

# The Probabilistic Method

## Techniques

- Union bound
- Argument from expectation
- Alterations
- The second moment method
- The (Lovasz) Local Lemma

## And much more

- Alon and Spencer, “The Probabilistic Method”
- Bolobas, “Random Graphs”

# Outline

- 1 The Union Bound Technique
- 2 The Argument from Expectation
- 3 Alteration Technique
- 4 Second Moment Method
- 5 The Local Lemma

# The Union Bound Technique: Main Idea

- $A$ : event our structure exists, want  $\text{Prob}[A] > 0$  or  $\text{Prob}[\bar{A}] < 1$

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We have seen this used in Ramsey number, magical graph,  $d$ -disjunct matrix examples.

# Example 1: Nice Tournaments

- A tournament is an orientation  $G$  of  $K_n$
- Think of  $u \rightarrow v$  as *player  $u$  beats player  $v$*
- Fix integer  $k$ ,  $G$  is **nice** if for every  $k$ -subset  $S$  of players there is another  $v$  who beats all of  $S$



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- Intuitively, nice tournaments may exist for large  $n$

# Existence of Nice Tournaments (Erdős, 1963)

- For every  $\{u, v\}$ , let  $u \rightarrow v$  with probability  $1/2$
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- So,  $n = \Omega(k^2 \cdot 2^k)$  is good!

## Example 2: 2-coloring of uniform hypergraphs

- Given a  $k$ -uniform hypergraph  $G = (V, E)$ , i.e.
  - $E$  is a collection of  $k$ -subsets of  $V$
- $G$  is 2-colorable iff each vertex in  $V$  can be assigned with red or blue such that there's no monochromatic edge



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### Theorem (Erdős, 1963)

Every  $k$ -uniform hypergraph with  $< 2^{k-1}$  edges is 2-colorable!

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# The Argument from Expectation: Main Idea

- $X$  a random variable with  $E[X] = \mu$ , then
  - There must exist a sample point  $\omega$  with  $X(\omega) \geq \mu$
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Have we seen this?



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## Theorem

For every graph  $G = (V, E)$ , there must be a cut with  $\geq |E|/2$  edges

## Example 2: $\pm 1$ Linear Combinations of Unit Vectors

### Theorem

Let  $\mathbf{v}_1, \dots, \mathbf{v}_n$  be  $n$  unit vectors in  $\mathbb{R}^n$ .

There exist  $\alpha_1, \dots, \alpha_n \in \{-1, 1\}$  such that

$$|\alpha_1 \mathbf{v}_1 + \dots + \alpha_n \mathbf{v}_n| \leq \sqrt{n}$$

and, there exist  $\alpha_1, \dots, \alpha_n \in \{-1, 1\}$  such that

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Specifically, choose  $\alpha_i \in \{-1, 1\}$  independently with prob.  $1/2$

$$\mathbb{E} [|\alpha_1 \mathbf{v}_1 + \dots + \alpha_n \mathbf{v}_n|^2] = \sum_{i,j} \mathbf{v}_i \cdot \mathbf{v}_j \mathbb{E}[\alpha_i \alpha_j] = \sum_i \mathbf{v}_i^2 = n.$$



## Example 3: Unbalancing Lights

### Theorem

For  $1 \leq i, j \leq n$ , we are given  $a_{ij} \in \{-1, 1\}$ . Then, there exist  $\alpha_i, \beta_j \in \{-1, 1\}$  such that

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- Choose  $\beta_j \in \{-1, 1\}$  independently with prob.  $1/2$ .
- $R_i = \sum_j a_{ij} \beta_j$ , then

$$\mathbb{E}[|R_i|] = 2 \frac{n \binom{n-1}{\lfloor (n-1)/2 \rfloor}}{2^n} \approx \left( \sqrt{\frac{2}{\pi}} + o(1) \right) n^{1/2}$$

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- Choose  $\alpha_i$  with the same sign as  $R_i$ , for all  $i$

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# Alteration Technique: Main Idea

- A randomly chosen object may not satisfy the property we want
- So, after choosing it we modify the object a little
- In non-elementary situations, the modification itself may be probabilistic
- Or, there might be more than one modification step

# Example 1: Independent Set

- $\alpha(G)$  denotes the maximum size of an independent set in  $G$
- Say  $G$  has  $n$  vertices and  $m$  edges
- **Intuition:**  $\alpha(G)$  is proportional to  $n$  and inversely proportional to  $m$
- **Line of thought:** on average a randomly chosen independent set has size  $\mu$  (proportional to  $n$  and inversely proportional to  $m$ )
- **Problem:** random subset of vertices may not be an independent set!!!

