

CS5275 – The Algorithm Designer’s Toolkit (S2 AY2025/26)

Lecture 6: Expanders – the power method

Recap

$$\text{Cheeger inequality: } \frac{\lambda_2}{2} \leq \Phi(G) \leq \sqrt{2\lambda_2}$$

Lemma:

- Let x be any vector orthogonal to $\mathbf{1}$.
- There is a polynomial-time algorithm that computes a cut with conductance at most $\sqrt{2R_N(x)}$.



Setting $x = v_2$ yields a cut with conductance at most $\sqrt{2\lambda_2}$.

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Lemma:

- Let x be any vector orthogonal to $\mathbf{1}$.
- There is a polynomial-time algorithm that computes a cut with conductance at most $\sqrt{2R_N(x)}$.



Setting $x = v_2$ yields a cut with conductance at most $\sqrt{2\lambda_2}$.

Our goal: Obtaining this in polynomial time.

From any vector $x \perp \mathbf{1}$ with $R_N(x) \leq \lambda_2 + \epsilon$, we get a cut with conductance at most $\sqrt{2(\lambda_2 + \epsilon)}$.

Setting

- Let M be a real symmetric $(n \times n)$ -matrix.

- Eigenvalues: $0 \leq \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$
- Eigenvectors v_1, v_2, \dots, v_n (orthonormal vectors)



Eigenvalue range for d -regular graphs:

- A (adjacency): $[-d, d]$ ✗
- $L = dI - A$ (Laplacian): $[0, 2d]$ ✓
- $N = I - \frac{1}{d}A$ (normalized Laplacian): $[0, 2]$ ✓

Setting

- Let M be a real symmetric $(n \times n)$ -matrix.
 - Eigenvalues: $0 \leq \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$
 - Eigenvectors v_1, v_2, \dots, v_n (orthonormal vectors)
 - **First goal:** Approximating the largest eigenvector v_n .
 - Find a vector x with $R_M(x) \geq (1 - \epsilon) \cdot \lambda_n$.
- ↑
- We will later extend this to:
- The second largest eigenvector v_{n-1} .
 - The smallest eigenvector v_1 .
 - The second smallest eigenvector v_2 (our main goal).

The power method

Algorithm POWER:

Input: a matrix M and a parameter k .

- Pick $x_0 \in \{-1,1\}^n$ uniformly at random.
- Return $x = M^k x_0$.

Claim: There is a choice of parameter $k \in O\left(\frac{\log n}{\epsilon}\right)$ such that $\Pr[R_M(x) \geq (1 - \epsilon) \cdot \lambda_n] \geq \frac{3}{16}$.

Proof sketch:

The matrix M^k has:

- Eigenvalues: $0 \leq \lambda_1^k \leq \lambda_2^k \leq \dots \leq \lambda_n^k$
- The same eigenvectors v_1, v_2, \dots, v_n

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Suppose $\lambda_{i^*} \leq (1 - \epsilon) \cdot \lambda_n < \lambda_{i^*+1}$.

Then $\lambda_{i^*}^k \leq (1 - \epsilon)^k \cdot \lambda_n^k$



$1/\text{poly}(n)$

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↓

$$x = M^k x_0 = \underbrace{c_1 \lambda_1^k v_1 + c_2 \lambda_2^k v_2 + \cdots + c_{i^*} \lambda_{i^*}^k v_{i^*}}_{\text{Negligibly small}} + \underbrace{c_{i^*+1} \lambda_{i^*+1}^k v_{i^*+1} + \cdots + c_n \lambda_n^k v_n}_{R_M(\cdot) \geq (1 - \epsilon) \cdot \lambda_n}$$

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\downarrow
1/poly(n)

To make this argument work, we need to start with a sufficiently large $c_n = \langle x_0, v_n \rangle$.

$$x_0 = c_1 v_1 + c_2 v_2 + \dots + c_i v_i + c_{i+1} v_{i+1} + \dots + c_n v_n$$

$$x = M^k x_0 = c_1 \lambda_1^k v_1 + c_2 \lambda_2^k v_2 + \dots + c_{i^*} \lambda_{i^*}^k v_{i^*} + c_{i^*+1} \lambda_{i^*+1}^k v_{i^*+1} + \dots + c_n \lambda_n^k v_n$$

Negligibly small

$R_M(\cdot) \geq (1 - \epsilon) \cdot \lambda_n$

The power method

Claim: for any unit vector \mathbf{v} , $\Pr \left[|\langle \mathbf{x}_0, \mathbf{v} \rangle| \geq \frac{1}{2} \right] \geq \frac{3}{16}$

