

local neighborhood R :

propagate boundary messages \rightarrow measure $\mu_R(x_R)$

(assumption of looking at neighborhood of distance $R-1$, entering boundary computed from μ_R through BP. \equiv messages at boundaries indep.)

assumption, internal measure well approximated by tree.

WRONG ASSUMPTION when:

loopy graphs (cliques)
long range correlations (long loops)

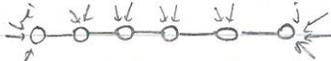
CLUSTER VARIATIONAL METHODS (Kikuchi)
GRAPHICAL MODEL APPROX-

SPARSE RANDOM GRAPHS

When getting long range correlations, what should we do with BP?

First, what correlations to measure?

\rightarrow connected correlations from distant variables: $\langle x_i x_j \rangle_c \equiv \langle x_i x_j \rangle - \langle x_i \rangle \langle x_j \rangle$



in 1d correlations always decay: $\langle x_i x_j \rangle_c \Big|_{|i-j|=r} \sim e^{-r/\xi}$

But the number of neighbors increases with distance: $\chi_T = \sum_i \chi_{i0} = \sum_r c(r) d(d-1)^{r-1}$
 $= \frac{d}{d-1} \sum_r \exp(-\frac{r}{\xi} + r \ln(d-1))$

d random regular graph

\hookrightarrow criticality for finite correlation length: $\xi_c = \frac{1}{\ln(d-1)}$

doi/07/2017

Define measure of how i and j are correlated:

$$\chi^{(2)} = \frac{1}{N} \sum_{i,j} \|\mu_{ij}(1, \cdot) - \mu_{i \cdot}(1, \cdot) \mu_{\cdot j}(1, \cdot)\| \rightarrow \text{norm over probability measures}$$

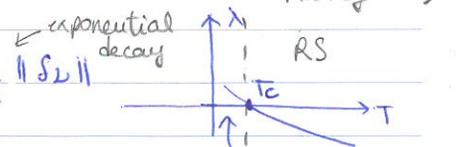
$$\Rightarrow \chi^{(m)} = \frac{1}{N^{m-1}} \sum_{i_1, \dots, i_m} \|\mu_{i_1, \dots, i_m}(1, \cdot) - \mu_{i_1, \dots, i_{m-1}}(1, \cdot) \mu_{i_m}(1, \cdot)\| \quad \text{eg: "Frobenius"} \quad \|A(x_i, x_j)\| = \frac{1}{2} \sum_{x_i, x_j} |A(x_i, x_j)|$$

The model is stable to small perturbation of all finite n , $\frac{\chi^{(n)}}{N} \rightarrow 0$ as $N \rightarrow \infty$

\rightarrow divergence of susceptibility \leftrightarrow instability of BP fixed points

In practice, should look at all $\chi^{(m)}$, but instead typically look at $\chi^{(2)}$ only (instability featured in pairwise models mainly)

\hookrightarrow perturbing the fixed point: $v + \delta v \rightarrow$ rate of decay? $\lambda = \lim_{t \rightarrow \infty} \frac{\|\delta v_t\|}{\|\delta v_0\|}$



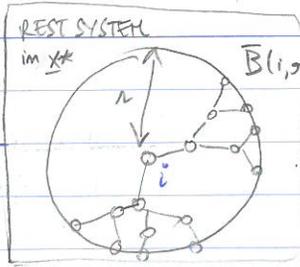
BP stops converging

can be measured by population dynamics

Instability making the RS aware unconnect.

POINT-TO-SET CORRELATION FUNCTION

Even if BP fixed points are stable, the system can be creating some kind of order in



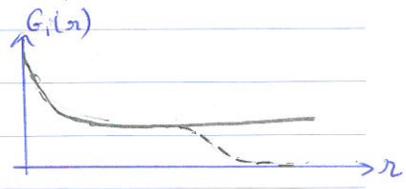
$$B(i, R) = \{j : |i-j| \leq R\}$$

a different way

Even if the root is not correlated with any finite set of variables, could be with the entirety of the boundary at $R \rightarrow +\infty$ divergent number of variables.

we want to look at: $G_i(R) = \|\mu_{i, B(i, R)}(\cdot, \cdot) - \mu_i(\cdot) \mu_{B(i, R)}(\cdot)\|$

And separate the cases where it decays or not with distance:



first experiment: Take system outside ball fixed x^* , then look inside the ball $\mu(x_B | x_{B^*})$

\rightarrow if $x_i \sim \mu(x_B | x_{B^*}) \approx x_i^*$?

in practice the same ...

second experiment: Take again equilibrium x^* , delete everything inside ball, can you guess x_i^* ?

