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Exploring Complex Free Energy Landscapes with Wang-Landau Sampling

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- Introduction
- Brief Review: Wang-Landau Algorithm
- Some characteristic problems
 - □ Spin glasses
 - □ "Lattice proteins"
 - □ "Real" proteins
- Conclusions/Outlook

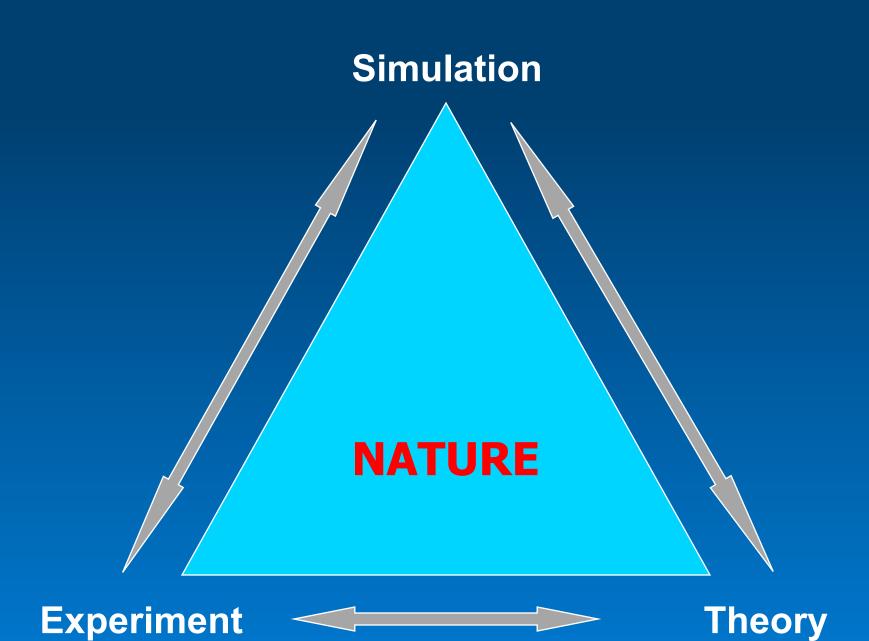


Background and motivation

Many systems in nature have complex or "rough" free energy landscapes in which there are many maxima and minima that may have widely spaced values of relevant thermodynamic parameters.

At "low" temperature, transitions between minima become very infrequent

Almost all models for such systems are impossible to treat analytically!



Reminder from Statistical Mechanics

The *Partition function* contains all thermodynamic

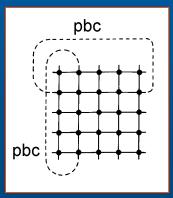
information:

$$Z = \sum_{all \ states} e^{-\mathcal{H}/k_B T}$$

Metropolis Monte Carlo approach: sample states via a random walk in probability space

The "fruit fly" of statistical physics: The Ising model

$$\mathcal{H} = -J \sum_{\langle i,j \rangle} \sigma_i \sigma_j , \quad \sigma_i = \pm 1$$



For a system of N spins have 2^N states!

Single spin-flip sampling for the Ising model

Produce the n^{th} state from the m^{th} state ... relative probability is $P_n/P_m \rightarrow$ need only the *energy difference*, *i.e.* $\Delta E = (E_n - E_m)$ between the states

Any transition rate that satisfies *detailed balance* is acceptable, usually the Metropolis form (*Metropolis et al, 1953*).

$$W(m \rightarrow n) = \tau_o^{-1} \exp(-\Delta E/k_B T), \quad \Delta E > 0$$

= τ_o^{-1} , $\Delta E < 0$

where τ_o is the time required to attempt a spin-flip.

MC Problems and Challenges

Statics: Monte Carlo methods are valuable, but near T_c \Rightarrow *critical slowing down* for 2^{nd} *order* transitions \Rightarrow *metastability* for 1^{st} *order* transitions and for systems with complex energy landscapes

:. Try to reduce characteristic time scales or circumvent them

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University of Georgia Athenian Science Acadamy			
This Simulational Nobel Prize			
Awarded to David Landau			
For Simulation of Outstanding			
work in Physics			
President <u>Kuni fun</u> Vice-President <u>Eddie Julien</u> Treasurer Janua & Yoliano J.			

The "Random Walk in Energy Space with a Flat Histogram" method

or "Wang-Landau sampling"

Wang and Landau, PRL (2001)

Wang-Landau sampling

Random Walk in Energy Space with a Flat Histogram

$$Z = \sum_{\substack{all \\ states}} e^{-\frac{2}{B}/k_B T} = \sum_{\substack{all \\ energies}} g(E)e^{-\frac{2}{B}/k_B T}$$

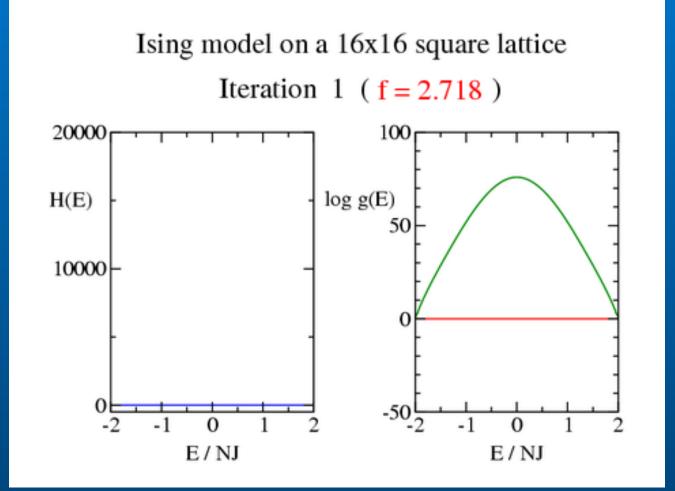
Estimate the *density of states* g(E) directly by performing a random walk in energy space:

- 1. Set g(E)=1; choose a modification factor (e.g. $f_0=e^1$)
- 2. Randomly flip a spin with probability:

bability:
$$p(E_1 \rightarrow E_2) = \min\left(\frac{g(E_1)}{g(E_2)}, \frac{g(E_1)}{g(E_2)}\right)$$

