

# Molecular rare event simulations

Peter Bolhuis

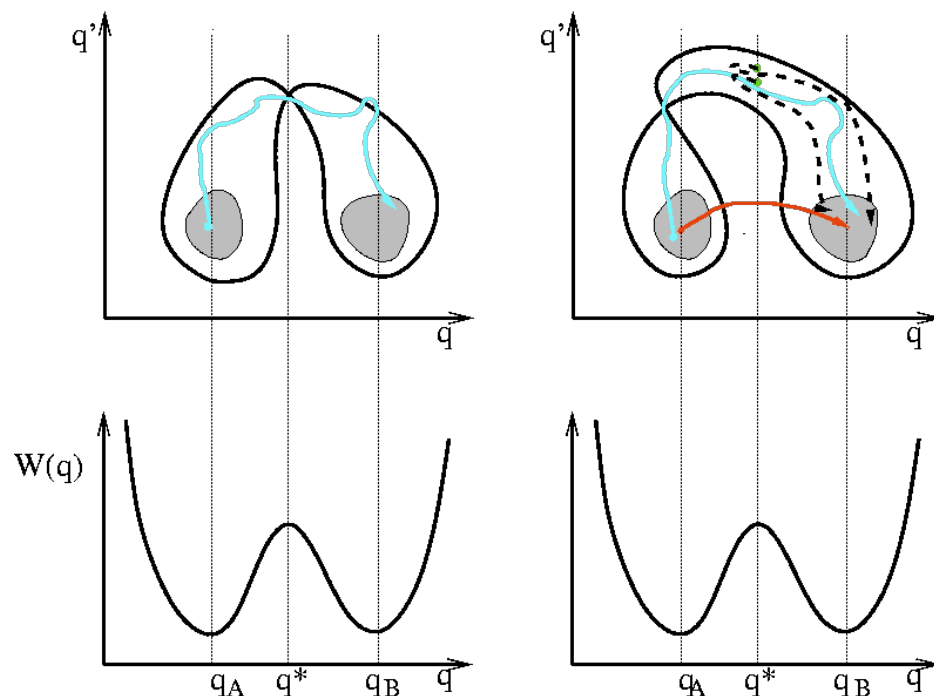
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# Outline

- Part 1
  - Rare events
  - The need for unbiased transition paths
  - Sampling the path ensemble
- Part 2
  - Analyzing the path ensemble
  - Calculation of rate constants
  - Transition state ensemble and reaction coordinate
- Part 3
  - Application to protein folding

# The reaction coordinate problem

If RC is not correct, transition states, rates and mechanism might be wrong.



$$W(q) = -kT \ln \int dq' \exp\{-\beta E(q, q')\}$$

Need for methods that create pathways without prior knowledge of the RC, e.g.

- Parallel replica, hyperdynamics, metadynamics, etc
- Nudged Elastic Band, string methods, etc
- Transition path sampling

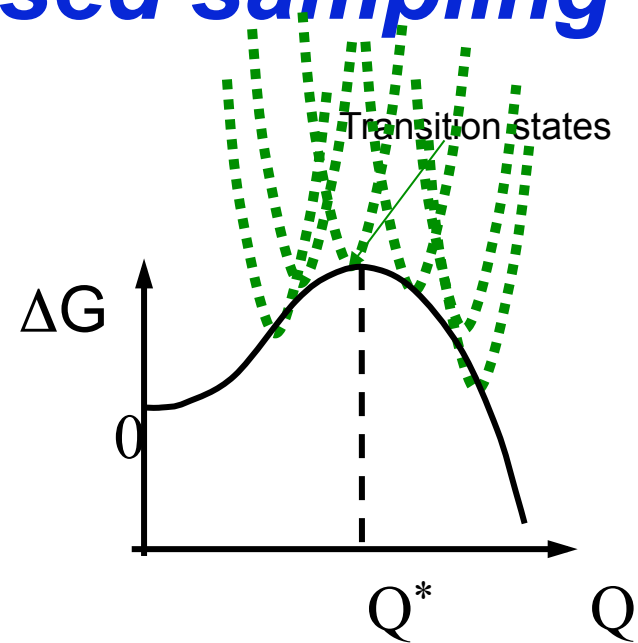
# *Breakdown of biased sampling*

Free energy landscape has barrier

Calculate FE by umbrella sampling

–by applying biasing potential

–as a function of order parameter  $Q$



# Breakdown of biased sampling

Free energy landscape has barrier

Calculate FE by umbrella sampling

–by applying biasing potential

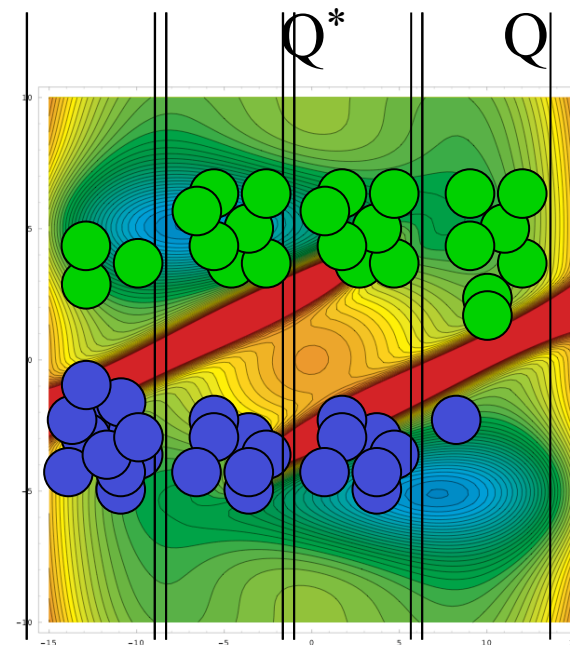
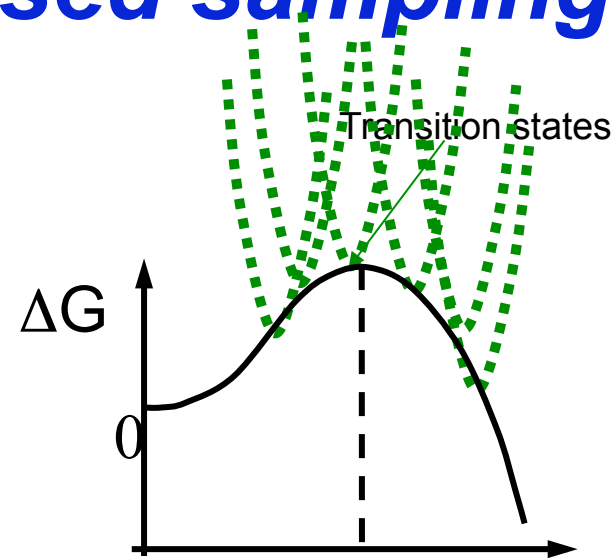
–as a function of order parameter  $Q$

Finding the correct reaction coordinate is difficult!

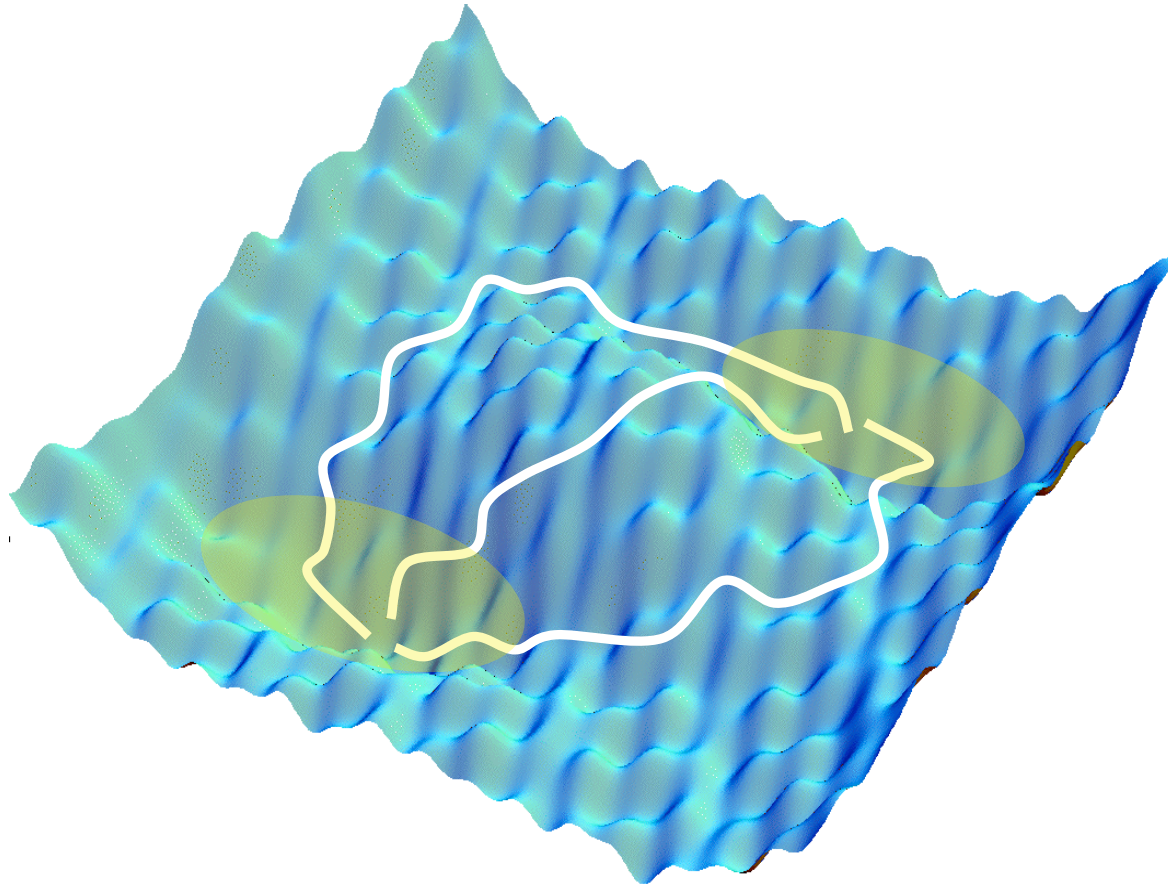
Rare events by biasing along reaction coordinate

Hysteresis because reaction coordinate not known in advance

Mechanism and kinetics are not correct



# *Two ended methods*



Methods that take the entire path and fix the begin and end point

# Nudged Elastic Band

Suitable for finding saddle points on complex PES

chain of states  $\{r^{(0)}, r^{(1)}, \dots, r^{(M)}\}$

define object function

$$S[r^{(0)}, r^{(1)}, \dots, r^{(M)}] = \sum_{i=0}^M V[r^{(i)}] + \frac{k}{2} \sum_{i=1}^M [r^{(i)} - r^{(i-1)}]^2$$

that should be minimized.

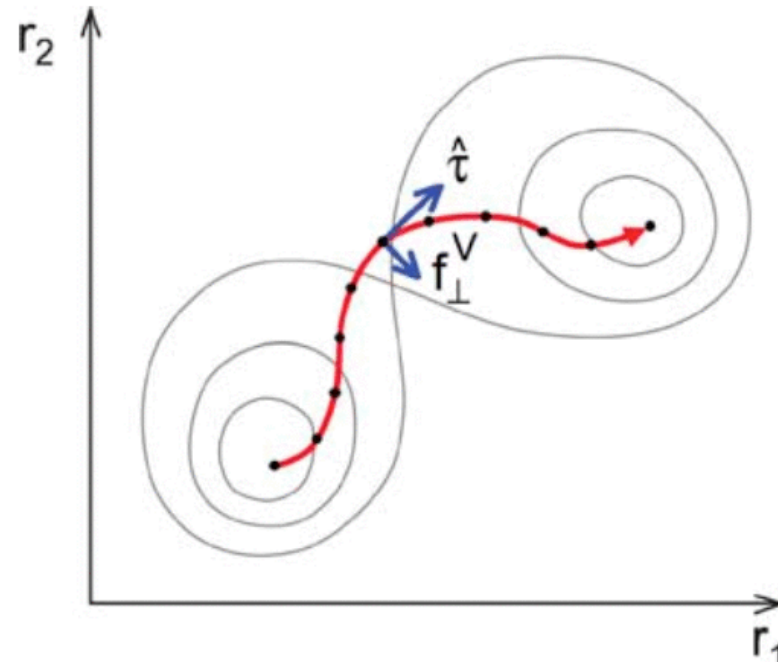
$$f^{\text{NEB}}[r^{(i)}] = f_{\perp}^V[r^{(i)}] + f_{\parallel}^S[r^{(i)}]$$

$$\hat{\tau} = \frac{r^{(i+1)} - r^{(i)}}{|r^{(i+1)} - r^{(i)}|}$$

H. Jonsson et al.

WorldScientific, Singapore, p.385(2000)

Han sur Lesse



# Minimize the action

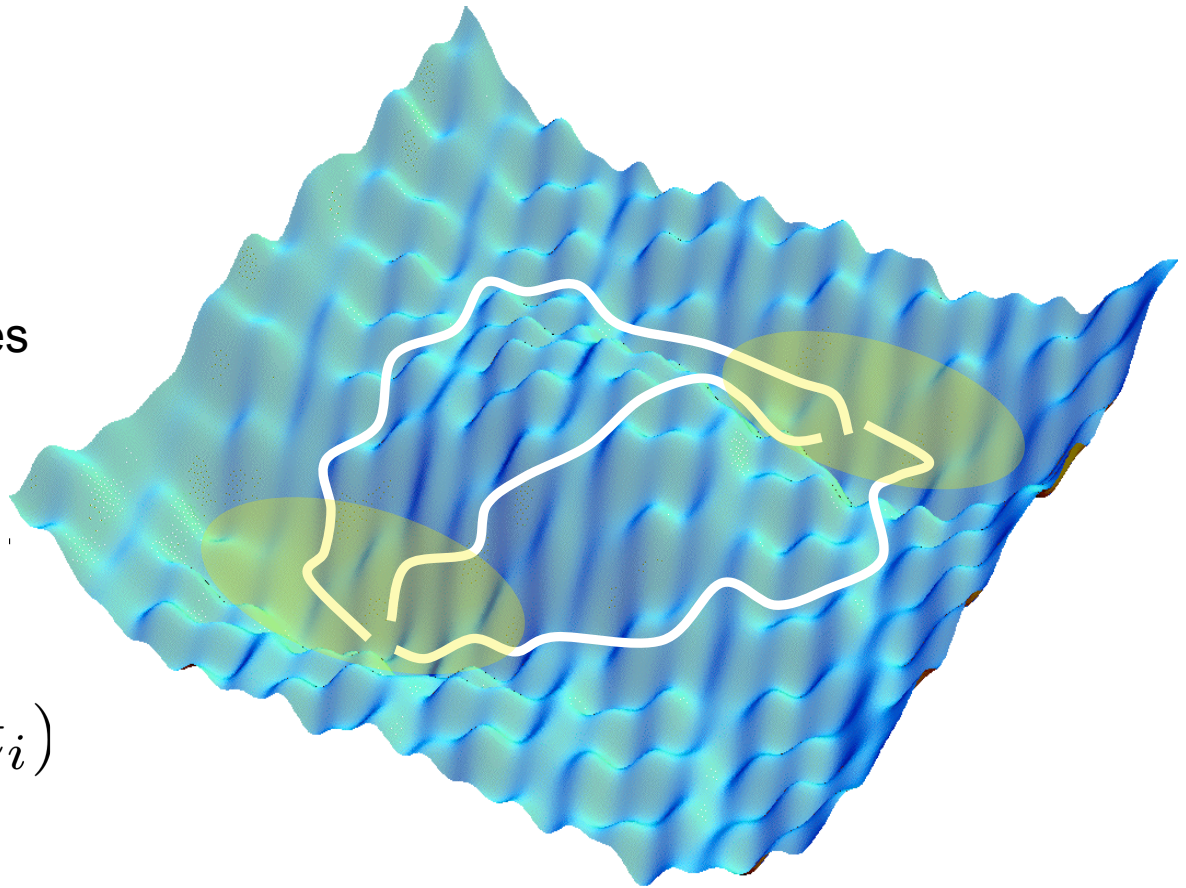
To get dynamical trajectories  
minimize action

$$S_{cont} = \int_{t_0}^{t_1} dt L(t)$$

$$S_{disc} = \Delta t \sum_{i=0}^{i_{max}} \mathcal{L}(t_i)$$

$$\mathcal{L}(r(t)) = \sum_{i=1}^N m_i \dot{r}_i^2 - U(r_1, r_2, \dots, r_N)$$

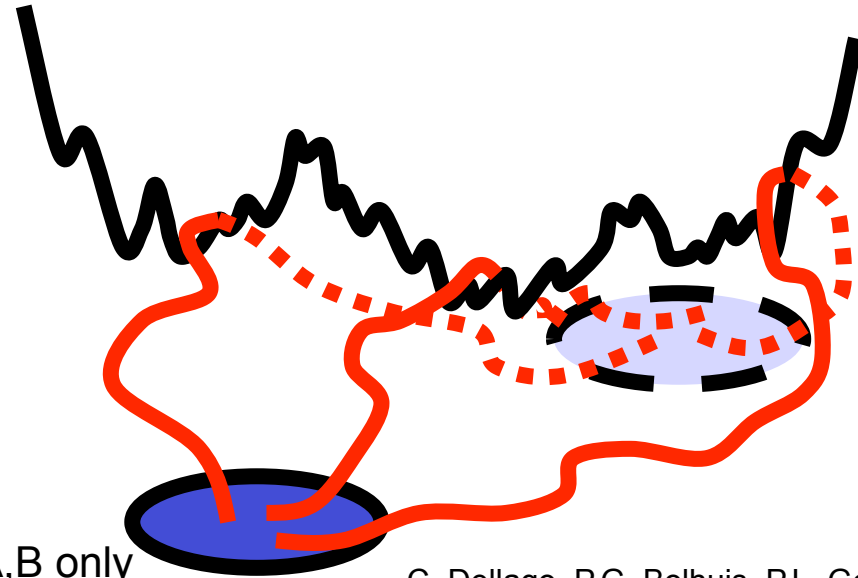
problem : only one trajectory is obtained





# Transition path sampling

Samples the path ensemble:  
all trajectories that lead over barrier



- Sampling by Monte Carlo
- Requires definition of stable states A,B only
- Results in ensemble of pathways
- Reaction coordinate is a result of simulation not an input
- Allows for calculation of rate constants

