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# Non-Markovian Dynamic Models of Protein Conformational Changes

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**Xuhui Huang**

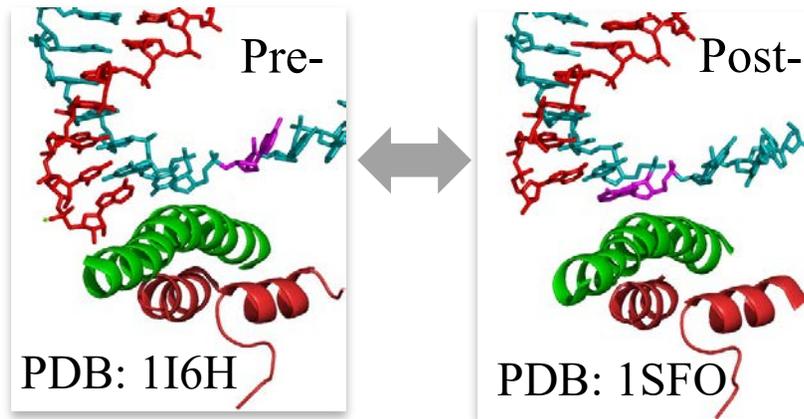
Department of Chemistry

University of Wisconsin-Madison



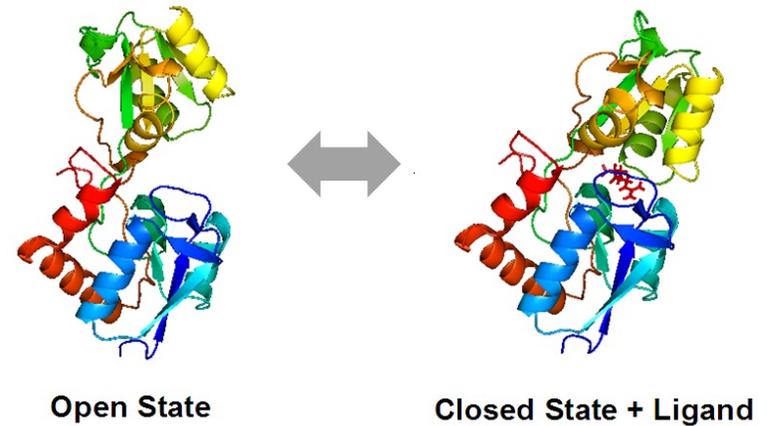
# Dynamics of Conformational Changes are Crucial for Protein Function

Dynamic and localized transitions between pairs of conformational states:



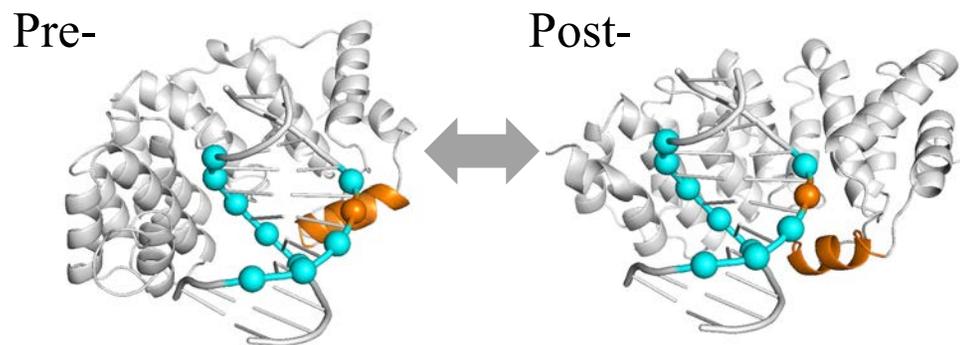
## RNA Polymerase translocation

*PNAS*, 7665, (2014); *Nat. Commun.*, 11244, (2016)



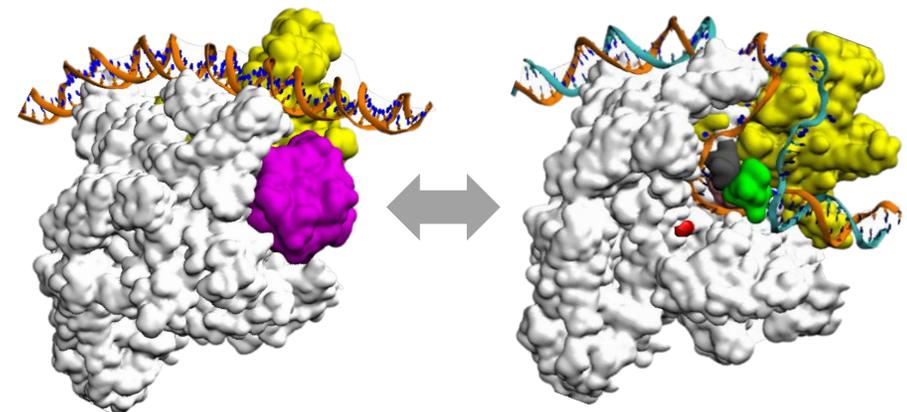
## Protein-ligand recognition

*PLOS. Comp. Bio.*, 7, e1002054, (2011)



## DNA repair protein translocates on dsDNA

*PNAS*, 117, 21889, (2020)



## DNA loading into RNA Polymerase

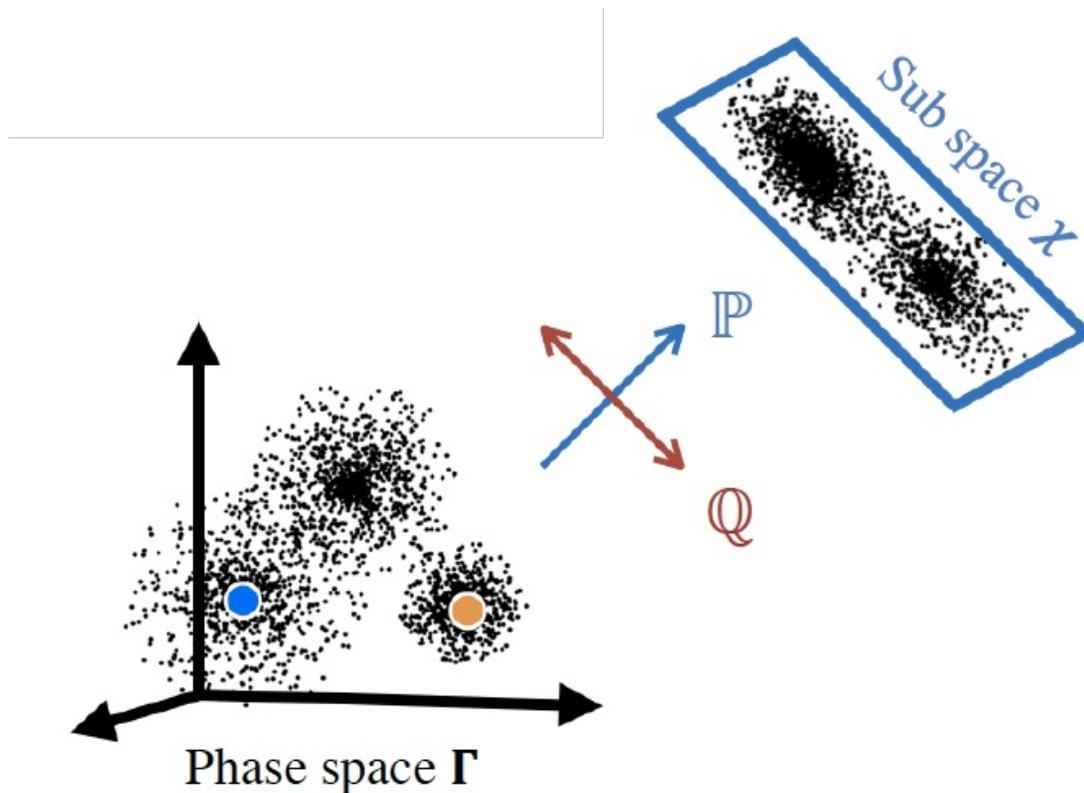
*PNAS*, 118(17), e2024324118, (2021)

# Projection Operator Approach of Protein Dynamics

Evolution of density in phase space satisfies Liouville's Equation:

$$\frac{\partial \rho(\Gamma, t)}{\partial t} = \mathcal{L} \rho(\Gamma, t) \quad \Gamma = (\mathbf{x}; \mathbf{p})$$

Mori-Zwanzig projection operator:  $\Gamma \rightarrow \chi$



$\mathbb{P}$ : slow variables  $\chi$

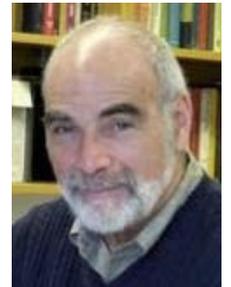
$\mathbb{Q}$ : fast variables  $\Gamma \cap \bar{\chi}$



Zwanzig



Mori

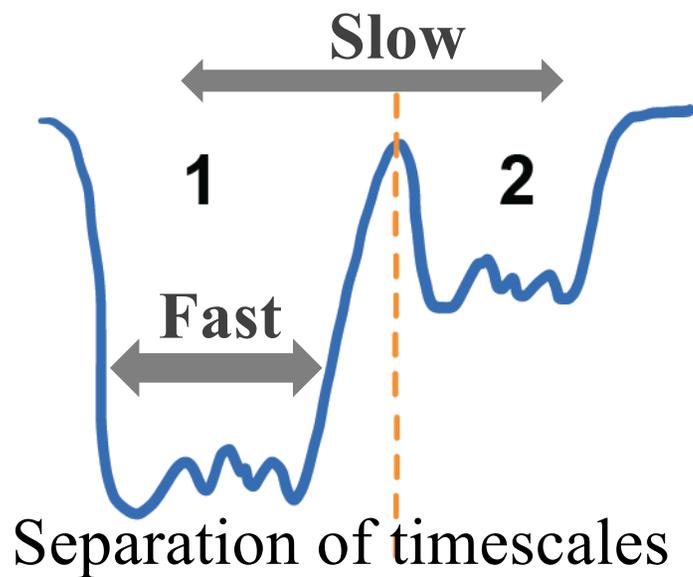


Berne

# Projecting Kinetics onto Coarse-grained States Introduces Memory

Hummer-Szabo projection operator:

$$\mathbb{P} := \sum_{j=1}^n |\rho(\Gamma; \text{eq})\chi_j(\mathbf{x})\rangle \cdot \pi_j^{-1} \langle \chi_j(\mathbf{x}) |$$



We choose  $|\chi\rangle$  to be the state indicator function  $\chi_i(\mathbf{x}) = 1$ : conformation  $\mathbf{x}$  belongs to state  $i$

$\mathbb{P}$ : Slow transitions between states  
 $\mathbb{Q}$ : Fast transitions within state

The projected kinetics satisfy a **Generalized Master Equation**:

$$\frac{\partial}{\partial t} \mathbf{T}(t) = \dot{\mathbf{T}}(0)\mathbf{T}(t) + \int_0^t \mathbf{K}(t')\mathbf{T}(t-t')dt'$$

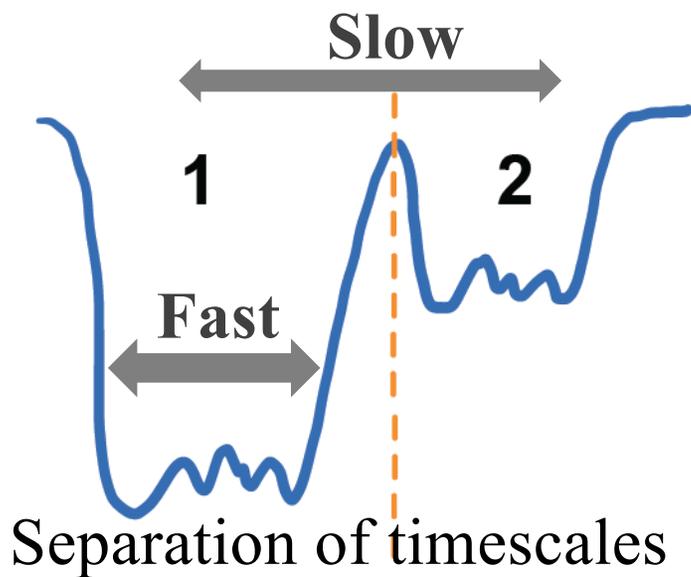
Memory kernel:  $\mathbf{K}(t) = \langle L e^{\mathbb{Q}Lt} \mathbb{Q}L \rangle_{\rho, \pi^{-1}}$

# Projecting Kinetics onto Coarse-grained States Introduces Memory

Hummer-Szabo projection operator:

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$\mathbb{P}$  : Slow transitions between states  
 $\mathbb{Q}$  : Fast transitions within state

Discretion of time (lag time:  $\tau$ ) is sufficiently long so that:  $\mathbb{P}e^{\mathcal{L}\tau}\mathbb{Q} \approx 0$

