Approximating the Bethe partition function

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Abstract

When belief propagation (BP) converges, it does so to a stationary point of the Bethe free energy $F$, and is often strikingly accurate. However, it may converge only to a local optimum or may not converge at all. An algorithm was recently introduced by Weller and Jebara for attractive binary pairwise MRFs which is guaranteed to return an $\epsilon$-approximation to the global minimum of $F$ in polynomial time provided the maximum degree $\Delta = O(\log n)$, where $n$ is the number of variables. Here we extend their approach and derive a new method based on analyzing first derivatives of $F$, which leads to much better performance and, for attractive models, yields a fully polynomial-time approximation scheme (FPTAS) without any degree restriction. Further, our methods apply to general (non-attractive) models, though with no polynomial time guarantee in this case, demonstrating that approximating $\log$ of the Bethe partition function, $\log Z_B = -\min F$, for a general model to additive $\epsilon$-accuracy may be reduced to a discrete MAP inference problem. This allows the merits of the global Bethe optimum to be tested.

1 INTRODUCTION

Undirected graphical models, also termed Markov random fields (MRFs), are flexible tools used in many areas including speech recognition, systems biology and computer vision. A set of variables and a score function is specified such that the probability of a configuration of variables is proportional to the value of the score function, which factorizes into sub-functions over subsets of variables in a way that defines a topology on the variables.

Three central problems are: (1) To evaluate the partition function $Z$, which is the sum of the score function over all possible settings, and hence is the normalization constant for the probability distribution; (2) Marginal inference, which is computing the probability distribution of a given subset of variables; and (3) Maximum a posteriori (MAP) inference, which is the task of identifying a setting of all the variables which has maximum probability.

All these are NP-hard, and (1) and (2) are closely related (marginals are a ratio of two partition functions). Variational methods show that the partition function may be obtained by minimizing the free energy over the marginal polytope, and that if instead the Bethe free energy (Bethe, 1935) is minimized over the local polytope, this should yield a good approximation\(^1\). Although this is not a formal result and there are cases where it performs poorly - typically when there are many short cycles with strong edge interactions (Wainwright & Jordan, 2008, § 4.1) - still, the approach has proved very popular and often strikingly accurate. One intuitively appealing way to perform this minimization is using the belief propagation message-passing algorithm (Pearl, 1988; Yedidia et al., 2001). Although performance is often excellent (McEliece et al., 1998; Murphy et al., 1999), when applied to models with cycles, termed loopy belief propagation (LBP), convergence is not guaranteed in general, even to a local minimum. Some conjectured that when LBP behaves poorly, it is likely that the Bethe approximation, as given by the global minimum, also performs poorly, but it has not previously been possible to test this.

Later approaches were developed based on gradient descent (Welling & Teh, 2001) or double-loop methods (Yuille, 2002) that do converge but only to a local minimum, and with no runtime guarantee. Recently, two methods with polynomial runtime were given for the important subclass of binary pairwise models: one returns an approximately stationary point (Shin, 2012), though its value may be far even from a local minimum; the other returns an $\epsilon$-approximate global optimum value (Weller & Jebara, 2013) but only for the restricted case of attractive models\(^2\). Both

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\(^1\)All terms are defined in §2.

\(^2\)An attractive model has all pairwise relationships of the type
these methods restrict the topology to have maximum degree $O(\log n)$, where $n$ is the number of variables.

1.1 CONTRIBUTION AND SUMMARY

We obtain results for binary pairwise MRFs by expanding on ideas from (Weller & Jebara, 2013). The approach is to construct a sufficient mesh of discretized points in such a way that the optimum mesh point $q^*$ is guaranteed to have $F(q^*)$ within $\epsilon$ of the true optimum. Our first derivative method typically results in a mesh that is much coarser (by many orders of magnitude, see §6.1), yet still sufficient, and admits adaptive methods to focus points in regions where $F$ may vary rapidly. This leads to a FPTAS for attractive models with no restriction on topology. In addition, we refine and extend the second derivative approach of (Weller & Jebara, 2013) to derive a method that performs well for very small $\epsilon$. With our new methods, both approaches apply to general binary pairwise models (not necessarily attractive) to reduce the problem of finding an $\epsilon$-approximate global optimum to solving a derived discrete optimization problem, which may be framed as multi-label MAP inference, where a rich family of methods already exists.

There are several motivations for this work:

- To our knowledge, we present the first way to solve for the global Bethe optimum (within $\epsilon$ accuracy) of a general binary pairwise MRF. Runtime is practical for small real-world problems.

- This now allows the accuracy of the global Bethe optimum to be tested.

- For attractive models, we obtain a fully polynomial time approximation scheme for any topology, thus answering an open theoretical question.

In §2, we establish notation and present preliminary results, then apply these in §3 to derive our new approach for mesh construction based on analyzing first derivatives of $F$. In §4 we revisit the second derivative approach of (Weller & Jebara, 2013). We show how this method can be refined and extended to yield better performance and also to admit non-attractive models, though for most cases of interest, unless $\epsilon$ is very small, the method of §3 is much superior.

In §5, we discuss the resulting discrete optimization problem. In certain settings this is tractable, and in general we mention several features that can make it easier to find a satisfactory solution, or at least to bound its value. Experiments are described in §6 demonstrating practical application of the algorithm. Conclusions are presented in §7.

1.1.1 Sketch of the overall algorithm

Input: Parameters for a general binary pairwise MRF (convert format using the reparameterization of §2.1 if required), and a desired accuracy $\epsilon$.

1. Preprocess by computing bounds on the locations of minima (see §2.4).

2. Construct a sufficient mesh using one of the methods in this paper. Indeed, all approaches are fast, so several may be used and the most efficient mesh selected.

3. Attempt to solve the resulting multi-label MAP inference problem, see §5.

4. If unsuccessful, but a strongly persistent partial solution was obtained, then improved location bounds may be generated (see §5.2.1), repeat from 2.

At anytime, one may stop and compute bounds on $F$, see §5.2.

1.2 RELATED WORK

In earlier work, a fully polynomial-time randomized approximation scheme (FPRAS) for the true partition function was derived (Jerrum & Sinclair, 1993), but only when singleton potentials are uniform (i.e. a uniform external field) and the resulting runtime is high at $O(\epsilon^{-2m^3n^{11}\log n})$. It was recently shown (Heinemann & Globerson, 2011) that models exist such that the true marginal probability cannot possibly be the location of a minimum of the Bethe free energy. Our work demonstrates an interesting connection between MAP inference techniques (NP-hard) and estimating the partition function $Z$ (#P-hard). A different connection was shown by using MAP inference on randomly perturbed models to approximate and bound $Z$ (Hazan & Jaakkola, 2012).

