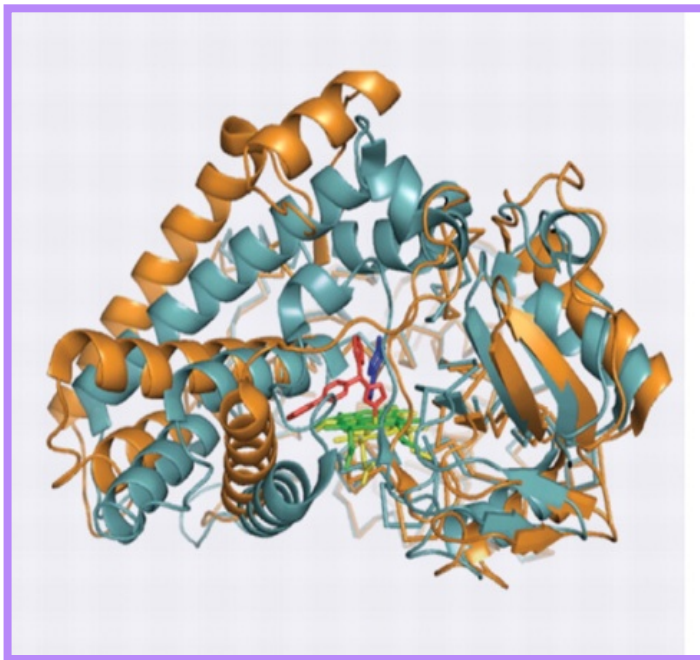


Intrinsically accessible motions enable **Optimal binding of substrate or drugs**



Conformational flexibility +
sequence variability mediates
substrate selectivity

- **Two conformations of P450-CYP2B4:**
open (orange) with a large substrate (bifonazole, red), and
closed (light blue) with the smaller substrate
4-(4-chlorophenyl) imidazole (blue)

See...

N. Tokuriki and D. S. Tawfik (2009) *Science* **324**: 203-207

Sequence evolution

an information-theoretic approach

Residue index

	<i>i</i>				<i>i</i> +5	<i>i</i> +7	<i>i</i> +9
	R				E	V	N
	E				K	V	N
	K				E	V	N
	R				D	V	S
	D				K	V	S
	D				K	V	S
	E				R	V	S

↑ correlated mutations

↑ conserved

Information entropy (Shannon, 1951)

$$S(i) = \sum_{x_i=1}^{20} P(x_i) \log \frac{1}{P(x_i)}$$

Mutual information (MI)

$$I(i, j) = \sum_{x_i=1}^{20} \sum_{y_j=1}^{20} P(x_i, y_j) \log \frac{P(x_i, y_j)}{P(x_i)P(y_j)}$$

for correlated mutations analysis (CMA)

Mutual Information without the influence of phylogeny

MI_p - to eliminate random noise and phylogenetic components

$$MI_p(i, j) = I(i, j) - APC$$

APC = Average product correction

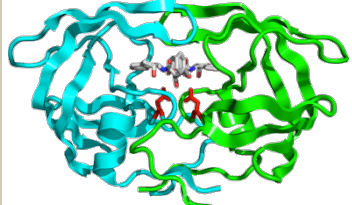
$$= [I(i, x) I(j, x)] / \langle I(i, j) \rangle$$

	R				E	V	N	
	E				K	V	N	
	K				E	V	N	
	R				D	V	S	
	D				K	V	S	
	D				K	V	S	
	E				R	V	S	

where $I(i, x)$ is the mean mutual information of column $i = \sum_j I(i, j)$

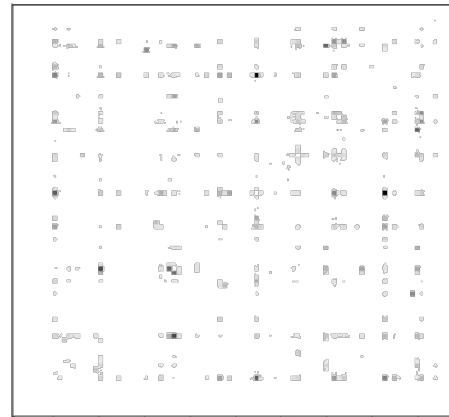
HIV-1 protease correlated mutation analysis (CMA)

MSA of HIV-1 protease



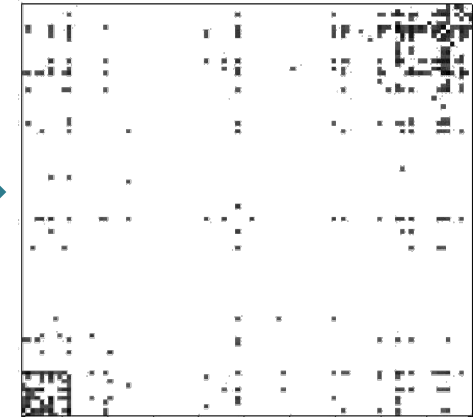
```
DKLIIQLLDDYPKCF  
FLKIIQLLDDYPKCF  
FLKIIQLLNDYPKCF  
FIKVVLELDEFKCF  
LEKATKLFTTYDKMI
```

MI matrix $I_{ij} = I(i, j)$

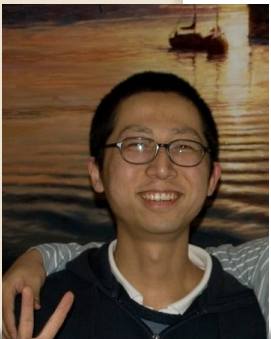


residue index

Shi and Malik (2000)
spectral clustering



reordered residue index



Dr. Ying Liu

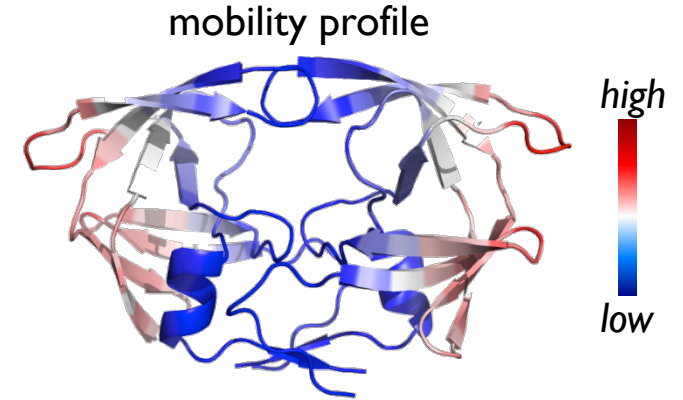
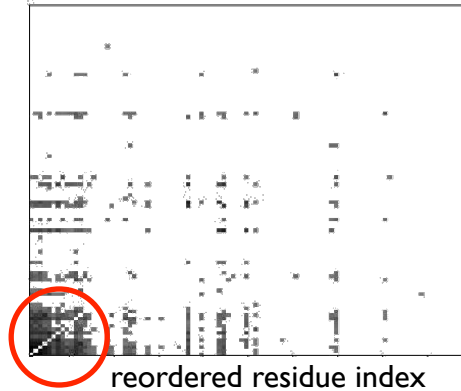
MDR mutations distinguished by CMA

MSA of HIV-1 protease
Stanford HIV Drug Resistance Database
<http://hivdb.stanford.edu/>

```

CTLVGTAIHEMMHALGFLHEQNREDRDDWVR
CDKFGIIVVHELGHVVGFWHEHTRPDREDHVV
CFRFGTVIHEFIHALGFYHAQSAYTRDDYVL
NFTVGS LIHEIGHAFGLIHEHQRPDRDDYVI
CLTYGTP IHELMHALGFFHEQNRHERDSYVR
CDKFGIIVVHELGHVVGFWHEHTRPDREKHVV
CDKFGVVVHELGHVVGFWHEHTRPDRENEFVG
CAYFGTIVHEIGHAIGFHEQSRPDRDDYIN
CVYHG I IQHELSHALGFYHEHTRSDRNKYVR
CINSGT I IHEVLHALGVHHEQARADRDGYVT
    
```

