

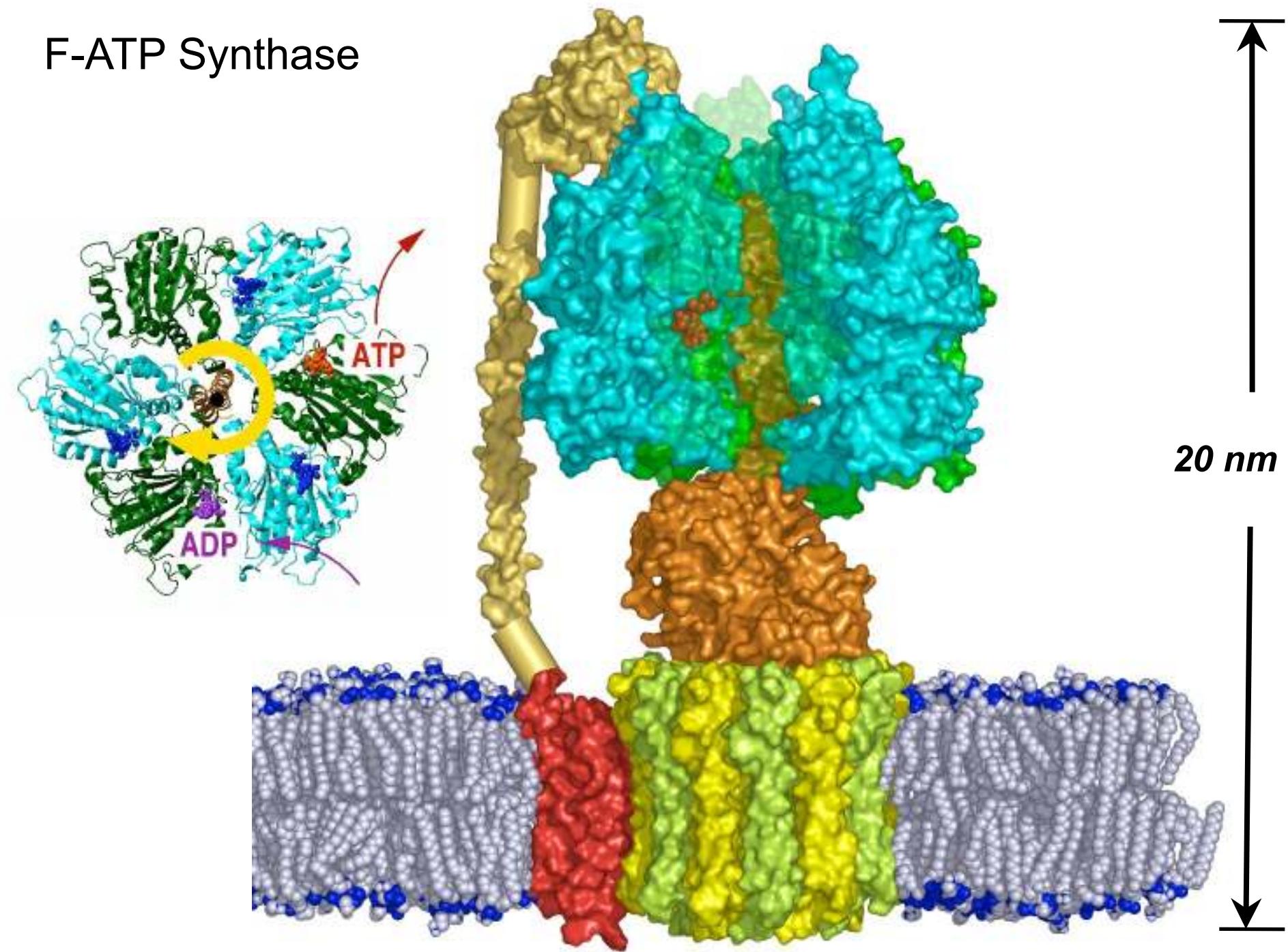


Positions available

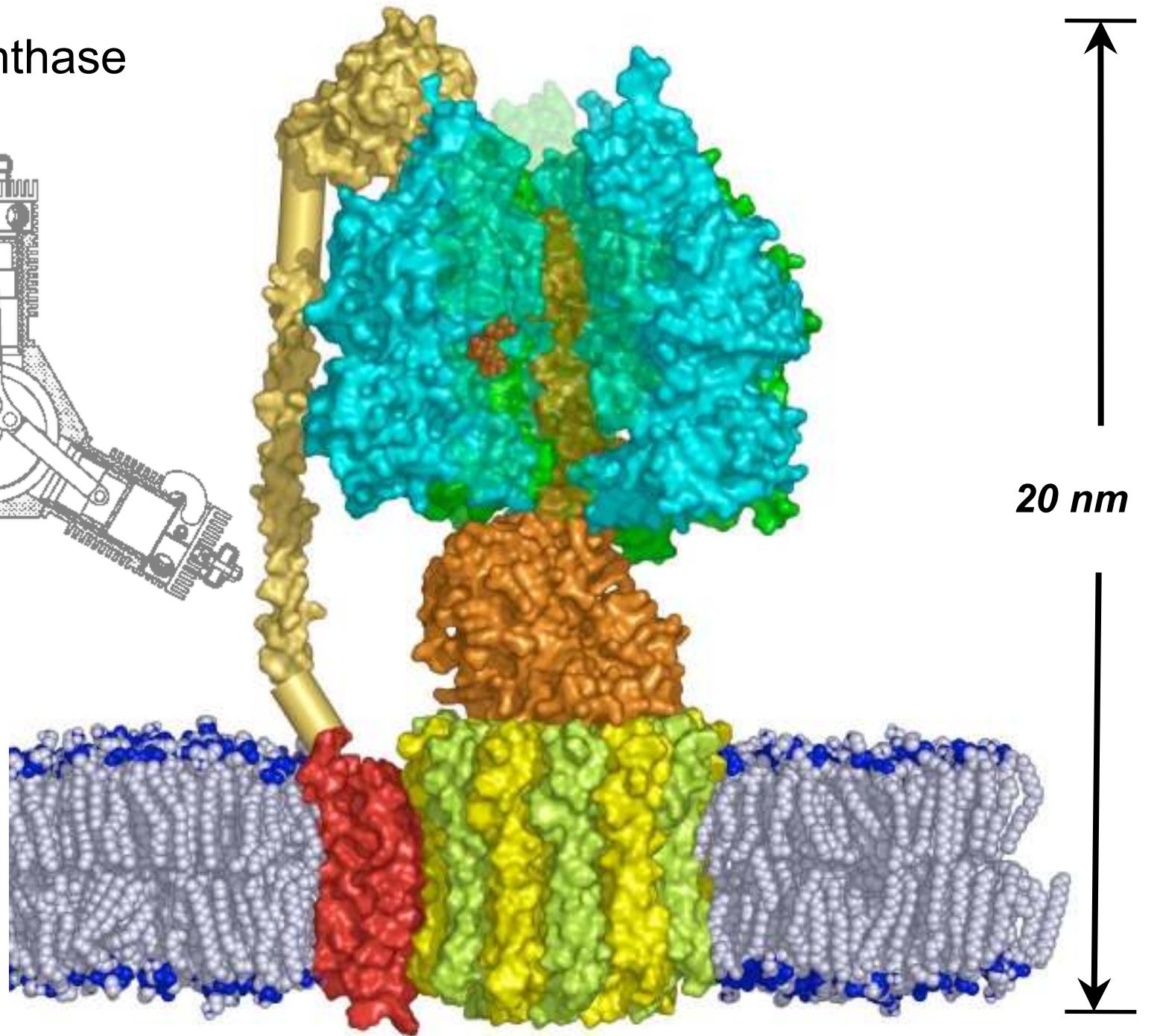
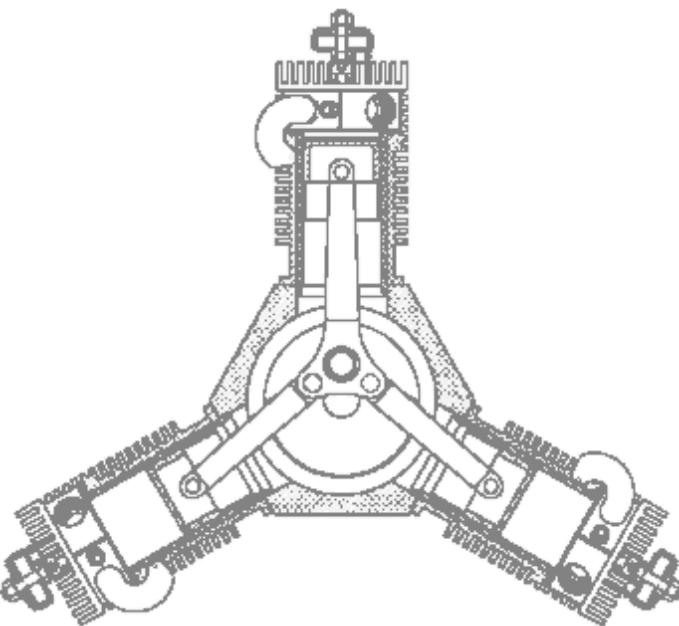
Proteins are Molecular Machines !

***Elementary steps:
Conformational motions***

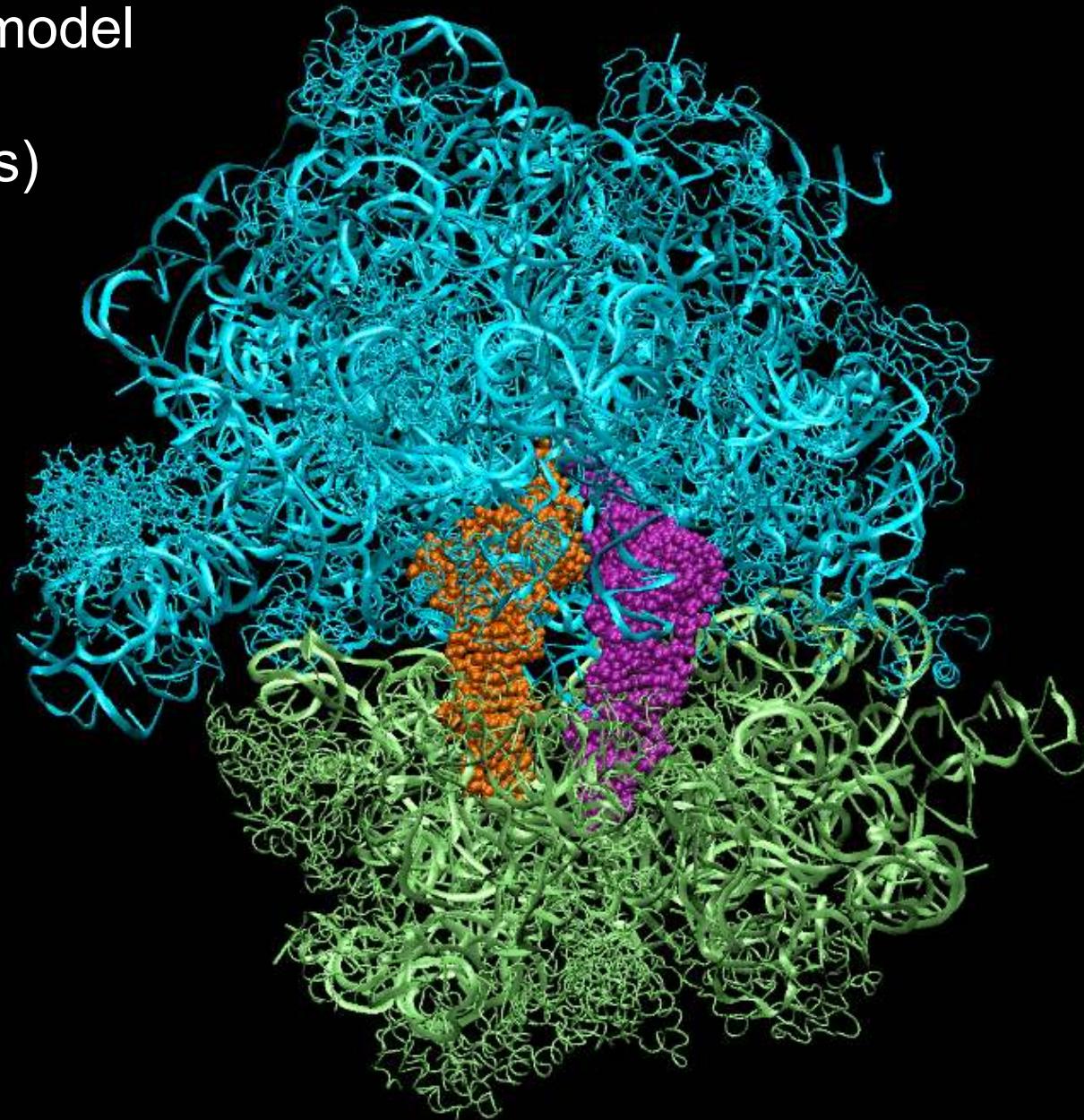
F-ATP Synthase



F-ATP Synthase



MD-Fit of
atomic xray model
to EM maps
(23 structures)



Reality



X-ray crystallography

„This is reality, not just simulations!“

Sir John Walker, European Biophysics Congress, London, 2007



Tur

J

K

L

M

Time resolved x-ray crystallography



single particle cryo EM



(C) Stacey Burgess

AFM



<http://go.to/arstanelver>

Molecular dynamics simulation



<http://go.to/arislanelver>

Molecular dynamics simulation



<http://go.to/arislanelver>

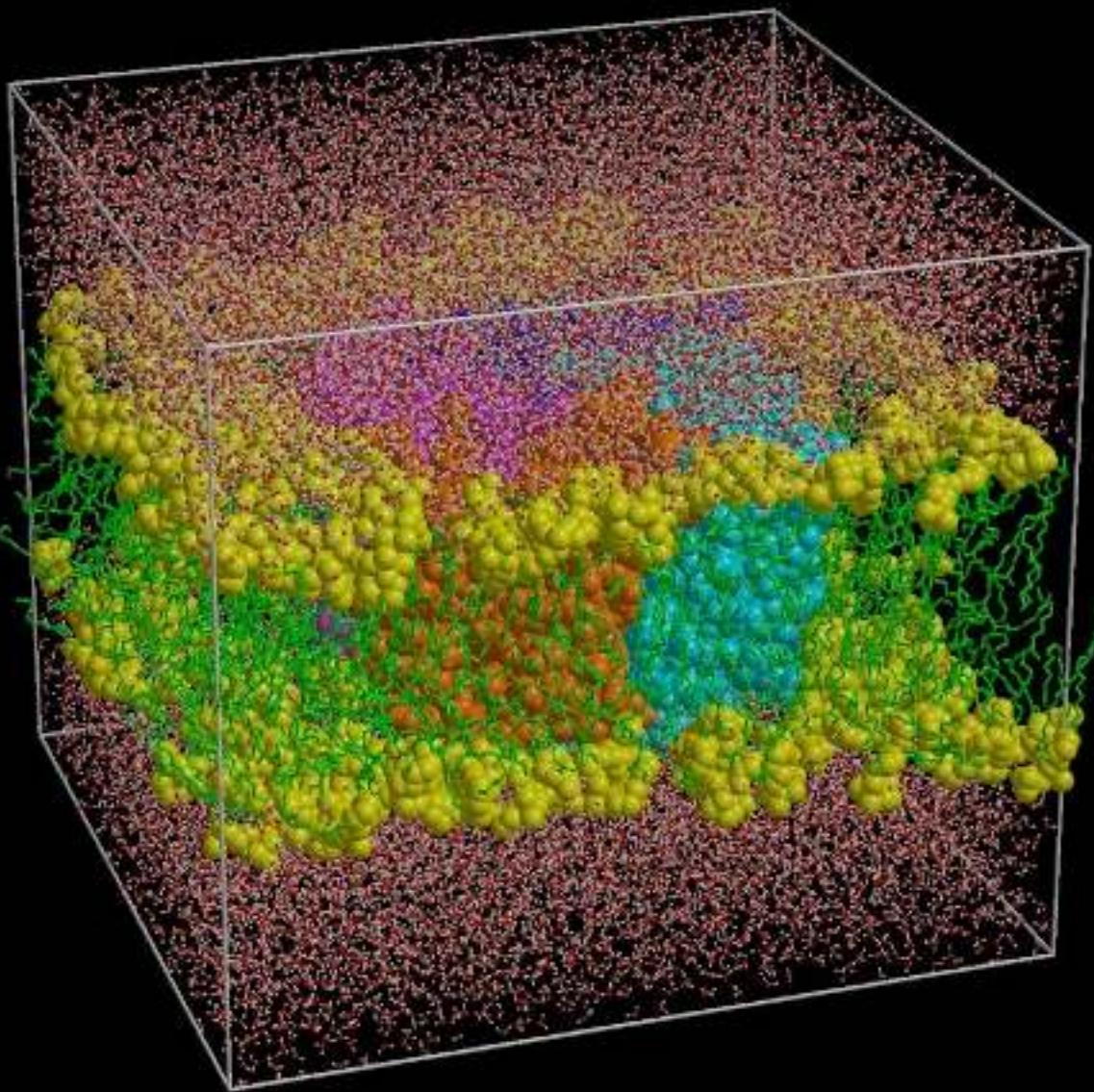
Molecular dynamics simulation



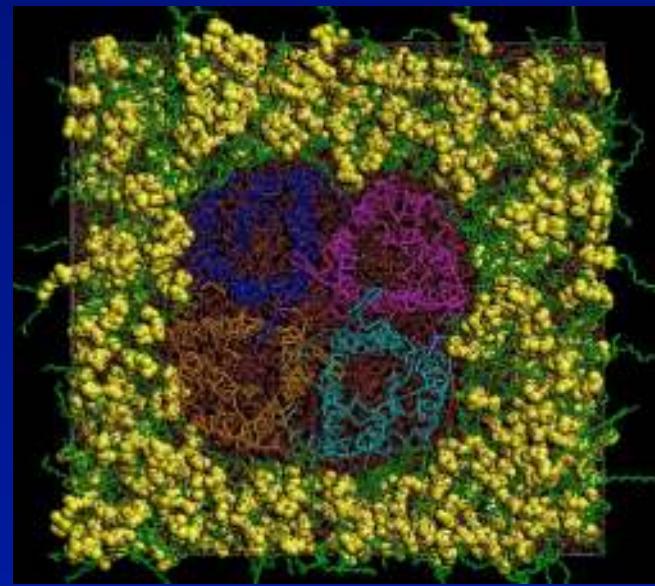
<http://go.to/arislanelver>

Molecular dynamics simulation

MD simulations of water transport

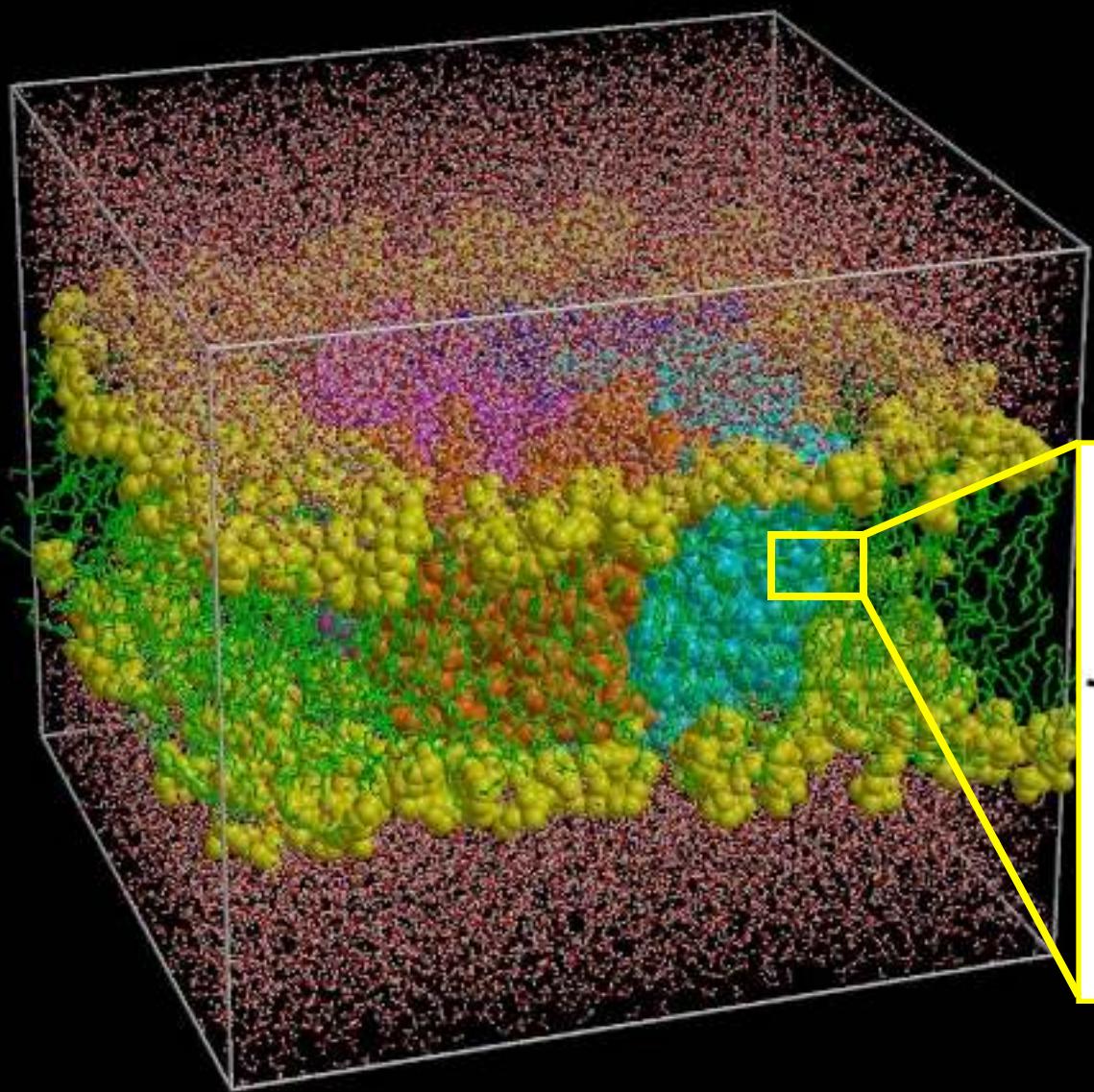


- ca. 100 000 atoms
- full electrostatics,
periodic boundary
- 10 ns simulation time

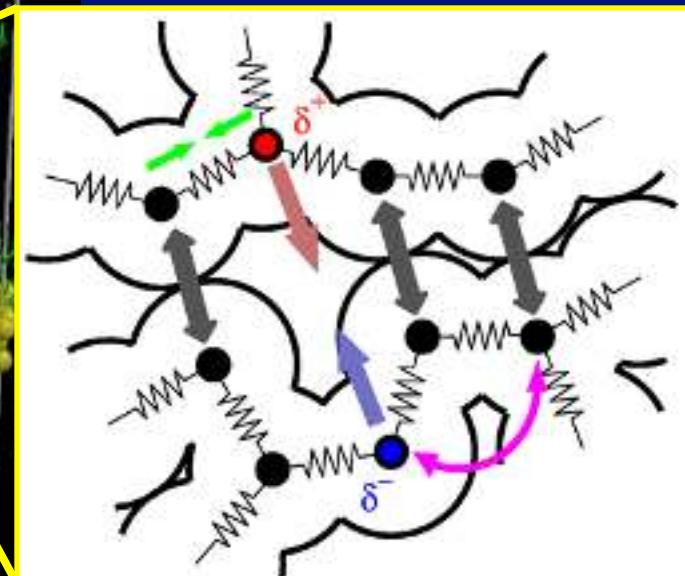


top view

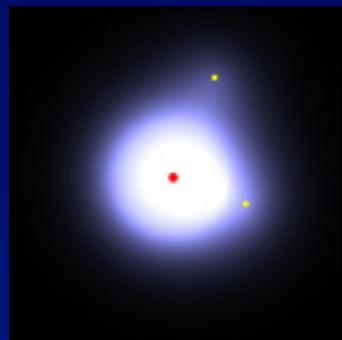
MD simulations of water transport



- ca. 100 000 atoms
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periodic boundary
- 10 ns simulation time



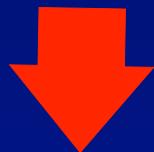
Molecular Dynamics Simulations



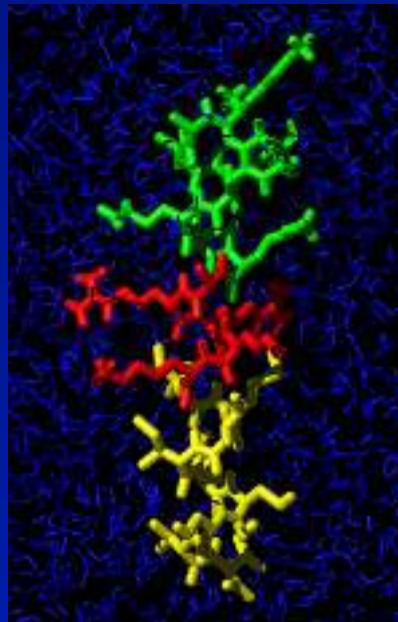
Schrödinger equation

$$i\hbar\partial_t\Psi(r, R) = H\Psi(r, R)$$

Born-Oppenheimer approximation



$$H_e\Psi_e(r; R) = E_e(R)\Psi_e(r; R)$$



Nucleic motion described classically

$$m_i \frac{d^2}{dt^2} \vec{R}_i = -\vec{\nabla}_i E(\vec{R})$$

Empirical Force field

$$E(\vec{R}) = \sum_{\text{bonded}} E_i(\vec{R}) + \sum_{\text{non-bonded}} E_i(\vec{R})$$

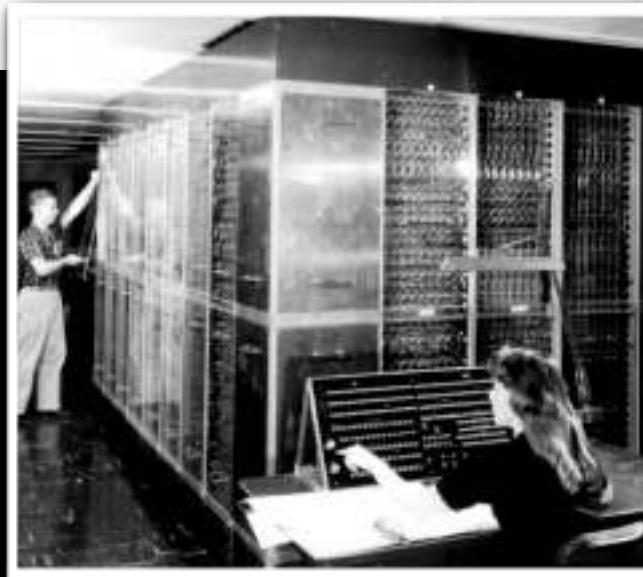
STUDIES OF NON LINEAR PROBLEMS

E. FERMI, J. PASTA, and S. ULAM
Document LA-1940 (May 1955).

ABSTRACT.

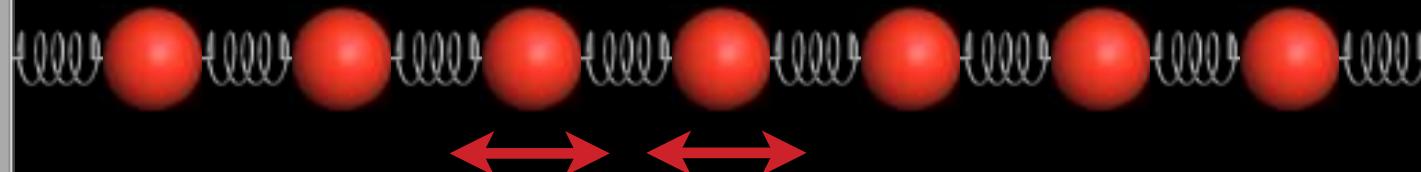
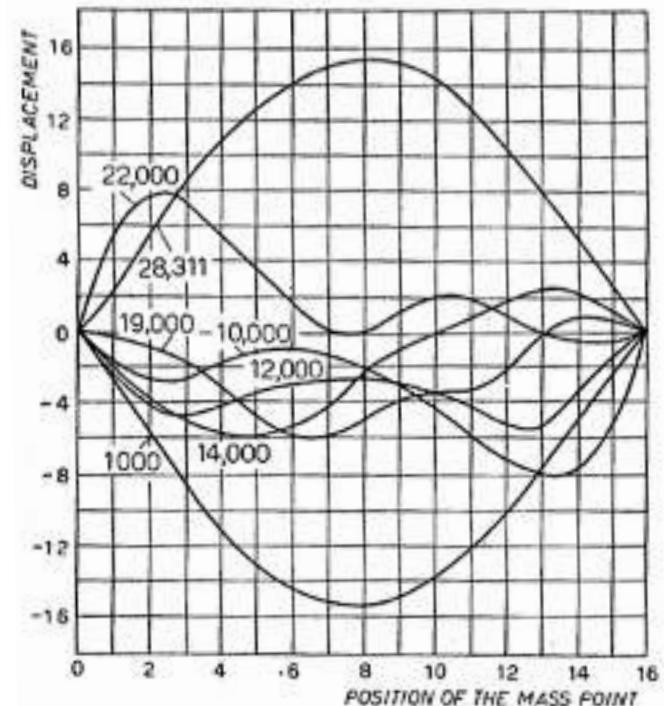
A one-dimensional dynamical system of 64 particles with forces between neighbors containing nonlinear terms has been studied on the Los Alamos computer MANIAC I. The nonlinear terms considered are quadratic, cubic, and broken linear types. The results are analyzed into Fourier components and plotted as a function of time.

The results show very little, if any, tendency toward equipartition of energy among the degrees of freedom.



http://knuth.cs.bilgi.edu.tr/%7Ecomp149-02/projects/history_of_cnt/the_dreamers/img/maniac.jpg

1955: A new field is born



High performance parallel computing



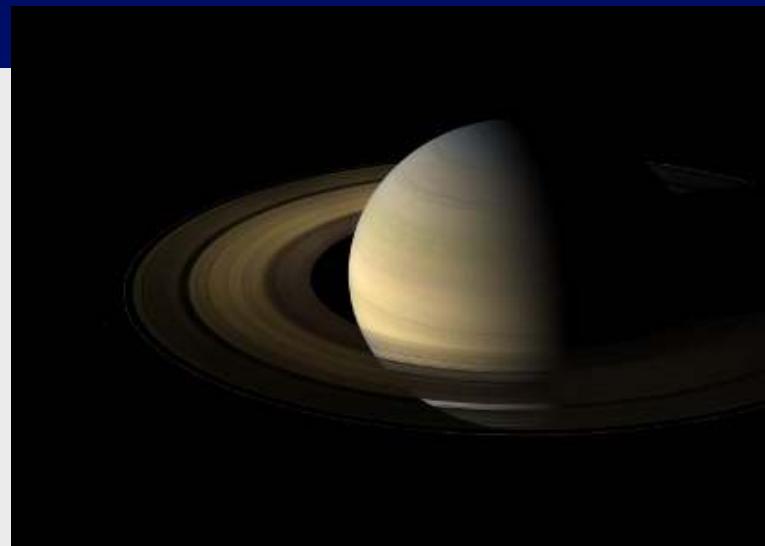
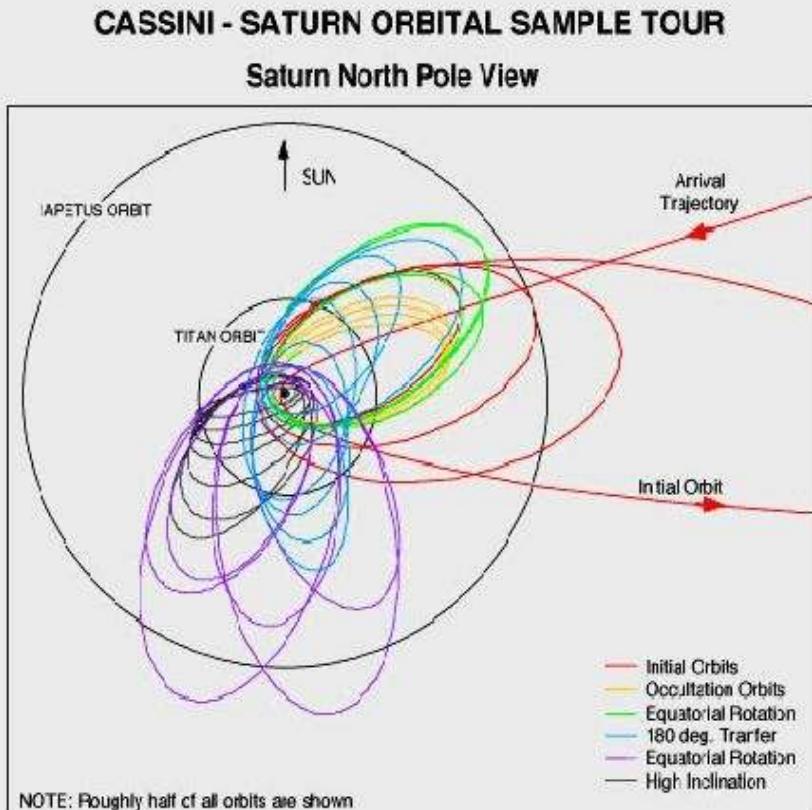
15 500 cores
150 GPUs

150 TFlop/s

12 TByte RAM
200 TByte disk

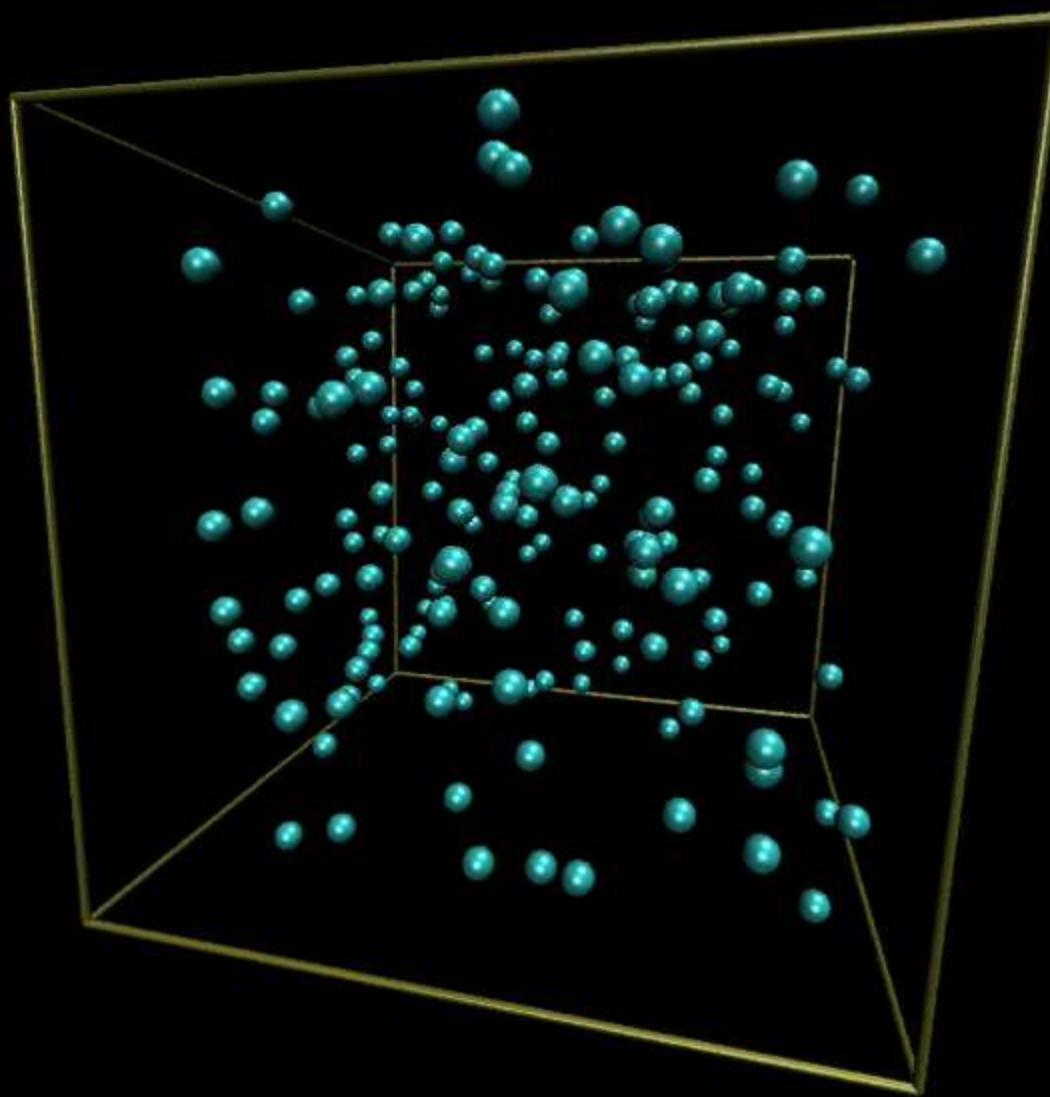
300 kW

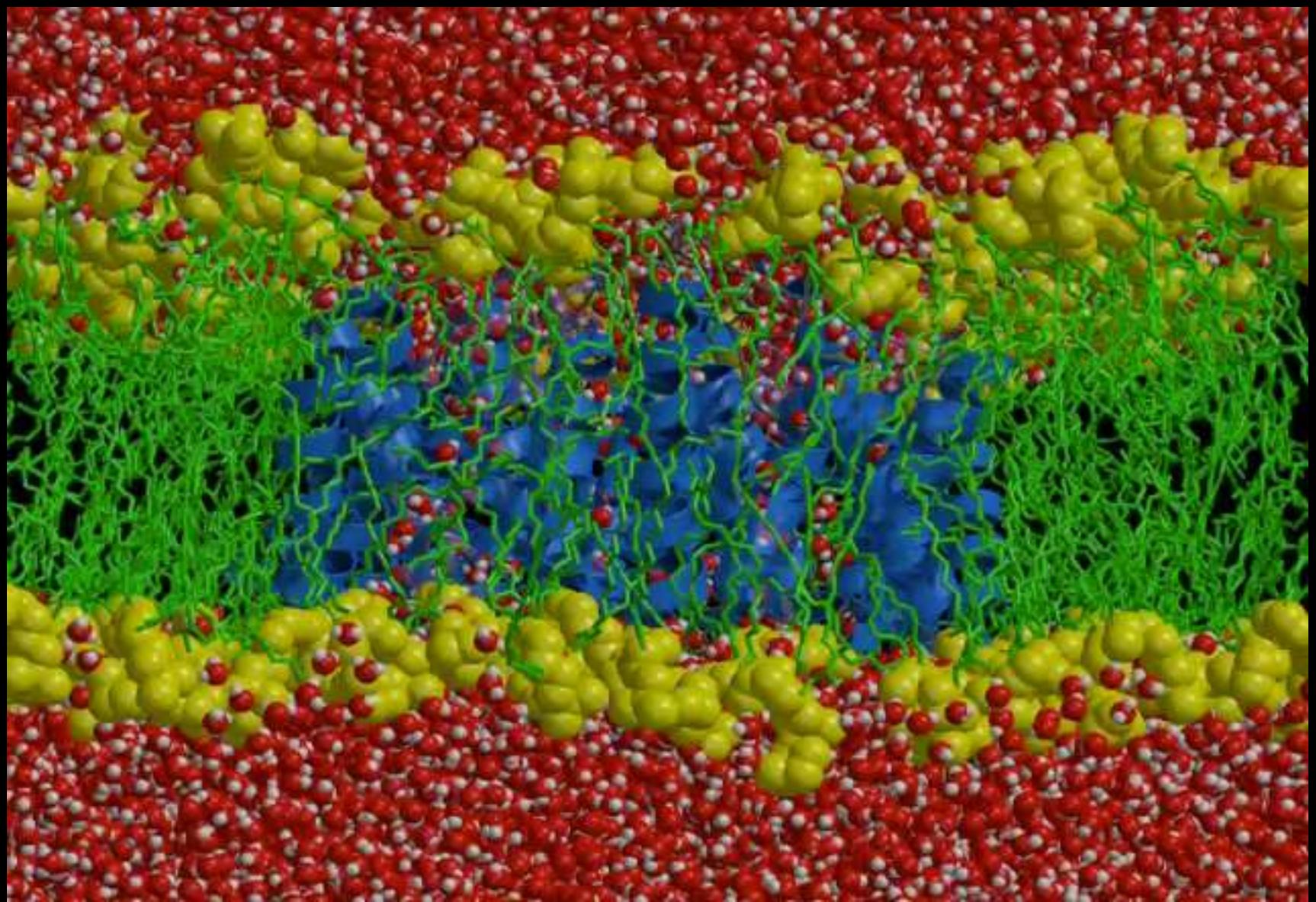
Cassini space probe trajectory to Saturn



Source: MPG, Max Planck Institute for Solar System Research

MD-Experiments with Argon Gas



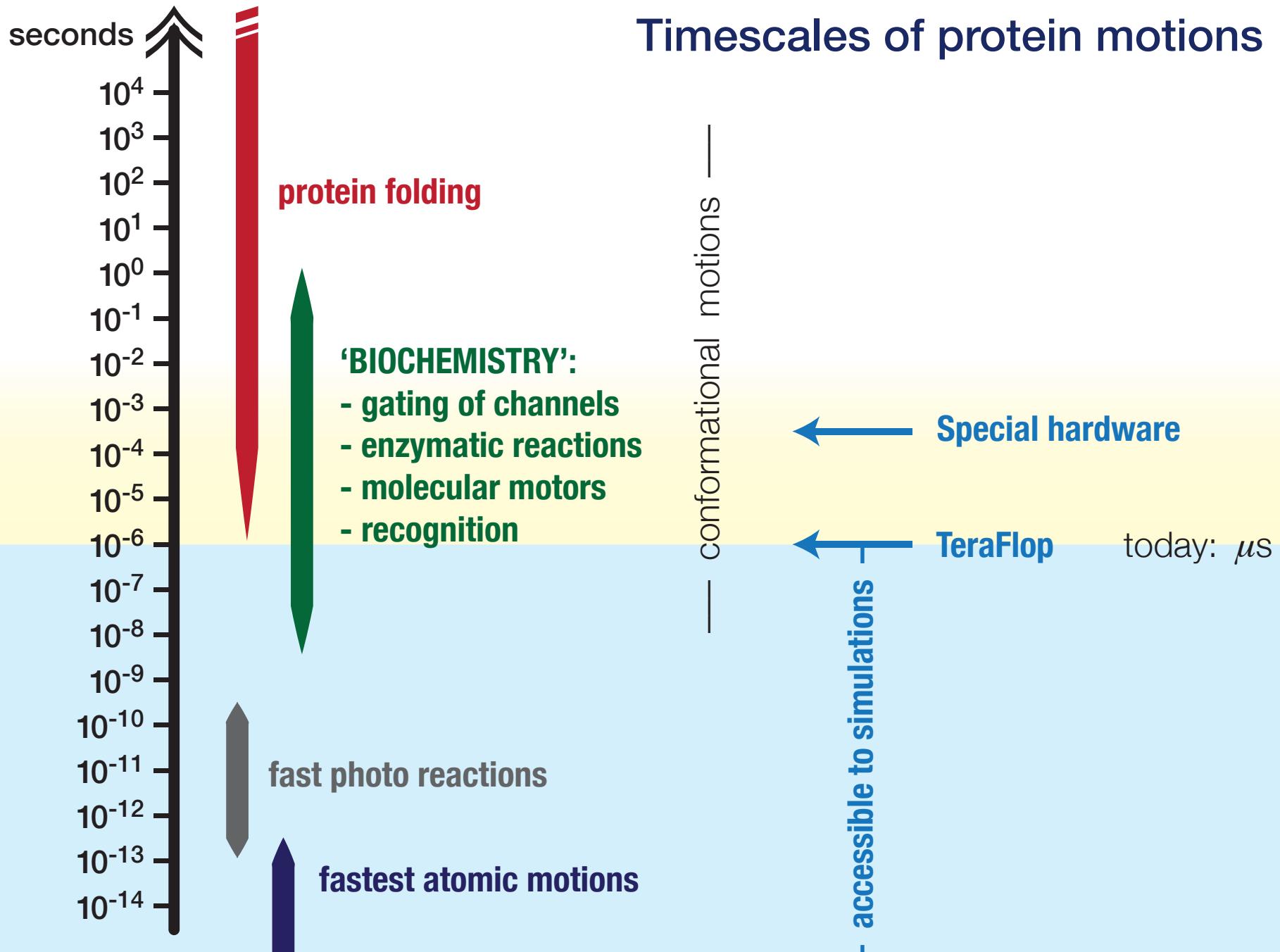


Molecular dynamics simulation, $1\text{s} \hat{=} 2 \cdot 10^{-11}\text{s}$

Water Permeation proceeds in steps

*one out of 16 full
spontaneous
permeation events
(2 ns)*





Towards a mechanistic understanding of protein function

(1) *Ligand unbinding revisited*



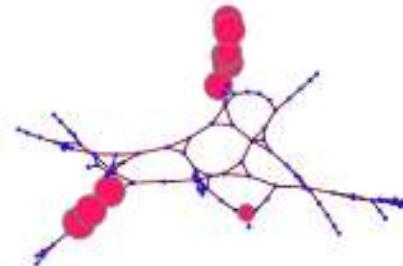
(2) *Ribosomal antibiotics mechanism*



(3) *Intrinsically Disordered Proteins*



(4) *The Dynasome*



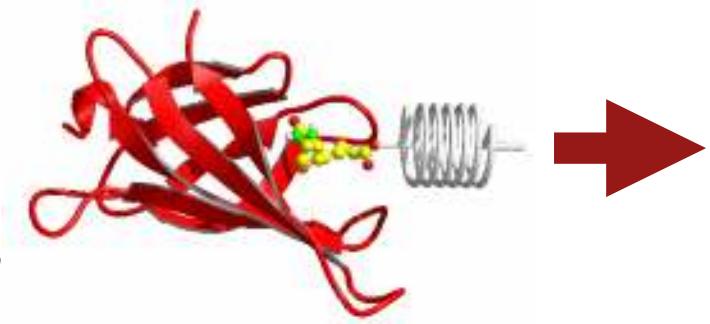
AFM+ X-ray + cryo EM + MD

*Lars Bock, Christian Blau, Michal Kolar, Andrea Vaiana, Andreas Russek,
Sarah Rauscher, Ulf Hensen*

*Holger Stark, Marina Rodnina (MPI Göttingen)
Roland Beckmann, Daniel Wilson (Univ. Munich)
Simon Scheuring (Cornell Univ.)*

Towards a mechanistic understanding of protein function

(1) *Ligand unbinding revisited*



(2) *Ribosomal antibiotics mechanism*

(3) *Intrinsically Disordered Proteins*

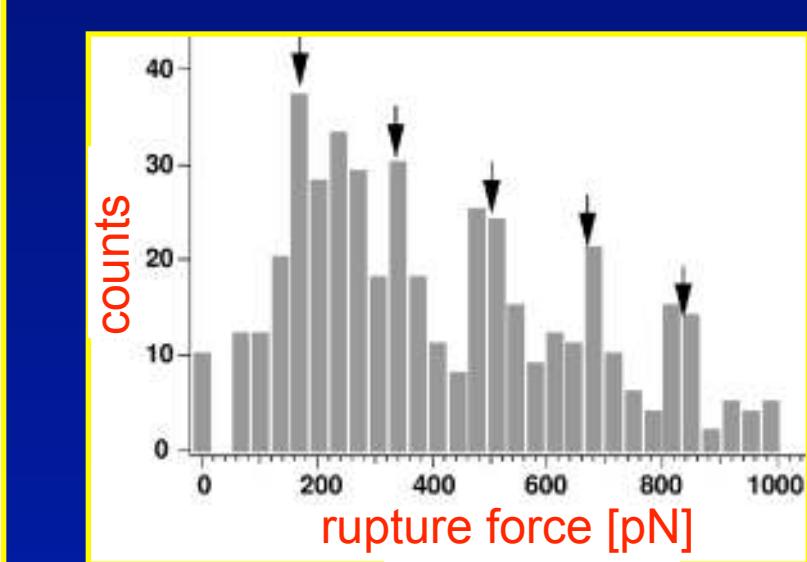
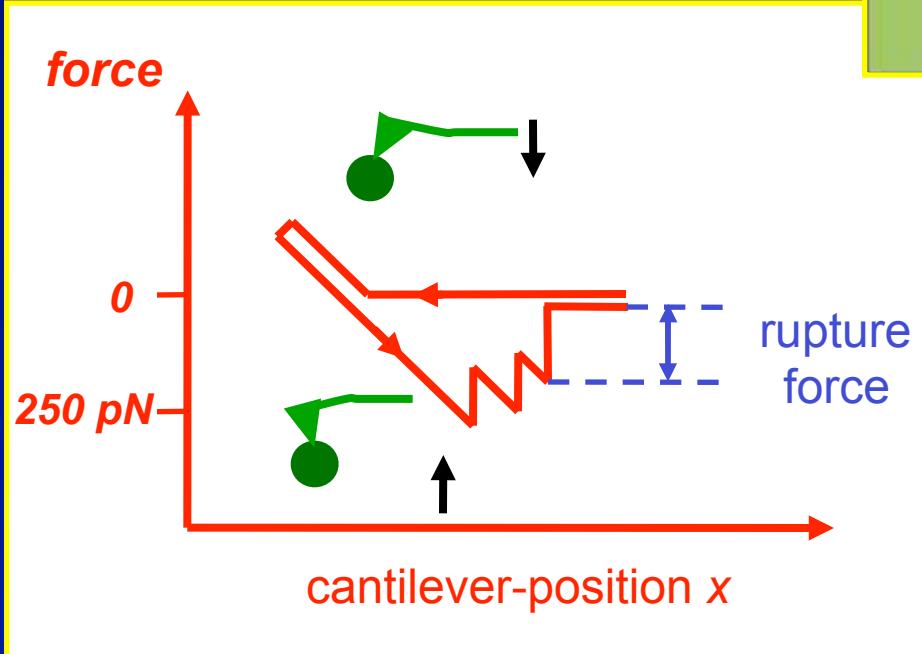
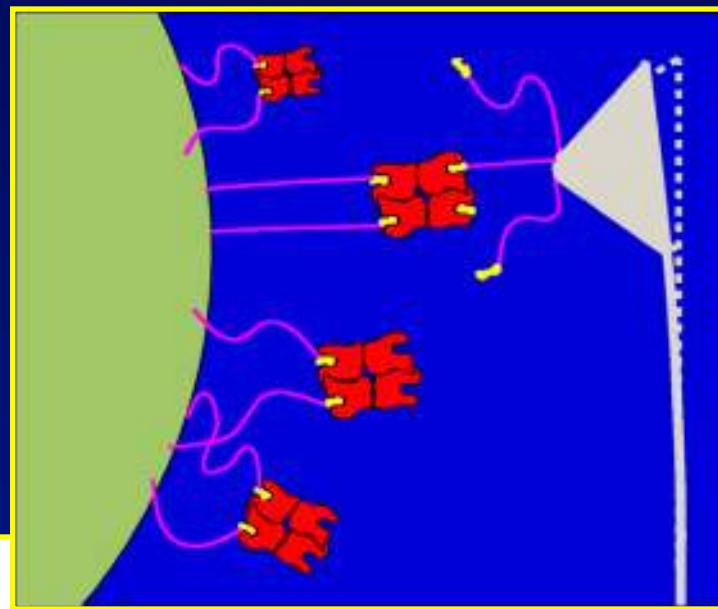
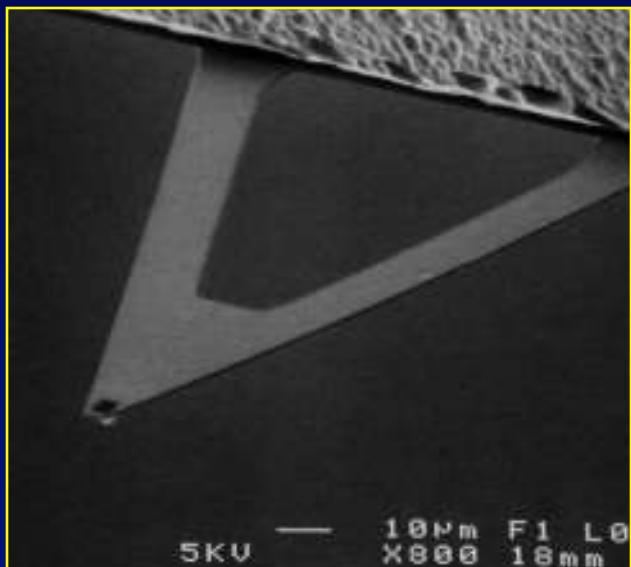
(4) *The Dynasome*

AFM+ X-ray + cryo EM + MD

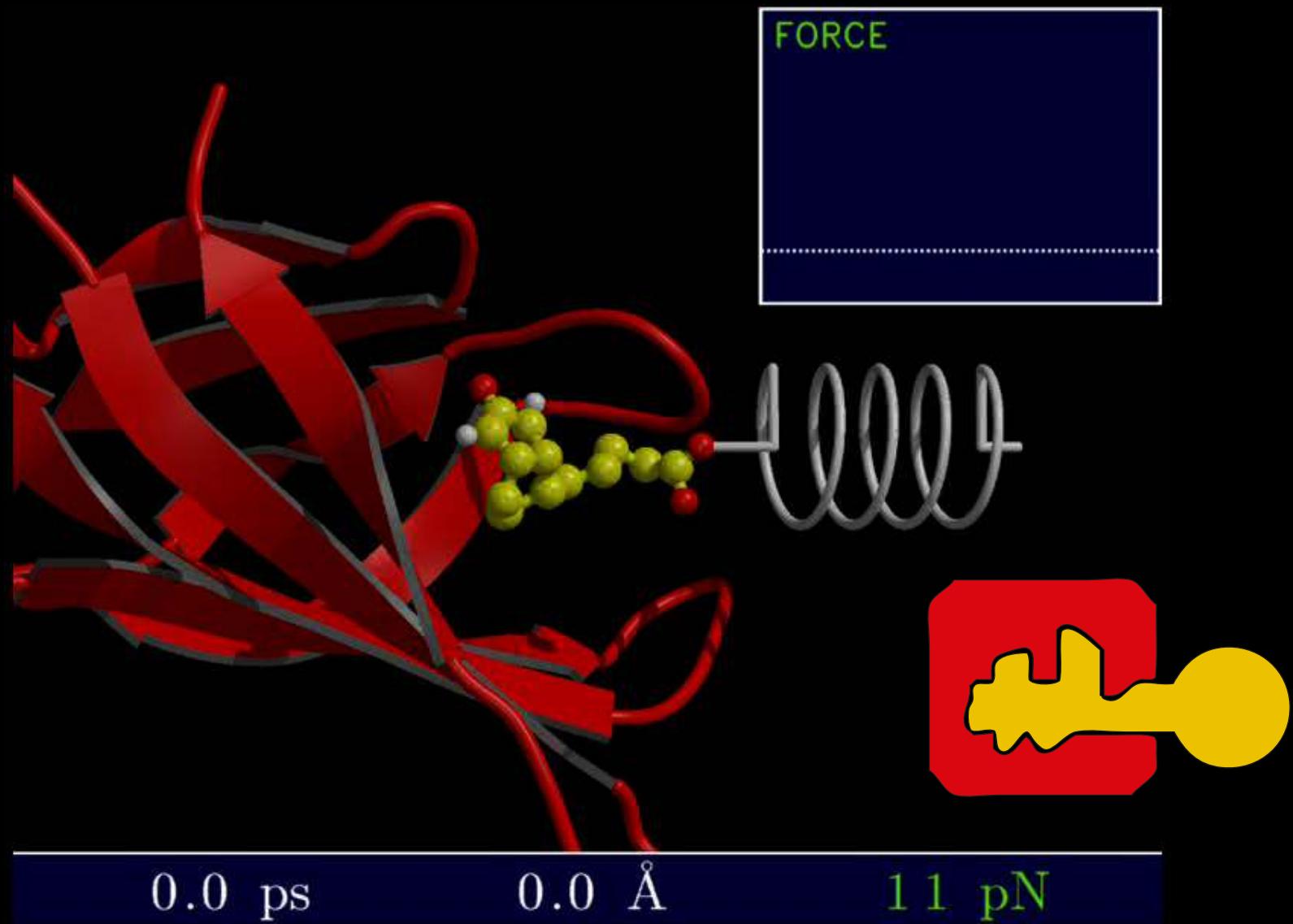
*Lars Bock, Christian Blau, Michal Kolar, Andrea Vaiana, Andreas Russek,
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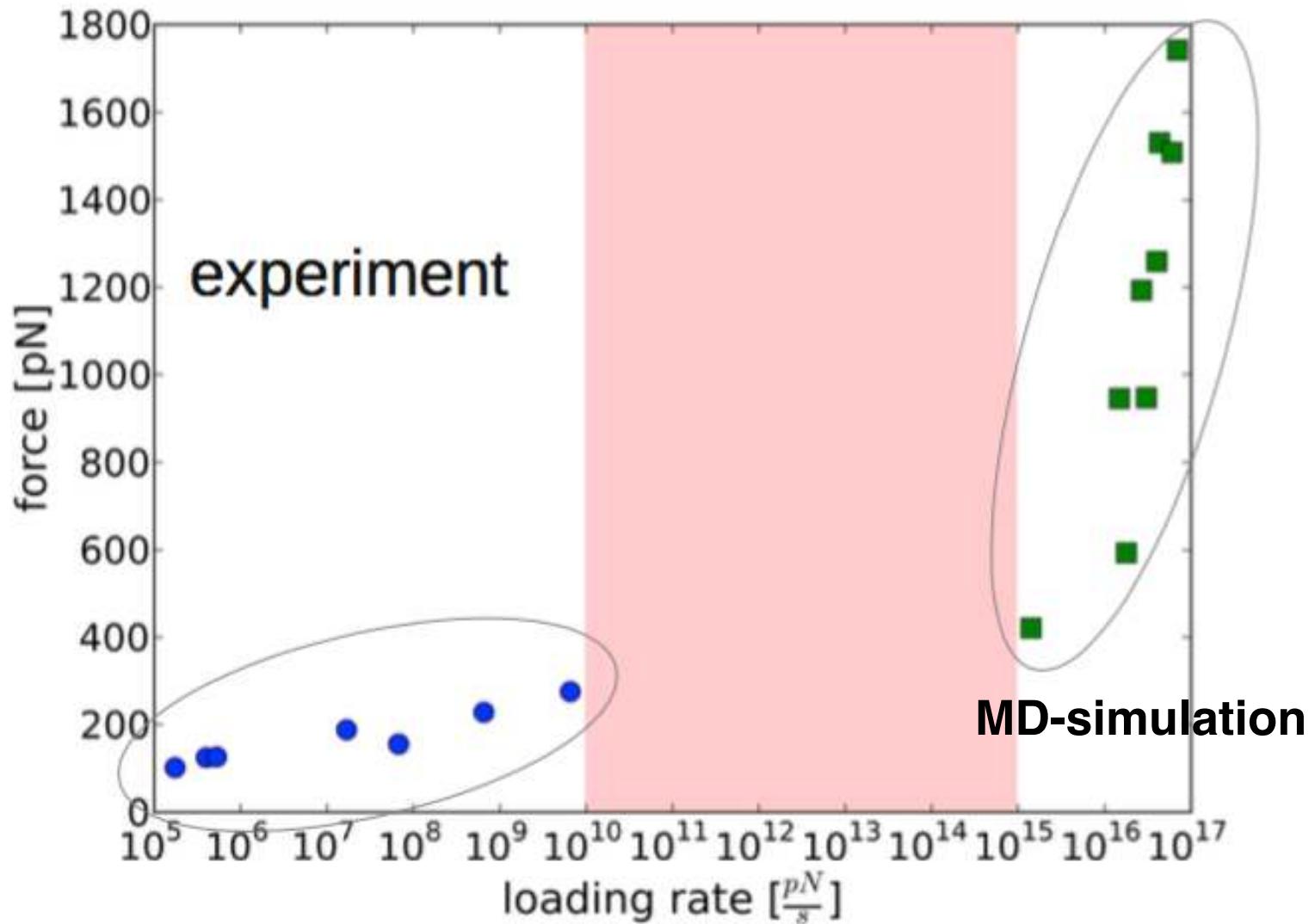
Single Molecule Force Spectroscopy



Force probe simulations



AFM unbinding: Simulation vs Experiment (1996)



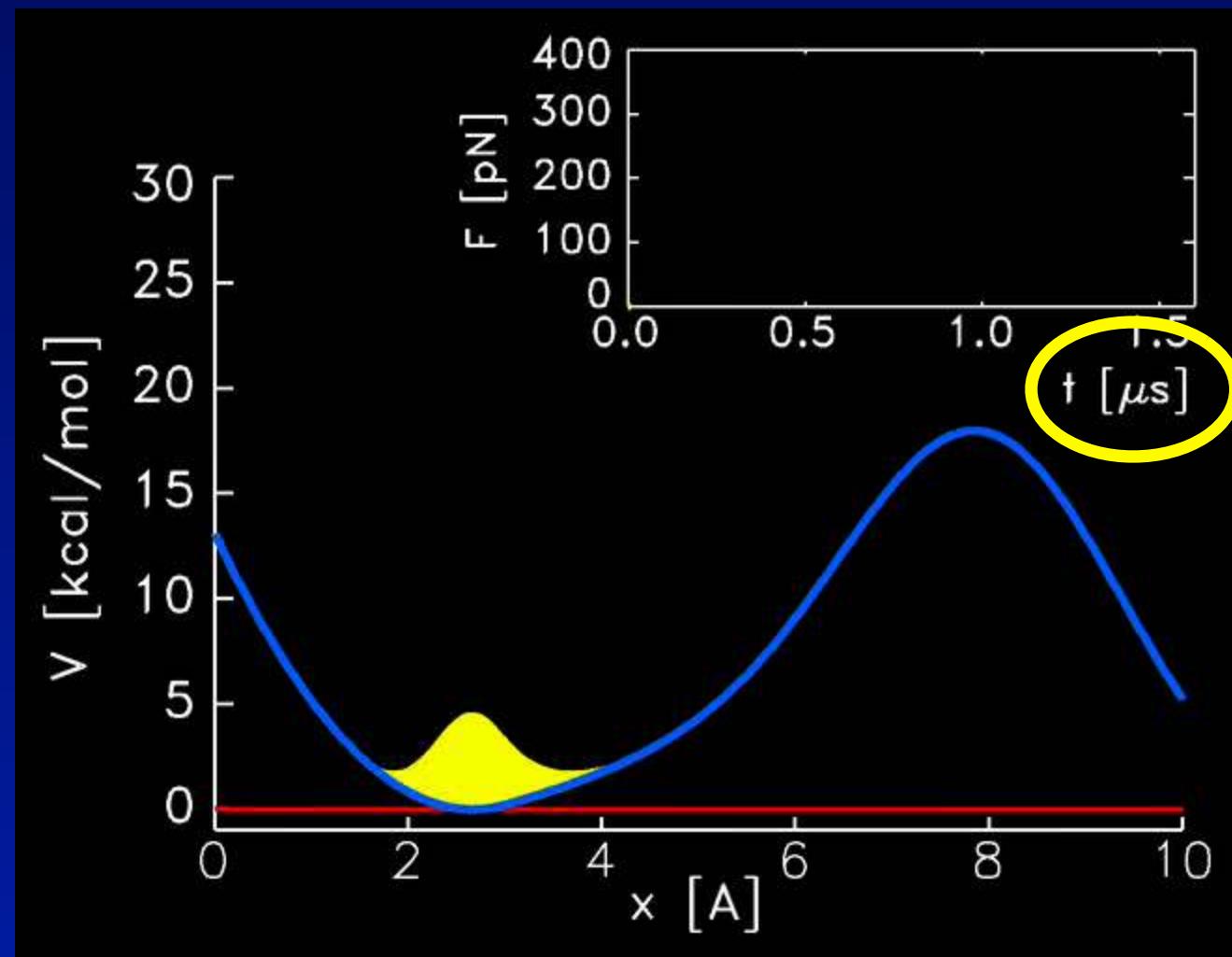
Unbinding forces depend on time scale due to activated barrier crossing: soft spring

$F(x)$:
applied force

$G(x) + V(x,t)$

$G(x)$:
energy landscape
of unperturbed
system

$V(x,t)$:
spring potential



$p(x)$: reaction coordinate probability distribution

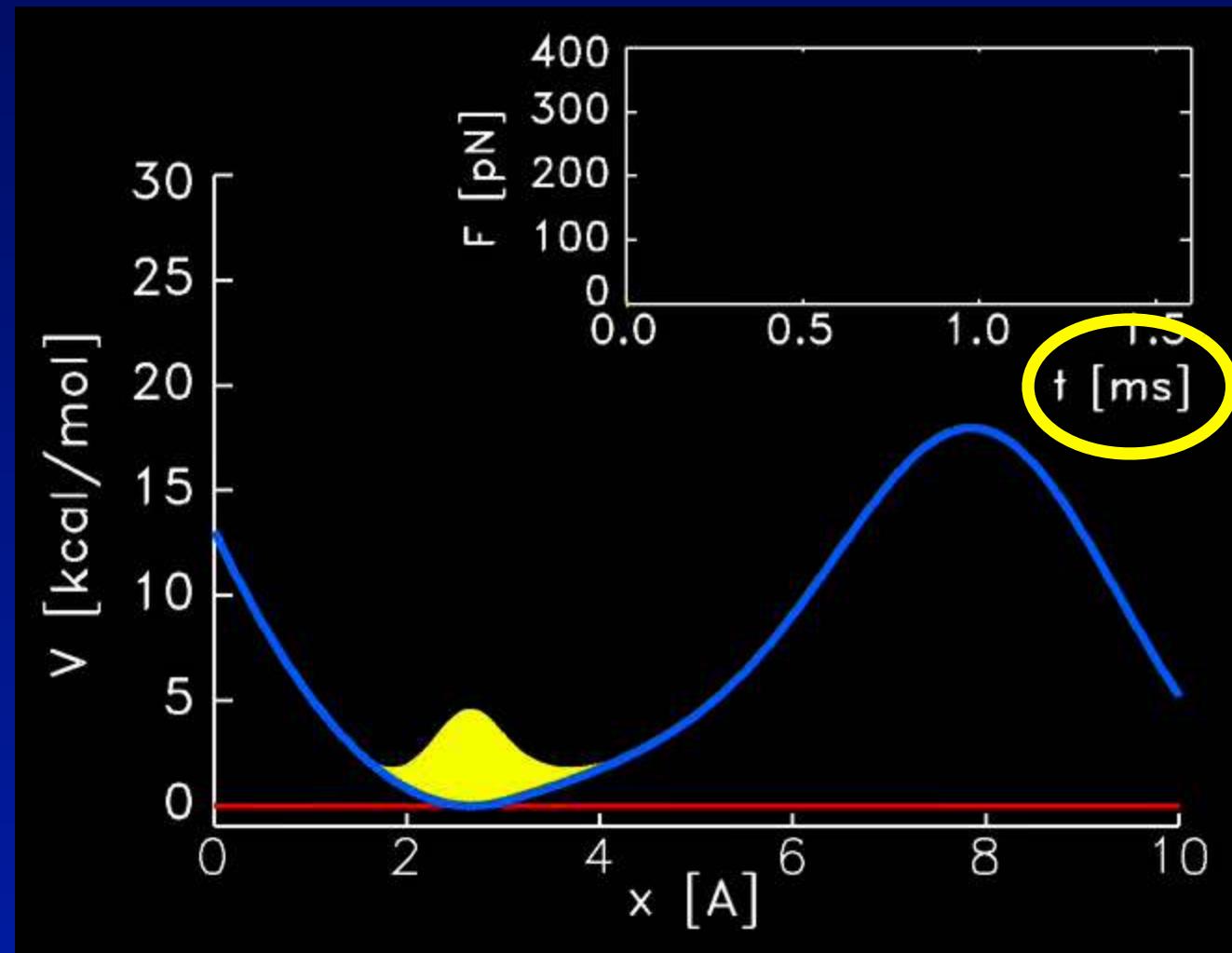
Same process, 10^3 times slower:

$F(x)$:
applied force

$G(x) + V(x,t)$

$G(x)$:
energy landscape
of unperturbed
system

$V(x,t)$:
spring potential



$p(x)$: reaction coordinate probability distribution

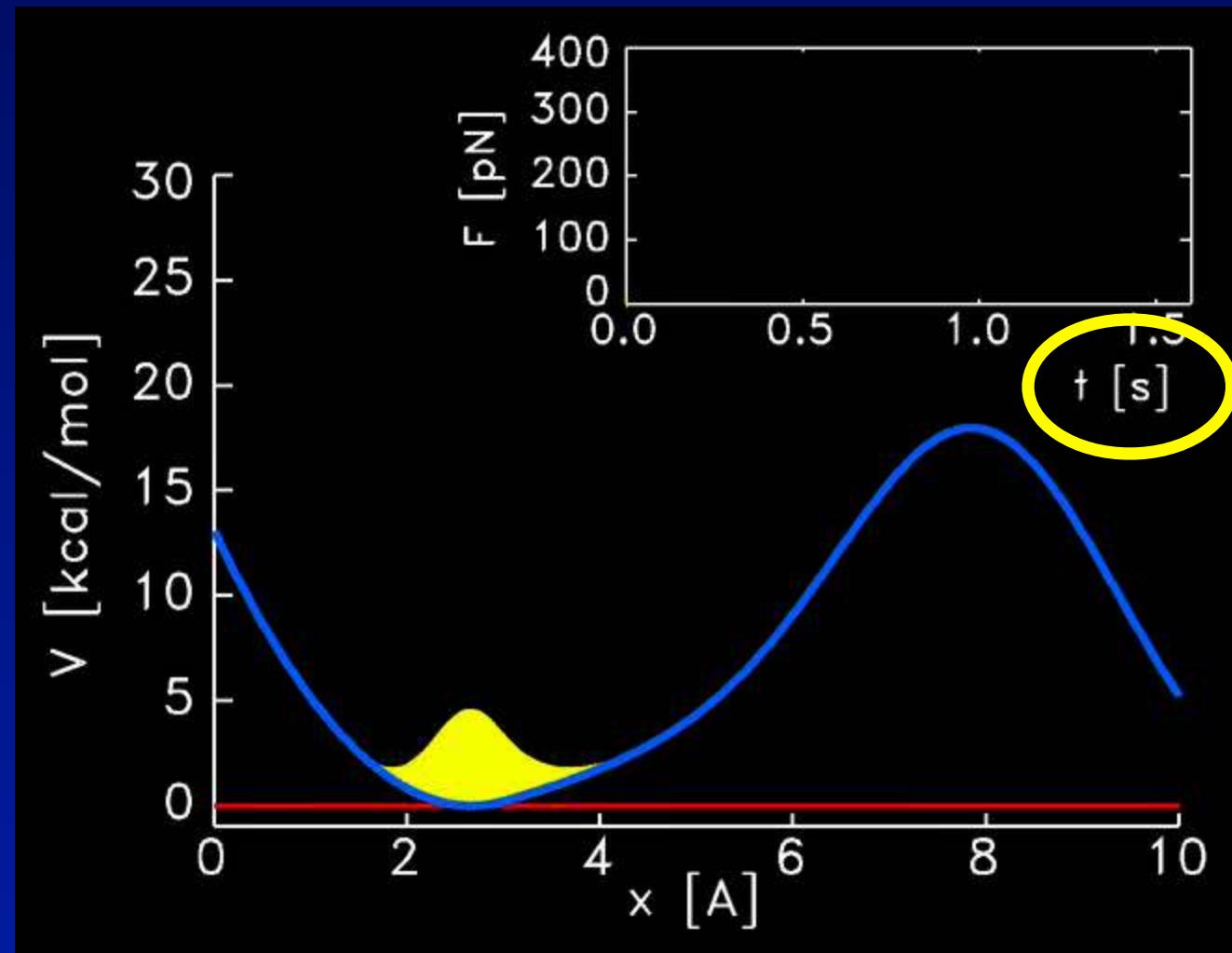
Same process, 10^6 times slower:

$F(x)$:
applied force

$G(x) + V(x,t)$

$G(x)$:
energy landscape
of unperturbed
system

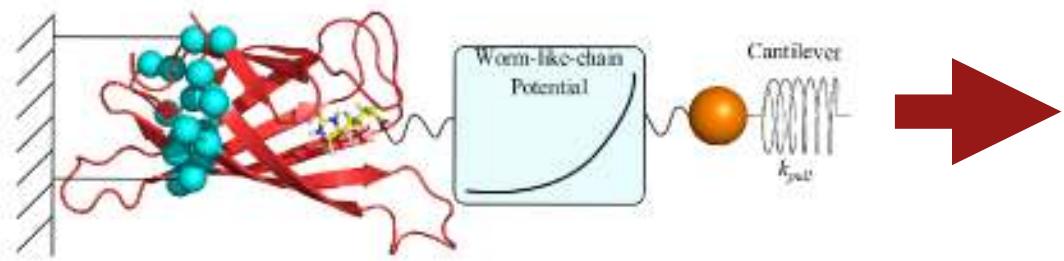
$V(x,t)$:
spring potential



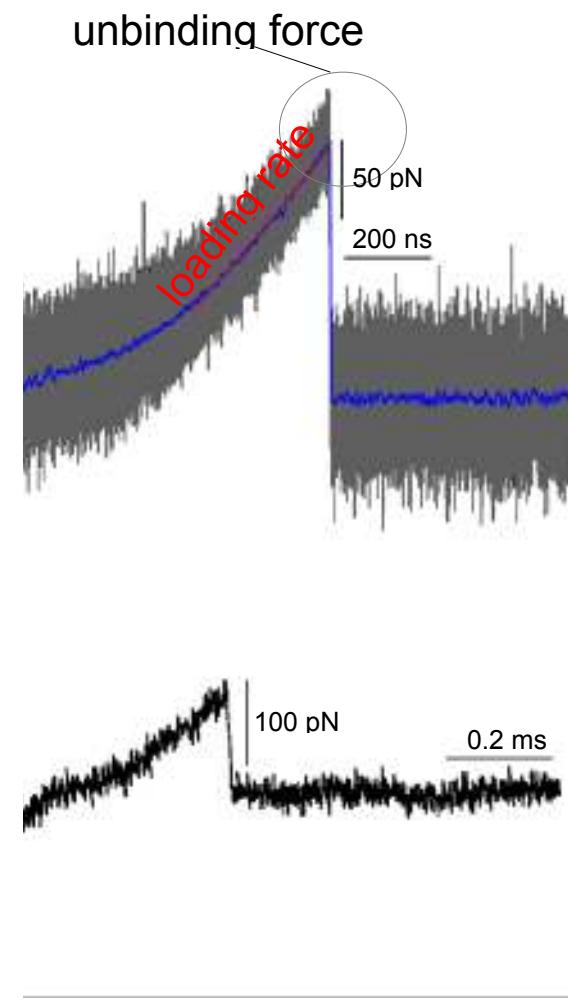
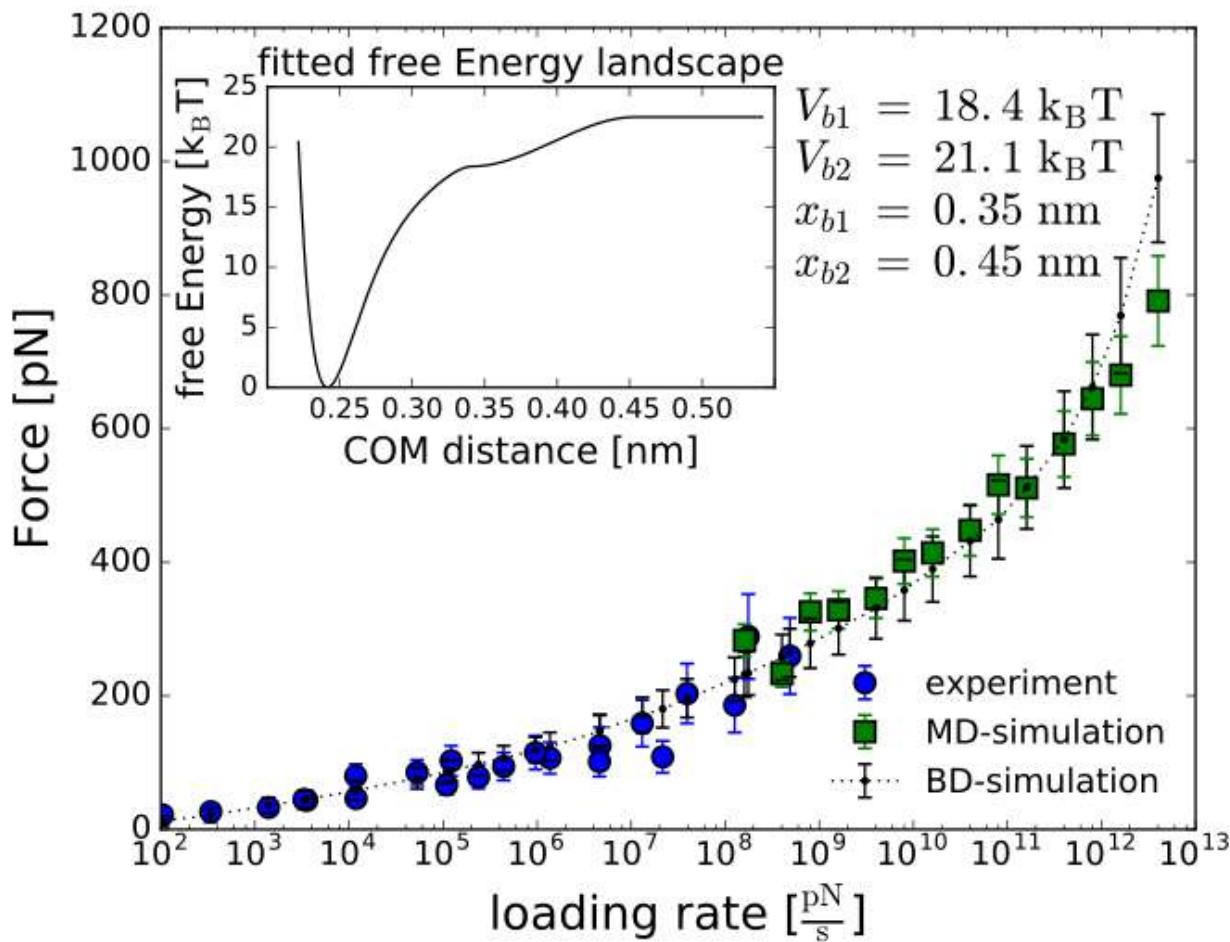
$p(x)$: reaction coordinate probability distribution

MD Simulation Methods

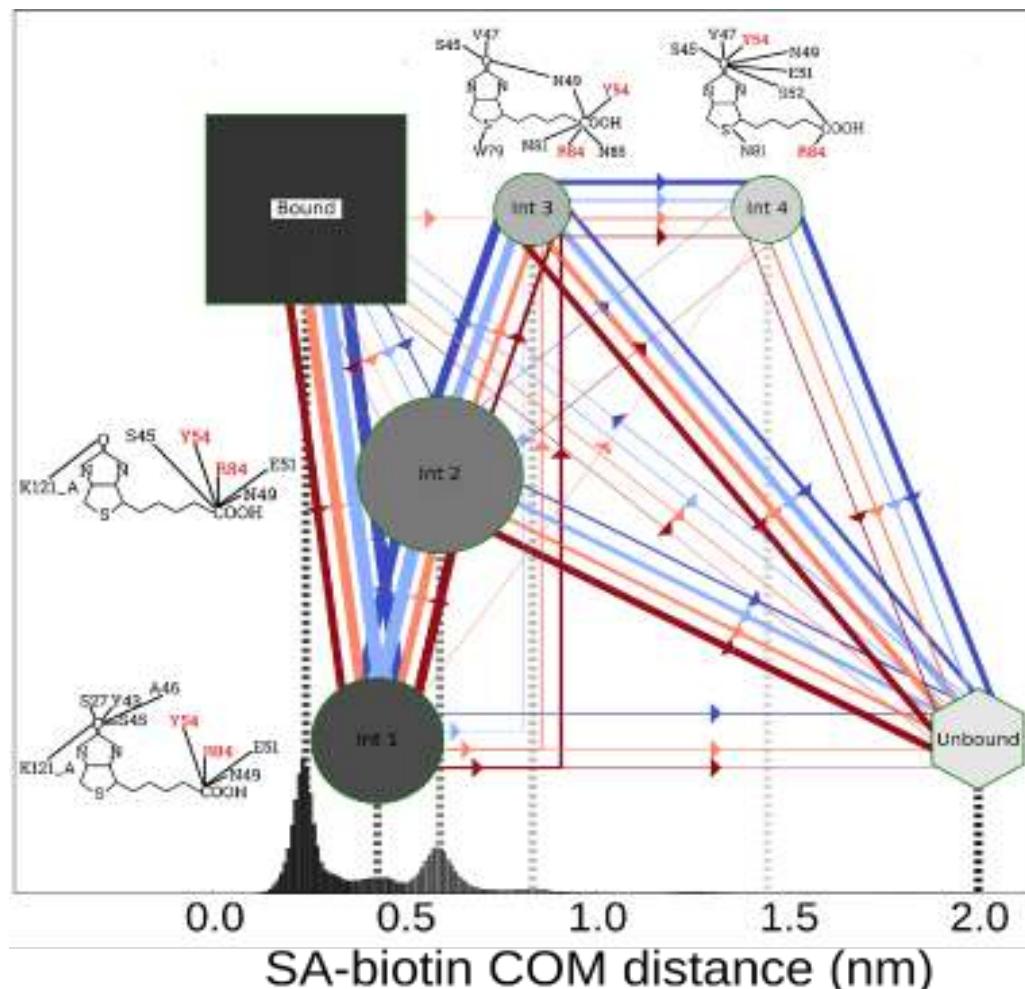
- Tetramer and monomer
- Pulling spring of cantilever
- Loading rates: $10^7 \dots 10^{13}$ pN/s
- Simulation lengths up to 8 μ s
- 10...20 simulations per velocity
- WLC-Potential to mimic PEG



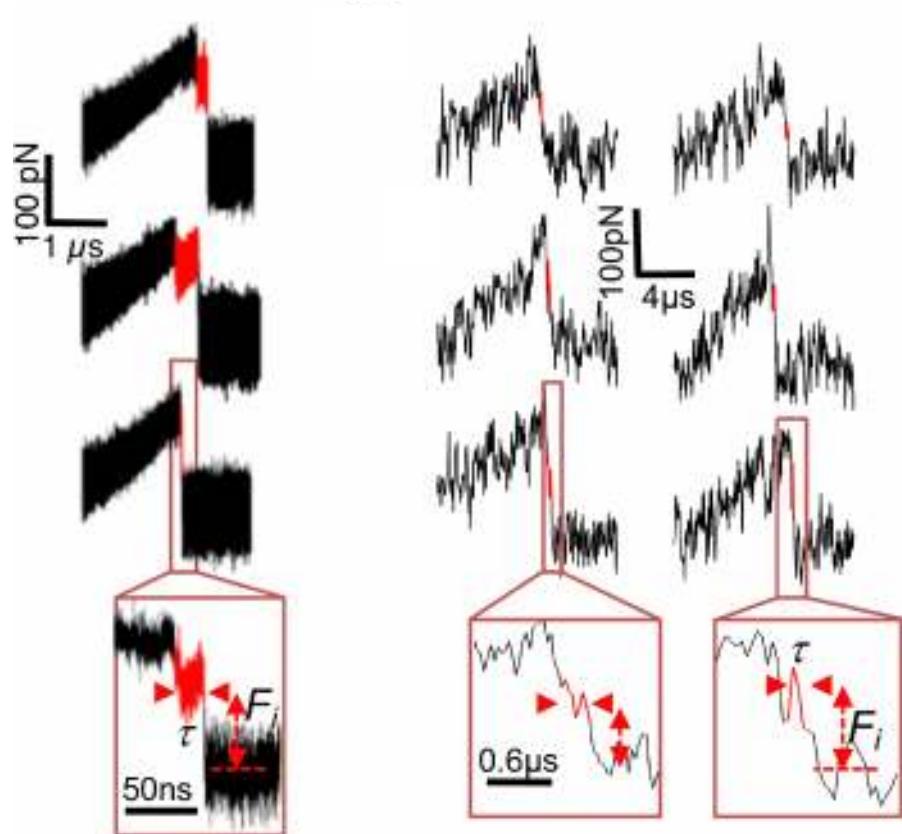
Exp + Sim -> Free energy landscape



Unbinding pathways change with loading rate

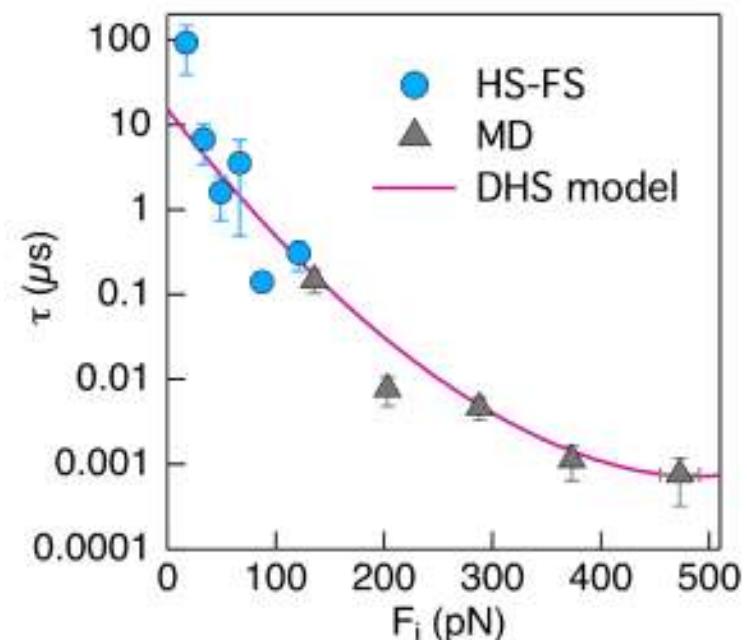


Outer Intermediate



Simulation

Experiment



$$\tau(F) = \tau_0 \left(1 - \frac{v F x^\ddagger}{\Delta G^\ddagger}\right)^{1-1/v} \exp\left(-\beta \Delta G^\ddagger [1 - \left(1 - \frac{v F x^\ddagger}{\Delta G^\ddagger}\right)^{1/v}]\right)$$

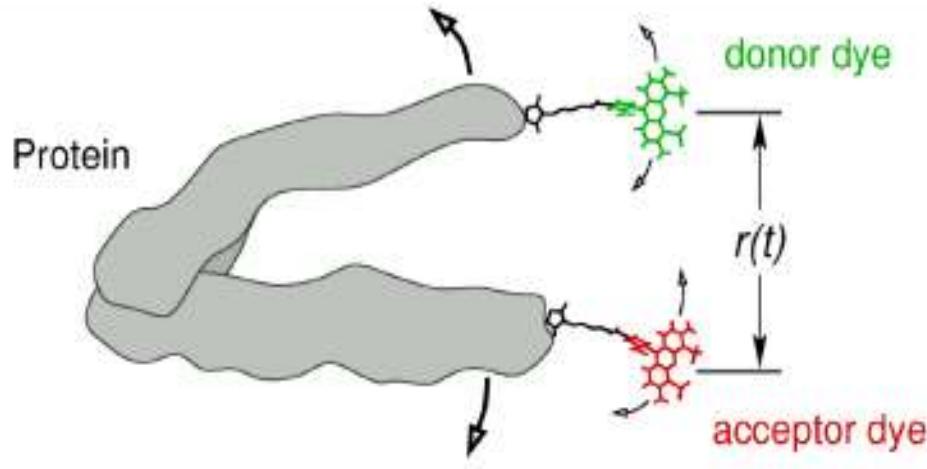
$$x^\ddagger = 0.23 \text{ nm}$$

$$\Delta G^\ddagger = 22.5 k_B T$$

[1] Dudko, O. K., Hummer, G. & Szabo, A. *Phys. Rev. Lett.* **96**, 108101 (2006).

Simulation of single molecule FRET experiments: FRET beyond $\kappa^2 = 2/3$

collab. U. Alexiev, C. Seidel, B. Schuler



Förster Formula:

$$\frac{I_A(t)}{I_A(t) + I_D(t)} = \frac{1}{1 + \left[\frac{r(t)}{r_0} \right]^6}$$

Usual assumption ($\kappa^2 = 2/3$):
dye motion isotropic
& uncorrelated

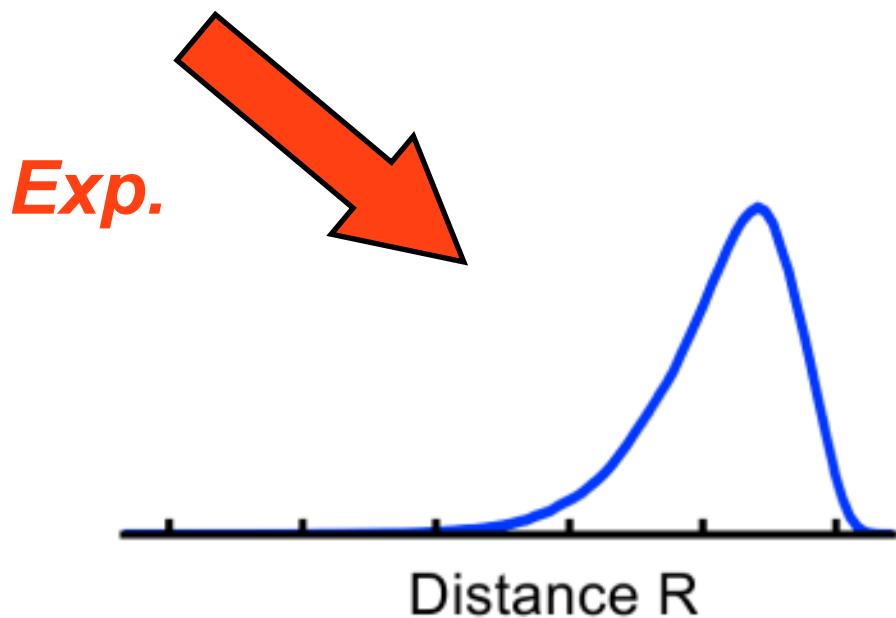
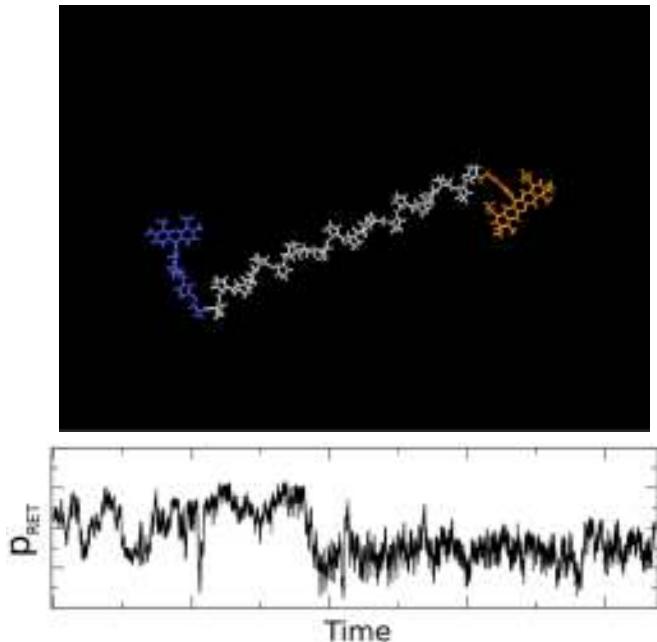
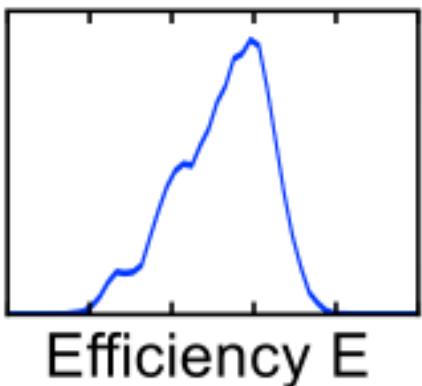
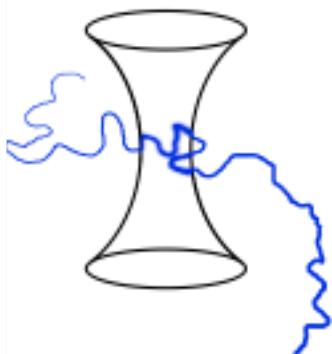


Martin
Höfling



Nicola
Lima

Can we improve distance measurements by combining FRET and MD?



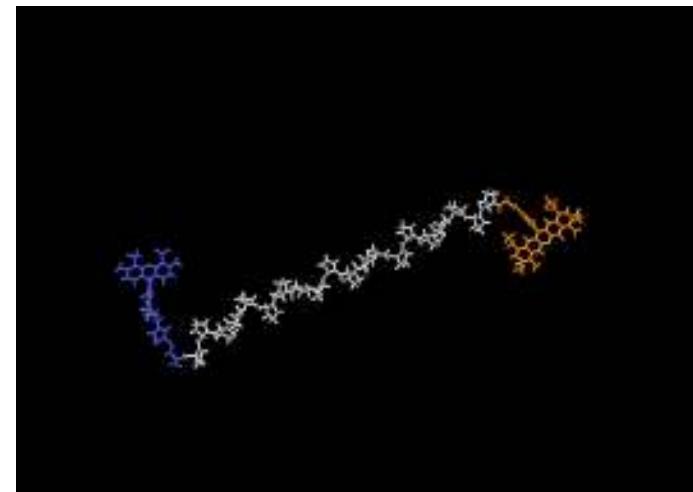
Exp.

Sim.

Procedure Outline

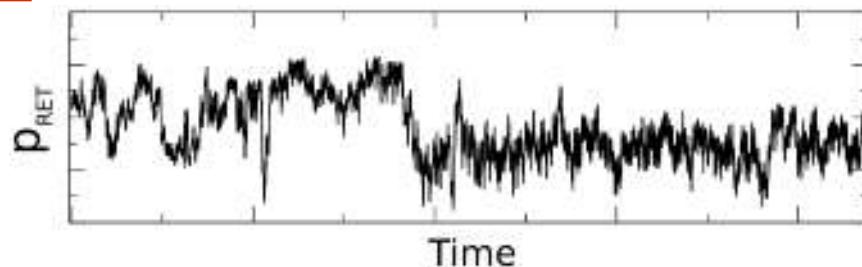
Step 1:

generate MD trajectories
--> $r(t)$, $\theta(t)$, $\varphi_1(t)$, $\varphi_2(t)$



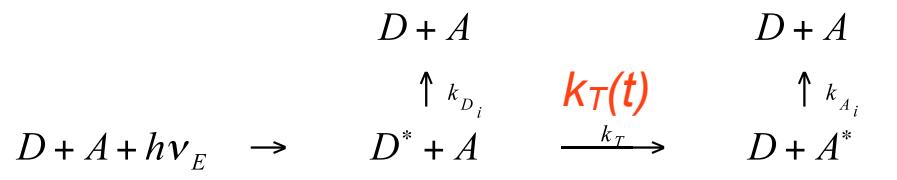
Step 2:

generate $k_{\text{RET}}(t)$



Step 3:

obtain photon statistics via MC



Step 4:

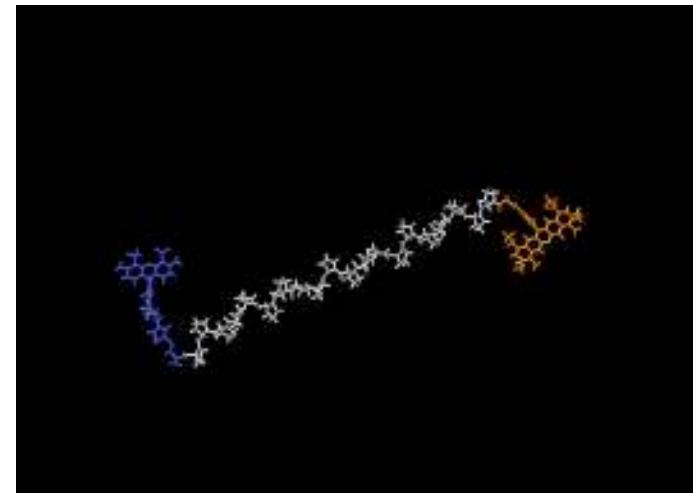
combine photon counts into bursts
from measured burst size statistics
--> efficiency histogram

$$E = \frac{n_A}{n_A + n_D}$$

Procedure Outline

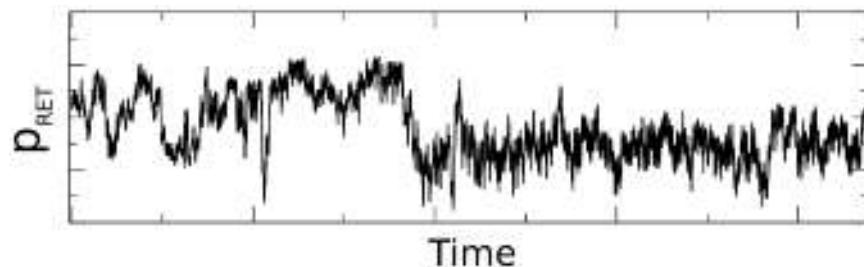
Step 1:

generate MD trajectories
--> $r(t)$, $\theta(t)$, $\varphi_1(t)$, $\varphi_2(t)$



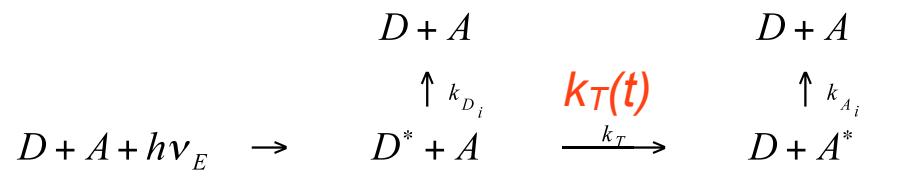
Step 2:

generate $k_{RET}(t)$



Step 3:

obtain photon statistics via MC



Step 4:

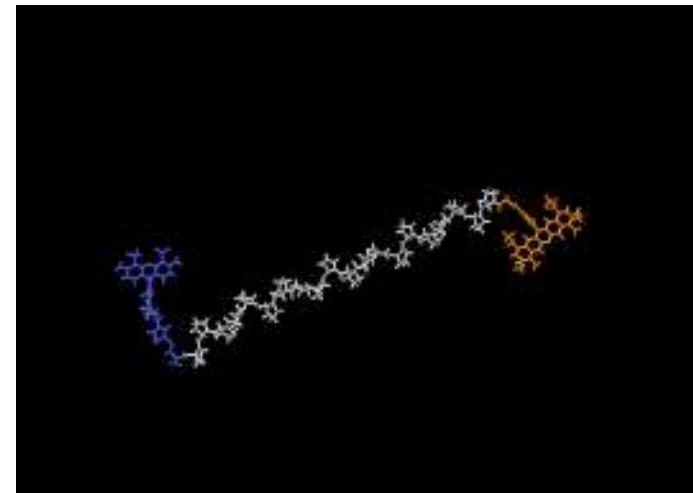
combine photon counts into bursts
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$$E = \frac{n_A}{n_A + n_D}$$

Procedure Outline

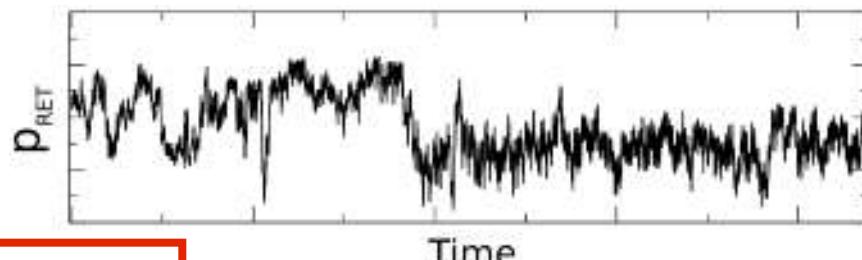
Step 1:

generate MD trajectories
--> $r(t)$, $\theta(t)$, $\varphi_1(t)$, $\varphi_2(t)$



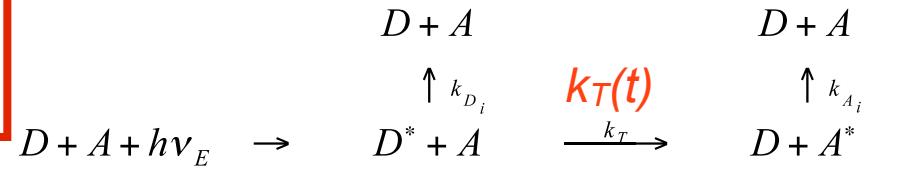
Step 2:

generate $k_{\text{RET}}(t)$



Step 3:

obtain photon statistics via MC



Step 4:

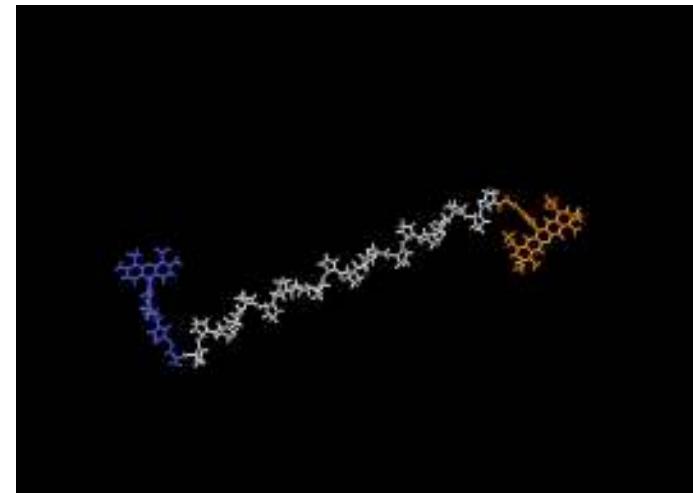
combine photon counts into bursts
from measured burst size statistics
--> efficiency histogram

$$E = \frac{n_A}{n_A + n_D}$$

Procedure Outline

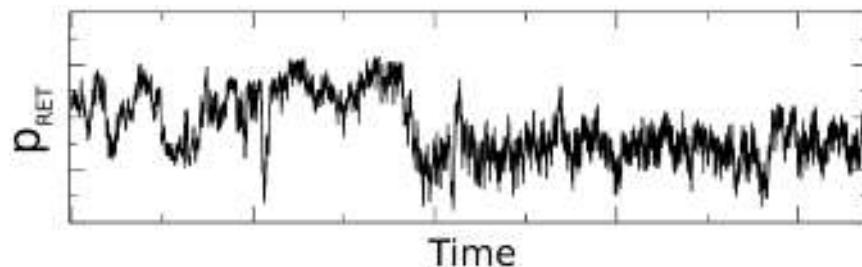
Step 1:

generate MD trajectories
--> $r(t)$, $\theta(t)$, $\varphi_1(t)$, $\varphi_2(t)$



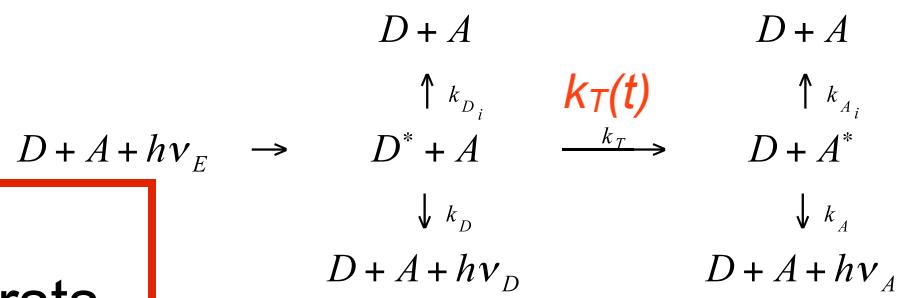
Step 2:

generate $k_{\text{RET}}(t)$



Step 3:

obtain photon statistics via MC

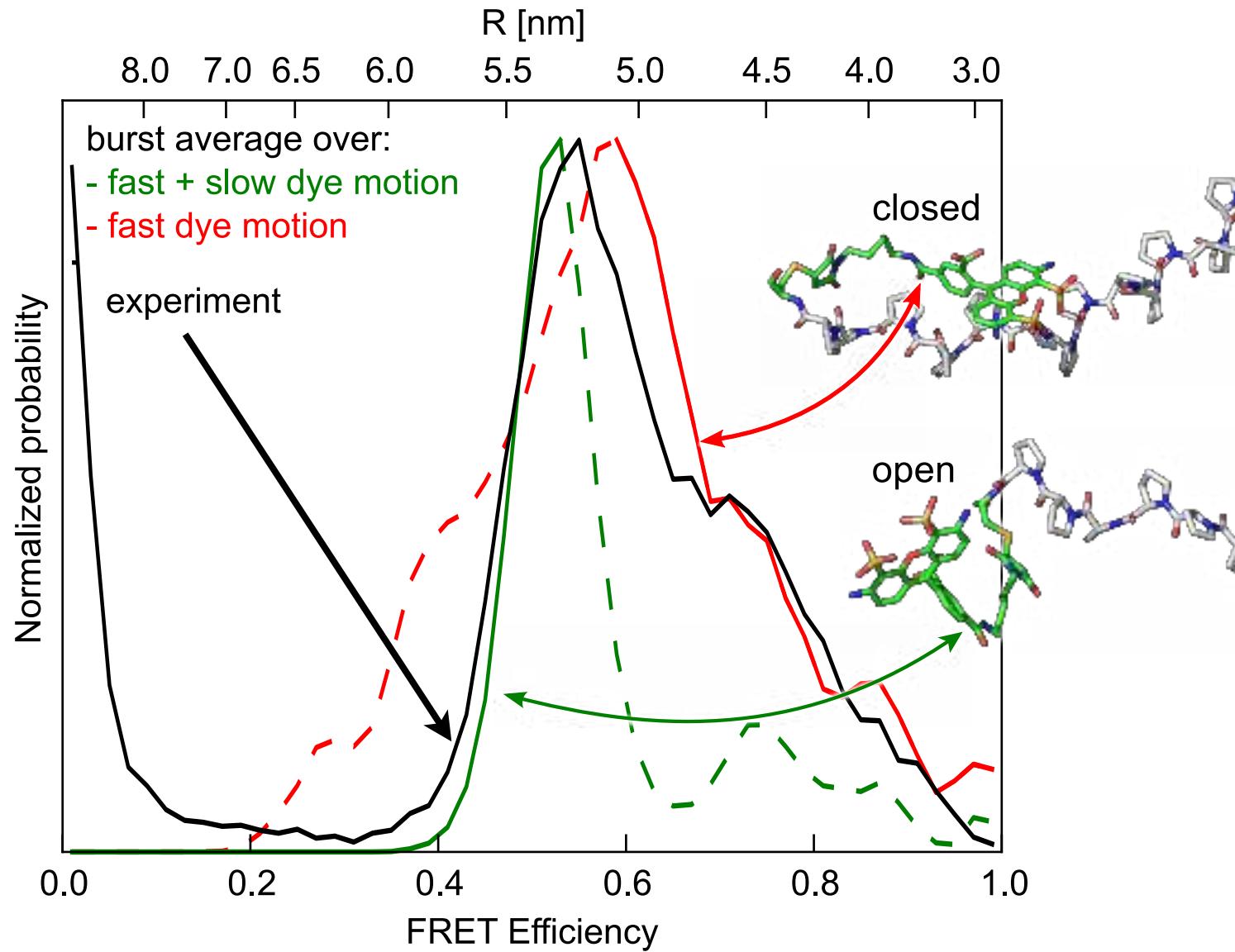


Step 4:

combine photon counts into bursts
from measured burst size statistics
--> efficiency histogram

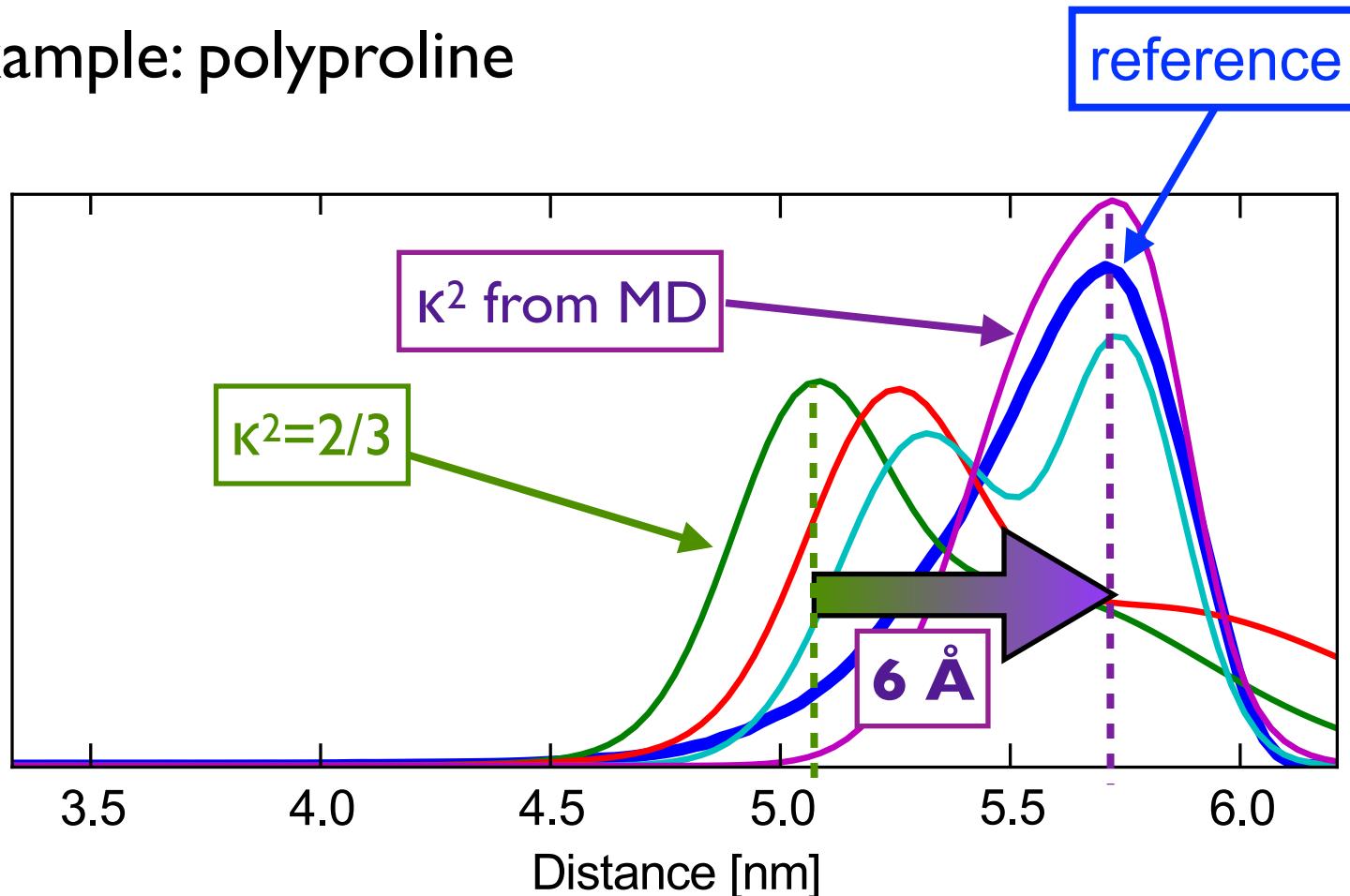
$$E = \frac{n_A}{n_A + n_D}$$

Simulation vs. Experiment

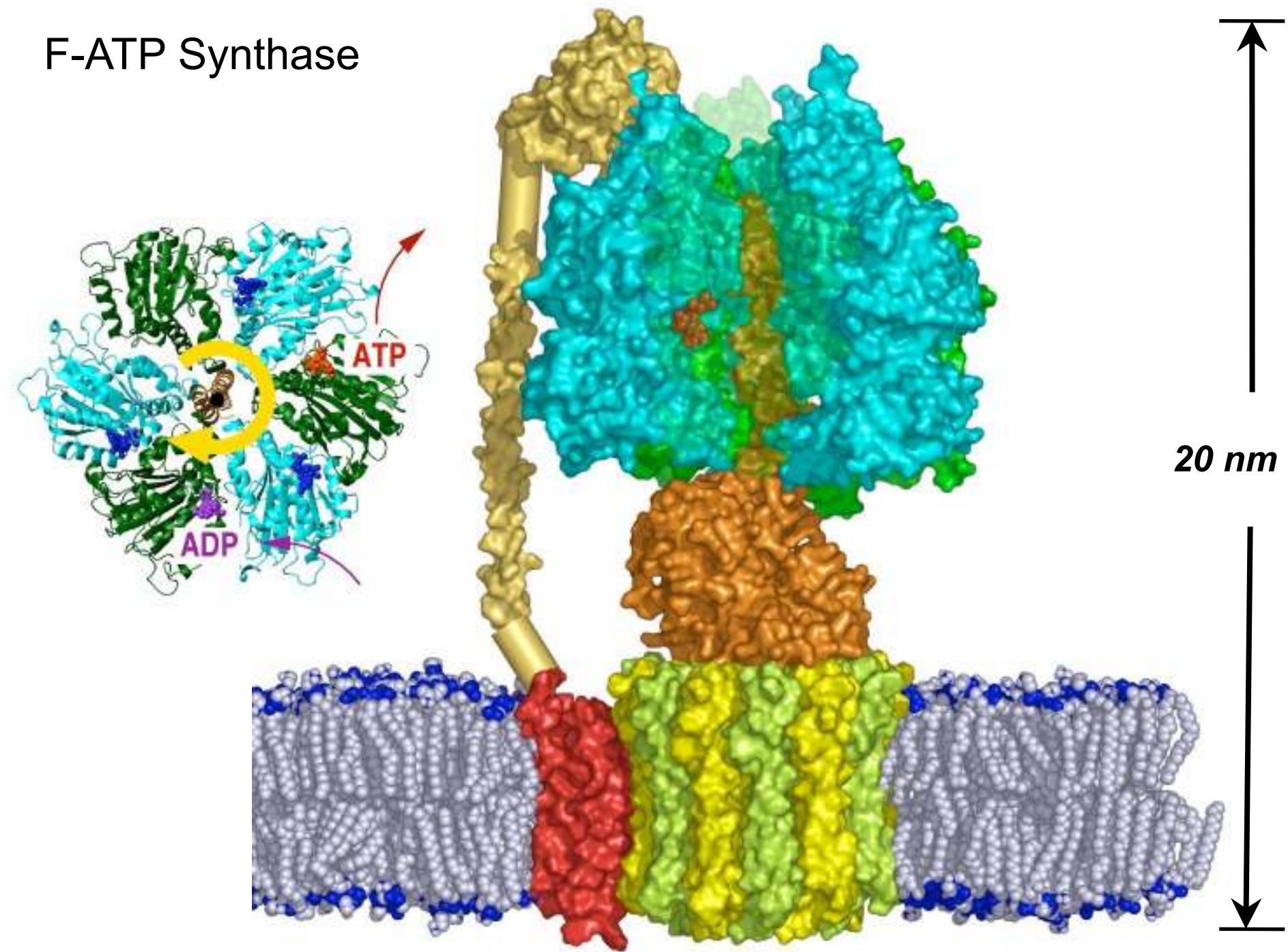


Can improved distance distributions be obtained? YES!

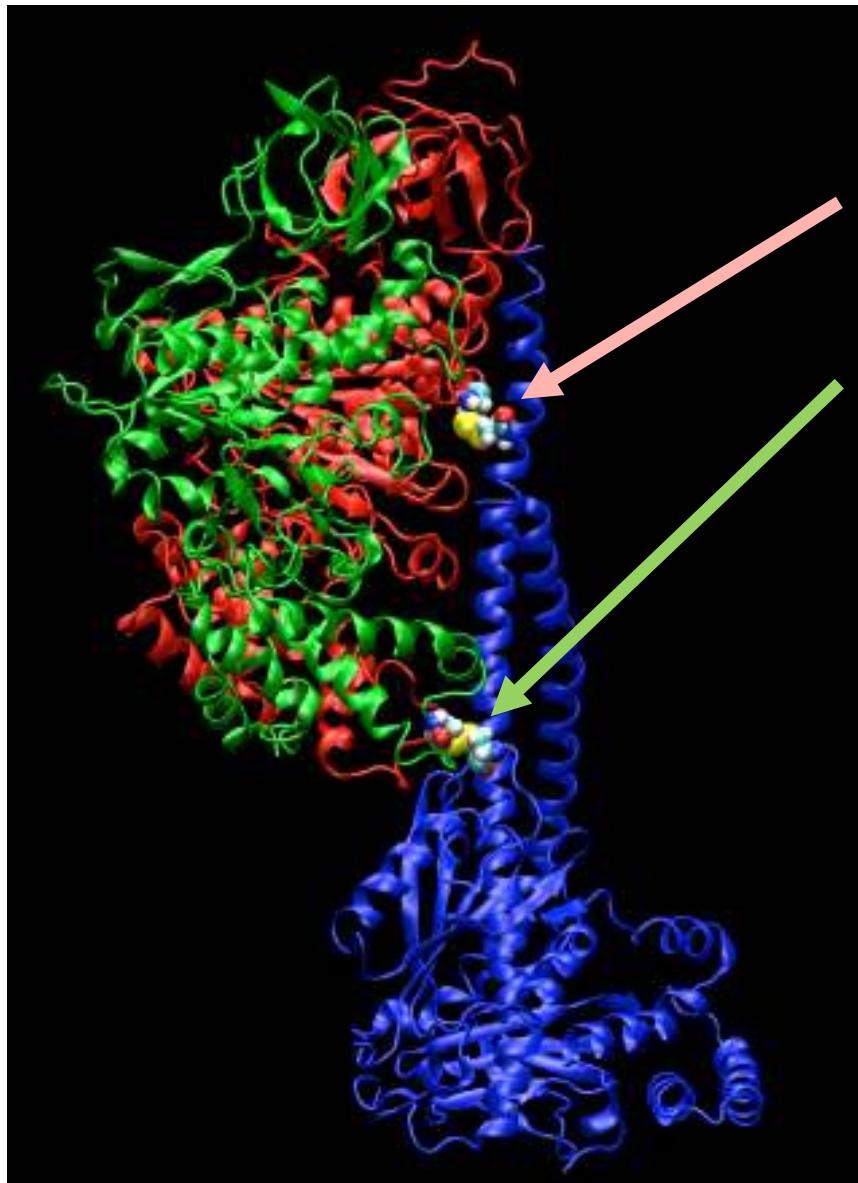
Example: polyproline



F-ATP Synthase



Elastic properties of the F₁-ATPase rotor – simulation setup



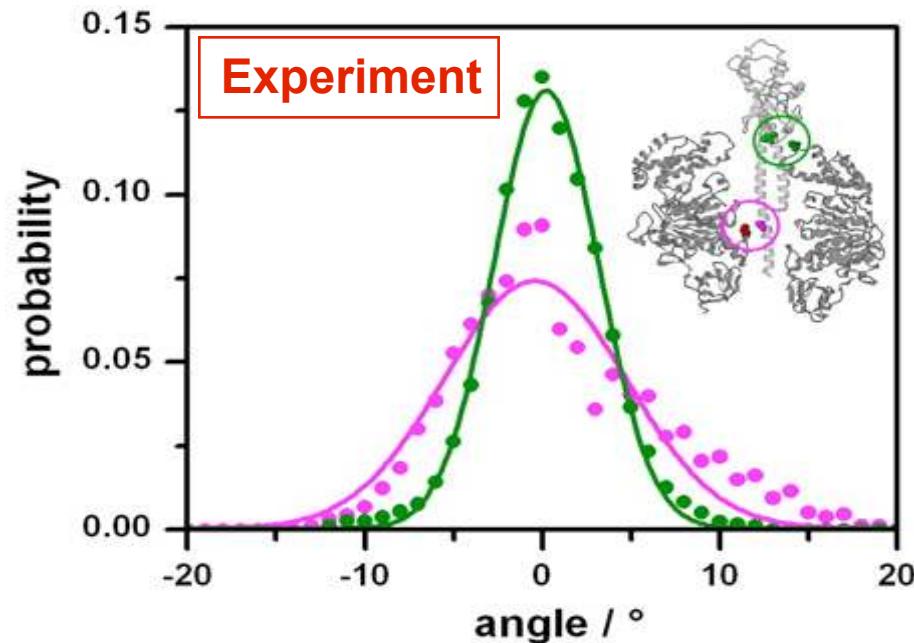
Disulfide bonds:

MIDDLE:

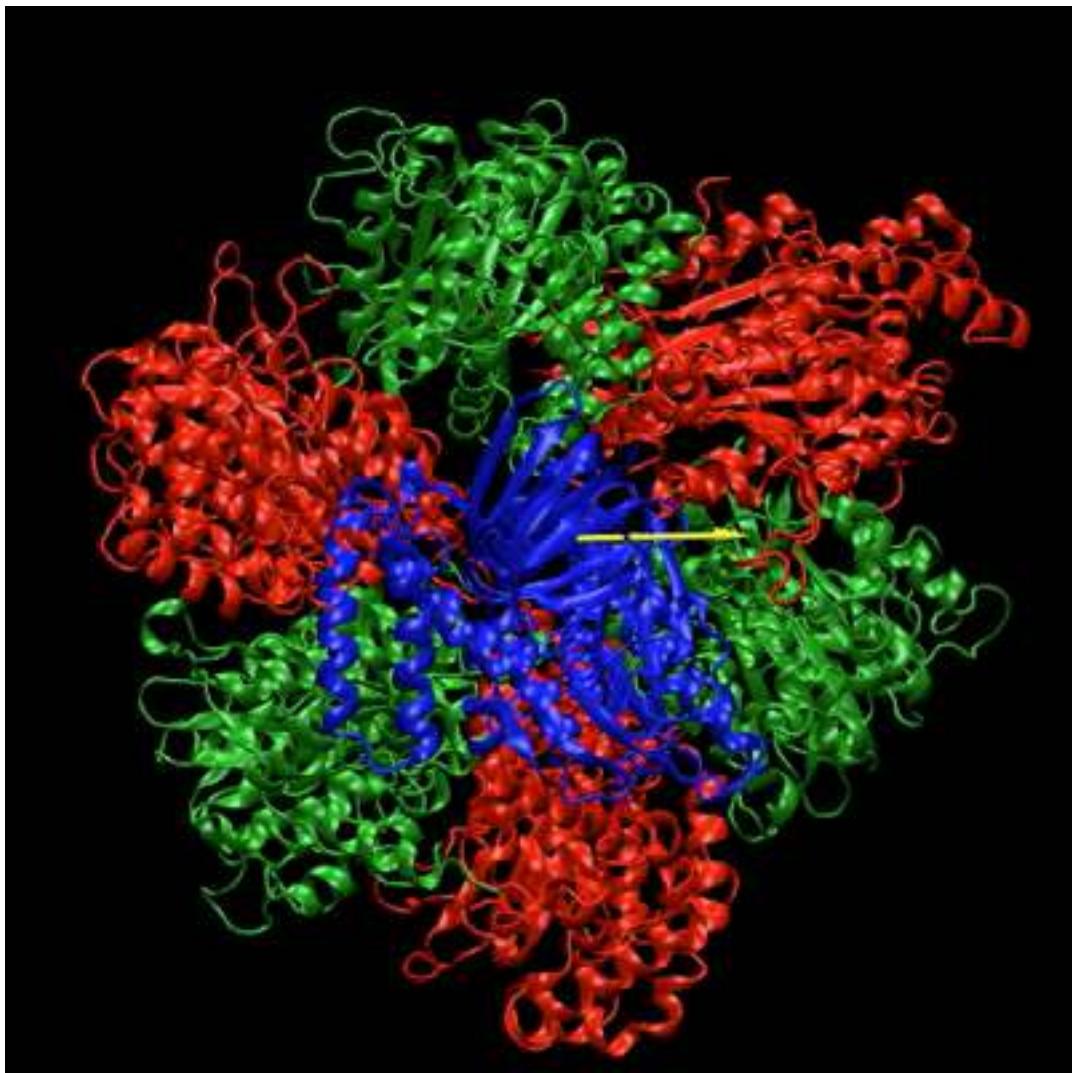
Cys (α_E -292) -- Cys (γ -256)

BOTTOM:

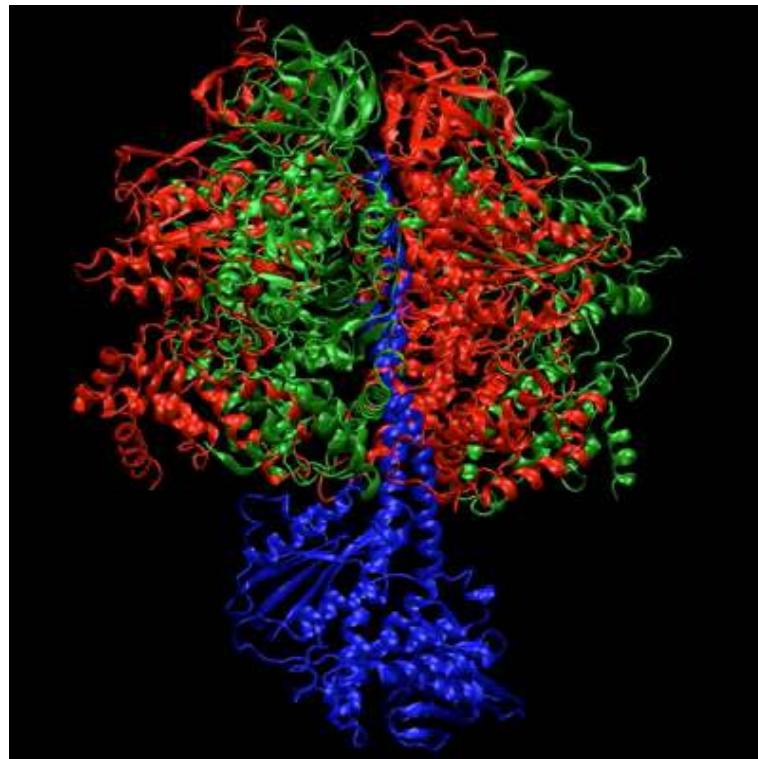
Cys (β_{TP} -395) -- Cys (γ -78)



Simulation of fluctuating gamma subunit within complete F1 -- 400 ns



Jacek Czub
(now Gdansk)



Elastic properties of the F₁-ATPase rotor – Results

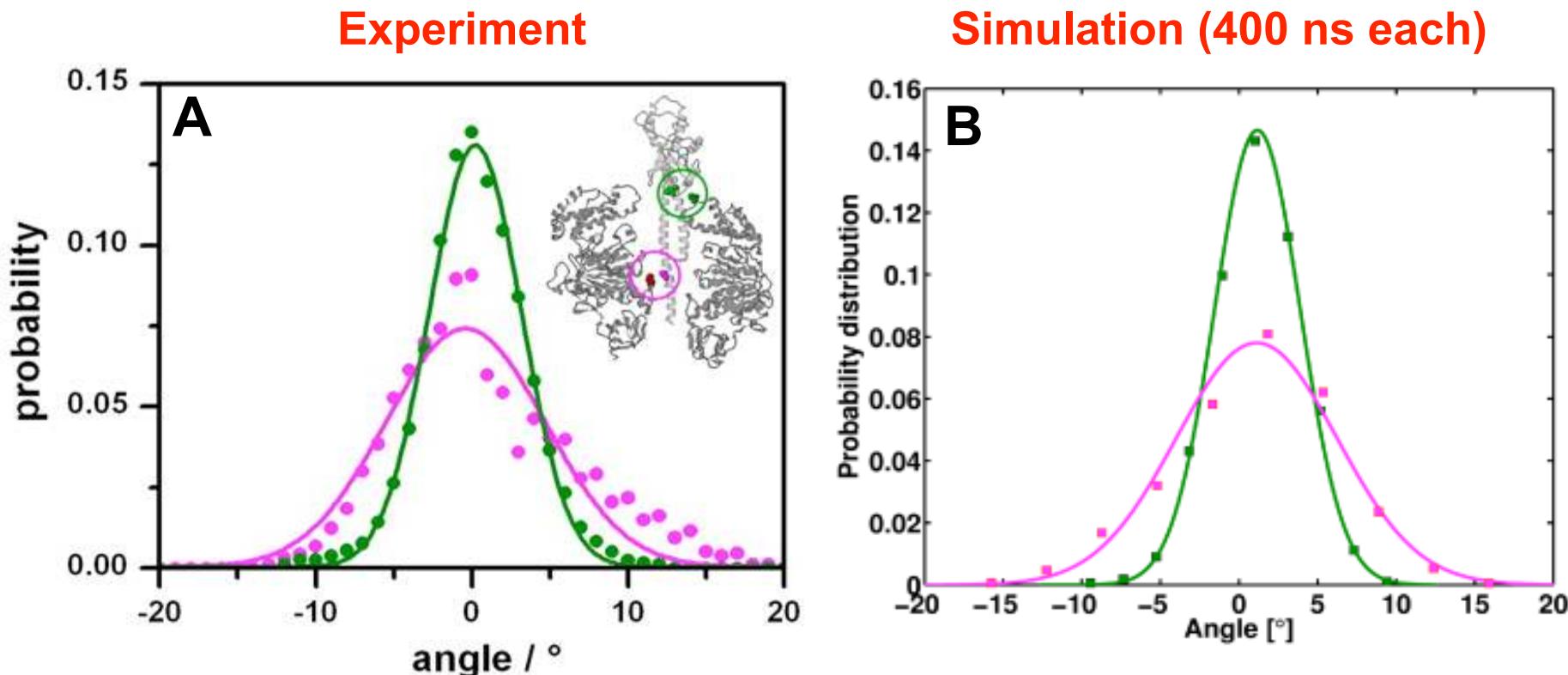
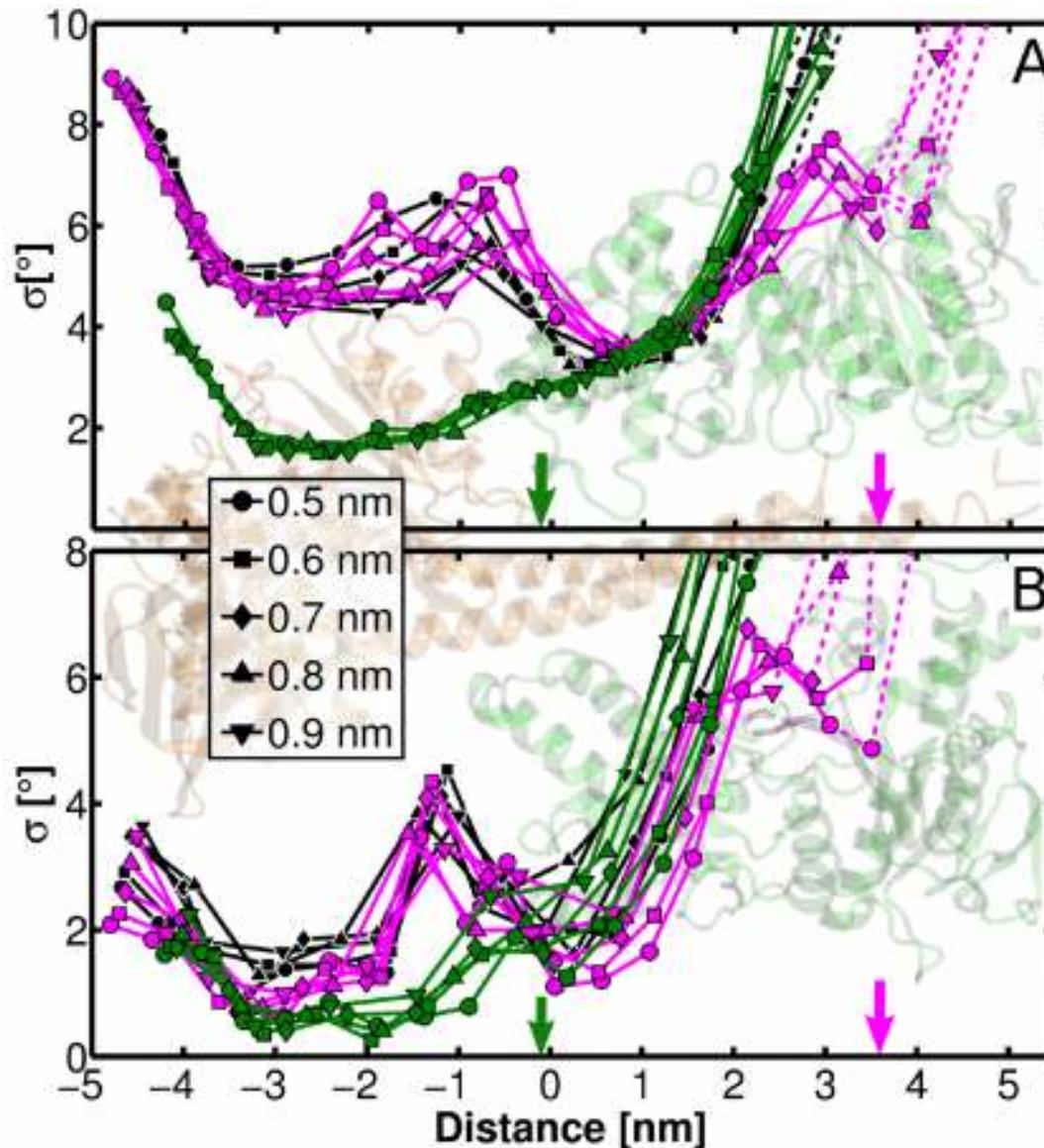
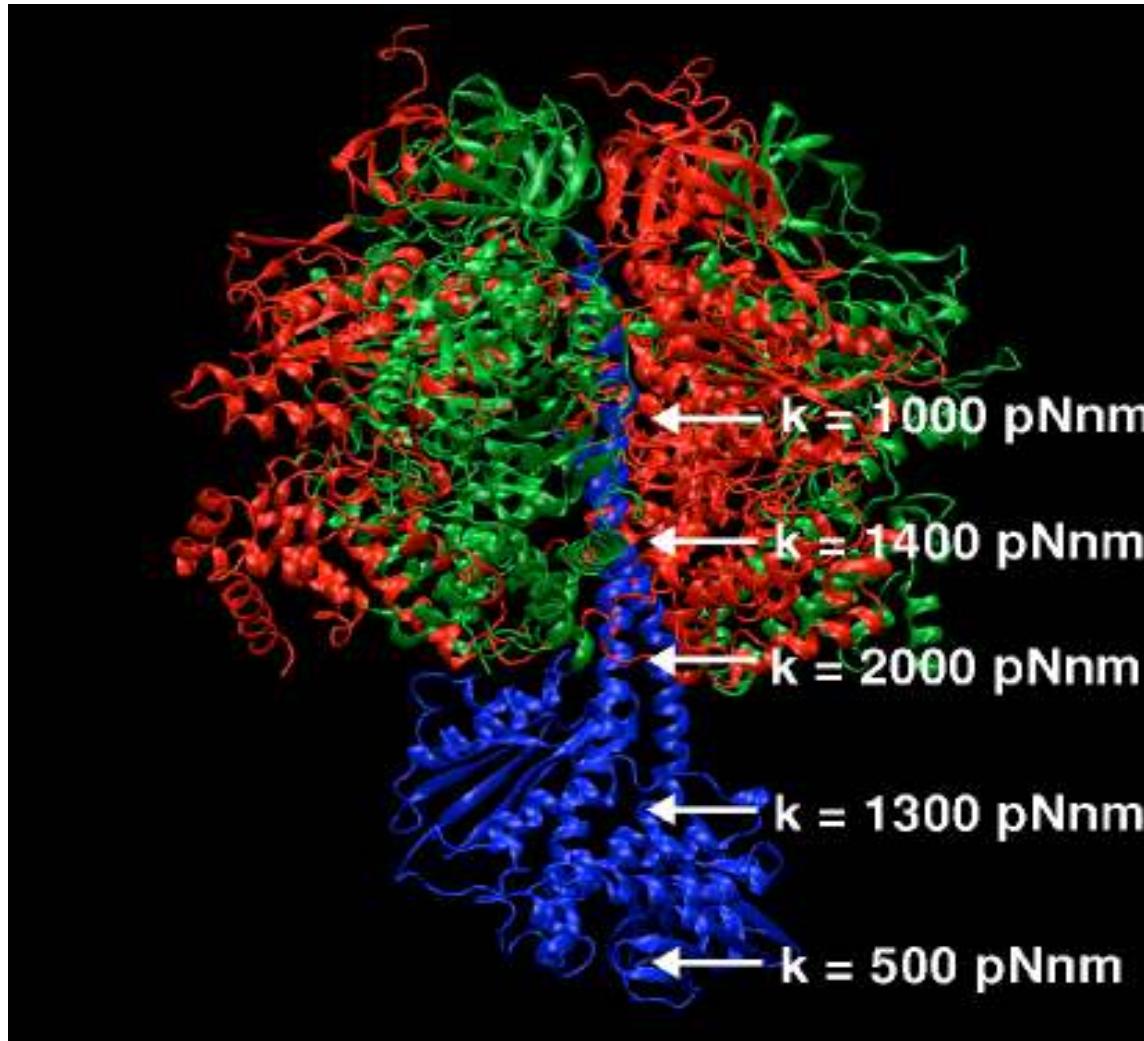


Figure: Distributions of the rotation angle observed in the experiment (Sielaff et al. PNAS 105:17760-, 2008) (A) and obtained from molecular dynamics simulations (B).

