

Outline

Day 1: Social Network analysis

Part 1:

- Fundamental concepts
- Visualization
- Connectivity and Cohesion
- Centrality
- Roles

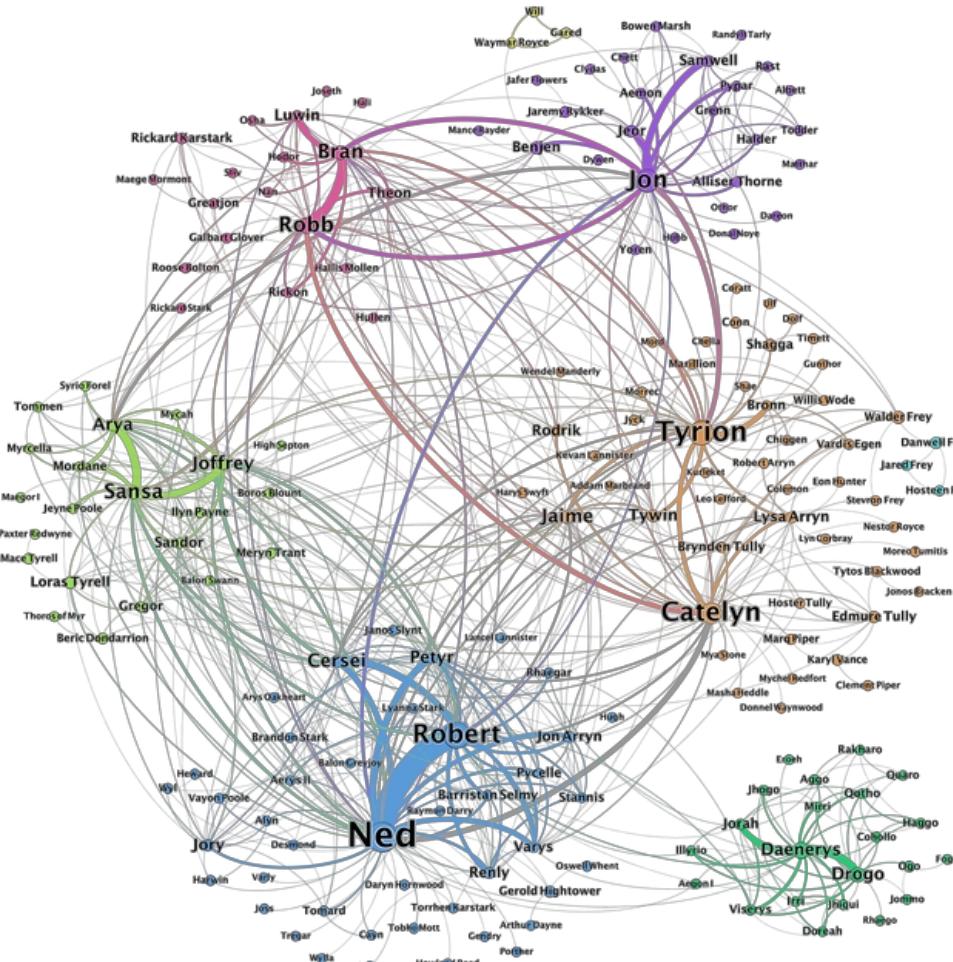
Day 2: Social media analysis

- Twitter APIs
- How to get data and what does the data look like
- Create a small network from twitter data and analyse it
- simple text analysis

Part 2:

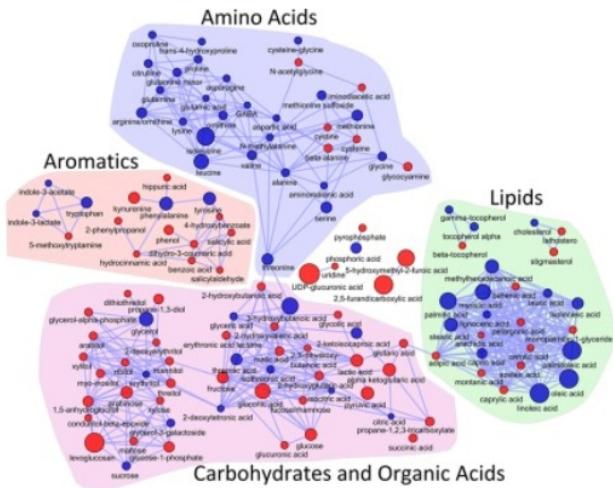
- Introduction to python library networkx
- apply concepts from part 1

Network Visualization and Theory: A "Very" Condensed Guide to Exploratory Social Network Analysis



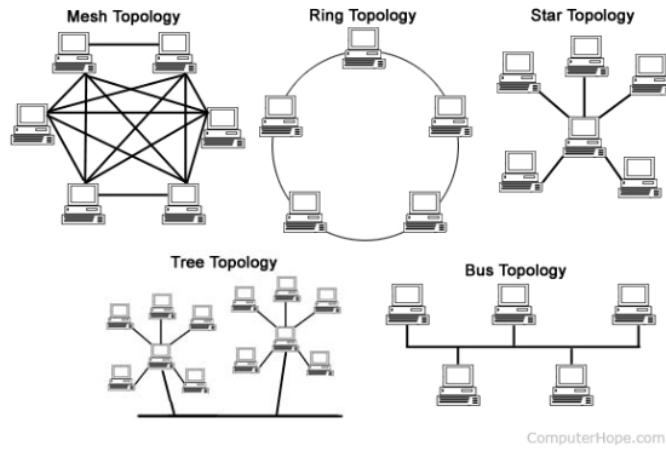
Nikolas Zöller and Jonathan H. Morgan

I. Main types of networks found in nature



Example of **biological networks**:
Nodes represent metabolites and
edges can be many things.

Source: <https://www.r-bloggers.com/tutorial-building-biological-networks/>



Source: <https://www.computerhope.com/jargon/n/network.htm>

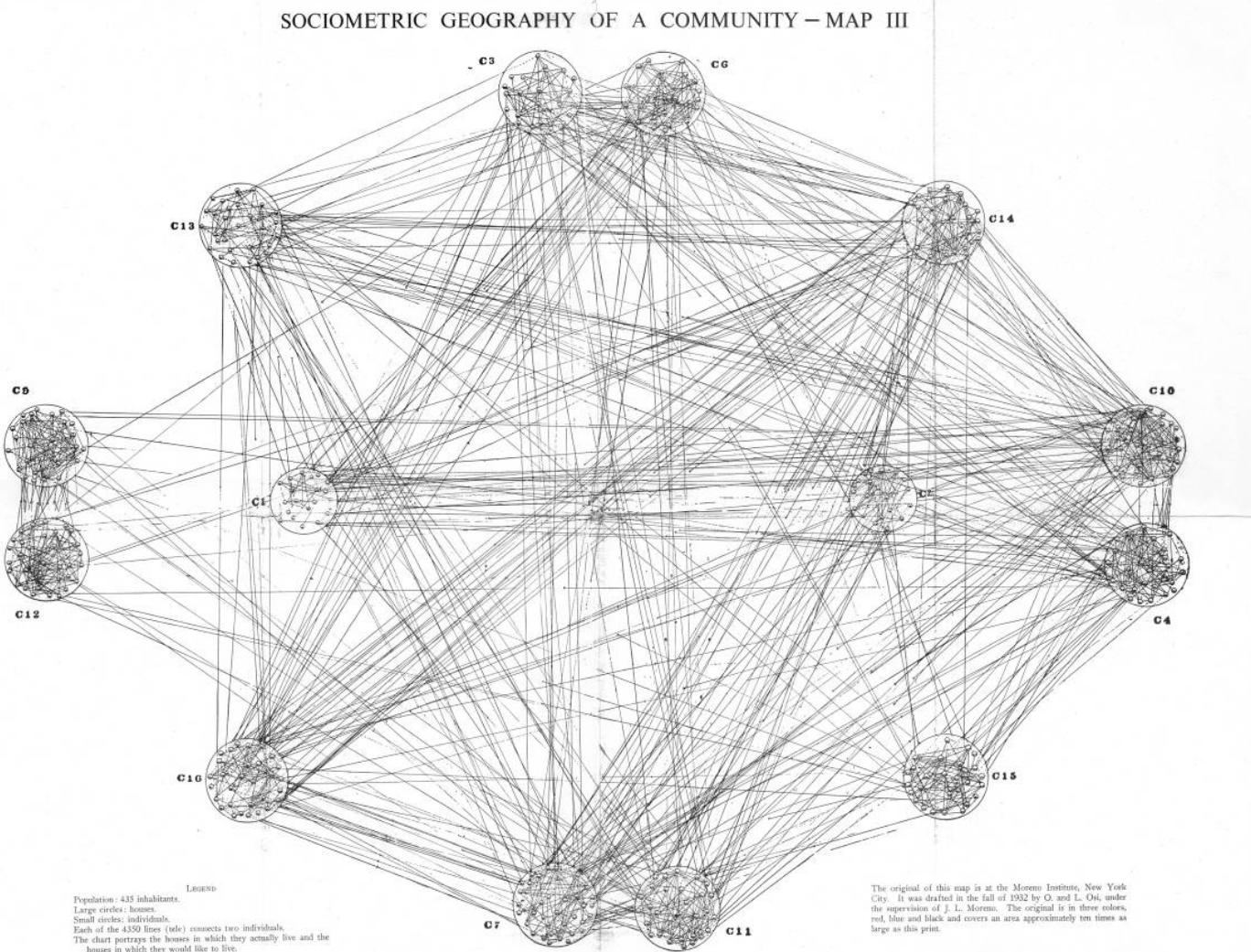
Social networks:

Facebook, Twitter, Wikipedia, etc.



Source:
<https://blog.stateofthedapps.com/blockchain-based-social-networks-1b7b729beb4d>

Sociometry and the Cultural Order: 1936



EMOTIONS MAPPED BY NEW GEOGRAPHY

Charts Seek to Portray the Psychological Currents of Human Relationships.

FIRST STUDIES EXHIBITED

Colored Lines Show Likes and Dislikes of Individuals and of Groups.

MANY MISFITS REVEALED

Dr. J. L. Moreno Calculates There Are 10 to 15 Million Isolated Individuals in Nation.

A new science, named psychological geography, which aims to chart the emotional currents, cross-currents and under-currents of human relationships in a community, was introduced here yesterday at the scientific exhibit of the Medical Society of the State of New York, which opens its 127th annual meeting here today at the Waldorf-Astoria.

The first series of maps of the new human geography were shown by Dr. Jacob L. Moreno of New York, consulting psychiatrist of the National Committee of Prisons and Prison Labor and director of research, New York State Training School for Girls, Hudson, N. Y. The maps represent studies of the forces of attraction and repulsion of individuals within a group toward one another and toward the group, as well as the attitude of the group as a whole toward its individual members and of one group toward another group.

Emotions are represented on these psychological maps by various colored lines. Red stands for liking; black for disliking. If individual A likes B a red line with an arrow points from A to B. If B reciprocates similarly a red line points from B to A. If he dislikes A this is indicated by a black line with an arrow pointing toward A. If B is merely indifferent the feeling is shown by a blue line.

Group of 500 Girls Studied.

Fundamentals

Fundamental Concepts

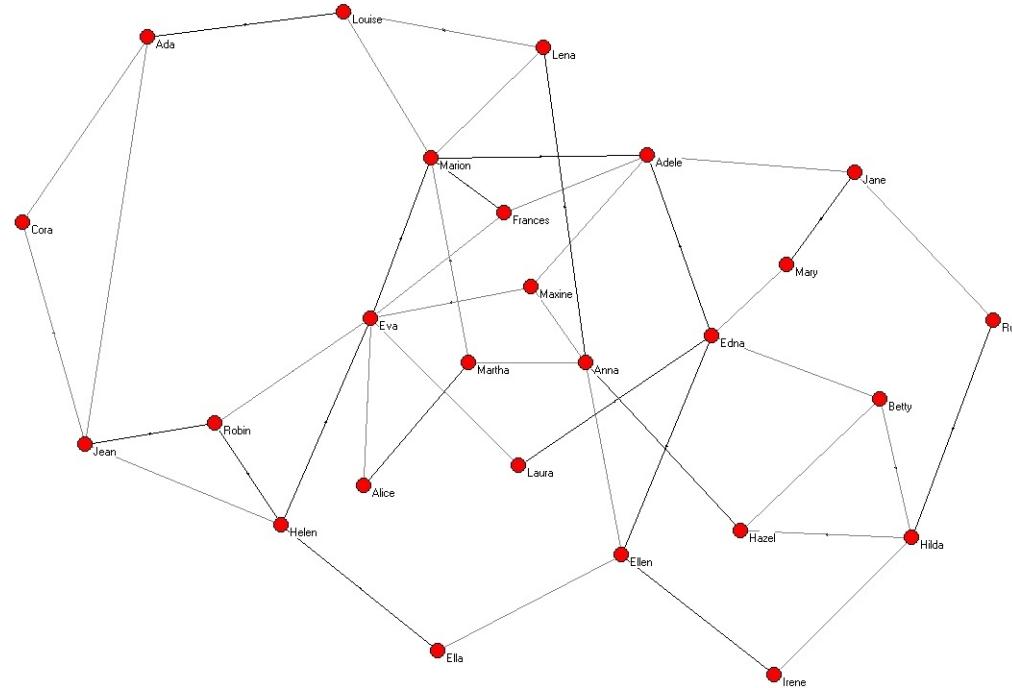
Graph: A set of *vertices* and a set of *lines* between pairs of vertices.

Key Elements of a Graph

Vertices, Nodes, or Dots

Lines, Edges, Links

Layout

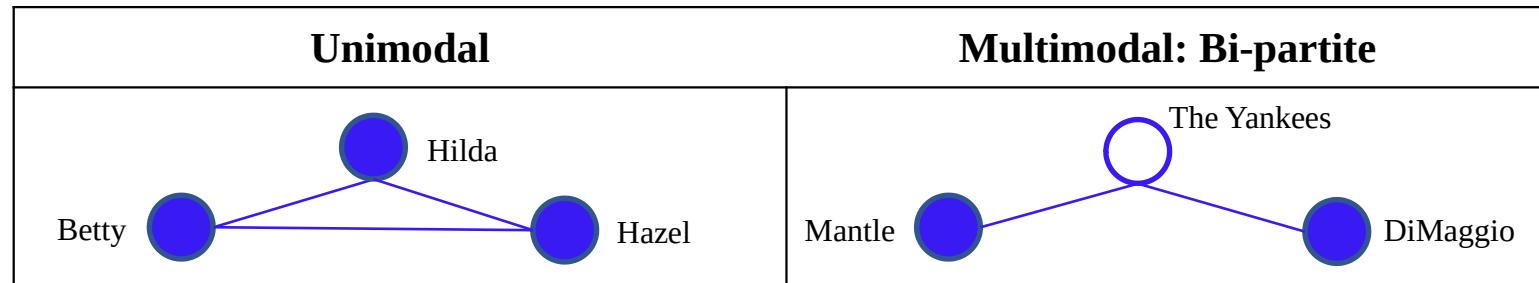


A **network** is a graph where the vertices are assigned attributes such as names (e.g., Laura or Intel), categories (e.g., messenger ribonucleic acid or sensory neurons), or continuous features such as size or weight).

