

Spin Glasses: A frustrating problem for statistical physics

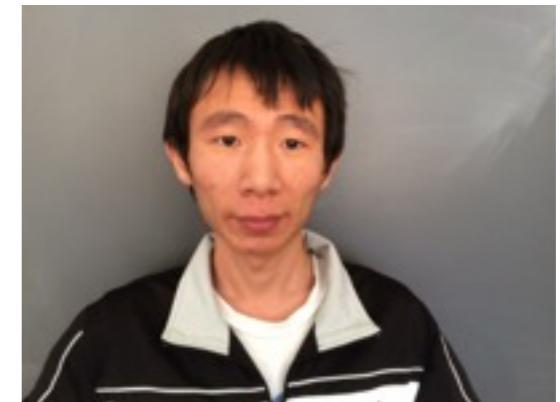
Jon Machta

*University of Massachusetts Amherst,
Santa Fe Institute*



Collaborators

- Helmut G. Katzgraber,
TAMU, SFI
- Wenlong Wang, *UMass, TAMU*
- Burcu Yucesoy, *UMass, Northeastern*



Outline

- Statistical Physics
- Spin Glasses
- Population Annealing
- Results
- Questions/Conclusions

Statistical Physics

- The study of the emergent properties of many component systems using probabilistic methods.
- Objects of study are statistical ensembles of system states or histories:
 - Thermal Equilibrium--Gibbs distribution:
$$P[\sigma] = \frac{1}{Z} \exp(-H[\sigma]/k_B T)$$
 - Non-equilibrium--stochastic dynamics

Gibbs Distribution

Thermal equilibrium: asymptotic stationary state in the absence of net fluxes of energy or mass. Described by a few parameters, e.g. temperature.

$$P[\sigma] = \frac{1}{Z} \exp(-H[\sigma]/k_B T)$$

$P[\sigma]$ = probability of state σ

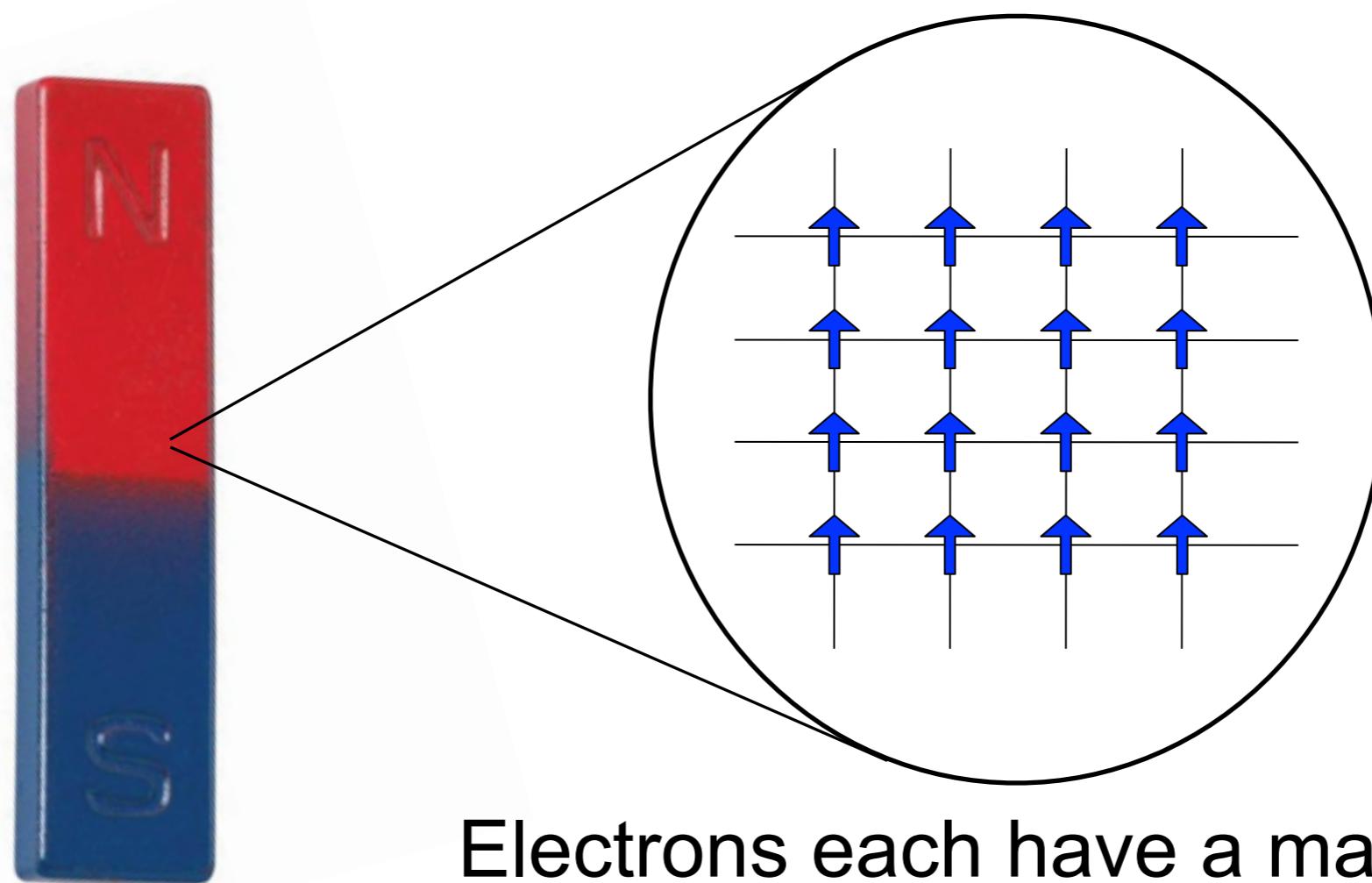
$H[\sigma]$ = energy of state σ T = temperature

Z = normalization (partition function)

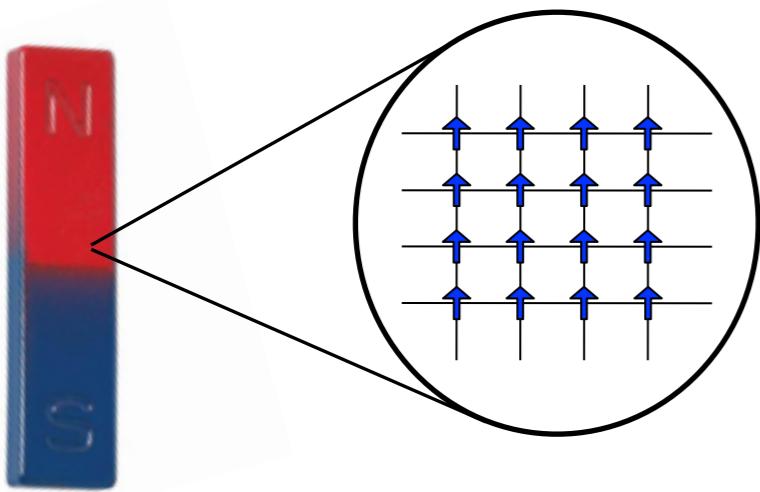
k_B = Boltzmann's constant

The Partition Function and Free energy

Magnetism



Ferromagnetism



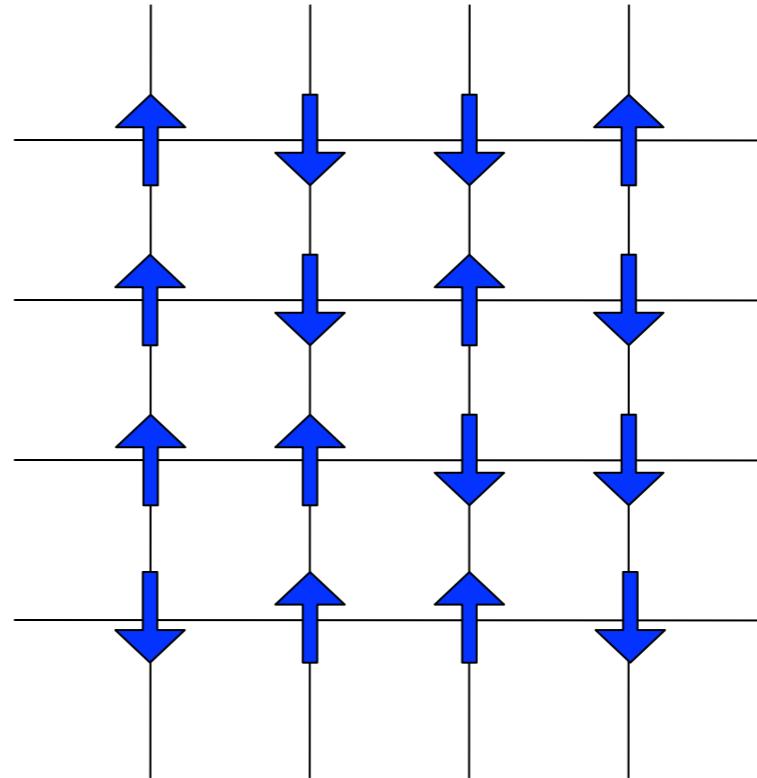
- Ferromagnetism (permanent magnetism) arises from the alignment of electron magnet moments, aka “spins.”
- Alignment is maintained over microscopic distances while the coupling distance between electrons is microscopic.

Ising Model

$$H [\sigma] = -J \sum_{(i,j)} s_i s_j$$

$$\sigma = \{s_i | i = 1, \dots, N\}$$

$$s_i = \pm 1 \quad \uparrow = +1 \quad \downarrow = -1$$

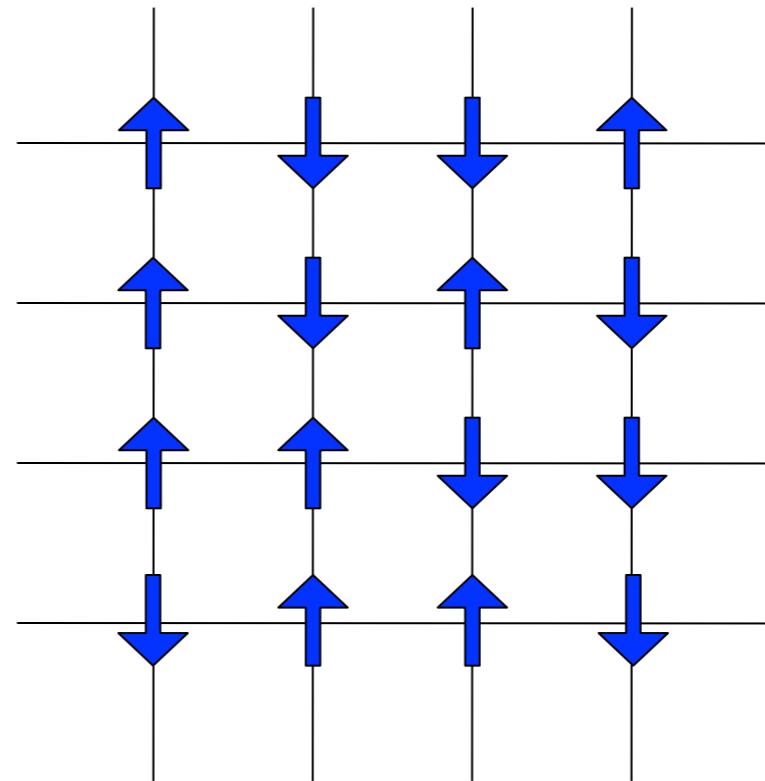


Ising Model

$$H[\sigma] = -J \sum_{(i,j)} s_i s_j$$

$$\sigma = \{s_i | i = 1, \dots, N\}$$

$$s_i = \pm 1 \quad \uparrow = +1 \quad \downarrow = -1$$



Aligned spins lower the energy
and vice versa:

$$\uparrow \text{---} \uparrow \text{ or } \downarrow \text{---} \downarrow \quad -J$$

$$\uparrow \text{---} \downarrow \text{ or } \uparrow \text{---} \downarrow \quad +J$$

Ising Model

$$H[\sigma] = -J \sum_{(i,j)} s_i s_j$$

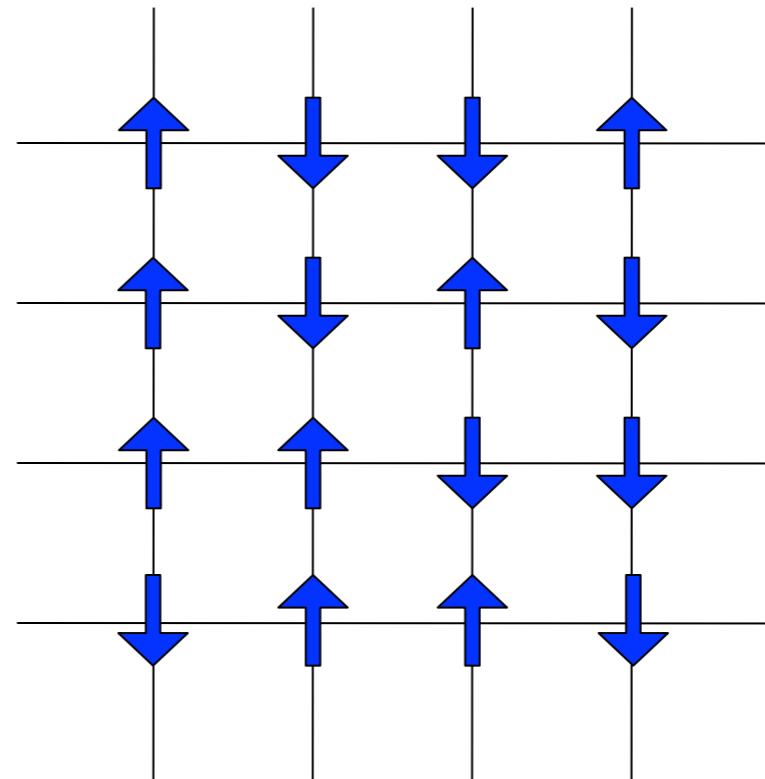
$$\sigma = \{s_i | i = 1, \dots, N\}$$

$$s_i = \pm 1 \quad \uparrow = +1 \quad \downarrow = -1$$

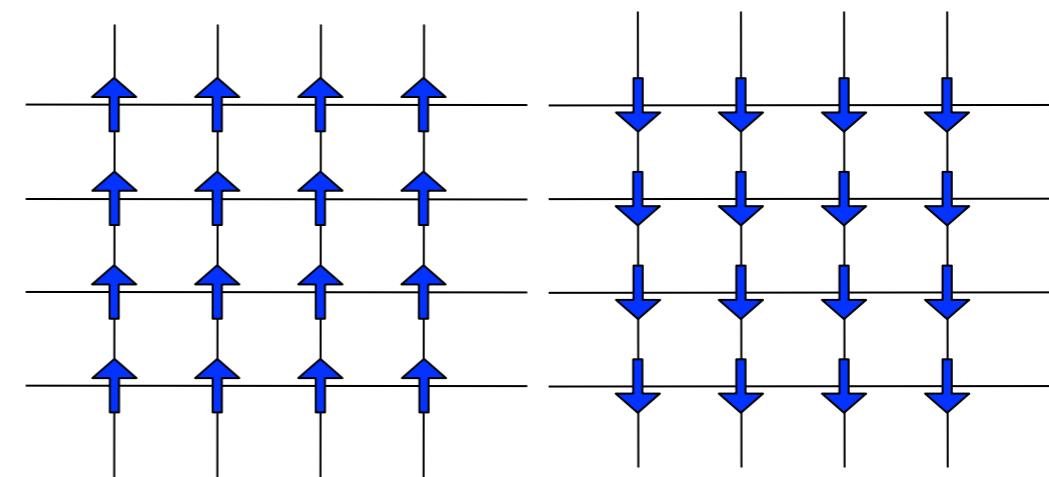
Aligned spins lower the energy and vice versa:

$$\uparrow \quad \uparrow \quad \text{or} \quad \downarrow \quad \downarrow \quad -J$$

$$\uparrow \quad \downarrow \quad \text{or} \quad \uparrow \quad \downarrow \quad +J$$



Two ground states:

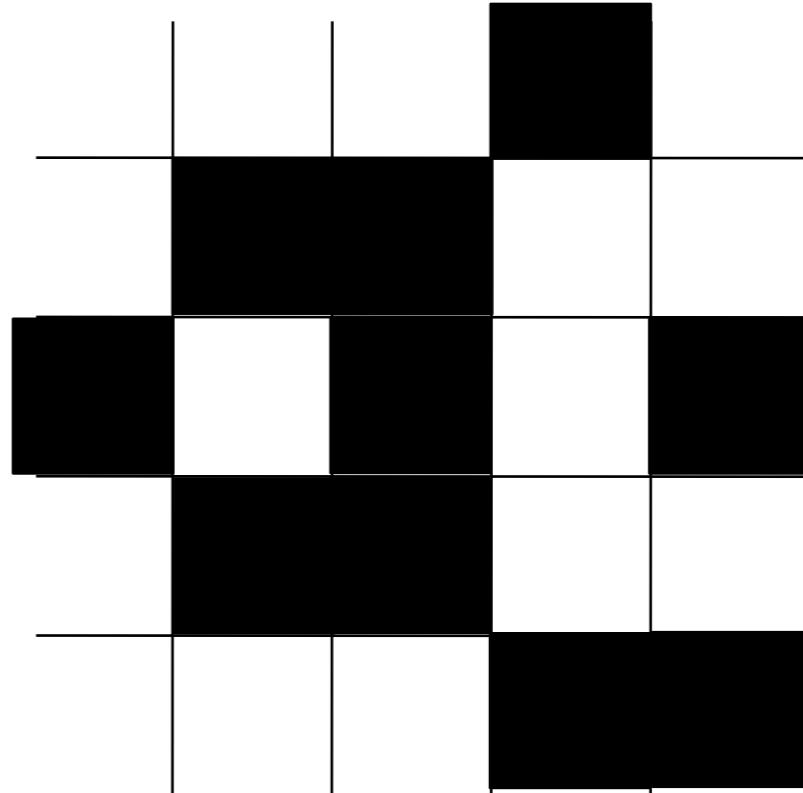


Ising Model Behavior

$$H [\sigma] = -J \sum_{(i,j)} s_i s_j$$

$$P [\sigma] = \frac{1}{\mathcal{Z}} \exp(-H [\sigma] / k_B T)$$

Gibbs Distribution

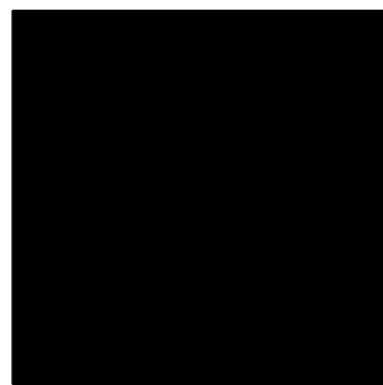
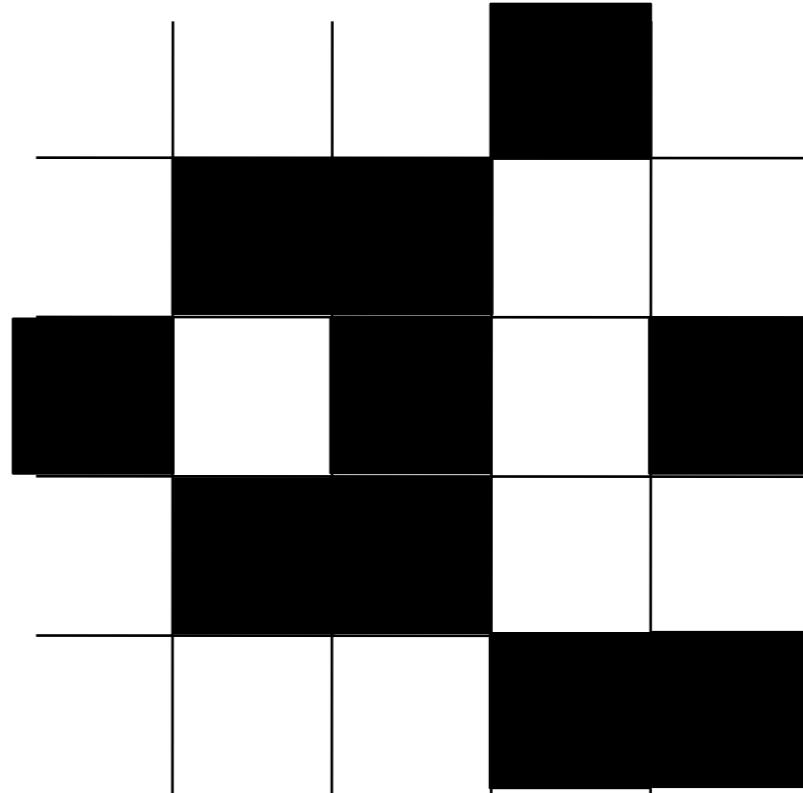


