

Oct. 19

- 1. Administrative**
- 2. Roles as relations
(blockmodels)**
- 3. Structural and regular
equivalence**
- 4. Discovering blocks
algorithmically**

| Précis feedback this week

| Proposal due Nov 9

Roles as Relations

Roles as relations

Sociology of roles

Roles are bundles of expectations in interaction

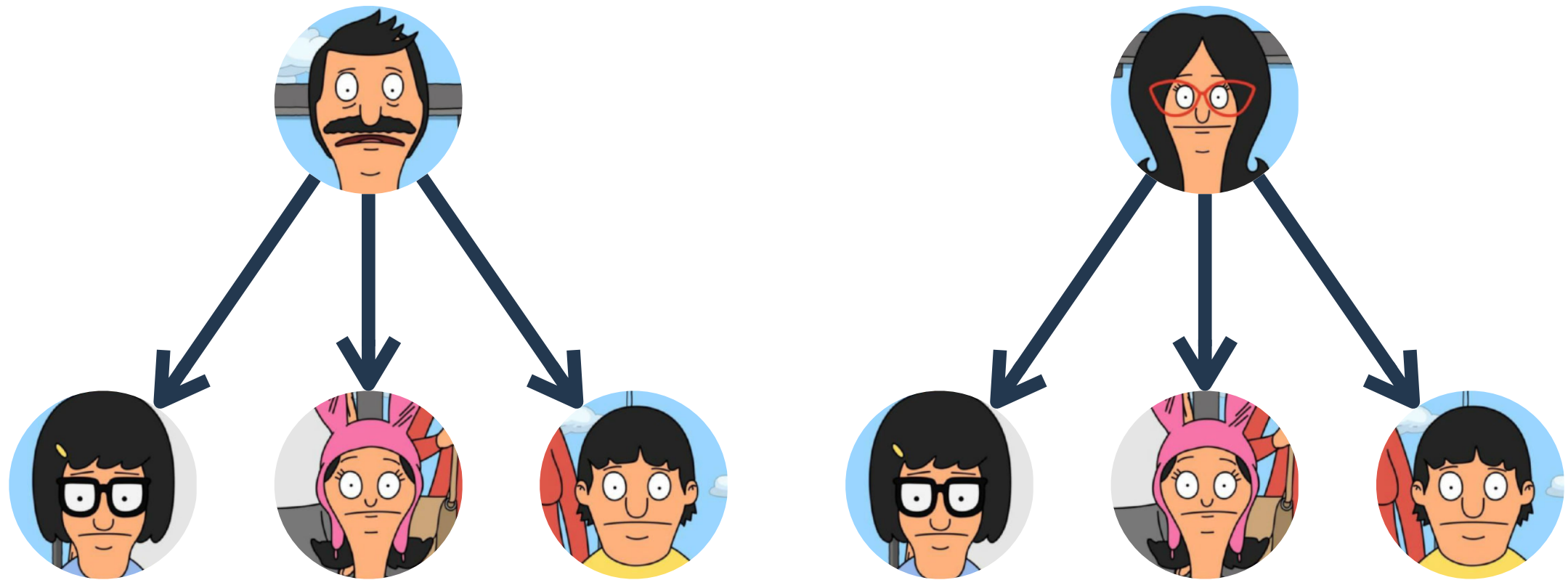
- ∴ the role of *parent* might be defined by expectations of caregiving toward certain children
- ∴ the role of *child* might be defined (in part) by expectations of obedience and dependence toward parents
- ∴ the role of *boxer* is defined by expectations of physical violence toward other boxers and deference toward a coach



