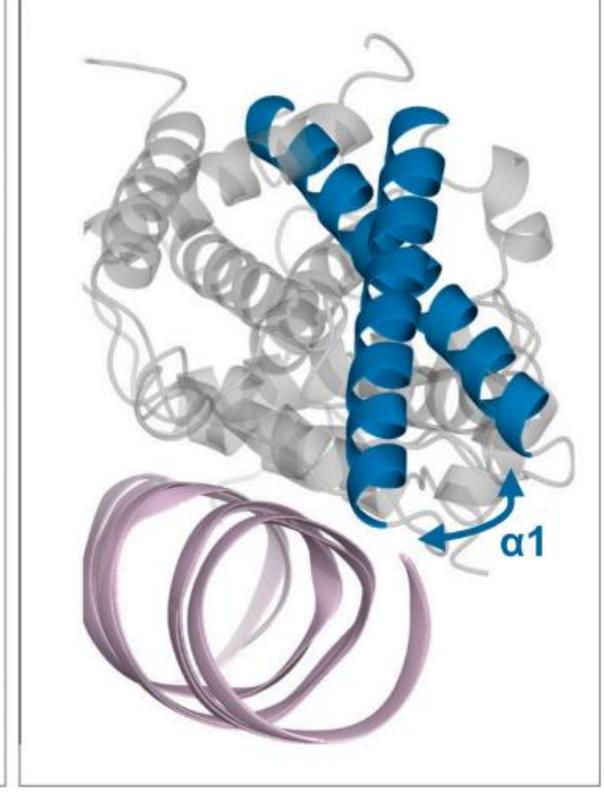




# Aligning (superposing) structures

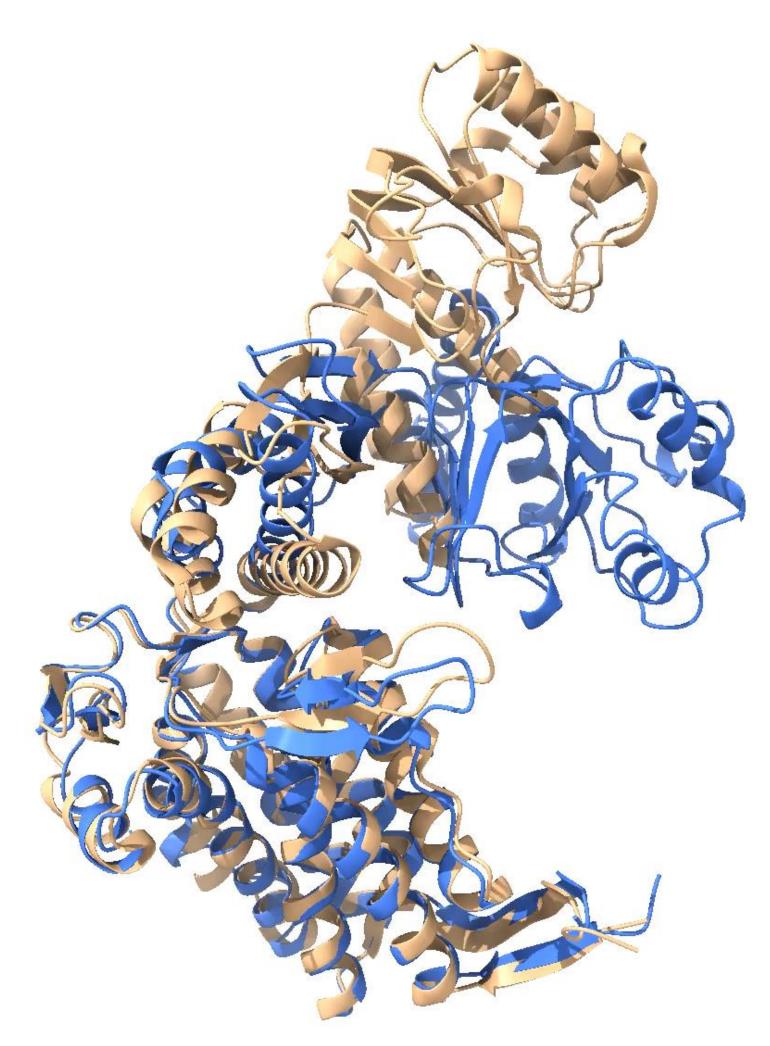
- Structure alignemnt is not identical to sequence alignment.
- Which one is preferred depends to the case study.
- Both can be informative.
- Automated structure alignments (e.g. Chimera-X "matchmaker" or Coot "SSM superpose") will align automatically two structures.
- You can show superposed structures seperately or overlapped.





# Aligning (superposing) multidomain proteins

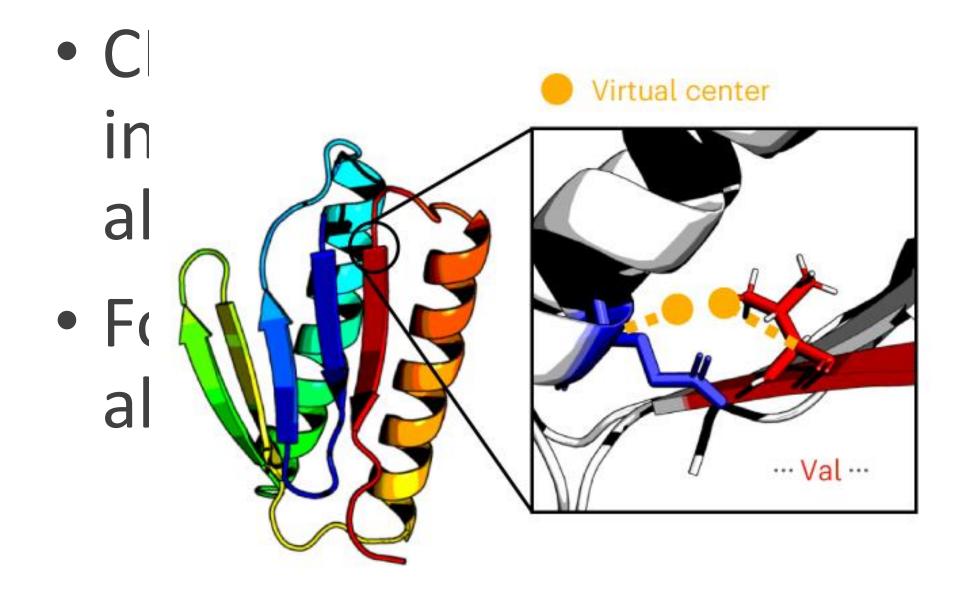
- Proteins are often put together by stiching together different domains.
- Domain movement needs to be taken into account during a structural alignment.
- Tools like RAPIDO, THESEUS, or [your brain] can be used to decide how to superpose.
- Superposition-independent structure comparisons are sometimes a good choice.

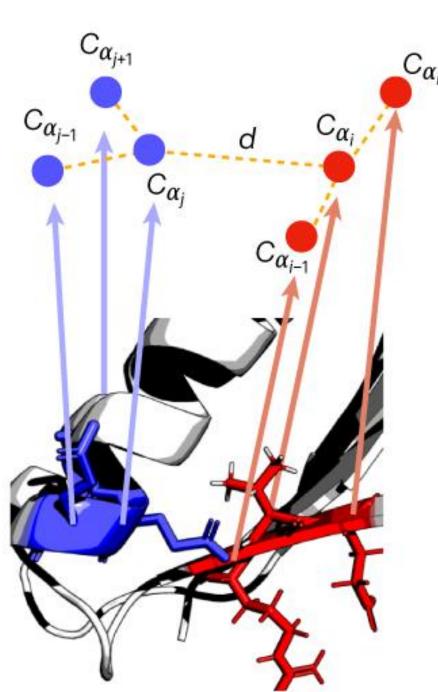


# Searching for structure similarity

• Looking for similar folds, regardless of sequence, can detect low similarity or cases that only a very small conserved core is conserved.

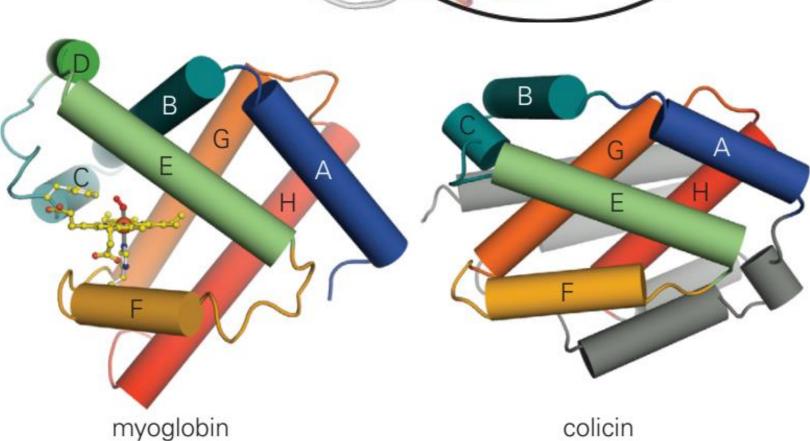
• DALI, CE, TM-align: iterative or stochastic optimisation of superpositions.