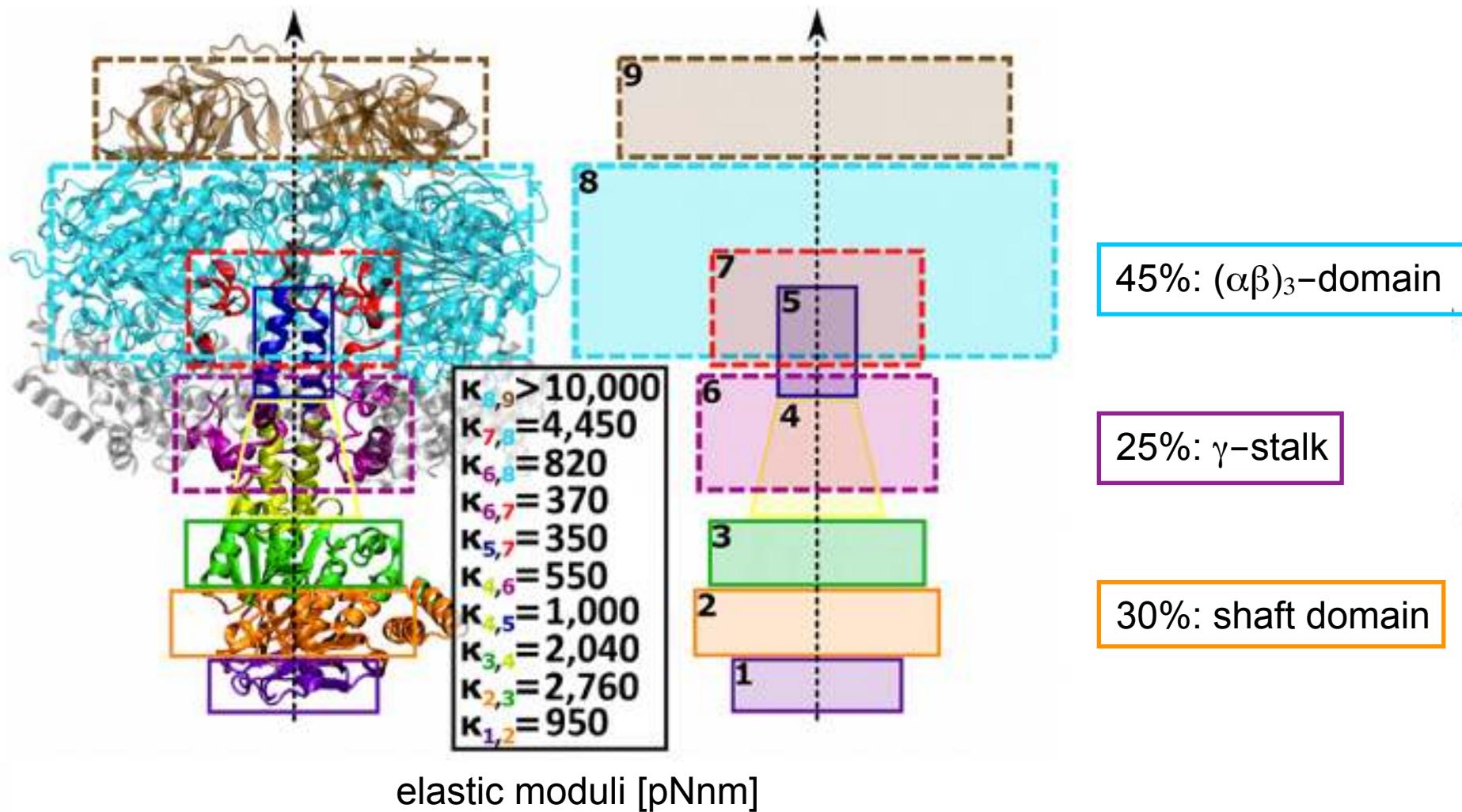
Elastic properties of the F₁-ATPase rotor – Fluctuation Analysis



Elastic properties of the F₁-ATPase rotor – Fluctuation Analysis

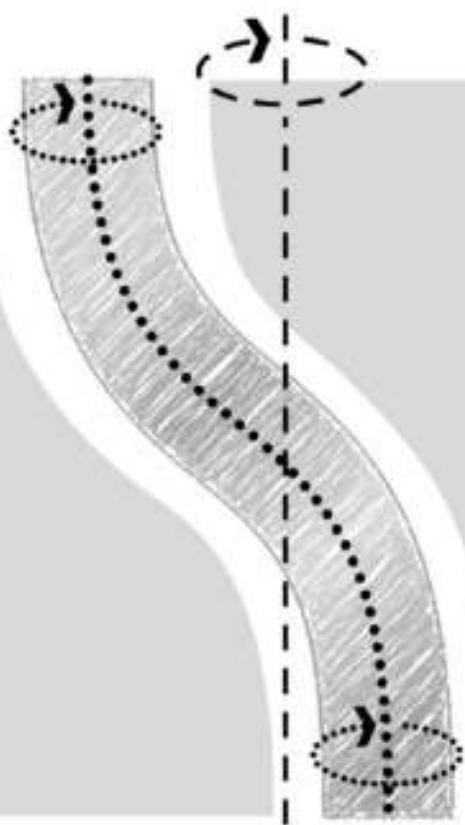


Elastic properties – conclusions

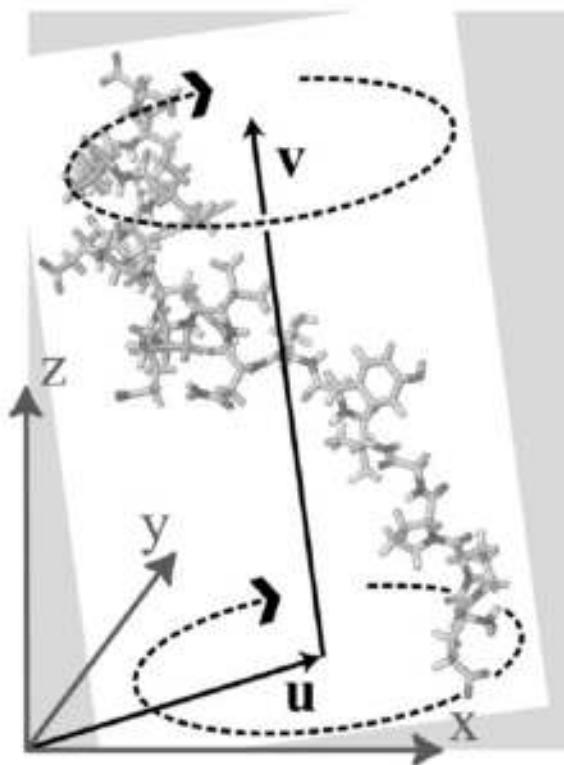


Driving Rotary motions with a flexible Axis

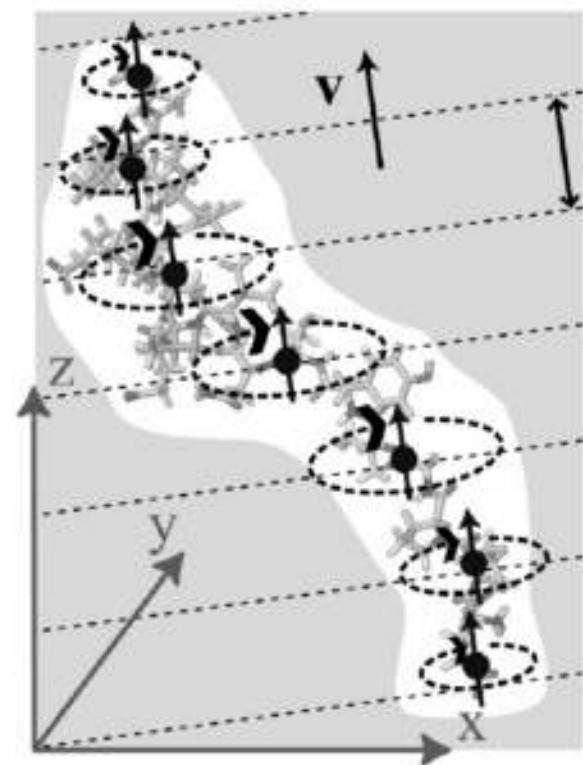
A



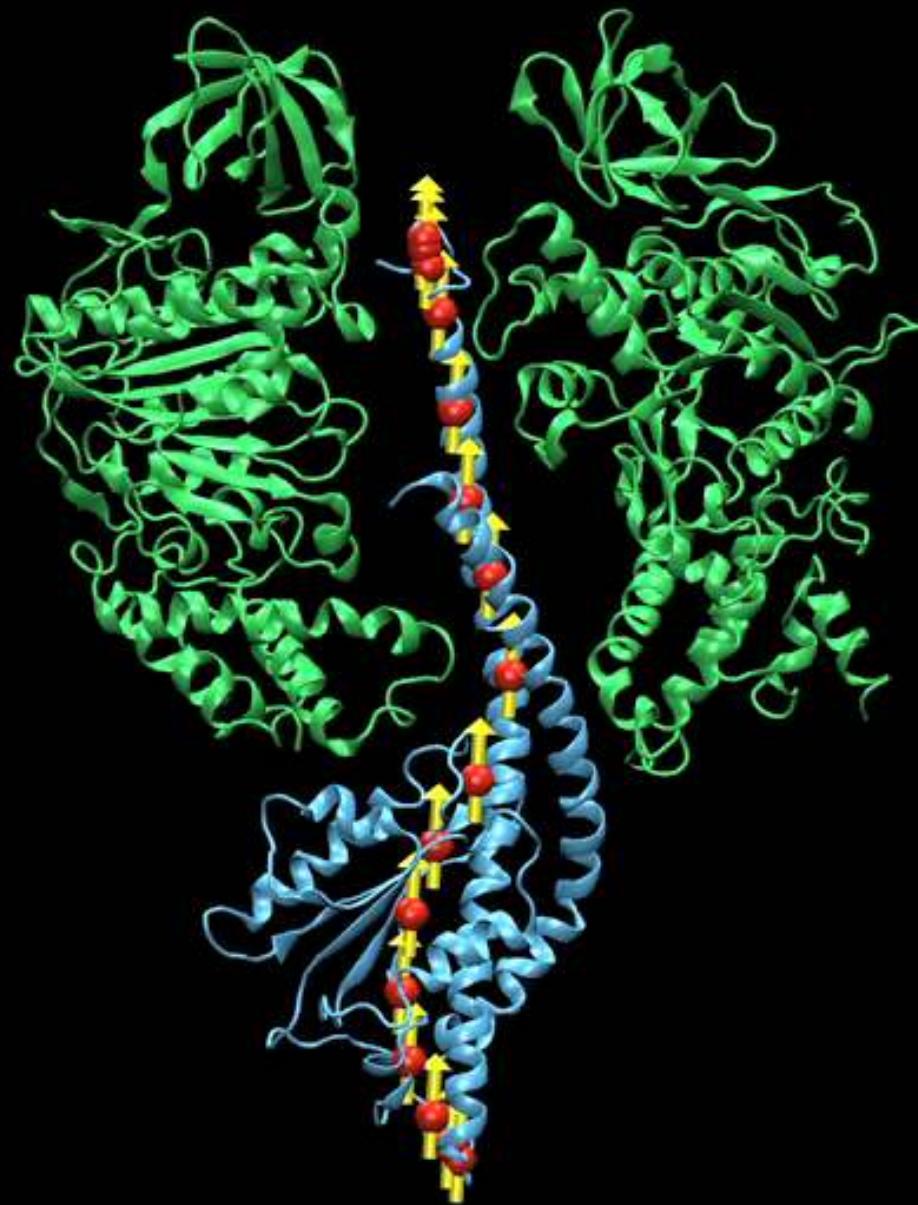
B fixed rotation



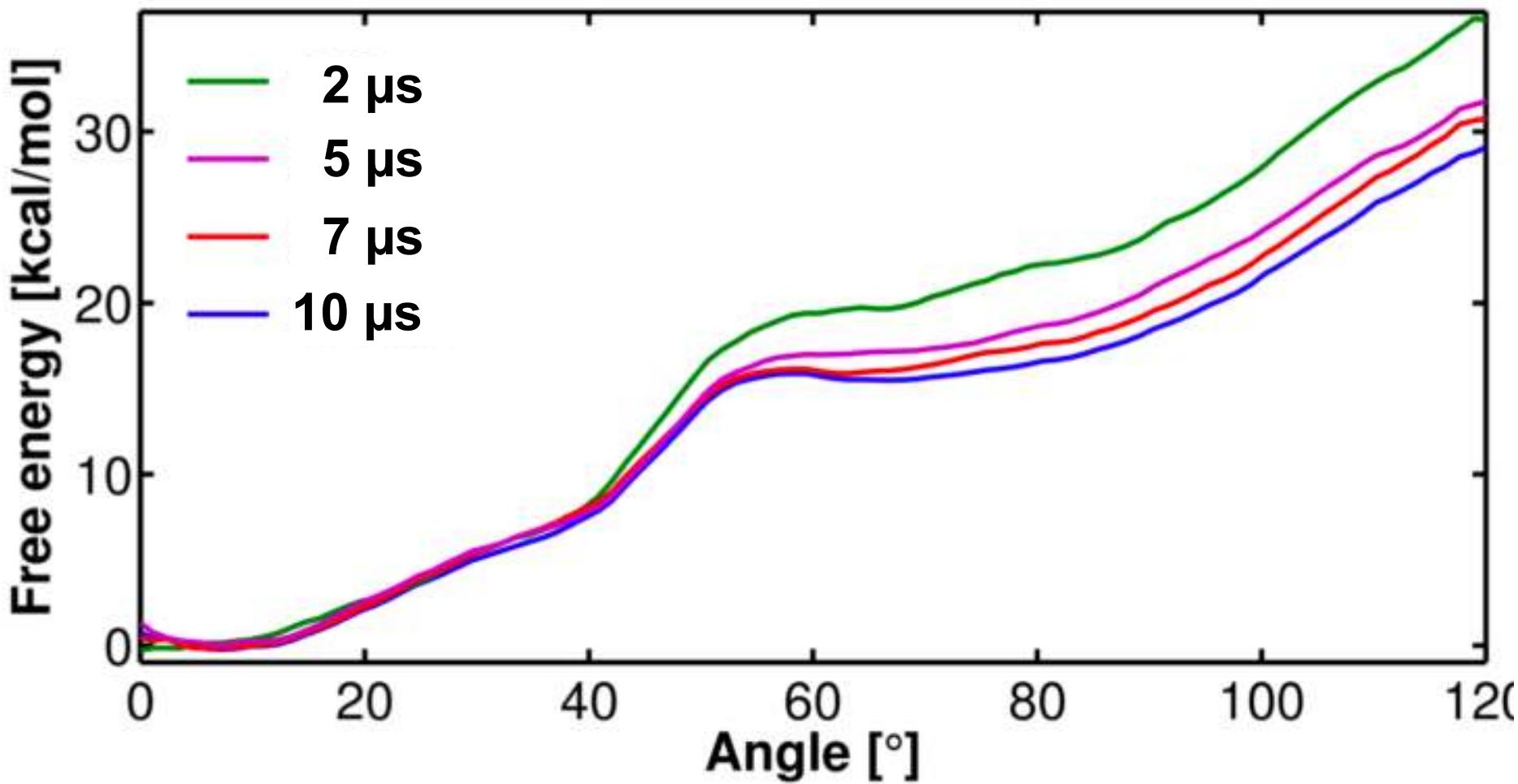
C flexible rotation



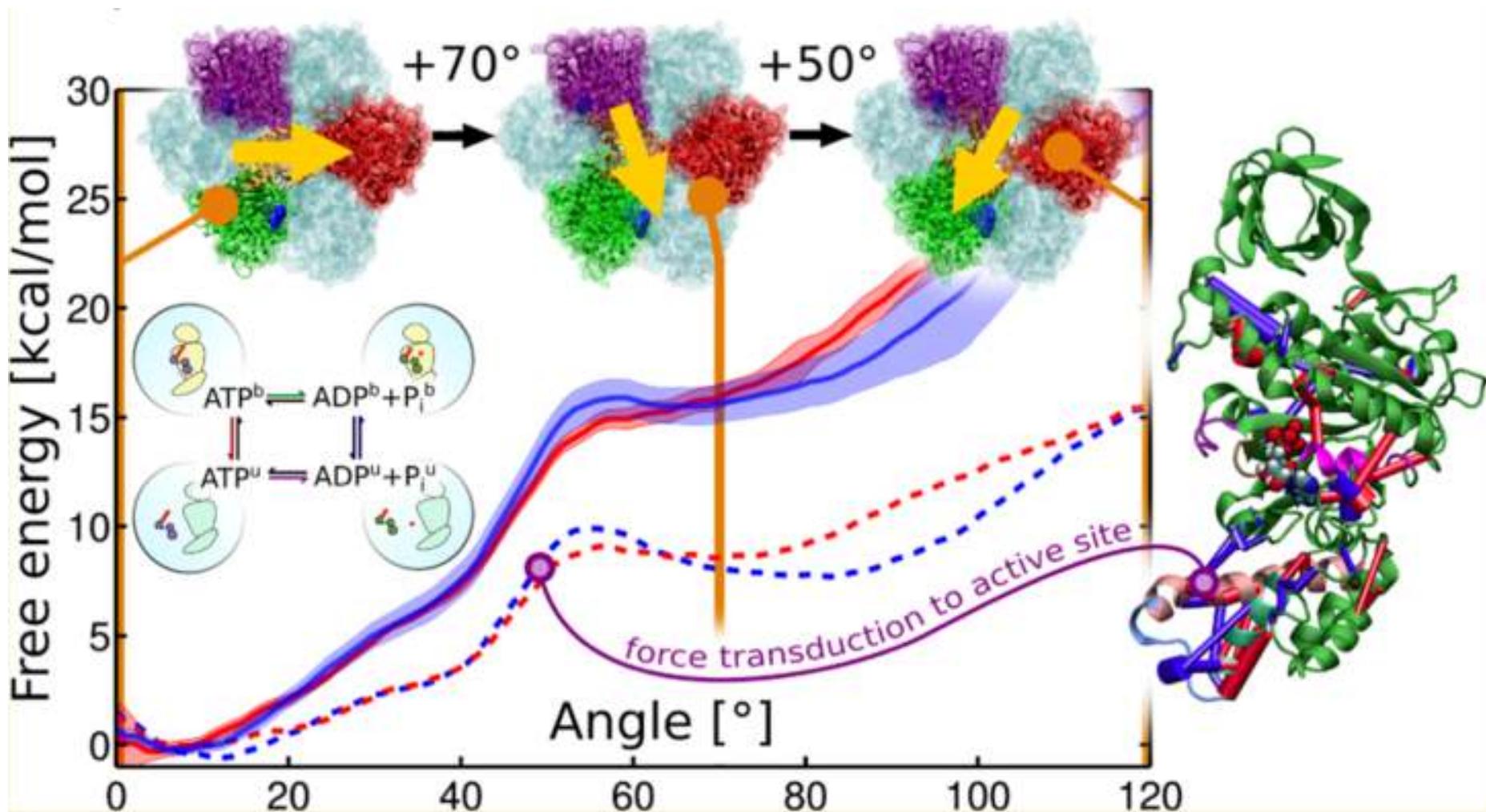
120° Gamma Subunit Rotation



Free energy landscape of gamma subunit rotation with bound ATP --> Convergence



Free energy landscape of gamma subunit rotation with bound ATP and ADP



Conformational changes upon gamma subunit rotation (in synthesis direction)

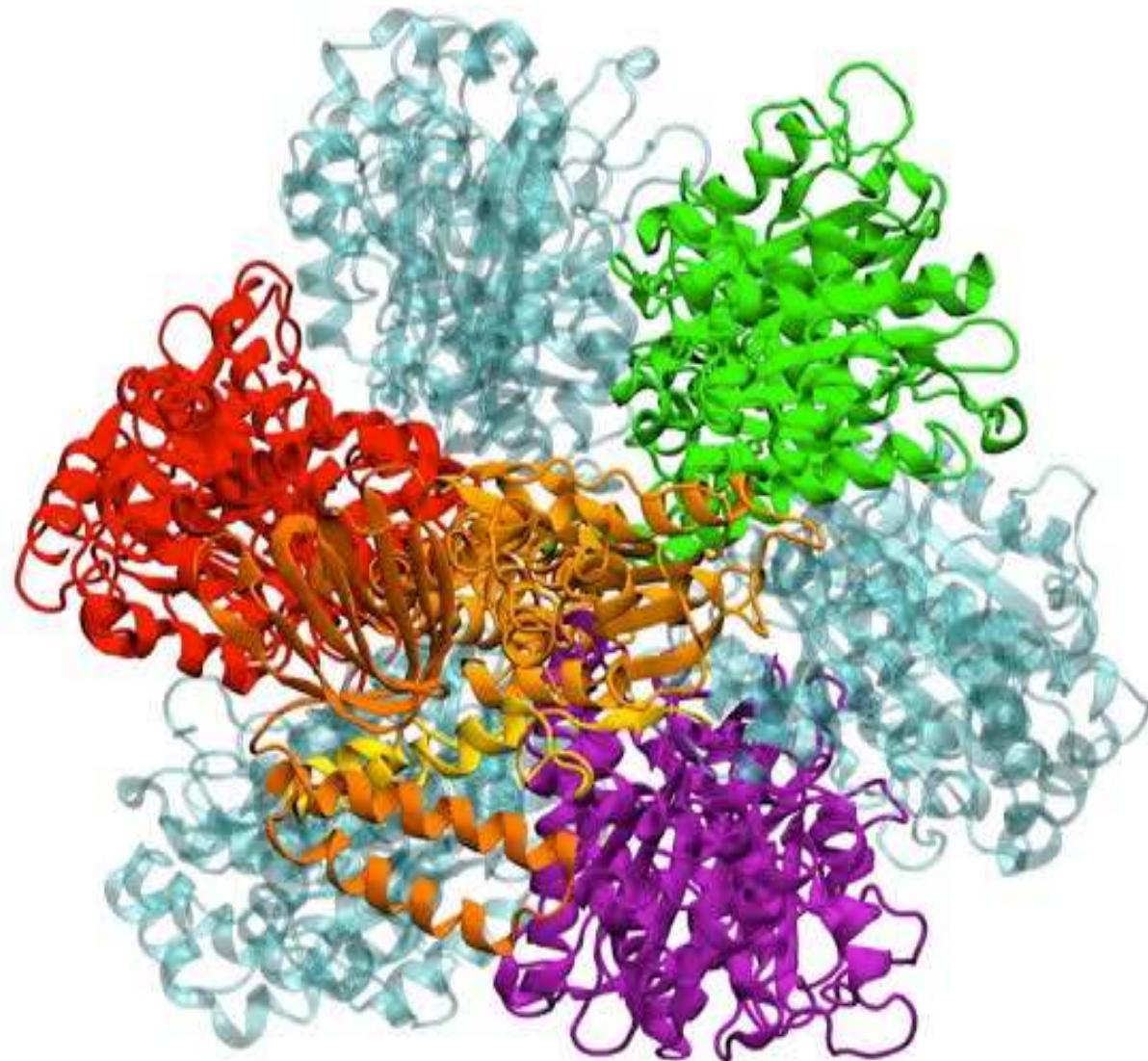
70° sub-step seen as metastable free energy minimum (pre ATP release)

Major free energy input via γ -rotation before 70° sub-step

=> Fine-tuned for 13 kcal/mol total energy turnover

=> compatible with kinetics

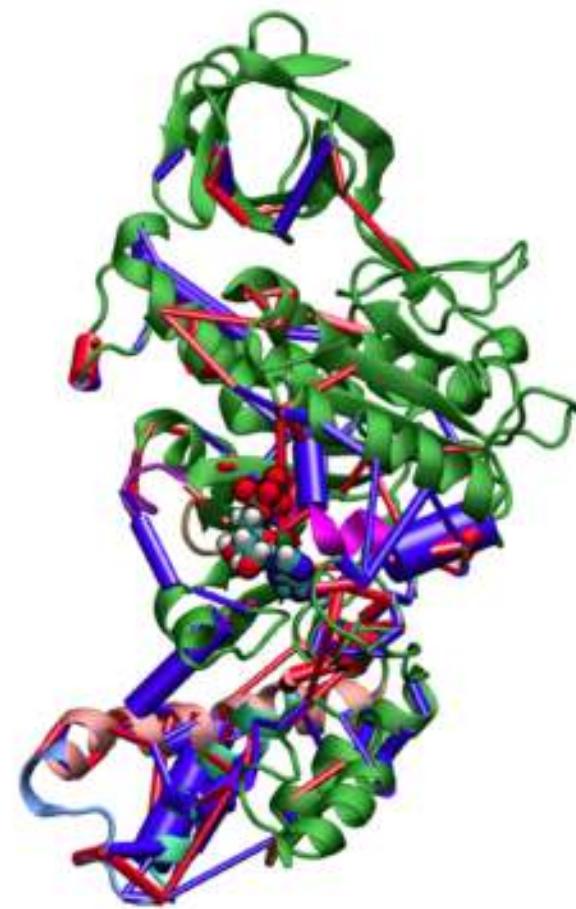
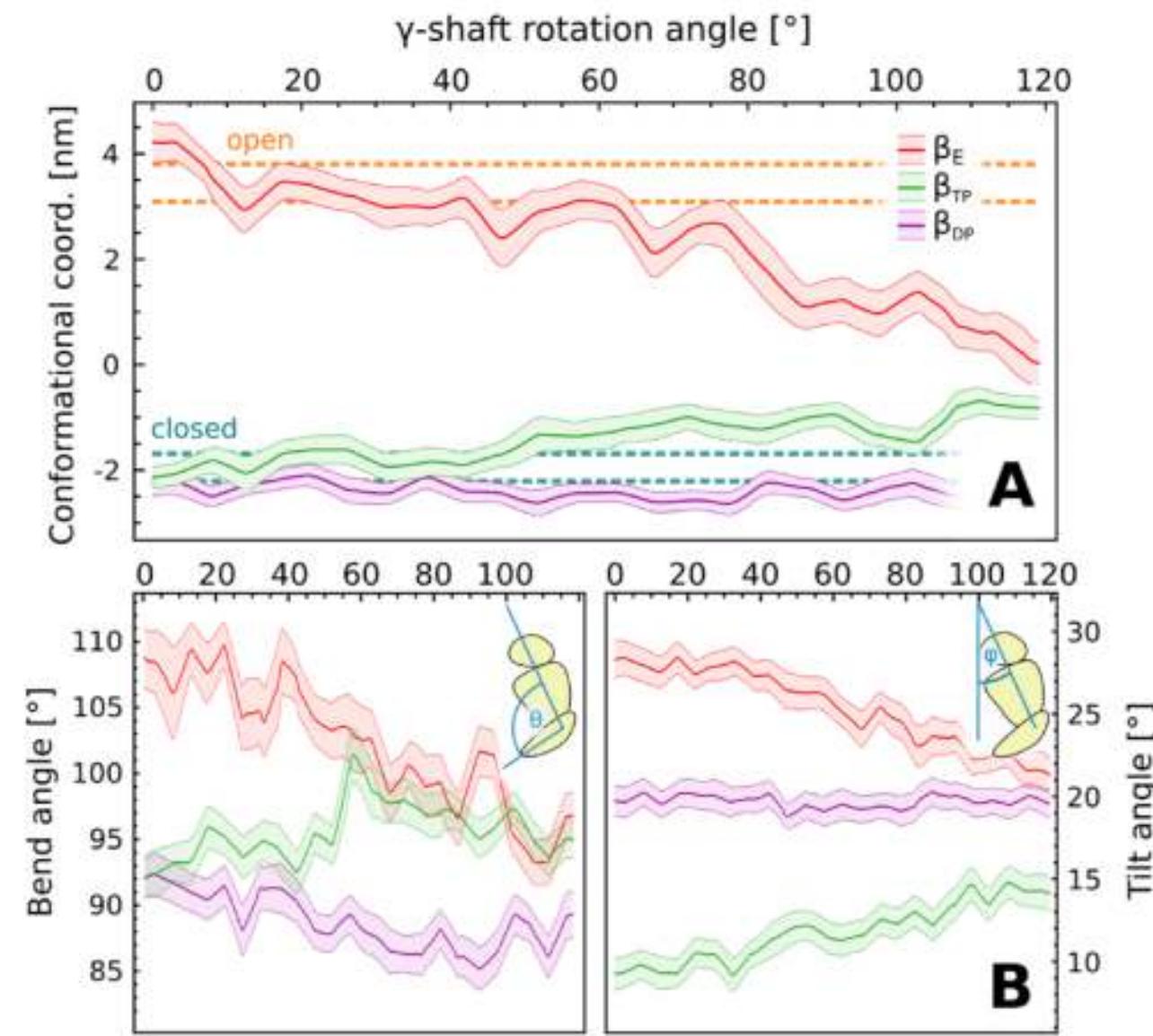
120° Gamma Subunit Rotation



0 ns

0°

Conformational changes upon gamma subunit rotation

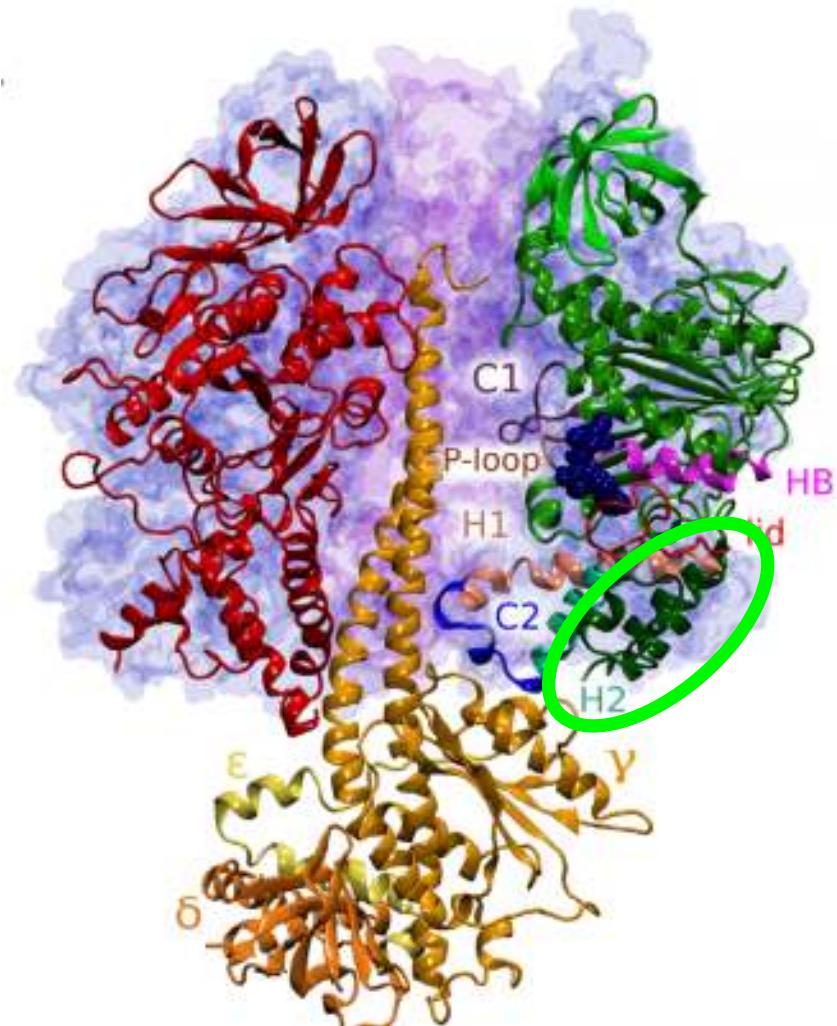


Conformational changes upon gamma subunit rotation (in synthesis direction)

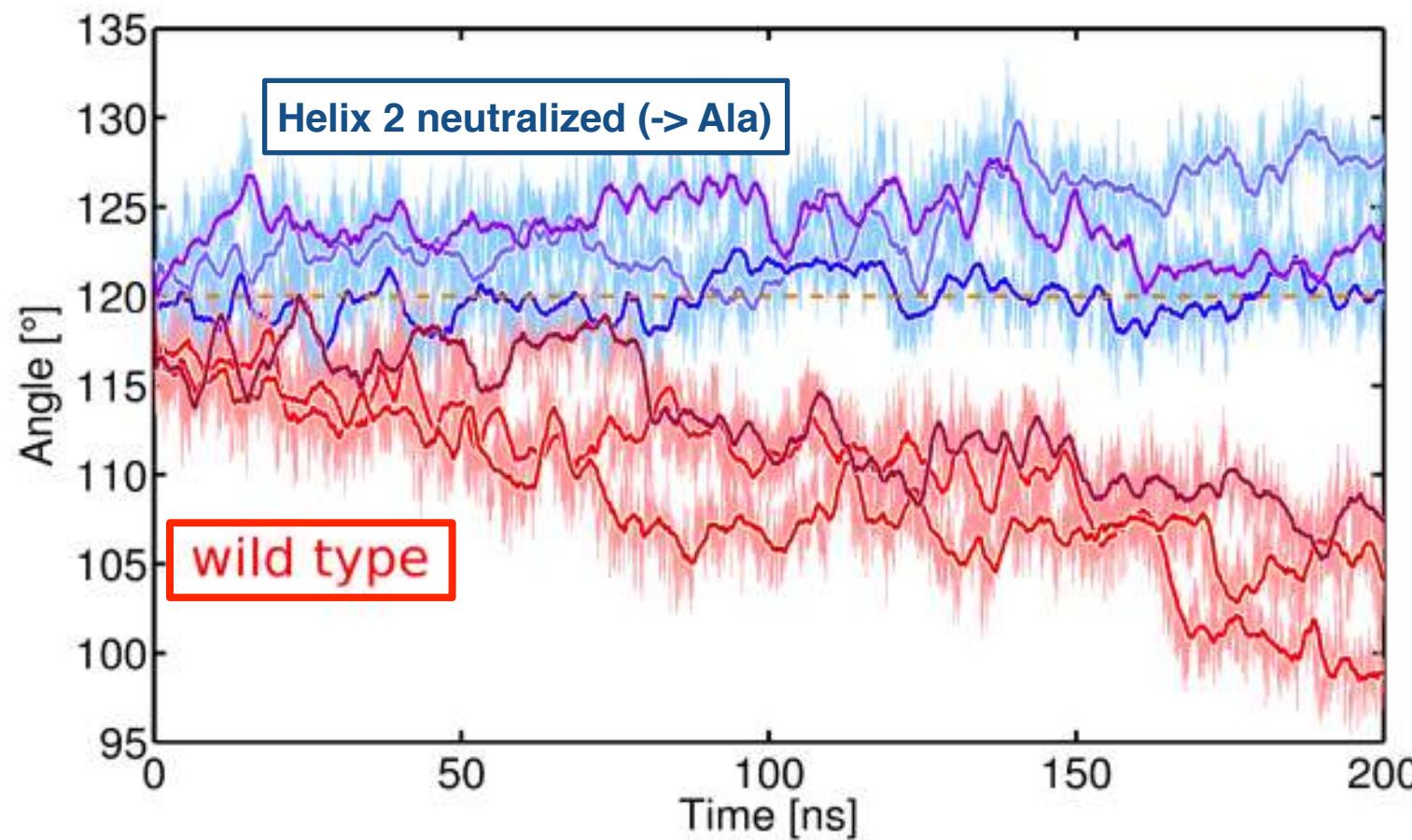
β_{TP} opens only partially during γ -rotation

=> full β_{TP} opening only after ATP release

=> Helix 2 as a gate-keeper



Electrostatic repulsion between H2 and gamma prevents completion of opening before ATP release



Conformational changes upon gamma subunit rotation (in synthesis direction)

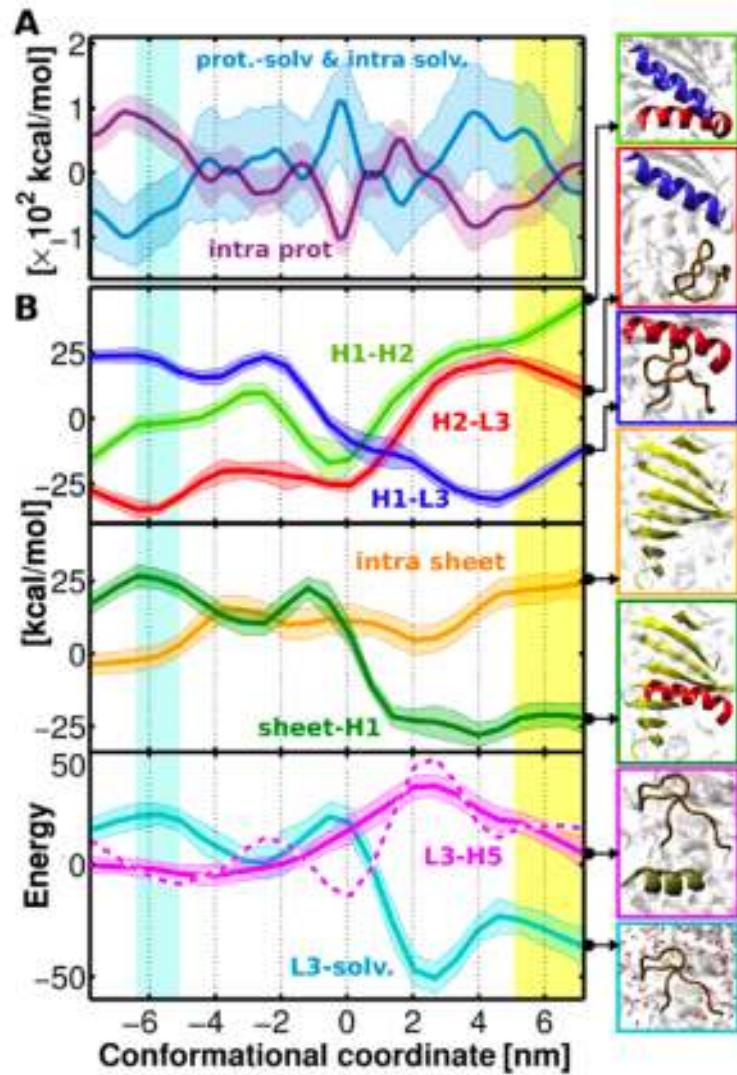
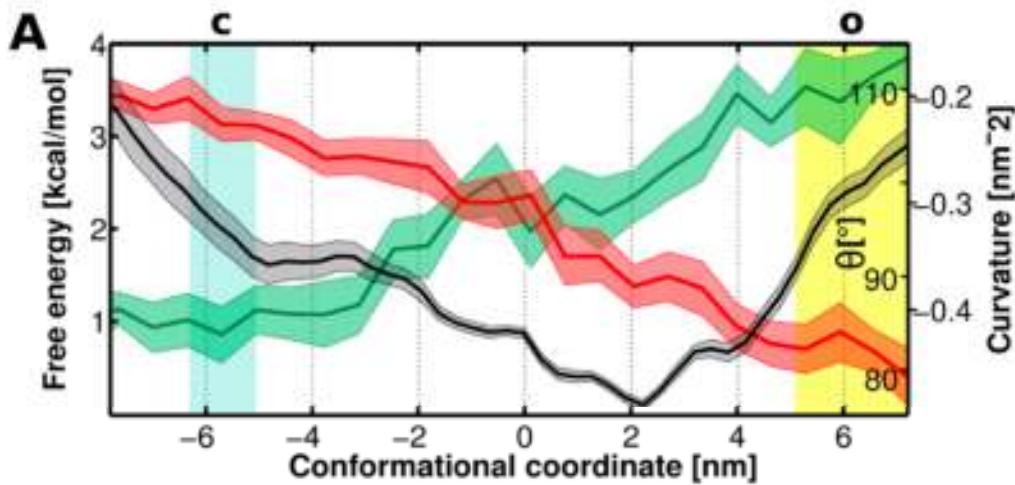
β_E closes spontaneously during γ -rotation, to stable half-open state

=> not the rate-limiting step

=> subsequent ADP binding allosterically contributes to full β_{TP} opening

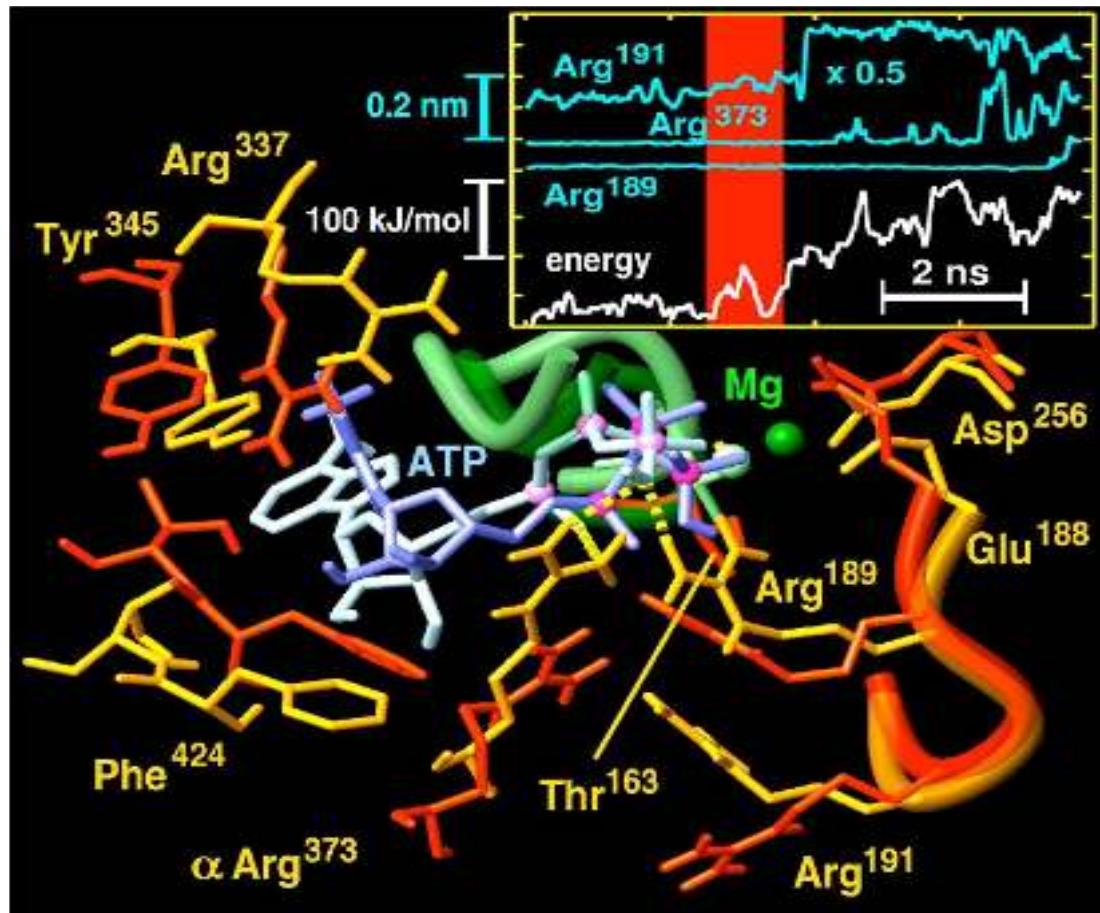
=> avoids 'waste' of energy through irreversible downhill ADP binding

Spontaneous closure of β_E is driven by competing interactions



Conformational changes upon gamma subunit rotation (in synthesis direction)

Affinity reduction for bound ATP
due to electrostatic
coupling with Arg finger(s)



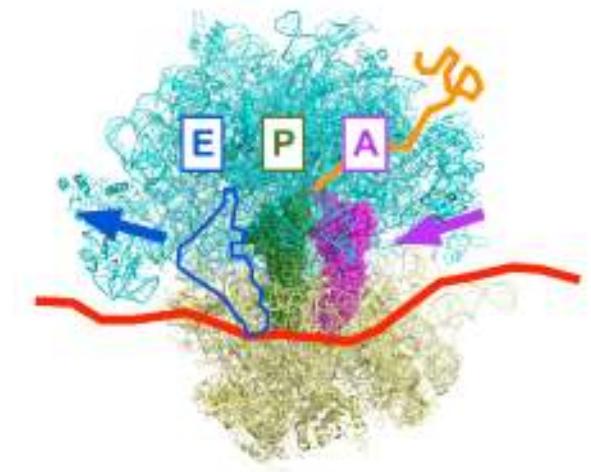
Towards a mechanistic understanding of protein function

(1) Ligand unbinding revisited

(2) Ribosomal antibiotics mechanism

(3) Intrinsically Disordered Proteins

(4) The Dynasome



AFM+ X-ray + cryo EM + MD

*Lars Bock, Christian Blau, Michal Kolar, Andrea Vaiana, Andreas Russek,
Sarah Rauscher, Ulf Hensen*

*Holger Stark, Marina Rodnina (MPI Göttingen)
Roland Beckmann, Daniel Wilson (Univ. Munich)
Simon Scheuring (Cornell Univ.)*

Ribosomal tRNA translocation and stalling: X-ray + cryoEM + MD

Lars Bock, Christian Blau, Andrea Vaiana

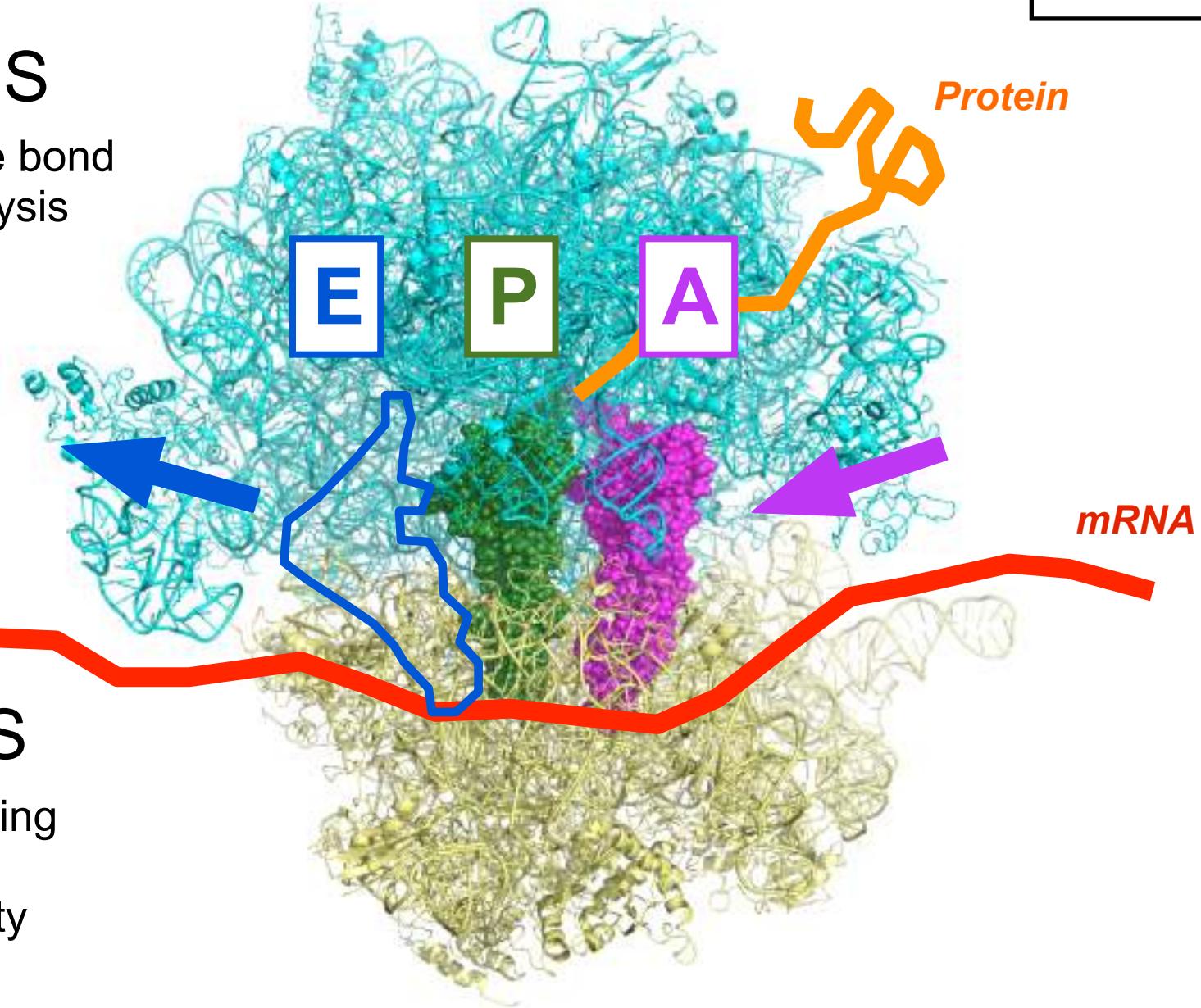
Collab.: Holger Stark, Marina Rodnina (MPI Göttingen)
Roland Beckmann, Daniel Wilson (Univ. Munich)

The Ribosome

2.5 MDa

50S
Peptide bond
catalysis

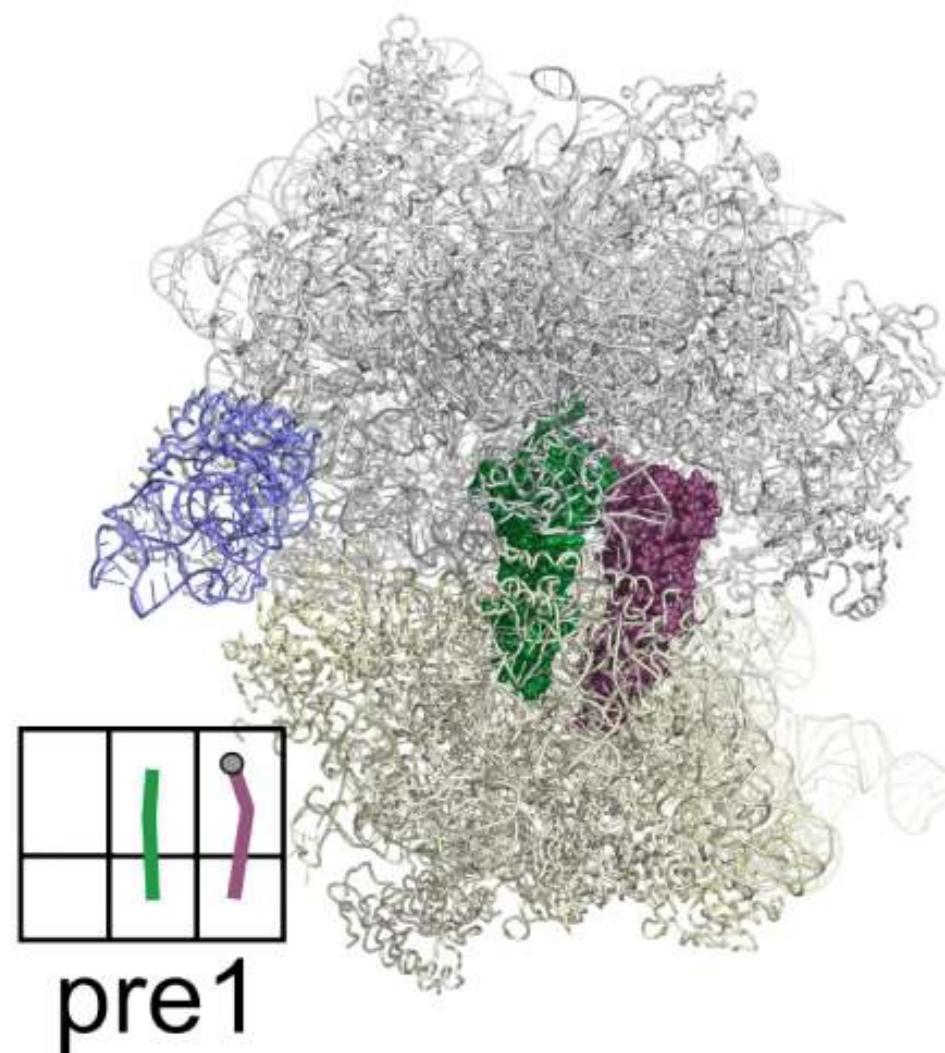
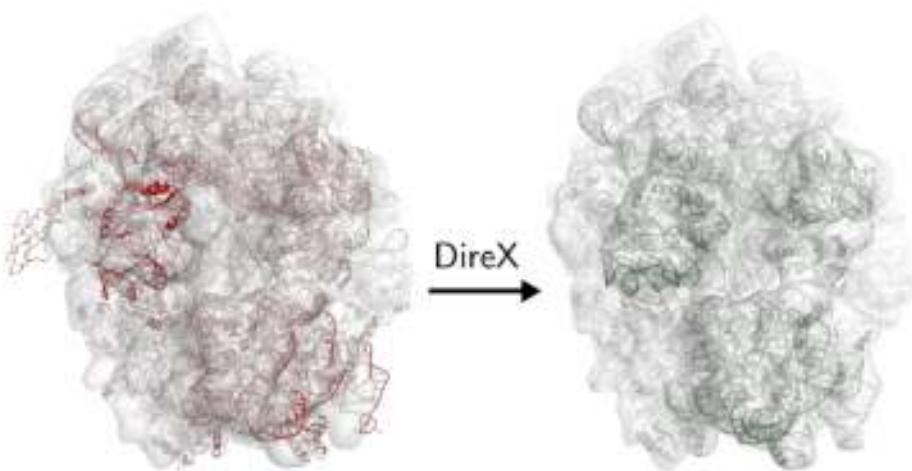
30S
Decoding
and
fidelity



Refinement of x-ray structure against Cryo-EM densities

Crystal structure [1]

Refined against 13 EM-maps
by flexible fitting (DireX [2])



[1] Zhang et al., 2009, Science

[2] Schröder et al., 2007, Structure

Correlation does not imply causality

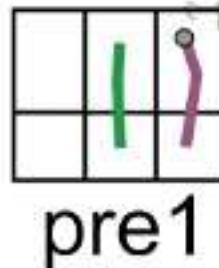
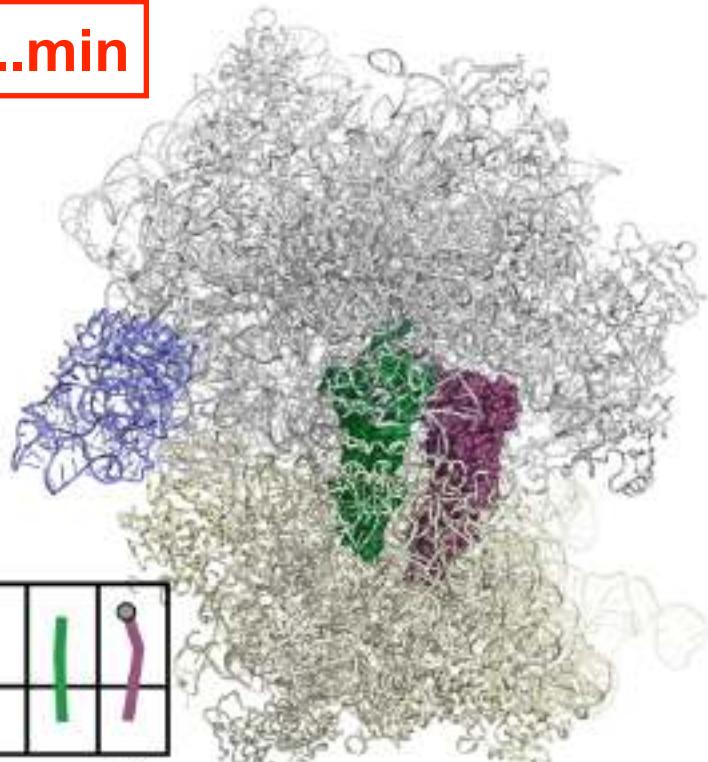


Multiple MD Simulations

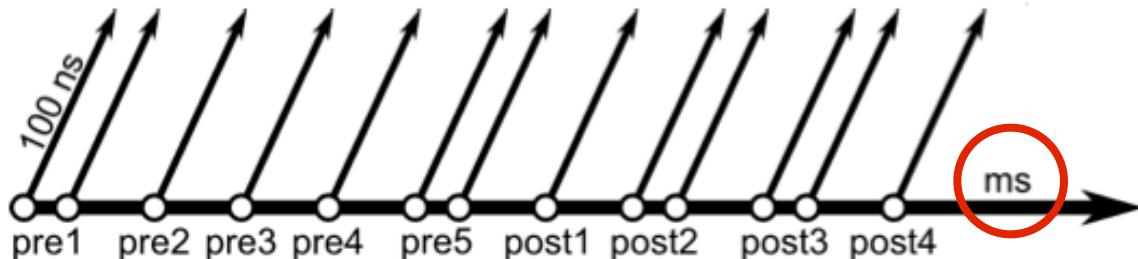
- 13 MD simulations (min one per state)
- at least 100 ns for each state
~1500 ns total simulation time

- Amber99sb force field
- GROMACS 4.0
- 150mM KCl 7mM Mg2Cl
- SPC/E water
- 2.2 M atoms
- NPT simulations

ms...min

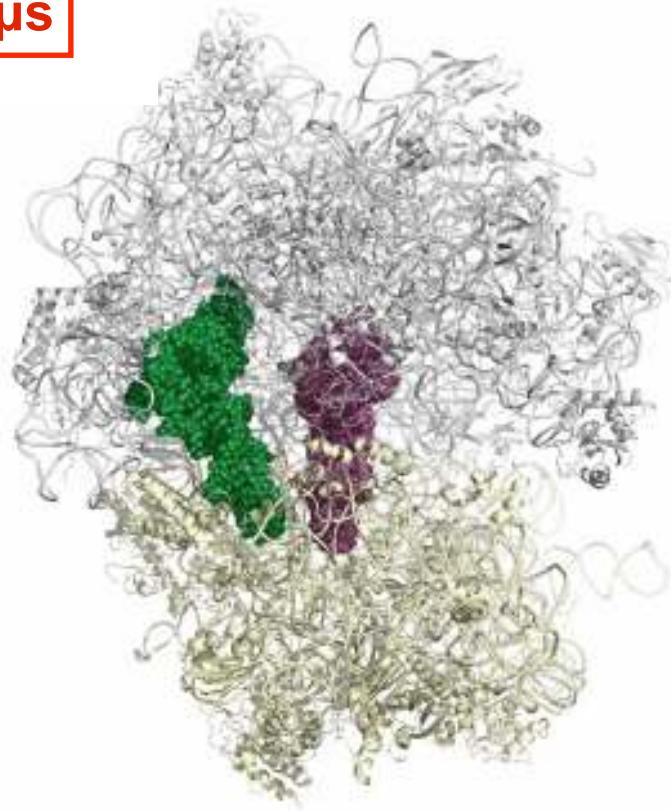


pre1

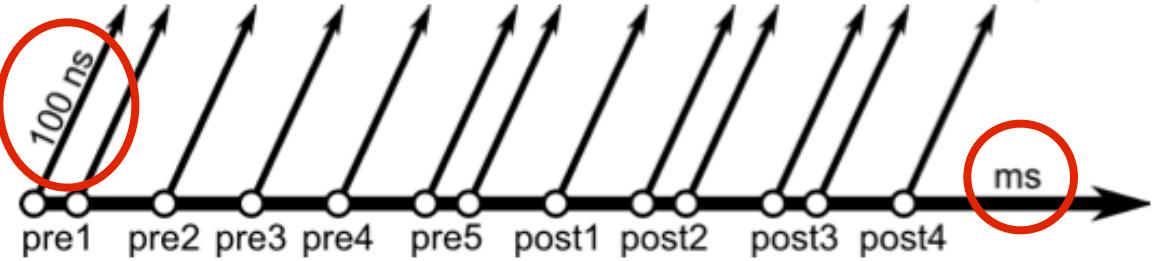
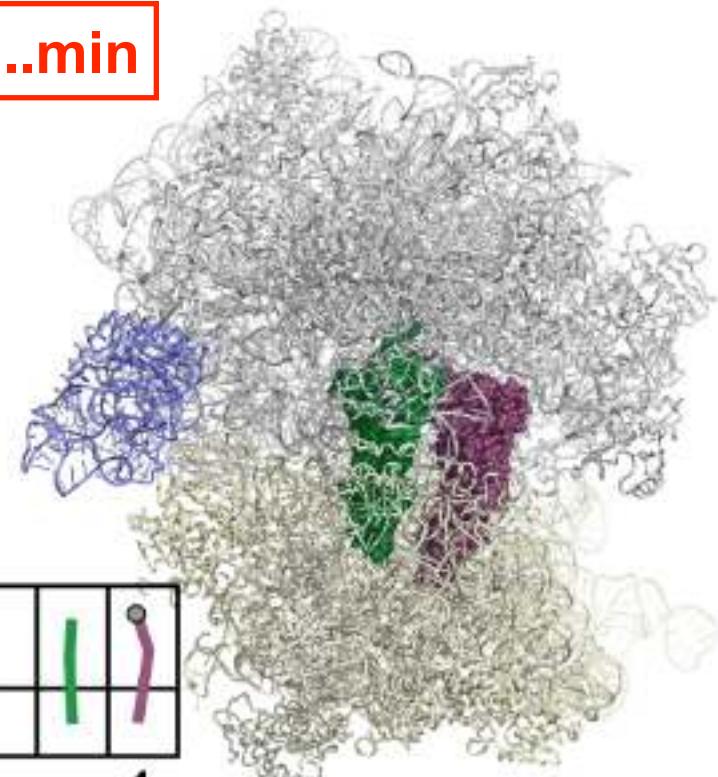


