

6.889 Sub-linear Time Algorithms

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Lecture 1

Topics:

- Overview
- Diameter of point set
- #Connected Components
- MST

Overview

- Big data - how do you access it?
too much to view it all?
can change by the time you
make a decision?
- e.g. what is "diameter" of facebook graph?
- Compromise:
"exactly", "for all", "there exists" statements
 \Rightarrow "approximately", "there is a large group" ...
- Models:
 - i) Random access queries - can access word of input in step
 - adj matrix vs. adj list
 - look i
 - 2) Samples - get sample of distribution/input in step

Course requirements :

- Scribing 25%
must be in latex
- Psets 35%
- Project 25%
- Class participation 15%
(includes grading)

Projects :

- groups of 1-3
- Possible ideas:
 - solve new problem (or try ideas + explain why they fail)
 - read + survey some papers
 - implement an algorithm (or two or three)

A first Example: Diameter of a point set

Input m points described by distance matrix D
 s.t. D_{ij} is distance from i, j

+ D is : 1) symmetric
 2) satisfies $\Delta \neq$
 i.e. $D_{ij} \leq D_{ik} + D_{kj} \quad \forall i, j, k$

Output

let i, j be s.t. D_{ij} is max $\Leftarrow D_{ij}$ is "diameter"

Output k, l s.t. $D_{kl} = \frac{D_{ij}}{2} \Leftarrow 2\text{-approximation}$

Algorithm

- Pick k arbitrarily
- Pick l to maximize D_{kl}
- Output k, l

runtime: $O(m) = O(\sqrt{n})$

Why does it work?

$$\begin{aligned} D_{ij} &\leq D_{ik} + D_{kl} & \Delta \neq \\ &= D_{ki} + D_{kl} & \text{Symmetry} \\ &\leq D_{ki} + D_{kl} & \text{choice of } l \\ &\leq 2D_{kl} \end{aligned}$$

How many connected components in G ?

Input $G = (V, E)$, ϵ adjacency list representation
 max degree d $|V| = n$
 $|E| = m \leq d \cdot n$

Output y s.t. if $C = \# \text{ conn comp}$
 then $C - \epsilon \cdot n \leq y \leq C + \epsilon n$ ← "additive approx to w/in ϵn "

A different characterization of # conn components:

notation: $\forall v$ let $n_v \equiv \# \text{ nodes in } v\text{'s conn comp.}$

observation: \forall connected component $A \subseteq V$
 $\sum_{u \in A} \frac{1}{n_u} = \sum_{u \in A} \frac{1}{|A|} = 1$

So new characterization of # conn comp:

$$C = \sum_{u \in V} \frac{1}{n_u}$$

Why is this better?

(computing $\frac{1}{n_u}$ needs $O(n)$ time?
 sum $O(n)$ terms? ← will estimate!

Estimating $C = \sum_{u \in V} \frac{1}{n_u}$:

Two ideas:

- 1) estimate $\frac{1}{n_u}$ quickly
- 2) estimate $\sum_u \frac{1}{n_u}$ via sampling bounds

Estimating $\frac{1}{n_u}$:

$$\text{def. } \hat{n}_u \equiv \min\{n_u, 2/\varepsilon\}$$

$$\hat{C} \equiv \sum_{u \in V} \frac{1}{\hat{n}_u}$$

$$\text{Lemma } \forall u \quad \left| \frac{1}{n_u} - \frac{1}{\hat{n}_u} \right| \leq \frac{\varepsilon}{2}$$

$$\text{Corr } |C - \hat{C}| \leq \frac{\varepsilon n}{2} \quad \leftarrow \text{ so if it is useful! can compute } \hat{C} \text{ faster,}$$

Pf of lemma

$$\text{if } n_u \leq 2/\varepsilon \text{ then } \hat{n}_u = n_u \text{ so } \left| \frac{1}{n_u} - \frac{1}{\hat{n}_u} \right| = 0$$

$$\text{else } n_u > 2/\varepsilon \text{ so } \hat{n}_u = 2/\varepsilon < n_u$$

$$\Rightarrow 0 \leq \frac{1}{n_u} - \frac{1}{\hat{n}_u} \leq \frac{1}{\hat{n}_u} = \frac{\varepsilon}{2}$$

↑ since $n_u > 0$

$$\Rightarrow \left| \frac{1}{\hat{n}_u} - \frac{1}{n_u} \right| \leq \frac{\varepsilon}{2} \quad \blacksquare$$

How long to compute \hat{n}_u ?