2 NOTATION & PRELIMINARIES

Our notation is similar to (Weller & Jebara, 2013) and (Welling & Teh, 2001). We focus on a binary pairwise model with $n$ variables $X_1, \ldots, X_n \in \mathbb{B} = \{0, 1\}$ and graph topology $(\mathcal{V}, \mathcal{E})$ with $m = |\mathcal{E}|$; that is $\mathcal{V}$ contains nodes $\{1, \ldots, n\}$ where $i$ corresponds to $X_i$, and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ contains an edge for each pairwise score relationship. Let $\mathcal{N}(i)$ be the neighbors of $i$. Let $x = (x_1, \ldots, x_n)$ be one particular configuration, and introduce the notion of energy $E(x)$ through\(^3\)

$$p(x) = \frac{e^{-\theta_i x_i}}{Z}, \quad E = \sum_{i \in \mathcal{V}} \theta_i x_i - \sum_{(i,j) \in \mathcal{E}} W_{ij} x_i x_j, \quad (1)$$

\(^3\)The probability or score function can always be reparameterized in this way, with finite $\theta_i$ and $W_{ij}$ terms provided $p(x) > 0 \ \forall x$, which is a requirement for our approach. There are reasonable distributions where this does not hold, i.e. distributions where $\exists x : p(x) = 0$, but this can often be handled by assigning such configurations a sufficiently small positive probability $\epsilon$. 
where the partition function $Z = \sum_x e^{-E(x)}$ is the normalizing constant, and $\{\theta_i, W_{ij}\}$ are parameters of the model.

Given any joint probability distribution $p(X_1, \ldots, X_n)$ over all variables, the (Gibbs) free energy is defined as $F_G(p) = E_p(E) - S(p)$, where $S(p)$ is the (Shannon) entropy of the distribution. Using variational methods, a remarkable result is easily shown (Wainwright & Jordan, 2008): minimizing $F_G$ over the set of all globally valid distributions (termed the marginal polytope) yields a value of $-\log Z$ at the true marginal distribution, given in (1).

This minimization is, however, computationally intractable, hence the approach of minimizing the Bethe free energy $F$ makes two approximations: (i) the marginal polytope is relaxed to the (Gibbs) free energy is defined as $\{\theta_i, W_{ij}\}$ are parameters of the model.

Thus we may consider the minimization of $F$ over $q = (q_1, \ldots, q_n) \in [0, 1]^n$.

We are interested in discretized pseudo-marginals where for each $q_i$, we restrict its possible values to a discrete mesh $\mathcal{M}_i$ of points in $[0, 1]$. The points may be spaced unevenly and we may have $\mathcal{M}_i \neq \mathcal{M}_j$. Let $N_i = |\mathcal{M}_i|$, and define $N = \sum_{i \in V} N_i$ and $\Pi = \prod_{i \in V} N_i$, the sum and product respectively of the number of mesh points in each dimension. Write $\mathcal{M}$ for the entire mesh. Let $\hat{q}$ be the location of a global optimum of $F$. We say that a mesh construction $\mathcal{M}(\epsilon)$ is sufficient if, given $\epsilon > 0$, it can be guaranteed that there exist $q^* \in \prod_{i \in V} \mathcal{M}_i$ s.t. $F(q^*) - F(\hat{q}) \leq \epsilon$.

We shall make use of the standard sigmoid function, $\sigma(\epsilon) = 1/(1 + \exp(-\epsilon))$ for various bounds.

### 2.1 Input Model Specification

Throughout this paper, we assume the reparameterization in (1) for all analysis, but a different specification is more natural for specifying models avoiding bias. We assume an input model is given with singleton terms $\theta_i$ as in (1), but with pairwise energy terms instead given by $-W_{ij} x_i x_j$. Throughout this paper, we assume the reparameterization in (1) for all analysis, but a different specification is more natural for specifying models avoiding bias. We assume a global optimum of $F$ over $q = (q_1, \ldots, q_n)$.

Thus we may consider the minimization of $F$ over $q = (q_1, \ldots, q_n) \in [0, 1]^n$.

The required transformation to convert from input model to the format of (1), simply takes $\theta_i \leftarrow \theta_i - \sum_{j \in N(i)} W_{ij}/2$, leaving $W_{ij}$ unaffected.

### 2.2 Submodularity

If all pairwise cost functions $f_{ij}$ over $\mathcal{M}_i \times \mathcal{M}_j$ from (5) are submodular, then the global discretized optimum may be found efficiently using graph cuts (Schlesinger & Flach, 2006). We require the following earlier result.

**Theorem 1** (Submodularity for any discretization of an attractive model, see (Weller & Jебара, 2013) Theorem 8, (Korč et al., 2012)). In a binary pairwise MRF, if an edge $(i, j)$ is attractive, i.e. $W_{ij} > 0$, then the multi-label discretized MRF for any mesh $\mathcal{M}$ is submodular for that edge. Hence if the MRF is fully attractive, then the multi-label discretized MRF is fully submodular for any discretization.

### 2.3 Flipping Variables

A useful technique for our analysis is to consider a model where some variables are flipped, i.e. given a model on $\{X_i\}$, consider a new model on $\{X'_i\}$ where $X'_i = 1 - X_i$ for some $i \in V$. New model parameters $\{\theta'_i, W'_{ij}\}$ may be identified as in (Weller & Jебара, 2013, §3) to preserve energies of all states up to a constant. If all variables are flipped, new parameters are given by
\[ W'_{ij} = W_{ij}, \quad \theta'_i = -\theta_i - \sum_{j \in N(i)} W_{ij}. \]  

(6)

If the original model was attractive, so too is the new. If only a subset \( R \subseteq V \) is flipped (this can be useful, for example, to make the model locally attractive around a variable by flipping those neighbors to which it has a repulsive edge), let \( X'_i = 1 - X_i \) if \( i \in R \), else \( X'_i = X_i \) for \( i \in S \), where \( S = V \setminus R \). Let \( E_t = \{ \text{edges with exactly } t \text{ ends in } R \} \) for \( t = 0, 1, 2 \). Then we obtain

\[
W'_{ij} = \begin{cases} 
W_{ij} & (i, j) \in E_0 \cup E_2, \\
-W_{ij} & (i, j) \in E_1,
\end{cases} \\
\theta'_i = \begin{cases} 
\theta_i + \sum_{(i,j) \in E_1} W_{ij} & i \in S, \\
-\theta_i - \sum_{(i,j) \in E_2} W_{ij} & i \in R.
\end{cases}
\]  

(7)

**Lemma 2.** Flipping variables changes affected pseudomarginal matrix entries' locations but not values. \( \boldsymbol{F} \) is unchanged up to a constant, hence the locations of stationary points are unaffected. Proof in (Weller & Jebara, 2013)

### 2.4 PRELIMINARY BOUNDS

We use the following earlier results.

**Lemma 3** ([Weller & Jebara, 2013] Lemma 2). \( \alpha_{ij} \geq 0 \Rightarrow \xi_{ij} \geq q_i q_j, \alpha_{ij} \leq 0 \Rightarrow \xi_{ij} \leq q_i q_j \).

**Lemma 4** (Upper bound for \( \xi_{ij} \) for an attractive edge, [Weller & Jebara, 2013] Theorem 6). If \( \alpha_{ij} > 0 \), then 
\[
\xi_{ij} - q_i q_j \leq \frac{\alpha_{ij} m (1 - M)}{1 + \alpha_{ij}},
\]
where \( m = \min(q_i, q_j) \) and \( M = \max(q_i, q_j) \).

