Lecture 11: Graph clustering and random walks

Nicolás Rivera John Sylvester Luca Zanetti Thomas Sauerwald

Lent 2020









- Geometric clustering: partition points in a Euclidean space
 - k-means, k-medians, k-centres, etc.



- Geometric clustering: partition points in a Euclidean space
 - k-means, k-medians, k-centres, etc.
- Graph clustering: partition vertices in a graph
 - modularity, conductance, min-cut, etc.

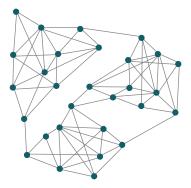


- Geometric clustering: partition points in a Euclidean space
 - k-means, k-medians, k-centres, etc.
- Graph clustering: partition vertices in a graph
 - modularity, conductance, min-cut, etc.



Graph clustering

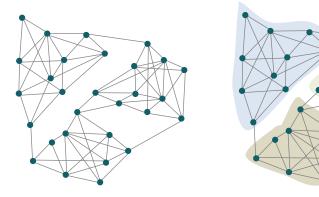
Partition the graph into pieces (clusters) so that vertices in the same piece have, on average, more connections among each other than with vertices in other clusters





Graph clustering

Partition the graph into pieces (clusters) so that vertices in the same piece have, on average, more connections among each other than with vertices in other clusters





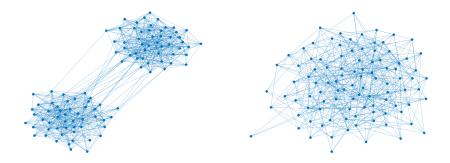
- Many practical applications, e.g.:
 - Community detection
 - Group webpages according to their topics
 - Find proteins performing the same function within a cell
 - Image segmentation
 - Identify bottlenecks in a network



- Many practical applications, e.g.:
 - Community detection
 - Group webpages according to their topics
 - Find proteins performing the same function within a cell
 - Image segmentation
 - Identify bottlenecks in a network
- Connections with different areas of mathematics and TCS, e.g.:
 - Random walk theory
 - Combinatorics
 - Theory of metric spaces
 - Approximation algorithms
 - Complexity theory



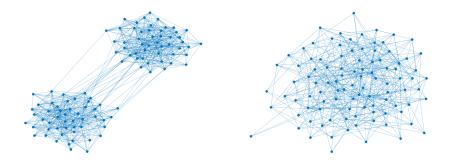
Which graph has a "cluster-structure"?





Relation between clustering and mixing

- Which graph has a "cluster-structure"?
- Which graph mixes faster?





Weighted graphs and random walks

G = (V, E, w) with weight function w, s.t.

- $w: V \times V \to \mathbb{R}_{\geq 0}$
- $w(x,y) > 0 \iff \{x,y\} \in E$
- w(x, y) = w(y, x)



Weighted graphs and random walks

G = (V, E, w) with weight function w, s.t.

- $w: V \times V \to \mathbb{R}_{\geq 0}$
- $w(x,y) > 0 \iff \{x,y\} \in E$
- w(x,y) = w(y,x)

The transition matrix of a lazy random walk on G is the n by n matrix P defined as

$$P(x,y) = \frac{w(x,y)}{2d(x)}, \qquad P(x,x) = \frac{1}{2}$$

where $d(x) = \sum_{z \in V} w(x, z)$. It has stationary distribution π s.t. $\pi(x) = \frac{d(x)}{\sum_{z} d(z)}$.



Weighted graphs and random walks

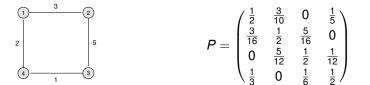
G = (V, E, w) with weight function w, s.t.

