

RANDOM

GRAPHS

Basic Models

$$G_{n,m} = ([n], E_{n,m})$$

Vertex set $[n] = \{1, 2, \dots, n\}$

Each graph with m edges

has same probability

$$\frac{1}{\binom{N}{m}},$$

$$N = \binom{n}{2}$$

$$G_{n,p} = ([n], E_{n,p})$$

Vertex set $[n]$

$$P_r(G_{n,p} = G) = p^{|E(G)|} (1-p)^{N - |E(G)|}$$

i.e. each edge occurs independently
with probability p .

Graph property \mathcal{P} .

$$p = \frac{m}{N}$$

$$P_r(G_{n,p} \in \mathcal{P}) = \sum_{\mu=0}^N P_r(G_{n,p} \in \mathcal{P} \mid |E_{n,p}| = \mu) \times P_r(|E_{n,p}| = \mu)$$

$$= \sum_{\mu=0}^N P_r(G_{n,\mu} \in \mathcal{P}) P_r(|E_{n,p}| = \mu)$$

$$\geq P_r(G_{n,m} \in \mathcal{P}) P_r(|E_{n,p}| = m)$$

$$P(|E_{n,p}| = m) = \binom{N}{m} p^m (1-p)^{N-m}$$

$$\approx (1+o(1)) \frac{N^N \sqrt{2\pi N} p^m (1-p)^{N-m}}{m^m (N-m)^{N-m} 2\pi \sqrt{m(N-m)}}$$

$m \rightarrow \infty$
 $N-m \rightarrow \infty$

$$\approx (1+o(1)) \sqrt{\frac{N}{2\pi m(N-m)}}$$

$$\geq \frac{1}{10\sqrt{m}}$$

So,

$$\Pr(G_{n,m} \in \mathcal{P}) \leq 10m^{1/2} \Pr(G_{n,p} \in \mathcal{P}).$$

Monotone Properties

A property is monotone increasing \nearrow if

$$G \in \mathcal{P} \implies G + e \in \mathcal{P}$$

e.g. connectivity

Monotone decreasing \searrow if

$$G \in \mathcal{P} \implies G - e \in \mathcal{P}$$

e.g. planarity

Suppose \mathcal{P} is \nearrow . $\rho = \frac{1}{\sqrt{3}}$

$$P_r(G_{n,p} \in \mathcal{P}) = \sum_{\mu=0}^N P_r(G_{n,\mu} \in \mathcal{P}) P_r(|E_{n,p}| = \mu)$$

$$\geq P_r(G_{n,m} \in \mathcal{P}) \sum_{\mu=m}^N P_r(|E_{n,p}| = \mu).$$

Central Limit Theorem \Rightarrow $\downarrow \geq \frac{1}{2} - o(1)$

$$P_r(G_{n,m} \in \mathcal{P}) \leq 3 P_r(G_{n,p} \in \mathcal{P}).$$

Graph Process:

$$G_0 = ([n], \emptyset), G_1, G_2, \dots, G_m, \dots, G_N = K_n$$

$$G_{m+1} = G_m \text{ plus random edge}$$

G_m and $G_{n,m}$ have same
distribution.

Markov Inequality

$X \geq 0$ is a random variable with finite mean μ .

$$P(X \geq t) \leq \frac{\mu}{t}$$

Proof

$$\begin{aligned} E(X) &= E(X|X < t) P(X < t) \\ &\quad + E(X|X \geq t) P(X \geq t) \\ &\geq t P(X \geq t). \end{aligned}$$



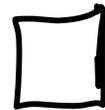
Chebyshev Inequality

X is a random variable with finite mean μ and variance σ^2 .

$$P(|X - \mu| \geq t) \leq \frac{\sigma^2}{t^2}$$

Proof

$$\begin{aligned} P(|X - \mu| \geq t\sigma) &= P((X - \mu)^2 \geq t^2\sigma^2) \\ &\leq \frac{E((X - \mu)^2)}{t^2\sigma^2} \\ &= \frac{\sigma^2}{t^2}. \end{aligned}$$



First Moment Method

Let X be a random variable with finite mean taking values in $\{0, 1, 2, \dots\}$.

$$P_r(X \neq 0) \leq E(X)$$

Proof

$$\begin{aligned} P_r(X \neq 0) &= P_r(X \geq 1) \\ &\leq \frac{E(X)}{1}. \end{aligned}$$

□

Second Moment Method

Let X be a non-negative random variable with finite mean and variance. Then

$$P(X > 0) \geq \frac{E(X)^2}{E(X^2)}$$

Proof

$$\text{Let } Y = \begin{cases} 0 & \text{if } X = 0 \\ 1 & \text{if } X > 0 \end{cases}$$

$$\text{So } XY = X$$

Cauchy-Schwarz inequality* in its

$$\mathbb{E}(XY)^2 \leq \mathbb{E}(X^2) \mathbb{E}(Y^2)$$

or

$$\mathbb{E}(X)^2 \leq \mathbb{E}(X^2) P(X > 0).$$

□

$$\begin{aligned} \mathbb{E}((X + tY)^2) &= \mathbb{E}(X^2) + 2t\mathbb{E}(XY) + t^2\mathbb{E}(Y^2) \\ &= (\mathbb{E}(X^2)^{1/2} + t\mathbb{E}(Y^2)^{1/2})^2 - 2t(\mathbb{E}(X^2)^{1/2}\mathbb{E}(Y^2)^{1/2} - \mathbb{E}(XY)) \\ &\geq 0 \text{ for all } t. \end{aligned}$$

Put $t = -\mathbb{E}(X^2)^{1/2}/\mathbb{E}(Y^2)^{1/2}$ to obtain $\mathbb{E}(X^2)^{1/2}\mathbb{E}(Y^2)^{1/2} - \mathbb{E}(XY) \geq 0$.

* Consider quadratic $\mathbb{E}((X + tY)^2) \geq 0$, as a function of t .

Evolution of a random graph.

We look at how $G_0, G_1, \dots, G_m, \dots$
evolves.

$\omega = \omega(n)$ denotes some slowly growing function e.g. $\omega = \log n$.

$$(1) \quad m \leq n^{1/2} / \omega$$

G_m is a matching whp

whp: with high probability
i.e. with probability $1 - o(1)$
as $n \rightarrow \infty$.

Let $p = \frac{m}{N}$ and let $X_2 =$ number of paths of length 2 in $G_{n,p}$.

$$\begin{aligned} E_p(X_2) &= 3 \binom{n}{3} p^2 \\ &\leq \frac{n^3 \times n}{N^2 \times w^2} \end{aligned}$$

$\rightarrow 0$.

$P_1(G_{n,p} \text{ contains path of length 2}) = o(1)$
monotone property

\Downarrow
 $P_1(G_{n,m} \text{ contains a path of length 2}) = o(1)$.

$$(ii) \quad m = \omega n^{1/2}, \quad m = o(n).$$

G_m contains a path of length 2 whp

Let $p = \frac{m}{n}$ and $X_2 = \#$ paths length 2.

$$\mathbb{E}(X_2) = 3 \binom{n}{3} p^2$$

$$\approx 2\omega^2$$

$$\rightarrow \infty$$

Does not imply $X_2 \neq 0$ whp.

Let \mathcal{P}_2 be the set of all paths of length two in K_n .

Let $\hat{X}_2 = \#$ of **isolated** paths of length 2 in $G_{n,p}$

$$\hat{X}_2 = \sum_{P \in \mathcal{P}_2} \mathbb{1}_{P \subseteq G_{n,p}}$$

$$E(\hat{X}_2) = 3 \binom{n}{3} p^2 (1-p)^{3(n-3)}$$

$$\geq (1-o(1)) \frac{n^3}{2} \cdot \frac{4p^2 n}{n^4} \cdot (1-6np)$$

$$\rightarrow \infty.$$

$$\begin{aligned} n &= o(n) \\ \Downarrow \\ np &= o(1) \end{aligned}$$

$$\hat{X}_2^2 = \sum_{P \in \mathcal{P}_2} \sum_{Q \in \mathcal{P}_2} \mathbb{1}_{P \in G_{n,p}} \mathbb{1}_{Q \in G_{n,p}}$$

$$= \sum_{P, Q \in \mathcal{P}_2} \mathbb{1}_{P \in G_{n,p}} \mathbb{1}_{Q \in G_{n,p}}$$

$P=Q$ or P, Q vertex disjoint

$$E(\hat{X}_2^2) = \sum_P \left\{ \sum_Q P_r(G_{n,p} \supseteq Q \mid G_{n,p} \supseteq P) \right\} \times P_r(G_{n,p} \supseteq P)$$

Expression inside $\{\}$ is same for all P .

$$= E(\hat{X}_2) \left(1 + \sum_{\substack{Q \cap \{1,2,3\} \\ = \emptyset}} P_r(G_{n,p} \supseteq Q \mid G_{n,p} \supseteq \checkmark_2) \right)$$

$$\leq E(\hat{X}_2) \left(1 + \binom{n}{3} p^2 (1-p)^{3(n-6)^*} \right)$$

$$\leq E(\hat{X}_2) \left(1 + (1-p)^{-3} E(\hat{X}_2) \right)$$

* Conditioning means no edge to $\{1,2,3\}$

So

$$P_r(\hat{X}_2 \neq 0) \geq \frac{E(\hat{X}_2)^2}{E(\hat{X}_2)(1 + (1-p)^{-3} E(\hat{X}_2))}$$

$$= \frac{1}{(1-p)^{-3} + E(\hat{X}_2)^{-1}}$$

$$\rightarrow 1.$$

not monotone

Thus $P_r(\underline{G_{n,p}} \geq \text{isolated 2-path}) \rightarrow \underline{1}$

$P_r(\underline{G_{n,p}} \geq \text{2-path}) \rightarrow \underline{1}$

$P_r(G_m \geq \text{2-path}) \rightarrow \underline{1}$

monotone

$$P_1(G_m \ni 2\text{-path}) = \begin{cases} 0(1) & m \ll n^{1/2} \\ 1 - 0(1) & m \gg n^{1/2} \end{cases}$$

We say that $n^{1/2}$ is the

threshold

for the existence of a 2-path in $G_{n,m}$

Probability "jumps" from
 ~ 0 to ~ 1

Small Trees

Fix $k \geq 3$.

$$m \leq \frac{n^{\frac{k-2}{k-1}}}{\omega}$$

$\Rightarrow G_m$ contains no tree with k vertices.

$$p = \frac{3}{2n} \approx \frac{3}{2n^{k/(k-1)}}$$

Let

$X_k =$ # of trees with k vertices in $G_{n,p}$

$$E(X_k) = \binom{n}{k} k^{k-2} p^{k-1}$$

$$\leq \left(\frac{ne}{k}\right)^k k^{k-2} \left(\frac{3}{2n^{k/(k-1)}}\right)^{k-1}$$

$$< \left(\frac{3e}{2}\right)^{k-1}$$

$\rightarrow 0$.

$P_r(G_{n,p} \text{ contains tree with } k \text{ vertices}) \rightarrow 0$
monotone



$P_r(G_m \text{ contains a tree with } k \text{ vertices}) \rightarrow 0.$

$$m = \omega n^{\frac{k-2}{k-1}}, \quad m = o(n)$$

$\Rightarrow G_m$ contains a copy of every
tree with k vertices.

$$p = \frac{m}{n}$$

Fix some tree T with k vertices.

$X_T = \#$ of isolated copies of T in $G_{n,p}$.

$$E(X_T) = \binom{n}{k} \frac{k!}{\text{aut}(T)} p^{k-1} (1-p)^{k(n-k)}$$

$$\approx^{**} \frac{(2w)^{k-1}}{\text{aut}(T)}$$

$\rightarrow \infty$.

* $\text{aut}(H) =$ no. of automorphisms of H

** $= (1 + o(1))$ times \dots

Let \mathcal{T} be the set of copies of T in K_n .

$$E(X_T^2) = \sum_{T_1, T_2 \in \mathcal{T}} P_r(T_2 \overset{i}{\subseteq} G_p \mid T_1 \overset{i}{\subseteq} G_p) \times P_r(T_1 \overset{i}{\subseteq} G_p)$$

$$= E(X_T) \left(1 + \sum_{\substack{T_2 \in \mathcal{T} \\ V(T_2) \cap [k] = \emptyset}} P_r(T_2 \subseteq G_p \mid \overset{\uparrow}{K} \subseteq G_p) \right)$$

↑ fixed copy of T on $[k]$.

$$\leq E(X_T) \left(1 + (1-p)^{-k} E(X_T) \right).$$

$$P_r(X_T \neq 0) \geq \frac{E(X_T)^2}{E(X_T)(1+(1-p)^{-k}E(X_T))}$$

$\rightarrow 1.$

$P_r(G_{n,p} \text{ contains isolated copy of } T) \rightarrow 1$
 \Downarrow

$P_r(G_{n,p} \text{ contains copy of } T) \rightarrow 1$
 \Downarrow

$P_r(G_m \text{ contains copy of } T) \rightarrow 1.$

Cycles

$m = O(n) \Rightarrow G_m$ is a forest, why

Suppose $m = n/w$

$$p = \sum_{k=3}^n \frac{3^k}{\omega^k n^k}$$

$X = \#$ of cycles in $G_{n,p}$

$$E(X) = \sum_{k=3}^n \binom{n}{k} \frac{(k-1)!}{2} p^k$$

$$\approx \sum_{k=3}^n \frac{n^k}{2^k} \cdot \frac{3^k}{\omega^k n^k}$$

$$= O(\omega^{-3})$$

$$\rightarrow 0.$$

$$P_r(G_{n,p} \text{ is not a forest}) = o(1)$$

\Downarrow

$$P_r(G_m \text{ is not a forest}) \approx o(1).$$

Poisson Convergence.

What happens if

$$m = c n^{(k-2)/(k-1)}$$

where $c > 0$ is constant?

Inclusion - Exclusion.

Lemma

Suppose A_1, A_2, \dots, A_r are events in some probability space Ω .

Suppose that f_1, f_2, \dots, f_s are boolean functions of A_1, A_2, \dots, A_s

Suppose $\alpha_1, \alpha_2, \dots, \alpha_s$ are reals. Then if

$$\sum_{i=1}^s \alpha_i P_r(f_i(A_1, A_2, \dots, A_r)) \geq 0 \quad (1)$$

whenever $P_r(A_i) = 0$ or 1 then (*)

holds in general.

Write

$$F_i = \bigcup_{S \in \mathcal{T}_i} \left(\left(\bigcap_{i \in S} A_i \right) \cap \left(\bigcap_{i \notin S} \bar{A}_i \right) \right)$$

so that

$$P_r(F_i) = \sum_{S \in \mathcal{T}_i} P_r \left(\left(\bigcap_{i \in S} A_i \right) \cap \left(\bigcap_{i \notin S} \bar{A}_i \right) \right)$$

and then LHS (1) becomes

$$\sum_{S \subseteq [r]} \beta_S P_r \left(\left(\bigcap_{i \in S} A_i \right) \cap \left(\bigcap_{i \notin S} \bar{A}_i \right) \right)$$

for some real β_S .

If (1) holds then $\beta_S \geq 0, \forall S$ since we can choose $A_i = \Omega, i \in S, A_i = \emptyset, i \notin S$.

□

For $X \subseteq [r]$ let $A_X = \bigcap_{i \in X} A_i$

$$S_t = \sum_{|X|=t} P_r(A_X)$$

$\mathcal{E} = \{ \text{none of } A_1, A_2, \dots, A_r \text{ occur} \}$

Lemma

$$P_r(\mathcal{E}) = \sum_{t=0}^r (-1)^t S_t \begin{cases} \leq 0 & r \text{ even} \\ \geq 0 & r \text{ odd} \end{cases}$$

We only need to check when

$$P_r(A_i) = \underline{1} \quad 1 \leq i \leq l$$

$$P_r(A_i) = 0 \quad l < i \leq r$$

$$P_r(\mathcal{E}) = \begin{matrix} \underline{1} & l = 0 \\ 0 & l \neq 0 \end{matrix}$$

$$S_r = \begin{pmatrix} l \\ r \end{pmatrix}$$

$l = 0$ trivial.

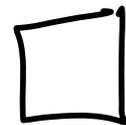
$$\underline{l > 0}$$

$$0 = \sum_{t=0}^r (-1)^t \binom{l}{t}$$

$$= \begin{cases} 0 & r \geq l \\ (-1)^r \binom{l-1}{r} & r < l \end{cases}$$

$$r \geq l$$

$$r < l$$



Back to random graphs

Let T_1, T_2, \dots, T_M be the list of copies of some fixed k vertex tree T .

$A_i = \{ T_i \text{ occurs as a component in } G_m \}$

Suppose $X \subseteq [M]$ with $|X| = t$, t fixed.

$P_r(A_X) = 0$ if $\exists i, j \in X$ such

that T_i, T_j share a vertex.

Suppose $T_i, i \in X$ are vertex disjoint.

$$Pr(A_X) = \frac{\binom{n-kt}{2} \binom{m-(k-1)t}{1}}{\binom{N}{m}}$$

Numerator = # ways of choosing m edges
so that A_X occurs

Now

$$\frac{A^B}{B!} \approx \binom{A}{B} = \frac{A^B}{B!} \left(1 - \frac{1}{A}\right) \left(1 - \frac{2}{A}\right) \dots \left(1 - \frac{B-1}{A}\right)$$

$$\approx \frac{A^B}{B!} \left(1 - \frac{B^2}{2A}\right)$$

So if A, B are functions of n and

$$\frac{B^2}{A} \rightarrow 0 \quad \text{as } n \rightarrow \infty$$

then

$$\binom{A}{B} \approx (1 + o(1)) \frac{A^B}{B!}$$

Consider $\binom{n-kt}{2}$ for $t \leq \log n$ say.

$$\begin{aligned}\binom{n-kt}{2} &= N \left(1 - \frac{kt}{n}\right) \left(1 - \frac{kt}{n-1}\right) \\ &= N (1 - O(kt/n))\end{aligned}$$

So $\frac{m^2}{\binom{n-kt}{2}} \rightarrow 0$ and

$$\begin{aligned}
\binom{\binom{n-kt}{2}}{m-(k-1)t} &= (1+o(1)) \frac{N(1-O(kt/n))^{m-(k-1)t}}{(m-(k-1)t)!} \\
&= \frac{(1+o(1)) N^{m-(k-1)t} (1-O(mkt/n))}{(m-(k-1)t)!} \\
&= (1+o(1)) \frac{N^{m-(k-1)t}}{(m-(k-1)t)!}
\end{aligned}$$

Similarly

$$\binom{N}{m} = (1+o(1)) \frac{N^m}{m!}$$

and so

$$\begin{aligned} \Pr(A_x) &= \frac{\binom{n-kt}{2}}{\binom{N}{m-(k-1)t}} \\ &= (1+o(1)) \frac{m!}{(m-(k-1)t)!} N^{-(k-1)t} = (1+o(1)) \left(\frac{m}{N}\right)^{(k-1)t}. \end{aligned}$$

So

$$\begin{aligned} S_T &\approx \frac{1}{T!} \binom{n}{k, k, k, \dots, k} \left(\frac{k!}{\text{aut}(T)} \right)^T \left(\frac{m}{N} \right)^{(k-1)T} \\ &\approx \frac{n^{kT}}{T! (k!)^T} \cdot \left(\frac{k!}{\text{aut}(T)} \right)^T \cdot \left(\frac{cn}{N} \right)^{(k-1)T} \\ &\approx \frac{\lambda^T}{T!} \end{aligned}$$

where $\lambda = \frac{(2c)^{k-1}}{\text{aut}(T)}$

Fix r large

$$P_r(\text{component copy of } T) =$$

$$\sum_{k=0}^r (-1)^k S_k + \theta_r$$

θ_r is non-positive if r is even
and non-negative if r is odd

$$= \sum_{k=0}^r (-1)^k (1 + o(1)) \frac{\lambda^k}{k!} + \theta_r$$

$$= (1 + o(1)) \sum_{k=0}^r (-1)^k \frac{\lambda^k}{k!} + \theta_r$$

[Here r can be thought of as a large constant while $n \rightarrow \infty$.]

$$(1 + o(1)) \sum_{k=0}^{2r-1} (-1)^k \frac{\lambda^k}{k!} \leq$$

$P_r(\nexists \text{ component copy of } T)$

$$\leq (1 + o(1)) \sum_{k=0}^{2r} (-1)^k \frac{\lambda^k}{k!}$$

Letting $r \rightarrow \infty$

$$P_r(\nexists \text{ component copy of } T) \Rightarrow e^{-\lambda}$$

If there is a copy of T which is not a component then either

(i) \exists cycle — $P_r(\text{cycle}) = o(1)$

(ii) T is part of a tree of size $> k$ — $P_r(\text{tree}) = o(1)$.

So

$$P_r(\exists \text{ copy of } T) \Rightarrow 1 - e^{-\lambda}.$$

Structure of graph when
 $m = \frac{1}{2} cn$, $0 < c < 1$ constant.

We will work in $G_{n,p}$

$$p = \frac{c}{n} \approx \frac{m}{n^2}$$

Cycles

Whp the are $\leq \log n$ edges on cycles.

Let $X_k = \#$ cycles of length k .

$$E(X_k) = \binom{n}{k} \frac{(k-1)!}{2} p^k$$

$$< \frac{n^k}{k!} \frac{(k-1)!}{2} \left(\frac{c}{n}\right)^k$$

$$= \frac{c^k}{2k}.$$

So if $X = 3X_3 + 4X_4 + \dots + nX_n$
 \Rightarrow # edges on cycles

then

$$E(X) \leq \sum_{k=3}^n k \cdot \frac{c^k}{2k} \ll \frac{1}{1-c}.$$

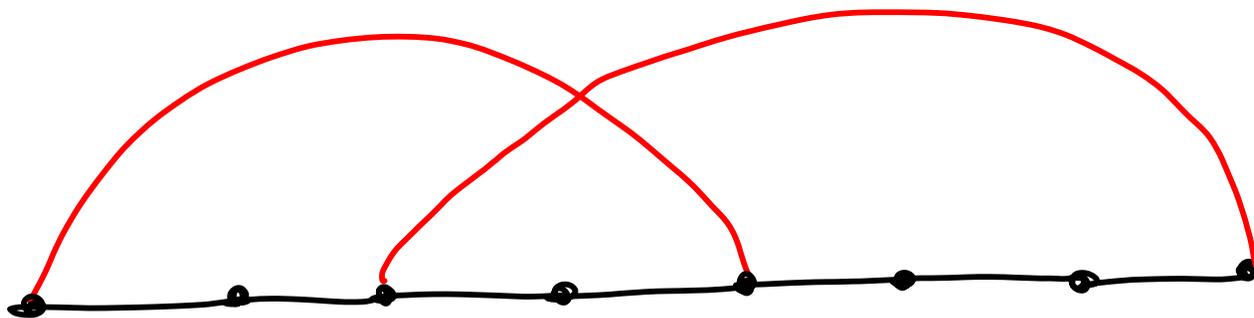
Applying the Markov inequality gives

$$P_r(X > \log n) \leq \frac{1}{(\log n)(1-c)} = o(1).$$

Claim: whp ~~∃~~ a pair of cycles that
are in the same component

Proof

If a pair exists then there is a
minimal pair C_1, C_2



$$E(\# C_3 C_2) \leq \sum_{k \geq 3} \binom{n}{k} \frac{k!}{2} k^2 p^{k+1}$$

$$\leq \frac{1}{n} \sum_{k \geq 3} C^{k+1} k^2$$

→ 0.

So whp every component contains at most one cycle.

We now show that whp
size of largest component
is $O(\log n)$.

Let X_k be the number of components of size k that are unicyclic
 $E(X_k)$

$$\leq \binom{n}{k} k^{k-2} \binom{k}{2} p^{1k} (1-p)^{k(n-k) + \binom{k}{2} - k}$$

$$\leq \frac{n^k}{k!} e^{-\frac{k(k-1)}{2n}} k^k \frac{c^k}{n^k} e^{-ck + ck(k-1)/2n + ck/2n}$$

$$\binom{n}{k} = \frac{n^k}{k!} \prod_{i=0}^{k-1} \left(1 - \frac{i}{n}\right) \quad \text{and} \quad 1 - x \leq e^{-x}$$

$$\leq \frac{n^k}{k!} e^{-\frac{k(k-1)}{2n}} k^k \frac{c^k}{n^k} e^{-ck + \frac{ck(k-1)}{2n}} + c/2$$

$$\leq (ce^{1-c})^k e^{c/2}$$

So if $w \rightarrow \infty$,

$P_r(\exists$ unicyclic component of size $\geq w)$

$$\leq \sum_{k=w}^n e^{c/2} (ce^{1-c})^k$$

$\rightarrow 0$

since $ce^{1-c} < 1$ for $c \neq 1$.

Now let X_k be the number of isolated trees.

Let
$$\alpha = c - 1 - \log c$$

Theorem

Suppose $w \rightarrow \infty$

(i) Whp \exists isolated trees of size

$$\frac{1}{\alpha} (\log n - \frac{5}{2} \log \log n) - w \leftarrow k_+$$

(ii) Whp \nexists an isolated tree of size

$$\geq \frac{1}{\alpha} (\log n - \frac{5}{2} \log \log n) + w \leftarrow k_+$$

Now let $X_k =$ number of isolated trees of size k .

$$E(X_k) = \binom{n}{k} k^{k-2} p^{k-1} (1-p)^{k(n-k) + \binom{k}{2} - k + 1}$$

(i) Suppose $k = O(\log n)$. Then

$$E(X_k) \approx \frac{(1+o(1))}{\sqrt{2\pi k}} \left(\frac{ne}{k}\right)^k k^{k-2} \left(\frac{c}{n}\right)^{k-1} e^{-ck}$$

$$= \frac{(1+o(1))}{\sqrt{2\pi}} \frac{n}{k^{5/2}} (ce^{1-c})^k$$

Putting $k = k_n$

we see that

$$\begin{aligned} E(X_{k_n}) &= \frac{(1+o(1))}{\sqrt{2\pi}} \frac{n}{k_n^{5/2}} (ce^{1-c})^{k_n} \\ &= \frac{(1+o(1))}{\sqrt{2\pi}} \cdot \frac{n}{k_n^{5/2}} \cdot \frac{(\log n)^{5/2} e^{\alpha n}}{n} \\ &\geq A e^{\alpha n}. \end{aligned}$$

We continue via second moment method.

$$E(X_k^2) \leq E(X_k) \left(1 + (1-p)^{-k} E(X_k) \right)$$

[Same argument as for fixed tree T of size k]

Thus

$$\frac{E(X_k)^2}{E(X_k^2)} \geq 1 - \frac{1}{2Ae^{\alpha w}} \rightarrow 1.$$

and we have (i).

For (ii) we go back to

$$E(X_k) = \binom{n}{k} k^{k-2} p^{k-1} (1-p)^{k(n-k) + \binom{k}{2} - k + 1}$$

$$\leq \frac{A}{\sqrt{k}} \left(\frac{ne}{k}\right)^k e^{-k^2/2n} k^{k-2} \left(\frac{c}{n}\right)^{k-1} e^{-ck + ck^2/2n}$$

$$\leq \frac{An}{k^{5/2}} (ce^{1-c})^k$$

and then

$$\sum_{k=k_+}^n E(X_k) \leq An \sum_{k=k_+}^n \frac{(ce^{1-c})^k}{k^{5/2}} = o(1).$$

Useful Identity

$$0 \leq c \leq 1 \text{ implies } \frac{1}{c} \sum_{k=1}^{\infty} \frac{k^{k-1}}{k!} (c e^{-c})^k = 1.$$

Proof

Assume first $c < 1$.

Let σ = number of vertices of $G_{n,p}$ that lie on unicyclic components.

$$n = \sum_{k=1}^n k X_k + \sigma$$

of lines of size k .

so

$$n = \sum_{k=1}^n k E(X_k) + E(\sigma)$$

$$(i) E(\sigma) \leq \log n$$

$$(ii) \sum_{k \geq k_+} k E(X_k) \leq \frac{1}{c} \sum_{k=k_+}^n \frac{(c e^{1-c})^k}{k^{3/2}} = o(1).$$

(iii) If $k < k_+$ then

$$\begin{aligned} E(X_k) &= \binom{n}{k} k^{k-2} p^{k-1} (1-p)^{k(n-k) + \binom{k}{2} - k + 1} \\ &= (1+o(1)) \frac{n}{c} \frac{k^{k-1}}{k!} (c e^{-c})^k \end{aligned}$$

So

$$n = \sum_{k=1}^n k E\binom{X}{k} + E(\sigma)$$

$$= 0(n) + \frac{n}{c} \sum_{k=1}^n \frac{k^{k-1}}{k!} (c e^{-c})^k$$

$$= 0(n) + \frac{n}{c} \sum_{k=1}^{\infty} \frac{k^{k-1}}{k!} (c e^{-c})^k$$

Now divide through by n .



Structure of graph when
 $m = \frac{1}{2} cn$, $c > 1$ constant.

We will work in $G_{n,p}$

$$p = \frac{c}{n} \approx \frac{m}{n^2}$$

Suppose now that X_k is the number of components of size k . Then

$$\begin{aligned}
 E(X_k) &\leq \binom{n}{k} k^{k-2} p^{k-1} (1-p)^{k(n-k)} \\
 &\leq \frac{A}{\sqrt{k}} \left(\frac{ne}{k}\right)^k e^{-k^2/2n} k^{k-2} \left(\frac{c}{n}\right)^{k-1} e^{-ck + ck^2/n} \\
 &\leq \frac{An}{k^{5/2}} (ce^{1-c} + ck/n)^k.
 \end{aligned}$$

Now let $B_1 = B_1(c)$ be small enough
so that

$$c e^{1-c+B_1} < 1.$$

and let $B_0 = B_0(c)$ be large enough
so that

$$(c e^{1-c+B_1})^{B_0 \log n} < \frac{1}{n^2}.$$

It follows that whp ~~∃~~ a component
of size $k \in [B_0 \log n, B_1 n]$

Our calculations for $c < 1$ can be repeated to show that if

$$\alpha = c - 1 - \log c$$

Theorem

Suppose $w \rightarrow \infty$

(i) Whp \exists an isolated line of size

$$\frac{1}{\alpha} (\log n - \frac{5}{2} \log \log n) - w \leftarrow k_-$$

(ii) Whp ~~\exists~~ an isolated line of size

$$\geq \frac{1}{\alpha} (\log n - \frac{5}{2} \log \log n) + w \leftarrow k_+$$

provided $w = O(\log n)$.

We can say a little more about components of size k , $k = O(\log n)$.

If we repeat the calculations for $c < 1$ then we find that if Y_k is the number of isolated trees of size

$$k = \frac{1}{\alpha} (\log n - \frac{5}{2} \log \log n) - w$$

then

$$E(Y_k) \geq A e^{\alpha w}$$

For some $A = A(c) > 0$.

$$E(Y_k^2) \leq E(Y_k) + E(Y_k)^2 (1-p)^{-k^2}$$

So

$$\text{Var}(Y_k) \leq E(Y_k) + E(Y_k)^2 ((1-p)^{-k^2} - 1)$$

$$\leq E(Y_k) + 2E(Y_k)^2 ck^2/n.$$

So

$$P_r(|Y_k - E(Y_k)| \geq \epsilon E(Y_k))$$

$$\leq \frac{1}{\epsilon^2 E(Y_k)} + \frac{2ck^2}{\epsilon^2 n}. \quad (*)$$

We now estimate the total number of vertices on small tree components i.e. size $\leq B_0 \log n$.

(i) $1 \leq k \leq k_0 = \frac{1}{2\alpha} \log n$

$$E \left(\sum_{k=1}^{k_0} k Y_k \right) \approx \frac{n}{c} \sum_{k=1}^{k_0} \frac{k^{k-1}}{k!} (ce^{-c})^k$$

$$\approx \frac{n}{c} \sum_{k=1}^{\infty} \frac{k^{k-1}}{k!} (ce^{-c})^k$$

Since $\frac{k^{k-1}}{k!} < e^{-k}$ and $ce^{1-c} < 1$.

Putting $\epsilon = \frac{1}{\log n}$ we see that

the probability that any Y_k deviates from its mean by more than $\pm \epsilon$ is at most (see (*) on p 6)

$$\sum_{k=1}^{k_0} \left[\frac{(\log n)^2}{n^{1/3}} + O\left(\frac{(\log n)^4}{n}\right) \right] = o(1).$$

Thus whp

$$\sum_{k=1}^{k_0} k Y_k \approx \frac{c}{c} \sum_{k=1}^{k_0} \frac{k^{k-1}}{k!} (ce^{-c})^k$$

$$\approx \frac{c}{c} \sum_{k=1}^{\infty} \frac{k^{k-1}}{k!} (ce^{-c})^k$$

$$= \frac{c}{c} \sum_{k=1}^{\infty} \frac{k^{k-1}}{k!} (\alpha e^{-\alpha})^k$$

where $0 < \alpha < 1$ and $\alpha e^{-\alpha} = ce^{-c}$

$$= \frac{c}{c} \alpha.$$

Now consider $k_0 < k \leq B_0 \log n$.

$$E \left(\sum_{k=k_0+1}^{B_0 \log n} k Y_k \right) \leq$$

$$\frac{n}{C} \sum_{k=k_0+1}^{B_0 \log n} \frac{An}{k^{3/2}} (ce^{1-c} + ck/n)^k$$

$$= o(n / (\log n)^{3/2}).$$

So, by the Markov inequality, whp,

$$\sum_{k=k_0+1}^{B_0 \log n} k Y_k = o(n).$$

Now consider the number of vertices Z_k on non-tree components with k vertices, $1 \leq k \leq B_0 \log n$.

$$E \left(\sum_{k=1}^{B_0 \log n} Z_k \right) \leq \sum_{k=1}^{B_0 \log n} \binom{n}{k} k^{k-2} \binom{k}{2} \left(\frac{c}{n} \right)^k \left(1 - \frac{c}{n} \right)^{k(n-k)}$$

$$\leq \sum_{k=1}^{B_0 \log n} \left(c e^{1-c+k/n} \right)^k$$

$$= O(1).$$

So, by the Markov inequality, whp

$$\sum_{k=1}^{B_0 \log n} Z_k = o(n).$$

So far: whp

there are $\approx \frac{n\alpha}{c}$

$$\alpha e^{-\alpha} = c e^{-c}$$

vertices on components of size k ,

$$1 \leq k \leq B_0 \log n.$$

The giant component.

Let $c_1 = c - \frac{\log n}{n^2}$ and $p_1 = \frac{c_1}{n}$

and define p_2 by

$$1-p = (1-p_1)(1-p_2).$$

Then

$$G_{n,p} = G_{n,p_1} \cup G_{n,p_2}$$

since probability e is not included in G_{n,p_2} is

$$(1-p_1)(1-p_2).$$

Note that

$$p_2 \geq \frac{\log n}{n^2}.$$

If $\alpha_1 e^{-\alpha_1} = c_1 e^{-c_1}$ then $\alpha_1 \approx c_1$ and
so by our previous analysis, whp,
 G_{n, p_1} has no components of size in the
range $[B_0 \log n, B_1 n]$.

Suppose there are components C_1, C_2, \dots, C_ℓ
with $|C_i| > B_0 n$. Thus $\ell \leq \frac{1}{B_0}$.

Now we add in the edges of G_{n, p_2} .

$$\begin{aligned}
& P_r(\exists i, j : \text{no } G_{n, p_2} \text{ edge joins } C_i, C_j) \\
& \leq \binom{l}{2} (1-p_2)^{(B_0 n)^2} \\
& \leq l^2 e^{-B_0^2 (\log n)^2} \\
& = o(1).
\end{aligned}$$

So whp $G_{n, p}$ has a **unique** component of size greater than $B_0 \log n$, and it is of size $(1 - \frac{\alpha}{c})n$.

Duality

Let $N = \frac{n\alpha}{c} \approx \#$ vertices outside giant whp.

Let $q = \frac{\alpha}{N} (= p)$.

Note that $\alpha < 1$ and $\#$ of isolated trees of size k is whp

$$\approx \frac{n}{c} \cdot \frac{k^{k-2}}{k!} (ce^{-c})^k$$

$$= \frac{N}{\alpha} \cdot \frac{k^{k-2}}{k!} (\alpha e^{-\alpha})^k.$$

Thus graph outside of giant component is asymptotically equal to $G_{N, \frac{\alpha}{N}}$ in distribution.

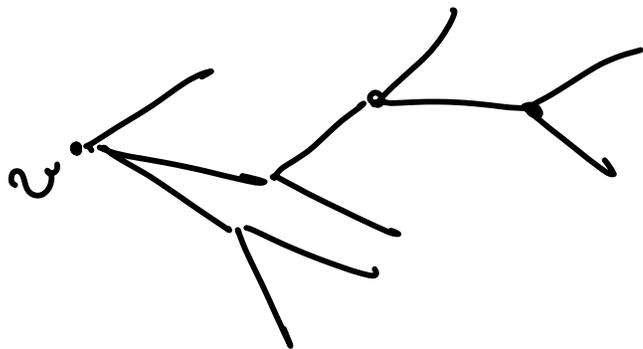
Branching Processes

If $p = c/n$ and $d(v)$ is the degree of vertex v then

$$\begin{aligned} P_r(d(v) = k) &= \binom{n-1}{k} p^k (1-p)^{n-1-k} \\ &= (1+o(1)) \frac{c^k e^{-c}}{k!} \end{aligned}$$

i.e. the degree distribution is asymptotically Poisson with mean c .

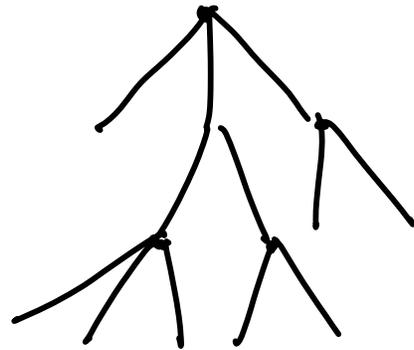
Since there are few "small" cycles,
locally, $G_{n,p}$ should look like



and this has led to a comparison with
Branching Processes.

It is not really so useful a method
for here, but it can be the right
approach for other models of a random
graph.

In a simple branching process there is an initial individual who "gives birth" to X_1 children and then dies. Each of the X_1 individuals give birth and die and so on.



The number of children X produced by an individual is a random variable independent of the number produced by any other.

Let

$$p_k = P_1(X = k), \quad k = 0, 1, 2, \dots$$

and

$$G(z) = \sum_{k=0}^{\infty} p_k z^k$$

is the **probability generating function**
(p.g.f.) of X .

Let

$$\begin{aligned} \mu &= E(X) \\ &= G'(1). \end{aligned}$$

Let X_t be the number of individuals in generation t . Thus

$$X_0 = 1$$

$$E(X_{t+1}) = \sum_{k=0}^{\infty} E(X_{t+1} | X_t = k) P_r(X_t = k)$$

$$= \sum_{k=0}^{\infty} k \mu P_r(X_t = k)$$

$$= \mu E(X_t)$$

and so

$$E(X_t) = \mu^t.$$

Let T denote the total size of the set of individuals produced.

$T = \infty$ is allowed and $\Pr(T = \infty)$ is one of the important parameters of the process.

Theorem

$\Pr(T < \infty) = y$ where y is the smallest non-negative root of $y = G(y)$.

In particular, $y = 1$ if $\mu \leq 1$.

Before proving this, let us consider the case where X has Poisson distribution with mean c .

$$G(z) = \sum_{k=0}^{\infty} \frac{c^k e^{-c}}{k!} z^k$$
$$= e^{c(z-1)}$$

From the Theorem, the "extinction probability"

y satisfies

$$y = e^{c(y-1)}$$

But then

$$cy e^{-cy} = c e^{-c}$$

Assume $c > 1$ and then $x = cy < 1$.

If we choose a vertex v and look at the BFS tree grown from v then (as we will check) this looks like our branching process.

If $T = \infty$ corresponds to being in the giant and v is chosen randomly, then

$$\Pr(v \in \text{Giant}) \approx 1 - y = 1 - \frac{x}{c}.$$

Proof of Theorem

Let G_T be the p.g.f. for X_T . Thus

$$\begin{aligned} G_{T+1}(z) &= \sum_{k=0}^{\infty} \sum_{l=0}^{\infty} P_r(X_{T+1}=k \mid X_T=l) P_r(X_T=l) z^k \\ &= \sum_{l=0}^{\infty} G_T(z)^l P_r(X_T=l) \\ &= G(G_T(z)) \end{aligned}$$

** If X, Y have p.g.f.'s f, g then $X+Y$
has p.g.f. $f * g$.

Let $y_{\tau} = P_r(X_{\tau} = 0)$ so that

$$y_{\tau} = G_{\tau}(0) = G(G_{\tau-1}(0)) = G(y_{\tau-1}).$$

Now y_{τ} is monotone increasing to $P_r(T < \infty)$
and so the continuity of G implies

$$y = G(y).$$

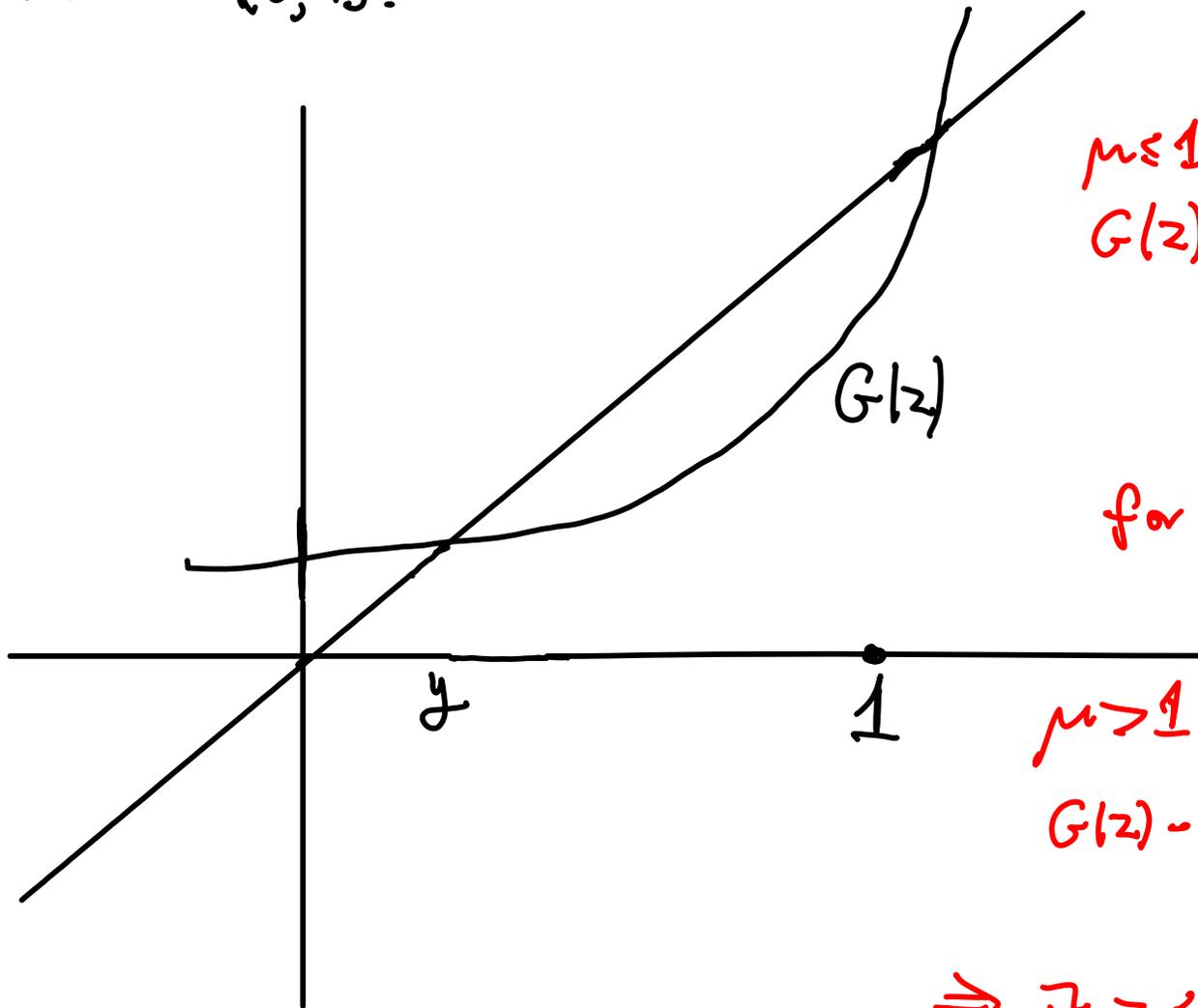
If ξ is any non-negative root of $z = G(z)$
then

$$y_1 = G(0) \leq G(\xi) = \xi$$

and

$$y_{\tau} \leq \xi \implies y_{\tau+1} = G(y_{\tau}) \leq G(\xi) = \xi.$$

G is strictly convex on $[0, 1]$ — $G''(z) = \sum_{k=2}^{\infty} k(k-1)p_k z^{k-2} > 0$
 for $z \in (0, 1]$.



