

$$P_{xy} = \frac{c_{xy}}{c_x} \quad \Pi_x = \frac{c_x}{c_G} \quad G \text{ connected}$$

\uparrow

Laplacian of G

$$L(G) = \begin{pmatrix} c_1 & & & \\ & c_2 & & \\ & & \ddots & \\ & & & c_n \end{pmatrix} - i \begin{pmatrix} & & j \\ & & -c_{ij} \end{pmatrix}$$

$$= \sum_e c_e \begin{pmatrix} u & 1 \\ v & -1 \end{pmatrix} \begin{pmatrix} u & -1 \\ -1 & v \end{pmatrix}$$

$$e = (u, v)$$

$$x^T L(G)x = \sum_{e=(u,v)} c_e (x_u - x_v)^2$$

Laplacian p.s.d. $\Rightarrow \lambda_i \geq 0$

$$0 = \lambda_1 \leq \lambda_2 \leq \dots \leq$$

all
1's
eigenvector

If G connected $\lambda_2 > 0$

Laplacian quadratic form highlights connection between Laplacian and cut structure

$$\text{take } \vec{x} \text{ so } x_i = \begin{cases} 1 & i \in S \\ 0 & i \notin S \end{cases}$$

$$\text{then } \vec{x}^T L_G \vec{x} = \sum_{\substack{e=(u,v) \\ u \in S, v \in \bar{S}}} c_e \quad \text{measures capacity of cut}$$

no small cuts \equiv "expansion" \equiv rapid mixing \equiv spectral gap

$\hat{\lambda}_2$ 2nd smallest eigenvalue of normalized Laplacian

$$\hat{L}(G) = D(G)^{-\frac{1}{2}} L(G) D(G)^{-\frac{1}{2}}$$

$T(\varepsilon)$ # steps for lazy rw. to converge to within ε of π

$$|q_j^\circ P_j^{T(\varepsilon)} - \pi_j| \leq \varepsilon \quad \forall j$$

$$T(\varepsilon) = \frac{1}{\hat{\lambda}_2} \log \left(\frac{n}{C\varepsilon} \right)$$

$$C = \frac{\max_e c_e}{\min_e c_e}$$

Connections to cut structure

$$\underline{\Phi}_G = \text{conductance of graph} = \min_{\emptyset \neq S \subset V} \phi(S)$$

$$\phi(S) = \frac{\sum_{e \text{ crosses } S-S} ce}{\min(\sum_{e \text{ incident to } v \in S} ce, \sum_{e \text{ incident to } v \in \bar{S}} ce)}$$

Cheeger's Inequality:

$$2\underline{\Phi}_G \geq \hat{\gamma}_2 \geq \frac{\underline{\Phi}_G^2}{2}$$

cuts w/ small conductance are obstacles to rapid mixing
in some sense only obstacles

Back to electrical flows:

∇ electric flow \vec{f} , \exists vector ϕ of vertex potentials

for unit s-t current, compute $\vec{\phi}$ by solving system

$$L_G \phi = \begin{pmatrix} 1 \\ -1 \end{pmatrix}_s^+$$

$$c_x \phi_x - \sum_{y \in N(x)} c_{xy} \phi_y = 0$$

$$c_s \phi_s - \sum_u c_{su} \phi_u = 1$$

$$\sum_u c_{su} (\phi_s - \phi_u) = \sum_u f_{su} = 1$$

$$\mathcal{E}_r(f) = f^T R f = \phi^T L(G) \phi$$

↗
diagonal matrix of
edge resistances

$$\sum_e c_e (\phi_u - \phi_v)^2 = \sum_e c_e \frac{f_e^2}{c_e^2} = \sum_e r_e f_e^2$$

Applications

Spectral Sparsification

[Spielman/Teng] [Spielman/Srivastava]

.....