C. Dellago, P.G. Bolhuis, P.L. Geissler  
Adv. Chem. Phys. **123**, 1 2002

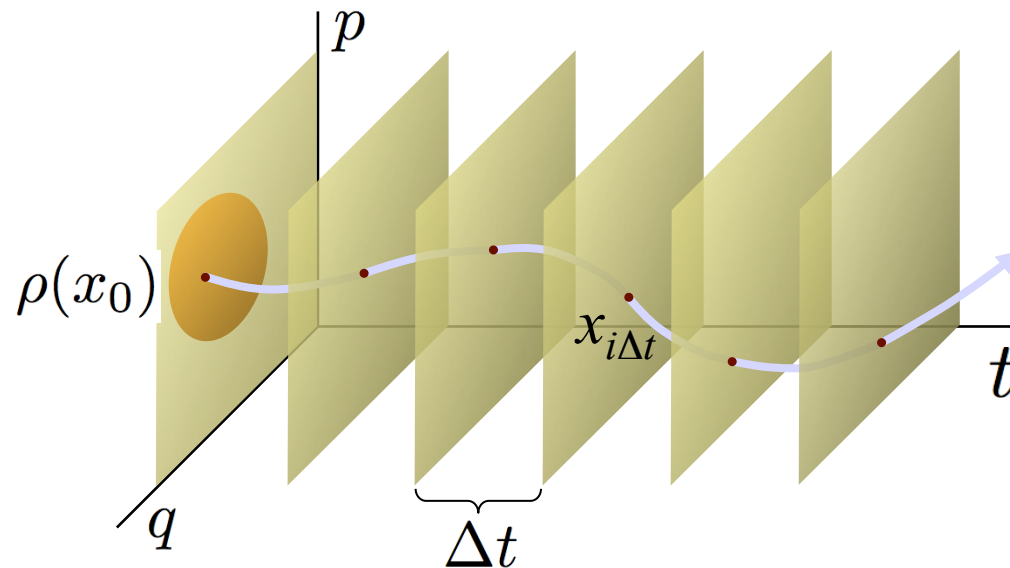
Apply when process of interest

- is a rare event
- is complex and reaction coordinate is not known

Examples: autodissociation of water, organic reactions in solution, protein folding

# Path probability density

$x(\mathcal{T}) \equiv \{x_0, x_{\Delta t}, x_{2\Delta t}, \dots, x_{\mathcal{T}}\}$       Path = Sequence of states



$$\mathcal{P}[x(\mathcal{T})] = \rho(x_0) \prod_{i=0}^{\mathcal{T}/\Delta t - 1} p(x_{i\Delta t} \rightarrow x_{(i+1)\Delta t})$$

# Transition probabilities

## Initial conditions

Canonical:  $\rho(x) = \exp\{-\beta\mathcal{H}(x)\}/Q$

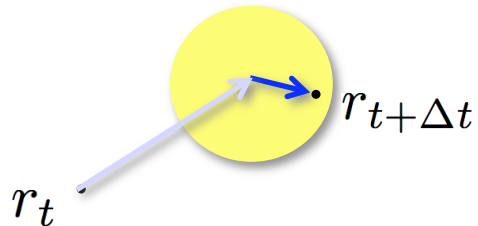
$$Q(\beta) = \int dx \exp\{-\beta\mathcal{H}(x)\}$$

Microcanonical:  $\rho(x) = \delta[E - \mathcal{H}(x)]/g(E)$

$$g(E) = \int dx \delta[E - \mathcal{H}(x)]$$

## Brownian dynamics

$$m\gamma\dot{r} = -\frac{\partial V(r)}{\partial r} + \mathcal{F}$$



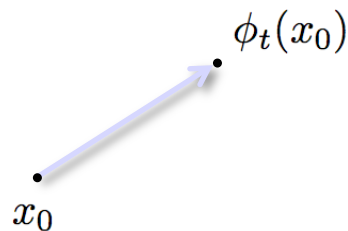
$$p(r_t \rightarrow r_{t+\Delta t}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(r_{t+\Delta t} - r_t + \frac{\Delta t}{\gamma m} \frac{\partial V}{\partial r})^2}{2\sigma^2}\right\}$$

$$\sigma^2 = \frac{2k_B T}{m\gamma} \Delta t$$

## Newtonian dynamics

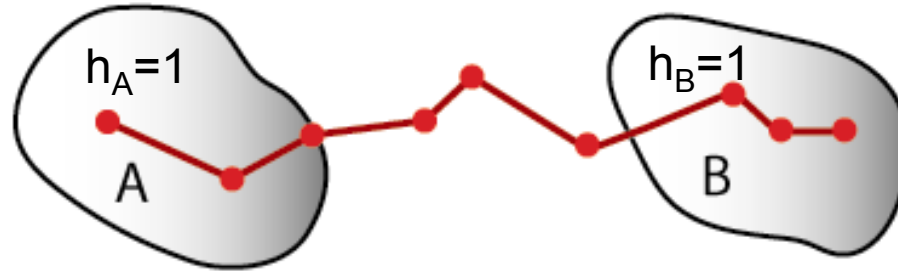
$$\dot{r} = \frac{\partial \mathcal{H}(r, p)}{\partial p}$$

$$\dot{p} = -\frac{\partial \mathcal{H}(r, p)}{\partial r}$$



$$p(x_t \rightarrow x_{t+\Delta t}) = \delta[x_{t+\Delta t} - \phi_{\Delta t}(x_t)]$$

# Transition path ensemble

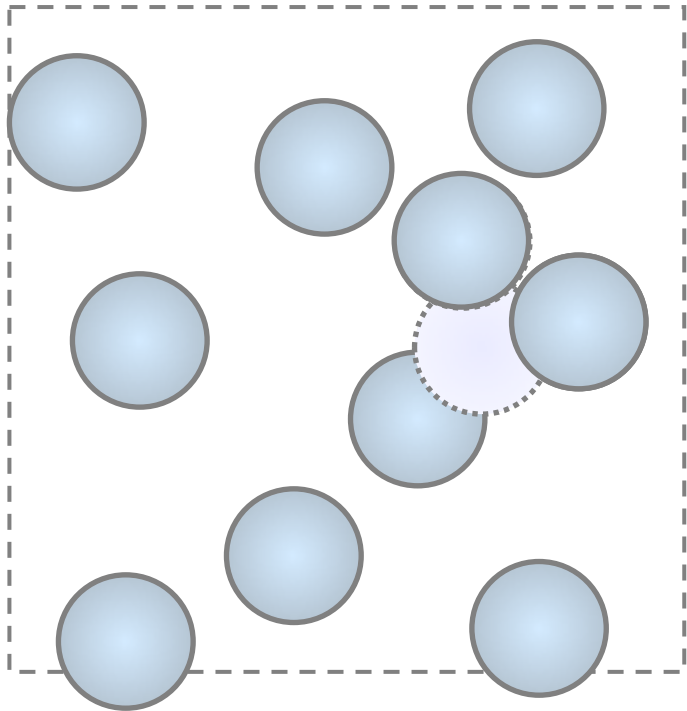


$$\mathcal{P}_{AB}[x(\mathcal{T})] \equiv h_A(x_0)\mathcal{P}[x(\mathcal{T})]h_B(x_T)/Z_{AB}(\mathcal{T})$$

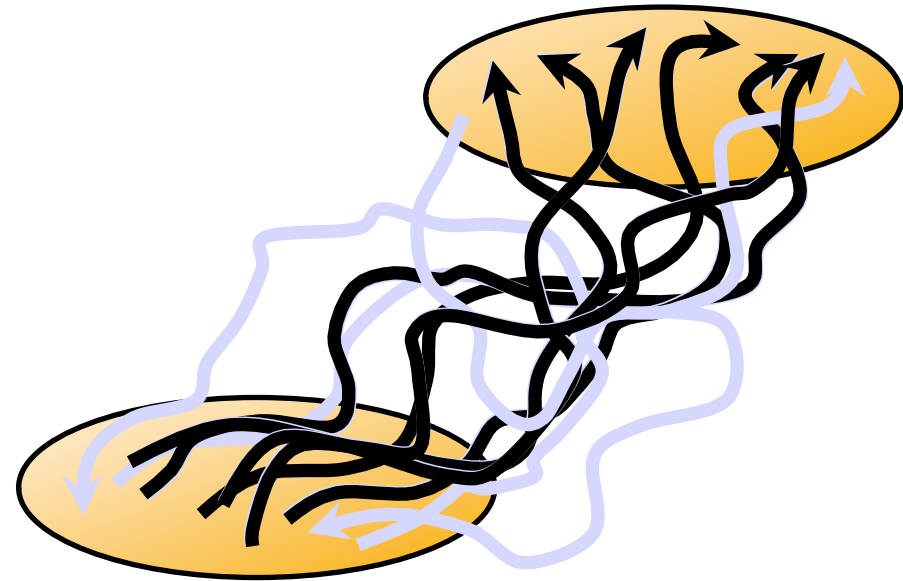
$$Z_{AB}(\mathcal{T}) \equiv \int \mathcal{D}x(\mathcal{T}) h_A(x_0)\mathcal{P}[x(\mathcal{T})]h_B(x_T)$$

$$\int \mathcal{D}x(\mathcal{T}) \equiv \int \cdots \int dx_0 dx_{\Delta t} dx_{2\Delta t} \cdots dx_T$$

# *Sampling the path ensemble*



**Monte Carlo  
simulation**

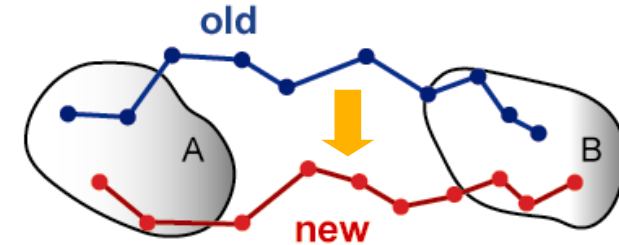


**transition path  
sampling**

# Metropolis MC of pathways

1. Generate **new** path from **old** one

$$x^{(o)}(\mathcal{T}) \longrightarrow x^{(n)}(\mathcal{T})$$



2. Accept **new** path according to **detailed balance**:

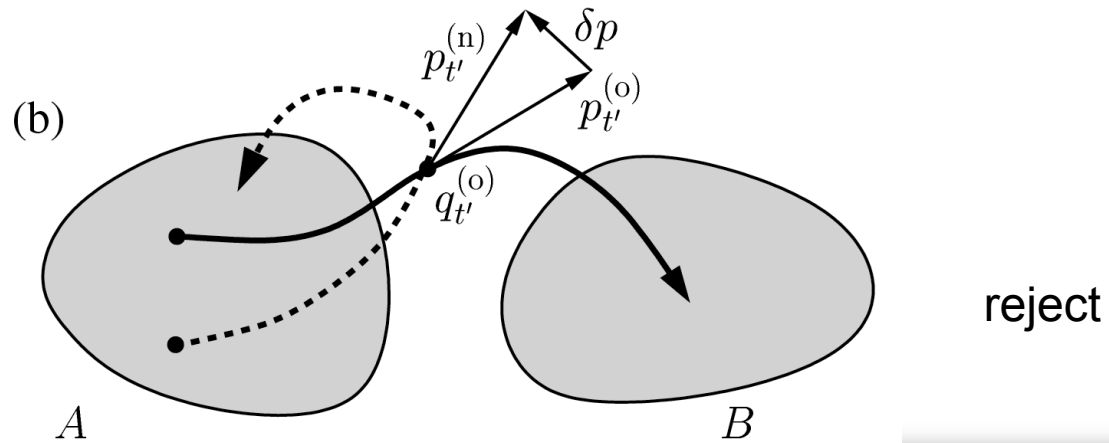
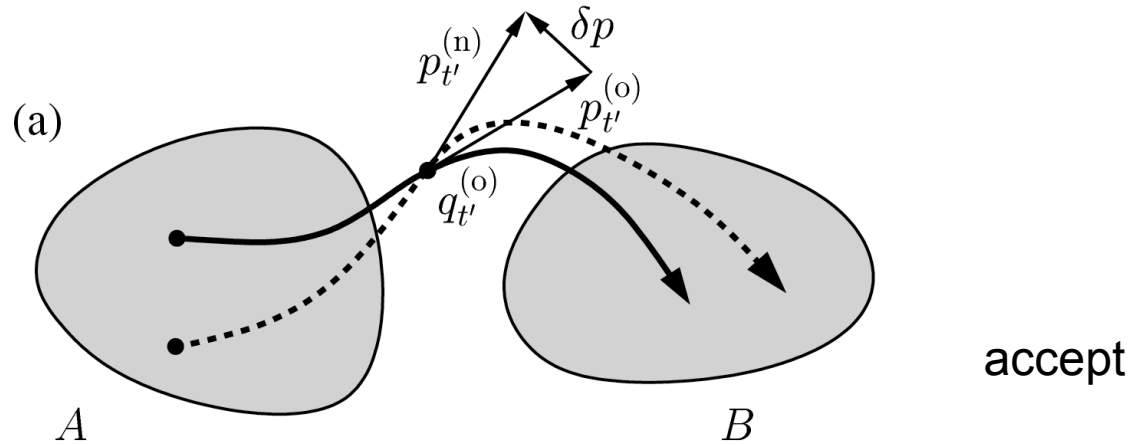
$$\mathcal{P}_{AB}[x^{(o)}(\mathcal{T})]\pi[x^{(o)}(\mathcal{T}) \rightarrow x^{(n)}(\mathcal{T})] = \mathcal{P}_{AB}[x^{(n)}(\mathcal{T})]\pi[x^{(n)}(\mathcal{T}) \rightarrow x^{(o)}(\mathcal{T})]$$

$$\pi[x^{(o)}(\mathcal{T}) \rightarrow x^{(n)}(\mathcal{T})] = P_{\text{gen}}[x^{(o)}(\mathcal{T}) \rightarrow x^{(n)}(\mathcal{T})] \times P_{\text{acc}}[x^{(o)}(\mathcal{T}) \rightarrow x^{(n)}(\mathcal{T})]$$

3. Satisfy detailed balance with the **Metropolis rule**:

$$P_{\text{acc}}[x^{(o)}(\mathcal{T}) \rightarrow x^{(n)}(\mathcal{T})] = h_A[x_0^{(n)}]h_B[x_T^{(n)}] \min \left\{ 1, \frac{\mathcal{P}[x^{(n)}(\mathcal{T})]P_{\text{gen}}[x^{(n)}(\mathcal{T}) \rightarrow x^{(o)}(\mathcal{T})]}{\mathcal{P}[x^{(o)}(\mathcal{T})]P_{\text{gen}}[x^{(o)}(\mathcal{T}) \rightarrow x^{(n)}(\mathcal{T})]} \right\}$$

# Shooting moves



$$P_{acc}[x^{(o)}(T) \rightarrow x^{(n)}(T)] = h_A(x_0^{(n)})h_B(x_T^{(n)})$$

$$h_A(t) = \begin{cases} 1 & \text{if } x_t \in A \\ 0 & \text{if } x_t \notin A \end{cases}$$

# Shooting algorithm

$$P_{\text{gen}}^{\text{f}}[x^{(o)}(\mathcal{T}) \rightarrow x^{(n)}(\mathcal{T})] = \prod_{i=t'/\Delta t}^{\mathcal{T}/\Delta t - 1} p\left(x_{i\Delta t}^{(n)} \rightarrow x_{(i+1)\Delta t}^{(n)}\right)$$

$$P_{\text{gen}}^{\text{b}}[x^{(o)}(\mathcal{T}) \rightarrow x^{(n)}(\mathcal{T})] = \prod_{i=1}^{t'/\Delta t} \bar{p}\left(x_{i\Delta t}^{(n)} \rightarrow x_{(i-1)\Delta t}^{(n)}\right)$$

$$P_{\text{gen}}[x^{(o)}(\mathcal{T}) \rightarrow x^{(n)}(\mathcal{T})] = p_{\text{gen}}[x_{t'}^{(o)} \rightarrow x_{t'}^{(n)}] \prod_{i=t'/\Delta t}^{\mathcal{T}/\Delta t - 1} p\left(x_{i\Delta t}^{(n)} \rightarrow x_{(i+1)\Delta t}^{(n)}\right) \times \prod_{i=1}^{t'/\Delta t} \bar{p}\left(x_{i\Delta t}^{(n)} \rightarrow x_{(i-1)\Delta t}^{(n)}\right)$$

$$P_{\text{acc}}[x^{(o)}(\mathcal{T}) \rightarrow x^{(n)}(\mathcal{T})] = h_A[x_0^{(n)}]h_B[x_{\mathcal{T}}^{(n)}] \min \left[ 1, \frac{\rho\left(x_0^{(n)}\right)}{\rho\left(x_0^{(o)}\right)} \prod_{i=0}^{t'/\Delta t - 1} \frac{p\left(x_{i\Delta t}^{(n)} \rightarrow x_{(i+1)\Delta t}^{(n)}\right)}{\bar{p}\left(x_{(i+1)\Delta t}^{(n)} \rightarrow x_{i\Delta t}^{(n)}\right)} \times \frac{\bar{p}\left(x_{(i+1)\Delta t}^{(o)} \rightarrow x_{i\Delta t}^{(o)}\right)}{p\left(x_{i\Delta t}^{(o)} \rightarrow x_{(i+1)\Delta t}^{(o)}\right)} \right]$$

$$\frac{p(x \rightarrow y)}{\bar{p}(y \rightarrow x)} = \frac{\rho_0(y)}{\rho_0(x)}$$

