

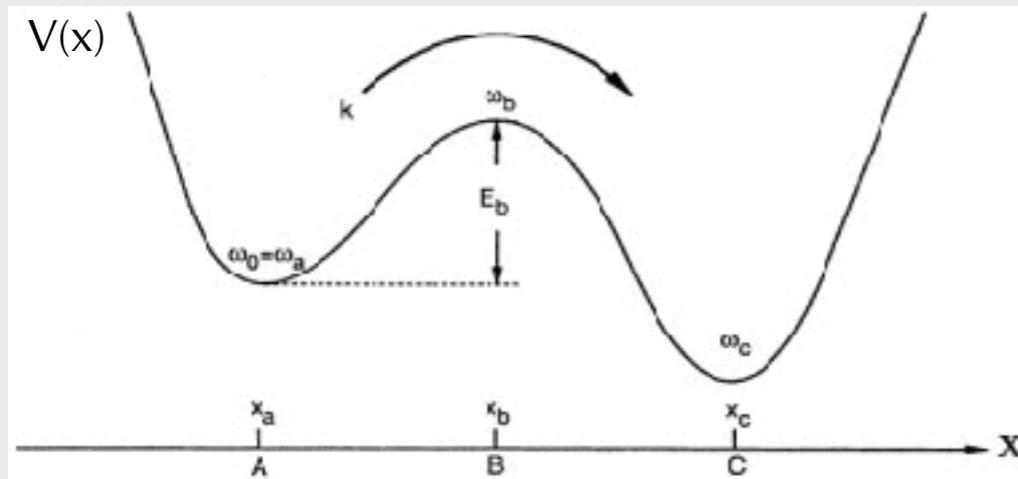
Characterizing energy landscapes: a survey

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Simple energy landscape

Potential energy minima A and C separated by a transition state B



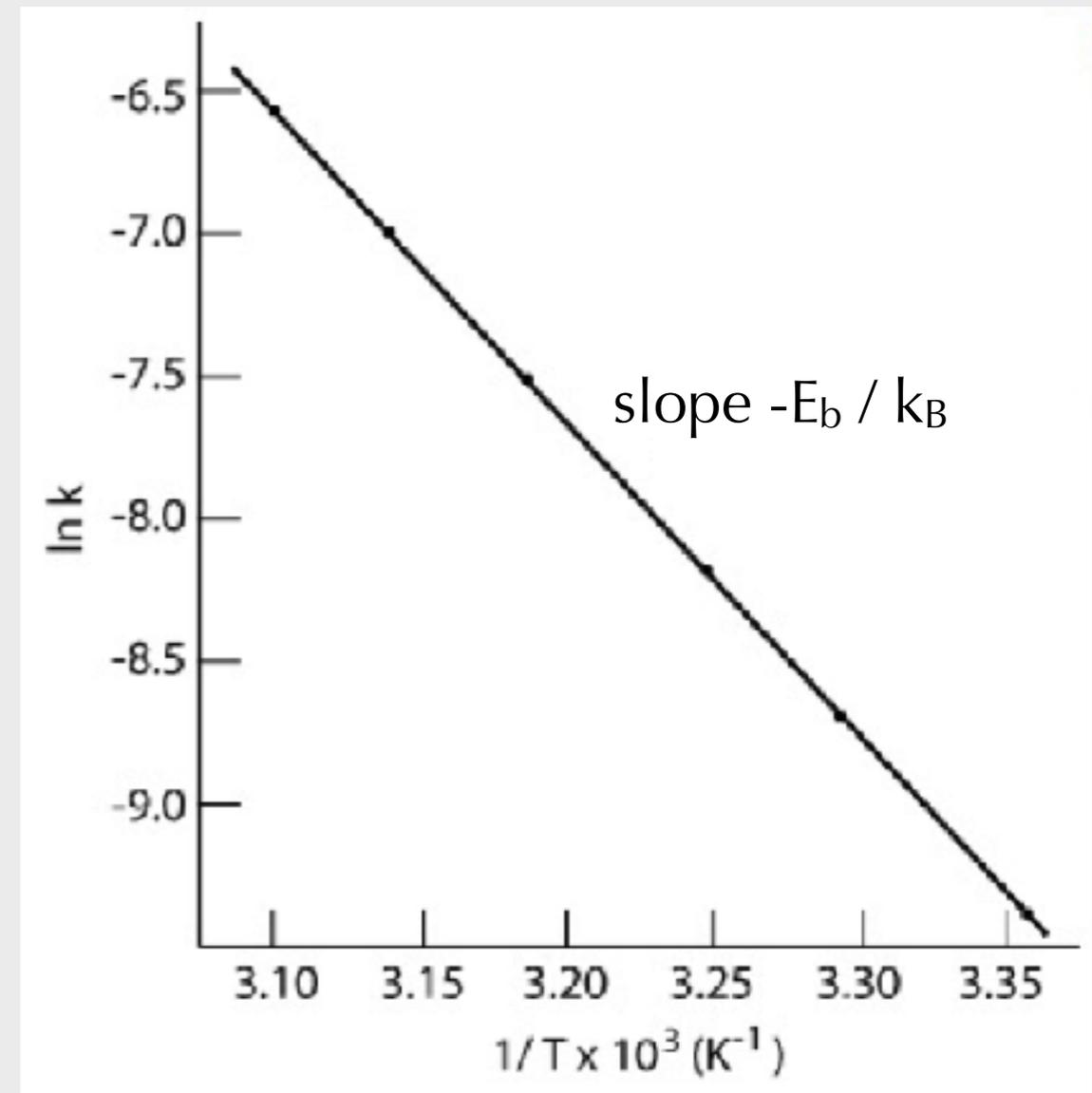
Rate of forward reaction k , units time^{-1}

Arrhenius: plotting $\ln k$ vs $1/T$ yields straight line

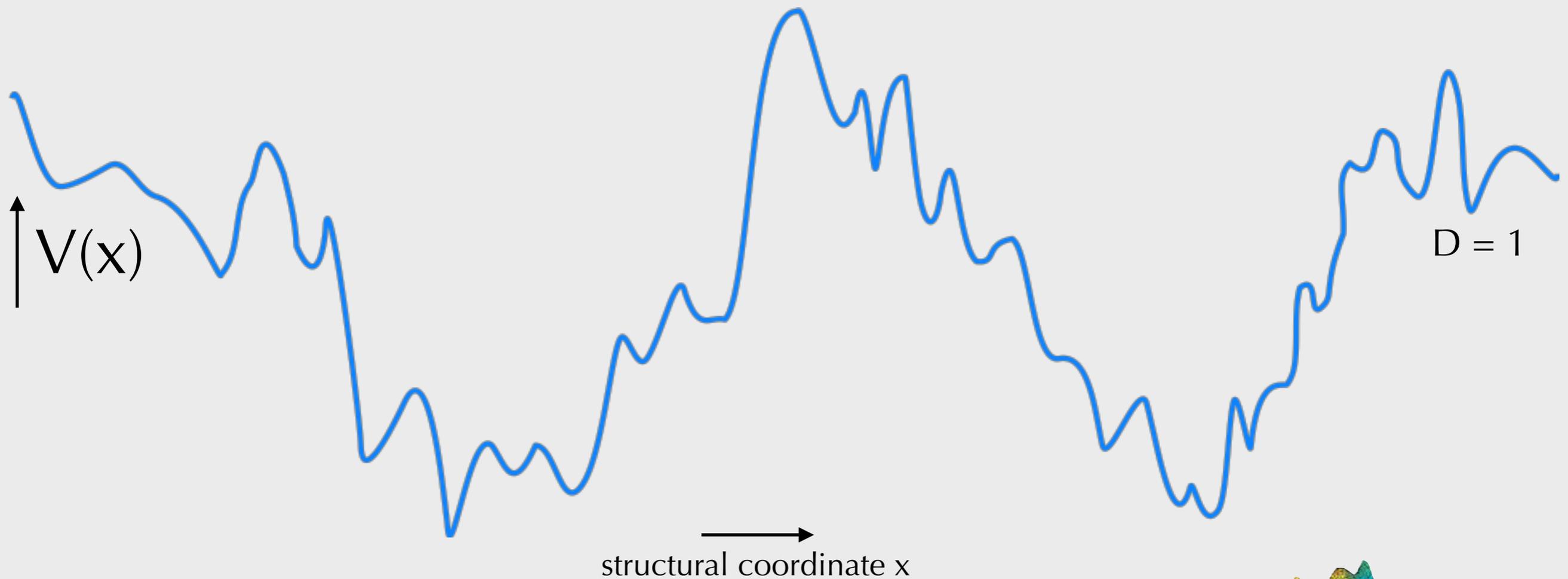
$$k = \mathcal{A} \exp(-E_b(X) / k_B T)$$

- k : rate constant
- E_b : barrier height (activation energy)
- \mathcal{A} : prefactor

Can estimate \mathcal{A} using harmonic transition state theory

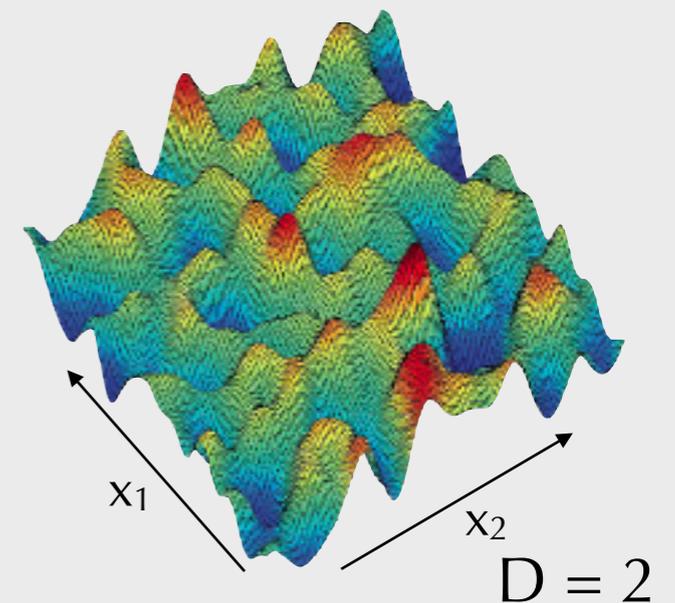


More complex situations



Potential energy V as a function of coordinates of N atoms

Defined over $D = 3N$ dimensional space



An early energy landscape conundrum: Levinthal's paradox

Christian Anfinsen: Denature an enzyme, then renature it again

Native catalytic activity is regained

→ Native structure must be at a global energy minimum

Cyrus Levinthal: take 100 residue protein, assume 10 backbone states/residue

e.g., \sim phi, psi torsion angles in staggered positions

Number of possible states $\approx 10^{100}$

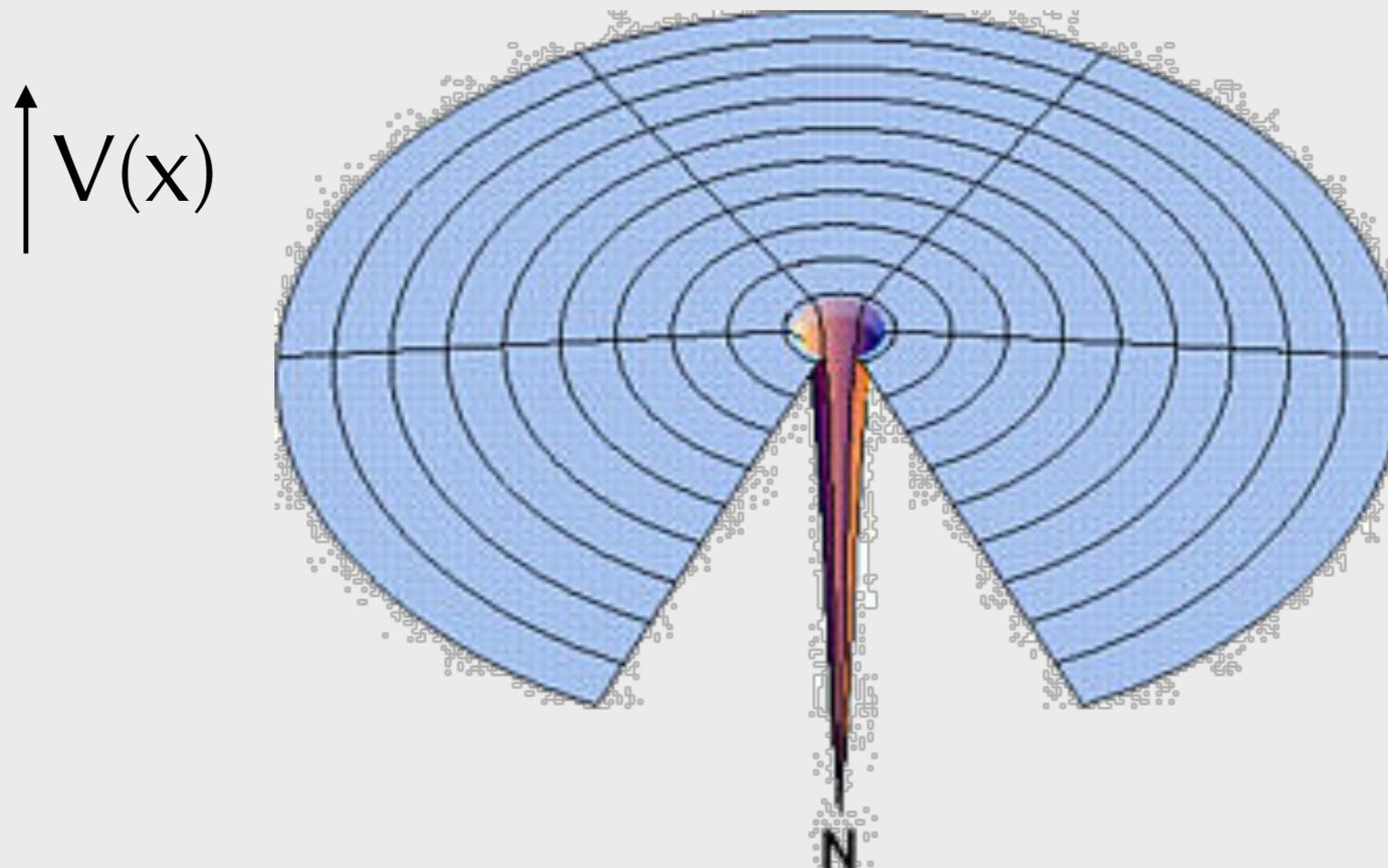
If 1 ps/state, exhaustive search $\gg 10 \times$ age of the universe

Yet proteins do find the native state, on μ s to s timescale

Implicit assumption: "golf course" energy landscape

- Levinthal's search assumes all non-native states have equal probabilities
- Implies that the potential energy surface is flat except for the native state

Finding native conformation unlikely (like a "hole in one")

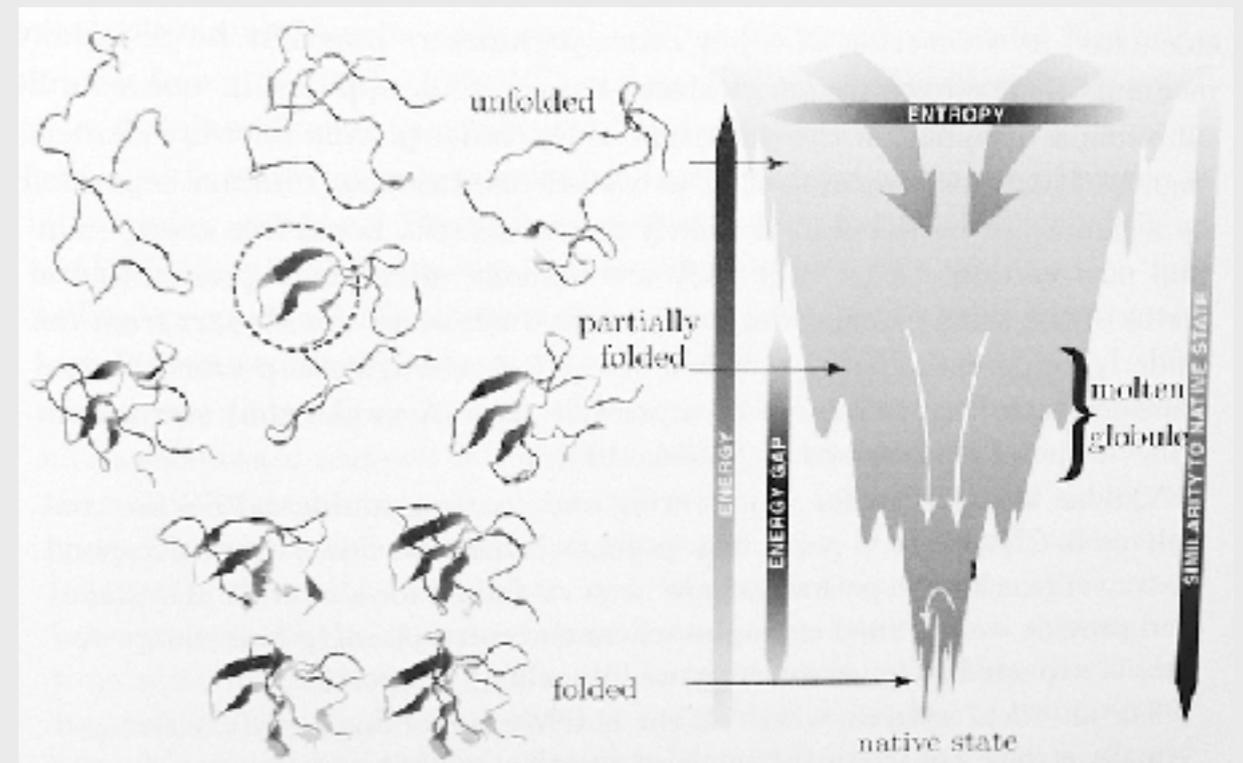
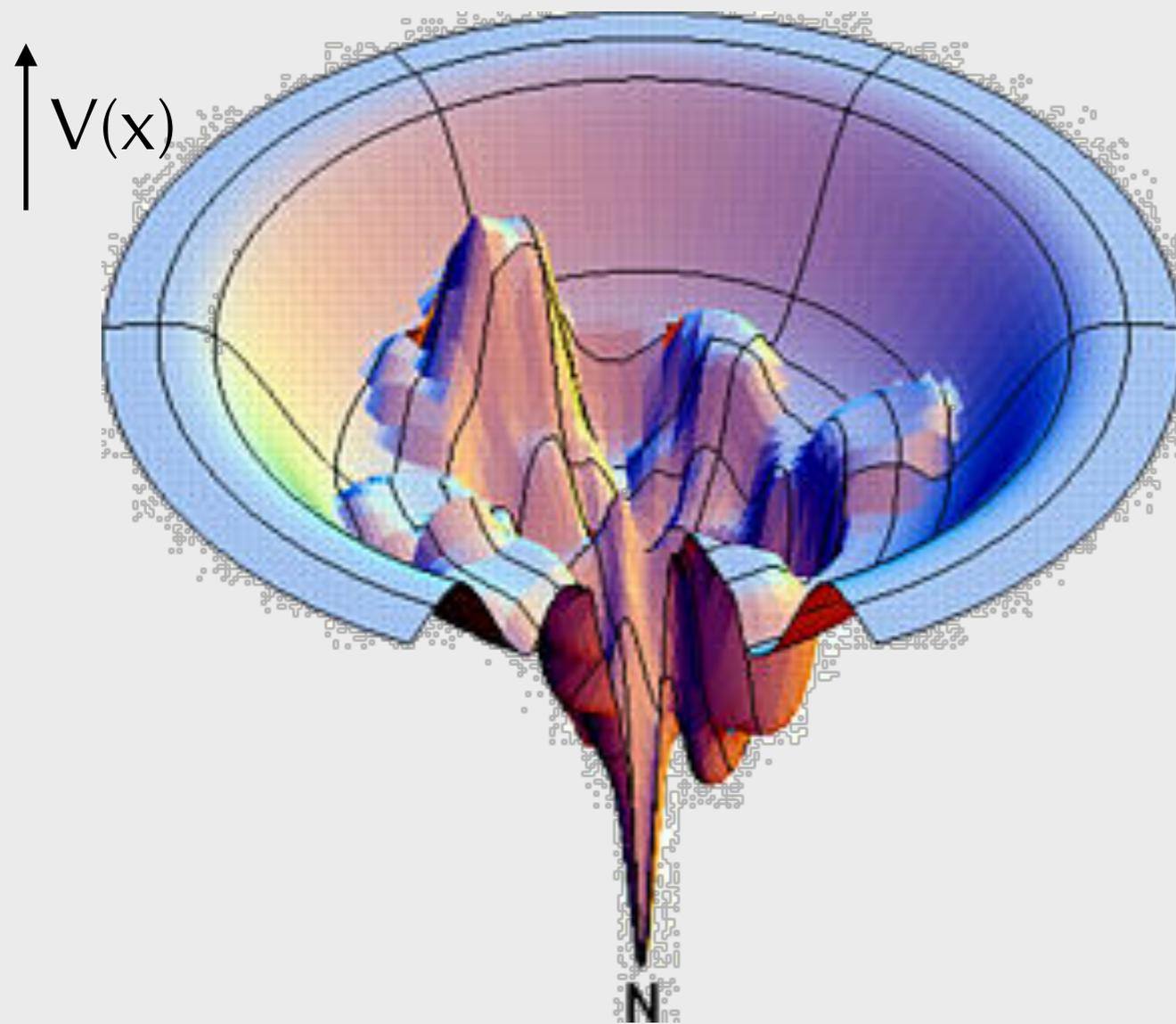


Resolution of paradox: folding funnel

Local interactions are quickly explored

Native-like local interactions are lower energy than the rest*

Energy decreases as the structure approaches the native form



* evolution selected them that way

Ken Dill, Peter Wolynes, ...

