



Subdiffusion and reaction networks in single-molecule biophysics

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Single-Molecule Experiments

- Experimental advances make it possible to study biochemical/biological progresses at **single-molecule level**
- Example: single-molecule enzymatic kinetics, single-molecule protein/DNA dynamics

“Everything that living things can do can be understood in terms of the jiggings and wiggings of atoms”

--- Richard Feynman

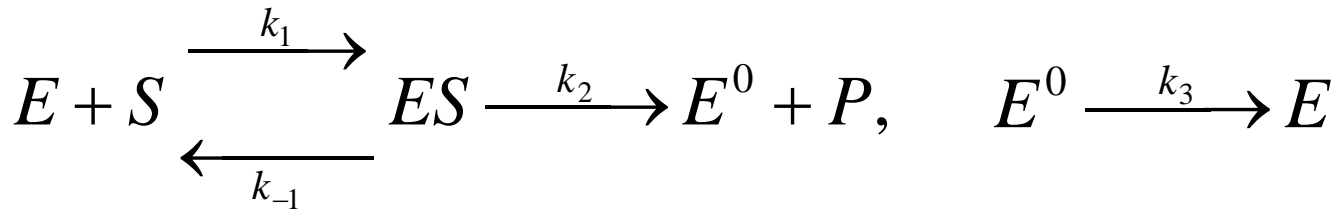
Single-Molecule Advantages

- Can measure molecular properties *individually*, instead of inferring from ensemble population statistics
- If the reaction/kinetic time is slow, ensemble experiments become almost impossible due to the *difficulty of synchronization*
- Single-molecule trajectory provides detailed *dynamic information*. In particular capture transient intermediates

Stochastic Challenges

- Require new stochastic modeling
 - Subdiffusion***
 - Enzymatic reaction***
- Data are noisier, and efficient inference methodology is needed

Michaelis-Menten Mechanism



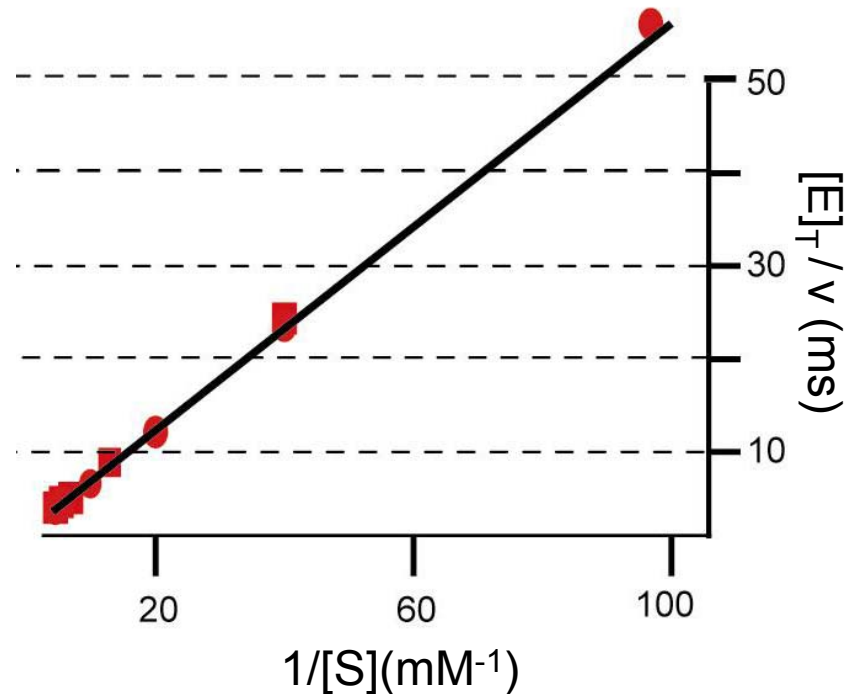
$$\begin{aligned} \frac{d[E]}{dt} &= -k_1[E][S] + k_{-1}[ES] \\ \frac{d[ES]}{dt} &= k_1[E][S] - (k_{-1} + k_2)[ES] \\ \frac{d[E^0]}{dt} &= \frac{d[P]}{dt} = k_2[ES] \end{aligned}$$



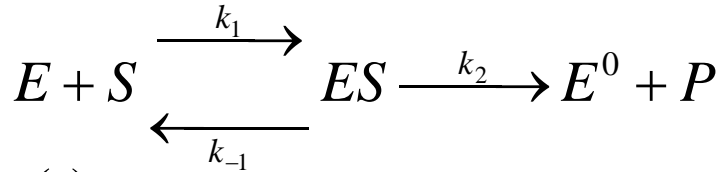
Classical Michaelis-Menten equation

$$v = \frac{v_{\max} [S]}{[S] + K_M}, \quad \begin{aligned} v_{\max} &= k_2 ([E] + [ES]) \\ K_M &= (k_{-1} + k_2) / k_1 \end{aligned}$$

Lineweaver-Burke plot



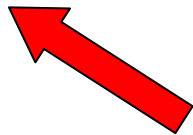
Single-molecule case



$$\frac{dP_E(t)}{dt} = -k_1[S]P_E(t) + k_{-1}P_{ES}(t)$$

$$\frac{dP_{ES}(t)}{dt} = k_1[S]P_E(t) - (k_{-1} + k_2)P_{ES}(t)$$

$$\frac{dP_{E^0}(t)}{dt} = k_2P_{ES}(t)$$

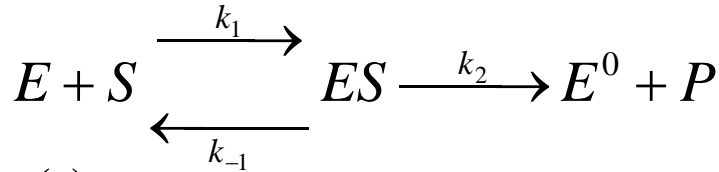


Turnover time:
first passage time

Three-state continuous-time
Markov chain

$$Q = \begin{pmatrix} -k_1[S] & k_1[S] & 0 \\ k_{-1} & -(k_{-1} + k_2) & k_2 \\ k_3 & 0 & -k_3 \end{pmatrix}$$

Single-molecule case



$$\frac{dP_E(t)}{dt} = -k_1[S]P_E(t) + k_{-1}P_{ES}(t)$$

$$\frac{dP_{ES}(t)}{dt} = k_1[S]P_E(t) - (k_{-1} + k_2)P_{ES}(t)$$

$$\frac{dP_{E^0}(t)}{dt} = k_2P_{ES}(t)$$

Turnover time distribution

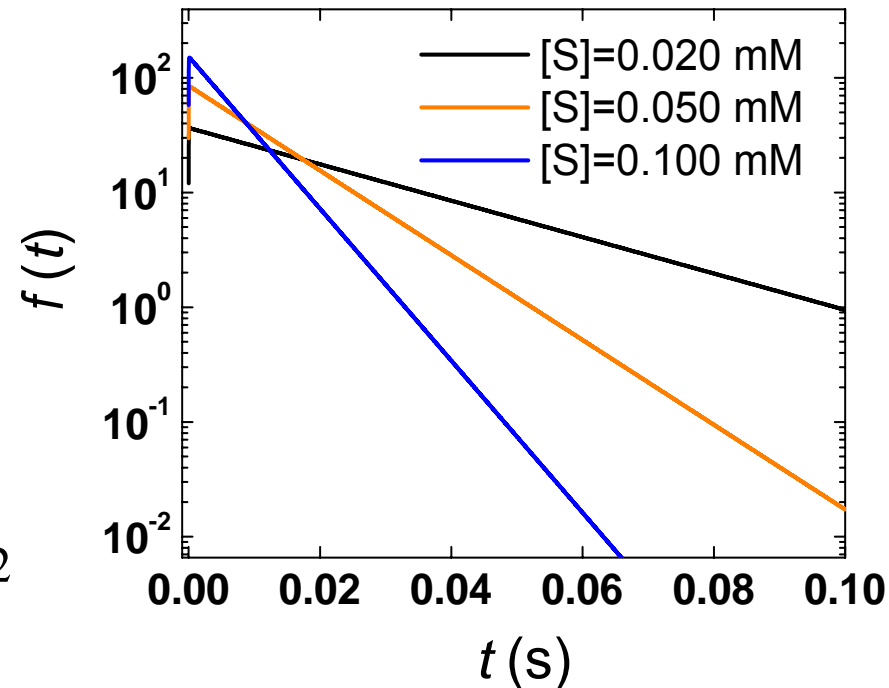
$$f(t) = \frac{k_1 k_2 [S]}{2A} [\exp(A+B)t - \exp(B-A)t]$$

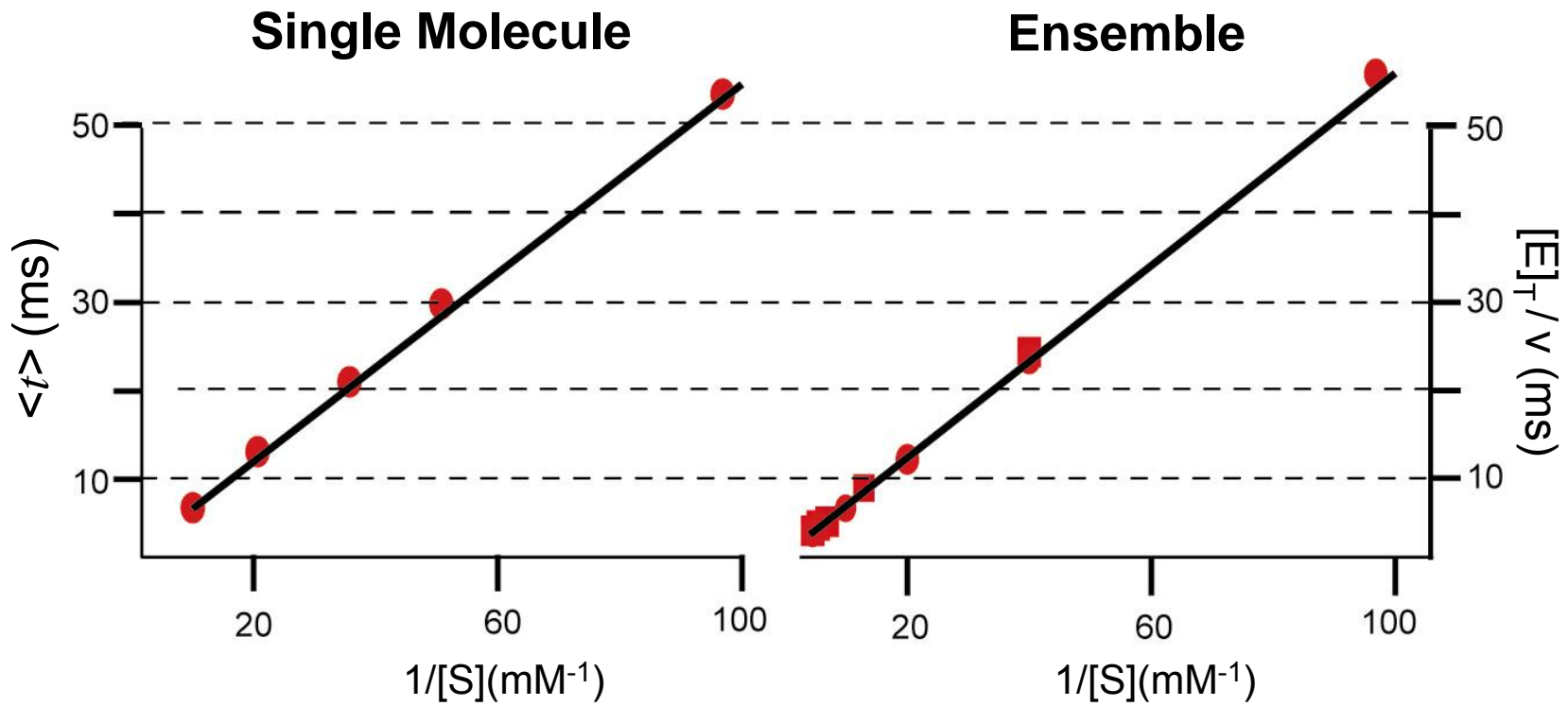
$$A = \sqrt{B^2 - k_1 k_2 [S]}, \quad B = -(k_1[S] + k_{-1} + k_2)/2$$

