

Supplementary material

Proof of Theorem 2.1

Algorithm SIMPLEHC correctly reconstructs the graph G if for every edge $e = \{i, j\}$ not in $E(G)$, at least one observed independent set vector $\sigma^{(k)}$ contains both i and j . Let $A_{ij}^k = \{\sigma_i^{(k)} = 0 \text{ or } \sigma_j^{(k)} = 0\}$ be the event that at least one of i or j is missing from $\sigma^{(k)}$, and let $A_{ij} = \bigcap_{k=1}^n A_{ij}^k$. We have by the union bound and independence of A_{ij}^k for different k ,

$$\mathbb{P}(\text{error}) \leq \mathbb{P}\left(\bigcup_{(i,j) \in E^c} A_{ij}\right) \leq \binom{p}{2} \mathbb{P}(\bigcap_{k=1}^n A_{ij}^k) = \binom{p}{2} \mathbb{P}(A_{ij}^1)^n \leq \binom{p}{2} (1 - \gamma)^n.$$

The last inequality is from Lemma 2.3, with the value of γ the quantity in the statement of the Lemma. To make $\mathbb{P}(\text{error})$ approach zero at the rate $1/p$ it suffices to take $n = 3\gamma^{-1} \log p$. This proves the theorem. \square

Proof of Theorem 2.2

Consider the set of graphs \mathcal{G}_m obtained by taking an arbitrary graph on m nodes with maximum degree d , and to each vertex v adding d nodes u_1, \dots, u_d with edges $\{v, u_i\}$. The total number of nodes is $p = m(d+1)$. Thus we are working with the set of graphs consisting of $m = p/(d+1)$ stars of degree d , with all remaining edges going between centers of stars.

The goal is to determine the correct subset of the $\binom{m}{2}$ remaining edges. Fix a constant $c > 0$ and consider any graph $G \in \mathcal{G}_m$ missing at least cm edges. Note that such graphs consist of almost all of \mathcal{G}_m (a proportion $1 - o(1)$).

We bound the number of samples required by the maximum-likelihood (ML) rule (equivalent to algorithm SIMPLEHC) to reconstruct G . As observed in Section 2, the ML graph contains the edge $e = \{i, j\}$ between star centers i and j if and only if none of the sets $\sigma^{(1)}, \sigma^{(2)}, \dots, \sigma^{(n)}$ contains both i and j . Thus, in order for ML to give the correct graph, for each missing edge $e = \{i, j\}$ it is necessary to observe a “witness” $\sigma^{(k)}$ with $\sigma_i^{(k)} = \sigma_j^{(k)} = 1$.

We proceed by upper bounding the probability of observing a witness for each of the cm missing edges. Each star center i is included in a particular random independent set $\sigma^{(k)}$ with probability at most

$$q = \frac{1}{2 \cdot (2\lambda)^d},$$

hence $\sigma^{(k)}$ is a witness for missing edge $\{i, j\}$ with probability at most q^2 . Hence the expected number of missing edges which within n samples have no witness is at least $cm(1 - q^2)^n$, and a second moment argument shows that one must take

$$n \geq (1 + o(1)) \frac{\log m}{-\log(1 - q^2)} = \Omega((2\lambda)^{2d} \log m),$$

where we used the fact that $-\log(1 - q^2) = q^2 + o(q^4)$ and $q^{-1} = (2\lambda)^d$. \square

Proof of Lemma 2.3

We can decompose the partition function as

$$\begin{aligned} Z_G &= \sum_I \lambda^{|I|} = \sum_{I \in S_{\emptyset, \emptyset}} \lambda^{|I|} + \sum_{I \in S_{\emptyset, j}} \lambda^{|I|} + \sum_{I \in S_{i, \emptyset}} \lambda^{|I|} + \sum_{I \in S_{i, j}} \lambda^{|I|} \\ &:= Z_{\emptyset, \emptyset} + Z_{\emptyset, j} + Z_{i, \emptyset} + Z_{i, j}, \end{aligned} \tag{4.4}$$

