

Eigenvalues and Random Walks (section 1.5 of “Spectral Graph Theory” by Fan Chung)

Weighted (undirected) graphs: we have a weight function $w: V \times V \rightarrow \mathbb{R}$ satisfying

(a) $w(u, v) = w(v, u)$

(b) $w(u, v) \geq 0$ and if u and v are not adjacent, $w(u, v) = 0$.

Then the degree d_v of a vertex v is defined by:

$$d_v = \sum_u w(u, v)$$

$$\text{vol } G = \sum_v d_v$$

The normalized Laplacian of G is still defined as $T^{-1/2}LT^{-1/2}$, so we have

$$\mathcal{L}(u, v) = \begin{cases} 1 - w(v, v) / d_v, & \text{if } u = v \\ -w(u, v) / (d_u d_v)^{1/2}, & \text{otherwise} \end{cases}$$

The Rayleigh quotient characterization for the eigenvalues can be readily generalized for weighted graphs.

Given a weighted graph G , we can define a random walk on it in a natural way, by specifying the transition probabilities:

$$P(u, v) = w(u, v) / d_u$$

Clearly, $\sum_v P(u, v) = 1$.

For our Markov chain, if the initial distribution is $f: V \rightarrow \mathbb{R}$, $\sum_v f(v) = 1$, the distribution after k steps is given by fP^k .

We call a Markov chain ergodic if there is a unique stationary distribution $\pi(v)$ satisfying

$$\lim fP^k(v) = \pi(v)$$

for any initial distribution f .

From the theory of finite Markov chains we know that the necessary and sufficient conditions for the ergodicity of P are:

- (i) irreducibility (for any u, v , there exists s , such that $P^s(u, v) > 0$)
- (ii) aperiodicity ($\text{GCD}\{s: P^s(u, u) > 0\} = 1$, which is a communicating class property)

It is easy to see that these two properties can be conveniently stated in the spectral terms. This is what we have for undirected graphs:

irreducibility is equivalent to the condition that G is connected, that is, $\lambda_1 > 0$.

aperiodicity is equivalent to the condition that G is not bipartite, that is, $\lambda_{n-1} < 2$.

A major problem of interest is the convergence rate of a given ergodic random walk:

Given an arbitrary initial distribution f , how many steps s are required for fP^s to be close to the stationary distribution?

As we will see shortly, the answer can be given in the terms of “spectral gap”, determined by λ_1 and λ_{n-1} .

We start with the L_2 -norm convergence: $\|fP^s - \pi\|_2$.

Note that $P = T^{-1}A = T^{-1/2}(I - \mathcal{L})T^{1/2}$.

The stationary distribution must satisfy $\pi P = \pi$ (if $a_s \rightarrow \pi$, then $a_s P \rightarrow \pi P$).

Since $(1T)P = 1A = (d_1, \dots, d_n) = 1T$, we see that $\pi = (1/\text{vol } G) (d_1, \dots, d_n)$ is a natural candidate for the stationary distribution.

Let $\{\varphi_i\}$ be the orthonormal eigenbasis of \mathcal{L} , where φ_i is associated with λ_i . Given an initial distribution f , we write $f T^{-1/2} = \sum_i a_i \varphi_i$.

We know that $\varphi_0 = (\text{vol } G)^{-1/2} 1T^{1/2}$, so $a_0 = (\text{vol } G)^{-1/2}$.

Then we have:

$$\|fP^s - \pi\| = \|fP^s - (1/\text{vol } G) 1T\| = \|fP^s - a_0 \varphi_0 T^{1/2}\| =$$

$$\|f T^{-1/2}(I - \mathcal{L})^s T^{1/2} - a_0 \varphi_0 T^{1/2}\| = \|(\sum_i a_i \varphi_i) (I - \mathcal{L})^s T^{1/2} - a_0 \varphi_0 T^{1/2}\| =$$

