

# multi-way spectral partitioning and higher-order Cheeger inequalities

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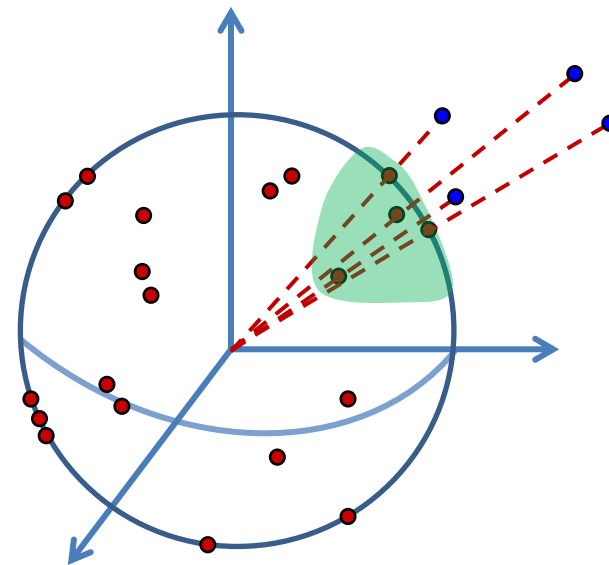
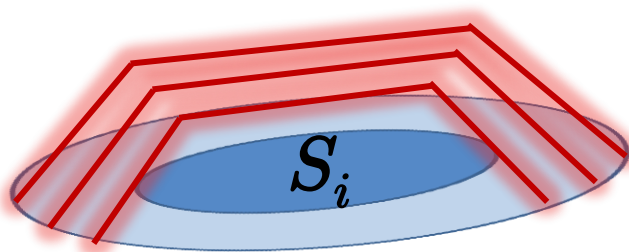
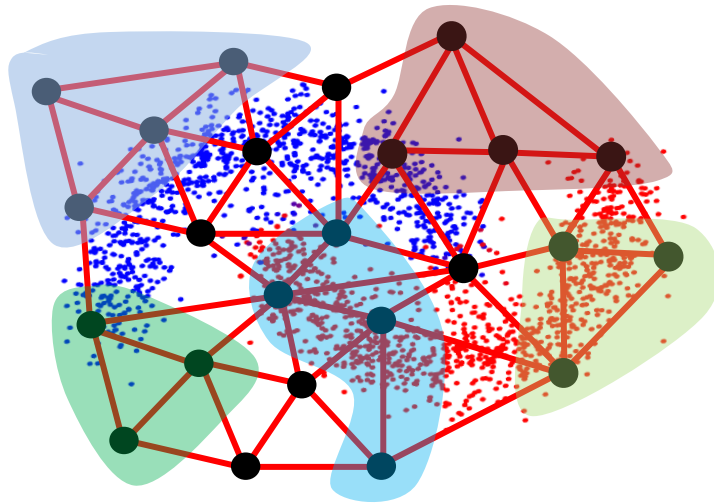
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# spectral theory of the Laplacian

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Consider a  $d$ -regular graph  $G = (V, E)$ .

Define the **normalized Laplacian**:  $L = I - \frac{1}{d}A$

(where  $A$  is the adjacency matrix of  $G$ )

$L$  is positive semi-definite with spectrum

$$0 = \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_{|V|} \leq 2$$

**Fact:**  $\lambda_2 = 0 \iff G$  is disconnected.

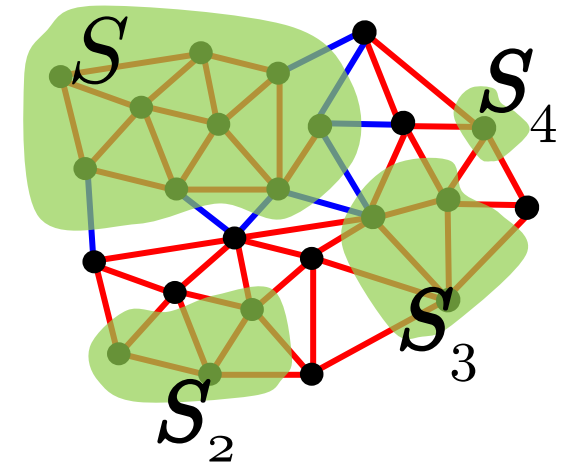
$$\lambda_2 = \min_{f \perp \mathbf{1}} \frac{\langle f, Lf \rangle}{\langle f, f \rangle} = \min_{f \perp \mathbf{1}} \frac{\frac{1}{d} \sum_{u \sim v} |f(u) - f(v)|^2}{\sum_{u \in V} f(u)^2}$$

# Cheeger's inequality

**Expansion:** For a subset  $S \subseteq V$ , define

$$\phi(S) = \frac{|E(S)|}{d|S|}$$

$E(S)$  = set of edges with one endpoint in  $S$ .



