

Random Walks and Mixing

15-859NN
2/8/21

Random Walk as a matrix-vector

$$G = (V, E, w); A_{ij} = w_{ij}; D_{ii} = \sum_j w_{ij}$$

Let $p_i^{(t)}$ \equiv prob at vertex V_i
at time t .

$p^{(0)}$ \equiv starting configuration.

Claim $A^T D^{-1} p^{(t)} = p^{(t+1)}$

note $\text{Prob}(V_i \text{ to } V_j) = \frac{w_{ji}}{d_i} = (A^T D^{-1})_{ji}$

$$\begin{array}{c} A^T \\ \boxed{\begin{array}{ccc} | & | & | \\ w_1^T & \dots & w_i^T & \dots & w_n^T \\ | & & | & & | \end{array}} \\ i \end{array} \cdot \begin{array}{c} D^{-1} \\ \boxed{\begin{array}{ccc} d_1^{-1} & & 0 \\ & \ddots & \\ 0 & & d_n^{-1} \end{array}} \end{array} = \begin{pmatrix} w_{i1}/d_i \\ \vdots \\ w_{in}/d_i \end{pmatrix}$$

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Note All col sums in $A^T D^{-1} \equiv 1$

Def $A^T D^{-1} \equiv$ transition matrix

In our case

$$A = A^T \text{ \& } \sum P_i^{(0)} = 1 \text{ \& } P_i^{(0)} \geq 0$$

Two Natural Questions

1) \exists dist \bar{P} s.t. $A D^{-1} \bar{P} = \bar{P}$?

(Stationary dist)

2) $\forall P_0 \quad \lim_{n \rightarrow \infty} (A D^{-1})^n P^{(0)} = \bar{P}$?

Answers

1) Yes & no

$$\text{Let } d = \sum d_i \quad \pi = \begin{pmatrix} d_1/d \\ \vdots \\ d_n/d \end{pmatrix} = 1/d D \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$$

pf

$$\begin{aligned} AD^{-1}\pi &= AD^{-1}(1/d) D \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} = \\ 1/d A^T \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} &= 1/d A \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} = 1/d \begin{pmatrix} d_1 \\ \vdots \\ d_n \end{pmatrix} = \pi \end{aligned}$$

thus $\tilde{d} = \begin{pmatrix} d_1 \\ \vdots \\ d_n \end{pmatrix}$ is an eigen vector
with value 1.

In general not unique

$$G \equiv \bullet \longleftrightarrow \bullet \quad A = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \text{ note } \lambda(\lambda) \neq \pm 1$$

$$\begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} 1 \\ -1 \end{pmatrix} = \begin{pmatrix} -1 \\ 1 \end{pmatrix} = - \begin{pmatrix} 1 \\ -1 \end{pmatrix}$$

2) In general no.

$$\begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix} \quad \left(\begin{pmatrix} 1 \\ 0 \end{pmatrix} \text{ will not converge} \right)$$

Thm If G is not bipartite
and connected then

$\forall P^{(0)} \quad |P^{(0)}|_1 = 1$ & $P^{(0)} \geq 0$ then

$$\lim_{k \rightarrow \infty} (AD^{-1})^k P^{(0)} = \mathbb{1}$$

2) We will prove convergence by answering
a more general question:

Question How fast does a
walk "mix" on G .

Goal: Use Spectral Thm.

Prob: A symmetric but AD^{-1} not!

We do a change of variables

$$AD^{-1} \longrightarrow \tilde{A} = D^{-1/2} A D^{-1/2} \quad (\tilde{A} \text{ sym})$$

$$p^{(k)} \longrightarrow \tilde{p}^{(k)} = D^{-1/2} p^{(k)}$$

$$\pi \longrightarrow \tilde{\pi} = D^{-1/2} \pi$$

Claim $AD^{-1}x = \lambda x$ iff $\tilde{A}\gamma = \lambda\gamma$
 where $\gamma = D^{-1/2}x$.

pf (\Rightarrow)

$$\begin{aligned} \tilde{A}\gamma &= (D^{-1/2} A D^{-1/2})(D^{-1/2}x) = D^{-1/2} A D^{-1}x \\ &= \lambda(D^{-1/2}x) = \lambda\gamma \end{aligned}$$

(\Leftarrow) Same.

