

# Optimized statistical ensembles

for slowly equilibrating classical and quantum systems

IPAM, January 2009

Simon Trebst  
Microsoft Station Q  
University of California, Santa Barbara

**Collaborators:** David Huse, Matthias Troyer, Emanuel Gull,  
Helmut Katzgraber, Stefan Wessel, Ulrich Hansmann

# Motivation

---

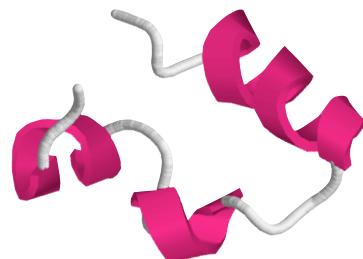
Many interesting phenomena in complex many-body systems  
arise only in the presence of

- **multiple energy scales**
- **complex energy landscapes**
- **slow equilibration**

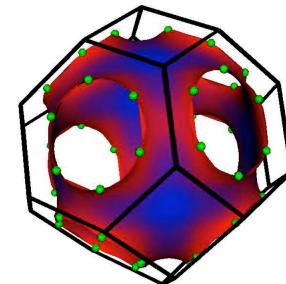
critical behavior



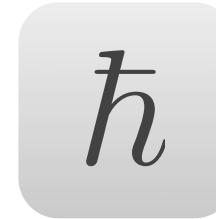
folding of proteins



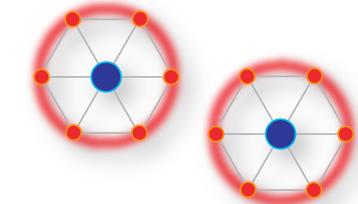
frustrated magnets



quantum systems



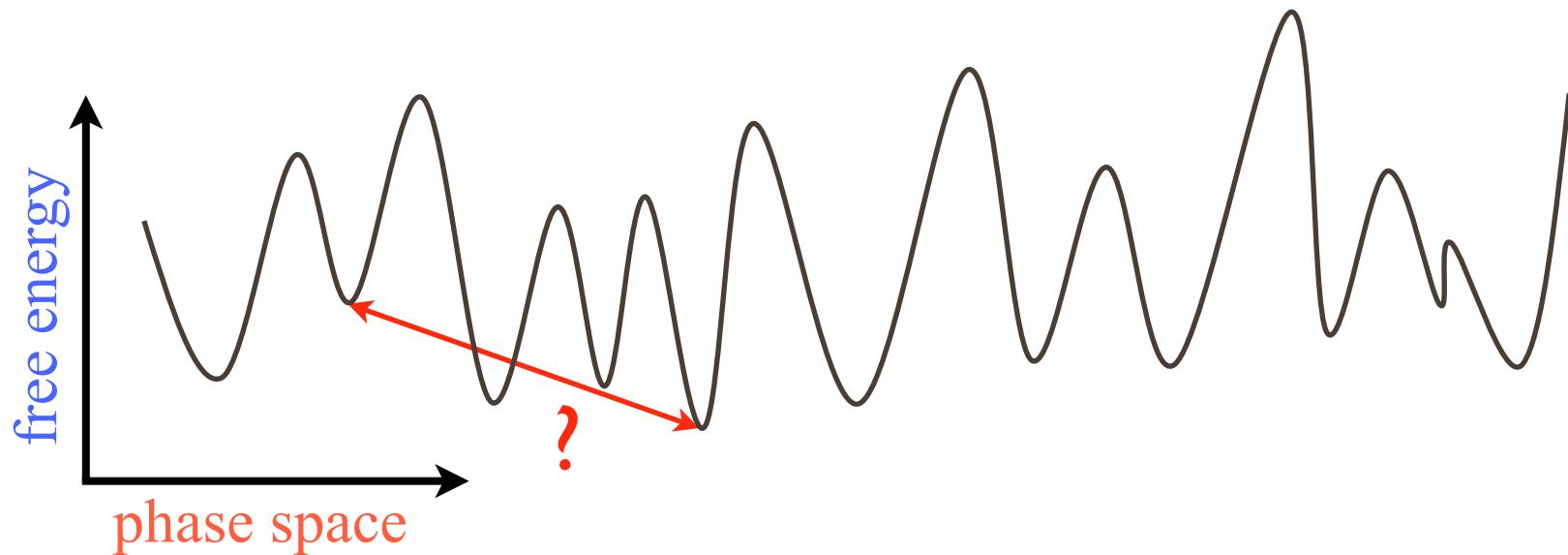
dense liquids



# Complex energy landscapes

---

Complex energy landscapes are characterized by **many local minima**.



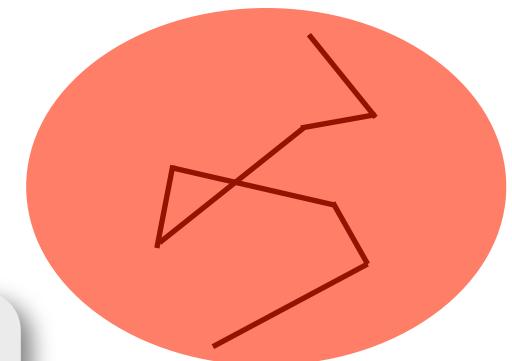
Slow equilibration due to suppressed tunneling.

*How can we efficiently simulate such systems?*

# Simulation of Markov chains

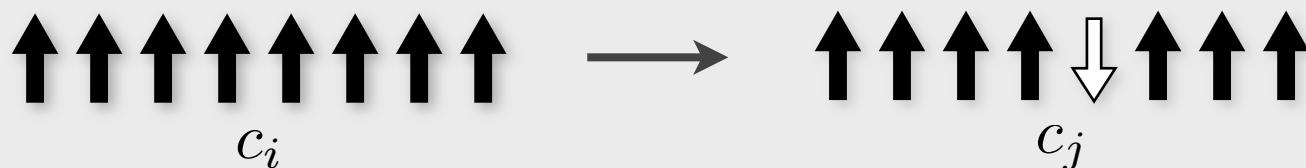
- Sample configurations in **phase space**

$$c_1 \rightarrow c_2 \rightarrow \dots \rightarrow c_i \rightarrow c_{i+1} \rightarrow \dots$$



**Metropolis algorithm (1953)**

propose a (small) change to a configuration



accept/reject the update with probability

$$p_{acc} = \min \left( 1, \frac{w(c_j)}{w(c_i)} \right)$$

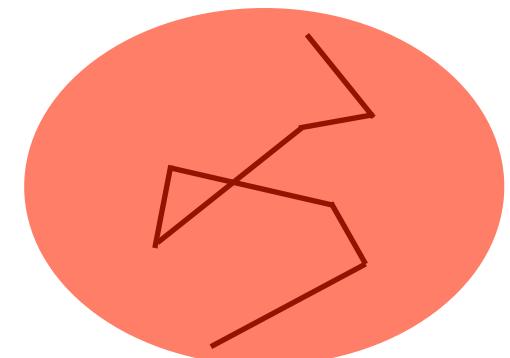
How do we choose  
these weights?

# Statistical ensembles

---

- Sample configurations in **phase space**

$$c_1 \rightarrow c_2 \rightarrow \dots \rightarrow c_i \rightarrow c_{i+1} \rightarrow \dots$$



- Project onto random walk in **energy space**

$$E_1 \rightarrow E_2 \rightarrow \dots \rightarrow E_i \rightarrow E_{i+1} \rightarrow \dots$$

- We define a **statistical ensemble**

$$w(c_i) = w(E_i) = \exp(-\beta E_i)$$

high dimensional

$$\downarrow E_i = H(c_i)$$



one dimensional

$$p_{acc}(E_1 \rightarrow E_2) = \min \left( 1, \frac{w(E_2)}{w(E_1)} \right) = \min (1, \exp(-\beta \Delta E))$$

# Statistical ensembles

---

- Sample configurations in **phase space**

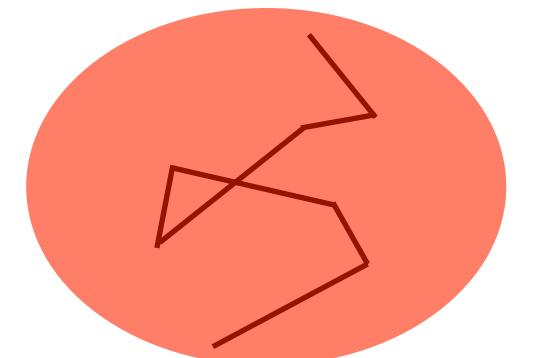
$$c_1 \rightarrow c_2 \rightarrow \dots \rightarrow c_i \rightarrow c_{i+1} \rightarrow \dots$$

- Project onto random walk in **energy space**

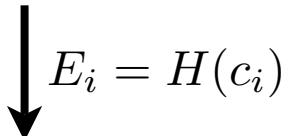
$$E_1 \rightarrow E_2 \rightarrow \dots \rightarrow E_i \rightarrow E_{i+1} \rightarrow \dots$$

- **Phase space:** The simulated system does a biased and Markovian random walk.

- **Energy space:** The projected random walk is **non-Markovian**, as memory is stored in the system's configuration.