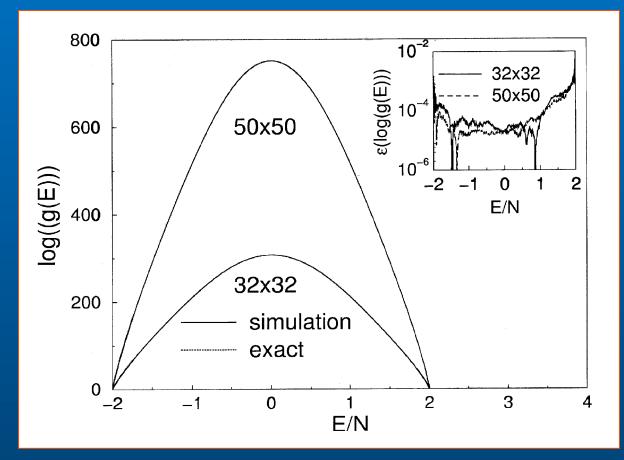
- 3. Set $g(E_i) \rightarrow g(E_i)^* f$, $H(E) \rightarrow H(E) + 1$
- 4. Continue until the histogram is "flat" decrease f, e.g. $f_{i+1} = f^{1/2}$
- 5. Repeat steps 2 4 until $f = f_{min} \sim exp(10^{-8})$
- 6. Calculate properties using final density of states g(E)

Density of States for the 2-dim Ising model



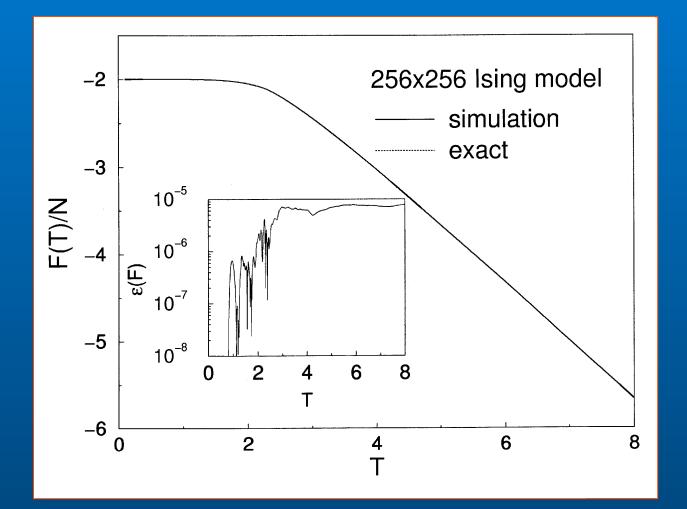
Density of States for the 2-dim Ising model

Compare exact results with data from random walks in energy space: *L*×*L lattices with periodic boundaries*



 ε = relative error (*exact solution is known for L* \leq 64)

Free Energy of the 2-dim Ising Model



 ϵ = relative error

Applications to "Complex" Systems

Spin glasses
"Lattice proteins"
"Real" proteins

A Magnetic System with Complex "Order" The EA (Edwards-Anderson) spin glass model in 3 dim:

$$\mathcal{H} = -\sum_{\langle i,j \rangle} J_{ij} \sigma_i \sigma_j, \sigma_i = \pm 1 \quad and \ J_{ij} = \pm J.$$

At T_c (if it exists) a spin glass state forms \Rightarrow get a "rough" energy landscape where multiple minima are separated by high energy barriers

A Magnetic System with Complex "Order"

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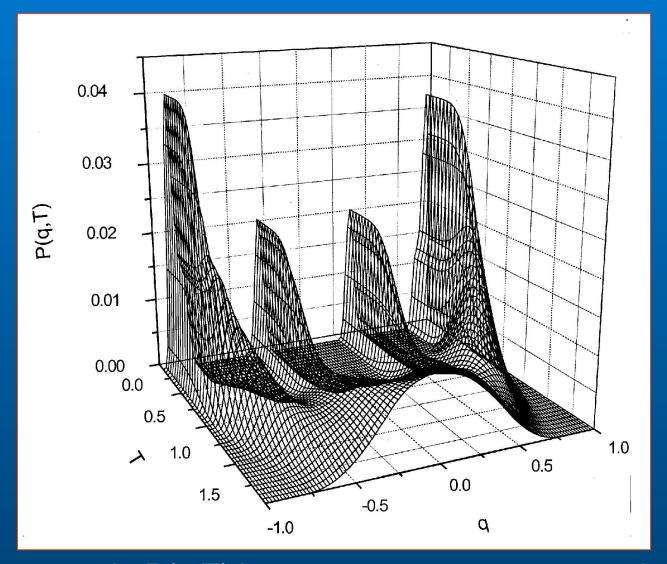
Define an Order Parameter 'q'

Overlap of a configuration with a groundstate . . . but must also take the configurational average over different bond distributions

Extend random walk \Rightarrow two-dimensional parameter space

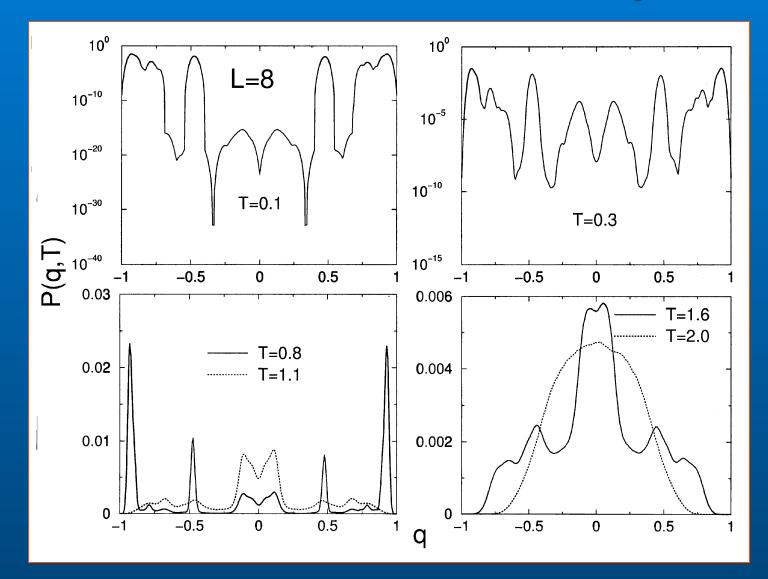
Distribution of States: LxLxL EA Spin Glass

L=6



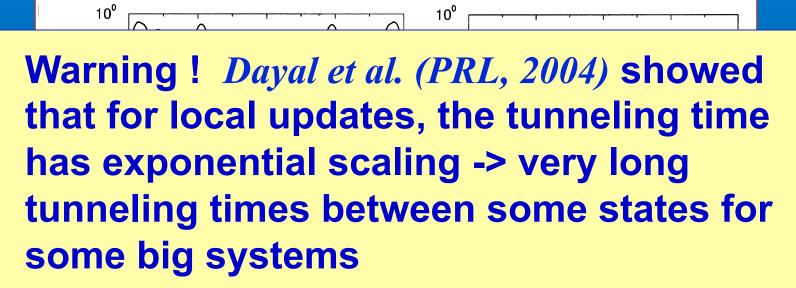
... For larger L, P(q,T) becomes even more complex!