**k-way expansion constant:**

$$\rho_G(k) = \min \{ \max \phi(S_i) : S_1, S_2, \dots, S_k \subseteq V \text{ disjoint} \}$$

**Theorem [Cheeger70, Alon-Milman85, Sinclair-Jerrum89]:**

$$\frac{\lambda_2}{2} \leq \rho_G(2) \leq \sqrt{2\lambda_2}$$

$\lambda_2 = 0 \iff G$  is disconnected.

## Miclo's conjecture

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$\lambda_k = 0 \iff G$  has at least  $k$  connected components.

$f_1, f_2, \dots, f_k : V \rightarrow \mathbb{R}$  first  $k$  (orthonormal) eigenfunctions

**spectral embedding:**  $F : V \rightarrow \mathbb{R}^k$

$$F(v) = (f_1(v), f_2(v), \dots, f_k(v))$$

**Higher-order Cheeger Conjecture [Miclo 08]:**

For every graph  $G$  and  $k \in \mathbb{N}$ , we have

$$\frac{\lambda_k}{2} \cdot \rho_G(k) \cdot C(k) \sqrt{\lambda_k}$$

for some  $C(k)$  depending only on  $k$ .

$$\rho_G(k) = \min \{ \max \phi(S_i) : S_1, S_2, \dots, S_k \subseteq V \text{ disjoint} \}$$

**Theorem:** For every graph  $G$  and  $k \in \mathbb{N}$ , we have

$$\frac{\lambda_k}{2} \cdot \rho_G(k) \cdot O(k^2) \sqrt{\lambda_k}$$

Also,  $\rho_G(k) \cdot O(\sqrt{\lambda_{2k} \log k})$

- actually, can put  $\lambda_{(1+\delta)k}$  for any  $\delta > 0$
- tight up to this  $(1+\delta)$  factor
- proved independently by [Louis-Raghavendra-Tetali-Vempala 11]

If  $G$  is planar (or more generally, excludes a fixed minor), then

$$\rho_G(k) \cdot O(\sqrt{\lambda_{2k}})$$

**Corollary:** For every graph  $G$  and  $k \in \mathbb{N}$ , there is a subset of vertices  $S$  such that  $|S| \leq \frac{n}{2k}$  and,

$$\phi(S) \leq O(\sqrt{\lambda_k \log k})$$

**Previous bounds:**

$$|S| \leq \frac{n}{\sqrt{k}} \quad \text{and} \quad \phi(S) \leq O(\sqrt{\lambda_k \log k})$$

[Louis-Raghavendra-Tetali-Vempala 11]

$$|S| \leq \frac{n}{k^{0.01}} \quad \text{and} \quad \phi(S) \leq O(\sqrt{\lambda_k \log_k n})$$

[Arora-Barak-Steurer 10]

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**Theorem:** For every graph  $G$  and  $k \in \mathbb{N}$ , we have

$$\rho_G(k) \leq O(k^2) \sqrt{\lambda_k}$$

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**Theorem:** For every graph  $G$  and  $k \in \mathbb{N}$ , we have

$$\rho_G(k) \cdot k^{O(1)} \sqrt{\lambda_k}$$



# Dirichlet Cheeger inequality

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For a mapping  $F : V \rightarrow \ell_2$ , define the **Rayleigh quotient**:

$$\mathcal{R}(F) = \frac{\frac{1}{\bar{d}} \sum_{u \sim v} \|F(u) - F(v)\|^2}{\sum_{u \in V} \|F(u)\|^2}$$