Dynamics, energetics, and driving forces from MD Simulations

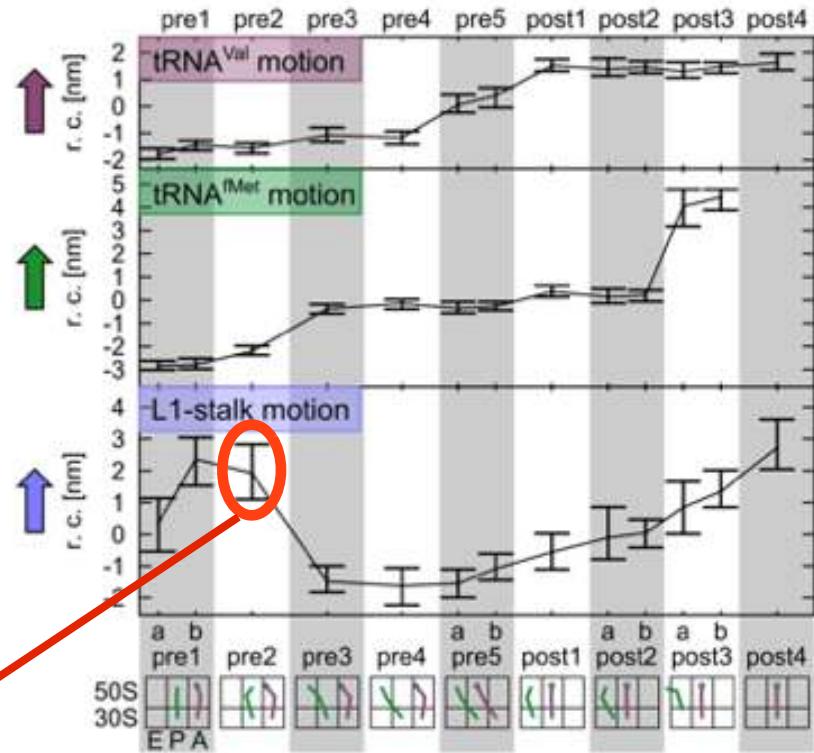
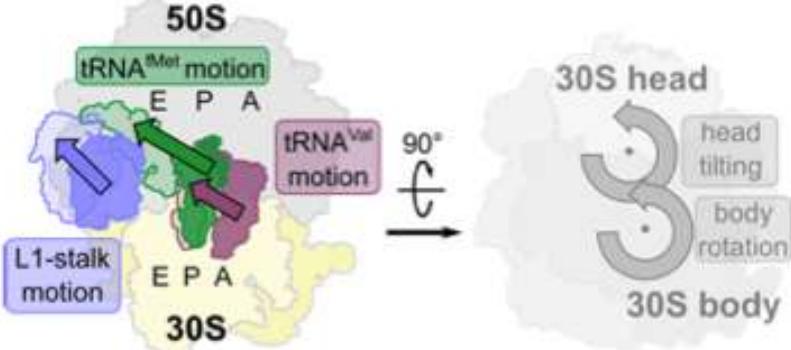
ns... μ s



ms...min



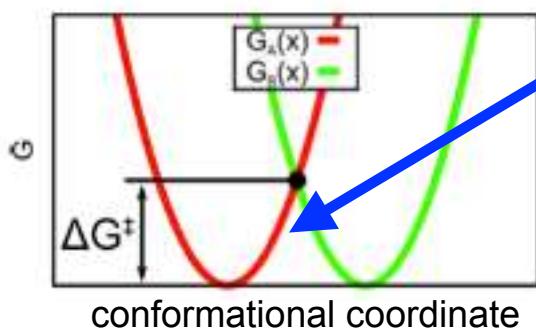
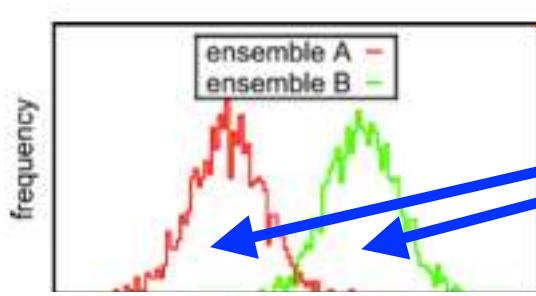
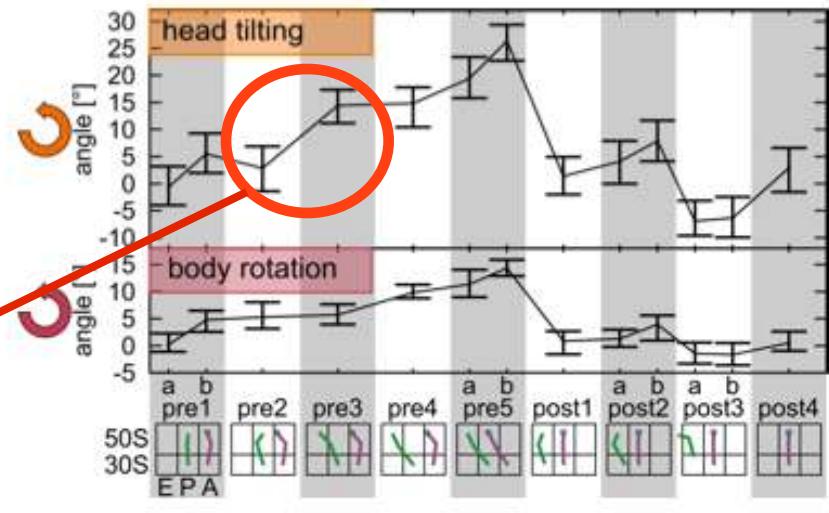
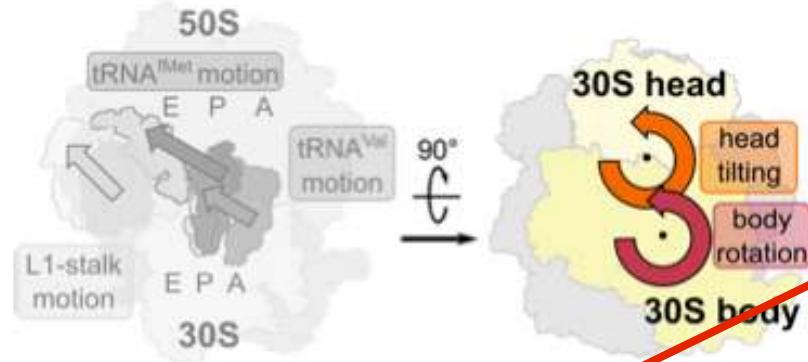
Coordinated conformational motions: L1 and tRNAs



structural fluctuations @ 100 ns

**Which motions limit translocational transition rates?
... and how are these overcome by the ribosome?**

Transition rate estimates from MD



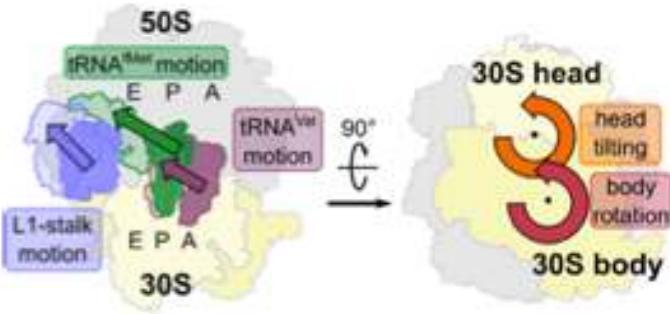
MD: fluctuations @ 100 ns

overlap -> barrier height

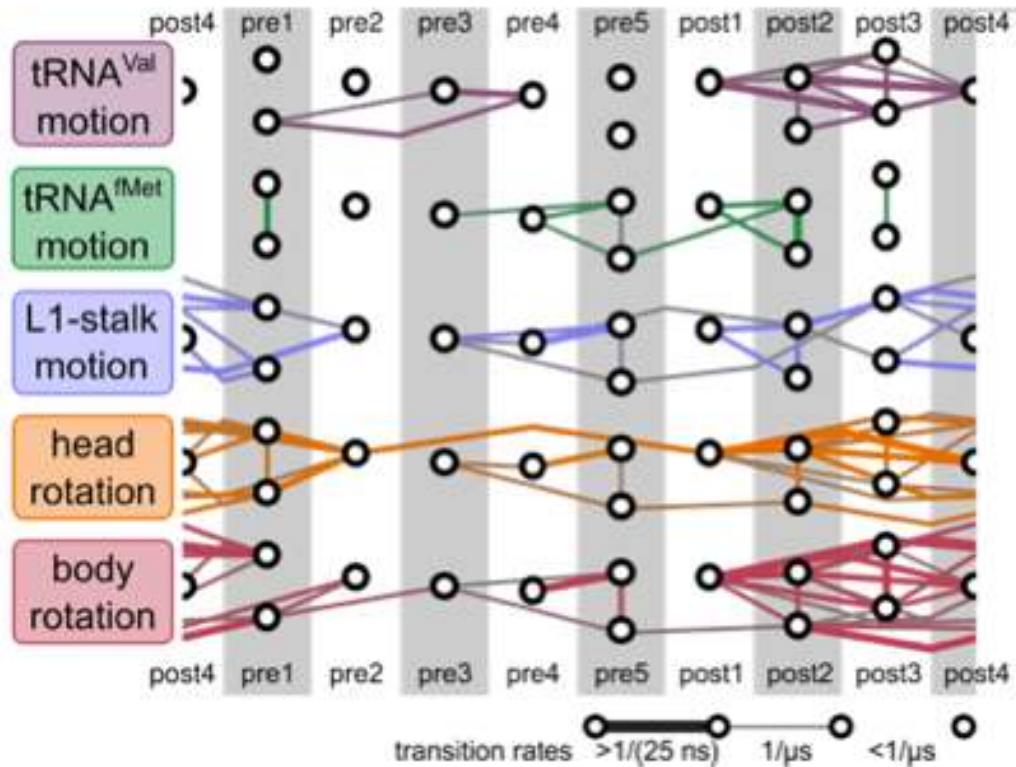
MD: Attempt frequency

$$k = A \exp(\Delta G^\ddagger / k_b T)$$

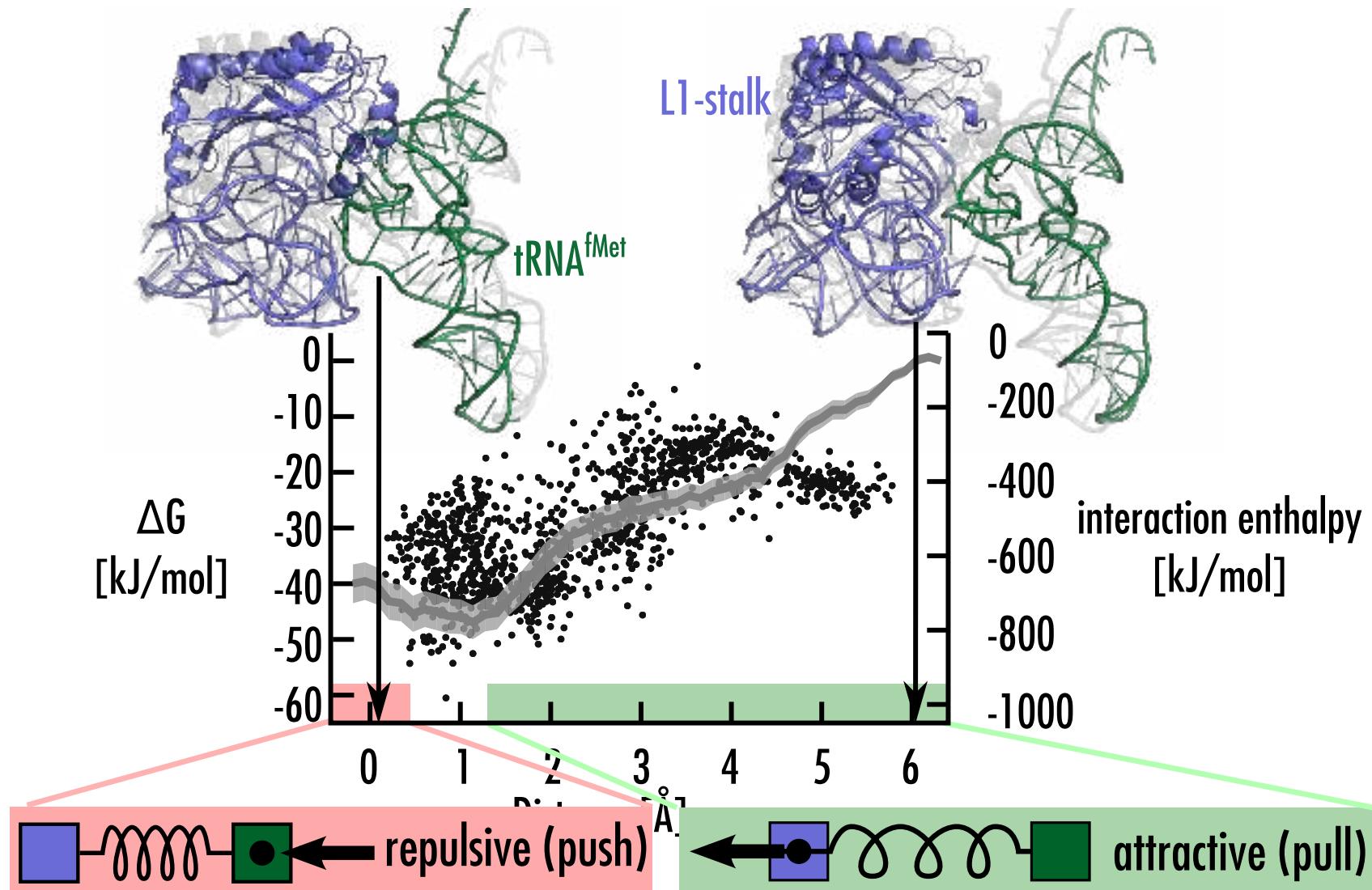
Rate-limiting: tRNA movement



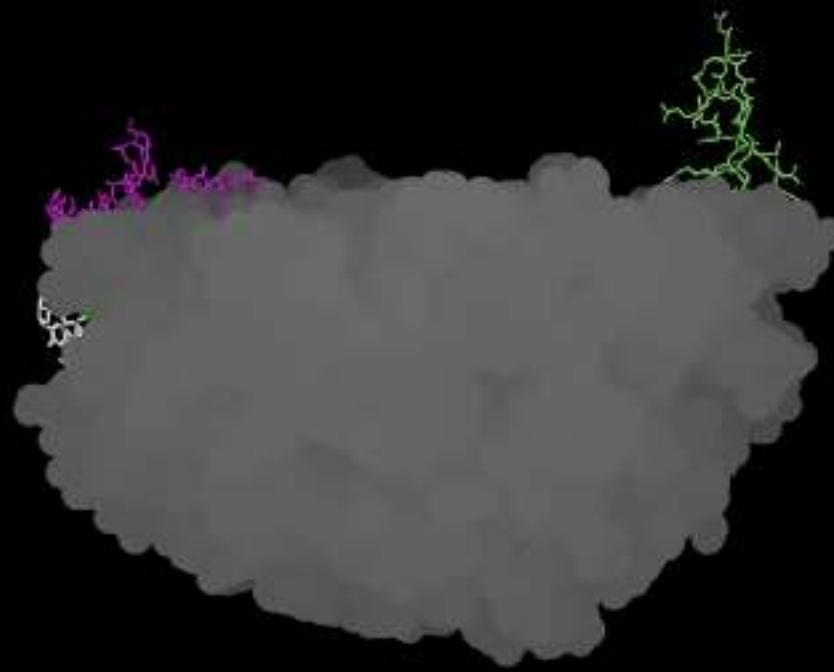
Most transition rates are determined by barriers which limit tRNA movement.



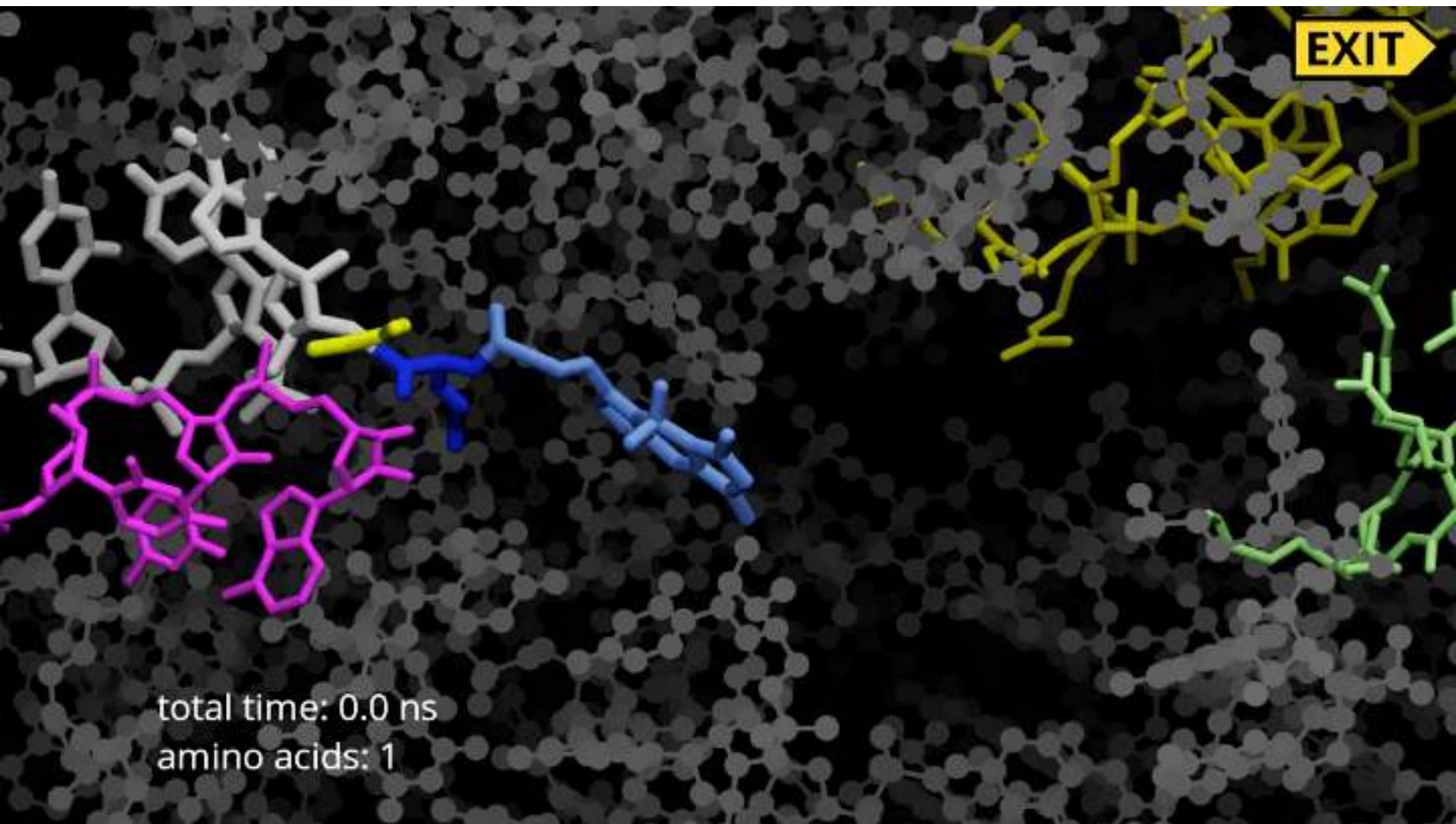
Local interactions: L1 stalk



Elongation dynamics of the nascent peptide in the exit tunnel

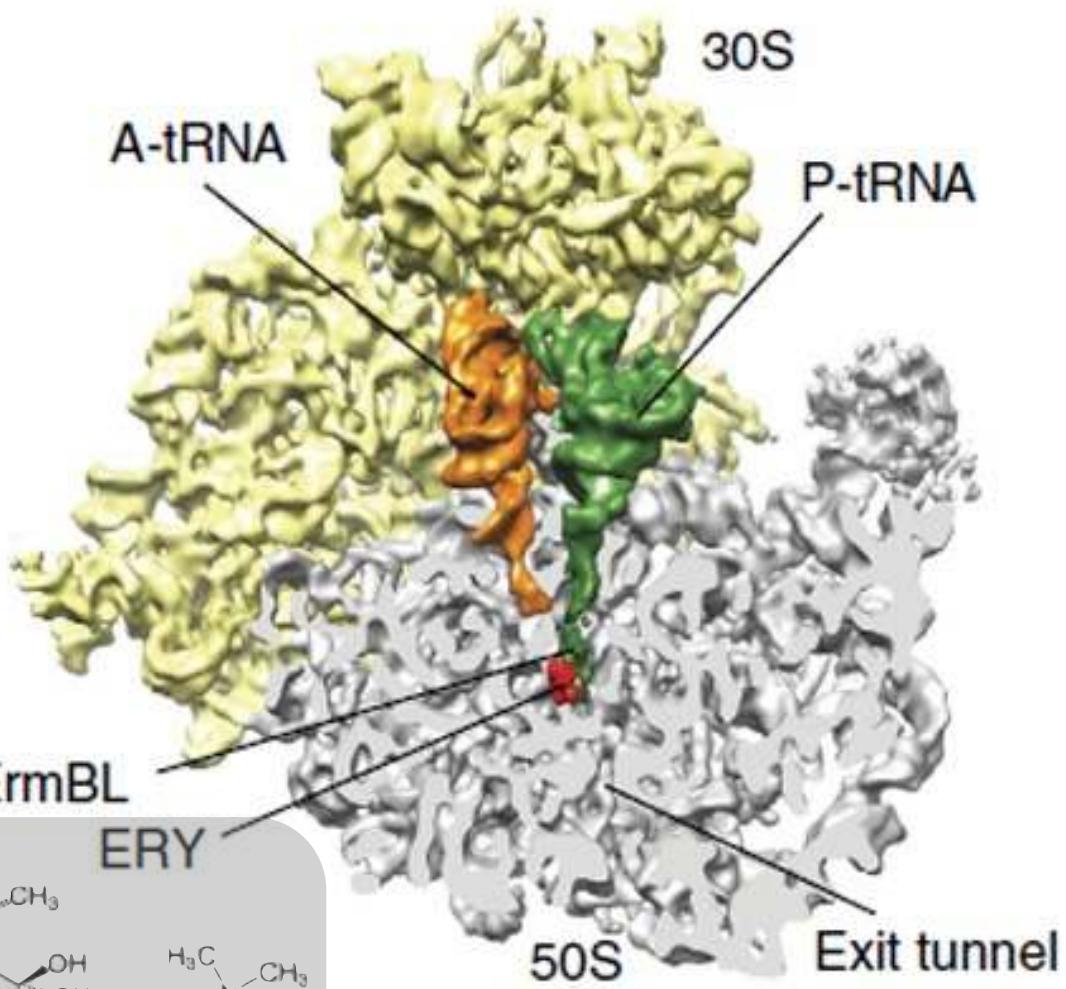
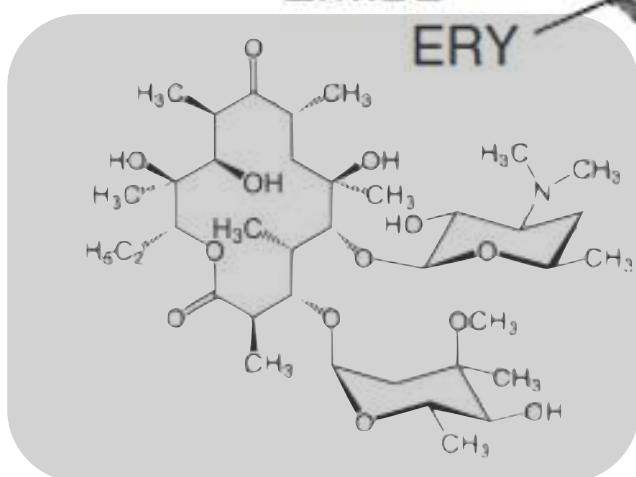


Elongation dynamics of the nascent peptide in the exit tunnel



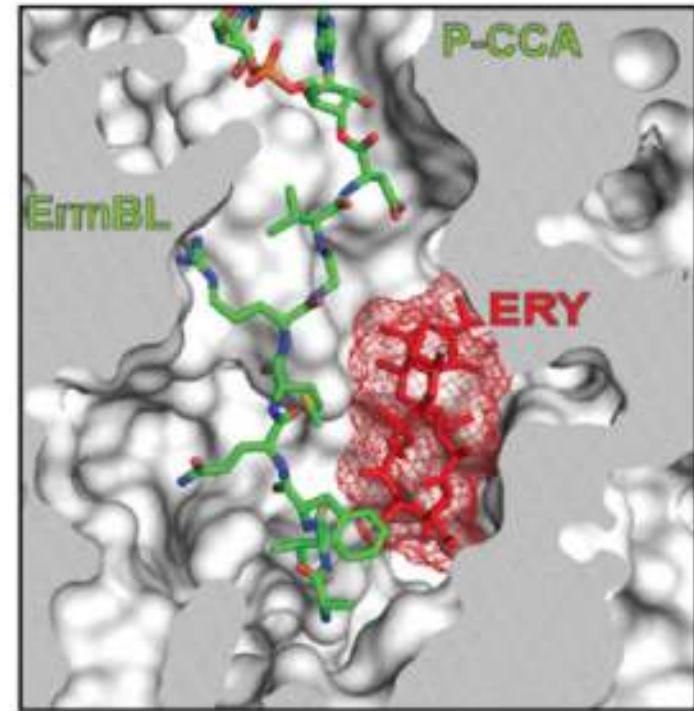
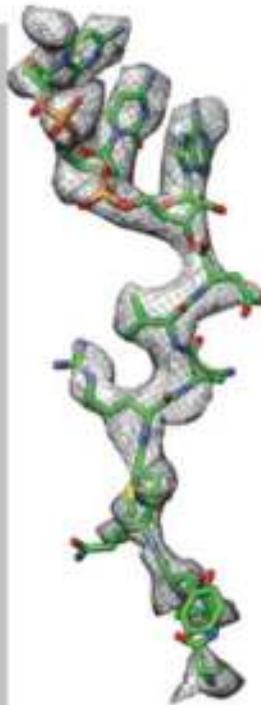
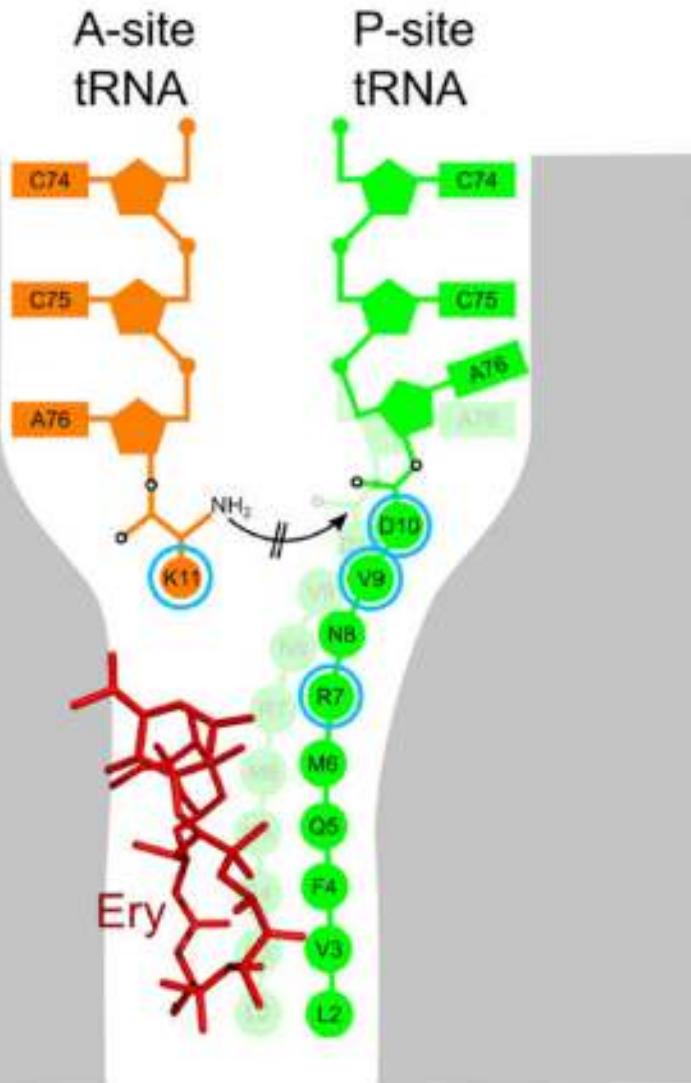
Erythromycin (Ery) binds in the exit tunnel

- Most peptides translated
 - Stalls the ribosome during ErmBL translation
(and others)



Arenz *et al* Nat. Commun. (2014)

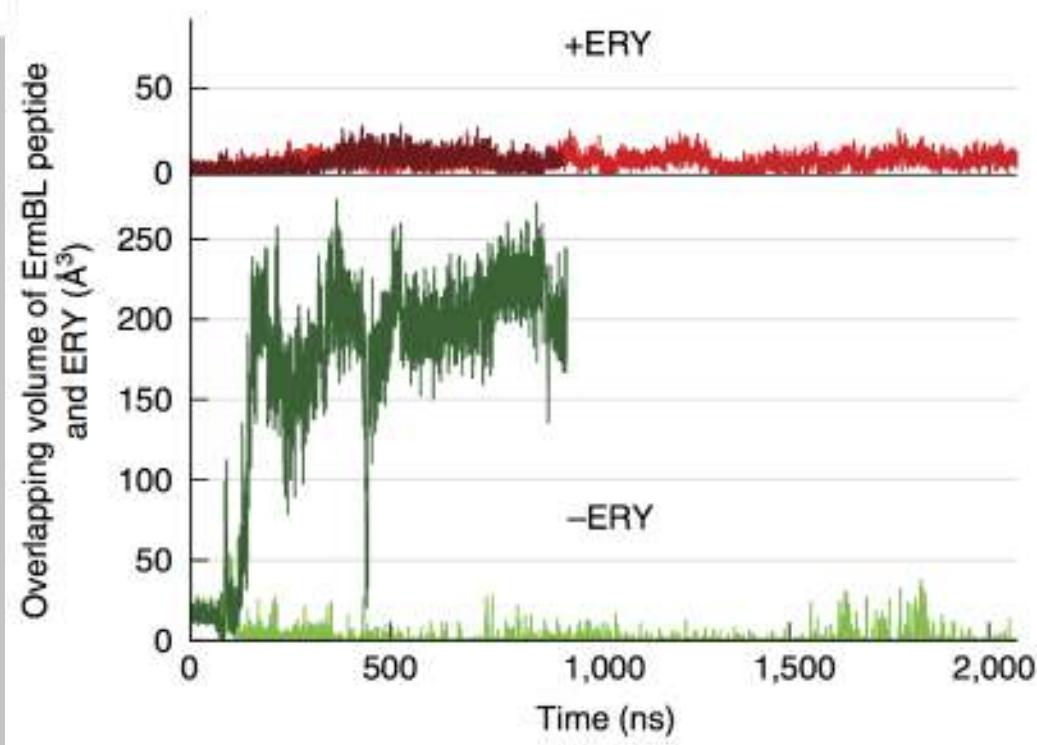
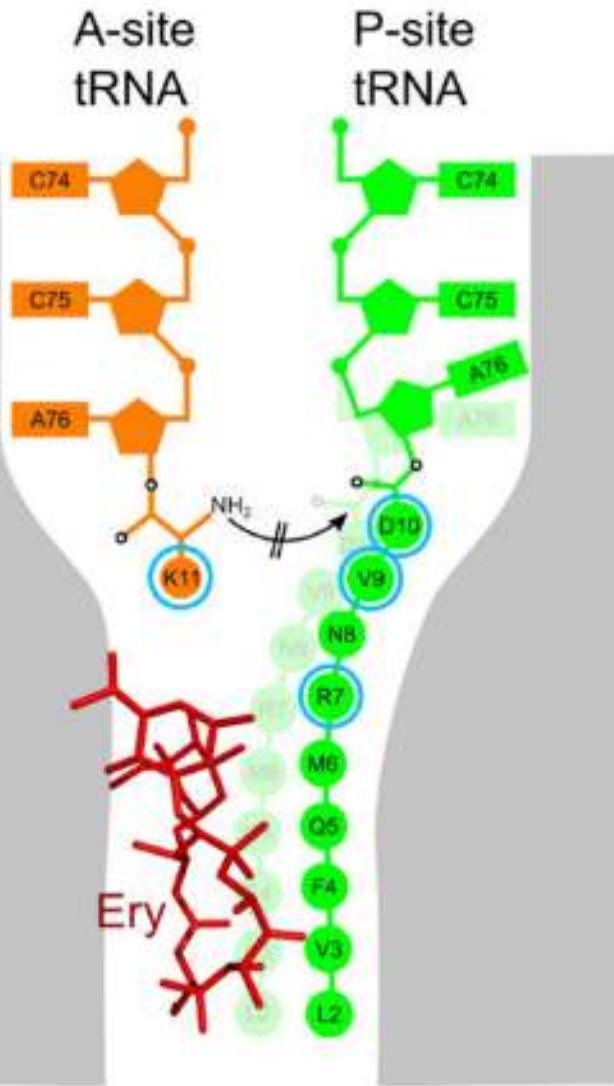
Erythromycin stalls the ribosome: Codon 10 of ErmBL



3.6 Å cryo-EM structure of
ErmBL stalled complex

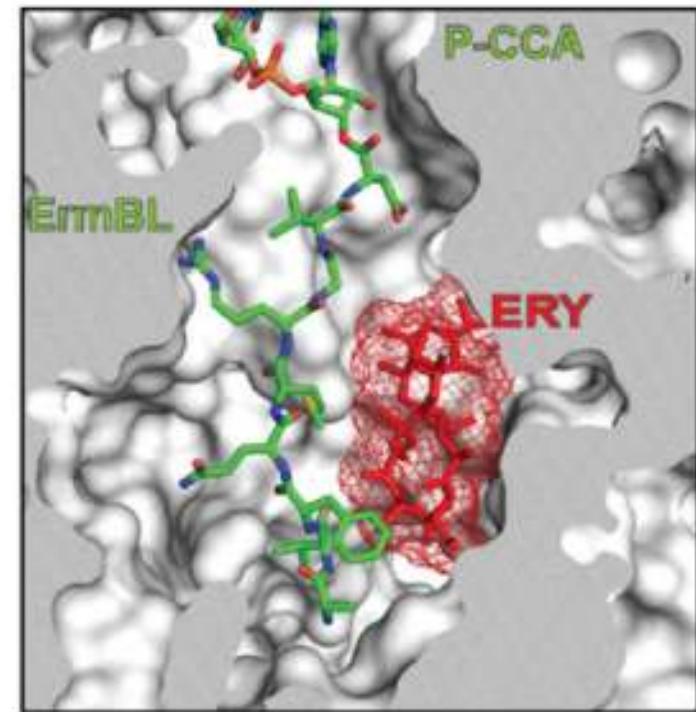
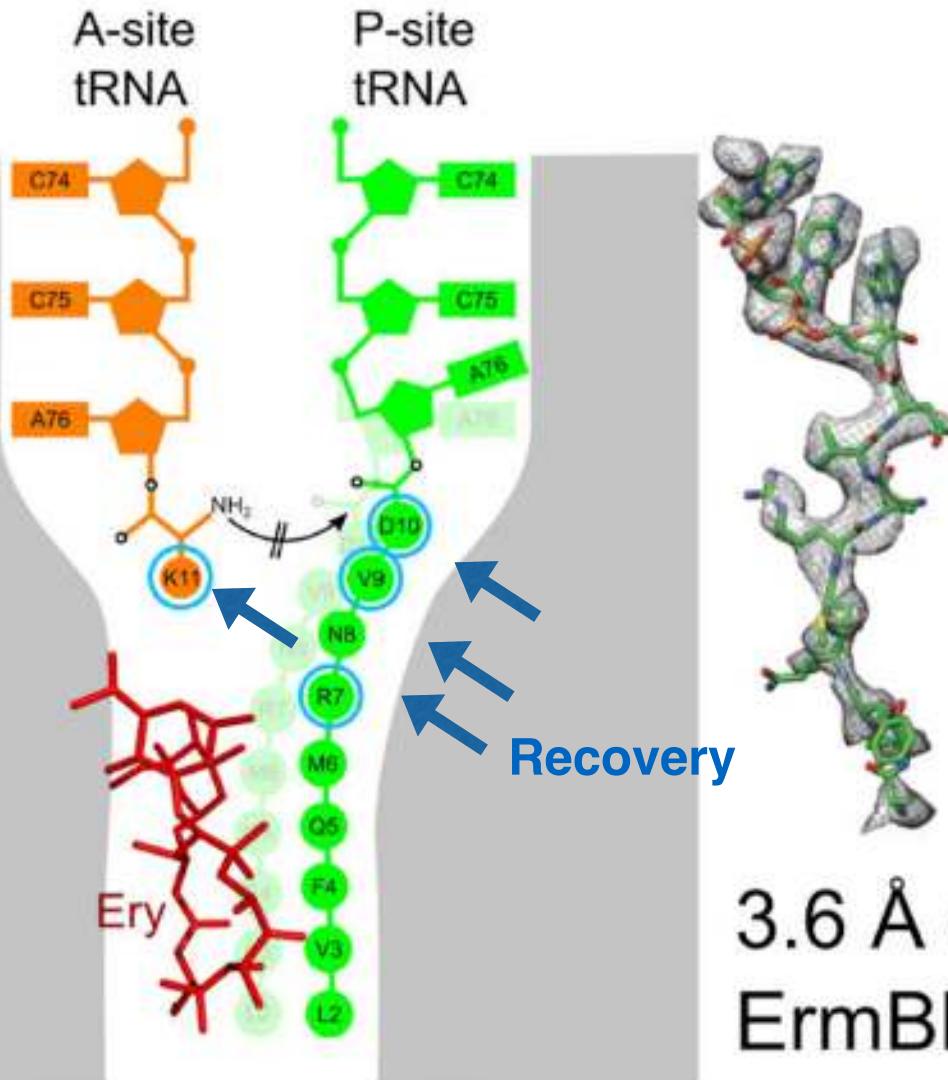
ErmBL with erythromycin

Erythromycin stalls the ribosome: Codon 10 of ErmBL



ErmBL with erythromycin

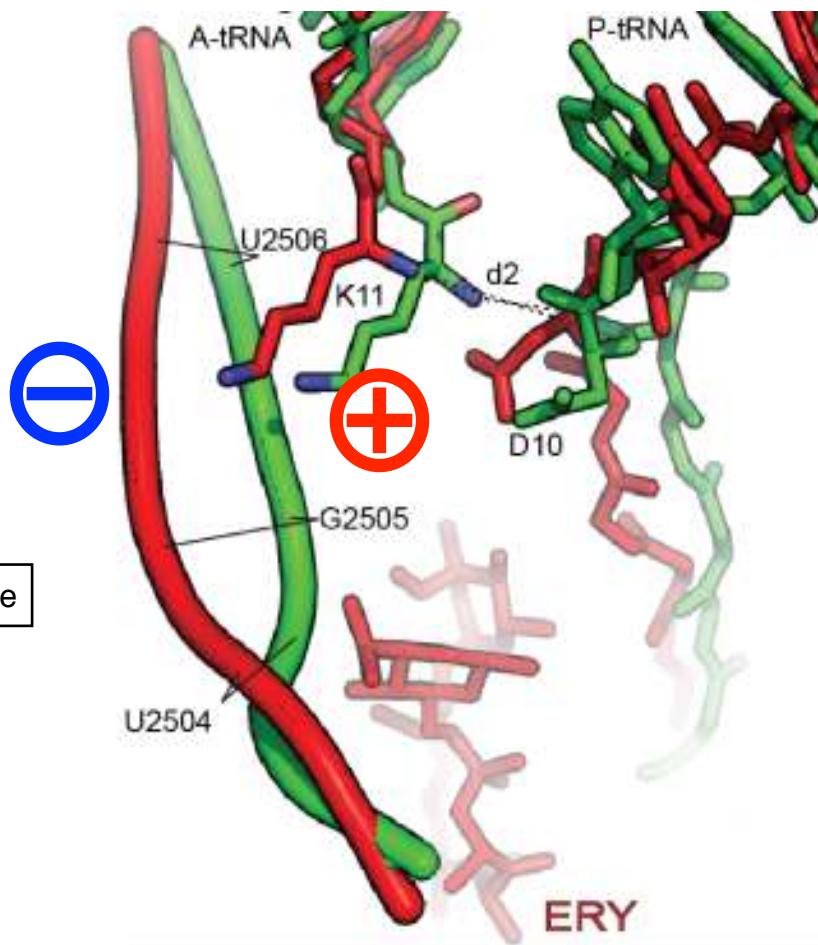
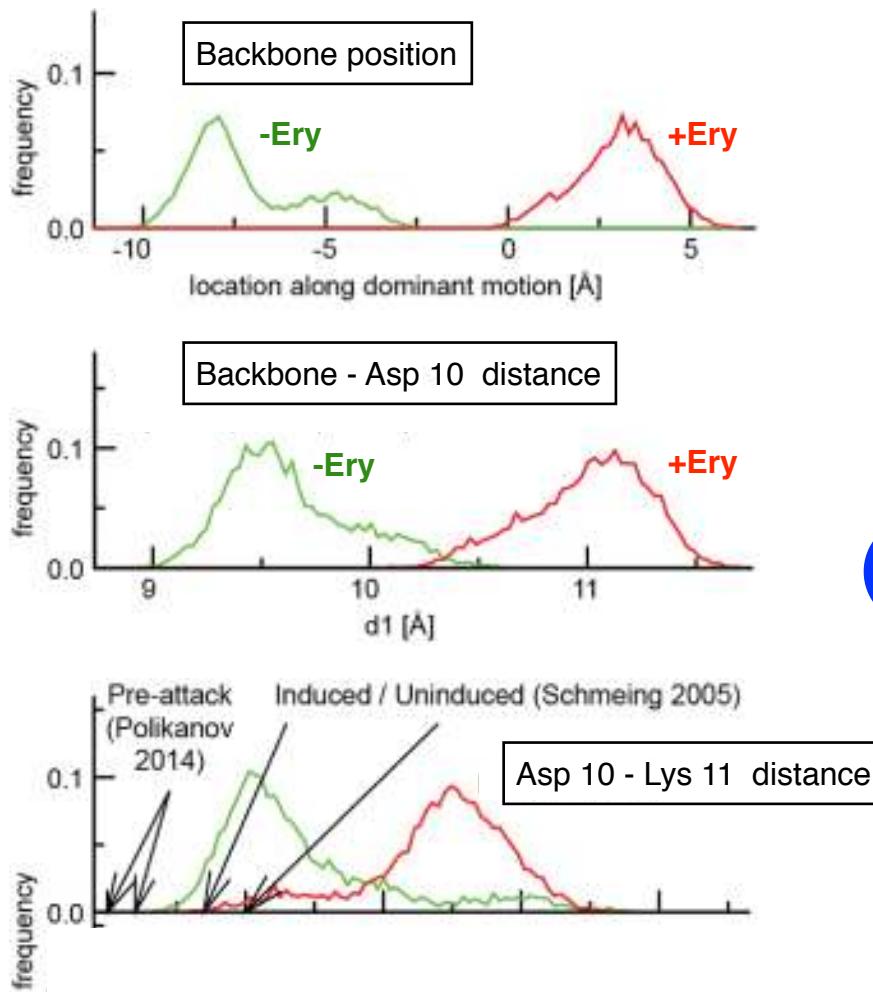
Erythromycin stalls the ribosome: Codon 10 of ErmBL



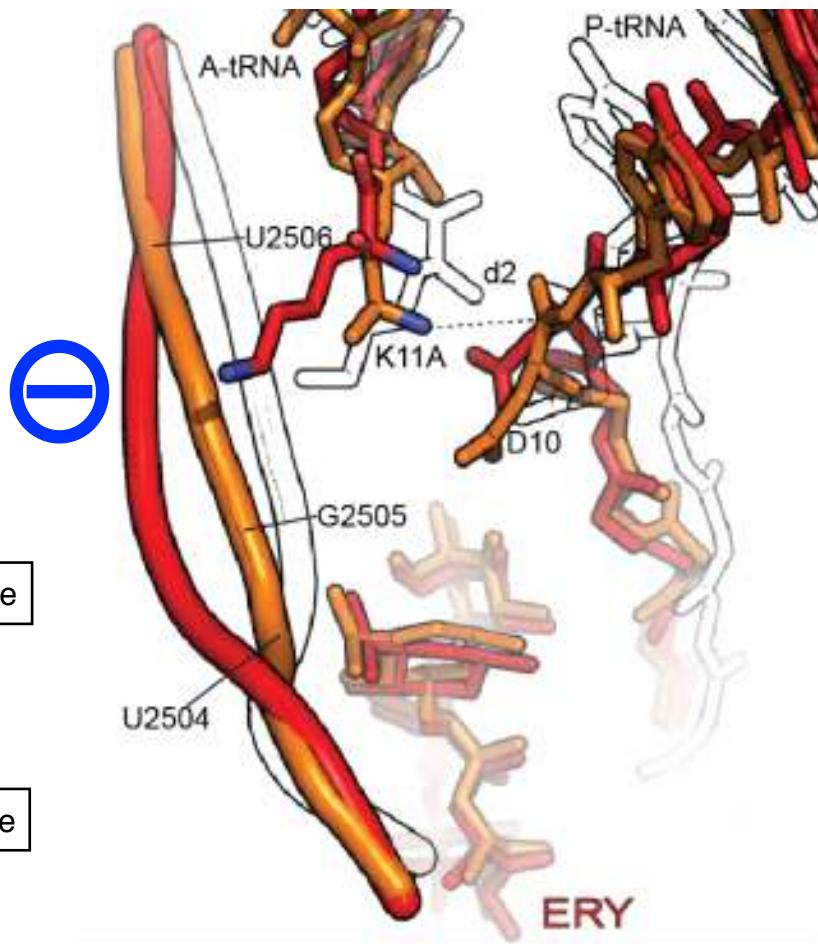
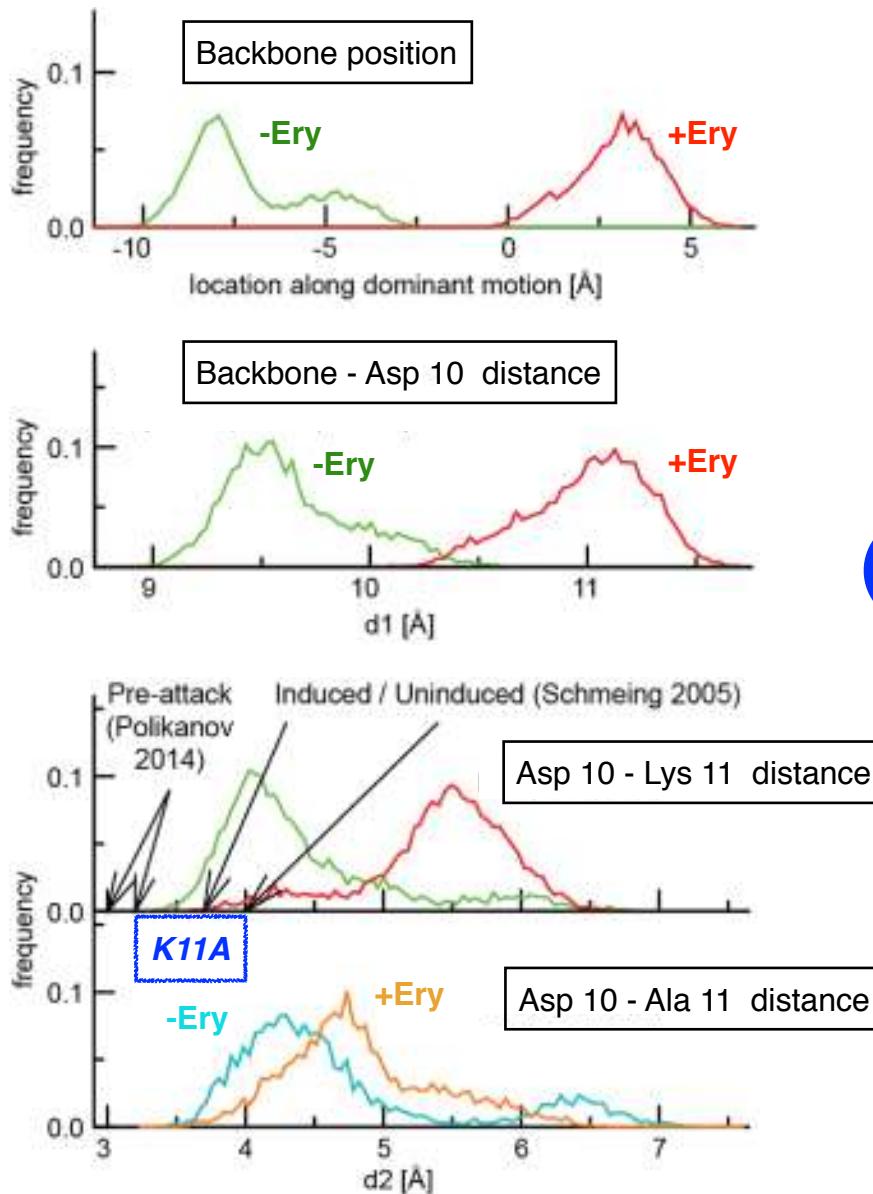
3.6 Å cryo-EM structure of
ErmBL stalled complex

ErmBL with erythromycin

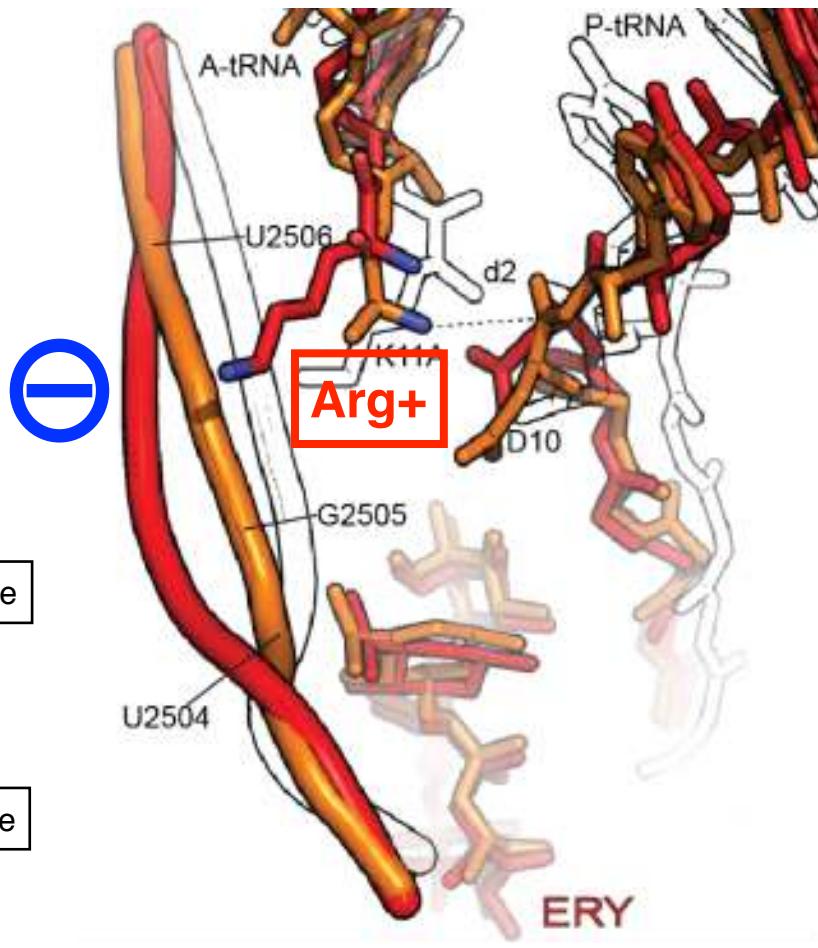
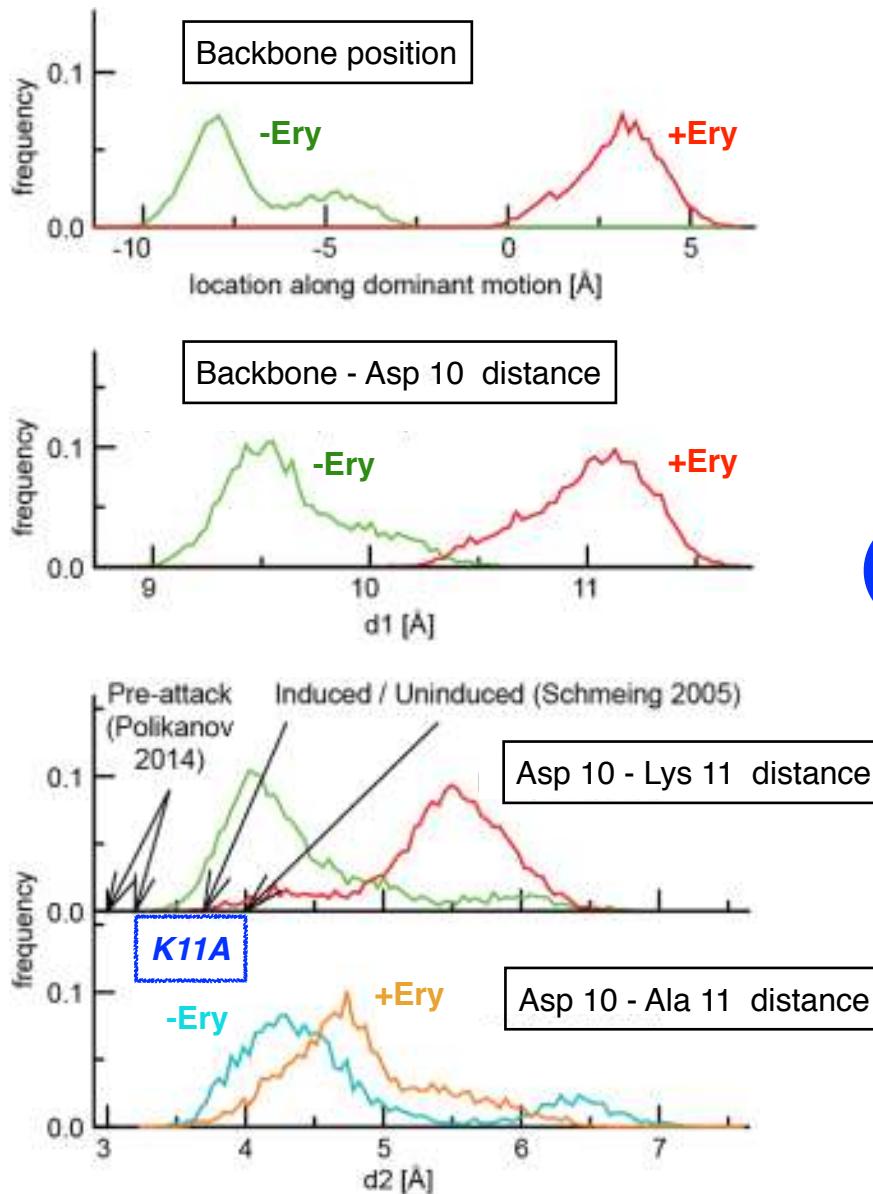
MD: Backbone shift increases NH₂-C distance



MD Predicts: K11R should enhance stalling

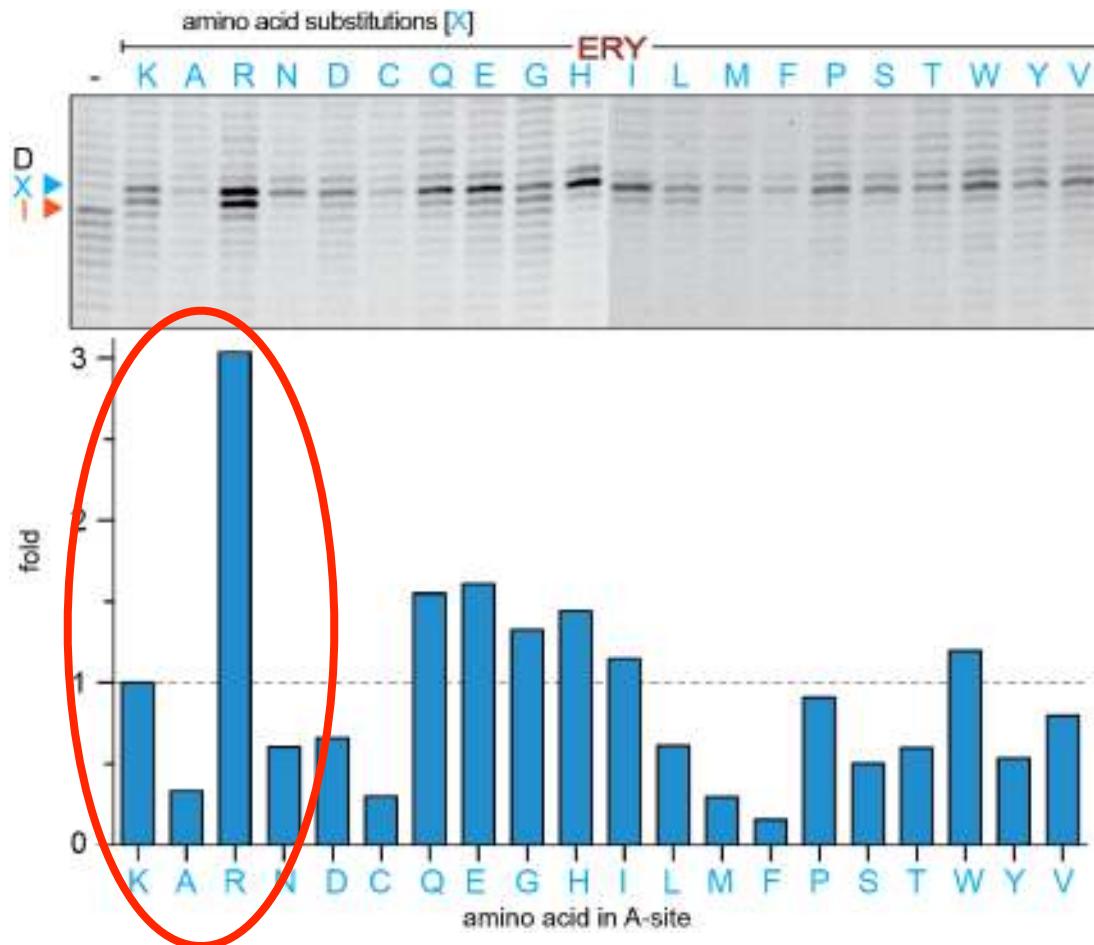


MD Predicts: K11R should enhance stalling



Prediction confirmed

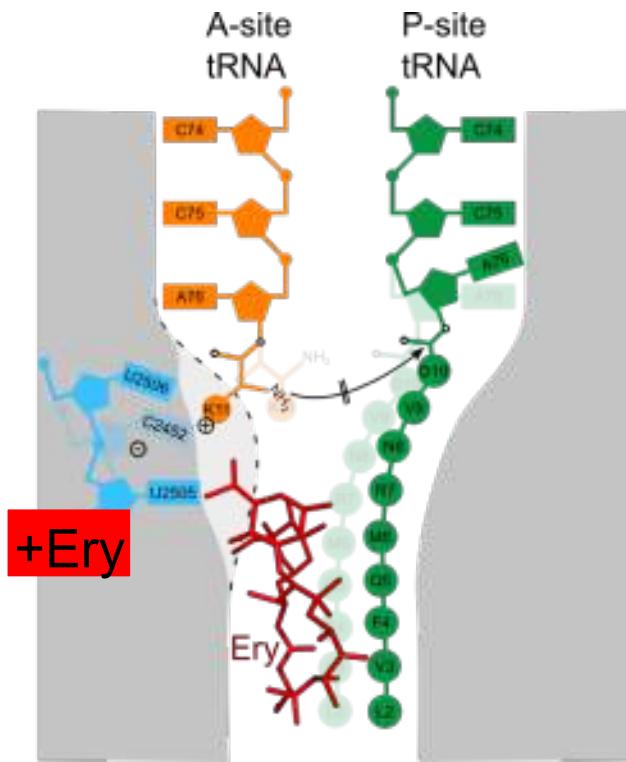
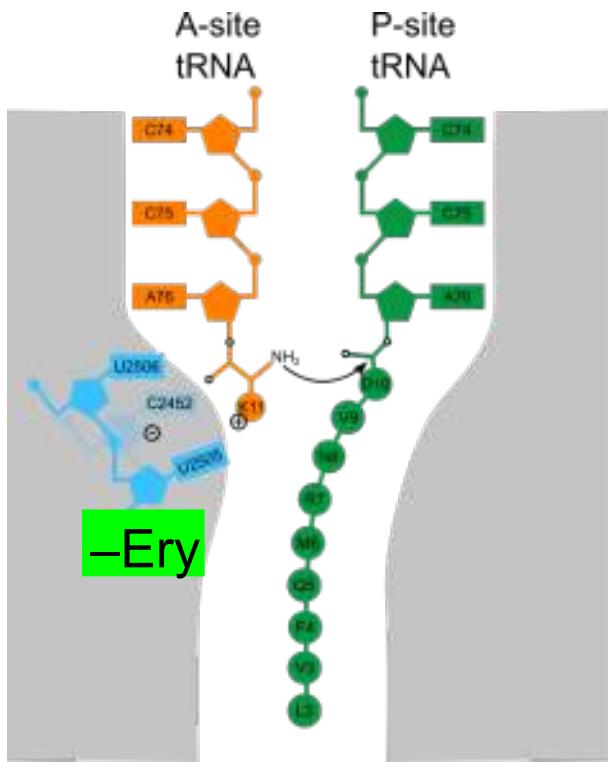
An Arg at codon 11 also stalls the ribosome



(Daniel Wilson, unpublished data)

Mechanism of stalling by erythromycin

Collaboration: Daniel Wilson (Univ. Munich)



+Erythromycin:

1) peptide conformation changed
→ P-site tRNA

2) A-site crevice perturbed → A-site amino acid K11 shifts

Distance between attacking NH₂ and carbonyl C increased

→ Inhibition of peptide bond formation

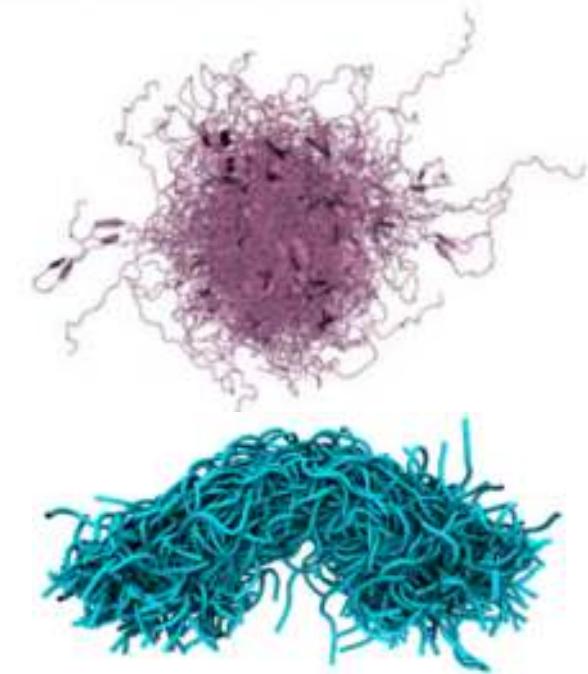
Towards a mechanistic understanding of protein function

(1) *Ligand unbinding revisited*

(2) *Ribosomal antibiotics mechanism*

(3) *Intrinsically Disordered Proteins*

(4) *The Dynosome*



AFM+ X-ray + cryo EM + MD

*Lars Bock, Christian Blau, Michal Kolar, Andrea Vaiana, Andreas Russek,
Sarah Rauscher, Ulf Hensen*

*Holger Stark, Marina Rodnina (MPI Göttingen)
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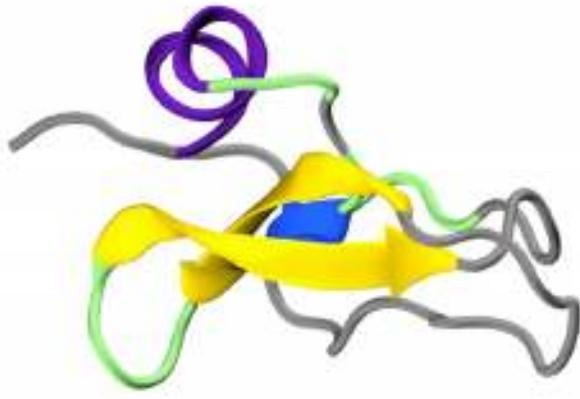
Folded vs. disordered proteins

***"This came directly from a computer
and is neither to be doubted nor disbelieved!"***

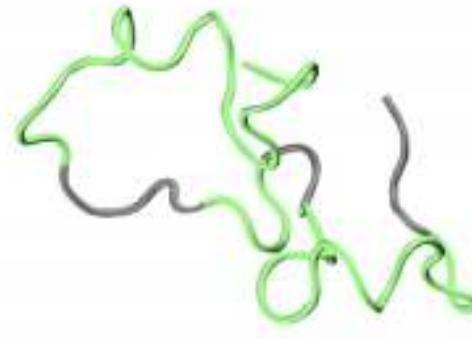
Found in an email-signature

Folded vs. disordered proteins

> 30% of eukaryotic proteins
> 75% cancer linked proteins



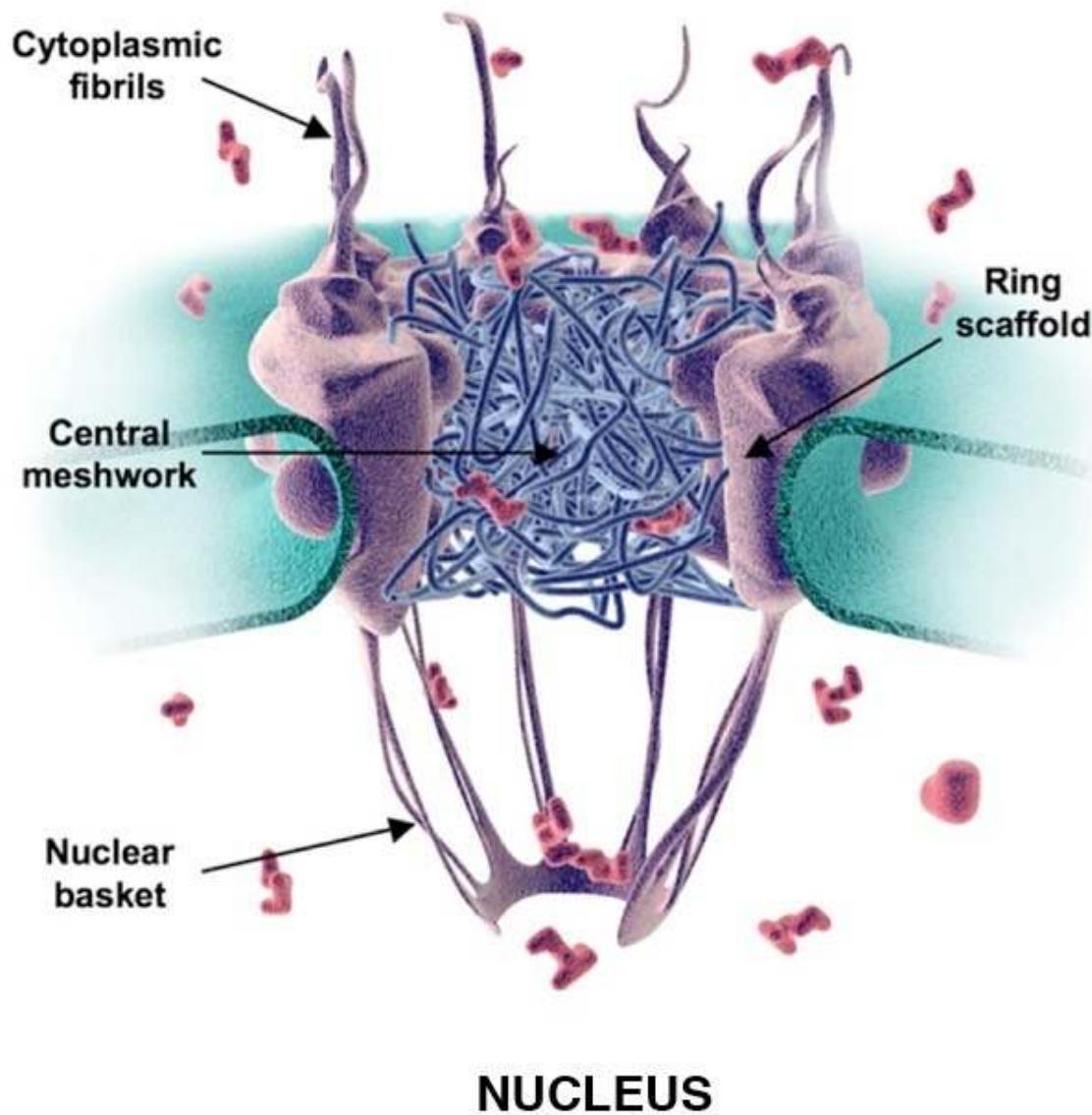
Folded



Disordered

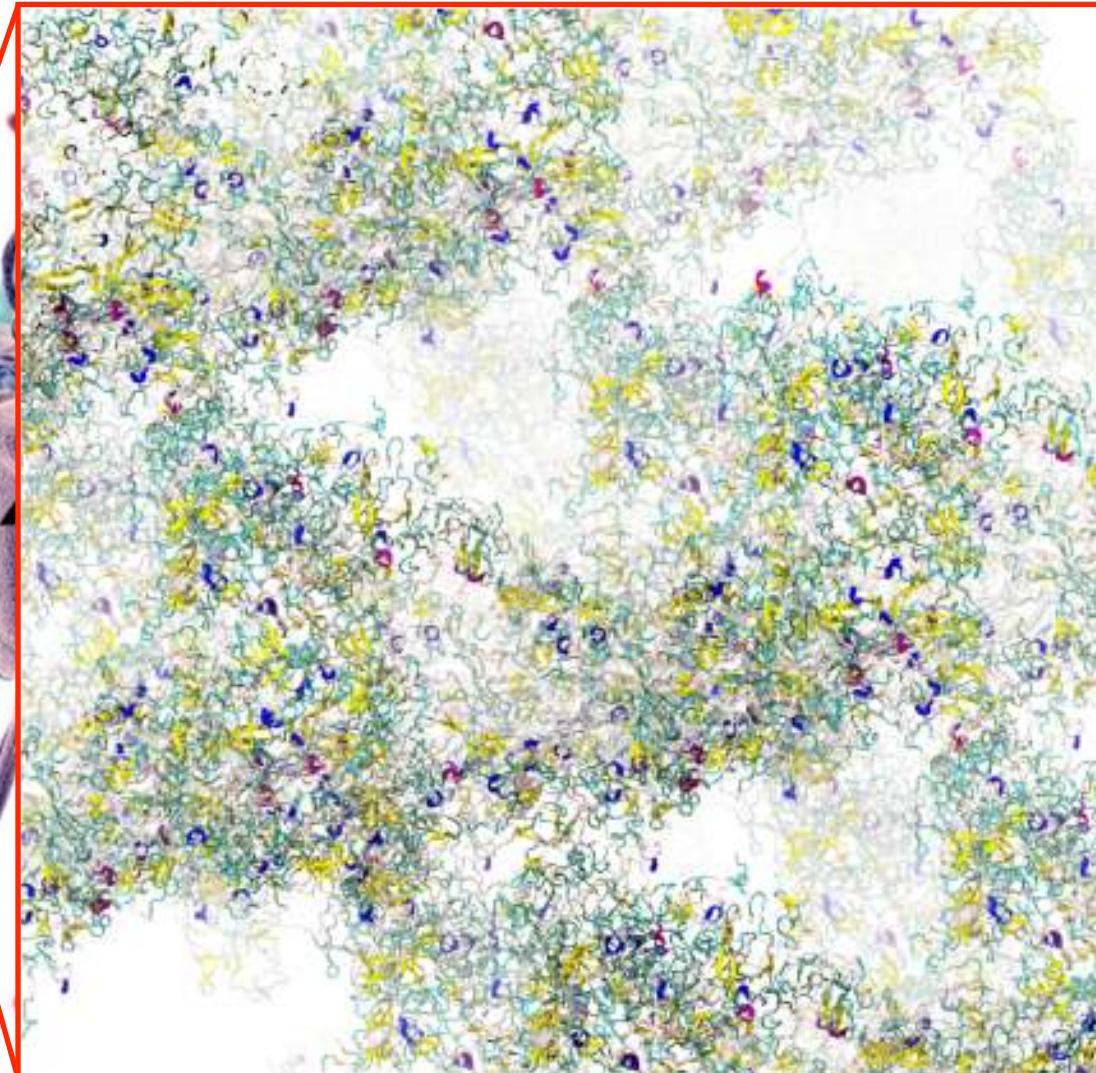
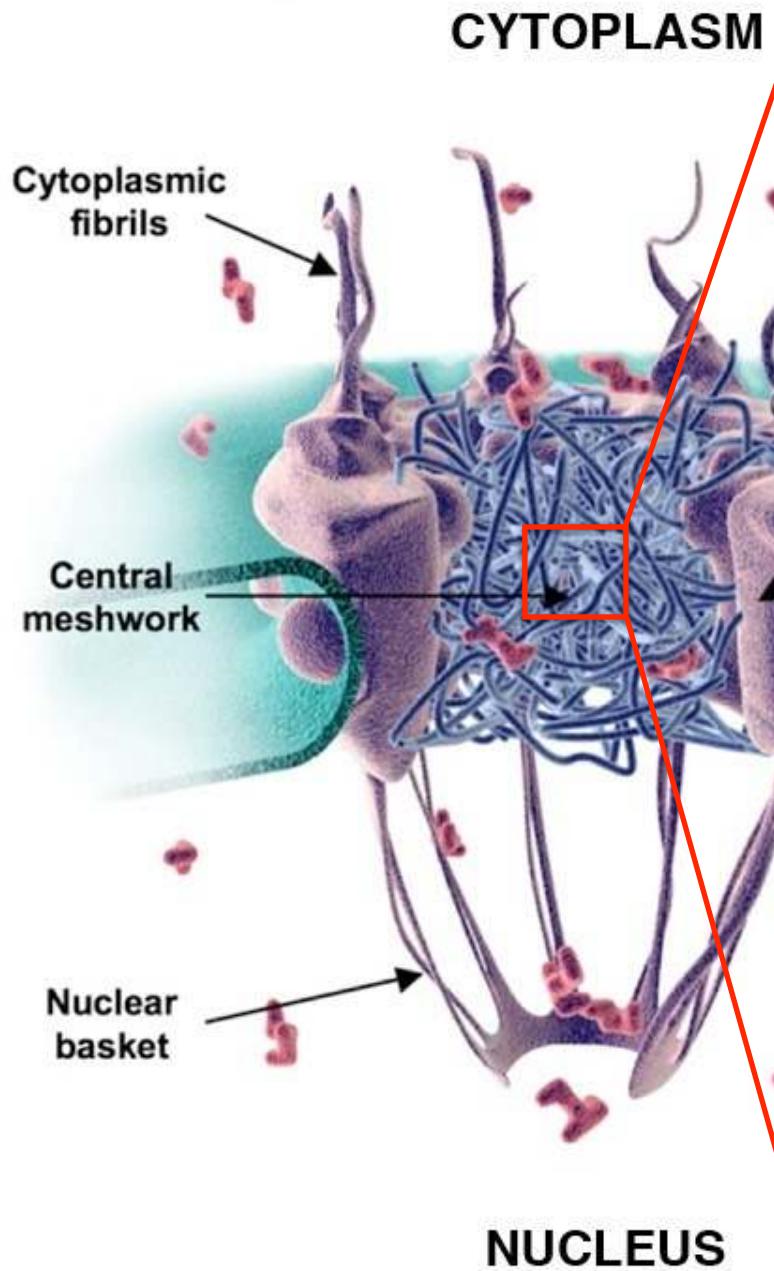
Nucleoporins are prototypic disordered proteins

CYTOPLASM



The nuclear pore complex is responsible for selective transport of macromolecules larger than 40 kDa into and out of the nucleus.