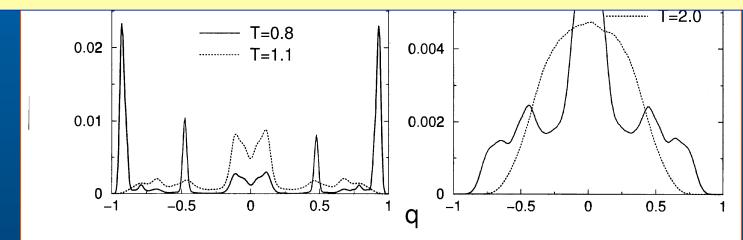
Distribution of States: LxLxL EA Spin Glass



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Distribution of States: LxLxL EA Spin Glass





... For larger L, P(q,T) becomes even more complex!

Groundstate Properties of the 3-d EA **Spin Glass**

Entopy and energy for the *L*×*L*×*L* simple cubic lattice

Wang-Landau sampling

Multicanonical sampling*

L	S_0	E_0	S_0
4	0.075 <u>+</u> 0.027	-1.734 <u>+</u> 0.006	0.0724 <u>+</u> 0.004
6	0.061 <u>+</u> 0.025	-1.767 <u>+</u> 0.024	0.0489 <u>+</u> 0.004
8	0.049 <u>+</u> 0.007	-1.779 <u>+</u> 0.016	0.0459 <u>+</u> 0.003
12	0.053 <u>+</u> 0.001	-1.780 <u>+</u> 0.012	0.0491 <u>+</u> 0.002
16	0.058 <u>+</u> 0.004	-1.776 <u>+</u> 0.004	
20	0.056+0.003	-1.774+0.004	

	${E}_0$
47	-1.7403 <u>+</u> 0.0114
49	-1.7741 <u>+</u> 0.0074
30	-1.7822 <u>+</u> 0.0081
23	-1.7843+0.0030

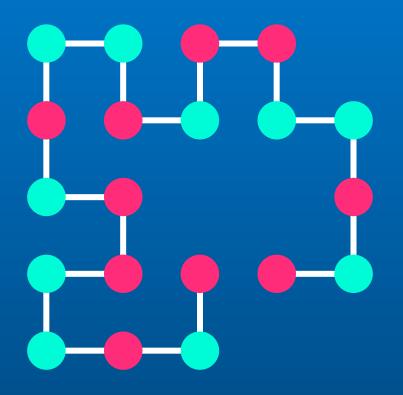
* Berg, Celik, and Hansmann (1993)

Applications to "Complex" Systems

Spin glasses *"Lattice proteins" "Real" proteins*

A Biological "Grand Challenge": Protein Folding

Real proteins are long polymers with side chains of different types and complicated interactions \Rightarrow simplify . . . but how much? A "Biologically inspired" problem The HP model of protein folding

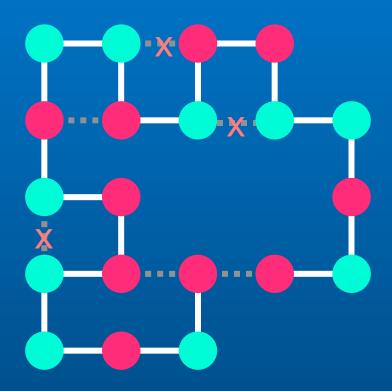


Amino acid = "bead"

Hydrophobic (H)Polar (P)

Protein sequence = "HPHPPHHPPP..."

Protein conformation = "self-avoiding walk" on a lattice, e.g. square (2D), cubic (3D) A "Biologically inspired" problem The HP model of protein folding



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Nearest-neighbor interactions between non-covalently bound neighbors

 $E_{HH} = -1, E_{HP} = 0, E_{PP} = 0 \implies$

Compact hydrophobic core / polar (hydrophilic) shell

(Dill, Biochemistry 1985; Lau, Dill, Macromolecules 1989)

A "Biologically inspired" problem The HP model of protein folding

Amino acid = "bead"

Hydrophobic (H)

Polar (P)

Protein sequence = "HPHPPHHPHPP..."

walk"

3D)

Sequences are chosen to mimic real proteins

Nearest-neighbor interactions between non-covalently bound neighbors

 $E_{HH} = -1, E_{HP} = 0, E_{PP} = 0 \implies$

Compact hydrophobic core / polar (hydrophilic) shell

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Wang-Landau sampling with pull moves

The importance of move sets

Local moves:

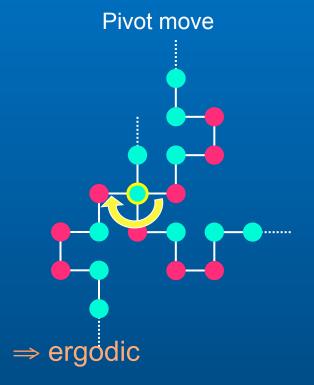
End flip (1 bond)

Kink flip (2 bonds)

Crankshaft (3 bonds)

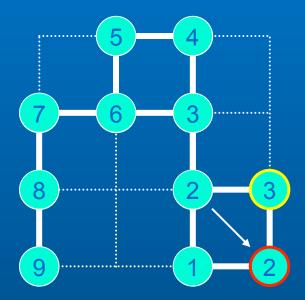


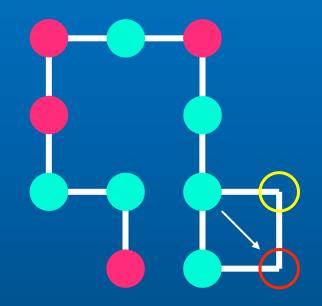
Non-local moves:



... but inefficient for dense conformations \Rightarrow high rejection probability Wang-Landau sampling with pull moves

Pull moves



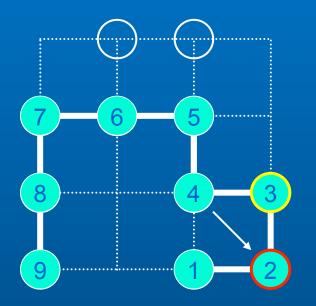


multi-bead move (Completes internally) multi-bead move (Pulls until the end of the sequence)

(Lesh et al., 2003)

Wang-Landau sampling with pull moves

Pull moves



Extensible to any dimension

Ergodic (complete)

Reversible $\Rightarrow n(A \rightarrow B) = n(B \rightarrow A)$ (detailed balance!)