Mixing as fun of error

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$$\text{Thus } \tilde{A} \tilde{\pi} = \tilde{\pi}$$

Def (New def of error!)

$$\text{Error: } \tilde{\epsilon}^{(k)} = \tilde{\pi} - \tilde{A}^k \tilde{p}^{(0)} = \tilde{\pi} - \tilde{p}^{(k)}$$

$$\text{Question? } (\tilde{\epsilon}^{(k)} = D^{-1/2} \epsilon^{(k)})$$

How fast does $\tilde{\epsilon}^k$ go to 0 with k ?
(If at all!)

$$\begin{aligned} \text{Note } \tilde{A} \tilde{\epsilon}^{(k)} &= \tilde{A} \tilde{\pi} - \tilde{A}^{k+1} \tilde{p}^{(0)} \\ &= \tilde{\pi} - \tilde{A}^{k+1} \tilde{p}^{(0)} = \tilde{\epsilon}^{(k+1)} \end{aligned}$$

$$\text{Thus } \tilde{\epsilon}^{(k)} = \tilde{A}^{(k)} \tilde{\epsilon}^{(0)}$$

A much simpler recurrence!

Claim $\tilde{\mathbf{z}}^{(b)} \perp \tilde{\mathbf{q}}$ i.e. $\tilde{\mathbf{z}}^{(b)T} \tilde{\mathbf{q}} = 0$ 7

i.e. $(\tilde{\mathbf{p}} - \tilde{\mathbf{p}}^{(b)})^T \tilde{\mathbf{q}} = 0$

to show: $\tilde{\mathbf{p}}^T \tilde{\mathbf{q}} = \tilde{\mathbf{p}}^{(b)T} \tilde{\mathbf{q}}$

$$\tilde{\mathbf{q}} = \mathbf{D}^{-1/2} \mathbf{q} = \begin{pmatrix} \frac{1}{\sqrt{d_1}} & & \\ & \ddots & \\ & & \frac{1}{\sqrt{d_n}} \end{pmatrix} \begin{pmatrix} d_1/d \\ \vdots \\ d_n/d \end{pmatrix} = \begin{pmatrix} \sqrt{d_1}/d \\ \vdots \\ \sqrt{d_n}/d \end{pmatrix}$$

$$\tilde{\mathbf{q}}^T \tilde{\mathbf{q}} = \sum \left(\frac{\sqrt{d_i}}{d} \right)^2 = \sum \frac{d_i}{d^2} = 1/d$$

$$\tilde{\mathbf{q}}^T \tilde{\mathbf{p}}^{(b)} = \left(\frac{\sqrt{d_1}}{d}, \dots, \frac{\sqrt{d_n}}{d} \right) \begin{pmatrix} p_1/\sqrt{d_1} \\ \vdots \\ p_n/\sqrt{d_n} \end{pmatrix}$$

$$= \sum p_i/d = (\sum p_i)/d = 1/d$$

(since $\sum p_i = 1$)

□

Spectral Thm

If A is real sym matrix then

1) Eigenvalues of A are real.

i.e. $Ax = \lambda x \Rightarrow \lambda$ is real

2) If $Ax = \lambda x$ & $Ay = \mu y$ & $\lambda \neq \mu$

then $x^T y = 0$ i.e. $x \perp y$.

3) \exists orthonormal bases

y_1, \dots, y_n (eigenvectors)

$$\text{s.t. } A = \begin{pmatrix} | & & | \\ y_1 & \dots & y_n \\ | & & | \end{pmatrix} \begin{pmatrix} \lambda_1 & 0 \\ & \ddots \\ 0 & \lambda_n \end{pmatrix} \begin{pmatrix} -y_1^T \\ \vdots \\ -y_n^T \end{pmatrix}$$

$$4) A = \sum_{i=1}^n \lambda_i y_i y_i^T$$

Perron-Frobenius Thm

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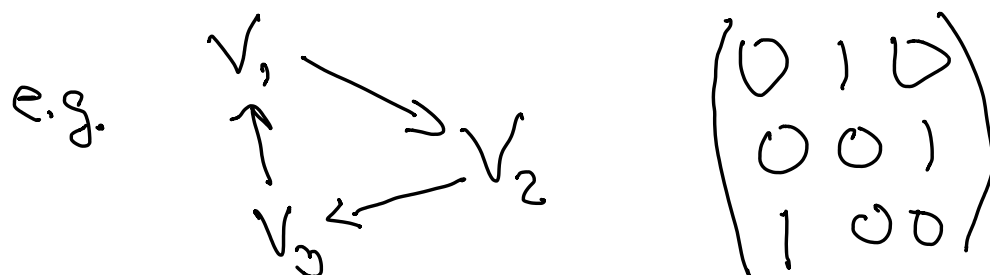
Suppose $A^{n \times n} \geq 0$

Graph(G) is strongly connected.

