

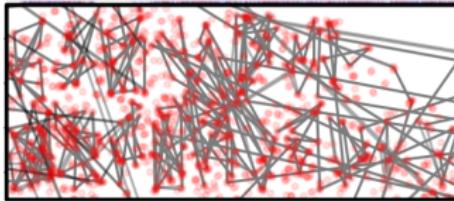
A Brief introduction to Social Network Analysis

From Descriptives to Statistical Inference

Zack W Almquist*

*Department of Sociology and School of Statistics
University of Minnesota

MPC Inequality and Methods Workshop





Peter M. Blau, Exchange and Power in Social Life, 1964

“To speak of social life is to speak of the association between people – their associating in work and in play, in love and in war, to trade or to worship, to help or to hinder. It is in the social relations men establish that their interests find expression and their desires become realized.”

J.L. Moreno, New York Times, April 13, 1933

“If we ever get to the point of charting a whole city or a whole nation, we would have . . . a picture of a vast solar system of intangible structures, powerfully influencing conduct, as gravitation does in space. Such an invisible structure underlies society and has its influence in determining the conduct of society as a whole.”



- Motivating Examples
 - Definitions
 - Network Data Collection
 - Descriptive Statistics
 - Node-level indices
 - Graph-level indices
 - Statistical Inference
 - Freeman, Linton (2004). *The Development of Social Network Analysis: A Study in the Sociology of Science*. Vancouver, BC, Canada: Empirical Press.
- Tools
 - R/RStudio
 - github
 - Other resources



Required Software

- github (<http://www.github.com>)
- R (<http://cran.r-project.org/>)
- RStudio (<http://www.rstudio.com/>)



- R Packages for SNA

- R packages:

```
install.packages("statnet")
install.packages("ergm")
install.packages("sna")
install.packages("network")
```

- R packages needed for installing from github

- R packages:

```
install.packages("devtools")
```

- R packages from github

- R packages:

```
install.packages("networkMethods")
install.packages("networkdata")
```



Examples: Some Types of Relationships

- Conceptual: shared or antithetic properties
 - E.g., similarity/difference in individual attributes, correlation among variables, inclusion/exclusion, surface matchings on proteins
- Co-categorical: shared membership
 - E.g., organizational co-membership, event co- participation, co-occurrence of words within texts
- Nominal: resulting from the behavior of ego
 - E.g., attributions of friendship/enmity, kinship (fictive or otherwise), causal narratives



Examples of Social Networks

For example:

- Macro-Level Networks
- Interpersonal Networks

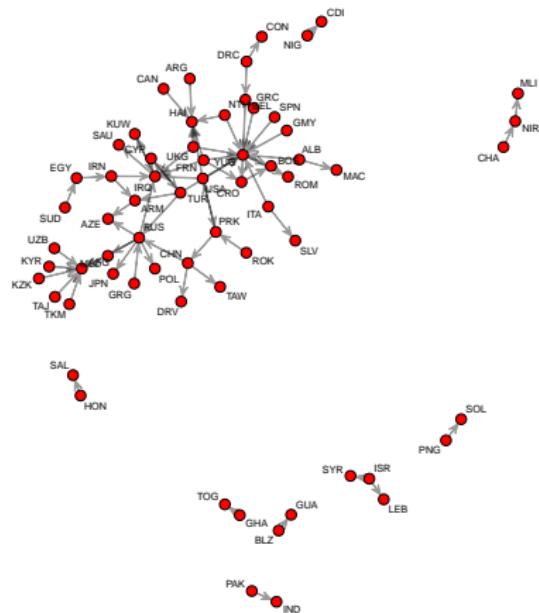


- International Relations
 - Militarized interstate disputes
- Migration Networks
 - County-to-county migration in the US
- Interorganizational Relations
 - Search and rescue (SAR) activities: Emergent multi-organizational networks (EMONs)



Militarized Interstate Disputes

1993 militarized interstate disputes (MIDs)

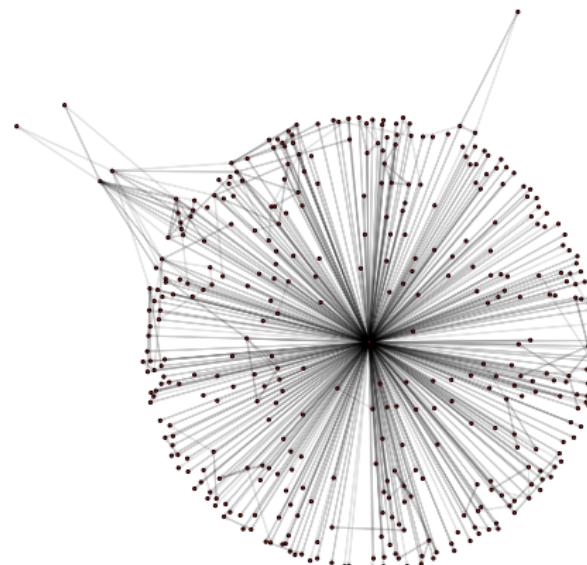


Correlates of War Project



County-to-County Migration in the US

IRS Migration Data, 2000–2001

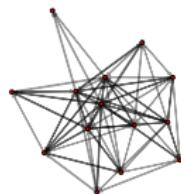


Threshold at 99%

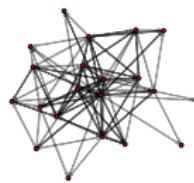


SAR EMONs, All Reported Ties, from Drabek et al 1981

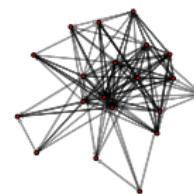
Cheyenne



HurrFrederic



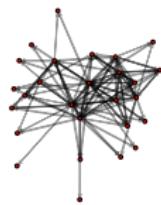
LakePomona



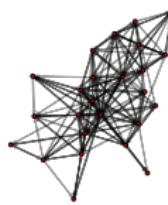
MtSi



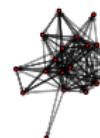
MtStHelens



Texas



Wichita

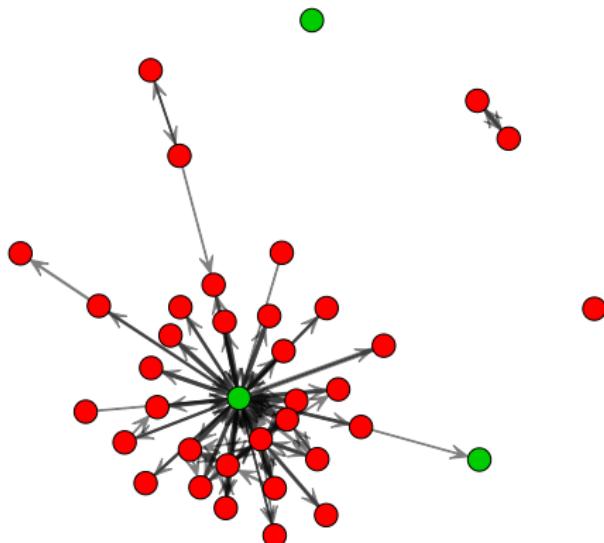




- Communication
 - WTC responder radio communications (aggregate and dynamic)
- Friendship
 - Perceived and estimated friendships among managers
- Interaction in Task Performance
 - WTC police reports
- Co-Participation
 - Research group co-participation in a large research project

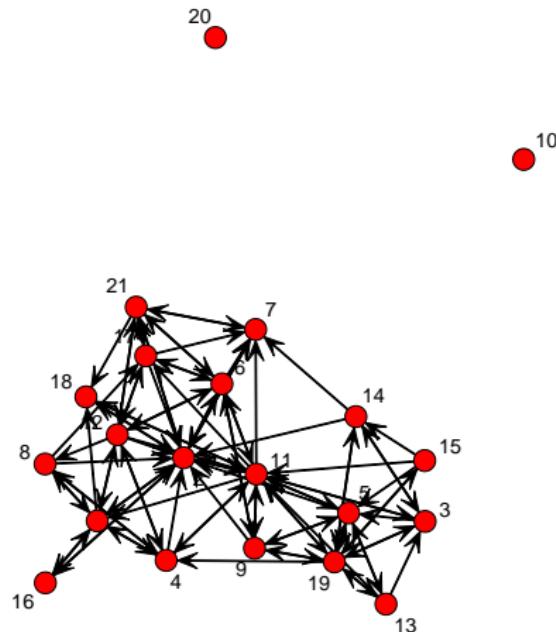


Data set coded by Butts et al. (2007)





David Krackhardt (1987) Perceived Friendships



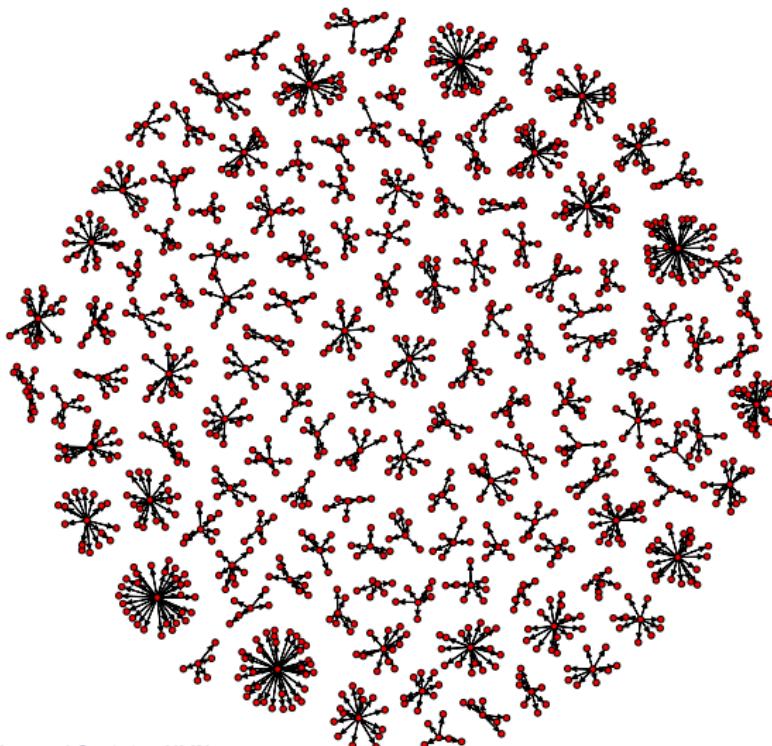


- Authorship
 - Authorship of articles in a large research project
- Hyperreferences
 - Citations among weblogs
- Functional Citations
 - Function calls in the Linux kernel



Co-Author Network from J. Yang and J. Leskovec (2012).

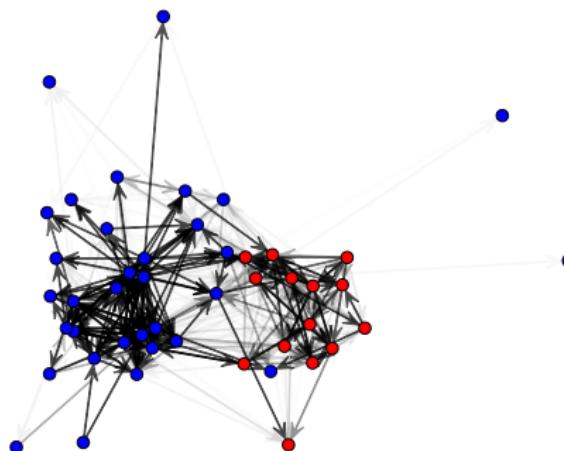
1% of the DBLP co-authorship network communities (Top 5,000)





Weblog Citation Network from Butts and Cross (2005)

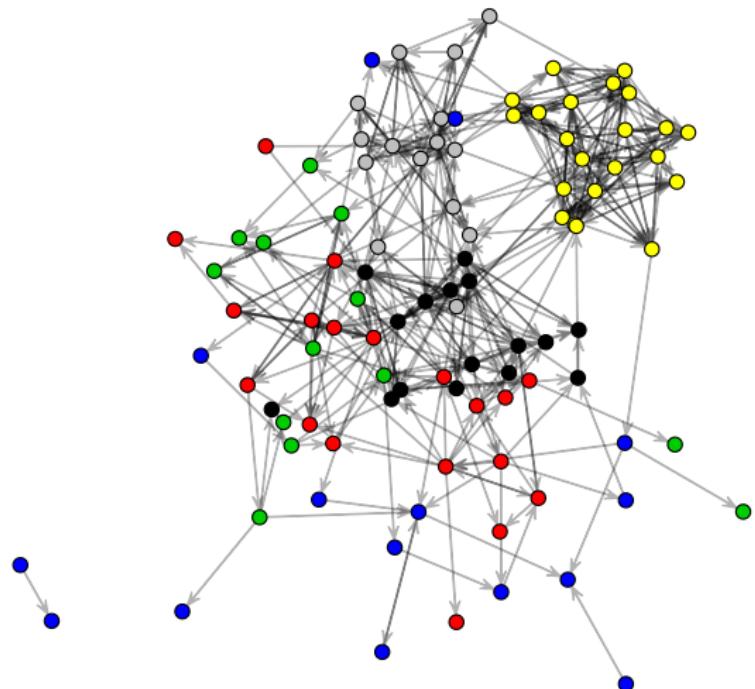
2004 RNC/DNC Credentialed Blogs Citation Network





Even More Networks You Can Find In Everyday Circumstances

- Acknowledgments in articles, CD liners
- Citations among scholars
- Commodity chains (whence did your printer come?) Email messages
- Entailment in ownership (I only own A if I also own B...) Flow of inter-office mail envelopes
- Hyperlinks (actually a kind of citation network)
- Item co-ownership (do we read the same books?) Speed-dial settings and address books





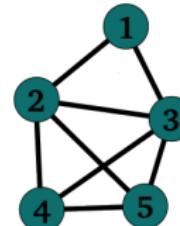
- Relationship: an irreducible property of two or more entities
 - Compare with properties of entities alone ("attributes")
- Focus: the properties and consequences of relations (rather than individual properties)
 - Entities can be persons, non-human animals, groups, locations, organizations, regions, etc.
 - Relationships can be communication, acquaintanceship, sexual contact, proximity, migration rate, alliance/conflict, etc.
 - Social network analysis: the study of relational data arising from social systems



Some Vocabulary

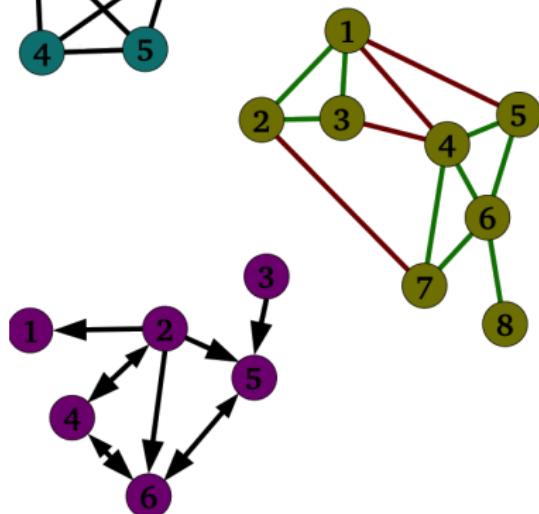
- **Network:** a collection of entities, together with a set of relations on those entities

- Entities: nodes, or vertices
- Relations: edges, or ties
 - Focus on dyadic relations
 - Directed vs. undirected edges
 - May be signed or valued



- Graph: a set of vertices together with a set of edges

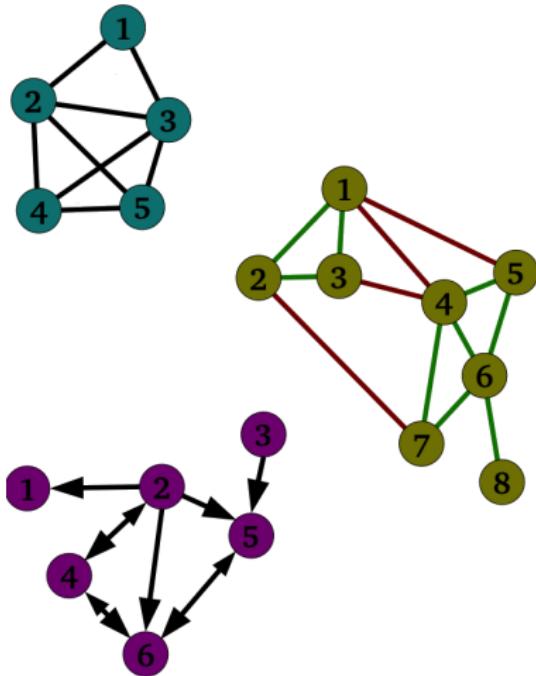
- Entities can be persons, non-human animals, groups, locations, organizations, regions, etc.
- Relationships can be communication, acquaintanceship, sexual contact, proximity, migration rate, alliance/conflict, etc.
- Mathematical representation of social structure





Sociometric Notation

- Based on *graph theory*
- Graph defined as $G = (V, E)$
 - Vertex set: $V = \{v_1, \dots, v_N\}$
 - Edge set: E
 - Undirected: $E \subseteq \{\{v_i, v_j\} : v_i, v_j \in V\}$
 - Directed: $E \subseteq \{(v_i, v_j) : v_i, v_j \in V\}$
 - Simple iff $\{v_i, v_i\}, (v_i, v_i) \notin E$
- Simple operations
 - $G_1 \cup G_2 = (V_1 \cup V_2, E_1 \cup E_2)$
 - $G_1 \cap G_2 = (V_1 \cap V_2, E_1 \cap E_2)$





Subgraphs and Cuts

- Subgraph

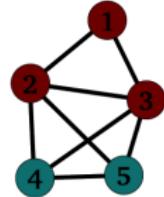
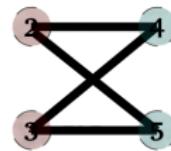
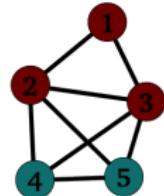
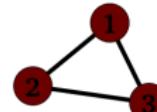
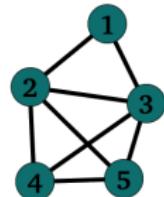
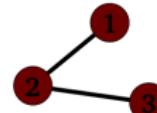
- Selection of vertices and edges from G
- $G_1 \subseteq G_2$ iff $V_1 \subseteq V_2, E_1 \subseteq E_2$

- Induced Subgraph

- Selection of vertices, w/all associated edges
- $G[S] = (S, \{e \in E : e \subseteq S \times S\})$

- Edge cut

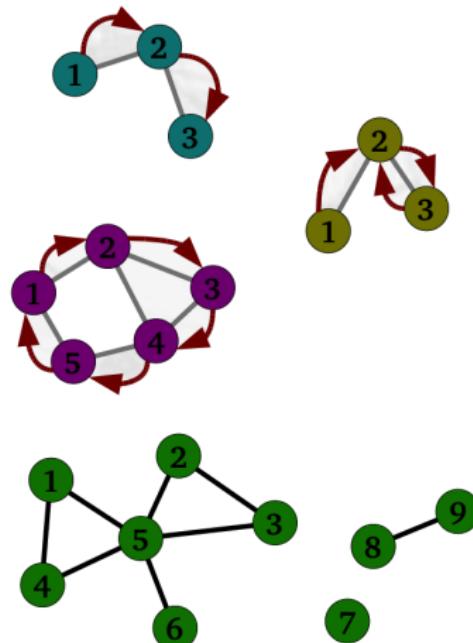
- $G[S_1, S_2] = \{\{s_1, s_2\} \in E : s_1 \in S_1, s_2 \in S_2\}$
- $G[S_1, S_2] = \{(s_1, s_2) \in E : s_1 \in S_1, s_2 \in S_2\}$





A Bit More Vocabulary

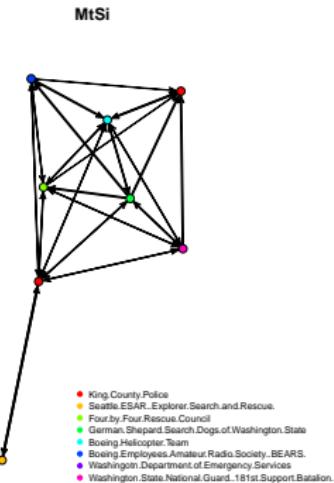
- Adjacency
 - i is adjacent to j iff i sends a tie to j
- Walks, paths, and cycles
 - *Path*: a sequence of adjacent vertices (and connecting edges) with no repetitions
 - *Walk*: like a path, but repetition is allowed
 - *Cycle*: like a path, but start/endpoints are the same
- Connectedness and components
 - i and j are connected iff an i,j path exists
 - *Component*: a maximal set of connected vertices
 - *Isolate*: a component of size 1





- Relational (network) data concerns connections among entities, rather than attributes of entities
 - Entities can be persons, organizations, concepts, etc.
 - Relations can be interaction, proximity, membership, etc.
- Two basic types (for now, at least!)
 - One-mode data: connections among one sort of entity
 - Two-mode data: connections among two sorts of entities

- Networks with one vertex class
- Represented by adjacency matrices
 - Vertices on rows and columns
 - $A_{ij} = 1$ if i sends a tie to j , else $A_{ij} = 0$
 - Can contain edge values, where applicable (A_{ij} is value of i,j edge)
 - Symmetric in undirected case
 - Diagonals represent self-ties
 - Often treated as undefined



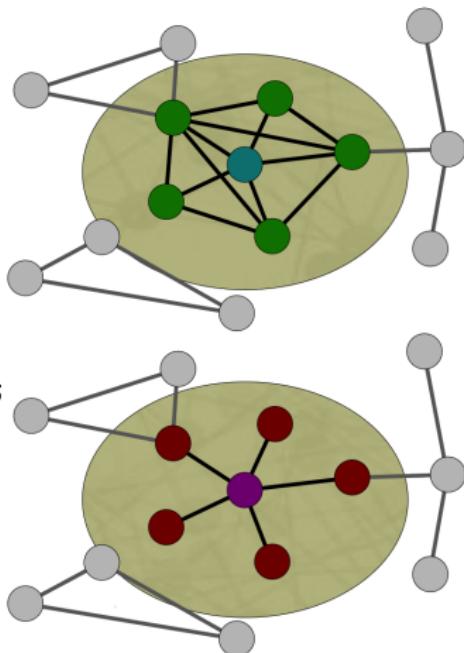
	1	2	3	4	5	6	7	8
1	0.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00
2	1.00	0.00	1.00	1.00	1.00	1.00	0.00	0.00
3	1.00	1.00	0.00	0.00	1.00	1.00	0.00	1.00
4	1.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00
5	1.00	1.00	1.00	0.00	0.00	1.00	0.00	1.00
6	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
7	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00

Table: Mt. Si SAR EMON, Confirmed Ties



Special Case: Ego Nets

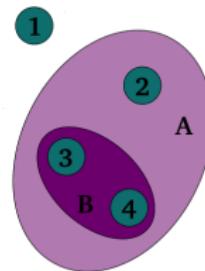
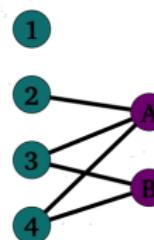
- Egocentric network: focal actor (“ego”) + neighbors (“alters”) + ties among alters
- What does it tell us?
 - Number of ties ego has (neighborhood size)
 - Triangles (3-cliques) containing ego
 - Connections among alters
 - Neighborhood composition (if asked)
- **Note:** Sometimes called *personal networks*



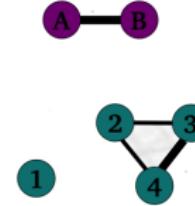


Two-Mode Data

- Networks with two vertex classes
 - Different entity types
 - Membership
 - Matching/containment
- Represented by incidence matrices
 - “Senders” on rows, “receivers” on columns
- Can be used to obtain “dual” representations



	A	B
1		
2	1	
3	1	1
4	1	1





Two-Mode Data

Regular Faculty

Name	Contact	Specialty
Cawo Abdi Associate Professor	1146 Social Sciences Building 612-624-3714 cabdi@umn.edu	Migration; Gender, Race, and Class; Family; Islam; Development Studies; Human Rights; Globalization; Africa; Middle East
Zack Almquist Assistant Professor of Sociology & Statistics	960 Social Sciences Building (Soc) & 372 Ford Hall (Stats) 612-624-1895 (Soc) & 612-625-1024 (Stats) almquist@umn.edu	Social Network Analysis, Mathematical and Computational Sociology, Spatial Analysis, Demography, Public Health, Methodology, and Human Judgement and Decision Making
Ron Aminzade Professor	1031 Social Sciences Building 612-624-9570 aminzade@umn.edu	Historical and Comparative, Political Sociology, Sociology of Development, Nationalism, Race Relations, Social Movements, Democratic Theory
Alejandro Baer Associate Professor & Director, Center for Holocaust & Genocide Studies	1133 Social Sciences Building (Soc) & 252 Social Sciences Building (CHGS) 612-624-7548 & 612-624-5014 aebaer@umn.edu	Social Memory Studies, Holocaust and Genocide Studies, Antisemitism, Sociology of Judaism, Sociology of Media and Communication, Qualitative Methods, Visual Sociology.
Joyce Bell Associate Professor	Off-site 2015-16 jmbell@umn.edu	American Race Relations; Social Movements; Work, Professions & Organizations
Yanjie Bian Professor	967 Social Sciences Building 612-624-9554 biany001@umn.edu	Economic sociology, Social networks, Social stratification, Chinese society
Elizabeth Boyle Professor & Chair	909 Social Sciences Building 612-624-3343 boyle014@umn.edu	Sociology of Law, Globalization, Children's and Women's Rights
	1036 Social Sciences Building	Political Sociology; Environmental Sociology; Social Movements; Network Analysis; Discourse Analysis; Institutions and Culture



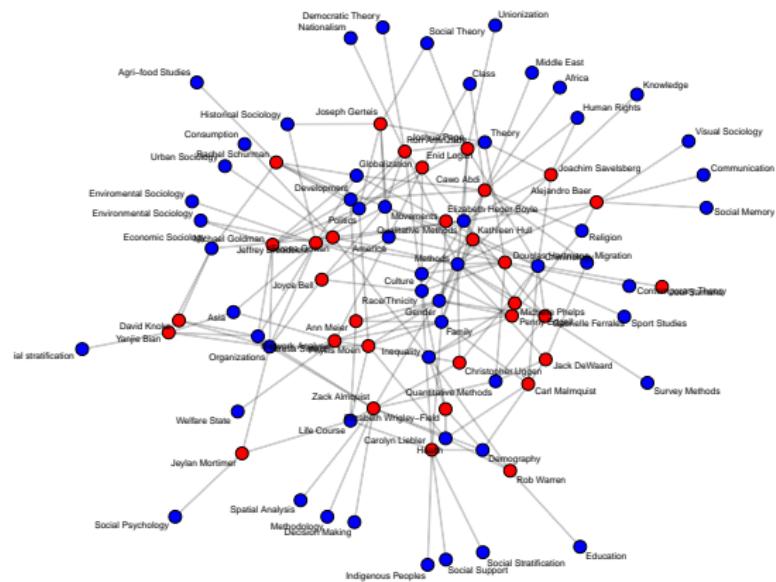
Two-Mode Data

The screenshot shows a Google Sheets spreadsheet titled "faculty2mode". The data is organized into two main sets of columns: faculty members (A-E) and topics (F-L). Faculty members include Cawo Abdi, Zack Almquist, Ron Aminzade, Alejandro Baer, Joyce Bell, Yanjie Bian, Elizabeth Boyle, Jeffrey Broader, Jack DeWaard, Penny Erdgel, and Gabriele Ferrale. Topics include Africa, Agri-food Studies, America, Asia, Class, Consumption, Contemporary TI, Criminology, Culture, Democratic Theor, Demography, Development, Economic Social, Education, Environmental So, Environmental S, Family, Gender, Globalization, Health, Historical Sociox, Human Judgeme, and Human Rights. The data is represented by binary values (0 or 1) indicating whether each faculty member is associated with each topic.

	A	B	C	D	E	F	G	H	I	J	K	L
1	Cawo Abdi	Zack Almquist	Ron Aminzade	Alejandro Baer	Joyce Bell	Yanjie Bian	Elizabeth Boyle	Jeffrey Broader	Jack DeWaard	Penny Erdgel	Gabriele Ferrale	
2	Africa	1	0	0	0	0	0	0	0	0	0	0
3	Agri-food Studier	0	0	0	0	0	0	0	0	0	0	0
4	America	0	0	0	0	1	0	0	0	0	0	0
5	Asia	0	0	0	0	0	1	0	1	0	0	0
6	Class	1	0	0	0	0	0	0	0	0	0	0
7	Consumption	0	0	0	0	0	0	0	0	0	0	0
8	Contemporary TI	0	0	0	0	0	0	0	0	0	0	0
9	Criminology	0	0	0	0	0	0	1	0	0	0	1
10	Culture	0	0	0	0	0	0	0	1	0	1	0
11	Democratic Theor	0	0	1	0	0	0	0	0	0	0	0
12	Demography	0	1	0	0	0	0	0	0	1	0	0
13	Development	1	0	1	0	0	0	0	0	0	0	0
14	Economic Social	0	0	0	0	0	1	0	0	0	0	0
15	Education	0	0	0	0	0	0	0	0	0	0	0
16	Environmental So	0	0	0	0	0	0	0	1	0	0	0
17	Environmental S	0	0	0	0	0	0	0	1	0	0	0
18	Family	1	0	0	0	0	0	1	0	0	1	0
19	Gender	1	0	0	0	0	0	0	0	0	1	1
20	Globalization	1	0	0	0	0	0	1	1	0	0	0
21	Health	0	1	0	0	0	0	0	0	0	0	0
22	Historical Sociox	0	0	0	0	0	0	0	1	0	0	0
23	Human Judgeme	0	0	0	0	0	0	0	0	0	0	0
24	Human Rights	1	0	0	0	0	0	0	0	0	0	0



Two-Mode Data





One-Mode Projections

- Let A be an $N \times M$ incidence matrix; the row-projection of A is the $N \times N$ matrix B such that

$$B_{ij} = \sum_{k=1}^M A_{ik} A_{jk}$$

- Likewise, the column projection of A is the $M \times M$ matrix C such that

$$C_{ij} = \sum_{k=1}^N A_{kj} A_{kj}$$

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

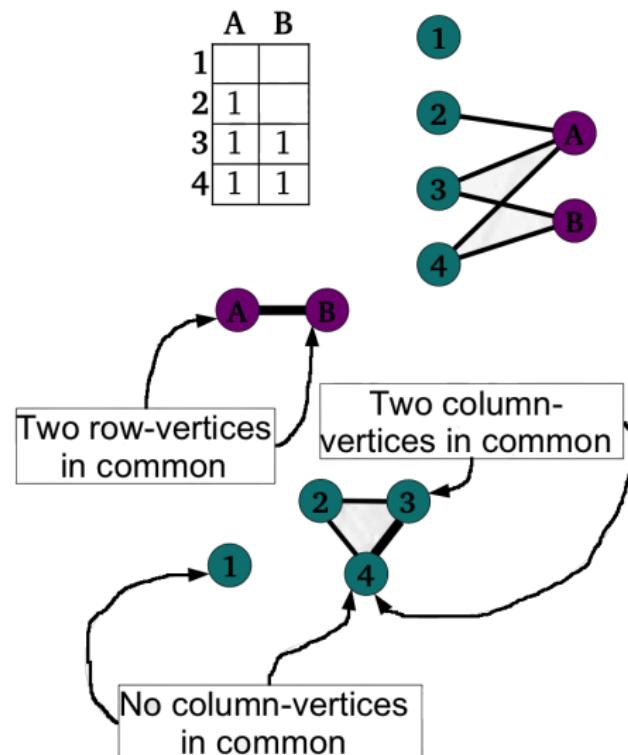
$$B = \begin{pmatrix} 2 & 1 & 1 & 1 \\ 1 & 2 & 1 & 1 \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 2 \end{pmatrix}$$

$$C = \begin{pmatrix} 2 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 3 \end{pmatrix}$$



What the Projections Mean

- Projections have simple meaning
 - Row: B_{ij} is the number of column elements shared by row elements i and j
 - Column: C_{ij} is the number of row elements shared by column elements i and j
 - Ex: Number of shared interests between two faculty; number of faculty having a given interest area in common





- To analyze network data, we must first collect it!
 - Many approaches exist – some better than others for particular purposes
 - Complex topic overall, but we will at least skim the surface...
- Two important concepts (not always separable):
 - Instruments: tools used to elicit information from respondents, assess presence/absence of ties from sensors or archival materials, etc.
 - Designs: protocols for determining how information should be elicited, who should be sampled, etc.



- Own-tie reports
 - Personal ties elicited from each ego
 - Standard instruments: roster and name generator
 - Pros: Easily implemented, most common design
 - Cons: Vulnerable to reporting error
- Egocentric network sampling
 - Personal ties elicited from ego, followed by induced ties
 - Standard instrument: name generator followed by roster
 - Pros: Well-suited to large-scale survey sampling; provides information on ego's neighborhood
 - Cons: Vulnerable to reporting error; false positives/negatives on own ties contaminate sampling of neighbors' ties



Instruments: Name Generators and Rosters

- Name generator: asks respondents to list names
 - E.g. “Think about the persons with whom you have talked in the past week. Please list all such persons in the following space.”
(followed by space to enter names)
- Pros:
 - Don't have to know name list; can use with large groups or organizations
- Cons:
 - High rate of forgetting; unclear boundary
- Roster: asks respondents to choose names from fixed list
 - E.g. “For each of the following persons, place a check in the associated blank if you have talked with him/her in the past week.”
(followed by check list)
- Pros:
 - More accurate, clear boundary
- Cons:
 - List may be prohibitively long, can be imposing; alters must be known in advance



- Common way to elicit ego nets: complete instrument followed by roster
 - Asked to name those with whom you discussed important matters
 - Then, asked to fill in same question for all pairs of persons named initially
- Pros:
 - Relatively easy to administer; don't need entire list of possible alters; don't have to ask about all group members
- Cons:
 - Step 1, step 2 questions have different error rates; may need large roster if many alters; hard to use with paper-based surveys



- Link-tracing
 - Personal ties elicited from ego; new ego(s) chosen from alters; process is iterated (possibly many times)
 - Standard instruments: multiwave own-report, RDS
 - Pros: Allows estimation of network properties for large and/or hard to reach populations; highly scalable; can be robust to poor seed sampling
 - Cons: Vulnerable to reporting error; reporting errors can contaminate design (but may be less damaging than ego net case); often difficult to execute
- Arc Sampling
 - Reports on third-party ties elicited from ego; multiple egos may be sampled for each third-party tie
 - Archival/observer data is a special case
 - Standard instrument: CSS
 - Pros: Very robust to reporting error (via modeling); can be very robust to missing data
 - Cons: Can impose large burden on respondents; can be difficult to execute



- Cognitive Social Structure (CSS)

- Ask each group member to report on all members' ties
- Ex: "Which of the following persons does Steve go to for help or advice?"

- Pros:

- Gets information on perception; can be used to get high-accurate estimates

- Cons:

- Hard to use; requires roster; doesn't scale well

- Respondent Driven Sampling (RDS)

- Combine standard network instrument with recruitment "tickets"
- Respondents given tickets to give to others; if they volunteer, both get paid

- Pros:

- Can use with hidden, vulnerable populations

- Cons:

- Difficult; expensive; complex to analyze; poorly understood



Coding Schemes as “Instruments”

- Can also think of coding schemes for archival materials as “instruments”
- Transcripts
 - Tag each line by sender/receiver
 - (i, j) tie if i sends to j
- Descriptive lists/tables
 - Common for two-mode data
 - Build entity/property table; fill in (i, j) as 1 if i th row entity has property j
- Video/Audio
 - Determine criterion for interaction
 - Find all interactions, code by sender/receiver
 - (i, j) tie if i sends to j
- Narrative documents
 - Determine criterion for interactions
 - As before, code by sender/receiver (or just by dyad, if not directed)
 - (i, j) tie if i sends to j , or $\{i, j\}$ tie if i and j interact



Coding Schemes as “Instruments”

- Can also think of coding schemes for archival materials as “instruments”
- Transcripts
 - Tag each line by sender/receiver
 - (i, j) tie if i sends to j
- Video/Audio
 - Determine criterion for interaction
 - Find all interactions, code by sender/receiver
 - (i, j) tie if i sends to j
- Narrative documents

A fun example

Adams, jimi (2015). Glee's McKinley High: Following Middle America's sexual taboos. *Network Science*, 3(2): 293 – 295.

http://journals.cambridge.org/abstract_S2050124215000168

$\{i, j\}$ tie if i and j interact



Related Issue: Network Boundary Problem

- Important problem: whence the vertex set?
 - If misspecified, theoretically relevant ties may be missed
- Typical cases
 - Exogenously defined
 - Physical region, group/cohort membership
 - Relationally defined
 - Isolated social unit (component), locally dense
 - Design defined
 - Alters named in ego net, link trace; sampled egos
- Major distinction: local versus global properties
 - Different sampling methods needed for each



Introduction to classic Social Network Metrics (Positional or Node-level indices)



- Node-level index: a real-valued function of a graph and a vertex
 - Purely structural NLIs depend only on unlabeled graph properties
 - I.e., $f(v, G) \rightarrow \mathbb{R}$
 - Invariant to node relabeling
 - Covariate-based NLIs use both structural and covariate properties
 - I.e., $f(v, G, X) \rightarrow \mathbb{R}$
 - Not labeling invariant

- Primary uses:
 - Quantify properties of individual positions
 - Describe local neighborhood
- Several common families:
 - Centrality
 - Ego-net structure
 - Alter covariate indices
- Centrality is the most prominent, and our focus in this workshop



- Returning to the core question: how do individual positions vary?
- One manner in which positions vary is the extent to which they are “central” in the network
 - Important concern of social scientists (and junior high school students)
- Many distinct concepts
 - No one way to be central in a network ? many different kinds of centrality
 - Different types of centrality aid/hinder different kinds of actions
 - Being highly central in one respect doesn't always mean being central in other respects (although the measures generally correlate)



Types of Centrality Measures

- One attempted classification by Koschützki et al. (2005):
 - Reach: Centrality based on ability of ego to reach other vertices
 - Degree, closeness
 - Flow Mediation: Centrality based on quantity/weight of walks passing through ego
 - Stress, betweenness
 - Vitality: Centrality based on effect of removing ego from the network
 - Flow betweenness (oddly), cutpoint status
 - Feedback: Centrality of ego defined as a recursive function of alter centralities
 - Eigenvector centrality, Bonacich Power



Degree

- Degree: number of direct ties

- Overall activity or extent of involvement in relation
- High degree positions are influential, but also may be subject to a great deal of influence from others

- Formulas:

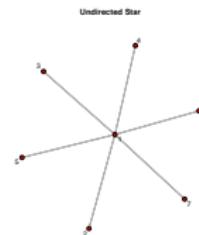
- Degree (undirected):

$$d(i, Y) = \sum_{j=1}^N Y_{ij}$$

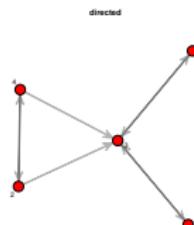
- Indegree $d_i(i, Y) = \sum_{j=1}^N Y_{ji}$
- Outdegree

$$d_o(i, Y) = \sum_{j=1}^N Y_{ij}$$

```
options(width=30) require(sna) require(network)
star<-network(cbind(rep(1,7),
matrix(rep(0,times=6,each=7), nc=6, nr=7)), directed=FALSE)
plot(star, main="Undirected Star",
label=1:7, edge.col=rgb(0,0,0,.3))
```



```
set.seed(9902211)
gplot(net<-rgraph(5), main="directed",
label=1:5, edge.col=rgb(0,0,0,.3))
```

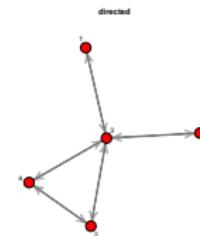




Interlude: Shortest Paths

- A shortest path from i to j is called an i,j geodesic
 - Can have more than one (but all same length, obviously)
 - The length of an i,j geodesic is called the geodesic distance from i to j
- Widely used, as we shall see...

```
set.seed(9902211)  
  
gplot(symmetrize(net[,]),main="directed",  
label=1:5,edge.col=rgb(0,0,0,.3))
```



```
sna::geodist(symmetrize(net[,]))
```

```
R > $counts  
R >      [,1] [,2] [,3] [,4] [,5]  
R > [1,]    1    1    1    1    1  
R > [2,]    1    1    1    1    1  
R > [3,]    1    1    1    1    1  
R > [4,]    1    1    1    1    1  
R > [5,]    1    1    1    1    1  
R >  
R > $gdist  
R >      [,1] [,2] [,3] [,4] [,5]  
R > [1,]    0    2    1    2    2  
R > [2,]    2    0    1    1    2  
R > [3,]    1    1    0    1    1  
R > [4,]    2    1    1    0    2  
R > [5,]    2    2    1    2    0
```



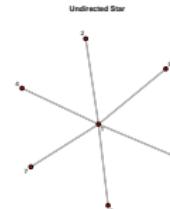
Betweenness

- Betweenness: tendency of ego to reside on shortest paths between third parties
 - Quantifies extent to which position serves as a bridge
 - High betweenness positions are associated with “broker” or “gatekeeper” roles; may be able to “firewall” information flow
- Formula

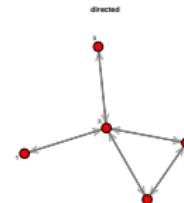
$$b(i, Y) = \sum_{j \neq i} \sum_{k \neq l} \frac{g'(j, k, l)}{g(j, k)}$$

Where $g(j, k)$ is the number of j, k geodesics, $g'(j, k, i)$ is the number of j, k geodesics including i

```
set.seed(9902211)
plot(star, main="Undirected Star",
label=1:7, edge.col=rgb(0,0,0,.3))
```



```
gplot(symmetric(net[,]), main="directed",
label=1:5, edge.col=rgb(0,0,0,.3))
```



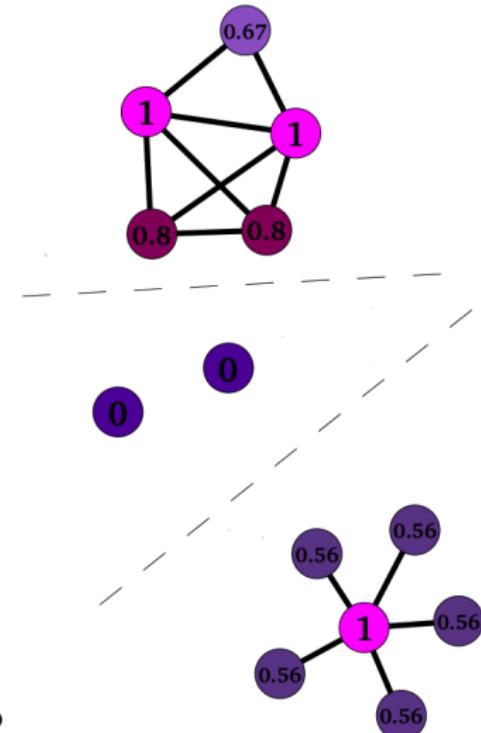


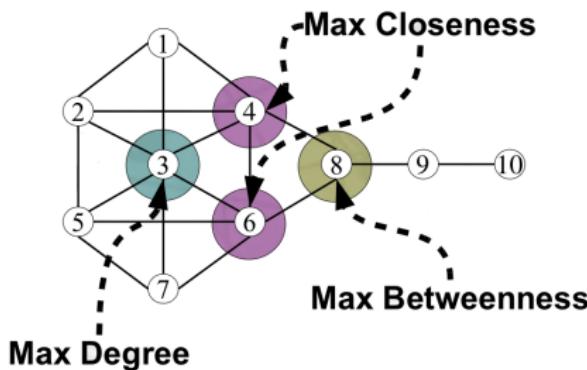
Closeness

- Closeness: ratio of minimum distance to other nodes to observed distance to other nodes
 - Extent to which position has short paths to other positions
 - High closeness positions can quickly distribute information, but may have limited direct influence
 - Limitation: not useful on disconnected graphs (may need to symmetrize directed graphs, too)
- Formula

$$c(i, Y) = \frac{N - 1}{\sum_{j=1}^N D(i, j)}$$

Where $D(i, j)$ is the distance from i to j





Top 3 by Degree

- 1: Node 3
- 2: Nodes 4 and 6
- 3: Nodes 2 and 5

Top 3 by Closeness

- 1: Nodes 4 and 6
- 2: Nodes 3 and 8
- 3: Nodes 2 and 5

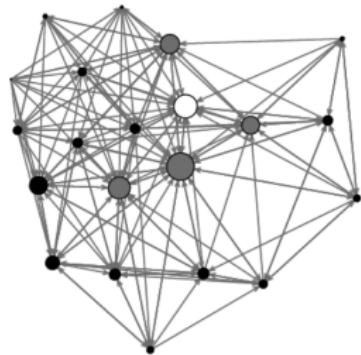
Top 3 by Betweenness

- 1: Node 8
- 2: Nodes 4 and 6
- 3: Node 9

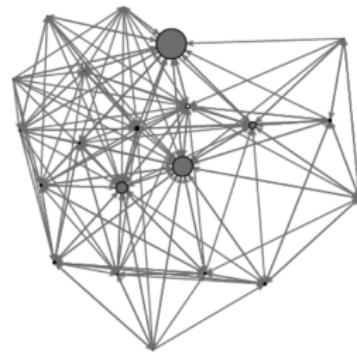


Classic Centrality Measures Compared

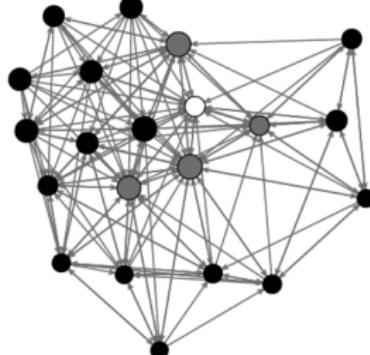
Krackhardt Office – Scaling by Indegree



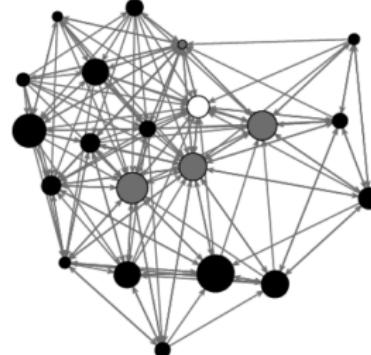
Krackhardt Office – Scaling by Betweenness



Krackhardt Office – Scaling by Closeness



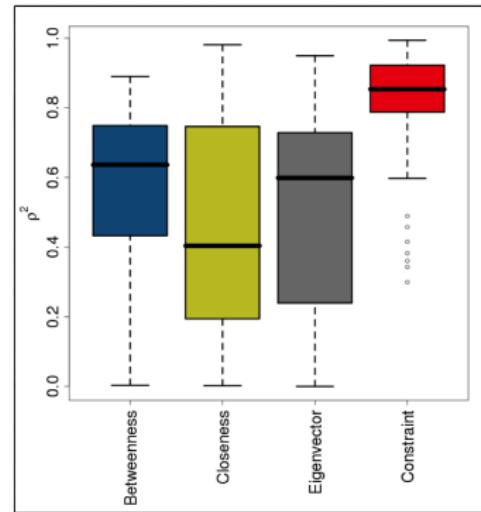
Krackhardt Office – Scaling by Accuracy





Relatedness of Centrality Indices

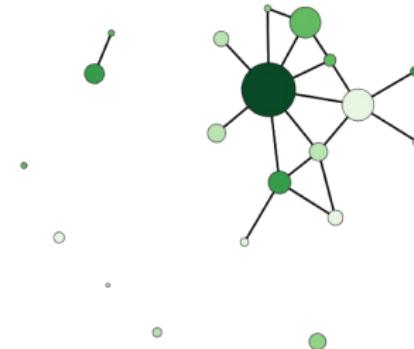
- Centrality indices are strongly correlated in practice
- Simple example: total degree versus “complex” NLIs
 - Squared correlations for sample UCINET data sets
 - Some diversity, but usually accounts for majority of variance
 - Theoretical insight: if you can capture degree, you can capture many other aspects of social position





Relating NLIs to Vertex Covariates

- Common question: are NLIs related to non-structural covariates?
 - Centrality to power or influence
 - Constraint to advancement
 - Diversity to attainment



(Texas SAR EMON Decision Rank Score (scale) vs. Degree (color), Mutually Reported “Continuous” Communication” - $p=0.86$)



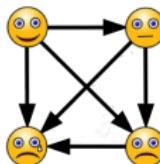
"Linear" Permutation Tests

- Simple, nonparametric test of association between vectors
 - Sometimes called "linear" or "vector" permutation test (or monte carlo test)
 - Tests marginal association against exchangeability null (independence conditional on marginal distributions)
- Null interpretation: "musical chairs" model
 - If we randomly switched the positions of people in the network (leaving structure as-is), what is the chance of observing a similar degree of association?
- Monte Carlo procedure:
 - Let $x_{obs} = (f(v_1, G), \dots, f(v_N, G))$ be the observed NLI vector, w/covariate vector y
 - Let $t_{obs} = s(x_{obs}, y)$
 - For i in $1, \dots, n$
 - Let $x^{(0)}$ be a random permutation of x_{obs}
 - Let $t^{(i)} = s(x^{(i)}, y)$
- Estimated p-values:
 - One-seided
 - $\Pr(t^{(i)} \leq t_{obs}) \approx \sum_i I(t^{(i)} \leq t_{obs})/n$
 - $\Pr(t^{(i)} \geq t_{obs}) \approx \sum_i I(t^{(i)} \geq t_{obs})/n$
 - Two-sided
 - $\Pr(|t^{(i)}| \geq |t_{obs}|) \approx \sum_i I(|t^{(i)}| \geq |t_{obs}|)/n$

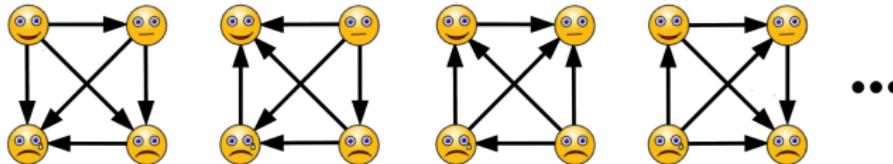


Understanding the Null Model

We Observed:



We Could Have Observed:

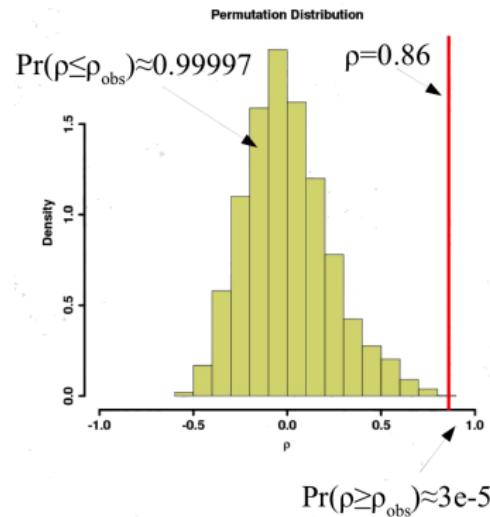


We Ask: *"Is the observed relationship extreme compared to what we would expect to see, if assignment to positions were independent of the covariate?"*



Texas SAR EMON Example

- Question: do organizations in constant communication w/many alters end up more/less prominent in the decision-making process?
 - Measure (s): correlation of decision rank score (y) with degree in confirmed "continuous communication" network (x_{obs})
 - Null: no relationship between degree and decision making
 - Alternative: decision making has linear marginal relationship w/degree



Results

- $t_{obs} = 0.86$;
 $\Pr(|t^{(i)}| \geq |t_{obs}|) \approx 3e-5$
- Correlation this large very



NLIs as Covariates

- NLIs can also be used as covariates (e.g., in regression analyses)
 - Modeling assumption: position properties predict properties of those who hold them
 - Conditioning on NLI values, so dependence doesn't matter (if no error in G)
 - NLIs as dependent variables are much more problematic; we'll revisit this problem when we discuss ERGs

- Things to keep in mind....
 - Make sure that your theory really posits a direct relationship w/the NLI
 - NLI distributions could be quite skewed or irregular; be sure this makes sense (e.g., via analysis of residuals)
 - Multiple NLIs may be strongly correlated; may not be able to distinguish among related measures in practice



Introduction to graph-level properties: Density, Reciprocity, the Dyad Census, and the Triad Census



- Earlier, we discussed the notion of node-level indices (mainly centrality)
 - Dealt with position of the individual within the network
- We will focus on properties at the graph level
 - Graph-level index: $f(v, G) \rightarrow \mathbb{R}$
 - Describes aggregate features of structure as a whole
- Provide complementary insight into social structure
 - Node-level properties tell you who's where, but graph- level properties provide the broader context



Density

- Density: fraction of possible edges which are present
 - Probability that a given graph edge is in the graph

- Formulas:

- Undirected: $\delta = \frac{2 \sum_{i=1}^N \sum_{j=i}^N Y_{ij}}{N(N-1)}$

- Directed: $\delta = \frac{2 \sum_{i=1}^N \sum_{j=1}^N Y_{ij}}{N(N-1)}$

```
library(sna)
undirected <- rgraph(10, mode = "graph")
directed <- rgraph(10, mode = "digraph")
gden(undirected, mode = "graph")

R > [1] 0.4222222

2 * sum(undirected[upper.tri(undirected)])/(NROW(directed) *
  (NROW(directed) - 1))

R > [1] 0.4222222

gden(directed, mode = "digraph")

R > [1] 0.5222222

sum(directed)/(NROW(directed) *
  (NROW(directed) - 1))

R > [1] 0.5222222
```



Size, Density, and Mean Degree

- Important fact: size, density, and mean degree are intrinsically related
 - Formally, $d_m = \delta(N - 1)$ [I.e., mean degree = density times size-1]
 - Also, $\delta = d_m/(N - 1)$ [I.e., density = mean degree over size-1]
- Simple fact, with non-obvious implications
 - If mean degree fixed, density falls with 1/group size
 - To maintain density, have to increase degree linearly, but actors can only support so many ties!
 - Thus, growing networks become increasingly sparse over time
 - Durkheim, Parsons, etc: modern social order depends on/produces norms of generalized exchange, since only tiny fraction of person can be directly related

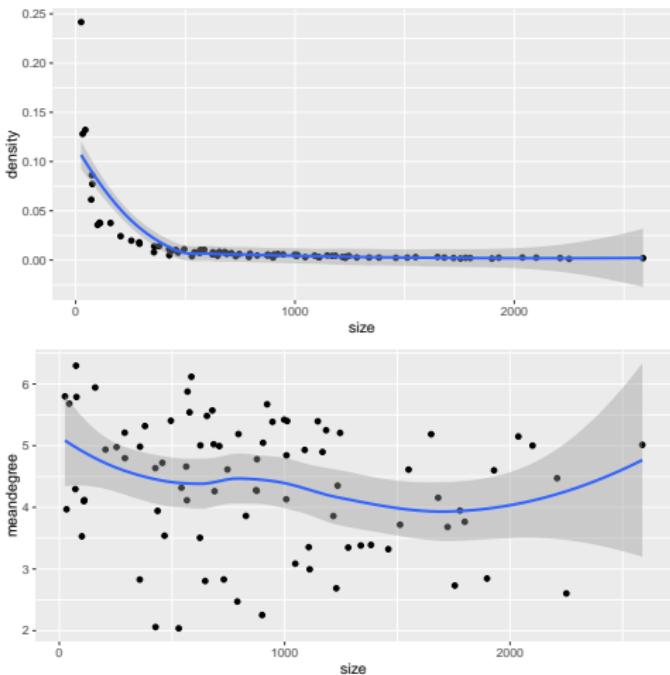


Illustration: Mean Degree Constancy and Density Decline

Add Health Example

```
library(ggplot2)
library(gridExtra)
library(networkdata)
data(addhealth)
data(addhealth)
data <- data.frame(size = sapply(addhealth,
  network.size), density = sapply(addhealth,
  gden))
data$meandegree <- data$density *
  (data$size - 1)

p1 <- ggplot(data, aes(size, density)) +
  geom_point() + geom_smooth()
p2 <- ggplot(data, aes(size, meandegree)) +
  geom_point() + geom_smooth()
grid.arrange(p1, p2, ncol = 1)
```



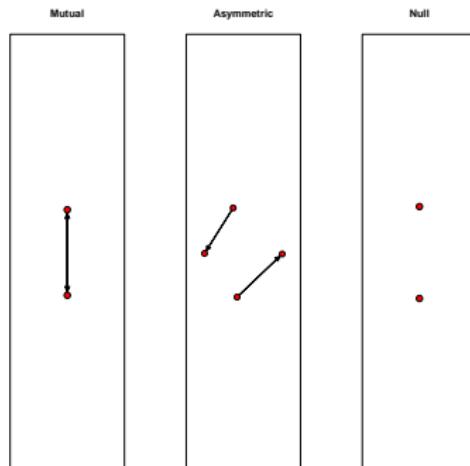
- Dyad census: a count of the number of mutual, asymmetric and null dyads in a network

- Mutual: (i, j) and (j, i)
- Asymmetric: (i, j) or (j, i) , but not both
- Null: neither (i, j) nor (j, i)
- Traditionally written as (M, A, N)

- Used as “building block”

- $M + A + N =$ Number of dyads
- $2M + A =$ Number of edges
- $(M + A/2)/(M + A + N) =$ Density

```
asym <- matrix(0, nc = 4, nr = 4)
asym[1, 4] <- 1
asym[3, 2] <- 1
mut <- matrix(c(0, 1, 1, 0), nc = 2)
null <- matrix(c(0, 0, 0, 0), nc = 2)
par(mfrow = c(1, 3))
gplot(mut, mode = "circle", main = "Mutual")
box()
gplot(asym, mode = "circle", main = "Asymmetric")
box()
gplot(null, mode = "circle", main = "Null")
box()
```





Reciprocity

```
graph <- rgraph(15)
gplot(graph)
```

- Reciprocity: tendency for relations to be symmetric
- Several notions:
 - Dyadic: probability that any given dyad is symmetric (mutual or null)

$$\frac{M + N}{M + A + N}$$

- Edgewise: probability that any given edge is reciprocated

$$\frac{2M}{2M + A}$$



```
dyad.census(graph)
```

```
R >           Mut  Asym  Null
R >   [1,]  19    64    22
```

```
grecip(graph, measure = "edgewise")
```

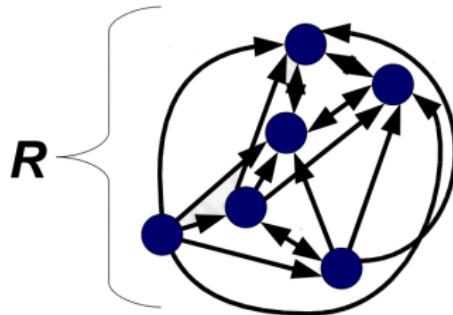
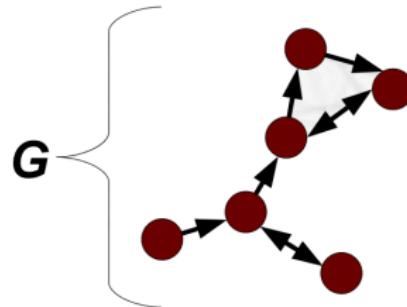
```
R >           Mut
R >   0.372549
```

```
grecip(graph, measure = "dyadic")
```

```
R >           Mut
R >   0.3904762
```

- Reachability graph

- Digraph, R , based on G such that (i,j) is an edge in R iff there exists an i,j path in G
 - If G is undirected or fully reciprocal, R will also be fully reciprocal
- Intuitively, an edge in R connects vertices which are connected in G
- Strong components of G (including cycles) form cliques in R

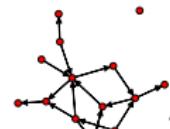




Hierarchy

- Hierarchy: tendency for structures to be asymmetric
- As with reciprocity, many notions; for instance...
 - Dyadic Hierarchy: 1- (Dyadic Reciprocity)
 - Intuition: extent to which dyads are asymmetric
 - Krackhardt Hierarchy:
 $1 - M/(M + A)$ in Reachability Graph
 - Intuition: for pairs which are in a contact, what fraction are asymmetric?

```
graph <- rgraph(15, tprob = 0.1)
gplot(graph)
```



```
hierarchy(graph, measure = "reciprocity")
```

```
R >      Mut  
R > 0.152381
```

```
hierarchy(graph, measure = "krackhardt")
```

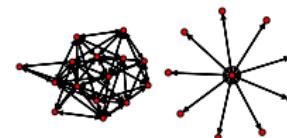
```
R > [1] 0.8333333
```



Centralization

- Centralization: extent to which centrality is concentrated on a single vertex
- Definition due to Freeman (1979):

$$C(G) = \sum_{i=1}^N \left(\max_v c(v, G) - c(i, G) \right)$$



```
graph <- rgraph(15, tprob = 0.5,
                mode = "graph")
par(mfrow = c(1, 2), mar = c(0,
                             0, 0, 0))
gplot(graph)
gplot(star)
```

```
cbind(centralization(graph, g = 1,
                      degree), centralization(graph,
                      g = 1, closeness))
```

```
R >           [,1]      [,2]
R > [1,] 0.2747253 0.1376352
```

```
cbind(centralization(star, g = 1,
                      degree), centralization(star,
                      g = 1, closeness))
```

```
R >           [,1]      [,2]
R > [1,] 1 0.5228758
```

- Defined for any centrality measure
- Often used with degree, betweenness, closeness, etc.
- Most centralized structure usually star network
 - True for most centrality measures



Centralization Versus Hierarchy

- Aren't centralization and hierarchy the same thing?
- No! Two very different ideas:
 - Hierarchy: asymmetry in interaction
 - Centralization: inequality in centrality
- Can have centralized mutual structures, hierarchical decentralized structures

- Bavelas, Leavitt and others studied work teams with four structural forms:



- Performance generally highest in centralized groups
 - Star, "Y" took least time, made fewest errors, used fewest messages
- Satisfaction generally highest in decentralized groups
 - Circle > Chain > "Y" > Star (but central persons had fun!)
- A lesson: optimal performance \neq optimal satisfaction...



- So far, we have been measuring properties of graphs (and modeling their effects)
- Next step: modeling graphs themselves
 - Long-running and ongoing research area
 - Will crop up repeatedly in the coming weeks
- A quick introduction to some basic families
 - We'll see some uses of these model families in the next lecture...



- Let $G = (V, E)$ be a graph. If E (and perhaps V) is a random set, then G is a random graph
 - Can consider G to be a random variable on some set \mathcal{G} of possible graphs ("multinomial" representation)
 - Write probability mass function (pmf) as $\Pr(G = g)$
- Let Y be the adjacency matrix of random graph G . Then Y is a random matrix
 - Write graph pmf as $\Pr(Y = y)$
 - Y_{ij} is a binary random variable which indicates the state of the (random) i, j edge
 - $\Pr(Y_{ij} = y_{ij})$ is the (marginal) probability of the Y_{ij} edge state



“Classical” Random Graphs

- Two families from the early (mathematical) literature:
 - The “N,M” family (Erdős-Rényi, size/density CUG)
 - Let M_m be the maximum number of edges in G . Then:

$$\Pr(G = g \mid N, M) = \binom{M_m}{M}^{-1}$$

- The “N,p” family (homogeneous Bernoulli graphs)

$$\Pr(G = g \mid N, p) = p^M(1 - p)^{M_m - M}$$

- Both used as baseline models, but very limited
 - No heterogeneity, (almost) no dependence
 - Starting point for more complex models



Relaxation 1: Intra-dyadic Independence

- First way to build richer models: relax independence
- Intra-dyadic dependence models
 - Allow for size, density, reciprocity effects
- Two parallel models
 - Dyad census conditioned CUG ($U|MAN$)
 - Let G have fixed dyad census M, A, N . Then

$$\Pr(G = g \mid M, A, N) = \frac{M! A! N!}{(M + A + N)!}$$

- Homogeneous dyadic multinomial family ($u|man$)

$$\Pr(G = g \mid m, a, n) = m^M a^A n^N$$



Relaxation 2: Homogeneity

- Second way to build richer models: relax homogeneity in edge probabilities
- Development for Bernoulli, multinomial cases:
- Inhomogeneous Bernoulli graph
 - Let $\Phi \in [0, 1]^{N \times N}$ be a parameter matrix, and $B(X = x | p)$ the Bernoulli pmf.

$$\Pr(G = g | \Phi) = \prod_{(i,j)} B(Y_{ij} = y_{ij} | \Phi_{ij})$$

- Inhomogeneous independent dyad graph
- Let $\Phi, \Psi \in [0, 1]^{N \times N}$ be parameter matrices w/ $\Phi_{ij} + \Psi_{ij} \leq 1$. Then

$$\Pr(G = g | \Phi, \Psi) = \prod_{(i,j)} [\Phi_{ij}y_{ij}y_{ji} + \Psi_{ij}(y_{ij}(1 - y_{ij}) + (1 - y_{ij})y_{ji}) + (1 - \Phi_{ij} - \Psi_{ij})(1 - y_{ij})(1 - y_{ij})]$$

- Intuitively, Φ sets the probability of mutuals, and Ψ sets the probability of asymmetrics
- Notation taken from Carter Butt's Social Network Methods Course at UCI



- Models without trivial cross-dyadic dependence still have many uses
 - Baseline models for null hypothesis testing
 - Mathematical tools for exploring the space of graphs
 - Serious data models (in the inhomogeneous case)
 - Start with inhomogenous family, model parameter matrix using regression-like model (see, e.g., `sna::netlogit`) and/or with latent variables (e.g. package `latentnet`)
 - Can be extremely effective, if sufficiently strong covariates are available
 - Dyad dependent models are much more complex, but we'll see them later...



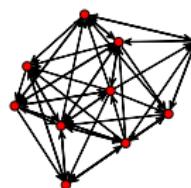
- Dyad census, etc.
 - Dyad census – most “foundational” structural element
- Triad and transitivity
 - Smallest nontrivial structural units
- Null hypothesis testing for GLIs
 - Application of random graphs



The Subgraph Census

- The dyad census counted all copies of the three dyadic isomorphism classes (M,A,N)
 - $G \cong H$ if there exists some relabeling f of $V(G)$: (u, v) in $E(G)$ iff $(f(u), f(v))$ in $E(H)$
- Generalization: subgraph census
 - Count of all subgraphs of a particular form (e.g., 2-stars, 3-cycles, etc)
 - Induced subgraph census: count of all induced subgraphs of a particular form (e.g., incomplete 2-paths – nulls count!)
 - Way of measuring network “composition”

```
g <- rgraph(10)
gplot(g)
```



```
dyad.census(g)
```

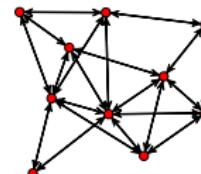
R >	Mut	Asym	Null
R > [1,]	17	19	9



From Dyads to Triads

- Famous observation of Simmel:
triads differ fundamentally from dyads
 - Possibility for exclusion,
alliance formation, etc.
- Structurally, triads are the first inseparable order
 - Dyads are separable: the edges of distinct $\{i, j\}$ and $\{k, l\}$ do not overlap
 - Triads are inseparable: every $\{i, j, k\}$ triad intersects $3(N - 3)$ other triads
- Triads are thus a “bridge” from local to global structure

```
g <- rgraph(10, mode = "graph")
gplot(g)
```



```
triad.census(g)
```

```
R >      003 012 102 021D 021U
R > [1,]   17   0   50   0   0
R >      021C 111D 111U 030T 030C
R > [1,]   0   0   0   0   0
R >      201 120D 120U 120C 210
R > [1,]   41   0   0   0   0
R >      300
R > [1,]   12
```

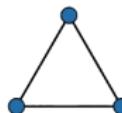
```
triad.classify(g)
```

```
R > [1] "102"
```

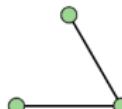


The Triad Census

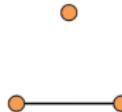
3



2



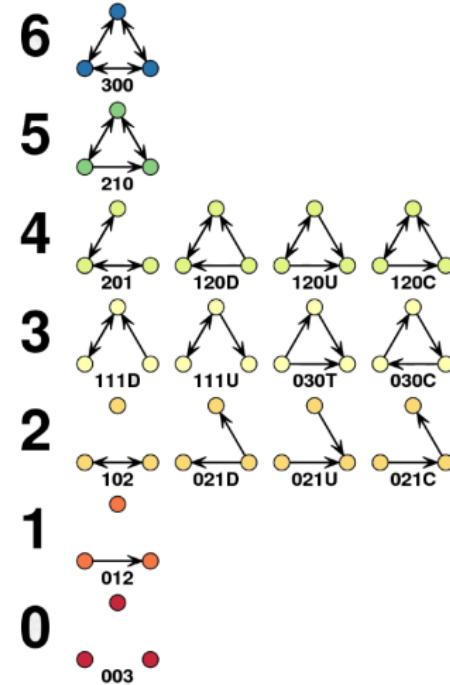
1



0



Undirected Case



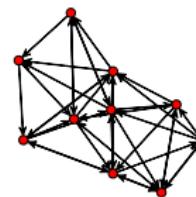
Directed Case



Transitivity

- Transitivity: condition such that (i, j) and (j, k) implies (i, k)
 - Usually assessed as fraction of completed two-paths
 - Can be directed or undirected
 - In directed, case, same as triangle/3-cycle/3-clique
- Many Uses
 - Measure of clustering
 - Also used to indicate dominance, hierarchy

```
g <- rgraph(10)  
gplot(g)
```



```
gtrans(g, measure = "weak")
```

```
R > [1] 0.3387097
```

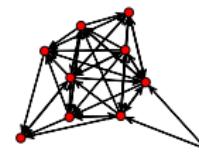
`gtrans` with `measure="weak"`: The fraction of potentially intransitive triads obeying the weak condition $(a \rightarrow b \rightarrow c \implies a \rightarrow c)$.



The “Forbidden Triad” and Weak Ties

- Granovetter (following Heider):
strong ties must be transitive
 - Weak ties, not so much
- Implications
 - No incomplete strong two-paths (“forbidden triad”)
 - Strong ties form cliques
 - All bridging ties are weak ties
 - Thus, weak ties can play an important role in bridging social systems

```
g <- rgraph(10)
gplot(g)
```



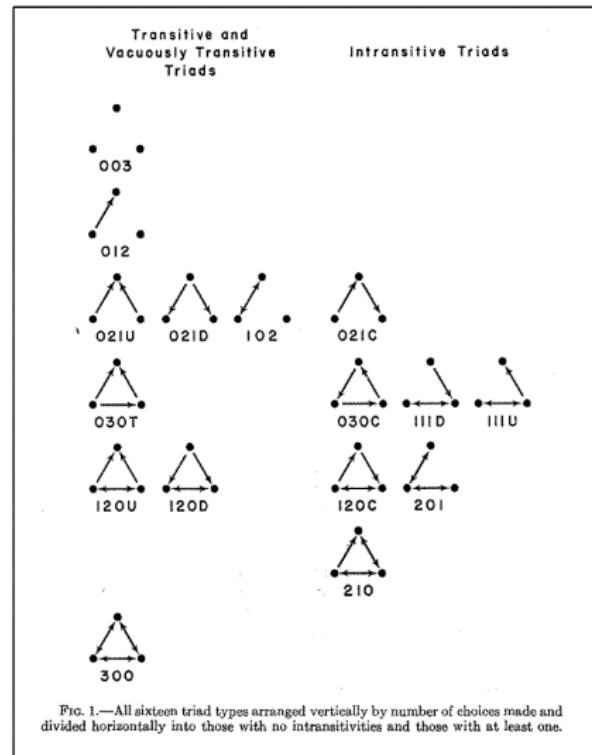
```
triad.census(g)
```

```
R >      003 012 102 021D 021U
R > [1,]    4   17   9   2   3
R >          021C 111D 111U 030T 030C
R > [1,]    13    6   11    8   0
R >          201 120D 120U 120C 210
R > [1,]    5    4   11    4   20
R >          300
R > [1,]    3
```



Transitivity and the Triad Census

- Transitivity bias implies that some triads should be over/underrepresented
- Weighting vector approach ($H+L$)
 - Let t be the triad census vector, and w be a “weighting vector” counting number of configurations satisfying a given hypothesis
 - $\tau = t^T w$ then counts the number of configurations present
 - Comparing τ to a null distribution allows one to test various hypotheses about structure
 - $H + L$ use Gaussian approximation, but we can use direct computation (which is much safer)





Null Hypothesis Testing for GLIs



- Last time, we introduced random graph models
 - Focused on simple cases with little or no heterogeneity or dependence among edges
- These models can be used as null models when assessing network structure
 - Goal is the detection of structural biases (departures from purely random structure)
 - Confirmatory use: specific biases predicted by prior theory
 - Exploratory use: identifying which biases are present, before attempting to build more complex models
 - Compare to the role of standard null hypothesis testing in the conventional statistics literature
 - Same basic idea, although some philosophical differences



Initial Concept: Baseline Models

- Baseline model: model which treats social structure as random, given some fixed constraints
 - Constraints could include size, density, etc.
- Method of baseline models (from Mayhew)
 - Identify potentially constraining factors
 - Compare observed properties to baseline model
 - Interpret deviations from baseline
 - May repeat with additional constraints
 - Note similarity to classical null hypothesis testing
 - Baseline model acts as null hypothesis
 - Useful even when baseline model is not “realistic”
 - Emphasis on triangulation to identify nature of biases; multiple baselines may be used to “pin down” complex behavior



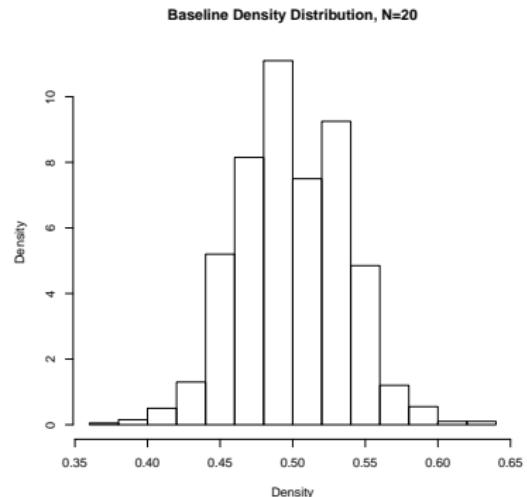
- Uniform conditional on size
 - Given number of individuals, all structures taken to be equally likely
- Uniform conditional on number of edges
 - Given number of individuals and interactions, structure is random (fixed density)
 - Valued version: condition on edge values (randomize over who gets edges)
- Uniform conditional on dyad census
 - Given number of individuals, mutual, asymmetric, and null relationships, structure is random (fixes density and reciprocity)
 - Valued version: condition on dyad pair values (randomize over who belongs to each dyad)
- Uniform conditional on all unlabeled properties
 - This is the permutation distribution.



Comparing Observations to Baseline

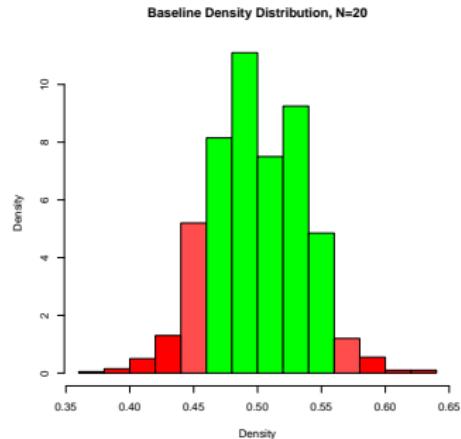
- To compare observations w/baseline behavior, must choose a statistic to evaluate
 - Should choose a statistic which reflects the type of property being examined
 - Obviously, cannot use a statistic on which one is conditioning
- Next, generate distribution of statistic under baseline model
 - Simulate networks from baseline model, then calculate statistic
- Finally, compare observed statistic to baseline distribution

```
library(sna)
baselineDensity <- sapply(1:1000,
  function(x) {
    gden(rgraph(20, mode = "graph"))
  })
save <- hist(baselineDensity, main = "Baseline Density Distribution",
  xlab = "Density", probability = TRUE,
  breaks = 10)
```



- Primary quantities of interest: probabilities of obtaining values greater than/equal to or less than/equal to observed value under baseline model
 - $\Pr(s(G) \leq s(G_{obs})) \approx 0$ implies that $s(G_{obs})$ is large compared to baseline
 - Small chance of observing a value that large under baseline
 - $\Pr(s(G) \geq s(G_{obs})) \approx 0$ implies that $s(G_{obs})$ is small compared to baseline
 - Small chance of observing a value that small under baseline

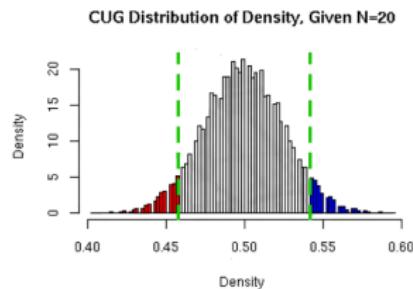
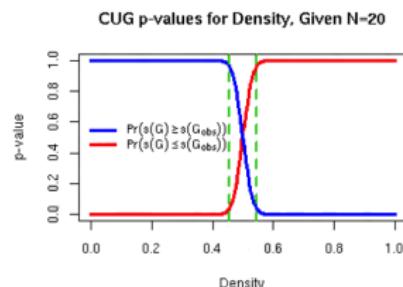
```
qt <- quantile(baselineDensity,
  prob = seq(0, 1, 0.025))[c("2.5%",
  "10%", "90%", "97.5%")]
col <- rep(rgb(0, 1, 0, 1), length(save$breaks))
col[save$breaks <= qt[1]] <- col[save$breaks >=
  qt[4]] <- rgb(1, 0, 0, 1)
col[save$breaks <= qt[2] & save$breaks >=
  qt[1]] <- col[save$breaks >=
  qt[3] & save$breaks < qt[4]] <- rgb(1,
  0, 0, 0.7)
hist(baselineDensity, main = "Baseline Density Distribution, N=20",
  xlab = "Density", probability = TRUE,
  breaks = 10, col = col)
```



- CUG test: use of conditional uniform baseline as a null hypothesis test
 - Propose that $s(G_{obs})$ is drawn from a baseline model
 - Reject at significance level p if

$$\Pr(s(G) \leq s(G_{obs})) < p \text{ (upper tail) or}$$

$$\Pr(s(G) \geq s(G_{obs})) < p \text{ (lower tail) or}$$
 - Conventional significance levels 0.05, 0.01, 0.001
- Interpretation
 - Rejection: Data shows noteworthy departure from model
 - Non-rejection: Data consistent with baseline model
 - Direction indicates nature of deviation





- Can perform CUG tests the “hard way”
 - Use tools like rgraph, rguman, rgnm to simulate baseline draws
 - Easier way: use the cug.test helper function
 - Can perform tests using several CUG baseline hypotheses
-
- cug.test syntax

```
args(cug.test)

R >   function (dat, FUN, mode = c("digraph", "graph"), cmode = c("size",
R >     "edges", "dyad.census"), diag = FALSE, reps = 1000, ignore.eval = TRUE,
R >     FUN.args = list())
R >   NULL
```



Example: International Trade in Complex Manufactured goods

- First, test density against size-conditioned model

```
library(networkdata)
data(trade)
cden <- cug.test(trade$MANUFACTURED_GOODS,
                 gden)
cden

R >
R > Univariate Conditional Uniform Graph Test
R >
R > Conditioning Method: size
R > Graph Type: digraph
R > Diagonal Used: FALSE
R > Replications: 1000
R >
R > Observed Value: 0.5615942
R > Pr(X>=Obs): 0
R > Pr(X<=Obs): 1
```

- Next, test reciprocity against density-conditioned model

```
crecip <- cug.test(trade$MANUFACTURED_GOODS,
                     grecip, cmode = "edges")
crecip

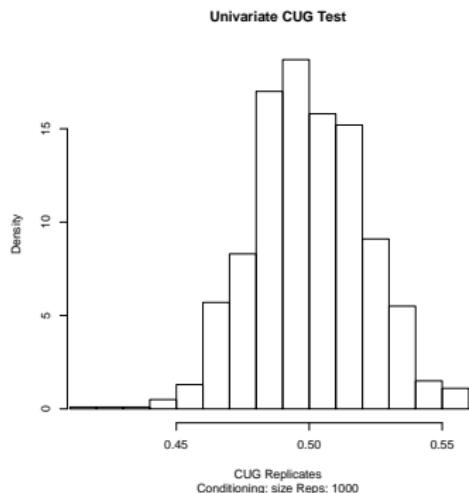
R >
R > Univariate Conditional Uniform Graph Test
R >
R > Conditioning Method: edges
R > Graph Type: digraph
R > Diagonal Used: FALSE
R > Replications: 1000
R >
R > Observed Value: 0.7101449
R > Pr(X>=Obs): 0
R > Pr(X<=Obs): 1
```



Example: International Trade in Complex Manufactured goods

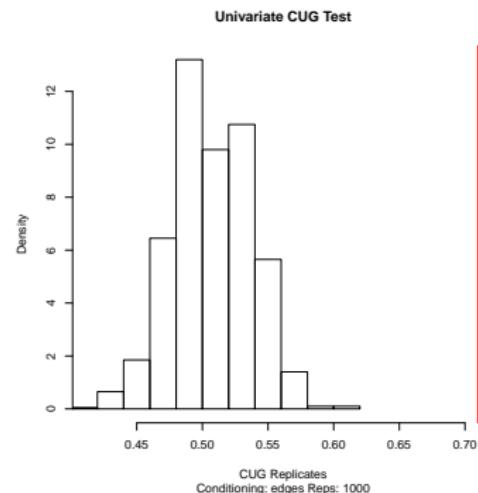
- First, test density against size-conditioned model

`plot(cden)`



- Next, test reciprocity against density-conditioned model

`plot(crecip)`





Example: International Trade in Complex Manufactured goods

- Now, test transitivity given the dyad census

```
library(networkdata)
data(trade)
ctrans <- cug.test(trade$MANUFACTURED_GOODS,
  gtrans, cmode = "dyad")
ctrans

R >
R > Univariate Conditional Uniform Graph Test
R >
R > Conditioning Method: dyad.census
R > Graph Type: digraph
R > Diagonal Used: FALSE
R > Replications: 1000
R >
R > Observed Value: 0.7860323
R > Pr(X>=Obs): 0
R > Pr(X<=Obs): 1
```

- Repeat for indegree centralization

```
c_cent_ind <- cug.test(trade$MANUFACTURED_GOODS,
  centralization, cmode = "dyad",
  FUN.arg = list(FUN = degree,
    cmode = "indegree"))
c_cent_ind

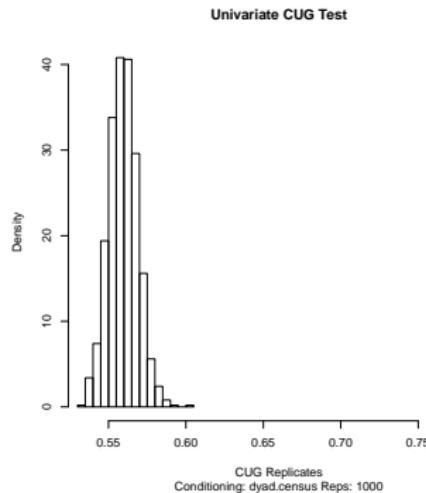
R >
R > Univariate Conditional Uniform Graph Test
R >
R > Conditioning Method: dyad.census
R > Graph Type: digraph
R > Diagonal Used: FALSE
R > Replications: 1000
R >
R > Observed Value: 0.2306238
R > Pr(X>=Obs): 0.414
R > Pr(X<=Obs): 0.863
```



Example: International Trade in Complex Manufactured goods

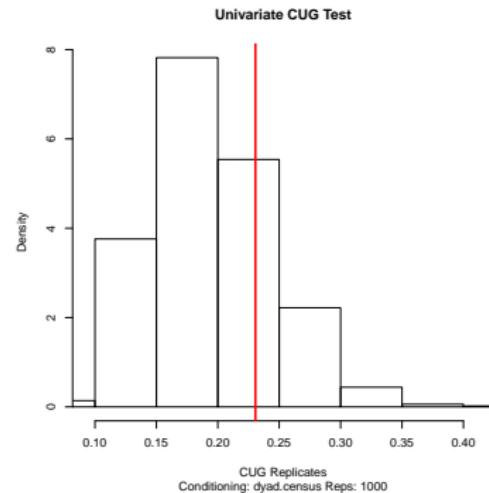
- Now, test transitivity given the dyad census

`plot(ctrans)`



- Repeat for indegree centralization

`plot(c_cent_ind)`





- Exponential Random Graph Models
- Temporal Network Models
- Spatial Network Models
- Cluster Analysis
- Latent Space Models
- Hierarchical Models (BERGM, HERGM, multilevel models)