

# Probabilistic Method and Random Graphs

## Lecture 11a. Lovász Local Lemma

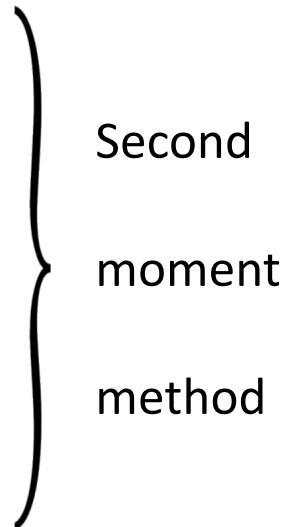
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<sup>1</sup>The slides are mainly based on Chapter 6 of Probability and Computing.

Comments, questions, or suggestions?

# Recap of Lecture 10

- Chebyshev's Ine.:  $\Pr(|X - \mathbb{E}[X]| \geq a) \leq \frac{\text{Var}[X]}{a^2}$
  - $\Pr(X = 0) \leq \Pr(|X - \mathbb{E}[X]| \geq \mathbb{E}[X]) \leq \frac{\text{Var}[X]}{\mathbb{E}[X^2]} \leq \frac{\text{Var}[X]}{(\mathbb{E}[X])^2}$ 
    - When  $X \geq 0$ ,  $\Pr(X > 0) > \frac{(\mathbb{E}[X])^2}{\mathbb{E}[X^2]}$
    - $\Pr(X > \theta \mathbb{E}[X]) \geq \frac{(1-\theta)^2 (\mathbb{E}[X])^2}{\text{Var}[X] + (1-\theta)^2 (\mathbb{E}[X])^2}$   
 $\geq (1-\theta)^2 \frac{(\mathbb{E}[X])^2}{\mathbb{E}[X^2]}, \theta \in (0,1)$
- 
- Second  
moment  
method

# Recap: applications

- Distinct Subset sum problem
  - Given  $n \in \mathbb{Z}^+$ ,  $f(n)$  is the max  $k$  such that:
    - $\exists S \subseteq [n], |S| = k, S$  has distinct subset sums
  - Erdős promised 500\$:  $f(n) = \lfloor \ln_2 n \rfloor + \Theta(1)$
  - $f(n) \leq \ln_2 n + \frac{1}{2} \ln_2 \ln_2 n + O(1)$ 
    - Improve by Hoeffding's inequality?
- Threshold function of  $G_{n,p}$ 
  - Clique number  $c(G) \geq 4$
  - $t(n) = n^{-\frac{2}{3}}$ 
    - The paradigm in estimating the variance of number of 4-cliques

# Recap: Lovász **local** lemma

- Can we avoid all bad events?
- Given bad events  $A_1, A_2, \dots, A_n$ , is  $\Pr(\cap_i \overline{A_i}) > 0$ ?
  - Applicable to **SAT**, coloring, Ramsey theory...
  - Challenging when dependent and highly probable
    - Dependency graph (not unique)
- **Yes** if  $\forall i, \Pr(A_i) \leq p, |\Gamma(A_i)| \leq d$  and  $4pd \leq 1$
- Any  $(k,s)$ -CNF is satisfiable if  $s \leq \frac{1}{4} \frac{2^k}{k}$
- $R(k) \geq k2^{\frac{k}{2}} \left[ \frac{\sqrt{2}}{e} + o(1) \right]$ . How about  $R(k, t)$ ?

# Non-symmetric LLL

- **Theorem:**  $\Pr(\cap_i \overline{A_i}) > 0$  if  $\forall i, \sum_{j \in \Gamma(A_i)} \Pr(A_j) < \frac{1}{4}$ 
  - [Spencer, 1975]
  - The sense of “local”
- Follow the proof of [symmetric LLL](#), with induction on  $m$  to show that  $\Pr(A|B_1, \dots, B_m) < 2\Pr(A)$
- Application to  $R(k, t)$ :

$$R(k, t) > t^{\frac{\binom{k}{2}-2}{k-2} + o(1)} \text{ with } k \text{ fixed and } t \rightarrow \infty$$

