

Expanders (or Expansion)

- We now start the first topic in our list of pseudorandom constructions.

↳ We want to construct a graph family that is very well-connected. (e.g. distance $O(\lg |V|)$).

- Application 1: Solve the problem of undirected graph connectivity in logspace (L or RL) .

→ derandomize?

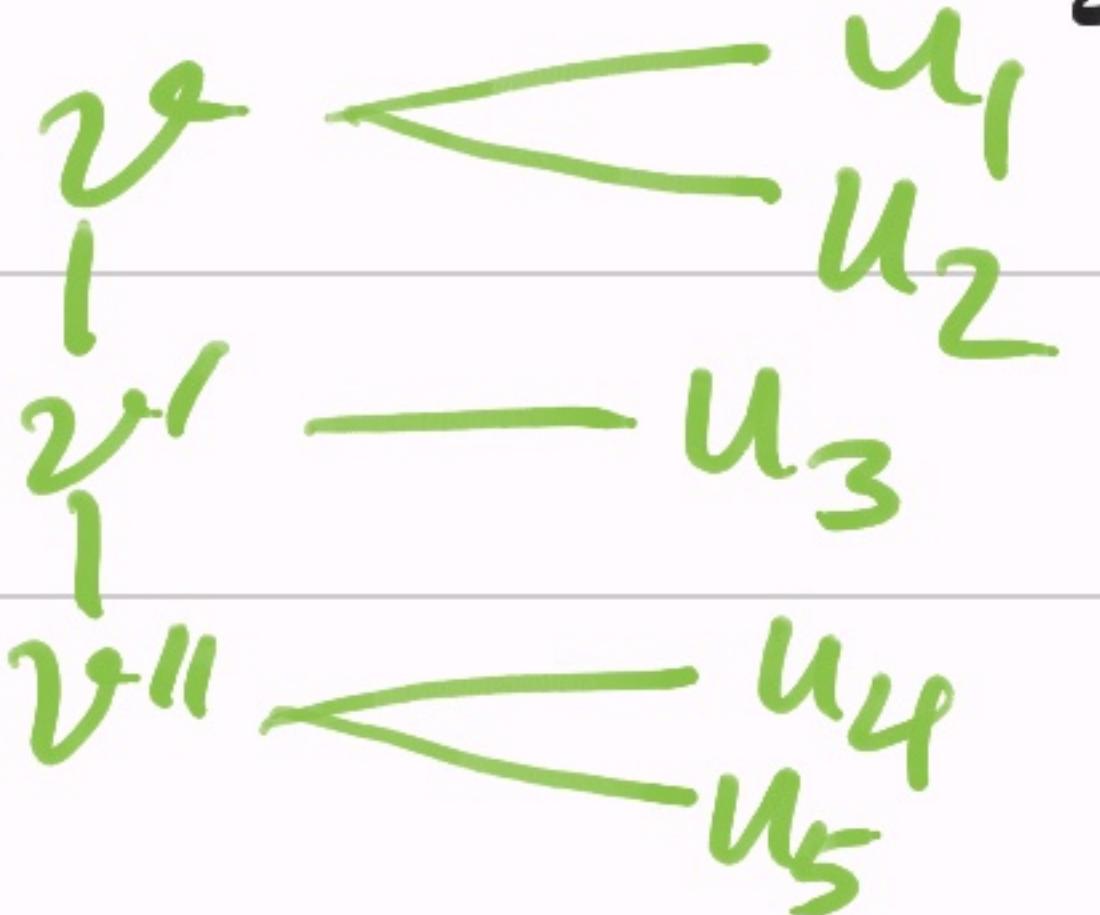
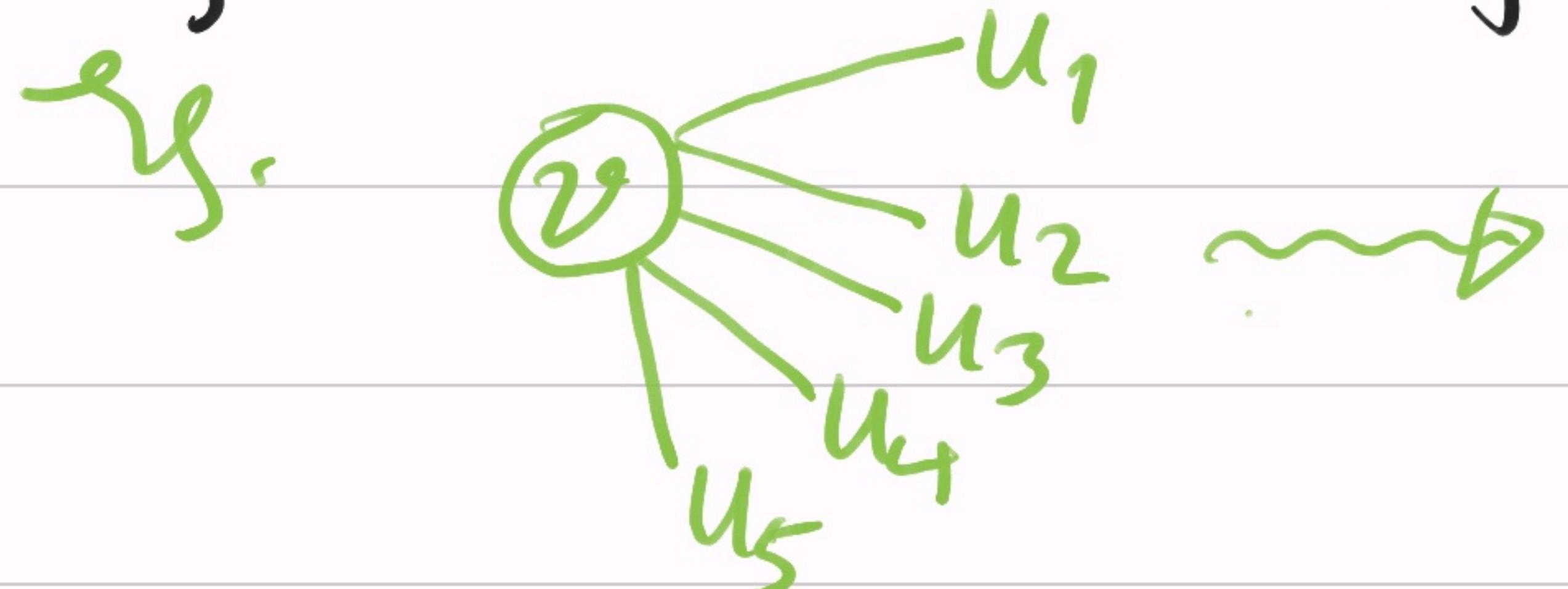
Defn: Upath := $\{(G, s, t) \mid \exists \text{ path } s \text{ to } t \text{ in the undirected graph } G\}$.