- $w: V \times V \to \mathbb{R}_{\geq 0}$
- $w(x,y) > 0 \iff \{x,y\} \in E$
- w(x,y) = w(y,x)

The transition matrix of a lazy random walk on G is the n by n matrix P defined as

$$P(x,y) = \frac{w(x,y)}{2d(x)}, \qquad P(x,x) = \frac{1}{2}$$

where $d(x) = \sum_{z \in V} w(x, z)$. It has stationary distribution π s.t. $\pi(x) = \frac{d(x)}{\sum_{z} d(z)}$.





How do we formalise the concept of cluster/bottleneck?



Let G = (V, E, w) and $\emptyset \neq S \subset V$. The conductance (edge expansion) of S is $\phi(S) := \frac{w(S, V \setminus S)}{\min\{\operatorname{vol}(S), \operatorname{vol}(V \setminus S)\}}$ where $w(S, V \setminus S) = \sum_{x \in S, y \notin S} w(x, y)$ and $\operatorname{vol}(S) = \sum_{x \in S} d(x)$.

Let G = (V, E, w) and $\emptyset \neq S \subset V$. The conductance (edge expansion) of S is $\phi(S) := \frac{w(S, V \setminus S)}{\min\{\operatorname{vol}(S), \operatorname{vol}(V \setminus S)\}}$ where $w(S, V \setminus S) = \sum_{x \in S, y \notin S} w(x, y)$ and $\operatorname{vol}(S) = \sum_{x \in S} d(x)$. The conductance of G is $\phi(G) := \min_{\emptyset \neq S \subset V} \phi(S)$

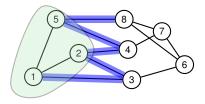


Let G = (V, E, w) and $\emptyset \neq S \subset V$. The conductance (edge expansion) of *S* is $\phi(S) := \frac{w(S, V \setminus S)}{\min\{\operatorname{vol}(S), \operatorname{vol}(V \setminus S)\}}$ where $w(S, V \setminus S) = \sum_{x \in S, y \notin S} w(x, y)$ and $\operatorname{vol}(S) = \sum_{x \in S} d(x)$. The conductance of *G* is $\phi(G) := \min_{\emptyset \neq S \subset V} \phi(S)$



Let G = (V, E, w) and $\emptyset \neq S \subset V$. The conductance (edge expansion) of *S* is $\phi(S) := \frac{w(S, V \setminus S)}{\min\{\operatorname{vol}(S), \operatorname{vol}(V \setminus S)\}}$ where $w(S, V \setminus S) = \sum_{x \in S, y \notin S} w(x, y)$ and $\operatorname{vol}(S) = \sum_{x \in S} d(x)$. The conductance of *G* is $\phi(G) := \min \phi(S)$

$$\phi(G) := \min_{\emptyset \neq S \subset V} \phi(S)$$

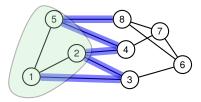


$$\phi(S) = \frac{5}{9}$$



Let G = (V, E, w) and $\emptyset \neq S \subset V$. The conductance (edge expansion) of S is $\phi(S) := \frac{w(S, V \setminus S)}{\min\{\operatorname{vol}(S), \operatorname{vol}(V \setminus S)\}}$ where $w(S, V \setminus S) = \sum_{x \in S, y \notin S} w(x, y)$ and $\operatorname{vol}(S) = \sum_{x \in S} d(x)$. The conductance of G is

$$\phi(G) := \min_{\emptyset \neq S \subset V} \phi(S)$$



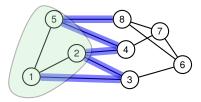
•
$$\phi(S) = \frac{5}{9}$$

• $\phi(G) \in [0, 1]$ and $\phi(G) = 0$ iff G is disconnected



Let G = (V, E, w) and $\emptyset \neq S \subset V$. The conductance (edge expansion) of S is $\phi(S) := \frac{w(S, V \setminus S)}{\min\{\operatorname{vol}(S), \operatorname{vol}(V \setminus S)\}}$ where $w(S, V \setminus S) = \sum_{x \in S, y \notin S} w(x, y)$ and $\operatorname{vol}(S) = \sum_{x \in S} d(x)$. The conductance of G is