$\mu \leq 1$:
 $G(z) > G(1) - G'(1)(1-z)$
 $= 1 - \mu(1-z)$
 $\geq z$
 for $0 \leq z < 1$

$\mu > 1$:
 $G(z) - z < 0 \quad z = 1 - \epsilon$
 $> 0 \quad z = 0$

$\Rightarrow \exists z < 1 - \epsilon$ s.t.
 $G(z) - z = 0.$

Thus

$$y = P_r(T < \infty) = \lim_{t \rightarrow \infty} P_r(T \leq t)$$

and we can write

$$P_r(T \leq t) = y - \sigma(t)$$

where $\sigma(t) \geq 0$ and $\lim_{t \rightarrow \infty} \sigma(t) = 0$.

Back to $G_{n,p}$, $p = c/n$ $c > 1$.

Suppose we choose a vertex a and do a BFS from a until either

(i) we have explored the component C_a containing a

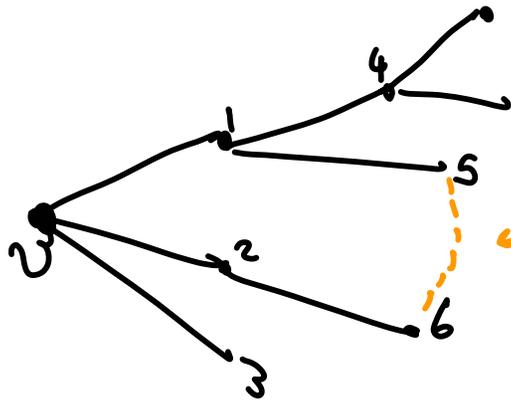
or

(ii) explored $w \rightarrow \infty$ vertices.*

Let T_a be the (partial) BFS tree produced.

We are going for ease of proof rather than best possible

Now fix a tree H with $\leq W = n^{\frac{1}{2}} (\log n)^3$ vertices and maximum degree $(\log n)^2$.



Let $d_i = \text{degree of } i$.
 We do not include these edges in def. of T_{a_i} $i = 0, 1, 2, \dots, l$

$$P_r(H = T_{a_i}) = \prod_{i=0}^l \binom{n_i}{d_i} p^{d_i} (1-p)^{n_i - d_i - (s_i)}$$

where

$$n_i = n - 1 - d_1 - \dots - d_{i-1}$$

$$= \left(\prod_{i=0}^l \frac{c^{d_i} e^{-c}}{d_i!} \right) \left(1 + O\left(\frac{c}{n}\right) \right)$$

$$= \left(\prod_{i=0}^l \frac{c^{d_i} e^{-c}}{d_i!} \right) \left(1 + o\left(\frac{\omega}{n}\right) \right)$$

$$= \Pr(H \text{ is branching process tree}) * (1 + o(1))$$

Thus,

$$\Pr(|C_a| < \omega) =$$

$$\Pr(|C_a| < \omega \wedge \Delta \geq (\log n)^2) +$$

$$\Pr(|C_a| < \omega \wedge \Delta \leq (\log n)^2)$$

$$\leq n \binom{n-1}{L} \left(\frac{c}{n}\right)^L$$

$$\leq n \left(\frac{ce}{L}\right)^L = o(1)$$

$$= o(1) + \sum_{H: |H| \leq \omega} \Pr((T_a = H) \wedge (\Delta(G \setminus C_a) \leq (\log n)^2))$$

$$= o(1) + \sum_{H: |H| \leq \omega} \Pr(T_a = H) \Pr(\Delta(G \setminus C_a) \leq (\log n)^2)$$

$$= o(1) + (1 + o(1)) \sum_{H: |H| \leq \omega} \Pr(T_a = H)$$

$$= o(1) + (1 + o(1)) \sum_{H: |H| \leq \omega} \Pr(H \text{ is branching process tree})$$

$$\stackrel{=} {=} o(1) + (1 + o(1)) \Pr(T_a \leq \omega) \approx \gamma.$$

Thus if
 $X_0 = \#\nu : |C_\alpha| < w, \quad w \rightarrow \infty$

then

$$E(X) = ny (1 - O(w/n) - \sigma(w)).$$

We next show, via Chebyshev, that
 X_0 is concentrated around its mean.

C_v

In constructing C_v we do not look at edges here i.e. they are unconditioned

We claim that for $b \neq a$

$$\begin{aligned} & \Pr(|C_b| < w \mid |C_a| < w) \quad (*) \\ & \approx \frac{|C_a|}{n} + (1 + o(1)) \Pr(|C_b| < \log n) \end{aligned}$$

\uparrow
 $\Pr(w \in C_a)$

\uparrow
Fixing C_a , we replace n by $n - |C_a|$ in computing $\Pr(|C_b| < w)$.

It follows from $\textcircled{*}$ on previous page that

$$E(X_0^2) \leq E(X_0) + E(X_0) \times \frac{\omega}{n} + (1 + o(1)) E(X_0)^2$$

i.e.

$$\text{Var}(X_0) \leq 2 E(X_0) + \eta E(X_0)^2$$

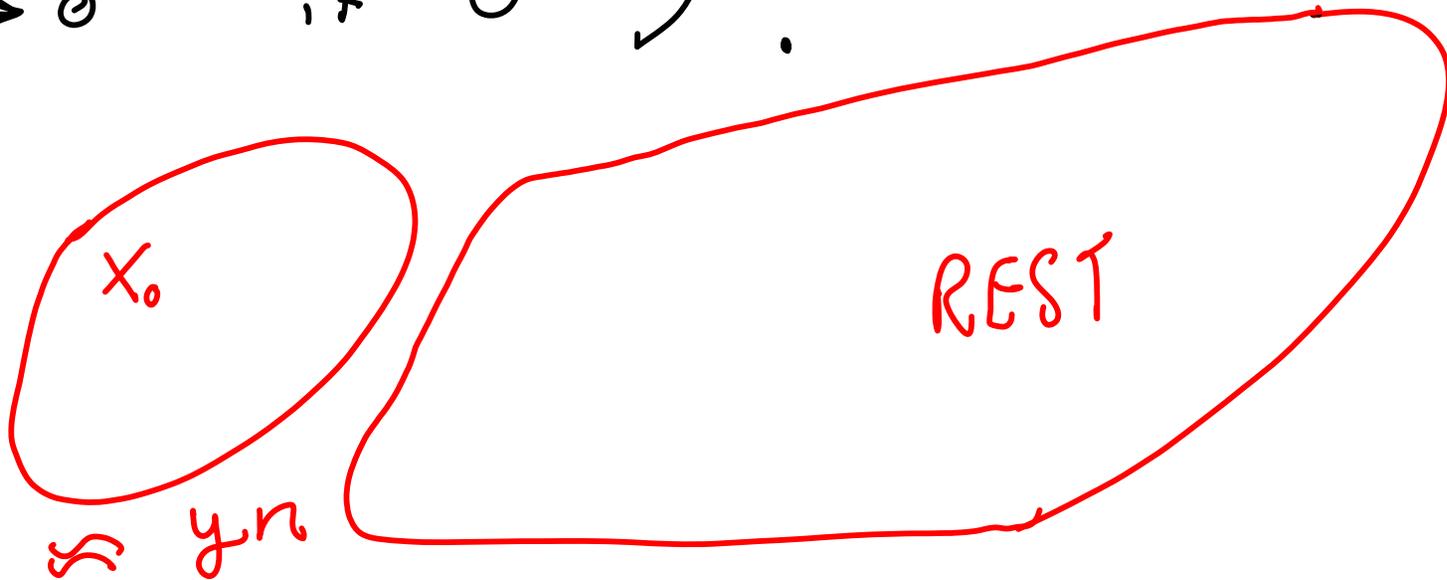
where $\eta \rightarrow 0$.

Then

$$P_r(|X_0 - E(X_0)| \geq \theta n)$$

$$\leq \frac{2E(X_0)}{\theta^2 n^2} + \frac{\gamma E(X_0)^2}{\theta^2 n^2}$$

$$\rightarrow 0 \quad \text{if} \quad \theta = \gamma^{1/3}.$$



Our aim now is to show that REST is connected, without using previous analysis.

Suppose $|C_v| \geq n^{\frac{1}{2}} (\log n)^3$ and we stop our DFS from v when we reach $n^{\frac{1}{2}} (\log n)^3$.



We argue next that whp

$$|N(S_a)| \geq n^{\frac{1}{2}} (\log n)$$

Indeed

$$P(\exists S, T: |S| = \underbrace{n^{\frac{1}{2}} (\log n)^3}_k, |T| = \underbrace{n^{\frac{1}{2}} \log n}_l : \bullet$$

S induces a connected subgraph and

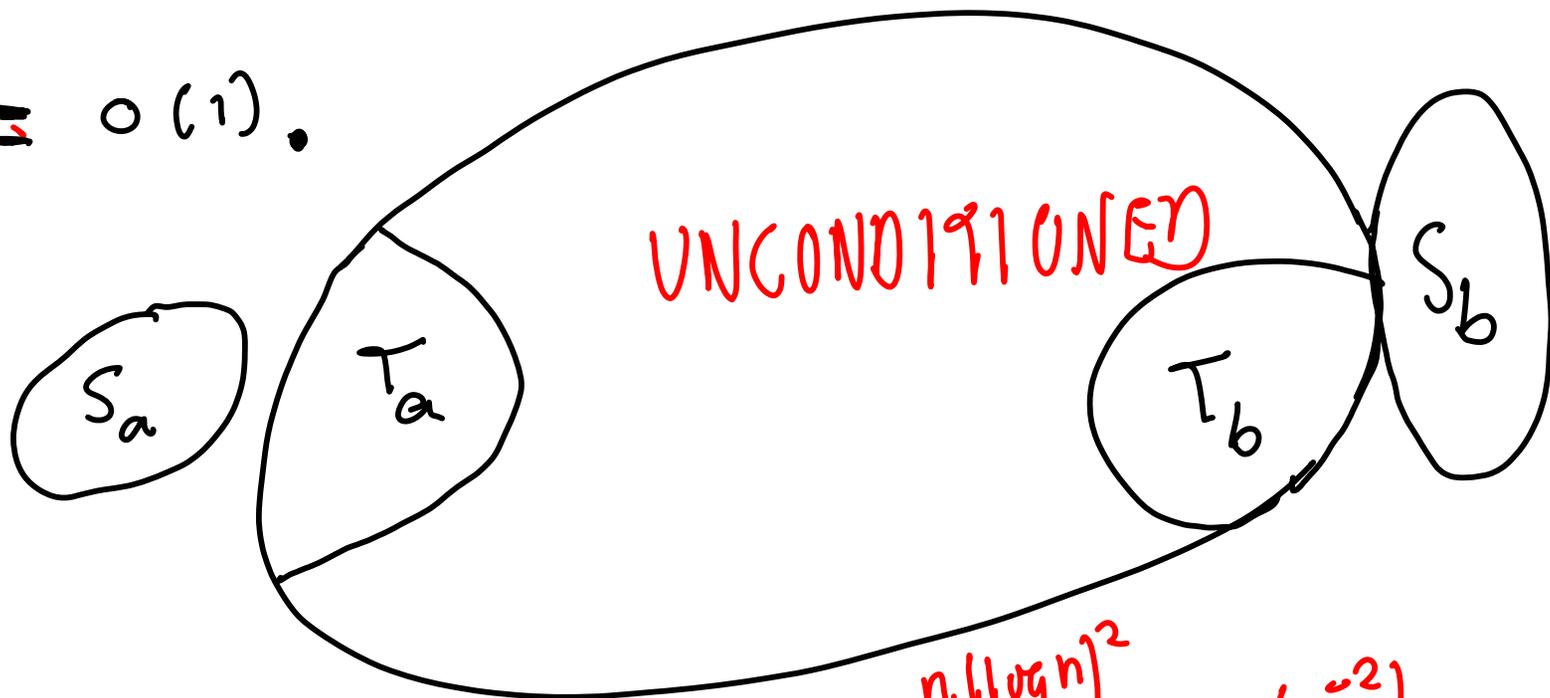
there are no $S: [n] \setminus (S \cup T)$

$$\leq \binom{n}{k} \binom{n}{l} k^{k-2} p^{k-1} (1-p)^{k(n-k-l)}$$

$$\geq \left(\frac{ne}{k}\right)^k \cdot \left(\frac{ne}{e}\right)^l \cdot k^{k-2} \left(\frac{c}{n}\right)^{k-1} e^{-ck(1-o(1))}$$

$$\geq n \left(c e^{1-c} \cdot n^{1/(\log n)^2} \right)^k \quad l \leq \frac{k}{(\log n)^2}$$

$\ll o(1)$.



$$P_r(\text{no } T_a, T_b \text{ edges}) \leq (1-p)^{n(\log n)^2} = o(n^{-2}).$$

This shows that vertices a_i ,
 $|C_a| \geq n^{\frac{1}{2}} (\log n)^3$ form a connected
component.

Connectivity of random graphs

Let $p = \frac{\log n + c_n}{n}$. We prove

$$\lim_{n \rightarrow \infty} P(G_{n,p} \text{ is connected}) = \begin{cases} 0 & c_n \rightarrow -\infty \\ e^{-e^{-c}} & c_n \rightarrow c \\ 1 & c_n \rightarrow +\infty \end{cases}$$

If $p_1 > p_2$ then we can write

$$G_{n,p_1} = G_{n,p_2} \vee G_{n,p_3}$$

where $(1 - p_1) = (1 - p_2)(1 - p_3)$

and so

$$\Pr(G_{n,p_1} \text{ is connected})$$

$$\geq \Pr(G_{n,p_2} \text{ is connected})$$

can replace "is connected"
by any monotone ↑ property.

It suffices to prove that

$$\Pr(G_{n,p} \text{ is connected}) \rightarrow e^{-e^{-c}}$$

when $p = \frac{\log n + c}{n}$.

Now

$$\begin{aligned} & \Pr(G_{n,p} \text{ is not connected}) \\ &= \Pr\left(\bigcup_{i=1}^{n/2} \exists \text{ a component of size } i\right) \end{aligned}$$

So we have

$$\Pr(\exists \text{ isolated vertex}) \leq$$

$$\Pr(G_{n,p} \text{ is not connected}) \leq$$

$$\Pr(\exists \text{ isolated vertex}) + \sum_{k=2}^{n/2} \Pr(\exists \text{ component of size } k)$$

Now

$$\sum_{k=2}^{n/2} P(\exists \text{ component of size } k)$$

$$\leq \sum_{k=2}^{n/2} E(\# \text{ of components of size } k)$$

$$\leq \sum_{k=2}^{n/2} \underbrace{\binom{n}{k} k^{k-2} p^{k-1} (1-p)^{k(n-k)}}_{u_k}$$

For $2 \leq k \leq 10$

$$u_k \leq \binom{n}{k} k^{k-2} \cdot \left(\frac{\log n + c}{n}\right)^{k-1} e^{-k(n-10) \frac{\log n + c}{n}} \leq (1+o(1)) \frac{e^{k(1-c)} (\log n)^{k-1}}{n^{k-1}}$$

and for $k \geq 10$

$$u_k \leq \left(\frac{ne}{k}\right)^k k^{k-2} \left(\frac{\log n + c}{n}\right)^{k-1} e^{-k(\log n + c)/2}$$

$$\leq n \left(\frac{e^{1-c/2+o(1)} \log n}{n^{1/2}} \right)^k$$

So

$$\sum_{k=2}^{n/2} u_k \leq (1+o(1)) \frac{e^{-c} \log n}{n} + \sum_{k=10}^{n/2} n^{1+o(1)-k/2}$$

$$= O(n^{o(1)-1}).$$

It follows that

$$\Pr(G_{n,p} \text{ is connected}) = \Pr(\nexists \text{ an isolated vertex}) + o(1).$$

So now let

X_0 = the number of isolated vertices in $G_{n,p}$.

Then

$$E(X_0) = n(1-p)^{n-1}$$

$$= n \exp\{(n-1) \log(1-p)\}$$

$$= n \exp\left\{- (n-1) \sum_{k=1}^{\infty} \frac{p^k}{k}\right\}$$

$$= n \exp\left\{- (\log n + c) + O\left(\frac{(\log n)^2}{n}\right)\right\}$$

$$\approx e^{-c}.$$

If we let

A_i be the event {vertex i is isolated}

and \downarrow

$$S_b = \sum_{\substack{X \subseteq [n] \\ |X|=b}} \Pr(A_X)$$

then

$$S_b = \binom{n}{b} (1-p)^{b(n-b) + \binom{b}{2}}$$

$$\approx e^{-bp} / b!$$

$$b = O(1).$$

Thus we deduce, as in our study of isolated trees,

that $\lim_{n \rightarrow \infty} \Pr(X_0 = 0) = e^{-e^{-c}}$

Hitting Time Version in Graph Process

Let $m_1^* = \min\{m : \delta(G_m) \geq 1\}$

$$m_c^* = \min\{m : G_m \text{ is connected}\}$$

We show

$$m_1^* = m_c^* \quad \text{whp}$$

Let

$$m_{\pm} = \frac{1}{2} n \log n \pm \frac{1}{2} n \log \log n$$

and

$$p_{\pm} = \frac{m}{N} \approx \frac{\log n \pm \log \log n}{2}$$

We first show that whp

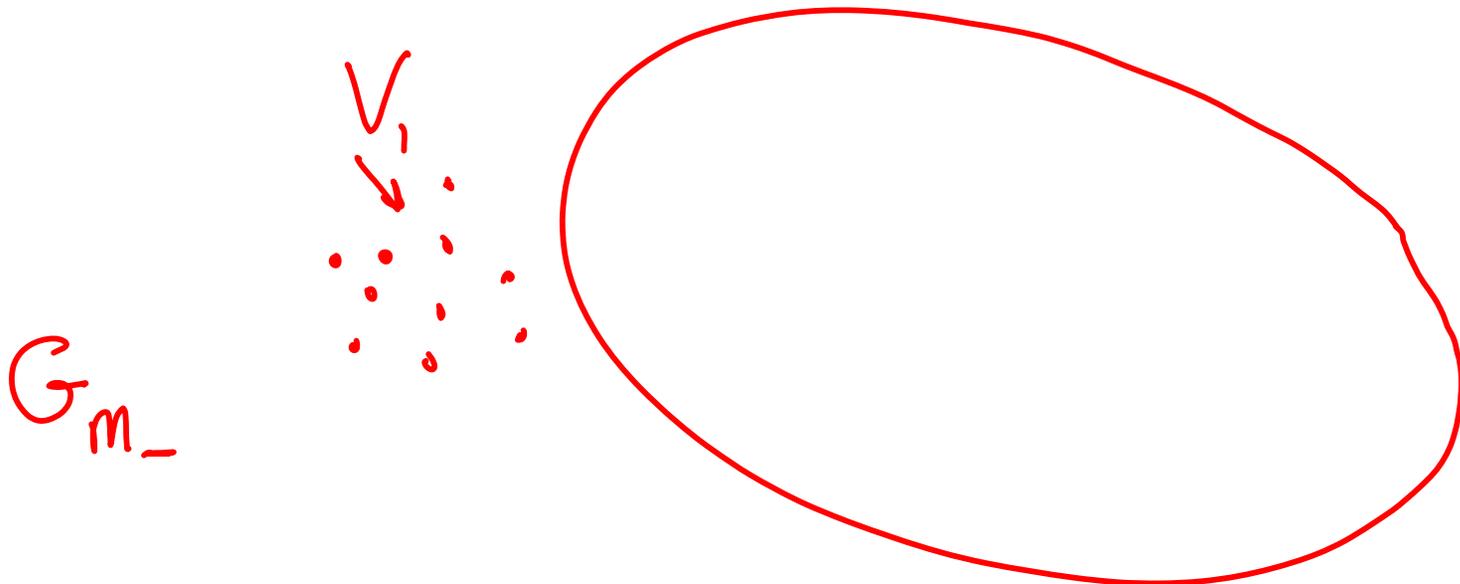
(i) $G_{m_{-}}$ consists of a giant connected component plus a set V_1 of $\leq 2 \log n$ vertices.

(ii) $G_{m_{+}}$ is connected.

Assume (i) and (ii).

It follows that whp

$$m_- \leq m_1^* \leq m_c^* \leq m_+$$



To create G_{m_+} we add $m_+ - m_-$ random edges.

$m_1^* = m_c^*$ if none of these edges is contained in V_1

Thus

$$\begin{aligned} \Pr(m_i^* < m_c) &\leq o(1) + (m_+ - m_1) \frac{\frac{1}{2}|V_1|^2}{N - m_+} \\ &= o(1) + \frac{n (\log \log n) * (2 (\log n)^2)}{\frac{1}{2}n^2 - o(n \log n)} \\ &= o(1). \end{aligned}$$

$$(1) \text{ Let } p = \frac{m}{N} \approx \frac{\log n - \log \log n}{n}$$

and let $X_1 = \#$ isolated vertices in $G_{n,p}$.

Then

$$E(X_1) = n(1-p)^{n-1}$$

$$= ne^{-np + o(np^2)}$$

$$\approx \log n.$$

$$E(X_1^2) = E(X_1) + n(n-1)(1-p)^{2n-3}$$

$$\leq E(X_1) + E(X_1)^2 (1-p)^{-3}$$

so

$$\text{Var}(X_1) \leq E(X_1) + 4E(X_1)^2 p$$

$$P_r(X_1 \geq 2 \log n) = P_r(|X_1 - E(X_1)| \geq (1+o(1))E(X_1))$$

$$\leq (1+o(1)) \left(\frac{1}{E(X_1)} + 4p \right)$$

$$= o(1)$$

Having $\geq 2 \log n$ isolated vertices is a monotone property and so whp

G_m has $< 2 \log n$ isolated vertices.

To show that the rest of G_m is a single component we let X_k , $2 \leq k \leq \frac{n}{2}$ be the number of components with k vertices in G_p .

Repeating the calculation on p5

$$E\left(\sum_{k=2}^{n/2} X_k\right) = O(n^{o(1)} - 1)$$

Let $\mathcal{E} = \{ \exists \text{ component of size } 2 \leq k \leq \frac{1}{2}n \}$

$$\begin{aligned} \Pr(G_n \in \mathcal{E}) &\leq O(\sqrt{n}) \Pr(G_{n, p} \in \mathcal{E}) \\ &= o(1) \end{aligned}$$

and this complete proof of (i).

(ii) G_{m_+} is connected whp.

This follows from $G_{n,p}$ is connected whp for $np - \log n \rightarrow \infty$
or by implication G_m is connected whp if $n \cdot \frac{m}{N} - \log n \rightarrow \infty$

$$\frac{nm_+}{N} = \frac{n \left(\frac{1}{2} n \log n + \frac{1}{2} n \log \log n \right)}{N}$$
$$\approx \log n + \log \log n.$$

k -connectivity.

Here we will prove that if $k = O(1)$

and

$$m = \frac{1}{2}n (\log n + (k-1) \log \log n + c_n)$$

then

$$\lim_{n \rightarrow \infty} \Pr(G_{n,m} \text{ is } k\text{-connected}) = \begin{cases} 0 & c_n \rightarrow -\infty \\ e^{-\frac{e^{-c}}{(k-1)!}} & c_n \rightarrow c \\ 1 & c_n \rightarrow \infty \end{cases}$$

$$\text{Let } p = \frac{\log n + (k-1) \log \log n + c}{n}$$

We will prove

$$(i) \quad \mathbb{E}(\# \text{ vertices of degree } \leq k-2) = o(1)$$

$$(ii) \quad \mathbb{E}(\# \text{ vertices of degree } k-1) \approx \frac{e^{-c}}{(k-1)!}$$

It then a simple matter to verify that

$$P(\delta(G_{n,p}) \geq k) \approx e^{-\frac{e^{-c}}{(k-1)!}}$$

$$\begin{aligned}
& E(\# \text{ vertices of degree } b \leq k-1) \\
&= n \binom{n-1}{b} p^b (1-p)^{n-1-b} \\
&\approx n \cdot \frac{n^b}{b!} \cdot \frac{(\log n)^b}{n^b} \cdot \frac{e^{-c}}{n (\log n)^{k-1}}
\end{aligned}$$

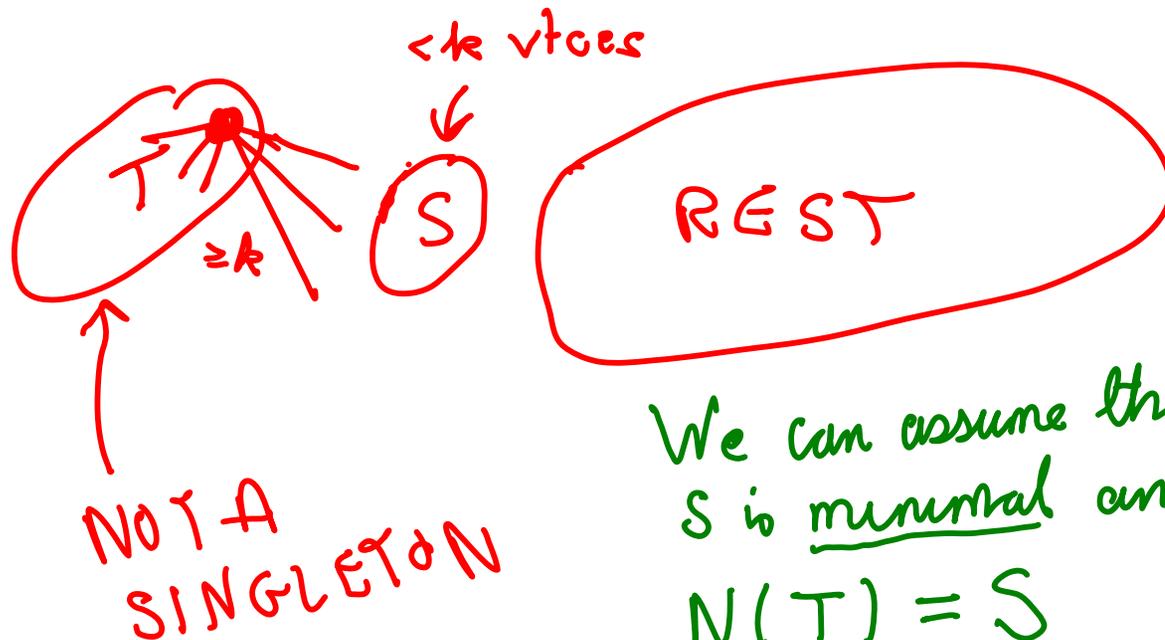
and (i) and (ii) follow immediately.

We now show that,

$P, (\exists S, |S| < k$ and $T, k - |S| + |S| |T| \leq \frac{1}{2}(n-s)$

T is a component of $G_{n,p} \setminus S = o(1)$.

This implies that if $\delta(G_{n,p}) \geq k$ then it is k -connected whp



We can assume that S is minimal and then $N(T) = S$

First moment :

$$E(\#S, T) \leq$$

Case 1 : $s+2 \leq t \leq \log n$

$$\begin{aligned} & \sum_{s=0}^{k-1} \sum_{t=s+2}^{\log n} \binom{n}{s} \binom{n}{t} t^{t-2} p^{t-1} (1-p)^{t(n-s-t)} \\ & \ll \sum_{s=0}^{k-1} \sum_{t=s+2}^{\log n} n^s \cdot \left(\frac{ne}{t}\right)^t \cdot t^{t-2} \cdot \left(\frac{e^{o(1)} \log n}{n}\right)^{t-1} \frac{e^{o((\log n)^2/n)}}{n^t (\log n)^{(k-1)t}} \\ & \ll \sum_{s=0}^{k-1} \sum_{t=s+2}^{\log n} (e^{1+o(1)} \log n)^t n^{s-t} \end{aligned}$$

$$= O(1).$$

Case 2 : $t > \log n$

$$\sum_{s=0}^{k-1} \sum_{t=\log n}^{\frac{1}{2}(n-s)} \binom{n}{s} \binom{n}{t} t^{t-2} p^{t-1} (1-p)^{t(n-s-t)}$$

$$\approx \sum_{s=0}^{k-1} \sum_{t=\log n}^{\frac{1}{2}(n-s)} n^s \left(\frac{ne}{t}\right)^t t^{t-2} \left(\frac{e^{o(1)} \log n}{n}\right)^{t-1} n^{-t/2}$$

$$\approx \sum_{s=0}^{k-1} \sum_{t=\log n}^{\frac{1}{2}(n-s)} n^{1+s-\frac{1}{2}t} (e^{o(1)} \log n)^t$$

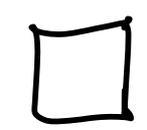
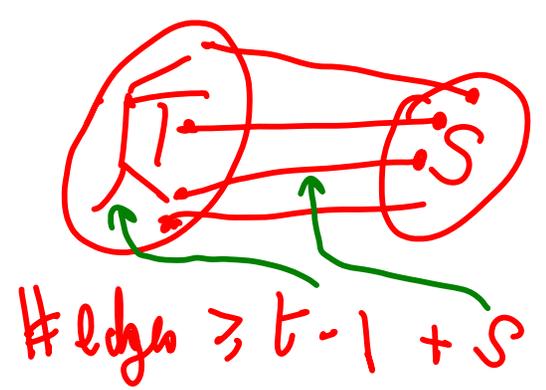
$$= o(1).$$

Case 3: $k-s+1 \leq t \leq s+1$

$$\sum_{s=0}^{k-1} \sum_{\substack{t \geq 2 \\ t \geq k-s+1}}^{s+1} \binom{n}{s} \binom{n}{t} t^{t-2} \binom{st}{s} p^{t-1+s} (1-p)^{t(n-s-t)}$$

$$\leq \sum_{s=0}^{k-1} \sum_t n^{s+t} 2^{st} \left(\frac{e^{o(1)} \log n}{n} \right)^{t-1+s} \frac{1+o(1)}{n^t}$$

$= o(1)$.



Perfect Matchings in Random Graphs

Let $K_{n,n,p}$ be the random **bipartite** graph with vertex bipartition $A=B=[n]$ in which each of the n^2 possible edges appears independently, with probability p .

Theorem

$$\text{Let } p = \frac{\log n + c_n}{n}.$$

$$\lim_{n \rightarrow \infty} \Pr(K_{n,n,p} \text{ has a perfect matching}) = \begin{cases} 0 & c_n \rightarrow -\infty \\ e^{-2e^{-c}} & c_n \rightarrow c \\ 1 & c_n \rightarrow \infty \end{cases}$$

$$= \lim_{n \rightarrow \infty} \Pr(\mathcal{S}(K_{n,n,p}) \geq 1).$$

Let $X_0 = \#$ isolated vertices.

$$E(X_0) = 2n(1-p)^n \\ \approx 2e^{-c}.$$

By previously used techniques we

$$\Pr(X_0 = 0) \approx e^{-2e^{-c}}.$$

We will now use Hall's condition.

$G = K_{n,n,p}$ contains a perfect matching iff

$$\forall S \subseteq A, |N(S)| \geq |S|. \quad (*)$$

It is convenient to replace (*) by

$$\forall S \subseteq A, |S| \leq \frac{1}{2}n, |N(S)| \geq |S| \quad (**)$$

$$\forall T \subseteq B, |T| \leq \frac{1}{2}n, |N(T)| \geq |T|.$$

$P_r(\exists v: v \text{ is isolated})$

$\leq P_r(\nexists \text{ a perfect matching}) \leq$

$P_r(\exists v: v \text{ is isolated}) +$

$P_r(\exists k, S \subseteq A, T \subseteq B, |S| = k \geq 2, |T| = k - 1$
 $N(S) \subseteq T \text{ and } e(S:T) \geq 2k - 2 \}$
 $\# S:T \text{ edges}$

? Why $e(S:T) \geq 2k-2$?

Take a pair S, T with $|S|+|T|$ as small as possible.

(i) If $|S| > |T|+1$, remove $|S|-|T|-1$ vertices from S

(ii) Suppose $\exists w \in T$ such that w has ≤ 2 nbs in S . Remove w and its (unique) nbr in S .

Repeat until (i) & (ii) do not hold. $|S|$ will stay at least 2 if $S \geq 1$.

$$\mathbb{E}(\# \text{ sets } S, T) \leq$$

$$2 \sum_{k=2}^{n/2} \binom{n}{k} \binom{n}{k-1} \binom{k(k-1)}{2k-2} p^k (1-p)^{k(n-k)}$$

$$\leq 2 \sum_{k=2}^{n/2} \left(\frac{ne}{k}\right)^k \left(\frac{ne}{k-1}\right)^{k-1} \left(\frac{ke(\log n + c)}{2n}\right)^{2k-2} e^{-npk(1-\frac{k}{n})}$$

$$\leq 8 \sum_{k=2}^{n/2} \underbrace{\left(\frac{e^{O(1)} (\log n)^2 n^{k/n}}{n} \right)^k}_{u_k}$$

u_k

Case 1: $2 \leq k \leq n^{3/4}$

$$u_k = n \left(\frac{e^{O(1)} (\log n)^2 n^{k/n}}{n} \right)^k$$

$$= e^{O(k)} n^{1 + O(1) - k}.$$

$$S_0 = 2 \sum_{k=2}^{n^{3/4}} u_k = O\left(\frac{1}{n}\right).$$

Case 2: $n^{3/4} < k \leq n/2$.

$$u_k = n \left(\frac{e^{O(1)} (\log n)^2 n^{k/n}}{n} \right)$$

$$\leq n^{1 - k/3}$$

So $\sum_{k=n^{3/4}}^{n/2} u_k = O(n^{-n^{3/4}/4})$.

So,

$$P_r(\nexists \text{ a perfect matching}) = \\ P_r(\exists \text{ isolated vertex}) + o(1).$$

We now consider $G_{n,p}$.

We could try to replace Hall's Theorem by Tutte's theorem, but it is simpler to use Hall's theorem.

Theorem

$$\text{Let } p = \frac{\log n + c_n}{n}.$$

$$\lim_{\substack{n \rightarrow \infty \\ n \text{ even}}} \Pr(G_{n,p} \text{ has a perfect matching}) = \begin{cases} 0 & c_n \rightarrow -\infty \\ e^{-e^{-c}} & c_n \rightarrow c \\ 1 & c_n \rightarrow \infty \end{cases}$$

$$= \lim_{n \rightarrow \infty} \Pr(\delta(G_{n,p}) \geq 1).$$

First of all if

$X_0 = \#$ of isolated vertices.

$$E(X_0) = n(1-p)^{n-1}$$
$$\approx e^{-c}$$

By previously used techniques we

$$\Pr(X_0=0) \approx e^{-e^{-c}}.$$

Suppose $n = 2m$ and $A = \{1, 2, \dots, m\}$

$$B = \{m+1, \dots, n\}$$

We will choose $A^* \subseteq A, B^* \subseteq B$ $|A^*| = |B^*| = s$

where s is small, such that whp $G_{n,p}$

contains a perfect matching between

$$\hat{A} = (A \setminus A^*) \cup B^*$$

and
$$\hat{B} = (B \setminus B^*) \cup A^*.$$

$$\text{Let } V_0 = \left\{ v : |N(v)| \leq \frac{\log n}{100} \right\}$$

$$A_0 = \left\{ v \in A \cap V_0 : |N(v) \cap A| > |N(v) \cap B| \right\}$$

$$B_0 = \left\{ w \in B \cap V_0 : |N(w) \cap B| > |N(w) \cap A| \right\}$$

$$A_1 = \left\{ v \in A \setminus A_0 : |N(v) \cap B| < \frac{\log n}{200} \right\}$$

$$B_1 = \left\{ w \in B \setminus B_0 : |N(w) \cap A| < \frac{\log n}{200} \right\}$$

Suppose

$$|A_0 \cup A_1| = |B_0 \cup B_1| + r$$

where $r \geq 0$.

Choose $R \subseteq B \setminus (B_0 \cup B_1)$

with $|R| = r$.

$$A^* = A_0 \cup A_1$$

$$B^* = B_0 \cup B_1 \cup R$$

We show that, conditional on $S \geq 1$,
there is w.h.p a perfect matching between
 \hat{A} and \hat{B} .

Lemma

Whp $|V_0| \leq n^{1/10}$.

Proof

$$\begin{aligned} E(|V_0|) &\leq n \sum_{k=0}^{\frac{1}{100} \log n} \binom{n-1}{k} p^k (1-p)^{n-1-k} \\ &\leq 2n \binom{n-1}{\frac{1}{100} \log n} p^{\frac{1}{100} \log n} \frac{e^{-c}}{n} \\ &\leq 2 \left(1000 e^{1+O(1)} \right)^{\frac{\log n}{100}} e^{-c}. \end{aligned}$$

Now use Markov inequality. □

Similarly, Whp

$$|A_1|, |B_1| \leq n^{2/3}.$$

Lemma

Whp $|A_i \cup B_i| \leq n^{6/10}$.

Proof

$$\begin{aligned} E(|V_0|) &\leq n \sum_{k=0}^{\frac{1}{200} \log n} \binom{\frac{1}{2}n-1}{k} p^k (1-p)^{\frac{1}{2}n-1-k} \\ &\leq 2n \binom{\frac{1}{2}n-1}{\frac{1}{200} \log n} p^{\frac{1}{200} \log n} \frac{e^{-c}}{n^{1/2}} \\ &\leq 2n^{1/2} (200e^{1+o(1)})^{\frac{\log n}{200}} e^{-c}. \end{aligned}$$

Now use Markov inequality.



Lemma

Why $v \in V_0, w \in A_1 \cup B_1 \Rightarrow N(v) \cap N(w) = \emptyset$

Proof

$\Pr(\exists v, w : N(v) \cap N(w) \neq \emptyset)$

$$\leq 3 \binom{n}{3} p^2 \left(\sum_{k=0}^{\frac{1}{2} \log n} \binom{n-3}{k} p^k (1-p)^{n-3-k} \right) \left(\sum_{k=0}^{\frac{1}{2} \log n} \binom{\frac{1}{2}n-3}{k} p^k (1-p)^{\frac{1}{2}n-3-k} \right)$$

$\leftarrow n^{\frac{1}{2}-\epsilon}$
 $\leftarrow n^{\frac{1}{2}-\epsilon}$

$$\leq 3 \binom{n}{3} \left(\frac{\log n + c}{n} \right)^2 n^{-4/3}$$

$= o(1).$



Lemma

Whp $\nexists v : |N(v) \cap (A \cup B \cup V_0)| \geq 3$

Proof

$$Pr(\exists v) \leq n \binom{n}{3} p^3$$

$$n \binom{n}{3} p^3 \left(\sum_{k=0}^{\frac{100 \log n}{\log 2}} \binom{\frac{1}{2}n-5}{k} p^k (1-p)^{\frac{1}{2}n-5-k} \right)^3$$

$$\leq n (\log n)^3 \cdot n^{-6/5}$$

$$= o(1).$$



Lemma

Whp $S \subseteq A \setminus (A_0 \cup A_1)$ implies

$$|N_B(S)| \geq \frac{\log n}{500} |S| \text{ for } |S| \leq \left(\frac{n}{\log n}\right)^3$$

Proof

We first show that whp

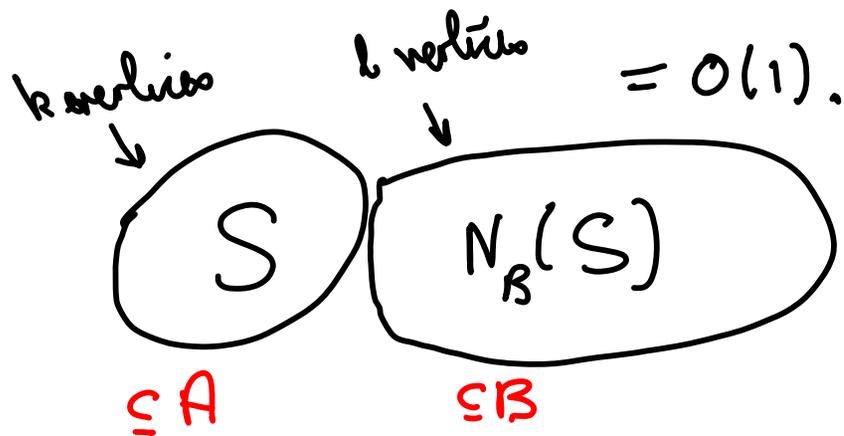
$$|S| \leq \frac{n}{10(\log n)^2} \text{ implies } e(S) < 2|S|.$$

↑ #edges inside S

$$P(\exists S: e(S) \geq 2|S|) \leq \frac{n}{10(\log n)^2} \leftarrow n_0$$

$$\sum_{k=4} \binom{n}{k} \binom{\binom{k}{2}}{2k} \rho^{2k} \leq \sum_{k=4}^{n_0} \left(\frac{ne}{k}\right)^k \left(\frac{ke}{2} \frac{(\log n + c)}{n}\right)^{2k}$$

$$= \sum_{k=4}^{n_0} \left(\frac{k}{n} \cdot \frac{e^3}{4} \cdot (\log n + c)^2\right)^k$$



$$k+l \leq \frac{n}{10(\log n)^2}$$

$$\frac{k \log n}{200} < 2(k+l)$$

$$\Rightarrow l > \frac{k \log n}{500}$$

$$\text{So } k \leq \frac{n}{(\log n)^3}$$



Lemma

Whp $\exists v \in A, u_1, u_2, u_3 \in B$ such that
 $u_i \in N(A, v \cup V_0) \cap N(v)$ for $i = 1, 2, 3$.

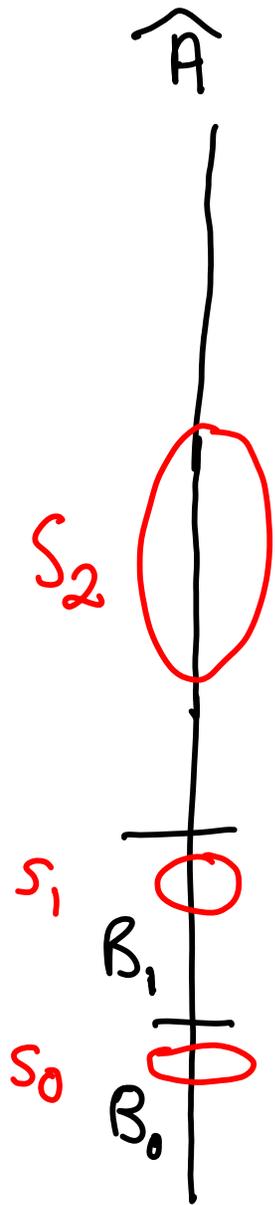
Proof

$$P(\neg) \leq n \binom{n}{3} p^3 \left(np \sum_{k=0}^{\log n / 100} \binom{\frac{1}{2}n}{k} p^k (1-p)^{n-k} \right)^3$$

$$\leq n (\log n)^2 n^{-6/5}$$

$$= o(1).$$





Try Hall Condition

$$(1) |S| \leq \frac{n}{(\log n)^3}$$

$$S = S_0 \cup S_1 \cup S_2$$

\uparrow \uparrow
 $S \cap B_0$ $S \cap B_1$

$$|N_B(S)| \geq$$

$$|S_0| + \frac{\log n}{600} |S_1| + \frac{\log n}{500} |S_2|$$

$$- 2|S_2|$$

$$\geq |S|.$$

$$(11) \frac{n}{2(\log n)^3} < |S| \leq \frac{n}{4}$$

Lemma

Whp $\exists S \subseteq A_0$, such that $|N_B(S)| \leq |S| + 2l$

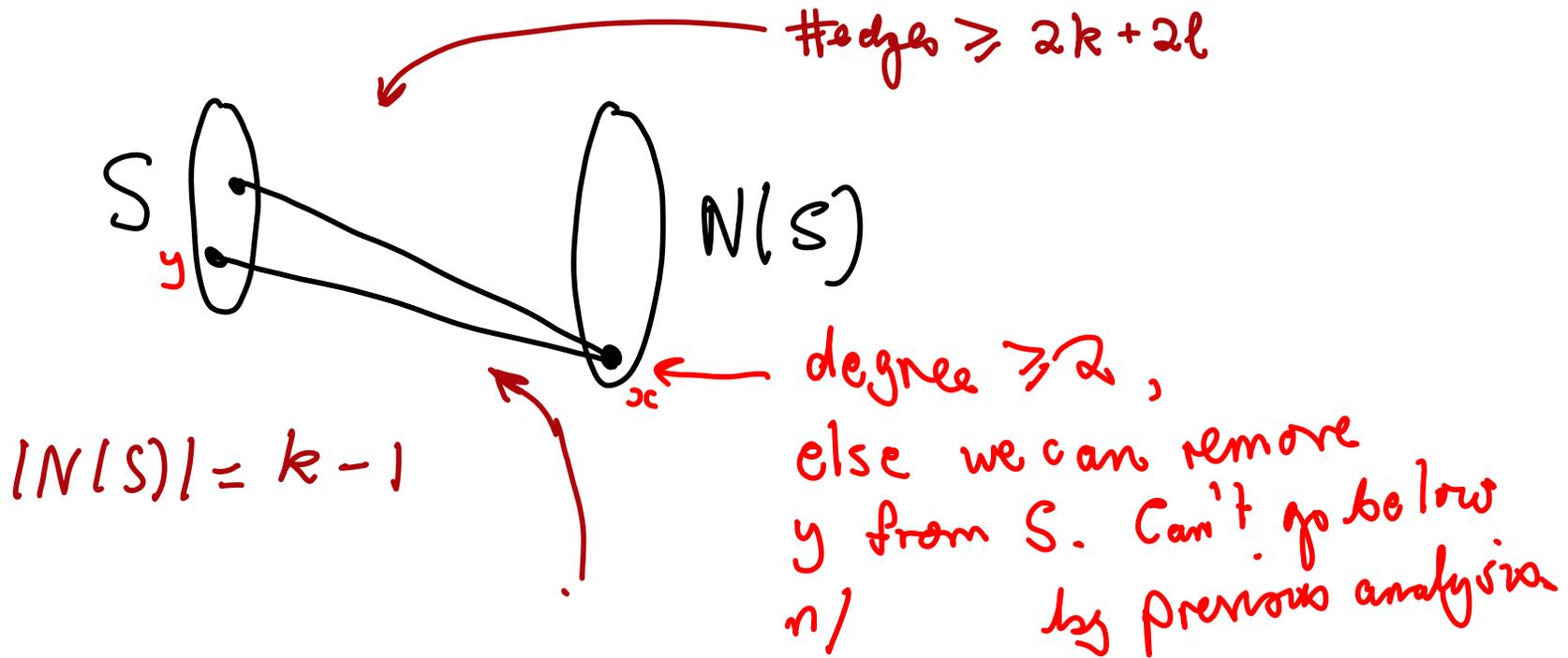
[This completes proof that Hall's condition holds whp.]

$$N_B(S) \geq N_B(S \setminus (A_0 \cup A_1)) - l \geq |S| - l - l + 2l.$$

Proof

As before we actually consider $S \subseteq A_0$,

$|S| \leq \frac{n}{4}$ and double our estimate.



