

# Probabilistic Symmetry and Network Models

## Lecture 1

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## 0. Introduction

If you had asked a probabilist in 1970 what was known about exchangeability, you would likely have received the answer "There's de Finetti's theorem: what else is there to say?" The purpose of these notes is to dispel this (still prevalent) attitude by presenting, in Parts II-IV, a variety of mostly post-1970 results relating to exchangeability. The selection of

From Aldous (1983). *Exchangeability and Related Topics*.

**Also:** O. Kallenberg. (2006). *Probabilistic Symmetries and Invariance Principles*.

**Today:** Mostly post-2015 results relating to exchangeability.

## ● Lecture 1: Basic symmetries and network sampling.

- H. Crane. (2018). *Probabilistic Foundations of Statistical Network Analysis*.
- H. Crane and W. Dempsey. (2018). Edge exchangeable models for interaction networks. *Journal of the American Statistical Association*.
- H. Crane and W. Dempsey. (2019). Relational exchangeability. *Journal of Applied Probability*.
- H. Crane and H. Towsner. (2018). Relatively exchangeable structures. *Journal of Symbolic Logic*.

## ● Lecture 2: Dynamic network models.

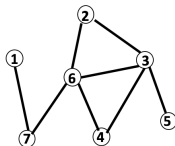
- H. Crane. (2015). Time-varying network models. *Bernoulli*, **21**(3):1670–1696.
- H. Crane. (2016). Dynamic random networks and their graph limits. *Annals of Applied Probability*.
- H. Crane. (2017). Exchangeable graph-valued Feller processes. *Probability Theory and Related Fields*.
- H. Crane. (2018). Combinatorial Lévy processes. *Annals of Applied Probability*.
- H. Crane and H. Towsner. (2019+). The structure of combinatorial Markov processes.



Book website: <http://www.harrycrane.com/networks.html>

# Notation and Terminology

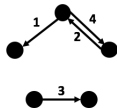
- **Network:** Abstract, non-mathematical concept. A structure of interconnected and/or interacting entities.
- **Graph:** a pair  $(V, E)$  consisting of sets  $V$  (vertices) and  $E \subset V \times V$  (edges).



- Encoded as  $\{0, 1\}$ -valued adjacency array  $\mathbf{y} = (y_{ij})_{i,j \in V}$  with

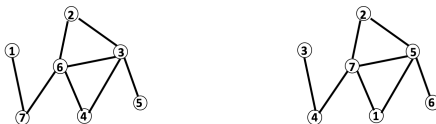
$$y_{ij} = \begin{cases} 1, & (i, j) \in E, \\ 0, & \text{otherwise.} \end{cases}$$

- **Edge-labeled graph:** Equivalence class of structures formed out of edge sequences (formal definition later).

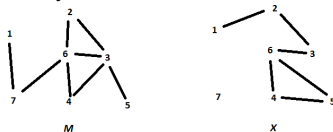


# Variations of exchangeability

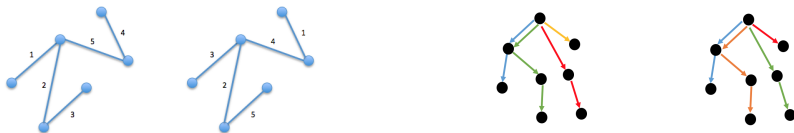
- 1 **Exchangeability** (conventional):  $\mathbf{X} =_{\mathcal{D}} \mathbf{X}^{\sigma} = (X_{\sigma(i)\sigma(j)})_{i,j \geq 1}$  for all permutations  $\sigma : \mathbb{N} \rightarrow \mathbb{N}$ .



- 2 **Relative exchangeability**:  $M$  represents heterogeneity of a population and  $\mathbf{X}$  is exchangeable **relative to** the symmetries of  $M$ .



- 3 **Relational exchangeability**: Exchangeability with respect to relabeling relations (species, edges, paths, networks, etc.)



## Exchangeable random graphs

- **Data:**  $\mathbf{Y} = (Y_{ij})_{i,j \in V} \in \{0, 1\}^{V \times V}$ .
- **Symmetries:** Any permutation  $\sigma : V \rightarrow V$  determines a **relabeling** map

$$\mathbf{y} \mapsto \mathbf{y}^\sigma := (y_{\sigma(i)\sigma(j)})_{i,j \in V}.$$



Graph on the right obtained by relabeling graph on left with  $\sigma(1) = 4, \sigma(2) = 2, \sigma(3) = 1, \sigma(4) = 7, \sigma(5) = 3, \sigma(6) = 5, \sigma(7) = 6$ .

## Definition ((Vertex) exchangeability)

A random graph  $\mathbf{Y} = (Y_{ij})_{i,j \in V}$  is (vertex) exchangeable if

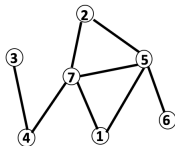
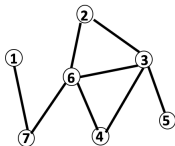
$$\mathbf{Y}^\sigma \stackrel{\mathcal{D}}{=} \mathbf{Y} \quad \text{for all permutations } \sigma : V \rightarrow V.$$

Equivalently,

$$\mathbb{P}(\mathbf{Y} \in A^\sigma) = \mathbb{P}(\mathbf{Y} \in A) \quad \text{for all permutations } \sigma : V \rightarrow V,$$

where  $A^\sigma = \{\mathbf{y}^\sigma : \mathbf{y} \in A\}$  obtained by relabeling all elements of  $A$  according to  $\sigma$ .