where $S_{ij} = \{I : i, j \in I\}$, $S_{i, \emptyset} = \{I : i \in I, j \notin I\}$, etc. Now, Z_G and Z_{G+e} are the same except Z_{G+e} does not have the last term $Z_{i, j}$. We bound the last term by first noting that

$$|S_{i, j}| \cdot 2^d \geq |S_{\emptyset, j}|. \tag{4.5}$$

This is because for each independent set I with $i \in I$, there are at most 2^d distinct independent sets I' with $i \notin I'$ with some subset of (at most d) neighbors of i included. One way of observing this is defining the map $f : S_{\emptyset,j} \rightarrow S_{i,j}$ by $I \mapsto \{i\} \cup I \setminus \mathcal{N}(i)$. The map f takes at most 2^d sets $I' \in S_{\emptyset,j}$ to each $I \in S_{i,j}$, which implies (4.5).

Now, each such set I' mapping to I has weight at most a factor λ^{d-1} larger than I , so

$$2^d \lambda^{d-1} Z_{i,j} \geq Z_{\emptyset,j}. \quad (4.6)$$

Similar reasoning gives

$$2^d \lambda^{d-1} Z_{i,j} \geq Z_{i,\emptyset}, \quad \text{and} \quad 2^{2d} \lambda^{2d-2} Z_{i,j} \geq Z_{\emptyset,\emptyset}. \quad (4.7)$$

Using these estimates, we obtain

$$\mathbb{P}(\{i,j\} \subseteq I) = \frac{\sum_{I:\{i,j\} \subseteq I} \lambda^{|I|}}{\sum_I \lambda^{|I|}} = \frac{Z_{i,j}}{Z} \geq \frac{1}{1 + 4 \cdot (2\lambda)^{d-1} + 4 \cdot (2\lambda)^{2d-2}},$$

proving the lemma. \square

Proof of Lemma 3.2

We start by defining restricted partition function summations: Let

$$\begin{aligned} S_{ab} &= \{\sigma \in \{0,1\}^p : \sigma_a = \sigma_b = 1\}, \\ S_{a\emptyset} &= \{\sigma \in \{0,1\}^p : \sigma_a = 1, \sigma_b = 0\}, \end{aligned}$$

and analogously for $S_{\emptyset b}$ and $S_{\emptyset\emptyset}$. We then define $Z_{ab} = \sum_{\sigma \in S_{ab}} \exp(H(\sigma))$ and again analogously for $Z_{a\emptyset}, Z_{\emptyset b}, Z_{\emptyset\emptyset}$.

We first prove case (i) of the lemma, in which we assume that $(a,b) \notin E(G)$ and lower bound the probability

$$\mathbb{P}(\sigma_a = 1 | \sigma_b = 1) = \frac{Z_{ab}}{Z_{ab} + Z_{\emptyset b}}.$$

To this end, consider the map $f : S_{\emptyset b} \rightarrow S_{ab}$ defined by taking a configuration σ , setting $\sigma_i = 0$ for neighbors $i \in N(a)$, and then setting $\sigma_a = 1$. Since the assumption $(a,b) \notin E(G)$ implies that $\sigma_a = \sigma_b = 1$ is a valid assignment to these variables, the definition of f implies in particular that $(f(\sigma))_b = 1$ if $\sigma_b = 1$, so indeed $f(\sigma) \in S_{ab}$ for $\sigma \in S_{\emptyset b}$.

Now, at most $2^{\deg(a)}$ sets are mapped by f to any one set (since the neighbors of a can be in any configuration), and for any $\sigma \in S_{\emptyset b}$, $\exp(H(f(\sigma))) \geq \exp(H(\sigma) - h(\deg(a) + 1))$. This shows that $2^{\deg(a)} \exp[h(\deg(a) + 1)] Z_{ab} \geq Z_{\emptyset b}$, and proves part (i) of the lemma.

