15-496/859X: Computer Science Theory for the Information Age Spring 2012 Carnegie Mellon University V. Guruswami & R. Kannan

PROBLEM SET 4 SOLUTION by Yuan Zhou

1. Let B be the indicator variable for the event  $N > 0$ , i.e.  $B = 1$  when  $N > 0$  and  $B = 0$  when  $N = 0$ . It is easy to check that  $NB = N$ . By Cauchy-Schwartz, we have

$$
\mathbf{E}[N]^2 = \mathbf{E}[NB]^2 \le \mathbf{E}[N^2] \mathbf{E}[B^2],
$$

which implies that

$$
\Pr[N > 0] = \mathbf{E}[B^2] \ge \frac{\mathbf{E}[N]^2}{\mathbf{E}[N^2]}.
$$

2. (a) Fix a set of  $(2 + \epsilon) \log_2 n$  vertices, the probability that there is an edge between each two of them is at most

$$
2^{-((2+\epsilon)\log_2 n)((2+\epsilon)\log_2 n -1)/2} \leq 2^{-(2+\epsilon)\log_2^2 n}.
$$

Since there are  $\binom{n}{(2+\epsilon)}$  $\binom{n}{(2+\epsilon)\log_2 n} \leq \frac{2^{(2+\epsilon)\log_2^2 n}}{(2\log_2 n)!}$  such set of vertices. By a union bound, the probability that there exists a clique of size  $(2 + \epsilon) \log_2 n$  is at most

$$
2^{-(2+\epsilon)\log_2^2 n} \cdot \frac{2^{(2+\epsilon)\log_2^2 n}}{(2\log_2 n)!} \le \frac{1}{(2\log_2 n)!} = n^{-w(1)}.
$$

Therefore, with probability  $(1 - n^{-w(1)})$ , there is no clique of size  $(2 + \epsilon) \log_2 n$ .

(b) Set  $k = (2 - \epsilon) \log_2 n$  for notational convenience. Let  $N_i$  be the indicator variable for the event that the *i*-th subset of size k forms a clique.  $(1 \leq i \leq {n \choose k})$  $\binom{n}{k}$ ). Let  $N = \sum_i N_i$  be the number of cliques of size k. We also use the notation  $S_i$  to denote the *i*-th subset. By Problem 1, we know that

$$
\Pr[N>0] \ge \frac{\mathbf{E}[N]^2}{\mathbf{E}[N^2]}.
$$

We are going to lower bound  $Pr[N > 0]$  by estimating calculating  $\frac{E[N]^2}{E[N^2]}$  $\frac{\mathbf{E}[N]^2}{\mathbf{E}[N^2]}$ . For  $\mathbf{E}[N]^2$ , we have

$$
\mathbf{E}[N]^2 = \left(\sum_i \mathbf{E}[N_i]\right)^2 = \left(\binom{n}{k} 2^{-k(k-1)/2}\right)^2 = \binom{n}{k}^2 2^{-k(k-1)}.
$$

For  $E[N^2]$  we have

$$
\mathbf{E}[N^2] = \sum_{i,j} \mathbf{E}[N_i N_j] = \sum_i \sum_{t=0}^k \sum_{j:|S_i \cap S_j| = t} \mathbf{E}[N_i N_j].
$$

Now, let  $f(t) = \sum_{j:|S_i \cap S_j|=t} \mathbf{E}[N_i N_j]$  so that  $\mathbf{E}[N^2] = \binom{n}{k}$  $\binom{n}{k} \sum_{t=0}^{k} f(t)$ . We see that

$$
f(t) = {k \choose t} {n-k \choose k-t} 2^{-k(k-1)+t(t-1)/2}.
$$

In all, we have

$$
\frac{\mathbf{E}[N]^2}{\mathbf{E}[N^2]} = \frac{\binom{n}{k}^2 2^{-k(k-1)}}{\binom{n}{k} \sum_{t=0}^k \binom{k}{t} \binom{n-k}{k-t} 2^{-k(k-1)+t(t-1)/2}} = \frac{\binom{n}{k}}{\sum_{t=0}^k \binom{k}{t} \binom{n-k}{k-t} 2^{t(t-1)/2}}.
$$

