

Lecture 4.1

Proof of Crucial Ratio Lemma by iterating twice through recursive relations.

Remarks

- With more care one can run the same argument for $\mathcal{D}_\Delta := \{d \in \mathbb{Z}_{\geq 0}^n : \sum_{i=1}^n d_i \text{ is even}, 1 \leq d_i \leq \Delta \text{ for all } i\}$ provided that $\Delta = o(n^6)$.
 → Approximation for ratios for ^{very} irregular & sparse sequences.
- Do 1 more iteration to get accuracy $(1 + O(\frac{d^3}{n^3}))$ which would be good enough for $d = o(\frac{n^{4/7}}{(\log n)^{1/7}})$.
 → Possible to do on paper, but tedious.

What remains to be done to prove Conjecture for $d = o(\frac{n^{2/5}}{\log n})$?
 Find $\mathcal{D} (= \mathcal{D}_m)$ and formulae y_d , for each $d \in \mathcal{D}_m$, such that

$$(1) \quad \frac{y_{d-e_a}}{y_{d-e_b}} = \frac{d_a}{d_b} \left(1 + \frac{d_a - d_b}{dn} \left(1 + \frac{M_2(d)}{dn} \right) + o\left(\frac{1}{d^{\text{diam}(S)}}\right) \right)$$

$$\text{and } \sum_{d \in \mathcal{D}_m} y_d = 1 + o(1). \quad (2)$$

$$\begin{aligned} \text{Conjecture says } y_d &= \Pr(\mathcal{B}_m(n) = d) \cdot \exp \left[\frac{1}{4} - \frac{\delta_2^2(d)}{4 \mu^2(1-\mu)^2} \right] \\ &= \frac{\prod_{i=1}^n \binom{n-1}{d_i}}{\binom{n(n-1)}{2m}} \cdot \frac{11 d_1^2}{H(d)} \end{aligned}$$

(1) is a calculation (sorry!)

$$\frac{\Pr(\mathcal{B}_m(n) = d - e_a)}{\Pr(\mathcal{B}_m(n) = d - e_b)} = \frac{d_a}{d_b} \frac{n - d_b}{n - d_a} = \frac{d_a}{d_b} \left(1 + \frac{d_a - d_b}{n} + O\left(\frac{d^2}{n^2}\right) \right)$$

(check!)

$$\text{and } \frac{H(d-e_a)}{H(d-e_b)} = \exp \left[\frac{(d_a-d_b) M_2}{(dn)^2} + \frac{d_a-d_b}{dn} - \frac{(d_a-d_b)}{n} + O\left(\frac{\log^2 n d^2}{n^2}\right) \right]$$

Exercise. Hint: Use $\chi_2(d-e_a) = \chi_2(d) - \frac{2d+1}{(n-1)^2} - \frac{2d_b}{(n-1)^2}$.

For (2): $\sum_{d \in \mathcal{D}_m} \Pr(\mathcal{D}_m(n) = d) \cdot H(d) = \sum_{\substack{d \in \mathcal{D}_m \\ d: \sum_i d_i = 2m}} \Pr(\mathcal{D}_m(n) = d) \cdot H(d) + O(n^{-23})$ (concentration lemma)

$$= \mathbb{E}_{\mathcal{D}_m} H(d) + o(1).$$

$$= \mathbb{E}_{\mathcal{D}_m} \exp \left[\frac{1}{4} - \frac{\chi_2^2(d)}{4n^2(1-\mu)^2} \right] + o(1)$$

$$\mu = \frac{m}{n} = \frac{2m}{n(n-1)} \text{ count on } \mathcal{D}_m.$$

$$\chi_2(d) = \frac{1}{(n-1)^2} \sum_i (d_i - d)^2$$

Lemma (Concentration)

With probability $1-o(1)$, $f(d) = \sum_{i=1}^n (d_i - d)^2$ satisfies

$$f(d) = \mathbb{E} f(d) (1+o(1)). \quad \text{in } \mathcal{D}_m(n).$$

E.g.: via Chebyshev's Inequality

or sharp concentration inequality (McDiarmid,

bounded differences, Azuma)

$$\mathbb{E} f(d) = \mathbb{E}_{\mathcal{D}_m} \sum_i (d_i - d)^2 = \sum_i \mathbb{E}_{\mathcal{D}_m} (d_i - d)^2 = n \cdot \text{Var}(d_1)$$

$$= n \cdot \left(\frac{2m}{n} \left(1 - \frac{1}{n}\right) \left(1 - \frac{2m}{n(n-1)-1}\right) \right)$$

$$\uparrow \text{Hypergeom} \left(\begin{matrix} n \\ n(n-1), n-1, 2m \end{matrix} \right)$$

$$\approx dn \left(1 - \frac{d}{n}\right) + O(d)$$

$$\Rightarrow \text{with prob } 1-o(1) \quad \chi_2^*(d) = \frac{d}{n} \left(1 - \frac{d}{n}\right) + o(1)$$

$$\Rightarrow \text{---} \text{---} \text{---} \quad H(d) = \exp \left[\frac{1}{4} - \frac{\chi_2^*(d)}{4n^2(1-\mu)^2} (1+o(1)) \right]$$

$$= 1+o(1)$$

$$\Rightarrow \mathbb{E}_{\mathcal{D}_m} H(d) = 1+o(1) + o(1) \cdot \max_{d \in \mathcal{D}_m} H(d) = 1+o(1).$$

