

# Random Graphs and Networks - 3<sup>rd</sup> LECTURE

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Recall: IRG is  $G(m, K)$  is s.t.

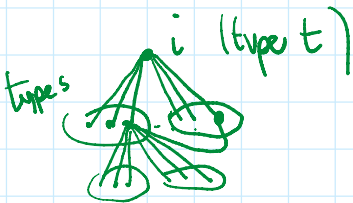
$$P(e=(i,j) \text{ is in } G(m, K)) = p(t(i), t(j)), \text{ indep. } \forall i, j \in [m], \text{ where } t: [m] \rightarrow T \text{ (type set)}$$

$$\bullet P(s, t) = \frac{K(s, t)}{m}$$

$$\text{Then, } \forall i \in [m] : d_{G(m, K)}(i) \stackrel{d}{\approx} \sum_{s \in T} \text{Poi}(\lambda(t, s))$$

s.t.  $t(i) = t$

$$\text{where } \lambda(t, s) = K(t, s) \cdot \mu(s)$$

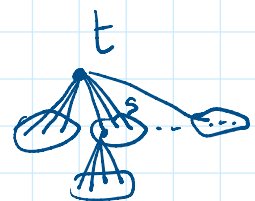


→ Multi-type BP with Poisson offspring distribution

$$\bullet \text{ Let } \Lambda = (\lambda(s, t))_{s, t \in T}$$

Assume that  $\text{Poi}(\lambda(s, t)) =$  law of the number of offsprings of type  $t$  generating from a vertex of type  $s$

independently for all vertices and types



## A. Extinction and survival probabilities

$$\bullet \text{ In the above setting, let } \nu = \sup_{x: |x| \leq 1} |\Lambda x|$$

• In the above setting, let  $V = \sup_{\underline{x}: |\underline{x}|=1} |\Lambda \underline{x}|$

(that is  $V$  is the maximal eigenvalue of  $\Lambda$ )

### Theorem [survival/extinction probabilities]

1.  $\underline{q}_n \neq \underline{0} \iff V > 1$ . Hence

• if  $V \leq 1 \implies$  the BP dies out with prob. 1

• if  $V > 1 \implies$  the BP survives with prob.  $q_n = \sum_{t \in T} q_n^{(t)}$

2.  $\underline{q}_n$  is the largest sol. of  $\underline{q}_n = \underline{1} - \underline{G}(\underline{1} - \underline{q}_n)$

(or equiv. if  $\underline{p}_n = \underline{1} - \underline{q}_n$  then  $\underline{p}_n = \underline{G}(\underline{p}_n)$ )

and explicitly:  $\underline{q}_n = \underline{1} - e^{-\Lambda \underline{q}_n}$ .

### B. Results

1. local structure: The IRG  $G(n, K)$  converges locally

in probability to a multi-type BP such that:

• the root has type  $t \in T$  with prob.  $\mu(t)$

• every vertex of type  $t \in T$  has type  $s$ -offspring distribution

$\text{Poi}(\lambda(t, s))$ , indep. for all  $s$ , where

$$\lambda(t, s) = K(t, s) \cdot \mu(s)$$

2. Phase transition: let  $\Lambda = (\lambda(s, t))_{s, t \in T}$  s.t.

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$$\therefore \text{if } \nu = \sup_{x: |x| \leq 1} |\lambda(x)| > 1$$

$$\text{if } \frac{|C_{\max}|}{n} \xrightarrow[n \rightarrow \infty]{\mathbb{P}} C_1, \quad \frac{|C_2|}{n} \xrightarrow[n \rightarrow \infty]{\mathbb{P}} 0$$

$$\text{ii: if } \nu \leq 1 \Rightarrow \frac{|C_{\max}|}{n} \xrightarrow[n \rightarrow \infty]{\mathbb{P}} 0$$

3. Small-world property: If  $\nu > 1$  then, conditionally on the event that  $U_1 \leftrightarrow U_2$ , where  $U_1, U_2$  are indep. Uniform  $[n]$ , it holds

$$\frac{\text{dist}_{G(n, \lambda)}(U_1, U_2)}{\log n} \xrightarrow[n \rightarrow \infty]{\mathbb{P}} \frac{1}{\log \nu}$$

**C.** A sub-family of IRG: Generalized Random Graphs (GRG)

- The connection probabilities  $P_{i,j}$ , for  $i, j \in [n]$  are moderated by vertex weights

Def: Let  $\underline{w} = (w_i)_{i \in [n]}$  vertex weight  $\stackrel{?}{\circ}$  assigned to every vertex of  $[n]$ .

Then,  $\forall i \neq j \in [n]$ , independently, set

$$P_{i,j} = \frac{w_i \cdot w_j}{L_n + w_i \cdot w_j}, \quad L_n = \sum_{j \in [n]} w_j$$

The resulting graph is called GRG and denoted by  $G(n, \underline{w})$  with law  $\mathbb{P}_{n, \underline{w}}$ .

with law  $\mathbb{P}_{m, \underline{w}}$ .

