

Based on lecture notes by Michael Mahoney, Dan Spielman, Luca Trevisan, etc.

# Random walks

- Let  $\mu^t$  be the probability distribution at time  $t$ .  
$$\mu^{t+1} = (AD^{-1})\mu^t$$
  - $(AD^{-1})(D\mathbf{1}) = A\mathbf{1} = (D\mathbf{1})$ .
  - Therefore, stationary distribution  $\mu_i^* = d_i / (\sum_j d_j)$ .
  - $AD^{-1}$  has the same eigenvalues as  $D^{-1/2}AD^{-1/2}$ .
- 
- Theorem: Let  $M$  be a  $n \times n$  matrix and let  $S$  be a  $n \times n$  invertible matrix. Then,  $M$  and  $SMS^{-1}$  have the same eigenvalues.
  - Let  $v$  an eigenvector of  $M$  with eigenvalue  $\lambda$ . Let  $v' \stackrel{\text{def}}{=} Sv$ . Then  
$$SMS^{-1}v' = SMS^{-1}Sv = S(\lambda v) = \lambda v'$$
  - (**H.W.**) Mixing time bounds for random walks on general graphs.

# How small can $\beta$ be?

- Let  $G$  be a  $d$ -regular graph, with eigenvalues  $d \geq \sigma_2 \geq \dots \geq \sigma_n$  where  $\max_{i \in \{2, \dots, n\}} |\sigma_i| \leq \beta$ .
- $\text{Tr}(A^2) = \sum_i e_i^T A^2 e_i = \sum_i \|Ae_i\|^2 = nd$
- $\text{Tr}(A^k)$  = number of walks of length  $k$  starting and ending at the same vertex.

$$nd = \text{Tr}(A^2) = \sum_i \sigma_i^2 \leq d^2 + (n - 1)\beta^2$$

- Therefore,  $\beta \geq \sqrt{\frac{n-d}{n-1}} \cdot \sqrt{d} = (1 - o(1))\sqrt{d}$
- It can be shown that  $\beta \geq 2\sqrt{d-1} - o(1)$

# Ramanujan Graphs

- Ramanujan graph: A  $d$ -regular graph is called a Ramanujan graph if  $\beta \leq 2\sqrt{d - 1}$
- For a random  $n$ -vertex  $d$ -regular graph,  $\beta \leq 2\sqrt{d - 1} + o(1)$  w.h.p. [Friedman - 03].
- Explicit constructions known for some values of  $d$  [Lubotzky, Philips, Sarnak - 88], etc.

# Expander mixing lemma

- Theorem: Let  $G$  be a  $d$ -regular graph on  $n$  vertices. Then for any  $S, T \subset V$

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

- For  $S \subseteq V$  and let  $\mathbf{1}_S$  be its indicator vector. Let  $\mathbf{1}_S = c_S \mathbf{1} + p_S$  where  $\langle p_S, \mathbf{1} \rangle = 0$ . Then  $\langle \mathbf{1}_S, \mathbf{1} \rangle = \langle c_S \mathbf{1}, \mathbf{1} \rangle + \langle p_S, \mathbf{1} \rangle = c_S n + 0$
- Fix  $S, T \subset V$ ,  $\mathbf{1}_S = (|S|/n)\mathbf{1} + p_S$  and  $\mathbf{1}_T = (|T|/n)\mathbf{1} + p_T$ .

$$\begin{aligned} |E(S, T)| &= \mathbf{1}_S^T A \mathbf{1}_T = \left( \frac{|S|}{n} \mathbf{1} + p_S \right)^T A \left( \frac{|T|}{n} \mathbf{1} + p_T \right) = \left( \frac{|S|}{n} \mathbf{1} + p_S \right)^T \left( d \frac{|T|}{n} \mathbf{1} + Ap_T \right) \\ &= d \frac{|S|}{n} \frac{|T|}{n} \mathbf{1}^T \mathbf{1} + \frac{|S|}{n} \mathbf{1}^T Ap_T + d \frac{|T|}{n} p_S^T \mathbf{1} + p_S^T Ap_T = d \frac{|S||T|}{n} + p_S^T Ap_T \end{aligned}$$

