

Random walks and the component structure of the vacant set

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Warwick

- ▶ Introduction: random walks and cover time
- ▶ How to estimate 'un-visit probability' and some examples

- ▶ Vacant set definition and main results
- ▶ Vacant set in $G_{n,p}$
- ▶ Vacant set in random r -regular graphs

Discrete random walk on a finite graph

- ▶ $G = (V, E)$ is a finite graph with n vertices and m edges.
($|V| = n, |E| = m$)
- ▶ Assume that G is connected, so that all vertices in G have at least one neighbour vertex,

- ▶ Simple random walk: move to a randomly chosen neighbour at each step
- ▶ A simple random walk is a (unbiased) Markov process
- ▶ Suppose that at step t the walk is at vertex $X(t) = v$
Let $d(v) = |N(v)|$ be the degree of vertex v , then for $w \in N(v)$

$$\Pr(X(t+1) = w) = \frac{1}{d(v)}$$

Cover time: Introduction

- ▶ $G = (V, E)$ is a connected graph. ($|V| = n, |E| = m$)
- ▶ Random walk W_v on G starting at $v \in V$
Let C_v be the **expected time** taken for W_v to visit every vertex of G
- ▶ The cover time of G is defined as $T_{cov} = \max_{v \in V} C_v$
- ▶ Starting vertex matters
- ▶ Graph with vertices u, v, w $C_v = C_u + 1$



Brief history

- ▶ AKLLR¹ For any connected graph $T_{cov} \leq 4mn$
- ▶ Application: Is there a path connecting vertex s to t ?
Test graph connectivity by random walk, in $O(n^3)$ steps with $O(\log n)$ storage.
- ▶ Good for exploring large networks.
This led to increased interest in **cover time**
- ▶ Feige (1995). Bounds for any connected G :

$$(1 - o(1))n \log n \leq T_{cov} \leq (1 + o(1))\frac{4}{27}n^3$$

¹Aleliunas, Karp, Lipton, Lovász and Rackoff. Random Walks, Universal Traversal Sequences, and the Complexity of Maze Problems. (1979)

Matthews bound for cover time

Hitting time from x to y , $\mathbf{E}_x T_y$, the expected time to reach destination vertex y , from start vertex x

$$T_{cov} \leq H_{\max} \left(1 + \frac{1}{2} + \cdots + \frac{1}{n} \right) = O(H_{\max} \log n)$$

where $H_{\max} = \max \mathbf{E}_x T_y$ is the maximum expected hitting time over all pairs (x, y)

e.g. Complete graph K_n , $H_{\max} = n - 1$, $T_{cov} \sim n \log n$

Geometric waiting time, probability visit y at next step $1/(n - 1)$

Convergence of random walk to stationarity

- ▶ Transition matrix of walk $P = (p_{i,j})$,
where $p_{i,j}$ is probability a walk at vertex i moves to vertex j
- ▶ Assume: **graph connected**, **walk not periodic**

$$P^t \rightarrow \Pi \quad \text{where} \quad \Pi_{i,j} = \pi_j$$

- ▶ For a random walk, stationary distribution

$$\pi_j = \frac{d(j)}{2|E|}$$

- ▶ The rate of convergence of the walk to π is given by

$$|P_u^t(x) - \pi_x| \leq (\pi_x/\pi_u)^{1/2} \lambda_2^t,$$

λ_2 is the second eigenvalue of the transition matrix P

- ▶ Many random graphs are expanders ($0 < \lambda_2 < 1$)
Walk is **Rapidly Mixing**. After $t = O(\log n)$ steps

$$|P_u^{(t)}(v) - \pi_v| \leq n^{-c}$$

Un-visit probability

- ▶ Estimate the **un-visit probability** of states
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- ▶ The expected hitting time of state v from stationarity can be approximated by

$$\mathbf{E}_{\pi} H_v \sim R_v / \pi_v$$

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- ▶ (Informally) Waiting time of first visit to v tends to geometric distn, success probability $p_v \sim \pi_v / R_v$

Estimate of Unvisit Probability

T_{mix} , a suitable mixing time of the walk.

π_v , the stationary distribution of v .

R_v , the expect number of returns to v by the walk in time T_{mix} .

