Randomness and Computation

or, “Randomized Algorithms”

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The Lovász Local lemma

In our work so far on the probabilistic method, we have often been concerned with avoiding “bad events”, our goal to prove existence of some structure that manages to avoid all the bad events.

Life (“life” meaning the proof of these results) would be easier if we were dealing with collections of bad events which were independent.

Recall that the collection of events $E_1, \ldots, E_N$ are *mutually independent* if for every $\{F_i : 1 \leq i \leq N\}$ such that F_i is either E_i or $\overline{E_i}$,

$$\Pr[\cap_{i=1}^N F_i] = \prod_{i=1}^N \Pr[F_i].$$

With mutual independence, we would only need the condition $E_i \in (0, 1)$ for all i to guarantee a structure without any bad events.

Unfortunately usually (monochromatic K_k, 4-cliques in $G_{n,p}$) we have to deal with situations where the bad events may be *dependent* (eg two vertex subsets f, f' each of size 4, may intersect).

The Lovász Local lemma

Definition (6.1)

A *dependency graph* for a set of events $E_1, \ldots, E_N$ is a graph $G = (V, E)$ such that $V = \{1, \ldots, N\}$ and for each $i = 1, \ldots, N$, the event i is mutually independent with the events $\{E_j \mid (i, j) \notin E\}$. The *degree* of the dependency graph is the max degree vertex of G.

Theorem (6.11, Lovász Local Lemma)

Let $E_1, \ldots, E_N$ be a set of events and assume we know $p \in (0, 1), d \in \mathbb{N}$ such that all the following conditions hold:

1. *For all i, $\Pr[E_i] \leq p$;*
2. *The degree of the dependency graph on $\{E_1, \ldots, E_N\}$ is $\leq d$;*
3. $4dp \leq 1$

Then

$$\Pr\left[\cap_{i=1}^N \overline{E_i}\right] > 0.$$

Proof of Lovász Local Lemma

The proof depends on showing the following claim by induction:

> *For $s = 0, 1, \ldots, n-1$, if $|S| \leq s$, $\Pr[\bigcap_{j \in S} \bar{E}_j] > 0$, and for every $k \in [n] \setminus S$,*
>
> $$\Pr[E_k \mid \bigcap_{j \in S} \bar{E}_j] \leq 2p.$$

After the claim is shown, it is not hard to obtain our result as follows:

$$\begin{aligned}
\Pr\left[\bigcup_{j=1}^n \bar{E}_j\right] &= \prod_{i=1}^n \Pr\left[\bar{E}_i \mid \bigcap_{j=1}^{i-1} \bar{E}_j\right] \\
&= \prod_{i=1}^n \left(1 - \Pr\left[E_i \mid \bigcap_{j=1}^{i-1} \bar{E}_j\right]\right) \\
&= \prod_{i=1}^n (1 - 2p) > 0.
\end{aligned}$$

The last step uses the fact that $4dp \leq 1$ (hence certainly $2p < 1$).

LLL: proof of Key Claim

Claim: Under the conditions of the LLL, if we take any $s = 0, \ldots, n-1$, and any $S \subseteq [n], |S| = s$, then for any $k \notin S$ we have

$$\Pr\left[E_k \mid \bigcap_{j \in S} \bar{E}_j\right] \leq 2p.$$

Base case ($s = 0$): Follows from assumption that $\Pr[E_j] \leq p$ for all j.

Induction step: Assume true for $0, 1, \ldots, s-1$. Next show for s.

First need to show $\Pr[\bigcap_{j \in S} \bar{E}_j]$ is > 0 (to be able to evaluate conditional expectation).

If $s = 1$ follows from assumptions ($\Pr[\bar{E}_j] > 1 - p$).

For $s > 1$, then we can use claim for $(s-1), \ldots, 0$ to show $\Pr[\bigcap_{j \in S} \bar{E}_j] \geq (1-2p)^s > 0$.

LLL: proof of Key Claim (cont'd.)

Induction step (cont'd): We want to show $\Pr\left[E_k \mid \bigcap_{j \in S} \bar{E}_j\right] \leq 2p$.

Consider E_k's node in the dependency graph, and let $S_1 = \{j \in S : E_j \text{ is a neighbour of } E_k\}$, $S_2 = S \setminus S_1$.

If $S_2 = S$, then E_k is mutually independent of all events in S. Done!