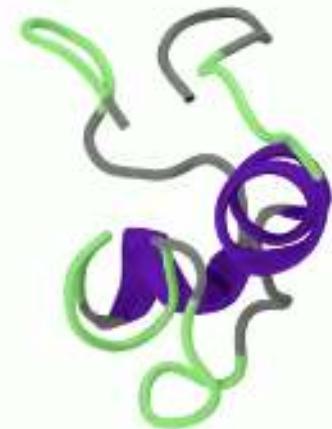
Nucleoporins are prototypic disordered proteins



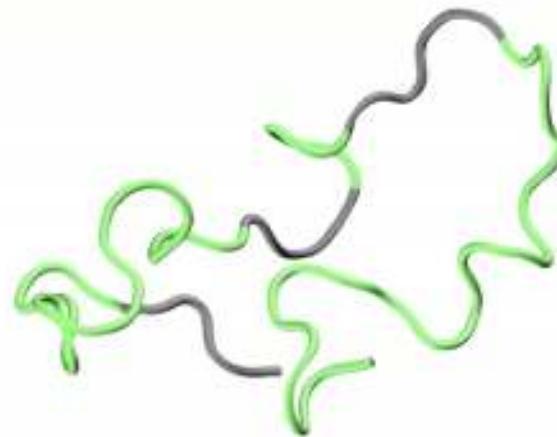
(unpublished data)

MD Simulations of Disordered Proteins

ff99sb*-ildn



CHARMM 22*

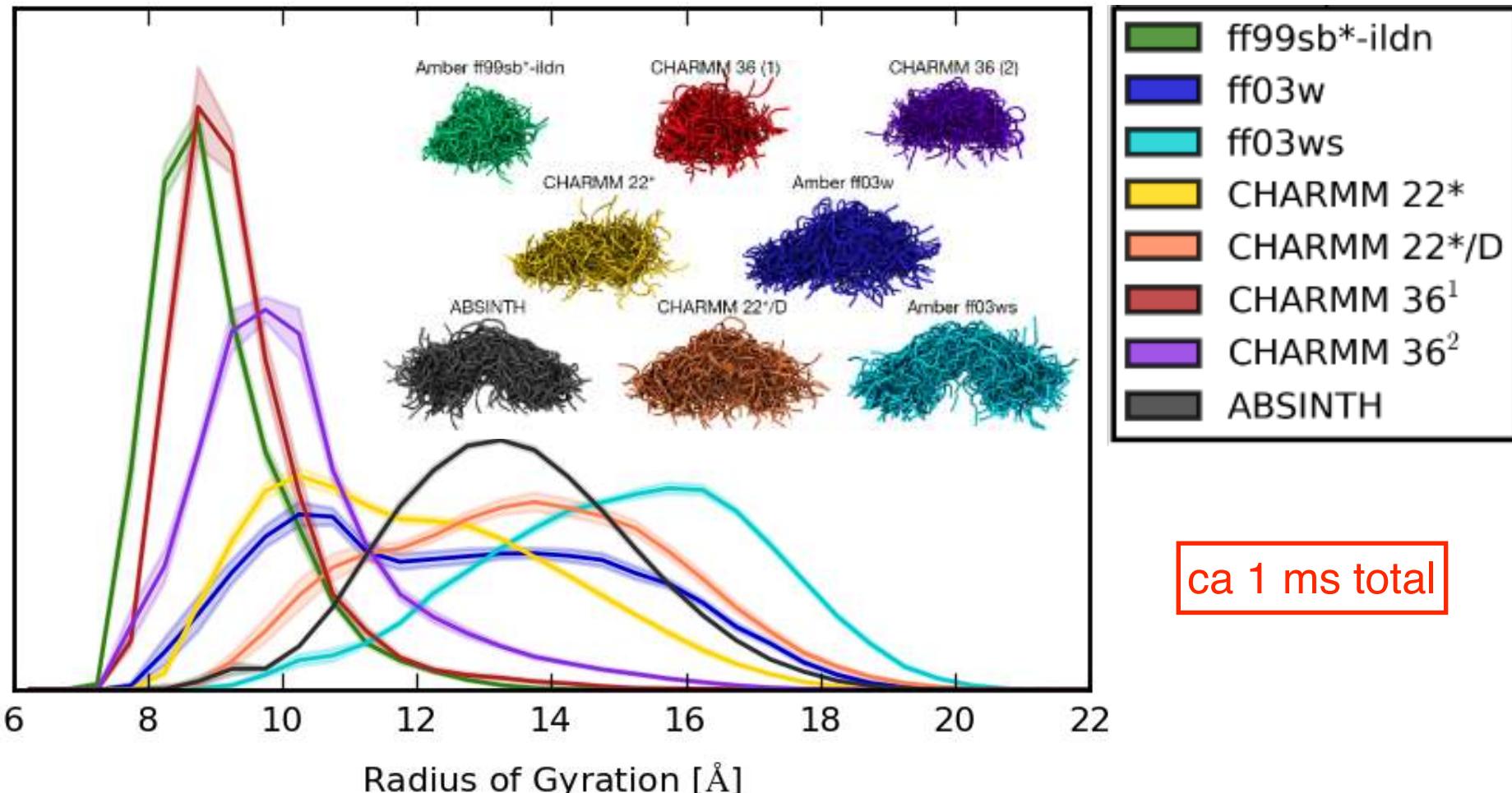


Force Fields Compared for Disordered Proteins

Force Field	Peptide Force Field	Water Model	References
ff99sb*-ildn	amber ff99sb*-ildn	TIP3P	Piana, S. <i>et al</i> (2011) <i>Biophys. J.</i> , 100 : L47-L49. Jorgensen, W. L. <i>et al</i> (1983) <i>J. Chem. Phys.</i> 79 : 926–935.
ff03w	amber ff03w	TIP4P/2005	Best, R. B. and Mittal, J. (2010) <i>J. Phys. Chem. B</i> , 114 : 14916–14923. Abascal J. L. and Vega C. (2005) <i>J. Chem. Phys.</i> 123 : 234505.
ff03ws	amber ff03ws	TIP4P/2005	Best, R. B., Zheng, W. and Mittal, J. (2014) <i>J. Chem. Theor. Comput.</i> , 10 : 5113–5124. Abascal J. L. and Vega C. (2005) <i>J. Chem. Phys.</i> 123 : 234505.
CHARMM 22*	CHARMM 22*	CHARMM-modified TIP3P	Piana, S. <i>et al</i> (2011) <i>Biophys. J.</i> , 100 : L47-L49. MacKerell, A. D. <i>et al</i> (1998) <i>J. Phys. Chem. B</i> 102 : 3586–3616.
CHARMM 22*/D	CHARMM 22*	TIP4P-D	Piana, S. <i>et al</i> (2011) <i>Biophys. J.</i> , 100 : L47-L49. Piana, S. <i>et al</i> (2015) <i>J. Phys. Chem. B</i> (online)
CHARMM 36¹	CHARMM 36	CHARMM-modified TIP3P	Best, R. B. (2012) <i>J. Chem. Theor. Comput.</i> 8 : 3257-3273. MacKerell, A. D. <i>et al</i> (1998) <i>J. Phys. Chem. B</i> 102 : 3586–3616.
CHARMM 36²	CHARMM 36	TIP3P	Best, R. B. (2012) <i>J. Chem. Theor. Comput.</i> 8 : 3257-3273. MacKerell, A. D. <i>et al</i> (1998) <i>J. Phys. Chem. B</i> 102 : 3586–3616.
ABSINTH	OPLS-AA/L	ABSINTH (implicit water)	Vitalis A. and Pappu R. V. (2009) <i>J Comput Chem</i> 30 : 673–699.

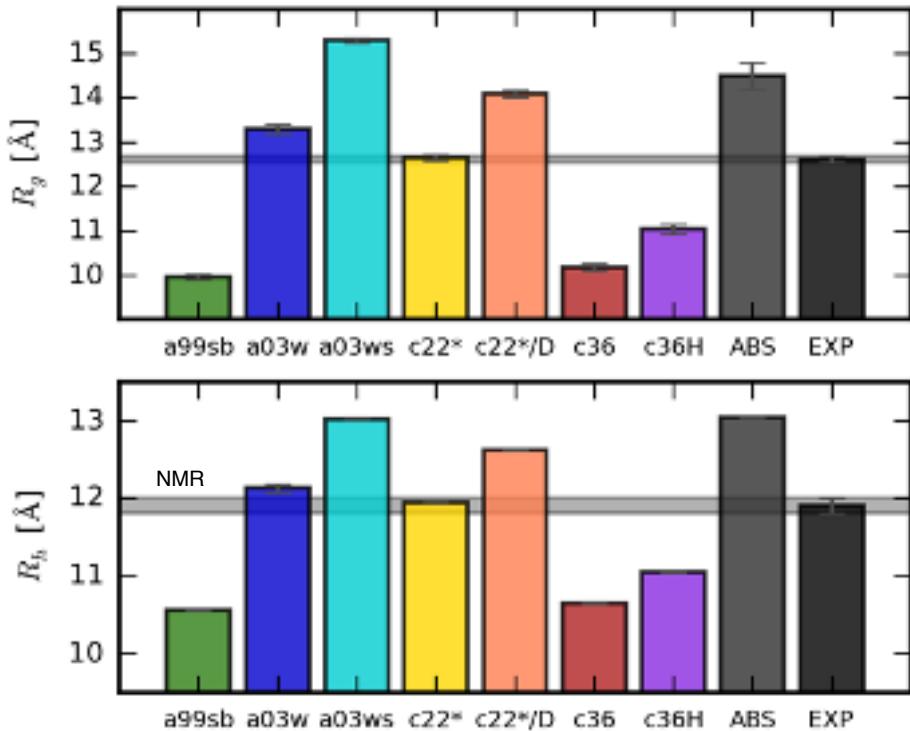
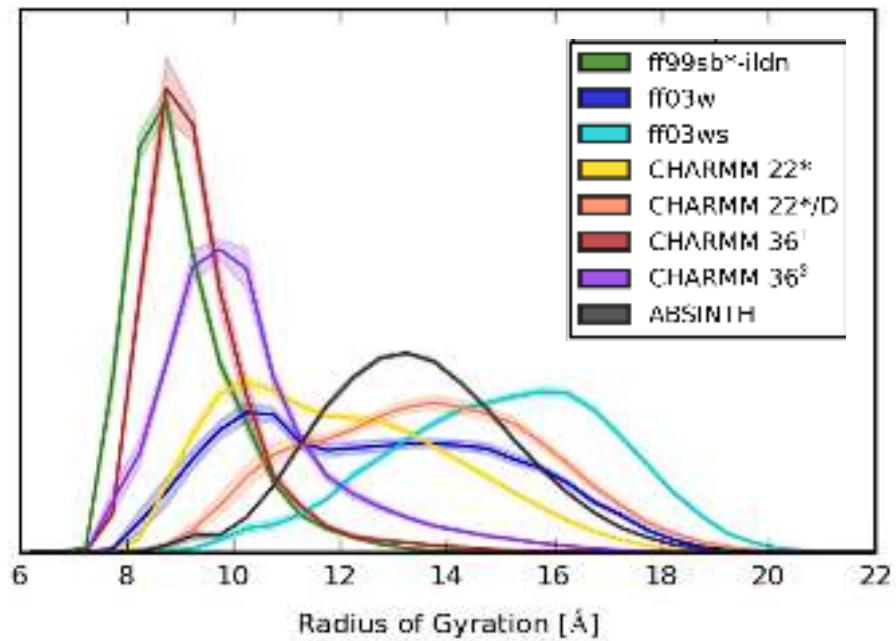
Force Fields Differ Dramatically in Compactness

Xiang, S. Q. et al Structure , 2162-2174 (2013).



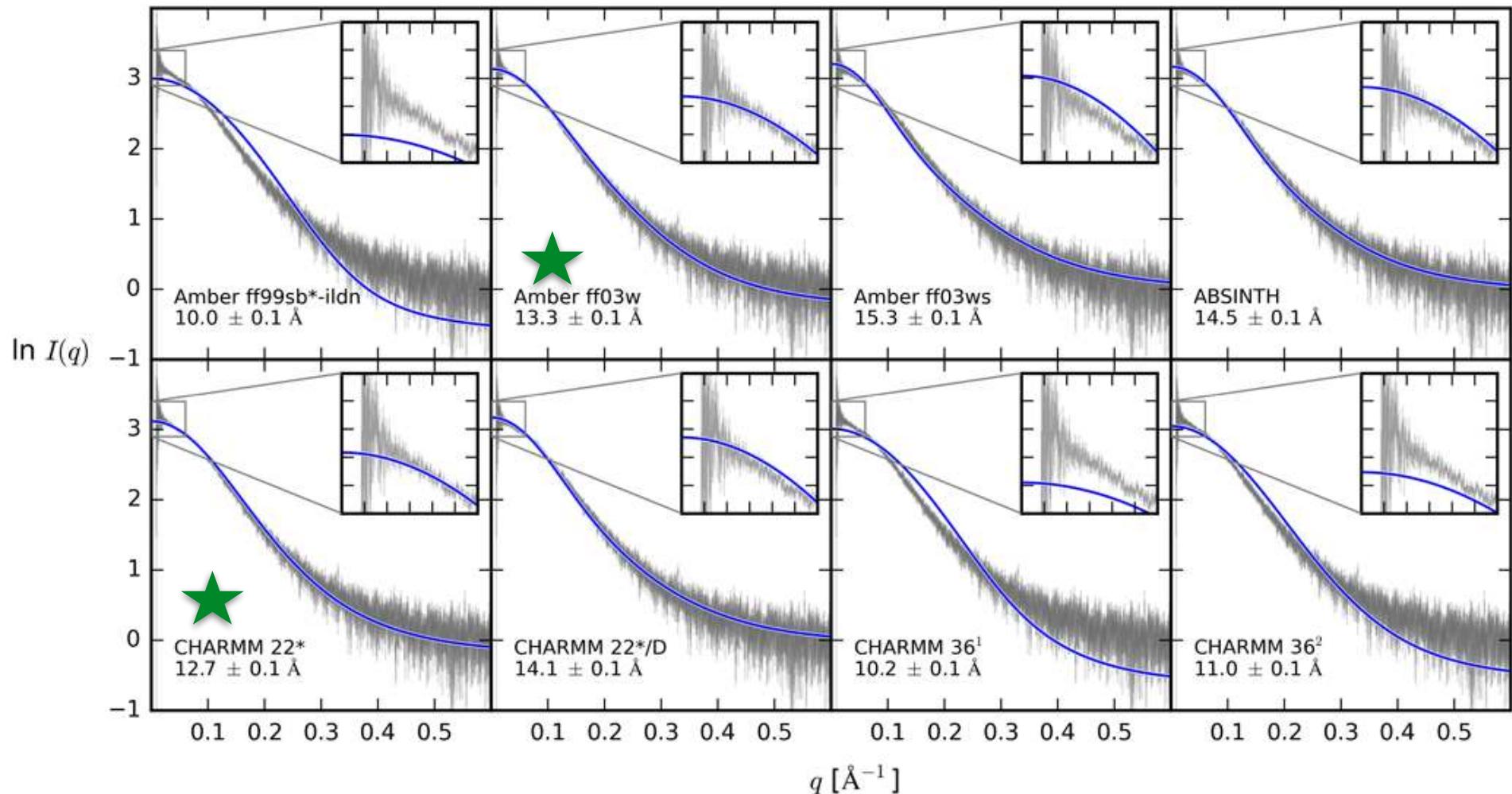
Comparison to Experiment

I. Small Angle X-Ray Scattering (Compactness)



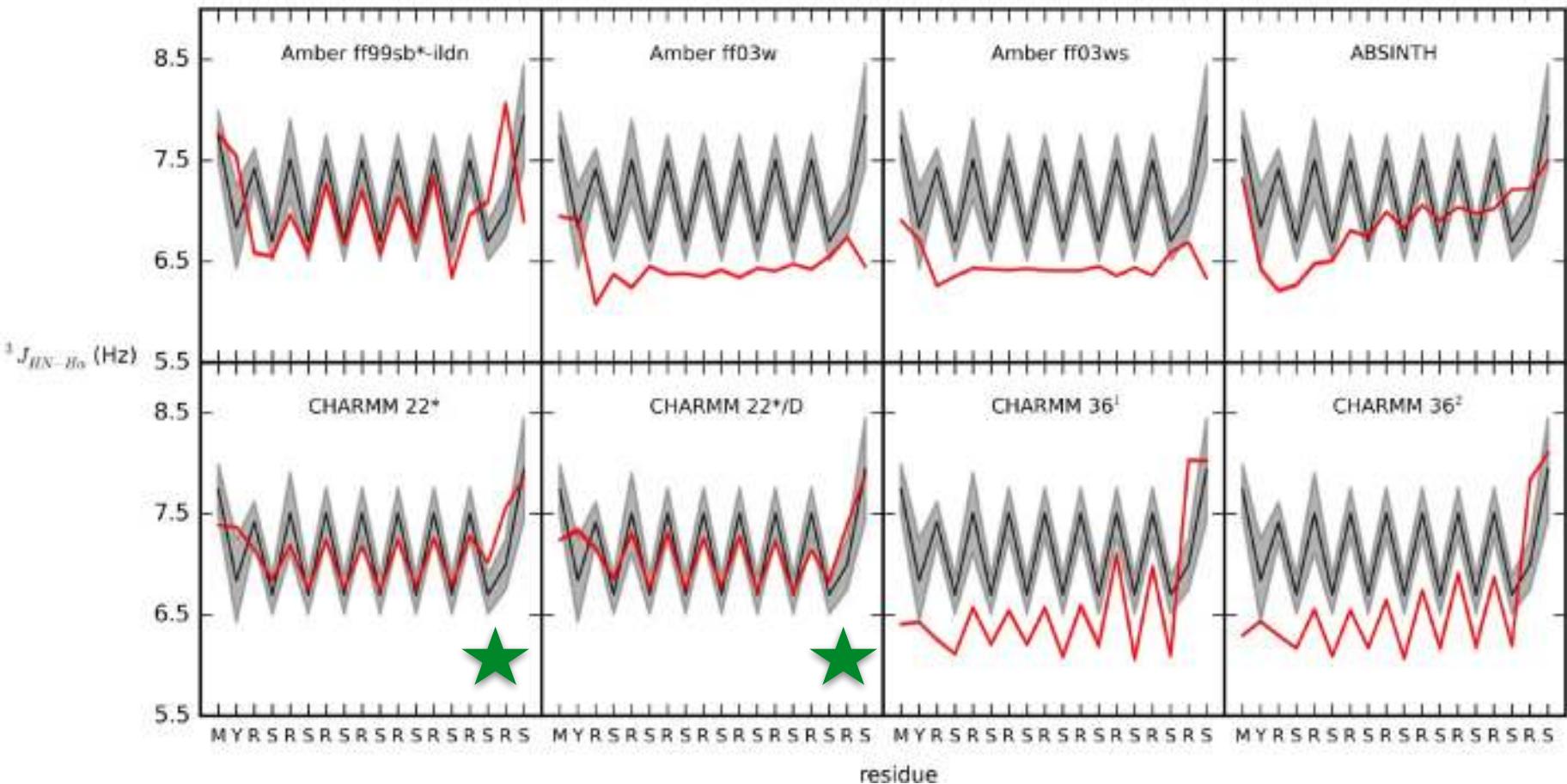
Comparison to Experiment

I. Small Angle X-Ray Scattering (Compactness)

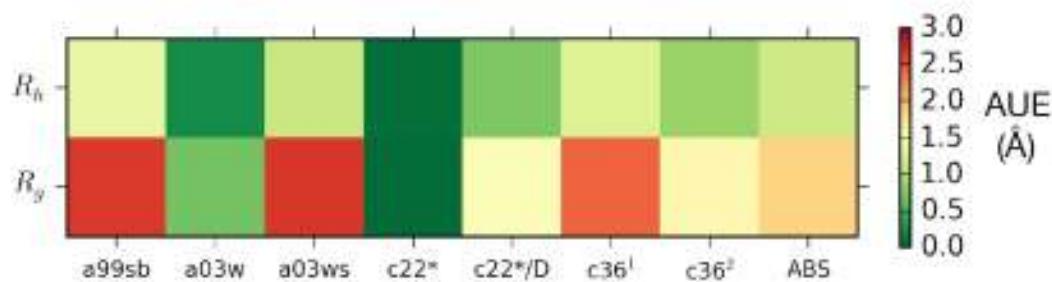
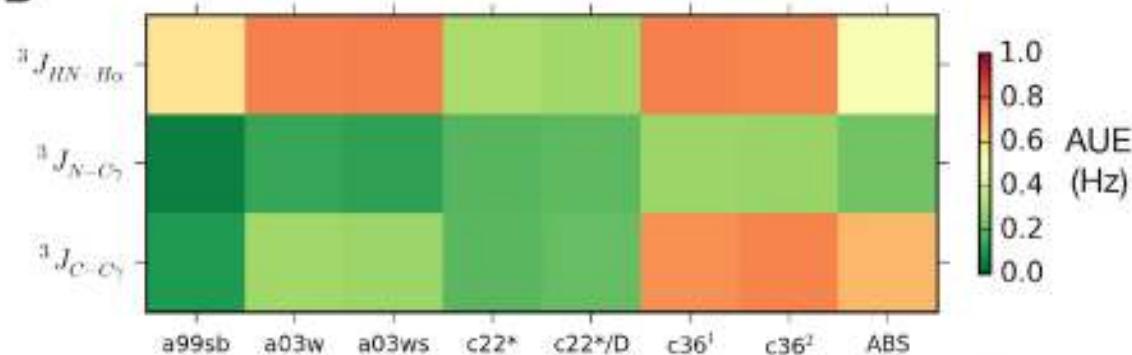
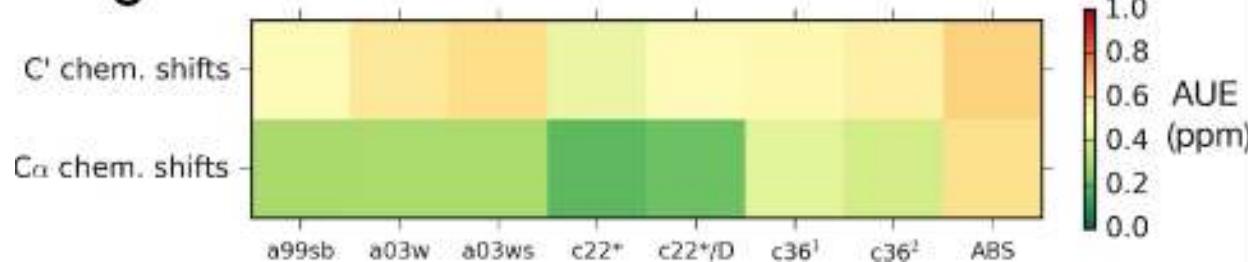


Comparison to Experiment

II. NMR 3J(HNHA)-Coupling (Secondary Structure)

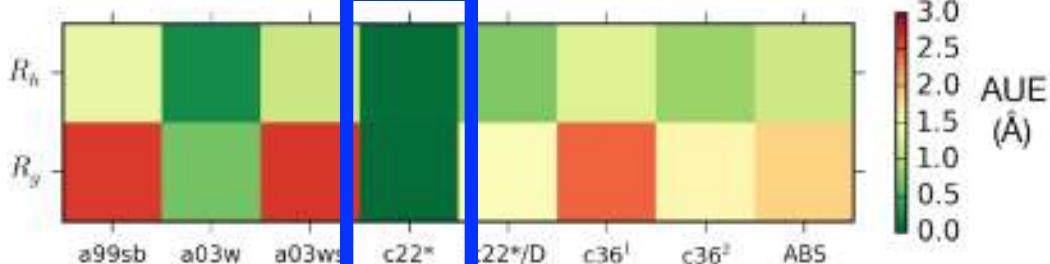


Summary: Comparison to Experiment

A**Chain Dimensions****B****Scalar Couplings****C****Chemical Shifts**

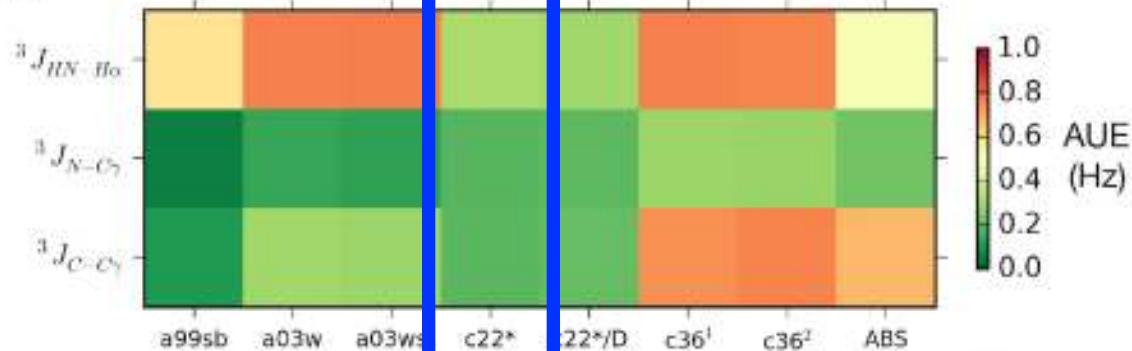
Summary: Comparison to Experiment

A



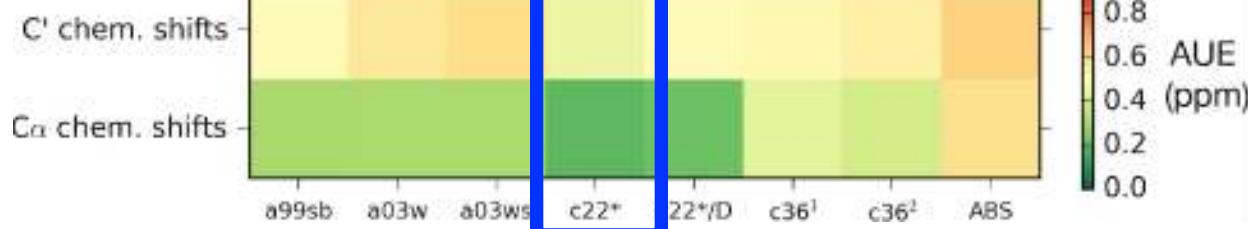
Chain Dimensions

B



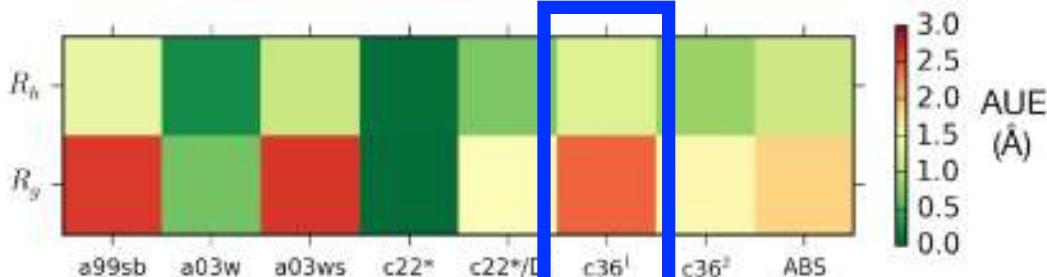
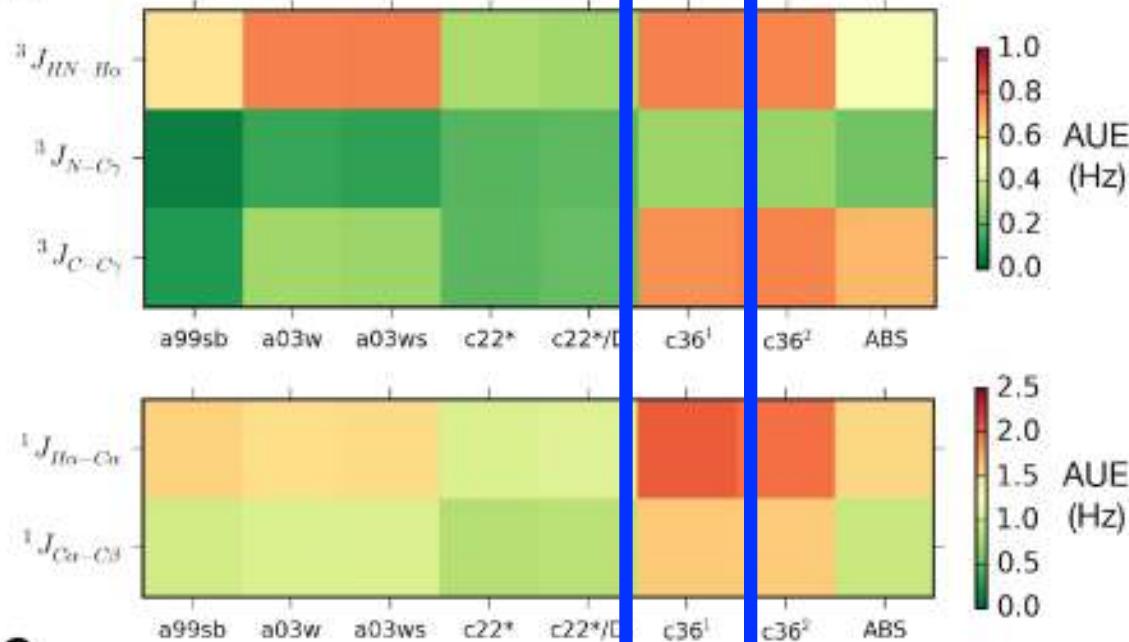
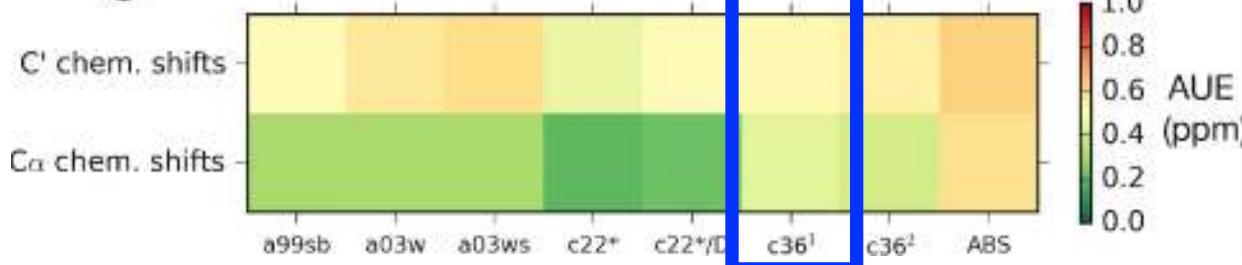
Scalar Couplings

C



Chemical Shifts

Summary: Comparison to Experiment

A**Chain Dimensions****B****Scalar Couplings****C****Chemical Shifts**

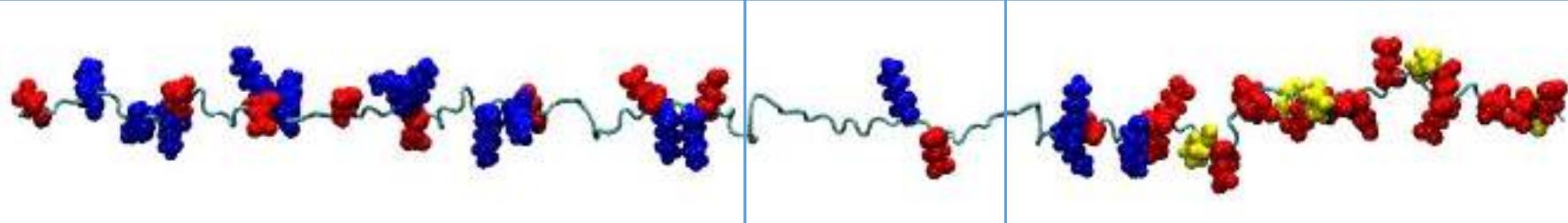
New Force Field Version:

Validated against 14 peptides and 15 proteins,
cumulative simulation time of more than 500 μ s

CHARMM36m: Improved conformational sampling in simulations of intrinsically disordered peptides

Jing Huang,¹ Sarah Rauscher,² Ting Ran,¹ Michael Feig,³ Bert de Groot,² Helmut
Grubmueller,² Alexander D. MacKerell Jr.^{1*}

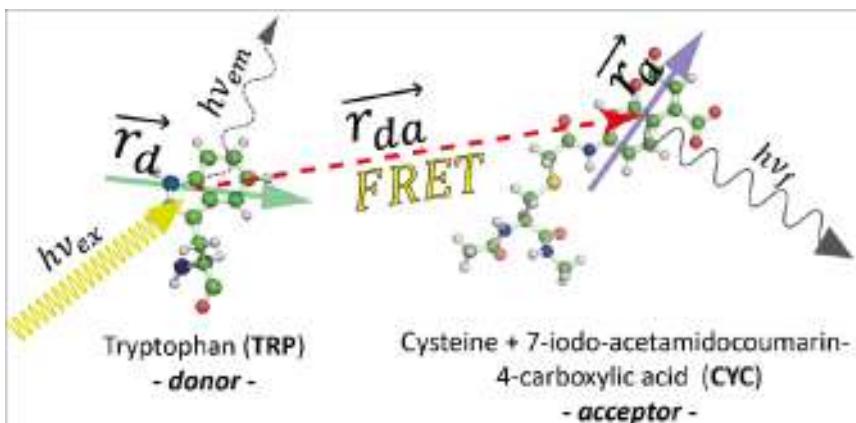
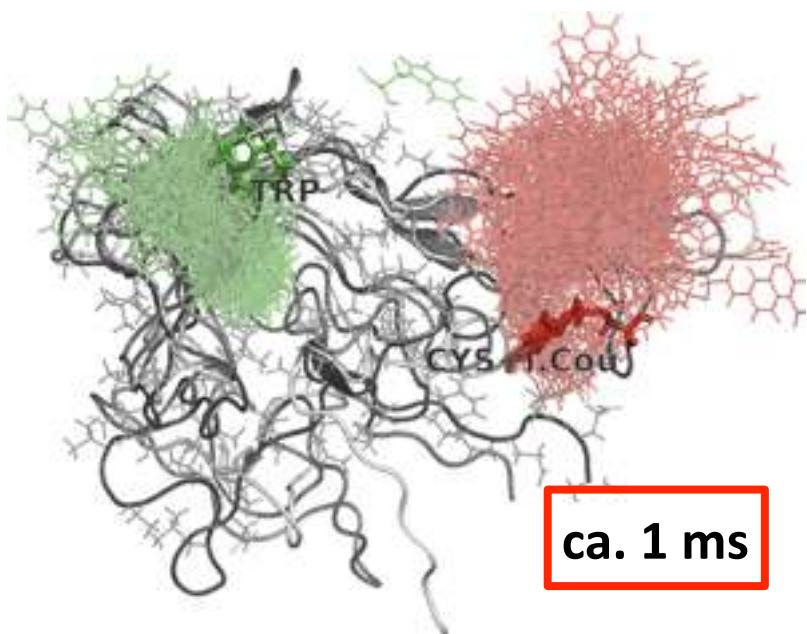
α -synuclein (α S)



N-terminus aa::1–60, +4e

NAC aa::61–95, -1e

C-terminus aa::



Collaborations

trFRET: Elisha Haas (Bar Illan)

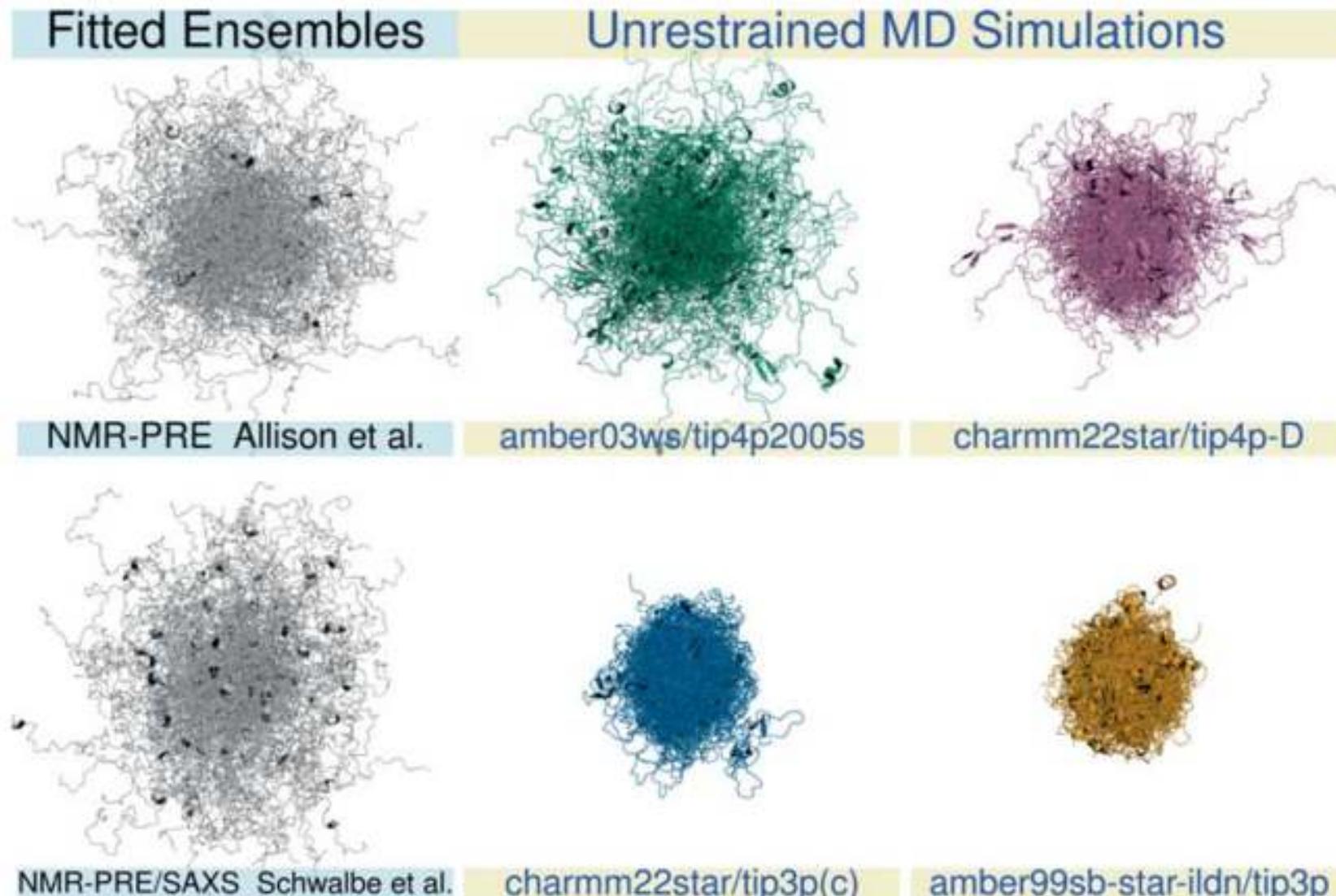
NMR/SAXS: Marcus Zweckstetter (MPIbpc)

Graen et al., JCTC (2014)

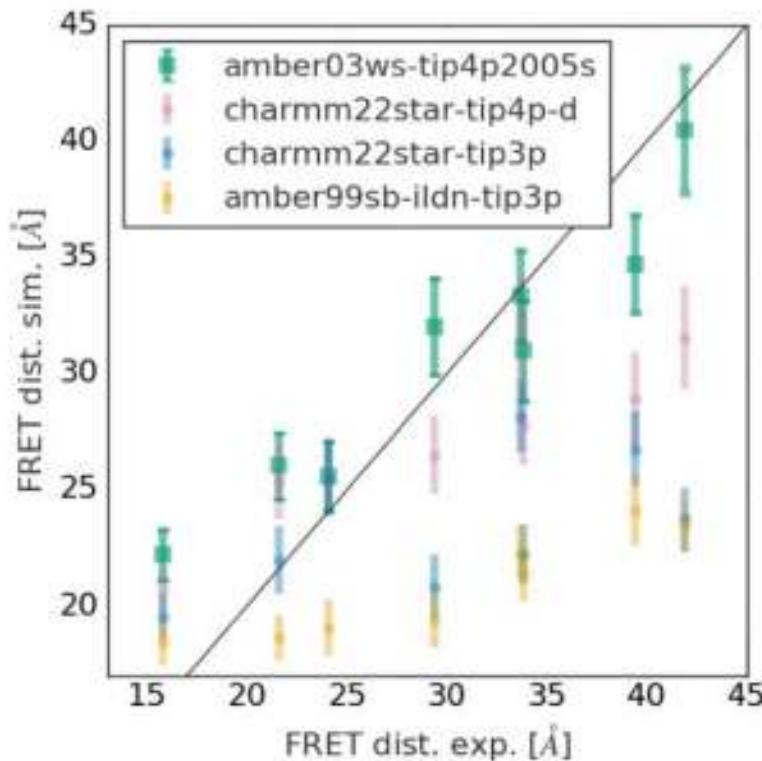
Höfling et al., PloS One (2011)

Höfling et al., Comp. Phys. Comm. (2013)

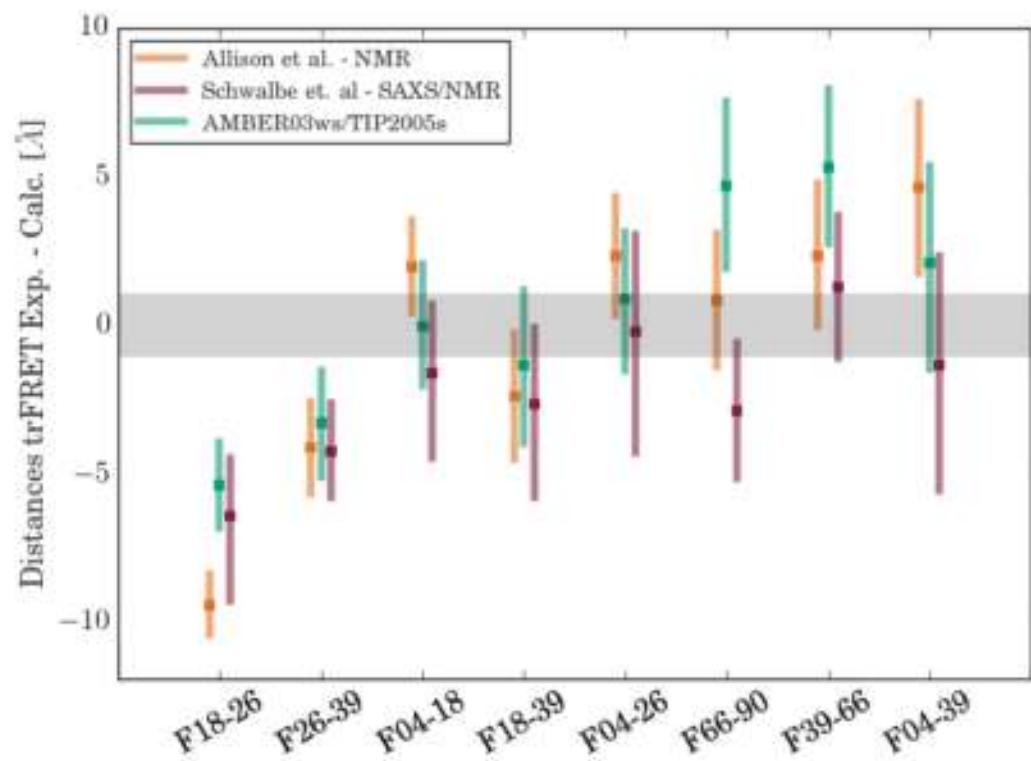
Structural Dynamics of Monomeric alpha-Synuclein on the ns- μ s Time Scale derived from MD Simulations



free MD vs FRET



restrained NMR ensembles and free MD vs FRET



Time scales, formation-, and dissociation rates



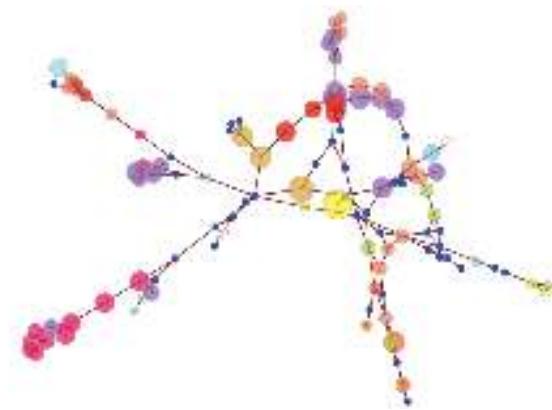
Towards a mechanistic understanding of protein function

(1) *Ligand unbinding revisited*

(2) *Ribosomal antibiotics mechanism*

(3) *Disordered Proteins*

(4) *The Dynosome*



AFM+ X-ray + cryo EM + MD

*Lars Bock, Christian Blau, Michal Kolar, Andrea Vaiana, Andreas Russek,
Benjamin von Ardenne*

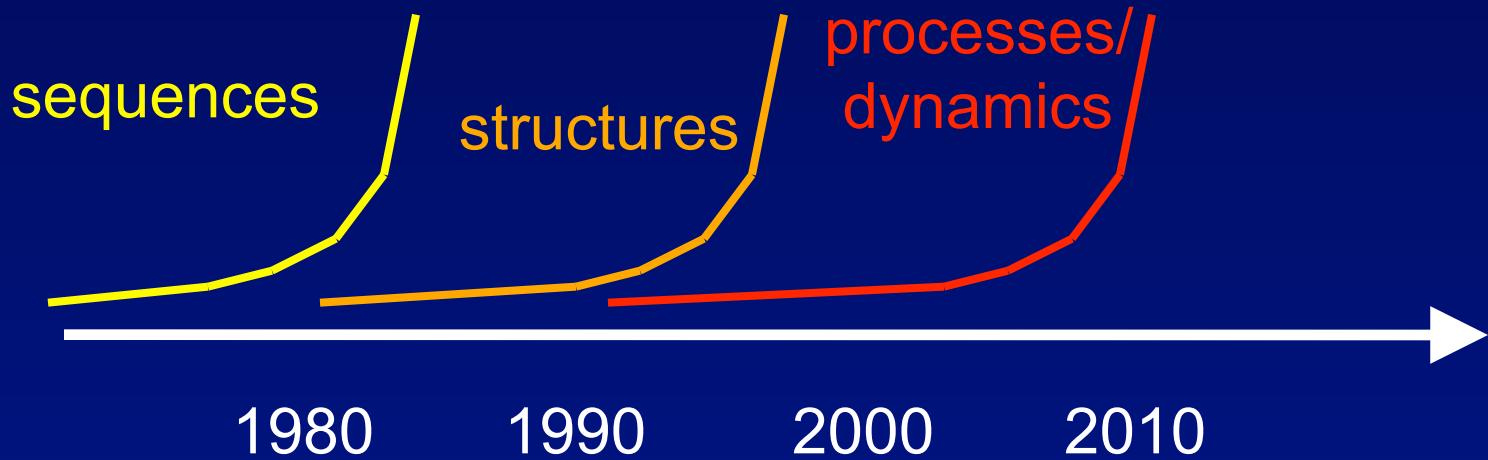
*Holger Stark, Marina Rodnina (MPI Göttingen)
Roland Beckmann, Daniel Wilson (Univ. Munich)
Simon Scheuring (Cornell Univ.)*

Charting the Protein Dynamics Landscape: The Dynosome

Ulf Hensen, Tim Meyer, Jürgen Haas, Rene Rex

Collab.: Gert Vriend (Nijmegen, NL)

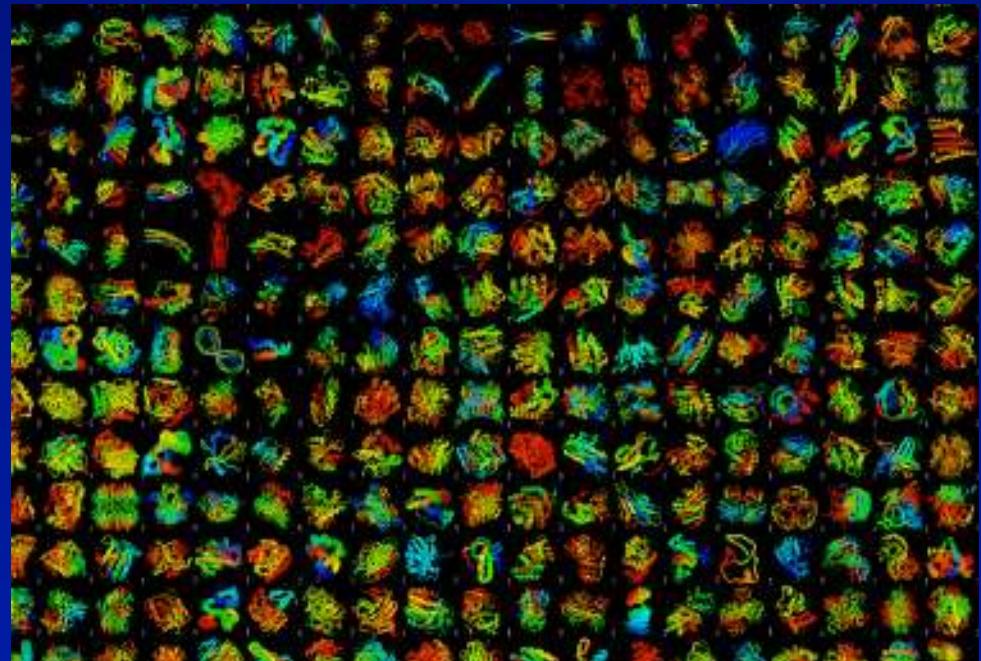
Perspective: The 'Dynasome'



Phylogenetic trees

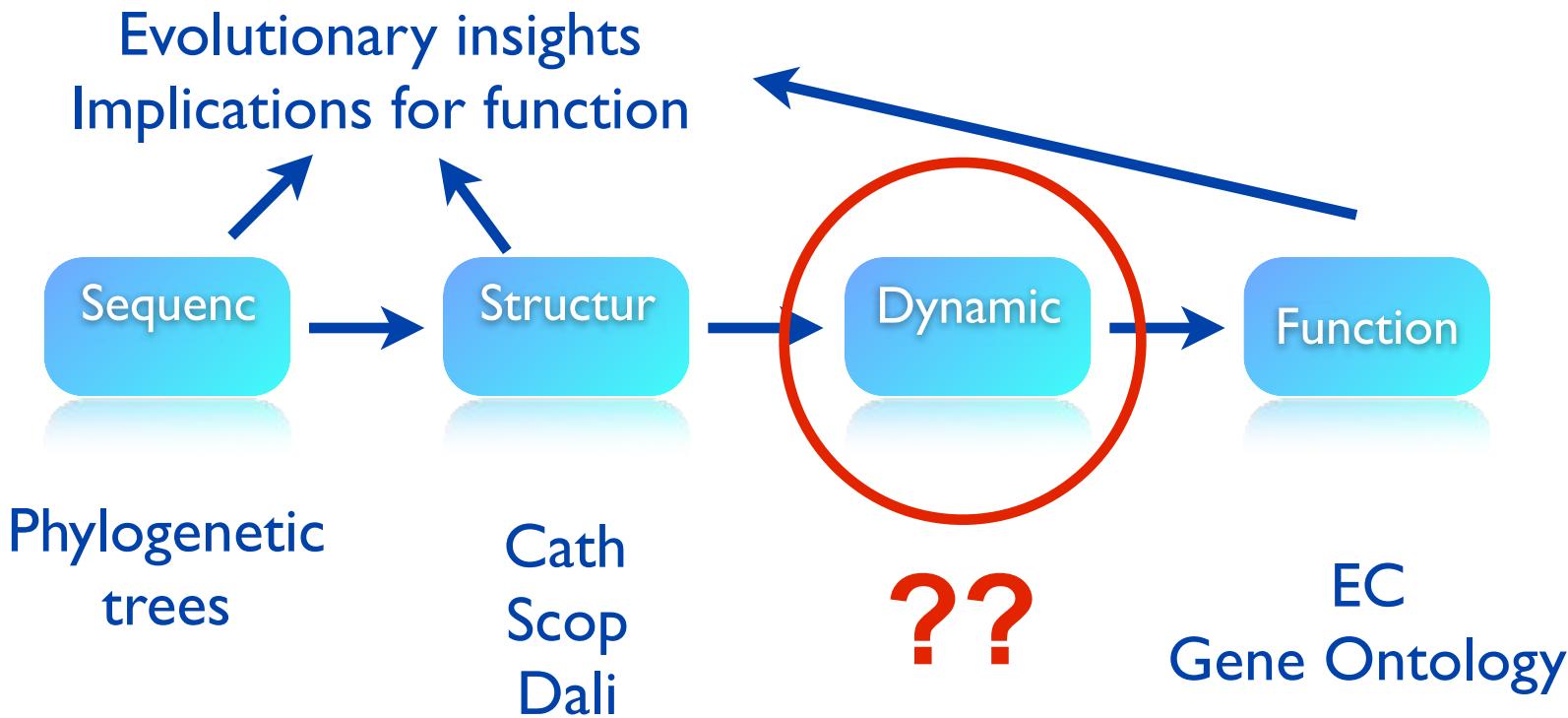
Protein structures fall
into families

-> **Can we also identify
and classify
dynamics motifs?**



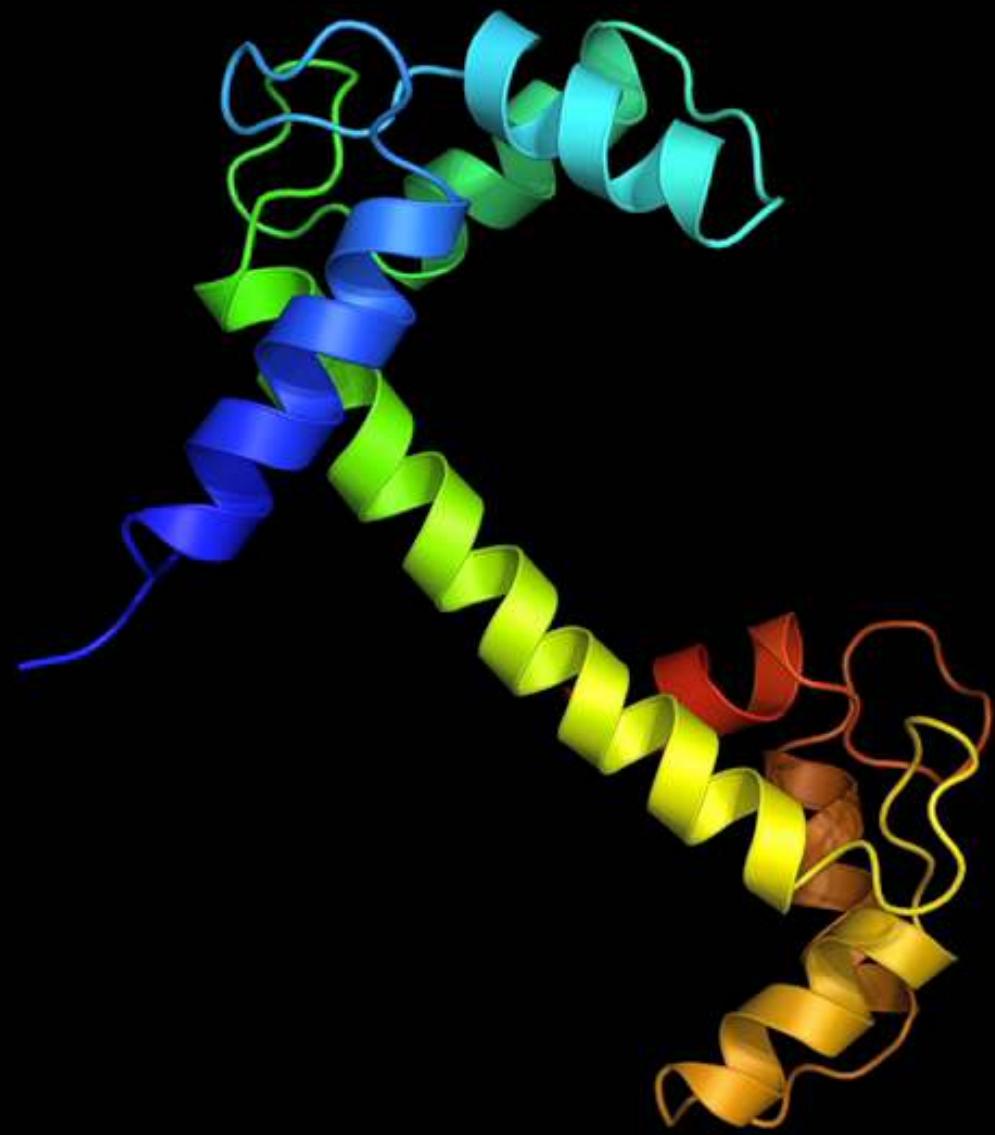
Exploring the protein dynamics space:

Structure / dynamics / function relationship



Ulf Hensen, Tim Meyer,
Jürgen Haas, René Rex,
Collaboration: Gert Vriend

Pang A, Arinaminpathy Y, Sansom M, Biggin P (2005) Proteins 61: 809–822.
Meyer T, de la Cruz X, Orozco M (2009) Structure 17: 88–95.
Jonsson AL, Scott KA, Daggett V (2009) Biophysical Journal 97: 2958–2966.

