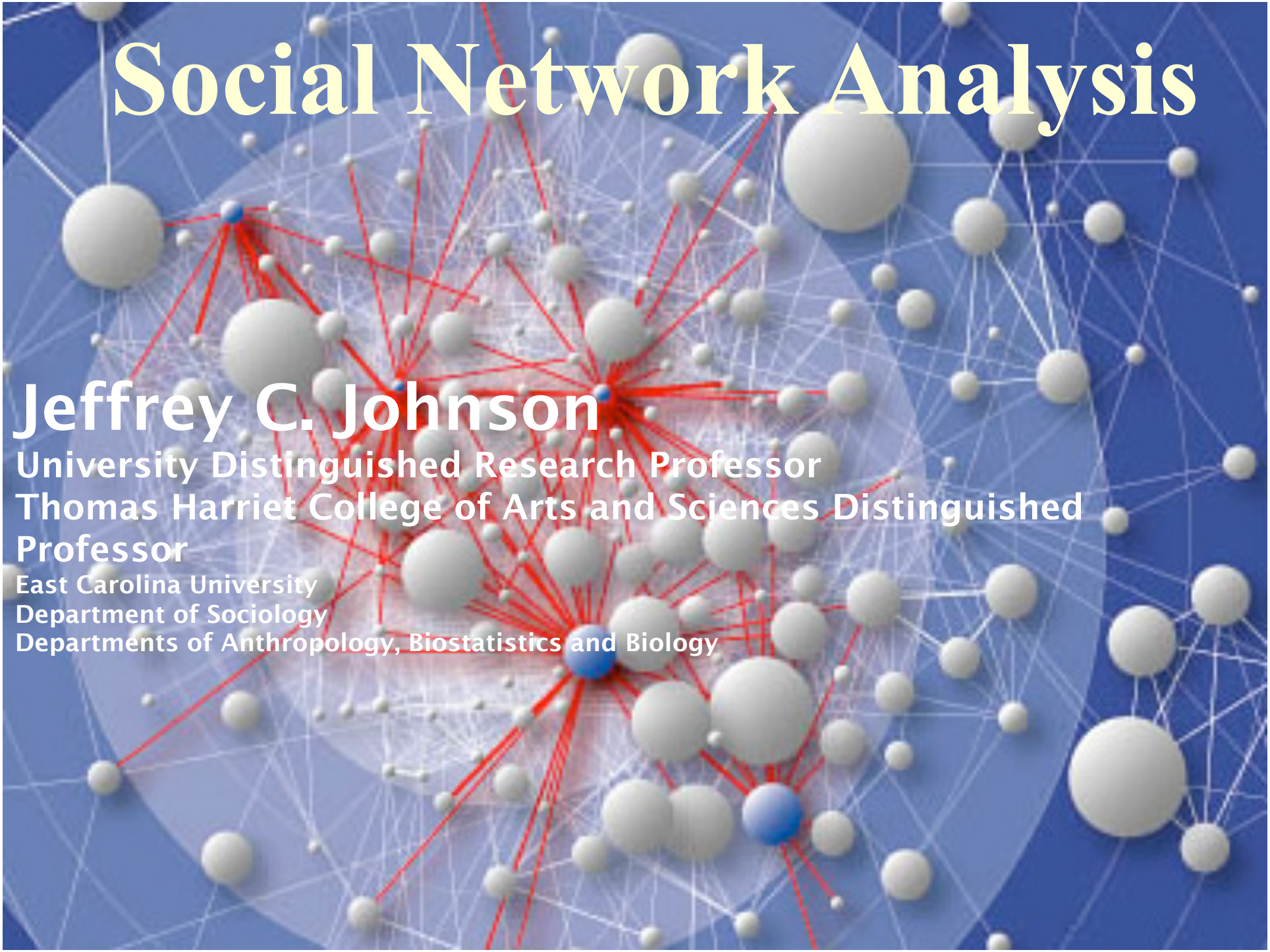


Social Network Analysis

Jeffrey C. Johnson

University Distinguished Research Professor
Thomas Harriet College of Arts and Sciences Distinguished Professor
East Carolina University
Department of Sociology
Departments of Anthropology, Biostatistics and Biology