Reaction rate: 

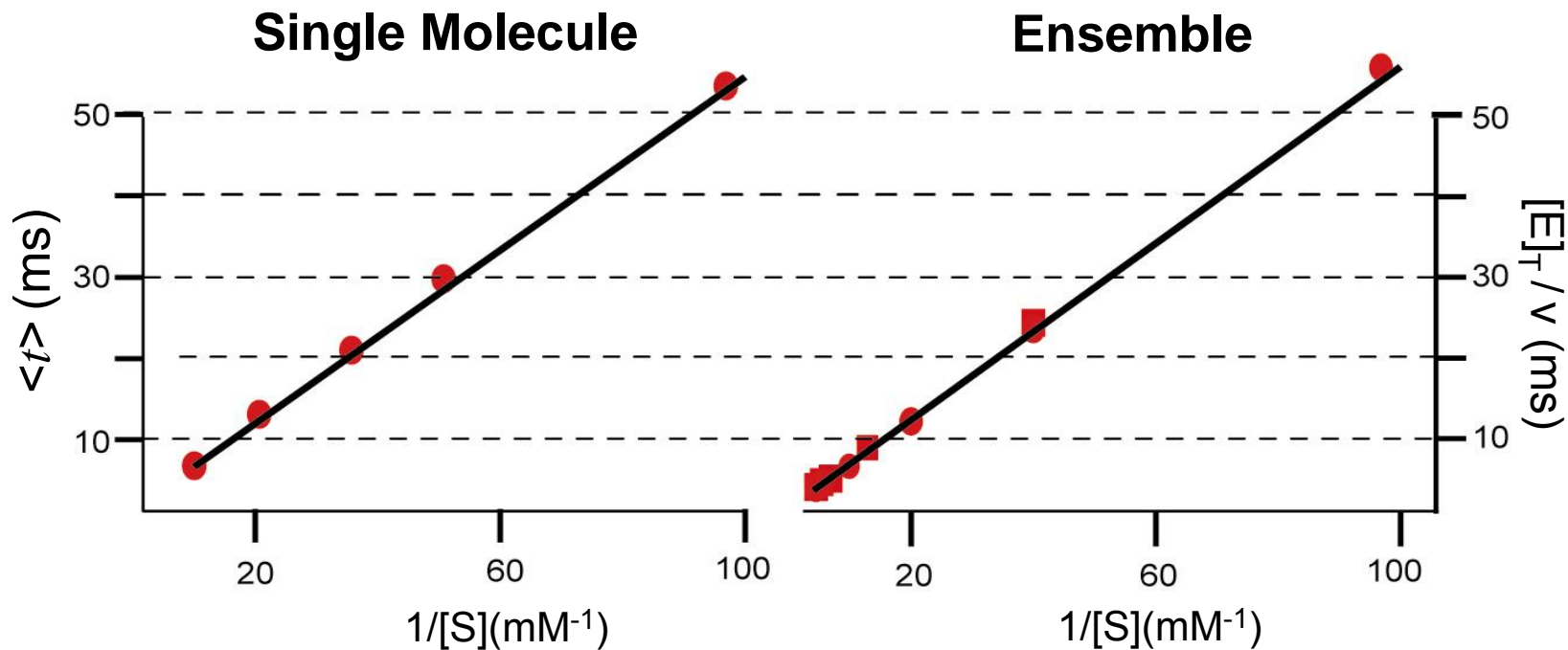
$$v = \frac{1}{\langle t \rangle} = \frac{k_2[S]}{[S] + K_M}$$

: Still obey the hyperbolic form





Obtained from English *et al.* (Nature Chem. Biol., 2, 87, 2006)'s single-molecule study of β -galactosidase

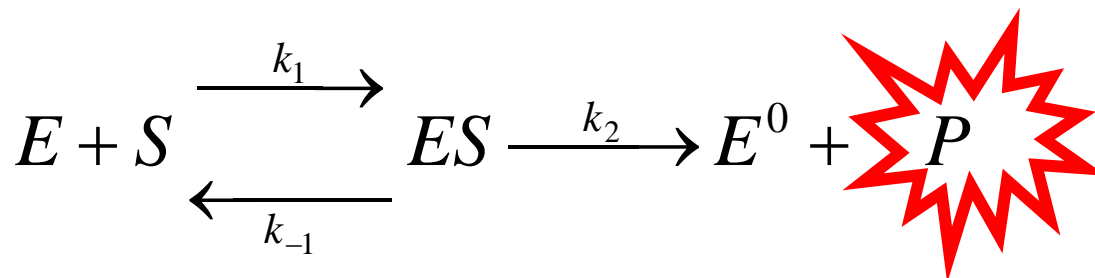


English *et al.*, Nature Chem. Biol., 2, 87 (2006)

β -galactosidase

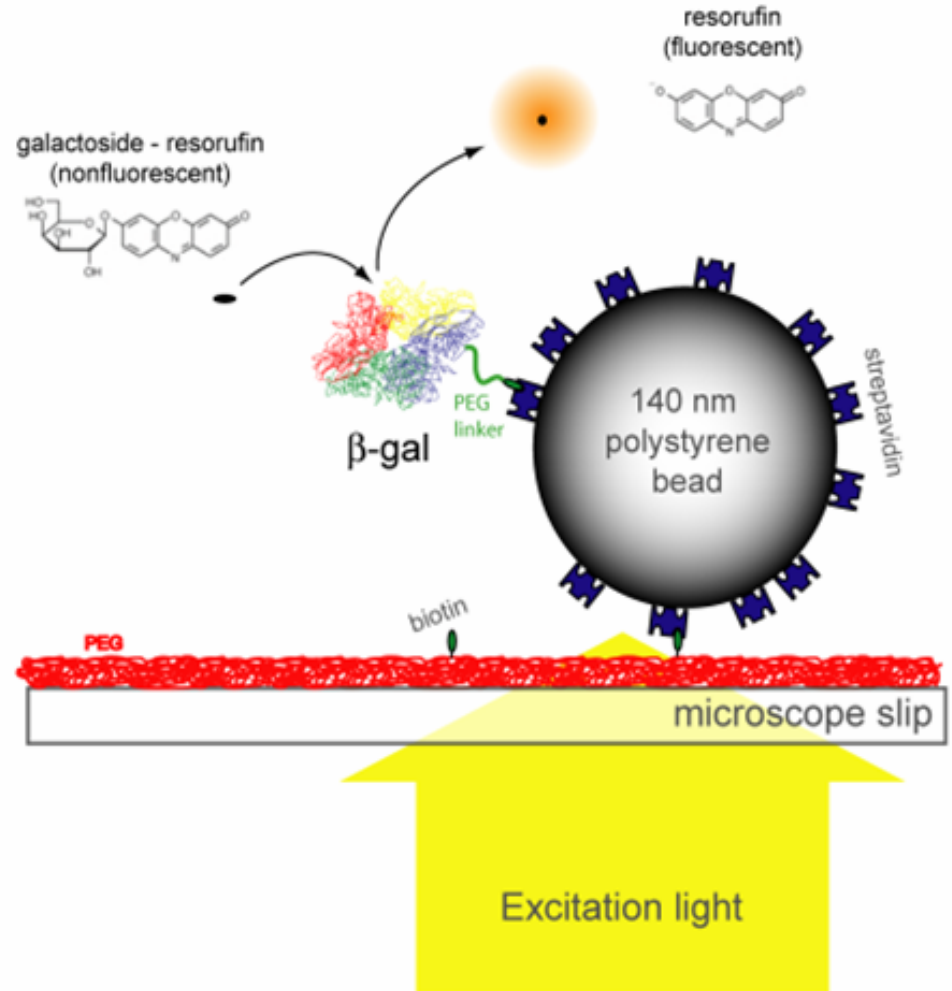
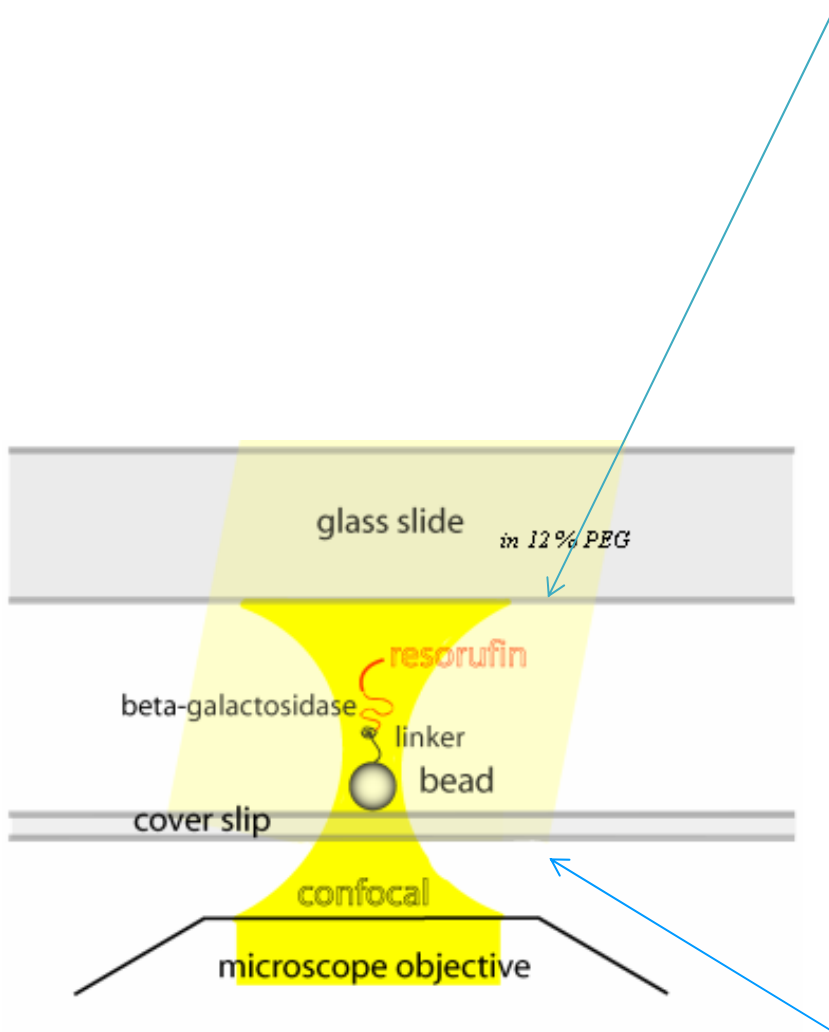
E. coli β -gal catalyzes Hydrolysis of Lactose

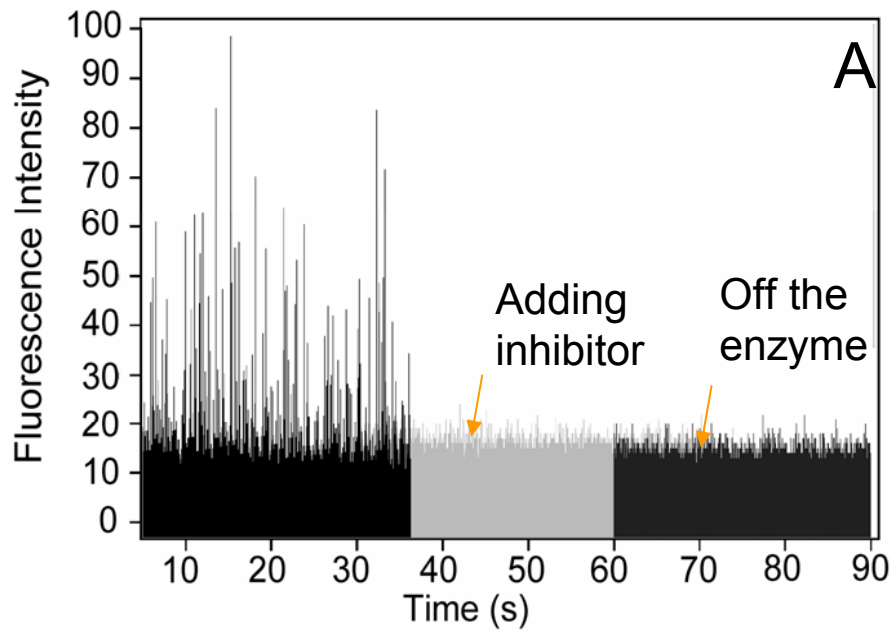
The experiment uses **photogenic** substrate