Algorithm compute \hat{n}_u

Do BFS starting from a until

- visit whole component of a
- or visit $2/\epsilon$ distinct nodes

Output # visited nodes

runtime

$$O(d \cdot \gamma_\epsilon)$$

\uparrow
time per step of BFS

How to estimate $\sum_u \frac{1}{\hat{n}_u}$?

Algorithm estimate \tilde{c}

$$r \leftarrow b/\epsilon^3$$

Choose $U = \{u_1, \dots, u_r\}$ random nodes

$\forall u \in U$
Compute \hat{n}_u via above algorithm

$$\text{Output } \tilde{c} = \frac{n}{r} \sum_{u \in U} \frac{1}{\hat{n}_u}$$

runtime

$$O((d/\epsilon) \cdot \gamma_\epsilon^3) = O(d/\epsilon^4)$$

Why is it good?

$$\text{Thm} \quad \Pr[|\tilde{C} - \hat{C}| \leq \varepsilon n/2] \geq 3/4$$

Pf

Chernoff Bnd: X_1, \dots, X_r iid $X_i \in [0, 1]$

$$S = \sum_{i=1}^r X_i \quad p = E[X_i] = E[S]/r$$

$$\text{Then: } \Pr\left[|\frac{S}{r} - p| \geq \delta p\right] \leq e^{-\Omega(rp\delta^2)}$$

$$\text{here } X_i = \frac{1}{\hat{n}_{u_i}}$$

$$p = E\left[\frac{1}{\hat{n}_{u_i}}\right] = \frac{1}{n} \cdot \sum_{u \in V} \frac{1}{\hat{n}_{u_i}} = \frac{\hat{C}}{n}$$

$$\delta = \frac{\varepsilon}{2}$$

$$\frac{S}{r} = \frac{1}{r} \sum_{i=1}^r \frac{1}{\hat{n}_{u_i}}$$

$\underbrace{\phantom{\sum_{i=1}^r \frac{1}{\hat{n}_{u_i}}}}_{\frac{C}{n}}$

$$\text{so } \Pr\left[|\frac{\tilde{C}}{n} - \frac{\hat{C}}{n}| \geq \frac{\varepsilon}{2} \cdot \frac{\hat{C}}{n}\right] = \Pr\left[|\tilde{C} - \hat{C}| \geq \frac{\varepsilon}{2} \cdot \hat{C}\right]$$

$$\leq e^{-(\frac{b}{\varepsilon} \cdot \frac{\hat{C}}{2} \cdot \frac{\varepsilon^2}{4})}$$

want this to be ≥ 2

Since $\frac{\varepsilon}{2} \leq \frac{1}{\hat{n}_u} \leq 1$

Summing over u : $\frac{\varepsilon n}{2} \leq \hat{C} \leq n$

so $\frac{\varepsilon}{2} \leq \frac{\hat{C}}{n} \leq 1$

so that probability $\leq e^{-2}$

pick $b \geq 16$

Now we are done:

$$\text{Corr. } \Pr[|C - \tilde{C}| \leq \varepsilon_n] \geq 3/4$$

$$\text{Pf. } |C - \tilde{C}| \leq |C - \hat{C}| + |\hat{C} - \tilde{C}| \quad \text{by } \Delta\neq$$

$\uparrow \qquad \qquad \uparrow$

$\text{always } \leq \frac{\varepsilon_n}{2}$ $\leq \frac{\varepsilon_n}{2} \text{ by thm}$
 by corr $\text{with prob } \geq 3/4$

Approximating Min Spanning Tree (MST)

Input $G = (V, E)$ adj list representation $n = |V|$
 max degree d
 each edge has weight $w_{uv} \in \{1..w\}$ $v \notin \text{adj}_u$
 ϵ G connected
 ie. $w_{uv} \notin E$

