
Social Networks

“Crash Course”

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Goal: Answer some questions

- ❖ What is “network science”?
- ❖ What do networks “look like”?
- ❖ How do we collect network data?
- ❖ What does network data “look like”?
- ❖ How do we analyze network data?

Schedule

- ❖ 9:00-9:30 Introductions and Overview
- ❖ 9:30-10:15 Basics of Network Science
- ❖ 10:15-10:30 Break
- ❖ 10:30-11:30 Network Data Structures and Analysis
- ❖ 11:30-12:00 Wrap-Up and Questions

Introductions

Who are you and why are you here?

Motivating Question

What determines whether a police officer activates their body-camera during an incident?

Empirical Example

Diffusion of Ideas and Technology: The Role of Networks in Influencing the Endorsement and Use of On-Officer Video Cameras

Journal of Contemporary Criminal Justice
2015, Vol. 31(3) 243–261

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Jacob T. N. Young¹ and Justin T. Ready¹

- ❖ <https://journals.sagepub.com/doi/10.1177/1043986214553380>

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Jacob T. N. Young¹ and Justin T. Ready¹

- ❖ Questions:
 - ❖ How do police officers “frame” body-worn cameras?
 - ❖ Is the meaning officers attribute to cameras created and transmitted in groups?

Empirical Example

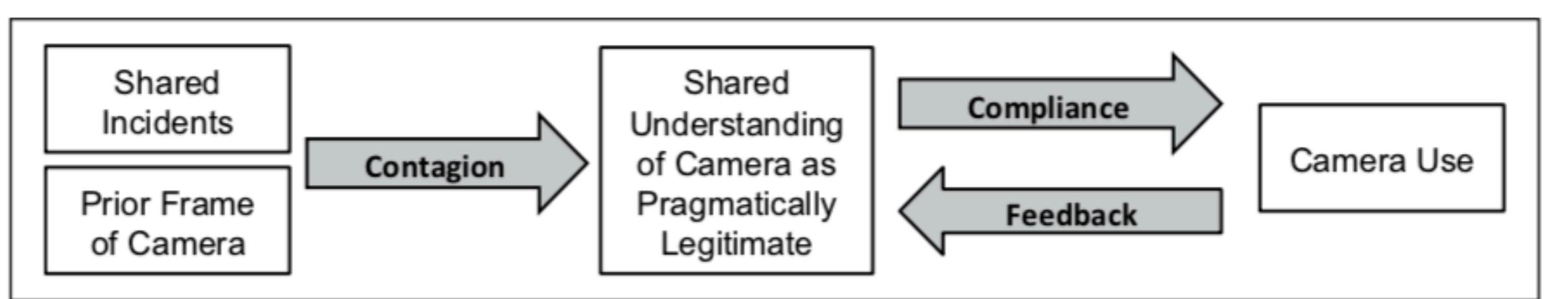


Figure 1. Diffusion of pragmatic legitimacy frame and compliance.

Network Science

- ❖ Network **science** is an approach to science that views the world as being composed of systems of actors connected through relational ties (i.e. a **network**).
- ❖ *What are some ways people can be connected?*

Network Science

- ❖ Network science takes these *relational structures* as the primary domain of interest:
 - ❖ How does the network matter? (explanan / IV)
 - ❖ What effects (affects?) the network? (explanandum / DV)

Network Analysis

- ❖ Network **analysis** is the set of tools used to study *relational variables*.
 - ❖ A set of methods for systematically understanding and identifying connections among actors.

Example

- ❖ Consider three different questions:
 - ❖ Are kids who are risk-seeking more likely to drink alcohol?
 - ❖ Are kids who have friends that drink alcohol more likely to drink alcohol?
 - ❖ Are kids who drink alcohol more likely to be popular?

Example

- ❖ Consider three different questions:
 - ❖ Are kids who are risk-seeking more likely to drink alcohol?
 - ❖ Are kids who have friends that drink alcohol more likely to drink alcohol?
 - ❖ Are kids who drink alcohol more likely to be popular?
- ❖ *How are these questions different? Is the causal logic the same? Are the policy implications the same? What are the variables?*

NEWS IN BRIEF

Sudden Death Of Aunt Creates Rupture In Family Gossip Pipeline

11/23/15 8:45am • SEE MORE: LOCAL ▾



<https://local.theonion.com/sudden-death-of-aunt-creates-rupture-in-family-gossip-p-1819578447>

Sudden Death Of Aunt Creates Rupture In Family Gossip Pipeline

VIRGINIA BEACH, VA—Grieving family members of local aunt Laurie Shelton confirmed Monday that the 48-year-old woman's unexpected death had caused a major breach in their gossip pipeline, suddenly disrupting access to the latest dirt on all their relatives. “Since Aunt Laurie passed, news about how Stephanie’s new boyfriend can’t hold down a job and updates on Uncle Jeff’s gambling habit have slowed to a trickle,” said Shelton’s niece Arielle, mourning the loss of a woman who for years had reportedly ensured a steady stream of the juiciest tidbits about relatives’ layoffs, unplanned pregnancies, personal bankruptcies, and misdemeanor shoplifting charges. “All the best gossip flowed through her, and now she’s gone. For all I know, the twins in North Carolina could have been caught smoking pot, Grandma could be back together with Leon, and Uncle Mike could be considering a vasectomy. It’s a devastating loss for the whole family.” Several in the family expressed hope that, for the time being, a sufficient supply of idle chatter could be rerouted through Cousin Staci to meet their immediate needs.

Sudden Death Of Aunt Creates Rupture In Family Gossip Pipeline

Conceptually, what does this story tell us about the relational structure of information transmission in the Shelton family?

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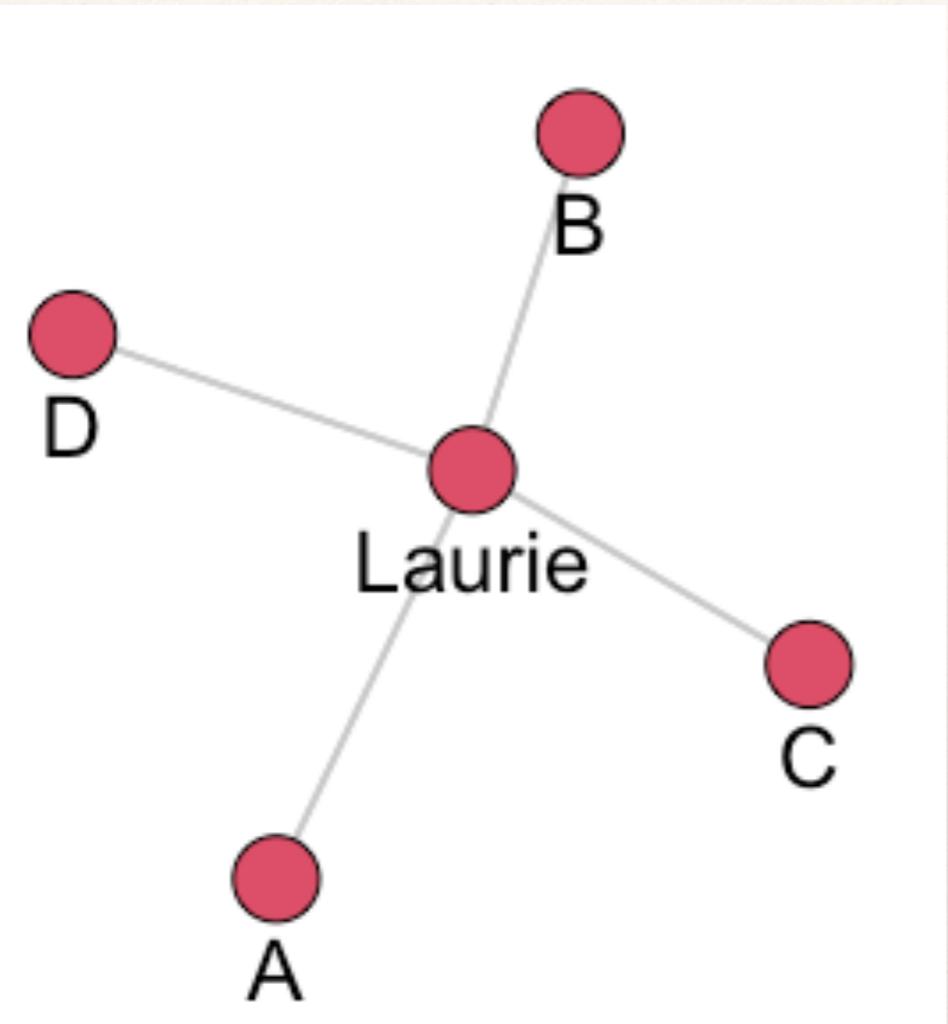
Sudden Death Of Aunt Creates Rupture In Family Gossip Pipeline

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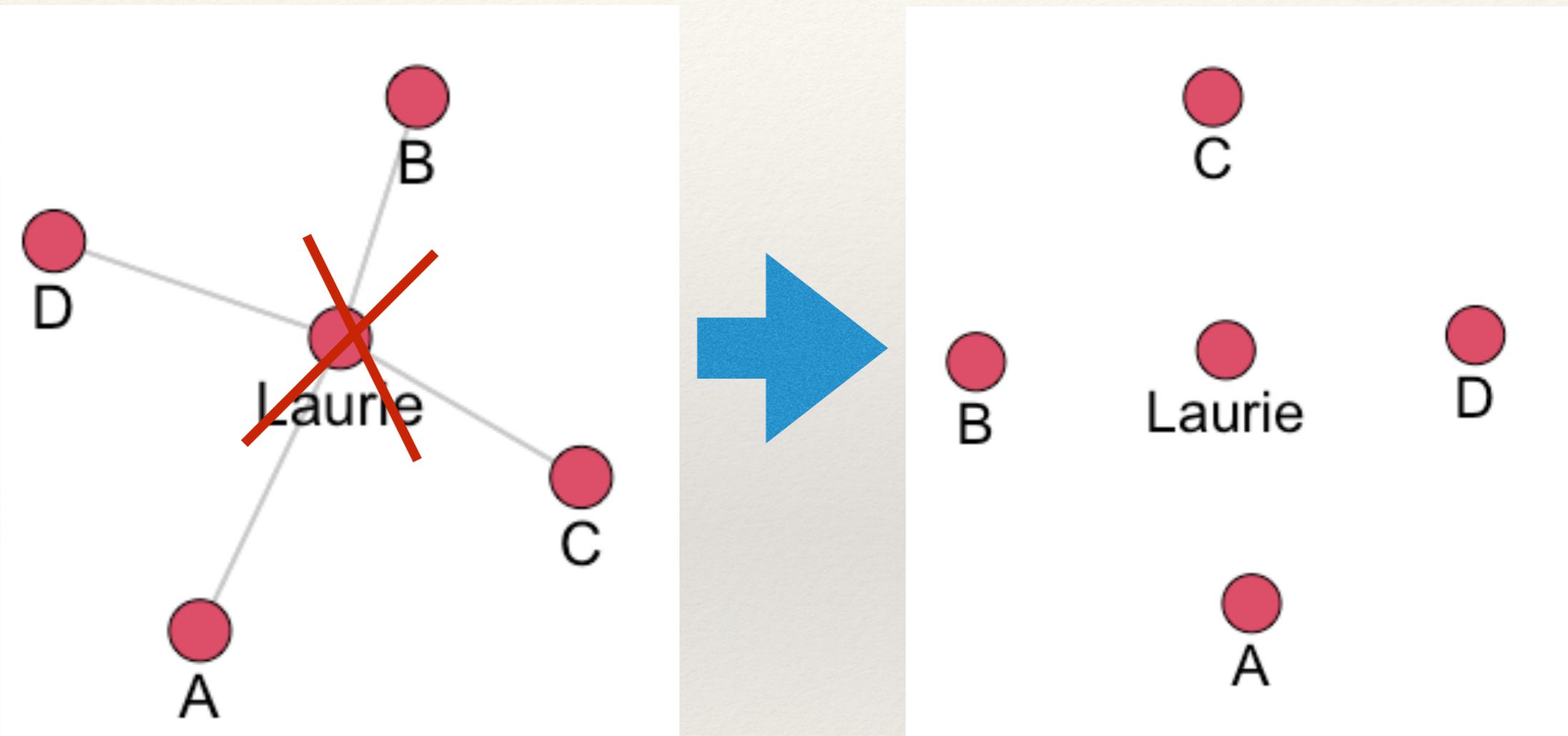
It is vulnerable...

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Sudden Death Of Aunt Creates Rupture In Family Gossip Pipeline

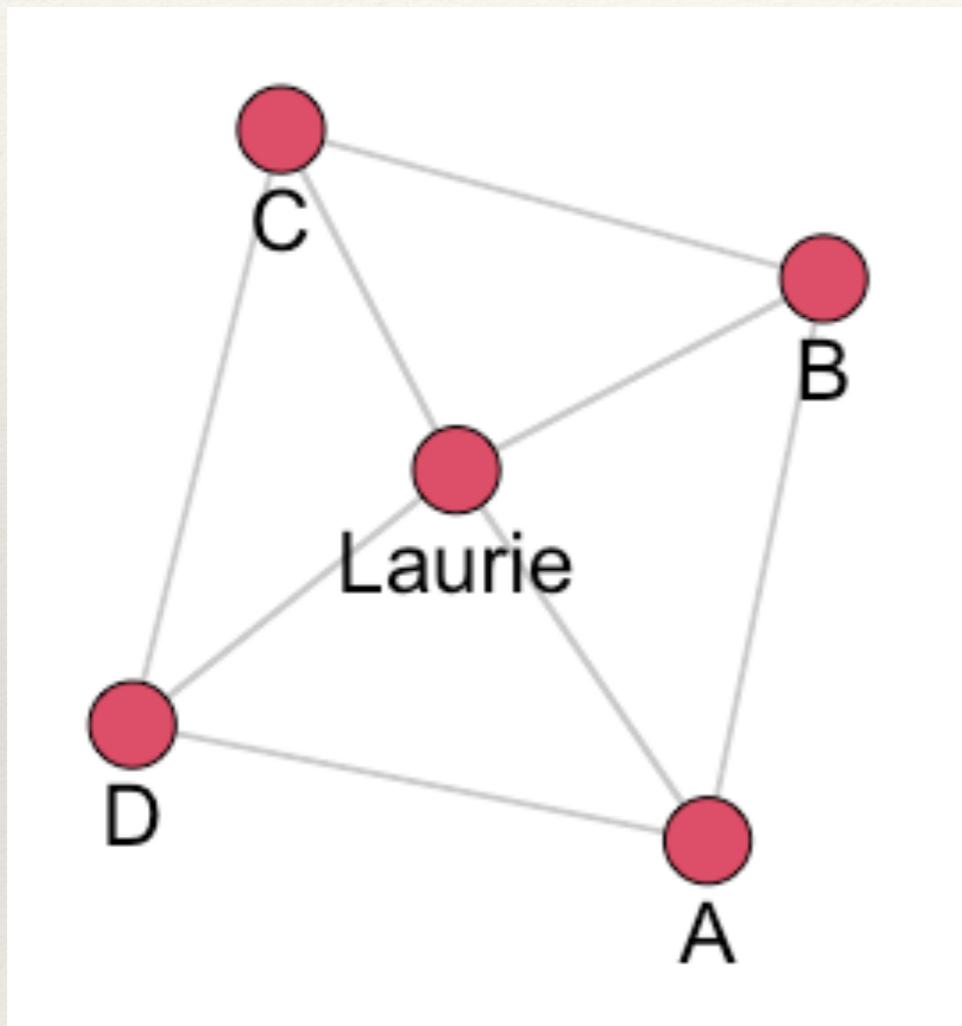


Sudden Death Of Aunt Creates Rupture In Family Gossip Pipeline

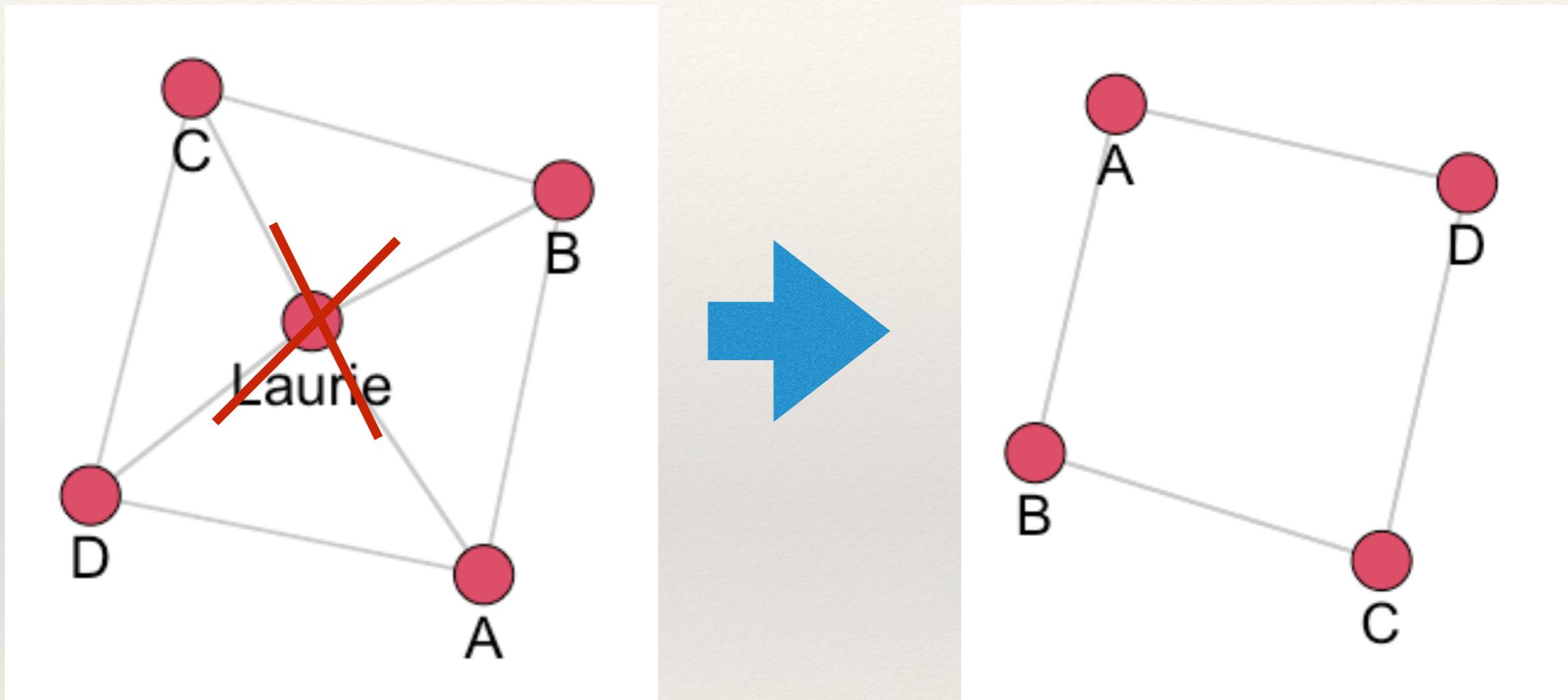


Why is it vulnerable?

Sudden Death Of Aunt Creates Rupture In Family Gossip Pipeline



~~Sudden Death Of Aunt Creates Rupture In Family Gossip Pipeline~~



Why is it not vulnerable?

The Point!

- ❖ These are topics that are inherently **relational**.
- ❖ *How do we go from theory to analysis?*

REMEMBER THIS?

- ❖ REMEMBER YOUR RESEARCH METHODS:
 - ❖ Conceptualization and Operationalization!
- ❖ Network science **conceptualizes** theoretical concepts that are inherently relational.
 - ❖ *Can you think of a relational theoretical concept?*
- ❖ Network research **operationalizes** theoretical constructs by drawing on the formal properties of graphs.
 - ❖ *Can you think of how that relational concept may be operationalized?*

Basic Data Elements

What do networks “look like”?

Basic Data Elements

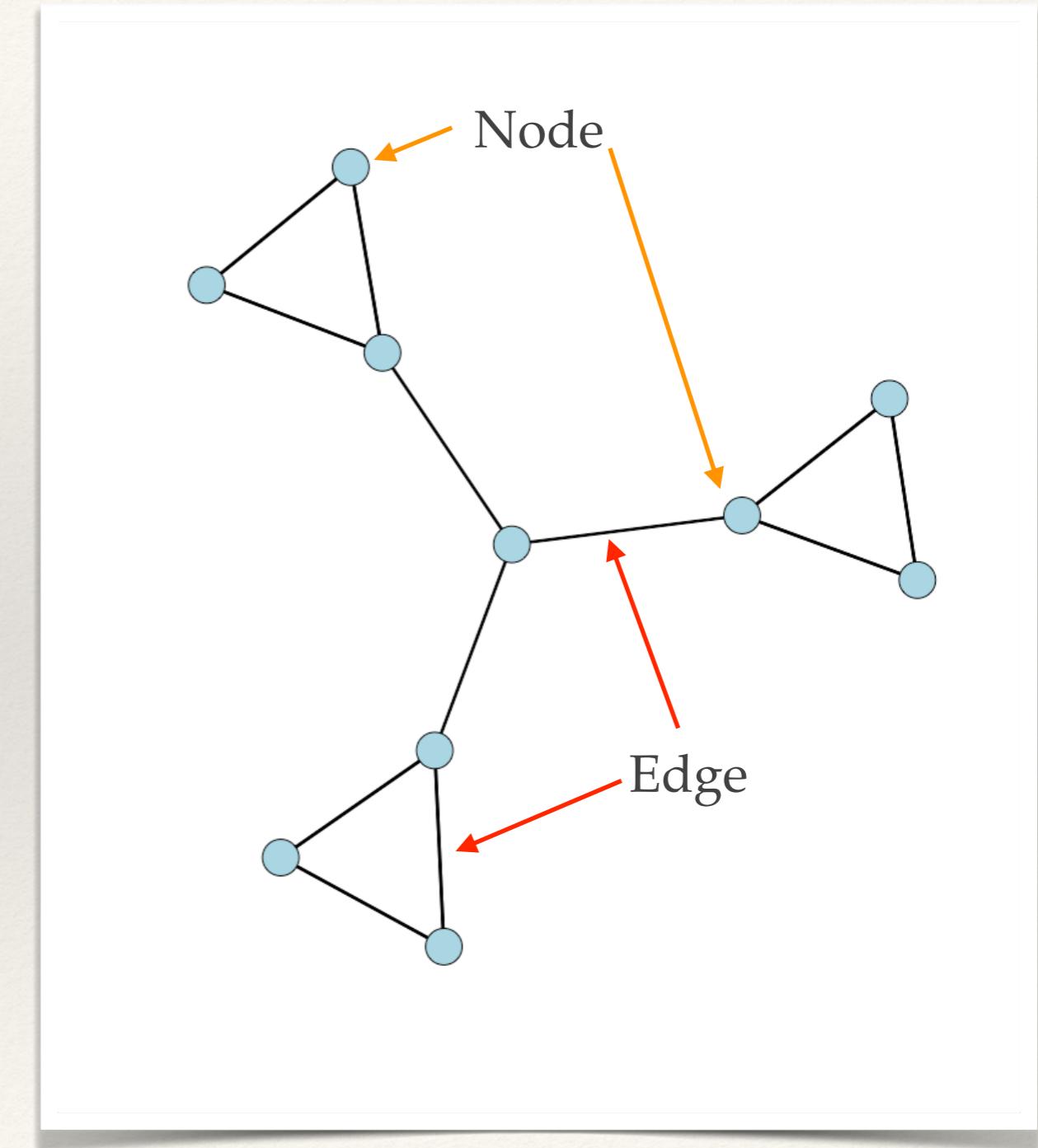
- ❖ Network (relational) data represent:
 - ❖ **Connections** (aka ties, arcs, edges, lines, ties) among,
 - ❖ **Entities** (aka nodes, vertices, actors, points, dots).
- ❖ I will use *node* to mean **entities** and *edge* to mean **connections**.