No time-consuming selfavoidance test required

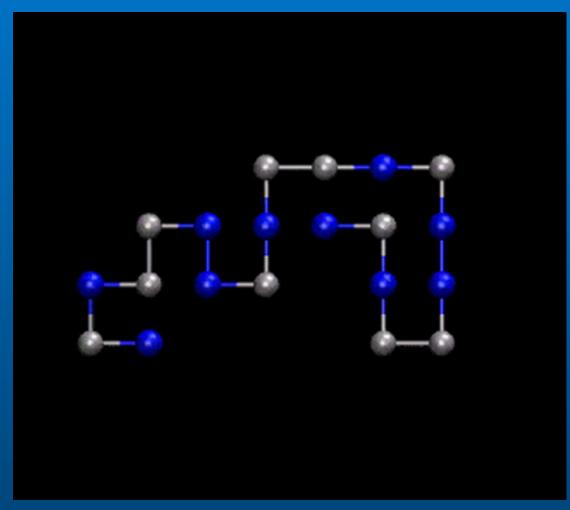
Good balance: local ↔ non-local "Close-fitting"

 \Rightarrow High acceptance ratio

⇒ Ideal for Wang-Landau sampling

Wang-Landau sampling of the HP model

• With pull moves

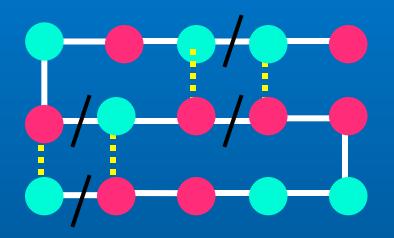


"Cut and join" moves

Initial HP configuration

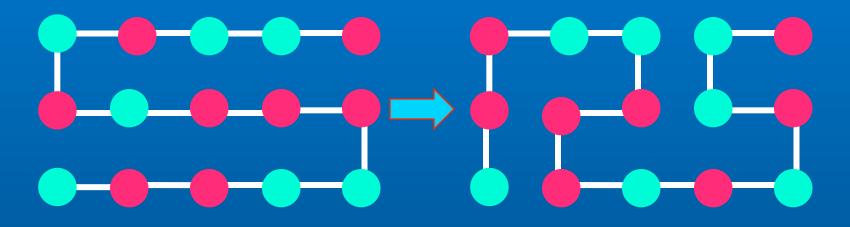
(Deutsch, J. Chem. Phys. 1997)

"Cut and join" moves



(Deutsch, J. Chem. Phys. 1997)

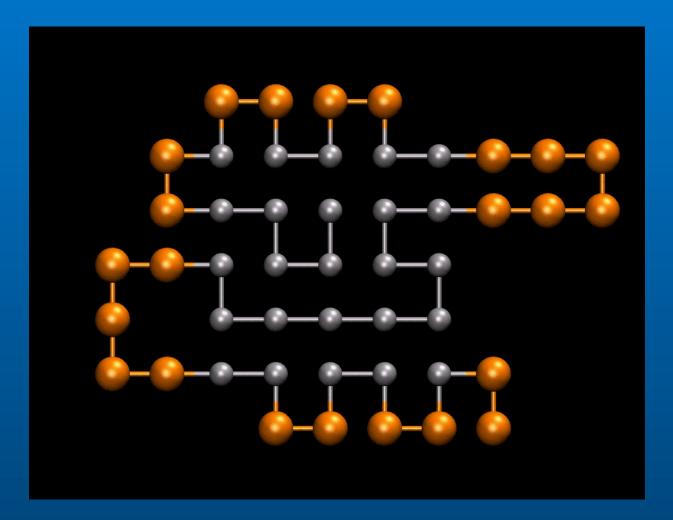
"Cut and join" moves



Note: For the HP model, the sequence of H's and P's **must** be maintained

(Deutsch, J. Chem. Phys. 1997)

"Cut and join"



Wang-Landau sampling of the HP Model 64mer in 2 dimensions (square lattice) Seq2D64

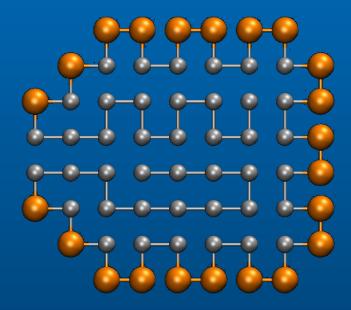
Ground state search

- Core directed chain-growth (Beutler, Dill 1996)
- PERM (Bastolla et al. 1998)

Density of states

- Multi-self-overlap ensemble (MSOE) (Chikenji et al. 1999)
- Equi-energy sampling (EES) (Kou et al. 2006)

Ground state (E = -42)



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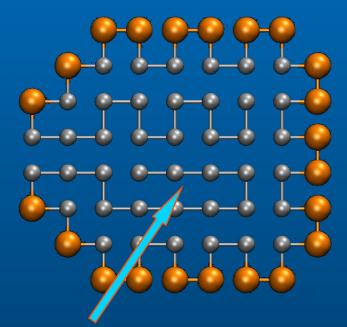
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Hydrophobic core

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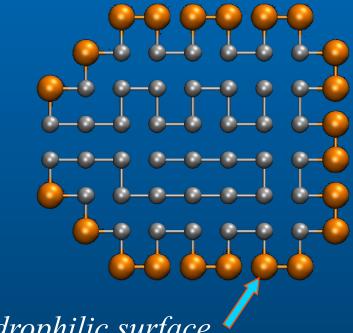
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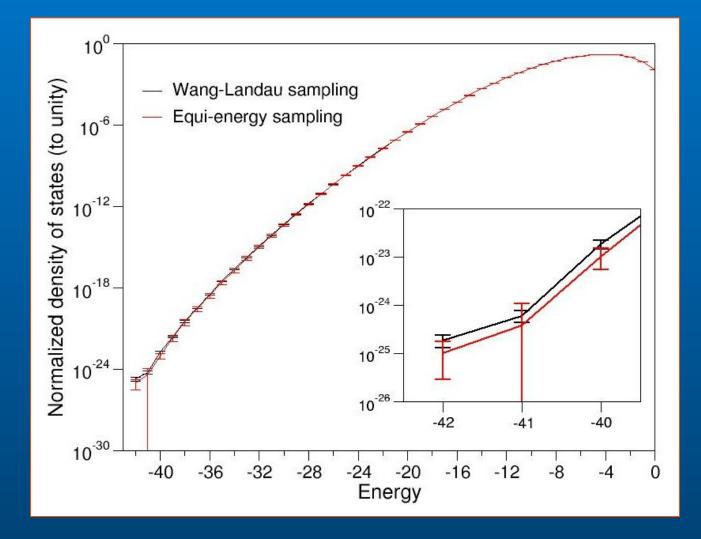