The model is called non-reconstructible or extremal, if $G_i(R) \xrightarrow{R \rightarrow \infty} 0 \forall i$.

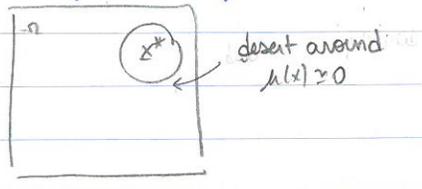
So in the end we have two different long range correlations types \rightarrow different phases?

Phases: REPLICA SYMMETRIC (RS): both correlations $x^{(n)}$ and $G_i(R)$ decay!

DYNAMICAL (DRSB): stable to small perturbation, $x^{(n)} < +\infty$, stable BP fixed point.
 $T_K < T < T_D$ [non-reconstructible $G_i(R) \rightarrow \text{cte}$]

csq: \rightarrow any local algorithm will have great trouble jumping barriers: size of sea movements diverging!
 \hookrightarrow breaking of ergodicity, stuck dynamics (slow to visit phase space...)

SPACE OF CONFIGURATIONS



\rightarrow as the system is stable under small perturbation \rightarrow can show that there must be exponentially many state:

- add one constraint
- killing finite fraction of solutions
- must have been exponentially many for thermodynamic observables to remain OK.

replica jargon: 1RSB $m=1$. $q = \int q_0$ with proba $1 - e^{-N\xi}$
 q_1 with proba $e^{-N\xi} \sim P(q) \sim \delta(q - q_0)$

\hookrightarrow weights of clusters: $w_j = e^{-N\xi} \rightarrow \sum w_j^2 = e^{-N\xi} \leftrightarrow$ proba $e^{-N\xi}$

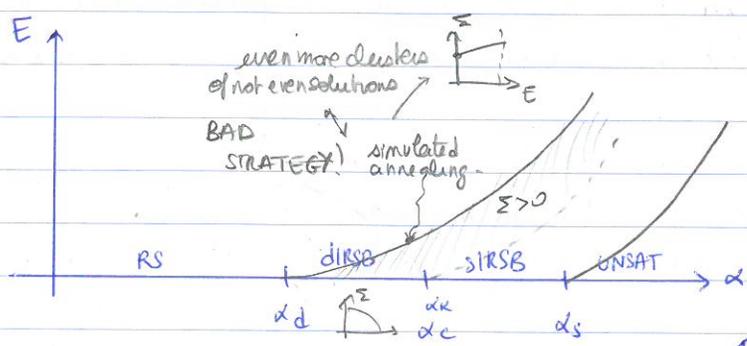
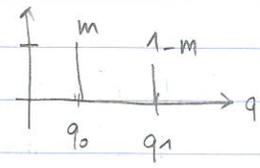
STATIC 1RSB (S1RSB) both correlations do not decay

$T < T_K$

BP is making wrong prediction csq $\rightarrow \Sigma = 0$

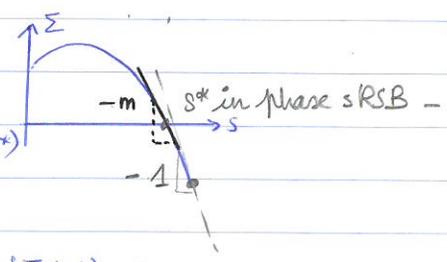
measure concentrates on $O(2)$ clusters.

