# Random graphs and networks

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February 26, 2019

## The Erdős-Rényi random graph

Def  $[n] := \{1, \ldots, n\}$ . Def  $K_n$  complete graph: vertex set [n], edge set  $\{\{s,t\} : s,t \in [n], s \neq t\}$ . Notation  $st = ts = \{s,t\}$ . Def  $\operatorname{ER}_n(p)$  Erdős-Rényi random graph with vertex set [n], random edge set: edges i.i.d. present with edge probability p. Def  $s \leftrightarrow t$  if s, t connected in  $\operatorname{ER}_n(p)$ .

 $\mathcal{C}(v) := \{ x \in [n] : v \leftrightarrow x \} \text{ connected component containing } v.$ 

Def  $C_{\max}$  largest connected component Set  $\lambda := pn$ . Let  $n \to \infty$  for fixed  $\lambda$ . Theorems 4.4 & 4.5 say that for  $\lambda < 1$ 

$$\mathbb{P}\big[(\kappa_{\lambda} - \varepsilon)\log(n) \le |\mathcal{C}_{\max}| \le (\kappa_{\lambda} + \varepsilon)\log(n)\big] \xrightarrow[n \to \infty]{} 1 \qquad \forall \varepsilon > 0,$$

with  $\kappa_{\lambda} := (\lambda - 1 - \log(\lambda))^{-1}$ . Theorem 4.8 says that for  $\lambda > 1$ 

$$\mathbb{P}[\zeta_{\lambda}n - n^{\nu} \le |\mathcal{C}_{\max}| \le \zeta_{\lambda}n + n^{\nu}] \xrightarrow[n \to \infty]{} 1 \qquad \forall \nu \in (\frac{1}{2}, 1),$$

for some  $0 < \zeta_{\lambda} < 1$ .

### Generalized Random Graphs

Edges independent but not identically distributed. Vertex *i* has weight  $w_i > 0$ . Graph  $\operatorname{GRG}_n(w)$ . Edge *ij* present with probab.  $p_{ij} := \frac{w_i w_j}{w_i w_j + \sum_k w_k}$ . Def  $W_n$  weight of unif chosen random vertex. Assume  $\exists W$  s.t.

- $\mathbb{P}[W_n \in \cdot] \Longrightarrow_{n \to \infty} \mathbb{P}[W \in \cdot],$
- $\mathbb{E}[W_n] \xrightarrow[n \to \infty]{} \mathbb{E}[W],$
- $\mathbb{E}[W_n^2] \xrightarrow[n \to \infty]{} \mathbb{E}[W^2].$

Typical choice

$$\mathbb{P}[W > x] \sim \operatorname{cst} \cdot x^{1-\tau}$$

Degree  $D_n$  of unif chosen random vertex has <u>mixed Poisson distribution</u>. (Compared to Pois( $\lambda$ ) for Erdős-Rényi.)

# The Configuration Model

In  $CM_n(d)$ , the degrees  $d_1, \ldots, d_n$  are given. Assume  $\sum_{i \in [n]} \overline{d_i}$  even.

- $\forall i$ , draw  $d_i$  half-edges out of i.
- Enumerate the half edges.
- Pair the first half edge to a unif chosen free partner.
- Continue till no half-edges left.

Result: <u>multigraph</u>: may contain <u>multiple edges</u> and <u>loops</u>.

In the Erased Configuration Model, all loops are erased, all multiple edges reduced to a single edge.

Assume  $\exists D \text{ s.t.}$ 

- $\mathbb{P}[D_n \in \cdot] \Longrightarrow_{n \to \infty} \mathbb{P}[D \in \cdot],$
- $\mathbb{E}[D_n] \xrightarrow[n \to \infty]{} \mathbb{E}[D],$
- $\mathbb{E}[D_n^2] \xrightarrow[n \to \infty]{} \mathbb{E}[D^2].$

Typical choice

$$\mathbb{P}[D=k] \sim \operatorname{cst} \cdot k^{-\tau}.$$

Recall  $\tau = 2.2, = 2.1$  observed in real networks.

If we choose  $\tau \in (1,2)$ , then after erasing multiple edges and loops  $\tau = 2$  (Theorem 7.24).

If we choose  $\tau > 2$ , then only few multiple edges and loops.

#### **Preferential Attachment Models**

Grow a multigraph with n vertices as follows. Fix  $\delta \ge -1$ . Let  $D_i(t) :=$  degree of i = 1, 2, ... at time t = 0, 1, 2, ... $D_1(0) := 1$  (half-edge) and  $D_i(0) := 0 \ \forall i \ge 2$ . Inductively for t = 0, 1, ...:

- Connect the half edge at t+1 to random  $i \in [t+1]$  chosen with probab. proportional to  $D_i(t) + \delta$  (weight of vertex).
- Add a half-edge to t + 2.

Sum of degrees  $\sum_{i=1}^{\infty} D_i(t) = 2t + 1.$ Sum of weights  $\sum_{i=1}^{\infty} (D_i(t) + \delta) = 2t + 1 + \delta(t+1).$ Probability to attach to  $i \in [t+1]$ 

$$\frac{D_i(t) + \delta}{2t + 1 + \delta(t+1)}.$$

More generally, fix m = 1, 2, ... and  $\delta \ge -m$ . For t = 0, 1, ...