Therefore,

$$
1 - \frac{\mathbf{E}[N]^2}{\mathbf{E}[N^2]}
$$
  
\n
$$
= \frac{\sum_{t=2}^k {k \choose t} {n-k \choose k-t} (2^{t(t-1)/2} - 1)}{\sum_{t=0}^k {k \choose t} {n-k \choose k-t} 2^{t(t-1)/2}} \quad \text{(since } {n \choose k} = \sum_{t=0}^k {k \choose t} {n-k \choose k-t})
$$
  
\n
$$
\leq \frac{\sum_{t=2}^k {k \choose t} {n-k \choose k-t} 2^{t(t-1)/2}}{\sum_{t=0}^k {k \choose t} {n-k \choose k-t} 2^{t(t-1)/2}} \quad \text{(again, by } {n \choose k} = \sum_{t=0}^k {k \choose t} {n-k \choose k-t})
$$
  
\n
$$
\leq k \cdot \frac{{k \choose t} {n-k \choose k-t} 2^{t(t-1)/2}}{{n \choose k}}|_{t=2}
$$

(by the fact given in the problem statement, for  $k < (2 - \epsilon) \log_2 n$ )

$$
\leq k \cdot \frac{k^4}{n^2} = o(1).
$$

- (c) Enumerate over all subsets of size  $(2 \epsilon) \log_2 n$  and check whether any of them forms a clique.
- (d) We start with a set  $S = \emptyset$  and  $T = [n]$ . We want to add vertices to S while keeping  $S$  a clique as the algorithm proceeds, and finally output  $S$ .  $T$  is to be maintained as the common neighbors of vertices in S. The algorithm repeats the following procedure, as long as  $T \neq \emptyset$ : choose an arbitrary vertex  $i \in T$ , move it to S, and remove all the vertices in  $T$  that are not connected to i. When this produce terminates, we see that  $S$ is always a clique.

It is easy to see that the algorithm runs in  $O(n^2)$  time for any graph. Now we are going to show that with high probability, S contains  $\Omega(\log n)$  vertices.

By a Chernoff bound, we see that for any  $|T| \ge \sqrt{n}$ , and any  $i \in T$ , the probability that *i* is connected to  $|T|/3$  vertices in T is at least  $1 - \exp(-\sqrt{n}/100)$ . Therefore, by a union bound, the probability that the algorithm proceeds for at least  $\log_3 \sqrt{n}$  steps is a union bound, the probability that the algorithm proceeds for at least  $\log_3 \sqrt{n}$  steps is<br>at least  $1 - (\log_3 \sqrt{n}) \exp(-\sqrt{n}/100) \ge 1 - \exp(-\sqrt{n}/200)$ . This also lower bounds the probability that  $|S| \ge \log_3 \sqrt{n}$ .

3. (a) The weak threshold is  $\Theta(1/n)$ . The probability that  $N(n, p)$  contains an even number is  $1 - (1 - p)^{n/2}$ . We see that when  $p = o(1/n)$ , this probability becomes  $1 - \exp(-o(1)) =$  $o(1)$ ; when  $p = \omega(1/n)$ , this probability becomes  $1 - \exp(-\omega(1)) = 1 - o(1)$ .

- (b) Since there are  $\Theta(n^2)$  triples  $(x, y, z)$  such that  $x + y = z$ , while each of these triples appears in  $N(n, p)$  with probability  $p^3$ , the expected number of these triples that appear in  $N(n,p)$  is  $\Theta(n^2/p^3)$ . For this number to be a constant, we need  $p^3 = \Theta(1/n^2)$ . Therefore, a reasonable guess for the threshold value would be  $\Theta(n^{-2/3})$ .
- 4. (a) Each assignment satisfies a random instance (with m) clauses with probability  $2^{-m}$ . Since there are  $2^n$  assignments, the expected number of satisfying assignments is  $2^{n-m}$ .
	- (b) By Markov inequality, we have

$$
\Pr[\mathcal{C}(n,m) \text{ satisfiable}] = \Pr[\text{#satisfying assignment for } \mathcal{C}(n,m) \ge 1] \le \mathbf{E}[\text{#satisfying assignment for } \mathcal{C}(n,m)] = 2^{n-m} = 2^{-\epsilon n} = o(1).
$$