A better golf course



Funnelled ELs are characteristic of self-structuring systems

Crystals

- Single, ordered state from highly diverse solution

Many biological systems...

- Folding of globular proteins / RNA
- Specific protein interactions
- Self-assembly (fibers, virus capsids, ...)

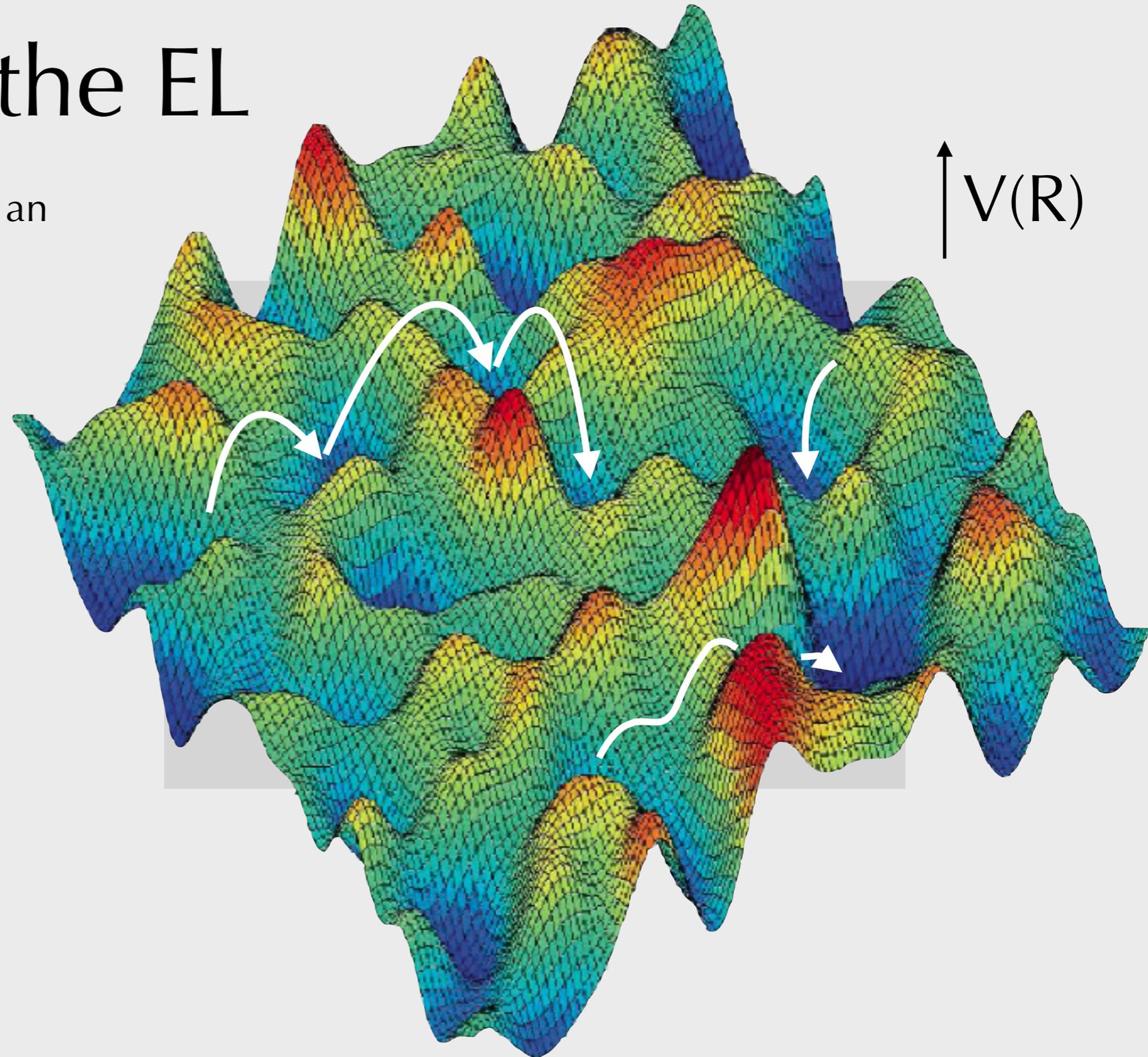
...but not all

- Misfolding/alternative structures (amyloids, ...)
- Intrinsically Disordered Proteins/Regions = ID[PR]s (promiscuous interactions, degradation pathways, ...)

Exploring the EL

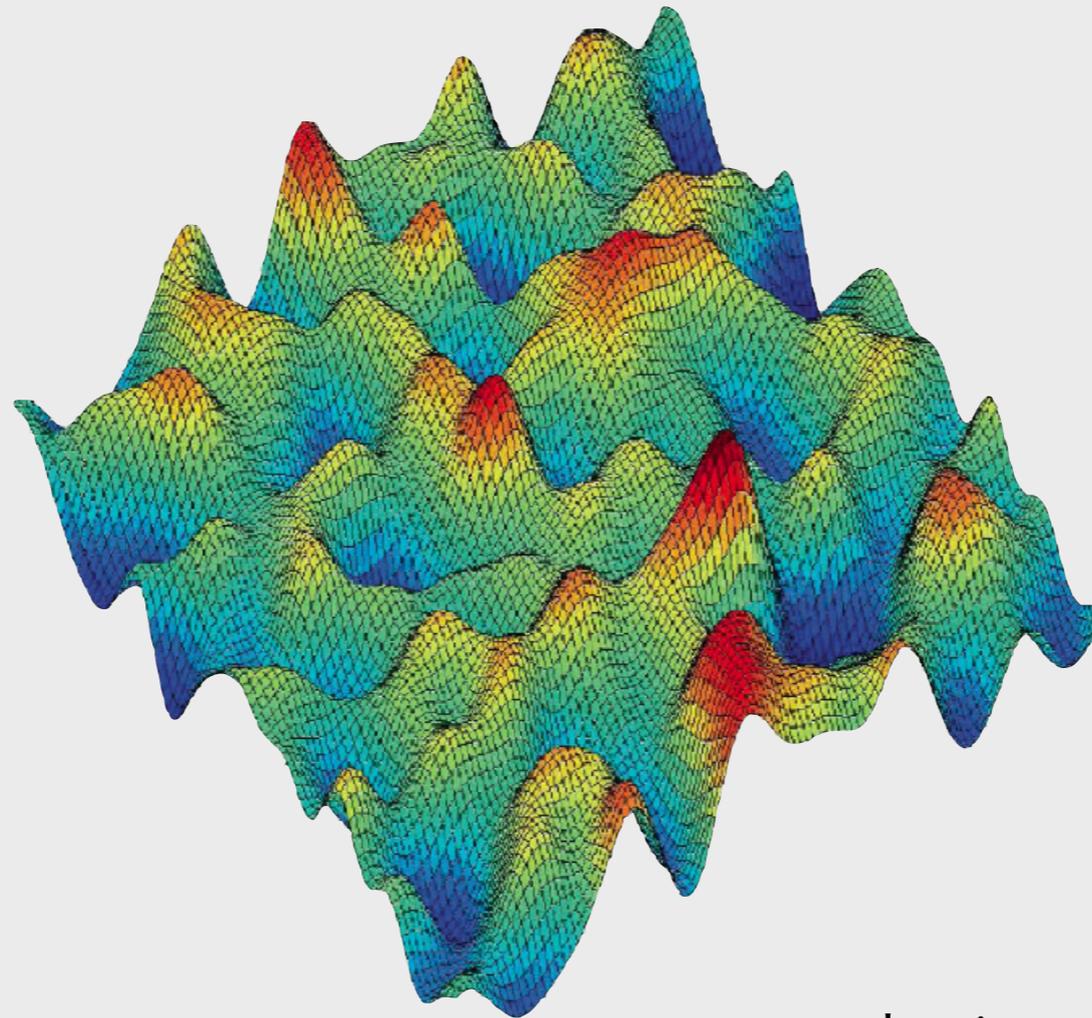
Where does knowledge of an EL come from?

- Optimisation
minimization, ...
- Local characterization
- Free exploration
- Guided exploration



Landmarks on an EL

↑ $V(R)$



Critical points: gradient = 0

minima

index 0: no negative eigenvalues in Hessian

saddle points

index 1, 2, ... $3N-1$ (number of negative eigenvalues)

maxima

index $3N$: negative eigenvalues only

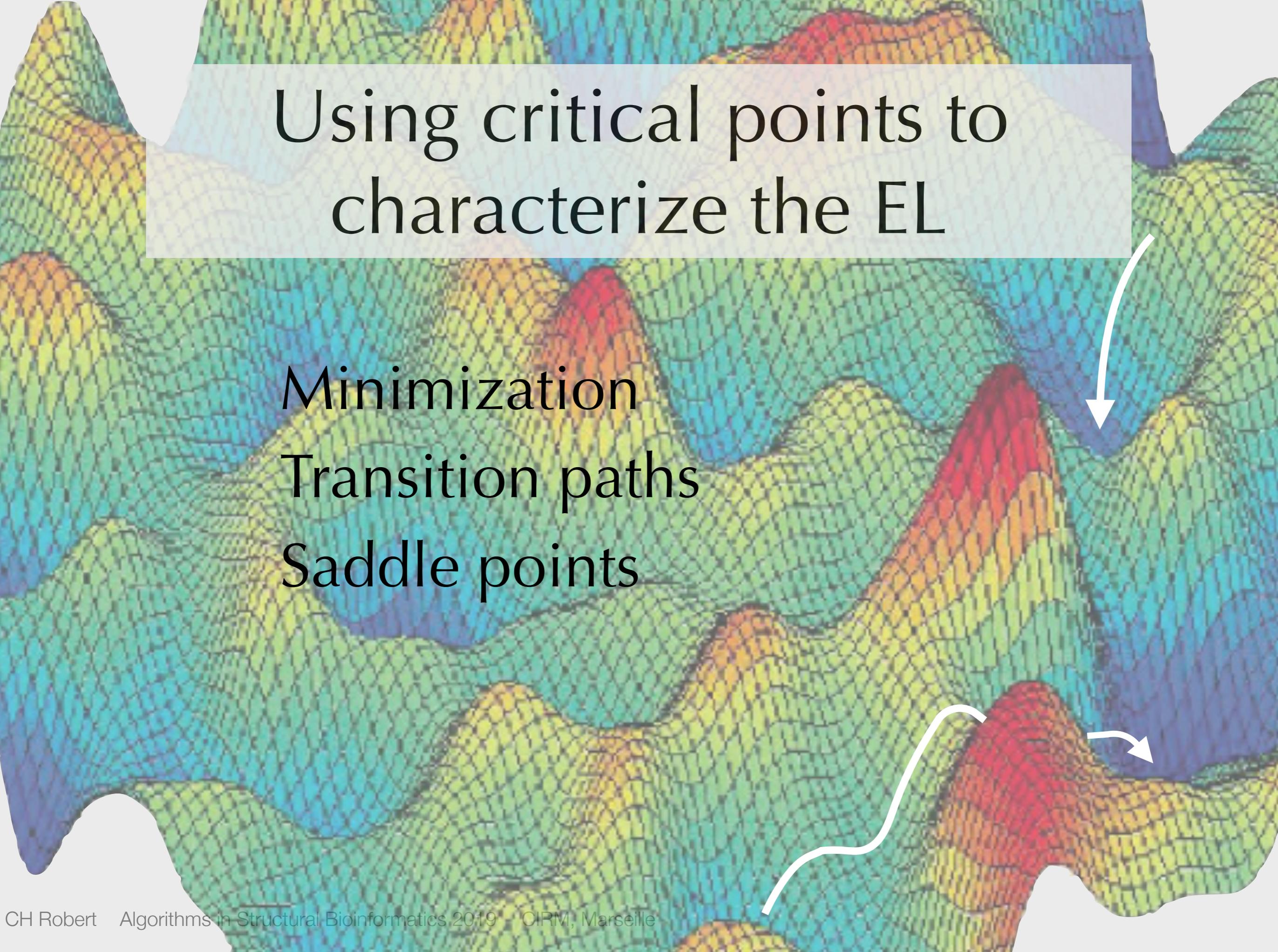
← number increases exponentially with D

← barriers between minima

...

Inflection points: curvature = 0

← may confuse some exploration algorithms



Using critical points to characterize the EL

Minimization
Transition paths
Saddle points

Minimization

1st derivative (gradient) approaches
steepest descent (-gradient of V)
conjugate gradients (keep list of productive directions)

2nd derivative (curvature of energy surface)
approaches

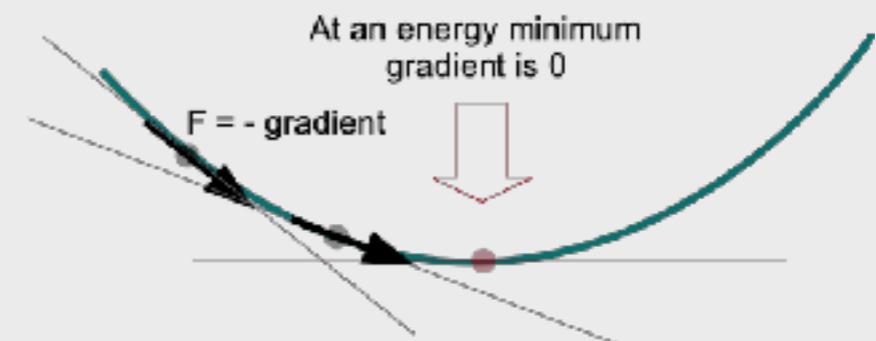
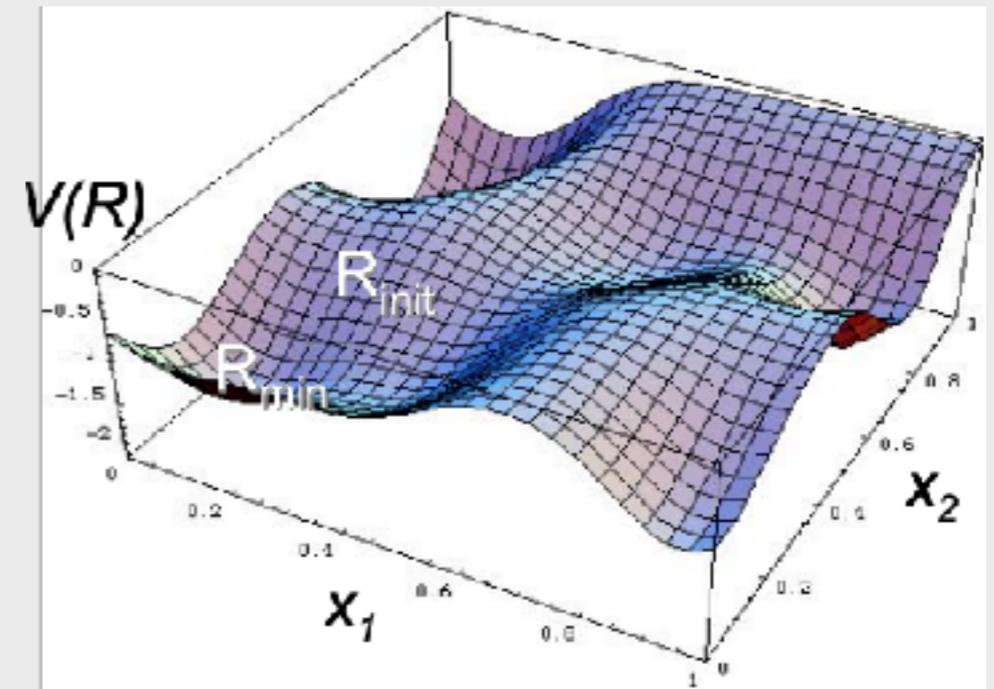
Approximate curvature matrix (Hessian, also used for NM)
Would find minimum in one step if surface were quadratic