# A Randomized Algorithm based on Alteration Technique

- Choose a random subset  $X$  of vertices where  $\text{Prob}[v \in X] = p$  (to be determined)
- Remove one end point from each edge in  $X$
- Let  $Y$  be the set of edges in  $X$
- Left with at least  $|X| - |Y|$  vertices which are independent

$$E[|X| - |Y|] = np - mp^2 = -m \left( p - \frac{n}{2m} \right)^2 + \frac{n^2}{4m}$$

## Theorem

*For any graph with  $n$  vertices and  $m$  edges, there must be an independent set of size at least  $n^2/(4m)$ .*

## Example 2: Dominating Set

- Given  $G = (V, E)$ ,  $S \subset V$  is a **dominating set** iff every vertex either is in  $S$  or has a neighbor in  $S$
- **Intuition:** graphs with high vertex degrees should have small dominating set
- **Line of thought:** a randomly chosen dominating set has mean size  $\mu$



# A Randomized Algorithm based on Alteration Technique

- Include a vertex in  $X$  with probability  $p$
- Let  $Y =$  set of vertices in  $V - X$  with no neighbor in  $X$
- Output  $X \cup Y$

$$\text{Prob}[u \notin X \text{ and no neighbor in } X] = (1 - p)^{\text{deg}(u)+1} \leq (1 - p)^{\delta+1}$$

where  $\text{deg}(u)$  is the degree of  $u$  and  $\delta$  is the minimum degree.

$$\mathbb{E}[|X| + |Y|] \leq n \left( p + (1 - p)^{\delta+1} \right) \leq n \left( p + e^{-p(\delta+1)} \right)$$

To minimize the RHS, choose  $p = \frac{\ln(\delta+1)}{\delta+1}$

## Theorem

*There exists a dominating set of size at most  $n \frac{1 + \ln(\delta+1)}{\delta+1}$*

## Example 3: 2-coloring of $k$ -uniform Hypergraphs

- $G = (V, E)$  a  $k$ -uniform hypergraph.
- **Intuition:** if  $|E|$  is relatively small,  $G$  is 2-colorable
- **We've shown:**  $|E| \leq 2^{k-1}$  is sufficient, but the bound is too small

### Why is the bound too small?

Random coloring disregards the structure of the graph.

Need some modification of the random coloring to improve the bound.

# A Randomized Algorithm

- 1 Order  $V$  randomly. For  $v \in V$ , flip 2 coins:
  - $\text{Prob}[C_1(v) = \text{HEAD}] = 1/2$ ;
  - $\text{Prob}[C_2(v) = \text{HEAD}] = p$
- 2 Color  $v$  **red** if  $C_1(v) = \text{HEAD}$ , **blue** otherwise
- 3  $D = \{v \mid v \text{ lies in some monochromatic } e \in E\}$
- 4 For each  $v \in D$  in the random ordering
  - **If**  $v$  is still in some monochromatic  $e$  in the first coloring and no vertex in  $e$  has changed its color, **then** change  $v$ 's color if  $C_2(v) = \text{HEAD}$
  - **Else** do nothing!

$$\begin{aligned}\text{Prob}[\text{Coloring is bad}] &\leq \sum_{e \in E} \text{Prob}[e \text{ is monochromatic}] \\ &= 2 \sum_{e \in E} \text{Prob}[e \text{ is red}] \\ &\leq 2 \sum_{e \in E} \left( \underbrace{\text{Prob}[e \text{ was red and remains red}]}_{A_e} \right. \\ &\quad \left. + \underbrace{\text{Prob}[e \text{ wasn't red and turns red}]}_{C_e} \right)\end{aligned}$$

$$\text{Prob}[A_e] = \frac{1}{2^k} (1 - p)^k.$$

# The Event $C_e$

Let  $v$  be the last vertex of  $e$  to turn blue  $\rightarrow$  red

- $v \in f \in E$  and  $f$  was blue (in 1st coloring) when  $v$  is considered
- $e \cap f = \{v\}$

For any  $e \neq f$  with  $|e \cap f| = \{v\}$ , let  $B_{ef}$  be the event that