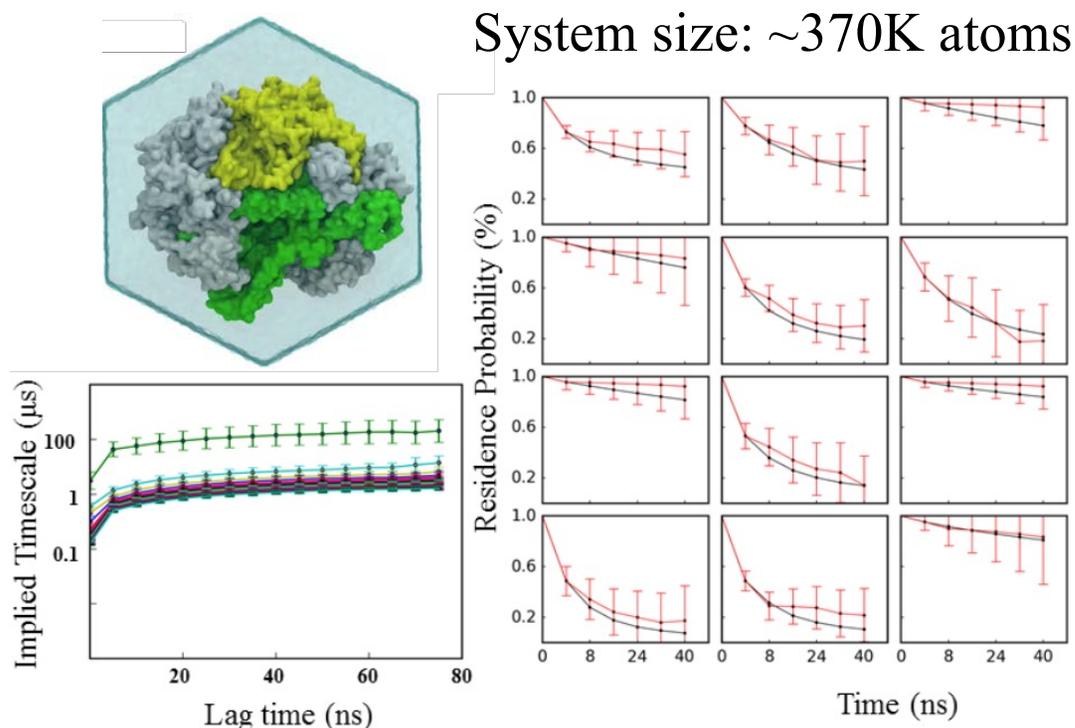
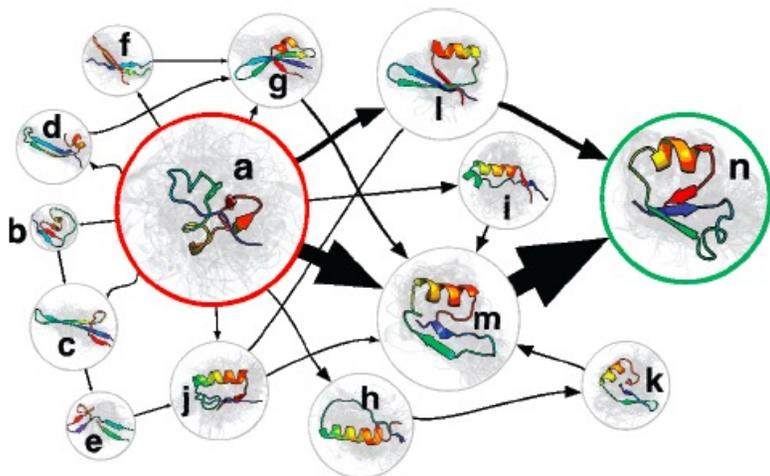
We obtain a **Markov State Model (MSM)**:

$$p(t + \tau) = \mathbf{T} p(t)$$

# MSMs are often non-Markovian due to Limited Length of MD Simulations

**NTL9 folding:**

**RNA Polymerase backtracking:**



**2000-state MSM:** lag time = 10ns.

**14-state model: Not Markovian**

Voelz *et al.* *JACS*, 132,5, (2010)

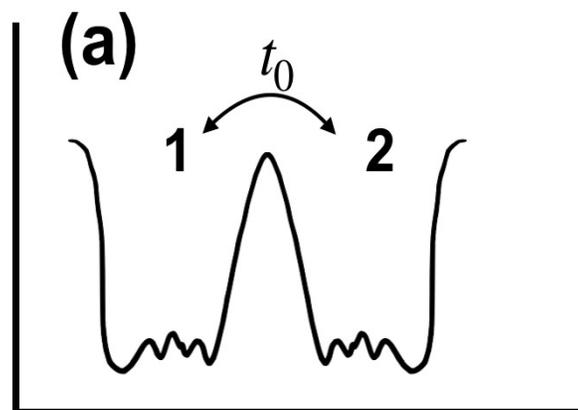
**800-state MSM:** lag time = 8ns (480  
100-ns MD simulations)

**4-state model: Not Markovian**

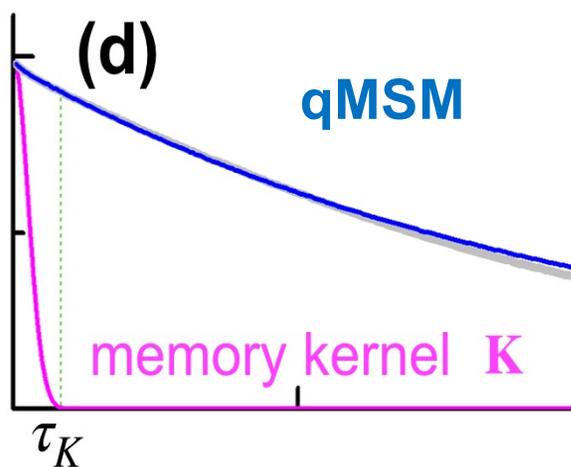
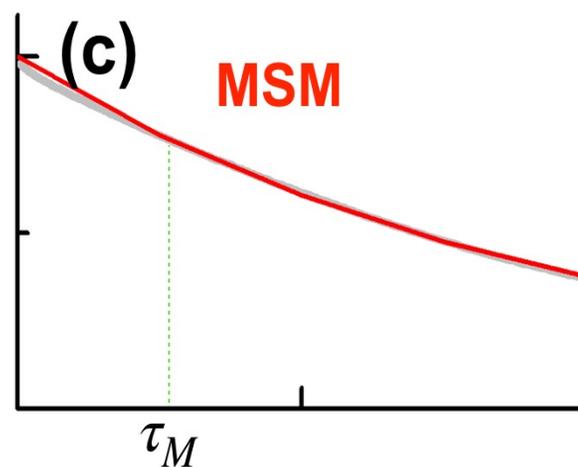
Da,..., Huang, *Nat. Communi.*, 7, 11244, (2016)

# Quasi-Markov State Model (qMSM) Theory

**Key Insights:** Due to separation of timescales, the memory kernel (mainly reflecting intra-state transition) decays faster than the Markovian lag time.



$$\tau_K \ll \tau_M$$

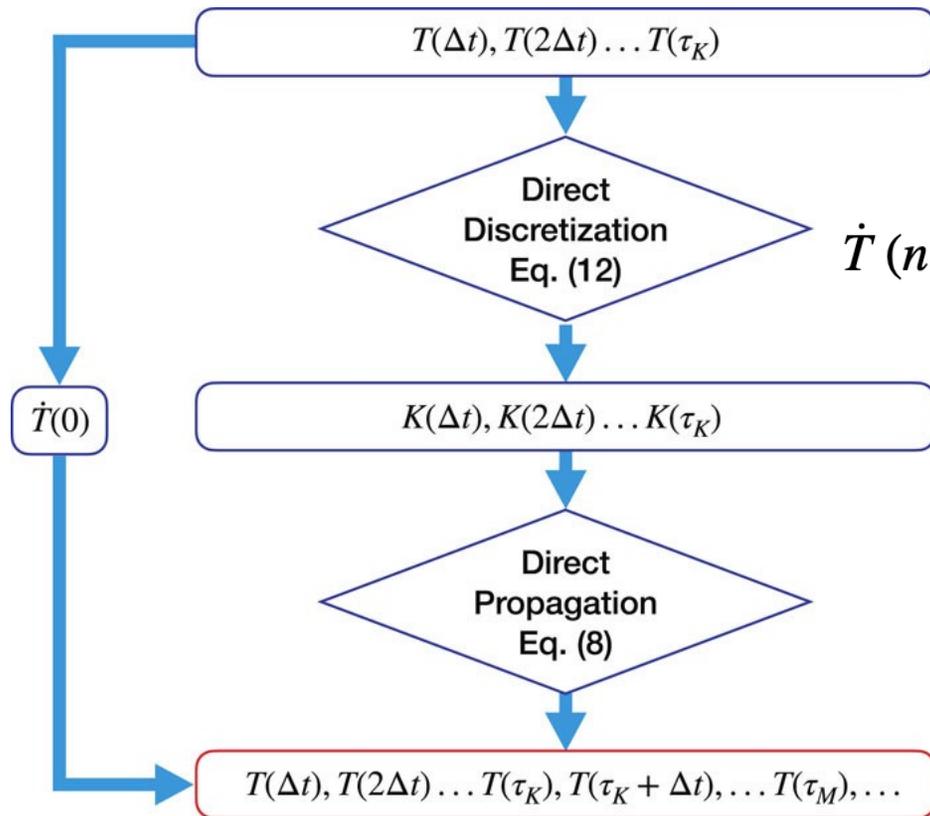


**Our approach:**  
Propagate dynamics using a Generalized Master Equation with memory kernel.

$$\tau_K < \tau_M < t_0$$

Cao *et al.* *J. Chem. Phys.*, 153, 014105, (2020)

# Computing Memory Kernel for Protein Dynamics



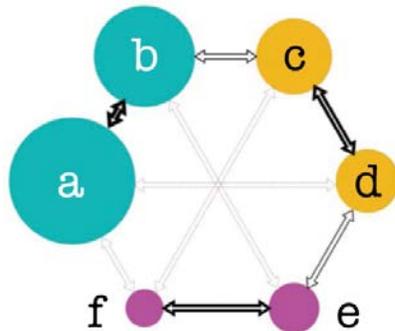
Direct discretization of GME:

$$\dot{T}(n\Delta t) = \dot{T}(0) T(n\Delta t) + \Delta t \sum_{m=1}^n \mathcal{K}(m\Delta t) T((n-m)\Delta t)$$

GME:

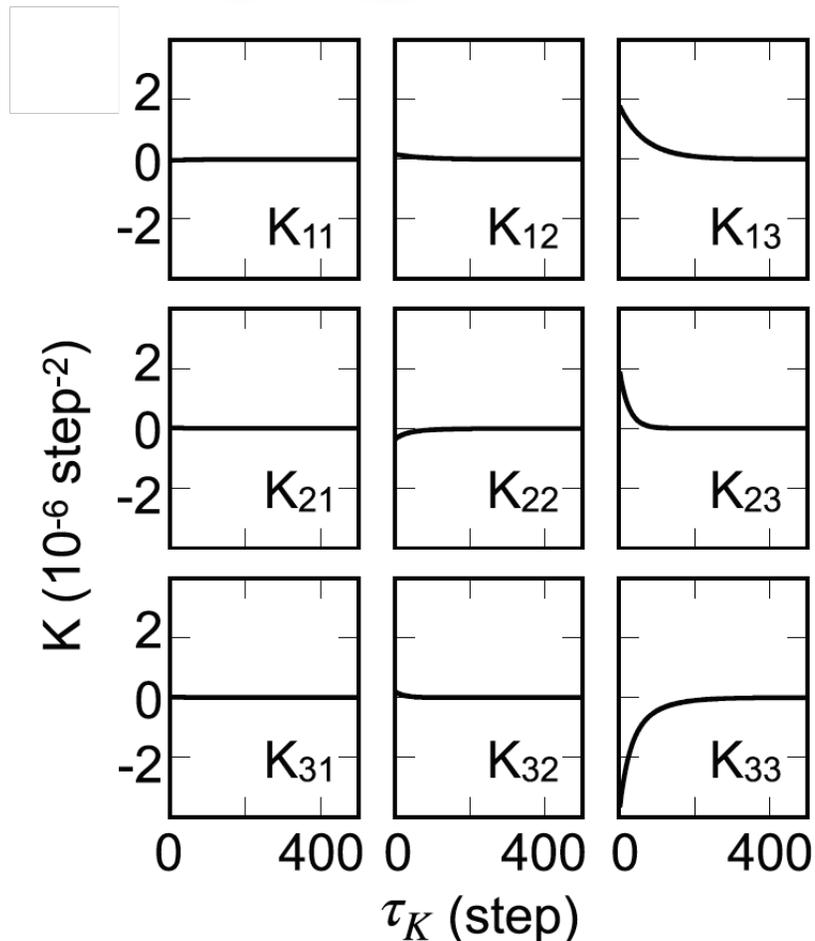
$$\dot{T}(t) = \dot{T}(0) T(t) - \int_0^{\min[\tau_K, t]} d\tau \mathcal{K}(\tau) T(t - \tau)$$

