

**L9**

**The Lovász Local Lemma**

(1)

$n \in \mathbb{N}$

$[n] = \{1, 2, \dots, n\}$ ,  $A_i \in \Sigma$  for  $i \in [n]$  - events in a prob. space.  $D = ([n], E)$  ( $E \subset [n] \times [n]$ ) is a dependency digraph for the ~~the~~ events  $A_1, \dots, A_n$  if:

$\forall i \in [n]: \exists C \subset \{j \in [n] \mid (i, j) \in E\}$  (i.e., some non-neighbours of  $i$ )  $\Rightarrow P_r(A_i \cap \bigcap_{j \in C} A_j) = P_r(A_i) \cdot \prod_{j \in C} P_r(A_j)$

$A_i$  is ~~mutually~~ independent of all the events  $\{A_j \mid (i, j) \notin E\}$ , of all "non-neighbours" of  $A_i$ .  
also means in terms of prob.

Here one should add that there is a lemma analogous to that of the previous lecture:

**Lemma**  $A$  is ~~mutually~~ independent of  $A_1, \dots, A_n$

$\Rightarrow A$  is ~~mutually~~ independent of  $A'_1, A'_2, \dots, A'_n$  where

each  $A'_i = \begin{cases} A_i \\ \text{or} \\ \bar{A}_i \end{cases}$  Proof. Like the previous lemma

$$P_r(A \cap B) = P_r(A) P_r(B) \Rightarrow P_r(A \cap \bar{B}) = P_r(A) - P_r(A \cap B) = P_r(A) - P_r(A) P_r(B) = P_r(A) (1 - P_r(B)) = P_r(A) P_r(\bar{B}), \dots$$

- exercise for you. ☒

Now back to the statement of the LLL.

Thm. (LLL-general ~~form~~ case)  $n \in \mathbb{N}$ ,  $A_1, \dots, A_n \in \Sigma$  are events (2)  
 in a pr. space,  $D = ([n], E)$  is a dep. digraph of  $A_1, \dots, A_n$   
 $x_1, \dots, x_n \in [0, 1]$ ,  $\forall i \in [n]: \Pr(A_i) \leq x_i \prod_{(i, j) \in E} (1 - x_j)$ .  
 Then  $\Pr(\bigcap_{i=1}^n \bar{A}_i) \geq \prod_{i=1}^n (1 - x_i) > 0$ .

Thm. (LLL-symmetric form)  $p \in [0, 1]$   
 $n \in \mathbb{N} (= \{1, 2, \dots\})$ ,  $A_1, \dots, A_n \in \Sigma$  are events in a pr. space,  
~~and~~  $\forall i \in [n]: A_i$  is ~~not~~ independent of ~~of~~ all of  $A_1, \dots, A_n$  but at most  $d$  events, ~~and~~ and  
 $\Pr(A_i) \leq p$  for every  $i \in [n]$ . Then

$$e p (d+1) \leq 1 \Rightarrow \Pr(\bigcap_{i=1}^n \bar{A}_i) > 0.$$

2.71828...

Proof of the general form: see the Pr. Method of N. Alon & J.H. Spencer, pp. 54-55 (1992 edition); not good, they write things like  $\Pr(A_i | \bigwedge_{j \in S} \bar{A}_j)$  without justifying that  $\Pr(\bigwedge_{j \in S} \bar{A}_j) > 0$ .

Instead, we prove a version of <sup>the</sup> symm. LLL from Mitzenmacher and Upfal, with weaker condition

Let  $p \leq 1$ . | Proof: Let  $S \subseteq [n]$ , ~~By~~ By

Induction on  $s = 0, 1, \dots, n-1$ : ( $|S| \leq s$ ,  $2 \notin S \Rightarrow$ )

$\Rightarrow Pr(\bigcap_{j \in S} \bar{A}_j) \leq 2p$ . For  $S \neq \emptyset$  we need

to show  $\dots = 2$  if  $S = \emptyset$  that also  $Pr(\bigcap_{j \in S} \bar{A}_j) > 0$ .

If  $s = 0 \checkmark (Pr(A_2) \leq p)$ . For the ind. step we must prove - true for  $s = 1$ , then  $Pr(\bar{A}_j) \geq 1 -$

$p > 0$ . For  $s > 1$ , wlog  $S = [s]$  and we have

$$Pr(\bigcap_{i=1}^s \bar{A}_i) = \frac{\prod_{i=1}^s Pr(\bigcap_{j=1}^i \bar{A}_j)}{\prod_{i=1}^{s-1} Pr(\bigcap_{j=1}^{i-1} \bar{A}_j)} \stackrel{Pr(\bar{X}) = 1 - Pr(X)}{=} \dots$$

$(\frac{A}{B} = \frac{A \cap C}{B \cap C} \text{ if } C \subseteq B)$

$> 0$  by induction

$$= \frac{\prod_{i=1}^s Pr(\bigcap_{j=1}^{i-1} \bar{A}_j) - Pr(A_i \cap \bigcap_{j=1}^{i-1} \bar{A}_j)}{\prod_{i=1}^{s-1} Pr(\bigcap_{j=1}^{i-1} \bar{A}_j)}$$

condit. probab.

$$= \prod_{i=1}^s (1 - Pr(A_i | \bigcap_{j=1}^{i-1} \bar{A}_j)) \geq \prod_{i=1}^s (1 - 2p) > 0.$$

$\leq 2p$  by the inductive assumption.