Unvisit Probability

$$\Pr(\mathcal{W}_u(\tau) \neq v : \tau = T_{mix}, \dots, t) \sim e^{-t\pi_v/R_v}$$

True under assumptions that hold for many e.g. random graph models. Asymptotics of generating function

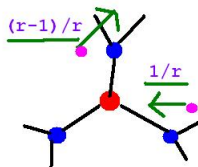
If the walk is rapidly mixing $T_{mix} = O(\log n)$, we can 'ignore' effect of visits during the mixing time when calculating T_{cov}

For random graphs we can estimate R_v from the graph structure for most vertices, (and bound it for all vertices)

Example: r -regular random graphs

How to calculate R_v for random r -regular graphs ?

If v is tree-like (not near any short cycles) then $R_v \sim \frac{r-1}{r-2}$



Same as: biased random walk on the half line $(0, 1, 2, \dots)$

$$\Pr(\text{go left}) = \frac{1}{r}, \quad \Pr(\text{go right}) = \frac{r-1}{r}$$

$$f = \Pr(\text{walk returns to origin}) = \frac{1}{r-1} \quad R_v \sim \frac{1}{1-f} = \frac{r-1}{r-2}$$

Example: r -regular random graphs

- ▶ $\pi_v = 1/n$
- ▶ T_{mix} the mixing time $O(\log n)$
- ▶ Most vertices are locally tree-like
For such vertices $R_v \sim (r-1)/(r-2)$, expected number of returns to start in infinite r -regular tree

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- ▶ Size of set of **unvisited** vertices $\mathcal{R}(t) \sim ne^{-t(r-2)/(r-1)n}$
- ▶ We know the size of $\mathcal{R}(t)$, the **vacant set**
- ▶ We can use this to calculate the cover time T_{cov}

Cover time T_{cov} of random walk on graph G

T_{cov} is the maximum expected time, over all start vertices u , for a random walk \mathcal{W}_u to visit all vertices of G .

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Let $np = c \log n$ and $(c - 1) \log n \rightarrow \infty$ then

$$T_{cov} \sim c \log \left(\frac{c}{c-1} \right) n \log n.$$

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3. Web-graphs $G(m, n)$ where $m \geq 2$

$$T_{cov} \sim \frac{2m}{m-1} n \log n$$

Directed graphs: random digraphs $D_{n,p}$

The main challenge for $D_{n,p}$, was to obtain the stationary distribution

Theorem

Let $np = d \log n$ where $d = d(n)$, and let $m = n(n-1)p$

Let $\gamma = np - \log n$, and assume $\gamma = \omega(\log \log n)$

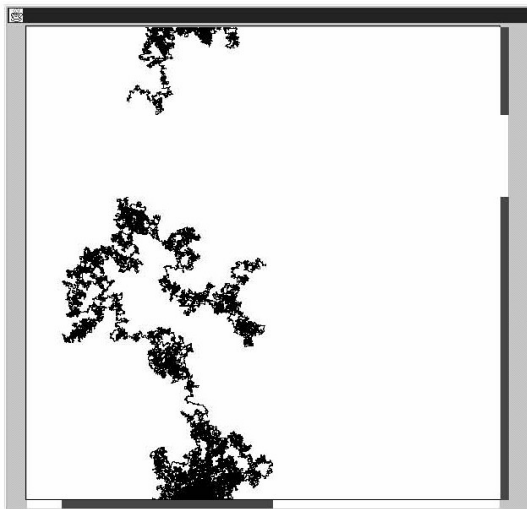
Then **whp**, for all $v \in V$,

$$\pi_v \sim \frac{\deg^-(v)}{m},$$

and

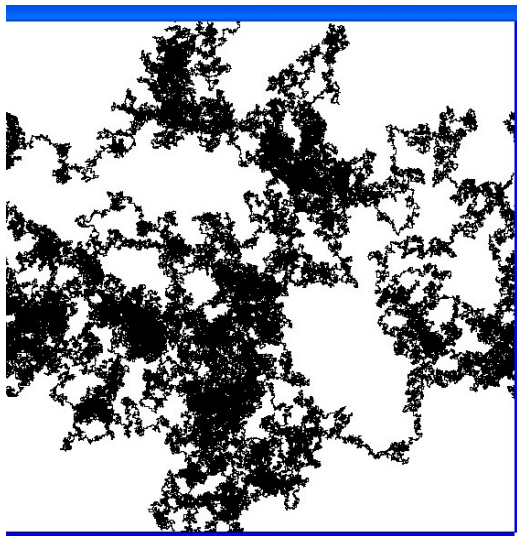
$$T_{\text{cov}} \sim d \log \left(\frac{d}{d-1} \right) n \log n$$

The vacant set of a random walk



Random walk on 600×600 toriodal grid. Black visited, white unvisited.

