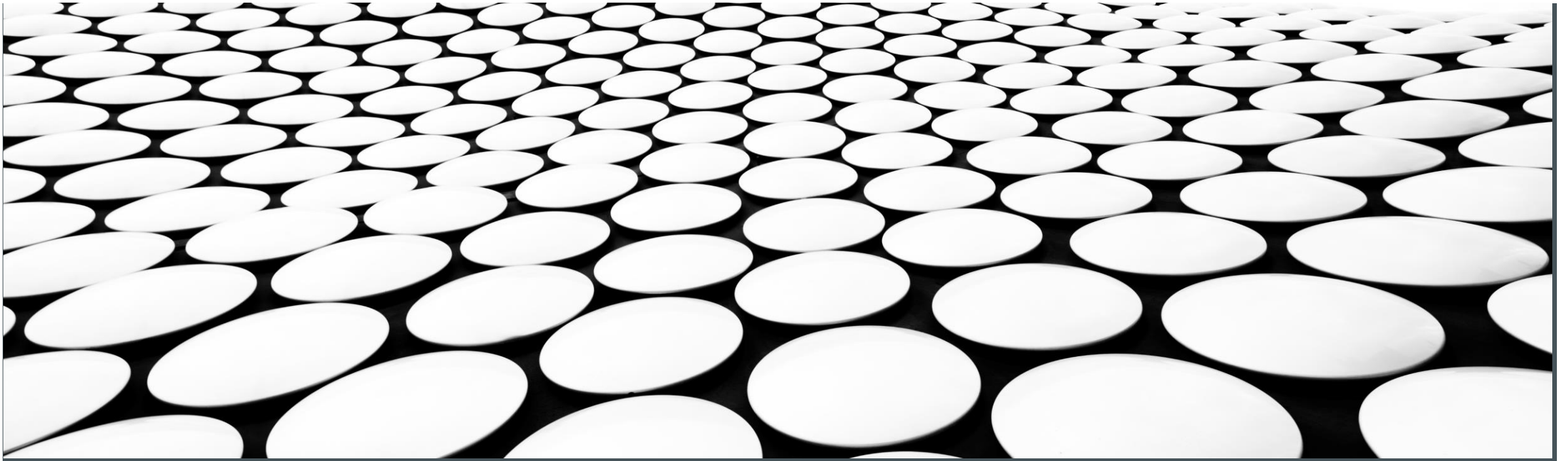


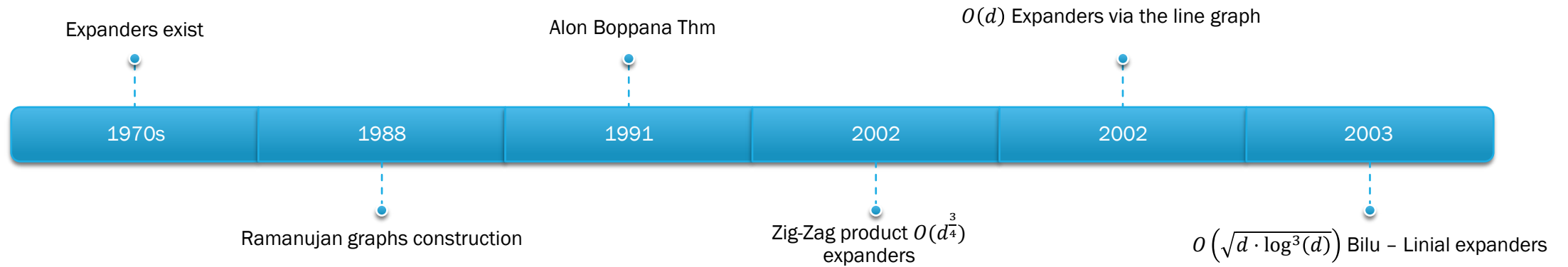
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# **BILU – LINIAL EXPANDERS**

ITAY COHEN AND KEDEM YAKIREVITCH

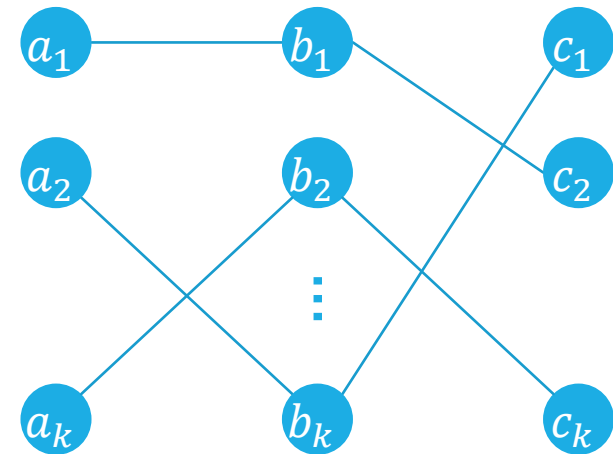
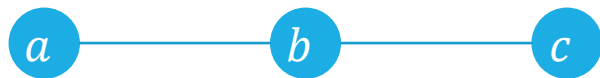


# BRIEF HISTORY



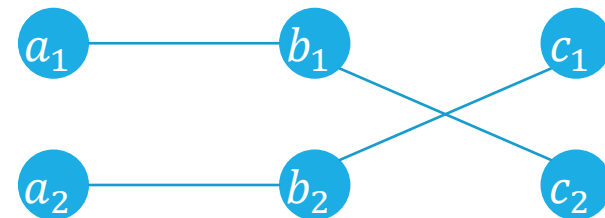
# GRAPH LIFTS

- A  $k$ -lift of a graph  $G = (V, E)$  is a new graph  $\hat{G} = (V', E')$ 
  - Each vertex  $v$  in  $G$  corresponds  $k$  vertices in  $\hat{G}$ , called the fiber of  $v$
  - Each edge  $e = (u, v)$  in  $G$  corresponds a perfect matching in the fibers of  $u$  and  $v$
- If  $G$  is  $d$  regular, so is  $\hat{G}$



## 2-LIFTS

- A 2-lift of a graph
  - Each vertex  $v$  in  $G$  corresponds 2 vertices in  $\hat{G}$ , called the fiber of  $v$
  - Each edge  $e = (u, v)$  in  $G$  corresponds **one of two** perfect matchings in the fibers of  $u$  and  $v$
- Description of a 2-lift can thus be done with one bit per edge
- Let 1 correspond “parallel” matching and let  $-1$  correspond “crossing” matching



## 2-LIFTS

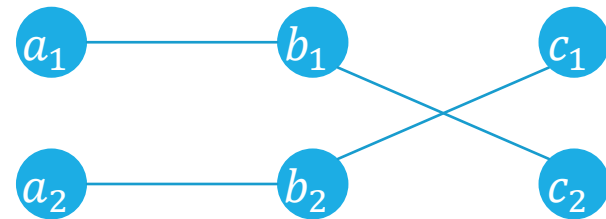
- Let  $s: E \rightarrow \{\pm 1\}$  be a signing of the edges

- $M_{u,v} = \begin{cases} 1 & u \sim v \\ 0 & \text{else} \end{cases}$

- $[M_s]_{u,v} = \begin{cases} s((u,v)) & u \sim v \\ 0 & \text{else} \end{cases}$

$$M = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

$$M_s = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$



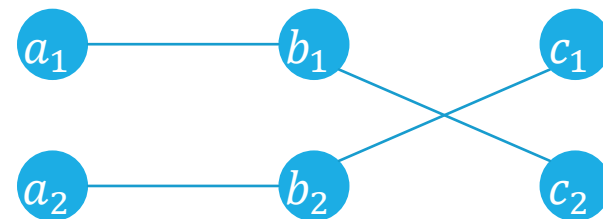
## 2-LIFTS LINEAR ALGEBRAIC PROPERTIES

- Denote  $M_1 = \begin{cases} 1 & M_s = 1 \\ 0 & M_s \neq 1 \end{cases}$  and  $M_{-1} = \begin{cases} 1 & M_s = -1 \\ 0 & M_s \neq -1 \end{cases}$

$$M = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad M_s = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & 0 \end{bmatrix} \quad M_1 = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad M_{-1} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

- Note that  $M = M_1 + M_{-1}$  and that  $M_s = M_1 - M_{-1}$
- Express  $M_{\hat{G}}$  using  $M_1$  and  $M_{-1}$

$$M_{\hat{G}} = \begin{bmatrix} M_1 & M_{-1} \\ M_{-1} & M_1 \end{bmatrix}$$



## 2-LIFTS EIGENVECTORS AND EIGENVALUES

- $M_{\hat{G}} = \begin{bmatrix} M_1 & M_{-1} \\ M_{-1} & M_1 \end{bmatrix}, \quad M = M_1 + M_{-1}, \quad M_S = M_1 - M_{-1}$

