Solving Marginal MAP Problems with NP Oracles and Parity Constraints

Yexiang Xue
Department of Computer Science
Cornell University
yexiang@cs.cornell.edu

Zhiyuan Li*
Institute of Interdisciplinary Information Sciences
Tsinghua University
lizhiyuan13@mails.tsinghua.edu.cn

Stefano Ermon
Department of Computer Science
Stanford University
ermon@cs.stanford.edu

Carla P. Gomes, Bart Selman
Department of Computer Science
Cornell University
{gomes,selman}@cs.cornell.edu

Abstract

Arising from many applications at the intersection of decision-making and machine learning, Marginal Maximum A Posteriori (Marginal MAP) problems unify the two main classes of inference, namely *maximization* (optimization) and *marginal inference* (counting), and are believed to have higher complexity than both of them. We propose `XOR_MMAP`, a novel approach to solve the Marginal MAP problem, which represents the intractable counting subproblem with queries to NP oracles, subject to additional parity constraints. `XOR_MMAP` provides a constant factor approximation to the Marginal MAP problem, by encoding it as a single optimization in a polynomial size of the original problem. We evaluate our approach in several machine learning and decision-making applications, and show that our approach outperforms several state-of-the-art Marginal MAP solvers.

1 Introduction

Typical inference queries to make predictions and learn probabilistic models from data include the *maximum a posteriori* (MAP) inference task, which computes the most likely assignment of a set of variables, as well as the *marginal inference* task, which computes the probability of an event according to the model. Another common query is the Marginal MAP (MMAP) problem, which involves both *maximization* (optimization over a set of variables) and *marginal inference* (averaging over another set of variables).

Marginal MAP problems arise naturally in many machine learning applications. For example, learning latent variable models can be formulated as a MMAP inference problem, where the goal is to optimize over the model's parameters while marginalizing all the hidden variables. MMAP problems also arise naturally in the context of decision-making under uncertainty, where the goal is to find a decision (optimization) that performs well on average across multiple probabilistic scenarios (averaging).

The Marginal MAP problem is known to be NP^{PP}-complete [18], which is commonly believed to be harder than both MAP inference (NP-hard) and marginal inference (#P-complete). As supporting evidence, MMAP problems are NP-hard even on tree structured probabilistic graphical models [13]. Aside from attempts to solve MMAP problems exactly [17, 15, 14, 16], previous approximate approaches fall into two categories, in general. The core idea of approaches in both categories is

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to effectively approximate the intractable marginalization, which often involves averaging over an exponentially large number of scenarios. One class of approaches [13, 11, 19, 12] use variational forms to represent the intractable sum. Then the entire problem can be solved with message passing algorithms, which correspond to searching for the best variational approximation in an iterative manner. As another family of approaches, Sample Average Approximation (SAA) [20, 21] uses a fixed set of samples to represent the intractable sum, which then transforms the entire problem into a restricted optimization, only considering a finite number of samples. Both approaches treat the optimization and marginalizing components separately. However, we will show that by solving these two tasks in an integrated manner, we can obtain significant computational benefits.

Ermon et al. [8, 9] recently proposed an alternative approach to approximate intractable counting problems. Their key idea is a mechanism to transform a counting problem into a series of optimization problems, each corresponding to the original problem subject to randomly generated XOR constraints. Based on this mechanism, they developed an algorithm providing a constant-factor approximation to the counting (marginalization) problem.

We propose a novel algorithm, called `XOR_MMAP`, which approximates the intractable sum with a series of optimization problems, which in turn are folded into the global optimization task. Therefore, we effectively reduce the original MMAP inference to *a single joint optimization* of polynomial size of the original problem.

We show that `XOR_MMAP` provides a constant factor approximation to the Marginal MAP problem. Our approach also provides upper and lower bounds on the final result. The quality of the bounds can be improved incrementally with increased computational effort.

We evaluate our algorithm on unweighted SAT instances and on weighted Markov Random Field models, comparing our algorithm with variational methods, as well as sample average approximation. We also show the effectiveness of our algorithm on applications in computer vision with deep neural networks and in computational sustainability. Our sustainability application shows how MMAP problems are also found in scenarios of searching for optimal policy interventions to maximize the outcomes of probabilistic models. As a first example, we consider a network design application to maximize the spread of cascades [20], which include modeling animal movements or information diffusion in social networks. In this setting, the marginals of a probabilistic decision model represent the probabilities for a cascade to reach certain target states (averaging), and the overall network design problem is to make optimal policy interventions on the network structure to maximize the spread of the cascade (optimization). As a second example, in a crowdsourcing domain, probabilistic models are used to model people's behavior. The organizer would like to find an optimal incentive mechanism (optimization) to steer people's effort towards crucial tasks, taking into account the probabilistic behavioral model (averaging) [22].

We show that `XOR_MMAP` is able to find considerably better solutions than those found by previous methods, as well as provide tighter bounds.

2 Preliminaries

Problem Definition Let $\mathcal{A} = \{0,1\}^m$ be the set of all possible assignments to binary variables $a_1, \ldots, a_m$ and $\mathcal{X} = \{0,1\}^n$ be the set of assignments to binary variables $x_1, \ldots, x_n$. Let $w(x, a) : \mathcal{X} \times \mathcal{A} \to \mathbb{R}^+$ be a function that maps every assignment to a non-negative value. Typical queries over a probabilistic model include the *maximization* task, which requires the computation of $\max_{a \in \mathcal{A}} w(a)$, and the *marginal inference* task $\sum_{x \in \mathcal{X}} w(x)$, which sums over $\mathcal{X}$.