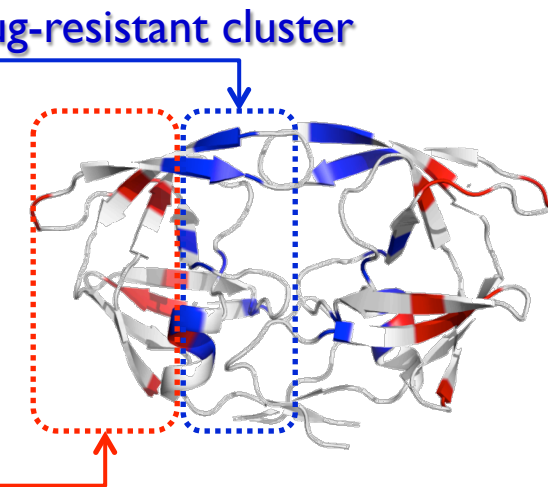
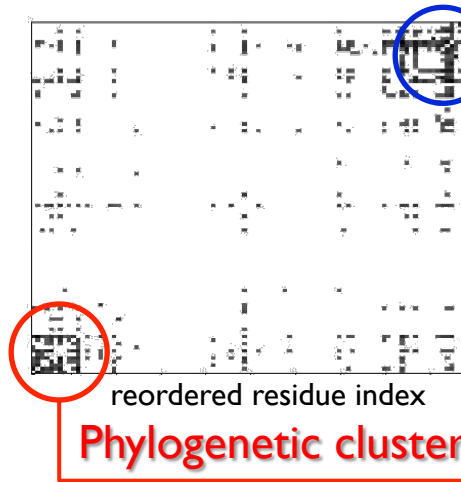
untreated



```

CTLVGTAIHEMMHALGFLHEQNREDRDDWVR
CDKFGIIVVHELGHVVGFWHEHTRPDREDHVV
CFRFGTVIHEFIHALGFYHAQSAYTRDDYVL
NFTVGS LIHEIGHAFGLIHEHQRPDRDDYVI
CLTYGTP IHELMHALGFFHEQNRHERDSYVR
CDKFGIIVVHELGHVVGFWHEHTRPDREKHVV
CDKFGVVVHELGHVVGFWHEHTRPDRENEFVG
CAYFGTIVHEIGHAIGFHEQSRPDRDDYIN
CVYHG I IQHELSHALGFYHEHTRSDRNKYVR
CINSGT I IHEVLHALGVHHEQARADRDGYVT
    
```

treated by at least
one drug



Summary

- two groups of correlated mutation sites

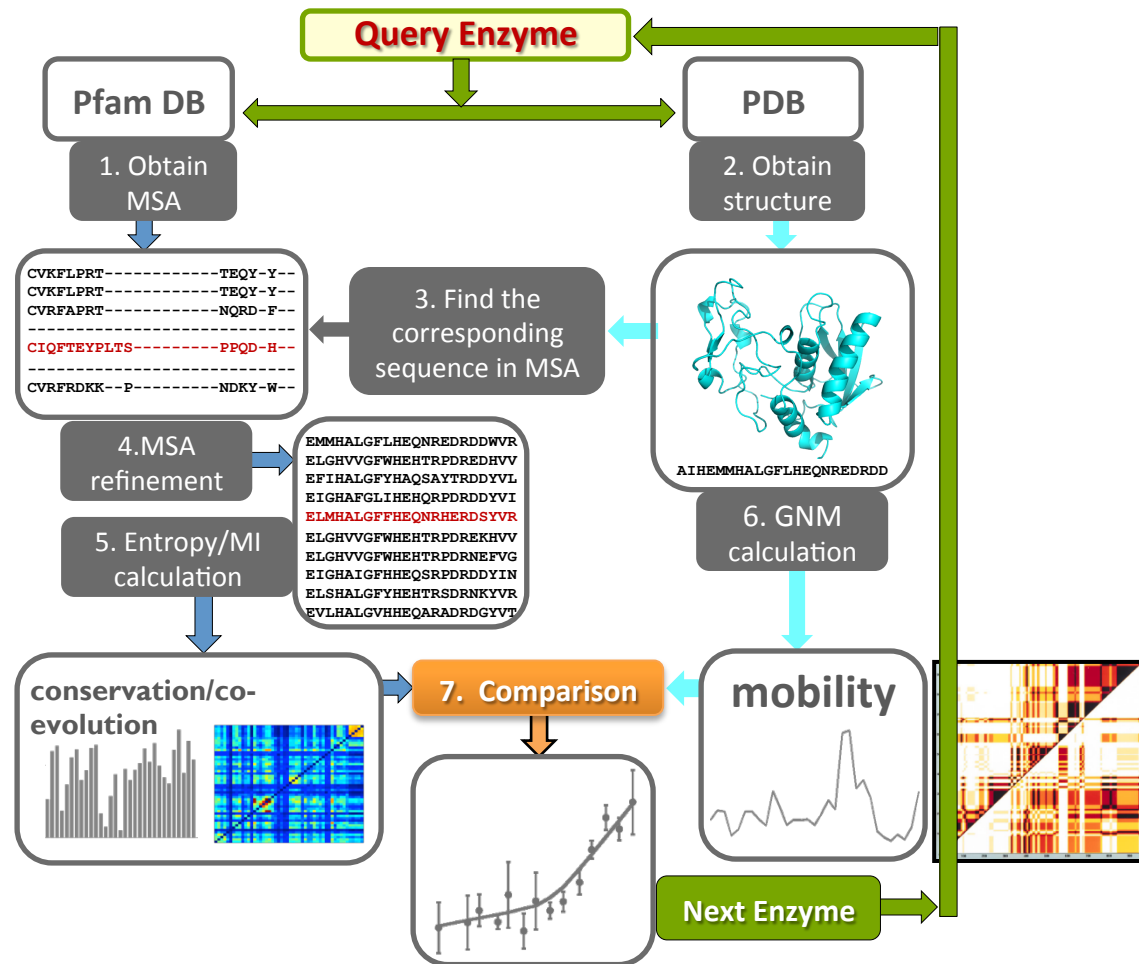
functional aspects	Structural location	structural dynamics
phylogenetic	exposed	mobile
multi-drug resistant	dimerization interface	restrained