$$\text{Proof: } R(k, t) > t \frac{\binom{k}{2}^{-2}}{k-2} + o(1)$$

- Randomly color edges of  $K_n$ ,  $p$  in red,  $(1 - p)$  in blue
- $S$ : a  $k$ -set of the vertices;  $T$ : a  $t$ -set of the vertices
- $A_S$ :  $S$  is a red clique;  $B_T$ :  $T$  is a blue clique
- $\Pr(A_S) = p^{\binom{k}{2}}$ ,  $\Pr(B_T) = (1 - p)^{\binom{t}{2}}$
- Any event has at most  $\binom{t}{2} \binom{n}{k-2}$  neighbors being  $A_S$ ,  
at most  $\binom{n}{t}$  neighbors being  $B_T$
- Let  $p = n^{-\epsilon - \beta + \delta}$ ,  $t = n^{\beta + \epsilon}$ ,  $\beta = \frac{k-2}{\binom{k}{2}^{-2}}$ ,  $0 < \delta < \epsilon$ ,  
we have  $\binom{t}{2} \binom{n}{k-2} p^{\binom{k}{2}} + \binom{n}{t} (1 - p)^{\binom{t}{2}} < \frac{1}{4}$

# A stronger non-symmetric LLL

- $\Pr(\cap \overline{A}_i) > 0$  if there are  $x_1, x_2, \dots, x_n \in (0,1)$  s.t.

$$\forall i, \Pr(A_i) \leq x_i \prod_{j \in \Gamma(A_i)} (1 - x_j)$$

- Similar proof, but

- Prove  $\Pr(A_i | \cap_{j=1}^t \overline{B}_j) \leq x_i$

- Use chain rule to lower-bound the numerator  $\Pr(\cap \overline{C}_j | \cap \overline{D}_j)$

- by  $\prod_{j \in \Gamma(A_i)} (1 - x_j)$

- Spencer, 1977



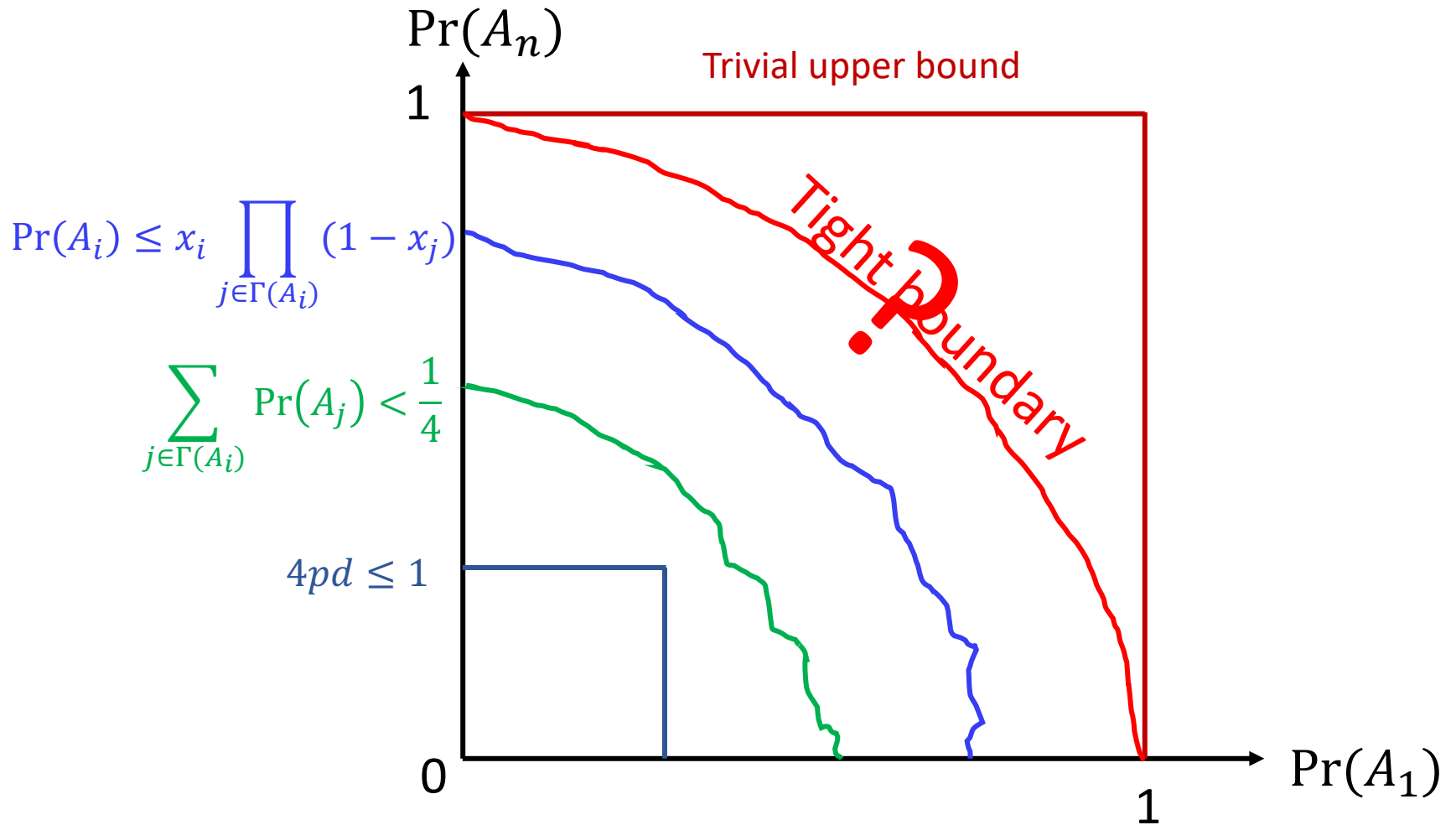
$$R(k, t) \geq c \left( \frac{t}{\ln t} \right)^{\frac{k+1}{2}} (1 - o(1))$$

