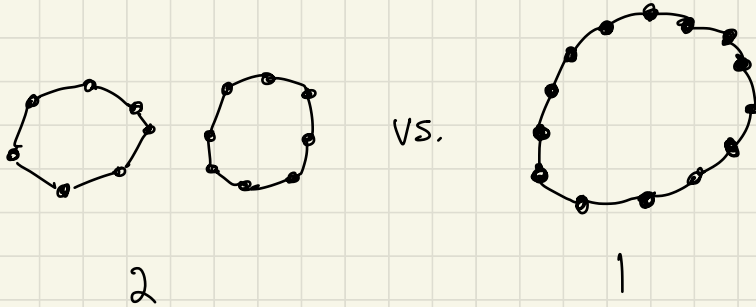


Lecture 3

Topics:

- Estimate number of connected components
- Estimate minimum spanning tree wt.

Estimating the number of connected components



need $\Omega(n)$ time

\Rightarrow multiplicative approx needs
linear time.

What about additive approx?

Additively estimate # of Connected Components

Given: Graph G , max degree Δ \leftarrow Adjacency list representation
parameter ε

$|V| = n$
 $|E| = m$

Output: let $C = \#$ conn comp in G

output y st.

$$C - \varepsilon n \leq y \leq C + \varepsilon n$$



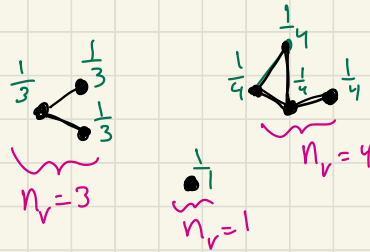
$$C = 3$$

Model: Adjacency list data structure

Main Insight:

A different characterization of # conn comp:

notation $\forall v$, let $n_v \equiv$ # nodes in v 's conn comp



observation: \forall conn comp $A \subseteq V$

$$\sum_{u \in A} \frac{1}{n_u} = \sum_{u \in A} \frac{1}{|A|} = 1$$

So # conn comp $C = \sum_{u \in V} \frac{1}{n_u}$

Why better?

maybe

not?

compute n_u

sum n

$O(n)$ time?

terms?

} estimate
estimate
estimate

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

1) estimate $\frac{1}{n_u}$ quickly \leftarrow additive error

2) estimate sum via sampling \leftarrow additive error but implies multiplicative error
bnds

First:

Estimate $\frac{1}{n_u}$: (if it gets really small, we don't need to know more)

def $\hat{n}_u \equiv \min \{ n_u, \frac{2}{\epsilon} \} \Rightarrow \frac{1}{\hat{n}_u} = \max \{ \frac{1}{n_u}, \frac{\epsilon}{2} \}$

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

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

Corr $|C - \hat{C}| \leq \frac{\epsilon n}{2}$

idea: if n_u is really big, can be hard to compute $\rightarrow 2/\epsilon$
but in this case $\frac{1}{n_u}$ is small $\leftarrow \leq \epsilon/2$

\Rightarrow never need $> 2/\epsilon$ BFS steps to compute \hat{n}_u to within $\epsilon/2$

why $\epsilon/2$?
why not 0?



we'll see later!!

$n_v \equiv \# \text{ nodes in } v\text{'s conn comp}$

Observation: $\forall \text{ conn comp } A \subseteq V$

$$\sum_{u \in A} \frac{1}{n_u} = \sum_{u \in A} \frac{1}{|A|} = 1$$

$$\# \text{ Conn comp } c = \sum_{u \in V} \frac{1}{n_u}$$

def $\hat{n}_u \equiv \min \{ n_u, \frac{2}{\epsilon} \}$

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

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

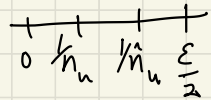
Corr $|c - \hat{c}| \leq \frac{\epsilon n}{2}$

Proof of lemma:

if $n_u < 2/\epsilon$ then $\hat{n}_u = n_u$ so $\frac{1}{\hat{n}_u} - \frac{1}{n_u} = 0$

if $n_u > 2/\epsilon$ then $\hat{n}_u = 2/\epsilon$ so

$$0 < \frac{1}{n_u} < \frac{1}{\hat{n}_u} = \frac{\epsilon}{2}$$



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

□

$n_v \equiv \# \text{ nodes in } v\text{'s conn comp}$

Observation: $\forall \text{ conn comp } A \subseteq V$

$$\sum_{u \in A} \frac{1}{n_u} = \sum_{u \in A} \frac{1}{|A|} = 1$$

$$\# \text{ conn comp } c = \sum_{u \in V} \frac{1}{n_u}$$

def $\hat{n}_u \equiv \min \{ n_u, 2/\epsilon \}$

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

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

Corr $|c - \hat{c}| \leq \frac{\epsilon n}{2}$

How do we compute \hat{n}_u ?