- For a real surface, very useful once we are near the minimum

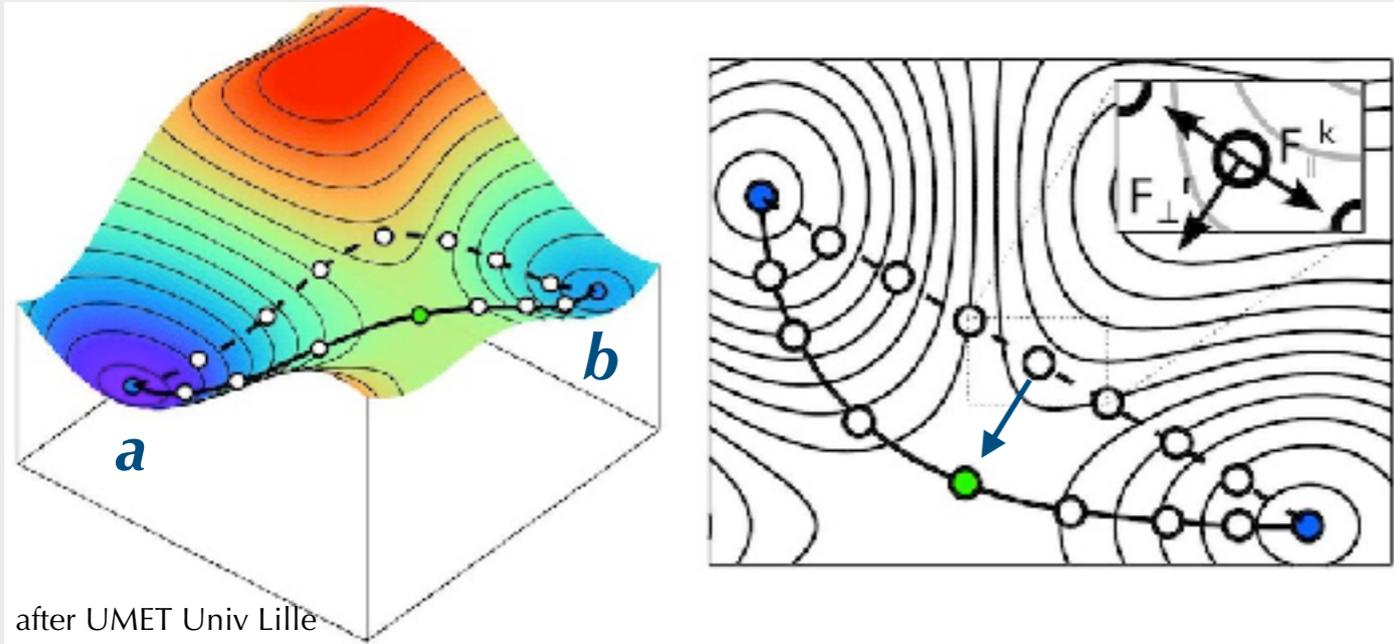
e.g., BFGS

Quality of minimization judged by magnitude of gradient

would be exactly zero at true minimum

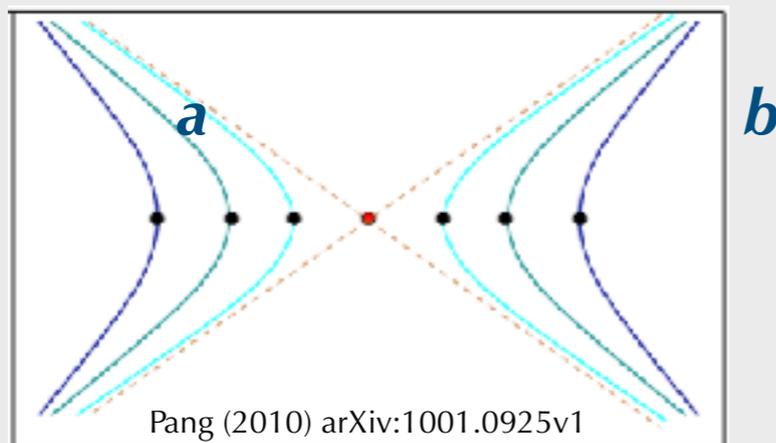


Transition paths



Nudged Elastic Band

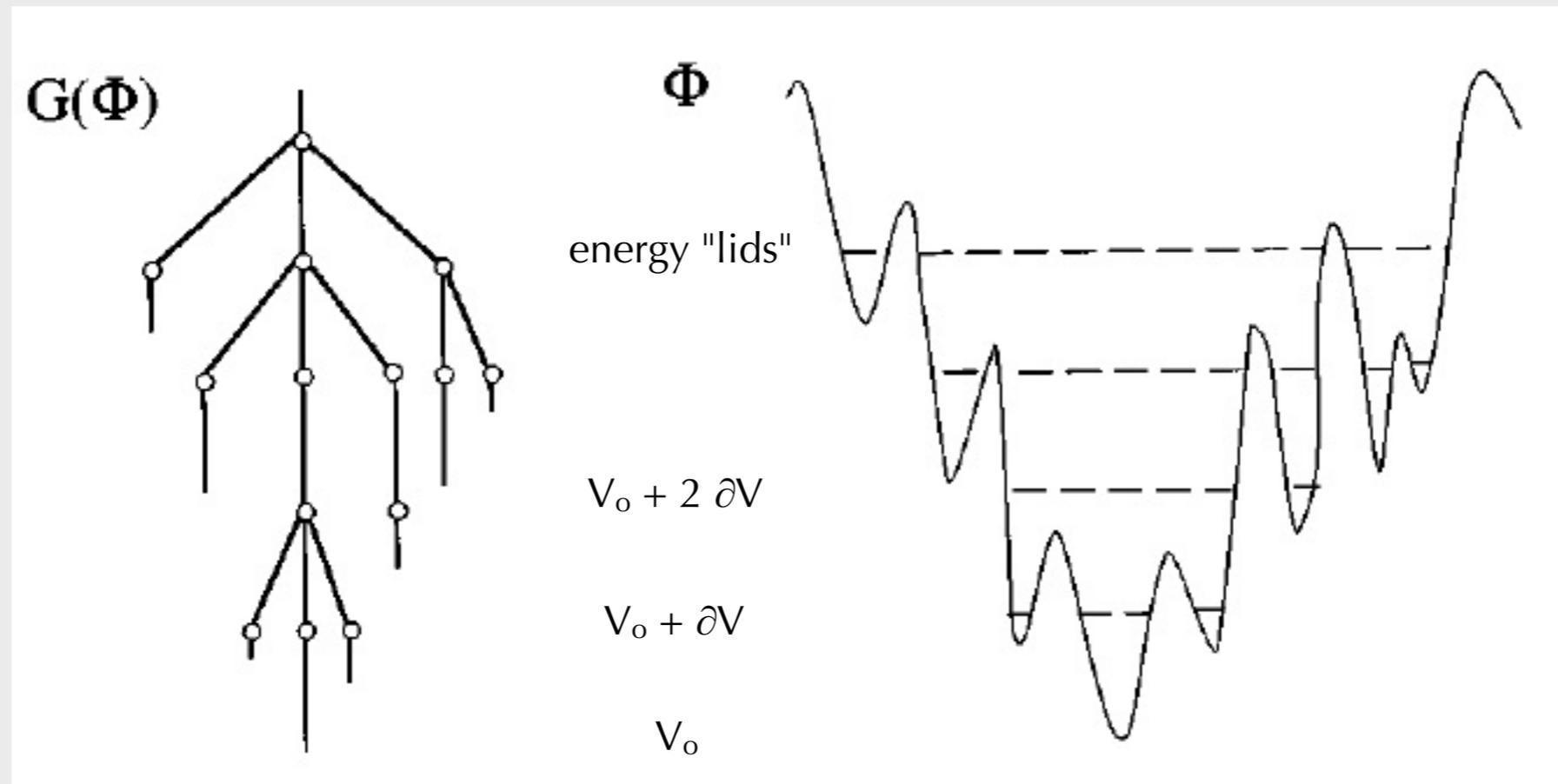
- “mountain pass problem” (index 1 saddle points)
- Guess initial points between fixed end-points a and b (e.g., by interpolation)
- Connect points by springs
- Minimize cost function $c(F_{\perp}, F_{\parallel})$ for the chain



Finding saddle points (an example)

- Use connectivity criteria between a and b in level sets
- Critical value is highest level set for which a and b are not connected
- General Morse index saddles

Picture the EL through disconnectivity graphs



Becker and Karplus (1997) J Chem Phys

Transform connected minima and saddle points into tree structure

Minima separated by the lowest index-1 saddle between $V(j)$ and $V(j+1)$ are connected at level j

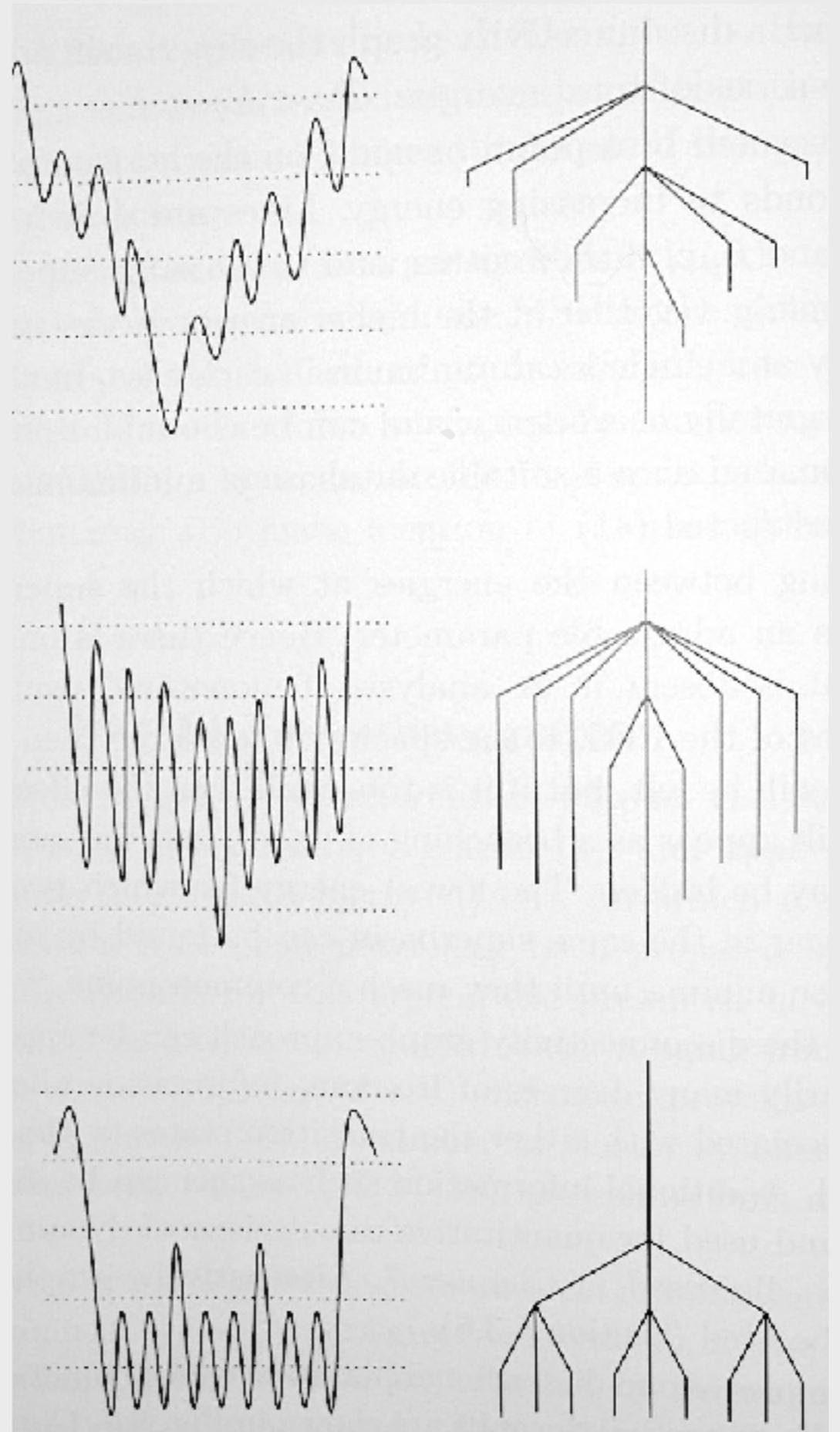
Minima coalesce into connected components (super-basins) at higher and higher energies

Examples of disconnectivity graphs

Different basin interconnectivities
give different classes of landscapes



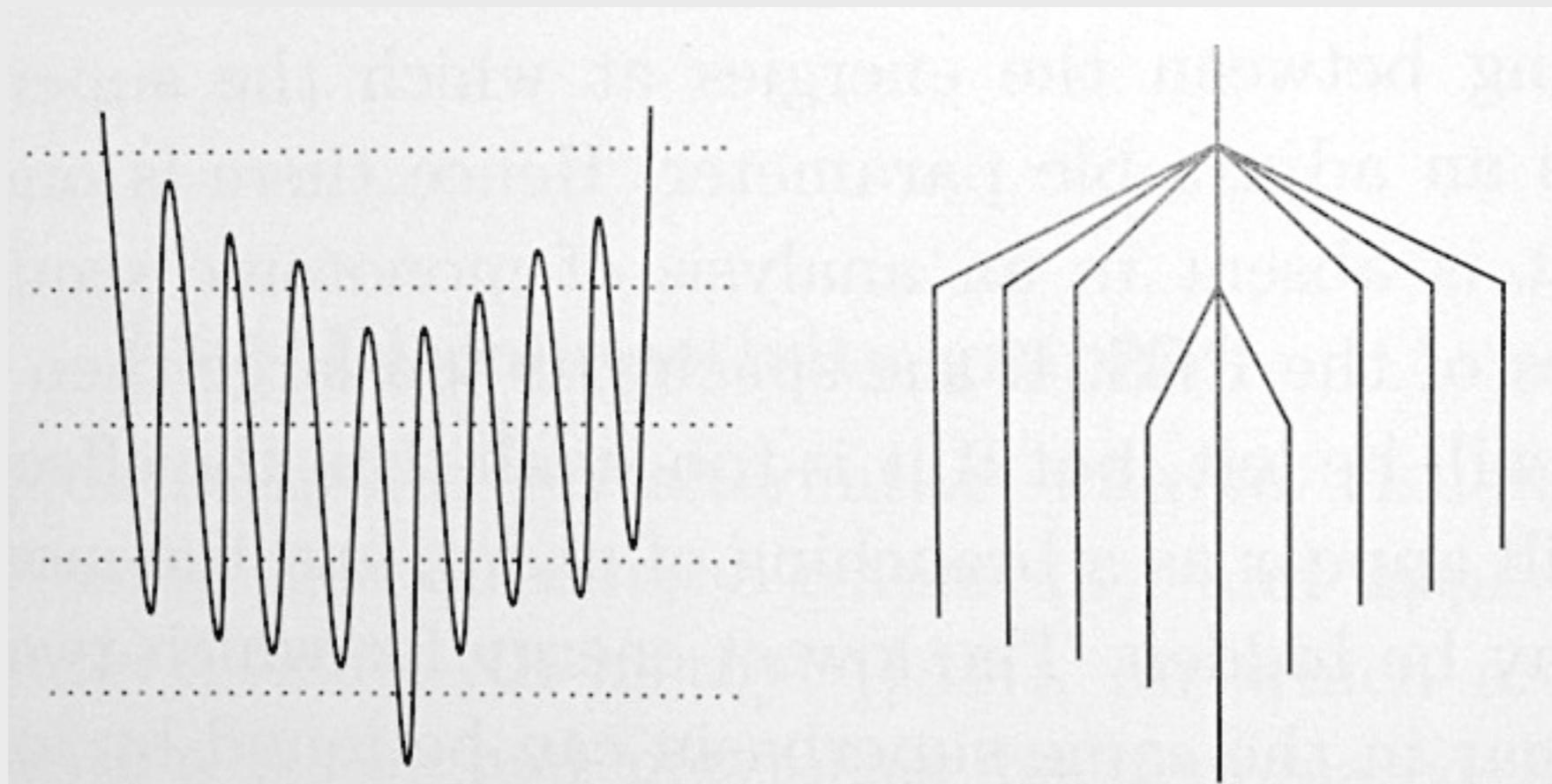
Different classes of dynamics



Non-funneled landscapes: frustration

Energy landscape prevents system from attaining the global energy minimum

- High temperatures— rapid configurational exploration
- Low temperatures— trapping
- → Global energy minimum difficult to reach



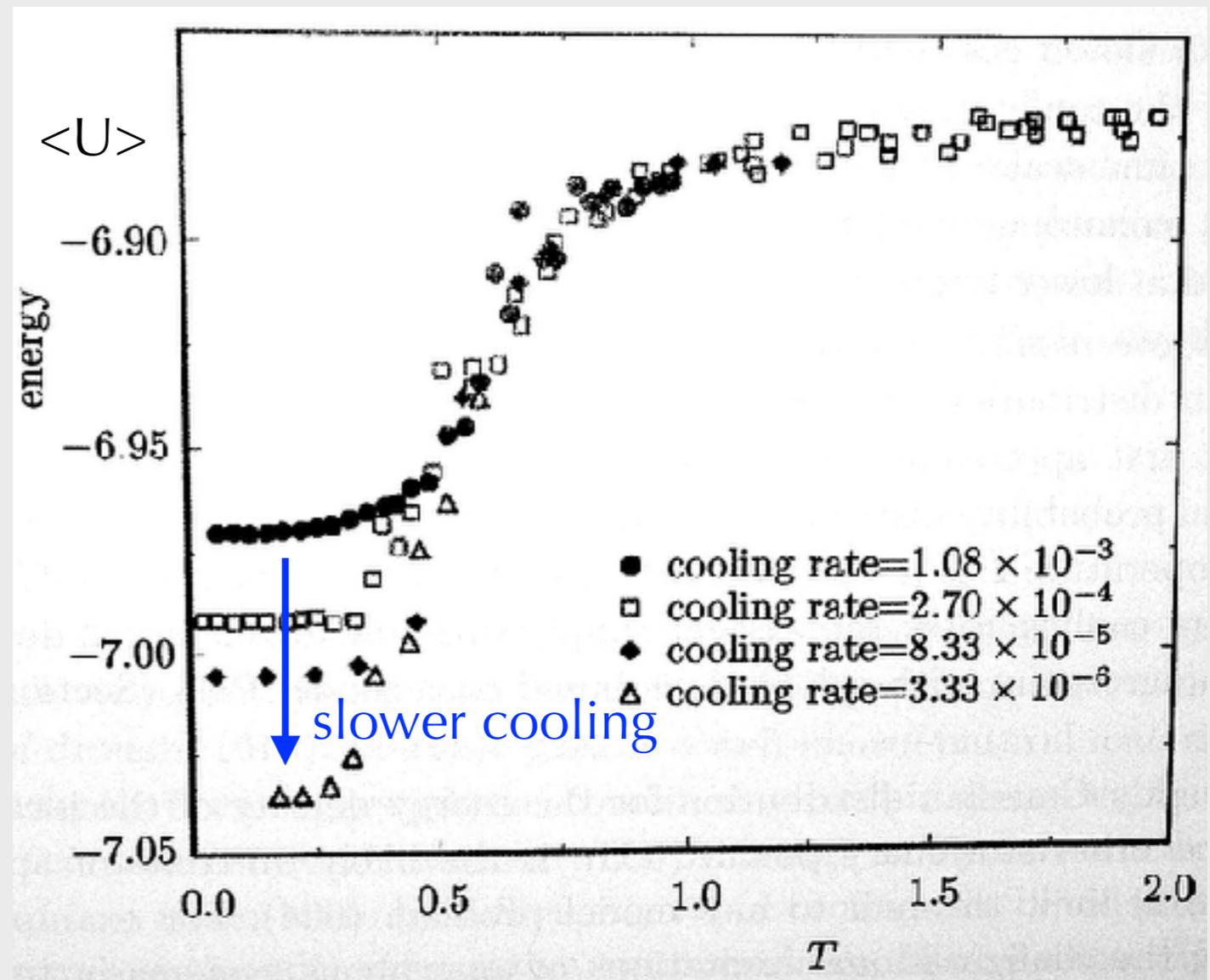
Frustrated systems: glassy behavior

Simple example: cooling of a binary
Lennard-Jones system using MD

Plot average energy of quenched
snapshots ("inherent structures")