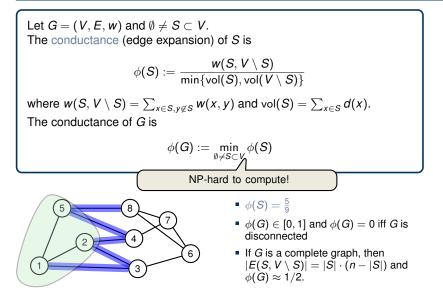
$$\phi(G) := \min_{\emptyset \neq S \subset V} \phi(S)$$



•
$$\phi(S) = \frac{5}{9}$$

- $\phi(G) \in [0, 1]$ and $\phi(G) = 0$ iff G is disconnected
- If G is a complete graph, then $|E(S, V \setminus S)| = |S| \cdot (n |S|)$ and $\phi(G) \approx 1/2$.







Cheeger's inequality Let *P* be the transition matrix of a lazy random walk of a graph G = (V, E, w) with eigenvalues $\lambda_1 \ge \cdots \ge \lambda_n$. Then, $\frac{1 - \lambda_2}{2} \le \phi(G) \le \sqrt{2(1 - \lambda_2)}$.



Cheeger's inequality Let *P* be the transition matrix of a lazy random walk of a graph G = (V, E, w) with eigenvalues $\lambda_1 \ge \cdots \ge \lambda_n$. Then, $\frac{1 - \lambda_2}{2} \le \phi(G) \le \sqrt{2(1 - \lambda_2)}$.

Spectral partitioning:



Cheeger's inequality Let *P* be the transition matrix of a lazy random walk of a graph G = (V, E, w) with eigenvalues $\lambda_1 \ge \cdots \ge \lambda_n$. Then, $\frac{1 - \lambda_2}{2} \le \phi(G) \le \sqrt{2(1 - \lambda_2)}$.

Spectral partitioning:

1. Let f_2 be the eigenvector corresponding to λ_2 .



Cheeger's inequality Let *P* be the transition matrix of a lazy random walk of a graph G = (V, E, w) with eigenvalues $\lambda_1 \ge \cdots \ge \lambda_n$. Then, $\frac{1 - \lambda_2}{2} \le \phi(G) \le \sqrt{2(1 - \lambda_2)}.$

Spectral partitioning:

- 1. Let f_2 be the eigenvector corresponding to λ_2 .
- 2. Order the vertices so that $f_2(u_1) \leq f_2(u_2) \leq \cdots \leq f_2(u_n)$



Cheeger's inequality Let *P* be the transition matrix of a lazy random walk of a graph G = (V, E, w) with eigenvalues $\lambda_1 \ge \cdots \ge \lambda_n$. Then, $\frac{1 - \lambda_2}{2} \le \phi(G) \le \sqrt{2(1 - \lambda_2)}$.

Spectral partitioning:

- 1. Let f_2 be the eigenvector corresponding to λ_2 .
- 2. Order the vertices so that $f_2(u_1) \leq f_2(u_2) \leq \cdots \leq f_2(u_n)$
- 3. Try all n 1 sweep cuts ({ $u_1, u_2, ..., u_k$ }, { $u_{k+1}, ..., u_n$ }) and return the one with smallest conductance



Cheeger's inequality Let *P* be the transition matrix of a lazy random walk of a graph G = (V, E, w) with eigenvalues $\lambda_1 \ge \cdots \ge \lambda_n$. Then, $\frac{1 - \lambda_2}{2} \le \phi(G) \le \sqrt{2(1 - \lambda_2)}.$

Spectral partitioning:

- 1. Let f_2 be the eigenvector corresponding to λ_2 .
- 2. Order the vertices so that $f_2(u_1) \leq f_2(u_2) \leq \cdots \leq f_2(u_n)$
- 3. Try all n 1 sweep cuts ({ $u_1, u_2, ..., u_k$ }, { $u_{k+1}, ..., u_n$ }) and return the one with smallest conductance

• It returns $\mathcal{S} \subset V$ such that $\phi(\mathcal{S}) \leq \sqrt{(1-\lambda_2)} \leq 2\sqrt{\phi(\mathcal{G})}$



Cheeger's inequality Let *P* be the transition matrix of a lazy random walk of a graph G = (V, E, w) with eigenvalues $\lambda_1 \ge \cdots \ge \lambda_n$. Then, $\frac{1 - \lambda_2}{2} \le \phi(G) \le \sqrt{2(1 - \lambda_2)}$.

Spectral partitioning:

- 1. Let f_2 be the eigenvector corresponding to λ_2 .
- 2. Order the vertices so that $f_2(u_1) \leq f_2(u_2) \leq \cdots \leq f_2(u_n)$
- 3. Try all n 1 sweep cuts ({ $u_1, u_2, ..., u_k$ }, { $u_{k+1}, ..., u_n$ }) and return the one with smallest conductance
- It returns $S \subset V$ such that $\phi(S) \leq \sqrt{(1 \lambda_2)} \leq 2\sqrt{\phi(G)}$
- no constant factor approximation (in the worst case)



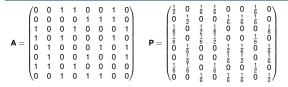
Cheeger's inequality Let *P* be the transition matrix of a lazy random walk of a graph G = (V, E, w) with eigenvalues $\lambda_1 \ge \cdots \ge \lambda_n$. Then, $1 = \lambda_2$

$$\frac{1-\lambda_2}{2} \leq \phi(G) \leq \sqrt{2(1-\lambda_2)}.$$

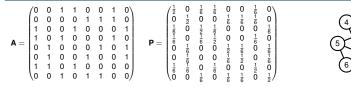
Spectral partitioning:

- 1. Let f_2 be the eigenvector corresponding to λ_2 .
- 2. Order the vertices so that $f_2(u_1) \leq f_2(u_2) \leq \cdots \leq f_2(u_n)$
- 3. Try all n 1 sweep cuts ({ $u_1, u_2, ..., u_k$ }, { $u_{k+1}, ..., u_n$ }) and return the one with smallest conductance
- It returns $S \subset V$ such that $\phi(S) \leq \sqrt{(1 \lambda_2)} \leq 2\sqrt{\phi(G)}$
- no constant factor approximation (in the worst case)
- mixing on G is $t_{mix} = O(\log(n)/\phi(G)^2)$.









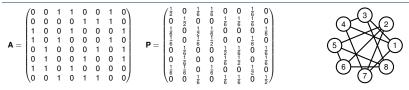




$1-\lambda_2\approx 0.13$

 $f_2 = (-0.425, +0.263, -0.263, -0.425, +0.425, +0.425, -0.263, +0.263)^T$



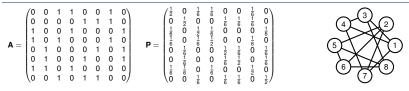


$1-\lambda_2\approx 0.13$

 $f_2 = (-0.425, +0.263, -0.263, -0.425, +0.425, +0.425, -0.263, +0.263)^T$

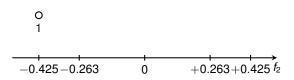
$$-0.425 - 0.263$$
 0 $+0.263 + 0.425 f_2$







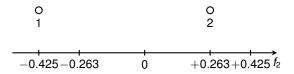
 $f_2 = (-0.425, +0.263, -0.263, -0.425, +0.425, +0.425, -0.263, +0.263)^T$







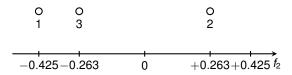
 $1-\lambda_2\approx 0.13$







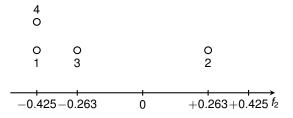
$1-\lambda_2 pprox 0.13$







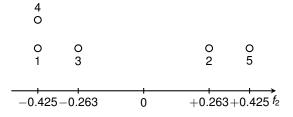








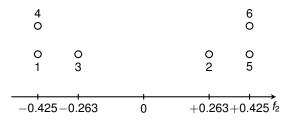








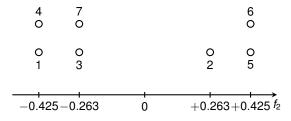








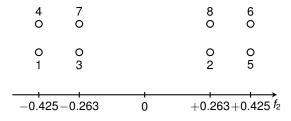
 $1 - \lambda_2 \approx 0.13$ $f_2 = (-0.425, +0.263, -0.263, -0.425, +0.425, +0.425, -0.263, +0.263)^T$







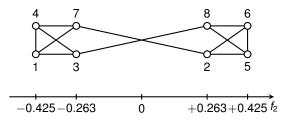
 $1 - \lambda_2 \approx 0.13$ $f_2 = (-0.425, +0.263, -0.263, -0.425, +0.425, +0.425, -0.263, +0.263)^T$