Ising Model Behavior

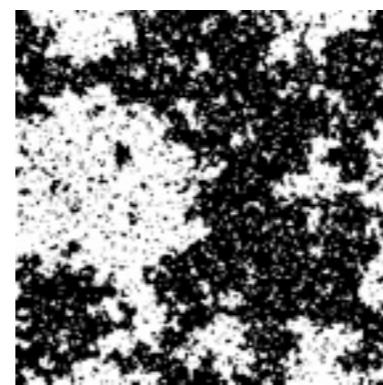
$$H [\sigma] = -J \sum_{(i,j)} s_i s_j$$

$$P [\sigma] = \frac{1}{\mathcal{Z}} \exp(-H [\sigma] / k_B T)$$

Gibbs Distribution



$T = 0$



$T = T_c$



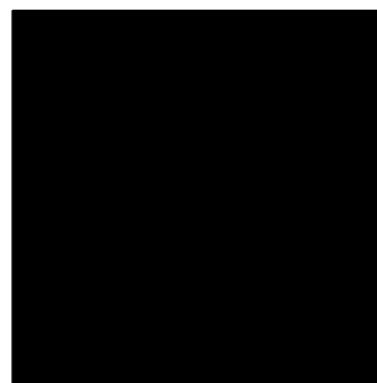
$T = \infty$

Ising Model Behavior

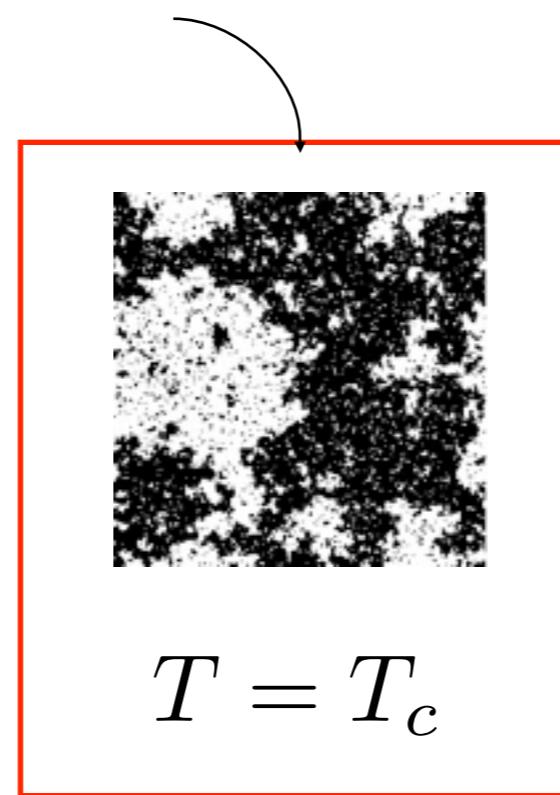
$$H [\sigma] = -J \sum_{(i,j)} s_i s_j$$

$$P [\sigma] = \frac{1}{\mathcal{Z}} \exp(-H [\sigma] / k_B T)$$

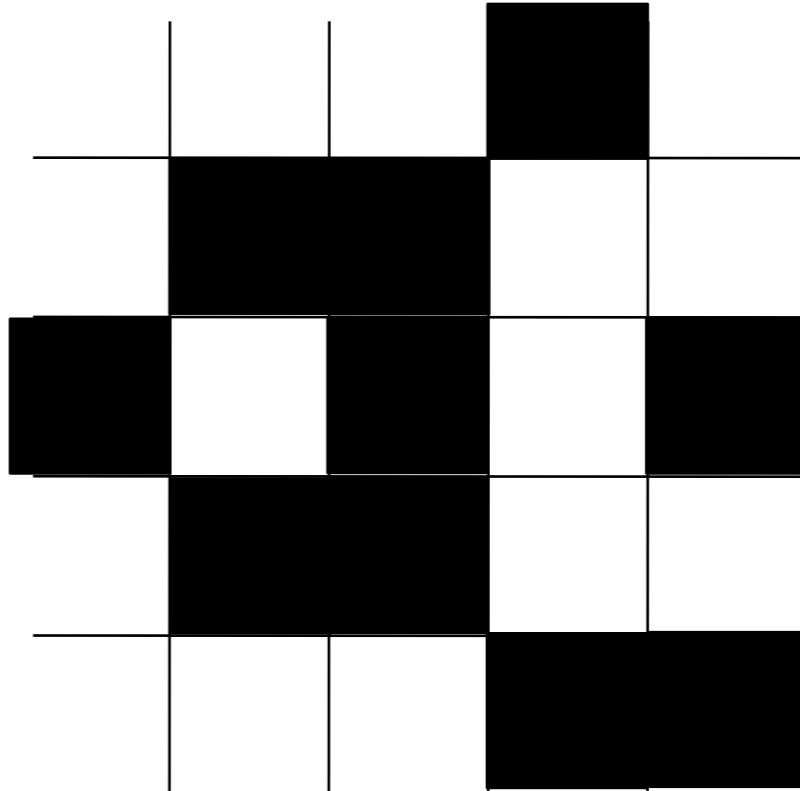
Critical point



$T = 0$



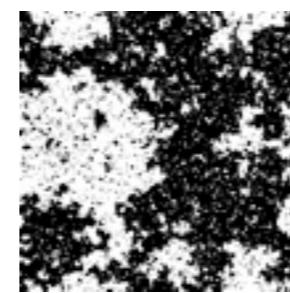
$T = T_c$



$T = \infty$



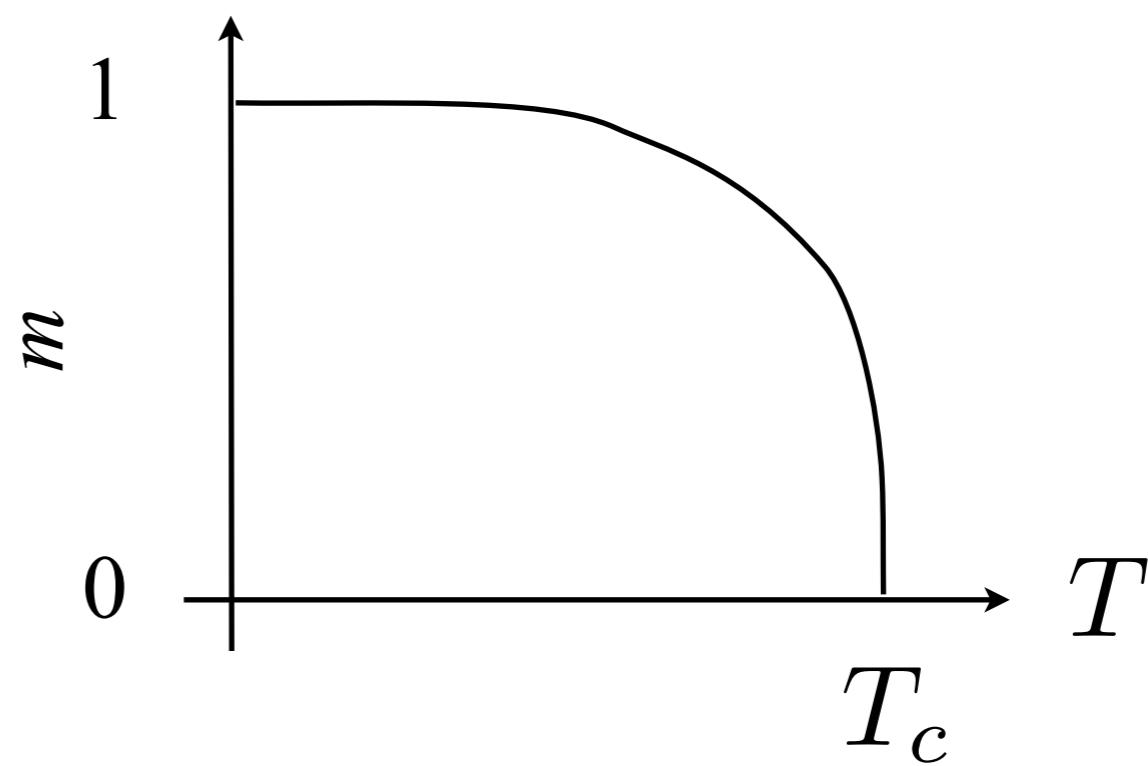
Order Parameter



$T \ll T_c$ $T = T_c$ $T \gg T_c$

Order parameter
(magnetization)

$$m = (1/N) \left\langle \left| \sum_i s_i \right| \right\rangle$$

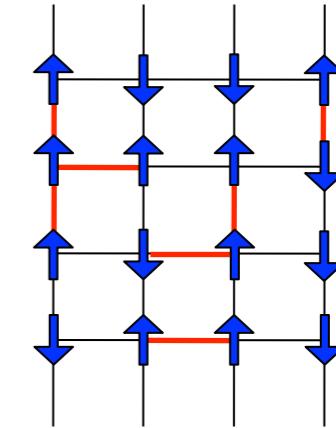


Pure States

- At low temperature the Gibbs distribution for the Ising model can be decomposed into a linear combination of two “pure states,” one mainly spin up and the other mainly spin down. The two pure states are related by the up-down symmetry of the energy function.

Spin Glasses

- Random magnetic alloys: CuMn, ...
- Ising spin glass (Edward-Anderson model, 1975)



$J > 0$, ferromagnetic

$J < 0$, antiferromagnetic

$$H[\sigma] = - \sum_{(i,j)} J_{ij} s_i s_j$$

$$s_i = \pm 1$$

J_{ij} are quenched (fixed) Gaussian random couplings with mean zero and variance one.

Frustration



Frustration



Frustration



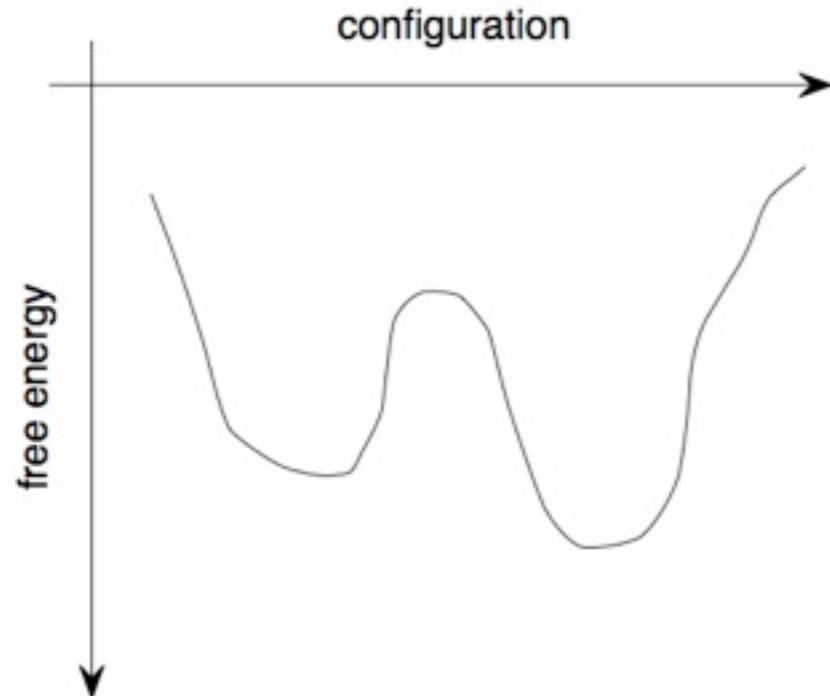
Frustration



Frustration



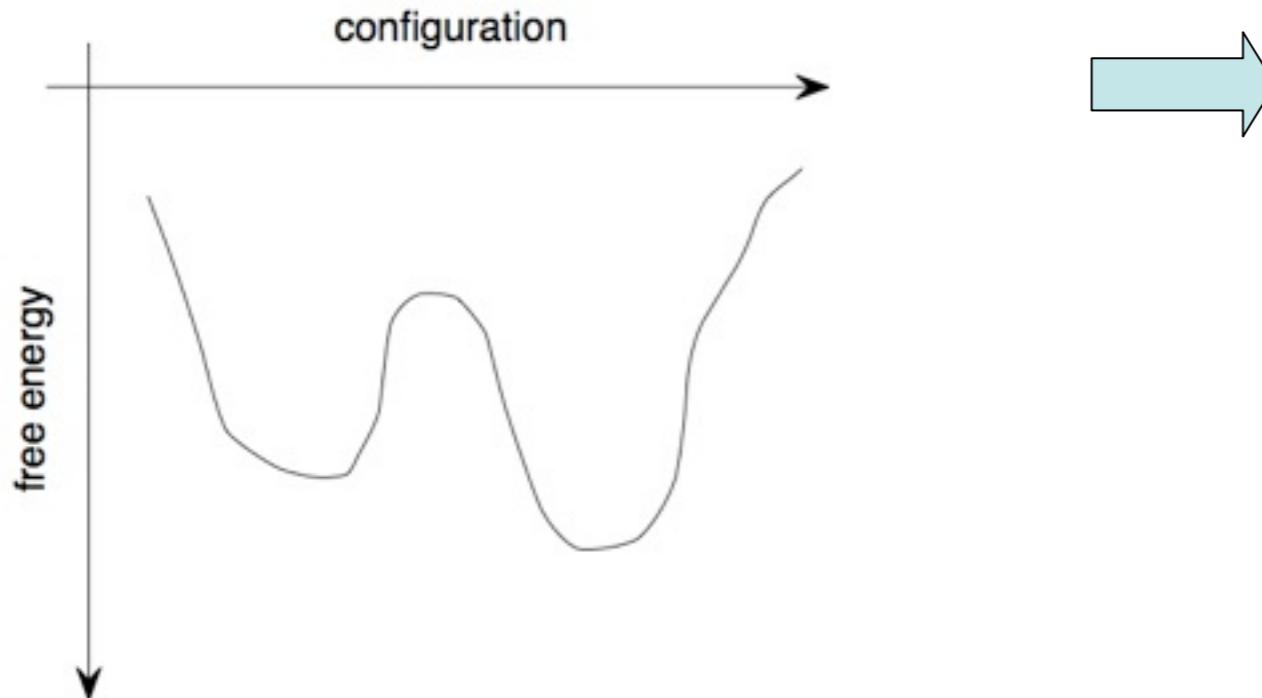
**Rough free energy
landscape.**



Frustration



**Rough free energy
landscape.**



Finding ground
states is NP-hard
(non-planar graphs)

Spin Glass Order

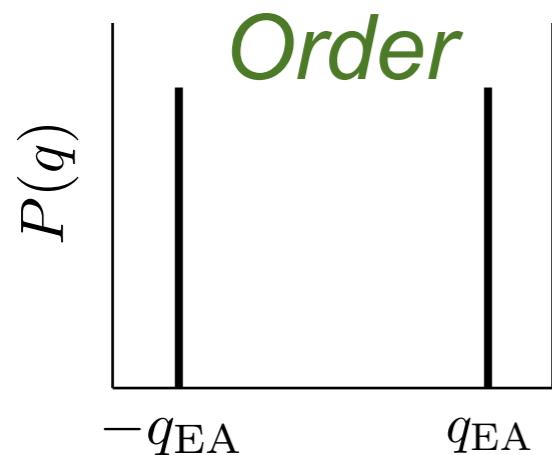
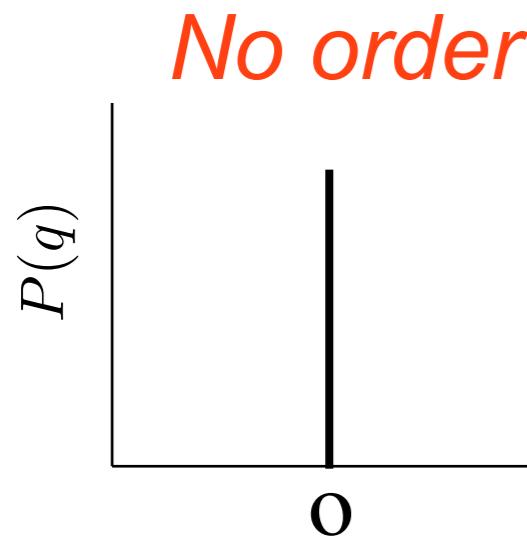
- Spin overlap:
$$q = \frac{1}{N} \sum_i s_i^{(1)} s_i^{(2)}$$

The superscripts refer to two independent spin configurations from the same problem instance.

Spin Glass Order

- Spin overlap:
$$q = \frac{1}{N} \sum_i s_i^{(1)} s_i^{(2)}$$

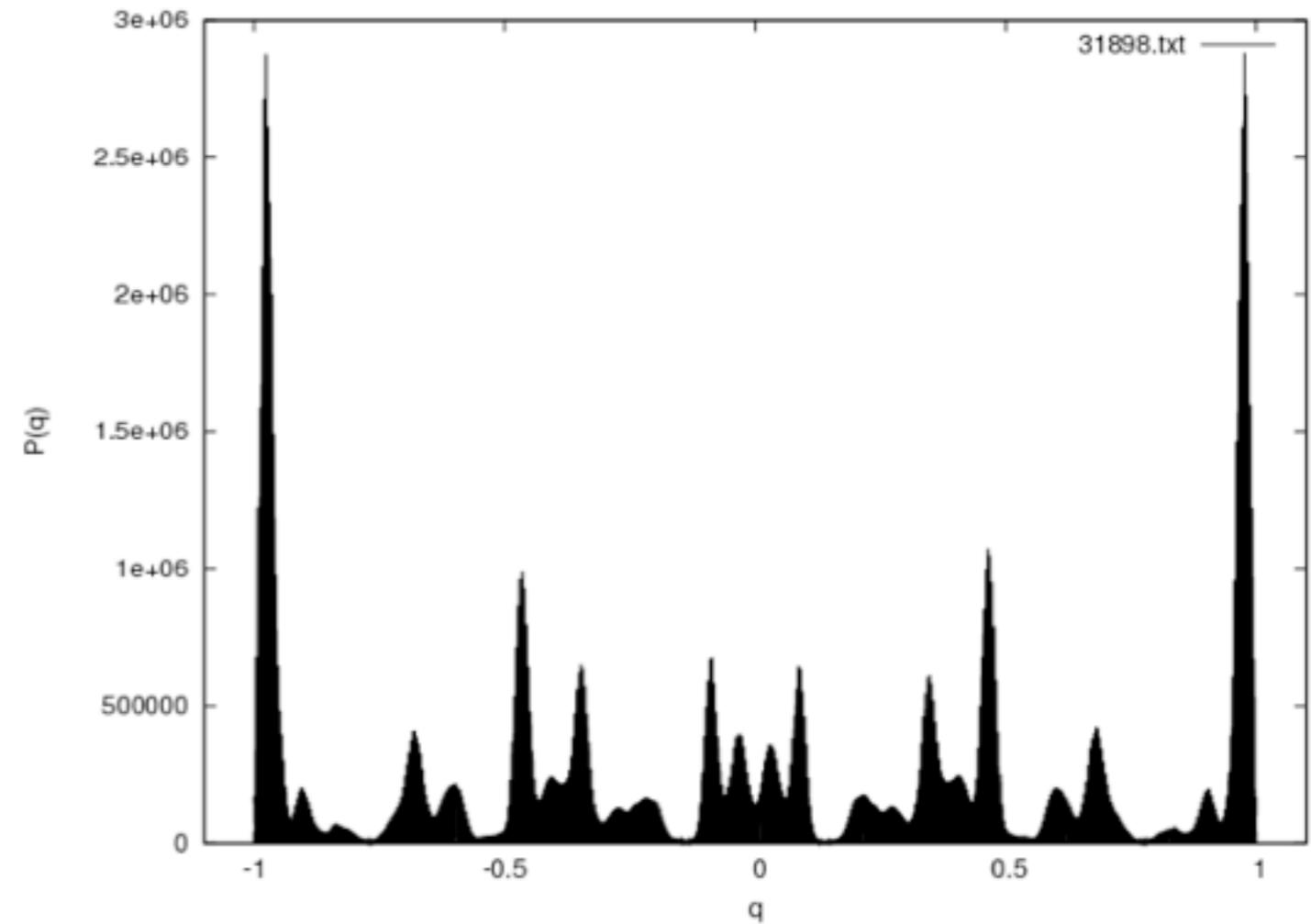
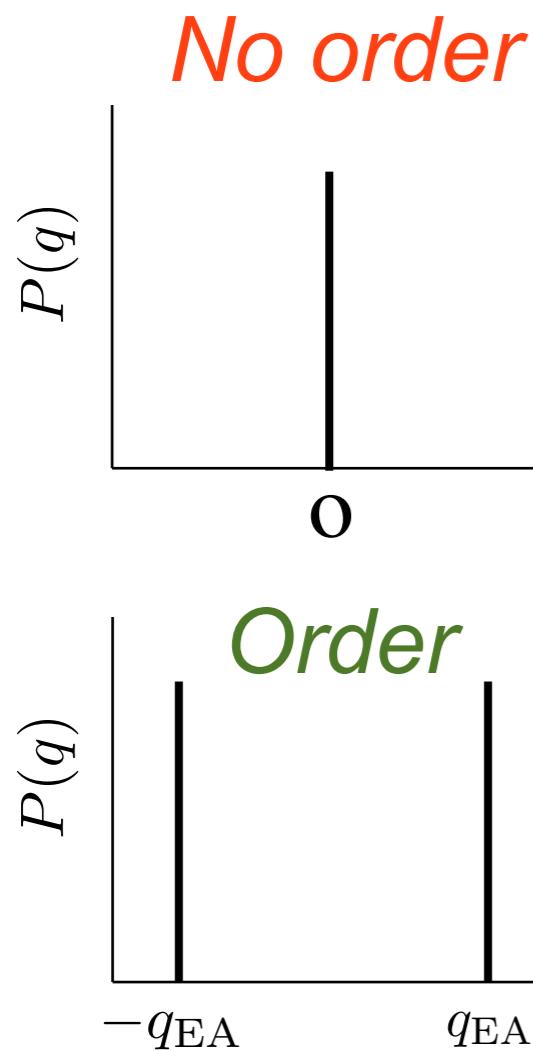
The superscripts refer to two independent spin configurations from the same problem instance.



Spin Glass Order

- Spin overlap:
$$q = \frac{1}{N} \sum_i s_i^{(1)} s_i^{(2)}$$

The superscripts refer to two independent spin configurations from the same problem instance.

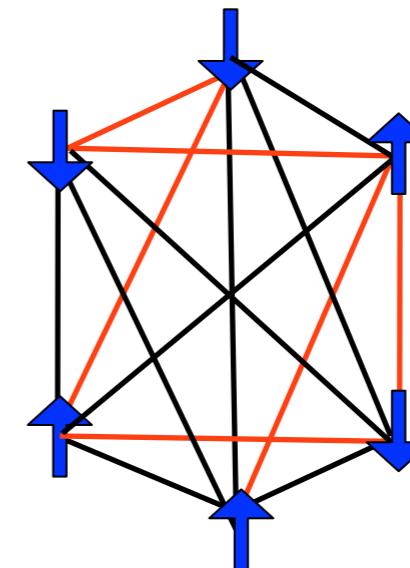


An example of an overlap histogram for a single 8x8x8 instance at low temperature.

Mean Field Theory

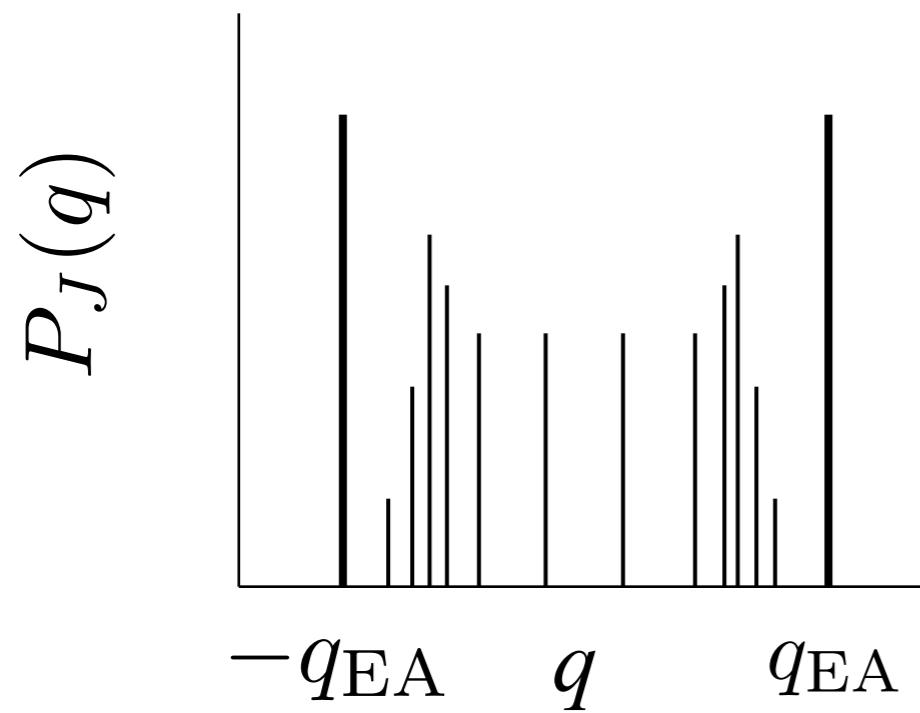
- Sherrington-Kirkpatrick model (1975)
 - Ising spin glass on the complete graph

$$H[\sigma] = \frac{1}{\sqrt{N}} \sum_{(i,j)} J_{ij} s_i s_j$$



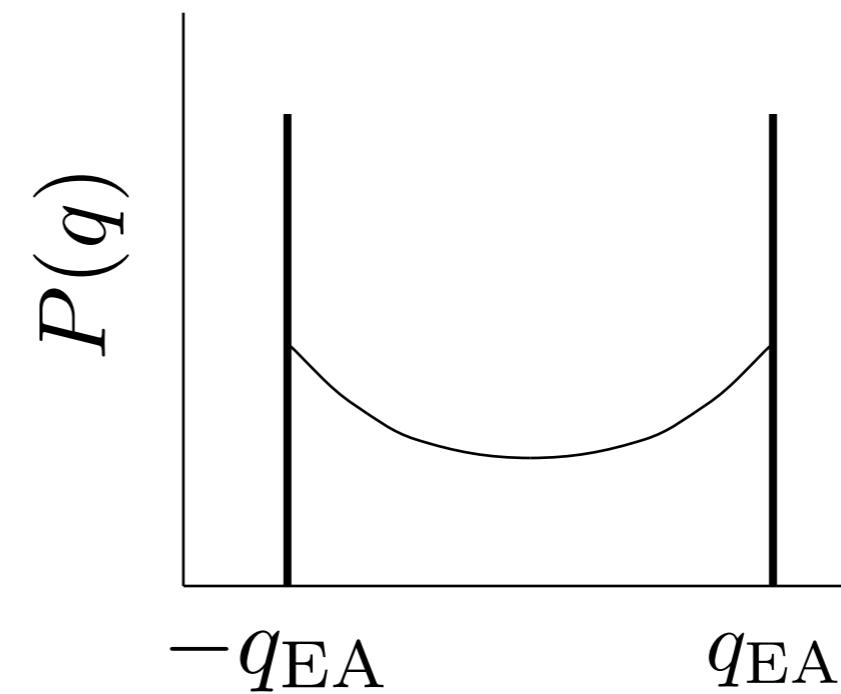
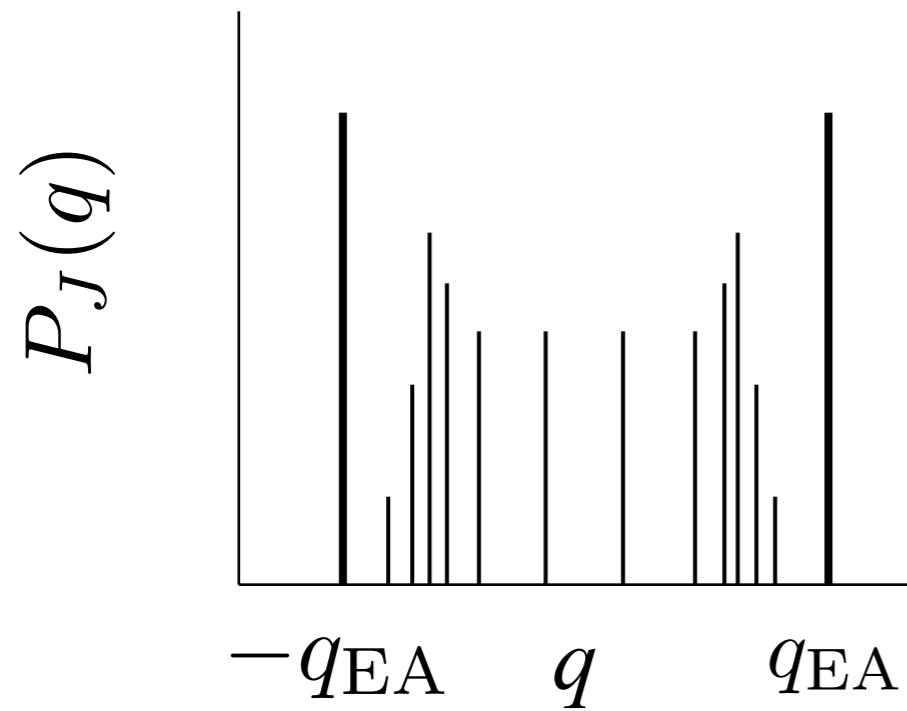
Parisi's solution for the SK Model (1979)