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To make this argument work, we need to start with a sufficiently large $c_n = \langle \mathbf{x}_0, \mathbf{v}_n \rangle$.

$$\mathbf{x}_0 = c_1 \mathbf{v}_1 + c_2 \mathbf{v}_2 + \cdots + c_i \mathbf{v}_i + c_{i+1} \mathbf{v}_{i+1} + \cdots + c_n \mathbf{v}_n$$

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Proof:

- $\mathbf{x}_0 = (x_1, x_2, \dots, x_n)$
- $\mathbf{v} = (v_1, v_2, \dots, v_n)$
- $Z = \langle \mathbf{x}_0, \mathbf{v} \rangle = \sum_{i=1}^n x_i v_i$

$$\mathbb{E}[Z] = \sum_{i=1}^n \mathbb{E}[x_i] v_i = 0$$

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$$\mathbb{E}[Z] = \sum_{i=1}^n \mathbb{E}[x_i] v_i = 0$$

$$\mathbb{E}[Z^2] = \sum_{i=1}^n \sum_{j=1}^n \mathbb{E}[x_i x_j] v_i v_j = \sum_{i=1}^n \mathbb{E}[x_i^2] v_i^2 = \sum_{i=1}^n v_i^2 = 1$$

$$\mathbb{E}[x_i x_j] = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases} \quad \mathbf{v} \text{ is a unit vector.}$$

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$$\mathbb{E}[Z^4] = \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^n \sum_{\ell=1}^n \underbrace{\mathbb{E}[x_i x_j x_k x_\ell]}_{\text{appears } \binom{4}{2} = 6 \text{ times}} v_i v_j v_k v_\ell = 3 \sum_{i=1}^n \mathbb{E}[x_i^2] v_i^2 \sum_{j=1}^n \mathbb{E}[x_j^2] v_j^2 - 2 \sum_{i=1}^n \mathbb{E}[x_i^4] v_i^4$$

$$i \notin \{j, k, \ell\} \rightarrow \mathbb{E}[x_i x_j x_k x_\ell] = 0$$

$$j \notin \{i, k, \ell\} \rightarrow \mathbb{E}[x_i x_j x_k x_\ell] = 0$$

$$k \notin \{i, j, \ell\} \rightarrow \mathbb{E}[x_i x_j x_k x_\ell] = 0$$

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For any $i \neq j$, $\mathbb{E}[x_i^2 x_j^2]$ appears $\binom{4}{2} = 6$ times.

For any i , $\mathbb{E}[x_i^4]$ appears once.

The power method

Claim: for any unit vector \mathbf{v} , $\Pr \left[|\langle \mathbf{x}_0, \mathbf{v} \rangle| \geq \frac{1}{2} \right] \geq \frac{3}{16}$

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$$\mathbb{E}[Z] = \sum_{i=1}^n \mathbb{E}[x_i] v_i = 0$$

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$$= 1$$

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$$= \sum_{i=1}^n v_i^4 \geq 0$$

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Claim: for any unit vector \mathbf{v} , $\Pr \left[|\langle \mathbf{x}_0, \mathbf{v} \rangle| \geq \frac{1}{2} \right] \geq \frac{3}{16}$

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- $Z = \langle \mathbf{x}_0, \mathbf{v} \rangle = \sum_{i=1}^n x_i v_i$
- $\mathbb{E}[Z] = 0$
- $\mathbb{E}[Z^2] = 1$
- $\mathbb{E}[Z^4] \leq 3$
- $\text{Var}[Z^2] = \mathbb{E}[Z^4] - \mathbb{E}[Z^2]^2 < \infty$

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- $\text{Var}[Z^2] = \mathbb{E}[Z^4] - \mathbb{E}[Z^2]^2 < \infty$

$$\begin{aligned}\Pr \left[|\langle \mathbf{x}_0, \mathbf{v} \rangle| \geq \frac{1}{2} \right] &= \Pr \left[|Z| \geq \frac{1}{2} \right] = \Pr \left[Z^2 \geq \frac{1}{4} \right] \\ &= \Pr \left[Z^2 \geq \delta \mathbb{E}[Z^2] \right] \geq (1 - \delta)^2 \frac{\mathbb{E}[Z^2]}{\mathbb{E}[Z^4]} \geq \left(\frac{3}{4} \right)^2 \cdot \frac{1}{3} = \frac{3}{16}\end{aligned}$$

$$\begin{array}{c} \delta = \frac{1}{4} \\ X = Z^2 \end{array}$$

Paley–Zygmund inequality: $\Pr[X \geq \delta \mathbb{E}[X]] \geq (1 - \delta)^2 \frac{\mathbb{E}[X]^2}{\mathbb{E}[X^2]}$, for $X \geq 0$, $\text{Var}[X] < \infty$, $\delta \in (0, 1)$