Else $|S_2| < s$, and there are some mutually dependent events (those in S_1) with E_k in the "conditional".

We re-write the conditional $\bigcap_{j \in S} \bar{E}_j$ as $F_{S_1} \cap F_{S_2}$, with

$$F_{S_1} =_{def} \bigcap_{j \in S_1} \bar{E}_j \qquad F_{S_1} =_{def} \bigcap_{j \in S_1} \bar{E}_j$$

LLL: proof of Key Claim (cont'd.)

Induction step (cont'd): ($|S_2| < s$ case) Our target quantity $\Pr\left[E_k \mid \bigcap_{j \in S} \bar{E}_j\right]$ is equal to

$$\Pr[E_k \mid F_{S_1} \cap F_{S_2}] = \frac{\Pr[E_k \cap F_{S_1} \cap F_{S_2}]}{\Pr[F_{S_1} \cap F_{S_2}]}.$$

We can use a trick to re-write top/bottom as

$$\begin{aligned} \Pr[E_k \cap F_{S_1} \cap F_{S_2}] &= \Pr[E_k \cap F_{S_1} \mid F_{S_2}] \cdot \Pr[F_{S_2}] \\ \Pr[F_{S_1} \cap F_{S_2}] &= \Pr[F_{S_1} \mid F_{S_2}] \cdot \Pr[F_{S_2}] \end{aligned}$$

We can cancel the common factor (well-defined - see end slide 5).

We will then argue about $\Pr[E_k \cap F_{S_1} \mid F_{S_2}]$ ("top") and $\Pr[F_{S_1} \mid F_{S_2}]$ ("bottom") separately.

LLL: proof of Key Claim (cont'd.)

Induction step (cont'd): ($|S_2| < s$ case) We have re-written our target quantity as

$$\frac{\Pr[E_k \cap F_{S_1} \mid F_{S_2}]}{\Pr[F_{S_1} \mid F_{S_2}]}.$$

"top": For sure, we have $\Pr[E_k \cap F_{S_1} \mid F_{S_2}] \leq \Pr[E_k \mid F_{S_2}]$. But E_k is mutually independent of all of F_{S_2} events (by definition of S_2). Hence $\Pr[E_k \mid F_{S_2}] = \Pr[E_k]$, which by assumption is $< p$.

"bottom": We have $\Pr[F_{S_1} \mid F_{S_2}]$ where $|S_2| < s$. So ... can use our I.H. with any individual events of F_{S_1}.

$$\begin{aligned} \Pr[F_{S_1} \mid F_{S_2}] &= \Pr\left[\bigcap_{i \in S_1} \bar{E}_i \mid \bigcap_{j \in S_2} \bar{E}_j\right] \\ &\geq 1 - \sum_{i \in S_1} \Pr\left[E_i \mid \bigcap_{j \in S_2} \bar{E}_j\right] \end{aligned}$$

LLL: proof of Key Claim (cont'd.)

Induction step (cont'd): ($|S_2| < s$ case) We have re-written our target quantity as

$$\frac{\Pr[E_k \cap F_{S_1} \mid F_{S_2}]}{\Pr[F_{S_1} \mid F_{S_2}]} \leq \frac{p}{Pr[F_{S_1} \mid F_{S_2}]}.$$

"top": For sure, we have $\Pr[E_k \cap F_{S_1} \mid F_{S_2}] \leq \Pr[E_k \mid F_{S_2}]$.
We have shown

$$\Pr[F_{S_1} \mid F_{S_2}] \quad \geq \quad 1 - \sum_{i \in S_1} \Pr\left[E_i \mid \bigcap_{j \in S_2} \bar{E}_j\right]$$

Now (because $|S_2| < s$, and fits our I.H.), we have that $\Pr\left[E_i \mid \bigcap_{j \in S_2} \bar{E}_j\right] \leq 2p$ for all $i \in S_1$.
We also know that S_1 (items dependent with E_k) has $\leq d$ items.
Hence we have $\Pr[F_{S_1} \mid F_{S_2}] \geq 1 - 2p \cdot d$, which is $\geq \frac{1}{2}$.

LLL: proof of Key Claim (wrapping-up.)