What is the component structure of vacant set?



Notation

Finite graph $G = (V, E)$.

\mathcal{W}_u Simple random walk on G , starting at $u \in V$

The **vacant set**. Vertices not yet visited by the walk

Can think of vacant set $\mathcal{R}(t)$ as coloured **red**,
and visited vertices $\mathcal{B}(t)$ as colored **blue**

$\mathcal{R}(t)$ Set of vertices not visited by \mathcal{W}_u up to time t

$\Gamma(t)$ Sub-graph of G induced by vacant set $\mathcal{R}(t)$

How large is $\mathcal{R}(t)$?

What is the likely component structure of $\Gamma(t)$?

Evolution of vacant set graph $\Gamma(t)$

It is a sort of random graph process in reverse

As the walk progresses the vacant set $\Gamma(t)$ is reduced from the whole graph G to a graph with no vertices

In the context of sparse random graphs, as the unvisited vertex set $\mathcal{R}(t)$ gets smaller, the edges inside $\Gamma(t)$ will get sparser and sparser.

Small sets of vertices don't induce many edges

One might expect that at some time $\Gamma(t)$ will break up into small components

This is basically what we prove

We say that $\Gamma(t)$ is **sub-critical** at step t , if all of its components are of size $O(\log n)$

We say that $\Gamma(t)$ is **super-critical** at step t , if it has a **unique giant component**, (of size $\Theta(\mathcal{R}(t))$) and all other components are of size $O(\log n)$

In the cases we consider there is a t^* , which is a (**whp**) threshold for transition from super-criticality to sub-criticality

Vacant set of $G_{n,p}$

We assume that

$$p = \frac{c \log n}{n}$$

where $(c - 1) \log n \rightarrow \infty$ with n , and $c = n^{o(1)}$. Let

$$t(\epsilon) = n (\log \log n + (1 + \epsilon) \log c)$$

Theorem

Let $\epsilon > 0$ be a small constant

Then **whp** we have

- (i) $\Gamma(t)$ is super-critical for $t \leq t(-\epsilon)$
- (ii) $\Gamma(t)$ is sub-critical for $t \geq t(\epsilon)$

Giant component of $\mathcal{R}(t)$ until $t > n \log \log n$

For $c > 1$ constant, Cover time T_{cov} of $G_{n,p}$ is $T_{cov} \sim n \log n$

Random graphs $G_{n,r}$

For $r \geq 3$, constant, let

$$t^* = \frac{r(r-1) \log(r-1)}{(r-2)^2} n$$

Theorem

Let $\epsilon > 0$ be a small constant. Then **whp** we have

- (i) $\Gamma(t)$ is super-critical for $t \leq (1 - \epsilon)t^*$
- (ii) For $t \leq (1 - \epsilon)t^*$, size of giant component is $\Omega(n)$
- (iii) $\Gamma(t)$ is sub-critical for $t \geq (1 + \epsilon)t^*$

e.g. for 3-regular random graphs $r = 3$, and $t^* = (6 \log 2) n$

Giant component for about $t^* = (6 \log 2)n$ steps

Cover time $T_{cov} \sim 2n \log n$

Related Work

Benjamini and Sznitman; Windisch:

Considered the d -dimensional toroidal grids $d \geq 5$.

Super-critical below $C_1 n$, sub-critical above $C_2 n$

Černý, Teixeira and Windisch:

Considered random r -regular graphs $G_{n,r}$

They showed sub-criticality for $t \geq (1 + \epsilon)t^*$

and existence of a unique giant component for $t \leq (1 - \epsilon)t^*$

These proofs use the concept of random interacements of continuous time random walks

Our proof: Discrete time

- ▶ Simple. Based on established random graph results
- ▶ Gives results for $G_{n,p}$
- ▶ Completely characterizes the component structure
- ▶ Proves that in the super-critical phase $t \leq t^*$, the second largest component of $G_{n,r}$ has size $O(\log n)$ **whp**
Gives the small tree structure of $\Gamma(t)$

Subsequent Work: Černý, Teixeira and Windisch:

Consider random r -regular graphs $G_{n,r}$

Investigate scaling window around t^* using annealed model

Component structure of vacant set of $G_{n,p}$

Distribution of edges in $\Gamma(t)$

Lemma

Consider a random walk on $G_{n,p}$

Conditional on $N = |\mathcal{R}(t)|$, $\Gamma(t)$ is distributed as $G_{N,p}$.

