

Spectral Graph Theory II

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Last time, we proved that

$$L\phi = \lambda\phi \quad \text{for some } \lambda \in \mathbb{R}$$

where L is the normalized Laplacian operator. We call ϕ an eigenvector of L .

We found ϕ by maximizing $\mathcal{E}[f]$ under the constraint that $\|f\|_2^2 = 1$. To find another eigenvector of L , we need only add the constraint

$$f \perp \phi.$$

We can repeat this process, optimizing over a lower-dimensional space each time, until we have n eigenvectors

$$\phi_0, \phi_1, \dots, \phi_{n-1}$$

with eigenvalues

$$0 = \lambda_0 \leq \lambda_1 \leq \dots \leq \lambda_{n-1} \leq 2.$$

The eigenvalues decrease with each iteration of the procedure above, since we are optimizing over a smaller set each time.

The last eigenvalue is zero because the last eigenvector is the 1-function:

$$L1 = I1 - K1 = 1 - 1 = 0.$$

The eigenvalues are uniquely determined, but not the eigenvectors. (for example, we could replace ϕ_k by $-\phi_k$.) We can fix a set of eigenvectors and then express any function f uniquely as

$$f = \hat{f}(0)\phi_0 + \hat{f}(1)\phi_1 + \dots + \hat{f}(n-1)\phi_{n-1}.$$

The number of eigenvalues that are 0 are the number of connected components in C . Moreover,

$$Lf = \lambda_0 \hat{f}(0)\phi_0 + \lambda_1 \hat{f}(1)\phi_1 + \dots + \lambda_{n-1} \hat{f}(n-1)\phi_{n-1}$$

It follows from orthonormality of the eigenvectors ϕ_i that

$$\langle f, g \rangle = \sum_{i=0}^n \hat{f}(i) \hat{g}(i).$$

And,

$$E(f) = \langle f, Lf \rangle = \sum_{i=0}^n \lambda_i \hat{f}(i)^2.$$

$$\|f\|_2^2 = \sum \hat{f}(i)^2$$

$$E[f] = \langle f, 1 \rangle.$$

$$\begin{aligned}\text{Var}[f] &= E[f^2] - E[f]^2 \\ &= \sum_{i=0}^{\infty} \hat{f}(i)^2.\end{aligned}$$

Conductance and the 2nd Eigenvalue

Observe that

$$\min_{\text{Var}[f]=1} E[f] = \lambda_1.$$

Put another way,

$$\lambda_1 \text{Var}[f] \leq E[f].$$

This follows from the fact that $\text{Var}[f]$ is the sum of non-negative numbers that add up to 1, whereas $E[f]$ is the sum of those same numbers multiplied by non-negative eigenvalues λ_i . λ_1 is the smallest eigenvalue that is possibly non-zero.

Recall the definition of conductance

Φ_G , the conductance of G , is

$$\min_{S: 0 < \text{vol}(S) \leq \frac{1}{2}} \{ \Phi(S) \}.$$

Note that a minimum bound on the conductance is

$$\Phi_a \geq \frac{1}{2} \min_{S: 0 < \text{vol}(S) \leq \frac{1}{2}} \left\{ \frac{\mathcal{E}[f]}{\text{Var}[1_S]} \right\},$$

because

$$\text{Var}[1_S] = \text{vol}(S)(1 - \text{vol}(S)) \geq \frac{1}{2} \text{vol}(S) = \frac{1}{2} \|1_S\|_2^2.$$

We can similarly express the second eigenvalue λ_1 as a minimization problem:

$$\lambda_1 = \min_{f: V \rightarrow \mathbb{R}, \text{Var}(f) \neq 0} \left\{ \frac{\mathcal{E}[f]}{\text{Var}[f]} \right\}.$$

Note: We can compute λ_1 efficiently, but computing the conductance of a graph is NP-hard. The values λ_1 and Φ_a are related to each other by Cheeger's Inequality.

Cheeger's Inequality

Theorem 1: $\frac{1}{2} \lambda_1 \leq \Phi_a \leq 2\sqrt{\lambda_1}.$

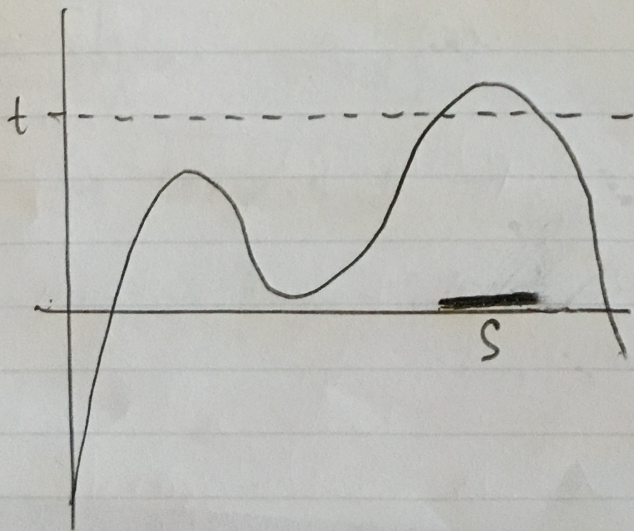
Proof: The first inequality follows from our formulation of λ_1 as a minimization problem:

$$\begin{aligned} \frac{1}{2} \lambda_1 &= \frac{1}{2} \min_{f: V \rightarrow \mathbb{R}, \text{Var}(f) \neq 0} \left\{ \frac{\mathbb{E}[f]}{\text{Var}(f)} \right\} \\ &\leq \frac{1}{2} \min_{S: 0 < \text{vol}(S) \leq \frac{1}{2}} \left\{ \frac{\mathbb{E}[1_S]}{\text{Var}[1_S]} \right\} \\ &\leq \Phi_a. \end{aligned}$$

The second inequality is proved by the theorem below.