Goals of Workshop

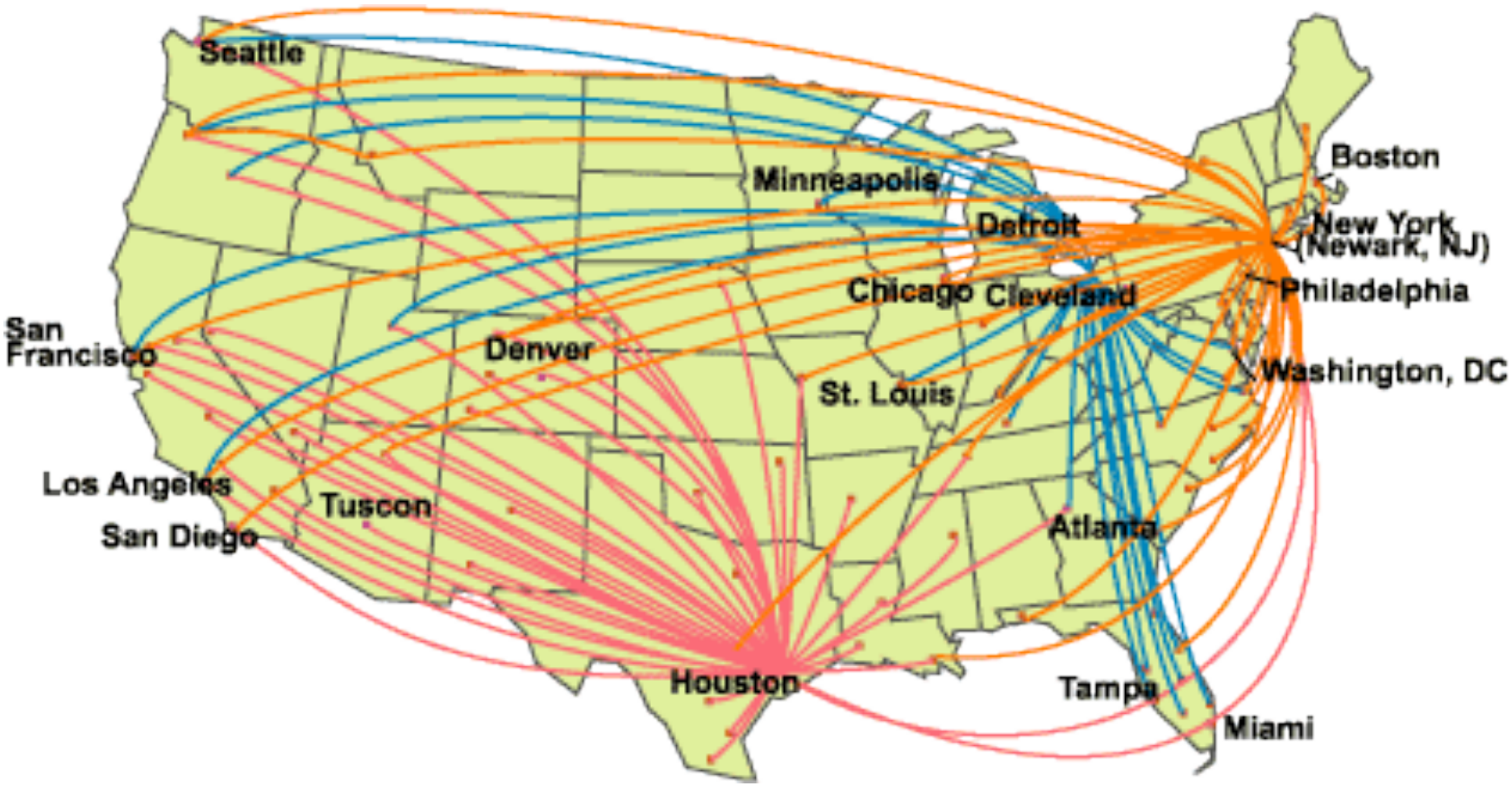
Understand network data-collection and management