Fundamental Concepts

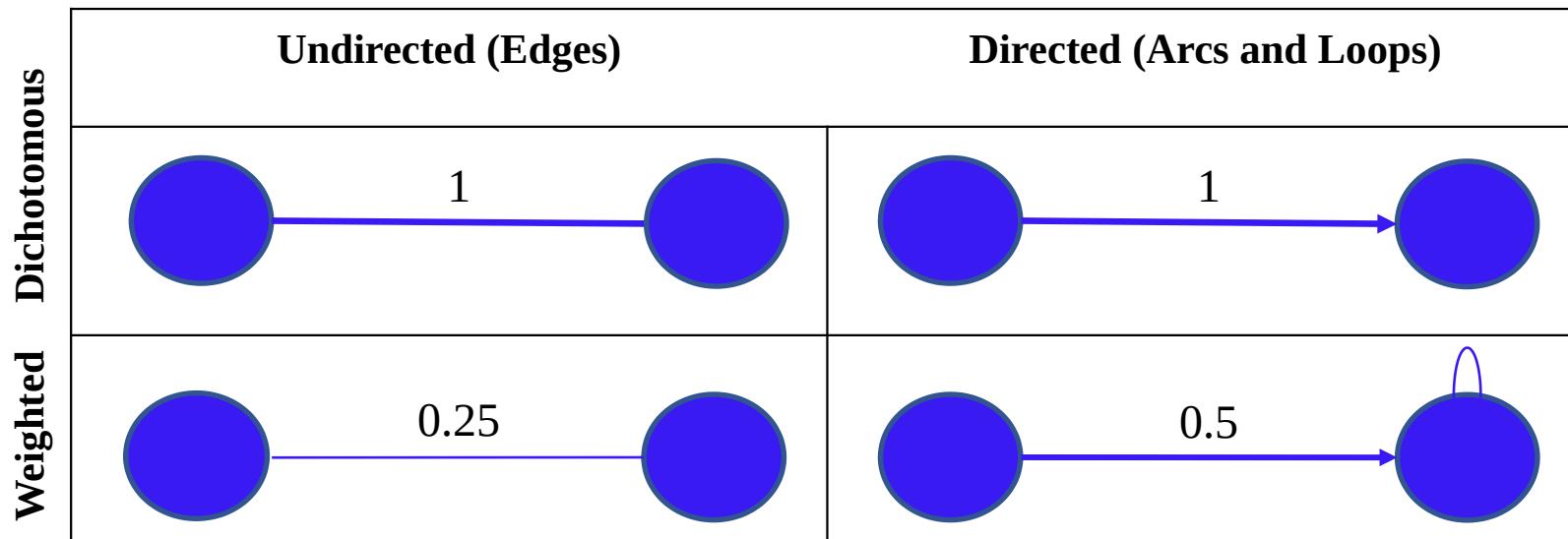
Networks can **differ** with respect to their nodes, edges, and layout

Nodes



Fundamental Concepts

Edges: Direction and Weight (e.g., frequency or distance) provide more information



Loops refer to arcs directed to oneself. Dichotomous networks are also called binary networks.

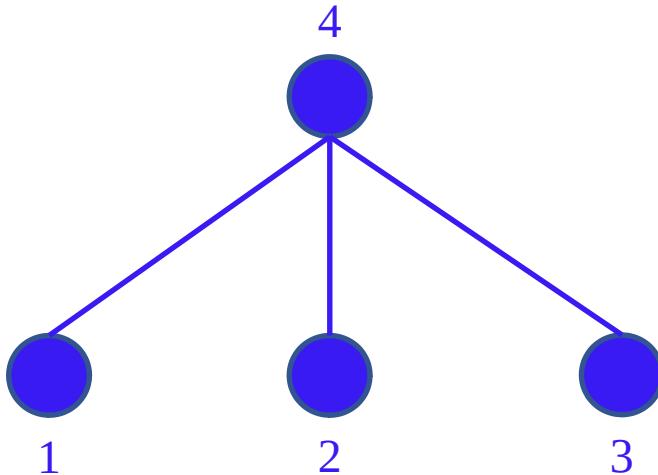
Multiplex networks refer to networks with more than one tie type (e.g., friends you ask advice from on important matters vs. friends you work with on projects).

Although some people may be connected through both types of ties; the ties are, nevertheless, different because they represent different kinds of relations.

Fundamental Concepts

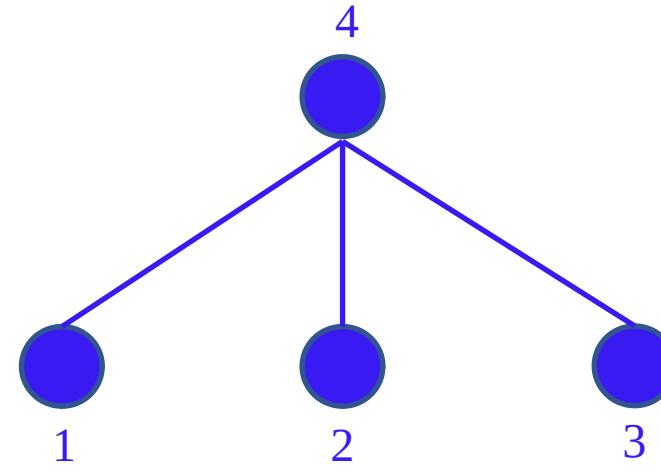
Data Structures

Adjacency Matrix



	1	2	3	4
1	0	0	0	1
2	0	0	0	1
3	0	0	0	1
4	1	1	1	0

Edgelist

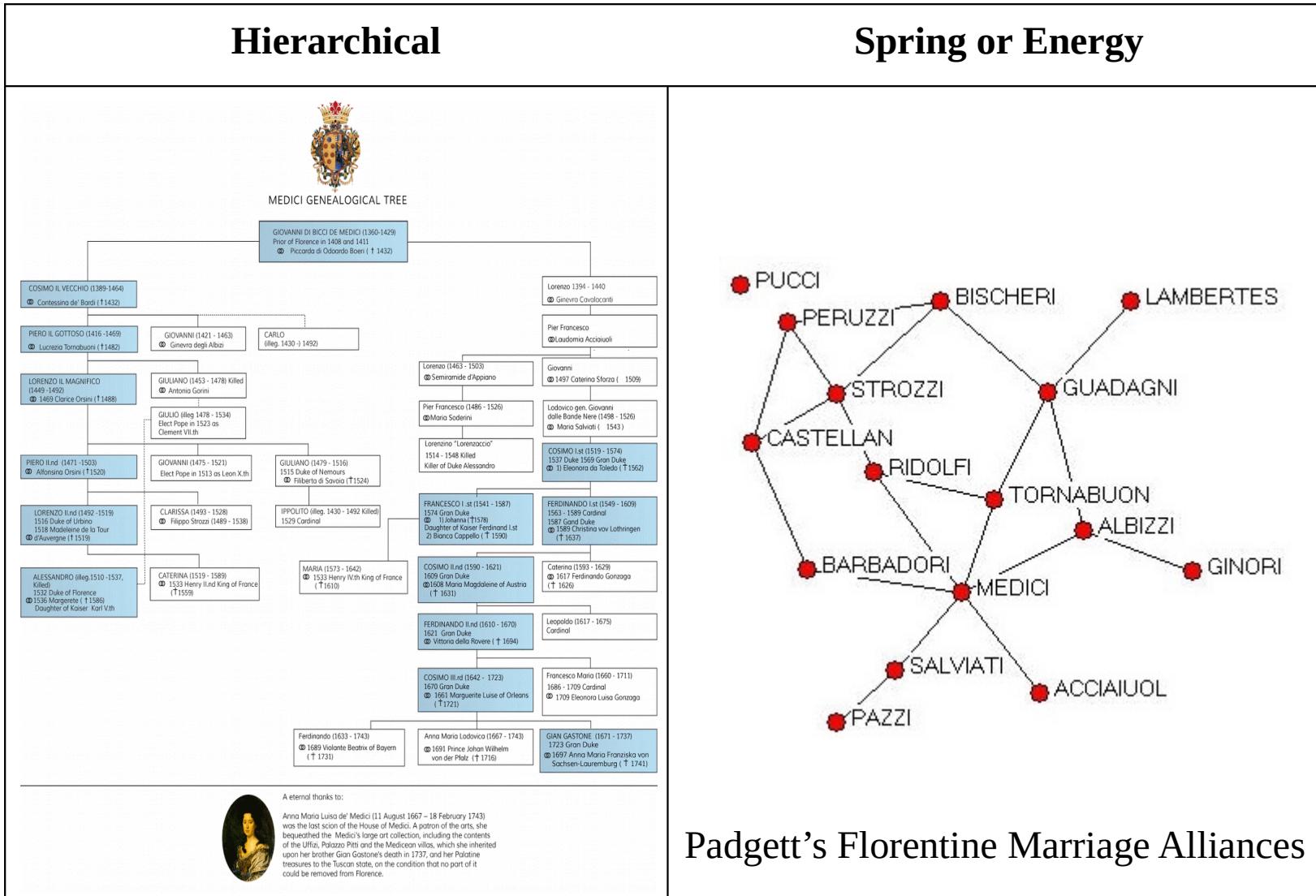


Sender	Target	Weight
1	4	1
2	4	1
3	4	1

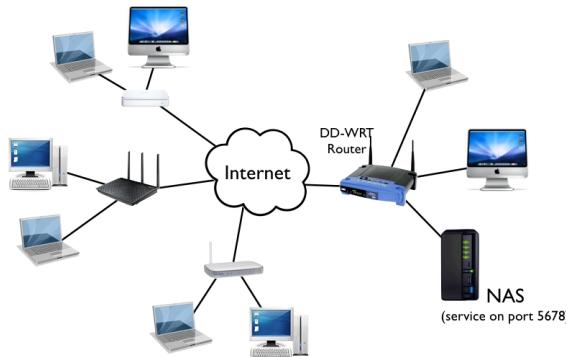
Visualization and a Little History

Fundamental Concepts

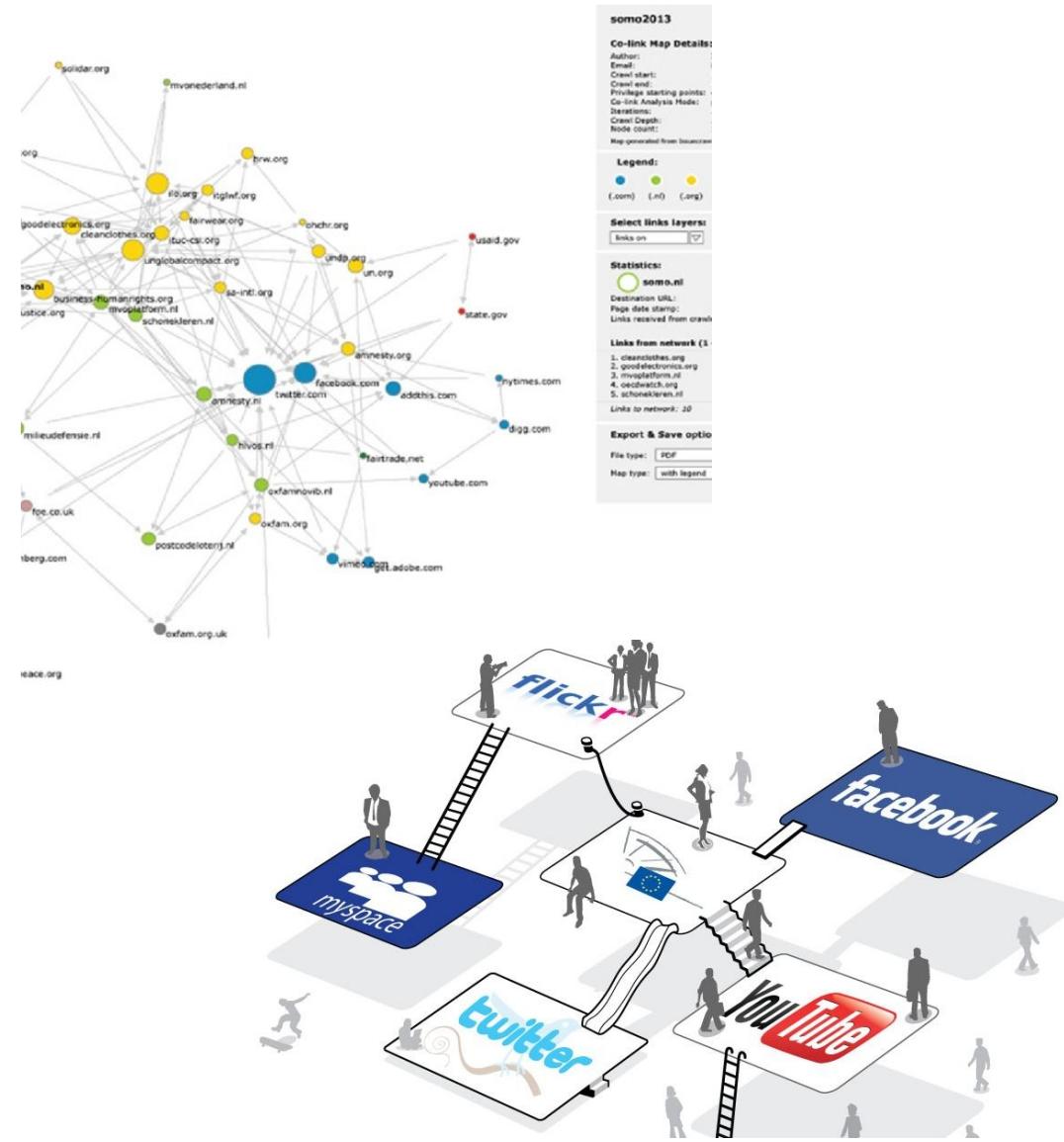
Layouts



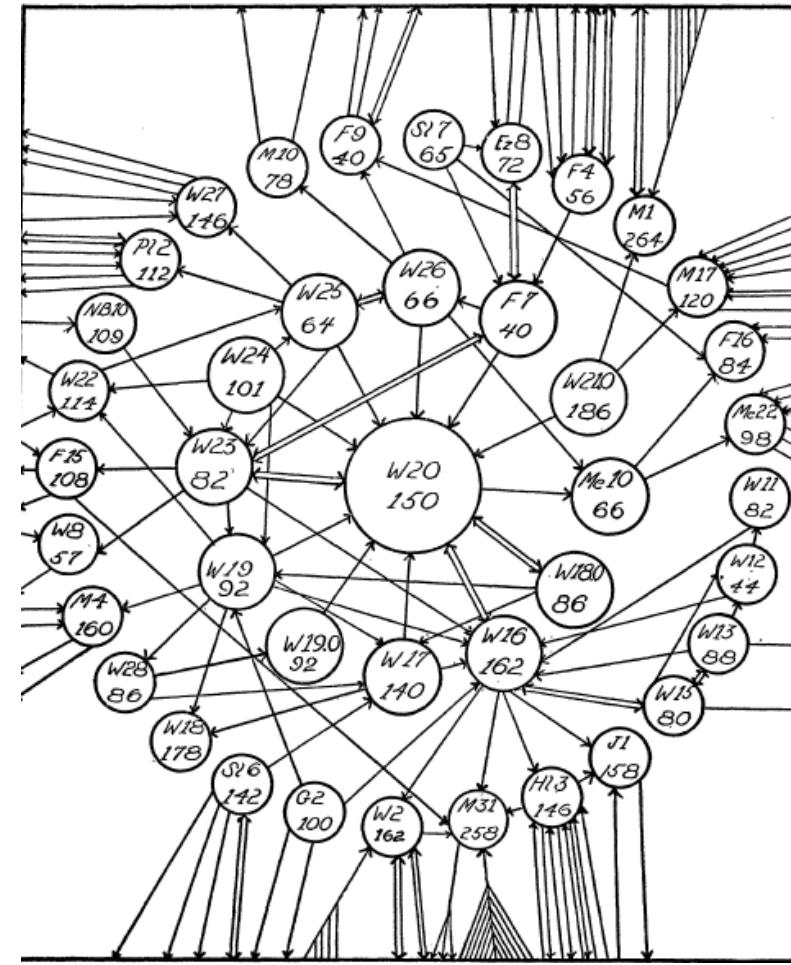
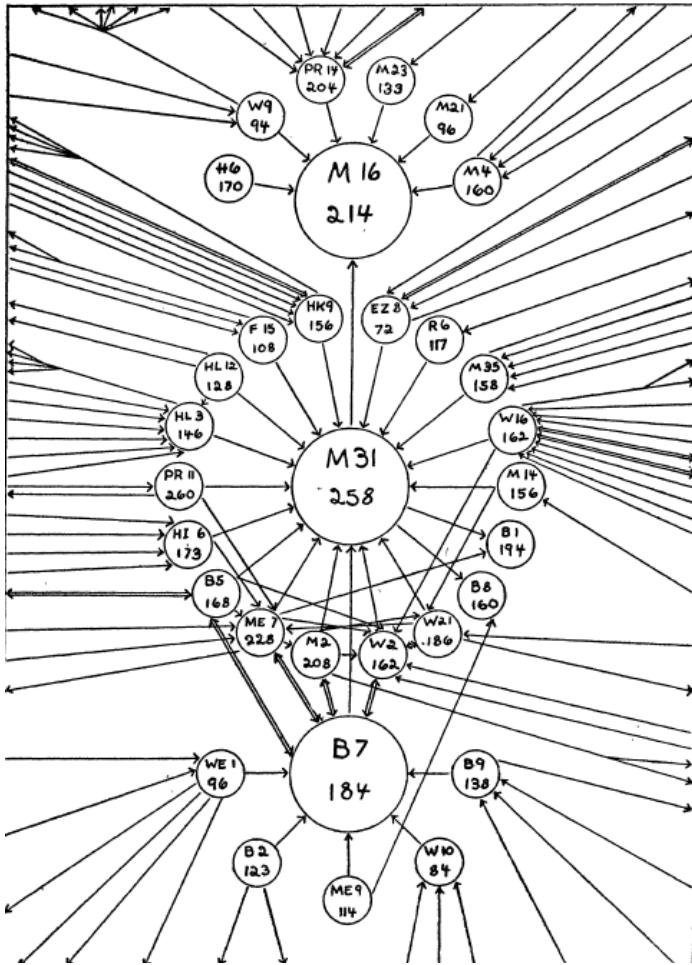
The internet infrastructure
→ geographical meaning