The power method

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- The same eigenvectors $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$

Suppose $\lambda_{i^*} \leq (1 - \epsilon) \cdot \lambda_n < \lambda_{i^*+1}$.

$$\mathbf{x}_0 = c_1 \mathbf{v}_1 + c_2 \mathbf{v}_2 + \dots + c_i \mathbf{v}_i + c_{i+1} \mathbf{v}_{i+1} + \dots + c_n \mathbf{v}_n$$



Assume $|c_n| = |\langle \mathbf{x}_0, \mathbf{v}_n \rangle| \geq \frac{1}{2}$.

$$\mathbf{x} = \mathbf{M}^k \mathbf{x}_0$$

$$\begin{aligned} R_{\mathbf{M}}(\mathbf{x}) &= \frac{\mathbf{x}^\top \mathbf{M} \mathbf{x}}{\mathbf{x}^\top \mathbf{x}} \\ &= \frac{\mathbf{x}_0^\top \mathbf{M}^{2k+1} \mathbf{x}_0}{\mathbf{x}_0^\top \mathbf{M}^{2k} \mathbf{x}_0} \\ &= \frac{\sum_{i=1}^n c_i^2 \lambda_i^{2k+1}}{\sum_{i=1}^n c_i^2 \lambda_i^{2k}} \end{aligned}$$

The power method

$$\mathbf{x}_0 = c_1 \mathbf{v}_1 + c_2 \mathbf{v}_2 + \cdots + c_i \mathbf{v}_i + c_{i+1} \mathbf{v}_{i+1} + \cdots + c_n \mathbf{v}_n$$

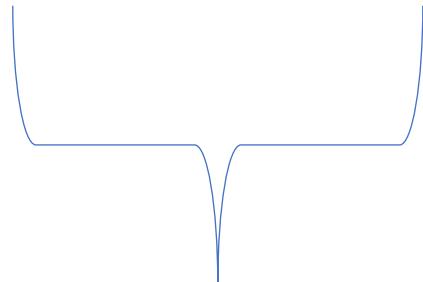


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$$\begin{aligned} R_{\mathbf{M}}(\mathbf{x}) &= \frac{\mathbf{x}^\top \mathbf{M} \mathbf{x}}{\mathbf{x}^\top \mathbf{x}} \\ &= \frac{\mathbf{x}_0^\top \mathbf{M}^{2k+1} \mathbf{x}_0}{\mathbf{x}_0^\top \mathbf{M}^{2k} \mathbf{x}_0} \\ &= \frac{\sum_{i=1}^n c_i^2 \lambda_i^{2k+1}}{\sum_{i=1}^n c_i^2 \lambda_i^{2k}} \\ &\geq \frac{(1 - \epsilon) \cdot \lambda_n \cdot \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}}{\sum_{i=1}^{i^*} c_i^2 \lambda_i^{2k} + \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}} \end{aligned}$$



The power method

$$x_0 = c_1 v_1 + c_2 v_2 + \cdots + c_i v_i + c_{i+1} v_{i+1} + \cdots + c_n v_n$$



Assume $|c_n| = |\langle x_0, v_n \rangle| \geq \frac{1}{2}$.

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Suppose $\lambda_{i^*} \leq (1 - \epsilon) \cdot \lambda_n < \lambda_{i^*+1}$.

$$\sum_{i=1}^n c_i^2 = \|x_0\|^2 = n$$

$$4 \cdot c_n^2 \leq 1$$

$$\begin{aligned} \sum_{i=1}^{i^*} c_i^2 \lambda_i^{2k} &\leq (1 - \epsilon)^{2k} \cdot \lambda_n^{2k} \cdot \sum_{i=1}^n c_i^2 \\ &= (1 - \epsilon)^{2k} \cdot n \cdot \lambda_n^{2k} \\ &\leq (1 - \epsilon)^{2k} \cdot 4n \cdot c_n^2 \lambda_n^{2k} \\ &\leq (1 - \epsilon)^{2k} \cdot 4n \cdot \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k} \end{aligned}$$



$$\begin{aligned} R_M(x) &= \frac{x^\top M x}{x^\top x} \\ &= \frac{x_0^\top M^{2k+1} x_0}{x_0^\top M^{2k} x_0} \\ &= \frac{\sum_{i=1}^n c_i^2 \lambda_i^{2k+1}}{\sum_{i=1}^n c_i^2 \lambda_i^{2k}} \\ &\geq \frac{(1 - \epsilon) \cdot \lambda_n \cdot \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}}{\sum_{i=1}^{i^*} c_i^2 \lambda_i^{2k} + \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}} \\ &\geq \frac{(1 - \epsilon) \cdot \lambda_n \cdot \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}}{(1 + (1 - \epsilon)^{2k} \cdot 4n) \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}} \end{aligned}$$

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- The same eigenvectors $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$

Suppose $\lambda_{i^*} \leq (1 - \epsilon) \cdot \lambda_n < \lambda_{i^*+1}$.

