Some recent results on the inverse Ising problem

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Outline of the talk

- Bethe approx. for inverse Ising problem
- Comparison among several mean-field approximations (IP, nMF, TAP, SM, Bethe...)
- Correlations normalization trick
- Major limitation in using TAP and Bethe in frustrated models with a field
- New method: pseudo-likelihood + decimation (Aurelien DECELLE)

Inverse Ising problem

• M configurations of N Ising variables ($s_i = \pm 1$) extracted from

$$P(s_1, \dots, s_N) = \frac{1}{Z(\boldsymbol{J}, \boldsymbol{h})} \exp\left[\sum_{i \neq j} J_{ij} s_i s_j + \sum_i h_i s_i\right]$$

[alternatively only magnetizations $m_i = \langle s_i \rangle$ and correlations $C_{ij} = \langle s_i s_j \rangle - m_i m_j$ are given]

• GOAL: estimate couplings and fields $(\boldsymbol{J},\boldsymbol{h})$

Monte Carlo -> unbiased solution ...but it is slow!



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Mean field approximations (MFA)

 $m^{ ext{MFA}}_i(oldsymbol{J},oldsymbol{h}) \ C^{ ext{MFA}}_{ij}(oldsymbol{J},oldsymbol{h})$

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$$m_i^{\text{MFA}}(\boldsymbol{J}, \boldsymbol{h}) = m_i$$

 $C_{ij}^{\text{MFA}}(\boldsymbol{J}, \boldsymbol{h}) = C_{ij}$

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Log-likelihood $L(\boldsymbol{J}, \boldsymbol{h} | \boldsymbol{s}) = \frac{1}{M} \log \prod_{k=1}^{M} P(\boldsymbol{s}^{(k)} | \boldsymbol{J}, \boldsymbol{h}) =$

$$=\sum_{i}h_{i}m_{i}+\sum_{ij}J_{ij}(C_{ij}+m_{i}m_{j})-\log Z(\boldsymbol{J},\boldsymbol{h})$$

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 $m_i = \partial F_{\rm MFA}(\boldsymbol{J}, \boldsymbol{h}) / \partial h_i$

Mean-field approximations (MFA) to the free-energy

naive mean-field (nMF)

$$F_{\rm nMF} = \sum_{i} \left[H\left(\frac{1+m_i}{2}\right) + H\left(\frac{1-m_i}{2}\right) \right] + \sum_{i} h_i m_i + \sum_{i \neq j} J_{ij} m_i m_j$$
$$H(x) \equiv -x \ln(x)$$

$$\frac{\partial F_{nMF}}{\partial m_i} = \sum_j J_{ij} m_j + h_i - \operatorname{atanh}(m_i) = 0$$
$$m_i = \tanh\left[h_i + \sum_j J_{ij} m_j\right]$$

• nMF + Onsager reaction term (TAP)

$$F_{\text{TAP}} = \sum_{i} \left[H\left(\frac{1+m_{i}}{2}\right) + H\left(\frac{1-m_{i}}{2}\right) \right] + \sum_{i} h_{i}m_{i} + \sum_{i \neq j} \left(J_{ij}m_{i}m_{j} + \frac{1}{2}J_{ij}^{2}(1-m_{i}^{2})(1-m_{j}^{2}) \right)$$

$$m_i = \tanh\left[h_i + \sum_j J_{ij}\left(m_j - J_{ij}(1 - m_j^2)m_i\right)\right]$$

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$$m_{i} = \tanh \left[h_{i} + \sum_{j} J_{ij} \left(m_{j} - J_{ij} (1 - m_{j}^{2}) m_{i} \right) \right]$$
reaction term

• Plefka expansion in small J

$$F_{\rm nMF} = \sum_{i} \left[H\left(\frac{1+m_i}{2}\right) + H\left(\frac{1-m_i}{2}\right) \right] + \sum_{i} h_i m_i + \sum_{i\neq j} J_{ij} m_i m_j$$

$$F_{\text{TAP}} = \sum_{i} \left[H\left(\frac{1+m_{i}}{2}\right) + H\left(\frac{1-m_{i}}{2}\right) \right] + \sum_{i} h_{i}m_{i} + \sum_{i \neq j} \left(J_{ij}m_{i}m_{j} + \frac{1}{2}J_{ij}^{2}(1-m_{i}^{2})(1-m_{j}^{2}) \right) \right]$$

• Bethe approximation (BA)

$$F_{BA} = \sum_{i \neq j} \left[H\left(\frac{(1+m_i)(1+m_j)+c_{ij}}{4}\right) + H\left(\frac{(1-m_i)(1-m_j)+c_{ij}}{4}\right) + H\left(\frac{(1+m_i)(1-m_j)-c_{ij}}{4}\right) + H\left(\frac{(1-m_i)(1+m_j)-c_{ij}}{4}\right) \right] + \sum_i (1-d_i) \left[H\left(\frac{1+m_i}{2}\right) + H\left(\frac{1-m_i}{2}\right) \right] + \sum_i h_i m_i + \sum_{i \neq j} J_{ij}(c_{ij}+m_i m_j)$$

