

Class 11: Agenda, Questions, and Links

1 Announcements

- HW5 was due today, HW6 due next Wednesday!

2 Recap/Questions?

Any questions from the minilectures and/or the quiz (second moment method and LLL)?

3 Practice with the LLL

Recall the k -SAT problem. There are n variables x_1, \dots, x_n . We consider clauses that look like $(x_{i_1} \vee x_{i_2} \vee \overline{x_{i_3}} \vee \dots \vee x_{i_k})$; that is, a clause is the OR of k literals. **For today, assume that each clause has k distinct variables that appear in it.** We have a formula φ that is the AND of m clauses. We would like to know: is φ satisfiable? That is, is there a way to assign values to the variables x_1, x_2, \dots so that φ evaluates to TRUE?

Group Work

Suppose that each variable x_i is in at most t clauses, for some parameter t that will depend on k and that you'll work out in this problem. Apply the LLL to get a statement like the following:

Suppose that each variable is in at most t clauses of φ . Then φ is satisfiable.

(You should try to get t to be as large as possible. It's not hard to see that the statement above is true if, say, $t = 1$, but you should get a value of t that grows with k .)

Hint: Recall that to apply the LLL, you need to define a probability distribution and a set of "bad" events. We set up this example in the minilecture video, we just didn't work out the conclusion. In the set-up of the video, we considered the probability distribution to correspond to assigning TRUE/FALSE to each variable x_1, \dots, x_n independently with probability $1/2$ each, and we defined the bad event A_i to be the event that clause i is not satisfied.

Group Work: Solutions

We claim that if each variable is in at most $t \leq 2^{k-2}k$ clauses, then the formula is satisfiable. To see this, consider a uniformly random assignment to x_1, \dots, x_n (ie setting each

x_i to be TRUE/FALSE independently with probability $1/2$). Define events A_1, \dots, A_m where A_i is the indicator random variable of the i th clause NOT being satisfied. For a clause with k variables to not be satisfied, all k variables must take the “bad” assignment, and hence:

$$\Pr[A_i] = 1/2^k.$$

To apply the LLL, we now need to reason about the dependencies. To that end, we claim that A_i is mutually independent of the set of clauses whose variable are disjoint from the variables in clause i , namely the set

$$S_i = \{A_j : \text{vbl}(\text{clause}_i) \cap \text{vbl}(\text{clause}_j) = \emptyset\}.$$

Indeed, no matter the assignment to variables that occur in the clauses in S_i , since none appear in the i th clause, they can't alter the probability of A_i . Now we simply count up the number of events not in the set S_i : namely

$$[\#j \text{ such that } \text{vbl}(\text{clause}_i) \cap \text{vbl}(\text{clause}_j) \neq \emptyset] \leq kt,$$

since there are k variables in clause i , and each of them is in at most t other clauses.

To conclude, each A_i is mutually independent of all but $d = kt$ other events, and hence by the LLL with $d = kt$ and $p = 2^{-k}$, we have that $\Pr[\bigcap_i \text{not}(A_i)] \geq (1 - 2p)^m > 0$ provided $dp \leq 1/4$, hence we want $kt \cdot 2^{-k} \leq 1/4$, which implies that want $t \leq 2^{k-2}/k$.

To put some concrete numbers in here, if $k = 10$, then as long as each variable appears in at most $2^{10-8}/8 = 25.6$ clauses, then the formula is always satisfiable, no matter the number of variables of clauses!!! Of course, now the big question on your mind should be “*Its great that we know such formulas are satisfiable, but how do we FIND a satisfying assignment efficiently?*” We'll get to this in the next set of minilectures, on the “Constructive LLL”!!

3.1 More Practice with LLL and Mutual Independence

Consider a set of equations over variables x_1, \dots, x_n , where each equation has the form $a_1x_{i_1} + a_2x_{i_2} + \dots + a_rx_{i_r} \equiv a_{r+1} \pmod{17}$, for some r (that might vary from equation to equation) and set of coefficients $a_1, \dots, a_r \in \{1, 2, \dots, 16\}$, and $a_{r+1} \in \{0, \dots, 16\}$. Additionally, suppose that each variable, x_i , occurs in at most 4 equations.

Group Work

Prove that there exists an assignment to the variables such that *none* of the equations are satisfied.

Hint: Recall that because 17 is prime, for any $a \in \{1, \dots, 16\}$ and any $b \in \{0, \dots, 16\}$, the equation $ax \equiv b \pmod{17}$ has a unique solution for $x \in \{0, \dots, 16\}$.

Hint: It might be helpful to go back to the definition of mutual independence when

arguing about the value of d when applying the LLL.

Group Work: Solutions

Consider the distribution given by assigning each variable x_i a uniformly random value in the set $\{0, \dots, 16\}$. Define the event A_i to be the indicator random variable representing whether the i th equation is satisfied. First, we claim that $\Pr[A_i] = 1/17$. To see this, consider an equation involving r variables, and note that whatever the assignment to the first $r - 1$ variables, over the randomness of assigning the r th variable, the probability the equation holds is $1/17$. This is true because after the first $r - 1$ variables are set, the equation becomes $a_r x_r \equiv a' \pmod{17}$, for some $a_r \neq 0$, and some value of a' , and this equation has a unique solution modulo 17 (because 17 is prime...).