Def $z = a + ib \in \mathbb{C}$

$$|z| = \sqrt{z^* z} = \sqrt{a^2 + b^2}$$

Spectral Radius $\rho(A) = \max_{\lambda \in \lambda(A)} |\lambda|$



$w \equiv 3\text{rd root of unity}$

$$\begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{pmatrix} \begin{pmatrix} 1 \\ w \\ w^2 \end{pmatrix} = \begin{pmatrix} w \\ w^2 \\ 1 \end{pmatrix} = w \begin{pmatrix} 1 \\ w \\ w^2 \end{pmatrix}$$

$\Rightarrow w$ is an eigenvalue

$$\lambda(A) = 1, w, w^2$$

Thm (PF)

1) $\rho(A)$ is a simple eigenvalue of A .

If x is its eigenvector then

$$\text{sign}(x_i) = \text{sign}(x_j) \neq 0 \quad \forall i, j$$

2) $\theta \in \lambda(A)$ & $|\theta| = \rho(A)$ then

$\theta/\rho(A)$ is an m th root of unity

and all cycles in $G(A)$ have

length a multiple of m .

3) Only non-neg eigenvector
is x .

pf maybe?

Back to the symmetric case. 12

Suppose eigenvalues are

$$-1 < \lambda_1 \leq \dots \leq \lambda_n = 1 \quad \left(\begin{array}{l} -1 < \lambda_1 \text{ true} \\ \text{by Sym Perron-F,} \\ \text{next lecture} \end{array} \right)$$

Orthonormal vectors are

$$y_1, \dots, y_n = \tilde{\Pi} \cdot d$$

We know that

$$\tilde{\xi}^{(0)} = \alpha_1 y_1 + \dots + \alpha_{n-1} y_{n-1}$$

$$\tilde{\xi}^{(1)} = \tilde{A} \tilde{\xi}^{(0)} = \lambda_1 \alpha_1 y_1 + \dots + \lambda_{n-1} \alpha_{n-1} y_{n-1}$$

$$\tilde{\xi}^{(k)} = \lambda_1^k \alpha_1 y_1 + \dots + \lambda_{n-1}^k \alpha_{n-1} y_{n-1}$$

We will show that:

The mixing rate determined by

$$\lambda = \max \{ |\lambda_1|, |\lambda_{n-1}| \}$$

What norm do we want our error? 13

$\|\varepsilon\|_1, \|\varepsilon\|_2, \|\varepsilon\|_\infty$?

Consider $\|\tilde{\varepsilon}^{(k)}\|_2$ (How does it compare to $\|\varepsilon^{(k)}\|_2$?)

Since y_i 's are orthonormal

$$\|\varepsilon^{(0)}\|_2 = \sqrt{\sum \alpha_i^2 \|y_i\|_2^2} = \sqrt{\sum \alpha_i^2}$$

Pick k s.t. $\lambda^k \leq 1/2$ (G not bipartite.)

$$\begin{aligned} \|\tilde{\varepsilon}^{(k)}\|_2 &= \sqrt{\sum \lambda_i^{2k} \alpha_i^2} \leq \sqrt{\sum \lambda^{2k} \alpha_i^2} \\ &= \lambda^k \sqrt{\sum \alpha_i^2} \leq \frac{1}{2} \sqrt{\sum \alpha_i^2} = \frac{1}{2} \|\tilde{\varepsilon}^{(0)}\|_2 \end{aligned}$$

Thus every k steps error goes down by $1/2$.

Def Mixing rate

$$\min_k 2 \|\varepsilon^{(k)}\| \leq \|\varepsilon^{(0)}\|$$

l_1 norm & Cauchy-Schwartz

(CS) $a, b \in \mathbb{R}^n$

$$(a^T b)^2 \leq (a^T a)(b^T b)$$

Def: If $a = \begin{pmatrix} a_1 \\ \vdots \\ a_n \end{pmatrix}$ then $|a| = \begin{pmatrix} |a_1| \\ \vdots \\ |a_n| \end{pmatrix}$

e.g. $b = \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$ a arbitrary

$$\begin{aligned} |a|_1^2 &= |a|^T \cdot b \leq |a|^T |a| \cdot n \\ &= a^T a \cdot n \end{aligned}$$