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Assume $|c_n| = |\langle \mathbf{x}_0, \mathbf{v}_n \rangle| \geq \frac{1}{2}$.

$$\begin{aligned} R_{\mathbf{M}}(\mathbf{x}) &= \frac{\mathbf{x}^\top \mathbf{M} \mathbf{x}}{\mathbf{x}^\top \mathbf{x}} \\ &= \frac{\mathbf{x}_0^\top \mathbf{M}^{2k+1} \mathbf{x}_0}{\mathbf{x}_0^\top \mathbf{M}^{2k} \mathbf{x}_0} \\ &= \frac{\sum_{i=1}^n c_i^2 \lambda_i^{2k+1}}{\sum_{i=1}^n c_i^2 \lambda_i^{2k}} \\ &\geq \frac{(1 - \epsilon) \cdot \lambda_n \cdot \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}}{\sum_{i=1}^{i^*} c_i^2 \lambda_i^{2k} + \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}} \\ &\geq \frac{(1 - \epsilon) \cdot \lambda_n \cdot \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}}{(1 + (1 - \epsilon)^{2k} \cdot 4n) \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}} \\ &= \frac{(1 - \epsilon) \cdot \lambda_n}{1 + (1 - \epsilon)^{2k} \cdot 4n} \\ &\in (1 - O(\epsilon)) \cdot \lambda_n \end{aligned}$$

$$k \in O\left(\frac{\log n}{\epsilon}\right)$$

The power method

Claim: There is a choice of parameter $k \in O\left(\frac{\log n}{\epsilon}\right)$ such that $\Pr[R_{\mathbf{M}}(\mathbf{x}) \geq (1 - \epsilon) \cdot \lambda_n] \geq \frac{3}{16}$.

with a change of variable: $\epsilon' \in \Theta(\epsilon)$

$$\mathbf{x}_0 = c_1 \mathbf{v}_1 + c_2 \mathbf{v}_2 + \cdots + c_i \mathbf{v}_i + c_{i+1} \mathbf{v}_{i+1} + \cdots + c_n \mathbf{v}_n$$



Assume $|c_n| = |\langle \mathbf{x}_0, \mathbf{v}_n \rangle| \geq \frac{1}{2}$.

This happens with probability $\geq \frac{3}{16}$.

$$\begin{aligned} R_{\mathbf{M}}(\mathbf{x}) &= \frac{\mathbf{x}^\top \mathbf{M} \mathbf{x}}{\mathbf{x}^\top \mathbf{x}} \\ &= \frac{\mathbf{x}_0^\top \mathbf{M}^{2k+1} \mathbf{x}_0}{\mathbf{x}_0^\top \mathbf{M}^{2k} \mathbf{x}_0} \\ &= \frac{\sum_{i=1}^n c_i^2 \lambda_i^{2k+1}}{\sum_{i=1}^n c_i^2 \lambda_i^{2k}} \\ &\geq \frac{(1 - \epsilon) \cdot \lambda_n \cdot \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}}{\sum_{i=1}^{i^*} c_i^2 \lambda_i^{2k} + \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}} \\ &\geq \frac{(1 - \epsilon) \cdot \lambda_n \cdot \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}}{(1 + (1 - \epsilon)^{2k} \cdot 4n) \sum_{i=i^*+1}^n c_i^2 \lambda_i^{2k}} \\ &= \frac{(1 - \epsilon) \cdot \lambda_n}{1 + (1 - \epsilon)^{2k} \cdot 4n} \\ &\in (1 - O(\epsilon)) \cdot \lambda_n \end{aligned}$$

Second largest eigenvector

- Let M be a real symmetric $(n \times n)$ -matrix.
 - Eigenvalues: $0 \leq \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$
 - Eigenvectors v_1, v_2, \dots, v_n (orthonormal vectors)
- **Done:** Find a vector x with $R_M(x) \geq (1 - \epsilon) \cdot \lambda_n$.
- **Next:** The second largest eigenvector v_{n-1} .

Given v_n , the goal is to find a vector $x \perp v_n$ with $R_M(x) \geq (1 - \epsilon) \cdot \lambda_{n-1}$.