Basic Data Elements

- ❖ A *node* can be anything that can link to something else.
- ❖ An *edge* can be anything that can record a connection between nodes.
- ❖ *What are some nodes and edges that come to mind?*

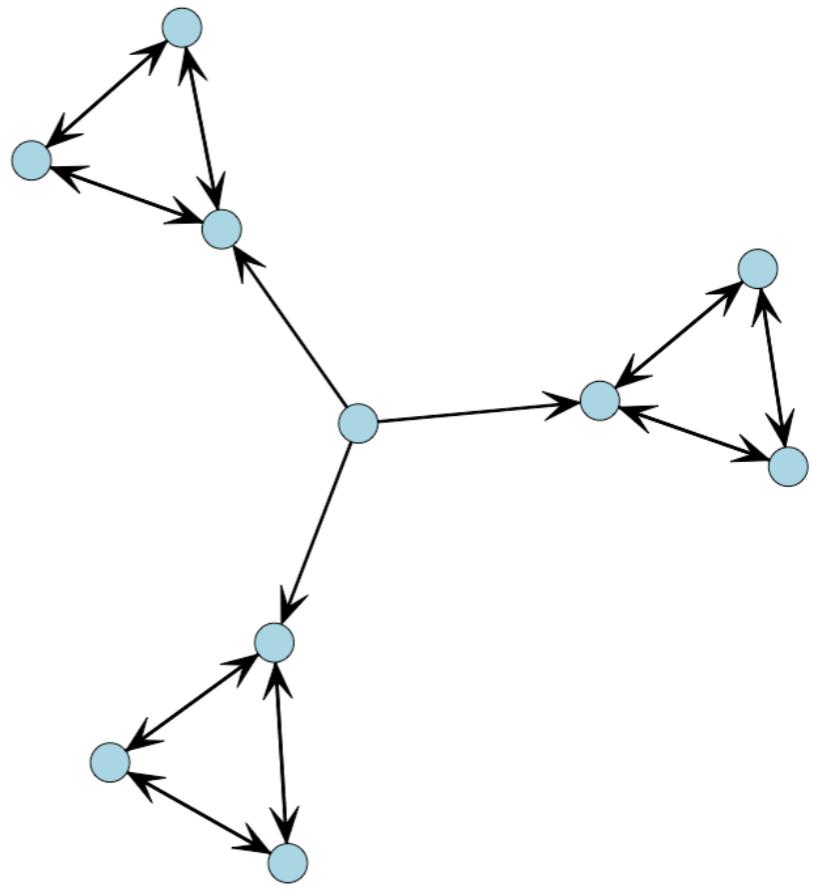
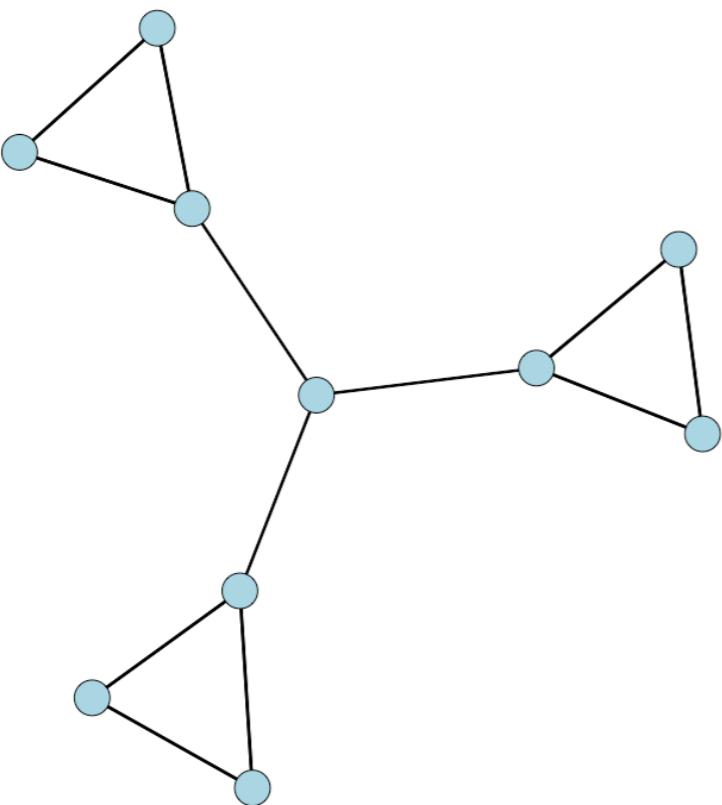
Basic Data Elements

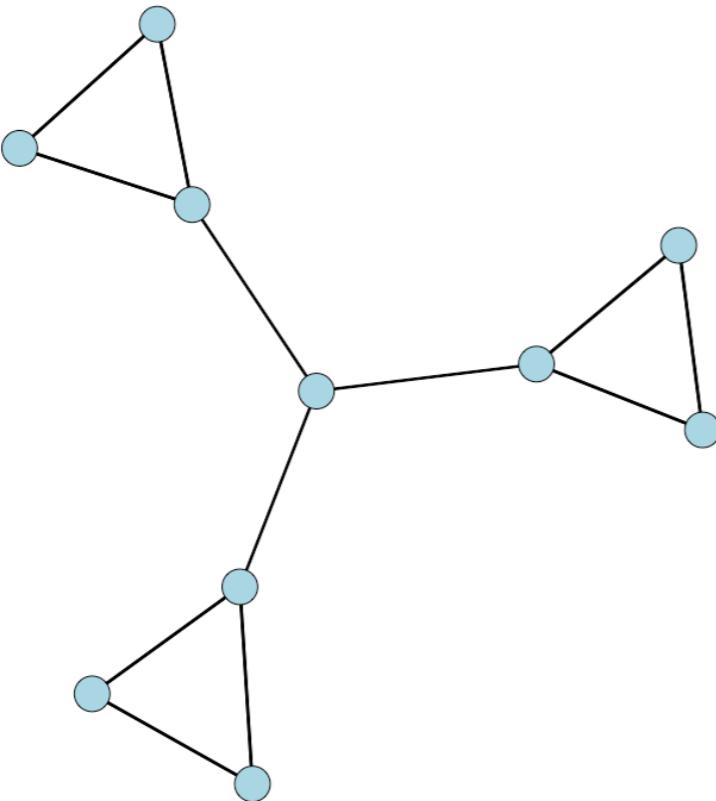
- ❖ On a graph, nodes are represented by *points* and edges are represented by *lines*.



Basic Data Elements

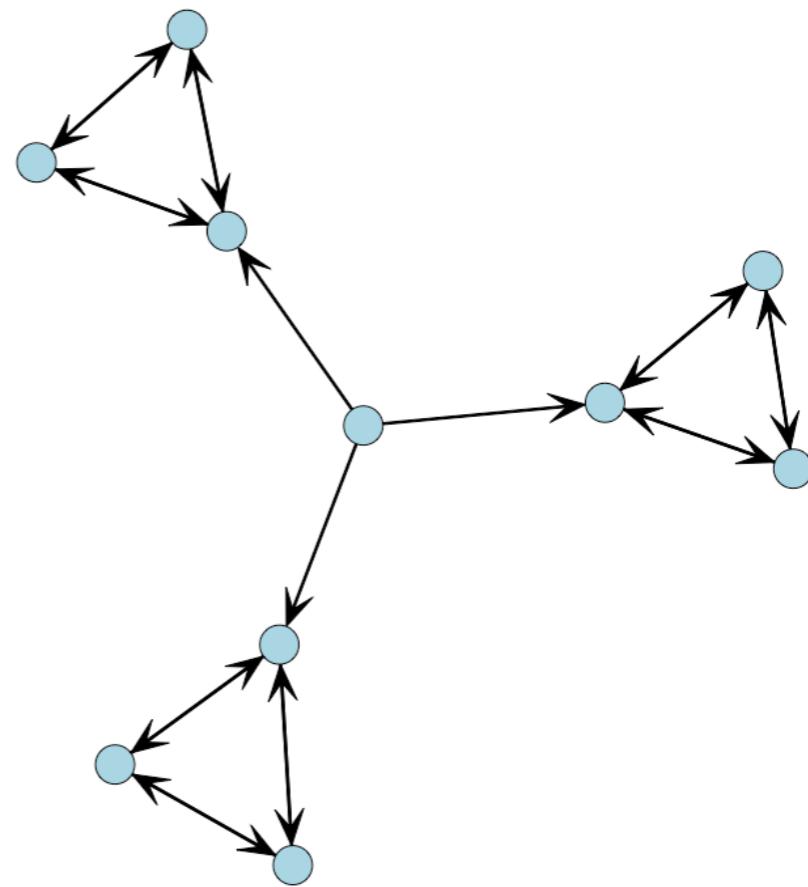
- ❖ Edges can be:
 - ❖ Directed or Undirected.





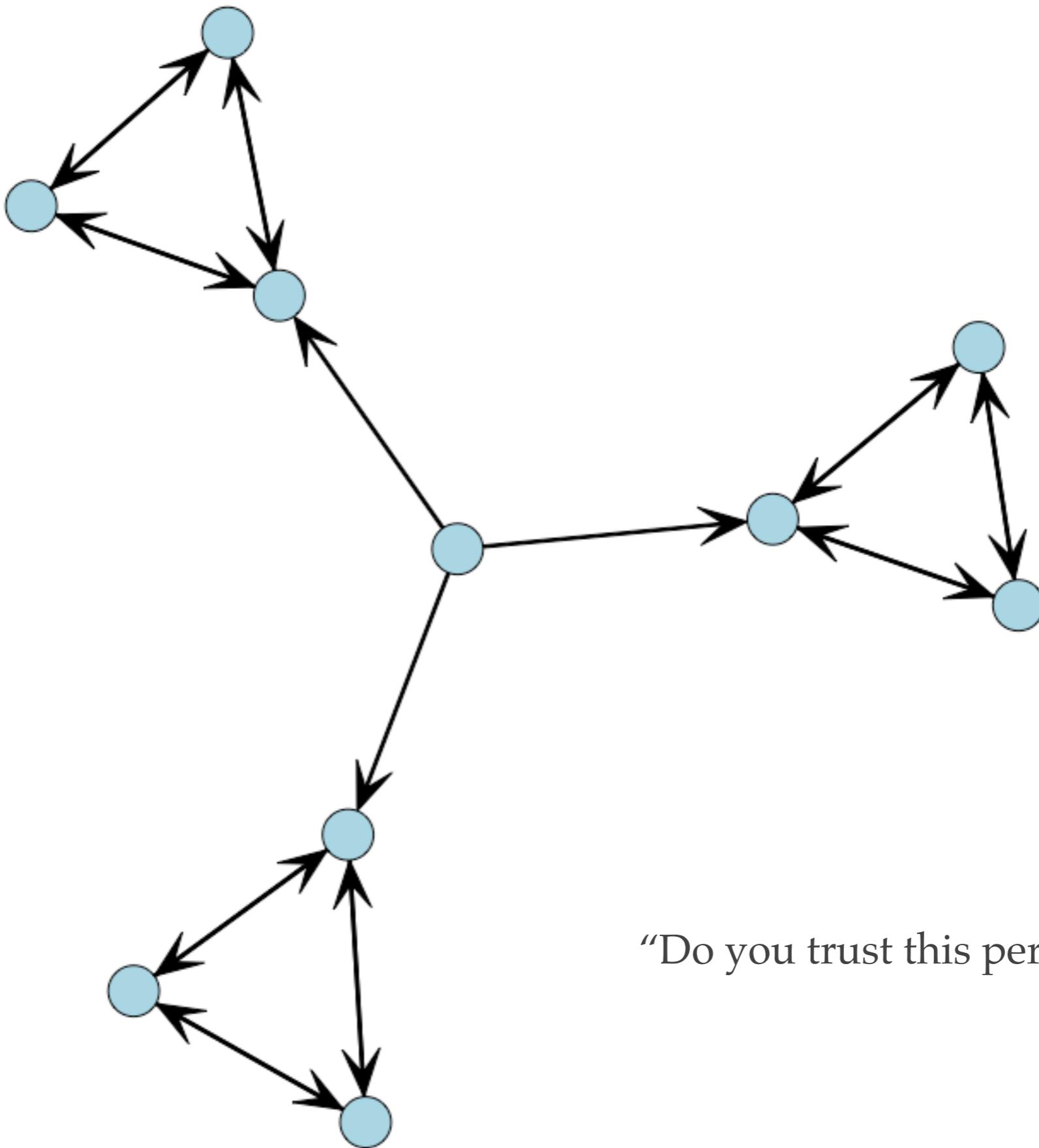
*How are these
structures
different?*

Suppose the edges
measure
communication...

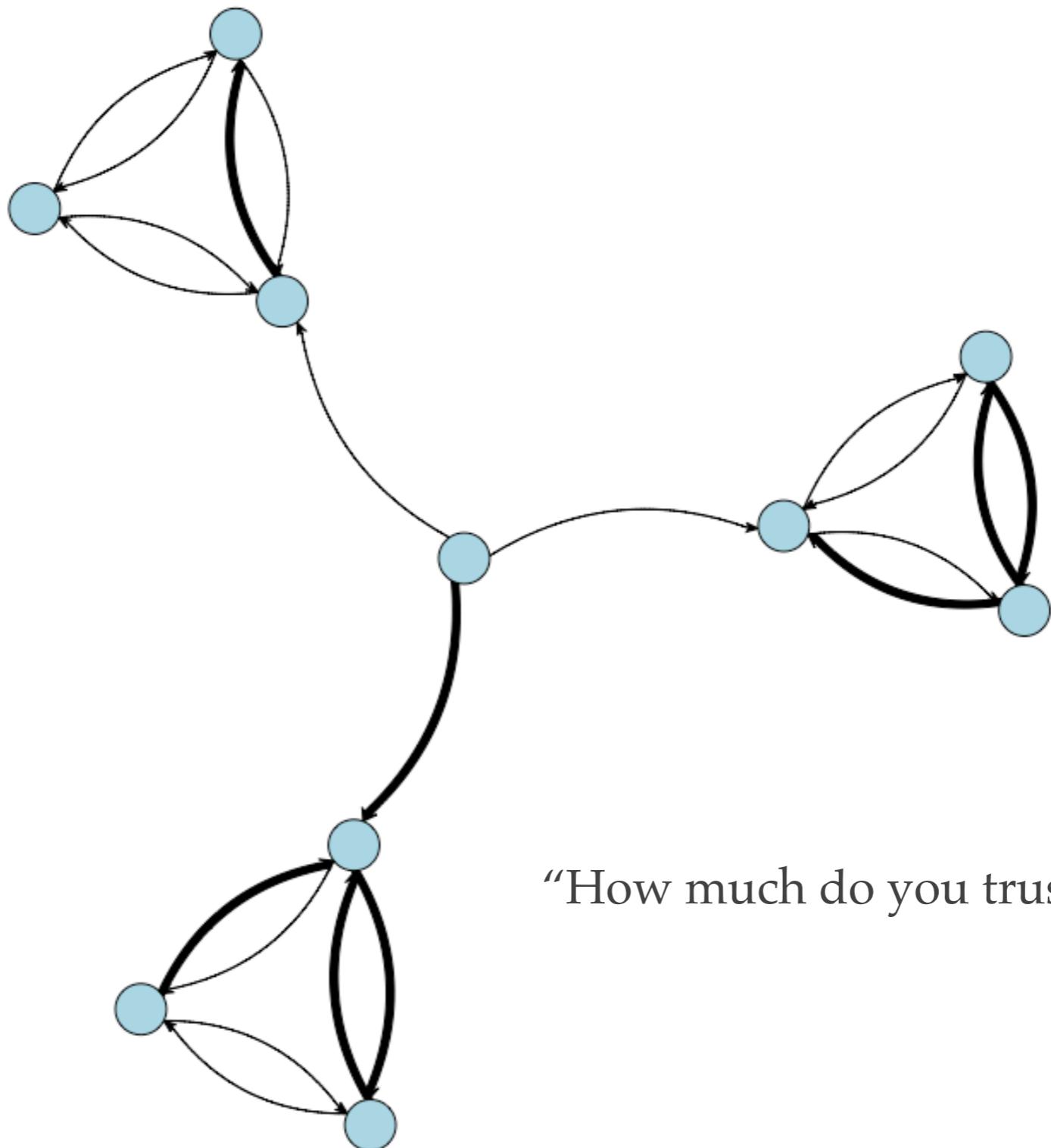


Basic Data Elements

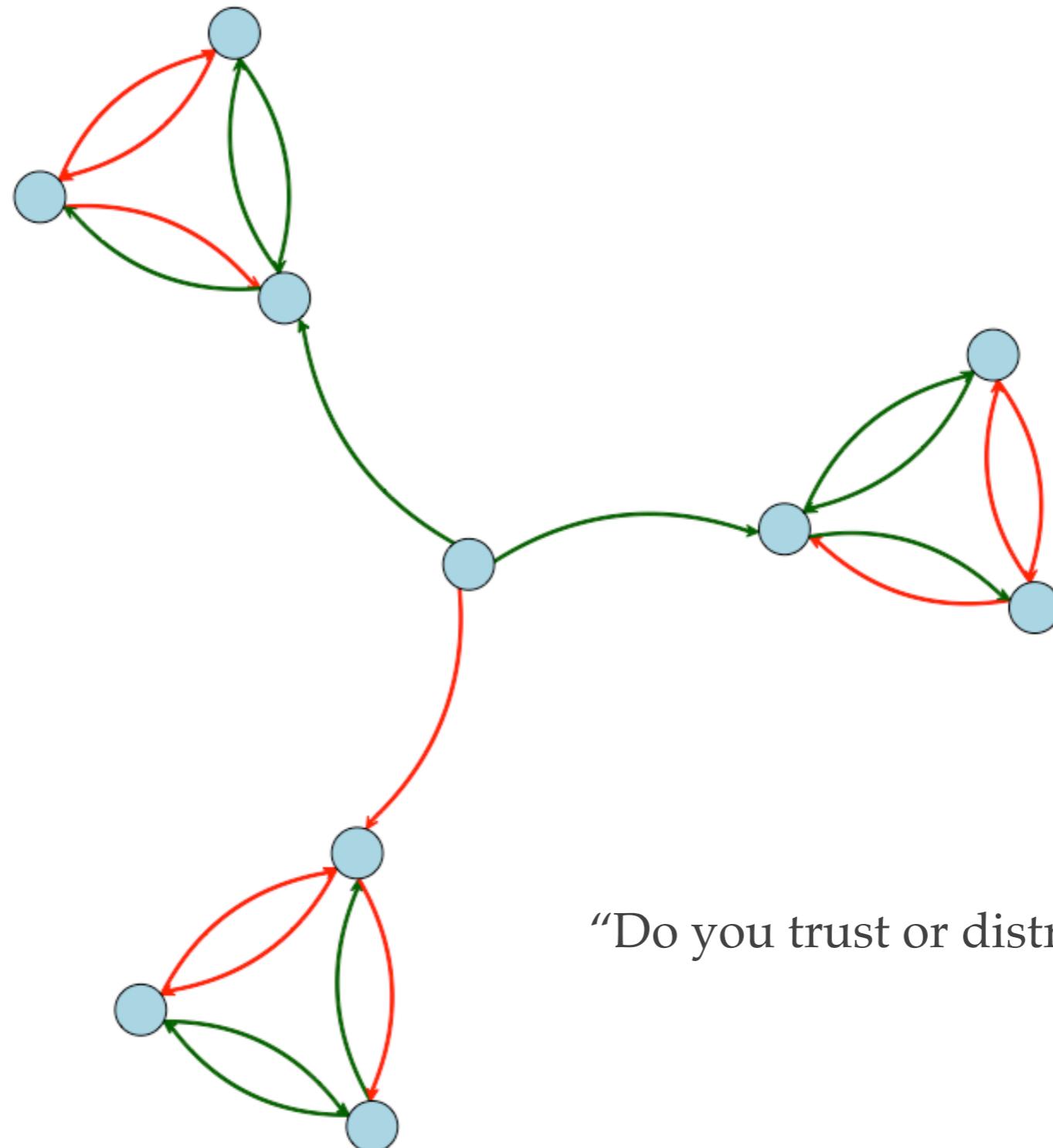
- ❖ **Edges** can be:
 - ❖ Binary (0/1; present/absent); Valued Integers (0/1/2...); Continuous Weights (0.24/1.76/ ...); Signed (+/-).



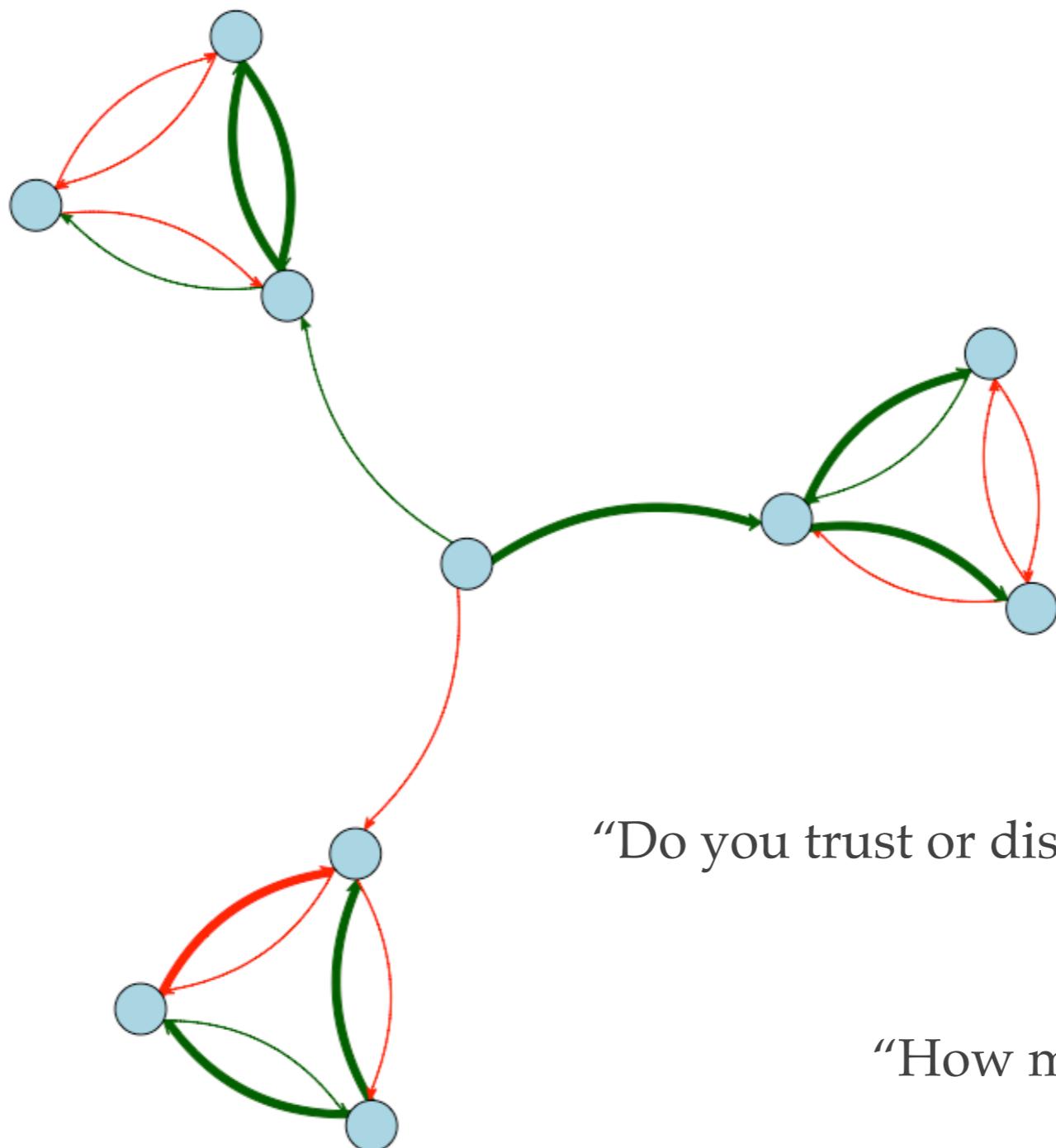
“Do you trust this person?”



“How much do you trust this person?”



“Do you trust or distrust this person?”



“Do you trust or distrust this person?”

“How much?”

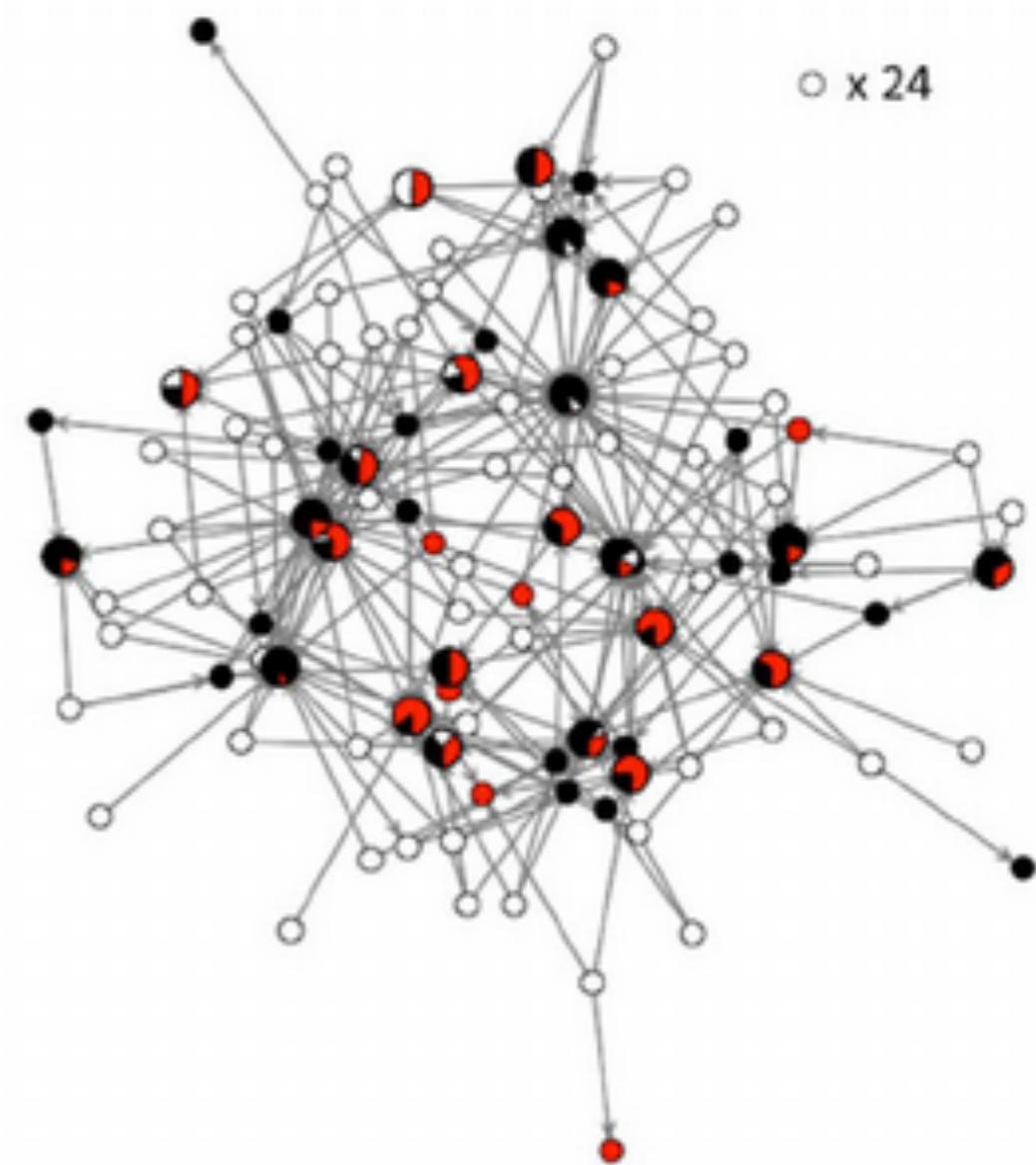
Basic Data Elements

- ❖ **Edges** can have different meanings and therefore be of different *types*.
 - ❖ Social relationships (sister, friend, likes, knows)
 - ❖ Interactions (has sex with, talks to, seeks advice from)
 - ❖ Flows (diseases, attitudes)

In the eye of the beholder: Meaning and structure of informal status in women's and men's prisons*

Derek A. Kreager¹ | Jacob T.N. Young² | Dana L. Haynie³ |
David R. Schaefer⁴ | Martin Bouchard⁵ | Kimberly M. Davidson¹

Positive/Negative/Neutral
Power nominations



(a)