For  $k = 0, 1, \dots, m - 1$ 

- Connect the half edge at t+1 to random  $i \in [t+1]$  chosen with probab. proportional to  $D_i(tm+k) + \delta/m$  (weight of vertex).
- If k < m 1, add another half-edge to t + 1.
- If k = m 1, add a half-edge to t + 2.

end end

Observation: model with  $\delta \ge -m$  and  $m \ge 2$  can be obtained from model with  $\delta' := \delta/m$  and m' := 1 by merging vertices in groups of m. Claim Choose I unif from [t + 1]. Then

$$\mathbb{P}\big[D_I \in \,\cdot\,\big] \underset{t \to \infty}{\Longrightarrow} \mathbb{P}\big[D \in \,\cdot\,\big]$$

for a r.v. D s.t.

$$\mathbb{P}[D=k] \sim \operatorname{cst} \cdot k^{-\tau}$$

with  $\tau = 3 + \delta/m$ .

# Levels of randomness

Let  $G_n(w)$  be a <u>deterministic</u> graph with vertex set [n] and vertex weights  $(w_i)_{i \in [n]}$ .

Then the empirical weight distribution and empirical distribution function

$$\mu_n := \frac{1}{n} \sum_{i=1}^n \delta_{w_i} \quad F_n(x) := \frac{1}{n} \sum_{i=1}^n \mathbf{1}_{\{w_i \le x\}}$$

are deterministic objects.

Let I(n) be uniformly distributed in [n]. Then

$$F_n(x) = \mathbb{P}[W_{I(n)} \le x]$$

Our assumption that  $\mathbb{P}[W_{I(n)} \in \cdot] \underset{n \to \infty}{\Longrightarrow} \mathbb{P}[W \in \cdot]$  for some W is equivalent to

 $F_n(x) \xrightarrow[n \to \infty]{} F(x)$  in all continuity points of F,

with  $F(x) := \mathbb{P}[W \le x]$ .

Let  $(w_i)_{i \in [n]}$  be i.i.d. with law  $\mu$ .

These define a  $\underline{\mathrm{random}}$  weighted graph with

$$F_n(x) \xrightarrow[n \to \infty]{p} F(x)$$
 in all continuity points of  $F$ ,

where  $\xrightarrow{\mathbf{p}}$  denotes convergence in probability. Let I(n) be uniformly distributed in [n] independent of  $(w_i)_{i \in [n]}$ . Then

 $\mathbb{P}\big[\big|\mathbb{P}[W_{I_n} \le x \,|\, (w_i)_{i \in [n]}] - F(x)\big| \ge \varepsilon\big] \underset{n \to \infty}{\longrightarrow} 0 \quad \text{in all continuity points of } F.$ 

Note two levels of randomness.

<u>Conditional</u> on  $(w_i)_{i \in [n]}$ , construct  $\operatorname{GRG}_n(w)$  with: edge ij present with probab.  $p_{ij} := \frac{w_i w_j}{w_i w_j + \sum_k w_k}$ . Now <u>three levels of randomness</u>:  $(w_i)_{i \in [n]}$ , the edges, and  $I_n$ . Similarly, construct configuration model with random degrees

- 1. Choose  $(d_i)_{i \in [n]}$  i.i.d. with law  $\mathbb{P}[D \in \cdot]$ .
- 2. Conditional on  $(d_i)_{i \in [n]}$ , randomly pair up half-edges.
- 3. Independently of  $(d_i)_{i \in [n]}$  AND the edges, choose uniform random vertex  $I_n \in [n]$ .

# Local limits

Let  $G_n$  be deterministic graphs with vertex set [n]. Let  $I_n$  uniformly distributed on [n]. Look at:

- $I_n$
- all neighbors of  $I_n$ .
- all neighbors of neighbors of  $I_n$ .
- etc.

Example The configuration model with  $d_i = 3$  for all i (and n even).

- $I_n$  has 3 neighbors.
- each neighbor of  $I_n$  has 3 neighbors.
- etc.

Moreover, for large n,

- $\mathbb{P}[I_n \text{ part of a triangle}] \xrightarrow[n \to \infty]{} 0.$
- $\mathbb{P}[I_n \text{ part of a cycle of length } 4] \xrightarrow[n \to \infty]{} 0.$
- $\mathbb{P}[I_n \text{ part of a cycle of length } k] \xrightarrow[n \to \infty]{} 0 \quad \forall k.$

The  $CM_n(d)$  locally looks like a 3-regular tree.

Example In the Erdős-Rényi random graph  $\text{ER}_n(\lambda/n)$ ,

- $I_n$  has  $\text{Pois}(\lambda)$  neighbors.
- each neighbor of  $I_n$  has  $Pois(\lambda)$  <u>further</u> neighbors.

 $\operatorname{ER}_n(\lambda/n)$  locally looks like a branching process with  $\operatorname{Pois}(\overline{\lambda})$  offspring distribution.