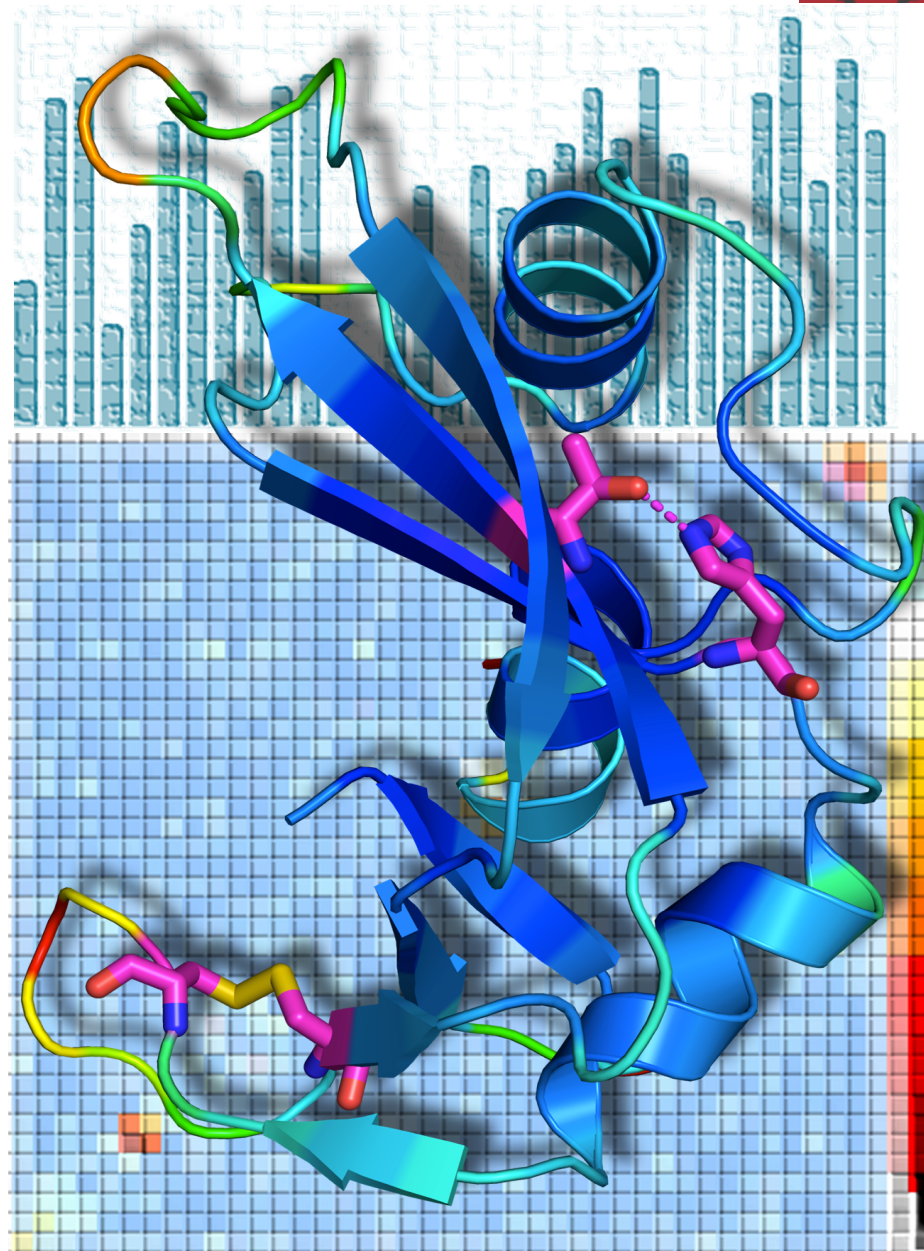
Questions:

- Are key mechanical sites (e.g. hinges) conserved?
- Is there any correlation between sequence variability and structural dynamics?
- How does the structure ensure substrate specificity *and* conformational adaptability?