Understand networks as matrices

Basic network measures and concepts

Basic analysis

Networks are Everywhere

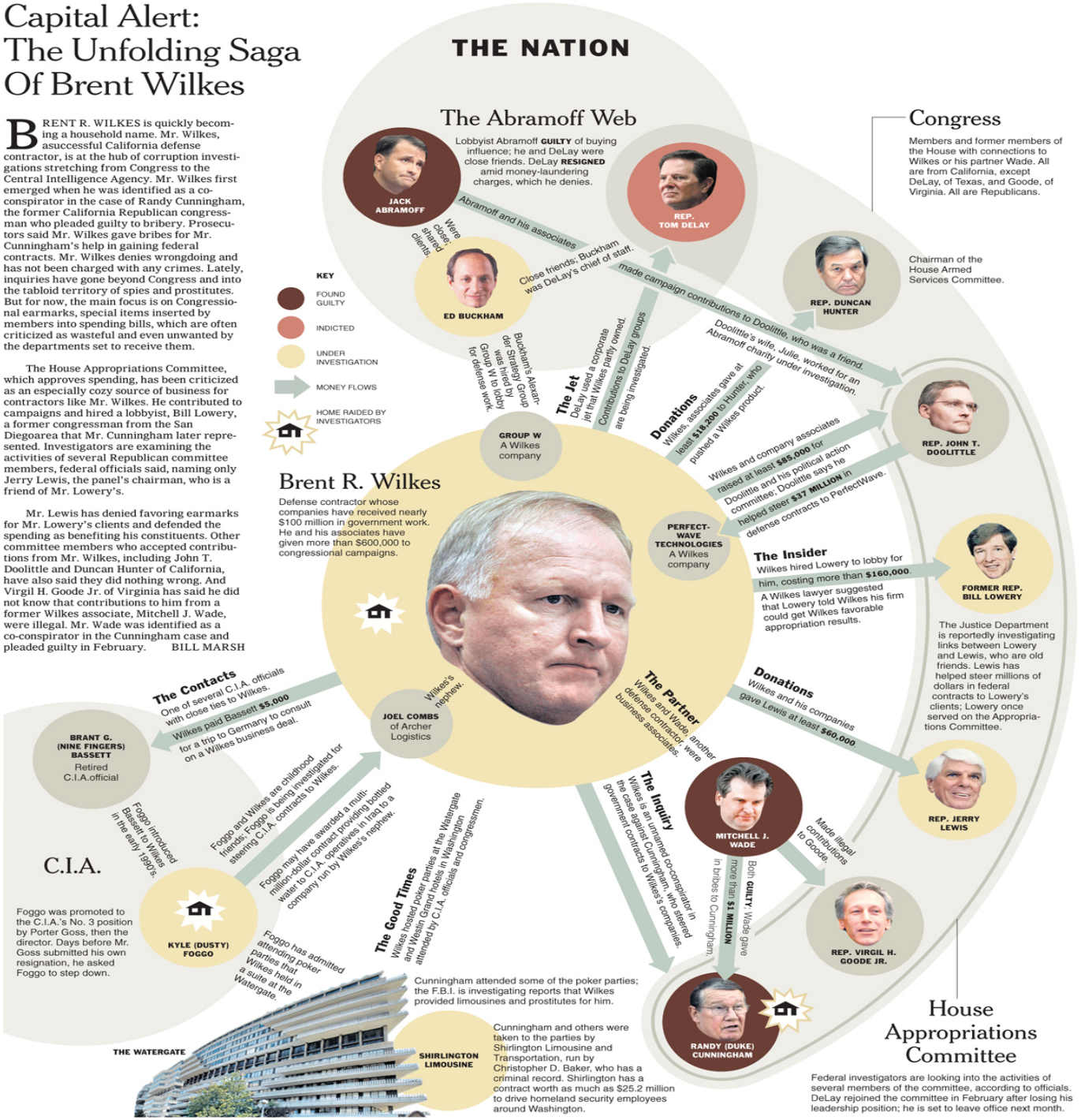


Capital Alert: The Unfolding Saga Of Brent Wilkes

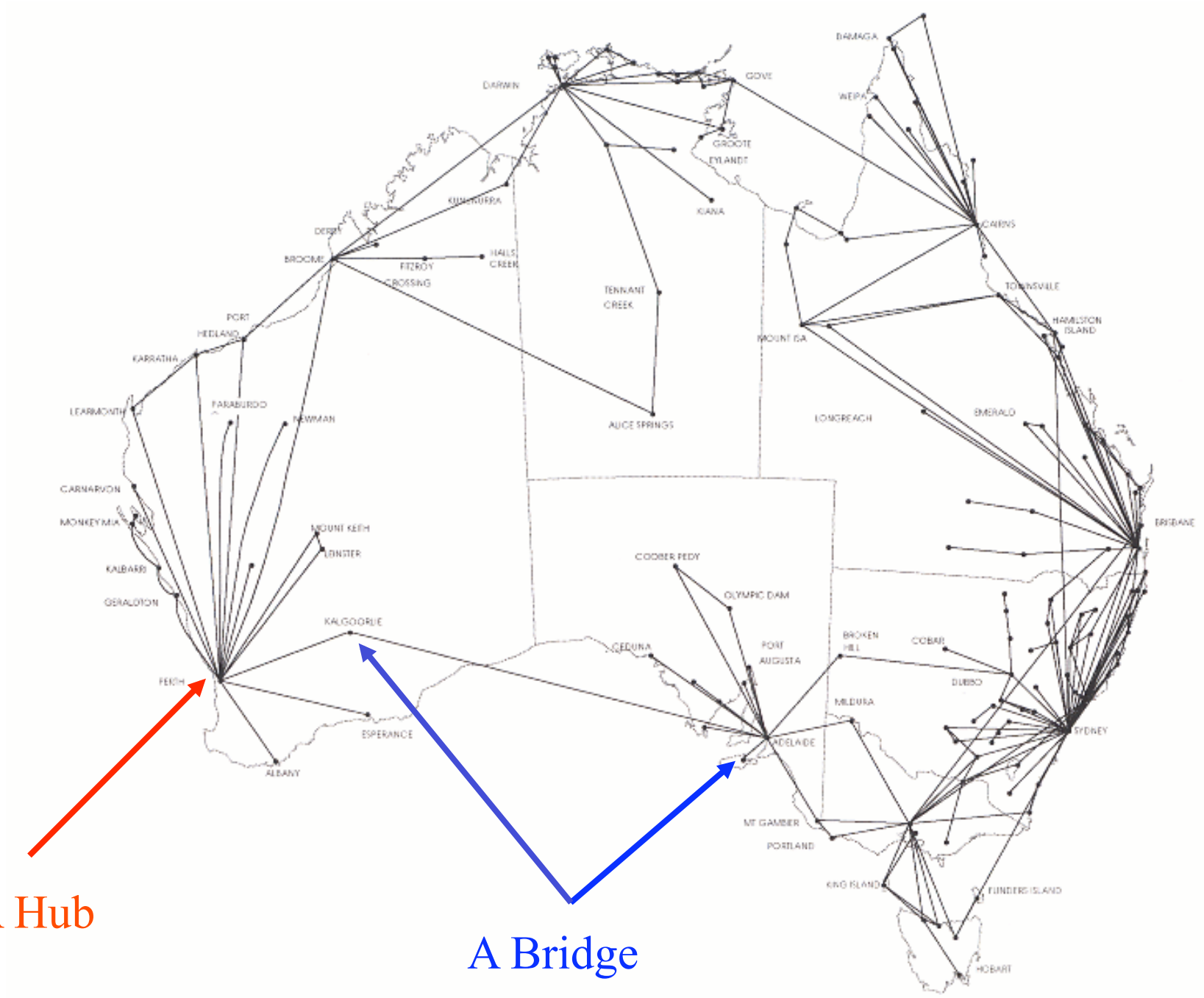
BRENT R. WILKES is quickly becoming a household name. Mr. Wilkes, asuccessful California defense contractor, is at the hub of corruption investigations stretching from Congress to the Central Intelligence Agency. Mr. Wilkes first emerged when he was identified as a co-conspirator in the case of Randy Cunningham, the former California Republican congressman who pleaded guilty to bribery. Prosecutors said Mr. Wilkes gave bribes for Mr. Cunningham's help in gaining federal contracts. Mr. Wilkes denies wrongdoing and has not been charged with any crimes. Lately, inquiries have gone beyond Congress and into the tabloid territory of spies and prostitutes. But for now, the main focus is on Congressional earmarks, special items inserted by members into spending bills, which are often criticized as wasteful and even unwanted by the departments set to receive them.