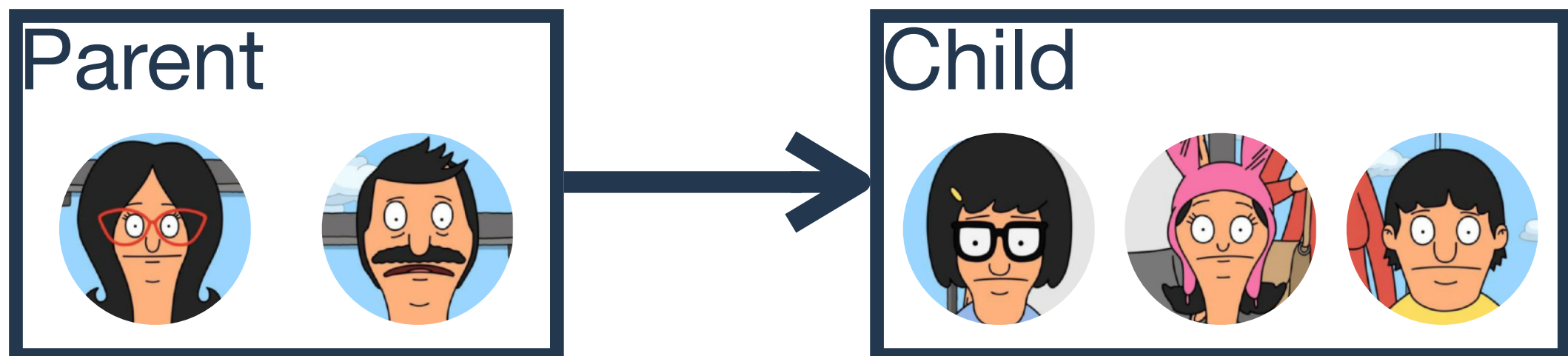
Roles are about *relations between categories*—
perfect for network analysis!

