

Discussions about Remark 1 on page (71). Solutions of
discrete-time heat eq. and distribution of a random walker.

Let $f_0 = \delta_{x_0}$, and $f : V \times \{0, 1, 2, \dots\} \rightarrow \mathbb{R}$ satisfies

$$\begin{cases} f(x, t+1) - f(x, t) = \Delta f(x, t), & t = 0, 1, 2, \dots, x \in V \\ f(x, 0) = f_0(x) \end{cases}$$

Recall the solution $f(\cdot, t) = P^t f_0(\cdot)$.

We calculate for $y \in V$,

$$\begin{aligned} f(y, t) &= P^t f_0(y) = P(P^{t-1} f_0)(y) \\ &= \frac{1}{d_y} \sum_{\substack{y_1 \in V \\ y_1 \sim y}} (P^{t-1} f_0)(y_1) = \frac{1}{d_y} \sum_{\substack{y_1 \in V \\ y_1 \sim y}} P(P^{t-2} f_0)(y_1) \\ &= \frac{1}{d_y} \sum_{\substack{y_1 \in V \\ y_1 \sim y}} \frac{1}{d_{y_1}} \sum_{\substack{y_2 \in V \\ y_2 \sim y_1}} (P^{t-2} f_0)(y_2) \\ &= \dots \\ &= \sum_{\substack{y_1 \in V \\ y_1 \sim y}} \sum_{\substack{y_2 \in V \\ y_2 \sim y_1}} \dots \sum_{\substack{y_{t-1} \in V \\ y_{t-1} \sim y_{t-2}}} \sum_{\substack{y_t \in V \\ y_t \sim y_{t-1}}} \frac{1}{d_y} \cdot \frac{1}{d_{y_1}} \dots \frac{1}{d_{y_{t-2}}} \cdot \frac{1}{d_{y_{t-1}}} f_0(y_t) \end{aligned}$$

Notice that $f_0(y_t)$ is only non zero at $y_t = x_0$. Therefore

$$\begin{aligned} f(y, t) &= \sum_{\substack{y_1, \dots, y_{t-1} \in V \\ y \sim y_1 \sim y_2 \sim \dots \sim y_{t-1} \sim x_0}} \frac{1}{d_y} \frac{1}{d_{y_1}} \dots \frac{1}{d_{y_{t-1}}} = \mathbb{P}(\text{The random walker} \\ & \hspace{15em} \text{arrives at } x_0 \in V \text{ after} \\ & \hspace{15em} t \text{ steps starting from } y \in V) \\ & = \frac{d_{x_0}}{d_y} \sum_{\substack{y_1, \dots, y_{t-1} \in V \\ y \sim y_1 \sim \dots \sim y_{t-1} \sim x_0}} \frac{1}{d_{y_1}} \dots \frac{1}{d_{y_{t-1}}} \frac{1}{d_{x_0}} \\ & = \frac{d_{x_0}}{d_y} \cdot \mathbb{P}(\text{The random walker arrives at } y \in V \text{ after } t \text{ steps} \\ & \hspace{15em} \text{starting from } x_0 \in V) \end{aligned}$$

(In fact, the above fact can be written as

$$d_y \mathbb{P}_y (X_t = x_0) = d_{x_0} \mathbb{P}_{x_0} (X_t = y)$$

This is certain symmetry property. In the term of Markov chains, this is called the reversibility.)

Therefore, Theorem 1 implies

$$\| \frac{d_{x_0}}{d} \mathbb{P}_{x_0} (X_t = \cdot) - \frac{d_{x_0}}{\text{vol}(G)} \| \leq \rho^n \sqrt{d_{x_0}}$$

$$\Rightarrow \sum_{y \in V} \left(\frac{d_{x_0}}{d_y} \mathbb{P}_{x_0} (X_t = y) - \frac{d_{x_0}}{\text{vol}(G)} \right)^2 d_y \leq \left(\rho^n \sqrt{d_{x_0}} \right)^2$$

$$\Rightarrow \sum_{y \in V} \left(\mathbb{P}_{x_0} (X_t = y) - \frac{d_{x_0}}{\text{vol}(G)} \right)^2 \frac{d_{x_0}^2}{d_y} \leq \left(\rho^n \sqrt{d_{x_0}} \right)^2$$

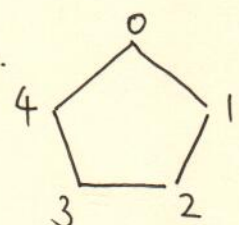
Corollary Let $G = (V, E)$ be a finite simple connected graph, Let $\{X_t\}$ be the associated simple random walk. Then we

have
$$\sum_{y \in V} \left(\mathbb{P}_{x_0} (X_t = y) - \frac{d_y}{\text{vol}(G)} \right)^2 \frac{d_{x_0}}{d_y} \leq \rho^{2n}$$

