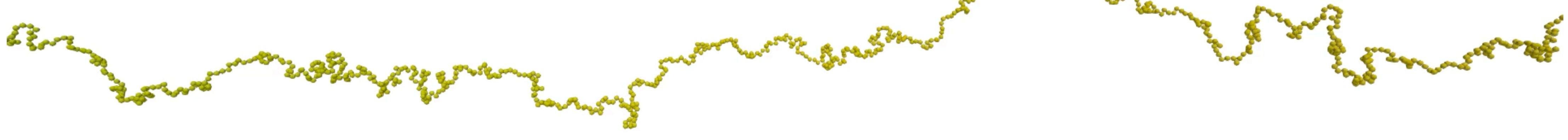
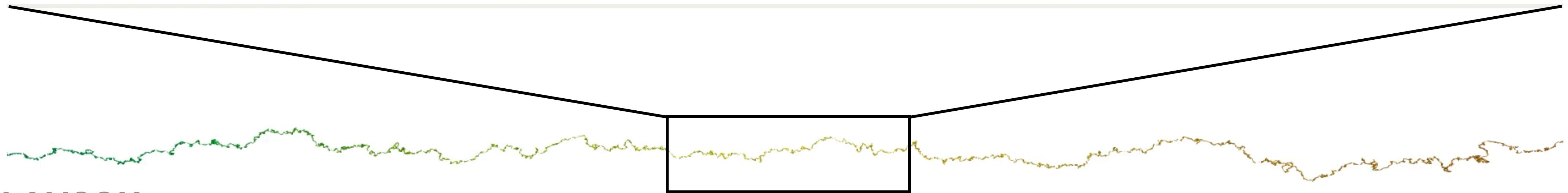


CHROMALENS: FLEXIBLE FILAMENTS AND TRANSIENT NETWORKS



Y
Z



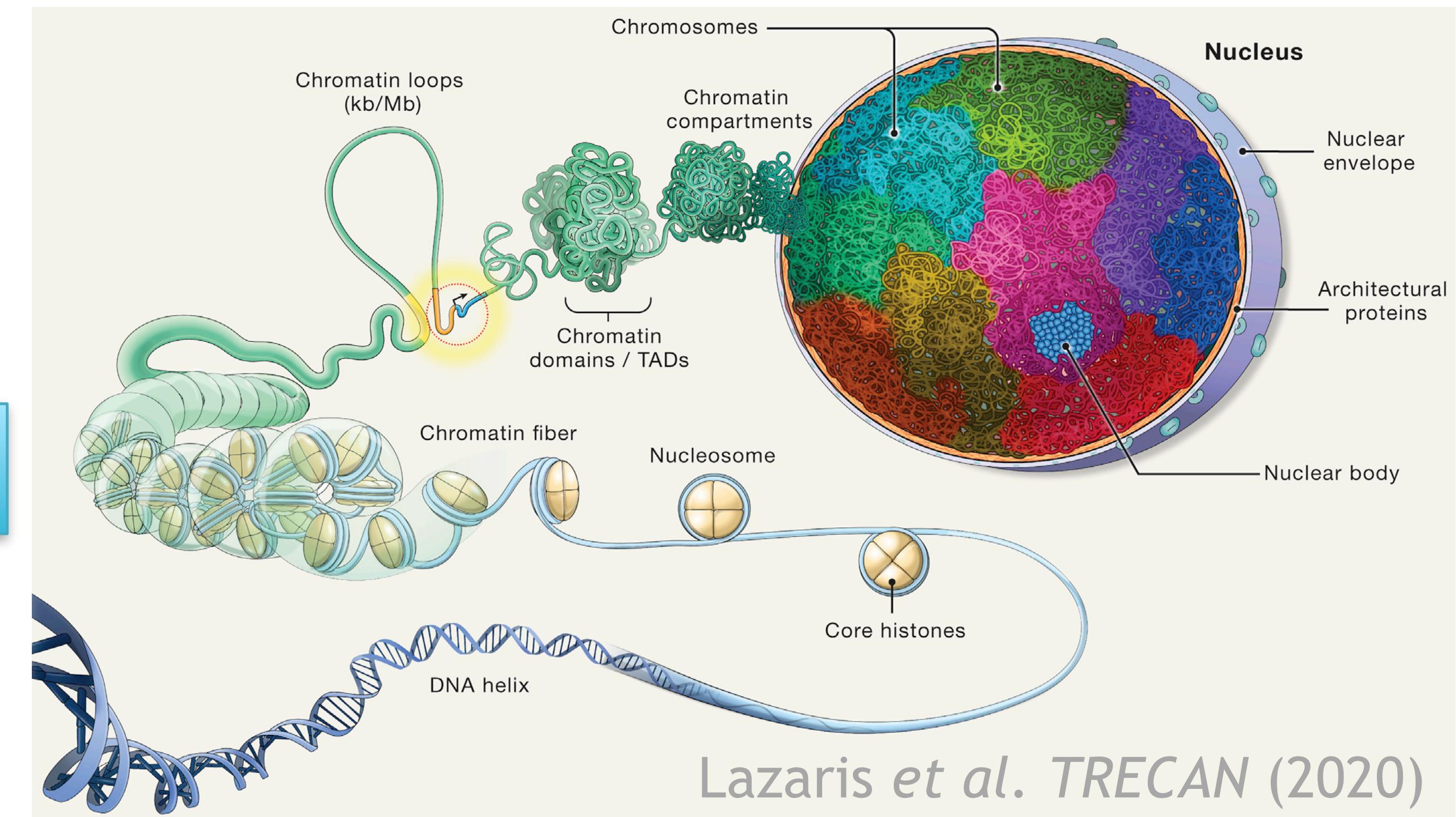
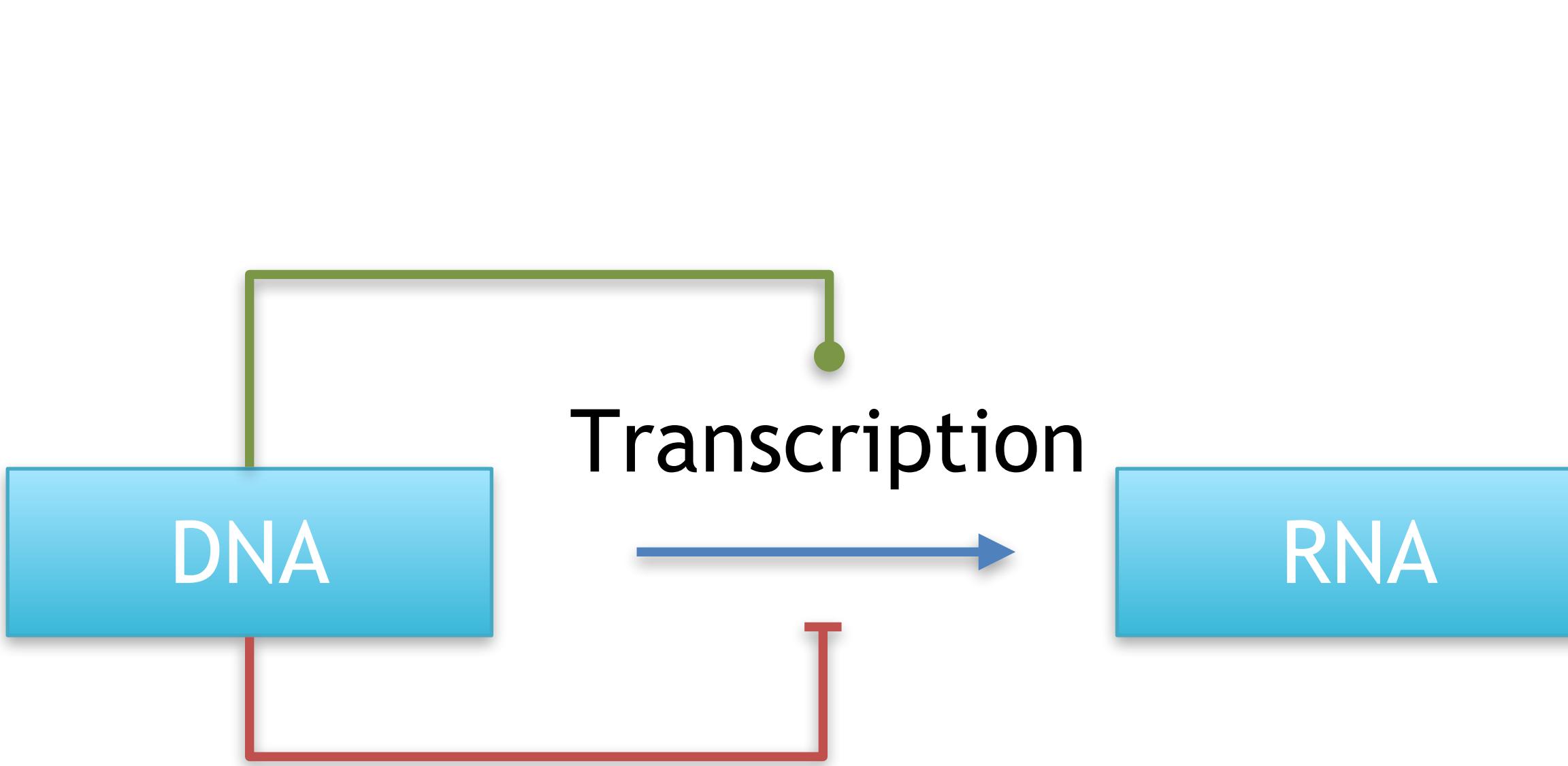
ADAM LAMSON
CENTER FOR COMPUTATIONAL BIOLOGY
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100 μm

Y
Z

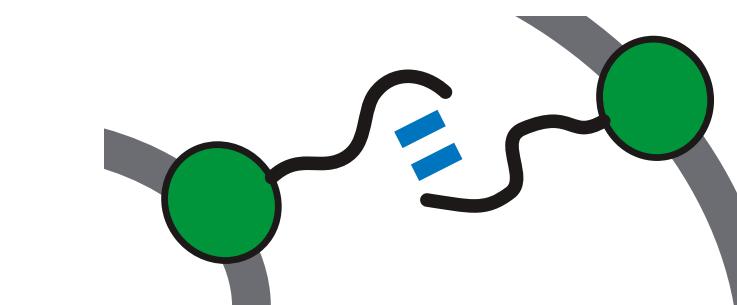
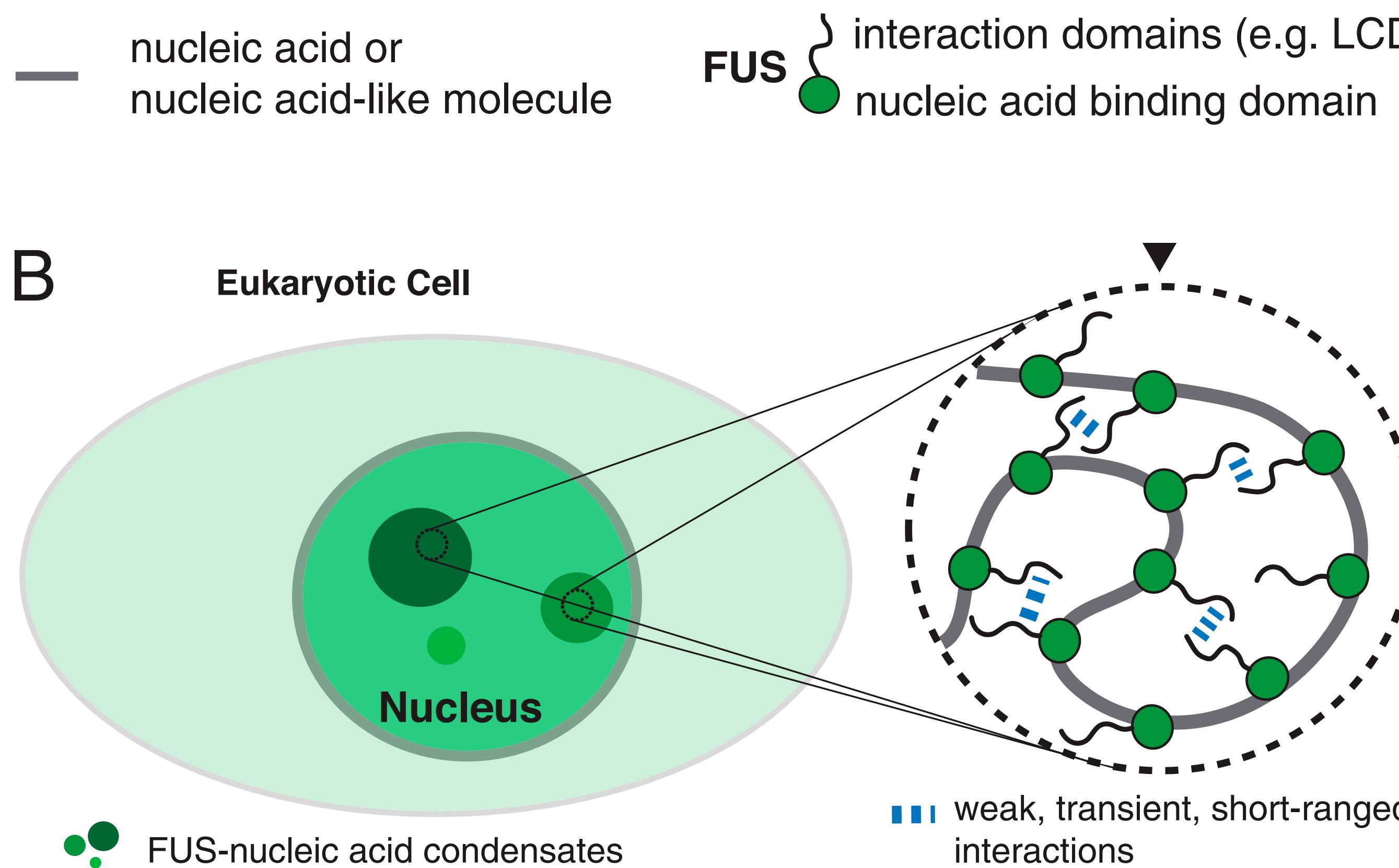
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DNA organizes and interacts with itself to regulate gene expression



DNA binding proteins with interacting disordered domains help organize the nucleus

Example:



Model property wish list:

- Transient: Time-scale associated with segment-segment interactions
- Reach: Length-scale independent of filament diameter
- Valency: Limit of attractive segment interactions
- Computationally scalable

