

Lecture 2

Topics:

- Sublinear time approximation of average degree
- Estimate number of connected components

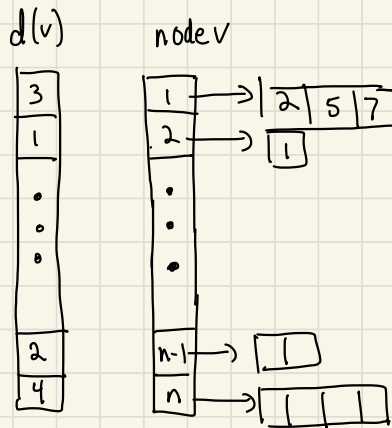
Last time

Estimating the average degree of a graph

def Average degree $\bar{d} = \frac{\sum_{u \in V} \deg(u)}{n} = \frac{2m}{n}$

Assume: G simple (no parallel edges, self-loops)
 $\Omega(n)$ edges (not "ultra-sparse")

Representation via adj list + degrees:



- degree queries: on v return $\deg(v)$
- neighbor queries: on (v, j) return j th
nbr of v

Estimating Average Degree

Given $G = (V, E)$

$\varepsilon \in (0, 1)$ approximation parameter

$\delta \in (0, 1)$ confidence

← lets assume
 $\delta = 1/4$

Output \tilde{d} st. $\Pr[|\tilde{d} - \bar{d}| \leq \varepsilon \bar{d}] \geq 1 - \delta$

where $\bar{d} = \frac{m}{n}$ (average degree)

Last time we saw that "naive sampling" i.e.

Pick $O(??)$ sample nodes v_1, \dots, v_s

output ave degree of sample:

$$\frac{1}{s} \sum_i \deg(v_i)$$

Does not work so well, although we did prove that if all $\deg(v)$ are in $[\Delta, 10\Delta]$ then constantly many samples are sufficient for the naive sampling algorithm

In general, we saw a handwavy argument that

- $\Omega(\ln)$ time is needed to give a multiplicative estimate for average degree (this used "ultrasparse" graphs)
- $\Omega(\sqrt{n})$ time is needed for estimating average degree, even when the average degree is > 1 .

Today we will see the general case, & a different algorithm

General Case: "Order" edges to control outdegree

Our plan:

define total order " \prec " on nodes:

↑ assume distinct IDs

def. $u \prec v$ if

- $\deg(u) < \deg(v)$

or • $\deg(u) = \deg(v)$

+ $ID(u) < ID(v)$

$\deg^+(u) = \#$ nbrs of u st. $u \prec v$



orient edges from small to large, $\deg^+(u)$ counts "out-edges"

Observation $\sum_{u \in V} \deg^+(u) = m = \frac{n}{2} \cdot \bar{d}$

(since each edge only counted once instead of twice as in $\sum_u \deg(u)$)

idea estimate average $\left(\deg^+(u) \right) \equiv \frac{1}{2} \cdot \bar{d}$

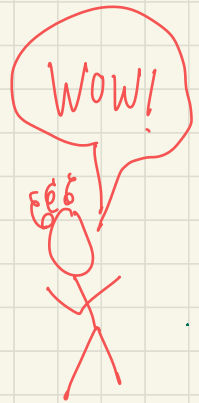
problem? we can query $\deg(u)$
not $\deg^+(u)$

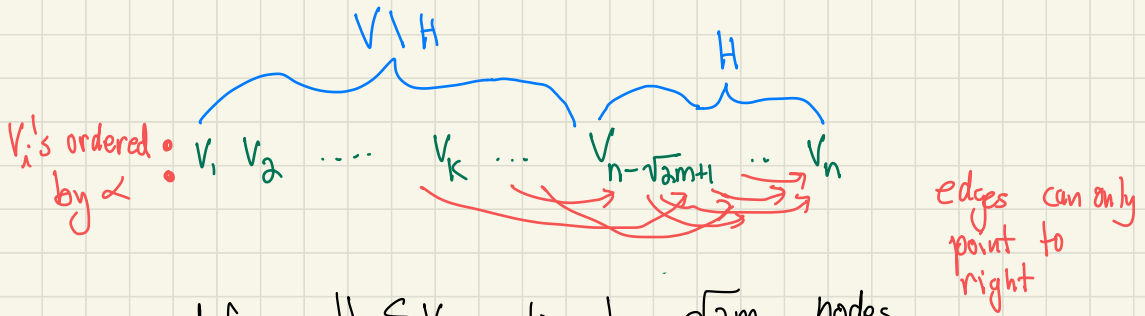
benefit:

Lemma $\forall v \in V \quad \deg^+(v) \leq \sqrt{2m}$

Proof

Consider order of v_n 's by \prec :





define $H \subseteq V$ to be $\sqrt{2m}$ nodes
with highest rank (degree) w.r.t. \prec

heavy nodes:

$\forall v \in H, \deg^+(v) \leq \sqrt{2m}$ since
edges "leaving" v go to bigger nodes
(which must also be in H)

light nodes:

$\forall v \in V \setminus H, \deg^+(v) \leq \deg(v) \leq \sqrt{2m}$:

Why?