- $f$  was blue in first coloring,  $e$  is red in the final coloring
- $v$  is the last of  $e$  to change color
- when  $v$  changes color,  $f$  is still blue

$$\text{Prob}[C_e] \leq \sum_{f:|f \cap e|=1} \text{Prob}[B_{ef}]$$

# The Event $B_{ef}$

- The random ordering of  $V$  induces a random ordering  $\sigma$  of  $e \cup f$
- $i_\sigma$  = number of vertices in  $e$  coming before  $v$  in  $\sigma$
- $j_\sigma$  = number of vertices in  $f$  coming before  $v$  in  $\sigma$

$$\text{Prob}[B_{ef} \mid \sigma] = \frac{1}{2^k} p \frac{1}{2^{n-1-i_\sigma}} (1-p)^{j_\sigma} \left( \frac{1+p}{2} \right)^{i_\sigma}$$

$$\begin{aligned} \text{Prob}[B_{ef}] &= \sum_{\sigma} \text{Prob}[B_{ef} \mid \sigma] \text{Prob}[\sigma] \\ &= \frac{p}{2^{2k-1}} \mathbb{E}_{\sigma}[(1-p)^{i_\sigma} (1+p)^{j_\sigma}] \\ &\leq \frac{p}{2^{2k-1}} \end{aligned}$$

# Putting it All Together

Let  $m = |E|$  and  $x = m/2^{k-1}$

$$\begin{aligned}\text{Prob}[\text{Coloring is bad}] &\leq 2 \sum_e (\text{Prob}[A_e] + \text{Prob}[C_e]) \\ &< 2m \frac{1}{2^k} (1-p)^k + 2m^2 \frac{p}{2^{2k-1}} \\ &= x(1-p)^k + x^2 p \\ &\leq 1\end{aligned}$$

as long as

$$m = \Omega\left(2^k \sqrt{\frac{k}{\ln k}}\right)$$

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# Second Moment Method: Main Idea

Use Chebyshev's Inequality.

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- **Open Problem:** (Erdős offered 500usd)

$$f(n) \leq \log_2 n + c?$$

## Example 1: Distinct Subset Sums

- A set  $A = \{a_1, \dots, a_k\}$  of positive integers has **distinct subset sums** if the sums of all subsets of  $A$  are distinct
- $f(n) =$  maximum  $k$  for which there's a  $k$ -subset of  $[n]$  having distinct subset sums
- **Example:**  $A = \{2^i \mid 0 \leq i \leq \lg n\}$

$$f(n) \geq \lfloor \lg n \rfloor + 1$$

- **Open Problem:** (Erdős offered 500usd)

$$f(n) \leq \log_2 n + c?$$

- **Simple information bound:**

$$2^k \leq nk \Rightarrow k < \lg n + \lg \lg n + O(1).$$

# A Bound for $f(n)$ Using Second Moment Method

## Line of thought

- Fix  $n$  and  $k$ -subset  $A = \{a_1, \dots, a_k\}$  with distinct subset sums
- $X =$  sum of random subset of  $A$ ,  $\mu = E[X]$ ,  $\sigma^2 = \text{Var}[X]$
- For any integer  $i$ ,

$$\text{Prob}[X = i] \in \left\{ 0, \frac{1}{2^k} \right\}$$

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- For any integer  $i$ ,

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- By Chebyshev, for any  $\alpha > 1$

$$\text{Prob}[|X - \mu| \geq \alpha\sigma] \leq \frac{1}{\alpha^2} \Rightarrow \text{Prob}[|X - \mu| < \alpha\sigma] \geq 1 - \frac{1}{\alpha^2}$$

- There are at most  $2\alpha\sigma + 1$  integers within  $\alpha\sigma$  of  $\mu$ ; hence,

$$1 - \frac{1}{\alpha^2} \leq \frac{1}{2^k}(2\alpha\sigma + 1)$$

- $\sigma$  is a function of  $n$  and  $k$



## More Specific Analysis

$$\sigma^2 = \frac{a_1^2 + \dots + a_k^2}{4} \leq \frac{n^2 k}{4} \Rightarrow \sigma \leq n\sqrt{k}/2$$

There are at most  $(\alpha n\sqrt{k} + 1)$  within  $\alpha\sigma$  of  $\mu$

$$1 - \frac{1}{\alpha^2} \leq \frac{1}{2^k}(\alpha n\sqrt{k} + 1)$$

Equivalently,

$$n \geq \frac{2^k \left(1 - \frac{1}{\alpha^2}\right) - 1}{\alpha\sqrt{k}}$$

Recall  $\alpha > 1$ , we get

$$k \leq \lg n + \frac{1}{2} \lg \lg n + O(1).$$

## Example 2: $\mathcal{G}(n, p)$ Model and $\omega(G) \geq 4$ Property

$\mathcal{G}(n, p)$

Space of random graphs with  $n$  vertices, each edge  $(u, v)$  is included with probability  $p$

Also called the **Erdős-Rényi Model**.