We now turn to case (ii), assuming that $(a,b) \in E(G)$. Consider the map $g : S_{ab} \rightarrow S_{\emptyset b}$ taking $\sigma \in S_{ab}$ and setting $\sigma_a = 0$ (removing node a from the independent set). The map g is one-to-one, and H increases by β due to resolving the conflict on edge (a,b) , but decreases by $h_a \leq h$ due to omitting node a : $\exp(H(g(\sigma))) \geq \exp(H(\sigma) + \beta - h)$. This shows that $Z_{ab} \geq e^{-\beta+h} Z_{\emptyset b}$, and completes the proof. \square

Proof of Lemma 3.5

We start by computing the probability that a particular sample $\sigma^{(i)}$ is in A_U , or equivalently that $\sigma_U = \mathbf{0}$. Let $W \subseteq V$ be any subset of nodes, and denote by x_W an assignment to the corresponding variables. Due to the antiferromagnetic nature of the interaction, the distribution (3.2) satisfies the monotonicity property $\mathbb{P}(\sigma_a = 1 | \sigma_W = x_W) \leq \mathbb{P}(\sigma_a = 1 | \sigma_W = x_W, \sigma_b = 0)$ for any neighbor $b \in N(a) \setminus W$. This monotonicity together with Bayes' rule gives

$$\begin{aligned} \mathbb{P}(\sigma_U = \mathbf{0}) &= \prod_{i=1}^{|U|} \mathbb{P}(\sigma_{u_i} = 0 | \sigma_{u_1} = \dots = \sigma_{u_{i-1}} = 0) \geq \prod_{i=1}^{|U|} \mathbb{P}(\sigma_{u_i} = 0 | \sigma_{N(u_i)} = \mathbf{0}) \\ &= \prod_{i=1}^{|U|} [1 + e^{h_i}]^{-1}. \end{aligned}$$

Denoting the last displayed quantity by q , we see that the number of samples obtained, $|A_U|$, stochastically dominates a $\text{Binom}(n, q)$ random variable. Hoeffding's inequality proves the lemma. \square

Proof of Lemma 4.4

Calculating correlation relative to the uniform distribution U (see Equation (4.1)), we have for $S \neq T$ with $|S \cap T| = \lambda$

$$\begin{aligned} \left\langle \frac{p_S}{U} - 1, \frac{p_T}{U} - 1 \right\rangle_U &= \sum_{x \in \{-1, +1\}^p} 2^{-p} (2^p p_S(x) - 1) (2^p p_T(x) - 1) \\ &= \sum_{x \in \{-1, +1\}^p} 2^p p_S(x) p_T(x) - 1. \end{aligned} \quad (4.8)$$

Now

$$\begin{aligned} \sum_{x \in \{-1, +1\}^p} 2^p p_S(x) p_T(x) &= \frac{2^p}{Z^2} \sum_x \exp(c \cdot (\chi_S(x) + \chi_T(x))) \\ &= \frac{2^p \cdot 2^{p-2N+\lambda}}{Z^2} \sum_{x_{S \cap T}} \sum_{x_{S \Delta T}} \exp(c \cdot (\chi_S(x) + \chi_T(x))) \\ &\stackrel{(a)}{=} \frac{2^p \cdot 2^{p-2N+\lambda}}{Z^2} \sum_{x_{S \cap T}} 2^{2N-2\lambda} \cdot \frac{1}{4} \cdot (e^{2c} + e^{-2c} + 2) \\ &= \frac{2^{2p-2}}{Z^2} (e^c + e^{-c})^2 \stackrel{(b)}{=} 1. \end{aligned}$$

Step (a) follows from the fact that for any fixed $x_{S \cap T}$, half the assignments to $x_{S \setminus T}$ result in $\chi_S = 1$ and half $\chi_S = -1$, and similarly for $x_{T \setminus S}$; step (b) is from the formula (4.3) for Z .

For the case $S = T$, we have

$$\begin{aligned} \sum_{x \in \{-1, +1\}^p} 2^p p_S(x) p_T(x) &= \frac{2^p}{Z^2} \sum_x \exp(c \cdot (\chi_S(x) + \chi_T(x))) \\ &= \frac{2^p \cdot 2^{p-1}}{Z^2} (e^{2c} + e^{-2c}) \\ &= \frac{2^{2p-2}}{Z^2} 2(e^c + e^{-c})^2 - \frac{4}{(e^c + e^{-c})^2} = 2 - \frac{4}{(e^c + e^{-c})^2}. \end{aligned}$$

Plugging this into (4.8) completes the proof. \square