▷ Upath $\in P$.

Theorem (Aleliunas, Karp, Lipton, Lovász, Rackoff '79):
 $\text{Upath} \in \text{RL}$ (randomized-logspace-algo)

Proof: Idea- Consider adjacency matrix A & simulate a random walk on graph G as matrix powering.

- Suppose G is the given undirected graph with n vertices.
- We need G to be d-regular (i.e. $\forall v \in V(G)$, $\deg(v) = d$).
- E.g. we can transform G to get $d=3$:



▷ Apply this gadget on all the vertices, in logspace: $O(\lg n)$.

- Now on, assume G to be $d(=3)$ -regular.
- On this we do a random walk, starting from \mathcal{D} , of length $300 \cdot n \lg n$.
 - ▷ Random walk is implementable in $O(\lg n)$ -space.
- Assume G to have self-loops: $(v, v) \in E(G)$, $\forall v \in V$.
- Defn: Let $A_{n \times n}$ be the normalized adjacency matrix of G , i.e. $A_{ij} := \# \text{edges}(i, j) / d$. A is symmetric stochastic matrix.
 - ▷ $\forall i \in [n]$, $A_{ii} = 1/d$.
 - ▷ A is symmetric, with entries in $\{0, 1/d\}$.
 - ▷ A 's row-sum, & column-sum, is 1.

- Idea: A transforms the probability vector

$$\vec{p} := (p_1, \dots, p_n)^T, \text{ where } p_i := \text{probability of being at vertex } i.$$

▷ At any stage of the walk: $\sum_{i=1}^n p_i = 1$.
 (Initially, $p_i = 1$ for $i = s$ & 0 otherwise.)

▷ In one-step of the random-walk the prob. vector changes as: $\vec{p} \mapsto \vec{q} := A \cdot \vec{p}$.

Pf: • By definition, $q_i := \Pr[\text{walk is at vertex } i]$
 $= \sum_{j=1}^n \Pr[\text{walk at } i \mid \text{previous was } j] \times \Pr[\text{prev} = j]$
 $= \sum_j A_{ji} \times p_j = \sum_j A_{ij} \cdot p_j = (A \cdot \vec{p})_i.$

$$\Rightarrow \bar{q} = A \cdot p.$$

- Let \vec{e}^8 be the elementary vector with 1 at the 8-th coordinate (& others 0).

▷ After l steps of the random-walk, the prob. vector is $(A^l \cdot \bar{e}^s)$.

- Next qn: How large is $(A \cdot \bar{e}^P)_t = \Pr[\text{reaching } t \text{ in } \ell \text{ rnd. steps}]?$

- Idea: Study the magnitude by using the eigenvalues λ of A , as the main technical tool.
(i.e. $A \cdot v = \lambda v$)

Exercise: Symmetric stochastic $A \Rightarrow$

eigenvalues $\lambda_1, \dots, \lambda_n$ are real &

$$|\lambda_n| \leq |\lambda_{n-1}| \leq \dots \leq |\lambda_1| = 1.$$

- Denote the uniform-prob. vector $(1/n, \dots, 1/n)^T =: \bar{1}$

$\triangleright A \cdot \bar{1} = \bar{1}$. [Thus, 1 is an eigenval & $\bar{1}$ is eigenvect. of A .]

- Denote $\bar{1}^\perp := \{v \in \mathbb{R}^n \mid \langle v, \bar{1} \rangle = 0\}$ is a subspace.
* vectors orthogonal to $\bar{1}$

$\triangleright \underline{\lambda(A)} := \max \{ \|Av\| \mid v \in \bar{1}^\perp \text{ & } \|v\|=1\}$ is the second largest eigenvalue of A .