# A Simple Kinetic Model

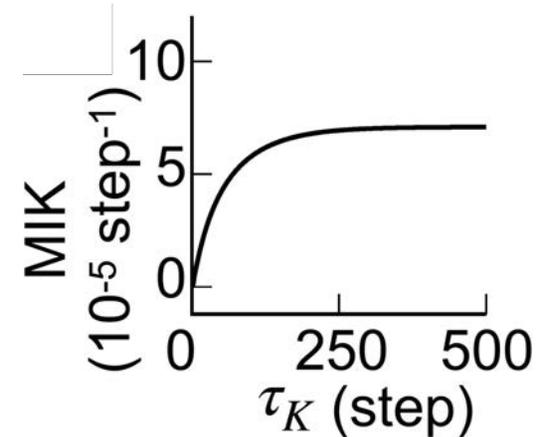


3-state

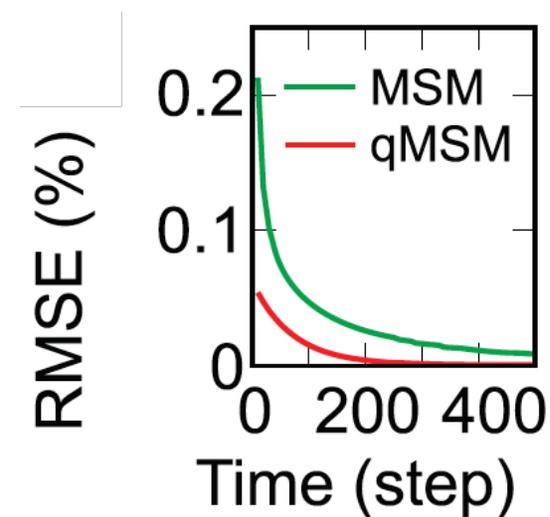
**Good lumping**



Memory Kernel Integral



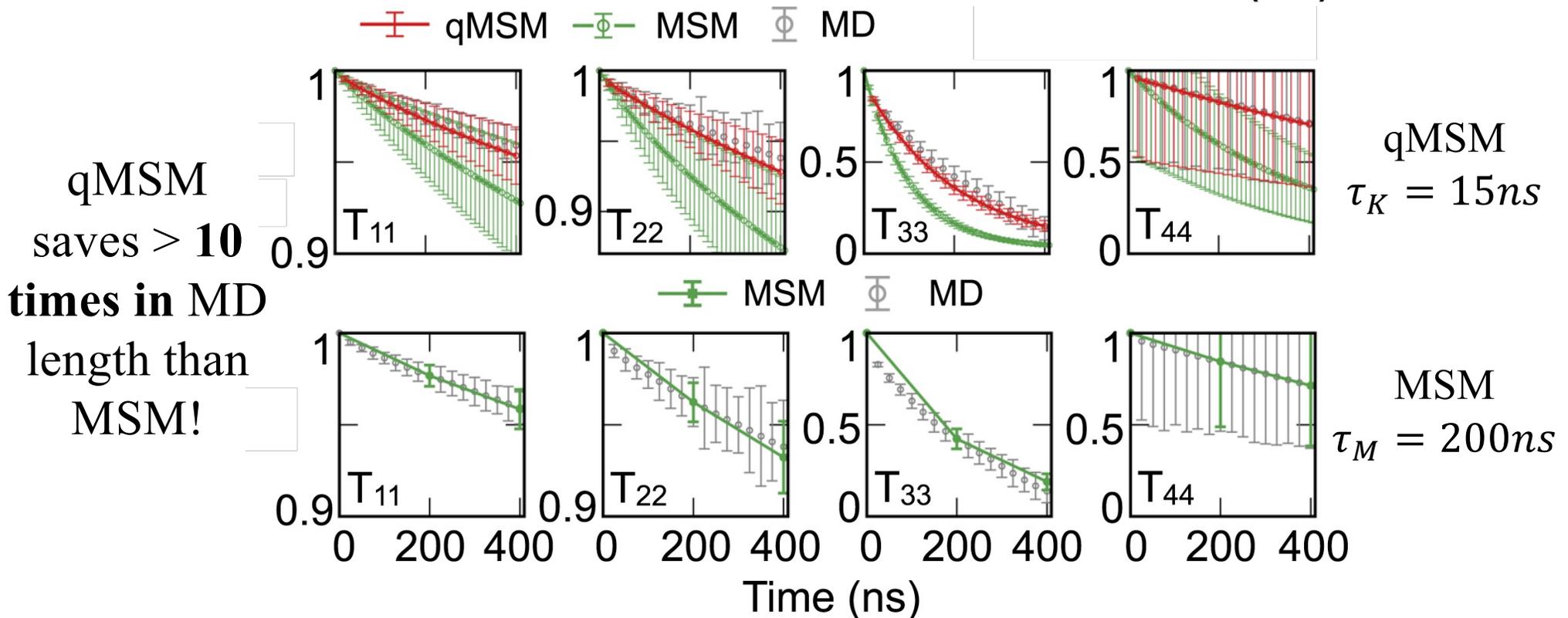
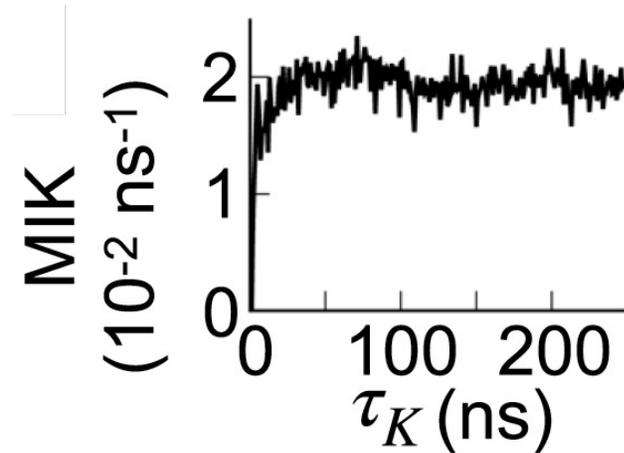
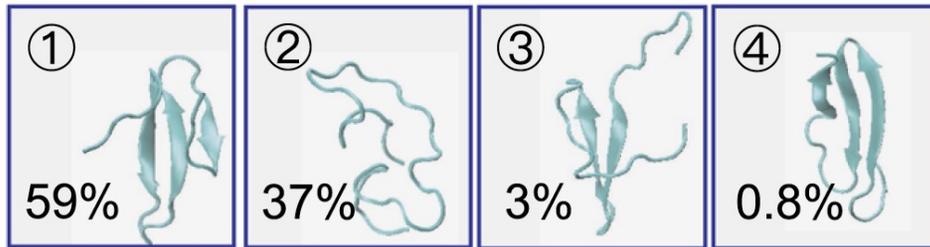
Root mean square errors of TPM



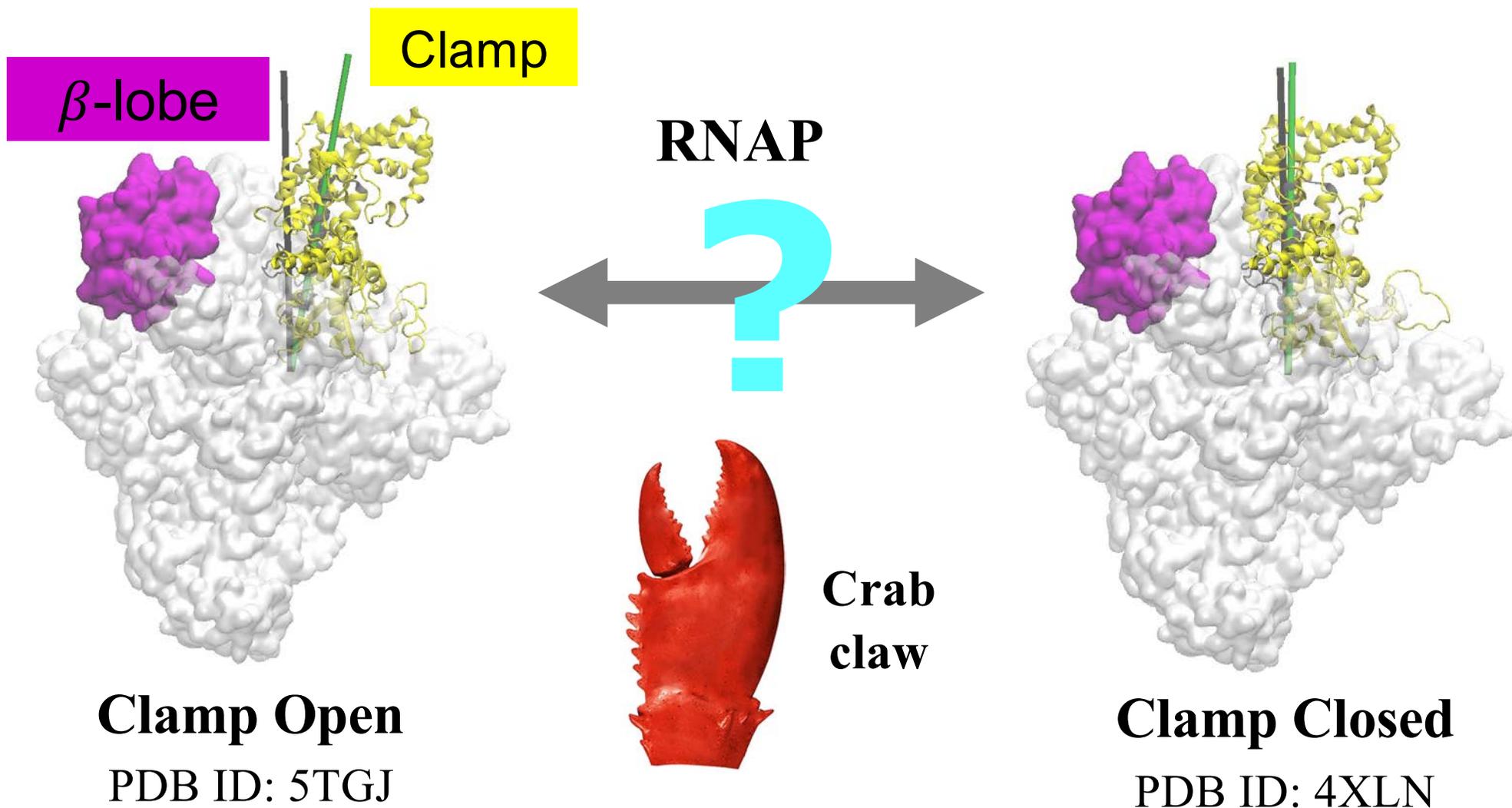
qMSM is more accurate than MSM.