- Let  $v$  be an eigenvector of  $M$  corresponding an eigenvalue  $\mu$ . Look at  $\begin{pmatrix} v \\ v \end{pmatrix}$

$$M_{\hat{G}} \cdot \begin{pmatrix} v \\ v \end{pmatrix} = \begin{bmatrix} M_1 & M_{-1} \\ M_{-1} & M_1 \end{bmatrix} \cdot \begin{pmatrix} v \\ v \end{pmatrix} = \begin{pmatrix} (M_1 + M_{-1})v \\ (M_1 + M_{-1})v \end{pmatrix} = \begin{pmatrix} Mv \\ Mv \end{pmatrix} = \mu \begin{pmatrix} v \\ v \end{pmatrix}$$

- Let  $v$  be an eigenvector of  $M_S$  corresponding an eigenvalue  $\mu$ . Look at  $\begin{pmatrix} v \\ -v \end{pmatrix}$

$$M_{\hat{G}} \cdot \begin{pmatrix} v \\ -v \end{pmatrix} = \begin{bmatrix} M_1 & M_{-1} \\ M_{-1} & M_1 \end{bmatrix} \cdot \begin{pmatrix} v \\ -v \end{pmatrix} = \begin{pmatrix} (M_1 - M_{-1})v \\ (M_{-1} - M_1)v \end{pmatrix} = \begin{pmatrix} M_S v \\ -M_S v \end{pmatrix} = \mu \begin{pmatrix} v \\ -v \end{pmatrix}$$

- These are  $2n$  orthogonal eigenvectors of  $M_{\hat{G}}$



# PLAN

- Start with a good graph  $G_0$  and 2-lift it many times
- Each time, choose a signing  $s$  with small eigenvalues
  - How can we find such a signing?
  - Does it even exist?





## GOOD SIGNINGS EXIST

- Every graph of maximal degree  $d$  has a signing with spectral radius  $O\left(\sqrt{d \cdot \log^3(d)}\right)$

## PROOF STEPS

- There exists a signing  $s$  such that  $\frac{|u^t M_s v|}{\|u\| \|v\|} \leq 10\sqrt{d \log d}$  for all  $u, v \in \{0,1\}^n$

- Let  $A \in S^n(\mathbb{R})$  such that  $\|A_i\|_1 \leq d$  and  $|A_{i,i}| = O\left(\alpha \left(\log\left(\frac{d}{\alpha}\right) + 1\right)\right)$ .

If for any two vectors  $u, v \in \{0,1\}^n$  we have  $\frac{u^t A v}{\|u\| \|v\|} \leq \alpha$

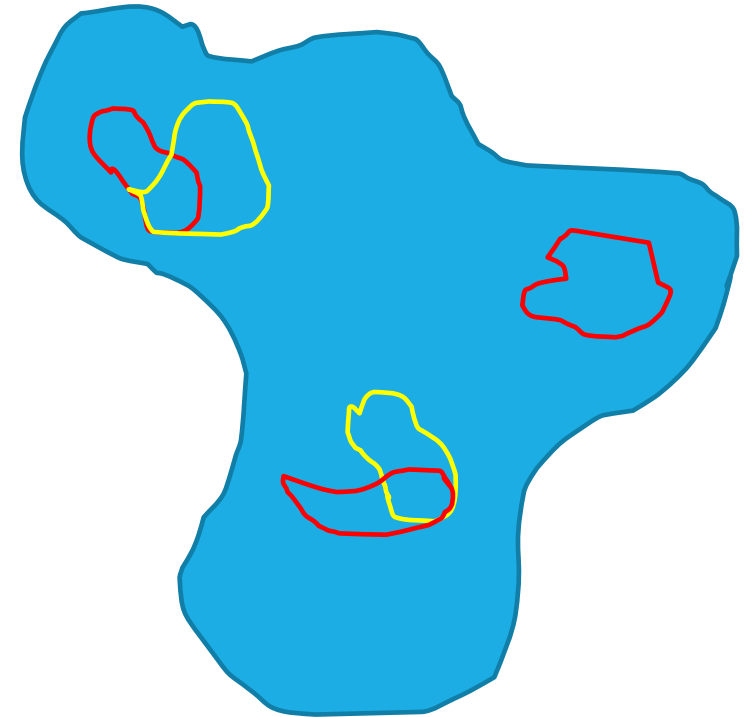
Then the spectral radius of  $A$  is  $O\left(\alpha \left(\log\left(\frac{d}{\alpha}\right) + 1\right)\right)$

- Plug  $\alpha = 10\sqrt{d \cdot \log(d)}$  to obtain the desired result

# GOOD SIGNINGS EXIST

- There exists a signing  $s$  such that  $\frac{|u^t M_s v|}{\|u\| \|v\|} \leq 10\sqrt{d \log d}$  for all  $u, v \in \{0,1\}^n$
- The vertices are  $V = \{1 \dots n\}$
- Denote  $S(v) = \{i \in [n] | v_i \neq 0\}$  the support of  $v$
- It suffices to prove for  $u, v$  such that  $S(u, v)$  is a connected component in  $G$ 
  - Denote  $S_1 \dots S_k$  the connected components of  $S(u, v)$  and decompose  $u = \sum u_i, v = \sum v_i$
  - For every  $i \neq j$  we have  $u_i^t M_s v_j = 0$

$$|u^t M_s v| \leq \sum |u_i^t M_s v_i| \leq \sum_{i=1}^k 10\sqrt{d \log(d)} \|u_i\| \|v_i\| \leq 10\sqrt{d \log(d)} \|u\| \|v\|$$



# GOOD SIGNINGS EXIST

- There exists a signing  $s$  such that  $\frac{|u^t M_s v|}{\|u\| \|v\|} \leq 10\sqrt{d \log d}$  for all  $u, v \in \{0,1\}^n$  when  $S(u, v)$  is a connected component
- Express  $u^t M_s v$  as  $\sum_{i \in S(v), j \in S(u)} (M_s)_{i,j}$ 
  - $(M_s)_{i,j}$  are independent random variables attaining values in  $\pm 1$  or  $\pm 2$  with probability  $\frac{1}{2}$
  - $\mathbb{E}(M_s) = 0$
  - Summing over  $e(S(u), S(v))$  elements
- Define  $B_{u,v}$  the bad event  $|u^t M_s v| > 10\sqrt{d \log d} \|u\| \|v\|$
- Hoeffding's Inequality

$$\mathbb{P}[|X - \mu| > t] \leq 2 \exp\left(\frac{2t^2}{\sum_{i=1}^m (b_i - a_i)^2}\right)$$

## GOOD SIGNINGS EXIST

- W.l.o.g,  $|S(u)| \geq \frac{1}{2}|S(u, v)|$

$$\begin{aligned}\mathbb{P}[B_{u,v}] &= \mathbb{P}\left[|v^t M_s u - 0| > 10\sqrt{d \log d} \|u\| \|v\|\right] \\ &\leq 2 \exp\left(-\frac{2 \cdot 100d \cdot \log(d) |S(u)||S(v)|}{16e(S(u), S(v))}\right) \\ &\leq 2 \exp\left(-\frac{100d \cdot \log(d) |S(u)||S(v)|}{8d|S(v)|}\right) \\ &\leq 2 \exp\left(-\frac{100 \log(d) \frac{|S(u, v)|}{2}}{8}\right) \\ &\leq d^{-6|S(u, v)|}\end{aligned}$$

# GOOD SIGNINGS EXIST

- For each pair of vectors  $u, v \in \{0,1\}^n$  there is a small probability to fail.  $\mathbb{P}[B_{u,v}] \leq d^{-6|S(u,v)|}$
- How many such pairs of vectors are there?
- Union bound wouldn't suffice