(since \mathcal{L} is symmetric, $\varphi_i \mathcal{L} = \lambda_i \varphi_i$)

$$= \left\| \sum_{i>0} a_i (1 - \lambda_i)^s \varphi_i T^{1/2} \right\| = \left\| \left(\sum_{i>0} a_i (1 - \lambda_i)^s \varphi_i \right) T^{1/2} \right\| \leq$$

$$\left(\left\| (x_1, \dots, x_n) T^{1/2} \right\| = \left\| (x_1 d_1^{1/2}, \dots, x_n d_n^{1/2}) \right\| \leq d_{\max}^{1/2} \left\| (x_1, \dots, x_n) \right\| \right)$$

$$\leq d_{\max}^{1/2} \left\| \sum_{i>0} a_i (1 - \lambda_i)^s \varphi_i \right\| \leq d_{\max}^{1/2} \left(\sum_{i>0} a_i^2 (1 - \lambda_i)^{2s} \right)^{1/2} \leq$$

$$\leq d_{\max}^{1/2} \left(\sum_{i>0} a_i^2 \right)^{1/2} \max_{i>0} |1 - \lambda_i|^s =$$

(define λ' as λ_1 if $(1 - \lambda_1) \geq (\lambda_{n-1} - 1)$ or as $(2 - \lambda_{n-1})$ otherwise)

$$= d_{\max}^{1/2} \left(\sum_{i>0} a_i^2 \right)^{1/2} |1 - \lambda'|^s \leq$$

$$\left(\sum_i a_i^2 = \left\| f T^{-1/2} \right\|^2 = \sum_i (f_i^2 / d_i) \leq (\sum_i f_i) / d_{\min} = 1 / d_{\min} \right)$$

$$\leq (d_{\max} / d_{\min})^{1/2} |1 - \lambda'|^s \leq \exp(-s\lambda') (d_{\max} / d_{\min})^{1/2} \text{ (since } (1 - \lambda') \leq \exp(-\lambda') \text{ on } [0, 1])$$

How many steps do we need to guarantee $\|fP^s - \pi\| \leq \varepsilon$?

$$s \geq (1/\lambda') \ln(1/\varepsilon \cdot (d_{\max}/d_{\min})^{1/2})$$

We can eliminate the dependence on λ_{n-1} by modifying the random walk slightly. Let's modify the weights in the following way:

$$w'(v, v) = w(v, v) + c d_v, \text{ where } c = (\lambda_1 + \lambda_{n-1}) / 2 - 1$$

(note that we have $c > 0$ if $(1 - \lambda_1) < (\lambda_{n-1} - 1)$)

and $w'(u, v) = w(u, v)$ if $u \neq v$.

Then we have $\lambda_k' = \lambda_k / (1 + c)$.

$$\text{So, } 1 - \lambda_1' = \lambda_{n-1}' - 1 = (\lambda_{n-1} - \lambda_1) / (\lambda_1 + \lambda_{n-1}).$$

This is called a *lazy* random walk.

A stronger notion of convergence: the *relative pointwise distance*.

We know that every row of matrix P of an ergodic random walk converges to π .

We define the relative pointwise distance as:

$$\Delta(s) = \max_{x,y} | P^s(y, x) - \pi(x) | / \pi(x)$$

Similar to the above, we can show that

$$\Delta(s) \leq \exp(-s\lambda') (\text{vol } G / d_{\min})$$

Why is the relative pointwise distance a stronger notion of convergence than the L_2 -norm one?

Given an initial distribution f , we have

$$| fP^s(x) - \pi(x) | / \pi(x) \leq \sum_y f(y) (| P^s(y, x) - \pi(x) | / \pi(x)) \leq \sum_y f(y) \Delta(s) \leq \Delta(s)$$

So, we obtained $\| fP^s - \pi \|_2 \leq \Delta(s) \|\pi\|_2$

The Total Variation distance.

$$\Delta_{\text{TV}}(s) = 1/2 \max_y \sum_x |P^s(y, x) - \pi(x)|$$

(half of the L_1 -distance)

Easy to see that $\Delta_{\text{TV}}(s) \leq \Delta(s) / 2$.

The case of directed graphs.

We can show the following:

If G is a strongly connected directed graph on n vertices, then we can define a lazy walk, such that after at most $t \geq 2/\lambda_1 ((-\ln \varphi_{\min}) + 2c)$ steps, we have

$$\Delta_{\text{TV}}(t) \leq \exp(-c)/2,$$

where φ is the normalized Perron vector.

A subtlety: for directed graphs, the Perron vector components and eigenvalues can be exponentially small in n . However, for certain “well-behaving” classes of graphs those values are of the order of $1 / \text{poly}(n)$. For instance, that holds true for *Eulerian* graphs (in-degree of each vertex is equal to its out-degree).