if not, $\deg(v) > \sqrt{2m}$ ← assume for contradiction

but all w in H have


$\deg(w) \geq \deg(v) > \sqrt{2m}$

so total degree $\sum_v d(v)$

$> |H| \cdot \sqrt{2m} + \underbrace{\text{something positive}}_{\text{contribution from } V \setminus H}$

$> \sqrt{2m} \cdot \sqrt{2m} = 2 \cdot m$

but sum of degrees $= 2 \cdot m$

$\rightarrow \leftarrow$
symbol for "contradiction" 

Algorithm:

$$k \leftarrow \frac{16}{\epsilon^2} \sqrt{n}$$

for $i=1$ to k

pick $v_i \in_r V$

pick $u_i \in_r N(v_i)$

if $v_i < u_i$ then $X_i \leftarrow 2 \deg(v_i)$
else $X_i \leftarrow 0$

$$\text{return } \tilde{d} = \frac{1}{k} \sum_{i=1}^k X_i$$

neighbor of v

(1)

(2)

Question to think about:
why the "2"?

Claim $E[X_i] = \bar{d}$

PF

$$E[X_i] = \sum_{v \in V} \Pr[v \text{ chosen in (1)}] \cdot E[X_i \mid v \text{ chosen in (1)}]$$

$$= \sum_{v \in V} \frac{1}{n} \cdot E[X_i \mid v \text{ chosen in (1)}]$$

$$= \frac{1}{n} \sum_{v \in V} \sum_{u \in N(v)} \Pr[u \text{ chosen in (2)} \mid v \text{ chosen in (1)}]$$

$$\times E[X_i \mid u \text{ chosen in (2)} + v \text{ chosen in (1)}]$$

$$= \frac{1}{n} \cdot \sum_{v \in V} \sum_{\substack{u \in N(v) \\ v \neq u}} \frac{1}{\deg(v)} \cdot 2 \cdot \deg(v)$$

if $v \neq u$
then
 $X_i = 2 \deg(v)$
else $X_i = 0$

$$= \frac{2}{n} \cdot \sum_{v \in V} \deg^+(v) = \frac{2m}{n} = \bar{d}$$

▀

But how many samples do we need to assure that we are close to expectation? Here is where we use graph properties!

def. $\text{Var}[X] = E[X^2] - E[X]^2$

Claim $\text{Var}[X_i] \leq 4\sqrt{2m} \bar{d}$

Pf $\text{Var}[X_i] = E[X_i^2] - E[X_i]^2 \leq E[X_i^2]$ ↘ as above

$$= \frac{1}{n} \sum_{v \in V} \sum_{\substack{u \in N(v) \\ v < u}} \frac{1}{\deg(v)} \underbrace{(2 \deg(v))^2}_{X_i^2}$$

$$= \frac{4}{n} \sum_{v \in V} \underbrace{\deg^+(v)}_{\leq \sqrt{2m}} \cdot \deg(v)$$

← key insight

$$\leq \frac{4}{n} \cdot \sqrt{2m} \sum_{v \in V} \deg(v)$$

$$\leq 4 \cdot \sqrt{2m} \cdot \bar{d}$$

■

2 useful facts about variance!

• Lemma let $Y = \frac{1}{k} \sum_{i=1}^k X_i$ where X_i 's are iid
then $\text{Var}[Y] = \frac{1}{k} \text{Var}[X]$

so can reduce variance by sampling averaging more!

important but pairwise independence is good enough

• Chebyshev's \neq : $\Pr[|X - E[X]| \geq b] \leq \frac{\text{Var}[X]}{b^2}$

Lemma $\Pr [|\tilde{d} - \bar{d}| \leq \varepsilon \bar{d}] \geq 3/4$

\tilde{d} = output
 \bar{d} = average

Pf

$E[\tilde{d}] = \bar{d}$ by lin of expectation

$\text{Var}[\tilde{d}] \leq \frac{4 \cdot \sqrt{2m}}{k} \cdot \bar{d}$

since $\bar{d} = E[\tilde{d}]$

$\Pr [|\tilde{d} - \bar{d}| \geq \varepsilon \bar{d}] = \Pr [|\tilde{d} - E[\tilde{d}]| \geq \varepsilon \bar{d}]$

$\leq \frac{\text{Var}[\tilde{d}]}{(\varepsilon \bar{d})^2}$

$\leq \frac{\frac{4 \sqrt{2m}}{k} \cdot \bar{d}}{\varepsilon^2 \bar{d}^2} = \frac{4 \sqrt{2m}}{\varepsilon^2 \bar{d} \cdot k}$

$= \frac{4 \sqrt{2m} \cdot n}{\varepsilon^2 \cdot 2m \cdot k} = \frac{4n}{\varepsilon^2 \sqrt{2m} \cdot k}$

$= \frac{\sqrt{n}}{4 \cdot \sqrt{2m}}$

pick $k = \frac{16}{\varepsilon^2} \sqrt{n}$

$\leq \frac{1}{4}$

since $\sqrt{\frac{n}{2m}} = \sqrt{\frac{1}{\bar{d}}}$
 ≤ 1 since we assumed $\bar{d} \geq 1$

\Rightarrow good estimate with prob $\geq 3/4$

How do we improve probability of success?

see HW 0!