# WW domain Folding

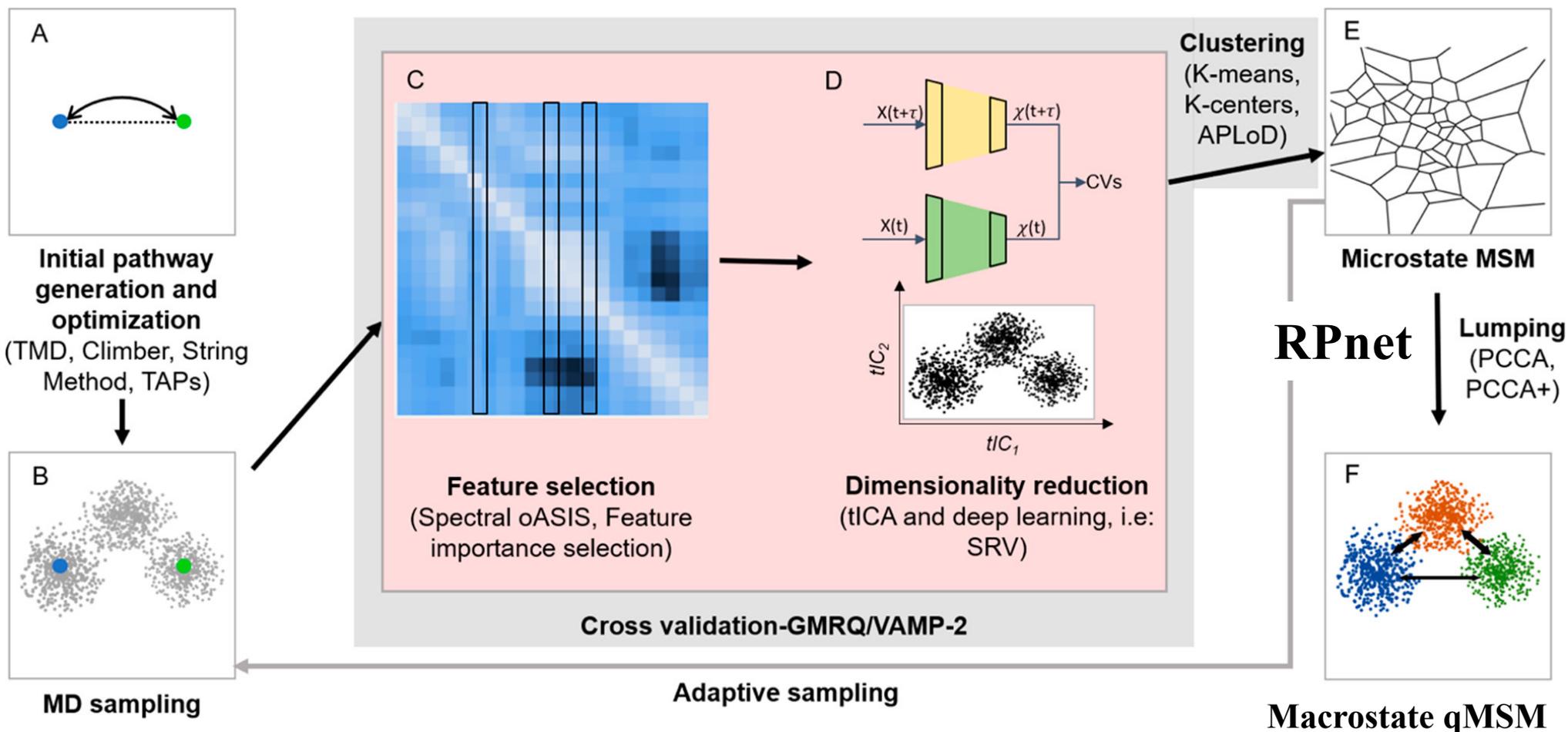
## 4-State



# Dynamics of RNAP Gate Opening is Crucial for DNA Promoter Loading

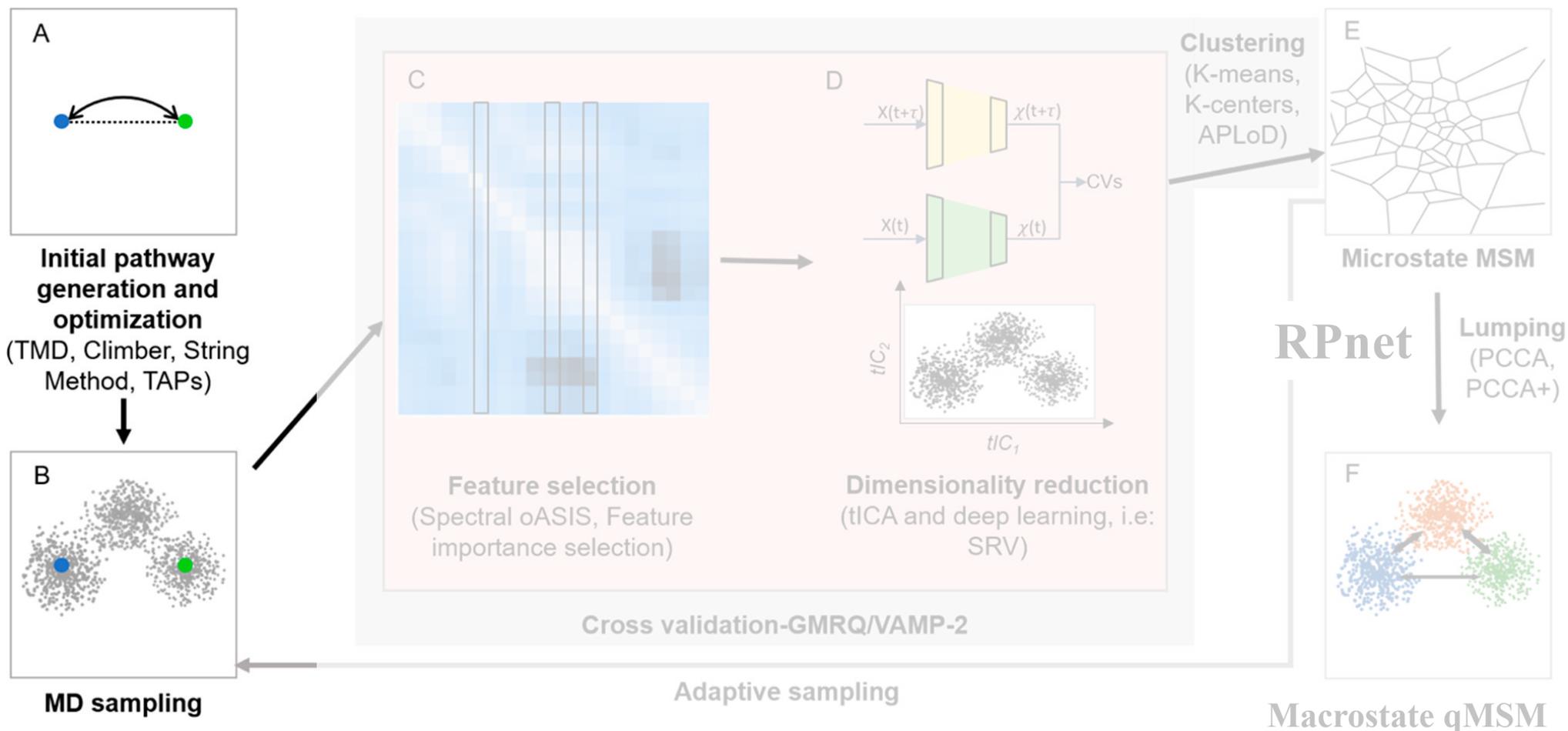


# Our Recipe for Constructing qMSMs to Study Functional Conformational Changes



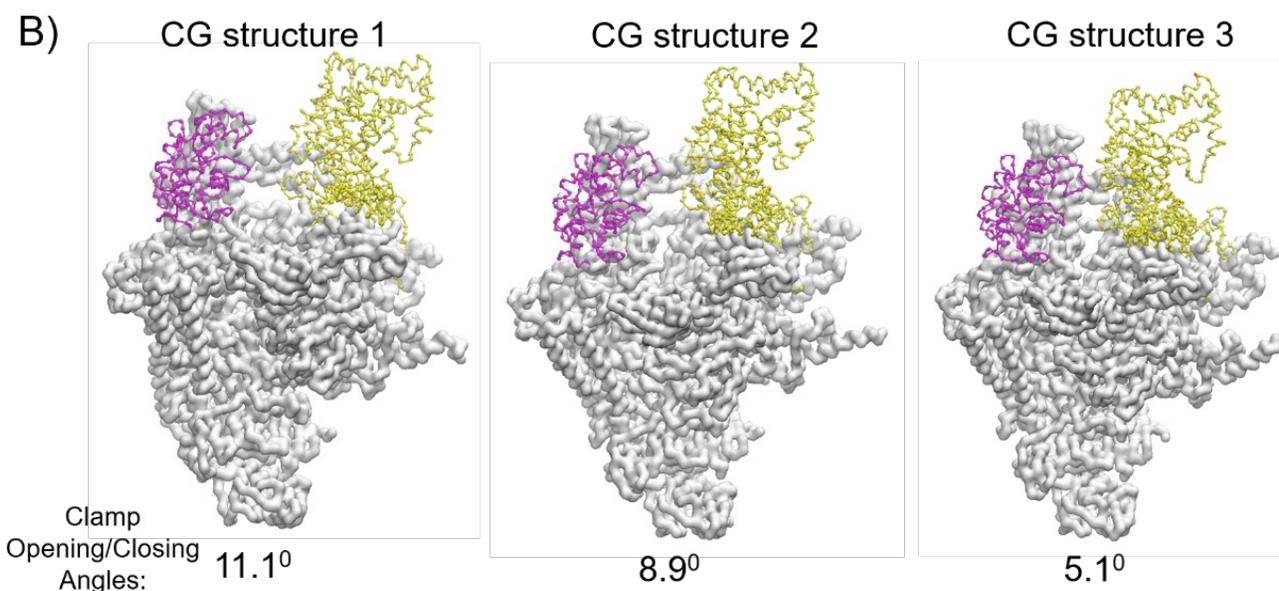
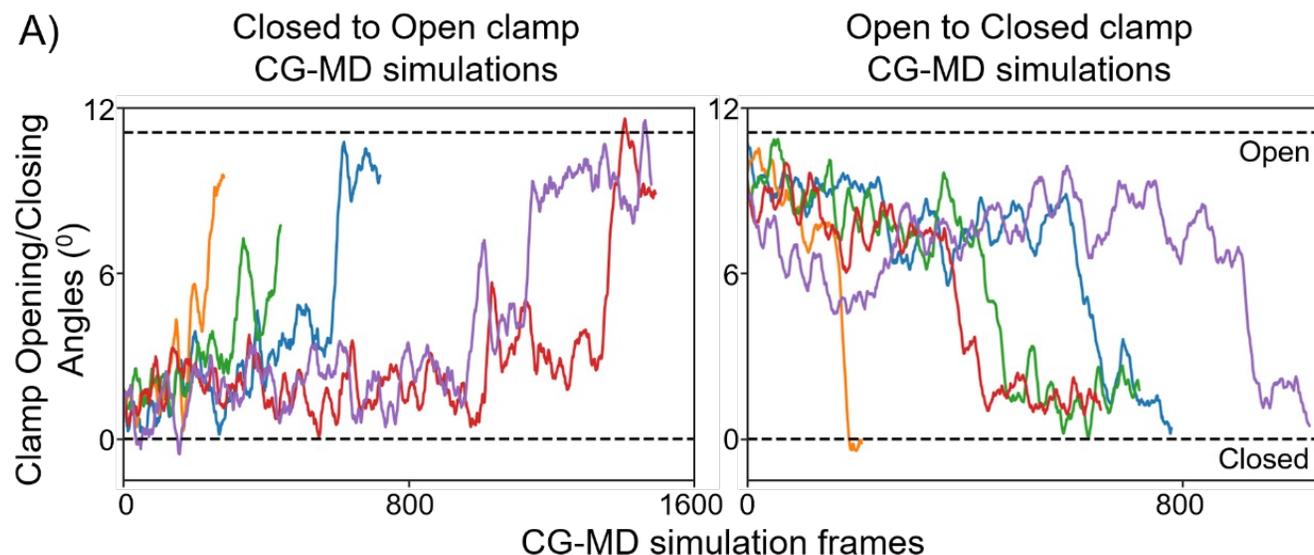
*JACS Au*, 1, 1330-1341, (2021)

# Our Recipe for Constructing qMSMs to Study Functional Conformational Changes



*JACS Au*, 1, 1330-1341, (2021)

# Coarse-Grained MD Simulations to Generate Initial Path

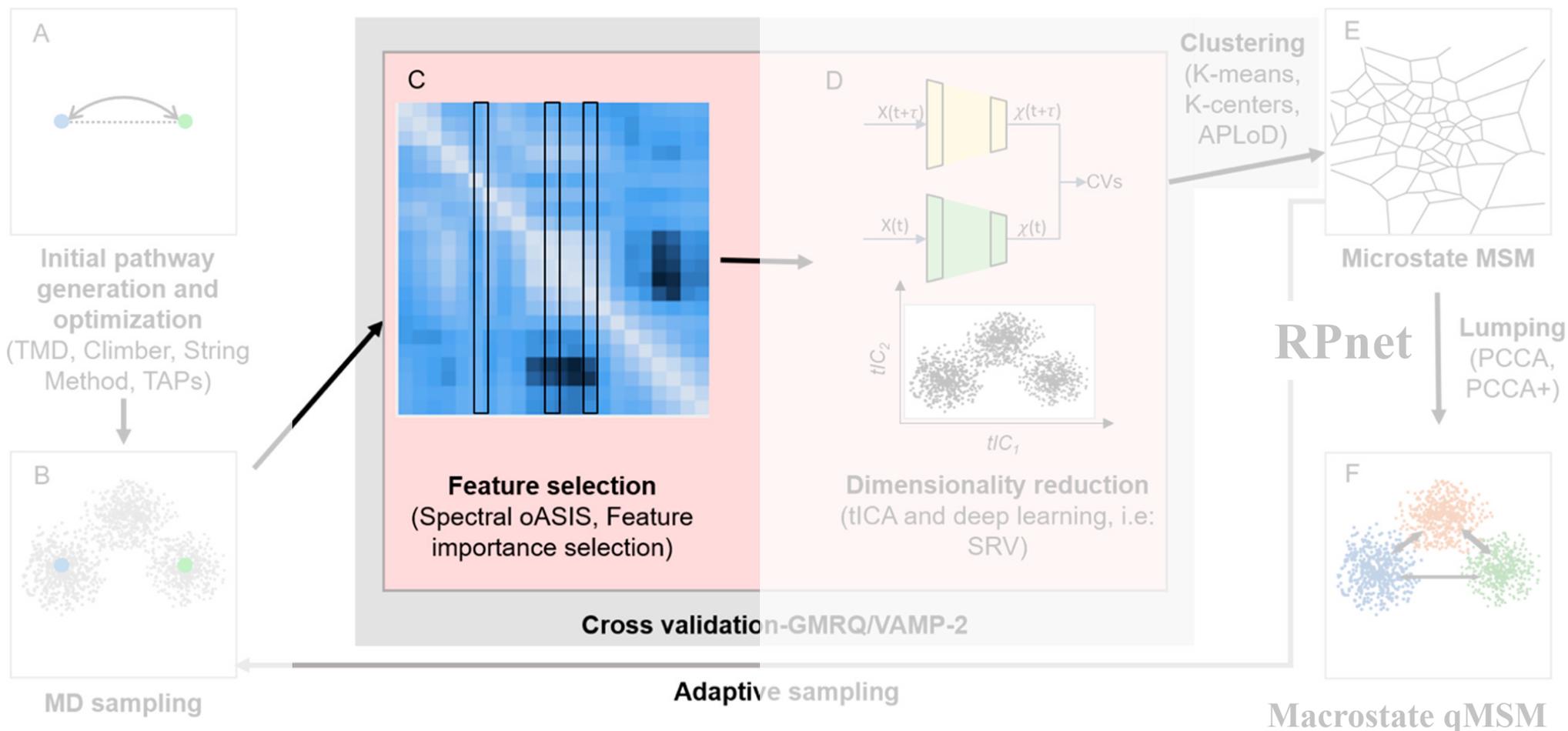


**Shoji Takada**  
**Kyoto U**

**CafeMol**

Back-map  
coarse-grained  
conformations to  
all-atom  
conformations.

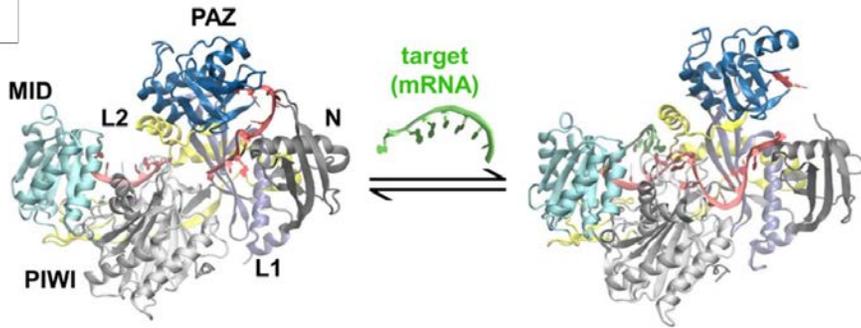
# Our Recipe for Constructing qMSMs to Study Functional Conformational Changes



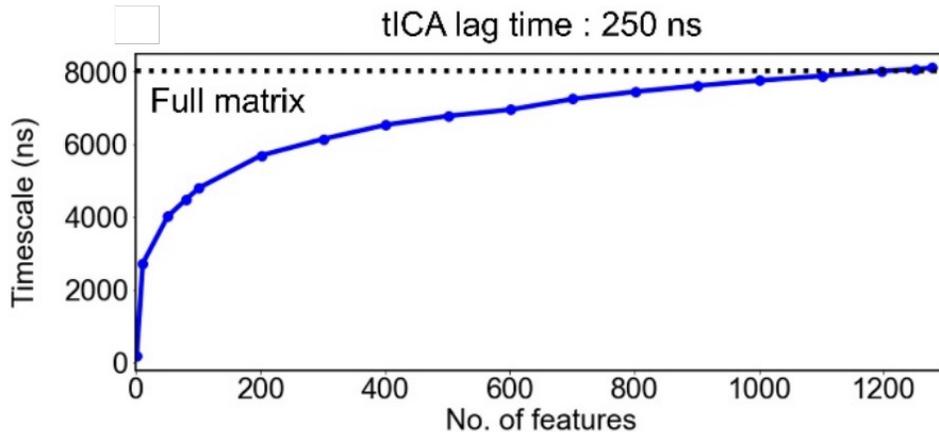
306 200-ns MD simulations

System size: 543K atoms

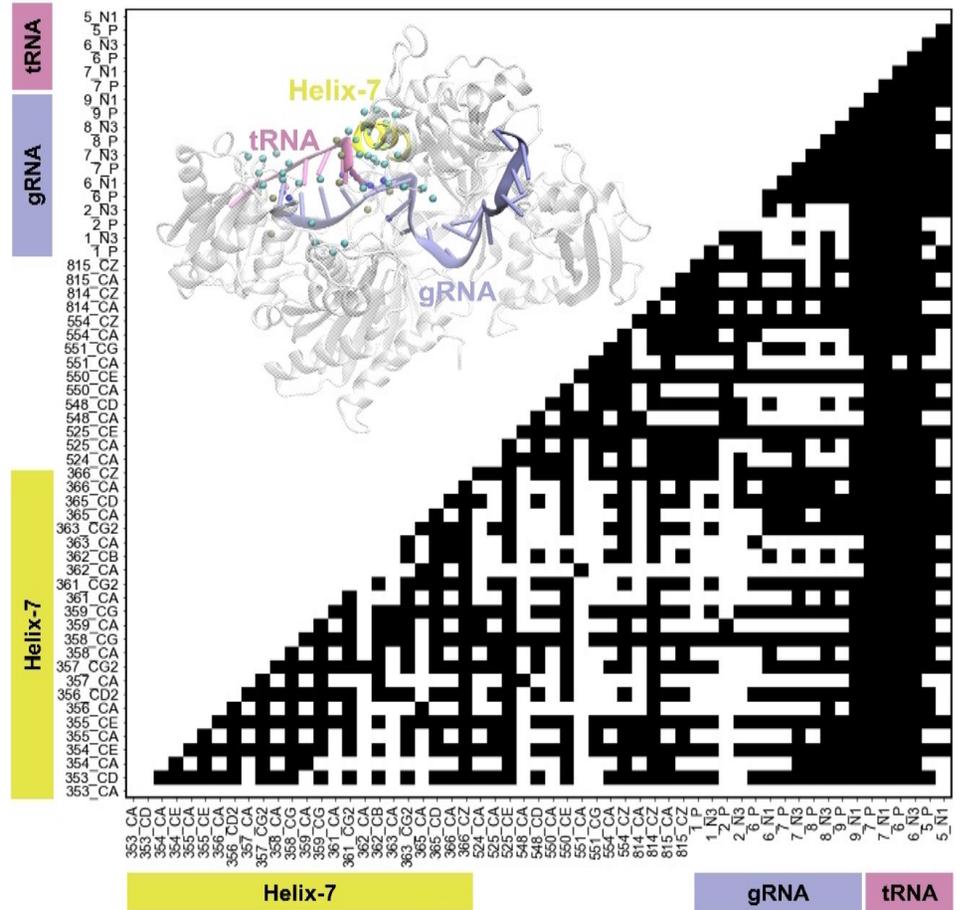
# Automatic Selection of Features that can Describe Protein Conformational Changes