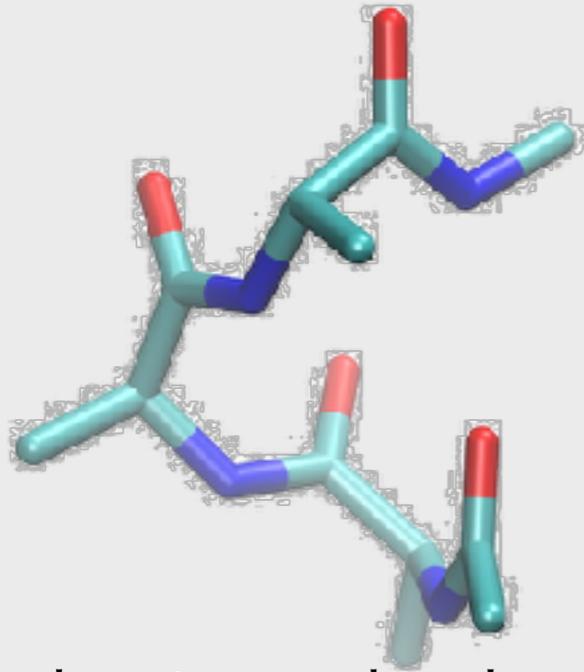
Slower cooling allows accessing lower
energy states, but

- amorphous
- no "native" structure
- global minimum not relevant



Sastry, Debenedetti, and Stillinger (1998) Nature 393, 554

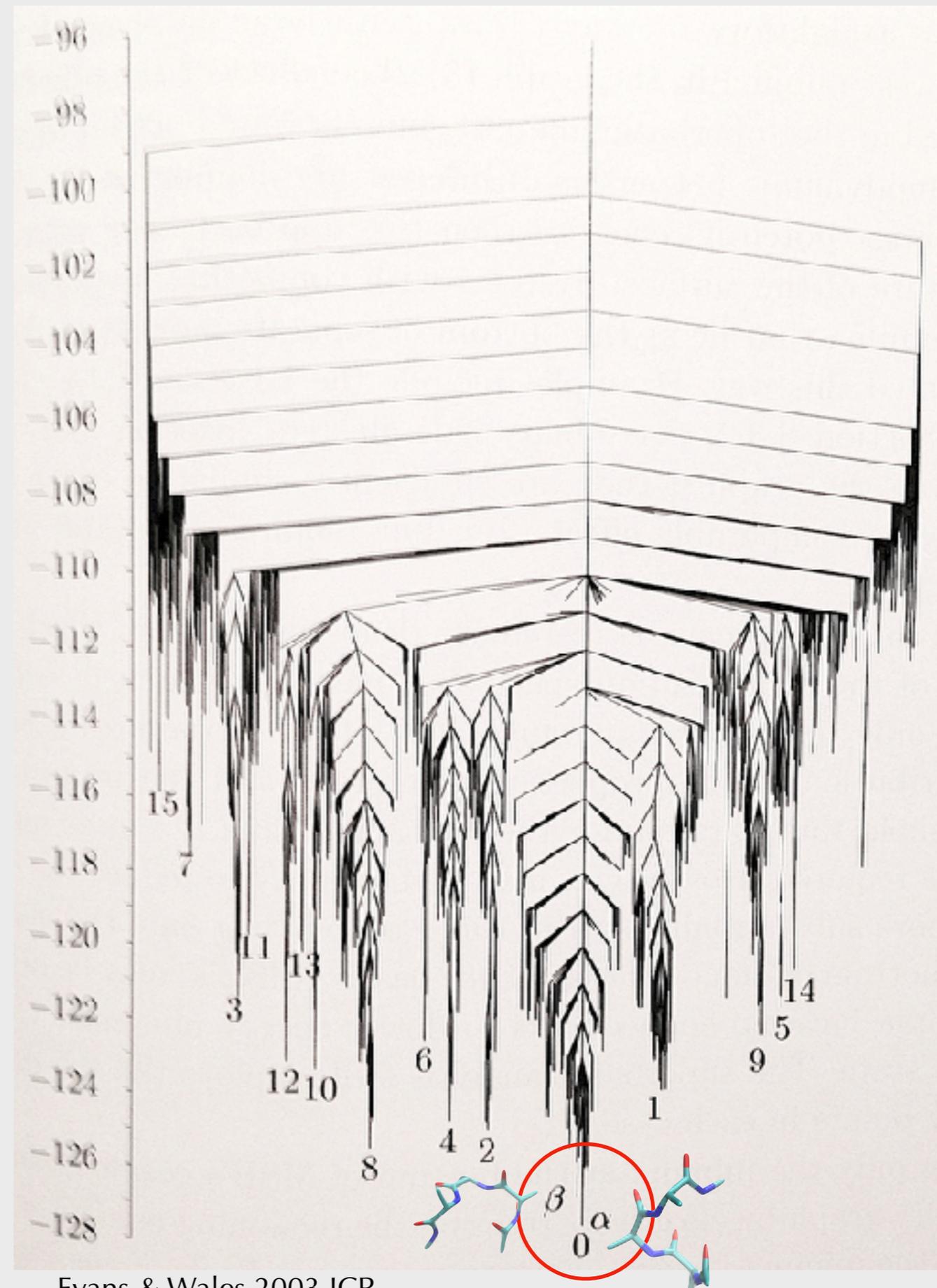
Disconnectivity graph for Alanine tetra- peptide Ac-(Ala)₃-NHMe



Blocked amino and carboxy termini:
four peptide bonds

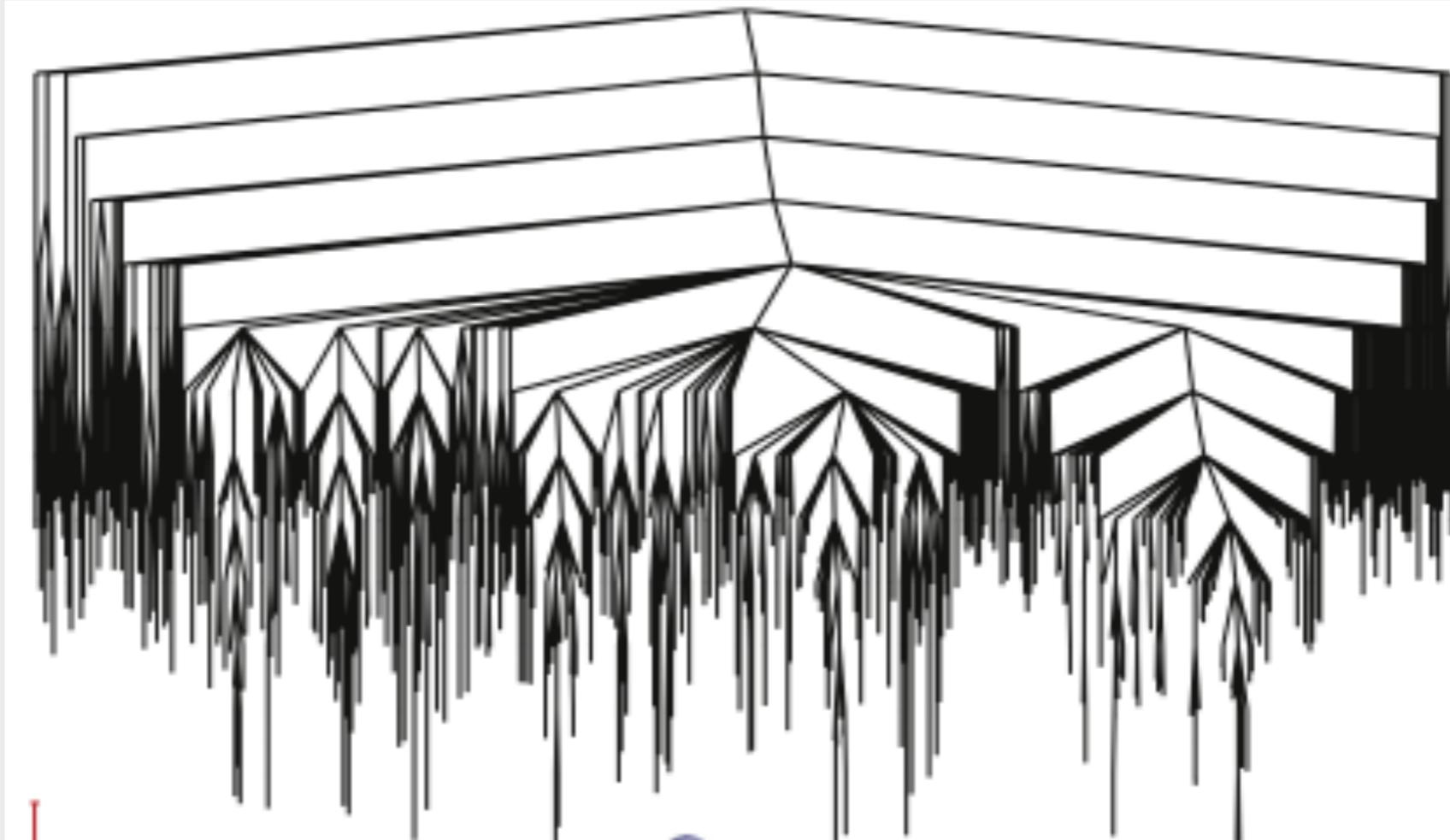
Can form one H-bonded turn of an
alpha helix

Extended (β) and helix (α)
approximately equal potential energy



Evans & Wales 2003 JCP

Limitations of disconnectivity graphs



Inconsistency: Minima shown exactly but saddle points only shown within ΔE

Only lowest transition states are seen

Multiple transition states can be hidden in an energy step

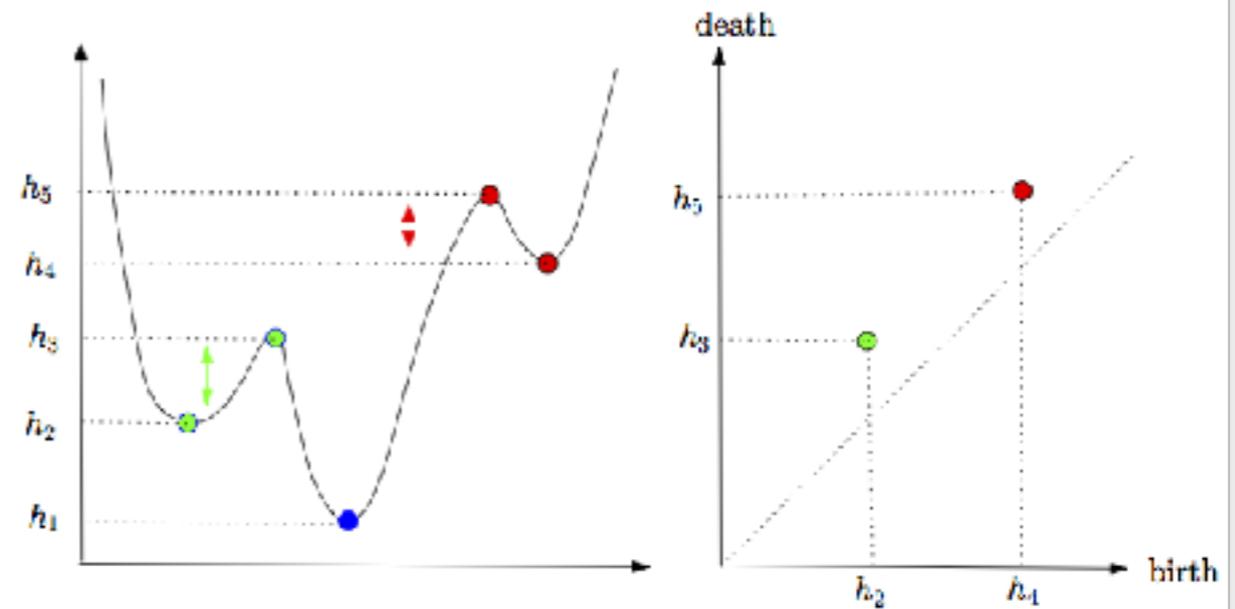
expand ΔE : gain visibility, lose transitions

reduce ΔE : gain transitions, lose visibility

Persistence analysis

▷ Rationale

- Sub-level sets: $M_t = f^{-1}(-\infty, t)$, $t \in \mathbb{R}$
- Birth and death of the **connected components** of M_t



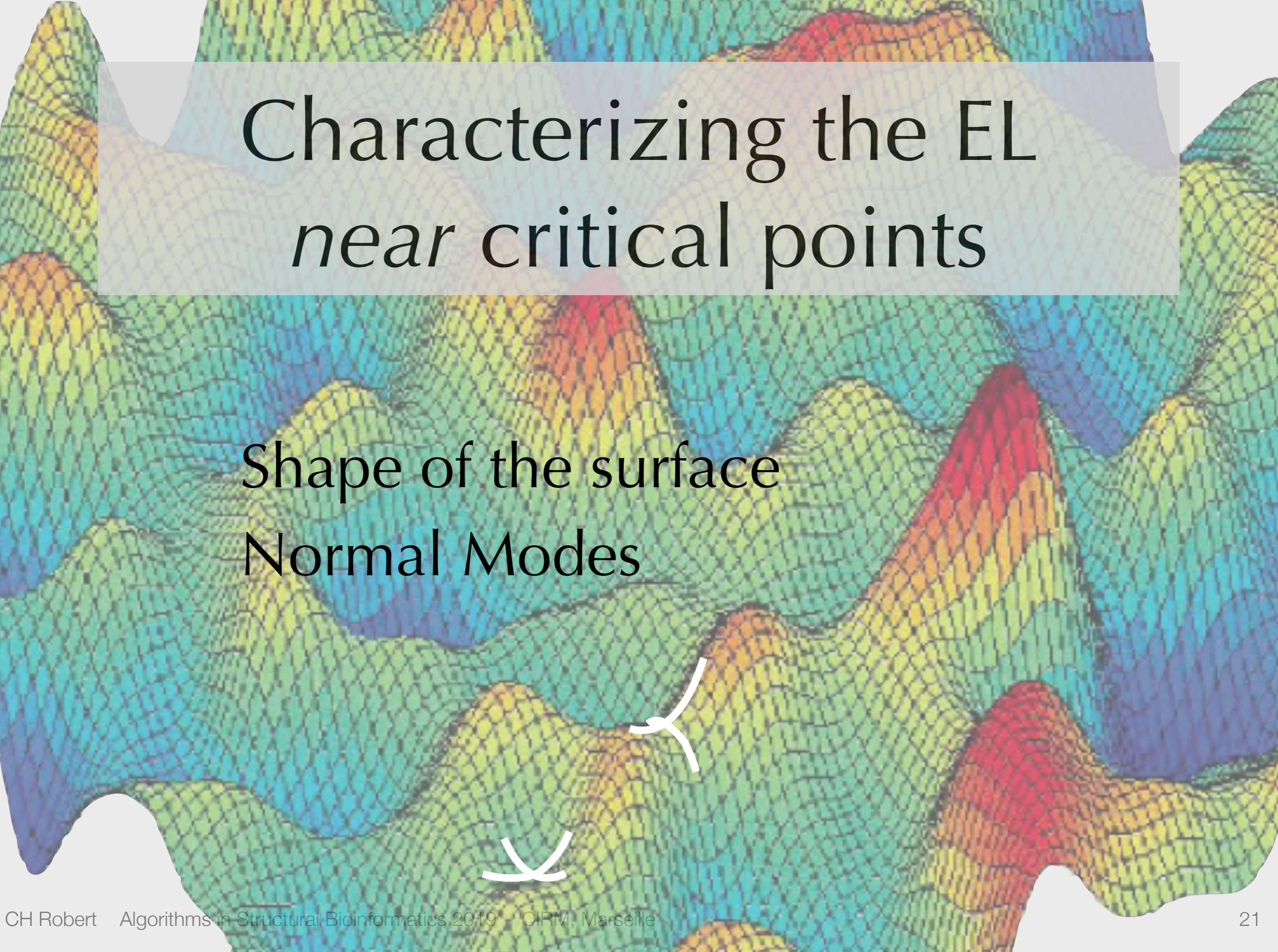
F. Cazals, course slide

Analyze connected components of sub-level sets as function of height (energy)

Plot *birth* of each additional component on x , *death* on y

- see the exact **persistence** of each component (height of saddle) directly
- natural mechanism to **denoise** landscape (*persistence* < *threshold*)

in the SBL

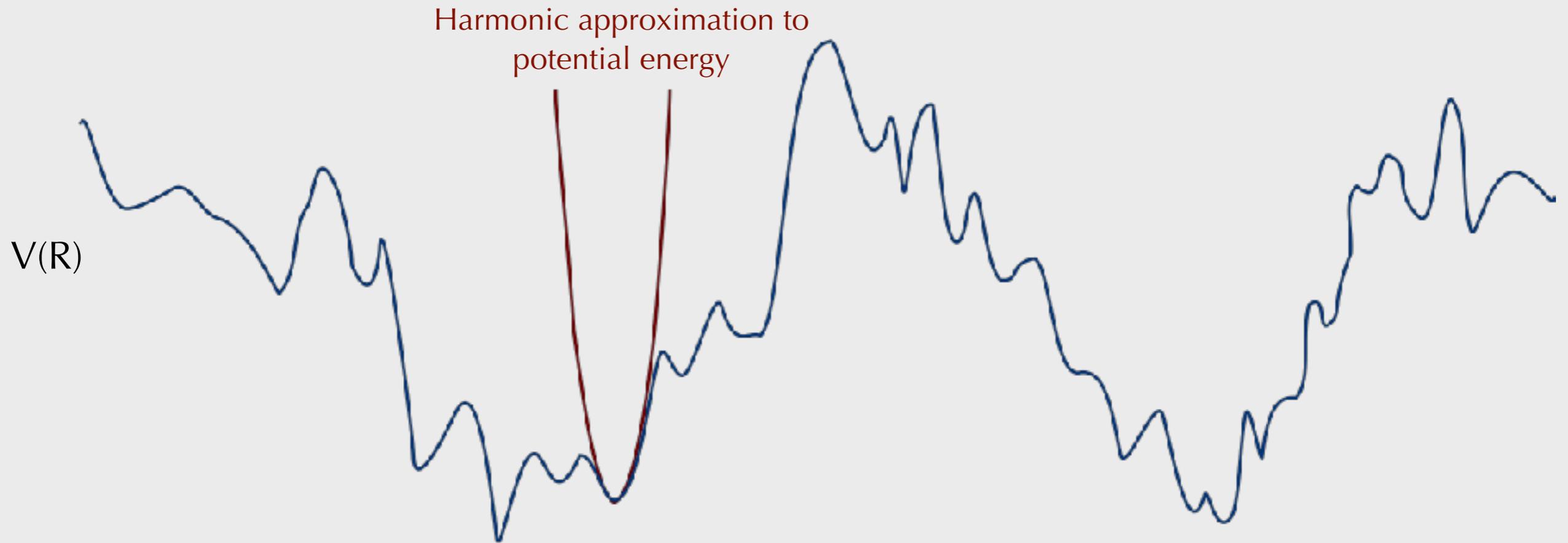


Characterizing the EL *near* critical points

Shape of the surface
Normal Modes



Idea behind NM



Restrict description to a single harmonic potential centered on a minimum-energy configuration

