

Spectral Graph Theory I - Christopher Ford

2/10/2015

- Agenda:
- 1) Graph theory review and vertex functions
 - 2) Local variance
 - 3) Random walks + random vertices
 - 4) Inner products (time permitting)


Graph Theory Review

- A graph G is defined by its vertices and edges.

$G = (V, E)$ where V is the set of vertices, E the set of edges

- for our graphs we assume the following:

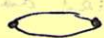
1) V, E are finite $\Rightarrow G$ is finite

2) no isolated vertices e.g. 
(no vertices of degree zero)

3) the edges do not have weights and are undirected

(though we can augment our analysis w/ parallel edges to account for this)

NOTE: parallel edges and self-loops are allowed



self-loops can be thought of as $1/2$ edges and contribute 1 to the degree of the vertex they are connected to.

NOTE: degree = # edges adjacent to a vertex. if degrees of all vertices are the same, the graph is regular

Vertex Functions

- useful to label vertices w/ a function

$f: V \rightarrow \mathbb{R}$ e.g. Google cows problem, voltages, indicator

indicator function: 0/1 if $v_i \in S, S \subseteq V$

$$f: V \rightarrow \mathbb{R} \equiv \begin{bmatrix} f(v_1) \\ f(v_2) \\ \vdots \\ f(v_n) \end{bmatrix}$$

can be thought of as a vector

Vector Functions Continued

note: addition and scaling of these functions are preserved:

$$(f + g)(v_i) = f(v_i) + g(v_i)$$

$$(c \cdot f)(v_i) = c \cdot (f(v_i))$$

⇒ linearity of functions

Local Variance

** the main idea of spectral graph theory **

In simple terms:

We have a function f that maps $V \rightarrow \mathbb{R}$. Want to know how much the function varies between adjacent vertices in the graph.

Def: local variance ("Dirichlet form", "analytic boundary size")

$$E(f) = \frac{1}{2} E_{u \sim v} [(f(u) - f(v))^2]$$

$u \sim v$ probability dist. across edges

Immediate observations:

1) $E(f) \geq 0$

2) $E(cf) = c^2 E(f)$

3) $E(f+c) = E(f)$

} same properties as original/traditional variance

#1 is trivial. #2: $E(cf) = \frac{1}{2} E_{u \sim v} [(c \cdot f(u) - c \cdot f(v))^2]$
 $= \frac{1}{2} E_{u \sim v} [c^2 (f(u) - f(v))^2]$
 $= \frac{c^2}{2} E_{u \sim v} [(f(u) - f(v))^2] = c^2 E(f)$

#3: $E(f+c) = \frac{1}{2} E_{u \sim v} [(f(u)+c - f(v)-c)^2]$
 $= \frac{1}{2} E_{u \sim v} [(f(u) - f(v))^2] = E(f)$

intuition for local variance:

- $E(f)$ is small when f doesn't differ much b/t adjacent vertices. f is "smooth" across ~~the~~ edges
- * $E(f)$ is large in the other case. f is "anti-smooth" or "rough" (not formal terms)

Example (time permitting)

$$f(v) = \begin{cases} 1 & v \in S \\ 0 & v \notin S \end{cases} \quad S \subseteq V$$

indicator function

$$f(v) = 1_S$$

$$E(f) = \frac{1}{2} \sum_{u,v} (f(u) - f(v))^2$$

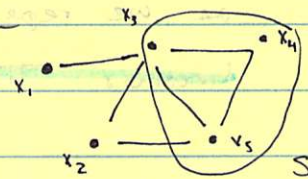
$$= \frac{1}{2} \sum_{u,v} [(1_S(u) - 1_S(v))^2]$$

$$= \frac{1}{2} \sum_{u,v} [1 \text{ if } (u,v) \text{ "crosses" } S]$$

↳ enters/exits the

$$= \Pr[u \rightarrow v \text{ "steps" out of } S] \text{ subset}$$

NOTE $(1_S(u) - 1_S(v))^2 = 1$ iff one of the vertices $\in S$, but not the other. 0 otherwise



$x_3, x_4, x_5 \in S$

$x_1 \notin S, x_2 \notin S, x_2 \rightarrow x_5$ "cross" S

Random Vertices + Random Walks

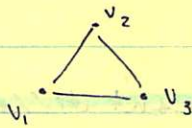
π : distribution of randomly selected vertices chosen by the following procedure