microRNA target recognition by RNA induced silencing complex



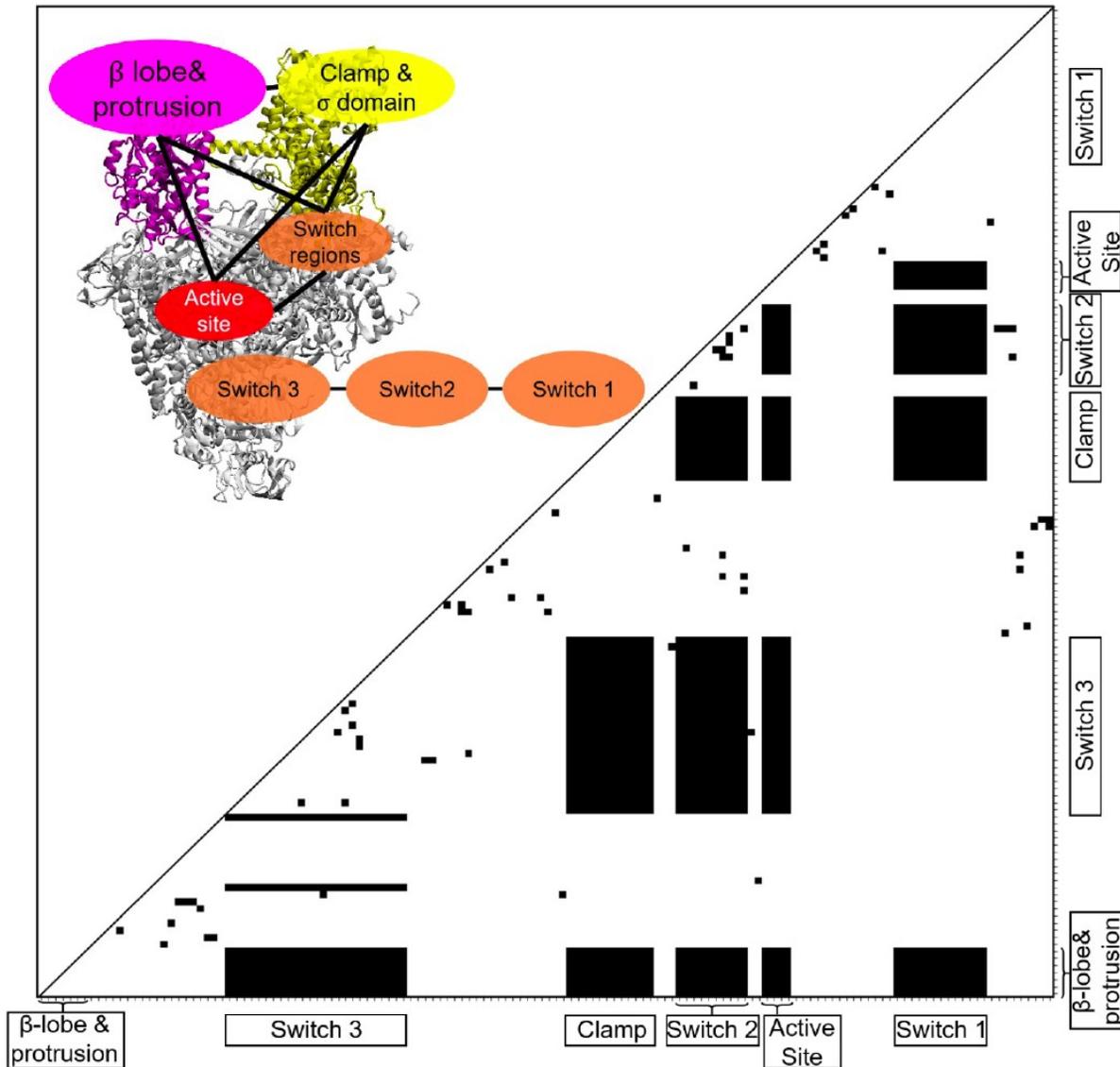
Spectral oASIS: *JCTC*, 14, 2771, (2018).



Spectral oASIS to choose 1,000 residue-residue distance features

*Communications Biology* 4 (1), 1345, (2021)

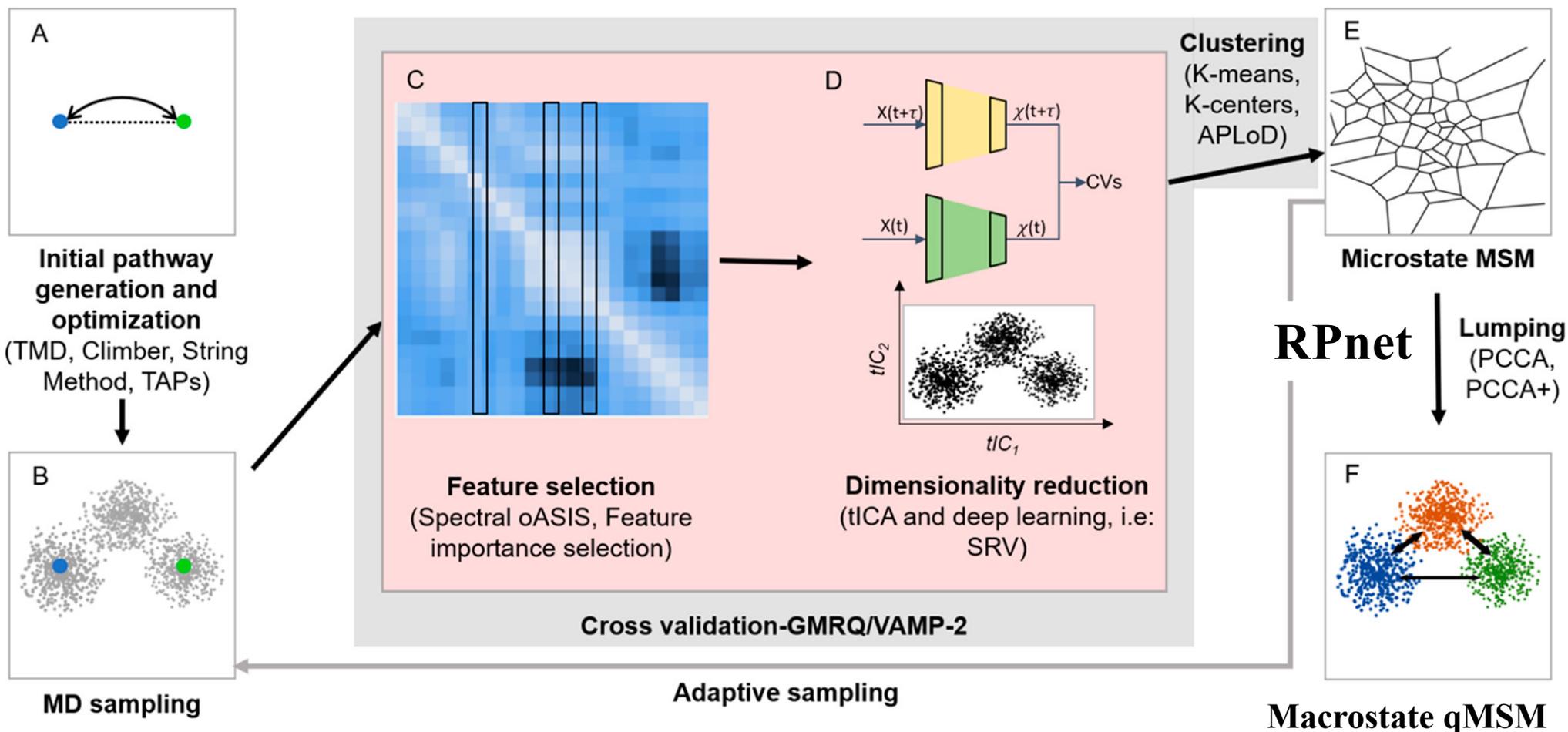
# Automatic Selection of Features that can Describe Protein Conformational Changes



We selected 1770 residue-residue pairwise distances that can best describe the RNAP gate opening.

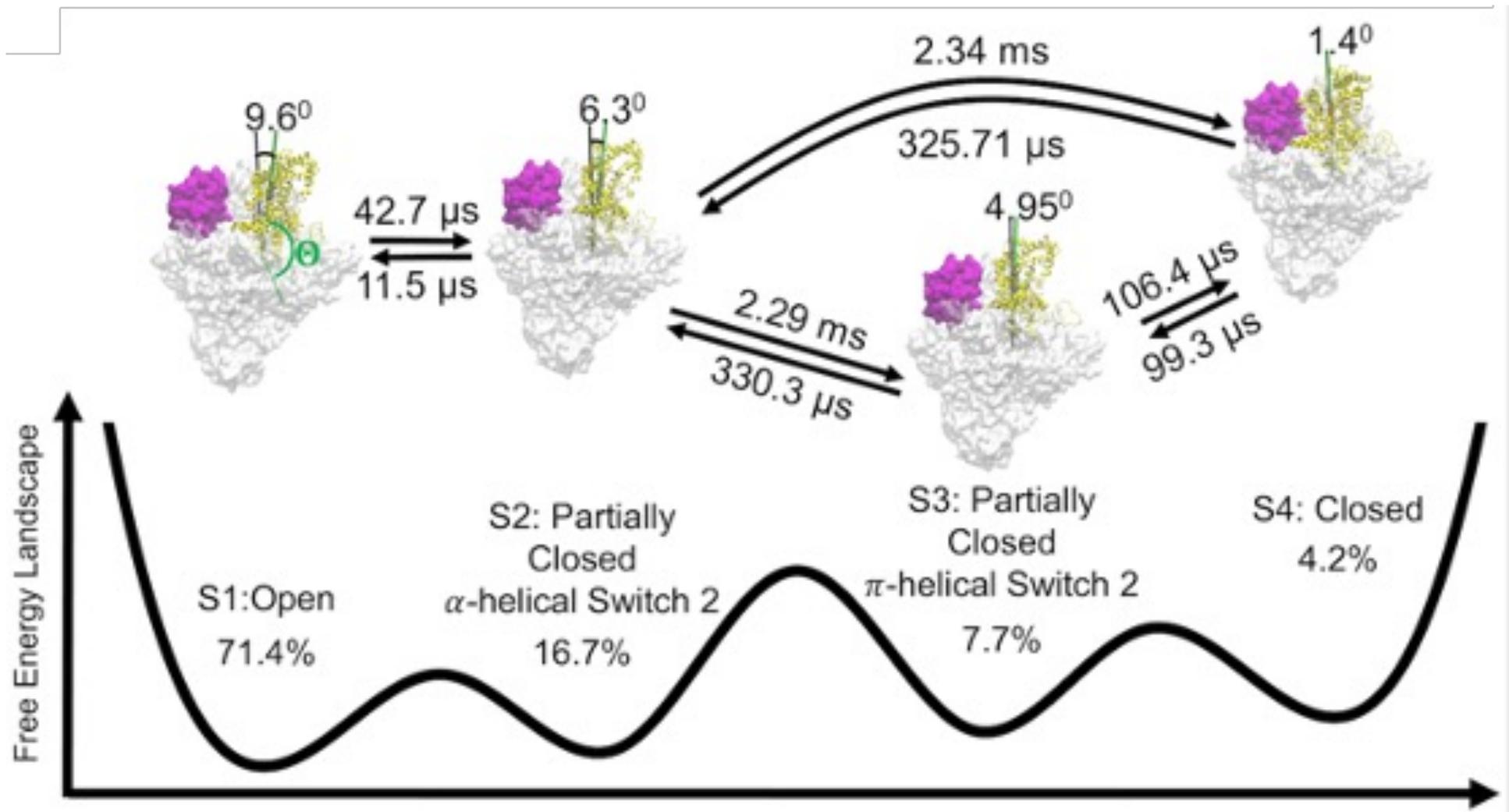
*Proc. Nat. Acad. Sci. U.S.A.*,  
118(17), e2024324118, (2021)

# Our Recipe for Constructing qMSMs to Study Functional Conformational Changes



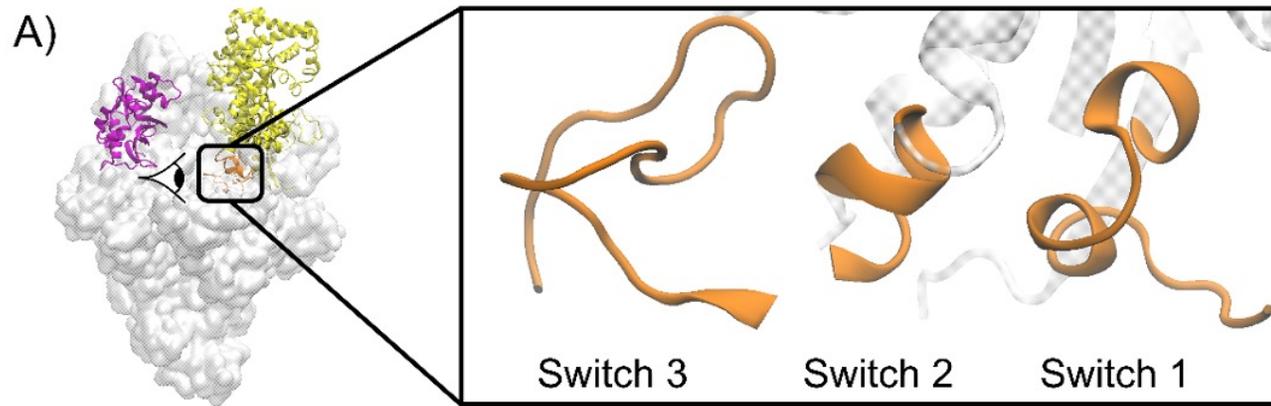
**RNAP gate dynamics: a 4-state qMSM model**

# Clamp Closing is Rate-Limiting and Occurs at Milliseconds



Two intermediate states with different conformations of Switch 2.

