

Expanders

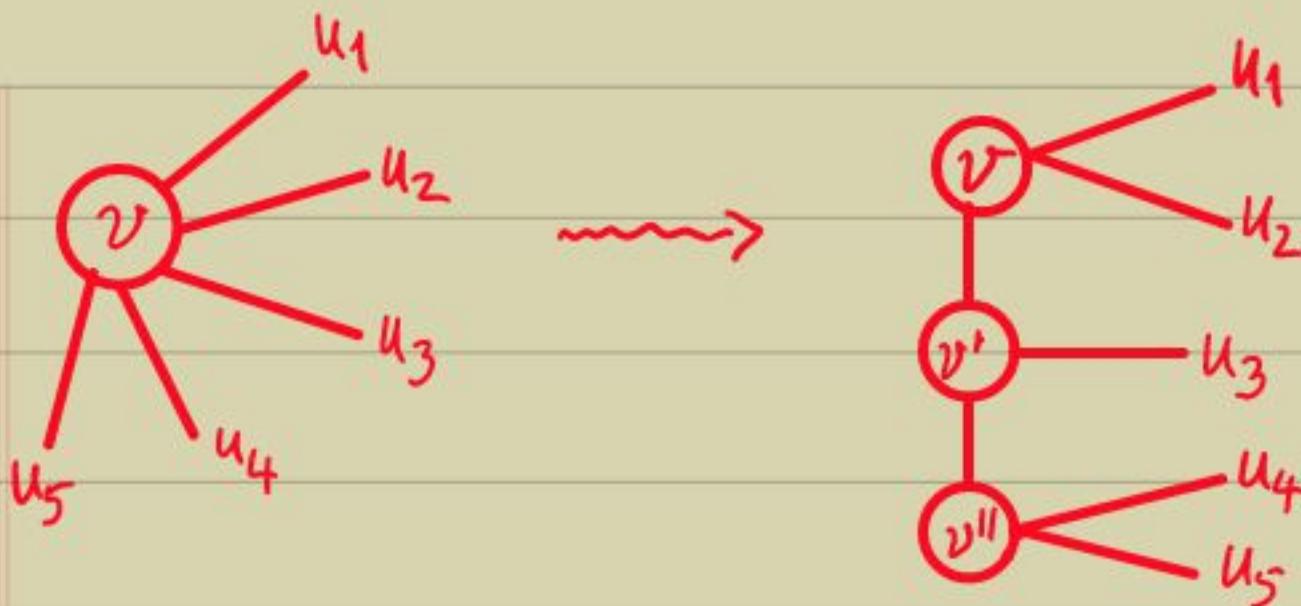
- We now start the first topic in our list of pseudorandom constructions.
- Motivation: Solving the problem of undirected connectivity in logspace (L or RL).

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

Theorem (Aleliunas, Karb, Lipton, Lovász, Rackoff 1979):
 $\text{Upath} \in \text{RL}$.

Pf:

- Suppose G is the given undirected graph with n vertices.
- Wlog we can assume G to be d-regular.
E.g. the following gadget achieves 3-regularity (in logspace):



- Now the algorithm is to do a random walk, starting from v , of length $300n^4 \ell n$.

Helps in

^{remembering} Assume that each vertex in G has a self-loop.
the history of the walk

- Let A be the normalized adjacency matrix of G . I.e. $A_{ij} := \#\text{edges}(i,j) / d$.

▷ A is symmetric with entries in $[0, 1]$.

▷ The row-sum, resp. col-sum, is 1.

(A is symmetric stochastic.)

- At any stage of the walk, $\bar{p} = (p_1, \dots, p_n)^T$ collects the probability p_i of being at the vertex i .

► In one step of the random walk the probability changes as \bar{p} to $\bar{q} = A\bar{p}$.

Pf:

$$\begin{aligned} q_i &:= \Pr[\text{walk is at } i] \\ &= \sum_{j \in [n]} \Pr[\text{walk was at } j] \cdot \Pr[\text{walk is at } i \mid \text{was at } j] \\ &= \sum_j p_j \cdot A_{ji} = (A \cdot \bar{p})_i. \end{aligned}$$

□

- Let \bar{e}^s be the elementary vector that is 1 at the s -th coordinate.

► After ℓ steps of the random walk, the probability vector is $A^\ell \cdot \bar{e}^s$.

- Now we study the action of A , by using its eigenvalues as the main tool.