Hydrophilic surface

A "Biologically inspired" problem

The HP Model of Protein Folding

Seq2D64

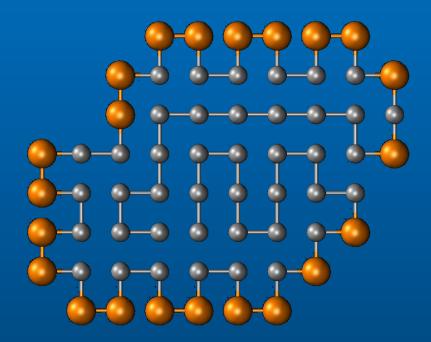


64er in 2 dimensions (square lattice)

Seq2D64

Ground state (E = -42)

 1^{st} excited state (E = -41)**



** highly degenerate

Wang-Landau Sampling of the HP model 103mer in 3 dimensions (simple cubic lattice) Seq3D103

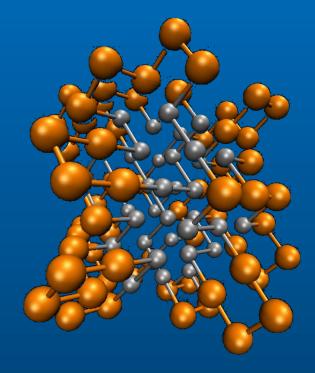
Ground state search

• Fragment regrowth MC (Zhang, Kou et al. 2007)

Density of states

• Multicanonical chain-growth (MCCG) (Bachmann, Janke 2003 / 2004)

Ground state (E = -58)

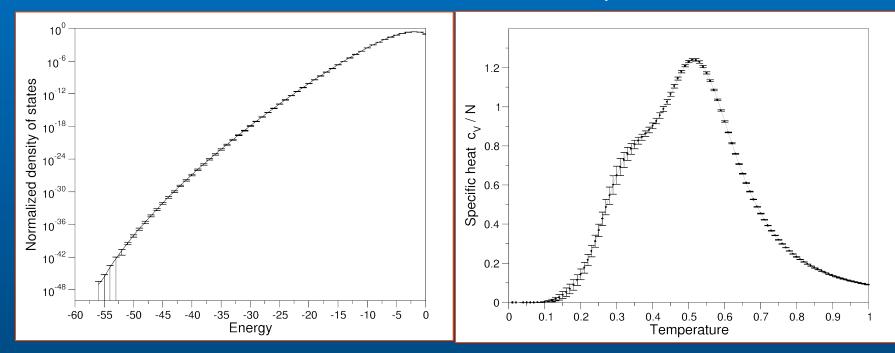


Seq3D103: Thermodynamic properties

Two-step folding process

Density of states

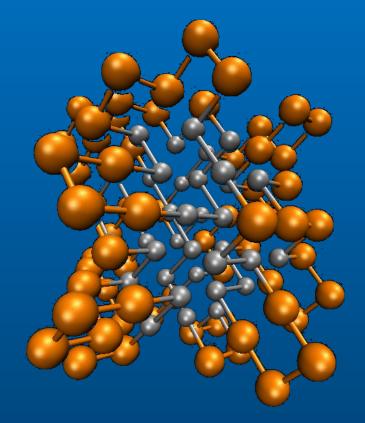
Specific heat



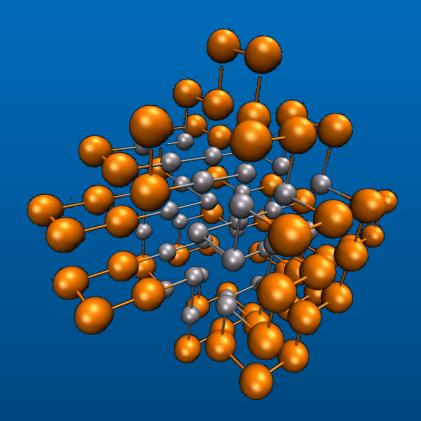
5 runs ≈ 80h_{CPU} / run

103mer in 3 dimensions (cubic lattice)

Ground state (E = -58)



 1^{st} excited state (E = -57)

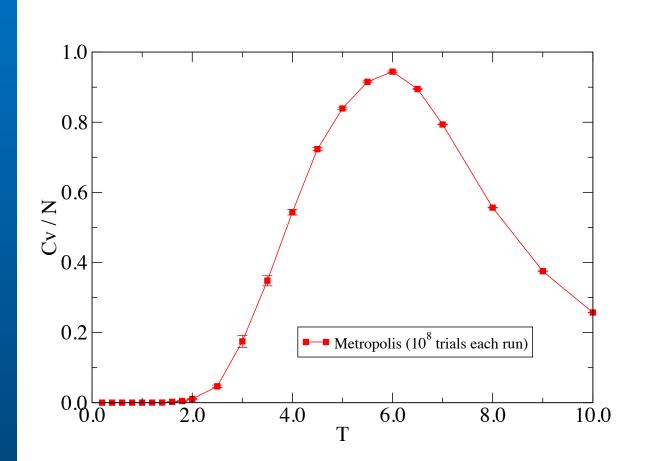


Now introduce an attractive surface:

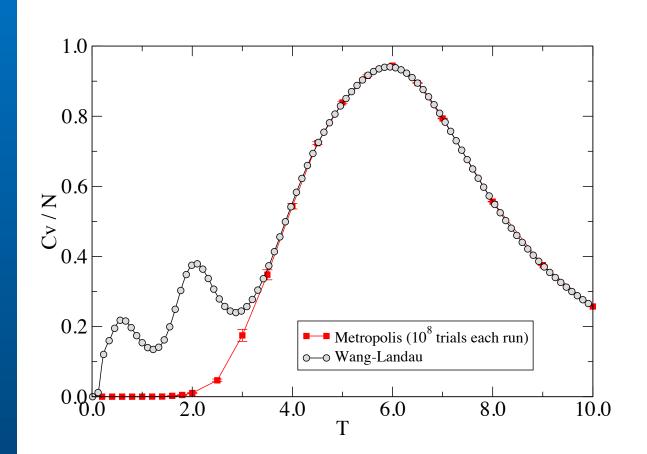
 $E_{HH} = H - H$ bond interaction energy $E_{SH} = H - surface$ interaction energy $E_{SP} = P - surface$ interaction energy

We have studied $E_{SH} = E_{SP}$, but other surfaces can be easily simulated !