Overview of collapsing filament models

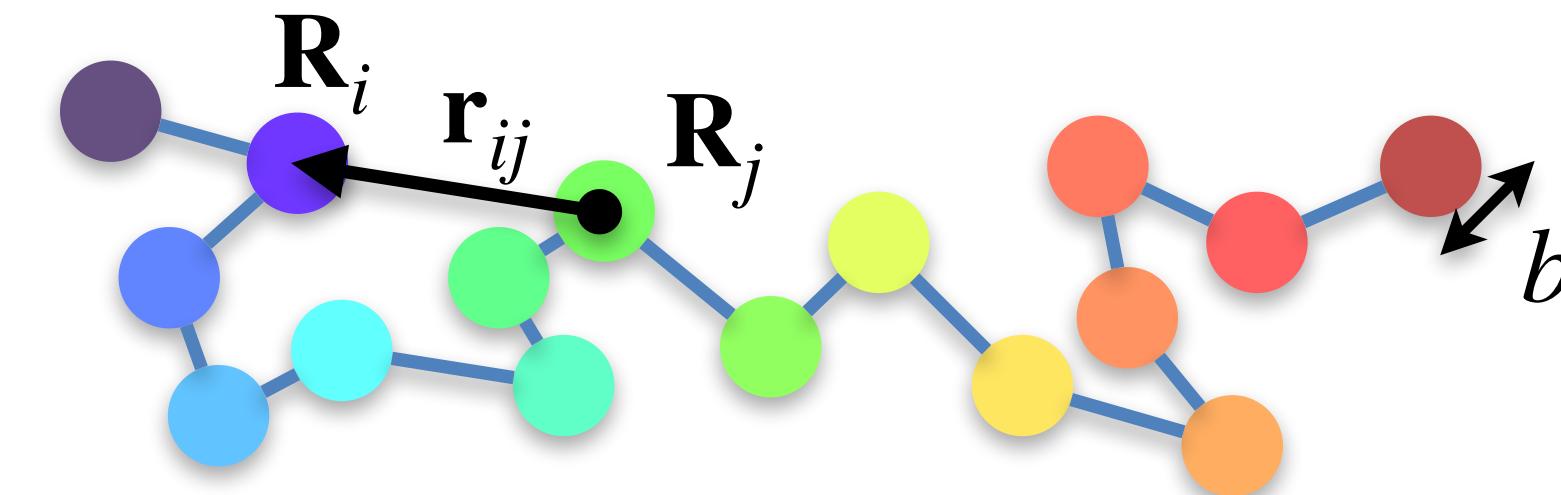
Equations of motion

ζ : drag coefficient

\mathbf{f}_i : Brownian noise

\mathbf{F}_{ij} : Other bead-bead forces

b : Bead diameter and
spring rest length

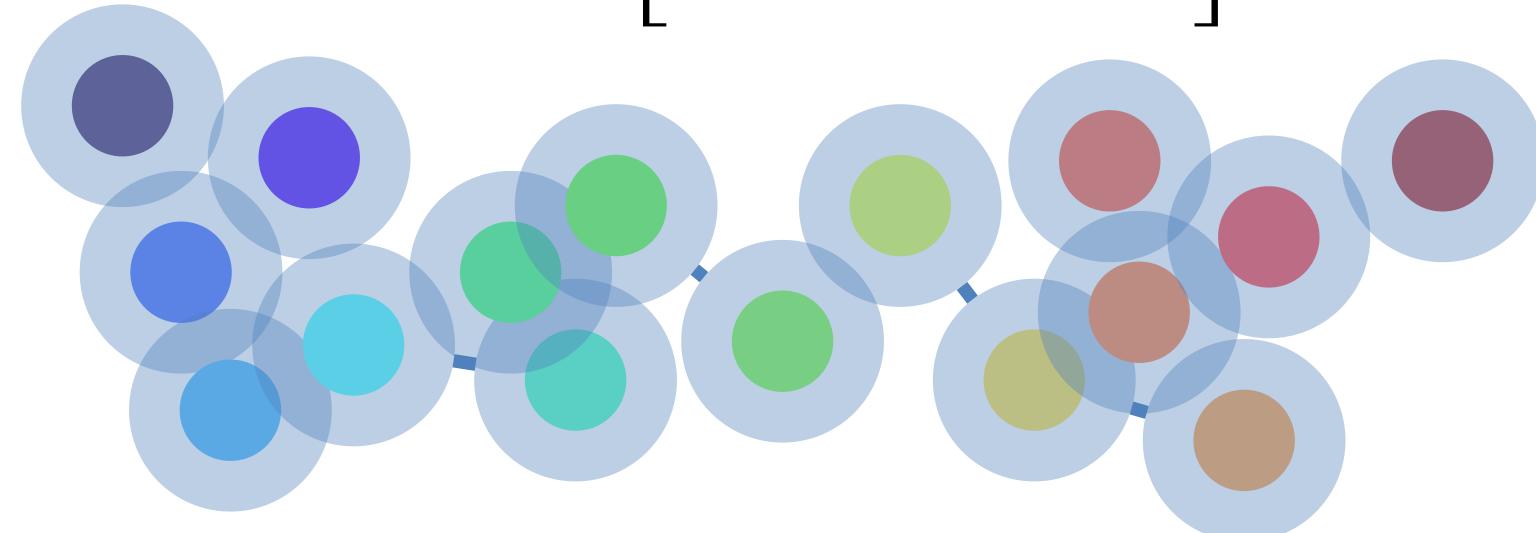


$$\zeta \dot{\mathbf{R}}_i = \mathbf{F}_{i-1,i} + \mathbf{F}_{i,i+1} + \sum_j \mathbf{F}_{ij}(\mathbf{r}_{ij}) + \mathbf{f}_i$$

Spring backbone forces

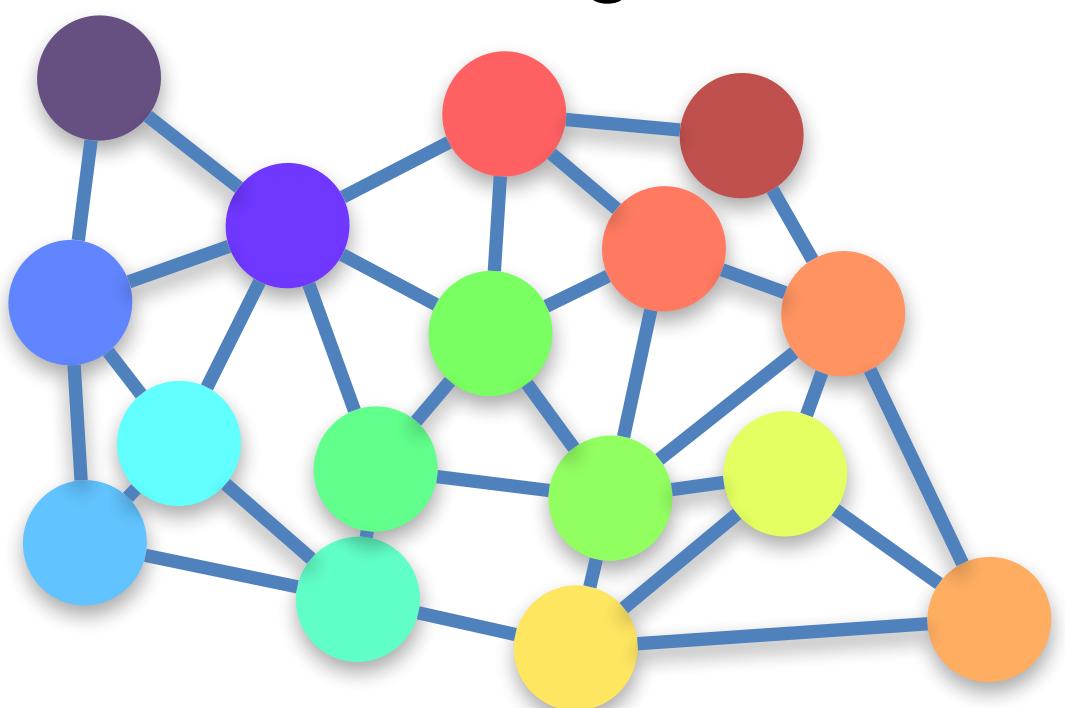
Lennard-Jones and coarse-grained potential models

$$\mathbf{F}^{LJ}(r_{ij}) = \frac{24\epsilon}{r_{ij}} \left[2\left(\frac{b}{r_{ij}}\right)^{12} - \left(\frac{b}{r_{ij}}\right)^6 \right] \hat{\mathbf{r}}_{ij}$$



- Computationally efficient
- No specific valency
- Length-scale affects repulsive force
- Time-scale affects attractive force

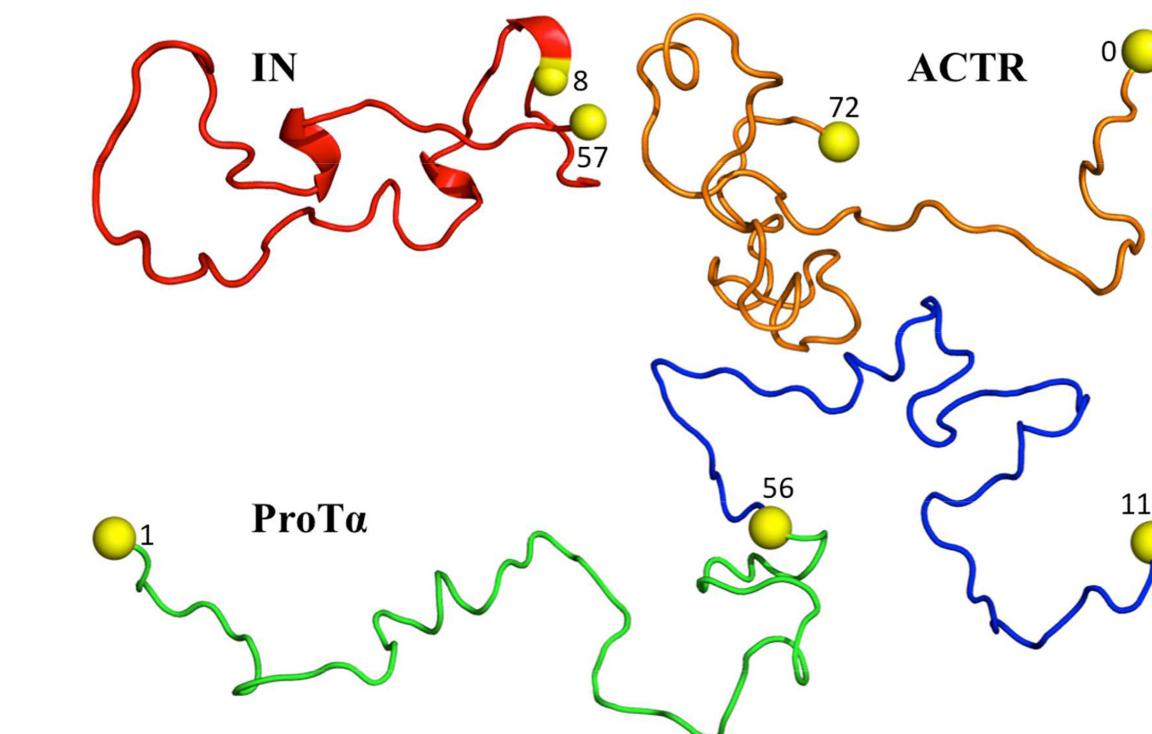
Gaussian network and Irreversible Binding models



- Computationally efficient
- Specifies interaction valency
- Defined average length between interacting polymer segments
- No transient kinetics

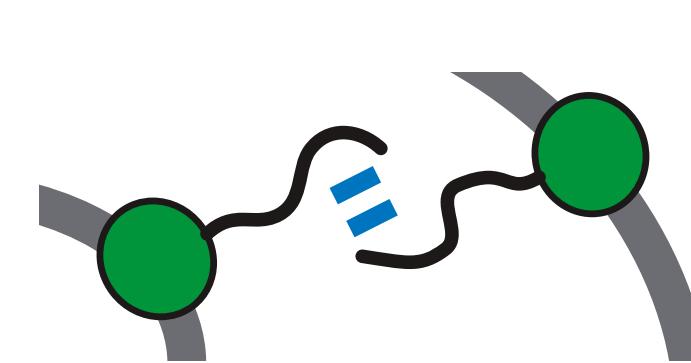
Atomistic force fields models

Valery Nguemaha et al. J Phys Chem B. (2018)

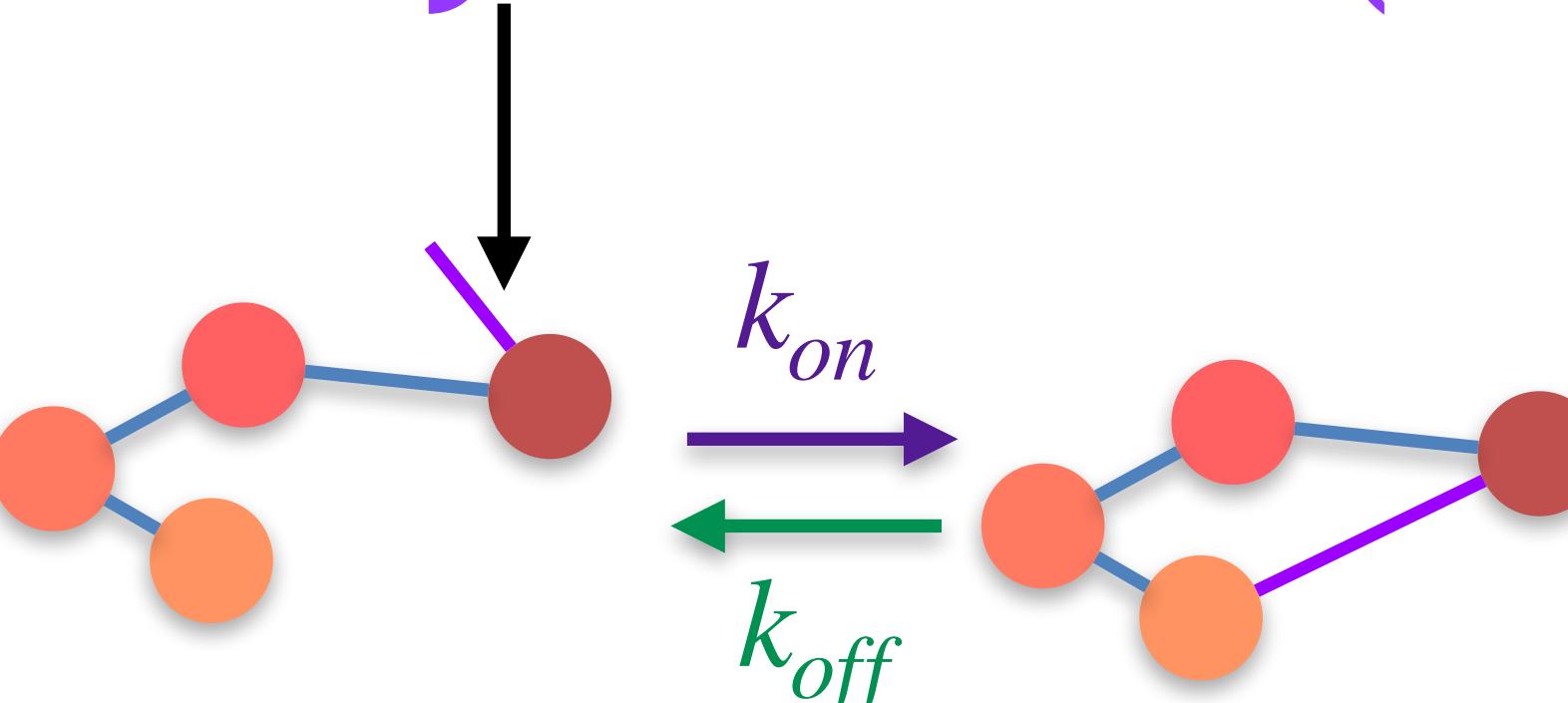


- Most accurate interactions between protein domains
- Computationally expensive!
- Unable to model large sections of DNA

Proposal: Transiently bound (sticky) tail model

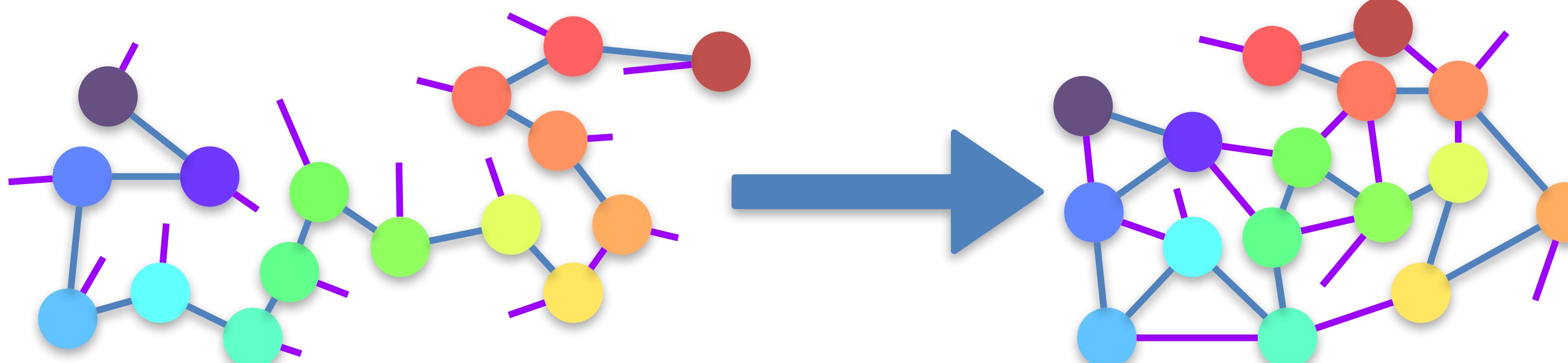


~



$$\frac{k_{on}(r_{ij})}{k_{off}} = K_e e^{-\beta \Delta U(r_{ij})}, \text{ where } U(r_{ij}) = \frac{\kappa_s}{2} (r_{ij} - \ell_s)^2$$