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Bethe approximation (BA) and cavity method

$$m_{i} = \frac{m_{i}^{(j)} + t_{ij} m_{j}^{(i)}}{1 + m_{i}^{(j)} t_{ij} m_{j}^{(i)}} \qquad m_{i}^{(j)} : \text{magnetization of i}$$

$$m_{j} = \frac{t_{ij} m_{i}^{(j)} + m_{j}^{(i)}}{1 + m_{i}^{(j)} t_{ij} m_{j}^{(i)}} \qquad \swarrow \begin{array}{c} t_{ij} \\ t_{ij} \end{array}$$

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 $m_i^{(j)} = f(m_i, m_j, t_{ij})$ $m_j^{(i)} = f(m_j, m_i, t_{ij})$

$$f(m_1, m_2, t) = \frac{1 - t^2 - \sqrt{(1 - t^2)^2 - 4t(m_1 - m_2 t)(m_2 - m_1 t)}}{2t(m_2 - m_1 t)}$$

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$$m_{i} = \tanh\left[h_{i} + \sum_{j} \operatorname{atanh}\left(t_{ij}f(m_{j}, m_{i}, t_{ij})\right)\right]$$

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$$m_i = \tanh\left[h_i + \sum_j \operatorname{atanh}\left(t_{ij}f(m_j, m_i, t_{ij})\right)\right]$$

Small J expansion gives nMF, TAP, ... $h_i + \sum_j \operatorname{atanh}\left(t_{ij}f(m_j, m_i, t_{ij})\right) \simeq h_i + \sum_j \left(J_{ij}m_j - J_{ij}^2(1 - m_j^2)m_i + \dots\right)$

Computing correlations by linear response

- Correlations are trivial in MFA $C_{ij} = 0$ in nMF, TAP and BA (between distant spins)
- Non trivial correlations can be obtained by using the linear response (Kappen Rodriguez, 1998)

$$C_{ij} = \frac{\partial m_i}{\partial h_j} , \qquad (C^{-1})_{ij} = \frac{\partial h_i}{\partial m_j}$$

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$$C_{ij} = \frac{\partial m_i}{\partial h_j} , \qquad (C^{-1})_{ij} = \frac{\partial h_i}{\partial m_j}$$

$$(C_{\rm nMF}^{-1})_{ij} = \frac{\delta_{ij}}{1 - m_i^2} - J_{ij} ,$$

$$(C_{\rm TAP}^{-1})_{ij} = \left[\frac{1}{1 - m_i^2} + \sum_k J_{ik}^2 (1 - m_k^2)\right] \delta_{ij} - \left(J_{ij} + 2J_{ij}^2 m_i m_j\right)$$

Computing correlations by linear response in BA

• Analytic expression for the correlations

$$(C_{\rm BA}^{-1})_{ij} = \left[\frac{1}{1-m_i^2} - \sum_k \frac{t_{ik}f_2(m_k, m_i, t_{ik})}{1-t_{ik}^2 f(m_k, m_i, t_{ik})^2}\right] \delta_{ij} - \frac{t_{ij}f_1(m_j, m_i, t_{ij})}{1-t_{ij}^2 f(m_j, m_i, t_{ij})^2}$$

- Coincide with the fixed point of Susceptibility Propagation
- No need to run any algorithm!



Improving correlations by a normalization trick

 In ferromagnetic models with loops, inferred correlations are too strong because of loops



- Usually $C_{ii}^{\text{MFA}} > 1$ which is unphysical
- Trick: enforce $C_{ii}^{\text{MFA}} = 1$ by a normalization

$$\widehat{C}_{ij} \equiv \frac{C_{ij}}{\sqrt{C_{ii}C_{jj}}}$$

More numerical results on estimating correlations



$$(C_{\rm nMF}^{-1})_{ij} = \frac{\delta_{ij}}{1 - m_i^2} - J_{ij} ,$$

$$(C_{\rm TAP}^{-1})_{ij} = \left[\frac{1}{1 - m_i^2} + \sum_k J_{ik}^2 (1 - m_k^2)\right] \delta_{ij} - \left(J_{ij} + 2J_{ij}^2 m_i m_j\right)$$







$$(C_{nMF}^{-1})_{ij} = \underbrace{\frac{1}{1 - m_{k}^{2}} - J_{ij}}_{I_{-}m_{k}^{2}} \rightarrow \underbrace{J_{ij}^{nMF} = -(C^{-1})_{ij}}_{I_{j}} = \underbrace{\frac{1}{1 - m_{t}^{2}} + \sum_{k} I_{k}^{2}(1 - m_{k}^{2})}_{I_{ij}} \delta_{ij} - (J_{ij} + 2J_{ij}^{2}m_{i}m_{j})}_{I_{ij}}$$