Pf: • Pick an orthonormal basis $\{b_1 = \bar{1}, b_2, \dots, b_n\}$ of \mathbb{R}^n st.
 b_i is an eigenvector corresponding to λ_i , $i \in [n]$.

$$\Rightarrow \bar{T}^\perp = \text{Span}_R \{ b_2, \dots, b_n \},$$

\Rightarrow Any vector $v \in \bar{T}^\perp$ can be written as: $v = \sum_{i \geq 2} \alpha_i b_i$

$$\Rightarrow Av = \sum_{i \geq 2} \alpha_i (Ab_i) = \sum_{i \geq 2} (\alpha_i \lambda_i) b_i$$

$$\Rightarrow \|Av\|^2 = \sum_{i \geq 2} (\alpha_i \lambda_i)^2 \Rightarrow \frac{\|Av\|^2}{\|v\|^2} = \frac{\sum \alpha_i^2 \lambda_i^2}{\sum \alpha_i^2} \leq \lambda_2^2$$

Also, $Ab_2 = \lambda_2 b_2 \Rightarrow \|Ab_2\|/\|b_2\| = \lambda_2$.

$\Rightarrow \lambda(A) := \max \|Av\|$, over unit vectors in \bar{T}^\perp ,
is exactly λ_2 .

□

$$\triangleright \lambda(A^\ell) \leq \lambda(A)^\ell.$$

Pf: • By defn of $\lambda(\cdot)$: $\|Av\| \leq \lambda(A) \cdot \|v\|$, $\forall v \in \mathbb{T}^\perp$.
• Also, $\langle Av, \mathbb{T} \rangle = \langle v, A\mathbb{T} \rangle = \langle v, \mathbb{T} \rangle = 0$, $\Rightarrow Av \in \mathbb{T}^\perp$.
 \Rightarrow A maps \mathbb{T}^\perp to itself; shrinking each vector
by a factor $\leq \lambda(A)$.
 $\Rightarrow \|A^\ell v\| \leq \lambda(A)^\ell \cdot \|v\|$, $\forall v \in \mathbb{T}^\perp$.
 $\Rightarrow \lambda(A^\ell) \leq \lambda(A)^\ell$. □

Exercise: $\lambda(A^\ell) = \lambda(A)^\ell$.

Lemma 1: \forall prob. vector \bar{p} , $\|A^\ell \bar{p} - \bar{t}\| < \lambda(A)^\ell$.

Pf: • $A^\ell \bar{p} - \bar{t} = A^\ell \cdot (\bar{p} - \bar{t})$ & $\langle \bar{p} - \bar{t}, \bar{t} \rangle = \langle \bar{p}, \bar{t} \rangle - \langle \bar{t}, \bar{t} \rangle$
 $= \gamma_h - \gamma_h = 0$.

$$\Rightarrow \|A^\ell(\bar{p} - \bar{T})\| \leq \lambda(A^\ell) \cdot \|\bar{p} - \bar{T}\| \leq \lambda(A)^\ell \cdot \|\bar{p} - \bar{T}\|$$

• Define $\bar{p}' := \bar{p} - \bar{T}$. $\Rightarrow \|\bar{p}\|^2 = \|\bar{p}'\|^2 + \|\bar{T}\|^2$

$$\Rightarrow \|\bar{p}'\|^2 < \|\bar{p}\|^2 = \sum_{i=1}^n p_i^2 \leq \sum_{i=1}^n p_i = 1.$$

$$\Rightarrow \|\bar{p}'\| < 1.$$

$$\Rightarrow \|A^\ell \bar{p} - \bar{T}\| \leq \lambda(A)^\ell \cdot \|\bar{p}'\| < \lambda(A)^\ell.$$

□

▷ The further $\lambda(A)$ is from 1, the faster is the convergence of $A^\ell \bar{p}$ to \bar{T} .

Defn: $1 - \lambda(A)$, or $1 - \lambda(G)$, is called the spectral gap of graph G .

▷ We wish it large for expansion!

Lemma 2: If d-regular, connected, n-vertex graph (with self-loops) : $1 - \lambda(G) \geq 1/8dn^3$. \leftarrow inverse-poly in input size!

Proof: Idea - Use the norm interpretation of $\lambda(G)$: where A acts on \mathbb{R}^n .

- Let $u \in \mathbb{R}^n$ be a unit vector & $v := Au$.

- We'll show: $1 - \|v\|^2 \geq 1/4dn^3$.