c<sub>α,,,</sub>conformations ence

uctu

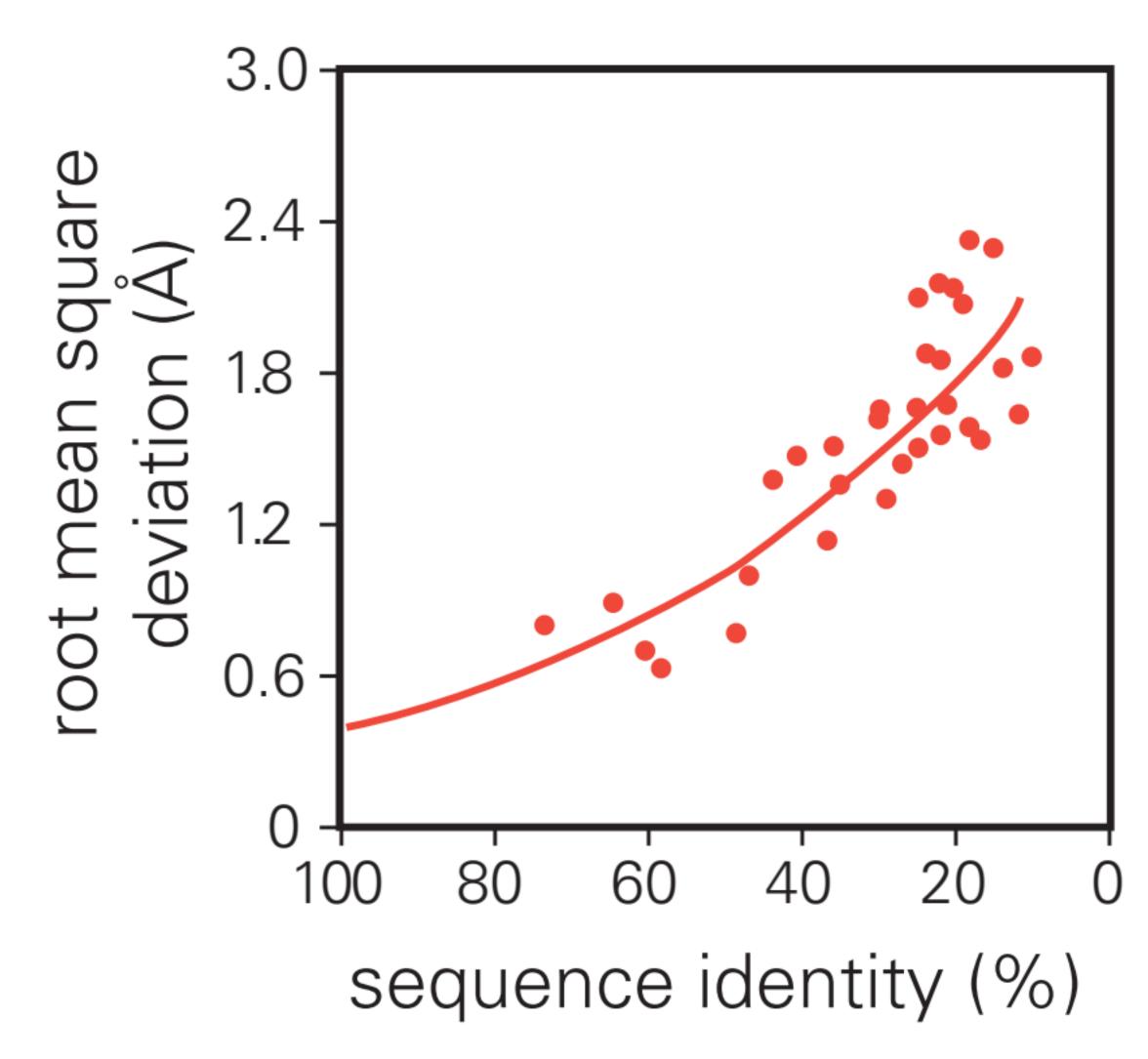


## Sequence and structure divergence

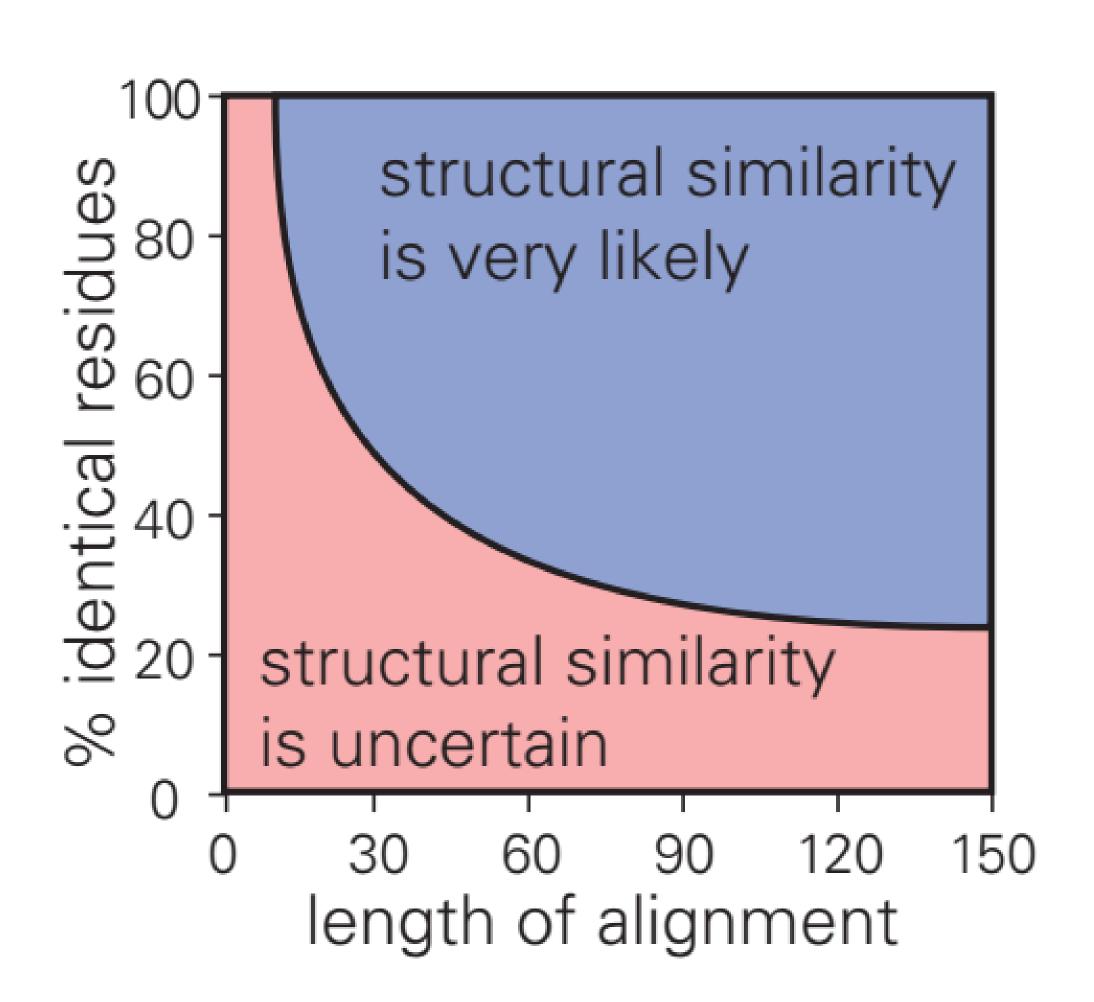
- Structure similarity can exist even with non-detectable sequence similarity.
- Structure similarity can exist even without homology
  - Homology: common evolutionary origin.
  - Similarity: based on amino-acid substitution matrix
  - Identity: what is says.
- Defining sequence similarity becomes complex in multi-domain proteins.
- Structure superpositions can help understand conservation.
- At what degree does sequence similarity guarantee structure similarity?

### Sequence and structure divergence

- A measure of the degree of structural overlap between two proteins is the root mean square (rms) deviation in the positions of  $C\alpha$  atoms in the common core between the two structures.
- The rms deviation should be calculated using residues within the common core, to be meaningful.
- Proteins that are related by ~50% or more sequence identity have common cores that are structurally very similar, with rms deviations that are less than ~1 Å.
- The rms deviation in backbone positions rises steadily as the level of sequence identity drops, and the deviations can exceed 2Å when the two proteins being compared share less than 20% sequence identity.



# How much can we tell about structure from sequence?

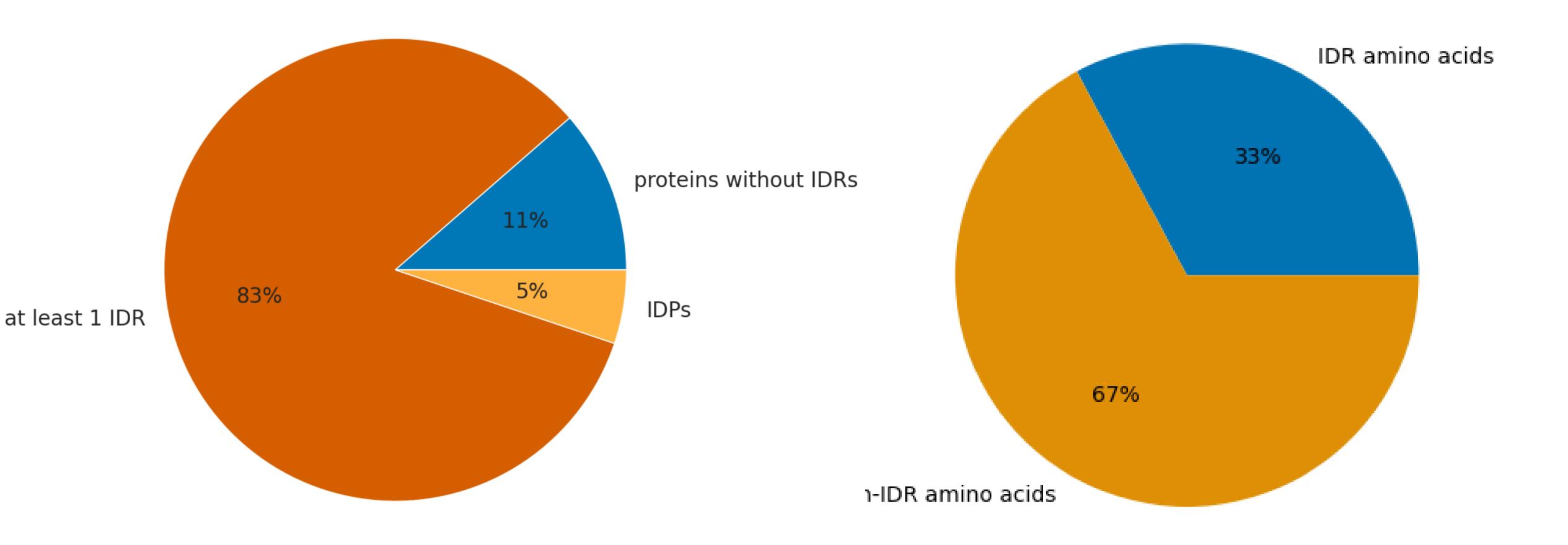


- ■Sequence comparisons become more informative when the lengths of the segments being compared are ~50 residues or greater.
- ■Similarity is virtually assured when the sequence identity between longer segments is greater than ~25%.
- ■Proteins that are related by less than ~25% sequence identity can have significantly different three-dimensional structures.

# Intrinsincly disordered proteins & residues

Proteins in the dataset (20,038 in total)

Amino acids in the dataset 10494750 in total)



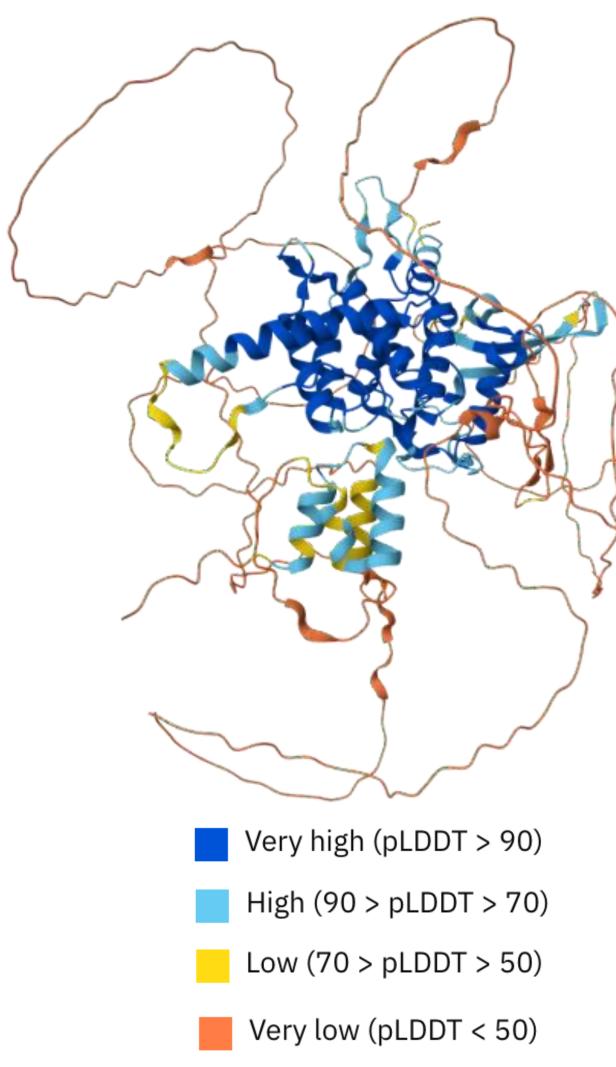
# Al redefines the limits on the information that can be extracted from sequences.

- AlphaFold3 and RosettaAllAtoms do an outstandign job modeling structures from sequence, even with shockingly little similarity.
- All these program learned from the public, free PDB data that costed billions to create and costs millions of public money to extend and maintain.
- You must however, be very critical on what you do with predicted models.