Let  $S_1 := \{j \in S \mid (a_{1j}) \in E\}$ ,  $S_2 := S \setminus S_1$ . ④

$S_2 = S \Rightarrow A_2$  is ~~not~~ indep. of the  $\bar{A}_i \mid i \in S$ ,

and  $\Pr(A_2 \mid \bigcap_{j \in S} \bar{A}_j) = \dots = \Pr(A_2) \leq P \leq 2p$ .

Let  $|S_2| < N$ . We introduce <sup>the</sup> notation

$F_S := \bigcap_{j \in S} \bar{A}_j$  and similarly for  $F_{S_1}$  and  $F_{S_2}$ . So

$$F_S = F_{S_1} \cap F_{S_2} \text{ and } \Pr(A_2 \mid F_S) = \frac{\Pr(A_2 \cap F_S)}{\Pr(F_S)}$$

$$N \leq \Pr(A_2 \cap F_S) = \Pr(A_2 \cap F_{S_1} \cap F_{S_2}) =$$

$$= \Pr(A_2 \cap F_{S_1} \mid F_{S_2}) \underbrace{\Pr(F_{S_2})}_{> 0}$$

~~$$= \Pr(A_2 \cap F_{S_1}) \Pr(F_{S_2})$$~~

$$D = \Pr(F_S) = \Pr(F_{S_1} \cap F_{S_2}) =$$

$$= \Pr(F_{S_1} \mid F_{S_2}) \underbrace{\Pr(F_{S_2})}_{> 0} \Rightarrow \Pr(A_2 \mid F_S) =$$

$$\frac{N}{D} = \frac{\Pr(A_2 \cap F_{S_1} \mid F_{S_2})}{\Pr(F_{S_1} \mid F_{S_2})} \quad \left( \begin{array}{l} \text{holds for} \\ S_2 = \emptyset \\ \text{as well} \end{array} \right)$$

$$N = \Pr(A_2 \cap F_{S_1} | F_{S_2}) \leq \Pr(A_2 | F_{S_2}) = \Pr(A_2) \leq p \quad (5)$$

$\uparrow$   $\Pr(A \cap B) \leq \Pr(A)$   $\uparrow$   $\Pr(A_2) \leq p$   
 $S_2$  are un-weighted.

Since  $|S_2| < |S| = s$ , by induction:

$$D = \Pr(F_{S_1} | F_{S_2}) \stackrel{\text{def}}{=} \Pr(\bigcap_{i \in S_1} \bar{A}_i | \bigcap_{j \in S_2} \bar{A}_j) \geq$$

$$\Pr(\bigcup_{i \in S_1} A_i | \bigcap_{j \in S_2} \bar{A}_j) \geq 1 - \sum_{i \in S_1} \Pr(A_i | \bigcap_{j \in S_2} \bar{A}_j)$$

$\Pr(\bar{A} \cap B) = \Pr(\overline{A \cup B})$ ,  
de Morgan

$$\Pr(\bar{A}) = 1 - \Pr(A)$$

and the union bound

$$\geq 1 - \sum_{i \in S_1} 2p \stackrel{|S_1| \leq d}{\geq} 1 - 2pd \stackrel{\text{by } (*)}{\geq} \frac{1}{2}. \text{ Thus indeed}$$

$$\Pr(A_2 | F_S) = \frac{N}{D} \leq \frac{p}{1/2} = 2p.$$

$$\Pr(A_2 | \bigcap_{j \in S} \bar{A}_j)$$

(2 & 5)

To conclude,  $\Pr(\bigcap_{i=1}^w \bar{A}_i) =$   
 recall from above  $\downarrow$   
 $\prod_{i=1}^w (1 - \Pr(A_i | \bigcap_{j=1}^{i-1} \bar{A}_j)) \geq$

$$\geq \prod_{i=1}^w (1 - 2p) > 0, \text{ as } 2p < 1 \text{ by } (*). \quad \square$$

⑥

The LLL is from the article  
by Paul (Pál) Erdős (1913 - 1996) and  
László Lovász (1948) in 1975. In 1991,  
József Beck (1952) [not to be confused with  
the Polish politician József Beck (1894 - 1944)]  
found efficient algorithmization of LLL - typical  
application is an efficient ( $\in P$ ) randomized, or  
even deterministic, algorithm that for a given  
hypergraph with low degree finds a proper colo-  
ring. The algorithmic LLL was much impro-  
ved in 2010 by R.A. Moser and Gábor Tar-  
dos (1964) [arxiv:0903.0544, see also the  
Wikipedia article ~~Algor~~ Algorithmic Lovász local  
lemma]. Goedel Prize 2020!