Probability \leq

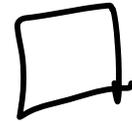
$$\sum_{k=\frac{n}{2(1+\epsilon)}}^{\frac{1}{4}n} \binom{\frac{1}{2}n}{k} \binom{\frac{1}{2}n}{k+2l} \binom{k(k+2l)}{2(k+2l)} p^{2k+4l} (1-p)^{k(\frac{1}{2}n-k-2l)}$$

$$\leq \sum_k \frac{n^k e^k}{2^k k^k} \cdot \frac{n^{k+2l} e^{k+2l}}{2^{k+2l} (k+2l)^{k+2l}} \left(\frac{ke(\log n + c)}{2n} \right)^{2k+4l} n^{-k/s}$$

$$\leq \sum_k \frac{n^k e^k}{2^k k^k} \cdot \frac{n^{k+2l} e^{k+2l}}{2^{k+2l} (k+2l)^{k+2l}} \left(\frac{k e (\log n + c)}{2n} \right)^{2k+4l} n^{-k/5}$$

$$\leq \sum_k \left(\frac{e^{O(1)} (\log n)^2}{n^{1/5}} \right)^k$$

$$= o(1).$$



$$\text{Check: } k^{2l} = \left(k^{2l/k} \right)^k = \left(e^{O(1)} \right)^k.$$

Hamilton Cycles in Random Graphs

Theorem

Let $m = \frac{1}{2}n(\log n + \log \log n + c_n)$. Then

$$\lim_{n \rightarrow \infty} \Pr(G_{n,m} \text{ is Hamiltonian}) = \begin{cases} 0 & c_n \rightarrow -\infty \\ e^{-e^{-c}} & c_n \rightarrow c \\ 1 & c_n \rightarrow \infty \end{cases}$$

$$= \lim_{n \rightarrow \infty} \Pr(\delta(G_{n,m}) \geq 2).$$

The proof of this is complicated and so we start by proving a weaker theorem.

Let $p = \frac{25 \log n}{n}$. Then

$G_{n,p}$ is Hamiltonian whp.

Write

$$G_{n,p} = G_{n,p_1} \cup G_{n,p_2}$$

where $p_1 = \frac{20 \log n}{n}$

and $1-p = (1-p_1)(1-p_2)$, $p_2 \approx \frac{5 \log n}{n}$

We first show that whp $G_1 = G_{n,p_1}$ has a Hamiltonian path.

Let $\lambda(G)$ denote the length of a longest path in G .

Let E_v be the event

$$\lambda(G_1 \setminus v) = \lambda(G_1)$$

Then

G_1 does not have a Hamiltonian path

$\Rightarrow \exists v: E_v$ occurs.

G , not Hamiltonian



\mathcal{E}_v occurs.

We show now that

$$Pr\left(\bigcup_v \mathcal{E}_v\right) \leq n Pr(\mathcal{E}_v) = o(1).$$

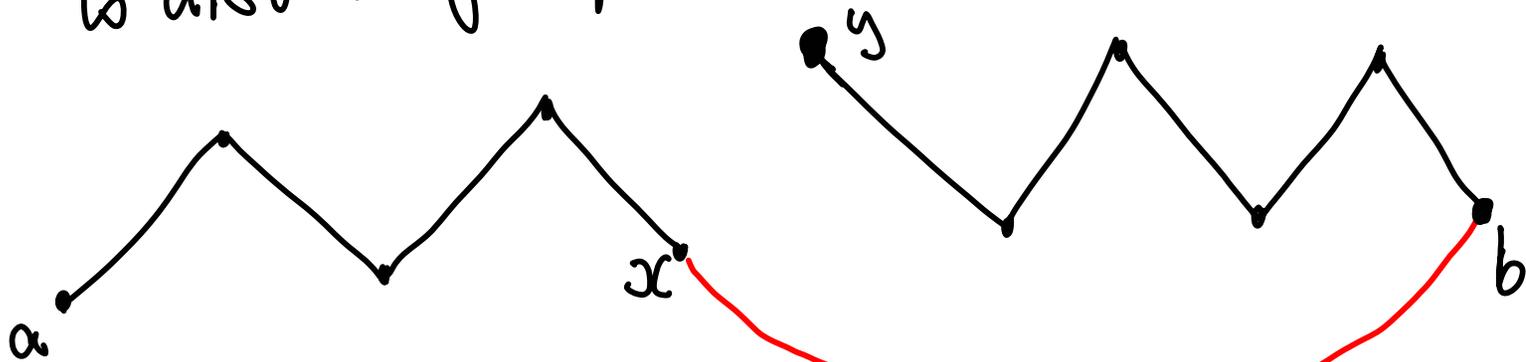
Posá Lemma

P is a longest path



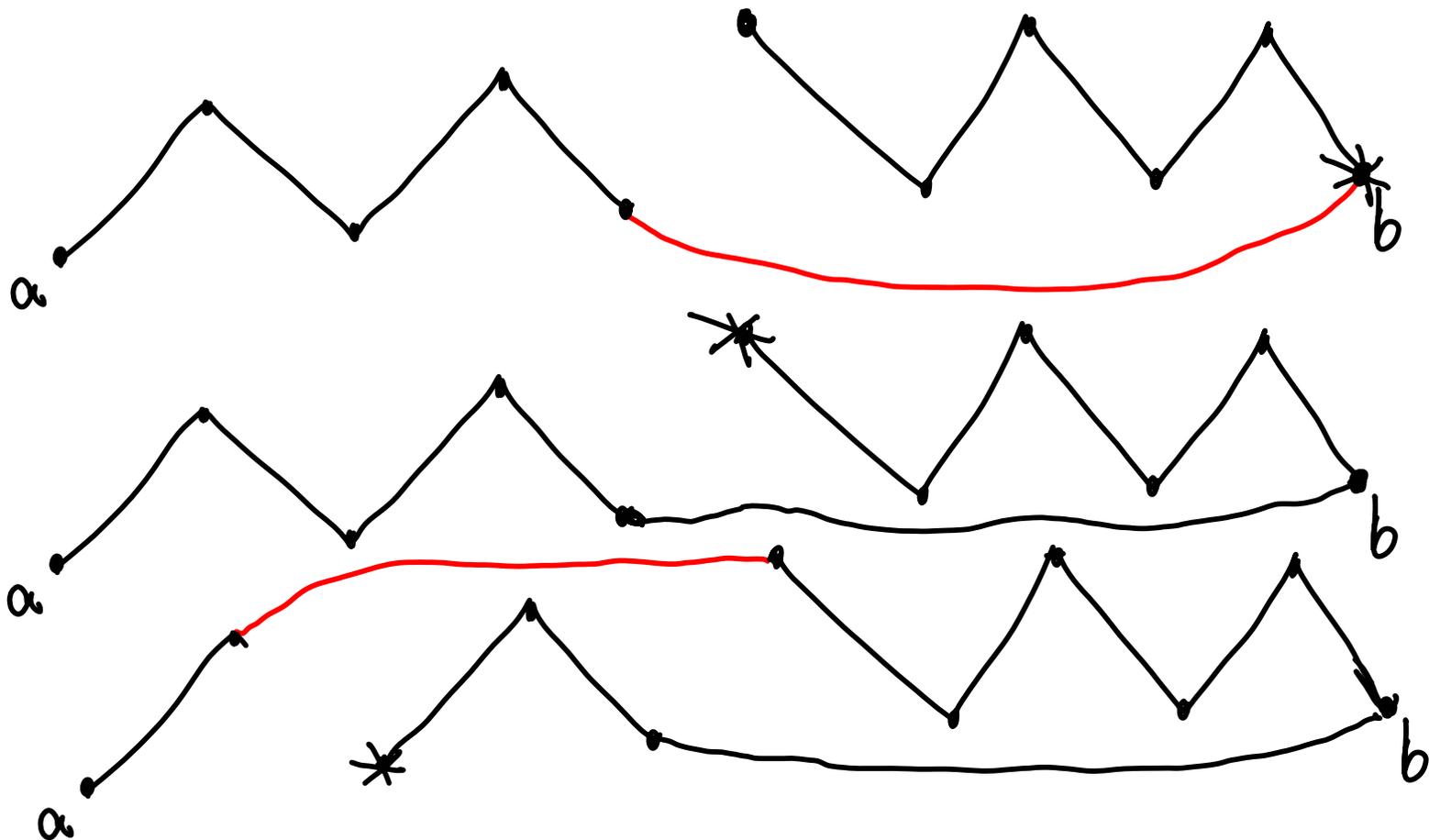
No edges from b go outside P .

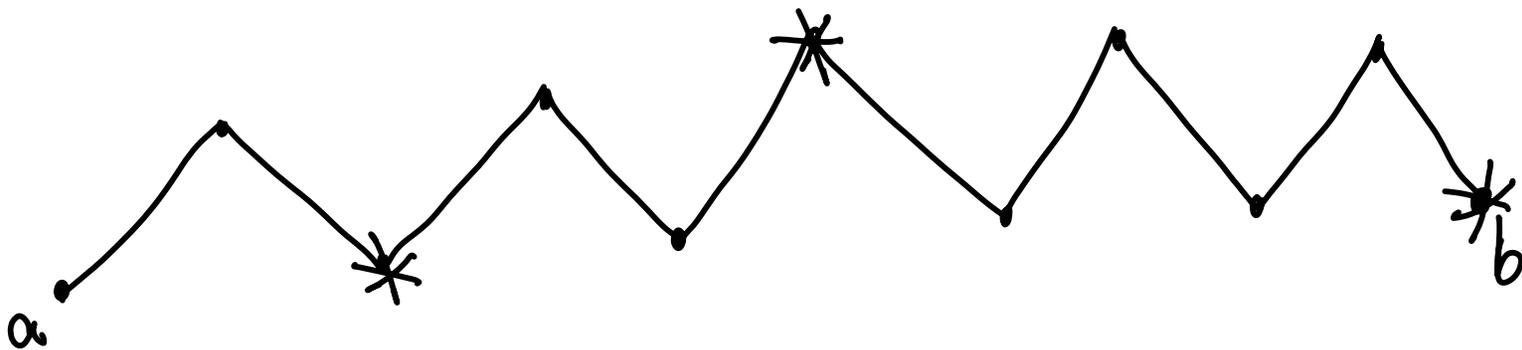
P' is also longest path:



P' is obtained by a rotation with a as fixed endpoint.

Now let END denote the set of v
 such that \exists longest path P_v from a to v
 such that P_v is obtained from P by
 a sequence of rotations with a fixed.





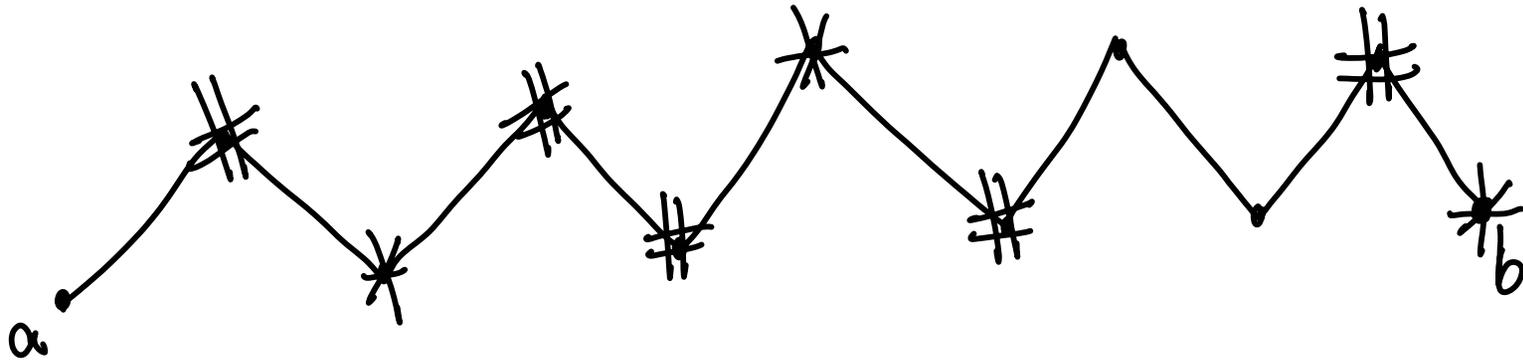
$$\text{END} = \{*\}$$

Lemma

If $v \in P \setminus \text{END}$ and v is adjacent to $w \in \text{END}$ then there exist $x \in \text{END}$ such that the edge $(x, v) \in P$ or $(v, x) \in P$.

Corollary

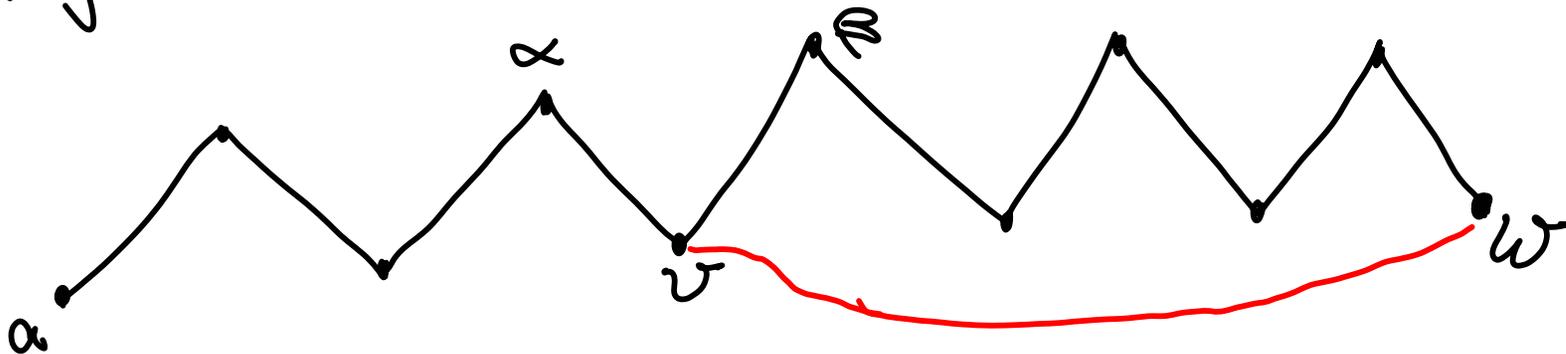
$$|\text{IN}(\text{END})| < 2|\text{END}|.$$

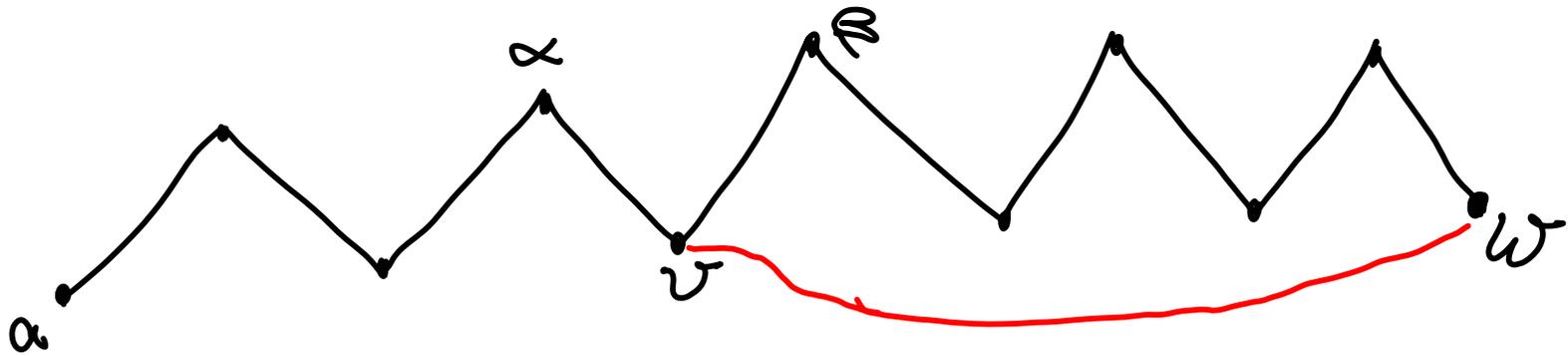


$$N(\text{END}) = \{ \# \}$$

Proof of Lemma

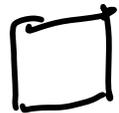
Suppose that x, y are the neighbours of v on P and that $v, x, y \notin \text{END}$ and that v is adjacent to $w \in \text{END}$. Consider P_{vw}





Now $\{\alpha, \beta\} = \{x, y\}$ because if
 a rotation deleted (α, v) say then
 α or v becomes an endpoint.

But then $\beta \in \text{END}$.



Lemma

Whyp $S \subseteq [n-1], |S| \leq \frac{1}{4}n \Rightarrow$

$$|N(S)| \geq 2|S|$$

in $G_1 \setminus \{n\}$

Proof

$$P(\exists S: |S| \leq \frac{1}{4}n \text{ and } |N(S)| < 2|S|) \leq$$

$$\sum_{k=1}^{\frac{n-1}{4}} \binom{n-1}{k} \binom{n-1}{2k} \underbrace{(1-p_1)^{k(n-1-3k)}}_{\leq}$$

$$\sum_{k=1}^{n/4} \left[\frac{ne}{k} \cdot \frac{n^2 e^2}{k^2} \cdot n^{-5} \right]^k = O(n^{-2}).$$

$$\leq e^{-kp_1/4} \\ \leq n^{-5k}$$

It follows that if P is a longest path in $G_1 \setminus \{n\}$ and END is defined w.r.t. P then

$$Pr(|END| \leq n/4) = O(n^{-2}).$$

Now the edges incident with n are unconditioned by $G_1 \setminus \{n\}$ and (see p3)

$$E_n \Rightarrow \nexists \text{ edge from } n \text{ to } END.$$

$$So \quad Pr(E_n) \leq O(n^{-2}) + (1-p_1)^{n/4} = O(n^{-2}).$$

$$So \quad Pr(G_1 \text{ does not have a Hamilton path}) = O(n^{-1}).$$

Now use the G_{n,p_2} edges.

Let P be a Hamilton path in G_1 and let

END be defined w.r.t. P .

By arguing as for $G_1 \setminus \{n\}$ we see that $|END| \geq \frac{n}{4}$

whp.

Let a be the fixed endpoint of P .

Then

$G_{n,p}$ not Hamiltonian \Rightarrow ~~\exists~~ a G_{n,p_2} edge from a to END .

Thus

$$P_r(G_{n,p} \text{ is not Hamiltonian}) = O(1) + (1-p_2)^{n/4} = o(1).$$

Let us now go to $G = G_{n,m}$, $m = \frac{1}{2}n(\log n + \log \log n + c)$
 and $G_{n,p}$, $p = \frac{m}{n}$.

Let a vertex of G be **large** if its degree is
 at least $\lambda = \frac{\log n}{100}$, and **small** otherwise.

Lemma
 Whp $v, w \in \text{SMALL} \Rightarrow \text{dist}(v, w) \geq 5$

Proof

$$P_r(\neg) \leq \binom{n}{2} \left(\sum_{l=0}^3 \binom{n}{l} p^{l+1} \right) \left(\sum_{k=0}^{\lambda} \binom{n}{k} p^k (1-p)^{n-k} \right)^2$$

$$\approx \frac{1}{2}n(\log n)^4 \left(\sum_{k=0}^{\lambda} \frac{(\log n)^k}{k!} \cdot \frac{e^{-c}}{n \log n} \right)^2$$

$$\approx \frac{1}{2} n (\log n)^4 \left(\sum_{k=0}^{\lambda} \frac{(\log n)^k}{k!} \cdot \frac{e^{-c}}{n \log n} \right)^2$$

$$\frac{u_{k+1}}{u_k} > 100$$

$$\leq n (\log n)^4 \left(\frac{(\log n)^{\lambda}}{\lambda!} \frac{e^{-c}}{n \log n} \right)^2$$

$$\lambda! \geq \left(\frac{\lambda}{e} \right)^{\lambda}$$

$$= O\left(\frac{(\log n)^3}{n} \cdot (100e)^{\frac{2 \log n}{100}} \right)$$

$$= O(n^{-3/4})$$

$$\text{So } P_r_m(\gamma) = O(m^{\frac{1}{2}} n^{-3/4}) = o(1)$$



Lemma

W.h.p. $|SMALL| \leq n^{1/4}$.

Proof

$$P_{r,p}(|SMALL| > n^{1/4})$$

$$\leq n \sum_{k=0}^{\log n / 100} \underbrace{\binom{n-1}{k} p^k (1-p)^{n-1-k}}_{u_k}$$

$$\begin{aligned} & u_{k+1} / u_k \\ &= \frac{n-1-k}{k+1} \cdot p \cdot \frac{1}{1-p} \\ &\geq 50. \end{aligned}$$

$$\leq 2n \left(\frac{nep \log n}{100n} \right)^{\frac{\log n}{100}} \cdot \frac{1}{n}$$

$$\leq n^{1/5}$$

Now apply Markov and monotonicity to go to $G_{n,m}$



Lemma

Whp ~~is~~ a cycle C_4 containing a small vertex.

Proof

$$P_p(\cdot) \leq \frac{1}{2} n^4 p^4 \sum_{k=0}^{\log n / 100} \binom{n}{k} p^k (1-p)^{n-1-k}$$

$$\leq (\log n)^4 n^{-3/4}$$

$$\text{So } P_p(\cdot) \leq O(m^{1/2} n^{-3/4}) = o(1).$$



Lemma

Whp, $\forall |S| \leq \frac{n}{(\log n)^3}$, $e(S) \leq 2|S|$

Proof

$\Pr_p \left[\exists S : |S| \leq \frac{n}{(\log n)^3} \text{ and } e(S) > 2|S| \right] \leq$

$$\sum_{s=4}^{\frac{n}{(\log n)^3}} \binom{n}{s} \binom{\binom{s}{2}}{2s} p^{2s}$$

$$\leq \sum_s \left(\frac{ne}{s} \cdot \left(\frac{se \log n}{2n} \right)^2 \right)^s$$

$$= \sum_s \left(\frac{e^3}{2} \cdot \frac{(\log n)^2}{n} \right)^s$$

$$= o(n^{-3}).$$

$$\text{So } \Pr_m(\neg) = O(m^{\frac{1}{2}} n^{-3}) = o(1).$$



Lemma

$$S \subseteq \text{LARGE}, \quad |S| \leq \frac{n}{\log n} \Rightarrow |N(S)| \geq \frac{\log n}{1000} |S|.$$

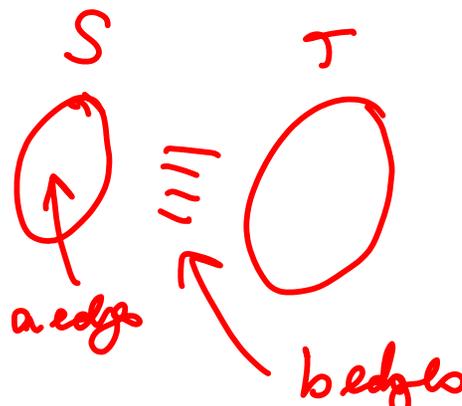
{large vertices}

Proof

$$(a) \quad 1 \leq |S| \leq \left(\frac{n}{\log n}\right)^3 \quad s = |S|$$

$$T = N(S)$$

$$t = |T|$$



$$2a + b \geq \frac{\log n}{100} s$$

$$a \leq 2s$$

$$\Downarrow$$

$$a + b \geq \frac{\log n}{200} s$$

$$P_p(\exists S) \leq \sum_{s=\sqrt{\lambda}}^{n/(\log n)^3} \sum_{t=0}^{\frac{\log n}{1000} s} \binom{n}{s} \binom{n}{t} \binom{s+t}{\frac{\log n}{200} s} p^{\frac{\log n}{200} s} (1-p)^{s(n-s-t)}$$

$$\leq \sum_{s,t} \left(\frac{ne}{s}\right)^s \left(\frac{ne}{t}\right)^t \left(\frac{(s+t)^2 e(100)}{2s \log n} \cdot \frac{(1+o(1)) \log n}{n}\right)^{s \log n / 200} \\ \times n^{-s(1 - 1/(\log n)^2)}$$

The summand increases with $t \ll n$ and so we can put $t = \frac{\log n}{1000} s$ and then very crudely

$$\leq n \sum_{s \geq \sqrt{n}} \left(\frac{ne}{s} \cdot \left(\frac{1000ne}{s \log n}\right)^{\frac{\log n}{1000}} \left(\frac{e(\log n)^2 s}{1000 n}\right)^{\frac{\log n}{200}} \left(\frac{1+o(1)}{n}\right)^s\right)^s$$

$$< n \sum_{s \geq \sqrt{n}} \left(\frac{e^6 (\log n)^9 s^4}{10^{12} n^4}\right)^{\frac{\log n}{1000} s}$$

$$= O(n^{-\Omega(\sqrt{n} \log n)}) \text{ and so } P_{r_m}(\neg) = o(1).$$

$$(b) \frac{n}{(\log n)^s} \leq |S| \leq \frac{n}{\log n}$$

$$Pr_p(\neg) \leq \sum_{s,t} \binom{n}{s} \binom{n}{t} \binom{st}{t} p^t (1-p)^{s(n-s-t)}$$

$S: T\text{-edge}$
 $T=N(S)$

$$\leq \sum_{s,t} \left(\frac{ne}{s} \right)^s \left(\frac{ne}{t} \right)^t (sep)^t n^{-s(1-\frac{s+t}{n})}$$

$u_{s,t}$

$$\frac{u_{s,t+1}}{u_{s,t}} = \frac{ne}{t+1} \cdot \left(\frac{t}{t+1} \right)^t \cdot (sep) \cdot n^{s/n}$$

$$\geq 10.$$

$$\text{So } P_1(\tau) \leq 2 \sum_s \left(\frac{ne}{s} \right)^s (10^3 e^{2+o(1)})^{\frac{s \log n}{1000}} n^{-s \left(1 - \frac{s(1+\log n/1000)}{n} \right)}$$

$$= 2 \sum_{s \geq \frac{n}{(\log n)^3}} \left(\frac{e}{s} \cdot (10^3 e^{2+o(1)})^{\frac{\log n}{1000}} \cdot n^{\frac{1}{1000} + o(1)} \right)^s$$

$$= O(n^{-\Omega(n^{1/2})})$$

and so

$$P_m(\tau) = o(1).$$



Suppose now that $X \subseteq E(G)$ and

(i) $|X| = \log n$

(ii) X is a matching

(iii) X is not incident with a small vertex

(iv) X avoids the edges of some longest path of G .

We say that X is *deletable*.

Let $G_X = G \setminus X$

Lemma

Suppose that $\delta(G) \geq 2$ and

(i) $v, w \in \text{SMALL} \Rightarrow \text{dist}(v, w) \geq 5$ and $v \notin \text{any } C_4$.

(ii) $S \subseteq \text{LARGE}, |S| \leq \frac{n}{\log n} \Rightarrow |N(S)| \geq \frac{\log n}{1000} |S|$.

(iii) X is deletable.

Then $S \subseteq [n], |S| \leq 10^{-4} n \Rightarrow |N_X(S)| \geq 2|S|$
↖ nbrs in G_X .

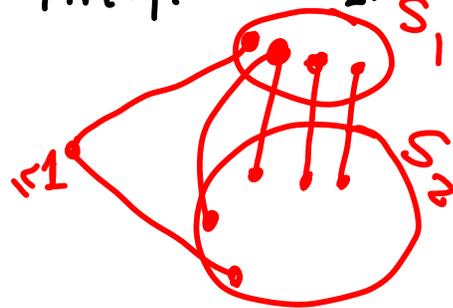
Proof

Let $S_1 = S \cap \text{SMALL}$ and $S_2 = S \setminus S_1$

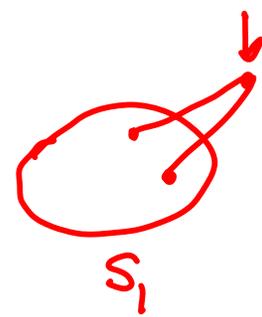
$$|N(S)| \geq |N(S_1)| + |N(S_2)| - |N(S_1) \cap S_2| - |N(S_2) \cap S_1| - |N(S_1) \cap N(S_2)|$$

$$\geq |N(S_1)| + |N(S_2)| - 2|N(S_1) \cap S_2| - |S_2|$$

$$\geq |N(S_1)| + |N(S_2)| - 3|S_2|.$$



DOES NOT HAPPEN



Now

$$|N(S_1)| \geq 2|S_1|$$

and

$$|N(S_2)| \geq 9|S_2|.$$

$$(i) |S_2| \leq \frac{n}{1000} \Rightarrow |N(S_2)| \geq \frac{1000n}{1000} |S_2|$$

$$(ii) |S_2| > \frac{n}{1000}. \text{ Take } S'_2 \subseteq S_2, |S'_2| = \frac{n}{1000}$$

$$|N(S_2)| \geq |N(S'_2)| - |S_2|$$

$$\geq \frac{n}{1000} - |S_2|$$

$$\geq 9|S_2|.$$

$$\text{So } |N(S)| \geq 2|S_1| + 6|S_2|$$

and

$$|N_X(S)| \geq |N(S)| - |S_2|$$

X is a matching and it avoids SMALL

$$\geq 2|S_1| + 5|S_2|$$

$$\geq 2|S|.$$

Summary

- (i) $\lim_{n \rightarrow \infty} P_r(\delta(G_{n,m}) \geq 2) = e^{-e^{-c}}$.
- (ii) $G_{n,m}$ is connected whp
- (iii) $|SMALL| \leq n^{1/4}$, $v, w \in SMALL \Rightarrow \text{dist}(v, w) \geq 5$,
 $\nexists C_4 : C_4 \cap SMALL \neq \emptyset$, whp.
- (iv) If $\delta(G) \geq 2$ and X is deletable then whp

$$|N_X(S)| < 2|S| \Rightarrow |S| \geq 10^{-4} n.$$

$\mathcal{G} = \{ \text{all graphs on } [n] \text{ with } m \text{ edges} \}$

$\mathcal{G}_0 = \{ G \in \mathcal{G} : \delta(G) \geq 2 \text{ and (ii) — (iv) hold} \}$

$\mathcal{G}_1 = \{ G \in \mathcal{G}_0 : G \text{ is not Hamiltonian} \}$

Coloring Argument

Suppose $G \in \mathcal{G}_1$ and X be deletable

Let P be a longest path in G_X .



Then

$$|END_X| \geq 10^{-4} n$$

(add subscript X to END)

Now for each $b \in END$, start with P_b and do all possible rotations, starting from P_b , but with b as a fixed endpoint. Let $END_X(b)$ be the set of endpoints produced.

We do a bit of re-naming

$$\text{END}_x \leftarrow \text{END}_x \cup \{a\}$$

$$\text{END}_x(a) \leftarrow \text{END}_x / \{a\}$$

Now we can say that for $b \in \text{END}$, we have

$$|\text{END}_x(b)| \geq \frac{n}{1000}$$

Now for $G \in \mathcal{G}$ and $X \subseteq E(G)$, $|X| = \omega = \log n$
choose some **fixed** longest path P_X of G_X .

Furthermore choose so that if $G, G' \in \mathcal{G}$ and

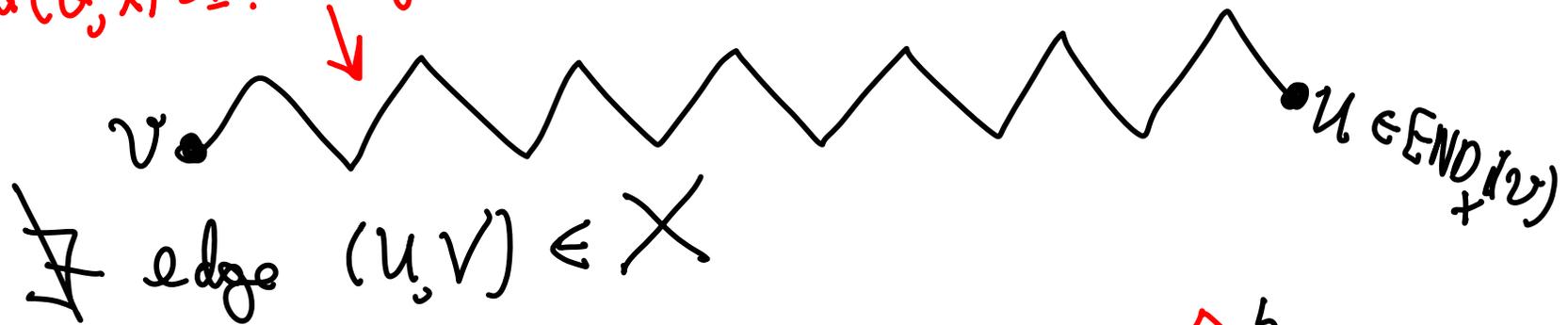
$G_X = G'_X$ then $P_X = P'_X$ i.e. path depends on G_X and
not G, X .

$$g(G, X) = \begin{cases} 1 & : \begin{array}{l} \text{(a) } G \in \mathcal{G}, \\ \text{(b) } X \cap E(P_X) = \emptyset \\ \text{(c) } X \text{ is deletable} \end{array} \\ 0 & : \text{otherwise} \end{cases}$$

Note that $a(G, X) = 1$ implies

If $u \in \text{END}_X(v)$ then $(u, v) \notin X$

$a(G, X) = 1$. Longest in $G - X$ and G

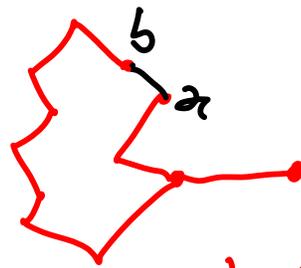


Either

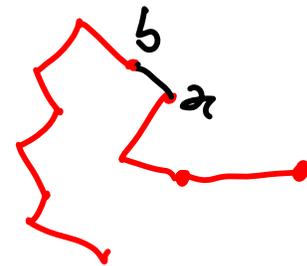
(i) $l(P_0) = n - 1$

$\Rightarrow G$ is Hamiltonian

(ii)



G is connected



longer path

Now a double counting estimate for $\sum_G \sum_X a(G, X)$.

(i) For $G \in \mathcal{G}_1$.

$$\begin{aligned} \sum_X a(G, X) &\geq \binom{m}{w} \left(1 - \frac{n + n^{\frac{1}{4}} \log n + w}{m - w}\right)^w \\ &\geq \binom{m}{w} / 10. \end{aligned}$$

$\left(1 - \frac{2n}{w}\right)^w$

Random choose w edges e_1, e_2, \dots

$$\Pr(a(G, X) = 1) \geq \prod_{i=0}^{w-1} \Pr(e_i \text{ avoids } P_X, \text{ SMALL}, e_1, \dots, e_{i-1} \mid e_1, \dots, e_{i-1})$$

So

$$|\mathcal{G}_1| \leq \frac{10}{\binom{m}{w}} \sum_{G \in \mathcal{G}} \sum_X a(G, X).$$

(ii) Now fix a graph H with $m-w$ edges.

$$\text{Let } S_H = \sum_{G, X: G_X = H} a(G, X).$$

If $S_H > 0$ then H has the expansion properties we expect and its END sets are large. Thus

$$S_H \leq \binom{N-m+w}{w} \left(1 - \frac{\binom{n/1000}{2}}{N}\right)^w \leq \binom{N-m+w}{w} e^{-(10^{-6} - o(w))w}.$$

There $\binom{N}{m-w}$ ways to add w edges to H . bounds
 the probability that a randomly chosen set of w
 edge avoids joining a to $\text{END}_H(a)$ for $a \in \text{END}_H$.

Thus

$$\sum_{G \in \mathcal{G}} \sum_X a(G, X) \ll \binom{N}{m-w} \binom{N-m+w}{w} e^{-\beta w}$$

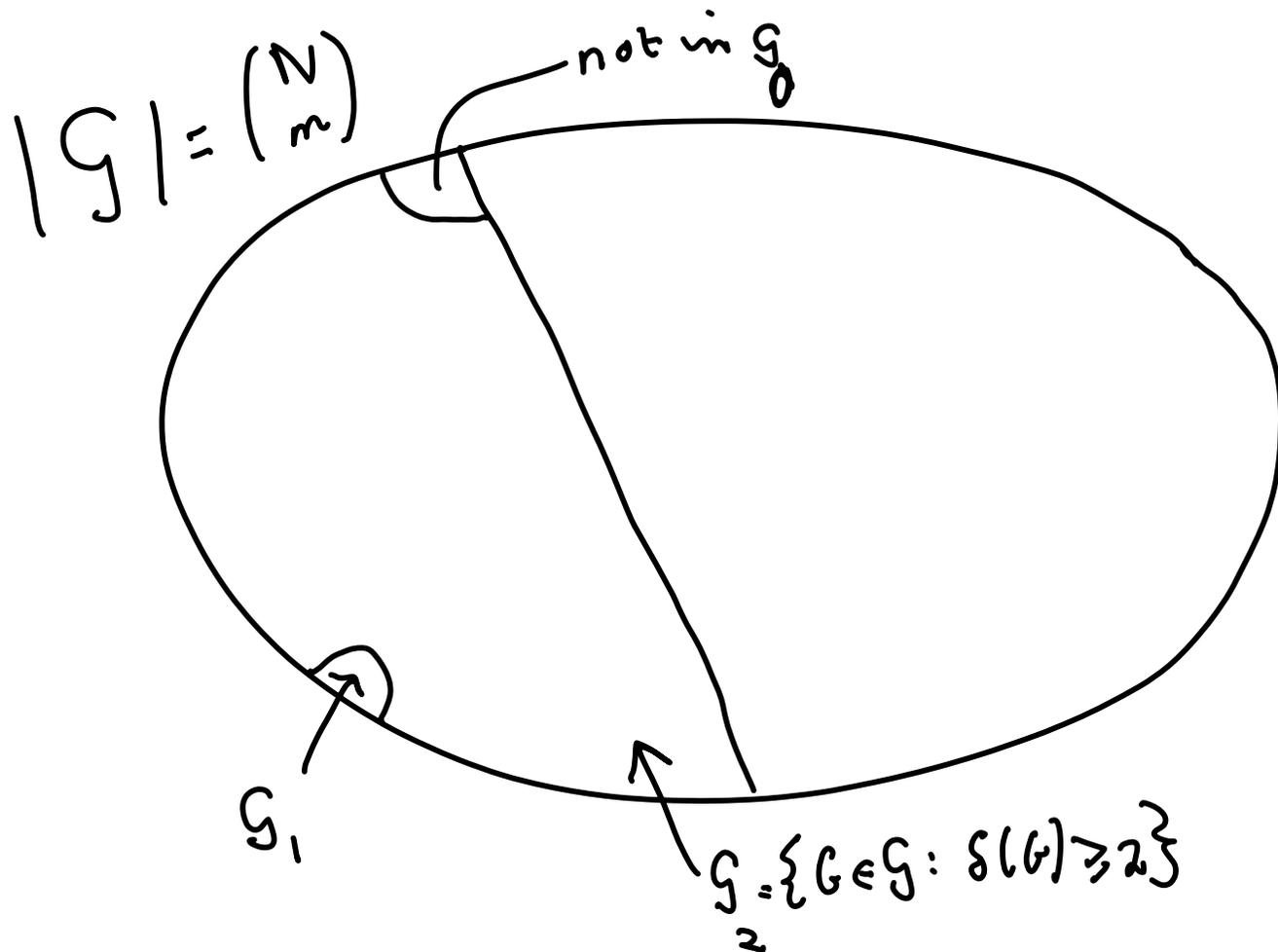
$\beta \approx 10^{-6}$

$$= \binom{N}{m} \binom{m}{w} e^{-\beta w}$$

and so

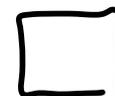
$$|g_1| \ll \frac{10}{\binom{m}{w}} \sum_{G \in \mathcal{G}} \sum_X a(G, X).$$

$$\ll 10 e^{-\beta w} \binom{N}{m}.$$



$$\Pr(G \text{ is not Ham} \ \& \ \delta(G) \geq 2) = \Pr(G \in (G_2 \setminus G_0) \cup G_1) = o(1).$$

$$\Pr(G \text{ is Ham} \ \& \ \delta(G) \geq 2) = e^{-e^{-c}} - o(1).$$



Separation of largest degrees,

Graph isomorphism and

edge coloring.

Lemma

Let $k = (n-1)p + x\sqrt{(n-1)pq}$, p constant, $q=1-p$,
where $x \leq (\log n)^2$ (for convenience).

Then

$$B_k = \binom{n-1}{k} p^k (1-p)^{n-1-k} = (1+o(1)) \sqrt{\frac{1}{2\pi npq}} e^{-x^2/2}.$$

Proof

Stirling's Formula gives

$$B_k = (1+o(1)) \sqrt{\frac{1}{2\pi npq}} \left(\frac{(n-1)p}{k} \right)^{\frac{k}{n-1}} \left(\frac{(n-1)q}{n-1-k} \right)^{1-\frac{k}{n-1}}.$$

New

$$\left(\frac{k}{(n-1)p} \right)^{k/n-1} = \left(1 + \alpha \sqrt{\frac{q}{p(n-1)}} \right)^{k/n-1}$$

$$= \exp \left\{ \left(\alpha \sqrt{\frac{q}{p(n-1)}} - \frac{\alpha^2}{2} \frac{q}{p(n-1)} + O(n^{-3/2}) \right) \left(p + \alpha \sqrt{\frac{pq}{n-1}} \right) \right\}$$

$$= \exp \left\{ \alpha \sqrt{\frac{pq}{n-1}} + \frac{\alpha^2}{2} \frac{q}{n-1} + O(n^{-3/2}) \right\}$$

$$\left(\frac{n-1-k}{(n-1)q} \right)^{1-k/n-1} = \left(1 - \alpha \sqrt{\frac{p}{q(n-1)}} \right)^{1-k/n-1}$$

$$= \exp \left\{ - \left(\alpha \sqrt{\frac{p}{q(n-1)}} + \frac{\alpha^2}{2} \cdot \frac{p}{q(n-1)} + O(n^{-3/2}) \right) \left(q - \alpha \sqrt{\frac{pq}{n-1}} \right) \right\}$$

$$= \exp \left\{ - \alpha \sqrt{\frac{pq}{n-1}} + \frac{\alpha^2}{2} \frac{p}{n-1} + O(n^{-3/2}) \right\}$$

So

$$\left(\frac{k}{(n-1)p} \right)^{\frac{k}{n-1}} \left(\frac{n-1-k}{(n-1)q} \right)^{1 - \frac{k}{n-1}} =$$

$$\exp \left\{ \frac{\partial c^2}{2(n-1)} + O(n^{-3/2}) \right\}$$

Substituting into

$$(1+o(1)) \sqrt{\frac{1}{2\pi n p q}} \left(\frac{(n-1)p}{k} \right)^{\frac{k}{n-1}} \left(\frac{(n-1)q}{n-1-k} \right)^{1 - \frac{k}{n-1}}^{n-1}$$

gives required expression.

□

Lemma

Let $\epsilon = \frac{1}{10}$ and p be constant

$$k_{\pm} = (n-1)p \pm (1 \pm \epsilon) \sqrt{2(n-1)pq \log n}.$$

Then whp

$$(i) \quad \Delta(G_{n,p}) \leq k_+$$

(ii) There are $\Omega(n^{2\epsilon(1-\epsilon)})$ vertices of degree at least k_-

(iii) ~~\exists~~ $u \neq v$ such that $d(u), d(v) \geq k_-$
and $|d(u) - d(v)| \leq 10$.

