

June 10-14, 2013

Hands-on Workshop on Computational Biophysics

by

The Theoretical and Computational Biophysics Group
(**TCBG**)

and

The National Center for Multiscale Modeling of
Biological Systems (**MMBioS**)

Workshop Program

Mon, June 10: Introduction to Protein Structure and Dynamics - *Klaus Schulten*

Tue, June 11: Statistical Mechanics of Proteins; Force Field Parameterization-
Klaus Schulten and Emad Tajkhorshid

Wed, June 12: Simulating Membrane Proteins - *Emad Tajkhorshid*

Thu, June 13: Collective Dynamics of Proteins Using Elastic Network Models -
Ivet Bahar, Tim Lezon and Ahmet Bakan

Fri, June 14: Druggability Simulations, and Analyzing Sequence Patterns and
Structural Dynamics - *Ivet Bahar and Ahmet Bakan*

Workshop Program

Thu, June 13: Collective Dynamics of Proteins Using Elastic Network Models -

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Fri, June 14: Druggability Simulations, and Analyzing Sequence Patterns and Structural Dynamics - *Ivet Bahar and Ahmet Bakan*

Workshop Program

Thu, June 13: Collective Dynamics of Proteins Using Elastic Network Models -

Ivet Bahar, Tim Lezon and Ahmet Bakan

Fr

St 9:00 – 9:45 am: Elastic Network Model, Collective (Normal) Modes: Definitions, Assumptions (1) *Ivet Bahar*

9:45 – 10:15 am: Applications and Comparison with Ensembles of Experimental Structures (2) *Ivet Bahar*

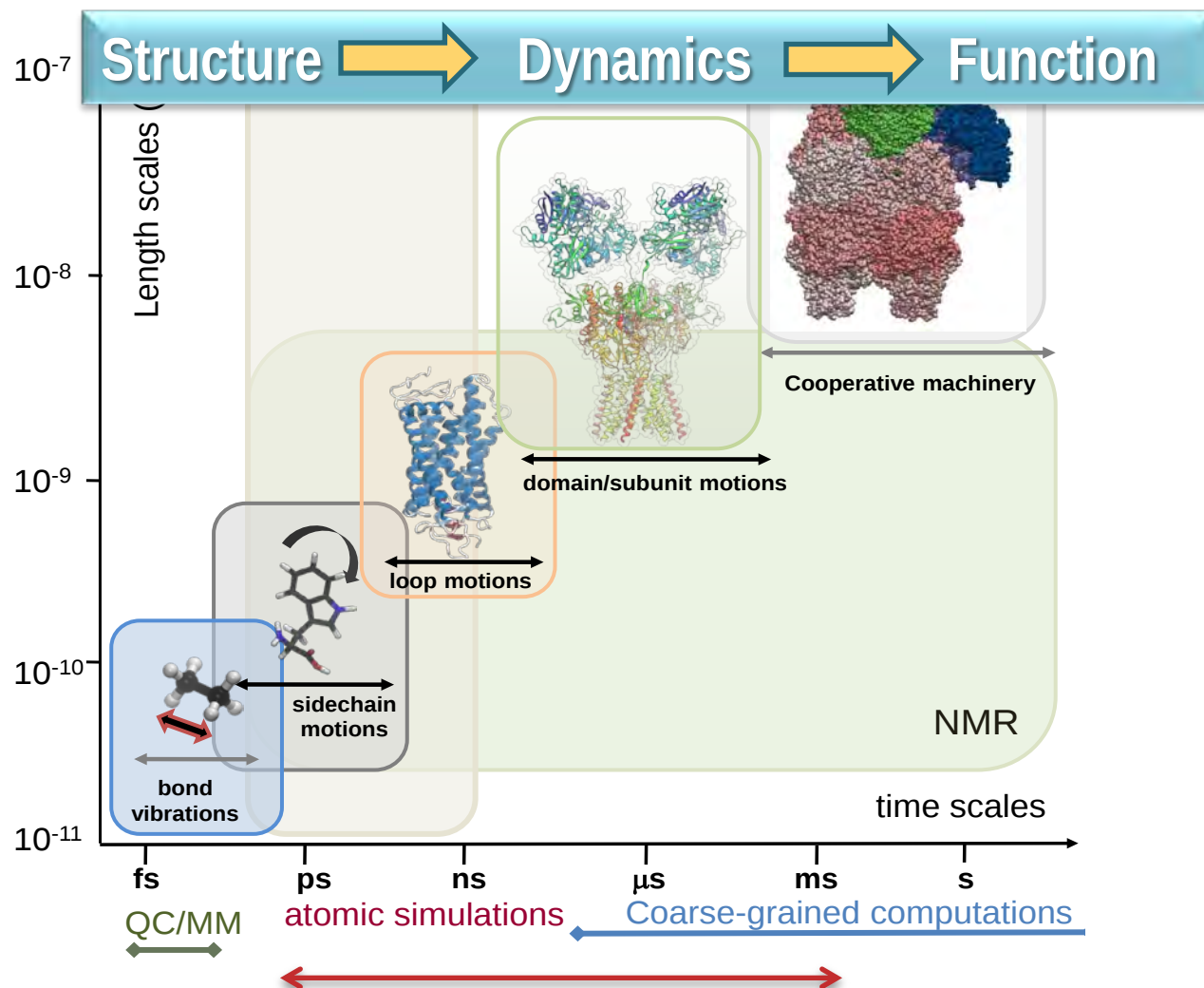
Coffee Break

10:30 – 12:00pm ProDy Overview and Applications (3) *Tim Lezon, Ahmet Bakan*

1. Bahar, Lezon, Yang & Eyal (2010) *Annu Rev Biophys* **39**: 23-42;

2. Bakan & Bahar (2009) *Proc Natl Acad Sci* **106**, 14349-54; 3. Bakan et al. (2011) *Bioinformatics* **27**:1575-77.

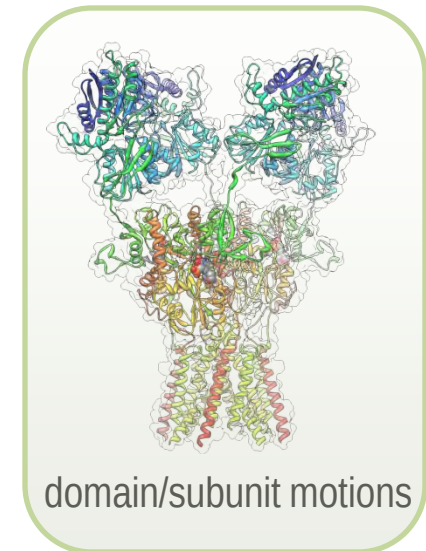
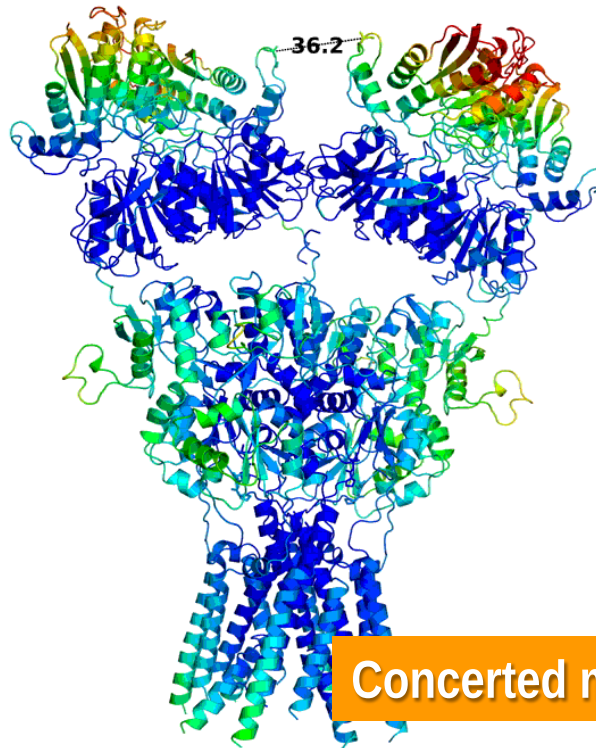
Each structure encodes a **unique** dynamics



Each structure encodes a **unique** dynamics

Structure → Dynamics → Function

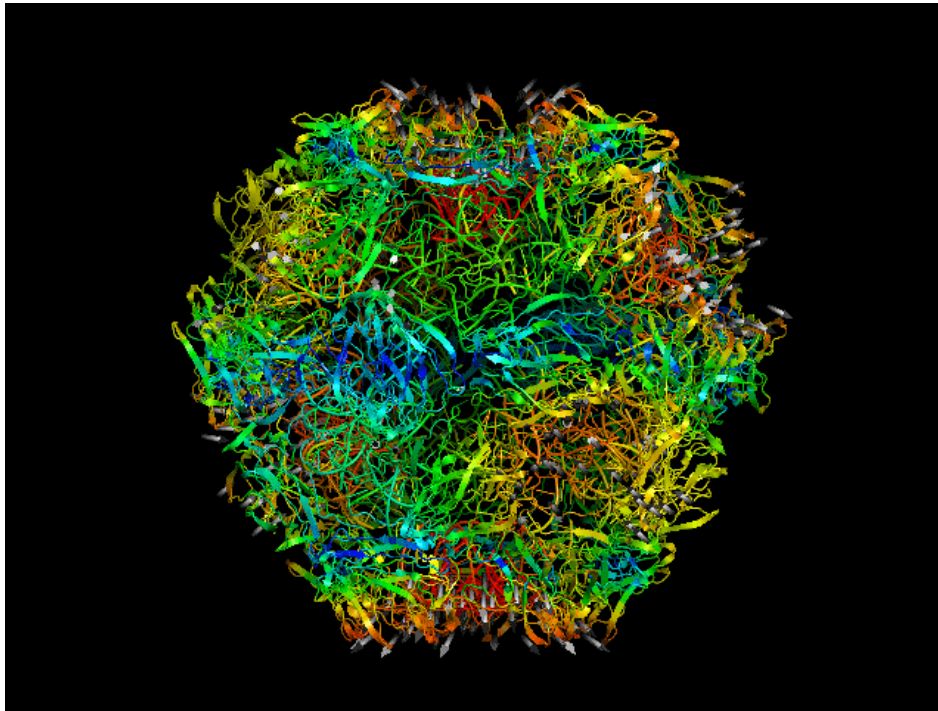
Signaling dynamics of AMPARs and NMDARs



Concerted movements of signaling molecules

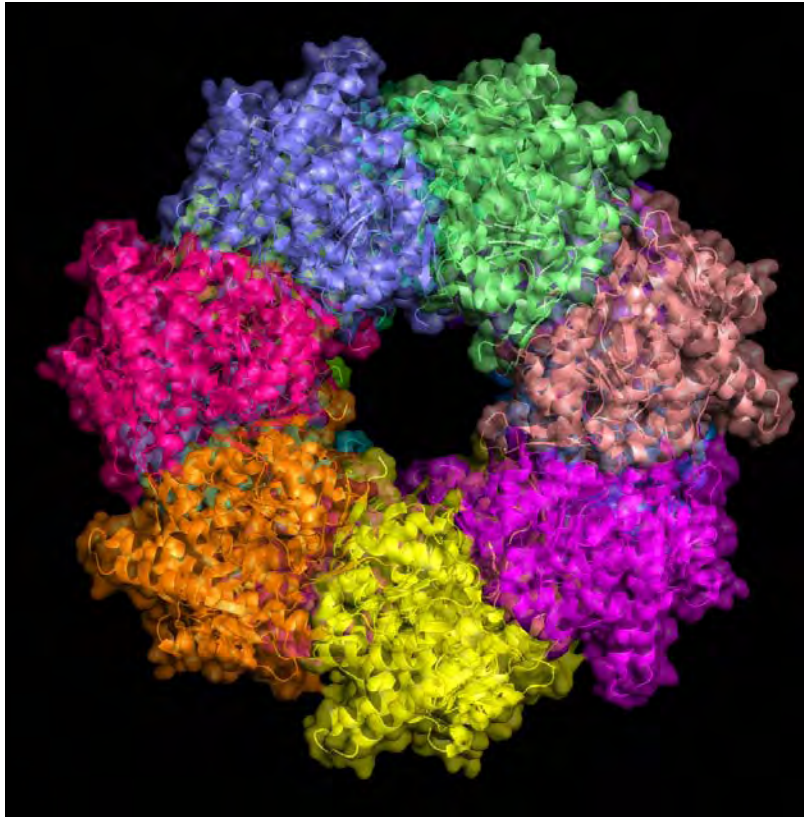
Many proteins are **molecular machines**

And mechanical properties become more important in complexes/assemblies



STMV dynamics (Zheng Yang)

Representation of structure as a network



Why network models?

