

Spectral analysis of undirected random walks

Lecture 1

Probability

Events, probabilities,
conditional probabilities,
union bound

Random variables,
expected value,
linearity of expectation
Markov's inequality

Algorithms

Approx. 3-SAT,

Big idea: we only want the average

$$\begin{array}{l} \text{Linearity of Expectation} \\ E[X+Y] = E[X] + E[Y] \quad (\text{stochastic variables}) \\ \text{"average sum = sum of averages"} \end{array}$$

let $Y_i = \begin{cases} 1 & \text{if } i\text{th clause satisfied} \\ 0 & \text{otherwise} \end{cases}$ ($i=1, \dots, m$)

$$E[Y_i] = 7/8 \quad (1 \text{ clause case})$$

$$E[\text{\# clauses satisfied}] = E\left[\sum_{i=1}^m Y_i\right] = \sum_{i=1}^m E[Y_i] = 7/8 m$$

let $Y_i = \begin{cases} 1 & \text{if } i\text{th clause satisfied} \\ 0 & \text{otherwise} \end{cases}$

$$Z = \sum_{i=1}^m Y_i = \text{\# clauses satisfied}$$

$$E[Z] = \frac{1}{2} E[Z | x_1 = \text{true}] + \frac{1}{2} E[Z | x_1 = \text{false}]$$

$\Rightarrow$ either $E[Z | x_1 = \text{true}]$ or $E[Z | x_1 = \text{false}]$ is $\geq E[Z]$!

QuickSort,

Random divide and conquer

① pick random 'pivot'

② Divide A into two parts



Expected running time of QuickSort

For each $i, j \in [n]$ w/ $i < j$,

$X_{ij} = \begin{cases} 1 & \text{if } i\text{th smallest element is compared to } j\text{th smallest} \\ 0 & \text{otherwise} \end{cases}$

$\sum_{i,j} X_{ij}$ = total # comparisons made by the algorithm
 $\approx$ total running time

$E[\sum_{i,j} X_{ij}]$ = average running time

$E[\sum_{i,j} X_{ij}] = \sum_{i,j} E[X_{ij}]$ Linearity of Expectation: $E[aX+bY] = aE[X] + bE[Y]$ (average case! not worst case!)

now analyze $E[X_{ij}]$ in isolation

$$E[X_{ij}] = \Pr[X_{ij} = 1] = \Pr[i\text{th element is compared to } j\text{th}]$$

i th and j th elem selected before any element in between happens w/ probability $\frac{2}{j-i+1}$

$$E[X_{ij}] = \frac{2}{j-i+1}$$

$$E[\sum_{i,j} X_{ij}] = \sum_{i,j} E[X_{ij}]$$

$$= \sum_{i,j} \frac{2}{j-i+1} = 2 \sum_{i,j} \frac{1}{j-i+1}$$

$$\leq 2n \left(\frac{1}{1} + \frac{1}{2} + \dots + \frac{1}{n} \right)$$

$$\leq O(n \log n) \quad \text{with harmonic series}$$

Quickselect (HW)

Lecture 2

Probability

Hash Functions,

Universal Hash Functions

$h: [n] \rightarrow k$ s.t. for all pairs $i, j \in [n]$,
 $\Pr[h(i) = h(j)] \leq \frac{1}{k}$ (much weaker than ideal hash)

e.g. $h(x) = (ax + b) \bmod p \bmod k$

where • p prime, $> k$

• a in $\{1, \dots, p-1\}$ unif. random

• b in $\{0, \dots, p-1\}$ unif. random



Markov's Inequality

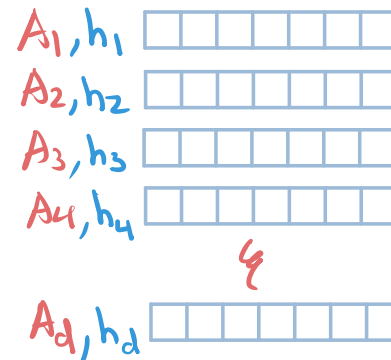
Markov's Inequality (special case)

Let $X \geq 0$ be nonnegative RV

$$\Pr[X \geq 2E[X]] \leq \frac{1}{2}$$

Algorithms

Frequency Estimation, Heavy Hitters (in streams)



estimate f_i w/
 $\min_{j=1, \dots, d} A_j[h_j(i)]$

Lecture 3

Probability

k-wise independence,
higher order moments
(generalizing universal hash
functions and Markov's inequality)

Algorithms

Hash tables w/
chaining +
linear probing

k-wise independent hash functions

$$h: [U] \rightarrow [m]$$

s.t. for any k keys $x_1, x_2, \dots, x_k \in [U]$,
 k values $y_1, y_2, \dots, y_k \in [m]$,

$$P[h(x_1)=y_1, h(x_2)=y_2, \dots, h(x_k)=y_k] = \frac{1}{m^k}$$

eg. $h(x) = a_0 + a_1x + a_2x^2 + \dots + a_{k-1}x^{k-1} \pmod{p}$

where $p \geq U$ prime,
 $a_0, a_1, \dots, a_{k-1} \in [p]$ indep, uniformly random

Important lemma

let $X_1, \dots, X_n \in \{0, 1\}$ be 4-wise independent
and $\mu = E[X_1 + \dots + X_n]$. then for $\beta > 0$,

$$P[X_1 + \dots + X_n \geq \mu + \beta] \leq \frac{4 \max\{\mu, \mu^3\}}{\beta^4}$$

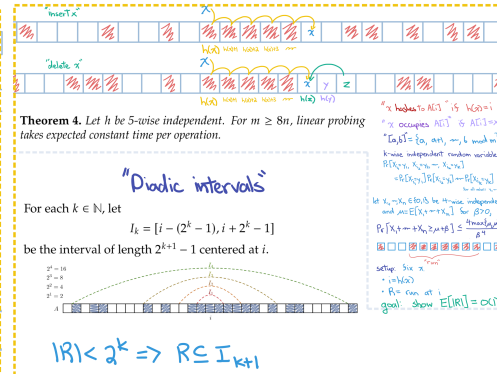
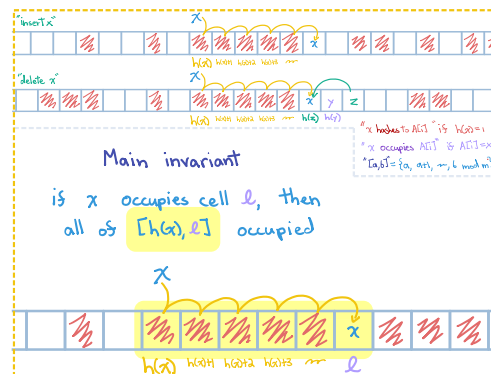
k-wise independent random variables
 $P[X_1=y_1, X_2=y_2, \dots, X_k=y_k]$

$$= P[X_1=y_1] P[X_2=y_2] \dots P[X_k=y_k]$$

for all values $y_1, \dots, y_k$

Main invariant

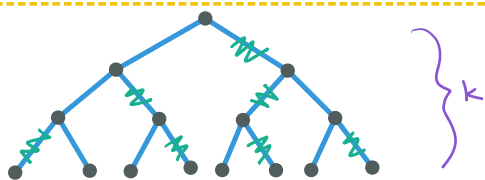
if x occupies cell i , then
all of $[h(x), i]$ occupied



Lecture 4

Probability

Galton-Watson processes



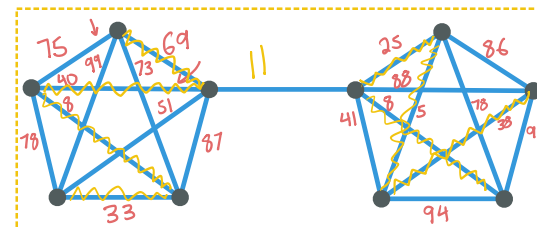
let T = complete binary tree of height k ,
w/ every edge deleted w/ prob $\leq 1/2$

Fact: $P[\text{some leaf connected to root}] \geq \frac{1}{k}$

"Galton-Watson process"

Algorithms

Random Contractions for min cut



Randomized contractions

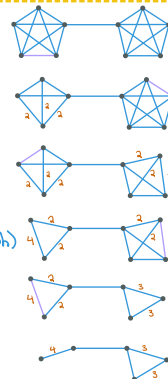
Input: $G=(V,E)$, weights $c \in \mathbb{R}_{\geq 0}^E$
(unweighted)