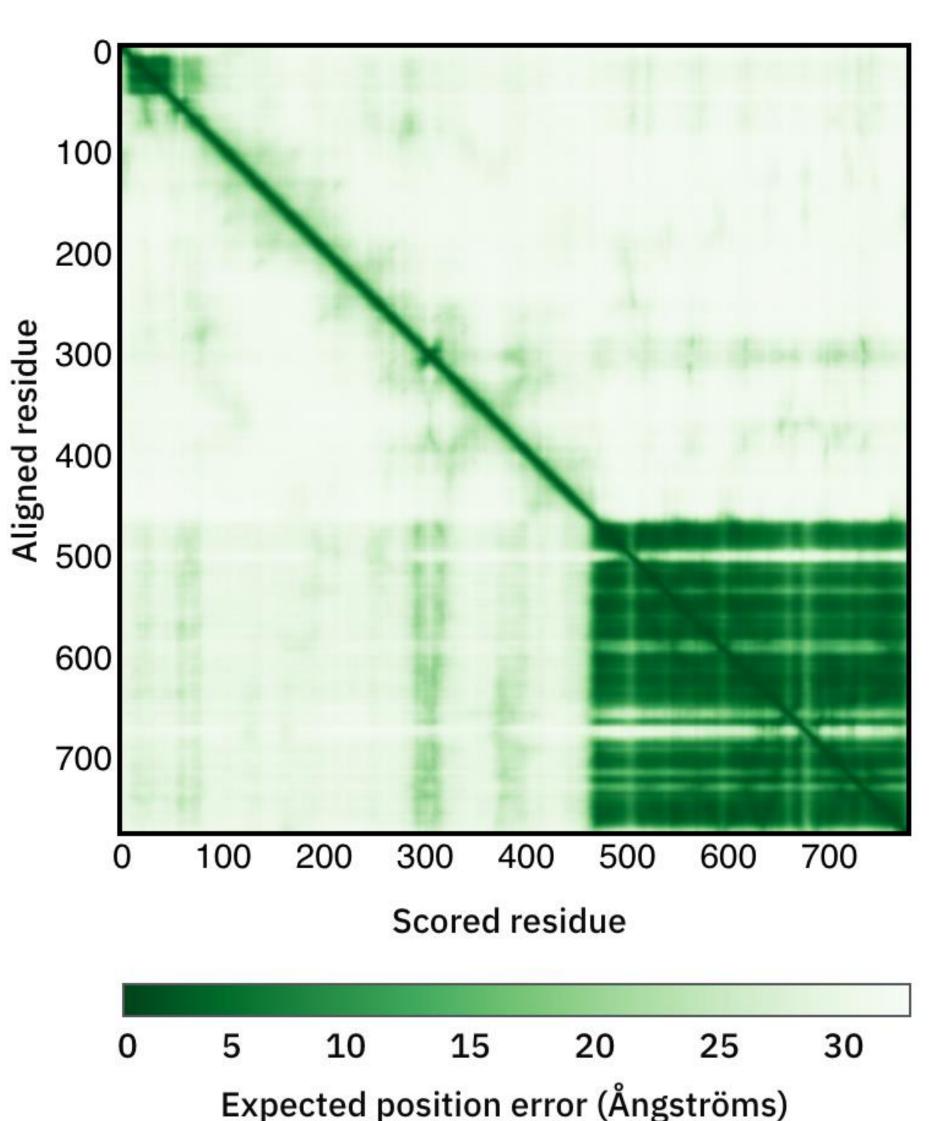
• AlphaFold3 provides excellent validation criteria.

### pLDDT:predicted local distance difference test

- AlphaFold produces a per-residue estimate of its confidence on a scale from 0 100. This confidence measure is called pLDDT
- AlphaFold models are colored by pLDDT
  - Regions with pLDDT > 90 are expected to be modelled to high accuracy. These should be suitable for any application that benefits from high accuracy (e.g. characterising binding sites).
  - Regions with pLDDT between 70 and 90 are expected to be modelled well (a generally good backbone prediction).
  - Regions with pLDDT between 50 and 70 are low confidence and should be treated with caution.
  - The 3D coordinates of regions with pLDDT < 50 often have a ribbon-like appearance and should not be interpreted.



# PAE: predicted alignment error



- The colour at (x, y) indicates AlphaFold's expected position error at residue x if the predicted and true structures were aligned on residue y.
- PAE within a structural core domain will be low (dark green)
- If the PAE is generally low for residue pairs x, y from two different domains, it indicates that AlphaFold predicts well-defined relative positions and orientations for them.
- If the PAE is generally high for residue pairs x, y from two different domains, then the relative positions and/or orientations of these domains in the 3D structure are uncertain and should not be interpreted.
- The PAE x-y is not the same as y-x

# On the asymmetry of the PAE matrix



- From the perspective of the lighthouse the position of the boat cannot be accurately determined
- From the perspective of the boat the position of the lighthouse is clear.



### What does the model tell us?

#### The importance of PAE plots

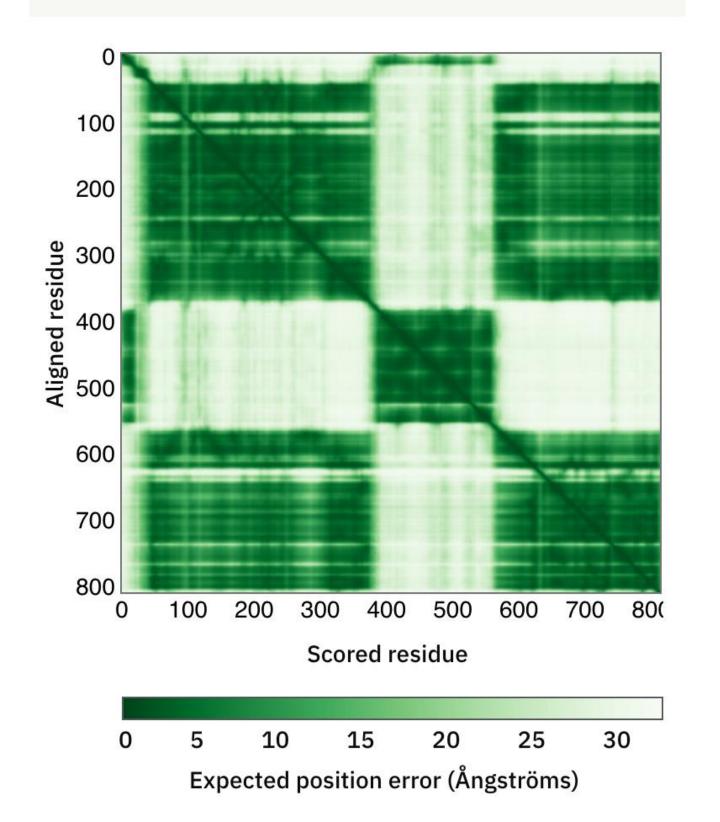
Thymidine Hydroxylase

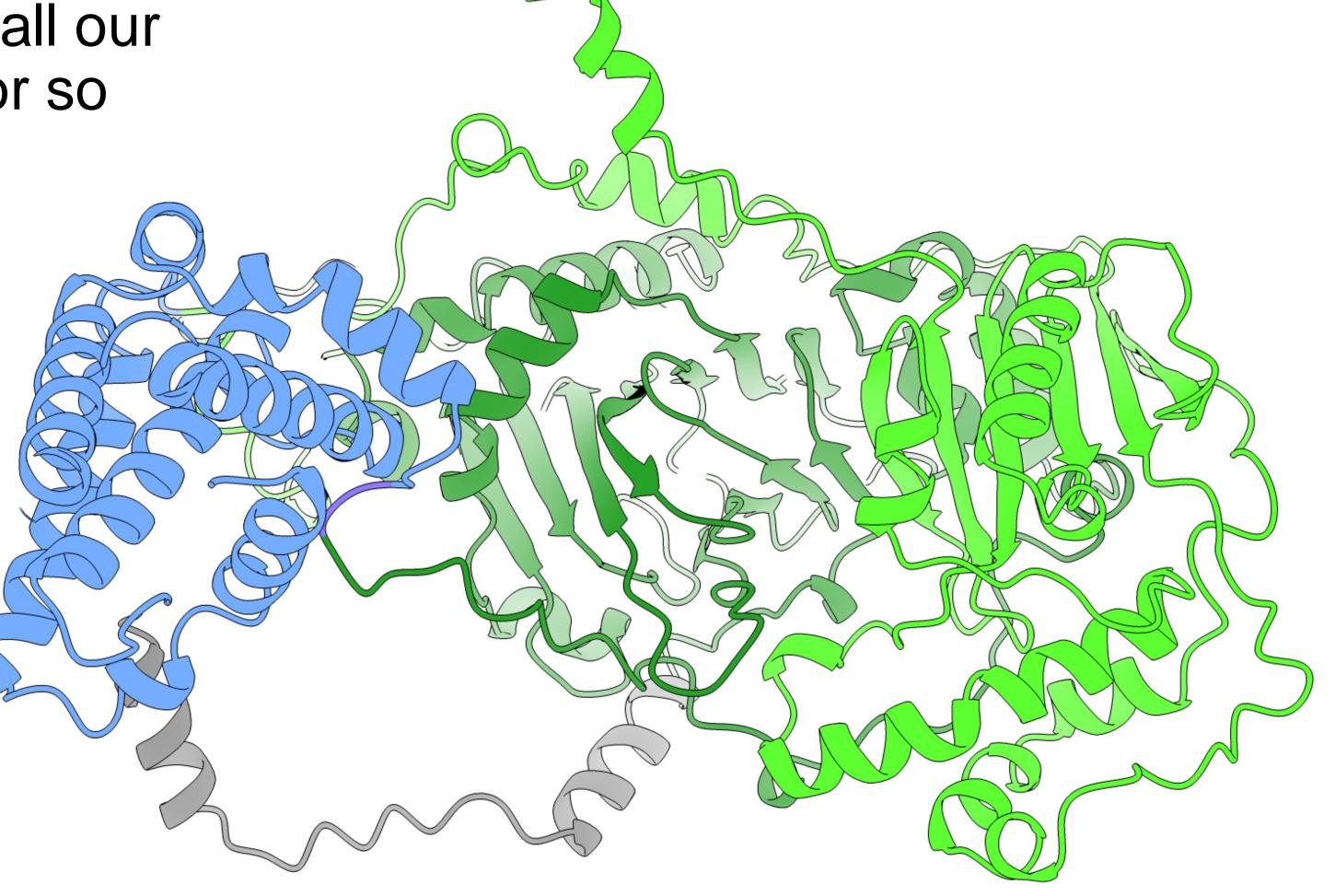
DBD

TH

 AlphaFold model confirms all our work for the last 15 years or so

Predicted aligned error (PAE)





### Are predictions enough?

#### No. You still need experiments

JBP1 is an Fe-dependent thymidine hydroxylase.

Where is the iron?

Published Online: 16 June, 2023 | Supp Info: http://doi.org/10.26508/lsa.202302150 Downloaded from life-science-alliance.org on 15 May, 2024