Lecture 4.2

Summary: we proved

Thm If $\log^2 n \ll d \ll n^{2/5} / \log n$ then

$$|g(n, d)| = \binom{2}{m} \Pr(D_m(n) = d) \cdot \exp\left[\frac{1}{4} + o(1)\right],$$

where $m = dn/2$.

Moreover, for all $d \in \mathcal{D}_m$,

$$\Pr(D(G_{nm}) = d) = \Pr(D_m(n) = d) \cdot \exp\left[\frac{1}{4} - \frac{\delta_2^2(d)}{4n^2(1/n)^2} + o(1)\right]$$

$\underbrace{\hspace{10em}}_{1+o(1) \text{ w.h.p. in } \mathcal{D}_m(n)}$

Pf summary

- define local change graph S , $\text{diam}(S) \leq 10\sqrt{d \log n} \cdot n$.

- CRL: $\frac{\Pr(D(G_{nm}) = d - e_a)}{\Pr(D(G_{nm}) = d - e_b)} = [\text{formula}] \left(1 + o\left(\frac{1}{\text{diam}(S)}\right)\right)$

- Calculation: $\frac{Y_{d-e_a}}{Y_{d-e_b}} = [\text{SAME formula}] \left(1 + o\left(\frac{1}{\text{diam}(S)}\right)\right)$

- (Sharp) concentration: $\sum_{d \in \mathcal{D}_m} Y_d = \sum_{d \in \mathcal{D}_m} \mathbb{E}_d H(d) + O(n^{-23})$
 $= 1 + o(1)$

□

Larger d ?

1st, 3rd & 4th point: standard toolbox

CRL $\rightarrow$ need to get finer approximation for $R_{\text{exp}}(d)$.

Lecture 4.3

Recursive relations

$$(1) \quad R_{a|b}(d) = \frac{da}{db} \cdot \frac{1 - \text{Bad}_{a|b}(d - e_b)}{1 - \text{Bad}_{b|a}(d - e_a)} \quad \text{for odd } d$$

$$(1.5) \quad \text{Bad}_{a|b}(d) = \frac{1}{da} \left(P_{ab}(d) + \sum_{r \neq a|b} Y_{a|r|b}(d) \right) \quad \text{even } d$$

$$(2) \quad P_{av}(d) = dv \left(\sum_{b \neq v} R_{(b,a)}(d - e_v) \frac{1 - P_{bv}(d - e_b - e_v)}{1 - P_{av}(d - e_a - e_v)} \right)^{-1}$$

$$(3) \quad Y_{a|v|b}(d) = \frac{P_{av}(d) (P_{bv}(d - e_a - e_v) - Y_{a|v|b}(d - e_a - e_v))}{1 - P_{av}(d - e_a - e_v)}$$

Assuming things are well-defined (e.g. realisable in $P_{av}(d)$).

Start with $P_{av}(d) = O\left(\frac{d}{n}\right) \ll 1$.

→ iterate applying (3), (1.5), (1), (2)

& get better & better approximations of $R_{a|b}(d)$.

What's the improvement after 1 round of iterations?

after 1st round $R_{a|b}(d) = \frac{da}{db} (1 + O(\frac{d}{n}))$

2nd $R_{a|b}(d) = \frac{da}{db} (\text{stth.} + O(\frac{d^2}{n^2}))$

3rd round $\frac{da}{db} (1 + \text{sth. more complicated} + O(\frac{d^3}{n^3}))$

?

k rounds $R_{a|b}(d) = \text{Formula} (1 + O((\frac{d}{n})^k))$

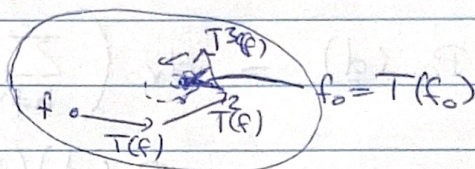
For which d is $(\frac{d}{n})^k$ precise enough? $(\frac{d}{n})^k = o\left(\frac{1}{n \log \log n}\right)$

$$\Leftrightarrow d \ll n^{\frac{k-1}{2k+1}} (\log n)^{1/2}$$

$$\Leftrightarrow d \ll n^{1 - \frac{2}{2k+1}} (\log n)^{\frac{1}{2k+1}}$$

In theory: $\forall \varepsilon > 0$, $d = n^{1-\varepsilon}$, need $O(1)$ iterations to obtain desired accuracy.