① while $|E| > 1$

 Ⓐ sample $e \in E$ in proportion to c

 Ⓑ "contract" e

② return set of edges (in original graph)
 contracted to remaining edge



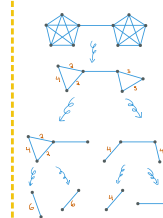
Amplification by branching

Instead of restarting at the beginning, restart partway through

High-level algorithm

① randomly contract until prob.
of ruining the min-cut is $\sim 1/2$

② Branch:
make two copies of current graph
recurse on both copies



Lecture 5

Probability

Multiplicative Chernoff Bound

Multiplicative Chernoff bound

let $X_1, \dots, X_n \in [0, 1]$ be independent

$$\mu = E[X_1 + \dots + X_n]$$

$$\epsilon \in (0, 1)$$

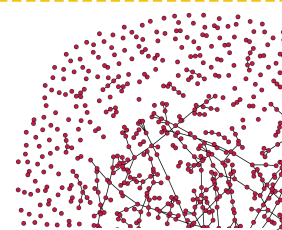
- $P[X_1 + \dots + X_n \geq (1 + \epsilon)\mu] \leq e^{-\epsilon^2 \mu / 3}$
- $P[X_1 + \dots + X_n \leq (1 - \epsilon)\mu] \leq e^{-\epsilon^2 \mu / 2}$

Algorithms (/ results)

Random graphs & the giant component

Erdős-Rényi graphs $G(n, p)$

- n vertices
- each edge sampled independently w/ probability p



Theorem 5.3. Consider a random graph $G \sim \mathcal{G}(n, p)$ for $p = c/n$, where c is a constant.

- If $c > 1$, then with high probability, there is exactly one connected component of G with $\Omega(n)$ vertices, and all other components have size $\leq O(\log n)$.
- For $c < 1$, then with high probability, all connected components of G has size $< O(\log n)$.

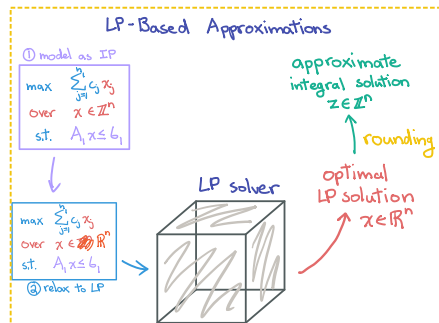
Lecture 6

Probability (& techniques)

Approximations via linear programming & randomized rounding

Linear programs (LPs)
Similar to IPs, except no integrality constraints

min/max $\sum_{j=1}^n c_j x_j$ linear objective
over $x \in \mathbb{R}^n$ linear integral variables
st. $A_1 x \leq b_1$ linear constraints
 $A_2 x = b_2$
 $A_3 x \geq b_3$



Continuous optimization vs Discrete optimization

randomization

Algorithms

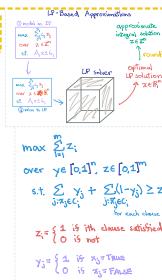
Max Sat Set Cover Covering Integer Programs

For each variable x_j , independently, randomly set $x_j = 1$ with probability p_j , and $x_j = 0$ otherwise.

$$E[\# \text{ sat. clauses}] \geq (1 - 1/e) \text{OPT}$$

k	oblivious	LP	average
1	1/2	$z_i \geq (3/4)z_i$	$\geq (3/4)z_i$
2	3/4	$(3/4)z_i \geq (3/4)z_i$	$\geq (3/4)z_i$
3	7/8	$(1 - 1/e)z_i \geq (3/4)z_i$	$\geq (3/4)z_i$
4	15/16	$(1 - 1/e)z_i \geq (3/4)z_i$	$\geq (3/4)z_i$
5	31/32	$(1 - 1/e)z_i \geq (3/4)z_i$	$\geq (3/4)z_i$
...	...	...	...
k	$1 - 1/2^k$	$(1 - 1/e)z_i \geq (3/4)z_i$	$\geq (3/4)z_i$

Can we get $\frac{3}{4}$ -APX?



Rounding LP solution
 $x \in [0, 1]^n \rightsquigarrow F \subseteq \{S_1, \dots, S_n\}$

For each set S_j , independently, take S_j with probability x_j .

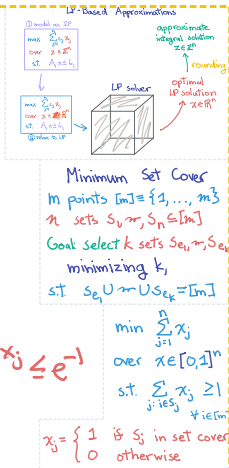
$$E[|F|] = \sum x_j \leq \text{OPT}$$

Fix a point i .

$$E[\# \text{ sets in } F \text{ covering } i] = \sum_{j \in S_i} x_j \geq z_i$$

$$P[F \text{ not cover } i] = \prod_{j \in S_i} (1 - x_j) \leq e^{-\sum_{j \in S_i} x_j} \leq e^{-z_i}$$

$$P[F \text{ cover } i] \geq 1 - e^{-1}$$



Lecture 7

Probability

Continuous Random Variables

Variance, Chebyshev's Variance Reduction

Median trick

Variance

$$\text{Var}(X) = E[(X - E[X])^2] = E[X^2] - (E[X])^2$$

Chebyshev's inequality

$$P[|X - E[X]| \geq d] \leq \frac{\text{Var}(X)}{d^2}$$

"median trick", "median of means"

- ① take mean to reduce variance, get constant prob. of error
- ② take median to amplify success prob. exponentially

Algorithms

Distinct Elements

1, 2, 3, ..., 14, 15, 16, ...

Algorithm w/
limited space

Goal: estimate # of distinct elements in the stream

Suppose you had an ideal hash function

$$h: [m] \rightarrow [0, 1]$$

and the following facts:

let $Y_1, \dots, Y_k \in [0, 1]$ independent and uniformly random

$$X = \min \{Y_1, \dots, Y_k\}$$

$$\text{then } E[X] = \frac{1}{k+1}$$

$$\textcircled{1} X \leftarrow 1$$

② for each element e

$$\textcircled{a} X \leftarrow \min\{X, h(e)\}$$

$$/* E[X] = \frac{1}{k+1}, k = (\text{\# distinct elements}) */$$

$$\textcircled{3} \text{ return } \frac{1}{X} - 1$$

$$\text{recall } E[X] = \frac{1}{k+1}$$

$$\text{goal: show } |X - E[X]| \leq \frac{\epsilon}{k+1}$$

w/ good prob.

$$P[|X - E[X]| \geq \frac{\epsilon}{k+1}]$$

$$\leq \text{Var}(X) \cdot \left(\frac{k+1}{\epsilon}\right)^2 \leftarrow \text{Chebyshev's inequality}$$

where

$$\text{Var}(X) = \frac{k}{(k+1)^2(k+2)} \approx \frac{1}{k^2}$$

Q: how to reduce $\text{Var}(X)$?

we can get $(1 \pm \epsilon)$ -APX

w/ 10% error prob. in $O(\frac{1}{\epsilon^2})$ space

what about high probability?

① make q copies $Y_1, \dots, Y_q$ of

② return median of $Y_1, \dots, Y_q$

Algo correct $\Leftrightarrow \geq \frac{1}{2}$ of Y_i 's correct

let $Z = \# \text{correct } Y_i$'s $E[Z] = \frac{q}{2}$

$$P[Z \leq (1 - \frac{\epsilon}{4})E[Z]] \leq e^{-\left(\frac{\epsilon}{4}\right)^2 E[Z]/2} \leq \frac{1}{n^{O(n)}} \text{ for } q = O(\log n)$$

ideal hash $h: [m] \rightarrow [0, 1]$

let $Y_1, \dots, Y_k \in [0, 1]$

indep. and unifs. rand.

$$X = \min \{Y_1, \dots, Y_k\}$$

$$\text{then } E[X] = \frac{1}{k+1}$$

$$\text{and } E[X^2] = \frac{2}{(k+1)(k+2)}$$

$$\text{Var}(X) = E[(X - E[X])^2]$$

$$X_1, \dots, X_q \text{ indep. copies of } X$$

$$\bar{X} = \frac{1}{q}(X_1 + \dots + X_q)$$

$$\text{Var}(\bar{X}) = \frac{1}{q} \text{Var}(X)$$

$$P[X_1 + \dots + X_q \leq (1 - \epsilon)q] \leq e^{-\epsilon^2 q/4}$$

Lecture 8

Probability

Gaussian random variables

Gaussian random variables

$$x \sim \mathcal{N}(\mu, \sigma^2)$$

mean variance

Def: the nicest, most pleasant, convenient random variable ever

Fact let $x \sim \mathcal{N}(\mu, \sigma^2)$, $d \in \mathbb{R}$.

