

## Lecture 4

Expander Mixing Lemma EML

$G$  d-reg graph  $G = (V, E)$

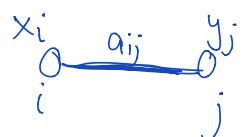
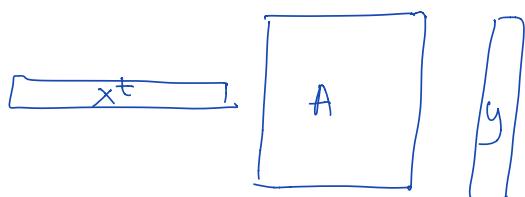
$A$  adj matrix  $A(i,j) = \# \text{edges bet } i \& j$

$M$  normalized, i.e.  $M = \frac{1}{d} \cdot A$ .

$A$  is also a quadratic form

$$x^t A y = \sum_{i,j=1}^n A_{ij} x_i y_j$$

$x = (x_1, \dots, x_n)$   
 $y = (y_1, \dots, y_n)$



$$\vec{x} = \overrightarrow{\mathbb{1}}_S \quad \vec{y} = \overrightarrow{\mathbb{1}}_T = \begin{cases} 1 & i \in T \\ 0 & i \notin T \end{cases}$$

For  $S, T \subset V$

$$\|S^T A\|_T = \sum_{i,j=1}^n A_{ij} \|S(i)\|_T(j)$$

$$= \sum_{i \in S} \sum_{j \in T} A_{ij}$$

$$= |E(S, T)|$$

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# edges from  $S$  to  $T$

$$i, j \in S \cap T \quad A_{ij} + A_{ji}$$

Expander Mixing Lemma :

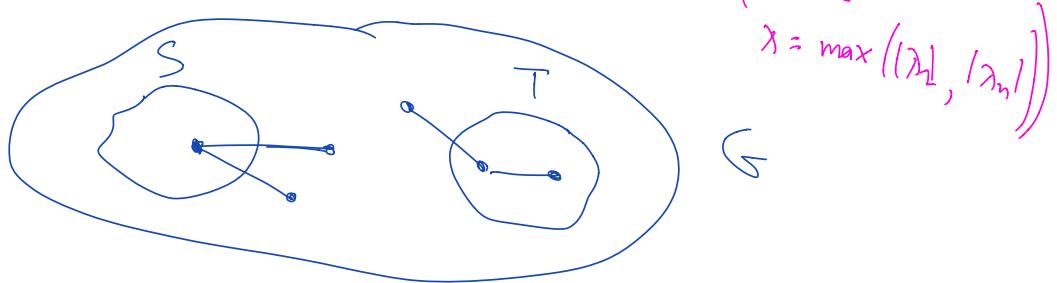
Let  $G$  be a  $d$ -reg graph, let  $d = \lambda_1 \geq \lambda_2 \geq \dots$  be the ev of its adj mat.

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

$\Rightarrow$

(where

$$\lambda = \max(|\lambda_1|, |\lambda_n|)$$



$|S| d \cdot \frac{|T|}{n}$  - expected number of edges from  $S$  to  $T$  if each  $v$  had chosen its nbrs randomly.

Proof:  $x = \prod_S$   $y = \prod_T$   $x, y \in \mathbb{R}^V$

Let  $u_1 \dots u_n$  be orthonormal eigenvectors of  $A$ .

(Recall  $\mathbb{R}^V$  has an inner product  $\langle x, y \rangle = \sum_{i=1}^n x_i y_i$ ,  $\|x\| = (\sum x_i^2)^{1/2} = \sqrt{\langle x, x \rangle}$ )

$$u_1 = \frac{1}{\sqrt{n}} \cdot \vec{1} \quad (\|u_1\| = \sqrt{\sum_{i=1}^n \left(\frac{1}{\sqrt{n}}\right)^2} = 1)$$

$$x = \sum_{i=1}^n \alpha_i u_i \quad \text{for some coeffs } \alpha_1 \dots \alpha_n$$

$$y = \sum_{j=1}^n \beta_j u_j \quad \dots \quad \beta_1 \dots \beta_n$$

$$\langle x, u_j \rangle = \langle \sum_{i=1}^n \alpha_i u_i, u_j \rangle$$

$$= \sum_{i=1}^n \alpha_i \langle u_i, u_j \rangle = \underline{\alpha_j}$$

$$\alpha_1 = \langle x, u_1 \rangle = \sum_{i=1}^n x(i) u_1(i) = \sum_{i \in S} u_1(i) = \frac{|S|}{n}$$

$$\beta_1 = \frac{|\Pi|}{\sqrt{n}}$$

$$\overrightarrow{Ay} = A \left( \sum_{j=1}^n \beta_j u_j \right) = \sum_{j=1}^n \beta_j \underbrace{A u_j}_{\lambda_j u_j} = \sum \beta_j \lambda_j u_j$$

$$\langle \overrightarrow{x}, \overrightarrow{Ay} \rangle = \left\langle \sum_{i=1}^n \alpha_i u_i, \sum_{j=1}^n \beta_j \lambda_j u_j \right\rangle$$

$$= \sum_{ij} \alpha_i \beta_j \lambda_j \langle u_i, u_j \rangle$$

$$= \sum_{i=1}^n \alpha_i \beta_i \lambda_i \cdot 1$$

$$\langle x, Ay \rangle = x^T A y$$

$$= \sum_i x_i (\underline{Ay})_i = \sum_i x_i \sum_j A_{ij} y_j = \sum A_{ij} x_i y_j$$

$$= x^T A y$$

$$= |E(S, T)|$$

$$|E(S, T)| = \alpha_1 \beta_1 \cdot d + \underbrace{\sum_{i>1} \alpha_i \beta_i}_{\cdot}$$

$$= \frac{|S|}{\sqrt{n}} \cdot \frac{|T|}{\sqrt{n}} \cdot d + \downarrow$$

$$\left| E(S, T) - |S| \cdot |T| \cdot \frac{d}{n} \right| = \left| \sum_{i>1} \alpha_i \beta_i \beta_i \right| \leq \sum_{i>1} |\alpha_i \beta_i|$$

where  $\lambda = \max(|\lambda_1|, |\lambda_2|)$ .

$$\sum_{i>1} |\alpha_i| |\beta_i| \leq \underbrace{\left( \sum_{i>1} \alpha_i^2 \right)^{1/2}}_{\text{Cauchy-Schwarz}} \cdot \left( \sum_{i>1} \beta_i^2 \right)^{1/2} \leq \|\mathbf{1}_S^\perp\| \cdot \|\mathbf{1}_T^\perp\|$$

[ Recall  $\langle x, x \rangle = \langle \sum \alpha_i u_i, \sum \alpha_i u_i \rangle = \sum \alpha_i^2$ , so  $\|x\| = (\sum \alpha_i^2)^{1/2}$  ]

$$\|\mathbf{1}_S^\perp\| = \left( \sum_{i=1}^n \|\mathbf{1}_S(i)\|^2 \right)^{1/2} = \sqrt{5}$$

Conclusion:  $|E(S, T) - \frac{d|S| \cdot |T|}{n}| \leq \lambda \cdot \sqrt{|S| \cdot |T|}$



## Applications

- Independent Set in  $G \subseteq V$  if  $|E(S, S)| = 0$ .

Def: A graph  $G$  is an  $(n, d, \lambda)$  graph if it is  $d$ -reg &  $\max(\lambda_2, |\lambda_n|) \leq \lambda$ .

Claim: max ind. set in an  $(n, d, \lambda)$ -graph  
 $|S| \leq \frac{\lambda}{d} \cdot n$ .

Proof: Suppose  $S \subseteq V$  is s.t.  $E(S, S) = 0$ .

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

$$\frac{d \cdot |S|}{n} \leq \lambda$$

$$|S| \leq \frac{\lambda \cdot n}{d}$$

Corollary:  $\chi(G) \geq \frac{d}{\lambda}$

- Expanders have small diameter  $O(\log h)$

Enough to prove that if  $|S| \leq \frac{h}{2}$

$$E(S, \bar{S}) > \varepsilon \cdot |S|.$$

$$\begin{aligned} E(S, S) &\leq \underbrace{\frac{d|S|^2}{n}}_{\text{---}} + \underbrace{\lambda \cdot |S|}_{\text{---}} \\ \frac{E(S, \bar{S})}{|S|} &\geq \frac{d \cdot |S| - \left( \text{---} \right)}{|S|} \\ &= d - \frac{d|S|}{n} - \lambda = d \left( 1 - \frac{|S|}{n} \right) - \lambda \end{aligned}$$

$$\text{If } |S| \leq \frac{h}{3} \text{ this is } \geq \frac{2}{3}d - \lambda \geq \frac{d}{2} - \lambda$$

$$\text{If } \lambda < \frac{d}{2} \quad \frac{E(S, \bar{S})}{|S|} \geq \varepsilon = \frac{d}{2} - \lambda$$