Thus, $\|v\|^2 \leq 1 - 1/4dn^3$.

$$\Rightarrow \|v\| \leq (1 - 1/4dn^3)^{1/2} < 1 - 1/8dn^3.$$

$\triangleright 1 - \|v\|^2 = \sum_{i,j \in [n]} A_{ij} \cdot (u_i - v_j)^2$ [quadratic form in the Laplacian of G]

Rf: RHS = $\sum A_{ij} \cdot u_i^2 - 2 \sum A_{ij} u_i v_j + \sum A_{ij} \cdot v_j^2$

$$= \sum_i (\sum_j A_{ij}) \cdot u_i^2 - 2 \cdot \langle Au, v \rangle + \sum_j (\sum_i A_{ij}) \cdot v_j^2$$

$$= \sum u_i^2 - 2 \langle Au, v \rangle + \sum v_j^2 = \|u\|^2 - 2 \langle v, v \rangle + \|v\|^2$$

$$= 1 - \|v\|^2 = \text{LHS. } \square$$

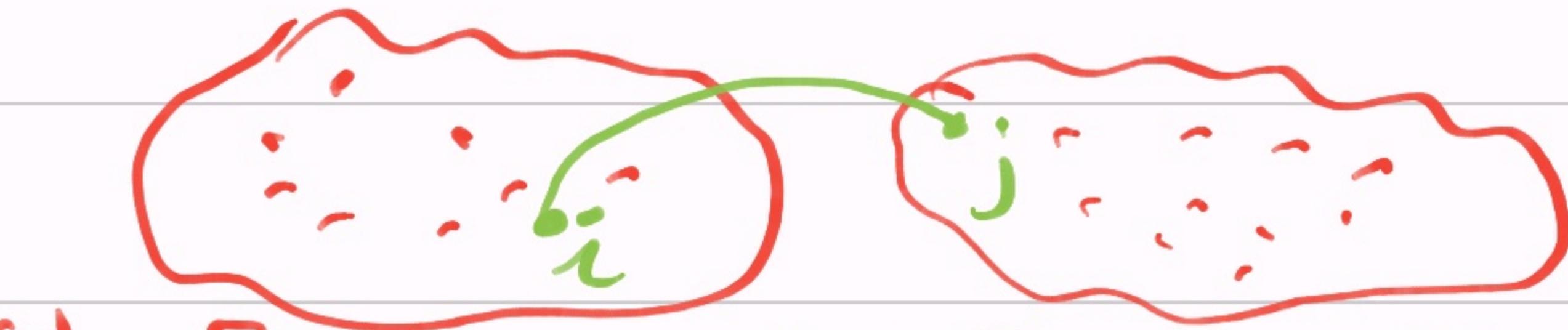
- Thus, it suffices to show: $\exists i, j, A_{ij} \cdot (u_i - v_j)^2 \geq \frac{1}{4dn^3}$.
 - If $\exists i, (u_i - v_i)^2 \geq \frac{1}{4n^3}$ then we are done.
 - So, assume: $\forall i, |u_i - v_i| < \frac{1}{2n^{1.5}}$. ≤ 0
 - Sort the coordinates of u : $u_1 \geq u_2 \geq \dots \geq u_n$.
- $\triangleright \sum u_i = 0 \quad \& \quad \sum u_i^2 = 1. \quad \geq 0$
- \Rightarrow either $u_1 \geq \frac{1}{\sqrt{n}}$ or $u_n \leq -\frac{1}{\sqrt{n}}$.
- $\triangleright u_1 - u_n \geq \frac{1}{\sqrt{n}}$.

$\Rightarrow \exists i_0, u_{i_0} - u_{i_0+1} > 1/h^{1.5}$ (by averaging)

$\Rightarrow \exists \text{edge } (i, j) \in E(G) \text{ s.t.}$

$i \in [i_0] \text{ & } j \in [i_0]^c.$

$\triangleright u_i - u_j > 1/h^{1.5} \text{ & } (i, j) \in E.$



$$\Rightarrow A_{ij} \cdot (u_i - v_j)^2 \geq \frac{1}{d} \cdot (|u_i - u_j| - |u_j - v_j|)^2$$

$$> \frac{1}{d} \cdot \left(\frac{1}{h^{1.5}} - \frac{1}{2n^{1.5}} \right)^2 = \frac{1}{4dn^3}$$

$$\Rightarrow 1 - \|v\|^2 > 1/4dn^3$$

$$\Rightarrow 1 - \lambda(G) > 1/8dn^3.$$

□

Lemma 3: Let $\ell := 10dn^3\lg n = 30n^3\lg n$. If s, t are connected in G , then $\Pr[\text{rnd. walk reaches } t \text{ at the } \ell\text{-th step}] > 1/2n$.

Proof:

- Let \bar{P} be the prob. vector at the ℓ -th-step,
- Lemmas 2 & 1 $\Rightarrow \|A^\ell \cdot \bar{e}^s - \bar{1}\|_1 \leq (1 - \frac{1}{8dn^3})^\ell$

$$\leq (1 - \frac{1}{8dn^3})^{10dn^3\lg n} < e^{-5\lg n/4} < \frac{1}{2n^{1.5}}.$$

- By Cauchy-Schwarz inequality :

$$\|A^\ell \cdot \bar{e}^s - \bar{1}\|_1 \leq \|A^\ell \cdot \bar{e}^s - \bar{1}\|_2 \cdot \sqrt{n} < \frac{1}{2n}.$$

$$\Rightarrow |(A^\ell \cdot \bar{e}^s - \bar{1})_t| < \frac{1}{2n} \Rightarrow (A^\ell \cdot \bar{e}^s)_t > \frac{1}{n} - \frac{1}{2n} = \frac{1}{2n}.$$

$$\Rightarrow \Pr[\text{reaching } t \text{ at } \ell\text{-th step}] > \frac{1}{2n}. \quad \square$$

- Thus, by continuing the rnd. walk for a longer amount we can bring the prob. above $3/4$.

$$\text{Is. } \left(1 - \frac{1}{2n}\right)^{4n} \leq e^{-2} < 1/4.$$

$\triangleright \ell := 40dn^4\lg n = 120n^4\lg n$ makes error $< 1/4$.