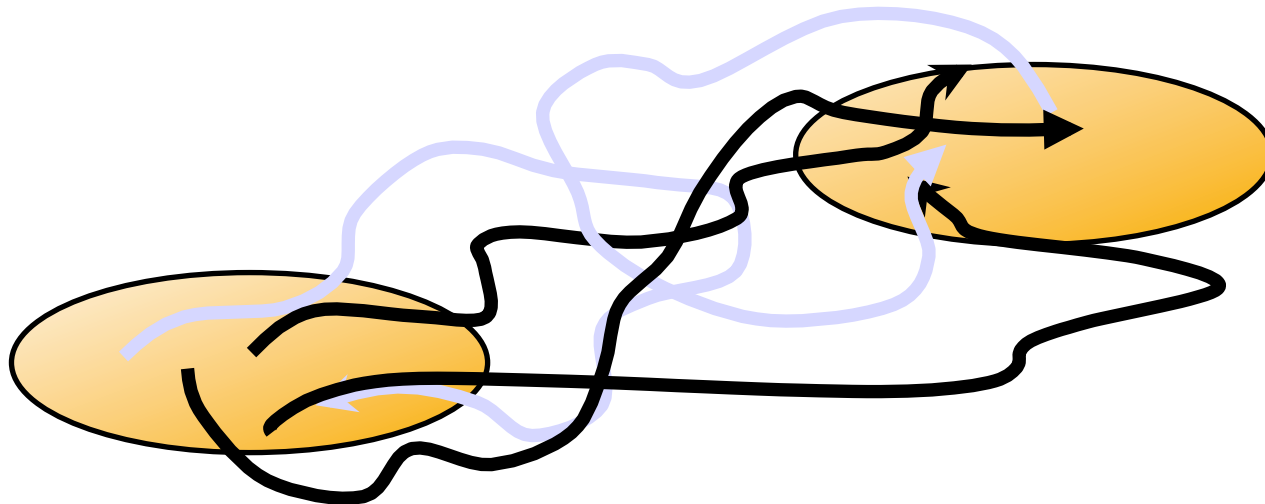
$$P_{\text{acc}}[x^{(o)}(\mathcal{T}) \rightarrow x^{(n)}(\mathcal{T})] = h_A[x_0^{(n)}]h_B[x_{\mathcal{T}}^{(n)}] \min \left[ 1, \frac{\rho(x_{t'}^{(n)})}{\rho(x_{t'}^{(o)})} \right]$$

$$P_{\text{acc}}[x^{(o)}(\mathcal{T}) \rightarrow x^{(n)}(\mathcal{T})] = h_A[x_0^{(n)}]h_B[x_{\mathcal{T}}^{(n)}]$$

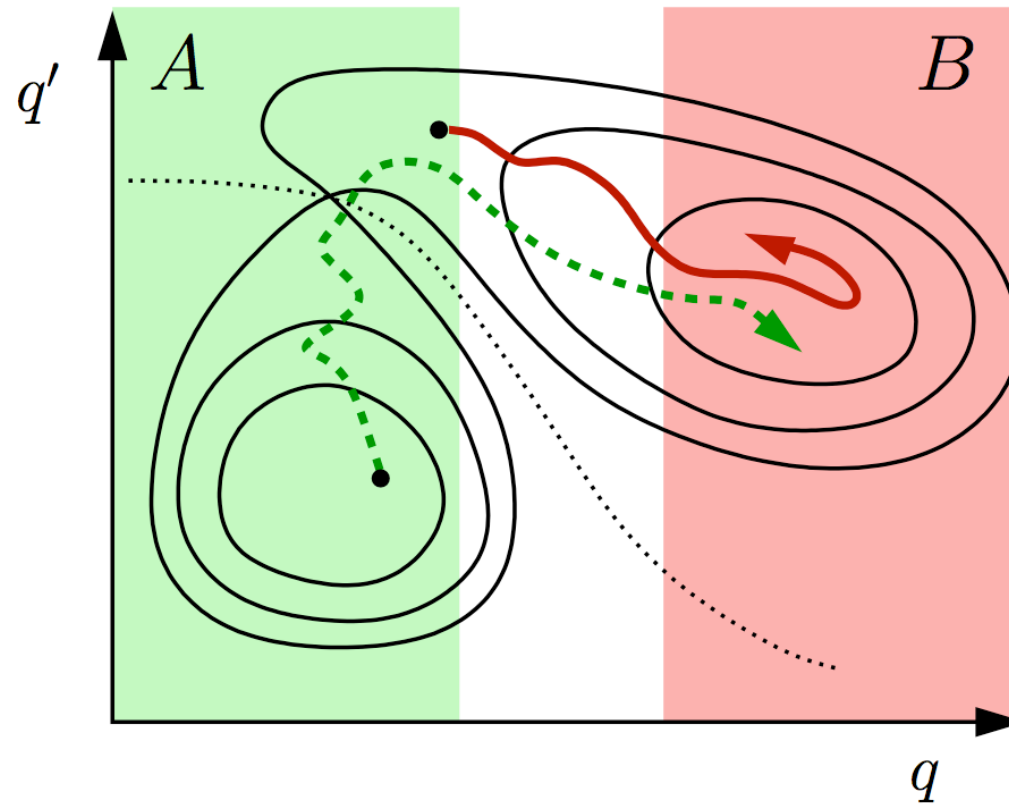


# Standard TPS algorithm

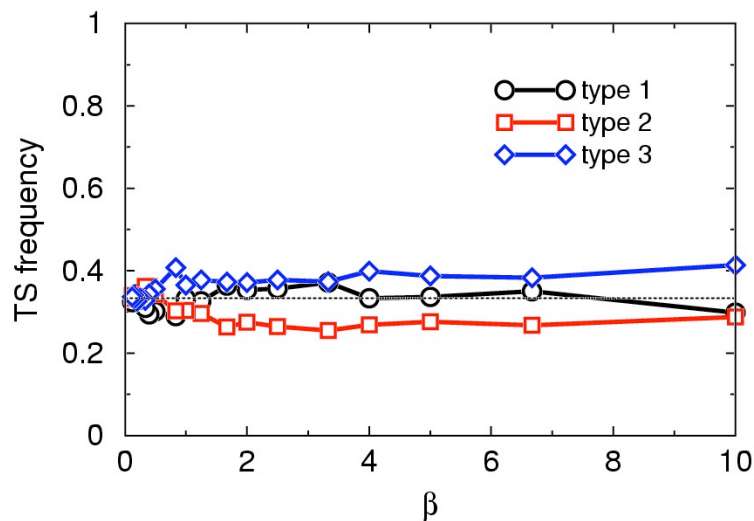
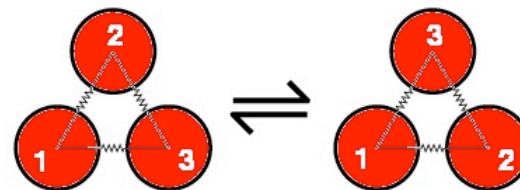
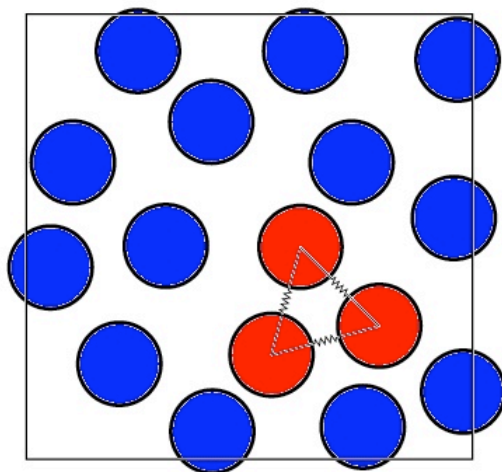
- take existing path
- choose random time slice  $t$
- change momenta slightly at  $t$
- integrate forward and backward in time to create new path of length  $L$
- accept if A and B are connected, otherwise reject and retain old path
- calculate averages
- repeat



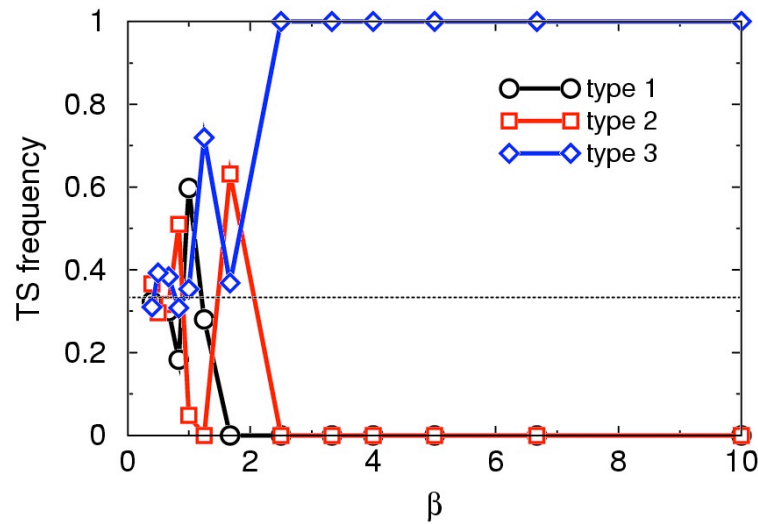
# *Definition of the stable states*



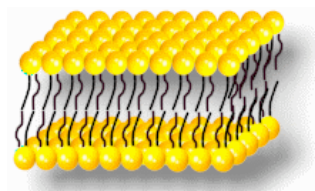
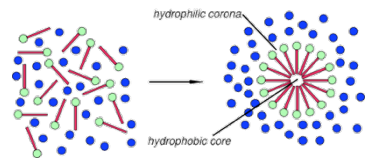
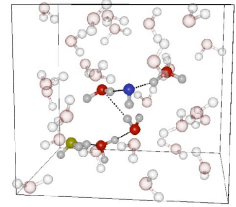
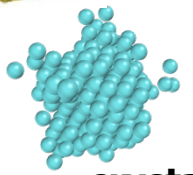
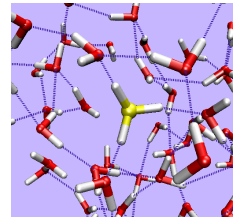
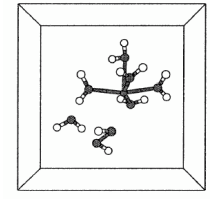
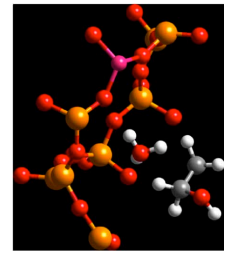
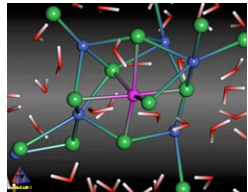
# Parallel tempering



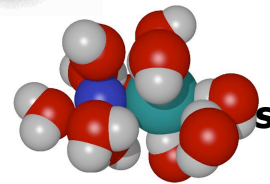
with parallel tempering



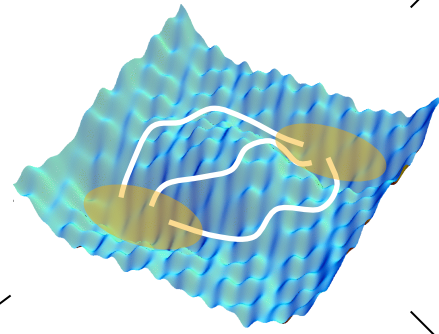
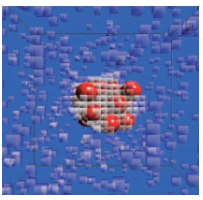
without parallel tempering



**complex fluids**



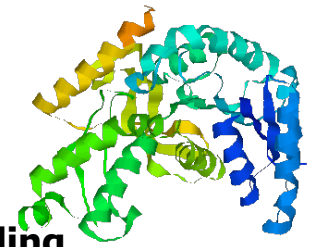
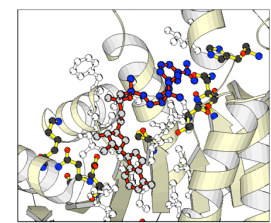
**solvent effects**



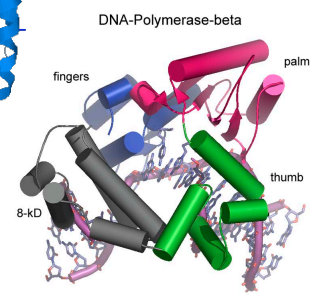
**catalysis**

**reactions**

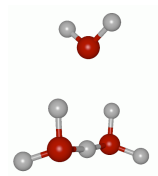
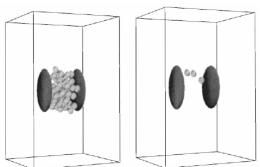
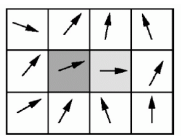
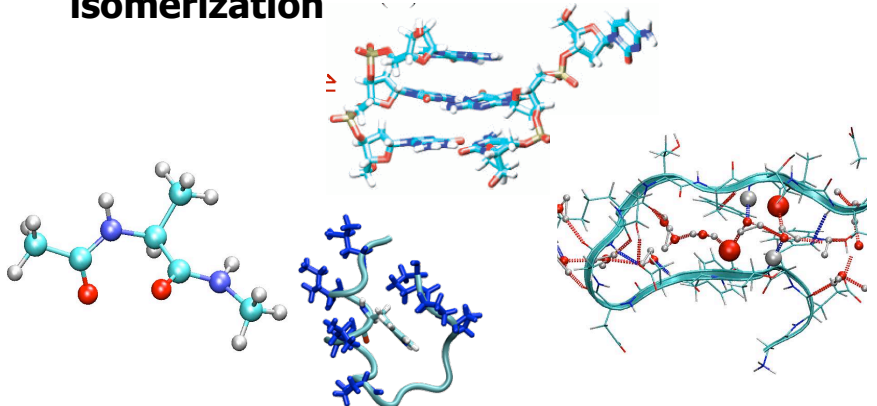
**enzyme reactions**



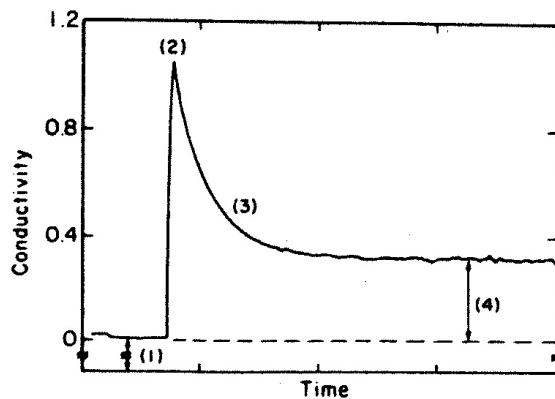
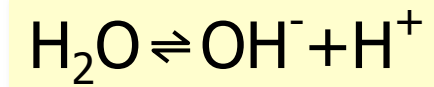
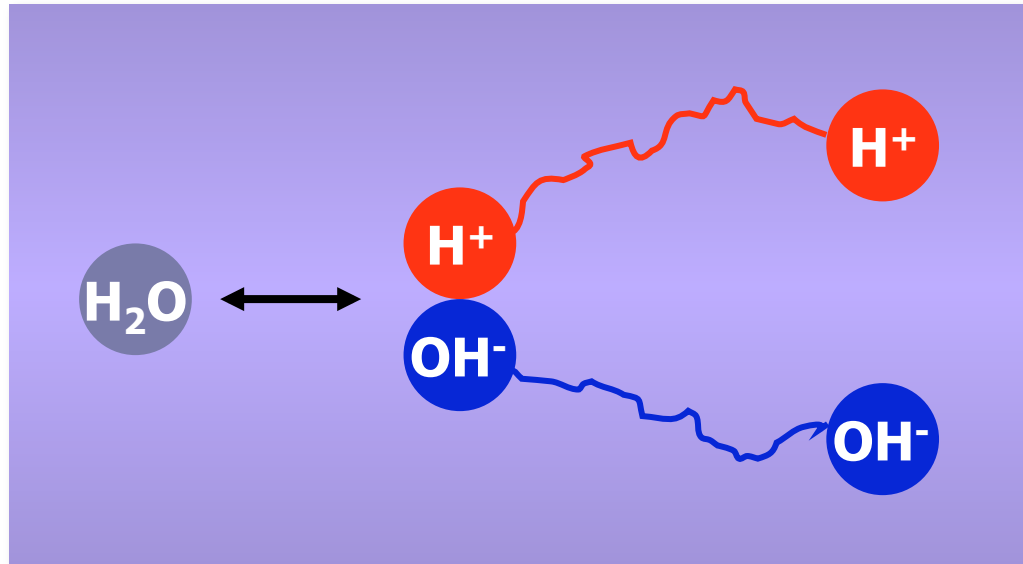
**folding & binding**



