

## Homework 2

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**Homework guidelines:** You may work with other students, as long as (1) they have not yet solved the problem, (2) you write down the names of all other students with which you discussed the problem, and (3) you write up the solution on your own. No points will be deducted, no matter how many people you talk to, as long as you are honest. If you already knew the answer to one of the problems (call these "famous" problems), then let me know that in your solution writeup – it will not affect your score, but will help me in the future. It's ok to look up famous sums and inequalities that help you to solve the problem, but don't look up an entire solution.

The following problems are **NOT** to be turned in.

- Consider an algorithm that returns a *random satisfying assignment* to any given DNF with  $n$  variables and  $\text{poly}(n)$  clauses. Every satisfying assignment must be returned with non-zero probability (not necessarily uniform). Given an input DNF formula  $\phi$  on  $n$  variables, the algorithm must satisfy the following requirements:
  - Every satisfying assignment  $\{x_1, x_2, \dots, x_n\} \in \{0, 1\}^n$ , must have non-zero probability of being output (need not be uniform).
  - Assignments that do not satisfy  $\phi$ , have zero probability of being output

Does there exist such an algorithm that uses at most  $\sqrt{n}$  random bits?

- Suppose you are given  $n$  boxes, each containing between 1 and  $k$  balls, where  $n \gg k$ . However, you do not know the number of balls in each box. All you can do is pick one of the boxes, and count the number of balls inside (assume this takes  $O(1)$  time). The goal of this problem is to design an algorithm to choose an *uniformly random ball*.
  1. The naive algorithm of viewing each box uses  $\mathcal{O}(n)$  run-time. Show that this task can be performed with  $\mathcal{O}(k)$  expected run-time.
  2. What if counting the number of balls in a box that contains  $d$  balls, actually takes  $O(d)$  time, instead of  $\mathcal{O}(1)$ ? In this case, what is the best run-time you can achieve?

The following problems are to be turned in.

1. **(Pairwise independence)** A *pairwise independent* space on  $n$  variables is a subset  $S \subseteq \{-1, +1\}^n$  such that for every  $i \neq j \in \{1, \dots, n\}$ , if  $\mathbf{x}$  is uniformly-random element of  $S$  then  $(\mathbf{x}_i, \mathbf{x}_j)$  is a pair of independent bits each drawn uniformly from  $\{-1, +1\}$ . The size of the pairwise independent space is  $|S|$ .

- (a) In class, we stated without proof, a construction which generates  $n = 2^l - 1$  pairwise independent bits, from  $l = \log(n + 1)$  truly random bits<sup>1</sup>. In other words, this is a

<sup>1</sup>Note that we used  $\{0, 1\}$  random bits in class, and considered the *parity* of all  $n$  possible non-empty subsets. Here, we will use  $\{-1, +1\}$  random bits, and consider the *product* of the elements in all possible subsets. You can easily check that this leads to the same outcome when replacing 0 with  $-1$ .

pairwise independent space of size  $2^l = n + 1$ . Prove that the bits are indeed pairwise independent.

Any algorithm that generates  $n$  pairwise independent random bits, will sample from a pairwise independent space  $S = \{\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \dots, \mathbf{x}^{(s)}\}$ , where  $s = |S|$ .

Arrange the vectors in  $S$  into a matrix  $S$ , with rows corresponding to  $\mathbf{x}^{(i)}$ .

- (b) Interpret the condition of pairwise independence in terms of the columns of  $S$ . Using this, prove that  $S$  must contain at least  $n$  vectors (think about the rank of  $S$ ).
- (c) Show that this implies that construction is optimal, in the sense that every pairwise independent space on  $n$  variables, requires at least  $\log n$  truly random bits.

You can solve this part by assuming the statement of (b).

2. Let  $\{M_1, M_2, \dots, M_k\}$  be a collection of subsets of  $[n]$ .<sup>2</sup> Given a set  $S$  containing  $N$  integers, we randomly assign weights  $w_x \in \mathcal{R}$  to each  $x \in [n]$ . We also define the weight of  $M_i$  to be the sum of the weights of its elements i.e.  $w(M_i) = \sum_{x \in M_i} w_x$ . The goal of this problem is to prove that it is likely that there is only one minimum weight set. To clarify, a unique minimum weight  $M_i$  is one, such that, for every other  $M_j$ , we have  $w(M_j) > w(M_i)$ . We will prove that

$$\mathbb{P}[\text{There is a unique } w(M_i) \text{ of minimum weight}] \geq 1 - \frac{n}{|S|}.$$

The astonishing fact is that this holds, even if the collection of sets  $\{M_1, M_2, \dots, M_k\}$  comprises of all  $2^n$  subsets of  $[n]$ . We begin by defining the quantity  $\alpha(x)$  for all  $x \in [n]$ .

$$\alpha(x) = \min_{i \in [k], x \notin M_i} w(M_i) - \min_{i \in [k], x \in M_i} w(M_i \setminus \{x\})$$

Note that above, we use the set-minus notation  $M_i \setminus \{x\}$  to denote the set  $M_i$  with the element  $x$  removed. In other words,  $w(M_i \setminus \{x\}) = w(M_i) - w_x$ .