#### Research Article

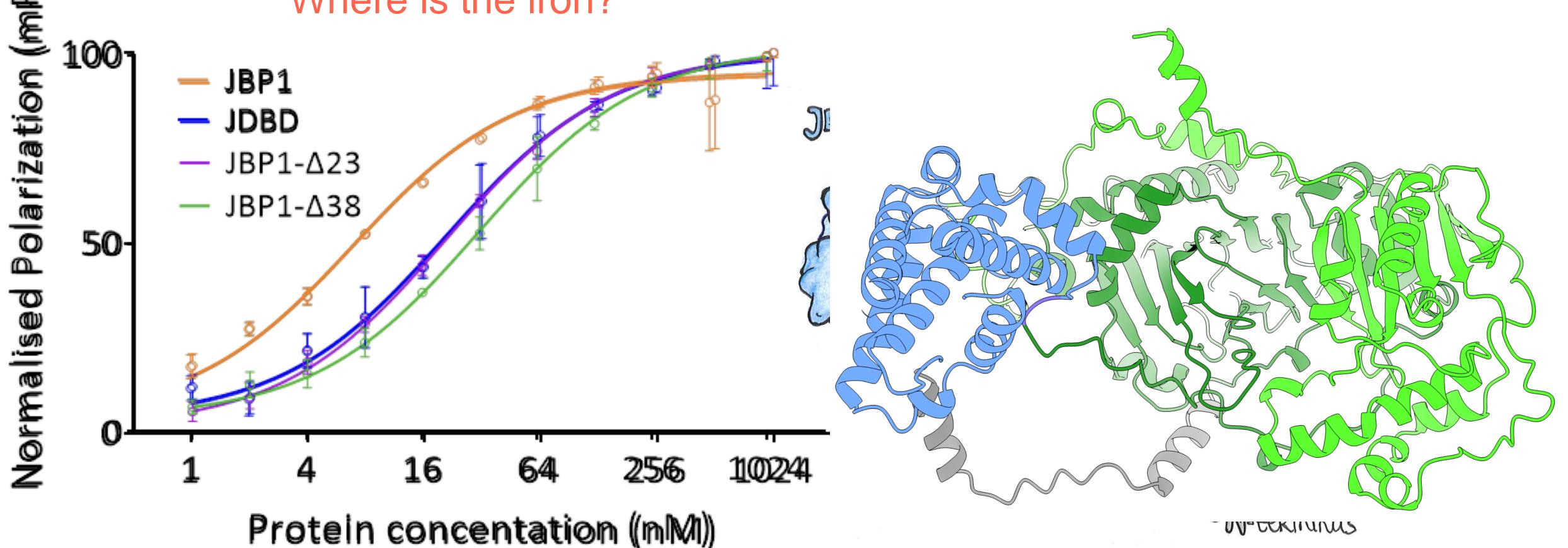






#### Distant sequence regions of JBP1 contribute to J-DNA binding

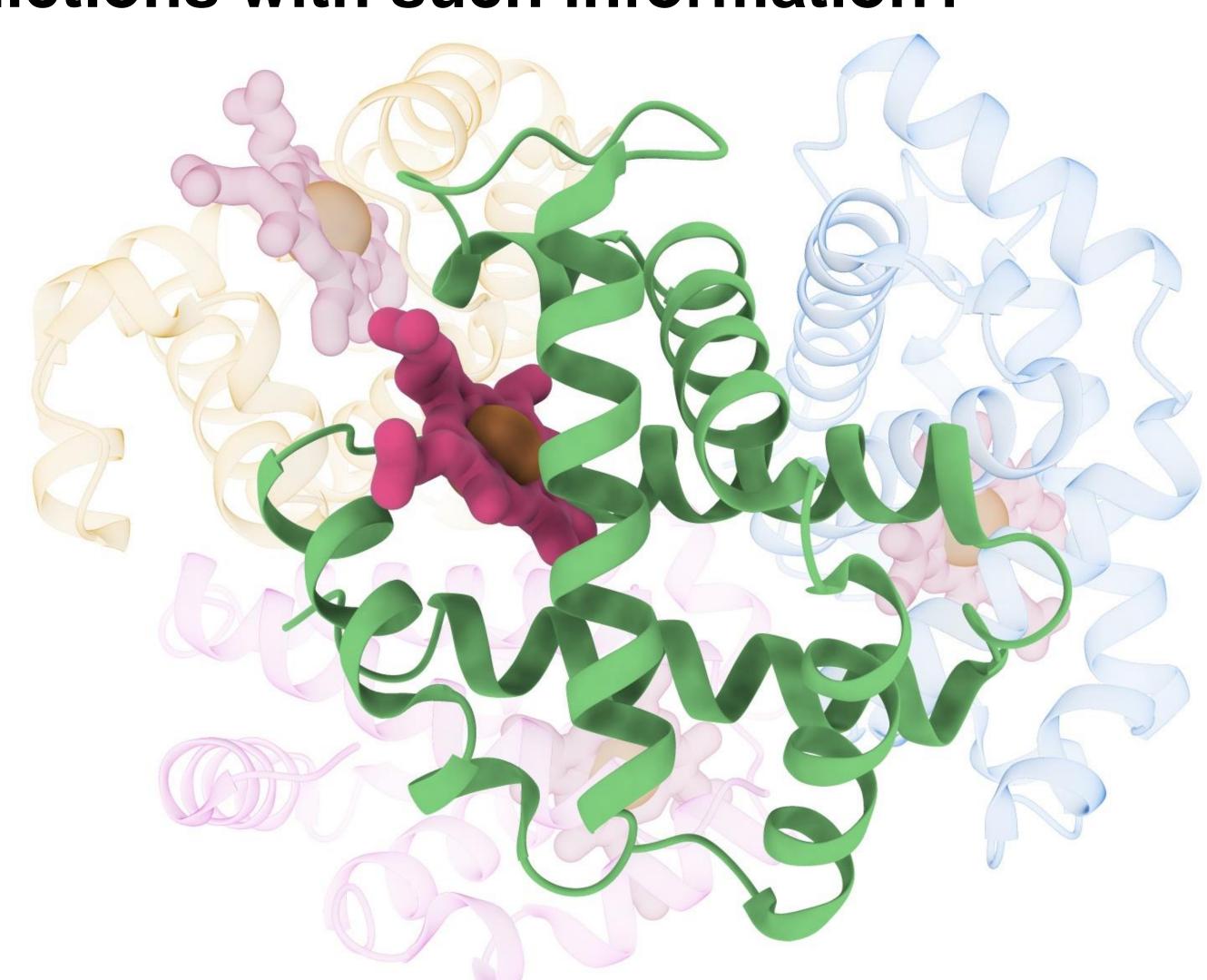
Ida de Vries<sup>1</sup>, Danique Ammerlaan<sup>1</sup>, Tatjana Heidebrecht<sup>1</sup>, Patrick HN Celie<sup>1</sup>, Daan P Geerke<sup>2</sup>, Robbie P Joosten<sup>1</sup>, Anastassis Perrakis<sup>1</sup>



### Things are missing from protein structure predictions?

#### ... how do we enrich these predictions with such information?

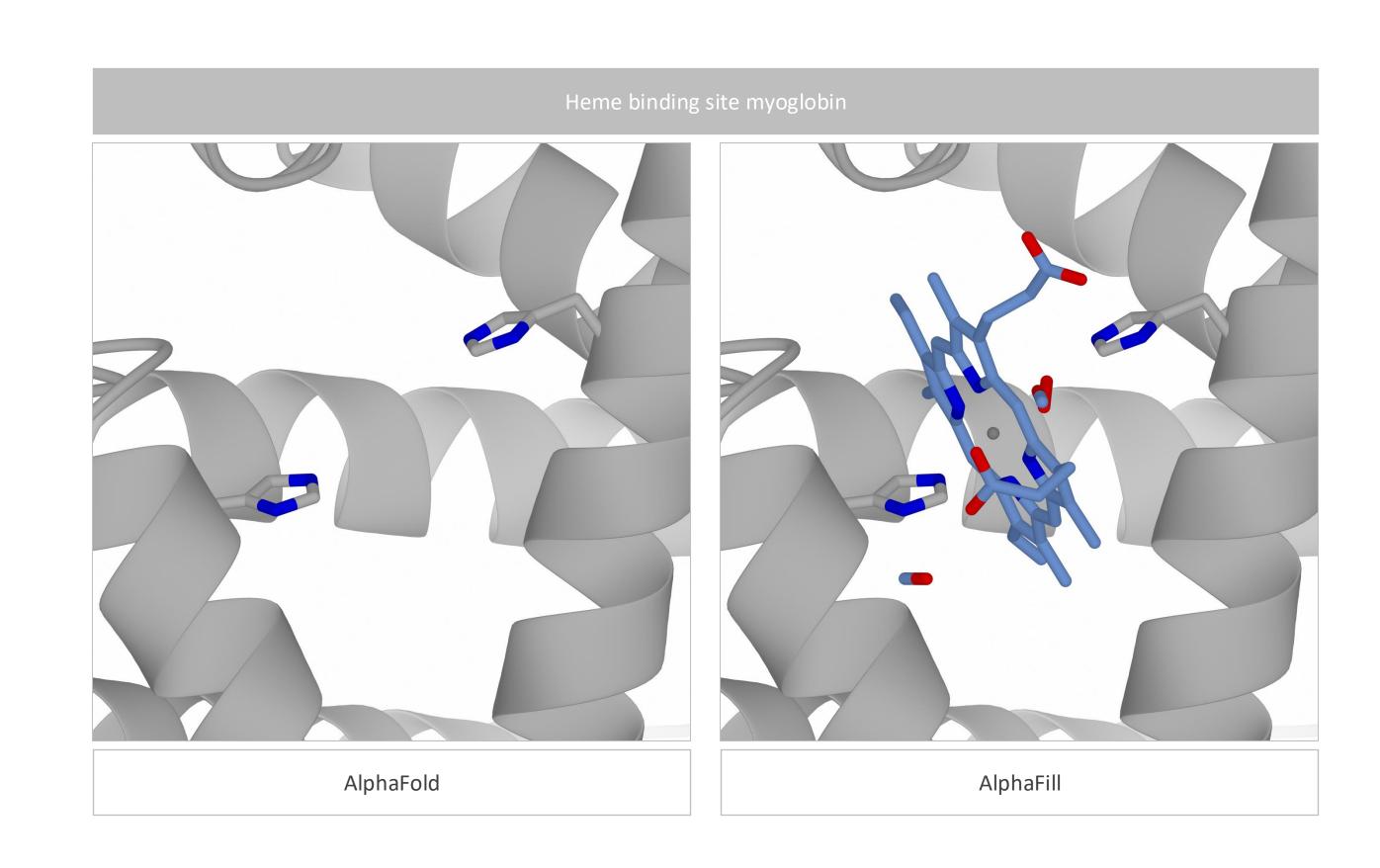
- Proteins miss heir conactors
- There is no point ion on ligands
- Multimers are models monomers
- There be by a great in the PB
- Can we transpurptig no form the PDB to Alph Fold model



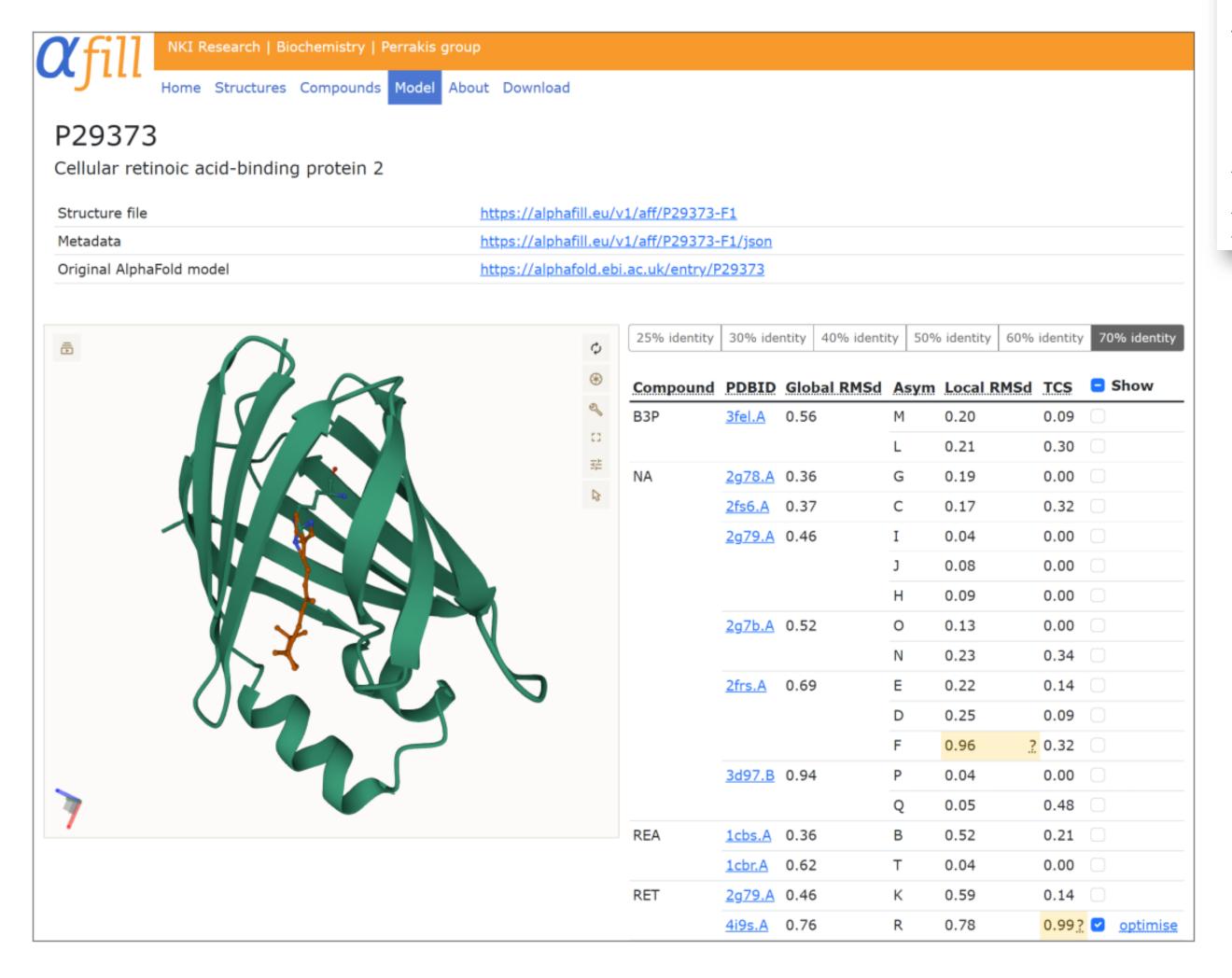
### A summary of the AlphaFill resource

#### Using AlphaFold DataBase June 2022

- Apply to the AlphaFold database: 995k predicted protein structures
  - Model organism proteomes
  - Proteomes relevant to global health
  - Swiss-Prot
- AlphaFill:
  - 586k AlphaFold models with transplants
  - 12 million transplanted compounds
- All the recently added AlphaFold models will be generated "on the fly"



## The AlphaFill databank



#### nature methods



Resource

https://doi.org/10.1038/s41592-022-01685-y

# AlphaFill: enriching AlphaFold models with ligands and cofactors

Received: 10 December 2021

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Accepted: 18 October 2022

Anastassis Perrakis **©** <sup>1,3</sup> ⊠

NKI Research | Blochemistry | Perrakis group
Home Structures Compounds Model About Download

P29373
Ligand RET (RETINAL) with identifier R optimized with Yasara

Structure file https://alphafill.eu/v1/aff/P29373-F1/optimized/A.R

Original Optimised
Transplant clash score (Å) 0.99 0.29

#### Does JBP1 now have its Fe?

No.