Induction step (cont'd): ($|S_2| < s$ case) We have re-written our target quantity as

$$\frac{\Pr[E_k \cap F_{S_1} \mid F_{S_2}]}{\Pr[F_{S_1} \mid F_{S_2}]} \leq \frac{p}{Pr[F_{S_1} \mid F_{S_2}]}.$$

We now have $Pr[F_{S_1} \mid F_{S_2}] \geq \frac{1}{2}$.
Hence we get

$$\frac{\Pr[E_k \cap F_{S_1} \mid F_{S_2}]}{\Pr[F_{S_1} \mid F_{S_2}]} \leq \frac{p}{\frac{1}{2}} = 2p,$$

as required.

We had already proved that this "claim" gives us the LLL. □

SAT and k-SAT (standard probabilistic method)

Recall that in propositional logic, a *Boolean variable* x_i can take on 0 or 1 values, a *literal* is either x_i or $\overline{x_i}$, and for the set of variables $\{x_j \mid 1 \leq j \leq n\}$ a SAT problem is any conjunction (AND) of a set of clauses, each individual clause being a disjunction (OR) of literals. For example,

$$\{x_4, \overline{x_7}, \overline{x_8}\}, \{\overline{x_1}, \overline{x_3}, \overline{x_5}\}, \{x_1, x_2, \overline{x_6}\}, \{x_3, x_8, \overline{x_4}\}$$

is an instance of SAT. Since all clauses are of length 3, the one above is also an instance of 3-SAT.

Suppose we have m clauses, with k_i literals in the ith clause, $1 \leq i \leq m$. Then on a *uniform random* assignment of boolean values to the n variables, the probability clause i is *satisfied* is $(1 - 2^{-k_i})$. (2^{k_i} is the probability we would set all k_i literals of this clause to be false.)

SAT and k-SAT (standard probabilistic method)

Suppose we have m clauses, with k_i literals in the ith clause, $1 \leq i \leq m$. Then on a *uniform random* assignment of boolean values to the n variables, the expected number of *satisfied* clauses is $\sum_{i=1}^{m}(1 - 2^{-k_i})$.

- This is at least $m \cdot (1 - 2^{-k})$, where $k = \min_{i=1}^{m} k_i$.
- If the instance is k-SAT (all clauses length k), the expected number of satisfied clauses is *exactly* this.
- Hence (by probabilistic method) there is at least one assignment to $\{x_1, \ldots, x_n\}$ with at least $\sum_{i=1}^{m}(1 - 2^{-k_i})$ satisfied clauses.
- Can't get any condition guaranteeing "satisfiability" (all m clauses) even for k-SAT as $m \cdot (1 - 2^{-k})$ is strictly less than m. Would need to do a different kind of analysis.

k-SAT with Lovász Local Lemma

Now consider the “bad events" E_i to be the event where clause i becomes unsatisfied, and consider the dependency graph.

Theorem (6.13)

If we have a k-SAT formula where no variable appears in more than $T = \frac{2^k}{4k}$ clauses, then that formula has some satisfying assignment.

Proof We assume a uniform random assignment to all the x_j and let E_i be the event that all the k variables get the “wrong" assignment. $\Pr[E_i] \leq 2^{-k}$ for all i.

The event E_i is mutually dependent of any $E_{i'}$ such that clause i' shares no logical variables with clause i. For each of the variables in clause i, they may appear in $T = \frac{2^k}{4k}$ clauses, so taking all k variables, there are at most $k \cdot T = \frac{2^k}{4}$ clauses which share *some* variable(s) with clause i. So $d \leq \frac{2^k}{4}$.

Then $4dp \leq 4 \cdot \frac{2^k}{4} \cdot 2^{-k} = 1$, and the LLL implies there is some assignment where none of the bad events occur (ie, all clauses are satisfiable).

LLL: can we de-randomize?

The only negative aspect of using LLL is that we don’t get an explicit randomized process linked to the existence result. So we don’t have a handle on how we might go about finding such a object.

There are ways to convert a LLL result into an explicit construction, but usually you need a lower dependency value.

We won’t cover this (see Sections 6.8, 6.10 of the book)

Notes

Reading

- Section 6.6 of the book presents the “Conditional Expectation Inequality" and shows how to shorten the proof of the “no clique with 4 vertices" half of Theorem 6.8 - ie, 6.8(b) of Lecture 12.
- Section 6.7 from the book deals with the Lovasz Local Lemma.

Doing

- Coursework 2 is due 24th March at 4pm (GMT).
- The final tutorial sheet will be shipped soon, tutorials will take place in week 11 (Tues 31st March, Wed 1st April).