Theorem 2: Let f be a non-constant function such that $\mathbb{E}[f] \leq \lambda_1 \text{Var}[f]$. Then, $\exists S \subset V$ such that $0 < \text{vol}(S) \leq \frac{1}{2}$ and $\Phi(S) \leq 2\sqrt{\lambda_1}$.

In fact, there exists a set S of the form $S = \{u: f(u) > t\}$ or $S = \{u: f(u) < t\}$ for some value t . This result allows us to approximately solve the sparsest cut problem.



Definition: A function $g: V \rightarrow \mathbb{R}$ is convex if $g \geq 0$ and $\text{vol}(\{u: g(u) \neq 0\}) \leq \frac{1}{2}$.

We can assume f is convex in our proof of Theorem 2, but we lose a factor of 2 in the inequality $E[f] \leq \lambda \text{Var}[f]$.

Lemma [Coarea Formula]: For a non-negative function $g: V \rightarrow \mathbb{R}^+$,

$$\int_0^\infty \text{Pr}_{u,v}[(u,v) \text{ crosses } g^{>t} \text{ boundary}] dt \\ = E_{u,v}[|g(u) - g(v)|]$$

where $g^{>t} = \{u: g(u) > t\}$.

Proof:

$$\int_0^\infty \text{Pr}_{u,v}[(u,v) \text{ crosses } g^{>t} \text{ boundary}] dt \\ = \int_0^\infty \text{Pr}[t \text{ is between } g(u) \text{ and } g(v)] dt \\ = E_{u,v} \left[\int_0^\infty \mathbb{1}_{\{t \text{ is between } g(u) \text{ and } g(v)\}} dt \right] \\ = E_{u,v}[|g(u) - g(v)|].$$

Corollary: Let g be convex. Then

$$E[|g(u) - g(v)|] \geq 2 \Phi_a E_{u,v}[g(u)].$$

Proof:

$$\begin{aligned} E[|g(u) - g(v)|] &= \int_0^\infty 2 P_{u,v} [u \in S, v \in S] dt \\ &= \int_0^\infty 2 E[1_{g > t}] dt \\ &= 2 \int_0^\infty \Phi(g^{>t}) \text{vol}(g^{>t}) dt \\ &\geq 2 \Phi_a \int_0^\infty P_{u,v} [u \in g^{>t}] dt \\ &= 2 \Phi_a \int_0^\infty P_{u,v} [g(u) \geq t] dt \\ &= 2 \Phi_a E_{u,v} [g(u)] \end{aligned}$$

Proof of Theorem 2:

Assuming g is convenient and not always zero, by the corollary above,

$$\Phi_a \leq \frac{E_{u,v} [|g(u) - g(v)|]}{2E_{u,v} [g(u)]}$$

Let f be a convenient function such that

$$\frac{E[f]}{\text{Var}[f]} \leq 2\lambda_1$$

(Recall that we lose a factor of 2 here by requiring that f be convenient.)

Next, let $g = f^2$. g is still non-negative and $g(u) = 0$ iff $f(u) = 0$, so g is also convenient.

$$\begin{aligned}
 E_{u,v} [|f(u)^2 - f(v)^2|] &= E_{u,v} [|f(u) - f(v)| \cdot |f(u) + f(v)|] \\
 &\leq \sqrt{E_{u,v} [(f(u) - f(v))^2]} \sqrt{E_{u,v} [(f(u) + f(v))^2]} \\
 &\leq \sqrt{2\lambda_1 E[f]} \sqrt{E_{u,v} [2f(u)^2 + 2f(v)^2]} \\
 &\leq \sqrt{4\lambda_1 E_{u,v} [f(u)^2]} \cdot 2 \sqrt{E_{u,v} [f(u)^2]} \\
 &= 4\sqrt{\lambda_1} E_{u,v} [f(u)^2].
 \end{aligned}$$

Thus,

$$\begin{aligned}
 \Phi_a &\leq \frac{E_{u,v} [|f(u)^2 - f(v)^2|]}{2E_{u,v} [f(u)^2]} \\
 &\leq \frac{4\sqrt{\lambda_1} E_{u,v} [f(u)^2]}{2E_{u,v} [f(u)^2]} \\
 &= 2\sqrt{\lambda_1}.
 \end{aligned}$$

Now, using Theorem 1, how can we efficiently compute an approximately minimal conductance set S.C.V.?

Given G , it is possible to compute a value $\tilde{\lambda}_1$ and a function $f: V \rightarrow \mathbb{R}$ such that

$$a) \quad |\tilde{\lambda}_1 - \lambda_1| \leq \epsilon,$$

$$b) \quad \mathbb{E}[f] \leq \tilde{\lambda}_1 \text{Var}[f]$$

In time either

$$\tilde{O}(n) \cdot \frac{1}{\epsilon}$$

or

$$\text{poly}(n) \cdot \log\left(\frac{1}{\epsilon}\right)$$