- A vertex exchangeable distribution assigns equal probability to isomorphic graphs.





A sequence  $\mathbf{X} = (X_1, X_2, \dots)$  is **exchangeable** if

$$\mathbf{X}^\sigma = (X_{\sigma(1)}, X_{\sigma(2)}, \dots) =_{\mathcal{D}} \mathbf{X} \quad \text{for all permutations } \sigma : \mathbb{N} \rightarrow \mathbb{N}.$$

## Theorem (de Finetti)

*Let  $\mathbf{X} = (X_1, X_2, \dots)$  be a countable, exchangeable  $\{0, 1\}$ -valued sequence. Then there exists a unique probability measure  $\mu$  on  $[0, 1]$  such that the finite-dimensional distributions of  $\mathbf{X}$  are given by*

$$Pr((X_1, \dots, X_n) = (x_1, \dots, x_n)) = \int_0^1 p^{\sum_i x_i} (1 - p)^{n - \sum_i x_i} \mu(dp).$$

- Intuition:
  - Pick a coin with a random heads-probability (according to  $\mu$ ).
  - Toss the coin repeatedly to generate  $\mathbf{X}$ .
- An exchangeable sequence is a mixture of i.i.d. sequences.
- Analogous theorem holds for countably exchangeable sequences in any nice enough probability space.

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Let  $\mathbf{X} = (X_1, X_2, \dots)$  be an exchangeable  $\{0, 1\}$ -valued sequence. Then there exists a measurable function  $\phi : [0, 1] \times [0, 1] \rightarrow \{0, 1\}$  such that  $\mathbf{X} =_{\mathcal{D}} \mathbf{X}^* = (X_1^*, X_2^*, \dots)$ , where

$$X_j^* = \phi(U_\emptyset, U_{\{j\}}), \quad j \geq 1,$$

for  $U_\emptyset, (U_{\{j\}})_{j \geq 1}$  i.i.d. Uniform $[0, 1]$ .

- Pick a coin with a random heads-probability (according to  $\mu$ ).
- Toss the coin repeatedly to generate  $\mathbf{X}$ .
- Shared dependence on  $U_\emptyset$  is the only source of dependence among variables.
- Fix  $U_\emptyset = \alpha$ , then  $X_j^* = \phi(\alpha, U_{\{j\}})$  is i.i.d.

*Exchangeable sequence is conditionally i.i.d.*

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$$\mathbf{Y}^\sigma = (Y_{\sigma(i)\sigma(j)})_{i,j \geq 1} \stackrel{\mathcal{D}}{=} \mathbf{Y} \quad \text{for all permutations } \sigma : \mathbb{N} \rightarrow \mathbb{N}.$$

## Theorem (Aldous–Hoover–Kallenberg)

Let  $\mathbf{Y}$  be the adjacency array of an exchangeable random graph with vertex set  $\mathbb{N}$ .

Then there exists a measurable function  $\phi : [0, 1]^4 \rightarrow \{0, 1\}$  such that

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Decomposes structure of exchangeable random graph:

- Global effect:  $U_\emptyset$
- Vertex effects:  $U_{\{i\}}, U_{\{j\}}$
- Edge effects:  $U_{\{i,j\}}$

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- **Vertex effects:**  $U_{\{i\}}, U_{\{j\}}$  (shared by all edges involving given vertex)
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Decomposes structure of exchangeable random graph:

- Global effect:  $U_\emptyset$
- Vertex effects:  $U_{\{i\}}, U_{\{j\}}$
- Edge effects:  $U_{\{i,j\}}$  (only for edge between  $i$  and  $j$ )

## Definition (Dissociated array)

A random array  $\mathbf{Y} = (Y_{ij})_{i,j \geq 1}$  is **dissociated** if

$\mathbf{Y} |_S$  and  $\mathbf{Y} |_T$  are independent for all  $S, T \subseteq \mathbb{N}$  such that  $S \cap T = \emptyset$ .

Fix  $U_\emptyset = \alpha$  in Aldous–Hoover: for  $S \cap T = \emptyset$ :

- $\mathbf{Y}^* |_S = (\phi(\alpha, U_{\{i\}}, U_{\{j\}}, U_{\{i,j\}}))_{i,j \geq S}$  depends on  $U_{\{i\}}, U_{\{j\}}, U_{\{i,j\}}$  indexed by  $S$ .
- $\mathbf{Y}^* |_T = (\phi(\alpha, U_{\{i\}}, U_{\{j\}}, U_{\{i,j\}}))_{i,j \geq T}$  depends on  $U_{\{i\}}, U_{\{j\}}, U_{\{i,j\}}$  indexed by  $T$ .