**isomerization**



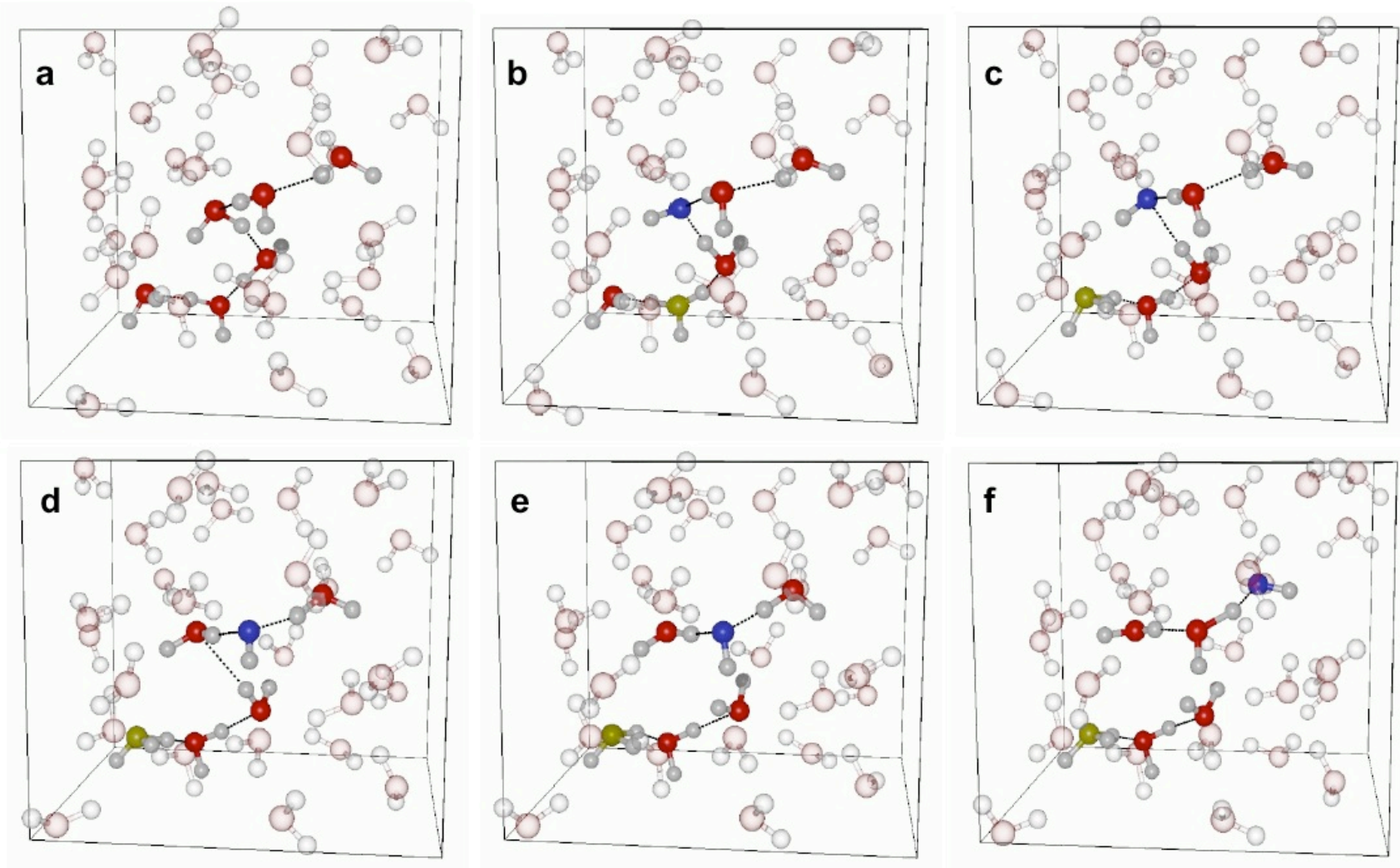
# Autoionization in liquid water



Average life time > 10 h

M. Eigen and L. De Maeyer, *Z. Elektrochemie* **59**, 987 (1955)

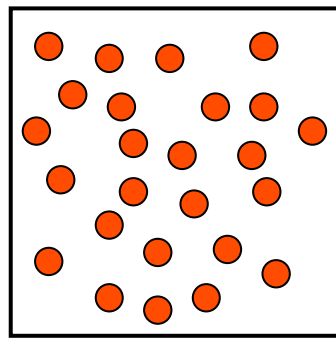
# Autoionization in liquid water



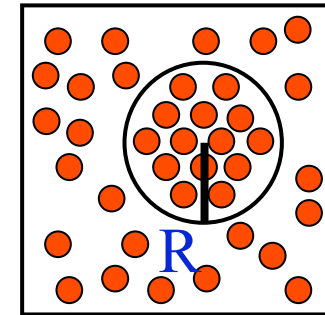
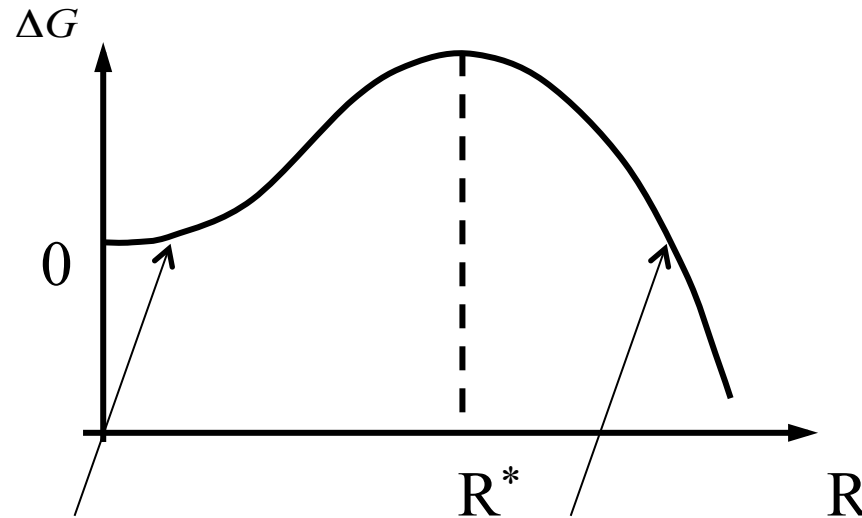
32 waters, BLYP functional CPMD code  
10 uncorrelated trajectories of 200 fs,

*P. L. Geissler, C. Dellago, D. Chandler, J. Hutter,  
M. Parrinello, Science* **291**, 2121 (2001).

# Classical nucleation (1926)



Liquid



Crystal nucleus

$$\Delta G = 4\pi R^2 \gamma - \frac{4}{3}\pi R^3 \rho \Delta\mu_{ls}$$

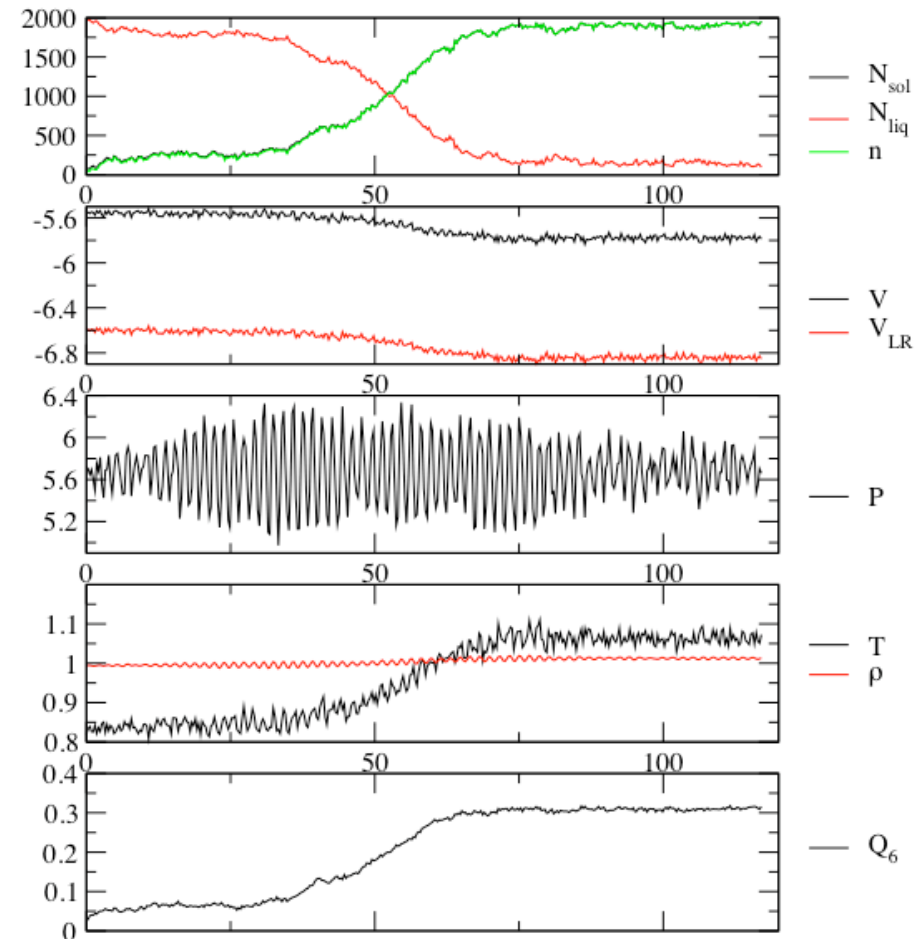
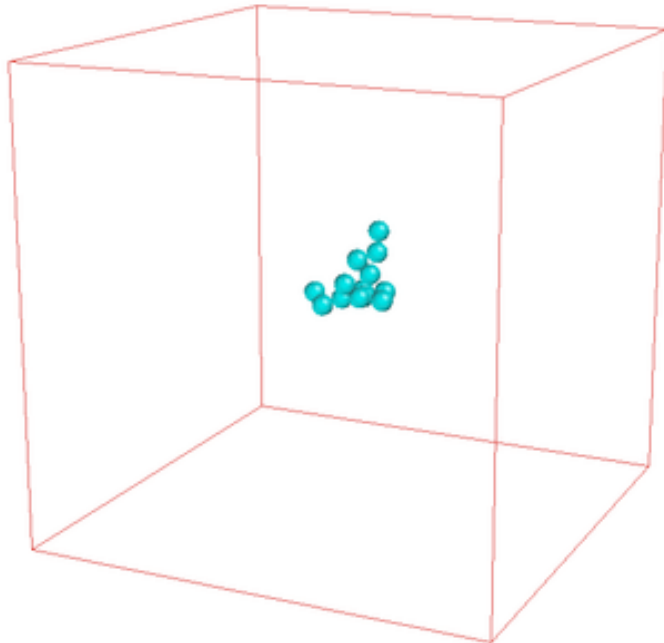
surface →      ← bulk

- How does the crystal form?
- What is the structure of the critical nucleus
- Is classical nucleation theory correct?
  - What is the barrier?
  - Rate constant

$\gamma$  : surface tension  
 $\Delta\mu$  : chem. pot difference  
 $\rho$  : density

# Path sampling of nucleation

TIS in NPH ensemble, as density and temperature change (*Daniele Moroni*)  
 $N=10000$ ,  $P=5.68$   $H=1.41$  (25 % undercooling)



D. Moroni, P. R. ten Wolde, and P. G. Bolhuis, *Phys. Rev. Lett.* **94**, 235703 (2005)

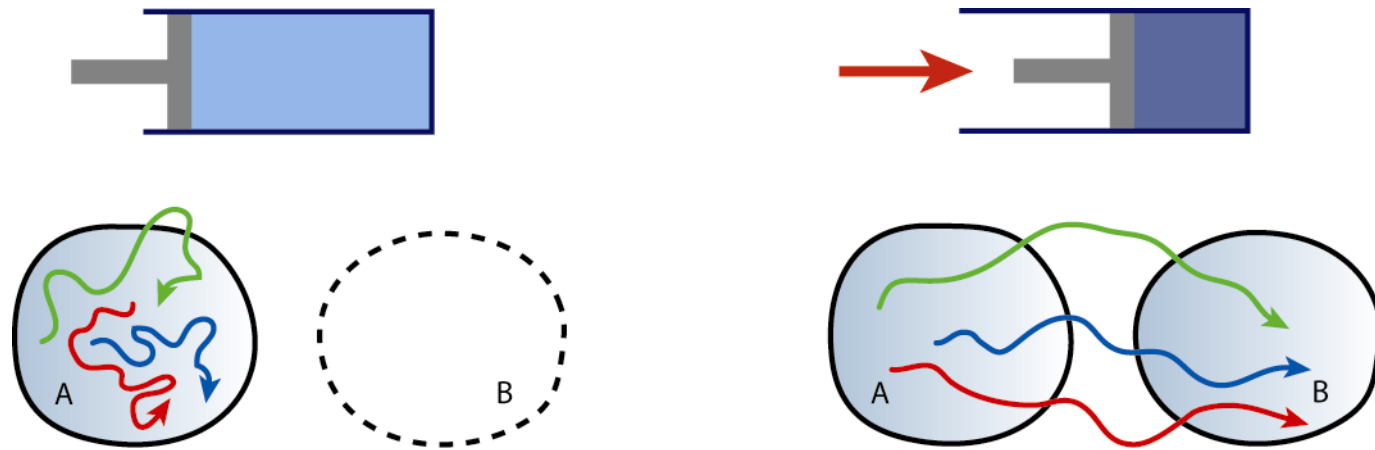


# *Sampling paths is only the beginning*

- *Eugene Wigner: "It is nice to know that the computer understands the problem. But I would like to understand it too."*
- Path ensemble needs to be further explored to obtain:
  - Rate constants
  - Free energy
  - Transition state ensembles
  - Mechanistic picture
  - Reaction coordinate
- Illustrative example: crystal nucleation

# Free energy of paths

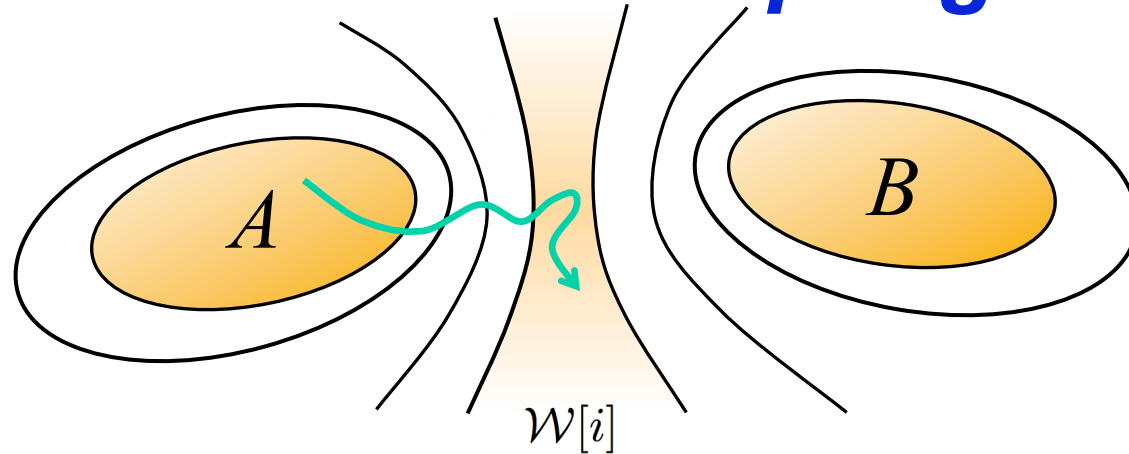
$$C(t) = \frac{\int \mathcal{D}x(t) h_A(x_0) \mathcal{P}[x(t)] h_B(x_t)}{\int \mathcal{D}x(t) h_A(x_0) \mathcal{P}[x(t)]} = \frac{Z_{AB}(t)}{Z_A}$$



$$W_{AB}(t) \equiv -\ln \frac{Z_{AB}(t)}{Z_A}$$

P.G. Bolhuis, D. Chandler, C. Dellago, and P.L. Geissler, *Annu. Rev. Phys. Chem.* **53**, 291 (2002)  
C. Dellago and P. L. Geissler, *AIP Conf. Proc.* **690**, (2003)  
P. L. Geissler and C. Dellago, *JPC B* **108**, 6667 (2004)

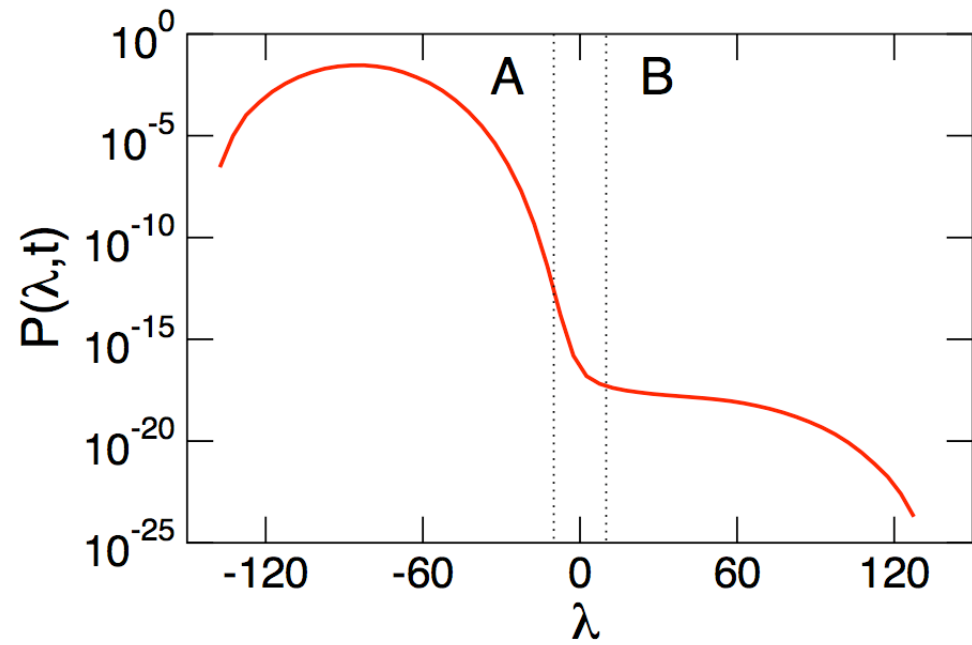
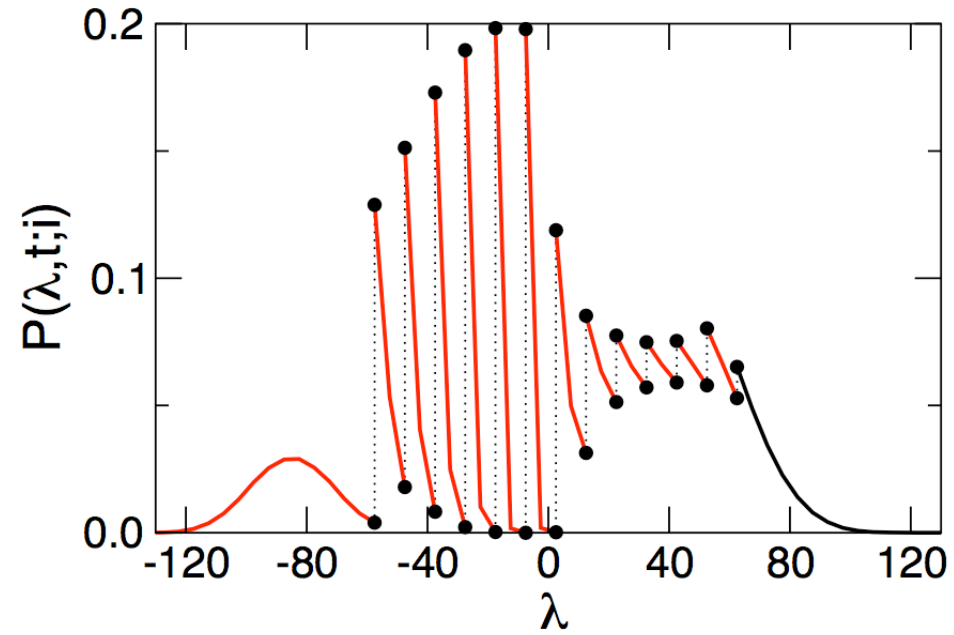
# ***Umbrella sampling***