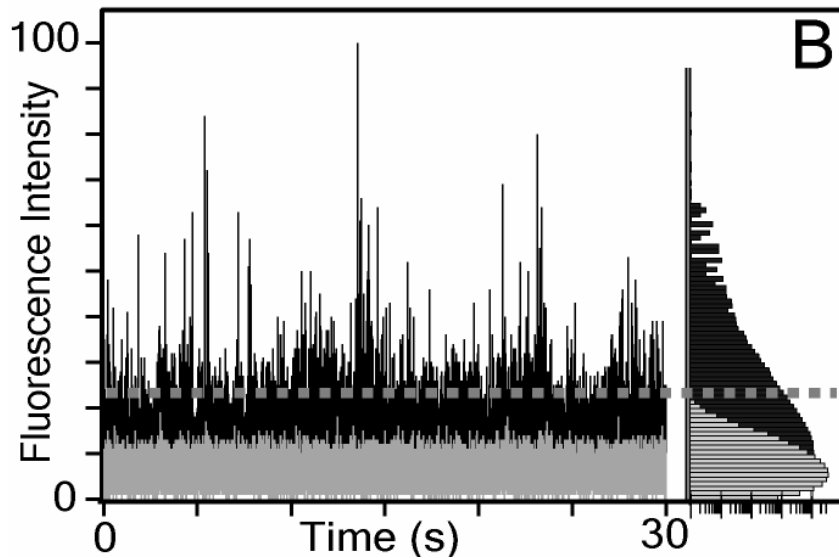
Single Molecule Turnover Experiment of β -galactosidase

Each enzymatic turnover creates a fluorescent burst



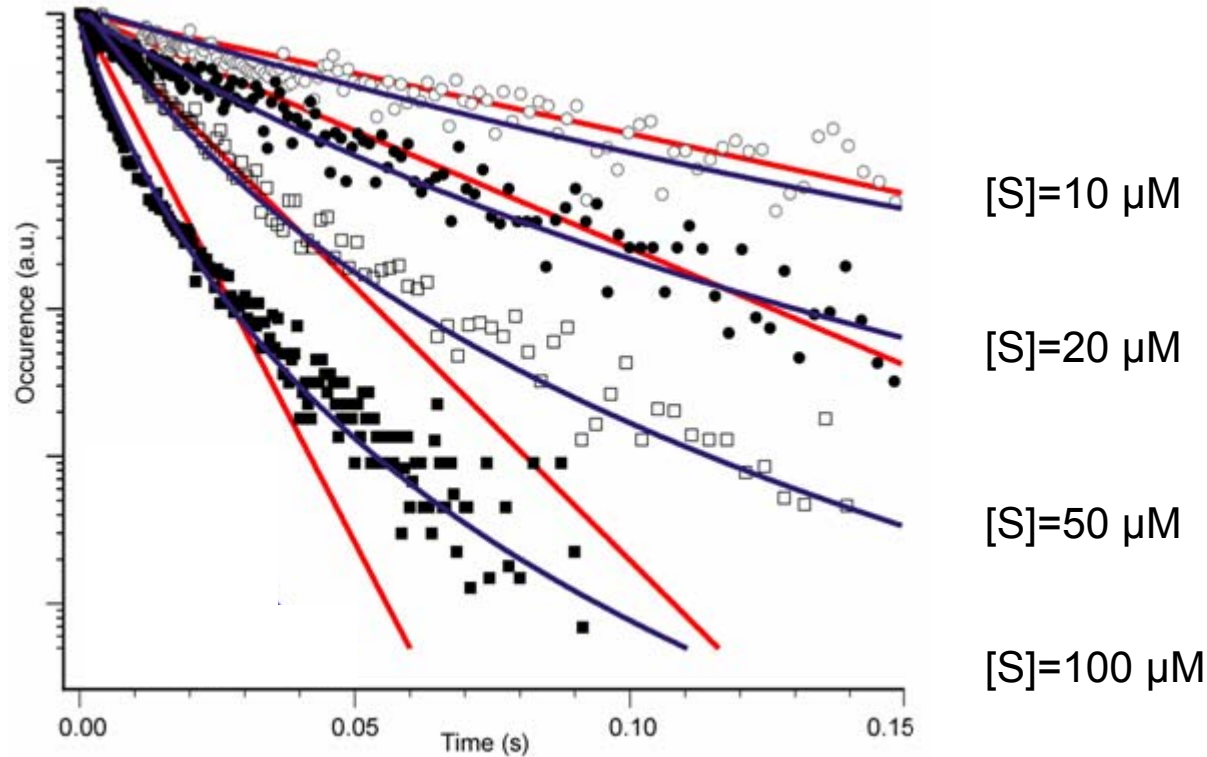


Low Substrate
Concentration
 $20\mu\text{M}$



High Substrate
Concentration
 $100\mu\text{M}$

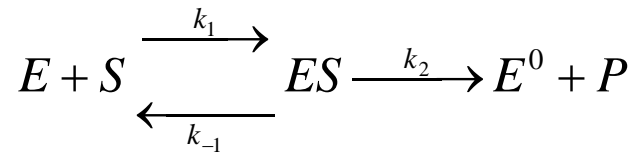
Multi-exponential Distributions of Turnover Times



- Multi-exponential decay at high substrate concentration
- Mono-exponential decay at low substrate concentration

Memory between successive turnover times

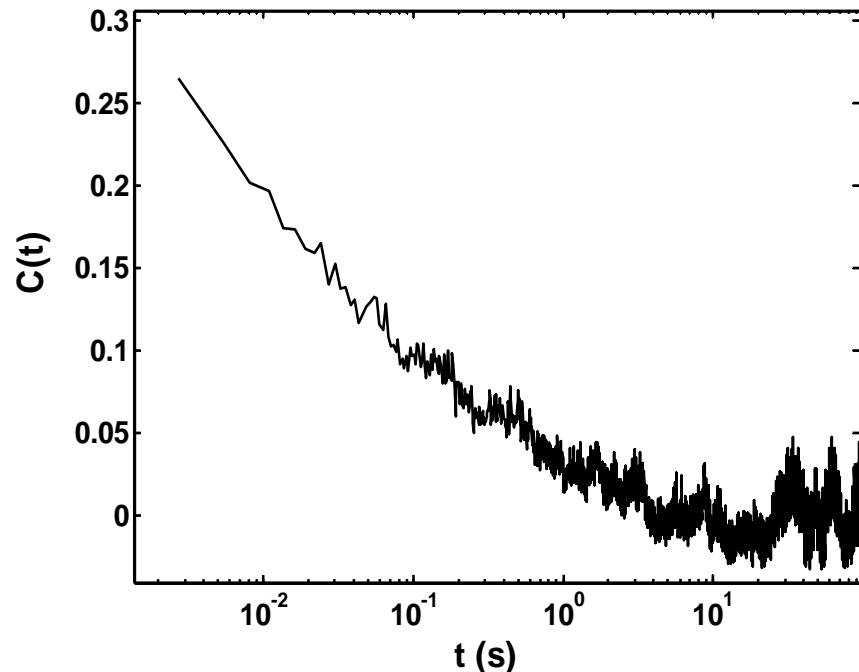
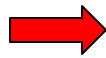
- Under Michaelis-Menten Mechanism

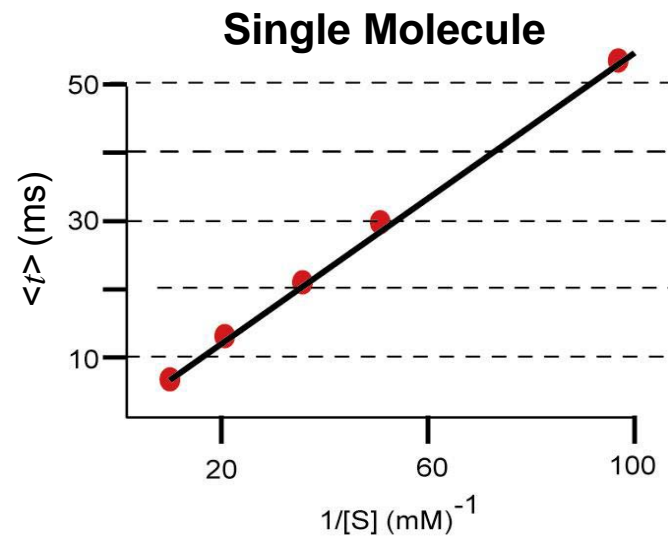
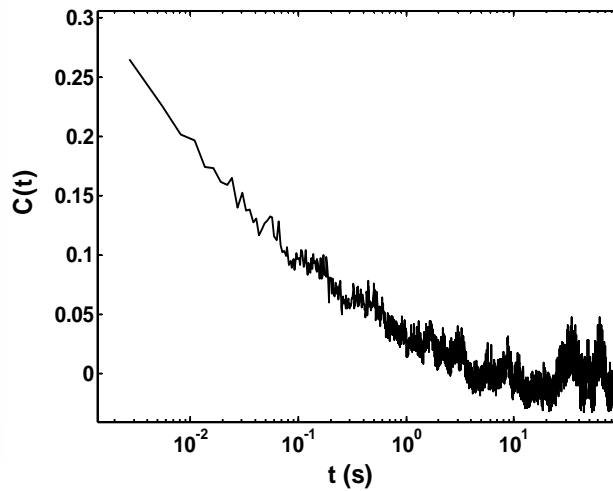
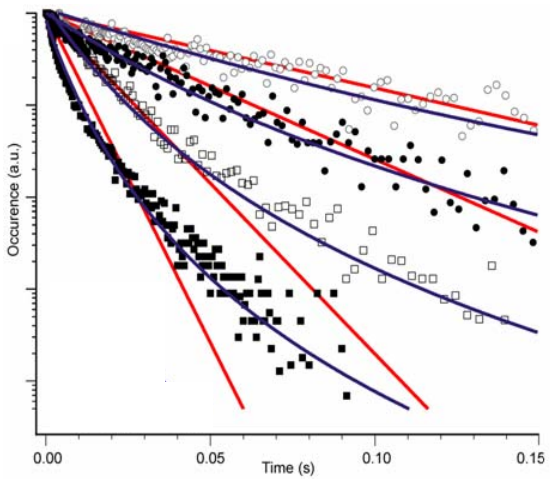