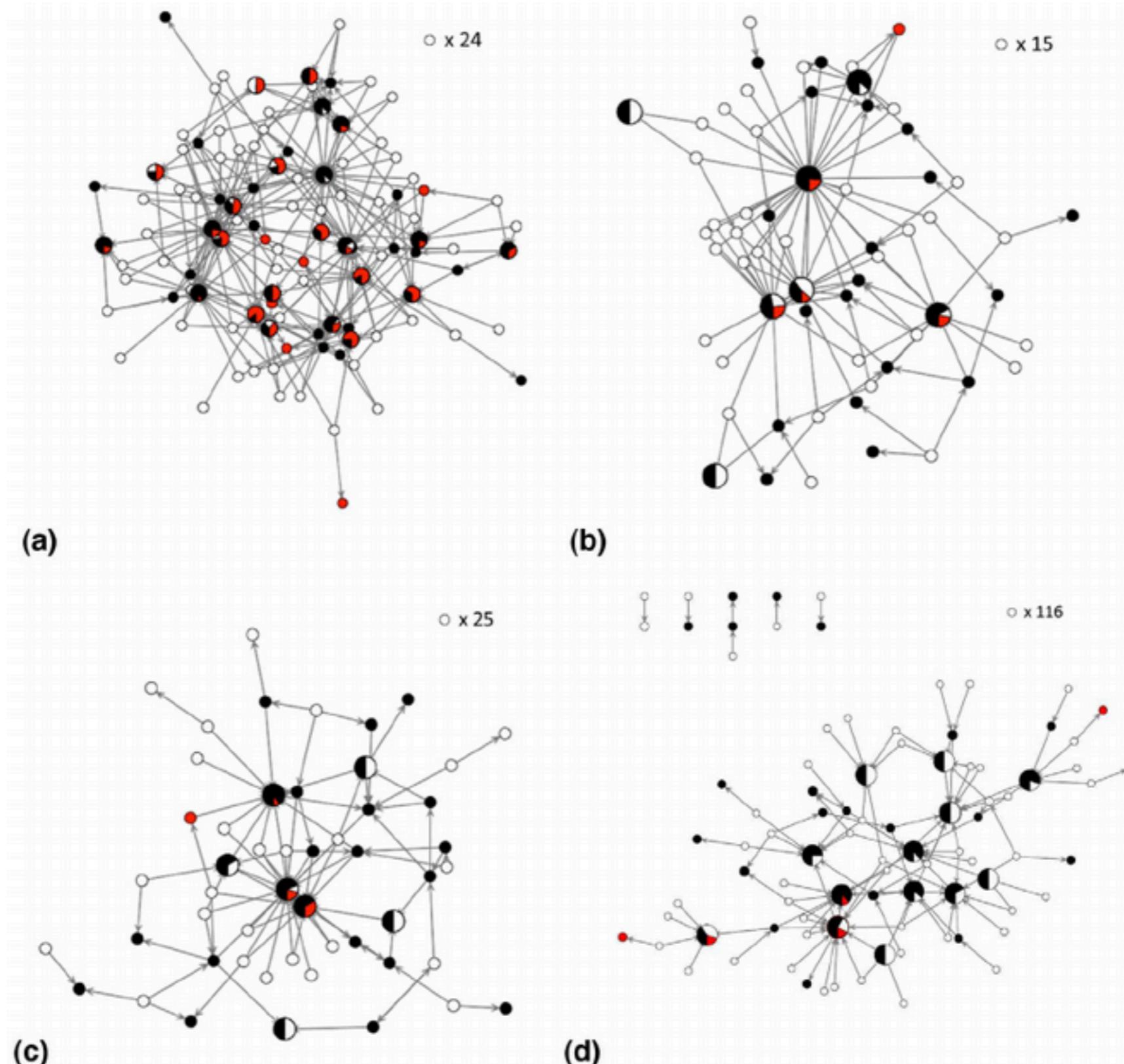
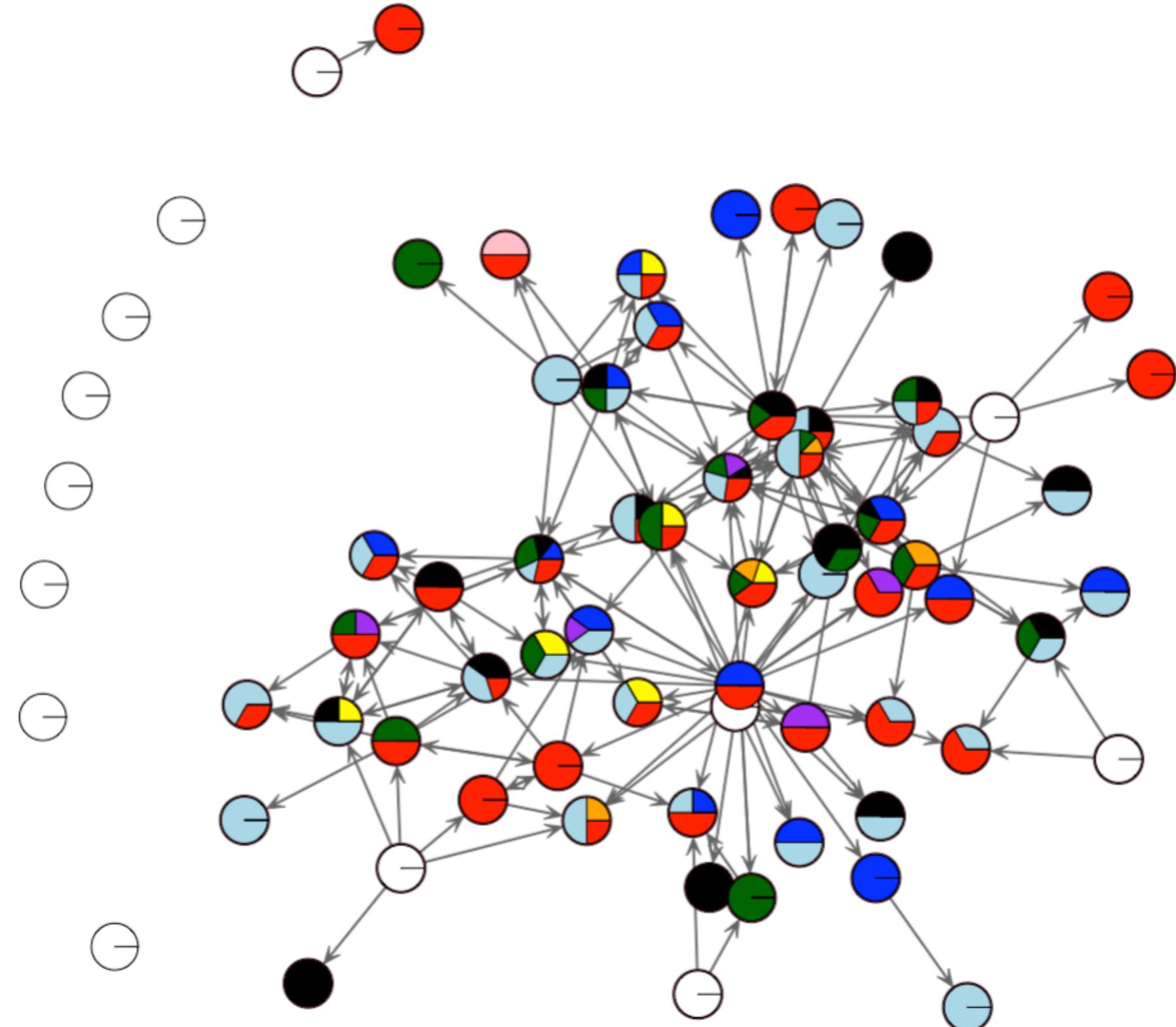


FIGURE 1 Balance of positive, neutral, and negative ties in the status networks of (a) Unit 1, (b) Unit 2, (c) Unit 3, and (d) Men's Unit [Color figure can be viewed at wileyonlinelibrary.com]

Notes: Nodes sized by indegree, isolate frequencies listed in top-right of each graph, and pie charts reflect proportion of incoming nominations that are positive [black], neutral [white], and negative [red].

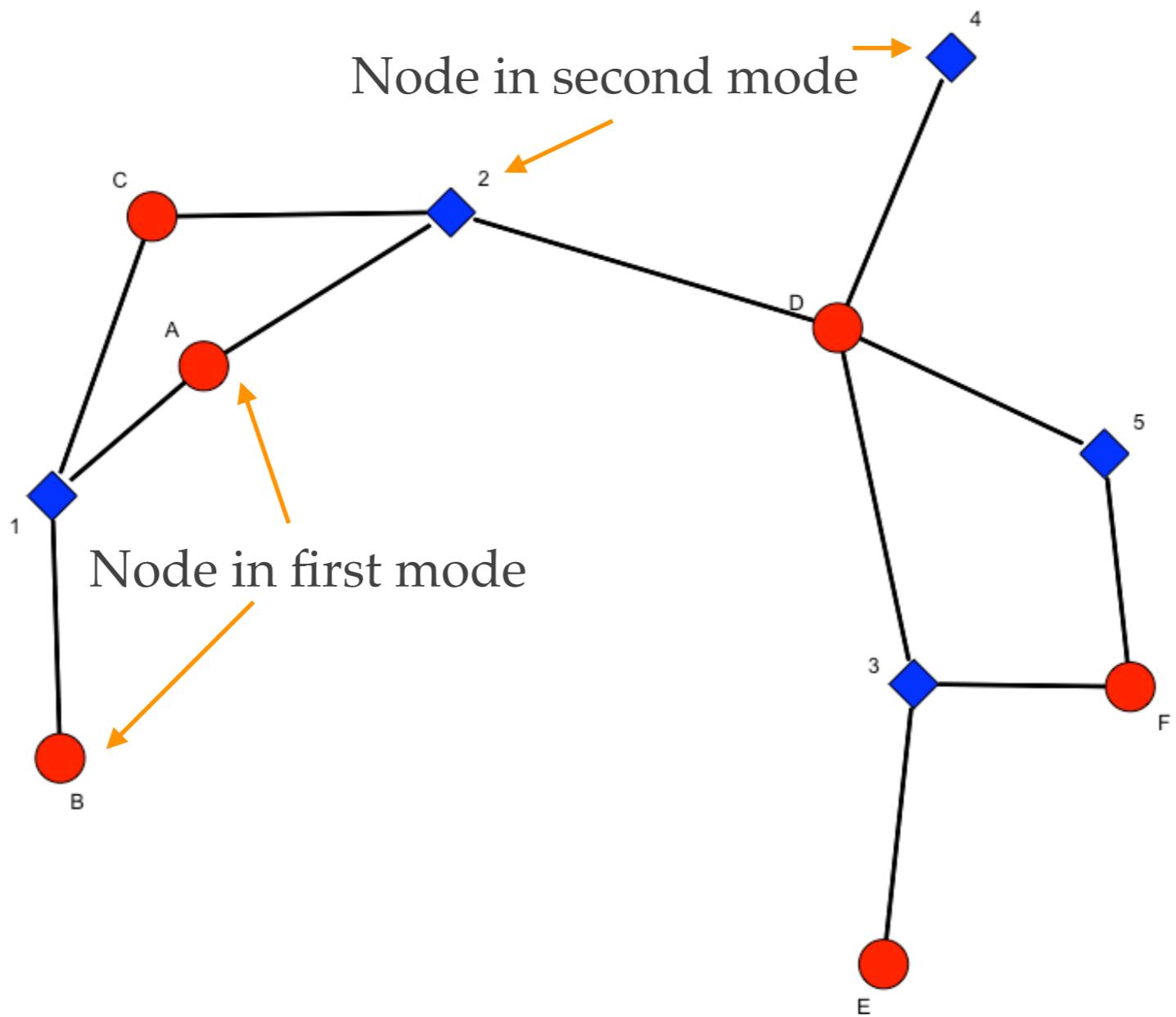
Family Role
Nominations
among
Incarcerated
Women

Good Behavior Family Network
(w/ Non-Roles Noms)

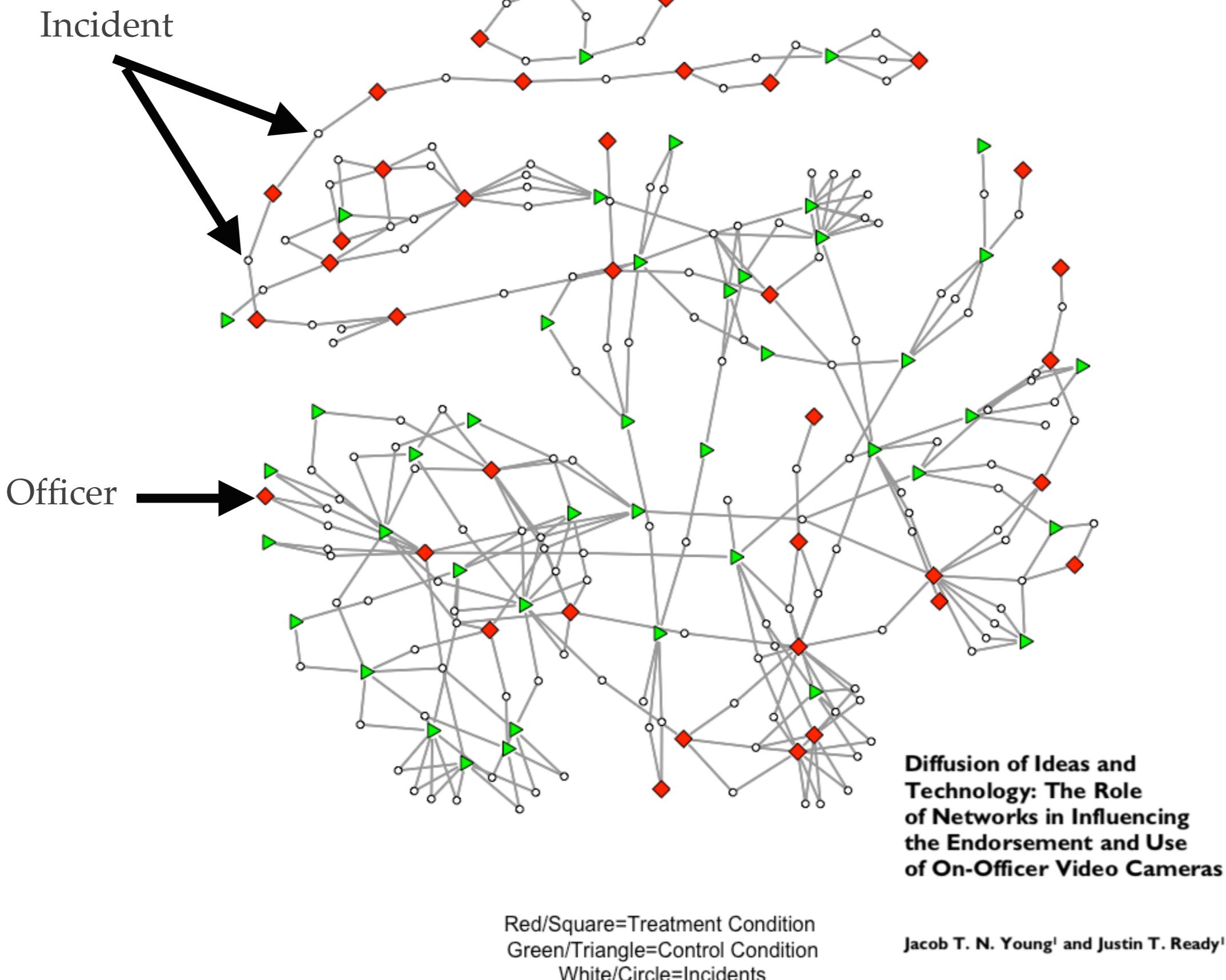


Basic Data Elements

- ❖ *Networks* can differ with respect to their **nodes**:
 - ❖ One-mode/uni-partite (connections among one type of node).
 - ❖ Multi-mode/multi-partite (connections among two or more types of nodes).



Bipartite Graph of Incidents and Officers by Treatment or Control Condition



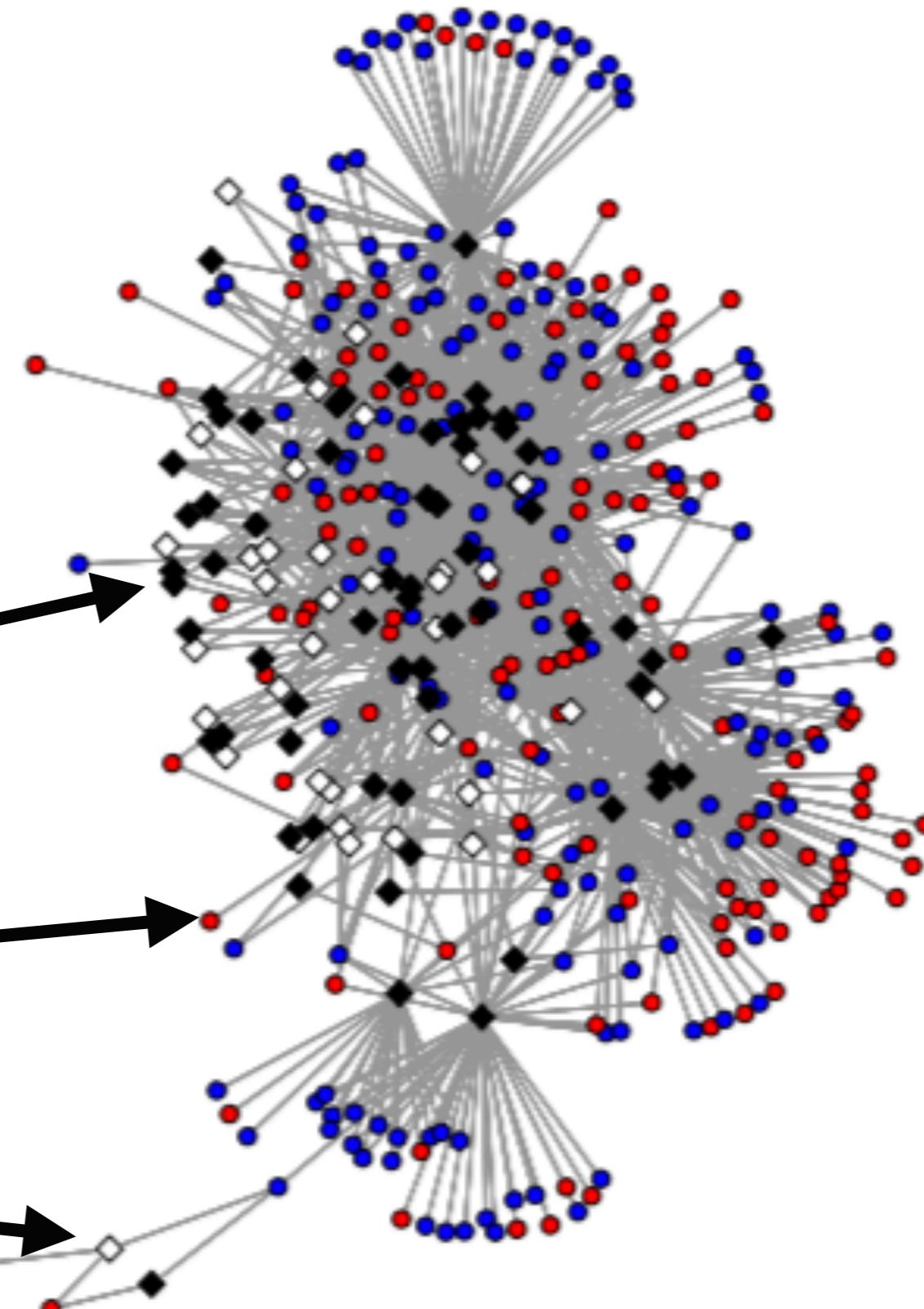
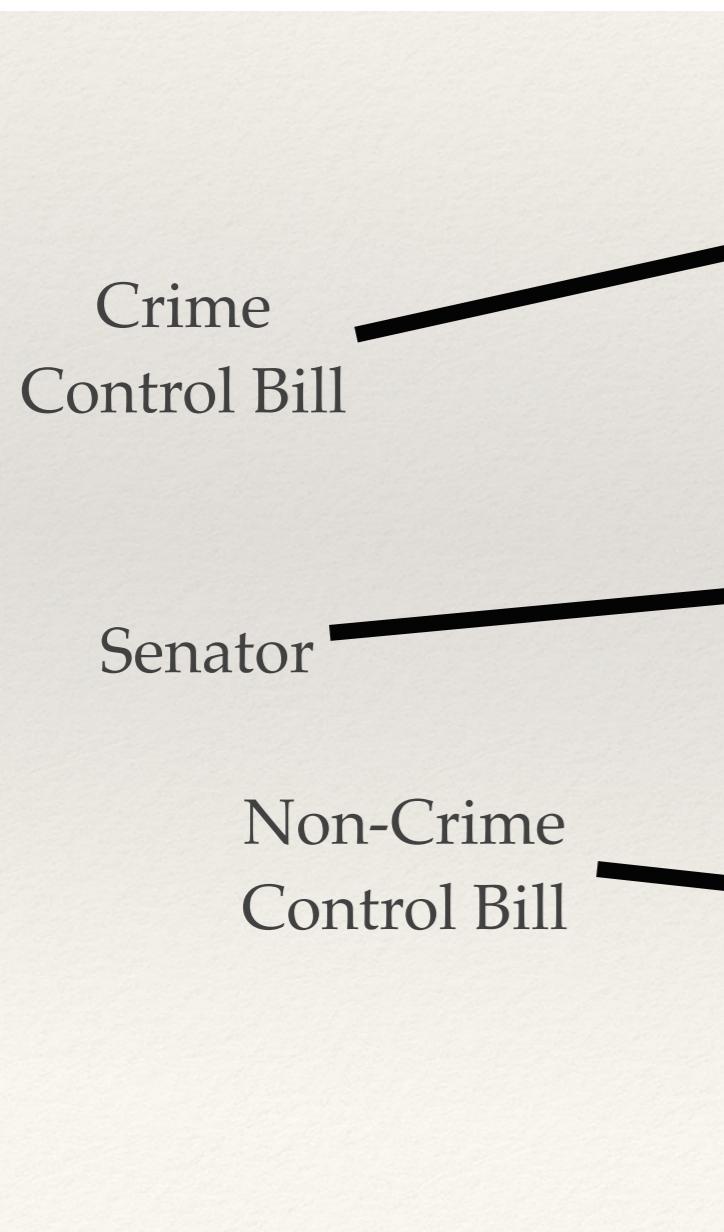
B: Plot of 291 Signers of 101 Bills in the Senate

Am J Crim Just (2018) 43:197–221
DOI 10.1007/s12103-017-9395-5



The “Tough on Crime” Competition: a Network Approach to Understanding the Social Mechanisms Leading to Federal Crime Control Legislation in the United States from 1973–2014