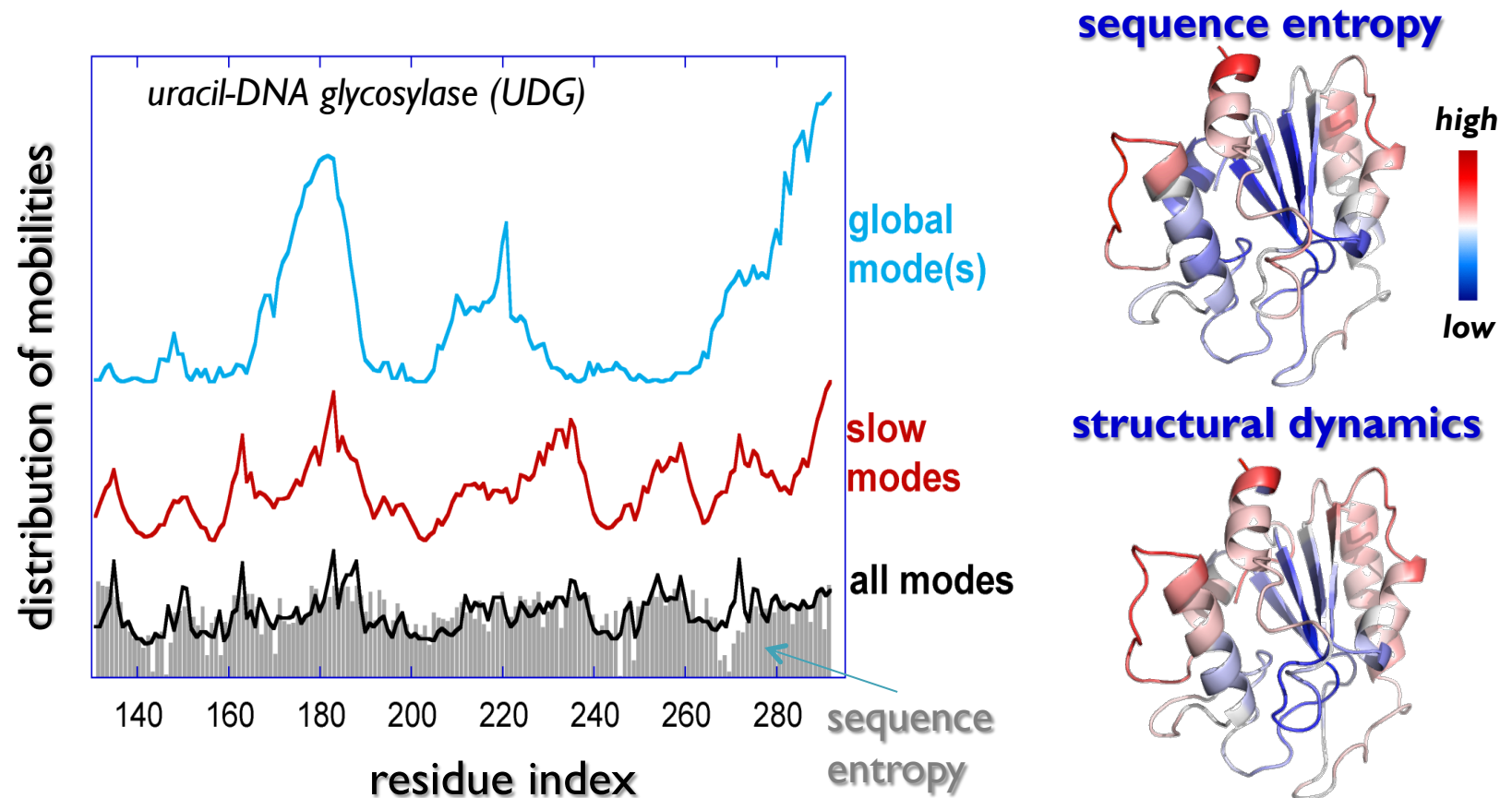
A systematic study of a set of enzymes



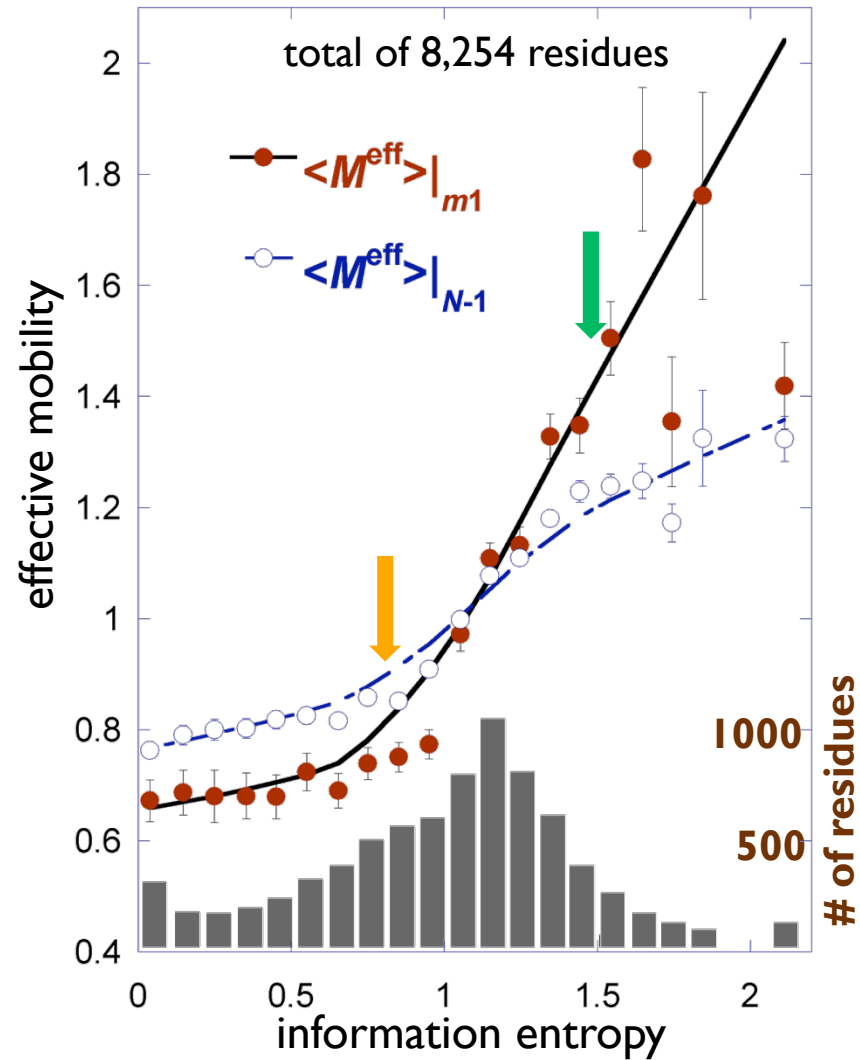
Evol



Correlation between sequence entropy & conformational mobility

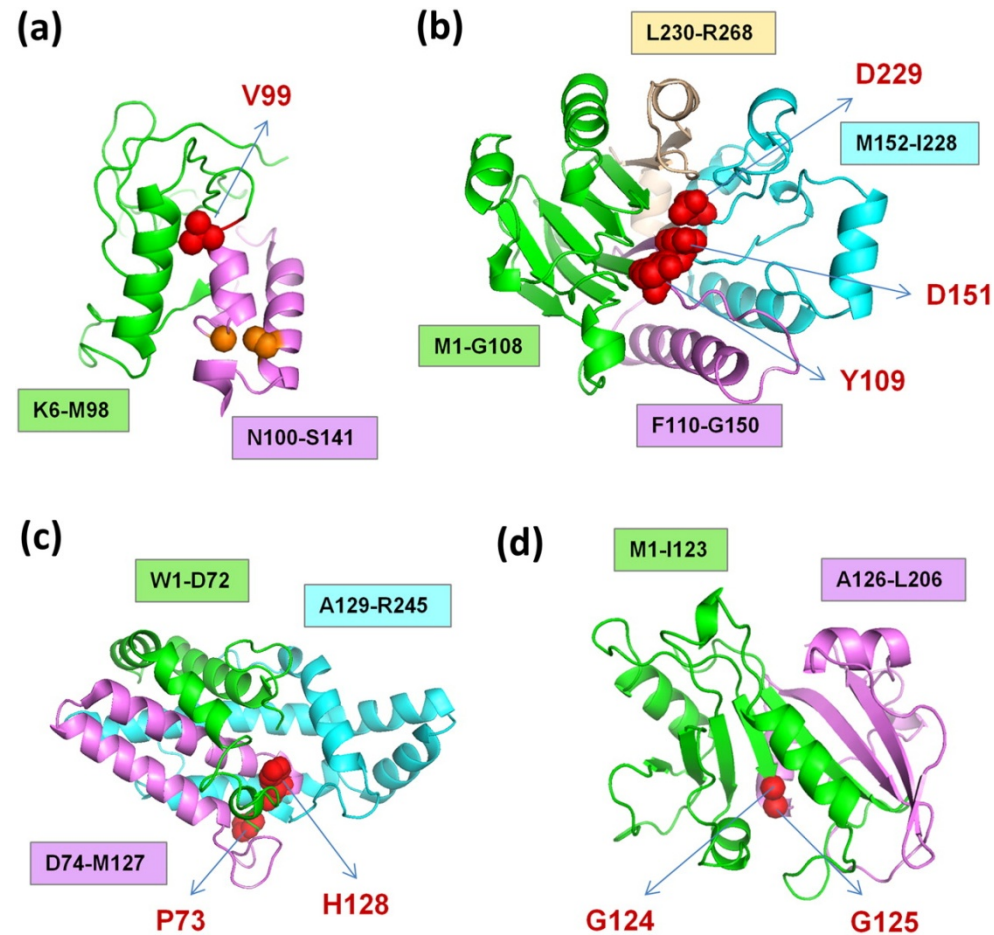


Mobility increases with sequence entropy



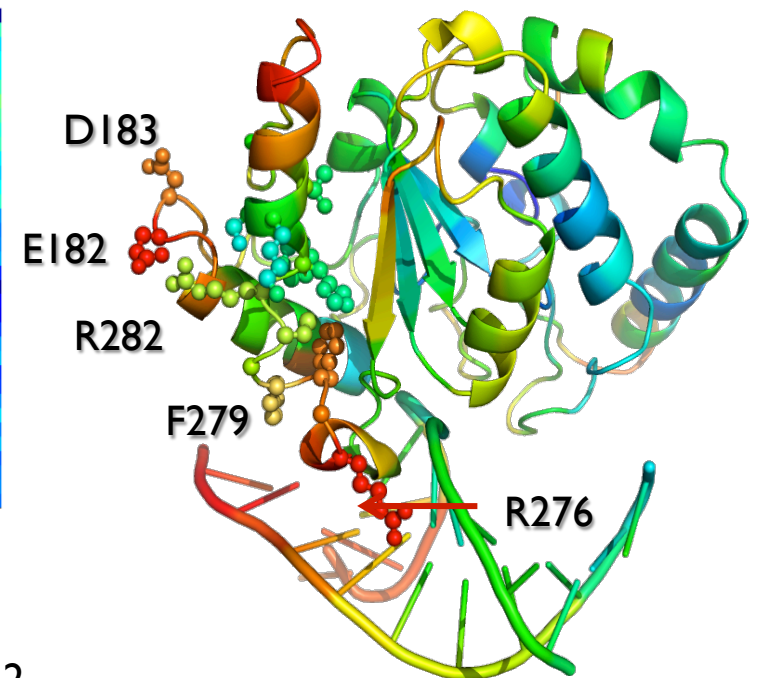
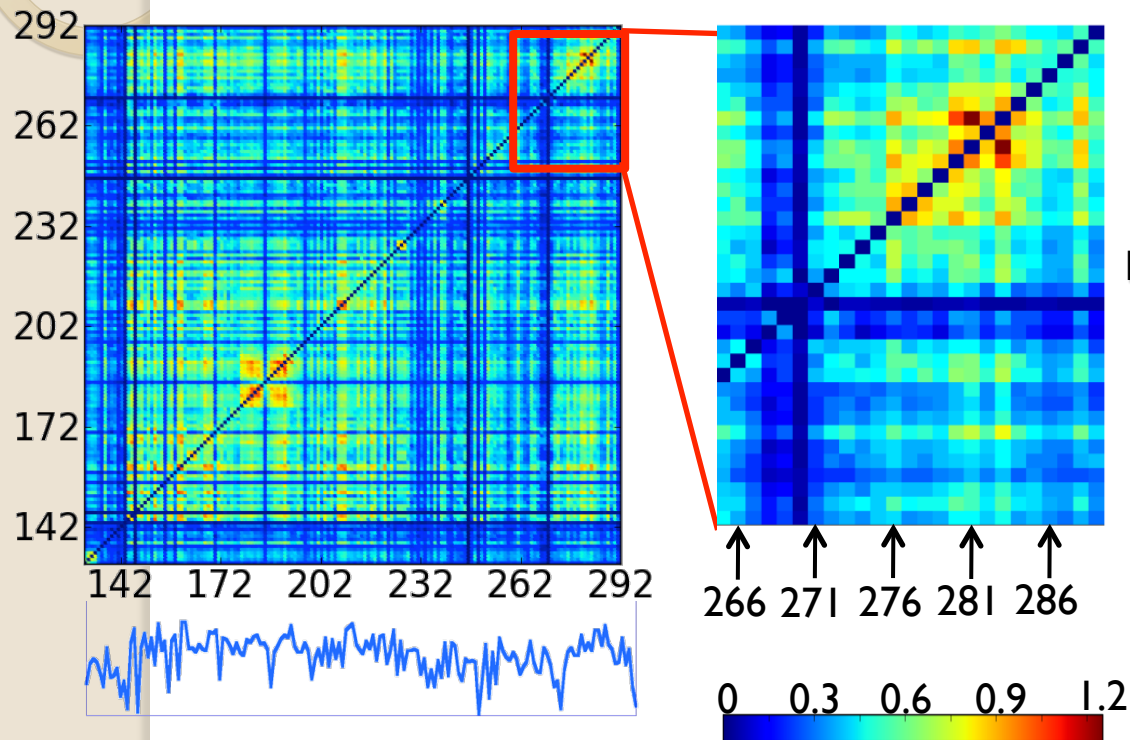
Hinge sites are evolutionarily conserved