We first prove that as $x \rightarrow \infty$

$$\frac{1}{x} e^{-x^2/2} \left(1 - \frac{1}{x^2}\right) \leq \int_x^\infty e^{-y^2/2} dy \leq \frac{1}{x} e^{-x^2/2}. \quad (***)$$

Proof

$$\int_x^\infty e^{-y^2/2} dy = - \int_x^\infty \frac{1}{y} (e^{-y^2/2})' dy$$

$$= - \left[\frac{1}{y} e^{-y^2/2} \right]_x^\infty - \int_x^\infty \frac{1}{y^2} e^{-y^2/2} dy$$

$$= \frac{1}{x} e^{-x^2/2} + \left[\frac{1}{y^3} e^{-y^2/2} \right]_x^\infty + 3 \int_x^\infty \frac{1}{y^4} e^{-y^2/2} dy \quad \square$$

(i) Let X be the number of vertices of degree k .

$$E(X_k) = (1+o(1)) \sqrt{\frac{n}{2\pi pq}} \exp\left\{-\frac{1}{2} \left(\frac{k - (n-1)p}{\sqrt{(n-1) pq}}\right)^2\right\}$$

assuming that $k \leq k_2 = (n-1)p + (\log n)^2 \sqrt{(n-1) pq}$.

But if $k > k_2$ then

$$E(X_k) \leq E(X_{k_2}) \quad - \text{binomial} \rightarrow \text{after mean}$$

$$\approx n \exp\left\{-\Omega((\log n)^4)\right\}$$

$$= o(1).$$

$$\text{So if } Y_k = X_k + X_{k+1} + \dots$$

$$E(Y_k) \approx \sum_{l=k}^{k_L} \sqrt{\frac{n}{2\pi pq}} \exp\left\{-\frac{1}{2} \left(\frac{l - (n-1)p}{\sqrt{(n-1) pq}}\right)^2\right\}$$

$$\approx \sum_{l=k}^{\infty} \sqrt{\frac{n}{2\pi pq}} \exp\left\{-\frac{1}{2} \left(\frac{l - (n-1)p}{\sqrt{(n-1) pq}}\right)^2\right\}$$

$$\approx \sqrt{\frac{n}{2\pi pq}} \int_{\lambda=k}^{\infty} \exp\left\{-\frac{1}{2} \left(\frac{\lambda - (n-1)p}{\sqrt{(n-1) pq}}\right)^2\right\} d\lambda$$

If $k = (n-1)p + x\sqrt{(n-1)pq}$ then

$$\sqrt{\frac{n}{2\pi pq}} \int_{\lambda=k}^{\infty} \exp \left\{ -\frac{1}{2} \left(\frac{\lambda - (n-1)p}{\sqrt{(n-1)pq}} \right)^2 \right\} d\lambda$$

$$= \sqrt{\frac{n}{2\pi pq}} \cdot \sqrt{(n-1)pq} \cdot \int_{y=x}^{\infty} e^{-y^2/2} dy$$

$$\approx \frac{n}{\sqrt{2\pi}} \cdot \frac{1}{x} \cdot e^{-x^2/2}$$

When $k = k_+$, $x = (1+\epsilon)\sqrt{2 \log n}$ and (i) follows.

When $k = k_{\epsilon}$, $x = (1 - \epsilon) \sqrt{2 \log n}$

and $E(Y_{k_{\epsilon}}) = \Omega(n^{2\epsilon(1-\epsilon)}) \rightarrow \infty$.

We use the second moment method to show concentration.

$$E(Y_k(Y_{k-1} - 1)) = n(n-1) \sum_{k \leq k_1, k_2 \leq k_{\epsilon}} P_r(d(1) = k_1 \wedge d(2) = k_2)$$

$$= n(n-1) \left[\sum_{k_1, k_2} P(\hat{d}(1) = k_1 - 1 \wedge \hat{d}(2) = k_2 - 1) + (1-p) P(\hat{d}(1) = k_1 \wedge \hat{d}(2) = k_2) \right]$$

where $\hat{d} = \# \text{nbrs in } \{3, 4, \dots, n\}$.

$$= n(n-1) \sum_{k_1, k_2} \left[p P(\hat{d}(1) = k_1 - 1) P(\hat{d}(2) = k_2 - 1) + (1-p) P(\hat{d}(1) = k_1) P(\hat{d}(2) = k_2) \right]$$

$$\frac{P(\hat{d}(1) = k_1 - 1)}{P(\hat{d}(1) = k_1)} = \frac{\binom{n-2}{k_1-1} (1-p)}{\binom{n-2}{k_1} p} = \frac{k_1 (1-p)}{(n-2-k_1) p} = 1 + \tilde{O}(n^{-1/2}).$$

$$= n(n-1) \sum_{k_1, k_2} \left[P(\hat{d}(1) = k_1) P(\hat{d}(2) = k_2) (1 + \tilde{O}(n^{-1/2})) \right]$$

$$= n(n-1) \sum_{k_1, k_2} \left[P(\hat{d}(1) = k_1) P(\hat{d}(2) = k_2) (1 + \tilde{O}(n^{-1/2})) \right]$$

$$\frac{P(\hat{d}(1) = k_1)}{P(d(1) = k_1)} = \frac{\binom{n-2}{k_1}}{\binom{n}{k_1}} (1-p)^{-2} = 1 + \tilde{O}(n^{-1/2})$$

$$= n(n-1) \sum_{k_1, k_2} \left[P(d(1) = k_1) P(d(2) = k_2) (1 + \tilde{O}(n^{-1/2})) \right]$$

$$= E(Y_k) (E(Y_k) - 1) (1 + \tilde{O}(n^{-1/2}))$$

So, with $k = k_-$,

$$P_r(Y_{k_-} \leq \frac{1}{2} E(Y_{k_-}))$$

$$\leq \frac{E(Y_{k_-}(Y_{k_-} - 1)) + E(Y_{k_-}) - E(Y_{k_-})^2}{E(Y_{k_-})^2 / 4}$$

$$= O\left(\frac{1}{n^{2\epsilon(1-\epsilon)}}\right)$$

$$= o(1).$$

This completes the proof of the second part.

$$P_r(\neg(iii)) \leq o(1) + \binom{n}{2} \sum_{k_1=k_2}^{k_L} \sum_{|k_2-k_1| \leq 10} P_r(d(1)=k_1 \wedge d(2)=k_2)$$

$$= o(1) + \sum_{k_1, k_2} \binom{n}{2} \left[p P(\hat{d}(1)=k_1-1) P(\hat{d}(2)=k_2-1) + (1-p) P(\hat{d}(1)=k_1) P(\hat{d}(2)=k_2) \right]$$

Now

$$\sum_{k_1, k_2} P(\hat{d}(1)=k_1-1) P(\hat{d}(2)=k_2-1)$$

$$\leq 2n(1+o(n^{-1/2})) \sum_{k_1} P_r(\hat{d}(1)=k_1-1)^2$$

and

$$\sum_{k_1} P_r(\hat{d}^{(1)} = k_1 - 1)^2 \lesssim \frac{1}{2\pi p q n} \int_{y=x}^{\infty} e^{-y^2} dy,$$

where $x = \frac{k_1 - (n-1)p}{\sqrt{(n-1)pq}} \lesssim (1-\epsilon)\sqrt{2 \log n}$

$$= \frac{1}{\sqrt{8\pi p q n}} \int_{z=x\sqrt{2}}^{\infty} e^{-z^2/2} dz$$

$$\lesssim \frac{1}{\sqrt{8\pi p q n}} \cdot \frac{1}{x\sqrt{2}} \cdot e^{-2(1-\epsilon)^2}$$

We get a similar bound for $\sum_{k_1} P_r(\hat{d}^{(1)} = k_1)^2$.

Thus

$$P_r(\gamma(\text{iii})) = o\left(n^{2-1-2(1-\epsilon)^2}\right) \\ = o(1).$$

□

Edge Colouring

The **Chromatic Index** $\chi'(G)$ of graph G is the minimum number of colors that can be used to color the edges of G so that if 2 edges share a vertex, they have a different color.

Vizing's Theorem states that

$$\Delta(G) \leq \chi'(G) \leq \Delta(G) + 1.$$

Also, if there is a unique vertex of maximum degree, then $\chi'(G) = \Delta(G)$.

So $\chi'(G_{n,p}) = \Delta(G_{n,p})$ whp.

Graph Isomorphism

In this section we describe a procedure for ordering the vertices of a graph G .

If it succeeds then it is possible

to quickly tell if $G \cong H$, for **any** H .

Algorithm

Input G . Parameter L .

Step 1

Re-label vertices so that degrees satisfy

$$d_G(v_1) \geq d_G(v_2) \geq \dots \geq d_G(v_n)$$

If $\exists i \leq L$ such that $d_G(v_i) = d_G(v_{i+1})$: **FAIL**

Step 2

For $i > L$ let:

$$X_i = \{ j \in \{1, 2, \dots, L\} : (v_i, v_j) \in G \}$$

Re-label vertices so that these sets satisfy

$$X_{L+1} \supseteq X_{L+2} \supseteq \dots \supseteq X_n \quad \text{— lexicographic ordering.}$$

If $\exists i > L$ such that $X_i = X_{i+1}$: **FAIL**.

Suppose now that the above algorithm succeeds for G .

Given an n -vertex graph H we run the algorithm on H .

(i) If algorithm fails $G \not\cong H$.

(ii) Suppose ordering of $V(H)$ is w_1, w_2, \dots, w_n . Then

$G \cong H \iff v_i \rightarrow w_i$ is an isomorphism.

Claim

Let $\rho = p^2 + q^2$ and $L = 3 \log_{1/\rho} n$.

Then whp the algorithm succeeds on $G = G_{n,p}$.

Proof

We have already proved that Step 1 succeeds whp.

We must now show that $X_i \neq X_j \neq i, j$ whp but there is slight problem because edges (v_i, v_j) are conditioned due to us knowing v_i has a high degree.

Fix i, j and let $\widehat{G}_{i,j} = G \setminus \{i, j\}$.

Now if i, j are not high degree vertices then the L largest degree vertices in $G, \widehat{G}_{i,j}$ will coincide, whp.

This is because there is whp, a gap ≥ 10 between high vertex degrees in G .

Thus

$$P_r(\text{Step 2 fails}) \leq$$

$$o(1) + \sum_{1 \leq i < j \leq n} P_r(i, j \text{ have same nbrs among } L \text{ largest degree vertices in } \widehat{G}_{i,j})$$

$$= o(1) + \binom{n}{2} \rho^L$$

$$= o(1).$$



Automorphisms

It follows from the previous section that
whp, $G_{n,p}$ has no non-trivial automorphisms.

For \downarrow $\sigma: [n] \rightarrow [n]$ is an automorphism, then

(i) $\sigma(v_i) = v_i$, $1 \leq i \leq \ell$
where v_i is the vertex with the i th largest
degree.

(ii) $\sigma(v) = v$ for $v \notin \{v_1, v_2, \dots, v_\ell\}$.

This is because all of the sets X_v are
distinct.

Janson's Inequality

Suppose that $0 \leq p_i \leq 1$ for $i=1, 2, \dots, M$.

Let X be a random subset of $[M]$ where

$$P_i(i \in X) = p_i$$

independently for $i \in [M]$

Let $S_1, S_2, \dots, S_\ell \subseteq [M]$ and let

$$Z_i = \begin{cases} 1 & S_i \subseteq X \\ 0 & S_i \not\subseteq X \end{cases}$$

Let $Z = Z_1 + Z_2 + \dots + Z_b$

Count the number of S_i that occur.

Let

$$\mu = E(Z) = \sum_{i=1}^b p_i$$

and

$$\Delta^* = \frac{1}{2} \sum_{S_i \cap S_j \neq \emptyset} E(Z_i Z_j).$$

Theorem

$$P_i(Z \leq \mu - t) \leq e^{-t^2/2\Delta^*}.$$

Proof

$$\text{Let } \psi(s) = E(e^{-sZ}), \quad s \geq 0.$$

$$\Pr(Z \leq \mu - t) = \Pr(e^{s(\mu - t - Z)} \geq 1)$$

$$\leq E(e^{s(\mu - t - Z)})$$

$$= e^{s(\mu - t)} \psi(s).$$

Write

$$\log \Pr(Z \leq \mu - t) \leq \log \Psi(s) + s(\mu - t)$$

TO BE SHOWN $\leq -\frac{\mu^2}{\Delta^*} (1 - e^{-s\Delta^*/\mu}) + s(\mu - t)$.

If $t = \mu$ we simply let $s \rightarrow \infty$. Otherwise

to minimize RHS we take

$$s = -\frac{\mu}{\Delta^*} \log\left(1 - \frac{t}{\mu}\right)$$

and then

$$\log \Pr(Z \leq \mu - t) \leq -\frac{\mu}{\Delta^*} \left(t + (\mu - t) \log\left(1 - \frac{t}{\mu}\right) \right)$$

$$\log \Pr(Z \leq \mu - t) \leq -\frac{\mu}{\Delta^*} \left(t \cdot (\mu - t) \log \left(1 - \frac{t}{\mu} \right) \right)$$

$$\leq -\frac{\mu}{\Delta^*} \left(t - (\mu - t) \frac{t}{\mu} \right)$$

$$= -\frac{t^2}{2\Delta^*}$$

TO BE SHOWN

$$\log \Psi(s) \leq -\frac{\mu^2}{\Delta^*} (1 - e^{-s\Delta/\mu}).$$

Now

$$\log \Psi(s) = \int_{u=0}^s \frac{\Psi'(u)}{\Psi(u)} du$$

and

$$\begin{aligned} \Psi'(u) &= -E(Ze^{-uZ}) \\ &= -\sum_{i=1}^M E(Z_i e^{-uZ}). \end{aligned}$$

For each $i \in [M]$ we write

$$Z = X_i + Y_i$$

where

$$X_i = \sum_{j: S_j \cap S_i \neq \emptyset} Z_j.$$

Then

$$E(Z_i e^{-uZ}) = p_i E(e^{-uX_i} e^{-uY_i} | Z_i = 1)$$

$$\text{FKG inequality} \geq p_i E(e^{-uX_i} | Z_i = 1) E(e^{-uY_i} | Z_i = 1)$$

$$= p_i E(e^{-uX_i} | Z_i = 1) E(e^{-uY_i})$$

$$\begin{aligned}
&= p_i E(e^{-uX_i} | Z_i=1) E(e^{-uY_i}) \\
&\geq p_i E(e^{-uX_i} | Z_i=1) \psi(u).
\end{aligned}$$

So

$$\begin{aligned}
\frac{\psi'(s)}{\psi(s)} &\leq -\mu \sum_{i=1}^M \frac{p_i}{\mu} E(e^{-sX_i} | Z_i=1) \\
&\leq -\mu \sum_{i=1}^M \frac{p_i}{\mu} e^{-E(sX_i | Z_i=1)} \quad \text{Jensen} \\
&\leq -\mu \exp \left\{ -\sum_{i=1}^M E\left(\frac{s p_i}{\mu} X_i | Z_i=1\right) \right\} \\
&= -\mu \exp \left\{ -\frac{s}{\mu} \sum_{i=1}^M E(X_i | Z_i=1) P(Z_i=1) \right\}
\end{aligned}$$

$$= -\mu \exp \left\{ -\frac{s}{M} \sum_{i=1}^M E(X_i | Z_i=1) P(Z_i=1) \right\}$$

$$= -\mu e^{-s\Delta^*/\mu}$$

$$\sum_{i=1}^M E(X_i | Z_i=1) P(Z_i=1)$$

$$= \sum_{i=1}^M \sum_{j: S_j \cap S_i \neq \emptyset} P(Z_j=1 | Z_i=1) P(Z_i=1)$$

$$= \Delta^*$$

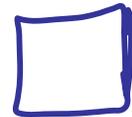
S₀

$$\frac{\psi'(s)}{\psi(s)} \leq -\mu e^{-s\Delta^*/\mu} \cdot$$

$$\log \psi(s) = \int_{u=0}^s \frac{\psi'(u)}{\psi(u)} du$$

$$\leq - \int_{u=0}^s \mu e^{-u\Delta^*/\mu} du$$

$$= -\frac{\mu^2}{\Delta^*} (1 - e^{-s\Delta^*/\mu}) \cdot$$



Now let

$$\Delta = \frac{1}{2} \sum_{\substack{S_i \cap S_j \neq \emptyset \\ S_i \neq S_j}} E(Z_i Z_j).$$

Theorem

$$(i) \Pr(Z=0) \leq e^{-\mu + \Delta}$$

$$(ii) \Pr(Z=0) \leq e^{-\frac{\mu^2}{\mu + \Delta}}$$

(ii) follows directly from first theorem.)

For (1) we have (see p 8)

$$\frac{\psi'(s)}{\psi(s)} \approx - \sum_i p_i E(e^{-sX_i} | z_i=1).$$

So

$$\log(P(Z=0)) = \int_0^{\infty} (\log \psi(s))' ds$$

$$\approx - \int_0^{\infty} \sum_i p_i E(e^{-sX_i} | z_i=1) ds$$

$$= - \sum_i p_i \int_{s=0}^{\infty} E(e^{-sX_i} | z_i=1) ds$$

$$= - \sum_i p_i E\left(\frac{1}{X_i} \mid z_i=1\right)$$

$$\leq - \sum_i p_i E\left(1 - \frac{1}{2}(X_i - z_i) \mid z_i=1\right)$$

$$\frac{1}{X_i} = \frac{1}{(X_i - z_i) + z_i} = \frac{1}{(X_i - z_i) + 1} \geq 1 - \frac{1}{2}(X_i - z_i)$$

↑ integer

$$\leq - \sum_i p_i E\left(1 - \frac{1}{2}(X_i - Z_i) \mid Z_i = 1\right)$$

$$= -\mu + \Delta.$$



The diameter of Random Graphs

Theorem

Let $d \geq 2$ be a fixed positive integer. Suppose that $c > 0$ and

$$p^d n^{d-1} = \ln(n^2/c).$$

Then

$$\lim_{n \rightarrow \infty} \Pr(\text{diameter } G_{n,p} = k) = \begin{cases} e^{-c/2} & : k = d \\ 1 - e^{-c/2} & : k = d+1. \end{cases}$$

(a) Whp $\text{diam}(G) \geq d$.

Fix $v \in V$ and let

$$N_k(v) = \{w : \text{dist}(v, w) = k\}.$$

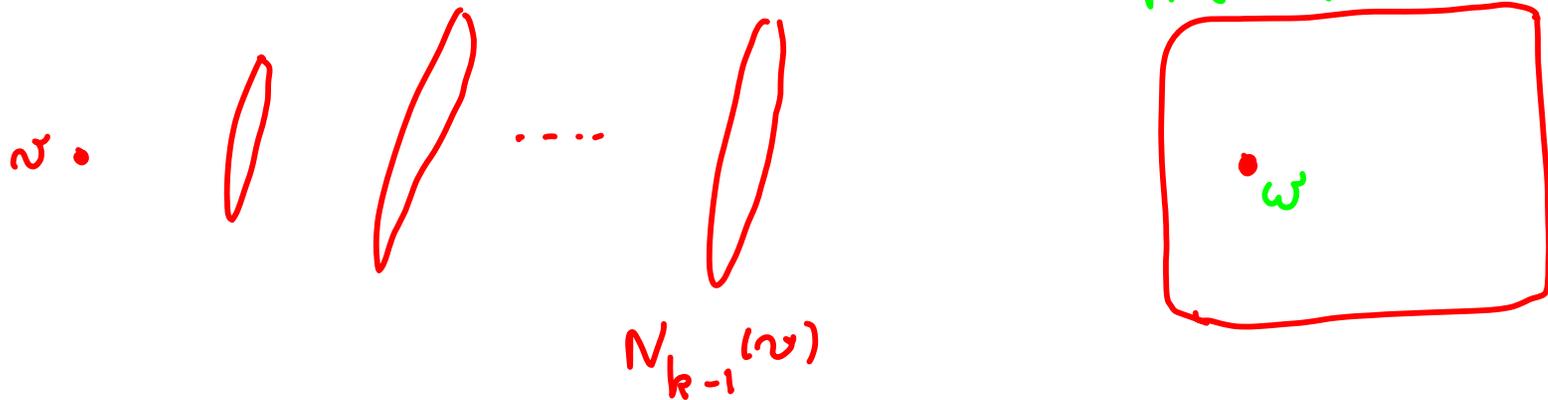
We show that whp, for $0 \leq k < d$,

$$\begin{aligned} |N_k(v)| &\leq (2np)^k \\ &\leq (2n \ln n)^{k/d} \\ &= o(n). \end{aligned}$$

We observe that given $N_i(\omega)$, $i = 0, 1, \dots, k-1$,

that $|N_k(\omega)|$ is distributed as

$$\text{Bin} \left(n - \sum_{i=0}^{k-1} |N_i(\omega)|, \underbrace{1 - (1-p)^{|N_{k-1}(\omega)|}}_{\text{Pr}(\omega \in N_k(\omega))} \right)$$



Let $\mathcal{E}_i = \{ |N_i(v)| \leq (2np)^i \}$.

Condition on $\mathcal{E}_0, \mathcal{E}_1, \dots, \mathcal{E}_{k-1}$.

Does not condition on edge from $N_{k-1}(v)$ to $V \setminus \bigcup_{i=0}^{k-1} N_i(v)$.

$|N_k(v)|$ is distributed as $\text{Bin}(\nu, q)$

where

$\nu < n$ and

$$q = 1 - (1-p)^{|N_{k-1}(v)|}$$

$$\leq |N_{k-1}(v)| p.$$

$$\leq (2np)^{k-1} p < 1.$$

Thus

$$E(|N_k(v)| \mid \mathcal{E}_0, \mathcal{E}_1, \dots, \mathcal{E}_{k-1})$$

$$= \nu \downarrow$$

$$\leq np \mid N_{k-1}(v) \mid.$$

Chernoff bound gives

$$Pr(|N_k(v)| \geq (2np)^k \mid \mathcal{E}_0, \mathcal{E}_1, \dots, \mathcal{E}_{k-1})$$

$$\leq Pr(\text{Bin}(n, \mid N_{k-1}(v) \mid p) \geq (2np)^k \mid \mathcal{E}_{k-1})$$

$$\leq Pr(\text{Bin}(n, (2np)^{k-1} p) \geq (2np)^k)$$

$$\begin{aligned} &\leq \Pr(\text{Bin}(n, (2np)^{k-1} p) \geq (2np)^k) \\ &\leq e^{-\frac{(2np)^{k-1} np}{3}} \\ &\ll n^{-2}. \end{aligned}$$

So

$$\Pr\left(\bigcup_{L=0}^{d-1} N_i(v) = [n]\right) \ll$$

$$\sum_{k=1}^{d-1} \Pr(\overline{E}_k \mid \mathcal{E}_1, \dots, \mathcal{E}_{k-1}) =$$

$$O(n^{-2}).$$

(b) Why $\text{diam}(G) \leq d+1$.

Proof

For $v, w \in [n]$. Then for $1 \leq k < d$,

Let $\mathcal{F}_k = \left\{ |N_k(v)| \geq \left(\frac{np}{2}\right)^k \right\}$.

$$\Pr(\overline{\mathcal{F}}_k \mid \mathcal{E}_1, \mathcal{F}_1, \dots, \mathcal{E}_{k-1}, \mathcal{F}_{k-1}) =$$

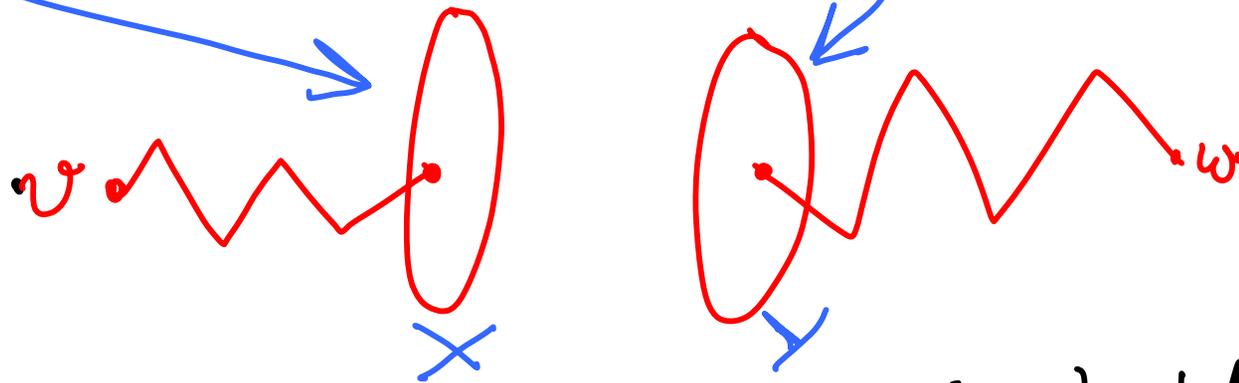
$$\Pr\left(\text{Bin}\left(\underbrace{n - \sum_{i=0}^{k-1} |N_i(v)|}_{n - o(n)}, \underbrace{1 - (1-p)^{|N_{k-1}(v)|}}_{\geq \frac{3}{4} \cdot \left(\frac{np}{2}\right)^{k-1} p}\right) \leq \left(\frac{np}{2}\right)^k\right)$$

$$\leq e^{-\Omega\left(\left(\frac{np}{2}\right)^k\right)} = o(n^{-3}).$$

So with probability $1 - O(n^{-3})$,

$$|N_{\lfloor d/2 \rfloor}(v)| \geq \left(\frac{np}{2}\right)^{\lfloor d/2 \rfloor} \quad \text{and}$$

$$|N_{\lceil d/2 \rceil}(w)| \geq \left(\frac{np}{2}\right)^{\lceil d/2 \rceil}.$$



Either $X \cap Y \neq \emptyset$ and $\text{dist}(v, w) \leq \lfloor d/2 \rfloor + \lceil d/2 \rceil = d$

or

$$\Pr(\nexists X:Y \text{ edge}) \leq (1-p) \left(\frac{np}{2}\right)^d$$

$$\begin{aligned}
P_r(\nexists X:Y \text{ edge}) &\leq (1-p)^{\binom{np}{2}^d} \\
&\leq \exp\left\{-\binom{np}{2}^d p\right\} \\
&\leq \exp\left\{-(2-o(1))np \ln n\right\} \\
&= o(n^{-3}).
\end{aligned}$$

So

$$P_r(\exists v,w: \text{dist}(v,w) > d+1) = o(n^{-1}).$$

$$p^d n^{d-1} = \ln(n^2/c).$$

Now consider d or $d+1$ as diameter.

We use Janson's inequality.

For $v, w \in [n]$ let

$$\mathcal{A}_{v,w} = \left\{ v, w \text{ are not joined by a path of length } d \right\}$$

For x_1, x_2, \dots, x_{d-1} let

$$\mathcal{B}_{\underbrace{x_1, x_2, \dots, x_{d-1}}_x} = \left\{ (v, x_1, x_2, \dots, x_{d-1}, w) \text{ is a path in } G_{n,p} \right\}.$$

Let $Z = \sum_{x = x_1, \dots, x_{d-1}} Z_x \leftarrow \begin{cases} 1 : \mathcal{B}_x \text{ occurs} \\ 0 : \neg \mathcal{B}_x \text{ occurs} \end{cases}$

$$\mu = E(Z) = (n-2)(n-3) \dots (n-d) p^d \\ \approx \ln(n^2/c).$$

Let $\Delta = \sum_{\substack{x = x_1, x_2, \dots, x_{d-1} \\ y = y_1, y_2, \dots, y_{d-1}}} \Pr(\mathcal{B}_x \wedge \mathcal{B}_y)$

v, x, w and v, y, w share an edge

$$x \neq y$$

$$\leq \sum_{c=1}^{d-1} n^{2(d-1)-c} P^{2d-c}$$

↑
edges in common
between x and y

$$= O\left(\sum_{c=1}^{2d-2} n^{2(d-1)-c} - \frac{d-1}{d}(2d-c) (\log n)^{\frac{2d-c}{d}}\right)$$

$$= \tilde{O}(n^{-c/d})$$

$$= o(1),$$

Applying $P_r(Z=0) \leq e^{-\mu+\Delta}$ we get

$$P_r(Z=0) \leq (1+o(1)) \frac{c}{n^2}.$$

On the other hand the FKG inequality implies

$$\begin{aligned} P_r(Z=0) &\geq (1-p^d)^{(n-2)(n-3)\dots(n-d)} \\ &= (1-o(1)) \frac{c}{n^2} \end{aligned}$$

So

$$P_r(\mathcal{A}_{v,w}) = P_r(Z=0) = (1+o(1)) \frac{c}{n^2}.$$

So $E(\#\nu, w : \mathcal{A}_{\nu, w} \text{ occurs}) \approx \frac{c}{2}$
and we should expect that

$$P_r(\nexists \nu, w : \mathcal{A}_{\nu, w} \text{ occurs}) \approx e^{-c/2}. \quad (1)$$

Indeed, if we choose $\nu_1, w_1, \nu_2, w_2, \dots, \nu_k, w_k$,
 k constant, we find that

$$P_r(\mathcal{A}_{\nu_1, w_1} \wedge \mathcal{A}_{\nu_2, w_2} \wedge \dots \wedge \mathcal{A}_{\nu_k, w_k}) \quad (2)$$
$$\approx \left(\frac{c}{n^2}\right)^k$$

and (1) follows as in previous arguments.

For (2) we define

$$Z = Z_1 + Z_2 + \dots + Z_k$$

where

$Z_i = \#$ paths of length d from v_i to w_i .

We need to show that the corresponding $\Delta = o(1)$
 and then we need to show that $1 \leq r < s \leq k$

$$\Delta_{r,s} = \sum_{\substack{x = x_1, x_2, \dots, x_{d-1} \\ y = y_1, y_2, \dots, y_{d-1}}} \Pr(\mathcal{B}_x^r \cap \mathcal{B}_y^s) = o(1)$$

v_r, x, w_r and v_s, y, w_s share an edge

$$x \neq y$$

But

$$\Delta_{r,s} \leq \sum_{c=1}^{d-1} n^{2(d-1)-c} p^{2d-c}$$
$$= o(1)$$

as before.



Independence and Chromatic Number

Theorem

Suppose $0 < p < 1$ is constant and $b = \frac{1}{1-p}$.

Then why

$$\alpha(G_{n,p}) \approx 2 \log_b n$$

$\alpha(G)$ = size of largest independent set in G .

Proof

Let $X_k = \#$ of independent sets of size k .

$$(1) \text{ Let } k = \lceil 2 \log_b n \rceil$$

$$E(X_k) = \binom{n}{k} (1-p)^{\binom{k}{2}}$$

$$\leq \left(\frac{ne}{k(1-p)^{1/2}} \cdot (1-p)^{k/2} \right)^k$$

$$\leq \left(\frac{e}{k(1-p)^{1/2}} \right)^k$$

$$= o(1).$$

(ii) Let now

$$k = \lfloor 2 \log_b n - 3 \log_b \log_b n \rfloor$$

Let $\Delta^* = \sum_{\substack{i, j \\ S_i \cap S_j}} \Pr(S_i \cap S_j \text{ are independent in } G_{n,p})$

where $S_1, S_2, \dots, S_{\binom{n}{k}}$ are all k -subsets of $[n]$

and $S_i \cap S_j$ iff $|S_i \cap S_j| \geq 2$.

$$\Pr(X_k = 0) \leq \exp\left\{-\frac{E(X_k)^2}{\Delta^*}\right\}$$

Janson's
Inequality

$$\frac{\Delta^*}{E(X_k)^2} = \frac{\binom{n}{k} (1-p)^{\binom{k}{2}} \sum_{j=2}^k \binom{n-k}{k-j} \binom{k}{j} (1-p)^{\binom{k}{2} - \binom{j}{2}}}{\left(\binom{n}{k} (1-p)^{\binom{k}{2}} \right)^2}$$

$$= \sum_{j=2}^k \underbrace{\frac{\binom{n-k}{k-j} \binom{k}{j}}{\binom{n}{k}} (1-p)^{-\binom{j}{2}}}_{u_j}$$

$$\frac{u_j}{u_2} \leq \left(\frac{k}{n-2k} \cdot \frac{k e}{j-2} \cdot (1-p)^{-\frac{j+1}{2}} \right)^{j-2} \quad j > 2$$

< 1.

$$S_0 \quad \frac{E(X_k)^2}{\Delta^*} \asymp \frac{1}{k u_2} \asymp \frac{n^2(1-p)}{k^5}$$

$$S_0 \quad \Pr(X_k = 0) \leq e^{-\Omega(n^2 / (\log n)^5)}, \quad (*)$$



Theorem

$$X(G_{n,p}) \approx \frac{n}{2 \log_b n}$$

Proof

$$(i) \quad X(G_{n,p}) \geq \frac{n}{\alpha(G_{n,p})}$$

$$\approx \frac{n}{2 \log_b n}$$

(ii)

Let $\nu = \frac{n}{(\log n)^2}$. It follows from (*)
on p5 that

$$P_1(\exists S: |S| \geq \nu \text{ and } S \not\subseteq \text{independent set of size} \\ \geq k_0 = 2 \log_6 n - 3 \log_6 \log_6 n)$$

$$\leq \binom{n}{\nu} \exp \left\{ -\Omega \left(\frac{\nu^2}{(\log n)^5} \right) \right\}$$

$$= o(1).$$

So assume that every set of size $\geq \nu$
contains an independent set of size $\geq k_0$.

So we repeatedly

Choose an independent set of size k_0 .

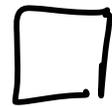
Give it a new colour.

Repeat until number of uncoloured vertices is $\leq \gamma$.

Give each remaining vertex its own colour.

Number of colours used

$$\leq \frac{n}{k_0} + \gamma \approx \frac{n}{2 \log_b n}.$$



Performance of Greedy Algorithm

Algorithm (GREEDY)

k is current colour

A is current set of vertices that might get color k in current round.

U is current set of uncoloured vertices.

begin
 $k \leftarrow 0$; $A \leftarrow [n]$; $U \leftarrow [n]$;
while $U \neq \emptyset$;

begin

$k \leftarrow k + 1$; $A \leftarrow U$;

START ITERATION

Choose $v \in A$ and give it colour k ;

$U \leftarrow U \setminus \{v\}$

$A \leftarrow A \setminus (\{v\} \cup N(v))$

if $A \neq \emptyset$

otherwise

end

Theorem

Whp GREEDY uses $\approx \frac{n}{\log_b n}$ colours
(about twice as many as it "should").

Proof

At the start of an iteration the edges inside U are unexamined. Suppose that

$|U| \geq \nu = \frac{n}{(\log n)^2}$. We show that $\approx \log_b n$

vertices get colour k .

Each iteration chooses a **maximal** independent set from the remaining uncolored vertices.

$P_r(\exists S : |S| \leq \underbrace{\log_2 n - 3 \log_2 \log_2 n}_{k_0} \text{ and } S \text{ is maximal independent})$

$$\leq \sum_{s=1}^{k_0} \binom{n}{s} (1-p)^{\binom{s}{2}} (1 - (1-p)^s)^{n-s}$$

$$\leq \sum_{s=1}^{k_0} \left[\frac{ne}{s} (1-p)^{\frac{s-1}{2}} \right]^s e^{-n(1-p)^s}$$

$$\leq \sum_{s=1}^{k_0} \left(ne^{1+(1-p)^s} (1-p)^{\frac{s-1}{2}} \right)^s e^{-n(1-p)^s}$$

$$\leq \sum_{s=1}^{k_0} \left(n e^{1+(1-p)^s} (1-p)^{\frac{s-1}{2}} \right)^s e^{-n(1-p)^s}$$

$$\leq \sum_{s=1}^{k_0} (n e^2)^s e^{-n(1-p)^s}$$

$$\leq k_0 (n e^2)^{k_0} e^{-(\log_b n)^3}$$

$$\leq e^{-(\log_b n)^3/2}.$$

So the probability that we fail to use $\geq k_0$ colours while $|U| \geq \nu$ is at most $n e^{-(\log_b \nu)^3/2} = o(1)$.

On the other hand let

$$k_1 = \log_b n + 2 \log_b \log_b n$$

consider one round. Let $U_0 = V$ and suppose u_1, u_2, \dots get colour k and $U_{i+1} = U_i \setminus (\{u_i\} \cup N(u_i))$.

Then

$$E(|U_{i+1}| \mid U_i) \leq |U_i| (1-p)$$

and so

$$E(|U_{k_1}|) \leq n (1-p)^{k_1}.$$

So

$$Pr(k_1 \text{ vertices coloured in a round}) \leq \frac{1}{(\log_b n)^2}$$

$$Pr(2k_1 \text{ vertices coloured in a round}) \leq \frac{1}{n^2}$$

So let

$$\delta_i = \begin{cases} 1 & \leq k_1 \text{ colours used in Round } i \\ 0 & \text{otherwise} \end{cases}$$

We see that

$$P(\delta_i = 1 \mid \delta_1, \delta_2, \dots, \delta_{i-1}) = 1 - O(1/(\log n)^2)$$

and deduce that w.h.p. $O(n/(\log n)^2)$ rounds colour more than k_1 vertices and no round colours more than $2k_1$ vertices.



Concentration

Theorem

$$P\left(|X(G_{n,p}) - E(X(G_{n,p}))| \geq t\right) \leq 2e^{-\frac{t^2}{2n}}$$

Proof

Write $X = Z(\gamma_1, \gamma_2, \dots, \gamma_n)$ where

$$\gamma_j = \{ (i, j) \in E(G_{n,p}) : i < j \}.$$

Then

$$|Z(\gamma_1, \dots, \gamma_i, \dots, \gamma_n) - Z(\gamma_1, \dots, \hat{\gamma}_i, \dots, \gamma_n)| \leq 1$$

and the theorem follows from a martingale inequality.

□

Concentration from Martingales

A sequence of random variables $X_0, X_1, \dots, X_n, \dots$

where $X_i = X_i(A_0, A_1, \dots, A_i)$

is called a **martingale w.r.t. $A_0, A_1, \dots, A_n, \dots$**

Nb: $E(X_{i+1} | A_0, A_1, \dots, A_i) = X_i$

\swarrow this is a random variable.

$$X_{i+1}(\omega) = \int_{\hat{\omega} : \begin{matrix} A_j(\hat{\omega}) = A_j(\omega) \\ 0 \leq j \leq i \end{matrix}} X_{i+1}(\hat{\omega}) \Pr(\hat{\omega})$$

Theorem

Suppose that X_0, X_1, \dots, X_n is a martingale,
w.r.t. A_0, A_1, \dots, A_n and

$$a_i \leq X_{i+1} - X_i \leq b_i, \quad i = 1, 2, \dots, n.$$

Then

$$P_r(|X_n - X_0| \geq t) \leq 2e^{-2t^2 / \sum_i (b_i - a_i)^2}.$$

Proof

We first consider $P_r(X_n - X_0 \geq t)$

For $\lambda > 0$. Then

$$\begin{aligned} \Pr(X_n - \mu \geq t) &= \Pr(e^{\lambda(X_n - X_0 - t)} \geq 1) \\ &\leq E(e^{\lambda(X_n - X_0 - t)}) \\ &= e^{-\lambda t} E(e^{\lambda(X_n - X_0)}) \\ &= e^{-\lambda t} E\left(\exp\left\{\sum_{i=0}^n \lambda Y_i\right\}\right) \end{aligned}$$

where $Y_i = X_i - X_{i-1}$.

$$= e^{-\lambda t} E\left(\prod_{i=0}^n e^{\lambda Y_i}\right)$$

We show that

$$E\left(\prod_{i=0}^n e^{\lambda Y_i}\right) \leq e^{\frac{\lambda^2}{8} (b_n - a_n)^2} E\left(\prod_{i=0}^{n-1} e^{\lambda Y_i}\right) \quad (1)$$

and then induction gives

$$E\left(\prod_{i=0}^n e^{\lambda Y_i}\right) \leq \exp\left\{\lambda^2 \sum_{i=1}^n (b_i - a_i)^2 / 8\right\}$$

and

$$Pr(X_n - X_0 \geq t) \leq \exp\left\{-\lambda t + \lambda^2 \sum_{i=1}^n (b_i - a_i)^2 / 8\right\}$$

Now choose

$$\lambda = \frac{4t}{\sum_{i=1}^n (b_i - a_i)^2}.$$

Proof of (1).

$$E\left(\prod_{i=0}^n e^{\lambda Y_i}\right)$$

$$= E\left(\prod_{i=0}^{n-1} e^{\lambda Y_i} E\left(e^{\lambda Y_n} \mid A_0, A_1, \dots, A_{n-1}\right)\right)$$

and we obtain (1) from

$$E\left(e^{\lambda Y_n} \mid A_0, A_1, \dots, A_{n-1}\right) \approx e^{\lambda^2 (b_n - a_n)^2 / 8} \quad (2)$$

Proof of (2)

Y_n satisfies

(i) $E(Y_n) = 0$ and (ii) $a_n \leq Y_n \leq b_n$

$$(E(Y_n) = E(E(X_n - X_{n+1} | A_0, A_1, \dots, A_{n-1})) = 0)$$

Now if $a_n \leq Y_n \leq b_n$

$$e^{\lambda Y_n} \leq \frac{Y_n - a_n}{b_n - a_n} e^{\lambda b_n} + \frac{b_n - Y_n}{b_n - a_n} e^{\lambda a_n}$$

and so

$$E(e^{\lambda Y_n}) \leq \frac{b_n}{b_n - a_n} e^{\lambda a_n} - \frac{a_n}{b_n - a_n} e^{\lambda b_n}$$

$$E(e^{\lambda Y_n}) \leq \frac{b_n}{b_n - a_n} e^{\lambda a_n} - \frac{a_n}{b_n - a_n} e^{\lambda b_n}$$

$$= e^{f(y)}$$

where if $p = -a_n / (b_n - a_n)$, $y = (b_n - a_n) \lambda$,

$$f(y) = -py + \ln(1 - p + pe^y)$$

$$f''(y) = \frac{p(1-p)e^{-y}}{(p + (1-p)e^{-y})^2} \leq \frac{1}{4}$$

$$\left[\frac{AB}{(A+B)^2} \leq \frac{1}{4} \right]$$

and so

$$f(y) \leq \frac{y^2}{8}$$

proving (2).

For the lower bound

$$P_r(X_n - X_0 \leq -t) = P_r(-X_n + X_0 \geq t)$$

$$\leq e^{-2t^2 / \sum_i (b_i - a_i)^2}$$



Sometimes our sequence is a **submartingale** or a **supermartingale**.

$$E(X_{i+1} | \dots) \leq X_i \quad E(X_{i+1} | \dots) \geq X_i$$

To bound $\Pr(X_n - X_0 \geq t)$ we used

$$e^{\lambda Y_n} \leq \frac{Y_n - a_n}{b_n - a_n} e^{\lambda b_n} + \frac{b_n - Y_n}{b_n - a_n} e^{\lambda a_n}$$

$$= \underbrace{Y_n}_{\geq 0} \left[\frac{e^{\lambda b_n} - e^{\lambda a_n}}{b_n - a_n} \right] + \frac{b_n}{b_n - a_n} e^{\lambda a_n} - \frac{a_n}{b_n - a_n} e^{\lambda b_n}$$

$E(Y_n) \leq 0$ for a supermartingale.

So our estimate for $\Pr(X_n - X_0 \geq t)$ is valid for supermartingales. For $\Pr(X_n - X_0 \leq -t)$, it is valid for submartingales.

We now prove a similar, but slightly different version:

Theorem

Suppose that X_0, X_1, \dots, X_n is a martingale, w.r.t. A_0, A_1, \dots, A_n and

for $0 \leq a_i \leq 1$, $i=1, 2, \dots, n$,

$$-a_i \leq X_{i+1} - X_i \leq 1 - a_i, \quad i=1, 2, \dots, n.$$

Let $a = \frac{1}{n}(a_1 + \dots + a_n)$ and $\bar{a} = 1 - a$. Then

$$P_i(|X_n - X_0| \geq nt) \leq \left(\left(\frac{a}{a+t} \right)^{a+t} \left(\frac{\bar{a}}{\bar{a}-t} \right)^{\bar{a}-t} \right)^n$$

for $t \leq \bar{a}$.