three-state continuous-time **Markov** chain

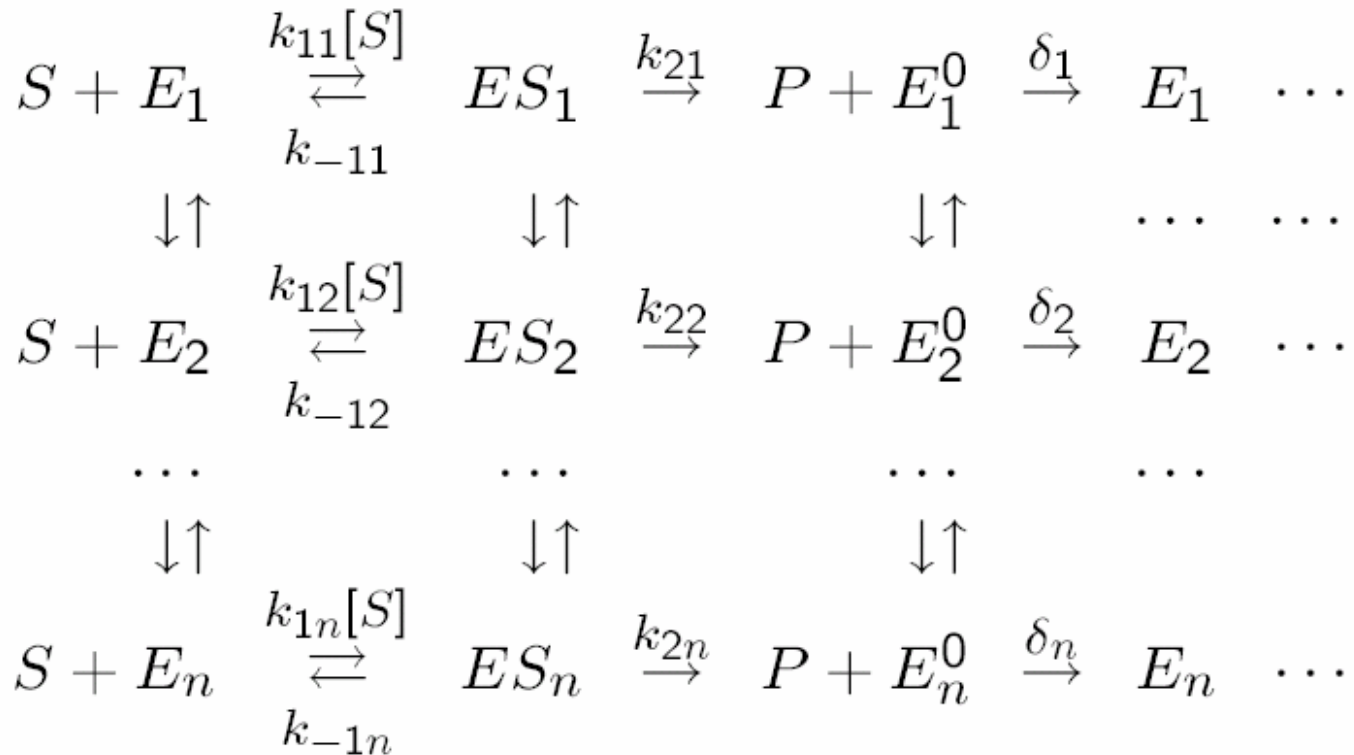
- Successive turnover times should have **NO** correlation

Experimental data

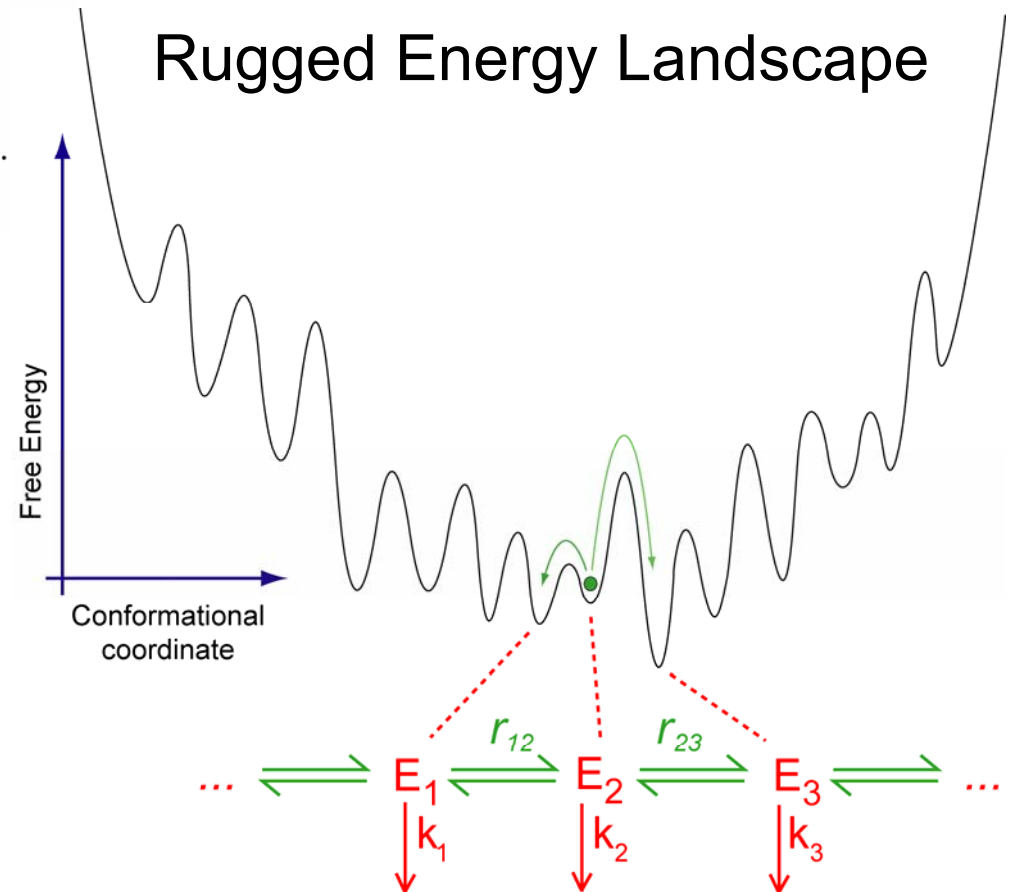
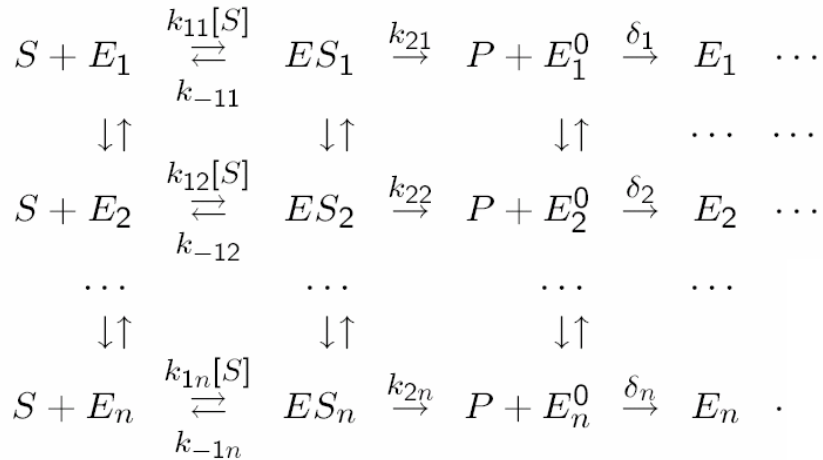




Dynamic disorder – the fluctuation of enzyme

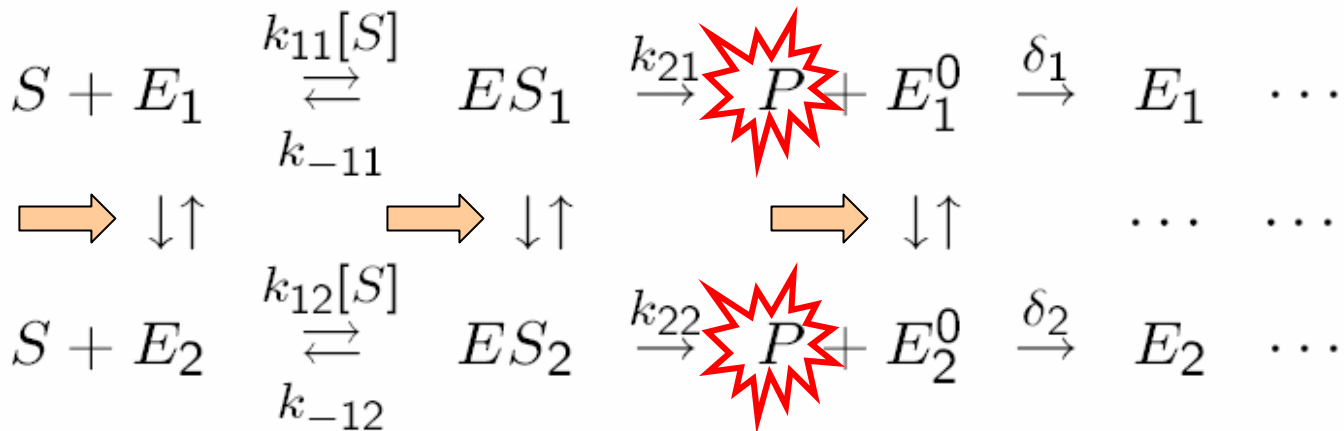


Dynamic disorder – the fluctuation of enzyme



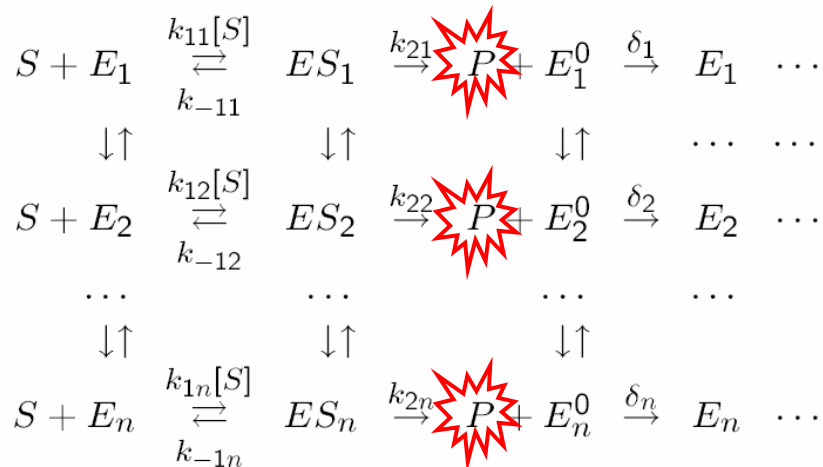
Explain the memory

If conformers intervert slowly



Transitions will stay in one channel for a quite while before going to the next

Naturally give rise to the strong correlation



→ Can be solved via Laplace transform and matrix algebra

Kou et al., *J. Phys. Chem. B*, 109, 19068 (2005)

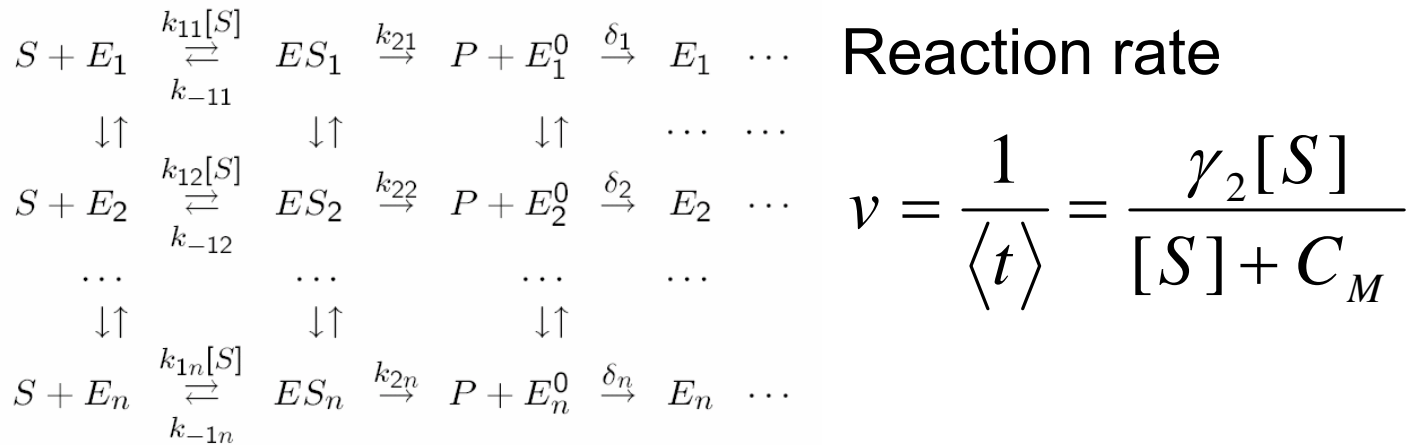
Under physically meaningful conditions

Single Molecule Michaelis-Menten Equation

$$v = \frac{1}{\langle t \rangle} = \frac{\gamma_2 [S]}{[S] + C_M}$$

$$\gamma_2 = \left[\int_0^\infty \frac{p(k_2)}{k_2} dk_2 \right]^{-1} \quad C_M = \frac{\gamma_2 + k_{-1}}{k_1}$$