AlphaFill depends on the existence of homologous structures.



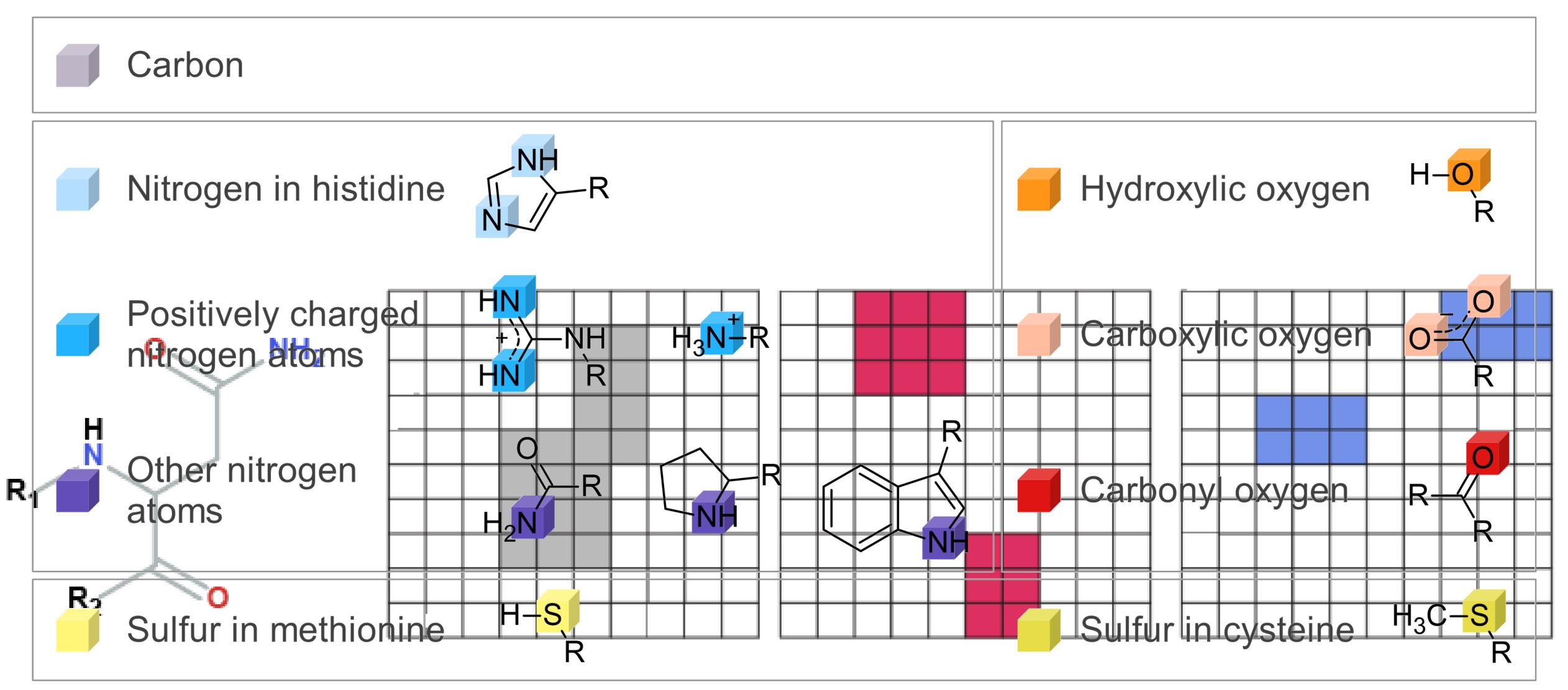
#### AlphaFill is based on homologous structures

#### Can we go beyond that?

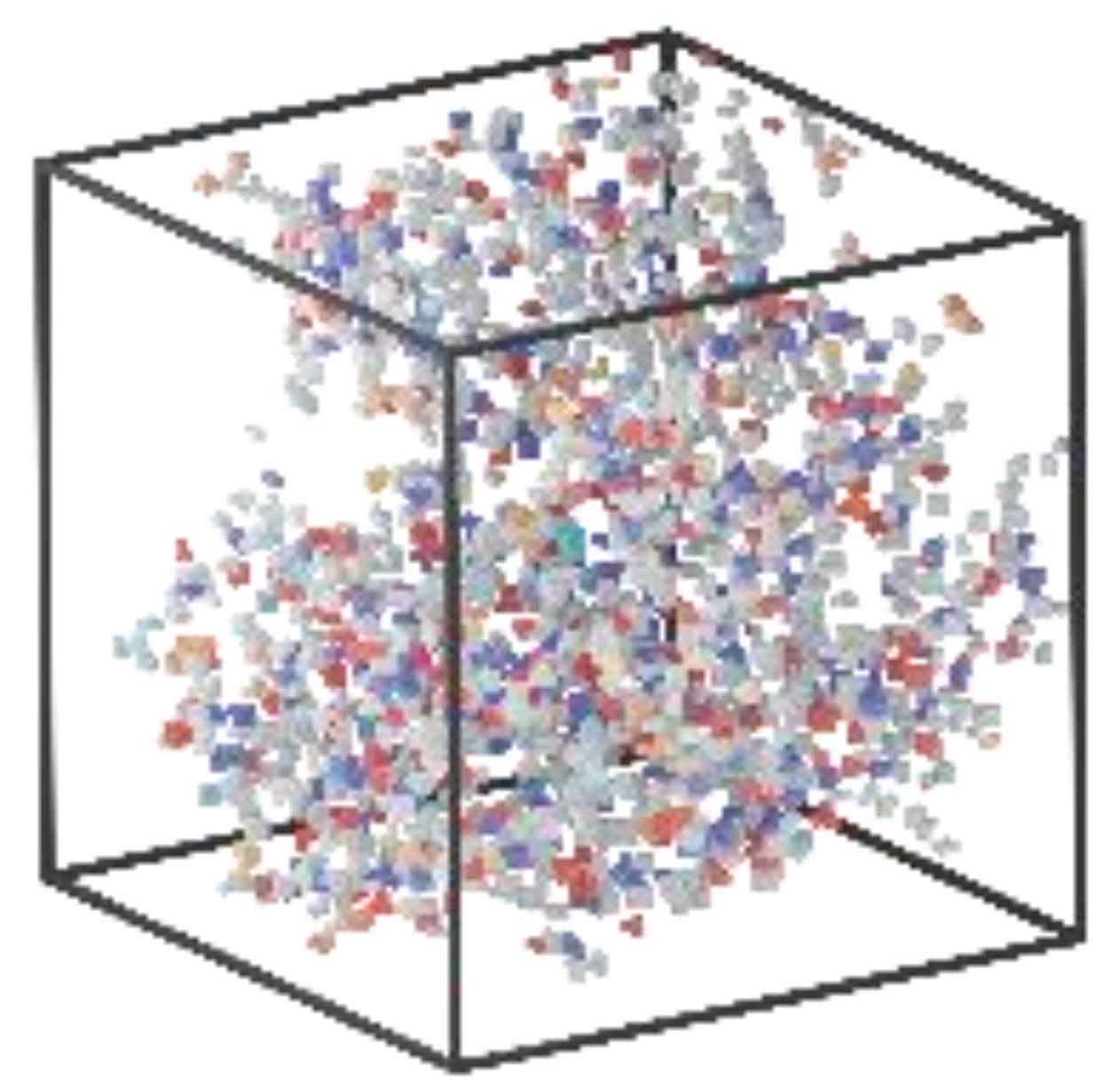
- We have thousand of ligand-binding events in experimental structures.
- And AlphaFill offers even more such reliable observations.
- Can we train an AI to learn what defines binding of specific ligands?
- ... at least for an easy case, e.g. for metals
  - no rotational and conformational freedom
- and while doing that think of what defines ligand binding?

### How should we describe a protein to an Al?

Why not as an image?