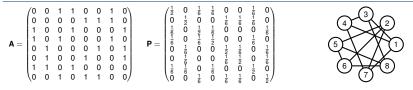




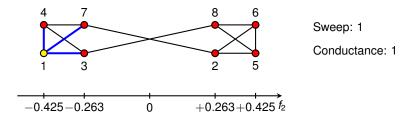
 $1-\lambda_2 pprox 0.13$



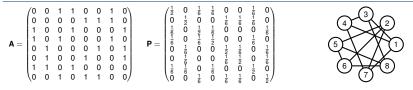




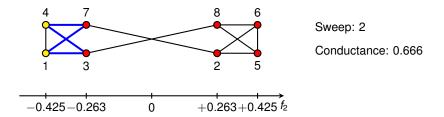
 $1-\lambda_2 pprox 0.13$



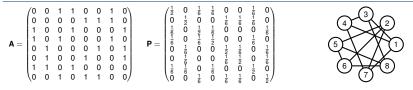




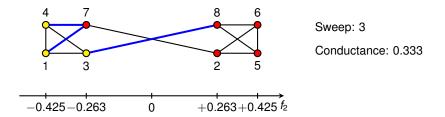
 $1-\lambda_2 pprox 0.13$



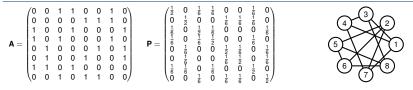




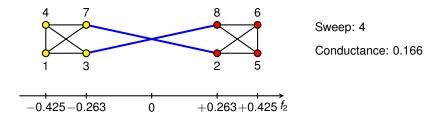
 $1-\lambda_2 pprox 0.13$



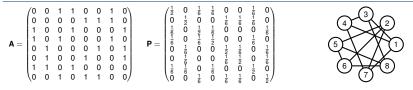




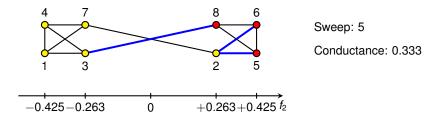
 $1-\lambda_2 pprox 0.13$



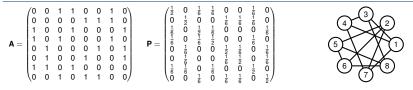




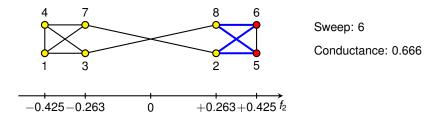
 $1-\lambda_2 pprox 0.13$



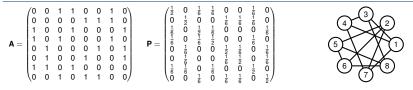




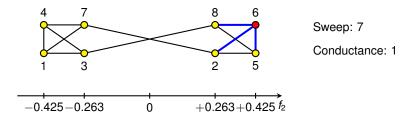
 $1-\lambda_2 pprox 0.13$



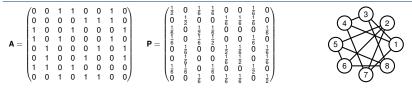




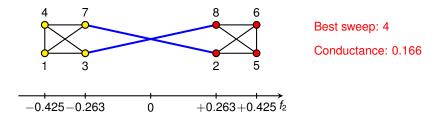
 $1-\lambda_2 pprox 0.13$







 $1-\lambda_2 pprox 0.13$





Let's start with a simplified example: $G = (V_1 \cup V_2, E)$

- disconnected with connected components supported on V₁ and V₂
- $|V_1| = |V_2| = n$
- regular (i.e., all vertices have the same degree)



Let's start with a simplified example: $G = (V_1 \cup V_2, E)$

- disconnected with connected components supported on V₁ and V₂
- $|V_1| = |V_2| = n$
- regular (i.e., all vertices have the same degree)

$$1 - \lambda_2 = \min_{\substack{f \in \mathbb{R}^n \setminus \{0\} \\ f \perp 1}} \frac{\sum_{\{u, v\} \in E} (f(u) - f(v))^2}{2d \sum_{u \in V} f(u)^2}$$



Let's start with a simplified example: $G = (V_1 \cup V_2, E)$

- disconnected with connected components supported on V₁ and V₂
- $|V_1| = |V_2| = n$
- regular (i.e., all vertices have the same degree)

We want to find $f: V \to \mathbb{R}$ such that $f \perp 1$ minimises

$$1 - \lambda_2 = \min_{\substack{f \in \mathbb{R}^n \setminus \{0\} \\ f \perp 1}} \frac{\sum_{\{u, v\} \in E} (f(u) - f(v))^2}{2d \sum_{u \in V} f(u)^2}$$

• If *f* is constant on V_1 and V_2 , $1 - \lambda_2 = 0$ (no edges between V_1 and V_2)



Let's start with a simplified example: $G = (V_1 \cup V_2, E)$

- disconnected with connected components supported on V₁ and V₂
- $|V_1| = |V_2| = n$
- regular (i.e., all vertices have the same degree)

$$1 - \lambda_{2} = \min_{\substack{f \in \mathbb{R}^{n} \setminus \{0\} \\ f \perp 1}} \frac{\sum_{\{u, v\} \in E} (f(u) - f(v))^{2}}{2d \sum_{u \in V} f(u)^{2}}$$

- If f is constant on V_1 and V_2 , $1 \lambda_2 = 0$ (no edges between V_1 and V_2)
- We want $f \perp 1 \implies \sum_{u} f(u) = 0$



Let's start with a simplified example: $G = (V_1 \cup V_2, E)$

- disconnected with connected components supported on V₁ and V₂
- $|V_1| = |V_2| = n$
- regular (i.e., all vertices have the same degree)

$$1 - \lambda_{2} = \min_{\substack{f \in \mathbb{R}^{n} \setminus \{0\} \\ f \perp 1}} \frac{\sum_{\{u, v\} \in E} (f(u) - f(v))^{2}}{2d \sum_{u \in V} f(u)^{2}}$$

- If f is constant on V_1 and V_2 , $1 \lambda_2 = 0$ (no edges between V_1 and V_2)
- We want $f \perp 1 \implies \sum_{u} f(u) = 0$

• choose
$$f(u) = \begin{cases} 1 & \text{if } u \in V_1 \\ -1 & \text{if } u \notin V_2 \end{cases}$$