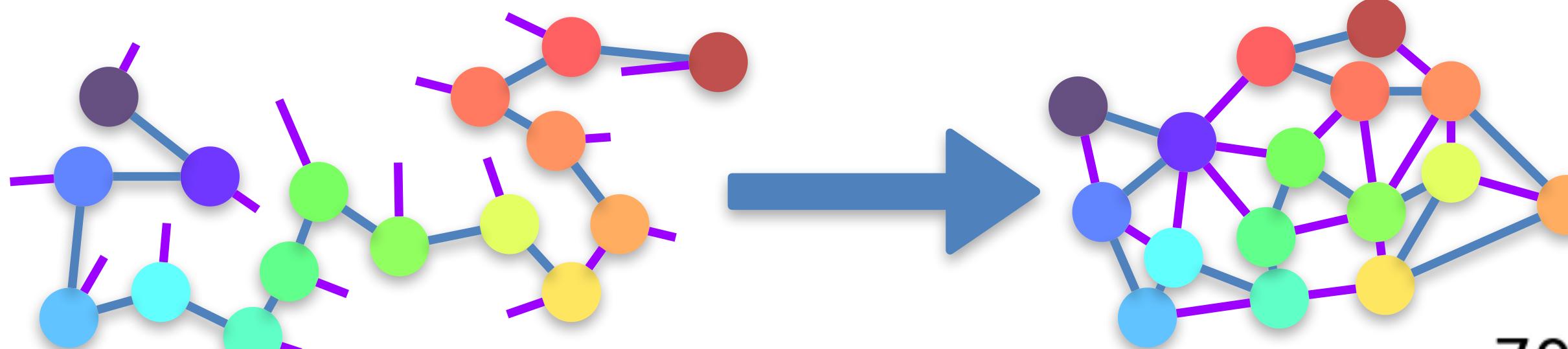
$$\text{So } \mathbf{F}_{ij} = -\partial_{\mathbf{r}_{ij}} U = -\kappa_s(r_{ij} - \ell_s)\hat{r}_{ij}$$



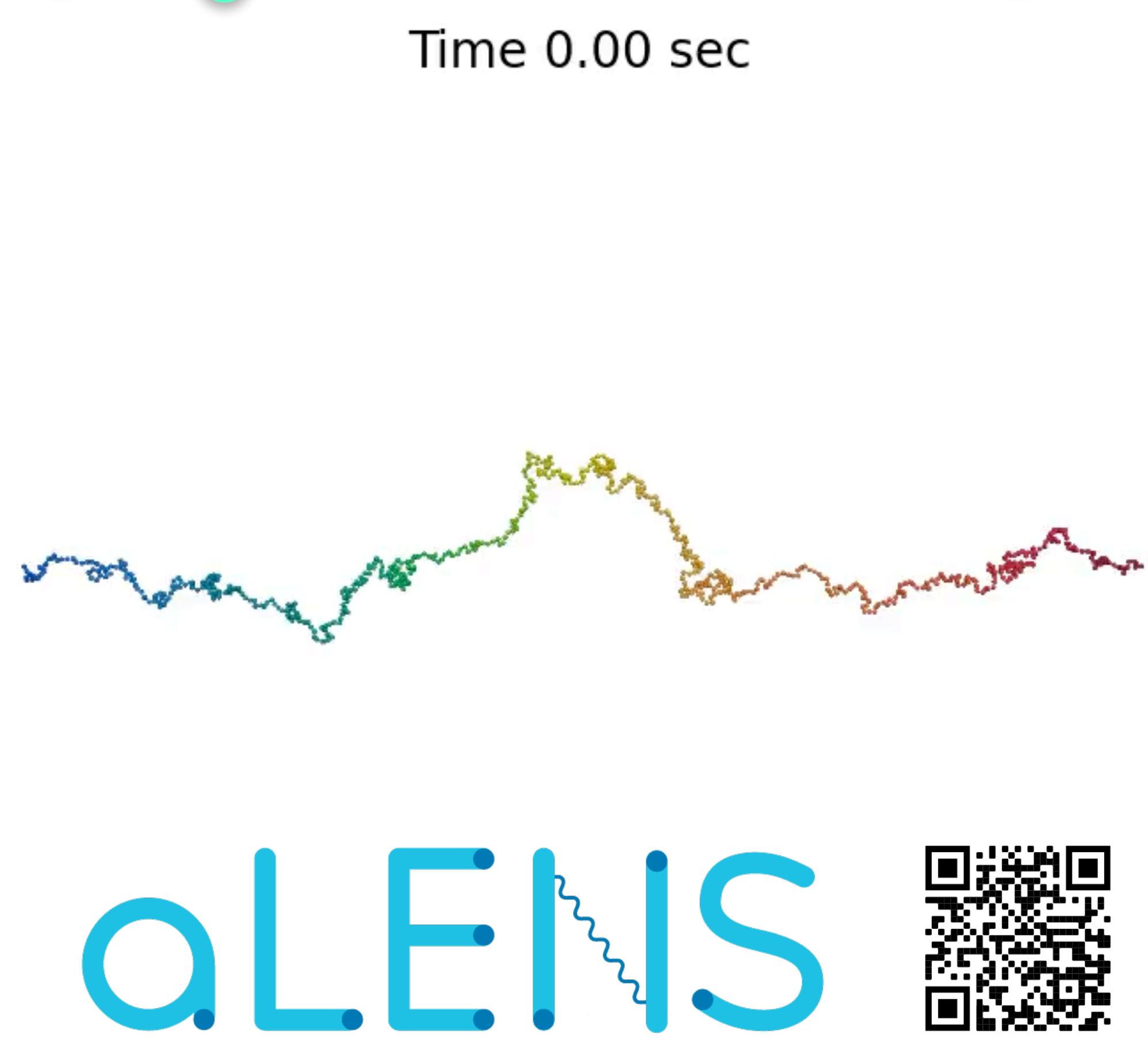
Tail parameters

- k_{on} : Binding rate
- k_{off} : Unbinding rate
- K_e : Binding affinity
- ℓ_s : Rest length
- κ_s : Spring constant

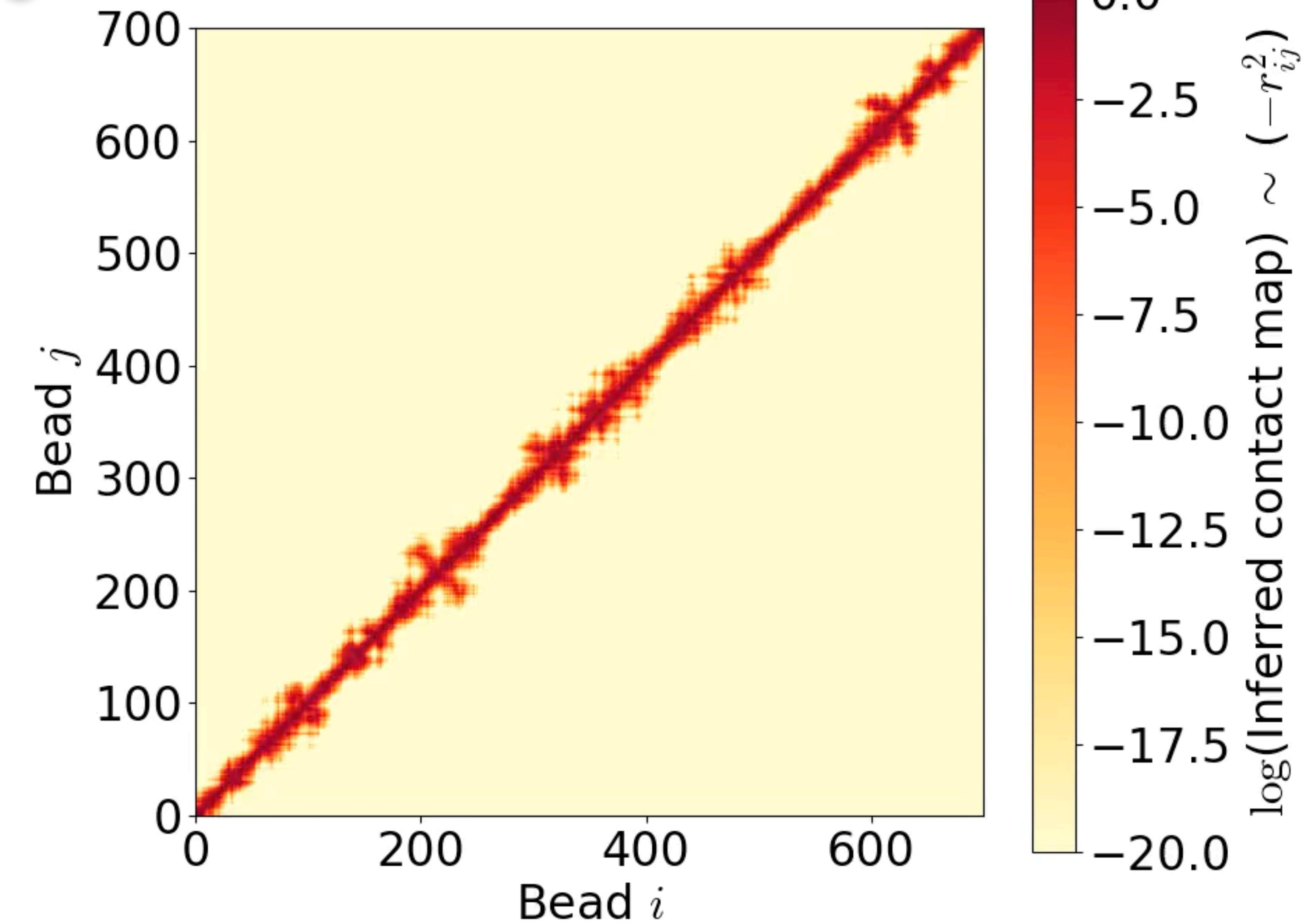
Transient binding tails compacts filaments



Time 0.00 sec

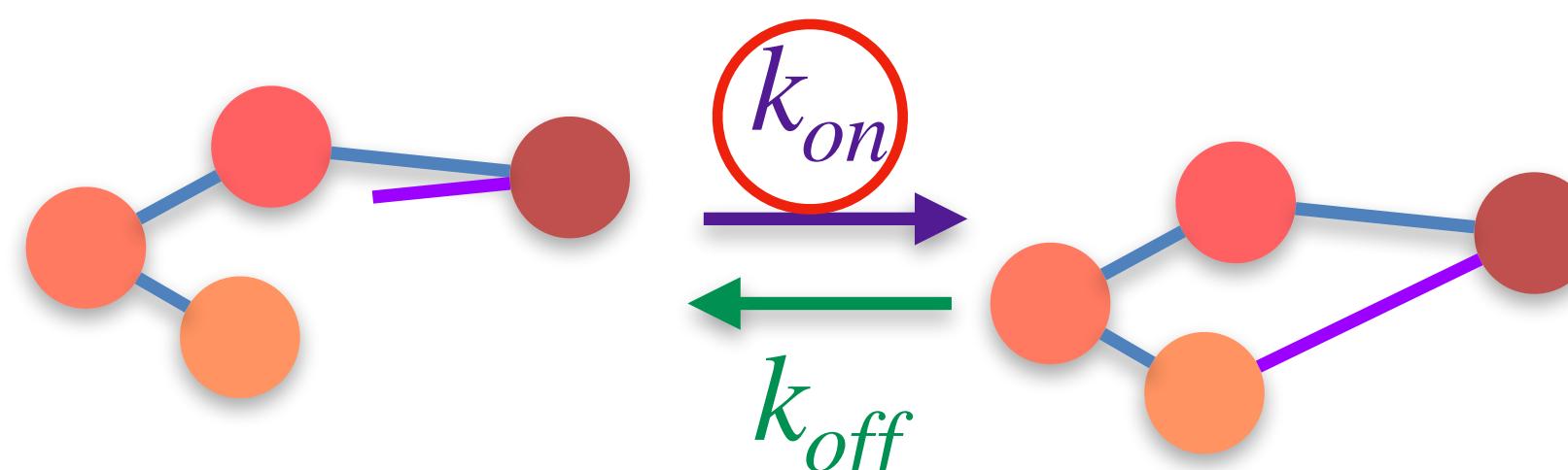


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How do the kinetics affect collapse rate?

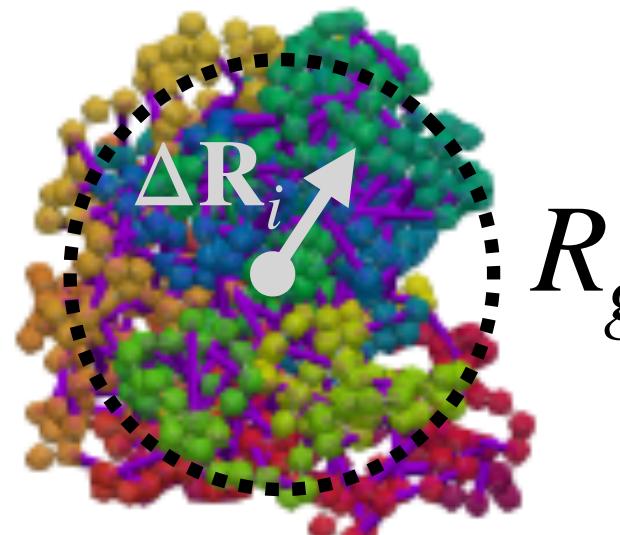
Sticky end parameters
 k_o : Unbinding rate
 K_e : Binding affinity
 ℓ_s : Rest length
 κ_s : Spring constant