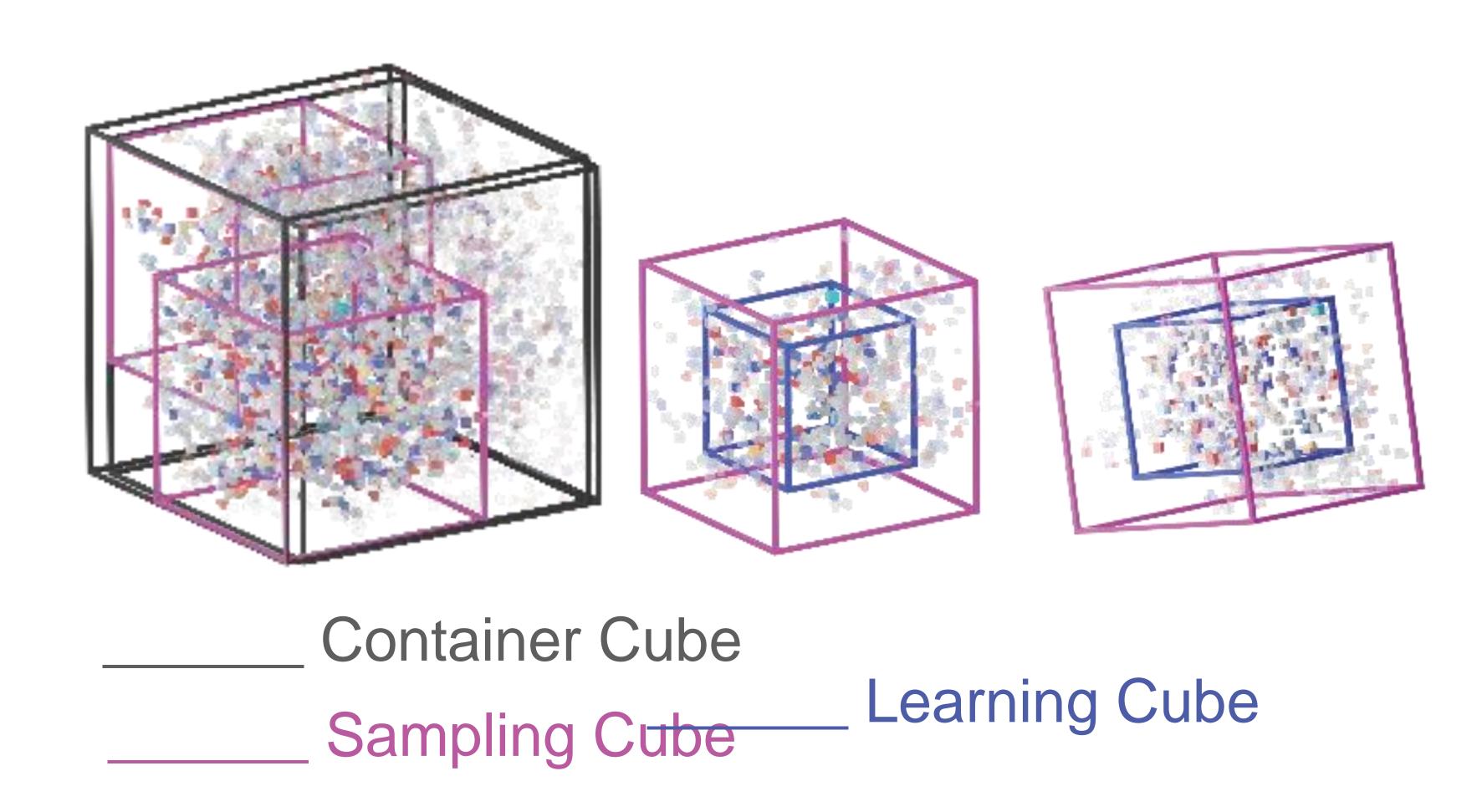


## A whole protein as a 3D "color"-image



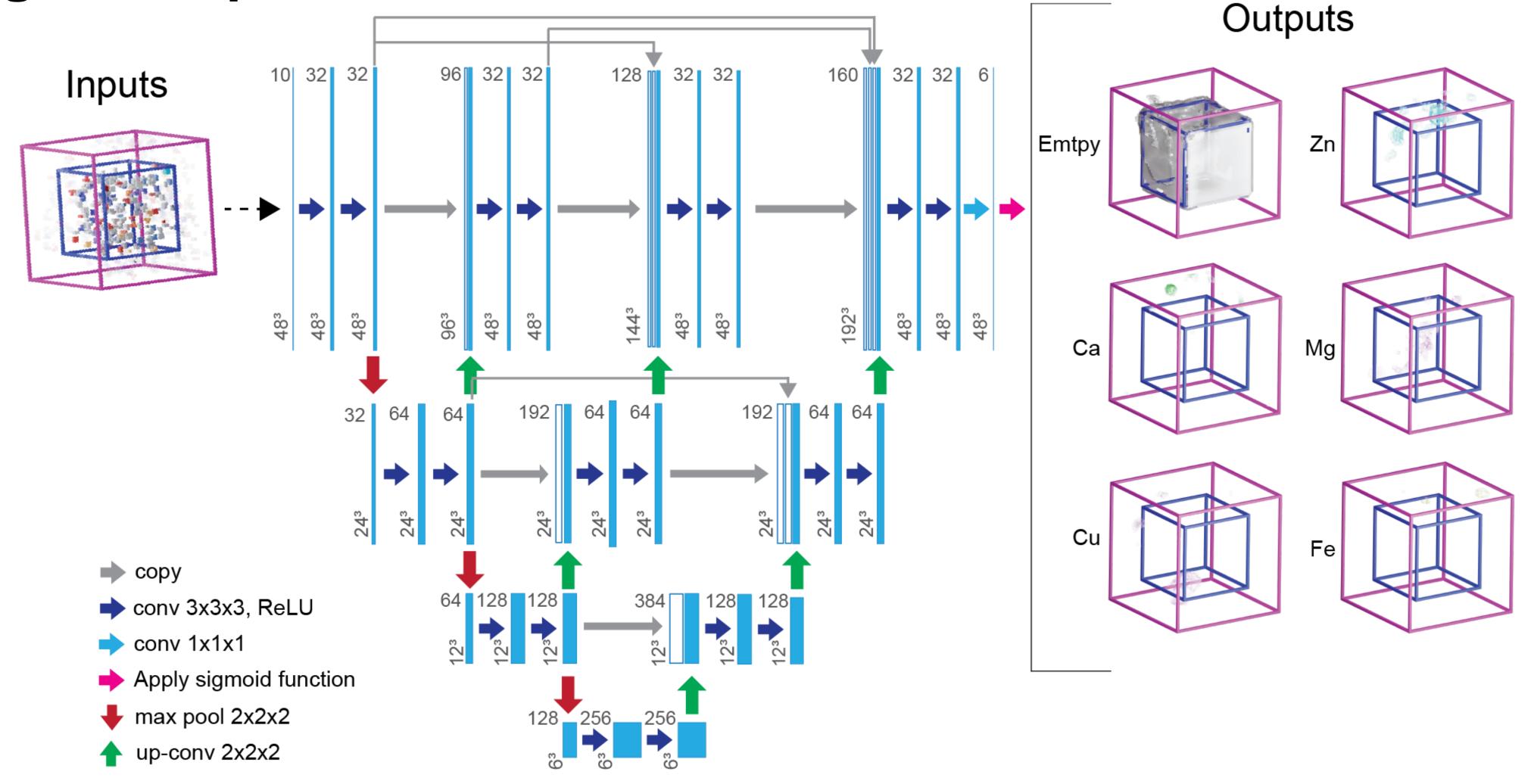
## Tricks and tips to learn in 3D

Pretty standard in image recognition Al



#### Learning to recognize metals in protein images

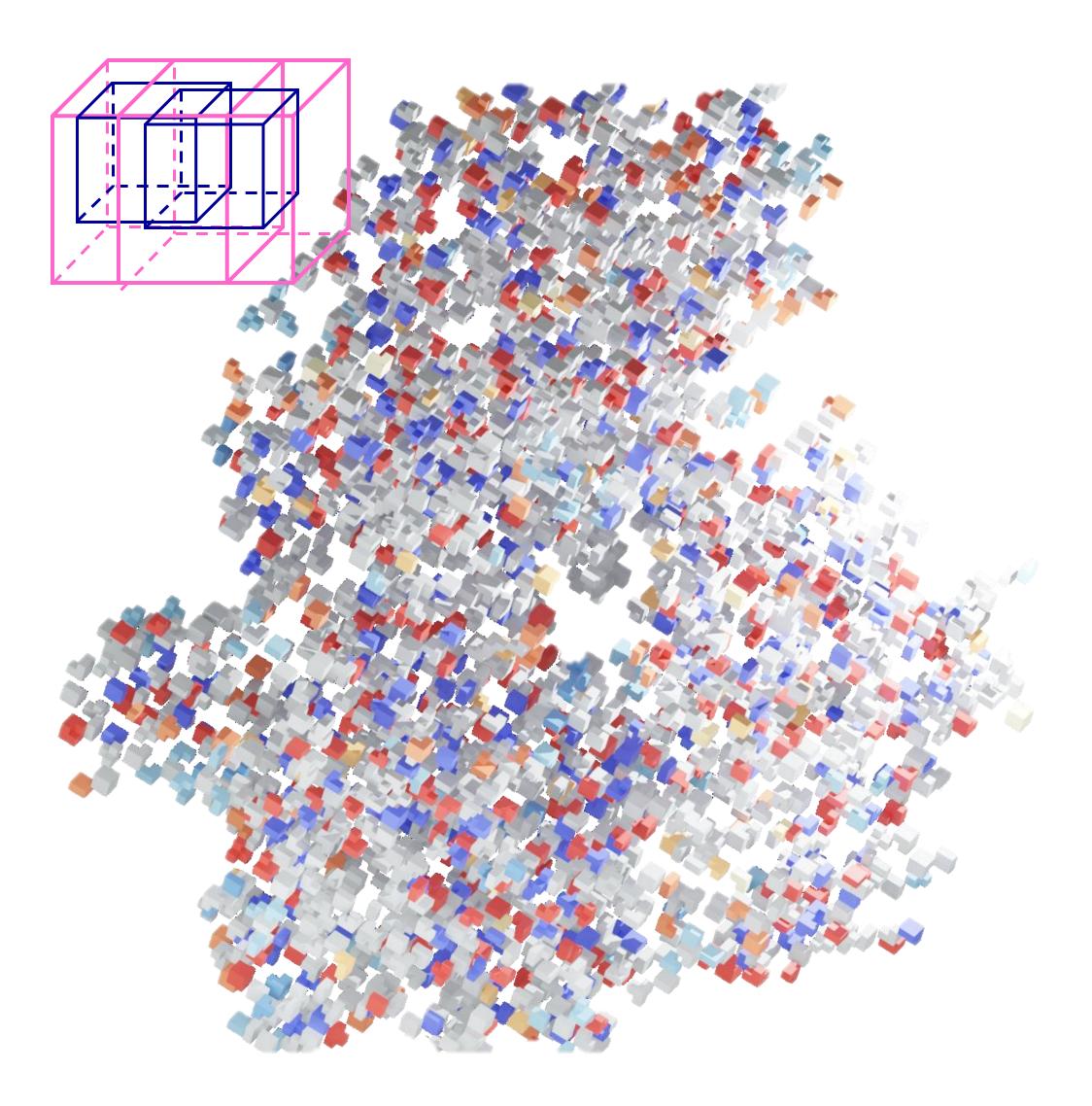
Using an adapted UNET++



## Metal prediction using Al

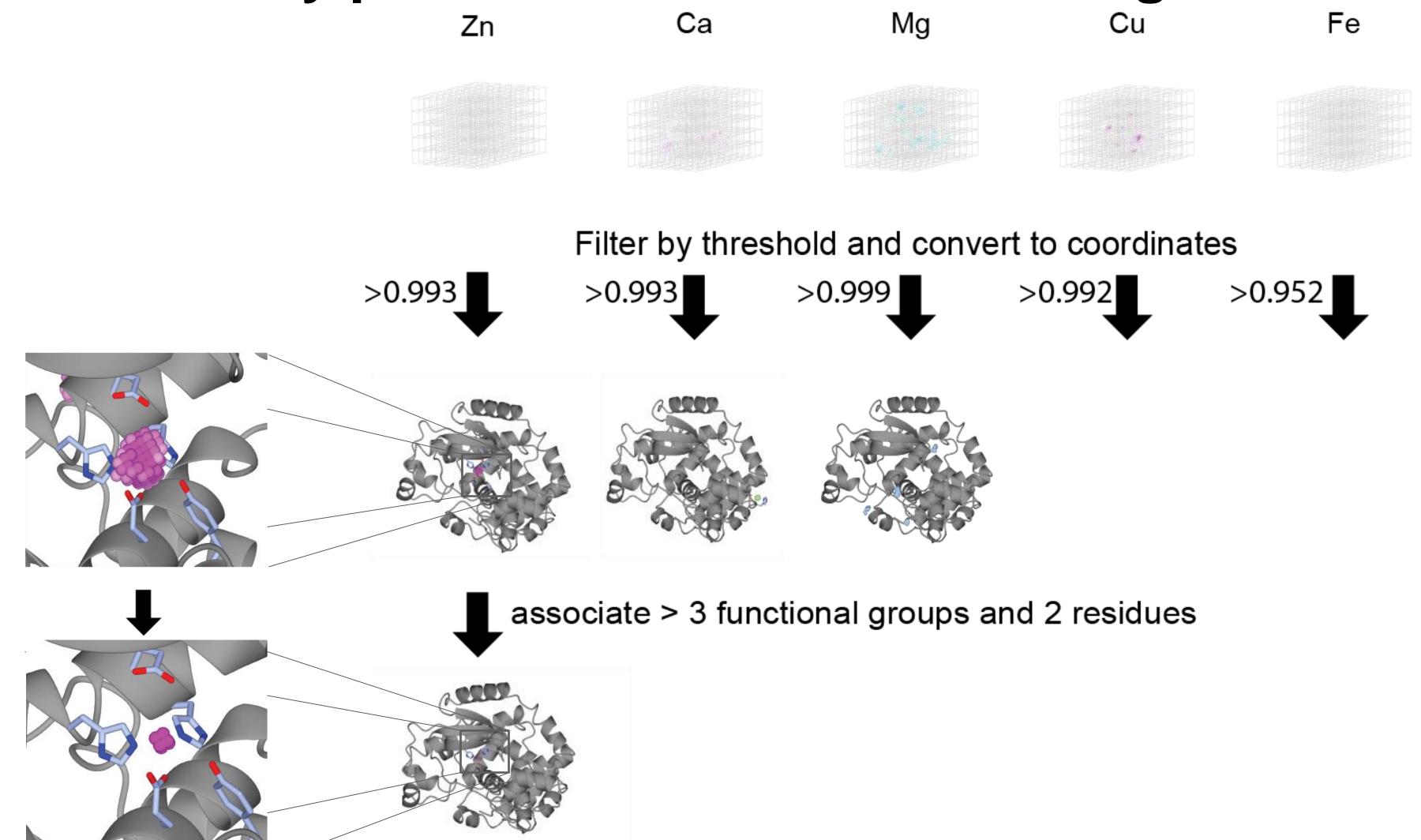
#### Scanning the target

- Start with simplest case: metal ions
  - Most common: Zn, Mg, Ca, Fe, Cu
- Provide chemistry to the computer
- Learn what a metal binding site looks like
- Find metal binding sites in proteins