- (a) Calculate the probability (over the choice of weights) that  $\alpha(x)$  is equal to  $w(x)$  for a *specific*  $x \in [n]$ . Next, upper bound the probability that this happens for *some*  $x \in [n]$ . Specifically, show that:

$$\mathbb{P}[\exists x \text{ such that } \alpha(x) = w(x)] \leq \frac{n}{|S|}$$

- (b) Now, we show that it is unlikely to that two distinct  $M_j$  and  $M_l$  have the same minimum weight (compared to all other  $w(M_i)$  where  $i \in [k]$ ). Apply the result from part (a) for some suitable  $x$ , to obtain the main result:

$$\mathbb{P}[\text{There is a unique } w(M_i) \text{ of minimum weight}] \geq 1 - \frac{n}{|S|}.$$

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<sup>2</sup>This notation  $[n]$  stands for the set of integers  $\{1, 2, \dots, n\}$ .

3. **Parallel Perfect Matchings:** In class, we used PIT to check whether a bipartite graph  $G$  contains a perfect matching. In this problem, we will think about the problem of actually *finding* a perfect matching using PIT. The techniques developed in this problem can be used to show that a perfect matching can be computed quickly in parallel (though we will not work out all of the details).

- (a) *Reducing Search to Decision problems sequentially:* To begin, let us consider a black box algorithm  $\mathcal{A}$  (we don't know how the internals of  $\mathcal{A}$  work), that checks whether a given graph  $G$  contains a perfect matching not,

$$\mathcal{A}(G) = \begin{cases} 1, & \text{if } G \text{ contains a perfect matching.} \\ 0, & \text{otherwise,} \end{cases}$$

and runs in time  $T_{\mathcal{A}}^{seq}(G)$ . Use this to construct a sequential algorithm  $\mathcal{B}$ , that *finds* a perfect matching in time  $\mathcal{O}(m \cdot T_{\mathcal{A}}^{seq}(G))$ .

We recap the algorithm from class. Given a bipartite graph  $G = (L \cup R, E)$ , where  $|L| = |R| = n$ ,  $E \subseteq L \times R$  (all edges go between left and right set), and  $|E| = m$ , we constructed a  $n \times n$  matrix  $A$  with entries:

$$A_{u,v} = \begin{cases} X_{u,v}, & \text{if } (u,v) \in E \\ 0, & \text{otherwise} \end{cases}$$

Subsequently, for each  $(u,v) \in E$ , we assigned *random values* to variables  $X_{u,v} \leftarrow x_{u,v}$ , and evaluated the determinant of the resulting matrix:

$$\text{Det}(A) = \sum_{\sigma \text{ is a permutation of } [n]} \text{sign}(\sigma) \cdot \prod_{u \in L} A_{u,\sigma(u)}$$

- (b) In this part, we restrict our attention to the case that the graph  $G$  has *exactly one perfect matching*. Obtain an algorithm, that is given an oracle for determinant computations, and uses it to find this unique perfect matching, with the restriction that all calls to the determinant oracle must be made *simultaneously* (in parallel). Thus the parameters for each call to the determinant oracle cannot depend on any of the values returned from other calls to the determinant oracles.

Now, for every edge  $e = (u,v) \in E$ , we assign a *random integer weight*  $w_{u,v}$ , and define the weight of a matching to be the sum of the weights on all its edges. As we proved in the previous Problem 2, even if  $G$  contains many perfect matchings (there could be exponentially many), it probably contains only one of minimum weight.

- (c) If we assign values  $2^{w_{u,v}}$  to the variables  $X_{u,v}$ , what can you conclude about the value of the determinant? Specifically, if the weight of the minimum weight perfect matching is  $w^*$ , how does the value of the determinant relate to  $2^{w^*}$ ?
- (d) Does this property (from the previous part) still hold, if the random weights  $w_{u,v}$  result in more than one minimum weight perfect matching?

- (e) How can you detect whether a specific edge  $e$  is in the *minimum weight* perfect matching or not, using a single call to the determinant oracle?
- (f) Now, you are ready to put all of the pieces together, and present a *randomized* algorithm for finding a perfect matching, that makes all calls to the determinant oracle simultaneously.