

# Mixed Membership Stochastic Blockmodels

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STAT 572 Intro Talk  
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1. Notation and motivation
2. Previous blockmodels
3. The Mixed Membership Stochastic Blockmodel
4. Conclusion and next steps

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# Network theory: notation

- Individuals  $p, q \in \{1, \dots, N\}$ .
- We observe relations/interactions  $R(p, q)$  on *pairs* of individuals.
- Here we assume  $R(p, q) \in \{0, 1\}$ ,  $R(p, p) = 0$ , but do not assume  $R(p, q) = R(q, p)$  (we deal with *directed* networks).

# Network theory: data representations

p	q	R(p,q)
1	2	1
2	3	1
3	2	1

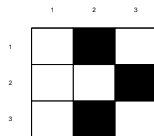
Table



Graph

$$\begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix}$$

Adjacency matrix  
 $i, j$  element is  
 $R(i, j)$

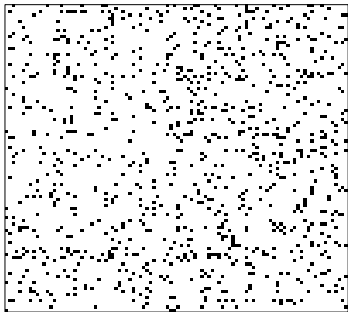


Adjacency matrix,  
black=1, white=0

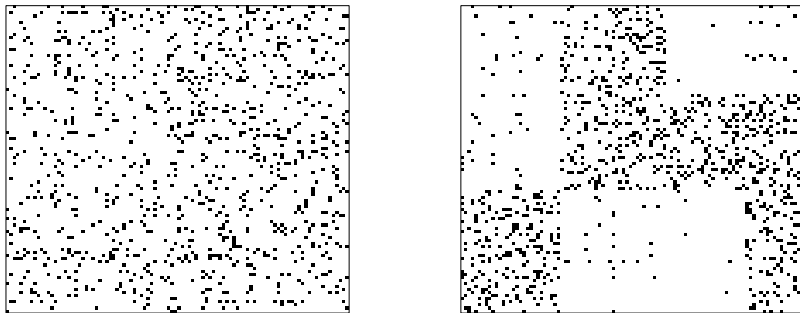
# The Problem: Scientific Motivation

- We believe the relations are a function of unobserved groupings among the individuals.
- We want to recover the groups so we can a) predict new relations or b) interpret the existing network structure.
- Example: Monk network.

# The Problem: Pictures



# The Problem: Pictures



**Figure:** Two visualizations of the same binary adjacency matrix. Each filled-in square represents a directed edge. Left: ordered randomly. Right: ordered by group membership.



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# Brief blockmodel history

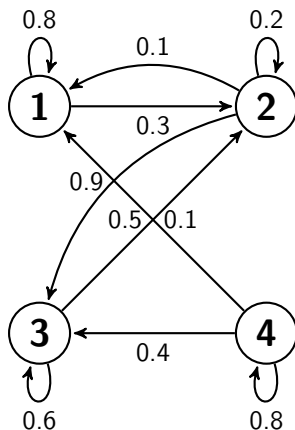
- 1975: CONCOR developed by Harrison White and colleagues
- 1983: Holland, Laskey & Leinhardt introduce *stochastic* blockmodel for blocks known *a priori*.
- 1987: Wasserman & Anderson extend to *a posteriori* estimation.
- 2004: Kemp, Griffiths & Tenenbaum allow unknown and unlimited number of blocks in the Infinite Relational Model.

# Infinite Relational Model

- Observe binary relations  $R(p, q)$  between nodes  $p, q \in \{1, \dots, N\}$ .
- Each node  $p$  is a member of exactly one block of  $K$  total blocks,  $K \leq N$  unknown. Let  $z_p$  be an indicator vector of block membership for node  $p$ , i.e.  $z_p = (0, 1, 0)$ .
- $B$  is a  $K \times K$  matrix of block relationships. If  $p$  is in block  $g$  and  $q$  is in block  $h$  then the probability of observing an interaction from node  $p$  to node  $q$  is  $B_{gh}$ .
- $R(p, q) \sim \text{Bernoulli}(z_p^T B z_q)$ .
- For example, if  $p$  is in block 3 and  $q$  is in block 2 then  $P(R(p, q) = 1) = B_{32}$ .

# Block structure

$$\begin{pmatrix} .8 & .3 & 0 & 0 \\ .1 & .2 & .9 & 0 \\ 0 & .5 & .6 & 0 \\ .1 & 0 & .4 & .8 \end{pmatrix}$$

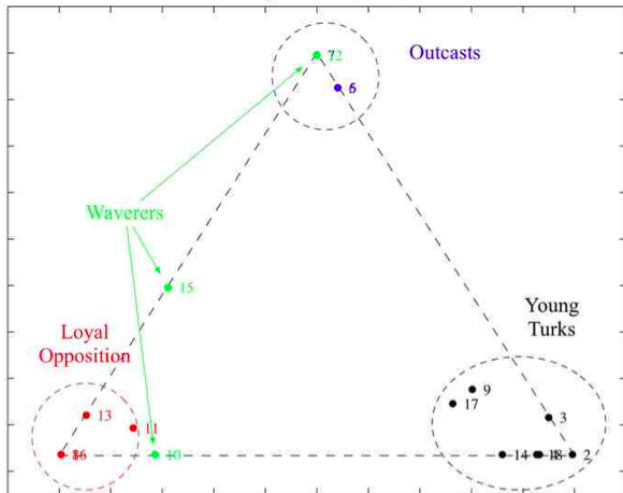


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# The Mixed Membership Stochastic Blockmodel

- Previous models assume each node is assumed to belong to exactly one latent block - e.g.  $z_p = (0, 1, 0, 0)$ .
- Instead, in the MMB we assume each node has a distribution  $\pi_p$  over the latent blocks.
- For each interaction from  $p$  to  $q$ , both  $p$  and  $q$  draw a particular block to be a part of for the interaction:  $z_{p \rightarrow q} \sim \text{Discrete}(\pi_p)$ ,  $z_{p \leftarrow q} \sim \text{Discrete}(\pi_q)$ .
- Then  $R(p, q) \sim \text{Bernoulli}(z_{p \rightarrow q}^T B z_{p \leftarrow q})$ .
- $K$  chosen by BIC.

Breiger et al. (1975)



- 1 Ambrose
- 2 Boniface
- 3 Mark
- 4 Winfrid
- 5 Elias
- 6 Basil
- 7 Simplicius
- 8 Berthold
- 9 John Bosco
- 10 Victor
- 11 Bonaventure
- 12 Amand
- 13 Louis
- 14 Albert
- 15 Ramuald
- 16 Peter
- 17 Gregory
- 18 Hugh

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# Conclusion and next steps

- Blockmodels allow clustering nodes from observed network data.
- MMB extends blockmodels to let nodes be in different groups to different extents, but commit to one group during any given interaction.
- Next steps: estimation...