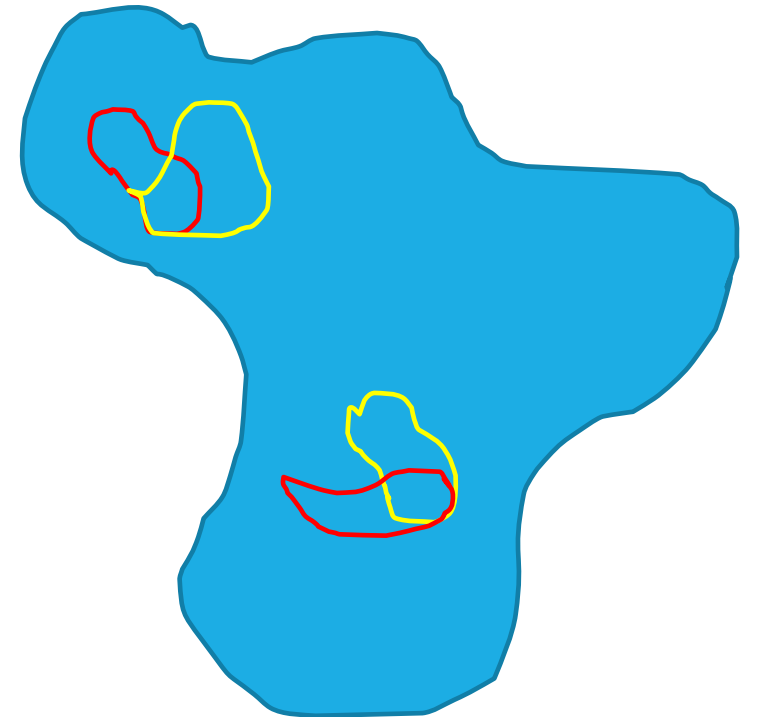
# LOVASZ LOCAL LEMMA

- Let  $H$  be a dependency graph
  - $A_1 \dots A_n$  are vertices corresponding bad events
  - $A_i \sim A_j$  if  $A_i$  and  $A_j$  are dependent
  - Bounded degree  $d$
- If  $\mathbb{P}[A_i] \leq \frac{1}{4d}$  then  $\mathbb{P}[\overline{A_1} \wedge \dots \wedge \overline{A_n}] > 0$
- If we assign each event  $A_i$  a quantity  $x_i \in [0,1]$  such that for all  $i$  we get  $\mathbb{P}[A_i] \leq x_i \prod_{A_j \sim A_i} (1 - x_j)$

$$\mathbb{P}[\overline{A_1} \wedge \dots \wedge \overline{A_n}] > \prod_{i=1}^n (1 - x_i) > 0$$

# DEPENDENCY GRAPH

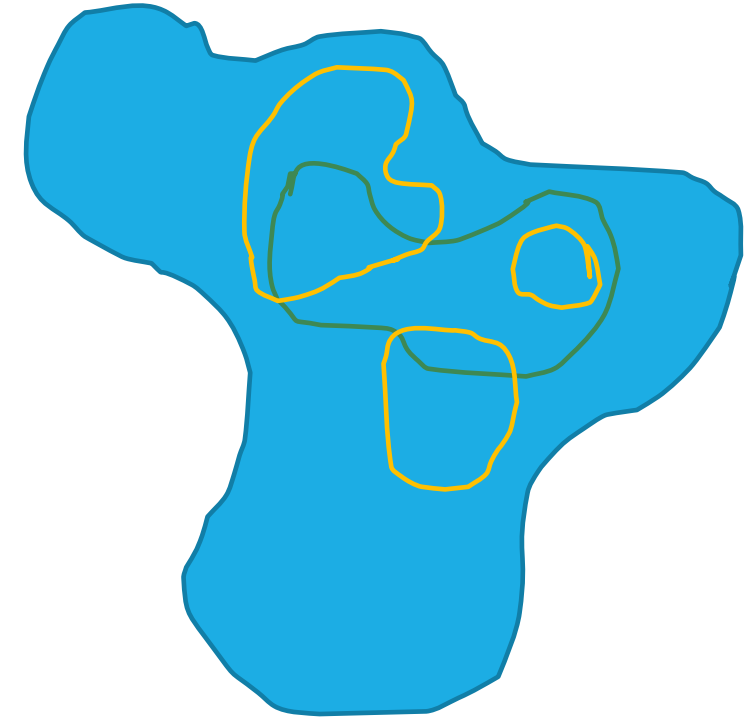
- Each vertex corresponds a bad event  $B_{u,v}$ , which happens with probability  $\mathbb{P}[B_{u,v}] \leq d^{-6|S(u,v)|}$ 
  - Only when  $S(u, v)$  form a connected component
- $B_{u,v}$  and  $B_{u',v'}$  are independent if  $S(u, v) \cap S(u', v') = \emptyset$
- How does the dependency graph look like?

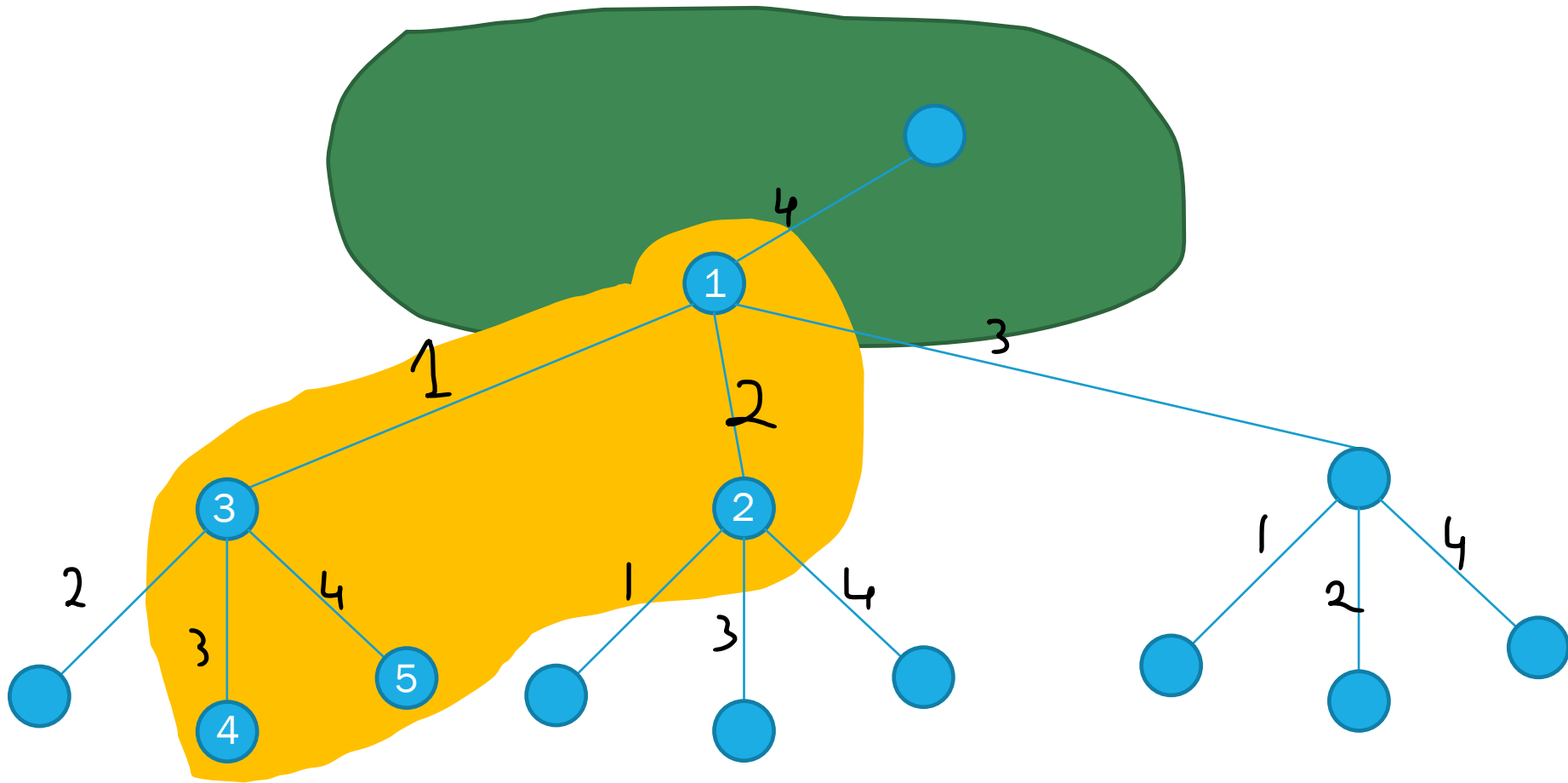




# DEPENDENCY GRAPH

- Let  $B_{u,v}$  be such that  $|S(u,v)| = k$ 
  - How many sets  $S(u',v')$  of size  $l$  can depend on  $B_{u,v}$ ?
    - At most  $k \binom{d(l-1)}{l-1} \leq k(de)^{l-1}$