**Lemma:** For any mapping  $F : V \rightarrow \ell_2$ , there exists a subset

$$S \subseteq \text{supp}(F) = \{v \in V : F(v) \neq 0\}$$

such that:  $\phi(S) \leq \sqrt{2\mathcal{R}(F)}$

# Miclo's disjoint support conjecture

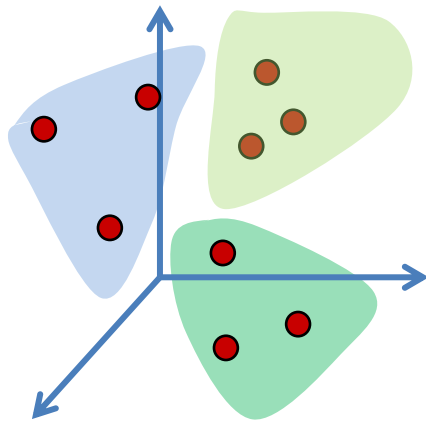
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**Conjecture [Miclo 08]:**

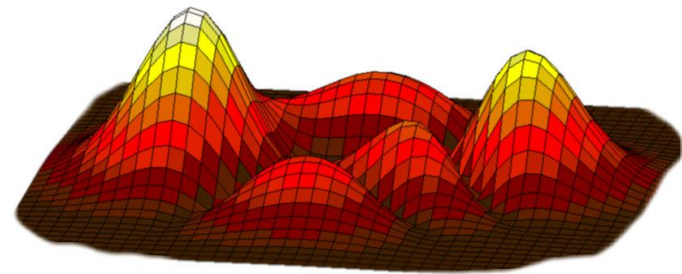
For every graph  $G$  and  $k \in \mathbb{N}$ , there exist disjointly supported functions  $\psi_1, \psi_2, \dots, \psi_k : V \rightarrow \mathbb{R}$  so that for  $i=1, 2, \dots, k$ ,

$$\mathcal{R}(\psi_i) \leq C(k) \lambda_k$$

**Localizing eigenfunctions:**  $F(v) = (f_1(v), f_2(v), \dots, f_k(v))$



$$\mathcal{R}(F) \leq \lambda_k$$



$$\mathbb{R}^k$$

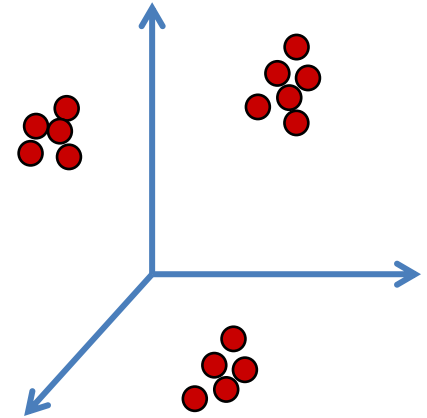
**Isotropy:** For every unit vector  $x \in \mathbb{R}^k$

$$\sum_{v \in V} \langle x, F(v) \rangle^2 = 1$$

||

$$x^T M M^T x = \|x\|^2$$

$$M = \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_k \end{pmatrix}$$



**Total mass:**  $\sum_{v \in V} \|F(v)\|^2 = k$

Define the **radial projection distance** on  $V$  by,

$$d_F(u, v) = \left\| \frac{F(u)}{\|F(u)\|} - \frac{F(v)}{\|F(v)\|} \right\|$$

**Fact:**  $\|F(u)\| \cdot d_F(u, v) \leq 2 \|F(u) - F(v)\|$

**Isotropy gives:** For every subset  $S \subseteq V$ ,

$$\text{diam}(S, d_F) \cdot \frac{1}{2} \implies \sum_{v \in S} \|F(v)\|^2 \cdot \frac{2}{k} \sum_{v \in V} \|F(v)\|^2$$

Want to find  $k$  regions  $S_1, S_2, \dots, S_k \subseteq V$  such that,

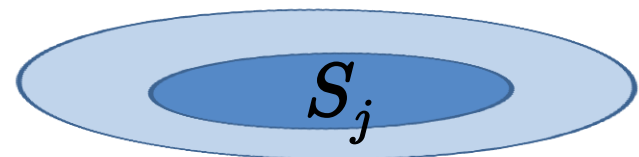
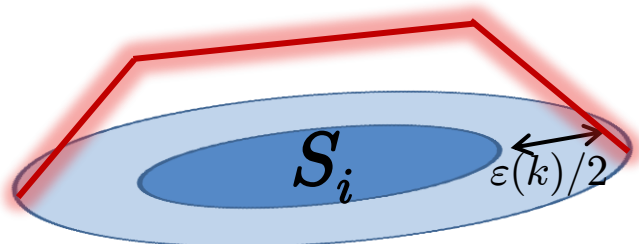
**mass:** 
$$\sum_{v \in S_i} \|F(v)\|^2 \asymp 1$$