- 1) choose a random edge $u \sim v$
- 2) output u (or v , identical by symmetry)

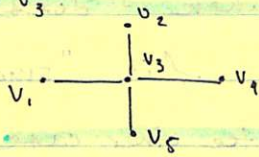
think of π as a distribution across vertices weighted by their degree
more degree \rightarrow more likely to be chosen in step 1.

$$\pi[v] = \frac{\text{deg}(v)}{|E|} \cdot \frac{1}{2} \quad (\text{pick edge adj. to } v, \text{ output } v \text{ as endpoint})$$

example:



$$\pi(v_1) = \pi(v_2) = \pi(v_3) = \frac{1}{3}$$



$$\pi(v_1) = \pi(v_2) = \pi(v_4) = \pi(v_3) = \frac{1}{8}$$

$$\pi(v_3) = \frac{4}{2 \cdot 4} = \frac{1}{2}$$

Application to random walks:

- ① picking u from π then picking v as a uniformly random neighbor of u is the same as
- ② drawing an edge uniformly at random $u \sim v$

PS.

$$\text{prob of getting } uv \text{ from ①} = \underbrace{\frac{\text{deg}(u)}{2|E|}}_{\text{pick } u} \times \underbrace{\frac{1}{\text{deg}(u)}}_{\text{select } v} = \frac{1}{2|E|} = \text{prob of picking random edge}$$

procedure ① is essentially a 1-step random walk. by repeating this step, we go on longer and longer walks. as we repeat, the distribution of the end pt. of our walk becomes π .

pick it randomly.

formally, let $t \in \mathbb{N}$. pick $u \sim \pi$. Do a random walk starting @ u taking t steps. distribution of v , the end pt. of the walk is π .

π is also known as the stationary distribution on vertices. Also known as limiting / invariant distribution.

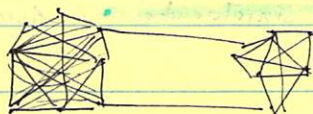
Suppose we don't start @ a random point. Say we start @ a pt. u_0 . Under what cases will the dist. of v . not converge to π ?

- ① G is disconnected
- ② G is bipartite (know which half you're in by even/odd steps)

When will it take a long time to converge to π ? Consider

e.g.

①



two cliques not "well connected"

vs.

②



completely connected.

① should take longer than ②

in e.g. ①, let $f = 1_S$ when S is one of the cliques.

$E(f)$ is small.

roughly: fast convergence \Rightarrow high $E(f)$

slow convergence \Rightarrow low $E(f)$

Global Variance + Global Mean

let $u \sim \pi$, and $f: V \rightarrow \mathbb{R}$

(u randomly selected from π)

$f(u)$ is a random variable w/ the following parameters.

mean $E(f) := E[F]$

variance: $\text{Var}(f) := E_{u \sim \pi} [(f(u) - \mu)^2]$

$$= E_{u \sim \pi} [f^2(u)] - E[F]^2$$

$$= \frac{1}{2} E_{u, v \sim \pi} [(f(u) - f(v))^2]$$

known as the global variance b/c takes into account all u, v pairs, not just those w/ edges b/t them

Spectral graph theory compares local and global variances.

e.g. if for all f , $E(f)$ larger $\text{Var}(f)$, graph is an expander (mix quickly)

Inner Products

Want a way to measure the "similarity" of functions on our graph.

let $f, g : V \rightarrow \mathbb{R}$

$$\langle f, g \rangle_{\pi} = E_{u \sim \pi} [f(u)g(u)] \quad \text{measures similarity.}$$

similar to an inner product, but scaled by π .

$$\text{e.g. } \langle f, g \rangle_{\pi} = \begin{bmatrix} f(v_1) \\ f(v_2) \\ \vdots \\ f(v_n) \end{bmatrix} \cdot \begin{bmatrix} g(v_1) \\ g(v_2) \\ \vdots \\ g(v_n) \end{bmatrix} = f(v_1)g(v_1) + f(v_2)g(v_2) + \dots + f(v_n)g(v_n)$$

Note: $\langle f, g \rangle_{\pi} = \langle g, f \rangle_{\pi}$ (obvious) associativity

$$\langle a \cdot f + g, h \rangle_{\pi} = a \langle f, h \rangle_{\pi} + \langle g, h \rangle_{\pi} \quad \text{linearity}$$

$$\langle f, f \rangle_{\pi} \geq 0 \quad \text{and} \quad = 0 \text{ iff } f=0$$