- Replica symmetry breaking (RSB)
- Overlap distribution not self-averaging
- Countable infinity of “pure states”
- Ultrametricity



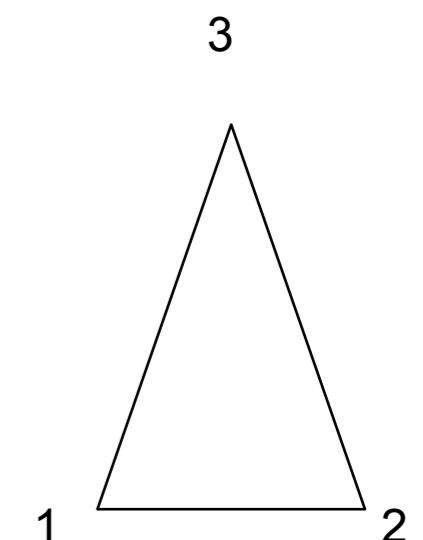
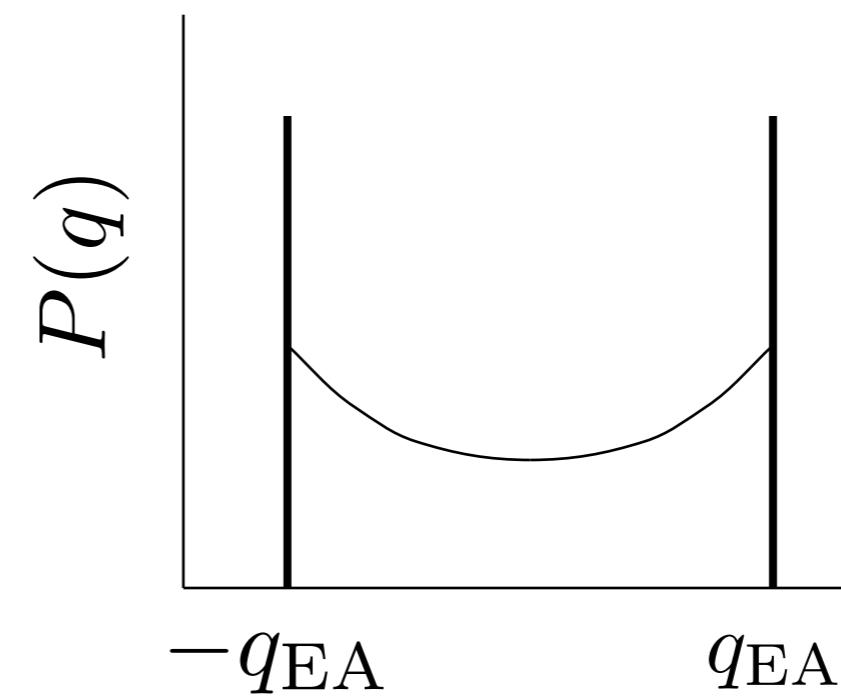
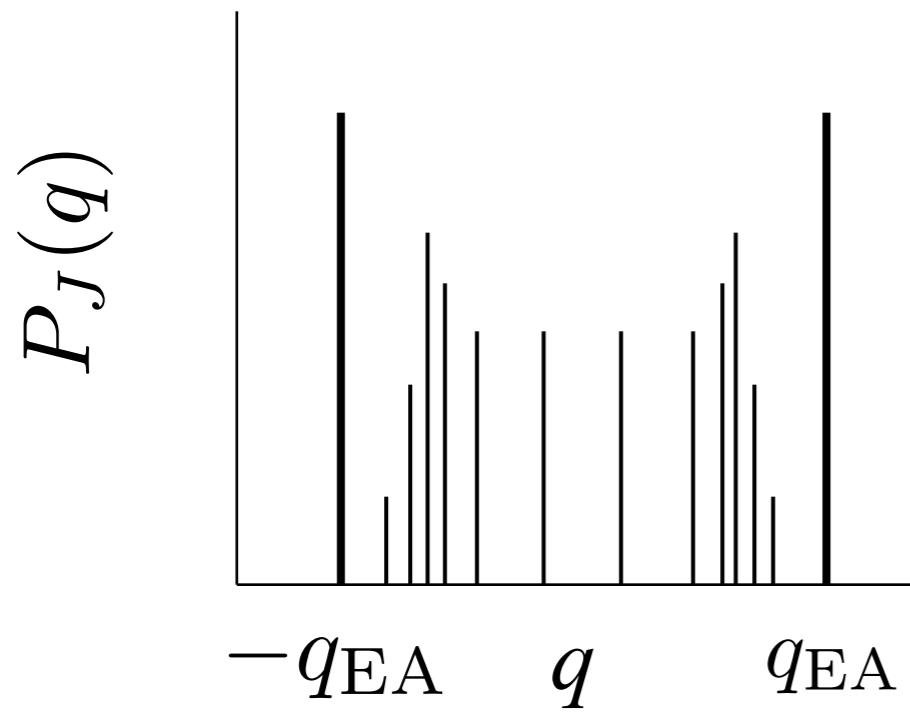
Parisi's solution for the SK Model (1979)

- Replica symmetry breaking (RSB)
- Overlap distribution not self-averaging
- Countable infinity of “pure states”
- Ultrametricity



Parisi's solution for the SK Model (1979)

- Replica symmetry breaking (RSB)
- Overlap distribution not self-averaging
- Countable infinity of “pure states”
- Ultrametricity



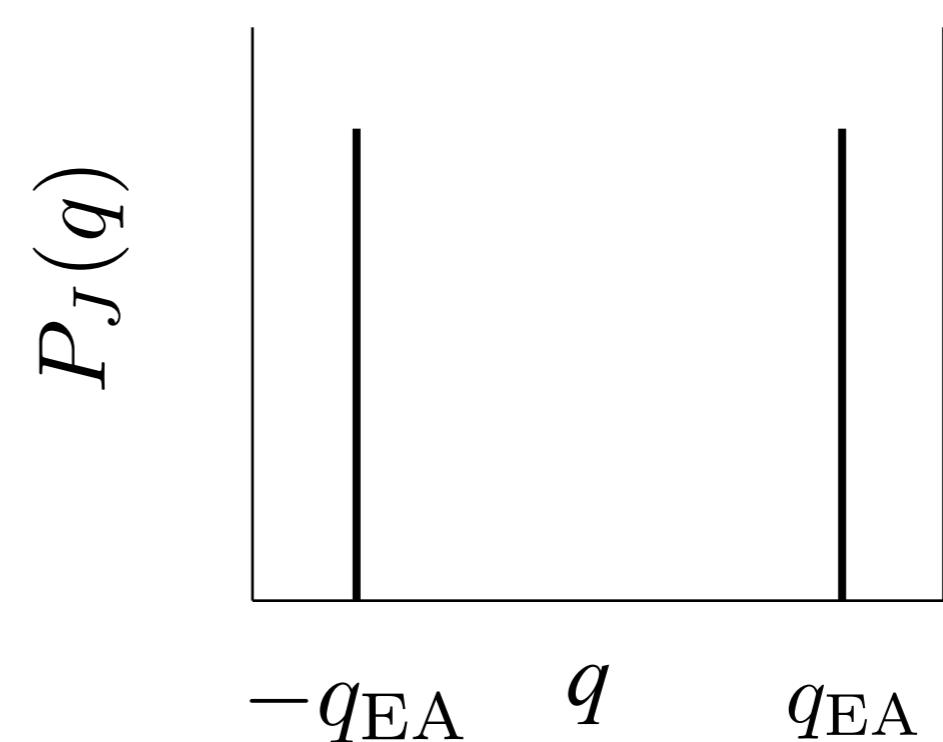
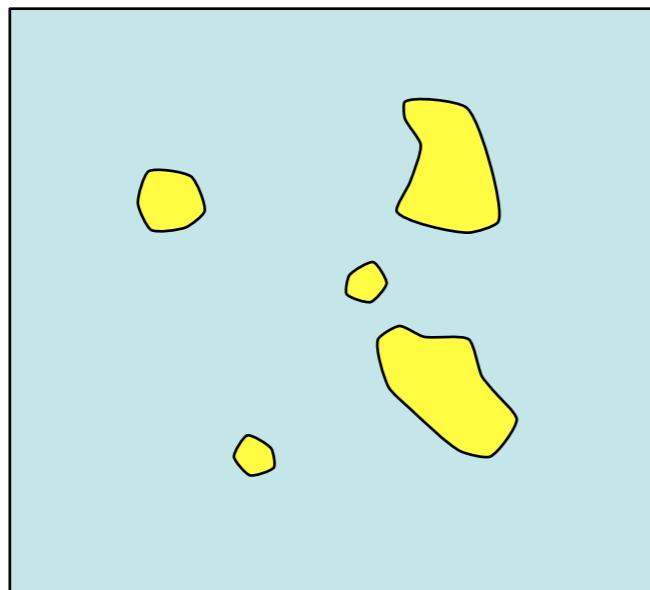
What about finite d ?

- Mean field (complete graph) results are often qualitatively correct for finite-dimensional systems.
- Does RSB apply to the three-dimensional Ising spin glass (Edwards-Anderson model)?

Droplet Picture

Fisher & Huse, Bray & Moore 1985

- Low temperature phase of 3D Ising spin glass consists of a pair of pure states related by up-down symmetry (similar to the ordinary Ising model).
- Low lying excitations are isolated compact “droplets” of flipped spins.



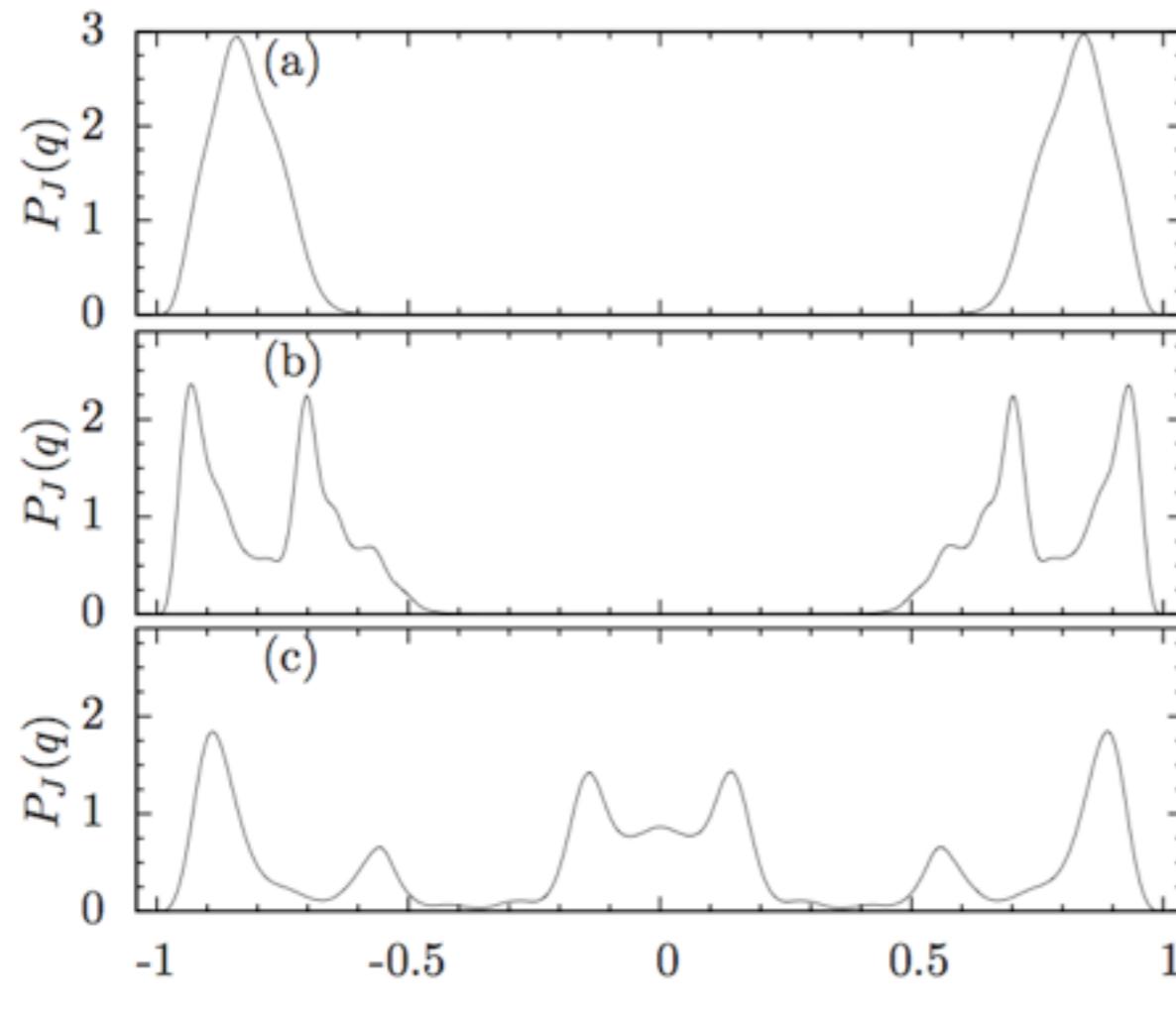
RSB vs Droplet

- Spin overlap:
$$q = \frac{1}{N} \sum_i s_i^{(1)} s_i^{(2)}$$

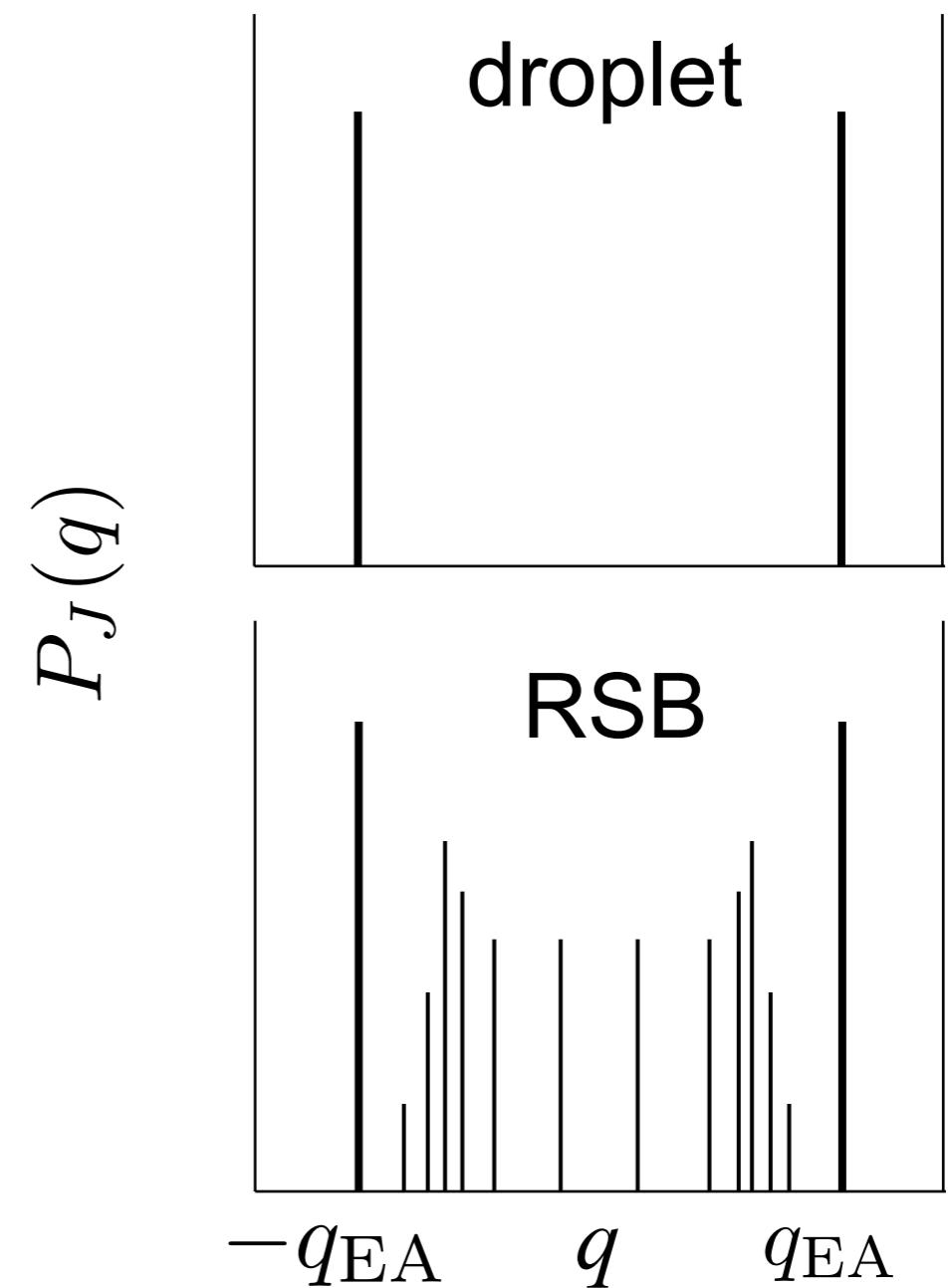
RSB vs Droplet

- Spin overlap:

$$q = \frac{1}{N} \sum_i s_i^{(1)} s_i^{(2)}$$



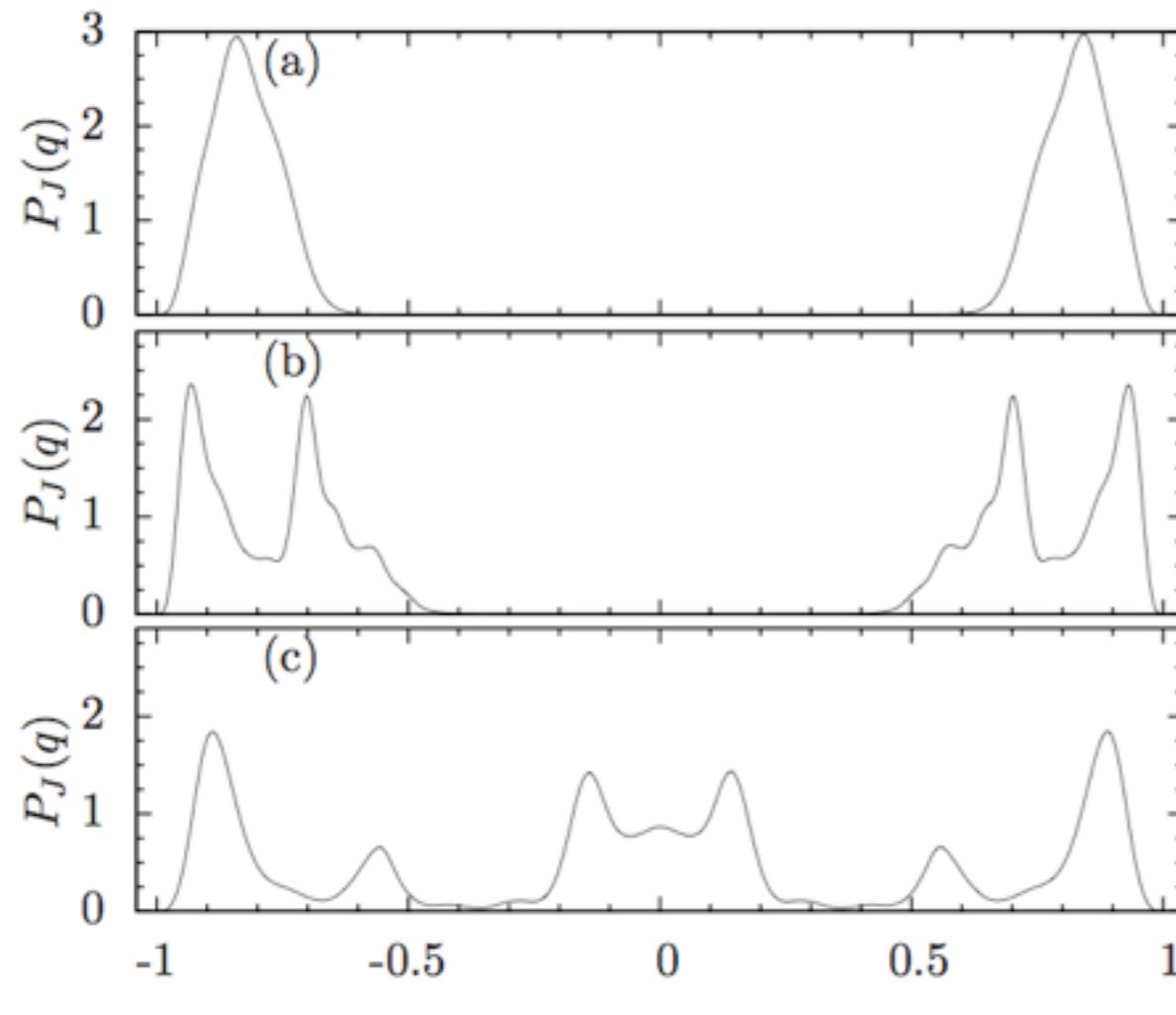
An example of overlap distributions for three disorder instances.