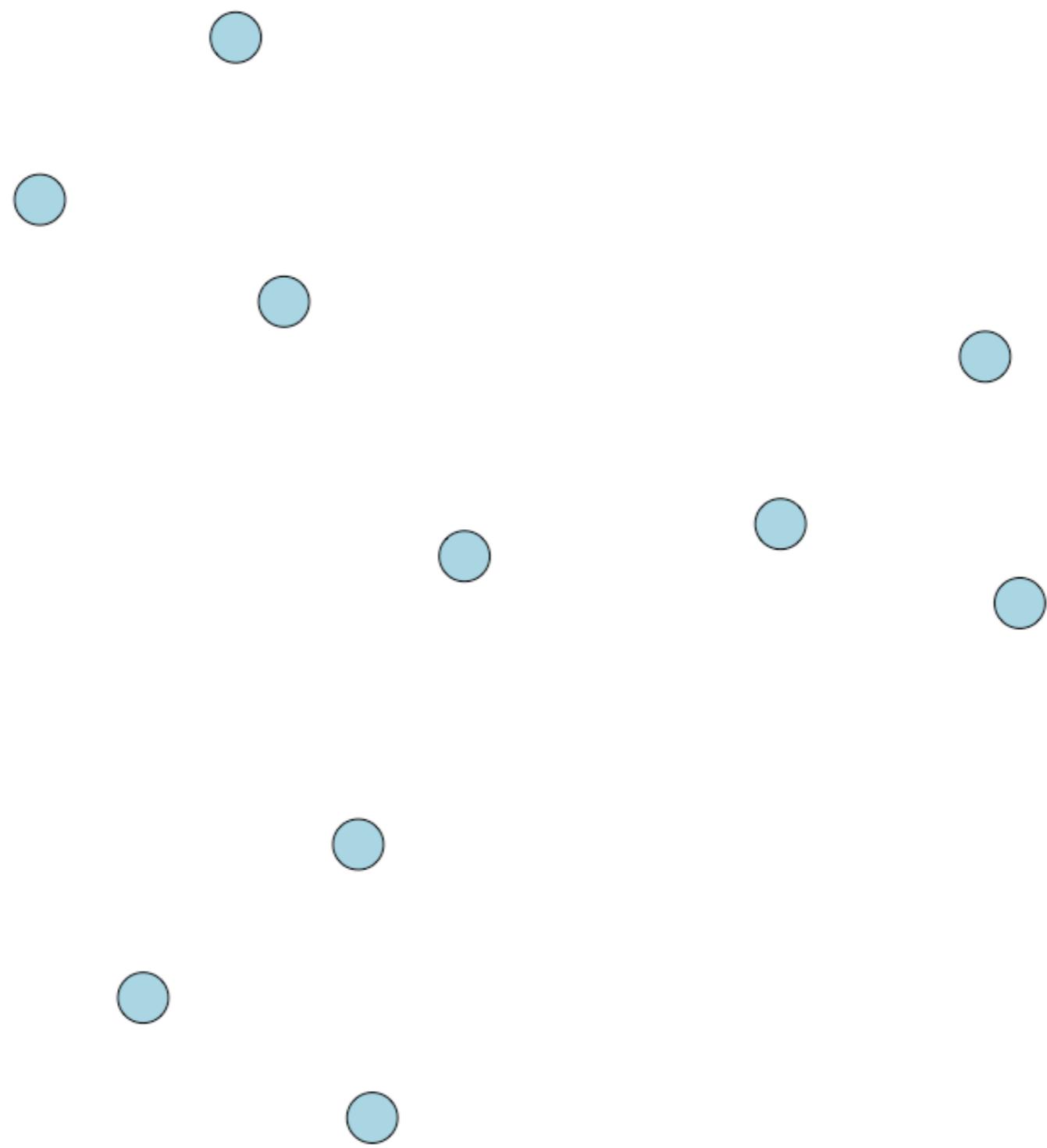
John A. Shjarback¹ · Jacob T. N. Young²

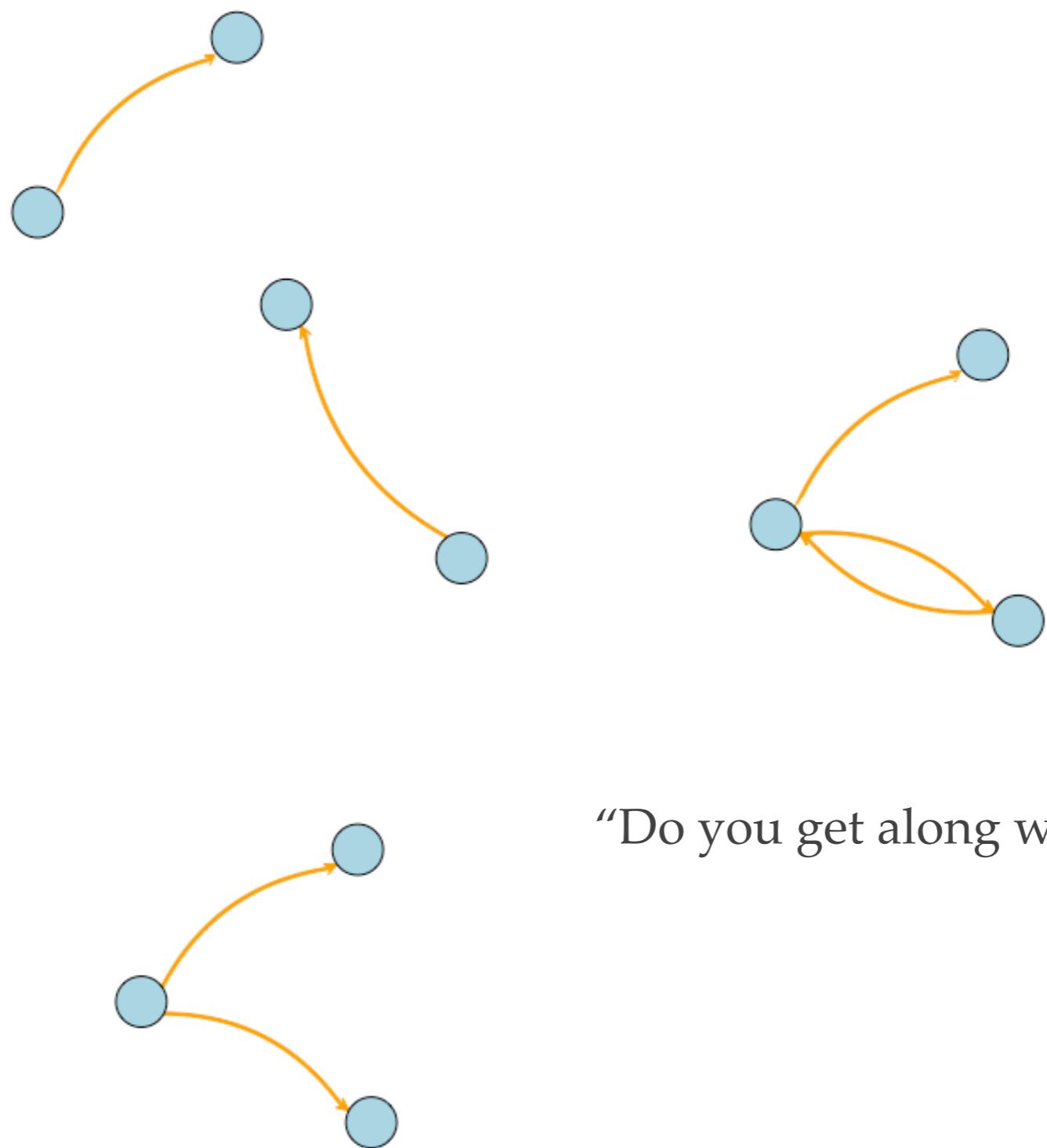


Democrats = Blue; Republicans = Red; CC Bills = Black; NCC Bills = White

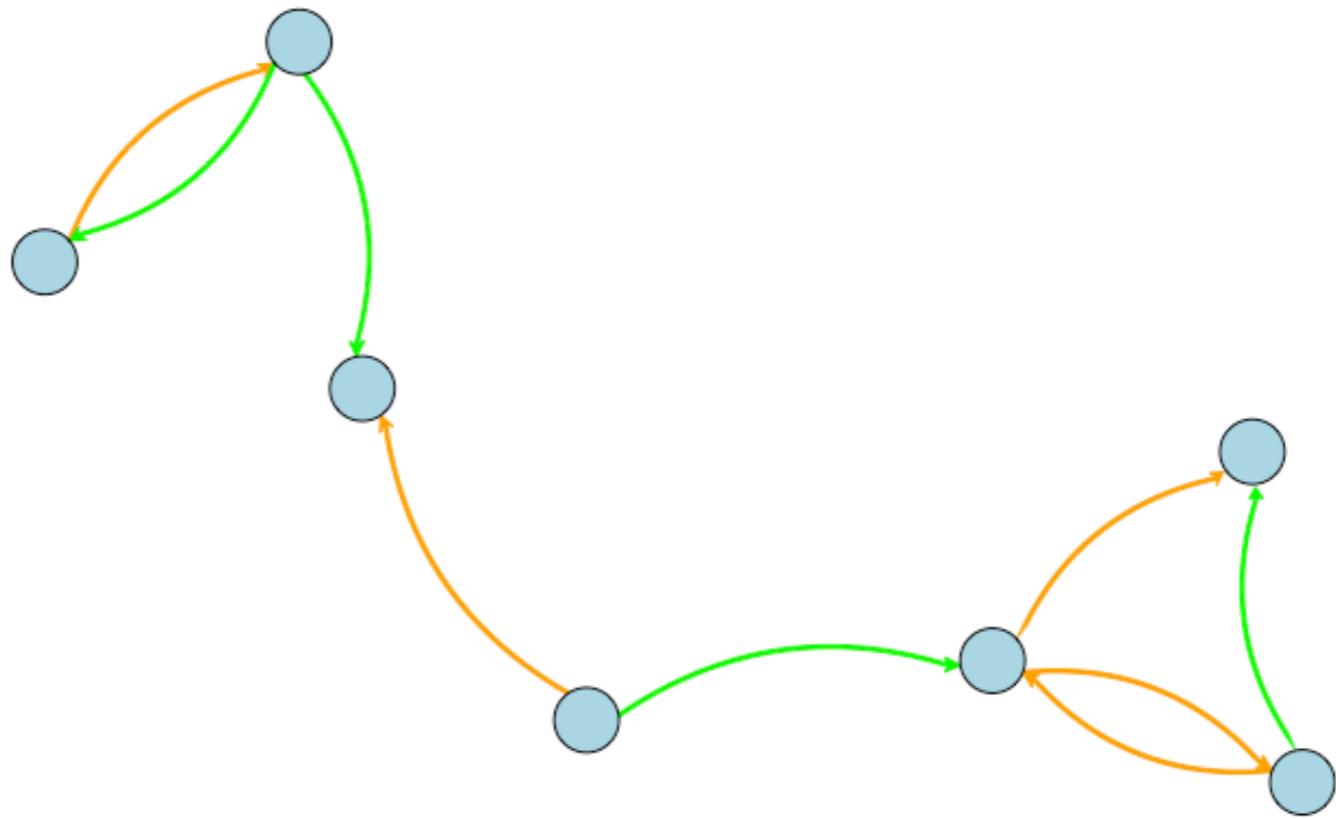
Basic Data Elements

- ❖ *Networks* can differ with respect to their **edges**:
 - ❖ Simplex (connections among nodes are of one type).
 - ❖ Multiplex (connections among nodes are of multiple types).



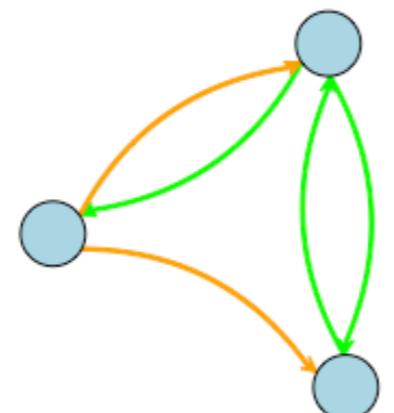


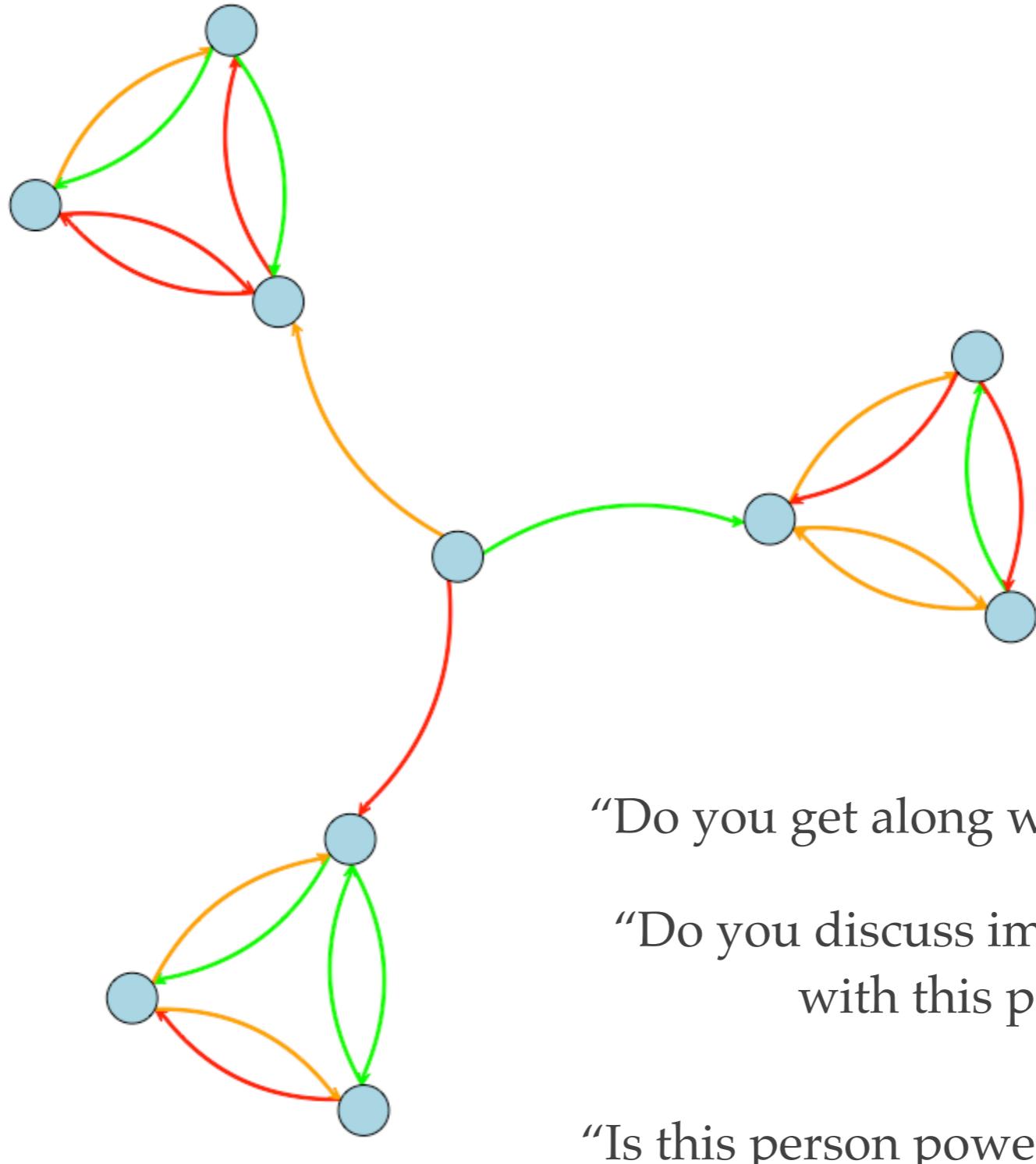
“Do you get along with this person?”



“Do you get along with this person?”

“Do you discuss important matters
with this person?”





“Do you get along with this person?”

“Do you discuss important matters
with this person?”

“Is this person powerful/influential?”

Summary

- ❖ *Relational* data can take many different forms and be represented many different ways.

Questions?

Network Data Collection

How do we collect network data?

Network Data Collection

- ❖ Where do network data come from?
 - ❖ **Everywhere!**
 - ❖ Types of data collection:
 - ❖ Observational (e.g. Miller project)
 - ❖ Archival (e.g. Capone project)
 - ❖ Questionnaires (e.g. Add Health, GSS)

Instruments and Design

- ❖ *Instruments* are the tools used to elicit information from respondents.
- ❖ *Design* corresponds to the protocol for determining how information should be elicited, who should be sampled, etc.
- ❖ Examples:
 - ❖ Ego-centric networks
 - ❖ Partial networks
 - ❖ Complete (global) networks

Ego-Centric Networks

- ❖ Data on a focal actor (ego) and ties to neighbors (alters) and the ties among the alters.
 - ❖ *Instrument:* name generator
 - ❖ “who are the people with whom you discuss important matters?”
 - ❖ For each person named, “which of these individuals discuss important matters”?
 - ❖ Why?-costs, generalizability, interest in local structure.

Partial Network

- ❖ Ego networks, plus some amount of tracing to reach contacts of contacts.
- ❖ *Instrument:* tracing mechanism
 - ❖ Using tickets to trace across a network
 - ❖ Why?-difficult to reach population, hard to specify sampling frame.
 - ❖ **Does this instrument seem familiar?**

Complete (Global) Network

- ❖ Data on all actors within a particular (defined) boundary, sampling frame is known.
 - ❖ *Instruments:*
 - ❖ roster
 - ❖ “For each of the following persons, please indicate whom you trust to share personal information with?”
 - ❖ Free response
 - ❖ “Who are the people in this prison that you trust with person information about you?”

Things to consider...

- ❖ Domain:
 - ❖ “What type of network is this?”
- ❖ Sample:
 - ❖ “What is the population of interest and how was it sampled?”
- ❖ Temporality:
 - ❖ “Are the data cross-sectional or longitudinal?”
 - ❖ “Is it a panel or continuous measurement?”
- ❖ Tie Meaning:
 - ❖ “Are ties discrete events or enduring states?”
- ❖ Instrument:
 - ❖ “How was the information collected?”

Things to keep in mind...

- ❖ Butts (2009: 24)
 - ❖ Representational formalism:
 - ❖ “Researchers begin with a finite set of identifiable entities...”
 - ❖ “This representational framework is quite restrictive. To represent a system in this way, we must be able to reduce it to a well-defined set of discrete components whose interactions are strictly dyadic in nature...; although such a framework may seem so restrictive as to useless, its typical purpose is to serve as an approximation...”
 - ❖ *What does this mean?*

More things to keep in mind...

- ❖ *What is the level of analysis?*
 - ❖ Dyad Level
 - ❖ “are individuals whose offices are close to each other more likely to be friends?”
 - ❖ Node Level
 - ❖ “are more popular youth more likely to engage in unprotected sex?”
 - ❖ Network Level
 - ❖ “do viruses spread faster in particular network structures?”

Questions?

Break!

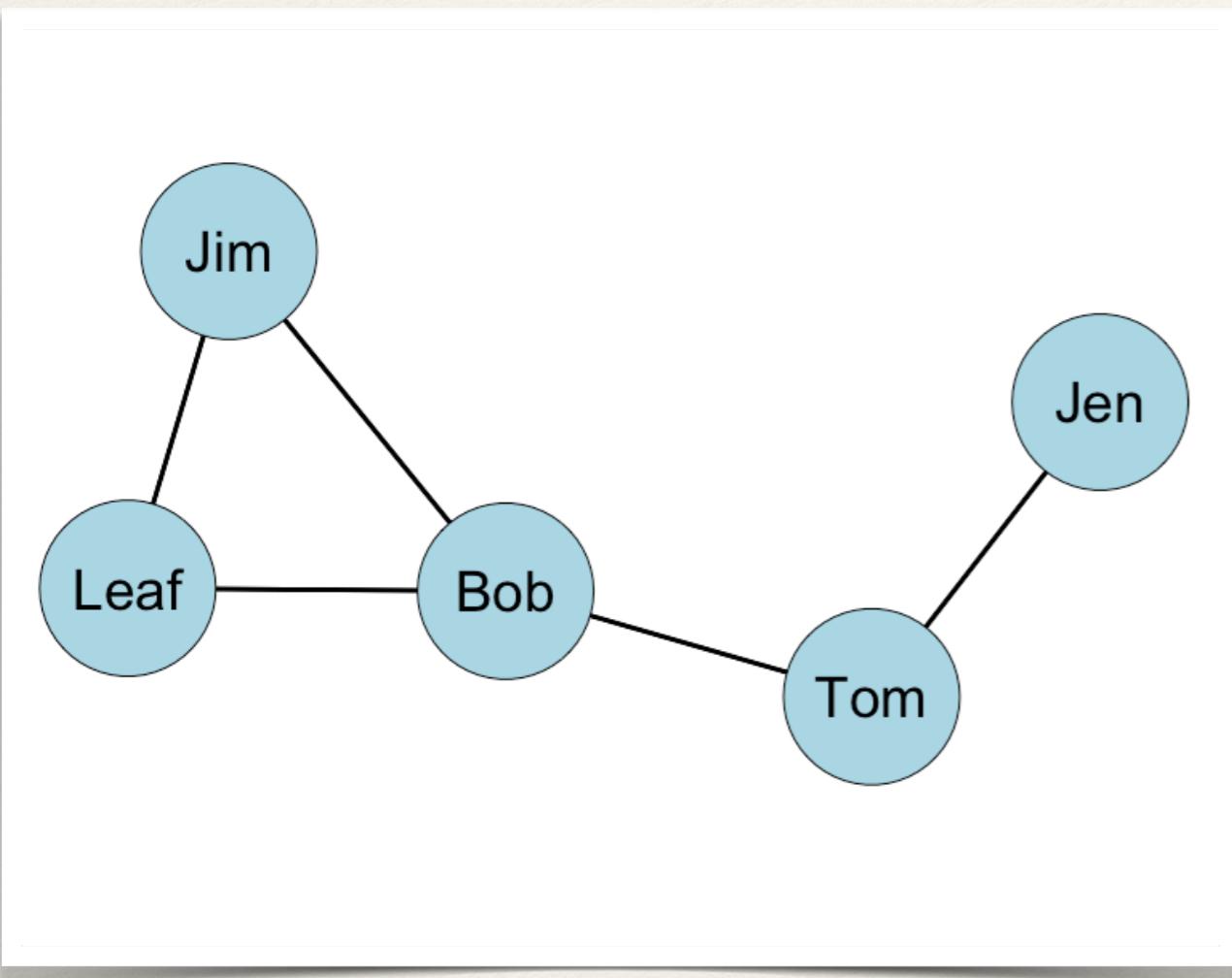
Representing Networks with Graphs and Matrices

What do network data “look like”?

Sociometric Notation

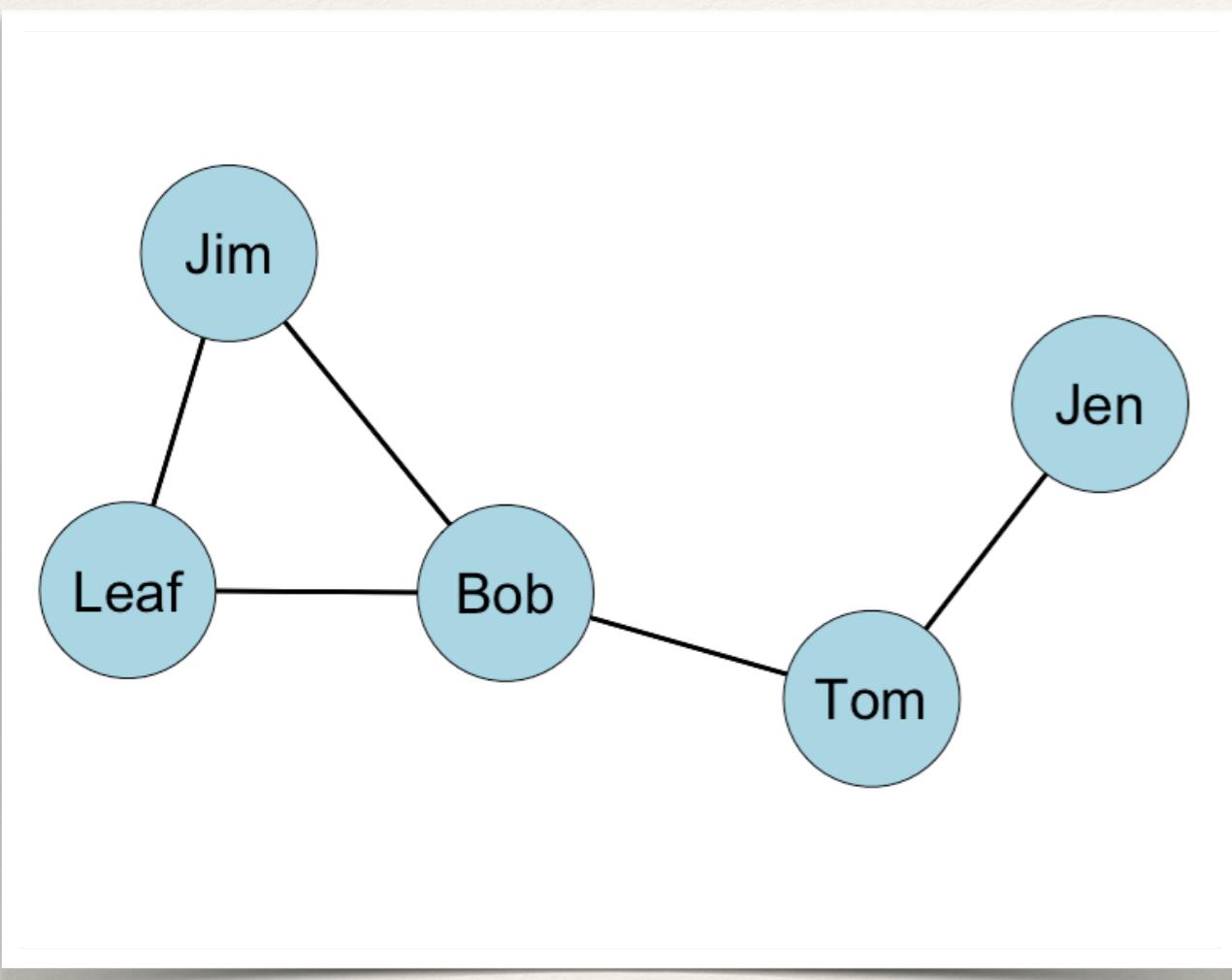
- ❖ For a set of relations, X , we can define a matrix which represents these relations.
- ❖ We commonly use an *adjacency matrix*, where each node / vertex is listed on the row and the column.
- ❖ The i_{th} row and the j_{th} column X_{ij} records the value of a tie from i to j .
- ❖ In this approach, X , can be thought of as a variable.
 - ❖ The presence or absence of values in the cells represent variation.

Example: Undirected, Binary Network



	Jen	Tom	Bob	Leaf	Jim
Jen					
Tom					
Bob					
Leaf					
Jim					

Example: Undirected, Binary Network

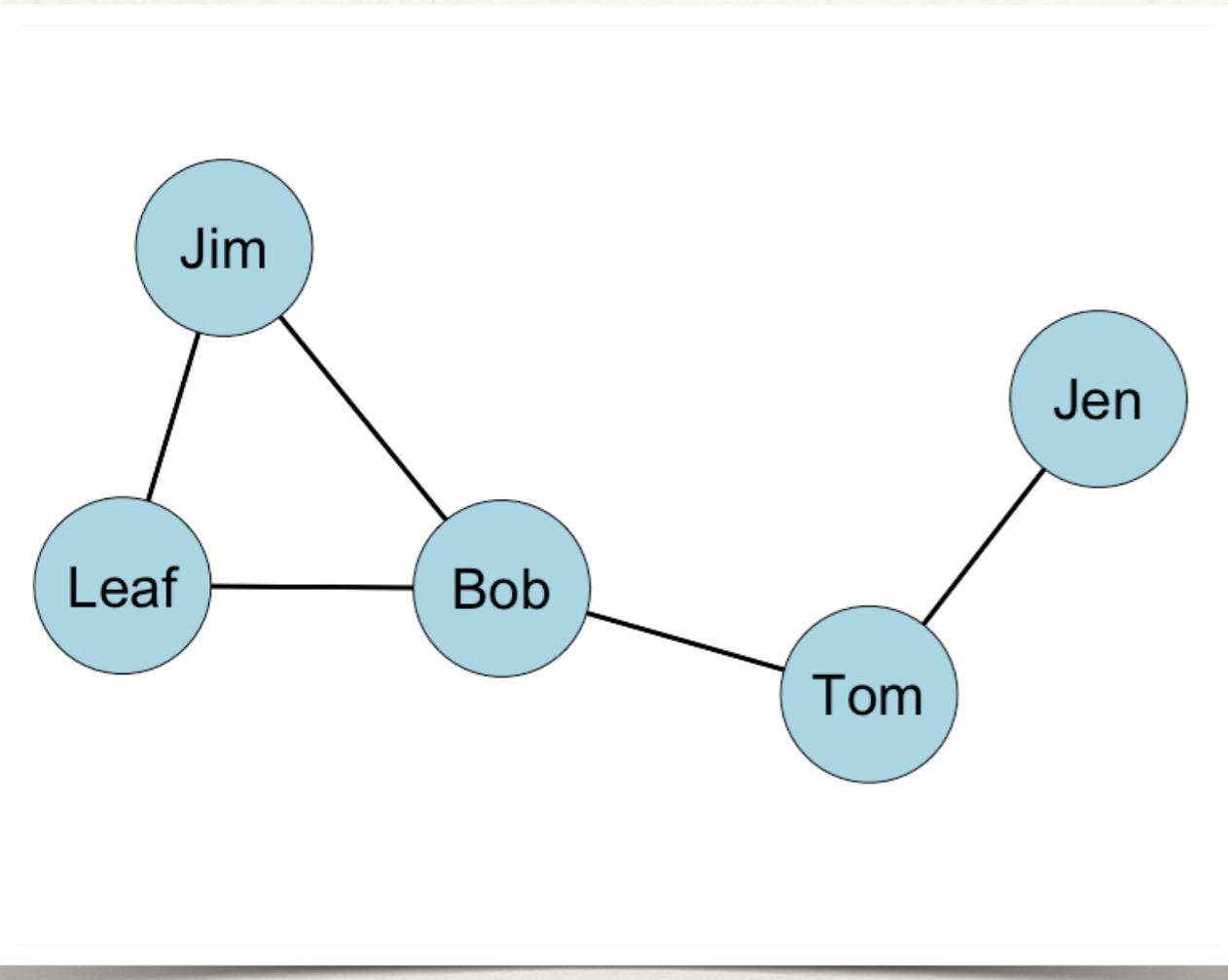


Graph or Sociogram

	Jen	Tom	Bob	Leaf	Jim
Jen					

Adjacency Matrix or Sociomatrix

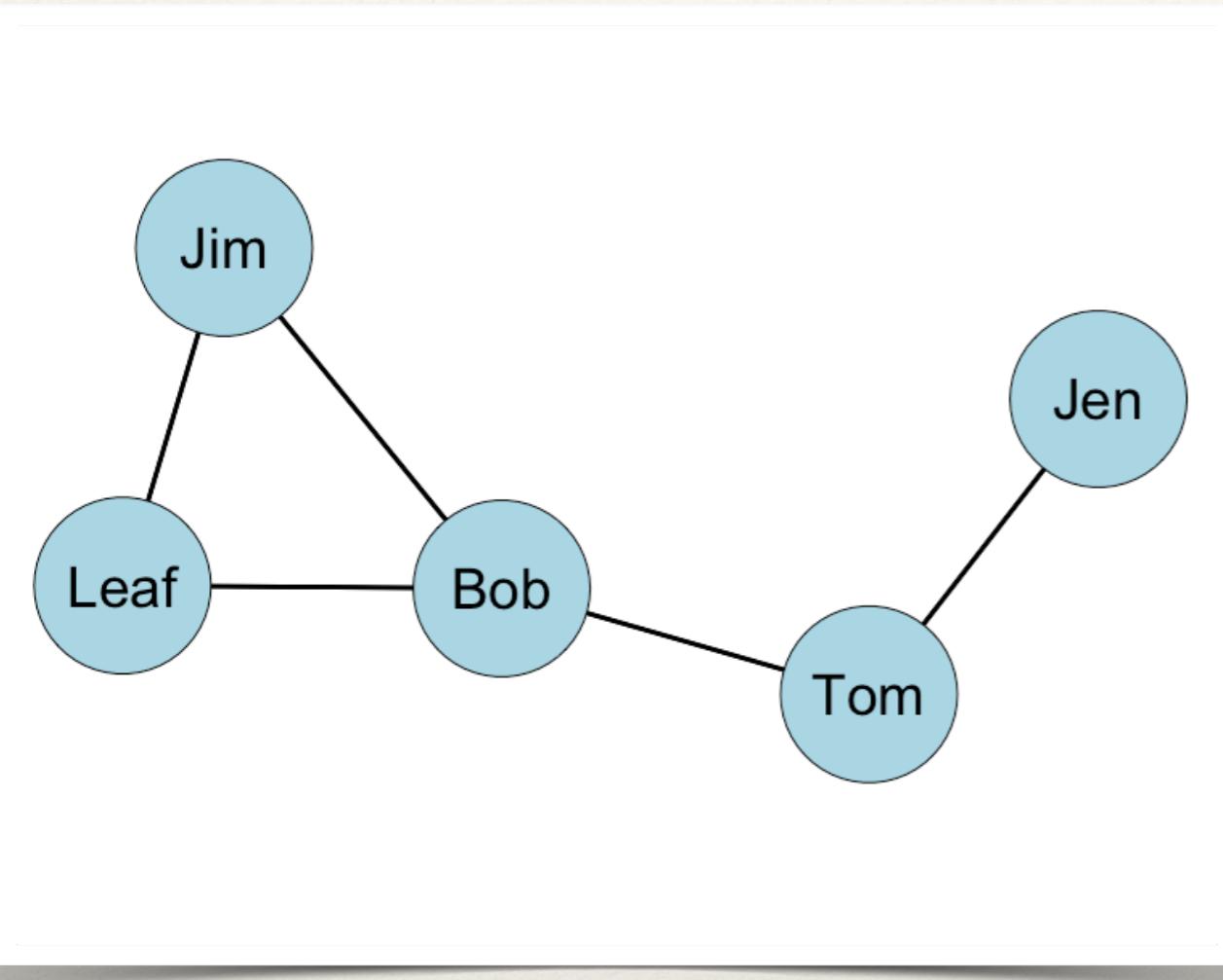
Example: Undirected, Binary Network



	Jen	Tom	Bob	Leaf	Jim
Jen					

We don't allow (in the simple case) self-nominations, so the diagonal is undefined.