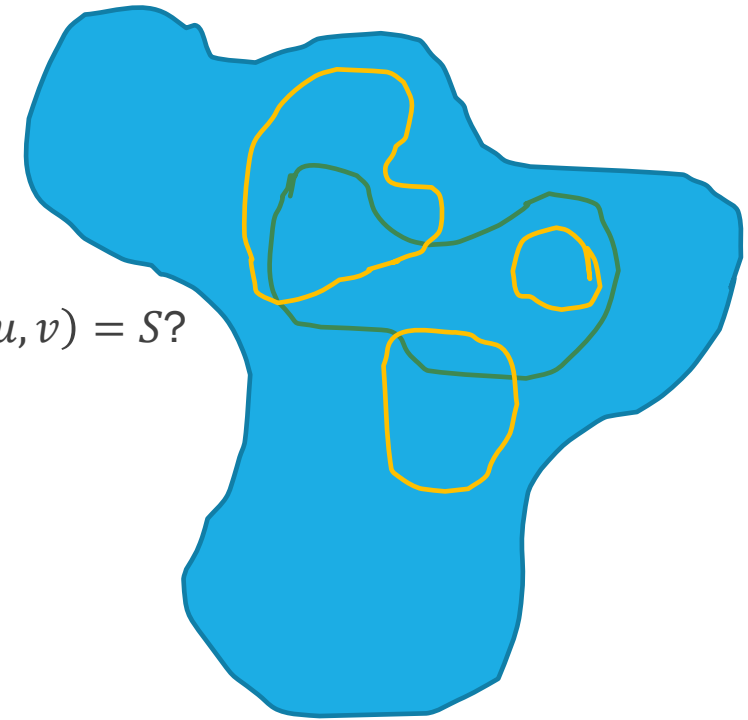




- (1,2)
- (1,1)
- (3,3)
- (3,4)

# DEPENDENCY GRAPH

- Let  $B_{u,v}$  be such that  $|S(u, v)| = k$ 
  - How many sets  $S(u', v')$  of size  $l$  can depend on  $B_{u,v}$ ?
    - At most  $k \binom{d(l-1)}{l-1} \leq k(de)^{l-1}$
- For a given support  $S \subseteq [n]$ , how many pairs of vectors  $u, v$  are there such that  $S(u, v) = S$ ?
  - At most  $3^{|S|}$
- Together, at most  $3k(3de)^{l-1}$  neighbors of weight  $l$



# LOVASZ LOCAL LEMMA

- Let  $H$  be a dependency graph
  - $A_1 \dots A_n$  are vertices corresponding bad events
  - $A_i \sim A_j$  if  $A_i$  and  $A_j$  are dependent
  - Bounded degree  $d$
- If  $\mathbb{P}[A_i] \leq \frac{1}{4d}$  then  $\mathbb{P}[\overline{A_1} \wedge \dots \wedge \overline{A_n}] > 0$
- If we assign each event  $A_i$  a quantity  $x_i \in [0,1]$  such that for all  $i$  we get  $\mathbb{P}[A_i] \leq x_i \prod_{A_j \sim A_i} (1 - x_j)$

$$\mathbb{P}[\overline{A_1} \wedge \dots \wedge \overline{A_n}] > \prod_{i=1}^n (1 - x_i) > 0$$

# LOVASZ LOCAL LEMMA

- Choose  $x_{u,v} = d^{-3k} = d^{-3|S(u,v)|}$

$$\begin{aligned}x_{u,v} \prod_{B_{u',v'} \sim B_{u,v}} (1 - x_{u',v'}) &= d^{-3k} \prod_{B_{u',v'} \sim B_{u,v}} (1 - d^{-3|S(u',v')|}) \\ &= d^{-3k} \prod_{l \in [n]} (1 - d^{-3l})^{3k \cdot (3de)^{l-1}} \\ &\geq d^{-3k} \exp\left(2 \cdot 3k \sum_{l \in [n]} d^{-3l} \cdot (3de)^{l-1}\right) \\ &\geq d^{-3k} e^{-3k} \\ &\geq d^{-6k}\end{aligned}$$

- Thus,  $\mathbb{P}[\overline{\bigwedge B_{u,v}}] > 0$

## GOOD SIGNINGS EXIST

- $0 < \mathbb{P}[\overline{\bigwedge B_{u,v}}] = \mathbb{P}\left[\forall u, v \in \{0,1\}^n: \frac{u^t M_s v}{\|u\| \|v\|} \leq 10\sqrt{d \log(d)}\right]$
- There is a strictly positive probability for such a signing  $s$
- Particularly, there exists such a signing, which finishes the proof

## PROOF STEPS

- There exists a signing  $s$  such that  $\frac{|u^t M_s v|}{\|u\| \|v\|} \leq 10\sqrt{d \log d}$  for all  $u, v \in \{0,1\}^n$

- Let  $A \in S^n(\mathbb{R})$  such that  $\|A_i\|_1 \leq d$  and  $|A_{i,i}| = O\left(\alpha \left(\log\left(\frac{d}{\alpha}\right) + 1\right)\right)$ .

If for any two vectors  $u, v \in \{0,1\}^n$  we have  $\frac{u^t A v}{\|u\| \|v\|} \leq \alpha$

Then the spectral radius of  $A$  is  $O\left(\alpha \left(\log\left(\frac{d}{\alpha}\right) + 1\right)\right)$

- Plug  $\alpha = 10\sqrt{d \cdot \log(d)}$  to obtain the desired result

# CONVERSE MIXING LEMMA

- The Expander Mixing Lemma states that for all  $S, T \subseteq V$  holds

$$\left| e(S, T) - \frac{d}{n} |S||T| \right| \leq \lambda \sqrt{|S||T|}$$

- Suppose we have for some graph  $G$  and some value  $\alpha > 0$  that all  $S, T \subseteq V$  with  $S \cap T = \emptyset$  uphold

$$\left| e(S, T) - \frac{d}{n} |S||T| \right| \leq \alpha \sqrt{|S||T|}$$

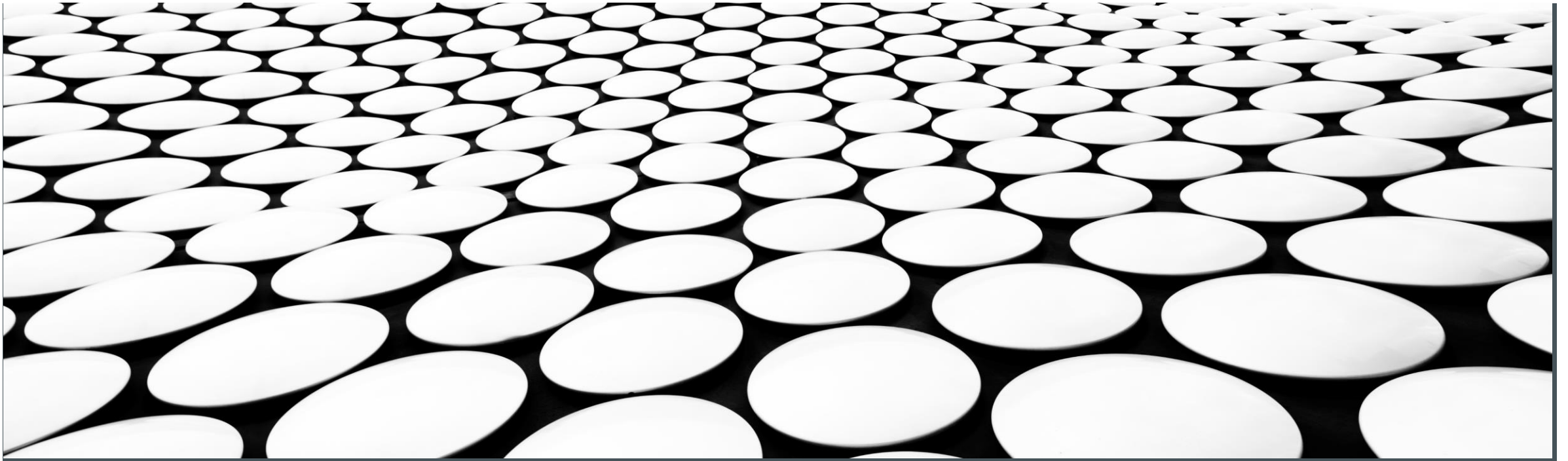
- We would like to say something about the spectral gap of  $G$ .

$$\frac{\left| u^t (M_G - \frac{d}{n} \mathbb{J}) v \right|}{\|u\| \|v\|} = \frac{\left| u^t M_G v - \frac{d}{n} u^t \mathbb{J} v \right|}{\|u\| \|v\|} = \frac{\left| e(S, T) - \frac{d}{n} |S||T| \right|}{\sqrt{|S||T|}} \leq \alpha$$



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# **BILU – LINIAL EXPANDERS – CONSTRUCTION**



# WHAT NOW?

- A remark about a converse to the Expander Mixing Lemma
- Almost all 2-lifts are “good” (with assumptions on the initial graph)
  - So iteratively lifting yields a “good” expander of arbitrary size w.h.p.
- Derandomization which gives a (weakly) explicit construction (deterministic, in polynomial time)
  
- If time permits:
  - A few words about trying to get a strongly explicit construction
  - A few words about the proof of the super technical lemma, and possible interesting byproducts