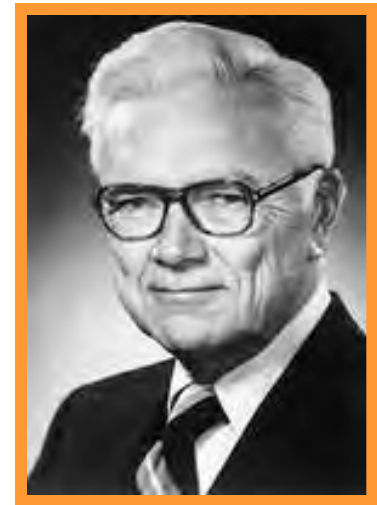
- for large systems' collective motions & long time processes beyond the capability of full atomic simulations
- to incorporate structural data in the models – at multiple levels of resolution
- to take advantage of theories of polymer physics, spectral graph methods, etc.

Physics-based approach

- Statistical Mechanics of Polymers
- Theory of Rubber Elasticity

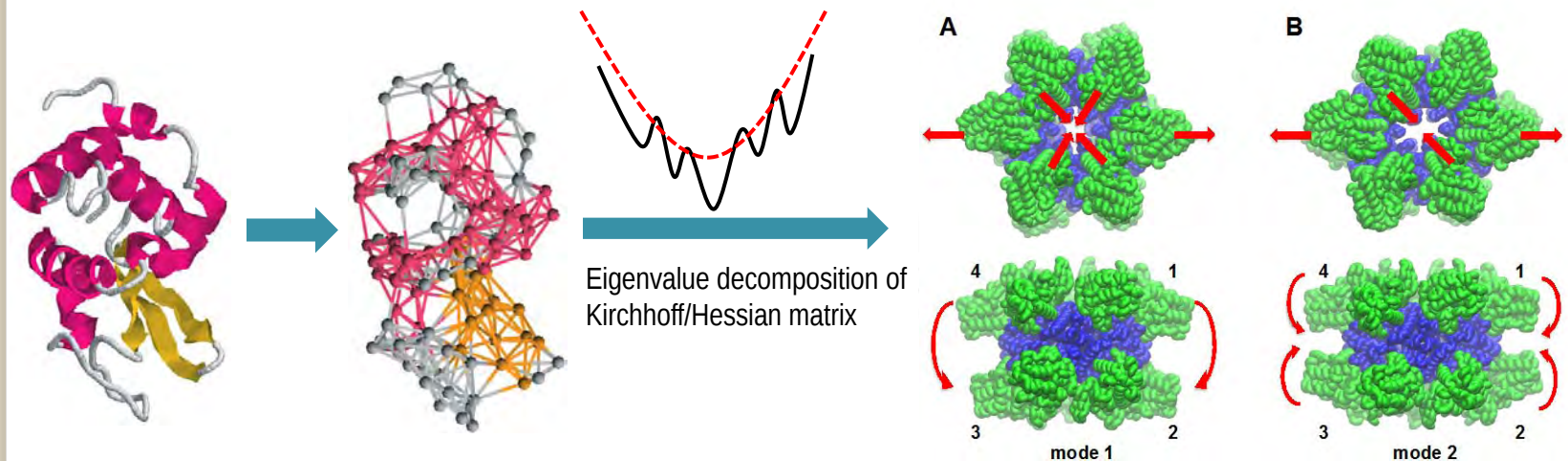


Elastic Network Model for Proteins



Paul J. Flory (1910-1985)
Nobel Prize in Chemistry 1974

Collective motions using elastic network models (ENM)

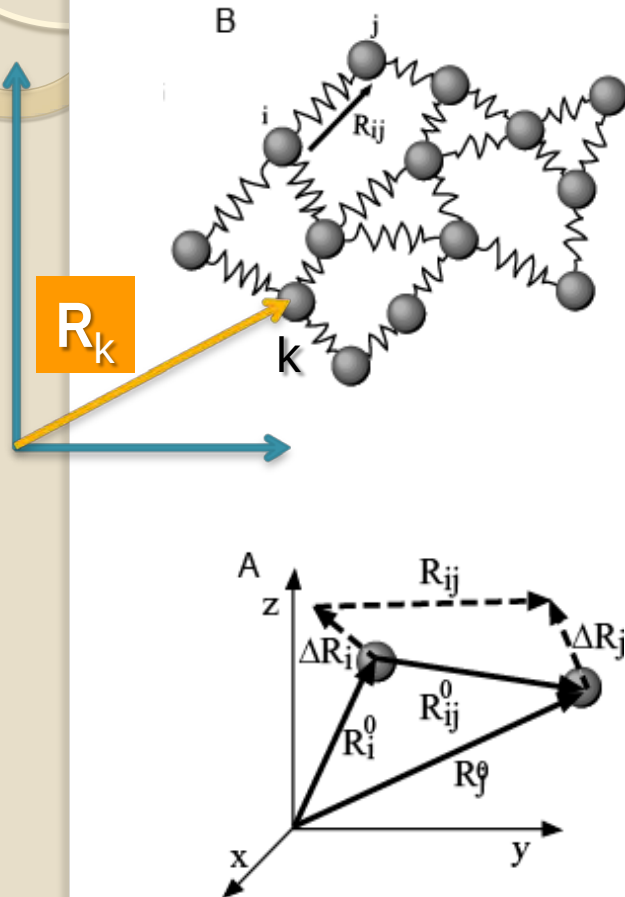


GNM: Bahar et al *Fold & Des* 1996; Haliloglu et al. *Phys Rev Lett* 1997

ANM: Doruker et al. *Proteins* 2000; Atilgan et al, *Biophys J* 2001

Based on theory of elasticity for
polymer networks by **Flory, 1976**

Gaussian network model (GNM)



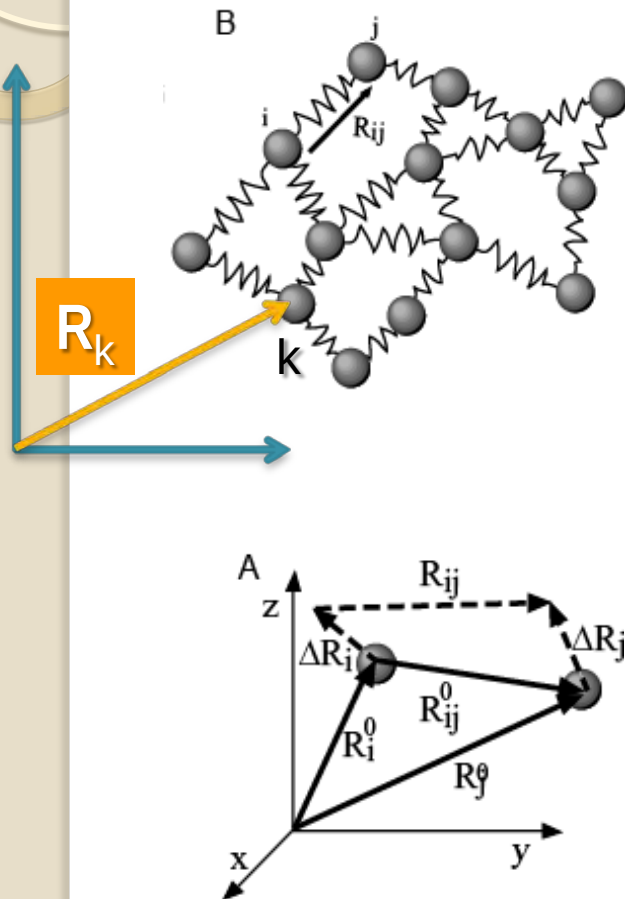
- Each node represents a residue
- Residue positions, R_i , identified by their α -carbons' coordinates
- Springs connect residues located within a cutoff distance (e.g., 10 Å)

→ Nodes are subject to **Gaussian fluctuations** ΔR_i
 → Inter-residue distances R_{ij} also undergo Gaussian fluctuations

$$\rightarrow \Delta R_{ij} = \Delta R_j - \Delta R_i$$

Fluctuations in residue positions

Gaussian network model (GNM)



Fluctuation vector:

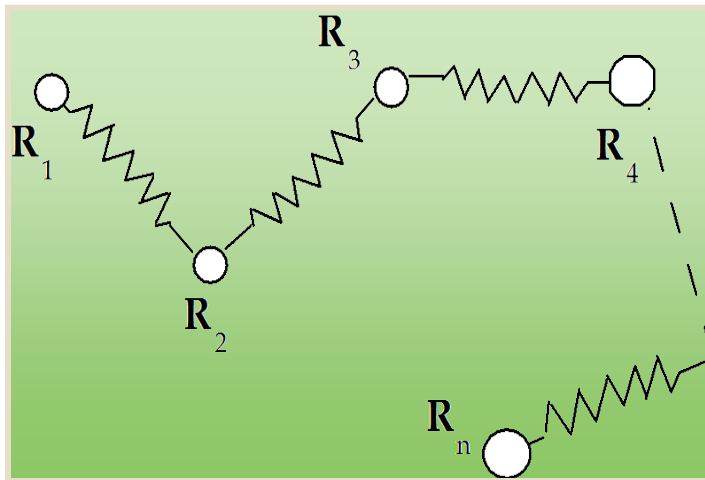
$\rightarrow \Delta R =$

$$\begin{bmatrix} \Delta R_1 \\ \Delta R_2 \\ \Delta R_3 \\ \Delta R_4 \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \Delta R_N \end{bmatrix}$$

Fluctuations in residue positions

Rouse model for polymers

Classical bead-and-spring model



$$\Delta \mathbf{R}_{12} = \mathbf{R}_{12} - \mathbf{R}_{12}^0$$

Kirchhoff matrix

$$\Gamma = \begin{bmatrix} 1 & -1 & & & \\ -1 & 2 & -1 & & \\ & -1 & 2 & -1 & \\ & & \ddots & \ddots & \ddots \\ & & & -1 & 2 & -1 \\ & & & & -1 & 1 \end{bmatrix}$$

$$\begin{aligned} V_{\text{tot}} &= (\gamma/2) [(\Delta R_{12})^2 + (\Delta R_{23})^2 + \dots (\Delta R_{N-1,N})^2] \\ &= (\gamma/2) [(\Delta R_2 - \Delta R_1)^2 + (\Delta R_3 - \Delta R_2)^2 + \dots \end{aligned}$$

Rouse model for polymers

Kirchhoff matrix

$$\Gamma = \begin{bmatrix} 1 & -1 & & & & \\ -1 & 2 & -1 & & & \\ & -1 & 2 & -1 & & \\ & & & \ddots & \ddots & \\ & & & & -1 & 2 & -1 \\ & & & & & -1 & 1 \end{bmatrix}$$