Vibrational dynamics only

Dynamics depend on the shape of the energy minimum at that point

Total vibrational energy

Kinetic plus harmonic potential energy

$$E_{vib} = T(\dot{\mathbf{R}}) + V_{harmonic}(\mathbf{R})$$

$$\mathbf{R} = \begin{matrix} \text{atom 1} & \text{atom 2} & \dots & \text{atom N} \\ \hline (x_1, y_1, z_1), & (x_2, y_2, z_2), & \dots, & (x_N, y_N, z_N) \end{matrix}$$

↓

$$\mathbf{x} = [x_1 \ x_2 \ x_3 \ x_4 \ x_5 \ x_6 \ \dots \ x_{3N}]$$

Expand potential energy V about a position \mathbf{x}_0 at an energy minimum

$$V(\mathbf{x}) = V(\mathbf{x}_0) + \sum_i^{3N} \left(\frac{\partial V}{\partial x_i} \right)_{\mathbf{x}_0} (x_i - x_{i0}) + \frac{1}{2!} \sum_{i,j}^{3N} \left(\frac{\partial^2 V}{\partial x_i \partial x_j} \right)_{\mathbf{x}_0} (x_i - x_{i0})(x_j - x_{j0}) + \dots$$

Hessian matrix of second-order partial derivatives describes the **curvature at the minimum**

$$E_{vib} = \frac{1}{2} \sum_{\text{atoms}, a}^N m_a (v_{ax}^2 + v_{ay}^2 + v_{az}^2) + \frac{1}{2} \sum_{i,j}^{3N} \left(\frac{\partial^2 V}{\partial x_i \partial x_j} \right)_{\mathbf{x}_0} (x_i - x_{i0})(x_j - x_{j0})$$

Inconvenient form: $T(\dot{\mathbf{R}})$ sums over atoms, $V(\mathbf{R})$ over Cartesian coordinates

Root-mass weighting gives eigensystem

Introduce root-mass weighted coordinate displacements

$$\xi_i = \sqrt{m_i}(x_i - x_{i0})$$
$$E_{\text{vib}} = \frac{1}{2} \sum_i^{3N} \dot{\xi}_i^2 + \frac{1}{2} \sum_{i,j}^{3N} \left(\frac{\partial^2 V}{\partial \xi_i \partial \xi_j} \right)_0 \xi_i \xi_j$$

Symmetric form

$$E_{\text{vib}} = \frac{1}{2} \dot{\xi}^T \dot{\xi} + \frac{1}{2} \xi^T H \xi \quad (\text{Note: Hessian becomes } H, \text{ a force-constant matrix})$$

Can find matrix A that diagonalizes H

$$L = A^T H A \quad L = \begin{bmatrix} \omega_1^2 & 0 & 0 & \dots & 0 \\ 0 & \omega_2^2 & 0 & \dots & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & 0 & 0 & \dots & \omega_{3N}^2 \end{bmatrix}$$

Eigenvalues ω_i^2

Eigenvectors \mathbf{q}_i : columns of A^T

Normal modes: molecular motions can be decomposed into independent oscillators

$$\begin{aligned} E_{vib} &= E_1 + E_2 + \dots \\ &= \boxed{\frac{1}{2}\dot{q}_1^2 + \frac{1}{2}\omega_1^2 q_1^2} + \boxed{\frac{1}{2}\dot{q}_2^2 + \frac{1}{2}\omega_2^2 q_2^2} + \dots \end{aligned}$$

E oscillator 1 **E oscillator 2**

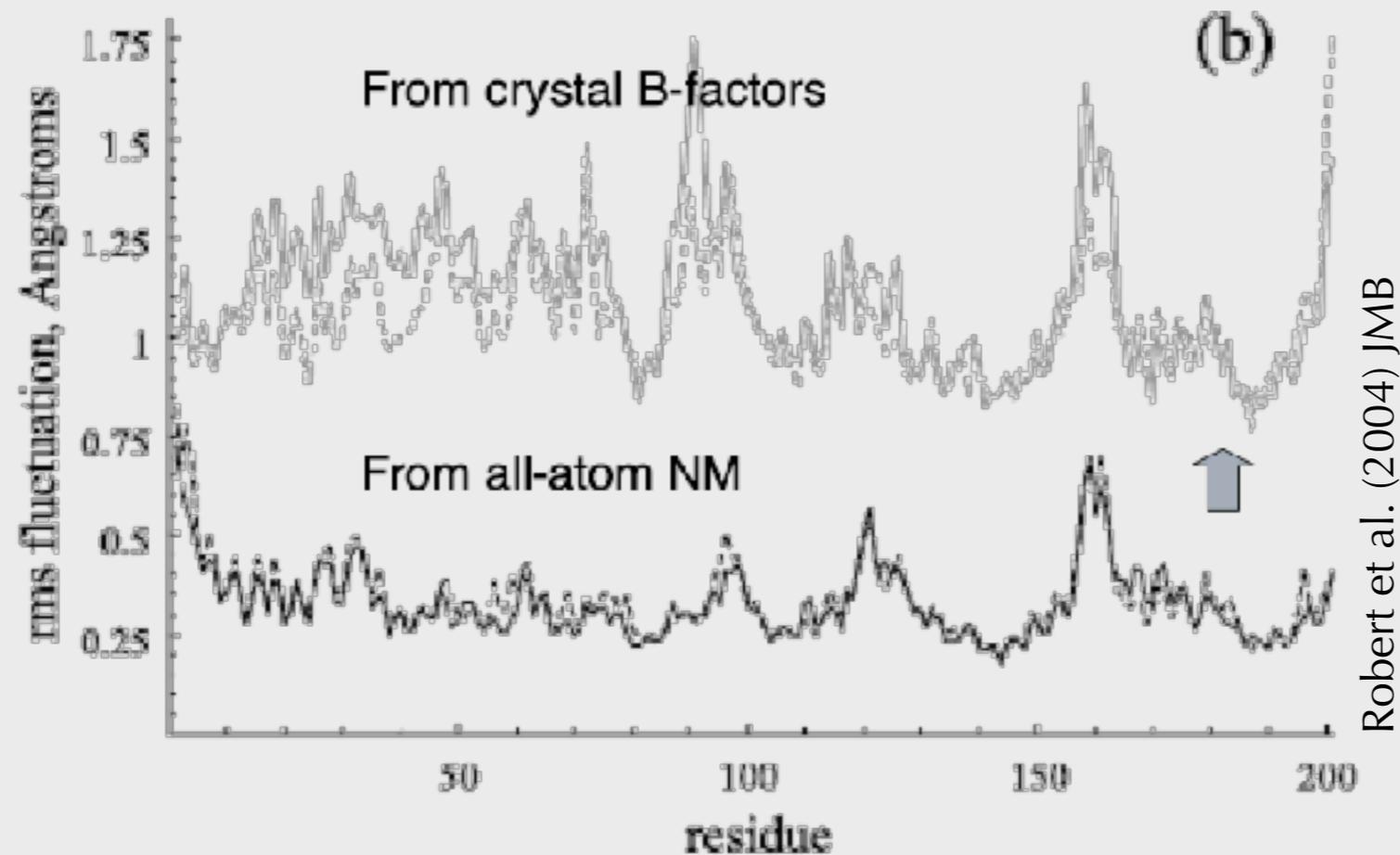
Because L is diagonal, the total energy is that of **3N independent oscillators** along the q 's

Each normal coordinate q_i is an oscillating function of time along eigenvector q_i , frequency is ω_i

$$q_i(t) = \sqrt{(2 E_i)/\omega_i} \cos(\omega_i t + \varphi_i)$$

Note: angular frequencies (radians/sec) typically converted to wavenumber cm^{-1} by $\bar{\nu} = \omega/2\pi c$

NM provides info on flexibility

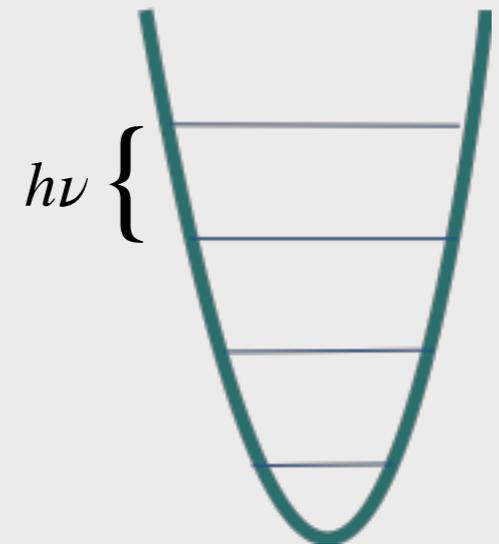
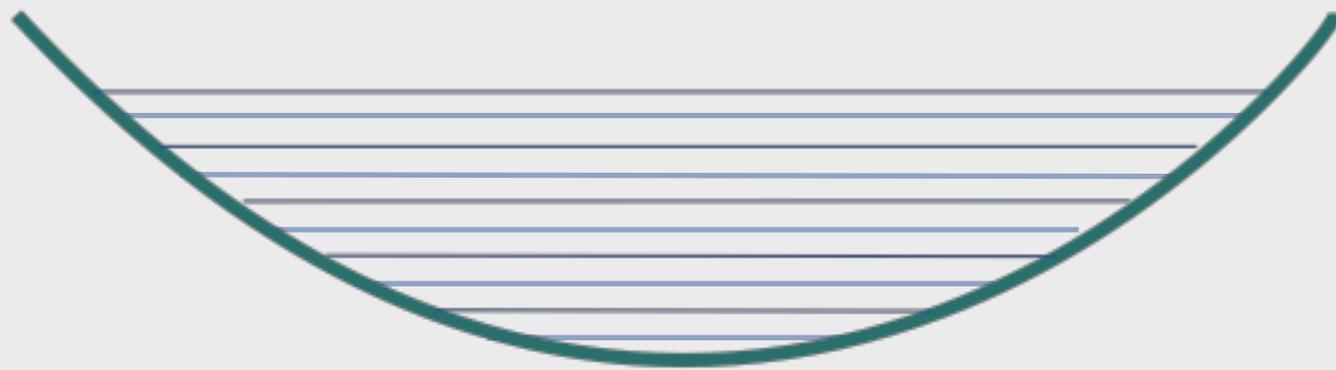


Calculate average squared atom displacements from modes

$$\langle \delta_i^2 \rangle = k_B T \sum_{k=1}^{3N-6} \frac{q_{3i,k}^2 + q_{3i+1,k}^2 + q_{3i+2,k}^2}{\omega_k^2} \quad (\text{for atom } 0 \dots N-1)$$

Correlate well with temperature factors (B-values) in xtal structures

Using NM for entropy estimation



Typical vibrational frequencies: $2 \lesssim \bar{\nu} \lesssim 2000 \text{ cm}^{-1}$

- Energy level spacing is on the order of $k_B T$ (207 cm^{-1}): $1/100 \lesssim \frac{h\nu}{k_B T} \lesssim 10$

Quantum harmonic oscillator

- Partition function $q = \sum_{n=0}^{\infty} \exp^{-\epsilon_n/k_B T}$ where $\epsilon_n = h\nu(n + 1/2)$

Vibrational entropy is f(occupation of excited states)

- $S_{\text{vib}} = k_B \sum_i^{3N-6} \left\{ -\ln(1 - \exp^{-h\nu_i/k_B T}) + \frac{h\nu_i/k_B T}{\exp^{h\nu_i/k_B T} - 1} \right\}$

Lower frequency NM \rightarrow smaller spacing \rightarrow larger entropy contribution

Why use this? e.g., MM-PBSA endpoint calcs of ΔG_{assoc}

Ala tetrapeptide free-energy landscape

Superposition approximation for basins

→ Thermodynamics

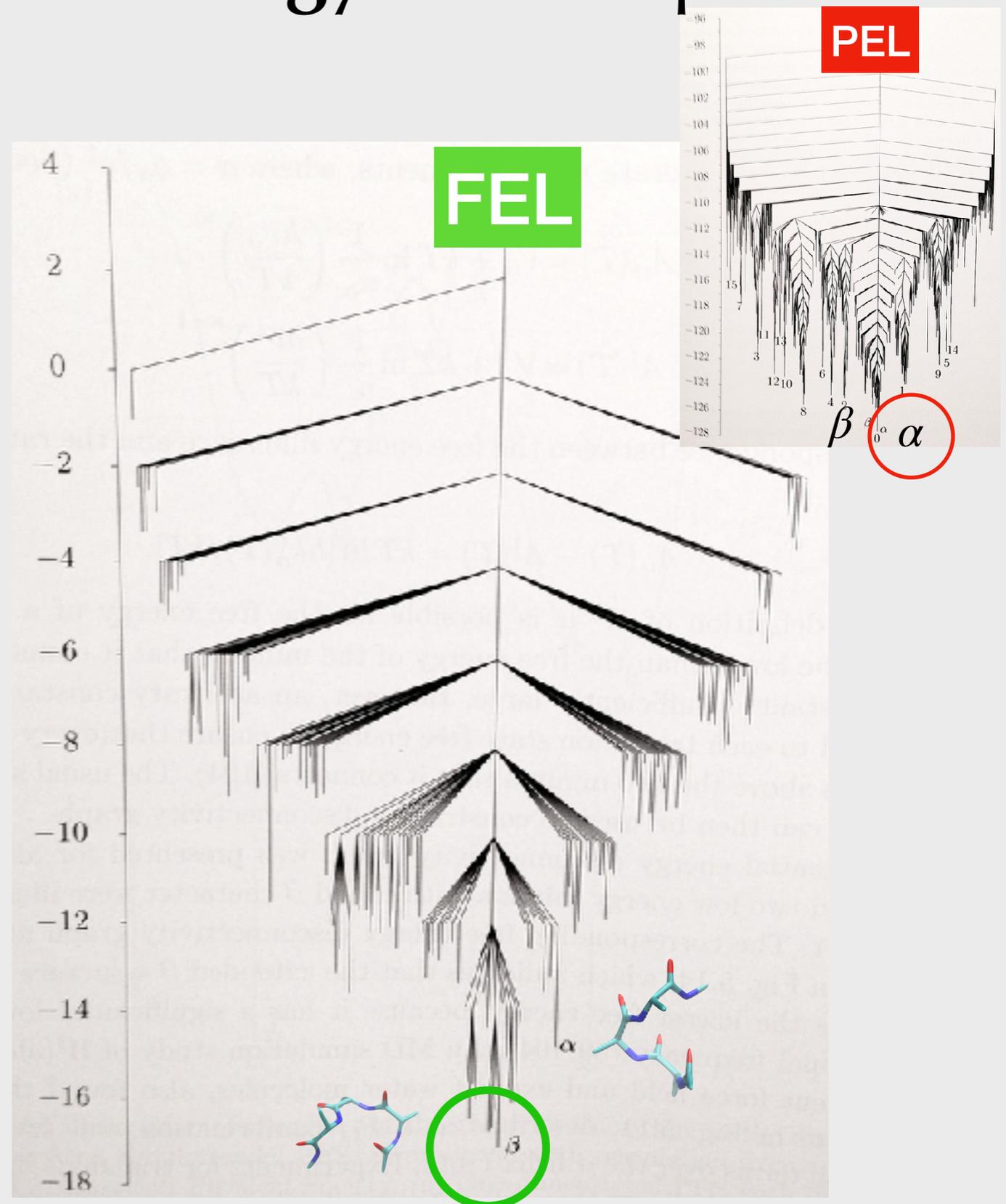
... for basins and transition points

→ Free Energy Landscape

- FEL is $f(T)$

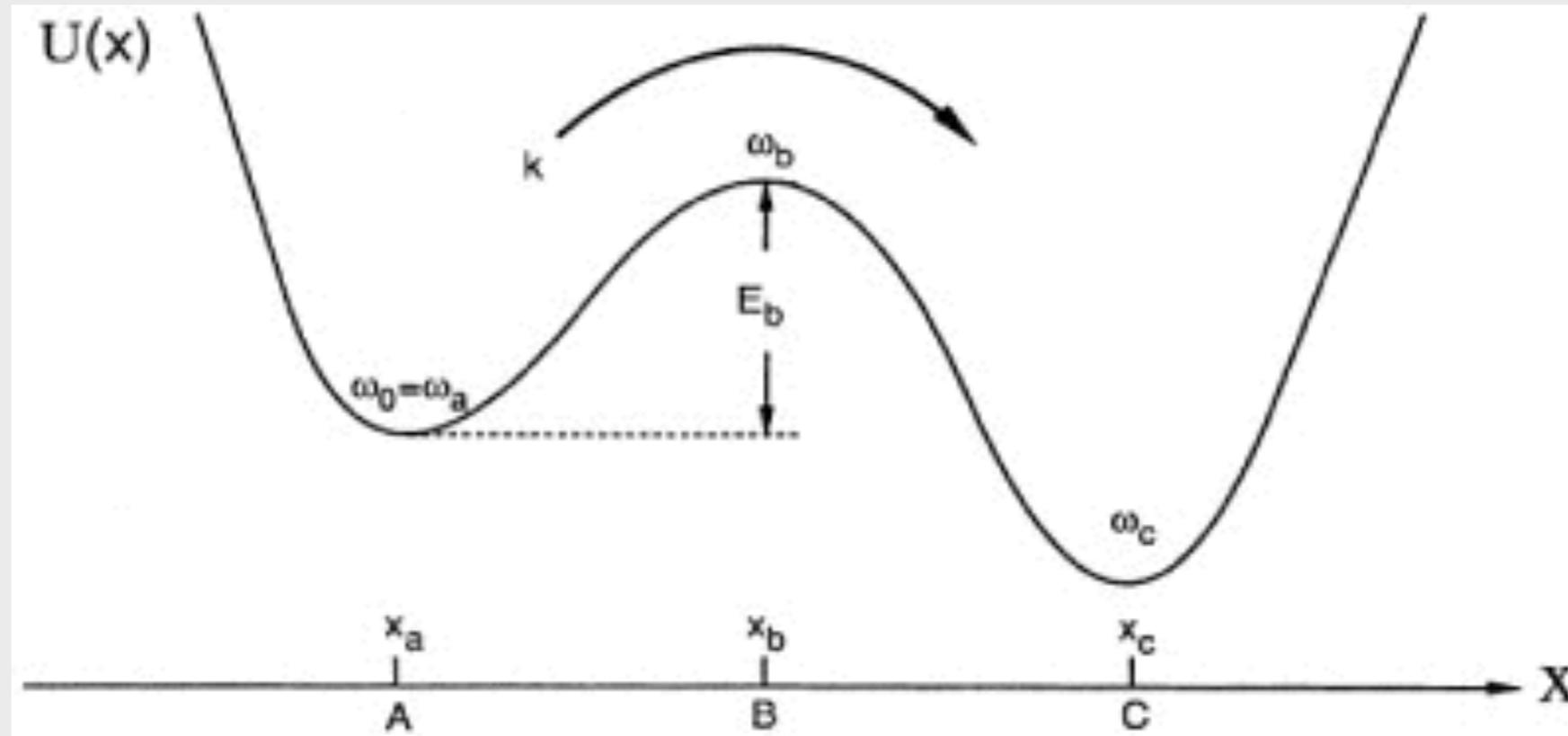
Extended β form is more stable at 298K

- lower vibrational mode frequencies than alpha helix → higher entropy
- agrees with MD sampling studies (Krivov&Karplus 2002 PRL)



Evans & Wales 2003 JCP

NM for kinetics: transition state theories depend on critical points and their shapes



Rate of forward reaction

$$k = \mathcal{A} \exp(- E_b(X) / k_B T)$$

E_b saddle point energy

saddle point: productive vibrational frequency ω_b

minima: vibrational partition functions q_A and q_B to estimate prefactor \mathcal{A}

What do the NM vectors represent?