Algorithm:

Do BFS from u until

OR

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

$\hat{n}_u \leftarrow n_u$

$\hat{n}_u \leftarrow 2/\epsilon$

Output $\#$ visited nodes

runtime: $O(\Delta \cdot 1/\epsilon)$ \leftarrow max $\#$ of nodes visited
 \uparrow
time per step of BFS

actually, $O(\Delta + 1/\epsilon)$ suffices ... why?

(we will come back to this)

$n_v \equiv \#$ nodes in v 's conn comp

Observation: \forall conn comp $A \subseteq V$

$$\sum_{u \in A} \frac{1}{n_u} = \sum_{u \in A} \frac{1}{|A|} = 1$$

$$\begin{aligned} \# \text{ Conn comp } c &= \sum_{u \in V} \frac{1}{n_u} \\ &= n \cdot (\text{average value of } \frac{1}{n_u}) \end{aligned}$$

def $\hat{n}_u \equiv \min \{ n_u, \frac{2}{\epsilon} \}$

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

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

Corr $|c - \hat{c}| \leq \frac{\epsilon n}{2}$

How to estimate $\sum_u \frac{1}{n_u}$?

Algorithm estimate \hat{c}

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

b is a constant

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

$\forall u_i \in U$

compute \hat{n}_{u_i} via above algorithm

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

average value of sample U where $|U|=r$

runtime:

$$O\left(\frac{n}{\epsilon} \cdot \frac{1}{\epsilon^3}\right) = O\left(\frac{n}{\epsilon^4}\right)$$

$\underbrace{\hspace{2cm}}_{\text{algorithm to compute } \hat{n}_u}$

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

average value

$n_V \equiv \#$ nodes in V 's conn comp

Observation: \forall conn comp $A \subseteq V$

$$\sum_{u \in A} \frac{1}{n_u} = \sum_{u \in A} \frac{1}{|A|} = 1$$

$$\# \text{ conn comp } c = \sum_{u \in V} \frac{1}{n_u}$$

Theorem:

$$\Pr [|\tilde{c} - \hat{c}| \leq \frac{\epsilon n}{2r}] \geq 3/4$$

Proof

Chernoff Bound:

Given X_1, \dots, X_r iid $X_i \in [0, 1]$

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

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

here, let $X_i = \frac{1}{\hat{n}_{u_i}}$ for each sampled $u_i \in U$

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

recall $\tilde{c} = \frac{1}{r} \sum_{i=1}^r \frac{1}{\hat{n}_{u_i}}$ - Output = \tilde{c}

$$\text{let } p = E[X_i] = \frac{1}{n} \sum_{u \in V} \frac{1}{\hat{n}_{u_i}} = \frac{\hat{c}}{n}$$

$$\text{let } \delta = \frac{\epsilon}{2}$$

recall $r = b/\varepsilon^3$

$$1 \leq \hat{n}_u \leq 2/\varepsilon \quad (\text{from definition})$$

so $1 \geq \frac{1}{\hat{n}_u} \geq \varepsilon/2$

$$\Rightarrow n \geq \sum_{u \in V} \frac{1}{\hat{n}_u} \geq \frac{\varepsilon n}{2}$$

$\underbrace{\hspace{10em}}_{\equiv \hat{c}}$

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

$$\Pr[|\tilde{c} - \hat{c}| \geq \frac{\varepsilon n}{2}] \leq \Pr[|\tilde{c} - \hat{c}| \geq \frac{\varepsilon}{2} \cdot \hat{c}]$$

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

$$\leq e^{-\Omega(rp\delta^2)}$$

$$= e^{-\Omega(b/\varepsilon^3 \cdot \frac{\hat{c}}{n} \cdot \frac{\varepsilon^2}{4})} \leq e^{-\Omega(b)}$$

this is why we set $\frac{1}{\hat{n}_u}$ to $\frac{\varepsilon}{2}$ instead of 0

pick const b big enough so that $e^{-\Omega(b)} \leq 1/4$



Finishing up:

We had

$$|C - \hat{C}| \leq \frac{\varepsilon}{2} \cdot n$$

by earlier corollary

now we have $|\hat{C} - \tilde{C}| \leq \frac{\varepsilon}{2} n$

\Downarrow

$$|C - \tilde{C}| \leq \varepsilon n \quad \text{by } \Delta \neq$$

\uparrow \uparrow
\uparrow output
conn
comp



Approximate Min Spanning Tree (MST)

Input (1) $G = (V, E)$

adjacency list representation

$$n = |V|$$

max degree Δ

each edge has weight

$$w_{uv} \in \{1..w\} \cup \{\infty\}$$

Connected

↑ ie. $w_{uv} \notin E$
 assumption that
 edges integral
 not necessary

(2) ε

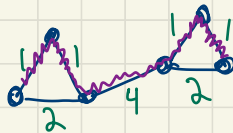
Output

let $M = \min_{\substack{T \text{ spans } G \\ \text{tree}}} \sum_{(i,j) \in T} w_{ij}$

$$\sum_{(i,j) \in T} w_{ij}$$

$$\sum_{(i,j) \in T} w_{ij}$$

output \hat{M} st. $(1-\varepsilon) \cdot M \leq \hat{M} \leq (1+\varepsilon) \cdot M$