high dimensional



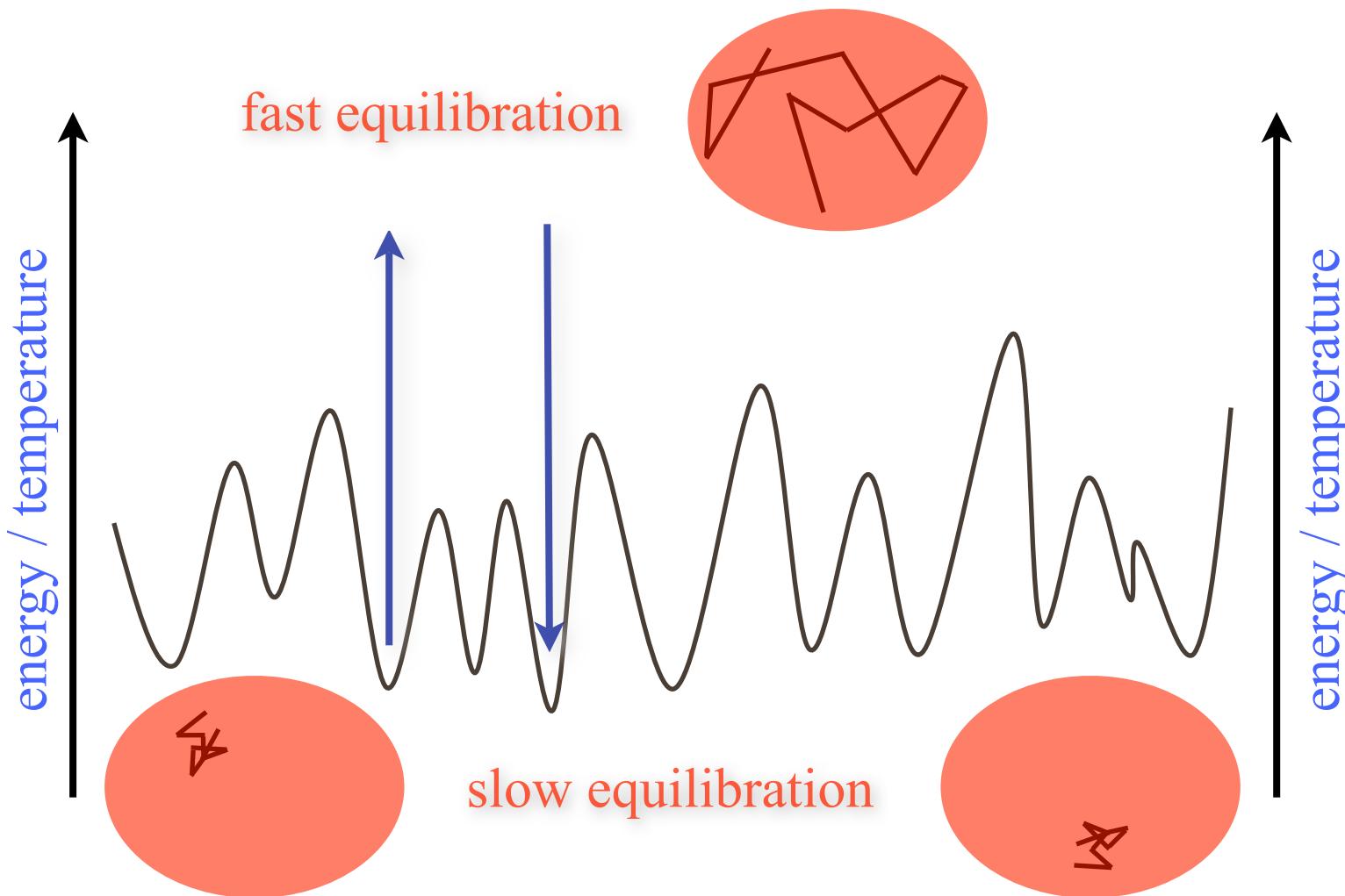
$$E_i = H(c_i)$$

one dimensional

# Random walks in energy

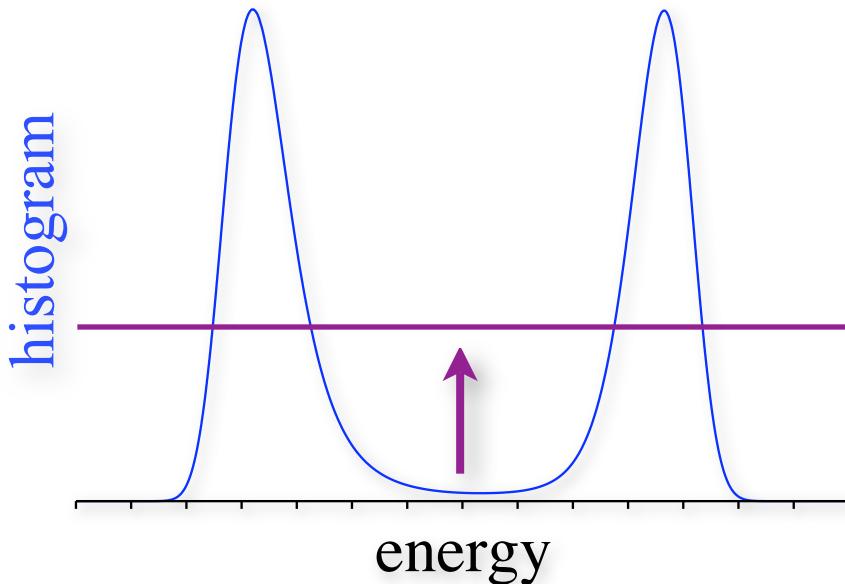
---

Random walk in temperature space increases equilibration.



# Extended ensemble simulations

- **Broaden the sampled energy space**, e.g. by sampling a flat histogram.



$$w(E) = \exp(-\beta E)$$

$$\downarrow$$

$$w(E) = 1/g(E)$$

density of states

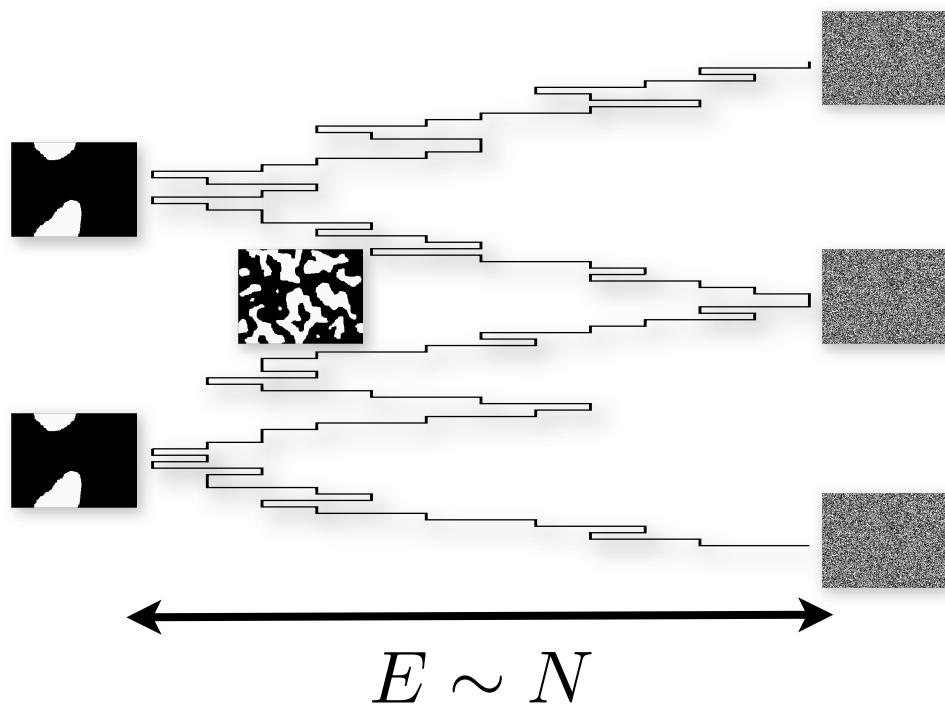
$$n_w(E) = w(E) g(E)$$

histogram

weight / ensemble

Wang-Landau algorithm ('01)

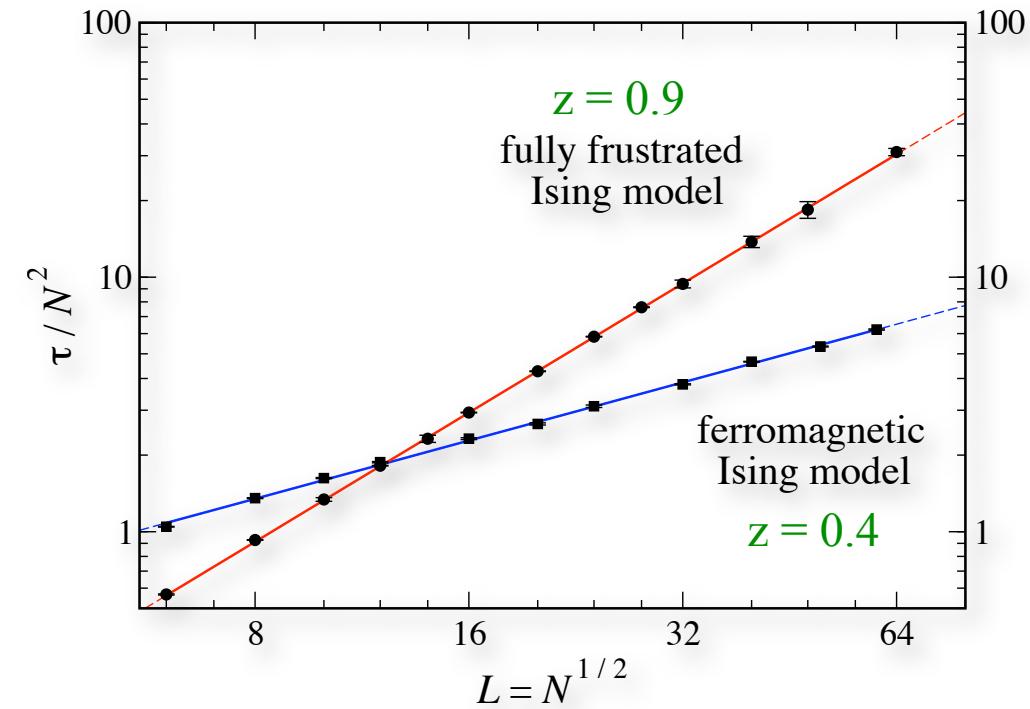
# How well does this work?



The energy range scales like  $N$ .

$$\tau \sim N^2$$

The round-trip time  
should scale like  $N^2$ .



