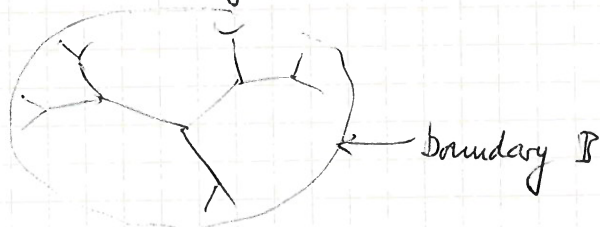


Cavity method

Originally for the SK model ($\rightarrow$ interpret the replica solution without replicas!) $\Leftrightarrow$ understanding the physics of the hierarchical block structure.

Cavity approach: much more direct, easier to grasp;
applicable to finite connectivity graphs $\Rightarrow$ approximate scheme for finite d glasses!

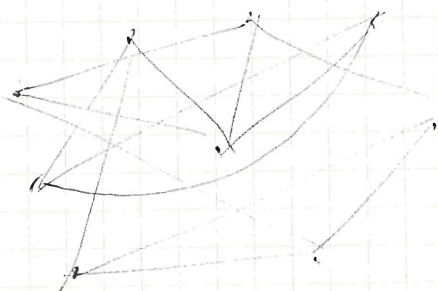
Key idea: 1. Graph = tree:



$\Leftrightarrow$ exactly solvable by iteration from outside in!

$\Rightarrow$ first step below!

2. Random graphs: no (free) boundary $\Rightarrow$ frustration (possibly)
But: locally looks tree like:



$\Leftarrow$ random graph of fixed connectivity $c = 3$

Important property: loops are large, typically $\sim \log(N_{\text{sites}})$

$\Rightarrow$ Portions of diameter $\ll \log(N_{\text{sites}})$ are typically loop-free
 $\rightarrow$ look like a tree!

Notations: i : sites

D_i : all neighbors linked with i

$\langle ij \rangle$: link from i to j

$D_i \setminus j$: D_i without the neighbor j



Solution on a tree

Problems:
considered

We restrict here to two-body interactions (like spin glasses, or Potts models, etc.)

Generalization to p-spin interactions are possible
see notes on MF glasses.

spins: $H = - \sum_{\langle ij \rangle} J_{ij} s_i s_j \quad (+ \sum \varphi_i s_i)$

two body term

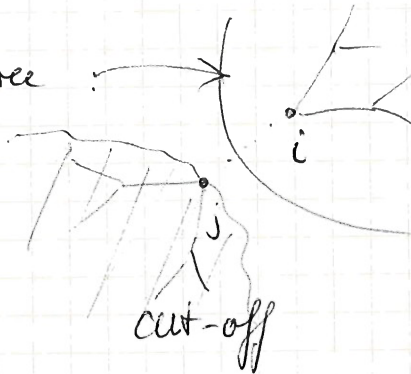
sometimes added: one body term

But: more generally:

$$\sum_{\langle ij \rangle} E(\sigma_i, \sigma_j)$$

σ_i : discrete variable with r different states.
e.g.: $E(\sigma_i, \sigma_j) = \delta(\sigma_i, \sigma_j) \Leftrightarrow$ Potts model

Consider subtree:



Partition function restricted to subtree, with σ_i fixed:

$$\equiv Z_{i \rightarrow j}(\sigma_i)$$

$\langle ij \rangle$ is eliminated

$\Rightarrow$ Probability to see σ_i on the sub-tree: $\eta_{i \rightarrow j}(\sigma_i) = \frac{Z_{i \rightarrow j}(\sigma_i)}{\sum_{\sigma_i'} Z_{i \rightarrow j}(\sigma_i')}$

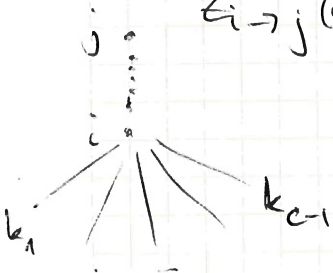
on full tree: $\eta_i(\sigma_i) = \frac{Z_i(\sigma_i)}{\sum_{\sigma_i'} Z_i(\sigma_i')}$

Solution of the tree: via recursion for $Z_{i \rightarrow j}(\sigma_i)$:

$$Z_{i \rightarrow j}(\sigma_i) = e^{\varphi_i(\sigma_i)} \prod_{k \in \text{children } j} \left(\sum_{\sigma_k} Z_{k \rightarrow i}(\sigma_k) e^{-\beta E(\sigma_i, \sigma_k)} \right)$$

$\equiv \varphi_k(\sigma_i, \sigma_k)$

with initial conditions on the boundary $Z_{k \rightarrow j}(\varphi_k)$.