$$\text{then } x+d \sim \mathcal{N}(\mu+d, \sigma^2)$$

$$dx \sim \mathcal{N}(d\mu, d^2\sigma^2)$$

Fact let $x_1 \sim \mathcal{N}(\mu_1, \sigma_1^2)$, $x_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$

$$\text{then } x_1 + x_2 \sim \mathcal{N}(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$

Fact let $x \sim \mathcal{N}(0, 1)$, $t < \frac{1}{2}$

$$\text{then } E[e^{tx^2}] = \frac{1}{\sqrt{1-2t}}$$

Algorithms

Dimensionality reduction

Bag-of-words

literally any sentence is fine

any ↑ is literally sentence English
five encodes text in high dimensions

Lemma 8.8. Let $A \sim \mathcal{N}^{k \times d}$ be a random matrix where each coordinate A_{ij} is an independently drawn sample from $\mathcal{N}$. Let $\epsilon > 0$ be sufficiently small. For any vector x ,

$$\mathbb{P}\left[(1-\epsilon)\|x\|^2 \leq \frac{1}{k}\|Ax\|^2 \leq (1+\epsilon)\|x\|^2\right] \geq 1 - 2e^{-k/8}$$

$$k \left\{ \left[\frac{1}{k} \|Ax\|^2 \right] \leftarrow \alpha_i \right.$$

$$E[\|Ax\|^2] = \sum_{i=1}^k E[(Ax)_i^2] = k\|x\|^2$$

$$E[(\sum_{i=1}^k A_{ij} x_j)^2] = \|x\|^2$$

$$A_{ij} x_j \sim \mathcal{N}(0, x_j^2)$$

$$\sum_{j=1}^n A_{ij} x_j \sim \mathcal{N}(0, \|x\|^2)$$

$$(Ax) \sim \mathcal{N}^k(0, \|x\|^2)$$

$$\Pr[\|Ax\|^2 \geq k\|x\|^2 \cdot (1+\epsilon)] \leq e^{-\epsilon^2 k/8}$$

Dimensionality Reduction - high level

$O(\log n)$ dimensions suffice

where $n = \# \text{ points}$

$$\mathbb{R}^{\text{very large}} \xrightarrow{f(x)} \mathbb{R}^{O(\log n)}$$

One can map n points into $\mathbb{R}^{O(\log n/\epsilon^2)}$ while preserving all distances up to $(1 \pm \epsilon)$ -APX

Lecture 9

Probability

Locality-sensitive hashing

Fix $\theta \in [0, \pi]$. given q , either:

(a) output $p \in P$ w/ $\angle(p, q) \leq 4\theta$

(b) declare no $p \in P$ w/ $\angle(p, q) \leq \theta$

define $h: S^{d-1} \rightarrow \{-1, 1\}^k$ by

$$h_i(x) = \text{sign}(\langle g_i, x \rangle) \text{ w/ } g_i \sim N^d$$

$$k = \pi(\log(n)/2\theta)$$



d-dimensional sphere

when querying y :

• if there is $x \in P$ w/ $\angle(x, y) \leq \theta$, then it collides w/ probability $\geq 1/\sqrt{n}$

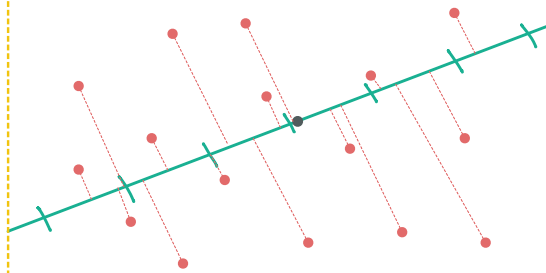
• expect to collide w/ at most one point $x \in P$ w/ $\angle(x, y) > 2\theta$

Lemma let $\bullet x, y \in S^{d-1}$
 $\bullet g \sim N^d$
 then

$$P[\text{sign}(\langle g, x \rangle) \neq \text{sign}(\langle g, y \rangle)] = \frac{\angle(x, y)}{\pi}$$

Random line embedding & Buckets

$$h(x) = \lfloor \langle g, x \rangle + d \rfloor \text{ w/ } g \sim N^d, d \in [0, 1] \text{ unifs. rand.}$$

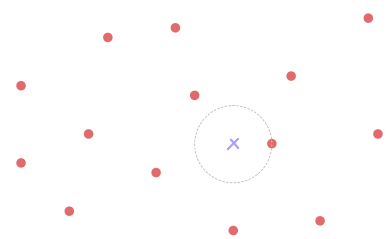


Algorithms

Approximate nearest neighbors

Nearest neighbor search

Input: n points $P \subset \mathbb{R}^d$



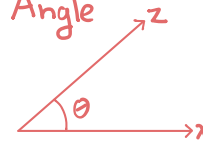
Query: given $q \in \mathbb{R}^d$, find closest point in P to q

Types of distances

• Euclidean distance

$$\|x - z\|_2 = \sqrt{\sum_i (x_i - z_i)^2}$$

• Angle



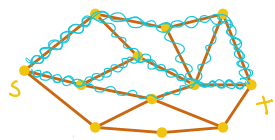
Lecture 10

Probability (and techniques)

LP duality

L_1 -metric embeddings

Max Flow Min Cut



Path Packing LP

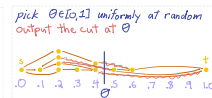
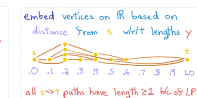
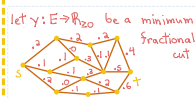
maximize $\sum_{p \in P} x_p$
over $x: P_{st} \rightarrow \mathbb{R}_{\geq 0}$
(all s-t paths)

s.t. $\sum_{p \in P} x_p \leq c_e$ for all edges e
"Ax ≤ c" (capacity of e)

Path Covering LP (i.e. cut)

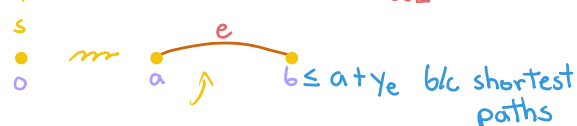
minimize $\sum_{e \in E} c_e y_e$
over $y: E \rightarrow \mathbb{R}_{\geq 0}$
(total capacity of "fractional cut")

s.t. $\sum_{e \in P} y_e \geq 1$ for all $p \in P_{st}$
"A'y ≥ b" (continuous analog of s-t cut)



$E[\text{capacity of cut}]$

$$\stackrel{\text{(linearity of expectation)}}{=} \sum_{e \in E} c_e \Pr[e \text{ cut}] \leq \sum_{e \in E} c_e y_e$$

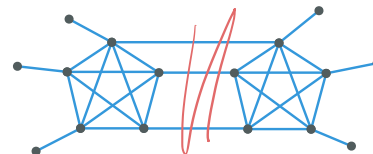


Algorithms

Sparsest Cut

Special case: uniform sparsest cut
w/ uniform demands $b(u,v) = 1 \quad \forall u,v$

$$\text{"sparsity"} = \frac{c(\delta(s))}{|S| |T|}$$



useful primitive for graph partitioning, divide & conquer

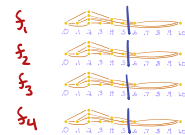
Q: how to round LP to sparse cut?

min $\sum_{e \in E} c_e d(u,v)$ over metrics $d: V \times V \rightarrow \mathbb{R}_{\geq 0}$
s.t. $\sum_{i=1}^k b_i d(s_i, t_i) \geq 1$

Suppose $d(u,v)$ was of the form

$$d(u,v) = \sum_{i=1}^k |\xi_i(u) - \xi_i(v)| \quad \text{for } \xi_i: V \rightarrow [0,1]^k$$

(assume $\min \xi_i(a) = 0, \max \xi_i(a) = 1$)



" L_1 -metric"

Lecture 11

Probability (and techniques)

Algorithms

Other metric-based problems
(sometimes via correspondence between cuts $\leftrightarrow$ metrics)