*Every exchangeable random graph is a mixture of dissociated, exchangeable graphs.*

## Example:

- Erdős–Rényi model: all edges are i.i.d. ( $\phi$  depends only on last argument.)
- Graphon models: let  $g : [0, 1] \times [0, 1] \rightarrow [0, 1]$ , let  $U_1, U_2, \dots$  i.i.d. Uniform $[0, 1]$  and let

$$\mathbb{P}(Y_{ij} = 1 \mid U_i, U_j) = g(U_i, U_j), \quad i, j \geq 1.$$

# Graph limits

Let  $G = (G_{ij})_{i,j \in \mathbb{N}}$  be a countable graph and  $F = (F_{ij})_{1 \leq i,j \leq m}$  be a graph with vertex set  $[m] = \{1, \dots, m\}$ .

- For each  $n \geq 1$ , define

$$t_n(F, G) = \frac{1}{n^{\downarrow m}} \sum_{\text{injections } \psi: [m] \rightarrow [n]} \mathbf{1}(G^\psi = F).$$

- The **homomorphism density of  $F$  in  $G$**  is the limit

$$t(F, G) = \lim_{n \rightarrow \infty} t_n(F, G) \quad \text{if the limit exists.}$$

- $G$  possesses a **graph limit** if  $t(F, G)$  exists for all finite  $F$ , for all  $m \geq 1$ .

## Corollary

*Graph limits  $\longleftrightarrow$  exchangeable, dissociated probability measures on countable graphs.*

### Immediate implications:

- Dense structure: Exchangeable random graph  $\implies$  dense or empty w.p. 1.
- Representative sampling: normalizing constant  $1/n^{\downarrow m}$  interpreted as assigning equal probability (uniform distribution) on all  $\psi$ -sampling maps.

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## Open Problem

*Define and study an interesting notion of asymptotics for sparse/complex networks.*

## Relative exchangeability

## Definition (Relative exchangeability)

*Invariance with respect to the symmetries of another structure.*

Population  $\mathbb{N} = \{1, 2, \dots\}$  divides into two classes, e.g., male and female.

- Define  $C = (C_1, C_2, \dots)$  by

$$C_i = \begin{cases} 1, & i \text{ is male,} \\ 0, & \text{otherwise.} \end{cases}$$

- $(X_1, X_2, \dots)$  is relatively exchangeable with respect to  $C$ , i.e.,  $\mathbf{X}^\sigma =_{\mathcal{D}} \mathbf{X}$  for permutations  $\sigma : \mathbb{N} \rightarrow \mathbb{N}$  that fix  $C$ .

<b>C</b>	1	1	0	1	0	0	1
<b>X</b>	$X_1$	$X_2$	$X_3$	$X_4$	$X_5$	$X_6$	$X_7$
<b>X'</b>	$X_2$	$X_4$	$X_3$	$X_1$	$X_6$	$X_5$	$X_7$

$\mathbf{X} =_{\mathcal{D}} \mathbf{X}'$

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## Theorem

Let  $C = (C_1, C_2, \dots)$  be  $[k]$ -valued sequence\* and  $\mathbf{X} = (X_1, X_2, \dots)$  be relatively exchangeable with respect to  $C$ . Then there exists a measurable  $\phi : [k] \times [0, 1]^2 \rightarrow \{0, 1\}$  such that  $\mathbf{X} =_{\mathcal{D}} \mathbf{X}^* = (X_i^*)_{i \geq 1}$  with

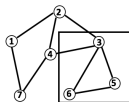
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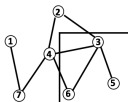


## Definition (Relatively exchangeable random graph)

$\mathbf{Y}$  is relatively exchangeable with respect to  $G$  if, for all  $S \subseteq \mathbb{N}$ ,  $\mathbf{Y} \mid_S^\sigma =_{\mathcal{D}} \mathbf{Y} \mid_S$  for all automorphisms  $\sigma$  of  $G \mid_S$ .



G



Y



(a)



(b)

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## Theorem (C. 2017)

Let  $G = (\mathbb{N}, E)$  be an undirected graph\* and  $\mathbf{Y}$  be relatively exchangeable with respect to  $G$ . There exists  $\phi : \{0, 1\} \times [0, 1]^4 \rightarrow \{0, 1\}$  such that  $\mathbf{Y} =_{\mathcal{D}} \mathbf{Y}^* = (Y_{ij}^*)_{i,j \geq 1}$  with

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- relatively exchangeable (structural) component
- exchangeable (Aldous–Hoover) component

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- exchangeable (Aldous–Hoover) component

$\mathfrak{M}$ : general combinatorial structure

$\mathbf{Y}$  is  $\mathfrak{M}$ -exchangeable (exchangeable relative to  $\mathfrak{M}$ ):

**Sequence:**  $\mathfrak{M} = (M_1, M_2, \dots) \in \{0, 1\}^{\mathbb{N}}$ ,

$$Y_i = \phi(M_i, U_\emptyset, U_{\{i\}}), \quad i \geq 1.$$

**Graph:**  $\mathfrak{M} = (M_{ij})_{i,j \geq 1} \in \{0, 1\}^{\mathbb{N} \times \mathbb{N}}$ ,

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**Lack of interference:** *Both exhibit strong local dependence on  $\mathfrak{M}$ .*

- Does this lack of interference hold in general? No.
- What properties must  $\mathfrak{M}$  satisfy to get the representation?

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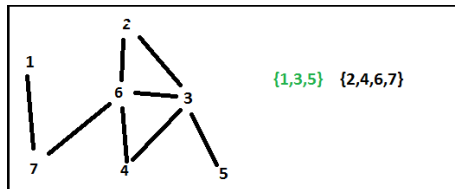
## General setting:

- **signature:**  $\mathcal{L} = \{i_1, \dots, i_r\}$  with  $1 \leq i_1 \leq \dots \leq i_r$ .
- **$\mathcal{L}$ -structure:**  $\mathfrak{M} = (\mathfrak{M}^1, \dots, \mathfrak{M}^r)$  with each  $\mathfrak{M}^j$  a symmetric  $i_j$ -ary relation  $\mathfrak{M}^j \subseteq \mathbb{N}^{i_j}$ .
- **adjacency array:**  $\mathfrak{M} = (\mathfrak{M}^1, \dots, \mathfrak{M}^r)$  corresponds to a collection of  $\{0, 1\}$ -valued arrays  $\mathfrak{M}^j = (\mathfrak{M}_s^j, s \in \mathbb{N}^{i_j})$  with

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## Example:

- $\mathcal{L} = \{1, 2\}$ : Graph with colored vertices



$M$

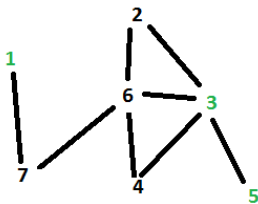
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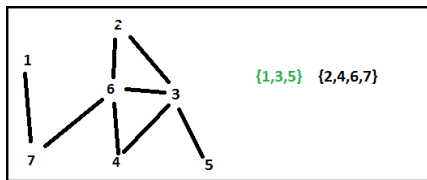


# Relative exchangeability

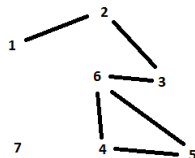
- population structure:  $\mathfrak{M} = (\mathfrak{M}^1, \dots, \mathfrak{M}^r)$  with each  $\mathfrak{M}^j = (\mathfrak{M}_s^j, s \in \mathbb{N}^j)$  for  $j \geq 1$ .
- random structure:  $\mathbf{Y} = (Y_{ij})_{i,j \geq 1}$ .

## Definition

$\mathbf{Y}$  is relatively exchangeable with respect to  $\mathfrak{M}$  if  $\mathbf{Y} |_{\mathcal{S}}^{\sigma} =_{\mathcal{D}} \mathbf{Y} |_{\mathcal{S}}$  for all permutations  $\sigma : \mathcal{S} \rightarrow \mathcal{S}$  such that  $\mathfrak{M} |_{\mathcal{S}}^{\sigma} = \mathfrak{M} |_{\mathcal{S}}$ .



M



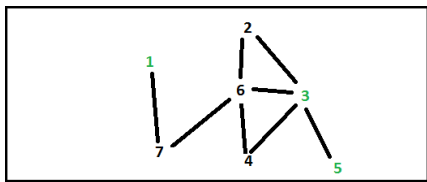
X

# Relative exchangeability

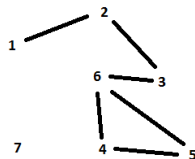
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$M$



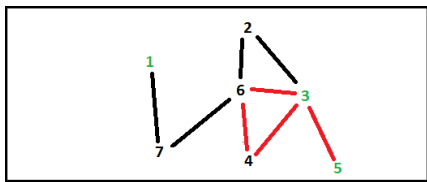
$X$

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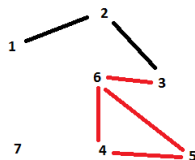
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M



X

## Theorem (C.-Towsner, 2018)

Let  $\mathbf{Y} = (Y_{ij})_{i,j \geq 1}$  be relatively exchangeable with respect to  $\mathfrak{M} = (\mathfrak{M}^1, \dots, \mathfrak{M}^r)$ . Then there exists  $\phi$  such that  $\mathbf{Y} =_{\mathcal{D}} \mathbf{Y}^*$  with

$$Y_{ij} = \phi(\mathfrak{M}|_{\{i,j\}}, U_{\emptyset}, U_{\{i\}}, U_{\{j\}}, U_{\{i,j\}}), \quad (i, j) \in \mathbb{N}, \quad (1)$$

for  $U_{\emptyset}, (U_{\{i\}})_{i \geq 1}, (U_{\{i,j\}})_{j \geq i \geq 1}$  i.i.d.  $\text{Uniform}[0, 1]$  and  $\mathfrak{M}|_S := (\mathfrak{M}^1|_S, \dots, \mathfrak{M}^r|_S)$ .

Representation in (3) holds only under strong condition on  $\mathfrak{M}$ :

- **ultrahomogeneous**: every embedding  $\mathfrak{N} \rightarrow \mathfrak{M}$  extends to an automorphism of  $\mathfrak{M}$ .
- **$n$ -disjoint amalgamation ( $n$ -DAP)**: Let  $K$  (set of finite structures) be closed under isomorphism. For every  $(\mathfrak{G}_i)_{1 \leq i \leq n}$  satisfying
  - $\mathfrak{G}_i \in K$ ,
  - $|\mathfrak{G}_i| = [n] \setminus \{i\}$ ,
  - and  $\mathfrak{G}_i|_{[n] \setminus \{i,j\}} = \mathfrak{G}_j|_{[n] \setminus \{i,j\}}$  for all  $1 \leq i, j \leq n$ ,
 there exists  $\mathfrak{G} \in K$  with  $|\mathfrak{G}| = n$  such that  $\mathfrak{G}|_{[n] \setminus \{i\}} = \mathfrak{G}_i$  for all  $1 \leq i \leq n$ .

- 3-DAP (sets):  $\mathfrak{G}_i \in \{\{1, 3\}, \{1, 2\}, \{2, 3\}\}$  extends to  $\{1, 2, 3\}$ .
- 3-DAP fails (partitions):  $\mathfrak{G}_i \in \{1/3, 12, 2/3\}$  cannot be extended to a partition of  $[3]$ .

## Relational/Edge exchangeability

# Species sampling

Sample animals and record their species

bear, deer, bear, wolf, ...  
 $X_1$     $X_2$     $X_3$     $X_4$

- Element-labeled sequence:  $X_1, X_2, X_3, X_4, \dots$

1 3   2   4  
●   ●   ●  
bear   deer   wolf

- Relationally-labeled structure:  $\sim_X \equiv \{1, 3\}, \{2\}, \{4\}, \dots$

1 3   2   4  
●   ●   ●

## Invariance:

- $(X_1, X_2, \dots) =_{\mathcal{D}} (X_{\sigma(1)}, X_{\sigma(2)}, \dots)$ : observed species representative of all species.

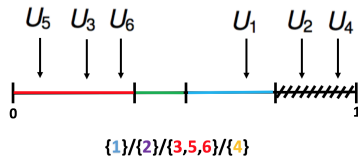
1 3   2   4                      1   2 4   3  
●   ●   ●                      ●   ●   ●  
bear   deer   wolf                      deer   bear   wolf

- $\sim_{X^\sigma} =_{\mathcal{D}} \sim_X$ : *relation* among observed species is representative of the relation of all species.

1 3   2   4                      1   2 4   3  
●   ●   ●                      ●   ●   ●

# Kingman's paintbox representation

- **Partition of  $[n]$ :**  $\pi = B_1/B_2/\dots/B_k$  with nonempty, disjoint subsets such that  $\bigcup_{j=1}^k B_j = [n] = \{1, \dots, n\}$ .
- Take a partition of  $[0, 1]$  and generate  $\Pi$  randomly by taking  $U_1, U_2, \dots$  i.i.d.  $\text{Uniform}[0, 1]$ :



- Define  $\Pi(\mathbf{X}) \equiv \sim_{\mathbf{X}}$  by

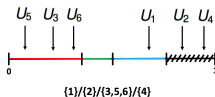
$$i \sim_{\mathbf{X}} j \iff U_i \text{ and } U_j \text{ in same sub-interval.}$$

## Theorem

$\Pi(\mathbf{X})$  from the paintbox process is an exchangeable random partition of  $\mathbb{N}$ .

# Kingman's paintbox representation

**Partition of  $[n]$ :**  $B_1/B_2/\dots/B_k$  with nonempty, disjoint subsets such that  $\bigcup_{j=1}^k B_j = [n]$ .



## Theorem (Kingman, 1978)

Let  $\Pi$  be an exchangeable partition of  $\mathbb{N}$ . Then there exists a unique probability measure  $\phi$  on

$$\mathcal{F}_{\mathbb{N}}^{\downarrow} = \{(f_0, f_1, \dots) : \sum_{i \geq 0} f_i = 1 \text{ and } f_1 \geq f_2 \geq \dots \geq 0\}$$

so that  $\Pi$  can be generated by  $\epsilon_{\phi}(\cdot) = \int_{\mathcal{F}_{\mathbb{N}}^{\downarrow}} \epsilon_f(\cdot) \phi(df)$ :

- $f \sim \phi$ ,
- $X_1, X_2, \dots$  conditionally i.i.d. from  $P(X_i = j \mid f) = f_j, j \geq 0$ .
- Let  $\Pi$  be partition induced by  $(X_1, X_2, \dots)$ .

Example:  $(X_1, X_2, \dots) = (3, 0, 1, 0, 1, 1) \implies \Pi = \{1\}/\{2\}/\{3, 5, 6\}/\{4\}$

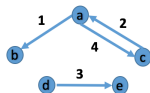


# Interaction sampling

- Sample phone calls (interactions) from database:

$$\underbrace{a \rightarrow b}_{X_1}, \quad \underbrace{c \rightarrow a}_{X_2}, \quad \underbrace{d \rightarrow e}_{X_3}, \quad \underbrace{a \rightarrow c}_{X_4}, \quad \dots$$

- Represent  $X_1, X_2, \dots$  (sequence of edges) by



- $(X_1, X_2, \dots) =_{\mathcal{D}} (X_{\sigma(1)}, X_{\sigma(2)}, \dots)$  implies equal probability for

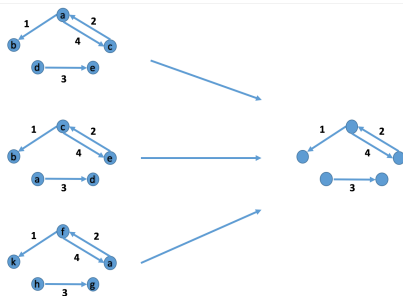


# Edge-labeled structure

- Call sequence:



- Phone call network: treats only structure induced by observed calls. (Vertices identified only through their edge relations to one another.)



- Formally,

$$\mathcal{E}_{\mathbf{X}} = \{\mathbf{X}' \mid \exists \rho : \{a, b, \dots\} \rightarrow \{a, b, \dots\} \text{ s.t. } \rho(\mathbf{X}') = \mathbf{X}\},$$

where  $\rho(\mathbf{X}') = (\rho(X_1), \rho(X_2), \dots)$ .

- Formally, edge-labeled graph induced by  $\mathbf{x} = (x_i)_{i \geq 1}$ :

$$\mathcal{E}_{\mathbf{x}} = \{\mathbf{x}' \mid \exists \rho : \{a, b, \dots\} \rightarrow \{a, b, \dots\} \text{ s.t. } \rho(\mathbf{x}') = \mathbf{x}\},$$

where  $\rho(\mathbf{x}') = ((\rho(x'_{11}), \rho(x'_{12})), (\rho(x'_{21}), \rho(x'_{22})), \dots)$ .

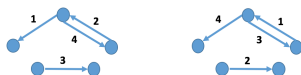
- Define the **relabeling of  $\mathbf{y} = \mathcal{E}_{\mathbf{x}}$  by  $\sigma : \mathbb{N} \rightarrow \mathbb{N}$**  by

$$\mathbf{y}^{\sigma} = \{\mathbf{x}' \mid \exists \rho : \{a, b, \dots\} \rightarrow \{a, b, \dots\} \text{ s.t. } \rho(\mathbf{x}') = \mathbf{x}^{\sigma}\}.$$

## Definition (Edge exchangeability)

$\mathbf{Y}$  is **edge exchangeable** if  $\mathbf{Y}^{\sigma} =_{\mathcal{D}} \mathbf{Y}$  for all permutations  $\sigma : \mathbb{N} \rightarrow \mathbb{N}$ .

- Edge exchangeable  $\implies$  assign equal probability to



## Theorem (Representation theorem)

Let  $\mathbf{Y}$  be an infinite edge exchangeable random graph then

$$\mathbf{Y} \sim \epsilon_\phi = \int_{\mathcal{F}_{\mathbb{N} \times \mathbb{N}}^\downarrow} \epsilon_f(\cdot) \phi(df)$$

for measure  $\phi$  on

$$\mathcal{F}_{\mathbb{N} \times \mathbb{N}}^\downarrow := \left\{ (f_{(i,j)})_{i,j \geq -1} : f_{(i,j)} \geq 0, \sum_{i,j \geq -1} f_{(i,j)} = 1, \sum_{j \geq 0} f_{(i,j)} \geq \sum_{j \geq 0} f_{(i+1,j)}, \quad i \geq 1 \right\}$$

- 1 Draw  $f \sim \phi$ ,
- 2 Given  $f$ , draw edges i.i.d.  $\mathbb{P}\{X_k = (i,j) \mid f\} = f_{(i,j)}$ .

Edge types:

- isolated interactions:  $f_{(i,j)}$  for  $i, j \geq 0$
- one-off interaction:  $f_{(i,j)}$  for  $i \leq 0$  and  $j \geq 1$  or  $i \geq 1$  and  $j \leq 0$ .
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## Theorem (Representation theorem)

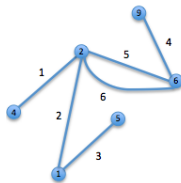
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$$\epsilon_\phi(\cdot) = \int_{\mathcal{F}_{\mathbb{N} \times \mathbb{N}}^\downarrow} \epsilon_f(\cdot) \phi(df).$$

- Generate  $\mathbf{Y}$  by first sampling  $f \sim \phi$  and, given  $f = (f_{(i,j)})_{i,j \geq -1}$ , putting  $\mathbf{Y} = \mathbf{Y}(X_1, X_2, \dots)$  for  $X_1, X_2, \dots$  i.i.d. from

$$\mathbb{P}\{X_k = (i, j) \mid f\} = f_{(i,j)}, \quad i, j \geq -1.$$

- For example:  $X_1 = (2, 4)$ ,  $X_2 = (1, 2)$ ,  $X_3 = (1, 5)$ ,  $X_4 = (6, 9)$ ,  $X_5 = (2, 6)$ ,  $X_6 = (2, 6)$ , generates



## Theorem (Representation theorem)

Let  $\mathbf{Y}$  be an infinite edge exchangeable random graph. Then there exists a unique probability measure  $\phi$  on  $\mathcal{F}_{\mathbb{N} \times \mathbb{N}}^{\downarrow}$  such that  $\mathbf{Y} \sim \epsilon_{\phi}$ , where

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## Open Problem

Prove anything about edge exchangeability that's not already in

- H. Crane and W. Dempsey. (2018). *Edge exchangeable models for interaction networks*. Journal of the American Statistical Association.
- H. Crane and W. Dempsey. (2019). *Relational exchangeability*. Journal of Applied Probability.
- S. Janson. (2017). *On edge exchangeable graphs*. arXiv:1702.06396.



Generate a sequence of edges  $(E_i)_{i \geq 1}$  as follows.

- Label elements in order of appearance.
- $D(j)$ : degree of vertex labeled  $j$ .
- Choose elements in edge  $i$ , denoted  $E_i(1)$  and  $E_i(2)$ , by

$$\text{pr}(E_i(r) = j \mid \text{past}) \propto \begin{cases} D(j) - \alpha, & j = 1, \dots, N_i \\ \theta + \alpha N_i, & j = N_i + 1. \end{cases}$$

Any realization of  $n$  interactions  $\mathbf{Y}_n = E$  occurs with probability

$$\alpha^{v(E)} \frac{(\theta/\alpha)^{\uparrow v(E)}}{\theta^{\uparrow m_n(E)}} \prod_{k=2}^{\infty} \exp\{N_k(E) \log((1 - \alpha)^{\uparrow(k-1)})\},$$

where

- $v(E)$  is the number of nonisolated vertices in  $E$ ,
- $(N_k(E))_{k \geq 0}$  gives the number of vertices with degree  $k$  for each  $k \geq 0$ ,
- $M_k(E)$  is the number of  $k$ -ary edges in  $E$ ,
- $m_n(E) = \sum_{k \geq 1} k M_k(E)$  is the total degree of  $E$ , and
- $x^{\uparrow j} = x(x+1) \cdots (x+j-1)$  is the ascending factorial function.

## Hollywood model: Basic facts

$(\mathbf{Y}_n)_{n \geq 1}$  obeys Hollywood process with parameter  $(\alpha, \theta)$  for  $0 < \alpha < 1$  and  $\theta > -\alpha$ .

- For each  $n \geq 1$ ,

$$p_n(k) = N_k(\mathbf{Y}_n)/v(\mathbf{Y}_n), \quad k \geq 1$$

is the empirical degree distribution of  $\mathbf{Y}_n$ , where  $N_k(\mathbf{Y}_n)$  is the number of vertices with degree  $k \geq 1$  and  $v(\mathbf{Y}_n)$  is the number of vertices in  $\mathbf{Y}_n$ , respectively.

### Theorem (Power law (C–D, 2018))

For every  $k \geq 1$ ,

$$p_n(k) \sim \alpha k^{-(\alpha+1)}/\Gamma(1-\alpha) \quad \text{a.s. as } n \rightarrow \infty,$$

that is,  $\mathbf{Y}$  exhibits power law degree distribution with exponent  $\gamma = \alpha + 1 \in (1, 2)$ .

### Theorem (Sparsity (C–D, 2018))

The expected number of vertices in  $\mathbf{Y}_n$  satisfies

$$E(v(\mathbf{Y}_n)) \sim \frac{\Gamma(\theta + 1)}{\alpha \Gamma(\theta + \alpha)} (\mu n)^\alpha \quad \text{as } n \rightarrow \infty, \quad (2)$$

where  $\mu = \sum_{k \geq 1} k \nu_k$  is the mean edge arity. Furthermore, if  $1/\mu < \alpha < 1$ , then  $(\mathbf{Y}_n)_{n \geq 1}$  is sparse almost surely.

$(\mathbf{Y}_n)_{n \geq 1}$  obeys Hollywood process with parameter  $(\alpha, \theta)$  for  $0 < \alpha < 1$  and  $\theta > -\alpha$ .

- For each  $n \geq 1$ ,

$$p_n(k) = N_k(\mathbf{Y}_n)/v(\mathbf{Y}_n), \quad k \geq 1$$

is the empirical degree distribution of  $\mathbf{Y}_n$ , where  $N_k(\mathbf{Y}_n)$  is the number of vertices with degree  $k \geq 1$  and  $v(\mathbf{Y}_n)$  is the number of vertices in  $\mathbf{Y}_n$ , respectively.

### Open Problem

Analyze other properties of graphs  $(\mathbf{Y}_n)_{n \geq 1}$  generated from Hollywood $(\alpha, \theta)$  process, e.g.,

- *distribution of triangles,*
- *distribution of component sizes,*
- *distribution/behavior of any other network statistics.*

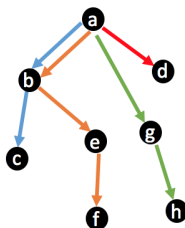
More general forms

## Example: Path sampling

Sample paths between IP addresses:

$$\underbrace{a \rightarrow b \rightarrow e \rightarrow f}_{X_1}, \quad \underbrace{a \rightarrow d}_{X_2}, \quad \underbrace{a \rightarrow b \rightarrow c}_{X_3}, \quad \underbrace{a \rightarrow g \rightarrow h}_{X_4}, \quad \dots$$

- Induced network: Relational structure observed by sampling paths representative of paths sampled by traceroute.