Roles as relations

Network relations



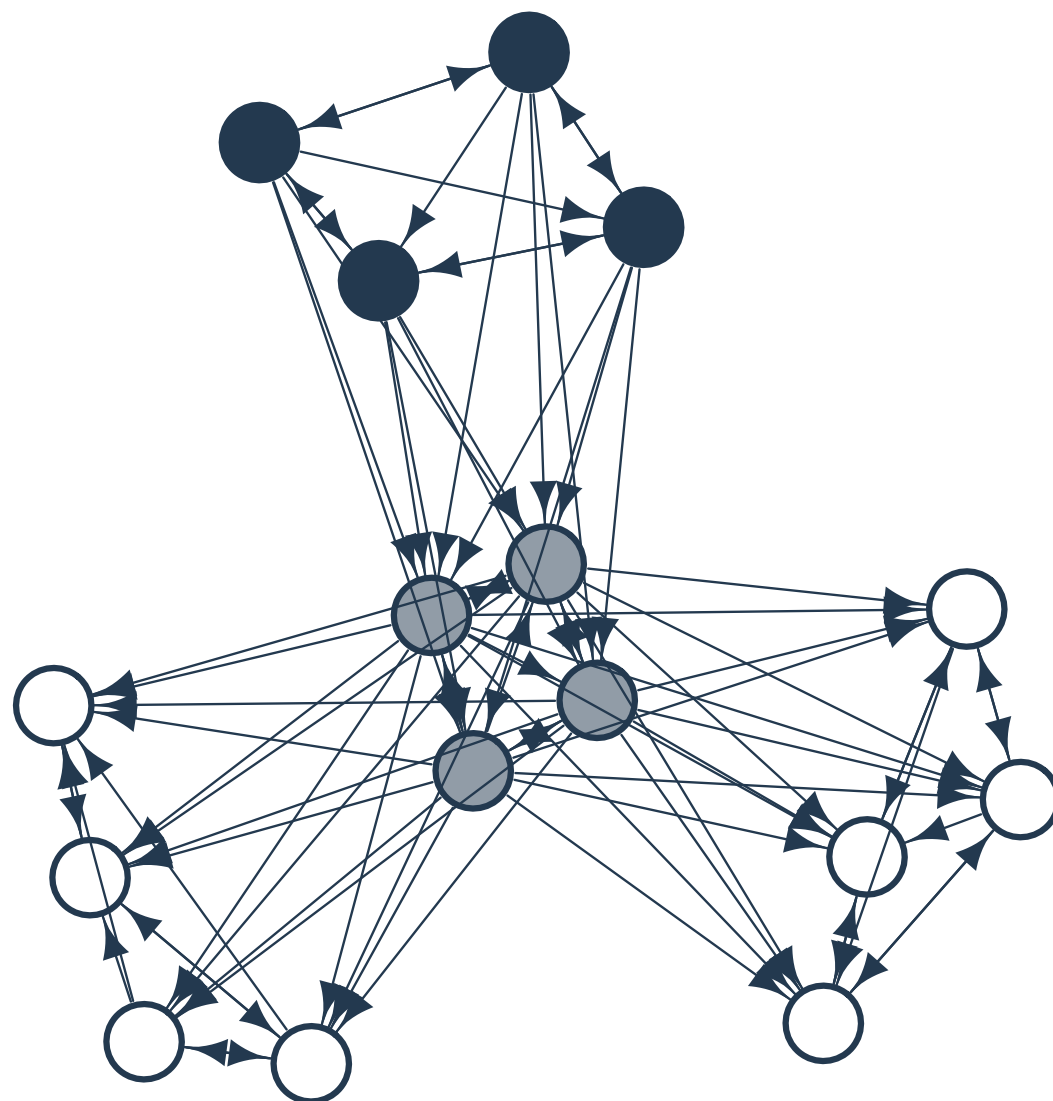
Role relations



Roles as relations

Blockmodelling aims to formalize this intuition

- ∴ Somewhat vague term, refers to methods, models, and theories that focus on the relational nature of roles
- ∴ Find categories of actors in “equivalent” positions in a network



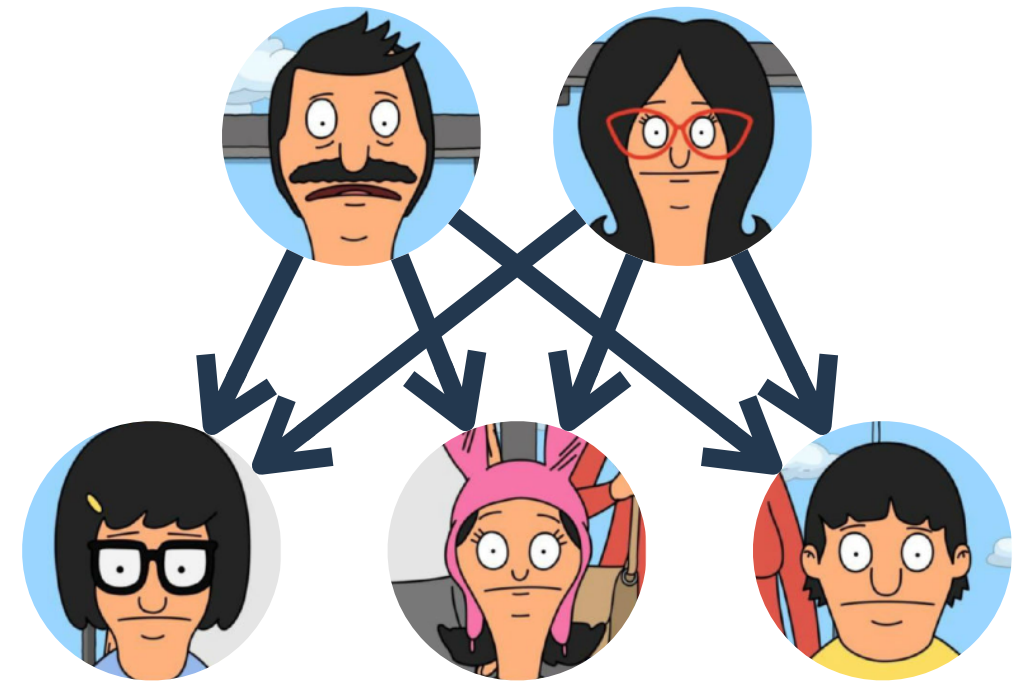
Structural & Regular Equivalence

Equivalence

Two major forms of “equivalence” of network position: *structural* and *regular*

Structural equivalence

- ∴ Two actors are *structurally equivalent* if they have the same ties to the same set of actors
- ∴ E.g. Bob and Linda Belcher are structurally equivalent in their role as “caregiver of Tina, Louise, and Gene”
- ∴ In a *sociogram*, this means swapping labels does not change the network
- ∴ In an *adjacency matrix*, this means having identical rows and columns



		1	2	3	4	5
Bob	1	0	0	1	1	1
Linda	2	0	0	1	1	1
Tina	3	0	0	0	0	0
Louise	4	0	0	0	0	0
Gene	5	0	0	0	0	0