Buy-at-bulk network design
k-median clustering
metric labeling
group Steiner tree
metrical task systems
vehicle routing
hierarchical placement
distributed k-server
covering Steiner tree
⋮



these problems are easy for tree metrics

Approximation by tree metrics

Input: undirected $G=(V,E)$ w/ edge weights $w:E \rightarrow \mathbb{R}_{\geq 0}$

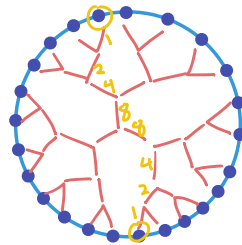
(High-level)
Goal: compute tree T (containing V as nodes)
so that shortest paths on T are close to T

$$d_T(u,v) \geq d_G(u,v)$$

$$\text{For } e=f_u,v \quad \begin{matrix} \text{(distance in } T) \\ \text{(stretch } e) = \frac{d_T(u,v)}{d_G(u,v)} \\ \text{(distance in } G) \end{matrix}$$

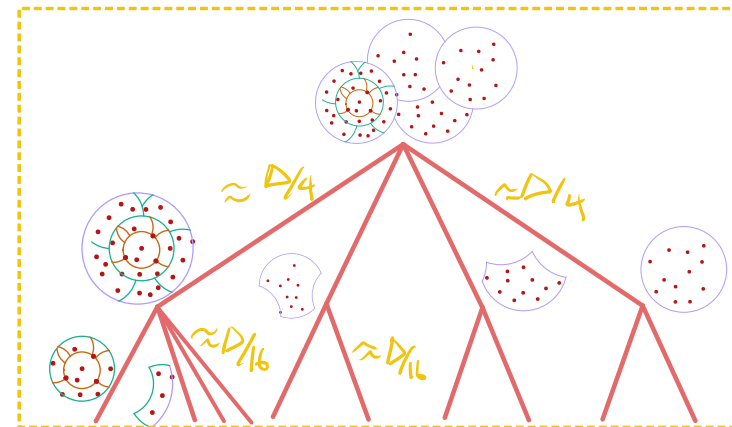
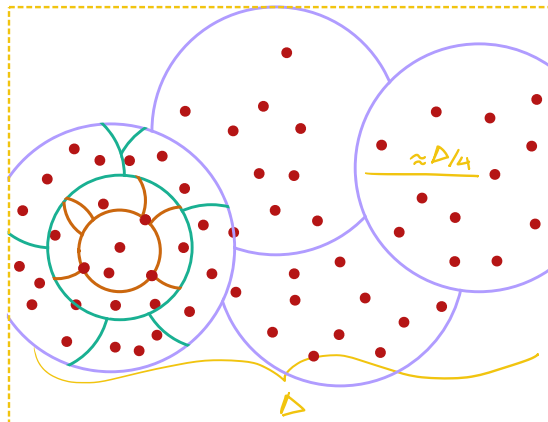
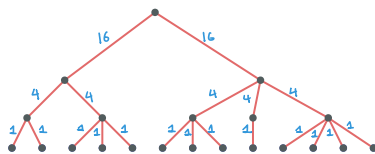
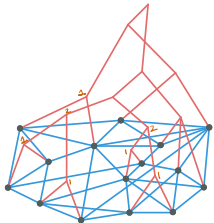
ideally

$$(\text{stretch } e) = \text{polylog}(n) \quad \forall e$$



Randomized Tree metrics

Theorem In randomized polynomial time,
randomized hierarchical dominating tree metric w/
 $E[\text{stretch } e] \leq O(\log n) \quad \forall e \in E$



Lecture 12

Probability (and techniques)

Additive Chernoff Inequality

Double-sampling

VC dimension

Additive Chernoff bound

let $X_1, \dots, X_n \in [0, 1]$ be independent

$$\mu = E[X_1 + \dots + X_n] / n$$

- $P[\frac{X_1 + \dots + X_n}{n} \geq \mu + \epsilon] \leq e^{-2\epsilon^2 n}$
- $P[\frac{X_1 + \dots + X_n}{n} \leq \mu - \epsilon] \leq e^{-2\epsilon^2 n}$

Algorithms

ϵ -samples and ϵ -nets

ϵ -sample $|M_Q(r) - \mu(r)| \leq \epsilon \quad \forall r \in R$

let Q sample k points w/ repetition
 $k = O\left(\frac{\ln(g(|P|))}{\epsilon^2}\right) \Rightarrow \epsilon$ -sample $k = O\left(\frac{\ln(g(|P|))}{\epsilon^2}\right) \Rightarrow \epsilon$ -net (w/ constant probability)

ϵ -sample theorem [VC71]
 $k \geq O\left(\frac{\ln(g(2k))}{\epsilon^2}\right) \Rightarrow \epsilon$ -sample (w/ constant probability)

e.g. $g(n) = O(n^d)$
 $k \geq O\left(\frac{d \ln(d/\epsilon)}{\epsilon^2}\right) \Rightarrow \epsilon$ -sample
 ↑ independent of $|P|$ (!)

$P[\frac{X_1 + \dots + X_n}{n} \geq \mu + \epsilon], P[\frac{X_1 + \dots + X_n}{n} \leq \mu - \epsilon] \leq e^{-2\epsilon^2 n}$ $g(n) = \max\{|RAQ| : \text{asf, lalsn}\}$

$\mu(r) = \frac{|P \cap r|}{|P|}$
 $M_Q(r) = \frac{|Q \cap r|}{|Q|}$
 $RAQ = \{r \cap q : r \in R, q \in Q\}$

ϵ -sample $|M_Q(r) - \mu(r)| \leq \epsilon \quad \forall r \in R$

let Q sample k points w/ repetition
 $k = O\left(\frac{\ln(g(|P|))}{\epsilon^2}\right) \Rightarrow \epsilon$ -sample $k = O\left(\frac{\ln(g(|P|))}{\epsilon^2}\right) \Rightarrow \epsilon$ -net (w/ constant probability)

ϵ -net theorem [HW87]
 $k \geq O\left(\frac{\ln(g(2k))}{\epsilon^2}\right) \Rightarrow \epsilon$ -net (w/ constant probability)

e.g. $g(n) = O(n^d)$
 $k \geq O\left(\frac{d \ln(d/\epsilon)}{\epsilon^2}\right) \Rightarrow \epsilon$ -net
 ↑ independent of $|P|$ (!)

$P[\frac{X_1 + \dots + X_n}{n} \geq \mu + \epsilon], P[\frac{X_1 + \dots + X_n}{n} \leq \mu - \epsilon] \leq e^{-2\epsilon^2 n}$ $g(n) = \max\{|RAQ| : \text{asf, lalsn}\}$

$\mu(r) = \frac{|P \cap r|}{|P|}$
 $M_Q(r) = \frac{|Q \cap r|}{|Q|}$
 $RAQ = \{r \cap q : r \in R, q \in Q\}$

Lecture 13

Probability
(and techniques)

Algorithms
(models and applications)

Consistency model

PAC learning model

Generalization error

Occam's Razor

Generalization by growth

Lecture 14

Probability
(and techniques)

Algorithms
(models and applications)

Entropy

(Optimal)
Error-Correcting
Codes

Lecture 15

Probability (and techniques)

Algorithms (models and applications)

Lovász Local Lemma

Moser's resampling
algorithm

Lecture 16

Probability (and techniques)

Algorithms (models and applications)

Random Walks

Stationary Distribution

Perron-Frobenius Theorem

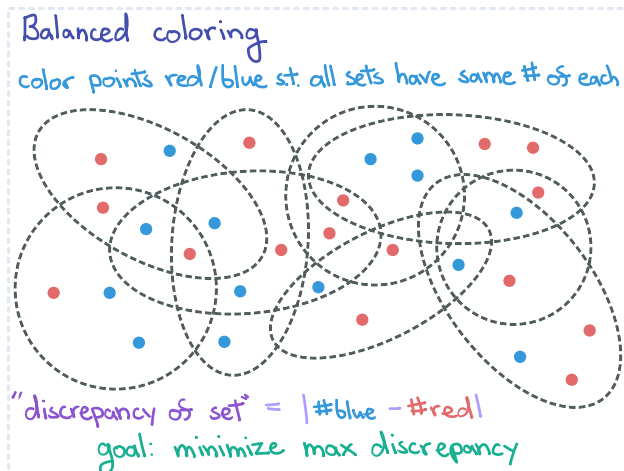
Pagerank

Lecture 17

Probability (and techniques)