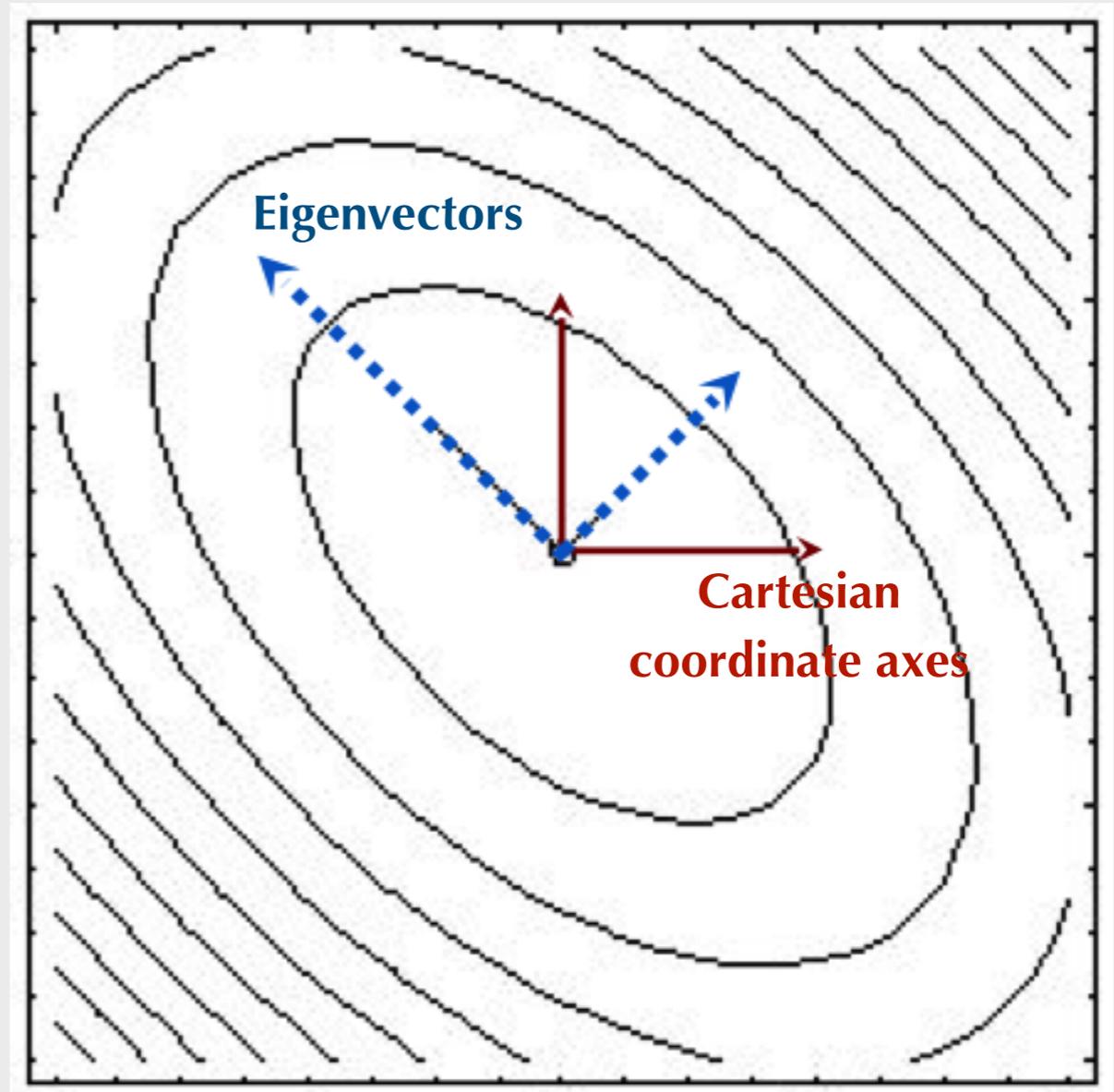
Eigenvectors: principal axes of the (hyper) paraboloid describing the minimum

“Natural” coordinate axes

Deforming along an eigenvector q_1

- produces a 1D vibration involving all the atoms
- has **no effect** on vibration along q_2
 - no rotational component : each $\mathbf{Lq} = \lambda\mathbf{q}$.
- Can thus speak of the energy of that mode.

Orthogonal (normal) modes of vibration



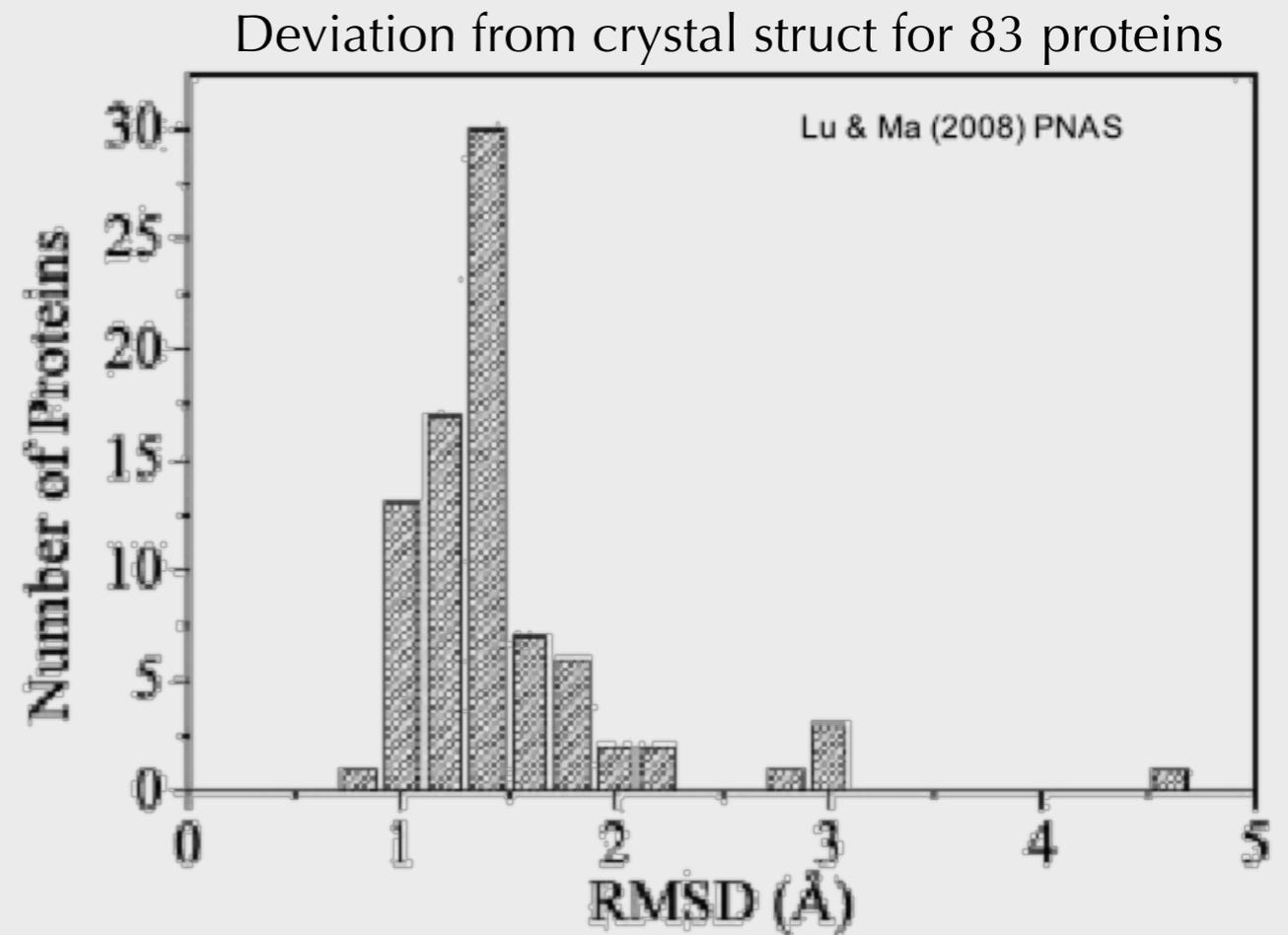
Normal modes summary

Advantages

- Analytical
- Less computationally demanding than MD
- Standard atomic forcefields*
- Identify correlated motions

Disadvantages

- Extensive minimization
 - Can be costly
 - Structural deviation
- Diagonalize large matrices ($3N \times 3N$)
 - Memory/time
- Dependence on initial structure
- Solvent effects poorly incorporated
 - Single solvent configuration if any
 - Heuristic distance-dependent dielectric

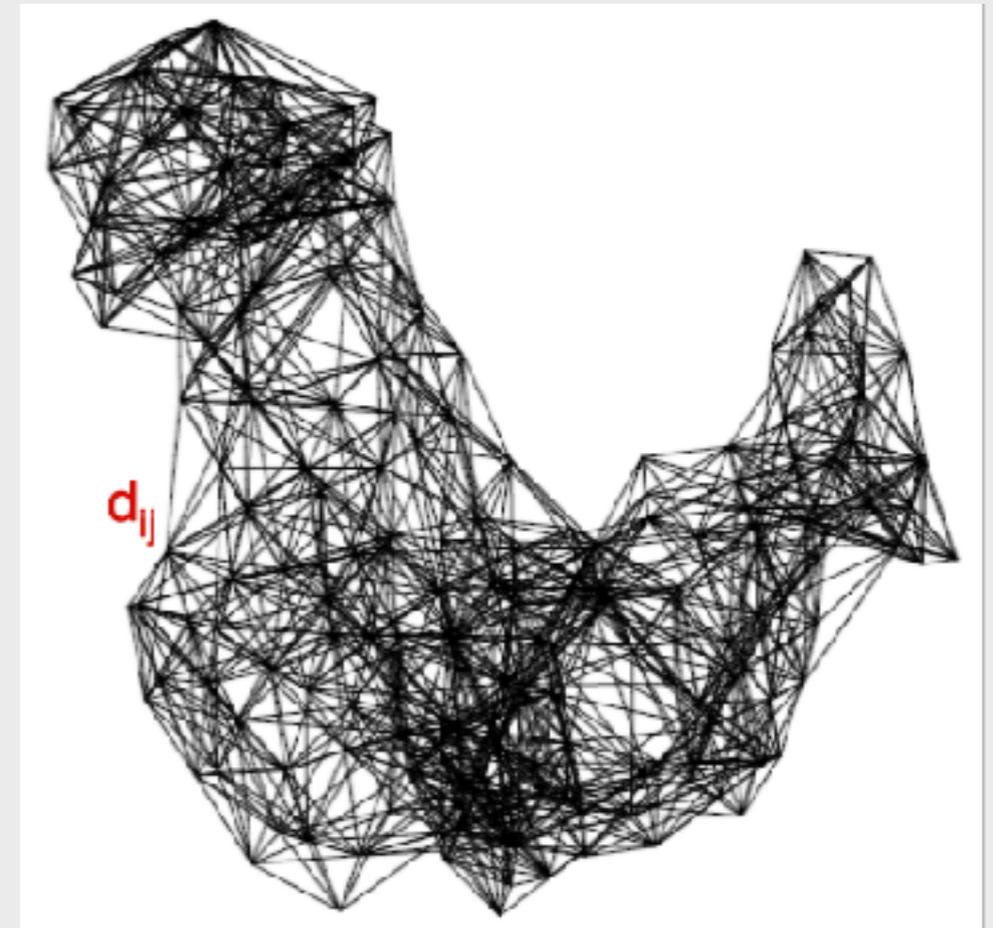


Elastic Network Models (ENM)

$$V_{\text{ENM}} = \sum_{i,j} C_{ij} (d_{ij} - d_{ij}^o)^2 \quad \forall d_{ij} < d_{\text{cutoff}}$$

Simplified harmonic potential

- Based on Tirion (1996) PRL
- d_{ij}^o are from initial structure
 - **no energy minimization**
 - **no structural deviation**
 - **fast**



Global exploration of the EL

Ensemble-less methods
Ensemble approaches

one more thing about NM...

Normal modes information can extend far beyond x_0



In proteins, lowest-frequency NM directions predict directions of conformational change

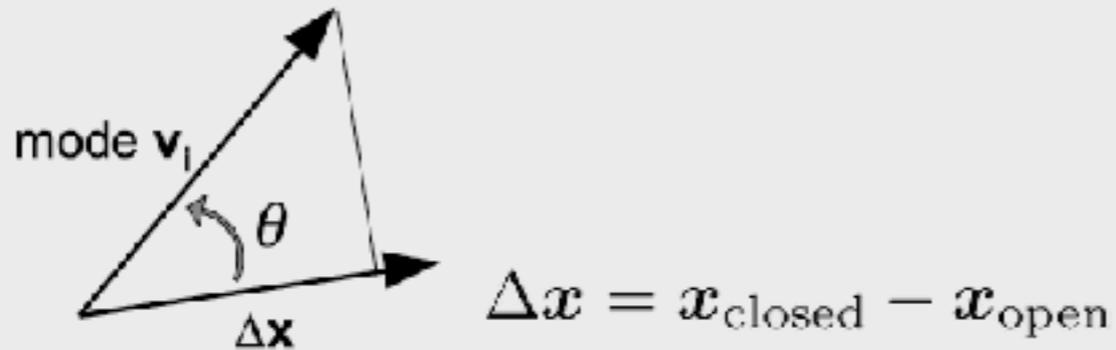
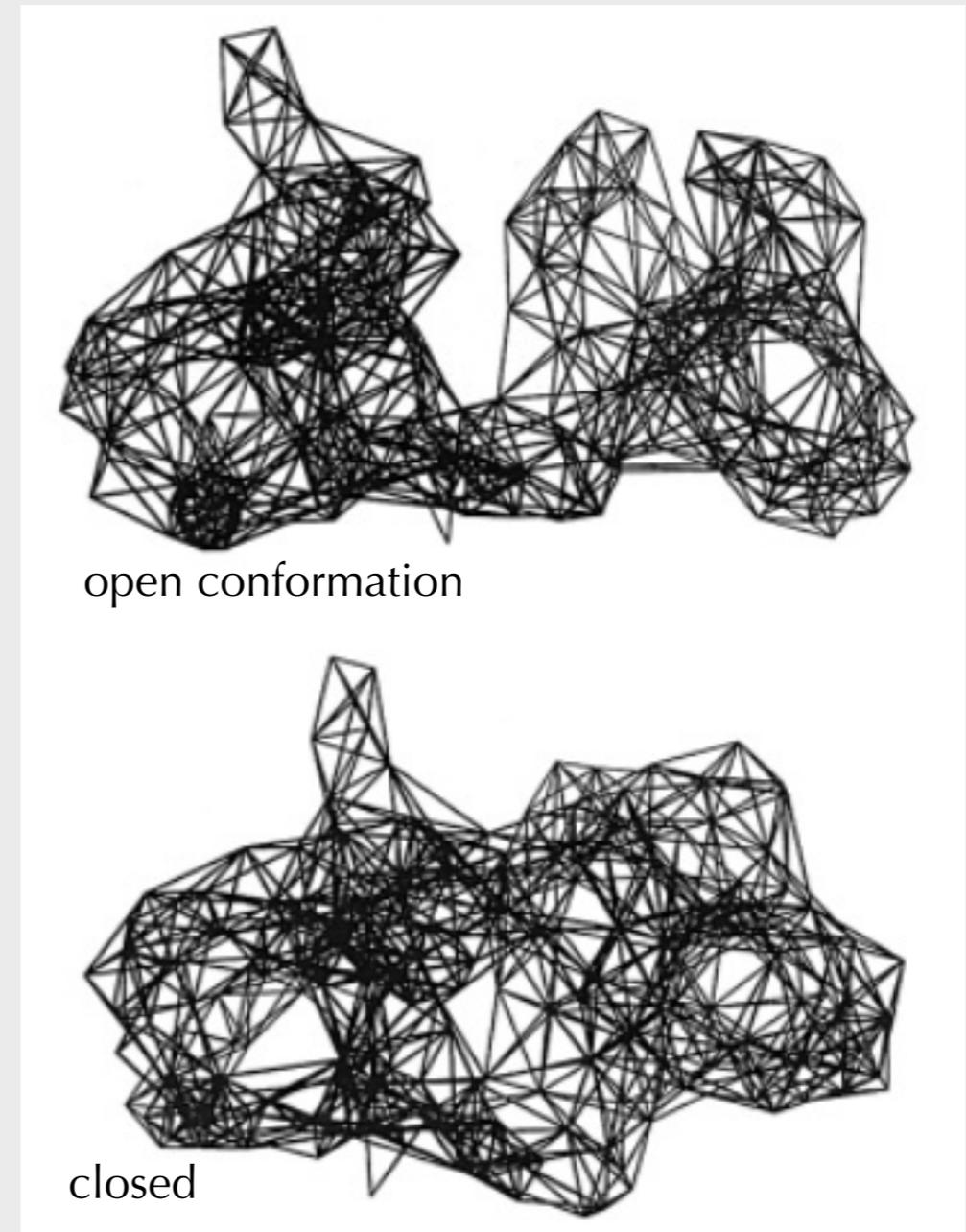


Table III. Overlap of the mode the most involved in the conformational change of proteins of various sizes and motion types, when the ‘open’ or ‘closed’ conformations are considered

Protein	Overlap	
	Open	Closed
Citrate synthase	0.83	0.57
Calmodulin	0.50	0.37
Che Y protein	0.32	0.34
Dihydrofolate reductase	0.72	0.64
Diphtheria toxin	0.58	0.37
Enolase	0.33	0.30
LAO binding protein	0.84	0.40
Triglyceride lipase	0.30	0.17
Maltodextrin binding protein	0.86	0.77
Thymidylate synthase	0.56	0.40



Tama and Sanejouand (2001) Prot Eng 14, 1

Conformational exploration with NM

Displace along eigenvectors

- Random linear combinations
- Displace along a chosen mode(s)
- Restrain projection along chosen mode(s)