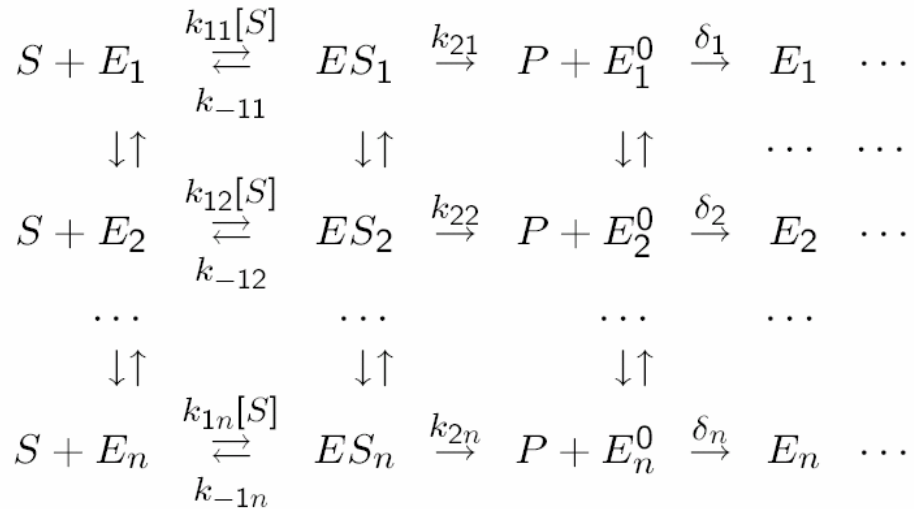
Weighted harmonic mean



If one of the following conditions holds:

- | | | |
|---|---|----------------------------|
| (a) slow interconversion between E_i | } | Quasi static |
| (b) slow interconversion between ES_i | | |
| (c) fast interconversion between E_i | | |
| (d) fast interconversion between ES_i | | |
| (e) $k_{-1i} \gg k_{2i}$ | | Quasi equilibrium |
| (f) $k_{2i}/k_{-1i} = \text{const}$ | | Conformational equilibrium |

Turnover Time distribution for fluctuating enzymes



Quasi Static Limit:

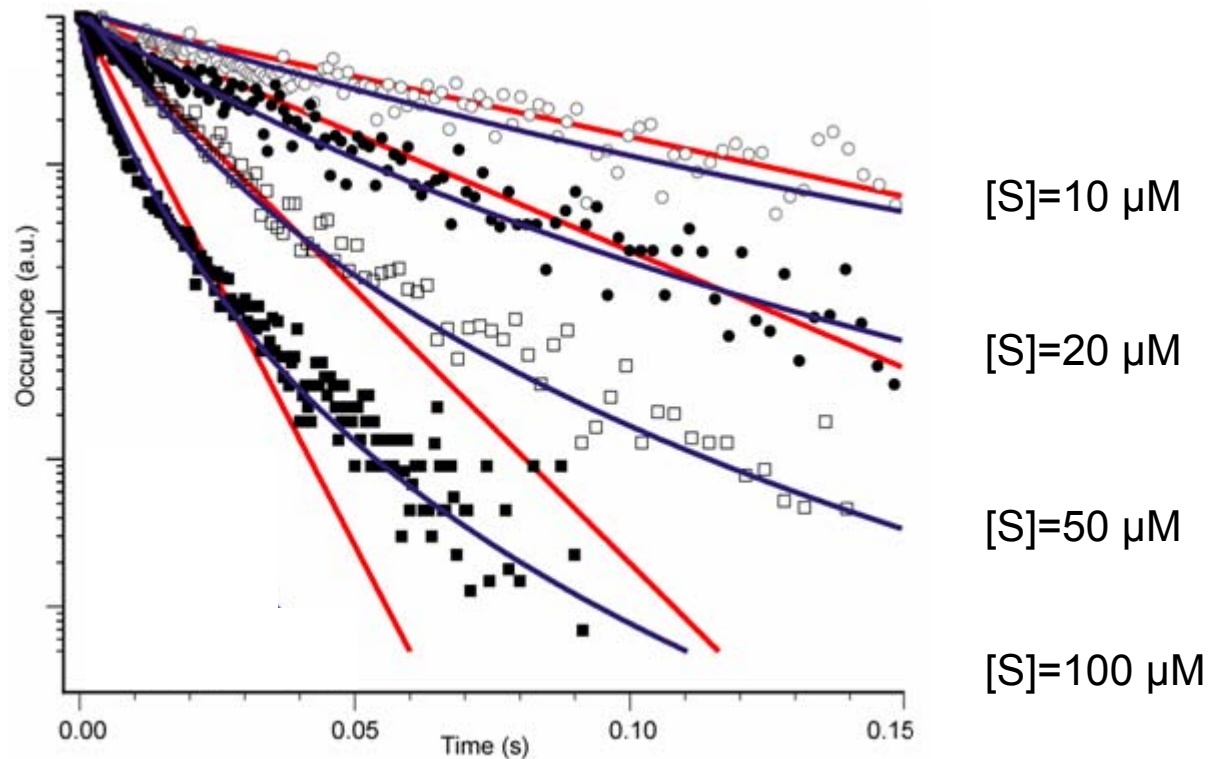
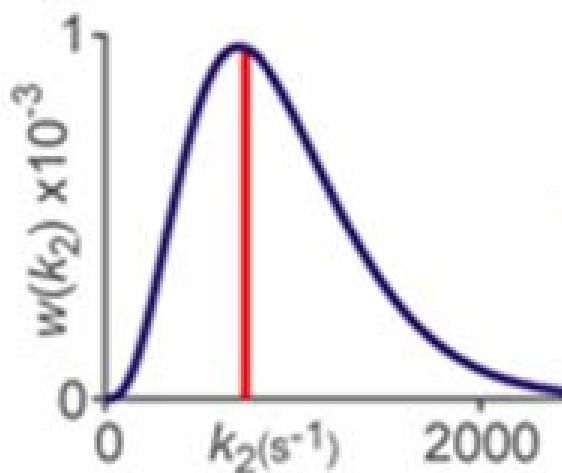
$$f(t) = \int_0^{\infty} dk_2 w(k_2) \frac{k_1 k_2 [S]}{2A} [\exp(A + B)t - \exp(B - A)t]$$

$$A = \sqrt{B^2 - k_1 k_2 [S]}, \quad B = -(k_1 [S] + k_{-1} + k_2) / 2$$

Multi-exponential Distributions of Turnover Times

Gamma Distribution

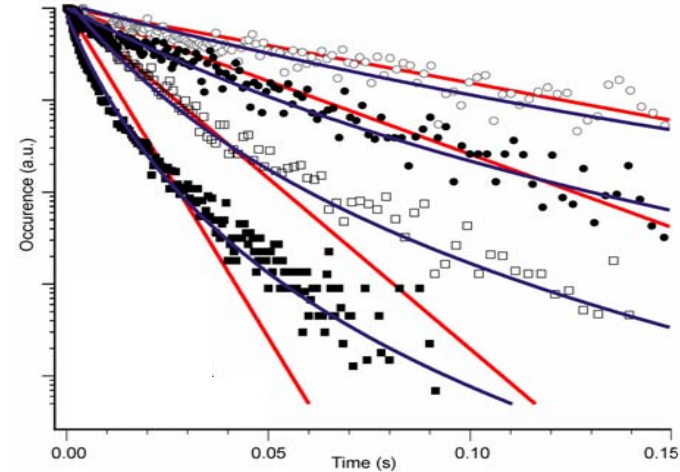
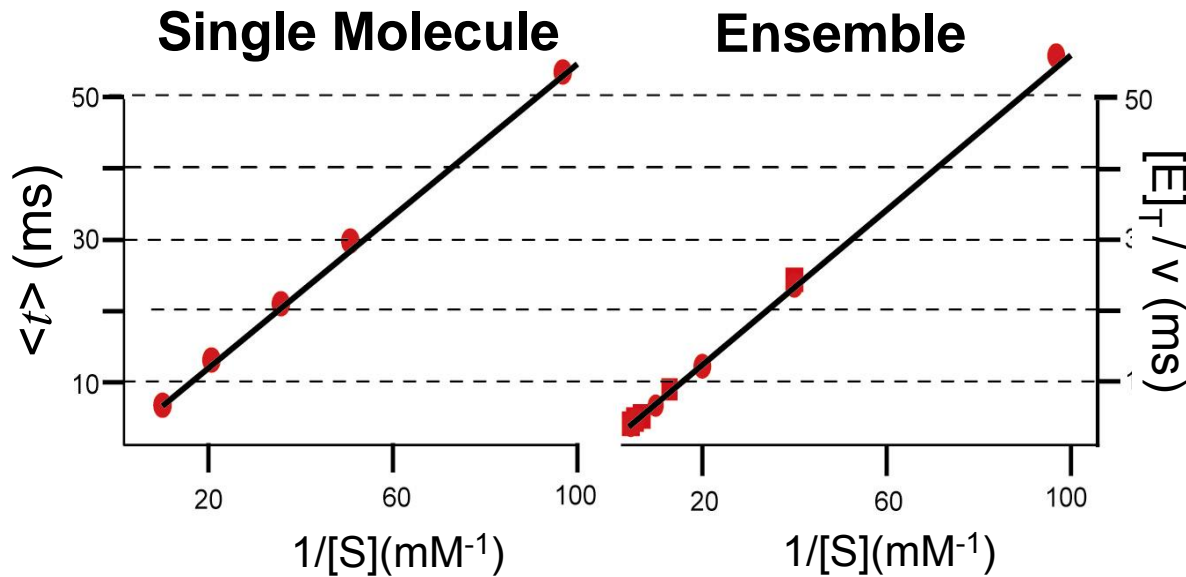
$$w(k_2) = \frac{1}{b^a \Gamma(a)} k_2^{a-1} \exp(-k_2/b)$$



$$k_1 = 5 \times 10^7 \text{ M}^{-1} \text{ s}^{-1}$$

$$k_{-1} = 1.83 \times 10^4 \text{ s}^{-1}$$

$$a = 4.2, b = 224 \text{ s}^{-1}$$



Consequences:

- (a) Single Molecule reconciled with ensemble study
- (b) Dynamic disorder might be masked in ensemble studies!
- (c) The apparent k_2 and K_M of the Michaelis-Menten equation are complex functions of the k_2 and K_M of a large distribution of conformers, different from their conventional interpretations.

Brownian diffusion

- Brownian motion described by Langevin equation

$$m \frac{dv_t}{dt} = -\zeta v_t + F(t)$$

where $F(t)$ is white noise process satisfying

$$\langle F(t)F(t') \rangle = \zeta k_B T \cdot \delta(t - t')$$

by **fluctuation-dissipation** theorem.