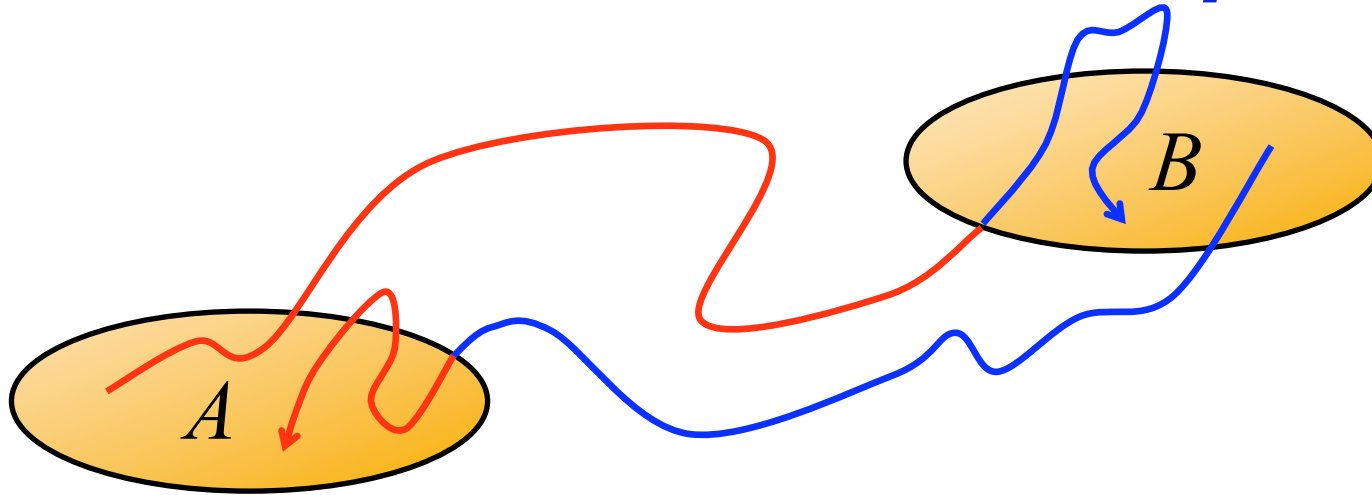
$$P_A(\tilde{\lambda}, t) = \frac{\int \mathcal{D}x(t) h_A(x_0) \mathcal{P}[x(t)] \delta[\tilde{\lambda} - \lambda(x_t)]}{Z_A} = \langle \delta[\tilde{\lambda} - \lambda(x_t)] \rangle_A$$

$$C(t) = \exp[-W_{AB}(t)] = \int_{\lambda_{\min}^B}^{\lambda_{\max}^B} d\lambda P_A(\lambda, t)$$

$$\begin{aligned} P_{A\mathcal{W}[i]}(\tilde{\lambda}, t) &= \frac{\int \mathcal{D}x(t) h_A(x_0) \mathcal{P}[x(t)] h_{\mathcal{W}[i]}(x_t) \delta[\tilde{\lambda} - \lambda(x_t)]}{\int \mathcal{D}x(t) h_A(x_0) h_{\mathcal{W}[i]}(x_t)} \\ &= \langle \delta[\tilde{\lambda} - \lambda(x_t)] \rangle_{A\mathcal{W}[i]}. \end{aligned}$$



# Transition interface sampling



Overall states in phase space:

**A**  
**B**

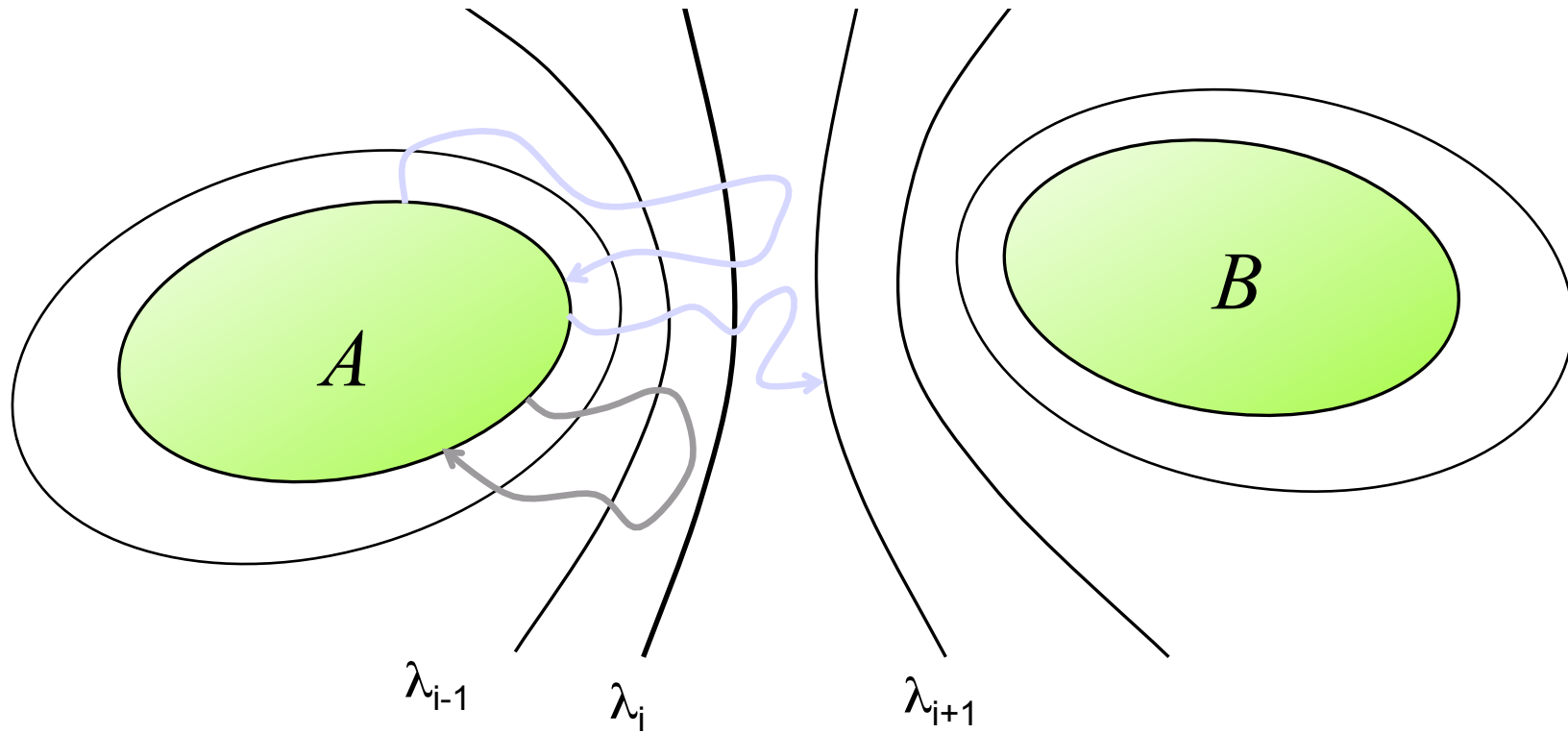
going back in time **A** reached first

going back in time **B** reached first

$$C(t) \equiv \frac{\langle h_A(x_0) h_B(x_t) \rangle}{\langle h_A \rangle}$$

$$k_{AB} = \frac{\langle h_A(x_0) \dot{h}_B(x_0) \rangle}{\langle h_A \rangle} = \frac{\langle \phi_{AB} \rangle}{\langle h_A \rangle}$$

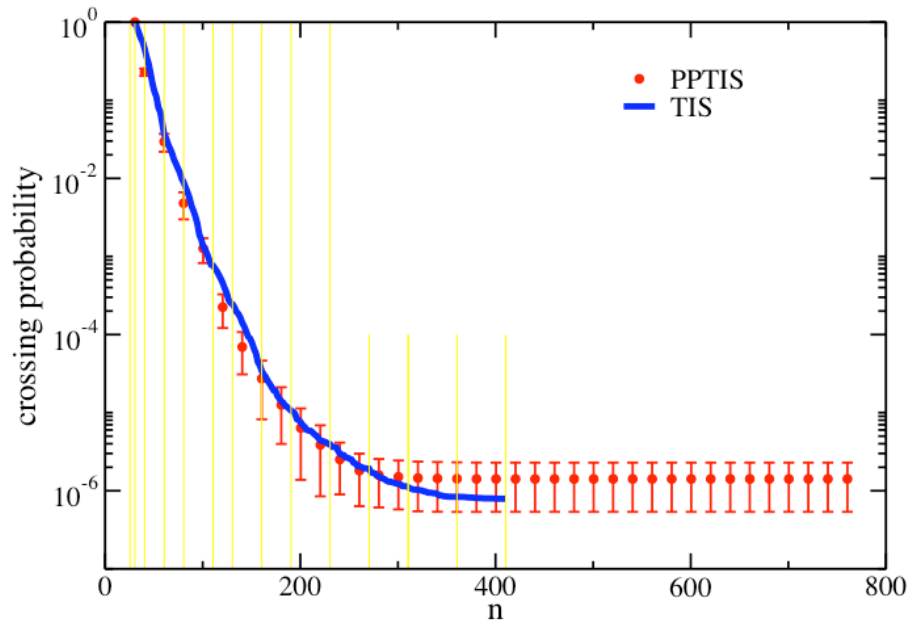
T. S. van Erp, D. Moroni and P. G. Bolhuis, *J. Chem. Phys.* **118**, 7762 (2003)  
T. S. van Erp and P. G. Bolhuis, *J. Comp. Phys.* **205**, 157 (2005)



$P_A(\lambda_{i+1} | \lambda_i)$  = probability that path crossing  $i$  for first time after leaving  $A$  reaches  $i+1$  before  $A$

$$k_{AB}^{TIS} = \frac{\langle \phi_{AB} \rangle}{\langle h_{\mathcal{A}} \rangle} = \frac{\langle \phi_{AB} \rangle}{\langle h_{\mathcal{A}} \rangle} \prod_{i=1}^{n-1} P_A(\lambda_{i+1} | \lambda_i) = \Phi_A \prod_{i=1}^{n-1} P_A(\lambda_{i+1} | \lambda_i)$$

# TIS results for nucleation



$$\mathcal{P}_A(B|1) = \prod_{i=1}^{n-1} \mathcal{P}_A(i+1|i) = 8 \times 10^{-7}$$

$$\frac{\langle \phi_{A1} \rangle}{\langle h_A \rangle} = 1.29$$

$$k_{AB} = (1.0 \pm 0.8) \times 10^{-6}$$

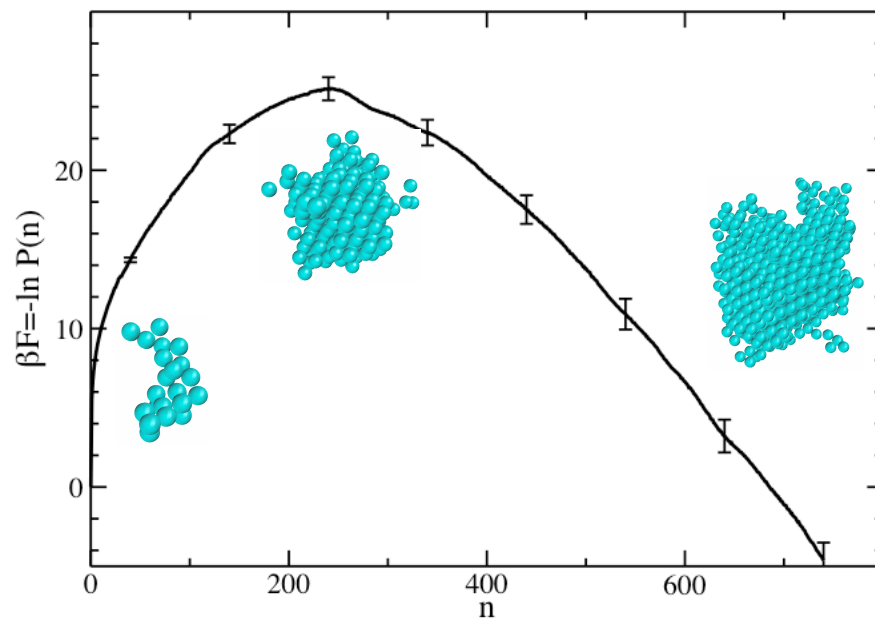
Memory loss reasonable

Free energy follows directly

*Moroni, van Erp, Bolhuis, PRE, 2005*

Agrees with ten Wolde (1995)

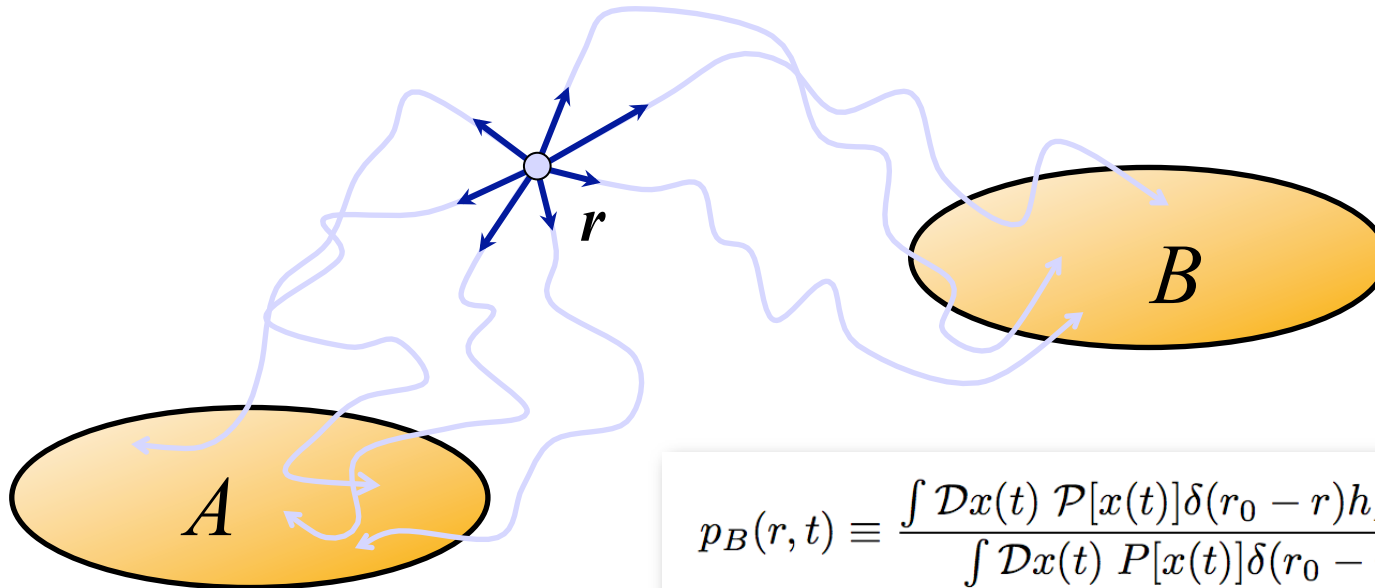
Structural analysis?



# Committor

(aka *p*-fold, splitting probability)

$p_B(r, t) =$  Probability that a trajectory initiated at  $r$  relaxes into  $B$



$$p_B(r, t) \equiv \frac{\int \mathcal{D}x(t) \mathcal{P}[x(t)] \delta(r_0 - r) h_B(x_t)}{\int \mathcal{D}x(t) \mathcal{P}[x(t)] \delta(r_0 - r)}$$

$$p_B(r, t) \approx \frac{1}{N} \sum_{i=1}^N h_B(x_t^{(i)})$$

$$\sigma = \sqrt{\langle (p_B^{(N)} - p_B)^2 \rangle} = \sqrt{\frac{p_B(1 - p_B)}{N}}$$

L. Onsager, *Phys. Rev.* **54**, 554 (1938).

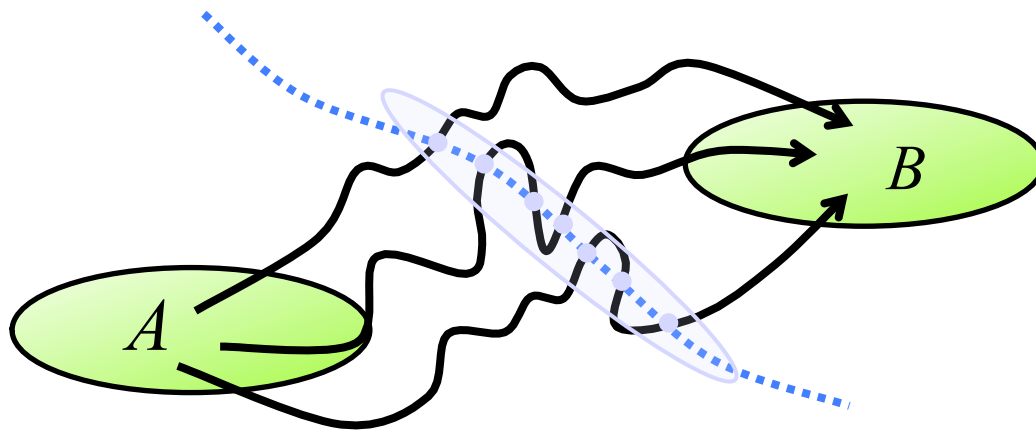
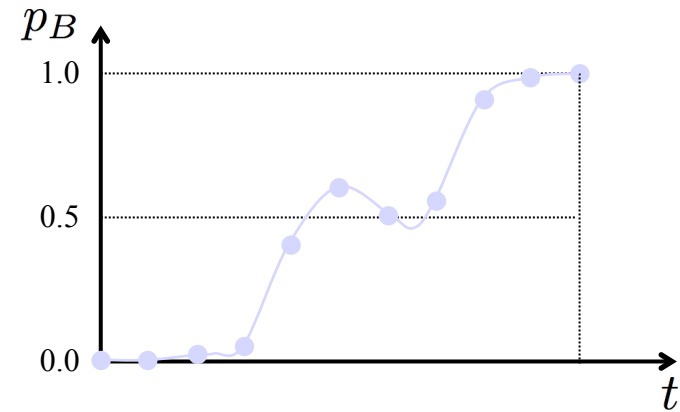
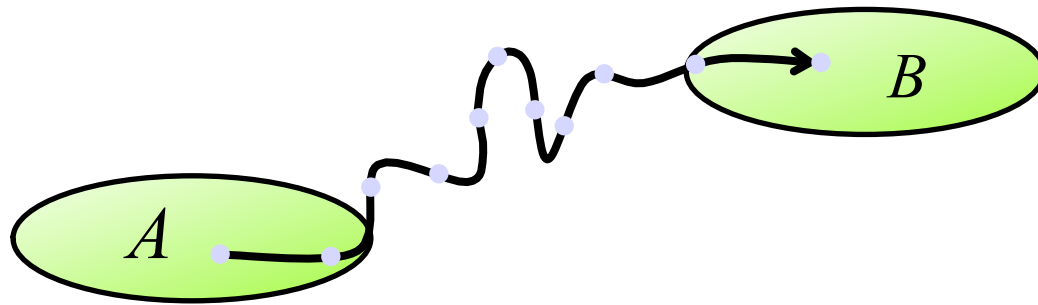
M. M. Klosek, B. J. Matkowsky, Z. Schuss, *Ber. Bunsenges. Phys. Chem.* **95**, 331 (1991)