Thus $|a|_1 \leq \sqrt{n} |a|_2$

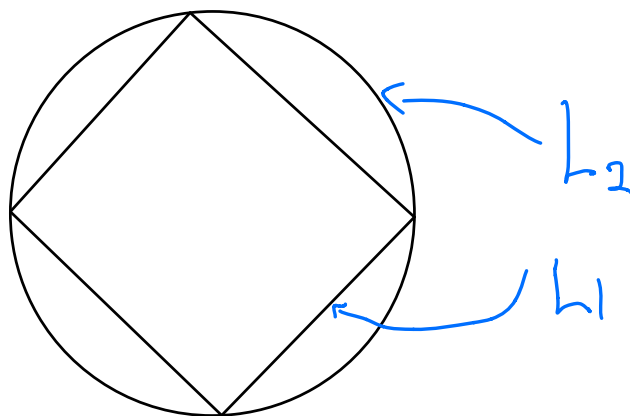
Claim Mixing rate in L_1 is

$$O(\log n \text{ (Mixing in } L_2))$$

(Better estimates for L_1 error are harder!)

pf note

$$|a|_2 \leq |a|_1$$



$$|\varepsilon_{\log n, k}|_1 \leq \sqrt{n} |\varepsilon_{\log n, k}|_2$$

$$\leq \left(\frac{1}{2^{\log n}}\right) \sqrt{n} |\varepsilon_0|_2$$

$$\leq \frac{1}{2} |\varepsilon_0|_2 \leq \frac{1}{2} |\varepsilon_0|_1$$

PROOF OF SPECTRAL THEOREM

Theorem 1 (Spectral Theorem). *Let $A \in \mathbb{R}^{n \times n}$ be a real symmetric matrix. Then*

- (1) *All eigenvalues of A are real.*
- (2) *There exists an orthogonal matrix Q and a diagonal matrix Λ such that $A = Q\Lambda Q^T$.*

Proof. We have proved (1) in the class. Only need to prove (2). We make an induction on n .

When $n = 1$, the claim is obvious. Now assume that the claim is valid for $n = m$, that is, for any $m \times m$ -real symmetric matrix A , there exists an orthogonal matrix Q and diagonal matrix Λ such that $A = Q\Lambda Q^T$. Let us consider $(m+1) \times (m+1)$ -real symmetric matrix A . By (1), A has a real eigenvalue λ with eigenvector α . We see that all entries of α must be real numbers. By Gram-Schmidt process, we may assume that there exists an orthonormal basis q_1, \dots, q_n with $q_1 = \alpha$. Let $P := (q_1 q_2 \cdots q_n)$ and $C := P^T A P = (c_{ij})_{(m+1) \times (m+1)}$. We claim that $c_{11} = \lambda$ and $c_{i1} = 0$ for $i \neq 1$. In fact, note that P is an orthogonal matrix, we have $AP = PC$, that is, $A(q_1 q_2 \cdots q_n) = (q_1 q_2 \cdots q_n)C$. Therefore, we have $Aq_1 = \sum_{i=1}^{m+1} c_{i1} q_i$. But $q_1 = \alpha$ is an eigenvector, so $\lambda q_1 = \sum_{i=1}^{m+1} c_{i1} q_i$. Since q_1, \dots, q_n are linearly independent. So $c_{11} = \lambda$ and $c_{i1} = 0$ for $i \neq 1$. So C has four blocks like $\begin{pmatrix} \lambda & \star \\ 0 & \tilde{A} \end{pmatrix}$. Note that

$C = P^T A P$ is symmetric(why ?), thus $\star = 0$. So $C = \begin{pmatrix} \lambda & 0 \\ 0 & \tilde{A} \end{pmatrix}$ and

\tilde{A} has to be symmetric matrix with the size $m \times m$. By induction, there exists an orthogonal matrix Q and diagonal matrix Λ such that $\tilde{A} = Q\Lambda Q^T$. Therefore

$$C = \begin{pmatrix} \lambda & 0 \\ 0 & \tilde{A} \end{pmatrix} = \begin{pmatrix} \lambda & 0 \\ 0 & Q\Lambda Q^T \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & Q \end{pmatrix} \begin{pmatrix} \lambda & 0 \\ 0 & \Lambda \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & Q \end{pmatrix}^T$$

Therefore

$$A = PCP^T = P \begin{pmatrix} 1 & 0 \\ 0 & Q \end{pmatrix} \begin{pmatrix} \lambda & 0 \\ 0 & \Lambda \end{pmatrix} (P \begin{pmatrix} 1 & 0 \\ 0 & Q \end{pmatrix})^T$$

and we easily check $P \begin{pmatrix} 1 & 0 \\ 0 & Q \end{pmatrix}$ is an orthogonal matrix and we are done. □

Consider Random walks on path graph $\equiv P_n$

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We will show that $\lambda = \lambda(P_n) \approx (1 - 1/n^2)$

Note $(1 - 1/n^2)^{n^2} \approx 1/e$

Thus mixing rate for P_n is $\approx n^2$!