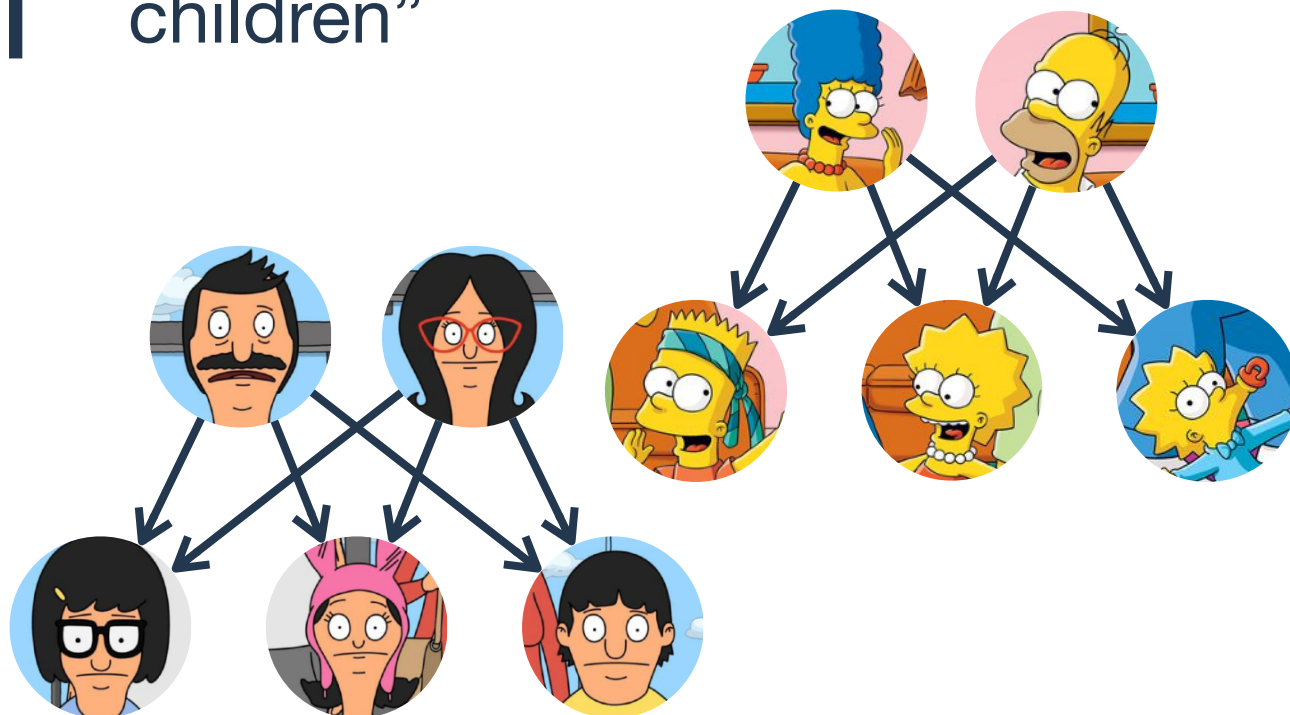
Equivalence

Two major forms of “equivalence” of network position: *structural* and *regular*

Regular equivalence

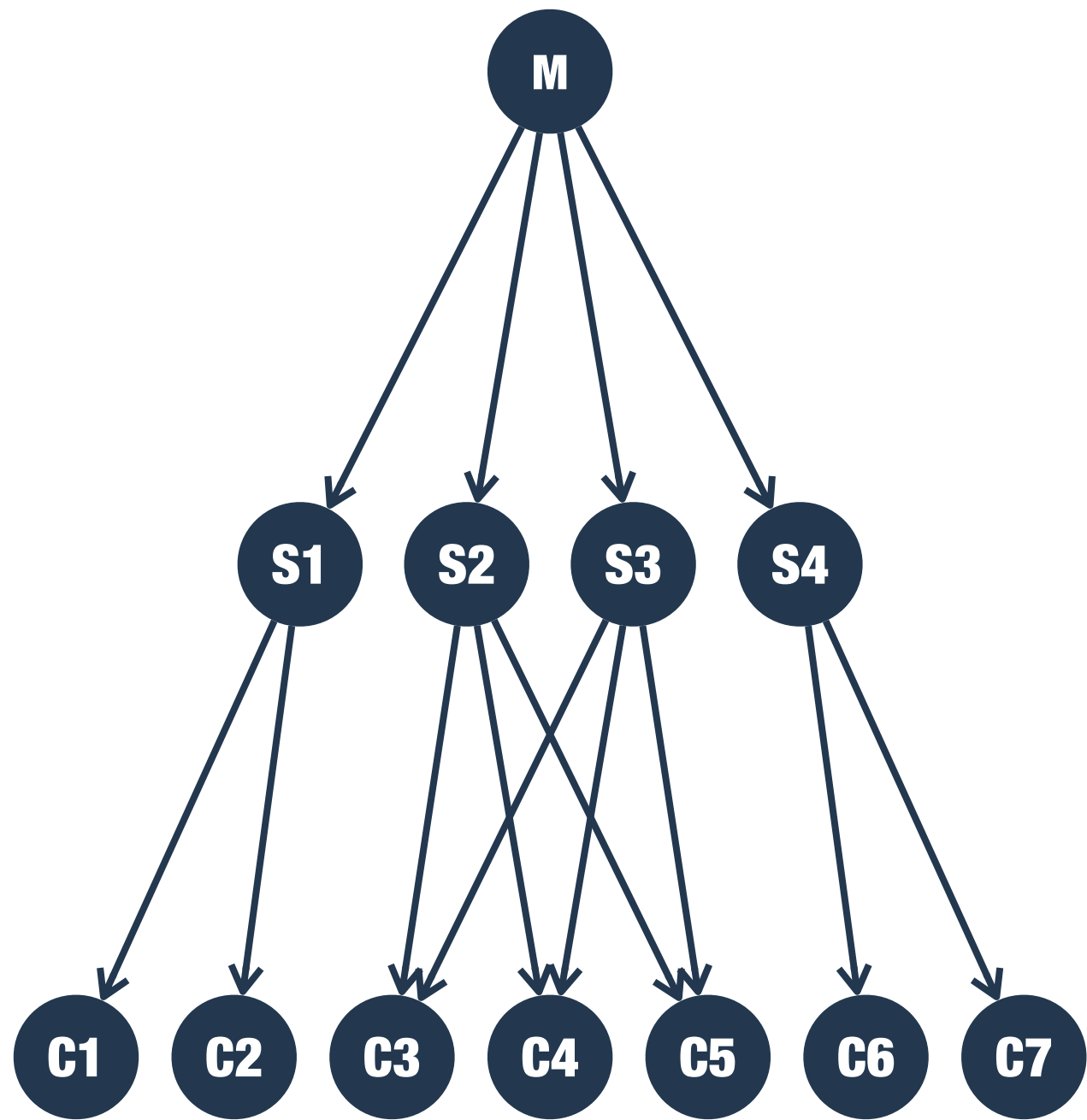
∴ Two actors are *regularly equivalent* if they have ties to the same *type* of actors

∴ E.g. Linda Belcher and Marge Simpson are regularly equivalent in their role as “caregiver of children”



		1	2	3	4	5	6	7	8	9	10
Bob	1	0	0	0	0	1	1	1	0	0	0
Linda	2	0	0	0	0	1	1	1	0	0	0
Marge	3	0	0	0	0	0	0	0	1	1	1
Homer	4	0	0	0	0	0	0	0	1	1	1
Tina	5	0	0	0	0	0	0	0	0	0	0
Louise	6	0	0	0	0	0	0	0	0	0	0
Gene	7	0	0	0	0	0	0	0	0	0	0
Bart	8	0	0	0	0	0	0	0	0	0	0
Lisa	9	0	0	0	0	0	0	0	0	0	0
Maggie	10	0	0	0	0	0	0	0	0	0	0

Equivalence



A restaurant with seven customers (C),
four servers (S), and a floor manager (M)

Comparing *structural* and *regular* equivalence

Structural:

- ∴ C1 and C2 (both served by S1)
- ∴ S2 and S3 (both serving C3, C4, C5 and reporting to M)
- ∴ *Not* S1 and S2 (serving different customers)

Regular:

- ∴ C1–C7 (all served by servers)
- ∴ S1–S4 (all serving customers and reporting to a manager)
- ∴ “*Customer*” and “*server*” are *mutually dependent categories*

Example



Example

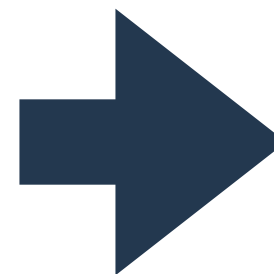
West Side Story Jets vs Sharks

Friendship	R	T	I	A	B	C	P
Riff	•	1	1	1	•	•	•
Tony	1	•	1	1	•	•	•
Ice	1	1	•	1	•	•	•
Action	1	1	1	•	•	•	•
Bernardo	•	•	•	•	•	1	1
Chino	•	•	•	•	1	•	1
Pepe	•	•	•	•	1	1	•