→ Partition function of full tree, restricted to σ_i on site i :

$$Z_i(\sigma_i) = \prod_{k \in \partial i} \left(\sum_{\sigma_k} Z_{k \rightarrow i}(\sigma_k) \psi_{ik}(\sigma_i, \sigma_k) \right)$$

↑
all now!

⇒ Recursion for probabilities:

$$\eta_{i \rightarrow j}(\sigma_i) = \frac{(e^{\varphi(\sigma_i)})}{Z_{i \rightarrow j}} \prod_{k \in \partial i \setminus j} \left(\sum_{\sigma_k} \eta_{k \rightarrow i}(\sigma_k) \psi_{ik}(\sigma_i, \sigma_k) \right)$$

normalization: $Z_{i \rightarrow j} = \sum_{\sigma_i} (e^{\varphi(\sigma_i)}) \prod_{k \in \partial i \setminus j} \left(\sum_{\sigma_k} \eta_{k \rightarrow i}(\sigma_k) \psi_{ik}(\sigma_i, \sigma_k) \right)$

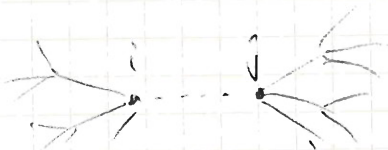
Full tree: $\eta_i(\sigma_i) = \frac{Z_i(\sigma_i)}{\sum_{\sigma_i'} Z_i(\sigma_i')} = \frac{1}{Z_i} \prod_{k \in \partial i} \left(\sum_{\sigma_k} \eta_{k \rightarrow i}(\sigma_k) \psi_{ik}(\sigma_i, \sigma_k) \right)$

with norm. $Z_i = \sum_{\sigma_i} \left[\prod_{k \in \partial i} \left(\sum_{\sigma_k} \eta_{k \rightarrow i}(\sigma_k) \psi_{ik}(\sigma_i, \sigma_k) \right) \right]$

Note: $\eta_i(\sigma_i)$ is the Gibbs probability to see σ_i

$$\Rightarrow \langle \sigma_i \rangle = \sum_{\sigma_i} \sigma_i \eta_i(\sigma_i)$$

Free energy?



Define "link free energy" (energy gained upon linking together i and j)

$$\begin{aligned} "e^{-\beta f_{ij}}" &\equiv Z_{ij} = \sum_{\sigma_i, \sigma_j} \eta_{j \rightarrow i}(\sigma_j) \eta_{i \rightarrow j}(\sigma_i) \psi_{ij}(\sigma_i, \sigma_j) \\ &= \sum_{\sigma_i, \sigma_j} Z_{j \rightarrow i}^{-1} \left(\prod_{k \in \partial j \setminus i} \left(\sum_{\sigma_k} \eta_{k \rightarrow j}(\sigma_k) \psi_{jk}(\sigma_j, \sigma_k) \right) \right) \eta_{i \rightarrow j}(\sigma_i) \psi_{ij}(\sigma_i, \sigma_j) \\ &= \frac{1}{Z_{j \rightarrow i}} \cdot Z_j \quad \text{and similarly: } = \frac{Z_i}{Z_{i \rightarrow j}} \end{aligned}$$



$$Z_{\text{tree, tot}} = \left(\prod_{k \in \text{Boundary } B} Z_{k \rightarrow j} \right) \cdot \prod_{j \in 1^{\text{st}} \text{ generation}} Z_{j \rightarrow j'} \cdot \prod_{j' \in 2^{\text{nd}} \text{ generation}} Z_{j' \rightarrow j''} \cdots$$

Diagram of a tree structure with root, 1st gen, 2nd gen, and boundary B.