Exercise: A has real eigenvalues $\lambda_1, \dots, \lambda_n$ with $|\lambda_n| \leq |\lambda_{n-1}| \leq \dots \leq |\lambda_1| = 1$.

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

Since $A \cdot \bar{1} = \bar{1}$ we have $\bar{1}$ as an eigenvector. Consider $\bar{1}^\perp := \{v \in \mathbb{R}^n \mid \langle v, \bar{1} \rangle = 0\}$.
 (vectors orthogonal to $\bar{1}$)

- ▷ $\lambda_2 := \max \{ \|Av\| \mid v \in \bar{1}^\perp \text{ & } \|v\|=1\}$
 is the second largest eigenvalue of A .

Pf:

- Since A is symmetric we can find an orthonormal basis $\{b_1, \dots, b_n\}$ of \mathbb{R}^n s.t. b_1 is an eigenvector of λ_1 and $b_1 = \bar{1}$.

$$\Rightarrow \bar{1}^\perp = \text{span}\{b_2, \dots, b_n\}$$

$$\Rightarrow \text{for a } v = \sum_{i>1} \alpha_i b_i \in \bar{1}^\perp,$$

$$Av = \sum_{i>1} \alpha_i \lambda_i b_i$$

$$\Rightarrow \frac{\|Av\|^2}{\|v\|^2} = \frac{\|\sum_{i>1} \alpha_i \lambda_i b_i\|^2}{\|\sum_{i>1} \alpha_i b_i\|^2} = \frac{\sum_{i>1} \alpha_i^2 \lambda_i^2}{\sum_{i>1} \alpha_i^2} \leq \lambda_2.$$

$\Rightarrow \max \|Av\| \text{ over unit vectors in } \bar{1}^\perp$
 is exactly λ_2 .

□

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

Pf:

- By the definition of $\lambda(\cdot)$,
 $\|A_v\| \leq \lambda(A) \cdot \|v\|$, for $v \in \bar{1}^\perp$.
- Also, $\langle Av, \bar{1} \rangle = \langle v, A\bar{1} \rangle = \langle v, \bar{1} \rangle = 0$,
for $v \in \bar{1}^\perp$.

$\Rightarrow A$ maps $\bar{1}^\perp$ to itself, shrinking each vector by a factor of (\leq) $\lambda(A)$.

$$\Rightarrow \|A^t v\| \leq \lambda(A)^t \cdot \|v\|, \text{ for } v \in \bar{1}^\perp$$

$$\Rightarrow \lambda(A^t) \leq \lambda(A)^t.$$

□

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

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

Pf:

- We use the eigenvector decomposition.
 - Let $\bar{p} = \alpha \cdot \bar{1} + \bar{p}'$, where $\bar{p}' \in \bar{1}^\perp$, $\alpha \in \mathbb{R}$.
- $$\Rightarrow \frac{1}{n} = \langle \bar{p}, \bar{1} \rangle = \alpha \cdot \langle \bar{1}, \bar{1} \rangle + \langle \bar{p}', \bar{1} \rangle \Rightarrow \alpha = 1.$$

$$\Rightarrow \bar{\beta} = \bar{1} + \bar{\beta}'.$$

$$\Rightarrow A^\ell \cdot \bar{\beta} = A^\ell \cdot \bar{1} + A^\ell \cdot \bar{\beta}' = \bar{1} + A^\ell \cdot \bar{\beta}'$$

$$\Rightarrow \|A^\ell \cdot \bar{\beta} - \bar{1}\| = \|A^\ell \cdot \bar{\beta}'\| \leq \lambda(A)^\ell \cdot \|\bar{\beta}'\|$$

• Also, $\|\bar{\beta}\|^2 = \|\bar{1}\|^2 + \|\bar{\beta}'\|^2$

$$\Rightarrow \|\bar{\beta}'\| < \|\bar{\beta}\| \leq \left(\sum_{i=1}^n k_i\right)^2 = 1.$$

$$\Rightarrow \|A^\ell \cdot \bar{\beta} - \bar{1}\| < \lambda(A)^\ell.$$

□

▷ Thus, the further $\lambda(A)$ is from 1, the faster is the convergence of $A^\ell \cdot \bar{\beta}$ to $\bar{1}$!

- $1 - \lambda(A)$, or $1 - \lambda(G)$, is called the spectral gap of the graph G .
We wish it large.

Lemma 2: \forall d-regular, connected G (with self-loops),
 $1 - \lambda(G) \geq 1/8dn^3$.