→ weights of each cluster δ : $\sum_{\delta} W_{\delta}^2 = 1 - m \rightarrow$



generic picture, can change according to model

↳ interpretation of m : $W(\#sd = e^{Ns}) = e^{N\Sigma(s)}$
 $Z(m) = \sum_{\delta} e^{N\delta m} = \int ds e^{N\delta m + N\Sigma(s)} = e^{Nms^* + N\Sigma(s^*)}$
 clusters $\rightarrow \delta$



⇒ total number of solutions = $Z(1)$ → dominated by $\left\{ \begin{array}{l} \Sigma(s^*) = 0 \\ \rho(s) \sim e^{-m(s-s_0^*)} \end{array} \right.$

$$\sum_{\delta} W_{\delta}^2 = \int ds e^{2Ns} e^{N\Sigma(s-s_0^*)}$$

ENSEMBLE RANDOM (GRAPHICAL) MODEL

We can introduce randomness \rightarrow

- $G(V_i, E)$
- $\Psi_i = e^{B H_i X_i} \quad H_i \sim p_0(H_i)$
- $\Psi_{ij} = e^{B J_{ij} X_i X_j} \quad J_{ij} \sim p_0(J_{ij})$

↳ this disorder is then incorporated into the BP algorithm: $\mu_{i \rightarrow a} \stackrel{d}{=} f_i[\{ \hat{\mu}_{i \rightarrow b} \}_b; H_i]$
 $\mu_{a \rightarrow i} \stackrel{d}{=} \hat{f}_a[\{ \mu_{a \rightarrow b} \}_b; J_{ij}]$

→ How can we compute ensemble average without sampling different problems and converging BP on each?

Density evolution equation → compute directly the disorder average:

- one way to see that: $\mu_{i \rightarrow a}$ RV. of H_i , and solve in terms of distributions
- another way: "self-averaging", statistical treatment by drawing messages at random and iterating from a ^{10⁵ is enough} huge sample of messages (\sim experiments)
- ↳ random incoming messages $P(\mu)$ → random outgoing messages

→ population dynamics \equiv density evolution:

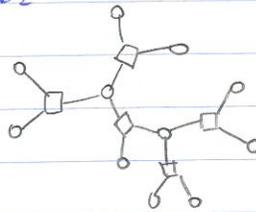
equations in probability $\left\{ \begin{array}{l} P(\mu) = \mathbb{E}_{H, J} \left(\int \prod_{i=1}^q d\hat{P}(\hat{\mu}_1) d\hat{P}(\hat{\mu}_2) \dots d\hat{P}(\hat{\mu}_q) \mathbb{1}(\mu = f[\hat{\mu}_1, \dots, \hat{\mu}_q; H_i]) \right) \\ \hat{P}(\hat{\mu}) = \end{array} \right.$

RANDOM XORSAT: Kauzmann = SAT

THE MODEL: N binary variables: $x_i \in \{0, 1\}$; $M = \alpha N$ constraints in the form of linear equations mod 2

$k=3 \rightarrow$ number of variables per constraint: $x_2 + x_4 + x_7 = b_1 \equiv Hx = b$ $H_{ij} \in \{0, 1\}$
 $x_{13} + x_{24} + x_5 = b_2$

\hookrightarrow all constraints chosen at random $\rightarrow |D_i| = \text{Poisson}(\alpha k)$
 (M k -tuples at random). $|D_a| = k$



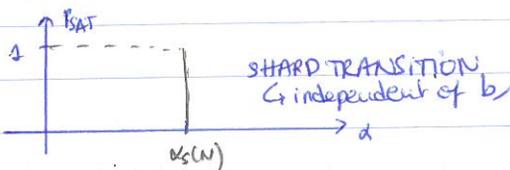
THE MEASURE: $\mu(x) = \frac{1}{Z} \prod_a \Psi_a(x_{D_a})$

constraints -
 \swarrow
 nodes -

RE: percolating ratio from branching ratio $(k-1)\alpha k = 1$ work way above percolation threshold not to be trivial (at least one loop).

\hookrightarrow with the change of variable: $s_i = (-1)^{x_i}$ $T_a = (-\mathbb{1})^{b_a}$ $\rightarrow H = \sum_a (1 - T_a \prod_{i \in D_a} s_i) \equiv$ Spine k -spin model! \rightarrow cavity rather than replica.