36mer in 3 dimensions (cubic lattice) with a surface $E_{SH} = E_{SP} = E_{HH}/12$

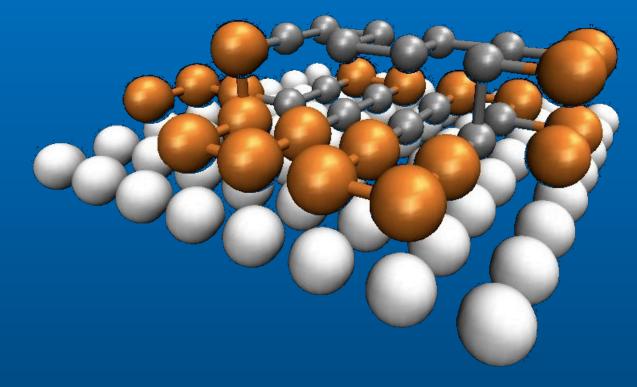


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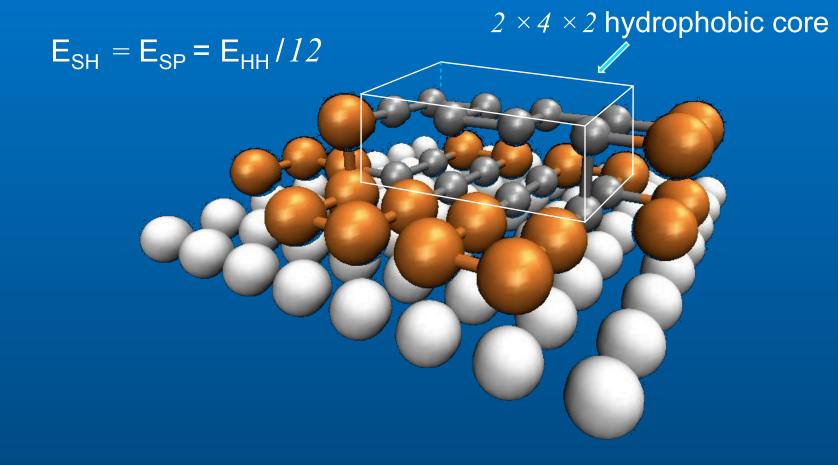


36mer in 3 dimensions (cubic lattice) with a surface

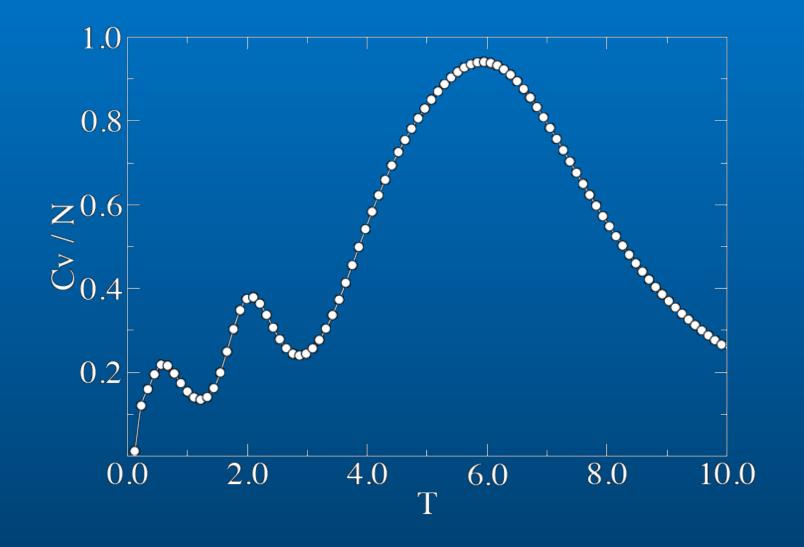
$E_{SH} = E_{SP} = E_{HH} / 12$



36mer in 3 dimensions (cubic lattice) with a surface



36mer in 3 dimensions (cubic lattice) with a surface $E_{SH} = E_{SP} = E_{HH} / 12$



36mer in 3 dimensions (cubic lattice) with a surface $E_{SH} = E_{SP} = E_{HH} / 12$ 1.0 0.8 $\frac{2^{0.6}}{2_{0.4}}$ 0.2 2.0 4.0 8.0 10.0 0.0 6.0

36mer in 3 dimensions (cubic lattice) with a surface $E_{SH} = E_{SP} = E_{HH} / 12$ 1.0 0.8 $\frac{2^{0.6}}{2_{0.4}}$ 0.2 2.0 4.0 8.0 10.0 0.0 6.0

36mer in 3 dimensions (cubic lattice) with a surface $E_{SH} = E_{SP} = E_{HH} / 12$ 1.0 0.8 0.2

0.0 2.0 4.0 6.0 8.0 10.0 T

36mer in 3 dimensions (cubic lattice) with a surface $E_{SH} = E_{SP} = E_{HH} / 12$ 1.0 0.8 0.2 2.0 10.0 4.0 8.0 6.0 Т Groundstate

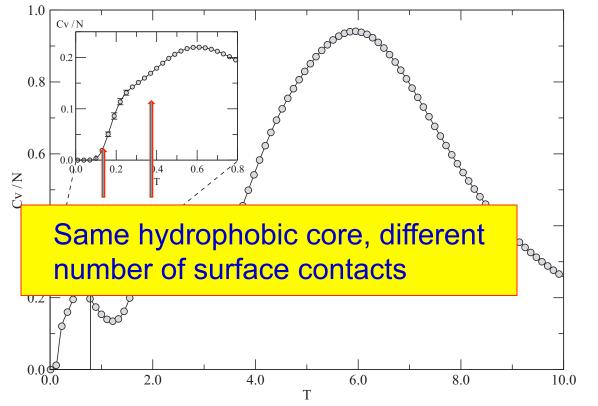
36mer in 3 dimensions (cubic lattice) with a surface $E_{SH} = E_{SP} = E_{HH} / 12$

Specific heat of 36mer, 3D with a surface attractive to both H & P monomers ($\epsilon/\epsilon_s = 12$) p = 0.8, $f_{min} = 10^{-8}$, 20% pull moves, 80% bond-rebridging 1.0 Cv/N0000 poor 0.2 0.8 0.1 0.6 0.2 0.4 0.6 Cv / N°°°°°°°°°°°°°°°°° 0.4 0.2 0.0 2.0 4.0 6.0 8.0 10.0