Arising naturally from many machine learning applications, the following *Marginal Maximum A Posteriori* (Marginal MAP) problem is a joint inference task, which combines the two aforementioned inference tasks:

$$\max_{a \in \mathcal{A}} \sum_{x \in \mathcal{X}} w(x, a). \tag{1}$$

We consider the case where the counting problem $\sum_{x \in \mathcal{X}} w(x, a)$ and the maximization problem $\max_{a \in \mathcal{A}} \#w(a)$ are defined over sets of exponential size, therefore both are intractable in general.

Counting by Hashing and Optimization Our approach is based on a recent theoretical result that transforms a counting problem to a series of optimization problems [8, 9, 2, 1]. A family of functions $\mathcal{H} = \{h : \{0,1\}^n \to \{0,1\}^k\}$ is said to be *pairwise independent* if the following two conditions

Algorithm 1: `XOR_Binary`($w : \mathcal{A} \times \mathcal{X} \to \{0, 1\}$, a_0, k)

Sample function $h_k : \mathcal{X} \to \{0, 1\}^k$ from a pair-wise independent function family;
Query an NP Oracle on whether
$\mathcal{W}(a_0, h_k) = \{x \in \mathcal{X} : w(a_0, x) = 1, h_k(x) = \mathbf{0}\}$ is empty;
Return **true** if $\mathcal{W}(a_0, h_k) \neq \emptyset$, otherwise return **false**.

hold for any function h randomly chosen from the family $\mathcal{H}$: (1) $\forall x \in \{0, 1\}^n$, the random variable $h(x)$ is uniformly distributed in $\{0, 1\}^k$ and (2) $\forall x_1, x_2 \in \{0, 1\}^n$, $x_1 \neq x_2$, the random variables $h(x_1)$ and $h(x_2)$ are independent.

We sample matrices $A \in \{0, 1\}^{k \times n}$ and vector $b \in \{0, 1\}^k$ uniformly at random to form the function family $\mathcal{H}_{A,b} = \{h_{A,b} : h_{A,b}(x) = Ax + b \bmod 2\}$. It is possible to show that $\mathcal{H}_{A,b}$ is pairwise independent [8, 9]. Notice that in this case, each function $h_{A,b}(x) = Ax + b \bmod 2$ corresponds to k parity constraints. One useful way to think about pairwise independent functions is to imagine them as functions that randomly project elements in $\{0, 1\}^n$ into 2^k buckets. Define $B_h(g) = \{x \in \{0, 1\}^n : h_{A,b}(x) = g\}$ to be a "bucket" that includes all elements in $\{0, 1\}^n$ whose mapped value $h_{A,b}(x)$ is vector g ($g \in \{0, 1\}^k$). Intuitively, if we randomly sample a function $h_{A,b}$ from a pairwise independent family, then we get the following: $x \in \{0, 1\}^n$ has an equal probability to be in any bucket $B(g)$, and the bucket locations of any two different elements x, y are independent.

3 XOR_MMAP Algorithm

3.1 Binary Case

We first solve the Marginal MAP problem for the binary case, in which the function $w : \mathcal{A} \times \mathcal{X} \to \{0, 1\}$ outputs either 0 or 1. We will extend the result to the weighted case in the next section. Since $a \in \mathcal{A}$ often represent decision variables when MMAP problems are used in decision making, we call a fixed assignment to vector $a = a_0$ a "solution strategy". To simplify the notation, we use $\mathcal{W}(a_0)$ to represent the set $\{x \in \mathcal{X} : w(a_0, x) = 1\}$, and use $\mathcal{W}(a_0, h_k)$ to represent the set $\{x \in \mathcal{X} : w(a_0, x) = 1 \text{ and } h_k(x) = \mathbf{0}\}$, in which h_k is sampled from a pairwise independent function family that maps $\mathcal{X}$ to $\{0, 1\}^k$. We write $\#w(a_0)$ as shorthand for the count $|\{x \in \mathcal{X} : w(a_0, x) = 1\}| = \sum_{x \in \mathcal{X}} w(a_0, x)$. Our algorithm depends on the following result:

Theorem 3.1. *(Ermon et. al.[8]) For a fixed solution strategy $a_0 \in \mathcal{A}$,*

- *Suppose $\#w(a_0) \geq 2^{k_0}$, then for any $k \leq k_0$, with probability $1 - \frac{2^c}{(2^c-1)^2}$, Algorithm* `XOR_Binary`*($w, a_0, k - c$)=**true**.*
- *Suppose $\#w(a_0) < 2^{k_0}$, then for any $k \geq k_0$, with probability $1 - \frac{2^c}{(2^c-1)^2}$, Algorithm* `XOR_Binary`*($w, a_0, k + c$)=**false**.*

To understand Theorem 3.1 intuitively, we can think of h_k as a function that maps every element in set $\mathcal{W}(a_0)$ into 2^k buckets. Because h_k comes from a pairwise independent function family, each element in $\mathcal{W}(a_0)$ will have an equal probability to be in any one of the 2^k buckets, and the buckets in which any two elements end up are mutually independent. Suppose the count of solutions for a fixed strategy $\#w(a_0)$ is 2^{k_0}, then with high probability, there will be at least one element located in a randomly selected bucket if the number of buckets 2^k is less than 2^{k_0}. Otherwise, with high probability there will be no element in a randomly selected bucket.

Theorem 3.1 provides us with a way to obtain a rough count on $\#w(a_0)$ via a series of tests on whether $\mathcal{W}(a_0, h_k)$ is empty, subject to extra parity functions h_k. This transforms a counting problem to a series of NP queries, which can also be thought of as optimization queries. This transformation is extremely helpful for the Marginal MAP problem. As noted earlier, the main challenge for the marginal MAP problem is the intractable sum embedded in the maximization. Nevertheless, the whole problem can be re-written as a single optimization if the intractable sum can be approximated well by solving an optimization problem over the same domain.