Flat-histogram sampling

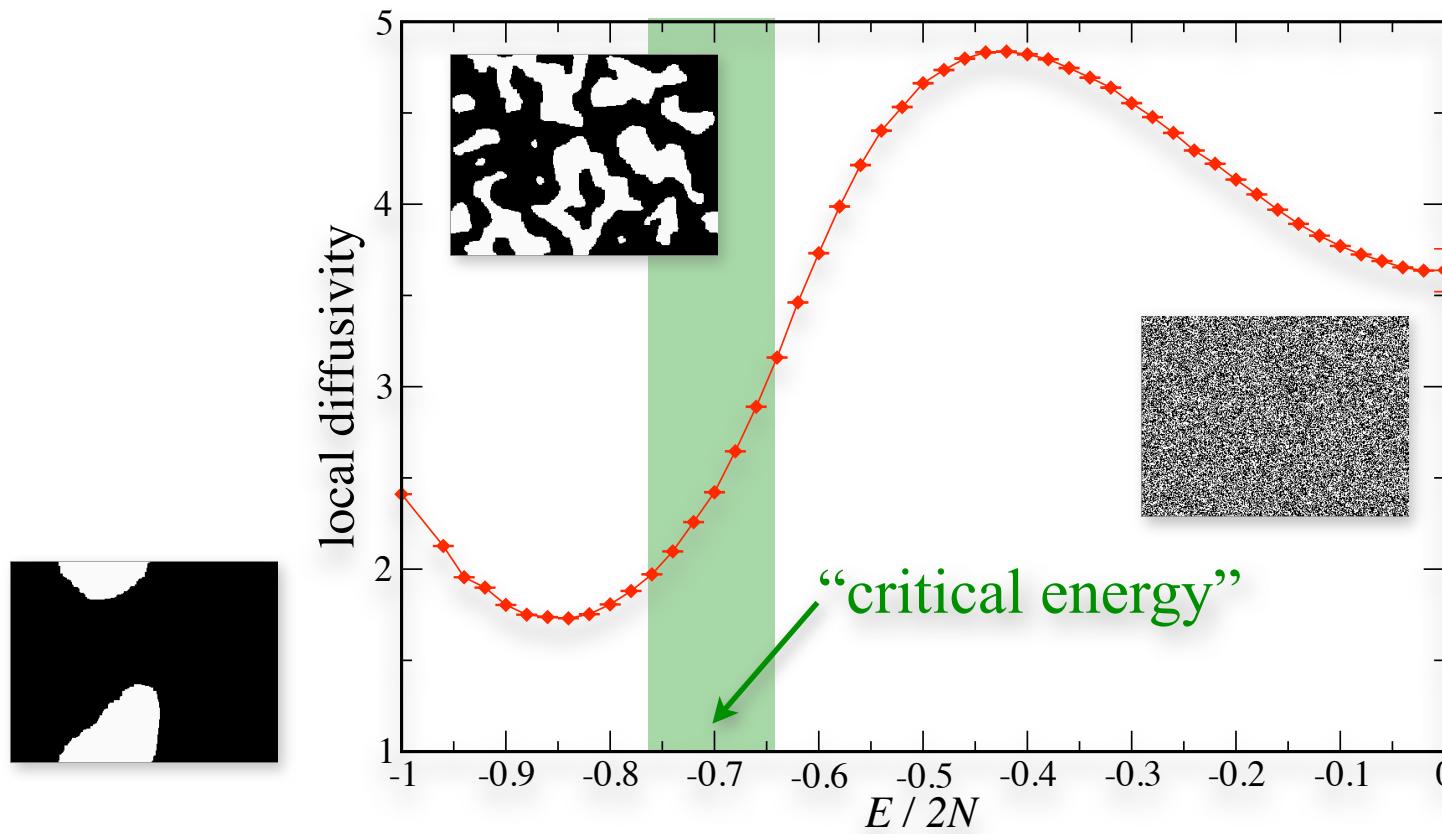
$$\tau \sim N^{2+z}$$

Critical slowing down.

# The problem: local diffusivity

---

$$D(E, t_D) = \langle [E(t) - E(t + t_D)]^2 \rangle / t_D$$



- The **local diffusivity** is NOT independent of the energy.

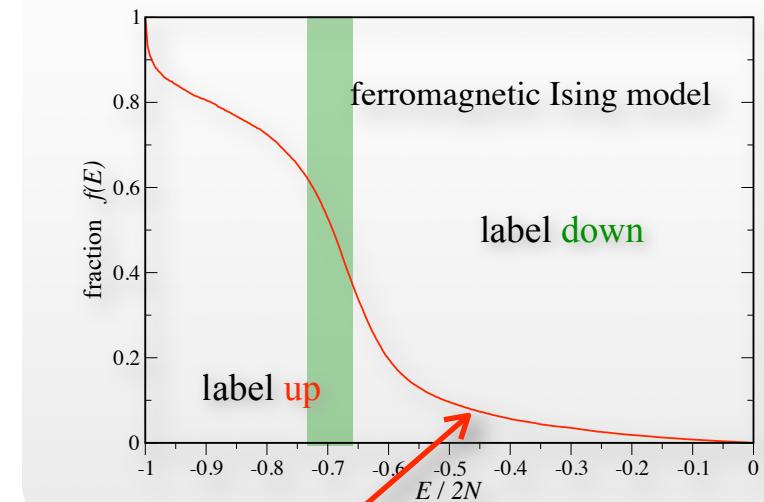
# Optimizing the ensemble

Measure the **current** in the energy interval

$$j = D(E) n_w(E) \frac{df}{dE}$$

Diagram illustrating the components of the current calculation:

- current** (purple arrow pointing to  $j$ )
- histogram** (blue arrow pointing to  $n_w(E)$ )
- local diffusivity** (green arrow pointing to  $D(E)$ )
- derivative of fraction** (red arrow pointing to  $\frac{df}{dE}$ )



Determine the **local diffusivity**.

**Maximize** current by varying histogram/ensemble.

Phys. Rev. E **70**, 046701 (2004).

# Optimizing the ensemble (cont'd)

**Optimal histogram** turns out to be

$$n_w^{(opt)}(E) \propto \frac{1}{\sqrt{D(E)}}$$

## Ensemble optimization algorithm

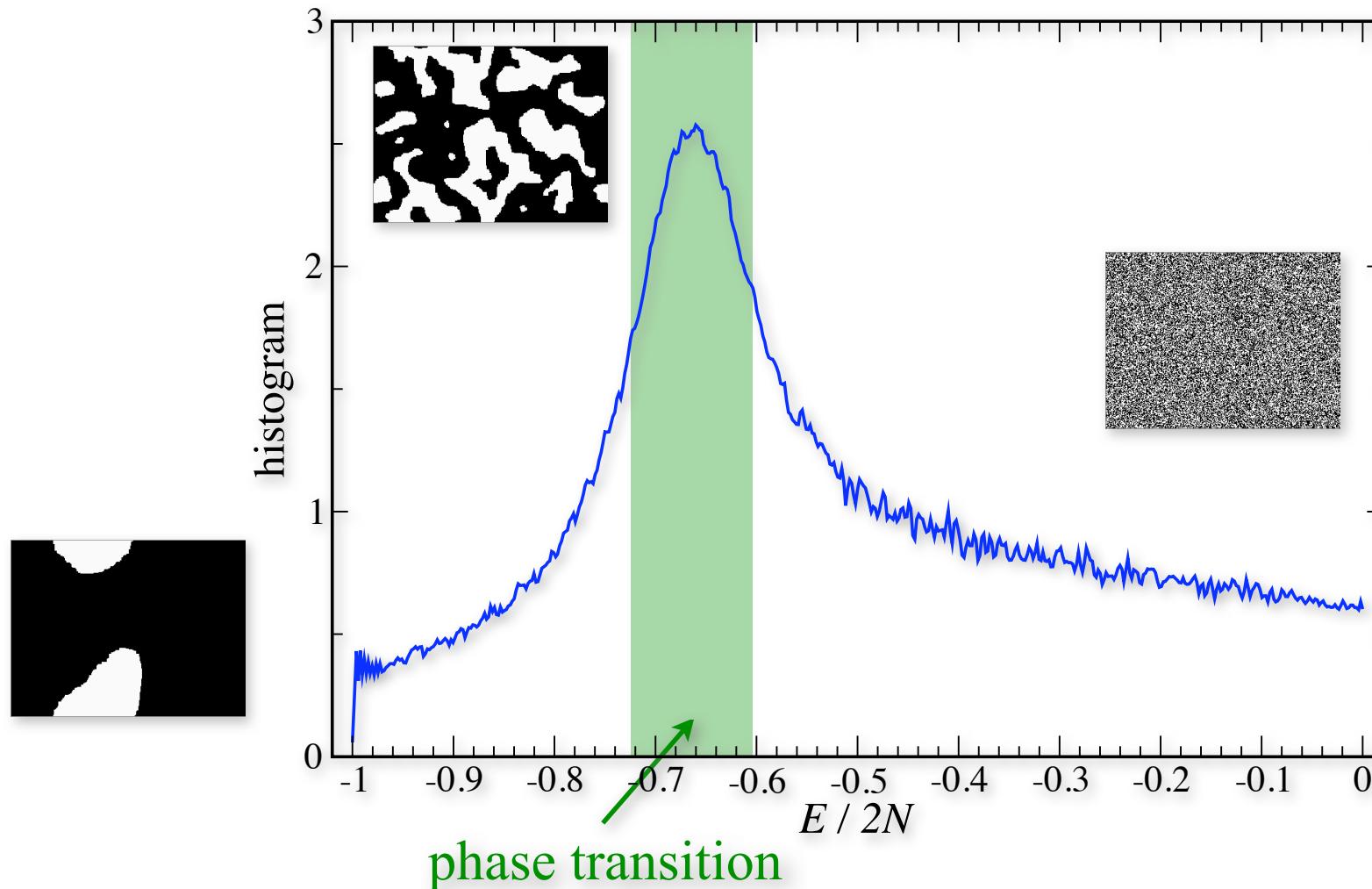
**Feedback** the local diffusivity

$$w'(E) \propto w(E) \cdot \sqrt{\frac{df}{dE} \cdot \frac{1}{n_w(E)}}$$

and **iterate** feedback until convergence.

# Optimized histogram

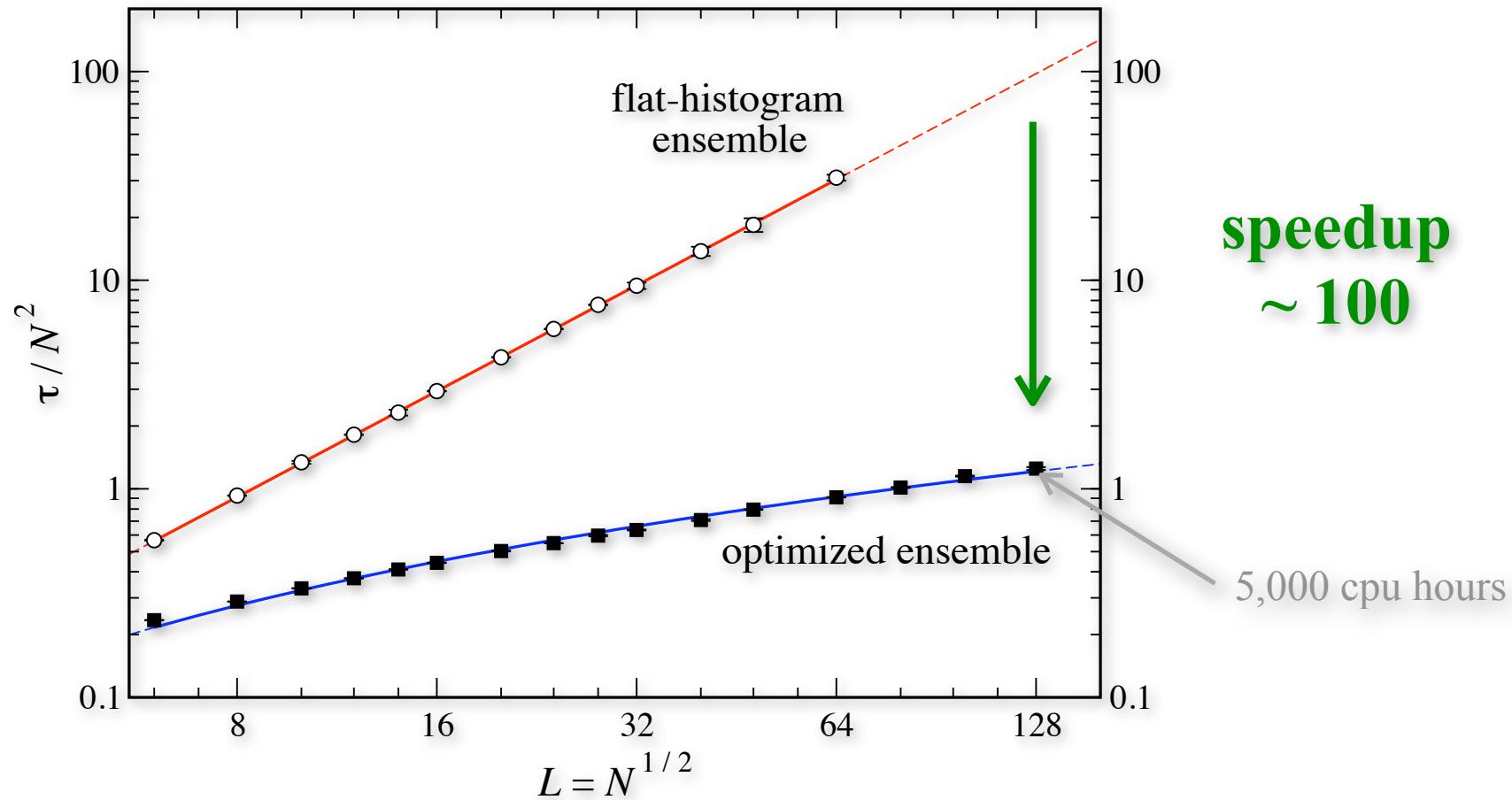
---



- **Feedback reallocates resources** towards the critical energy.