$$k_{on}(r_{ij}) = K_e k_o e^{-\beta \Delta U(r_{ij})}, \quad k_{off} = k_o$$

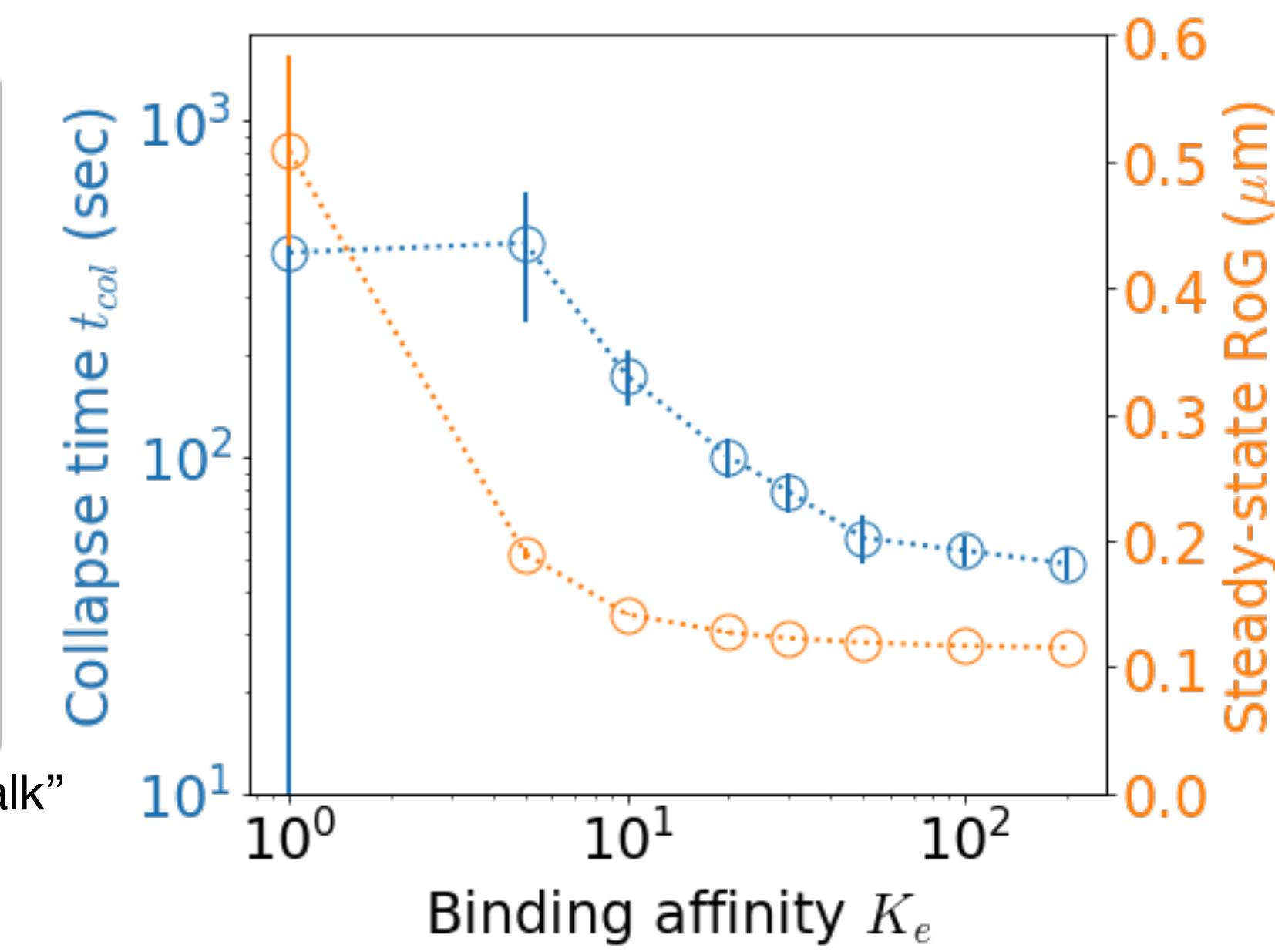
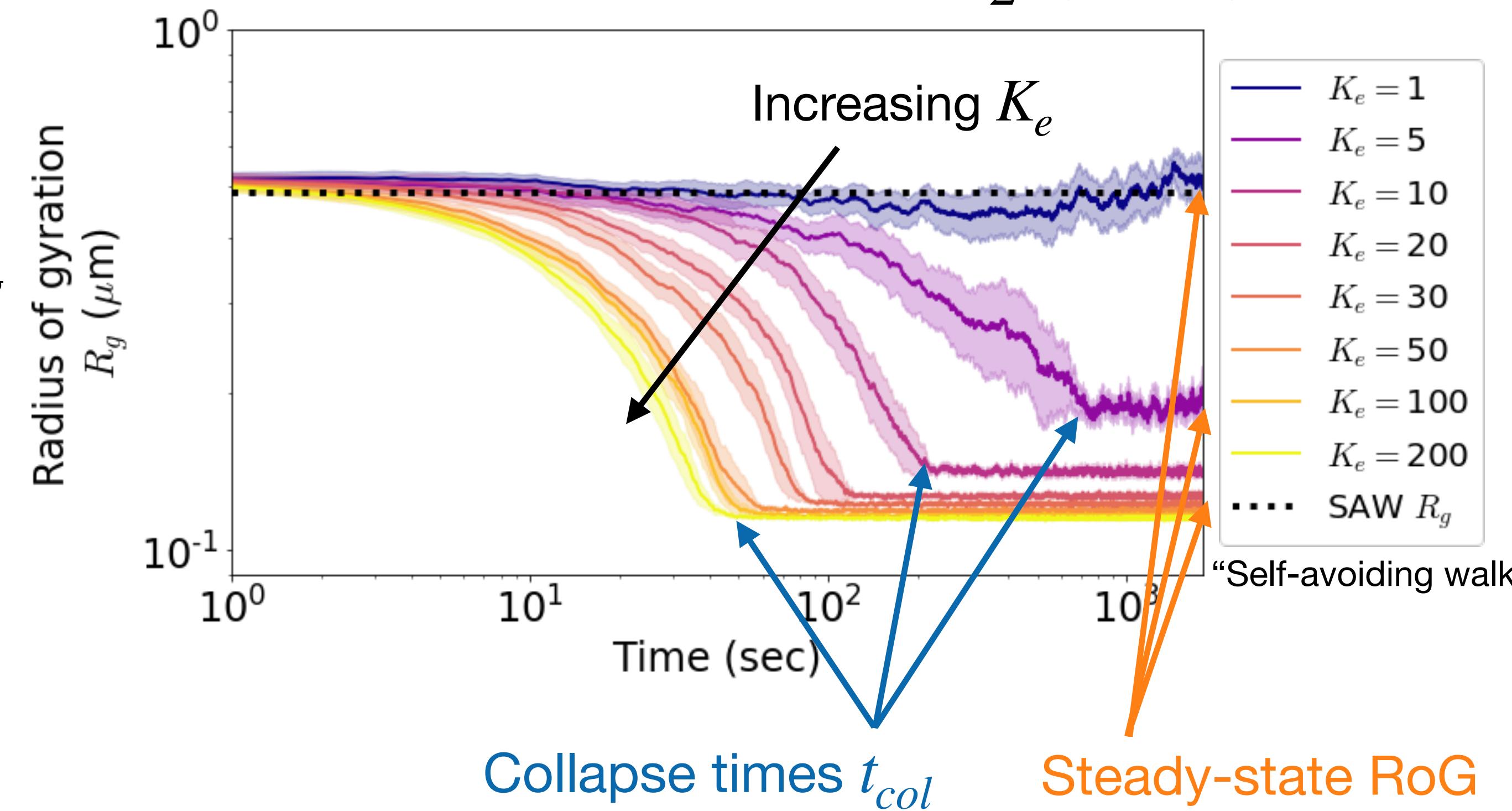
$$U(r_{ij}) = \frac{\kappa_s}{2} (r_{ij} - \ell_s)^2$$

$$\Delta R = R_i - R_{com}$$

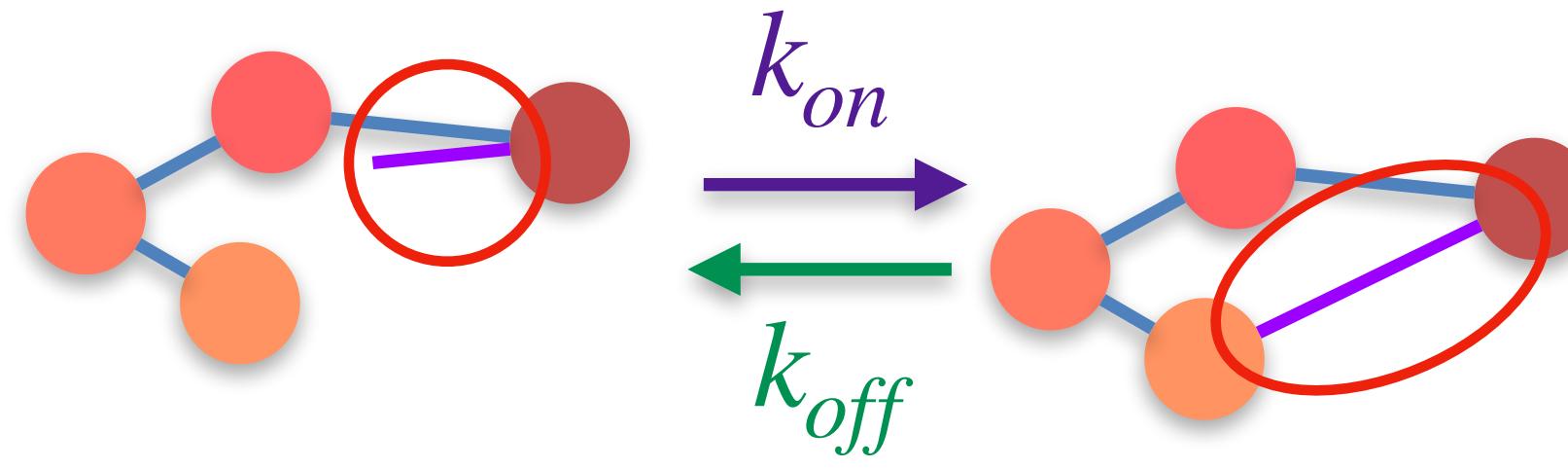


$$\Delta R_i = R_i - R_{com}$$

$$R_g = \sqrt{\frac{1}{N} \sum_i \Delta R_i^2}$$

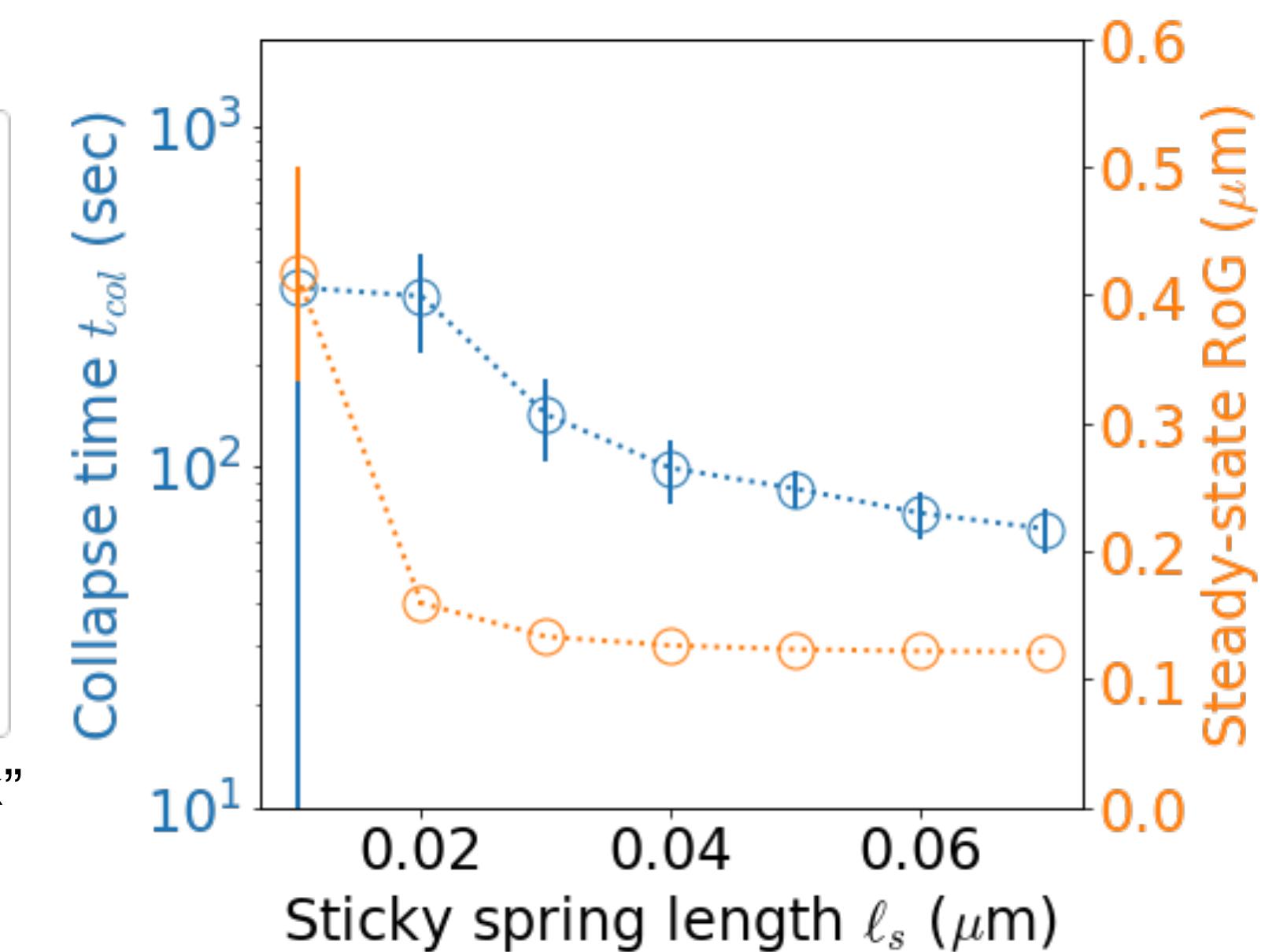
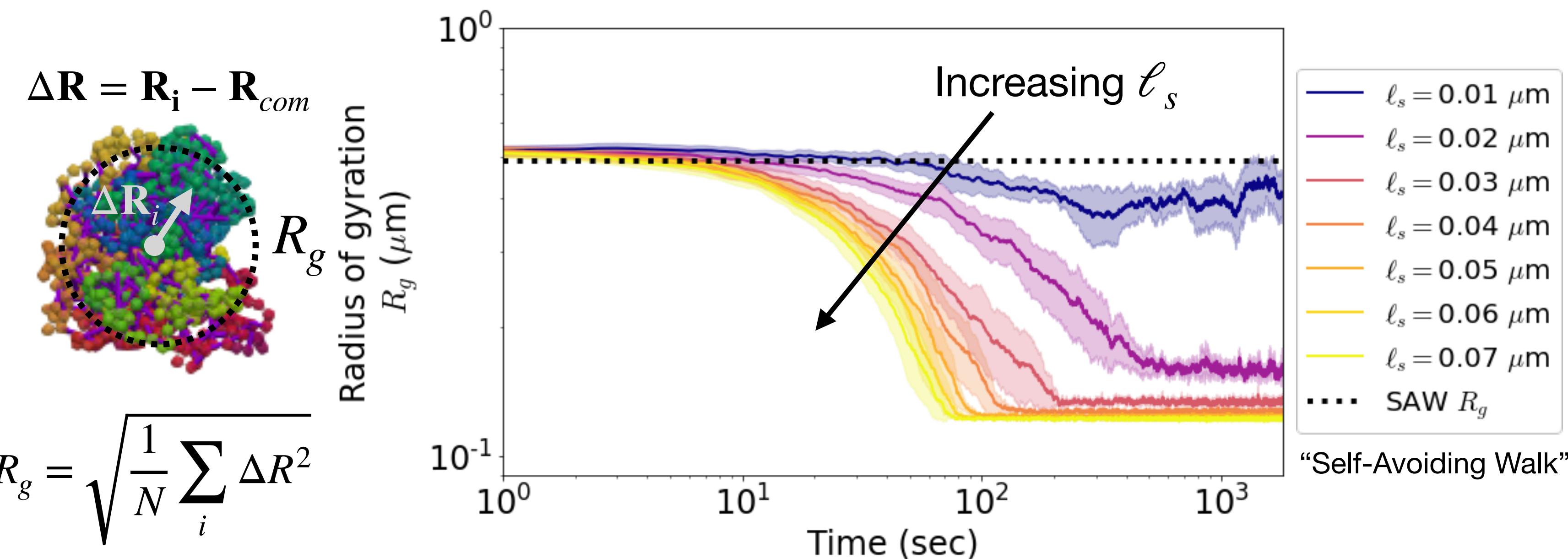


What about the physical characteristics of the tails?



$$k_{on}(r_{ij}) = K_e k_o e^{-\beta \Delta U(r_{ij})}, \quad k_{off} = k_o$$

$$U(r_{ij}) = \frac{\kappa_s}{2} \left(r_{ij} - \ell_s \right)^2$$



Binding affinity and tail length dictate the probability of a single tail being bound