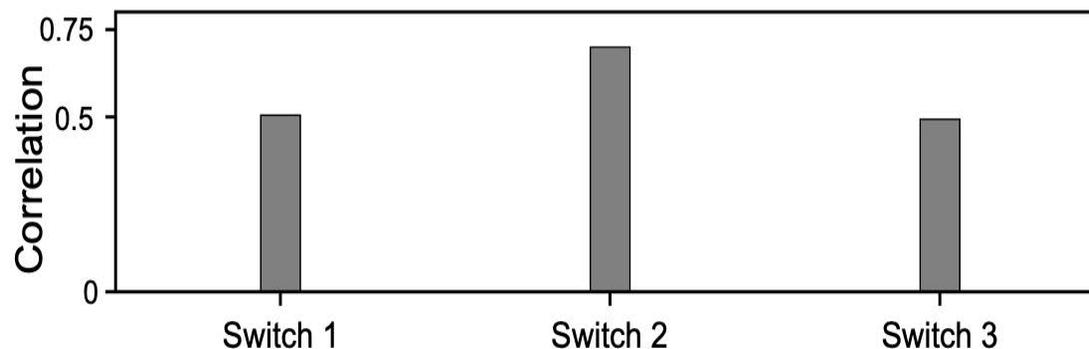
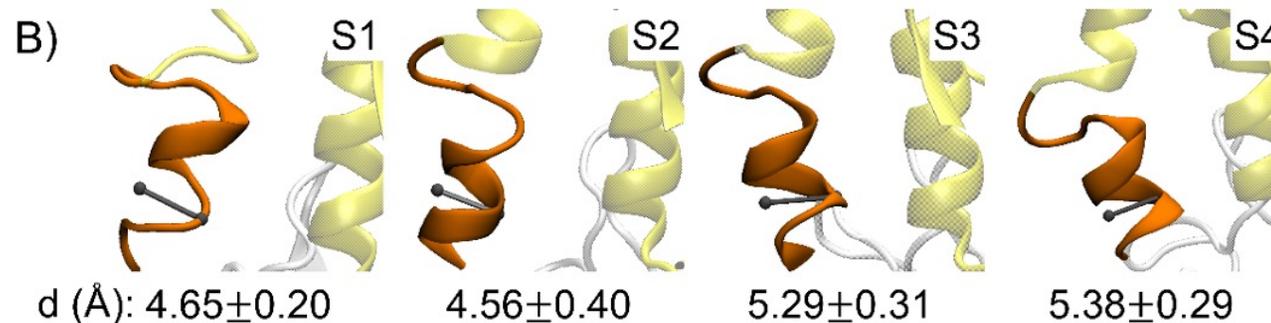
# Clamp Closing is Dynamically Correlated with the Switch-2 Region



Switch-2 conformation:

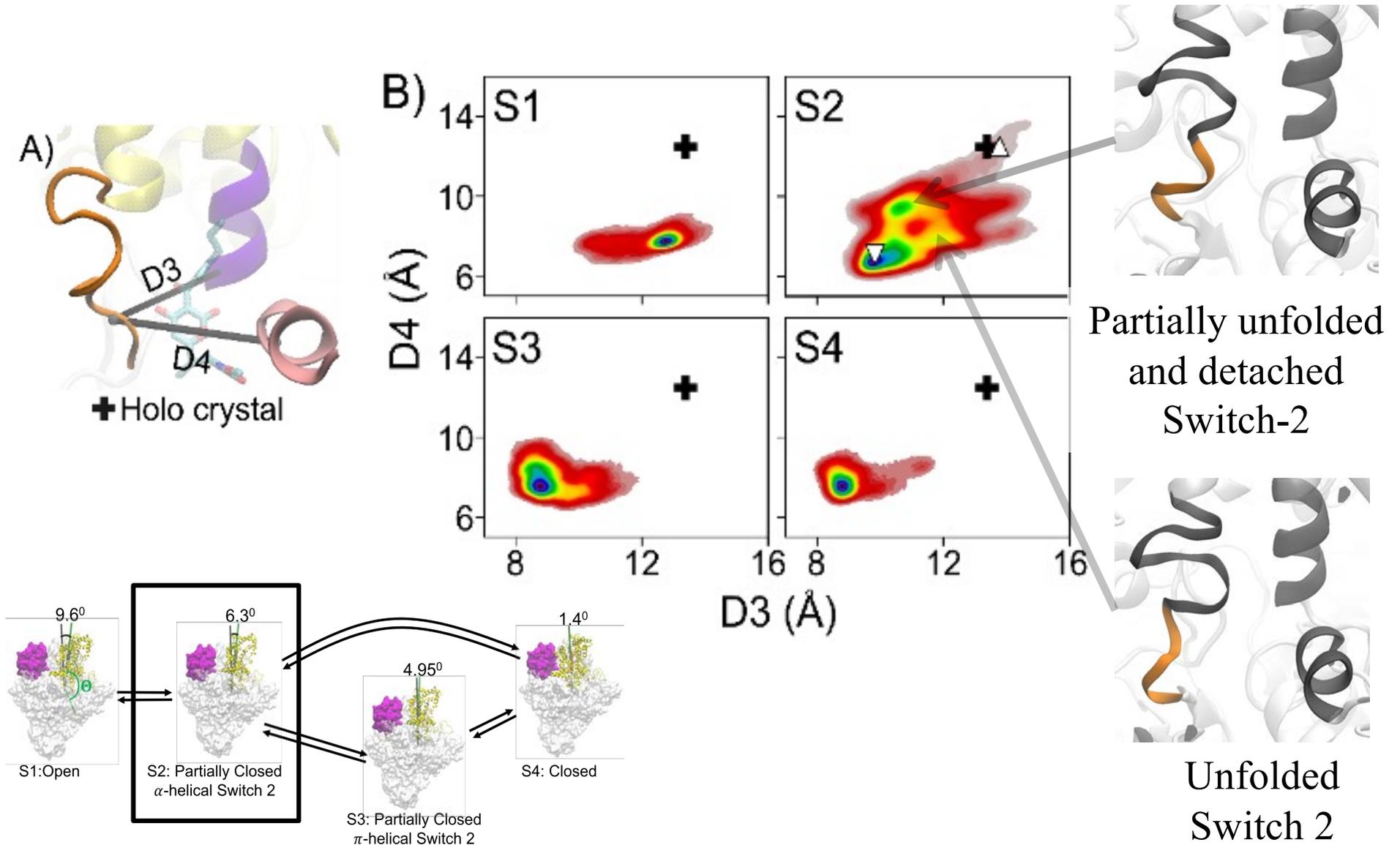
**S1-S2:** alpha-helix

**S3-S4:** pi-helix

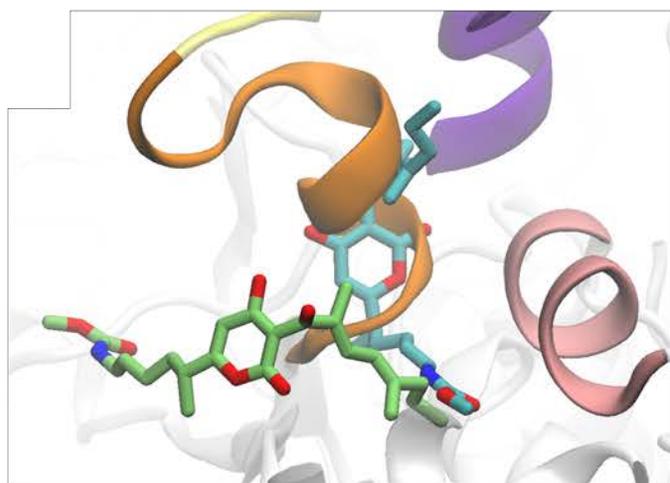


RNAP Clamp-Switch 2 has highest dynamic correlation.

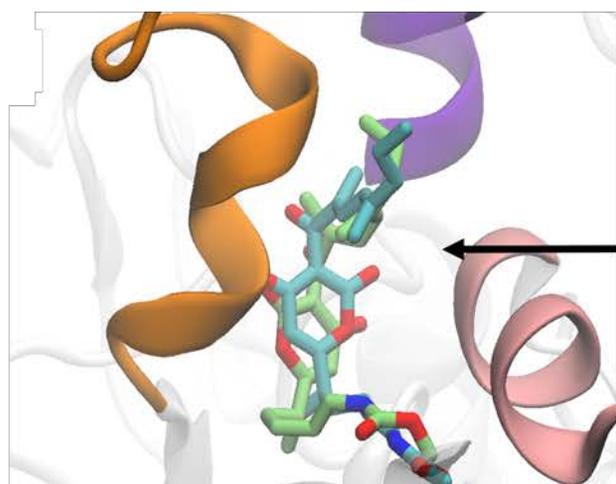
# Unfolded Switch-2 Conformations are Spontaneously Sampled by the Partially Closed Intermediate State



# Unfolded Switch-2 Conformations Allow the Binding of Antibiotics Myx

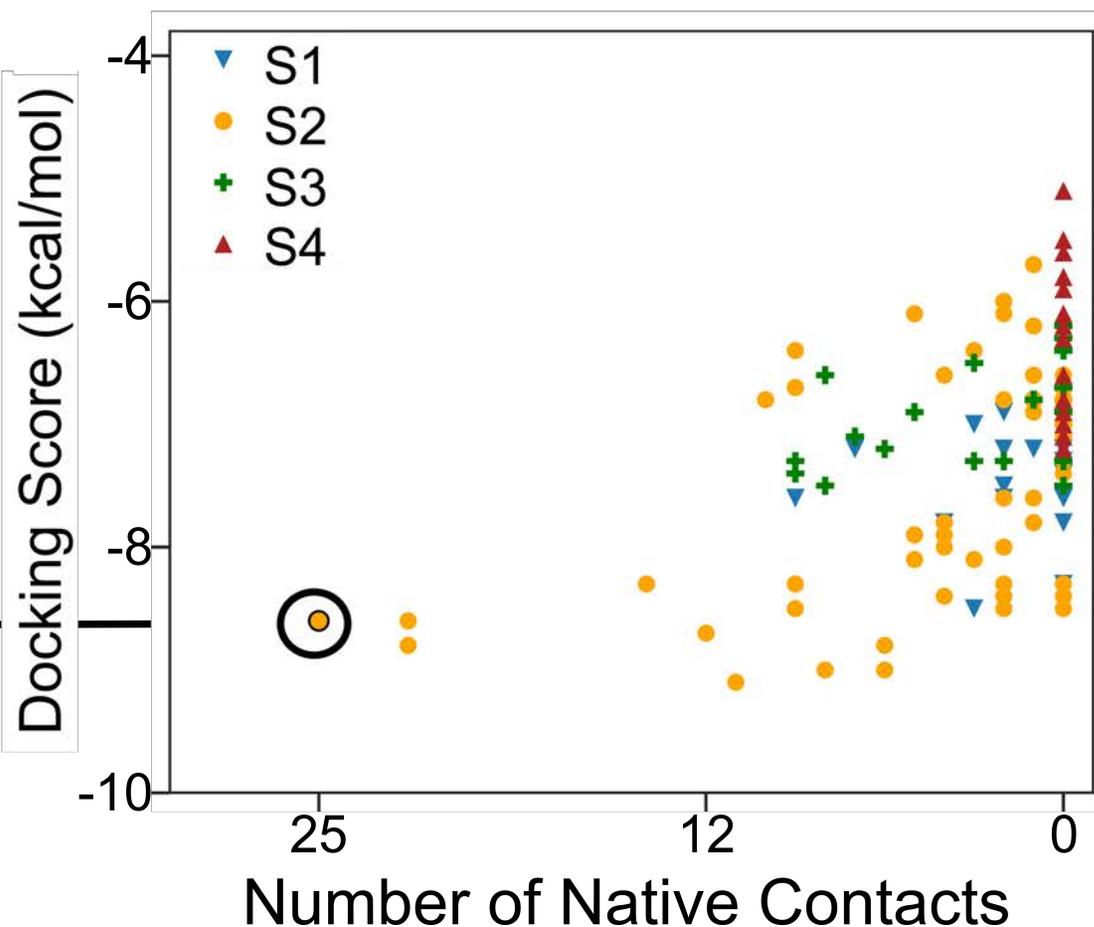


▽ Folded

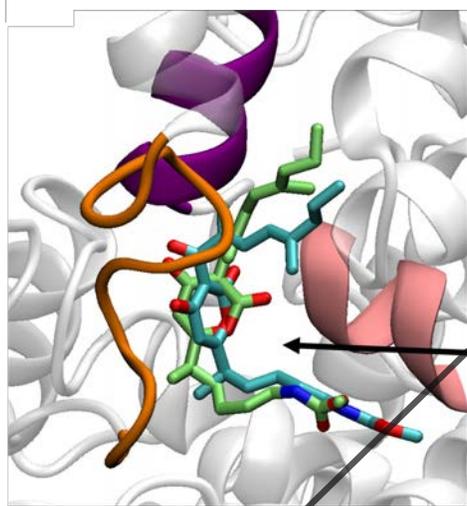


△ Detached

Partially unfolded and detached Switch-2 conformations allow sufficient space for the binding of antibiotics Myx