V. Pande, A. Y. Grosberg, T. Tanaka, E. I. Shakhnovich, *J. Chem. Phys.* **108**, 334 (1998)



# Transition state ensemble

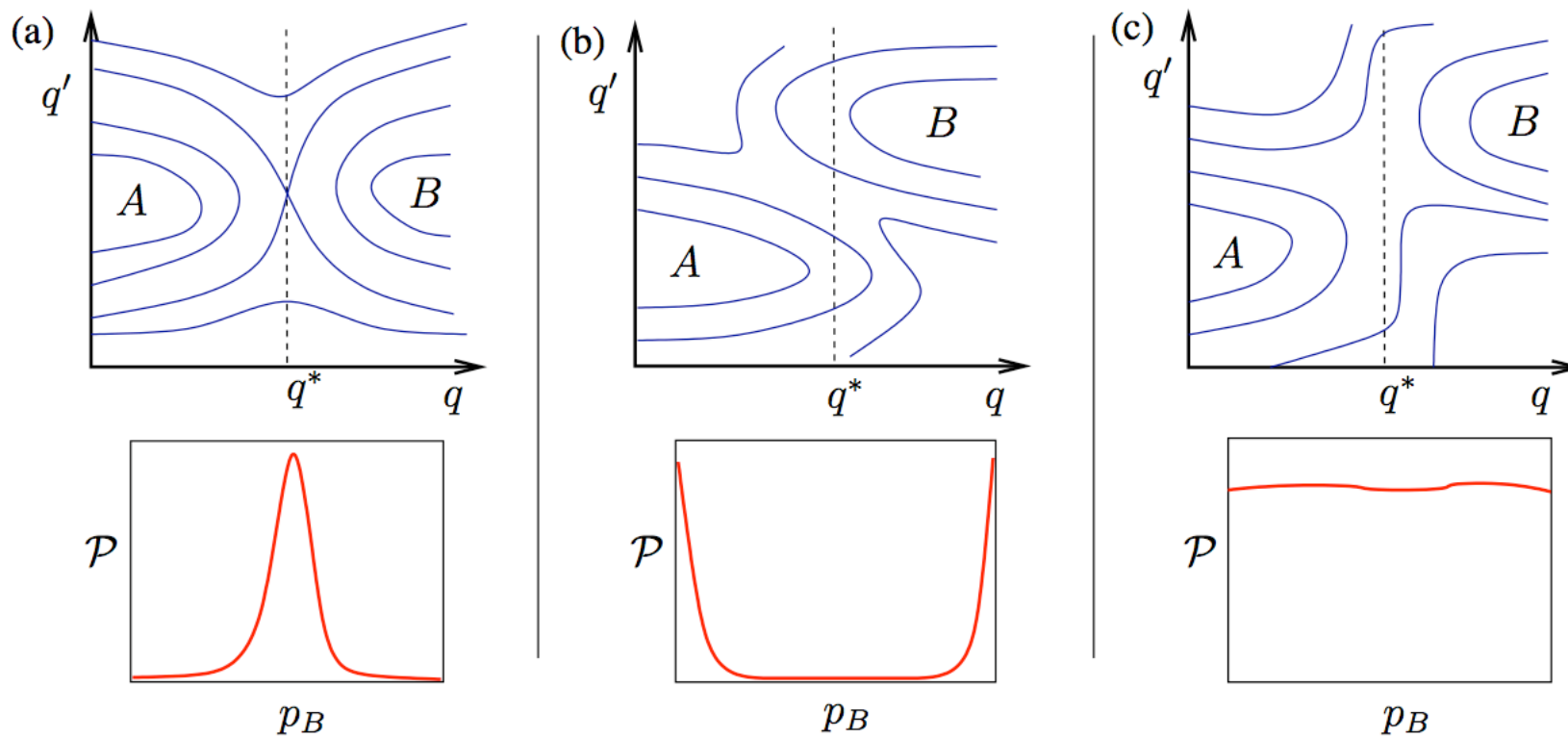
$r$  is a transition state (TS) if  $p_B(r) = p_A(r) = 0.5$



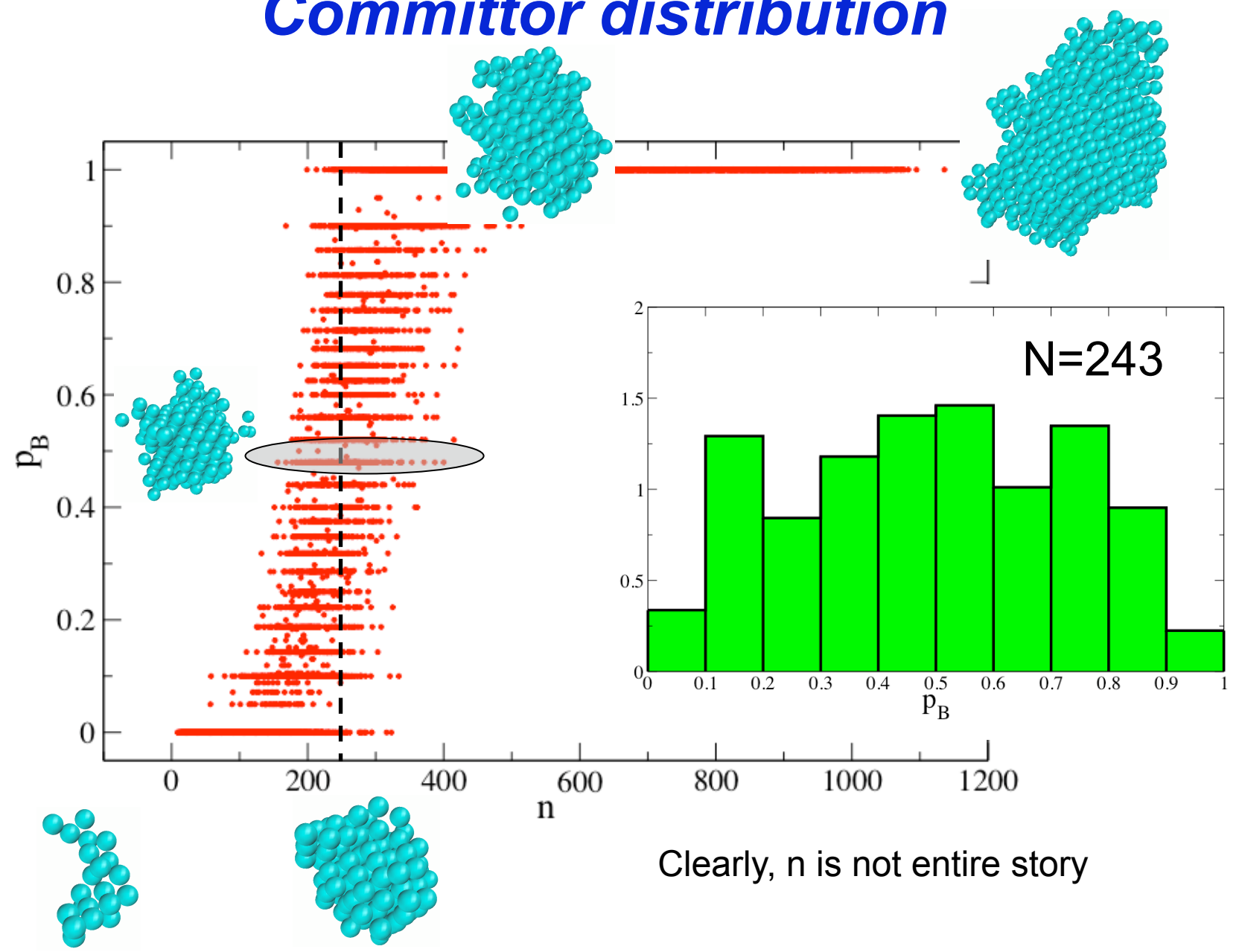
**TSE:**

Intersections of transition pathways with the  $p_B = 1/2$  surface

# Committor distributions



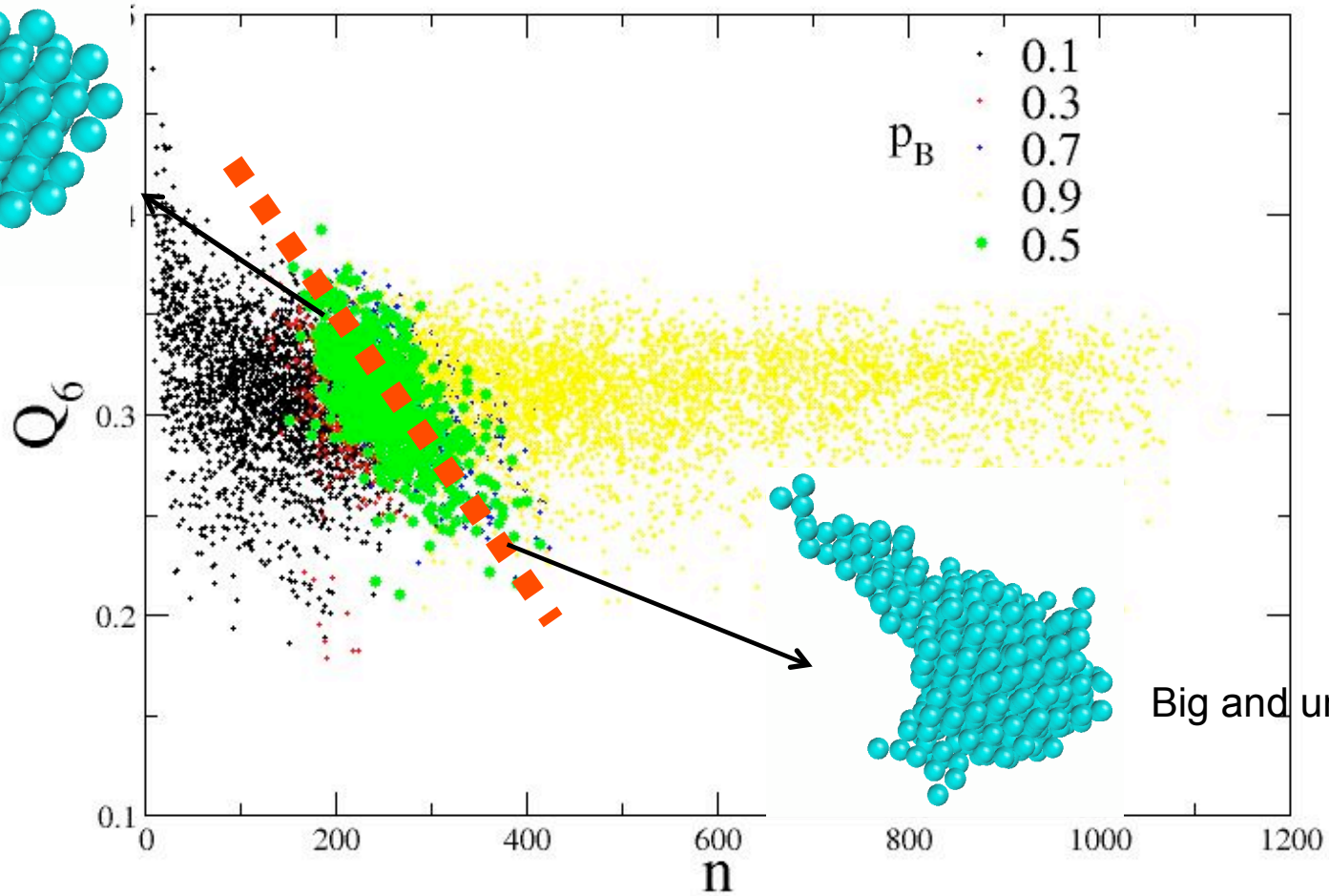
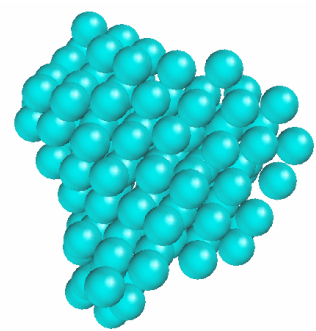
# Committer distribution



Clearly,  $n$  is not entire story

# Structure

Small and structured



Big and unstructured

# Outline

- Part 1
  - Rare events
  - The need for unbiased transition paths
  - Sampling the path ensemble
- Part 2
  - Analyzing the path ensemble
  - Calculation of rate constants
  - Transition state ensemble and reaction coordinate
- **Part 3**
  - **Application to protein folding**

# Folding of Trp-cage

20-residue protein NLYIQ WLKDG GPSSG RPPPS

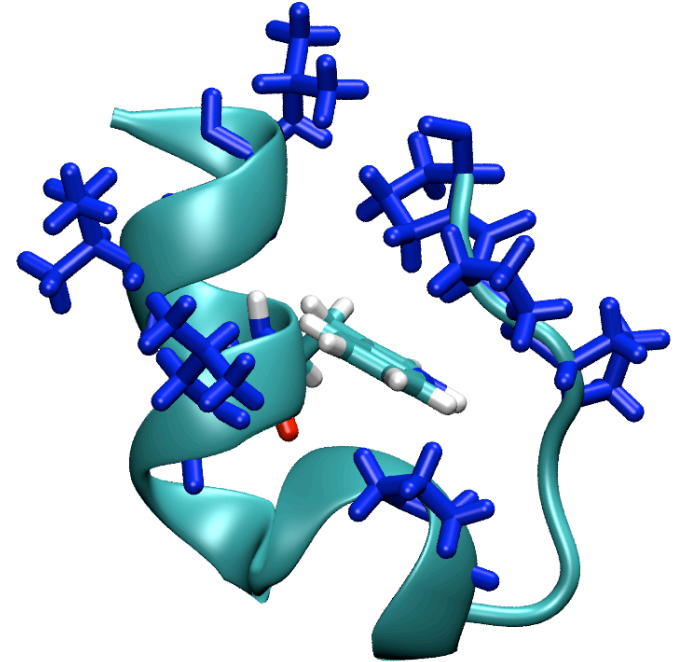
2-state folder, experimental rate 4  $\mu$ s

(Andersen et al, Nature 2002, Zhou et al. PNAS 2004, others)

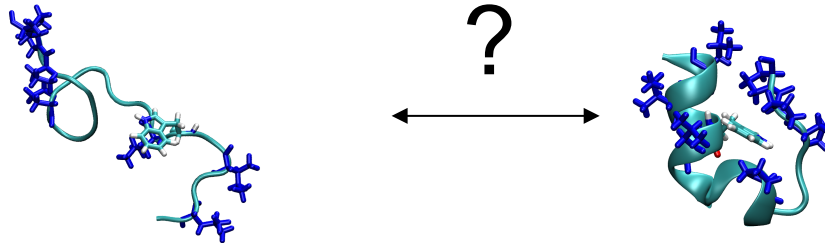
**System:**

**1L2Y in 2800 SPC waters**

**OPLSAA, PME, Nose-Hoover, GROMACS**



What is folding mechanism in explicit water at 300K?



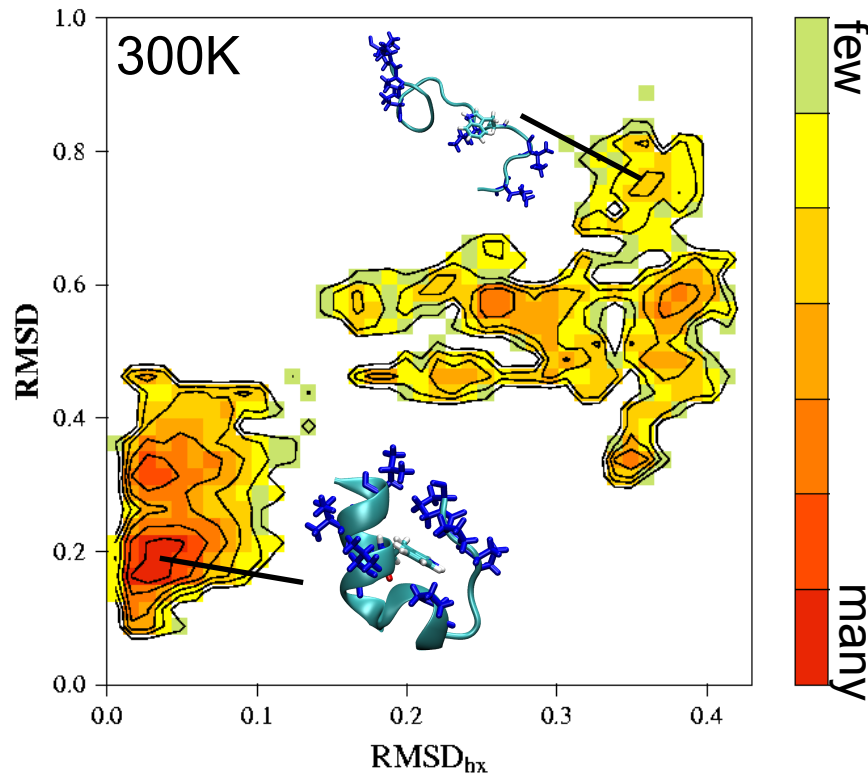
**Strategy:**

- Stable states by PT/REM
- Mechanism by path sampling

**Jarek Juraszek and P.B., PNAS 2006**

# Replica exchange of Trp-cage

initially folded

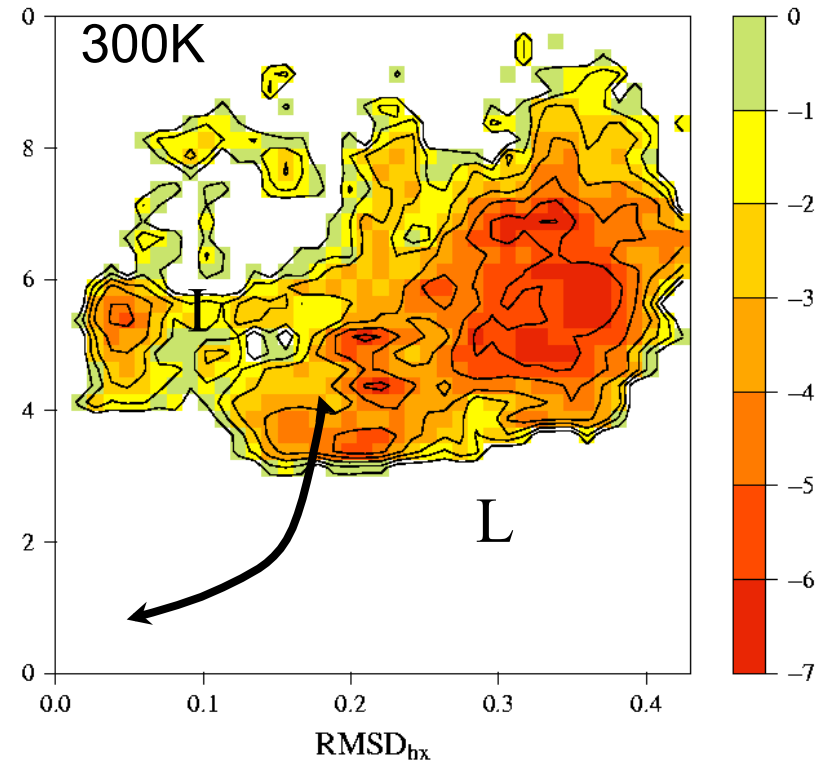


64 replicas

Temp range 272-555K

30 ns per replica

initially unfolded



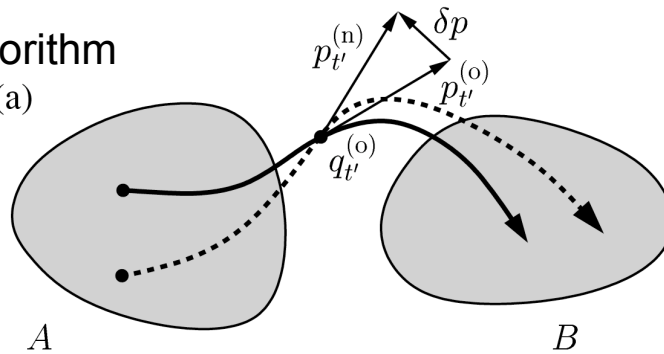
barrier towards native state not  
crossed:

**Path sampling**

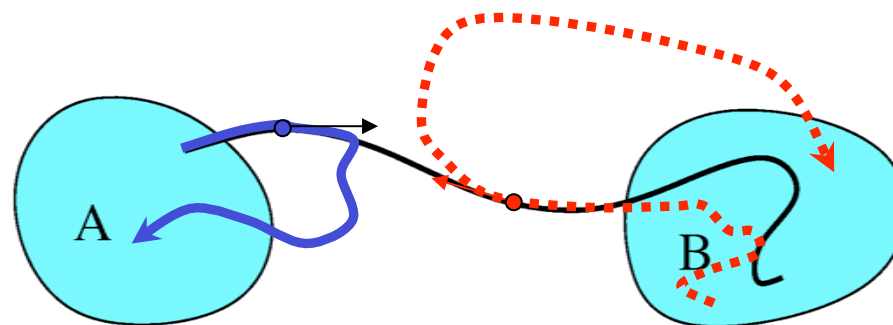
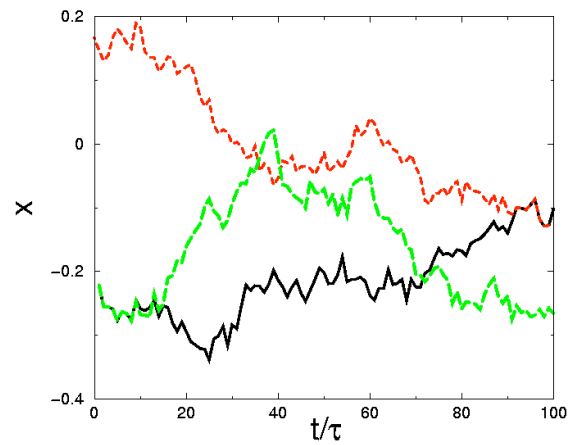
# Acceptance problem

Original shooting algorithm

(a)



has problems with long paths ( $>1\text{ps}$ ) because of molecular chaos (even with  $dp \rightarrow 0$ )

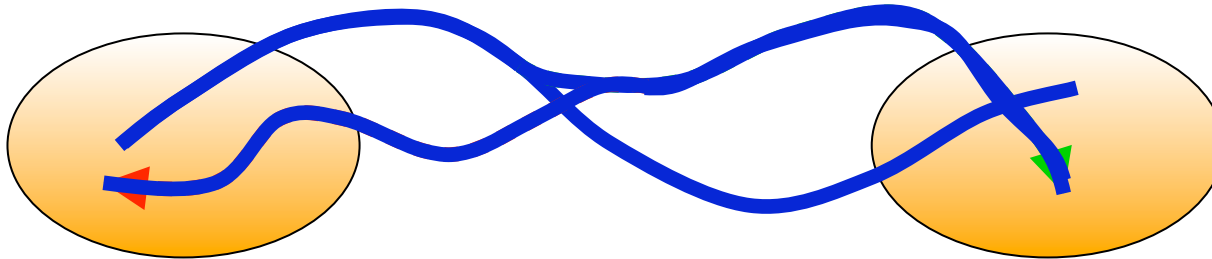


Result: very low acceptance



# Modified path sampling

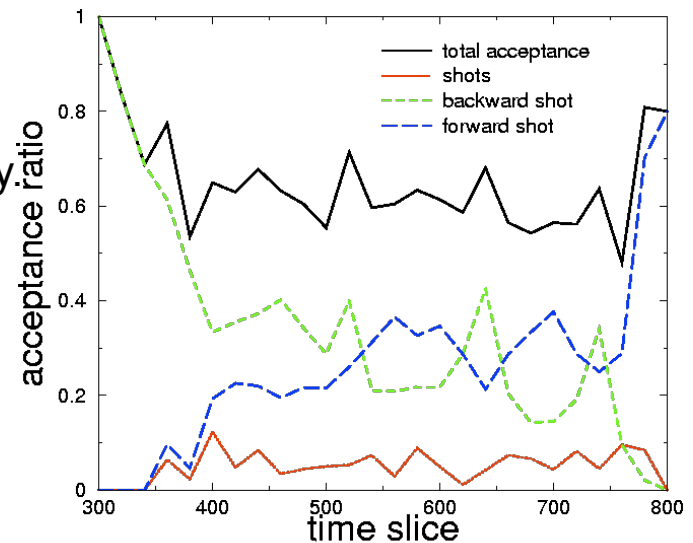
Long paths require stochastic sampling.



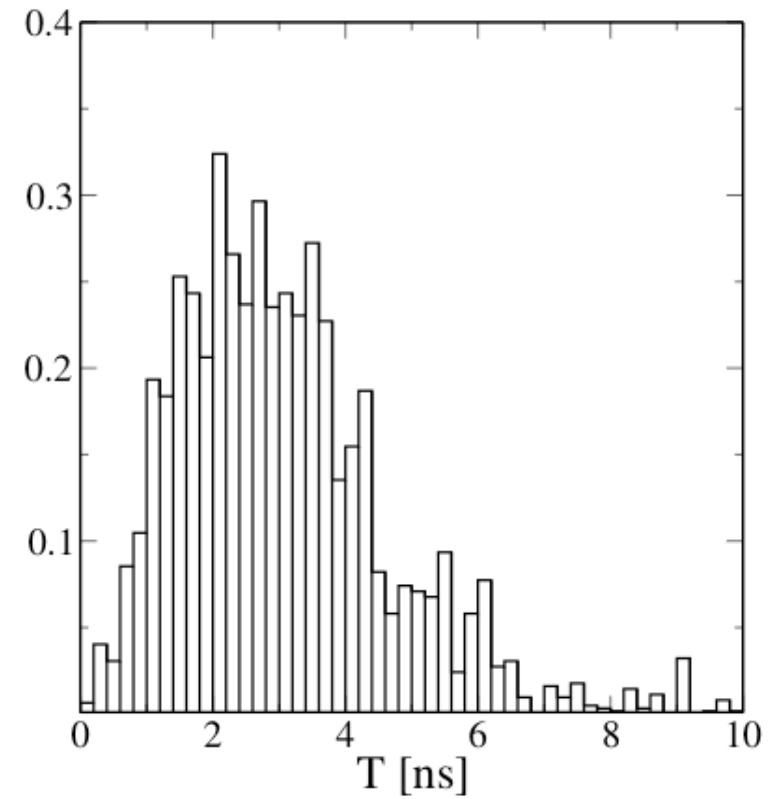
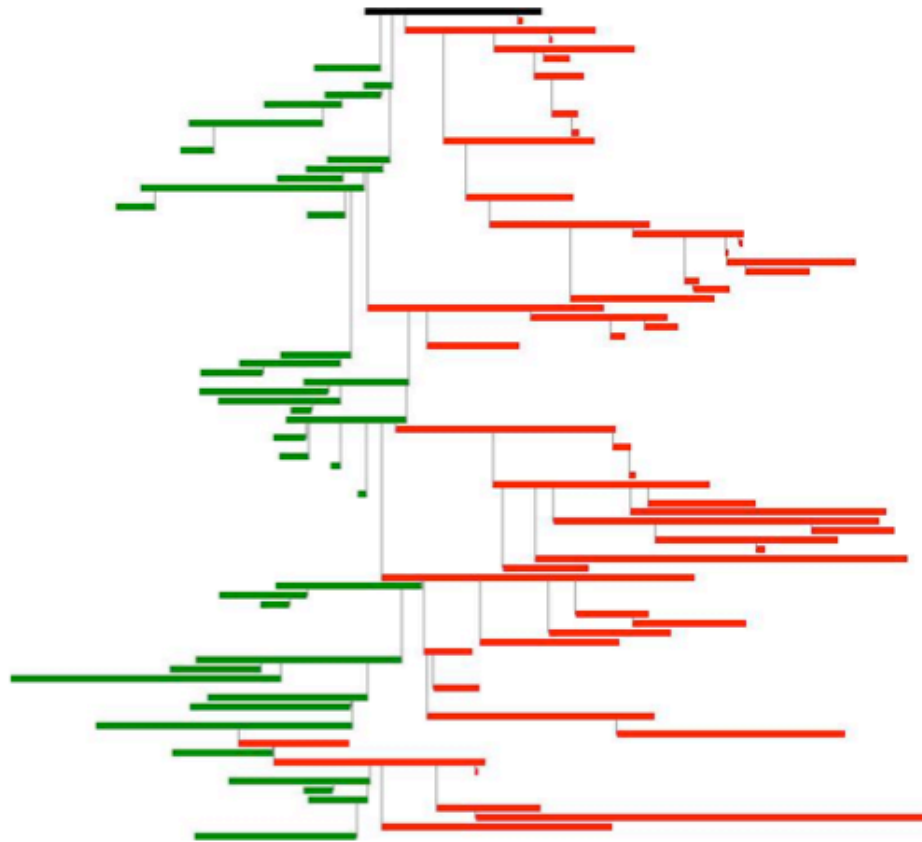
Shoot a trajectory using stochastic thermostat in just one arbitrary direction.

Path length fluctuates, no shifting moves necessary.

- Higher acceptance (>50% instead of <10%)
- Allows shorter trajectories
- No true deterministic dynamics

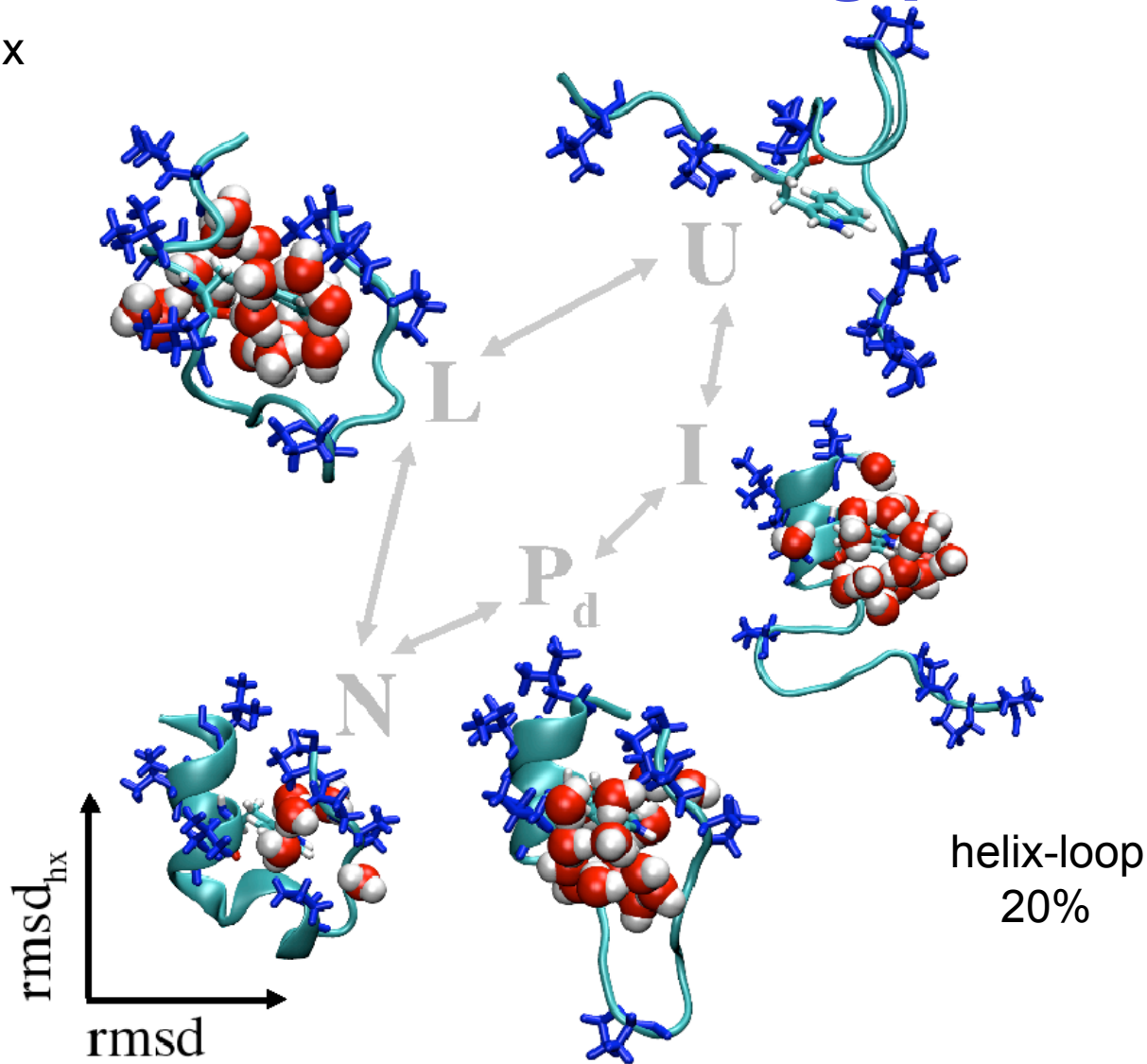


# *Path sampling indicators*

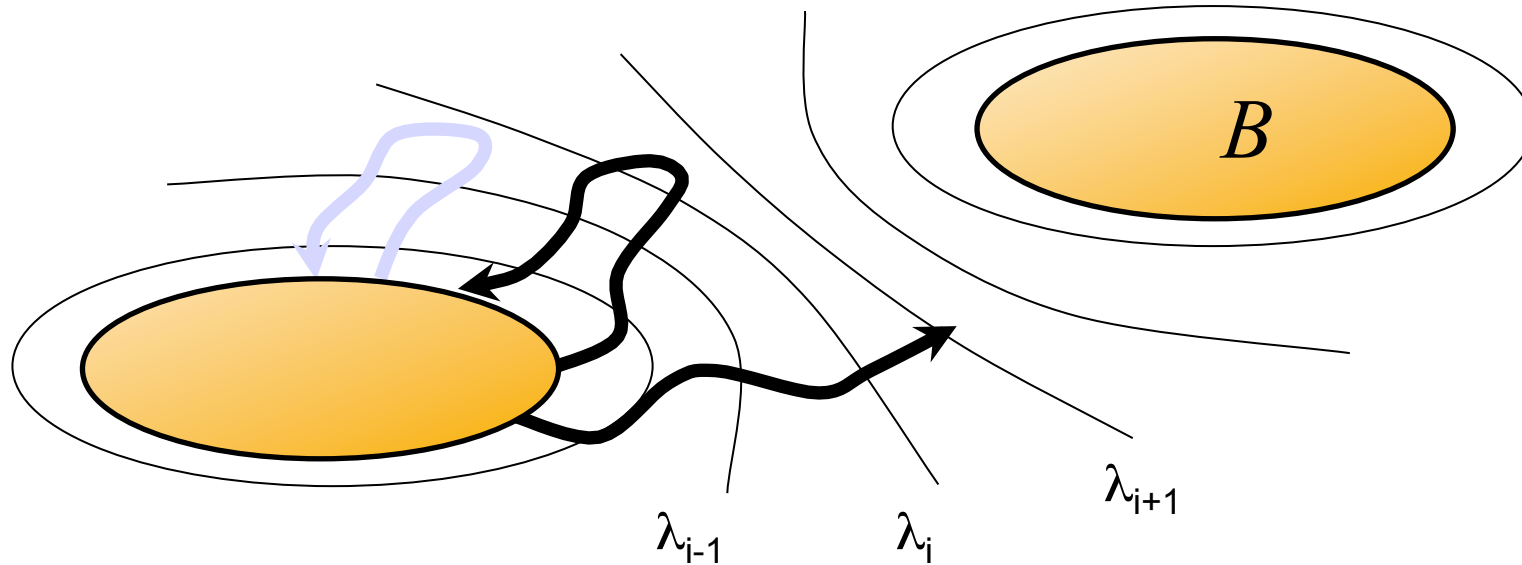


# *TPS reveals two folding pathways*

loop-helix  
80%



# Rates by Transition interface sampling



$P_A(\lambda_{i+1} | \lambda_i)$  = probability that path crossing  $i$  for first time after leaving A reaches  $i+1$  before A

$$k_{AB} = \frac{\langle \phi_{AB} \rangle}{\langle h_{\mathcal{A}} \rangle} = \frac{\langle \phi_A \rangle}{\langle h_{\mathcal{A}} \rangle} P_A(\lambda_B | \lambda_A) = \frac{\langle \phi_A \rangle}{\langle h_{\mathcal{A}} \rangle} \prod_{i=1}^{n-1} P_A(\lambda_{i+1} | \lambda_i)$$