We will first observe that

$$E(e^{\lambda Y_n}) \leq (1-a_n)e^{-\lambda a_n} + a_n e^{\lambda(1-a_n)}$$

so that

$$P_t(X_n - X_0 \geq nt) \leq e^{-\lambda nt} \prod_{k=1}^n \left[(1-a_k)e^{-\lambda a_k} + a_k e^{\lambda(1-a_k)} \right]$$

$$= e^{-\lambda n(a+t)} \prod_{k=1}^n (1 - a_k + a_k e^{\lambda})$$

$$\leq e^{-\lambda n(a+t)} (1 - a + a e^{\lambda})^n$$

Now put

$$e^{\lambda} = \frac{(a+t)(1-a)}{a(1-a-t)}.$$

Corollary

Under the conditions above:

$$(i) \quad \Pr(|X_n - X_0| \geq t) \leq 2e^{-2t^2/n}$$

$$(ii) \quad \Pr(X_n - X_0 \geq \epsilon an) \leq \left((1+\epsilon)^{1+\epsilon} e^{-\epsilon} \right)^{an} \\ \leq e^{-\frac{\epsilon^2 an}{2(1+\epsilon/3)}}$$

$$(iii) \quad \Pr(X_n - X_0 \leq -\epsilon an) \leq e^{-\epsilon^2 an/2} \quad \bullet$$

(1)

Let

$$f(t) = \ln \left(\left(\frac{a}{a+t} \right)^{a+t} \left(\frac{\bar{a}}{\bar{a}-t} \right)^{\bar{a}-t} \right)$$

$$f'(t) = \ln \left(\frac{a(\bar{a}-t)}{(a+t)\bar{a}} \right)$$

$$f''(t) = - \left((a+t)(\bar{a}-t) \right)^{-1} \leq -4$$

$f(0) = f'(0) = 0$ and so

$$f(t) \leq -2t^2.$$

(ii)

$$\Pr(X_n - X_0 \geq \epsilon an) \leq \left[e^{-\lambda a(1+\epsilon)} (1 - a + ae^{-\lambda}) \right]^n$$

Now let $e^{-\lambda} = 1 + \epsilon$

$$\leq \left[(1+\epsilon)^{-a(1+\epsilon)} (1 + a\epsilon) \right]^n$$

$$\leq \left[(1+\epsilon)^{-(1+\epsilon)} e^{\epsilon} \right]^{an}$$

and now use

$$(1+\epsilon) \ln(1+\epsilon) - \epsilon \geq \frac{3\epsilon^2}{6+2\epsilon}$$

to get second inequality in (ii).

(iii)

$$f(t) = \ln \left(\left(\frac{a}{a+t} \right)^{a+t} \left(\frac{\bar{a}}{\bar{a}-t} \right)^{\bar{a}-t} \right)$$

$$h(x) = f(-ax) \text{ for } 0 \leq x \leq 1.$$

$$h''(x) = a^2 f''(-ax) = -\frac{a}{(1-x)(\bar{a}+xa)} \leq -a$$

and so

$$f(-ax) \leq -ax^2/2.$$

Doob Martingale

$$\Omega = \{A_1, A_2, \dots, A_n\}$$

Let $Z = Z(A_1, A_2, \dots, A_n)$ be a random variable with $E(Z) = 0$.

Define random variables, $X_0 = 0$ and

$$X_i = E(Z | A_1, A_2, \dots, A_i), \quad 1 \leq i \leq n$$

Claim

X_0, X_1, \dots, X_n is a martingale w.r.t.

A_0, A_1, \dots, A_n with $X_0 = E(Z) = 0$ and $X_n = Z$.

Proof

$$E(X_{i+1} | A_0, A_1, \dots, A_i)$$

$$= E\left(E(X_{i+1} | A_0, A_1, \dots, A_{i+1}) | A_0, A_1, \dots, A_i \right)$$

given A_0, \dots, A_i we are
averaging X_{i+1} over A_{i+1}

$$= X_i .$$



Case 1

$$Z = Z_1 + Z_2 + \dots + Z_n$$

where Z_1, Z_2, \dots, Z_n are independent.

Put
$$X_i = \sum_{j=1}^i (Z_j - E(Z_j)).$$

$$X_{i+1} = X_i + Z_{i+1} - E(Z_{i+1})$$

$$E(X_{i+1} | X_i, X_{i-1}, \dots, X_1) = X_i$$

and all the derived inequalities apply.

In particular if $0 \leq Z_i \leq 1$ and $E(Z_i) = a_i$
then we get bounds on

$$P_r(|Z - \sum a_i| \geq t)$$

by considering

$$\hat{Z}_i = Z_i - a_i \in [-a_i, 1 - a_i].$$

Case 2

$Z = Z(A_1, \dots, A_n)$ and A_1, A_2, \dots, A_n
are independent.

Theorem

1P

$a_i \leq Z(A_1, \dots, A_i, \dots, A_n) - Z(A_1, \dots, \hat{A}_i, \dots, A_n) \leq b_i$
for all $i, A_1, A_2, \dots, A_n, \hat{A}_i$ then

$$Pr(|Z - E(Z)| \geq t) \leq 2e^{-\frac{t^2}{\sum_{i=1}^n (b_i - a_i)^2}}$$

We can assume w.l.o.g. that $E(Z) = 0$.
 Now define $X_i = E(Z | A_1, \dots, A_i)$ as before

$$X_{i+1} - X_i =$$

$$\sum_{\hat{A}_{i+1}, \dots, \hat{A}_n}$$

$$\left(Z(A_1, \dots, A_{i+1}, \hat{A}_{i+2}, \dots, \hat{A}_n) - Z(A_1, \dots, A_i, \hat{A}_{i+1}, \dots, \hat{A}_n) \right) \\ \times P_r(\hat{A}_{i+2}) \times P_r(\hat{A}_{i+3}) \times \dots \times P_r(\hat{A}_n)$$

$$\in [a_i, b_i]$$

$$\text{So } a_i \leq X_{i+1} - X_i \leq b_i.$$



In $G_{n,p}$ we can take

(i) $A_1, A_2, \dots, A_{\binom{n}{2}}$ as independent 0-1 random variables defining G .

(ii) $A_i = \{ (j,i) : j \leq i \text{ and } (j,i) \in E(G_{n,p}) \}$

Case 3

For $G_{n,m}$ we need a slight modification.

Suppose

$$Z = Z(u_1, u_2, \dots, u_m)$$

where u_1, u_2, \dots, u_m is a random permutation
of $\{1, 2, \dots, N\}$.

Suppose that

one interchange 

$$a_i \leq Z(u_1, \dots, u_i, \dots, u_m) - Z(u_1, \dots, \hat{u}_i, \dots, u_m) \leq b_i$$

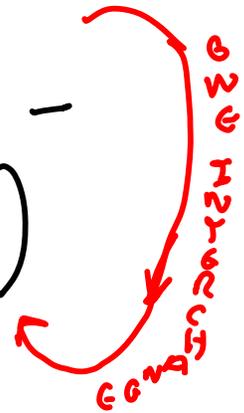
then

$$\Pr(|Z - E(Z)| \geq t) \leq 2e^{-t^2 / \sum_{i=1}^m (b_i - a_i)^2}$$

Now define $X_i = E(Z | u_1, u_2, \dots, u_i)$

$$X_{i+1} - X_i =$$

$$\int_{\hat{u}_{i+1}, \dots, \hat{u}_N} (Z(u_1, \dots, u_i, \hat{u}_{i+1}, \dots, \hat{u}_j = u_{i+1}, \dots, \hat{u}_N) - Z(u_1, \dots, u_i, u_{i+1}, \dots, \hat{u}_{i+1}, \dots, \hat{u}_N)) \times \frac{1}{(N-i)!}$$



Small Subgraphs

Let H be a fixed graph.

We use the notation n_H, e_H for the number of vertices and edges of G .

Also let

$$p_H = \frac{e_H}{v_H}.$$

Lemma

Let X_H denote the number of copies of

H in $G_{n,p}$.

$$E(X_H) = \binom{n}{v_H} \frac{v_H!}{\text{aut}(H)} p^{e_H}$$

where

$\text{aut}(H)$ is the number of automorphisms of H .

Proof

K_n contains $\binom{n}{v_H} a_H$ distinct copies of H , where a_H is the number of copies of H in K_{v_H} . Thus

$$E(X_H) = \binom{n}{v_H} a_H p^{e_H}$$

and all we need to show is that

$$a_H \times \text{aut}(H) = v_H!$$

Each permutation σ of $[v_H]$ defines a **unique** copy of H as follows:

A copy of H corresponds to a set of e_H edges of K_{v_H} . The copy H_σ corresponding to σ has edge $\{(\alpha_{\sigma(i)}, \gamma_{\sigma(i)}) : 1 \leq i \leq e_H\}$ where $\{(\alpha_i, \gamma_i) : 1 \leq i \leq e_H\}$ is some fixed copy of H in K_{v_H} .

But $H_\sigma = H_{\tau\sigma}$ iff $\forall i \exists j$ such that $(\alpha_{\tau\sigma(i)}, \gamma_{\tau\sigma(i)}) = (\alpha_{\sigma(j)}, \gamma_{\sigma(j)})$ i.e. τ is an automorphism of H .

□

Theorem

Suppose $\rho = o(n^{-1/\rho_H})$. Then whp, $G_{n,\rho}$ contains no copies of H .

Proof

Suppose that $\rho = \frac{1}{\omega} n^{-1/\rho_H}$ where $\omega(n) \rightarrow \infty$. Then

$$\begin{aligned} E(X_H) &\leq n^{\nu_H} \omega^{-e_H} n^{-e_H/\rho_H} \\ &= \omega^{-e_H} \\ &\rightarrow 0. \end{aligned}$$

□

Now consider the case where $n^{1/\rho_H} p \rightarrow \infty$.

Suppose $p = \omega n^{-1/\rho_H}$ where $\omega \rightarrow \infty$.

Then for some constant $c_H > 0$

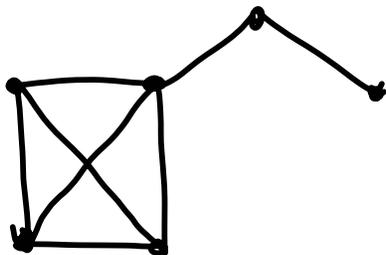
$$\begin{aligned} E(X_H) &\geq c_H n^{2\nu_H} \omega^{e_H} n^{-e_H/\rho_H} \\ &= c_H \omega^{e_H} \\ &\rightarrow \infty. \end{aligned}$$

This is not enough to show that w.h.p.

$G_{n,p}$ contains a copy of H .

Suppose

$H =$



$$n_H = 6$$

$$e_H = 8$$

Let $p = n^{-5/7}$. Then $1/p_H > \frac{5}{7}$ and so

$$E(X_H) \approx c_H n^{6 - 8 \times 5/7} \rightarrow \infty.$$

On the other hand, if $\hat{H} = K_4$ then

$$E(X_{\hat{H}}) \leq n^{4 - 6 \times 5/7} \rightarrow 0$$

and so whp there are no copies of \hat{H} and hence no copies of H .

Theorem

$$\text{Let } \rho_H^* = \max_{\substack{H' \in H \\ v_{H'} > 0}} \rho_{H'}.$$

(a) If $n^{-1/\rho_H^*} \rho \rightarrow 0$

then $\text{whp } X_H = 0.$

(b) If $n^{-1/\rho_H^*} \rho \rightarrow \infty$

then $\text{whp } X_H > 0.$

Proof

(a) follows from p5 because in this case there is whp, an $H' \subseteq H$ such that $X_{H'} = 0$.

(b) We use the second moment method:

$$P_r(X_H > 0) \geq \frac{E(X_H)^2}{E(X_H^2)}$$

$$E(X_H^2) = \sum_{i,j=1}^{N_H} P(H_i \wedge H_j)$$

$$= E(X_H) \sum_{j=1}^{N_H} P(H_j | H_1)$$

H_1, H_2, \dots
are all copies
of H in \mathcal{K}_n .

$$\leq E(X_H)^2 + E(X_H) \sum_{\substack{H' \subseteq H \\ H' \neq H \\ e_{H'} > 0}} n^{\nu_H - \nu_{H'}} P^{e_H - e_{H'}}$$



$H' \subseteq H$
 $H' \neq H$
 $e_{H'} > 0$

So

$$\frac{E(X_H^2)}{E(X_H)^2} - 1 \leq \underbrace{c_H}_{\text{constant}} \sum_{\substack{H' \subseteq H \\ H' \neq H \\ e_{H'} > 0}} n^{-\nu_{H'}} P^{-e_{H'}}$$

But

$$\sum_{\substack{H' \subseteq H \\ H' \neq H}}$$

$H' \subseteq H$
 $H' \neq H$

$$\rho^{-2e_{H'}} \rho^{-e_{H'}}$$

$$= \sum_{\substack{H' \subseteq H \\ H' \neq H \\ e_{H'} > 0}}$$

$H' \subseteq H$
 $H' \neq H$
 $e_{H'} > 0$

$$\rho^{e_{H'} \left(\frac{1}{\rho_H^*} - \frac{1}{\rho_{H'}} \right)} \omega^{-e_{H'}}$$

$$\rho = \omega n^{-1} / \rho_H^*$$

$$= O(\omega^{-1})$$

Thus

$$\frac{E(X_H^2)}{E(X_H)^2} = 1 + o(1)$$

□

Every monotone property has a threshold

Let \mathcal{G} be a monotone increasing property of graphs. Assume $\bar{K}_n \notin \mathcal{G}$ and $K_n \in \mathcal{G}$.

Given $0 < \epsilon < 1$ we define $p(\epsilon)$ by

$$\Pr(G_{n, p(\epsilon)} \in \mathcal{G}) = \epsilon.$$

$p(\epsilon)$ exists because

$\Pr(G_{n, p} \in \mathcal{G})$ is a polynomial in p that increases from 0 ($p=0$) to 1 ($p=1$).

Theorem

$p^* = p(\frac{1}{2})$ is a threshold for G .

Proof

Suppose G_1, G_2, \dots, G_k are independent

copies of $G_{n,p}$. Then

(i) $G_1 \cup G_2 \cup \dots \cup G_k \stackrel{\text{same distribution as}}{\approx} G_{n, \underbrace{1 - (1-p)^k}_{\leq kp}} \stackrel{\text{coupling}}{\leq} G_{n, kp}$.

(ii) With this coupling

$$G_{n, kp} \not\in G \Rightarrow G_1, G_2, \dots, G_k \not\in G.$$

So

$$\Pr(G_{n, kp} \notin \mathcal{G}) \leq \Pr(G_{n, p} \notin \mathcal{G})^k.$$

(i) Suppose now $p = p^*$ and $k = w \rightarrow \infty$

$$\Pr(G_{n, wp^*} \notin \mathcal{G}) \leq 2^{-w} = o(1).$$

(ii) Now suppose $p = p^*/w$.

$$\frac{1}{2} = \Pr(G_{n, p^*} \notin \mathcal{G}) \leq \Pr(G_{n, p^*/w} \notin \mathcal{G})^w$$

So $\Pr(G_{n, p^*/w} \notin \mathcal{G}) \geq 2^{-1/w} = 1 - o(1).$

□

Expected Length of Minimum Spanning Tree

Let $X_e, e \in E(K_n)$ be a collection of independent uniform $[0, 1]$ random variables.

Consider X_e to be the length of edge e .

Let L_n be the length of the minimum spanning tree of K_n .

Theorem

$$\lim_{n \rightarrow \infty} E(L_n) = \zeta(3) = \sum_{k=1}^{\infty} \frac{1}{k^3} = 1.202 \dots$$

Proof

Suppose that $T = T(\{X_e\})$ is the minimum spanning tree, unique with probability one.

$$L_n = \sum_{e \in T} X_e$$

$$= \sum_{e \in T} \int_{p=0}^1 \mathbb{1}_{p \leq X_e} dp$$

$$= \int_{p=0}^1 \sum_{e \in T} \mathbb{1}_{p \leq X_e} dp$$

$$a = \int_0^1 \mathbb{1}_{x \leq a} dx$$

$$= \int_{p=0}^1 \sum_{e \in \mathcal{T}} \mathbb{1}_{p \leq X_e} dp$$

$$= \int_{p=0}^1 |\{e \in \mathcal{T} : X_e \geq p\}| dp$$

$$= \int_{p=0}^1 (\kappa(G_p) - 1) dp$$

$$E(L_n) = \int_{p=0}^1 (E(\kappa(G_p) - 1)) dp$$

$\kappa(G) = \#$ components of G .

$G_p =$ graph induced by edges e with $X_e \geq p$

$\equiv G_{n,p}$

So we estimate $E(\kappa(G_p))$.

$$(i) \quad p \geq \frac{6 \log n}{n} \Rightarrow E(\kappa(G_p)) = 1 + o(1).$$

$$\begin{aligned} E(\kappa(G_p)) &\leq 1 + n \Pr(G_p \text{ is not connected}) \\ &\leq 1 + n \sum_{k=1}^{\frac{1}{2}n} \binom{n}{k} k^{k-2} p^{k-1} (1-p)^{k(n-k)} \\ &\leq 1 + n^2 \sum_{k=1}^{\frac{1}{2}n} \left(n e \cdot \frac{6 \log n}{n} \cdot \frac{1}{n^3} \right)^k \\ &= 1 + o(1). \end{aligned}$$

$$E(L_n) = \int_{p=0}^{\frac{6 \log n}{n}} E(\kappa(G_p) - 1) dp + o(1)$$

$$= \int_{p=0}^{\frac{6 \log n}{n}} E(\kappa(G_p)) dp + o(1)$$

Write

$$\kappa(G_p) = \sum_{k=1}^{(\log n)^2} A_k + \sum_{k=1}^{(\log n)^2} B_k + C$$

of k -components
that are trees

of k -components
that are not trees

components of
size $\geq (\log n)^2$

↓
C

$$E(A_k) = \binom{n}{k} k^{k-2} p^{k-1} (1-p)^{k(n-k) + \binom{k}{2} - k + 1}$$

$$= (1 + o(1)) n^k \cdot \frac{k^{k-2}}{k!} p^{k-1} (1-p)^{kn}$$

uniform in p

$$E(B_k) \leq \binom{n}{k} k^{k-2} \binom{k}{2} p^k (1-p)^{k(n-k)}$$

$$\leq (1 + o(1)) (np e^{1-np})^k$$

$$\leq (1 + o(1))$$

$$C \leq \frac{n}{(\log n)^2}$$

$$\int_{p=0}^{\frac{6 \log n}{n}} \sum_{k=1}^{(\log n)^2} E(B_{k,p}) dp \leq \frac{6 \log n}{n} \cdot (\log n)^2 \cdot (1 + o(1))$$

$$= o(1).$$

$$\int_{p=0}^{\frac{6 \log n}{n}} C dp \leq \frac{6 \log n}{n} \cdot \frac{n}{(\log n)^2} = o(1)$$

$$E(L_n) =$$

$$o(1) + (1 + o(1)) \sum_{k=1}^{(\log n)^2} n^k \cdot \frac{k^{k-2}}{k!} \int_{p=0}^{\frac{6 \log n}{n}} p^{k-1} (1-p)^{kn} dp$$

$$\sum_{k=1}^{(\log n)^2} n^k \cdot \frac{k^{k-2}}{k!} \int_{p=\frac{6 \log n}{n}}^1 p^{k-1} (1-p)^{kn} dp$$

$$\leq \sum_{k=1}^{(\log n)^2} n^k e^k \int_{p=\frac{6 \log n}{n}}^1 n^{-6k} dp = o(1).$$

$$E(L_n) =$$

$$o(1) + (1 + o(1)) \sum_{k=1}^{(\log n)^2} n^k \cdot \frac{k^{k-2}}{k!} \int_{p=0}^1 p^{k-1} (1-p)^{kn} dp$$

$$= o(1) + (1 + o(1)) \sum_{k=1}^{(\log n)^2} n^k \cdot \frac{k^{k-2}}{k!} \frac{(k-1)! (k(n-k))!}{(k(n-k+1))!}$$

$$= o(1) + (1 + o(1)) \sum_{k=1}^{(\log n)^2} n^k k^{k-3} \prod_{i=1}^k \frac{1}{k(n-k)+i}$$

$$= o(1) + (1 + o(1)) \sum_{k=1}^{(\log n)^2} \frac{1}{k^3}$$

$$= o(1) + (1 + o(1)) \sum_{k=1}^{\infty} \frac{1}{k^3} .$$



Random Graphs with a Fixed Degree Sequence.

Let $\underline{d} = (d_1, d_2, \dots, d_n)$

where $d_1 + d_2 + \dots + d_n = 2M$ is even.

Let $G_{n, \underline{d}} = \left\{ \begin{array}{l} \text{simple graphs with vertex set } [n] \\ \text{such that degree } d(i) = d_i, i \in [n] \end{array} \right\}$

$G_{n, \underline{d}}$ is chosen randomly from $G_{n, \underline{d}}$.

We assume that $d_1, d_2, \dots, d_n \geq 1$ and that $\sum d_i (d_i - 1) = \Omega(n)$.

Configuration model

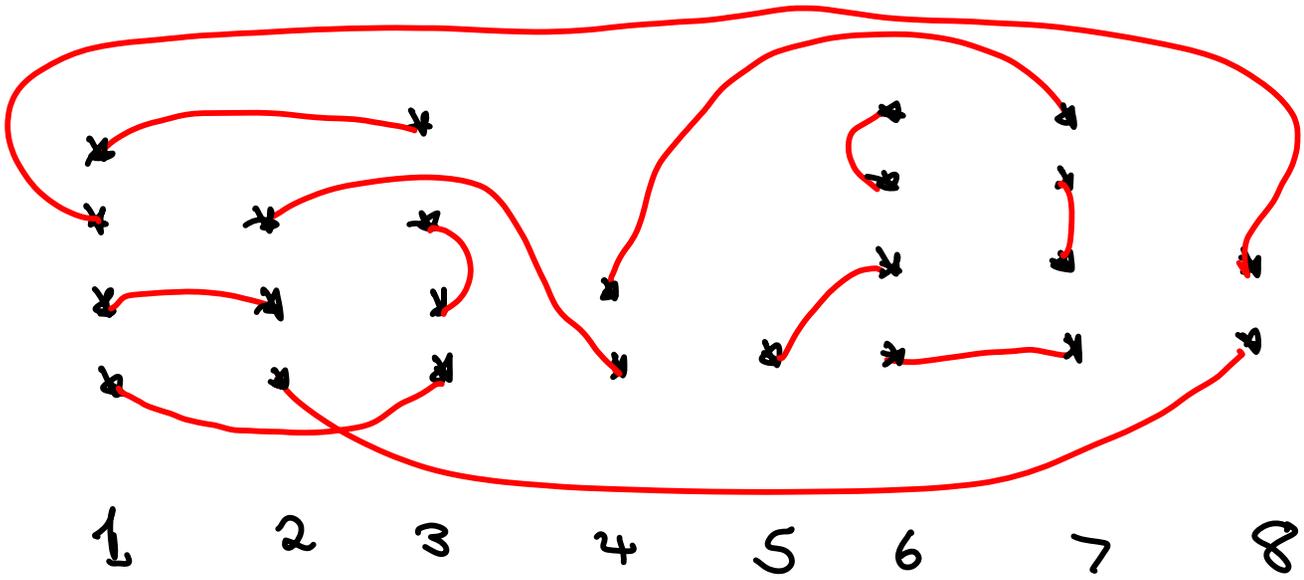
Let W_1, W_2, \dots, W_n be a partition of W , where
 $|W_i| = d_i$ for $1 \leq i \leq n$.

For $x, y \in W$ define $\phi(x)$ by $x \in W_{\phi(x)}$.

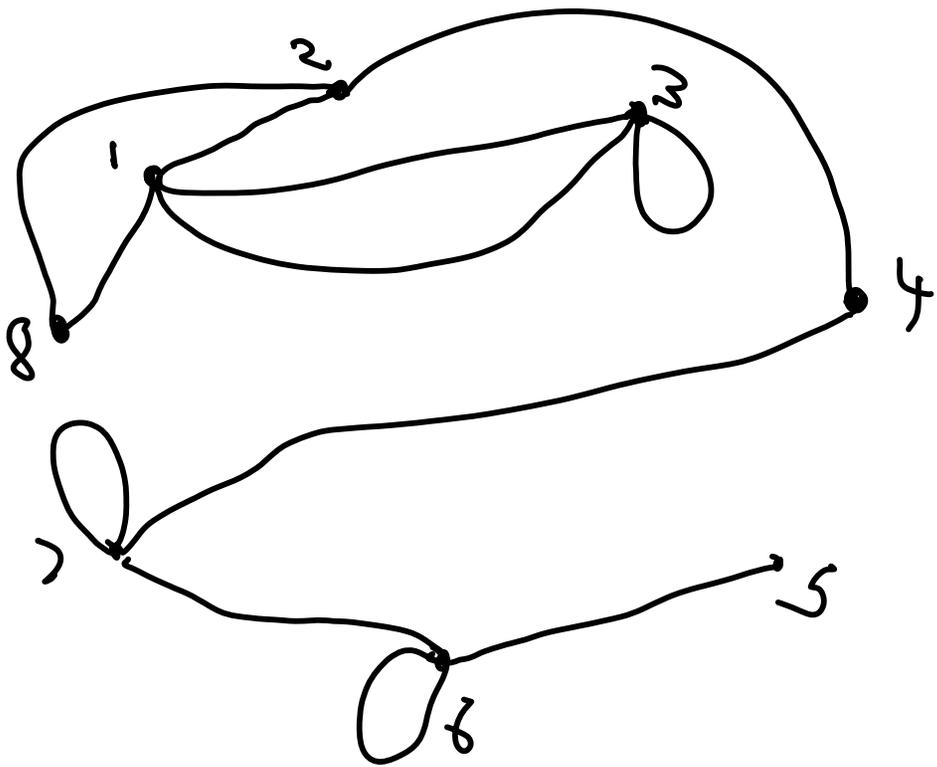
Let F be a partition of W into m parts
(a configuration).

Given F we define the (multi) graph $\gamma(F)$

$$\gamma(F) = ([n], \{(\phi(x), \phi(y)) : (x, y) \in F\})$$



4



Lemma

If $G \in \mathcal{G}_{n, \underline{d}}$, then

$$|\gamma^{-1}(G)| = \prod_{i=1}^n d_i!$$

Proof

Arrange the edges of G in lexicographic order. Now go through the sequence of $2m$ symbols, replacing each i by a new member of W_i . We get all F for which $\gamma(F) = G$.

□

Corollary

If F is chosen uniformly at random from Ω (the set of configurations) and $G_1, G_2 \in \mathcal{G}_{n,d}$ then

$$P_r(\chi(F) = G_1) = P_r(\chi(F) = G_2).$$

so we can choose a random F and accept $\chi(F)$ iff there are no loops or multiple edges.

The next question is: What is

$P_r(\gamma|F)$ is simple)

(i)

Since

$$|\Omega| = \frac{(2m)!}{m! 2^m}$$

(ii)

Take d_i "distinct" copies of i for $i=1, 2, \dots, n$ and take a permutation of these $2m$ symbols. Read off F , pair by pair.

Each distinct F arises in $m! 2^m$ ways.

(i) & (ii) will tell us how big is $G_{n,d}$.

Alternative Construction of F

Begin

$$U = W; F = \emptyset;$$

For $i = 1, 2, \dots, m$ do

Begin

Choose x *arbitrarily* from U ;

Choose y *randomly* from $U \setminus \{x\}$;

$$F := F \cup \{(x, y)\};$$

$$U := U \setminus \{x, y\}$$

End

Each F arises with probability $\frac{1}{(2m-1)(2m-3)\dots 1}$
 $= |\Omega|^{-1}$.

Let $\Delta = \max \{d_1, d_2, \dots, d_n\}$.

Notation: $F \stackrel{\text{ran}}{\in} \Omega \equiv F$ is chosen uniformly from Ω .

Lemma

Assume that $\Delta \leq n^{1/6}$ and $F \stackrel{\text{ran}}{\in} \Omega$. Then whp

(a) $\gamma(F)$ has no double loops

(b) $\gamma(F)$ has $\leq \Delta \log n$ loops

(c) $\gamma(F)$ has no triple edges.

(d) $\gamma(F)$ has no adjacent double edges.

(e) $\gamma(F)$ has $\leq \Delta^2 \log n$ double edges.

Proof

(a)

$P_r(F \text{ contains a double loop})$

$$\sum_{i=1}^n \binom{d_i}{4} \cdot 3 \cdot \left(\frac{1}{2m-3} \right)^2$$

$$\leq n \Delta^4 m^{-2}$$

$$= O(1),$$

(b)

Let $k_1 = \Delta \log n$.

$$Pr(F \text{ has } \geq k_1 \text{ loops}) \leq o(1) +$$

$$\sum_{l=1}^n \binom{d_i}{2}^{x_i} \left(\frac{1}{2m - 2k_1} \right)^{k_1}$$

$x_1 + \dots + x_n = k_1$
 $x_i = 0, 1$

$$\leq o(1) + \left(\frac{\Delta}{2m} \right)^{k_1} \sum_{l=1}^n d_i^{x_i}$$

$x_1 + x_2 + \dots + x_n = k_1$

$$\leq o(1) + \left(\frac{\Delta}{2m} \right)^{k_1} \frac{(d_1 + \dots + d_n)^{k_1}}{k_1!} \leq o(1) + \left(\frac{\Delta e}{k_1} \right)^{k_1} = o(1).$$

(c)

$P_2(F \text{ contains a triple edge})$

$$\approx \sum_{1 \leq i < j \leq n} \binom{d_i}{3} \binom{d_j}{3} \cdot 6 \cdot \left(\frac{1}{2m-5} \right)^3$$

$$\approx \Delta^4 \left(\sum d_i \right)^2 n^{-3}$$

$$= o(1).$$

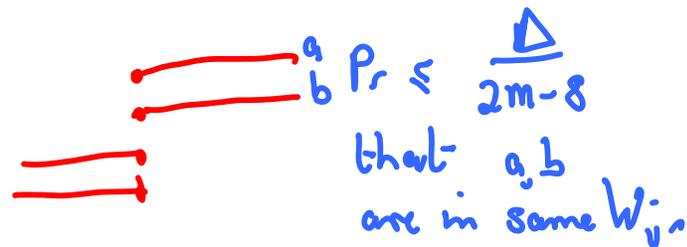
(d)

$P_r(F \text{ contains 2 adjacent double edges}) \leq$

$$\sum_{i=1}^n \binom{d_i}{2} \left(\frac{\Delta}{2m-8} \right)^2$$

$$\leq \frac{\Delta^3}{(2m-8)^2} \sum_{i=1}^n d_i$$

$$= o(1).$$

 $P_r \leq \frac{\Delta}{2m-8}$
that a, b
are in same W_{ij} .

(e) Let $k_2 = \Delta^2 \log n$.

$P_r(F \text{ has } \geq k_2 \text{ double edges})$

$$o(1) + \sum_{\substack{\alpha_1 + \dots + \alpha_n = k_2 \\ \alpha_i = 0, 1}} \prod_{i=1}^n \left[\binom{d_i}{2} \frac{\Delta}{2m - 4k_2} \right]^{\alpha_i}$$

$$o(1) + \left(\frac{\Delta^2}{m} \right)^{k_2} \sum_{\alpha_1 + \dots + \alpha_n = k_2} \prod_{i=1}^n d_i^{\alpha_i}$$

$$\leq o(1) + \left(\frac{\Delta^2}{m} \right)^{k_2} \frac{(2m)^{k_2}}{k_2!}$$

$$= o(1).$$



Switchings

Let now

$$\Omega_{i,j} = \{ F \in \Omega : F \text{ has } i \text{ loops, } j \text{ double edges and no double loops or triple edges and no vertex incident with 2 double edges} \}$$

Lemma (Sutherland) Let $M_1 = 2M$ and $M_2 = \sum_i d_i(d_i - 1)$

For $i \leq k_1$, and $j \leq k_2$

$$\frac{|\Omega_{i-1, j}|}{|\Omega_{i, j}|} = \frac{2iM_1}{M_2} \left(1 + \mathcal{O}\left(\frac{\Delta^3}{\hbar}\right) \right)$$

$$\frac{|\Omega_{0, j-1}|}{|\Omega_{0, j}|} = \frac{4jM_1^2}{M_2^2} \left(1 + \mathcal{O}\left(\frac{\Delta^3}{\hbar}\right) \right).$$

Corollary

$$\frac{|\Omega_{0,0}|}{|\Omega|} = (1 + o(1)) e^{-\lambda(\lambda+1)}$$

where $\lambda = \frac{M_2}{2M_1}$.

Thus

$$|G_{n,d}| \approx e^{-\lambda(\lambda+1)} \frac{1}{\prod_{L=1}^n d_L!} \frac{(2m)!}{m! 2^m}$$

Proof It follows from the switching lemma that $i \leq k_1$ and $j \leq k_2$ implies

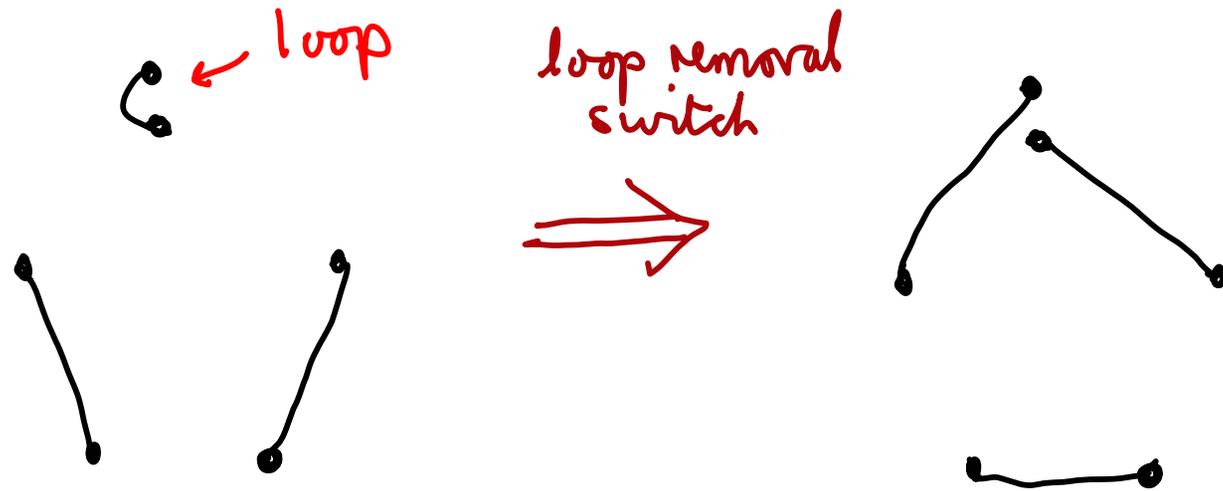
$$\frac{|\Omega_{i,j}|}{|\Omega_{0,0}|} = (1 + o(1)) \frac{\lambda^{i+2j}}{i! j!}$$

Therefore

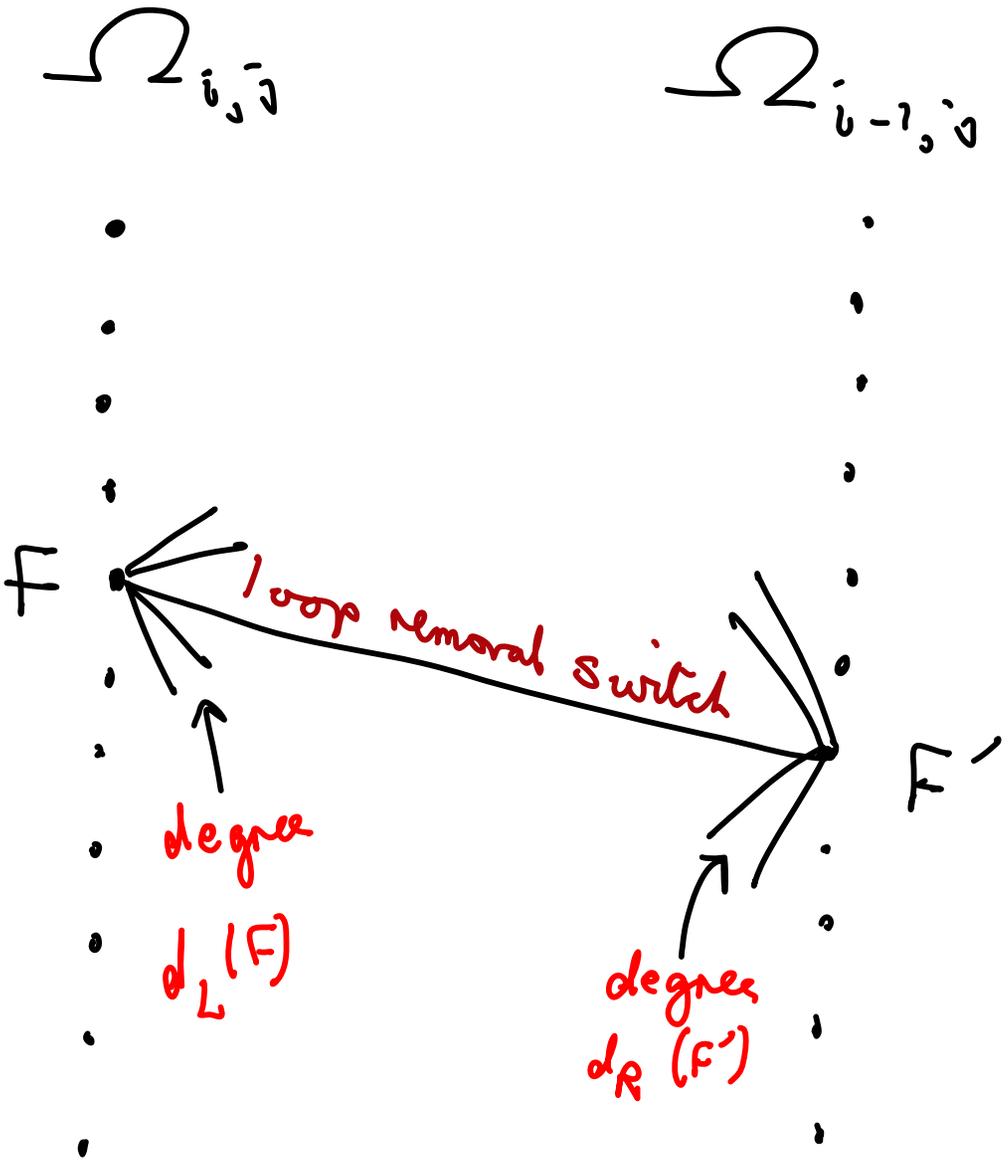
$$\begin{aligned} (1 + o(1)) |\Omega| &= (1 + o(1)) |\Omega_{0,0}| \sum_{i=0}^{\lambda_1} \sum_{j=0}^{\lambda_2} \frac{\lambda^{i+2j}}{i! j!} \\ &= (1 + o(1)) |\Omega_{0,0}| e^{\lambda(\lambda+1)}. \end{aligned}$$

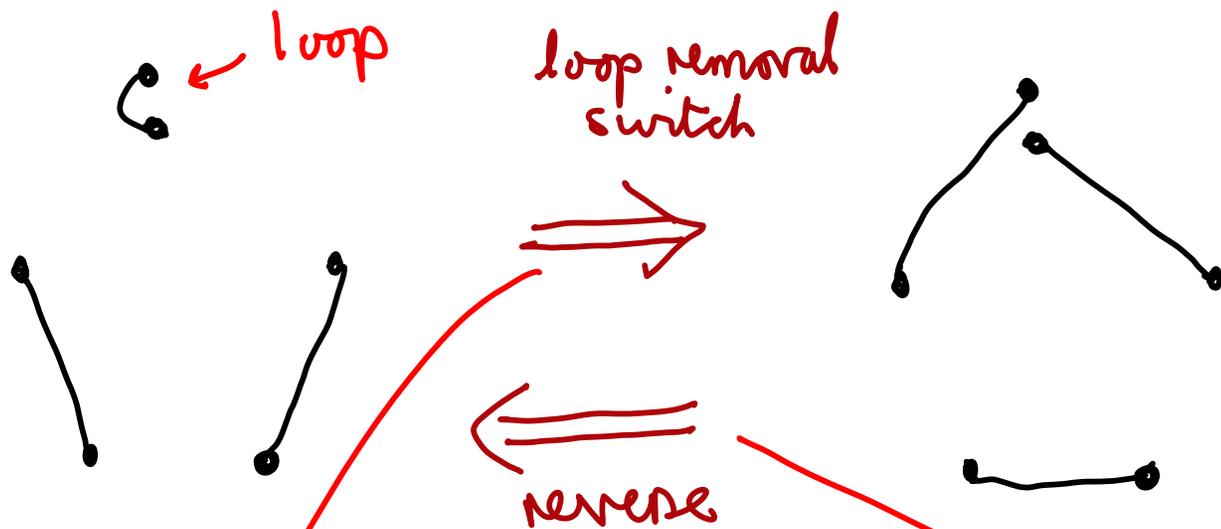


Proof of switching lemma



In general this operation takes a member F of $\Omega_{i,j}$ to a member F' of $\Omega_{i-1,j}$ unless it creates new loops or multiple edges.





$$\begin{aligned} \# \text{choices} &\leq i \times M_1^2 \\ &\geq i \times M_1^2 - \tilde{O}(i M_1 \Delta^2) \end{aligned}$$

$$\begin{aligned} \# \text{choices} &\leq M_1 M_2 / 2 \\ &\geq M_1 M_2 / 2 - \tilde{O}((M_1 + M_2) \Delta^3) \end{aligned}$$

Now

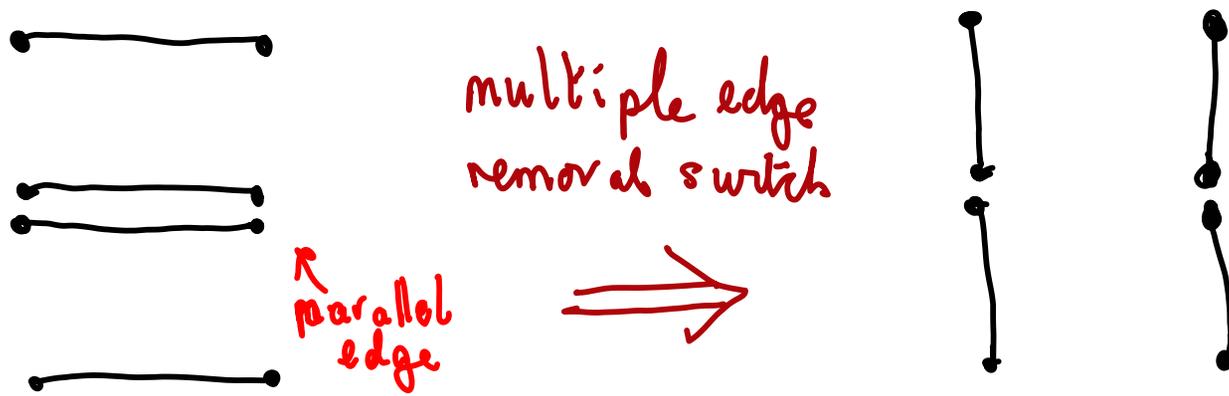
$$\sum_{F \in \Omega_{i,j}} d_L(F) = \sum_{F' \in \Omega_{i-1,j}} d_R(F')$$

$$\begin{aligned} & \approx iM_1^2 |\Omega_{i,j}| \\ & \geq iM_1^2 |\Omega_{i,j}| \\ & \times (1 - \tilde{O}(i\Delta^2/M_1)) \end{aligned}$$

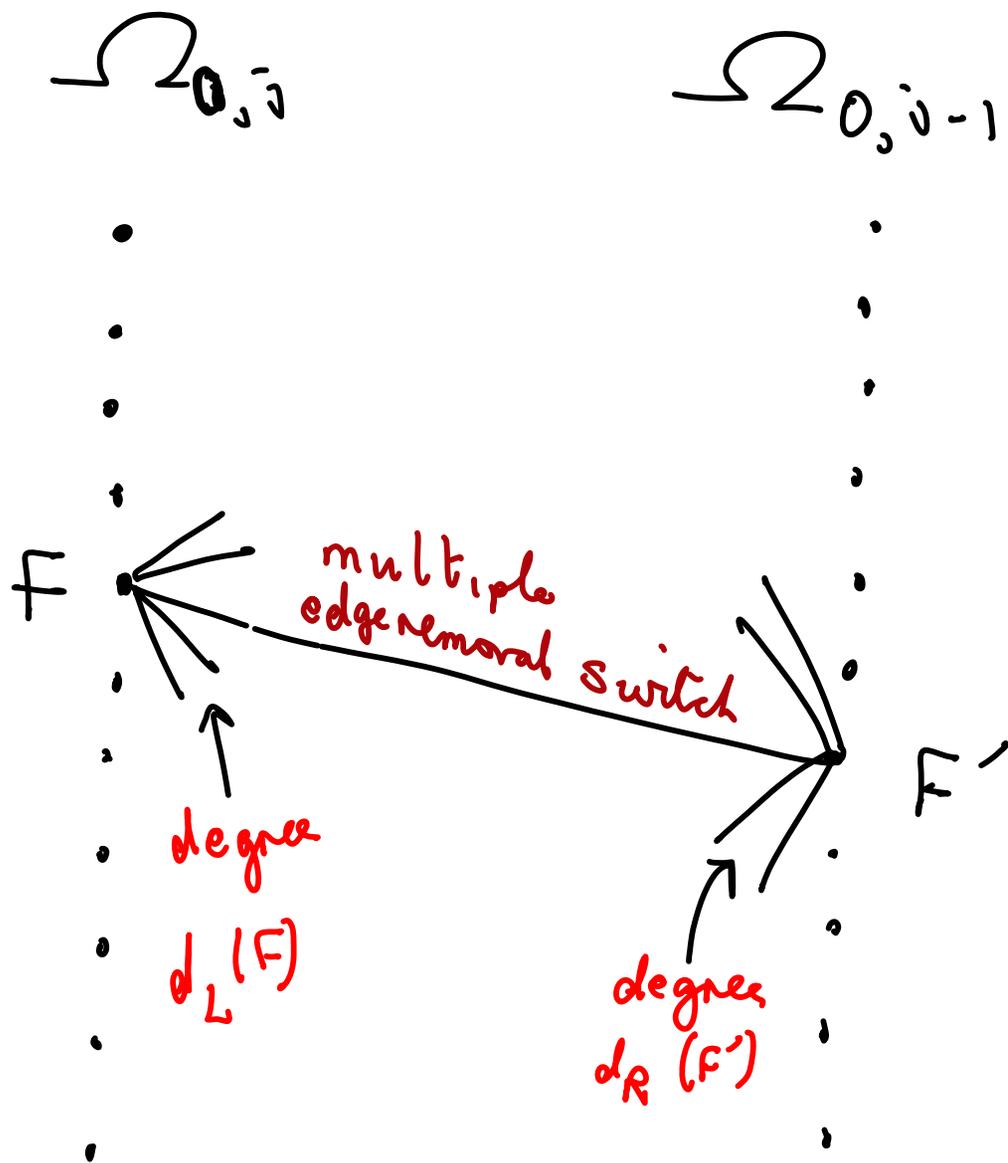
$$\begin{aligned} & \leq \frac{1}{2} M_1 M_2 |\Omega_{i-1,j}| \\ & \geq \frac{1}{2} M_1 M_2 |\Omega_{i-1,j}| \\ & \times (1 - \tilde{O}\left(\frac{\Delta^3}{M_1} + \frac{\Delta^3}{M_2}\right)) \end{aligned}$$

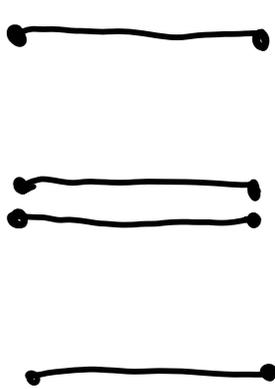
So

$$\frac{|\Omega_{i-1,j}|}{|\Omega_{i,j}|} = \frac{2iM_1}{M_2} \left(1 + \tilde{O}\left(\frac{\Delta^3}{M_1}\right)\right)$$



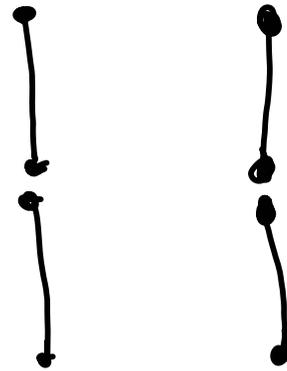
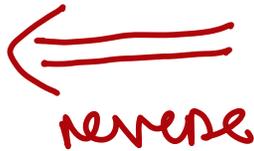
In general this operation takes a member F of $\Omega_{i,j}$ to a member F' of $\Omega_{i,j-1}$ unless it creates new loops or multiple edges.