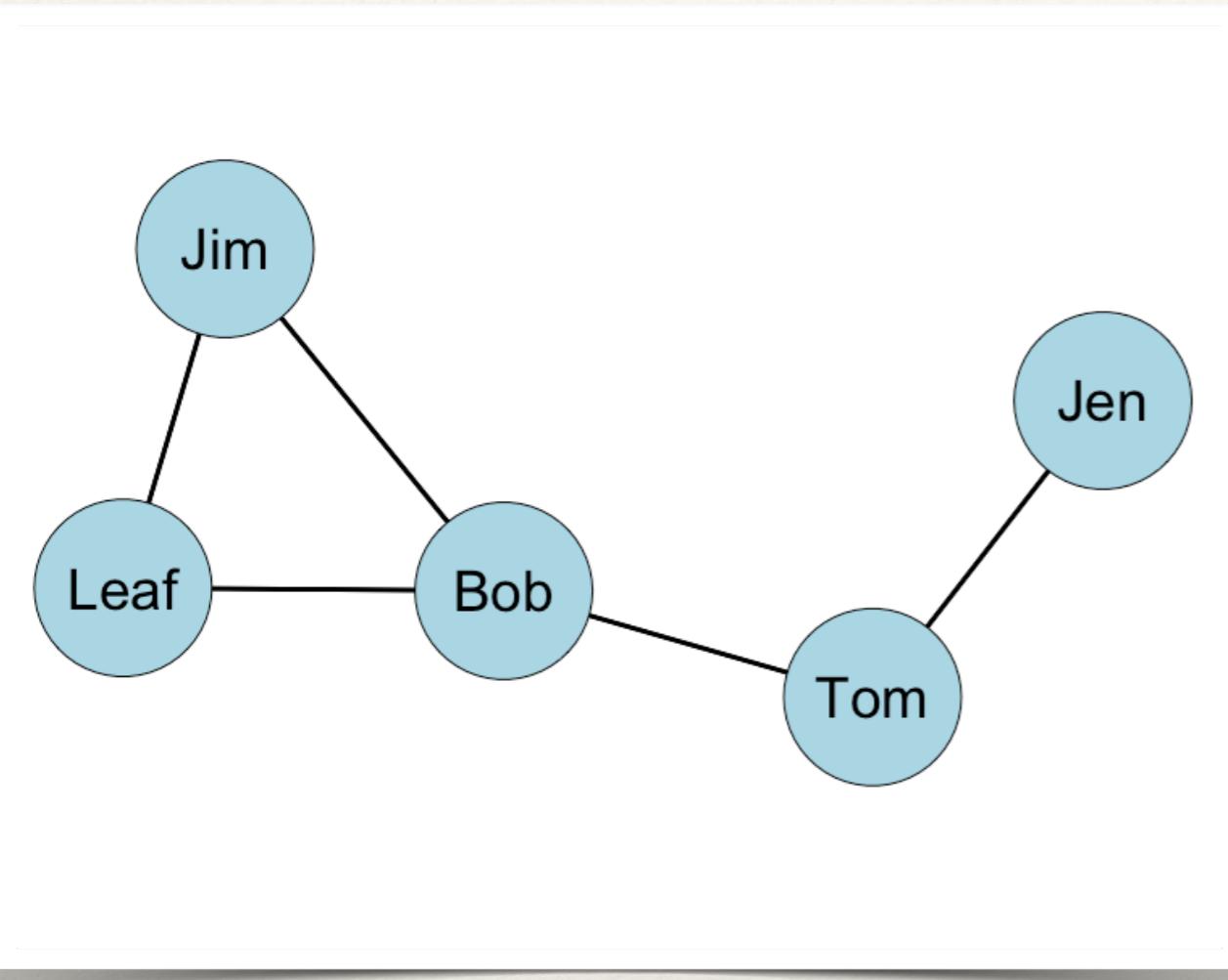
Example: Undirected, Binary Network



	Jen	Tom	Bob	Leaf	Jim
Jen		1	0	0	0
Tom					
Bob					
Leaf					
Jim					

In the first row, i sends to the second row
only: $X_{12} = 1$; $X_{15} = 0$

Example: Undirected, Binary Network

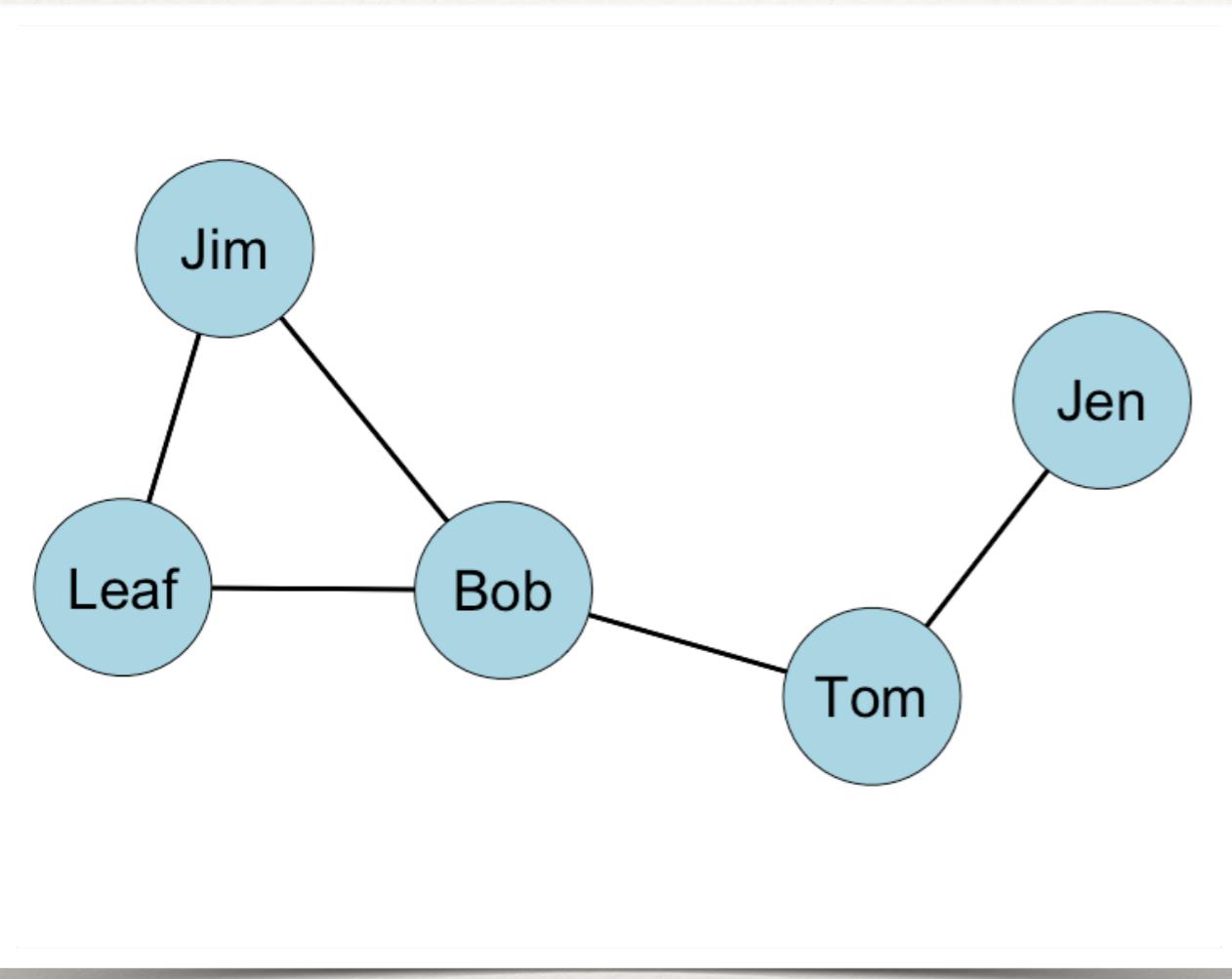


	Jen	Tom	Bob	Leaf	Jim
Jen		1	0	0	0
Tom	1				
Bob	0				
Leaf	0				
Jim	0				

Since this is *undirected*, it is **symmetric** about the diagonal.

This means that the *i*th column is the transposition of the *i*th row.

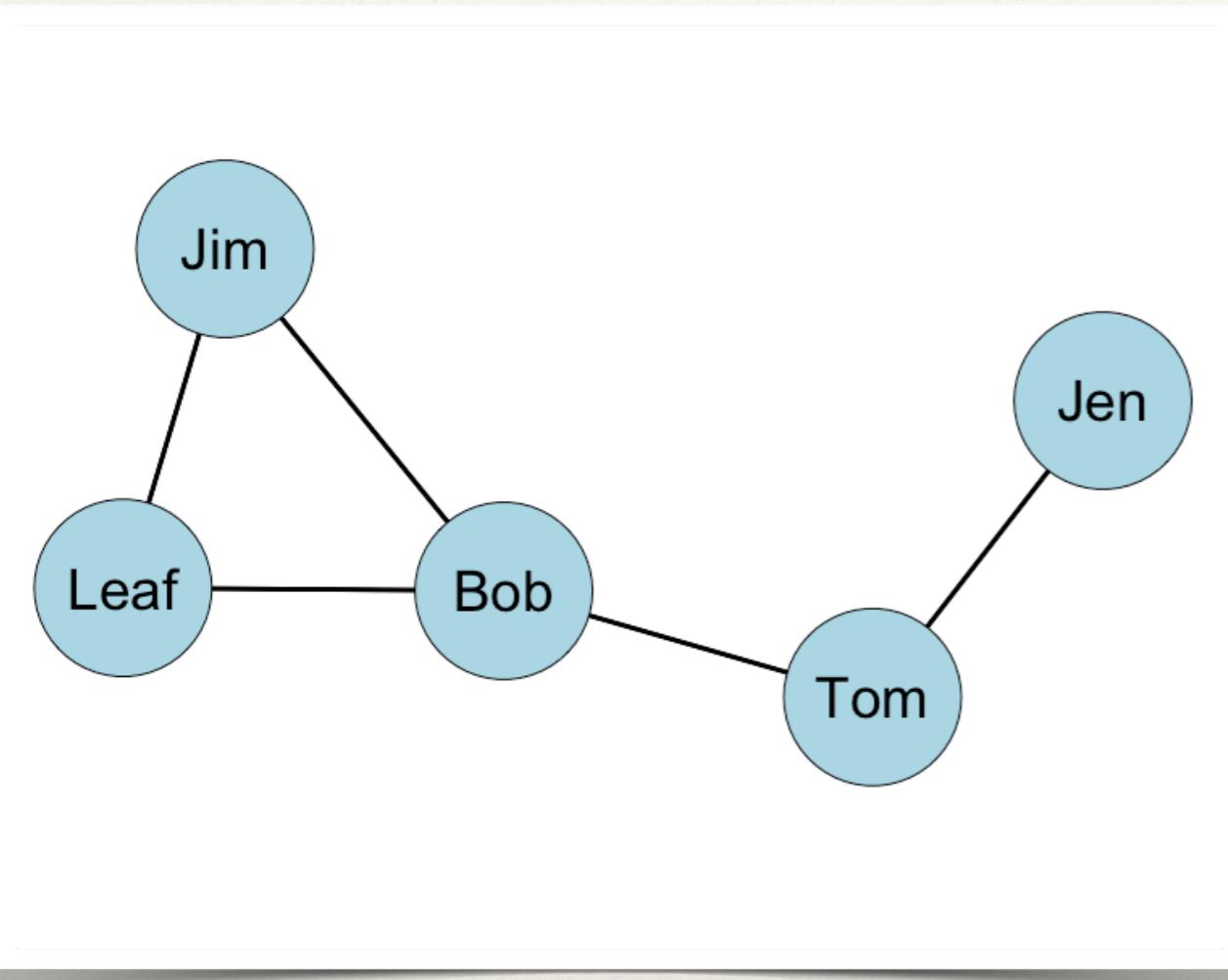
Example: Undirected, Binary Network



	Jen	Tom	Bob	Leaf	Jim
Jen	1	0	0	0	0
Tom	1				
Bob	0				
Leaf	0				
Jim	0				

What does the rest of the matrix look like?

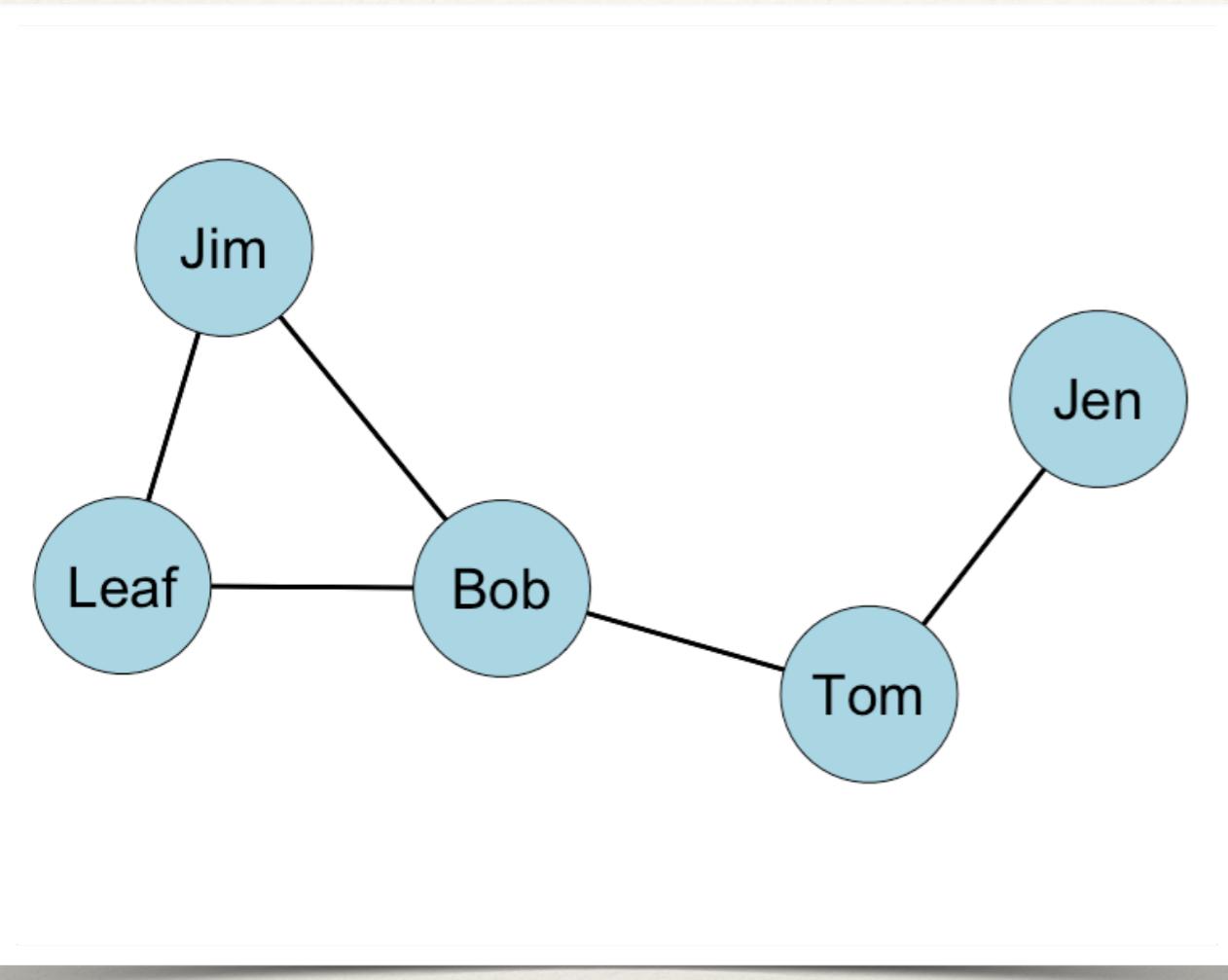
Example: Undirected, Binary Network



It looks like this.

	Jen	Tom	Bob	Leaf	Jim
Jen		1	0	0	0
Tom	1		1	0	0
Bob	0	1		1	1
Leaf	0	0	1		1
Jim	0	0	1	1	

Example: Undirected, Binary Network

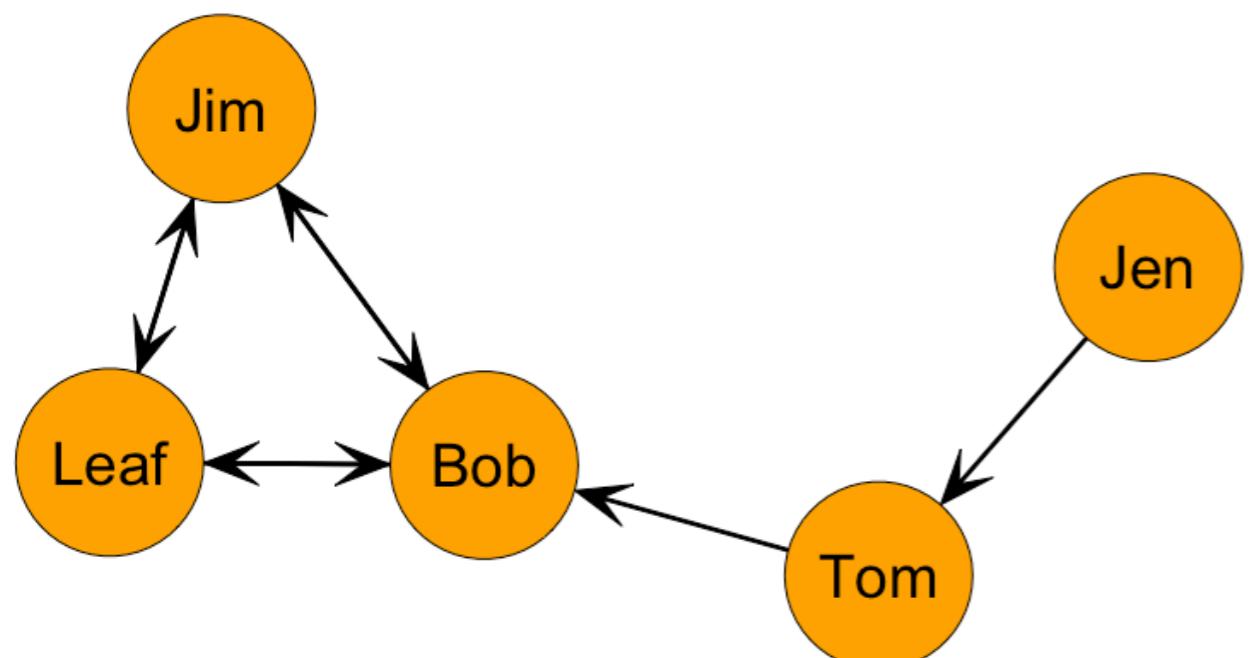


It looks like this.

	Jen	Tom	Bob	Leaf	Jim
Jen	0	1	0	0	0
Tom	1	0	1	0	0
Bob	0	1	0	1	1
Leaf	0	0	1	0	1
Jim	0	0	1	1	0

Let's add zeros to the diagonals. (will explain this later...)

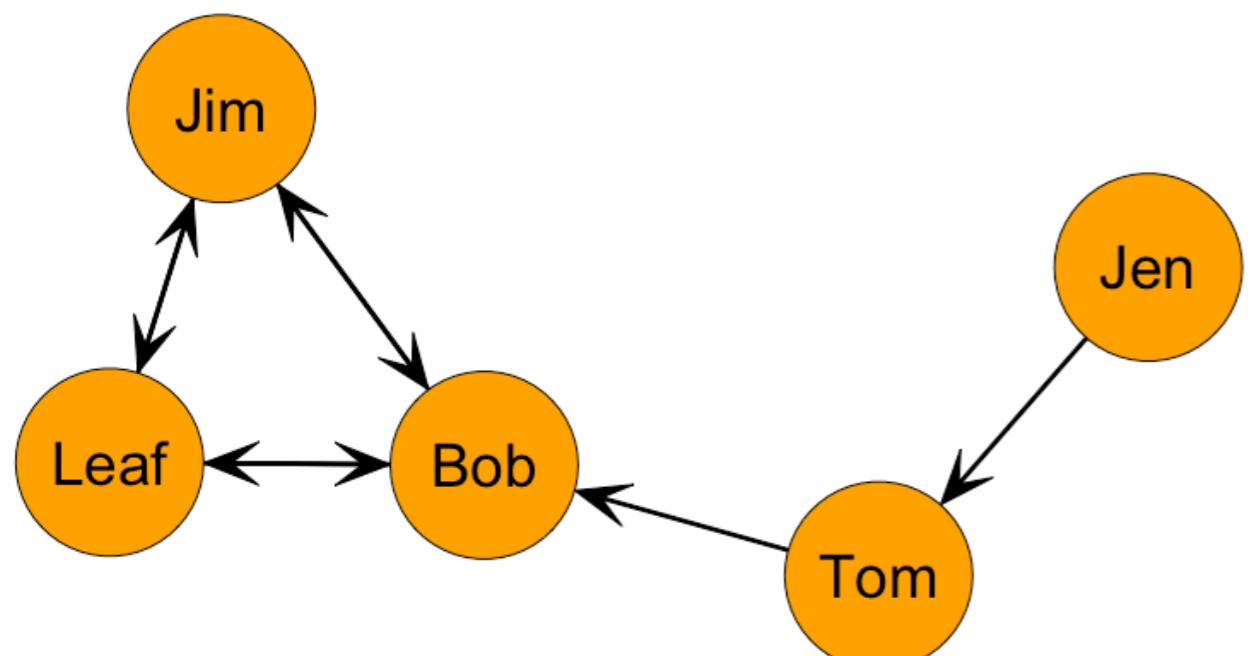
Example: Directed, Binary Network



	Jen	Tom	Bob	Leaf	Jim
Jen					
Tom					
Bob					
Leaf					
Jim					

What's different about a directed network?