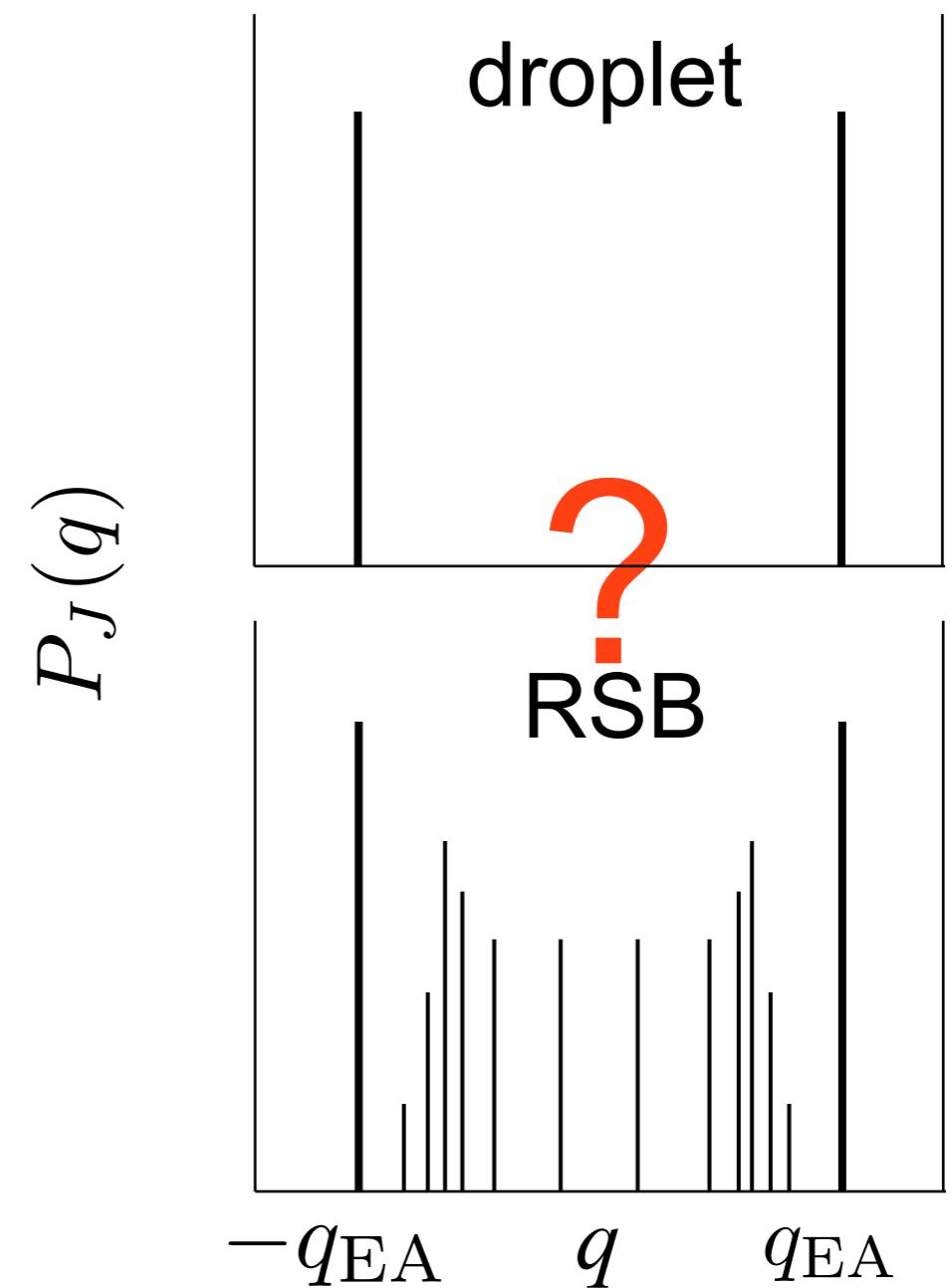
RSB vs Droplet

- Spin overlap:

$$q = \frac{1}{N} \sum_i s_i^{(1)} s_i^{(2)}$$



An example of overlap distributions for three disorder instances.

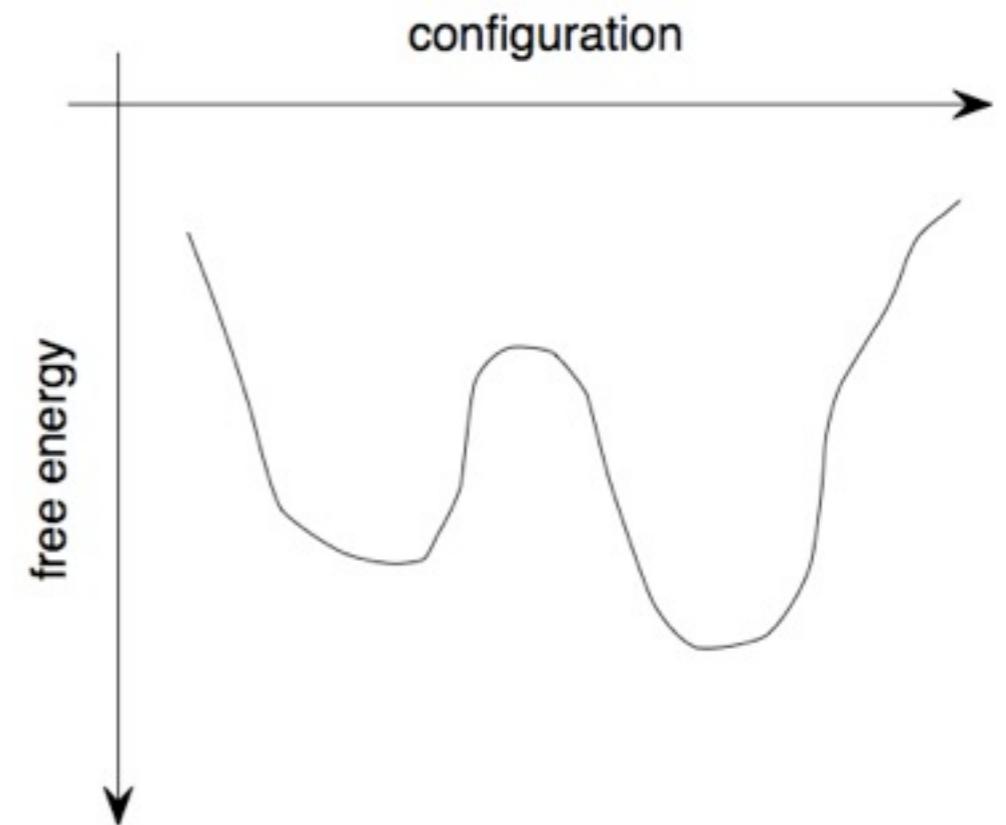


Computational Studies of Spin Glasses

- Find ground states using branch and bound or genetic algorithms.
- Find ground states, sample thermal states and compute free energies using polynomial time algorithms in 2D
- Find ground states, sample thermal states and estimate free energies using Monte Carlo methods for $d > 2$ and the complete graph
 - Parallel tempering
 - **Population annealing**

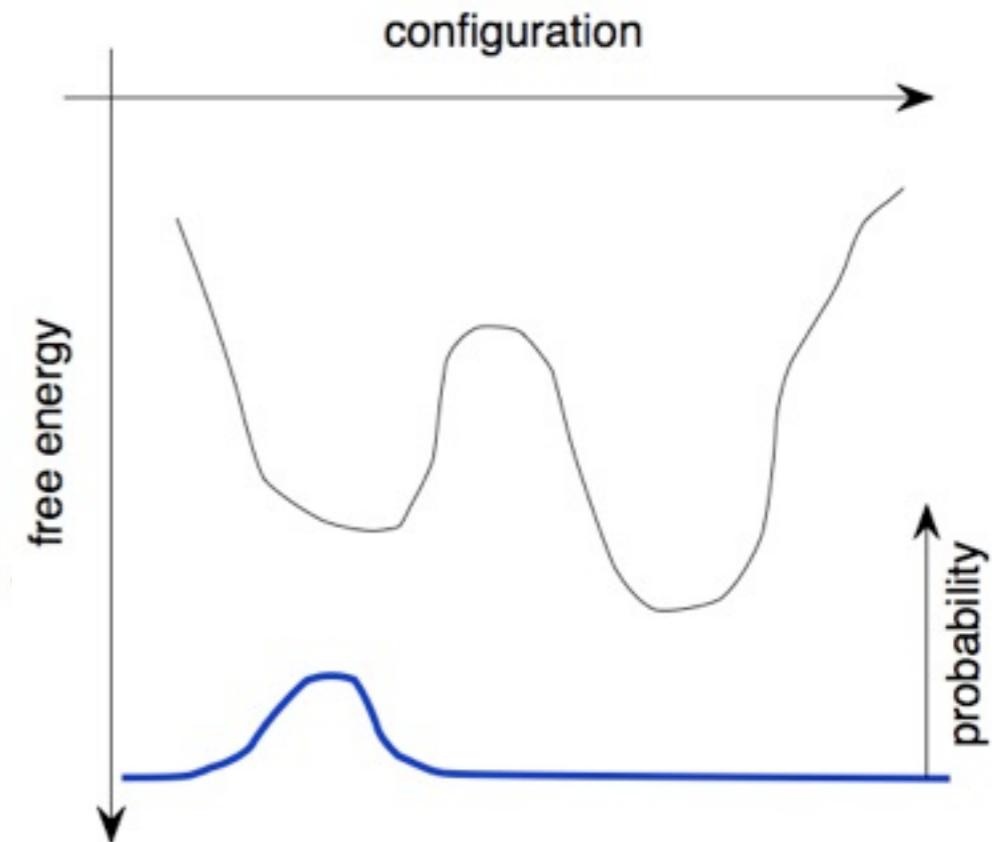
Problem

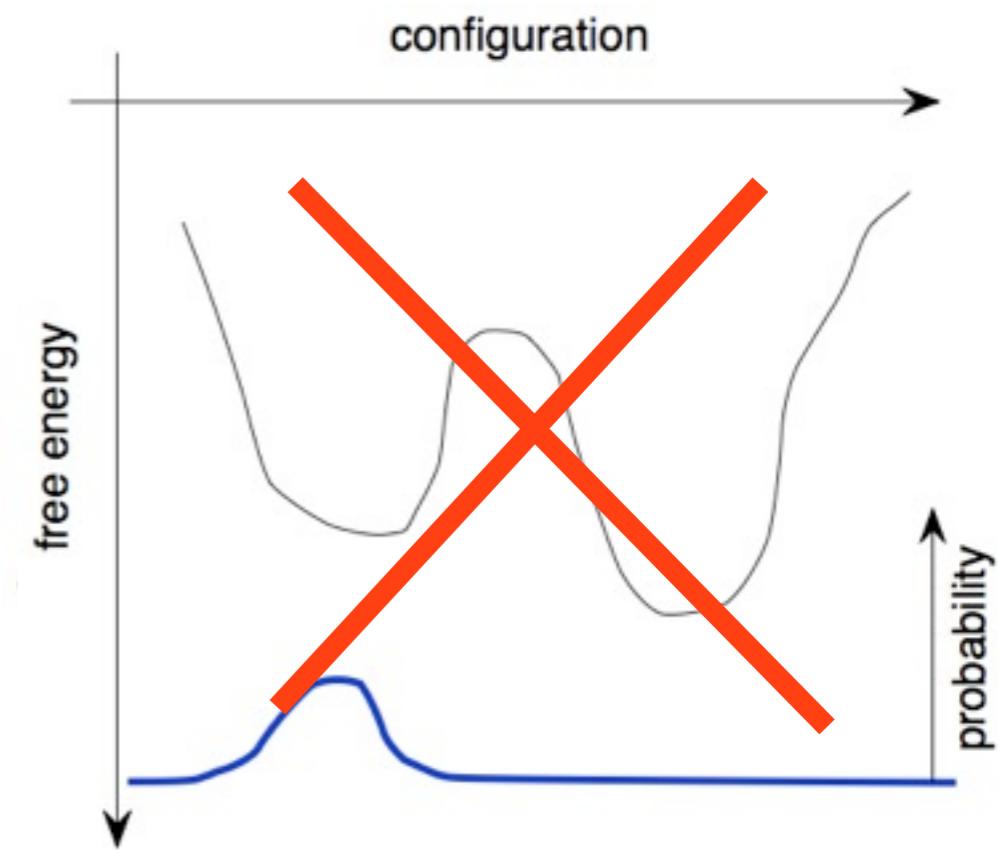
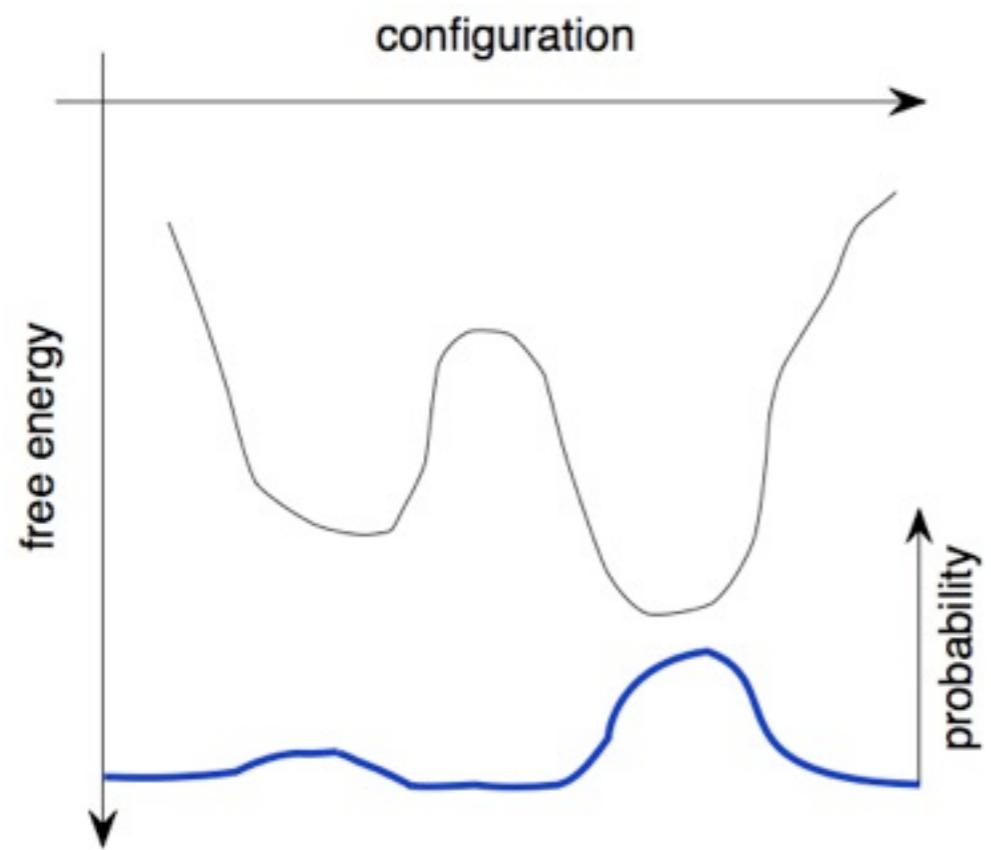
- Markov chain Monte Carlo (MCMC) at a single temperature such as the Metropolis-Hastings algorithm gets stuck in local minima.



Problem

- Markov chain Monte Carlo (MCMC) at a single temperature such as the Metropolis-Hastings algorithm gets stuck in local minima.





Population Annealing



K. Hukushima and Y. Iba, in *THE MONTE CARLO METHOD IN THE PHYSICAL SCIENCES: Celebrating the 50th Anniversary of the Metropolis Algorithm*, edited by J. E. Gubernatis (AIP, 2003), vol. 690, pp. 200–206.



- Modification of *simulated annealing* for equilibrium sampling.
- A *population* of replicas is cooled according to an annealing schedule. Each replica is acted on by the Metropolis-Hastings at the current temperature.
- During each temperature step, the population is differentially reproduced (*resampled*) according to the correct Boltzmann re-weighting to maintain equilibrium.
- *See:* Phys. Rev. E 82, 026704 (2010); E 92, 063307 (2015)

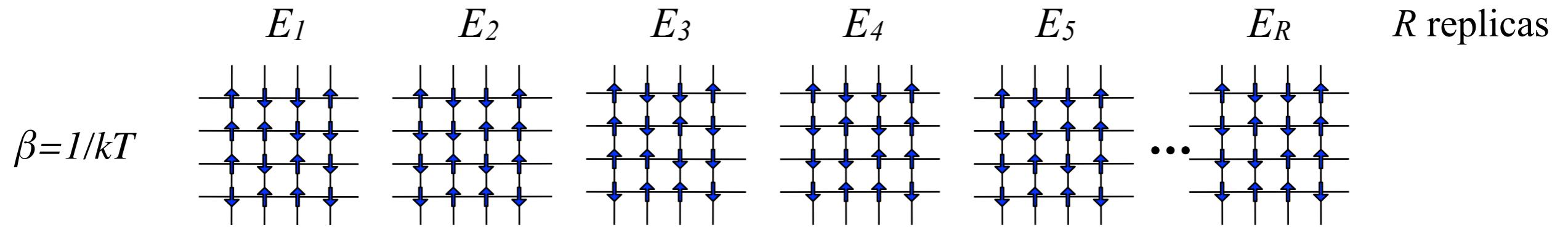
Population Annealing is related to...

→ Simulated annealing

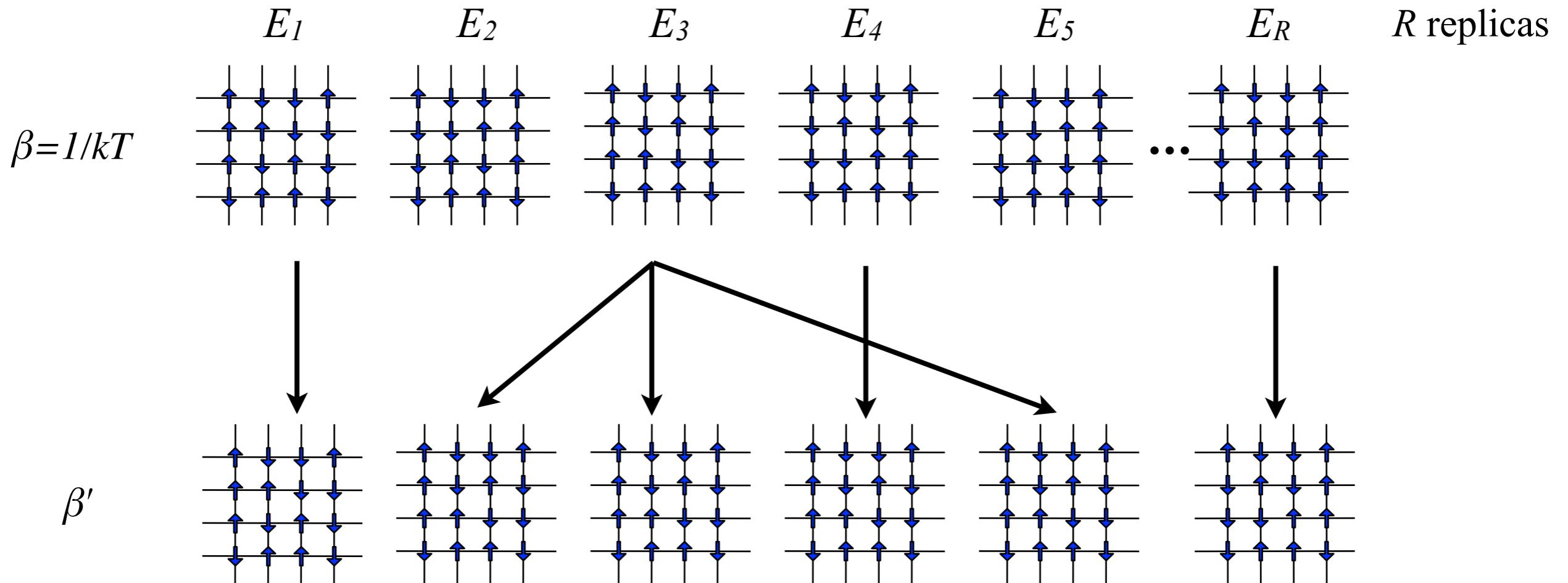
→ Sequential Monte Carlo

- See e.g. “Sequential Monte Carlo Methods in Practice”, A. Doucet, et. al. (2001)
- aka Particle Filters
- Nested Sampling, Skilling
- Go with the Winners, Grassberger (2002)
- Diffusion (quantum) Monte Carlo
- Nonequilibrium Equality for Free Energy Differences, Jarzynski (1997)
- Histogram Re-weighting, Swendsen and Ferrenberg (1988)

Population Annealing

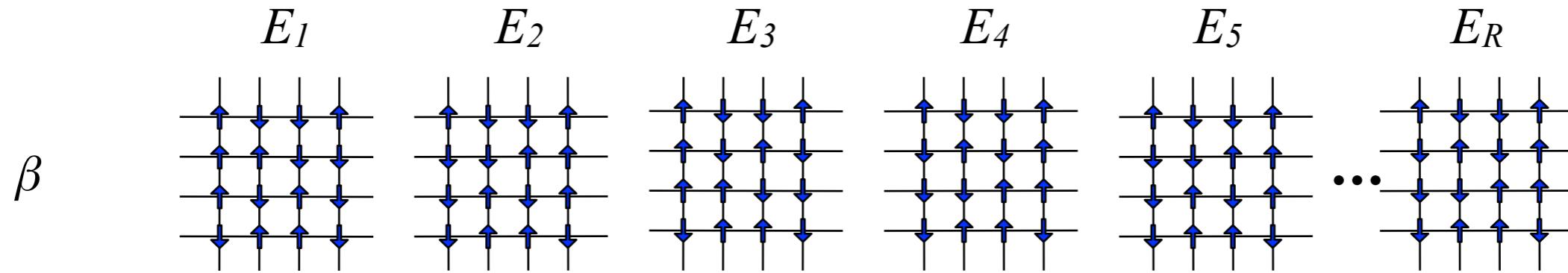


Population Annealing



Population annealing = simulated annealing with differential reproduction (resampling) of replicas

Temperature Step

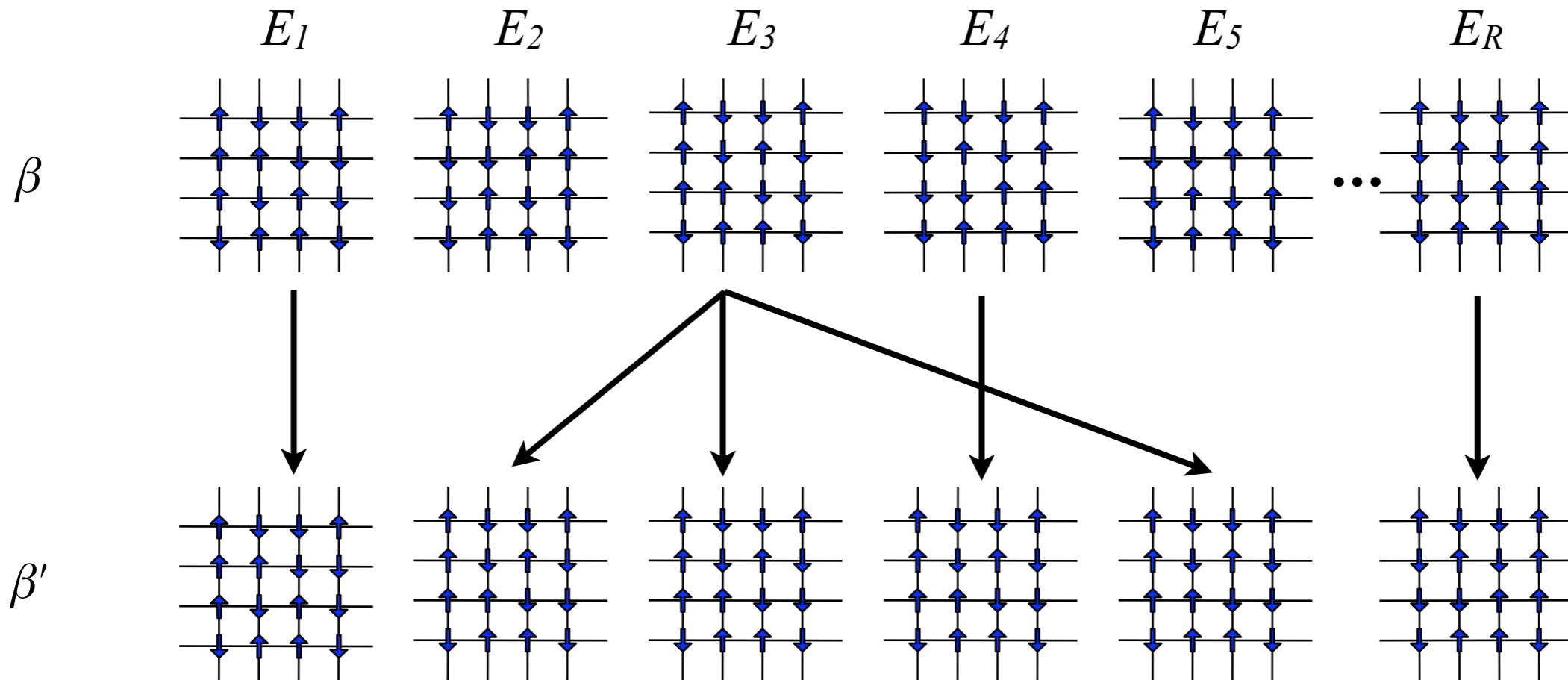


$$\tau_j(\beta, \beta') = \frac{\exp [-(\beta' - \beta)E_j]}{Q(\beta, \beta')}$$

$$Q(\beta, \beta') = \frac{\sum_{j=1}^R \exp [-(\beta' - \beta)E_j]}{R}$$

Replica j is reproduced n_j times where n_j is an integer random variate with mean τ_j .

