Adding loops to mean field approximation for disordered models

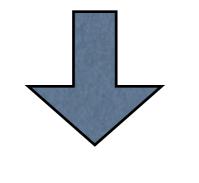
Federico Ricci-Tersenghi Sapienza University of Rome

- Replica cluster variational method,
 T. Rizzo, A. Lage-Castellanos, R. Mulet and F. Ricci-Tersenghi,
 J. Stat. Phys. 139, 375 (2010).
- Inference algorithm for finite-dimensional spin glasses: Belief Propagation on the dual lattice,
 A. Lage-Castellanos, R. Mulet, F. Ricci-Tersenghi and T. Rizzo,
 Phys. Rev. E 84, 046706 (2011).
- Characterizing and Improving Generalized Belief Propagation Algorithms on the 2D Edwards-Anderson Model,
 E. Dominguez, A. Lage-Castellanos, R. Mulet, F. Ricci-Tersenghi and T. Rizzo,
 J. Stat. Mech. P12007 (2011).
- Replica cluster variational method: the replica symmetric solution for the 2d random bond Ising model,
 A. Lage-Castellanos, R. Mulet, F. Ricci-Tersenghi and T. Rizzo, arxiv:1204.0439

Models of interest

SPIN GLASSES on D-dimensional lattices

 $H = -\sum_{(i,j)} J_{ij} \sigma_i \sigma_j$ disorder (random couplings) frustration



COMPLEXITY

What we want to know

- Physical properties: (free-)energy and correlations
 -> nature of low T phase
- <u>Single sample</u>: site specific $\begin{cases} p_i(\sigma_i) = \sum_{\vec{\sigma} \setminus \sigma_i} e^{-\beta H}/Z \\ p_{ij}(\sigma_i, \sigma_j) = \sum_{\vec{\sigma} \setminus \sigma_i, \sigma_j} e^{-\beta H}/Z \end{cases}$
- <u>Average case</u>: global quantities

$$f = \langle \ln Z \rangle_J \quad m = \frac{1}{N} \sum_i m_i \quad q = \frac{1}{N} \sum_i m_i^{(1)} m_i^{(2)}$$

Mean field approximations

Variational approach

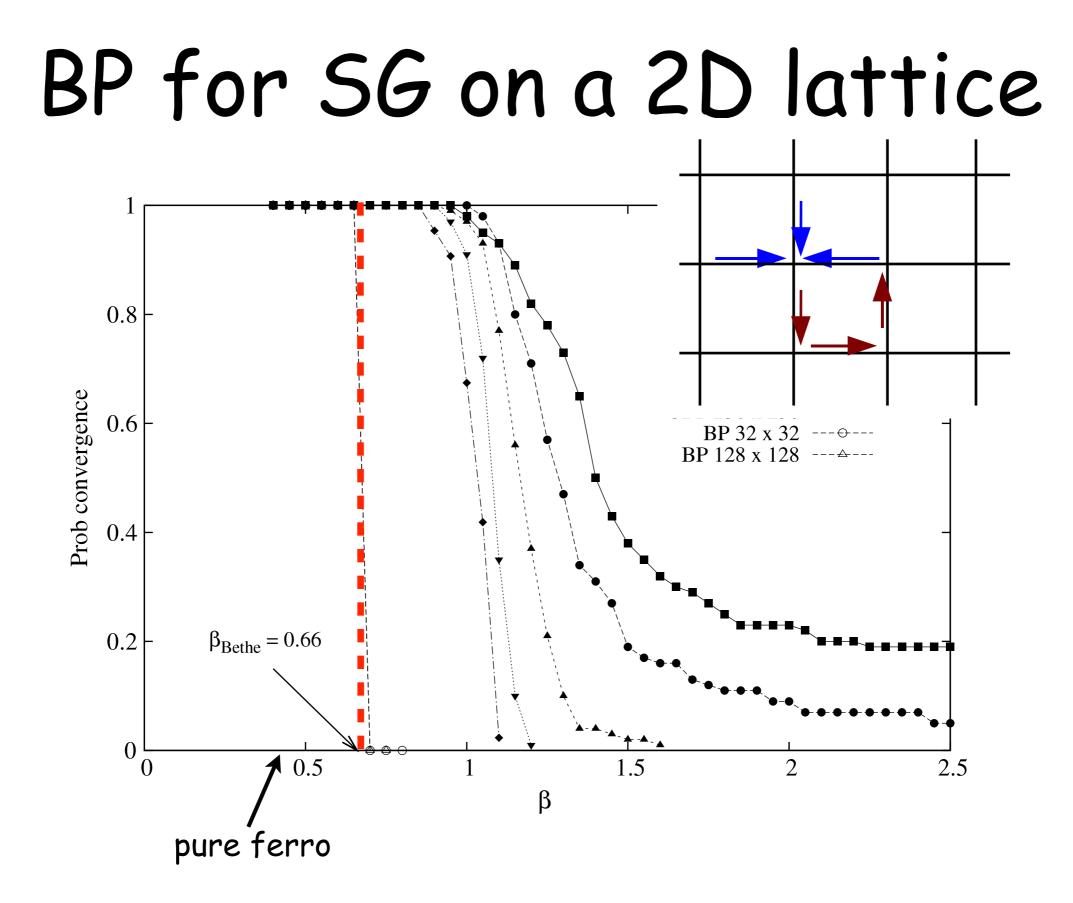
$$F = U - TS = \sum_{\vec{\sigma}} H(\vec{\sigma}) P(\vec{\sigma}) + T \sum_{\vec{\sigma}} P(\vec{\sigma}) \ln P(\vec{\sigma})$$

Short description, few parameters: magnetizations (MF) $P_{MF}(\vec{\sigma}) = \prod_{i} b_i(\sigma_i) = \prod_{i} \frac{1 + m_i \sigma_i}{2}$

and correlations (Bethe) $P_{Bethe}(\vec{\sigma}) = \prod_{ij} \frac{b_{ij}(\sigma_i, \sigma_j)}{b_i(\sigma_i)b_j(\sigma_j)} \prod_i b_i(\sigma_i)$

Bethe approximation

- Exact on trees
- Marginalization conditions $\sum b_{ij}(\sigma_i, \sigma_j) = b_i(\sigma_i)$ σ_{j} $\tanh(\beta u_{j\to i}) = \tanh(\beta J_{ij}) \tanh(\beta \sum u_{k\to j})$ $k \in \partial j \setminus i$ $m_i = \tanh(\beta \sum u_{j \to i})$ $i \in \partial i$ $\bigotimes k \in \partial j \setminus i$ • Belief Propagation (BP)



Improving BP (loop corrections)

- Montanari, Rizzo, JSTAT 2005
- Parisi, Slanina, JSTAT 2006
- Chertkov, Chernyak, JSTAT 2006 (loop calculus)

all based on existence of BP fixed point!

Cluster Variation Method Kikuchi 1951

$$F = \sum_{\vec{\sigma}} H(\vec{\sigma}) P(\vec{\sigma}) + T \sum_{\vec{\sigma}} P(\vec{\sigma}) \ln P(\vec{\sigma})$$

energy (easy) entropy (hard)

• Mean field • $P_{MF}(\vec{\sigma}) = \prod_i b_i(\sigma_i) = \prod_i \frac{1 + m_i \sigma_i}{2}$

• Bethe •
$$P_{Bethe}(\vec{\sigma}) = \prod_{ij} \frac{b_{ij}(\sigma_i, \sigma_j)}{b_i(\sigma_i)b_j(\sigma_j)} \prod_i b_i(\sigma_i)$$

• Plaquette CVM • $\{b_i, b_{ij}, b_{ijkl}\}$

Region graph approximation

Yedidia Freeman Weiss, IEEE-IT 2005

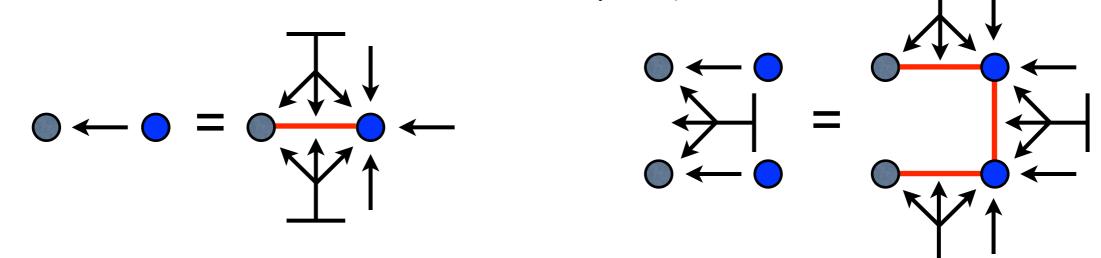
- Disorder -> heterogeneities
- Choose an arbitrary set of regions (containing all interactions)

$$F_{RGA} = \sum_{r \in \mathbb{R}} c_r \left(\sum_{x_r} b_r E_r + \sum_{x_r} b_r \ln b_r \right)$$

