

Random Graphs and Hypergraphs

Based on the course *Random Graphs and Hypergraphs* (049014) by Omer Bobrowski, Technion, 2021.

The main source for the course is *Introduction to Random Graphs* by Frieze & Karonski.

The summary covers the first 8 weeks of the course, focusing on random graphs under the simple model of edges drawn independently according to *Bernoulli*(p). The (un-summarized) rest of the course focused on random *hypergraphs* (i.e. with hyper-edges, which can connect more than 2 nodes together).

Summarized by Ido Greenberg in 2021.

Contents

Introduction	2
Basic tools	2
Random graph process & thresholds.....	3
Vertex degrees	3
Connectivity	4
Local limits	4
Cycles	5
Other topics	6

Notations:

- $G = (V, E)$, $e_G = |E|$, $e_v = |V|$
- $[n] = \{1, \dots, n\}$
- $a_n \ll b_n \Leftrightarrow a_n = o(b_n)$, $\gg \Leftrightarrow \omega$, $\sim \Leftrightarrow \Theta$, $\approx \Leftrightarrow a_n/b_n \rightarrow 1$
- w.h.p = with high probability (asymptotically)

Introduction

1. Default scope: undirected & unweighted graphs.
2. **Random graphs models:**
 - a. $G \sim G(n, p)$: n vertices; edges randomly placed independently w.p. p .
 - i. Ignores structures in the graph (e.g. if $(x,y), (y,z)$ are edges, it often should increase the probability of the edge (x,z)).
 - ii. Probability of a specific graph is $P(G) = p^{|E|}(1-p)^{N-|E|}$ ($N := \binom{n}{2}$).
 - b. $G \sim G(n, M)$: M random edges (equivalently: $G(n, p)$ conditioned on $|E| = M$).
 - i. Asymptotically equivalent to $G(n, p)$ with $p = M/N$.
 - c. $G \sim G(n, d)$ – **random d -regular graph**: uniform dist. over n -sized d -regular graphs.
 - d. $G \sim G(n, r)$ – **geometric rand. graph**: nodes are i.i.d in $[0,1]^d$, connected if distance $\leq r$.
 - e. **Preferential attachment** model: generate by induction – iteratively add a new node and connect it to existing nodes with probabilities proportional to their current degrees.
 - i. Respects the structure of Hubs (well-connected nodes get more new edges).
3. The course focuses on the simple $G(n, p)$, despite its lack of structure.
4. Applications examples:
 - a. Network analysis, e.g. epidemic spread.
 - b. The probabilistic methods: proving existence of objects based on their probability (in a suitable probabilistic model) being positive. For example: existence of certain colorings in graphs.
5. **Extended graph models:**
 - a. **Hypergraph**: $E \subset 2^V$ rather than V^2 (*hyper-edges* are subsets of nodes rather than pairs).
 - i. **Simplicial Complex**: hypergraph that is closed to inclusion, i.e. $\forall e \in E$, all the subsets of e are also in E .
 - b. Applications examples:
 - i. High-dimensional networks (connections are more general than pairs).
 - ii. Triangulation – connections come in triplets.

Basic tools

6. Some bounds:
 - a. $1 + x \leq e^x$
 - b. $(1 - \epsilon)^n \approx e^{-\epsilon n}$ ($\epsilon \rightarrow 0, n\epsilon^2 \rightarrow 0$)
 - c. $\binom{n}{k} \approx \frac{n^k}{k!}$ ($k = o(\sqrt{n})$)
 - d. $\binom{n}{k} \leq \left(\frac{en}{k}\right)^k$
7. Probabilistic tools:
 - a. **Markov inequality** (1st moment argument): $X \geq 0 \Rightarrow P(X \geq a) \leq \mu/a$
 - i. For integer X and $a := 1$: $P(X > 0) \leq \mu$
 - b. **Chebyshev inequality** (2nd moment argument): $\forall a > 0: P(|X - \mu| \geq a) \leq \sigma^2/a^2$
 - i. Private case for $X \geq 0$: $P(X = 0) \leq \frac{\sigma^2}{\mu^2}$
 - c. $\text{Binom}(n, \gamma/n) \rightarrow^D \text{Poisson}(\gamma)$ (convergence in distribution).
8. **Method of Moments**: $[\forall k: EX_n^k \rightarrow EX^k] \Rightarrow [X_n \rightarrow^D X]$ (assuming all moments are finite).

9. **Factorial moment:** $E((S_n)_k) := E[S_n(S_n - 1) \dots (S_n - k + 1)]$
 a. $E((S_n)_k) \rightarrow \lambda^k \Rightarrow S_n \rightarrow^D \text{Poisson}(\lambda)$.

