### Making maximum entropy and linear response estimates consistent

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joint work with Jack Raymond

Two very old problems...  

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

- DIRECT problem: given model parameters  $\{J_{ij}, h_i\}$ , compute average values  $\langle s_i \rangle$  and correlations  $\langle s_i s_j \rangle$ (or equivalently marginal probabilities)
- INVERSE problem:

given measured mean values and correlations, estimate model parameters (previously known as Boltzmann machine learning)

#### ...with a common difficulty

• Compute the free-energy

 $F(\boldsymbol{J},\boldsymbol{h}) = \log Z(\boldsymbol{J},\boldsymbol{h}) = \log \sum_{\{s_i\}} \exp\left(\sum J_{ij} s_i s_j + \sum_i h_i s_i\right)$ 

The sum is over exponentially many terms

- Resort to mean field approximations (MFA)
  - few parameters to be fixed self-consistently
  - fast to compute, but inexact!

naive mean-field (nMF)  $\bullet$ only N parameters  $m_i = \langle s_i \rangle$  $H(x) \equiv -x \ln(x)$  $F_{\rm nMF} = \sum_{i} \left[ H\left(\frac{1+m_i}{2}\right) + H\left(\frac{1-m_i}{2}\right) \right] + \sum_{i} h_i m_i + \sum_{i,j} J_{ij} m_i m_j$  $\frac{\partial F_{\rm nMF}}{\partial m_i} = \sum_j J_{ij} m_j + h_i - \operatorname{atanh}(m_i) = 0$  $m_i = \tanh \left| h_i + \sum_j J_{ij} m_j \right|$ 

• nMF + Onsager reaction term (TAP)

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

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

Plefka expansion in small J

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

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

nice discussion in T. Tanaka, PRE, 1998

• Bethe approximation (BA) nMF + nearest neighbors correlations parameters  $c_{ij} = \langle s_i s_j \rangle - m_i m_j$ 

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

• Bethe approximation (BA)

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

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

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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 (LR)

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

#### Computing correlations by linear response in BA

• Analytic expression for the correlations (FRT, JSTAT, 2012)

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

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

From correlations to marginals...or better "beliefs"

$$b_{i}(\sigma_{i}) = \frac{1 + m_{i}\sigma_{i}}{2}$$

$$b_{ij}(\sigma_{i}, \sigma_{j}) = \frac{(1 + m_{i}\sigma_{i})(1 + m_{j}\sigma_{j}) + C_{ij}\sigma_{i}\sigma_{j}}{4}$$

$$b_{ijk}(\sigma_{i}, \sigma_{j}, \sigma_{k}) = \dots$$

$$b_{ijkl}(\sigma_{i}, \sigma_{j}, \sigma_{k}, \sigma_{l}) = \dots$$
Useful if variables  
are correlated  
(e.g. form a clique  
or a loop)

Cluster Variational Method (CVM) or Region Graph Approx.

$$F = E - S$$

$$E(b, J, H) = -\sum_{i < j} \operatorname{Tr} b_{ij} J_{ij} \sigma_i \sigma_j - \sum_i \operatorname{Tr} b_i H_i \sigma_i$$
$$= -\sum_{i < j} J_{ij} (C_{ij} + m_i m_j) - \sum_i H_i m_i$$
$$S(b) = -\sum_R c_R \operatorname{Tr} b_R \log b_R$$

#### Limits of MFA

- Impossible to use large regions in CVM (too many parameters to optimize over) in general the largest region used is the smallest loop/clique in the graph
- Strong need for corrections to MFA that are able to take into account the effect of short loops and small local structures

#### How loops make MFA fail

e.g. Bethe approximation, high temperature phase

• maximum entropy

$$\langle \sigma_i \sigma_j \rangle_c^{\mathrm{BA}} = c_{ij}^* = \tanh(\beta J_{ij}) < \langle \sigma_i \sigma_j \rangle_c^{\mathrm{exact}}$$

• linear response  $\chi_{ii} = 1 + \sum_{j \in \partial i} u_{j \to i,i} \neq 1$ ferromagnet  $\chi_{ij}^{BA} > \langle \sigma_i \sigma_j \rangle_c^{exact}$ 

#### Make MFA more consistent

"Consistency is more important than truth" (S. Ting)

 Add to the free-energy Lagrange multipliers to enforce (at the fixed point)

$$\chi_{ii} = 1 - m_i^2 \qquad \chi_{ij} = c_{ij}$$

• The entropy term changes to (for nMF and Bethe)

$$S_{\lambda}^{N} = -\sum_{i} \operatorname{Tr} \left[ b_{i} \log b_{i} \right] - \sum_{i} \lambda_{i} \left( \left( 1 - m_{i}^{2} \right) - \chi_{ii} \right) / 2$$
$$S_{\lambda}^{B} = S_{\lambda}^{N} - \sum_{ij \in I} \left\{ \operatorname{Tr} \left[ b_{ij} \log \left( \frac{b_{ij}}{b_{i} b_{j}} \right) \right] - \lambda_{ij} \left( C_{ij} - \chi_{ij} \right) \right\}$$