Typical applications

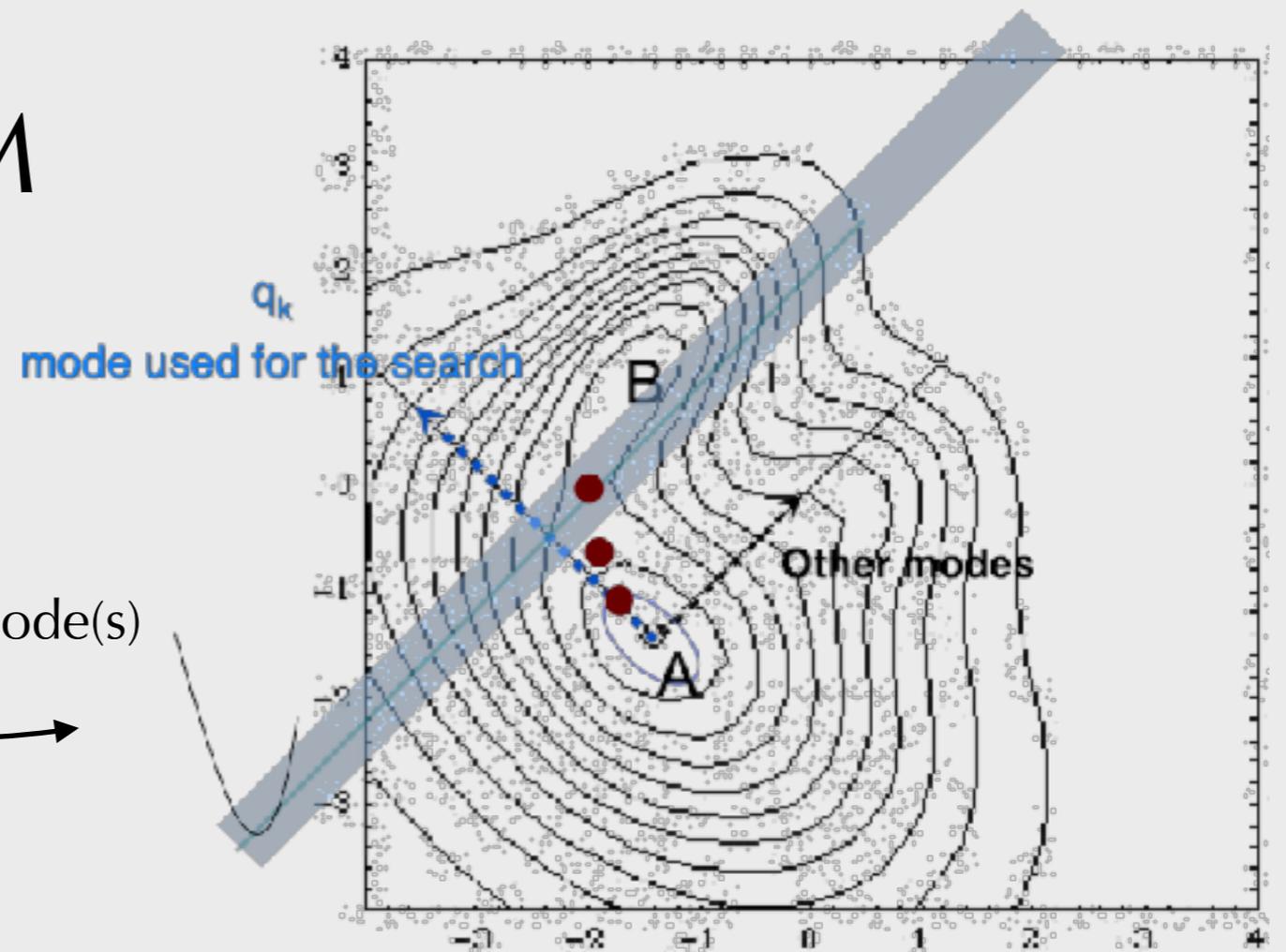
Studying mechanisms

Flexible docking

Crystal structure refinement

Cryo EM

...



see Perahia, Hinson, Sanejouand, Delarue, Zacharias, Chacon, Grudinin ...

Global optimization

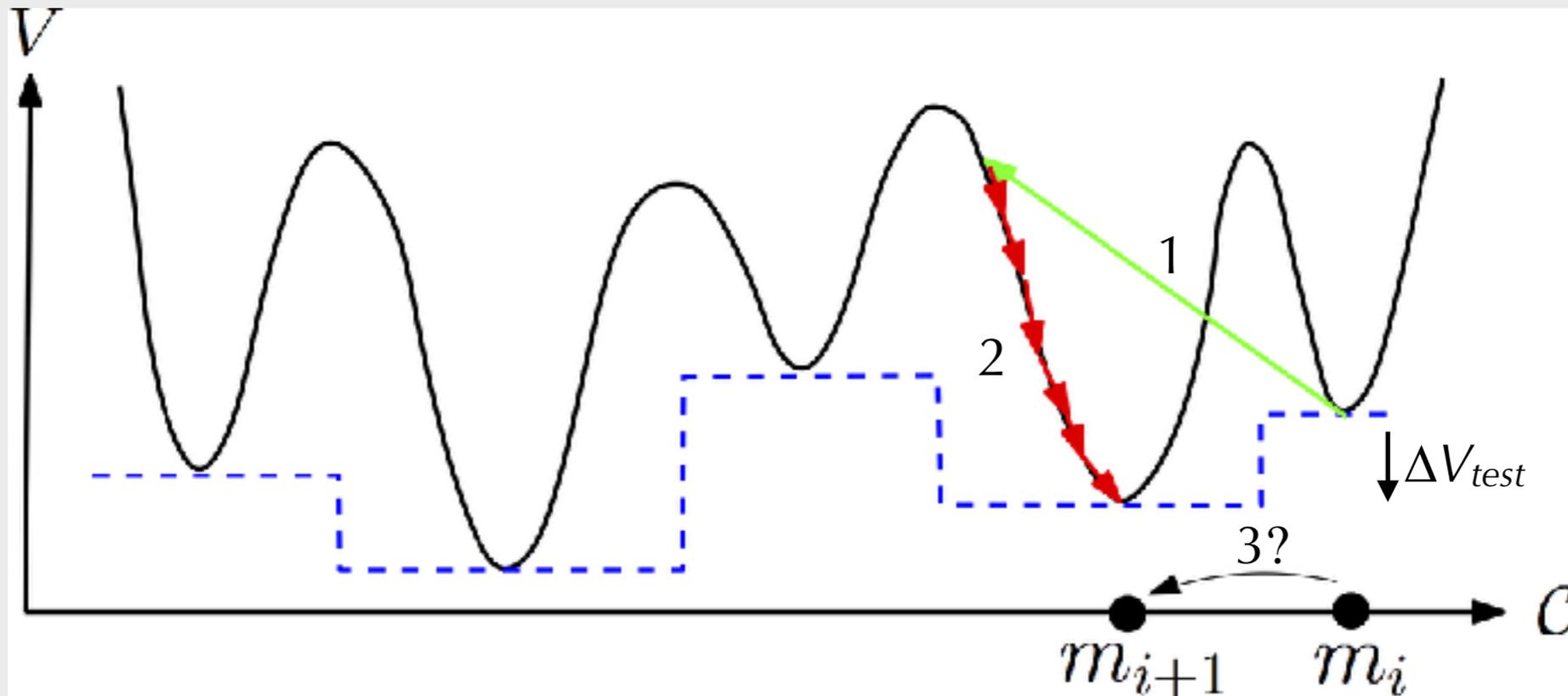
Explicit goal is to find low-energy structures

Structure prediction

Implicit goals:

- Exploration
 - explore far reaches of conformational space
- Exploitation
 - find low-energy structures

Global minimization/exploration with Basin Hopping



aka “Monte Carlo minimization”, Li and Scheraga PNAS 1987

Monte Carlo move followed by minimization before Metropolis test

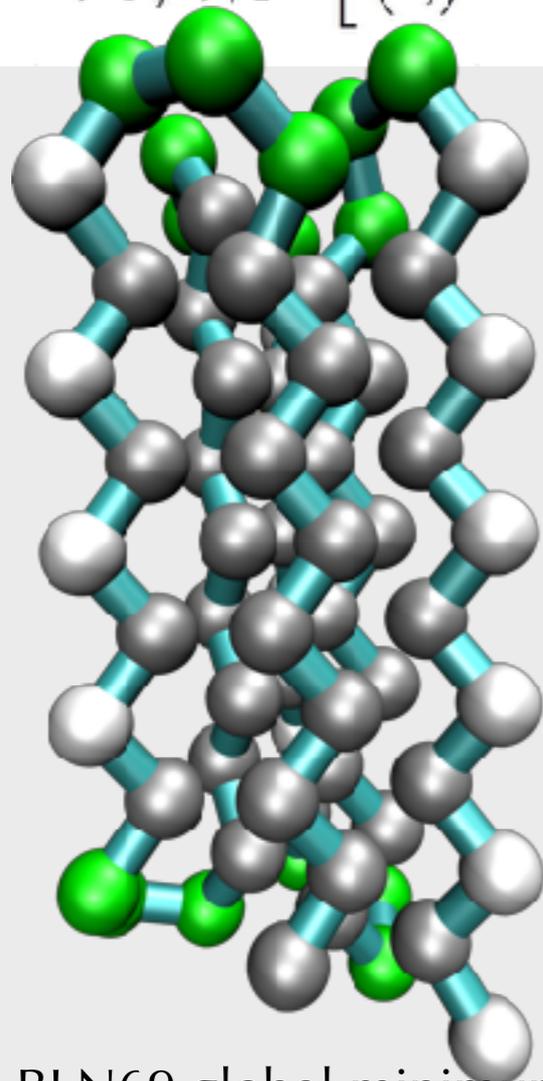
BH transforms EL to remove all barriers

- If unchecked even samples chirality changes
- → Ensemble sampling of transformed surface

Efficient for finding global minimum in somewhat large systems (100 - 1000 atoms)

Frustrated folding of a model protein

$$V_{\text{BLN}} = \frac{1}{2}K_r \sum_{i=1}^{N-1} (R_{i,i+1} - R_c)^2 + \frac{1}{2}K_\theta \sum_{i=1}^{N-2} (\theta_i - \theta_c)^2$$
$$+ \varepsilon \sum_{i=1}^{N-3} [A_i(1 + \cos \phi_i) + B_i(1 + 3 \cos \phi_i)]$$
$$+ 4\varepsilon \sum_{i=1}^{N-2} \sum_{j=i+2}^N C_{ij} \left[\left(\frac{\sigma}{R_{ij}} \right)^{12} - D_{ij} \left(\frac{\sigma}{R_{ij}} \right)^6 \right]$$



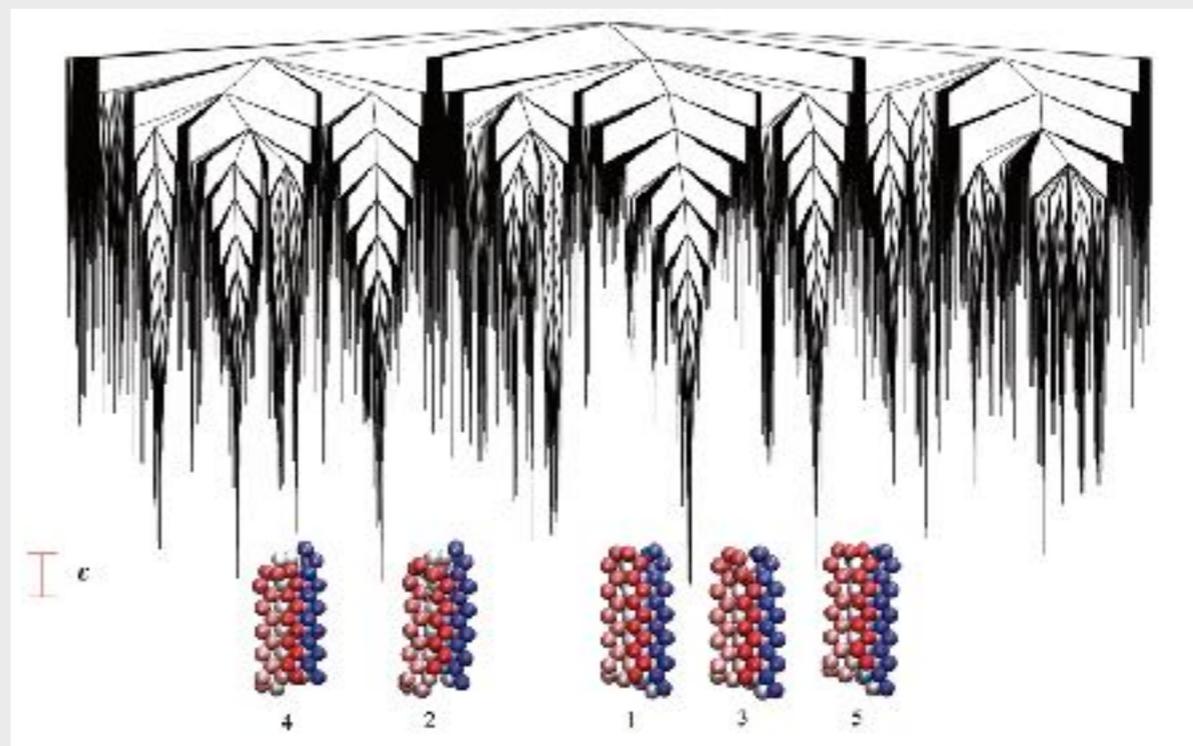
BLN69 global minimum:
a β -barrel

BLN coarse-grained model

- Hydrophobic, hydrophilic, Neutral
- Honeycutt & Thirumalai PNAS (1990)
- Head-Gordon PNAS (2003)

Highly frustrated EL

- Numerous low-energy structures in deep funnels
- Extensive BH studies ($\sim 10^6$ minima)



Oakley, Wales & Johnston J Phys Chem (2011)

BH + Voronoi bias: *hybrid explorer*

Combine two strategies

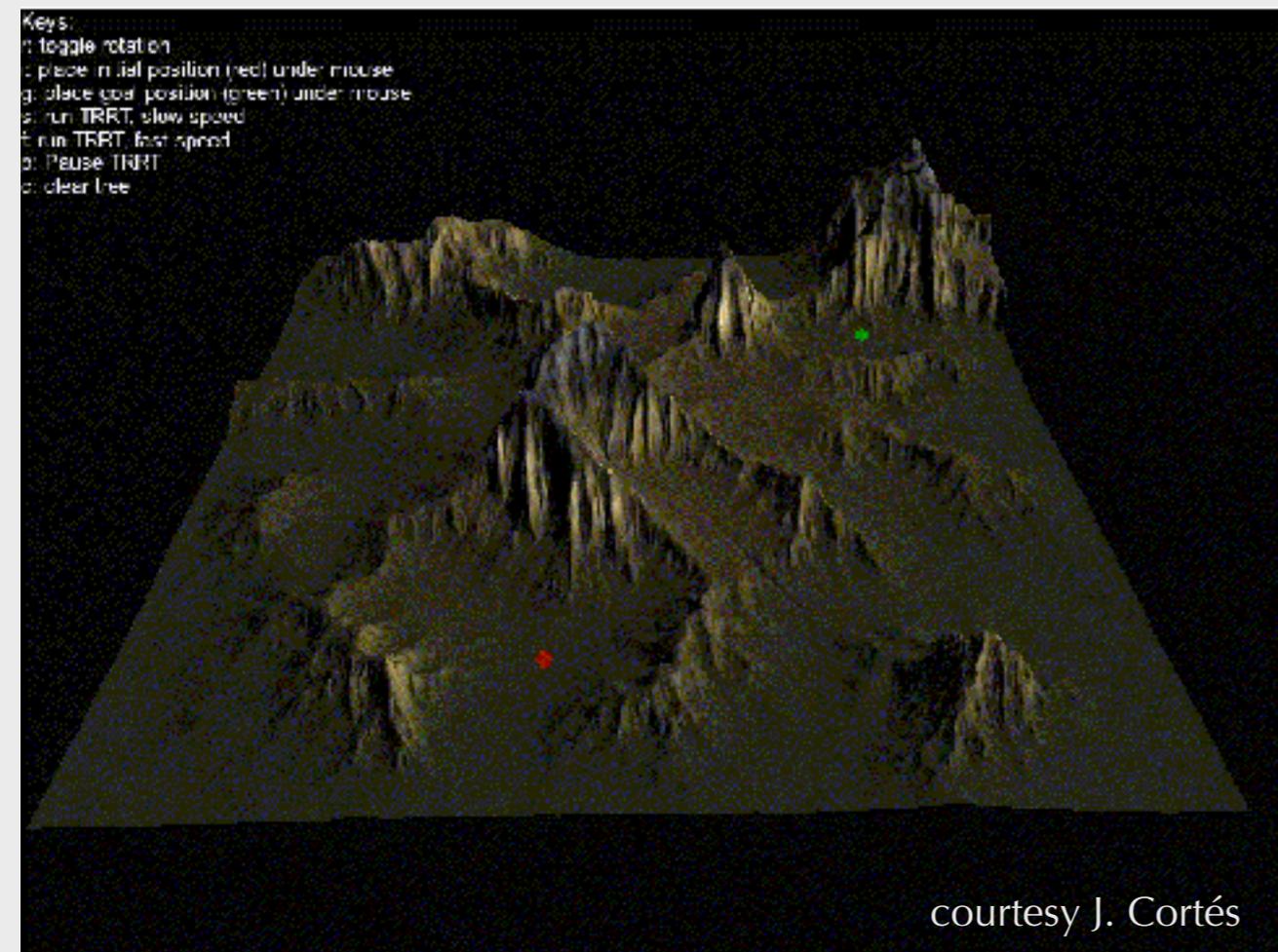
1) **T-RRT**: Voronoi bias (*taboo-ish*)

- Temperature controlled Rapidly-expanding Random Tree
- Jaillet, et al. (2011) J Comp Chem

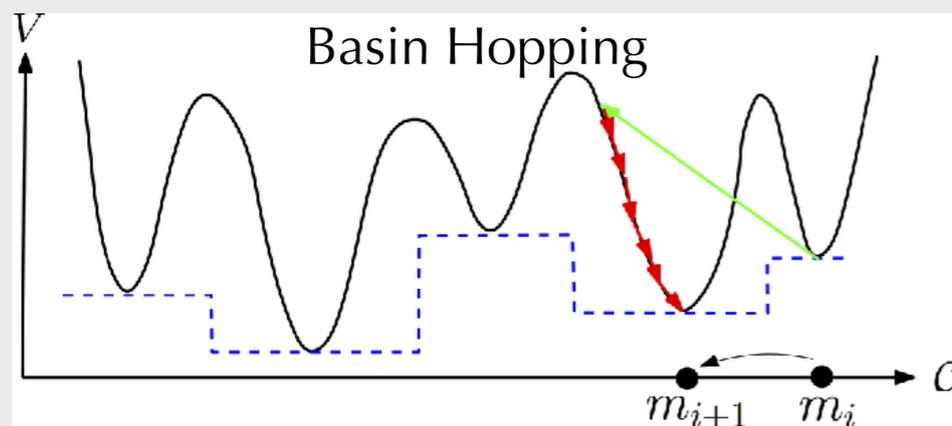
2) Monte Carlo minimization (**Basin Hopping**)

- Li & Scheraga (1987) PNAS

→ Basin hopping threads biased towards unexplored regions



+



Cazals et al. (2015) J Comp Chem
Roth et al. (2016) J Comp Chem

Hybrid explorer efficiently finds low-energy structures

Model system

BLN coarse grained protein model (69 amino acids)