Temperature Step

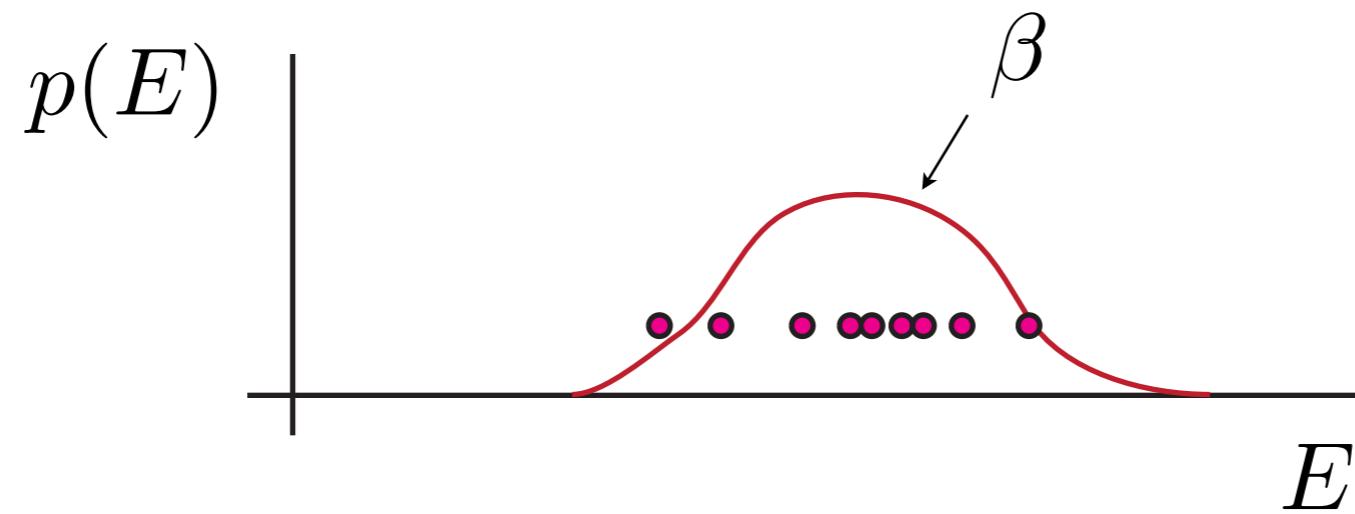


$$\tau_j(\beta, \beta') = \frac{\exp [-(\beta' - \beta)E_j]}{Q(\beta, \beta')}$$

$$Q(\beta, \beta') = \frac{\sum_{j=1}^R \exp [-(\beta' - \beta)E_j]}{R}$$

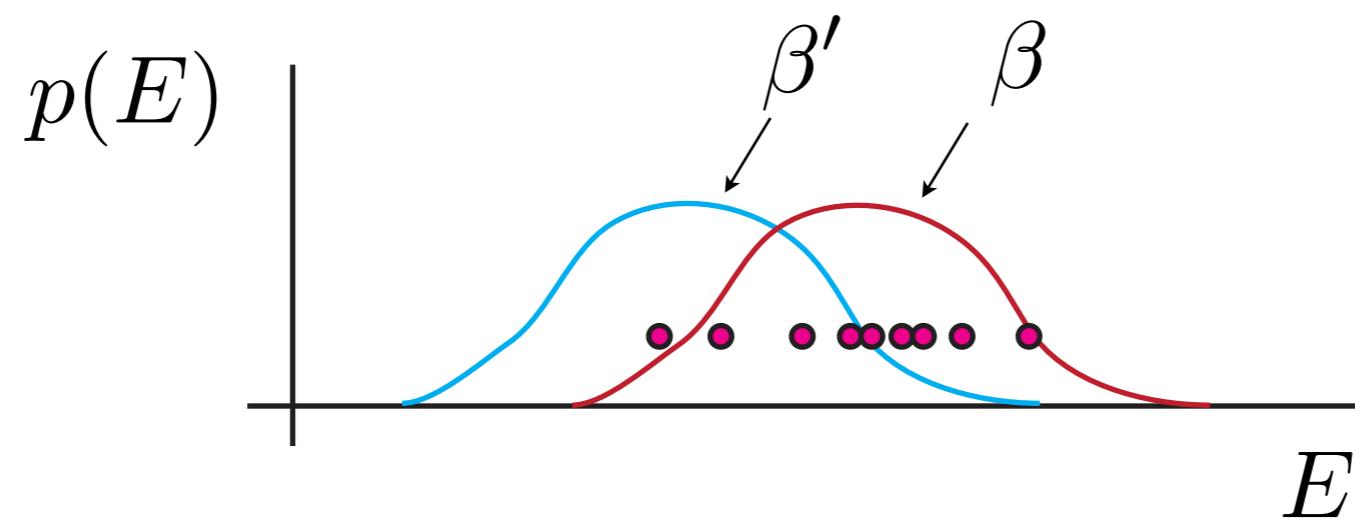
Replica j is reproduced n_j times where n_j is an integer random variate with mean τ_j .

Systematic Errors

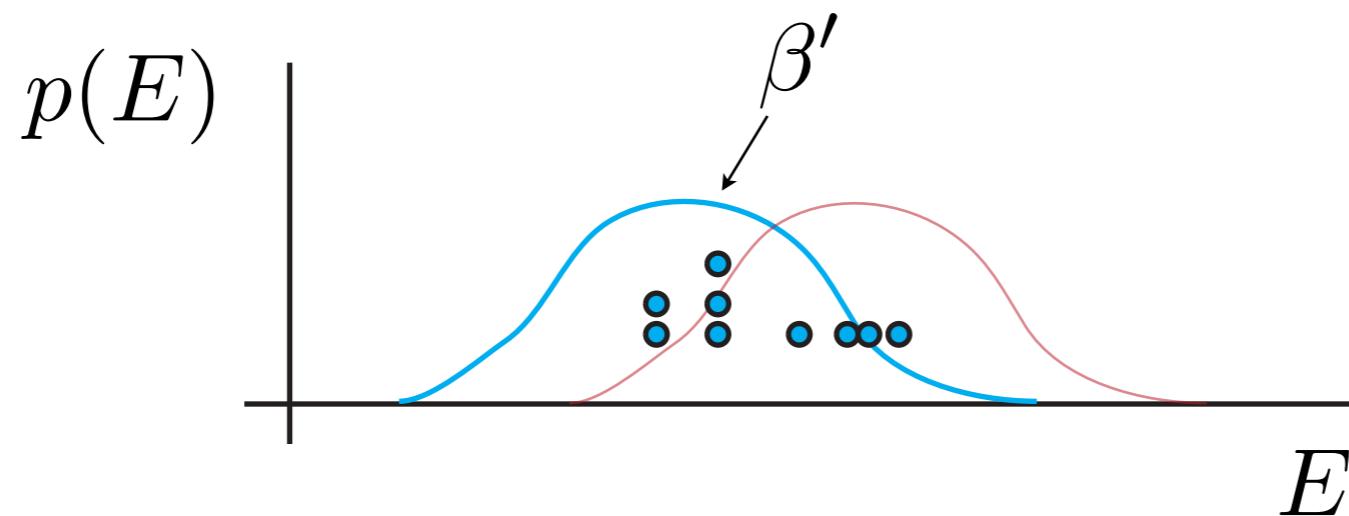


Population represents the Gibbs distribution at β

Systematic Errors



Systematic Errors



Resampled population represents the Gibbs distribution at β'

... but new population is biased toward high energy and correlated

Direct Estimate of Free Energy

$$Q(\beta, \beta') = \frac{\sum_{j=1}^R \exp [-(\beta' - \beta)E_j]}{R}$$

$$-\beta_k F(\beta_k) = \sum_{\ell=k}^K \ln Q(\beta_{\ell+1}, \beta_\ell) + \beta_K F(\beta_K)$$

Derivation:

$$\begin{aligned} \frac{Z(\beta')}{Z(\beta)} &= \frac{\sum_\gamma e^{-\beta' E_\gamma}}{Z(\beta)} \\ &= \sum_\gamma e^{-(\beta' - \beta)E_\gamma} \left(\frac{e^{-\beta E_\gamma}}{Z(\beta)} \right) \\ &= \langle e^{-(\beta' - \beta)E_\gamma} \rangle_\beta \\ &\approx \frac{1}{R} \sum_{j=1}^R e^{-(\beta' - \beta)E_j} = Q(\beta, \beta'). \end{aligned}$$

Weighted Averaging

JM, PRE82,26704(2010)

- Results from small population runs are biased.
- Results from independent runs can be combined and biases reduced using *weighted* averages.
- Observables from each run weighted by the exponential of the free energy estimator for that run.

$$\overline{A}(\beta) = \sum_{m=1}^M \tilde{A}_m(\beta) \omega_m(\beta) \quad \omega_m(\beta) = \frac{R_m e^{-\beta \tilde{F}_m(\beta)}}{\sum_{i=1}^M R_m e^{-\beta \tilde{F}_i(\beta)}}$$

Weighted Averaging

Imagine population annealing with unlimited resources and let the population in each run m grow according to unnormalized weights

$$\tau_i = \exp [-(\beta' - \beta)E_i]$$

$$\mathfrak{R}_m = R_m \prod_{\beta_k} Q_m(\beta_k) = e^{-\beta \tilde{F}_m(\beta)}$$

final population of run m

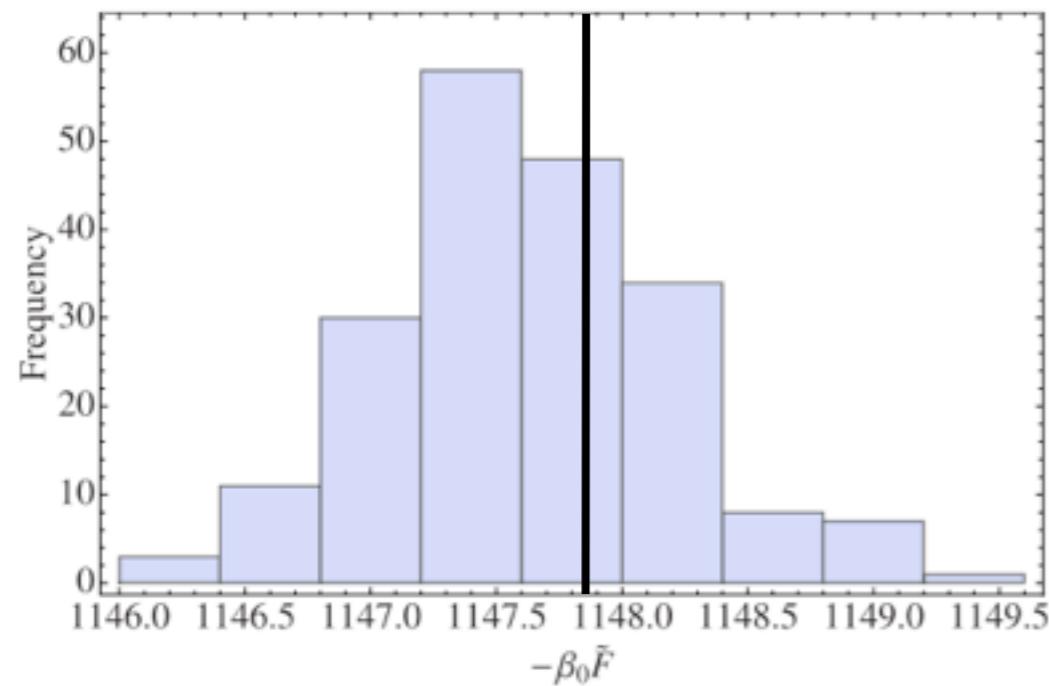
$$\mathfrak{R}_1 \quad \mathfrak{R}_2 \quad \mathfrak{R}_3 \quad \dots \quad \mathfrak{R}_M$$

.....

An ordinary average over the combined populations of unlimited PA is equivalent to a weighted average with standard PA

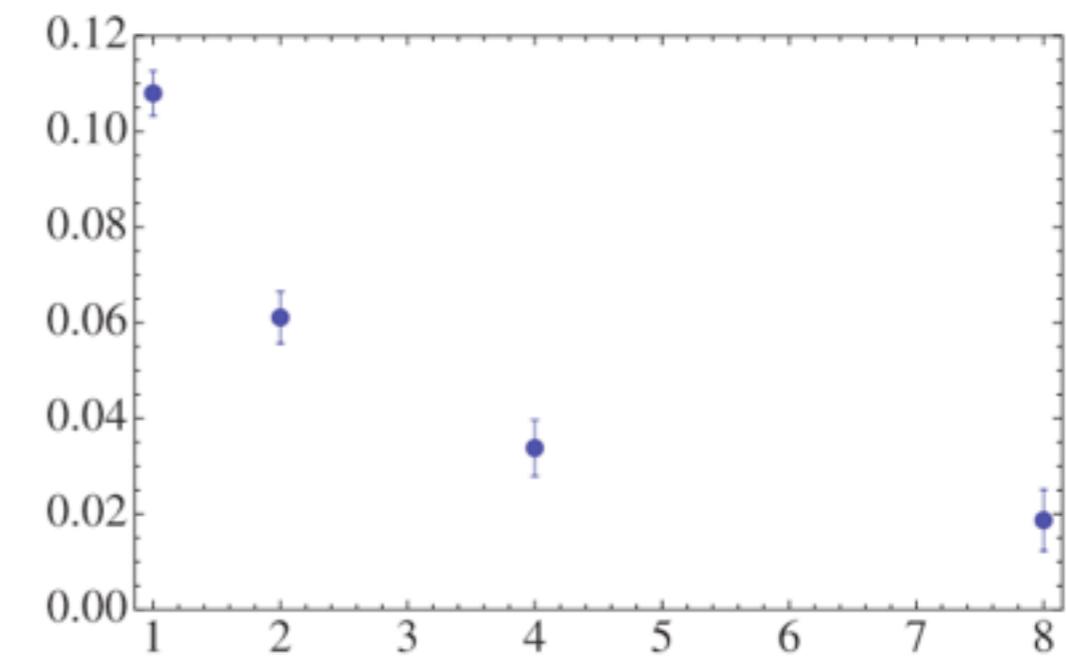
Weighted Averaging

histogram



free energy

systematic error



number of runs

Systematic Errors

If an observable is a function of the free energy estimator there will be a systematic error (bias) proportional to the variance of the free energy estimator.

$$\delta A_{\text{systematic}} \approx -(\text{Var} \beta \tilde{F}) \frac{d\tilde{A}}{\beta d\tilde{F}} \approx -\frac{\rho_0}{R} \frac{dA}{\beta dF}$$

$$\rho_0 = \lim_{R \rightarrow \infty} R \text{Var} \beta \tilde{F}$$

Systematic Errors

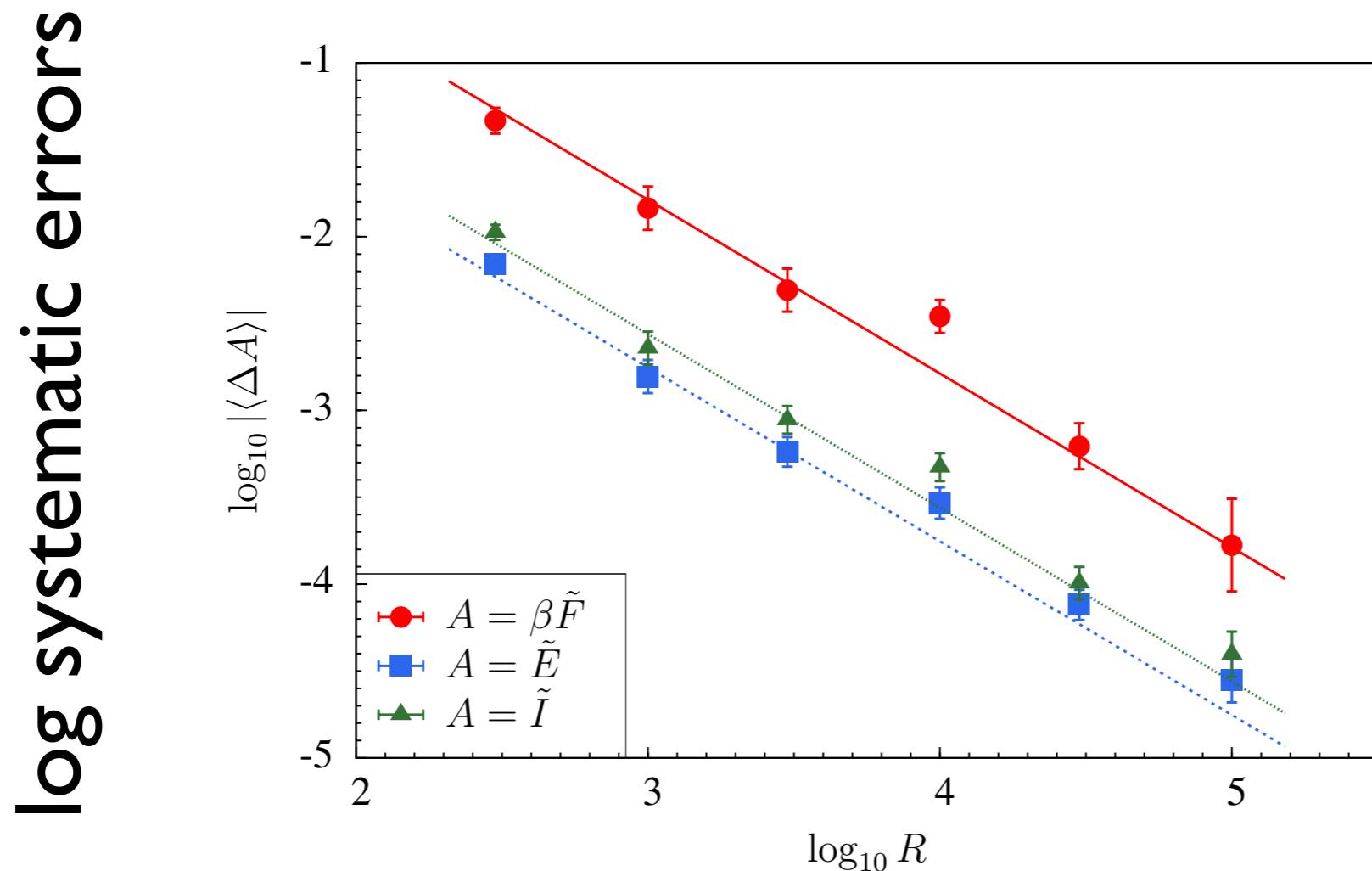
If an observable is a function of the free energy estimator there will be a systematic error (bias) proportional to the variance of the free energy estimator.

$$\delta A_{\text{systematic}} \approx -(\text{Var} \beta \tilde{F}) \frac{d\tilde{A}}{\beta d\tilde{F}} \approx -\frac{\rho_0}{R} \frac{dA}{\beta dF}$$

$$\rho_0 = \lim_{R \rightarrow \infty} R \text{Var} \beta \tilde{F}$$

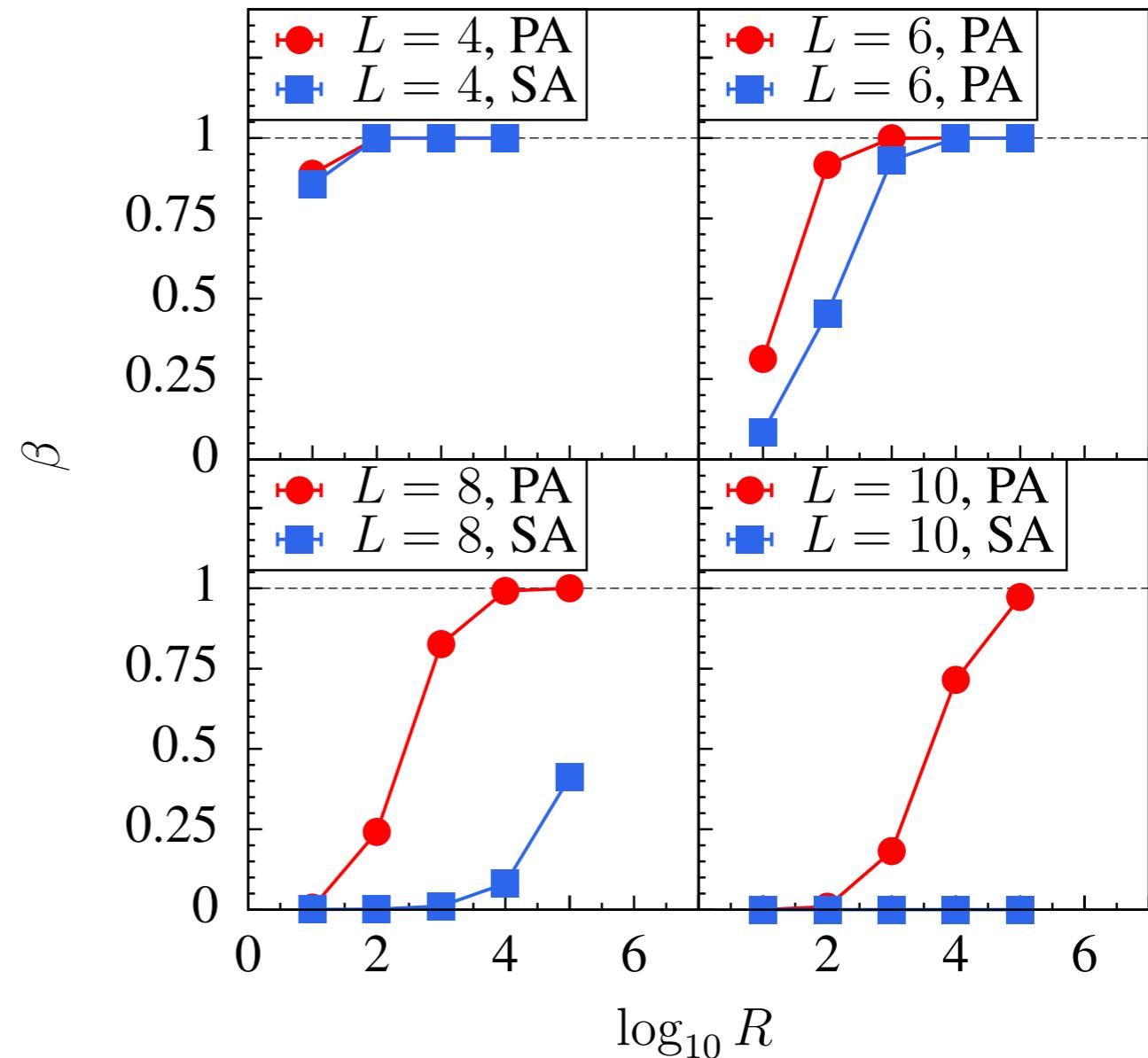
ρ_0 is the population size scale for systematic errors
(like the exponential autocorrelation time for MCMC)