**Theorem 5** ([Weller & Jebara, 2013] Theorem 4). For general edge types (associative or repulsive), let \( W_i = \sum_{j \in N(i): W_{ij} > 0} W_{ij}, V_i = -\sum_{j \in N(i): W_{ij} < 0} W_{ij} \). At any stationary point of the Bethe free energy, \( \sigma(\theta_i - V_i) \leq q_i \leq \sigma(\theta_i + W_i) \).

For the efficiency of our overall approach, it is very desirable to tighten these bounds on locations of minima of \( \boldsymbol{F} \) since this both reduces the search space and allows a lower density of discretizing points in the mesh. For our theoretical results, we do not assume this can be done but in practice, it can be attempted efficiently by running either of the following two algorithms: Bethe bound propagation (BBP) from (Weller & Jebara, 2013, §6), or using the approach from (Mooij & Kappen, 2007) which we term MK. Either method can achieve striking results quickly, though MK is our preferred method\(^4\) - this considers cavity fields around each variable and determines the range of possible beliefs after iterating LBP, starting from any initial values;

\(^4\)Both BBP and MK are anytime methods that converge quickly, and can be implemented such that each iteration runs in \( O(m) \) time. MK takes a little longer but can yield tighter bounds.

Since any minimum of \( \boldsymbol{F} \) corresponds to a fixed point of LBP (Yedidia et al., 2001), this bounds all minima.

Let the lower bounds obtained for \( q_i \) and \( 1 - q_i \) respectively be \( A_i \) and \( B_i \) so that \( A_i \leq q_i \leq 1 - B_i \), and let the Bethe box be the orthotope given by \( \prod_{i \in V} [A_i, 1 - B_i] \). Define \( \eta_i = \min(A_i, B_i) \), i.e. the closest that \( q_i \) can come to the extreme values of 0 or 1.

### 2.5 DERIVATIVES OF \( \boldsymbol{F} \)

In ([Welling & Teh, 2001], first partial derivatives of the Bethe free energy are derived as

\[
\frac{\partial \boldsymbol{F}}{\partial q_i} = -\theta_i + \log Q_i, \\
\frac{\partial^2 \boldsymbol{F}}{\partial q_i \partial q_j} = \frac{1}{T_{ij}} q_j (1 - q_i) - \frac{1}{T_{ij}} q_i (1 - q_j) \\
\frac{\partial^2 \boldsymbol{F}}{\partial q_i \partial q_j} = \frac{1}{T_{ij}} (q_i q_j - \xi_{ij}), \\
\end{array}
\]  

where \( T_{ij} = q_i q_j (1 - q_i) (1 - q_j) - (\xi_{ij} - q_i q_j)^2 \)

(8)

(9)

Incorporating all singleton terms gives the following result.

**Theorem 7** (All terms of the Hessian, see [Weller & Jebara, 2013] §4.3 and Lemma 9). Let \( H \) be the Hessian of \( \boldsymbol{F} \) for a binary pairwise model, i.e. \( H_{ij} = \frac{\partial^2 \boldsymbol{F}}{\partial q_i \partial q_j}, d_i = \text{degree of variable } X_i \), then

\[
H_{ii} = -\frac{d_i - 1}{q_i (1 - q_i)} + \sum_{j \in N(i)} \frac{q_j (1 - q_j)}{T_{ij}} \geq \frac{1}{q_i (1 - q_i)}, \\
H_{ij} = \begin{cases} 
\frac{q_i q_j - \xi_{ij}}{T_{ij}} & (i, j) \in E, \\
0 & (i, j) \notin E, i \neq j.
\end{cases}
\]

### 3 NEW APPROACH: GRADMESH

We develop a new approach to constructing a sufficient mesh \( \mathcal{M} \) by analyzing bounds on the first derivatives of \( \boldsymbol{F} \). To help distinguish between methods, we call the new first derivative approach gradMesh, and the earlier, second derivative approach curvMesh. The new gradMesh approach yields several attractive features:

- For attractive models, we obtain an FPTAS with worst case runtime \( O(e^{-\Delta} n^3 m^3 W^3) \) and no restriction on topology, unlike earlier work (Weller & Jebara, 2013) which required max degree \( \Delta = O(\log n) \).
Our sufficient mesh is typically dramatically coarser than the earlier method of (Weller & Jebara, 2013) unless \( \epsilon \) is very small, leading to a much smaller subsequent MAP problem. Here, the sum of the number of discretizing points in each dimension, \( N = O \left( \frac{n m W}{\epsilon^2} \right) \). For comparison, the earlier method, even after our improvements in §4, forms a mesh with \( N = O \left( \frac{1}{\epsilon^2} \right) \exp \left[ \frac{1}{2} W (1 + \Delta/2 + T) \right] \).

As an example, for the model in the experiment of §6.2, our new approach with the adaptive minsum method (see §3.1.2), yields a mesh with \( N = 8 \) that is 8 orders of magnitude smaller than the earlier method. See §6.1 for more comparisons.

The approach immediately handles a general model with both attractive and repulsive edges. Hence approximating \( \log Z_B \) may be reduced to a discrete multi-label MAP inference problem. This is valuable due to the availability of many MAP techniques, see §5.

First consider a model which is fully attractive around variable \( X_i \), i.e. \( W_{ij} > 0 \forall j \in \mathbb{N}(i) \). From (8) and Lemma 3, we obtain

\[
\frac{\partial F}{\partial q_i} = -\theta_i + \log q_i \leq -\theta_i + \log \frac{q_i}{1 - q_i}.
\]

Using one \( O(m) \) iteration of the belief propagation algorithm (BBP) derived in (Weller & Jebara, 2013, Supplement), allows us to refine the bounds for variable \( X_i \) of (11) based on the \( [A_j, 1 - B_j] \) location bounds on its neighbors \( j \in \mathbb{N}(i) \), to show

\[
\frac{\partial F}{\partial q_i} \leq f^L_i(q_i) \leq f^U_i(q_i),
\]

where

\[
f^L_i(q_i) = -\theta_i - W_i + \log \frac{q_i}{1 - q_i} + \log U_i
\]

\[
f^U_i(q_i) = -\theta_i + V_i + \log \frac{q_i}{1 - q_i} - \log L_i.
\]

\( L_i, U_i \) are each \( > 1 \) with \( \log L_i + \log U_i \leq V_i + W_i \). They are computed as

\[
L_i = \prod_{j \in \mathbb{N}(i)} L_{ij}, \quad U_i = \prod_{j \in \mathbb{N}(i)} U_{ij},
\]

with

\[
L_{ij} = \begin{cases} 
1 + \frac{1}{1 + \alpha_{ij}(1-B_j)(1-A_j)} & \text{if } W_{ij} > 0 \\
1 + \frac{1}{1 + \alpha_{ij}(1-B_j)(1-A_j)} & \text{if } W_{ij} < 0
\end{cases}
\]

\[
U_{ij} = \begin{cases} 
1 + \frac{1}{1 + \alpha_{ij}(1-A_j)(1-B_j)} & \text{if } W_{ij} > 0 \\
1 + \frac{1}{1 + \alpha_{ij}(1-A_j)(1-B_j)} & \text{if } W_{ij} < 0
\end{cases}
\]

See Figure 1 for an example. We make the following observations:

- The upper bound is equal to the lower bound plus the constant \( D_i = V_i + W_i - \log L_i - \log U_i \geq 0 \).
- The bound curves are monotonically increasing with \( q_i \), ranging from \(-\infty\) to \(+\infty\) as \( q_i \) ranges from 0 to 1.
- A necessary condition to be within the Bethe box is that the upper bound is \( \geq 0 \) and the lower bound is \( \leq 0 \). Hence, anywhere within the Bethe box, we must have bounded derivative, \( \left| \frac{\partial F}{\partial q_i} \right| \leq D_i \). BBP generates \( \{[A_j, 1 - B_j] \} \) bounds by iteratively updating with \( L_i, U_i \) terms. In general, however, we may have better bounds from any other method, such as MK, which lead to higher \( L_i \) and \( U_i \) parameters and lower \( D_i \).