- Therefore,

$$\left| |E(S, T)| - \frac{d}{n} |S||T| \right| = |p_S^T A p_T| \leq \|p_S\| \|A p_T\|$$

- $\|A p_T\| = \sqrt{p_T^T A^T A p_T} \leq \sqrt{\beta^2 p_T^T p_T} = \beta \|p_T\|$

$$\left| |E(S, T)| - \frac{d}{n} |S||T| \right| \leq \|p_S\| \|A p_T\| \leq \beta \|p_S\| \|p_T\| \leq \beta \|\mathbf{1}_S\| \|\mathbf{1}_T\| = \beta \sqrt{|S||T|}$$

# Laplacian Matrix

- $L = D - A$  and  $L\mathbf{1} = 0$ .

- $\mathcal{L} = D^{-1/2}LD^{-1/2}$  and  $\mathcal{L}(D^{1/2}\mathbf{1}) = D^{-1/2}LD^{-1/2}(D^{1/2}\mathbf{1}) = D^{-1/2}L\mathbf{1} = 0$

$$\begin{aligned}x^T L x &= x^T (D - A)x = \sum_i d_i x_i^2 - 2 \sum_{ij \in E} A_{ij} x_i x_j = \sum_i \left( \sum_j A_{ij} \right) x_i^2 - 2 \sum_{ij \in E} A_{ij} x_i x_j \\&= \sum_{ij \in E} A_{ij} (x_i - x_j)^2\end{aligned}$$

$$\lambda_2 = \min_{x \perp D^{1/2}\mathbf{1}} \frac{x^T \mathcal{L} x}{x^T x} = \min_{x \perp D^{1/2}\mathbf{1}} \frac{(D^{-1/2}x)^T L (D^{-1/2}x)}{x^T x} = \min_{y \perp D\mathbf{1}} \frac{y^T Ly}{y^T Dy} = \min_{y \perp D\mathbf{1}} \frac{\sum_{ij \in E} A_{ij} (y_i - y_j)^2}{\sum_i d_i y_i^2}$$

- If  $y = D^{-1/2}x$ , then  $\langle x, D^{1/2}\mathbf{1} \rangle = \langle y, D\mathbf{1} \rangle$ .

# Laplacian Matrix

- Let  $x \in \{0,1\}^n$  and let  $S_x = \{i : x_i \neq 0\}$ .
- For a pair of vertices  $i$  and  $j$ ,  $(x_i - x_j)^2$  indicates whether  $i$  and  $j$  are separated by  $S_x$ .

$$\frac{\sum_{ij \in E} A_{ij} (x_i - x_j)^2}{\sum_i d_i x_i^2} = \frac{\sum_{i \in S_x, j \in V \setminus S_x} A_{ij}}{\sum_{i \in S_x} d_i}$$

- Therefore,

$$\phi_G = \min_{S : \text{vol}(S) \leq \text{vol}(V)/2} \phi(S) = \min_{x \in \{0,1\}^n : \langle x, D\mathbf{1} \rangle \leq \sum_i d_i/2} \frac{\sum_{ij \in E} A_{ij} (x_i - x_j)^2}{\sum_i d_i x_i^2}$$

- $\langle x, D\mathbf{1} \rangle = \sum_i d_i x_i = \text{vol}(S_x)$

$$\lambda_2/2 \leq \phi_G$$

$$\lambda_2 = \min_{y \perp D\mathbf{1}} \frac{\sum_{ij \in E} A_{ij} (y_i - y_j)^2}{\sum_i d_i y_i^2}$$

- Fix any  $S \subset V$  such that  $\text{vol}(S) \leq \text{vol}(V)/2$ , and let  $x$  be the indicator vector of  $S$ ,  
i.e.  $x_i = \begin{cases} 1 & \text{if } i \in S \\ 0 & \text{if } i \notin S \end{cases}$
- Let  $y = x + c\mathbf{1}$  such that  $\langle y, D\mathbf{1} \rangle = 0$ .

$$0 = \langle y, D\mathbf{1} \rangle = \langle x, D\mathbf{1} \rangle + c\langle \mathbf{1}, D\mathbf{1} \rangle = \sum_i d_i x_i + c \sum_i d_i$$