**separation:**  $d_F(S_i, S_j) \geq \varepsilon(k)$  for all  $i \neq j$

Then define  $\psi_i : V \rightarrow \mathbb{R}^k$  by,

$$\psi_i(v) = F(v) \cdot \max\left(0, 1 - \frac{2d_F(v, S_i)}{\varepsilon(k)}\right)$$

so that  $\psi_1, \psi_2, \dots, \psi_k$  are disjointly supported and  $\psi_i|_{S_i} \equiv F|_{S_i}$



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**Claim:** 
$$\mathcal{R}(\psi_i) \leq \frac{O(k)}{\varepsilon(k)^2} \cdot \mathcal{R}(F)$$

Want to find  $k$  regions  $S_1, S_2, \dots, S_k \subseteq V$  such that,

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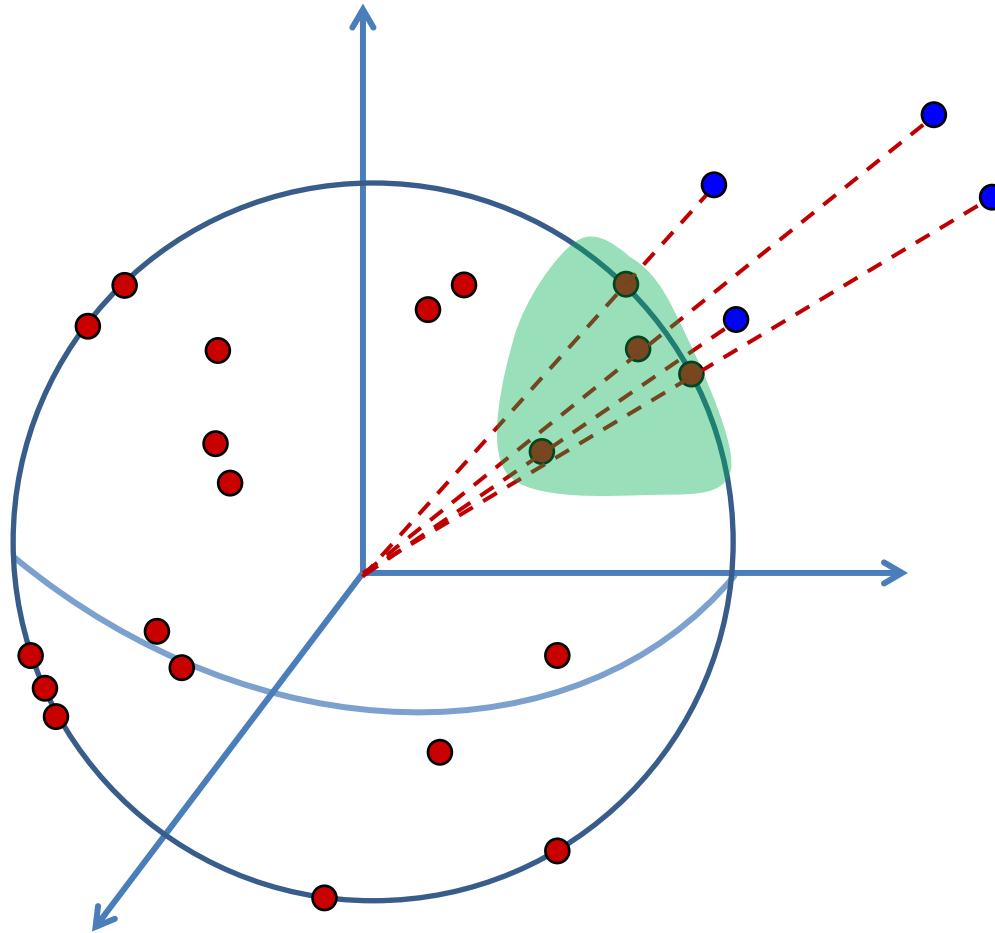
For every subset  $S \subseteq V$ ,

$$\text{diam}(S, d_F) \cdot \frac{1}{2} \implies \sum_{v \in S} \|F(v)\|^2 \cdot \frac{2}{k} \sum_{v \in V} \|F(v)\|^2$$