## CONVERSE MIXING LEMMA

- The Expander Mixing Lemma states that for all  $S, T \subseteq V$  holds

$$\left| e(S, T) - \frac{d}{n} |S||T| \right| \leq \lambda \sqrt{|S||T|}$$

- Suppose we have for some graph  $G$  and some value  $\alpha > 0$  that all  $S, T \subseteq V$  with  $S \cap T = \emptyset$  uphold

$$\left| e(S, T) - \frac{d}{n} |S||T| \right| \leq \alpha \sqrt{|S||T|}$$

- We would like to say something about the spectral gap of  $G$ . Denote  $\mathbb{1}_X$  to be the indicator function,  $O$  the all-ones matrix:

$$\alpha \geq \frac{\left| e(S, T) - \frac{d}{n} |S||T| \right|}{\sqrt{|S||T|}} = \frac{\left| \mathbb{1}_S^t M_G \mathbb{1}_T - \frac{d}{n} \mathbb{1}_S^t O \mathbb{1}_T \right|}{|\mathbb{1}_S| |\mathbb{1}_T|} = \frac{\left| \mathbb{1}_S^t (M_G - \frac{d}{n} O) \mathbb{1}_T \right|}{|\mathbb{1}_S| |\mathbb{1}_T|}$$

## CONVERSE MIXING LEMMA

- Now we have  $\alpha \geq \frac{|u^t(M_G - \frac{d}{n}O)v|}{|u||v|}$  for all  $u, v \in \{0,1\}^n$  with  $S(u) \cap S(v) = \emptyset$
- The lemma - “Let  $A \in M_{n \times n}$  a real symmetric matrix such that the  $l_1$  norm of each row is at most  $d$ , and all diagonal entries are, in absolute value,  $O\left(\alpha * \left(\log\left(\frac{d}{\alpha}\right) + 1\right)\right)$ . Assume that for any  $u, v \in \{0,1\}^n$  with  $S(u) \cap S(v) = \emptyset$  we have  $\frac{|u^tAv|}{|u||v|} \leq \alpha$ , then all eigenvalues of  $A$  are  $O\left(\alpha * \left(\log\left(\frac{d}{\alpha}\right) + 1\right)\right)$  “
- The matrix  $\left(M_G - \frac{d}{n}O\right)$  upholds the assumptions of the lemma, so we get a bound on its eigenvalues.
- It shares all eigenvalues (except  $\lambda_1 = d$ ) with  $M_G$  (why?)

# MOST 2-LIFTS ARE GOOD

- We saw every  $d$ -regular graph  $G$  had a 2-lift  $\hat{G}$  with all new eigenvalues  $O\left(\sqrt{d \log^3 d}\right)$
- For construction to be feasible we want to be able to find good 2-lifts
- Would be nice if most 2-lifts were good
  - But we will have to add some restrictions on  $G$ .
- The intuition – condition that makes sure that  $u, v$  with small supports work.
  - (recall during the previous proof we saw the chance of each ‘bad event’ was  $\leq d^{-6*|S(u,v)|}$ , so we only need worry about small supports)
- Definition: a graph  $G$  is  $(\beta, t)$  – *sparse* if for any  $u, v \in \{0,1\}^n$  with  $|S(u, v)| \leq t$  holds  $|u^t M_G v| \leq \beta * |u||v|$

# MOST 2-LIFTS ARE GOOD

- Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$  – *sparse* (with  $\gamma(d) = 10\sqrt{d \log_2 d}$ ).  
and let  $\hat{G}$  be the 2-lift from a random signing  $s$ . So w.h.p. –

1. for all  $u, v \in \{0,1\}^n$  :  $\frac{|u^t M_s v|}{\|u\| \|v\|} \leq \gamma(d) = 10\sqrt{d \log d}$

this means the eigenvalues of  $\hat{G}$  will be bounded as before

2.  $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$  – *sparse*

this means we can continue inductively

Working memory

# MOST 2-LIFTS ARE GOOD

- First we prove (1)
- Recall the ‘bad events’ -  $\mathbb{P} \left[ \frac{|u^t M_S v|}{\|u\| \|v\|} > \gamma(d) \right] \leq d^{-6|S(u,v)|}$
- For a given value of  $k$  there are at most  $n \binom{d(k-1)}{k-1} \leq n(de)^{k-1}$  connected subgraphs of size  $k$  in  $G$
- Each of those might have as many as  $3^k$  options for  $u, v$
- If  $k = |S(u, v)| \leq \lceil \log_2 n \rceil$  we have (1) for free ( $G$  is  $(\gamma(d), \lceil \log_2 n \rceil)$  – sparse)
- $Pr((1) \text{ fails}) \leq \sum_{k > \lceil \log_2 n \rceil} 3^k n (de)^{k-1} * d^{-6k} \leq \frac{1}{2d} n^{-5 \log_2 d + 4.03}$   
 $= O\left(\frac{1}{poly(n^{\log_2 d})}\right)$

Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$  – sparse So w.h.p. –

1. for all  $u, v \in \{0,1\}^n : \frac{|u^t M_S v|}{\|u\| \|v\|} \leq \gamma(d)$

2.  $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$  – sparse

Working memory

# MOST 2-LIFTS ARE GOOD

Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$  – sparse So w.h.p. –

(V) 1. for all  $u, v \in \{0,1\}^n$  :  $\frac{|u^t M_S v|}{\|u\| \|v\|} \leq \gamma(d)$

2.  $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$  – sparse

- Now we want (2) – meaning  $|u^t M_{\hat{G}} v| \leq \gamma(d) \|u\| \|v\|$  for all  $u, v \in \{0,1\}^{2n}$  such that  $|S(u, v)| \leq 1 + \lceil \log_2 n \rceil$
- Because we care about  $|u^t M_{\hat{G}} v| / \|u\| \|v\|$  we may assume each vertex in  $S(u)$  is connected (in  $\hat{G}$ ) to some vertex in  $S(v)$ 
  - otherwise drop it to get a harder bar to clear
- $M_{\hat{G}} = \begin{bmatrix} M_1 & M_{-1} \\ M_{-1} & M_1 \end{bmatrix}, \quad M_G = M_1 + M_{-1}, \quad M_S = M_1 - M_{-1}$

Working memory

New:

$S(u, v)$  is connected in  $\hat{G}$   
 $|S(u, v)| \leq 1 + \lceil \log_2 n \rceil$

$$M_{\hat{G}} = \begin{bmatrix} M_1 & M_{-1} \\ M_{-1} & M_1 \end{bmatrix},$$

$$M_G = M_1 + M_{-1},$$



# MOST 2-LIFTS ARE GOOD

- We would like to use our assumption that  $G$  is  $(\gamma(d), \lceil \log_2 n \rceil)$  – *sparse*
- For that we want subsets of  $V_G$  and not  $V_{\hat{G}}$ 
  - Consider fibers in  $\hat{G}$
- $u = (u_1, u_2)$     $u_{OR} = u_1 \vee u_2$     $u_{AND} = u_1 \wedge u_2$

Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$  – *sparse* So w.h.p. –

(V) 1. for all  $u, v \in \{0,1\}^n$  :  $\frac{|u^t M_s v|}{\|u\| \|v\|} \leq \gamma(d)$