www → no geographical meaning

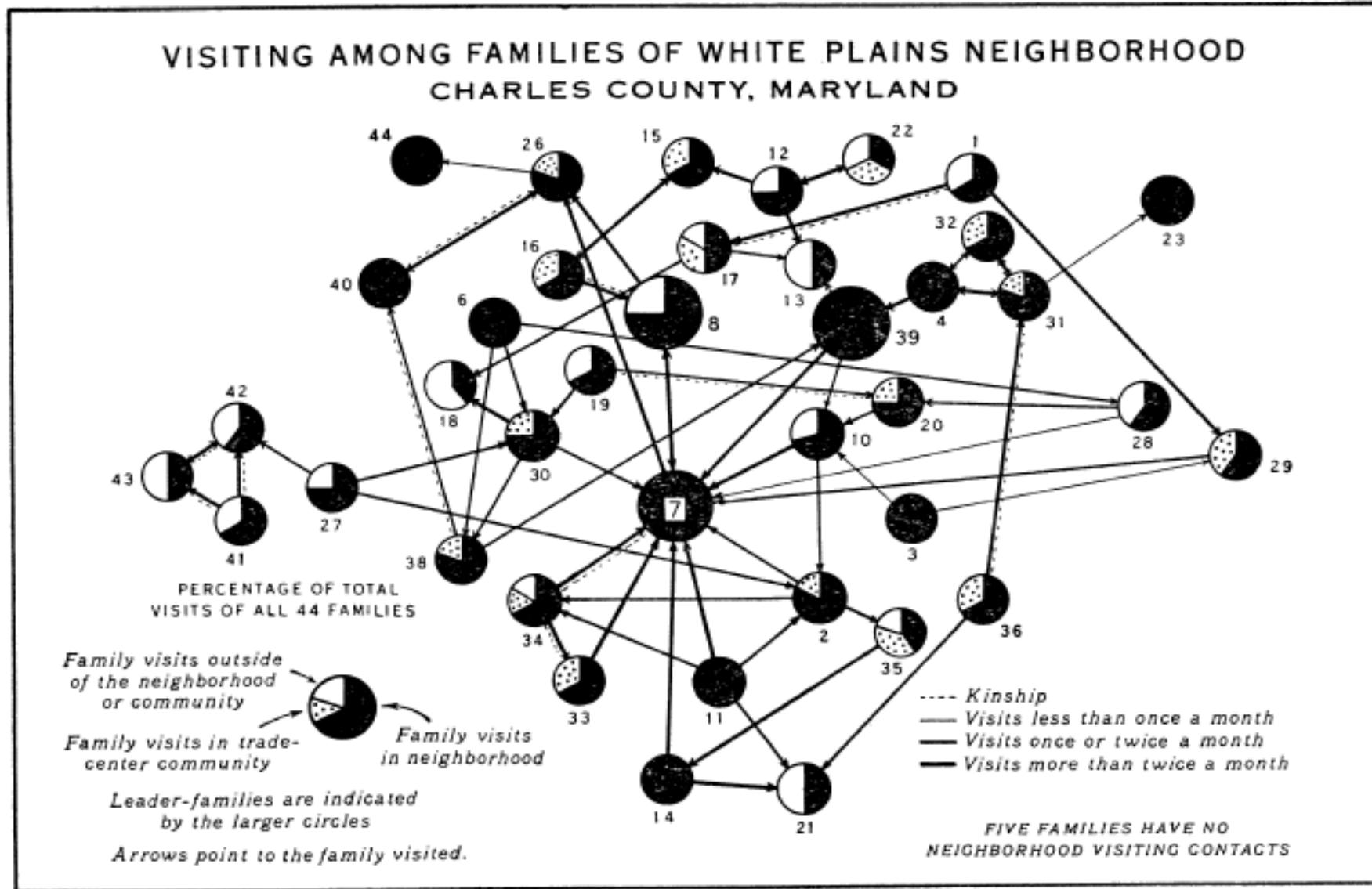


Lundberg & Steel 1938: Visualizing Directed Ties

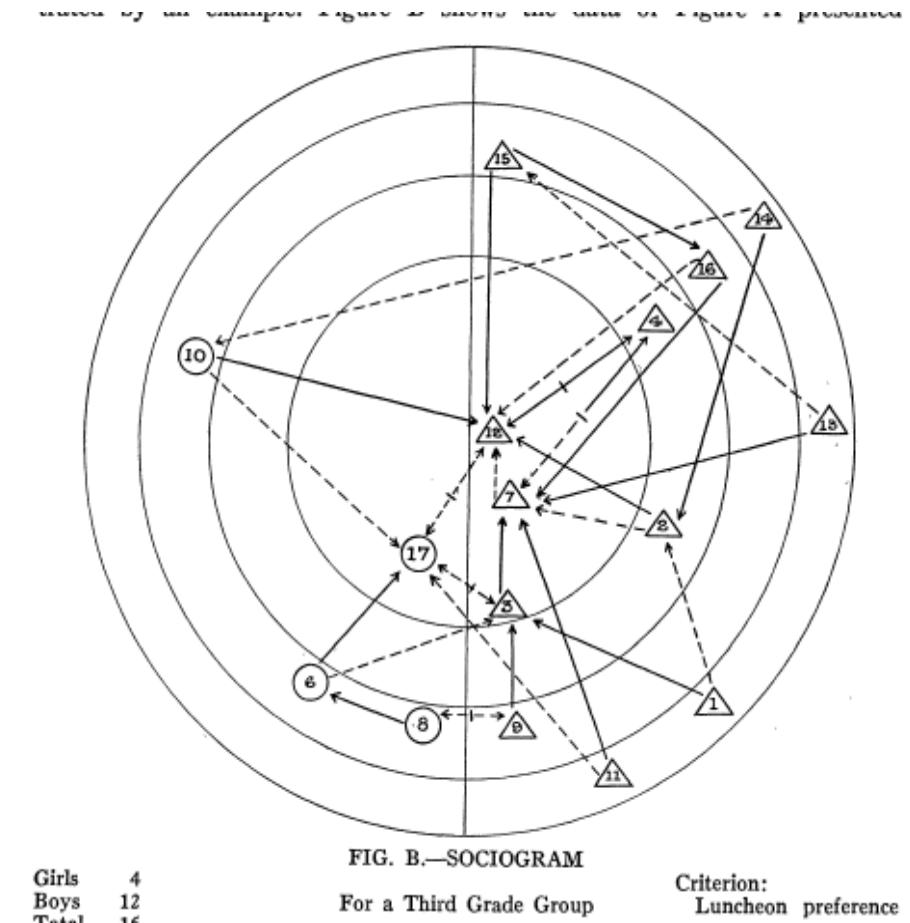


Moreno's idea was quickly taken up in community studies, as the social analog to "atoms" in physics....

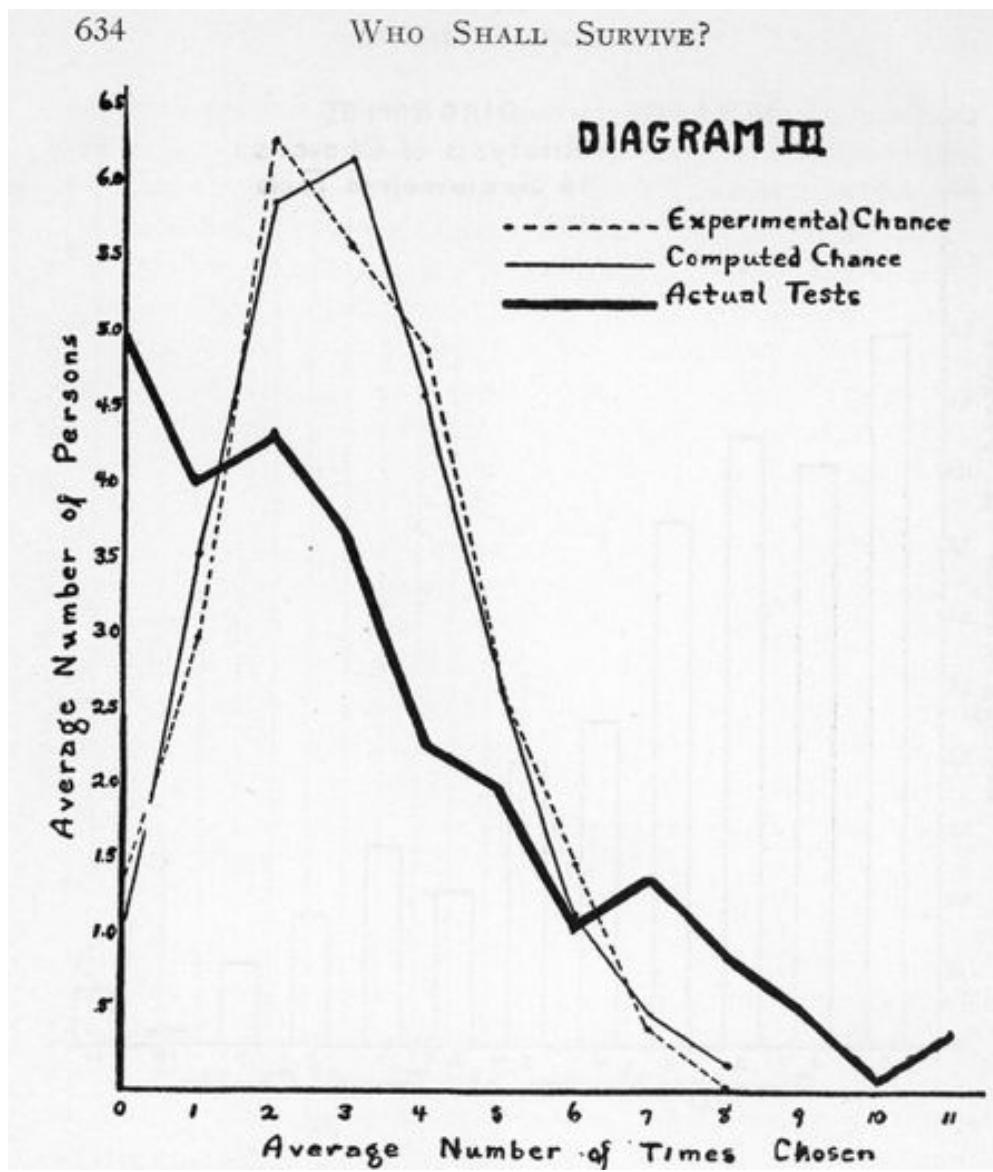
Charles Loomis 1948: Early Example of Layered Information



Northaway's (1940) Target Sociograms



More than Sociograms: The First Long-Tailed Distribution Observed in a Social Network?



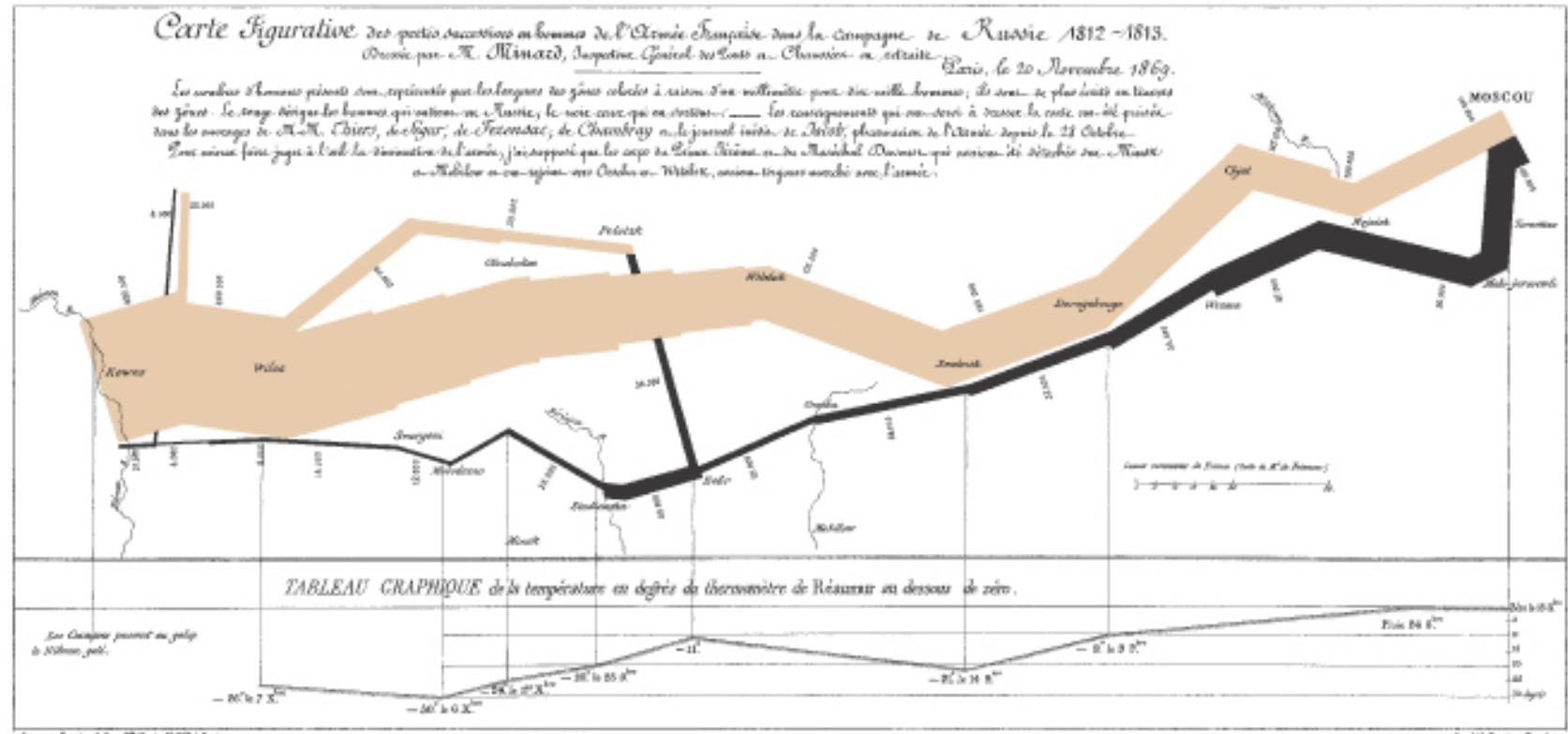
Goals to Aspire to When Visualizing a Network

Clarity

Scaling

Effective Layering information

Effective use of color



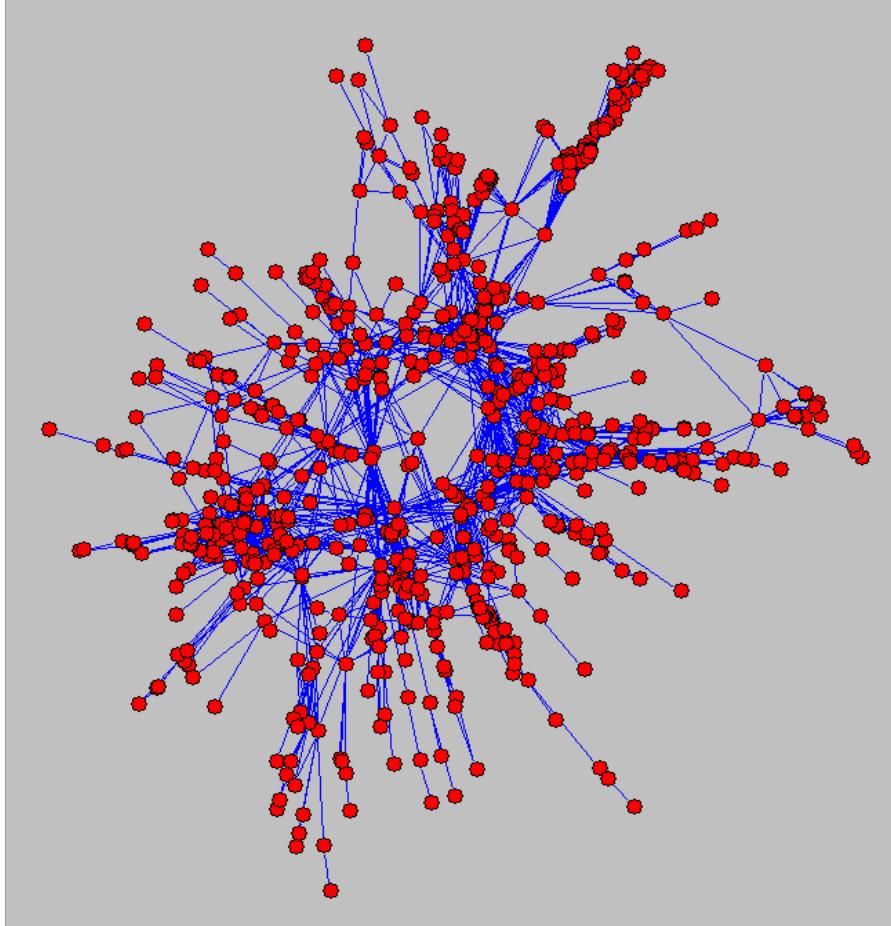
Napoleon's March to Moscow The War of 1812

Charles Joseph Minard

This classic of Charles Joseph Minard (1781-1859), the French engineer, shows the terrible fate of Napoleon's army in Russia. Described by E.J. Marey as 'one of the greatest pieces of history told by an artist', this combination of data map and time-series, drawn in 1869, portrays the devastating losses suffered in Napoleon's Russian campaign of 1812. Beginning at the left on the Polish-Russian border near the Niemen River, the thick band shows the size of the army (420,000 men) it invaded Russia in June 1812. The width of the band indicates the size of the army at each place on the map. In September, the army reached Moscow, which was by then sacked and deserted, with 100,000 men. The path of Napoleon's retreat from Moscow is depicted by the darkest, lower band, which is linked to a temperature

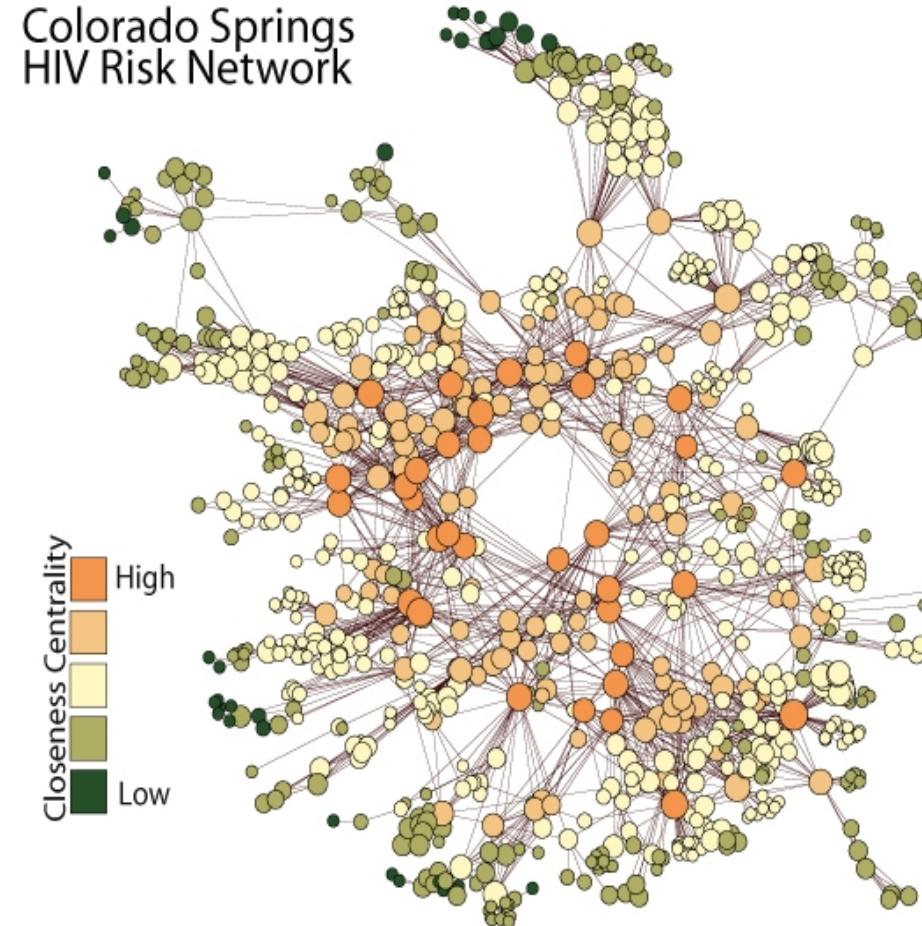
scale and dates at the bottom of the chart. It was a bitterly cold winter, and many froze on the march out of Russia. As the graphic shows, the crossing of the Berezina River was a disaster, and the army finally struggled back into Poland with only 10,000 men remaining. Also shown are the movements of auxiliary troops, as they sought to protect the rear and the flank of the advancing army. Minard's graphic tells a rich, coherent story with its mathematical data, far more enlightening than just a single number bouncing along over time. Six variables are plotted: the size of the army, its location on a two-dimensional surface, direction of the army's movement, and temperature on various dates during the retreat from Moscow. It may well be the best statistical graphic ever drawn.

Example of an Effective Sociogram



Before: Out-of-the-Box

Colorado Springs
HIV Risk Network

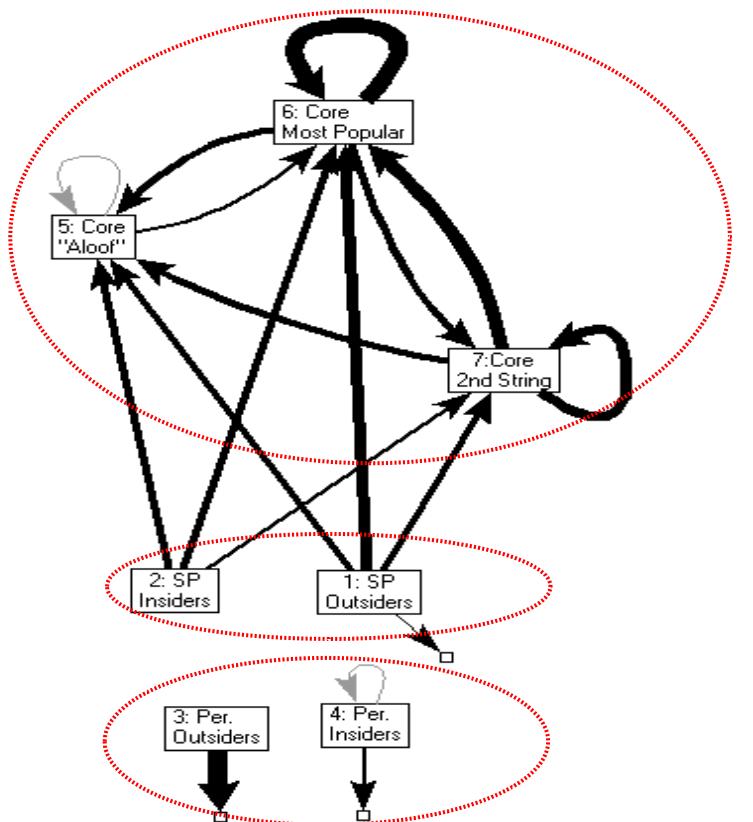


After: Moody 2007

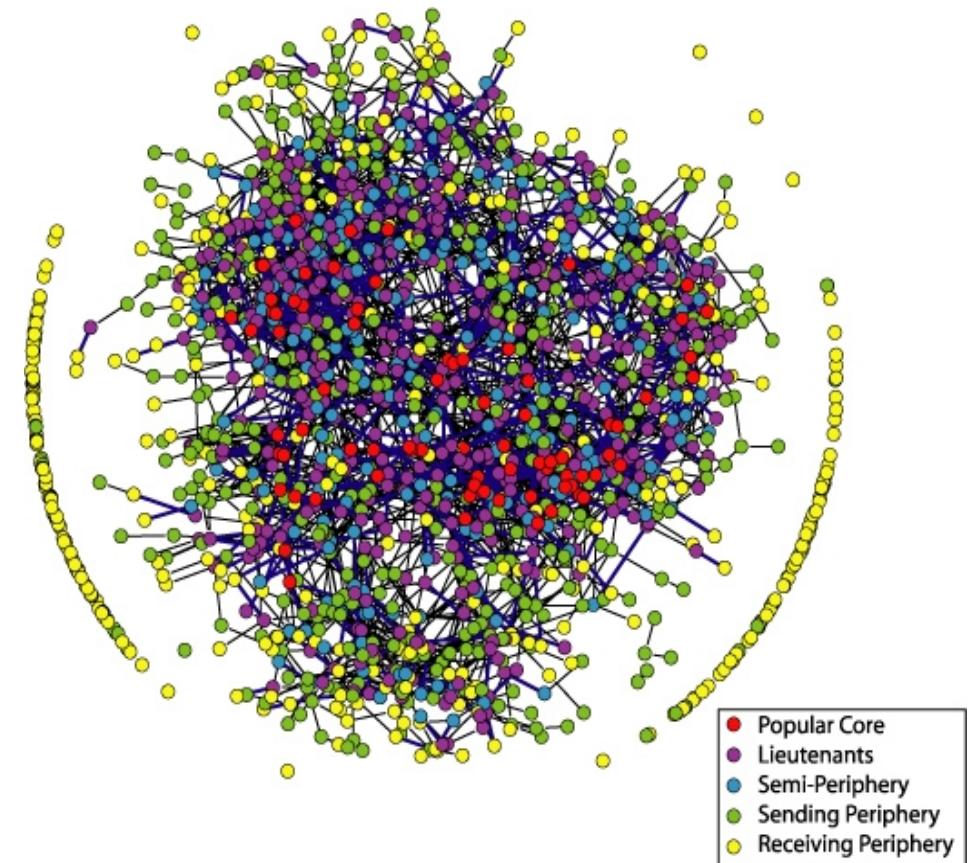
Visualization Challenges

Network Specific graphic problem: Which social space?

For example, are we trying to show the distinctiveness of the nodes or the general topology of the network?



Reduced Block
Model



Labeled Sociogram

Basic Tradeoffs & Considerations

Network Visualization Challenges/Considerations

Model of Social Space

Resolution (Local or Global)

Multiple Relations

Dynamics

Density

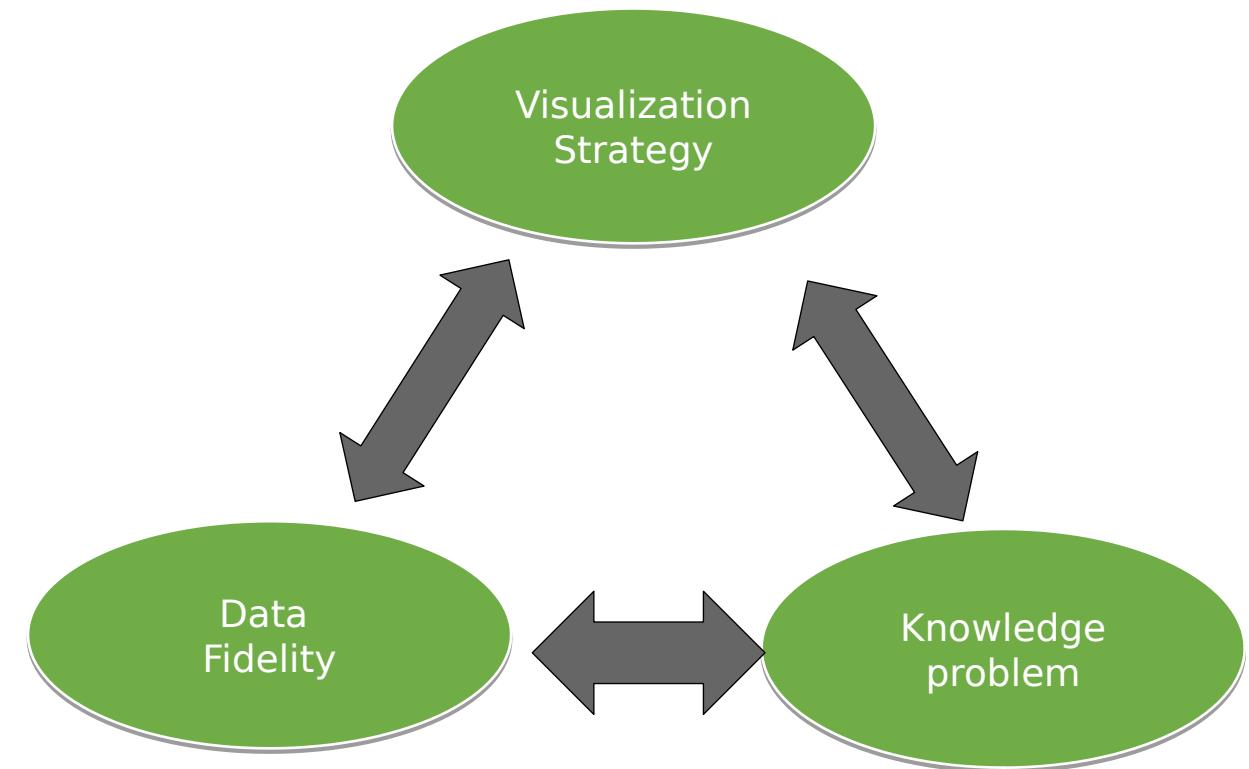
Node-Level Attributes

Edge-Level Attributes

Hierarchical Ordering

Diffusion Potential

Exploration or Communication

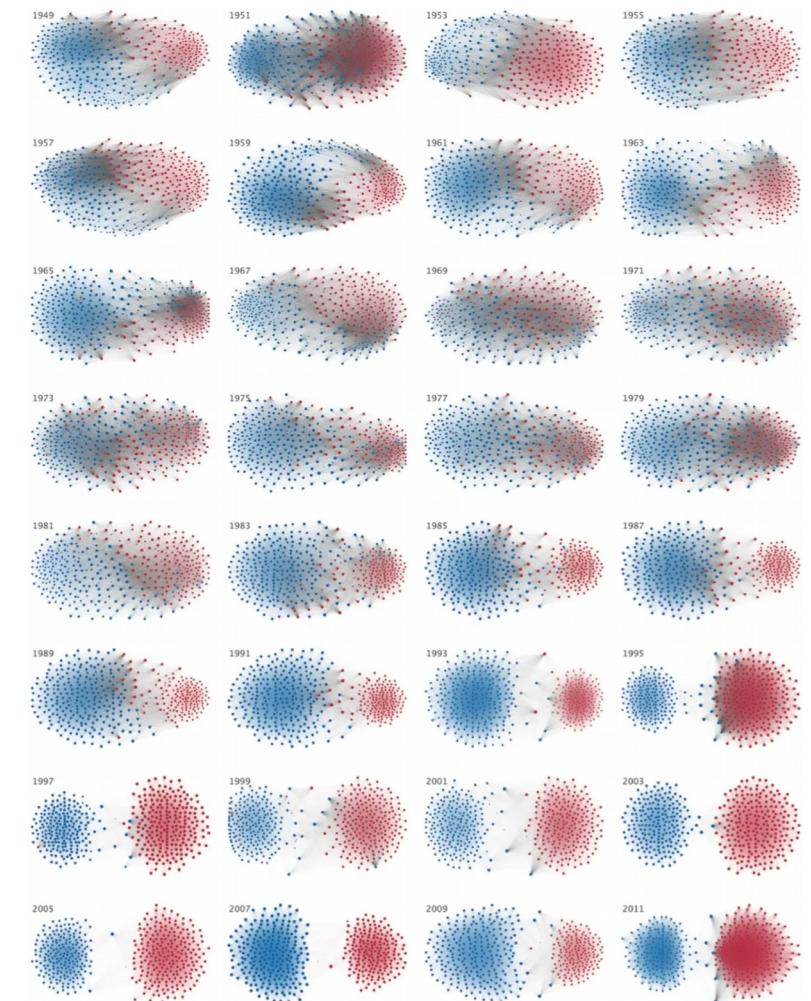
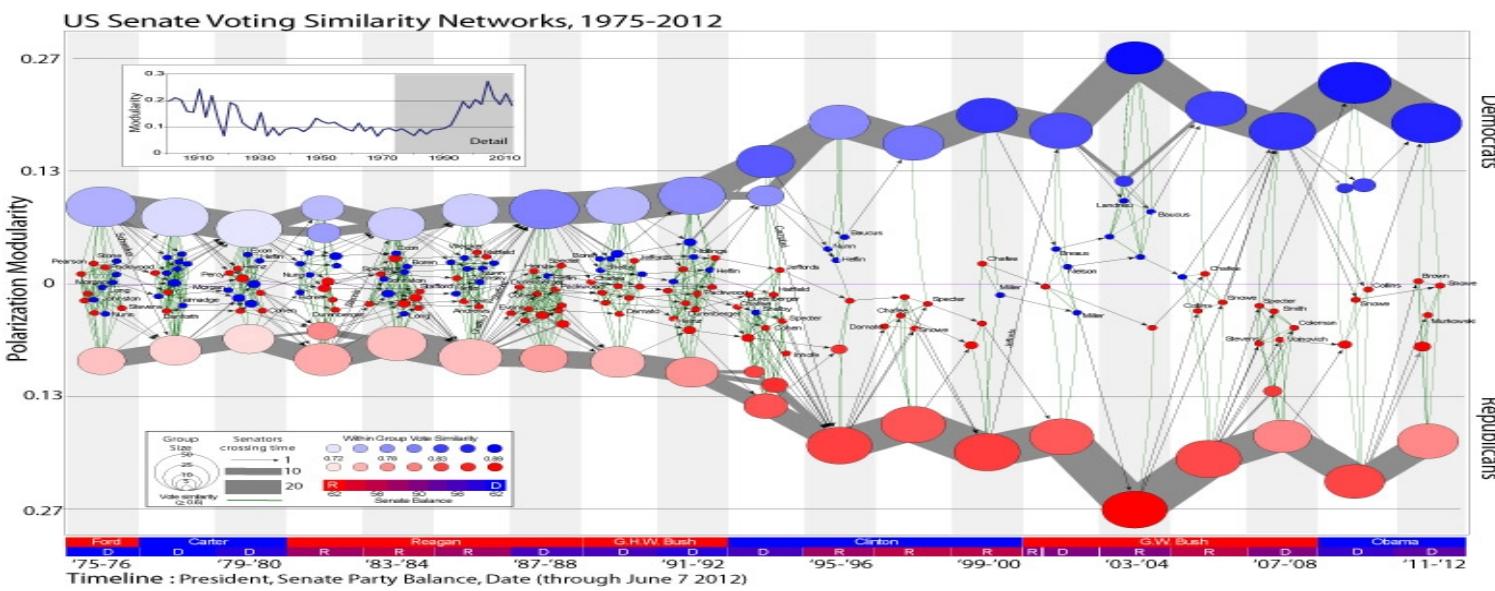


Final Goals When Visualizing a Network

Repeatable: Same data should produce the same picture

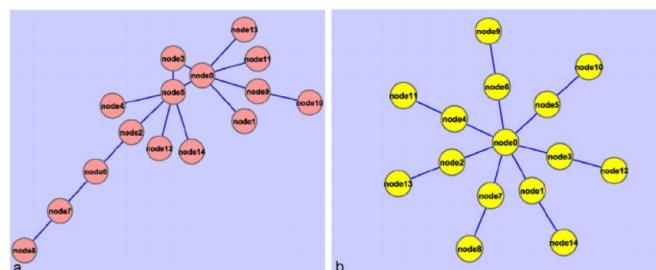
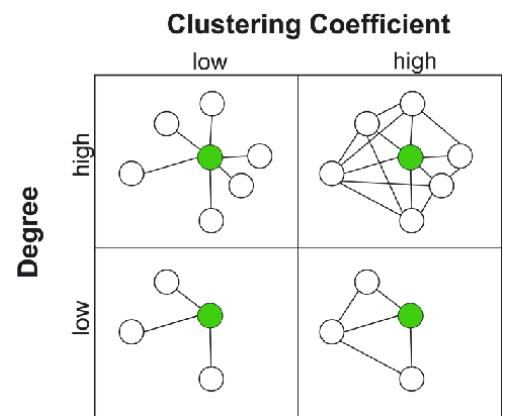
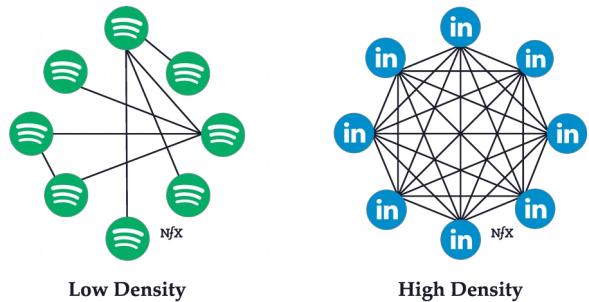
Quantification: Most features in the graph should be translatable to a measurement in the graph

Relevant: Either give us something new to theorize about, or use the visualization a theory building tool.



Connectivity and Cohesion

System-Level Measures

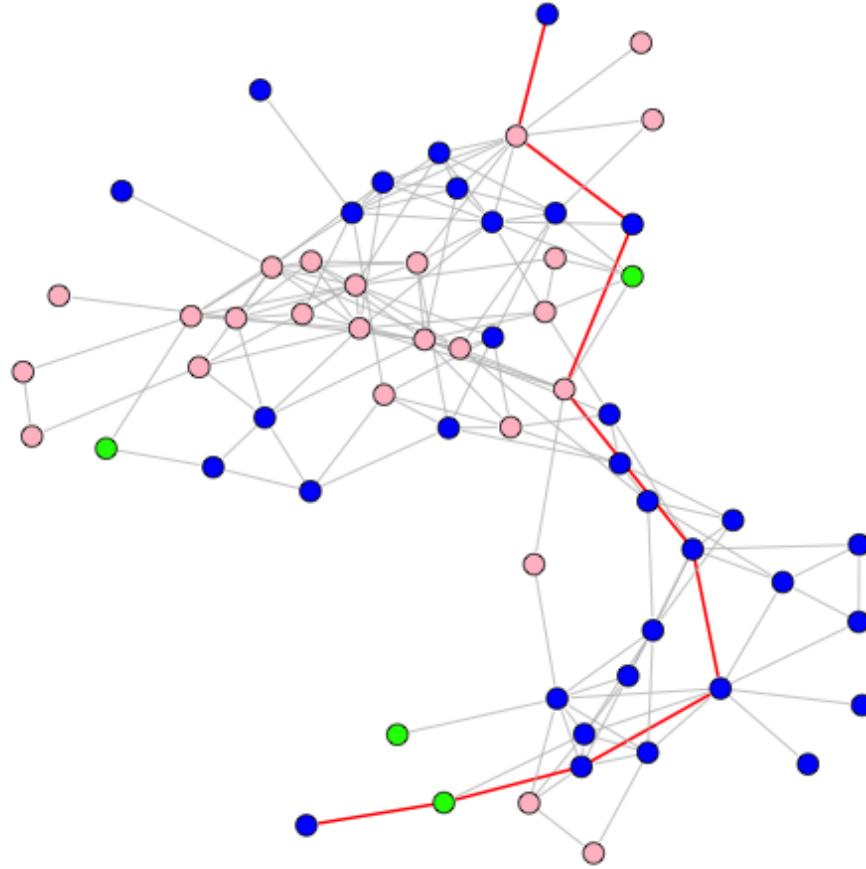


Density: The proportion of actually connected ties over all possible connections. Dense networks are highly connected networks where information, diseases, or resources can quickly move across the network.

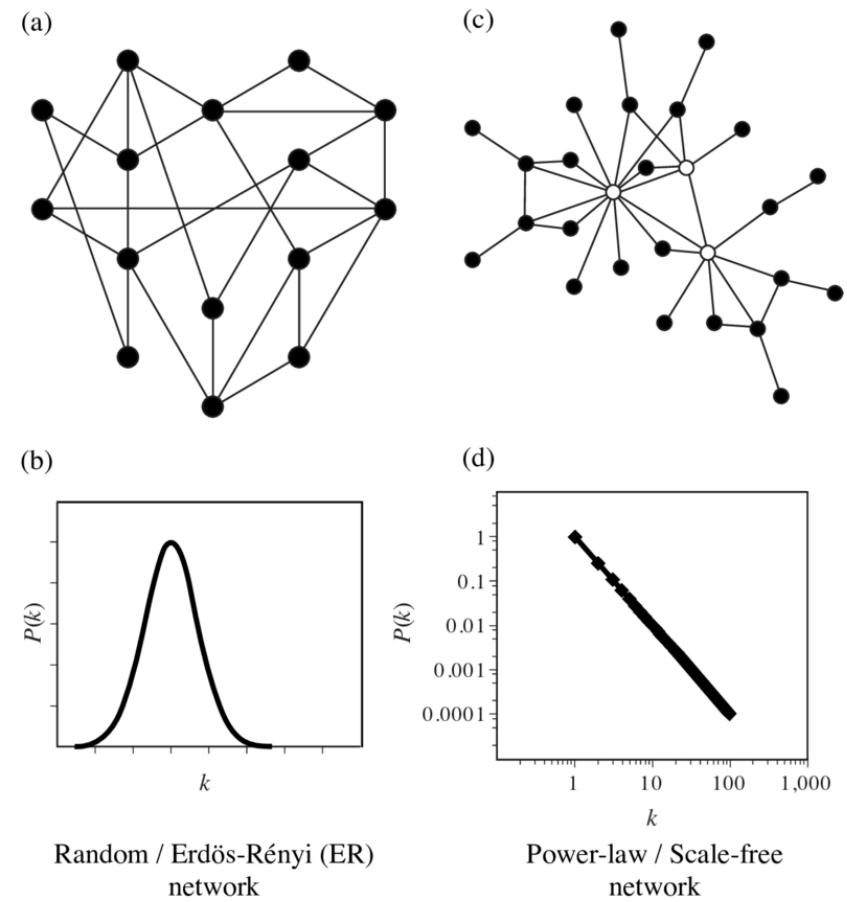
Clustering: The proportion of closed triads over the total number of triads both closed and open

Diameter: The longest geodesic distance in the network.

Particularly Important System-Level Measures

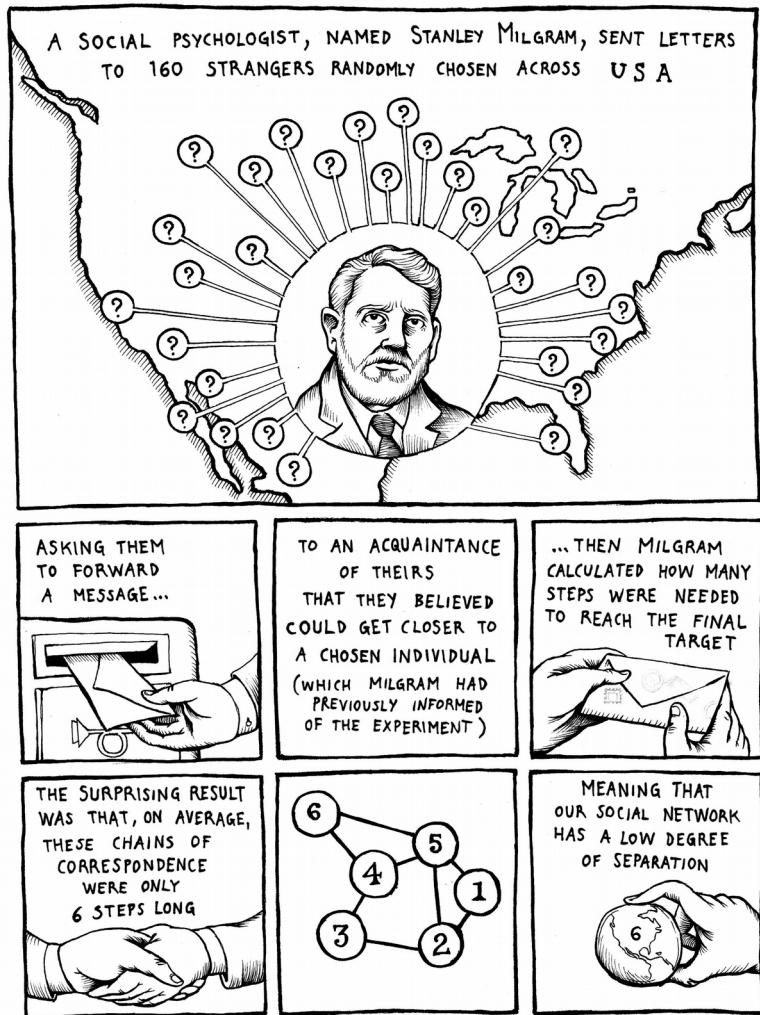


Geodesic (Shortest-Path) Distance and Average Geodesic Distances

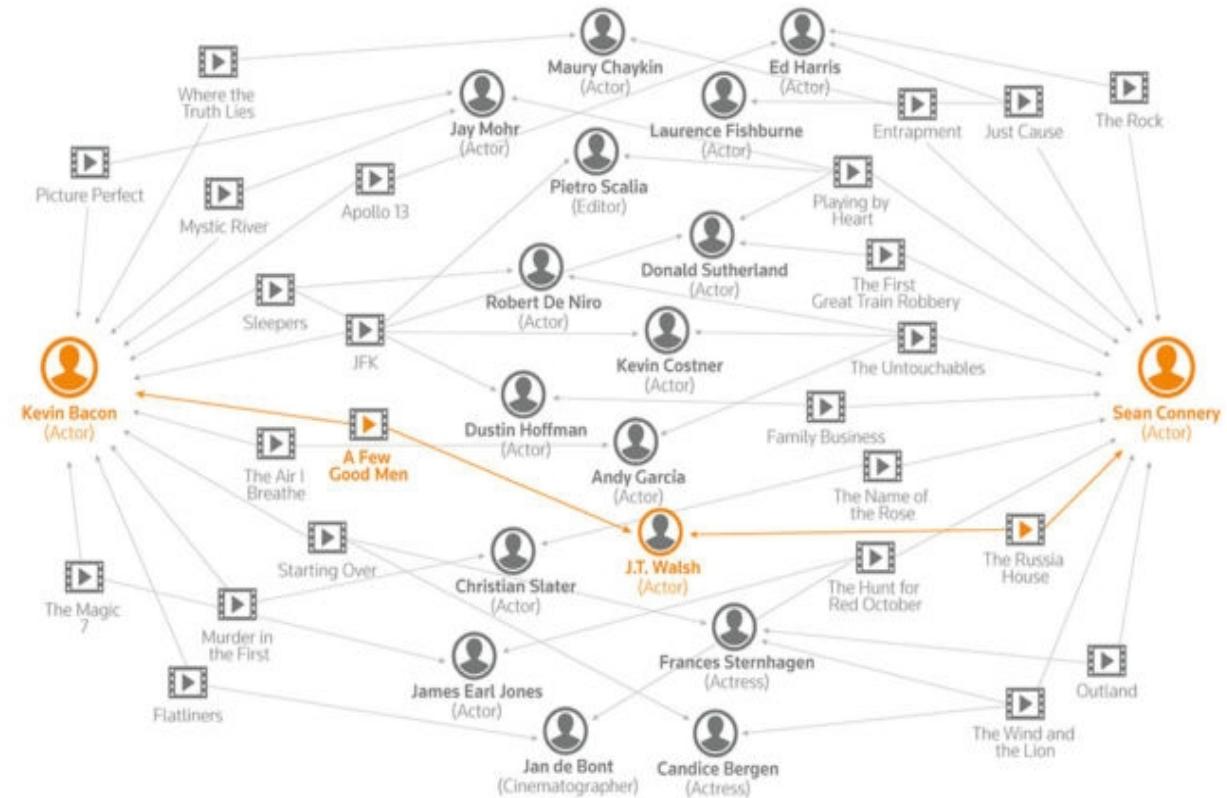


Degree Distribution

A Small-Worlds: Stanley Milgram and Kevin Bacon

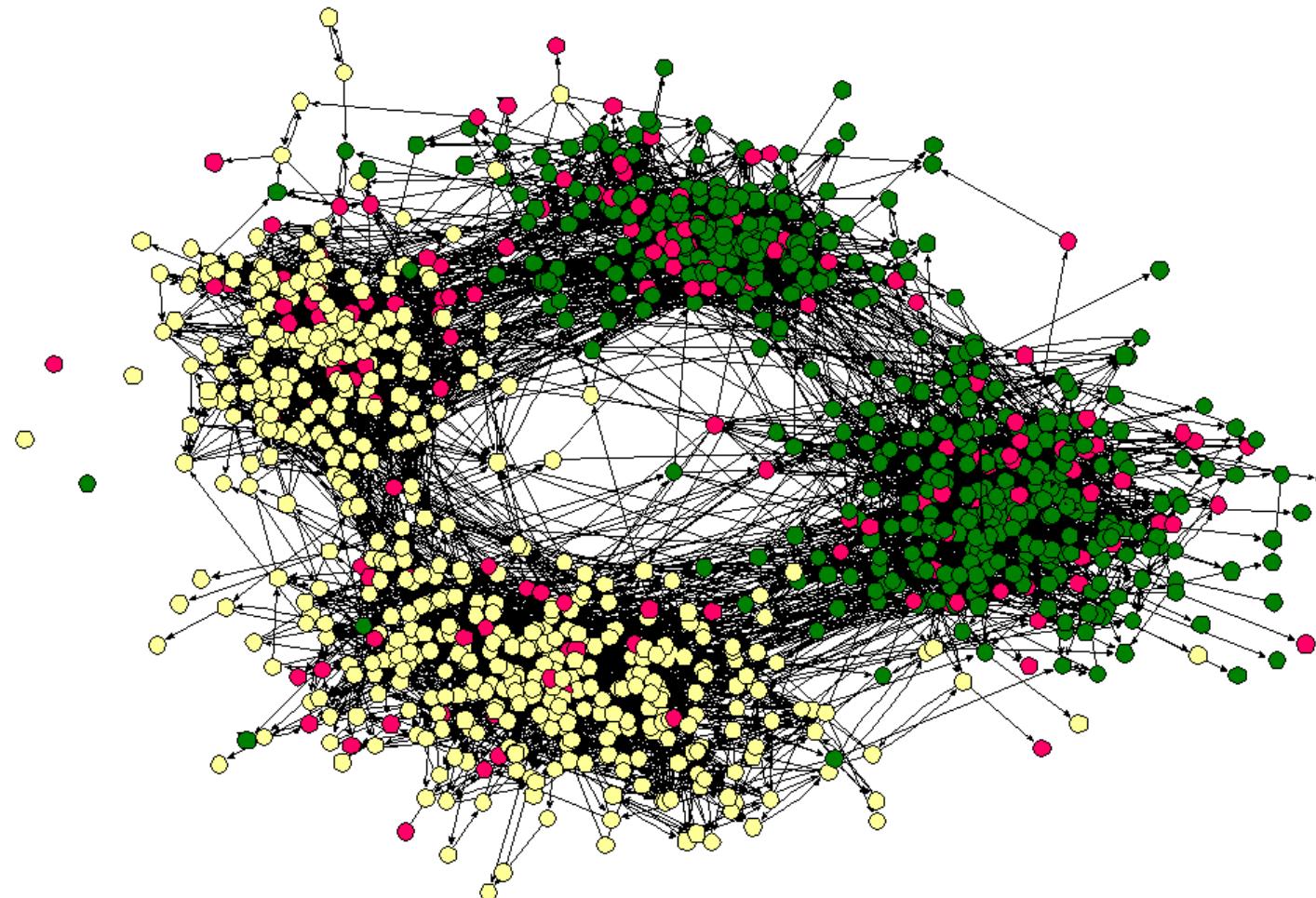


Small World: Stanley Milgram experiment



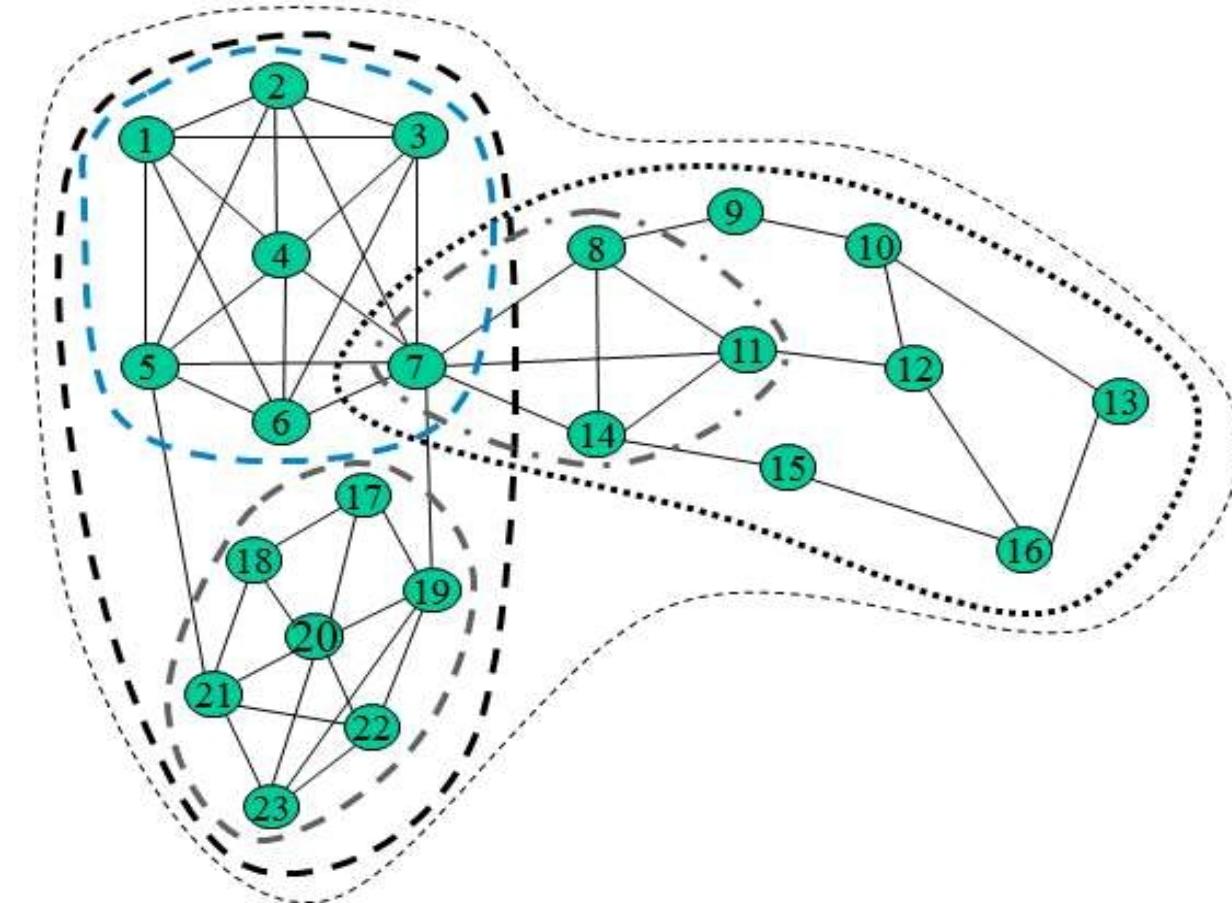
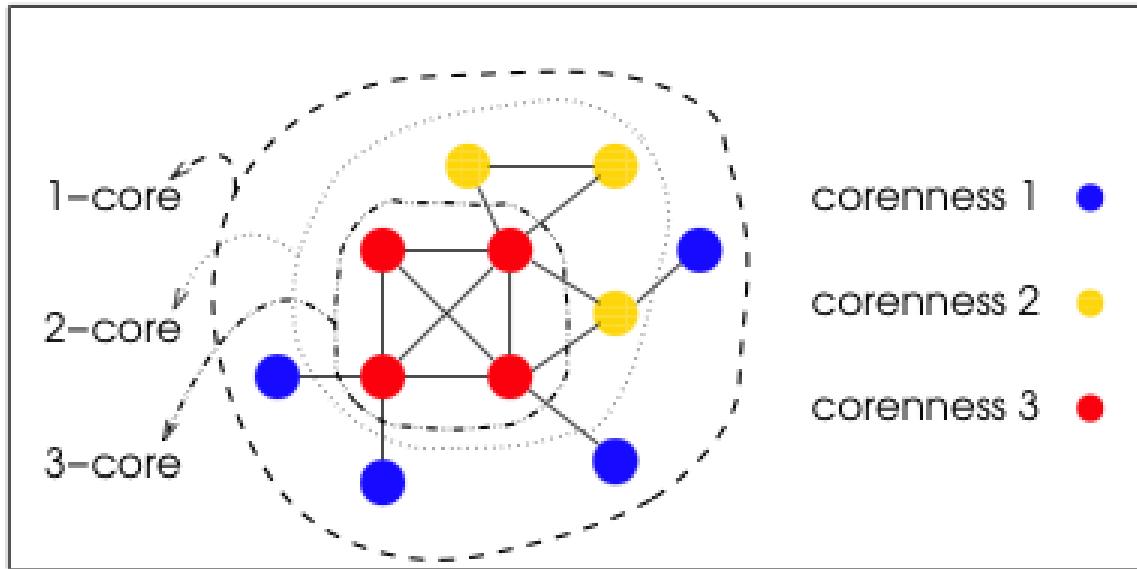
The Shortest Path from Kevin to Sean through Movies

Meso-Level View: Homophily



Moody 2001: Friendship Segregation in a U.S.
High School

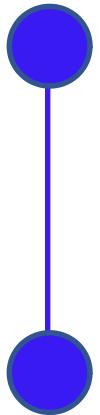
Meso-Level View: Cohesiveness and Embeddedness



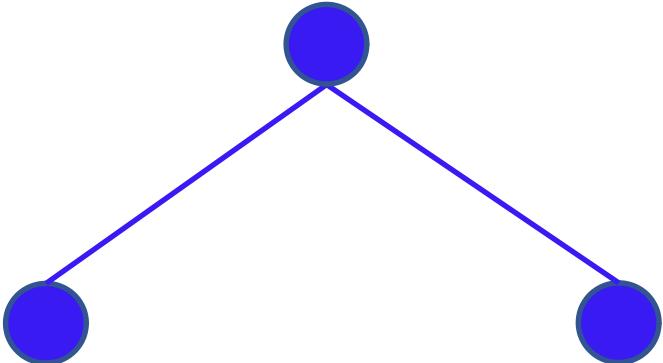
Embeddedness: Identify cohesive groups in a network, then remove k-cut sets to identify successively deeper embedded groups.

Triads: The Building Blocks of Networks

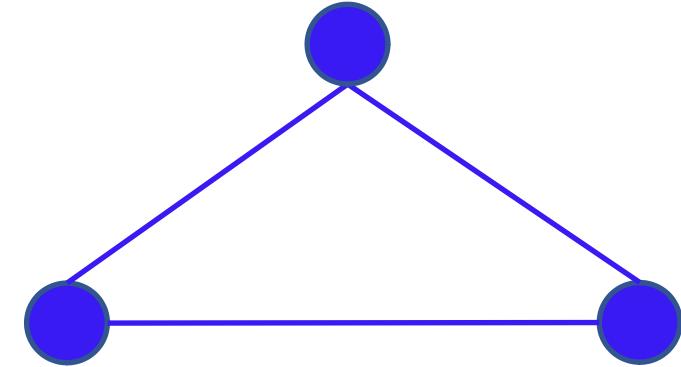
Dyad



Tryads



Open Triad

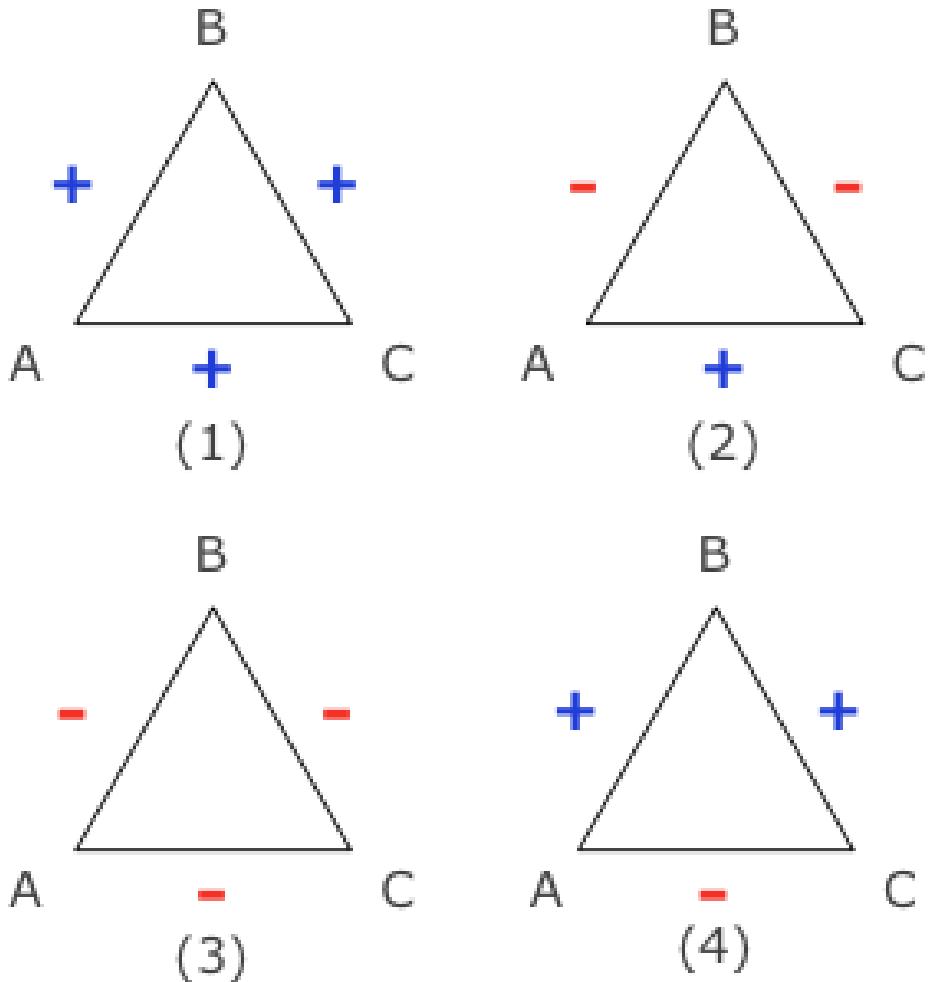


Closed Triad

Transitivity refers to the extent to which nodes making up a dyad that are also connected to a third node will both be connected to that third node: if $a \rightarrow b$ and $b \rightarrow c$ then $a \rightarrow c$

In social networks, high transitivity can indicate social closure mechanisms that might be important such as mutualism, shared costs, a common enemy or threat, or social sanctioning.

Heider: Structural Balance Theory

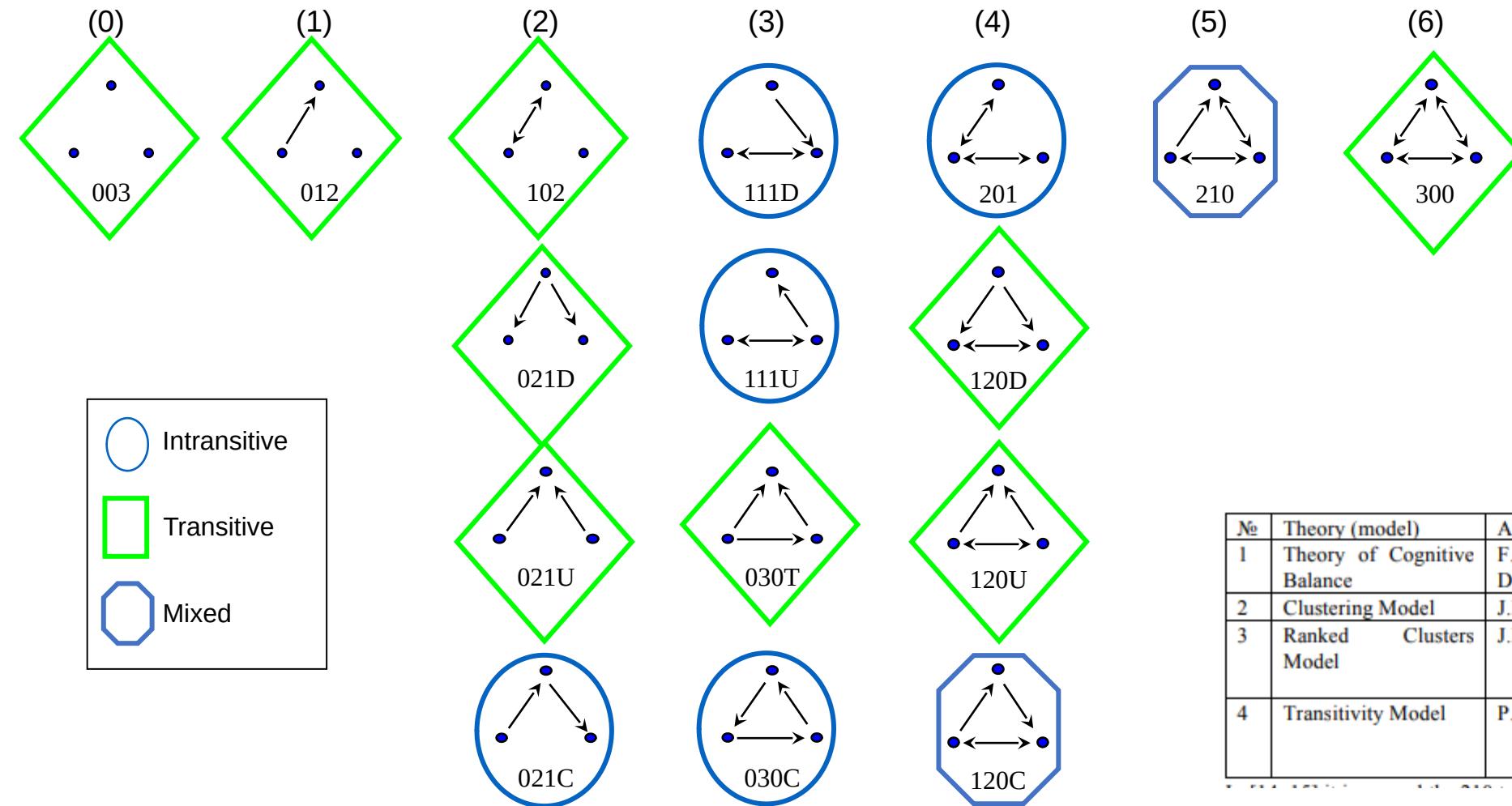


Positive ties are transitive:
The friend of a friend is a friend

Negative ties are intransitive:
The friend of a friend is not a friend

→ Leads to Segregation,
Polarization, Homophily

The Triad Census



No	Theory (model)	Authors	Permitted Triad Types
1	Theory of Cognitive Balance	F.Heider, D.Cartwright, F.Harary	300, 102
2	Clustering Model	J.Davis	300, 102, 003
3	Ranked Clusters Model	J.Davis, S. Leinhardt	300, 102, 003, 120D, 120U, 030T, 021D, 021U
4	Transitivity Model	P.W.Holland, S.Leinhardt	300, 102, 003, 120D, 120U, 030T, 021D, 021U, 012, 210.

Centrality

1 IA

18 VIIIA

	8000 1979 DC Degree	2 II A	Periodic Table of Network Centrality												518 1989 IC Information C				
1	224 1971 BC Betweenness	239 2008 EBC Endpoint BC	3 III A	4 IV B	5 V B	6 VI B	7 VII B	8 VIII B	9 VIIIB	10 VIIIB	11 I B	12 IIB	13 IIIA	14 IVA	15 VA	16 VIA	17 VIIA		
2	942 1966 CC Closeness	239 2008 PBC Proxy BC	224 1971 EBC Edge BC	53 2009 CBC Commun. BC	236 2007 ΔC Delta Cent.	5 2010 MDC MD Cent.	0 2015 EYC Entropy C.	2 2013 CAC Comm. Ability	56 2007 EPTC Entropy PC	281 1971 CCoef Clust. Coef.	42 2012 PeC PeC	427 2007 BN Bottleneck	43 2009 EI Essentiality I.	573 2006 e-kPC e-disjoint kPC	573 2006 v-kPC v-disjoint kPC	80 2006 HYPSC Hypergraphs	279 1997 AFF Affiliation C.	399 2001 α-C α-Cent.	178 1995 ECC Eccentricity
3	1279 1972 EC Eigenvector	239 2008 LSBC LscaledBC	979 2005 RWBC RWalk BC	477 1991 TEC Total Effects	42 2009 LI Lobby Index	11 2008 MC Mod Cent.	0 2014 COMCC Community C.	45 2012 ECCoef ECCoef	0 2015 SMD Super Mediat.	1 2014 UCC United Comp.	4 2012 WDC WDC	119 2008 MNC MNC	43 2009 KL Clique Level	179 2005 BIP Bipartivity	426 1988 GPI GPI Power	116 1991 kRPC Reachability	58 2007 SCodd odd Subgraph	586 2004 RWCC RWalk CC	
4	8053 1999 PR Page Rank	239 2008 DSBC DScaled BC	291 1953 σ Stress	477 1991 IEC Immediate Eff.	1 2014 DM Degree Mass	10 2012 LAPC Laplacian C.	0 2012 ABC Attentive BC	1699 2001 STRC Straightness C	0 2015 SNR Silent Node R.	15 2011 HPC Harm. Prot.	26 2011 LAC Local Average	119 2008 DMNC DMNC	3 2013 LR Lurker Rank	2457 1987 β-C β Cent.	x x HYP Hyperbolic C.	27 2012 kEPC k-edge PC	13 2007 FC Functional C.	0 2014 HCC Hierar. CC	
5	484 2005 SC Subgraph	613 1991 FBC Flow BC	14 2012 RLBC RLimited BC	477 1991 MEC Mediative Eff.	69 2010 LEVC Leverage Cent.	35 2010 TC Topological C.	X X SDC Sphere Degree	15 2010 ZC Zonal Cent.	14 2013 CI Collab. Index	11 2013 CoEWC CoEWC	45 2012 NC NC	108 2010 MLC Moduland C.	X X RSC Resolvent SC	1 2014 SWIPD SWIPD	36 2009 XXXX LinComb	0 2014 BCPR BCPR	0 2014 TPC Tunable PC	0 2015 EDCC Effective Dist.	

citations	year
C	Name

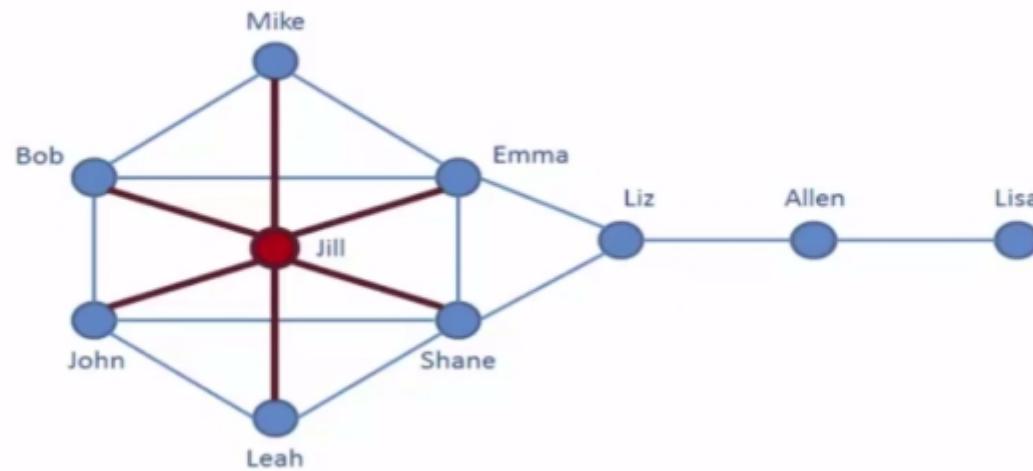
8000 1979 Freeman Conceptual	942 1966 Sabidussi Axiomatic	573 2006 Borgatti/Everett Conceptual	1130 2005 Borgatti Conceptual	24 2014 Boldi/Vigna Axiomatic	252 1974 Nieminen Axiomatic	6 1981 Kishi Axiomatic	3 2012 Kitti Axiomatic	3 2009 Garg Axiomatic
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2065 1934 Moreno Historic	1546 1950 Bavelas Historic	780 1948 Bavelas Historic	1475 1951 Leavitt Historic	297 1992 Borgatti/Everett Conceptual	3649 2001 Jeong et al. Empirical	4167 1998 Tsai/Ghoshal Empirical	961 1993 Ibarra Empirical	71 2008 Valente Empirical
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- “Traditional”
- Betweenness-like
- Friedkin Measures
- Miscellaneous
- Path-based
- Specific Network Type
- Spectral-based
- Closeness-like

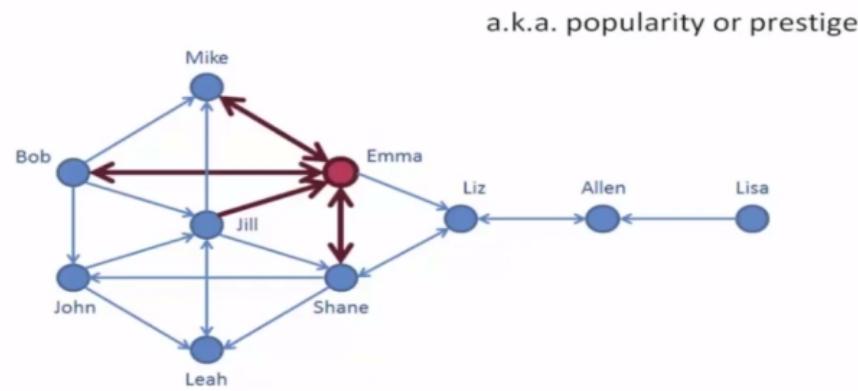
Common Measures of Centrality

Degree Centrality: A node's degree centrality refers to the number of ties it has.

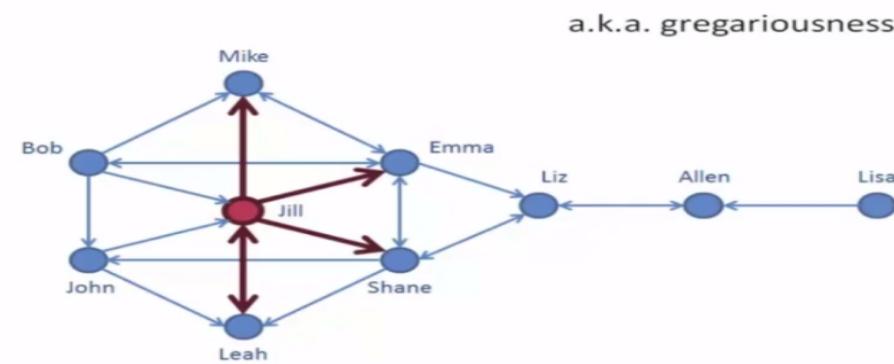


Common Measures of Centrality

In-Degree Centrality: A node's in-degree centrality refers to the number of ties it receives.



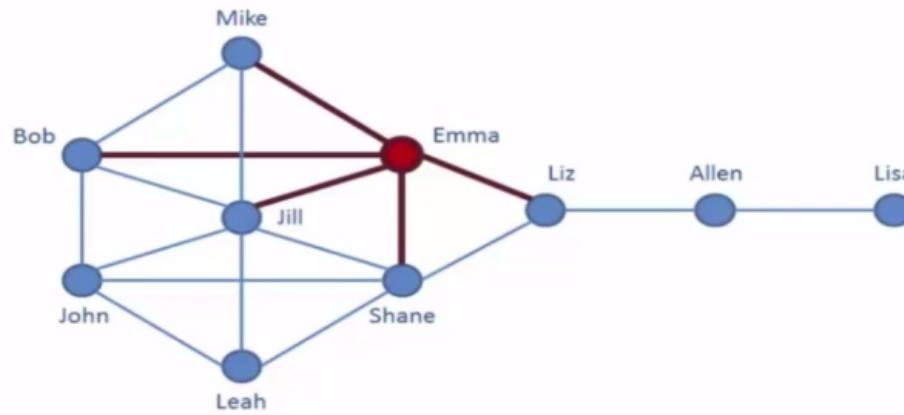
Out-Degree Centrality: A node's out-degree centrality refers to the number of ties it sends.



Note: To calculate these measures, you need to have a directed network.

Common Measures of Centrality

Closeness Centrality: The closeness centrality of a node is the average length of the shortest path between the node and all other nodes. The most central the node the closer it is to all the other nodes.

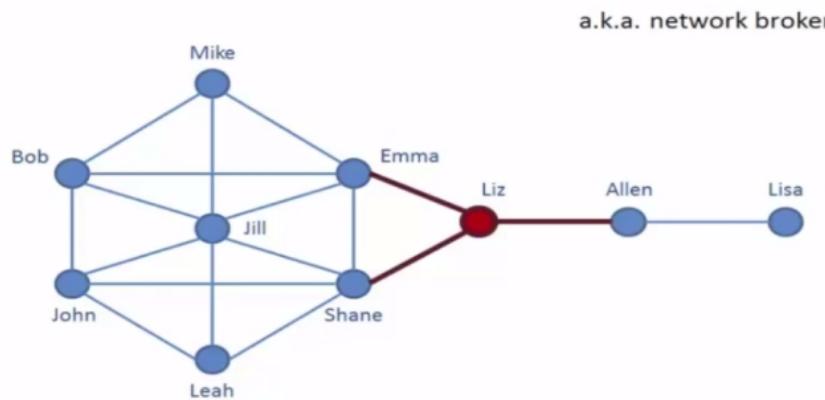


Note: Shane's closeness centrality is equivalent to Emma's.

Closeness centrality like degree centrality can be calculated in terms of closest **to** (incoming ties) and **from** (outgoing ties) in directed networks.

Common Measures of Centrality

Betweenness Centrality: A node's betweenness centrality is the number of times a node acts as a bridge along the shortest path between two other nodes.

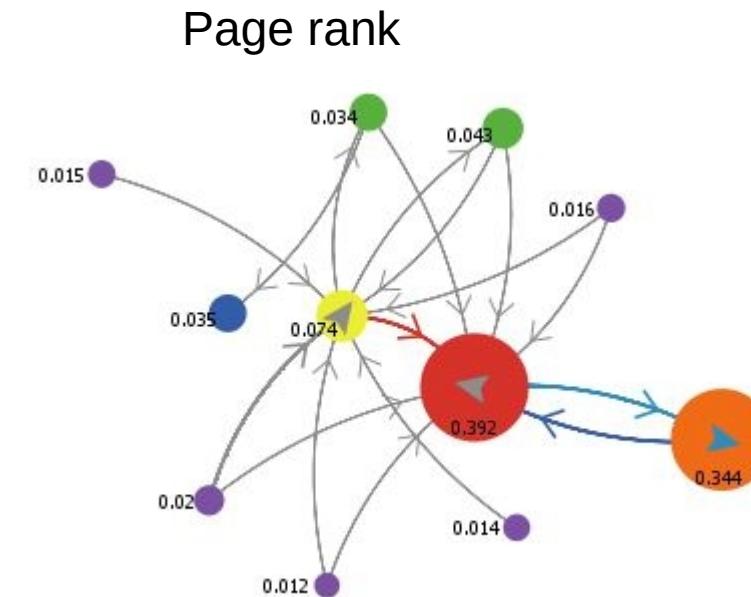
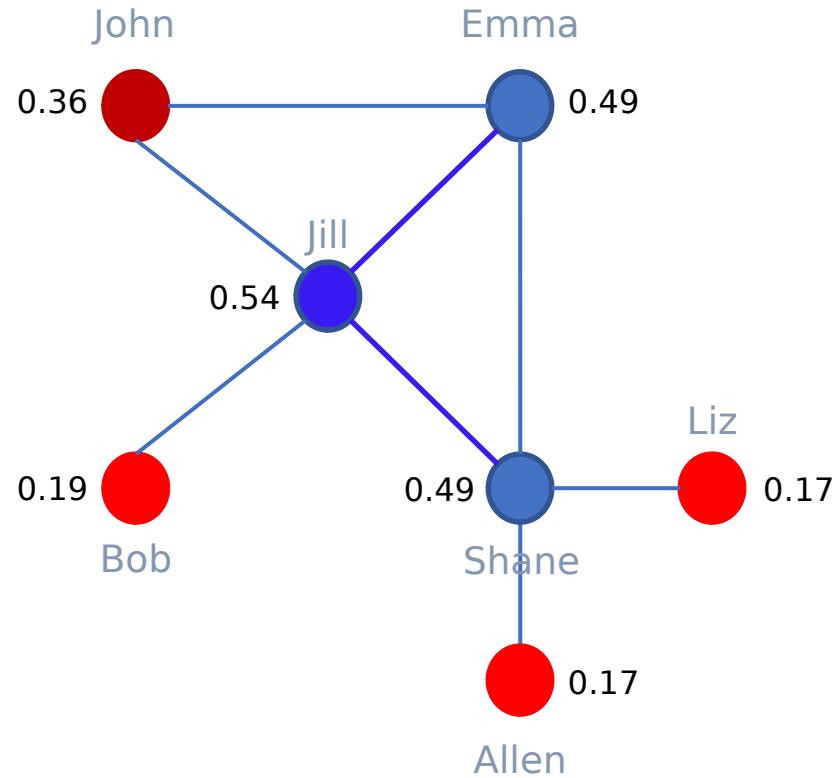


Betweenness Centrality is calculated by:

1. For each pair of nodes, compute the shortest paths between them.
2. For each pair of nodes, determine the fraction of shortest paths through the node in question.
3. Sum this fraction over all pairs of nodes.

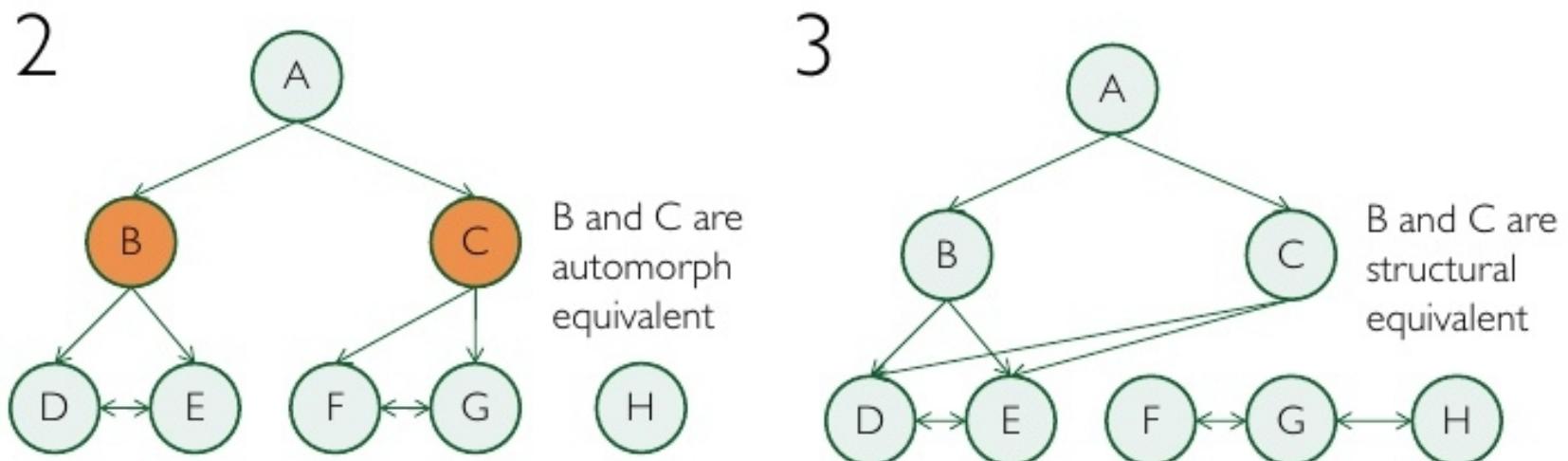
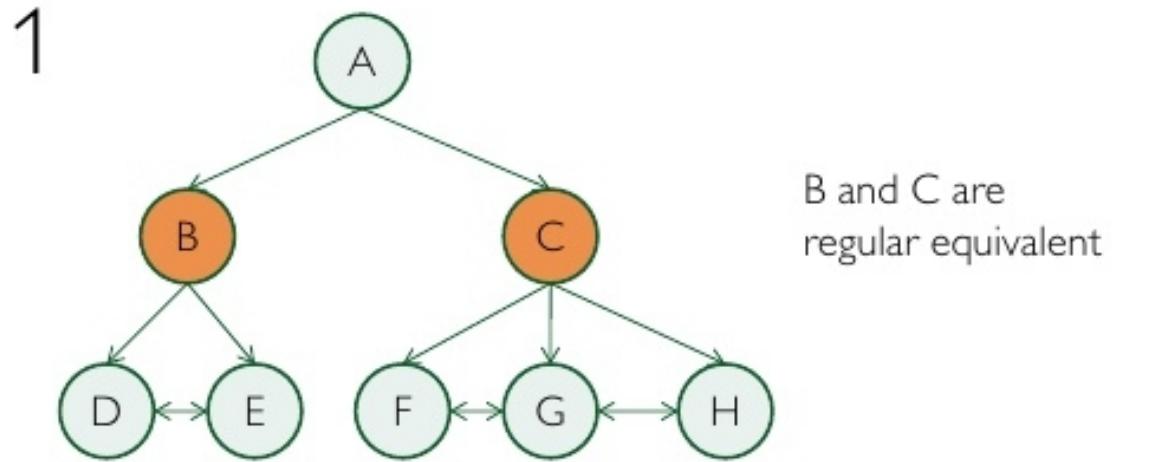
Common Measures of Centrality

Eigenvector Centrality: A node's eigenvector centrality measures its influence in terms of how connected the node is to other highly connected nodes.



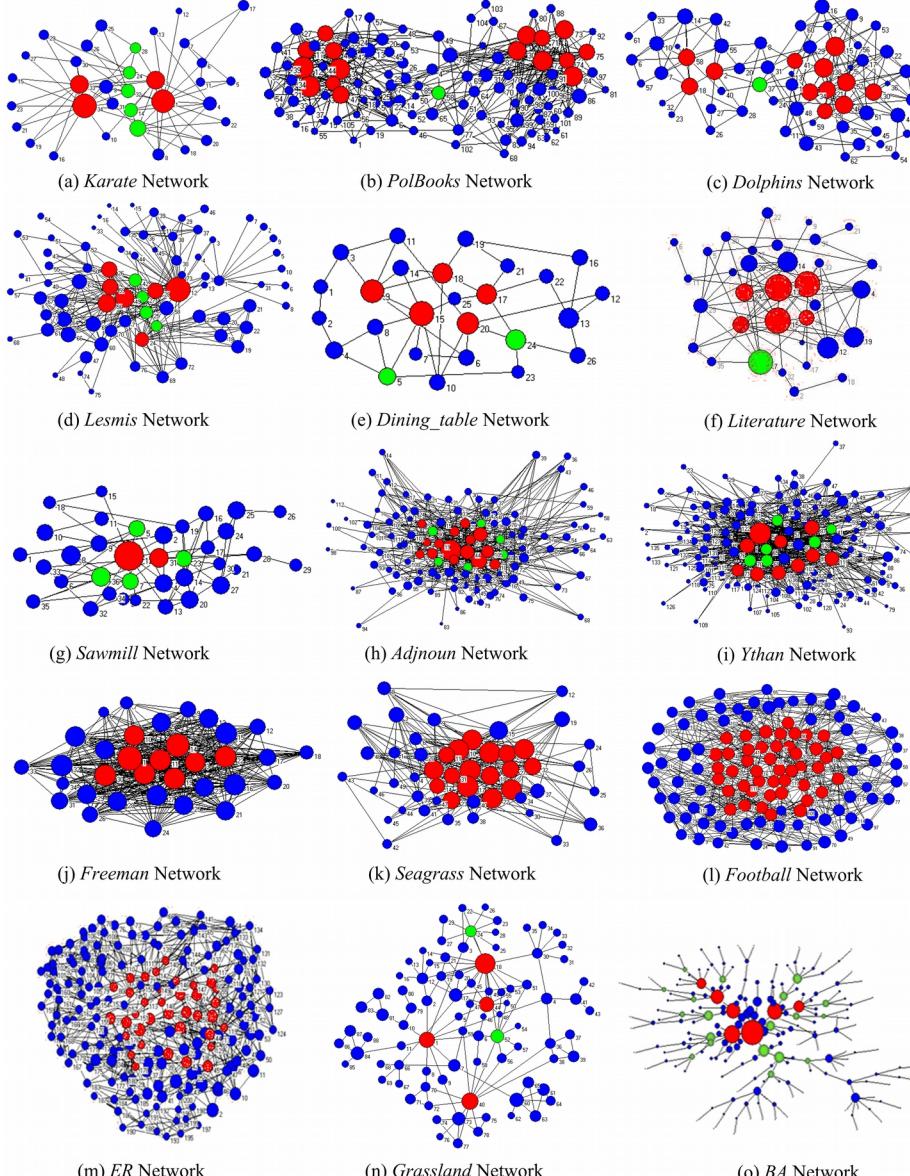
Roles

Identifying Roles in Networks: Structural Equivalence



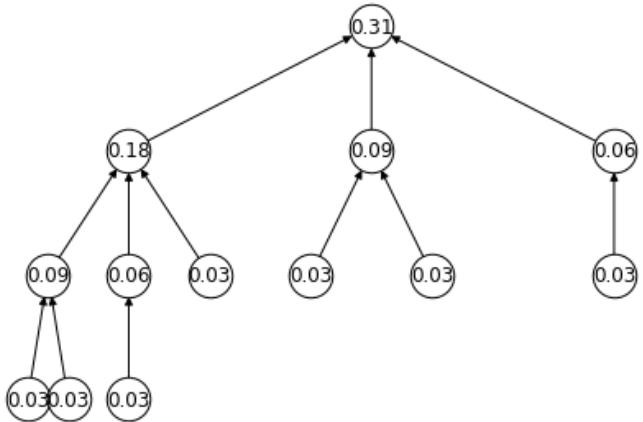
Identifying Roles in Networks

They use several centrality measures to find roles:
degree,
betweenness centrality
and eigenvector centrality



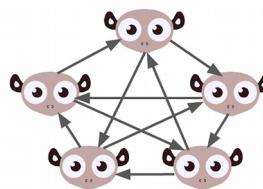
Hierarchy in networks

PageRank



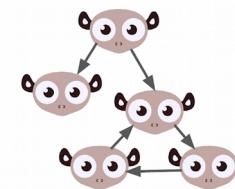
A complex network graph illustrating a fully connected structure. The graph consists of 10 nodes arranged in two columns of five. Each node is a white circle with a black border, and each is labeled with the value '0.08' inside. Every node in the left column is connected to every node in the right column by a directed edge, with all arrows pointing from left to right. This results in a total of 45 directed edges.

Flow hierarchy



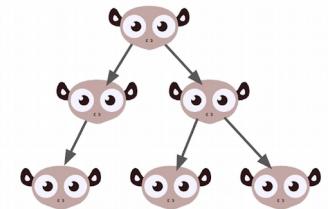
Low hierarchy

(flow hierarchy = 0%)



Some hierarchy

(flow hierarchy = 40%)



High hierarchy

(flow hierarchy = 100%)

$$h = \frac{\sum_{i=1}^L e_i}{L}, \quad e_i = 0 \text{ if edge } i \text{ is in a cycle, } 1 \text{ otherwise}$$

Calculate hierarchy value for the whole network
→ useful to compare networks

Structural Holes: Why Some Roles Are More Advantageous than Others

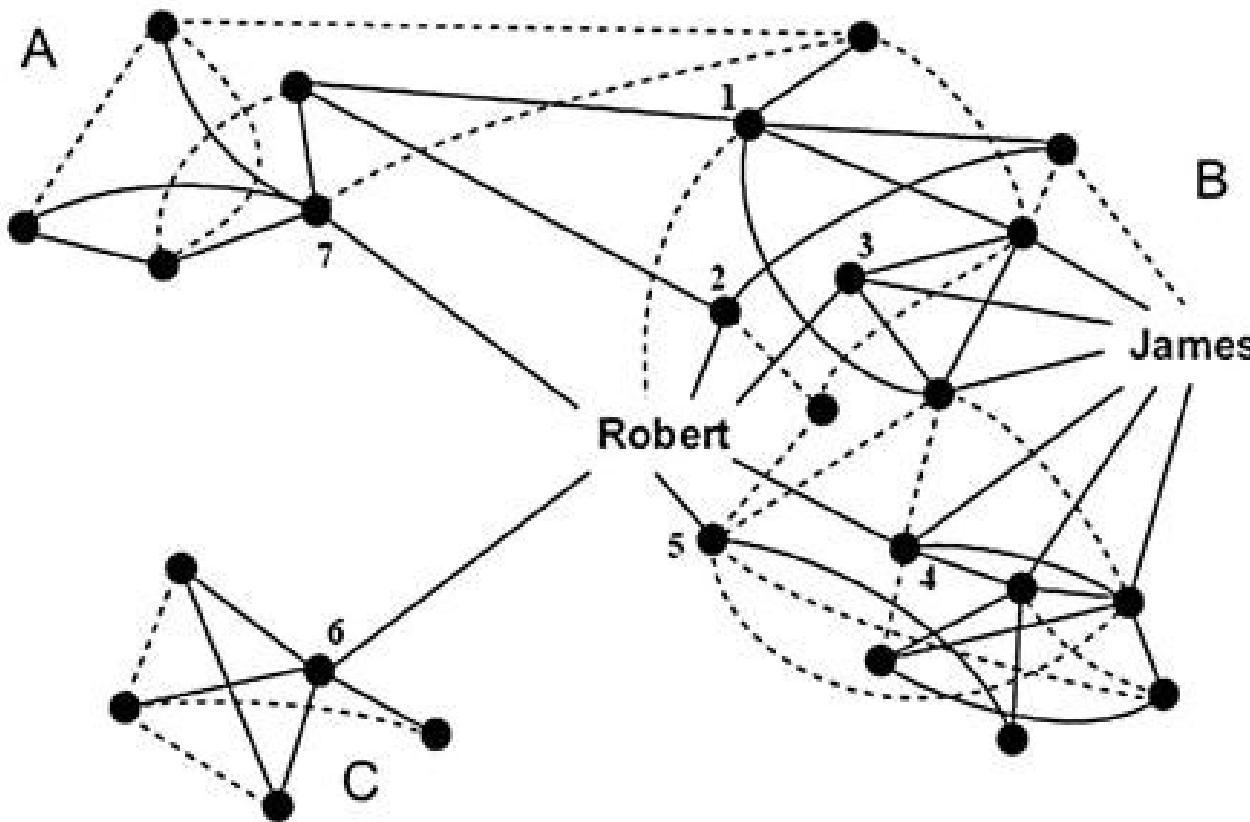


Figure 1. Robert Fills a Structural Hole in the Network.

From: Mauro F. Guillen, Randall Collins, Paula England, and Marshall Meyer, eds. "The Social Capital of Structural Holes," in *New Directions in Economic Sociology* (New York: Russell Sage Foundation, 2002).

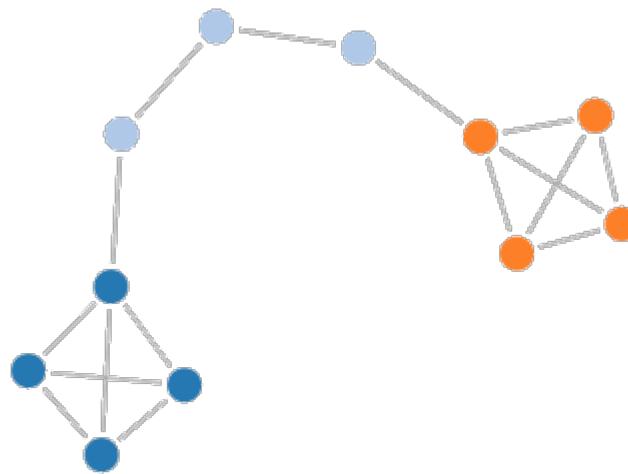
Social Capital Theory

LEADING SCHOLARS:

- Pierre Bourdieu in sociology (1984)
- Robert Putnam in political science (1993, 1996)
- James Coleman in education psychology (1988)
- Francis Fukuyama in economic history (1996)



Part 2: Network analysis with networkx



NetworkX