

# Fast Convergence of Belief Propagation to Global Optima: Beyond Correlation Decay

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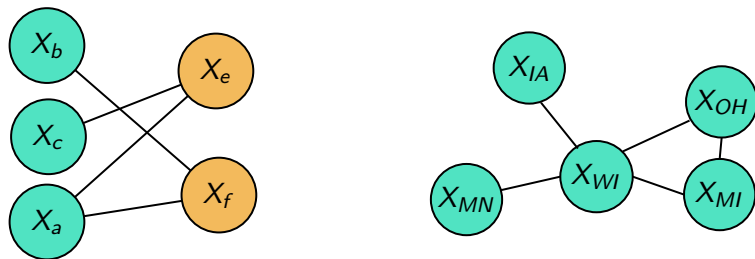
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# Graphical models

**Ising model:** For  $x \in \{\pm 1\}^n$ ,

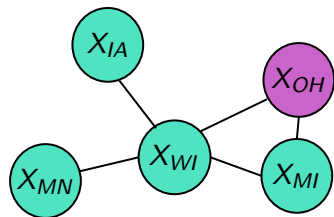
$$\Pr(X = x) = \frac{1}{Z} \exp \left( \frac{1}{2} x^T J x + h^T x \right)$$

Natural model of correlated random variables. Some examples: Hopfield networks, Restricted Boltzmann Machine (RBM) = bipartite Ising model.



Popular model in ML, natural and social sciences, etc.

**Inference:** Given  $J, h$  compute properties of the model. E.g.  $\mathbb{E}[X_i]$  or  $\mathbb{E}[X_i | X_j = x_j]$ .



$$\mathbb{E}[X_{WI} | X_{OH} = +1] = ?$$

**Problem:** inference in Ising models (e.g. approximating  $\mathbb{E}[X_i]$ ) is NP-hard! Natural markov chain approaches (e.g. Gibbs sampling) may mix very slowly.

**Variational objectives** (Mean-Field/VI, Bethe):

$$\Phi_{MF}(x) = \frac{1}{2}x^T Jx + h^T x + \sum_i H \left( \text{Ber} \left( \frac{1+x_i}{2} \right) \right)$$

$$\Phi_{Bethe}(P) = \mathbb{E}_P \left[ \frac{1}{2}X^T JX + h^T X \right] + \sum_E H_P(X_E) - \sum_i (\text{deg}(i) - 1)H_P(X_i)$$

**Message-passing algorithms** (MF/VI, BP):

$$x^{(t+1)} = \tanh^{\otimes n}(Jx^{(t)} + h)$$

$$\nu_{i \rightarrow j}^{(t+1)} = \tanh \left( h_i + \sum_{k \in \partial i \setminus j} \tanh^{-1}(\tanh(J_{ik})\nu_{k \rightarrow i}^{(t)}) \right)$$

**Non-convex** objective — when do these algorithms find **global optima**?

# Our Assumption

We suppose, following Dembo-Montanari '10, that the model is **ferromagnetic**:

$$J_{ij} \geq 0, h_i \geq 0 \quad \text{for all } i, j$$

- I.e. neighbors want to align.
- This assumption is **necessary**: if we don't have it, computing the optimal mean-field approximation, even approximately, is NP hard.
- Objective typically has sub-optimal critical points. (cf. correlation decay)

# Our Theorems

Fix a ferromagnetic Ising model  $(J, h)$  with  $m$  edges and  $n$  nodes.

## Theorem (Mean-Field Convergence)

Let  $x^*$  be a global maximizer of  $\Phi_{MF}$ . Initializing with  $x^{(0)} = \vec{1}$  and defining  $x^{(1)}, x^{(2)}, \dots$  by iterating the mean-field equations, for every  $t \geq 1$ :

$$0 \leq \Phi_{MF}(x^*) - \Phi_{MF}(x^{(t)}) \leq \min \left\{ \frac{\|J\|_1 + \|h\|_1}{t}, 2 \left( \frac{\|J\|_1 + \|h\|_1}{t} \right)^{4/3} \right\}$$

## Theorem (BP Convergence)

Let  $P^*$  be a global maximizer of  $\Phi_{Bethe}$ . Initializing  $\nu_{i \rightarrow j}^{(0)} = 1$  for all  $i \sim j$  and defining  $\nu^{(1)}, \nu^{(2)}, \dots$  by BP iteration,

$$0 \leq \Phi_{Bethe}(P^*) - \Phi_{Bethe}^*(\nu^{(t)}) \leq \sqrt{\frac{8mn(1 + \|J\|_\infty)}{t}}.$$

The poster: Poster 174, Wednesday 10:45-12:45

The paper: <https://arxiv.org/abs/1905.09992>