Let's start with a simplified example: $G = (V_1 \cup V_2, E)$

- disconnected with connected components supported on V₁ and V₂
- $|V_1| = |V_2| = n$
- regular (i.e., all vertices have the same degree)

$$1 - \lambda_{2} = \min_{\substack{f \in \mathbb{R}^{n} \setminus \{0\} \\ f \perp 1}} \frac{\sum_{\{u, v\} \in E} (f(u) - f(v))^{2}}{2d \sum_{u \in V} f(u)^{2}}$$

- If f is constant on V_1 and V_2 , $1 \lambda_2 = 0$ (no edges between V_1 and V_2)
- We want $f \perp 1 \implies \sum_{u} f(u) = 0$

• choose
$$f(u) = \begin{cases} 1 & \text{if } u \in V_1 \\ -1 & \text{if } u \notin V_2. \end{cases}$$

•
$$f \perp 1$$
 and $1 - \lambda_2 = 0$



Let's start with a simplified example: $G = (V_1 \cup V_2, E)$

- disconnected with connected components supported on V₁ and V₂
- $|V_1| = |V_2| = n$
- regular (i.e., all vertices have the same degree)

We want to find $f: V \to \mathbb{R}$ such that $f \perp 1$ minimises

$$1 - \lambda_{2} = \min_{\substack{f \in \mathbb{R}^{n} \setminus \{0\} \\ f \perp 1}} \frac{\sum_{\{u, v\} \in E} (f(u) - f(v))^{2}}{2d \sum_{u \in V} f(u)^{2}}$$

- If f is constant on V_1 and V_2 , $1 \lambda_2 = 0$ (no edges between V_1 and V_2)
- We want $f \perp 1 \implies \sum_{u} f(u) = 0$
- choose $f(u) = \begin{cases} 1 & \text{if } u \in V_1 \\ -1 & \text{if } u \notin V_2. \end{cases}$
- $f \perp 1$ and $1 \lambda_2 = 0$

Hope: If $\phi(G)$ is small, a similar construction can give us a small spectral gap





Proof of the "easy" direction $(1 - \lambda_2)/2 \le \phi(G)$

Proof: Recall that
$$1 - \lambda_2 = \min_{\substack{f \in \mathbb{R}^n \setminus \{0\} \\ f \perp 1}} \frac{\sum_{\{u,v\} \in E} (f(u) - f(v))^2}{2d \sum_{u \in V} f(u)^2}$$

• Take $S \subset V$ minimising $\phi(G)$



Proof of the "easy" direction $(1 - \lambda_2)/2 \le \phi(G)$

Proof: Recall that
$$1 - \lambda_2 = \min_{\substack{f \in \mathbb{R}^n \setminus \{0\} \\ f \perp 1}} \frac{\sum_{\{u,v\} \in \mathcal{E}} (f(u) - f(v))^2}{2d \sum_{u \in V} f(u)^2}$$

- Take $S \subset V$ minimising $\phi(G)$
- Construct $f \in \mathbb{R}^n$ s.t. $f(u) = \begin{cases} 1/|S| & \text{if } u \in S \\ -1/|V \setminus S| & \text{if } u \notin S. \end{cases}$



Proof of the "easy" direction $(1 - \lambda_2)/2 \le \phi(G)$

Proof: Recall that
$$1 - \lambda_2 = \min_{\substack{f \in \mathbb{R}^n \setminus \{0\} \\ f \perp 1}} \frac{\sum_{\{u,v\} \in \mathcal{E}} (f(u) - f(v))^2}{2d \sum_{u \in V} f(u)^2}$$

• Take
$$S \subset V$$
 minimising $\phi(G)$

• Construct
$$f \in \mathbb{R}^n$$
 s.t. $f(u) = \begin{cases} 1/|S| & \text{if } u \in S \\ -1/|V \setminus S| & \text{if } u \notin S. \end{cases}$

•
$$\langle f_2, 1 \rangle = \sum_u f(u) = \sum_{u \in S} \frac{1}{|S|} + \sum_{u \notin S} \frac{-1}{|V \setminus S|} = 0$$