$$Z_{\text{root}} = 0$$

$$= z_0 \cdot \prod_{j \in \partial_0} \underbrace{Z_{j \rightarrow 0}}_{= \frac{z_j}{z_0}} \prod_{k \in \partial_{j \rightarrow 0}} Z_{k \rightarrow j} \cdots \prod_{k \in \text{boundary}} Z_{k \rightarrow k'}$$

$$= z_0 \prod_{j \in \partial_0} \frac{z_j}{z_0} \prod_{k \in \partial_{j \rightarrow 0}} \left(\frac{z_k}{z_j} \right) \prod \cdots$$

$$\Rightarrow \boxed{Z_{\text{tree, tot}} = \frac{\prod_{i \text{ sites}} z_i}{\prod_{\text{links } \langle ij \rangle} z_{ij}}}$$

$$\Rightarrow F_{\text{tree}} = -T \log Z_{\text{tree, tot}} = \sum_i f_i - \sum_{\langle ij \rangle} f_{ij}$$

$\parallel$ $\parallel$
 $-T \log z_i$ $-T \log z_{ij}$

Simplest case: • No disorder in H

• graph is regular (equal connectedities)

$\Rightarrow$ all sites are statistically equivalent $\Rightarrow$ expect $\eta_{i \rightarrow j}(\sigma_i)$ independent of i !

But more precisely: Graph: - take tree like neighborhood of site i ;
 - "leaves" of that tree are connected to the rest of the ~~tree~~ ^{graph}.

Assume a homogeneous $\eta(\sigma_{\text{leaves}})$ on those leaves k .

$\Rightarrow$ Recursion from generation g to $g+1$:

$$\eta_{g+1}(\sigma) = \frac{1}{z_g} \sum_{\sigma_1 \cdots \sigma_{c-1}} \eta_g(\sigma_1) \cdots \eta_g(\sigma_{c-1}) \psi(\sigma, \sigma_1) \cdots \psi(\sigma, \sigma_{c-1})$$
 here: indep of link!

(5)



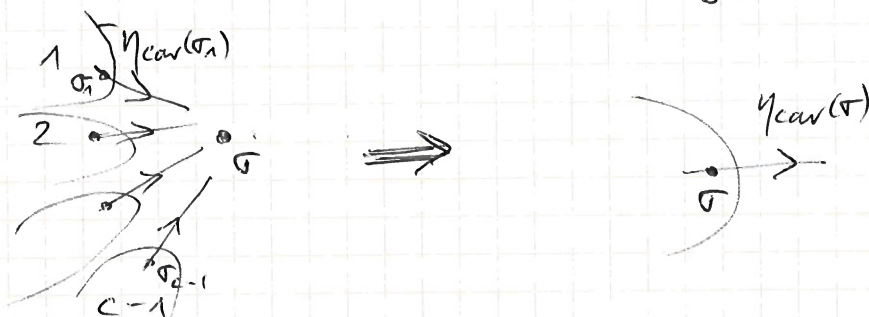
Iteration $\Rightarrow$ fixed point $\eta_g(\sigma) \xrightarrow{g \rightarrow \infty} \eta_{\text{car}}(\sigma)$

where η_{car} solves:

$$\eta_{\text{car}}(\sigma) = \frac{1}{z_{\text{car}}} \sum_{\sigma_1, \dots, \sigma_{c-1}} \eta_{\text{car}}(\sigma_1) \psi(\sigma, \sigma_1) \eta_{\text{car}}(\sigma_2) \psi(\sigma, \sigma_2) \dots \eta_{\text{car}}(\sigma_{c-1}) \psi(\sigma, \sigma_{c-1})$$

$$= \frac{1}{z_{\text{car}}} \left(\sum_{\sigma'} \eta_{\text{car}}(\sigma') \psi(\sigma, \sigma') \right)^{c-1}$$

$\uparrow$ normalization ensuring $\sum_{\sigma} \eta_{\text{car}}(\sigma) = 1$



messages / probabilities η propagate forward to σ on neighbors $\sigma_1, \dots, \sigma_{c-1}$

$\Rightarrow$ free energy? Homogeneity $\Rightarrow z_i = z_{\text{site}}$ for all i
 $z_{ij} = z_{\text{link}}$ for all $\langle ij \rangle$

$$z_{\text{site}} = \sum_{\sigma} \left(\sum_{\sigma'} \eta_{\text{car}}(\sigma') \psi(\sigma, \sigma') \right)^c$$