# Performance of optimized ensemble

---

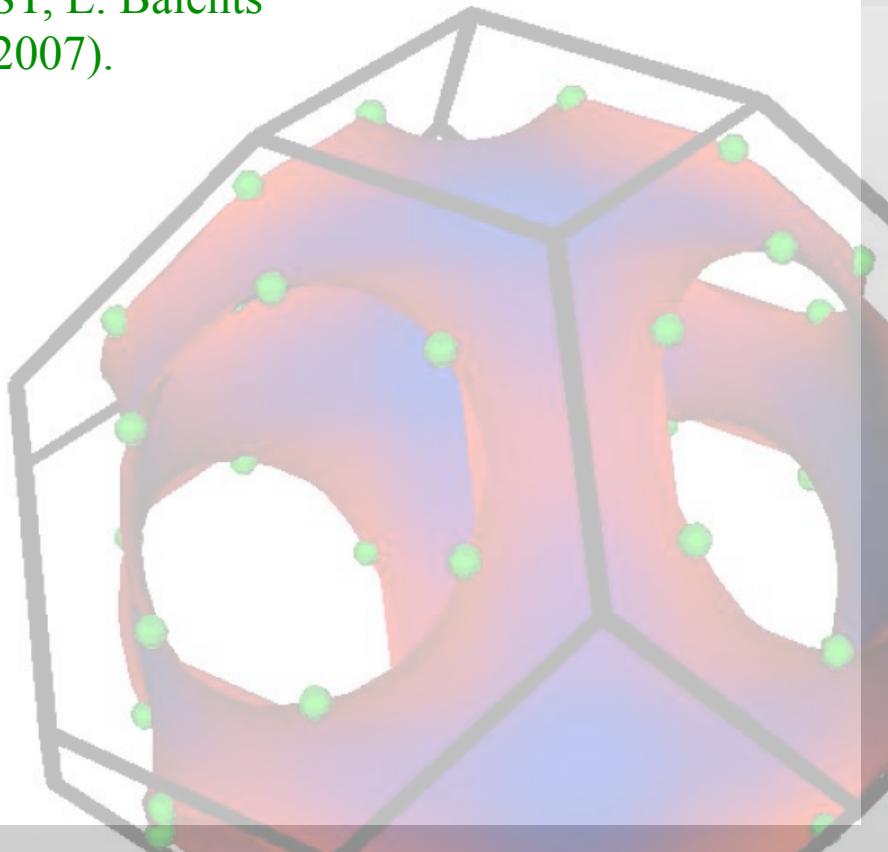


The round-trip times scale like  $O([N \log N]^2)$ .

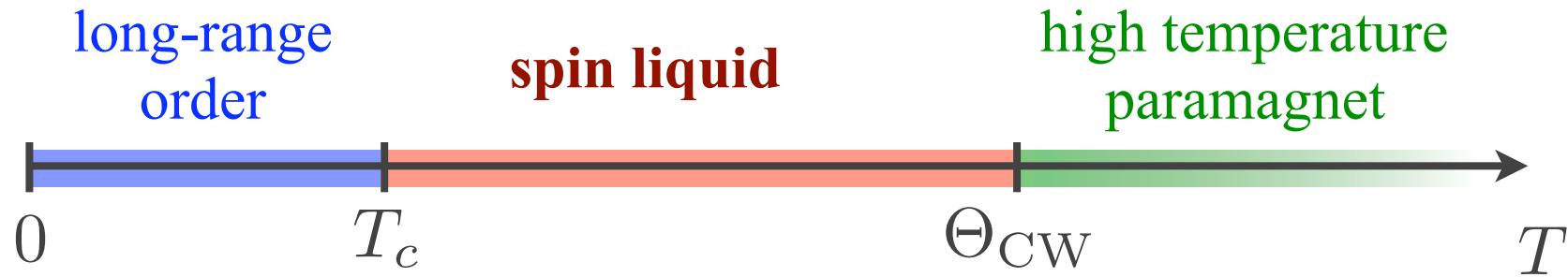
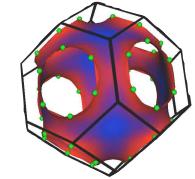
Example

# Order by disorder transitions & spiral spin liquids

D. Bergman, J. Alicea, E. Gull, ST, L. Balents  
Nature Physics 3, 487 (2007).



# Frustrated magnets



frustration parameter

$$f = \frac{\Theta_{\text{CW}}}{T_c}$$

“highly frustrated”

$$f > 5 - 10$$

**spin liquid**

system **fluctuates** amongst low-energy configurations, but **no** long-range order

**Curie-Weiss law**

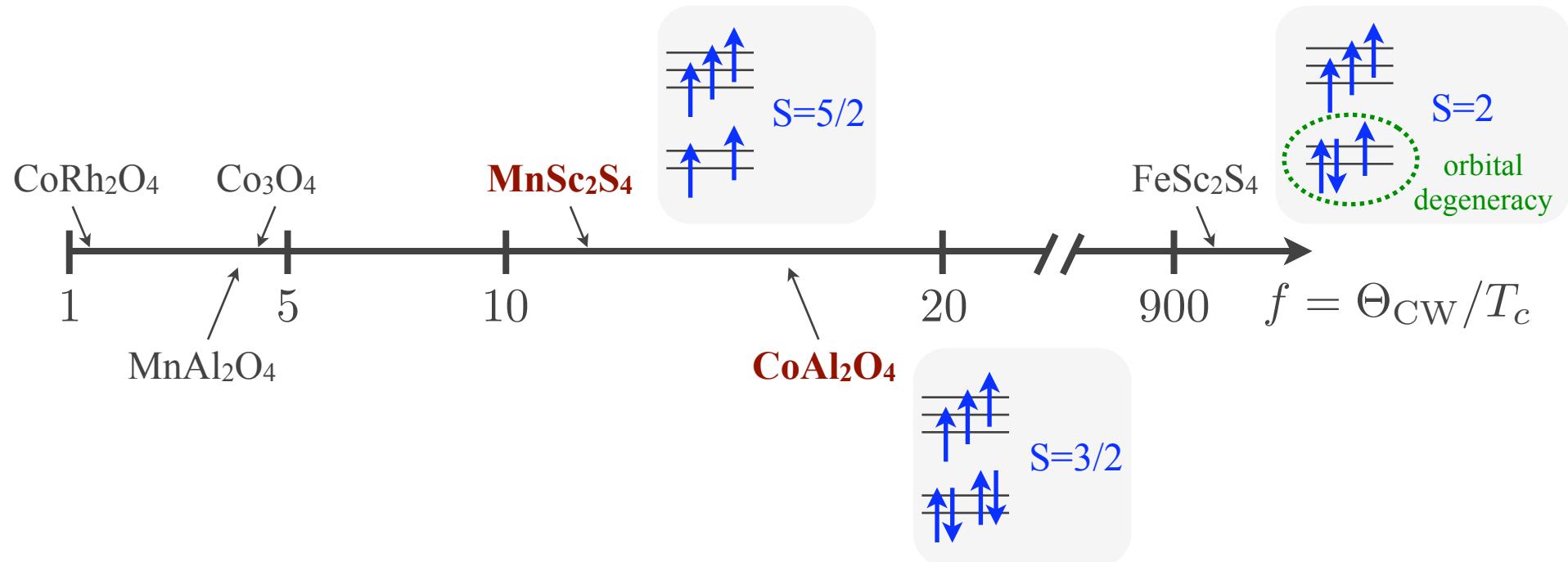
$$\chi \sim \frac{1}{T - \Theta_{\text{CW}}}$$

# Diamond lattice antiferromagnets: Materials

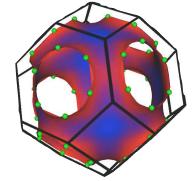
V. Fritsch *et al.*, PRL **92**, 116401 (2004); N. Tristan *et al.*, PRB **72**, 174404 (2005); T. Suzuki *et al.* (2007)

Many materials take on the **normal spinel** structure  $\text{AB}_2\text{X}_4$ .