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Chevnoff's, or Cernov's, bounds  
[in fact, after Herman Chevnoff (1923)]  
cf. Leopold Vietoris (1891 - 2002)  
- wrote a paper on trig-sums at the age  
103]

Recall the notion of a random variable  $\oplus$

[for a prob. space  $(\Omega, \Sigma, Pr)$ , it is a function  $X: \Omega \rightarrow \mathbb{R}$  that is  $(\Sigma)$ -measurable, which means that  $\forall a \in \mathbb{R}: \{\omega \in \Omega \mid X(\omega) \leq a\} \in \Sigma$ ] and of independence of  $r$  variables

[real  $r$  variables  $X, Y$  are independent if  $\forall a, b \in \mathbb{R}: Pr[X \leq a \& Y \leq b] =$

$$= Pr(\{\omega \in \Omega \mid X(\omega) \leq a\}) = Pr[X \leq a] Pr[Y \leq b]$$

Similarly for several  $r$  variables  $x_1, x_2, \dots, x_n$

[Theorem (essentially <sup>Бернуштейн</sup> Bernstein, 1924)]

[Sergey N. Bernstein (1880-1968)]

$x_1, \dots, x_n$  are  $\pm 1$ -valued  $r$  variables, independent,  $Pr(x_i = 1) = Pr(x_i = -1) = \frac{1}{2}$  and

[ $X := x_1 + x_2 + \dots + x_n$ ] then  $\forall$  real  $t > 0$ :

$$Pr(X \geq t) < e^{-t^2/2\sigma^2} \text{ and } Pr(t \leq X) < -||-,$$

where  $\sigma = \sqrt{n}$ .

~~where~~  $(\sigma = \sqrt{\text{Var}(X)} = \sqrt{n})$

Proof. Just the 1<sup>st</sup> ineq., the other follows by symmetry (which ~~means~~ <sup>means</sup> really  $= n$ ). We set

$Y := e^{\mu X}$  where  $\mu > 0$  is to be determined.

$\Pr[X \geq t] = \Pr[Y \geq e^{\mu t}]$ . By Markov's ineq.

$\Pr[Y \geq q] \leq \frac{EY}{q}$ . But  $EY = E[\exp(\mu$

$\cdot (X_1 + X_2 + \dots + X_n)] = E \prod_{i=1}^n e^{\mu X_i} \stackrel{\text{independence of } X_i}{=} \prod_{i=1}^n E e^{\mu X_i}$

$= \left(\frac{e^{\mu} + e^{-\mu}}{2}\right)^n \leq e^{n\mu^2/2}$ . Hence

Because  $\frac{e^x + e^{-x}}{2} = 1 + \frac{1}{2!}x^2 + \frac{1}{4!}x^4 + \dots \leq 1 + \frac{1}{1!} \frac{x^2}{2} + \frac{1}{2!} \left(\frac{x^2}{2}\right)^2 + \dots = e^{x^2/2}$

$\Pr[Y \geq e^{\mu t}]$

$\leq \frac{EY}{e^{\mu t}} \leq e^{n\mu^2/2 - \mu t}$ . The last expression is minimized by setting  $\mu = \frac{t}{n}$ , thus

$\Pr(X \geq t) \leq e^{-t^2/2n} (= e^{-t^2/2\sigma^2})$   $\square$

An obvious application is, of course, coin



flipping.  $X_1, \dots, X_n$  tosses of a fair coin (9  
 (  $\Pr(X_i=1) = \Pr(X_i=-1) = \frac{1}{2}$  ). Then for  $X :=$   
 $X_1 + \dots + X_n$  ( $n$  tosses) we have:

$$\Pr\left(\left|X - \frac{n}{2}\right| \geq \frac{n}{4}\right) \leq 2 e^{-\frac{(n/4)^2}{2n}} =$$

$$= 2 e^{-n/32} \text{ or } \Pr(|X| \geq 10\sqrt{n}) \leq$$

$$\leq 2 e^{-(10\sqrt{n})^2/2n} = 2 e^{-50} = \text{much stro.}$$

near bounds than those provided by Chebyshev's  
 ineq.

More general Theorem (from Hoeffding  
 and VanderVaer)  $X_1, X_2, \dots, X_n$  indep. r. variables,  
 (see also Appendix in Alon & Spencer)

$X_i \in [0, 1]$ ,  $X := X_1 + X_2 + \dots + X_n$ ,  $\sigma^2 = \text{Var } X =$   
 $= \sum_{i=1}^n \text{Var } X_i$ . Then  $\forall$  real  $t \geq 0$ :

$$\Pr(X \geq \mathbb{E}X + t) < e^{-\frac{t^2}{2(\sigma^2 + t/3)}}$$

and  $\Pr(X \leq \mathbb{E}X - t) < \frac{1}{2}$ .

Thank you.