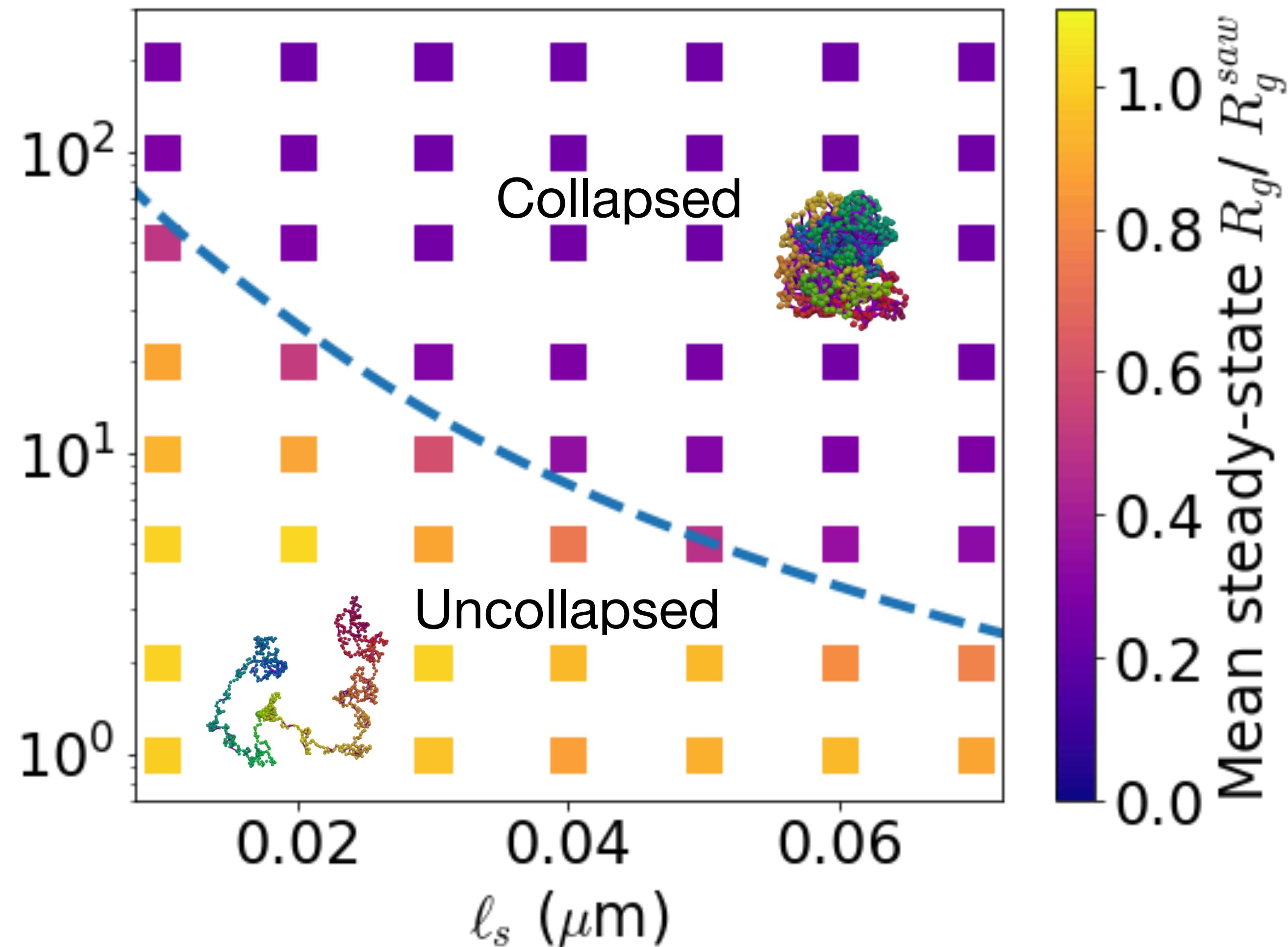
Sticky end parameters
 k_o : Unbinding rate
 K_e : Binding affinity
 ℓ_s : Rest length
 κ_s : Spring constant
 $\rho(\mathbf{r})$: Bead density

Probability of a single sticky tail being bound

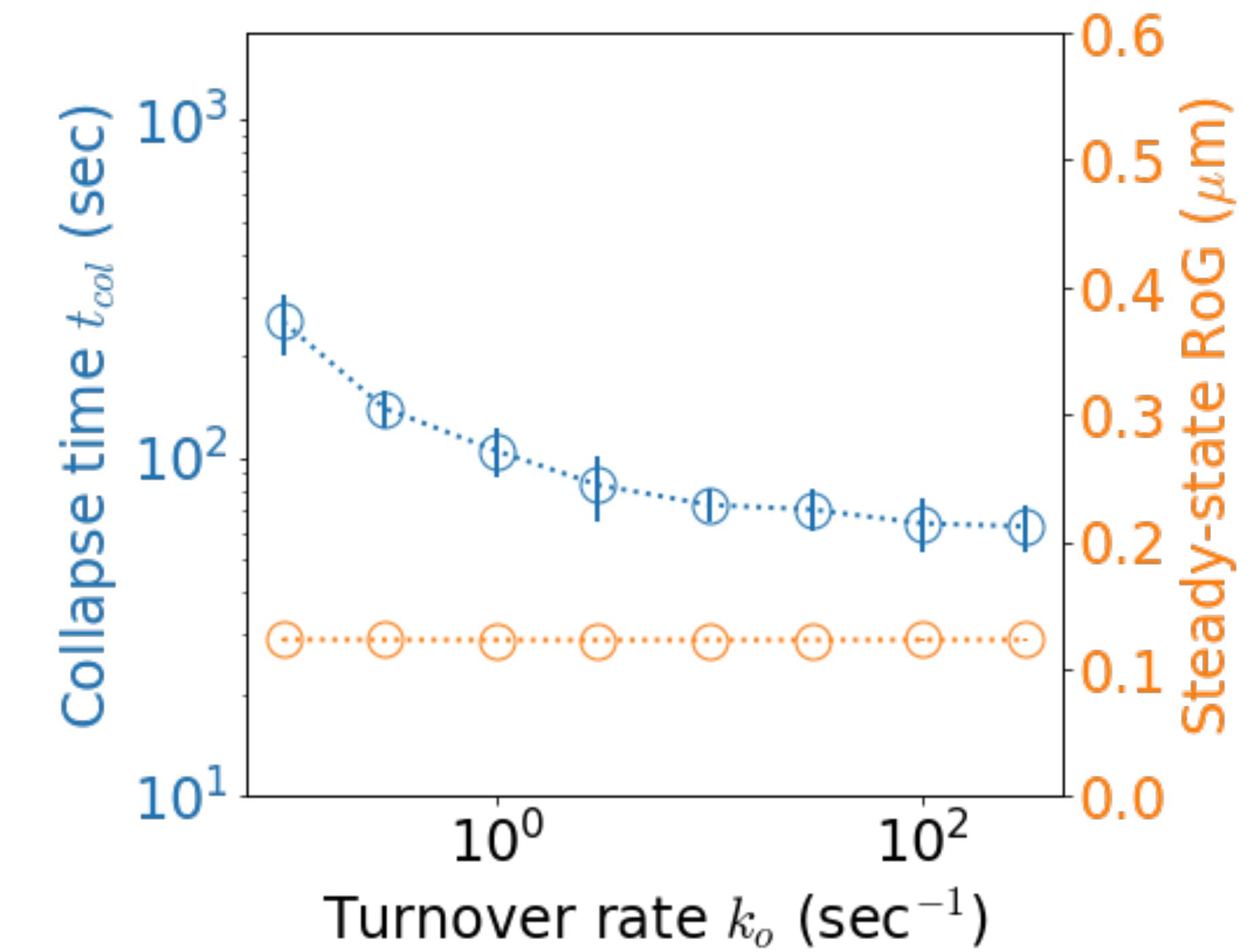
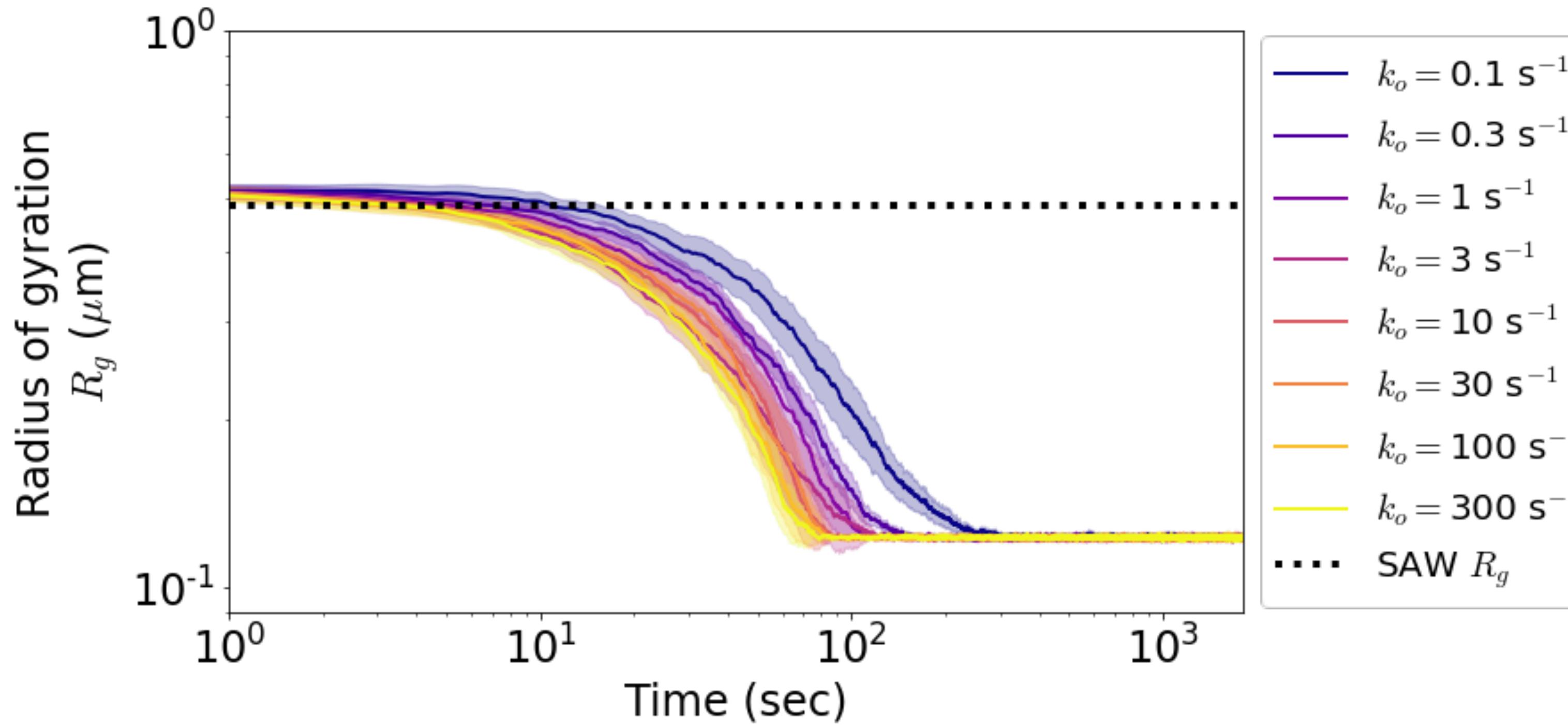
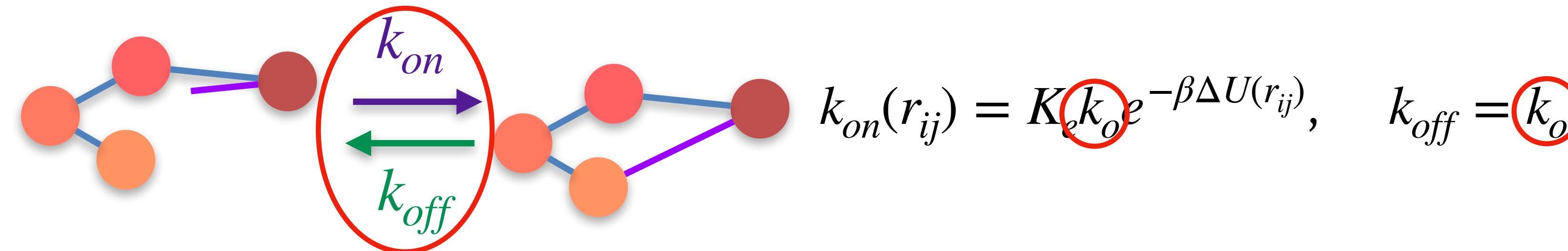
$$\Psi_B = \int d\mathbf{r} \frac{k_{on}(\mathbf{r})}{k_{off}} \rho(\mathbf{r}) = 4\pi \rho_o K_e \int d\mathbf{r} \exp\left(\frac{-\beta\kappa_s}{2}(r - \ell_s)^2\right)$$

Assume critical value for the Ψ_B and solve for K_e as a function of ℓ_s

$$K_e(l_s) = \frac{\Psi_{crit}}{4\pi\rho_o\ell_s^3} \left[\frac{\sqrt{\frac{\pi}{2}} (\beta\kappa_s\ell_s^2 + 1) \left(\text{erf}\left(\sqrt{\frac{\beta\kappa_s\ell_s^2}{2}}\right) + 1 \right)}{\left(\beta\kappa_s\ell_s^2\right)^{3/2}} + \frac{e^{-\frac{1}{2}\beta\kappa_s\ell_s^2}}{\beta\kappa_s\ell_s^2} \right]^{-1}$$

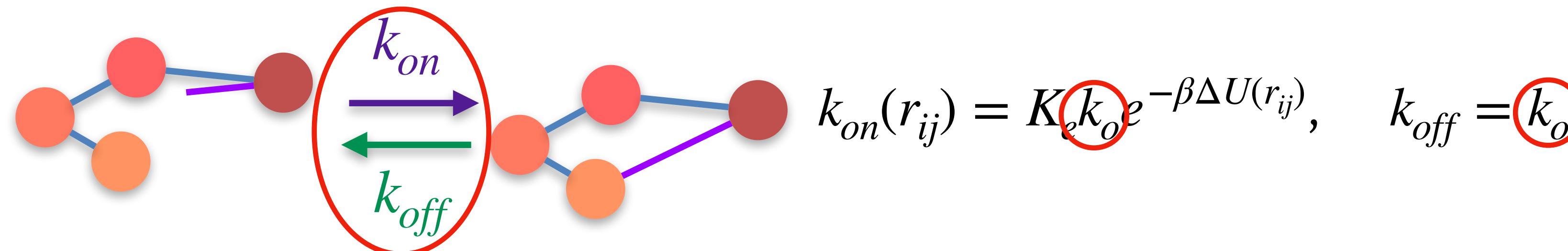


The tail turnover rate affects collapse rate but not steady-state radius of gyration