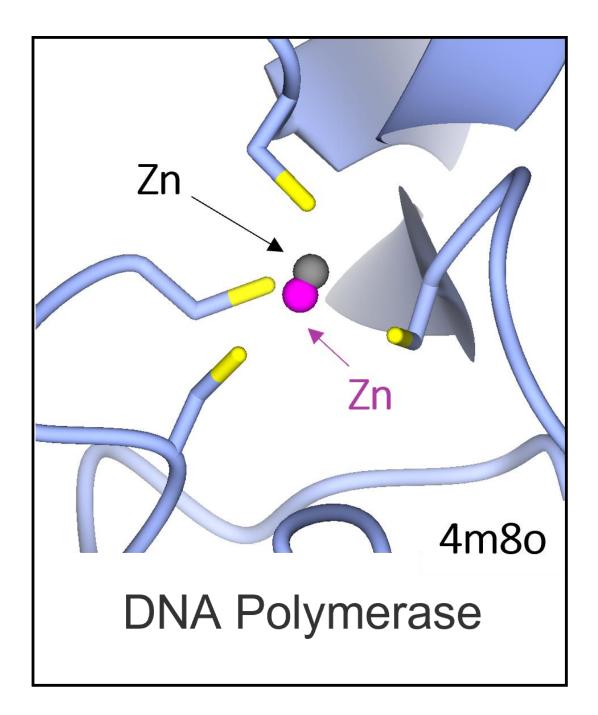
## Post-processing by probability

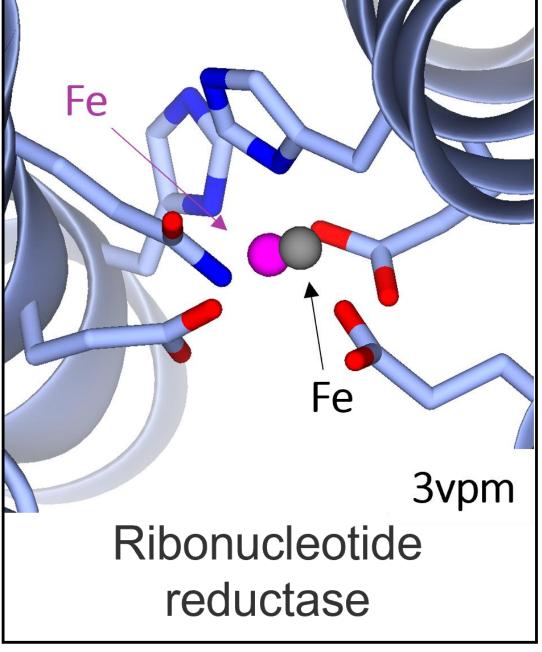
Filter results by probabilities and surroundings

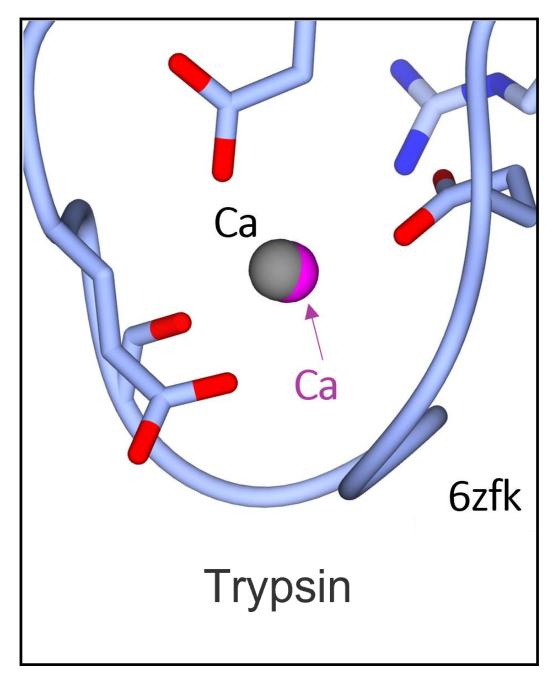


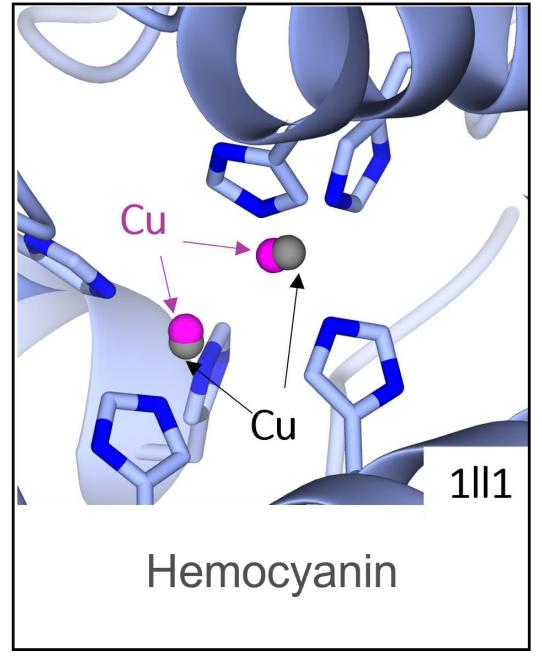
### Finding Metals

#### In PDB structures of the "left-out" validation set





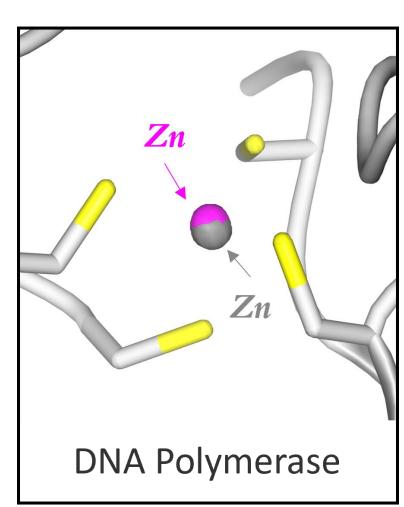




## Overall performance

	Zn	Ca	Mg	Cu	Fe
Known metal binding sites	27	13	19	20	12
Re-discovered	26	12	16	19	10
Not discovered	1	1	3	1	2
Newly discovered	5	4	14	2	3

Re-discovered

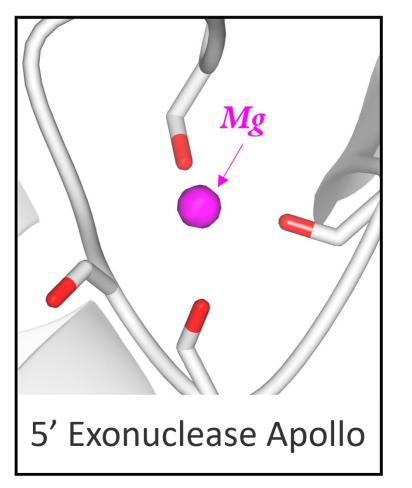


Newly discovered

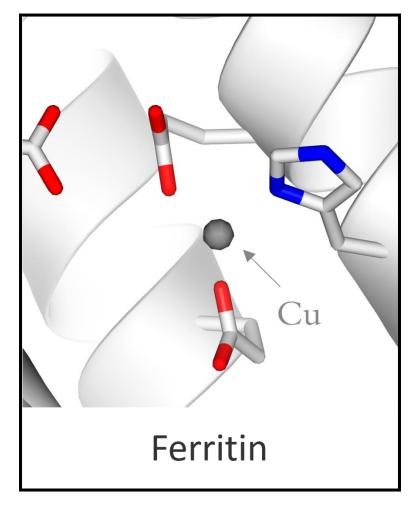
Miss-identified

Oxidase

False positive



Not discovered

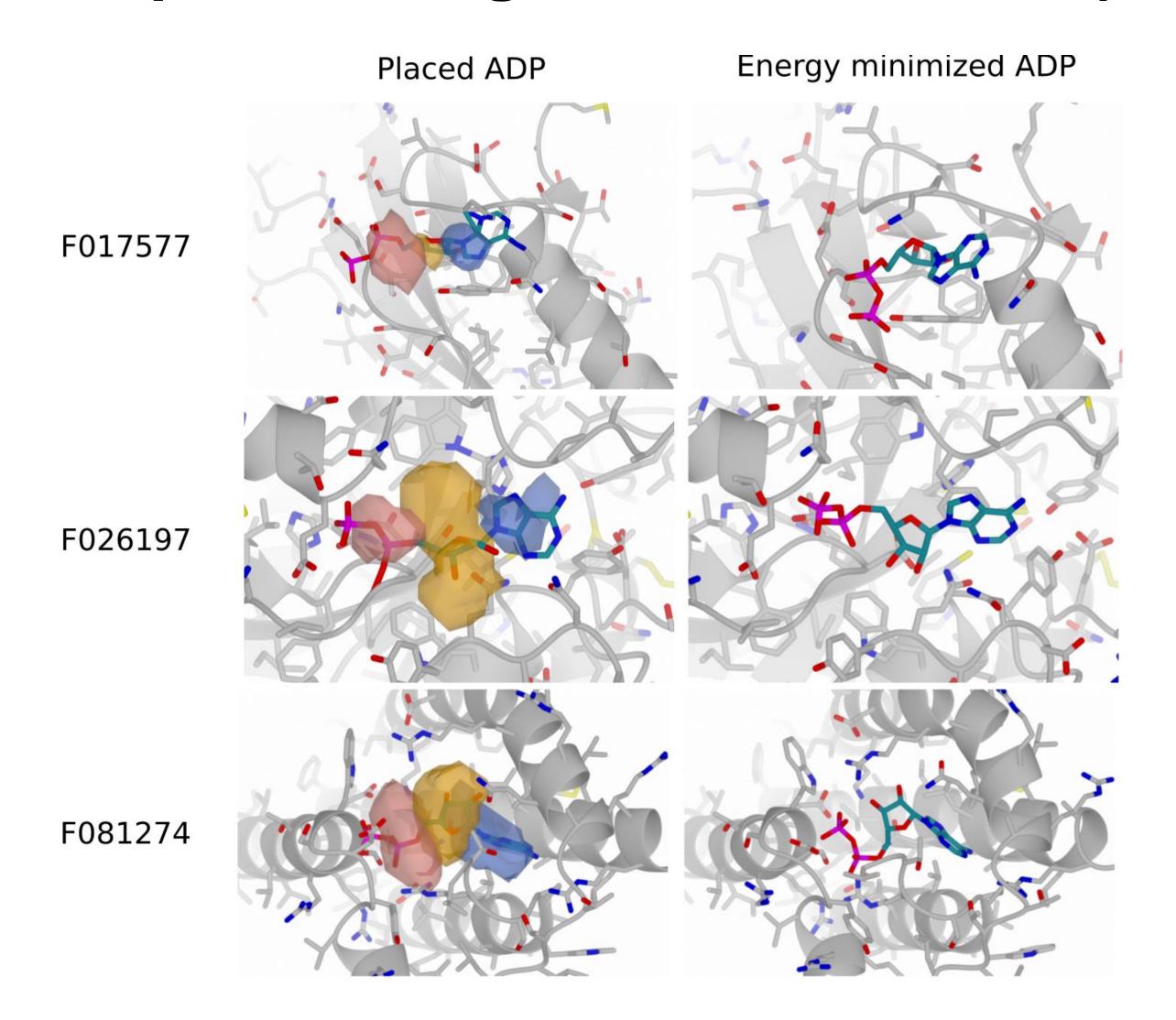


Metal ion in PDB-REDO

Metal ion predicted by neural network

## Finding more complex blocks

#### Phosphates, sugars, nucleobases (to build nucleotide)



	Nucleotide prediction
Total tested	1365
Re-discovered	710
Not discovered	655
Newly discovered	157