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

A different characterization of MST:

def $E^{(i)} = \{ (u,v) \mid w_{u,v} \in \{1..i\} \}$ edges of $w_t \leq i$

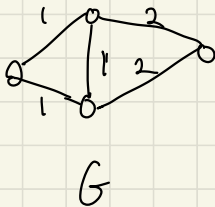
$G^{(i)} = (V, E^{(i)})$

$C^{(i)} = \# \text{ conn comp of } G^{(i)}$

Some examples:

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

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



$C^{(1)} = 2$

$$E^{(i)} = \{(u,v) \mid w_{u,v} \in \{1 \dots i\}\}$$

$$G^{(i)} = (V, E^{(i)})$$

$$C^{(i)} = \# \text{ conn comp of } G^{(i)}$$

Kruskal's idea for MST:
(paraphrased)

Use as many wt 1 edges as you can
then only need wt 2 edges to connect
current components

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

Total MST wt:

$$M = 1 \cdot (\# \text{ wt 1 edges}) + 2 \cdot (\# \text{ wt 2 edges})$$

$$= (n-1) + \underbrace{\# \text{ wt 2 edges}}_{C^{(i)} - 1}$$

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

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

Kruskal's \Rightarrow
this is same
 \forall MSTs why?

Pf. let $\alpha_i = \#$ edges of wt i in any MST of G

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

$$= C^{(l)} - 1$$

$$C^{(0)} = n$$

$$M = \sum_{i=1}^w i \cdot \alpha_i$$

$$= \sum_{i=1}^w \alpha_i + \sum_{i=2}^w \alpha_i + \dots + \sum_{i=w}^w \alpha_i$$

$\underbrace{\hspace{10em}}_{\alpha_w}$

$$= \underbrace{C^{(0)} - 1}_{n-1} + C^{(1)} - 1 + C^{(2)} - 1 + \dots + C^{(w-1)} - 1$$

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

$$E^{(i)} = \{ (u,v) \mid w_{u,v} \in \{1 \dots i\} \}$$

$$G^{(i)} = (V, E^{(i)})$$

$$C^{(i)} = \# \text{ conn comp of } G^{(i)}$$

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



Approximation algorithm:

$$E^{(i)} = \{(u,v) \mid w_{u,v} \in \{1..i\}\}$$

$$G^{(i)} = (V, E^{(i)})$$

$$C^{(i)} = \# \text{ conn comp of } G^{(i)}$$

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

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

$\hat{C}^{(i)}$ ← approx # conn comp of $G^{(i)}$ to within

$\frac{\epsilon}{2w} \cdot n$ additive error

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

let $\epsilon' = \frac{\epsilon}{2w}$

Runtime:

$$\tilde{O}\left(\frac{\Delta}{(\epsilon')^4}\right) = \tilde{O}\left(\frac{\Delta w^4}{\epsilon^4}\right)$$

per call to approx-CC

Total: $\tilde{O}\left(\frac{\Delta w^5}{\epsilon^4}\right)$

how do you work with $G^{(i)}$?

since calling approx-CC on subgraphs of G , can't save factor of Δ in approx-CC

Can improve to $O\left(\frac{\Delta w}{\epsilon^2} \log \frac{\Delta w}{\epsilon}\right)$

need $\Omega\left(\frac{\Delta w}{\epsilon^2}\right)$

No dependence on n !!!

Approximation algorithm:

$$E^{(i)} = \{ (u,v) \mid w_{u,v} \in \{1..i\} \}$$

$$G^{(i)} = (V, E^{(i)})$$

$$C^{(i)} = \# \text{ conn comp of } G^{(i)}$$

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

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

$\hat{C}^{(i)} \leftarrow$ approx $\#$ conn comp of $G^{(i)}$ to within

$\frac{\epsilon}{2w} \cdot n$ additive error

Output $\hat{M} = n - w + \sum_{i=1}^{w-1} \hat{C}^{(i)}$ let $\epsilon' = \frac{\epsilon}{2w}$

Approximation guarantee:

Call approx $\#cc$ with "failure" prob $\delta \leq \frac{1}{4w}$

how?
HW0

$\Pr[\text{all calls give } \epsilon' n \text{ approx}] \geq 1 - \frac{w}{4w}$

union bound

If \uparrow happens, $|M - \hat{M}| \leq w \cdot \frac{\epsilon}{2w} \cdot n = \frac{\epsilon n}{2}$ ← additive error bound

since $M \geq n - 1 \geq \frac{n}{2}$ $|M - \hat{M}| \leq \epsilon M$ ← mult error bound

mult error bound

Which edges are on MST?

What if w is big?