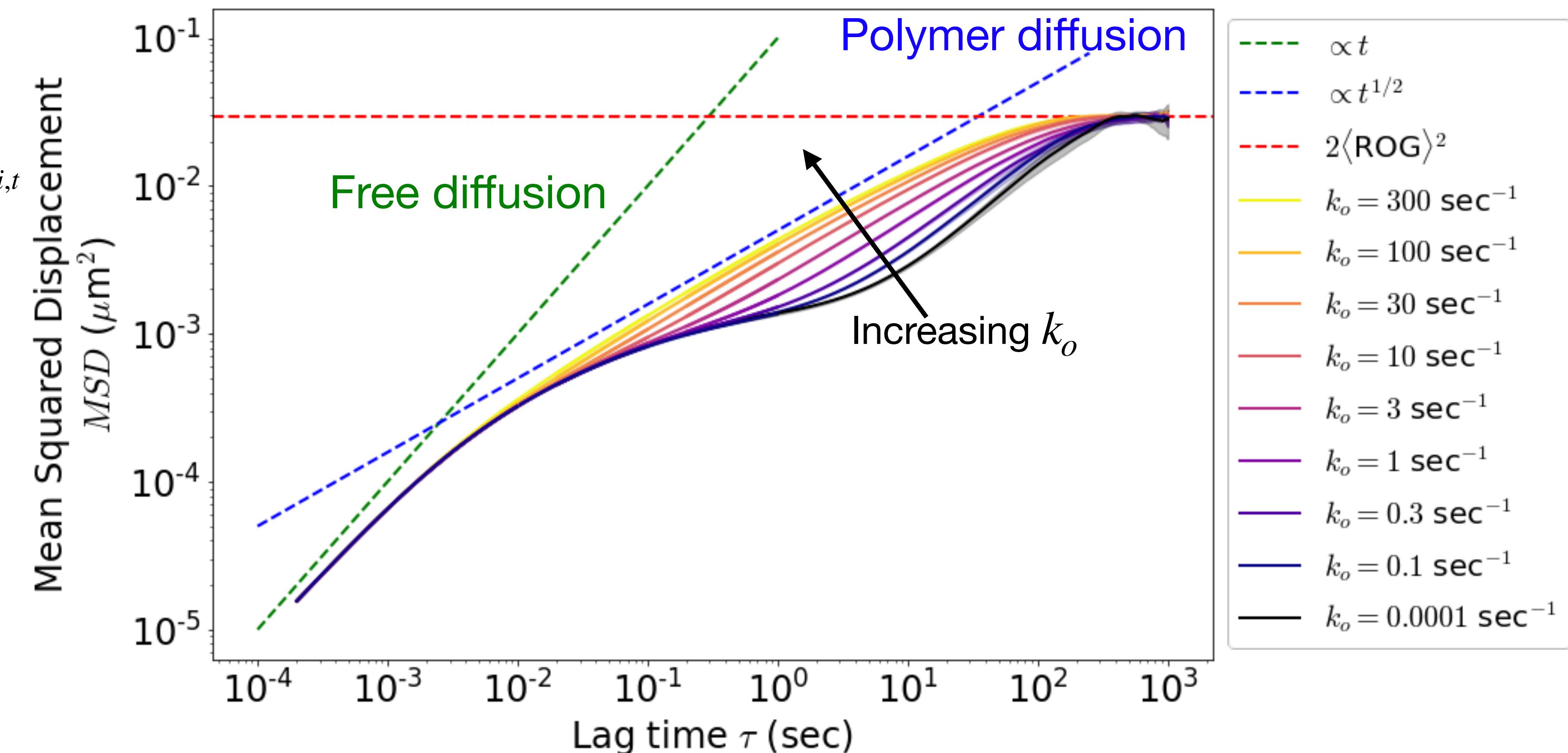
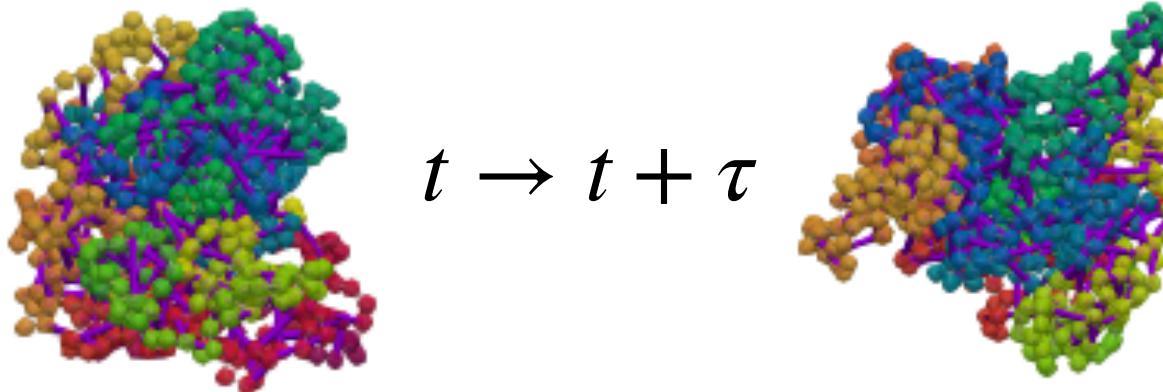


Binding turnover dictates the amount of anomalous diffusion inside collapsed polymer

Sticky end parameters
 k_o : Unbinding rate
 K_e : Binding affinity
 ℓ_s : Rest length
 κ_s : Spring constant

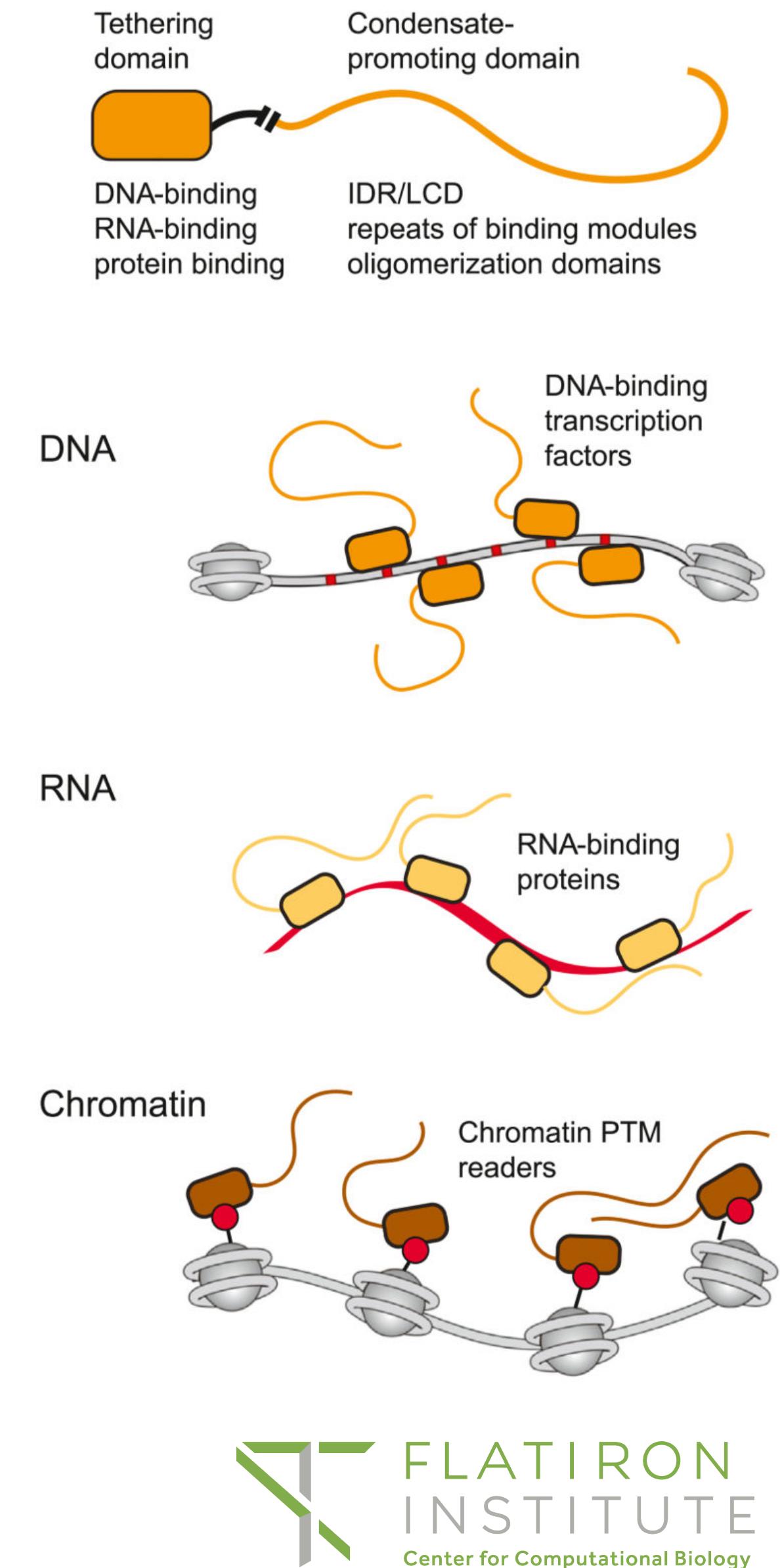
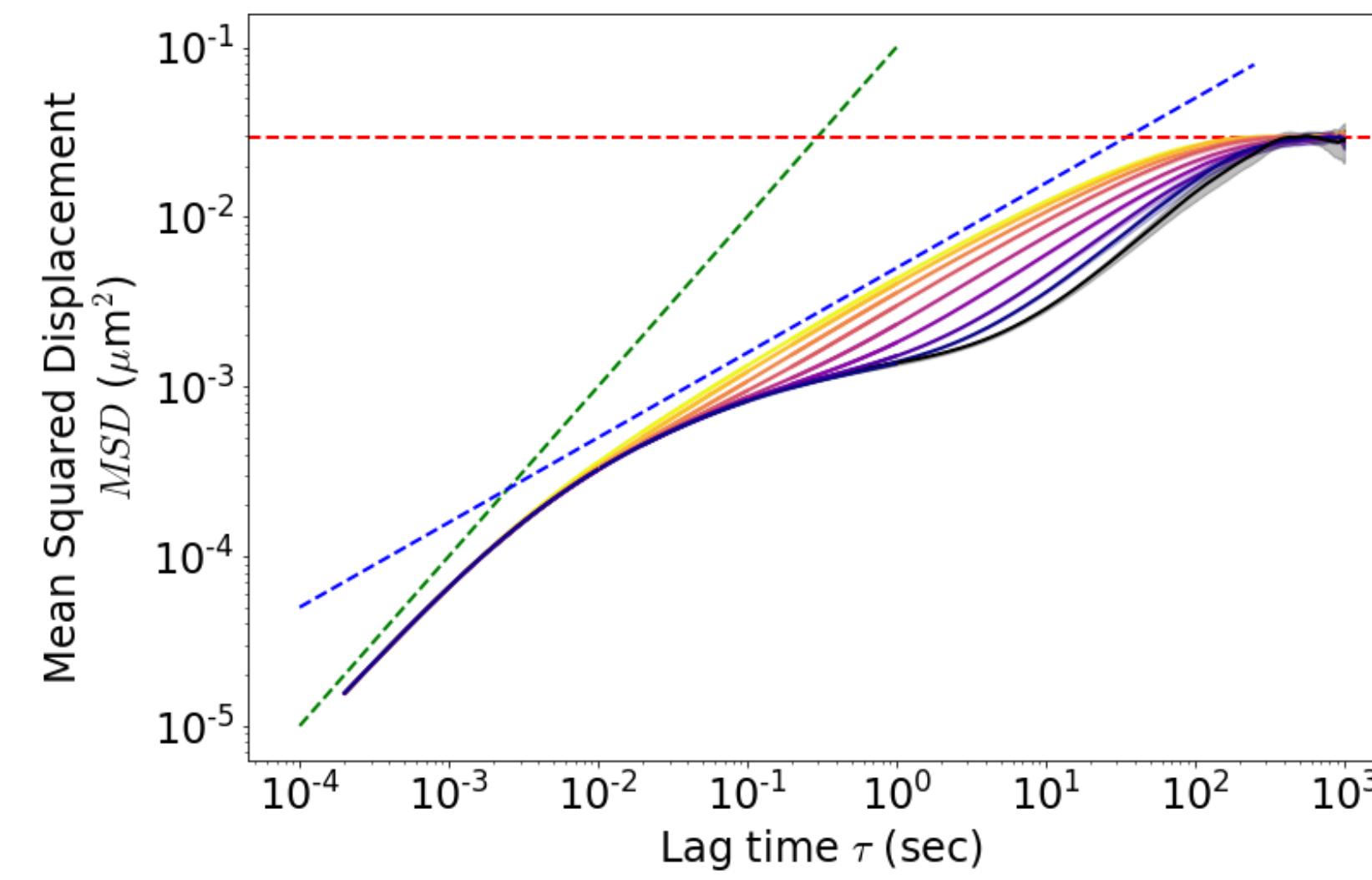
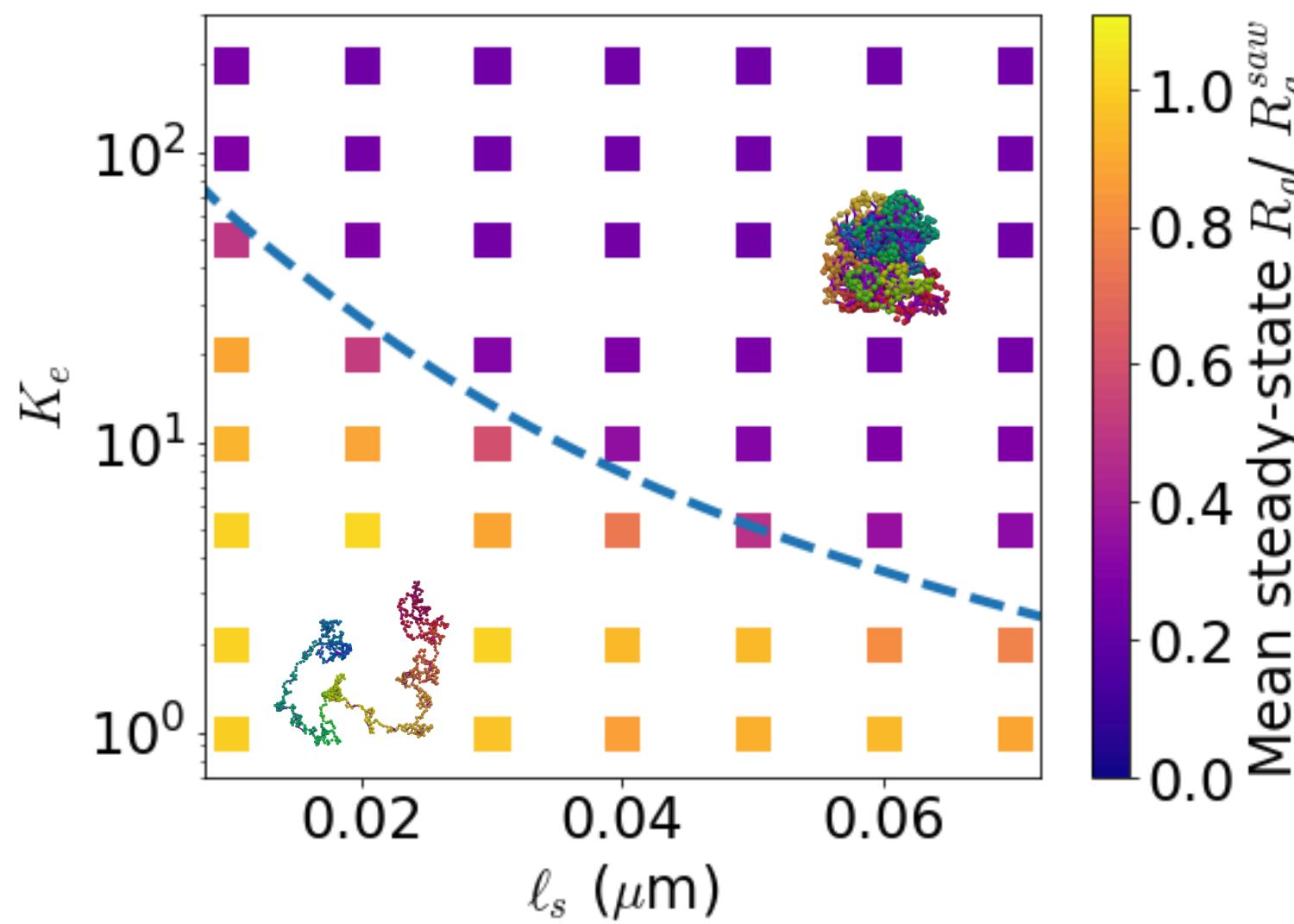


$$MSD(\tau) = \langle |\Delta \mathbf{R}_i(\tau + t) - \Delta \mathbf{R}_i(t)|^2 \rangle_{i,t}$$



Take aways

- The sticky tail model is a simplified yet computationally efficient and general model for filaments bound by proteins with attractive domains.
- We can predict polymer collapse based on the kinetic and physical parameters of tails.
- Period of tail binding cycle dictates reorganization speed of condensed polymers.



Thank you!