despite their moderate-to-high exposure to environment



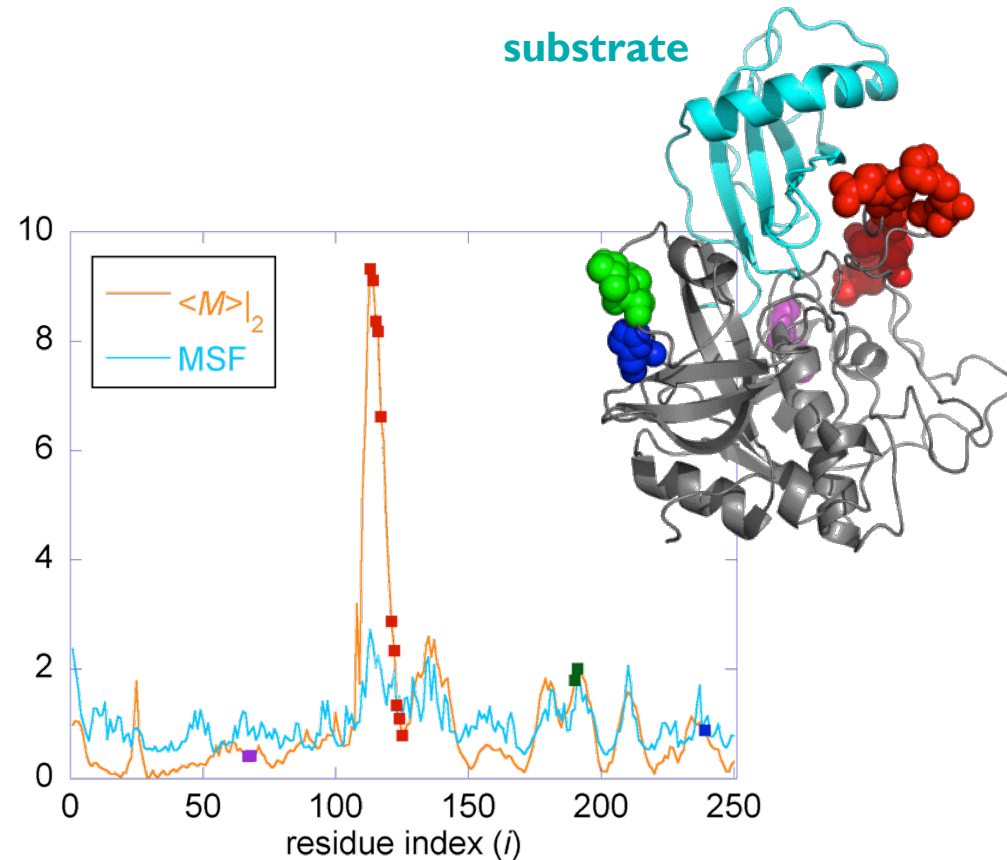
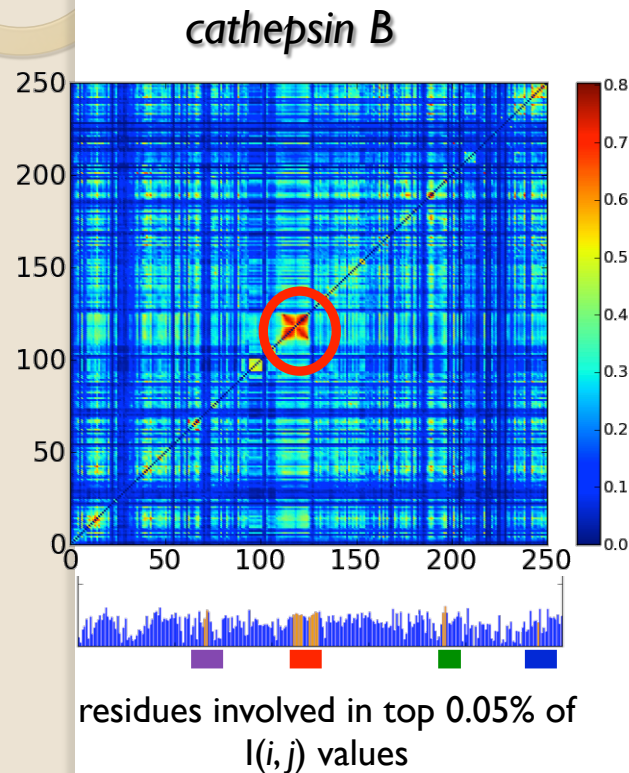
3

Amino acids involved in intermolecular recognition are distinguished by **their co-evolution propensities**



3

Amino acids involved in intermolecular recognition are distinguished by **their high global mobility**



Summary

Four types of functional sites

Functional site	Mobility in global modes	Sequence evolution	Dominant Feature
Chemical (catalytic, ligand binding)	Minimal	Conserved	high fidelity, precision
Core	Minimal	Conserved	high stability
Hinge sites	Minimal	Conserved	rotational flexibility
Substrate recognition (specific)	High	High co-evolution propensity	adaptability

There are several methods for evaluating sequence co-evolution

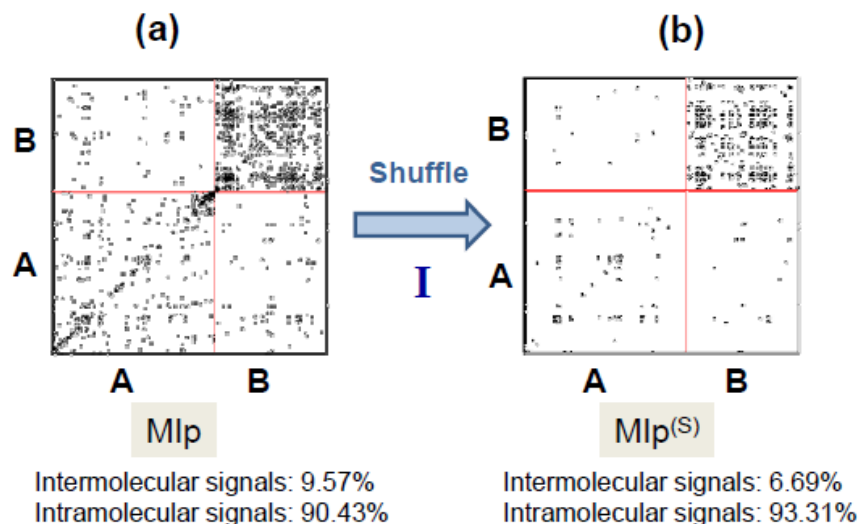
Mao W, Kaya C, Dutta A, Horovitz A, Bahar I (2015)

[Comparative Study of the Effectiveness and Limitations of Current Methods for Detecting Sequence Coevolution](#) *Bioinformatics* pii: btv103 PMID: 25697822