We therefore design Algorithm `XOR_MMAP`, which is able to provide a constant factor approximation to the Marginal MAP problem. The whole algorithm is shown in Algorithm 3. In its main procedure

Algorithm 2: `XOR_K`($w : \mathcal{A} \times \mathcal{X} \to \{0,1\}, k, T$)

Sample T pair-wise independent hash functions
$h_k^{(1)}, h_k^{(2)}, \ldots, h_k^{(T)} : \mathcal{X} \to \{0,1\}^k$;
Query Oracle

$$\max_{a \in \mathcal{A}, x^{(i)} \in \mathcal{X}} \sum_{i=1}^{T} w(a, x^{(i)}) \quad \text{s.t.} \quad h_k^{(i)}(x^{(i)}) = \mathbf{0}, i = 1, \ldots, T. \tag{2}$$

Return **true** if the max value is larger than $\lceil T/2 \rceil$, otherwise return **false**.

Algorithm 3: `XOR_MMAP`($w : \mathcal{A} \times \mathcal{X} \to \{0,1\}$,$n = \log_2 |\mathcal{X}|$,$m = \log_2 |\mathcal{A}|$,$T$)

$k = n$;
while $k > 0$ **do**
  if `XOR_K`(w, k, T) **then**
    Return 2^k;
  end
  $k \leftarrow k - 1$;
end
Return 1;

`XOR_K`, the algorithm transforms the Marginal MAP problem into an optimization over the sum of T replicates of the original function w. Here, $x^{(i)} \in \mathcal{X}$ is a replicate of the original x, and $w(a, x^{(i)})$ is the original function w but takes $x^{(i)}$ as one of the inputs. All replicates share common input a. In addition, each replicate is subject to an independent set of parity constraints on $x^{(i)}$. Theorem 3.2 states that `XOR_MMAP` provides a constant-factor approximation to the Marginal MAP problem:

Theorem 3.2. *For $T \geq \frac{m \ln 2 + \ln(n/\delta)}{\alpha^*(c)}$, with probability $1 - \delta$, `XOR_MMAP`$(w, \log_2 |\mathcal{X}|, \log_2 |\mathcal{A}|, T)$ outputs a 2^{2c}-approximation to the Marginal MAP problem: $\max_{a \in \mathcal{A}} \#w(a)$. $\alpha^*(c)$ is a constant.*

Let us first understand the theorem in an intuitive way. Without losing generality, suppose the optimal value $\max_{a \in \mathcal{A}} \#w(a) = 2^{k_0}$. Denote a^* as the optimal solution, ie, $\#w(a^*) = 2^{k_0}$. According to Theorem 3.1, the set $\mathcal{W}(a^*, h_k)$ has a high probability to be non-empty, for any function h_k that contains $k < k_0$ parity constraints. In this case, the optimization problem $\max_{x^{(i)} \in \mathcal{X}, h_k^{(i)}(x^{(i)}) = \mathbf{0}} w(a^*, x^{(i)})$ for one replicate $x^{(i)}$ almost always returns 1. Because $h_k^{(i)}$ $(i = 1 \ldots T)$ are sampled independently, the sum $\sum_{i=1}^{T} w(a^*, x^{(i)})$ is likely to be larger than $\lceil T/2 \rceil$, since each term in the sum is likely to be 1 (under the fixed a^*). Furthermore, since `XOR_K` maximizes this sum over all possible strategies $a \in \mathcal{A}$, the sum it finds will be at least as good as the one attained at a^*, which is already over $\lceil T/2 \rceil$. Therefore, we conclude that when $k < k_0$, `XOR_K` will return `true` with high probability.

We can develop similar arguments to conclude that `XOR_K` will return **false** with high probability when more than k_0 XOR constraints are added. Notice that replications and an additional union bound argument are necessary to establish the probabilistic guarantee in this case. As a counter-example, suppose function $w(x, a) = 1$ if and only if $x = a$, otherwise $w(x, a) = 0$ ($m = n$ in this case). If we set the number of replicates $T = 1$, then `XOR_K` will almost always return 1 when $k < n$, which suggests that there are 2^n solutions to the MMAP problem. Nevertheless, in this case the true optimal value of $\max_x \#w(x, a)$ is 1, which is far away from 2^n. This suggests that at least two replicates are needed.

Lemma 3.3. *For $T \geq \frac{\ln 2 \cdot m + \ln(n/\delta)}{\alpha^*(c)}$, procedure `XOR_K`(w,k,T) satisfies:*

- *Suppose $\exists a^* \in \mathcal{A}$, s.t. $\#w(a^*) \geq 2^k$, then with probability $1 - \frac{\delta}{n 2^m}$, `XOR_K`$(w, k - c, T)$ returns* `true`.
- *Suppose $\forall a_0 \in \mathcal{A}$, s.t. $\#w(a_0) < 2^k$, then with probability $1 - \frac{\delta}{n}$, `XOR_K`$(w, k + c, T)$ returns* **false**.

Proof. **Claim 1:** If there exists such a^* satisfying $\#w(a^*) \geq 2^k$, pick $a_0 = a^*$. Let $X^{(i)}(a_0) = \max_{x^{(i)} \in \mathcal{X}, h_{k-c}^{(i)}(x^{(i)}) = \mathbf{0}} w(a_0, x^{(i)})$, for $i = 1 \ldots, T$. From Theorem 3.1, $X^{(i)}(a_0) = 1$ holds with probability $1 - \frac{2^c}{(2^c - 1)^2}$. Let $\alpha^*(c) = D(\frac{1}{2} \| \frac{2^c}{(2^c-1)^2})$. By Chernoff bound, we have

$$\Pr\left[\max_{a \in \mathcal{A}} \sum_{i=1}^{T} X^{(i)}(a) \leq T/2\right] \leq \Pr\left[\sum_{i=1}^{T} X^{(i)}(a_0) \leq T/2\right] \leq e^{-D(\frac{1}{2} \| \frac{2^c}{(2^c-1)^2})T} = e^{-\alpha^*(c)T}, \tag{3}$$

where

$$D\left(\frac{1}{2} \| \frac{2^c}{(2^c - 1)^2}\right) = 2\ln(2^c - 1) - \ln 2 - \frac{1}{2}\ln(2^c) - \frac{1}{2}\ln((2^c - 1)^2 - 2^c) \geq (\frac{c}{2} - 2)\ln 2.$$