### Question

Does a “typical”  $G \in \mathcal{G}(n, p)$  satisfy a given property?

- Is  $G$  connected?
- Does  $G$  have a 4-clique?
- Does  $G$  have a Hamiltonian cycle?

# Threshold Function

- As  $p$  goes from 0 to 1,  $G \in \mathcal{G}(n, p)$  goes from “typically empty” to “typically full”
- Some property may become more likely or less likely

# Threshold Function

- As  $p$  goes from 0 to 1,  $G \in \mathcal{G}(n, p)$  goes from “typically empty” to “typically full”
- Some property may become more likely or less likely
- The property *having a 4-clique* will become more likely

## Threshold Function

$f(n)$  is a threshold function for property  $P$  if

- When  $p \ll f(n)$  almost all  $G \in \mathcal{G}(n, p)$  **do not** have  $P$
  - When  $p \gg f(n)$  almost all  $G \in \mathcal{G}(n, p)$  **do** have  $P$
- 
- It is not clear if any property has threshold function

# The $\omega(G) \geq 4$ Property

- Pick  $G \in \mathcal{G}(n, p)$  at random
- $S \in \binom{V}{4}$ ,  $X_S$  indicates if  $S$  is a clique
- $X = \sum_S X_S$  is the number of 4-clique
- $\omega(G) \geq 4$  iff  $X > 0$

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Natural line of thought:

$$\mathbb{E}[X] = \sum_S \mathbb{E}[X_S] = \binom{n}{4} p^6 \approx \frac{n^4 p^6}{24}$$

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Natural line of thought:

$$E[X] = \sum_S E[X_S] = \binom{n}{4} p^6 \approx \frac{n^4 p^6}{24}$$

- When  $p = o(n^{-2/3})$ , we have  $E[X] = o(1)$ ; thus,

$$\text{Prob}[X > 0] \leq E[X] = o(1)$$

# The $\omega(G) \geq 4$ Property

More precisely

$$p = o\left(n^{-2/3}\right) \implies \lim_{n \rightarrow \infty} \text{Prob}[X > 0] = 0$$

## In English

When  $p = o\left(n^{-2/3}\right)$  and  $n$  sufficiently large, almost all graphs from  $\mathcal{G}(n, p)$  do not have  $\omega(G) \geq 4$



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More precisely

$$p = o\left(n^{-2/3}\right) \implies \lim_{n \rightarrow \infty} \text{Prob}[X > 0] = 0$$

## In English

When  $p = o\left(n^{-2/3}\right)$  and  $n$  sufficiently large, almost all graphs from  $\mathcal{G}(n, p)$  do not have  $\omega(G) \geq 4$

- What about when  $p = \omega\left(n^{-2/3}\right)$ ?
- We know  $\lim_{n \rightarrow \infty} E[X] = \infty$
- But it's not necessarily the case that  $\text{Prob}[X > 0] \rightarrow 1$
- Equivalently, it's not necessarily the case that  $\text{Prob}[X = 0] \rightarrow 0$
- Need more information about  $X$

# Here Comes Chebyshev

Let  $\mu = E[X]$ ,  $\sigma^2 = \text{Var}[X]$

$$\begin{aligned}\text{Prob}[X = 0] &= \text{Prob}[X - \mu = -\mu] \\ &\leq \text{Prob}[\{X - \mu \leq -\mu\} \cup \{X - \mu \geq \mu\}] \\ &= \text{Prob}[|X - \mu| \geq \mu] \\ &\leq \frac{\sigma^2}{\mu^2}\end{aligned}$$

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Thus, if  $\sigma^2 = o(\mu^2)$  then  $\text{Prob}[X = 0] \rightarrow 0$  as desired!