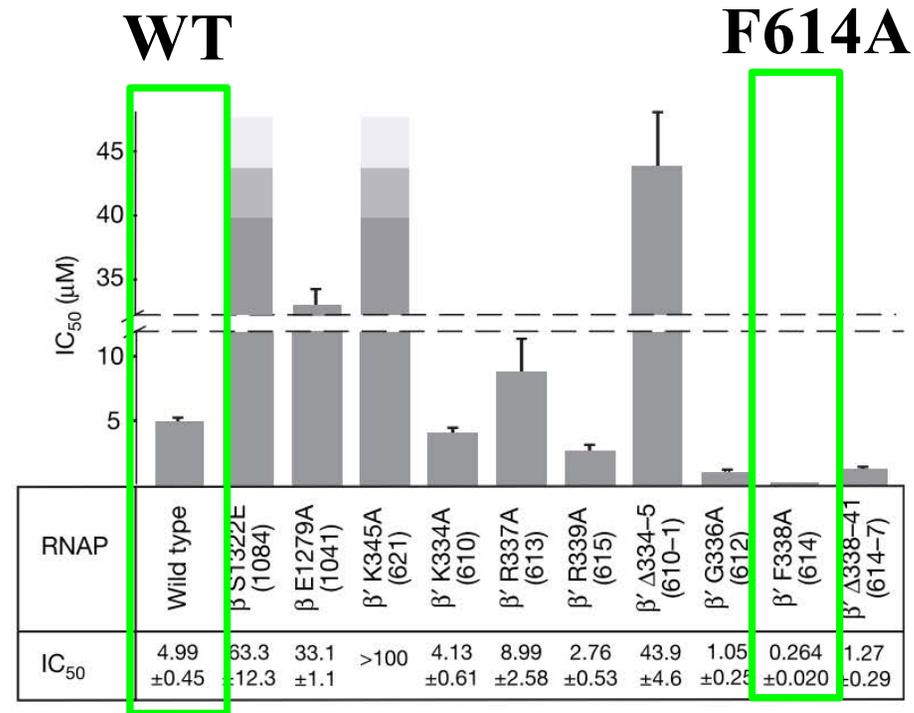
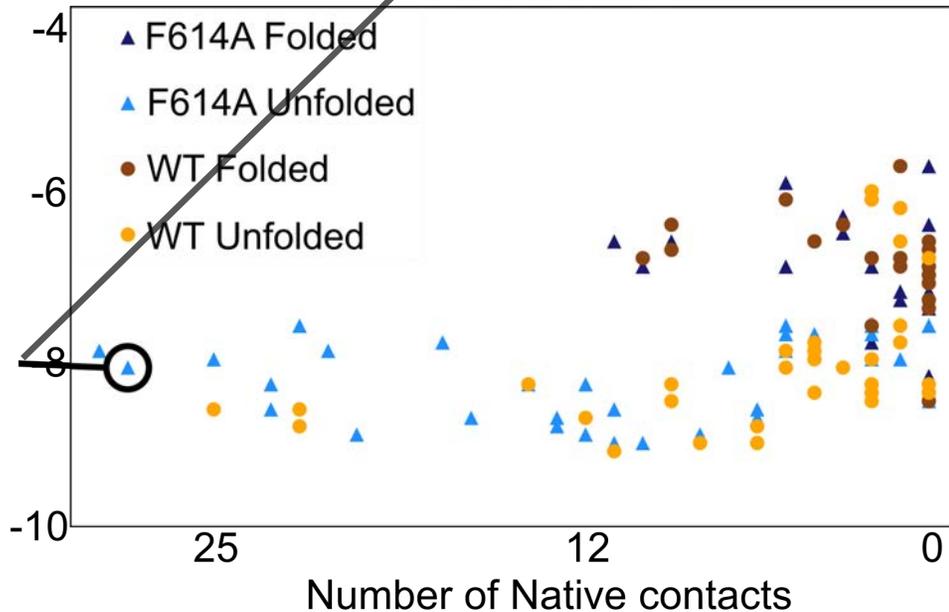


# F614A Mutant Causes Hypersensitivity to Myx



F614A allows for more favourable binding with Myx by providing more space in the binding pocket

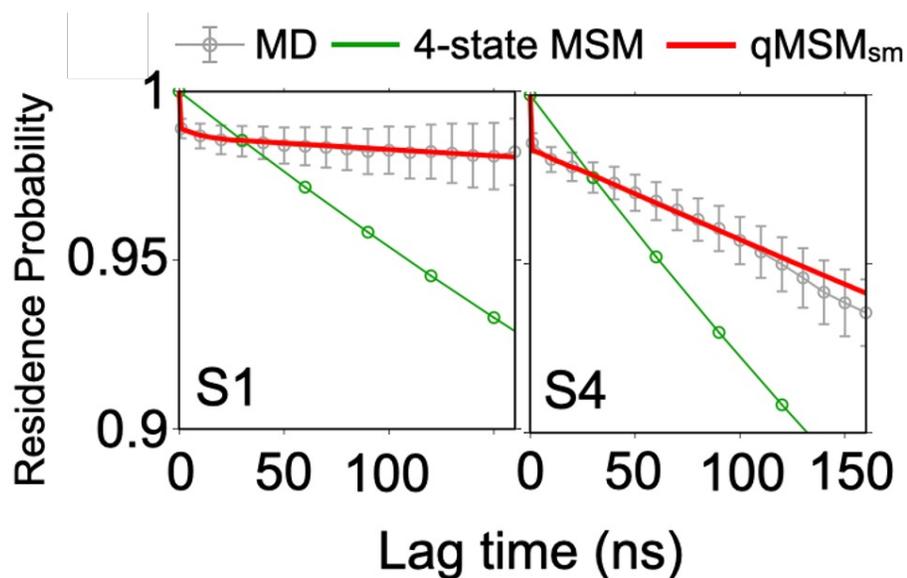
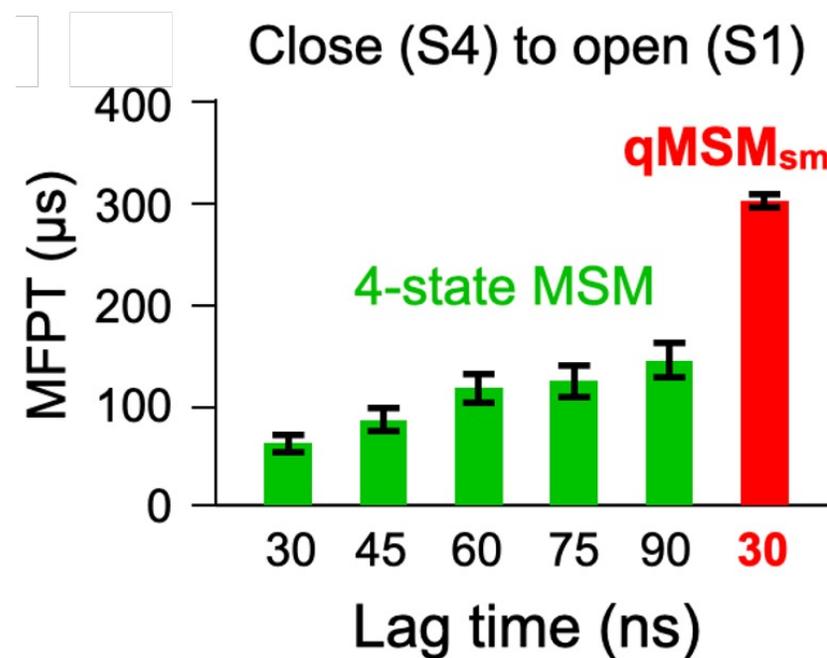
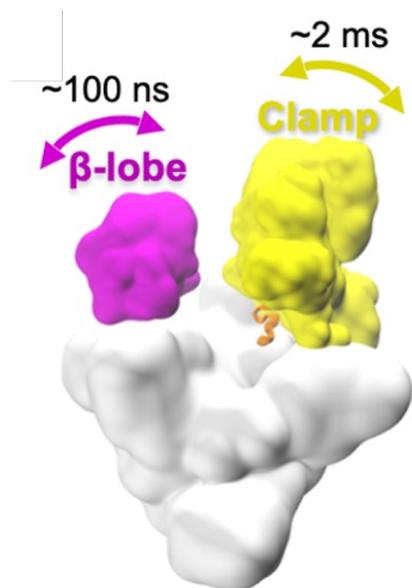
Lime: docking structure to F614A RNAP  
Blue: Myx-bound Crystal structure



*Thermus thermophilus* RNAP

Belogurov et al. *Nature*, 457:332, (2009)

# qMSMs Greatly Outperform MSMs



For MSM, it requires a lag time as long as 2000 ns in order to build a Markovian model (estimated by GME).

*Proc. Nat. Acad. Sci. U.S.A.*,  
118(17), e2024324118, (2021)

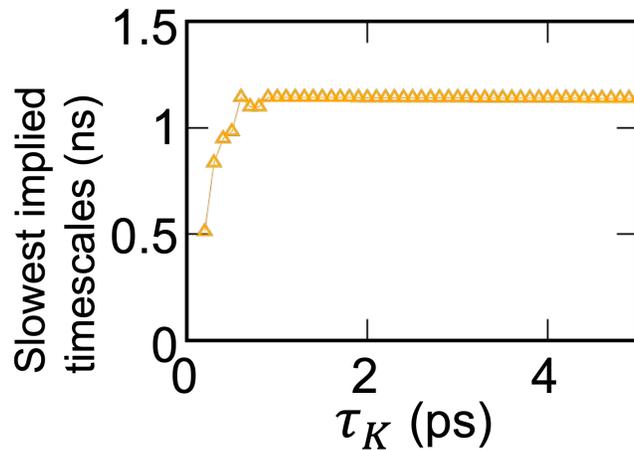
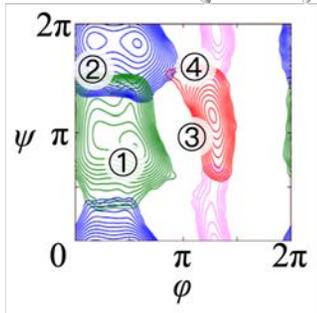
# **Overcoming the Challenges that still Face GME Models**



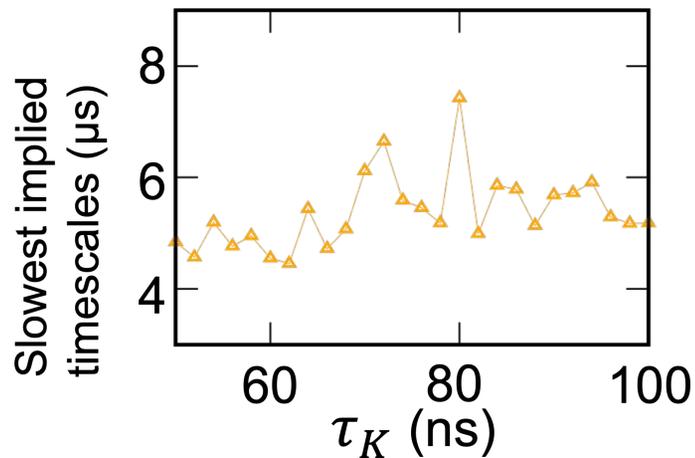
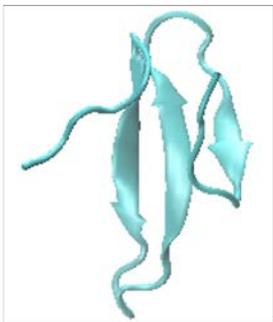
# Numerical Instability of Memory Kernels for Complex Systems

—△— qMSM

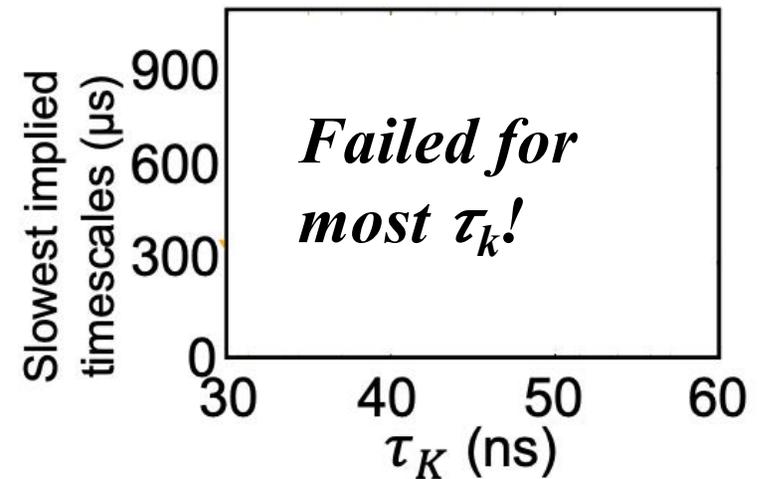
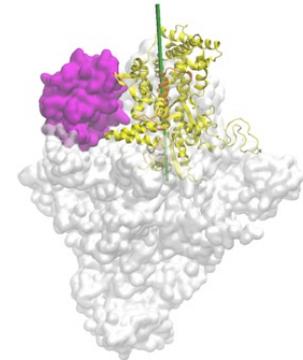
Alanine dipeptide