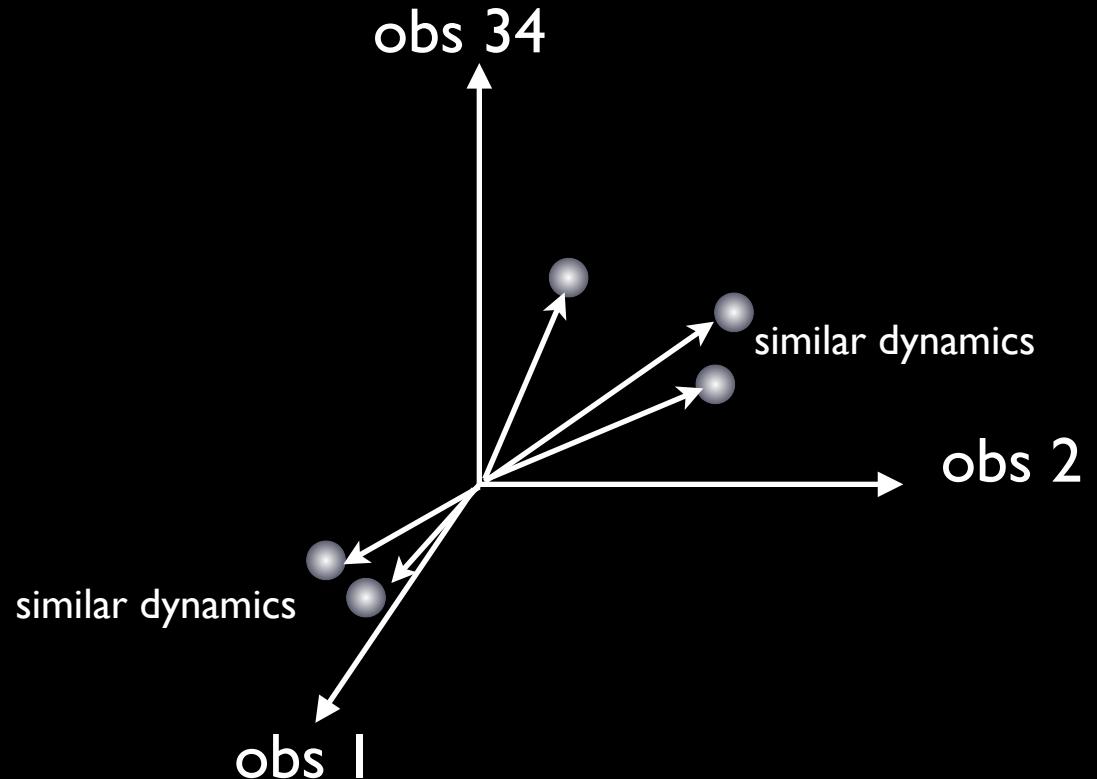


34 Dynamics observables

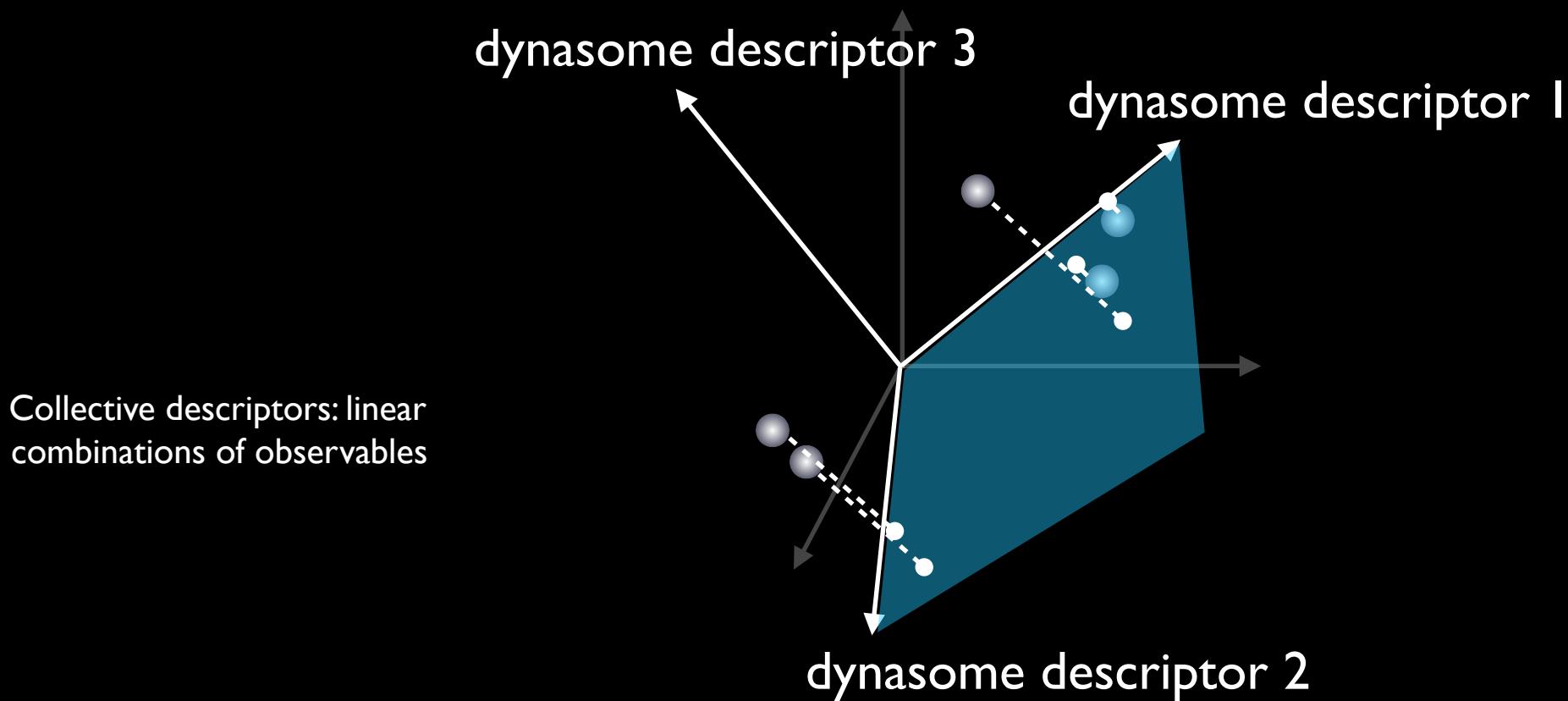
from 100 ns Simulations of 112 representative proteins

Index	Symbol	Description
1, ..., 5	$\lambda_1, \dots, \lambda_5$	Eigenvalues 1, ... 5
6	m^λ	Slope of the middle third of the eigenvalue spectrum
7	χ_λ^2	R^2 value of that fit
8, ..., 12	\cos_1, \dots, \cos_5	Cosine content of the principal components 1-5
13, 14, 15	$\chi_{N,1}^2, \chi_{N,2}^2, \chi_{N,3}^2$	Goodness of fit of a Gaussian fit to principal components 1-3
16, ..., 20	$f_1^{\text{acf}}, \dots, f_5^{\text{acf}}$	Friction constant derived from a fit to the autocorrelation function of principal components 1-5
21	$\mu(\gamma)$	Measure of the average ruggedness of the energy landscape: Average slope of a linear fit to the time dependent eigenvalue spectrum λ .
22	$\text{skew}(\gamma)$	Skewness of the distribution of these ruggedness values (6) of each collective degree of freedom.
23	$\text{kurt}(\gamma)$	Kurtosis thereof.
24	μ^{RMSD}	Average root-mean square deviation from the X-ray structure
25	c_v^{RMSD}	Coefficient of variation thereof
26	μ^{RMSF}	Average residual fluctuations with respect to the average ensemble structure
27	c^{rg}	Coefficient of variation of the radius of gyration
28, ..., 31	$c^{\text{struct}}, c^\alpha, c^\beta, c^{\text{turn}}$	Coefficient of variation of secondary structure content: total, α -helix, β -sheet, turn
32	μ^{SAS}	Average solvent accessible surface
33	c^{SAS}	Coefficient of variation thereof
34	S_{RMSF}	RMSF entropy

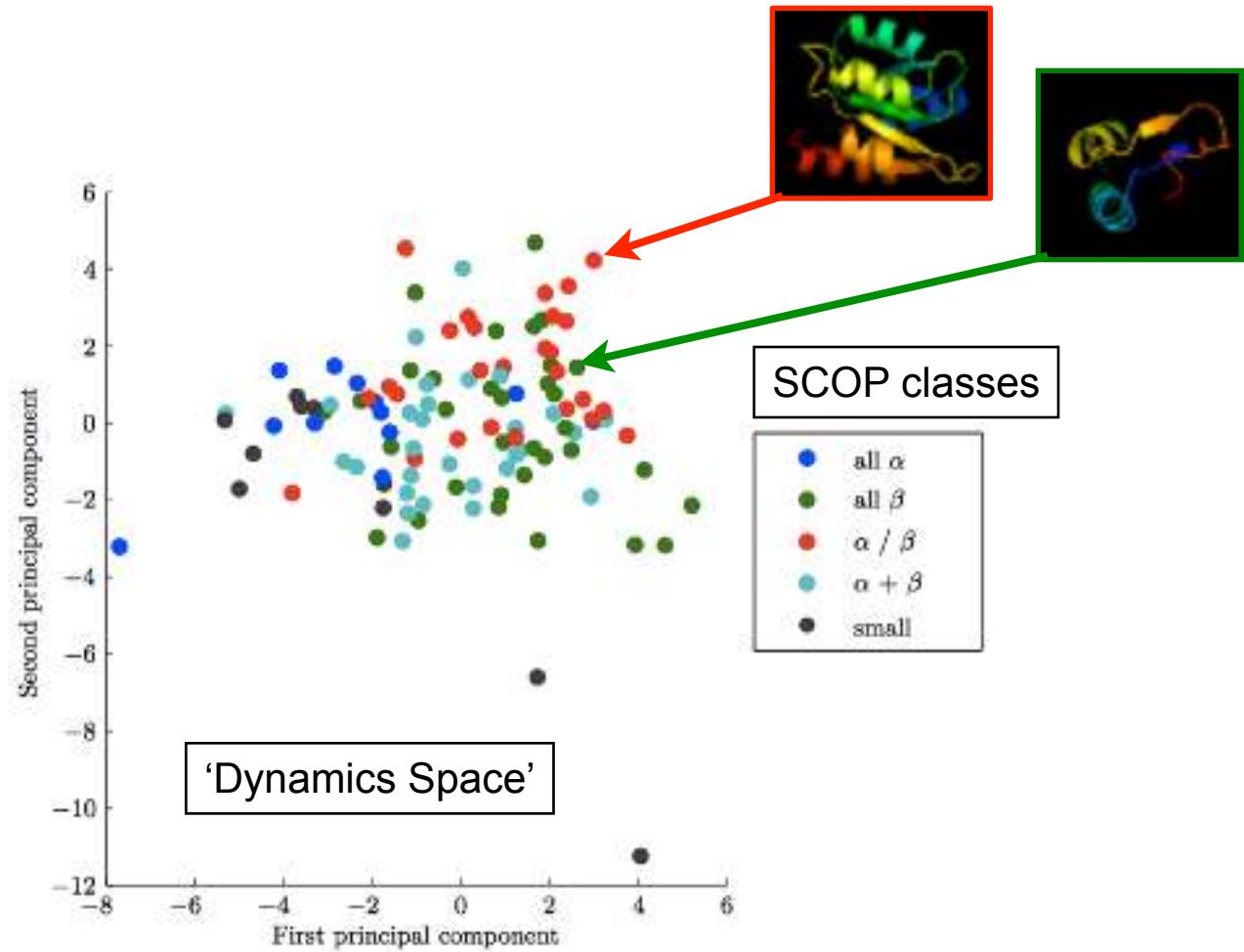
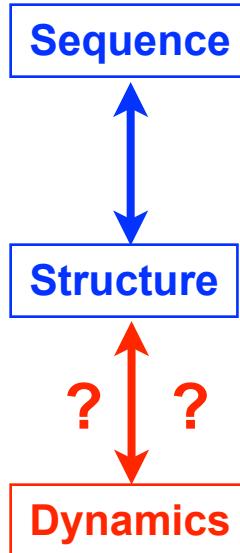
Each protein -> vector in dynamics space



Projection into essential subspace: PCA



Structure / dynamics relationship



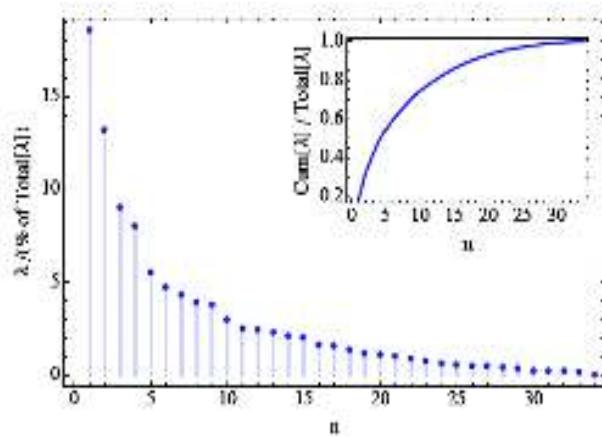
Questions:

- What is the meaning of the principal components?
- Does similar structure imply similar dynamics?
- Does similar dynamics require similar structure?
- How does function correlate with dynamics?

Collective dynamics descriptors

Descriptor 2	
$f_1^{\text{acf}}(-)$	(12 %)
f_2^{acf}	(-) (8 %)
f_4^{acf}	(-) (7 %)
$\chi_{\mathcal{N},1}^2(-)$	(7 %)
kurt(γ)(+)	(7 %)

Kinetics



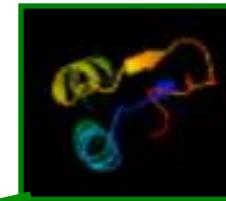
Slow

fast

'Dynamics Space'

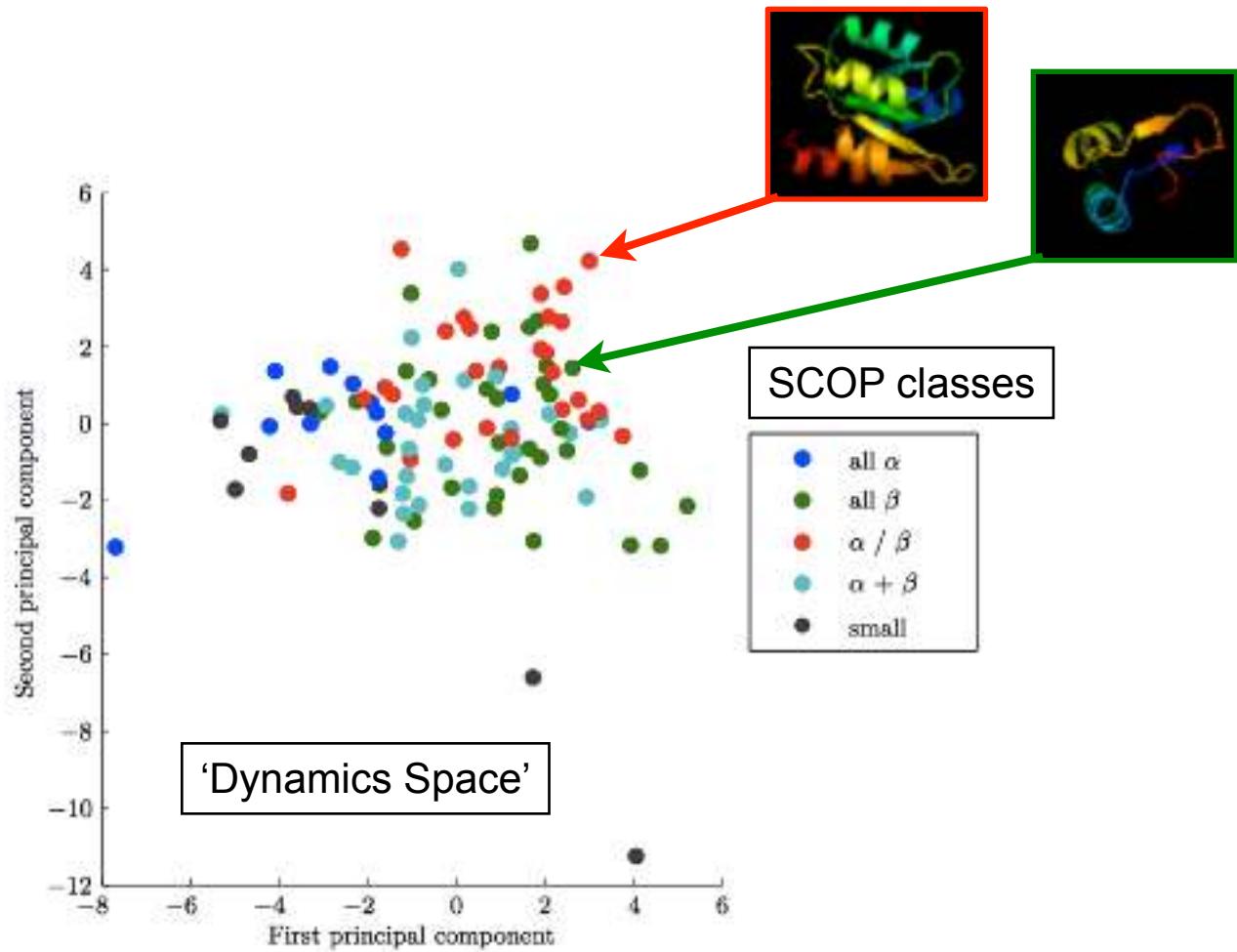
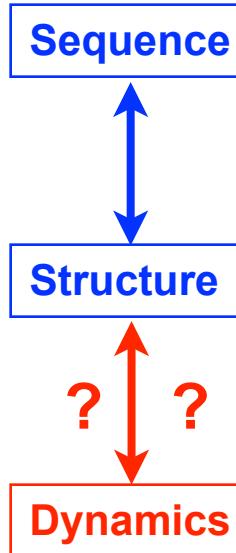
flexible rigid

Thermodynamics



Descriptor 1	
μ^{RMSF}	(-) (10 %)
μ^{RMSD}	(-) (9 %)
c^{rg}	(-) (9 %)
skew(γ)	(+) (7 %)
$\mu(\gamma)$	(+) (7 %)

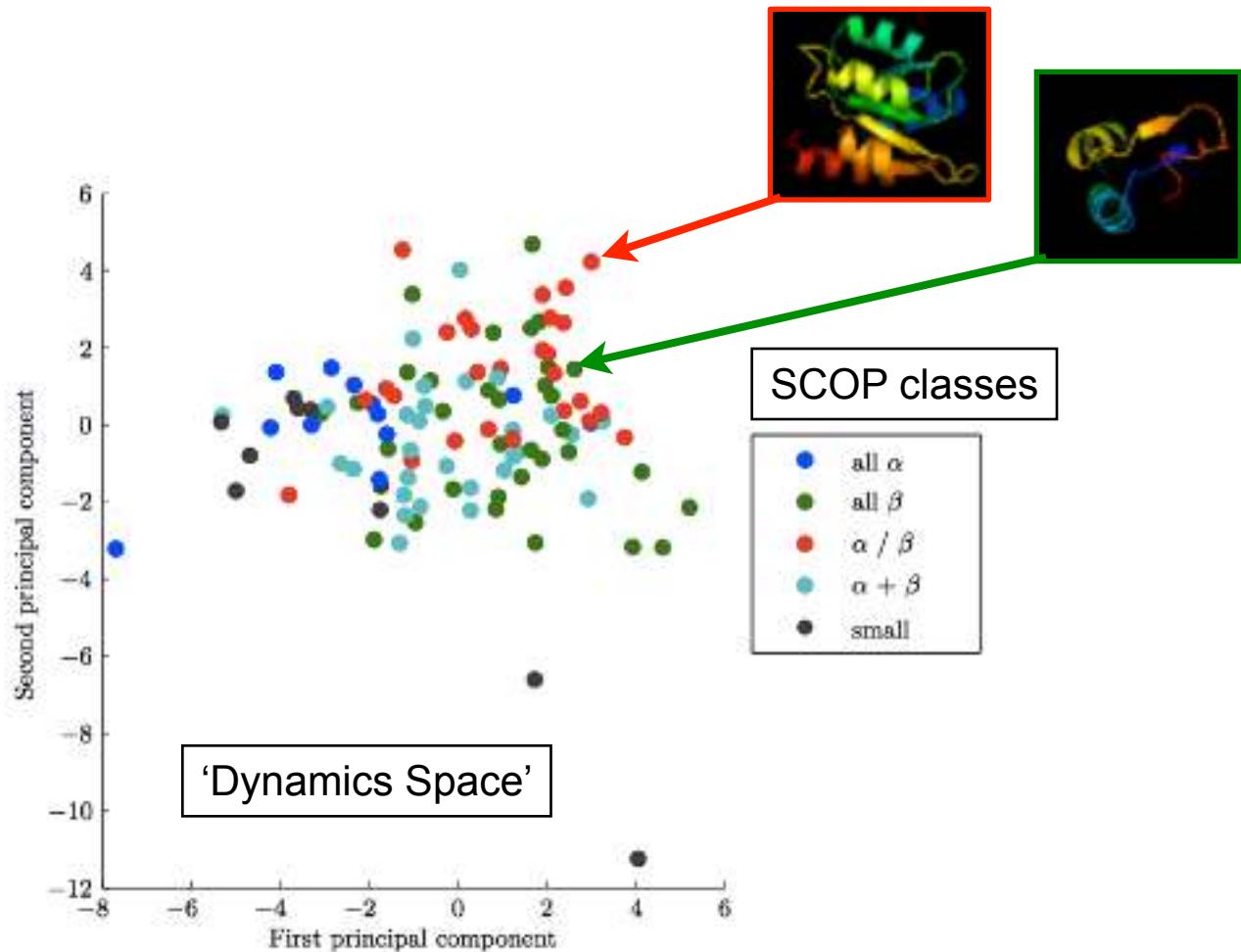
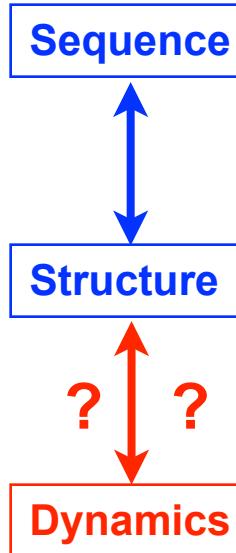
Structure / dynamics relationship



Questions:

- What is the meaning of the principal components?
- Does similar structure imply similar dynamics?
- Does similar dynamics require similar structure?
- How does function correlate with dynamics?

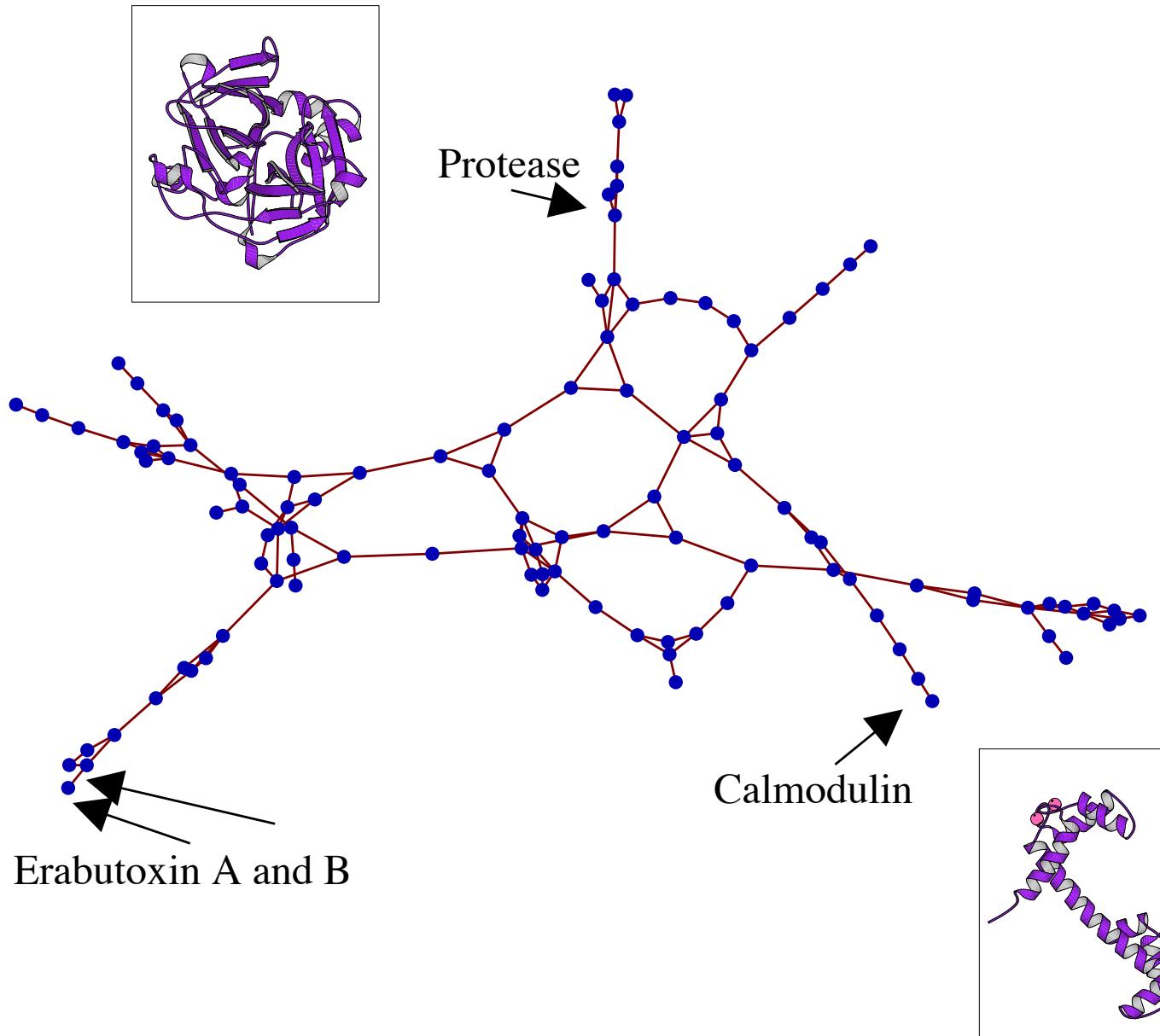
Structure / dynamics relationship



Questions:

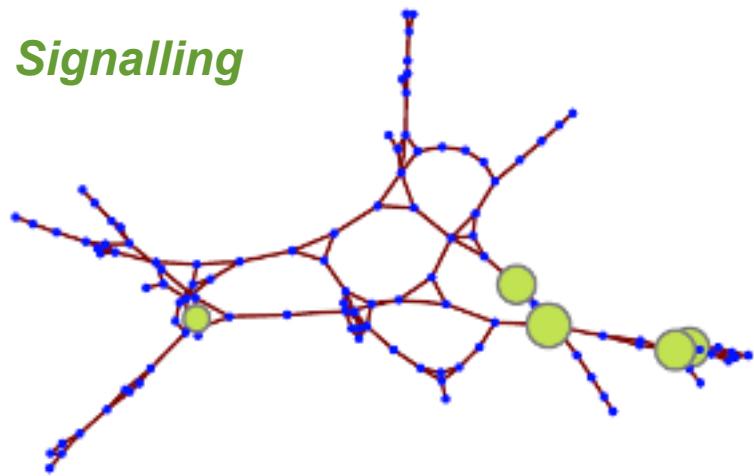
- What is the meaning of the principal components?
- Does similar structure imply similar dynamics?
- Does similar dynamics require similar structure?
- How does function correlate with dynamics?

The fine structure or the dynasome

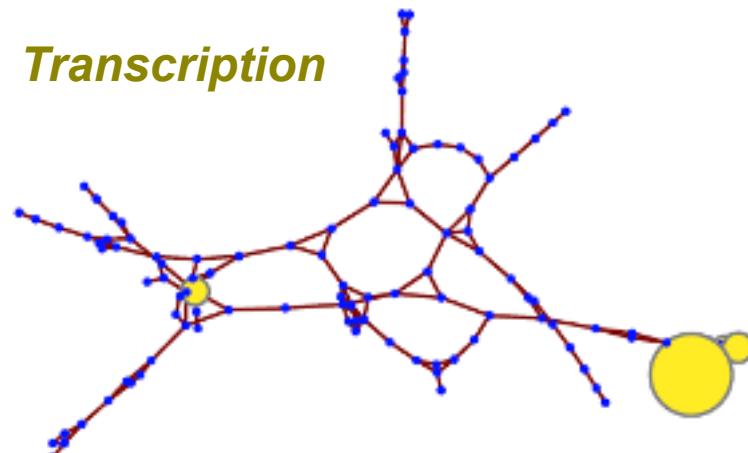


Dynamics correlates with function!

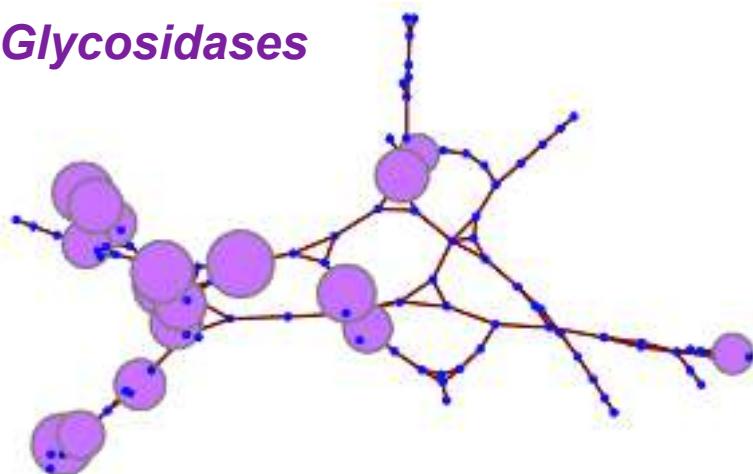
Signalling



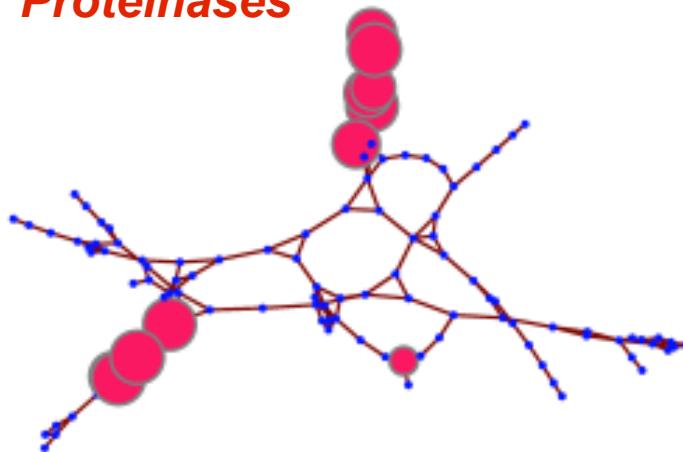
Transcription



Glycosidases

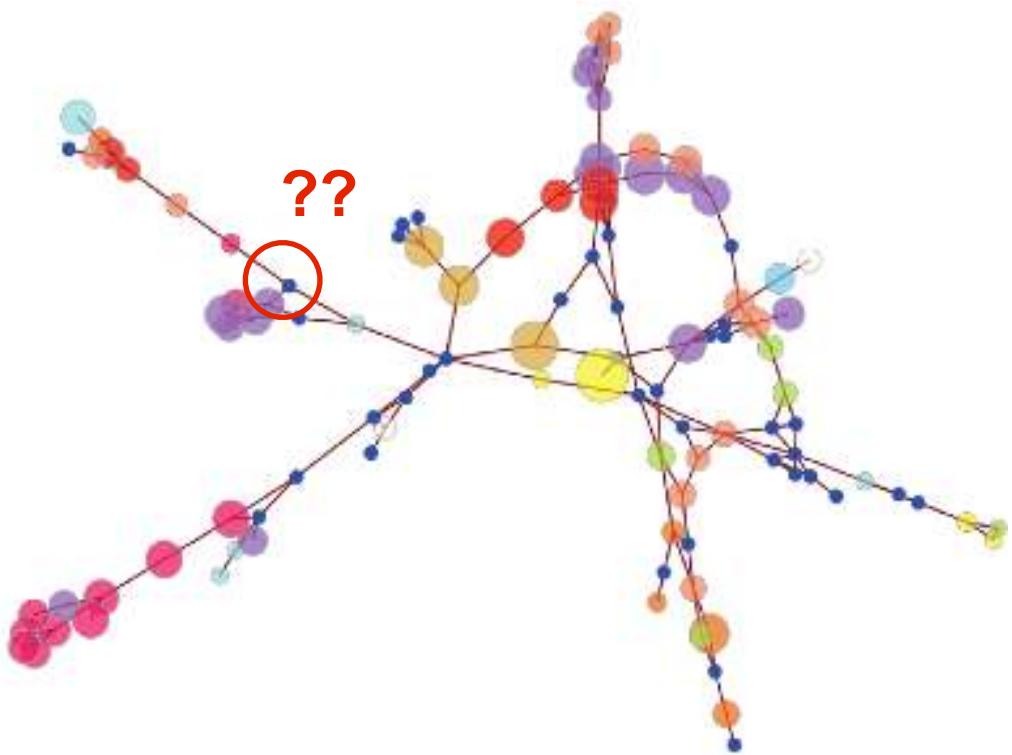


Proteinases



Protein Function Prediction

- I. New protein of unknown function:
2. Based on its dynamics, determine its position in the graph.
3. function from closest cluster.



<i>dyn</i>	<i>struct</i>	<i>random</i>
46 %	32 %	11 %

Femtoseconds XFEL single molecule diffraction ('diffract and destroy')

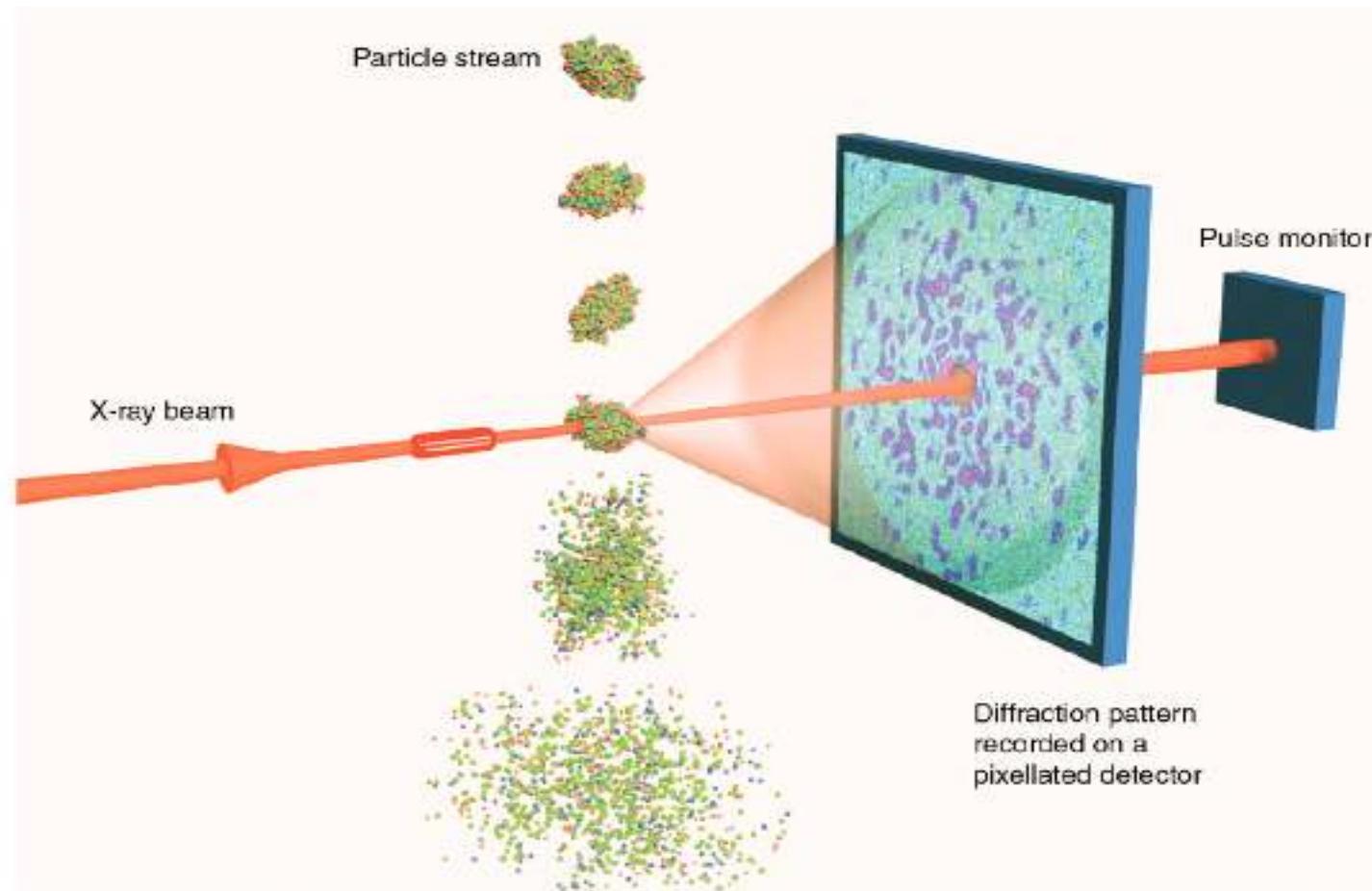
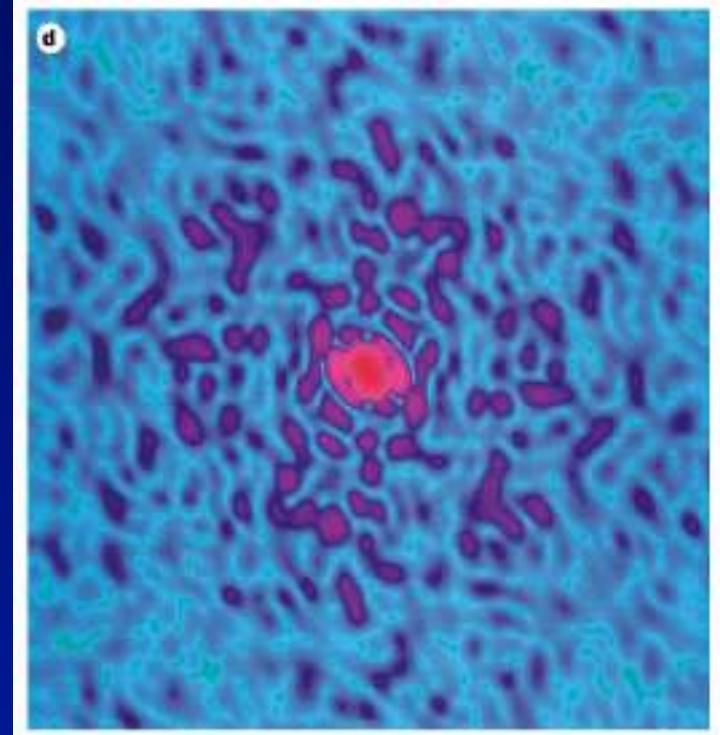
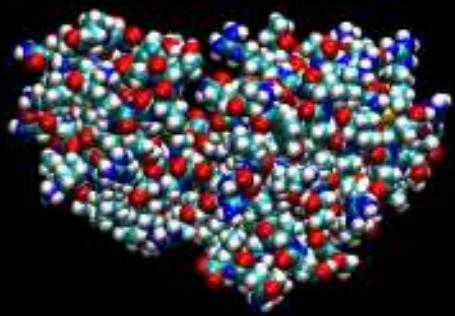


Illustration from Gaffney and Chapman (2007), Science 316, 1444

Structure determination from XFEL fs xray pulses?

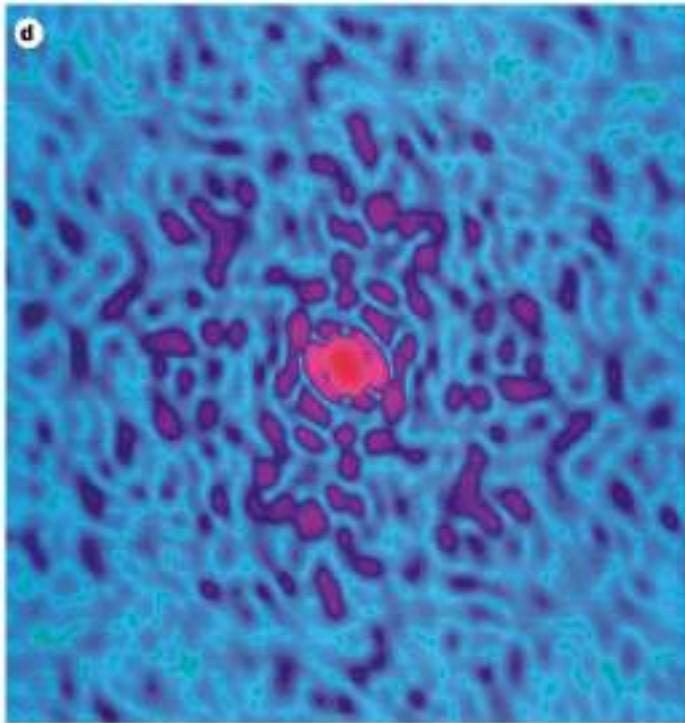


R. Neutze et al., Nature 406, 752-757

G. Groenhof & H. Grubmuller

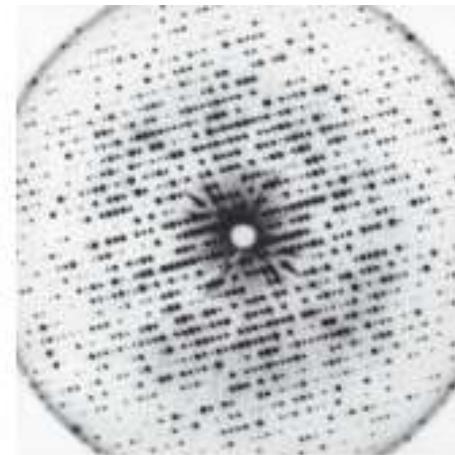
Lysozyme Coulomb explosion after XFEL xray pulse exposure
Simple Force Field!

Ideal case: continuous diffraction pattern (infinite intensity)

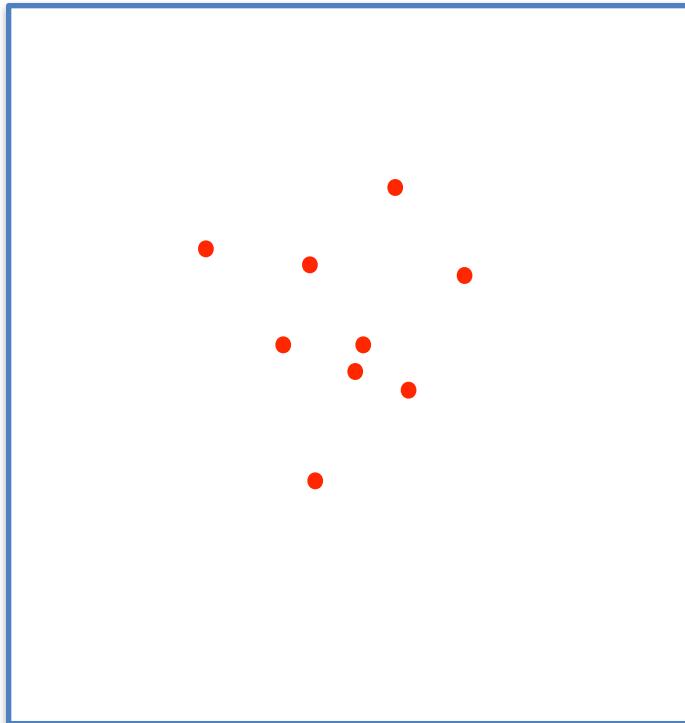


(calculated!)

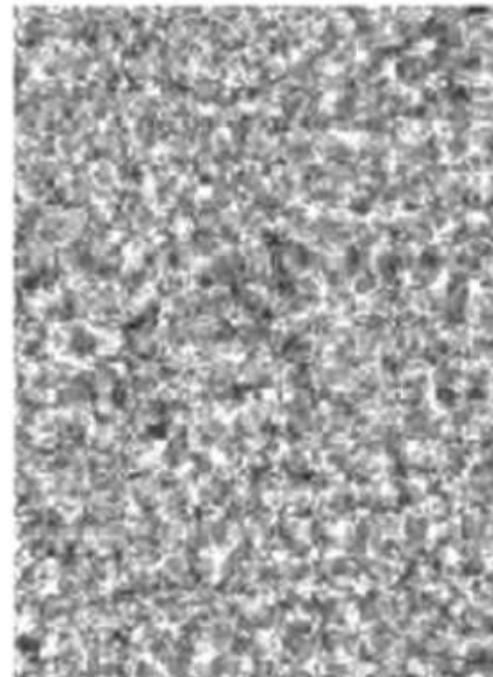
Fourier Transform
no phases
BUT: continuous sampling
-> phase reconstruction
much easier



Reality: extreme low photon statistics (Poisson limit)

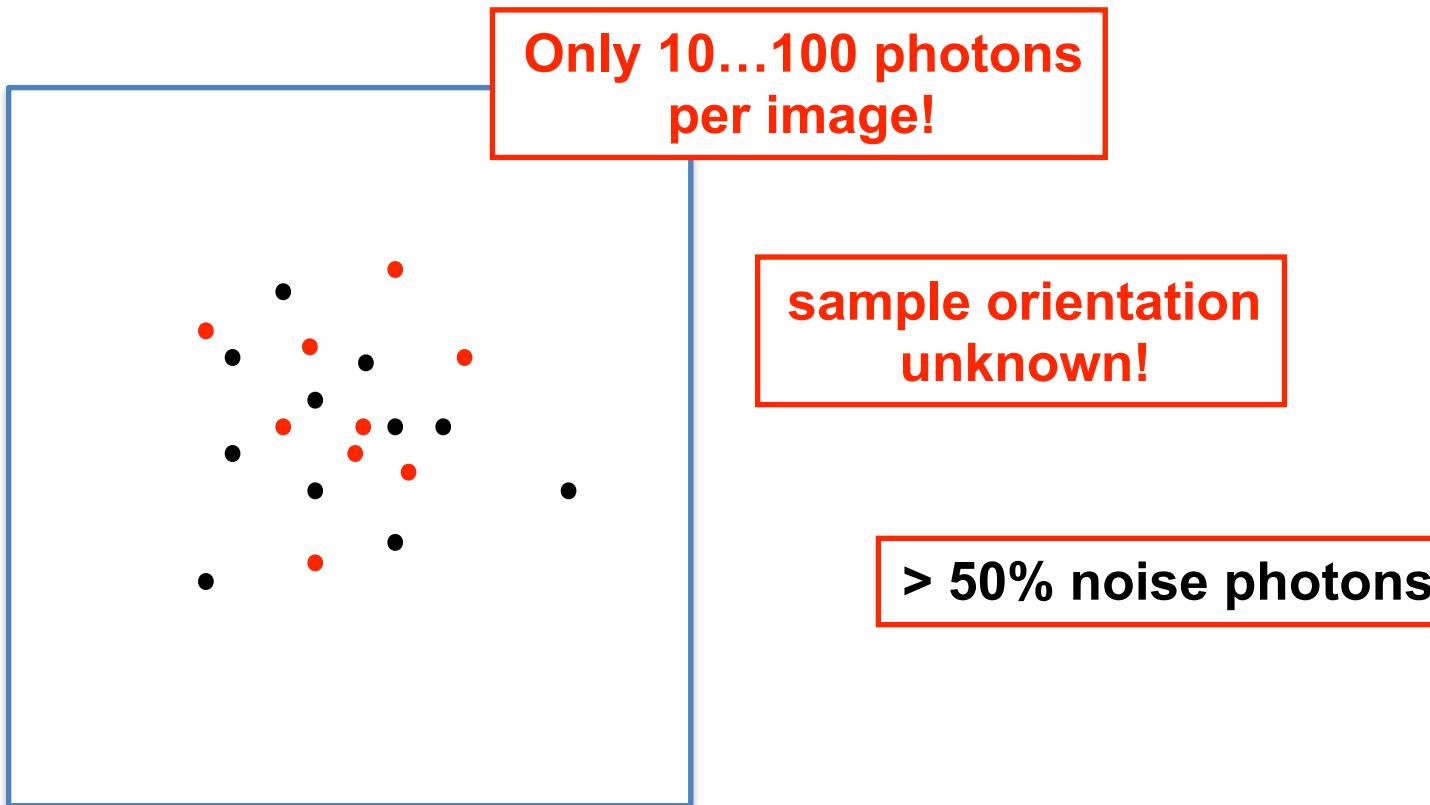


Only 10...100 photons per image!

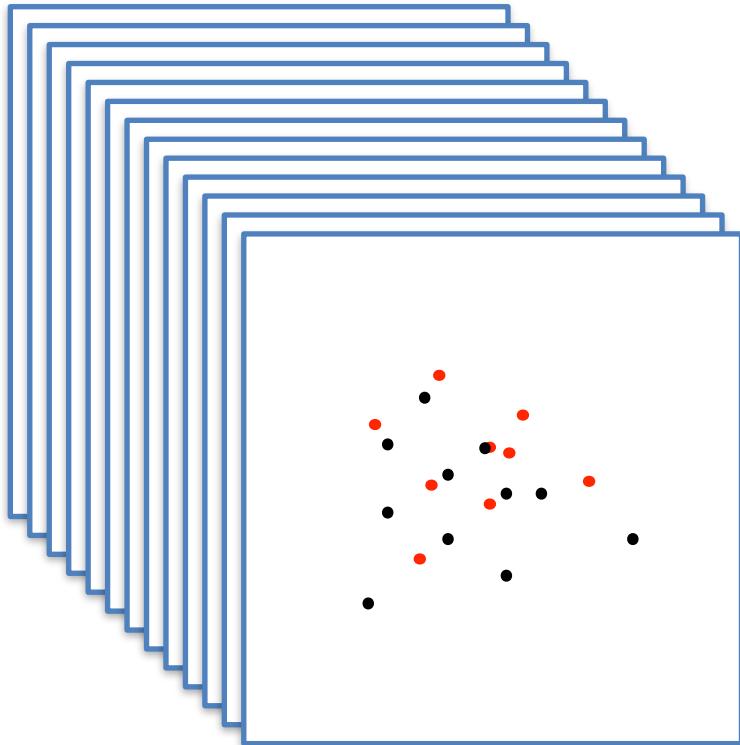


Single Molecule Cryo-EM

Reality: extreme low photon statistics (Poisson limit)



Reality: extreme low photon statistics (Poisson limit)

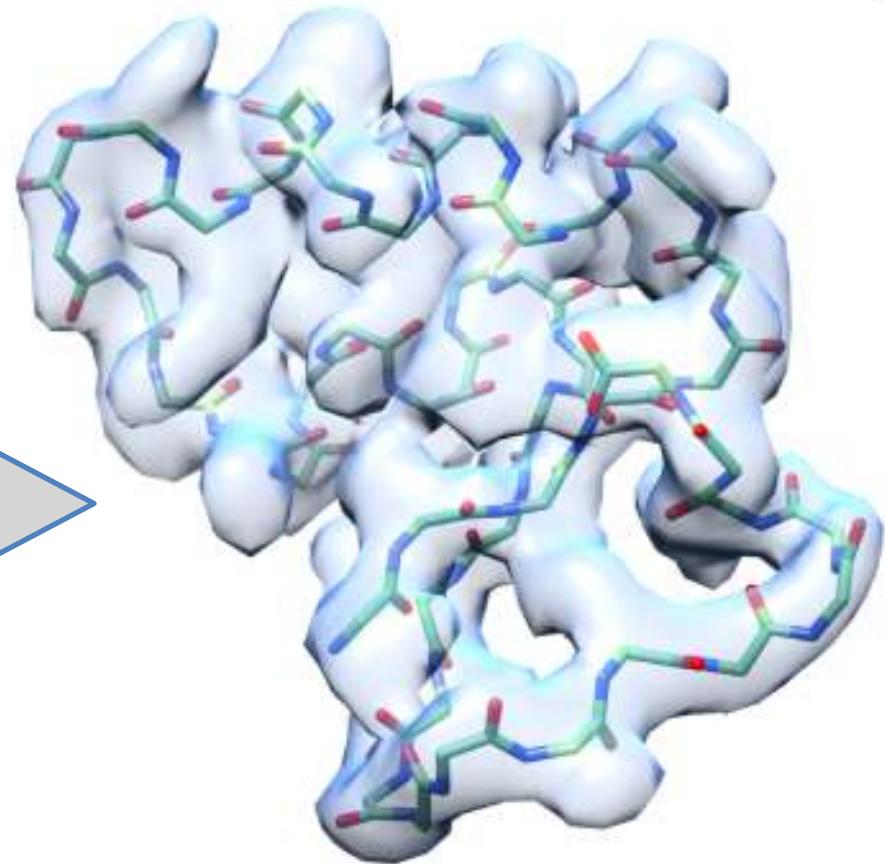
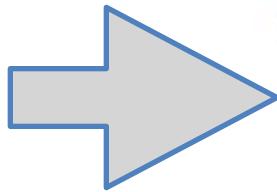
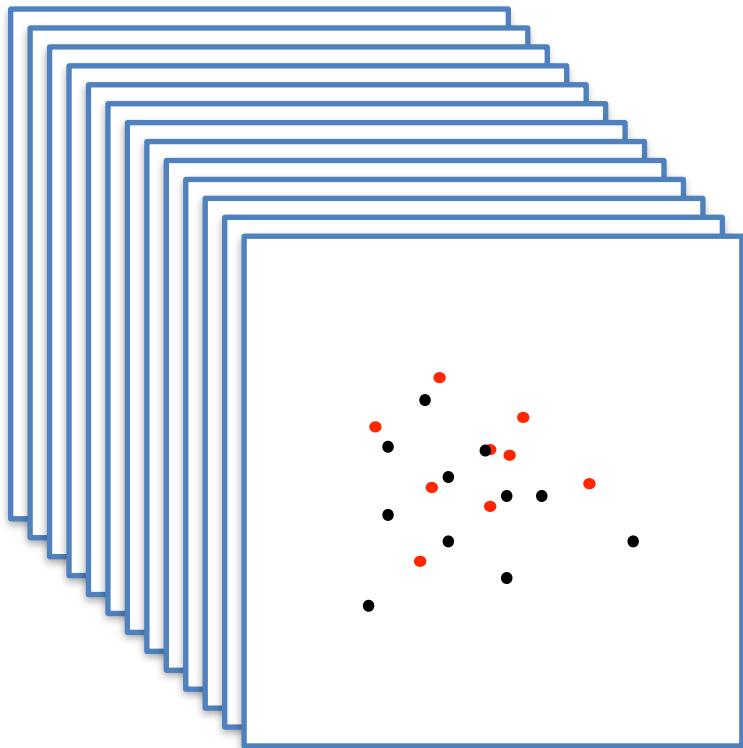


BUT: $10^6 \dots 10^9$ images

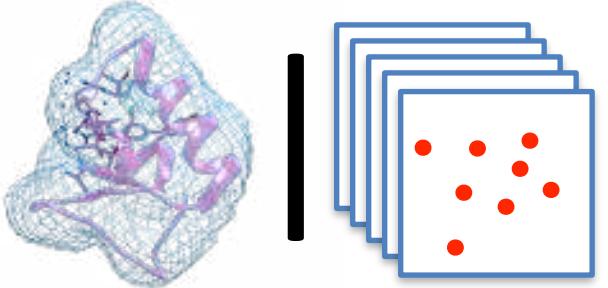
(27000 pulses /sec)

How few photons will do?

**state of the art:
>300 photons per image**



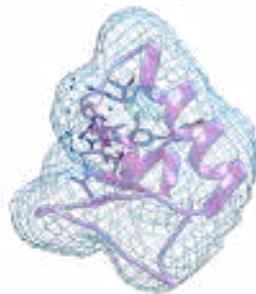
Trick #1: Maximize

$$P(\text{ } | \text{ })$$


Benjamin von Ardenne

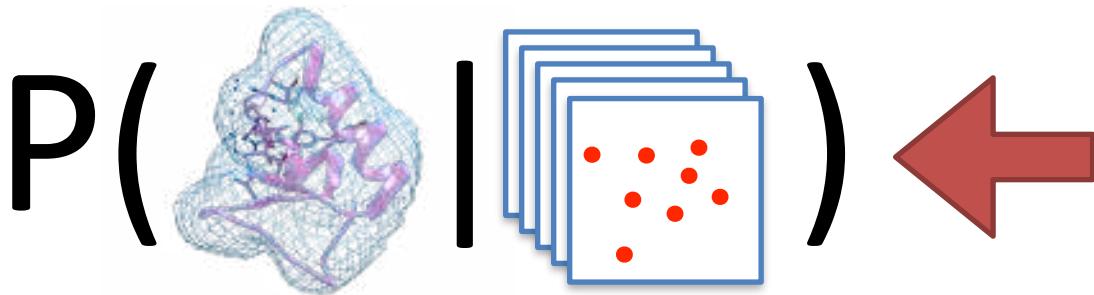
Martin Mechelke

Find the one



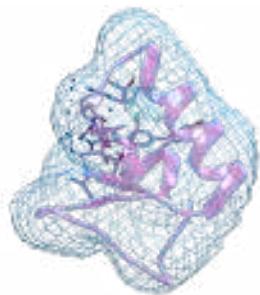
for which $P(|)$ ist largest

Trick #1: Maximize

$$P(\text{ } | \text{ })$$


A large blue wireframe shape is on the left. A vertical bar is positioned between the wireframe and the stack of squares. To the right of the bar is a stack of four smaller blue squares, each containing several red dots. A large red arrow points from the text "we can NOT calculate this" to the stack of squares.

Find the one



for which $P(|)$ ist largest

Bayes' formula

$$P(\text{protein structure} \mid \text{experimental data}) \sim P(\text{experimental data} \mid \text{protein structure}) \times P(\text{protein structure})$$

MD or Markov chain sampling techniques,
Gaussian ensembles

we can calculate this

The diagram illustrates the application of Bayes' formula to protein structure prediction. It shows the two main components of the formula: the posterior probability $P(\text{protein structure} \mid \text{experimental data})$ and the prior probability $P(\text{protein structure})$.

The first term, $P(\text{protein structure} \mid \text{experimental data})$, is represented by a protein structure model (a blue wireframe) and a stack of experimental data points (red dots). This term is highlighted with a red border.

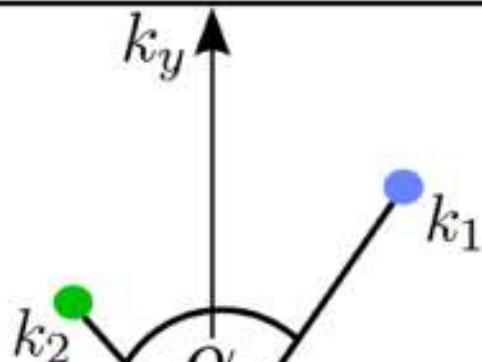
The second term, $P(\text{experimental data} \mid \text{protein structure}) \times P(\text{protein structure})$, is represented by a stack of experimental data points and a protein structure model. A red arrow points up from this term to a box containing text about sampling techniques.

A red arrow points down from the first term to a box containing the text "we can calculate this".

Wozniak et al., PNAS (2008)
Schröder et al., Comp. Phys. Comm (2004)
Margittai et al., PNAS (2003)
Schröder et al., J. Chem. Phys. (2003)

Trick #3: New correlation method

Two Photons

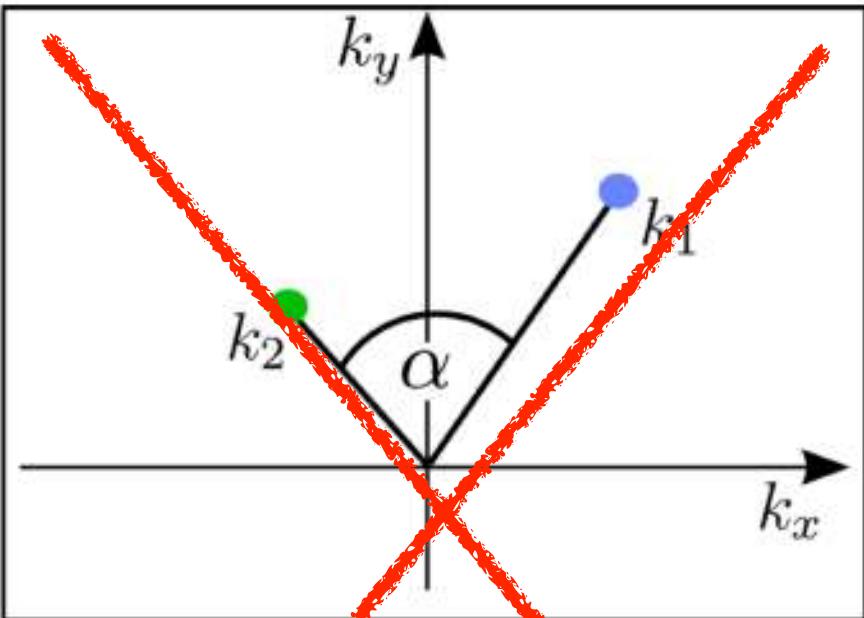


$$c_{k_1, k_2, \alpha} = \sum_l P_l (\cos(\alpha)) \cdot \sum_m A_{lm}(k_1)(\omega) A_{lm}^*(k_2)$$

Analytical inversion exists
BUT: underdetermined

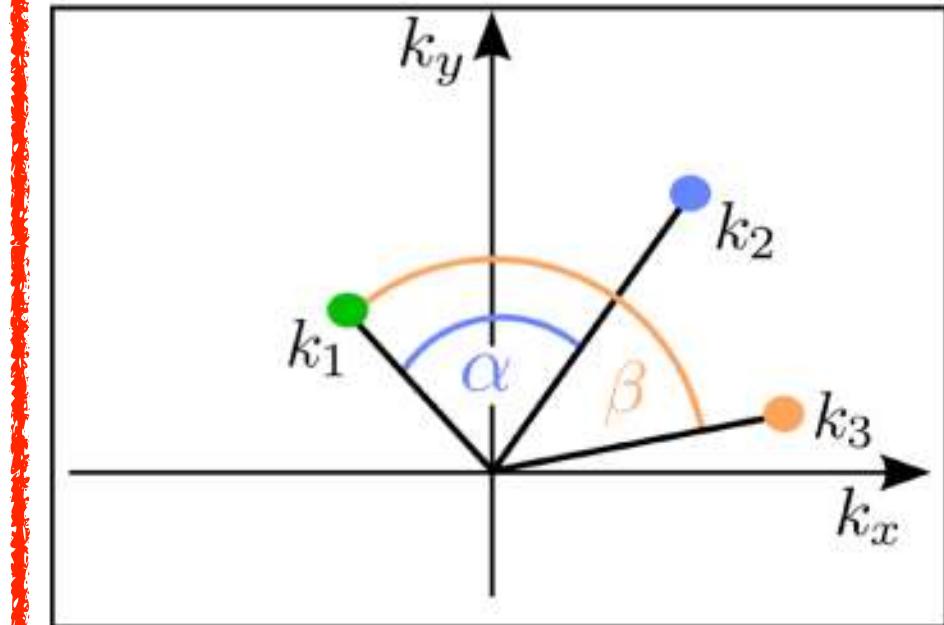
3-photon correlations DQ encode structure

Two Photons



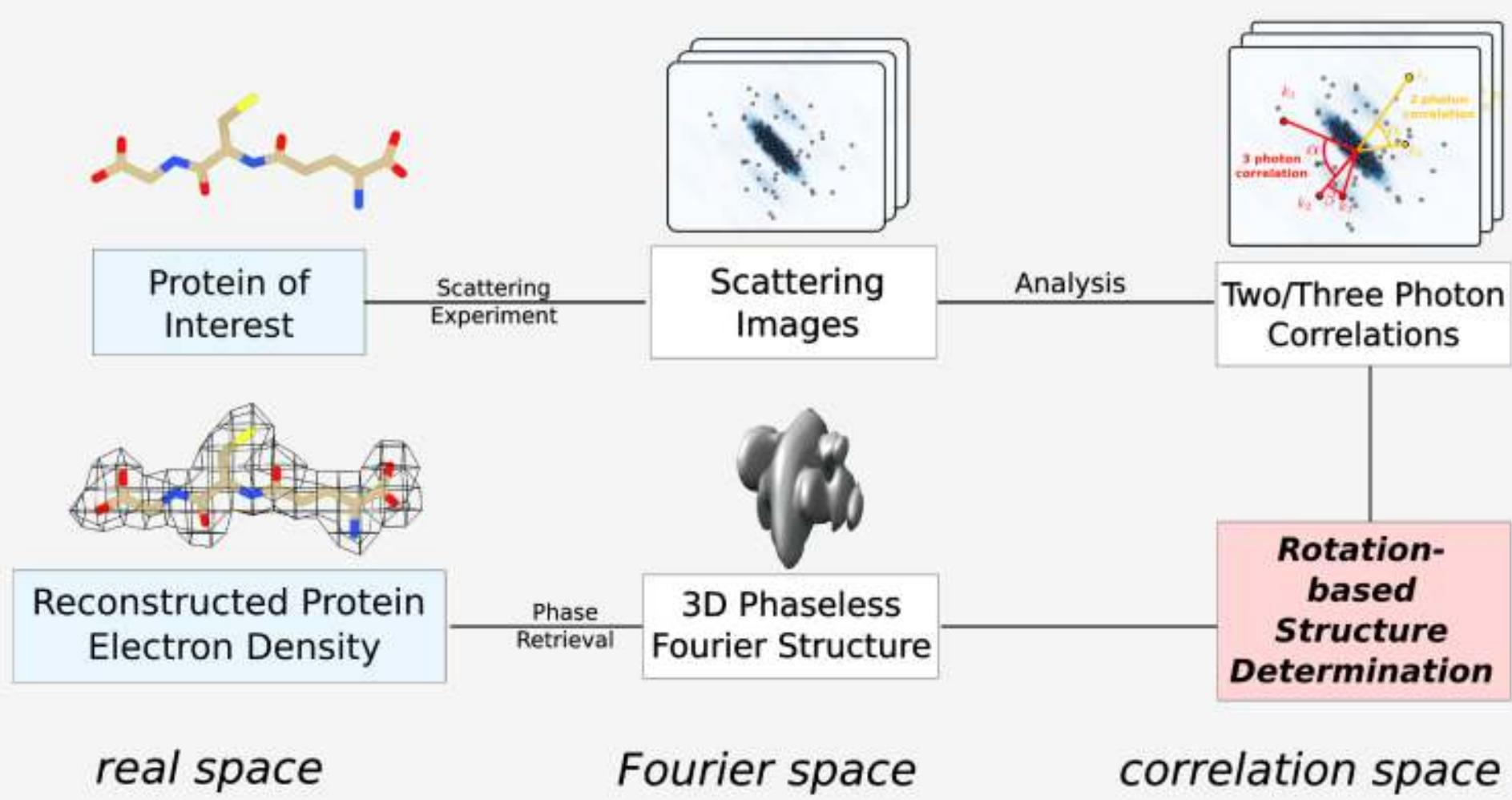
$$c_{k_1, k_2, \alpha} = \sum_l P_l(\cos(\alpha)) \cdot \sum_m A_{lm}(k_1)(\omega) A_{lm}(k_2)$$

Three Photons



$$t_{k_1, k_2, k_3, \alpha, \beta} = \sum_{l_1 l_2 l_3} \sum_{m_1 m_2 m_3} A_{l_1 m_1}(k_1) \cdot A_{l_2 m_2}(k_2) A_{l_3 m_3}^*(k_3) \cdot f(l_1, l_2, l_3, m_1, m_2, m_3, \alpha, \beta)$$

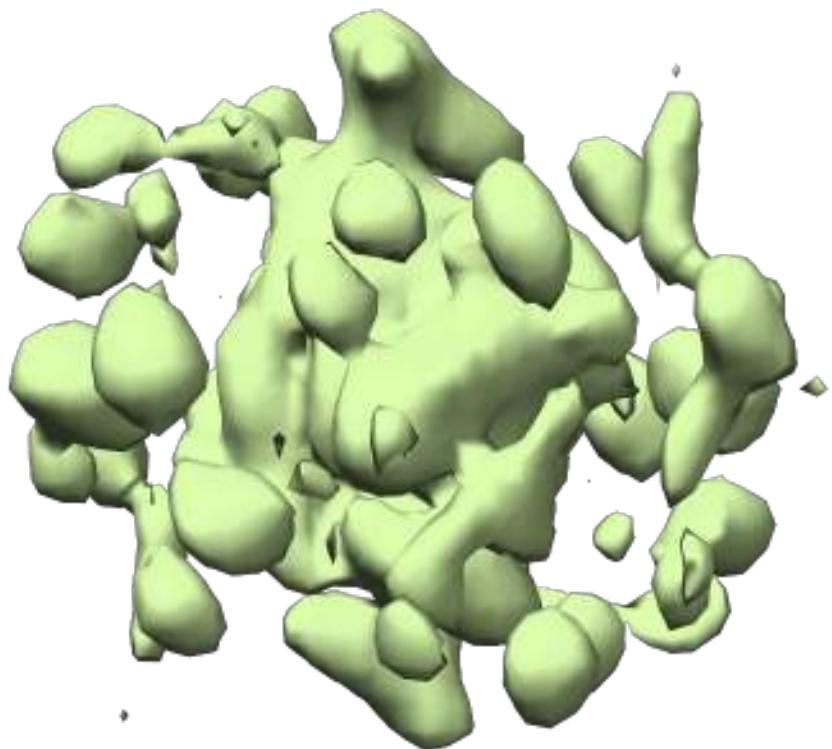
New: 3-photon correlation method



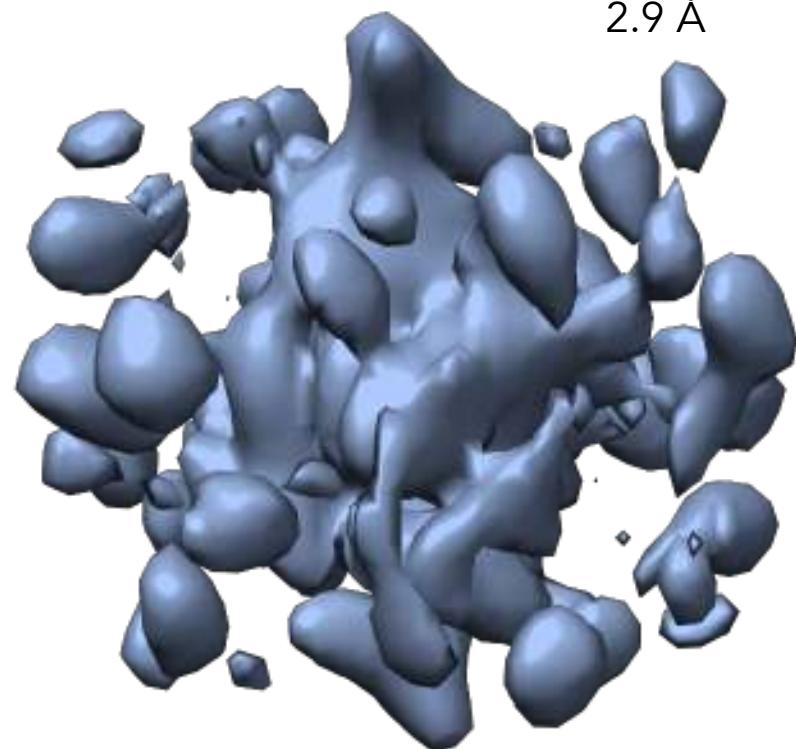
Fourier density derived from 3-photon correlations

$$I(\mathbf{k}(k, \varphi, \theta)) = \sum_{l=0}^L \sum_{m=-l}^l A_{lm}(k) Y_{lm}(\varphi, \theta)$$