## Lemma

*For any random variable  $X$*

$$\text{Prob}[X = 0] \leq \frac{\text{Var}[X]}{(E[X])^2}$$

# PTCF: Bounding the Variance

Suppose  $X = \sum_{i=1}^n X_i$

$$\text{Var}[X] = \sum_{i=1}^n \text{Var}[X_i] + \sum_{i \neq j} \text{Cov}[X_i, X_j]$$

If  $X_i$  is an indicator for event  $A_i$  and  $\text{Prob}[X_i = 1] = p_i$ , then

$$\text{Var}[X_i] = p_i(1 - p_i) \leq p_i = \mathbf{E}[X_i]$$

If  $A_i$  and  $A_j$  are independent, then

$$\text{Cov}[X_i, X_j] = \mathbf{E}[X_i X_j] - \mathbf{E}[X_i] \mathbf{E}[X_j] = 0$$

If  $A_i$  and  $A_j$  are **not** independent (denoted by  $i \sim j$ )

$$\text{Cov}[X_i, X_j] \leq \mathbf{E}[X_i X_j] = \text{Prob}[A_i \cap A_j]$$

# PTCF: Bounding the Variance

## Theorem

Suppose

$$X = \sum_{i=1}^n X_i$$

where  $X_i$  is an indicator for event  $A_i$ . Then,

$$\text{Var}[X] \leq \text{E}[X] + \sum_i \text{Prob}[A_i] \underbrace{\sum_{j:j \sim i} \text{Prob}[A_j | A_i]}_{\Delta_i}$$

# PTCF: Bounding the Variance

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## Corollary

If  $\Delta_i \leq \Delta$  for all  $i$ , then

$$\text{Var}[X] \leq \text{E}[X](1 + \Delta)$$



## Back to the $\omega(G) \geq 4$ Property

$$\begin{aligned}\Delta_S &= \sum_{T \sim S} \text{Prob}[A_T \mid A_S] \\ &= \sum_{|T \cap S|=2} \text{Prob}[A_T \mid A_S] + \sum_{|T \cap S|=3} \text{Prob}[A_T \mid A_S] \\ &= \binom{n-4}{2} \binom{4}{2} p^5 + (n-4)p^3 = \Delta\end{aligned}$$

## Back to the $\omega(G) \geq 4$ Property

$$\begin{aligned}\Delta_S &= \sum_{T \sim S} \text{Prob}[A_T \mid A_S] \\ &= \sum_{|T \cap S|=2} \text{Prob}[A_T \mid A_S] + \sum_{|T \cap S|=3} \text{Prob}[A_T \mid A_S] \\ &= \binom{n-4}{2} \binom{4}{2} p^5 + (n-4)p^3 = \Delta\end{aligned}$$

So,

$$\sigma^2 \leq \mu(1 + \Delta)$$

- **Recall:** we wanted  $\sigma^2/\mu^2 = o(1)$  – OK as long as  $\Delta = o(\mu)$
- **Yes!** When  $p = \omega(n^{-2/3})$ , certainly

$$\Delta = \binom{n-4}{2} \binom{4}{2} p^5 + (n-4)p^3 = o(n^4 p^6)$$

# The $\omega(G) \geq 4$ Property: Conclusion

## Theorem

$f(n) = n^{-2/3}$  is a threshold function for the  $\omega(G) \geq 4$  property

With essentially the same proof, we can show the following.

Let  $H$  be a graph with  $v$  vertices and  $e$  edges. Define the *density*  $\rho(H) = e/v$ . Call  $H$  *balanced* if every subgraph  $H'$  has  $\rho(H') \leq \rho(H)$

## Theorem

The property " $G \in \mathcal{G}(n, p)$  contains a copy of  $H$ " has threshold function  $f(n) = n^{-v/e}$ .

# What Happens when $p \approx$ Threshold?

## Theorem

*Suppose  $p = cp^{-2/3}$ , then  $X$  is approximately Poisson( $c^6/24$ )  
In particular,  $\text{Prob}[X = 0] \rightarrow 1 - e^{-c^6/24}$*

# Outline

- 1 The Union Bound Technique
- 2 The Argument from Expectation
- 3 Alteration Technique
- 4 Second Moment Method
- 5 The Local Lemma**