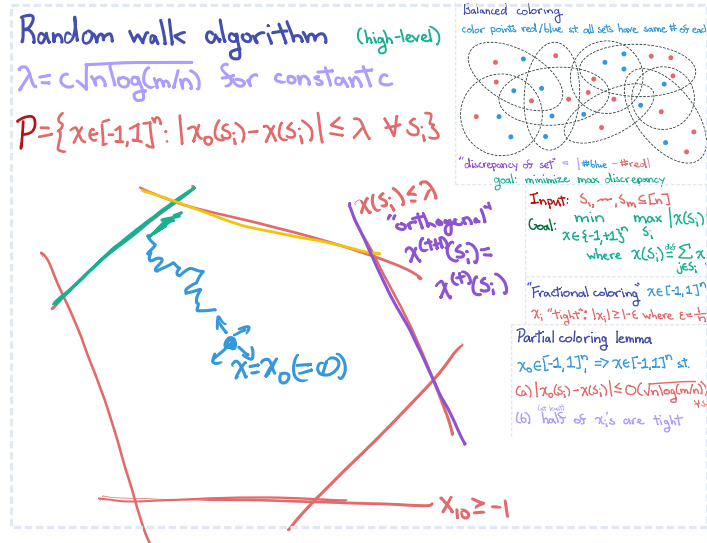
High-dimensional random walks

More fun w/ Gaussians



Algorithms (models and applications)

Discrepancy minimization



Lecture 18

Probability (and techniques)

Algorithms (models and applications)

Hitting times

Cover times

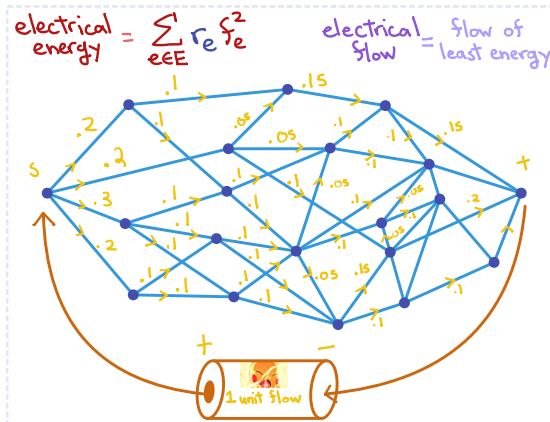
Electrical networks

Connectivity
in $O(\log n)$ space

random walk terminology:

Hitting time $H(s, t)$ = expected # steps until a random walk from s reaches t

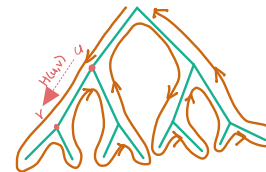
Cover time $C(s)$ = expected # steps until a random walk from s visits every vertex



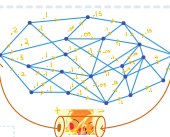
Lemma $H(u, v) + H(v, u) = 2m \cdot (\text{energy of unit flow } (u, v))$

Theorem $C(s) \leq 2mn$

proof Six traversal of spanning tree



$$\begin{aligned} \text{total time} &= \sum_{u, v \in V} H(u, v) + H(v, u) \\ &= 2m \sum_{u, v \in V} (\text{energy of unit flow } (u, v)) \leq 2m(n-1) \end{aligned}$$



electrical energy = $\sum_{e \in E} r_e f_e^2$
electrical flow = least energy

des $B: \mathbb{R}^E \rightarrow \mathbb{R}^V$ by
(BS) $_v$ = net flow at v
 $d_v = \begin{cases} -1 & \text{if } v \text{ is } s \\ 1 & \text{if } v \text{ is } t \\ 0 & \text{otherwise} \end{cases}$

min $\frac{1}{2} \sum_{e \in E} r_e f_e^2$ s.t. $BS = d$
(electrical energy) (is a typical)

effective resistance of d = optimum value/energy

Ohm's law: $f = R^{-1} B^T p$
for electric flow by electric potentials p
 $L = BR^{-1}B^T \in \mathbb{R}^{V \times V}$
(effective resist. of d) $\leq \langle d, L^{-1}d \rangle$

Lecture 19

Probability (and techniques)

Algorithms (models and applications)

Spectral theorem
for symmetric maps

Spectral analysis of
random walks

Let R have eigenvalues

$$\mu_1 = 1 \geq \mu_2 \geq \dots \geq \mu_n \geq -1$$

Theorem. let $\gamma = 1 - \max\{\mu_2, |\mu_n|\}$

$$\|R^k x - s\| \leq (1 - \gamma)^k \sqrt{\frac{\Delta_{\max}}{\Delta_{\min}}}$$

↑
stationary
distribution

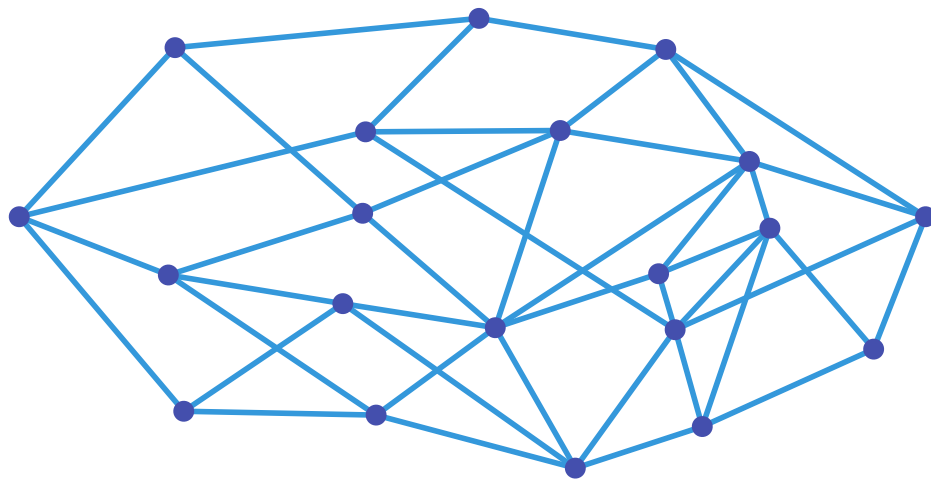
Lecture 19

Probability (and techniques)

Algorithms (models and applications)

Spectral theorem
for symmetric maps

Spectral analysis of
random walks



Laplacian

$$L \in \mathbb{R}^{n \times n}$$

(symmetric, positive semidefinite)

Rank-1 matrix

$$u \otimes v \quad \text{where } u, v \in \mathbb{R}^n$$

(aka. uv^T)

defined by $\langle x, (u \otimes v) y \rangle = \langle x, u \rangle \langle v, y \rangle$

as a matrix:

$$u \otimes v = \begin{bmatrix} u_1 v_1 & u_1 v_2 & \cdots & u_1 v_n \\ u_2 v_1 & u_2 v_2 & & u_2 v_n \\ \vdots & \vdots & \ddots & \vdots \\ u_n v_1 & u_n v_2 & & u_n v_n \end{bmatrix}$$

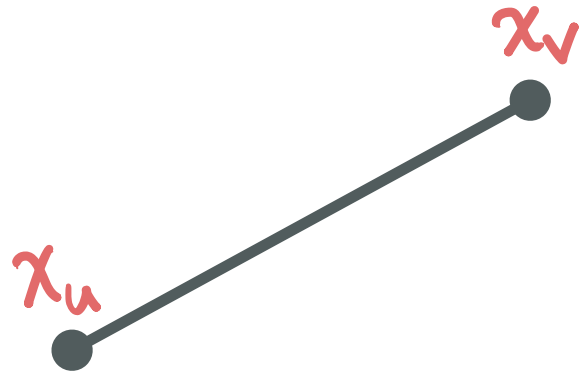
Laplacian of an edge $e = \{u, v\}$

Rank-1 matrix
 $u \otimes v$ where $u, v \in \mathbb{R}^n$
 $\langle x, (u \otimes v) y \rangle = \langle x, u \rangle \langle v, y \rangle$

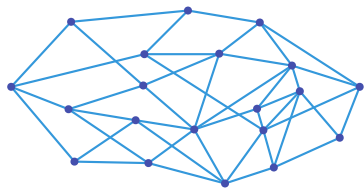
$$L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{V \times V}$$

($1_u = \{0, 1\}$ -indicator vector for u)

$$\langle x, L_e x \rangle = (x_u - x_v)^2$$



Laplacian of



$G=(V,E)$ w/ edge weights $w \in \mathbb{R}_{\geq 0}^E$

$$L = \sum_{e \in E} w(e) L_e$$

$$\langle x, Lx \rangle = \sum_{\substack{e \in E \\ e=\{u,v\}}} w(e) (x_u - x_v)^2$$