Proof This follows easily from the principle of deferred decisions. We do not have to expose the existence or absence of edges between the unvisited vertices of $\mathcal{R}(t)$ \square

Thus to find the super-critical/ sub-critical phases, we only need high probability estimates of $|\mathcal{R}(t)|$ as t varies

This, we know how to do, from our work on cover time of random graphs

Size of vacant set $\mathcal{R}(t)$ in $G_{n,p}$

Analysis of $G_{n,p}$ for $p = c \log n/n$

1. $\mathbf{E}(|\mathcal{R}(t)|) \sim \sum_v e^{-t\pi_v/R_v}$

Size of vacant set $\mathcal{R}(t)$ in $G_{n,p}$

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1. $\mathbf{E}(|\mathcal{R}(t)|) \sim \sum_v e^{-t\pi_v/R_v}$
2. Almost all vertices have \sim average degree $np = c \log n$
Thus $\pi_v \sim 1/n$

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Analysis of $G_{n,p}$ for $p = c \log n/n$

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2. Almost all vertices have \sim average degree $np = c \log n$
Thus $\pi_v \sim 1/n$
3. Probability of retracing an edge at next step $1/d(v) = o(1)$
Thus $R_v = 1 + o(1)$ for all $v \in V$
4. Size of vacant set $\mathbf{E}(|\mathcal{R}(t)|) \sim ne^{-(1+o(1))t/n}$.
5. We can use Chebyshev to show that $|\mathcal{R}(t)|$ is concentrated

If $t_\theta = n(\log \log n + (1 + \theta) \log c)$ then

$$\mathbf{E}(|\mathcal{R}(t)|) \sim \frac{n}{c^{1+\theta} \log n} = \frac{1}{c^\theta p}$$

Size of 'giant' component

- ▶ Recall that $np = c \log n$,

If $t_\theta = n(\log \log n + (1 + \theta) \log c)$ then $\mathbf{E}(|\mathcal{R}(t)|) \sim 1/(c^\theta p)$

So, at t_θ ,

$$\mathbf{E}(|\mathcal{R}(t_\theta)|p) \sim \frac{1}{c^\theta}$$

- ▶ Threshold criteria for random graph $G_{N,p}$ is $Np \sim 1$
- ▶ When $\theta = 0$, then $\mathbf{E}(|\mathcal{R}(t_\theta)|p) \sim 1$
- ▶ The threshold t^* occurs at around $\theta = 0$ i.e.

$$t^* \sim n(\log \log n + \log c)$$

- ▶ Size of giant is order $|\mathcal{R}(t_\theta)|$. As $t \rightarrow t^*$ from below, size of 'giant' is order $|\mathcal{R}(t^*)| \sim 1/p = n/(c \log n)$
- ▶ Above t^* max component size collapses to $O(\log n)$

Component structure of
vacant set of random
 r -regular graphs
for $r \geq 3$, constant.

Reminder: Vacant set of r -regular random graphs

▶ $\mathbf{E}(|\mathcal{R}(t)|) \sim \sum_v e^{-t\pi_v/R_v}$

Reminder: Vacant set of r -regular random graphs

- ▶ $\mathbf{E}(|\mathcal{R}(t)|) \sim \sum_v e^{-t\pi_v/R_v}$
- ▶ $\pi_v = 1/n$
- ▶ Most vertices are locally tree-like
For such vertices $R_v \sim (r-1)/(r-2)$,
expected number of returns to start in infinite r -regular tree
- ▶
$$\mathbf{Pr}(v \text{ unvisited in } T_{mix, \dots, t}) \sim e^{-t(r-2)/(r-1)n}$$
- ▶ A similar upper bound can be obtained for the $o(n)$ non-tree-like vertices
- ▶ Size of vacant set $\mathcal{R}(t) \sim ne^{-t(r-2)/(r-1)n}$