\( F \) is continuous on \([0, 1]^n\) and differentiable everywhere in \((0, 1)^n\) with partial derivatives satisfying (12). \( f^L_i(q_i) \) and \( f^U_i(q_i) \) are continuous and integrable. Indeed, using the notation \( \left[ \hat{\phi}(x) \right]_{x=a}^{x=b} = \hat{\phi}(b) - \hat{\phi}(a) \),

\[
\int_a^b C + \log \frac{q_i}{1 - q_i} \, dq_i = \left[ C q_i + q_i \log q_i + (1 - q_i) \log (1 - q_i) \right]_{q_i=a}^{q_i=b}
\]

for \( 0 \leq a \leq b \leq 1 \), which relates to the binary entropy function \( H(p) = -p \log p - (1 - p) \log (1 - p) \), recall the definition of \( F \). We remark that although \( \frac{\partial F}{\partial q_i} \) tends to \(-\infty\) or \(+\infty\) as \( q_i \) tends to 0 or 1, the integral converges (taking \( 0 \log 0 = 0 \)).

Hence if \( \hat{q} = (\hat{q}_1, \ldots, \hat{q}_n) \) is the location of a global minimum, then for any \( q = (q_1, \ldots, q_n) \) in the Bethe box,

\[
F(q) - F(\hat{q}) \leq \sum_{i: q_i \leq \hat{q}_i} f^L_i(q_i) dq_i + \sum_{i: q_i < \hat{q}_i} f^U_i(q_i) dq_i.
\]
To construct a sufficient mesh, a simple initial bound relies on $|\frac{\partial f}{\partial q_i}| \leq D_i$. If mesh points $M_i$ are chosen s.t. in dimension $i$ there must be a point $q^*_i$ within $\gamma_i$ of a global minimum (which can be achieved using a mesh width in each dimension of $\gamma_i$), then by setting $\gamma_i = \frac{\epsilon}{nD_i}$, we obtain $F(q^*_i) - F(q) \leq \sum_i D_i \frac{\epsilon}{nD_i} = \epsilon$. It is easily seen that $N_i \leq 1 + \frac{1}{\gamma_i} \sum_i D_i$, hence the total number of mesh points, $N = \sum_{i \in V} N_i$, satisfies

$$N \leq 2n + \frac{n}{2\epsilon} \sum_i D_i \leq 2n + \frac{n}{\epsilon} \sum_{(i,j) \in E} |W_{ij}|$$

$$= O\left(\frac{n}{\epsilon} \sum_{(i,j) \in E} |W_{ij}|\right) = O\left(\frac{nmW}{\epsilon}\right), \quad (15)$$

since $D_i \leq V_i + W_i = \sum_{j \in N(i)} |W_{ij}|$. Here $W = \max_{(i,j) \in E} |W_{ij}|$ and $m = |E|$ is the number of edges.

If the initial model is fully attractive, then by Theorem 1 we obtain a submodular multi-label MAP problem which is solvable using graph cuts with worst case runtime $O(N^3) = O(\epsilon^{-3}n^3m^3W^3)$ (Schlesinger & Flach, 2006; Greig et al., 1989; Goldberg & Tarjan, 1988).

Note from the first expression in (15) that if we have information on individual edge weights then we have a better bound using $\sum_{(i,j) \in E} |W_{ij}|$ rather than just $mW$.

For comparison, the earlier second derivative approach of (Weller & Jebara, 2013) has runtime $O(\epsilon^{-2}n^{3/2}W^{3/2})$, where, even using the improved method in §4 here, $\Omega = O(\Delta e^{W(1+\Delta/2)+T})$. Unless $\epsilon$ is very small, the new first derivative approach is typically dramatically more efficient and more useful in practice. Further, it naturally handles both attractive and repulsive edge weights in the same way.

### 3.1 REFINEMENTS, ADAPTIVE METHODS

Since the resulting multi-label MAP inference problem (which is not submodular in general) is NP-hard (Shimony, 1994), it is helpful to minimize its size. As noted above, setting $\gamma_i = \frac{\epsilon}{nD_i}$, which we term the simple method, yields a sufficient mesh, where $|\frac{\partial F}{\partial q_i}| \leq D_i = V_i + W_i - \log L_i - \log U_i$. However, since the bounding curves are monotonic with $f_i^U \geq 0$ and $f_i^L \leq 0$, a better bound for the magnitude of the derivative is available by setting $D_i = \max\{f_i^U(1 - B_i), -f_i^L(A_i)\}$.

#### 3.1.1 The minsum method

We define $N_i = \text{the number of mesh points in dimension } i$, with sum $N = \sum_{i \in V} N_i$ and product $\Pi = \prod_{i \in V} N_i$. For a fully attractive model, the resulting MAP problem may be solved in time $O(N^3)$ by graph cuts (Theorem 1, (Schlesinger & Flach, 2006; Greig et al., 1989; Goldberg & Tarjan, 1988)), so it is sensible to minimize $N$. In other cases, however, it is less clear what to minimize. For example, a brute force search over all points would take time $\Theta(\Pi)$.

Define the spread of possible values in dimension $i$ as $S_i = 1 - B_i - A_i$ and note $N_i = 1 + \frac{1}{\gamma_i D_i}$ is required to cover the whole range. To minimize $N$ while ensuring the mesh is sufficient, consider the Lagrangian $\mathcal{L} = \sum_{i \in V} S_i - \lambda(\epsilon - \sum_{i \in V} \gamma_i D_i)$, where $D_i$ is set as in the simple method ($\S 3.1$). Optimizing gives

$$\gamma_i = \frac{\epsilon}{\sum_{j \in V} \sqrt{S_j D_j}} \sqrt{\frac{S_i}{D_i}} \quad \text{and} \quad N \leq 2n + \frac{1}{2\epsilon} \left(\sum_{i \in V} \sqrt{S_i D_i}\right)^2 \quad (16)$$

which we term the minsum method. Note $D_i \leq d_i W$ where $d_i$ is the degree of $X_i$, hence $(\sum_{i \in V} \sqrt{S_i D_i})^2 \leq W (\sum_{i \in V} \sqrt{d_i})^2$. By Cauchy-Schwartz and the handshake lemma, $(\sum_{i \in V} \sqrt{d_i})^2 \leq \pi \sum_{i \in V} d_i = 2mn$, with equality iff the $d_i$ are constant, i.e. the graph is regular.