Convergence in Population Size



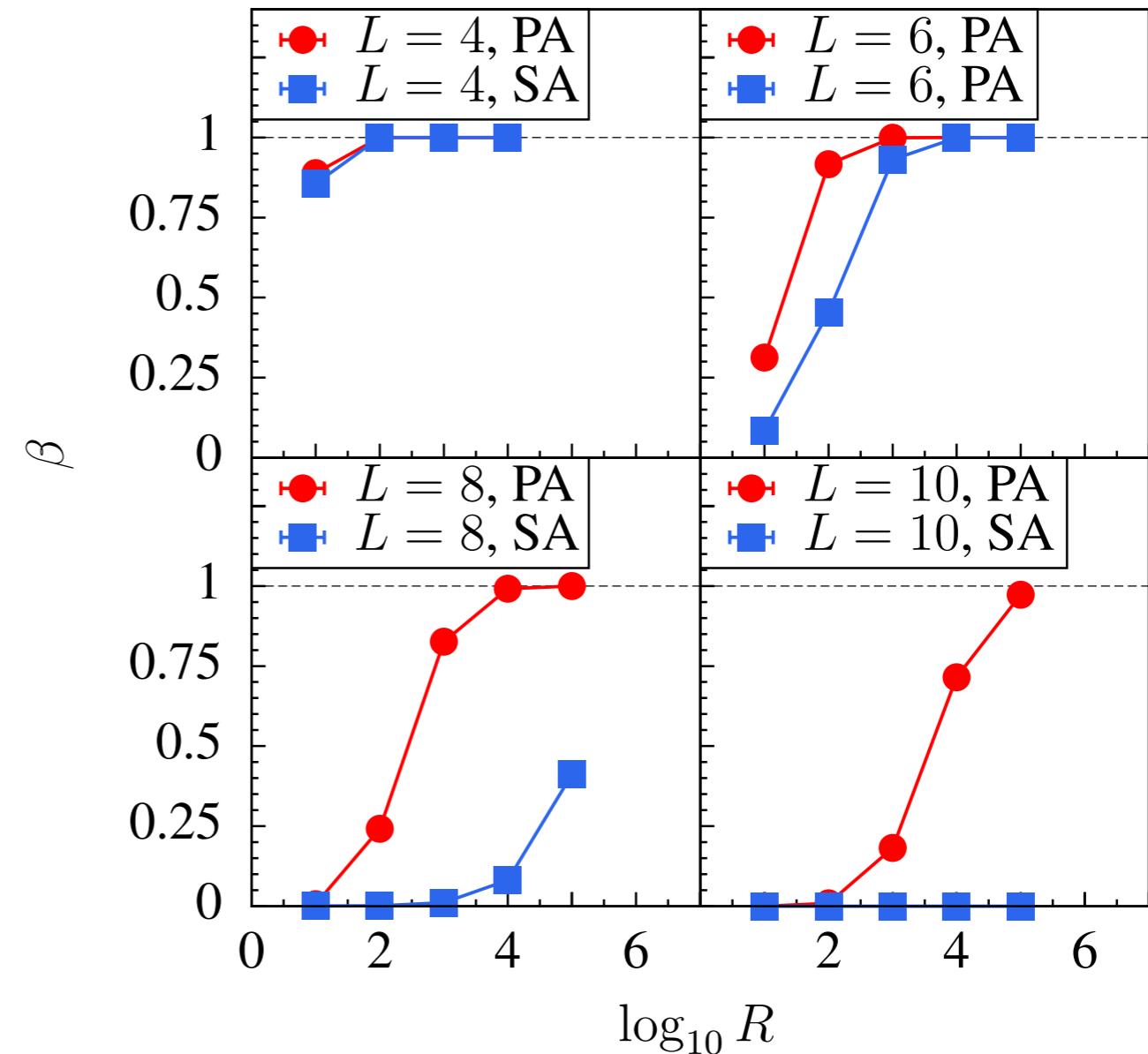
Compare PA and SA for finding GS's

- Simulate a population of R replicas with resampling (PA) and without resampling (SA) holding the annealing schedule fixed.
- Do for many spin glass instances.
- The vertical axis is the disorder averaged probability of finding the true ground state.



Compare PA and SA for finding GS's

- Simulate a population of R replicas with resampling (PA) and without resampling (SA) holding the annealing schedule fixed.
- Do for many spin glass instances.
- The vertical axis is the disorder averaged probability of finding the true ground state.



Population annealing is far more efficient than simulated annealing with almost no overhead

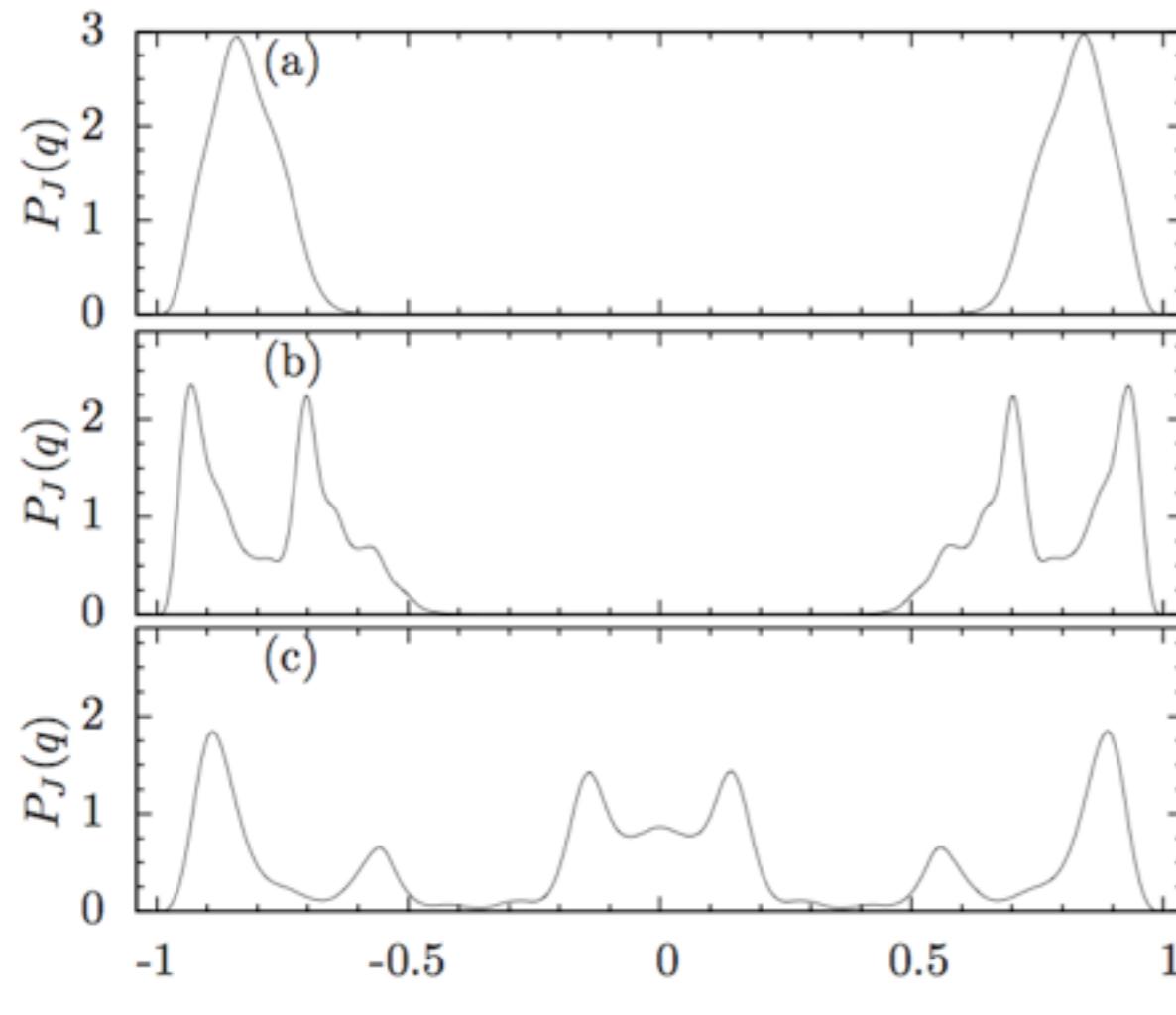
RSB vs Droplet

- Spin overlap:
$$q = \frac{1}{N} \sum_i s_i^{(1)} s_i^{(2)}$$

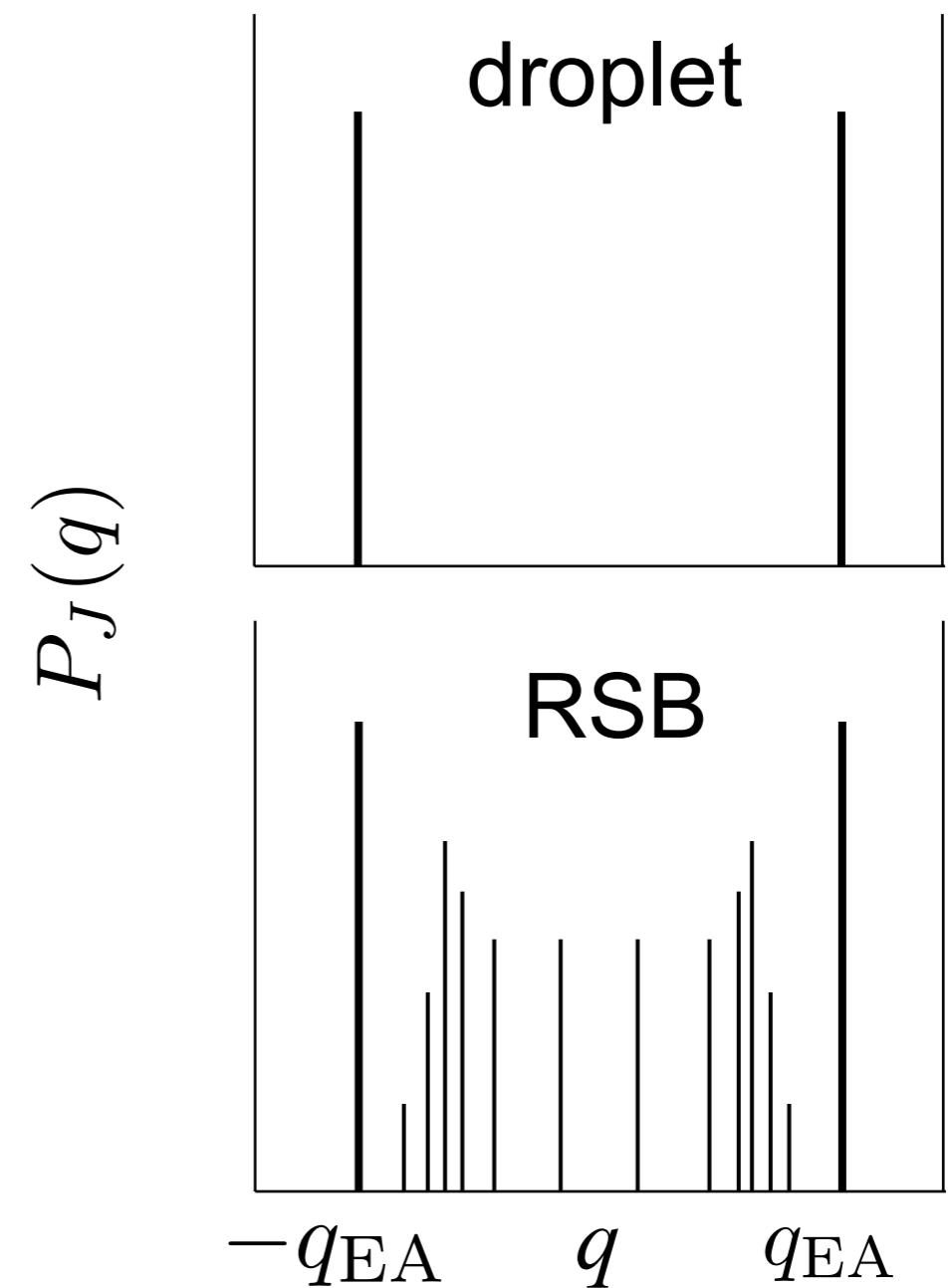
RSB vs Droplet

- Spin overlap:

$$q = \frac{1}{N} \sum_i s_i^{(1)} s_i^{(2)}$$



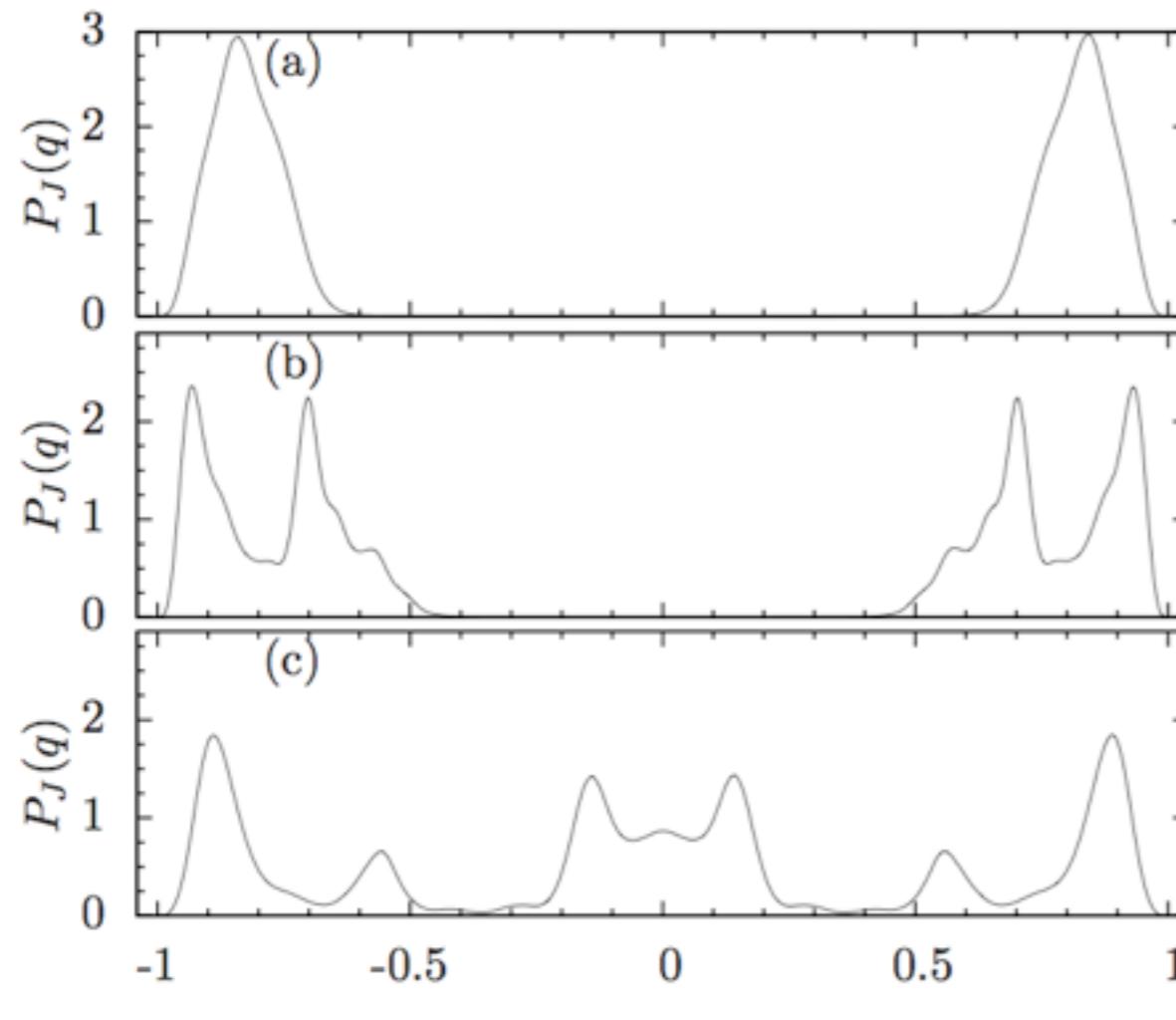
An example of overlap distributions for three disorder instances.



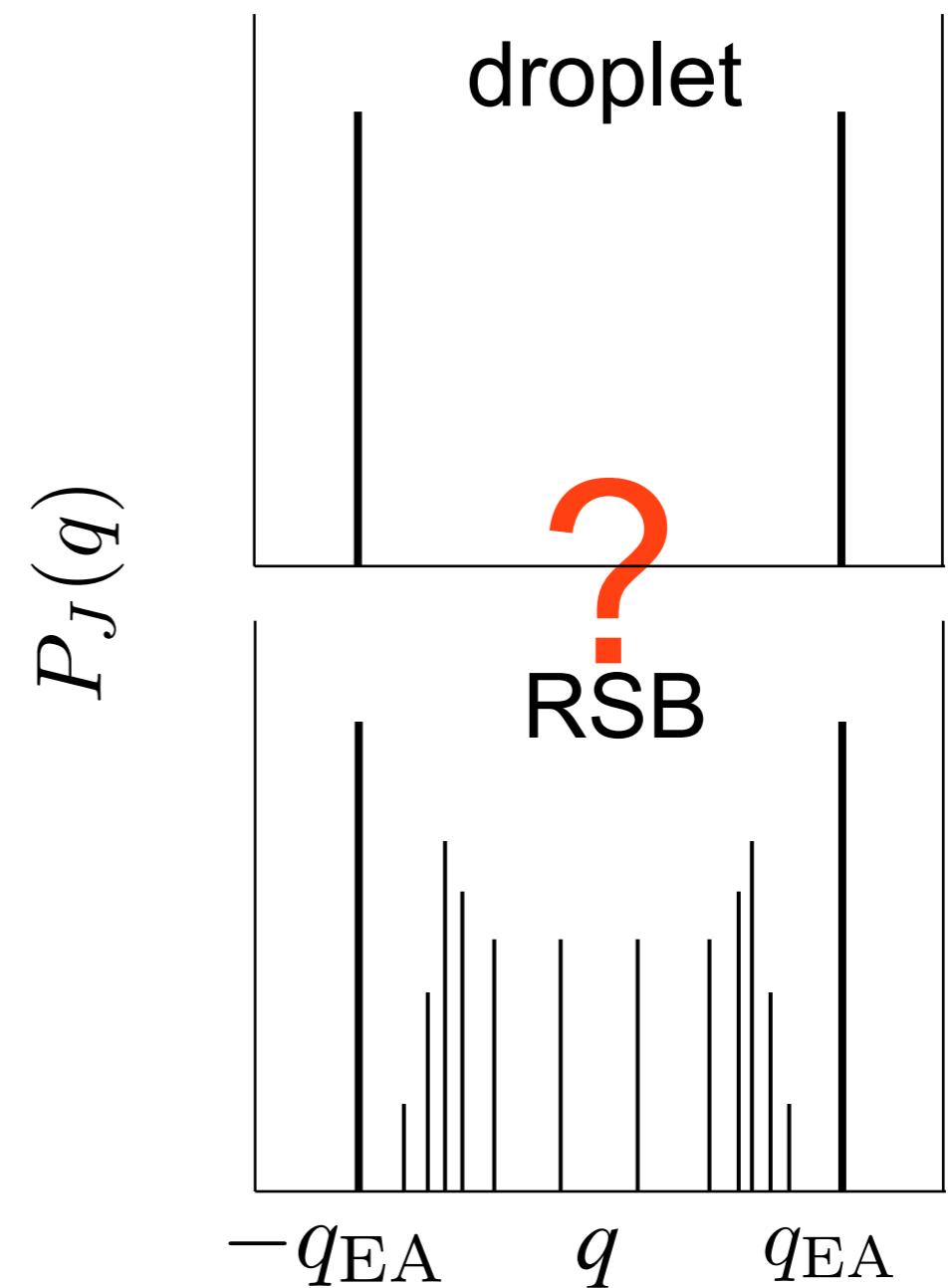
RSB vs Droplet

- Spin overlap:

$$q = \frac{1}{N} \sum_i s_i^{(1)} s_i^{(2)}$$



An example of overlap distributions for three disorder instances.