For $T \geq \frac{\ln 2 \cdot m + \ln(n/\delta)}{\alpha^*(c)}$, we have $e^{-\alpha^*(c)T} \leq \frac{\delta}{n2^m}$. Thus, with probability $1 - \frac{\delta}{n2^m}$, we have $\max_{a \in \mathcal{A}} \sum_{i=1}^{T} X^{(i)}(a) > T/2$, which implies that `XOR_K`$(w, k-c, T)$ returns $\mathbf{true}$.

Claim 2: The proof is almost the same as Claim 1, except that we need to use a union bound to let the property hold for all $a \in \mathcal{A}$ simultaneously. As a result, the success probability will be $1 - \frac{\delta}{n}$ instead of $1 - \frac{\delta}{n2^m}$. The proof is left to supplementary materials. □

Proof. (Theorem 3.2) With probability $1 - n\frac{\delta}{n} = 1 - \delta$, the output of n calls of `XOR_K`(w, k, T) (with different $k = 1 \dots n$) all satisfy the two claims in Lemma 3.3 simultaneously. Suppose $\max_{a \in \mathcal{A}} \#w(a) \in [2^{k_0}, 2^{k_0+1})$, we have (i) $\forall k \geq k_0 + c + 1$, `XOR_K`$(w, k, T)$ returns **false**, (ii) $\forall k \leq k_0 - c$, `XOR_K`(w, k, T) returns $\mathbf{true}$. Therefore, with probability $1 - \delta$, the output of `XOR_MMAP` is guaranteed to be among $2^{k_0 - c}$ and $2^{k_0 + c}$. □

The approximation bound in Theorem 3.2 is a worst-case guarantee. We can obtain a tight bound (e.g. 16-approx) with a large number of T replicates. Nevertheless, we keep a small T, therefore a loose bound, in our experiments, after trading between the formal guarantee and the empirical complexity. In practice, our method performs well, even with loose bounds. Moreover, `XOR_K` procedures with different input k are not uniformly hard. We therefore can run them in parallel. We can obtain a looser bound at any given time, based on all completed `XOR_K` procedures. Finally, if we have access to a polynomial approximation algorithm for the optimization problem in `XOR_K`, we can propagate this bound through the analysis, and again get a guaranteed bound, albeit looser for the MMAP problem.

Reduce the Number of Replicates We further develop a few variants of `XOR_MMAP` in the supplementary materials to reduce the number of replicates, as well as the number of calls to the `XOR_K` procedure, while preserving the same approximation bound.

Implementation We solve the optimization problem in `XOR_K` using Mixed Integer Programming (MIP). Without losing generality, we assume $w(a, x)$ is an indicator variable, which is 1 iff (a, x) satisfies constraints represented in Conjunctive Normal Form (CNF). We introduce extra variables to represent the sum $\sum_i w(a, x^{(i)})$ which is left in the supplementary materials. The XORs in Equation 2 are encoded as MIP constraints using the Yannakakis encoding, similar as in [7].

3.2 Extension to the Weighted Case

In this section, we study the more general case, where $w(a, x)$ takes non-negative real numbers instead of integers in $\{0, 1\}$. Unlike in [8], we choose to build our proof from the unweighted case because it can effectively avoid modeling the median of an array of numbers [6], which is difficult to encode in integer programming. We noticed recent work [4]. It is related but different from our approach. Let $w : \mathcal{A} \times \mathcal{X} \to \mathbb{R}^+$, and $M = \max_{a,x} w(a, x)$.

Definition 3.4. *We define the embedding $\mathcal{S}_a(w, l)$ of $\mathcal{X}$ in $\mathcal{X} \times \{0, 1\}^l$ as:*

$$\mathcal{S}_a(w, l) = \left\{ (x, y) | \forall 1 \leq i \leq l, \frac{w(a, x)}{M} \leq \frac{2^{i-1}}{2^l} \Rightarrow y_i = 0 \right\}. \quad (4)$$

Lemma 3.5. *Let $w'_l(a, x, y)$ be an indicator variable which is 1 if and only if (x, y) is in $\mathcal{S}_a(w, l)$, i.e., $w'_l(a, x, y) = \mathbf{1}_{(x,y) \in \mathcal{S}_a(w,l)}$. We claim that*

$$\max_a \sum_x w(a, x) \leq \frac{M}{2^l} \max_a \sum_{(x,y)} w'_l(a, x, y) \leq 2 \max_a \sum_x w(a, x) + M 2^{n-l}.^2 \quad (5)$$

Proof. Define $S_a(w, l, x_0)$ as the set of (x, y) pairs within the set $S_a(w, l)$ and $x = x_0$, ie, $S_a(w, l, x_0) = \{(x, y) \in S_a(w, l) : x = x_0\}$. It is not hard to see that $\sum_{(x,y)} w'_l(a, x, y) = \sum_x |S_a(w, l, x)|$. In the following, first we are going to establish the relationship between $|S_a(w, l, x)|$ and $w(a, x)$. Then we use the result to show the relationship between $\sum_x |S_a(w, l, x)|$

[2] If w satisfy the property that $\min_{a,x} w(a, x) \geq 2^{-l-1} M$, we don't have the $M 2^{n-l}$ term.

