

Goal: consider general random graph models and be able to model scale-free property

→ The simplest way to generalize  $G(n, p)$  is to consider edge-connectivities that are independent but not identical:  $(P_e)_{e \in E_n}$  so that,  $\forall e \in E_n$

$$X_e(G) = \begin{cases} 1 & \text{if } e \in G \\ 0 & \text{if } e \notin G \end{cases} \Rightarrow X_e \sim B_e(P_e)$$

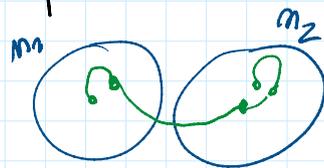
and  $(X_e)_{e \in E_n}$  are all independent.

→ This leads to the definition of Inhomogeneous RG

### Inhomogeneous Random Graph

**A.** Motivating example: 2-type random graph

- We divide the vertex-set  $[n]$  in 2 groups:
  - group of type 1 of size  $m_1$
  - group of type 2 of size  $m_2$



→ We assign a probability connection to an edge  $(i, j)$  depending on the type of  $i$  and of  $j$ . Hence

$$t: [n] \rightarrow \{1, 2\} \quad \text{and set } \boxed{P(i, j) = P(t(i), t(j))}$$

$i \rightarrow t(i) = \text{type}(i)$

This is represented by a  $2 \times 2$  symmetric matrix:

$$\begin{pmatrix} P(1,1) & P(1,2) \\ P(1,2) & P(2,2) \end{pmatrix} \rightarrow \text{connection with stochastic block model}$$

This model is specified by

This model is specified by:

- The sizes  $m_1$  and  $m_2$  of the two groups, that should increase with  $n$  to avoid triviality. Equivalently, we consider a probability density  $\mu: \{1, 2\} \rightarrow [0, 1]$  s.t.

$$m_1 = \mu(1) \cdot m \quad \text{and} \quad m_2 = \mu(2) \cdot m$$

- A  $2 \times 2$  symmetric matrix providing the edge-connectivities as function of types.

Comment: Inspired by ER random graph, we mainly deal with edges connectivities:

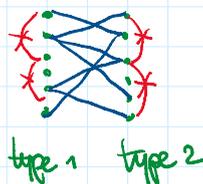
$$s, t \in \{1, 2\} \quad P(s, t) = \frac{K(s, t)}{m} \quad (\text{sparse regime})$$

So some matrix  $K = (K(s, t))_{s, t \in \{1, 2\}}$  symmetric, non-negative (irreducible, bounded).

Examples:

$$1. \quad K = \begin{pmatrix} \lambda & \lambda \\ \lambda & \lambda \end{pmatrix} \Rightarrow G(m, \frac{\lambda}{m})$$

$$2. \quad K = \begin{pmatrix} 0 & \lambda \\ \lambda & 0 \end{pmatrix} \Rightarrow \text{Bipartite random graph}$$



Consider the degree of a vertex:

- let  $j \in [m]$  s.t.  $t(j) = 1$ . Then

$$d(j) = \sum_{k \in [m]} \mathbb{1}_{\{k \sim j\}} = \underbrace{\sum_{\substack{k: \\ t(k)=1}}^{m_1} \mathbb{1}_{\{k \sim j\}}}_{\text{Be}(P(m))} + \underbrace{\sum_{\substack{k: \\ t(k)=2}}^{m_2} \mathbb{1}_{\{k \sim j\}}}_{\text{Be}(P(1,2))}$$

by independence

by independence of edges  $\rightarrow$

$$\stackrel{K \in [m]}{\text{Be}(P(n))} \stackrel{t(n)=1}{\text{Be}(P(n))} \stackrel{t(n)=2}{\text{Be}(P(1,2))}$$

$$\stackrel{d}{=} \text{Bin}( \mu(1) \cdot m, \frac{K(1,1)}{m} ) + \text{Bin}( \mu(2) \cdot m, \frac{K(1,2)}{m} ) \quad (\text{indep.})$$

$$\approx \text{Poi}( \mu(1) \cdot K(1,1) ) + \text{Poi}( \mu(2) \cdot K(1,2) )$$

### B. Definition of IRG

- Let  $T = \text{set of types}$  and  $\mu$  a probability measure on  $T$ , so that  $\mu(t) \cdot m = \#\{\text{vertices of type } t\}$ .

Hyp: to simplify the discussion we assume  $|T| < \infty$ , though in general it may be  $|T| = \infty$  (countable or more)

- Let  $K = (K(st))_{s,t \in T}$  a symmetric, non-negative matrix (irreducible, bounded), called kernel, s.t.  $\forall i, j \in [m]$

$$P(i, j) = P(t(i), t(j)) = \frac{K(t(i), t(j))}{m}$$

where  $t: [m] \rightarrow T$

The resulting graph is denoted  $G(m, K)$ , and it has law denoted by  $P_{m, K}$ .