Second largest eigenvector

Algorithm POWER:

Input: a matrix \mathbf{M} and a parameter k .

- Pick $\mathbf{x}_0 \in \{-1,1\}^n$ uniformly at random.
- Return $\mathbf{x} = \mathbf{M}^k \mathbf{x}_0$.

This restricts ourselves to $\text{span}\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_{n-1}\}$.



- Pick $\mathbf{x}_0 \in \{-1,1\}^n$ uniformly at random.
- $\mathbf{x}'_0 = \mathbf{x}_0 - \langle \mathbf{x}_0, \mathbf{v}_n \rangle \cdot \mathbf{v}_n$
- Return $\mathbf{x} = \mathbf{M}^k \mathbf{x}'_0$.

Second largest eigenvector

Claim: for any unit vector \mathbf{v} , $\Pr \left[|\langle \mathbf{x}_0, \mathbf{v} \rangle| \geq \frac{1}{2} \right] \geq \frac{3}{16}$

$$\langle \mathbf{x}'_0, \mathbf{v}_{n-1} \rangle = \langle \mathbf{x}_0, \mathbf{v}_{n-1} \rangle$$

We still have:

$$\Pr \left[|\langle \mathbf{x}'_0, \mathbf{v}_{n-1} \rangle| \geq \frac{1}{2} \right] \geq \frac{3}{16}$$

The same analysis:

There is a choice of parameter $k \in O\left(\frac{\log n}{\epsilon}\right)$ such that $\Pr[R_{\mathbf{M}}(\mathbf{x}) \geq (1 - \epsilon) \cdot \lambda_{n-1}] \geq \frac{3}{16}$.

Algorithm POWER:

Input: a matrix \mathbf{M} and a parameter k .

- Pick $\mathbf{x}_0 \in \{-1,1\}^n$ uniformly at random.
- Return $\mathbf{x} = \mathbf{M}^k \mathbf{x}_0$.

- Pick $\mathbf{x}_0 \in \{-1,1\}^n$ uniformly at random.
- $\mathbf{x}'_0 = \mathbf{x}_0 - \langle \mathbf{x}_0, \mathbf{v}_n \rangle \cdot \mathbf{v}_n$
- Return $\mathbf{x} = \mathbf{M}^k \mathbf{x}'_0$.

Approximating \boldsymbol{v}_1 and \boldsymbol{v}_2

- Let \mathbf{M} be a real symmetric $(n \times n)$ -matrix.
 - Eigenvalues: $0 \leq \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$
 - Eigenvectors $\boldsymbol{v}_1, \boldsymbol{v}_2, \dots, \boldsymbol{v}_n$ (orthonormal vectors)
- Suppose we know an upper bound $c \geq \lambda_n$
- Consider $c\mathbf{I} - \mathbf{M}$:
 - Same eigenvectors: $\boldsymbol{v}_1, \boldsymbol{v}_2, \dots, \boldsymbol{v}_n$
 - Eigenvalues: $c - \lambda_1 \geq c - \lambda_2 \geq \dots \geq c - \lambda_n \geq 0$

Now we can use the same method to approximate \boldsymbol{v}_1 and \boldsymbol{v}_2 .

Computing a low-conductance cut

- Approximating the second largest eigenvector of $2I - N$:
 - We get a vector $x \perp \mathbf{1}$ with

$$R_{2I-N}(x) = 2 - R_N(x) \geq (1 - \epsilon) \cdot (2 - \lambda_2)$$



$$R_N(x) \leq 2 - (1 - \epsilon) \cdot (2 - \lambda_2) \leq \lambda_2 + 2\epsilon$$



$$\epsilon' = 2\epsilon$$

We get a cut with conductance at most $\sqrt{2(\lambda_2 + \epsilon')}$.

Summary

- Let M be a real symmetric $(n \times n)$ -matrix.
 - Eigenvalues: $0 \leq \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$
 - Eigenvectors v_1, v_2, \dots, v_n



We showed how to approximate them efficiently.



Many applications in theory and in practice.

Outlook

- We finished the discussion of these two topics:
 - Conductance approximation.
 - Spectral graph theory.
- **Next:** The probabilistic aspect of expanders.



This includes **random walks** and their applications.

References

- **Main reference:**
 - Lecture 4.2 of <https://sites.google.com/site/thsaranurak/teaching/Expander>
 - Chapter 9 of <https://lucatrevisan.github.io/books-expanders-2016.pdf>
- **Additional/optional reading:** The power method in distributed computing.
 - “Distributed Sparsest Cut via Eigenvalue Estimation” by Yannic Maus and Tijn de Vos
<https://arxiv.org/pdf/2508.19898>