Rivalry	R	T	I	A	B	C	P
Riff	•	•	•	•	1	1	1
Tony	•	•	•	•	1	1	1
Ice	•	•	•	•	1	1	1
Action	•	•	•	•	1	1	1
Bernardo	1	1	1	1	•	•	•
Chino	1	1	1	1	•	•	•
Pepe	1	1	1	1	•	•	•

Example

Friendship	R	T	I	A	B	C	P
Riff	0	1	1	1	0	0	0
Tony	1	0	1	1	0	0	0
Ice	1	1	0	1	0	0	0
Action	1	1	1	0	0	0	0
Bernardo	0	0	0	0	0	1	1
Chino	0	0	0	0	1	1	1
Pepe	0	0	0	0	1	1	0



	J	S
J	1	0
S	0	1

Example

Jets, Jet Girls, Sharks, and Shark Girls

		1	2	3	4	5	6	7	8	9	10	11
Riff	1		1	1	1	1						
Tony	2	1		1	1							
Ice	3	1	1		1		1					
Action	4	1	1	1								
Velma	5	1					1					
Graziella	6			1		1						
Bernardo	7								1	1		1
Chino	8							1		1		
Pepe	9							1	1		1	
Consuelo	10									1		1
Anita	11							1			1	

Example

Jets, Jet Girls, Sharks, and Shark Girls

		1	2	3	4	5	6	7	8	9	10	11
Riff	1	Complete				Col. Reg.		Null			Null	
Tony	2											
Ice	3											
Action	4											
Velma	5	Row Regular				Comp.		Null			Null	
Graziella	6											
Bernardo	7	Null				Null		Complete			Col. Reg.	
Chino	8											
Pepe	9											
Consuelo	10	Null				Null		Row Regular			Comp.	
Anita	11											

Example



Null-block-crossed lovers

		1	2	3	4	5	6	7	8	9	10	11	12
Riff	1		1	1	1	1							
Tony	2	1		1	1								1
Ice	3	1	1		1		1						
Action	4	1	1	1									
Velma	5	1					1						
Graziella	6			1		1							
Bernardo	7								1	1		1	
Chino	8							1		1			
Pepe	9							1	1		1		
Consuelo	10									1		1	1
Anita	11							1			1		1
Maria	12		1								1	1	

Discovering Blocks Algorithmically

Discovering block structure

Normally, network data does not come pre-sorted

∴ *Block structure not apparent until rows and columns are re-ordered*

		1	2	3	4	5	6	7	8	9	10	11	12
Ice	1		1				1	1					1
Graziella	2	1									1		
Bernardo	3				1					1		1	
Chino	4			1						1			
Maria	5							1	1			1	
Riff	6	1						1			1		1
Tony	7	1				1	1						1
Consuelo	8					1				1		1	
Pepe	9			1	1				1				
Velma	10		1				1						
Anita	11			1		1			1				
Action	12	1					1	1					

Discovering block structure

There are two main approaches to *fitting* (a.k.a. *estimating*) block structure

Traditional blockmodelling

- ⋮ Define which blocks are “allowed”
- ⋮ Re-arrange rows and columns in the adjacency matrix until it (approximately) fits the pattern
- ⋮ Effective way to look for expected patterns, e.g. a core-periphery structure
- ⋮ Can take advantage of multiple relations on a group, (friend, enemy, authority, etc.)

Stochastic blockmodelling

- ⋮ Assume that there is some number of *latent* blocks in a network
- ⋮ Edges within and between blocks follow simple probabilistic patterns (e.g. “actors in block A have a 10% chance to connect to any actor in block B”)
- ⋮ Algorithms try to simultaneously discover the number of blocks, the membership of the blocks, and the edge probability between blocks

Discovering block structure

Stochastic
block model
(SBM)



		1	2	3	4	5	6	7	8	9	10	11	12
Riff	1	1.0				0.25		0.0			0.08		
Tony	2												
Ice	3												
Action	4												
Velma	5	0.25				1.0		0.0			0.0		
Graziella	6												
Bernardo	7	0.0				0.0		1.0			0.22		
Chino	8												
Pepe	9												
Consuelo	10	0.08				0.0		0.22			1.0		
Anita	11												
Maria	12												