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Group leaders

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Olga Troyanskaya



Collaborators

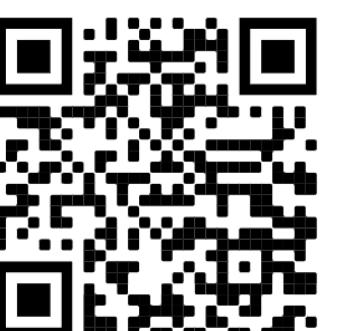
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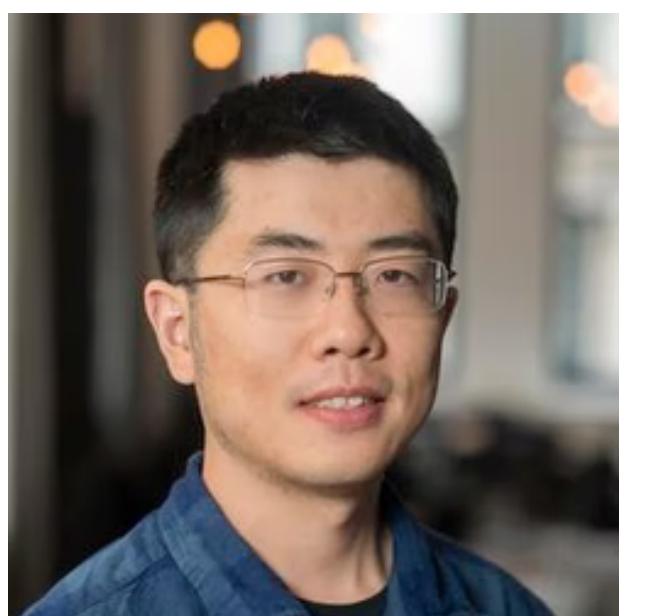
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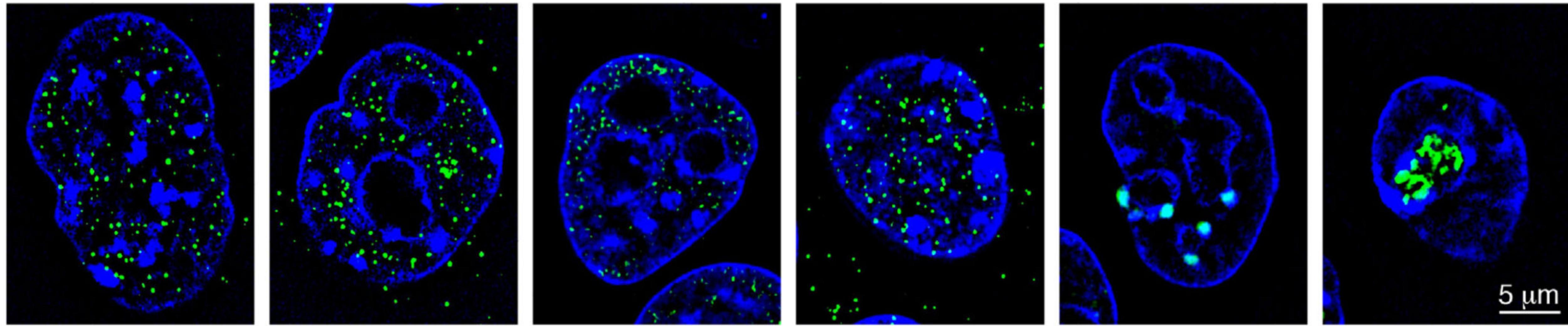
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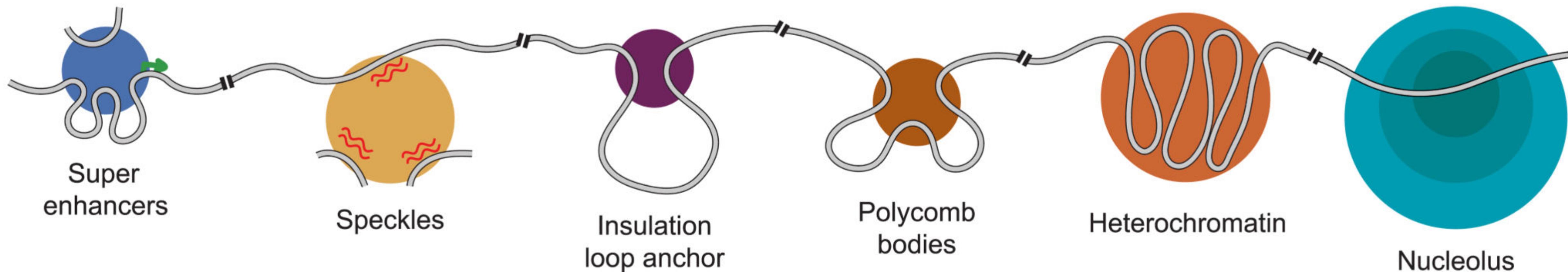
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Backup slides

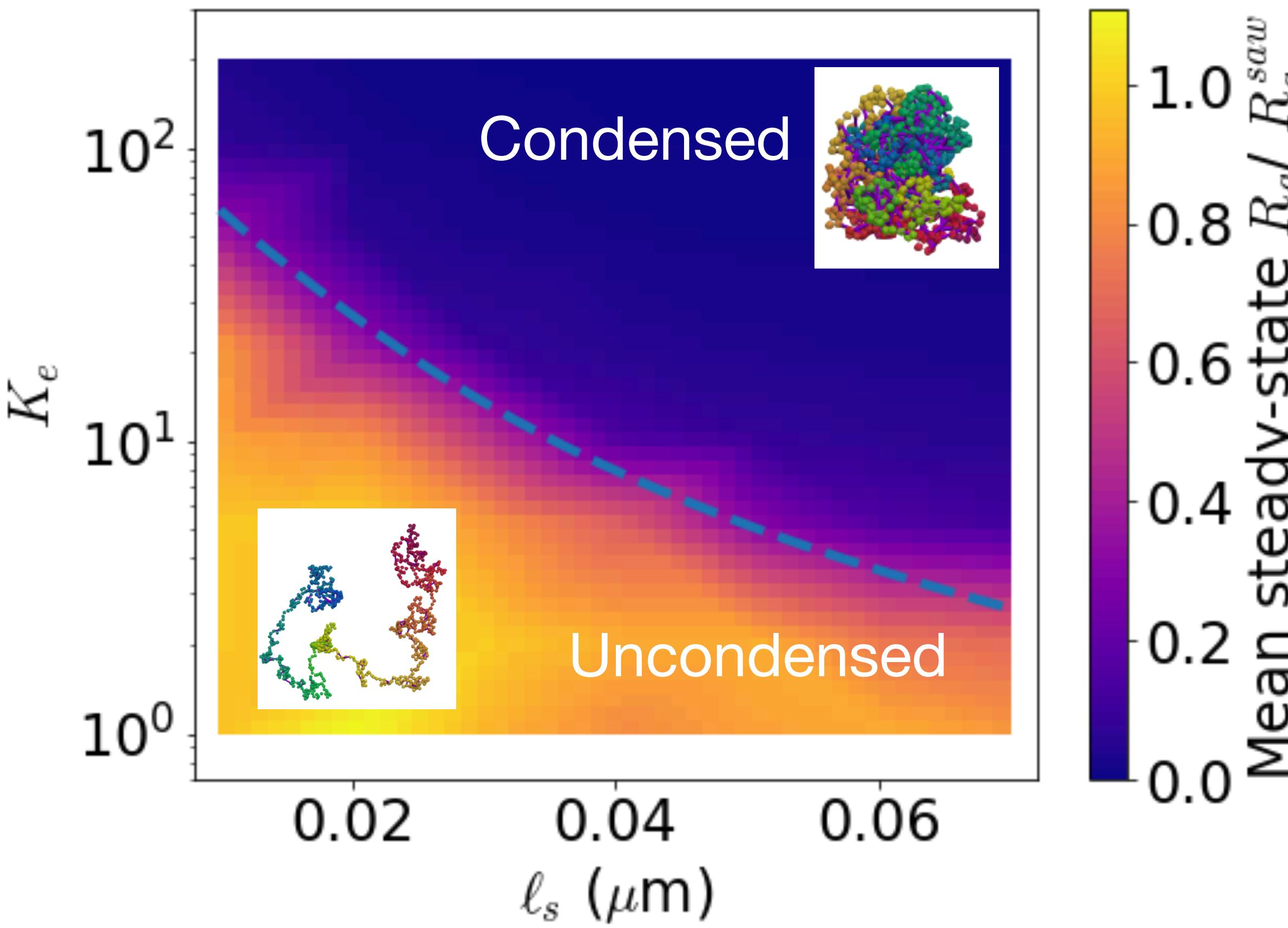
Different types of nuclear condensates



(B)



Interpolated map of condensed and uncondensed states with fitted boundary



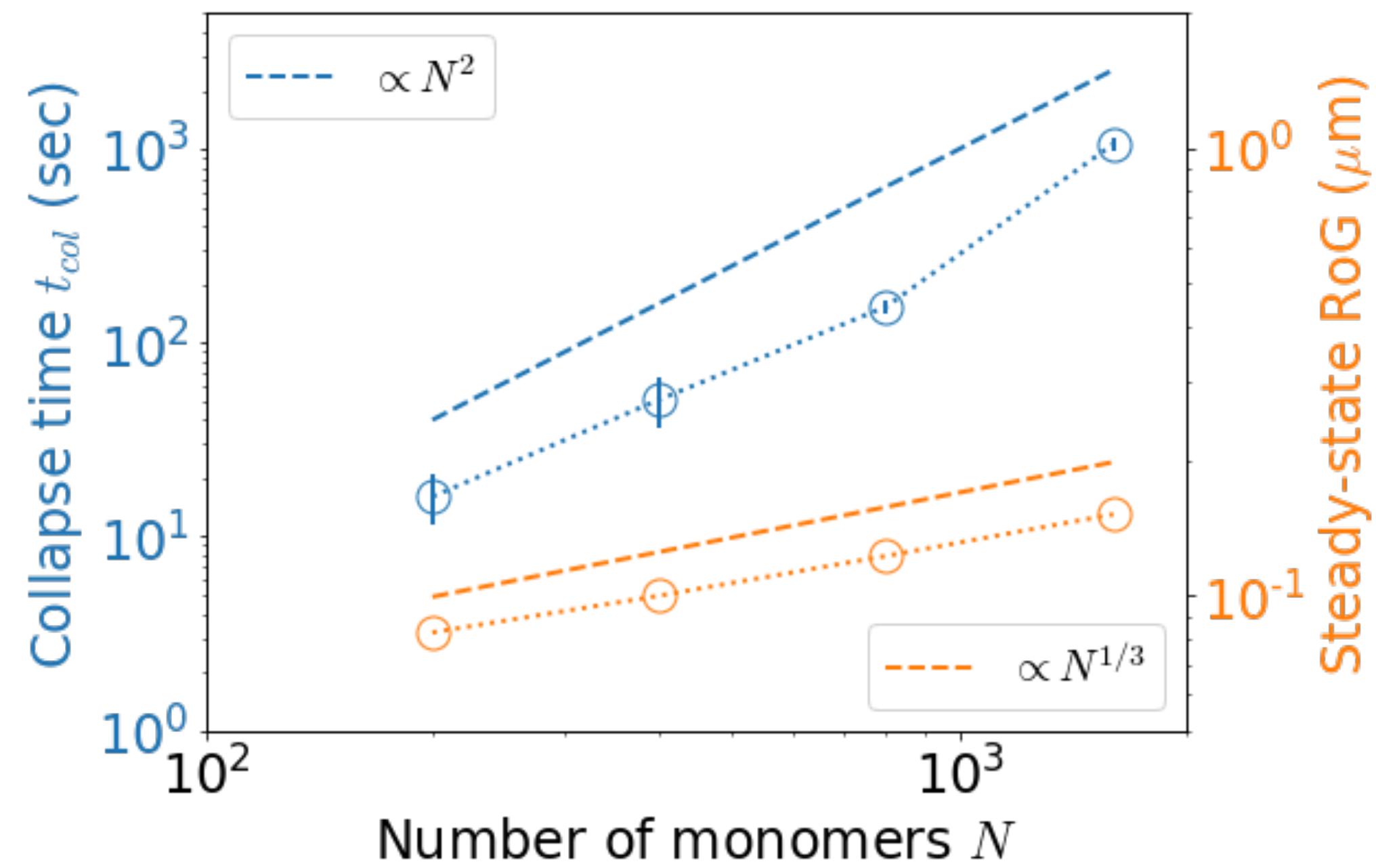
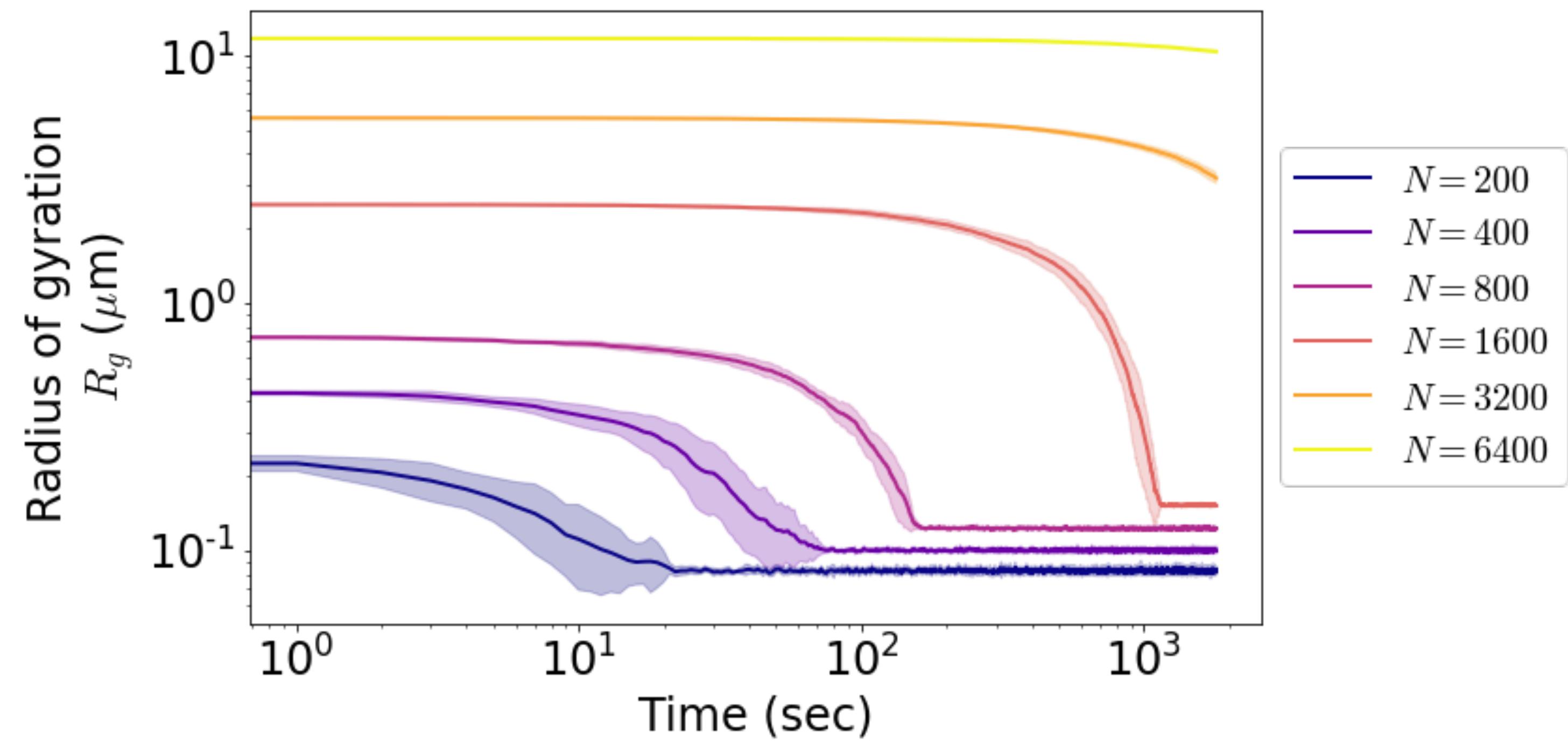
Depending on what value of ρ_o you use, $\Psi_{crit} \approx \{1 - 100\}$

$$\Psi_B = \int d\mathbf{r} \frac{k_{on}(\mathbf{r})}{k_{off}} \rho(\mathbf{r}) = 4\pi\rho_o K_e \int d\mathbf{r} \exp\left(\frac{-\beta k_s}{2}(r - l_s)^2\right)$$