Т

36mer in 3 dimensions (cubic lattice) with a surface $E_{SH} = E_{SP} = E_{HH} / 12$

Specific heat of 36mer, 3D with a surface attractive to both H & P monomers ($\epsilon/\epsilon_{s} = 12$) p = 0.8, f_{min} = 10⁻⁸, 20% pull moves, 80% bond-rebridging



Applications to "Complex" Systems

Spin glasses
"Lattice proteins"
"Real" proteins

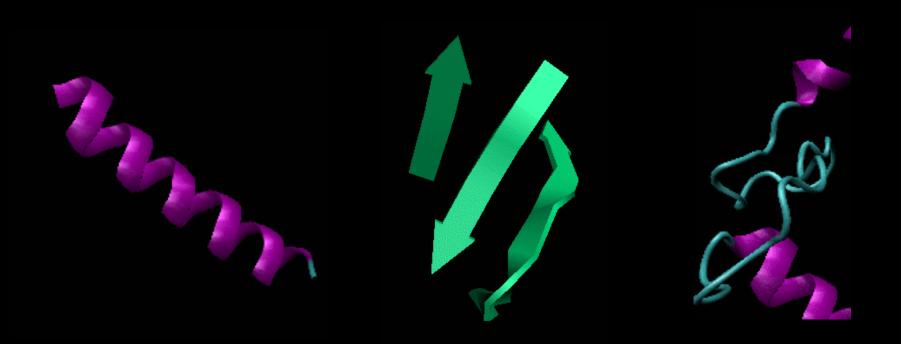
What is a protein?

Primary structure: Sequence of amino acid residues

EITLIFGVMAGVIGTILLISY

What is a protein?

Secondary structure: H-bonds of backbone atoms



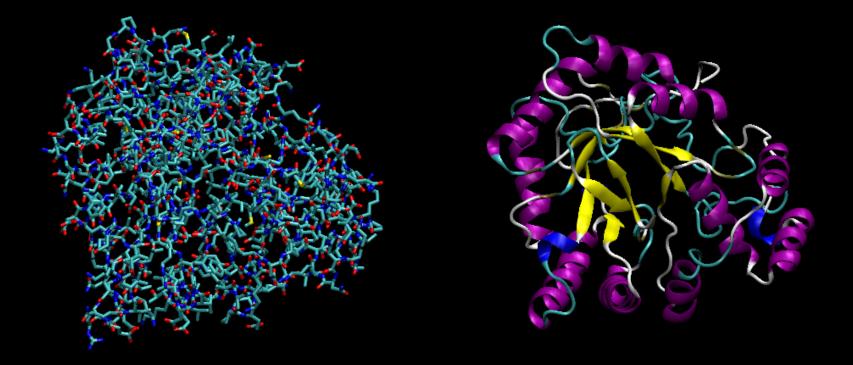
Alpha-helix

Beta-sheet



What is a protein?

Tertiary structure: 3-dim arrangement of atoms



balls & sticks

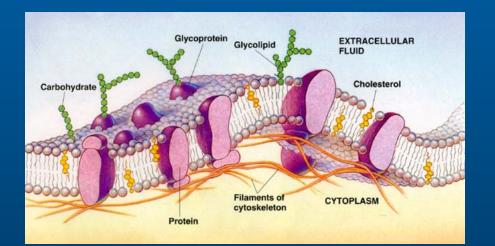
helices & arrows

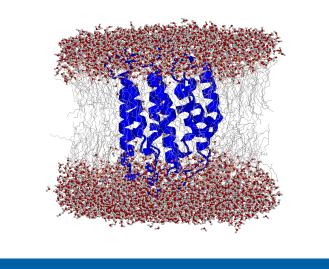
What is a membrane protein?

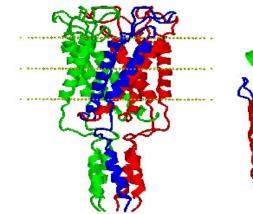
Roles in biological process:

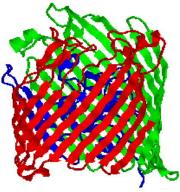
- Receptors;
- Channels, gates and pumps;
- Electric/chemical potential;
- Energy transduction

> 50% new drug targets are membrane proteins (MP).







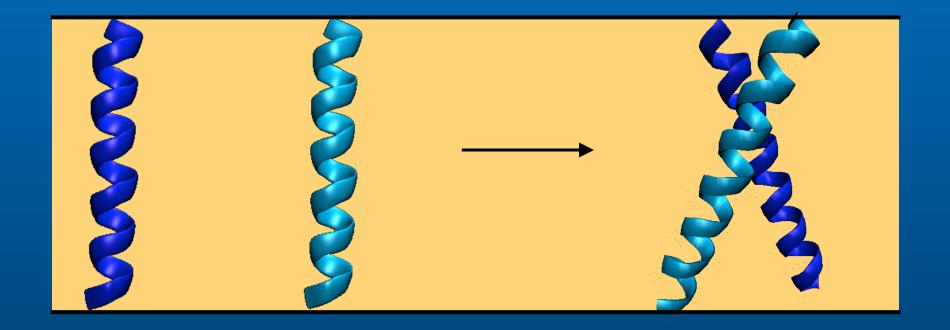


Helical structure

Beta structure

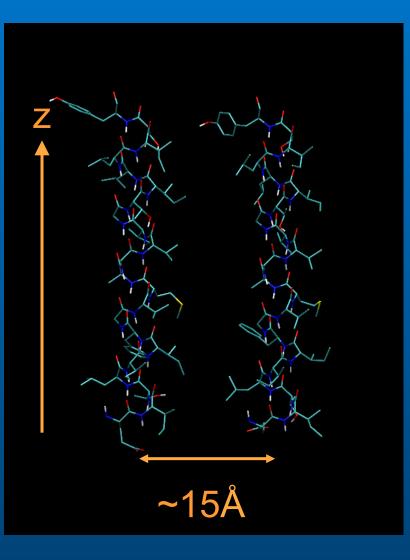
Folding process of GPA

Single helix stable in the membraneAssociation of helices



(Popot, Engelman, Biochemistry, 1990)

Wang-Landau sampling of a GPA model*



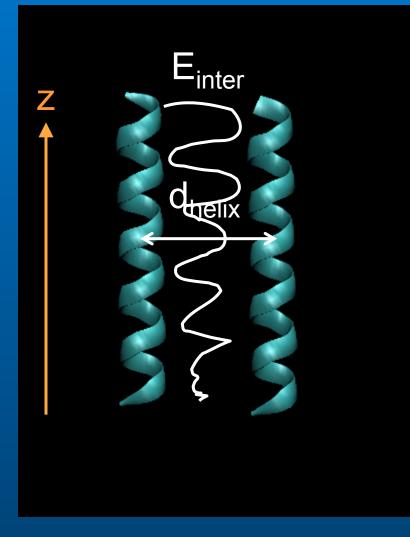
>Unified-atom model
>Total: 368 atoms
>2 helices (22 amino-acids)