Proof: Recall that
$$1 - \lambda_2 = \min_{\substack{f \in \mathbb{R}^n \setminus \{0\}\\f \perp 1}} \frac{\sum_{\{u,v\} \in E} (f(u) - f(v))^2}{2d \sum_{u \in V} f(u)^2}$$

• Take
$$S \subset V$$
 minimising $\phi(G)$

• Construct $f \in \mathbb{R}^n$ s.t. $f(u) = \begin{cases} 1/|S| & \text{if } u \in S \\ -1/|V \setminus S| & \text{if } u \notin S. \end{cases}$

•
$$\langle f_2, 1 \rangle = \sum_u f(u) = \sum_{u \in S} \frac{1}{|S|} + \sum_{u \notin S} \frac{-1}{|V \setminus S|} = 0$$

•
$$\sum_{u \in V} f(u)^2 = \sum_{u \in S} \frac{1}{|S|^2} + \sum_{u \notin S} \frac{1}{|V \setminus S|^2} \ge \frac{1}{|S|}$$



Proof: Recall that
$$1 - \lambda_2 = \min_{\substack{f \in \mathbb{R}^n \setminus \{0\} \\ f \perp 1}} \frac{\sum_{\{u,v\} \in \mathcal{E}} (f(u) - f(v))^2}{2d \sum_{u \in V} f(u)^2}$$

• Take
$$S \subset V$$
 minimising $\phi(G)$

• Construct
$$f \in \mathbb{R}^n$$
 s.t. $f(u) = \begin{cases} 1/|S| & \text{if } u \in S \\ -1/|V \setminus S| & \text{if } u \notin S. \end{cases}$

•
$$\langle f_2, 1 \rangle = \sum_u f(u) = \sum_{u \in S} \frac{1}{|S|} + \sum_{u \notin S} \frac{-1}{|V \setminus S|} = 0$$

•
$$\sum_{u \in V} f(u)^2 = \sum_{u \in S} \frac{1}{|S|^2} + \sum_{u \notin S} \frac{1}{|V \setminus S|^2} \ge \frac{1}{|S|}$$

•
$$\sum_{\{u,v\}\in E} (f(u) - f(v))^2 \le \sum_{\substack{\{u,v\}\in E\\ u\in S, v\notin S}} \frac{4}{|S|^2} = \frac{4|E(S, V\setminus S)|}{|S|^2}$$



Proof: Recall that
$$1 - \lambda_2 = \min_{\substack{f \in \mathbb{R}^n \setminus \{0\} \\ f \perp 1}} \frac{\sum_{\{u,v\} \in E} (f(u) - f(v))^2}{2d \sum_{u \in V} f(u)^2}$$

• Take $S \subset V$ minimising $\phi(G)$

• Construct $f \in \mathbb{R}^n$ s.t. $f(u) = \begin{cases} 1/|S| & \text{if } u \in S \\ -1/|V \setminus S| & \text{if } u \notin S. \end{cases}$

•
$$\langle f_2, 1 \rangle = \sum_u f(u) = \sum_{u \in S} \frac{1}{|S|} + \sum_{u \notin S} \frac{-1}{|V \setminus S|} = 0$$

•
$$\sum_{u \in V} f(u)^2 = \sum_{u \in S} \frac{1}{|S|^2} + \sum_{u \notin S} \frac{1}{|V \setminus S|^2} \ge \frac{1}{|S|}$$

•
$$\sum_{\{u,v\}\in E} (f(u) - f(v))^2 \le \sum_{\substack{\{u,v\}\in E\\ u\in S, v\notin S}} \frac{4}{|S|^2} = \frac{4|E(S, V\setminus S)|}{|S|^2}$$

•
$$1-\lambda_2\leq rac{4|E(S,V\setminus S)|}{2d|S|^2}\cdot rac{1}{1/|S|}=2\phi(S)=2\phi(G).$$



Spectral partitioning example