### Comments:

- We may assume that  $w_i > 0$  (otherwise  $i$  is isolated)
- The weights  $\underline{w} = (w_i)_{i \in \mathbb{N}}$  may be deterministic or random: e.g. taken to be iid r.v.  $(w_i)_{i \in \mathbb{N}} \rightarrow$  double source of randomness.
- Notice that if  $w_i = c \ \forall i \in \mathbb{N}$ , then we obtain ER random graph (Specifically  $\sim G(m, \frac{c}{m+c})$ )
- There are different choices of  $P_{ij} = \phi(\underline{w})$   
[Chung-Lo model, Norros-Perttinen model]
- Let  $T = [0, 1]$  set of types and assign to each vertex  $i \in [m]$  the type  $t_m(i) = \frac{i}{m} \in T, \ \forall m \in \mathbb{N}$

$$\text{Then set } K\left(\frac{i}{m}, \frac{j}{m}\right) = w_i \cdot w_j \cdot \frac{m}{ln}$$

$$\text{and } P_{ij} = \frac{K\left(\frac{i}{m}, \frac{j}{m}\right)}{m + K\left(\frac{i}{m}, \frac{j}{m}\right)}$$

- For given  $i \in [m]$ :

$$\begin{aligned} \mathbb{E}_{m, \underline{w}}(d_G(i)) &= \mathbb{E}_{m, \underline{w}}\left(\sum_{j \in [m]} \mathbb{1}_{\{i \sim j\}}\right) \\ &= \sum_{j \in [m]} \frac{w_i \cdot w_j}{ln + w_i \cdot w_j} \approx \frac{w_i}{ln} \sum_{j \in [m]} w_j = \boxed{w_i} \end{aligned}$$

## Assumptions on weights

Let  $W_m := w_U$ , where  $U \sim \text{Uniform}[m]$

a.  $\exists W^{(2.o.)}$  st.  $\boxed{W_m \xrightarrow{d} W}$

Equiv:  $P(W_m \leq x) = \frac{1}{m} \sum_{j \in [m]} \mathbb{1}_{\{w_j \leq x\}} \rightarrow P(W \leq x)$

empirical weight distribution

$\forall x \in \mathbb{R}$

(or convergence in probability)

$\hookrightarrow$  If  $\underline{w} = (w_i)_{i \in \mathbb{N}}$  iid 2.o., it is immediately verified by

LLN with  $W \stackrel{d}{=} w_i$

b.  $\boxed{E(W_m) \xrightarrow{m \rightarrow \infty} E(W)} < \infty$

$\hookrightarrow$  if  $\underline{w} = (w_i)_{i \in \mathbb{N}}$  iid 2.o., then  $E(W_m) = h(\underline{w})$  is a 2.o., and the convergence in b. is replaced by

$$E(W_m) \xrightarrow{P, m \rightarrow \infty} E(W)$$

Remark: under this assumption we can deduce that

$$E_{n, \underline{w}}[|E(G)|] \approx E(W) \cdot \frac{n}{2} \rightarrow \text{sparse regime}$$

Theorem 1: Under conditions a. and b.:

1.  $d_{G(n, W)}(U) \xrightarrow{m \rightarrow \infty} D$ , where  $D$  has mixed Poisson dist.:

$$P(D=k) = E\left[\frac{W^k}{k!} e^{-W}\right], \text{ where } W \text{ is as in a., b.}$$

As a consequence if  $W$  is st.

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$$(H) \quad P(W \geq x) \simeq c \cdot x^{-(\tau-1)} \quad \text{as } x \rightarrow \infty$$

$$\Rightarrow \underline{P(D \geq x)} \simeq \underline{P(W \geq x)} \simeq \underline{c \cdot x^{-(\tau-1)}} \quad \left[ \begin{array}{l} \text{scale-free} \\ \text{property} \end{array} \right]$$

2. If  $\nu := \frac{E(W^2)}{E(W)} > 1$  (also  $\infty$ ), then in  $G(n, \underline{w})$

$$\frac{|C_{\max}|}{n} \xrightarrow[n \rightarrow \infty]{\mathbb{P}} C_{\underline{w}}, \quad \frac{|C_2|}{n} \xrightarrow[n \rightarrow \infty]{\mathbb{P}} 0 \quad \left[ \begin{array}{l} \text{high connectivity} \\ \downarrow \\ \text{Phase transition} \end{array} \right]$$

$$\text{while if } \nu \leq 1 \Rightarrow \frac{|C_{\max}|}{n} \xrightarrow[n \rightarrow \infty]{\mathbb{P}} 0$$

3. If  $\nu > 1$  then, conditionally on the event that  $U_1 \leftrightarrow U_2$ , where  $U_1, U_2$  indep. Uniform  $[n]$ ,

$$\text{dist}_{G(n, \underline{w})}(U_1, U_2) \xrightarrow[n \rightarrow \infty]{\mathbb{P}} \frac{1}{\log \nu} \quad \left[ \begin{array}{l} \text{small world} \\ \text{property} \end{array} \right]$$

Remark: If  $\nu = \infty$  (which happens if  $E(W^2) = \infty$ ),

$$\text{result 3. reads as } \frac{\text{dist}_{G(n, \underline{w})}(U_1, U_2)}{\log n} \xrightarrow{\mathbb{P}} 0$$

This suggests on ultra-small world behavior, that indeed can be proved under hypothesis (H) with  $\tau \in (2, 3)$  so that

$$\frac{\text{dist}_{G(n, \underline{w})}(U_1, U_2)}{\log \log n} \xrightarrow{\mathbb{P}} \frac{2}{|\log(\tau-2)|}$$

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