2.  $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$  – *sparse*

Working memory

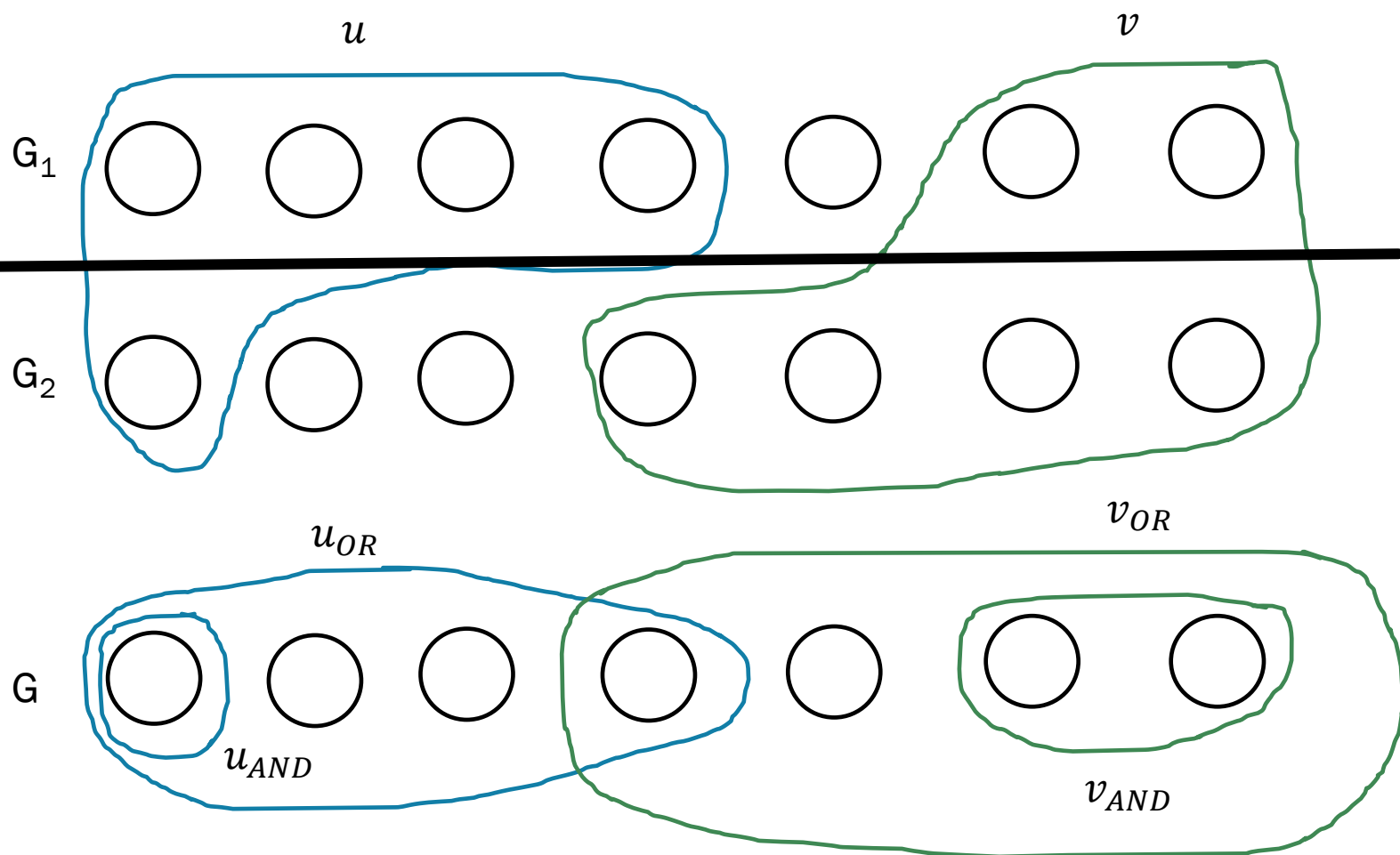
$S(u, v)$  is connected in  $\hat{G}$

$$|S(u, v)| \leq 1 + \lceil \log_2 n \rceil$$

$$M_{\hat{G}} = \begin{bmatrix} M_1 & M_{-1} \\ M_{-1} & M_1 \end{bmatrix},$$

$$M_G = M_1 + M_{-1},$$

$$u = (u_1, u_2) \quad u_{OR} = u_1 \vee u_2 \quad u_{AND} = u_1 \wedge u_2$$



$$u = (u_1, u_2)$$

$$|u|^2 = |u_{OR}|^2 + |u_{AND}|^2$$

$$u_{OR} + u_{AND} = u_1 + u_2$$

$$|S(u, v)| \geq |S(u_{OR}, v_{OR})|$$

Note:  $u, v \in \{0, 1\}^{2n}$

$u_{OR}, v_{OR} \in \{0, 1\}^n$

# MOST 2-LIFTS ARE GOOD

Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$  – sparse So w.h.p. –

(V) 1. for all  $u, v \in \{0,1\}^n : \frac{|u^t M_s v|}{\|u\| \|v\|} \leq \gamma(d)$

2.  $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$  – sparse

- $u_{OR}, u_{AND}$  will be our subsets in  $G$  for applying  $(\gamma(d), \lceil \log_2 n \rceil)$  – sparseness
- $|u|^2 = |u_{OR}|^2 + |u_{AND}|^2 ; u_{OR} + u_{AND} = u_1 + u_2 ; |S(u, v)| \geq |S(u_{OR}, v_{OR})|$   
 $u^t M_{\hat{G}} v = u_1^t M_1 v_1 + u_2^t M_{-1} v_1 + u_1^t M_{-1} v_2 + u_2^t M_1 v_2 \leq u_{OR}^t M_G v_{OR} + u_{AND}^t M_G v_{AND}$
- If  $|S(u_{OR}, v_{OR})| \leq \lceil \log_2 n \rceil$  we get from  $G$  being  $(\gamma(d), \lceil \log_2 n \rceil)$  – sparse :
- $u^t M_{\hat{G}} v \leq u_{OR}^t M_G v_{OR} + u_{AND}^t M_G v_{AND} \leq \gamma(d) * (|u_{OR}| |v_{OR}| + |u_{AND}| |v_{AND}|) \leq \gamma(d) * (|u| |v|)$
- Which is precisely (2). Which leaves the case of  $|S(u_{OR}, v_{OR})| \geq 1 + \lceil \log_2 n \rceil$

Working memory

$S(u, v)$  is connected in  $\hat{G}$

$$|S(u, v)| \leq 1 + \lceil \log_2 n \rceil$$

$$M_{\hat{G}} = \begin{bmatrix} M_1 & M_{-1} \\ M_{-1} & M_1 \end{bmatrix}$$

$$M_G = M_1 + M_{-1},$$

New:

$$u = (u_1, u_2)$$

$$u_{OR} = u_1 \vee u_2 ; u_{AND} = u_1 \wedge u_2$$

$$|S(u, v)| \geq |S(u_{OR}, v_{OR})|$$

$$u^t M_{\hat{G}} v \leq u_{OR}^t M_G v_{OR} + u_{AND}^t M_G v_{AND}$$

$$|S(u_{OR}, v_{OR})| \geq 1 + \lceil \log_2 n \rceil$$

# MOST 2-LIFTS ARE GOOD

- From  $|S(u, v)| \geq |S(u_{OR}, v_{OR})|$ , we get  $|S(u, v)| = |S(u_{OR}, v_{OR})| = 1 + \lceil \log_2 n \rceil$
- So  $S(u, v)$  cannot contain both vertices from a fiber of  $\hat{G}$ 
  - In particular,  $u_{AND} = v_{AND} = \vec{0}$  and so  $|u| = |u_{OR}|$ ;  $|v| = |v_{OR}|$
- We want to apply  $G$ 's  $(\gamma(d), \lceil \log_2 n \rceil)$ -sparseness to  $u^t M_{\hat{G}} v \leq u_{OR}^t M_G v_{OR}$
- Only problem is  $|S(u_{OR}, v_{OR})|$  is too big by 1
- By taking one vertex out of  $S(v)$  we get:
- $u_{OR}^t M_G v'_{OR} \leq \gamma(d) \sqrt{|S(u)| |S(v) - 1|}$

Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$  - sparse So w.h.p. -

(V) 1. for all  $u, v \in \{0,1\}^n$  :  $\frac{|u^t M_S v|}{\|u\| \|v\|} \leq \gamma(d)$

2.  $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$  - sparse

Working memory

$S(u, v)$  is connected in  $\hat{G}$

$$|S(u, v)| \leq 1 + \lceil \log_2 n \rceil$$

$$u = (u_1, u_2)$$

$$u_{OR} = u_1 \vee u_2 ; u_{AND} = u_1 \wedge u_2$$

$$|S(u, v)| \geq |S(u_{OR}, v_{OR})|$$

$$u^t M_{\hat{G}} v \leq u_{OR}^t M_G v_{OR} + u_{AND}^t M_G v_{AND}$$

$$|S(u_{OR}, v_{OR})| \geq 1 + \lceil \log_2 n \rceil$$

New:

$$|S(u, v)| = |S(u_{OR}, v_{OR})| = 1 + \lceil \log_2 n \rceil$$

$$|u| = |u_{OR}| ; |v| = |v_{OR}|$$

$$u^t M_{\hat{G}} v \leq u_{OR}^t M_G v_{OR}$$

# MOST 2-LIFTS ARE GOOD

Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$  - sparse So w.h.p. -

(V) 1. for all  $u, v \in \{0,1\}^n$  :  $\frac{|u^t M_S v|}{\|u\| \|v\|} \leq \gamma(d)$

2.  $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$  - sparse

- taking one vertex out of  $S(v)$  gives -  $u_{OR}^t M_G v'_{OR} \leq \gamma(d) \sqrt{|S(u)| |S(v) - 1|}$

- Summing over all candidates for vertices to take out gives

$$|S(v) - 2| * u_{OR}^t M_G v_{OR} \leq |S(v)| \gamma(d) \sqrt{|S(u)| |S(v) - 1|}$$

- We are trying to prove  $u_{OR}^t M_G v_{OR} \leq \gamma(d) \frac{|S(v)| - 1}{|S(v)| - 2} \sqrt{|S(u_{OR})| |S(v_{OR})|}$ .