Example: Directed, Binary Network

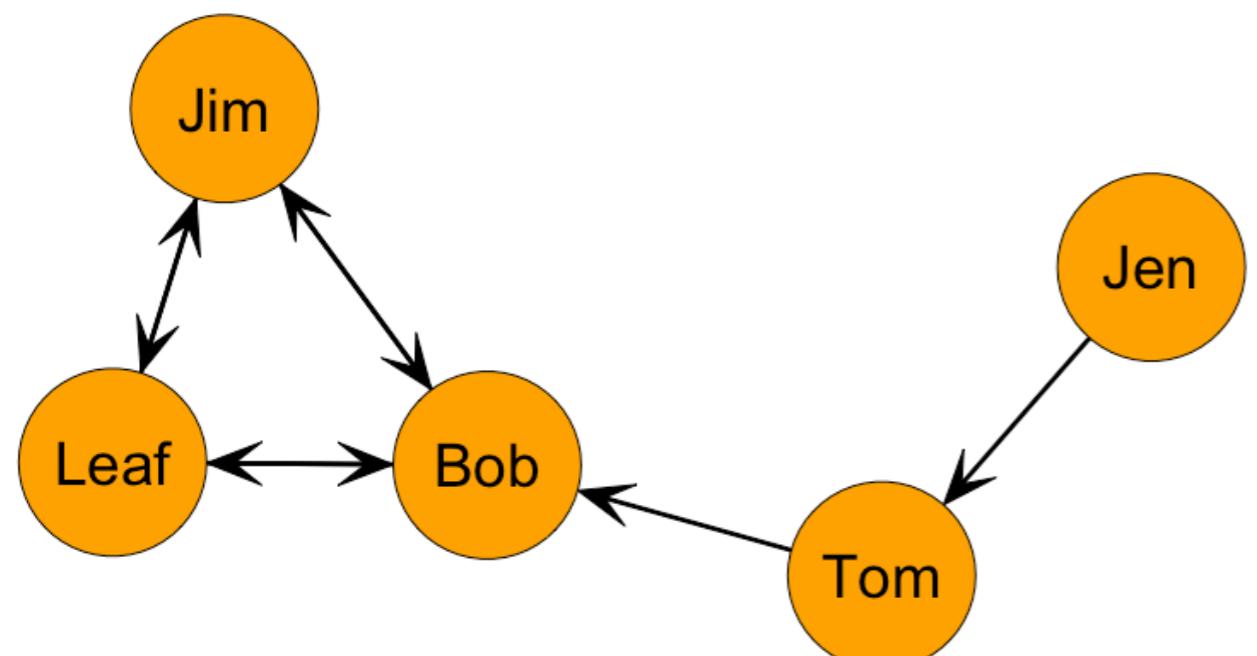


	Jen	Tom	Bob	Leaf	Jim
Jen					
Jim					

In the first row, i sends to the second row:

$$X_{12} = 1$$

Example: Directed, Binary Network

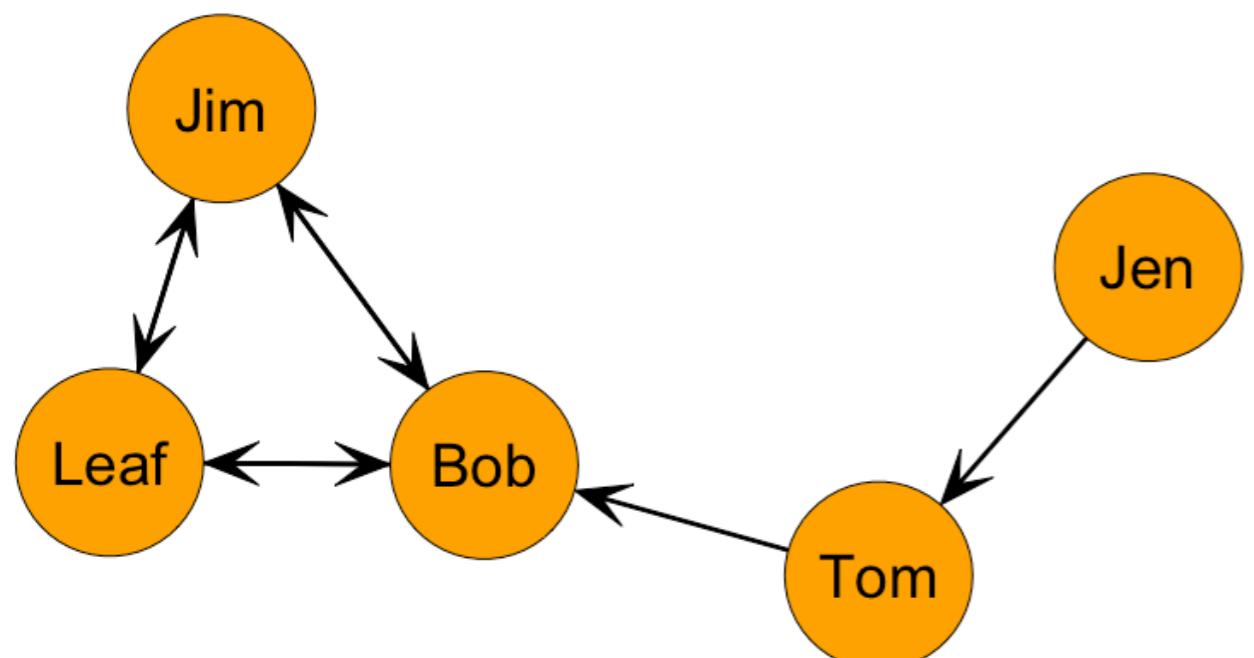


	Jen	Tom	Bob	Leaf	Jim
Jen					1
Tom		0			
Bob					
Leaf					
Jim					

But in the second row, j does not send:

$$X_{21} = 0$$

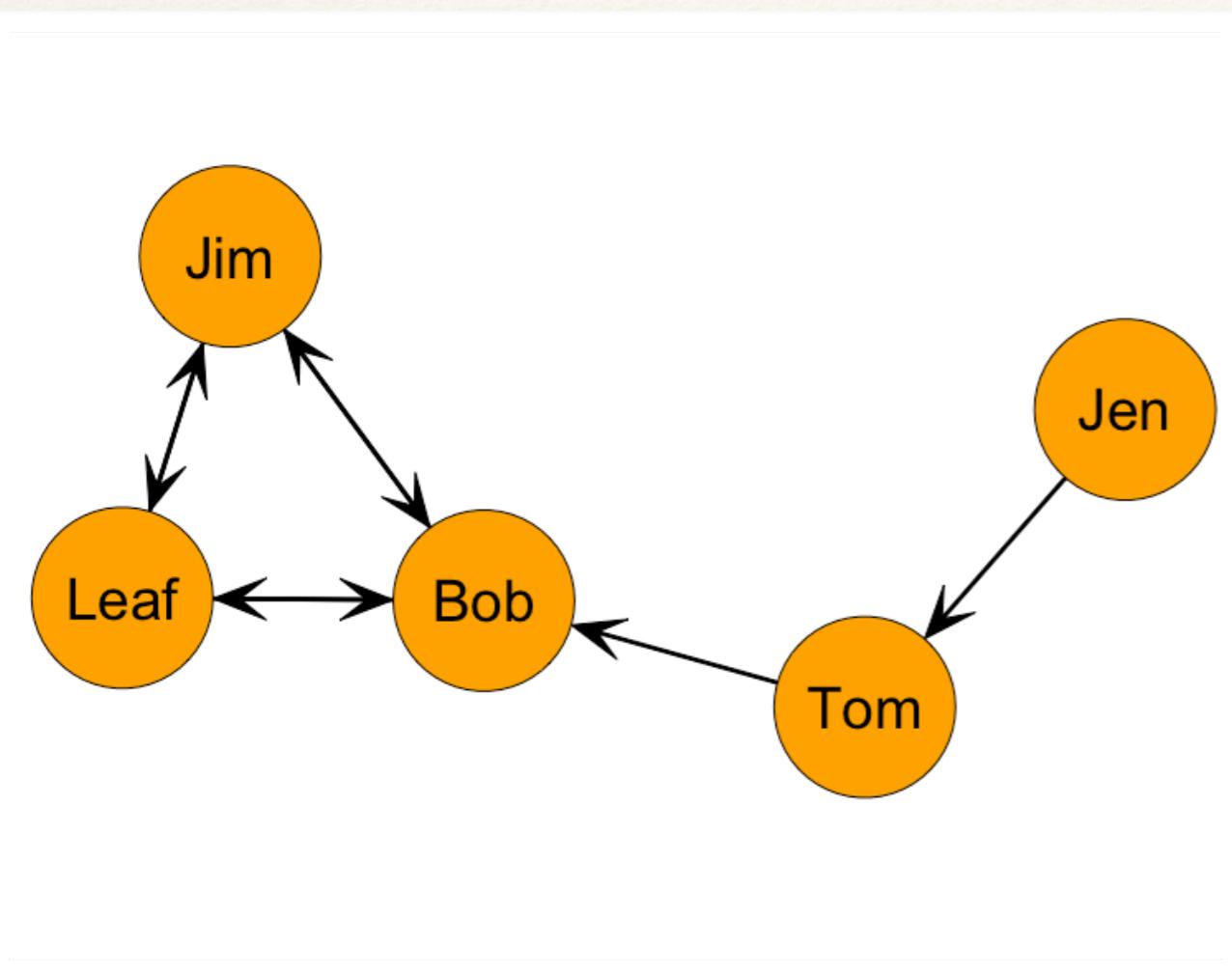
Example: Directed, Binary Network



	Jen	Tom	Bob	Leaf	Jim
Jen					1
Tom				0	
Bob					
Leaf					
Jim					

The Jen/Tom dyad is **asymmetric**. So, directed graphs permit asymmetry.

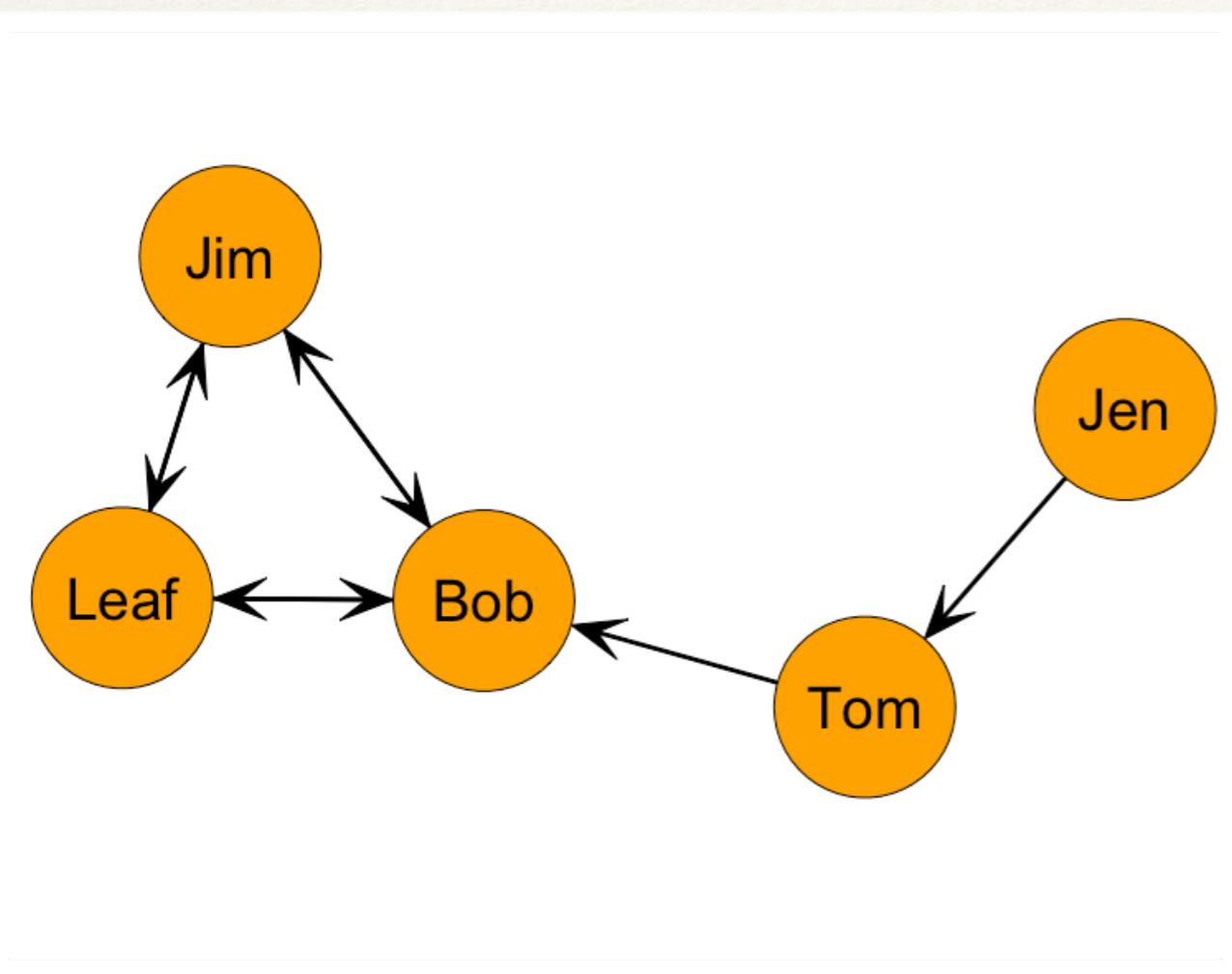
Example: Directed, Binary Network



	Jen	Tom	Bob	Leaf	Jim
Jen					1
Tom				0	
Bob					
Leaf			1		
Jim					

What about the Leaf/Bob dyad? Is it **asymmetric** or is it **symmetric**?

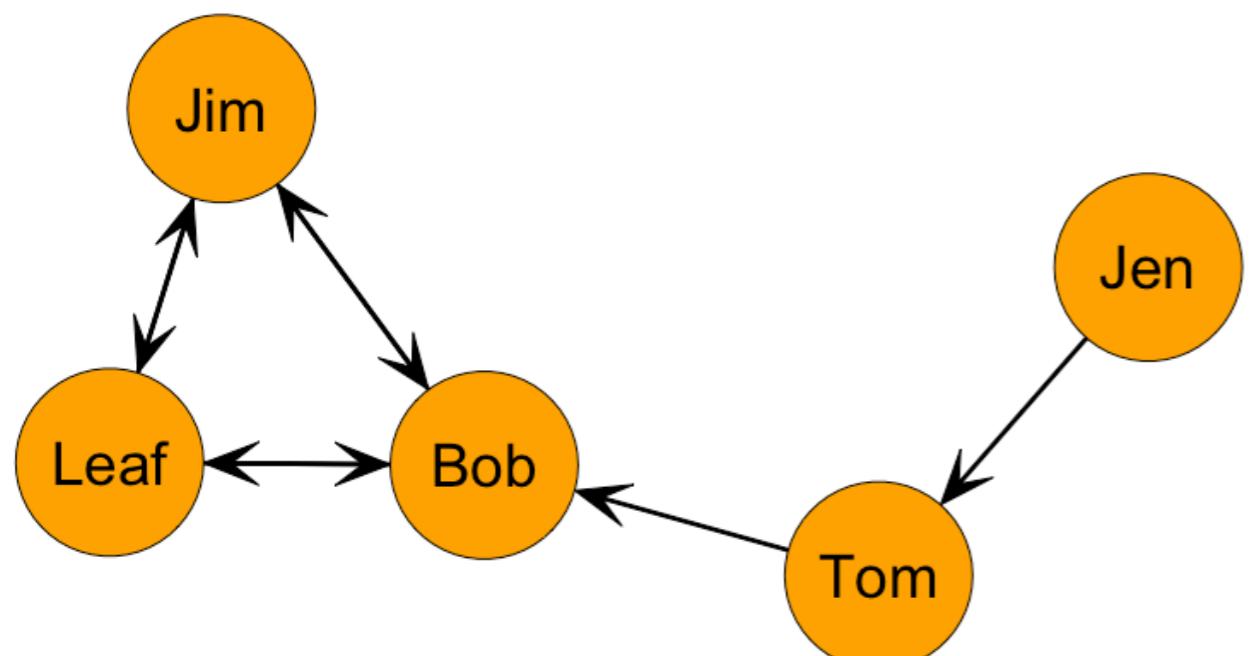
Example: Directed, Binary Network



	Jen	Tom	Bob	Leaf	Jim
Jen					1
Tom				0	
Bob					1
Leaf				1	
Jim					

What does the rest of the matrix look like?

Example: Directed, Binary Network



It looks like this.

Let's add zeros to the diagonals. (will explain this later...)

	Jen	Tom	Bob	Leaf	Jim
Jen	0	1	0	0	0
Tom	0	0	1	0	0
Bob	0	0	0	1	1
Leaf	0	0	1	0	1
Jim	0	0	1	1	0

Extensions

- ❖ We can use matrices to represent other types of network data.
 - ❖ Valued, Weighted, Signed, etc.
 - ❖ Multiple modes

Questions?

Basic Network Analysis

Description vs. Inference

- ❖ Description
 - ❖ What proportion of possible ties are observed? (density)
 - ❖ Who has the most ties? (degree centrality)
 - ❖ Are there clusters in the network? (graph modularity / subgroup analysis)
- ❖ Inference
 - ❖ How did this graph form? (Exponential random graph models)
 - ❖ Why do nodes change their edges? (Stochastic actor based models)
 - ❖ Do edges/nodes influence nodes/edges? (Co-evolution models)

When we say a *node* is “central”
what do we mean conceptually?

Conceptualization

- ❖ “Centrality” can mean different things:
 - ❖ How many ties do you have? (degree)
 - ❖ How many people do you connect? (betweenness)
 - ❖ How far/near are you from people in the network? (closeness)

Conceptualization

- ❖ “Everyone agrees, it seems, that centrality is an important structural attribute of networks. All concede that it is related to a high degree to other important group properties and processes. But there consensus ends.” (Freeman, 1978/1979: 217)
- ❖ The type of measure we use depends on the substantive question of interest.
 - ❖ Various measures of centrality are correlated, but they operationalize different concepts.

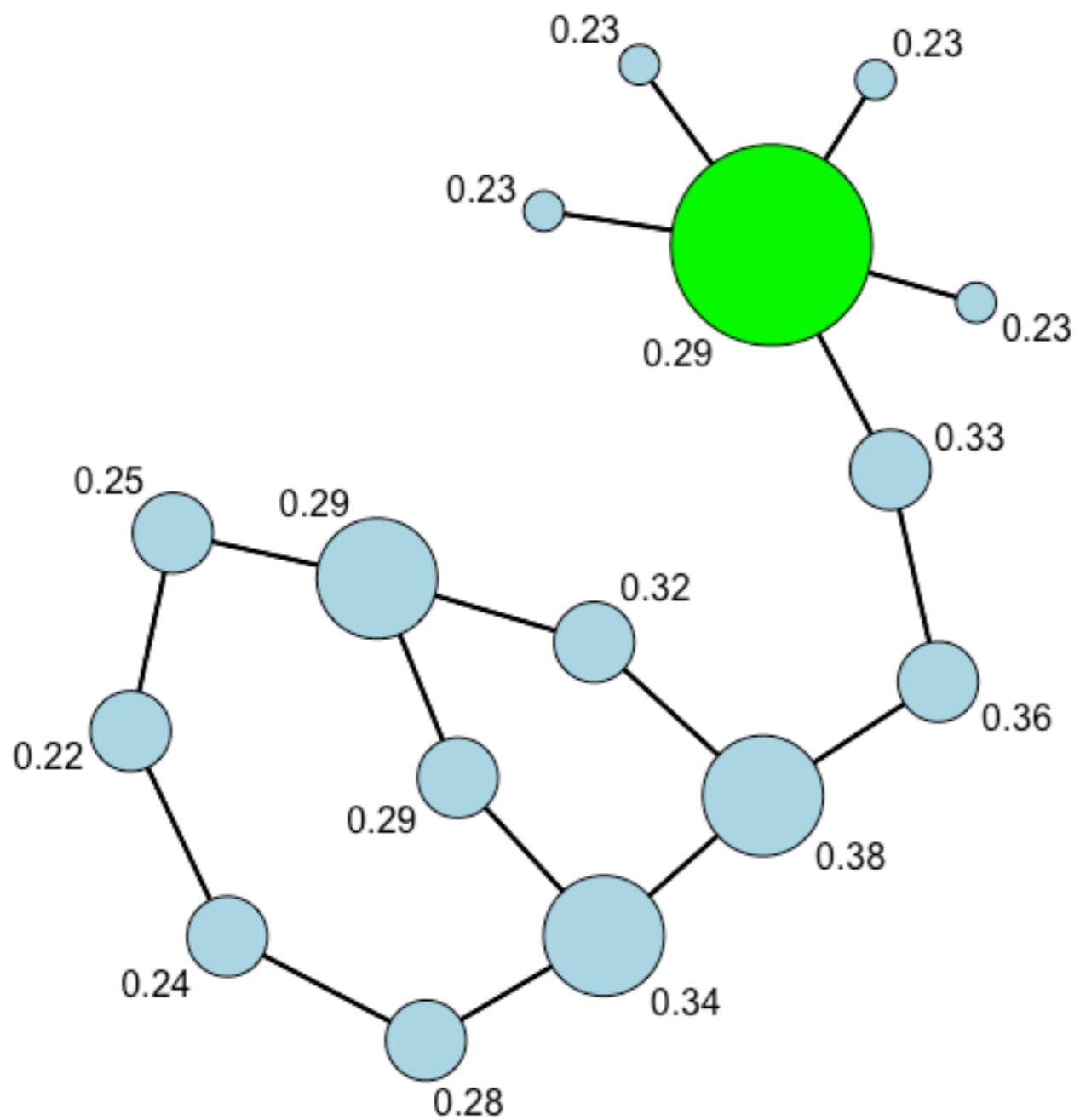
Comparing Measures of Centrality

	Low Degree	Low Closeness	Low Betweenness
High Degree		Embedded in cluster that is far from the rest of the network	Ego's connections are redundant - communication bypasses him/her
High Closeness	Key player tied to important/active alters		Probably multiple paths in the network, ego is near many people, but so are others
High Betweenness	Ego's few ties are crucial for network flow	Very rare. Would mean that ego monopolizes the ties from a small number of people to many others	

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High Degree, Low Closeness



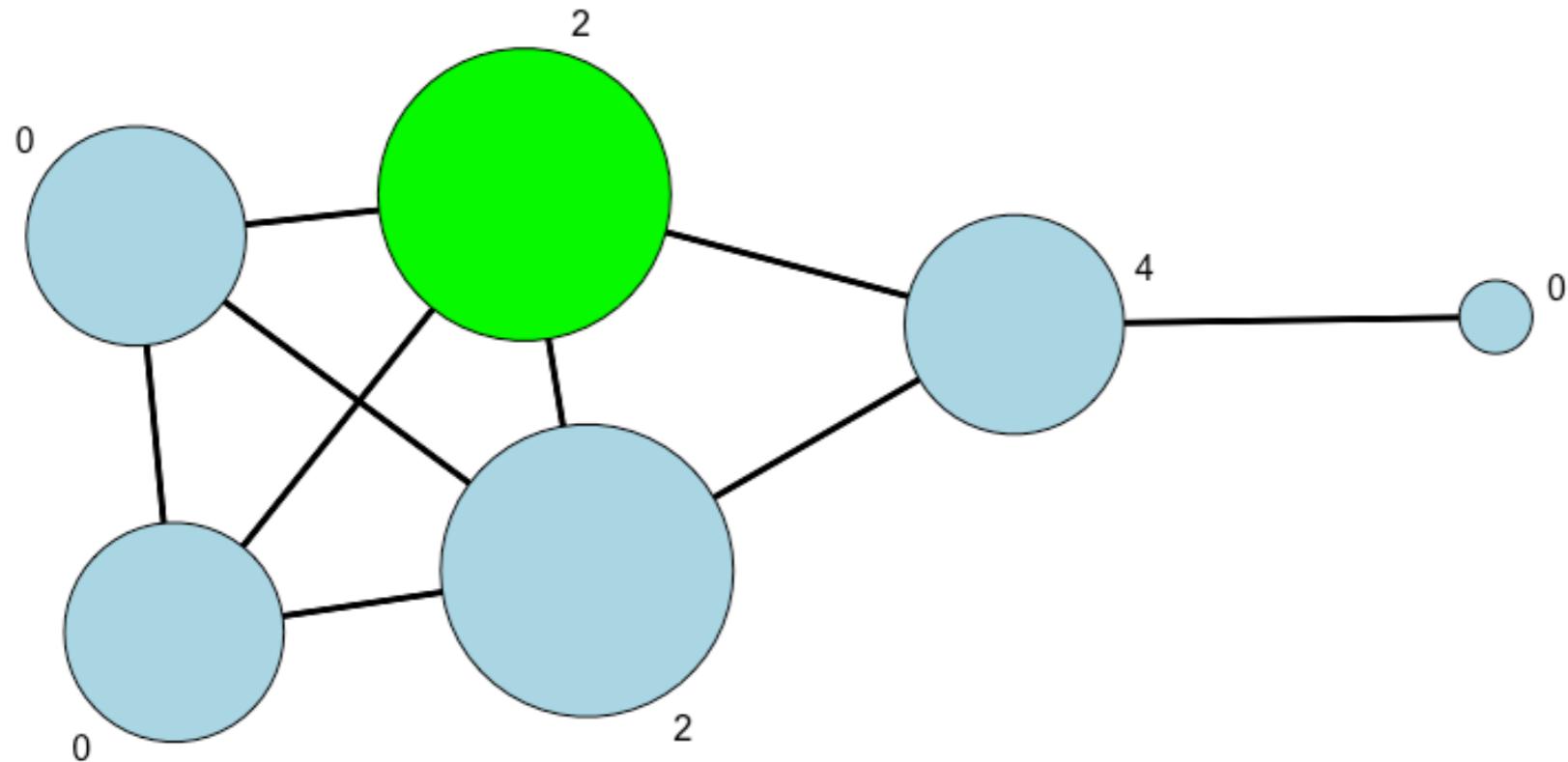
*Nodes sized by
degree*

*Nodes labeled by
closeness
centrality*

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High Degree, Low Betweenness



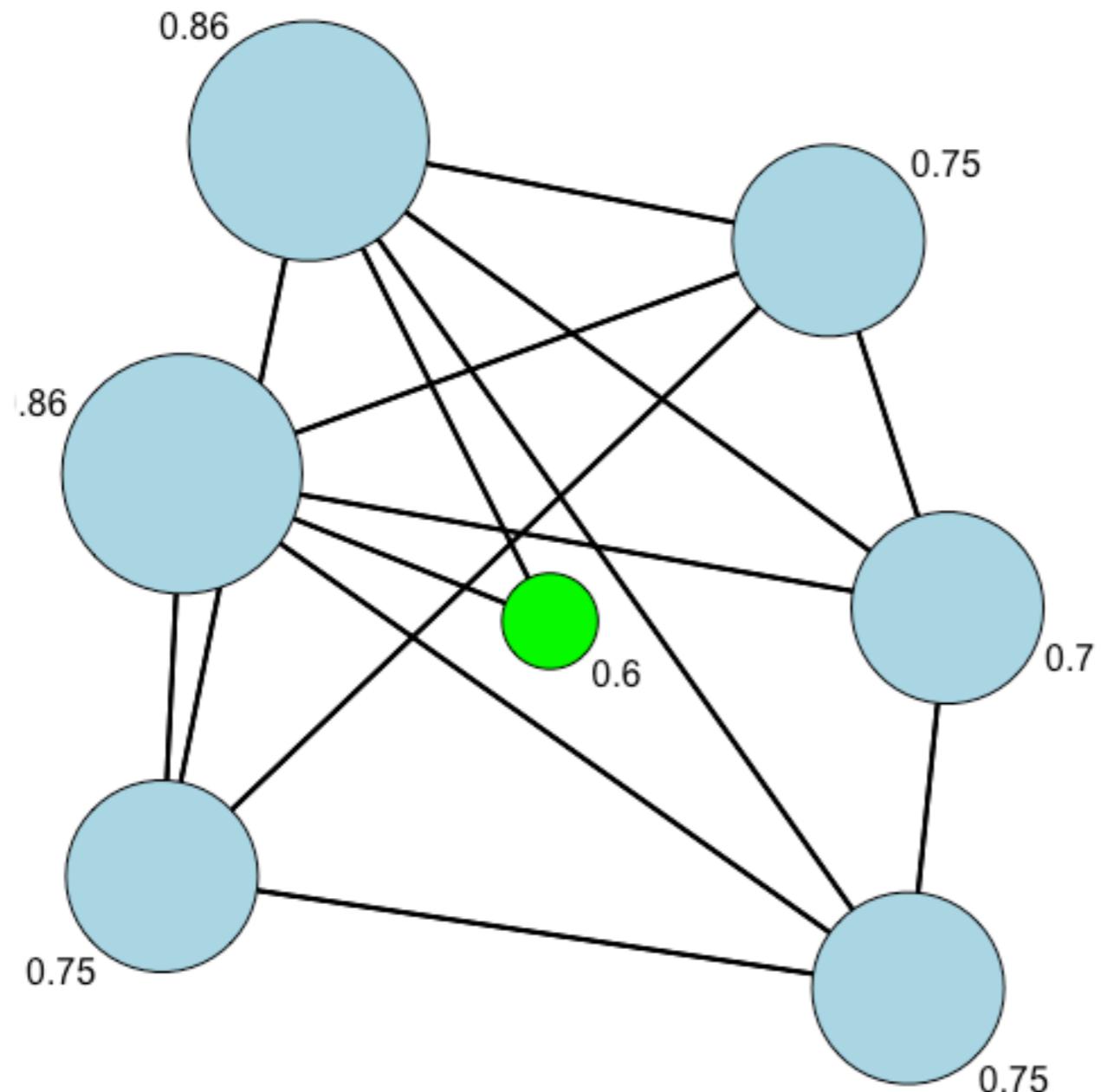
*Nodes sized by
degree*

*Nodes labeled by
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High Closeness, Low Degree