- Solving the equation
mean square displacement $x(t) = \int_0^t v(s) ds$

$$\langle x(t)^2 \rangle \sim 2 \frac{k_B T}{\zeta} t, \text{ for large } t$$

--- Corner stone for statistical mechanics

Subdiffusion

- Brownian diffusion, however, cannot explain subdiffusion:

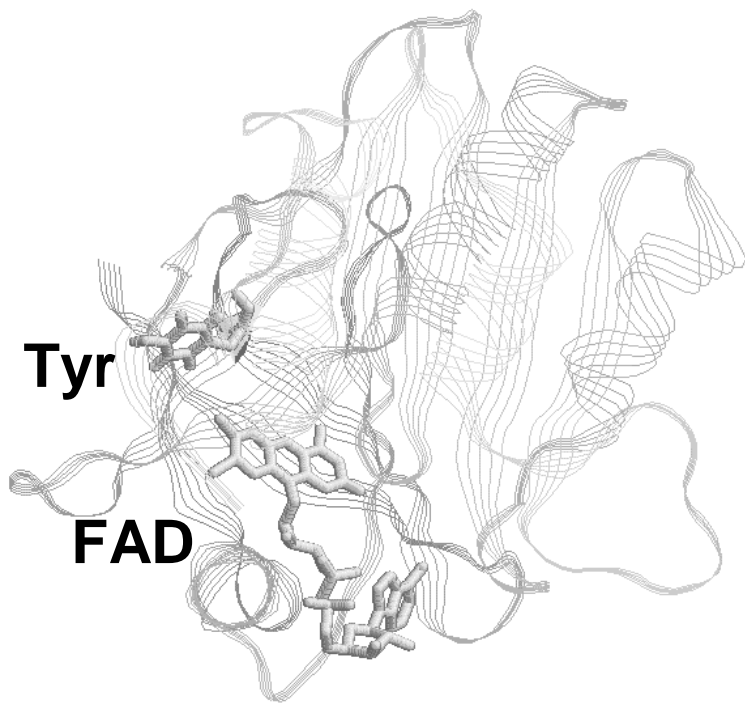
$$\langle x(t)^2 \rangle \propto t^\alpha, \quad 0 < \alpha < 1$$

- Distance fluctuation between electron transfer donor and acceptor within a single protein molecule

Yang *et al.*, *Science*, 302, 266 (2003)

Conformational fluctuation within a protein

Yang *et al.* (*Science*, 302, 266, 2003) studied flavin-enzyme **Fre**: catalyzes the reduction of flavin, which contains a flavin adenine dinucleotide (**FAD**) and a tyrosine (**Tyr**).

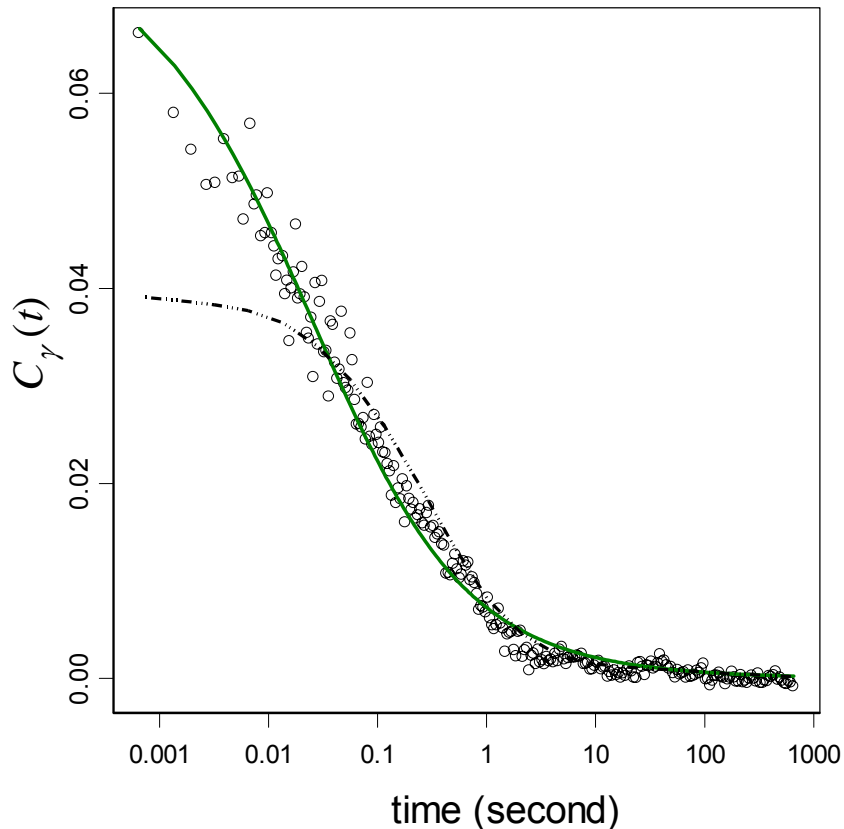


Fluorescence lifetime of FAD varies due to **electron transfer** from Tyr, depending on the distance between ET donor and acceptor

$$\gamma^{-1}(t) = [k_0 e^{-\beta(X_{eq} + X_t)}]^{-1}$$

Autocorrelation function $\langle \Delta\gamma^{-1}(0) \Delta\gamma^{-1}(t) \rangle$

$$\Delta\gamma^{-1}(t) = \gamma^{-1}(t) - \langle \gamma^{-1}(t) \rangle$$



- Need tools beyond Langevin equation and BM.
- The model: Generalized Langevin equation with fractional Gaussian noise (GLE with fGn).

Generalized Langevin Equation with fGn

- Langevin equation $m \frac{dv_t}{dt} = -\zeta v_t + F(t)$
- Generalized Langevin equation $m \frac{dv_t}{dt} = -\zeta \int_{-\infty}^t v_u K(t-u) du + G_t,$
- **Fluctuation-dissipation theorem** links memory kernel $K(t)$ with fluctuating force $E\{G_t G_s\} = \zeta k_B T \cdot K(t-s)$
- Key question: How to introduce the noise structure?
- Understand the white noise: White noise is the derivative of the Wiener process $F_t = \frac{d}{dt} B_t$
- $B(t)$ is the unique process: (i) Gaussian, (ii) independent increment, (iii) stationary increment, (iv) self-similar

- Natural generalization: (i) Gaussian (ii) stationary increment (iii) self-similar.

- The **ONLY** candidate fBM $B^{(H)}(t)$, $0 < H < 1$
 $E\{B_t^{(H)}\} = 0$, and covariance function

$$E\{B_t^{(H)} B_s^{(H)}\} = (|t|^{2H} + |s|^{2H} - |t-s|^{2H}) / 2 \quad \text{for } t, s \geq 0.$$

when $H = 1/2$, reduces to $B(t)$.

- Fractional Gaussian noise $F^{(H)}(t) = \frac{dB_t^{(H)}}{dt}$:
 Gaussian & stationary.

- Memory kernel

$$K_H(t) = E\{F^{(H)}(0)F^{(H)}(t)\}$$

$$= H(2H-1)|t|^{2H-2}, \text{ for } t \neq 0$$

- Spectral density

$$\tilde{K}_H(\omega) = \int_{-\infty}^{\infty} e^{it\omega} K_H(t) dt = \Gamma(2H+1) \sin(H\pi) |\omega|^{1-2H}$$

Toward subdiffusion

- Applying Fourier transform on

$$m \frac{dv_t}{dt} = -\zeta \int_{-\infty}^t v_u K_H(t-u) du + F_t^{(H)},$$

$v(t)$ Gaussian $E\{v(t)\} = 0$,

$$C(t) = E\{v(0)v(t)\} = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{it\varpi} \tilde{C}(\varpi) d\varpi$$

$$\tilde{C}(\varpi) = \frac{k_B T \zeta \tilde{K}_H(\varpi)}{\left| \zeta \tilde{K}_H^+(\varpi) - i\varpi m \right|^2}$$

- For displacement $X(t) = \int_0^t v(s) ds$

$$E\{X(t)^2\} = \int_0^t \int_0^t E\{v(s)v(u)\} du ds$$

$$E\{X(t)^2\} \sim \frac{k_B T}{\zeta} \frac{2 \sin(2H\pi)}{\pi H (2H-1)(2H-2)} t^{2-2H} \propto t^{2-2H}$$

- $H > 1/2$ leads to subdiffusion!

Harmonic potential

- For harmonic potential $U(x) = \frac{1}{2} m \omega^2 x^2$, model becomes

$$m \frac{d^2 x(t)}{dt^2} = -\zeta \int_{-\infty}^t \frac{dx(u)}{du} K_H(t-u) du - \frac{dU(x)}{dx} + F^{(H)}(t)$$

- Overdamped limit:

$$m \omega^2 x(t) = -\zeta \int_{-\infty}^t \frac{dx(u)}{du} K_H(t-u) du + F^{(H)}(t)$$

- Solution: stationary Gaussian

$$\langle x(t) \rangle = 0$$

$$C_x(t) = \langle x(0)x(t) \rangle = \frac{k_B T}{m \omega^2} E_{2-2H} \left(-\frac{m \omega^2}{\zeta \Gamma(2H+1)} t^{2-2H} \right)$$

$$E_\alpha(z) : \text{Mittag-Leffler function} \quad E_\alpha(z) = \sum_{k=1}^{\infty} z^k / \Gamma(\alpha k + 1)$$

$$\begin{aligned}
 C_{xx}(t) &= E\{X(0)X(t)\} \\
 &= \frac{k_B T}{m\omega^2} E_{2-2H} \left(-\frac{m\omega^2}{\zeta\Gamma(2H+1)} t^{2-2H} \right)
 \end{aligned}$$

$$E_{\alpha}(z) = \sum_{k=0}^{\infty} z^k / \Gamma(\alpha k + 1)$$

- For all H ,

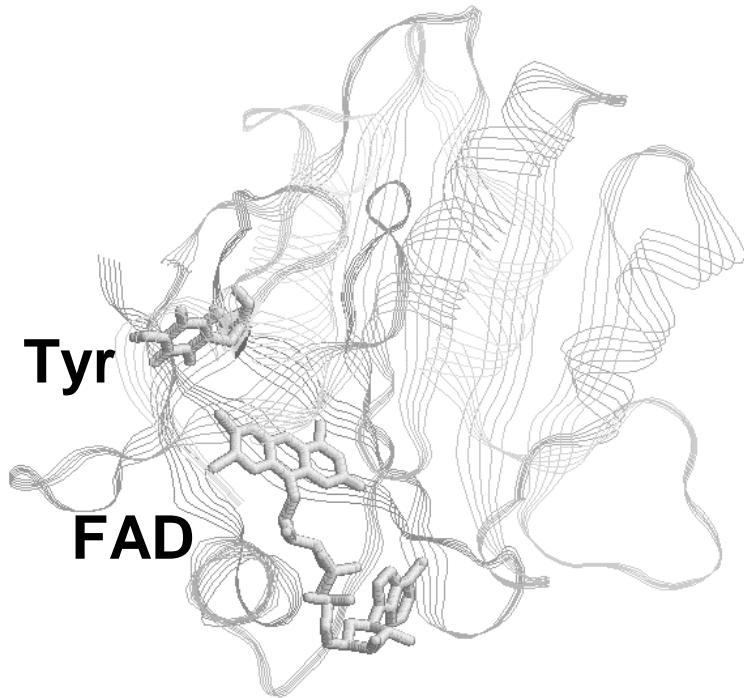
$$C_{xx}(0) = E\{X(0)X(0)\} = \frac{k_B T}{m\omega^2}$$

the **thermal equilibrium** value.