### C. Vertex-degree sequence of $G(m, K)$

- Let  $j \in [m]$  s.t.  $t(j) = t \in T$

$$d(j) = \sum_{i \in [m]} \mathbb{1}_{\{i \sim j\}} = \sum_{s \in T} \sum_{\substack{i \in [m]: \\ t(i) = s}} \mathbb{1}_{\{i \sim j\}}$$

stays for  $d_{\text{in}}(j)$

$$d \sim \text{Bin}( m \cdot \mu(s), \frac{K(s, t)}{m} ) \approx \text{Poi}( \sum_{s \in T} \mu(s) K(s, t) ) = \text{Poi}( h(t) )$$

shows for  $d_{G(m,K)}(t)$

$$\stackrel{t(i)=s}{=} \sum_{s \in T} \text{Bin} \left( m \cdot \mu(s), \frac{K(s,t)}{m} \right) \approx \text{Poi} \left( \underbrace{\sum_{s \in T} \mu(s) K(s,t)}_{\substack{K \cdot \mu(t) \\ \stackrel{\mu(t,s)}{=} \lambda(t)}} \right) = \text{Poi}(\lambda(t))$$

• Let  $U \sim \text{Uniform}[m]$  and consider  $d(U)$

$$P(d(U)=k) = \frac{1}{m} \sum_{i \in [m]} \mathbb{1}(d(i)=k) = \sum_{t \in T} \sum_{\substack{i \in [m]: \\ t(i)=t}} \frac{\mathbb{1}\{d(i)=k\}}{m}$$

empirical distr. of a vertex degree

Averaging w.r.t.  $P_{m,K}$ , we get:

$$\begin{aligned} P_{m,K}(d(U)=k) &= \sum_{t \in T} \sum_{\substack{i \in [m] \\ t(i)=t}} \frac{P_{m,K}(d(i)=k)}{m} \\ &= \sum_{t \in T} \sum_{\substack{i \in [m] \\ t(i)=t}} \frac{1}{m} \frac{\lambda(t)^k}{k!} e^{-\lambda(t)} = \\ &= \sum_{t \in T} \mu(t) \cdot \frac{\lambda(t)^k}{k!} e^{-\lambda(t)} \end{aligned}$$

called mixed Poisson distribution

In short:  $d_{G(m,K)}(U) \stackrel{d}{\approx} \text{Poi}(Z)$  st.  $Z$  is random:  
 $P(Z = \lambda(t)) = \mu(t)$

Consequence:

1° FACT: It is possible to consider kernel  $K$  st.

$$P_{m,K}(d(U) > k) \approx P(Z > k)$$

where  $P(Z = \lambda(t)) = \mu(t)$  and  $\lambda = K \cdot \mu$

2° FACT: It is possible to prepare  $\lambda$  (and hence  $K$ ) so that  
 $P(Z > k) \sim c \cdot k^{-(\tau-1)} \quad \text{as } k \rightarrow \infty$

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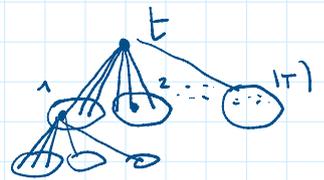
$\rightarrow P_{m|k}(\mathcal{L}(U) > k) \sim c \cdot k^{-(\tau-1)} \rightarrow$  scale-free behavior

## D. Multi-type branching processes

- Assign to each individual a type  $t \in T$
- Provide a branching rule that depends on the type (of parent and child)

1. Start with 1 individual of given type  $t \in T$

2. Let  $\underline{j} = (j_1, \dots, j_{|T|}) \in \mathbb{N}_0^{|T|}$  and consider the joint offspring density



$$P_{\underline{j}}^{(t)} = \mathbb{P} \left( \begin{array}{l} \text{a vertex of type } t \text{ gives rise} \\ \text{to offspring } \underline{j}: j_1 \text{ of type } 1, \dots \\ \dots \\ j_{|T|} \text{ of type } |T| \end{array} \right), \quad \forall t \in T, \forall \underline{j} \in \mathbb{N}_0^{|T|}$$

Assume that each individual of type  $t$ , indep. of the others, produce offsprings of given type according to  $P_{\underline{j}}^{(t)}$ .

We will focus on the case in which:

$$P_{\underline{j}}^{(t)} = \prod_{s \in T} P_{j_s}^{(t,s)}, \quad \text{where } \left( P_{j_s}^{(t,s)} \right)_{j_s \in \mathbb{N}_0} \leftrightarrow \text{Poi}(\lambda(t,s))$$

Notation:  $\forall s, t \in T$

•  $Z_{m,s}^{(t)} := \#$  vertices in generation  $m$  of type  $s$  and parent  $t$

•  $\underline{Z}_m^{(t)} = (Z_{m,s}^{(t)})_{s \in T}$

•  $\zeta^{(t)} := \mathbb{P}(\underline{Z}_m^{(t)} \neq \underline{0}, \forall m \in \mathbb{N})$

- $\mathcal{G}^{(t)} := \mathbb{P}(\underline{Z}_m^{(t)} \neq \underline{0}, \forall m \in \mathbb{N})$

and let  $\underline{G} = (G^{(t)})_{t \in T}$

- $G^{(t)} : [0, 1]^{|T|} \rightarrow \mathbb{R}$  s.t

$$G^{(t)}(\underline{q}) = \sum_{\underline{j} \in \mathbb{N}_0^{|T|}} P_{\underline{j}}^{(t)} \cdot \prod_{s \in T} q_s^{j_s}$$

Notice that if  $(P_{\underline{j}_s}^{(t,s)})_{\underline{j}_s \in \mathbb{N}_0} \leftrightarrow \text{Poi}(\lambda(t,s))$ , then

$$\begin{aligned} G^{(t)}(\underline{q}) &= \mathbb{E} \left( \prod_{s \in T} q_s^{Z_{1s}^{(t)}} \right) = e^{\sum_{s \in T} \lambda(t,s) (q_s - 1)} \\ &= e^{\Lambda(\underline{q} - \underline{1})(t)} \end{aligned}$$

where  $\Lambda = (\lambda(s,t))_{s,t \in T}$ .