- So assume  $u_{OR}^t M_G v_{OR} > \gamma(d) \sqrt{|S(u_{OR})| |S(v_{OR})|}$ , suppose  $|S(u_{OR})| \leq |S(v_{OR})|$

- Regularity gives  $u_{OR}^t M_G v_{OR} \leq d |S(u_{OR})|$

- Together we get  $\frac{|S(u_{OR})|}{|S(v_{OR})|} > \frac{\gamma(d)^2}{d^2} = \frac{100 \log_2 d}{d}$

Working memory

$S(u, v)$  is connected in  $\hat{G}$

$$u = (u_1, u_2) \quad u_{OR} = u_1 \vee u_2$$

$$|S(u, v)| = |S(u_{OR}, v_{OR})| = 1 + \lceil \log_2 n \rceil$$

$$|u| = |u_{OR}| ; |v| = |v_{OR}|$$

$$u^t M_{\hat{G}} v \leq u_{OR}^t M_G v_{OR}$$

New:

$$1 \geq \frac{|S(u_{OR})|}{|S(v_{OR})|} > \frac{\gamma(d)^2}{d^2} = \frac{100 \log_2 d}{d}$$

$$\frac{u_{OR}^t M_G v_{OR}}{\leq \sqrt{\frac{|S(v)|}{|S(v)| - 1} \frac{\gamma(d)(|S(v)| - 1)}{|S(v)| - 2} \sqrt{|S(u)| |S(v)|}}}$$

$$|S(u_{OR})| \leq |S(v_{OR})| \geq \frac{\log_2 + 1}{2}$$

# MOST 2-LIFTS ARE GOOD

Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$  - sparse So w.h.p. -

(V) 1. for all  $u, v \in \{0,1\}^n$  :  $\frac{|u^t M_S v|}{\|u\| \|v\|} \leq \gamma(d)$

2.  $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$  - sparse

- Edges in  $\hat{G}$  from  $S(u)$  to  $S(v)$  come from edges in  $G$  between  $S(u_{OR})$  and  $S(v_{OR})$ . Since no fiber is contained in  $S(u, v)$  each edge survives with  $p=0.5$

$$\mathbb{E}[u^t M_{\hat{G}} v] \leq \frac{1}{2} \mathbb{E}[u_{OR}^t M_G v_{OR}] \leq \left( \frac{1}{2} \sqrt{\frac{|S(v)|}{|S(v)|-1}} \right) \gamma(d) \sqrt{|S(u_{OR})| |S(v_{OR})|}$$

- By multiplicative Chernoff bound  $\mathbb{P}(X > (1 + \delta)\mu) \leq \exp\left(-\frac{\delta^2 \mu}{3}\right)$  ( $\delta < 1$ )

$$\begin{aligned} \mathbb{P}(u^t M_{\hat{G}} v > \gamma(d) \sqrt{|S(u)| |S(v)|}) &\leq \exp\left(-0.1 \gamma(d) \sqrt{|S(u)| |S(v)|}\right) \\ &\leq \exp(-0.05 \gamma(d) (\log_2 n + 1)) \left(10 \sqrt{\frac{\log_2 d}{d}}\right) = \exp(-5 \log_2 d (1 + \log_2 n)) \end{aligned}$$

Working memory

$S(u, v)$  is connected in  $\hat{G}$

$$u = (u_1, u_2) \quad u_{OR} = u_1 \vee u_2$$

$$|S(u, v)| = |S(u_{OR}, v_{OR})| = 1 + \lceil \log_2 n \rceil$$

$$|u| = |u_{OR}| ; |v| = |v_{OR}|$$

$$u^t M_{\hat{G}} v \leq u_{OR}^t M_G v_{OR}$$

$$\leq \sqrt{\frac{|S(v)|}{|S(v)|-1}} \gamma(d) \sqrt{|S(u)| |S(v)|}$$

$$\frac{|S(u_{OR})|}{|S(v_{OR})|} > \frac{100 \log_2 d}{d}$$

$$|S(u_{OR})| \leq |S(v_{OR})| \geq \frac{\log_2 n + 1}{2}$$

# MOST 2-LIFTS ARE GOOD

Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$  - sparse So w.h.p. -

(V) 1. for all  $u, v \in \{0,1\}^n$  :  $\frac{|u^t M_s v|}{\|u\| \|v\|} \leq \gamma(d)$

2.  $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$  - sparse

- For specific  $u, v$  with  $|S(u, v)| = 1 + \lceil \log_2 n \rceil$  we got  
$$\mathbb{P}\left(u^t M_{\hat{G}} v > \gamma(d) \sqrt{|S(u)| |S(v)|}\right) < \exp(-5 \log_2 d (1 + \log_2 n))$$
- There are at most  $2n \binom{d(k-1)}{k-1} \leq 2n(de)^{k-1}$  connected subgraphs of size  $k$  in  $\hat{G}$  and each has at most  $3^k$  partitions to  $u, v$ . we care about  $k = 1 + \lceil \log_2 n \rceil$
- Union bound gives us the chance of a signing to be bad is  $O\left(\frac{1}{\text{poly}(n^{\log_2 d})}\right)$
- woohoo

Working memory

$S(u, v)$  is connected in  $\hat{G}$

$|S(u, v)| = 1 + \lceil \log_2 n \rceil$

# FIRST ALGORITHM

- Start with  $(\gamma(d), \lceil \log_2 n_0 \rceil)$  – *sparse*  $d$ -regular graph
- Pick a random signing and create the 2-lift graph
- Keep going until the graph is of the desired size
- Guaranteed to have  $O\left(\frac{1}{\text{poly}(n^{\log_2 d})}\right)$  chance to end up with a bad graph
- Could repeat the process until you get a good one



# DETERMINISTIC ALGORITHM

- Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$  – *sparse* (with  $\gamma(d) = 10\sqrt{d \log_2 d}$ ). Then there is a deterministic polynomial time algorithm for finding a signing  $s$  of  $G$  such that the following hold:
  1. the spectral radius of  $G_s$  is  $O\left(\sqrt{d \log^3 d}\right)$
  2.  $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$  – *sparse*
- We want to reconstruct our argument for bounding the probability of a ‘bad’ signing in a concise way so we can derandomize it (non of that “for all  $u, v \in \{0,1\}^n$ ” stuff, too many of those...)
  - We swapped that out for a concise statement about the spectral radius of  $G_s$

# MOST 2-LIFTS ARE GOOD (AGAIN)

Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$ -sparse (with  $\gamma(d) = 10\sqrt{d \log_2 d}$ ). Then there is a deterministic polynomial time algorithm for finding a signing  $s$  of  $G$  such that the following hold:

1. the spectral radius of  $G_s$  is  $O(\sqrt{d \log^3 d})$
2.  $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$ -sparse

- For every closed path  $p$  in  $G$  of length  $l = 2\lceil \log_2 n \rceil$  define  $Y_p = \prod_{e \in p} s(e)$
- Name  $Y := \sum_p Y_p$  and note that  $Y = \text{Tr}(M_s^l)$  to get
- $\mathbb{E}[Y] = \mathbb{E}[\text{Tr}(M_s^l)] = \mathbb{E}[\sum_{\mu \in \text{spec}(M_s)} \mu^l] = O(\sqrt{d(\log_2 d)^3})^l$ 
  - **The last equation** is due the bound we showed on the probability of bad  $\mu$ .
  - we got  $p \leq d^{-2l}$  and the worst an eigenvalue could be is  $d$ , so this is good enough to bound the effect on  $\mathbb{E}[n * \mu^l]$  to be  $< 1$
  - $\mathbb{E}[Y]$  is positive because  $l$  is even (why is it not identically zero?)
- Making sure  $Y$  is small will ensure (1)
  - By small we mean close to its expected value

Working memory  
 $s$  is a random signing

New:  
 $l = 2\lceil \log_2 n \rceil$   
 $\mathbb{E}[Y] = O(\sqrt{d(\log_2 d)^3})^l$   
If  $Y$  is small,  $s$  upholds (1)