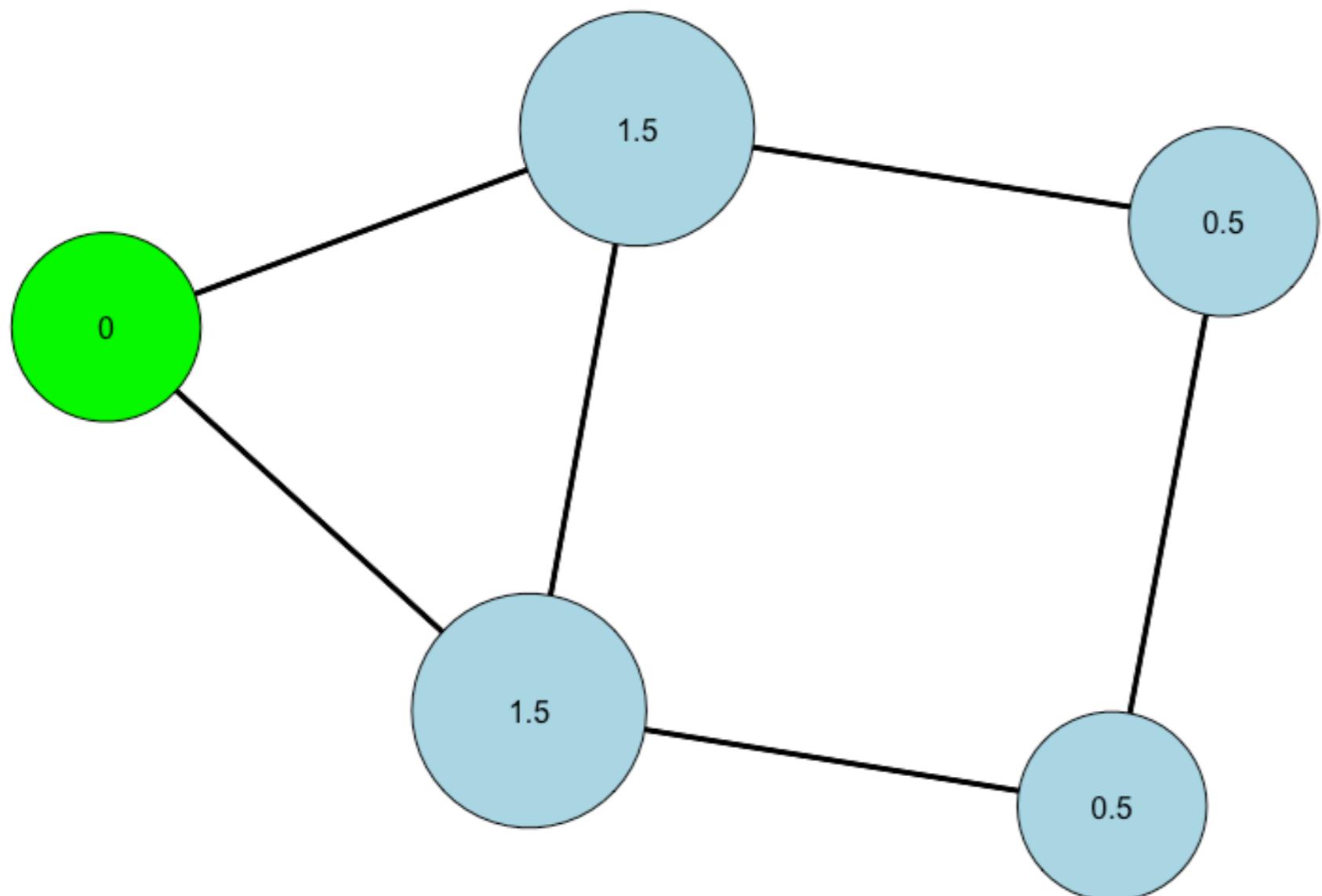
*Nodes sized by
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High Closeness, Low Betweenness



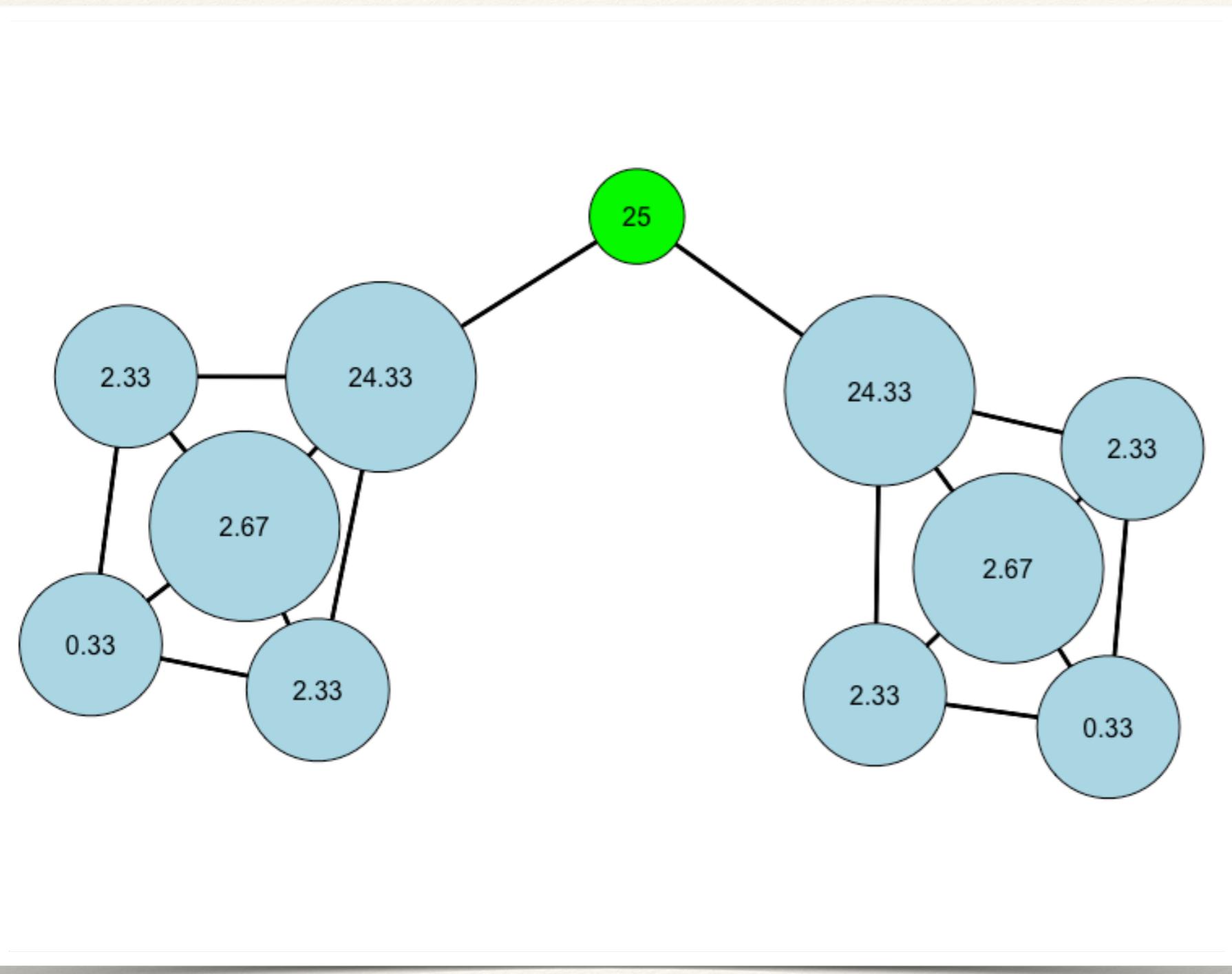
*Nodes sized by
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High Betweenness, Low Degree



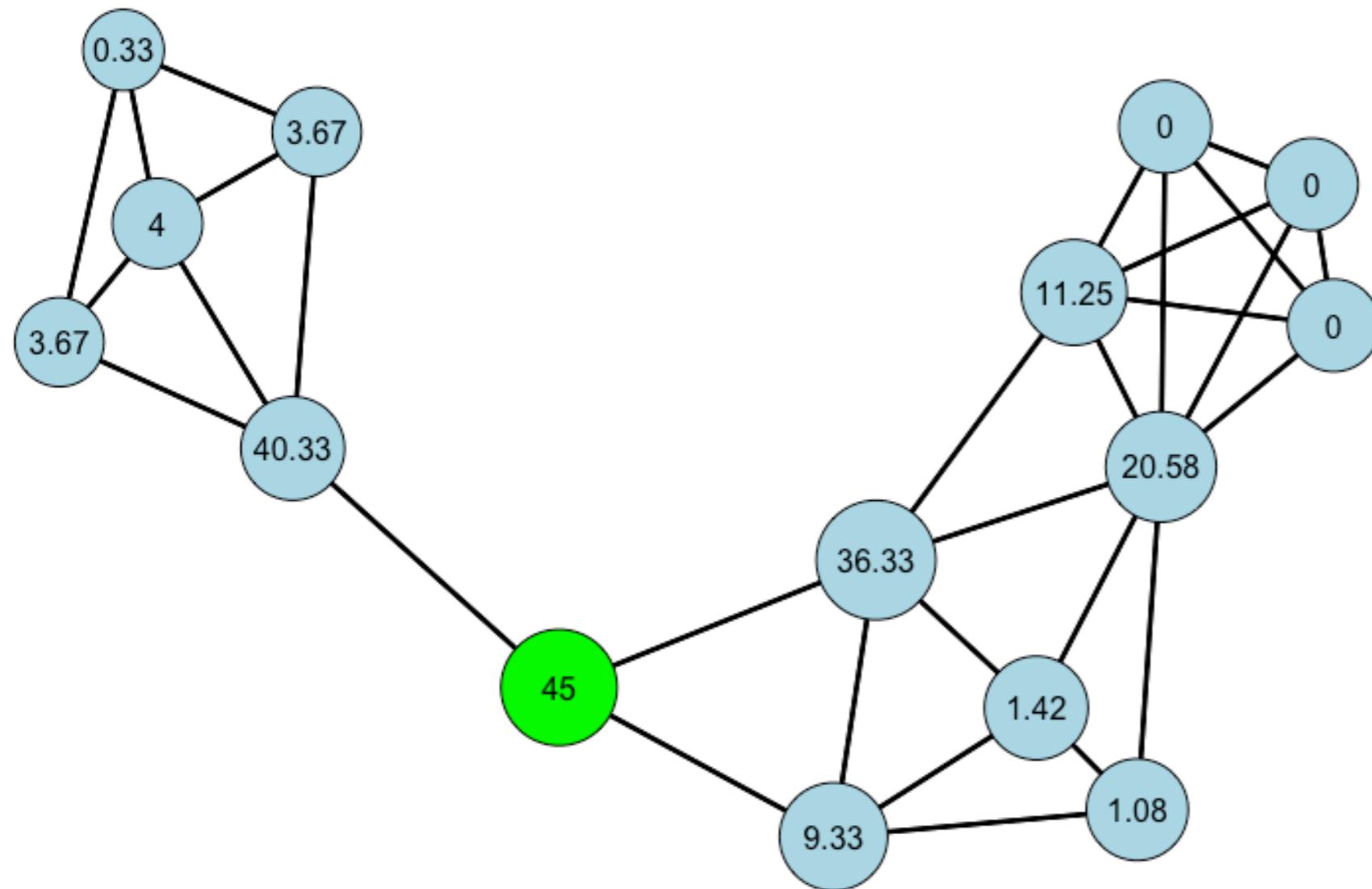
*Nodes sized by
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High Betweenness, Low Closeness



Network Analysis

- ❖ What sort of analysis you do depends on the question:
 - ❖ Do attitudes spread through simple or complex processes? (diffusion)
 - ❖ Do adolescents sort into subgroups? (modularity)
 - ❖ Are particular networks more vulnerable than others? (degree assortativity)
 - ❖ And so on...

Summary

- ❖ Network analysis can be simple or complex, descriptive or inferential.
- ❖ But, remember the crucial steps:
 - ❖ **Conceptualizing** theoretical concepts that are inherently relational.
 - ❖ **Operationalizing** theoretical constructs by drawing on the formal properties of graphs.

Questions?

Examples from my research

Example

- ❖ Young, J. T. N. (2013). “Role Magnets”? An Empirical Investigation of Popularity Trajectories for Life-Course Persistent Individuals During Adolescence. *Journal of youth and adolescence*. <http://link.springer.com/article/10.1007%2Fs10964-013-9946-0>.
- ❖ Goal: Examine the developmental trajectory of popularity during adolescence for violent individuals.
- ❖ Concept: Popularity
- ❖ Operationalization: Indegree Centrality
- ❖ Expectation: violent individuals should experience an increase in popularity during adolescence, then a decline.

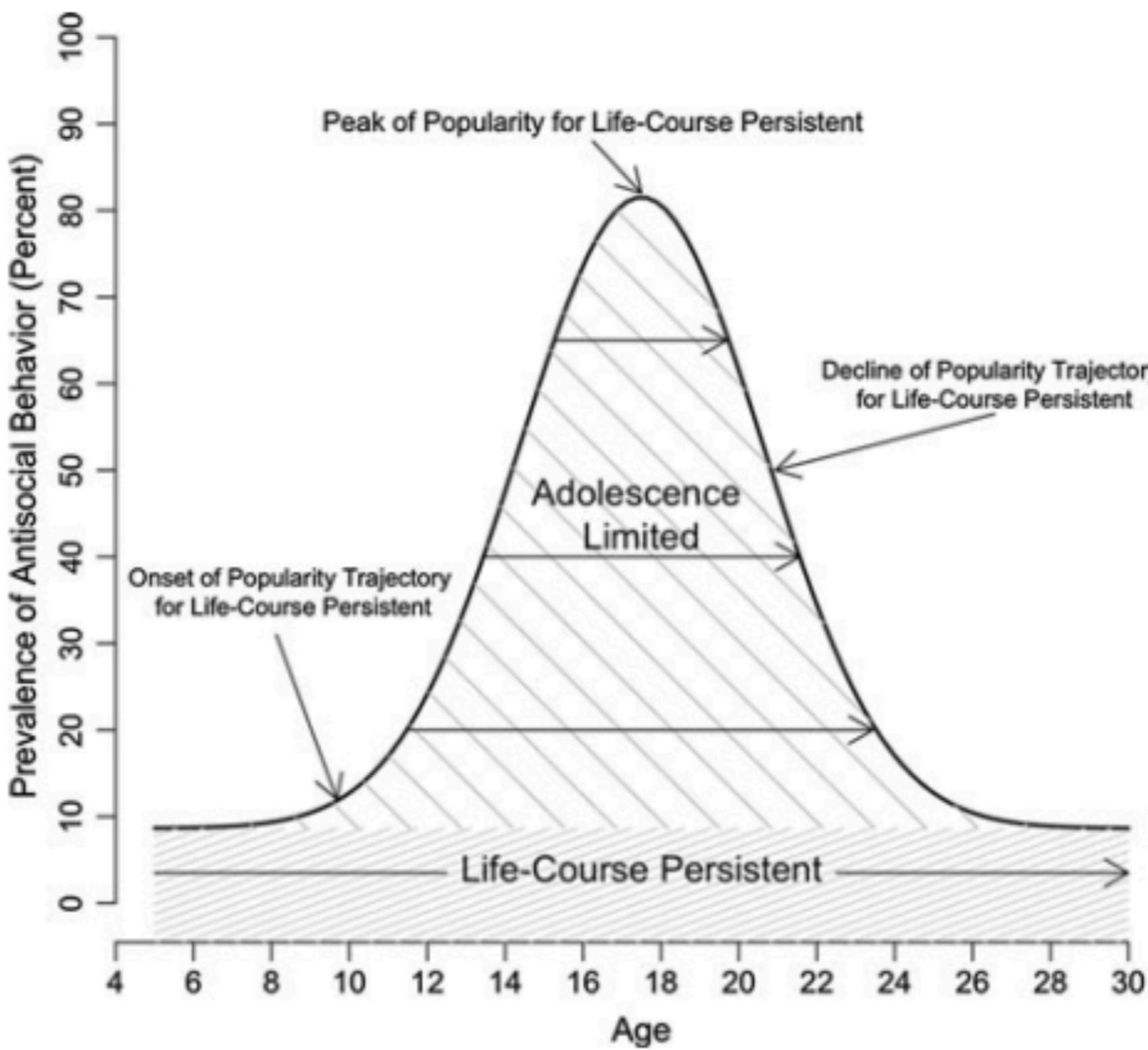


Fig. 1 Hypothetical illustration of the prevalence of antisocial behavior. *Arrow length* represents duration of participation in antisocial behavior

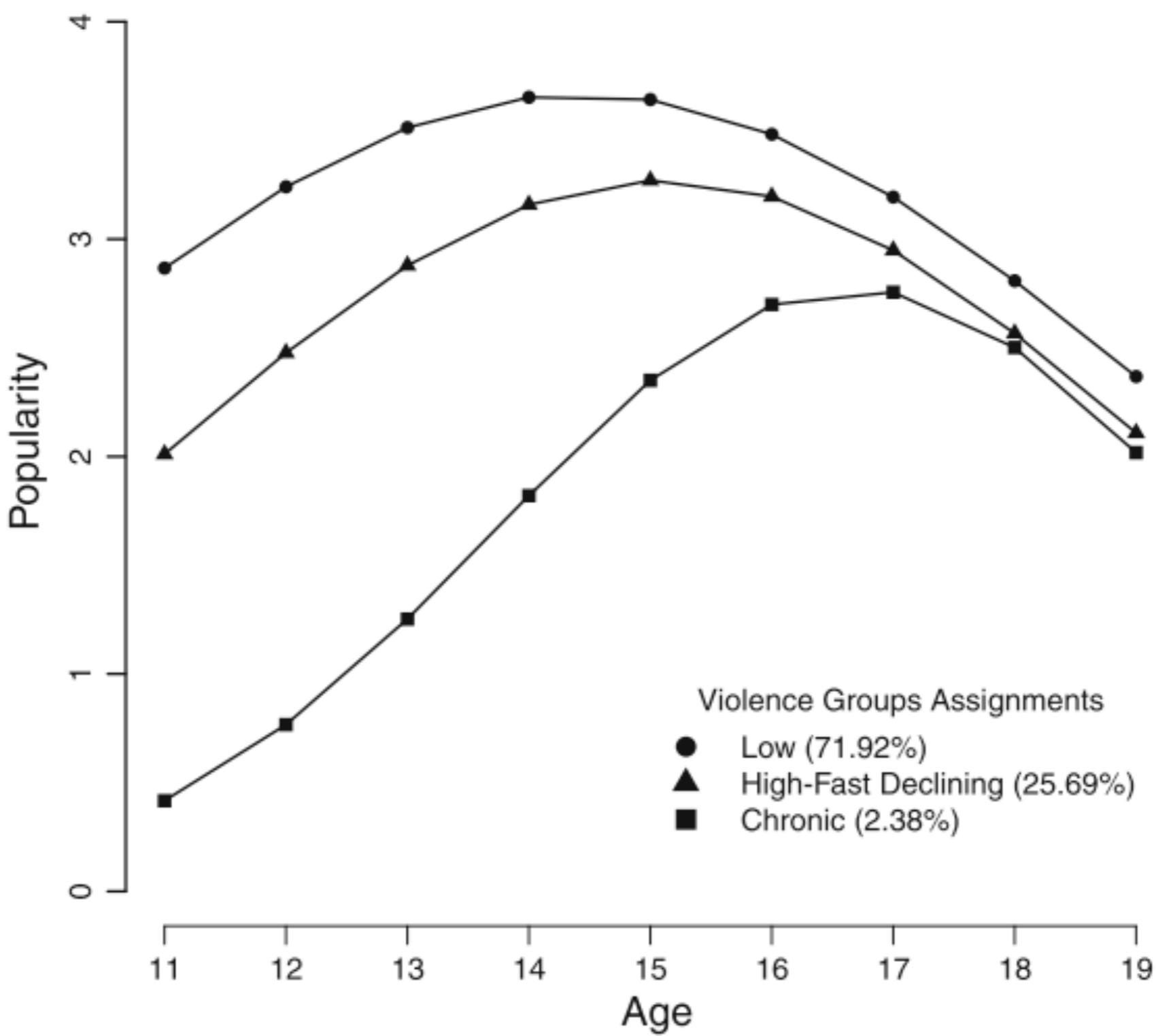
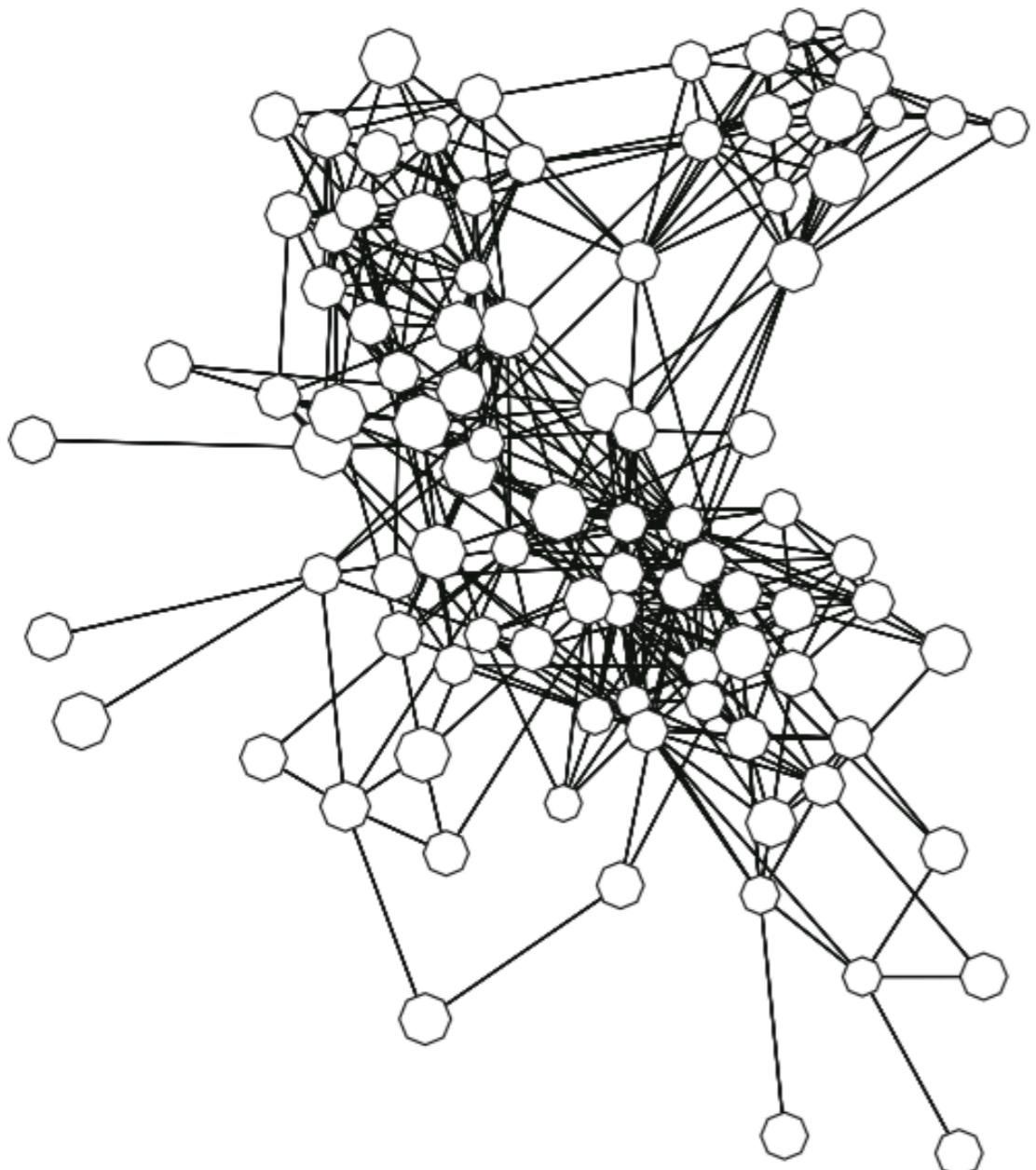


Fig. 3 Predicted growth trajectories for popularity by age and violence trajectory group

Example

- ❖ Young, J. T. N. (2011). How Do They “End Up Together”? A Social Network Analysis of Self-Control, Homophily, and Adolescent Relationships. *Journal of Quantitative Criminology*, 27(3), 251–273. <https://doi.org/10.1007/s10940-010-9105-7>.
- ❖ Question: What generates the correlation between an individuals level of self-control and his/her peers?
 - ❖ Concept: Homophily
 - ❖ A node-based mechanism: Selective mixing
 - ❖ A structural mechanism: Transitivity