Threshold

Let

$$t^* = \frac{r(r-1) \log(r-1)}{(r-2)^2} n.$$

Theorem

Let $\epsilon > 0$ be a small constant. Then **whp** we have

- (i) $\Gamma(t)$ is super-critical for $t \leq (1 - \epsilon)t^*$,
- (ii) For $t \leq (1 - \epsilon)t^*$, size of giant component is $\Omega(n)$
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Proof outline for r -regular random graph

- ▶ Generate the graph in the configuration model using the random walk
- ▶ Graph $\Gamma(t)$ induced by vacant set $\mathcal{R}(t)$ is random
- ▶ Estimate un-visit probability of vertices to find size of $\mathcal{R}(t)$
- ▶ Estimate degree sequence \mathbf{d} of $\Gamma(t)$ in the configuration model, using size of vacant set $\mathcal{R}(t)$, and number of unvisited edges $\mathcal{U}(t)$
- ▶ Given the degree sequence \mathbf{d} of $\Gamma(t)$, we can use Molloy-Reed condition for existence of giant component in a random graph with fixed degree sequence
- ▶ Estimate number of small trees in configuration model

Degree sequence of $\Gamma(t)$

Vacant set size

$$|\mathcal{R}(t)| = (1 + o(1))N_t \text{ where } N_t = ne^{-\frac{(r-2)t}{(r-1)n}}$$

Vertex degree

Let $D_s(t)$ the number of unvisited vertices of $\Gamma(t)$ with $r - s$ visited neighbours and of degree s in $\Gamma(t)$

For $0 \leq s \leq r$, and for ranges of t given below, **whp**

$$D_s(t) \sim N_t \binom{r}{s} p_t^s (1 - p_t)^{r-s}$$

where

$$p_t = e^{-\frac{(r-2)^2 t}{(r-1)r n}}$$

Range of validity is $o(n) \leq t \leq \Theta(n \log n)$

Includes t^*

Uniformity

Lemma

Consider a random walk on G_r . Conditional on $N = |\mathcal{R}(t)|$ and degree sequence $\mathbf{d} = d_{\Gamma(t)}(v)$, $v \in \mathcal{R}(t)$, then $\Gamma(t)$ is distributed as $G_{N,\mathbf{d}}$, the random graph with vertex set $[N]$ and degree sequence \mathbf{d} .

Proof Basic idea: Reveal G_r using the random walk. Suppose that we condition on $\mathcal{R}(t)$ and the *history of the walk*, $\mathcal{H} = (W_u(0), W_u(1), \dots, W_u(t))$. If G_1, G_2 are graphs with vertex set $\mathcal{R}(t)$ and if they have the same degree sequence then substituting G_2 for G_1 will not conflict with \mathcal{H} . Every extension of G_1 is an extension of G_2 and vice-versa. \square

Thus we only need:

Good model of component structure of $G_{N,\mathbf{d}}$

High probability estimates of the degree sequence $D_s(t)$ of $\Gamma(t)$.

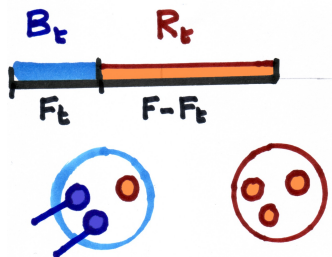
Main variables

By calculating un-visit probabilities in various ways, we can estimate the size at step t of

- ▶ $\mathcal{R}(t)$ the set of **unvisited** vertices
- ▶ $\mathcal{U}(t)$ the set of **unvisited** edges
- ▶ $D_s(t)$ the number of unvisited vertices of degree s in $\Gamma(t)$
ie number of **unvisited vertices** with $r - s$ edges incident
with visited vertices $\mathcal{B}(t)$

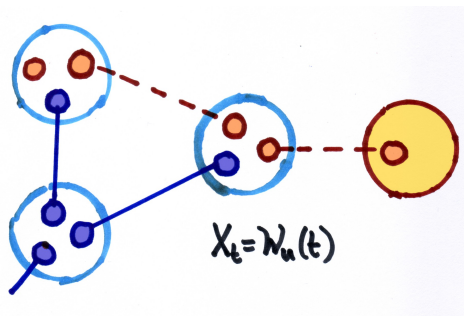
Annealed process

We use the random walk to generate the graph in the configuration model as a random pairing F