Maximum achievable:
2.9 Å

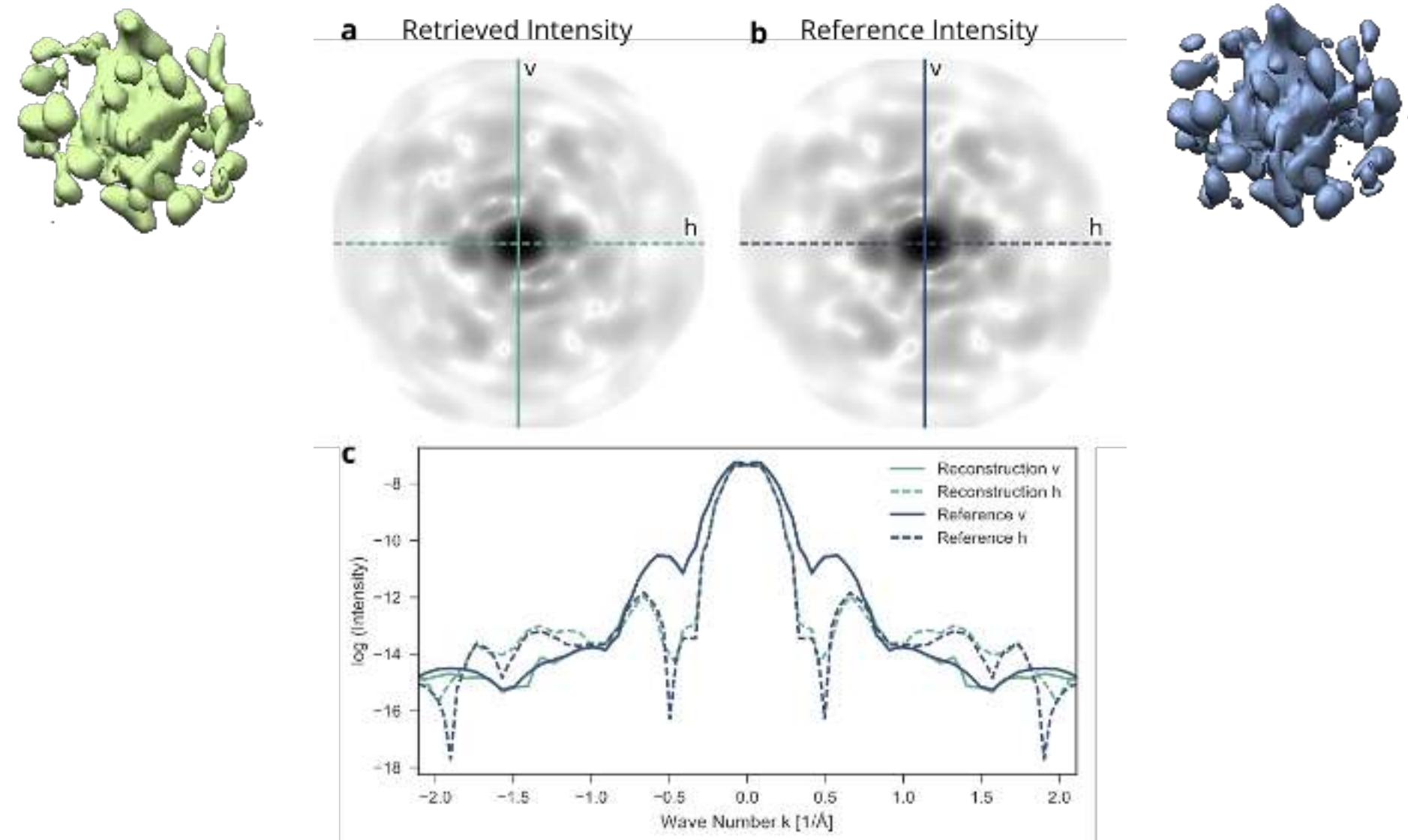


Retrieved Intensity
K=26, L=18



Original Intensity
K=26, L=18

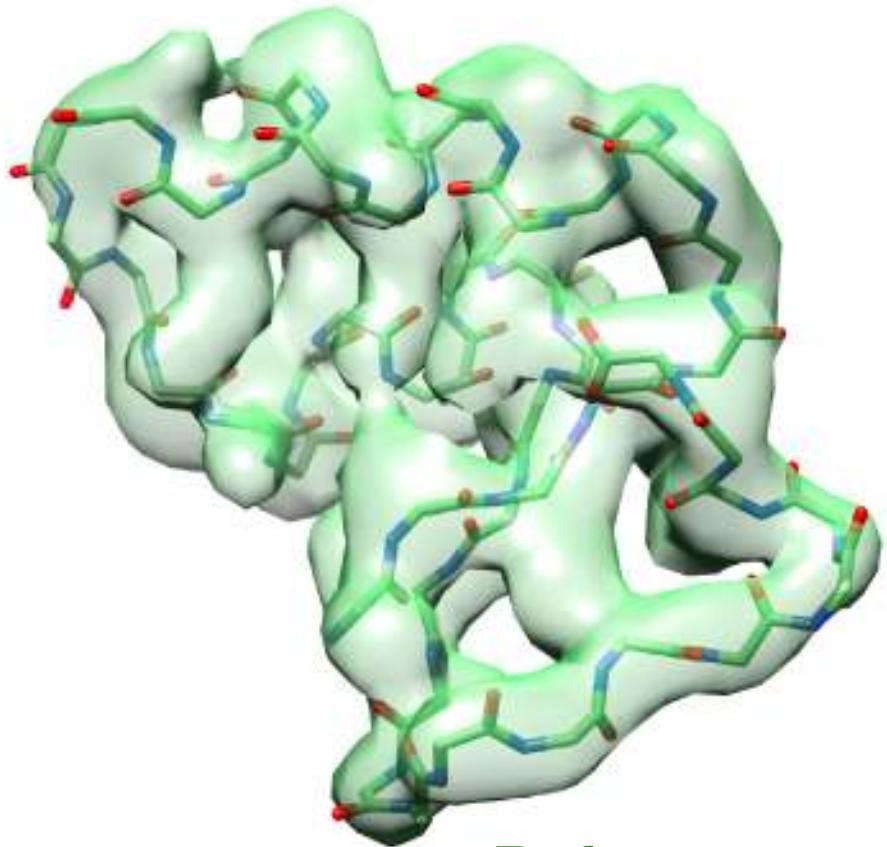
Fourier density derived from 3-photon correlations



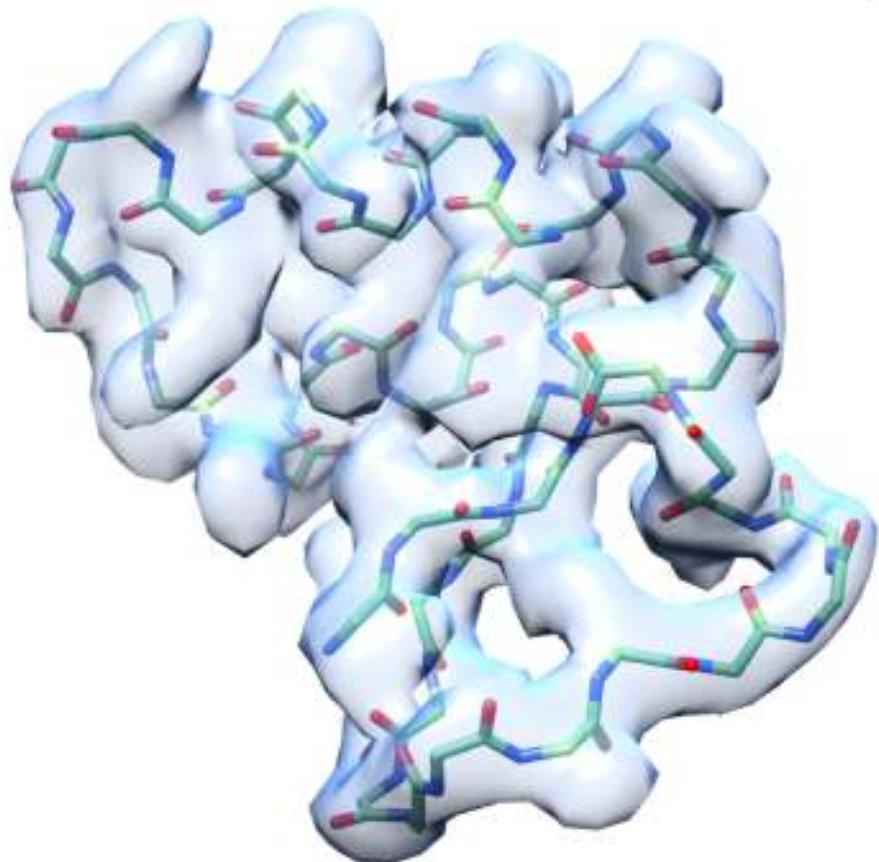
ca 10^8 photon-triples

B. von Ardenne & HG, Nature Comm. 9:2375 (2018)

New: 3-photon correlation method

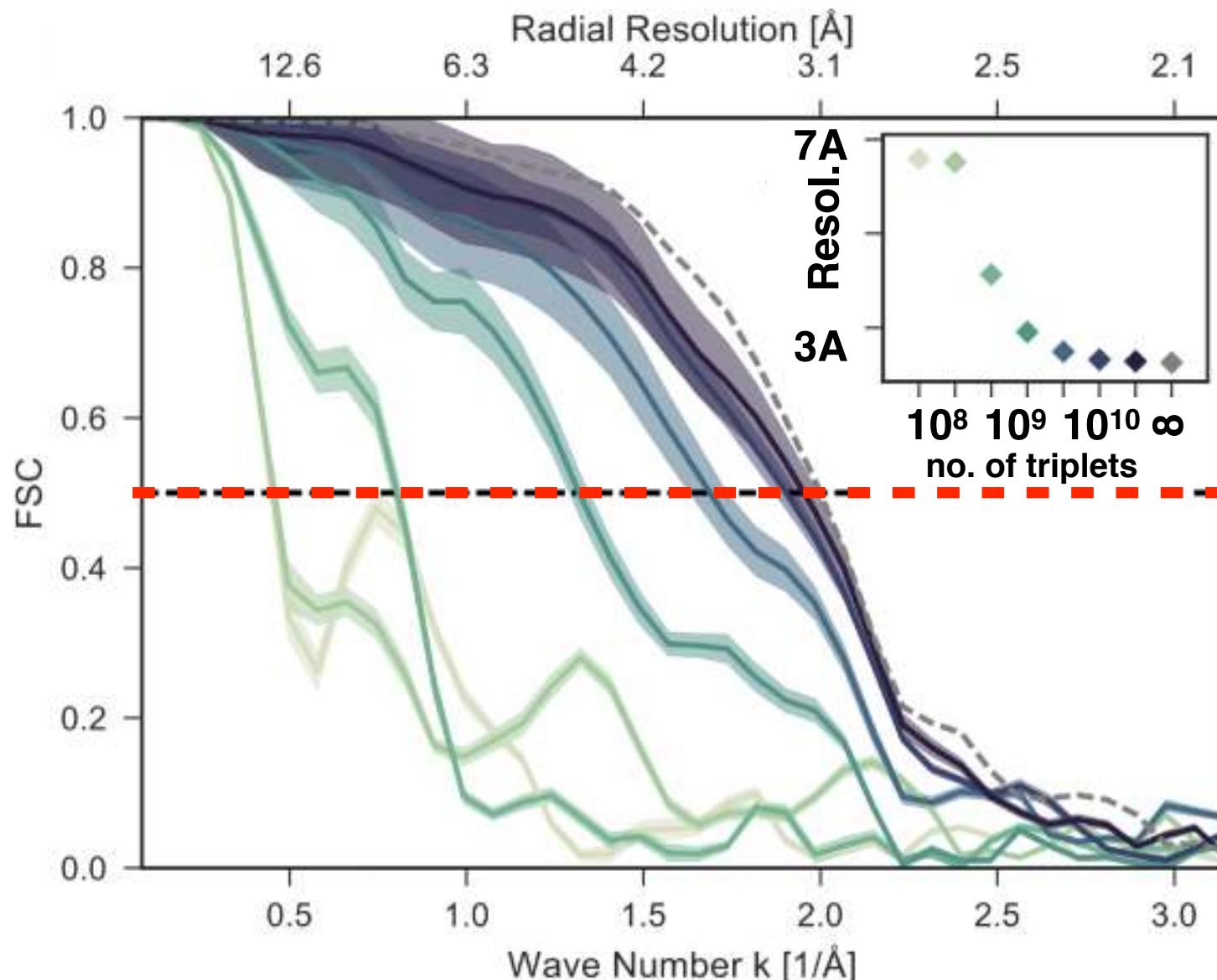


Reference

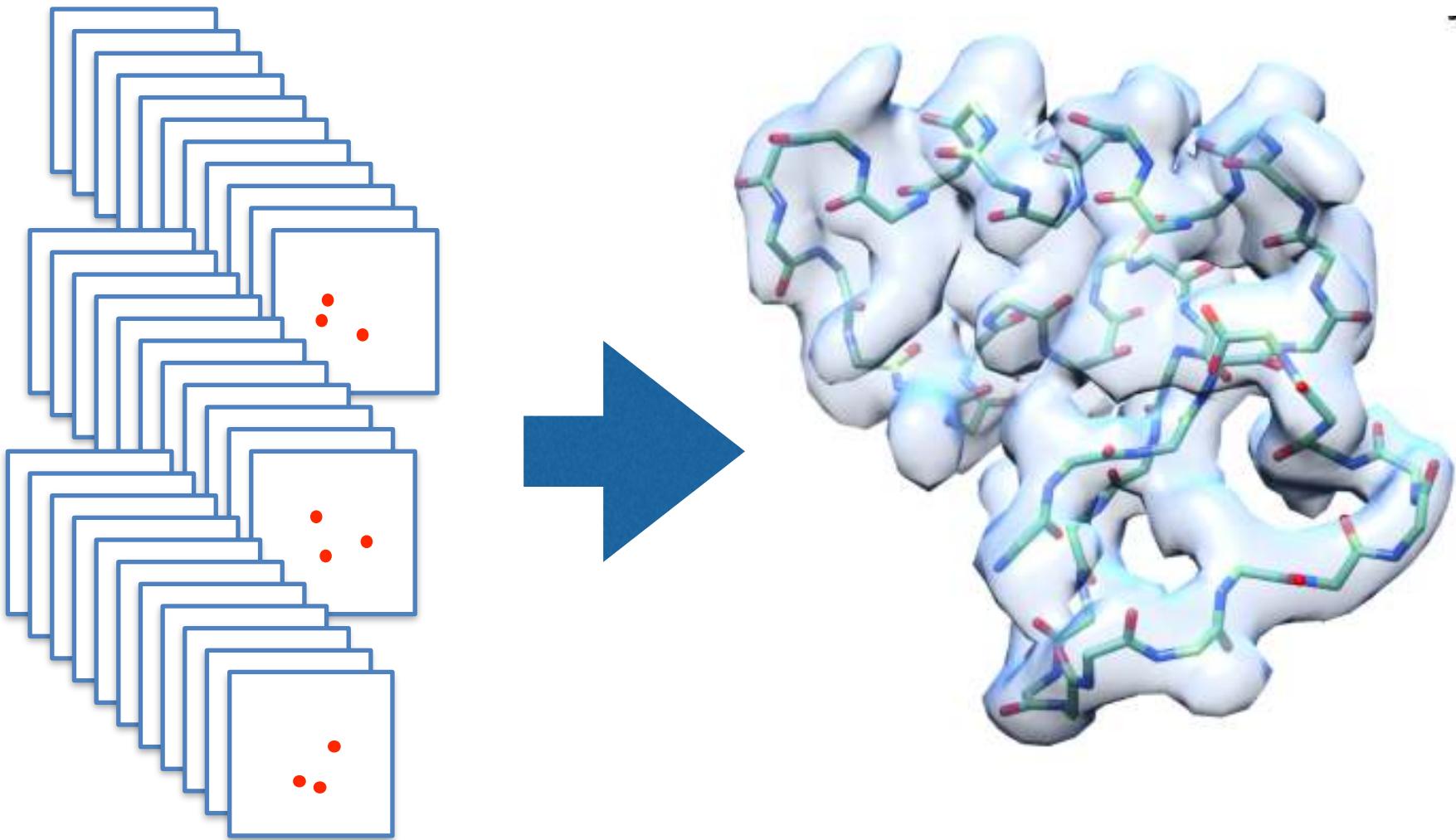


ca 4×10^7 pictures, 10 photons per picture

What resolution can be achieved?

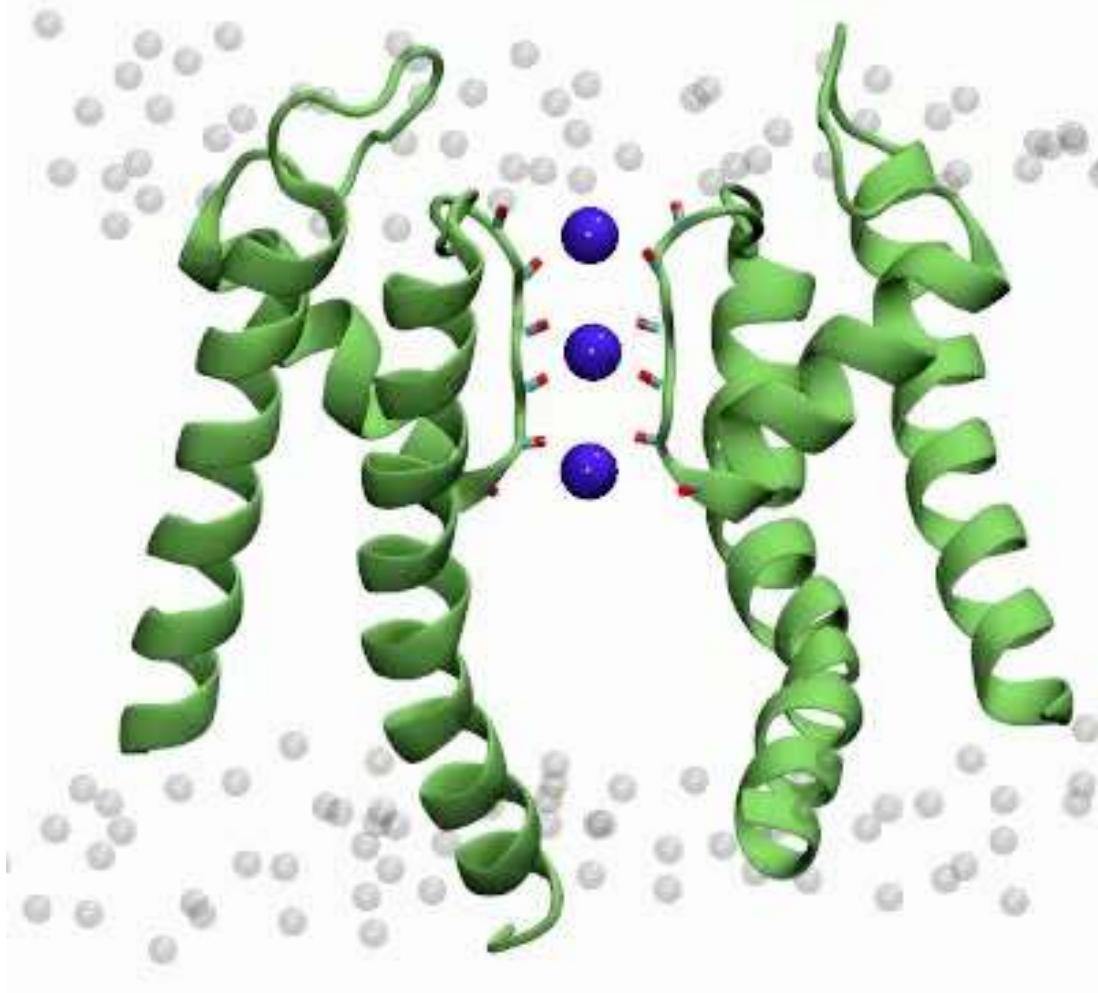


3 photons per picture suffice! (for REALLY many pictures)



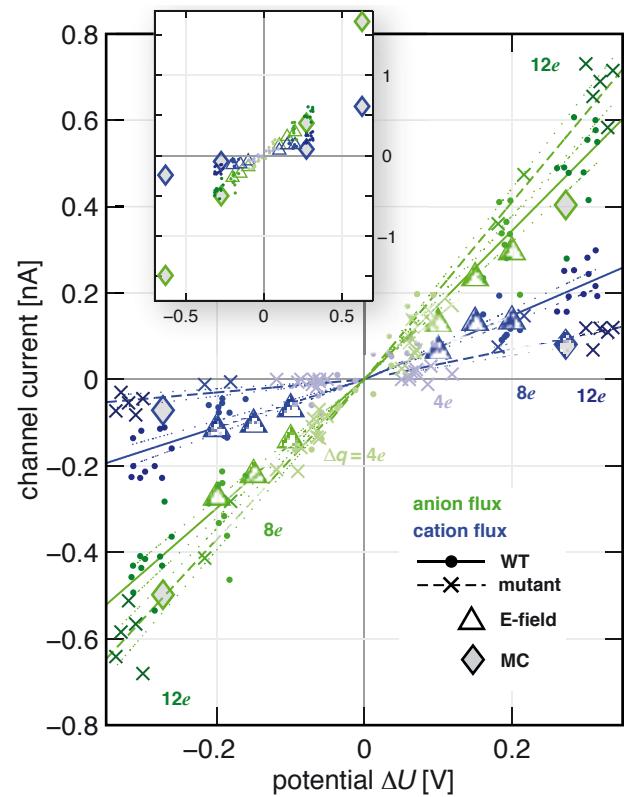
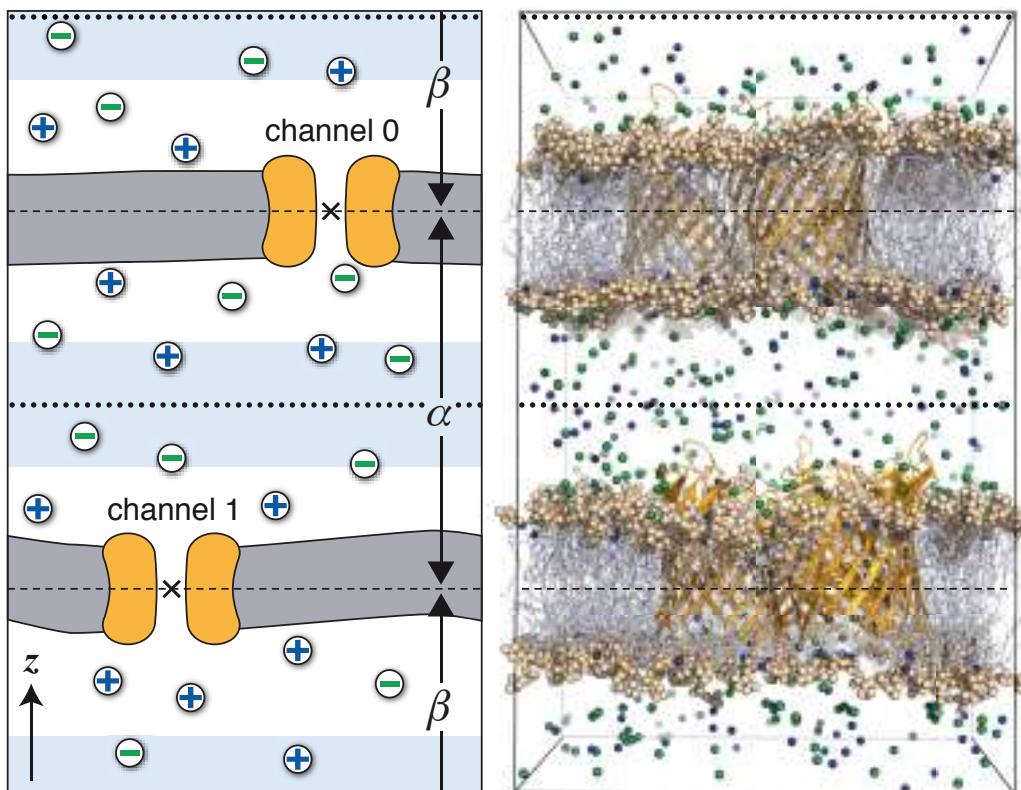
(simulated experiment)

Computational electrophysiology



Potassium channel

Computational electrophysiology

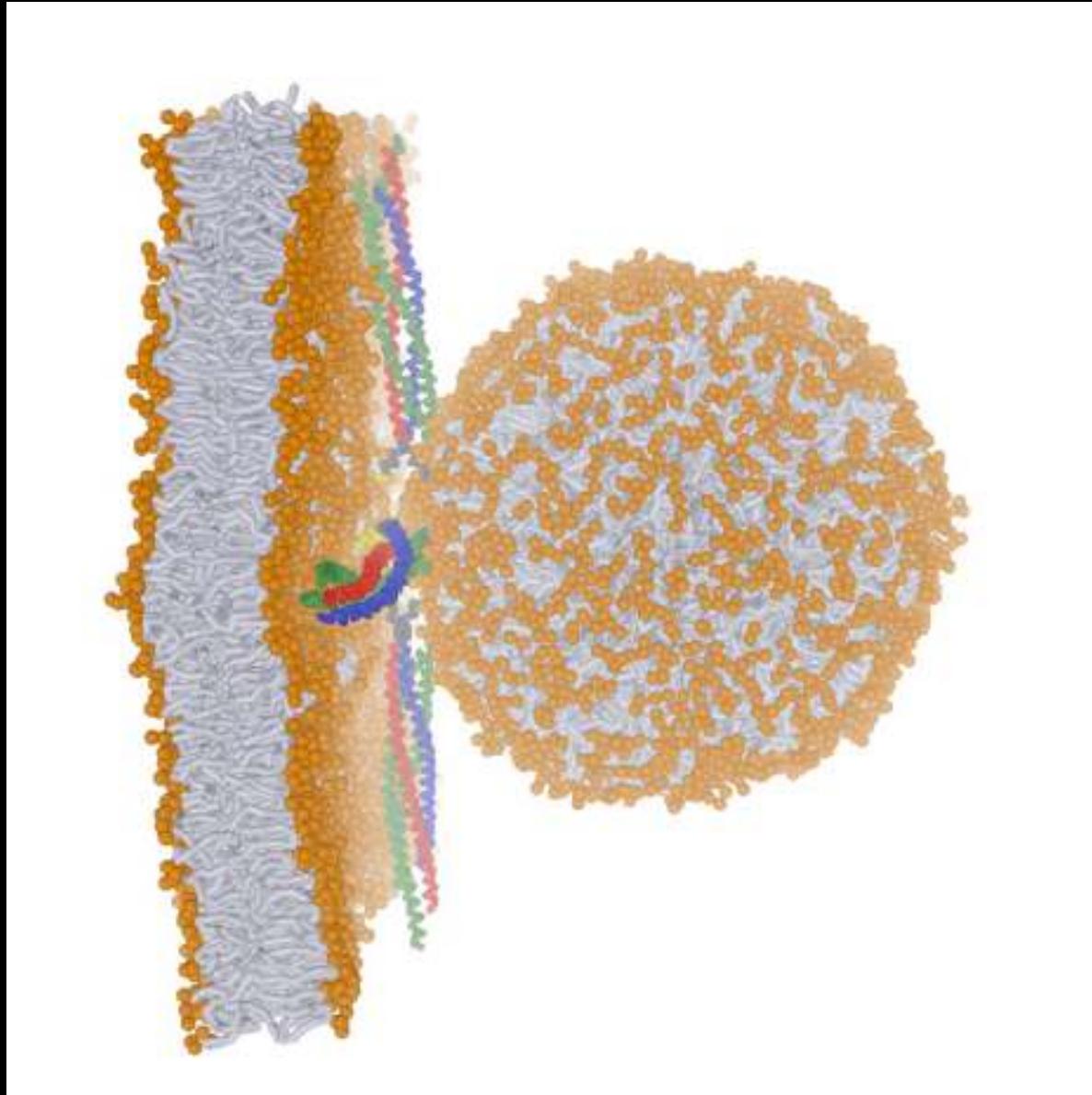
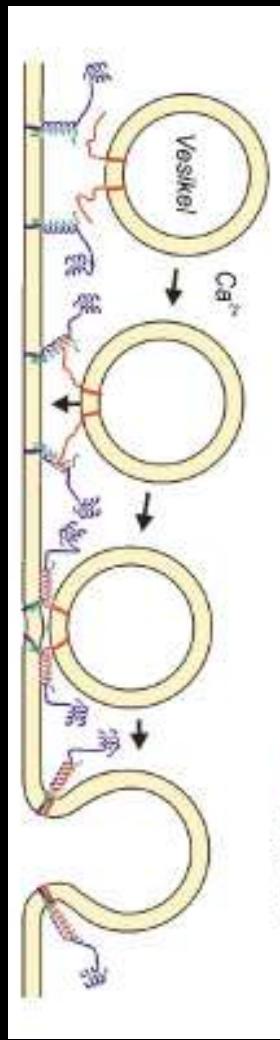
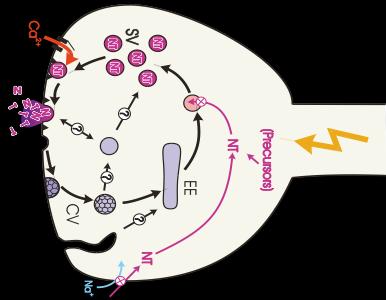


Ulrich
Zachariae

Carsten
Kutzner

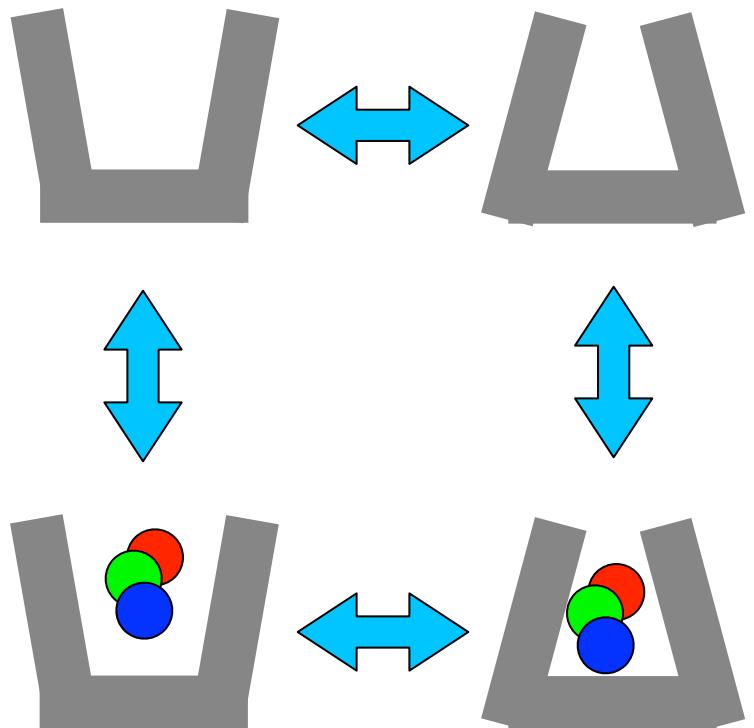
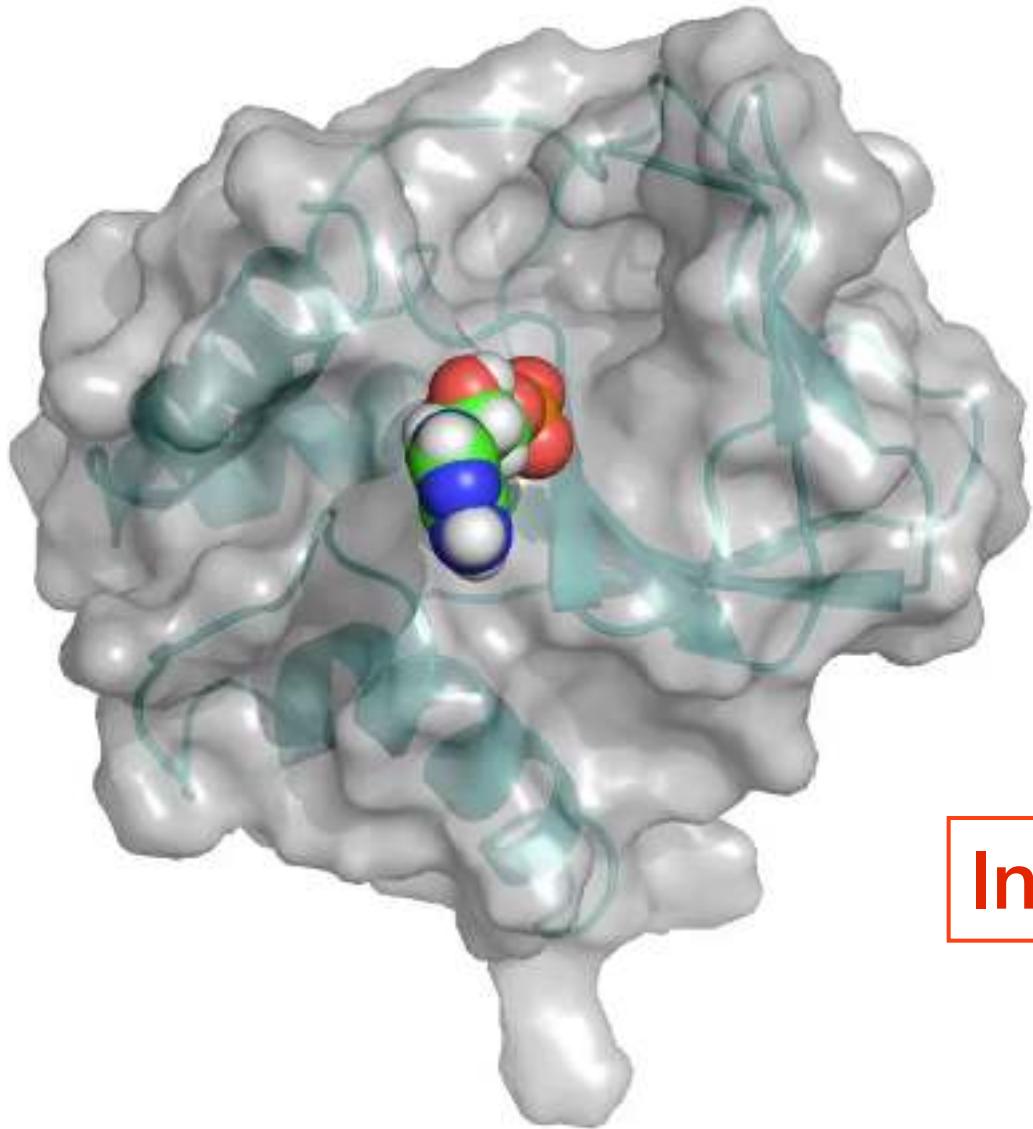
Bert
de Groot

Synaptic fusion



First principles docking: MloK1

Collab. Benjamin Kaupp



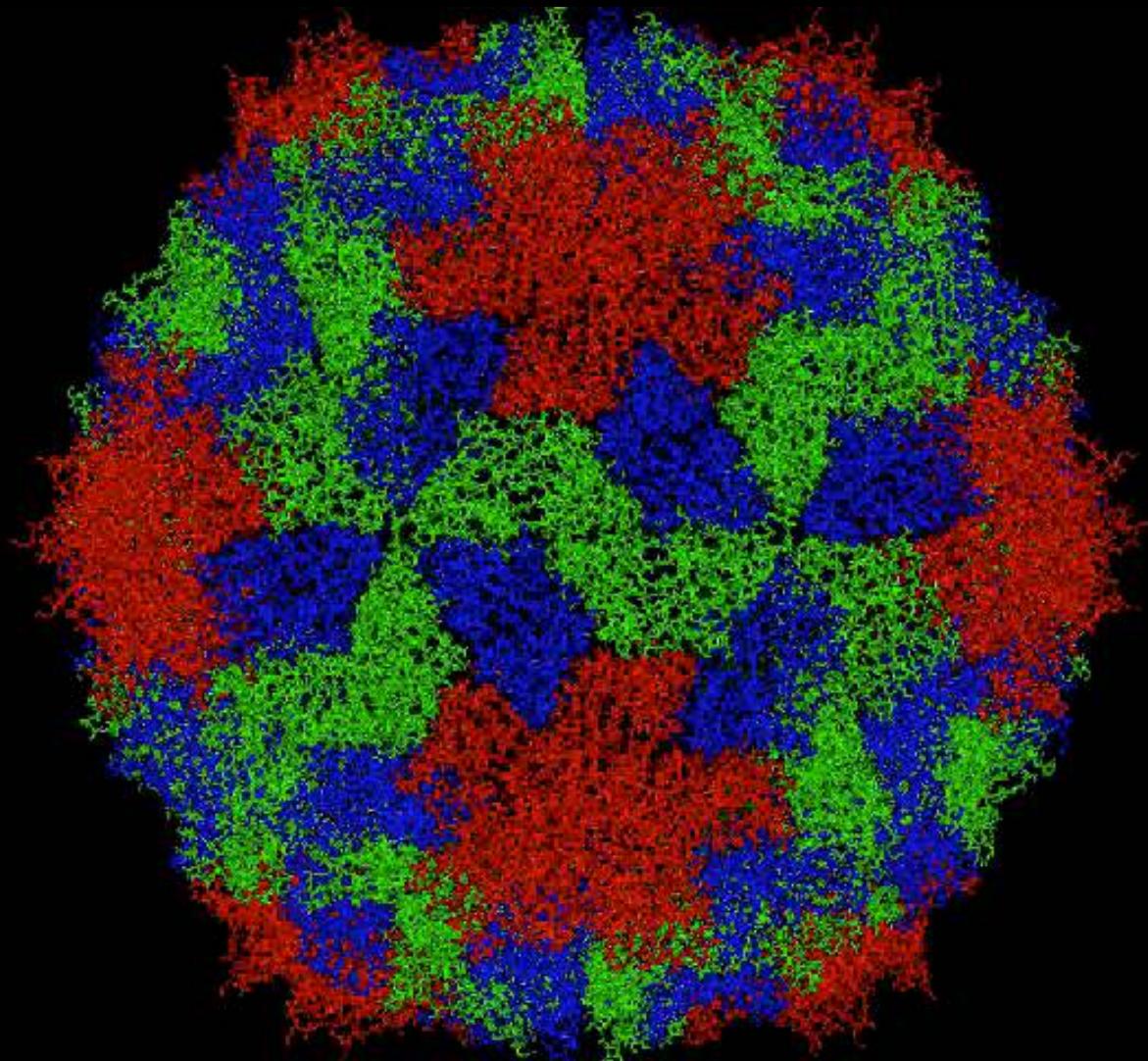
Induced Fit

MloK1 – a cyclic nucleotide modulated ion channel



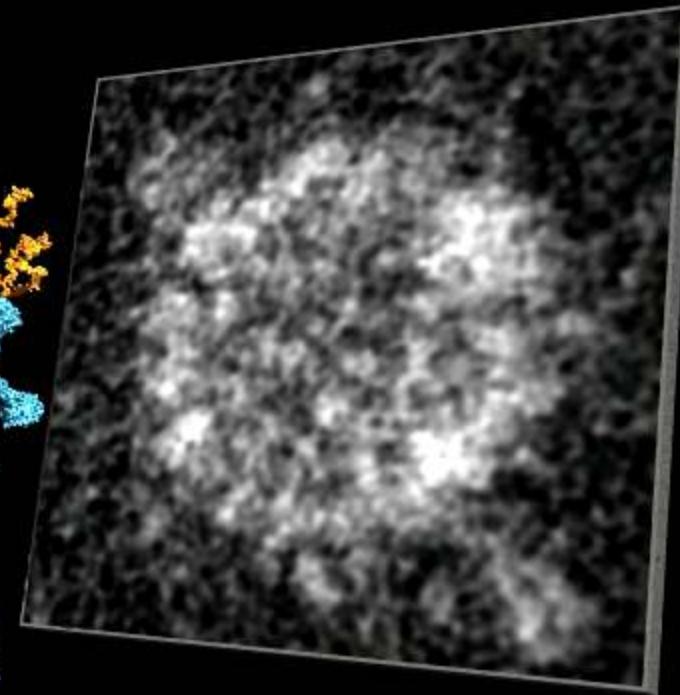
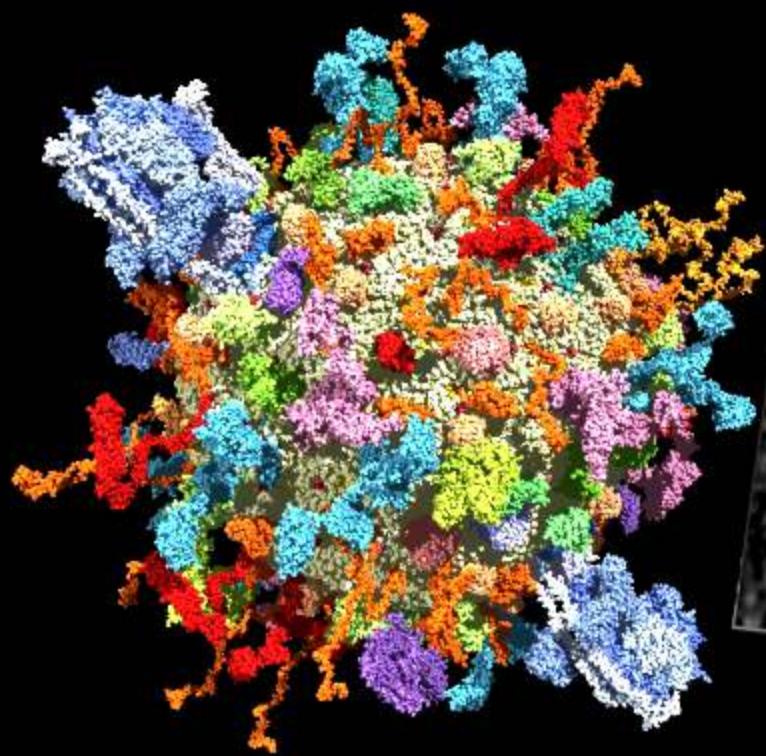
Bela Voss

Southern Bean Mosaic Virus – Mechanical Properties

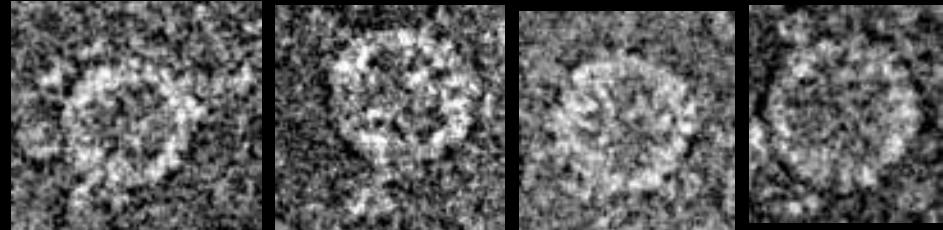


~4,500,000 particles

Anatomy of a Synaptic Vesicle



Simulated EM image



EM images by D. Riedel and R. Jahn

What have we learned ?

(1) AFM + force probe MD -> Overlap, 11 orders total

- Solved puzzle of too low AFM forces
- Unbinding free energy landscape, 3rd barrier
- Loading rate dependent unbinding paths

(2) Combined mechanism for erythromycin stalling:

- Perturbation of peptide conformation
- Perturbation of A-site crevice

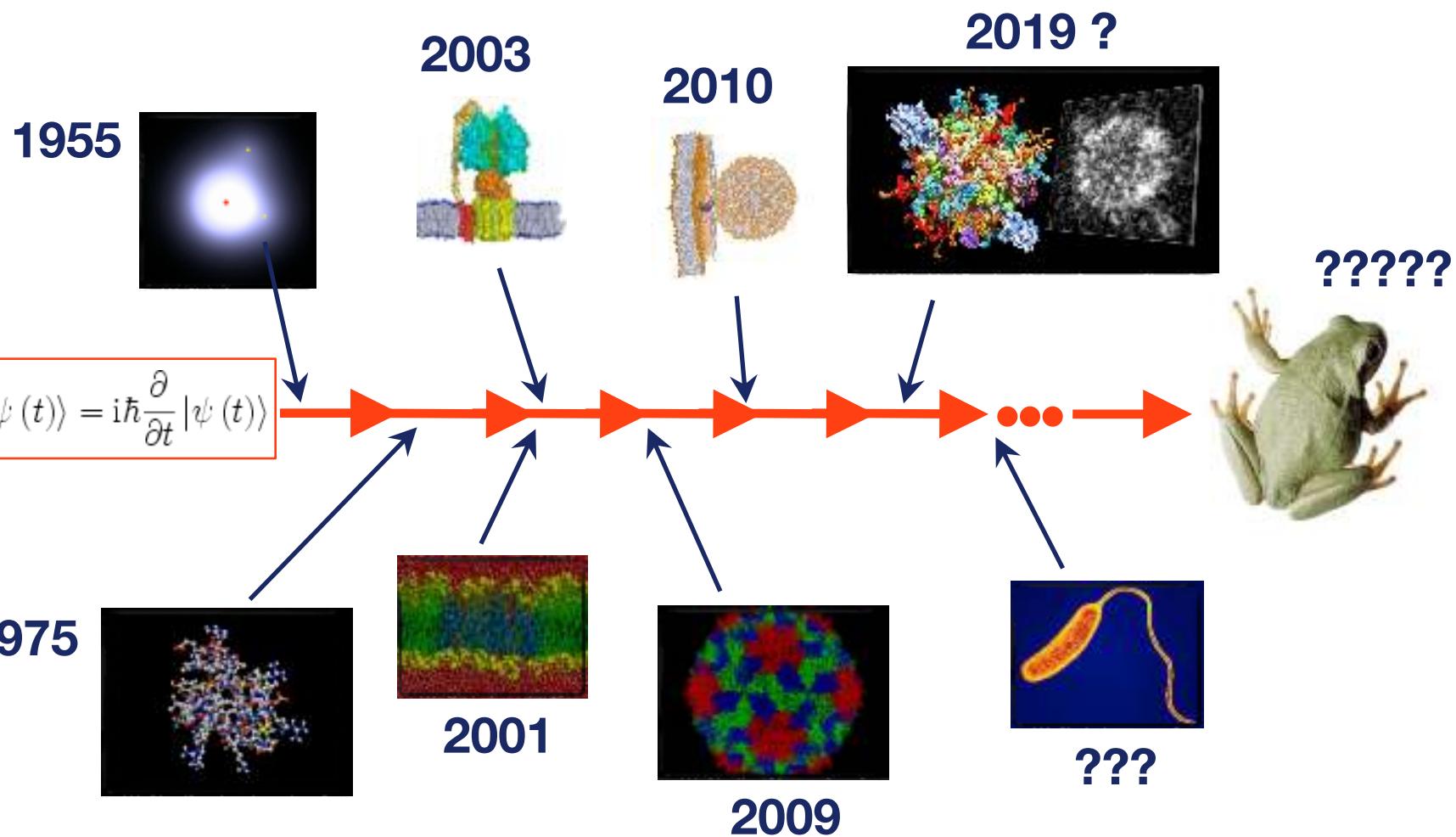
(3) Intrinsically disordered proteins:

- CHARMM36m
- First principles alpha-Synuclein ensemble

(4) The Dynosome:

Structure -> Dynamics -> Function

Towards a *fundamental understanding of life* processes from *first principles*





Positions available

ABCE1: A simpler prototypic ATPase motor domain

(collaboration: Robert Tampe, Univ. Frankfurt)

AKA: RLI, PIXIE (archaea/eukaryotes)

Translation termination:

Separation of ribosomal subunits

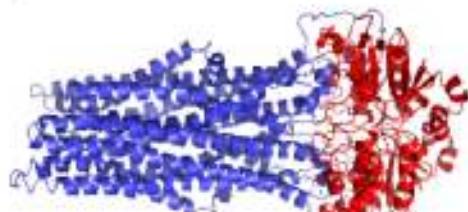
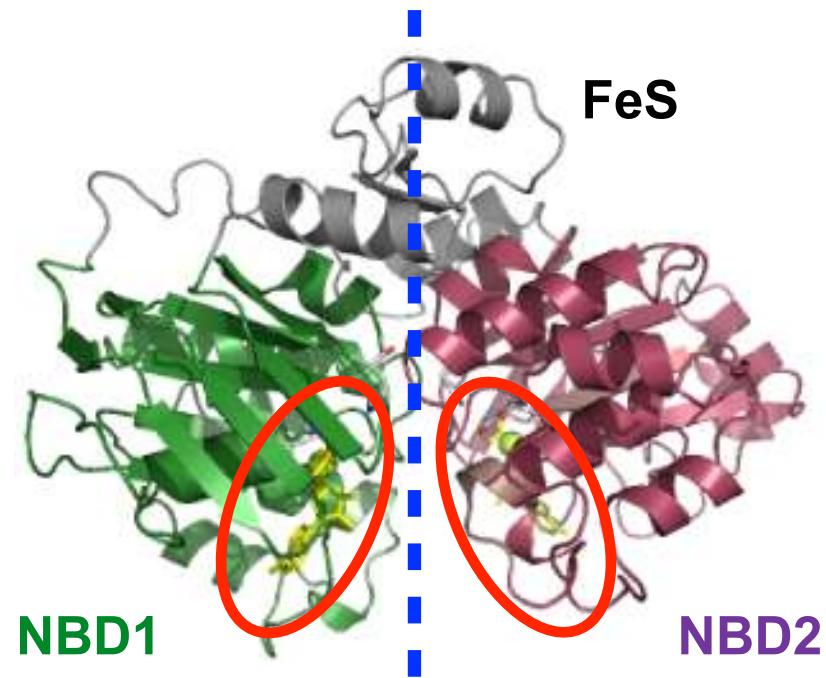
(Pisareva et al. EMBOJ, 2011)

Stall recovery

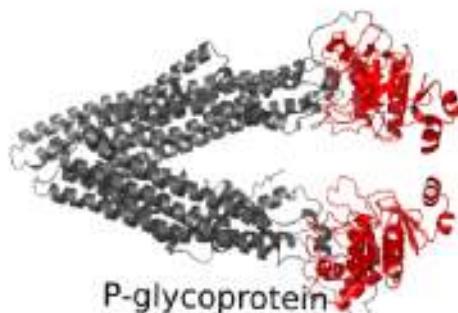
(Preis et al. CelRep, 2014)

Maybe translation initiation

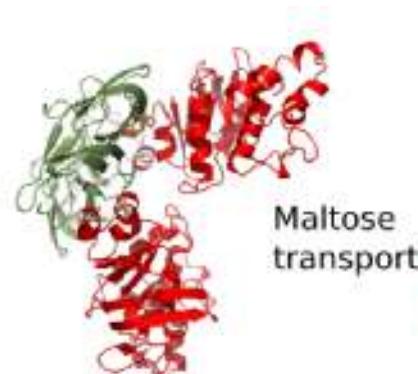
(Heuer et al. NSMB 2017)



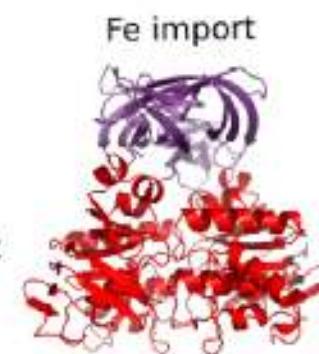
MDR (sav1866)



P-glycoprotein

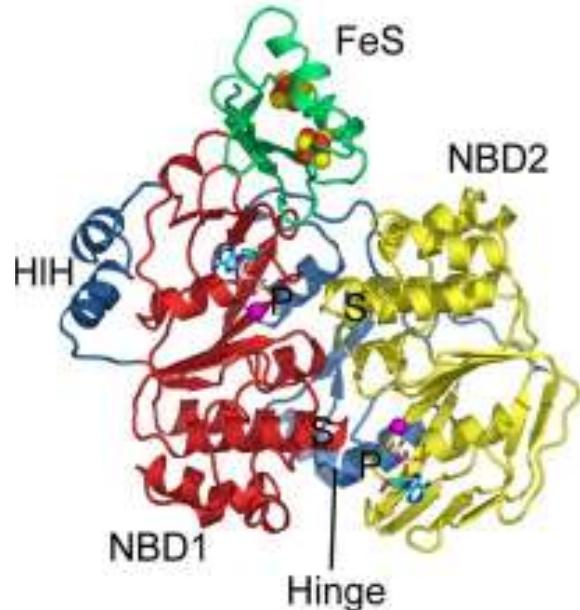


Maltose transport



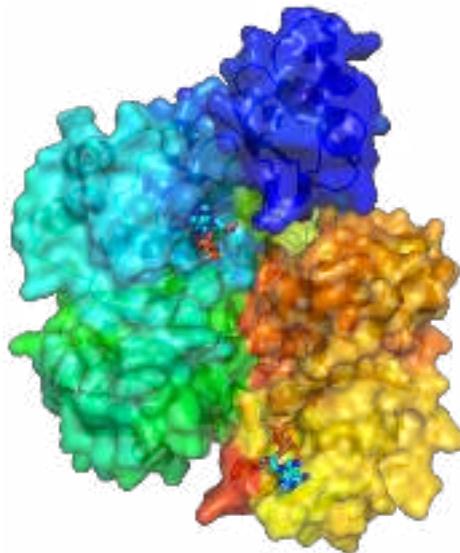
Fe import

ABCE1: Two nucleotide binding sites, open/closed



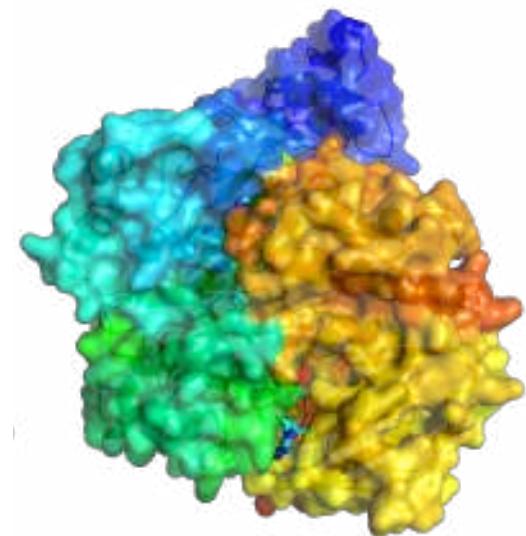
Annette Karcher et al. JBC 2008

OPEN



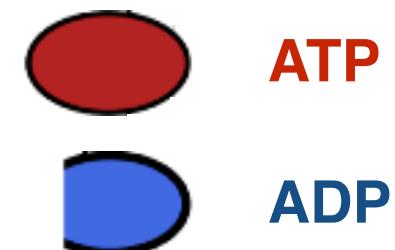
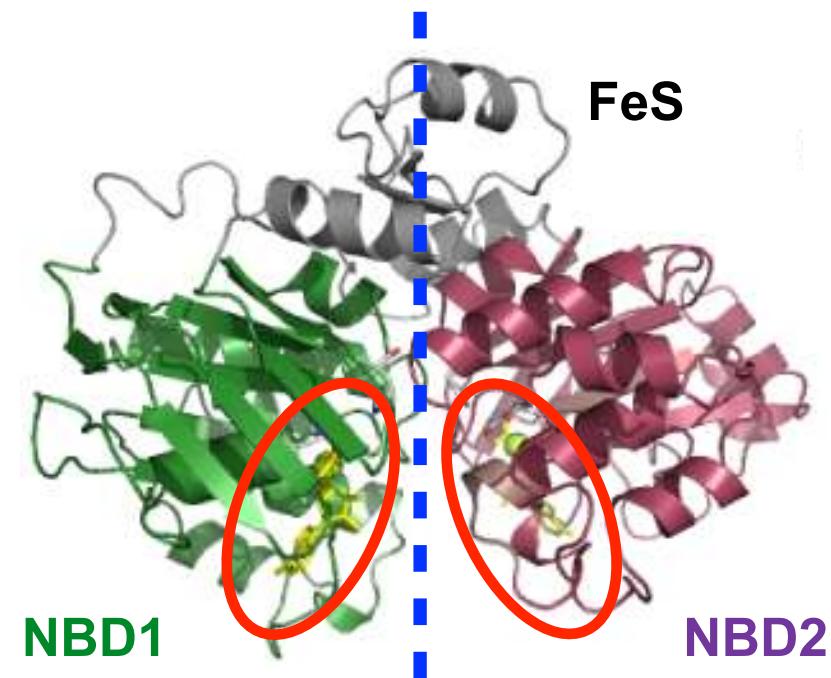
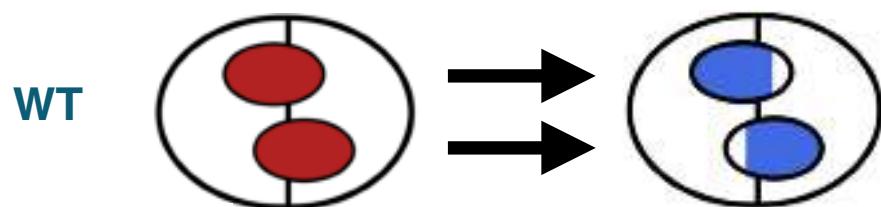
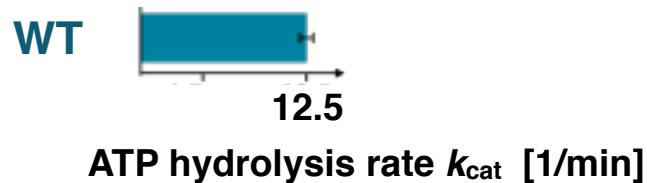
Karcher et al., J Biol
Chem, 2008

CLOSED

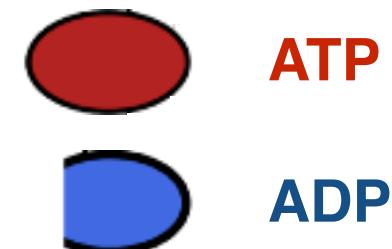
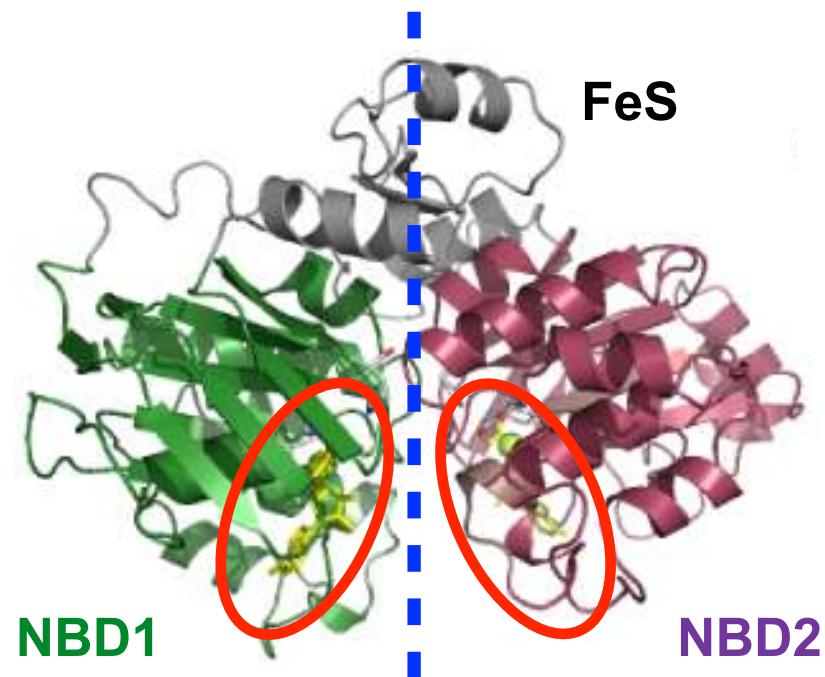
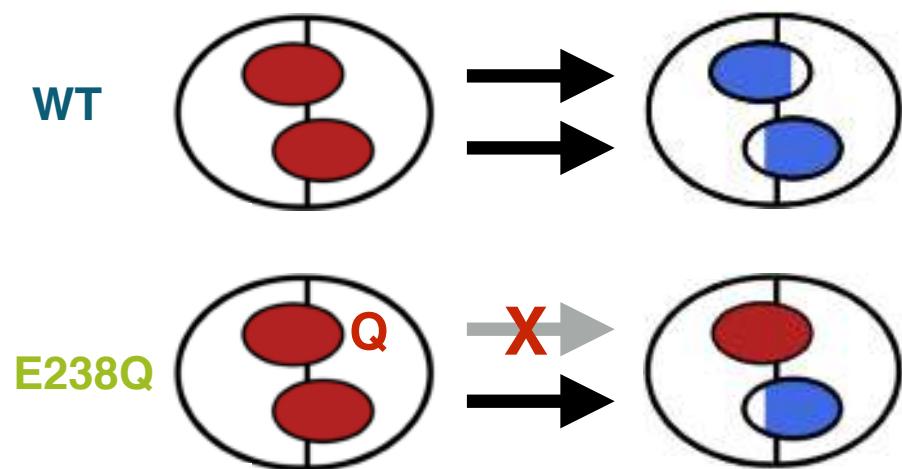
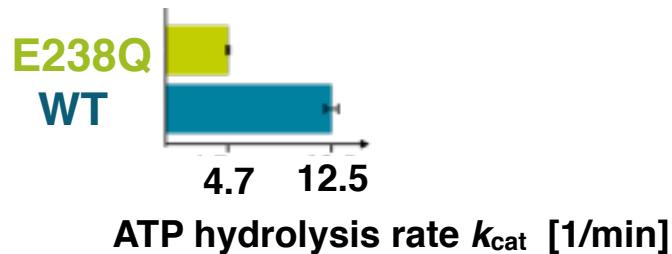


Heuer et al., Nat Struct Mol Biol, 2017

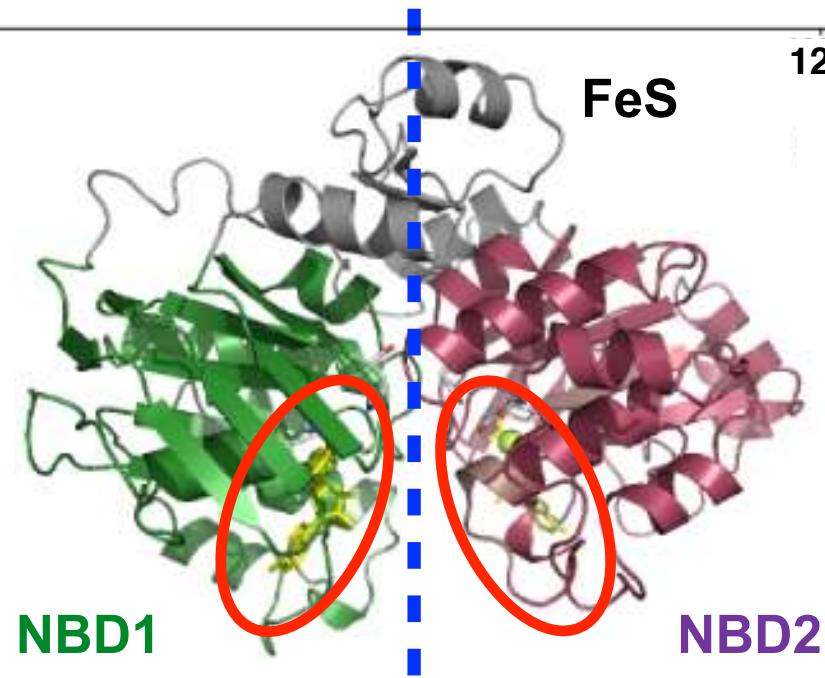
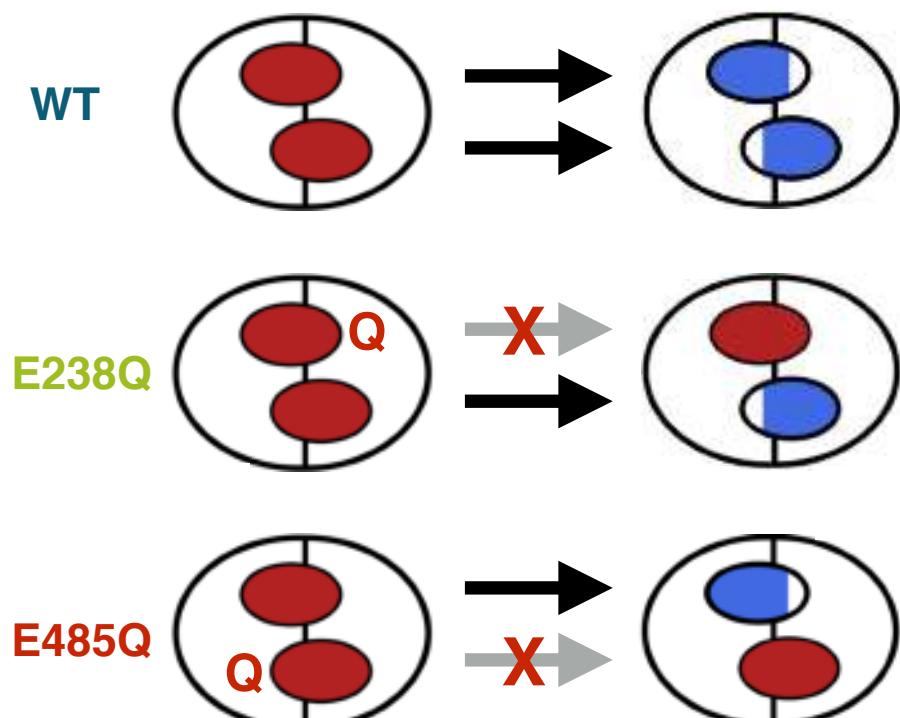
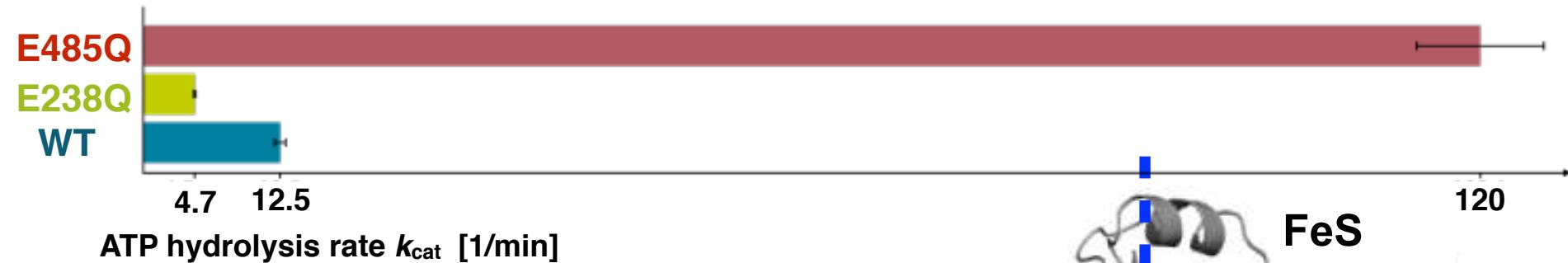
ABCE1: Both nucleotide binding sites hydrolise ATP



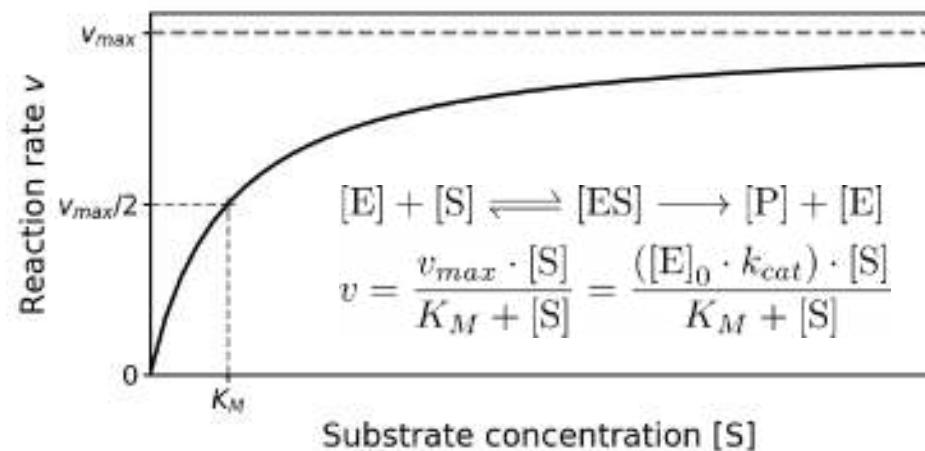
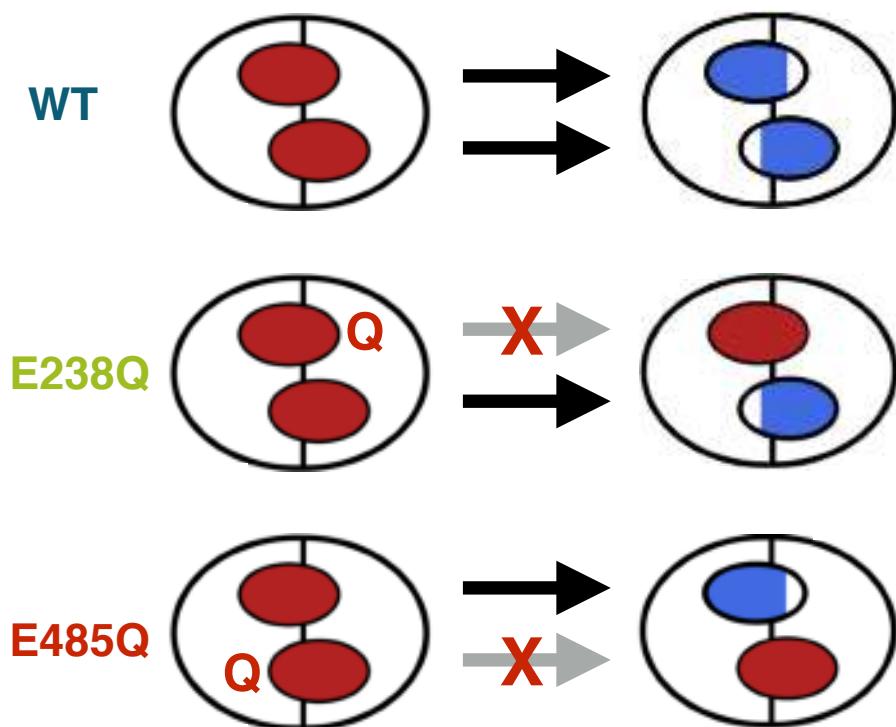
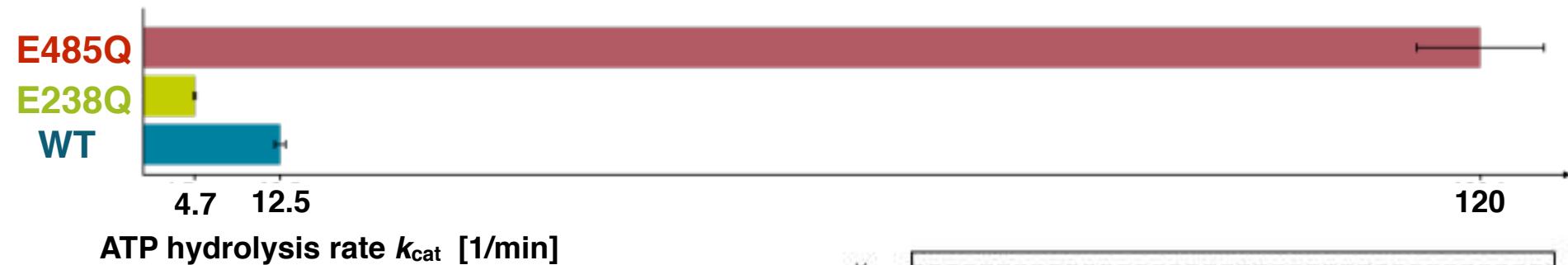
Block binding site 1: half hydrolysis rate



Block binding site 2: 10-fold hydrolysis rate!