- This rnd-walk is in logspace (rnd.), as we need to store the current vertex label ; which has only $O(\lg n)$ -bits.

\Rightarrow Upath $\in RL$.

(also outputs a path!)

□

- Qn: Can it be derandomized?

This was an intriguing question for three decades; to solve it several tools were developed.

- Idea: Convert G to G' - a graph with constant spectral gap, so that $\ell = O(\lg n)$ suffices to reach t from s .

Then, one can exhaustively look for all $O(\lg n)$ -length options from s , in \mathbb{L} . [$\because d=3$]

- G' motivates Expanders: 'highly'-connected graphs. We'll see two definitions.

- Defn (algebraic):
- We call a graph G an (n, d, λ) -expander if G is n -vertex, d -regular & $\lambda(G) \leq \lambda$.
 - A (d, λ) -expander family $\{G_n\}_{n \geq 1}$ is s.t.
 $\forall n$, G_n is (n, d, λ) -expander.

- Alon-Boppana '86 showed that $\lambda(G) \geq 2\sqrt{d-1}/d$.

Exercise: Show $\lambda(G) > 1/\sqrt{d}$ [by using $\text{tr}(A^2)$].

▷ Graphs with $\lambda = 2\sqrt{d-1}/d$ are called Ramanujan Graphs. Their explicit constructions are known due to (Lubotzky-Phillips-Sarnak '88). ↩

$$d = p^k + 1, \text{ prime } p.$$

Defn (Combinatorial): We call G an (n, d, ρ) -edge-expander if G is n -vertex, d -regular st. $\forall S \subseteq V(G)$ of $|S| \leq n/2$, $|E(S, \bar{S})| \geq \underbrace{\rho \cdot d \cdot |S|}_{\delta_{\max}}$

edges $S \times \bar{S} \cap \vec{E}(G)$

- Note: In the algebraic-defn. we want λ to be small $\approx 2/\sqrt{d}$.
While, in the combinatorial-defn. we want ρ to be large $\approx 1/2$. (Why $1/2$?)

- Next, we show the equivalence of these two defns.

Theorem 1: G is an (n, d, λ) -expander \Rightarrow
" " " $(n, d, \frac{1-\lambda}{2})$ -edge-expander.

Theorem 2: G is an (n, d, p) -edge expander \Rightarrow
" " " $(n, d, 1 - p^2/2)$ -expander.

Cheeger's Inequality: $\frac{1-\lambda(G)}{2} \leq p(G) \leq \sqrt{2(1-\lambda(G))}$.
 p measures bottlenecks in a graph

Pf. of Thm. 1: • The #edges out of S are estimated by
considering $Z := \sum_{i,j \in [n]} A_{ij} \cdot (x_i - x_j)^2$. or Laplacian quadratic form

- Define $\bar{x} \in \mathbb{R}^n$ as: $x_i := \begin{cases} |S| & \text{if } i \in S, \\ -|S| & \text{if } i \notin S \end{cases}$

$\triangleright \bar{x} \in T^\perp$.

$$\begin{aligned} \Rightarrow Z_{\bar{x}} &= \sum_{(i,j) \in S^2} + \sum_{(i,j) \in \bar{S}^2} + \sum_{(i,j) \in S \times \bar{S} \cup \bar{S} \times S} \\ &= 0 + 0 + 2 \cdot \sum_{(i,j) \in S \times \bar{S}} A_{ij} \cdot (x_i - x_j)^2 \\ &= 2n^2 \cdot \sum_{(i,j) \in S \times \bar{S}} A_{ij} \\ &= (2n^2/d) \cdot \#E(S, \bar{S}). \end{aligned}$$

$$\begin{aligned} \bullet \text{On the other hand, } Z &= \sum A_{ij} x_i^2 - 2 \sum A_{ij} x_i x_j + \sum A_{ij} x_j^2 \\ &= \sum_i (\sum_j A_{ij}) x_i^2 - 2 \cdot \langle A\bar{x}, \bar{x} \rangle + \sum_j (\sum_i A_{ij}) x_j^2 \\ &= \|A\bar{x}\|^2 - 2 \cdot \langle A\bar{x}, \bar{x} \rangle + \|\bar{x}\|^2 \geq 2 \cdot \|\bar{x}\|^2 - 2\lambda \cdot \|\bar{x}\|^2 \\ &\quad [\|A\bar{x}\| \leq \lambda \cdot \|\bar{x}\| \text{ &} |\langle \bar{y}, \bar{x} \rangle| \leq \|\bar{y}\| \cdot \|\bar{x}\|.] \end{aligned}$$

$$\Rightarrow \#E(S, \bar{S}) \cdot (2n^2/d) = Z \geq 2 \cdot \| \vec{x} \|^2 \cdot (1-\lambda) \\ = 2(1-\lambda) \cdot (|S| \cdot |\bar{S}|^2 + |\bar{S}| \cdot |S|^2)$$