How to break into subsets? **Randomly...**

# random partitioning

$\mathbb{R}^k$



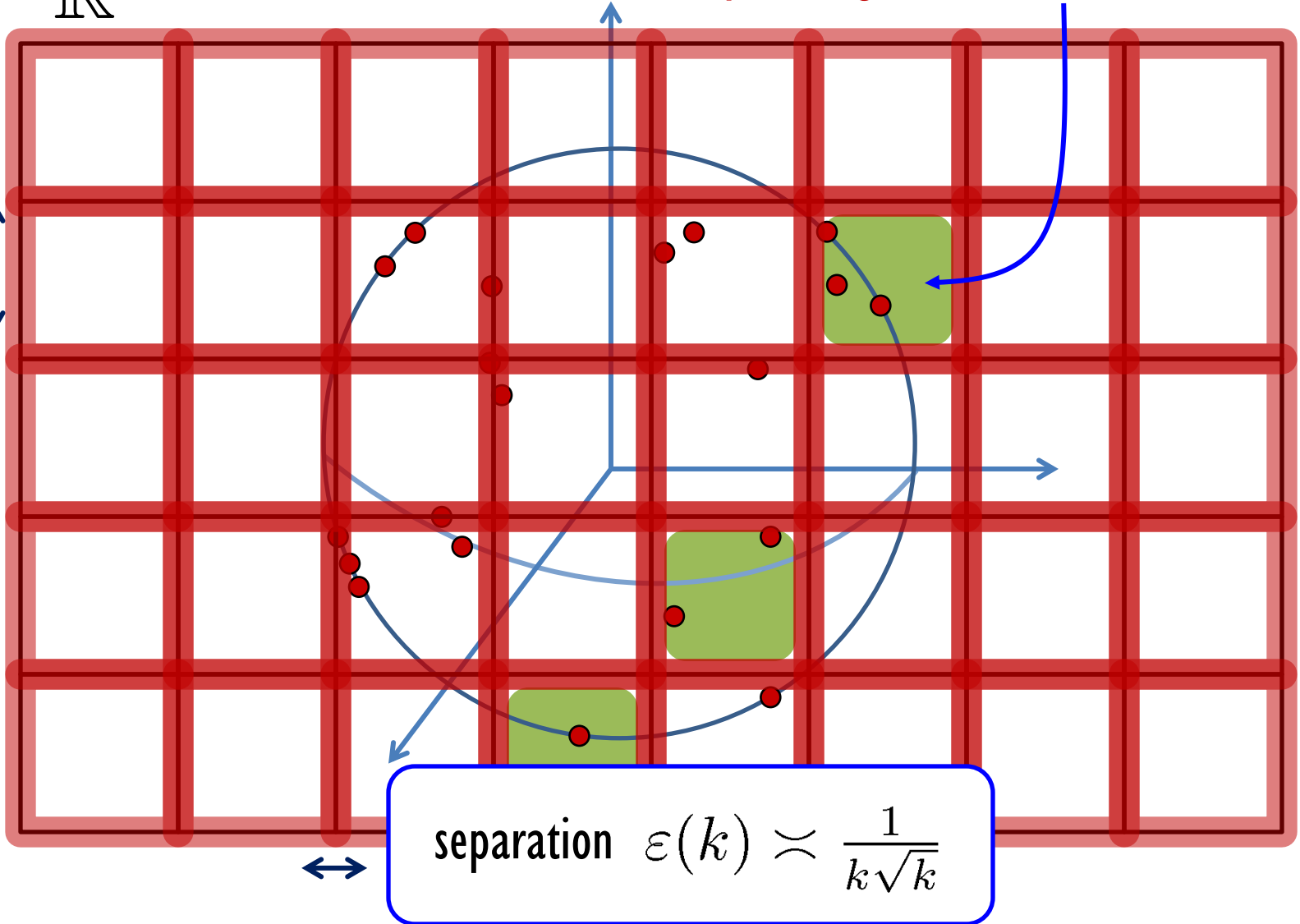


# random partitioning

$\mathbb{R}^k$

spreading  $\Rightarrow \leq 0.5$  mass

$$\frac{1}{2\sqrt{k}}$$

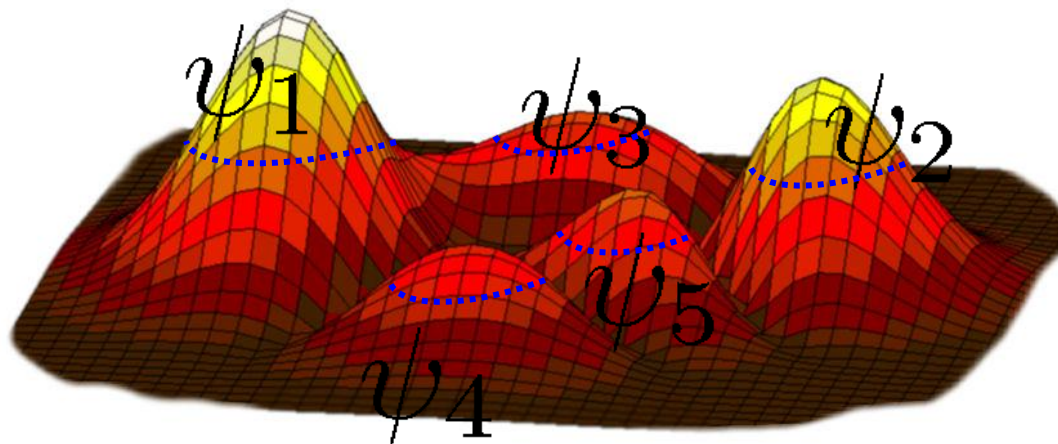
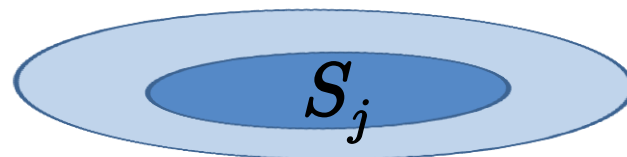
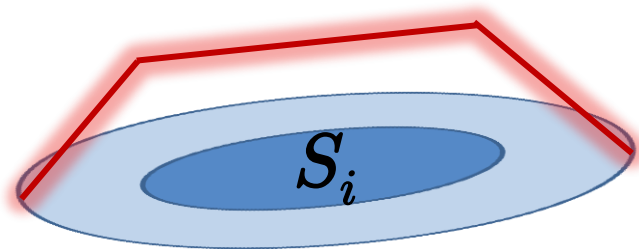


separation  $\varepsilon(k) \asymp \frac{1}{k\sqrt{k}}$

We found  $k$  regions  $S_1, S_2, \dots, S_k \subseteq V$  such that,

**mass:** 
$$\sum_{v \in S_i} \|F(v)\|^2 \asymp 1$$

**separation:** 
$$d_F(S_i, S_j) \geq \frac{1}{2k\sqrt{k}} \text{ for all } i \neq j$$