# MOST 2-LIFTS ARE GOOD (AGAIN)

- Now we want to encode (2) as the expectancy of a random variable
- We saw that for  $u, v \in \{0,1\}^{2n}$  with  $|S(u, v)| \leq \lceil \log_2 n \rceil$  we get the sparseness condition directly from  $G$  being  $(\gamma(d), \lceil \log_2 n \rceil)$ -sparse. Also,  $S(u, v)$  connected is good enough
- for  $u, v$  with  $S(u, v)$  connected and  $|S(u, v)| = 1 + \lceil \log_2 n \rceil$  define
 
$$Z_{u,v} = \begin{cases} d^l & u^t M_{\hat{G}} v > \gamma(d) \sqrt{|S(u)||S(v)|} \\ 0 & \text{otherwise} \end{cases}$$
- Want to bound  $\mathbb{E}[Z]$  for  $Z := \sum Z_{u,v}$ . We saw  $P(Z_{u,v} \neq 0) < \exp(-5 \log_2 d (1 + \log_2 n))$ 
  - Using the whole  $u_{OR}, v_{OR}$  mess, all the assumptions still hold, this bound holds for any such  $u, v$
- The number of  $(u, v)$  pairs is at most  $2n * 3(3ed)^{\log_2 n}$  so by the union bound we get
- $\mathbb{E}[Z] < 2n * 3(3ed)^{\log_2 n} * d^{\left(\left(2 - \frac{5}{\ln(2)}\right) \log_2 n\right)} < d^{-3 \log_2 n}$

Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$ -sparse (with  $\gamma(d) = 10\sqrt{d \log_2 d}$ ). Then there is a deterministic polynomial time algorithm for finding a signing  $s$  of  $G$  such that the following hold:

- the spectral radius of  $G_s$  is  $O(\sqrt{d \log^3 d})$
- $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$ -sparse

Working memory

$s$  is a random signing

$$l = 2 \lceil \log_2 n \rceil$$

$$\mathbb{E}[Y] = O\left(\sqrt{d(\log_2 d)^3}\right)^l$$

If  $Y$  is small,  $s$  upholds (1)

New:

$$\mathbb{E}[Z] < d^{-3 \log_2 n}$$

If  $Z = 0$ ,  $s$  upholds (2)

If  $Z \neq 0$ ,  $Z \geq d^{2 \lceil \log_2 n \rceil}$

## MOST 2-LIFTS ARE GOOD (AGAIN)

- Now combine the whole thing into one random variable
- Let  $X = Y + Z$  clearly  $\mathbb{E}[Y] \approx \mathbb{E}[X] < d^{2\lceil \log_2 n \rceil}$
- So if  $X$  is less than its expected value,  $Z = 0$  and  $Y = X \leq \mathbb{E}[X] \approx \mathbb{E}[Y]$
- So if  $X \leq \mathbb{E}[X]$  we know that (1) and (2) hold
- All that remains is finding a signing which gives a small value of  $X$
- Note that  $Y$  and  $Z$  are each a sum of  $\text{poly}(n^{\log_2 d})$  – many random variables, and the conditional expectation of each one (if we pre-assign some of the edges of  $s$ ) can be computed in poly-time

Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$  – sparse (with  $\gamma(d) = 10\sqrt{d \log_2 d}$ ). Then there is a deterministic polynomial time algorithm for finding a signing  $s$  of  $G$  such that the following hold:

1. the spectral radius of  $G_s$  is  $O(\sqrt{d \log^3 d})$
2.  $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$  – sparse

Working memory

$s$  is a random signing

$$l = 2\lceil \log_2 n \rceil$$

$$\mathbb{E}[Y] = O\left(\sqrt{d(\log_2 d)^3}\right)^{2\lceil \log_2 n \rceil}$$

If  $Y$  is small,  $s$  upholds (1)

$$\mathbb{E}[Z] < d^{-3 \log_2 n}$$

If  $Z = 0$ ,  $s$  upholds (2)

$$\text{If } Z \neq 0, Z \geq d^{2\lceil \log_2 n \rceil}$$

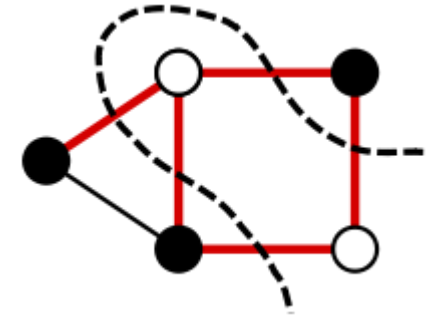
New:

$\mathbb{E}[Y_p], \mathbb{E}[Z_{u,v}]$  can be computed in poly-time even under conditional partial  $s$

if  $X \leq \mathbb{E}[X]$  (1) and (2) hold

# SHORT DETOUR - MAX CUT

- Given graph  $G$ , find  $S \subseteq V$  such that  $e(S, V \setminus S)$  is maximal (weighted case -  $\sum_{e \in e(S, V \setminus S)} w_e$ )
- NP-hard
- Can be randomly approximated:
  - Put each vertex in  $S$  or  $V \setminus S$  with probability 0.5
  - $E[\text{size of cut}] = \frac{1}{2} \sum_e w_e$
- This algorithm can be derandomized!



# DERANDOMAZATION – THE METHOD OF CONDITIONAL EXPECTATION

- At each step in the algorithm, what will the expected size of the final cut be?
- $\mathbb{E}[\textit{final cut}] = \sum_{e \textit{ already in cut}} w_e + \frac{1}{2} \sum_{e \textit{ is undecided}} w_e$
- This can be computed in poly time
- Note that for each unassigned vertex  $v$  we have:
- $\mathbb{E}[\textit{final cut}] = \frac{1}{2} \mathbb{E}[\textit{final cut} | v \textit{ in } S] + \frac{1}{2} \mathbb{E}[\textit{final cut} | v \textit{ in } V \setminus S]$
- So at least one of **these** is no less than  $\mathbb{E}[\textit{final cut}]$ .
- Place  $v$  so that the expected size of the final cut is largest, and continue to the next vertex
- We are guaranteed to get a cut of size  $\geq \mathbb{E}[\textit{final cut} | \textit{nothing assigned yet}] = \frac{1}{2} \sum w_e$

# DERANDOMAZATION

- We had  $X = Y + Z$  such that if  $X \leq \mathbb{E}[X]$  (1) and (2) hold
- $Y = \sum_p Y_p ; Z = \sum_{u,v} Z_{u,v}$
- $\mathbb{E}[Y_p], \mathbb{E}[Z_{u,v}]$  can be computed in poly-time even under conditional partial  $s$
- For each edge  $e$ :
  - Compute expected value of  $X$  if  $s(e) = 1$  and if  $s(e) = -1$
  - Give  $e$  the sign which yields a lower expected value of  $X$
  - Continue to next edge
- The signing you get will be good (deterministically!)

Let  $G$  be  $d$ -regular and  $(\gamma(d), \lceil \log_2 n \rceil)$ -sparse (with  $\gamma(d) = 10\sqrt{d \log_2 d}$ ). Then there is a deterministic polynomial time algorithm for finding a signing  $s$  of  $G$  such that the following hold:

1. the spectral radius of  $G_s$  is  $O(\sqrt{d \log^3 d})$
2.  $\hat{G}$  is  $(\gamma(d), 1 + \lceil \log_2 n \rceil)$ -sparse

Working memory

$s$  is a random signing

$\mathbb{E}[Y_p], \mathbb{E}[Z_{u,v}]$  can be computed in poly-time even under conditional partial  $s$

if  $X \leq \mathbb{E}[X]$  (1) and (2) hold

## ON AN UNRELATED NOTE (1)

- The construction is weakly explicit but not strongly explicit.
- Turns out there's a construction by Naor and Naor which lets us create a  $(k, \epsilon)$  – wise independent sample space.
- With parameter choice of  $k = d \log_2 n$  ,  $\epsilon = d^{-2d \log_2 n}$  the size of the sample space will be  $\text{poly}(n^{\log_2 d})$
- Using these random coin-tosses for giving signs to the edges gives chance of failure will be  $\leq 1/n$ 
  - Won't go into more details, though there are plenty



## ON AN UNRELATED NOTE (2)

- The super-technical lemma states - “Let  $A \in M_{n \times n}$  a real symmetric matrix such that the  $l_1$  norm of each row is at most  $d$ , and all diagonal entries are, in absolute value,  $O\left(\alpha * \left(\log\left(\frac{d}{\alpha}\right) + 1\right)\right)$ . Assume that for any  $u, v \in \{0,1\}^n$  with  $S(u) \cap S(v) = \phi$  we have  $\frac{|u^t A v|}{|u||v|} \leq \alpha$ , then all eigenvalues of  $A$  are  $O\left(\alpha * \left(\log\left(\frac{d}{\alpha}\right) + 1\right)\right)$  “
- It proves this claim by taking any vector  $x$ , and bounding its Rayleigh Quotient by splitting it into a sum of several multiples of 0,1-vectors (by the range of the entry size - 0.5-1, 0.25-0.5, 0.125-0.25 and so on) and using the lemma's assumption on each pair of those.
- This lets us get from a large eigenvalue to a counter-example of combinatorial edge expansion (S and T such that  $\left|e(S, T) - \frac{d}{n} |S||T|\right|$  is large. (note that we lose a factor of  $\log$ )
  - This is cool (and could maybe even be useful for someone at some point? But mostly cool)



**QUESTIONS?**