$$\Rightarrow \#E(S, \bar{S}) \geq \left(\frac{d}{2n^2}\right) \cdot 2(1-\lambda) \cdot |S| \cdot |\bar{S}| \cdot n = \frac{(1-\lambda)d}{n} \cdot |S| \cdot |\bar{S}| \\ \geq \frac{(1-\lambda)d}{n} \cdot \frac{n}{2} \cdot |S| = \left(\frac{1-\lambda}{2}\right) \cdot d \cdot |S|$$

$$\Rightarrow \rho(G) \geq (1-\lambda)/2 \quad \&$$

G is an $(n, d, \frac{1-\lambda}{2})$ -edge-expander.

D

Pf. of Thm 2: • Assume G to be an (n, d, ρ) -edge-expander.
• We again estimate Z ; use \vec{u} = eigenvector of $\lambda_2(A)$.

- Pick \bar{u} : $A \cdot \bar{u} = \underline{\lambda_2} \cdot \bar{u}$ & $\bar{u} \in T^\perp$ & $\bar{u} \neq \bar{0}$.
 $\Rightarrow \bar{u}$ has +ve & -ve coordinates ; let us collect them in \bar{v} & \bar{w} resp.

$$\Rightarrow \bar{u} =: \bar{v} + \bar{w} ; \bar{v}, -\bar{w} \in (R_{\geq 0})^n.$$

- Wlog \bar{v} has $\leq \gamma_2$ nonzero entries (else we use $-\bar{u}$).
- Consider $Z := \sum_{i < j \in [n]} A_{ij} \cdot (\underbrace{v_i^2 - v_j^2}_{\geq 0})$. & assume $v_1 \geq v_2 \geq \dots \geq v_n \geq 0$.

- We'll show: Claim 1: $Z \geq p \cdot \| \bar{v} \|^2$ (use edge-expansion)
Claim 2: $Z \leq \sqrt{2(1-\lambda_2)} \cdot \| \bar{v} \|^2$ (matrix analysis)

► The two claims will prove Theorem 2.

Pf. of Claim 1: • Recall in \bar{v} : $v_1 \geq v_2 \geq \dots \geq v_n \geq 0$ &

$$v_i = 0, \forall i > n/2.$$

$$\cdot Z = \sum_{i < j} A_{ij} \cdot (v_i^2 - v_j^2) \quad [\text{Idea: Relate to } E([k], [k+1 \dots n])]$$

$$= \sum_{i < j} A_{ij} \cdot \sum_{i \leq k < j} (v_k^2 - v_{k+1}^2)$$

$$= \sum_{k=1}^{n/2} \#E([k], [k+1 \dots n]) \cdot \frac{1}{d} \cdot (v_k^2 - v_{k+1}^2)$$

$$\geq \sum_k \left(\rho dk/d \right) \cdot (v_k^2 - v_{k+1}^2) = \rho \cdot \sum_{k=1}^{n/2} (kv_k^2 - kv_{k+1}^2)$$

$$= \rho \cdot \sum_{1 \leq k \leq \lfloor n/2 \rfloor} (kv_k^2 - (k-1)v_k^2) = \rho \cdot \sum_k v_k^2 = \rho \cdot \|\bar{v}\|^2. \quad \square$$

Pf. of claim 2: • Z & λ_2 are fundamentally related.

Idea: Use $\langle A\bar{u}, \bar{v} \rangle$ & recalculate Z .

$$\bullet \langle A\bar{u}, \bar{v} \rangle = \langle \lambda_2 \bar{u}, \bar{v} \rangle = \langle \lambda_2 \bar{v} + \lambda_2 \bar{w}, \bar{v} \rangle = \lambda_2 \|\bar{v}\|^2$$

$$\bullet \quad " = \langle A\bar{v}, \bar{v} \rangle + \langle A\bar{w}, \bar{v} \rangle \leq \langle A\bar{v}, \bar{v} \rangle .$$

$$\Rightarrow \lambda_2 \leq \langle A\bar{v}, \bar{v} \rangle / \|\bar{v}\|^2$$

$$\Rightarrow 1 - \lambda_2 \geq (1/\|\bar{v}\|^2 - \langle A\bar{v}, \bar{v} \rangle) / \|\bar{v}\|^2 \quad [\xrightarrow{\text{We want to}} \text{"reach"} Z.]$$

$$\begin{aligned} D_2(\|\bar{v}\|^2 - \langle A\bar{v}, \bar{v} \rangle) &= 2\|\bar{v}\|^2 - 2 \sum_{i,j} A_{ij} v_i v_j \\ &= \sum_{i,j} A_{ij} v_i^2 + \sum_{i,j} A_{ij} v_j^2 - \sum_{i,j} A_{ij} \cdot 2v_i v_j \\ &= \sum_{i,j} A_{ij} \cdot (v_i - v_j)^2 \end{aligned}$$

$$\Rightarrow 1 - \lambda_2 \geq \frac{\left[\sum_{i,j} A_{ij} \cdot (v_i - v_j)^2 \right]}{2 \cdot \|v\|^2} \cdot \frac{\left[\sum_{i,j} A_{ij} \cdot (v_i + v_j)^2 \right]}{\left[\sum_{i,j} A_{ij} \cdot (v_i + v_j)^2 \right]}$$