**Focus:** Spinels with **magnetic A-sites** (only).



# Frustration in the diamond lattice



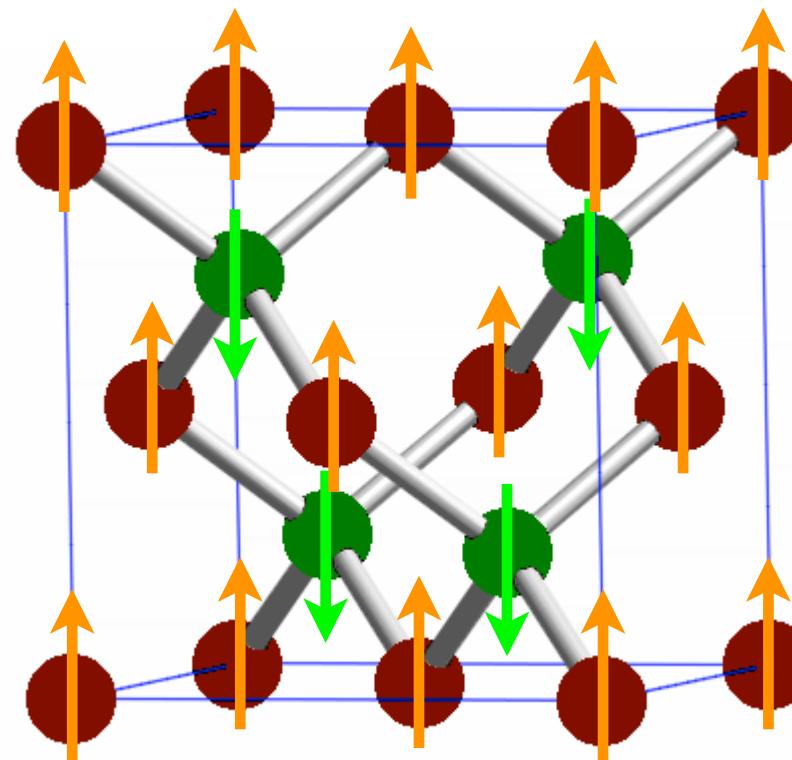
Naive Hamiltonian

$$H = J_1 \sum_{\langle ij \rangle} \vec{S}_i \cdot \vec{S}_j$$

antiferromagnetic

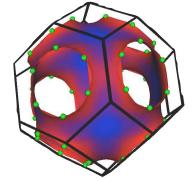
classical spins  
 $S=3/2, S=5/2$

diamond lattice  
two FCC lattices  
coupled via  $J_1$



bipartite lattice  
no frustration

# Frustration in the diamond lattice



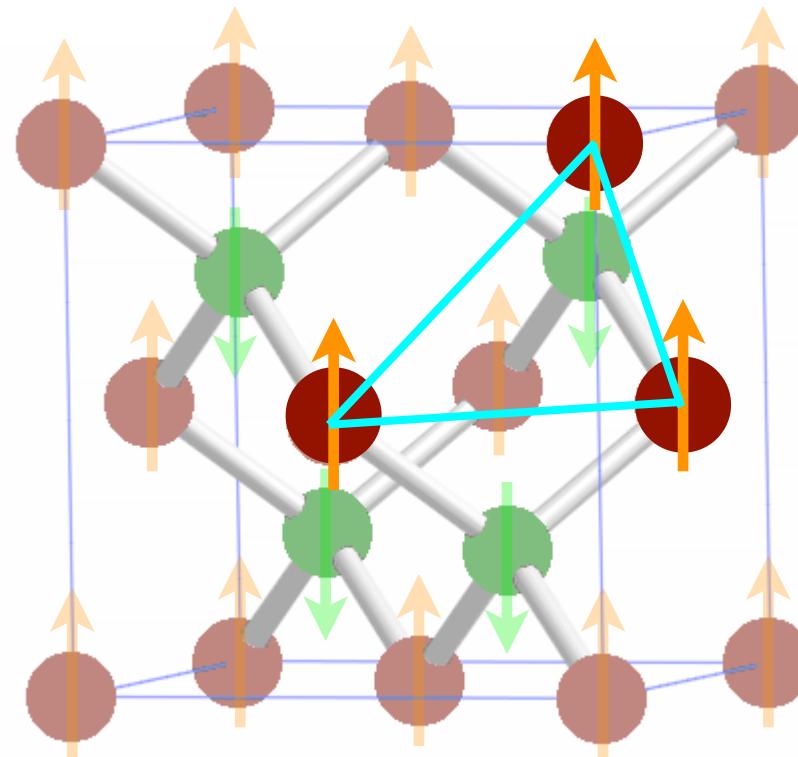
2nd neighbor  
exchange

$$H = J_1 \sum_{\langle ij \rangle} \vec{S}_i \cdot \vec{S}_j + J_2 \sum_{\langle\langle ij \rangle\rangle} \vec{S}_i \cdot \vec{S}_j$$

$$J_1 \approx J_2$$

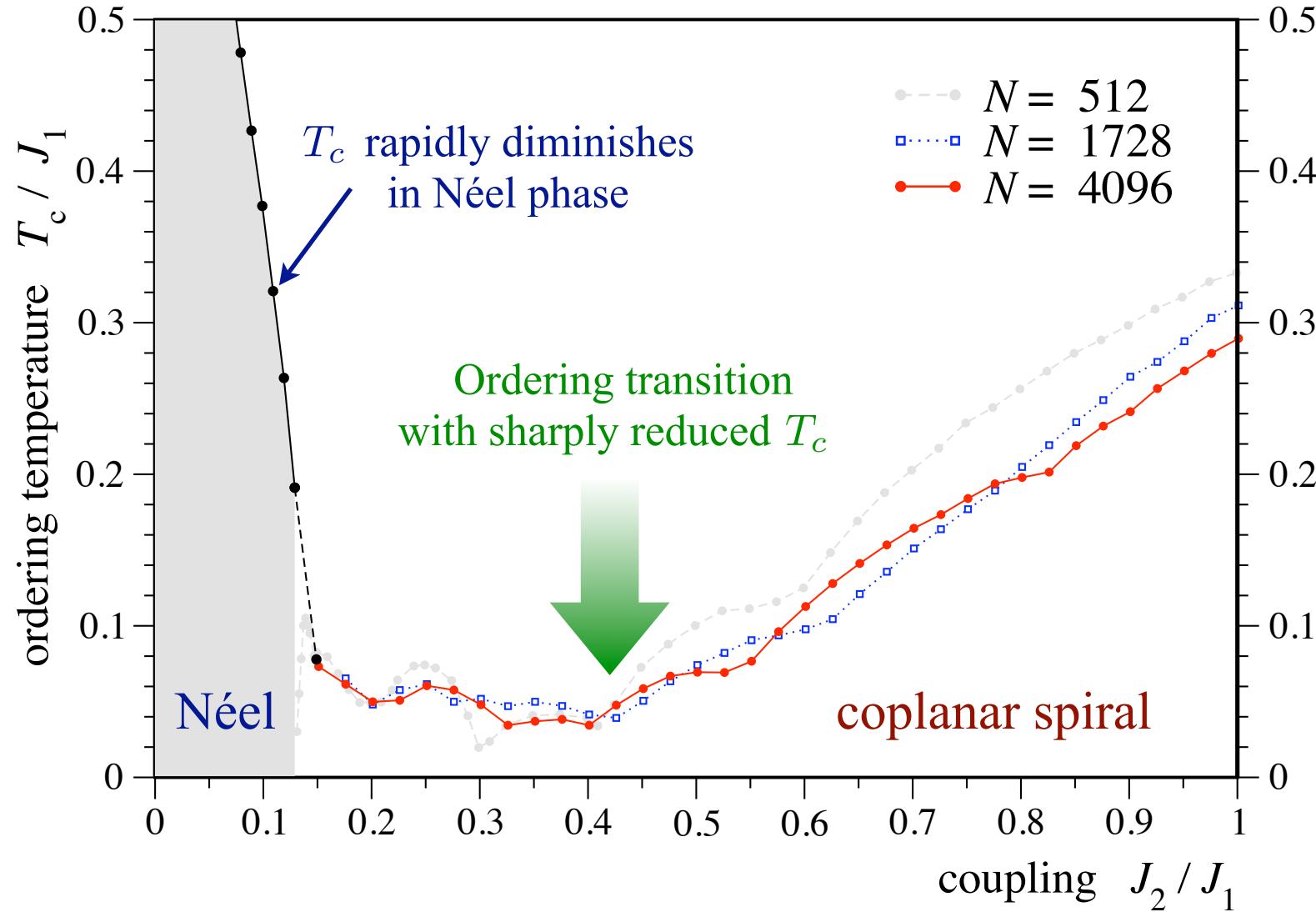
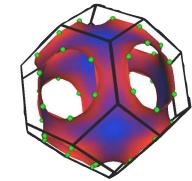
similar exchange path

W. L. Roth, J. Phys. **25**, 507 (1964)

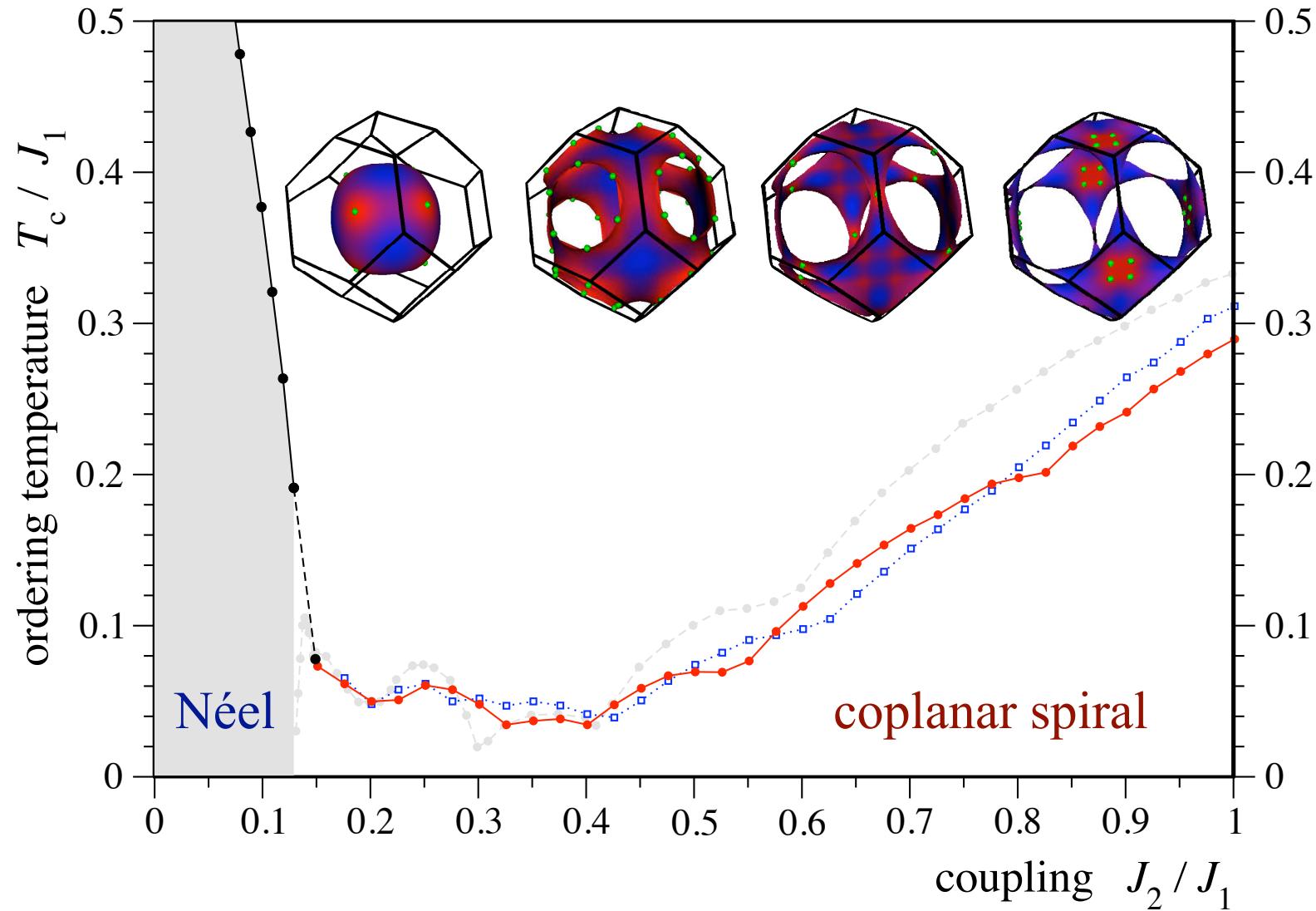
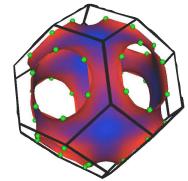