THE NUMBER OF SOLUTIONS: $Z = \begin{cases} 2^{N - \text{rank}(H)} & \text{if } b \in \text{Image}(H) \rightarrow \#b = 2^{\text{rank}(H)} \\ 0 & \text{otherwise} \end{cases}$



\hookrightarrow one can show that in the thermodynamic limit \rightarrow

PLANTED MODEL: As we do not care for the actual choice of b , we'll choose $b=0$.

Indeed, $S = \{x : Hx = b\} \Rightarrow \forall x^* \in S \quad S = x^* + S_0 \rightarrow$ equivalent under one translation
 $S_0 = \{x : Hx = 0\}$ \hookrightarrow same properties for S and S_0

\hookrightarrow constraint generated at random $\rightarrow H$ full rank typically $|S| = |S_0| = 2^{N-\pi}$

Important property: 2 classes of variables \rightarrow frozen $x_i = 0 \forall x \in S_0$
 \downarrow prove an EXERCISE \rightarrow free $x_i = \begin{cases} 0 & \text{proba } 1/2 \\ 1 & \text{proba } 1/2 \end{cases}$

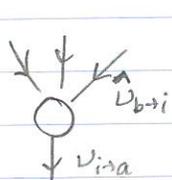
percolation, loop, frustration \swarrow
 EASY BOUNDS: $\frac{1}{k(k-1)} < \alpha_s < 1$ \leftarrow inversion of H

BELIEF PROPAGATION EQUATIONS:

We'll denote the uniform $(1/2, 1/2)$ marginal by $* (x) = 1/2 \delta(x) + 1/2 \delta(x-1)$

and the delta on 0 marginal by $0 (x) = \delta(x)$

property: $\{u^{(i)}, v^{(i)}\} \in \{0, *\}^2 \Rightarrow \{u^{(i+1)}, v^{(i+1)}\} \in \{0, *\}^2$ (stable under BP equations)



$v_{i \rightarrow a} = \begin{cases} 0 & \text{if at least 1 } v_{b \rightarrow i} = 0 \\ * & \text{otherwise (every incoming = *)} \end{cases}$

$u_{a \rightarrow i} = \begin{cases} 0 & \text{if all } v_{j \rightarrow a} = 0 \\ * & \text{otherwise} \end{cases}$

"has more zero than \tilde{v} "

Rk: there is a partial ordering w.r.t to the messages: $\tilde{v} \succ \tilde{u}$ if $\tilde{v} = 0 \Rightarrow v = 0$
 \rightarrow stable under BP: if $v^{(t)} \succ \tilde{v}^{(t)} \Rightarrow v^{(s)} \succ \tilde{v}^{(s)} \forall s > t$.

\hookrightarrow BPFIXED POINTS:

1st case $\{ \tilde{v}^{(t)}, \tilde{v}^{(0)} \} = *$ \rightarrow already a fixed point

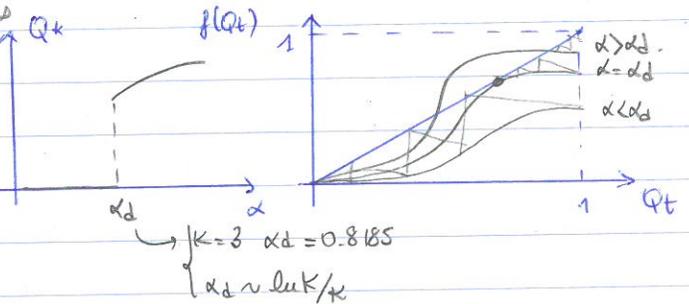
2nd case $\{ \tilde{v}^{(t)}, \tilde{v}^{(0)} \} = 0$ \rightarrow will follow the evolution with Q_t = fraction of $v=0$ messages

$Q_0 = 1$

$$Q_{t+1} = \sum_{k=0}^{\infty} e^{-\alpha k} \frac{(\alpha k)^e}{e!} [1 - \tilde{Q}_t^e] \quad \text{with } \tilde{Q}_t = Q_t^{k-1} \Rightarrow \begin{cases} Q_{t+1} = 1 - e^{-\alpha k Q_t^{k-1}} \\ Q_0 = 1 \end{cases} = f(Q_t)$$

degree

probability all incoming messages are trivial



\rightarrow we initialized BP to very special conditions \rightarrow message concentrated on the planted configuration \rightarrow if it belongs to a finite cluster, will sp out over and only over this planted cluster $\rightarrow Q^* > 0$.

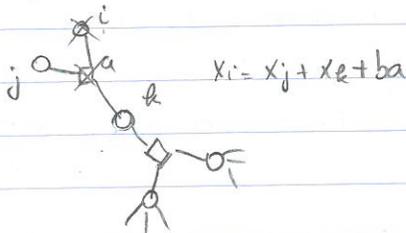
Rk: Reconstruction problem with boundaries $v=0$ \rightarrow the number of zeros while going toward the center/root of the ball/tree \Rightarrow less and less 0 according to $Q^{t+1} = f(Q^t)$.

Phases: $\begin{cases} \alpha < \alpha_d: \text{strong correlation decay } Q \rightarrow 0: \text{Replica symmetric} \\ \alpha > \alpha_d: \text{clusters, can we understand them better?} \end{cases}$

Idea: Try to keep the dense part of the tree only (should be during this transition!)

\rightarrow Remove leaf by keeping track of the value ~~remaining~~ ^{deleted} variables should take

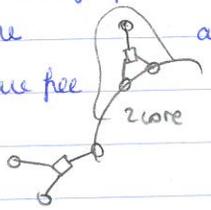
\rightarrow As long as there are leaves remove them + corresponding clause \equiv smart gaussian elimination



Is if nothing left eventually \rightarrow go back constructing graph from random assignment to last eliminated variable

→ start existing for $\alpha > \alpha_d$.

→ if something left \Rightarrow 2-core \Rightarrow subgraph $|\alpha| > 2 \forall i \oplus$ all frozen $\hat{v}, \nu = 0$
 \hookrightarrow directly implied by the core also frozen \rightarrow BACKBONE (of cluster)
 \hookrightarrow the remaining variables are free



\Rightarrow one to one correspondence between BP messages \Leftrightarrow topology.

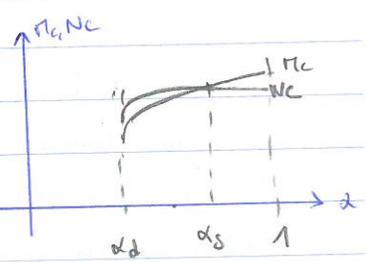
In this special CSP core = label for the cluster \rightarrow all solutions share same core configurations.
 \hookrightarrow so that counting clusters = counting core configurations.

SIZE OF THE CORE:

$$\begin{cases} \mathbb{P}[\hat{v}=0] = \hat{Q}^* \\ \mathbb{P}[\nu=0] = Q^* \end{cases} \quad \text{with } \begin{cases} Q^* = 1 - e^{-\alpha k \hat{Q}^*} \\ \hat{Q}^* = Q^{k-1} \end{cases}$$

\hookrightarrow expected number of variables in core $N_c = N [1 - e^{-\alpha k \hat{Q}^*} - k \alpha \hat{Q}^* e^{-k \alpha \hat{Q}^*}]$
 $M_c = N \alpha \hat{Q}^* (1 - e^{-k \alpha \hat{Q}^*})$

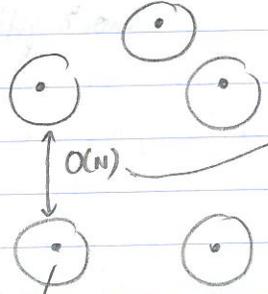
solution on the core: $2^{N_c - M_c} \equiv e^{\Sigma N} \rightarrow \Sigma = \frac{N_c - M_c}{N} \ln 2$
 analytic expression for complexity



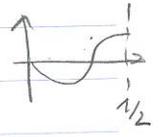
SOLUTION IN SPACE OF CONFIGURATIONS FOR $\alpha_d < \alpha < \alpha_s$

e^{NS} configurations of core

clusters of equal size (given special topology) of internal entropy $e^{NS} = 2^{N - M} e^{-NS}$