Random graph process & thresholds

10. **Random graph process:** $T_1 \dots T_N \sim \text{unif}[0,1]$ i.i.d ($N := \binom{n}{2}$). $\mathbf{E}_t := \{e \in [N] : T_e \leq t\}$.
 a. Adding edges as t increases; $\forall t \in [0,1] : G_t \sim G(n, t)$.
11. A set A of graphs is **monotone increasing** if $G \in A \Rightarrow G + \{e\} \in A$ (adding edges keeps us in the set; e.g. "all graphs with min degree 5"). A is also termed *property*.
 a. **Monotone decreasing** is defined similarly.
 b. Claim: A is increasing & $t_1 < t_2 \Rightarrow P_{t_1}(A) \leq P_{t_2}(A)$. (since $G_{t_1} \subset G_{t_2}$)
12. $p^*(n)$ is a **threshold** for A if: $\lim_n P_t(A) = \begin{cases} 0 & \text{if } t \ll p^* \\ 1 & \text{if } t \gg p^* \end{cases}$
 a. A **sharp threshold:** $\lim_n P_t(A) = \begin{cases} 0 & \text{if } t \leq (1 - \epsilon)p^* \\ 1 & \text{if } t \geq (1 + \epsilon)p^* \end{cases}$
 b. Intuition: a threshold on p beyond which, the RG suddenly satisfies A 's condition.
 c. Example: $A = \{\text{graphs with at least one edge}\} \Rightarrow \#\text{edges} \sim \text{Binom}\left(\binom{n}{2}, p\right) \Rightarrow P(\text{no edges}) \approx (1 - p)^{n^2/2} \approx e^{-pn^2/2} \Rightarrow p^* = n^{-2}$ is a threshold.
 d. Example: $A = \{\text{graphs with isolated node}\}$ (decreasing) $\Rightarrow p^* = \frac{\log n}{n}$ (sharp thresh).
13. **Theorem: every nontrivial monotone increasing property ($\phi \notin A$) has a threshold.**
 a. Proof: $P_p(A)$ increases polynomially in p from 0 to 1, so $\exists p^* : P_{p^*}(A) = 0.5$, and we can show that it satisfies the threshold property.
 b. **Kalai & Friedgut:** (almost) every nontrivial A has a **sharp threshold**.

Vertex degrees

14. Denote $X_d :=$ number of vertices with degree d .
15. Example – **non-isolated nodes (X_0):**
 a. $E[X_0] = \sum_{v \in V} (1 - p)^{n-1} = n(1 - p)^{n-1} \approx ne^{-np}$.
 b. **Theorem:**
 i. $np = \log n - \omega(n) \Rightarrow \frac{X_0 - EX_0}{\sqrt{\text{Var}(X_0)}} \rightarrow^D N(0,1)$
 ii. $np = \log n + c \Rightarrow X_0 \rightarrow^D \text{Poisson}(e^{-c})$
 iii. $np = \log n + \omega(n) \Rightarrow X_0 \rightarrow^D 0$
 c. Proof relies on Stein's method (i), method of moments (ii), and Markov inequality (iii).
16. While $X_0(p)$ decreases with p from n to 0, $X_d(p)$ isn't monotone, since $X_d(0) = X_d(1) \approx 0$.
17. **Behavior of X_d :** $E[X_d] = n \binom{n-1}{d} (1-p)^{n-d-1} p^d \approx \frac{n(np)^d}{d!} e^{-np}$. In particular:
 a. $np \ll n^{-1/d} \Rightarrow EX_d \rightarrow 0, X_d \rightarrow 0$
 b. $np = cn^{-1/d} \Rightarrow EX_d \rightarrow \frac{c^d}{d!}, X_d \rightarrow \text{Poisson}$
 c. $n^{-1/d} \ll np \leq \log n + d \log^2 n + \omega(n) \Rightarrow EX_d \rightarrow \infty, \frac{X_d - EX_d}{\sqrt{\text{Var}(X_d)}} \rightarrow N(0,1)$
 d. $np = \log n + d \log^2 n + c \Rightarrow EX_d \rightarrow \frac{e^{-c}}{d!}, X_d \rightarrow \text{Poisson}$
 e. $np = \log n + d \log^2 n + \omega(n) \Rightarrow EX_d \rightarrow 0, X_d \rightarrow 0$ ($\log^2 = \log \log$)

18. **Min/max degree** $(\delta(G), \Delta(G))$:a. Note: $E[d_v] = (n-1)p \approx np$.