$J_2$  generates  
**strong frustration**

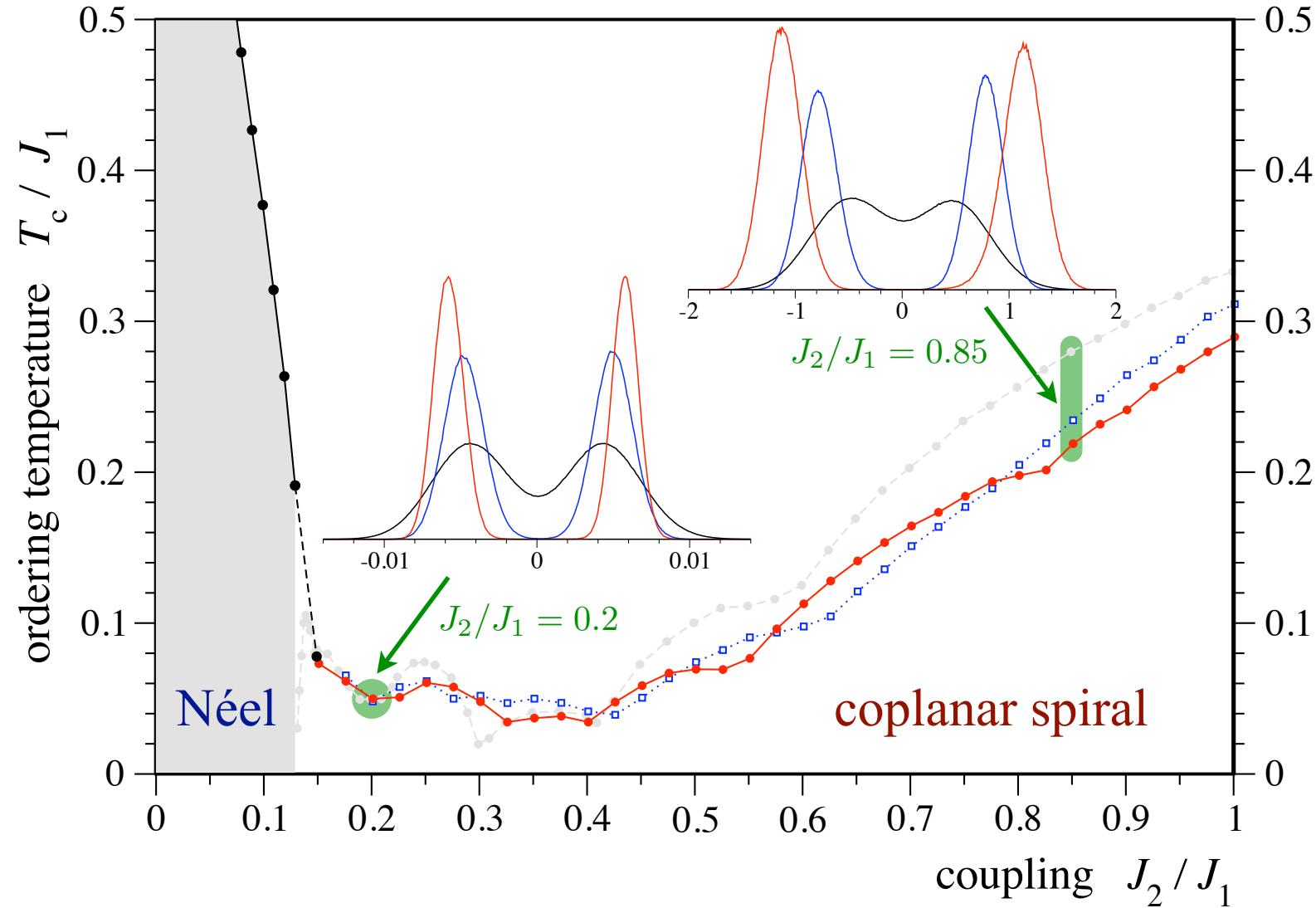
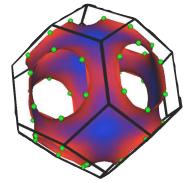
# Phase diagram

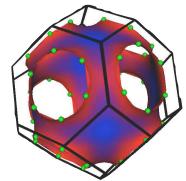


# Spiral surfaces



# First-order transitions

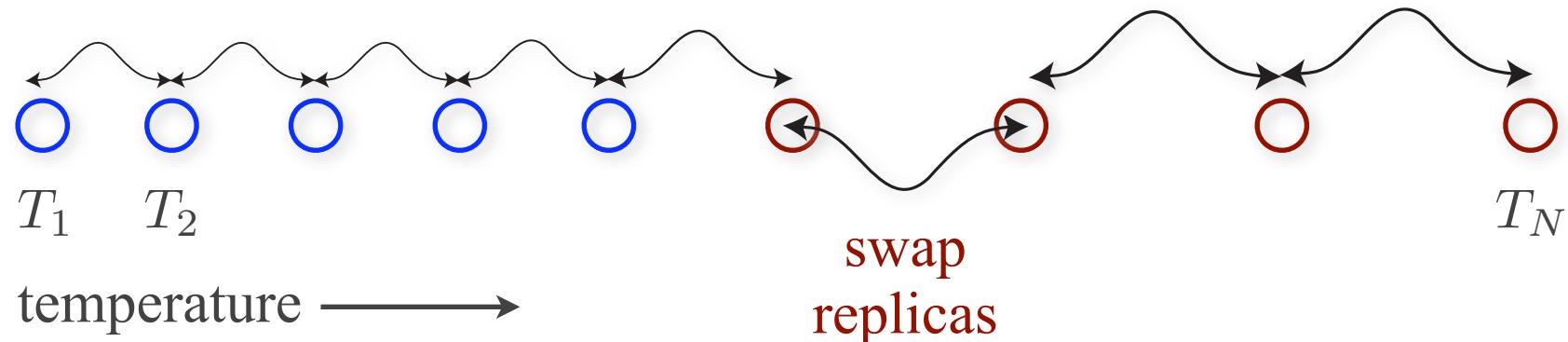




# Parallel tempering

K. Hukushima and Y. Nemoto, J. Phys. Soc. Jpn. **65**, 1604 (1996)

Simulate **multiple replicas** of the system at various temperatures.

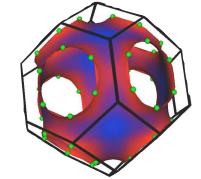


$$p(E_i, T_i \rightarrow E_{i+1}, T_{i+1}) = \min(1, \exp(\Delta\beta\Delta E))$$

Single replica performs **random walk** in temperature space.

How do we choose the temperature points?

# Ensemble optimization



## Feedback algorithm

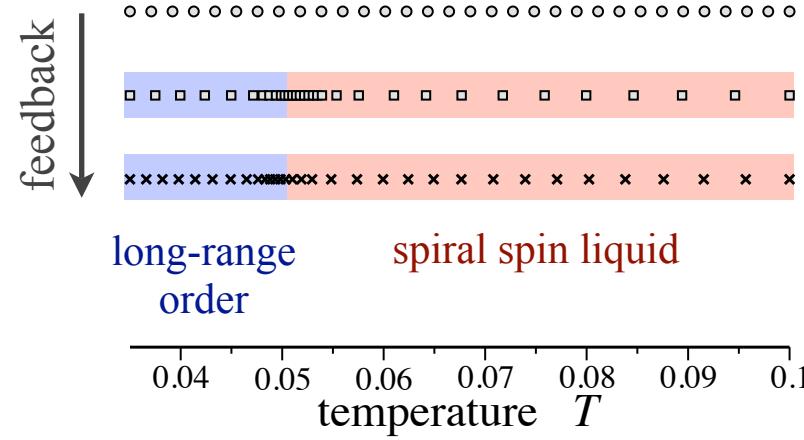
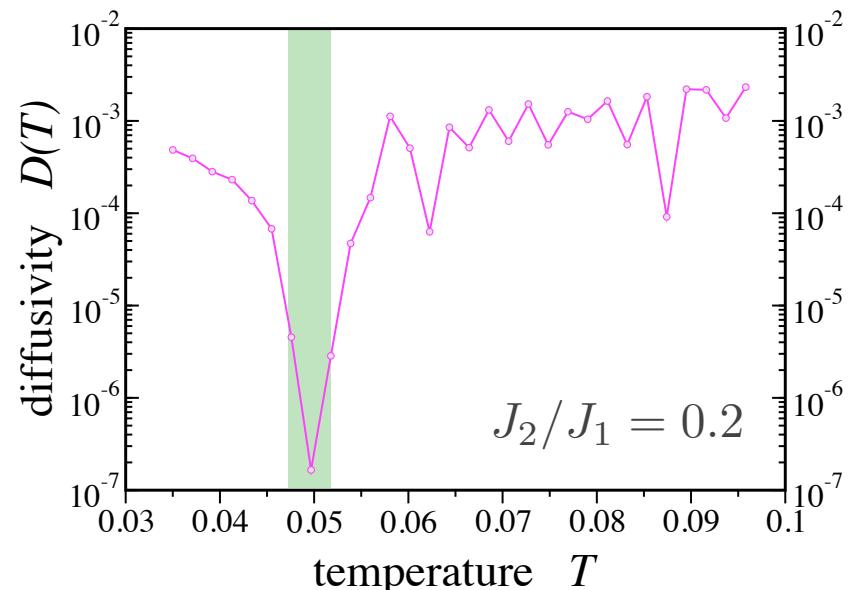
Measure **local diffusivity**  $D(T)$  of current in temperature space.

**Optimal choice** of temperatures

$$\eta^{\text{opt}}(T) \sim \frac{1}{\sqrt{D(T)}}$$

density of  
 $T$ -points

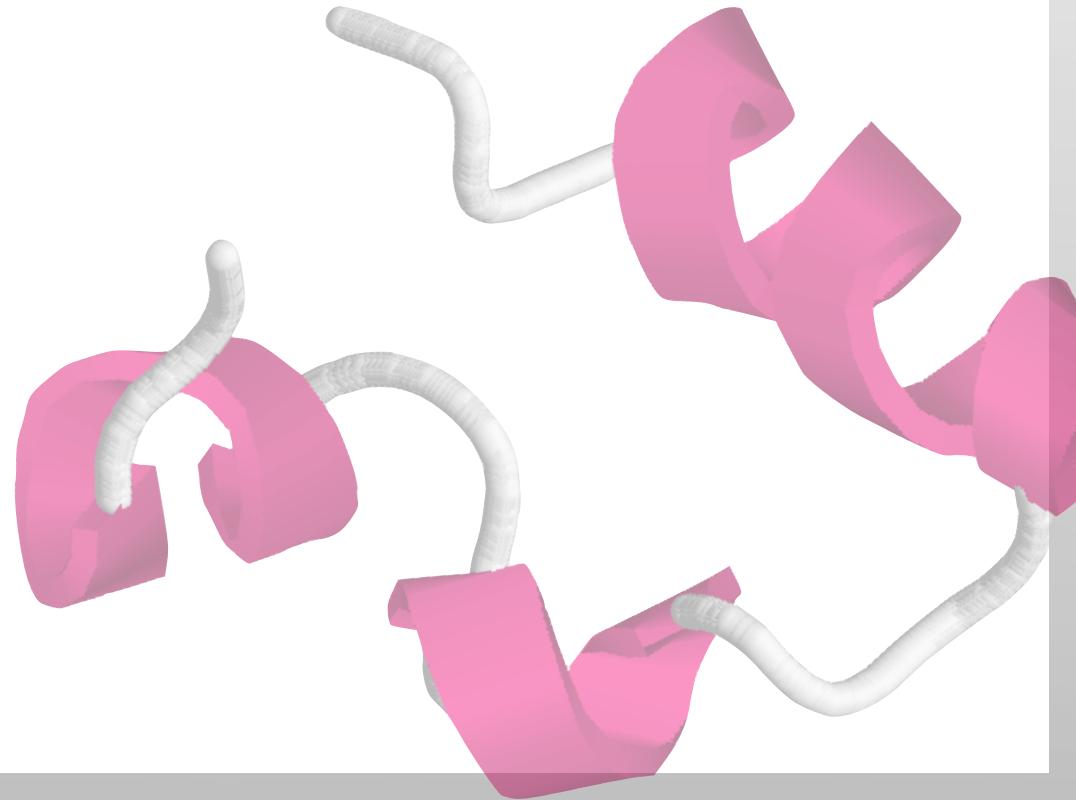
Iterate feedback of diffusivity.