Rank-1 matrix
 $u \otimes v$ where $u, v \in \mathbb{R}^n$
 $\langle x, (u \otimes v) y \rangle = \langle x, u \rangle \langle v, y \rangle$

Laplacian of $e = \{u, v\}$

$$L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{V \times V}$$

($1_u = \{0,1\}$ -indicator vector for u)

$$\langle x, L_e x \rangle = (x_u - x_v)^2$$

$$L = \sum_{e \in E} w(e) L_e$$

$$\langle x, Lx \rangle = \sum_{\substack{e \in E \\ e = \{u, v\}}} w(e) (x_u - x_v)^2$$

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 $u \otimes v$ where $u, v \in \mathbb{R}^n$
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 Laplacian of $e = \{u, v\}$
 $L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{V \times V}$
($1_u = \{0, 1\}$ -indicator vector for u)
 $\langle x, L_e x \rangle = (x_u - x_v)^2$

$A \in \mathbb{R}^{n \times n}$ is positive semi-definite if:

- A is symmetric
- $\langle x, Ax \rangle \geq 0 \quad \forall x$

(A is positive definite if it is positive semi-definite &)

- A is invertible

Recall:

$$Ax = \lambda x$$

“eigenvalue”

“eigenvector”

Lemma every linear map A has an eigenvalue $\lambda \in \mathbb{C}$ and eigenvector $x \in \mathbb{C}^n$

Rank-1 matrix
 $u \otimes v$ where $u, v \in \mathbb{R}^n$
 $\langle x, (u \otimes v) y \rangle = \langle x, u \rangle \langle v, y \rangle$

Laplacian of $e = \{u, v\}$
 $L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{n \times n}$
($1_u = \{0, 1\}$ -indicator vector for u)
 $\langle x, L_e x \rangle = (x_u - x_v)^2$

Laplacian of 
 $L = \sum_{e \in E} w(e) L_e$
 $\langle x, Lx \rangle = \sum_{e = \{u, v\}} w(e) (x_u - x_v)^2$

positive semi-definite A :

- A is symmetric
- $\langle x, Ax \rangle \geq 0 \quad \forall x$

Lemma every linear map A has an eigenvalue $\lambda \in \mathbb{C}$ and eigenvector $x \in \mathbb{C}^n$

Lemma: $L \in \mathbb{R}^{n \times n}$ symmetric,

$x \in \mathbb{R}^n$ maximizes $\langle x, Lx \rangle$ over $\|x\|=1$

$\Rightarrow Lx = \mu x$ for $\mu = \langle x, Lx \rangle$

note: $\mu = \langle x, Lx \rangle \in \mathbb{R}$

Rank-1 matrix
 $u \otimes v$ where $u, v \in \mathbb{R}^n$
 $\langle x, (u \otimes v) y \rangle = \langle x, u \rangle \langle v, y \rangle$

Laplacian of $e = \{u, v\}$

$$L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{n \times n}$$

($1_u = \{0, 1\}$ -indicator vector for u)

$$\langle x, L_e x \rangle = (x_u - x_v)^2$$

Laplacian of 

$$L = \sum_{e \in E} w(e) L_e$$

$$\langle x, Lx \rangle = \sum_{e = \{u, v\}} w(e) (x_u - x_v)^2$$

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- $\langle x, Ax \rangle \geq 0 \quad \forall x$

"eigenvalue"

$$Ax = \lambda x$$

"eigenvector"

Lemma: $L \in \mathbb{R}^{n \times n}$ symmetric,
 $x \in \mathbb{R}^n$ maximizes $\langle x, Lx \rangle$ over $\|x\|=1$
 $\Rightarrow Lx = \mu x$ for $\mu = \langle x, Lx \rangle$

proof.

claim: for $u \in \mathbb{R}^n$,

if $\langle u, x \rangle = 0$, then $\langle u, Lx \rangle = 0$.

if claim is true:

$$\Rightarrow Lx \in \text{span}(x)$$

$$\Rightarrow Lx = \mu_1 x \text{ for some } \mu_1 \in \mathbb{R}$$

$$\Rightarrow \mu_1 = \mu_1 \langle x, x \rangle = \langle x, Lx \rangle$$

Rank-1 matrix
 $u \otimes v$ where $u, v \in \mathbb{R}^n$
 $\langle x, (u \otimes v) y \rangle = \langle x, u \rangle \langle v, y \rangle$

Laplacian of $e = \{u, v\}$
 $L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{n \times n}$
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 $\langle x, L_e x \rangle = (x_u - x_v)^2$

Laplacian of 
 $L = \sum_{e \in E} w(e) L_e$
 $\langle x, Lx \rangle = \sum_{e = \{u, v\}} w(e) (x_u - x_v)^2$

positive semi-definite A :

- A is symmetric
- $\langle x, Ax \rangle \geq 0 \quad \forall x$

"eigenvalue"
 $Ax = \lambda x$
 "eigenvector"

$L \in \mathbb{R}^{n \times n}$ symmetric,
 $x \in \mathbb{R}^n$ maximizes $\langle x, Lx \rangle$ over $\|x\|=1$

claim: if $\langle u, x \rangle = 0$, then $\langle u, Lx \rangle = 0$.

let $u \in \mathbb{R}^n$ w/ $\langle u, x \rangle = 0$, $\|u\|=1$

define $f(\varepsilon) = \frac{\langle x + \varepsilon u, L(x + \varepsilon u) \rangle}{1 + \varepsilon^2}$

(note: $\|x + \varepsilon u\|^2 = \|x\|^2 + \varepsilon^2 \|u\|^2 = 1 + \varepsilon^2$)

f is max'd at $\varepsilon = 0$

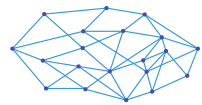
$$f'(0) = 0$$

$$f'(x) = \sim \sim$$

$$f(0) = 0$$

Rank-1 matrix
 $u \otimes v$ where $u, v \in \mathbb{R}^n$
 $\langle x, (u \otimes v) y \rangle = \langle x, u \rangle \langle v, y \rangle$

Laplacian of $e = \{u, v\}$
 $L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{n \times n}$
($1_u = \{0, 1\}$ -indicator vector for u)
 $\langle x, L_e x \rangle = (x_u - x_v)^2$

Laplacian of 
 $L = \sum_{e \in E} w(e) L_e$
 $\langle x, Lx \rangle = \sum_{e = \{u, v\}} w(e) (x_u - x_v)^2$

positive semi-definite A :

- A is symmetric
- $\langle x, Ax \rangle \geq 0 \quad \forall x$

"eigenvalue"
 $Ax = \lambda x$
 "eigenvector"

Rank-1 matrix
 $u \otimes v$ where $u, v \in \mathbb{R}^n$
 $\langle x, (u \otimes v) y \rangle = \langle x, u \rangle \langle v, y \rangle$

Laplacian of $e = \{u, v\}$

$$L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{V \times V}$$

($1_u = \{0, 1\}$ -indicator vector for u)

$$\langle x, L_e x \rangle = (x_u - x_v)^2$$

Laplacian of 

$$L = \sum_{e \in E} w(e) L_e$$

$$\langle x, Lx \rangle = \sum_{e = \{u, v\}} w(e) (x_u - x_v)^2$$

positive semi-definite A :

- A is symmetric
- $\langle x, Ax \rangle \geq 0 \quad \forall x$

"eigenvalue" $\swarrow$

$$Ax = \lambda x$$

$\nwarrow$ "eigenvector"

Lemma: $L \in \mathbb{R}^{n \times n}$ symmetric,
 $x \in \mathbb{R}^n$ maximizes $\langle x, Lx \rangle$ over $\|x\|=1$
 $\Rightarrow Lx = \mu x$ for $\mu = \langle x, Lx \rangle$

proof.

✓ for $u \in \mathbb{R}^n$,

if $\langle u, x \rangle = 0$, then $\langle u, Lx \rangle = 0$.