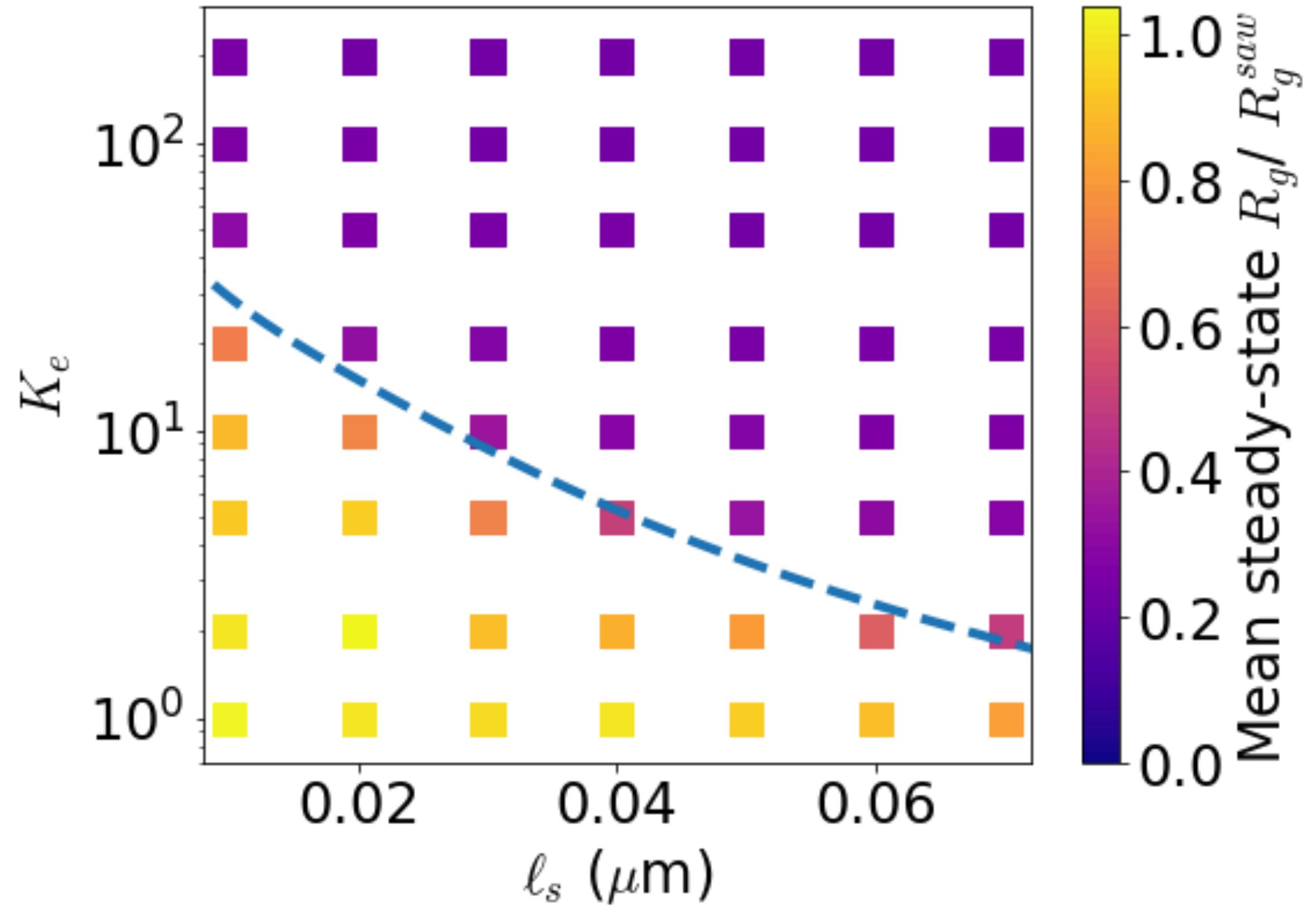
$$\Psi_B = \int d\mathbf{r} \frac{k_{on}(\mathbf{r})}{k_{off}} \rho(\mathbf{r}) = 4\pi\rho_o K_e \int dr r^2 \exp\left(\frac{-\beta k_s}{2}(r - l_s)^2\right)$$

Assume critical value for Ψ_B and solve for K_e as a function of l_s

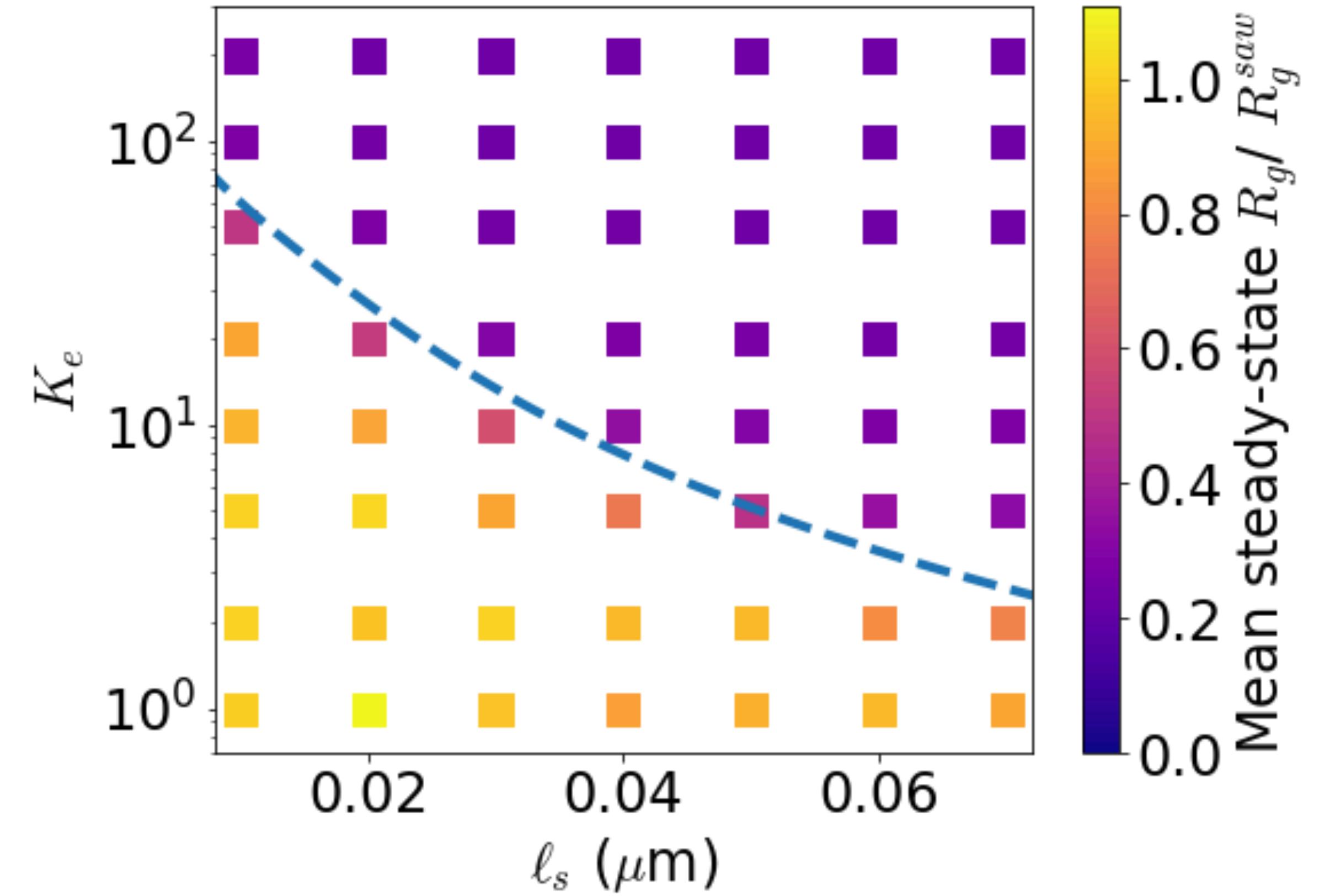
$$K_e(l_s) = \frac{\Psi_{crit}}{4\pi\rho_o} \left[\frac{\sqrt{\frac{\pi}{2}} (\beta k_s l_s^2 + 1) \left(\operatorname{erf}\left(\frac{l_s \sqrt{\beta k_s}}{\sqrt{2}}\right) + 1 \right)}{(\beta k_s)^{3/2}} + \frac{l_s e^{-\frac{1}{2}\beta k_s l_s^2}}{\beta k_s} \right]^{-1}$$

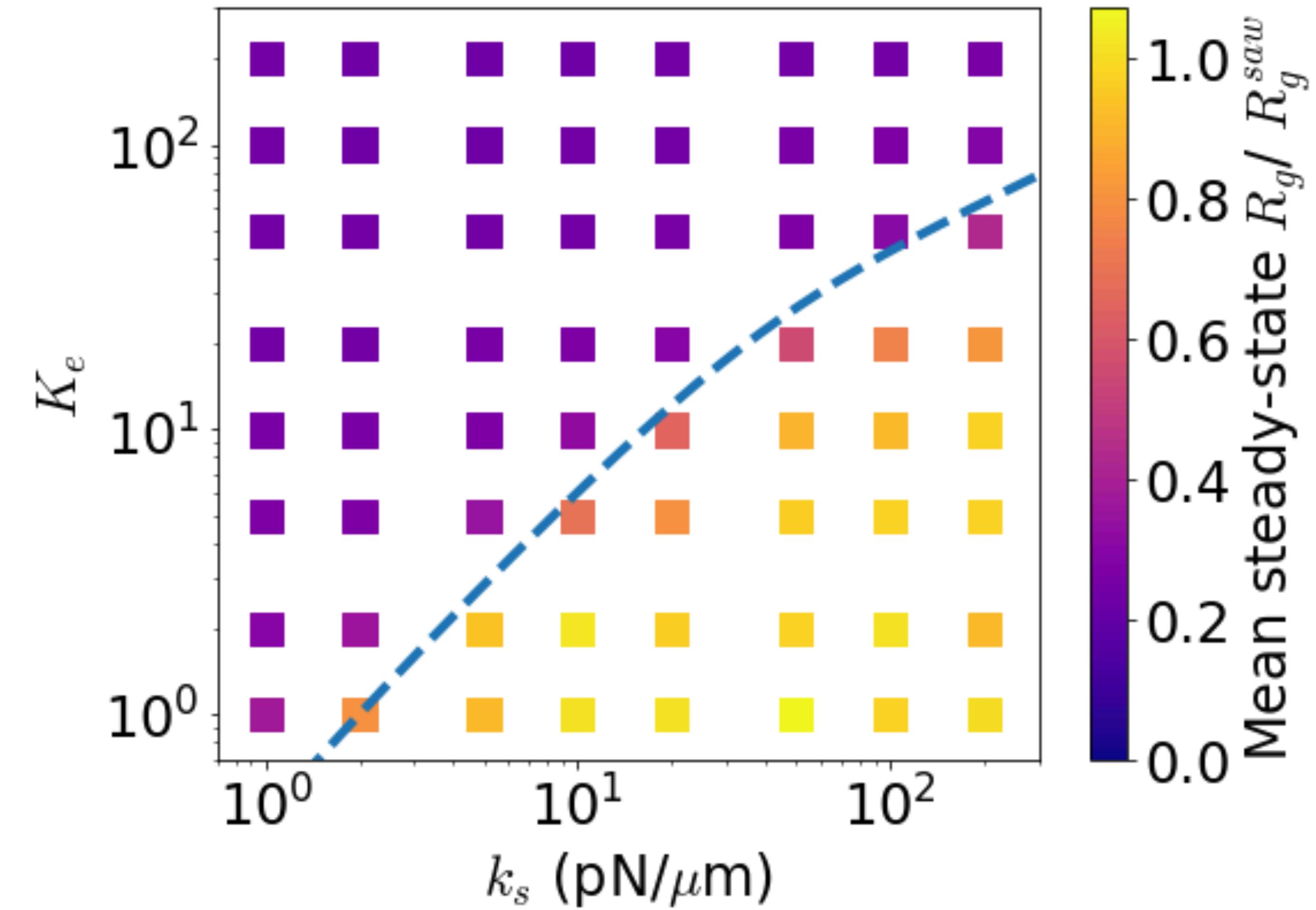


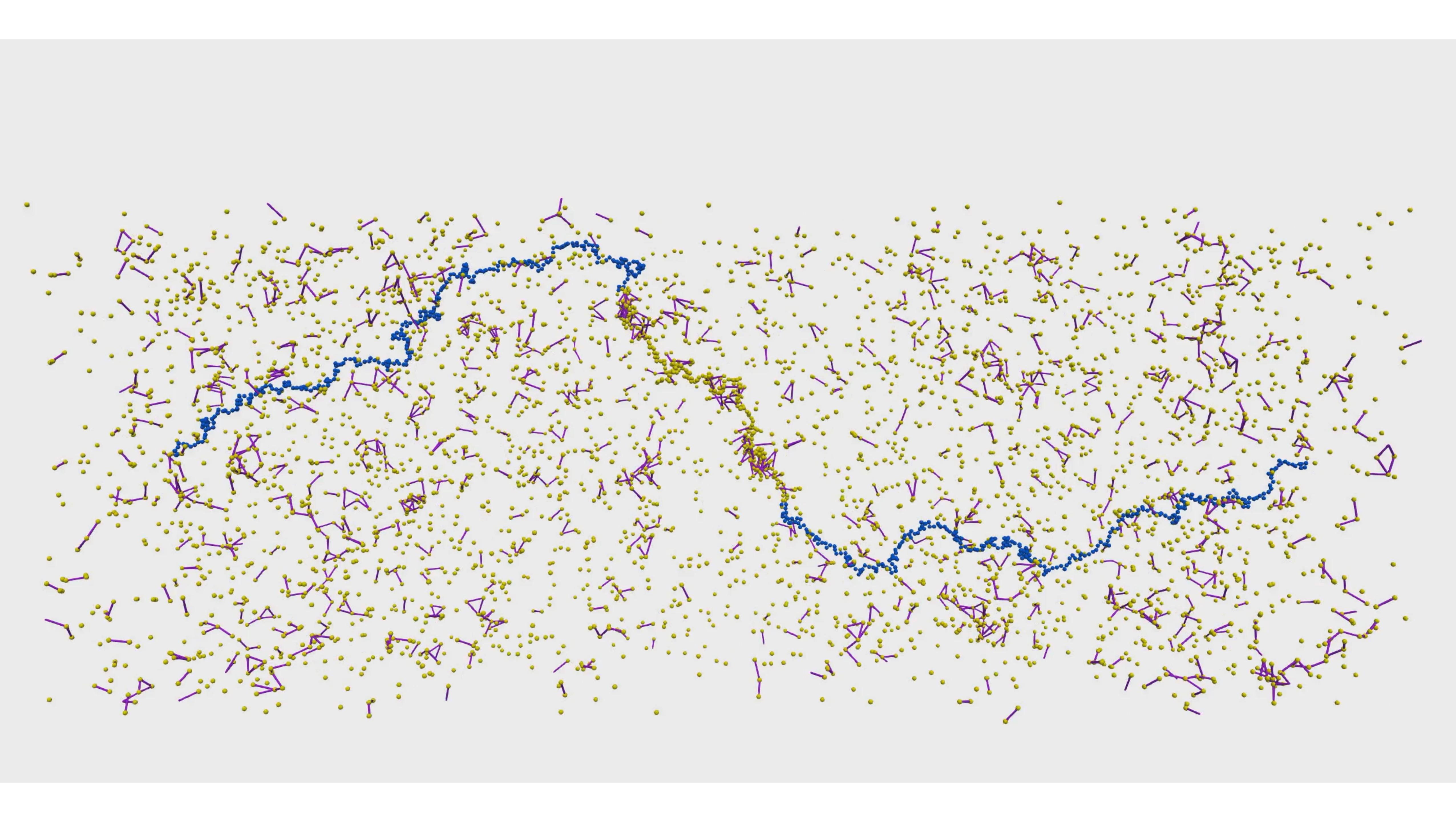
$\kappa = 25 \text{ pN}/\mu\text{m}$



$\kappa = 50 \text{ pN}/\mu\text{m}$







Comparison with potential-based simulations (LAMMPS)