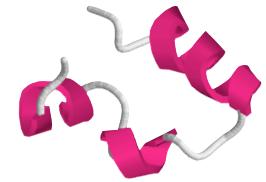
Example

# Folding of a (small) protein

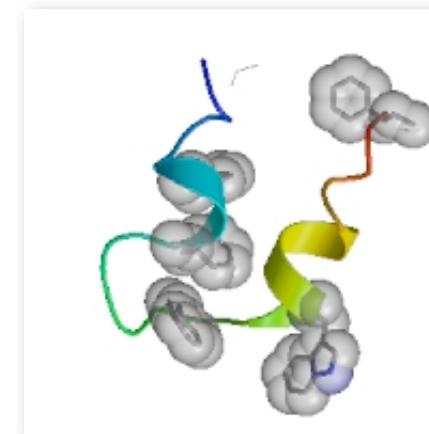
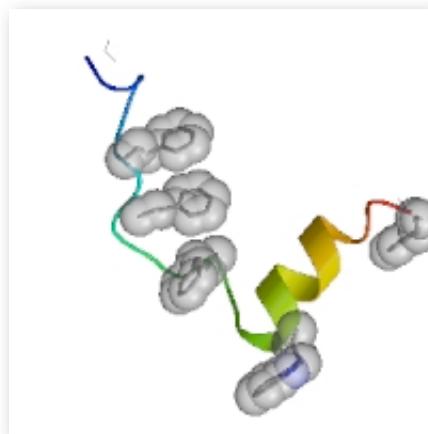
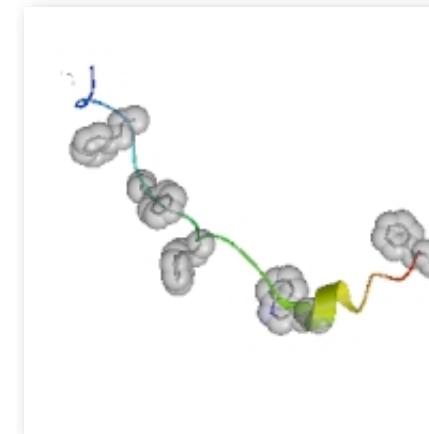
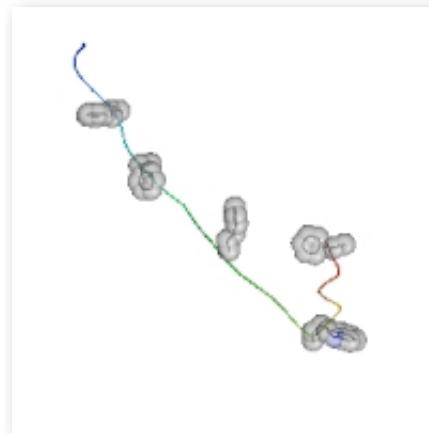
ST, M. Troyer, U.H.E. Hansmann  
J. Chem. Phys. **124**, 174903 (2006).



# A small protein: HP-36



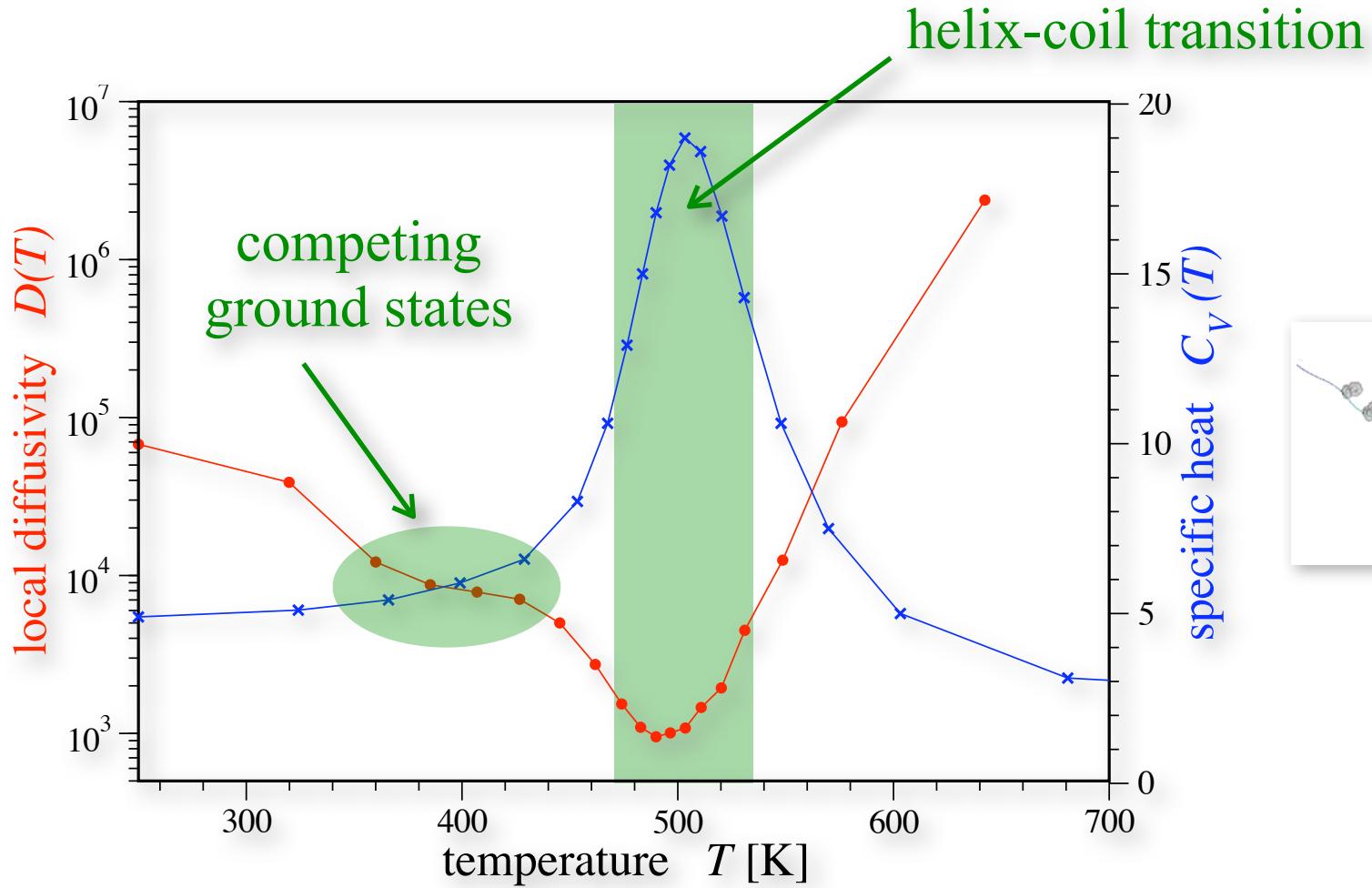
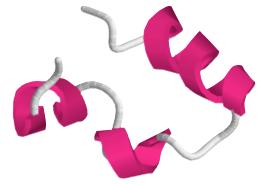
*The chicken villin headpiece*



folding@home project

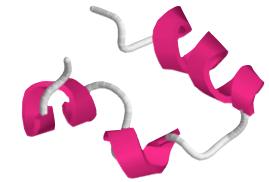
folding time: 4.3 microseconds

# Random walk in temperature

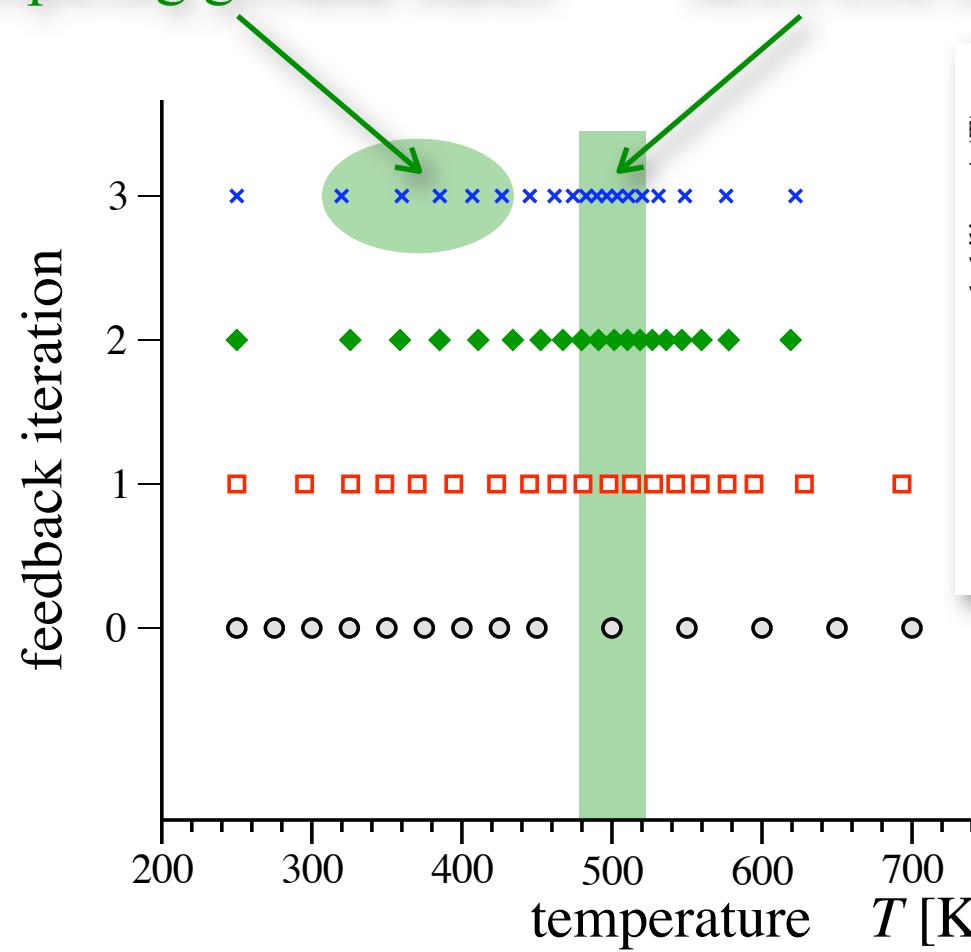


- **Multiple temperature scales** are revealed by the local diffusivity.