- Therefore,  $c = -\text{vol}(S) / \text{vol}(V)$ .
- Note that for any  $i, j$ , we have  $y_i - y_j = x_i - x_j$ . Therefore,

$$\sum_{ij \in E} A_{ij} (y_i - y_j)^2 = \sum_{ij \in E} A_{ij} (x_i - x_j)^2 = \sum_{i \in S, j \in V \setminus S} A_{ij}$$

$$\begin{aligned}
\sum_i d_i y_i^2 &= \sum_i d_i (x_i + c)^2 = \sum_i d_i x_i^2 + c^2 \sum_i d_i + 2c \sum_i d_i x_i \\
&= \text{vol}(S) + \left( \frac{\text{vol}(S)}{\text{vol}(V)} \right)^2 \text{vol}(V) - 2 \frac{\text{vol}(S)}{\text{vol}(V)} \text{vol}(S) = \text{vol}(S) \left( 1 - \frac{\text{vol}(S)}{\text{vol}(V)} \right) \\
&\geq \frac{1}{2} \text{vol}(S)
\end{aligned}$$

- Therefore,

$$\lambda_2 \leq \frac{\sum_{ij \in E} A_{ij} (y_i - y_j)^2}{\sum_i d_i y_i^2} \leq 2 \frac{\sum_{i \in S, j \in V \setminus S} A_{ij}}{\text{vol}(S)} = 2\phi(S)$$

- Lemma 1: There exists a polynomial time algorithm that takes a graph  $G = (V, E)$  and an  $x \in \mathbb{R}_{\geq 0}^n$ , and computes an  $S \subseteq \text{supp}(x)$  such that

$$\frac{\sum_{i \in S, j \in V \setminus S} A_{ij}}{\sum_{i \in S} d_i} \leq \frac{\sum_{i,j} A_{ij} |x_i - x_j|}{\sum_i d_i x_i}$$

- Without loss of generality assume that  $x_1 \geq x_2 \geq \dots \geq x_n \geq 0$ .
- For  $i < j$ , writing  $x_i - x_j = \sum_{l=i}^{j-1} (x_l - x_{l+1})$  and  $x_i = \sum_{l=i}^n (x_l - x_{l+1})$  where  $x_{n+1} \stackrel{\text{def}}{=} 0$ .

$$\frac{\sum_{i,j} A_{ij} |x_i - x_j|}{\sum_i d_i x_i} = \frac{\sum_{i < j} A_{ij} \sum_{l=i}^{j-1} (x_l - x_{l+1})}{\sum_i d_i \sum_{l=i}^n (x_l - x_{l+1})} = \frac{\sum_{l=1}^n ((x_l - x_{l+1}) \sum_{i \in [l], j \in V \setminus [l]} A_{ij})}{\sum_{l=1}^n ((x_l - x_{l+1}) \sum_{i \in [l]} d_i)}$$

- $(x_l - x_{l+1})$  will appear for  $ij$  when  $i \leq l$  and  $j \geq l + 1$ .

- Fact: For  $a_1, \dots, a_n, b_1, \dots, b_n, c_1, \dots, c_n > 0$ , we have

$$\frac{c_1 a_1 + \dots + c_n a_n}{c_1 b_1 + \dots + c_n b_n} \geq \min_i \frac{a_i}{b_i}$$

- Let  $\alpha = \min_i a_i/b_i$ . Then  $a_i \geq \alpha b_i \forall i$ . Therefore,

$$\frac{c_1 a_1 + \dots + c_n a_n}{c_1 b_1 + \dots + c_n b_n} \geq \frac{c_1 \alpha b_1 + \dots + c_n \alpha b_n}{c_1 b_1 + \dots + c_n b_n} = \alpha$$

$$\frac{\sum_{ij} A_{ij} |x_i - x_j|}{\sum_i d_i x_i} = \frac{\sum_{l=1}^n \left( (x_l - x_{l+1}) \sum_{i \in [l], j \in V \setminus [l]} A_{ij} \right)}{\sum_{l=1}^n \left( (x_l - x_{l+1}) \sum_{i \in [l]} d_i \right)} \geq \min_{l: (x_l - x_{l+1}) > 0} \frac{\sum_{i \in [l], j \in V \setminus [l]} A_{ij}}{\sum_{i \in [l]} d_i}$$

- Therefore,  $S = [l^*]$  for optimal  $l^*$  above suffices. Since  $(x_{l^*} - x_{l^*+1}) > 0$ ,  $S \subseteq \text{supp}(x)$ .

- Lemma 2: There exists a polynomial time algorithm that takes a graph  $G = (V, E)$  and a  $y \in \mathbb{R}_{\geq 0}^n$ , and computes an  $S \subseteq \text{supp}(y)$  such that

$$\frac{\sum_{i \in S, j \in V \setminus S} A_{ij}}{\sum_{i \in S} d_i} \leq \sqrt{2 \frac{y^T L y}{y^T D y}}$$

- Idea: Use Lemma 1 with  $x$ , where  $x_i \stackrel{\text{def}}{=} y_i^2$ . Note that  $\text{supp}(x) = \text{supp}(y)$

$$\begin{aligned} \sum_{ij} A_{ij} |x_i - x_j| &= \sum_{ij} A_{ij} |y_i - y_j| (y_i + y_j) \leq \sqrt{\sum_{ij} A_{ij} (y_i - y_j)^2} \sqrt{\sum_{ij} A_{ij} (y_i + y_j)^2} \\ &= \sqrt{y^T L y} \sqrt{\sum_{ij} A_{ij} (y_i^2 + y_j^2 + 2y_i y_j)} \leq \sqrt{y^T L y} \sqrt{2 \sum_{ij} A_{ij} (y_i^2 + y_j^2)} = \sqrt{y^T L y} \sqrt{2 \sum_i d_i y_i^2} \end{aligned}$$

- Therefore,

$$\frac{\sum_{ij} A_{ij} |x_i - x_j|}{\sum_i d_i x_i} \leq \frac{\sqrt{y^T L y} \sqrt{2 \sum_i d_i y_i^2}}{\sum_i d_i y_i^2} = \sqrt{2 \frac{y^T L y}{y^T D y}}$$

- Lemma 3: There exists a polynomial time algorithm that takes a graph  $G = (V, E)$  and a  $z \in \mathbb{R}^n$  such that  $\langle z, D\mathbf{1} \rangle = 0$ , and computes an  $S$  such that  $\text{vol}(S) \leq \text{vol}(V)/2$  and  $\phi(S) \leq \sqrt{2 \frac{z^T L z}{z^T D z}}$ .
- Idea: (1) Shift every entry of  $z$  such that volume of the support of the positive part of  $z$  and the negative part of  $z$  is at most half of the total volume. (2) Use Lemma 2 on only the positive part or the negative part, whichever is “better”.
- For  $a \in \mathbb{R}$ , let  $a^+ \stackrel{\text{def}}{=} \max\{a, 0\}$  and  $a^- \stackrel{\text{def}}{=} \max\{-a, 0\}$ . Note that  $a = a^+ - a^-$ .
- Let  $u = z + c\mathbf{1}$  for an appropriate constant  $c$  such that  $\text{vol}(\text{supp}(u^+)), \text{vol}(\text{supp}(u^-)) \leq \text{vol}(V)/2$
- $\sum_{ij} A_{ij} (z_i - z_j)^2 = \sum_{ij} A_{ij} (u_i - u_j)^2$
- $\sum_i d_i u_i^2 = \sum_i d_i (z_i + c)^2 = \sum_i d_i z_i^2 + c^2 \sum_i d_i + 2 \sum_i d_i z_i \geq \sum_i d_i z_i^2$ .  

$$\frac{\sum_{ij} A_{ij} (u_i - u_j)^2}{\sum_i d_i u_i^2} \leq \frac{\sum_{ij} A_{ij} (z_i - z_j)^2}{\sum_i d_i z_i^2}$$

- Claim:  $(a - b)^2 \geq (a^+ - b^+)^2 + (a^- - b^-)^2$ .

If  $a, b \geq 0$ , then  $a^+ = a, b^+ = b, a^- = b^- = 0$ .

If  $a \geq 0, b < 0$ , then  $a^+ = a, b^+ = 0, a^- = 0, b^- = -b$ . Therefore,

$$(a - b)^2 = a^2 + b^2 - 2ab \geq a^2 + b^2 = (a^+ - b^+)^2 + (a^- - b^-)^2$$

- Therefore,  $\sum_{ij \in E} A_{ij}(u_i - u_j)^2 \geq \sum_{ij \in E} A_{ij}(u_i^+ - u_j^+)^2 + \sum_{ij \in E} A_{ij}(u_i^- - u_j^-)^2$

- $\sum_i d_i u_i^2 = \sum_i d_i (u_i^+)^2 + \sum_i d_i (u_i^-)^2$

$$\frac{\sum_{ij \in E} A_{ij}(u_i - u_j)^2}{\sum_i d_i u_i^2} \geq \frac{\sum_{ij \in E} A_{ij}(u_i^+ - u_j^+)^2 + \sum_{ij \in E} A_{ij}(u_i^- - u_j^-)^2}{\sum_i d_i (u_i^+)^2 + \sum_i d_i (u_i^-)^2}$$

$$\geq \min \left\{ \frac{\sum_{ij \in E} A_{ij}(u_i^+ - u_j^+)^2}{\sum_i d_i (u_i^+)^2}, \frac{\sum_{ij \in E} A_{ij}(u_i^- - u_j^-)^2}{\sum_i d_i (u_i^-)^2} \right\}$$

- Use Lemma 2 on the minimizer above.

- Without loss of generality, assume that  $z_1 \geq \dots \geq z_n$ . Then

$$\min_l \phi([l]) \leq \sqrt{2 \frac{z^T L z}{z^T D z}}$$

where  $\phi(S) = \frac{\sum_{i \in S, j \in V \setminus S} A_{ij}}{\min\{\text{vol}(S), \text{vol}(V \setminus S)\}}$ . (**why?**)

### Cheeger's Inequality

- Use Lemma 3 with  $z = D^{-1/2}v_2$ . Then  $\langle z, D\mathbf{1} \rangle = 0$  and  $\frac{z^T L z}{z^T D z} = \lambda_2$ .
- Cycle:  $\phi_G = 2/n$  and  $\lambda_2 = 1 - \cos \frac{2\pi}{n} \approx \Theta\left(\frac{1}{n^2}\right)$ . Therefore,  $\phi_G = \Theta(\sqrt{\lambda_2})$

# Hypercube

- $V = \{-1,1\}^d$  and  $\{x, y\} \in E$  if  $x$  and  $y$  differ in exactly one coordinate.
- $\chi_S \stackrel{\text{def}}{=} \prod_{i \in S} x_i$ , where  $S \subseteq [d]$ . Therefore,  $\chi_S \in \{-1,1\}^{2^d}$
- Theorem:  $\chi_S$  is an eigenvector of the normalized adjacency matrix with eigenvalue  $1 - 2|S|/d$ .
- Let  $S \neq T$ . Then

$$\begin{aligned}\langle \chi_S, \chi_T \rangle &= \sum_{x \in \{-1,1\}^d} (\prod_{i \in S} x_i \prod_{i \in T} x_i) = 2^d \mathbb{E}_{x \sim \{-1,1\}^d} \left( (\prod_{i \in S \cap T} x_i^2) (\prod_{i \in S \Delta T} x_i) \right) \\ &= 2^d \prod_{i \in S \Delta T} \mathbb{E}_{x_i \sim \{-1,1\}} x_i = 0\end{aligned}$$

- Fix  $S \subseteq [d]$ . Then for any  $x \in \{-1,1\}^d$

$$\begin{aligned}(A\chi_S)_x &= \sum_{y \in N(x)} \chi_S(y) = \sum_{y \in N(x)} \prod_{j \in S} y_j = \sum_{i \in S} (-\prod_{j \in S} x_j) + \sum_{i \notin S} (\prod_{j \in S} x_j) \\ &= (d - 2|S|)\prod_{j \in S} x_j = (d - 2|S|)\chi_S(x)\end{aligned}$$

- Therefore,  $A\chi_S = (d - 2|S|)\chi_S$
- Therefore, eigenvalues of  $\mathcal{L}$  are  $\left\{\frac{2i}{d} : i = 0, \dots, d\right\}$  where  $2i/d$  has multiplicity  $\binom{d}{i}$ .
- Let  $S_i = \{x \in V : x_i = 1\}$ .

$$\phi_G \leq \phi(S_i) = \frac{1}{d} = \frac{\lambda_2}{2}$$