- ▶ B_t blue config. points at step t which form discovered pairing F_t
- ▶ R_t red config. points at step t This will form un-generated pairing $F - F_t$
- ▶ Visited vertices may have config. points in R_t , corresponding to **unexplored edges**

Next configuration pairing



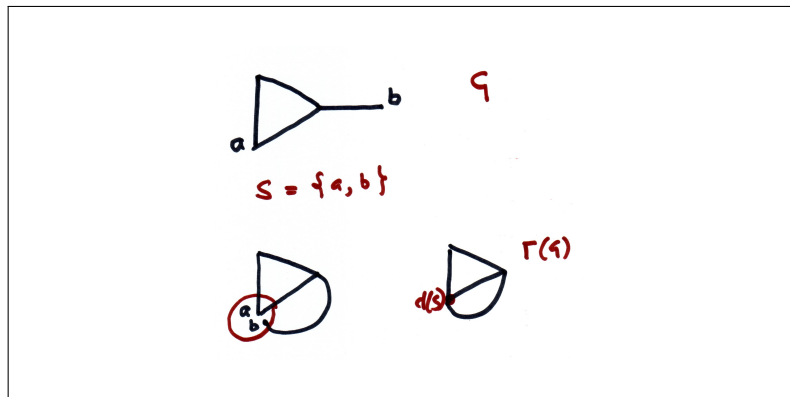
At step t walk located at vertex $X_t \in \mathcal{B}(t)$

Probability walk moves to an unvisited vertex?

Given the walk selects a red config. point of X_t (if any), the probability this is paired with an config. point in $\mathcal{R}(t)$ is

$$\frac{r|\mathcal{R}(t)|}{|R_t| - 1}$$

Shrinking Vertices: First visit to a set of vertices S



S subset of vertices of G

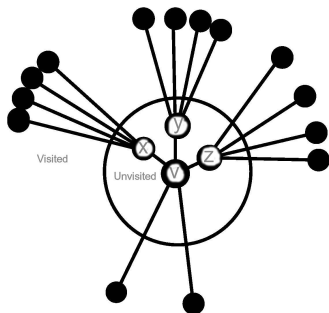
$\gamma(S)$ is S shrunk to a vertex

$H(G)$ is G with S shrunk to $\gamma(S)$

$\Pr_G(S \text{ unvisited at step } t) \sim \Pr_{H(G)}(\gamma(S) \text{ unvisited at step } t)$

Degree of unvisited vertex

Vertex v has 3 unvisited neighbours x, y, z and 2 visited neighbours a, b , so $s = 3$, $r - s = 2$



Calculate probability that exactly $\{v, x, y, z\}$ are unvisited, and a, b visited from probability that $\{v, x, y, z\}$ are unvisited, $\{v, x, y, z, a\}$ are unvisited etc. Contract e.g. $\{v, x, y, z\}$ to a single vertex γ of degree 20 with 3 loops

The degree sequence of $\mathcal{R}(t)$

To analyse the degree sequence of $\Gamma(t)$ we prove

Lemma

If the neighbours of v in G are w_1, w_2, \dots, w_r then

$$\begin{aligned} \Pr(v, w_1, \dots, w_s \in \mathcal{R}_t, w_{s+1}, \dots, w_r \in \mathcal{B}(t)) \\ \sim e^{-\frac{(r-2)t}{(r-1)n}} p_t^s (1 - p_t)^{r-s} \end{aligned}$$

where $p_t = e^{-\frac{t(r-2)^2}{n(r-1)r}}$

We write

$$\begin{aligned} & \Pr_{\mathcal{W}}(\{v, w_1, \dots, w_s\} \subseteq \mathcal{R}(t) \text{ and } \{w_{s+1}, \dots, w_r\} \subseteq \mathcal{B}(t)) \\ &= \sum_{X \subseteq [s+1, r]} (-1)^{|X|} \Pr_{\mathcal{W}}(\{v, w_1, \dots, w_s\} \cup X \subseteq \mathcal{R}(t)) \\ &\sim \sum_{X \subseteq [s+1, r]} (-1)^{|X|} e^{-tp_{\gamma_X}}, \end{aligned}$$

where

$$p_{\gamma_X} \sim \frac{((r-2)(s+|X|)+r)(r-2)}{r(r-1)n}.$$

To prove this we contract $\{v, w_1, \dots, w_s\} \cup X$ to a single vertex γ_X creating $\Gamma_X(t)$.