- For $H = 1/2$, recovers the Brownian diffusion result

$$C_{xx}(t) = E\{X(0)X(t)\} = \frac{k_B T}{m\omega^2} e^{-2\frac{m\omega^2}{\zeta}t}$$

Back to experiment

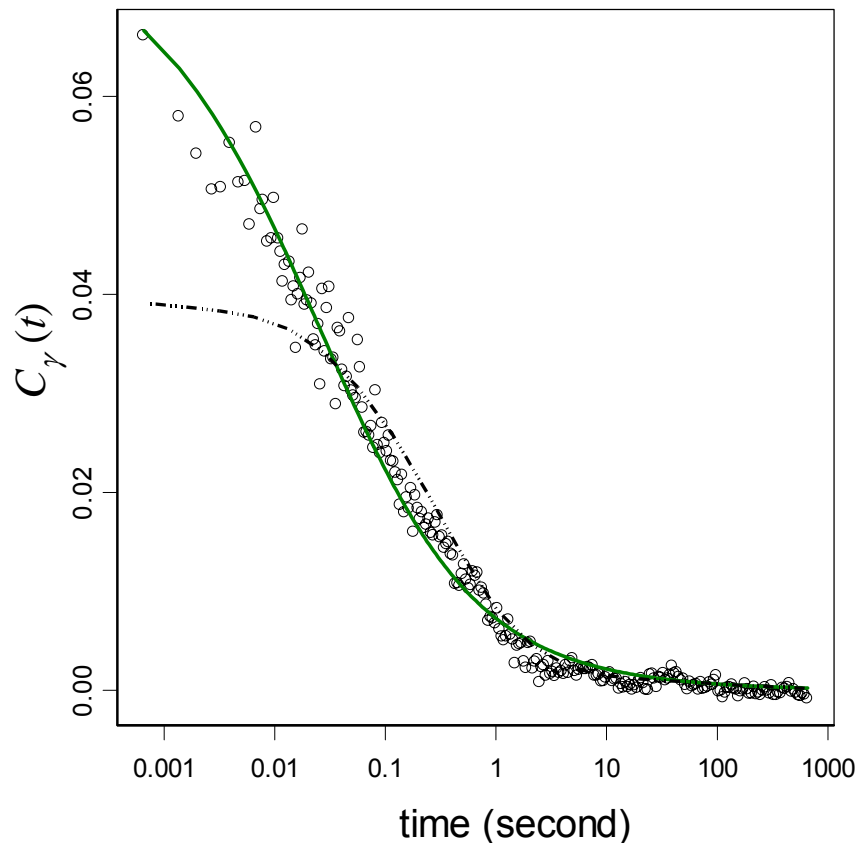


Fluorescence lifetime of FAD depends on the distance between ET donor and acceptor

$$\gamma^{-1}(t) = [k_0 e^{-\beta(X_{eq} + X_t)}]^{-1}$$

- ⇒ Model $X(t)$ by GLE with fGn under harmonic potential
easy calculation of lifetime autocorrelation

Fitting experimental autocorrelation



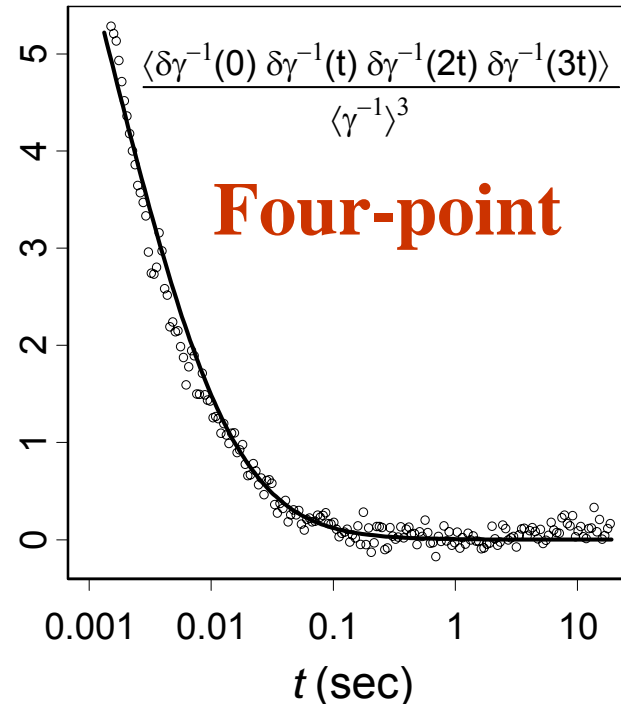
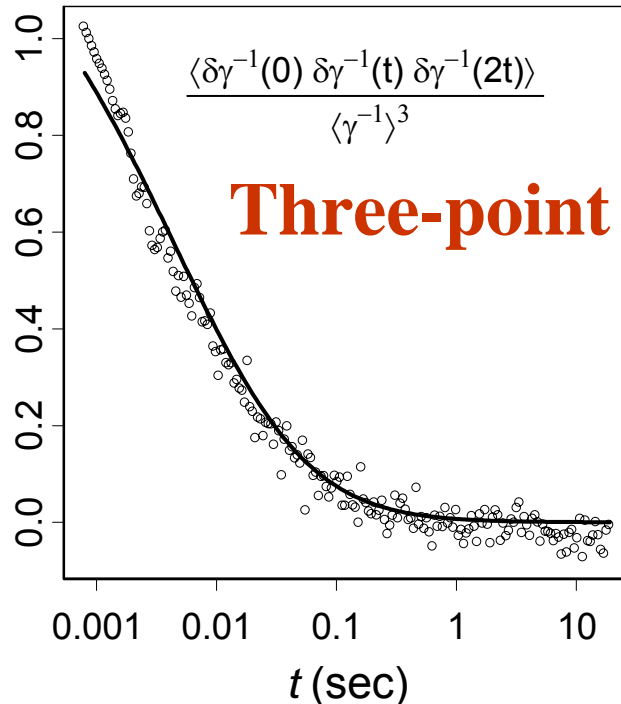
$$H \quad \frac{\zeta}{m\omega^2} \quad \frac{k_B T}{m\omega^2} \beta^2$$

0.74 0.40 0.81

Kou and Xie, *Phys. Rev. Lett.*, **93**, 180603 (2004).

Higher order autocorrelation functions

$$\delta\gamma^{-1}(t) := \gamma^{-1}(t) - \langle \gamma^{-1}(t) \rangle$$



Same parameters:

| | | |
|------|---------------------------|-----------------------------------|
| H | $\frac{\zeta}{m\omega^2}$ | $\frac{k_B T}{m\omega^2} \beta^2$ |
| 0.74 | 0.40 | 0.81 |

A prediction for three-point autocorrelation

- GLE with fGn predicts time symmetry

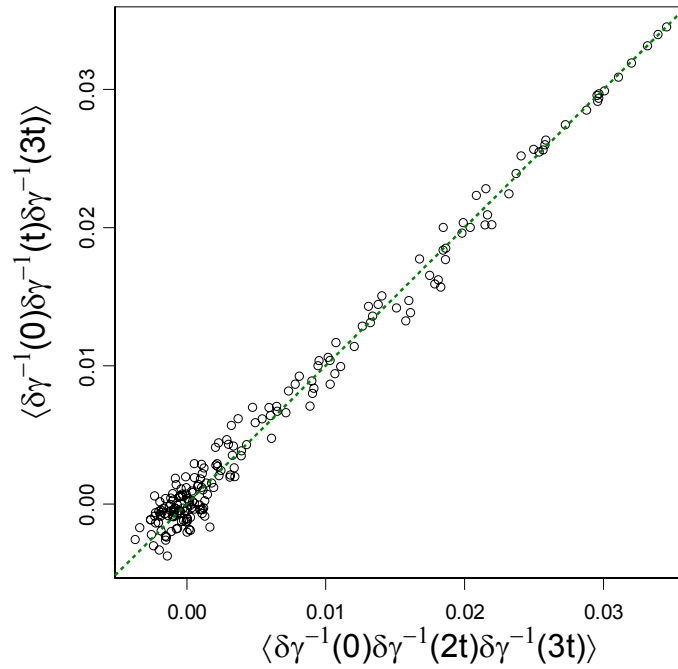
$$\begin{aligned} & \langle \delta\gamma(0)^{-1} \delta\gamma(t_1)^{-1} \delta\gamma(t_1 + t_2)^{-1} \rangle \\ &= \langle \delta\gamma(0)^{-1} \delta\gamma(t_2)^{-1} \delta\gamma(t_1 + t_2)^{-1} \rangle \end{aligned}$$

- In particular



$$\begin{aligned} & \langle \delta\gamma^{-1}(0) \delta\gamma^{-1}(t) \delta\gamma^{-1}(3t) \rangle \\ &= \langle \delta\gamma^{-1}(0) \delta\gamma^{-1}(2t) \delta\gamma^{-1}(3t) \rangle \text{ for all } t \end{aligned}$$

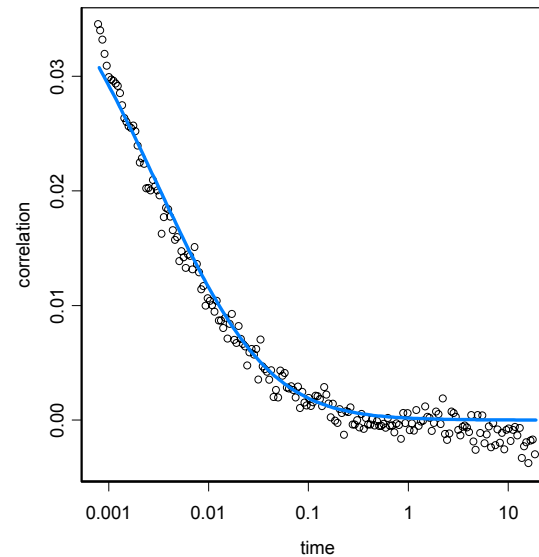
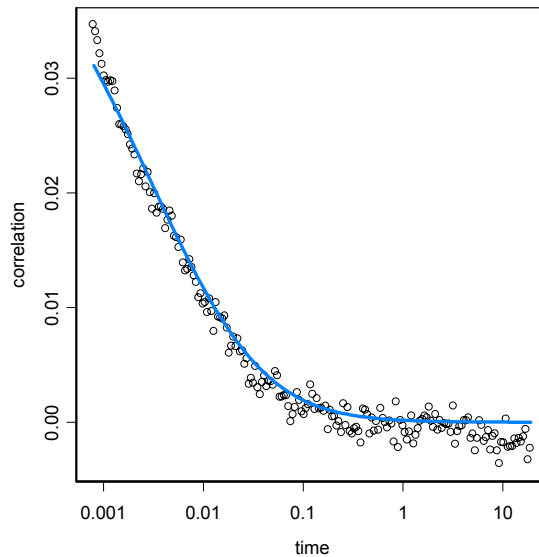
- Check with experiments:



$\langle \delta\gamma^{-1}(0) \delta\gamma^{-1}(t) \delta\gamma^{-1}(3t) \rangle$
 versus
 $\langle \delta\gamma^{-1}(0) \delta\gamma^{-1}(2t) \delta\gamma^{-1}(3t) \rangle$