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Rouse model for polymers

Fluctuation vector

Kirchhoff matrix

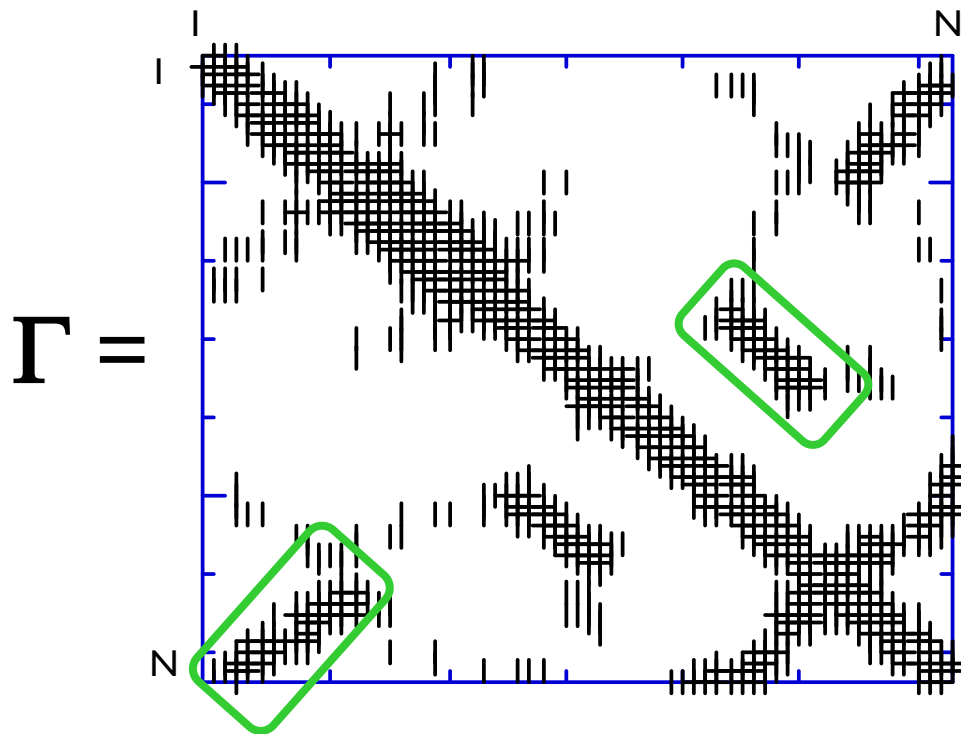
$$(\gamma/2) [\Delta R_1 \quad \Delta R_2 \quad \Delta R_3 \quad \dots \quad \Delta R_N] \begin{bmatrix} 1 & -1 & & & \\ -1 & 2 & -1 & & \\ & -1 & 2 & -1 & \\ & & & \ddots & \ddots \\ & & & & -1 & 2 & -1 \\ & & & & & 1 & 1 \end{bmatrix} \begin{bmatrix} \Delta R_1 \\ \Delta R_2 \\ \Delta R_3 \\ \vdots \\ \Delta R_N \end{bmatrix} =$$

$$V_{\text{tot}} = (\gamma/2) \Delta R^T \Gamma \Delta R$$

$$\begin{aligned} V_{\text{tot}} &= (\gamma/2) [(\Delta R_{12})^2 + (\Delta R_{23})^2 + \dots + (\Delta R_{N-1,N})^2] \\ &= (\gamma/2) [(\Delta R_2 - \Delta R_1)^2 + (\Delta R_3 - \Delta R_2)^2 + \dots \end{aligned}$$

Kirchhoff matrix for inter-residue contacts

For a protein of N residues



$$\Gamma_{ik} = \begin{cases} -1 & \text{if } r_{ik} < r_{\text{cut}} \\ 0 & \text{if } r_{ik} > r_{\text{cut}} \end{cases}$$

$$\Gamma_{ii} = - \sum_k \Gamma_{ik}$$

Γ provides a complete description of contact topology!

Statistical mechanical averages

For a protein of N residues

$$\langle \Delta \mathbf{R}_i \cdot \Delta \mathbf{R}_j \rangle = (1 / Z_N) \int (\Delta \mathbf{R}_i \cdot \Delta \mathbf{R}_j) e^{-V / k_B T} d \{ \Delta \mathbf{R} \}$$

$$= (3 k_B T / \gamma) [\Gamma^{-1}]_{ij}$$

Γ provides a complete description of contact topology!



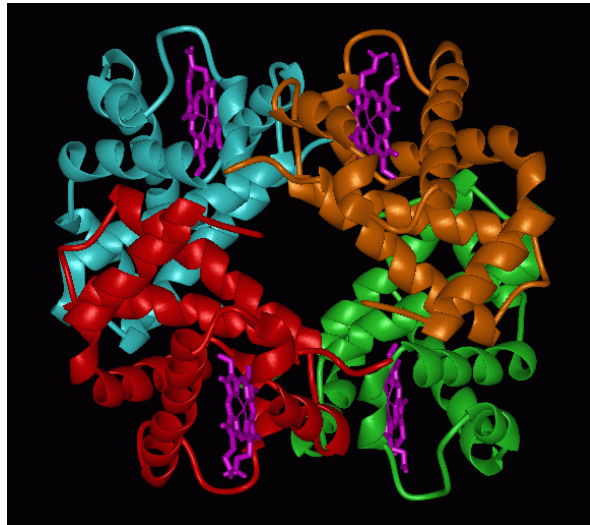
Kirchhoff matrix determines the mean-square fluctuations

$$[\Gamma^{-1}]_{ii} \sim \langle (\Delta \mathbf{R}_i)^2 \rangle$$

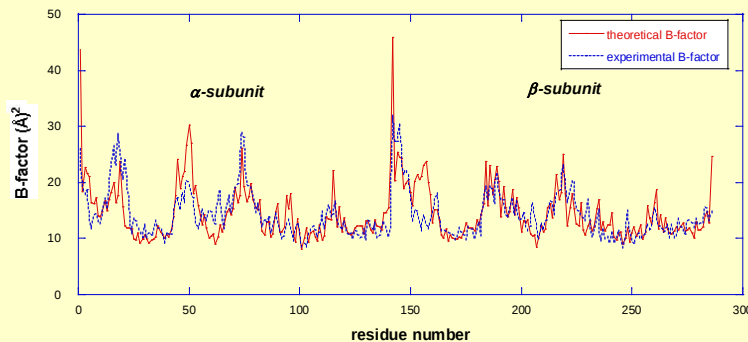
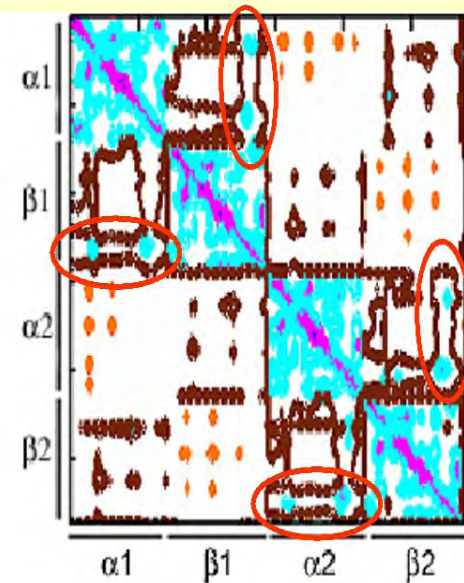
And cross-correlations between residue motions

$$[\Gamma^{-1}]_{ij} \sim \langle \Delta \mathbf{R}_i \cdot \Delta \mathbf{R}_j \rangle$$

I. Application to hemoglobin



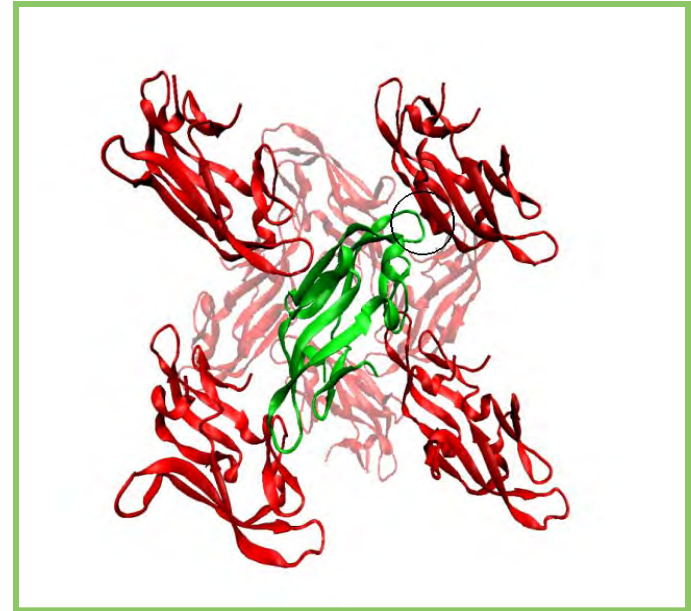
$$B_i = 8\pi^2/3 \langle (\Delta R_i)^2 \rangle$$



B- factors – Comparison with experiments

Intradimer cooperativity – Symmetry rule (Yuan et al. JMB 2002; Ackers et al. PNAS 2002.)

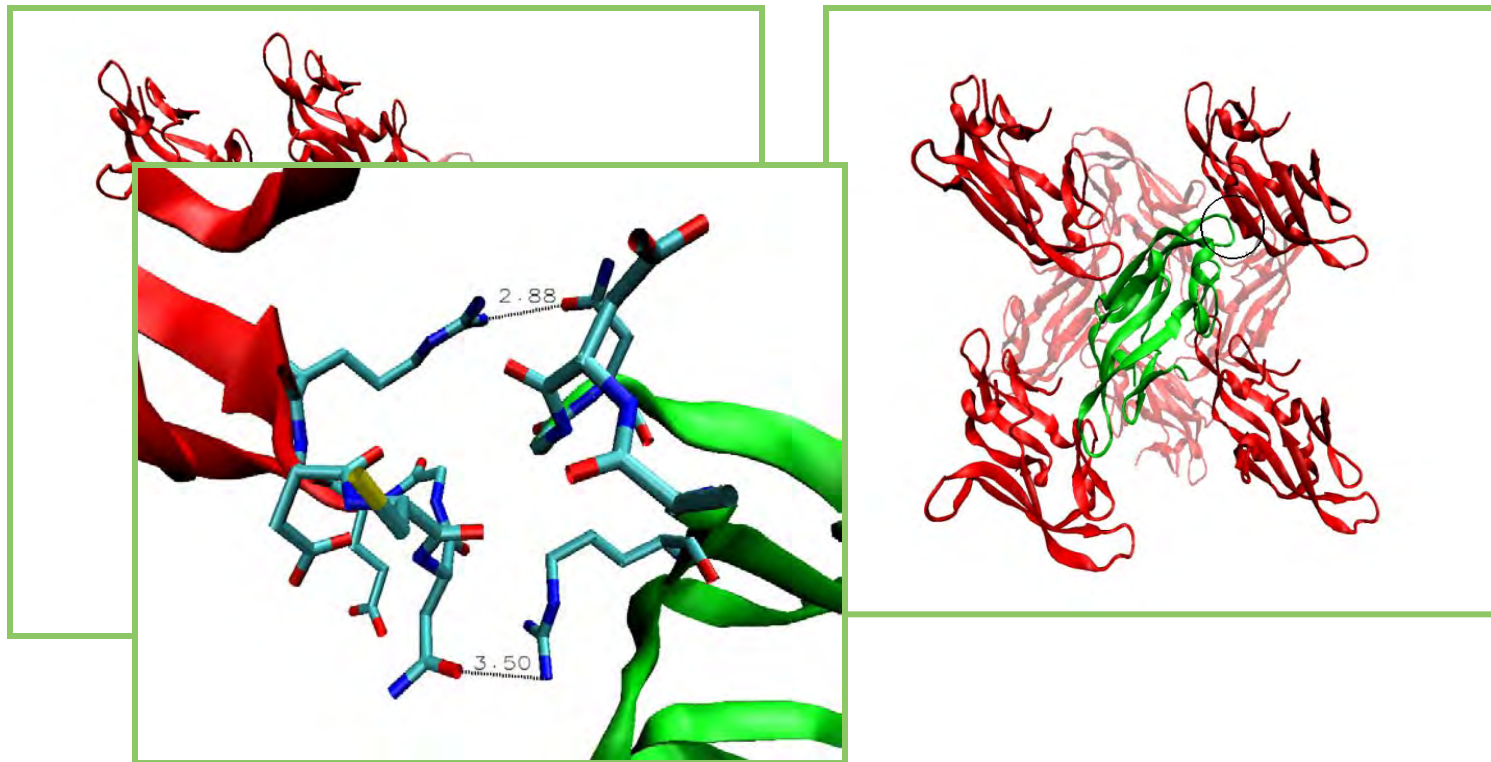
B-factors are affected by crystal contacts