- Follow the proof of  $R(k, t) > t^{\frac{\binom{k}{2}-2}{k-2}+o(1)}$ 
  - Define events  $A_S$  and  $B_T$  for any  $k$ -set  $S$  and  $t$ -set  $T$
  - Let  $p = c_1 n^{-\beta}$ ,  $t = c_2 n^\beta \ln n$ ,  $x_S = (1 + \epsilon) \Pr(A_S)$   
 $x_T = e^{c_3 n^\beta \ln^2 n} \Pr(A_S)$ , with  $\beta = \frac{2}{k+1}$ ,  $\epsilon > 0$
  - Apply LLL
- Best until 2010
  - Bohman&Keevash:  $R(k, t) \geq c \left( \frac{t}{\ln t} \right)^{\frac{k+1}{2}} (\ln t)^{\frac{1}{k-2}}$

# Major open problem

- Determine  $\alpha(k)$  s.t.  $R(k, t) = t^{\alpha(k)+o(1)}$
- [Spencer 1975](#):  $\alpha(k) \geq \frac{\binom{k}{2}-2}{k-2}$
- Spencer 1977:  $\alpha(k) \geq \frac{k+1}{2} = \frac{\binom{k}{2}-1}{k-2}$ 
  - Best for 40+ years
  - How tight is it?
- $\alpha(k) \leq k - 1$  since  $R(k, t) \leq \binom{k+t-2}{k-1}$
- Conjecture:  $\alpha(k) = k - 1$ 
  - Yes for  $k = 3$
  - Known for larger  $k$

- This local lemma is so strong. Is it ultimate?



Local lemma is to determine a curve surrounding a *safe zone*.  
 Safe:  $\Pr(\cap_i \bar{A}_i) > 0$  any set of events with the probabilities

# Tight Bound of Lovász **local** lemma

- General (Non-symmetrical) case
- $\Pr(\cap \overline{A}_i) > 0$  if

$$\forall S \in \text{ind}(G), \sum_{T \supseteq S} (-1)^{|T \setminus S|} \prod_{i \in T} p_i > 0$$

- By James B. Shearer @IBM in 1985

James Shearer



# Tight Bound of Lovász **local** lemma

- Symmetrical case

- $\Pr(\bigcap \overline{A_i}) > 0$  if

$$p < \begin{cases} \frac{(d-1)^{d-1}}{d^d} & \text{when } d > 1 \\ \frac{1}{2} & \text{when } d = 1 \end{cases}$$

- **Corollary:**  $\Pr(\bigcap A_i) > 0$  if  $edp \leq 1$

# Application

- Any  $(k,s)$ -CNF is satisfiable if  $s \leq \frac{1}{e} \frac{2^k}{k}$ 
  - Known: satisfiable if  $s \leq \frac{1}{4} \frac{2^k}{k}$
  - Tight bound of  $s$ :  $\left( \frac{2}{e} + o\left(\frac{1}{\sqrt{k}}\right) \right) \frac{2^k}{k}$   
[Gebauer et al. 2011]
  - Can we efficiently find a satisfying assignment?



# Algorithmic aspects

- **Like** other probabilistic methods, LLL proves existence non-constructively
- **Unlike** other probabilistic methods, LLL doesn't lead to efficient algorithms
  - Directly sampling has an *exponentially small* lower bound of success probability
  - Say,  $\Pr(\cap \overline{A_i}) \geq \prod(1 - x_i)$  for general version
- Is there an efficient, constructive proof?