# Previous proposals for fixing the diagonal terms $\chi_{ii}$

- Kappen, Rodriguez (Neur. Comp., 1998) MF + self-couplings  $J_{ii}$
- Opper, Winter (PRL, PRE, 2001) TAP +  $\lambda_i$
- FRT (JSTAT, 2012) normalized correlations j useful for inverse pb.

$$\widehat{\chi}_{ij} \equiv \frac{\chi_{ij}}{\sqrt{\chi_{ii}\chi_{jj}}}$$

- Yasuda, Tanaka (PRE, 2013) Bethe +  $\lambda_i$ 

## Improvement by normalizing correlations (diluted 2D Ising)



#### General framework



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$$F_{\lambda} = F_{\text{MFA}}(\{m_i\}, \{C_{ij}\}, \ldots) + \sum_i \lambda_i m_i^2 + \sum_{i < j} \lambda_{ij} C_{ij}$$

### Maximum Entropy equations from free-energy minimization

$$\partial_{m_i} F_{\lambda} = \operatorname{atanh}(m_i) + \partial_{m_i} S^{2+} - H_i - \sum_j J_{ij} m_j + \lambda_i m_i = 0$$

$$\partial_{C_{ij}} F_{\lambda} = \partial_{C_{ij}} S^{2+} - J_{ij} + \lambda_{ij} = 0$$

 $\partial_{C_{ijk}}F_{\lambda} = \partial_{C_{ijk}}S^{2+} = 0$  Higher order correlation parametrs are fixed by standard maximum entropy

#### General framework

$$F_{\lambda} = F_{\text{MFA}}(\{m_i\}, \{C_{ij}\}, \ldots) + \sum_i \lambda_i m_i^2 + \sum_{i < j} \lambda_{ij} C_{ij}$$

Linear Response equations from quadratic exp. around the free-energy mininum

$$\partial^2 F_{\lambda} \quad \Rightarrow \quad [\chi^{-1}]_{ij} = \Phi_{ij} - J_{ij}$$

# Some comments before showing results...

- Bethe/CVM free-energies are not convex adding parameters it not obvious to improve!
- $\lambda$  parameters measure how wrong is the MFA e.g. on a random graph with Bethe approx.  $\lambda \to 0$
- $J_{ij} \rightarrow J_{ij} + \lambda_{ij}$  would naively imply stronger correlations and also more unstable Susc. Prop. but this is not the case!

#### Models studied

We are starting with exactly solvable models to check the new method

- Ising variables
- 2D topology (square and triangular lattices)
- homogeneous -> Fourier transform solution
- both ferromagnetic and frustrated

...willing to arrive to a general purpose algorithm!

#### Ferromagnet on a 2D square lattice

$$u = \hat{u}_{J+\lambda}(h) \equiv \operatorname{atanh}[\tanh(J+\lambda)\tanh(h)]$$
$$h = 3u + (\lambda_0 - 4\lambda)m \qquad \text{Modified BP}$$
$$m = \tanh(h+u)$$

#### Modified SuscP leading to

$$\chi_x = \frac{1 - m^2}{(2\pi)^2} \int_{-\pi}^{\pi} dq_1 \int_{-\pi}^{\pi} dq_2 \frac{\cos(q_1)^x}{\phi_0 - 2\phi_1[\cos(q_1) + \cos(q_2)]}$$

$$\phi_0 = 1 + 4 \frac{\widehat{u}'^2}{1 - \widehat{u}'^2} - (1 - m^2)\lambda_0$$
$$\phi_1 = \frac{\widehat{u}'}{1 - \widehat{u}'^2} - (1 - m^2)\lambda$$

#### Nearest-neighbor correlation (2D square lattice)



#### Nearest-neighbor correlation (2D triangular lattice, $\lambda_0 = 0$ )





#### Nearest-neighbor correlation (2D triangular lattice)



#### Inverse problem

- Use the CVM for the free-energy including all pairs (Bethe) or all triplets (Plaquette)
- Solve equations in  $J_{ij}, H_i$  and eventually  $\lambda$  given (exact) correlations and magnetizations
- Measured the error on the inferred couplings by

$$\Delta_J = \sqrt{\frac{\sum_{i < j} (J'_{ij} - J_{ij})^2}{\sum_{i < j} J^2_{ij}}}.$$

### Inverse problem from exact statistics (2D triangular lattice, $\lambda_0 = 0$ )



## Inverse problem from MC data (diluted 2D square lattice, $\lambda_0 = 0$ )



#### Summary

New general framework to force in CVM the consistency between maximum entropy estimates and linear response ones.

Several improvements achieved

- better high temperature expansions
- better correlation estimates
- smaller errors in estimating couplings

...still working for a fast message passing algorithm ;-)