and $\sum_x w(x,a)$. Case (i): If $w(a,x)$ is sandwiched between two exponential levels: $\frac{M}{2^l}2^{i-1} < w(a,x) \leq \frac{M}{2^l}2^i$ for $i \in \{0,1,\ldots,l\}$, according to Definition 3.4, for any $(x,y) \in S_a(w,l,x)$, we have $y_{i+1} = y_{i+2} = \ldots = y_l = 0$. This makes $|S_a(w,l,x)| = 2^i$, which further implies that

$$\frac{M}{2^l} \cdot \frac{|S_a(w,l,x)|}{2} < w(a,x) \leq \frac{M}{2^l} \cdot |S_a(w,l,x)|, \tag{6}$$

or equivalently,

$$w(a,x) \leq \frac{M}{2^l} \cdot |S_a(w,l,x)| < 2w(a,x). \tag{7}$$

Case (ii): If $w(a,x) \leq \frac{M}{2^{l+1}}$, we have $|S_a(w,l,x)| = 1$. In other words,

$$w(a,x) \leq 2w(a,x) \leq 2\frac{M}{2^{l+1}}|S_a(w,l,x)| = \frac{M}{2^l}|S_a(w,l,x)|. \tag{8}$$

Also, $M2^{-l}|S_a(w,l,x)| = M2^{-l} \leq 2w(a,x) + M2^{-l}$. Hence, the following bound holds in both cases (i) and (ii):

$$w(a,x) \leq \frac{M}{2^l}|S_a(w,l,x)| \leq 2w(a,x) + M2^{-l}. \tag{9}$$

The lemma holds by summing up over $\mathcal{X}$ and maximizing over $\mathcal{A}$ on all sides of Inequality 9. □

With the result of Lemma 3.5, we are ready to prove the following approximation result:

Theorem 3.6. *Suppose there is an algorithm that gives a c-approximation to solve the unweighted problem:* $\max_a \sum_{(x,y)} w'_l(a,x,y)$*, then we have a* $3c$*-approximation algorithm to solve the weighted Marginal MAP problem* $\max_a \sum_x w(a,x)$.

Proof. Let $l = n$ in Lemma 3.5. By definition $M = \max_{a,x} w(a,x) \leq \max_a \sum_x w(a,x)$, we have:

$$\max_a \sum_x w(a,x) \leq \frac{M}{2^l} \max_a \sum_{(x,y)} w'_l(a,x,y) \leq 2\max_a \sum_x w(a,x) + M \leq 3\max_a \sum_x w(a,x).$$

This is equivalent to:

$$\frac{1}{3} \cdot \frac{M}{2^l} \max_a \sum_{(x,y)} w'_l(a,x,y) \leq \max_a \sum_x w(a,x) \leq \frac{M}{2^l} \max_a \sum_{(x,y)} w'_l(a,x,y).$$

□

4 Experiments

We evaluate our proposed algorithm `XOR_MMAP` against two baselines – the Sample Average Approximation (SAA) [20] and the Mixed Loopy Belief Propagation (Mixed LBP) [13]. These two baselines are selected to represent the two most widely used classes of methods that approximate the embedded sum in MMAP problems in two different ways. SAA approximates the intractable sum with a finite number of samples, while the Mixed LBP uses a variational approximation. We obtained the Mixed LBP implementation from the author of [13] and we use their default parameter settings. Since Marginal MAP problems are in general very hard and there is currently no exact solver that scales to reasonably large instances, our main comparison is on the relative optimality gap: we first obtain the solution a_{method} for each approach. Then we compare the difference in objective function $\log \sum_{x\in\mathcal{X}} w(a_{method},x) - \log \sum_{x\in\mathcal{X}} w(a_{best},x)$, in which a_{best} is the best solution among the three methods. Clearly a better algorithm will find a vector a which yields a larger objective function. The counting problem under a fixed solution a is solved using an exact counter ACE [5], which is only used for comparing the results of different MMAP solvers.

Our first experiment is on unweighted random 2-SAT instances. Here, $w(a,x)$ is an indicator variable on whether the 2-SAT instance is satisfiable. The SAT instances have 60 variables, 20 of which are randomly selected to form set $\mathcal{A}$, and the remaining ones form set $\mathcal{X}$. The number of clauses varies from 1 to 70. For a fixed number of clauses, we randomly generate 20 instances, and the left panel of Figure 1 shows the median objective function $\sum_{x\in\mathcal{X}} w(a_{method},x)$ of the solutions found by the three approaches. We tune the constants of our `XOR_MMAP` so it gives a $2^{10} = 1024$-approximation ($2^{-5} \cdot sol \leq OPT \leq 2^5 \cdot sol$, $\delta = 10^{-3}$). The upper and lower bounds are shown in dashed lines. SAA uses 10,000 samples. On average, the running time of our algorithm is reasonable. When

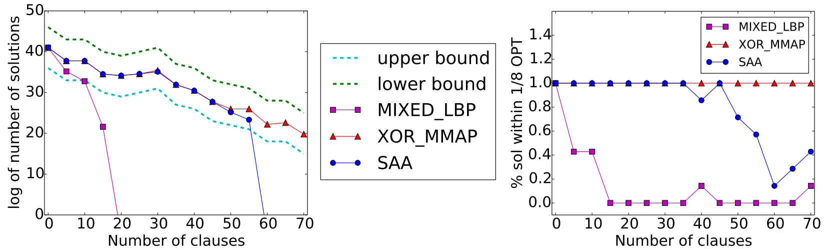

Figure 1: (Left) On median case, the solutions a_0 found by the proposed Algorithm XOR_MMAP have higher objective $\sum_{x \in \mathcal{X}} w(a_0, x)$ than the solutions found by SAA and Mixed LBP, on random 2-SAT instances with 60 variables and various number of clauses. Dashed lines represent the proved bounds from XOR_MMAP. (Right) The percentage of instances that each algorithm can find a solution that is at least 1/8 value of the best solutions among 3 algorithms, with different number of clauses.