Two X-ray structures for a designed sugar-binding protein LKAMG

1

B-factors are affected by crystal contacts

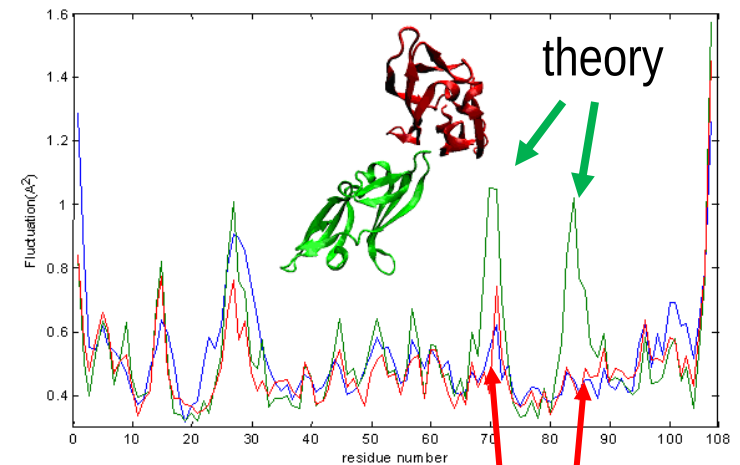
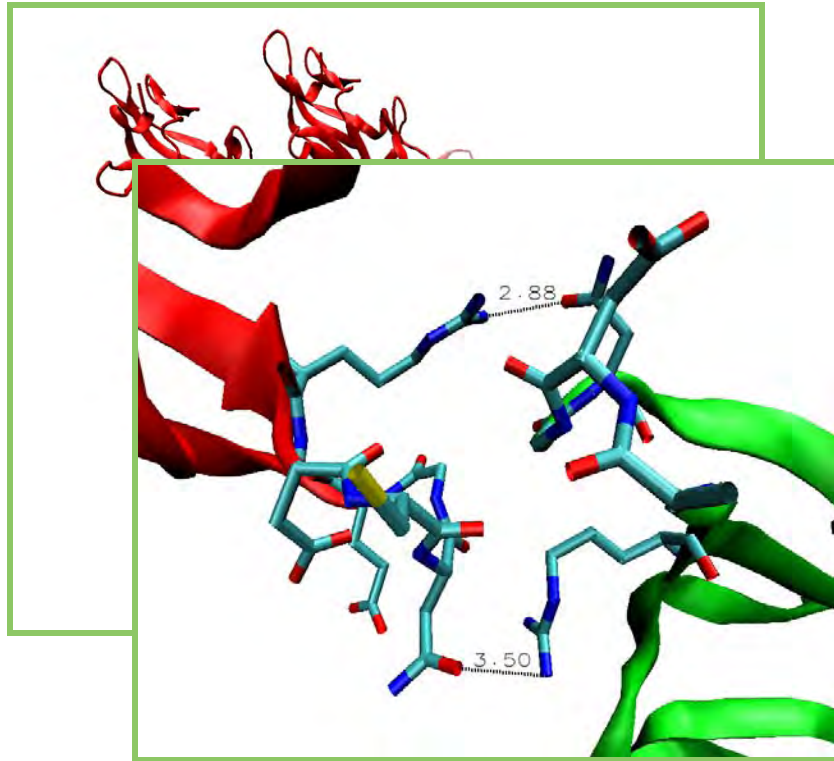


Particular loop motions are curtailed by intermolecular contacts in the crystal environment causing a discrepancy between theory and experiments

FOR MORE INFO...

Liu, Koharudin, Gronenborn & Bahar (2009) *Proteins* 77, 927-939.

Agreement between theory and experiments upon inclusion of crystal lattice effects into the GNM



Crystal contacts

Particular loop motions are curtailed by intermolecular contacts in the crystal environment causing a discrepancy between theory and experiments



Collective Motions Encoded by the Structure: **Normal Modes**

Several modes contribute to dynamics

$$\langle \Delta \mathbf{R}_i \cdot \Delta \mathbf{R}_j \rangle = \sum_k \text{Contribution of mode } k [\Delta \mathbf{R}_i \cdot \Delta \mathbf{R}_j]_k$$

$$\langle \Delta \mathbf{R}_i \cdot \Delta \mathbf{R}_j \rangle = (3k_B T / \gamma) \left[\boldsymbol{\Gamma}^{-1} \right]_{ij}$$

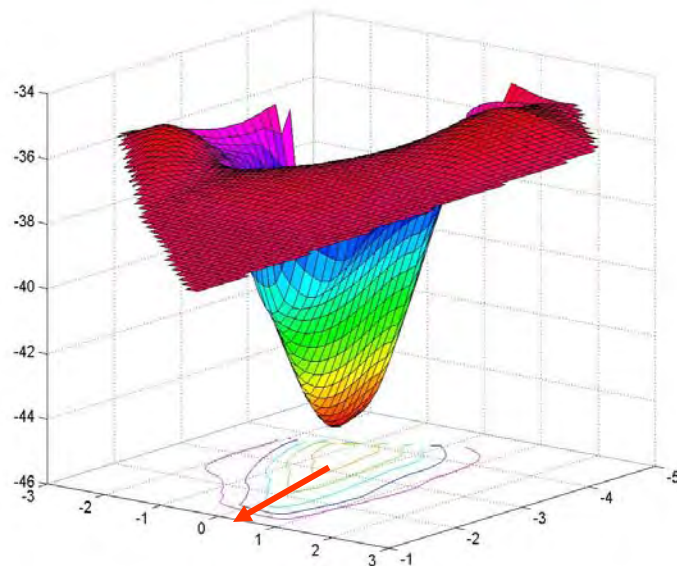
Contribution of mode k

$$[\Delta \mathbf{R}_i \cdot \Delta \mathbf{R}_j]_k = (3k_B T / \gamma) \left[\lambda_k^{-1} \mathbf{u}_k \mathbf{u}_k^T \right]_{ij}$$

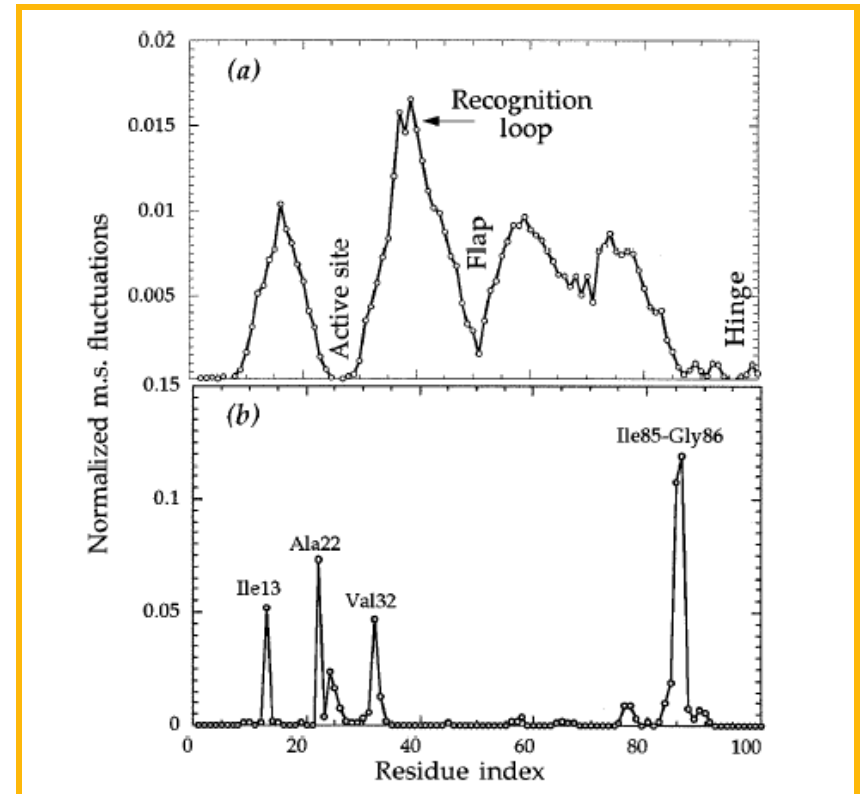
expressed in terms of the kth eigenvalue λ_k and eigenvector $\mathbf{u}_k$

FOR MORE INFO...

Several modes contribute to dynamics

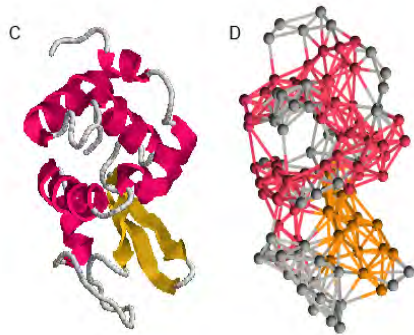


The first mode selects the 'easiest' collective motion

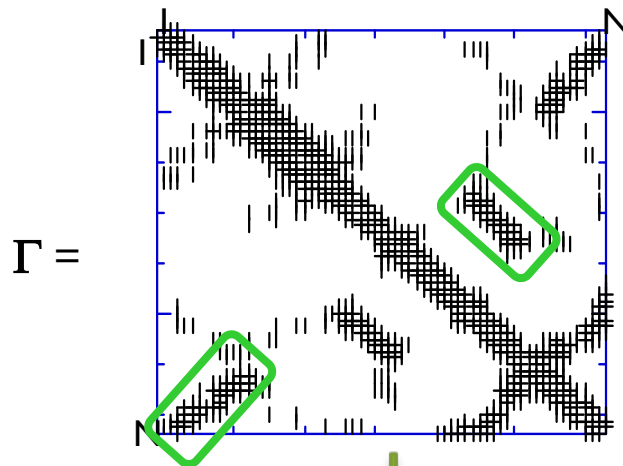


FOR MORE INFO...

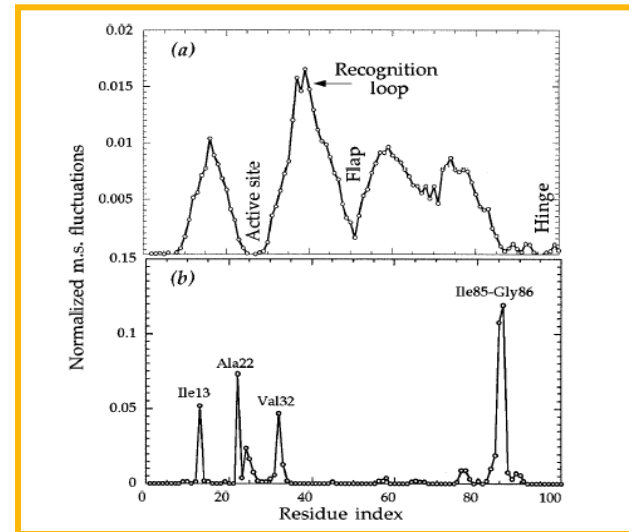
Gaussian network model (GNM)