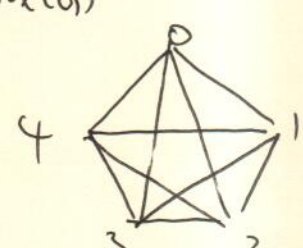
In particular, we have $\left| \mathbb{P}_{x_0} (X_t = y) - \frac{d_y}{\text{vol}(G)} \right| \leq \rho^n \sqrt{\frac{d_y}{d_{x_0}}}$.

If G is non-bipartite, we have

$$\mathbb{P}_{x_0} (X_t = y) \rightarrow \frac{d_y}{\text{vol}(G)} \text{ as } t \rightarrow \infty.$$

Example 1. C_5  limit: $\frac{1}{5}$

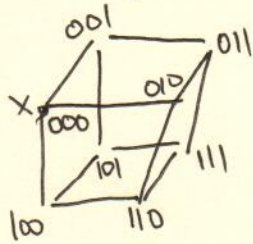
	0	1	2	3	4
t=0	0	0	1	0	0
t=1	0	1/2	0	1/2	0
t=2	1/4	0	1/2	0	1/4
t=3	1/8	3/8	0	3/8	1/8
t=4	1/4	1/6	3/8	1/6	1/4

K_5  limit: $\frac{4}{20} = \frac{1}{5}$

	0	1	2	3	4
t=0	0	0	1	0	0
t=1	1/4	1/4	0	1/4	1/4
t=2	3/16	3/16	1/4	3/16	3/16
t=3	13/64	13/64	3/16	13/64	13/64
t=4	5/256	5/256	13/64	5/256	5/256

The convergence is much faster in K_5 than in C_5 . (78)

Example 2, 3-Hypercube x_0



	000	110	101	011	100	010	001	111
$t=0$	1	0	0	0	0	0	0	0
$t=1$	0	0	0	0	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	0
$t=2$	$\frac{1}{3}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	0	0	0	0
$t=3$	0	0	0	0	$\frac{7}{27}$	$\frac{7}{27}$	$\frac{7}{27}$	$\frac{2}{9}$
$t=4$	$\frac{7}{27}$	$\frac{20}{81}$	$\frac{20}{81}$	$\frac{20}{81}$	0	0	0	0

We see $P_{x_0}(X_t = \cdot)$ does not converge.

Theorem 3. Let $G=(V, E)$ be a bipartite graph, Let V^+, V^- be a bipartition of V . Then for any function f_0 on V , consider the function \tilde{f}_0 on V that takes two values as follows:

$$\tilde{f}_0(x) = \begin{cases} \frac{2}{\text{vol}(G)} \sum_{y \in V^+} f_0(y) dy, & \text{if } x \in V^+ \\ \frac{2}{\text{vol}(G)} \sum_{y \in V^-} f_0(y) dy, & \text{if } x \in V^- \end{cases}$$

Then, we have for all even t

$$\|f(\cdot, t) - \tilde{f}_0\| \leq S^n \|f_0\|$$

where $S = \max(|1 - \lambda_2|, |\lambda_{N-1} - 1|) = 1 - \lambda_2$.

Consider the function \hat{f}_0 on V that takes two values as follows

$$\hat{f}_0(x) = \begin{cases} \frac{2}{\text{vol}(G)} \sum_{y \in V^-} f_0(y) dy, & \text{if } x \in V^+ \\ \frac{2}{\text{vol}(G)} \sum_{y \in V^+} f_0(y) dy, & \text{if } x \in V^- \end{cases}$$

Then we have for all odd t

$$\|f(\cdot, t) - \hat{f}_0\| \leq S^n \|f_0\|$$

Proof: This follows from a similar strategy as in the proof of Thm 1. Let $\{f_k\}_{k=1}^N$ be an orthogonal basis of eigenfunctions. Then

$$P^t f_0 = \sum_{k=1}^N a_k (1-\lambda_k)^t f_k, \quad \text{where } a_k = (f_0, f_k)$$

$$\text{Recall } a_1 f_1 = \frac{1}{\text{vol}(G)} \sum_{y \in V} f_0(y) dy.$$

Observe that

$$f_N(x) = \begin{cases} \frac{1}{\sqrt{\text{vol}(G)}}, & \text{if } x \in V_0^+ \\ -\frac{1}{\sqrt{\text{vol}(G)}}, & \text{if } x \in V_0^- \end{cases}$$

is the eigenfunction to $\lambda_N = 2$.