- Numerator estimate: $\geq \left(\sum_{i,j} A_{ij} \cdot |v_i^2 - v_j^2| \right)^2$ [by Cauchy-Schwarz inequality]

- Denominator estimate:

$$\begin{aligned} D \frac{1}{2} \cdot \sum_{i,j} A_{ij} \cdot (v_i + v_j)^2 &= \frac{1}{2} \sum A_{ij} \cdot (v_i^2 + v_j^2) + \sum A_{ij} \cdot v_i v_j \\ &= \|v\|^2 + \sum_{i,j} A_{ij} v_i v_j \leq \|v\|^2 + \frac{1}{2} \cdot \sum A_{ij} (v_i^2 + v_j^2) \\ &= 2 \cdot \|v\|^2. \end{aligned}$$

$$\Rightarrow \sum_{i,j} A_{ij} (v_i + v_j)^2 \leq 4 \cdot \|v\|^2.$$

Combining all inequalities: $1 - \lambda_2 \geq \frac{4z^2}{2\|v\|^2 \cdot 4\|v\|^2}$

$$\Rightarrow 1 - \lambda_2 \geq z^2 / 2 \cdot \|v\|^4$$

$$\Rightarrow z \leq \sqrt{2(1-\lambda_2)} \cdot \|v\|^2. \quad \square$$

\Rightarrow Thus, Theorem 2 is proved.

\square

\rightarrow Laplacian quadratic form $Z(G) := \sum_{i,j} A_{ij} \cdot (x_i - x_j)^2$.
 It carries information about expansion & sparsest-cut!

Application — Error-reduction using expanders. (explicit)

- Recall that a problem $L \in \text{BPP}$ with an algorithm $M(n)$ of error-probability $\leq 1/3$, using r random bits, can also be solved with a much smaller error $= 2^{-k}$.

The naive way is to repeat $M(n)$, k -times using (rk) random bits. Qn: Can you do better?
→ We'll show that by "walking in an expander" we can reduce rnd. bits to $r + O(k)$.

* additive!

- Idea:
- Start with an $(2^r, d, 0.1)$ -expander graph G , for constant d . Assume that the neighbors of any vertex in G are listable in $\text{poly}(r)$ -time.
 - Choose a vertex $v_0 \in V(G)$ at random & do a random-walk for k -steps; going to $v_1, \dots, v_k \in V(G)$.
 - Use strings $v_0, v_1, \dots, v_k \in \{0,1\}^r$ as "random" strings to run $M(x)$ $(k+1)$ -times!
 - Finally, output the majority-vote of the $(k+1)$ outputs.
 - We'll show that error-prob $\leq 2^{-k}$, & we used only $(r + k \cdot \lg d) = r + O(k)$ random bits!
 $\ll (r \cdot k)$

- First, we found the prob. of the rnd-walk, being confined to bad vertices B (e.g. v_i 's on which $M(n)$ is wrong).

Theorem (Ajtai, Komlós, Szemerédi, '87): Let G be an (n, d, λ) -expander & $B \subseteq V(G)$, $|B| = \beta \cdot n$. Then, $\Pr_{\text{rnd.walk in } G} [V_i \in [0 \dots k], v_i \in B] \leq (\beta + \lambda)^k$. rexp small!

• Once we've this, we'll upper-bound the prob. of $(\exists^{1/2})$ of $\{v_0, \dots, v_k\}$ being in B .

Proof of Thm: • Let A be the normalized adjacency matrix of G .

• Idea: express the probability as a matrix product
 (using the submatrix $A_{B \times B}$) & then analyze using
spectral-norm of A & $|B|$.

• Let $\underline{P} := P_B$ be the $n \times n$ identity matrix with the
 rows corresponding to $[n] \setminus B$ set to 0.
 $\triangleright P^2 = P$ & $P \cdot AP = A_{B \times B}$.

Claim 1: $\Pr_{\text{walking}} [v_i, v_i \in B] = \| (PA)^k \cdot P \bar{1} \|_1$

Pf:

- The prob. of $v_0 \in B$ is $\|P \cdot \bar{1}\|_1$.
- Prob. of being in B after 1-step is $\|PA \cdot P \bar{1}\|_1$.
- Induct to K . □

$$\triangleright (PA)^2 \cdot P\bar{T} = PA \cdot \underbrace{PA \cdot P\bar{T}}_{PAP} = \underbrace{PAP \cdot PAP}_{PAP} \cdot \bar{T} = (PAP)^2 \cdot \bar{T}$$

$$\triangleright (PA)^k \cdot P\bar{T} = (PAP)^k \cdot \bar{T}$$

- Now, we'll study the spectral norm of PAP , i.e. the factor by which it shrinks a vector.

Claim 2: $\forall \bar{v} \in \mathbb{R}^n$, $\|PAP \cdot \bar{v}\| \leq (\beta + \lambda) \cdot \|\bar{v}\|$

Pf: • Assume that \bar{v} is supported on B . (else, replace \bar{v} by $P\bar{v}$ in the inequality. This cannot increase RHS.)