Kirchhoff matrix for inter-residue contacts



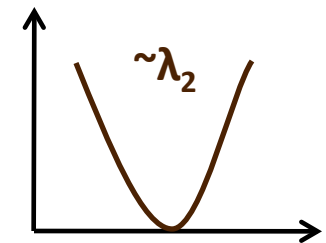
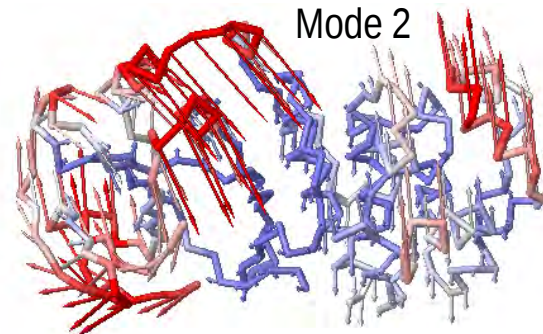
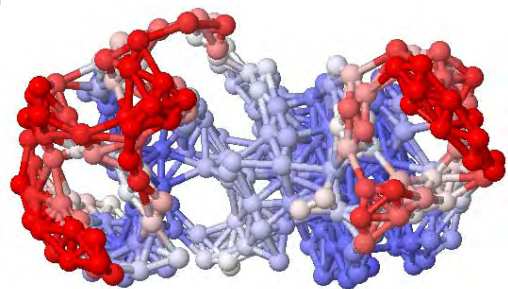
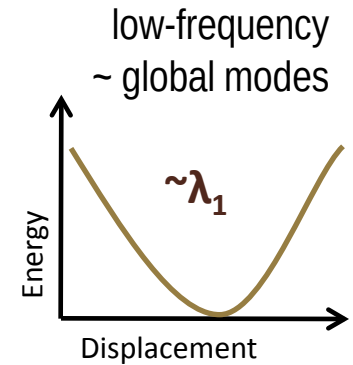
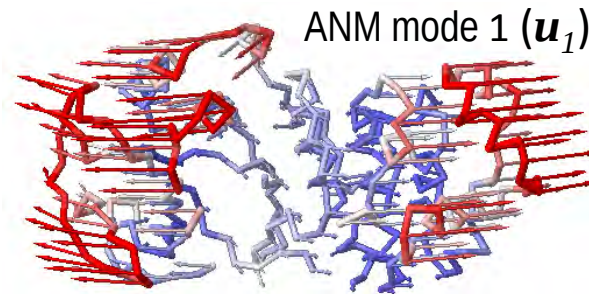
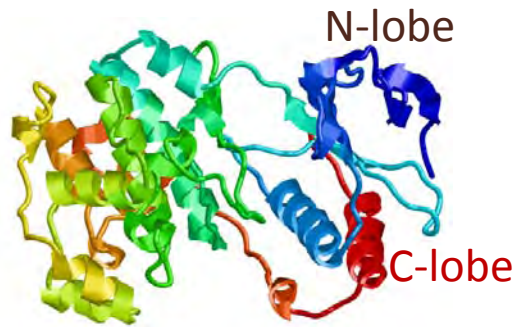
$$[\Delta \mathbf{R}_i \cdot \Delta \mathbf{R}_i]_k = (3k_B T / \gamma) [\lambda_k^{-1} \mathbf{u}_k \mathbf{u}_k^T]_{ii}$$



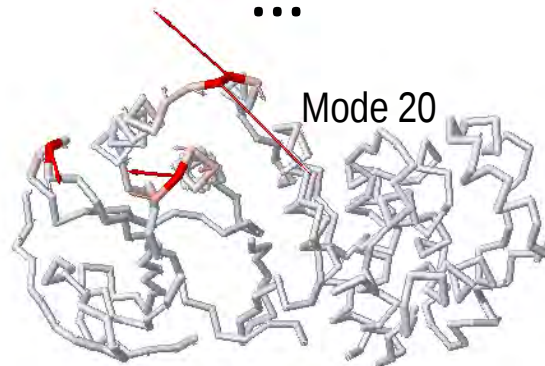
Several modes of motion contribute to dynamics

$$\langle \Delta \mathbf{R}_i \cdot \Delta \mathbf{R}_j \rangle = (1 / Z_N) \int (\Delta \mathbf{R}_i \cdot \Delta \mathbf{R}_j) e^{-V / k_B T} d\{ \Delta \mathbf{R} \} = (3k_B T / \gamma) [\Gamma^{-1}]_{ij}$$

Anisotropic Network Model (ANM)

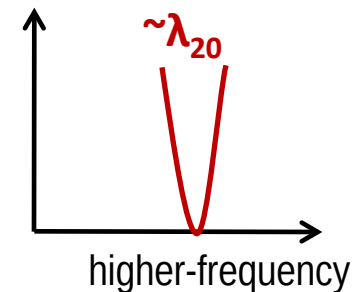


...



...

$$\lambda_1 < \lambda_2 < \lambda_3 < \dots$$



$$\mathbf{H} = \sum_{i=1}^{3N-6} \lambda_i \mathbf{u}_i \mathbf{u}_i^T$$

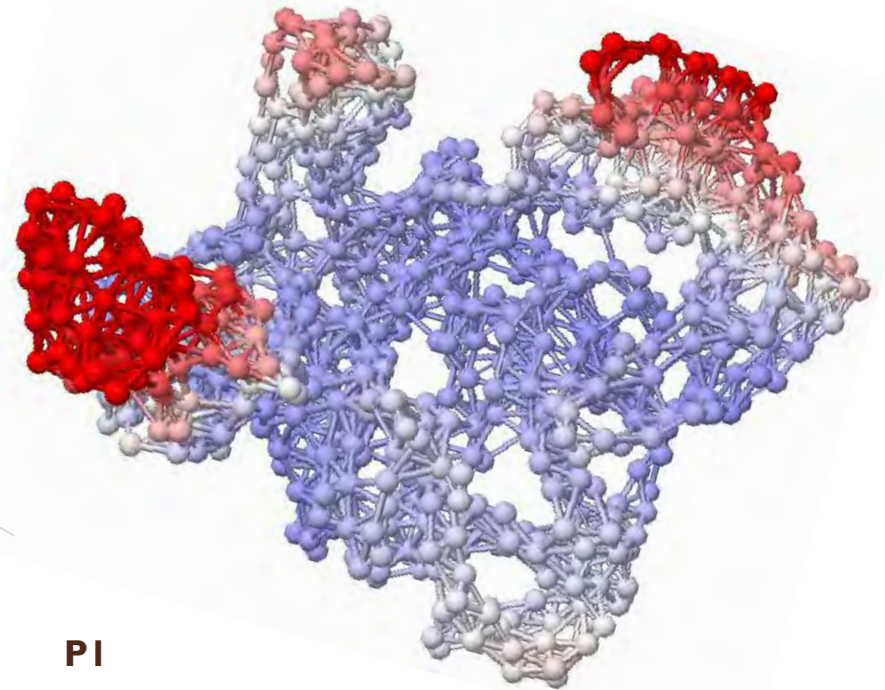
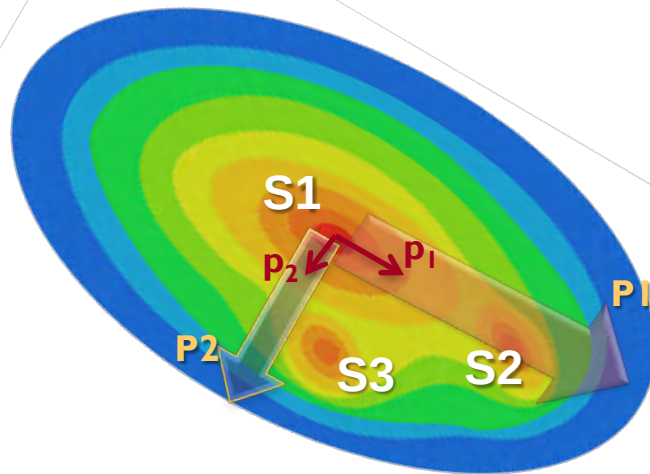
$$\mathbf{H}^{(ij)} = \frac{\gamma}{(R_{ij}^0)^2} \begin{bmatrix} X_{ij}X_{ij} & X_{ij}Y_{ij} & X_{ij}Z_{ij} \\ Y_{ij}X_{ij} & Y_{ij}Y_{ij} & Y_{ij}Z_{ij} \\ Z_{ij}X_{ij} & Z_{ij}Y_{ij} & Z_{ij}Z_{ij} \end{bmatrix}$$

Total of $321 \times 3 - 6 = 957$ modes

Allosteric changes in conformation

ANM (anisotropic network model)

Elastic Network Models are particularly useful for exploring the allosteric dynamics of large multimeric structures



Comparison with experimental data shows that **the functional movements are those predicted by the ENM to be intrinsically encoded by the structure**

Session I: Plotting $\langle(\Delta R_i)^2\rangle$ and contributions of selected modes

- `from prody import *`
- `anm = calcANM('l cot', selstr='calpha')`
- `anm, cot = calcANM('l cot', selstr='calpha')`
- `anm`
- `cot`
- `figure()`
- `showProtein(cot)`
- `figure()`
- `showSqFlucts(anm)`
- `figure()`
- `showSqFlucts(anm[0])`
- `showSqFlucts(anm[:10])`
- `figure()`
- `showSqFlucts(anm[:10], label='10 modes')`
- `legend()`

Session 2: Viewing color-coded animations of individual modes

- `writeNMD('cot_anm.nmd', anm, cot)`
- *Start VMD*
- *select* Extensions → Analysis → Normal Mode Wizard
- *Select* 'Load NMD File'

Session 3: Cross-correlations

$\langle \Delta \mathbf{R}_i \cdot \Delta \mathbf{R}_j \rangle$ between fluctuations

- `cross_corr = calcCrossCorr?`
- `cross_corr = calcCrossCorr(anm[0])`
- `figure()`
- `showCrossCorr(anm[0])`
- `writeHeatmap('anm_cross1.hm', cross_corr)`

Session 4:

Viewing cross-correlations using VMD

- *VMD – Load file*
- *Select cot_anm.nmd (from your local folder)*
- *Load HeatMap*
- *open anm_cross1.hm (from your local folder)*

Ensembles of structures

- Structural changes accompanying substrate (protein) binding
- Structural changes induced by, or stabilized upon, ligand binding



Ubiquitin
140 structures
1732 models

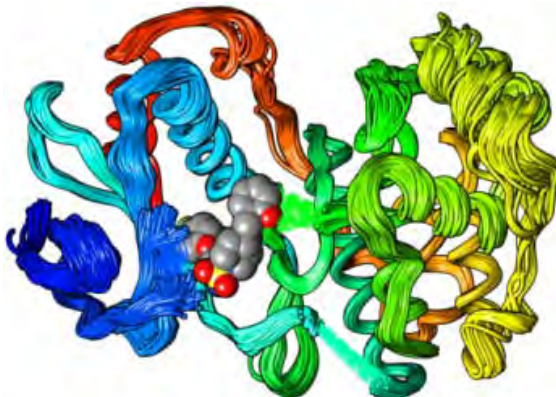
Ensembles of structures

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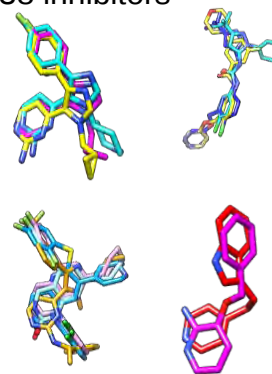


Ubiquitin
140 structures
1732 models

p38 MAP kinase
(182 structures)