# Lovasz Local Lemma: Main Idea

- Recall the union bound technique:
  - want to prove  $\text{Prob}[A] > 0$
  - $\bar{A} \Rightarrow$  (or  $\Leftrightarrow$ ) some bad events  $B_1 \cup \dots \cup B_n$
  - done as long as  $\text{Prob}[B_1 \cup \dots \cup B_n] < 1$
- Could also have tried to show

$$\text{Prob}[\bar{B}_1 \cap \dots \cap \bar{B}_n] > 0$$

- Would be much simpler if the  $B_i$  were **mutually independent**, because

$$\text{Prob}[\bar{B}_1 \cap \dots \cap \bar{B}_n] = \prod_{i=1}^n \text{Prob}[\bar{B}_i] > 0$$

## Main Idea

**Lovasz Local Lemma** is a sort of generalization of this idea when the “bad” events are not mutually independent

# PTCF: Mutual Independence

## Definition (Recall)

A set  $B_1, \dots, B_n$  of events are said to be or **mutually independent** (or simply **independent**) if and only if, for any subset  $S \subseteq [n]$ ,

$$\text{Prob} \left[ \bigcap_{i \in S} B_i \right] = \prod_{i \in S} \text{Prob}[B_i]$$

## Definition (New)

An event  $B$  is **mutually independent of** events  $B_1, \dots, B_k$  if, for any subset  $S \subseteq [k]$ ,

$$\text{Prob} \left[ B \mid \bigcap_{i \in S} B_i \right] = \text{Prob}[B]$$

**Question:** can you find  $B, B_1, B_2, B_3$  such that  $B$  is mutually independent of  $B_1$  and  $B_2$  but not from all three?

## Definition

Given a set of events  $B_1, \dots, B_n$ , a directed graph  $D = ([n], E)$  is called a **dependency digraph** for the events if every event  $B_i$  is independent of all events  $B_j$  for which  $(i, j) \notin E$ .

- What's a dependency digraph of a set of mutually independence events?
- Dependency digraph is **not unique!**



# The Local Lemma

## Lemma (General Case)

Let  $B_1, \dots, B_n$  be events in some probability space. Suppose  $D = ([n], E)$  is a dependency digraph of these events, and suppose there are real numbers  $x_1, \dots, x_n$  such that

- $0 \leq x_i < 1$
- $\text{Prob}[B_i] \leq x_i \prod_{(i,j) \in E} (1 - x_j)$  for all  $i \in [n]$

Then,

$$\text{Prob} \left[ \bigcap_{i=1}^n \bar{B}_i \right] \geq \prod_{i=1}^n (1 - x_i)$$

# The Local Lemma

## Lemma (Symmetric Case)

Let  $B_1, \dots, B_n$  be events in some probability space. Suppose  $D = ([n], E)$  is a dependency digraph of these events with maximum out-degree at most  $\Delta$ . If, for all  $i$ ,

$$\text{Prob}[B_i] \leq p \leq \frac{1}{e(\Delta + 1)}$$

then

$$\text{Prob} \left[ \bigcap_{i=1}^n \bar{B}_i \right] > 0.$$

The conclusion also holds if

$$\text{Prob}[B_i] \leq p \leq \frac{1}{4\Delta}$$

# Example 1: Hypergraph Coloring

- $G = (V, E)$  a hypergraph, each edge has  $\geq k$  vertices
- Each edge  $f$  intersects at most  $\Delta$  other edges
- Color each vertex randomly with red or blue
- $B_f$ : event that  $f$  is monochromatic

$$\text{Prob}[B_f] = \frac{2}{2^{|f|}} \leq \frac{1}{2^{k-1}}$$

- There's a dependency digraph for the  $B_f$  with max out-degree  $\leq \Delta$

## Theorem

$G$  is 2-colorable if

$$\frac{1}{2^{k-1}} \leq \frac{1}{e(\Delta + 1)}$$

## Example 2: $k$ -SAT

### Theorem

*In a  $k$ -CNF formula  $\varphi$ , if no variable appears in more than  $2^{k-2}/k$  clauses, then  $\varphi$  is satisfiable.*

## Example 3: Edge-Disjoint Paths

- $\mathcal{N}$  a directed graph with  $n$  inputs and  $n$  outputs
- From input  $a_i$  to output  $b_i$  there is a set  $P_i$  of  $m$  paths
- In switching networks, we often want to find (or want to know if there exists) a set of edge-disjoint  $(a_i \rightarrow b_i)$ -paths

### Theorem

*Suppose  $\delta nk \leq m$  and each path in  $P_i$  share an edge with at most  $k$  paths in any  $P_j$ ,  $j \neq i$ . Then, there exists a set of edge-disjoint  $(a_i \rightarrow b_i)$ -paths.*