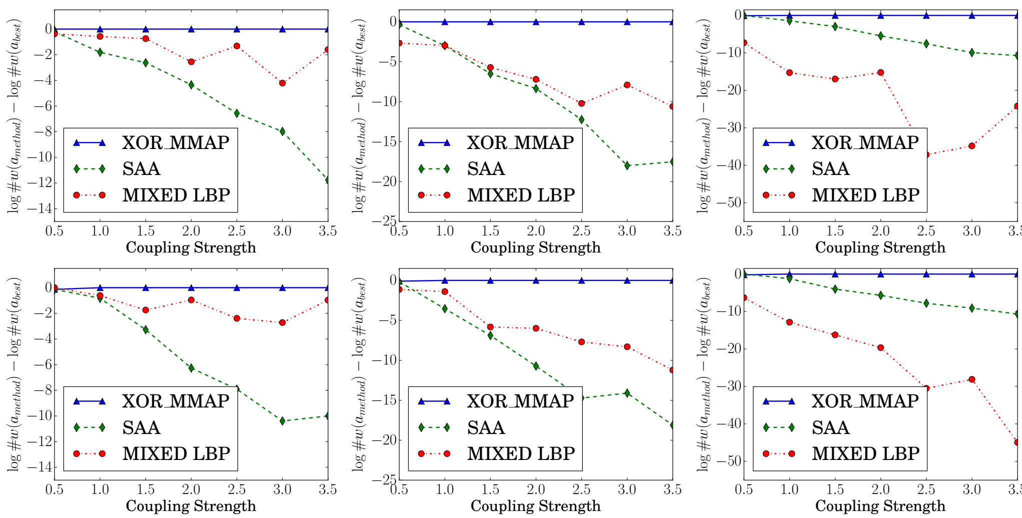

Figure 2: On median case, the solutions a_0 found by the proposed Algorithm XOR_MMAP are better than the solutions found by SAA and Mixed LBP, on weighted 12-by-12 Ising models with mixed coupling strength. (Up) Field strength 0.01. (Down) Field strength 0.1. (Left) 20% variables are randomly selected for maximization. (Mid) 50% for maximization. (Right) 80% for maximization.

enforcing the 1024-approximation bound, the median time for a single XOR_k procedure is in seconds, although we occasionally have long runs (no more than 30-minute timeout).

As we can see from the left panel of Figure 1, both Mixed LBP and SAA match the performance of our proposed XOR_MMAP on easy instances. However, as the number of clauses increases, their performance quickly deteriorates. In fact, for instances with more than 20 (60) clauses, typically the a vectors returned by Mixed LBP (SAA) do not yield non-zero solution values. Therefore we are not able to plot their performance beyond the two values. At the same time, our algorithm XOR_MMAP can still find a vector a yielding over 2^{20} solutions on larger instances with more than 60 clauses, while providing a 1024-approximation.

Next, we look at the performance of the three algorithms on weighted instances. Here, we set the number of replicates $T = 3$ for our algorithm XOR_MMAP, and we repeatedly start the algorithm with an increasing number of XOR constraints k, until it completes for all k or times out in an hour. For SAA, we use 1,000 samples, which is the largest we can use within the memory limit. All algorithms are given a one-hour time and a 4G memory limit.

The solutions found by XOR_MMAP are considerably better than the ones found by Mixed LBP and SAA on weighted instances. Figure 2 shows the performance of the three algorithms on 12-by-12 Ising models with mixed coupling strength, different field strengths and number of variables to form set $\mathcal{A}$. All values in the figure are median values across 20 instances (in $\log_{10}$). In all 6 cases in Figure 2, our algorithm XOR_MMAP is the best among the three approximate algorithms. In general, the difference in performance increases as the coupling strength increases. These instances are

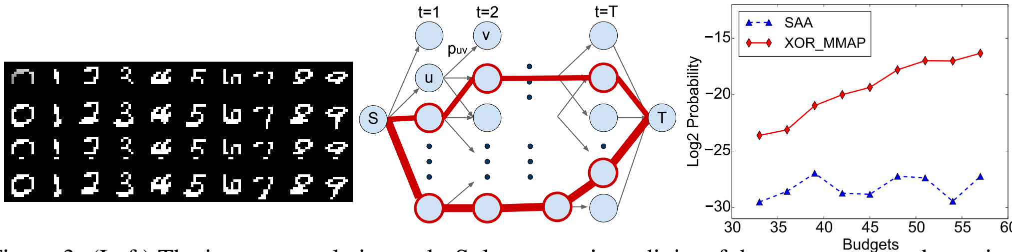

Figure 3: (Left) The image completion task. Solvers are given digits of the upper part as shown in the first row. Solvers need to complete the digits based on a two-layer deep belief network and the upper part. (2nd Row) completion given by `XOR_MMAP`. (3rd Row) SAA. (4th Row) Mixed Loopy Belief Propagation. (Middle) Graphical illustration of the network cascade problem. Red circles are nodes to purchase. Lines represent cascade probabilities. See main text. (Right) Our `XOR_MMAP` performs better than SAA on a set of network cascade benchmarks, with different budgets.

challenging for the state-of-the-art complete solvers. For example, the state-of-the-art exact solver AOBB with mini-bucket heuristics and moment matching [14] runs out of 4G memory on 60% of instances with 20% variables randomly selected as max variables. We also notice that the solution found by our `XOR_MMAP` is already close to the ground-truth. On smaller 10-by-10 Ising models which the exact AOBB solver can complete within the memory limit, the median difference between the log10 count of the solutions found by `XOR_MMAP` and those found by the exact solver is 0.3, while the differences between the solution values of `XOR_MMAP` against those of the Mixed BP or SAA are on the order of 10.