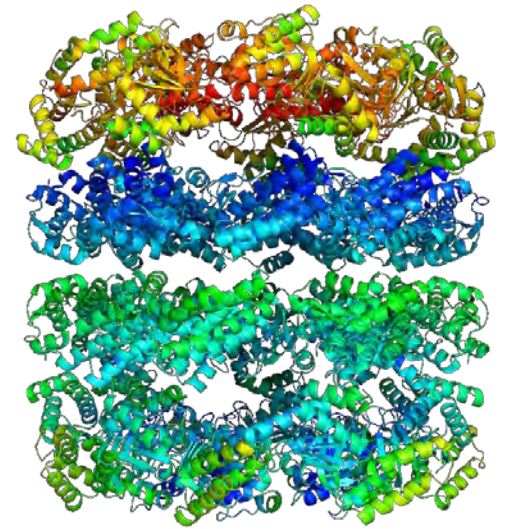


p38 inhibitors



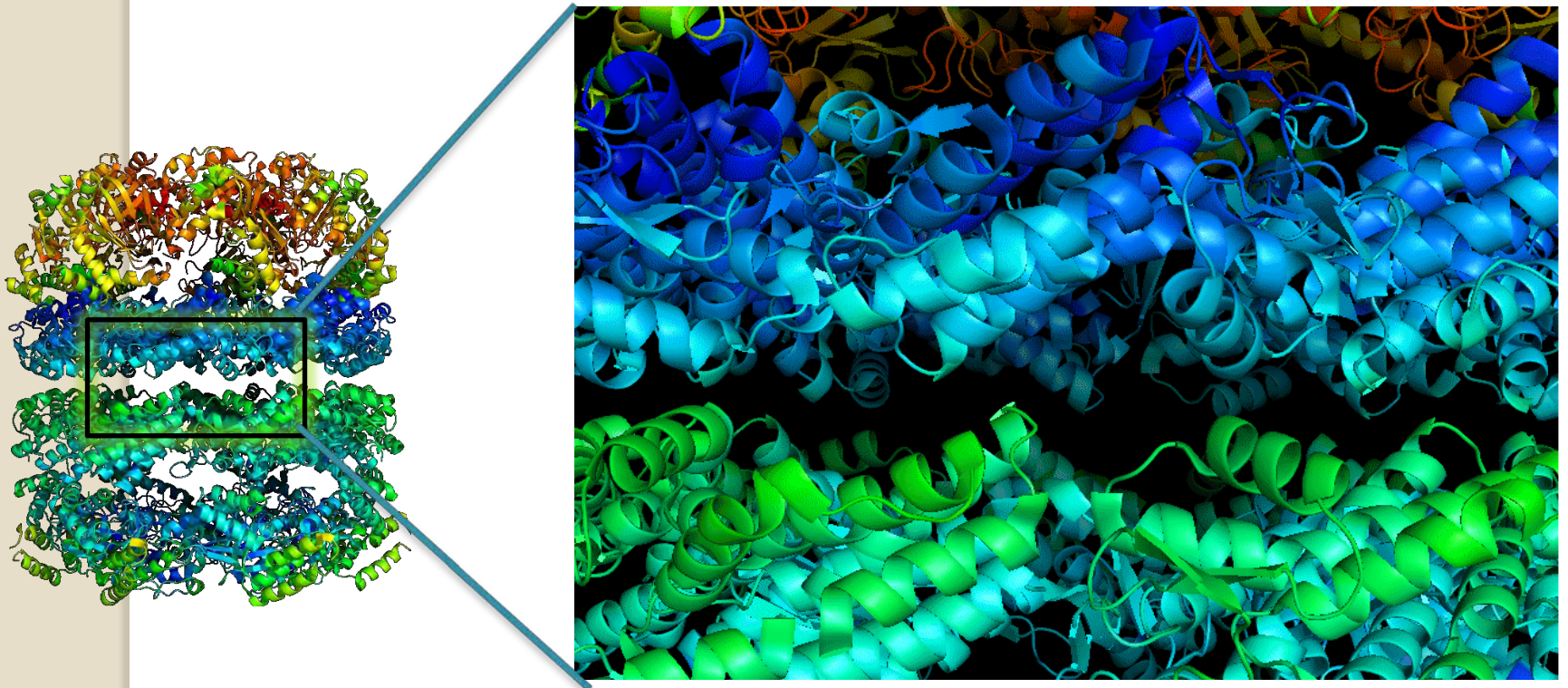
Ensembles of structures

- Structural changes accompanying substrate (protein) binding
- Structural changes induced by, or stabilized upon, ligand binding
- Alternative conformations sampled during allosteric cycles

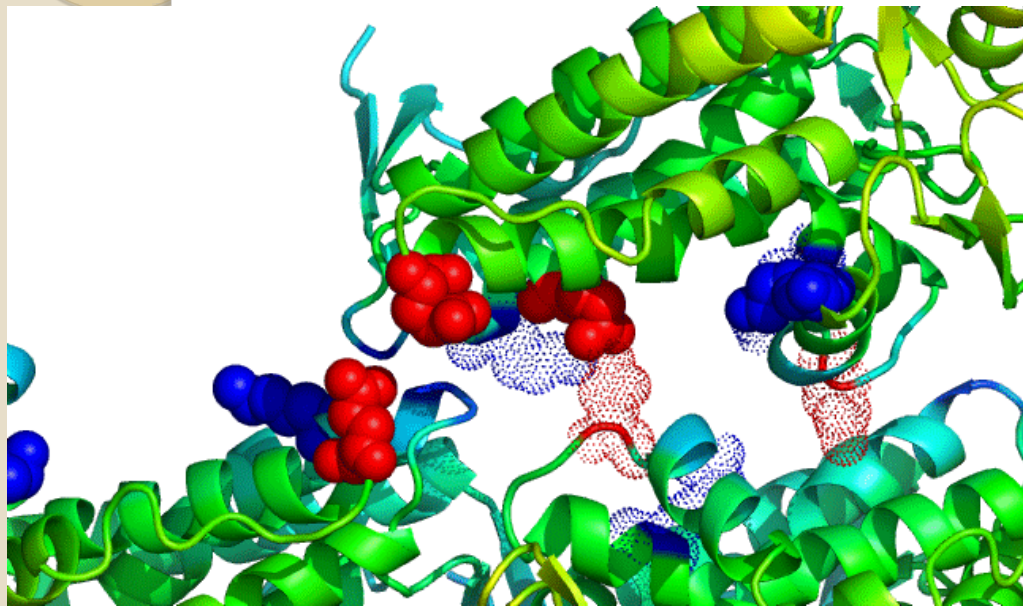


Yang et al. *PLoS Comp Biol* 2009

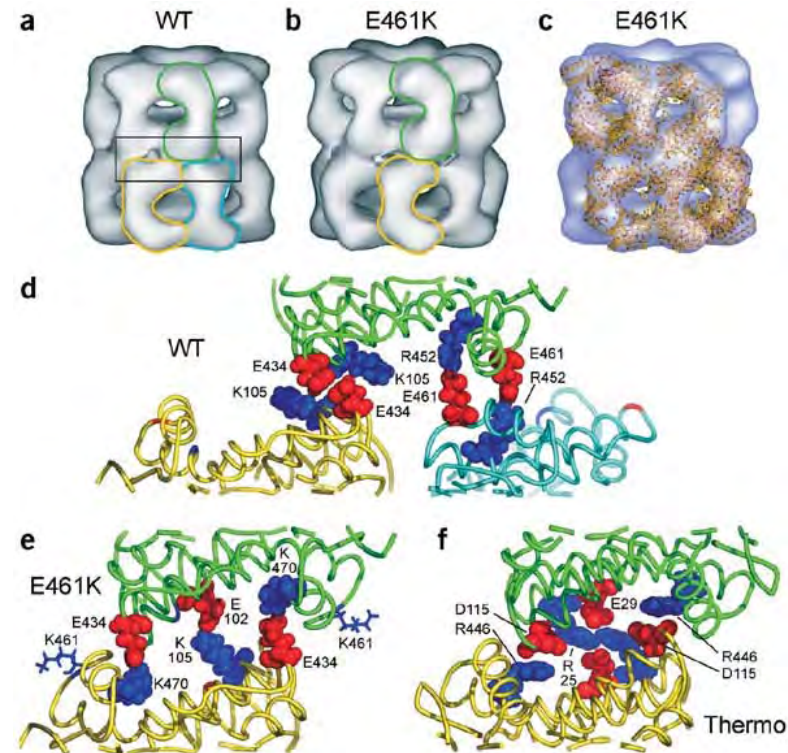
Redistribution of interactions at interfaces



Mutations may stabilize conformers along soft modes – which may be dysfunctional

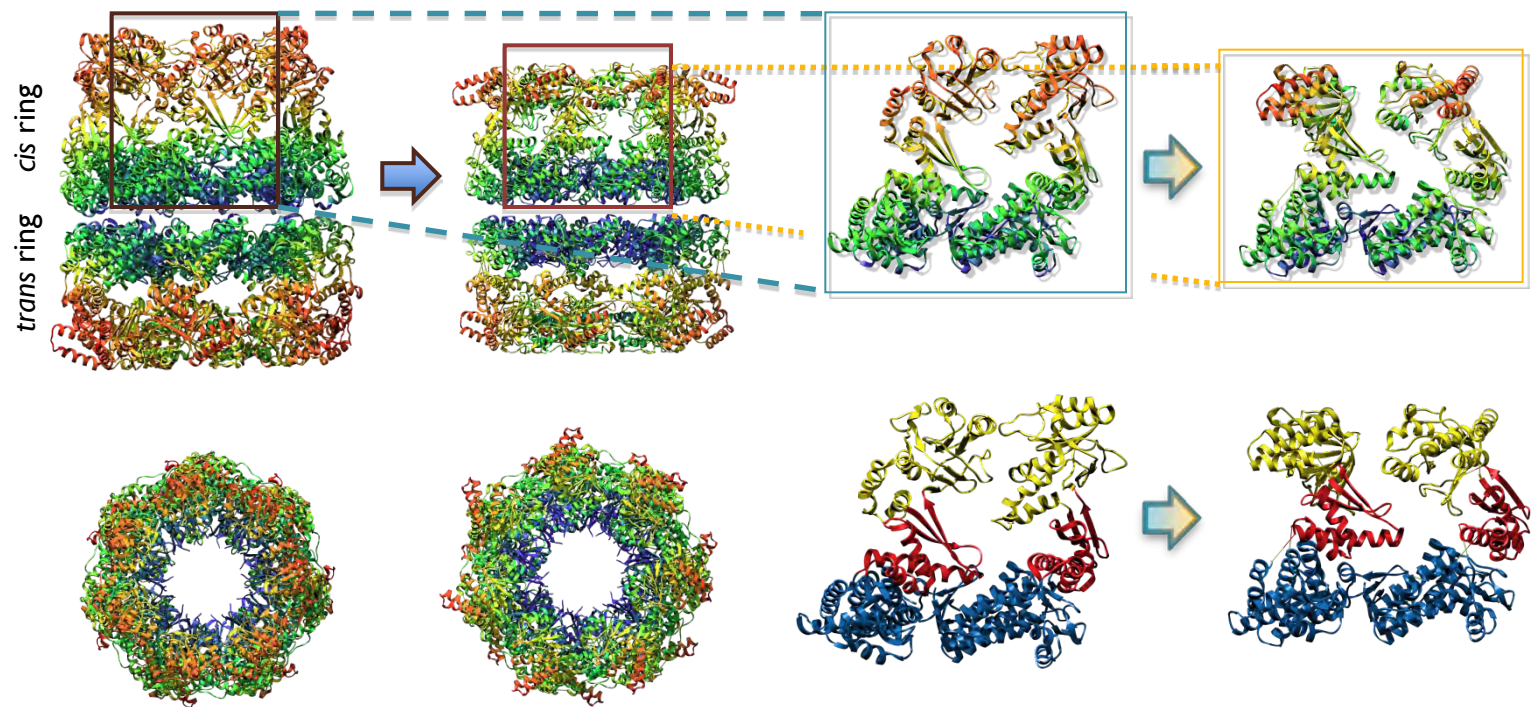


E461 mutant is a deformed structure along mode 1



E461K mutation causes disruption of inter-ring transfer of ATP-induced signal (Sewell et al NSB 2004)

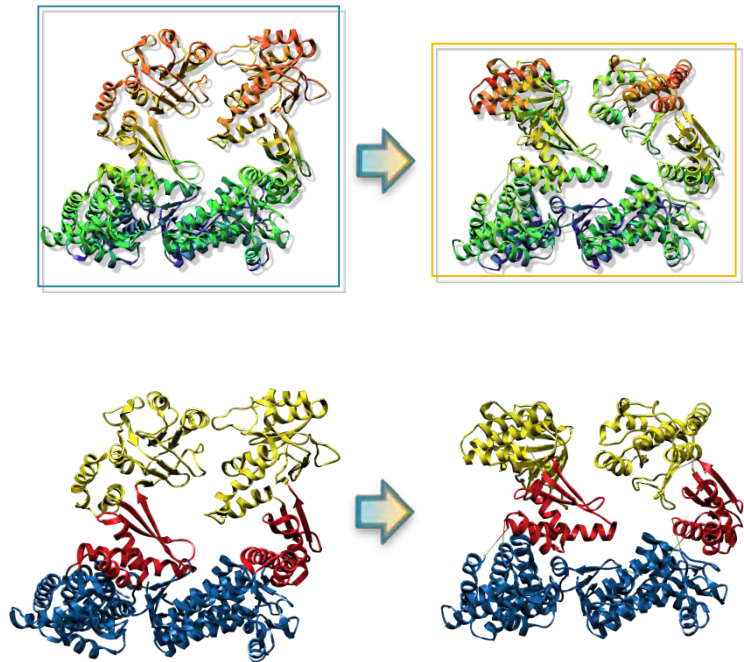
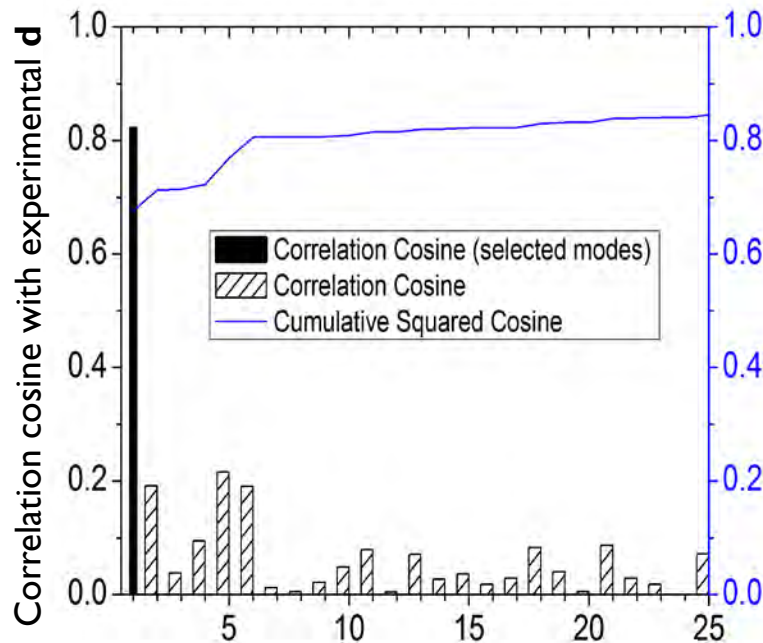
Passage between the R and T state of GroEL



See...