Problem 2: that does not get us up to $d = \Theta(\frac{n}{\log n})$ or even $d = \epsilon n$.

$$T(f)$$
$$p = p(a, b, \underline{d})$$


$$p \in \binom{n}{2} \times \mathbb{Z}_{\geq 0}^n \rightarrow \mathbb{R}_{\geq 0}$$

$$P_{av}(d)$$

$$y: \binom{(n)}{3} \times \mathbb{Z}_{\geq 0}^n \rightarrow \mathbb{R}_{\geq 0} \quad y(a, v, b, d) \quad y_{a,v,b,d}$$

$$r: [n]^2 \times \mathbb{Z}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0} \quad r(a, b, d), \quad r_{a,b}(d)$$

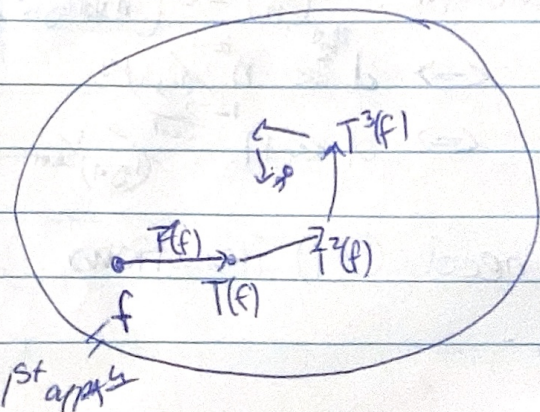
$$(i) \quad R(p, y)(a, b, d) = \frac{da}{db} \cdot \frac{1 - \text{bad}(p, y)(a, b, d - e_b)}{1 - \text{bad}(p, y)(a, b, d - e_a)},$$

$$(ES) \quad \text{bad}(p, y)(a, b, d) = \frac{1}{d_a} \left(\cancel{p_{ab}}(d) + \sum_{v \neq a, b} y_{avb}(d) \right)$$

$$(2) \mathcal{P}(p_{gr})(a, r, d) = d_v \left(\sum_{b \neq v} r_{b,a} (d - e_v) \frac{1 - p_{br} (d - e_b - e_v)}{1 - p_{av} (d - e_a - e_v)} \right)^{-1}$$

$$(3) \quad y(p, y)(a, v, b, d) = \frac{p_{av}(d)(p_{bv}(d - e_a - e_v) - \gamma_{avb}(d - e_a - e_v))}{1 - p_{av}(d - e_a - e_v)}$$

Observation : "real" probabilities & ratios P_{air} , γ_{arb} & R_{arb} are "fixed points"



$$R(P, Y) = R$$

$$P(P, R) = P$$

$$y(p, y) = y.$$

Lecture 4 ②

Operators are "contractive" for probability-like p & y :

Call (p, y) μ -probability-like on $\mathcal{D}_0 \leftarrow \text{some set} \subseteq \mathbb{Z}_{\geq 0}^n$

$$(P1) \quad 0 \leq p_{av}(d) \leq \mu \quad \forall d \in \mathcal{D}_0$$

$$(P2) \quad \sum_{a \neq b} y_{avb}(d) \leq \mu \cdot d_a \quad \forall d \in \mathcal{D}_0, a, b \in [n] \text{ distinct.}$$

$$(P3) \quad 0 \leq y_{avb}(d) \leq \mu \cdot p_{av}(d) \quad \forall d \in \mathcal{D}_0 \text{ \& } a, v, b \in [n] \text{ distinct.}$$

Exercise: Show that $\text{real}(P, y)$ is μ -probability-like

on $\mathcal{B}_{16 \log n}(\mathcal{D}_m)$, assuming $n \log^3 n \leq m = o(n^2)$

$$\text{where } \mu = 5 \cdot \frac{m}{\binom{n}{2}}.$$

Hint: Use Simple Switching lemma & Recursion for y_{avb} .

Contraction lemma $(p, y), (p', y')$ are μ -probability-like on $\mathcal{D}_0$
 r, r' fctns.

$$(a) \quad \text{If } p \equiv p'(1 \pm \xi) \text{ \& } y \equiv y'(1 \pm \xi) \\ \text{then } R(p, y) = R(p', y')(1 + O(\mu \cdot \xi))$$

$$(b) \quad \text{If } p \equiv p'(1 \pm \xi) \text{ \& } r = r'(1 \pm \mu \xi) \\ \text{then } P(p, r) = P(p', r')(1 + O(\mu \xi))$$

$$(c) \quad \text{If } p = p'(1 \pm \mu \xi) \text{ and } y = y'(1 \pm \xi) \\ \text{then } y(p, y) = y(p', y')(1 + O(\mu \xi))$$

[w/o proof]

Take $(p, y, r) = (P, Y, R)$

and (p', y', r') are guessed formulae: