Apparition de la composante géante pour un hypergraphe aléatoire

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Outline

Giant component for random graphs

G(n, p)
 G(n, (d_i)ⁿ₁)

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- Hypergraphs
- Random hypergraphs
- Branching process approximation

3 Giant component for random hypergraphs

- Result
- Exploring process
- Differential equation approximation for Markov chains

G(n, p) $G(n, (d_i)_1^n)$

Erdős-Rényi graphs

[Erdős and Rényi, *On the evolution of random graphs*, Publ. Math. Inst. Hungar. Acad. Sci., 1960]

- Model : G(n,p) with $p = \frac{c}{n}$ $C_1(n) =$ largest connected component of $G\left(n, \frac{c}{n}\right)$
- Sub-critical phase : $c \leq 1$ (no giant component)

 $|C_1(n)| = o_p(n)$

• Super-critical phase : c > 1 (giant component of order n)

$$\exists \rho > 0, |C_1(n)| = \rho n + o_p(n)$$

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G(n, p) $G(n, (d_i)_1^n)$

Graphs with given degree sequence $(d_i)_1^n$

[Molloy and Reed, A critical point for random graphs with a given degree sequence, Rand. Struct. Alg., 1995]

- Model :
 - For each $n \in \mathbb{N}$, $(d_i)_1^n$ sequence of non-negative integers such that there exists a graph with degree sequence $(d_i)_1^n$
 - G(n, (d_i)ⁿ₁) random graph with degree sequence (d_i)ⁿ₁, uniformly chosen among all possibilities
- Conditions :

 $\exists (p_k)_{k=1}^{\infty}$ probability distribution such that :

(i)
$$\sharp\{i: d_i = k\}/n \rightarrow p_k \text{ as } n \rightarrow \infty$$
, for every $k \ge 0$
(ii) $\sum_k kp_k \in (0; \infty)$
(iii) $p_1 > 0$

(iv)
$$\sum_i d_i^2 = O(n)$$

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G(n, p) $G(n, (d_i)_1^n)$

Graphs with given degree sequence $(d_i)_1^n$

 $D\sim (p_k)_{k=1}^\infty$ $C_1(n)=$ largest connected component of $G\left(n,(d_i)_1^n
ight)$

- Theorem :
 - Sub-critical phase : E [D(D − 1)] ≤ E [D] (no giant component)

$$|C_1(n)| \underset{n\to\infty}{=} o_p(n)$$

 Super-critical phase : E [D(D − 1)] > E [D] (giant component of order n)

$$\exists \rho > 0, |C_1(n)| = \rho n + o_p(n)$$

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Hypergraph : definition

- V and E finite sets
- $\mathsf{Hypergraph}: \gamma \subset \mathit{V} \times \mathit{E}$



Degree of a vertex v = its number of edges

Weight of a hyper-edge e = its number of edges

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Hypergraphs Random hypergraphs Branching process approximation

• Degree and weight functions :

$$\mathbf{d} : \left\{ \begin{array}{ll} V & \to & \mathbb{N} \\ v & \mapsto & \mathbf{d}(v) = \text{degree of } v \end{array} \right.$$
$$\mathbf{w} : \left\{ \begin{array}{ll} E & \to & \mathbb{N} \\ e & \mapsto & \mathbf{w}(e) = \text{weight of } e \end{array} \right.$$

• Degree and weight frequency vectors :

 $\mathbf{p} = (p_1, ..., p_L) : p_d =$ number of vertices of degree d $\mathbf{q} = (q_1, ..., q_L) : q_w =$ number of hyper-edges of weight w

Correspondence

$$\begin{aligned} \mathbf{p} &= (|\mathbf{d}^{-1}(\{1\})|, ..., |\mathbf{d}^{-1}(\{L\})|) = \mathbf{n}(\mathbf{d}) \\ \mathbf{q} &= (|\mathbf{w}^{-1}(\{1\})|, ..., |\mathbf{w}^{-1}(\{L\})|) = \mathbf{n}(\mathbf{w}) \end{aligned}$$

Hypergraphs Random hypergraphs Branching process approximation



$$\mathbf{p} = (2, 2, 1, 0)$$

 $\mathbf{q} = (1, 2, 0, 1)$

$$m = \sum_{d=1}^{L} dp_d = \sum_{w=1}^{L} wq_w$$
 (number of edges)

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Hypergraphs Random hypergraphs Branching process approximation

Random hypergraphs

- $\mathbf{p} = (p_1, ..., p_L)$ and $\mathbf{q} = (q_1, ..., q_L)$ fixed vectors such that $\sum_{d=1}^{L} dp_d = \sum_{w=1}^{L} wq_w = m$
- Choose V, E finite sets, d degree function and w weight function such that $\mathbf{n}(\mathbf{d}) = N\mathbf{p}$ and $\mathbf{n}(\mathbf{w}) = N\mathbf{q}$, for $N \in \mathbb{N}^*$
- $G(\mathbf{d}, \mathbf{w}) = \text{set of all hypergraphs on } V \times E$ with degree function \mathbf{d} and weight function \mathbf{w}
- Γ random hypergraph taken uniformly at random in $G(\mathbf{d}, \mathbf{w})$ ($\Gamma \sim U(\mathbf{d}, \mathbf{w})$)
- Number of edges = Nm, number of vertices = $N||p||_1$, number of hyper-edges = $N||q||_1$



Hypergraphs Random hypergraphs Branching process approximation

Size of the largest component when $N \rightarrow \infty$?

Connected component of a given vertex :



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EXPLORATION ALGORITHM



Need to explore a proportion α of the vertices

Branching process approximation : a way to guess the result

 $\mathsf{\Gamma} \thicksim U(\mathsf{d}, \mathbf{w})$ converges locally, when $\mathit{N} \rightarrow \infty$, to a tree

Corresponding random tree :

- Alternating one : generation of nodes of type V / generation of nodes of type E
- Except root, each node of type V has d-1 offsprings with probability $\frac{dp_d}{m}$
- Each of type E has w 1 offsprings with probability $\frac{wq_w}{m}$



Algorithm on the tree

- Step 0 : Let $\alpha > 0$ and turn each vertex into alive with probability α
- Step 1a : turn into alive all individuals of type *E* having some alive vertex as an offspring
- Step 1b : turn into alive all individuals of type V having some alive hyper-edge as an offspring
- Repeat step 1 infinitely often



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How to guess the result

Definitions

$$s_0 = g_0 = 1$$

 $s_n = \mathbb{P}(\text{after } n \text{ steps, a hyper-edge } e \text{ is not alive})$

 $g_{n+1} = \mathbb{P}(\text{after } n \text{ steps, a vertex } v \text{ is not alive})$

$$s_n = \sum_{w} \frac{wq_w}{m} (g_n)^{w-1}$$

=: $\sigma(g_n)$
$$g_{n+1} = (1-\alpha) \sum_{d} \frac{dp_d}{m} (s_n)^{d-1}$$

=: $\phi_{\alpha}(g_n)$

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How to guess the result

 φ_α maps continuously [0, 1] to [0, 1) and is increasing, so (g_n)_{n≥0} converges to

$$z_{\alpha}^{*} = \text{largest root of } \phi_{\alpha}(z) = z \text{ in } [0,1)$$

• Proportion of alive vertices :

$$P(\alpha) = 1 - (1 - \alpha) \sum_{d} \frac{p_d}{\|p\|_1} \left(\sigma(z_{\alpha}^*)\right)^d$$

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Hypergraphs Random hypergraphs Branching process approximation

Two different behaviours



Coupechoux - Lelarge Giant component for random hypergraphs

Hypergraphs Random hypergraphs Branching process approximation

• D random variable such that $\mathbb{P}(D=d) \propto p_d$

$$\phi_D(z) = \sum_{d=1}^L \frac{p_d}{\|p\|_1} z^d$$

• W random variable such that $\mathbb{P}(W=w) \propto q_w$

$$\phi_W(z) = \sum_{w=1}^L \frac{q_w}{\|q\|_1} z^w$$

$$f_lpha(z) = z - (1-lpha) rac{1}{\mathbb{E}\left[D
ight]} \phi_D' \left(rac{1}{\mathbb{E}\left[W
ight]} \phi_W'(z)
ight)$$

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When $N \to \infty$, is there a giant component of order N?

- $C_1(N) = \text{largest connected component of } \Gamma \sim U(\mathbf{d}, \mathbf{w})$
- D random variable such that $\mathbb{P}(D=d) \propto p_d$
- W random variable such that $\mathbb{P}(W=w) \propto q_w$

Theorem

Case (i) If
$$\mathbb{E}[D(D-1)] \mathbb{E}[W(W-1)] \leq \mathbb{E}[D] \mathbb{E}[W]$$

then for each $\epsilon > 0$, $\mathbb{P}\left(\frac{|C_1(N)|}{N} > \epsilon\right) \xrightarrow[N \to \infty]{} 0$
(there is no giant component)
Case (ii) If $\mathbb{E}[D(D-1)] \mathbb{E}[W(W-1)] > \mathbb{E}[D] \mathbb{E}[W]$
then, there exists $\lambda > 0$ such that, for each $\epsilon > 0$
 $\mathbb{P}\left(\left|\frac{|C_1(N)|}{N} - \lambda\right| > \epsilon\right) \xrightarrow[N \to \infty]{} 0$
(there exists a giant component of order N)

Exploring process

- Exploring the component of a given vertex
- Active vertices = those we want to explore the component
- $\alpha >$ 0 : activate each vertex independently with proba α
- 3 types of vertices : sleeping, alive, dead
 - **sleeping** = we haven't explored it
 - alive = we must explore it
 - **dead** = we have explored it

Exploring process : algorithm

- Initially, label active vertices as alive, and non-active ones as sleeping
- 2 While there is a vertex that is alive do
- Schoose a vertex v uniformly at random among all alive vertices
- Solution For all hyper-edges e that contains v but no dead vertex do
- Second For all sleeping vertices *u* connected with *e* do
 - Label *u* as alive
- 2 Label v as dead

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Jumping chain

• Sequence of random hypergraphs

•
$$\Gamma_0 = \Gamma \sim U(\mathbf{d}, \mathbf{w})$$

- $\Gamma_n = \Gamma_{n-1} \setminus \{ \text{dead vertex and its hyper-edges} \}$
- $\mathbf{D}_n, \mathbf{W}_n = \text{degree and weight functions of } \Gamma_n$
- Conditionally on the past, $\Gamma_n \sim U(\mathbf{D}_n, \mathbf{W}_n)$

Markov chain

 $\begin{cases} \xi_n^{d,d',0} = \text{ nb of non active vertices with current degree d and initial degree d'} \\ \xi_n^{d,d',1} = \text{ nb of active vertices with current degree d and initial degree d'} \\ \xi_n^w = \text{ nb of hyper-edges with current weight w} \end{cases}$

•
$$\xi_n = \left(\xi_n^{d,d',k}, \xi_n^w : 0 \le d \le d', \ k \in \{0,1\}, \ 0 \le w\right)$$

• $(\xi_n)_{n\geq 0}$ is a Markov chain

Differential equation approximation

- (X_t) continuous-time Markov chain with jump chain (ξ_n)
- Coordinate functions :

$$Y_t = \left(\frac{X_t^{d,d,0}}{N}, \frac{X_t^w}{N} : 1 \le d \le L, 1 \le w \le L\right)$$

- Estimation of the generator
- Differential equation approximation :

$$\begin{cases} x_t^w = e^{-tw}q_w \\ x_t^{d,d,0} = \sigma(e^{-t})^d (1-\alpha)p_d \end{cases}$$

Terminal values

Proportion of dead vertices

• End of the algorithm

 $\iff \text{number of edges connected with alive vertices} = 0 \\ \iff \sum_{w} w x_t^w - \sum_{d} dx_t^{d,d,0} = 0 \\ \iff f_{\alpha}(e^{-t}) = 0$

• Proportion of dead vertices :

$$P(\alpha) = 1 - \frac{|\{\text{remained vertices}\}|}{|\{\text{initial vertices}\}|} \\ = 1 - \frac{1}{\|p\|_1} \sum_d \sigma(z_\alpha^*)^d (1 - \alpha) p_d$$

Result Exploring process Differential equation approximation for Markov chains

Two different behaviours



Coupechoux - Lelarge Giant component for random hypergraphs

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Conclusion

- As for random graphs, existence of a phase transition for the appearance of the giant component
- Branching process : a way to guess the result
- Markov chain : a tool for proving it

Conclusion

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- Branching process : a way to guess the result
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Thanks for your attention !

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How to guess the result

Definitions

 $s_0 = g_0 = 1$

 $s_n = \mathbb{P}(\text{after } n \text{ steps, a hyper-edge } e \text{ isn't alive})$

 $g_{n+1} = \mathbb{P}(\text{after } n \text{ steps, a vertex } v \text{ isn't alive})$

 $g_{n+1}^d = \mathbb{P}(a \text{ vertex of degree } d \text{ isn't alive at time } n)$

$$s_n = \mathbb{P}(\text{every offspring of } e \text{ wasn't alive at time } n-1)$$

$$= \sum_w \mathbb{P}(e \text{ has } w-1 \text{ offsprings}) (\mathbb{P}(\text{a given offspring } v \text{ isn't alive at time } n-1))^{w-1}$$

$$= \sum_w \frac{wq_w}{m} (g_n)^{w-1}$$

$$=: \sigma(g_n)$$

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How to guess the result

$$g_{n+1}^{d} = \mathbb{P}(\text{a vertex } v \text{ of degree } d \text{ isn't alive at time } n | v \in V_A) \mathbb{P}(v \in V_A) \\ + \mathbb{P}(\text{a vertex } v \text{ of degree } d \text{ isn't alive at time } n | v \notin V_A) \mathbb{P}(v \notin V_A) \\ = (1 - \alpha) \mathbb{P}(\text{a vertex } v \text{ of degree } d \text{ isn't alive at time } n | v \notin V_A) \\ = (1 - \alpha) \mathbb{P}(\text{none of the } d - 1 \text{ offsprings of } v \text{ is alive at time } n) \\ = (1 - \alpha) s_n^{d-1} \\ = (1 - \alpha) (\sigma(g_n))^{d-1}$$

$$g_{n+1} = \sum_{d} \mathbb{P}(v \text{ isn't alive at time } n | v \text{ has degree } d) \mathbb{P}(v \text{ has degree } d)$$
$$= (1 - \alpha) \sum_{d} \frac{dp_{d}}{m} (\sigma(g_{n}))^{d-1}$$
$$=: \phi_{\alpha}(g_{n})$$

Result Exploring process Differential equation approximation for Markov chains

Graphs with clustering





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Upper bound : idea

For each $\alpha > {\rm O}$:

- $P_N(\alpha)$ = proportion of alive vertices at the end of the algorithm
- $P(\alpha) = \lim_{N \to \infty} P_N(\alpha)$ (limit in probability)
- If we activate some vertex in $C_1(N)$, then

$$\frac{|C_1(N)|}{Nn} \le P_N(\alpha)$$

• The probability of activating no vertex in $C_1(N)$ tends to 0 (when $N \to \infty$)