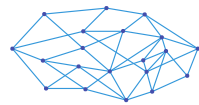
$\Rightarrow Lx \in \text{span}(x)$

$\Rightarrow Lx = \mu_1 x$ for some $\mu_1 \in \mathbb{R}$

$\Rightarrow \mu_1 = \mu_1 \langle x, x \rangle = \langle x, Lx \rangle$

Rank-1 matrix
 $u \otimes v$ where $u, v \in \mathbb{R}^n$
 $\langle x, (u \otimes v) y \rangle = \langle x, u \rangle \langle v, y \rangle$

Laplacian of $e = \{u, v\}$
 $L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{n \times n}$
 $(1_u = \{0, 1\}$ -indicator vector for u)
 $\langle x, L_e x \rangle = (x_u - x_v)^2$

Laplacian of 
 $L = \sum_{e \in E} w(e) L_e$

$\langle x, Lx \rangle = \sum_{e = \{u, v\}} w(e) (x_u - x_v)^2$

positive semi-definite A :

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- $\langle x, Ax \rangle \geq 0 \quad \forall x$

"eigenvalue"
 $Ax = \lambda x$
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Lemma: $L \in \mathbb{R}^{n \times n}$ symmetric,
 $x \in \mathbb{R}^n$ maximizes $\langle x, Lx \rangle$ over $\|x\|=1$
 $\Rightarrow Lx = \mu x$ for $\mu = \langle x, Lx \rangle$

Rank-1 matrix
 $u \otimes v$ where $u, v \in \mathbb{R}^n$
 $\langle x, (u \otimes v) y \rangle = \langle x, u \rangle \langle v, y \rangle$

Laplacian of $e = \{u, v\}$
 $L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{n \times n}$
 $(1_u = \{0, 1\}$ -indicator vector for u)
 $\langle x, L_e x \rangle = (x_u - x_v)^2$

Spectral theorem. $L \in \mathbb{R}^{n \times n}$ symmetric

then $L = \lambda_1 (v_1 \otimes v_1) + \dots + \lambda_n (v_n \otimes v_n)$

where $\lambda_1, \dots, \lambda_n \in \mathbb{R}$

$v_1, \dots, v_n$ orthonormal basis

$$Lv_k = \sum_i \lambda_i (v_i \otimes v_i) v_k = \sum_i \lambda_i \langle v_i, v_k \rangle v_i = \lambda_k v_k$$

Laplacian of 
 $L = \sum_{e \in E} w(e) L_e$
 $\langle x, Lx \rangle = \sum_{e = \{u, v\}} w(e) (x_u - x_v)^2$

positive semi-definite A :

- A is symmetric
- $\langle x, Ax \rangle \geq 0 \quad \forall x$

"eigenvalue"
 $Ax = \lambda x$
 "eigenvector"

Spectral theorem. $L \in \mathbb{R}^{n \times n}$ symmetric

$$\text{then } L = \lambda_1 (v_1 \otimes v_1) + \dots + \lambda_n (v_n \otimes v_n)$$

where $\lambda_1, \dots, \lambda_n \in \mathbb{R}$

$v_1, \dots, v_n$ orthonormal basis

proof let $v_n \max \langle v_n, L v_n \rangle$ s.t. $\|v_n\|=1$

$$\lambda_n = \langle v_n, L v_n \rangle$$

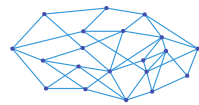
$$A = L - \lambda_n (v_n \otimes v_n) \quad \checkmark \text{ symmetric}$$

$$A v_n = L v_n - \lambda_n v_n = 0$$

$$\gamma = \{x \in \mathbb{R}^n : \langle x, v_n \rangle = 0\}$$

Rank-1 matrix
 $u \otimes v$ where $u, v \in \mathbb{R}^n$
 $\langle x, (u \otimes v) y \rangle = \langle x, u \rangle \langle v, y \rangle$

Laplacian of $e = \{u, v\}$
 $L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{V \times V}$
($1_u = \{0, 1\}$ -indicator vector for u)
 $\langle x, L_e x \rangle = (x_u - x_v)^2$

Laplacian of 
 $L = \sum_{e \in E} w(e) L_e$
 $\langle x, L x \rangle = \sum_{e = \{u, v\}} w(e) (x_u - x_v)^2$

positive semi-definite A :
• A is symmetric
• $\langle x, A x \rangle \geq 0 \quad \forall x$

Lemma: $L \in \mathbb{R}^{n \times n}$ symmetric,
 $x \in \mathbb{R}^n$ maximizes $\langle x, L x \rangle$ over $\|x\|=1$
 $\Rightarrow L x = \mu x$ for $\mu = \langle x, L x \rangle$

Claim: A maps Y into Y

$\forall y \in Y,$

$$\langle v_n, Ay \rangle = \langle Av_n, y \rangle = \langle 0, y \rangle = 0$$

$$A: Y \rightarrow Y$$

$$A = \lambda_1(v_1 \otimes v_1) + \dots + \lambda_{n-1}(v_{n-1} \otimes v_{n-1})$$

by induc.

$$L = A + \lambda_n(v_n \otimes v_n)$$

Rank-1 matrix
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 $\langle x, (u \otimes v)y \rangle = \langle x, u \rangle \langle v, y \rangle$

Laplacian of $e = \{u, v\}$
 $L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{V \times V}$
 $(1_u = \{0, 1\}$ -indicator vector for u)
 $\langle x, L_e x \rangle = (x_u - x_v)^2$

Laplacian of 
 $L = \sum_{e \in E} w(e) L_e$
 $\langle x, Lx \rangle = \sum_{e = \{u, v\}} w(e) (x_u - x_v)^2$

positive semi-definite A :

- A is symmetric
- $\langle x, Ax \rangle \geq 0 \quad \forall x$

Lemma: $L \in \mathbb{R}^{n \times n}$ symmetric,
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Spectral theorem. $L \in \mathbb{R}^{n \times n}$ symmetric

$$L = \lambda_1 (v_1 \otimes v_1) + \dots + \lambda_n (v_n \otimes v_n)$$

where $\lambda_1, \dots, \lambda_n \in \mathbb{R}$

$v_1, \dots, v_n$ orthonormal basis

For $x \in \mathbb{R}^n$, write

$$x = d_1 v_1 + \dots + d_n v_n \quad (\text{unique, } d_i = \langle x, v_i \rangle)$$

$$Lx = \lambda_1 (v_1 \otimes v_1)x + \dots + \lambda_n (v_n \otimes v_n)x$$

$$\begin{aligned} & \langle v_1, x \rangle = d_1 \\ &= \lambda_1 \underline{d_1} v_1 + \lambda_2 \underline{d_2} v_2 + \dots + \lambda_n \underline{d_n} v_n \end{aligned}$$

Rank-1 matrix
 $u \otimes v$ where $u, v \in \mathbb{R}^n$
 $\langle x, (u \otimes v)y \rangle = \langle x, u \rangle \langle v, y \rangle$

Laplacian of $e = \{u, v\}$

$$L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{n \times n}$$

($1_u = \{0, 1\}$ -indicator vector for u)

$$\langle x, L_e x \rangle = (x_u - x_v)^2$$

Laplacian of 

$$L = \sum_{e \in E} w(e) L_e$$

$$\langle x, Lx \rangle = \sum_{e = \{u, v\}} w(e) (x_u - x_v)^2$$

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- A is symmetric
- $\langle x, Ax \rangle \geq 0 \quad \forall x$

Lemma: $L \in \mathbb{R}^{n \times n}$ symmetric,
 $x \in \mathbb{R}^n$ maximizes $\langle x, Lx \rangle$ over $\|x\|=1$
 $\Rightarrow Lx = \mu x$ for $\mu = \langle x, Lx \rangle$

Lecture 19

Probability (and techniques)

Algorithms (models and applications)

✓ Spectral theorem
for symmetric maps

Spectral analysis of
random walks

Recall:

$$\text{score}_3(v) = \sum_{(u,v) \in E} \frac{\text{score}_3(u)}{\deg^+(u)}$$



let $\Delta^V = \{x \in \mathbb{R}_V^{\geq 0} : \sum_v x_v = 1\} = \{\text{distributions over } V\}$

Theorem there exists $x \in \Delta^V$ s.t.

$$x_v = \sum_{(u,v) \in E} \frac{x_u}{\deg^+(u)} \quad \forall v \in V.$$

If G is strongly connected, then x is unique and strictly positive.

Theorem, restated: every random walk has a stationary distribution. If G is strongly connected, then this distribution is unique.