If instead $\Pi$ is minimized, rather than $N$, a similar argument shows that the simple method ($\S 3.1$) is optimal.

#### 3.1.2 Adaptive methods

The previous methods rely on one bound $D_i$ for $|\frac{\partial F}{\partial q_i}|$ over the whole range $[A_i, 1 - B_i]$. However, we may increase efficiency by using local bounds to vary the mesh width across the range. A bound on the maximum magnitude of
the derivative over any sub-range may be found by checking just \(-f_i^U\) at the lower end and \(f_i^U\) at the upper end.

This may be improved by using the exact integral as in (14). First, constant proportions \(k_i > 0\) should be chosen with \(\sum_i k_i = 1\). Next, the first or smallest mesh point \(\gamma_1 \in M_i\) should be set s.t. \(\int_{A_i} f_i^U(q_i) dq_i = k_i \epsilon\). This will ensure that \(\gamma_1\) covers all points to its left in the sense that \(F[q_i = \gamma_1[i] - F[q_i \in [A_i, \gamma_1]]] \leq k_i \epsilon\) where all other variables \(q_j, j \neq i\), are held constant at any values within the Bethe box. \(\gamma_1\) also covers all points to its right up to what we term its reach, i.e. the point \(r_1\) s.t. \(\int_{r_1} f_i^L(q_i) dq_i = k_i \epsilon\). Next, \(\gamma_2\) is chosen as before, using \(r_1\) as the left extreme rather than \(A_i\), and so on, until the final mesh point is computed with reach \(\geq 1 - B_i\). This yields an optimal mesh for the choice of \(\{k_i\}\).

If \(k_i = \frac{1}{n}\), we achieve an optimized adaptive simple method. If \(k_i = \frac{\sqrt{s_i d_i}}{\sum_{j \in V} \sqrt{s_j d_j}}\), we achieve an adaptive minsum method. For many problems, this adaptive minsum method will be the most efficient.

Integrals are easily computed using (13). To our knowledge, computing optimal points \(\{\gamma_i^2\}\) is not possible analytically, but each may be found with high accuracy in just a few iterations using a search method, hence total time to compute the mesh is \(O(N)\), which is negligible compared to solving the subsequent MAP problem.

4 REVISITING THE SECOND DERIVATIVE APPROACH: CURVMESH

We shall review and then refine the second derivative approach used in (Weller & Jebara, 2013, §5). Since it is a second derivative approach, which we call curvMesh, the mesh size (measured by \(N\), the total number of points summed over the dimensions) grows as \(O(e^{-1/2})\) rather than as \(O(e^{-1})\) in the new first derivative gradMesh approach. In practice, however, particularly for harder cases where \(n\) and \(W\) are above small values, unless \(\epsilon\) is very small, the gradMesh method of §3 is much more efficient.

As in this paper, the possible location of a global minimum \(\hat{q}\) was first bounded in the Bethe box given by \(\prod_{i \in V} [A_i, 1 - B_i]\). Next an upper bound \(\Lambda\) was derived on the maximum possible eigenvalue of the Hessian \(H\) of \(F\) anywhere within the Bethe box, where it was required that all edges be attractive. Then a mesh of constant width in every dimension was introduced s.t. the nearest mesh point \(q^*\) to \(\hat{q}\) was at most \(\gamma\) away in each dimension. Hence the \(L_2\) distance \(\delta\) satisfies \(\delta^2 \leq n\gamma^2\) and by Taylor’s theorem, \(F(q^*) \leq F(\hat{q}) + \frac{1}{2} \Lambda \delta^2\). A was computed by bounding the maximum magnitude of any element of \(H\). Considering Theorem 7, this involves separate analysis of diagonal \(H_{ii}\) terms, which are positive and were bounded above by the term \(b\); and edge \(H_{ij}\) terms, which are negative for attractive edges, whose magnitude was bounded above by \(a\). Then \(\Omega\) was set as \(\max(a, b)\), and \(\Sigma\) as the proportion of non-zero entries in \(H\). Finally, \(\Lambda \leq \sqrt{\Omega(H^T H)} \leq \sqrt{\Sigma n^2 \Omega^2} = n\Omega \sqrt{\Sigma}\).

4.1 IMPROVED BOUND FOR AN ATTRACTIVE MODEL

We improve the upper bound for \(\Lambda\) by improving the \(a\) bound for attractive edges to derive \(\tilde{a}\), a better upper bound on \(-H_{ij}\). Essentially, a more careful analysis allows a potentially small term in the numerator and denominator to be canceled before bounding. Writing \(\tilde{\eta} = \min_{i \in V} \eta_i(1 - \eta_i)\), i.e. the closest that any dimension can come to 0 or 1, the result is that

\[-H_{ij} \leq \left(\frac{\alpha_{ij}}{1 + \alpha_{ij}}\right) \sqrt{\tilde{\eta} \left(1 - \left(\frac{\alpha_{ij}}{1 + \alpha_{ij}}\right)^2\right)}\]

(17)

Thus, \(\tilde{a} = O(e^{W(1 + \Delta/2 + \epsilon)\epsilon})\) which compares favorably to the earlier bound in (Weller & Jebara, 2013), where \(a = O(e^{W(1 + \epsilon)\epsilon})\). Recall \(b = O((\Delta e^{W(1 + \epsilon)\epsilon})\epsilon)\) and \(\Omega = \max(a, b)\), so using the new \(\tilde{a}\) bound, now \(\Omega = O((\Delta e^{W(1 + \Delta/2)\epsilon})\epsilon)\). Details and derivations are in the supplement.

4.2 EXTENDING TO A GENERAL MODEL

Using flipping arguments from §2.3, we are able to extend the method of (Weller & Jebara, 2013) to apply to general (non-attractive) models. Interestingly, the bounds derived for \(\Omega = \max(a, b)\) take exactly the same form as for the purely attractive case, except that now \(-W \leq W_{ij} \leq W\), whereas previously it was required that \(0 \leq W_{ij} \leq W\). Details and derivations are in the supplement.

5 RESULTING MULTI-LABEL MAP

After computing a sufficient mesh, it remains to solve the multi-label MAP inference problem on a MRF with the same topology as the initial model, where each \(q_i\) takes values in \(M_i\). In general, this is NP-hard (Shimony, 1994).

5.1 TRACTABLE CASES

If it happens that all cost functions are submodular (as is always the case if the initial model is fully attractive by Theorem 1), then as already noted, it may be solved efficiently using graph cut methods, which rely on solving a max flow/min cut problem on a related graph, with worst case runtime \(O(N^3)\) (Schlesinger & Flach, 2006; Greig et al., 1989; Goldberg & Tarjan, 1988). Using the Boykov-Kolmogorov algorithm (Boykov & Kolmogorov, 2004),
performance is typically much faster, sometimes approaching \(O(N)\). This submodular setting is the only known class of problem which is solvable for any topology.