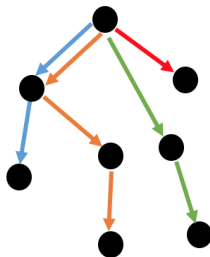


## Example: Path sampling

Sample paths between IP addresses:

$$\underbrace{a \rightarrow b \rightarrow e \rightarrow f}_{X_1}, \quad \underbrace{a \rightarrow d}_{X_2}, \quad \underbrace{a \rightarrow b \rightarrow c}_{X_3}, \quad \underbrace{a \rightarrow g \rightarrow h}_{X_4}, \quad \dots$$

- Induced network: Relational structure observed by sampling paths representative of paths sampled by traceroute.

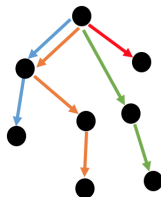
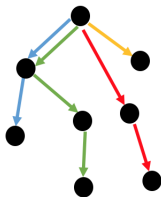


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- Induced network: Relational structure observed by sampling paths representative of paths sampled by traceroute.
- path exchangeability: assign equal probability to



Let

- $\mathcal{R}$  be a set of relations on a finite set (singleton sets, edge, hyperedges, paths, graphs, etc.) and
- $\mathcal{F}_{\mathcal{R}}^{\downarrow}$  be the “ranked simplex” indexed by the elements of  $\mathcal{R}$ .

**$\mathcal{R}$ -structure**: structure obtained by removing element labels (taking equivalence class) of sequence from  $\mathcal{R}$ . (Gluing edge, paths, etc. together.)

## Theorem (C.-Dempsey, 2019)

Let  $Y$  be an infinite relationally exchangeable  $\mathcal{R}$ -structure. Then there exists a unique probability measure  $\phi$  on  $\mathcal{F}_{\mathcal{R}}^{\downarrow}$  such that  $Y \sim \epsilon_{\phi}$ , where

$$\epsilon_{\phi}(\cdot) = \int_{\mathcal{F}_{\mathcal{R}}^{\downarrow}} \epsilon_f(\cdot) \phi(df).$$

*H. Crane and W. Dempsey. (2019). Relational exchangeability. Journal of Applied Probability.*



## Theorem (Aldous–Hoover, C.-Towsner)

Let  $X = (X^1, \dots, X^{r'})$  be relatively exchangeable with respect to  $\mathfrak{M} = (\mathfrak{M}^1, \dots, \mathfrak{M}^r)$ . Then there exists  $g = (g_1, \dots, g_{r'})$  such that  $\mathbf{X} =_{\mathcal{D}} \mathbf{X}^*$  with

$$X_s^{*j} = g_j(\mathfrak{M}|_{\{s_1, \dots, s_{j'}\}}, (U_t)_{t \subseteq \{s_1, \dots, s_{j'}\}}), \quad s = (s_1, \dots, s_{j'}) \in \mathbb{N}^{j'}, \quad (3)$$

for  $(U_t)_{t \subseteq \mathbb{N}: |t| \leq \max j'_i}$  i.i.d.  $\text{Uniform}[0, 1]$  and  $\mathfrak{M}|_S := (\mathfrak{M}^1|_S, \dots, \mathfrak{M}^r|_S)$ .

- Aldous–Hoover:  $\mathfrak{M} = \emptyset$  or any perfectly symmetric structure ( $\text{Aut}(\mathfrak{M}) = \mathbf{Sym}(\mathbb{N})$ ).
- Stochastic blockmodel:  $\mathfrak{M} \in [k]^{\mathbb{N}}$  (labeled classes) or  $\mathfrak{M} \in \mathcal{P}_{\mathbb{N}}$  (unlabeled).

## Theorem (Kingman, C.-Dempsey)

Let  $Y$  be an infinite relationally exchangeable  $\mathcal{R}$ -structure. Then there exists a unique probability measure  $\phi$  on  $\mathcal{F}_{\mathcal{R}}^{\downarrow}$  such that  $Y \sim \epsilon_{\phi}$ , where

$$\epsilon_{\phi}(\cdot) = \int_{\mathcal{F}_{\mathcal{R}}^{\downarrow}} \epsilon_f(\cdot) \phi(df).$$

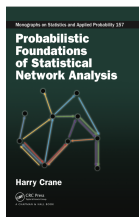
### Special cases:

- Kingman: Paintbox process (random equivalence relations).
- C.-Dempsey: Edge exchangeability (random interaction networks).

- H. Crane and W. Dempsey. (2018). Edge exchangeable models for interaction networks. *Journal of the American Statistical Association*.
- H. Crane and W. Dempsey. (2019). Relational exchangeability. *Journal of Applied Probability*.
- H. Crane and H. Towsner. (2018). Relatively exchangeable structures. *Journal of Symbolic Logic*.
- H. Crane and H. Towsner. (2018). Relatively exchangeable structures with equivalence relations. *Archive of Mathematical Logic*.
- H. Crane. (2018). *Probabilistic Foundations of Statistical Network Analysis*.

See also:

- D. Aldous. (1983). *Exchangeability and Related Topics*.



\* More information available at [www.harrycrane.com/networks.html](http://www.harrycrane.com/networks.html)