↑ parallel edge

multiple edge removal switch



$$\begin{aligned} \# \text{choices} &: \approx j \times M_1^2 \\ &\geq j \times M_1^2 - \tilde{O}(j M_1 \Delta^2) \end{aligned}$$

$$\begin{aligned} \# \text{choices} &\leq M_2^2/4 \\ &\geq M_2^2/4 - \tilde{O}(M_2 \Delta^3) \end{aligned}$$

Now

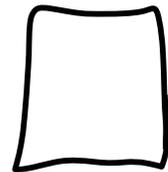
$$\sum_{F \in \Omega_{0,j}} d_L(F) = \sum_{F' \in \Omega_{0,j-1}} d_R(F')$$

$$\begin{aligned} &\leq j M_1^2 |\Omega_{0,j}| \\ &\geq j M_1^2 |\Omega_{0,j}| \\ &\quad \times (1 - \tilde{O}\left(\frac{\Delta^2}{M_1}\right)) \end{aligned}$$

$$\begin{aligned} &\leq \frac{1}{4} M_2^2 |\Omega_{0,j-1}| \\ &\leq \frac{1}{4} M_2^2 |\Omega_{0,j-1}| \\ &\quad \times \left(1 - \tilde{O}\left(\frac{\Delta^3}{M_2}\right)\right) \end{aligned}$$

So

$$\frac{|\Omega_{0,j-1}|}{|\Omega_{0,j}|} = \frac{4j M_1^2}{M_2^2} \left(1 + \tilde{O}\left(\frac{\Delta^3}{M_2}\right)\right)$$



So $\forall F \in \Omega,$

$$P_r(\chi(F) \text{ is simple}) \approx e^{-\lambda(\lambda+1)}$$

where $\lambda = \frac{\sum d_i(d_i-1)}{2 \sum d_i}$,

So for any (multi) graph property \mathcal{P}

$$P_r(G_{n,d} \in \mathcal{P}) \approx (1+o(n)) e^{-\lambda(\lambda+1)} P_r(\chi(F) \in \mathcal{P})$$

assuming $\Delta \leq n^{1/3}$ [Not best known.]

$$\Pr(G_{n,d} \in \mathcal{P}) \leq (1+o(1)) e^{\lambda(\lambda+1)} \Pr(\mathcal{Y}(F) \in \mathcal{P})$$

This is particularly useful if $\lambda = O(1)$

e.g. random r -regular graphs where

r is a constant. Here $\lambda = \frac{r-1}{2}$.

Theorem

Let $G_{n,r}$ denote a random r -regular graph, $r \geq 3$ constant, vertex set $[n]$.

Then whp $G_{n,r}$ is r -connected.

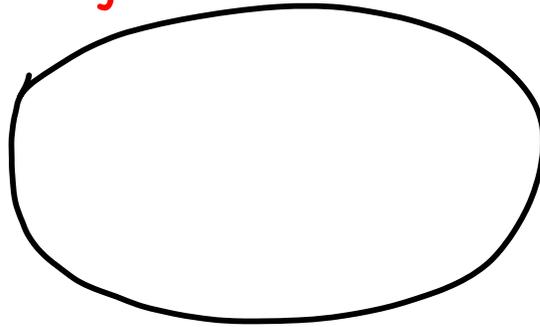
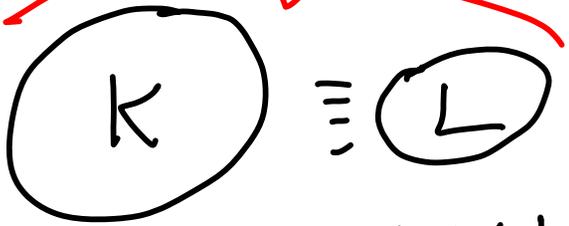
Corollary

If n is even then whp $G_{n,r}$ has a perfect matching.

[An r -edge connected, r -regular graph, with n even, has a perfect matching.]

Proof

$$\left. \begin{array}{l} \# \text{edges } \leq k+l \\ \text{incident with} \\ k \end{array} \right\} \geq \frac{r_{k+l}}{2}$$



$$l = |L| \leq r-1$$

$$L = N(K)$$

r_0

$$(i) \cdot \frac{r}{r-2} \leq k = |K| \leq n e^{-10}$$

$$P_r(\exists K, L) \leq \sum_{k,l} \binom{n}{k} \binom{n}{l} \left(\frac{r_{k+l}}{2} \right) \left(\frac{r_{k+l}}{r^n} \right)^{\frac{r_{k+l}}{2}}$$

$$\leq \sum_{k,l} n^{-\left(\frac{r}{2}-1\right)k + \frac{l}{2}} \frac{e^{k+l}}{k^k l^l} 2^{rk} (k+l)^{\frac{r_{k+l}}{2}}$$

$$\leq \sum_{k,l} n^{-\left(\frac{r}{2}-1\right)k + \frac{l}{2}} \frac{e^{k+l}}{k^k l^l} 2^{rk} (k+l)^{\frac{r(k+l)}{2}}$$

$$\left(\frac{k+l}{e}\right)^{l/2} \leq e^{k/2} \quad \left(\frac{k+l}{k}\right)^{k/2} \leq e^{l/2}$$

$$(k+l)^{rk/2} \leq k^{rk/2} e^{lr/2}$$

$$\frac{r-1}{2k} < \frac{r}{2} - 1$$

$$k > \frac{r-1}{r-2}$$

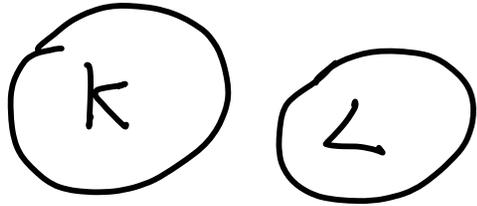
$$\leq C_r \sum_{k=r}^{n/10} \sum_{l=0}^{r-1} n^{-\left(\frac{r}{2}-1\right)k + \frac{l}{2}} e^{3k/2} k^{(r-2)k/2}$$

\uparrow
 constant

$$= C_r \sum_{k=r_0}^{n/10} \sum_{l=0}^{r-1} \left(n^{-\left(\frac{r}{2}-1\right)k + \frac{l}{2k}} e^{3/2} k^{\frac{r}{2}-1} 2^r \right)^k$$

$$= o(1).$$

$$(ii) 2 \leq k \leq \frac{r}{r-2} \leq 3$$



KVL contains

$$\frac{rk}{2} + l \geq k + l + 1 \text{ edges}$$

$P_r(\exists S: s=|S| \leq r-1+3, \text{ contains } s+1 \text{ edges})$

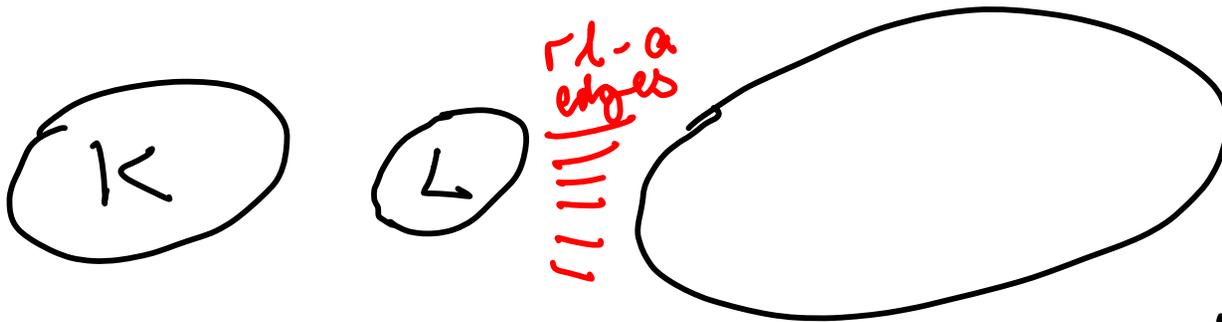
$$\leq \sum_{s=4}^{r+2} \binom{n}{s} \binom{rs/2}{s+1} \left(\frac{rs}{rn}\right)^{s+1}$$

$$\leq \sum_{s=4}^{r+2} n^s \cdot 2^{rs/2} \cdot s^{s+1} \cdot n^{-s-1}$$

$$= o(1)$$

$$(iii) \quad ne^{-10} < k \leq \frac{n}{2}$$

$$\phi(2m) = \frac{(2m)!}{m! 2^m} \approx 2^{\frac{1}{2}} \left(\frac{2m}{e}\right)^m$$



$$P_r(\exists K, L) \leq \sum_{k, l, a} \binom{n}{k} \binom{n}{l} \binom{r l}{a} \frac{\phi(rk + rl - a) \phi(r(n-k-l) + a)}{\phi(rn)}$$

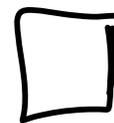
$$\leq C_r \sum_{k, l, a} \left(\frac{ne}{k}\right)^k \left(\frac{ne}{l}\right)^l \frac{\binom{rk + rl - a}{r} \binom{r(n-k-l) + a}{r}}{(rn)^{rn}}$$

$$\leq C_r \sum_{k, l, a} \left(\frac{ne}{k}\right)^k \left(\frac{ne}{l}\right)^l e^{O(1)} \left(\frac{k}{n}\right)^{rk} \left(1 - \frac{k}{n}\right)^{r(n-k)}$$

$$= C_r \sum_{k, l, a} \left(\frac{ne}{k}\right)^k \left(\frac{ne}{l}\right)^l e^{O(l)} \left(\frac{k}{n}\right)^{rk} \left(1 - \frac{k}{n}\right)^{r(n-k)}$$

$$\leq C_r \sum_{k, l, a} \left(\left(\frac{k}{n}\right)^{r-1} \cdot e^{1-r/2} \cdot n^{\frac{r}{k}} \right)^k$$

$$= O(1)$$



Differential Equations Method

Consider the following simple process:

We start with n isolated vertices

$1, 2, \dots, n$.

At a general step, we choose a (still)

isolated vertex v and add an edge

to a randomly chosen w .

Question: how long before there are no isolated vertices?

Let

$X(t)$ = # isolated vertices
after t steps.

$$X(0) = n$$

$$\mathbb{E}(X(t+1) - X(t) \mid X(t)) = -1 - \frac{X(t)}{n-1}. \quad (*)$$

Now put $t = \tau n$, $0 \leq \tau \leq 1$

and $n x(\tau) = X(t)$.

(*) on p2 suggest that

$$x'(\tau) = -1 - x(\tau)$$

given

$$x(\tau) = 2e^{-\tau} - 1.$$

In which case we would expect that
the process ends when $t \approx n \ln 2$.

We now consider the following greedy algorithm for finding an independent set in a graph.

GREEDY

begin

$I \leftarrow \emptyset; A \leftarrow V;$

While $A \neq \emptyset$ do

Choose $v \in A;$

$I \leftarrow I \cup \{v\}; A \leftarrow A \setminus (\{v\} \cup N(v))$

[Random Choice]

end ^{od} _{output} I

Greedy produces an independent set.
We begin by studying the likely
size of the output, if G is a random
 r -regular graph.

We use the configuration model
of r -regular graphs i.e. $W = W_1 \cup W_2 \cup \dots \cup W_n$
where $W_i = [(i-1)r+1, ir]$

We will expose the random pairing of W as the algorithm progresses i.e. not before.

If vertex i is placed in the independent set I , then and only then, do we expose the pairs involving W_i .

Let the **degree** of a vertex i at a general step of the algorithm be the number of exposed pairs involving W_i .

Thus a general step of GREEDY involves

- (i) Choose a vertex of degree **zero**.
- (ii) Expose the pairs involving w_i .

Let $t = |I|$ be the number of steps taken so far and let P_t refer to the current set of exposed pairs.

Let $X(t)$ be the number of vertices of degree zero.

The number of vertices in the set chosen by GREEDY is t_0 , where $X(t_0) = 0$.

$$E(X(t+1) - X(t) | \mathcal{P}_t) =$$

$$-1 - \frac{X(t)r}{n-2t} + O\left(\frac{1}{n}\right) \quad (*)$$

$v \in I$ \nearrow -1 \nearrow $\frac{X(t)r}{n-2t}$ \nearrow $O\left(\frac{1}{n}\right)$ \nearrow $(*)$
 assuming $t \leq \left(\frac{1}{2} - \alpha\right)n$

We expose r pairs associated with v .
 For first pair there are still $r(X(t)-1)$ points
 associated with vertices of degree zero,
 (excluding v). There are $r(n-2t)$ points unpaired
 altogether. So the probability of pairing
 with vertex of degree zero is $\frac{r(X(t)-1)}{r(n-2t)-1} = \frac{X(t)}{n-2t} + O\left(\frac{1}{n}\right)$.

Repeat r times to get $(*)$.

Putting $t = \tau n$ and $X(t) = nx(\tau)$, this suggests that we solve

$$x'(\tau) = -1 - \frac{rx(\tau)}{1-2\tau}$$

$$x(0) = 1.$$

$$\text{Solution: } x(\tau) = \frac{(r-1)(1-2\tau)^{r/2} - (1-2\tau)}{r-2}$$

The smallest positive solution to $x(\tau) = 0$ is

$$\tau_0 = \frac{1}{2} \left(1 - \left(\frac{1}{r-1} \right)^{2/(r-2)} \right)$$

and then number of vertices in independent set chosen by GREEDY is whp, $\approx \tau_0 n$.

For the following:

$q_0, q_1, \dots, q_t, \dots, q_n \in S$ is a random process.

$H_t = (q_0, q_1, \dots, q_t)$ is the history to time t .

$X(0), X(1), \dots, X(t), \dots$ are random variables where

$$X(t) = X_t(H_t).$$

$D \subseteq \mathbb{R}^2$ is open and connected and

$$\left(0, \frac{X_0(q_0)}{r_0}\right) \in S$$

[We can assume
[q_0 is fixed

We further assume

$$(i) \quad |X(t)| \leq C_0 n, \quad \forall t < T_D \text{ where } C_0 \text{ is constant.}$$

$$(ii) \quad |X(t+1) - X(t)| \leq \beta = \beta(n) \geq 1, \quad \forall t < T_D$$

$$(iii) \quad |E(X(t+1) - X(t) | \mathcal{H}_t) - f(t/n, X(t)/n)| \leq \lambda_0, \\ \forall t < T_D$$

(iv) $f(t, x)$ is **continuous** and satisfies a **Lipschitz** condition on $D_n \{(t, x) : t \geq 0\}$

$$\text{i.e.} \quad |f(x) - f(x')| \leq L \|x - x'\|_\infty.$$

Example 1

$$H_B = (i_1, i_2), (i_3, i_4), \dots, (i_{2t-1}, i_{2t}) \quad 1 \leq i_k \leq n$$

$$X_B(H_B) = n - |\{i_1, i_2, \dots, i_{2t}\}| \quad C_0 = 1$$

$$f(t, x) = -1 - x$$

$$\lambda_0 = \frac{1}{n-1}$$

$$L = 1$$

$$D = (-1, 1)^2$$

Example 2

$$W = [r, n]$$

$$H_v = (i_1, i_2), (i_3, i_4), \dots, (i_{2v-1}, i_{2v}) \quad 1 \leq i_k \leq rn$$

$$X_v(H_v) = n - |\{a : \exists s \text{ s.t. } i_s \in W_a\}|$$

$$f(v, \alpha) = -1 - \frac{r\alpha}{1-2v}$$

$$C_0 = 1$$

$$\lambda_0 = \frac{1}{2}n$$

$$L = \frac{r}{2}\alpha$$

$$D = (-1, \frac{1}{2} - \alpha) \times (0, 1)$$

Theorem

Suppose $\lambda > \lambda_0$ and C is sufficiently large and

$\sigma = \inf \{ \tau : (\tau, z(\tau)) \notin D_0 = \{ (t, z) \in D : \text{distance of } (t, z) \text{ to boundary of } D \geq C\lambda \} \}$

where $z(t)$, $0 \leq \tau \leq \sigma$ be the unique solution to

$$\dot{z}(\tau) = f(\tau, z) \quad (*)$$

$$z(0) = \frac{x_0(\tau_0)}{n}$$

With probability $1 - O\left(\frac{\beta}{\lambda} \exp\left(-\frac{n\lambda^3}{\beta^3}\right)\right)$

$$X(t) = n z(t/n) + O(\lambda n)$$

uniformly in $0 \leq t \leq \sigma n$.

Proof

$$\text{Let } \omega = \left\lceil \frac{n\lambda}{\beta} \right\rceil.$$

We can assume that $\frac{\lambda}{\beta} \geq n^{-1/3}$ else there is nothing to prove.

We study the concentration of $X(t+\omega) - X(t)$,

so assume that $(t/n, X(t/n)) \in D_0$.

For $0 \leq k \leq \omega$ we have

$$\text{Note that } \left| \frac{X(t+k)}{n} - \frac{X(t)}{n} \right| \leq \frac{k\beta}{n} \leq 2\lambda$$

$$\text{So } \left\| \left(\frac{t+k}{n}, \frac{X(t+k)}{n} \right) - \left(\frac{t}{n}, \frac{X(t)}{n} \right) \right\|_{\infty} \leq 2\lambda$$

and so $\underbrace{\quad}_{\text{is in } D}$, assuming $C \geq 2_0$.

$$\mathbb{E} (X(t+k+1) - X(t+k) \mid H_{t+k}) =$$

$$f\left(\frac{t+k}{n}, \frac{X(t+k)}{n}\right) + \theta_k = \quad |\theta_k| \leq \lambda$$

$$f\left(\frac{t}{n}, \frac{X(t)}{n}\right) + \psi_k + \theta_k = \quad |\psi_k| \leq \frac{L\beta k}{n}$$

$$f\left(\frac{t}{n}, \frac{X(t)}{n}\right) + \rho$$

where $|\rho| \leq 2L\lambda$.

Now, given H_t , let

$$Z_k = X(t+k) - X(t) - k f\left(\frac{t}{n}, \frac{X(t)}{n}\right) - 2kL\lambda.$$

Then

$$E(Z_k - Z_{k-1} | Z_0, \dots, Z_{k-1}) \leq 0$$

i.e. Z_0, Z_1, \dots, Z_w is a **supermartingale**.

Also

$$|Z_k - Z_{k-1}| \leq \beta + \left| f\left(\frac{t}{n}, \frac{X(t)}{n}\right) \right| + 2L\lambda$$

$$\leq K\beta$$

where $K_0 = O(1)$.

$O(1)$ by continuity and boundedness of S .

So, conditional on H_F ,

$$\begin{aligned} \Pr(X(t+\omega) - X(t) - \omega f(t/n, X(t/n)) \geq 2L\omega\lambda + K_0\beta\sqrt{2\alpha\omega}) \\ \leq e^{-\alpha}. \end{aligned}$$

Similarly,

$$\begin{aligned} \Pr(X(t+\omega) - X(t) - \omega f(t/n, X(t/n)) \leq -2L\omega\lambda - K_0\beta\sqrt{2\alpha\omega}) \\ \leq e^{-\alpha}. \end{aligned}$$

Here we produce a **supermartingale** or equivalently consider $-X(t)$.

Thus

$$Pr(|X(t+w) - X(t) - w f(t/n, X(t/n))| \geq \overbrace{2Lw\lambda + K_0\beta\sqrt{2\alpha w}}^{\text{err}}) \leq 2e^{-\alpha}.$$

We will choose

$$\alpha = \frac{n\lambda^3}{\beta^3}$$

so that $w\lambda$ and $\beta\sqrt{2\alpha w}$ are both $\Theta(n\lambda^2/\beta)$ giving

$$\text{err} \leq K_1 \frac{n\lambda^3}{\beta}$$

Now let $k_j = jw$ for $j = 0, 1, \dots, j_0 = \lfloor \sigma n/w \rfloor$.

We will show by induction that

$$P_j(\exists i \leq j : |X(k_j) - z(k_j/n)| \geq B_j) \leq 2j e^{-\alpha}$$

where

$$B_j = B \left(\left(1 + \frac{Lw}{n} \right)^j - 1 \right) \frac{n\lambda^2}{\beta}$$

and where B is another constant.

The induction begins with $z(0) = \frac{X(0)}{n}$.

Note that $B_{j_0} = O\left(\frac{n\lambda^2}{\beta}\right) = O(\lambda n)$.

Now write

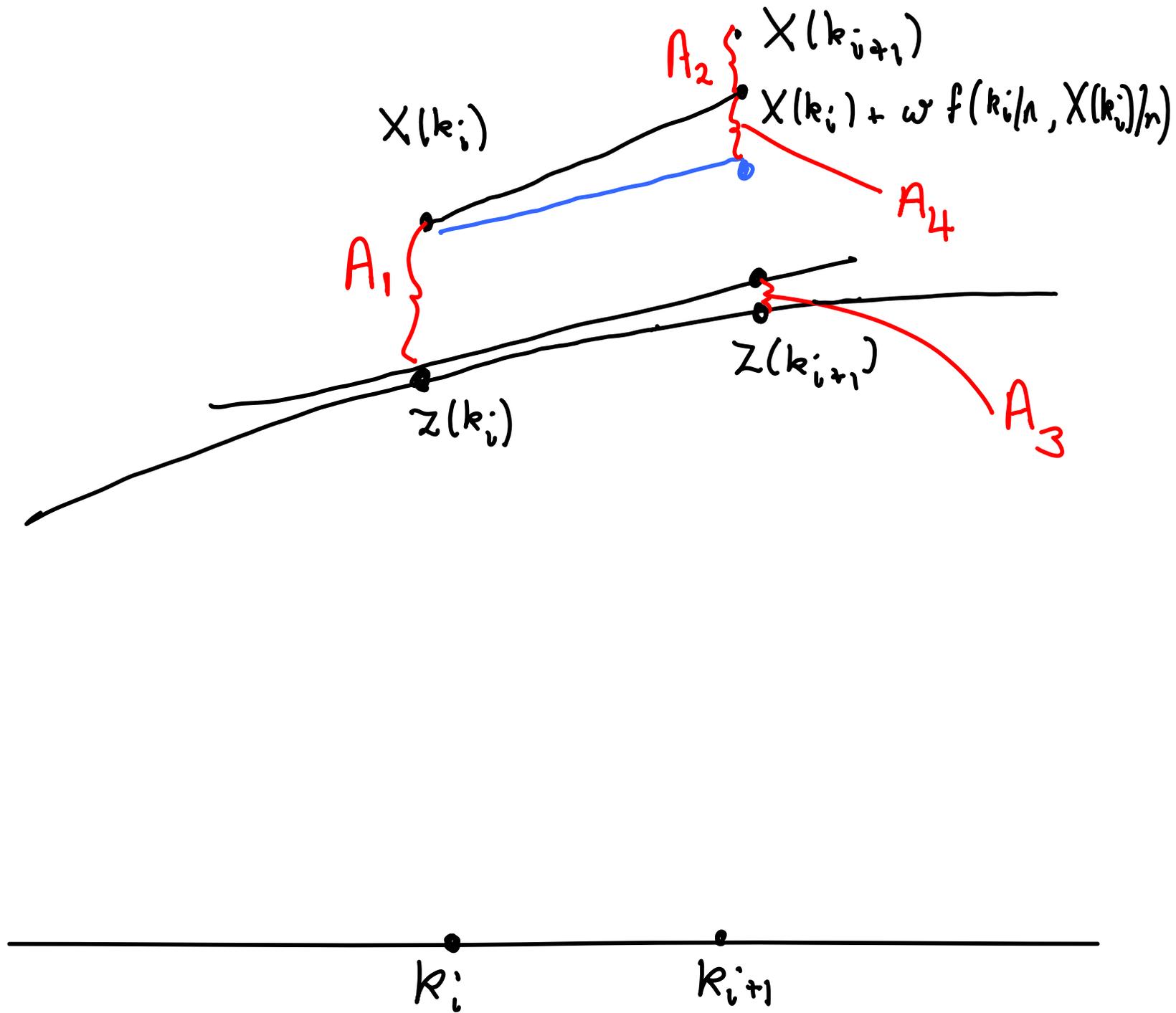
$$|X(k_{i+1}) - z(k_{i+1}/n)n| = |A_1 + A_2 + A_3 + A_4|$$

$$A_1 = X(k_i) - z(k_i/n)n$$

$$A_2 = \cancel{X(k_{i+1})} - X(k_i) - \omega f(k_i/n, X(k_i/n))$$

$$A_3 = \omega z'(k_i/n) + z(k_i/n)n - z(k_{i+1}/n)n$$

$$A_4 = \omega f(k_i/n, X(k_i/n)) - \omega z'(k_i/n)$$



$$A_i = X(k_i) - z(k_i/n) n$$

The induction gives

$$\|A_i\| \leq B_i.$$

$$A_2 = X(k_{i+1}) - X(k_i) - \omega f(k_i/n, X(k_i/n))$$

$$|A_2| \leq K_1 \frac{n \lambda^2}{\beta}$$

with probability $1 - 2e^{-\alpha}$.

$$A_3 = \omega z'(k_i/n) + z(k_i/n)n - z(k_{i+1}/n)n$$

$$|A_3| \leq L \frac{\omega^2}{n^2} \cdot n = L \frac{\omega^2}{n} \leq 2L n \frac{\lambda^2}{\beta^2}$$

$$A_4 = \omega f(k_i/n, X(k_i)/n) - \omega Z'(k_i/n)$$

$$|A_4| \leq \frac{\omega L A_1}{n} \leq \frac{\omega L}{n} B_i.$$

Thus, for some $B > 0$,

$$B_{i+1} \leq |A_1| + |A_2| + |A_3| + |A_4|$$

$$\leq \left(1 + \frac{\omega L}{n}\right) B_i + B n^{\frac{\lambda^2}{\beta}}.$$

Finally consider $k_i \leq t < k_{i+1}$.

From "time" k_i to t , the change in X and nZ is at most $\omega\beta = O(n\lambda)$.



The above proof generalises easily to the case where

(i) $X(t)$ is replaced by $X_1(t), X_2(t), \dots, X_\alpha(t)$ where $\alpha = O(1)$.

(ii) Condition (iii) on P11 holds with probability $1 - \gamma$.

This adds $O(n\gamma)$ to the error probability.

We simply condition on (iii) always holding.

Eigenvalues of Random Graphs

Theorem

Suppose $(\ln n)^5 \leq np \leq n - (\ln n)^5$.

Let A denote the adjacency matrix of

$G_{n,p}$. Let the eigenvalues of A be

$\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$. Then whp

(i) $\lambda_1 \approx np$

(ii) $|\lambda_i| \leq \underbrace{2(\ln n)^2}_{\downarrow} \sqrt{np(1-p)} \quad 2 \leq i \leq n.$

With more work \downarrow can be replaced by $2 + o(1)$.

Main Lemma

Let J be the all 1's matrix and

$M = pJ - A$. Then why

$$\|M\| \leq 2(\log n)^2 \sqrt{np(1-p)}$$

$$\|M\| = \max_{|x|=1} |Mx| = |\lambda_1(M)|$$

We first show that the lemma implies the theorem.

Let \underline{e} denote the all 1's vector.

$$\begin{aligned} (a) \quad |A\underline{e} - np\underline{e}| &= |M\underline{e}| \\ &\leq \|M\| \cdot |\underline{e}| \\ &\leq 2(\log n)^2 n \sqrt{p(1-p)} \end{aligned}$$

(b) Now suppose that $|\xi|=1$ and $\xi \perp \underline{e}$. Then $J\xi=0$ and

$$|A\xi| = |M\xi| \leq \|M\| \leq 2(\log n)^2 \sqrt{np(1-p)}$$

Now let $|x|=1$ and let $x = \alpha u + \beta y$
 where $u = \frac{1}{\sqrt{n}} \mathbf{1}$ and $y \perp \underline{e}$ and $|y|=1$. Then

$$|Ax| \leq |\alpha| |Au| + |\beta| |Ay|$$

We have

$$\begin{aligned} |Au| &= \frac{1}{\sqrt{n}} |A\underline{e}| \leq \frac{1}{\sqrt{n}} (np|\underline{e}| + \|M\| \cdot |\underline{e}|) \\ &\leq np + 2(\log n)^2 \sqrt{np(1-p)} \end{aligned}$$

$$|Ay| \leq 2(\log n)^2 \sqrt{np(1-p)}$$

Thus

$$\begin{aligned} |Ax| &\leq |\alpha| np + 2(|\alpha| + |\beta|) (\log n)^2 \sqrt{np(1-p)} \\ &\leq np + 3(\log n)^2 \sqrt{np(1-p)}. \end{aligned}$$

This implies that $\lambda_1 \leq (1+o(1))np$

But

$$|Au| \geq |(A+M)u| - |Mu|$$

$$= |pJu| - |Mu|$$

$$\geq np - 2(\log n)^2 \sqrt{np(1-p)}$$

implying $\lambda_1 \geq (1-o(1))np$.

Now

$$\lambda_2 = \min_{\xi} \max_{0 \neq \xi \perp \eta} \frac{|A\xi|}{|\xi|}$$

$$\leq \max_{0 \neq \xi \perp \eta} \frac{|A\xi|}{|\xi|}$$

$$\leq 2(\log n)^2 \sqrt{np(1-p)}$$

$$\lambda_n = \min_{|\xi|=1} \xi^T A \xi \geq \min_{|\xi|=1} \xi^T A \xi - \underbrace{p \xi^T J \xi}_{\geq 0}$$

$$= \min_{|\xi|=1} -\xi^T M \xi \geq -\|M\| \geq -2(\log n)^2 \sqrt{np(1-p)}$$

Proof of Main Lemma

Putting $\hat{M} = M - pI_n$ (zero's diagonal)

we see that

$$\|M\| \leq \|\hat{M}\| + \|pI_n\| = \|\hat{M}\| + p$$

and so we bound $\|\hat{M}\|$.

Letting m_{ij} denote (i,j) entry of \hat{M} we have

$$(i) \quad E(m_{ij}) = 0$$

$$(ii) \quad \text{Var}(m_{ij}) \leq p(1-p) \leftarrow \sigma^2.$$

(iii) $m_{ij}, m_{i'j'}$ are independent, unless $(i',j') = (i,j)$.

Now let $k \geq 2$ be an even integer.

$$\begin{aligned} \text{Trace}(\hat{M}^k) &= \sum_{i=1}^n \lambda_i (\hat{M})^k \\ &\geq \max \{ \lambda_1 (\hat{M})^k, \lambda_n (\hat{M})^k \} \\ &= \|\hat{M}\|^k. \end{aligned}$$

We estimate

$$\|\hat{M}\| \leq \text{Trace}(\hat{M}^k)^{1/k}$$

where

$$k = (\log n)^2.$$

$$E(\text{Trace}(\hat{M}^k)) = \sum_{i_0=1}^{\hat{n}} \sum_{i_1=1}^{\hat{n}} \cdots \sum_{i_{k-1}=1}^{\hat{n}} E(m_{i_0 i_1} m_{i_1 i_2} \cdots m_{i_{k-2} i_{k-1}} m_{i_{k-1} i_0})$$

So

$$\|\hat{M}\|^k \leq \sum_{\rho=2}^{k+1} E_{n,k,\rho}$$

where

$$E_{n,k,\rho} = \sum_{i_0=1}^{\hat{n}} \sum_{i_1=1}^{\hat{n}} \cdots \sum_{i_{k-1}=1}^{\hat{n}} \left| E \left(\prod_{j=0}^{k-1} m_{i_j i_{j+1}} \right) \right|$$

$|\{i_0, i_1, \dots, i_{k-1}\}| = \rho$

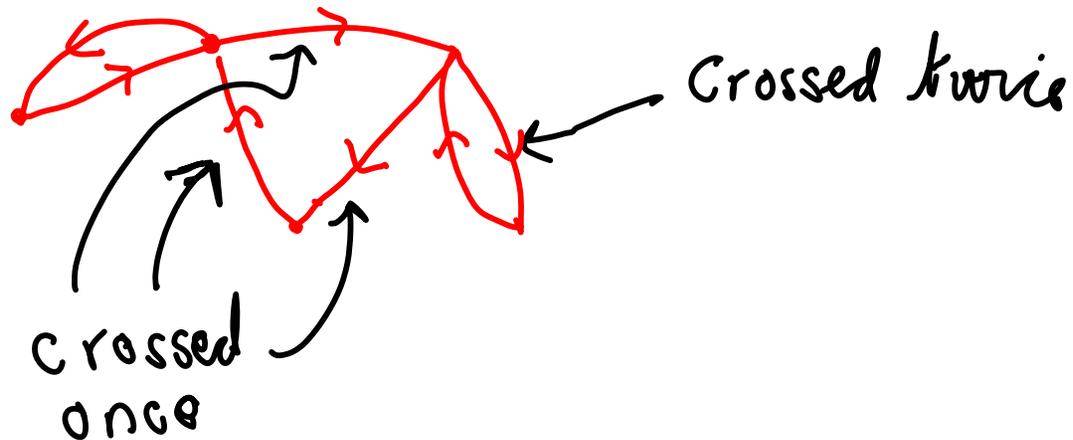
Note that $m_{i,i} = 0$ implies $E_{n,k,1} = 0$.

Each sequence $\underline{i} = i_0, i_1, \dots, i_{k-1}, i_0$ corresponds to a walk on $W(\underline{i})$ on K_n with n loops added.

Note that

$$E\left(\prod_{j=0}^{k-1} m_{i_j i_{j+1}}\right) = 0$$

if the walk $W(\underline{i})$ contains an edge that is crossed exactly once



On the other hand, $|m_{i_j}| \leq 1$ and so

$$\left| E \left(\prod_{j=0}^{k-1} m_{i_j} i_{j+1} \right) \right| \leq \sigma^{2(\rho-1)}$$

if each edge of $W(\underline{i})$ is crossed at least twice and if $|\{i_0, i_1, \dots, i_{k-1}\}| = \rho$.

Let $R_{k,\rho}$ denote the number of (k,ρ) -walks.

We use the following trivial estimates:

$$(i) \quad \rho > \frac{k}{2} + 1 \quad \text{implies} \quad R_{k,\rho} = 0$$

$$(ii) \quad \rho \leq \frac{k}{2} + 1 \quad \text{implies}$$

$$R_{k,\rho} \leq n^\rho k^k$$

choose
the ρ
distinct
vertices

number of
walks of length k

We have

$$\|\widehat{M}\|^k \leq \sum_{\rho=2}^{\frac{1}{2}k+1} R_{k,\rho} \sigma^{2(\rho-1)}$$

$$\leq \sum_{\rho=2}^{\frac{1}{2}k+1} n^{\rho} k^k \sigma^{2(\rho-1)}$$

$$\leq 2 n^{\frac{1}{2}k+1} k^k \sigma^k.$$

Thus

$$E(\|\hat{M}\|^k) \leq 2n^{\frac{k+1}{2}} k^k \sigma^k$$

Then

$$\begin{aligned} & P_r(\|\hat{M}\| \geq 2k\sigma n^{\frac{1}{2}}) \\ &= P_r(\|\hat{M}\|^k \geq (2k\sigma n^{\frac{1}{2}})^k) \\ &\leq \frac{E(\|\hat{M}\|^k)}{(2k\sigma n^{\frac{1}{2}})^k} \end{aligned}$$

$$\sim \frac{2n^{\frac{1}{2}k+1} k^k \sigma^k}{(2k\sigma n^{1/2})^k}$$

$$= \left(\frac{(2n)^{1/2k}}{2} \right)^k$$

$$= \left(\frac{1}{2} + o(1) \right)^k$$

$$= o(1).$$

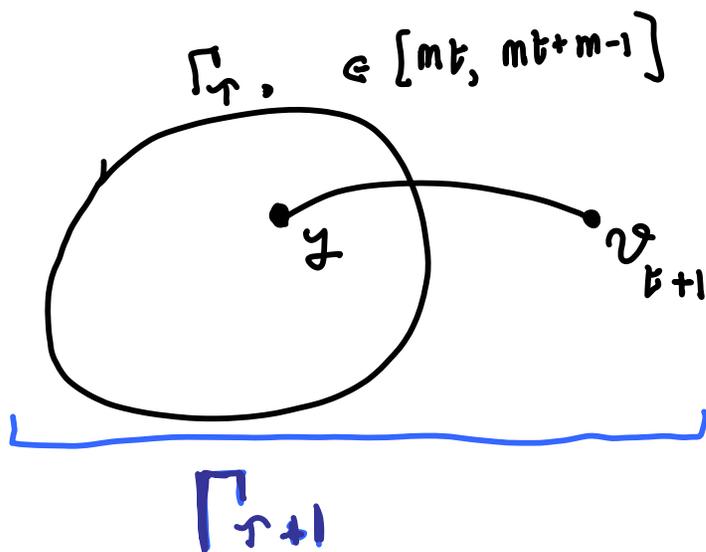
Preferential Attachment.

Fix $m > 0$, constant.

Sequence of graphs

$\Gamma_1, \Gamma_2, \dots, \Gamma_{m-1}, G_1, \Gamma_{m+1}, \Gamma_{m+2}, \dots, \Gamma_{2m-1}, G_2, \dots, \Gamma_{mt-1}, G_t, \dots$

$\Gamma_{(m-1)t+1}, \dots, \Gamma_{mt-1}, G_t$ have vertex set v_1, v_2, \dots, v_t



$$P_r(y=v) = \begin{cases} \frac{\deg(v, \Gamma_r)}{2r+1} & v \neq v_{t+1} \\ \frac{1}{2r+1} & v = v_{t+1} \end{cases}$$

Expected Degree Sequence.

$D_k(t)$ = # of vertices of degree k in G_t ,
 $m \leq k = \tilde{O}(t^{1/2})$.

$$\bar{D}_k(t) = E(D_k(t)).$$

$$E(D_k(t+1) | G_t) = D_k(t) + \mathbb{1}_{k=m} + E(k, t) + m \left(\frac{(k-1) D_{k-1}(t)}{2mt} - \frac{k D_k(t)}{2mt} \right)$$

$$|E(k, t)| = O \left(\sum_{i=2}^m \frac{(k-i)^i D_{k-i}(t)}{(mt)^i} \right) = O \left(\frac{k}{t} \right) = \tilde{O}(t^{-1/2}).$$

to account for multiple edges and denominator being $2mt + (s m)$.

$$D_k(t) \leq 2mt$$

Taking expectations over G_t ,

$$\bar{D}_k(t+1) = \bar{D}_k(t) + \mathbb{1}_{k=m} + \tilde{O}(t^{-1/2})$$

$$+ M \left(\frac{(k-1) \bar{D}_{k-1}(t)}{2mt} - \frac{k \bar{D}_k(t)}{2mt} \right)$$

Under the assumption $\bar{D}_k(t) \sim d_k t$ we are led to the recurrence

$$d_k = \mathbb{1}_{k=m} + [(k-1)d_{k-1} - kd_k]/2$$

or

$$d_k = \frac{k-1}{k+2} d_{k-1} + \frac{\mathbb{1}_{k=m}}{k+2} \times 2 \quad k \geq m$$

$$= 0 \quad k < m$$

$$d_k = \frac{k-1}{k+2} d_{k-1} + \frac{1_{k=m} \times 2}{k+2} \quad \begin{array}{l} k \geq m \\ k < m \end{array}$$

$$= 0$$

Therefore

$$d_m = \frac{2}{m+2}$$

$$d_k = d_m \prod_{l=m+1}^k \frac{l-1}{l+2}$$

$$= \frac{2m(m+1)}{k(k+1)(k+2)}$$

Theorem

$$|\bar{D}_k(t) - d_k t| = \tilde{O}(t^{1/2})$$

Proof

Let $\Delta_k(t) = \bar{D}_k(t) - d_k t$. Then

$$\Delta_k(t+1) = \frac{k-1}{2t} \Delta_{k-1}(t) + \left(1 - \frac{k}{2t}\right) \Delta_k(t) + \underbrace{\tilde{O}(t^{-1/2})}_{\leq \alpha t^{-1/2} (\log t)^\beta}.$$

Now assume inductively on t that

$$|\Delta_k(t)| \leq A t^{1/2} (\log t)^\beta \quad \forall k \geq 0$$

This is trivially true for small t (make A large)
and $k < m$.

So

$$|\Delta_k(t+1)| \leq \frac{k-1}{2t} |\Delta_{k-1}(t)| + \left| \left(1 - \frac{k}{2t}\right) \Delta_k(t) \right| + \alpha t^{-1/2} (\log t)^\beta$$

$$\leq \frac{k-1}{2t} A t^{1/2} (\log t)^\beta + \left(1 - \frac{k}{2t}\right) A t^{1/2} (\log t)^\beta + \alpha t^{-1/2} (\log t)^\beta$$

$$\leq (\log t)^\beta (A t^{1/2} + \alpha t^{-1/2})$$

$$(t+1)^{1/2} = t^{1/2} \left(1 + \frac{1}{t}\right)^{1/2} \geq t^{1/2} + \frac{1}{3t^{1/2}} \quad t \text{ large enough}$$

$$\leq (\log(t+1))^\beta \left(A (t+1)^{1/2} - \frac{1}{3t^{1/2}} \right) + \frac{\alpha}{t^{1/2}}$$

$$\leq A (\log(t+1))^\beta (t+1)^{1/2}$$



Concentration

$$P(|D_k(t) - \bar{D}_k(t)| \geq u) \leq 2 \exp\left\{-\frac{u^2}{8mt}\right\}.$$

Proof

Let $\gamma_1, \gamma_2, \dots, \gamma_{mt}$ be the sequence of choices made in the construction of G_t .

$$\begin{aligned} Z_i &= Z_i(\gamma_1, \gamma_2, \dots, \gamma_i) \\ &= E(D_k(t) \mid \gamma_1, \gamma_2, \dots, \gamma_i). \end{aligned}$$

Result follows from

$$|Z_i - Z_{i-1}| \leq 4.$$

For $\gamma_1, \gamma_2, \dots, \gamma_i$ and $\hat{\gamma}_0 \neq \gamma_i$. We define
map

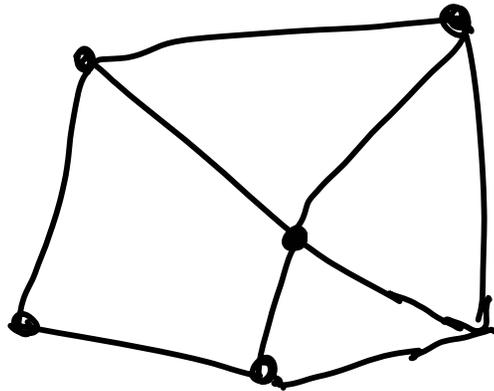
$$\gamma_1, \gamma_2, \dots, \gamma_{i-1}, \gamma_i, \gamma_{i+1}, \dots, \gamma_{mb}$$

\Downarrow measure preserving projection ϕ

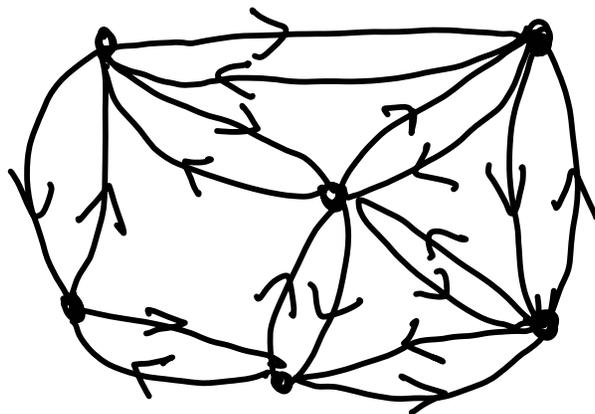
$$\gamma_1, \gamma_2, \dots, \gamma_{i-1}, \hat{\gamma}_i, \hat{\gamma}_{i+1}, \dots, \hat{\gamma}_{mb}$$

D_k changes by at most 4.

In preferential attachment we can view vertex choices as choices of a random arc



Choose vertex v
according to
degree



Choose
random arc



So Y_1, Y_2, \dots can be viewed as a sequence of arc choices.

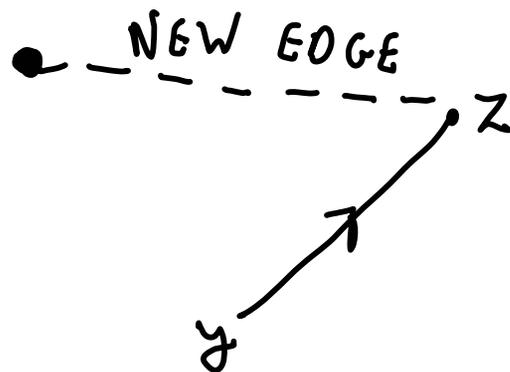
Let

$$Y_i = (x, v) \quad x > v$$

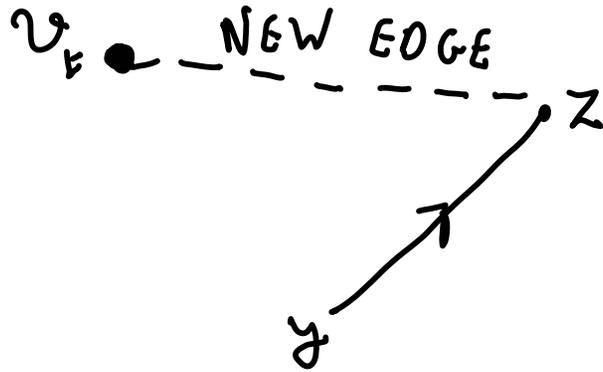
$$\hat{Y}_i = (\hat{x}, \hat{v}) \quad \hat{x} > \hat{v}$$

$$[x = \hat{x} \text{ if } i \bmod m \neq 1]$$

Now suppose $j > i$ and $Y_j = (y, z)$. Then

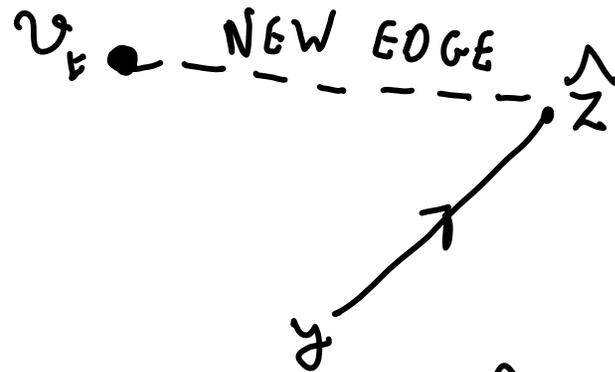
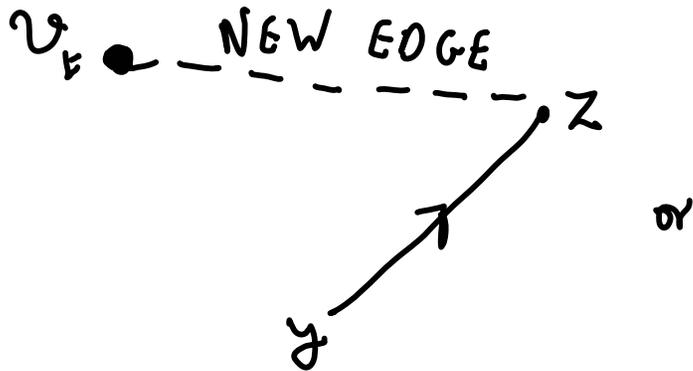


Now suppose $j > i$ and $Y_j = (y, z)$. Then



Only x, \hat{x}, v, \hat{v}
Change degree in
transformation.

In $\hat{}$ world



if (y, z) exists else

$$z = v \Rightarrow \hat{z} = \hat{v}$$

$$z = x \Rightarrow \hat{z} = \hat{x}$$

Maximum Degree

Fix $k \leq t$ and let $X_k = \text{degree of } v_k \text{ in } \Gamma_k$.

Lemma

$$\Pr(X_{mt} \geq A(t/k)^{1/2} (\log t)^2) = O(t^{-A/2}).$$

Proof

$$X_{mk} \leq 2m.$$

If $0 < \lambda < \frac{1}{\log t}$ then

$$E(e^{\lambda X_{l+1}} | X_l) = e^{\lambda X_l} \left(1 - \frac{X_l}{2l} + \frac{X_l}{2l} e^{\lambda} \right)$$

$$\leq e^{\lambda X_l} \left(1 - \frac{X_l}{2l} + \frac{X_l}{2l} (1 + \lambda(1 + \lambda)) \right)$$

$$\leq e^{\lambda \left(1 + \frac{1 + \lambda}{2l} \right) X_l}$$

So if we define a sequence

$$\lambda = \lambda_{m_l}, \lambda_{m_l+1}, \dots, \lambda_{m_t}$$

where

$$\lambda_{j+1} = \left(1 + \frac{1 + \lambda_j}{2j} \right) \lambda_j < 1 / \log t$$

then

$$E(e^{\lambda X_{mt}}) \approx E(e^{\lambda_{m,t+1} X_{m,t-1}})$$

$$\approx \dots \approx E(e^{\lambda_{m,t} X_{m,t}})$$

$$\approx e^{2m / \log t}.$$

$$\lambda_{j+1} \leq \left(1 + \frac{1 + 1/\log t}{2j} \right) \lambda_j$$

implies that

$$\lambda_{mt} \leq \lambda_{ml} \prod_{j=ml}^{mt} \left(1 + \frac{1 + 1/\log t}{2j} \right)$$

$$\leq \lambda_{ml} \exp \left\{ \sum_{j=ml}^{mt} \frac{1 + 1/\log t}{2j} \right\}$$

$$\leq 2(t/l)^{\frac{1}{2}} \lambda_{ml}$$

So argument works for

$$\lambda_{ml} = \frac{(l/t)^{\frac{1}{2}}}{2 \log t}.$$

This gives

$$E\left(\exp\left\{\underbrace{\frac{(t/l)^{1/2}}{2\log t}}_{\lambda} X_{mt}\right\}\right) \leq e^{2m/\log t}$$

Finally,

$$\begin{aligned} & P_r\left(X_{mt} \geq A(t/l)^{1/2}(\log t)^2\right) \\ & \leq e^{-\lambda A(t/l)^{1/2}(\log t)^2} E(e^{\lambda X_{mt}}) \\ & \leq e^{-A/2} e^{2m/\log t}. \end{aligned}$$

□

Largest component in $G_{n,p}$ near $p = 1/n$.

Theorem

Let $p = \frac{1}{n} + \frac{\lambda}{n^{4/3}}$ where $|\lambda| = O(1)$.

Let C_1, C_2, \dots denote the connected components

of $G_{n,p}$ where $|C_1| \geq |C_2| \geq \dots$. Then

$$(i) \quad E\left(\sum_i |C_i|^2\right) \leq \begin{cases} 3n^{4/3} & \lambda = 0 \\ 4n^{4/3} & 0 < |\lambda| \leq 1/10 \\ n^{4/3} [2 + 5|\lambda|^{2/3}] & |\lambda| \geq 1/10 \end{cases}$$

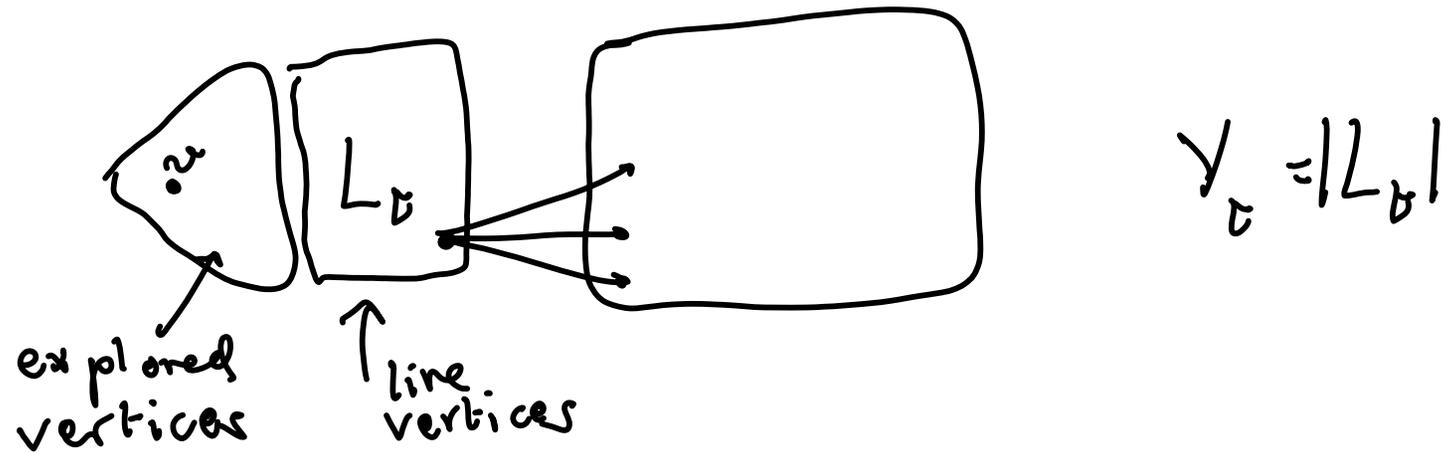
\Downarrow Markov

$$(ii) \quad P_r(|C_1| \geq \delta n^{2/3}) \leq \delta^{-2} (4 + 5\sqrt{|\lambda|}).$$

$$(iii) \quad P_r(|C_1| \leq \delta n^{2/3}) \leq (33 + 21|\lambda|) \delta^{8/5}.$$

if δ is sufficiently small and n sufficiently large.

For vertex v . In BFS from v we construct sequences of sets



$$\gamma_0 = 1$$

$$\gamma_v = \begin{cases} \gamma_{v-1} + \eta_v - 1, & \gamma_{v-1} > 0 \\ \eta_v & \gamma_{v-1} = 0 \end{cases}$$

where $\eta_v = B(n - \gamma_{v-1} - 1, p)$.

η_1, η_2, \dots are independent.

Note that if $C(v)$ is the component containing v then

$$|C(v)| = \min \{ t : \forall v = 0 \}.$$

$$\underline{\underline{d}} \uparrow.$$

$$S_t = 1 + \sum_{i=1}^t (\xi_i - 1)$$

ξ_1, ξ_2, \dots are indep.
copies of $B(n, p)$.

We couple so that $\gamma_1 \leq \xi_1, \gamma_2 \leq \xi_2, \dots$

It follows that

$$S_t \geq \gamma_t \quad \text{for } t = 0, 1, 2, \dots \uparrow$$

$$E(S_{t+1} - S_t | S_t) = np - 1.$$

Let

$$\hat{S}_t = S_t - t |np - 1|$$

Then

$$E(\hat{S}_{t+1} | \hat{S}_t) = (np - 1) - |np - 1| \leq 0$$

and so (\hat{S}_t) is a super-martingale.

Now fix an integer $H > 0$ and let

$$\delta = \min \{ t \geq 1 : S_t \geq H \text{ or } S_t = 0 \}$$

Note that

$$S_\delta \geq H \Rightarrow Y_\delta \leq S_\delta$$

$$\text{Let } \tau_0 = \min \{ t \geq 0 : Y_{\delta+t} = 0 \}$$

$$\tau \leq \delta + \tau_0 \mathbb{1}_{\{S_\delta \geq H\}}$$

$$[S_\delta = 0 \Rightarrow \tau \leq \delta]$$

$$E(\tau) \leq E(\gamma) + E(\tau_0 | S_\gamma \geq H) P(S_\gamma \geq H)$$

We prove

$$(i) P(S_\gamma \geq H) \leq \frac{1 + E(\gamma)(np-1)}{H}$$

$$(ii) E(\gamma) \leq \frac{H+2}{npq - 4H(np-1)}$$

We make sure denominator is positive.

$$(iii) E(\tau_0 | S_\gamma \geq H) \leq \left(\frac{2(H+np)}{p} \right)^{\frac{1}{2}}$$

So,

$$E(\tau) \leq$$

$$\frac{H+2}{npq - 4H|np-1|} + \left(\frac{2(H+np)}{p} \right) \leq \left(\frac{npq - 3H|np-1|}{npq - 4H|np-1|} \right) \cdot \frac{1}{H}$$

We choose H to (approximately) minimize the RHS.

$$\text{If } \lambda = 0$$

$$E(\tau) \leq \frac{H+2}{n-1} + \frac{\sqrt{2n(H+1)}}{H}$$

$$\text{Put } H = n^{1/3} \Rightarrow E(\tau) \leq 3n^{1/3}.$$

If $0 < |\lambda| < \frac{1}{10}$ then

$$E(\mathcal{T}) \leq 2(H+2) + \frac{\sqrt{(2+o(1))n(H+1)} \times 7}{6H}$$

Putting $H = n^{\frac{1}{3}}$ gives

$$E(\mathcal{T}) \leq 4n^{\frac{1}{3}}.$$

If $|\lambda| \geq \frac{1}{10}$ we put $H = \frac{n^{\frac{1}{3}}}{10|\lambda|}$ and then

$$E(\mathcal{T}) \leq 2H + \frac{\sqrt{(2+o(1))nH} \times 7}{6H}$$

$$\leq n^{\frac{1}{3}} \left[2 + 5|\lambda|^{\frac{1}{2}} \right].$$

Now write

$$E(\mathcal{T}) = E(|C(v)|)$$

$$= \frac{1}{n} \sum_{v=1}^n E(|C(v)|)$$

$$= \frac{1}{n} E\left(\sum_j |C_j|^2\right)$$

So

$$E\left(\sum_j |C_j|^2\right) \leq n E(\mathcal{T}).$$

Main tool [OPTIONAL STOPPING]

Let $Z_0, Z_1, \dots, Z_T, \dots$ be a random process.

T is a stopping time if the event $\{T \leq t\}$ depends only on Z_0, Z_1, \dots, Z_t and not on the future.

Optional Stopping

Suppose T is a stopping time.

(i) (Z_t) is a martingale $\Rightarrow E(Z_T) = E(Z_0)$.

(ii) (Z_t) is a supermartingale $\Rightarrow E(Z_T) \leq E(Z_0)$.

(iii) (Z_t) is a submartingale $\Rightarrow E(Z_T) \geq E(Z_0)$

We must also assume (Z_t) is bounded.

$$\begin{aligned}
 1 &= E(\hat{S}_0) \cong E(\hat{S}_\gamma) = E(S_\gamma) - E(\gamma)(np-1)^+ \\
 &\cong H P(S_\gamma \geq H) - E(\gamma)(np-1)^+
 \end{aligned}$$

so

$$P(S_\gamma \geq H) \leq \frac{1 + E(\gamma)(np-1)}{H}$$

Lemma

Given $S_Y \geq H$, the conditional distribution of $S_Y - H \stackrel{d}{\leq} B(n, p)$.

Proof

$$\xi = B(n, p) = I_1 + I_2 + \dots + I_n$$

Given $\xi \geq r$, $\xi - r \stackrel{d}{\leq} B(n, p)$. *

(Suppose $r = \sum_{j=1}^q I_j$ so that $\xi - r$ has distribution $\stackrel{d}{\leq} B(n - q, p)$.)

Conditioned on $\{Y = l\} \cap \{S_{l-1} = H - r\} \cap \{S_Y \geq H\}$,

$$S_Y - H \stackrel{d}{=} \xi_l - r \stackrel{d}{\leq} B(n, p).$$

Now average over l, r .

□

* $A \stackrel{d}{\leq} B$ if $P_r(A \geq x) \leq P_r(B \geq x)$, $\forall x$.

Write

$$S_y^2 = H^2 + 2H(S_y - H) + (S_y - H)^2$$

Then, lemma on p10 implies

$$\begin{aligned} E(S_y^2 | S_y \geq H) &\leq H^2 + 2Hnp + npq + (np)^2 \\ &\leq H^2 + 3H. \end{aligned}$$

Define

$$t \wedge \gamma = \min \{ t, \gamma \}.$$

and

$$A_t = S_{t \wedge \gamma}^2 - B(t \wedge \gamma)$$

where

$$B = npq - 2H|1 - np|.$$

We claim that

(A_t) is a sub-martingale

$$\begin{aligned}
E(S_{t+1}^2 - S_t^2 \mid S_t) &= \\
&2 E(S_t (\sum_{t+1} - 1)) + E((\sum_{t+1} - 1)^2) \\
&= 2 S_t (np - 1) + npq + 1 - np \\
&\cong \underbrace{npq - 2H \mid np - 1}_B, \quad \forall t \leq \delta.
\end{aligned}$$

$$E([S_{t+1}^2 - B(t+1)] - [S_t^2 - Bt] \mid S_t) \leq 0, \quad t \leq \delta.$$

So

$$A_0 \leq E(A_\gamma)$$

$$\text{or } 1 \leq E(S_\gamma^2) - BE(\gamma)$$

So

$$1 + BE(\gamma) \leq E(S_\gamma^2) = E(S_\gamma^2 | S_\gamma \geq H) P(S_\gamma \geq H)$$

$$\leq (H+3)(1 + E(\gamma) |np-1)$$

So

$$E(\gamma) \leq \frac{H+2}{B - (H+3) |np-1} \leq \frac{H+2}{npq - 4H |np-1}$$

We ensure this is positive.

Now consider

$$\tau_0 = \min\{t \geq 0 : Y_{\delta+t} = 0\}$$

$$Z_t = Y_{\delta+t \wedge \tau_0} + \sum_{j=1}^{t \wedge \tau_0} jP$$

If $t < \tau_0$ then

$$\sigma = (t+1) \wedge \tau_0$$

$$E(Z_{t+1} - Z_t | Z_t) = E(\mathcal{D}_{\delta+\sigma} + \sigma P)$$

$$= -1 + (n - Y_{\delta+t \wedge \tau_0} - (\delta+t \wedge \tau_0) + \sigma)P$$

$$\leq 0$$

and $Z_{t+1} = Z_t \cdot \mathbb{1}_{t \geq \tau_0}$.

So (Z_t) is a supermartingale.

$$H + np \geq E(S_\gamma | S_\gamma \geq H)$$

Lemma on p10

$$\geq E(Z_0 | S_\gamma \geq H)$$

$$S_\gamma \geq Y_\gamma$$

$$\geq E(Z_{\tau_0} | S_\gamma \geq H)$$

Optional Stopping

$$\geq E(\tau_0^2 | S_\gamma \geq H) \rho / 2$$

take sum only.

By Cauchy-Schwarz

$$E(\tau_0 | S_\gamma \geq H) \leq E(\tau_0^2 | S_\gamma \geq H)$$

$$\leq \left(\frac{2(H + np)}{\rho} \right)^{\frac{1}{2}}$$

Proof of (iii)

Fix $h = An^{1/3}$, $A = O(1)$ to be determined.

Stage 1

$$T_h = \begin{cases} \min \{ t \leq \frac{n}{8h} : Y_t \geq h \} & \leftarrow \text{set non-empty} \\ \frac{n}{8h} & \text{otherwise} \end{cases}$$

If $Y_{t-1} > 0$ then

$$Y_t^2 - Y_{t-1}^2 = (\eta_t - 1)^2 + 2(\eta_t - 1)Y_{t-1}.$$

If $Y_{t-1} \leq h$ then

$$E(Y_t^2 - Y_{t-1}^2 | Y_{t-1}) \geq (n-t-h) \rho q - 2(t+h) \rho h.$$

$$\geq \frac{1}{2}.$$

If $Y_{t-1} \neq 0$ then $E(Y_t^2 - Y_{t-1}^2) = E(\eta_t^2) \geq \frac{1}{2}$,
under these assumptions.

So $Y_{t \wedge T_h}^2 - \frac{1}{2}(t \wedge T_h)$ is a submartingale

and so

$$E(Y_{T_h}^2) - \frac{1}{2} T_h \geq 0.$$

Lemma on PIB \Rightarrow

$$E(Y_{T_h}^2) \leq h^2 + 3h \leq 2h^2.$$

So

$$2h^2 \geq E(Y_{T_h}^2) \geq \frac{1}{2} E(T_h) \geq \frac{T_1}{2} \Pr(T_h = \frac{n}{8h})$$

or

$$\Pr(T_h = \frac{n}{8h}) \leq \frac{32h^3}{n}.$$

$$\tau_0 = \begin{cases} \min \{ t \leq \delta n^{2/3} : \bigvee_{\tau_h+t} = 0 \} & \leftarrow \text{set non-empty} \\ \delta n^{2/3} & \text{otherwise} \end{cases}$$

$$M_t = h - \min \left\{ h, \bigvee_{\tau_h+t} \right\}.$$

if $0 < M_{t-1} < h$ then

$$M_t^2 - M_{t-1}^2 = (\mathcal{D}_{\tau_h+t} - 1)^2 + 2(1 - \mathcal{D}_{\tau_h+t})M_{t-1}$$

and so

$$\begin{aligned} E(M_t^2 - M_{t-1}^2 | M_{t-1}) &\leq npq + 2h \left(1 - \left(n - \frac{n}{8h} - \delta n^{2/3} \right) p \right) \\ &\leq 2(1 + A|\lambda|). \end{aligned}$$

If $Y_{t-1} \geq h$ then $M_{t-1} = 0$ and $M_t \leq 1$.

So $Z_t = M_{t \wedge T_0}^2 - 2(1 + A|\lambda|)(t \wedge T_0)$ is a

super martingale.

Now use P_h, E_h to denote conditioning on $\{Y_{\tau_h} \geq h\}$.

$Z_0 = 0$ and so

$$\begin{aligned} 0 &\geq E(Z_{T_0}) = E_h(M_{T_0}^2) - 2(1 + A|\lambda|)E(T_0) \\ &\geq E_h(M_{T_0}^2) - (1 + A|\lambda|)\delta n^{2/3}. \end{aligned}$$

So

$$P_h(T_0 < \delta n^{2/3}) \leq P_h(M_{T_0} \geq h) \leq \frac{E_h(M_{T_0}^2)}{h^2} \leq \frac{(1 + A|\lambda|)\delta n^{2/3}}{h^2}$$

implies

So

$$P(\tau_0 < \delta n^{2/3}) \leq P(\tau_h = \frac{n}{8h}) + P_h(\tau_0 < n^{2/3})$$

$$\leq \frac{32h^3}{n} + \frac{(1+|\lambda|) \cdot \delta n^{2/3}}{h^2}$$

or

$$P(\tau_0 < \delta n^{2/3}) \leq 32A^3 + \frac{(1+|\lambda|)\delta}{A^2}.$$

Putting $A = \delta^{1/5}$ for simplicity, we get

which gives

$$P(\tau_0 < \delta n^{2/3}) \leq (33 + 2|\lambda|) \delta^{3/5}.$$

We finally note that

$$|C_1| < \delta n^{2/3} \Rightarrow |C(v)| < \delta n^{2/3}$$

$$\Rightarrow \tau < \delta n^{2/3}$$

$$\Rightarrow \tau_0 < \delta n^{2/3}.$$

Perfect Matchings in Bipartite 2-OUT

$B_{k\text{-out}}$ is a random bipartite graph
with vertex partition $X \cup Y$ where $|X| = |Y| = n$.

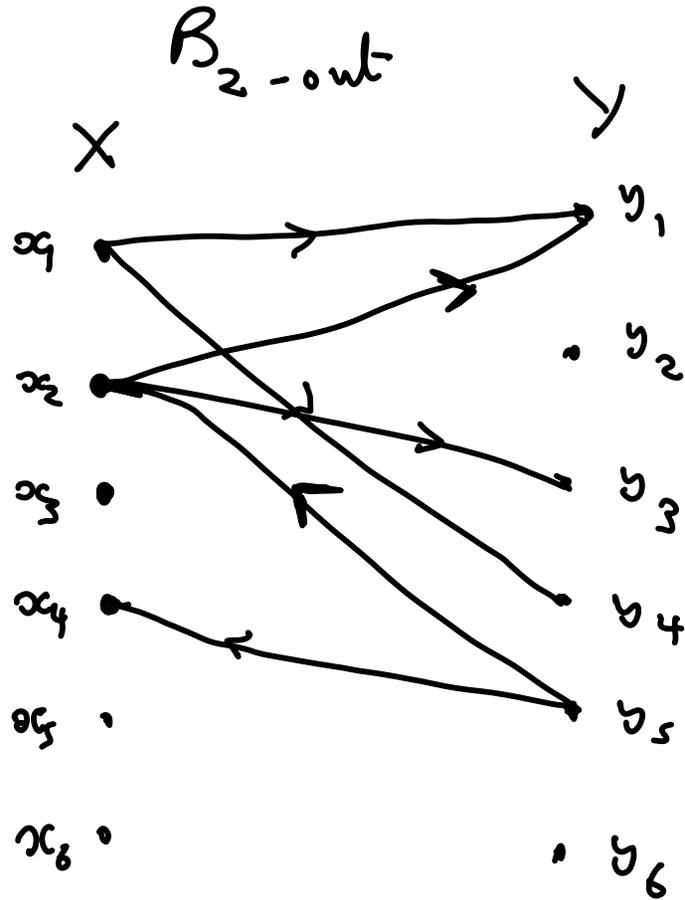
Each $x \in X$ chooses k random nbrs in Y

Each $y \in Y$ chooses k random nbrs in X .

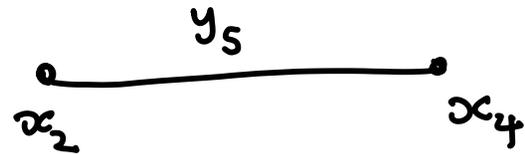
Theorem

$B_{2\text{-out}}$ has a perfect matching w.h.p.

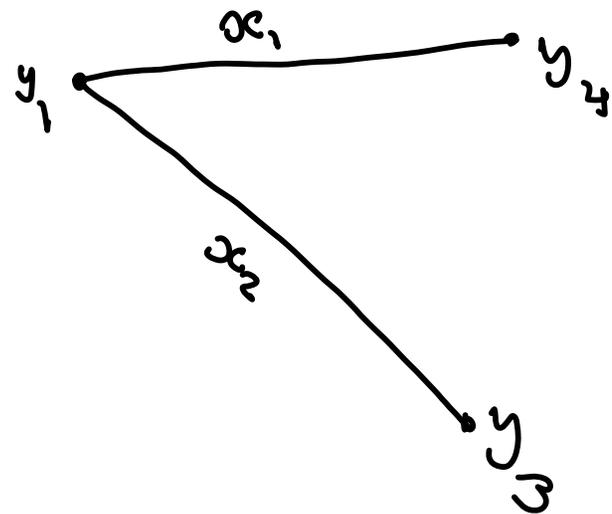
Algorithmic Proof



G_1 : n random edges

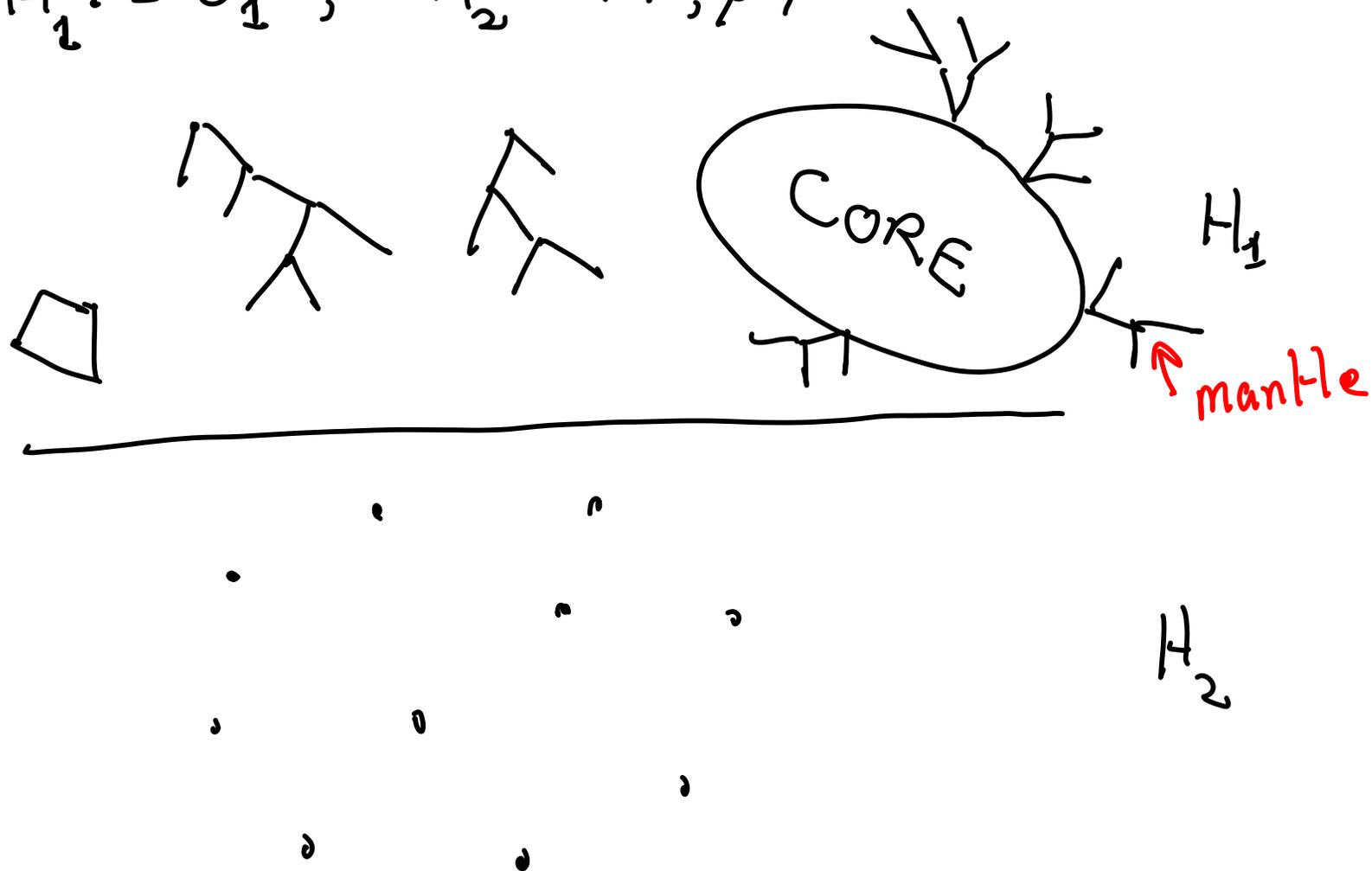


G_2 : n random edges

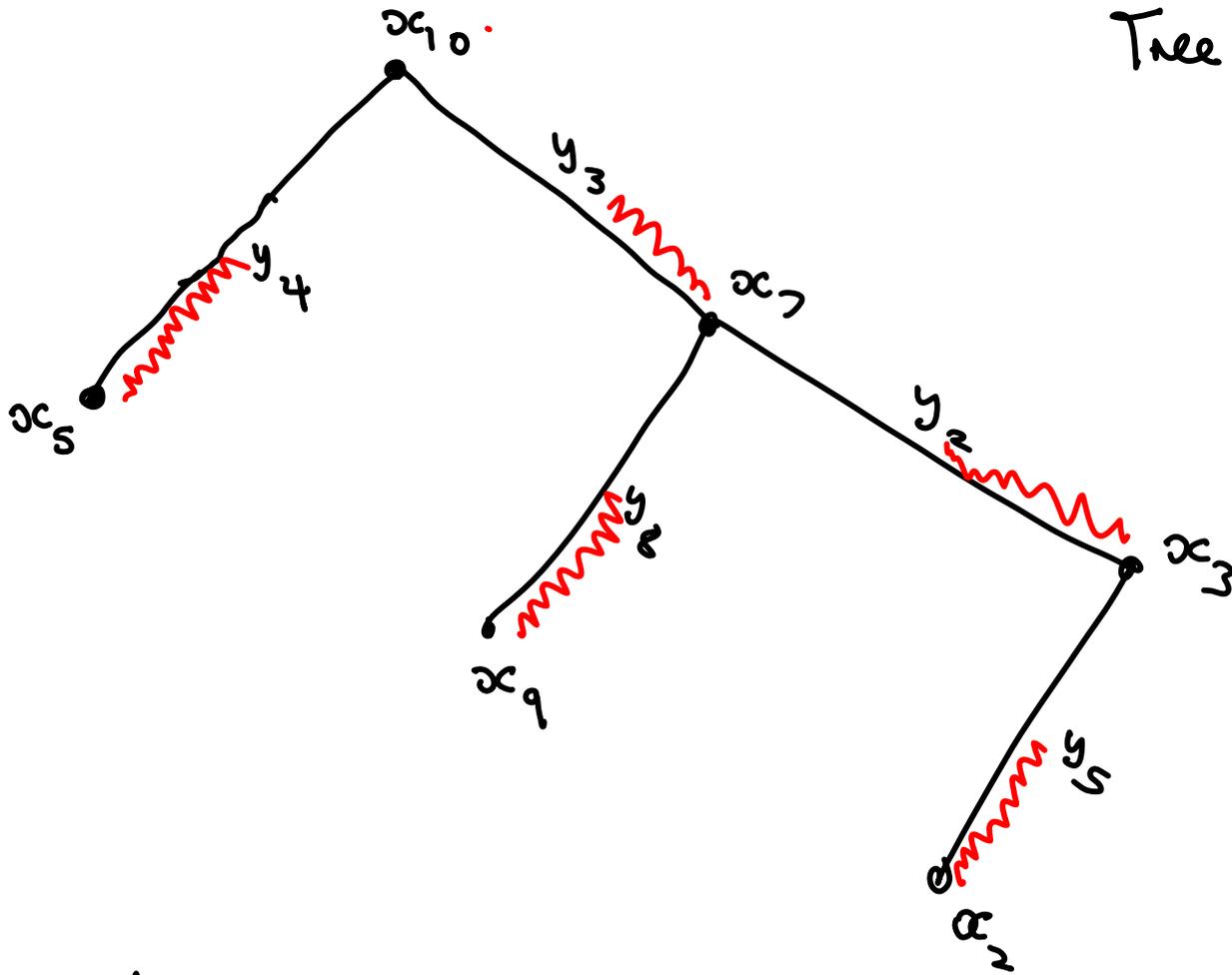


Algorithm

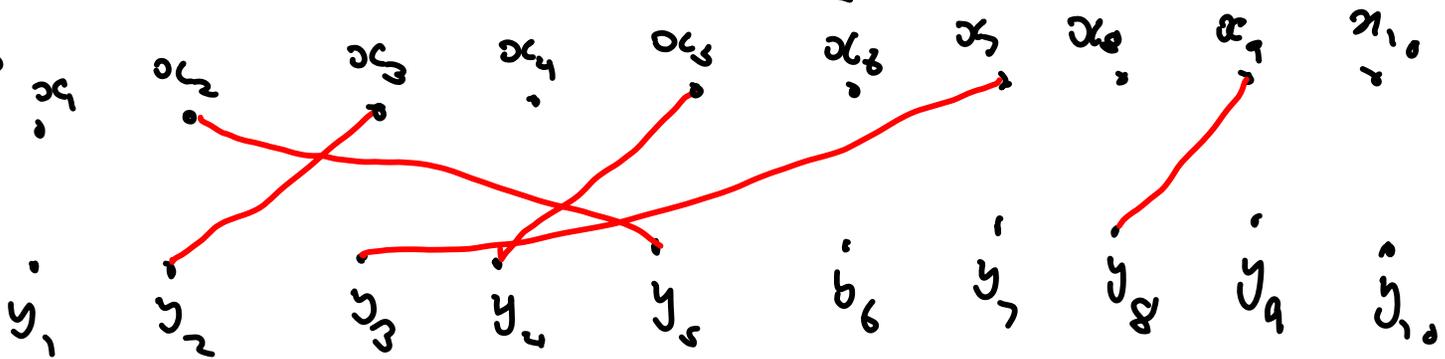
$$H_1 := G_1 ; \quad H_2 := (X, \emptyset)$$

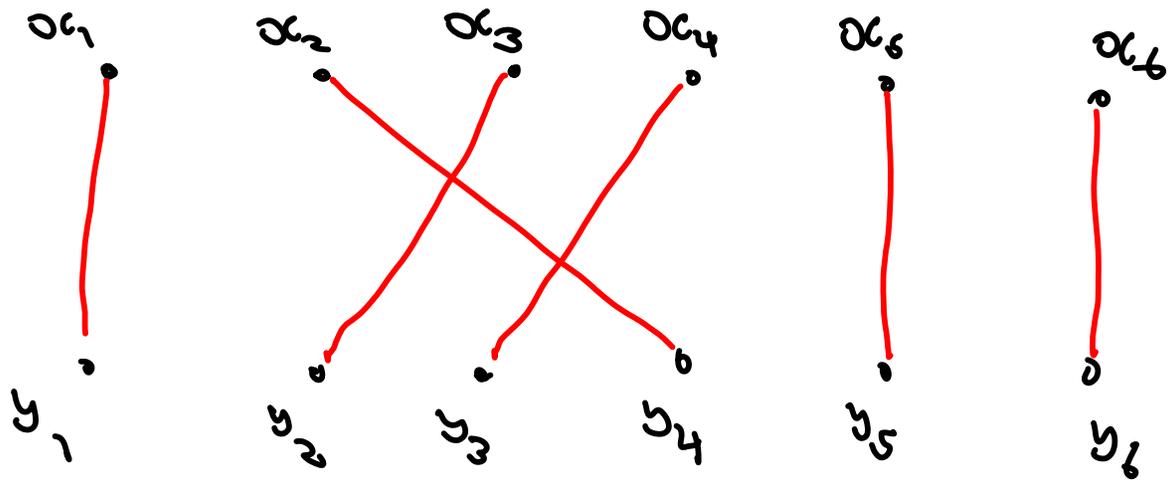
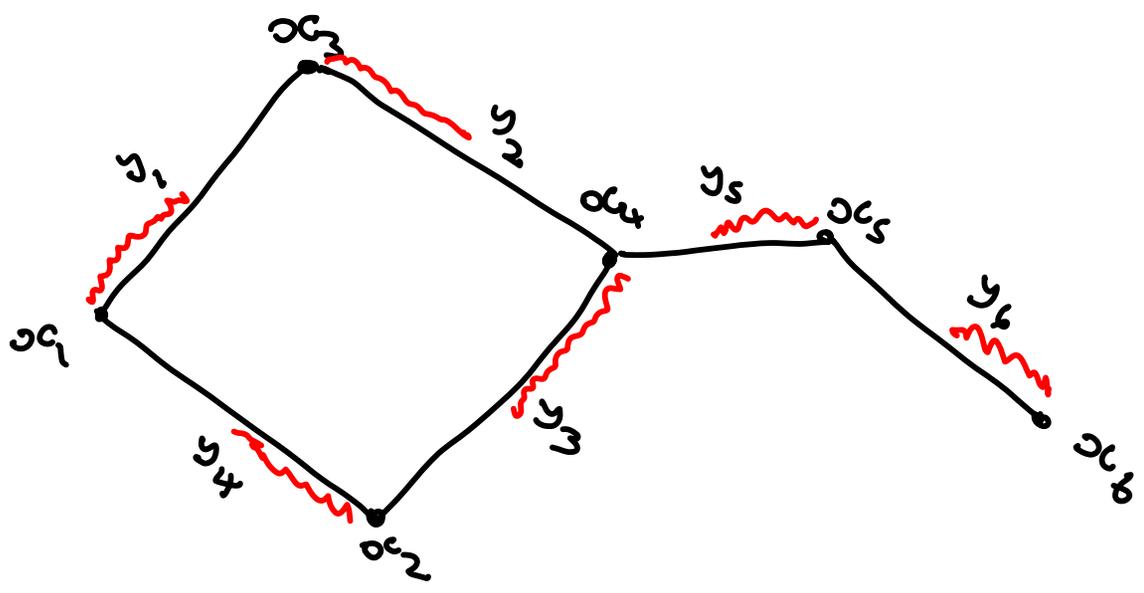


Tree in H_1



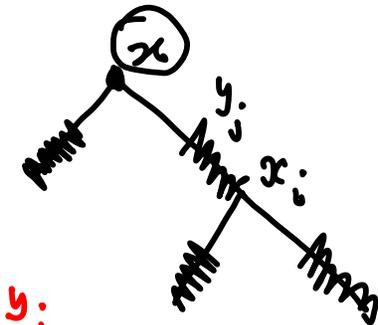
Yields





Step 1: If every isolated tree of H_1 contains a **marked** vertex: **FOUND PERFECT MATCHING.**

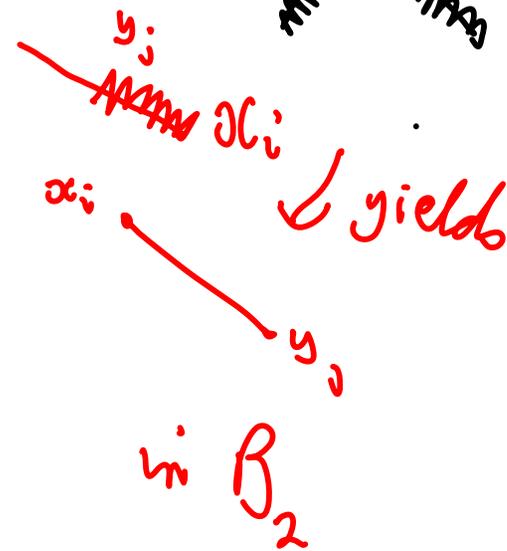
Step 2: Choose unmarked isolated tree T ;
 Choose root x for T ;
 Mark x .