Alternatively, the topological restriction of bounded treewidth allows tractable inference (Pearl, 1988). Further, under mild assumptions, this was shown to be the only restriction which will allow efficient inference for any cost functions (Chandrasekaran et al., 2008). We note that if the problem has bounded tree-width, then so too does the original binary pairwise model, hence exact inference (to yield the true marginals or the true partition function \(Z\)) on the original model is tractable using the junction tree algorithm, making our approximation result less interesting for this class. In contrast, although MAP inference is tractable for any attractive binary pairwise model, marginal inference and computing \(Z\) are not (Jerrum & Sinclair, 1993).

A recent approach reducing MAP inference to identifying a maximum weight stable set in a derived weighted graph (\(?; \)?) shows promise, allowing efficient inference if the derived graph is perfect. Further, testing if this graph is perfect can be performed in polynomial time (\(?; \) Chudnovsky et al., 2005).

### 5.2 INTRACTABLE MAP CASES

Many different methods are available, see (Kappes et al., 2013) for a recent survey. Some, such as dual approaches, may provide a helpful bound even if the optimum is not found. Indeed, a LP relaxation will run in polynomial time and return an upper bound on \(\log Z_B\) that may be useful. A lower bound may be found from any discrete point, and this may be improved using local search methods.

Note that the Bethe box bounds on each \(q_i \in [A_i, 1 - B_i]\) are worst case, irrespective of other variables. However, given a particular value for one or more \(q_i, j \in N(i)\), either BBP (Weller & Jebara, 2013, §6) or MK (Mooij & Kappen, 2007) can produce better bounds on \(q_i\), which may be helpful for pruning the solution space.

#### 5.2.1 Persistent partial optimization approaches

The multi-label implementation of quadratic pseudo-Boolean optimization termed MQPBO (Kohli et al., 2008), and Kovtun’s method (Kovtun, 2003), are examples of this class. Both consider LP-relaxations and run in polynomial time. In our context, the output consists of ranges (which in the best case could be one point) of settings for some subset of the variables. If any such ranges are returned, the strong persistence property ensures that any MAP solution satisfies the ranges. Hence, these may be used to update \(\{A_i, B_i\}\) bounds (padding the discretized range to the full continuous range covered by the end points if needed), compute a new, smaller, sufficient mesh and repeat until no improvement is obtained.

### 6 EXPERIMENTS

#### 6.1 COMPARISON TO EARLIER WORK

We compared the new mesh construction methods from this paper with the earlier approach in (Weller & Jebara, 2013), see Figure 2. We considered two values of \(\epsilon\): 1 (medium resolution) and 0.1 (fine resolution). For each value, we generated random MRFs on \(n\) variables, all pairwise connected, where \(\theta_i \sim U[-2, 2]\) and \(W_{ij} \sim U[-W, W]\), using the input convention of [2.1]. We show results first for fixed \(W = 5\) as \(n\) is varied from 3 to 20, then for fixed \(n = 10\) as \(W\) is varied from 1 to 10, generating 10 random models for each value. Of the various first derivative gradMesh methods, only minsum is shown since the others are very similar to those [4]; gradMesh is our new first derivative minsum method, see §3. For more details, see text of §6.1.

Note that \(N\) is shown on a log axis, thus we observe that the new methods dramatically outperform that of (Weller & Jebara, 2013) by many orders of magnitude for most cases of interest, even for small \(\epsilon\). Further, recall that \(N = \sum N_i\) is the sum of the number of mesh points in each dimension. The runtime of the overall algorithm is certainly \(\Omega(N)\), even for attractive models, and for general models is typi-

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3The original method of (Weller & Jebara, 2013) could only handle attractive models but we augment it as in §4.2. Plots for attractive models, where \(W_{ij} \sim U[0, W]\) are very similar to those shown.

4In practice, the adaptive methods typically produce a mesh with about half the number of points in each dimension.

5In our experiments on attractive models, the Boykov-
cally a significantly higher power, thus further demonstrating the benefit of the new methods.

6.2 POWER NETWORK

As a first step toward applying our algorithm to explore the usefulness of the global optimum of the Bethe approximation, here we consider one setting where LBP fails to converge, yet still we achieve reasonable results.

We aim to predict transformer failures in a power network (Rudin et al., 2012). Since the real data is sensitive, our experiments use synthetic data. Let $X_i \in \{0, 1\}$ indicate if transformer $i$ has failed or not. Each transformer has a probability of failure on its own which is represented by a singleton potential $\theta_i$. However, when connected in a network, a transformer can propagate its failure to nearby nodes (as in viral contagion) since the edges in the network form associative dependencies. We assume that homogeneous attractive pairwise potentials couple all transformers that are connected by an edge, i.e. $W_{ij} = W \ \forall (i, j) \in \mathcal{E}$. The network topology creates a Markov random field specifying the distribution $p(X_1, \ldots, X_n)$. Our goal is to compute the marginal probability of failure of each transformer within the network (not simply in isolation as in (Rudin et al., 2012)). Since recovering $p(X_i)$ is hard, we estimate Bethe pseudo-marginals $q_i = q(X_i = 1)$ through our algorithm, which emerge as the arg min when optimizing the Bethe free energy.

A single simulated sub-network of 55 connected transformers was generated using a random preferential attachment model, resulting in average degree 2 (see Figure 3 in the Appendix). Typical settings of $\theta_i = -2$ and $W = 4$ were specified (using the input model specification of §2.1). We attempted to run BP using the libDAI package (Mooij et al., 2012) but were unable to achieve convergence, even with multiple initial values, using various sequential or parallel settings and with damping. However, running our gradMesh adaptive minsum algorithm with $\epsilon = 1$ achieved reasonable results as shown in Table 1, where true values were obtained with the junction tree algorithm.

<table>
<thead>
<tr>
<th>$\epsilon = 1$ PTAS for $\log Z_B$</th>
<th>Error from true value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean $\ell_1$ error of single marginals</td>
<td>0.003</td>
</tr>
<tr>
<td>Log-partition function</td>
<td>0.26</td>
</tr>
</tbody>
</table>

Table 1: Results on simulated power network

It has been suggested that the Bethe approximation is poor when BP fails to converge (Mooij & Kappen, 2005). Our new method will allow this to be explored rigorously in future work. The initial result above is a promising first step and justifies further investigation.

7 DISCUSSION & FUTURE WORK

To our knowledge, we have derived the first $\epsilon$-approximation algorithm for $\log Z_B$ for a general binary pairwise model. Our approaches are useful in practice, and much more efficient than the earlier method of (Weller & Jебара, 2013). From experiments run, we note that the $\epsilon$ bounds for the adaptive minsum first derivative $\text{gradMesh}$ approach appear to be close to tight since we have found models where the optimum returned when run with $\epsilon = 1$ is more than 0.5 different to that for $\epsilon = 0.1$. When applied to attractive models, we guarantee a FPTAS with no degree restriction.

As described in §6.2, Bethe pseudo-marginals may be recovered from our approach by taking the $q^*$ that is returned as the arg min of $\mathcal{F}$ over the discrete mesh. However, although $\mathcal{F}(q^*)$ is guaranteed within $\epsilon$ of the optimum, there is no guarantee that $q^*$ will necessarily be close to a true Bethe optimum pseudo-marginal. For example, the surface could be very flat over a wide region, or the true optimum might be $\frac{\epsilon}{2}$ better at a location far from $q^*$. We sketch out how our approach may be used to bound the location of a global optimum pseudo-marginal, though note that there is no runtime guarantee. First pick an initial $\epsilon_1$ and run the main algorithm to find $q^*_1$. Now use any method to solve for the second best discretized mesh point $q^*_2$. If it happens that $\mathcal{F}(q^*_2) \geq \mathcal{F}(q^*_1) + \epsilon_1$ then, by the nature of the mesh construction, there must be a global minimum within the orthotope given by the neighboring mesh points of $q^*_1$ in each dimension⁴ and we terminate. On the other hand, if $\mathcal{F}(q^*_2) < \mathcal{F}(q^*_1)$ then we reduce $\epsilon$, for example to $\frac{\epsilon}{2}$ and repeat until we’re successful.

Future work includes further reducing the size of the mesh, considering how it should be selected to simplify the subsequent discrete optimization problem, and exploring applications. Importantly, we now have the opportunity to examine rigorously the performance of the global Bethe optimum. In addition, this will provide a benchmark against which to compare other (non-global) Bethe approaches that typically run more quickly, such as LBP or CCCP (Yuille, 2002). Another interesting avenue is to use our algorithm as a subroutine in a dual decomposition approach to optimize over a tighter relaxation of the marginal polytope.

References


⁴In fact, the optimum must be within a tighter orthotope based on the reach down and up, in each dimension, of $q^*_1$, see 3.1.2.


APPENDIX: SUPPLEMENTARY MATERIAL FOR APPROXIMATING THE BETHE PARTITION FUNCTION

Here we provide further details and proofs of several of the results in the main paper, using the original numbering.

4 REVISITING THE SECOND DERIVATIVE APPROACH

4.1 Improved bound for an attractive model

In this section, we improve the upper bound for $\Lambda$ (the maximum eigenvalue of the Hessian $H$) by improving the $a$ bound for attractive edges to derive $\tilde{a}$, an improved upper bound on $-H_{ij}$. Essentially, a more careful analysis allows a potentially small term in the numerator and denominator to be canceled before bounding.

Using Theorem 7, equation (9) and Lemma 4,

$$-H_{ij} = (\xi_{ij} - q_i q_j) \frac{1}{T_{ij}} \leq m(1 - M) \alpha_{ij} \frac{1}{(1 - m) M - m(1 - M) \left( \frac{\alpha_{ij}}{1 + \alpha_{ij}} \right)^2} \leq \left( \frac{\alpha_{ij}}{1 + \alpha_{ij}} \right) \frac{1}{(1 - m) M - m(1 - M) \left( \frac{\alpha_{ij}}{1 + \alpha_{ij}} \right)^2}$$

where $m = \min(q_i, q_j)$, $M = \max(q_i, q_j)$. Now we use the following result.

**Lemma 8.** For any $k \in (0,1)$, let $y = \min_{q_i \in [A_i, 1 - B_i], q_j \in [A_j, 1 - B_j]} (1 - m) M - m(1 - M) k$, then

$$y = \begin{cases} B_i A_j - (1 - B_i)(1 - A_j) k & \text{if } (1 - B_i) \leq A_j \text{ i range } \leq j \text{ range} \\ (1 - k) \min\{A_j(1 - A_j), B_i(1 - B_i)\} & \text{if } A_i \leq A_j \leq 1 - B_i \leq 1 - B_j \text{ ranges overlap, i lower} \\ (1 - k) \min\{A_j(1 - A_j), B_j(1 - B_j)\} & \text{if } A_i \leq A_j \leq 1 - B_j \leq 1 - B_i \text{ j range } \leq i \text{ range} \\ (1 - k) \min\{A_i(1 - A_i), B_i(1 - B_i)\} & \text{if } A_j \leq A_i \leq 1 - B_i \leq 1 - B_j \text{ i range } \leq j \text{ range} \\ (1 - k) \min\{A_i(1 - A_i), B_j(1 - B_j)\} & \text{if } A_j \leq A_i \leq 1 - B_j \leq 1 - B_i \text{ ranges overlap, j lower} \\ B_j A_i - (1 - B_j)(1 - A_i) k & \text{if } (1 - B_j) \leq A_i \text{ j range } \leq i \text{ range.} \end{cases}$$

**Proof.** The minimum is achieved by minimizing the larger and maximizing the smaller of $q_i$ and $q_j$. The result follows for cases where their ranges are disjoint. If ranges overlap, then the minimum is achieved at some $q_i = q_j$ in the overlap, with value $q_i(1 - q_i)(1 - k)$, which is concave and minimized at an extreme of the overlap range. \qed

Lemma 8 is useful in practice, and should be used to compute $\tilde{a} = \max_{(i,j) \in E} y$ of the bound above. To analyze the theoretical worst case, it is straightforward to see the corollary that $y \geq (1 - k) \bar{\eta}$, where $\bar{\eta} = \min_{e \in V} \eta_i(1 - \eta_i)$. This bound can be met, for example, if all ranges coincide. Hence, from (18), and with the reasoning for $\bar{\eta}$ from (Weller & Jebara, 2013) §5.3, where it is shown that $\frac{1}{\eta_i(1 - \eta_i)} = O(e^{T + \Delta W/2})$, and using $\alpha_{ij} = e^{W_{ij}} - 1$, we obtain

$$-H_{ij} \leq \left( \frac{\alpha_{ij}}{1 + \alpha_{ij}} \right) \frac{1}{\bar{\eta}} \left( 1 - \left( \frac{\alpha_{ij}}{1 + \alpha_{ij}} \right)^2 \right) = O(e^{W(1 + \Delta/2) + T}).$$

4.2 Extending the second derivative approach to a general (non-attractive) model

Here we extend the analysis of (Weller & Jebara, 2013) by considering repulsive edges to show that for a general binary pairwise model, we can still calculate useful bounds (which turn out to be very similar to the earlier bounds for attractive models) for a sufficient mesh width.
Our main tool for dealing with a repulsive edge is to flip the variable at one end (see §2.3) to yield an attractive edge, then we can apply earlier results. We denote the flipped model parameters with $\alpha'$. For example, if just variable $X_j$ is flipped, then $q^\prime_j = q(X^\prime_j) = q(1 - X_j) = 1 - q_j$. Since $\alpha_{ij} = e^{W_{ij}} - 1$ and here $W^\prime_{ij} = -W_{ij}$, the following relationship holds if one end of an edge is flipped,

$$\frac{\alpha^\prime_{ij}}{1 + \alpha^\prime_{ij}} = \frac{e^{-W_{ij}} - 1}{e^{-W_{ij}}} = 1 - e^{-W_{ij}} = -\alpha_{ij}. \quad (20)$$

Note that, for an attractive edge, $\frac{\alpha^\prime_{ij}}{1 + \alpha^\prime_{ij}} \in (0, 1)$, as is $-\alpha_{ij}$ for a repulsive edge. Recall that when we flip some set of variables, by construction $F' = F + \text{constant}$ (see §2.3).

The Hessian terms from Theorem 7 still apply. Our goal is to bound the magnitude of each entry $H_{ij}$ for a general binary pairwise model, then the earlier analysis will provide the result. Whereas for a fully attractive model, we assumed a maximum edge weight $W$ with $0 \leq W_{ij} \leq W$, now we assume $|W_{ij}| \leq W$.