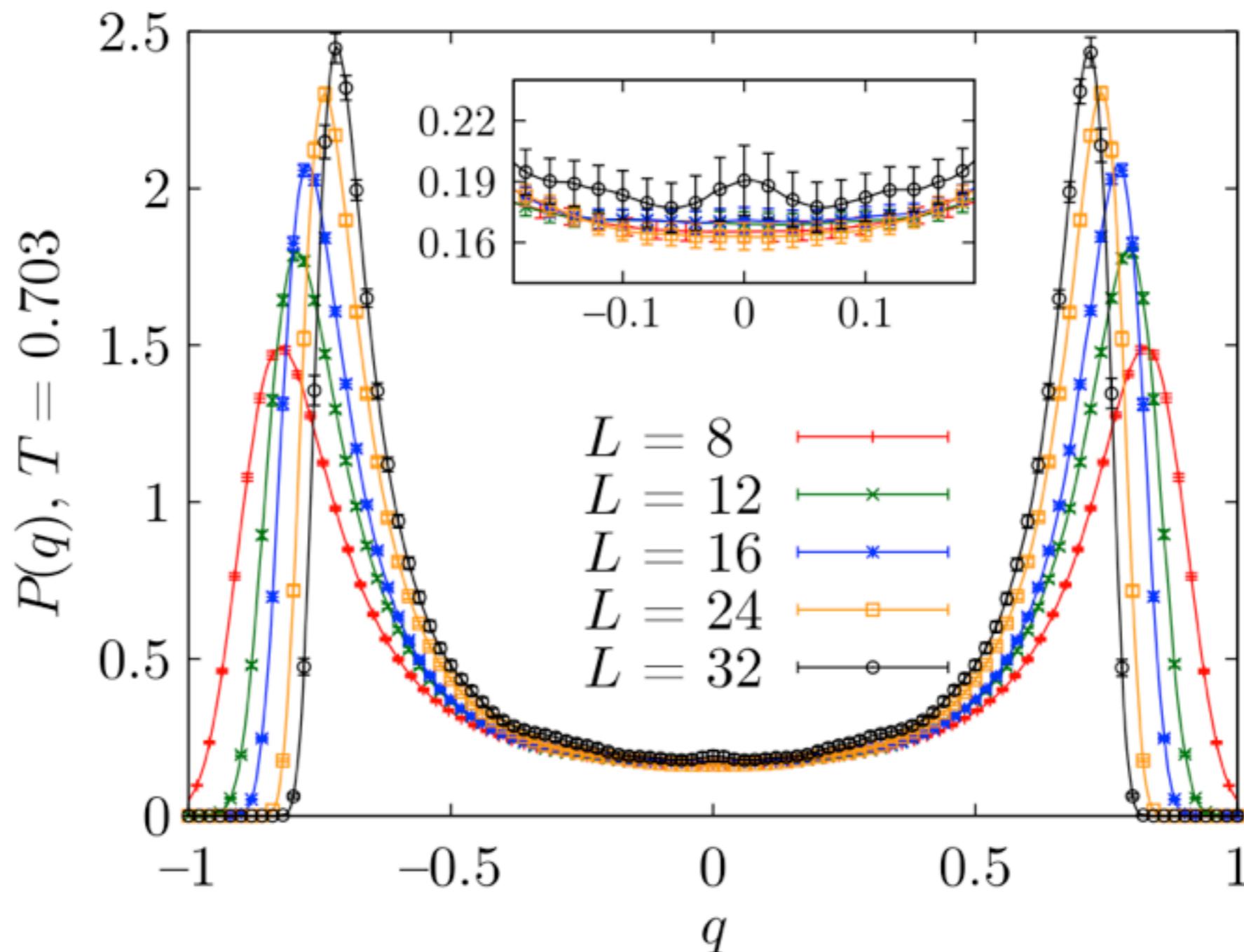


Nature of the spin-glass phase at experimental length scales

3D Ising spin glass

R Alvarez Baños^{1,2}, A Cruz^{1,2}, L A Fernandez^{1,3},
J M Gil-Narvion¹, A Gordillo-Guerrero^{1,4}, M Guidetti⁵,
A Maiorano^{1,6}, F Mantovani⁵, E Marinari⁶,
V Martin-Mayor^{1,3}, J Monforte-Garcia^{1,2},
A Muñoz Sudupe³, D Navarro⁷, G Parisi⁶,
S Perez-Gavirio^{1,6}, J J Ruiz-Lorenzo^{1,8}, S F Schifano⁵,
B Seoane^{1,3}, A Tarancón^{1,2}, R Tripiccione⁵ and D Yllanes^{1,3}

J. Stat. Mech. (2010) P06026

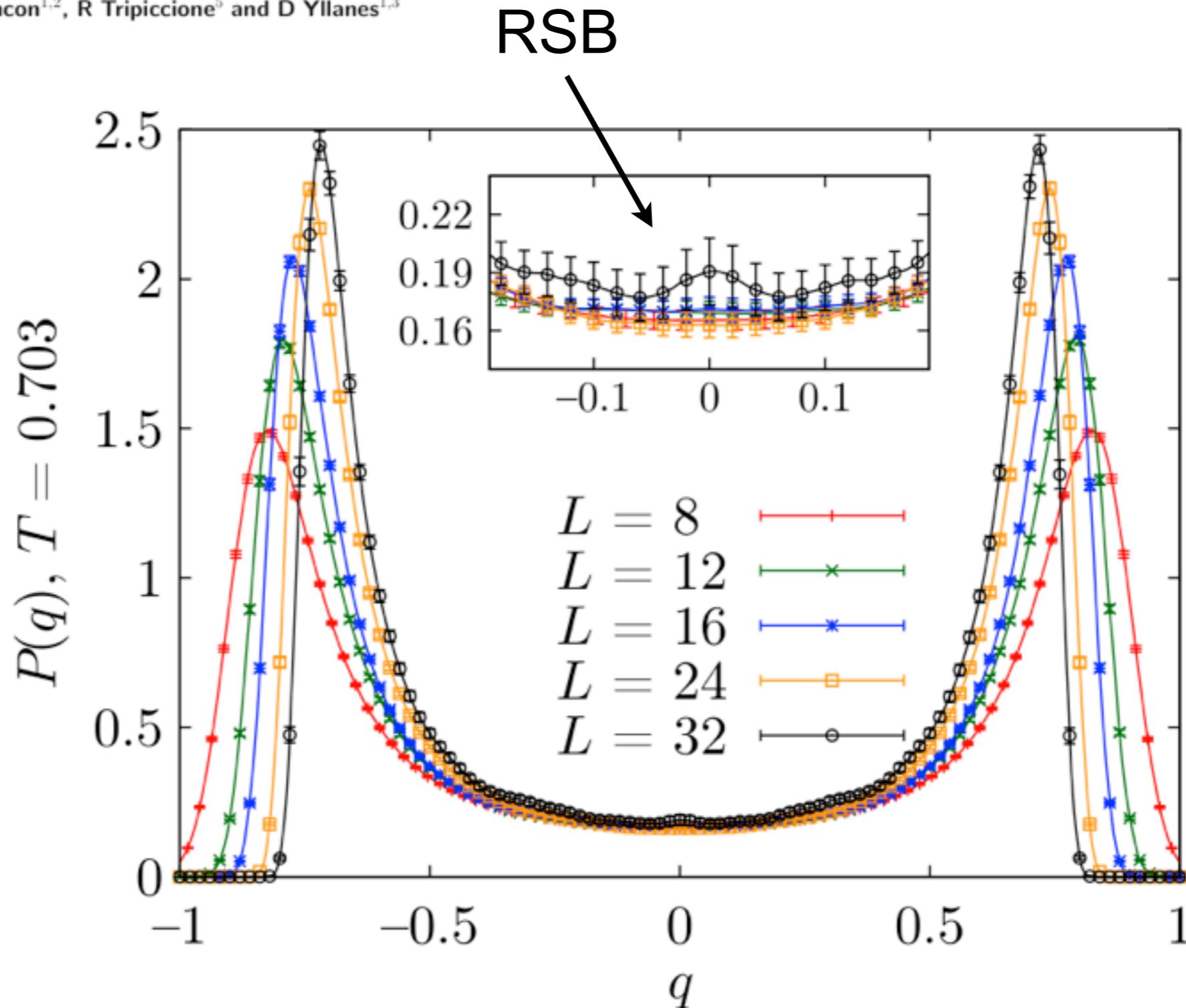


Nature of the spin-glass phase at experimental length scales

3D Ising spin glass

R Alvarez Baños^{1,2}, A Cruz^{1,2}, L A Fernandez^{1,3},
J M Gil-Narvion¹, A Gordillo-Guerrero^{1,4}, M Guidetti⁵,
A Maiorano^{1,6}, F Mantovani⁵, E Marinari⁶,
V Martin-Mayor^{1,3}, J Monforte-Garcia^{1,2},
A Muñoz Sudupe³, D Navarro⁷, G Parisi⁶,
S Perez-Gavirio^{1,6}, J J Ruiz-Lorenzo^{1,8}, S F Schifano⁵,
B Seoane^{1,3}, A Tarancón^{1,2}, R Tripiccione⁵ and D Yllanes^{1,3}

J. Stat. Mech. (2010) P06026

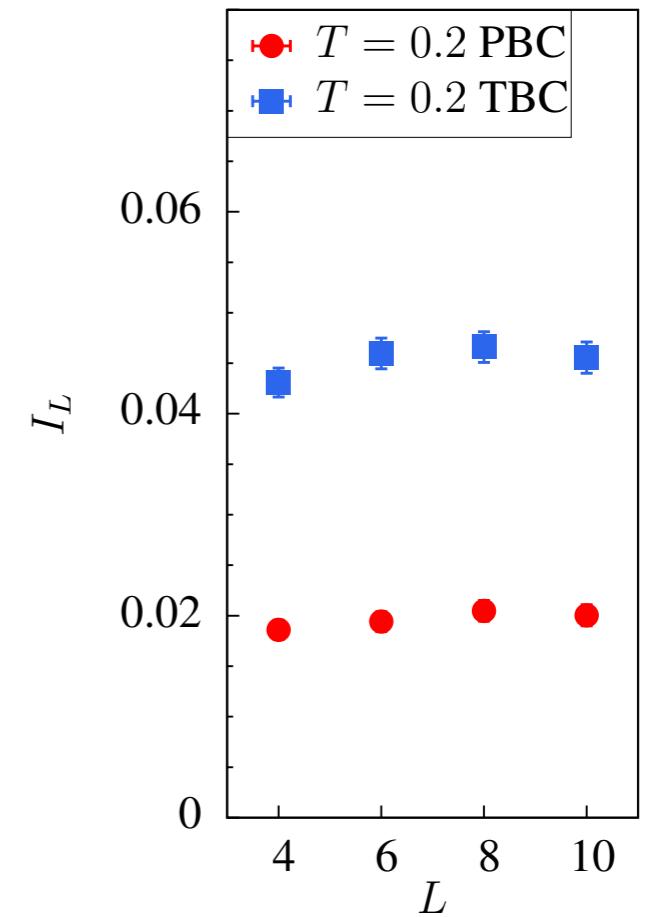
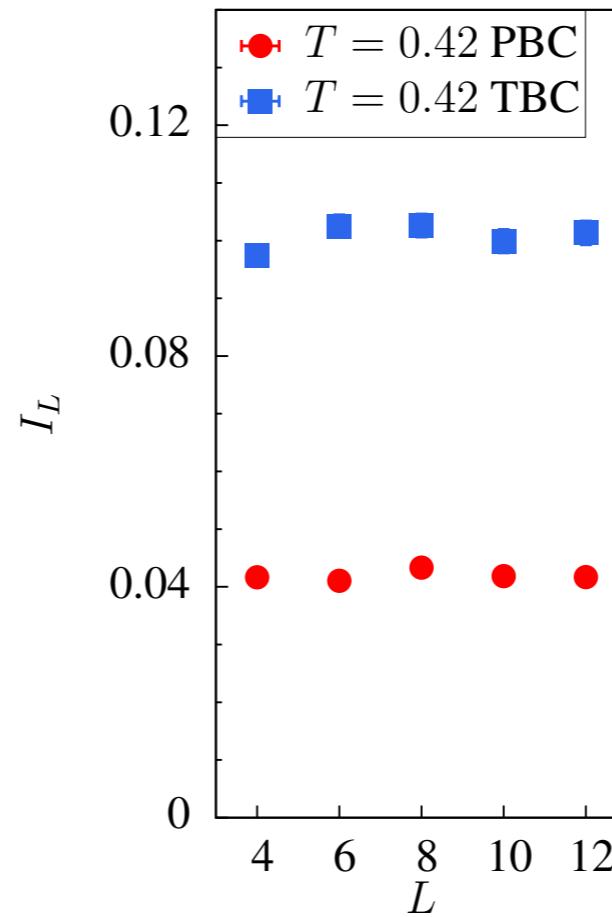
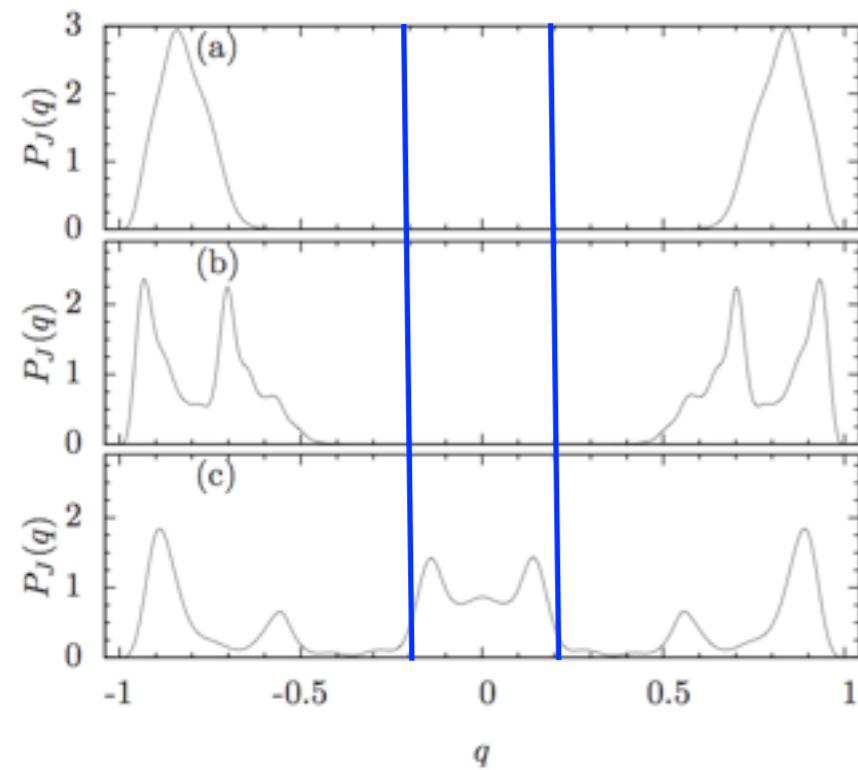


Overlap Near the Origin

$$I_J = \int_{-0.2}^{0.2} P_J(q) dq$$

Disorder averaged overlap near the origin

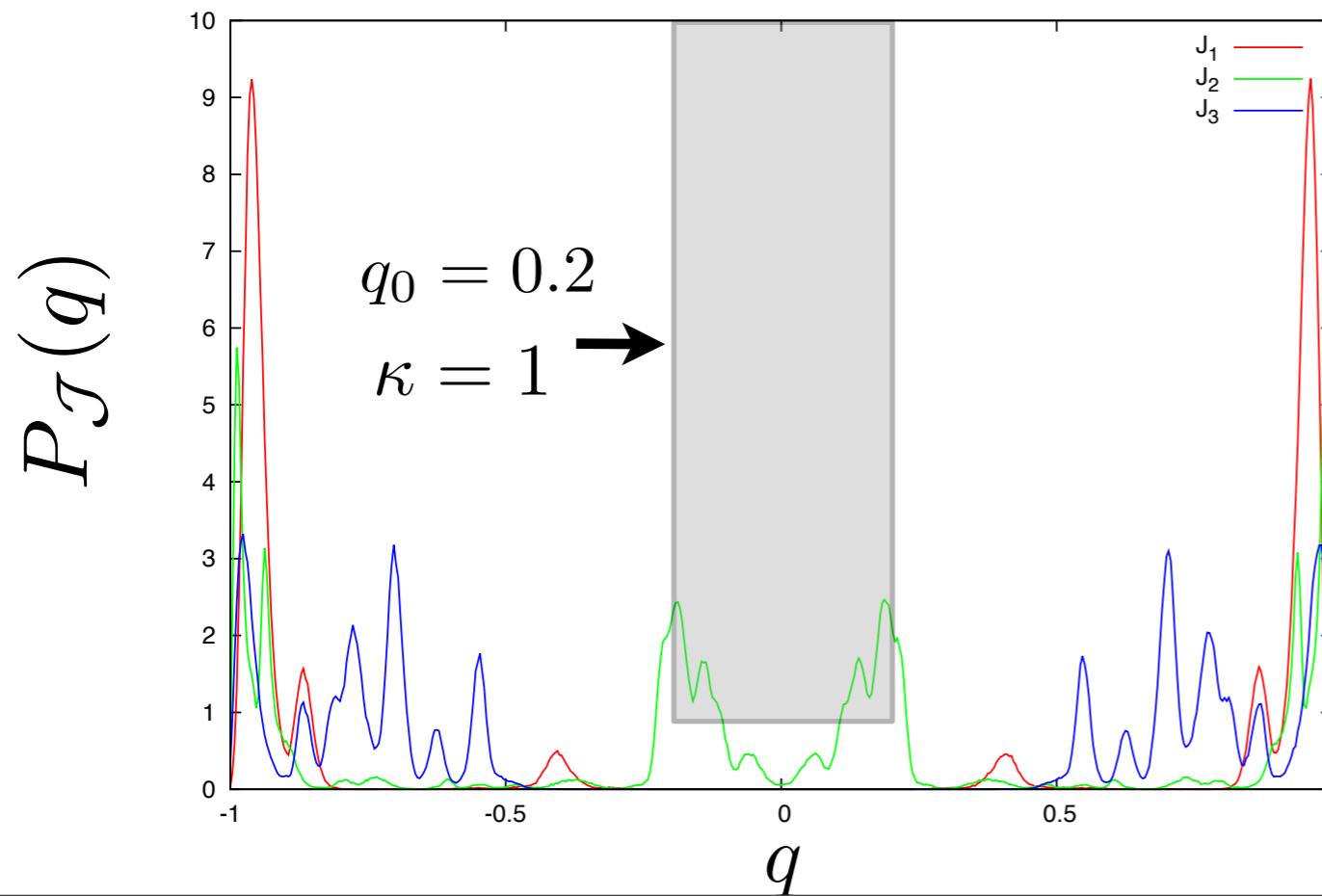
Overlap near the origin



$I > 0$ as $L \rightarrow \infty$ implies the RSB picture

RSB vs Droplet II

$$\Delta(q_0, \kappa) = \text{Prob} \left[\max_{|q| < q_0} \left\{ \frac{1}{2} (P_{\mathcal{J}}(q) + P_{\mathcal{J}}(-q)) \right\} > \kappa \right]$$