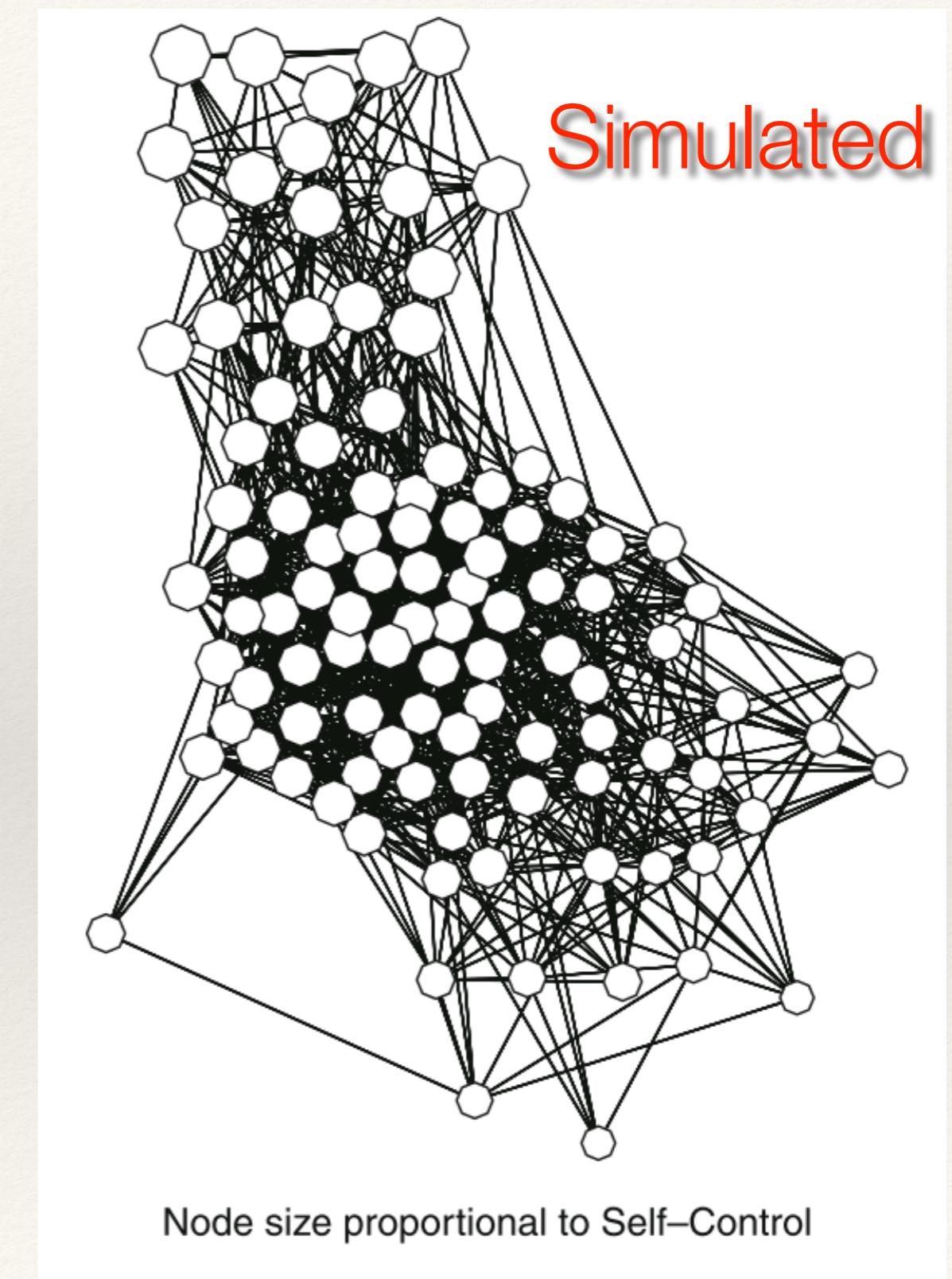
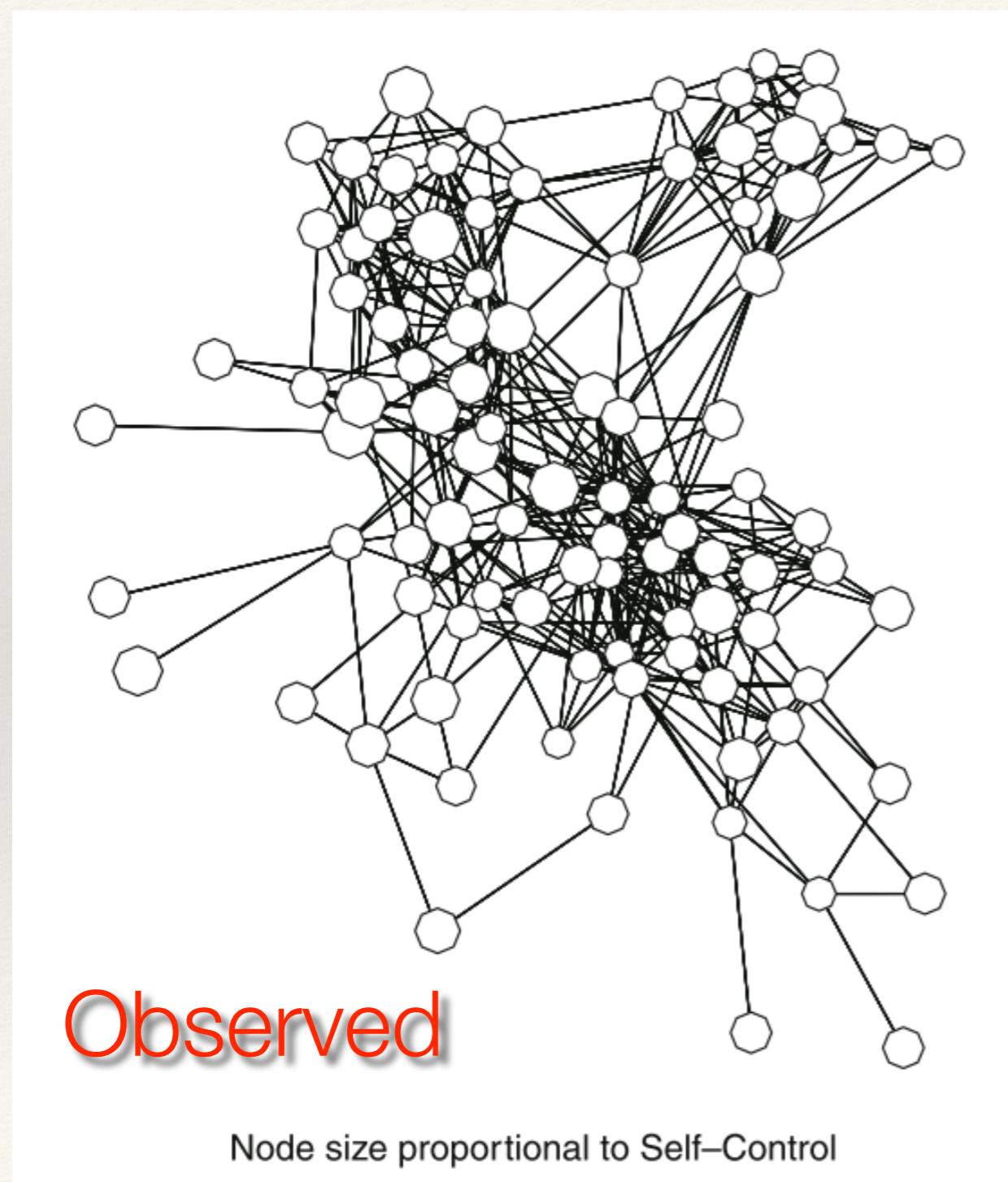
Exponential Random Graph models to the rescue!



Node size proportional to Self-Control

- ❖ Specify a model of how ties form.
- ❖ Then, compare the observed data to a model where ties form at random.

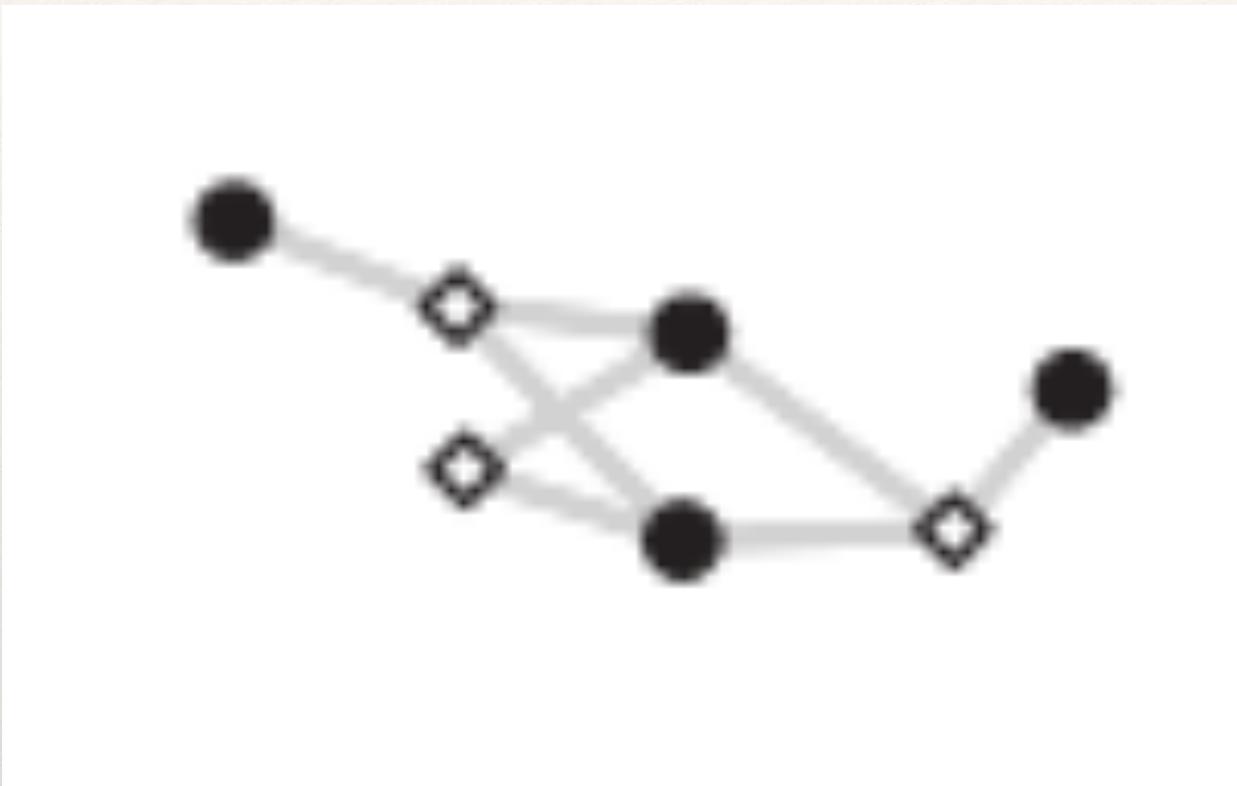
❖ *Take away?*



Example

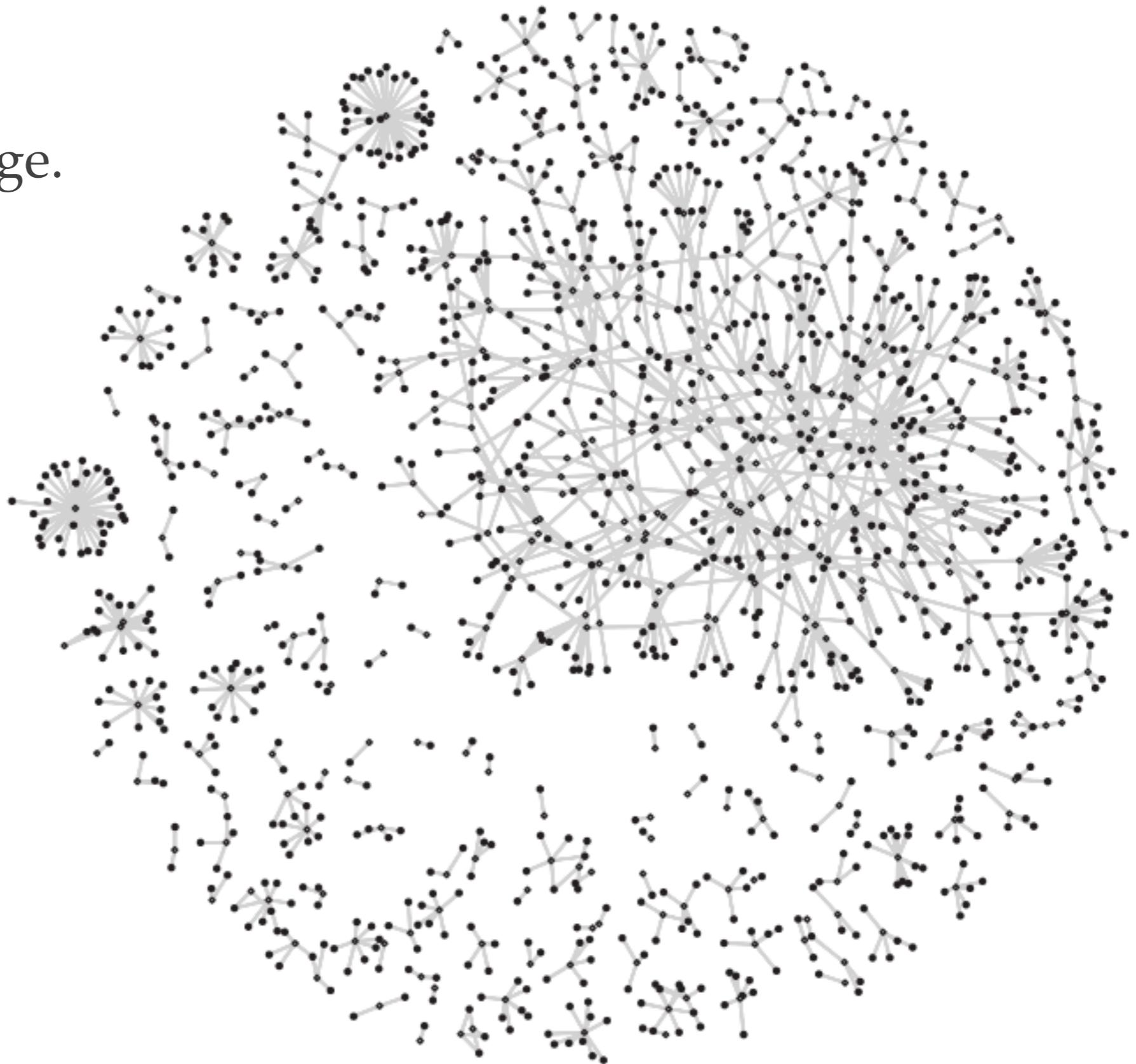
- ❖ Fahmy, C., & Young, J. T. N. (2015). Invisible Colleagues: The Informal Organization of Knowledge Production in Criminology and Criminal Justice. *Journal of Criminal Justice Education*, (June), 1–23. <https://doi.org/10.1080/10511253.2015.1051999>
- ❖ Question: how are acknowledgements organized?
 - ❖ Concept: informal knowledge production.
 - ❖ Measurement: acknowledgements in journals
 - ❖ a two-mode network

Example



- ❖ Articles in white
- ❖ Acknowledges in black
- ❖ *Anything about the structure of this stick out to you? (Other than being blurry)*

- ❖ 83% of nodes receive only 1 edge.
- ❖ 3 people had 10!



- ❖ What does it mean?

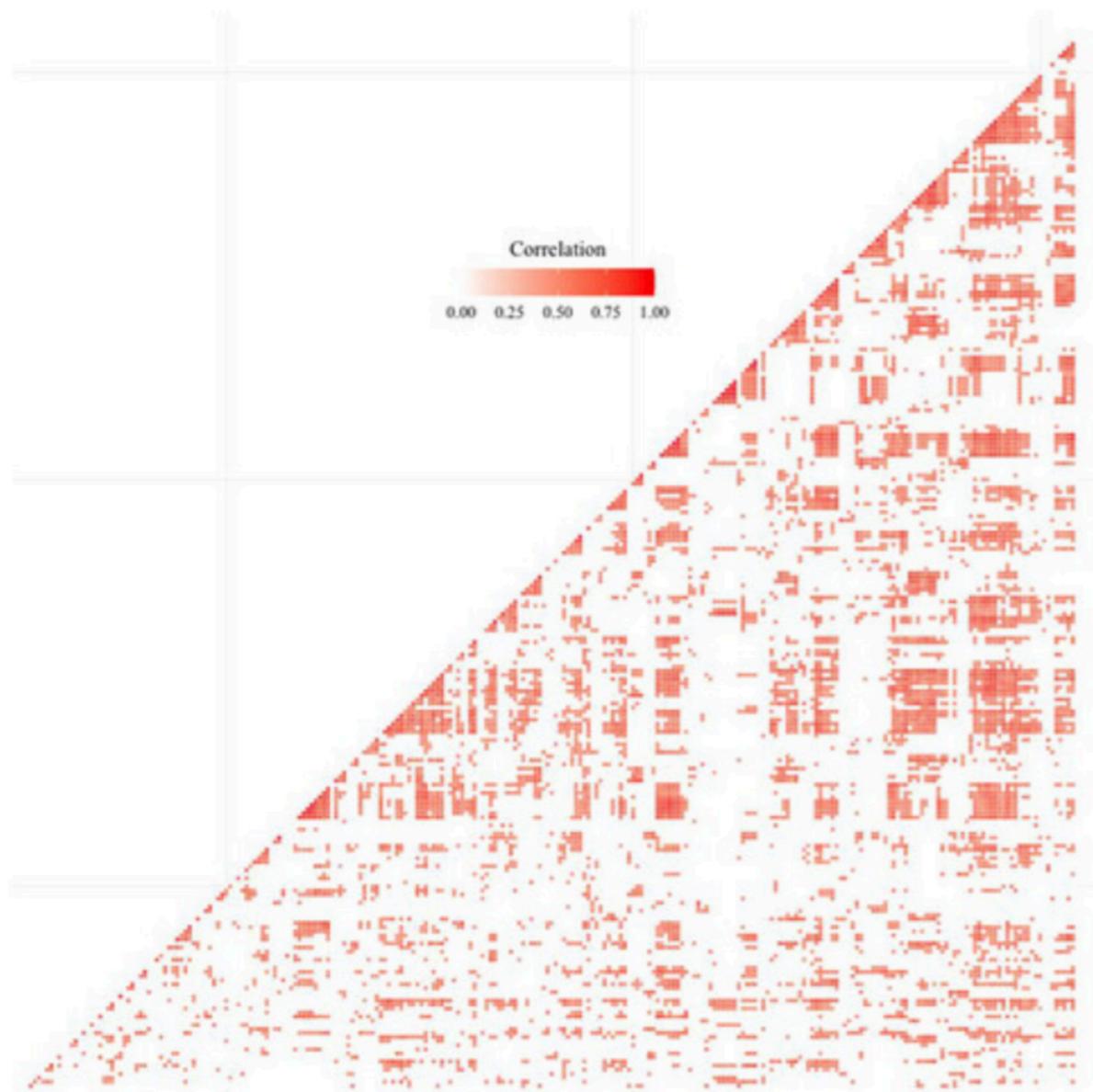


Example

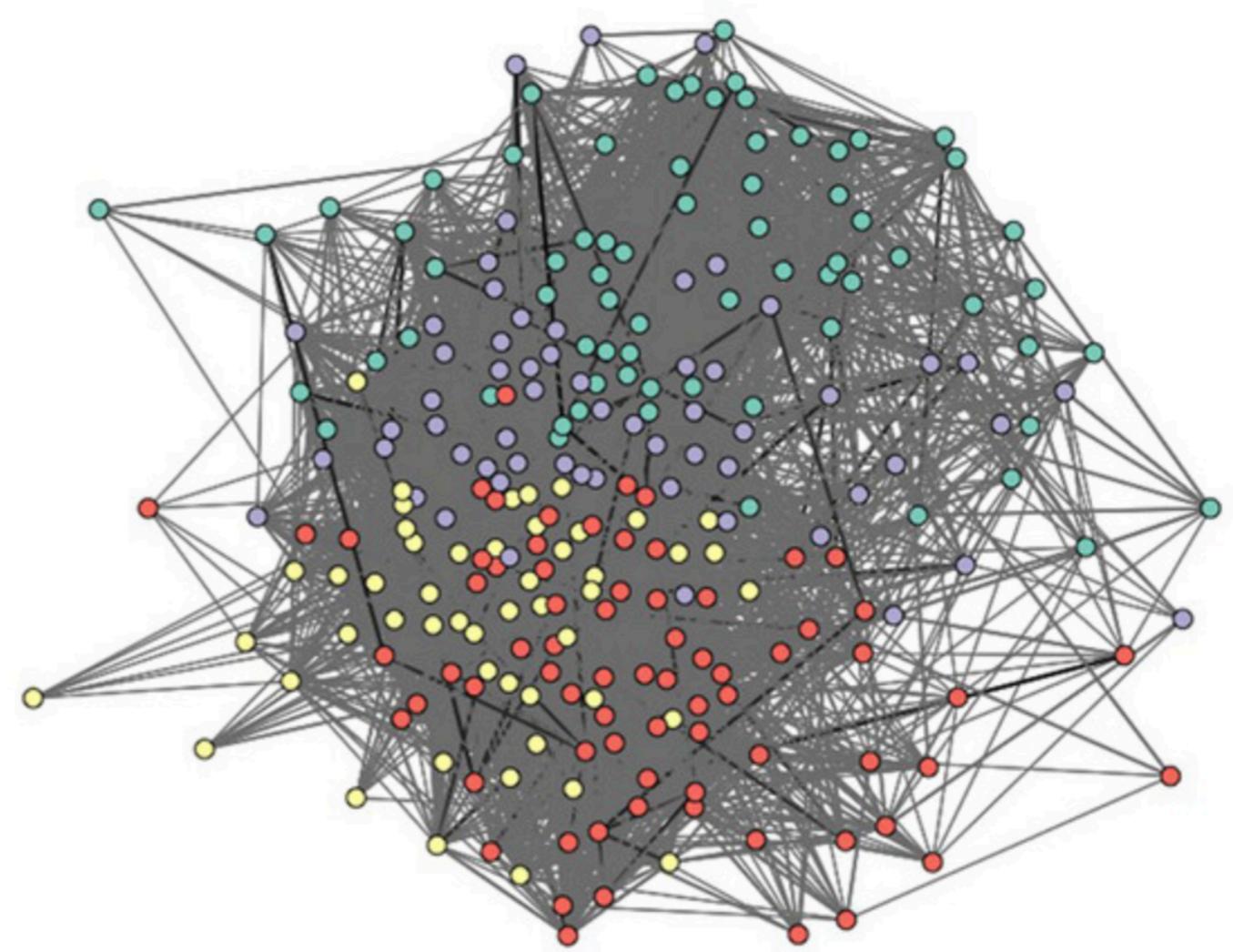
- ❖ Young, J. T. N., Meyers, T. J., & Morse, S. J. (2023). What is “prison culture”? Developing a theoretical and methodological foundation for understanding cultural schema in prison. *Criminology*, 61(3), 421-448. <https://doi.org/10.1111/1745-9125.12335>
- ❖ Question: what does it mean to say that a prison has a ‘culture’?
 - ❖ Concept: **culture** is a “shared understanding”
 - ❖ Measurement: modularity of an agreement matrix for two cultural domains (prison code and race)
 - ❖ Weighted sociomatrix

Example

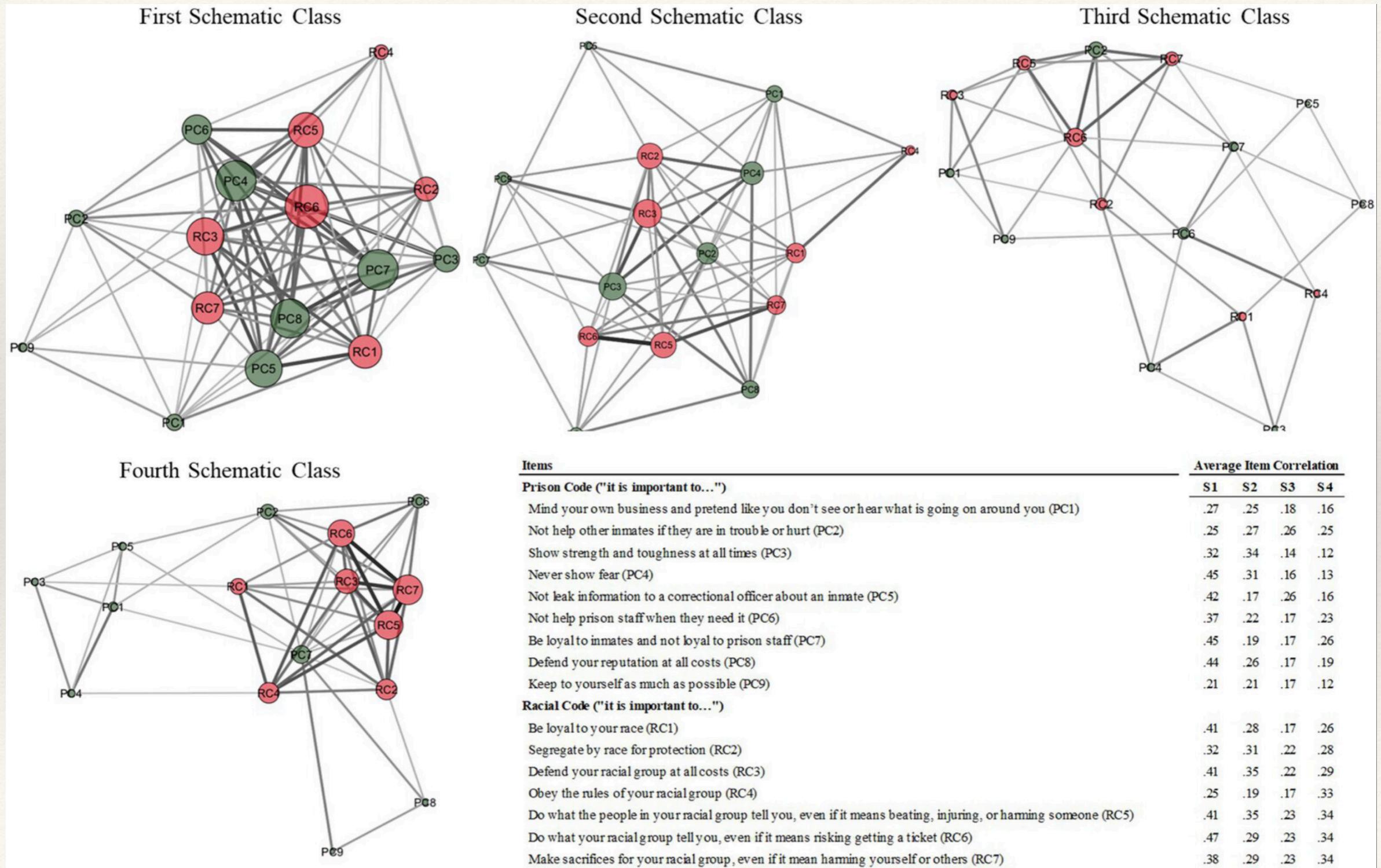
Correlations among Respondents for Prison & Racial Code Items



Weighted Network of Correlations among Respondents for Prison & Racial Code Items



Example



Where to go from here...

Resources

- ❖ The internet
- ❖ Check out professional associations
 - ❖ INSNA (insna.org)
- ❖ Journals
 - ❖ *Social Networks*
 - ❖ *Network Science*

Computation

- ❖ R (cran.r-project.org)
 - ❖ <https://jacobtnyoung.github.io/RWorkshop/>
- ❖ UCINET
 - ❖ <https://sites.google.com/site/ucinetsoftware/home>

WARNING! Shameless Plug!!!

Future Classes

- ❖ Got the network fever?



- ❖ Statistical Analysis of Network Data (CRJ 605) in Spring
 - ❖ <https://jacobtnyoung.github.io/SAND/>
- ❖ Network Criminology (CRJ 523) (TBD)
 - ❖ <https://jacobtnyoung.github.io/NetworkCriminology/>

Thank you!!!!

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jacob.young.1@asu.edu
<https://jacobtnyoung.github.io/>