### 4.2.1 Edge terms

First consider $H_{ij}$ for an edge $(i, j) \in E$. If the edge is attractive, then the earlier analysis holds (it makes no difference if other edges are attractive or repulsive). If it is repulsive, then $H_{ij} > 0$. Consider a model where just $X_j$ is flipped.

$$H_{ij} = \frac{\partial^2 F}{\partial q_i \partial q_j} = -\frac{\partial^2 F}{\partial q^\prime_i \partial q^\prime_j} = -H_{ij}'. \quad \text{Hence using (18) and (20), in practice an upper bound may be computed from Lemma 8 using $k = -\alpha_{ij}$ and $A^\prime_j = B_j, B^\prime_j = A_j$. The theoretical bound for an attractive edge from (19) becomes}$$

$$H_{ij} \leq \frac{-\alpha_{ij}}{\eta(1 - \alpha_{ij})}. \quad \text{As we should expect from the attractive case, the following result holds.}$$

**Lemma 9.** For a repulsive edge, $\frac{1}{1 - \alpha_{ij}^\prime} = O(e^{-W_{ij}})$.

**Proof.** Let $u = -W_{ij}$, then $\alpha_{ij} = e^{-u} - 1$ and $\frac{1}{1 - \alpha_{ij}^\prime} = \frac{1}{(1 - \alpha_{ij})(1 + \alpha_{ij})} = \frac{1}{e^{-u}(2 - e^{-u})} = O(e^u)$. □

Hence, noting that we may flip any neighbors $j$ of $i$ which are adjacent via repulsive edges to obtain $\frac{1}{\eta(1 - \eta)} = O(e^{T + \Delta W/2})$ as before, where now $W = \max_{(i, j) \in E} |W_{ij}|$, we see that for our new second derivative method, just as in the fully attractive case, $\tilde{a} = O(e^{W(1 + \Delta/2) + T})$.

For comparison interest, we also show how the earlier, worse bound for an attractive edge given in (Weller & Jebara, 2013) may similarly be combined with flipping to provide a worse upper bound for $H_{ij}$ when $(i, j)$ is repulsive. See (Weller & Jebara, 2013) §5.2: considering the proof of Lemma 10 and using (20) from this paper, we see that for a repulsive edge, the $K_{ij}$ minimum bound for $T_{ij}$ becomes $K_{ij} = \eta_i \eta_j (1 - \eta_i) (1 - \eta_j) (1 - \alpha_{ij}^\prime)$; then from (Weller & Jebara, 2013) Theorem 11, the equivalent bound is $H_{ij} \leq \frac{-\alpha_{ij}^\prime}{4K_{ij}}$ which gives $a = O(e^{W(1 + \Delta/2) + 2T})$ as it was for the fully attractive case.

We provide a further interesting result, deriving a lower bound for $\xi_{ij}$ for a repulsive edge. **Lemma 10** (Lower bound for $\xi_{ij}$ for a repulsive edge, analogue of Lemma 4). For any repulsive edge $(i, j)$, $q_i q_j - \xi_{ij} \leq -\alpha_{ij} p_{ij}$ where $p_{ij} = \min\{q_i q_j, (1 - q_i)(1 - q_j)\}$.

**Proof.** Consider a model where just variable $X_j$ is flipped, and let all new quantities be designated by the symbol $\prime$. Consider the joint pseudo-marginal (3). In the new model the columns are switched since $\mu^\prime_{ij}(a, b) = q(X^\prime_i = a, X^\prime_j = b) = q(X_i = a, X_j = 1 - b) = \mu_{ij}(a, 1 - b)$, hence

$$\mu^\prime_{ij} = \begin{pmatrix} 1 + \xi^\prime_{ij} - q_i - q_j & q_j - \xi^\prime_{ij} + \xi^\prime_{ij} \xi^\prime_{ij} \\
q_i - \xi^\prime_{ij} & \xi^\prime_{ij} \end{pmatrix} = \begin{pmatrix} q_j - \xi_{ij} & 1 + \xi_{ij} - q_i - q_j \\
q_i - \xi_{ij} & q_i - \xi_{ij} \end{pmatrix}. \quad (21)$$

Applying Lemma 4 to the new model, $\xi^\prime_{ij} - q'_i q'_j \leq \frac{\alpha^\prime_{ij}}{1 + \alpha^\prime_{ij}} m'(1 - M')$. Substituting in $\xi^\prime_{ij} = q_i - \xi_{ij}$ from (21) and using (20), we have $(q_i - \xi_{ij}) - q_i(1 - q_j) \leq -\alpha_{ij} m'(1 - M')$. Since $m' = \min\{q_i, 1 - q_j\}$ and $M' = \max\{q_i, 1 - q_j\}$, noting $q_i \leq 1 - q_j \Leftrightarrow q_i + q_j \leq 1 \Leftrightarrow q_i q_j \leq (1 - q_i)(1 - q_j)$, the result follows. □

Hence for a repulsive edge $(i, j)$, using (9), we have

$$T_{ij} = q_i q_j (1 - q_i)(1 - q_j) - (\xi_{ij} - q_i q_j)^2 \geq p_{ij} \mu_{ij} - \alpha^2_{ij} p^2_{ij},$$

where $P_{ij} = \max\{q_i q_j, (1 - q_i)(1 - q_j)\}$.  

4.2.2 Diagonal terms

Consider the $H_{ii}$ terms from Theorem 7, which is true for a general model. If all neighbors of $X_i$ are adjacent via attractive edges, then, as in (Weller & Jebara, 2013) Theorem 11, $H_{ii} \leq \frac{1}{\eta_i(1-\eta_i)} \left(1 - d_i + \sum_{j \in N(i)} \frac{1}{1 + \frac{\alpha_{ij}}{\alpha_{ji}}} \right)^2$.

If any neighbors are connected to $X_i$ by a repulsive edge, then consider a new model where those neighbors are flipped, so now all edges incident to $X_i$ are attractive, and designate the new model parameters with a $'$. As before, observe $F = F' + constant$, hence $H_{ii} = \frac{\partial^2 F}{\partial q_i^2} = \frac{\partial^2 F'}{\partial q_i'} = H'_{ii}$. Using (20) we obtain that for a general model,

$$H_{ii} \leq \frac{1}{\eta_i(1-\eta_i)} \left(1 - d_i + \sum_{j \in N(i): W_{ij} > 0} \frac{1}{1 - \left(\alpha_{ij} / (1 + \alpha_{ij})\right)} \right)^2 + \sum_{j \in N(i): W_{ij} < 0} \frac{1}{1 - \alpha_{ij}^2}.$$  \hspace{1cm} (22)

Similarly to the analysis in §4.2.1, using Lemma 9 gives that for a general model, $b = \max_{i \in V} H_{ii} = O(\Delta e^{W(1+\Delta/2)+T})$, just as for a fully attractive model, where now $W = \max |W_{ij}|$.

6.2 POWER NETWORK

Here we show the simulated sub-network used in the experiment.

![Sub-network used for the experiment described in the main text §6.2.](image)

Figure 3: Sub-network used for the experiment described in the main text §6.2.