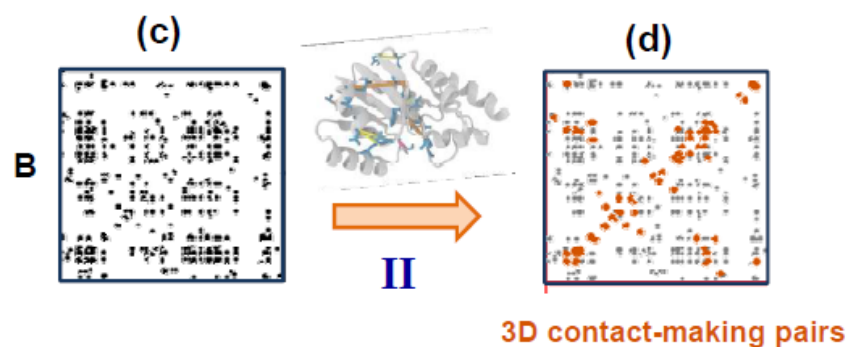
Four possible outcomes:

- True positive (TP) – correctly predicted to be a hit
- False positive (FP); predicted but it is a miss
- True negative (TN) – correctly predicted to be a miss
- False negative (FN) – predicted as a miss, but is a hit

Two criteria for assessing the performance of different methods



- Minimizing false positives (signals between non interacting proteins)



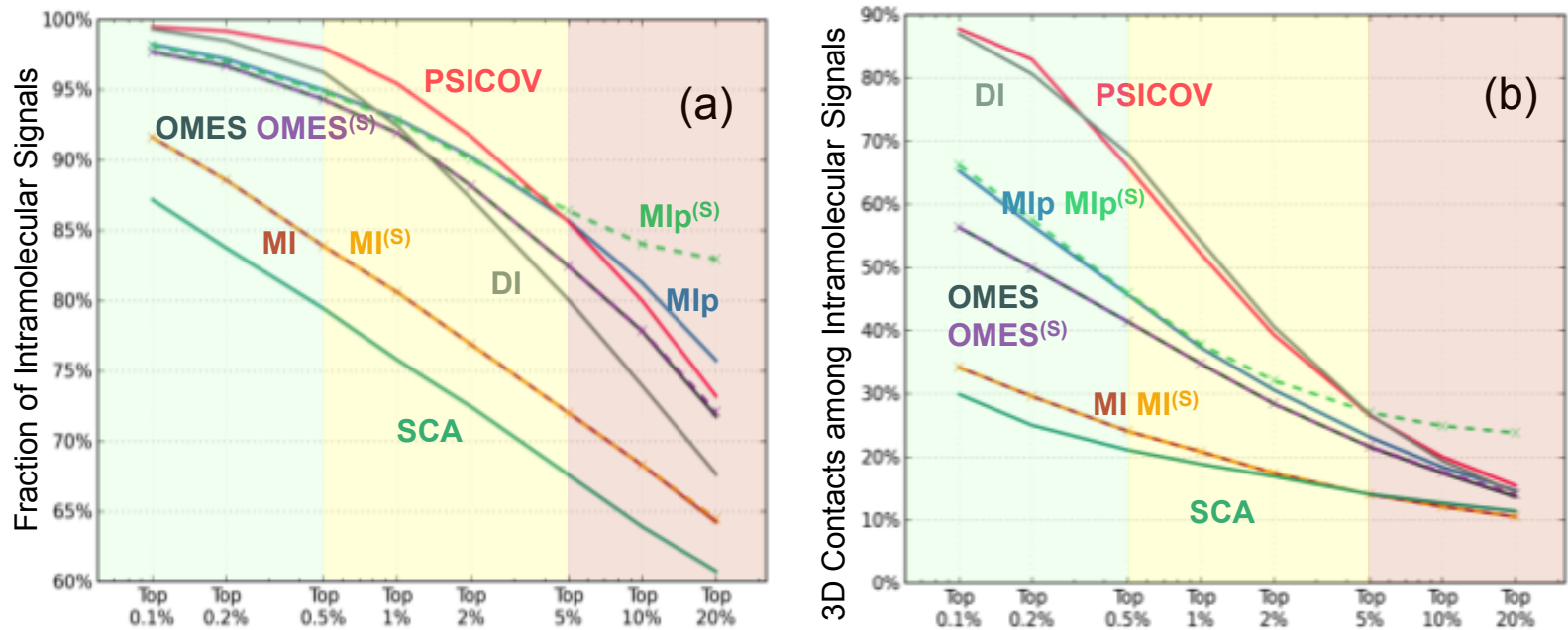
- Maximizing true positives (signals between contact making residues)

Screening of large databases

For testing 9 methods, including

- observed-minus-expected-squared ((OMES) (Kass and Horovitz, 2002)
- statistical coupling analysis (SCA) (Halabi et al., 2009; Lockless and Ranganathan, 1999).
- Direct Coupling Analysis (DCA or DI for Direct Information) (Morcos et al., 2011; Weigt et al., 2009),
- Protein Sparse Inverse COVariance (PSICOV) (Jones et al., 2012),

PSICOV and DI are the best



Average performance of the nine methods based on two criteria, absence of intermolecular FPs (a), and fraction of 3D contact making pairs (b) among different subsets of top-ranking signals. The signals are classified to 3 groups: strong coevolution signals (0.1-0.5%), intermediate signals (0.5-5%) and relatively weak signals (5-20%), which also refer to relatively small, intermediate, and high coverage of coevolving pairs. PSICOV and DI outperform other methods in the strong coevolution region. For the intermediate signal, OMES and Mlp exhibit performances similar to PSICOV and DI in panel a. Mlp^(s) shows the best performance in the weak signal regime. SCA and MI (and its shuffled version) have lower performance compared to all others for both criteria over the whole range.

Allosteric communication mechanisms explored by network models

- Diffusion of signal obeys a **Markov process**
- The structure is modeled as a network
- Network connectivity given by Γ

References

Laplacian based manifold methods (Belkin & Niyogi)

Chennubhotla & Bahar Mol Systems Biology (2006); PLoS Comp Bio (2007)



Markov Model of Network Communication

$\Gamma = \mathbf{D} - \mathbf{A}$ where \mathbf{A} = connectivity/affinity matrix and \mathbf{D} = diagonal matrix of degrees

A *discrete-time, discrete-state* Markov process is defined by setting the conditional probability of signal transduction from residue j to i as

$$m_{ij} = a_{ij} / d_j$$

The conditional probability matrix $\mathbf{M} = \{m_{ij}\}$, also called the Markov transition matrix, is

$$\mathbf{M} = \mathbf{A} \mathbf{D}^{-1}$$

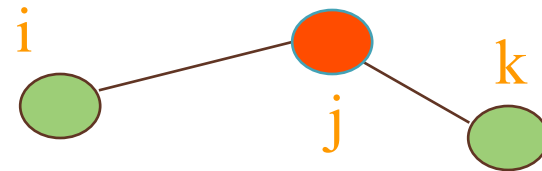
\mathbf{M} completely defines the stochastics of information transfer over the network of residues.