Output let $M = \min_{T \text{ spans } G} \{w(T)\}$
 \uparrow tree \uparrow tree touches every node \uparrow $\sum w_{ij}$
 \uparrow $(i,j) \in T$

output \hat{M} s.t. $(1-\epsilon)M \leq \hat{M} \leq (1+\epsilon)M$

Assumption on wts $\Rightarrow n-1 \leq w(T) \leq w(n-1)$

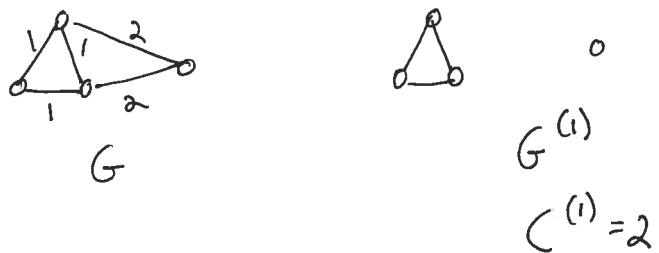
A different characterization of MST:

def $G^{(i)} = (V, E^{(i)})$ where $E^{(i)} = \{(u,v) \mid w_{uv} \in \{1..i\}\}$
 $C^{(i)} = \# \text{ conn comp of } G^{(i)}$

Some examples before characterization:

1) $w=1$ only size 1 weights + connected by assumption
here $M=n-1$

2) $w=2$ weights $\in \{1, 2\}$



idea of Kruskal:

use as many wt 1 edges as you can
only need wt 2 edges to connect the components

\Rightarrow need $C^{(1)} - 1$ wt 2 edges in MST

(recall that total # of edges is $n-1$)

Total wt of MST:

$$M = (n-1) + (C^{(1)} - 1) = n-2 + C^{(1)}$$

\uparrow
1 for each edge

\uparrow additional 1
for wt 2 edges

$$\underline{\text{Claim}} \quad M = n - w + \sum_{i=1}^{w-1} C^{(i)}$$

Pf.

let $\alpha_i = \# \text{ edges of wt } i \text{ in any MST of } G$

Kruskal's tells us that all MST's have
same value of α_i

why?

$$\begin{aligned} \sum_{i \geq 1} \alpha_i &= \# \text{ conn comp of } G^{(l)} - 1 \\ &= C^{(l)} - 1 \end{aligned}$$

where $C^{(0)} = n$ (no edges in $G^{(0)}$)

$$\begin{aligned} M &= \sum_{i=1}^w i \cdot \alpha_i \\ &= \sum_{i=1}^w \alpha_i + \sum_{i=2}^w \alpha_i + \sum_{i=3}^w \alpha_i + \dots + \sum_{i=w}^w \alpha_i \\ &\quad \underbrace{\phantom{\sum_{i=1}^w \alpha_i + \dots + \sum_{i=w}^w \alpha_i}}_{= \alpha_w} \\ &= (n-1) + (C^{(1)}-1) + (C^{(2)}-1) + \dots + (C^{(w-1)}-1) \\ &= n - w + \sum_{i=1}^{w-1} C^{(i)} \end{aligned}$$



Approximation Algorithm :

For $i = 1$ to $w-1$

$\hat{C}^{(i)} = \text{approx } \# \text{cc of } G^{(i)} \text{ to within } \frac{\epsilon'}{2w} \cdot n$ (additive error)

Output $\hat{M} = n - w + \sum_{i=1}^{w-1} \hat{C}^{(i)}$

ϵ'

\uparrow
adds $\text{poly}(\log \frac{w}{\epsilon})$
factor to runtime

Runtime :

$\tilde{O}(d/(\epsilon')^4) = \tilde{O}(dw^4/\epsilon^4)$ for each call to approx #cc.

Total $\tilde{O}(dw^5/\epsilon^4)$

\uparrow
how do you recompute $G^{(i)}$?
ignore edges of $wt > i$

(Can improve to $O(\frac{dw}{\epsilon^2} \log \frac{dw}{\epsilon})$)

+ need $\tilde{O}(dw/\epsilon^2)$

Approximation guarantee: "error" if approx error of approx #cc is too big ($> \epsilon'$) \leftarrow how? Hwo!

Call approx #cc with \tilde{O} error probability $\leq \frac{1}{4 \cdot w}$

$\Pr[\text{all calls to approx #cc give output that is } \epsilon' \text{ additive approx}] \geq 1 - \frac{w}{4w} \leftarrow$ union bound

If \nexists happens: $|M - \hat{M}| \leq w \cdot \frac{\epsilon n}{2w} = \frac{\epsilon n}{2} \leftarrow$ small additive error

\rightarrow since $M \geq n - 1 \geq n/2$, $|M - \hat{M}| \leq \epsilon M \leftarrow$ small multiplicative error

this is where we use lower bound on edge weights

Conclusion:

runtime depends only on $d, w, 1/\epsilon$
gives additive/multiplicative error