 Find an extremum by Generalized Belief Propagation (GBP)

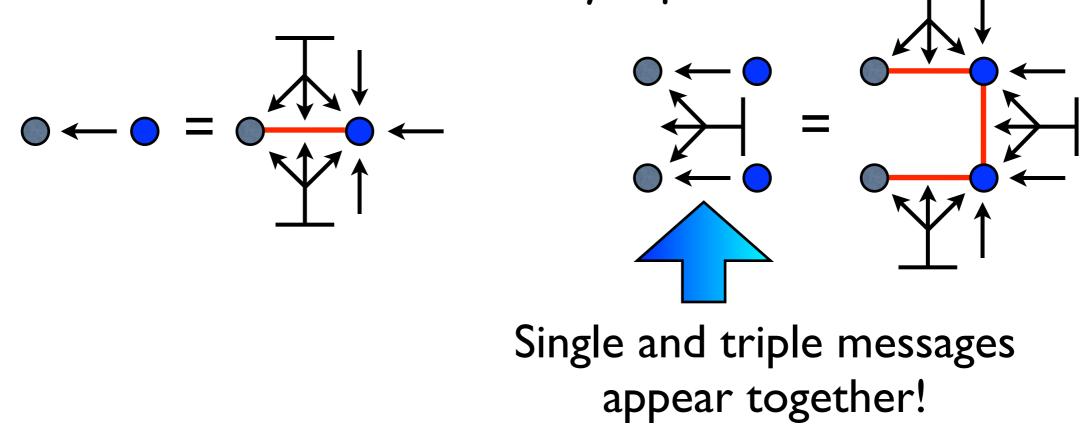
Square plaquette GBP

- 2 kind of self-consistency equations

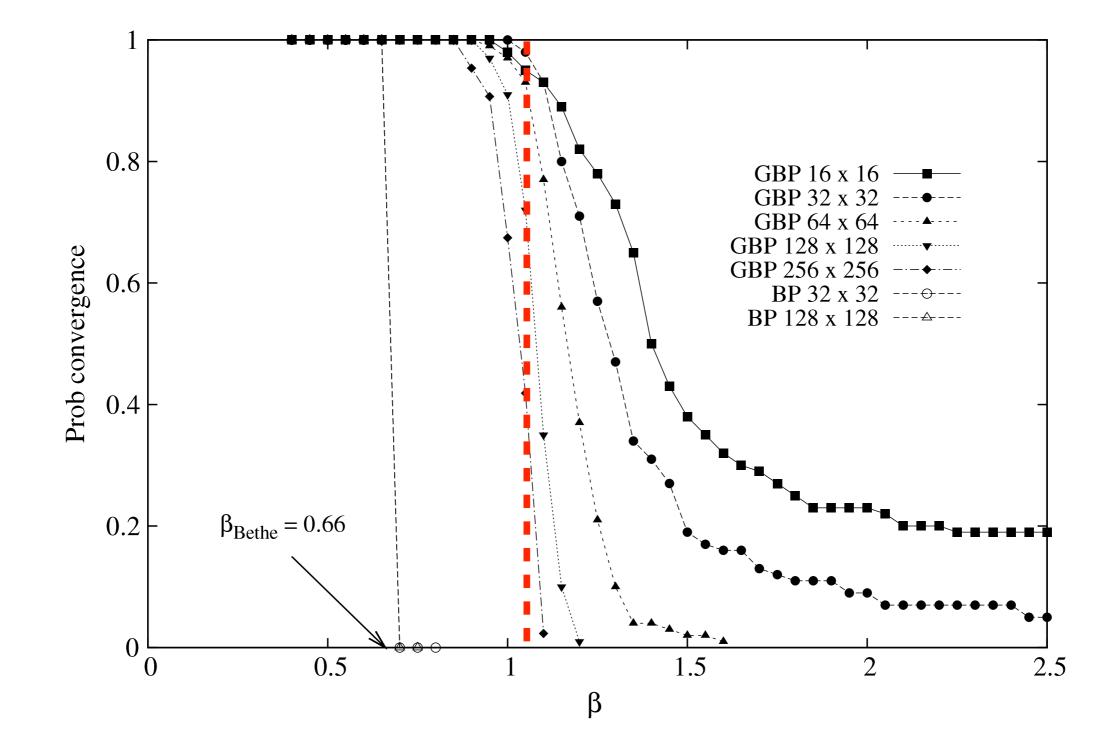


Square plaquette GBP

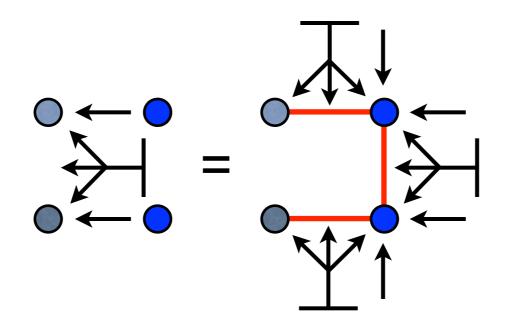
- 2 kind of messages (marginalizations) $\bullet \stackrel{u}{\leftarrow} \bullet$ (U, u_1, u_2)
- 2 kind of self-consistency equations



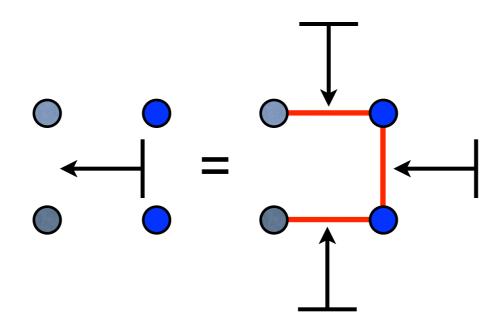
GBP for a SG on a 2D lattice



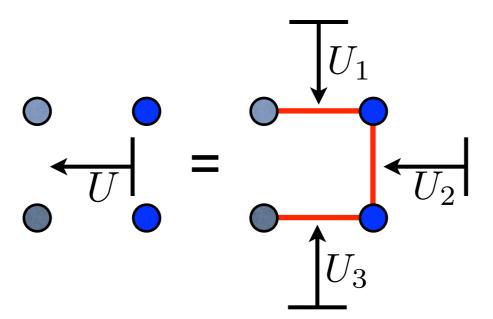
Exploit symmetries: $m_i = 0 \implies u = 0$