# improved quantitative bounds

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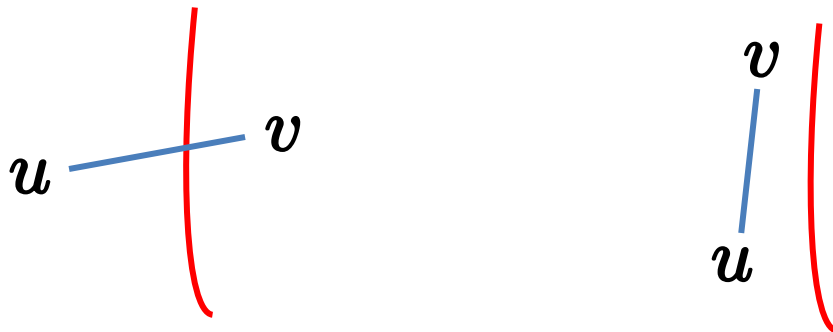
$$\rho_G(k) \cdot O(\sqrt{\lambda_{2k} \log k})$$

- Take only best  $k/2$  regions (gains a factor of  $k$ )
- Before partitioning, take a random projection into  $O(\log k)$  dimensions

**Recall the spreading property:** For every subset  $S \subseteq V$ ,

$$\text{diam}(S, d_F) \cdot \frac{1}{2} \implies \sum_{v \in S} \|F(v)\|^2 \cdot \frac{2}{k} \sum_{v \in V} \|F(v)\|^2$$

- With respect to a random ball in  $d$  dimensions...