• Similarly, assume \bar{v} to be non-negative & $\|\bar{v}\|_1 = 1$.

- Write $P\bar{v} = \bar{v} =: \alpha \cdot \bar{1} + \bar{z}$, for $\bar{z} \in \bar{1}^\perp$.
- Since $\langle n\bar{1}, \bar{v} \rangle = \langle (1, \dots, 1)^T, \bar{v} \rangle = \sum v_i = 1$, we get $1 = \langle n\bar{1}, \bar{v} \rangle = \langle n\bar{1}, \alpha \cdot \bar{1} + \bar{z} \rangle = \alpha \cdot \langle n\bar{1}, \bar{1} \rangle \Rightarrow \underline{\alpha = 1}$.
 $\Rightarrow \bar{v} = \bar{1} + \bar{z}$.
- $\Rightarrow PAP \cdot \bar{v} = PA \cdot \bar{v} = PA \cdot \bar{1} + PA \cdot \bar{z} = P \cdot \bar{1} + PA \cdot \bar{z}$
- $\Rightarrow \|PAP \cdot \bar{v}\| \leq \|P\bar{1}\| + \|PA\bar{z}\|$.
- We bound these resp. by $\beta\|\bar{v}\|$ & $\lambda\|\bar{v}\|$, proving the claim.

$\triangleright \|P\bar{1}\| \leq \beta\|\bar{v}\|$.

Pf: • $\|P \cdot \bar{1}\| = \sqrt{\beta n \cdot \frac{1}{n^2}} = \sqrt{\beta/n}$ 1 in B-positions only

• On the other hand, $1 = \sum_{i \in B} v_i = \langle \bar{e}_B, \bar{v} \rangle \leq \|\bar{e}_B\| \cdot \|\bar{v}\|$

$\Rightarrow 1 \leq \sqrt{\beta n} \cdot \|\bar{v}\| \Rightarrow \|P \cdot \bar{1}\| \leq \beta \cdot \|\bar{v}\|$. D

$$\triangleright \|PA\bar{z}\| < \lambda \cdot \|\bar{v}\|$$

Pf: • Since $\bar{z} \in \bar{T}^\perp$, we have $\|A\bar{z}\| \leq \lambda \cdot \|\bar{z}\|$

$$\Rightarrow \|PA\bar{z}\| \leq \|A\bar{z}\| \leq \lambda \cdot \|\bar{z}\|$$

$$\bullet \bar{v} = \bar{T} + \bar{z} \Rightarrow \|\bar{v}\|^2 = \|\bar{T}\|^2 + \|\bar{z}\|^2$$

$$\Rightarrow \|\bar{z}\| < \|\bar{v}\| \Rightarrow \|PA\bar{z}\| < \lambda \cdot \|\bar{v}\|. \quad \square$$

$$\Rightarrow \|PAP.v\| < (\beta + \lambda) \cdot \|\bar{v}\|. \quad \square \text{ (Claim 2)}$$

• Since we now know that the spectral norm of PAP is $< (\beta + \lambda)$, we can estimate the matrix-product:

$$\|(PA)^k \cdot P\bar{T}\|_1 \leq \sqrt{n} \cdot \|(PA)^k \cdot P\bar{T}\| = \sqrt{n} \cdot \|(PAP)^k \cdot \bar{T}\|$$

$$< \sqrt{n} \cdot (\beta + \lambda)^k \cdot \|\bar{T}\| = (\beta + \lambda)^k.$$

\square

• The above technique is strong enough to estimate the prob. of being at B at specified steps (in the random walk).

Eg. $I = \{0, 2, 4\}$ -th step you want to be in B ,
the $\Pr_{\text{walk}} [\forall i \in I, v_i \in B] = \| P^A \cdot A \cdot P^A \cdot A \cdot P \cdot T \|_1$.

Corollary: For $I \subseteq [0, \dots, k]$,
 $\Pr_{\text{walk in } G} [\forall i \in I, v_i \in B] < (\beta + \lambda)^{|I|-1}$.

(Exercise)

- Say, algorithm $M(n)$ uses $\underline{r_2}$ random bits & has error $\leq \underline{\beta}$. $\underline{N} := 2^{\underline{r_2}}$.

Define $\underline{B} \subseteq \{0,1\}^{\underline{r_2}}$ be the bad strings. $\triangleright |B| \leq \beta \cdot N$

- Employ an (N, d, λ) -expander G to walk.

$V(G) = \{0,1\}^{\underline{r_2}}$; $B \subseteq V(G)$ are bad vertices.

- Let v_0, v_1, \dots, v_k be the walk.

- The majority-vote $\{M(x, v_i) \mid i \in [0..k]\}$ is wrong iff $\exists I \subseteq [0..k]$, $|I| \geq \frac{k+1}{2}$ s.t. $\forall i \in I, v_i \in B$.

$\triangleright \Pr_{\text{walk}}[-] < 2^k \cdot (\beta + \lambda)^{(k-1)/2}$ Assuming $\beta + \lambda \leq 1/8$
we get error-prob $< 2^{-k/2}$; rnd-bits $\leq (r + k \lg d)$.