b. Theorem:

i. $np = c \in (0, \infty) \rightarrow \Delta(G) \approx \log n / \log^2 n$ ii. $np \gg \log n \rightarrow \delta(G) \approx \Delta(G) \approx np$

1. The proof uses Chernoff inequality.

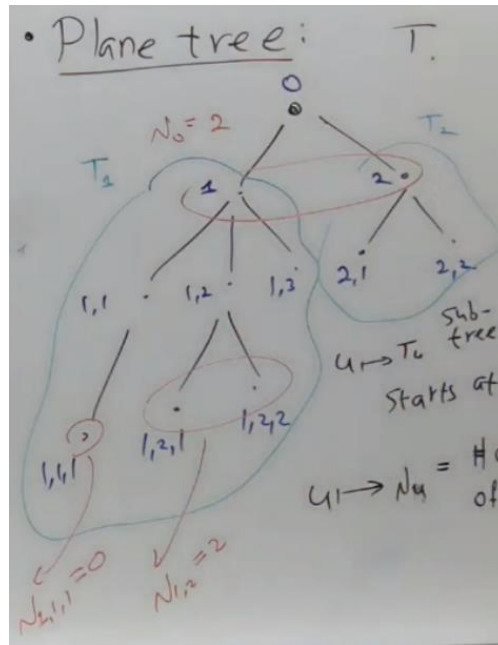
2. Convergence in probability: $\frac{\delta(G)}{np}, \frac{\Delta(G)}{np} \xrightarrow{P} 1$

Connectivity

19. What is the smallest p s.t. $G(n, p)$ is connected?a. If $np = \log n - \omega(n)$ then $X_0 > 0$ w.h.p $\rightarrow \exists$ isolated nodes \rightarrow disconnected.i. Otherwise \rightarrow no isolated nodes. Non-trivially, in this case we also have connectivity w.h.p. That is, dis-connectivity comes only from isolated nodes.20. **Theorem (Erdos & Renyi, 1959):** $\lim_n P(\text{connected}) = \begin{cases} 1 & np = \log n + \omega(n) \\ e^{-e^{-c}} & np = \log n + c \\ 0 & np = \log n - \omega(n) \end{cases}$ a. Also if $np = \log n + c$: $n_{\text{components}} \approx 1 + X_0 \rightarrow \text{Poisson}(e^{-c})$ (i.e. 1 large component + X_0 isolated nodes).b. The proof uses Cayley's formula for the number of spanning trees on k nodes (k^{k-2}), and calculates the probability of each spanning tree (which is essentially a connected graph).21. **Theorem – connected component size:** for $np = c \in (0, \infty)$ (i.e. the “disconnected limit”):a. If $c < 1$: all connected components are of size $O(\log n)$.b. If $c = 1$: largest component is $\approx n^{2/3}$.c. If $c > 1$: \exists a component of $\approx \left(1 - \frac{x^*}{c}\right)n$ nodes, and the other components are $O(\log n)$.i. $xe^{-x} = ce^{-c}$ has one solution $x = c$ and one $x < 1$. x^* is the smaller solution.ii. The proof shows that w.h.p, no components exist of size $[a \log n, bn]$; and that only $\frac{x^*}{c}n$ nodes reside on smaller components; thus all the other nodes are in larger components.iii. Then the proof shows that this “giant” component is unique. Note that if $bn > 0.5n$, the uniqueness is trivial since there are only n nodes. In general, we can assume multiple giant components at $c_1 = c - \epsilon > 1$, and show that when adding components to move from c_1 to c , then w.h.p we connect all the giant components together.

Local limits

22. What do we see when we explore a random graph – from an arbitrary node v , up to a distance r ?23. **Pointed graph:** (G, v^*) (for some $v^* \in V$); **Neighborhood** $[(G, v^*)]_r$: all nodes of distance $\leq r$ from v^* , along with the edges that connect them to v^* .24. **Plane tree:** labeling the nodes, subtrees & neighborhoods in a tree according to the corresponding paths from the root.