# k-way spectral partitioning algorithm

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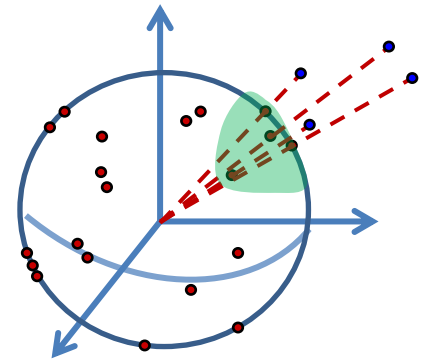
## ALGORITHM:

- 1) Compute the spectral embedding

$$F(v) = (f_1(v), f_2(v), \dots, f_k(v))$$

- 2) Partition the vertices according to the radial projection

$$d_F(u, v) = \left\| \frac{F(u)}{\|F(u)\|} - \frac{F(v)}{\|F(v)\|} \right\|$$



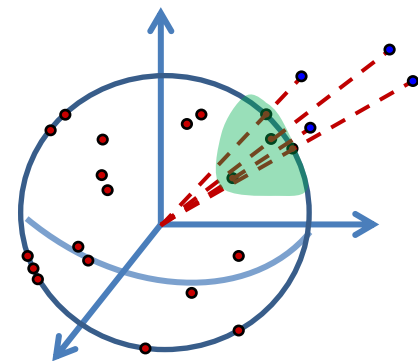
- 3) Perform a “Cheeger sweep” on each piece of the partition

# planar graphs: spectral + intrinsic geometry

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2) Partition the vertices according to the radial projection

$$d_F(u, v) = \left\| \frac{F(u)}{\|F(u)\|} - \frac{F(v)}{\|F(v)\|} \right\|$$



For planar graphs, we consider the induced shortest-path metric on  $G$ , where an edge  $\{u, v\}$  has length  $d_F(u, v)$ .

Now we can analyze the shortest-path geometry using

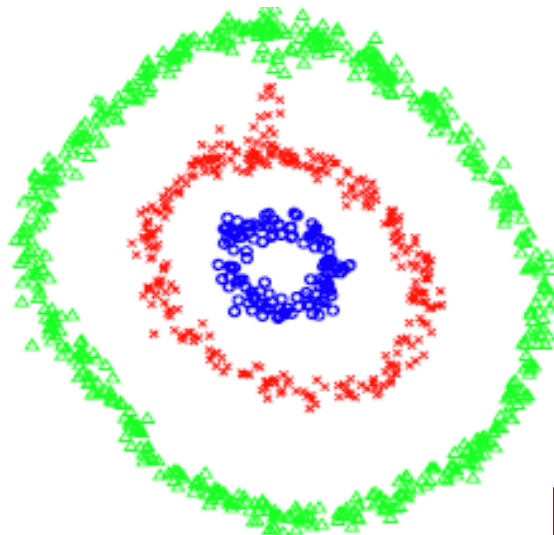
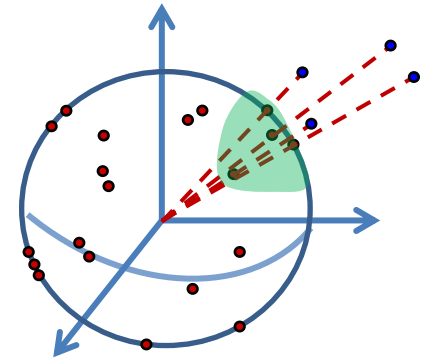
[Klein-Plotkin-Rao 93]

# planar graphs: spectral + intrinsic geometry

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$$d_F(u, v) = \left\| \frac{F(u)}{\|F(u)\|} - \frac{F(v)}{\|F(v)\|} \right\|$$



[Jordan-Ng-Weiss 01]

1)  $\rho_G(k) \leq O(k^2)\sqrt{\lambda_k}$  Can this be made  $\text{poly}(\log k)$ ?

2) Can [Arora-Barak-Steurer] be done geometrically?

We use  $k$  eigenvectors, find  $\asymp k$  sets, lose  $\sqrt{\log k}$ .

What about using  $\sqrt{n}$  eigenvectors to find  $n^{0.01}$  sets?

3) Small set expansion problem

There is a subset  $S \subseteq V$  with

$$|S| \leq \frac{n}{2k} \quad \text{and} \quad \phi(S) \leq O(\sqrt{\lambda_k \log k})$$

Tight for  $k \leq \text{poly}(\log n)$  (noisy hypercubes)

Tight for  $k \leq 2^{(\log n)^\epsilon}$  (short code graph)

[Barak-Gopalan-Hastad-Meka-Raghvendra-Steurer 11]