## Can we find new things?

#### Test in metagenome database of new folds

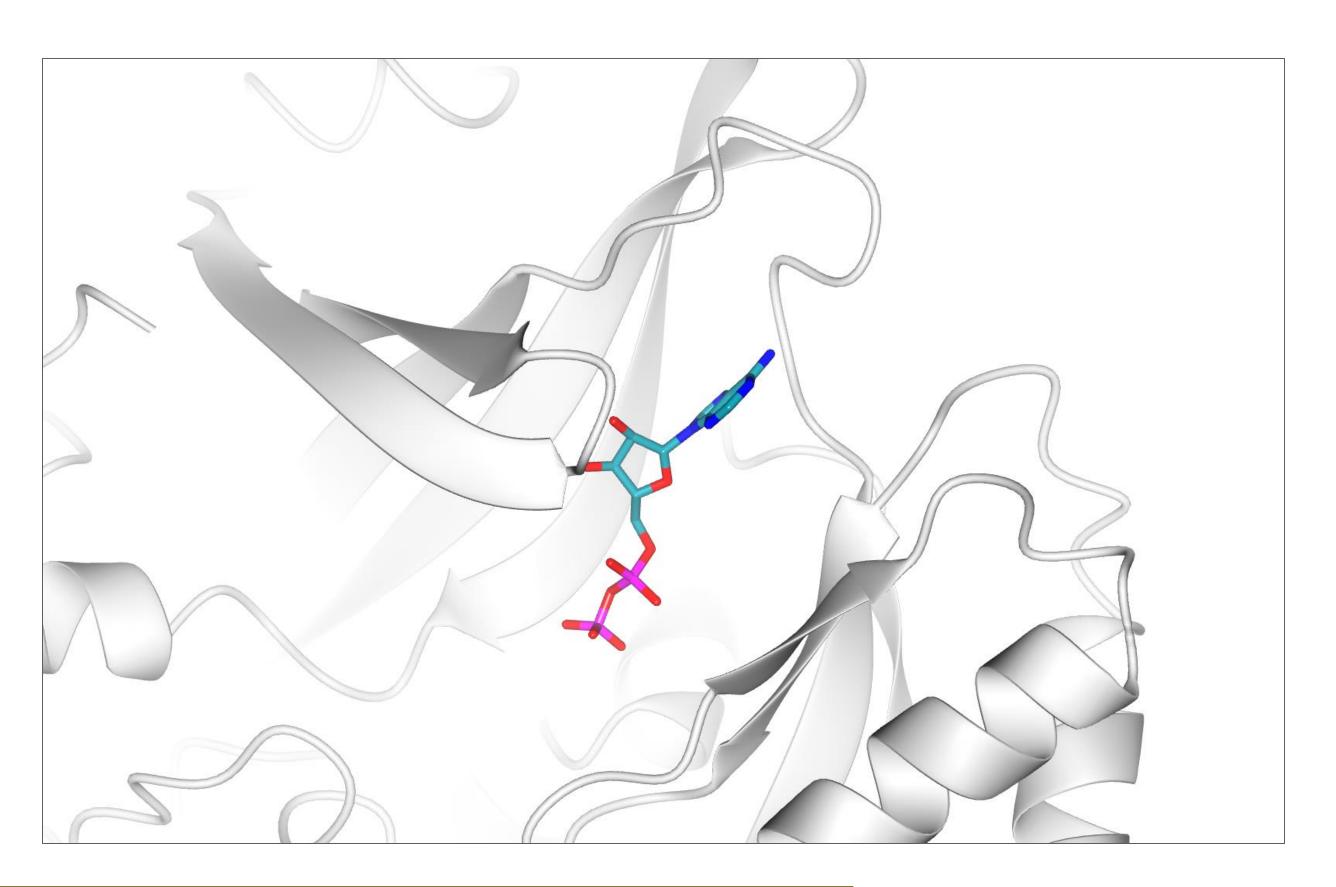
## Unraveling the functional dark matter through global metagenomics

https://doi.org/10.1038/s41586-023-06583-7
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Published online: 11 October 2023
Open access

Check for updates

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Natalia N. Ivanova<sup>2</sup>, I. Min Chen<sup>2</sup>, David Paez-Espino<sup>2</sup>, Evangelos Karatzas<sup>1</sup>,
Novel Metagenome Protein Families Consortium\*, Ioannis Iliopoulos<sup>7</sup>,
Konstantinos Konstantinidis<sup>8</sup>, James M. Tiedje<sup>9</sup>, Jennifer Pett-Ridge<sup>10</sup>, David Baker<sup>11,12,13</sup>,
Axel Visel<sup>2</sup>, Christos A. Ouzounis<sup>2,14,15</sup>, Sergey Ovchinnikov<sup>4</sup>, Aydin Buluç<sup>5,16</sup> &
Nikos C. Kyrpides<sup>2 ⋈</sup>

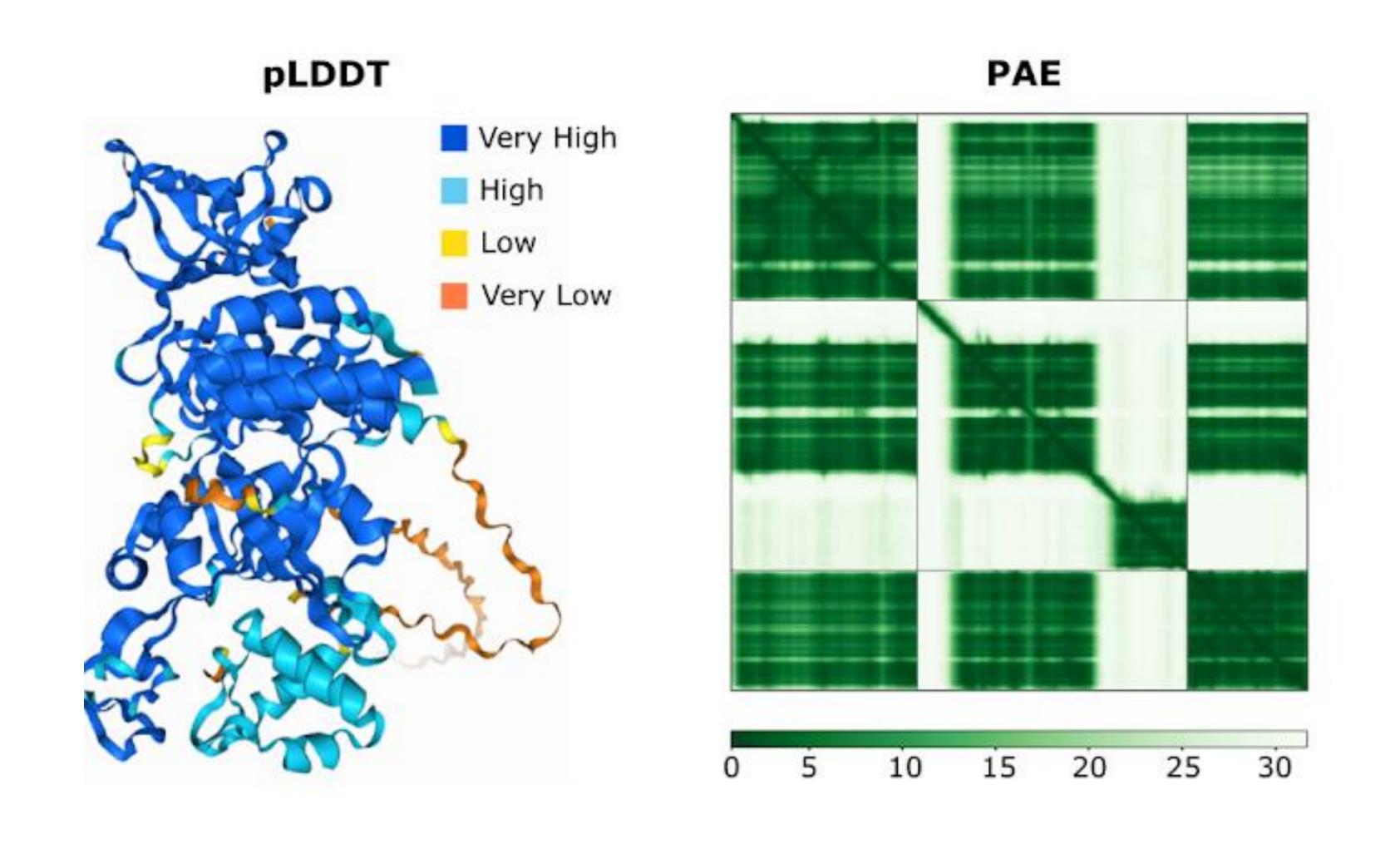
# Nucleotide prediction Total Tested 13096 Sites discovered 334



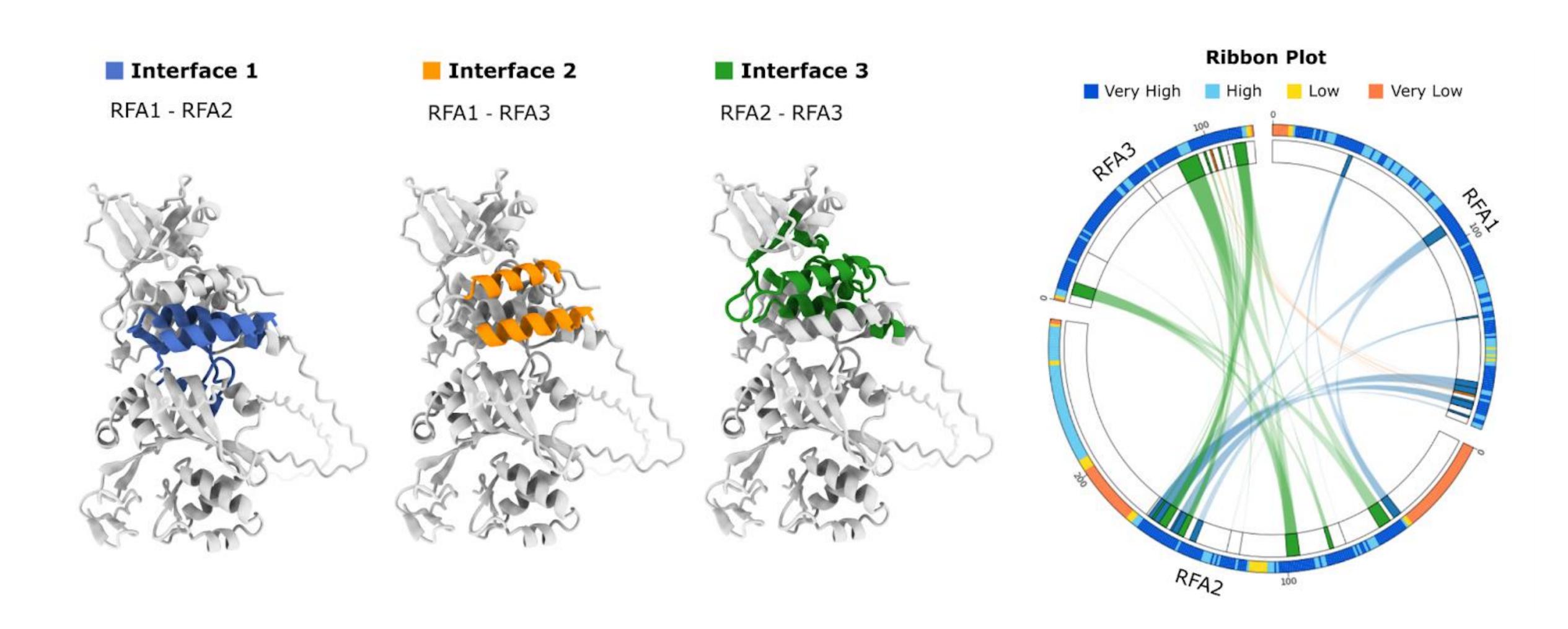
4 proteins produced, testing now ATP/ADP binding

TAMRA-ADP binds in all 4

## What you see in the AlphaFold Server



#### Plotting interfaces in 2D for easy inspection



#### Found 8 interfaces