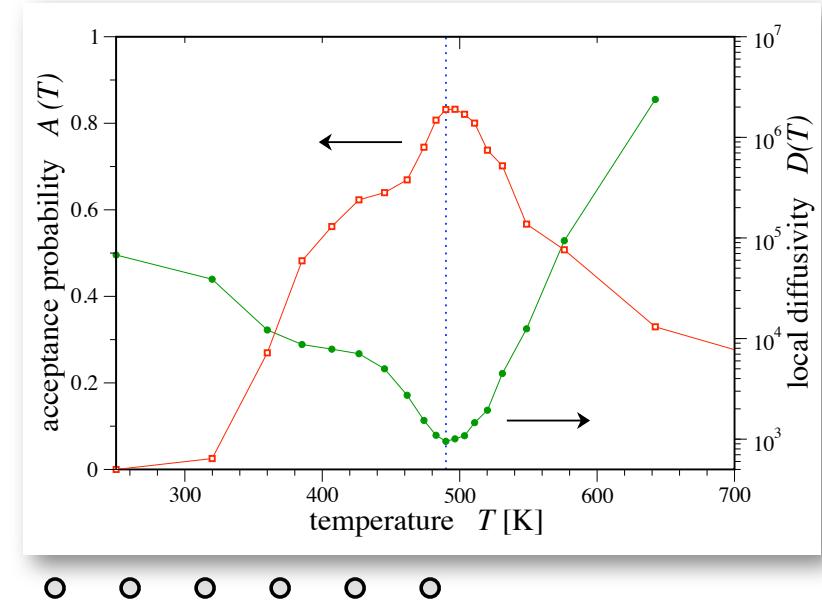
# Optimized temperature sets



competing ground states



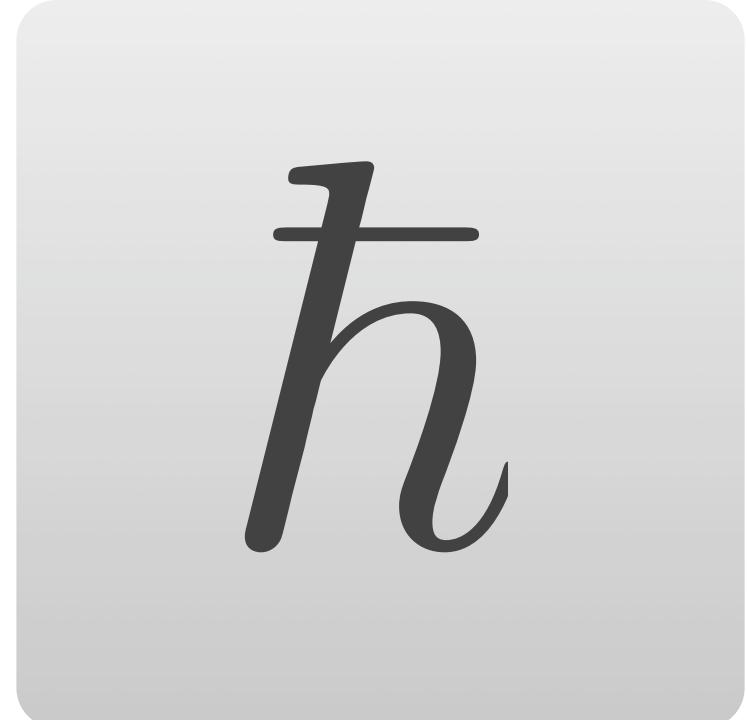
helix-coil transition



- Feedback reallocates resources towards the relevant temperature scales.

# Example Quantum systems

S. Wessel, N. Stoop, E. Gull, ST, M. Troyer  
J. Stat. Mech. P12005 (2007).



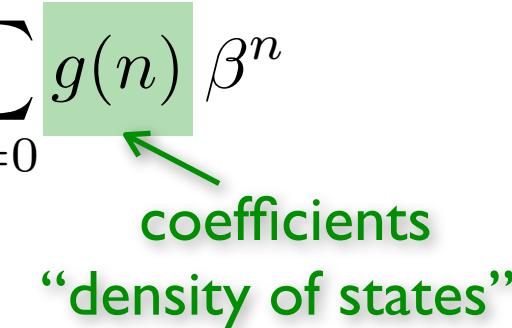
ℏ

# Quantum systems

$\hbar$

Reconsider the high-temperature series expansion

$$Z = \text{Tr } e^{-\beta H} = \sum_{n=0}^{\infty} \frac{\beta^n}{n!} \text{Tr } (-H)^n = \sum_{n=0}^{\infty} g(n) \beta^n$$

  
coefficients  
“density of states”

We can define a broad-histogram **ensemble in the expansion order**.

M. Troyer, S. Wessel & F. Alet, PRL **90**, 120201 (2003).

Stochastic series expansion (SSE) samples these coefficients

$n \rightarrow 0$

high temperatures

?

$$\langle n \rangle \propto \beta N$$

$n \rightarrow \infty$

low temperatures

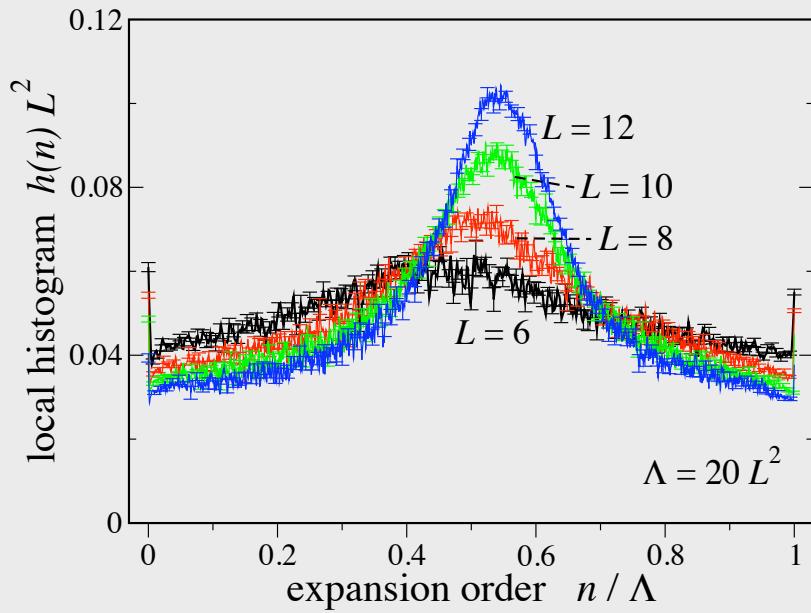
# Examples

$\hbar$

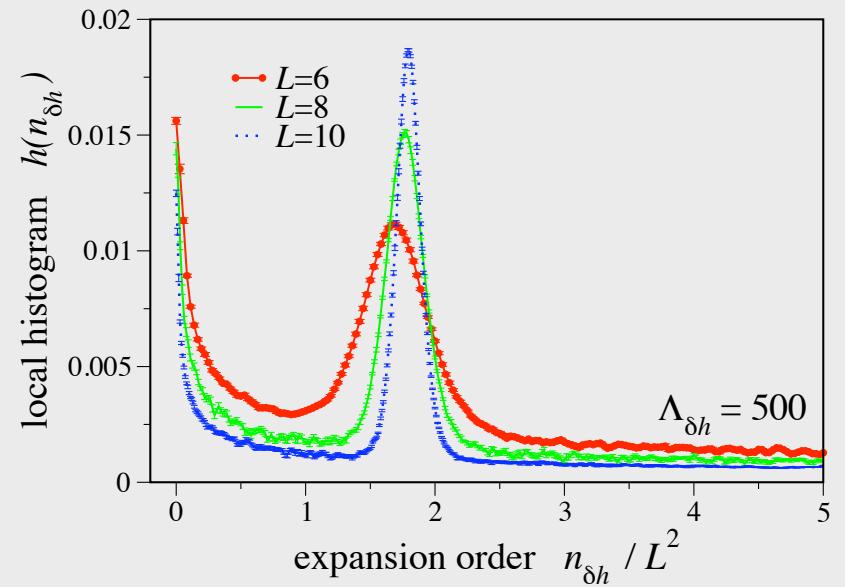
## Thermal first-order transition

hard-core bosons  
with next-nearest neighbor repulsion

$$H = -t \sum_{\langle i,j \rangle} (a_i^\dagger a_j + a_j^\dagger a_i) + V_2 \sum_{\langle\langle i,k \rangle\rangle} n_i n_k - \mu \sum_i n_i$$



## Spin-flop transition



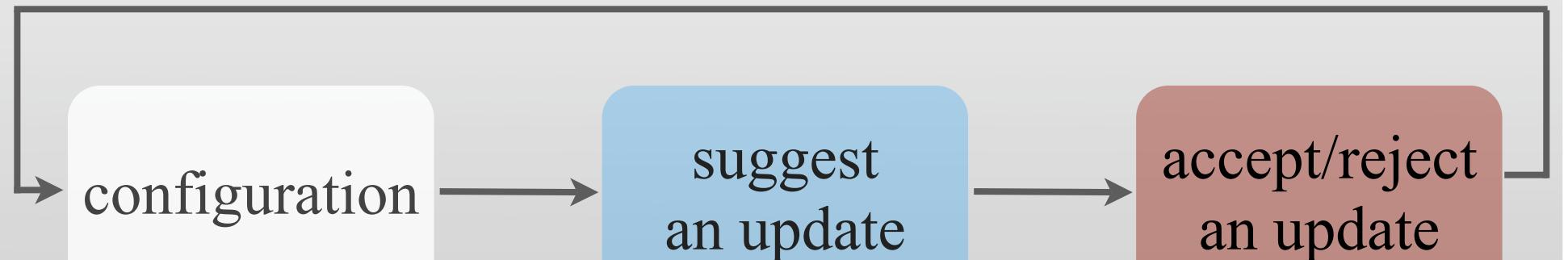
spin-1/2 XXZ model in a magnetic field

$$H = J \sum_{\langle i,j \rangle} [S_i^x S_j^x + S_i^y S_j^y + \Delta S_i^z S_j^z]$$

$$-h \sum_i S_i^z$$

# Summary

## Metropolis cycle



**non-local update schemes**  
loops, worms, ...

**unconventional  
statistical ensembles**

improve sampling efficiency  
& overcome entropic barriers