Therefore

$$\begin{aligned} a_N &= (f_0, f_N) = \sum_{y \in V} f_0(y) f_N(y) dy \\ &= \frac{1}{\sqrt{\text{vol}(G)}} \left(\sum_{y \in V^+} f_0(y) dy - \sum_{y \in V^-} f_0(y) dy \right). \end{aligned}$$

$$\text{Hence } a_N f_N(x) = \begin{cases} \frac{1}{\text{vol}(G)} \left(\sum_{y \in V^+} f_0(y) dy - \sum_{y \in V^-} f_0(y) dy \right) \\ \frac{1}{\text{vol}(G)} \left(\sum_{y \in V^-} f_0(y) dy - \sum_{y \in V^+} f_0(y) dy \right) \end{cases}$$

Notice that

$$a_1 f_1 + a_N f_N = \tilde{f}_0 \quad \text{and} \quad a_1 f_1 - a_N f_N = \tilde{\tilde{f}}_0.$$

We then have

$$P^t f_0 = \sum_{k=1}^N (1-\lambda_k)^t a_k f_k = \sum_{k=2}^{N-1} a_k (1-\lambda_k)^t f_k + a_1 f_1 + (1-\lambda_N)^t a_N f_N.$$

Since $(1-\lambda_N)^t = (-1)^t = \begin{cases} 1, & t \text{ even} \\ -1, & t \text{ odd} \end{cases}$, we obtain

$$P^t f_0 = \sum_{k=2}^{N-1} (1-\lambda_k)^t a_k f_k + a_1 f_1 + (-1)^t a_N f_N.$$

if t even, we have

$$\|P^t f_0 - \tilde{f}_0\|^2 = \sum_{k=2}^{N-1} (1-\lambda_k)^{2t} a_k^2 \leq \max_{2 \leq k \leq N-1} |1-\lambda_k|^{2t} \cdot \underbrace{\sum_{k=2}^{N-1} a_k^2}_{\leq \|f_0\|^2}$$

whereas t odd,

$$\|P^t f_0 - \tilde{f}_0\|^2 \leq \sum_{k=2}^{N-1} (1-\lambda_k)^{2t} a_k^2 \leq \max_{2 \leq k \leq N-1} |1-\lambda_k|^{2t} \sum_{k=2}^{N-1} a_k^2$$

This finishes the proof. □

Corollary: Let $G=(V,E)$ be a bipartite with $V=V^+ \cup V^-$.

Let $x_0 \in V^+$. Then for $y \in V$

$$P_{x_0}(X_t=y) \rightarrow \begin{cases} \frac{z dy}{\text{vol}(G)}, & \text{if } y \in V^+ \\ 0 & \text{if } y \in V^- \end{cases}$$

as $t \rightarrow \infty$, t even

$$\text{and } P_{x_0}(X_t=y) \rightarrow \begin{cases} 0, & \text{if } y \in V^+ \\ \frac{z dy}{\text{vol}(G)}, & \text{if } y \in V^- \end{cases}$$

as $t \rightarrow \infty$, t odd.

Back to the proof of Cheeger inequality: Observe that, we actually show that there exists $\Omega_1 \subseteq \text{supp}(f_+)$,

$\Omega_2 \subseteq \text{supp}(f_-)$, where $\Delta f + \lambda_2 f = 0$, s.t.

$$\max_{i=1,2} \phi(\Omega_i) \leq \sqrt{2\lambda_2}$$

$$\text{Therefore } \lambda_2 \geq \frac{1}{2} \left(\min_{\substack{\Omega_1, \Omega_2 \subseteq V \\ \Omega_1 \cap \Omega_2 = \emptyset \\ \Omega_i \neq \emptyset}} \max_{i=1,2} \phi(\Omega_i) \right)^2$$

~~We call Ω_1, Ω_2 a subpartition of V if $\Omega_1, \Omega_2 \subseteq V, \Omega_1 \cap \Omega_2 = \emptyset$.~~

Claim: $h = \min_{\substack{\Omega_1, \Omega_2 \subseteq V \\ \Omega_1 \cup \Omega_2 = V \\ \Omega_1, \Omega_2 \neq \emptyset}} \max_{i=1,2} \phi(\Omega_i) = \min_{\substack{\Omega_1, \Omega_2 \subseteq V \\ \Omega_1 \cap \Omega_2 = \emptyset \\ \Omega_1, \Omega_2 \neq \emptyset}} \max_{i=1,2} \phi(\Omega_i).$