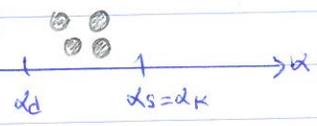
proof in the book / Brillouin exercise?
 # configurations at distance d $W(d) \rightarrow \frac{\ln W(d)}{N}$



EXACT PICTURE

at most $O(\ln N)$

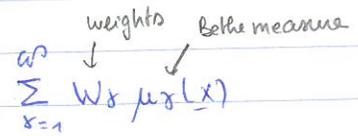
PHASE DIAGRAM:



\rightarrow The simplest CSP, that can be solved with basic graph structure argument (leaf removal) straightforwardly. Yet still feature clusters + sat sharp.

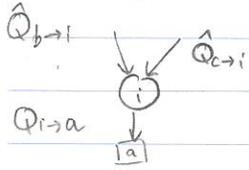
CAVITY METHOD WITH LONG RANGE CORRELATIONS:

Decompose the measure over different states: $\mu(x) = \sum_{s=1}^{\omega} W_s \mu_s(x)$



→ meta messages, IRSB cavity method: statistical distribution of fixed parts of BP

$$\begin{cases} \hat{Q}_{i \rightarrow a}(v) = \mathbb{P}[v_{i \rightarrow a}^{(i)} = v] \\ \hat{Q}_{a \rightarrow i}(\tilde{v}) = \mathbb{P}[v_{a \rightarrow i}^{(i)} = \tilde{v}] \end{cases} \rightarrow \text{make them locally consistent!}$$



now the messages $\hat{Q}_{b \rightarrow i}$ and $\hat{Q}_{c \rightarrow i}$ are not entirely independent, they need to be compatible!

e.g. for XORSAT \rightarrow case: $\hat{Q} = \frac{1}{2} \mathbb{1}(\tilde{v}=0) + \frac{1}{2} \mathbb{1}(\tilde{v}=1)$,

but getting $\begin{cases} \hat{v}_{b \rightarrow i} = 0 \\ \hat{v}_{c \rightarrow i} = 1 \end{cases}$ cannot be possible $\rightarrow \tilde{v}$ not a BP fixed point!

↳ XORSAT IRSB: $Q_{i \rightarrow a}(v) \propto \sum_{\{\tilde{v}_{b \rightarrow i}\}_{b \in \mathcal{N}(i)}} \prod \hat{Q}_{b \rightarrow i}(\tilde{v}_{b \rightarrow i}) \mathbb{1}(v = f(\{\tilde{v}_{b \rightarrow i}\})) \mathbb{1}(\{\tilde{v}_{b \rightarrow i}\} \text{ are compatible})$ - at least one solution allowed

GENERIC MODEL IRSB

CAVITY EQUATIONS: $\begin{cases} Q_{i \rightarrow a}(v) \propto \sum_{\{\tilde{v}_{b \rightarrow i}\}} \mathbb{1}(v = f_i(\{\tilde{v}_{b \rightarrow i}\})) Z_{i \rightarrow a}^m(\{\tilde{v}_{b \rightarrow i}\}) \prod_{b \in \mathcal{N}(i)} \hat{Q}_{b \rightarrow i}(\tilde{v}_{b \rightarrow i}) \\ \hat{Q}_{a \rightarrow i}(\tilde{v}) \propto \sum_{\{v_{j \rightarrow a}\}} \mathbb{1}(\tilde{v} = \hat{f}_a(\{v_{j \rightarrow a}\})) Z_{a \rightarrow i}^m(\{v_{j \rightarrow a}\}) \prod_{j \in \mathcal{N}(i)} Q_{j \rightarrow a}(v_{j \rightarrow a}) \end{cases}$

$Z_{i \rightarrow a} \equiv$ proportional to the entropy of solutions when merging branches

↳ corresponds to look at statistics of clusters according to $Z(m) = \sum_{\delta} e^{NS_{\delta} m}$

↳ $Z(s)$ Legendre transform