Exploit symmetries: $m_i = 0 \implies u = 0$

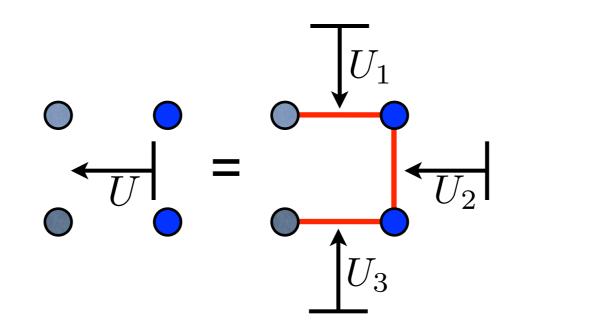


Exploit symmetries: $m_i = 0 \implies u = 0$



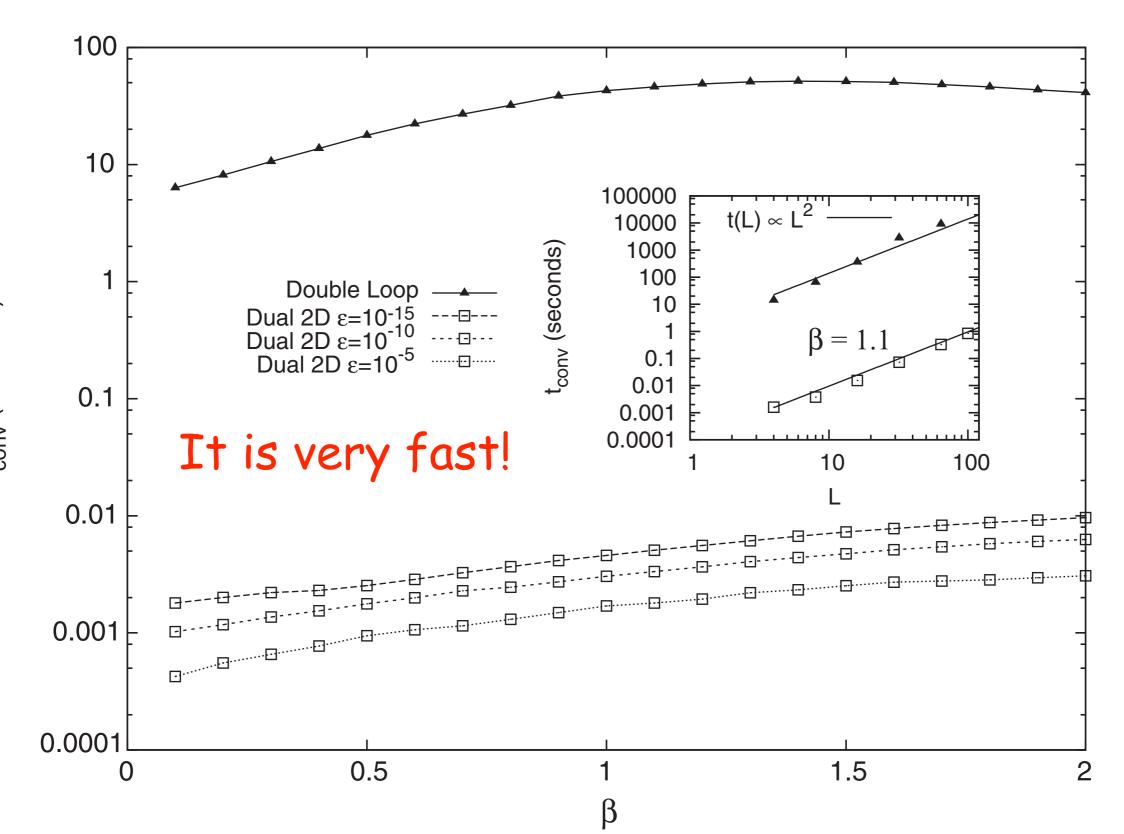
 $\tanh(\beta U) = \tanh(\beta(J_1 + U_1)) \tanh(\beta(J_2 + U_2)) \tanh(\beta(J_3 + U_3))$

Exploit symmetries: $m_i = 0 \implies u = 0$



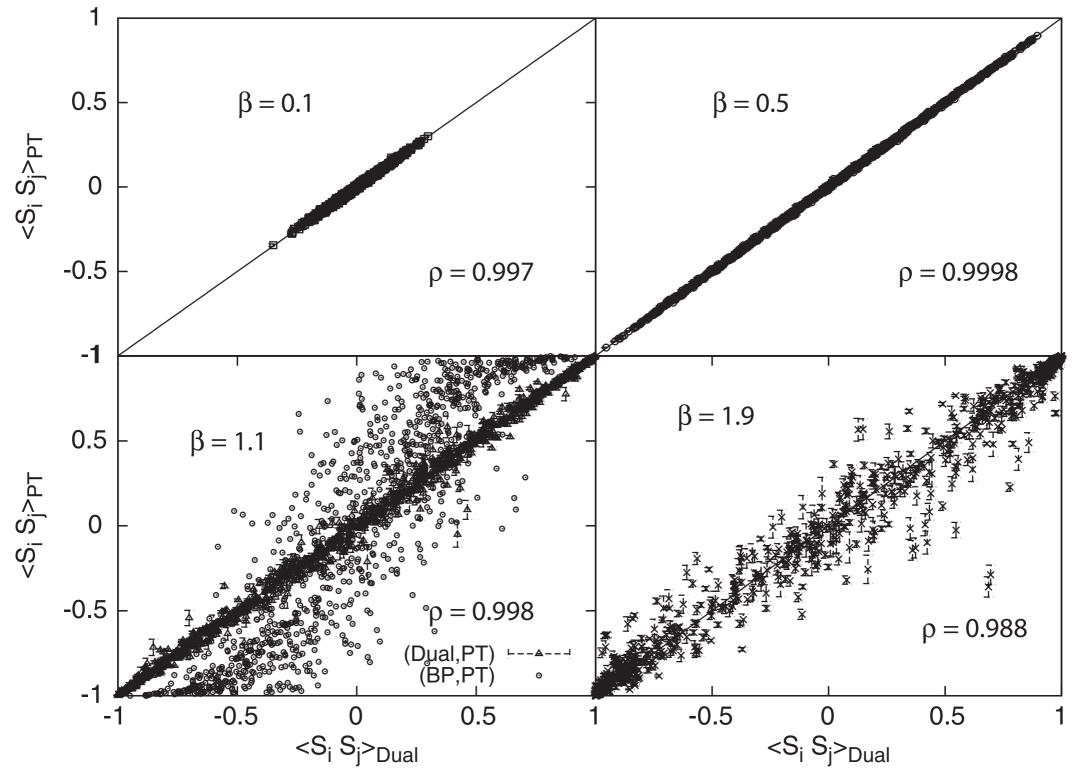
Dual algorithm

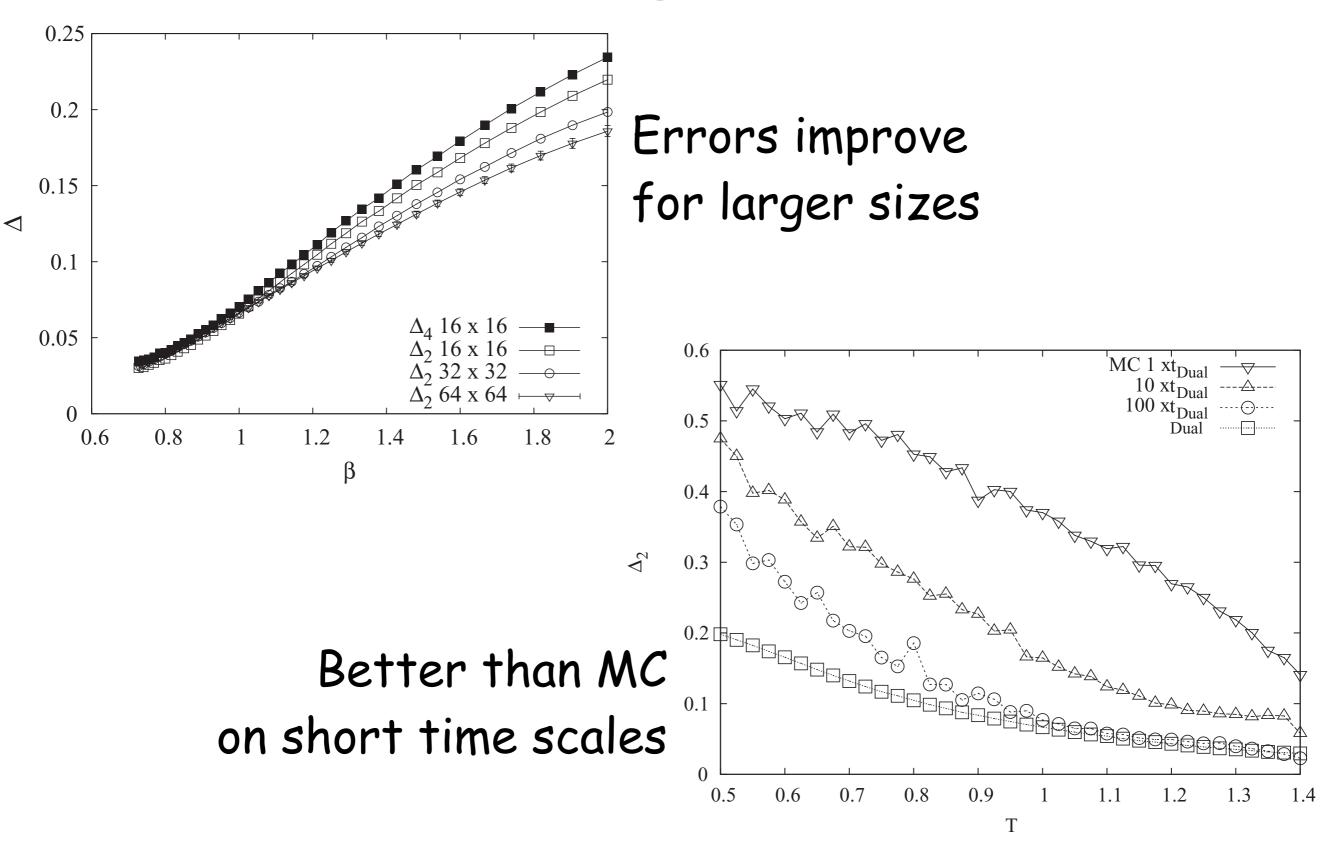
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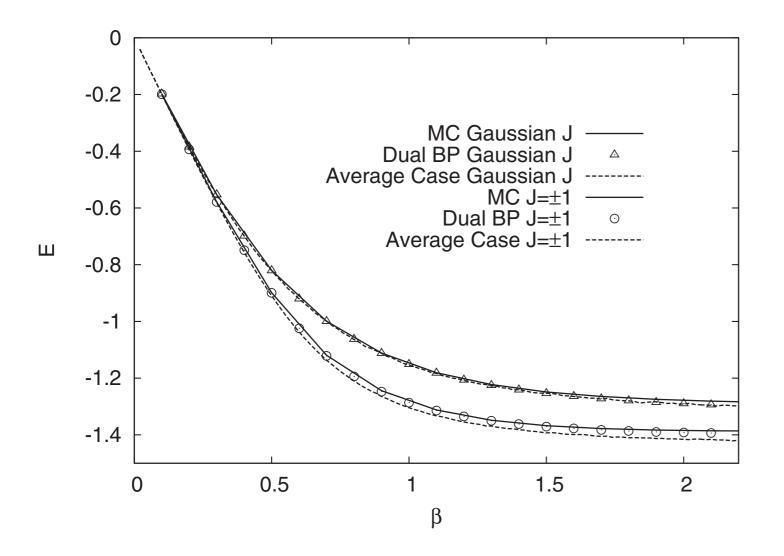
t_{conv} (seconds)