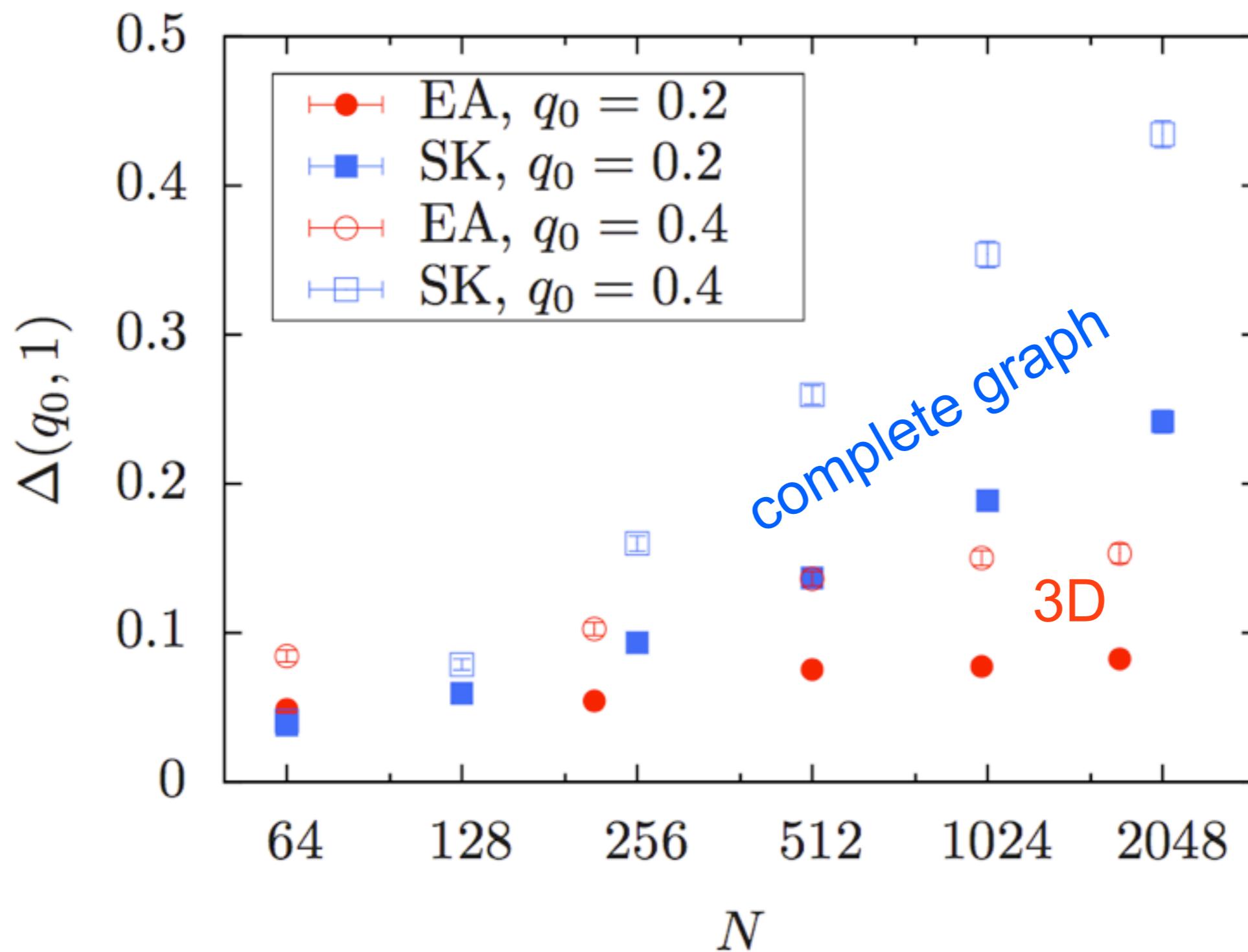


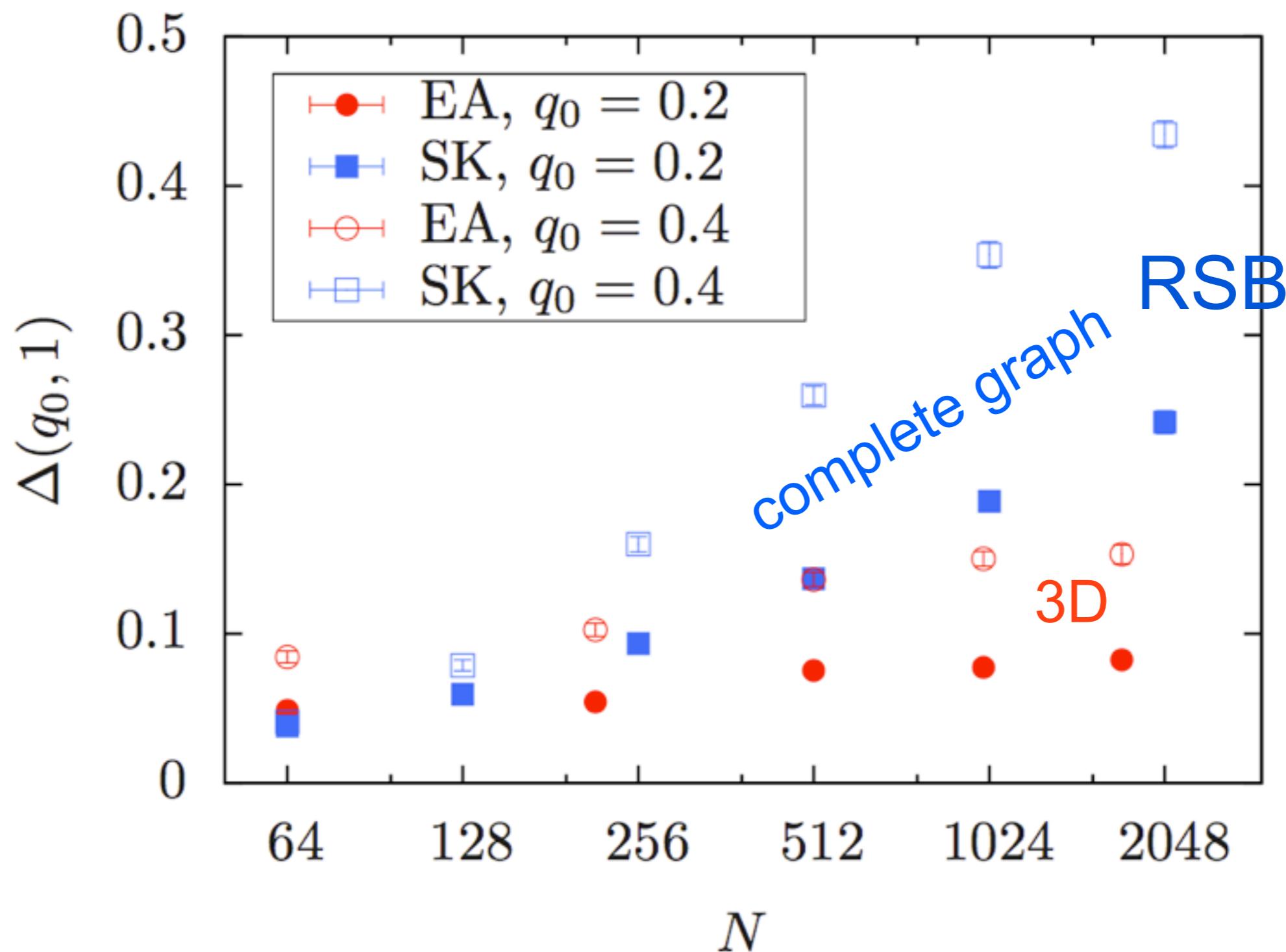
$\Delta(q_0, \kappa) \rightarrow 0$

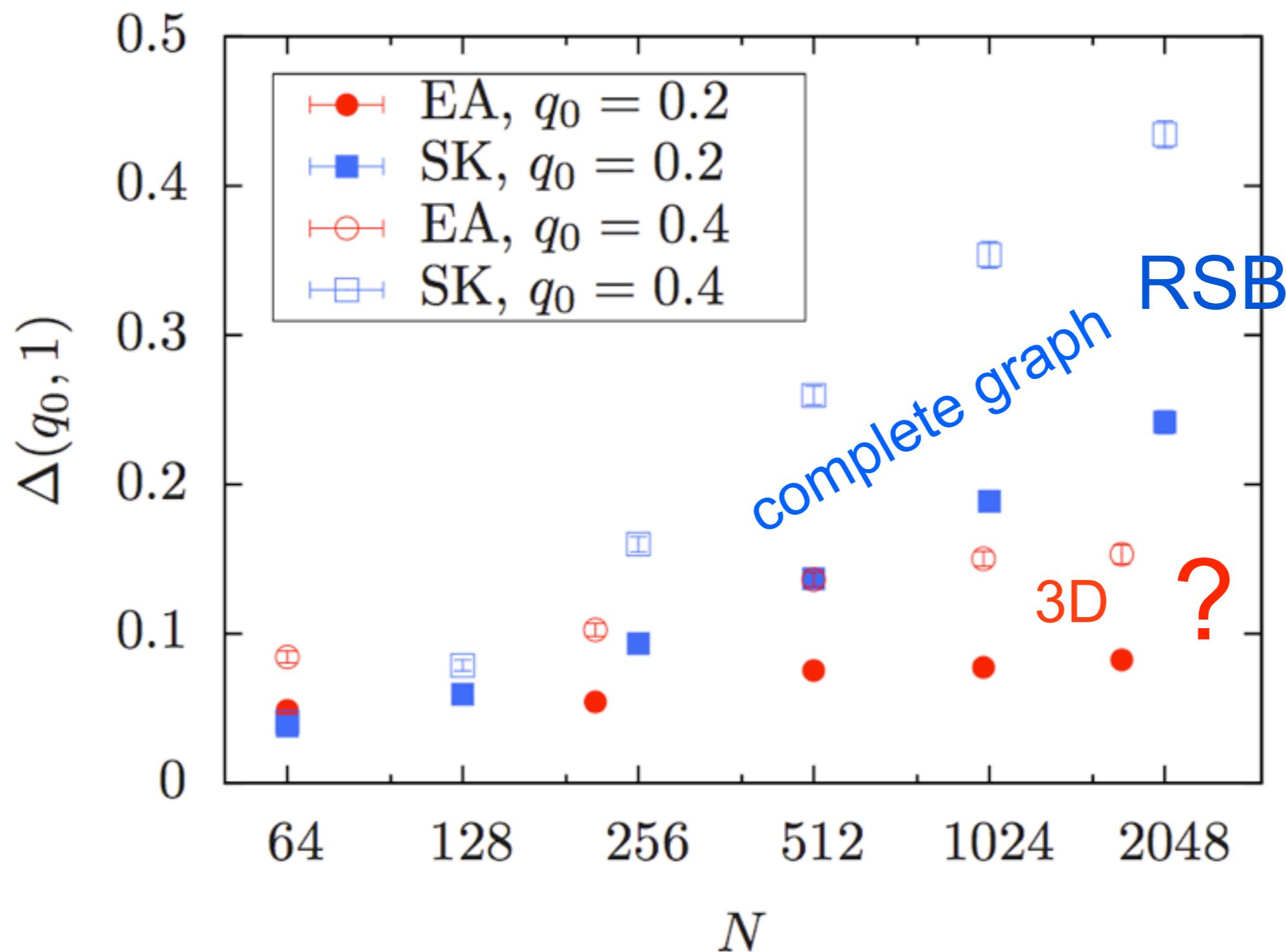
single pair of pure states

$\Delta(q_0, \kappa) \rightarrow 1$

many pairs of pure states







Chaos

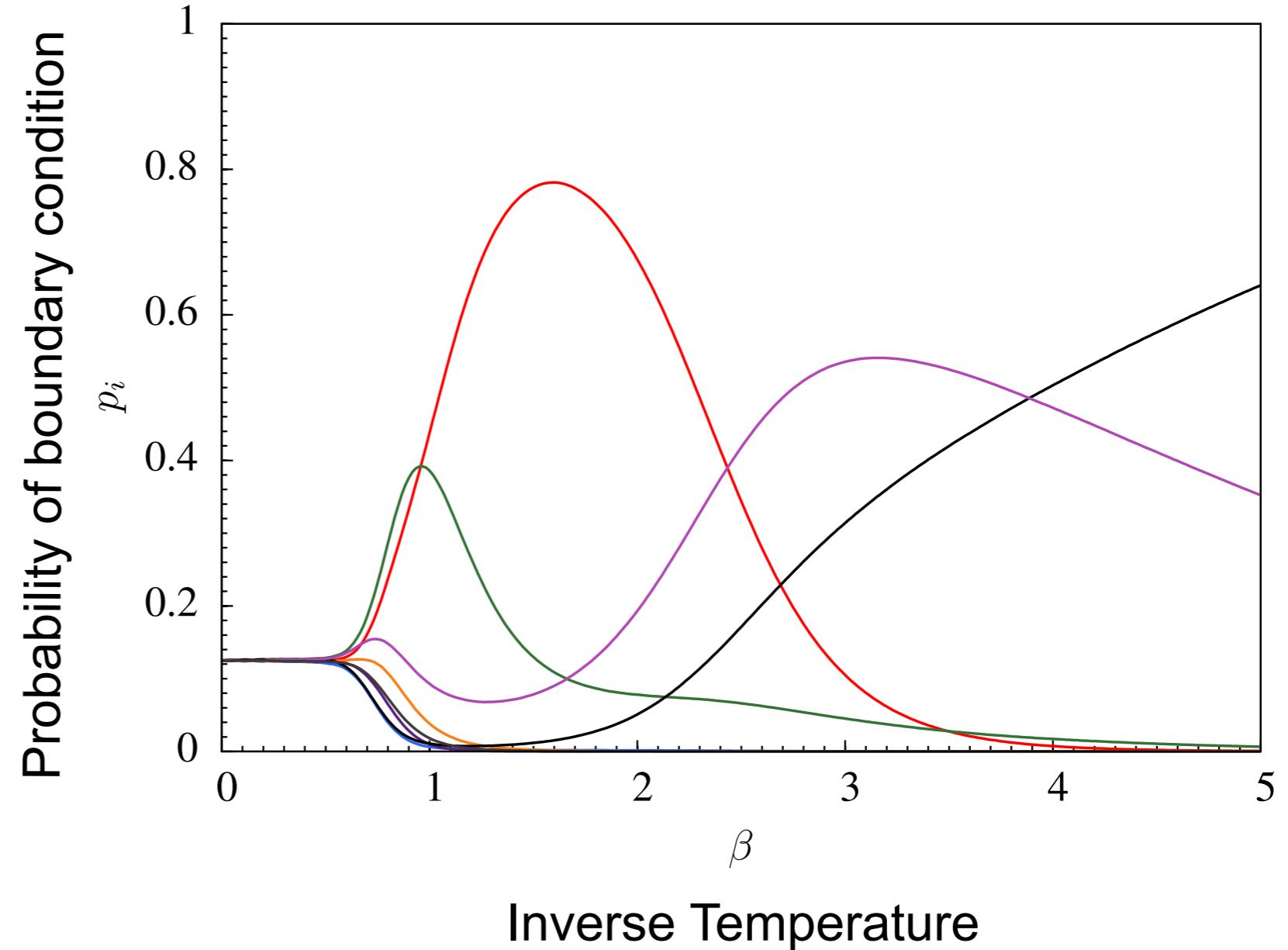
- A small change in the parameters (temperature, bond strengths,...) induces a large change in the spin configuration.

Thermal Boundary Conditions

- *What*: TBC ensemble includes the 2^d possible combinations of periodic and anti-periodic boundary conditions in the d spatial directions each with the correct Gibbs weight.
- *Why*:
 - Suppression of BC's that induce domain walls may lead to milder finite size corrections.
 - Access to a new measures of **chaos**, spin stiffness and other quantities.
- *See also*:
 - Thomas and Middleton, PRB 76, 220406(R) (2007)
 - Hasenbusch, Physica A 197, 423 (1993)

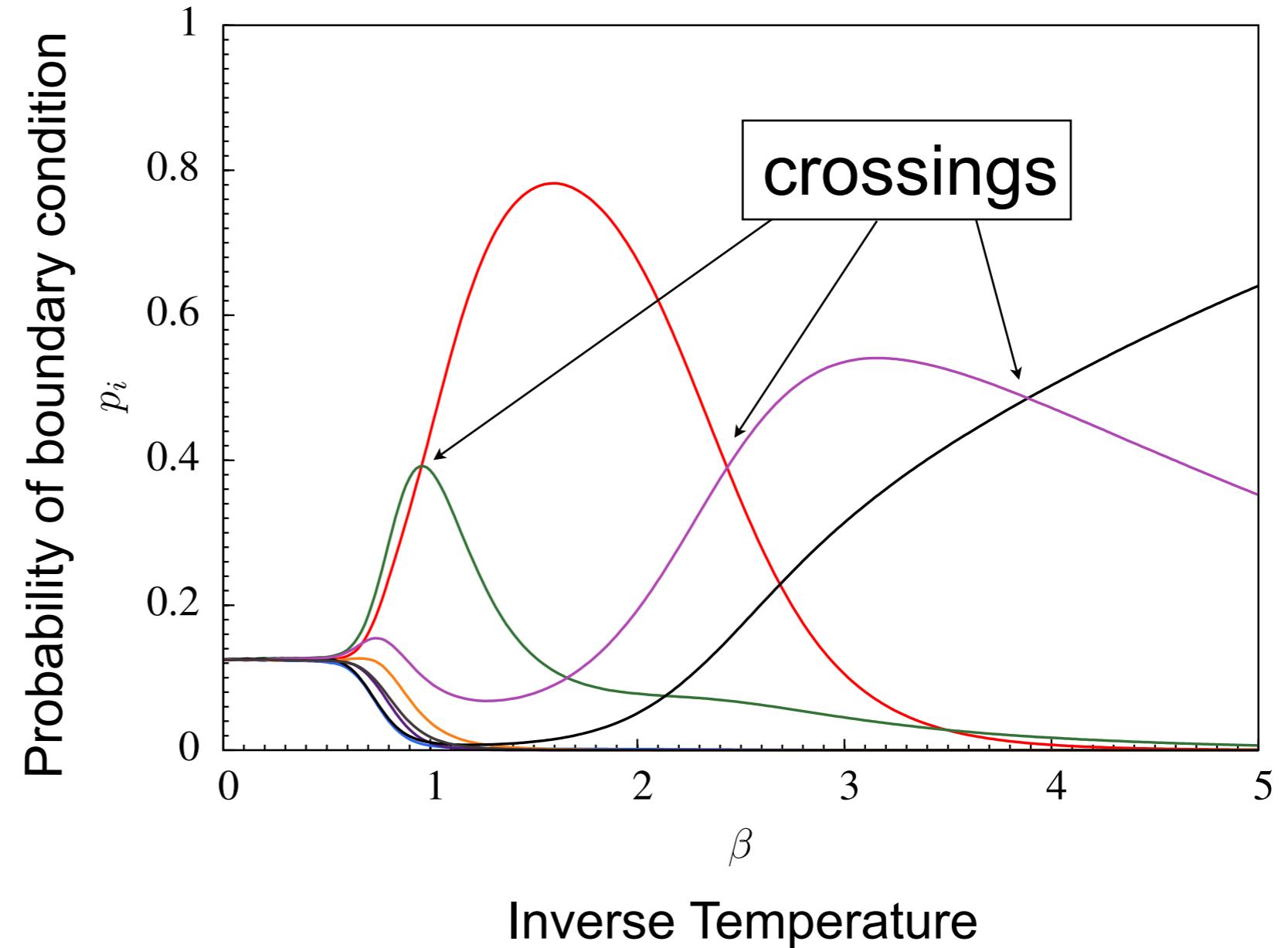
Temperature Chaos

- For many (but not all) disorder realizations the dominant boundary condition changes chaotically with temperature.

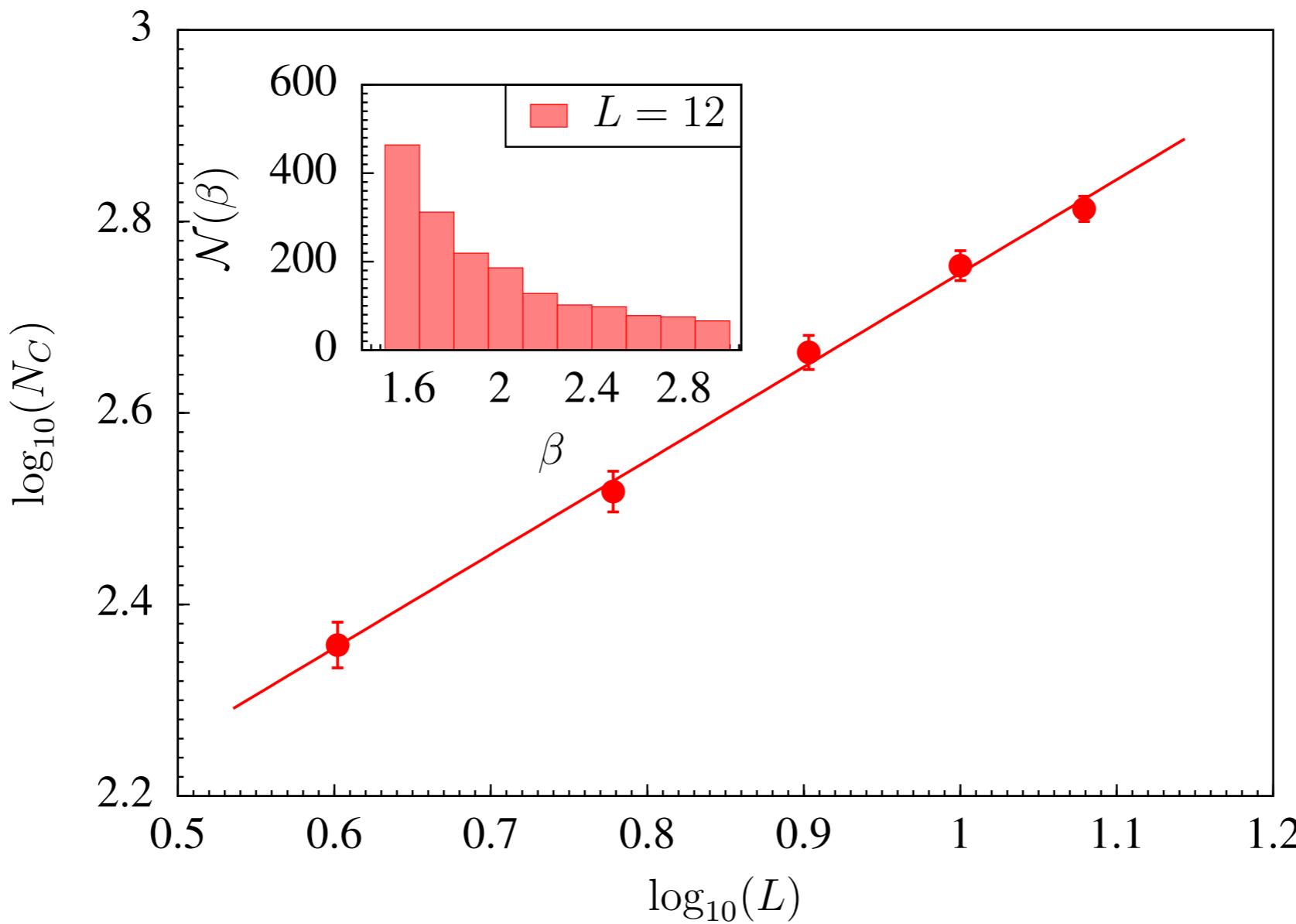


Temperature Chaos

- For many (but not all) disorder realizations the dominant boundary condition changes chaotically with temperature.



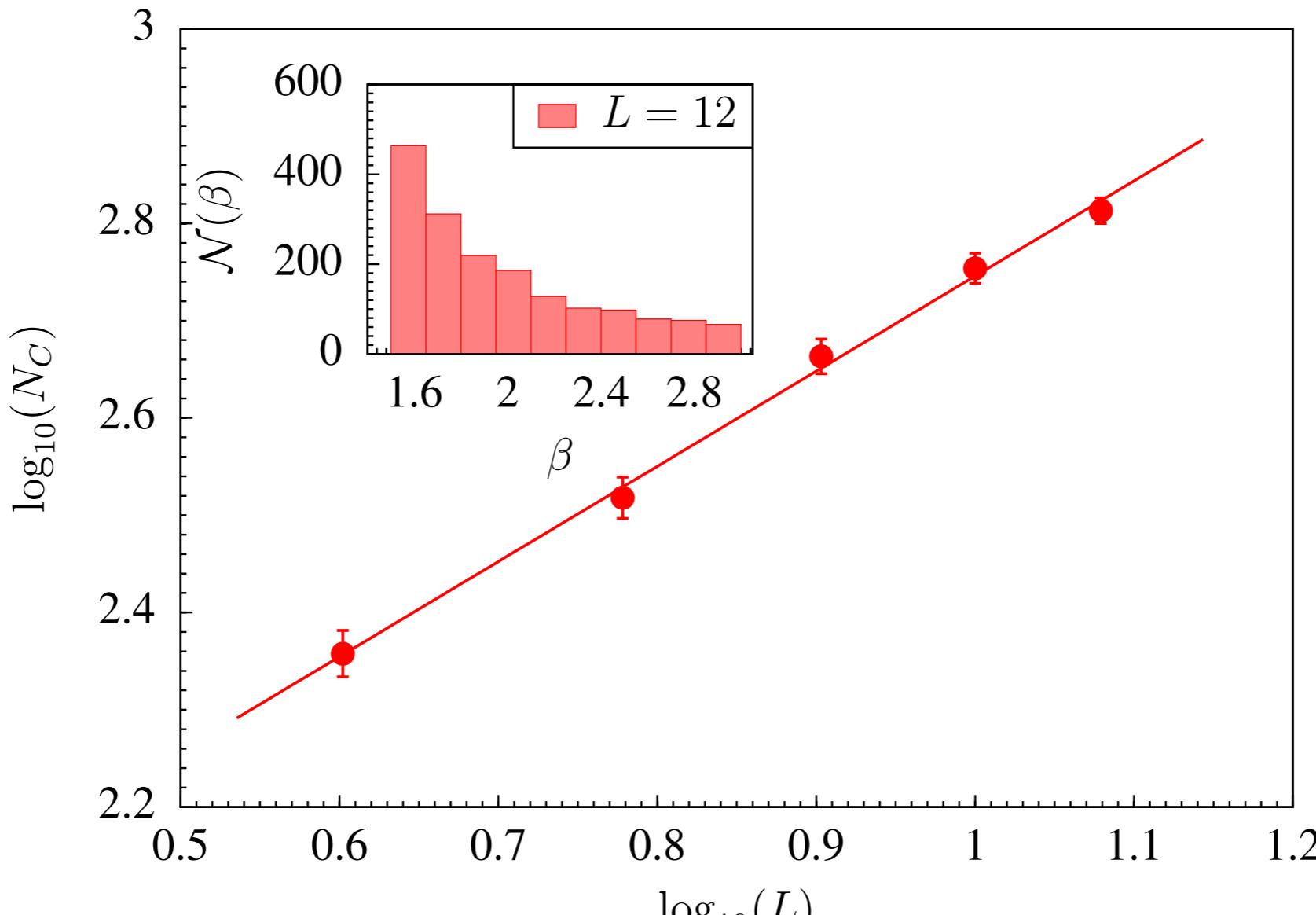
log number of crossings



log size

$$N_C \sim L^\zeta$$
$$\zeta \sim 0.96(5)$$

log number of crossings

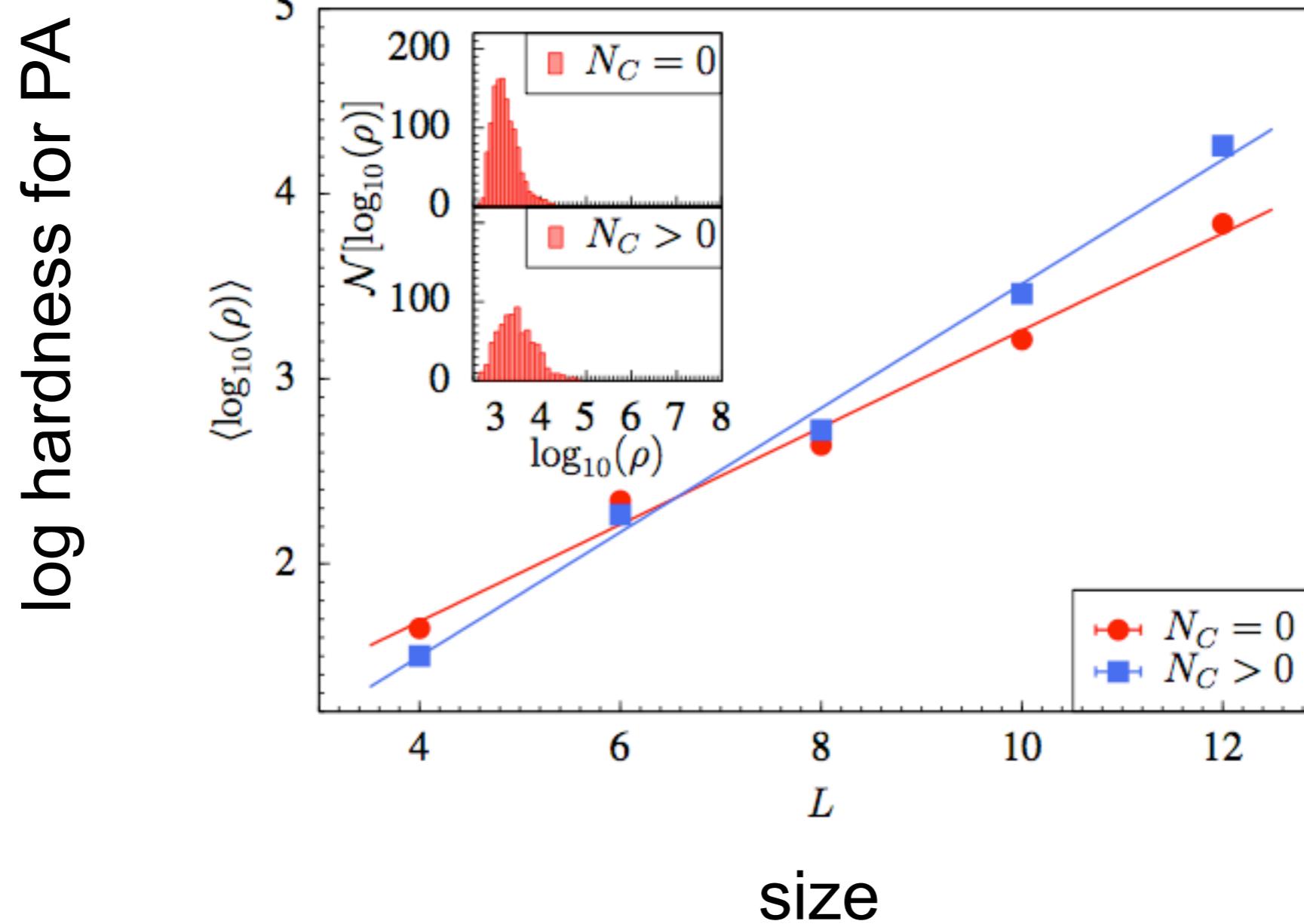


log size

$$N_C \sim L^\zeta$$
$$\zeta \sim 0.96(5)$$

Chaos increases roughly linearly with size

Temperature Chaos and Hardness



Questions

- Other ideas from CS about what makes an instance hard?
- Is sampling from the joint instance/solution distribution easier than first choosing a problem and then solving it?

Conclusions

- The spin glass is an example of an NP-hard problem relevant to physics.
- Population annealing is an effective algorithm for sampling thermal states and finding ground states of spin glasses.
- It is not known yet whether ordering occurs in the 3D spin glass via the many-state RSB picture or the simpler droplet picture with a single pair of pure states.
- Temperature chaos in spin glasses is associated with the hardness of an instance (for population annealing).