We also apply the Marginal MAP solver to an image completion task. We first learn a two-layer deep belief network [3, 10] from a 14-by-14 MNIST dataset. Then for a binary image that only contains the upper part of a digit, we ask the solver to complete the lower part, based on the learned model. This is a Marginal MAP task, since one needs to integrate over the states of the hidden variables, and query the most likely states of the lower part of the image. Figure 3 shows the result of a few digits. As we can see, SAA performs poorly. In most cases, it only manages to come up with a light dot for all 10 different digits. Mixed Loopy Belief Propagation and our proposed `XOR_MMAP` perform well. The good performance of Mixed LBP may be due to the fact that the weights on pairwise factors in the learned deep belief network are not very combinatorial.

Finally, we consider an application that applies decision-making into machine learning models. This network design application maximizes the spread of cascades in networks, which is important in the domain of social networks and computational sustainability. In this application, we are given a stochastic graph, in which the source node at time $t = 0$ is affected. For a node v at time t, it will be affected if one of its ancestor nodes at time $t - 1$ is affected, and the configuration of the edge connecting the two nodes is "on". An edge connecting node u and v has probability $p_{u,v}$ to be turned on. A node will not be affected if it is not purchased. Our goal is to purchase a set of nodes within a finite budget, so as to maximize the probability that the target node is affected. We refer the reader to [20] for more background knowledge. This application cannot be captured by graphical models due to global constraints. Therefore, we are not able to run mixed LBP on this problem. We consider a set of synthetic networks, and compare the performance of SAA and our `XOR_MMAP` with different budgets. As we can see from the right panel of Figure 3, the nodes that our `XOR_MMAP` decides to purchase result in higher probabilities of the target node being affected, compared to SAA. Each dot in the figure is the median value over 30 networks generated in a similar way.

5 Conclusion

We propose `XOR_MMAP`, a novel constant approximation algorithm to solve the Marginal MAP problem. Our approach represents the intractable counting subproblem with queries to NP oracles, subject to additional parity constraints. In our algorithm, the entire problem can be solved by a single optimization. We evaluate our approach on several machine learning and decision-making applications. We are able to show that `XOR_MMAP` outperforms several state-of-the-art Marginal MAP solvers. `XOR_MMAP` provides a new angle to solving the Marginal MAP problem, opening the door to new research directions and applications in real world domains.

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Appendix

Proof of Claim 2 of Lemma 3.3

The proof is almost the same as Claim 1, except that we need to use a union bound to let the property hold for all $a \in \mathcal{A}$ simultaneously. As a result, the success probability will be $1-\frac{\delta}{n}$ instead of $1-\frac{\delta}{n2^m}$. Let $Y_i(a) = \max_{x^{(i)}\in\mathcal{X}, h_{k+c}^{(i)}(x^{(i)})=\mathbf{0}} w(a_0, x^{(i)})$ for $i = 1, \dots, T$. If for all $a \in \mathcal{A}$, $\#w(a) < 2^k$, then for any fixed a_0,

$$\Pr\left[\sum_{i=1}^{T} Y_i(a_0) > \frac{T}{2}\right] \leq e^{-D\left(\frac{1}{2}\|\frac{2^c}{(2^c-1)^2}\right)T} \leq \frac{\delta}{n2^m}. \tag{10}$$

Using Union bound, we have:

$$\Pr\left[\max_{a\in\mathcal{A}} \sum_{i=1}^{T} Y_i(a) > \frac{T}{2}\right] \leq \Pr\left[\exists a \in \mathcal{A}, \sum_{i=1}^{T} Y_i(a) > \frac{T}{2}\right] \leq 2^m \frac{\delta}{n2^m} = \frac{\delta}{n}. \tag{11}$$

Therefore, w.p. $1-\frac{\delta}{n}$, we have $\forall a$, $\sum_{i=1}^{T} Y_i(a) \leq \frac{T}{2}$, which implies that `XOR_K` returns **false**.

Algorithm Variants to Reduce the Number of Replicates T

Algorithm 4: `XOR_K`+($w : \mathcal{A} \times \mathcal{X} \to \{0,1\}, k, T, q$)

Sample T pair-wise independent hash functions
$h_k^{(1)}, h_k^{(2)}, \dots, h_k^{(T)} : \mathcal{X} \to \{0,1\}^k$;
Query Oracle

$$\max_{a\in\mathcal{A}, x^{(i)}\in\mathcal{X}} \sum_{i=1}^{T} w(a, x^{(i)})$$
$$\textbf{s.t.} \quad h_k^{(i)}(x^{(i)}) = \mathbf{0}, \quad i = 1, \dots, T$$

Return **true** if the max value is no less than q, otherwise return **false**.

Algorithm 5: `XOR_MMAP`+($w : \mathcal{A} \times \mathcal{X} \to \{0,1\}$,$n = \log_2 |\mathcal{X}|$,$m = \log_2 |\mathcal{A}|$,$T$,$r$)

$k = n$;
while $k > 0$ **do**
  Run `XOR_K`(w, k, T) r times. Each time `XOR_K` returns either **true** or **false**;
  if *half independent trials return **true*** **then**
    Return 2^k;
  end
  $k \leftarrow k - 1$;
end
Return 1.

We develop a few variants of the original algorithm so as to reduce T – the number of replicates to guarantee a constant approximation bound.

Option 1: Use Binary Search in `XOR_MMAP`: Using binary search, we only need to check $\log_2 n$ outcomes (instead of n outcomes) of calls to function `XOR_K`(w, k, T) to nail down the correct k. Because our proof to Theorem 3.2 is relies on a probabilistic bound that all outcomes of the calls to `XOR_K`(w, k, T) satisfy the two claims of Lemma 3.3, with fewer checks to the outcomes of `XOR_K`(w, k, T), we can reduce the number of replicates T to $\lceil \frac{m \ln 2 + \ln \log_2 n + \ln(1/\delta)}{\alpha^*(c)} \rceil$, while preserving the same probabilistic bound.