FIP35 WW domain



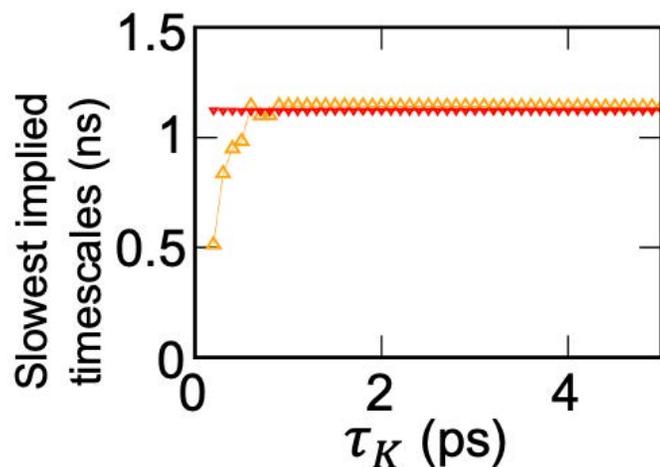
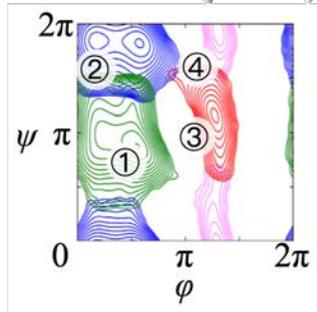
*Taq*  
RNAP



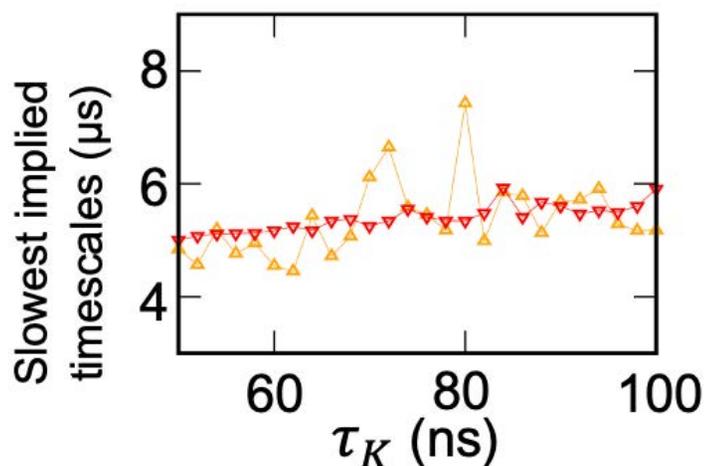
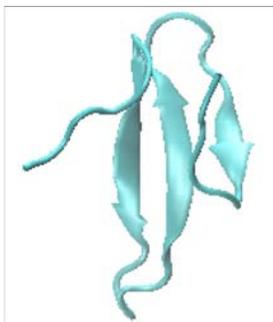
# A Smoothing Scheme Improves Numerical Stability of Memory Kernels, but Not Enough!

—▲— qMSM —▼— qMSM<sub>sm</sub>

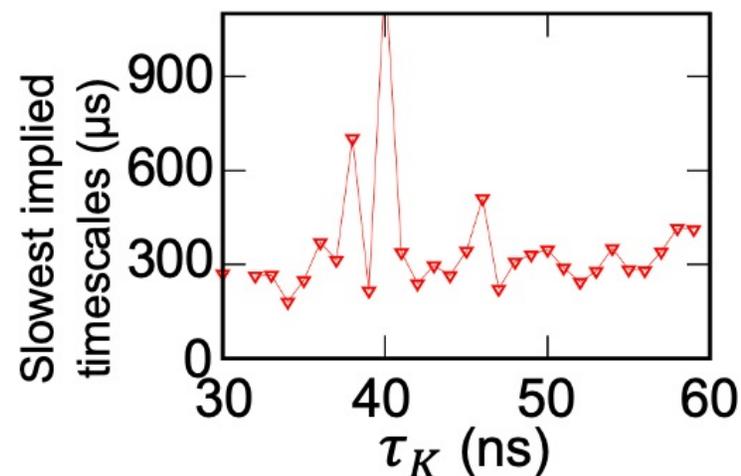
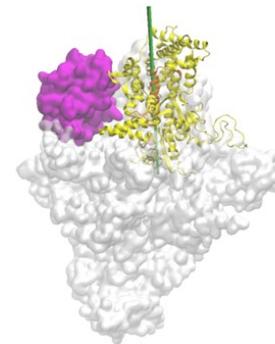
Alanine dipeptide



FIP35 WW domain



*Taq*  
RNAP

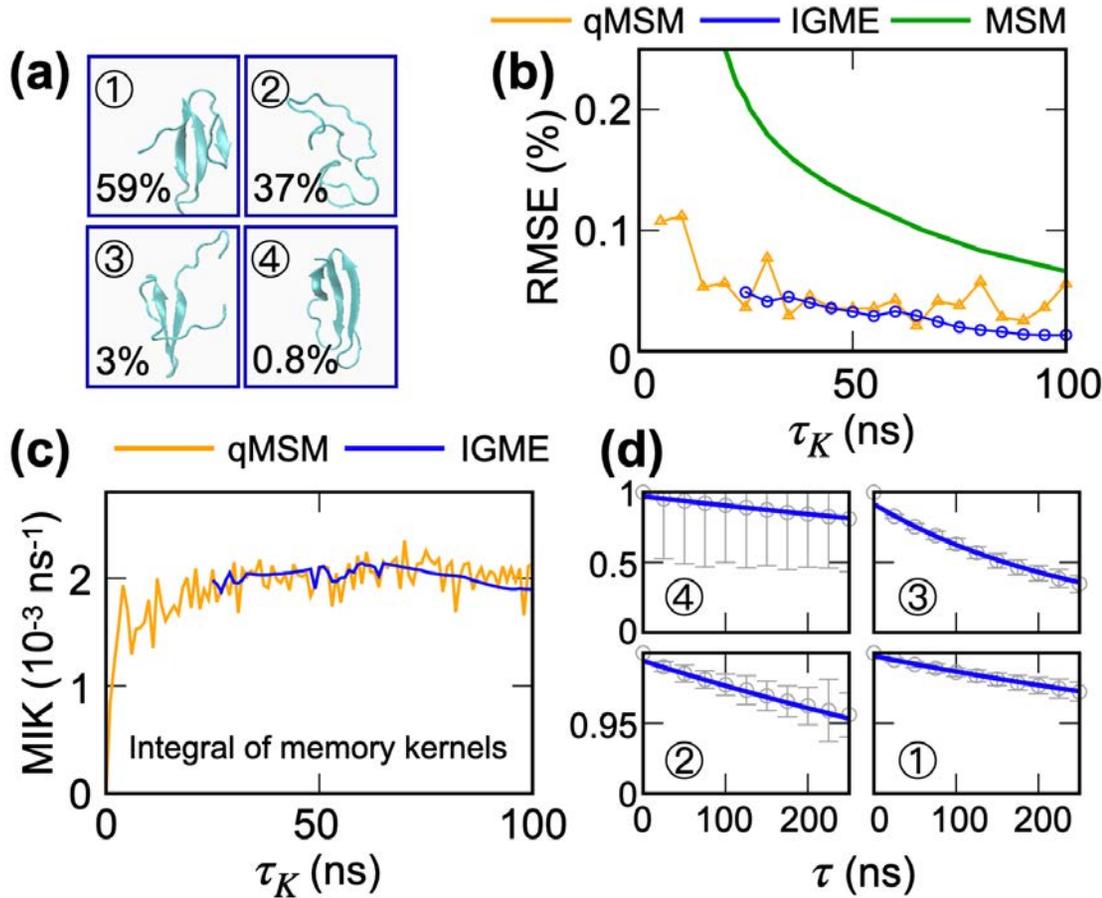


We fit time evolutions of TPM's eigenvalues to multiexponential functions and re-assemble TPMs based on smoothed eigenvalues.

# Integrative-GME (IGME) Method

Taylor expansion of the memory term in GME:

$$\frac{d}{dt} \ln T(t) = \dot{T}(0) - M_0(t) - \left( T(t)^{-1} \sum_{m=1}^n \frac{(-1)^m}{m!} \frac{d^m}{dt^m} T(t) \right) M_m(t)$$



Integrals of memory:

$$M_m(t) = \int_0^t K(s) s^m ds$$

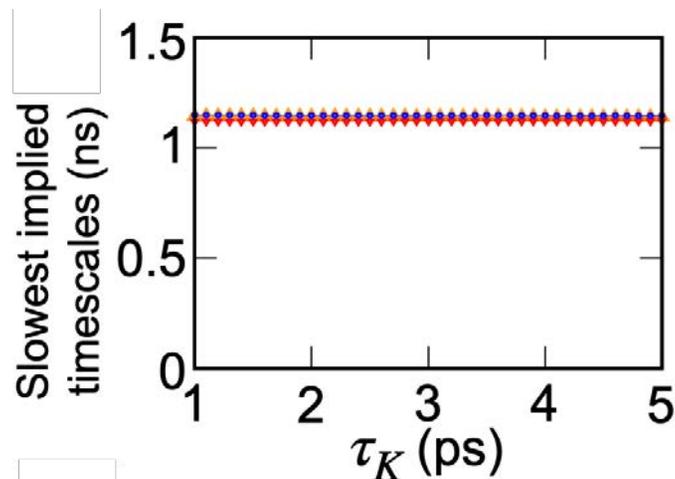
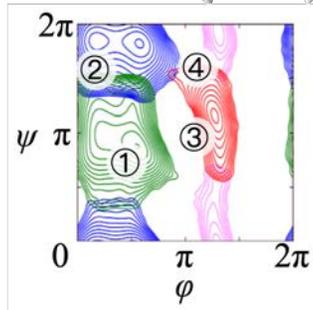
We solve this equation self-consistently.

IGME substantially outperforms qMSM in yielding stable estimations of dynamics!

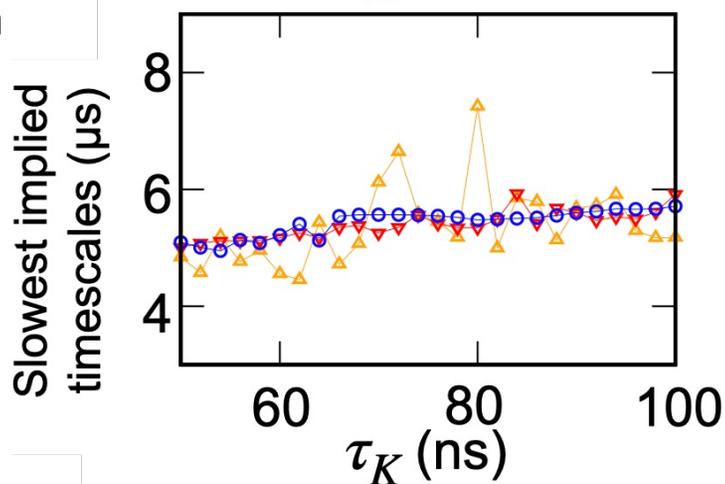
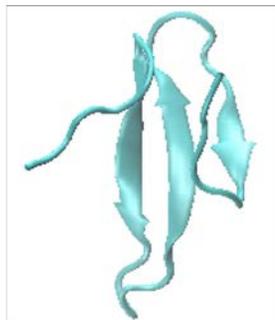
# Integrative-GME (IGME) Models are Stable

—▲— qMSM —▼— qMSM<sub>sm</sub> —○— IGME

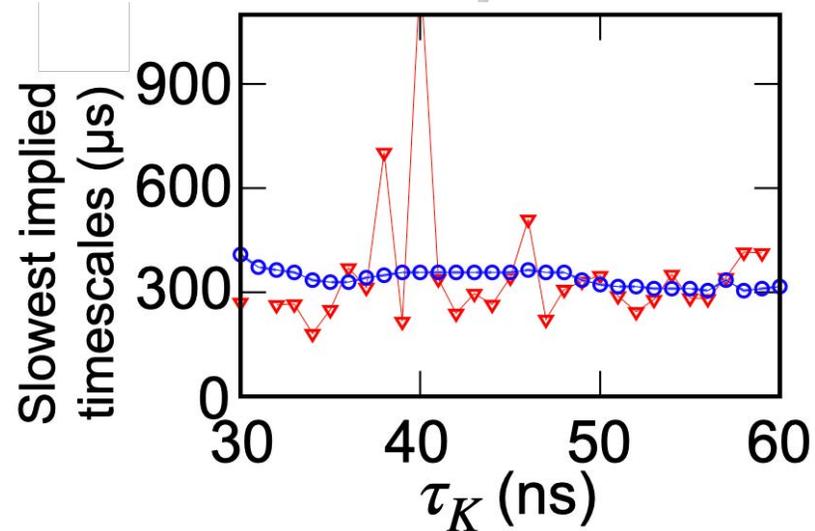
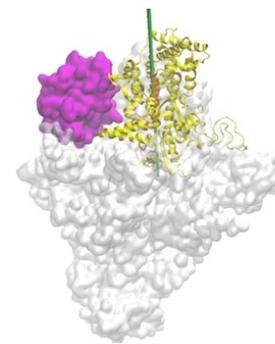
Alanine dipeptide



FIP35 WW domain



*Taq*  
RNAP



IGME provides a numerically robust way to propagate the GME because it only considers the integrals of the memory kernels.



# Integrative Generalized Master Equation: A Theory to Study Long-timescale Biomolecular Dynamics via the Integrals of Memory Kernels

**Working Paper**

[Siqin Cao](#) University of Wisconsin–Madison,  
[Yunrui Qiu](#) University of Wisconsin–Madison,  
[Michael Kalin](#) University of Wisconsin–Madison,  
[Xuhui Huang](#)  University of Wisconsin–Madison

## Abstract

The generalized master equation (GME) provides a powerful approach to study biomolecular dynamics via non-Markovian dynamic models built from molecular dynamics (MD) simulations. Previously, we have implemented the GME for biomolecular dynamics, namely the quasi Markov State Model (qMSM), where we explicitly calculate the memory kernel and propagate protein dynamics using a discretized GME. qMSM can be constructed with much shorter MD simulation trajectories than the Markov State Model (MSM). However, since qMSM needs to explicitly compute the time-dependent memory kernels, it is heavily affected by the

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### Version History

Jan 17, 2023 Version 2  
Dec 30, 2022 Version 1

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**IGME:** <https://github.com/xuhuihuang/IGME>

# Acknowledgement

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