# *N-L folding and unfolding rate*

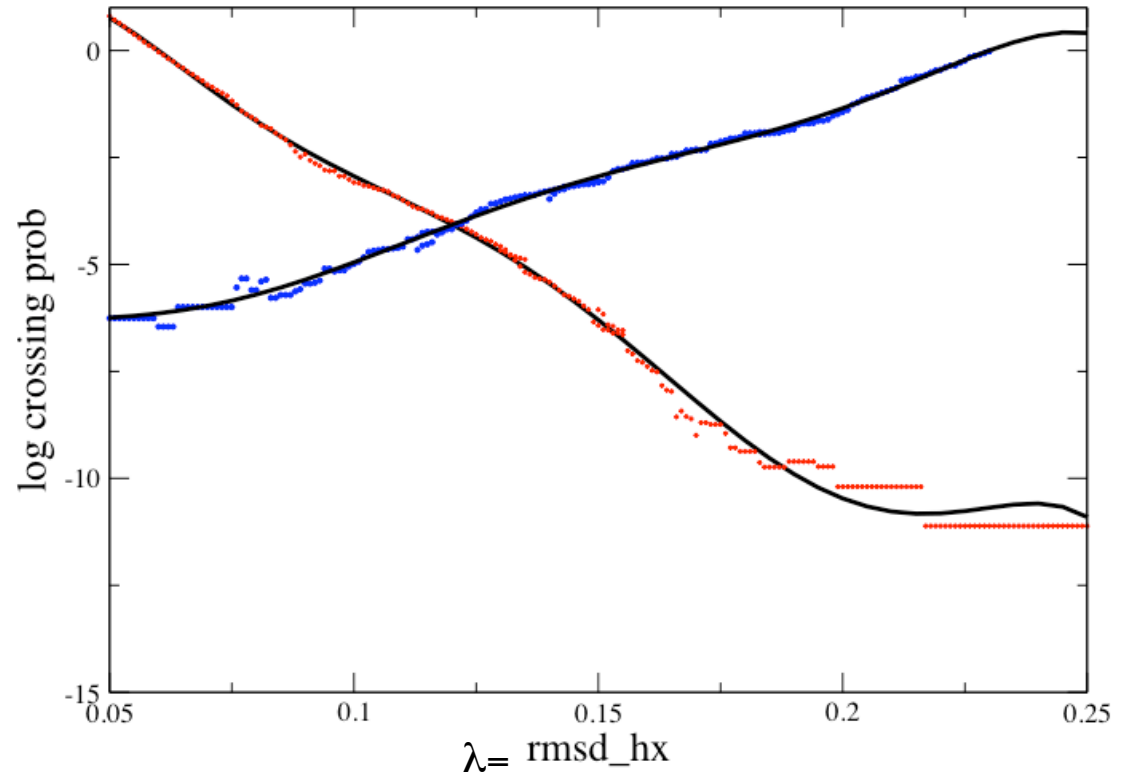
TIS, 6 interfaces

$\ln P_{\text{unf}} = -11$   
 $\Phi_A (\lambda = 0.06) = 6.6 \text{ ns}^{-1}$   
 $k_{\text{unf}} = 0.11 \text{ } \mu\text{s}^{-1}$

Exp:  $k_{\text{unf}} = 0.08 \text{ } \mu\text{s}^{-1}$

$\ln P_{\text{fol}} = -6.3$   
 $\Phi_A (\lambda = 0.23) = 1 \text{ ns}^{-1}$   
 $k_{\text{fol}} = 1.83 \text{ } \mu\text{s}^{-1}$

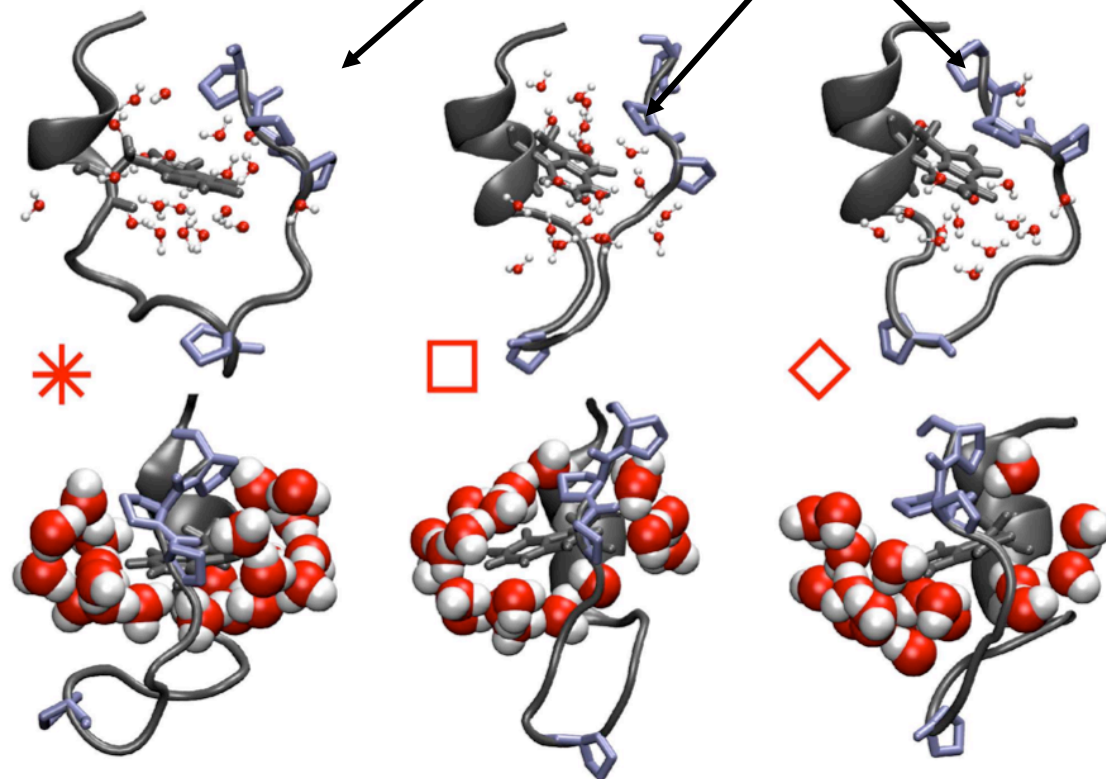
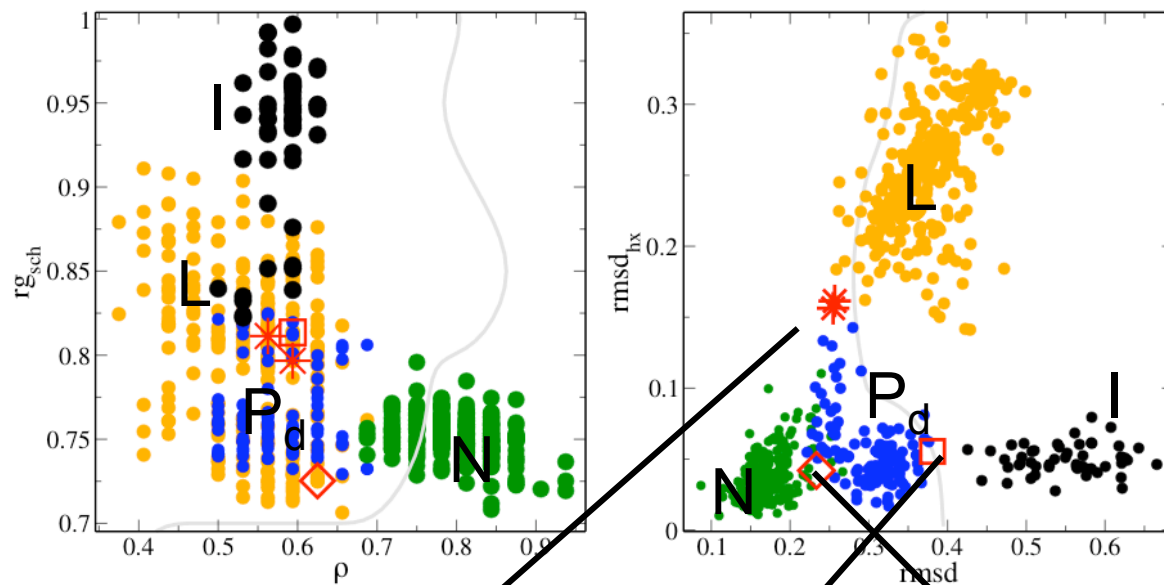
Exp.  $k_{\text{fol}} = 0.24 \text{ } \mu\text{s}^{-1}$



Difference in folding rate might be caused by L state being different from U state.

# TSE

TS can fall inside stable state in FE landscape

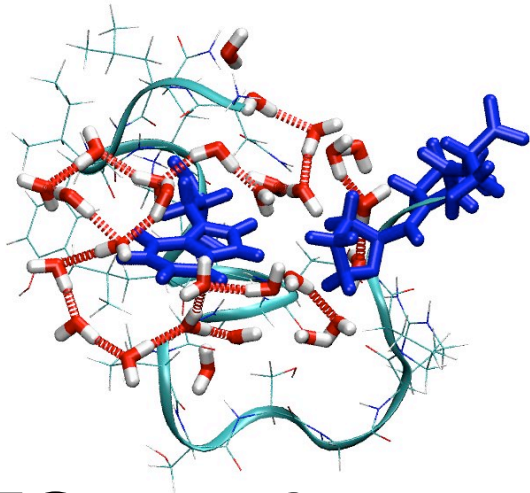


# *Water role in kinetics*

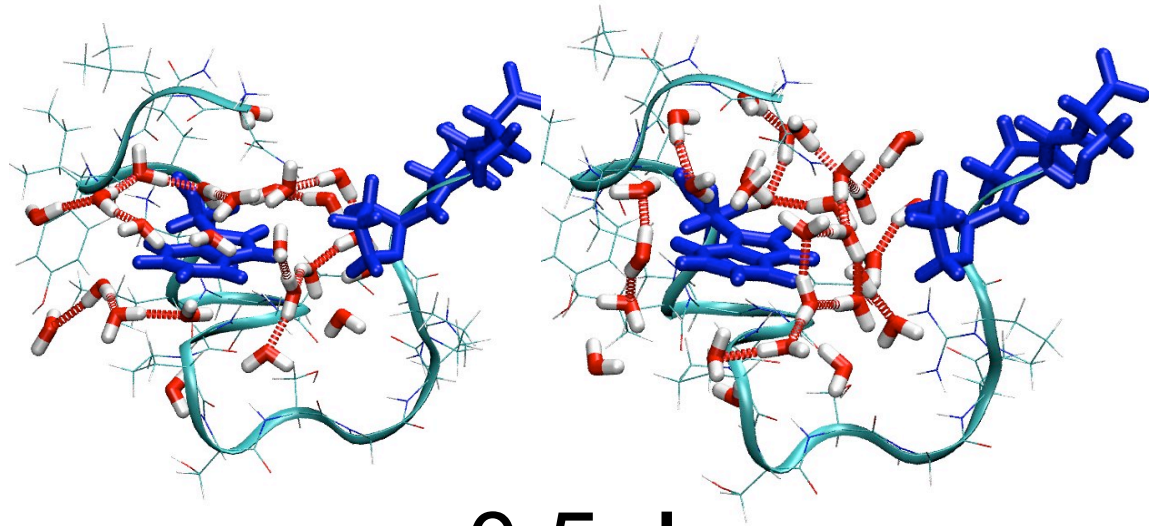
We can do a committor analysis:

- Start with TS and randomize waters, calculate committor

I-N path



TS:  $p_B = 0.5$



$p_B = 0.5$  !

# *Role of water*

- Water expulsion is last step upon folding.
- $P_{\text{fold}}$  calculations show instantaneous configuration of water is not important in reaction coordinate (for both L-N and I-N pathways).
  - Average path length is 3 ns: more than enough time to equilibrate
- Water plays a role, as implicit solvent predict different pathways and TS structure. Possible solution: some water molecules can play structural role:
  - Average residence time < 50 ps
  - Special very strongly bound bridging water molecules > 1 ns.
- In improved implicit solvent models these waters should be treated differently.



# Maximum likelihood estimation

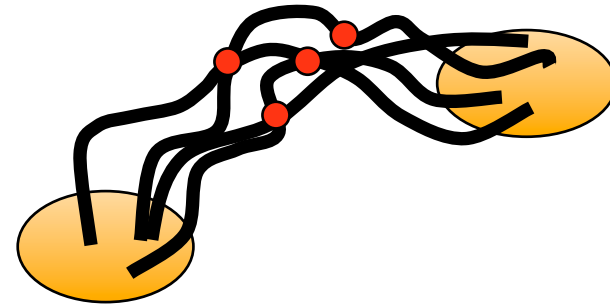
- Suppose we have TPS information, how do we get reaction coordinate  $r$  ?
- $p(\text{TP}|x)$  is the probability to be on a Transition Path provided we are at  $x$
- A model for this function could be

$$p(\text{TP}|r) \propto (1 - \tanh^2(r))$$

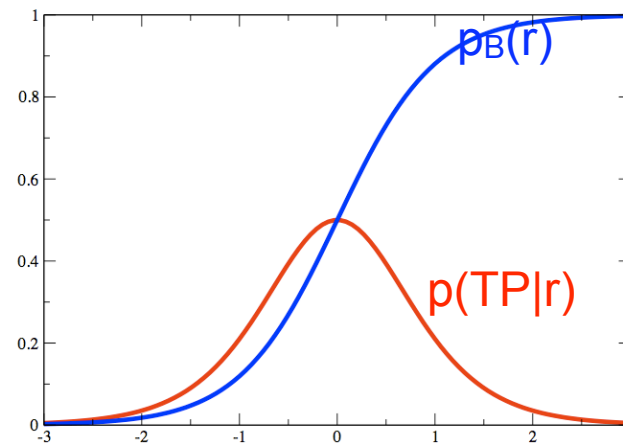
- For diffusive dynamics (or dynamics that quickly loses memory) this changes into a function of the committor  $p_B$

$$p(\text{TP}|r) = 2p_B(r)(1 - p_B(r))$$

- The question: what is  $r(x)$  ?



Peters & Trout, JCP 125 054108(2006)



# Maximum likelihood estimation

- we are searching for a reaction coordinate  $r(\mathbf{x})$  that describes the reaction best.
- $r(\mathbf{x})$  should be a combination of the collective variable  $q(\mathbf{x})$ , e.g.

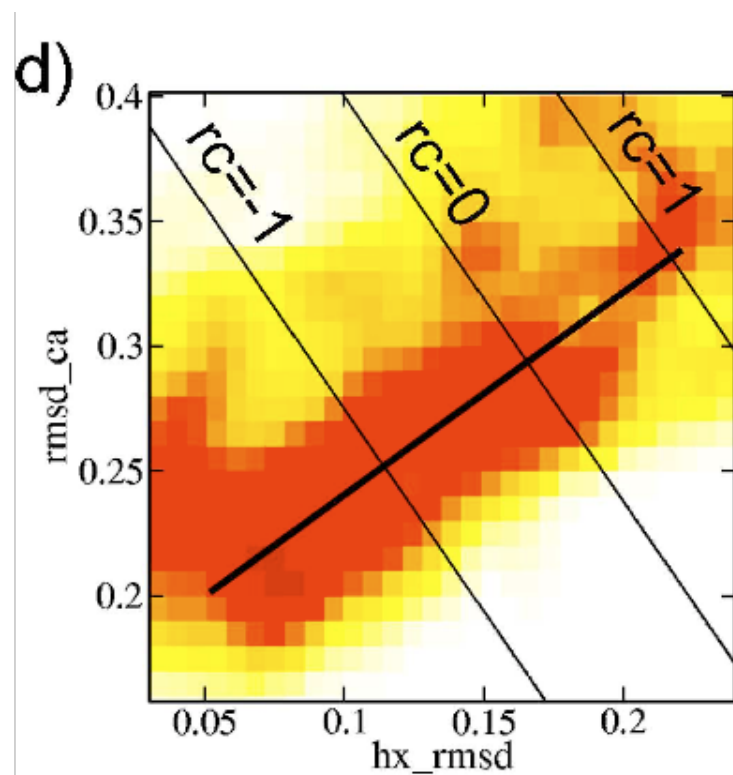
$$r(\mathbf{x}) = \sum_i \alpha_i q(\mathbf{x}) + \alpha_0$$

- suppose we have from aimless TPS shooting points  $\mathbf{x}$  and the outcomes of the trajectories:  $\{\mathbf{x}^A\}$  and  $\{\mathbf{x}^B\}$
- Then the likelihood of a model predicting this outcome would be

$$L(\alpha) = \prod_{i=1}^{N_B} p_B(r(q(\mathbf{x}_i^{(B)}))) \prod_{i=1}^{N_A} (1 - p_B(r(q(\mathbf{x}_i^{(B)}))))$$

- maximize this likelihood to obtain the optimal parameters  $\alpha$

# *Reaction coordinate analysis*



TPS

# Conclusions

- Separate folding pathways can be sampled with TPS
- Transition state ensemble (TSE) :
  - characterized by solvation
  - water dynamics probably no part of RC at TSE , water structure is.
  - does not always correspond with a FE landscape saddle
  - In general FE should not be trusted for kinetics (solution: flux through graphs, MSMs)
- Calculated TIS rate constant compares good to experiment for unfolding and less for folding: possibly a force field issue.

**Bridging time and length scales in biophysical problems  
requires a combination of techniques**

# Summary

- Rare events difficult to simulate
- need for good potentials
- need for good MD simulation
- need for free energy calculations
- need for order parameter free methods:
  - NEB, TPS , string method
- need for reaction coordinate analysis methods

# *Acknowledgements*



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**UC Berkeley**



**Phill Geissler**  
**UC Berkeley**



**Daniele Moroni**  
**Cambridge**



**Titus van Erp**  
**Univ Leuven**