Hitting time: a measure of communication efficiency between two endpoints

Based on all possible pathways

path	# of steps	Path Probability
$j \rightarrow i$	1	0.5
$j \rightarrow k \rightarrow j \rightarrow i$	3	0.5^2
$j \rightarrow k \rightarrow j \rightarrow k \rightarrow j \rightarrow i$	5	0.5^3



$$H(j, i) = 1 \times 0.5 + 3 \times 0.5^2 + \dots = \sum_{j=1}^{\infty} (2j - 1) \times 0.5^j = 3.$$

path	# of steps	Path Probability
$i \rightarrow j \rightarrow k$	2	0.5
$i \rightarrow j \rightarrow i \rightarrow j \rightarrow k$	4	0.5^2
$i \rightarrow j \rightarrow i \rightarrow j \rightarrow i \rightarrow j \rightarrow k$	6	0.5^3

$$H(k, i) = 2 \times 0.5 + 4 \times 0.5^2 + \dots = 2 \sum_{j=1}^{\infty} j \times 0.5^j = 4.$$

$P(t) = M P(0)$, where $M = AD^{-1}$ is the conditional prob matrix for signal diffusion

Fluctuations as determinant of communication

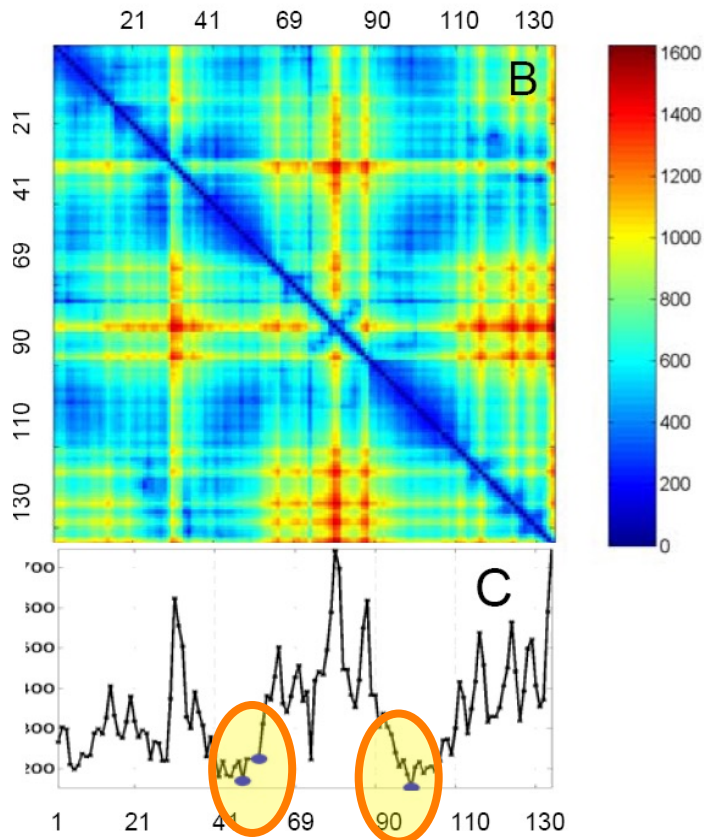
$$H(n, i) = 1 + \sum_{k=1}^{n-1} H(n, k) m_{ki}$$

Commute distance $\sim \langle (\Delta R_{ij})^2 \rangle$

$$H(j, i) = \sum_{k=1}^n [\Gamma_{ki}^{-1} - \Gamma_{ji}^{-1} - \Gamma_{kj}^{-1} + \Gamma_{jj}^{-1}] d_k$$

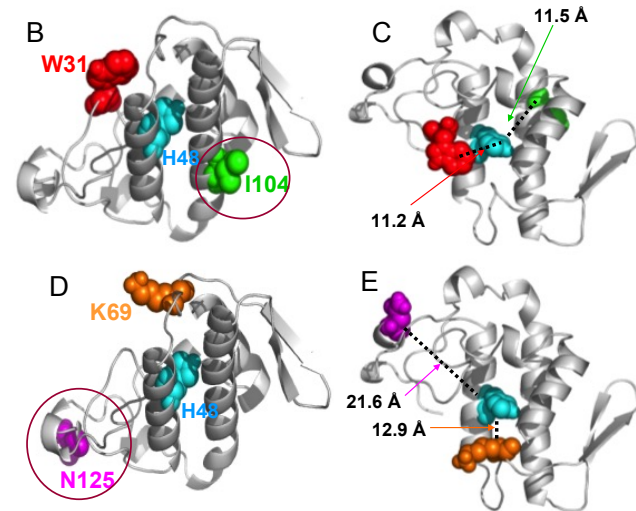
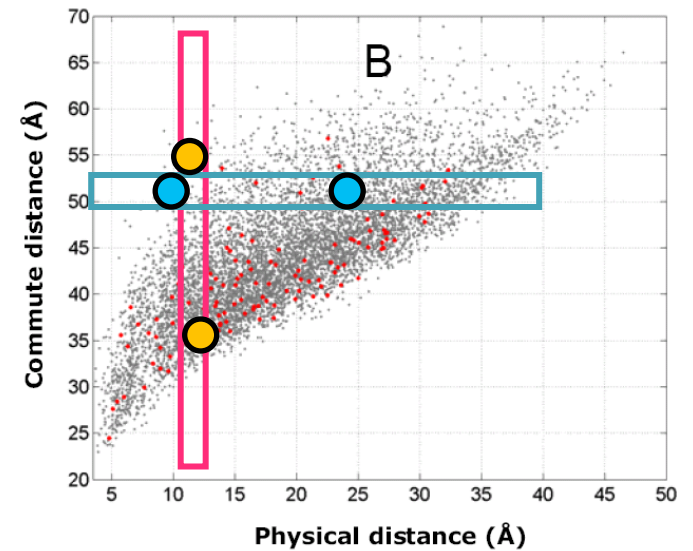
$$C(i, j) = [\Gamma_{ii}^{-1} + \Gamma_{jj}^{-1} - 2\Gamma_{ij}^{-1}] \sum_{k=1}^n d_k.$$

Communication times



Distribution of Commute Times for Phospholipase A2 (1bk9)

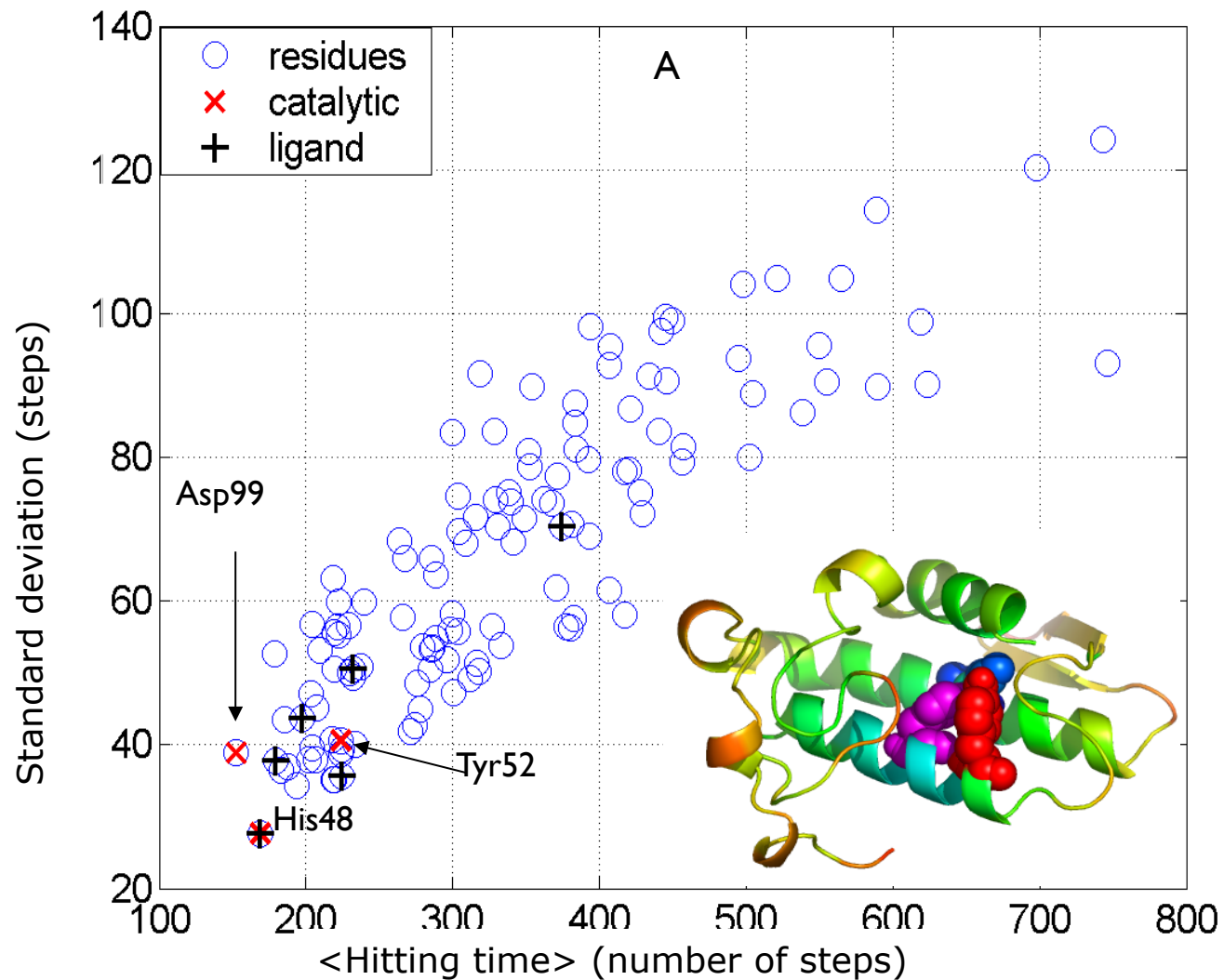
His48 ,Tyr52, Asp99 – catalytic residues