Rather accurate results



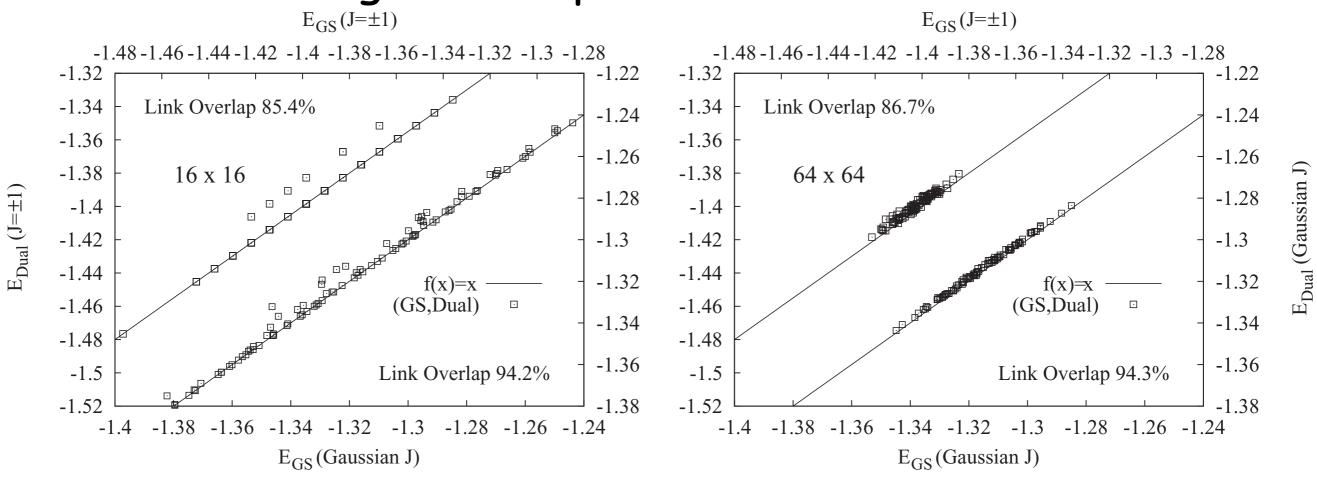


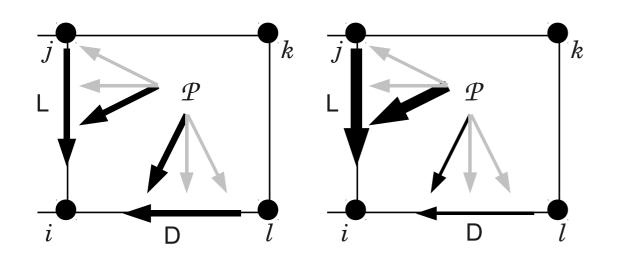
Not exact (even on the long run) but very fast and good enough for many applications



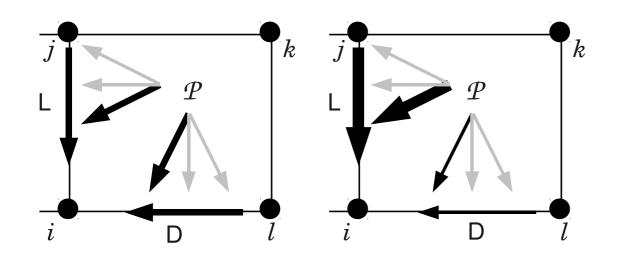
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Computing ground states by fixing variables according to dual-predicted correlations