Global minimum known

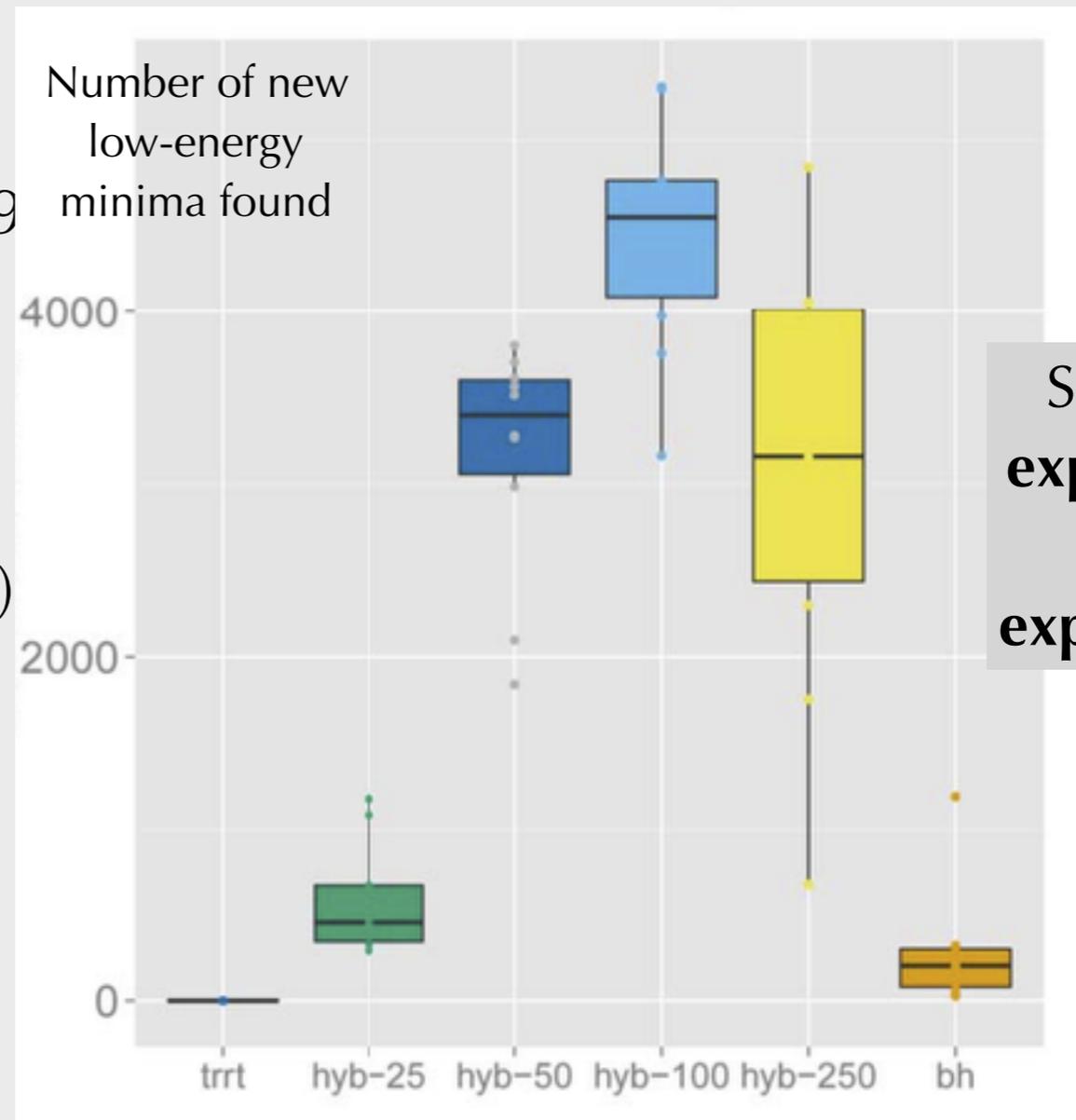
Gold standard database of minimum-energy structures (Oakley, et al. 2011)

Hybrid explorer

More low-energy minima

Wider exploration

Competitive run time



Synergy:
exploration
and
exploitation

...in the SBL

More T-RRT-
like



More basin-
hopping-like

Global minimization algorithms: pluses and minuses

Advantages:

- target low-energy structures (structure prediction)
- broad exploration

Disadvantages:

- no thermodynamic ensemble: averages not related to observables
- In Basin Hopping, MC move sets limiting for compact states

Thermodynamic sampling of the EL

MC or MD allows sampling in a thermodynamic ensemble

Averaging samples allows calculating observable properties

$n(E)$: density of states (energy states)

- A property of the entire energy landscape
- Grows rapidly with E

Boltzmann factor:

- Diminishes rapidly with E

$$W_B(E) = \exp^{-\beta E(X)}$$

Probability distribution:

- Peaks at average energy at T

$$P_{\text{can}}(E; T) \propto n(E) \exp^{-\beta E}$$

Berg and Neuhaus (1992) Phys Rev Lett

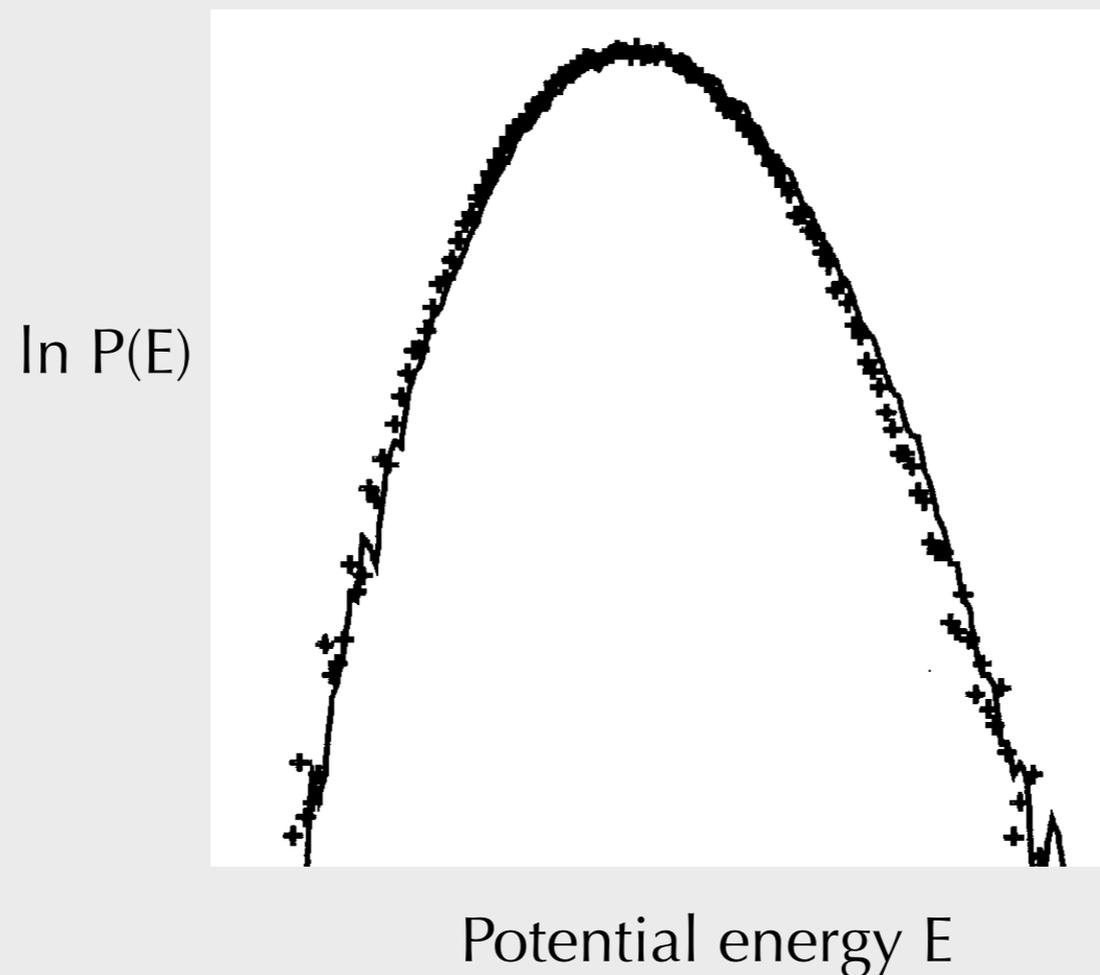
Mitsutake, Sugita & Okamoto (2001) Biopolymers

Canonical sampling

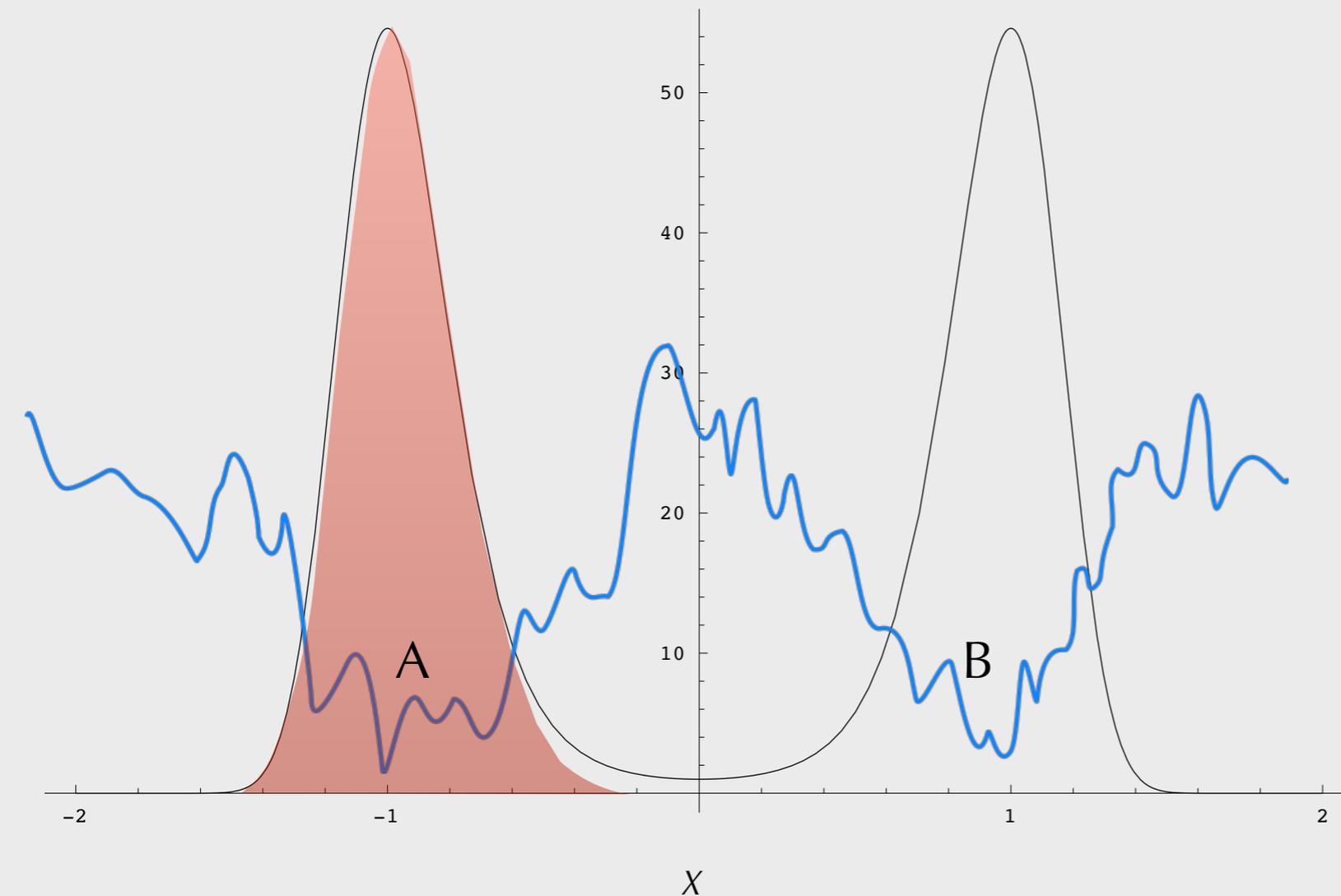
Probability distribution of $E(T)$ is approximately Gaussian around avg E

$$\ln P_{\text{can}} = a - b(E - \bar{E}(T))^2$$

But crossing barriers may require sampling high E transition regions...



Trapping in canonical simulations



- Transition regions are exponentially suppressed
- Simulation remains trapped in local (super-) basin

Here the true $P_{\text{can}}(T)$ is bimodal

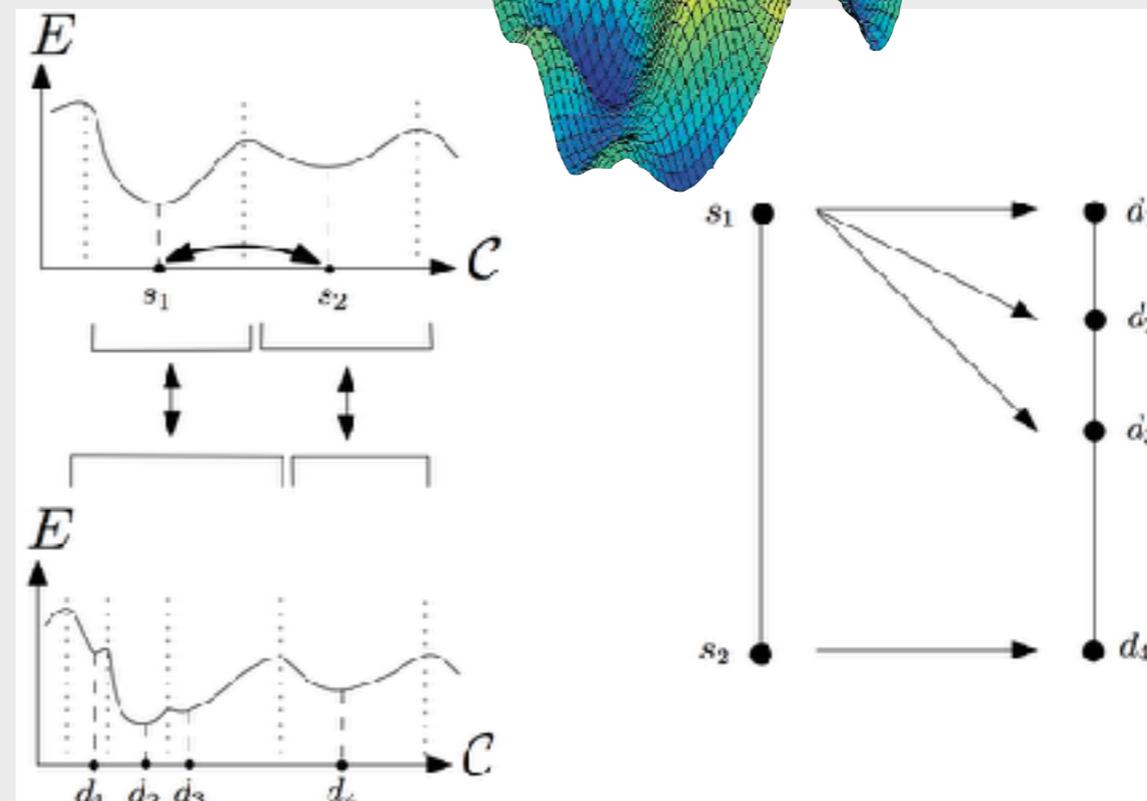
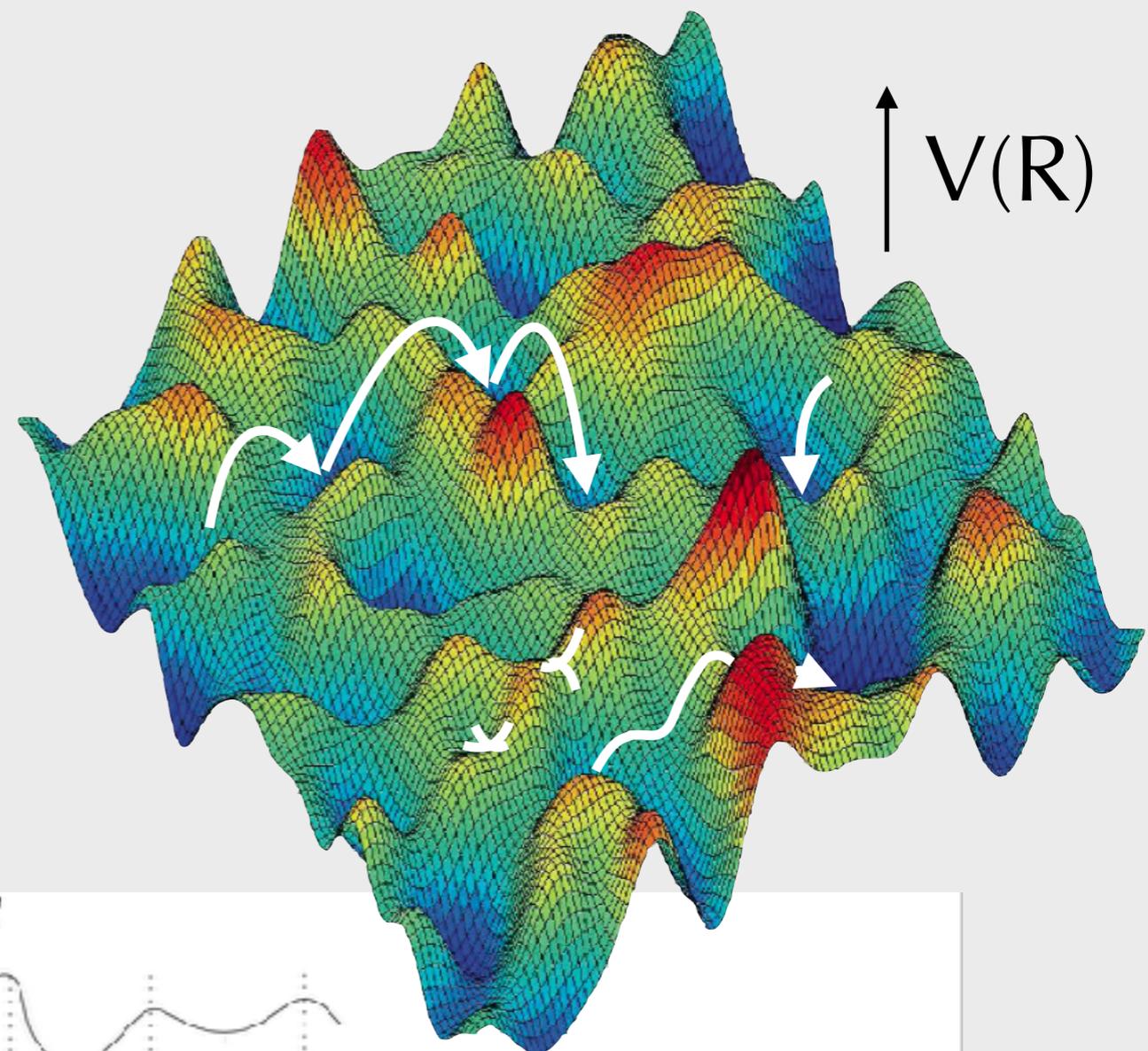
Sampled $P_{\text{sim}}(T)$ is not: poor sampling

Large swaths of the energy landscape may be ignored

→ Other approaches (e.g., REMD) sample better [...]

Summary

1. New and old methods* for exploring the EL of macromolecular systems both locally and globally
2. Ways to accommodate and compare** diverse data in simplified but still rich representations



* including robotics [Juan Cortés]

** ...also in the SBL [Frédéric Cazals]

Comparing 2 EL using the earthmover's distance

(Cazals et al. 2015)

Thanks

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and many others...



...you're done, stop talking