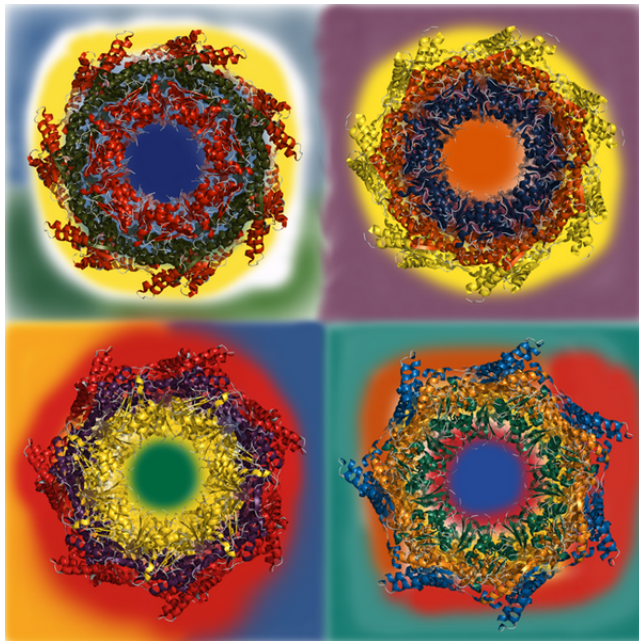
See also

Nadler, Lafon, Kevrekidis & Coifman (2005) Diffusion Maps, Spectral Clustering and Eigenfunctions of Fokker-Planck Operators, NIPS 18; Coifman et al (2005) PNAS 102, 7426.

Active sites are distinguished by effective communication properties



CONCLUSION

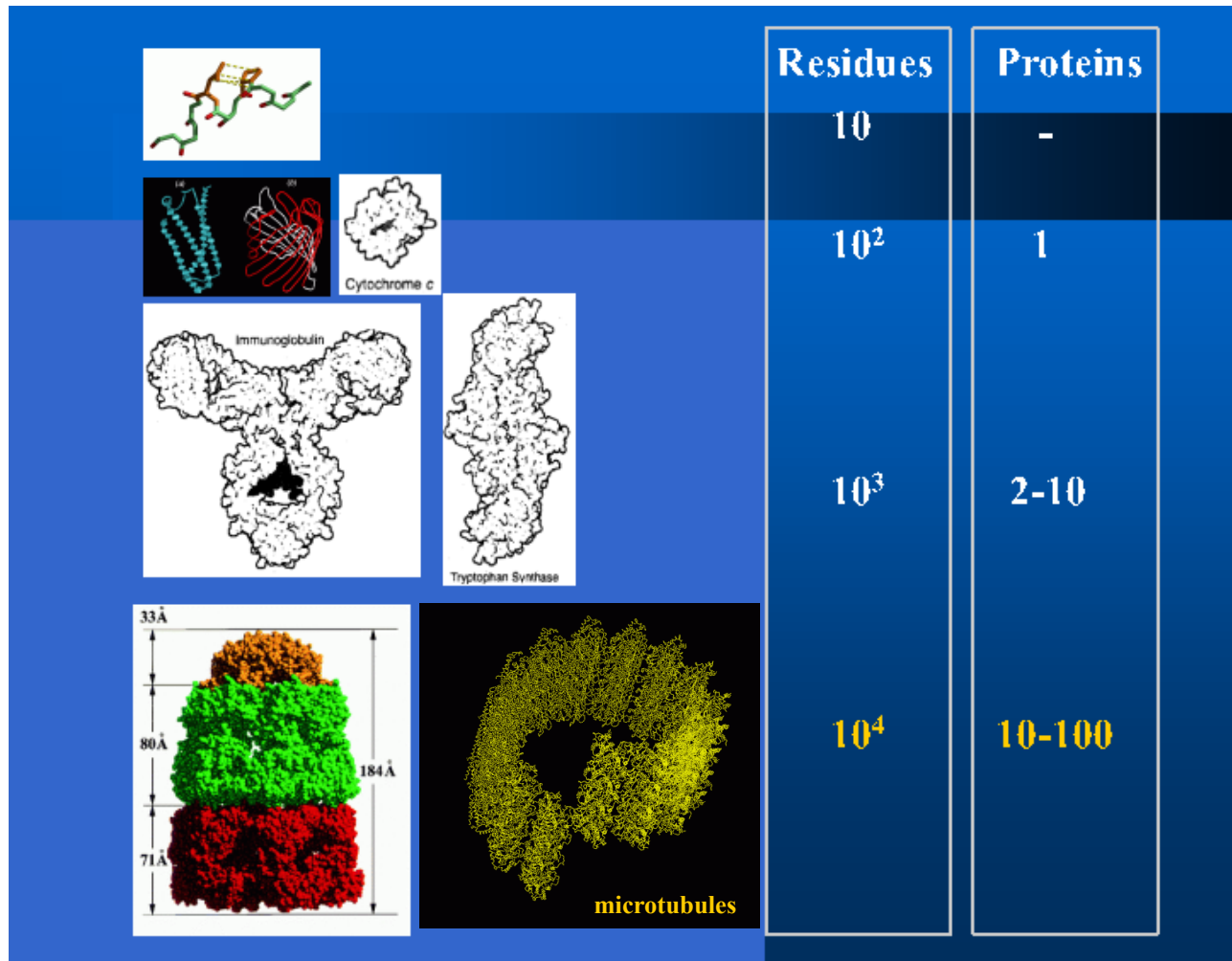


- Proteins are designed to favor functional changes in their structure. Pre-existing soft modes facilitate substrate binding.
- Collective mechanics/allosteric dynamics are mediated by conserved residues
- The intrinsic motions confer enhanced flexibility at substrate **recognition** sites
- Correlated mutations at recognition sites enable substrate specificity while conferring conformational adaptability
- Accurate modeling of protein dynamics is essential to assessing target druggability

Mechanics vs chemistry?

How does complexity scale with size of the system?

Increasing specificity/chemistry) ↑



↓ Dominance of molecular machinery



DISCUSSION

- Different tools for different time/length windows: MD cannot explore long-time processes for multimeric systems; ANM does not incorporate detailed atomic forces
- Not all evolutionarily correlated sites refer to structural or dynamic correlations
- Accurate modeling of protein dynamics is essential to computer-aided drug discovery, but not sufficient for quantitative evaluation of binding affinity
- Druggability simulations identify druggable sites, but not the type of drugs that optimally bind those sites



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Acknowledgment: NIH - 5 P41 GMI0371202