# Constructive Lovász Local Lemma

- Initiated by Jozsef Beck in 1991
  - Under strong conditions on neighborhood size
  - In terms of coloring, SAT ...
- Breakthrough by Robin Moser & Gabor Tardos in 2009, Kashyap Kolipaka and Mario Szegedy in 2011
  - Events are generated by independent random variables
  - If Shearer's condition is met, an assignment s.t. none events occurs can be found in linear time

Josze Beck



Gabor Tardos



Mario Szegedy

# The assignment algorithm

For  $X \in \mathcal{X}$  do

$v_X \leftarrow$  a random evaluation of  $X$

EndFor

While (some  $A$  occurs) do

    Arbitrarily pick an event  $A$  that occurs

    For  $X \in \text{vbl}(A)$  do

$v_X \leftarrow$  a random evaluation of  $X$

    EndFor

EndWhile

Return  $(v_X)_{X \in \mathcal{X}}$

- $\text{vbl}(A) \subset \mathcal{Y}$ : the set of variables determining  $A$

# Directions of LLL research

- Local conditions
  - Cluster LLL
  - Random walk
- Algorithms (Inspired by [Moser&Tardos](#))
  - Efficient beyond Shearer's bound?
  - Efficient for abstract events?

# Comparing probabilistic methods

- All dependent vs almost independent
  - Counting (union bound): mutually exclusive
  - First moment: linearity doesn't care dependence
  - Second moment: pairwise dependence
  - LLL: global dependence

# References

- Spencer. Ramsey's theorem-A new lower bound. 1975
- Spencer. Asymptotic lower bounds for Ramsey functions. 1977
- James B. Shearer. On a Problem of Spencer. 1985
- Robin Moser and Gabor Tardos. A constructive proof of the general Lovasz Local Lemma. 2009
- Polipaka and Szegidy. Moser and Tardos Meet Lovász. 2011
- <http://www.openproblemgarden.org/>

Thank you



# Appendix: Proof of Symmetric LLL

- Standard trick
  - Chain rule:  $\Pr(\cap_i \bar{A}_i) = \prod_{i=1}^n \Pr(\bar{A}_i | \cap_{j=1}^{i-1} \bar{A}_j)$ 
    - Valid only if each  $\cap_{j=1}^{i-1} \bar{A}_j$  has nonzero probability
  - Hold if each term  $\Pr(\bar{A}_i | \cap_{j=1}^{i-1} \bar{A}_j) > 0$
- **Claim:** for any  $t \geq 0$  and  $A, B_1, B_2, \dots, B_t \in S$ ,
  1.  $\Pr(\cap_{j=1}^t \bar{B}_j) > 0$
  2.  $\Pr(A | \cap_{j=1}^t \bar{B}_j) < x_i$

# Inductive proof of the claim

- **Basis:**  $t = 0$ . Both 1 and 2 of the claim hold
- **Hypothesis:** the claim holds for all  $t' < t$
- **Induction**
  - For **1**,  $\Pr(\bigcap_{j=1}^t \bar{B}_j)$   
$$= \Pr(\bar{B}_t | \bigcap_{j=1}^{t-1} \bar{B}_j) \Pr(\bigcap_{j=1}^{t-1} \bar{B}_j) > 0$$
  - For **2**, let  $\{C_1, \dots, C_x\} = \{B_1, \dots, B_t\} \cap \Gamma(A)$ , and  
$$\{D_1, \dots, D_y\} = \{B_1, \dots, B_t\} \setminus \Gamma(A)$$
    - $x \leq d, x + y = t$

# Proof: induction for 2

- If  $x = 0$ ,  $A$  is independent of  $\{B_1, \dots, B_t\}$  and  $\Pr(A | \bigcap_{j=1}^t \bar{B}_j) = \Pr(A) < \frac{1}{2d}$
- Assume  $x > 0$ . Then  $y < t$ .

$$\begin{aligned} \bullet \Pr(A | \bigcap_{j=1}^t \bar{B}_j) &= \frac{\Pr(A \cap (\bigcap_{j=1}^t \bar{B}_j))}{\Pr(\bigcap_{j=1}^t \bar{B}_j)} \\ &\leq \frac{\Pr(A \cap (\bigcap \bar{D}_j))}{\Pr((\bigcap \bar{C}_j) \cap (\bigcap \bar{D}_j))} = \frac{\Pr(A | \bigcap \bar{D}_j)}{\Pr((\bigcap \bar{C}_j) | \bigcap \bar{D}_j)} \end{aligned}$$

Use chain rule to lower-bound  $\Pr(\bigcap \bar{C}_j | \bigcap \bar{D}_j)$

[General case](#)