Z Yang, P Marek and I Bahar, *PLoS Comp Biology* 2009

The softest mode enables the passage $R \rightarrow T$ (with a correlation of 0.81)

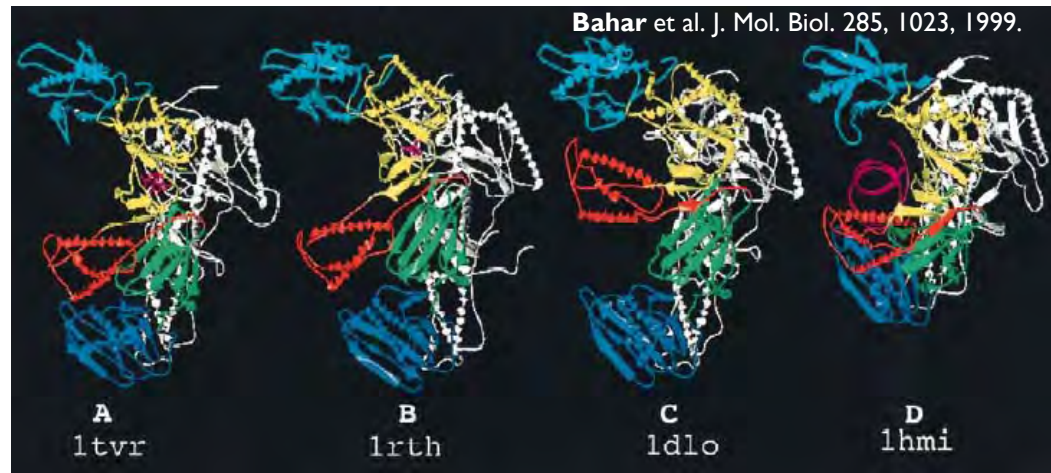


$$\mathbf{d} = [\Delta x_1 \quad \Delta y_1 \quad \Delta z_1 \quad \dots \quad \Delta z_N]^T$$

See...

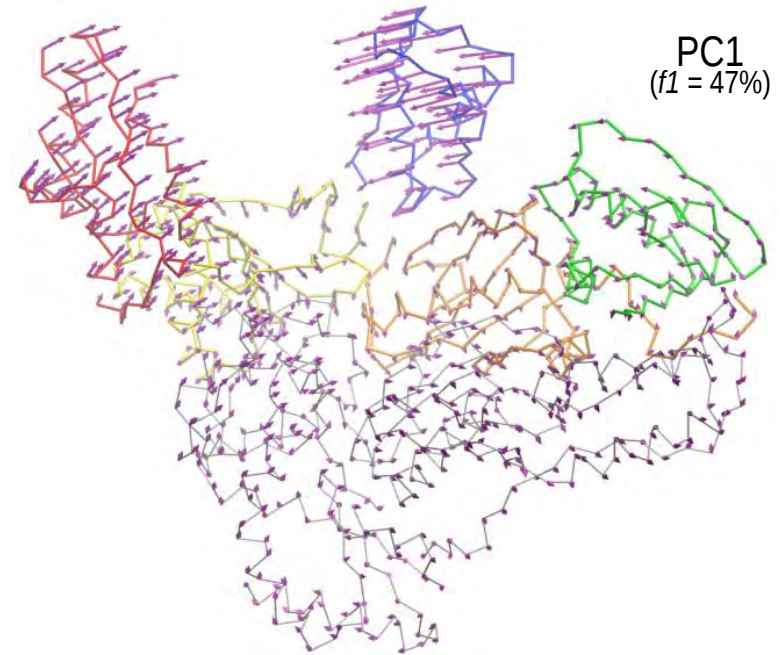
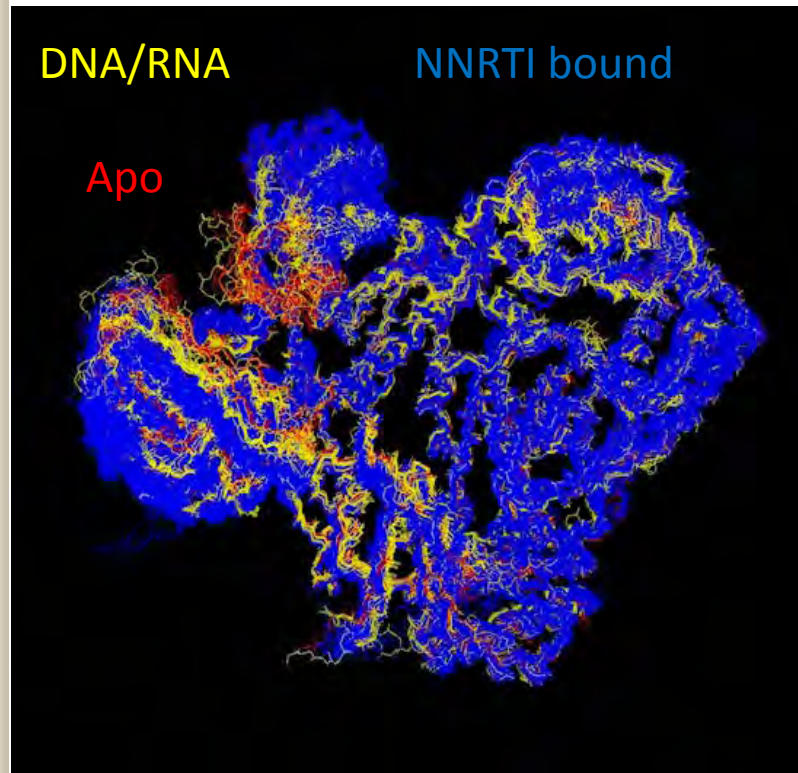
Dynamics inferred from known structures

Comparison of static structures available in the PDB for the same protein in different form has been widely used as an **indirect** method of inferring dynamics.



Different structures resolved for HIV-1 reverse transcriptase (RT)

Principal Component Analysis (PCA)

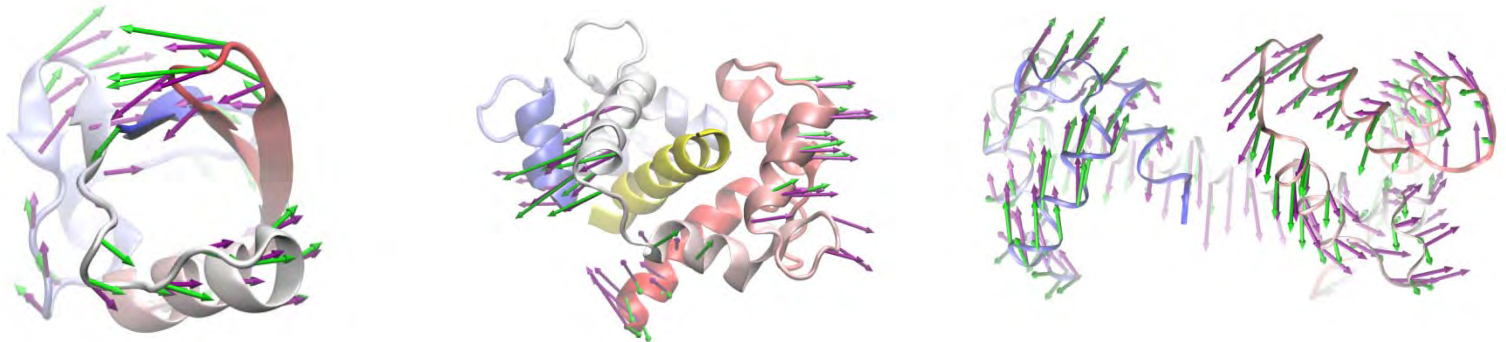


$$\mathbf{C}^{(ij)} = \begin{bmatrix} \langle \Delta x_i \Delta x_j \rangle & \langle \Delta x_i \Delta y_j \rangle & \langle \Delta x_i \Delta z_j \rangle \\ \langle \Delta y_i \Delta x_j \rangle & \langle \Delta y_i \Delta y_j \rangle & \langle \Delta y_i \Delta z_j \rangle \\ \langle \Delta z_i \Delta x_j \rangle & \langle \Delta z_i \Delta y_j \rangle & \langle \Delta z_i \Delta z_j \rangle \end{bmatrix}$$



$$\mathbf{C} = \mathbf{P} \mathbf{S} \mathbf{P}^T = \sum_{i=1}^{3N} \sigma_i \mathbf{p}^i \mathbf{p}^{iT}$$

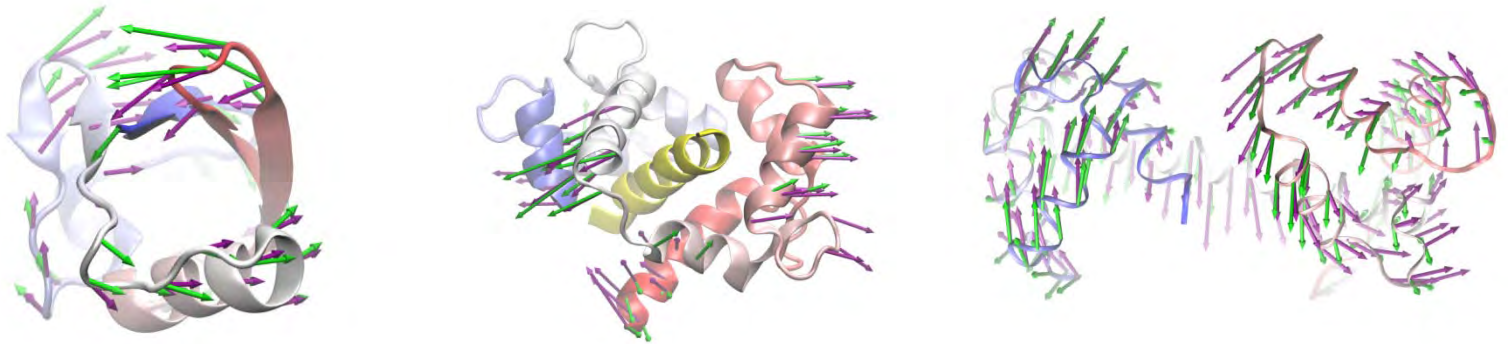
Global motions inferred from theory and experiments



→ PCA of the ensemble of resolved structures

→ ANM analysis of a single structure from the ensemble

Global motions inferred from theory and experiments



The intrinsic dynamics of enzymes plays a dominant role in determining the structural changes induced upon inhibitor binding