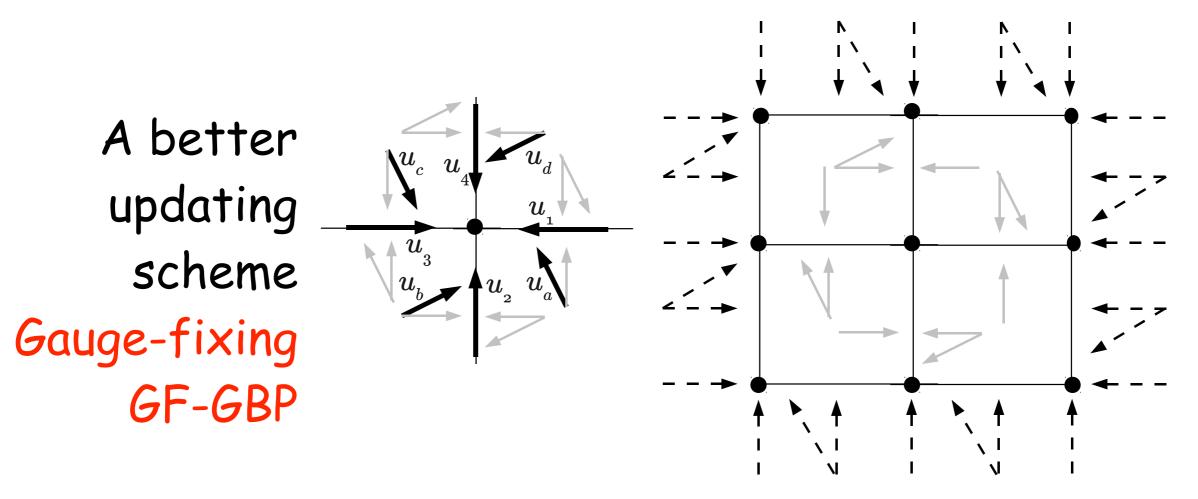


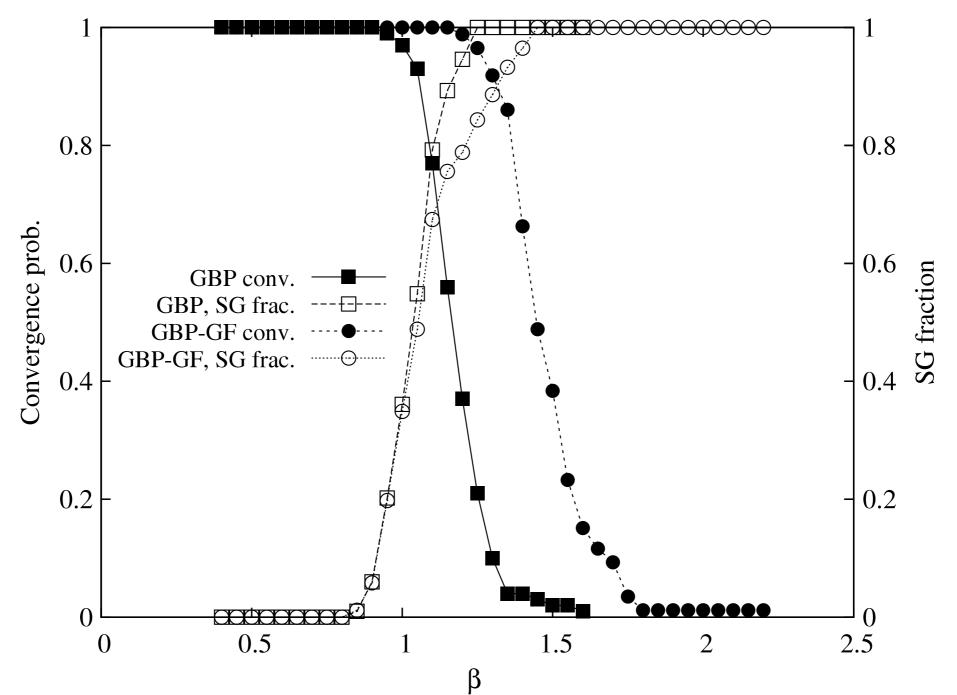


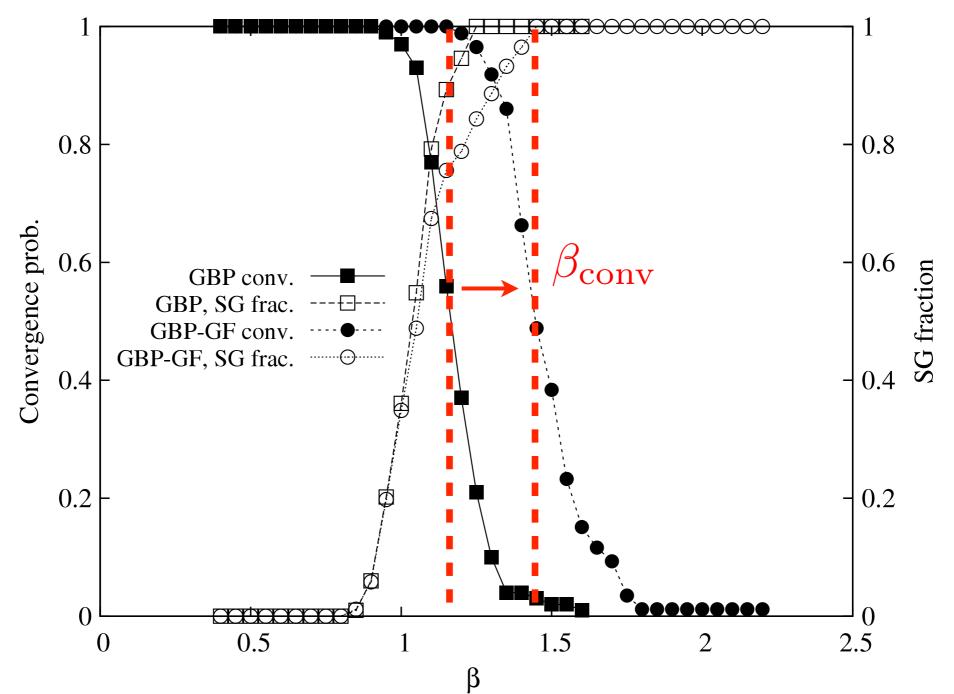
Fixing a gauge symmetry

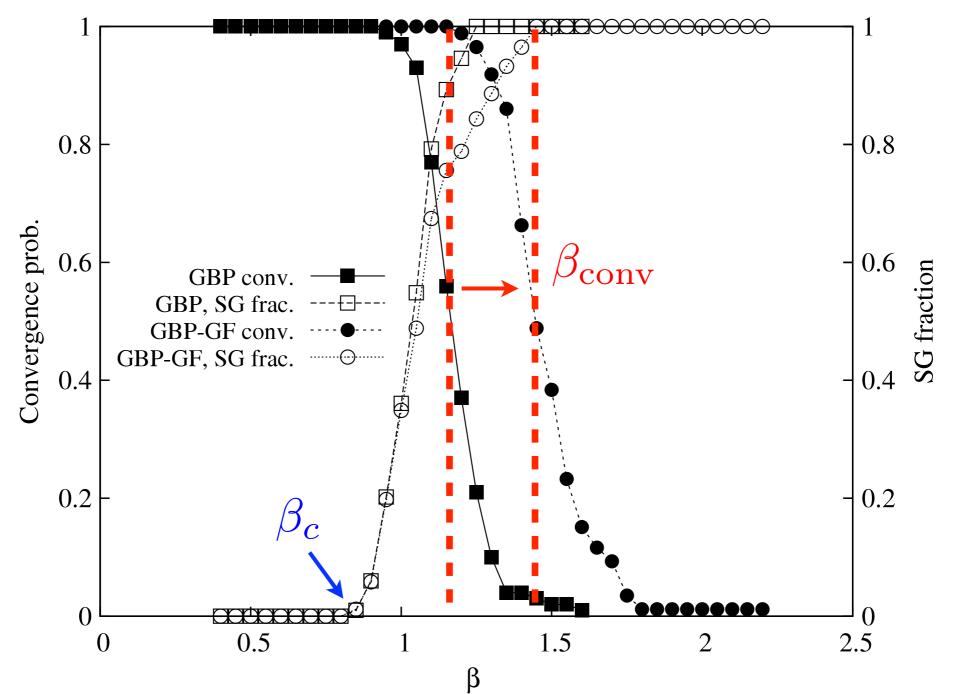


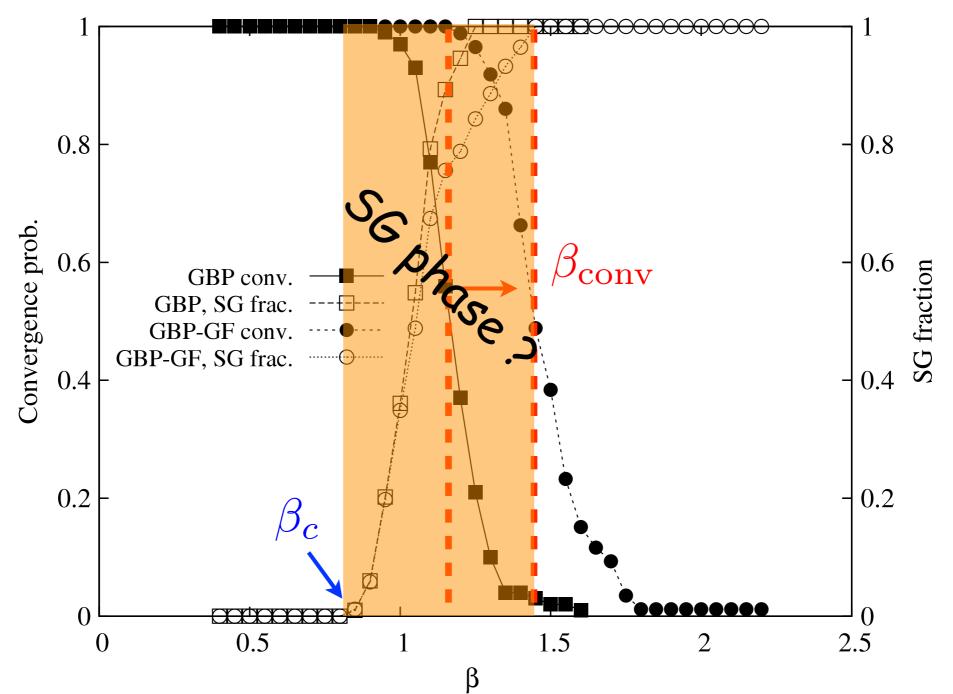
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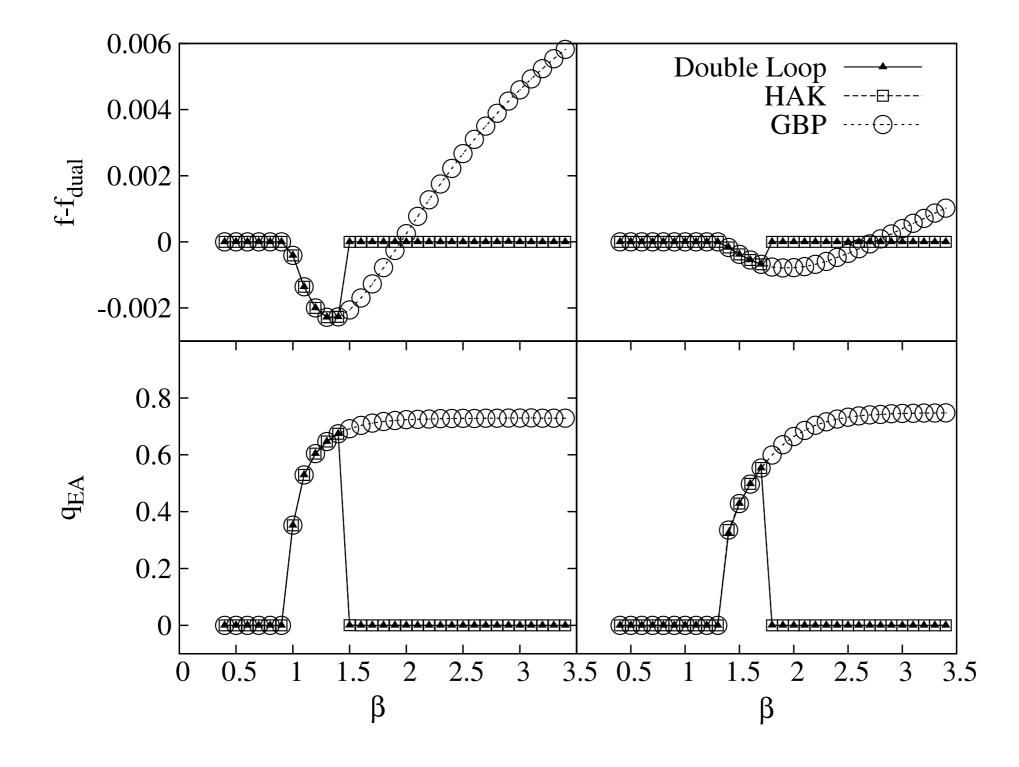