Option 2: Run `XOR_K` Multiple Times: Algorithm `XOR_MMAP`+ achieves similar approximation bounds with smaller T, but at the price of running the `XOR_K` procedure $r > 1$ times.

Theorem 5.1. *Let* $p = \frac{2^c}{(2^c-1)^2}$. *For* $T \geq \frac{m \ln 2 + \ln \frac{1}{p}}{\alpha^*(c)}$, $r \geq \frac{\ln \frac{n}{\delta}}{D(\frac{1}{2}\|p)}$, *with probability* $1-\delta$, `XOR_MMAP`+*(w,n,m,T, r) outputs a* 2^{2c}*-approximation to the Marginal MAP Problem:* $\max_{a\in\mathcal{A}} \#w(a)$.

Proofsketch. By the same argument in the proof of 3.3, for $T \geq \frac{m \ln 2 + \ln \frac{1}{p}}{\alpha^*(c)}$, we have

- Suppose $\exists a^* \in \mathcal{A}$, s.t. $\#w(a^*) \geq 2^k$, then with probability $1 - \frac{p}{2^m}$, `XOR_K`($w, k-c, T$) returns **true**.

- Suppose $\forall a_0 \in \mathcal{A}$, $\#w(a_0) < 2^k$, then with probability $1-p$, XOR_K$(w, k+c, T)$ returns **false**.

Then we can use r independent trials to amplify the success probability from $1-p$ to $1-e^{-D(\frac{1}{2}\|p)\cdot r}$, which is larger than $1-\delta/n$. Then we apply union bound for all $a \in \mathcal{A}$, to guarantee a 2^{2c}-approximation with probability larger than $1-\delta$.

Option 3: Biased XOR_K **Procedure**: Furthermore, instead of returning $\mathbf{true}$ if at least $\lceil T/2 \rceil$ replicates are 1 in the procedure XOR_K, we develop XOR_K+ which returns $\mathbf{true}$ if no less than q replicates are 1. Then q becomes a parameter that we can tune. As a result, we can further reduce the number of trials T.

Lemma 5.2. *Procedure* XOR_K+(w, k, T, q) *satisfies the following properties:*

- *Suppose* $\exists a^* \in \mathcal{A}$, *s.t.* $\#w(a^*) \geq 2^k$, *then with probability* $1 - e^{-D(\frac{T-q+1}{T}\|\frac{2^c}{(2^c-1)^2})T}$, XOR_K+$(w, k-c, T, q)$ *returns* $\mathbf{true}$.

- *Suppose* $\forall a_0 \in \mathcal{A}$, $\#w(a_0) < 2^k$, *then with probability* $1 - 2^m e^{-D(\frac{q}{T}\|\frac{2^c}{(2^c-1)^2})T}$, XOR_K+$(w, k+c, T, q)$ *returns* **false**.

Proofsketch. Let $X^{(i)}(a)$ and $Y^{(i)}(a)$ be defined in the same way as in the proof of Lemma 3.3. Similarly we have

$$\Pr\left[\max_{a\in\mathcal{A}} \sum_{i=1}^{T} X^{(i)}(a) \leq q-1\right] \leq \Pr\left[\sum_{i=1}^{T} X^{(i)}(a^*) \leq q-1\right] \leq e^{-D(\frac{T-q+1}{T}\|\frac{2^c}{(2^c-1)^2})T}, \quad (12)$$

and,

$$\Pr\left[\max_{a\in\mathcal{A}} \sum_{i=1}^{T} Y^{(i)}(a) \geq q\right] \leq \Pr\left[\forall a \in \mathcal{A}, \sum_{i=1}^{T} Y^{(i)}(a) \geq q\right] \leq 2^m e^{-D(\frac{q}{T}\|\frac{2^c}{(2^c-1)^2})T}. \quad (13)$$

Based on Lemma 5.2, we can reduce the number of independent trials T, by picking a q larger than $\frac{T}{2}$, which balances the right hand sides of (12) and (13). In other words, we pick $q^*(T)$ to minimize the max of the two values:

$$q^*(T) = \operatorname*{argmin}_{q > \frac{T}{2}} \max\{e^{-D(\frac{T-q+1}{T}\|\frac{2^c}{(2^c-1)^2})T}, 2^m e^{-D(\frac{q}{T}\|\frac{2^c}{(2^c-1)^2})T}\}. \quad (14)$$

The $q^*(T)$ picked in this way can further reduce the number of independent trials.

Represent $\max_{a,x^{(i)}} \sum_i w(a, x^{(i)})$ When the Unweighted $w(a, x^{(i)})$ Are Specified by CNF

The idea is to add extra binary variables for each replicate. Suppose $w(a, x^{(i)})$ is 1 if and only if the following CNF:

$$cl_{i,1} \wedge cl_{i,2} \ldots \wedge cl_{i,p}$$

is satisfiable. In this CNF, $cl_{i,j}$ ($j = 1, \ldots, p$) are clauses that range over variables $x^{(i)}$ and a. Introduce extra binary variable y_i for replicate $w(x^{(i)}, a)$. Then we can augment clause $cl_{i,j}$ to

$$cl_{i,j} \vee (y_i = 0),$$

and replace the global objective function from $\max_{a,x^{(i)}} \sum_i w(a, x^{(i)})$ to:

$$\max_{a,x^{(i)}} \sum_i y_i \quad \text{subject to} \quad (cl_{i,1} \vee (y_i = 0)) \wedge \ldots \wedge (cl_{i,p} \vee (y_i = 0)) \quad \forall i.$$

Similar encoding exists when we are solving $\max_{a,x^{(i)}} \sum_i w(a, x^{(i)})$ subject to extra parity constraints.