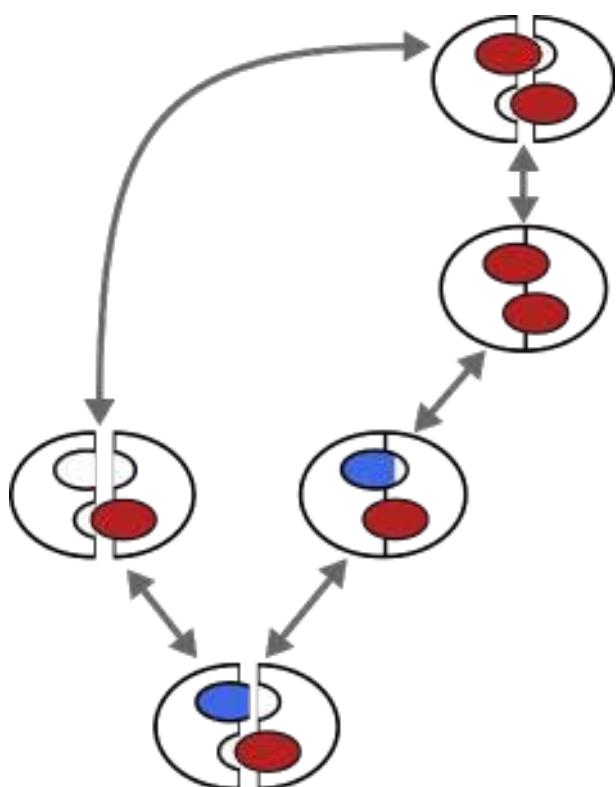


Measured k_{cat} and K_M (WT & 2 mutants)

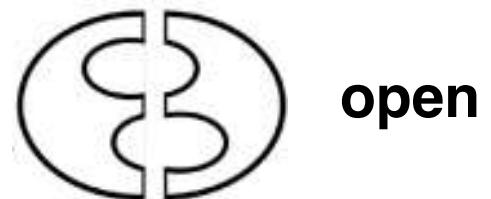


Protein	k_{cat} [min ⁻¹]	K_M [mM]
Wild type	12.5 ± 0.5	0.68 ± 0.05
E238Q	4.7 ± 0.1	0.20 ± 0.06
E485Q	122.1 ± 5.8	0.76 ± 0.12

ABCE1: A simple Markov State Model



Malte Schäffner



open



closed



ATP

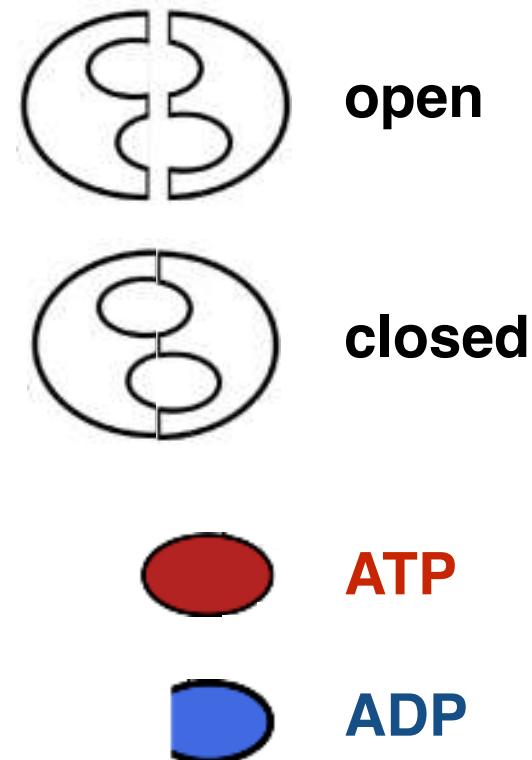
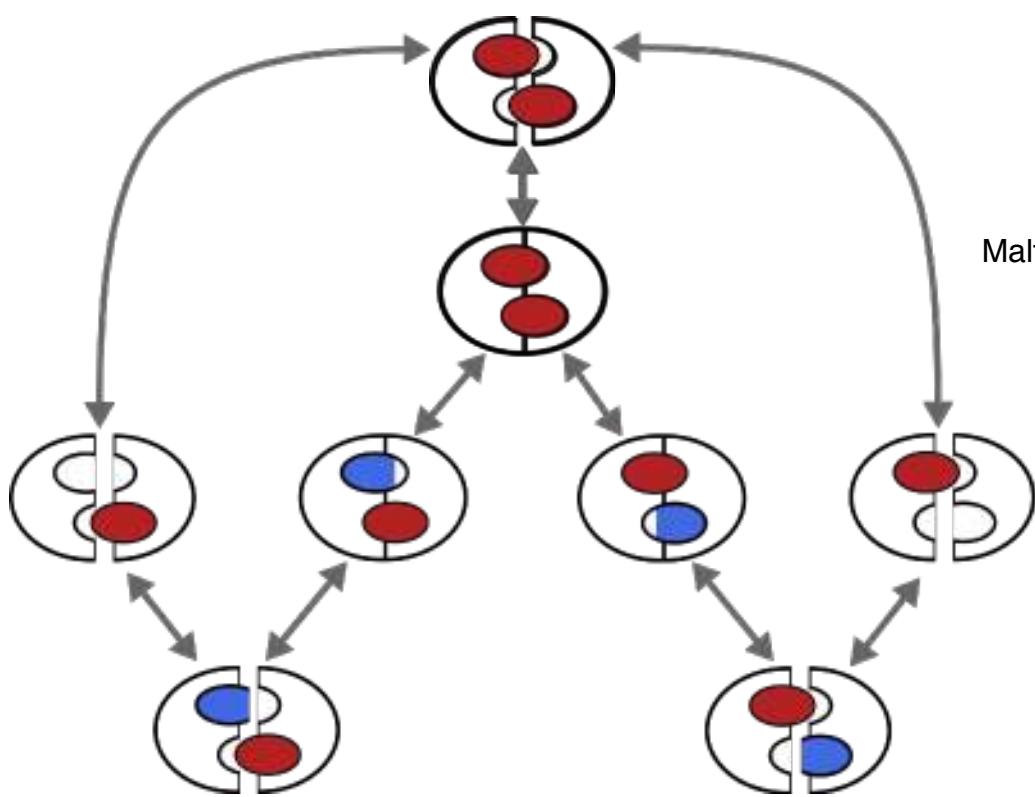


ADP

ABCE1: A simple Markov State Model



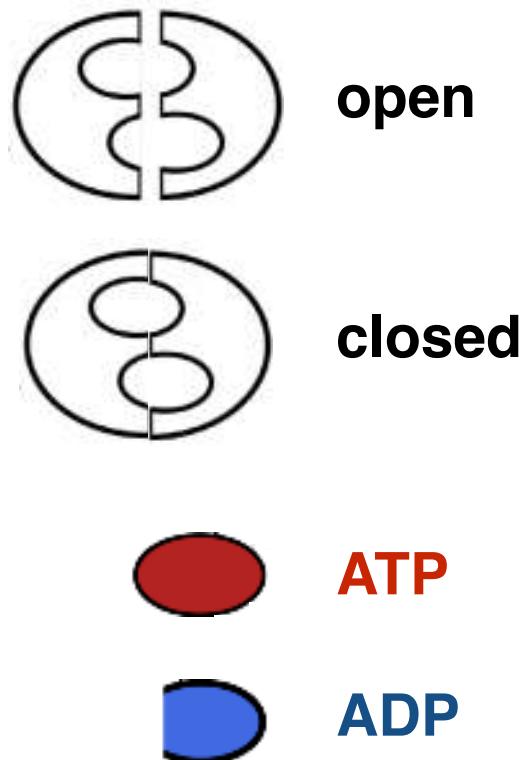
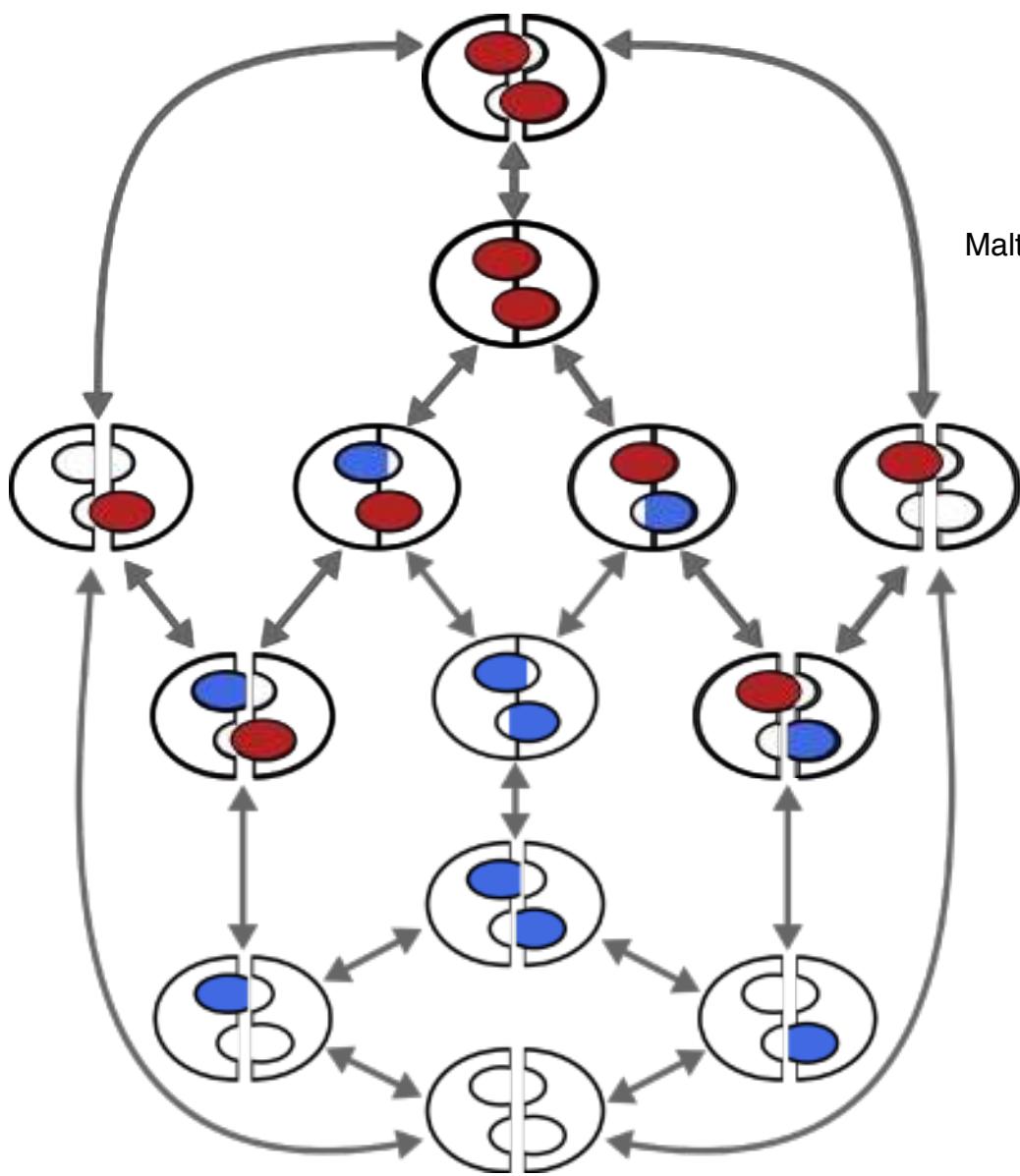
Malte Schäffner



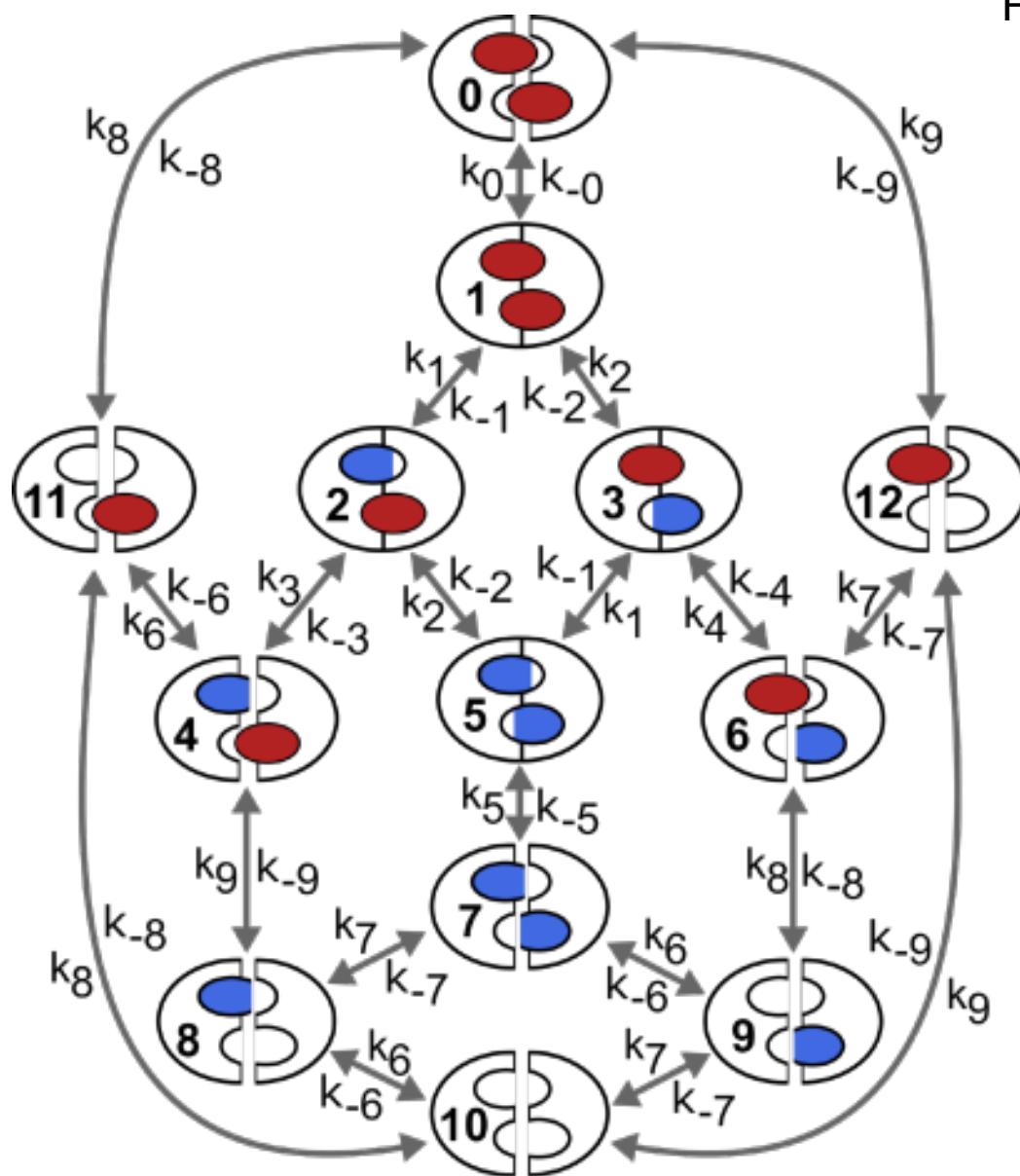
ABCE1: A simple Markov State Model



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ABCE1: 13 states , 30 independent rates $\{k_{ij}\}$



Rate coefficient Matrix \mathbf{M}

$$M_{ij} = k_{j \rightarrow i}$$

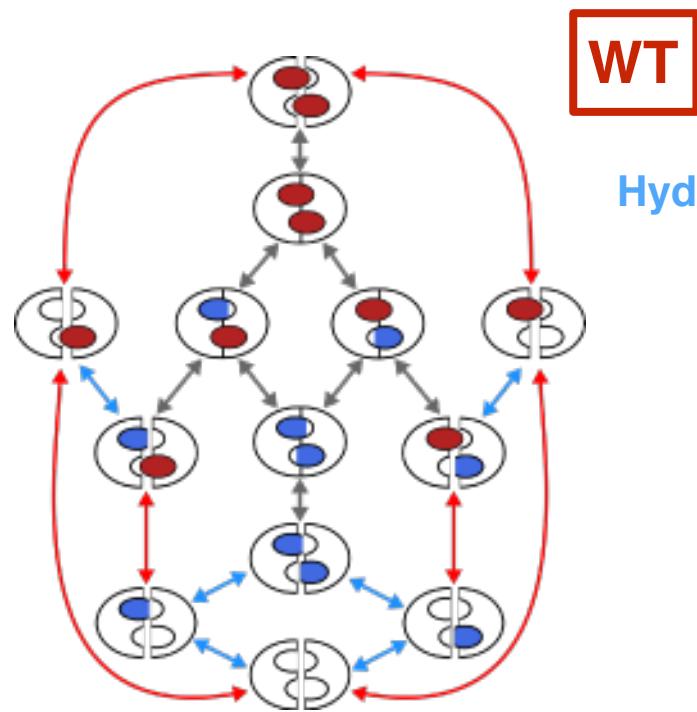
$$M_{ii} = - \sum k_{i \rightarrow j}$$

$$\mathbf{M} \cdot \mathbf{p} = \dot{\mathbf{p}}$$

Stationary state:

$$\mathbf{M} \cdot \hat{\mathbf{p}} = \mathbf{0}$$

Each set of 30 rates --> ATP hydrolysis rate



WT

Hydrolysis rates = Σ fluxes

Rate coefficient Matrix \mathbf{M}

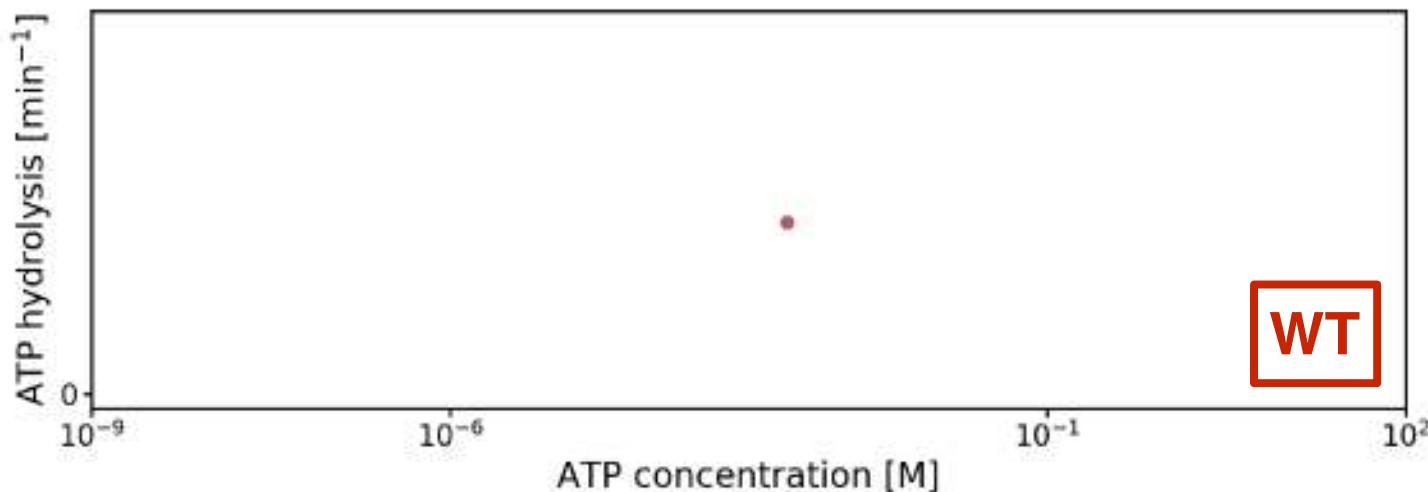
$$M_{ij} = k_{j \rightarrow i}$$

$$M_{ii} = - \sum k_{i \rightarrow j}$$

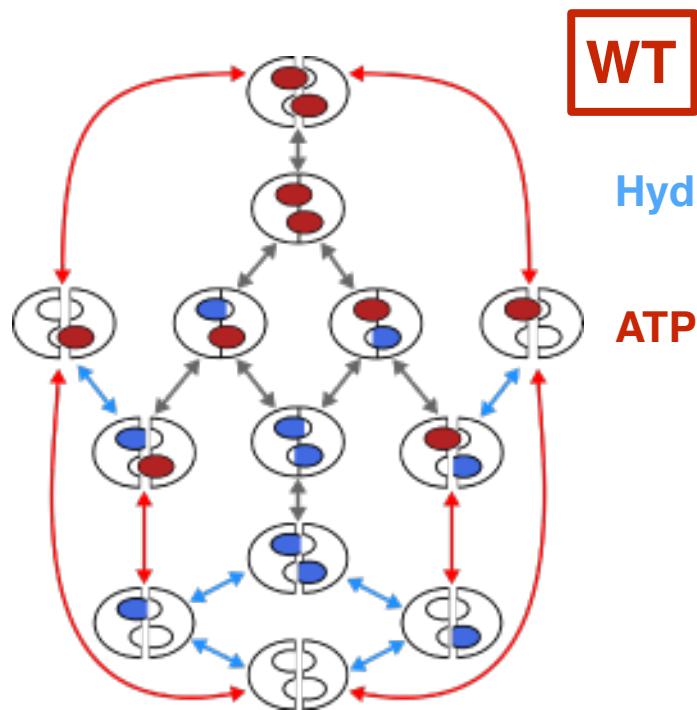
$$\mathbf{M} \cdot \mathbf{p} = \dot{\mathbf{p}}$$

Stationary state:

$$\mathbf{M} \cdot \hat{\mathbf{p}} = \mathbf{0}$$



Vary ATP concentration --> k_{cat} and K_M



Rate coefficient Matrix \mathbf{M}

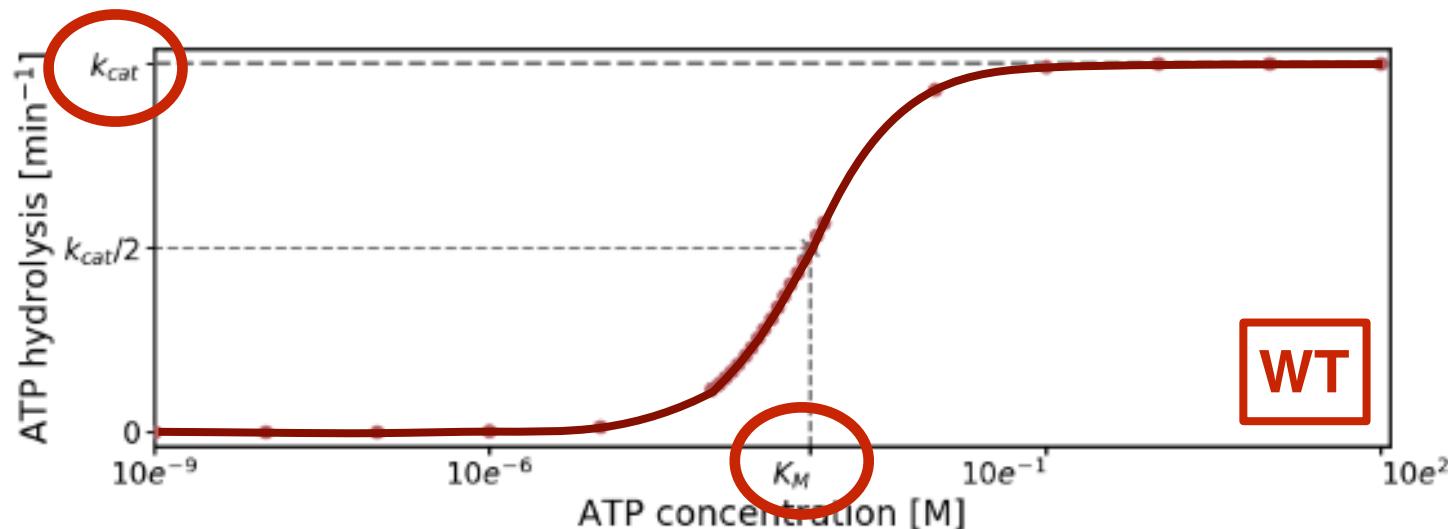
$$M_{ij} = k_{j \rightarrow i}$$

$$M_{ii} = - \sum k_{i \rightarrow j}$$

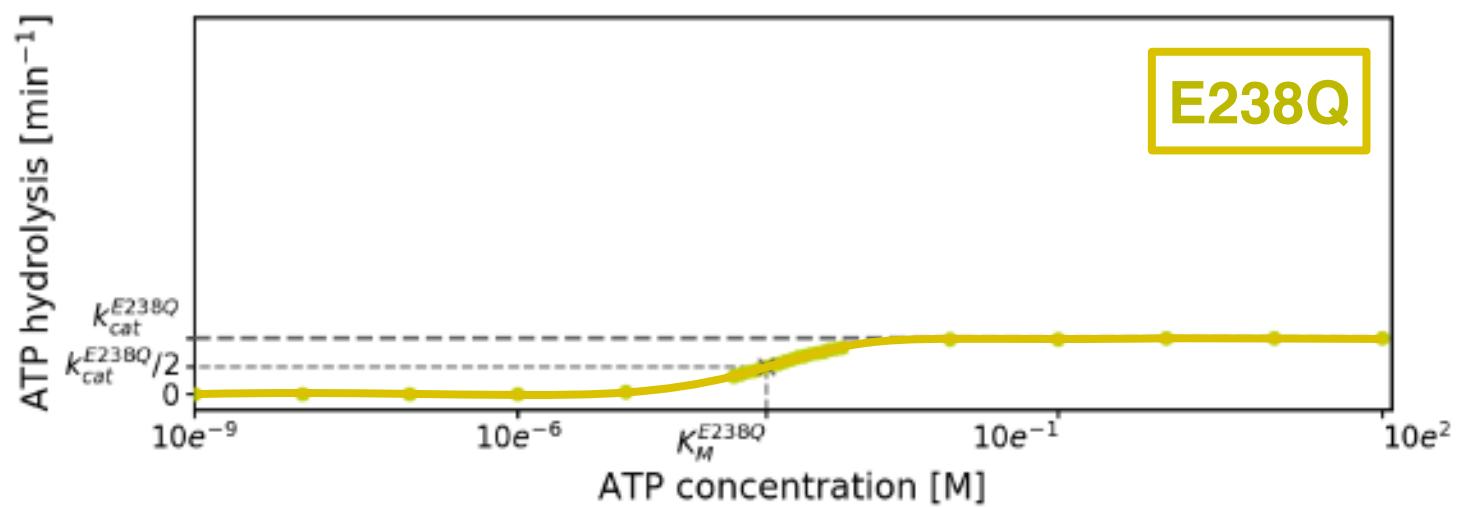
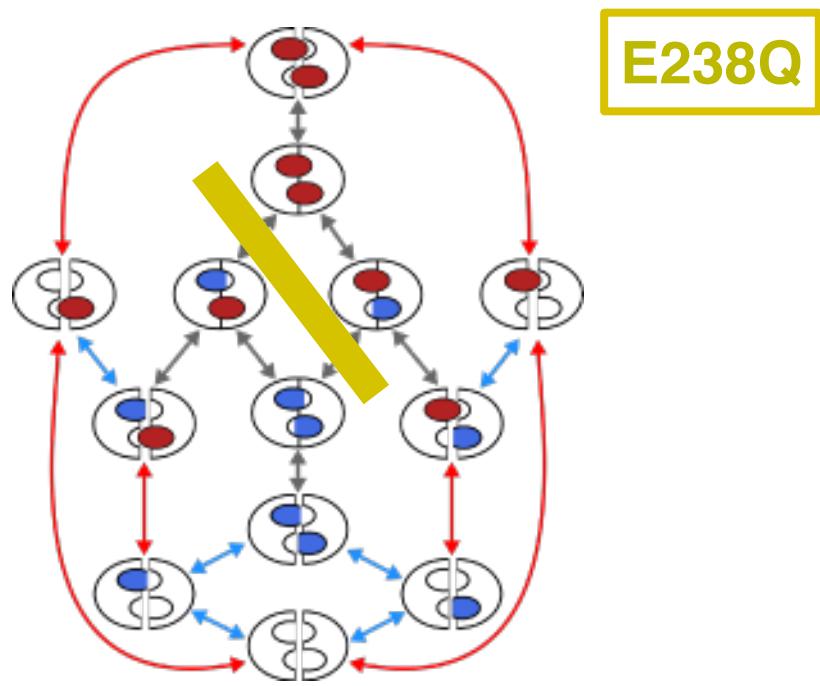
$$\mathbf{M} \cdot \mathbf{p} = \dot{\mathbf{p}}$$

Stationary state:

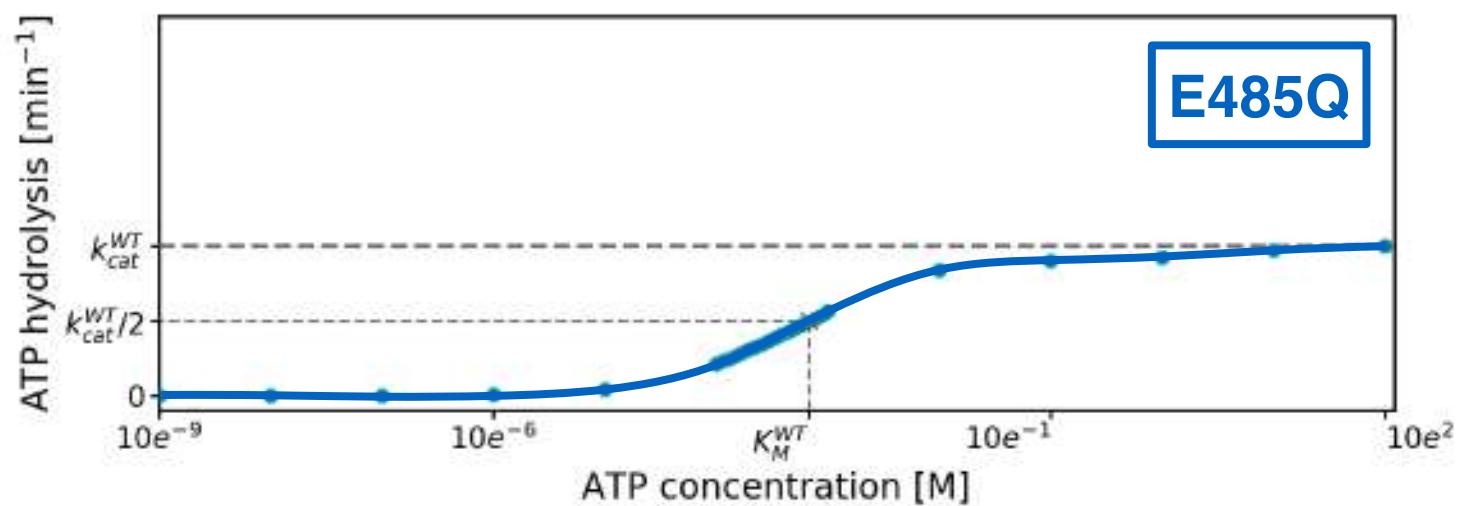
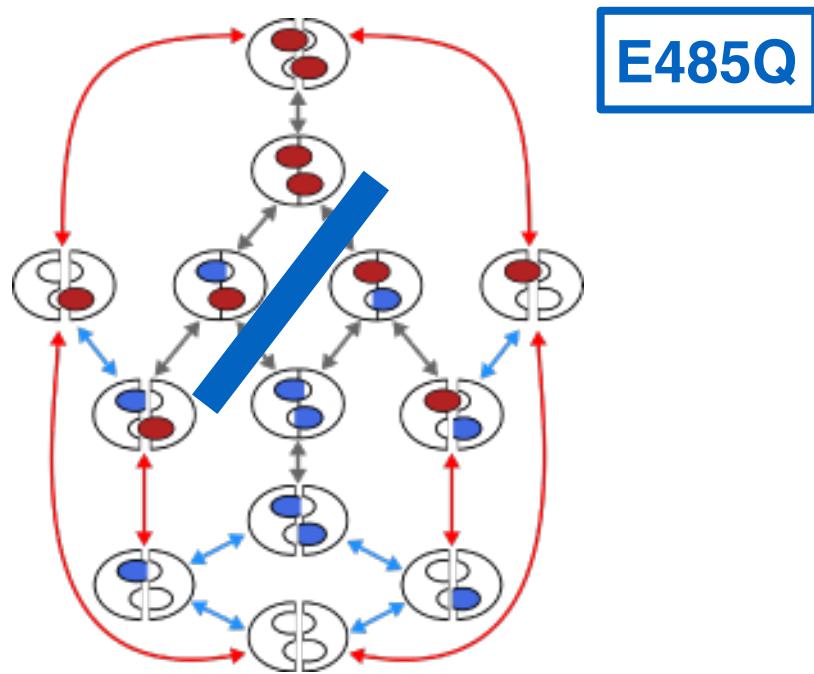
$$\mathbf{M} \cdot \hat{\mathbf{p}} = \mathbf{0}$$



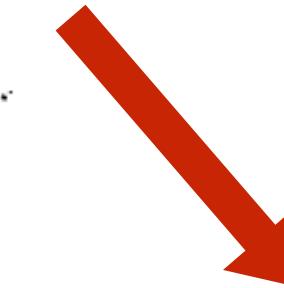
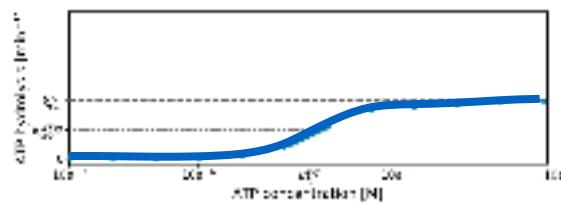
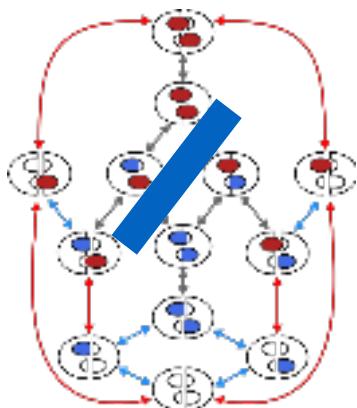
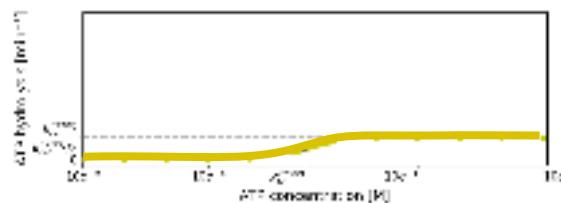
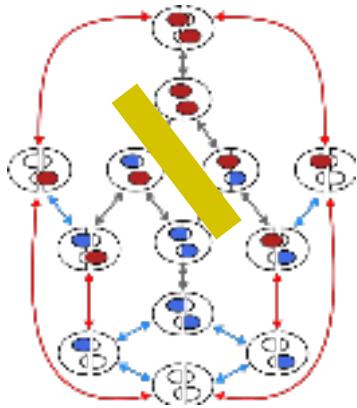
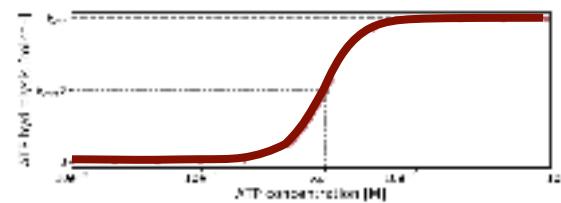
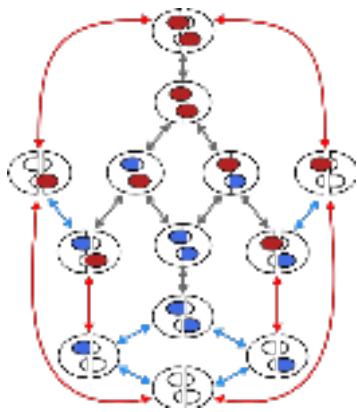
Block binding site 1 $\rightarrow k_{\text{cat}}$ and K_M for E238Q



Block binding site 2 $\rightarrow k_{\text{cat}}$ and K_M for E485Q



Compare $3 \times k_{\text{cat}}$ and K_M to experiment $\rightarrow p(\{k_{ij}\} \mid \{k_{\text{cat}}, K_M\})$

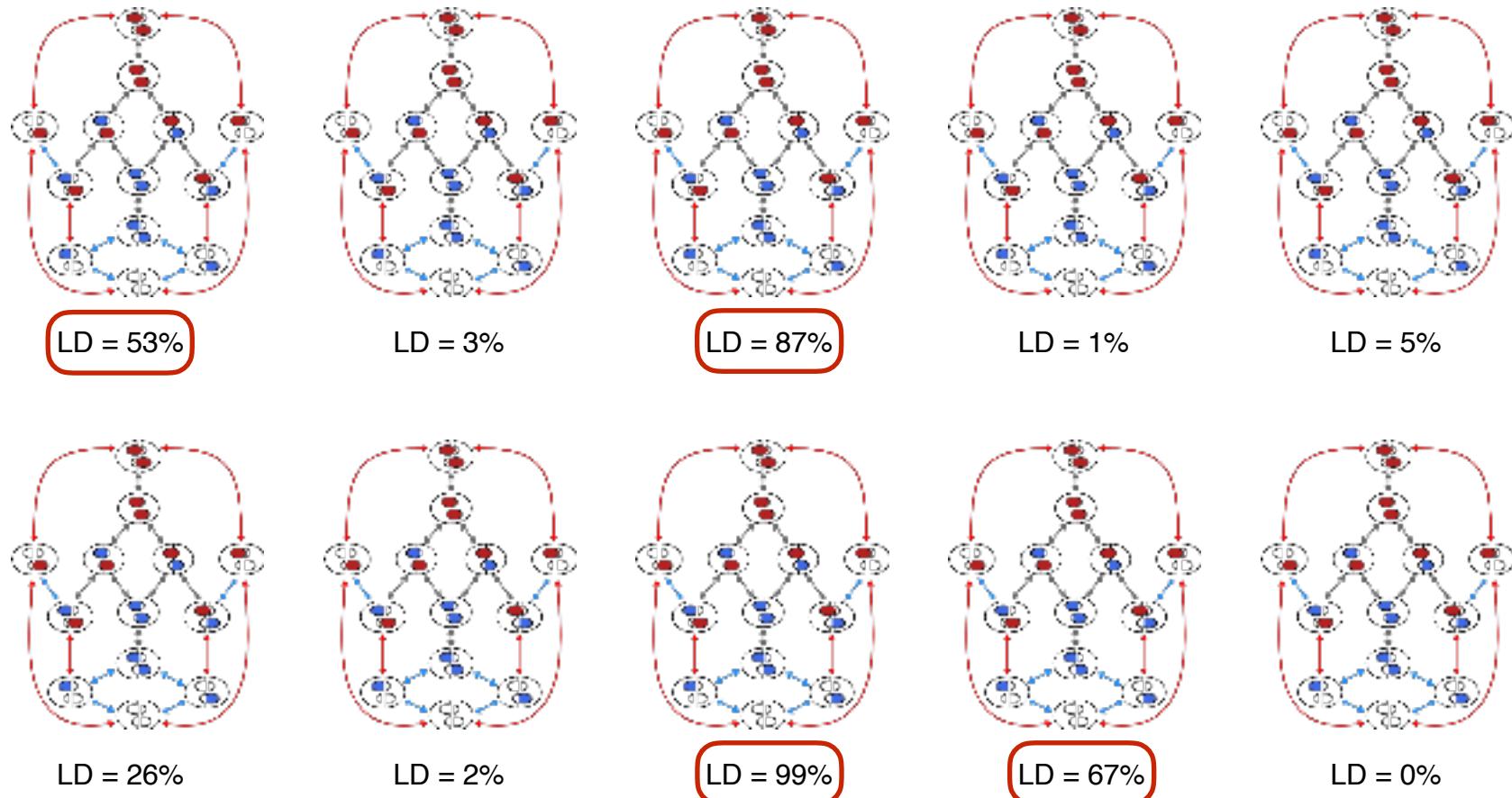


$$LD := \sqrt{\sum_i \left(\log \frac{k p_{\text{sim}i}}{k p_{\text{exp}i}} \right)^2}$$



Malte Schäffner (unpublished)

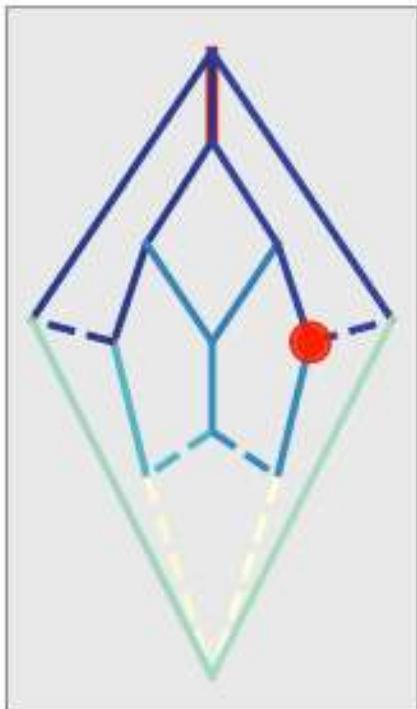
Exhaustive sampling of Markov models $\{k_{ij}\}$



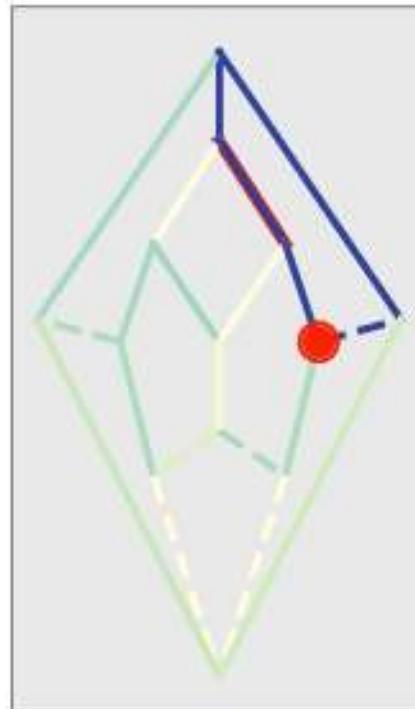
--> 10,000,000 sets of rate coefficients, enhanced sampling

Markov Models $\{k_{ij}\}$ that agree best with experiment

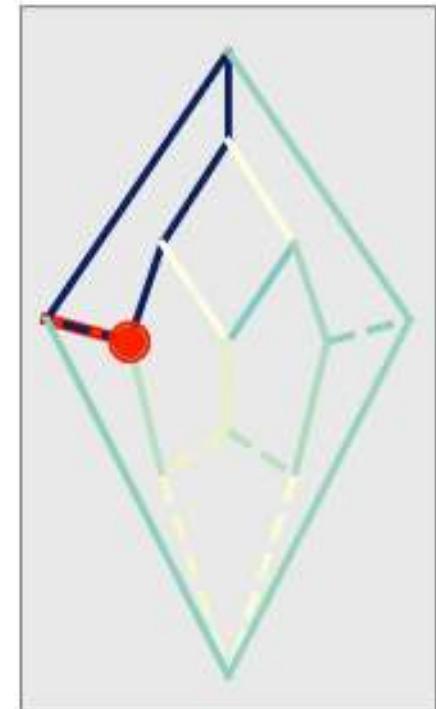
Wild type



E238Q



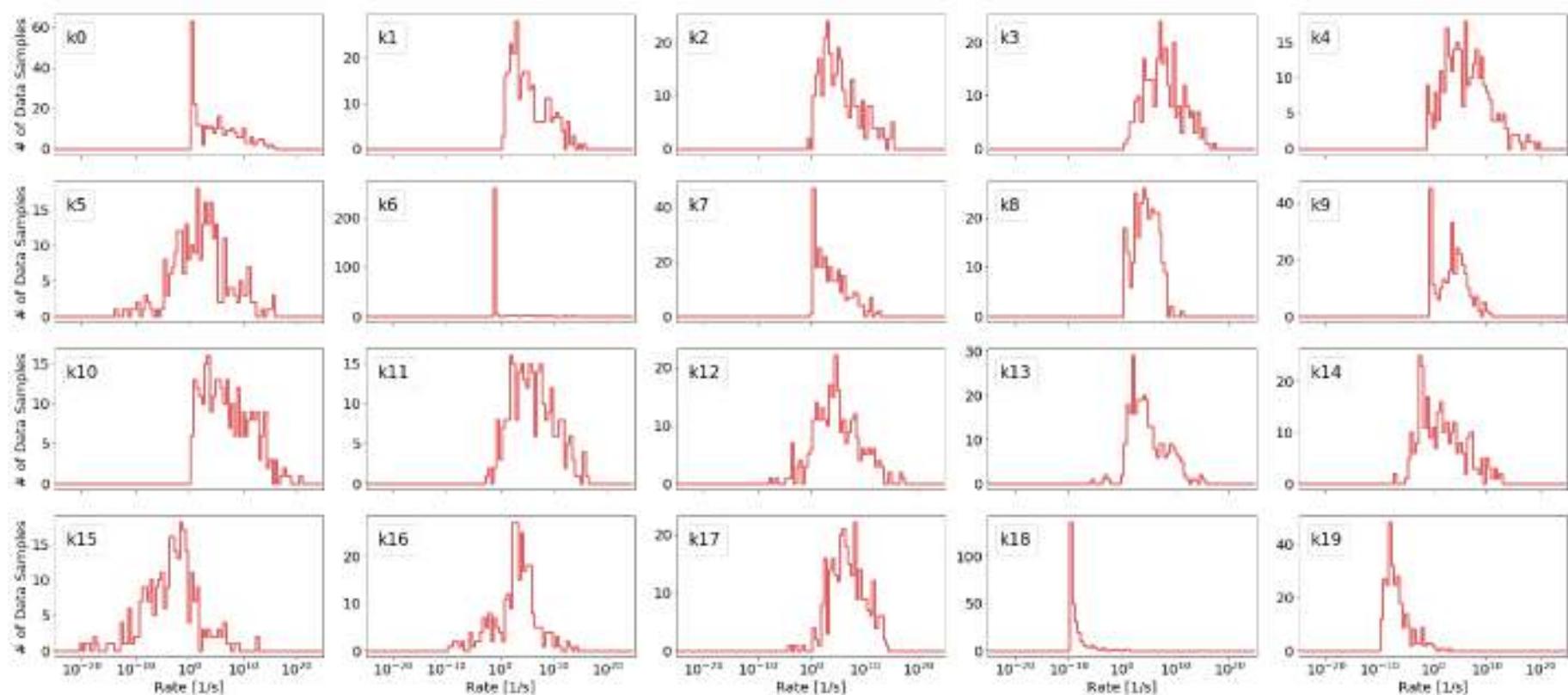
E485Q



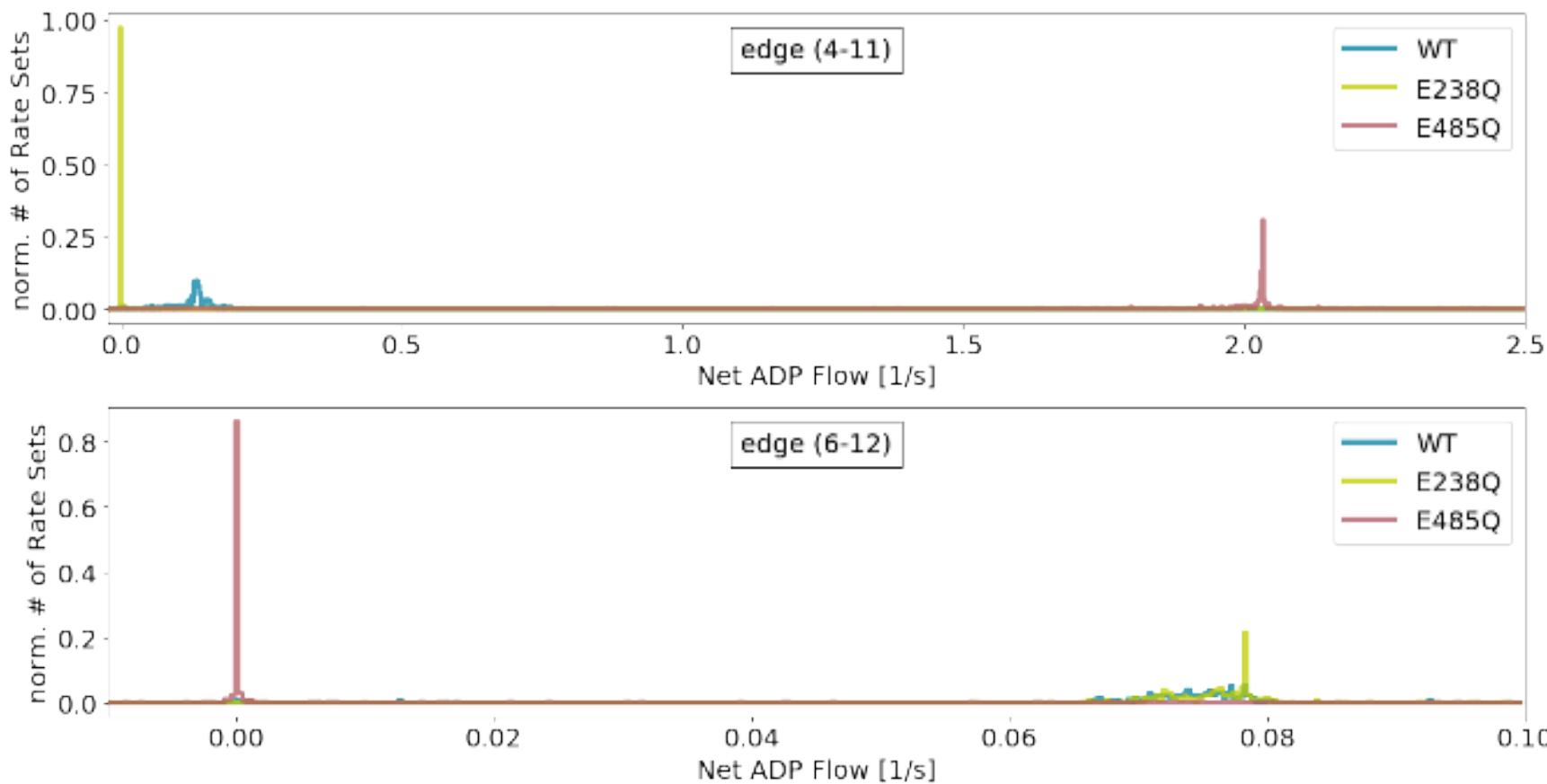
flux: *low* *high*
red: *bottleneck*

--> 10,000,000 sets of rate coefficients,
enhanced sampling

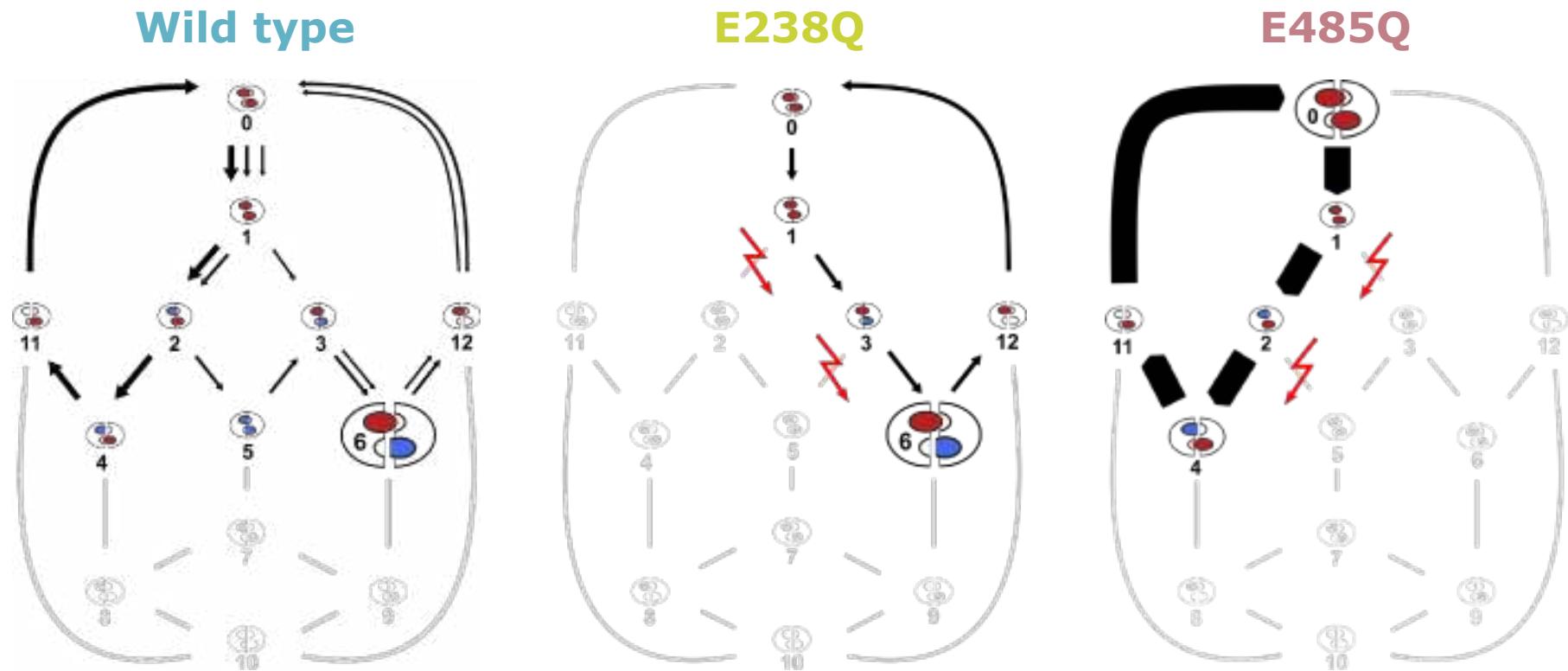
Broad distributions of rate coefficients



Narrow distributions of fluxes



ABCE1 Consensus Kinetic Model



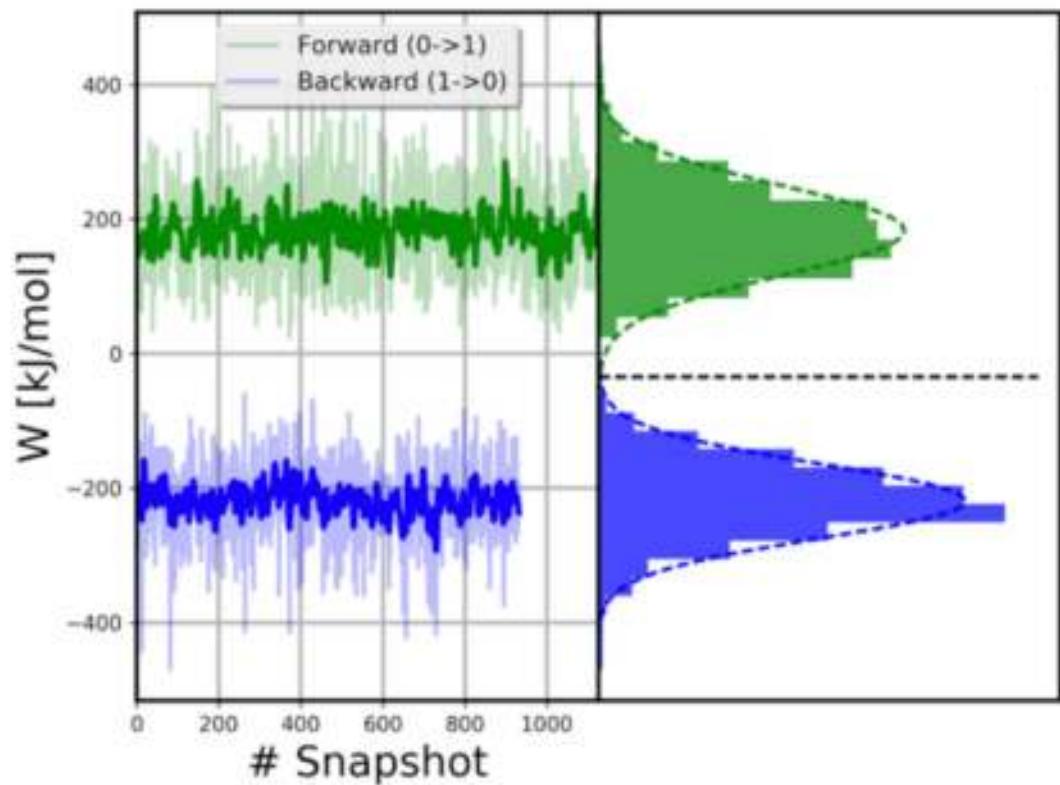
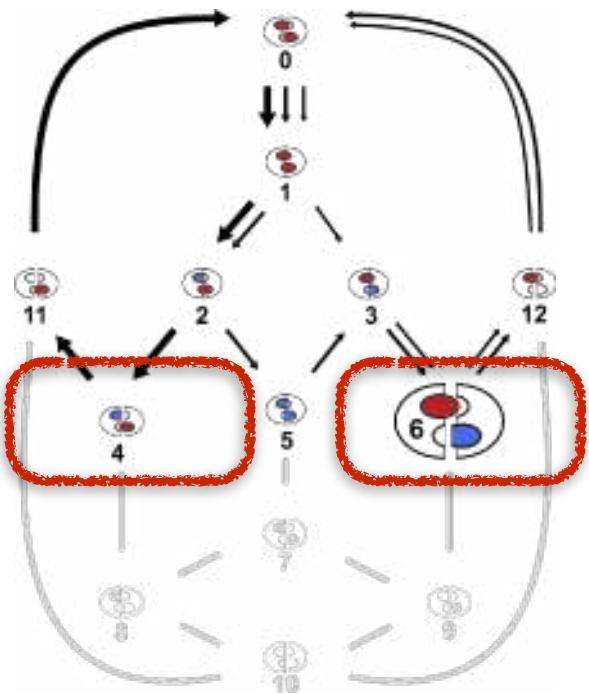
Line thickness: Flux

Symbol size: Population

Malte Schäffner (unpublished)

Prediction: Free energy difference (MD / Crooks NE-sampling)

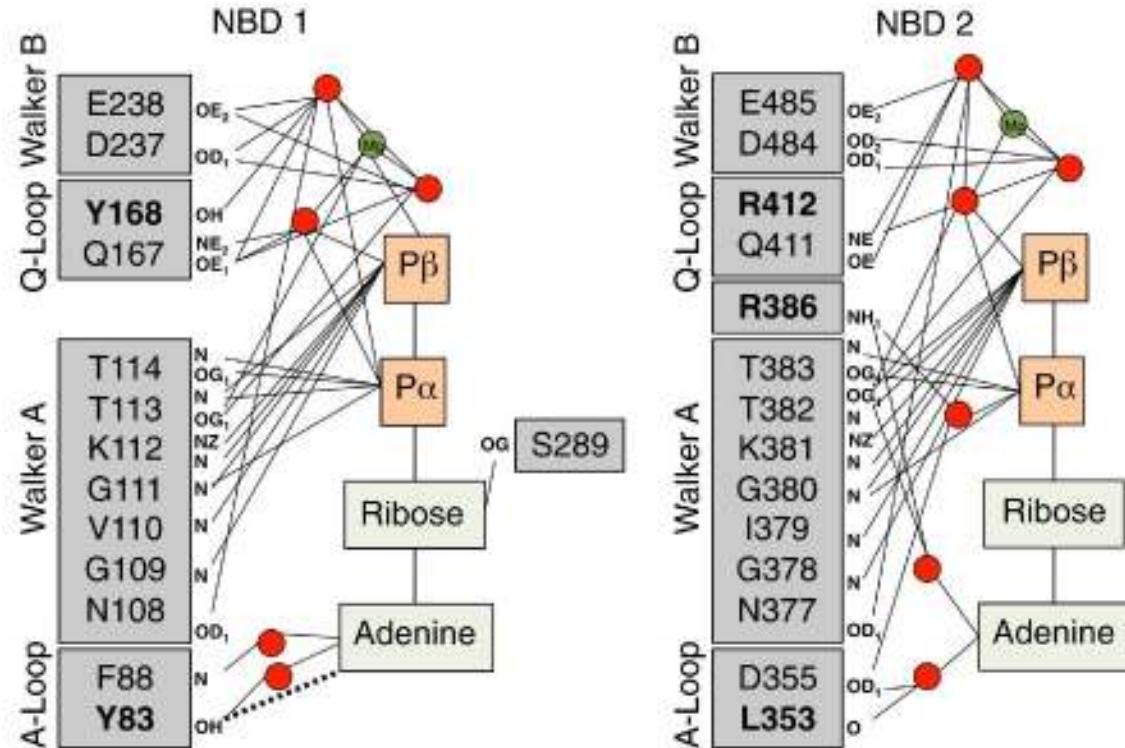
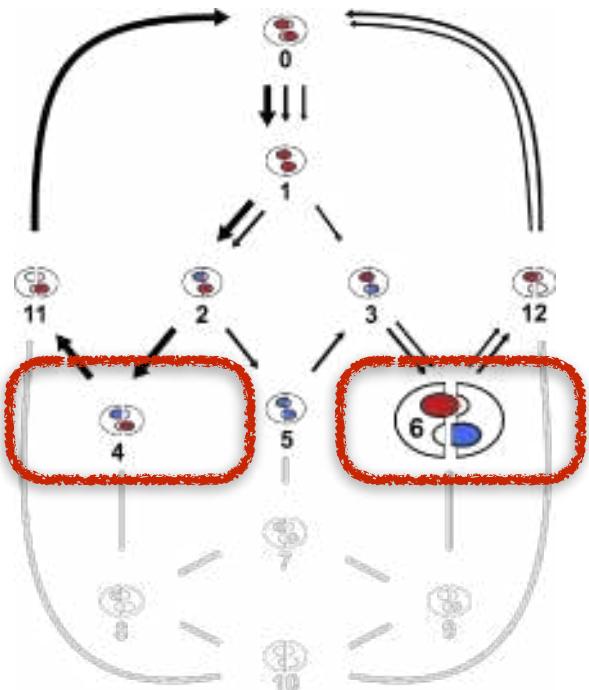
Wild type



$$\Delta G_{6-4} = -30 \text{ kJ/mol}$$

Prediction: Free energy difference (MD / Crooks NE-sampling)

Wild type



Barthelme et. al. PNAS 2011, Fig. S2

$$\Delta G_{6-4} = -30 \text{ kJ/mol}$$

Theory vs. Experiment: Occupancies