Step 3: Add edge with label α
 to H_2

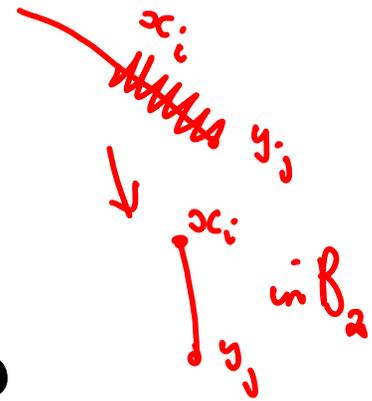
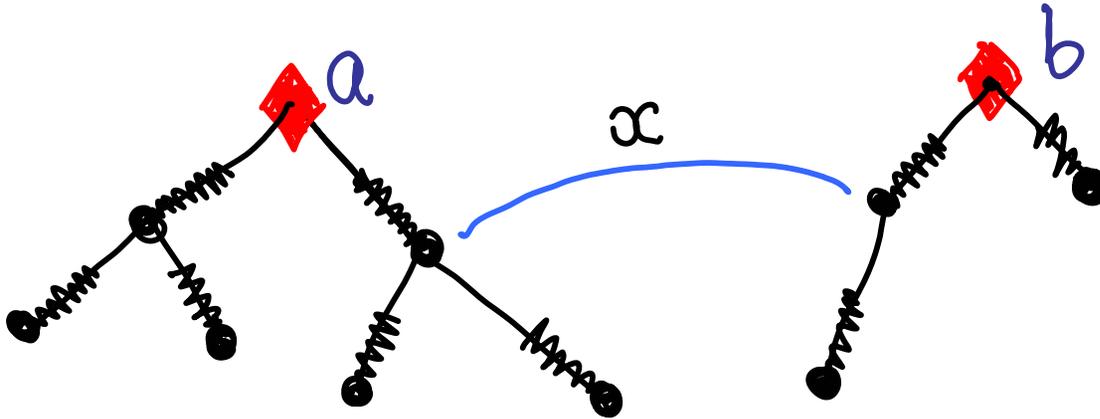


α choose y_i, y_j

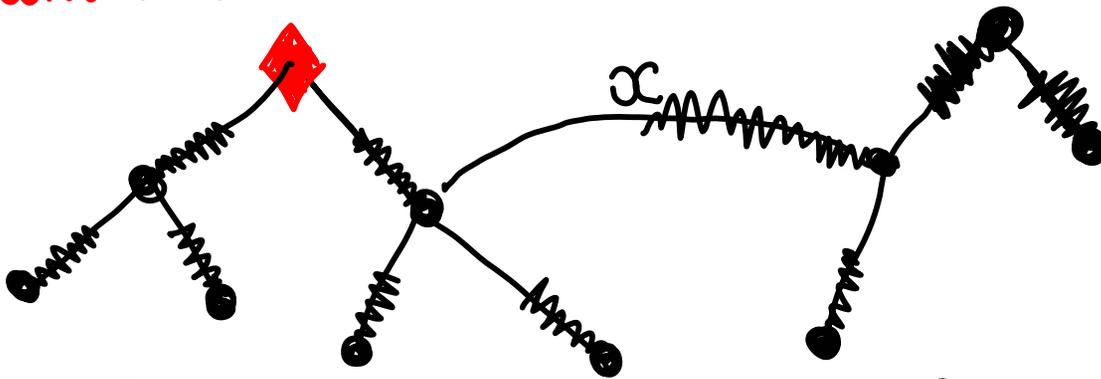


Step 4 : Possibilities.

(1)



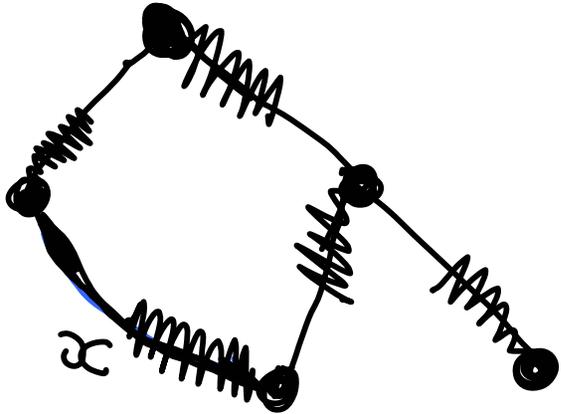
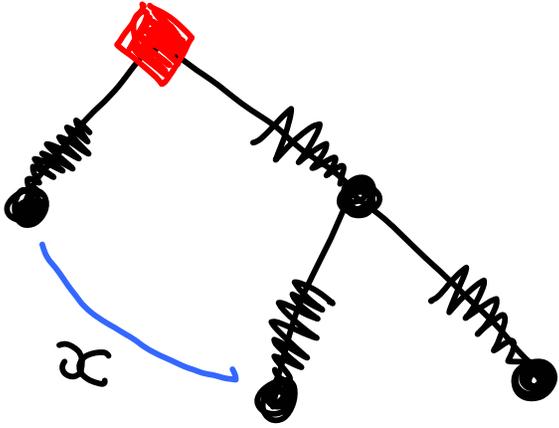
- - checked vertex
- ◆ - unchecked vertex



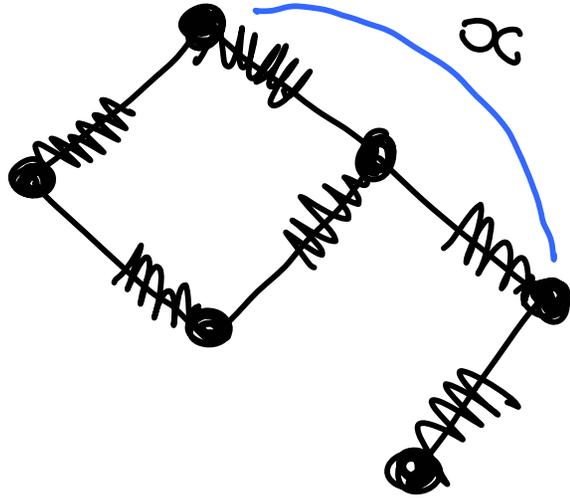
$\alpha \in E(H_1) \cap E(H_2)$

Give preference to vertex b if edge b in CORE of H_1 and edge a is not.

(ii)



(iii)



FAIL

In cases (i) & (ii) delete edge ∞
from H_1 .

Repeat from Step 1

Invariants

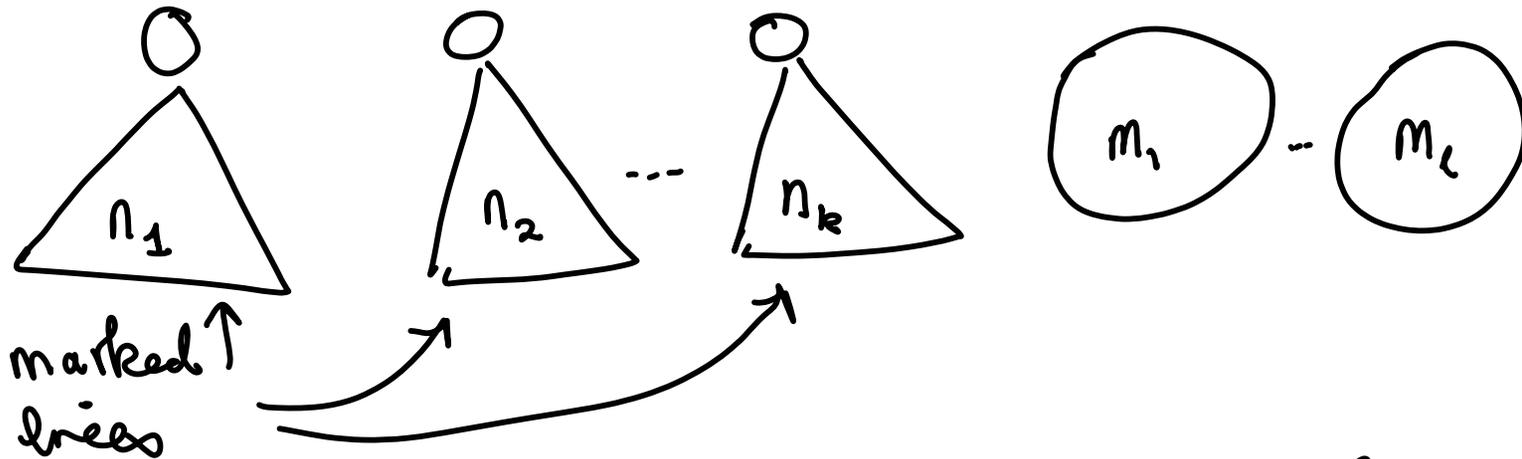
(i) # marked vertices = $n - \# \text{edges in } H_1$.

Each round marks one vertex and deletes one edge of H_1 .

(ii) # checked vertices = # edges of H_2 .

Each round checks one vertex and adds one edge to H_2 .

Suppose there are no unmarked lines.



vertices $n_1 + n_2 + \dots + n_k + m_1 + \dots + m_l = n$

edges $(n_1 - 1) + (n_2 - 1) + \dots + (n_k - 1) + (\geq m_1) + \dots + (\geq m_l) = n - k$

\Rightarrow $m_1 - m_l$ are unicyclic

The edges ~~gives~~ give a matching M_1 in B_2 of size $n - k$ covering all unmarked OG's.

Note # rounds = # edges lost = k

H_2 contains k edges, also yielding matching M_2 in B_2 .

x (marked in H_1)

~~~~~~~~~

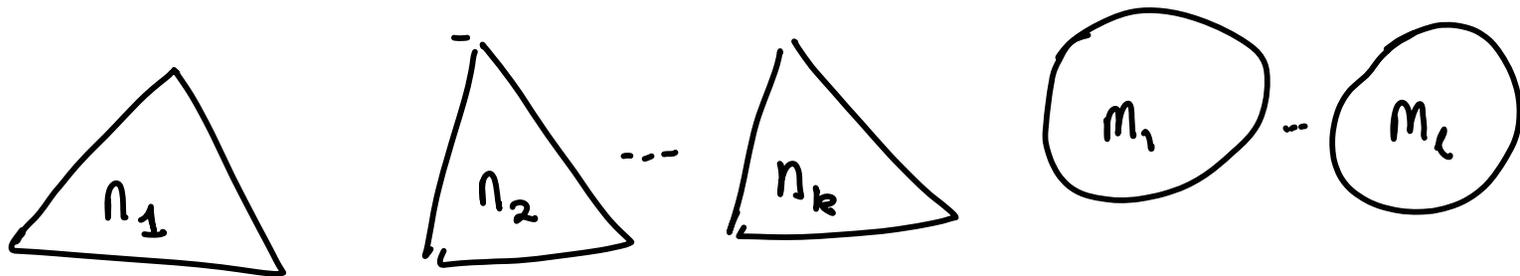
The ~~mmr~~ derived edge covers  $x$ .

$M_1$  does not cover  $x$ , but  $M_2$  does.

Finally, suppose that  $M_1$  does not cover  $y$   
i.e.  ~~$x$~~  ~~~~~~~~~ <sup>$y$</sup> . This edge was deleted and  
so  $y$  is a checked vertex of  $H_2$  and is  
covered by  $M_2$ .

Thus  $M_1 \cup M_2 = n$  edges covering  $X \cup Y$ , is **perfect matching**.

Conversely, suppose  $H_1$  consists of lines and unicyclic components



$$\begin{aligned} \# \text{ edges} &= n - k \\ &= n - \# \text{ marked vertices} \end{aligned}$$

So every line has a marked vertex and algorithm stops as soon as this happens.

# Probability of Failure

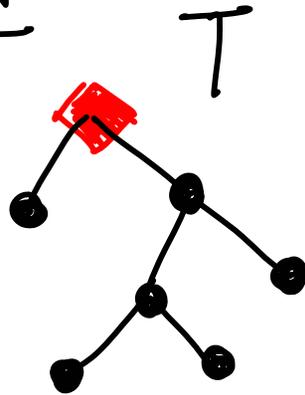
## Claim (proved below)

Why  $H_2$  consists only of trees and unicyclic components before  $.49n$  rounds.

Assume claim:  $H_2$  consists of  $\leq .49n$  random edges and so why only contains trees and unicyclic components and so case (ii) of Step 4 does not happen.

## Proof of Claim

Each  $H_2$ -tree  
has one  
unchecked  
vertex



Edge of  $H_1$  corr. to  
unchecked vertices of  
 $H_2$ .

If  corresponds to edge of CORE then  
our rule  $\Rightarrow$  every vertex of T corresponds  
to edge of CORE.

So # vertices left in (what was) CORE  
 $=$  # trees of  $H_2$  where every vertex corr. to  
an edge of CORE.

# Size of CORE

Suppose  $\partial G e^{-x} = 2e^{-2}$ ,  $0 < x < 1$ .

Then CORE has  $\approx (1 - \frac{x}{2})^2 n$  edges.

$$.4 \leq x \leq .41$$

$$.63 \leq (1 - \frac{x}{2})^2 \leq .64$$

Let  $Z = \#$  trees in  $H_2$  made up of vertices  $y \in V$   
 whose edge in  $H_1$  belongs to CORE.  $.49n$

$$E(Z) \leq o(1) + \sum_{k=1}^{(\log n)^2} \binom{n}{k} k^{k-2} \binom{.49n}{k-1} (k-1)! \left(\frac{1}{\binom{n}{2}}\right)^{k-1} \cdot (.64)^{k-1} \cdot \left(1 - \frac{k(n-k)}{\binom{n}{2}}\right)^{.49n}$$

$$\leq o(1) + .64n \sum_{k=1}^{(\log n)^2} \frac{k^{k-2}}{k!} (.64)^{k-1} \exp\left\{-\frac{.98k(n-k)}{(n-1)}\right\}$$

$$\leq .64n \sum_{k=1}^{(\log n)^2} \frac{k^{k-2}}{k!} (.64)^{k-1} \exp\left\{-\frac{.98k(n-k)}{(n-1)}\right\} + o(n)$$

$$\leq (1+o(1)) (.64)n \left( e^{-.98} \left( \frac{.6}{2} + \frac{3(.64)^3}{4} + \frac{16(.64)^3}{24} \right) + \sum_{k=5}^{(\log n)^2} \frac{1}{k^{5/2}} \cdot \frac{1}{.64} \cdot (.64e^{.02})^k \right)$$

$$\leq \frac{1}{3}$$

$$\leq \frac{1}{5^{5/2} \times .64 \times (1 - .65 \times e^{.02})}$$

$$\leq \frac{1}{15}$$

So, after .49 rounds,  
in expectation,

# edges left in CORE,

is  $\leq \frac{2}{5}$  of original,

and Chebyshev can be used to show this w.h.p.

But deleting  $\approx \frac{3}{5}$  of CORE's edges will whp  
leave just trees and unicyclic components:

Choose  $n$  random edges.

Build CORE

Delete  $\approx \frac{3}{5}$  of edges.

(i) Whp  $\approx \frac{3}{5}$  of edges of CORE are deleted.

(ii) Graph has  $\approx \frac{2}{5}n$  edges and so has only  
trees plus unicyclic components.

So whp algorithm finishes before  $.49n$   
rounds with a perfect matching.

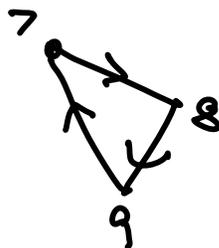
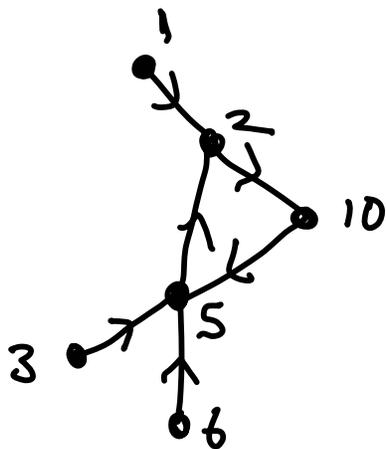
# Random Mappings

Let  $f$  be chosen uniformly at random from the set of all  $n^n$  mappings from  $[n] \rightarrow [n]$ .

Let  $D_f$  be the digraph  $([n], (x, f(x)))$

and let  $G_f$  be obtained from  $D_f$  by ignoring orientation.

|     |          |   |    |   |   |   |   |   |   |   |    |
|-----|----------|---|----|---|---|---|---|---|---|---|----|
| Ex: | $\alpha$ | 1 | 2  | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|     | $f(x)$   | 2 | 10 | 5 | 4 | 2 | 5 | 8 | 9 | 7 | 5  |



In general  $D_f$  consists of unicyclic components, where each such consists of a directed cycle  $C$  with trees rooted at each vertex of  $C$ .

## Thm 1

$$\Pr(G_p \text{ is connected}) \approx \sqrt{\frac{\pi}{2n}}$$

## Proof

Let  $T(n, k)$  denote the number of forests with vertex set  $[n]$ ,  $k$  trees, in which  $1, 2, \dots, k$  are in different trees. We show later that

$$T(n, k) = k n^{n-k-1}.$$

$$P_r(G_f \text{ is connected}) =$$

$$n^{-n} \sum_{k=1}^n \underbrace{\binom{n}{k} (k-1)!}_{\text{choose cycle of length } k} \underbrace{T(n, k)}_{\text{finish off mapping}}$$

$$= \frac{1}{n} \sum_{k=1}^n \underbrace{\prod_{j=0}^{k-1} \left(1 - \frac{j}{n}\right)}_{u_k}$$

if  $k \geq n^{3/5}$  then  $u_k \leq \exp\left\{-\frac{k(k-1)}{2n}\right\} \leq e^{-\frac{1}{3}n^{1/5}}$ .

if  $k < n^{3/5}$  then  $u_k = \exp\left\{-\frac{k^2}{2n} + O\left(\frac{k^3}{n^2}\right)\right\}$

So

$$Pr(G_f \text{ is connected}) =$$

$$\frac{1+o(1)}{n} \sum_{k=1}^{n^{1/5}} e^{-k^2/2n} + O(n e^{-n^{1/5}/3})$$

$$= \frac{1+o(1)}{n} \int_0^{\infty} e^{-x^2/2n} dx + O(n e^{-n^{1/5}/3})$$

$$= \frac{1+o(1)}{\sqrt{n}} \int_0^{\infty} e^{-y^2/2} dy + O(n e^{-n^{1/5}/3})$$

$$\sim \sqrt{\frac{\pi}{2n}}$$

Formula for  $T(n, k)$ :

$$T(n, 1) = n^{n-2}$$

Cayley's Formula

$$T(n, k) = \sum_{l=0}^{n-k} \binom{n-k}{l} (l+1)^{l-1} T(n-l-1, k-1)$$

# vertices in  $k$  tree  
is  $l+1$

$$= \sum_{l=0}^{n-k} \binom{n-k}{l} (l+1)^{l-1} (k-1) (n-l-1)^{n-k-l-1}$$

induction

Abel's Formula

$$\sum_{l=0}^m \binom{m}{l} (x+l)^{l-1} (y+m-l)^{m-l-1} = \left(\frac{1}{x} + \frac{1}{y}\right) (x+y+m)^{m-1}$$

Take  $m = n-k$ ,  $x = 1$ ,  $y = k-1$ .



Number of cycles:

Let  $Z_k = \#$  of cycles of length  $k$ .

$$E(Z_k) = \binom{n}{k} (k-1)! n^{-k} = \frac{1}{k} \prod_{j=0}^{k-1} \left(1 - \frac{j}{n}\right)$$

If  $Z = Z_1 + \dots + Z_n$  then

$$E(Z) = \sum_{k=1}^n \frac{1}{k} \prod_{j=0}^{k-1} \left(1 - \frac{j}{n}\right)$$

$$\sim \int_{-1}^{\infty} \frac{1}{x} e^{-x^2/2n} dx$$

$$\sim \log_e n.$$

Number of vertices on cycles:

$$E\left(\sum_{k=1}^n k Z_k\right) = \sum_{k=1}^n \prod_{j=1}^{k-1} \left(1 - \frac{j}{n}\right)$$

$$\sim \sqrt{\frac{\pi n}{2}}.$$

## Shortest Paths

Let the arcs of the complete digraph  $D_n$  on  $[n]$  be given independent lengths  $X_e$ ,  $e \in [n]^2$ .

Here  $X_e$  is exponential with mean 1

i.e.

$$P(X_e \geq t) = e^{-t}$$

for all  $t \geq 0$ .

## Theorem

Let  $X_{ij}$  = distance from  $i$  to  $j$ . Then

(i) For any **fixed**  $i, j$ ,

$$P\left(\left|\frac{X_{ij}}{\log n/n} - 1\right| \geq \epsilon\right) \rightarrow 0, \quad \forall \epsilon > 0$$

(ii) For any **fixed**  $i$ ,

$$P\left(\left|\frac{Z_i}{2 \log n/n} - 1\right| \geq \epsilon\right) \rightarrow 0, \quad \forall \epsilon > 0$$

Here  $Z_i = \max_j X_{ij}$

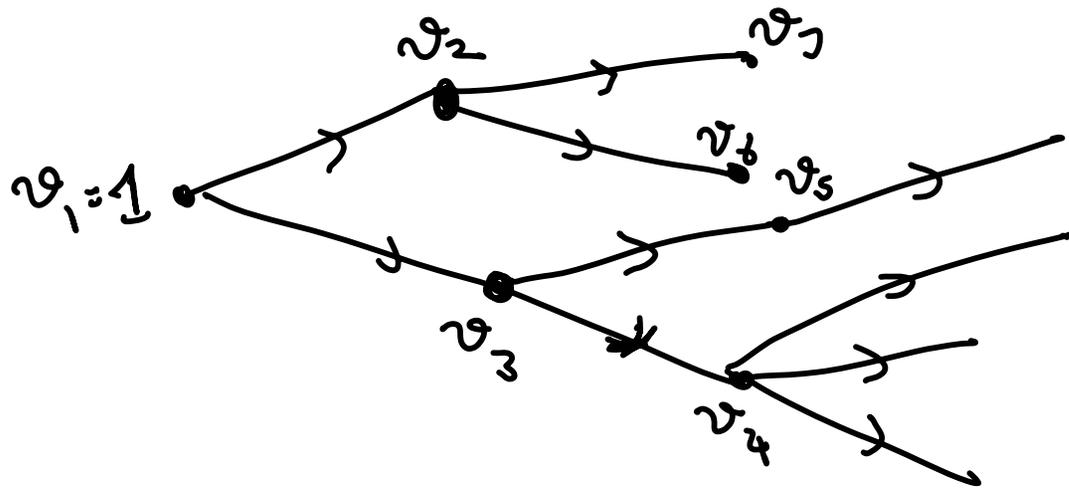
## Proof

Two main properties of exponential  $X$ :

$$(P1) \Pr(X > \alpha + \beta \mid X > \alpha) = \Pr(X > \beta).$$

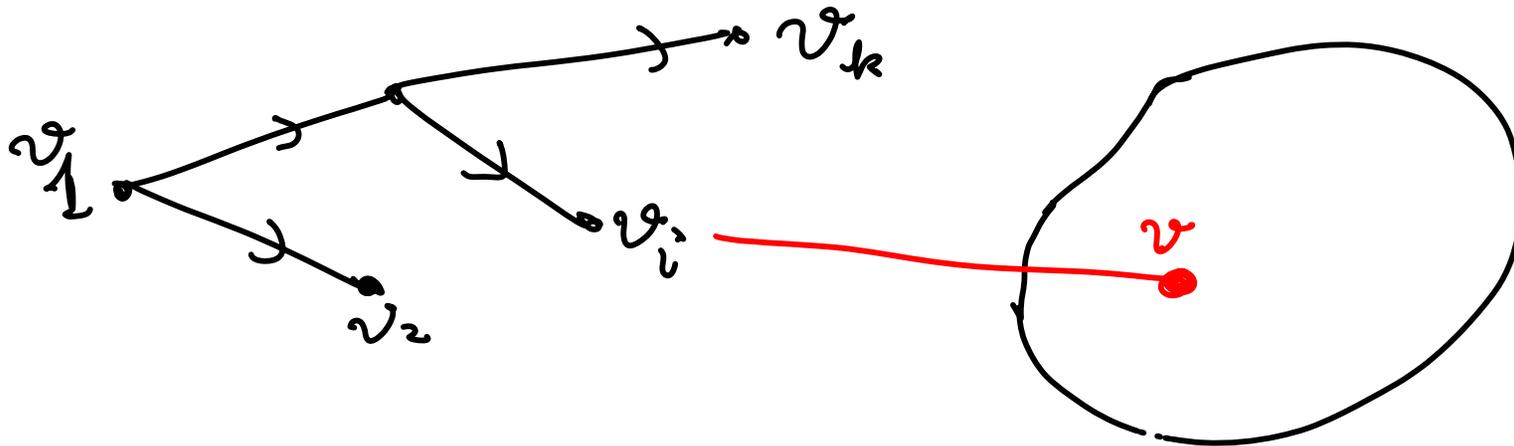
(P2) If  $X_1, X_2, \dots, X_m$  are independent exponentials then  $\min\{X_1, X_2, \dots, X_m\}$  is an exponential with mean  $1/m$ .

Fix  $i=1$  and consider Dijkstra's shortest path algorithm. This produces a tree



Suppose that vertices are added to the tree in the order  $v_1, v_2, \dots, v_n$  and that  $\text{dist}(v_1, v_i) = \gamma_i$ .

It follows from P1 (p3) that



$$Y_{k+1} = \min_{i=1, \dots, k} \left[ \underbrace{Y_i + X(v_i, v)}_{\geq Y_k} \right]$$

$\stackrel{d}{=} Y_k + \text{Exponential}$

So  $Y_{k+1} = Y_k + E_k$

where  $E_k$  is exponential with mean  $\frac{1}{k(n-k)}$  and is independent of  $Y_k$ .

So

$$E(Y_n) = \sum_{k=1}^{n-1} \frac{1}{k(n-k)}$$

$$= \frac{1}{n} \sum_{k=1}^{n-1} \left( \frac{1}{k} + \frac{1}{n-k} \right)$$

$$= \frac{2}{n} \sum_{k=1}^{n-1} \frac{1}{k}$$

$$\sim \frac{2 \log n}{n}.$$

$$\begin{aligned} \text{Also } \text{Var}(Y_n) &= \sum_{k=1}^{n-1} \text{Var}(E_{1/n}) = \sum_{k=1}^{n-1} \left( \frac{1}{k(n-k)} \right)^2 \\ &\leq 2 \sum_{k=1}^{n/2} \left( \frac{1}{k(n-k)} \right)^2 \leq \frac{8}{n^2} \sum_{k=1}^{n/2} \frac{1}{k^2} = O(n^{-2}) \end{aligned}$$

and we can use Chebyshev to prove (ii).

Now fix  $j=2$ . Then if  $i$  is defined by  $n_{i,j}=2$ , we see that  $i$  is uniform over  $\{2, 3, \dots, n\}$ .

$$\begin{aligned}
 \text{So } E(X_{1,2}) &= \frac{1}{n-1} \sum_{i=2}^n \sum_{k=1}^i \frac{1}{k(n-k)} \\
 &= \frac{1}{n-1} \sum_{k=1}^{n-1} \frac{n-k}{k(n-k)} \\
 &\stackrel{**}{=} \frac{\log_e n}{n}.
 \end{aligned}$$

For variance we have

$$X_{1,2} = \delta_2 Y_2 + \delta_3 Y_3 + \dots + \delta_n Y_n$$

where

$$\delta_i \in \{0,1\}; \delta_2 + \dots + \delta_n = 1; P(\delta_i = 1) = \frac{1}{n-1}$$

$$\text{Var}(X_{1,2}) = \sum_{i=2}^n \text{Var}(\delta_i Y_i)$$

$$+ \sum_{i \neq j} \text{Cov}(\delta_i Y_i, \delta_j Y_j)$$

$$\leq \sum_{i=2}^n \text{Var}(\delta_i Y_i)$$

$$\text{Cov}(\delta_i Y_i, \delta_j Y_j) = E(\delta_i Y_i \delta_j Y_j) - E(\delta_i Y_i) E(\delta_j Y_j) \leq 0$$

$\uparrow 0$

$$\begin{aligned}
\text{Var}(X_{1,2}) &\approx \sum_{i=2}^n \text{Var}(\beta_i Y_i) \\
&\ll \sum_{i=2}^n \frac{1}{n-1} \sum_{k=1}^{i-1} \left( \frac{1}{k(n-k)} \right)^2 \\
&= O\left(\frac{1}{n^2}\right).
\end{aligned}$$

Split sum  
at  $n/2$

We can now use Chebyshev.

## Digraphs

In this chapter we study the random digraph  $D_{n,p}$ . This has vertex set  $[n]$  and each of the  $n(n-1)$  possible edges occurs independently with probability  $p$ .

We will first study the size of the strong components of  $D_{n,p}$ .

Case 1:  $p = \frac{c}{n}$ ,  $c < 1$

We will show that in this case

### Theorem 1

whp

(i) all strong components of  $D_{n,p}$  are either cycles or single vertices.

(ii) The number of vertices on cycles is at most  $\omega$ , for any  $\omega = \omega(n) \rightarrow \infty$

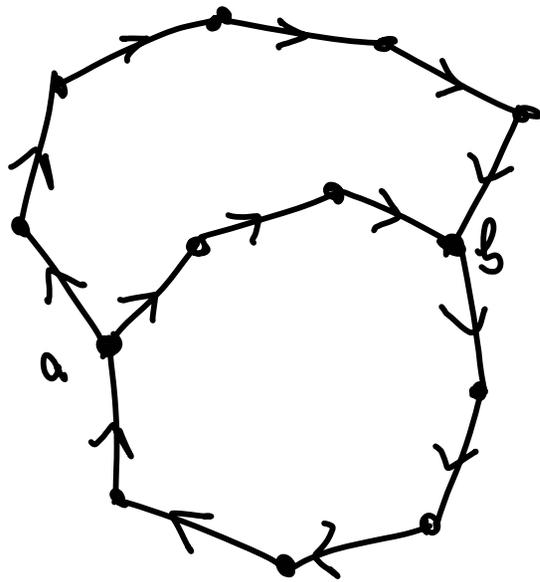
## Proof

The expected number of cycles is

$$\sum_{k=2}^n \binom{n}{k} (k-1)! \left(\frac{c}{n}\right)^k \leq \sum_{k=2}^n \frac{c^k}{k} = O(1).$$

Part (ii) now follows from the Markov inequality

To tackle (i) we argue that if there is a component that is not a cycle or single vertex then there is a cycle  $C$  and vertices  $a, b \in C$  and a path  $P$  from  $a$  to  $b$  that is internally disjoint from  $C$ .



However, the expected number of such sub-graphs is bounded by

$$\sum_{k=2}^n \sum_{l=1}^{n-k} \binom{n}{k} (k-1)! \left(\frac{c}{n}\right)^k \binom{n}{l} l! \left(\frac{c}{n}\right)^{l+1}$$

$$\leq \sum_{k=2}^{\infty} \sum_{l=1}^{\infty} \frac{c^{k+l+1}}{k n} = O\left(\frac{1}{n}\right).$$

Here  $l$  is the number of vertices on the path  $P$ , excluding  $a, b$ .



We now consider the case  $p = \frac{c}{n}$  where  $c > 1$ .

We will prove the following theorem that is a directed analogue of the existence of a giant component in  $G_{n,p}$ .

### Theorem 2

Let  $\alpha$  be defined by  $\alpha < 1$  and  $\alpha e^{-\alpha} = c e^{-c}$ .

Then whp  $D_{n,p}$  contains a unique strong component of size  $\sim (1 - \frac{\alpha}{c})^2 n$ . All other strong components are of logarithmic size.

General Strategy: For a vertex  $v$  let

$$D^+(v) = \{w : \exists \text{ path } v \text{ to } w \text{ in } D_{n,p}\}$$

$$D^-(v) = \{w : \exists \text{ path } w \text{ to } v \text{ in } D_{n,p}\}.$$

We will first prove

### Lemma 1

There exist constants  $\alpha, \beta$  (dependent only on  $c$ ) such that whp

$$\exists v \text{ such that } |D^\pm(v)| \in [\alpha \log n, \beta n].$$

## Proof

If there is a  $v$  such that  $|D^+(v)| = s$   
then  $D_{n,p}$  contains a forest of size  $s$ , rooted  
at  $v$  such that (i) all arcs are oriented away  
from  $v$  and (ii) there are no arcs  
oriented from  $V(T)$  to  $[n] \setminus V(T)$ .

The expected number of such trees is  
bounded above by

$$\binom{n}{s} s^{s-2} \left(\frac{c}{n}\right)^{s-1} \left(1 - \frac{c}{n}\right)^{s(n-s)} \leq$$

$$\frac{n}{cs^2} \left(ce^{1-c+s/n}\right)^s.$$

Now  $ce^{1-c} < 1$  for  $c \neq 1$  and so

there exists  $\beta$  such that when  $s \leq \beta n$

we can bound  $ce^{1-c+s/n}$  by some

constant  $\gamma < 1$  ( $\gamma$  depends only on  $c$ ).

In which case

$$\frac{n}{cs^2} \gamma^s \leq n^{-3} \text{ for } s \geq \frac{4}{\log^{1/2} \gamma} \log n.$$

□

Fix a vertex  $v \in [n]$  and consider a directed breadth first search from  $v$ .

Let  $S_0^+ = \{v\}$  and given  $S_0^+, S_1^+, \dots, S_k^+ \subseteq [n]$   
 let  $T_k^+ = \bigcup_{i=1}^k S_i^+$  and let

$$S_{k+1}^+ = \left\{ w \notin T_k^+ : \exists x \in T_k^+ \text{ s.t. } (x, w) \in E(D_{n,p}) \right\}.$$

Not surprisingly, we can show that the sub-graph  $\Gamma_k^+$  induced by  $T_k^+$  is close in distribution to the tree defined by

the first  $k+1$  levels of a Galton-Watson branching process with  $Po(c)$  as the distribution of the number of offspring from a single parent.

## Lemma 2

If  $\hat{S}_0, \hat{S}_1, \dots, \hat{S}_k$  and  $\hat{T}_k$  are defined with respect to the branching process and if  $k \leq k_0 = \log^3 n$  and  $s_0, s_1, \dots, s_k \leq \log^4 n$  then

$$P_r(|S_i^+| = s_i, 0 \leq i \leq k) = \left(1 + O\left(\frac{1}{n^{1+0.10}}\right)\right) P_r(|\hat{S}_i| = s_i, 0 \leq i \leq k).$$

Proof

$$P_r(|\hat{S}_i| = s_i, 0 \leq i \leq k) = \prod_{i=1}^k \frac{(c s_{i-1})^{s_i} e^{-c s_{i-1}}}{s_i!},$$

Furthermore, putting  $t_i := s_0 + s_1 + \dots + s_i$  we have

$$P_r(|S_i^+| = s_i, 0 \leq i \leq k) = \prod_{i=1}^k \binom{s_{i-1}(n-t_i)}{s_i} \left(\frac{c}{n}\right)^{s_i} \left(1 - \frac{c}{n}\right)^{s_{i-1}(n-t_i) - s_i}$$

and the lemma follows by simple estimations.  $\square$

### Lemma 3

$$(a) \Pr(|S_i^+| \geq s \log n \mid |S_{i-1}^+| = s) \leq n^{-10}.$$

$$(b) \Pr(|\hat{S}_i| \geq s \log n \mid |\hat{S}_{i-1}| = s) \leq n^{-10}.$$

Proof

(a)

$$\Pr(|S_i^+| \geq s \log n \mid |S_{i-1}^+| = s) \leq$$

$$\Pr(B(sn, \frac{c}{n}) \geq s \log n) \leq \binom{sn}{s \log n} \left(\frac{c}{n}\right)^{s \log n}$$

$$\leq \left(\frac{snec}{sn \log n}\right)^{s \log n}$$

$$\leq \left(\frac{ec}{\log n}\right)^{\log n}.$$

(b) is similar.

Next let

$$\mathcal{F} = \{ \exists i : |\mathcal{T}_i^+| > \log^2 n \}$$

Lemma 4

$$P_r(\mathcal{F}) = 1 - \frac{\alpha}{c} + o(1)$$

Proof

$$P_r(\mathcal{F}) = P_r(\mathcal{F}_1) + o(1)$$

where

$$\mathcal{F}_1 = \{ \exists i \leq \log^2 n : |\mathcal{T}_0^+|, \dots, |\mathcal{T}_{i-1}^+| < \log^2 n \leq |\mathcal{T}_i^+| \}$$

This follows from Lemma 3.

Applying Lemma 2 (on p/2) we see that

$$P_r(\mathcal{F}_1) = P_r(\widehat{\mathcal{F}}_1) + o(1)$$

where  $\widehat{\mathcal{F}}_1$  is defined w.r.t. the branching process.

Now let  $\widehat{\mathcal{E}}$  be the event that the branching process becomes extinct.

We write

$$P_r(\widehat{\mathcal{F}}_1) = P_r(\widehat{\mathcal{F}}_1 | \neg \widehat{\mathcal{E}}) P_r(\neg \widehat{\mathcal{E}}) + P_r(\widehat{\mathcal{F}}_1 \wedge \widehat{\mathcal{E}}). \quad (1)$$

To estimate (1) we first define

$$\begin{aligned} \rho &= P_1(\hat{E}) \\ &= \sum_{k=0}^{\infty} \frac{c^k e^{-c}}{k!} \rho^k. \end{aligned}$$

This is if the origin of the process has  $k$  children then each of the processes spawned by them must become extinct for  $E$  to occur.

Thus

$$\rho = e^{c\rho - c}.$$

Substituting  $\rho = \frac{c}{c}$  proves that

$$P_r(\widehat{\mathcal{E}}) = \frac{\sigma}{c} \quad \text{where} \quad \frac{\sigma}{c} = e^{\sigma} - c$$

and so  $\mathcal{E} = \mathcal{X}$ .

The lemma will follow from (1) [p16]

and this and  $P_r(\widehat{\mathcal{F}} | \neg \mathcal{E}) = 1 - o(1)$

(see Lemma 3 [p14]) and

$$P_r(\widehat{\mathcal{F}} \wedge \mathcal{E}) = o(1). \quad (2)$$

Let us break the first  $\log^2 n$  generations of the branching process into  $\log n$  rounds of length  $\log n$ .

If  $\bar{F} \cap \bar{E}$  occurs then we start each round with a non-zero population.

### Claim 1

Each member of this population has a probability of at least  $\epsilon > 0$  of producing  $\log^2 n$  descendants at depth  $\log n$ . Here  $\epsilon > 0$  depends only on  $C$

and so

$$P(\overline{F \cap E}) \leq (1 - \epsilon)^{\log n} = o(1).$$

If the current population of the process is  $S$  then the probability that it reach size at least  $\frac{C+1}{2}S$  in the next round is

$$\sum_{k \geq \frac{C+1}{2}S} \frac{(cS)^k e^{-cS}}{k!} \geq 1 - e^{-\alpha S}$$

for some constant  $\alpha > 0$  provided  $S \geq 100$ , say.

Now there is a positive probability  $\epsilon$ , say that a single object spawns at least 100 descendants and so there is a probability of at least

$$\epsilon \left( 1 - \sum_{s=100}^{\infty} e^{-\alpha s} \right)$$

that a single object spawns

$$\left(\frac{c+1}{2}\right)^{\log n} \gg \log^2 n$$

descendants at depth  $\log n$ .

This proves Claim 1 ([p19]) and completes

the proof of Lemma 4.



We state for future reference that the above argument supports the following claim.

Claim 2

$$P(\exists i: |S_i^+| \geq \log^2 n \text{ and } |T_i^+|)$$

We must now consider the probability that both  $D^+(v)$  and  $D^-(v)$  are large.

### Lemma 5

$$P(|D^-(v)| \geq \log^2 n \mid |D^+(v)| \geq \log^2 n) = 1 - \frac{\alpha}{c} + o(1).$$

### Proof

Expose  $S_0^+, S_1^+, \dots, S_{k_0}^+$  until either  $S_{k_0}^+ = \emptyset$

or we see that  $|T_{k_0}^+| \geq \log^2 n$ .

Now let  $G$  denote the set of edges/vertices defined by  $S_0^+, S_1^+, \dots, S_{k_0}^+$  we see that (see Lemma 2 [p12])

Let  $\mathcal{C}$  be the event that there are no edges from  $T_\ell^-$  to  $S_k^+$  where  $T_\ell^-$  is the set of vertices we reach through our BFS with  $v$ , up to the point where we first find that  $|D(v)| < \log^2 n$  or  $\geq \log^2 n$ . Then

$$P_r(\mathcal{C}) = 1 - \frac{1}{n^{1-o(1)}}$$

end

$$P_r(|S_i^-| = s_i, 0 \leq i \leq k \mid \mathcal{C}) = \prod_{i=1}^k \binom{s_{i-1}(n'-t_i)}{s_i} \left(\frac{s_i}{n}\right)^{s_i} \left(1 - \frac{s_i}{n}\right)^{s_{i-1}(n'-t_i) - s_i}$$

where  $n' = n - |T_k^+|$ .

Given this we can prove a conditional version of Lemma 2 and continue as before.  $\square$

We have now shown that if

$$S = \{v : |D^+(v)|, |D^-(v)| > 2 \log n\}$$

then

$$E(|S|) \approx (1 + o(1)) \left(1 - \frac{\alpha}{\epsilon}\right)^2 n.$$

We also claim that for any two vertices  $v, w$

$$P_r[v, w \in S] = (1 + o(1)) P_r(v \in S) P_r(w \in S) \quad (3)$$

and therefore the Chebyshev inequality implies

that whp

$$|S| \approx (1 + o(1)) \left(1 - \frac{\alpha}{\epsilon}\right)^2 n.$$

But (3) follows in a similar manner to the proof of Lemma 5 (p22).

All that remains of the proof of Theorem 2 is to show that

whp  $S$  is a strong component. (4)

(Any  $v \in S$  is in a strong component of size  $\leq 2 \log n$ ).

We prove (4) by arguing that

$$P_r(\exists v, w \in S : w \notin D^+(v)) = o(1). \quad (5)$$

For this we expose  $S_0^+, S_1^+, \dots, S_{t_0}^+$  until we find that  $|T_{t_0}^+(v)| \geq n^{\frac{1}{2}} \log n$ .

At the same time we expose  $S_0^-, S_1^-, \dots, S_{t_0}^-$  until  $|T_{t_0}^-(w)| \geq n^{\frac{1}{2}} \log n$ .

If  $w \notin D^+(v)$  then this experiment will have tried at least  $(n^{\frac{1}{2}} \log n)^2$  times to find an edge from  $D^+(v)$  to  $D^-(w)$  and failed every time.

The probability of this is at most

$$\left(1 - \frac{c}{n}\right)^{n \log^2 n} = o(n^{-2}).$$

This completes the proof of Theorem 2.



# Strong Connectivity Threshold

Here we prove

## Theorem 3

Suppose that  $p = \frac{\log n + c_n}{n}$ . Then

$$\lim_{n \rightarrow \infty} P_1(D_{n,p} \text{ is strongly connected}) = \begin{cases} 0 & c_n \rightarrow -\infty \\ e^{-2e^{-c}} & c_n \rightarrow c \\ 1 & c_n \rightarrow +\infty \end{cases}$$

$$= \lim_{n \rightarrow \infty} P_1(\nexists v \text{ such that } d^+(v) = 0 \text{ or } d^-(v) = 0).$$

## Proof

We leave it as an exercise to prove that

$$\lim_{n \rightarrow \infty} P_1(\nexists v \text{ such } d^+(v) = 0 \text{ or } d^-(v) = 0) = \begin{cases} 1 & C_n \rightarrow -\infty \\ 1 - e^{-2e^{-c}} & C_n \rightarrow c \\ 0 & C_n \rightarrow \infty \end{cases}$$

Given this, one only has to show that if  $C_n \rightarrow -\infty$

then why there does not exist a vertex  $v$

such that  $2 \leq |D^+(v)| \leq n/2$  or

$2 \leq |D^-(v)| \leq n/2$ .

But, here with  $s_{i+1} = |D^+(v)|$ ,

$$P(\exists v) \leq 2n \sum_{s=1}^{n/2} \binom{n}{s} (s+1)^{s-1} \left(\frac{c}{n}\right)^s (1-p)^{(s+1)(n-1-s)}$$

$$= o(1). \quad (\text{Exercise})$$

# Hamilton Cycles

Here we prove the following remarkable inequality:

## Theorem 4

$$P_r(D_{n,p} \text{ is Hamiltonian}) \geq P_r(G_{n,p} \text{ is Hamiltonian})$$

### Proof

Remark: This shows that if  $p = \frac{\log n + \log \log n + c}{n}$  then  $D_{n,p}$  is Hamiltonian whp. This result has been strengthened but it requires a much more difficult argument. The  $\log \log n$  can be eliminated.

## Proof

We consider a sequence of random digraphs

$\Gamma_0, \Gamma_1, \Gamma_2, \dots, \Gamma_N$ ,  $N = \binom{n}{2}$  defined as follows:

Let  $e_1, e_2, \dots, e_N$  be an enumeration of the edges of  $K_n$ . Each  $e_i = (v_i, w_i)$  gives rise to two directed edges  $\vec{e}_i = (v_i, w_i)$  and  $\overleftarrow{e}_i = (w_i, v_i)$ .

In  $\Gamma_i$  we include  $\vec{e}_j$  and  $\overleftarrow{e}_j$  independently of each other, with probability  $p$ , for  $j \leq i$ .

While for  $j > i$  we include both or neither with probability  $p$ .

Thus  $\Gamma_0^+$  is just  $G_{n,p}$  with each edge  $(v,w)$  replaced by a pair of directed edges  $(v,w), (w,v)$  and  $\Gamma_N^- = D_{n,p}$ . Theorem 4 follows from

$$P_i(\Gamma_i^+ \text{ is Hamiltonian}) \geq P_i(\Gamma_{i-1}^- \text{ is Hamiltonian})$$

To prove this we condition on the existence or otherwise of directed edges associated with  $e_w, \dots, e_{i-1}, e_{i+1}, \dots, e_N$ .

Let  $C$  denote this conditioning.

Either  $\mathcal{C}$  is such that

(a)  $\mathcal{C}$  gives us a Hamilton cycle without arcs associated with  $e_i$  or there is no Hamilton cycle even if both  $\vec{e}_i, \overleftarrow{e}_i$  occur

or  $\mathcal{C}$  is such that

(b)  $\exists$  a Hamilton cycle if at least one of  $\vec{e}_i, \overleftarrow{e}_i$  occurs.

In  $\Gamma_{i-1}$  this happens with probability  $p$

In  $\Gamma_i$  this happens with probability  $1 - (1-p)^2 > p$

[ We will never require that both  $\vec{e}_i, \overleftarrow{e}_i$  occur. ]

