

Definitions and logistics...

**Definition: Expander**

In this course we will deal with undirected graphs with edge weights unless otherwise stated. A graph  $G = (V, E)$  with normalized adjacency matrix  $A = D^{-1/2}AD^{-1/2}$ :

- is a **one-sided  $\lambda$ -expander** if the second largest eigenvalue  $\lambda_2(A) \leq \lambda$ ;
- is a **two-sided  $\lambda$ -expander** if  $\lambda_2(A), |\lambda_n(A)| \leq \lambda$ .

*Intuition: this graph is well-connected; in order to separate the graph, one needs to remove many graphs.*

### Examples that can be solved using spectral information

- (1) Given  $G = (V, E)$ , draw it in  $\mathbb{R}^n$  such that connected vertices are close to each other.
- (2) Find the sparsest cut  $S$  in  $G$  that minimizes  $|\partial S|/|S|$ .
- (3) A linear code  $C_k$  is a  $k$ -dimensional subspace of  $\mathbb{F}^n$ . Consider transmitting encoded information over a faulty channel so that extra information needs to be sent to overcome this. A few things we care about: (i) rate  $r$  (so not too much redundant information is needed), (ii) distance  $\delta = \min_{x \in C_k \setminus \{0\}} \text{hammingweight}(x)$  which measures the tolerance between two strings, and (iii) decoding which measures how efficient the algorithm is at decoding *into the uncorrected, redundant string*. Question: can we constraint a family  $\{C_k\}$  such that there exist  $r_0, \delta_0$ , and  $C > 0$  such that  $r(C_k) \geq r_0$ ,  $\delta(C_k) \geq \delta_0$ , and the decoding algorithm takes at most  $Cn$  time (constant rate, constant distance, and linear decoding time).
- (4) BPP (bounded probabilistic polynomial time): a language  $L$  if there exists a PPT-TM (probabilistic polytime Turing machine)  $M$  such that:
  - if  $x \in L$  then it accepts w.p.  $\geq 2/3$ , and
  - if  $x \notin L$ , then it rejects w.p.  $\geq 2/3$ .

To reduce error within  $\epsilon$  for a  $\ell$ -bit string, one naïve operation is to repeat for  $\ell \log \epsilon^{-1}$  times and take majority vote. Question: can we reduce this to  $\ell + \mathcal{O}(\log \epsilon^{-1})$ .

### Basic notations

- Given  $G = (V, E)$ , define the diagonal matrix  $D$ , adjacency matrix  $A$ , and normalized adjacency matrix (with abuse of notation  $A$ ), like before.
- Define  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$  be the eigenvalues sorted in decreasing values, with eigenvectors  $v_i$ .
- Define the Laplacian  $L = D - A$  and the normalized Laplacian  $\bar{L} = D^{-1/2}LD^{-1/2} = I - \bar{A}$ . Sort the spectrum of  $L$  in **increasing order**:  $\gamma_1 \leq \dots \leq \gamma_n$  with eigenvectors  $u_1, \dots, u_n$ .

Some facts.

- $\lambda_1 = 1$  and  $v_1 \propto D^{-1/2}\mathbf{1}$ . In addition,  $\lambda_n \geq -1$ .
- $\gamma_i = 1 - \lambda_i$  which explains why we sort the  $\gamma$ 's in increasing order. This further implies  $\gamma_1 = 0$ .
- $u_i = v_i$  — same eigenspace.
- Using the definition of  $\lambda$ -expanders: if  $G$  is a  $\lambda$ -expander, then  $\gamma_2 \geq 1 - \lambda$ .
- There is a variational perspective to define  $\lambda$ 's: given a matrix  $M$  with increasing spectrum  $\gamma_1 \leq \dots \leq \gamma_n$ , and eigenvalues are  $u_1, \dots, u_n$ , then

$$\gamma_i = \min_{x \perp \text{span}(u_1, \dots, u_{i-1})} \frac{x^T M x}{\langle x, x \rangle}.$$

- We want to write  $f^T L f$  and  $f^T \bar{L} f$  in nicer ways:

$$f^T L f = f^T D f - f^T A f = \sum_{v \in V} f(v)^2 d(v) - \sum_{(a,b) \in E} 2f(a)f(b) = \sum_{(a,b) \in E} (f(a) - f(b))^2.$$

Likewise,

$$f^T \bar{L} f = \sum_{(a,b) \in E} \left( \frac{f(a)}{\sqrt{d(a)}} - \frac{f(b)}{\sqrt{d(b)}} \right)^2.$$

## Conductance

### Definition: Conductance

Given  $G = (V, E)$  and  $S \subset V$ , define cut  $S$ 's conductance as

$$\varphi(S) = \frac{|\partial S|}{\min(\text{vol}(S), \text{vol}(S^c))}$$

where  $\partial S$  is the set of edges between  $(S, S^c)$ , and  $\text{vol}(S) = \sum_{a \in S} d(a)$ , and define the conductance of the graph by  $\varphi(G) = \min_{S \subset V} \varphi(S)$ .

Furthermore, the minimizer  $S$  gives the sparsest cut. Cheeger's inequality gives  $\gamma_2/2 \leq \varphi(G) \leq \sqrt{\gamma_2}$ . Equalities can be attained by hypercubes and cycles, respectively.

**Proof of  $\gamma_2/2 \leq \varphi(G)$ :** let  $S$  be the set minimizing  $\varphi(G)$  with  $\text{vol}(S) \leq 1/2 \text{vol}(V)$ . Let  $f = \mathbf{1}_S - |S|/n \cdot \mathbf{1}$ . It follows from  $(D - A)\mathbf{1} = \mathbf{0}$  that  $f^T L f = \mathbf{1}_S^T L \mathbf{1}_S = |\partial S|$ . On the other hand,

$$\begin{aligned} f^T D f &= \langle \mathbf{1}_S, D \mathbf{1}_S \rangle - 2 \langle \mathbf{1}_S, D |S|/n \mathbf{1} \rangle + \left( \frac{|S|}{n} \right)^2 \langle \mathbf{1}, D \mathbf{1} \rangle \\ &= \text{vol}(S) - \frac{2|S|}{n} \text{vol}(S) + \left( \frac{|S|}{n} \right)^2 \text{vol}(V). \end{aligned}$$

Since  $f^T D f = \text{vol}(S)$ . Recall that  $u_1 = D^{1/2} \mathbf{1}$  so that

$$\begin{aligned} \gamma_2 &= \min_{x \perp D^{1/2} \mathbf{1}} \frac{x^T D^{-1/2} L D^{-1/2} x}{\langle x, x \rangle} = \min_{f \perp \mathbf{1}} \frac{f^T L f}{f^T D f} \\ &\leq \frac{|\partial S|}{\text{vol}(S) - 2|S|\text{vol}(S)/n + |S|^2/n^2 \text{vol}(V)}. \end{aligned}$$

Rewrite the denominator as  $\text{vol}(S)[(1 - a)^2 + a^2]$  where  $a = |S/n|$  and since the bracketed term  $\geq 1/2$ , the claim follows.