Proof: It is enough to show any ~~subpartition~~ Ω_1, Ω_2 (81)

achieving the $\min_{\substack{\Omega_1, \Omega_2 \subseteq V \\ \Omega_1 \cap \Omega_2 = \emptyset \\ \Omega_1, \Omega_2 \neq \emptyset}} \max_{i=1,2} \phi(\Omega_i)$ can be replaced

by a partition: i.e., $\Omega'_1, \Omega'_2 \subseteq V$, $\Omega'_1 \sqcup \Omega'_2 = V$. W.l.o.g.,

suppose $\phi(\Omega_1) \geq \phi(\Omega_2)$.

Case (i): if $\text{vol}(\Omega_1) \leq \frac{1}{2} \text{vol}(G)$, then $\phi(\Omega_1) \geq \phi(\Omega_1^c)$

Hence $\max\{\phi(\Omega_1), \phi(\Omega_2)\} = \max\{\phi(\Omega_1), \phi(\Omega_1^c)\} = \phi(\Omega_1)$.

Case (ii) if $\text{vol}(\Omega_1) > \frac{1}{2} \text{vol}(G)$, then $\text{vol}(\Omega_2) \leq \frac{1}{2} \text{vol}(G)$

Hence $\phi(\Omega_2) \geq \phi(\Omega_2^c)$.

Therefore, $\max\{\phi(\Omega_2), \phi(\Omega_2^c)\} = \phi(\Omega_2) \leq \max\{\phi(\Omega_1), \phi(\Omega_2)\}$.

This finishes the proof. □

(II.3). λ_N , dual Cheeger constant and bipartiteness

Now, we switch to the other fact that

$\lambda_N = 2$ iff G is bipartite.

Like in the case of (II.2), we hope to quantify how close a graph is to be bipartite.

For any $\Omega \subseteq V$, we denote

$$E(\Omega) := E(\Omega, \Omega) = \sum_{u \in \Omega} \sum_{\substack{v \in \Omega \\ v \sim u}} 1 = 2 \cdot \# \text{ edges with both adj. vertices lying in } \Omega.$$

Definition (dual Cheeger constant / bipartiteness ^{ratio})

Given a finite simple graph $G = (V, E)$, its bipartiteness ratio is defined by

$$\beta = \min_{(V_1, V_2)} \frac{E(V_1) + E(V_2) + |\partial(V_1, V_2)|}{\text{vol}(V_1 \cup V_2)}$$

where the minimum is taken over all possible

(82)

$$V_1, V_2 \subseteq V \text{ s.t. } V_1 \cap V_2 = \emptyset, V_1 \cup V_2 \neq \emptyset.$$

Remark: Notice particularly that we allow one of V_1 and V_2 to be empty. Moreover, it is not required that $V_1 \cup V_2 = V$.

Theorem 1 (dual Cheeger inequality). We have

$$\frac{\beta^2}{2} \leq 2 - \lambda_N \leq 2\beta.$$

Lemma 1.3.1. We have

$$2 - \lambda_N = \min_{f \neq 0} \frac{\sum_{\{u,v\}} (f(u) + f(v))^2}{\sum_u f(u)^2 du}.$$

Proof: Recall $\lambda_N = \min_{f \neq 0} \max_{f \neq 0} R(f)$

$$= \max_{f \neq 0} \frac{\sum_{\{u,v\}} (f(u) - f(v))^2}{\sum_u f(u)^2 du}$$

Therefore, we have

$$2 - \lambda_N = \min_{f \neq 0} \left(2 - \frac{\sum_{\{u,v\}} (f(u) - f(v))^2}{\sum_u f(u)^2 du} \right)$$
$$= \min_{f \neq 0} \frac{2 \sum_u f(u)^2 du - \sum_{\{u,v\}} (f(u) - f(v))^2}{\sum_u f(u)^2 du}.$$

Observe that

$$\begin{aligned} \sum_{\{u,v\}} (f(u) - f(v))^2 &= \frac{1}{2} \sum_u \sum_{v: v \sim u} (f(u)^2 - 2f(u)f(v) + f(v)^2) \\ &= \frac{1}{2} \left[\sum_u f(u)^2 du \right] - \frac{1}{2} \sum_u \sum_{v: v \sim u} 2f(u)f(v) + \frac{1}{2} \sum_v f(v)^2 dv \\ &= \sum_u f(u)^2 du - \frac{1}{2} \sum_u \sum_{v: v \sim u} 2f(u)f(v). \end{aligned}$$