- a. **Galton-Watson Tree**: a plane tree with a distribution $\pi = (\pi_0, \pi_1, \dots)$, s.t. for each node in the tree, its number of children is drawn according to π . It is required that $\sum_{i=1}^{\infty} \pi_i = 1$ and $\pi_1 \leq 1$ ($\pi_1 = 1$ is the trivial case of an infinite path graph).
 - b. **Theorem – finiteness of GW trees**: let $T \sim GW_{\pi}$, and denote $z_0 := \min\{z \mid \sum_{k=0}^{\infty} \pi_k z^k = z\} \leq 1$. Then $P(|T| < \infty) = z_0$ and $[z_0 < 1 \Leftrightarrow E[\pi] = \sum_{k=0}^{\infty} k \pi_k > 1]$.
 - i. The last claim relies on a straightforward function exploration of $\sum_{k=0}^{\infty} \pi_k z^k - z$.
25. **Graph isomorphism $G_1 \cong G_2$** : a bijection (one-to-one & onto) $f: V_1 \rightarrow V_2$ with $(u, v) \in E_1 \Leftrightarrow (f(u), f(v)) \in E_2$. That’s essentially a relabeling of the nodes.
- a. **Pointed-graph isomorphism**: also require $f(v_1^*) = v_2^*$.
26. **Theorem – local limit of a pointed graph**: let $G \sim G(n, p)$ with $np = c$. Then the r -neighborhood satisfies $[(G, v^*)]_r \xrightarrow{n \rightarrow \infty} GW_{\pi}$, where $\pi = Poisson(c)$.
- a. Note that $E[\pi] = c \leq 1$, thus $P(|T| < \infty) = 1$ and $[(G, v^*)]_r$ is indeed finite.
 - b. The formal way to phrase the limit is through graph isomorphism – for $T \sim GW_{\pi}$ and $T^* = (T, u^*)$: $\forall t \in \mathbf{trees}: P([(G, v^*)]_r \cong t) = P([T^*] \cong t)$.
 - c. Conclusion: w.h.p, $[(G, v^*)]_r$ is a tree ($\sum_{t \in \mathbf{trees}} P([(G, v^*)]_r \cong t) \rightarrow 1$).

Cycles

27. Let G and denote by γ_k the **number of Hamiltonian cycles** of size k within G .
- a. Note: a Hamiltonian cycle forbids repetition of nodes, i.e. $|E| = |V| = k$.
 - b. Example: in the clique K_n , there are $\binom{n}{k}$ subsets of k nodes, each with $k!$ different cycles up to 2 reflections and k cyclic shifts, thus $\gamma_k = \binom{n}{k} (k-1)!/2$.
28. **Theorem**: let $G \sim G(n, p)$ with $np = c$. Then $\gamma_k \xrightarrow{n \rightarrow \infty} Poisson(c^k/2k)$ in distribution.
- a. **Total cycles**: $\Gamma := \sum_{k=3}^n \gamma_k$.
 - i. Claim: $E[\Gamma] \xrightarrow{n \rightarrow \infty} \Lambda_c := \frac{1}{2} \left(\log \frac{1}{1-c} - c - c^2/2 \right)$ (assuming $c < 1$).
 - ii. In fact, $\Gamma \rightarrow Poisson(\Lambda_c)$ (was not proved).

29. **Theorem (Erdos-Renyi, 1960) – probability of having no cycles:** let $G \sim G(n, p)$ with $np = c$. Then

$$\lim_{n \rightarrow \infty} P(G \text{ is acyclic}) = \begin{cases} \sqrt{1 - ce^{\frac{c}{2} + \frac{c^2}{4}}} & c < 1, \\ 0 & c \geq 1 \end{cases}$$

30. **Theorem (Hamiltonian cycle of size $k = n$):** let $G \sim G(n, p)$, $np = \log n + \log^2 n + c(n)$. Then

$$\lim_{n \rightarrow \infty} P(\gamma_n = 1) = \lim_{n \rightarrow \infty} P(\delta(G) \geq 2) = \begin{cases} 1 & c(n) \rightarrow \infty \\ e^{-e^{-c}} & c(n) \rightarrow c \in (0, \infty). \\ 0 & c(n) \rightarrow -\infty \end{cases}$$

- Note that necessarily $\gamma_n \in \{0, 1\}$, and that $\gamma_n = 1$ requires connectivity (hence $np \geq \log n$) and min degree $\delta \geq 2$.
- The ranges don't cover the whole R – possibly a mistake.
- Only the first case ($c(n) \rightarrow \infty$) was proven.

Other topics

31. **Diameter** = longest distance in the graph.

32. **Claims:**

- $np \gg \log n \rightarrow \text{diam}(G) \approx \log n / \log np$.
- $np = [n \log n^2 - \log c]^{1/d} \rightarrow \text{diam}(G)$ decreases with c from $d + 1$ to d .

33. **Independent set:** a subset of nodes that contains no edges. $\alpha(G) := |\text{largest independent set}|$.

34. **Claim:** $np = c \cdot n \rightarrow \alpha(G) \approx 2 \log_{1/(1-p)} n$.

- Chromatic number** ($\chi(G)$): minimal number of colors that allows coloring s.t. neighbors always have different colors.
- Corollary:** $\chi(G) \approx \frac{n}{2 \log_{1/(1-p)} n}$.