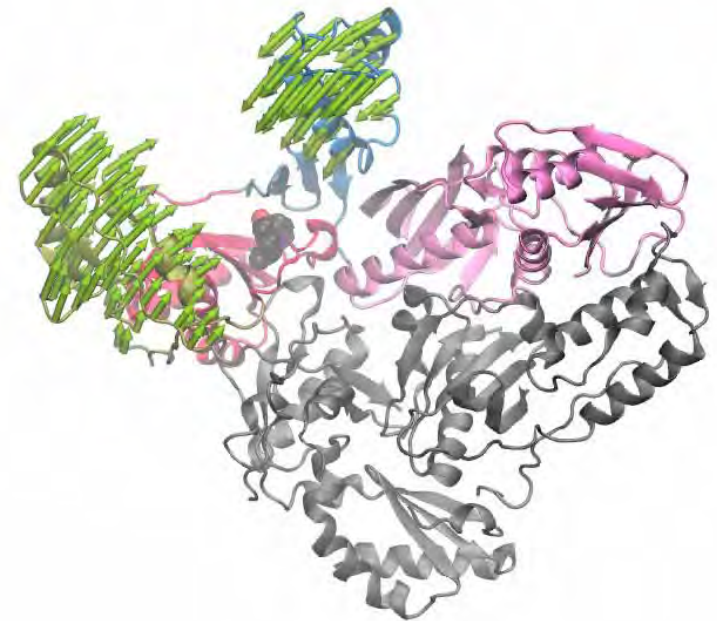
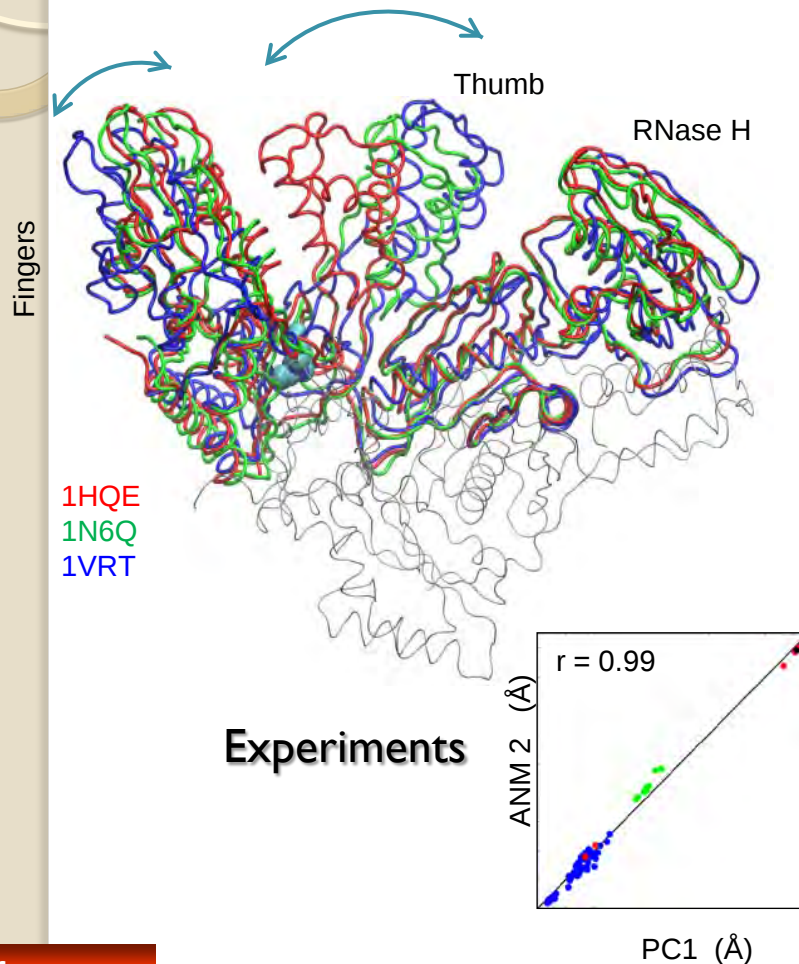
Ahmet Bakan and Ivet Bahar¹

Department of Computational Biology, School of Medicine, University of Pittsburgh, 3064 BST3, 3501 Fifth Avenue, Pittsburgh, PA 15213

Reference:

Bakan & Bahar (2009) PNAS 106, 14349-54

Induced Dynamics or Intrinsic Dynamics?

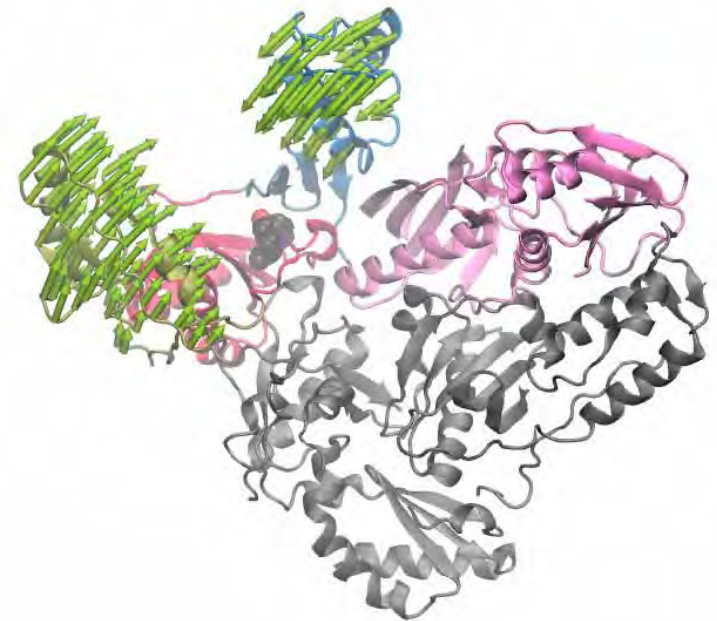
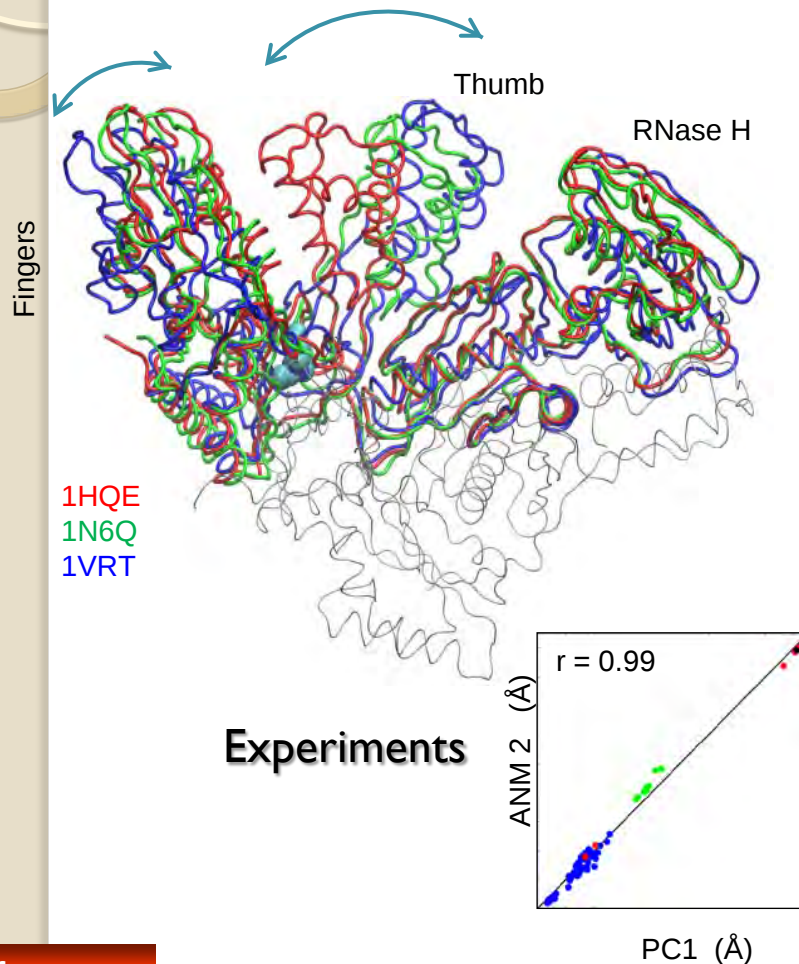


<http://www.youtube.com/watch?v=1OUzdm68YY>

References:

Bakan & Bahar (2009) PNAS 106, 14349-54.

Soft modes enable **functional** movements



<http://www.youtube.com/watch?v=1OUzdm68YY>

References:

Bakan & Bahar (2009) PNAS **106**, 14349-54.

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...

ProDy for exploring conformational space

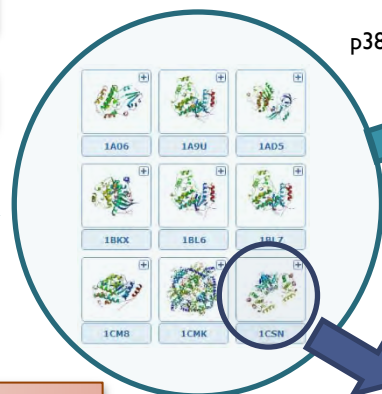
Protein Dynamics Analysis in Python

Usage example

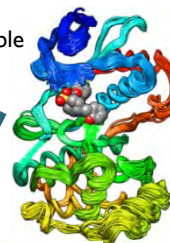
User inputs a protein sequence

```
>1A9U:A|PDBID|CHAIN
GSSHHHHHHSSGLVPRGSHMSQER
PTFYRQELNKTIWEVPERYQNLSPV
GSGAYGSVCAAFDTKTGLRVAVKK
LSRPFQSIHAKRTYRELRLKHKMKH
ENVIGLLDVFT.....
```

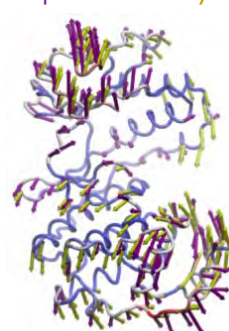
ProDy identifies, retrieves, aligns, and analyzes (PCA) structures that match the input sequence



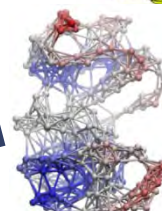
p38 ensemble
(PCA)



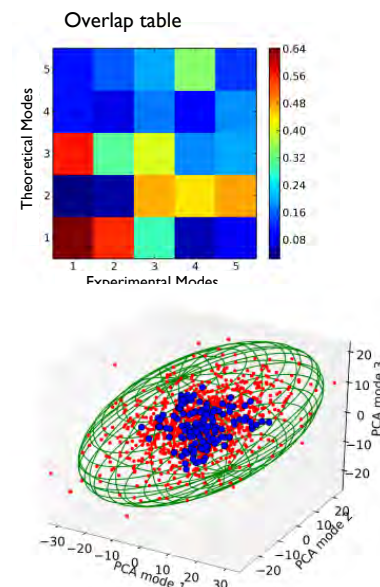
Experiment/Theory



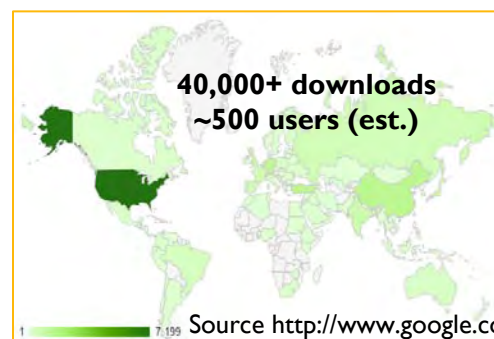
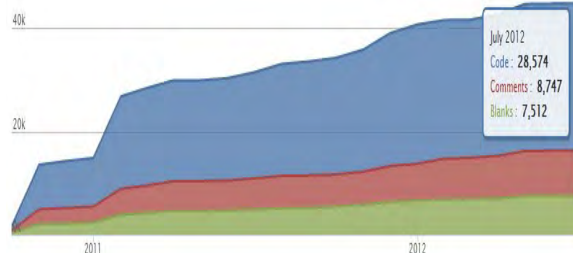
p38 network model
(ANM)



User can compare experimental and theoretical models



Growth of Source Code



Source <http://www.google.com/analytics/>

User can sample an ensemble of conformations along ANM modes for docking simulations

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Comp & Systems Biol,
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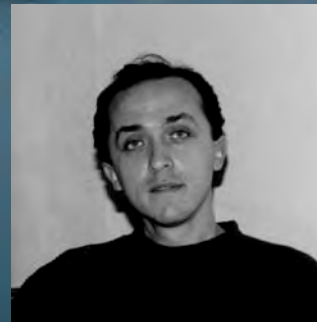
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