We now argue that each A_i is mutually independent of all but 4 other equations. This might seem counterintuitive, because there could be a large number of other equations sharing variables with each A_i . The argument will critically leverage the definition of mutual independence. Consider one of the equations: $a_1 x_{i_1} + a_2 x_{i_2} + \dots + a_r x_{i_r} \equiv a_{r+1} \pmod{17}$, and consider the set of equations S that do not include variable x_{i_1} . [By assumption, there are at most 4 equations not in set S .] We claim that the event that the equation in question is satisfied is mutually independent from all the events corresponding to equations in set S . To see why this holds, recall that for any fixed assignment to all variables except x_{i_1} , with respect to randomly assigning x_{i_1} , the probability the equation in question is satisfied is exactly $1/17$. Because the equations in set S do not involve x_{i_1} , conditioning on any outcomes for those equations does not change the distribution of x_{i_1} , and hence the probability the equation is satisfied is still exactly $1/17$ even when conditioning on any subset of outcomes of equations in S . This is precisely the definition of mutual independence.

To apply the LLL, we are hoping that $d \Pr[A_i] < 1/4$, which holds because $d = 4$, and $\Pr[A_i] = 1/17$.

4 Practice with the second moment method

In a graph $G = (V, E)$, say that a vertex v is **isolated** if it has no neighboring vertices.

Group Work

Let $G \sim G_{n,p}$ be a random graph where each edge is present independently with probability p , where $p = \frac{c \ln n}{n}$ for some constant $0 < c < 1$.

1. Use the Second Moment Method to show that, with probability at least $1 - o(1)$, there is some isolated vertex in G .

For this exercise, feel free to use the approximation $e^{-x} \approx 1 - x$ when x is small

without worrying about it.

Hint: Consider the random variable X that is the number of isolated vertices in G , and recall that the second moment method says that $\Pr[X = 0] \leq \frac{\text{Var}[X]}{(\mathbb{E}[X])^2}$.

Hint: When computing the variance of X , you may want to consider the following question: given two distinct vertices u, v of G , what is the probability that both u and v are isolated?

2. If you finish the previous part, what statement can you make about the case that $c > 1$?

Group Work: Solutions

1. First, let's make sure that the expected number of isolated vertices is reasonably large for $p = \frac{c \log n}{n}$ with $c < 1$. We do this by linearity of expectation:

$$\mathbb{E}[\# \text{ isolated vertices}] = n \Pr[v \text{ is isolated}] = n(1-p)^{n-1} \approx ne^{-p(n-1)} = n \cdot n^{-c(1-1/n)} \approx n^{1-c}.$$

When $c < 1$, $n^{1-c} \gg 1$, things are looking good in expectation.

To apply the second moment method, we need a bound on the variance of the number of isolated vertices. Letting X denote the number of isolated vertices, we have the following:

$$\begin{aligned} \text{Var}[X] &= \mathbb{E}[X^2] - (\mathbb{E}[X])^2 \\ &= \mathbb{E}\left[\sum_{u,v} \Pr[u \text{ and } v \text{ isolated}]\right] - (\mathbb{E}[X])^2 \\ &= \mathbb{E}\left[\sum_u \Pr[u \text{ and } u \text{ isolated}]\right] + \mathbb{E}\left[\sum_{u \neq v} \Pr[u \text{ and } v \text{ isolated}]\right] - (\mathbb{E}[X])^2 \\ &\approx n^{1-c} + n(n-1)(1-p)^{2n-3} - (\mathbb{E}[X])^2. \end{aligned}$$

In the above, we used the fact that for each of the $n(n-1)$ choices of $u \neq v$, for both to be isolated, all of the $2n-3$ potential edges connected to either of them must be absent. Now we just simplify: $(1-p)^{2n-3} \approx e^{-(2n-3)p} = n^{-c(2-3/n)} \approx n^{-2c}$.

$$n^{1-c} + n(n-1)(1-p)^{2n-3} - (\mathbb{E}[X])^2 \approx n^{1-c} + n^{2(1-c)} - (n^{1-c})^2 = n^{1-c}.$$

So, to conclude, we have

$$\Pr[X = 0] \leq \frac{\text{Var}[X]}{(\mathbb{E}[X])^2} \approx \frac{n^{1-c}}{n^{2(1-c)}} = n^{c-1}.$$

Hence for $c < 1$, this probability is $o(1)$.

2. In the case that $c > 1$, the expected number of isolated vertices is roughly $n^{1-c} \ll 1$, and hence by Markov's inequality, the probability that there are any isolated vertices (ie the probability that the number of isolated vertices is at least 1), is bounded by $\frac{\mathbb{E}[X]}{1} \approx n^{1-c} \ll 1$.