Theorem, restated: let G be a dir. graph and R the random walk linear map. Then R has an eigenvector $x \in \Delta^V$ w/ eigenvalue 1. If G is strongly connected, then x is the unique eigenvector w/ eigenvalue 1

Theorem: $G=(V,E)$ undirected, $w:E \rightarrow \mathbb{R}_{>0}$

let $R:\mathbb{R}^V \rightarrow \mathbb{R}^V$ be random walk map

then R has stationary distr. $s \in \Delta_V$ w/

$$s_v = \frac{\deg(v)}{2W}$$

$$\deg(v) = \sum_{e \in \mathcal{E}(v)} w(e)$$

$$W = \sum_{e \in E} w(e)$$

Proof $d \in \mathbb{R}^V$ be the degrees

$$D = \text{diag}(d)$$

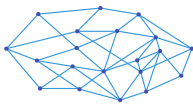
$$A = \text{adj. matrix} \in \mathbb{R}^{n \times n}$$

$$R = AD^{-1}$$

$$Rd = AD^{-1}d = A\mathbb{1} = d$$

Rank-1 matrix
 $u \otimes v$ where $u, v \in \mathbb{R}^n$
 $\langle x, (u \otimes v) y \rangle = \langle x, u \rangle \langle v, y \rangle$

Laplacian of $e = \{u, v\}$
 $L_e = (1_u - 1_v) \otimes (1_u - 1_v) \in \mathbb{R}^{V \times V}$
 $(1_u = \{0,1\}$ -indicator vector for u)
 $\langle x, L_e x \rangle = (x_u - x_v)^2$

Laplacian of 
 $L = \sum_{e \in E} w(e) L_e$

$$\langle x, Lx \rangle = \sum_{e=\{u,v\}} w(e) (x_u - x_v)^2$$

positive semi-definite A :

- A is symmetric
- $\langle x, Ax \rangle \geq 0 \quad \forall x$

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 $L = \lambda_1 (v_1 \otimes v_1) + \dots + \lambda_n (v_n \otimes v_n)$
 where $\lambda_1, \dots, \lambda_n \in \mathbb{R}$
 $v_1, \dots, v_n$ orthonormal basis

Let R have eigenvalues

$$\mu_1 = 1 \geq \mu_2 \geq \dots \geq \mu_n \geq -1$$

Theorem. let $\gamma = 1 - \max\{\mu_2, |\mu_n|\}$

$$\|R^k x - s\| \leq (1 - \gamma)^k \sqrt{\frac{\Delta_{\max}}{\Delta_{\min}}}$$

↑
stationary
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$$s_v = \frac{\deg(v)}{2W} \quad \deg(v) = \sum_{e \in \mathcal{E}(v)} w(e), \quad W = \sum_{e \in E} w(e)$$

Similar matrices

$A, B \in \mathbb{R}^{n \times n}$ are similar if

$$A = C^{-1}BC \text{ for some invertible } C \in \mathbb{R}^{n \times n}$$

let $A = C^{-1}BC$.

Lemma C restricts to isomorphism
between $\ker(A)$ and $\ker(B)$.

proof: if $Ax = 0$

$$B(Cx) = CAx = C0 = 0$$

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$$= 0$$

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Lemma

- A and B have same eigenvalues
- C maps eigenvectors of A to eigenvectors of B

why? $\forall \lambda$,

$$(A - \lambda I) = C^{-1}(B - \lambda I)C$$

if $Ax = \lambda x$

$$B(Cx) = CC^{-1}BCx = CAx = \lambda Cx$$

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$$Q = v_1 \otimes v_1 + \mu_2 (v_2 \otimes v_2) + \dots + \mu_n (v_n \otimes v_n)$$

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(also eigenvalues of R)

$D^{1/2} v_1 \leftrightarrow \text{stationary distribution}$

$$v_1 = \frac{\sqrt{d}}{\|\sqrt{d}\|} = \frac{\sqrt{d}}{\sqrt{\langle \mathbf{1}, d \rangle}}$$

$$v_1 \propto D^{-1/2} d = \sqrt{d}$$

$$\|\sqrt{d}\|^2 = \langle \sqrt{d}, \sqrt{d} \rangle = \langle \mathbf{1}, d \rangle$$

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$$R = D^{1/2} Q D^{-1/2}$$

$Q =$

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w/ $\mu_1 = 1 \geq \mu_2 \geq \dots \geq \mu_n$ (also eigenvalues of R)

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$$R^k x = (D^{1/2} Q D^{-1/2})^k x$$

$$= D^{1/2} Q^k D^{-1/2} x$$

$$= D^{1/2} \left(\frac{\sqrt{d} \otimes \sqrt{d}}{\langle \mathbf{1}, d \rangle} + \mu_2 (v_2 \otimes v_2) + \dots + \mu_n (v_n \otimes v_n) \right)^k D^{-1/2} x$$

$$= D^{1/2} \left(\frac{\sqrt{d} \otimes \sqrt{d}}{\langle \mathbf{1}, d \rangle} + \mu_2^k (v_2 \otimes v_2) + \dots + \mu_n^k (v_n \otimes v_n) \right)^k D^{-1/2} x$$

$$(v_i \otimes v_i)(v_j \otimes v_j) = \langle v_i, v_j \rangle v_i \otimes v_j$$

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$$= D^{1/2} \left(\frac{\sqrt{d} \otimes \sqrt{d}}{\langle \mathbf{1}, d \rangle} \right) D^{-1/2} x$$

$$+ D^{1/2} (\mu_2^k (v_2 \otimes v_2) + \dots + \mu_n^k (v_n \otimes v_n)) D^{-1/2} x$$

$$D^{1/2} \left(\frac{\sqrt{d} \otimes \sqrt{d}}{\langle \mathbf{1}, d \rangle} \right) D^{-1/2} = \frac{d \otimes \mathbf{1}}{\langle \mathbf{1}, d \rangle}$$

$$\frac{d \otimes \mathbf{1}}{\langle \mathbf{1}, d \rangle} x = \underbrace{\frac{d}{\langle \mathbf{1}, d \rangle}}_S \underbrace{\langle \mathbf{1}, x \rangle}_1$$

$$= \frac{d}{\langle \mathbf{1}, d \rangle} +$$

$$D^{1/2} (\mu_2^k (v_2 \otimes v_2) + \dots + \mu_n^k (v_n \otimes v_n)) D^{-1/2} x$$

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$$\|R^k x - \frac{d}{\langle 1, d \rangle}\|_2^2$$

$$\|D^{1/2} (\mu_2(v_2 \otimes v_2) + \dots + \mu_n(v_n \otimes v_n)) D^{-1/2} x\|_2^2$$

=

$$\Delta_{\max} \|(\mu_2(v_2 \otimes v_2) + \dots + \mu_n(v_n \otimes v_n)) D^{-1/2} x\|_2^2$$

$$\|S D^{-1/2} x\|^2 = \langle D^{-1/2} x, S^2 D^{-1/2} x \rangle$$

$$\leq \underbrace{\max\{\mu_2, \mu_n\}}_{(1-\delta)^k} \|D^{-1/2} x\|^2$$

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$$\langle x, Lx \rangle \leq \lambda_{\max} \|x\|^2$$

$$\|D^{-1/2}x\|^2 = \sum_v \frac{x_v^2}{\deg_v^2} \leq \frac{x_v^2}{\Delta_{\min}}$$

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 $\Rightarrow Lx = \mu x$ for $\mu = \langle x, Lx \rangle$

Spectral theorem. $L \in \mathbb{R}^{n \times n}$ symmetric
 $L = \lambda_1 (v_1 \otimes v_1) + \dots + \lambda_n (v_n \otimes v_n)$
where $\lambda_1, \dots, \lambda_n \in \mathbb{R}$
 $v_1, \dots, v_n$ orthonormal basis

Theorem: $G=(V, E)$ undirected, $w: E \rightarrow \mathbb{R}_{>0}$
then R has stationary distr. $s \in \Delta_V$ w/

$$s_v = \frac{\deg(v)}{2W} \quad \deg(v) = \sum_{e \in \mathcal{E}(v)} w(e), \quad W = \sum_{e \in E} w(e)$$

Lemma let $A = C^{-1}BC$.

- A and B have same eigenvalues
- C maps eigenvectors of A to eigenvectors of B

Normalized random walk matrix

$$Q = D^{-1/2} R D^{1/2} = D^{-1/2} A D^{1/2}$$

- $D = \text{diag}(d)$ w/ $d = \text{degrees}$
- $A = \text{adjacency matrix}$
- $R = A D^{-1} = \text{random walk matrix}$
- Q is symmetric!
- Q has same eigenvalues as R !