Given $G = (V, E, c)$ find $H = (V, F, w)$

sparse $|F| = O(n)$

s.t. H approximates G well

≡ all cuts approximately preserved ++

$$x^T L_H x \approx x^T L_G x \quad \forall x \quad (\text{eigenvalues } \approx \text{same})$$

↑
could be
cont here

Example: degree d expanders approx complete graph

sample edges w/ prob d effective resistance between endpoints

Solving symmetric diagonally dominant linear systems

$$Ax = b \quad A \text{ symm} \quad |A_{ii}| > \sum_{j \neq i} |A_{ij}|$$

[Spielman Tang] . . . [Kelner, Orecchia, Sidford, Zhu]

Numerous applications: scientific computing, machine learning, vision, ...
+ algorithmic applications - flow, sparsification, routing, etc.

reduces $\rightarrow L\phi = Y_{s,t}$ \equiv electrical flow problem

New alg: start w/ unit s-t flow (e.g. $s-t$ path)

If it was electrical flow \forall cycle $C \quad \sum_{e \in C} r_e f_e = 0$

- randomly sample cycle from well-chosen dist'n

- compute $\sum_{e \in C} r_e f_e$ & if not 0, add flow around cycle

to make this 0.

Show that w/ suitable data structures can be
implemented efficiently in not too many cycle updates

Max Flow

[Christiano et al., Srivastava/Rao]

- compute electrical flow by solving $L\phi = \mathbf{f}_{s,t}$ efficiently
capacities will be violated

Version 1 penalize congested edges by \uparrow re
repeat

Version 2 $(u \rightarrow v)$ overly congested

\Rightarrow create current sce at v of value = excess flow

remove current at u

repeat

Random Spanning Trees

Procedure: Fix ordering on vertices $v_1 = r, \dots, v_n$
 ↑
 root

Take r.w starting at v_2 till hit r , erasing any cycles.

Add ^{directed} edges on path to tree

If T spanning stop

If not, take first vertex in ordering that isn't visited

Take r.w erasing cycles until hit tree

repeat... till tree is spanning

This tree is uniformly random tree!!! [Wilson]

Claim: Suppose fix a root r & select oriented tree

w/ edges directed towards root with prob $\propto \prod_{e \in T} p_e^{\vec{c}_e}$

Then if orientation & root are forgotten

$$\Pr(T) \propto \prod_{e \in T} c_e$$

$$\text{fix } r: \Pr(\vec{T}) \propto \prod_{e \in T} p_e^{\vec{c}_e} = \frac{\prod_{e \in T} c_e}{\prod_{v \in V \setminus r} c_v}$$

$$\propto \frac{\prod_{e \in T} c_e}{\prod_v c_v} \quad \text{since } c_r \text{ same for } \vec{T}_r$$

$$\propto \prod_{e \in T} c_e \quad \text{since denom doesn't depend on } T$$

Theorem

Wilson's alg finds tree in \vec{T}_r w/ prob $\propto \prod_e p_e^{\vec{c}_e}$

therefore once root & orientations forgotten, find tree

$$\text{w/ prob } \propto \prod_{e \in T} c_e$$

Proof: Order in which cycles popped off stack doesn't matter

Lemma

$$\Pr((x,y) \in T) = c_{(x,y)} R_{x \leftrightarrow y}$$

Proof

Run Wilson's alg with root y , starting at x

$$\Pr(e \in T) = \Pr_x (\text{first hit } y \text{ walking along } e)$$

$$= \sum_f \Pr(\text{return to } x \text{ at time } + w_0 \text{ seeing } y) \frac{c_e}{c_x}$$

$$= E_x (\# \text{visits to } x \text{ w/o seeing } y) \frac{c_e}{c_x}$$

$$= c_x R_{x \leftrightarrow y} \frac{c_e}{c_x} = c_e R_{x \leftrightarrow y}$$

Negative correlation:

$$\Pr(e \in T \text{ and } f \in T) \leq \Pr(e \in T) \Pr(f \in T)$$

Proof:

$$\Pr(e \in T_G \cap f \in T_G) = \Pr(e \in T_G) \Pr(f \in T_G | e \in T_G)$$

$$= \Pr(e \in T_G) \Pr(f \in T_G | e)$$

empty if e fused
≡ resistance 0

$$\leq \Pr(f \in T_G)$$

↑
Rayleigh Monotonicity

These results used to get best known alg for TSP problems

Kirchoff's Matrix Tree Thm

$$\sum_T \prod_{e \in T} c_e = \frac{1}{n} \prod_{i=2}^n \lambda_i$$

\uparrow
Eigenvalues of Laplacian