We then estimate the probability that γ_X hasn't been visited by a random walk on $\Gamma_X(t)$. (**Unvisit probability**)

For this we argue that $|\{v, w_1, \dots, w_s\} \cup X| = s + |X| + 1$

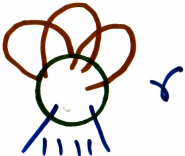
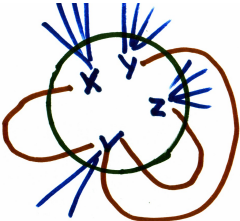
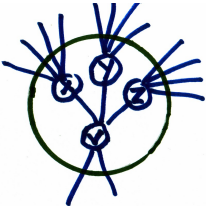
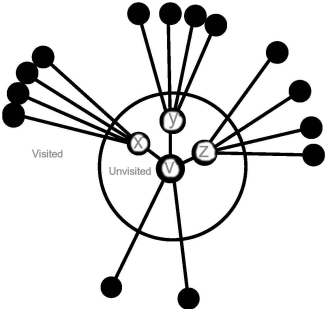
$$\pi_{\gamma_X} = \frac{r(s + |X| + 1)}{rn}$$

and

$$R_{\gamma_X} \sim \frac{(s + |X| + 1)r(r - 1)}{((r - 2)(s + |X|) + r)(r - 2)}$$

Expression for R_{γ_X} is obtained by considering the expected number of returns to the origin in an infinite tree with branching factor $r - 1$ at each non-root vertex. At the root there are $s + |X|$ loops and $(r - 2)(s + |X|) + r$ branching edges..

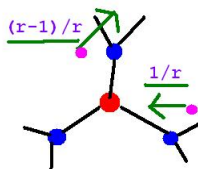
Example



Reminder, R_v for random r -regular graphs

A transition on the loops returns to γ_x immediately, and a transition on any other edge is (usually) like a walk in a tree

If v is tree-like (not near any short cycles) then $R_v \sim \frac{r-1}{r-2}$



Same as: random walk on the line $(0, 1, 2, \dots)$

$$\Pr(\text{go left}) = \frac{1}{r}, \quad \Pr(\text{go right}) = \frac{r-1}{r}$$

Molloy-Reed Condition

Theorem

Let $\lambda_0, \lambda_1, \dots, \lambda_r \in [0, 1]$ be such that $\lambda_0 + \lambda_1 + \dots + \lambda_r = 1$.

Suppose that $\mathbf{d} = (d_1, d_2, \dots, d_N)$ satisfies

$|\{j : d_j = s\}| = (1 + o(1))\lambda_s N$ for $s = 0, 1, \dots, r$.

Let $G_{n, \mathbf{d}}$ be chosen randomly from graphs with vertex set $[N]$ and degree sequence \mathbf{d} . Let

$$L = \sum_{s=0}^r s(s-2)\lambda_s.$$

- (a) If $L < 0$ then **whp** $G_{n, \mathbf{d}}$ is sub-critical.
- (b) If $L > 0$ then **whp** $G_{n, \mathbf{d}}$ is super-critical.

Furthermore the unique giant component has size βn where β is the solution to an equation derived from the degree sequence

Threshold for collapse of giant component

Degree sequence of $\Gamma(t)$ is (approximately) binomial $Bin(r, p_t)$

where $p_t = e^{-\frac{t(r-2)^2}{n(r-1)r}}$

Once we know the degree sequence we can use the Molloy-Reed criterion to see whether or not there is a giant component. G has a giant component iff $L > 0$, where

$$L = \sum_v d_v(d_v - 2).$$

Direct calculation gives $t^* = \frac{r(r-1)\log(r-1)}{(r-2)^2} n$ as the critical value

Heuristically, $t^* = \frac{r(r-1)\log(r-1)}{(r-2)^2}n$ can be obtained from the degree sequence of unvisited vertices

Branching outward from an unvisited vertex

The probability an edge goes to another unvisited vertex:

$$p_t = e^{-\frac{(r-2)^2 t}{(r-1)m}}$$

We need branching factor $(r-1)p_t > 1$, to have a chance to get a large component

At $t^* = \frac{r(r-1)\log(r-1)}{(r-2)^2}n$

$$\begin{aligned}(r-1)p_t &= (r-1)e^{-\frac{(r-2)^2 t}{(r-1)m}} \\ &= (r-1)e^{-\log(r-1)} \\ &= 1\end{aligned}$$

Enumerating tree components

These are small subgraphs of the underlying graph

How to count subgraphs of a given graph?