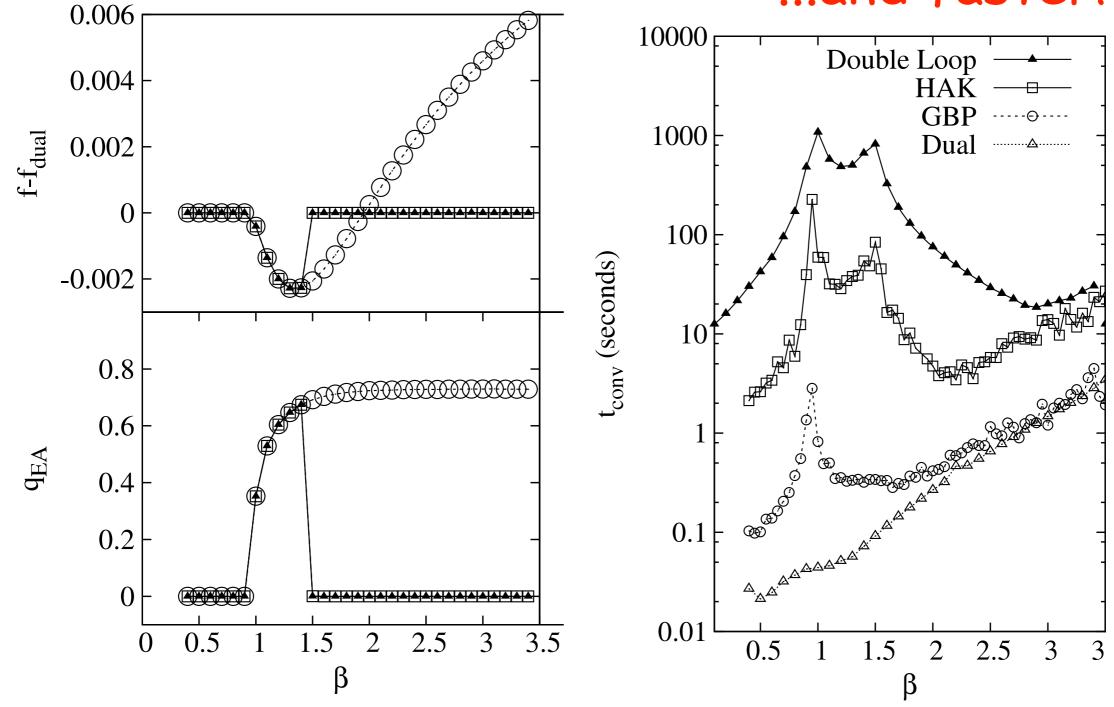






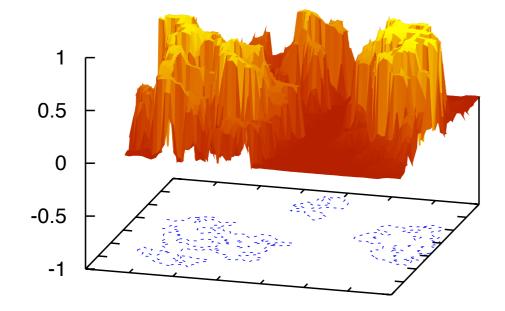


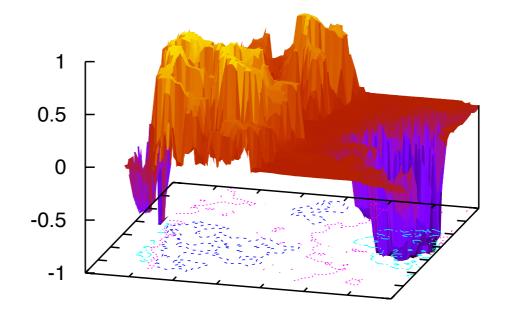
...and faster!

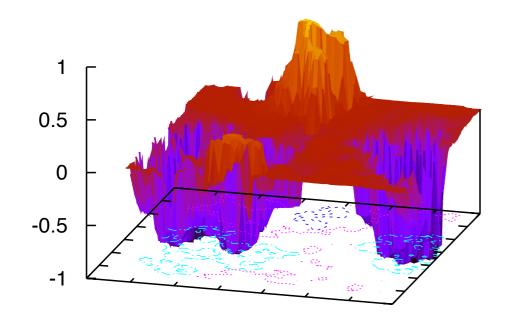


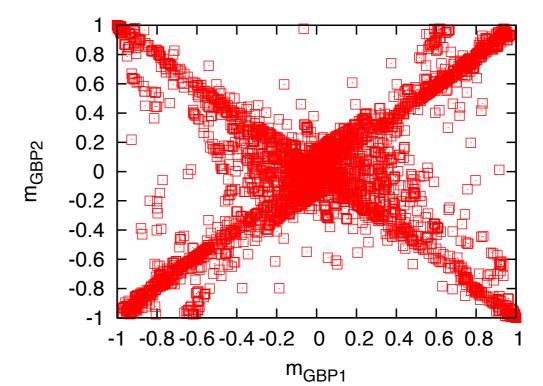
Relevance of SG solutions

 $T_c < T < T_{\rm conv}$

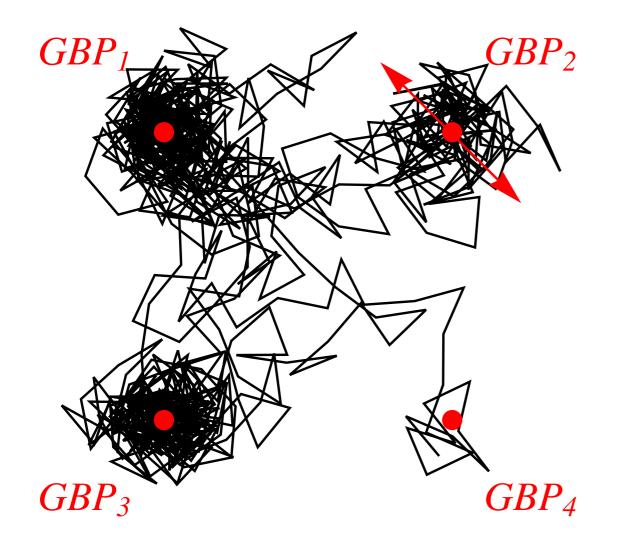






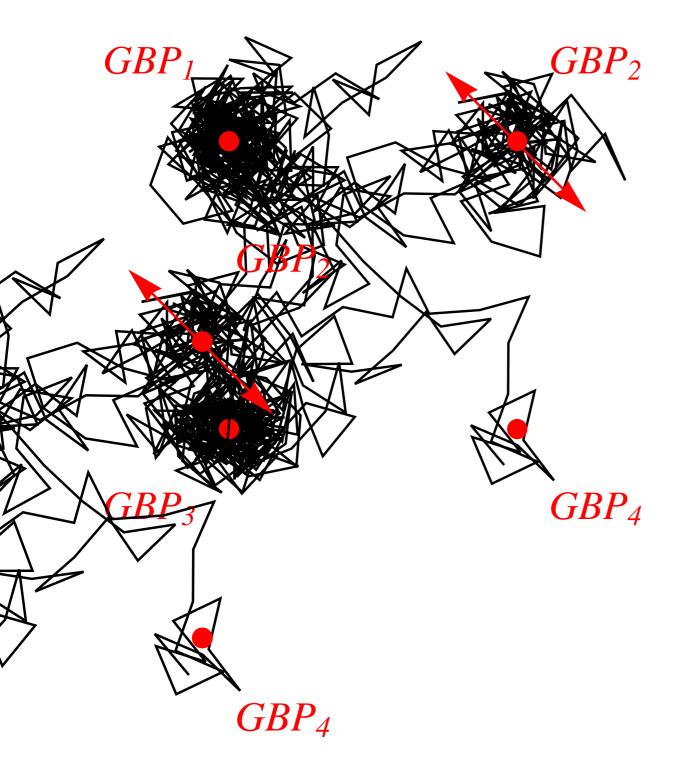


Relevance of SG solutions

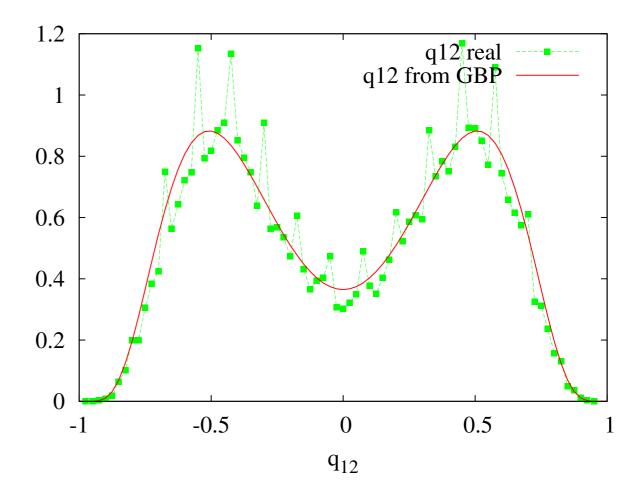


 $P(\vec{\sigma}) \simeq \sum e^{-\beta F_{\alpha}} P_{\alpha}(\vec{\sigma})$ $\alpha \in \text{GBP f.p.}$

Relevance of SG solutions



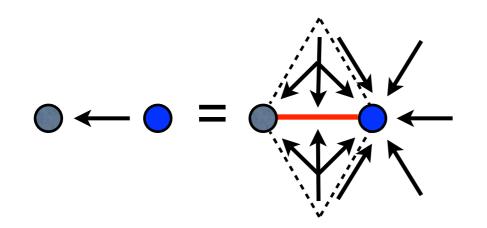
 $P(\vec{\sigma}) \simeq \sum e^{-\beta F_{\alpha}} P_{\alpha}(\vec{\sigma})$ $\alpha \in \text{GBP f.p.}$



Replica CVM a technical slide :-)

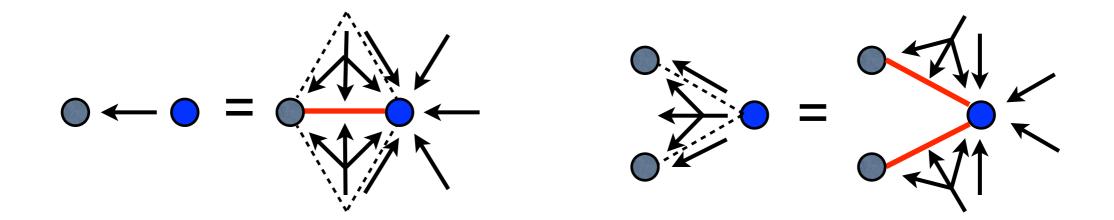
n-replicated free energy $\Phi(n) = -\frac{1}{n\beta N} \ln \operatorname{Tr} \left\langle \exp\left(\sum_{(ij)} \beta J_{ij} \sum_{a=1}^{n} s_i^a s_j^a\right) \right\rangle_{\mathbf{T}}$ **n-replicated spins** $\sigma_i \equiv \{s_i^1, \dots, s_i^n\}$ $\psi_r(\sigma_r) \equiv \prod_{i,j \in r} \langle \exp(\beta J_{ij} \sum_a s_i^a s_j^a) \rangle_J$ energy of region r $E_r = -\ln\prod_{i=1}^{n}\psi_{ij}(\sigma_i,\sigma_j) - \ln\prod_{i=1}^{n}\psi_i(\sigma_i)$ n-replicated CVM $F_K = \sum_{r \in R} c_r \left(\sum_{x_r} b_r E_r + \sum_{r_r} b_r \ln b_r \right)$ free energy

a second technical slide :- |



 $m_{(ij)\to j}(\sigma_j) \propto \sum_{\sigma_i} \psi_{(ij)}(\sigma_i, \sigma_j) M_{\alpha \to (ij)}(\sigma_i, \sigma_j) M_{\beta \to (ij)}(\sigma_i, \sigma_j) \prod_{k \in \partial i \setminus j} m_{(ki)\to i}(\sigma_i)$

a second technical slide :- |



$$m_{(ij)\to j}(\sigma_j) \propto \sum_{\sigma_i} \psi_{(ij)}(\sigma_i, \sigma_j) M_{\alpha \to (ij)}(\sigma_i, \sigma_j) M_{\beta \to (ij)}(\sigma_i, \sigma_j) \prod_{k \in \partial i \setminus j} m_{(ki)\to i}(\sigma_i)$$

$$\begin{split} M_{(ijk)\to(ij)}(\sigma_i,\sigma_j)m_{(ik)\to i}(\sigma_i)m_{(jk)\to j}(\sigma_j) \propto \sum_{\sigma_k}\psi_{(ik)}(\sigma_i,\sigma_k)\psi_{(jk)}(\sigma_j,\sigma_k) \\ &\prod_{\alpha\in\partial(ik)\setminus(ijk)}M_{\alpha\to(ik)}(\sigma_i,\sigma_k)\prod_{\beta\in\partial(jk)\setminus(ijk)}M_{\beta\to(jk)}(\sigma_j,\sigma_k)\prod_{l\in\partial k\setminus\{i,j\}}m_{l\to k}(\sigma_k) \end{split}$$

a third technical slide :-(

RS ansatz on
the messages
$$m(\sigma_i) = \int du \, q(u) \exp\left[\beta u \sum_{a=1}^n \sigma_i^a\right] (2 \cosh \beta u)^{-n}$$

$$M(\sigma_i, \sigma_j) \propto \int dU \, du_i \, du_j \, Q(U, u_i, u_j) \exp\left[\beta U \sum_{a=1}^n \sigma_i^a \sigma_j^a + \beta u_i \sum_{a=1}^n \sigma_i^a + \beta u_j \sum_{a=1}^n \sigma_j^a\right]$$

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analytic continuation for n->0

$$\begin{aligned} q(u) &= \int \prod_{i}^{k} dq_{i} \prod_{\alpha}^{p} dQ_{\alpha} \left\langle \delta(u - \hat{u}(\#)) \right\rangle_{J}, \\ R(U, u_{a}, u_{b}) &\equiv \int du_{i} du_{j} Q(U, u_{i}, u_{j}) q(u_{a} - u_{i}) q(u_{b} - u_{j}) = \\ &= \int \prod_{i}^{K} dq_{i} \prod_{\alpha}^{P} dQ_{\alpha} \left\langle \delta(U - \hat{U}(\#)) \delta(u_{a} - \hat{u}_{a}(\#)) \delta(u_{b} - \hat{u}_{b}(\#)) \right\rangle_{J} \end{aligned}$$

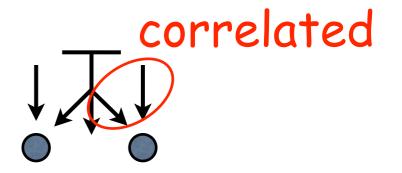
$$q(u) = \int \prod_{i}^{k} dq_{i} \prod_{\alpha}^{p} dQ_{\alpha} \langle \delta(u - \hat{u}(\#)) \rangle_{J} ,$$

$$R(U, u_{a}, u_{b}) \equiv \int du_{i} du_{j} Q(U, u_{i}, u_{j}) q(u_{a} - u_{i}) q(u_{b} - u_{j}) =$$

$$= \int \prod_{i}^{K} dq_{i} \prod_{\alpha}^{P} dQ_{\alpha} \langle \delta(U - \hat{U}(\#)) \delta(u_{a} - \hat{u}_{a}(\#)) \delta(u_{b} - \hat{u}_{b}(\#)) \rangle_{J}$$

Very hard to solve:

- convolution in $R(U, u_a, u_b)$
- non-positive defined $Q(U, u_i, u_j)$



no population dynamics

Hard to solve because are the right equations ...?

Paramagnetic solution stability analysis

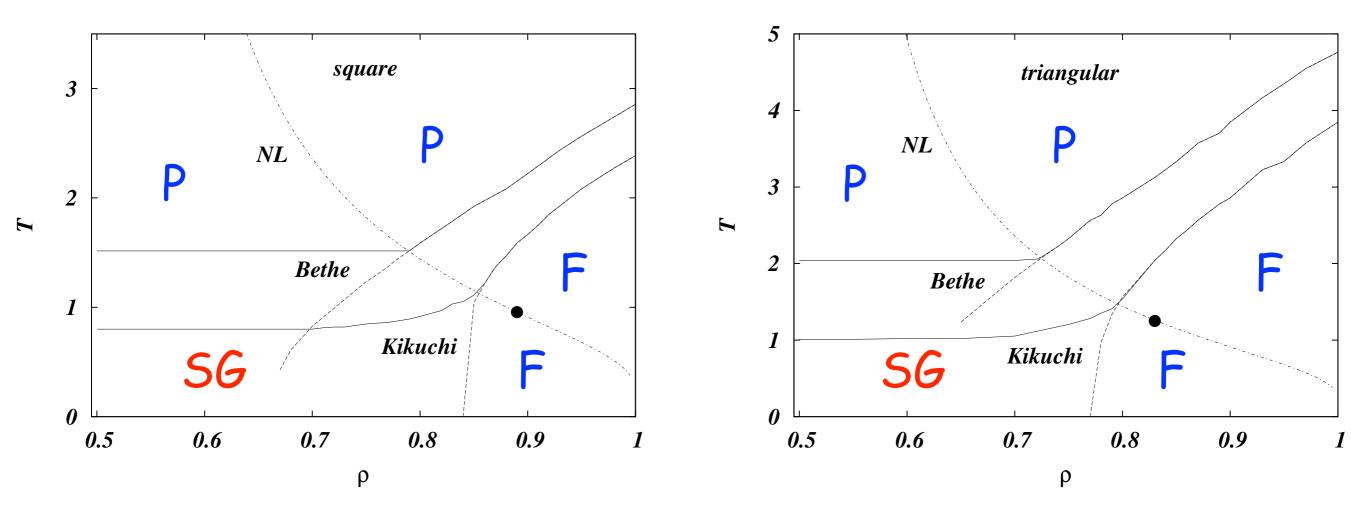
 $q(u) = \delta(u) \qquad Q(U, u_i, u_j) = a_0(U)\delta(u_1)\delta(u_2)$

first two moments $m = \int q(u) u \, du , \qquad a = \int q(u) u^2 du ,$ $M_i(U) = \iint Q(U, u_1, u_2) u_i \, du_i , \qquad a_{ij}(U) = \iint Q(U, u_1, u_2) u_i u_j \, du_1 du_2 ,$

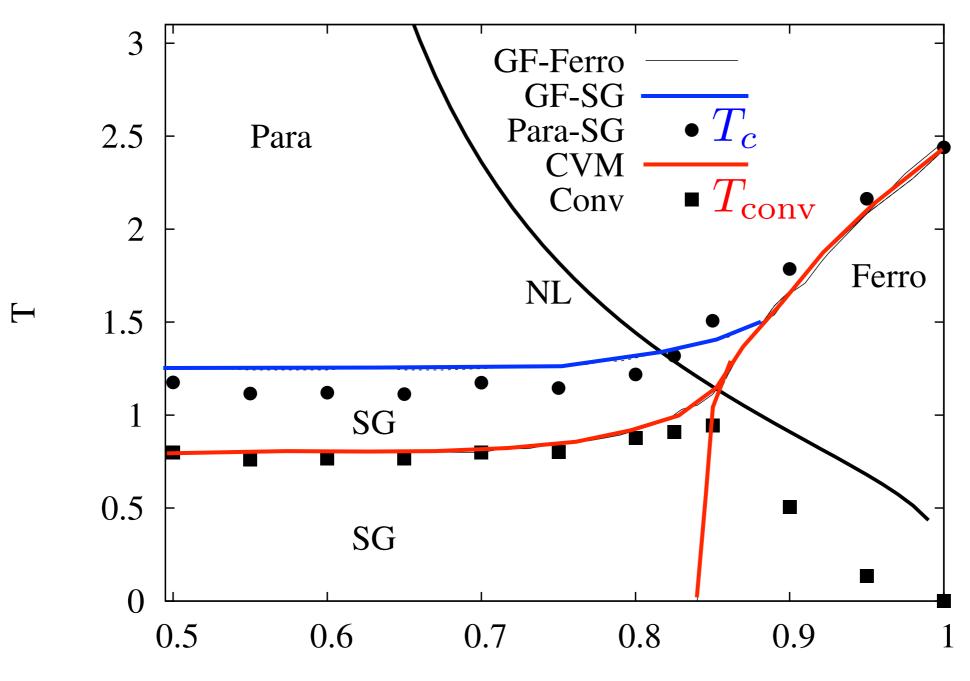
three phases:paramagnetic (P)m = 0a = 0spin glass (SG)m = 0 $a \neq 0$ ferromagnetic (F) $m \neq 0$ $a \neq 0$

2D Plaquette Replica CVM

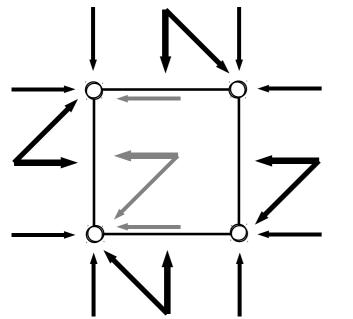
 $P(J) = \rho \,\delta(J-1) + (1-\rho)\delta(J+1)$



Replica CVM "explains" the behavior of GBP on given samples



Population dynamics for gauge-fixed messages

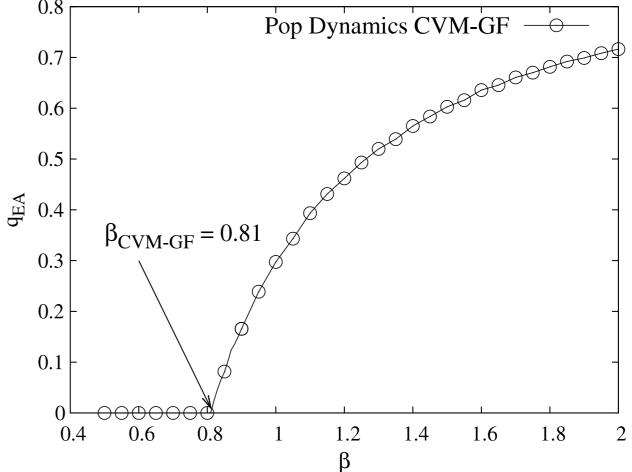


Choose randomly the external 4-fields and compute the internal 4-field. Repeat until convergence.

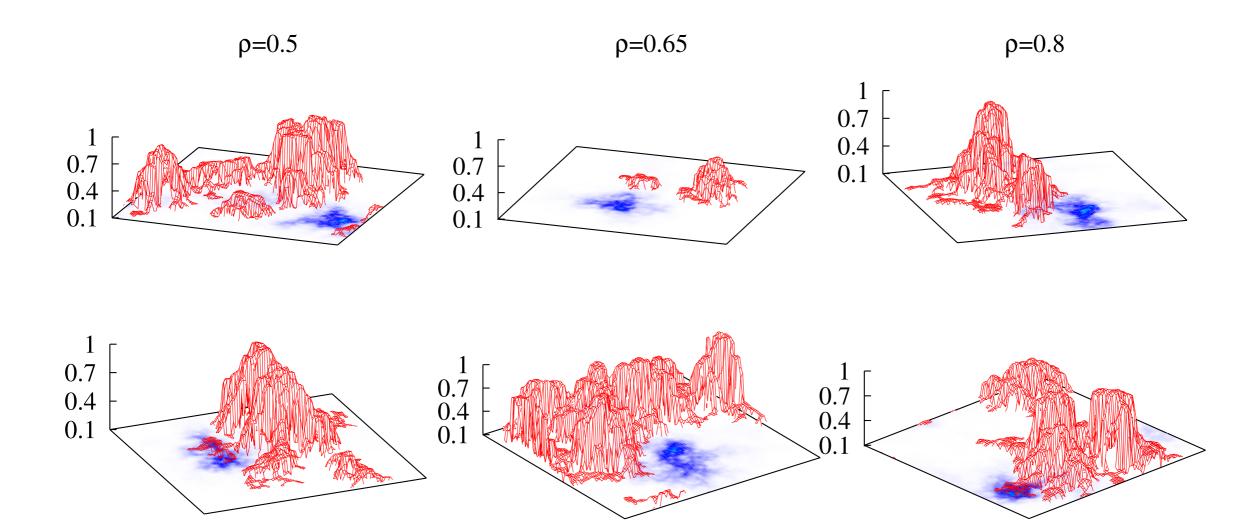
Population dynamics for gauge-fixed messages

Choose rai Choose rai and compu-Repeat un 0.8

Choose randomly the external 4-fields and compute the internal 4-field. Repeat until convergence.



Why T_{conv} and T_{CVM} are close?



Summary

- BP fails on regular lattices... and so improved methods based on BP
- GBP works better...
 much better if improved
 (dual algorithm, gauge fixing)
- SG solutions found by GBP are faithful
- Replica CVM improves largely Bethe (e.g. phase diagrams) and can "explain" GBP behavior