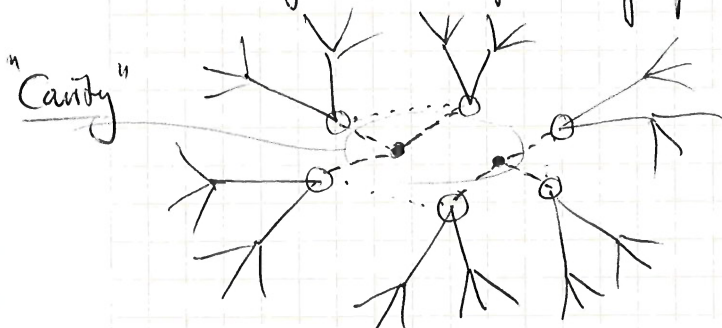
$$z_{\text{link}} = \sum_{\sigma_1, \sigma_2} \eta_{\text{car}}(\sigma_1) \eta_{\text{car}}(\sigma_2) \psi(\sigma_1, \sigma_2)$$

Free energy per site: $f = \frac{F}{N} = -T \left(\log z_{\text{site}} - \underbrace{\frac{\# \text{links}}{N}}_{\frac{c}{2}} z_{\text{link}} \right)$

"Cavity method" $\Leftrightarrow$ solve for $\eta_{\text{car}}(\sigma)$ fixed point!
 $\Rightarrow$ compute f

Reason why $f = f_{\text{site}} - \frac{c}{2} f_{\text{link}} ?$

Imagine incomplete graph:



~~2.c~~ sites have only $c-1$ neighbors

⇒ Two ways to complete the graph:

I) add two sites and connect them each to c of these sites (....)

II) Connect the $2c$ sites pairwise

⇒ The difference in gained free energy is

$$\Delta f^{(I)} = 2 \cdot f_{\text{site}}$$

⇒ ends up with two more sites in the graph
 $\Rightarrow F = F_{N+2} = F_{\text{refr}} + \Delta f^{(I)}$

$$\Delta f^{(II)} = c \cdot f_{\text{link}}$$

⇒ same number of sites $\Rightarrow F = F_N = F_{\text{refr}} + \Delta f^{(II)}$

$$\Rightarrow \text{For large graphs: } f = \frac{F_N}{N} \rightarrow f = \frac{\Delta f^{(I)} - \Delta f^{(II)}}{2} = f_{\text{site}} - \frac{c}{2} f_{\text{link}}$$

⚠ Assumption made:

1) The $2c$ sites are uncorrelated in the $N \rightarrow \infty$ limit

⇔ requires clustering property ⇔ system must be in a pure state (e.g. high T Gibbs state!).

2) The pure states of the system remain pure upon addition:

→ local perturbations (from coupling an extra spin) should not propagate to infinity! That's reasonable



Disordered Hamiltonians, fluctuating connectivities etc

$\Rightarrow \eta_i$ will depend on i (non-equivalence of sites)

To compute disorder-averaged free energy: suffices to know the distribution of η_i (as one varies the disorder)

$$\Rightarrow P[\eta_{\text{cav}}(\sigma)] \equiv \text{Probability}[\eta_{i \rightarrow j}(\sigma_i) = \eta_{\text{cav}}(\sigma_i)]$$

Self-consistency:

$$\eta_0(\sigma_0) = \frac{1}{Z_{\text{cavity}}} \sum_{\sigma_1, \dots, \sigma_{c-1}} \eta_{1 \rightarrow 0}^{\text{cav}}(\sigma_1) \dots \eta_{c-1 \rightarrow 0}(\sigma_{c-1}) \psi_1(\sigma_0, \sigma_1) \dots \psi_{c-1}(\sigma_0, \sigma_{c-1})$$

$$\equiv \mathcal{F}_J[\eta_{1 \rightarrow 0}, \dots, \eta_{c-1 \rightarrow 0}]$$

$\nwarrow$ disorder dependent functional

disorder

$$\rightarrow P[\eta_{\text{cav}}] = \int dP[\eta_{1 \rightarrow 0}] \dots dP[\eta_{c-1 \rightarrow 0}] \delta(\eta_{\text{cav}} - \mathcal{F}_J[\eta_{1 \rightarrow 0}, \dots, \eta_{c-1 \rightarrow 0}])$$

Example: SK model in a field! $\Rightarrow$ effective local fields depend on site i .

$$h_i = \sum_{j \neq i} J_{ij} + h_{\text{ext.}}$$

$$P[\eta_{\text{cav}}(s)] \Leftrightarrow P(h) : \text{distribution over disorder and/or sites!}$$

$\sim \exp(\beta h(s))$



Illustration:

Ising model:

$$\mathcal{H} = - \sum_{\langle i,j \rangle} J_{ij} s_i s_j$$

$$s_i = \pm 1$$

$$\Rightarrow \eta_{i \rightarrow j}(s_i) \equiv \frac{e^{\beta h_{i \rightarrow j} s_i}}{2 \cosh(\beta h_{i \rightarrow j})} \quad \leftarrow \text{parametrization of } \eta \text{ via the field } h_{i \rightarrow j}!$$

Check: $\eta_{i \rightarrow j}$ is normalized

• since $\eta_{i \rightarrow j}(s_i=+1) + \eta_{i \rightarrow j}(s_i=-1) = 1$ and only two values of η need to be fixed, one parameter suffices!

$$\text{namely: } h_{i \rightarrow j} = \frac{1}{2\beta} \log \frac{\eta_{i \rightarrow j}(1)}{\eta_{i \rightarrow j}(-1)}$$

$$\text{Note: } e^{\beta h s_i} = \cosh(\beta h) \cdot [1 + s_i \tanh(\beta h)] \quad \leftarrow e^{\pm x} = \cosh x \pm \sinh x$$

Can'ty recursion:

$$\eta_{i \rightarrow j}(s_i) = \frac{1}{Z_{i \rightarrow j}} \prod_{k \in \partial i \setminus j} \left(\sum_{s_k = \pm 1} \eta_{k \rightarrow i}(s_k) e^{\beta J_{ki} s_i s_k} \right)$$

$$\frac{1}{2} (1 + s_k \tanh(\beta h_{k \rightarrow i})) (\cosh \beta J_{ki} (1 + s_i s_k \tanh(\beta h_{ki})))$$

only even powers of s_k survive

$$= \frac{1}{Z_{i \rightarrow j}} \prod_{k \in \partial i \setminus j} \frac{\cosh(\beta J_{ki})}{2} [1 + s_i \tanh(\beta h_{k \rightarrow i}) \cdot \tanh(\beta J_{ki})]$$

$$\equiv 1 + s_i \tanh(\beta u_{k \rightarrow i})$$

with "message": $u_{k \rightarrow i} \equiv \frac{1}{\beta} \operatorname{atanh} [\tanh(\beta h_{k \rightarrow i}) \tanh(\beta J_{ki})]$

$$= \frac{e^{\beta h_{i \rightarrow j} s_i}}{2 \cosh(\beta h_{i \rightarrow j})} = \frac{1}{Z_{i \rightarrow j}} \prod_{k \in \partial i \setminus j} \frac{\cosh(\beta J_{ki})}{2} \frac{e^{\beta s_i u_{k \rightarrow i}}}{\cosh(\beta u_{k \rightarrow i})} \Rightarrow h_{i \rightarrow j} = \sum_{k \in \partial i \setminus j} u_{k \rightarrow i}$$



$z_{i \rightarrow j}$ can be computed easily, too.

$\Rightarrow$ The "cavity field" $h_{i \rightarrow j}$ is the sum of messages $u_{k \rightarrow i}$ from its neighbors down in the tree! or "Beliefs"

$\Leftrightarrow$ Belief propagation in combinatorial / Boolean optimization:

Belief $u_{i \rightarrow j}$ becomes stronger as $h_{i \rightarrow j}$ or J_{ij} increase!
and $u \rightarrow 0$ as h or $J \rightarrow 0$.

Interesting exercises:

I. Apply the homogeneous cavity method to a ^{Ising!} ferromagnet.

$\Rightarrow$ What is T_c ? What asymptotics do you find for large connectivity? $c \rightarrow \infty$

II. Apply to SK model:

Derive TAP equations from the cavity equations!

Note: $m_o = \tanh(\beta \sum_{j \in \partial o} u_{j \rightarrow o})$
 $\uparrow$ all neighbors

Express $u_{j \rightarrow o}$ in terms of $h_{j \rightarrow o}$, using that $J_{ij} \sim \frac{1}{N}$ is small!

$\Rightarrow$ Express "total field" $\sum_{k \in \partial j} u_{k \rightarrow j}$ on j = $\underbrace{h_{j \rightarrow o} + u_{o \rightarrow j}}_{\sum_{k \in \partial j, k \neq o} u_{k \rightarrow j}}$

$\Rightarrow$ Find TAP Equations: $m_o = \tanh(\beta (\sum_{j \in \partial o} J_{oj} u_j - u_o \sum_{j \in \partial o} J_{oj}^2 \beta (1 - u_j^2)))$