$$J_{ij}^{TAP} = \frac{\sqrt{1 - 8m_{i}m_{j}(C^{-1})_{ij}} - 1}{4m_{i}m_{j}}$$

$$J_{ij}^{BA} = -\operatorname{atanh}\left[\frac{1}{2(C^{-1})_{ij}}\sqrt{1 + 4(1 - m_{i}^{2})(1 - m_{j}^{2})(C^{-1})_{ij}^{2}} - m_{i}m_{j} - \frac{1}{2(C^{-1})_{ij}}\sqrt{\left(\sqrt{1 + 4(1 - m_{i}^{2})(1 - m_{j}^{2})(C^{-1})_{ij}^{2}} - 2m_{i}m_{j}(C^{-1})_{ij}\right)^{2} - 4(C^{-1})_{ij}^{2}}\right]$$

Normalization trick for the inverse Ising problem

TAP with m=0 $J_{ij}^{\text{TAP}} = -(C^{-1})_{ij}$

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$$(\widehat{C}_{\mathrm{TAP}})_{ij} = \frac{(C_{\mathrm{TAP}})_{ij}}{\sqrt{(C_{\mathrm{TAP}})_{ii}(C_{\mathrm{TAP}})_{jj}}} = \lambda_i \lambda_j (C_{\mathrm{TAP}})_{ij}$$

 λ_i are N new parameters to fix s.t. $\widehat{C}_{\mathrm{TAP}} = C$

More approximations for the inverse Ising problem

• Independent pair (IP) approximation

$$J_{ij}^{\rm IP} = \frac{1}{4} \ln \left(\frac{\left((1+m_i)(1+m_j) + C_{ij} \right) \left((1-m_i)(1-m_j) + C_{ij} \right)}{\left((1+m_i)(1-m_j) - C_{ij} \right) \left((1-m_i)(1+m_j) - C_{ij} \right)} \right)$$

• Sessak-Monasson (SM) small correlation expansion

$$J_{ij}^{\rm SM} = -(C^{-1})_{ij} + J_{ij}^{\rm IP} - \frac{C_{ij}}{(1 - m_i^2)(1 - m_j^2) - (C_{ij})^2}$$

More approximations for the inverse Ising problem

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$$J_{ij}^{\rm SM} = -(C^{-1})_{ij} + J_{ij}^{\rm IP} - \frac{C_{ij}}{(1-m_i^2)(1-m_j^2) - (C_{ij})^2}$$

[for m=0 can be derived in 2 lines, ask me if interested]

Numerical results for the inverse Ising problem



Numerical results for the inverse Ising problem



1.2



The resulting coupling is real only if

$$\Delta^{\mathrm{TAP}} \equiv 1 - 8m_i m_j (C^{-1})_{ij} \ge 0$$

The same happens also within the BA

$$\Delta^{\text{BA}} = \left(\sqrt{1 + 4(1 - m_i^2)(1 - m_j^2)(C^{-1})_{ij}^2} - 2m_i m_j (C^{-1})_{ij}\right)^2 - 4(C^{-1})_{ij}^2$$

A major problem for frustrated models in a field

Three spins interacting with a coupling J in a constant field h

 $P(s_1, s_2, s_3) \propto \exp[J(s_1s_2 + s_2s_3 + s_3s_1) + h(s_1 + s_2 + s_3)]$



Pseudo-likelihood method (PLM)

- Approximate $P(s) \simeq \prod P_i(s_i | s_{\setminus i})$
- Define the pseudo-log-likelihood as

$$PL(\boldsymbol{h}, \boldsymbol{J}|\boldsymbol{s}) = \langle \log P(\boldsymbol{s}|\boldsymbol{h}, \boldsymbol{J}) \rangle = \sum_{i} \langle \log P_{i}(\boldsymbol{s}|h_{i}, \boldsymbol{J}_{i}) \rangle = \sum_{i} f_{i}$$

$$f_i = h_i m_i + \sum_j J_{ij} (C_{ij} + m_i m_j) - \langle \log 2 \cosh \left(s_i (h_i + \sum_j J_{ij} s_j) \right) \rangle$$

- Maximize f_i to estimate h_i and J_{ij}
- For sparse models use an L1 regularization and maximize $f_i \lambda \sum |J_{ij}|$

$$f_i - \lambda \sum_j |J_{ij}|$$

PLM vs. MFA











Decimation procedure

- Run PLM
- Set to zero a constant fraction of couplings (those inferred to be the smallest)
- Re-run PLM only on couplings not set to zero (this is impossible within a MFA)
- Iterate until...











Summary of recent results about the inverse Ising pb. JSTAT (2012) PO8015

- Analytical expressions for the Bethe approx.
- Comparison of MFA in a wide temperature range
- Serious limitation of TAP and Bethe in a field
- Improvement in the inferred couplings by:
 - normalization trick (in weakly frustrated models)
 - PLM + decimation procedure