• Energy :

- CHARMM19
- Lipid potential
- Starting structure: parallel helices
- 7 Monte Carlo Moves: protein, helix, side-chain

*with Claire Gervais, IOB

Observables for GPA The HP model of protein folding

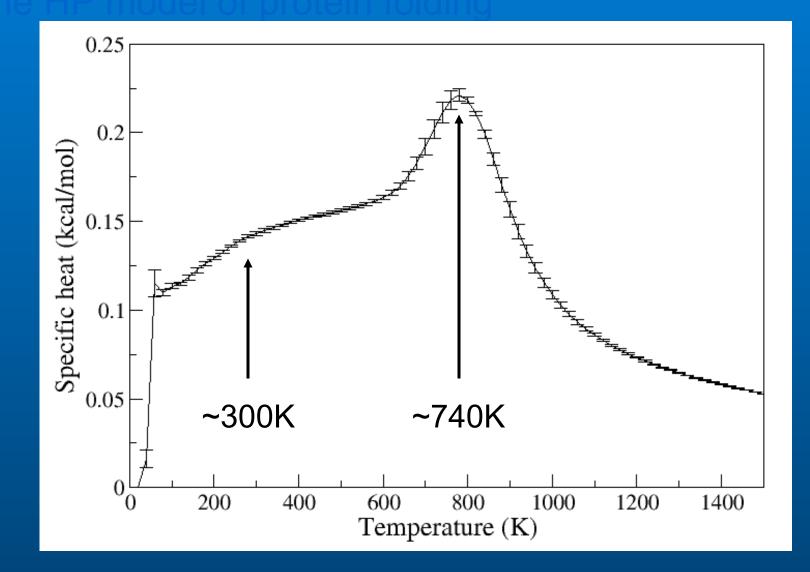


 helix-helix nonbond energy (E_{inter})

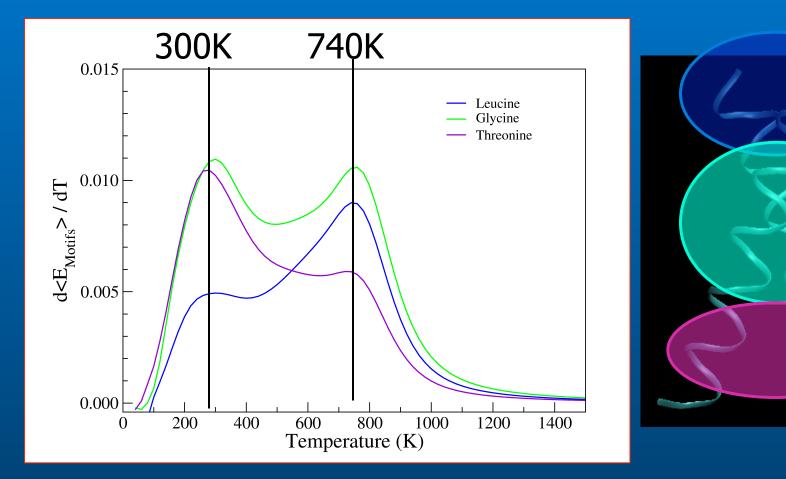
helix-helix distance (d_{helix})

• RMSD of C_{α} atoms

Specific heat



Results for GPA



Convergence towards native contacts dependent on position in structure

GPA Results

Study residue energies, heat capacities, etc.:

- First native contacts appear at ~740K
- Final native contacts at ~300K

 \rightarrow Gradual convergence to the native state

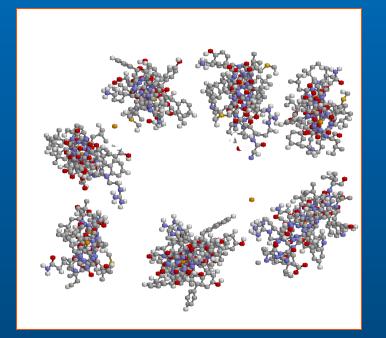
• Appearance of native contacts: Leucine \rightarrow Glycine \rightarrow Threonine

 \rightarrow Hierarchical acquisition of the native state

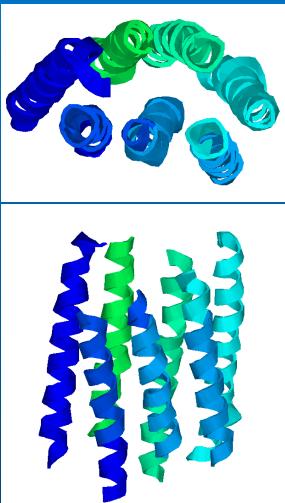
Docking of Bacteriorhodopsin

7 helices, 174 residues, 1619 atoms

- Rigid side-chains
- VDW + lipid-helix potential
- One month CPU time at f=2.781



(Zhong Chen, IOB, UGA)



A GEM structure with rmsd=3.0 Å was obtained in the self-assembly simulation of a 7-helix bundle

Summary

Systems with complex free energy landscapes are particularly challenging for computer simulations. Inventive Monte Carlo algorithms are beginning to make them accessible.

Characteristic examples include:

- Spin glasses (no connectivity constraints)
- "Lattice proteins" (rich, minimalistic model)

• Real proteins (force fields remain a problem)

Summary/Outlook

Systems with complex free energy landscapes are particularly challenging for computer simulations. Inventive Monte Carlo algorithms are beginning to make them accessible.

Parting thought: Research in coming decades will focus on complex systems. Inventive algorithms, together with petaflop/exaflop computers, offer great promise for the future.

Acknowledgments

Collaborators: Y.-W. Li F. Wang T. Wüst C. Gervais Y. Xu IOB, U. of Georgia

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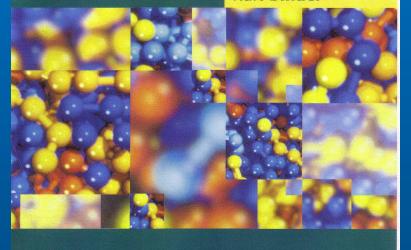
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THIRD EDITION

Learn more about Monte Carlo,

A Guide to **Monte-Carlo Simulations** in **Statistical Physics David P. Landau &** Kurt **Binder**



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