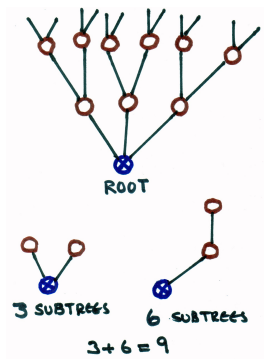
Rooted subtrees of the infinite r -regular tree

How to count subgraphs of a given graph?

Number of rooted k -subtrees of the infinite r -regular tree

$$\frac{r}{((r-2)k+2)} \binom{(r-1)k}{k-1}$$

Example $r = 3, ; k = 3$



Number of small components in $\Gamma(t)$

$N_t = \mathbf{E}|\mathcal{R}(t)|$. Expected size of vacant set

p_t probability of a red edge

$N(k, t)$: Number of **unvisited tree components** of $\Gamma(t)$ with k vertices

Theorem

Let ϵ be a small positive constant. Let $1 \leq k \leq \epsilon \log n$ and $\epsilon n \leq t \leq (1 - \epsilon)t_{k-1}$. Then **whp**:

$$N(k, t) \sim \frac{r}{k((r-2)k+2)} \binom{(r-1)k}{k-1} N_t p_t^{k-1} (1-p_t)^{k(r-2)+2}$$

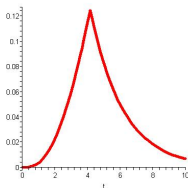
Vertices on small components of vacant set

Let

$$t^* = n \frac{r(r-1)}{(r-2)^2} \log(r-1).$$

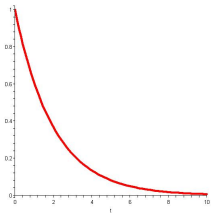
Theorem

Let $\mu(t)$ be the expected proportion of vertices on small trees
The function $\mu(t)$ increases from 0 at $t = 0$,
to a maximum value $\mu^* = 1/(r-1)^{r/(r-2)}$ as $t \rightarrow t^*$,
and decreases to 0 as $t \rightarrow (r-1)/(r-2) n \log n$

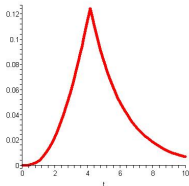


Example: $r = 3$. Vacant set as a function of $\tau = t/n$

Proportion of vertices in vacant set $N(t)/n \sim e^{-t/n((r-2)/(r-1))}$

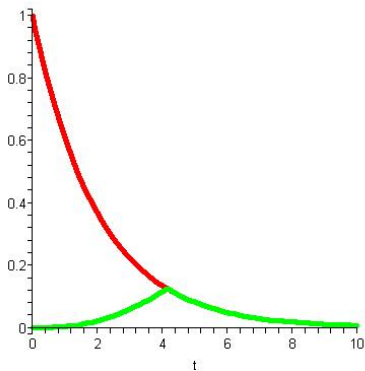


Proportion of vertices in unvisited tree components



Threshold: $r = 3$, $t^* = 6 \log 2$

$$t^* = \frac{r(r-1) \log(r-1)}{(r-2)^2} n$$



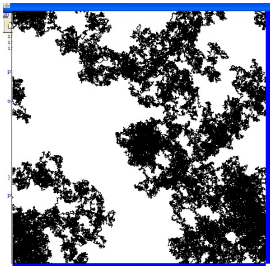
Propn. of vertices in vacant set, and on small tree components

Closing observations

- ▶ Random graphs $G(n, p)$ and random r -regular graphs exhibit threshold behavior
- ▶ The size of the giant component can be estimated in the super-critical range
- ▶ The number of small tree components of a given size can be estimated

- ▶ The technique can be applied to other problems e.g.
- ▶ Vacant net: sub-graph induced by the unvisited edges
- ▶ Upper bounds on sub-critical threshold for hypercube, high degree grids,...

THANK YOU



QUESTIONS