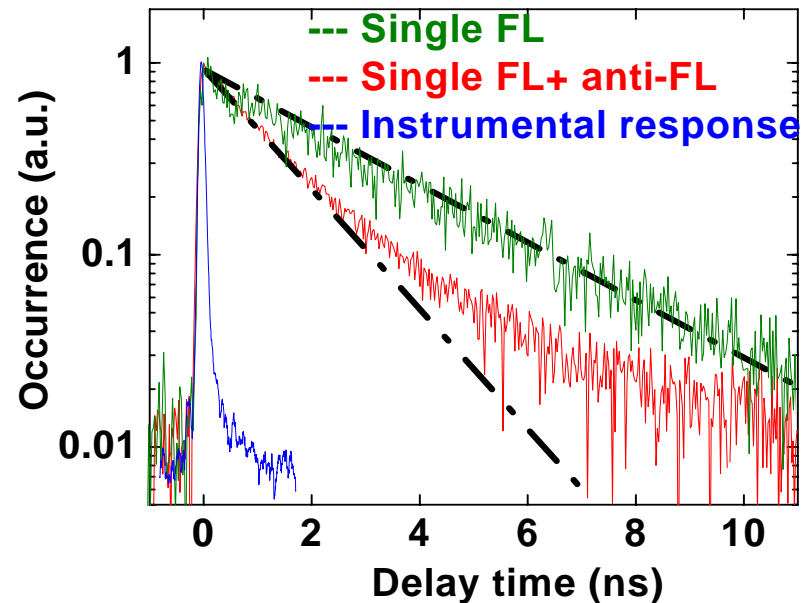
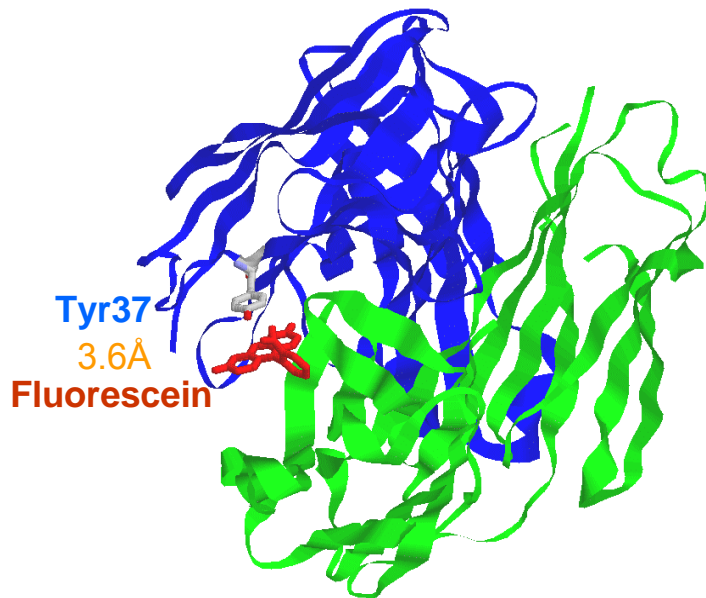
$\langle \delta\gamma^{-1}(0)\delta\gamma^{-1}(2t)\delta\gamma^{-1}(3t) \rangle$

$\langle \delta\gamma^{-1}(0)\delta\gamma^{-1}(t)\delta\gamma^{-1}(3t) \rangle$



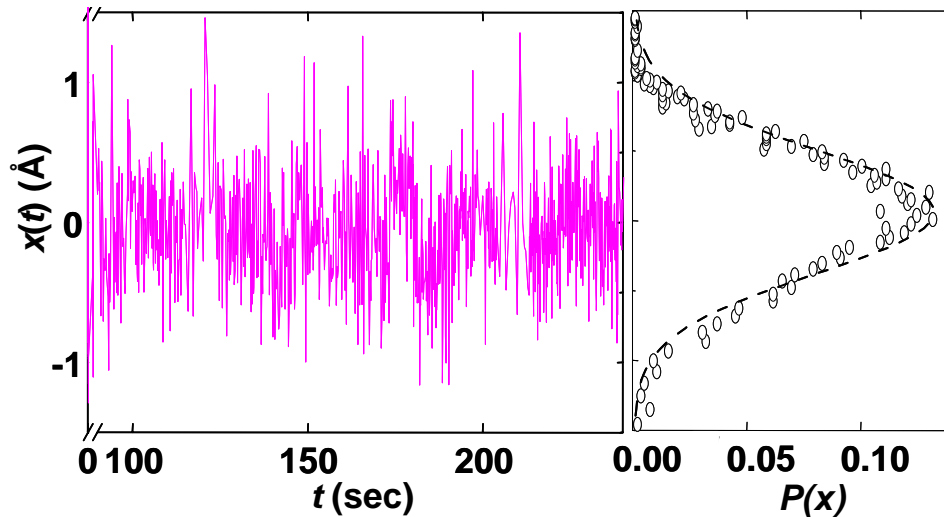
Another system

A protein complex formed by fluorescein (FL) and monoclonal anti-fluorescein (anti-FL)

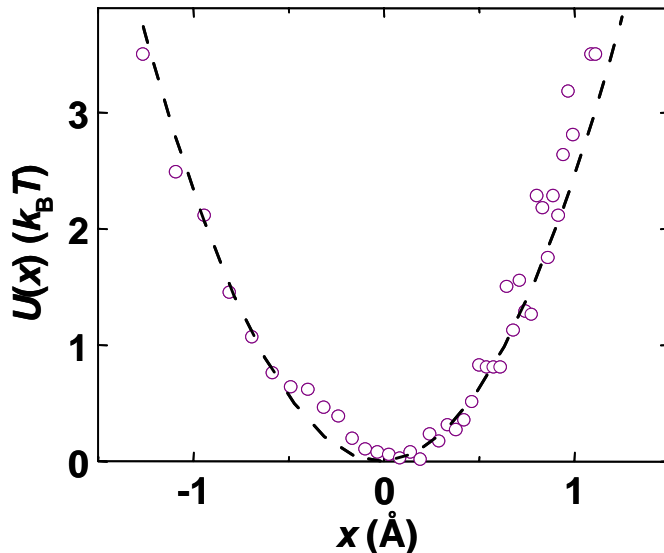


Min, *et al. Phys. Rev. Lett.* **94**, 198302 (2005).

Obtain distance fluctuation from $\gamma^{-1}(t) = [k_0 e^{-\beta(X_{eq} + X_t)}]^{-1}$



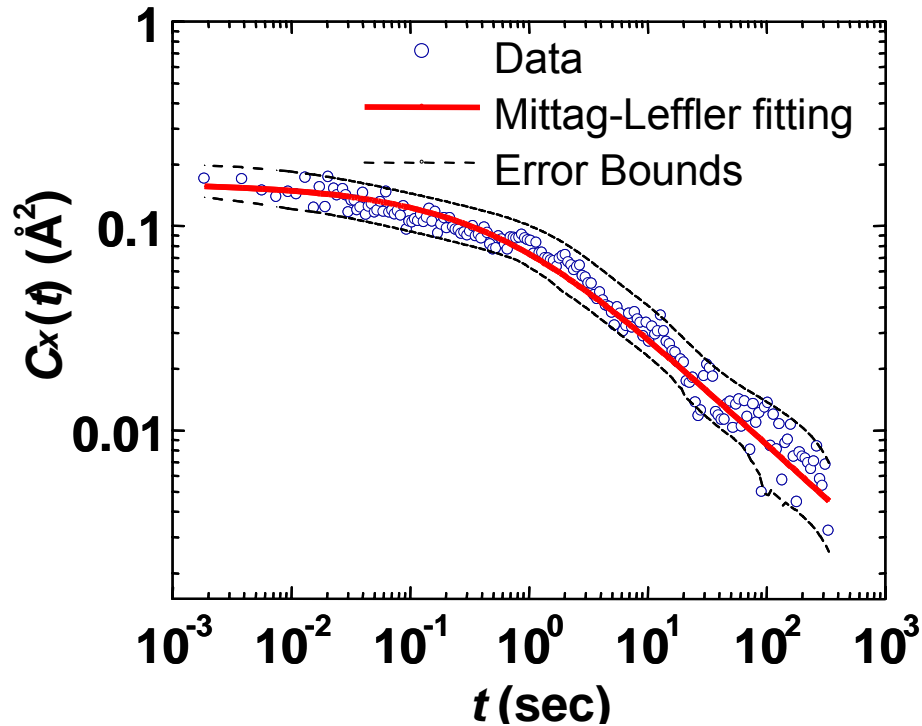
$$P(x) \propto \exp(-U(x) / k_B T)$$



Potential mean force

$$U(x) = -k_B T \ln P(x)$$

Autocorrelation of distance fluctuation



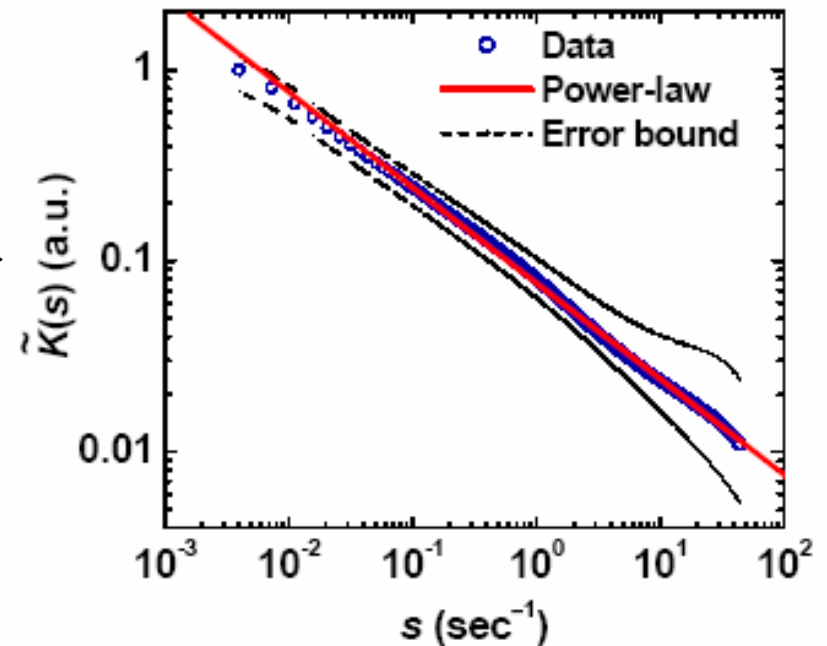
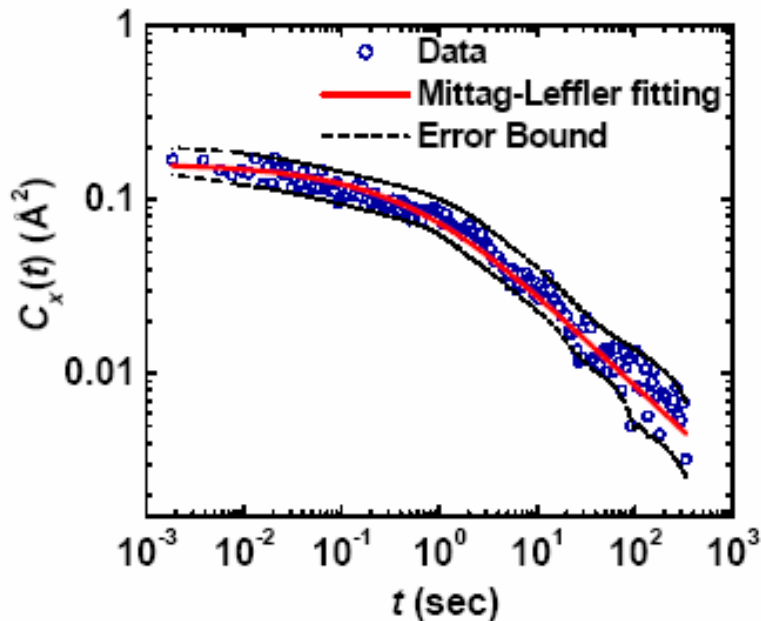
$$m\omega^2 x(t) = -\zeta \int_{-\infty}^t \frac{dx(u)}{du} K(t-u) du + F(t)$$

→ **one-to-one correspondence**

$$\tilde{K}(s) = \frac{m\omega^2}{\zeta} \frac{\tilde{C}_x(s)}{C_x(0) - s\tilde{C}_x(s)}$$

Memory kernel of conformational fluctuations

$$\tilde{K}(s) = \frac{m\omega^2}{\zeta} \frac{\tilde{C}_x(s)}{C_x(0) - s\tilde{C}_x(s)}$$



$$K(t) \propto t^{-\alpha-1} = t^{-0.51 \pm 0.07}$$

Summary

- Michaelis-Menten with dynamic disorder
 - Explains experimental data
 - Derive single-molecule Michaelis-Menten equation
 - Dynamic disorder might be masked in ensemble studies!
- Generalized Langevin Equation with fGn
 - Explains the observed conformational dynamics.
 - Experimentally obtain power law memory kernel

Summary (Continued)

- The connection: both highlight the conformation fluctuation:
 - An enzyme is a dynamic entity with conformational interconversion on a board range of time scales.
 - The interconverting conformers have different enzymatic reaction rate constants.



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