(c) When the two variables are both from the k variables (where  $a$  and  $b$  are differ), or both from the rest  $n - k$  variables, the probability that both a and b satisfy the random clause is  $1/2$ . In other cases, a and b cannot simultaneously satisfy the random clause. Therefore, the overall probability is

$$
\frac{1}{2} \cdot \frac{{k \choose 2} + {n-k \choose 2}}{{n \choose 2}} = \frac{k(k-1) + (n-k)(n-k-1)}{2n(n-1)}.
$$

(d) Let  $N_i$  be the indicator variable that the *i*-th assignment satisfies the random assignment (for  $1 \leq i \leq 2^n$ ). We have

$$
\mathbf{E}[N^2] = \sum_{i} \sum_{j} \mathbf{E}[N_i N_j]
$$
  
= 
$$
\sum_{i} \sum_{k=0}^{n} \sum_{j:\text{Assignment } j \text{ and assignment } i \text{ differ at } k \text{ places}} \left(\frac{k(k-1) + (n-k)(n-k-1)}{2n(n-1)}\right)^m
$$
  
= 
$$
\sum_{i} \sum_{k=0}^{n} {n \choose k} \cdot \left(\frac{k(k-1) + (n-k)(n-k-1)}{2n(n-1)}\right)^m
$$
  
= 
$$
\sum_{k=0}^{n} 2^n {n \choose k} \cdot \left(\frac{k(k-1) + (n-k)(n-k-1)}{2n(n-1)}\right)^m.
$$

(e) (Proof sketch.) Given an NAE instance, we construct a corresponding constraint graph by creating a vertex for each variable, and connecting two vertices by an undirected edge when the two corresponding variables are involved in a same NAE clause. Now our proof goes by two steps.

Step 1. We are going to prove that when  $m = (1 - \epsilon)n$ . the constraint graph has only  $O(1)$  cycles with probability at least  $1/2$ . This can be done by a first moment method. Step 2. We prove the claim that if the constraint graph has only  $t$  cycles, then over the random choices of clause types (i.e. whether to put negation on the related literals), the NAE instance is satisfiable with probability  $2^{-O(t)}$ .

Therefore, with probability  $2^{-O(1)}$ , a random NAE instance is satisfiable (when  $m =$  $(1 - \epsilon)n$ .

5. (a) Consider the process that one starts from  $v$ , and each time visits the only next vertex of the current vertex (since each vertex has out-degree exactly 1), until a vertex is revisited.

 $r(v) = k$  if and only if the process above runs for  $k - 1$  times before a vertex is revisited. Since all the choices of out-going edges are independent, we have

$$
\Pr[r(v) = k] = \prod_{i=1}^{k-1} \left(1 - \frac{i}{n}\right) \cdot \frac{k}{n}.
$$

(b) Note that for any  $t$ ,

$$
\Pr[r(v) \ge t] = \sum_{k=t}^{n} \prod_{i=1}^{k-1} \left( 1 - \frac{i}{n} \right) \cdot \frac{k}{n}
$$
  
= 
$$
\left( \prod_{i=1}^{t-1} \left( 1 - \frac{i}{n} \right) \right) \left( \frac{t}{n} + \left( 1 - \frac{t}{n} \right) \left( \frac{t+1}{n} + \left( 1 - \frac{t+1}{n} \right) \left( \frac{t+2}{n} + \cdots \right) \right) \right)
$$
  
= 
$$
\prod_{i=1}^{t-1} \left( 1 - \frac{i}{n} \right).
$$

Therefore,

$$
\Pr[r(v) \le \sqrt{n}/10] = 1 - \Pr[r(v) \ge \sqrt{n}/10 + 1]
$$
  
=1 -  $\prod_{i=1}^{\sqrt{n}/10} \left(1 - \frac{i}{n}\right) \le 1 - \left(1 - \sum_{i=1}^{\sqrt{n}/10} \frac{i}{n}\right) = \frac{(\sqrt{n}/10)(\sqrt{n}/10 - 1)}{2n} \le \frac{1}{3},$ 

and

$$
\Pr[r(v) \ge 10\sqrt{n}] = \prod_{i=1}^{10\sqrt{n}-1} \left(1 - \frac{i}{n}\right) \le \prod_{i=\sqrt{n}}^{10\sqrt{n}-1} \left(1 - \frac{i}{n}\right) \le \left(1 - \frac{\sqrt{n}}{n}\right)^{9\sqrt{n}} \le \frac{1}{3}.
$$