The House Appropriations Committee, which approves spending, has been criticized as an especially cozy source of business for contractors like Mr. Wilkes. He contributed to campaigns and hired a lobbyist, Bill Lowery, a former congressman from the San Diegoarea that Mr. Cunningham later represented. Investigators are examining the activities of several Republican committee members, federal officials said, naming only Jerry Lewis, the panel's chairman, who is a friend of Mr. Lowery's.

Mr. Lewis has denied favoring earmarks for Mr. Lowery's clients and defended the spending as benefiting his constituents. Other committee members who accepted contributions from Mr. Wilkes, including John T. Doolittle and Duncan Hunter of California, have also said they did nothing wrong. And Virgil H. Goode Jr. of Virginia has said he did not know that contributions to him from a former Wilkes associate, Mitchell J. Wade, were illegal. Mr. Wade was identified as a co-conspirator in the Cunningham case and pleaded guilty in February. BILL MARSH



Sources: Times reporting; The San Diego Union-Tribune (total Wilkes contributions, Wilkes-Hunter); The Washington Post (Wilkes-Doolittle); The Sacramento Bee (Abramoff-Doolittle); The Los Angeles Times (Wilkes-Lewis); Taxpayers for Common Sense; Center for Responsive Politics


DARWIN
GOVE
DAMAGA
WEIPA
GROOTE EYLANDT
KUNUNURRA
KIANA
CAIRNS
DERBY
BROOME
FITZROY CROSSING
HALLS CREEK
TENNANT CREEK
TOWNSVILLE
HAMILTON ISLAND
PORT HEDLAND
MOUNT ISA
KARRATHA
LEARMONTH
PARABURDOO
NEWMAN
ALICE SPRINGS
LONGREACH
EMERALD
CARNARVON
MONKEYMIA
BRISBANE
MOUNT KEITH
LEINSTER
KALBARRI
COOBER PEDY
GERALDTON
OLYMPIC DAM
KALGOORLIE
CEDUNA
PORT AUGUSTA
BROKEN HILL
COBAR
PERTH
DUBBO
MILDURA
ESPERANCE
SYDNEY
ADELAIDE
ALBANY
MT GAMBIER
PORTLAND
KING ISLAND
FLINDERS ISLAND
HOBART
A Hub
A Bridge

And They Have Implications

The Medieval River Trade Network of Russia Revisited

Social Networks (1978/79) 1:285-292

Forrest R. Pitts
*University of Hawaii**

Medieval trade and communication along the rivers of Russia are considered as a social network. Two measures are presented. An intermediate node occurrence rate (Shimbel's stress index) provides a measure of centrality. The short path distances to all other places are summed to provide a system-effort measure Of accessibility. Both measures show Moscow to have been most central and accessible with aggregate least effort.

Figure 1. *Russian trade routes in the 12th - 13th centuries.*

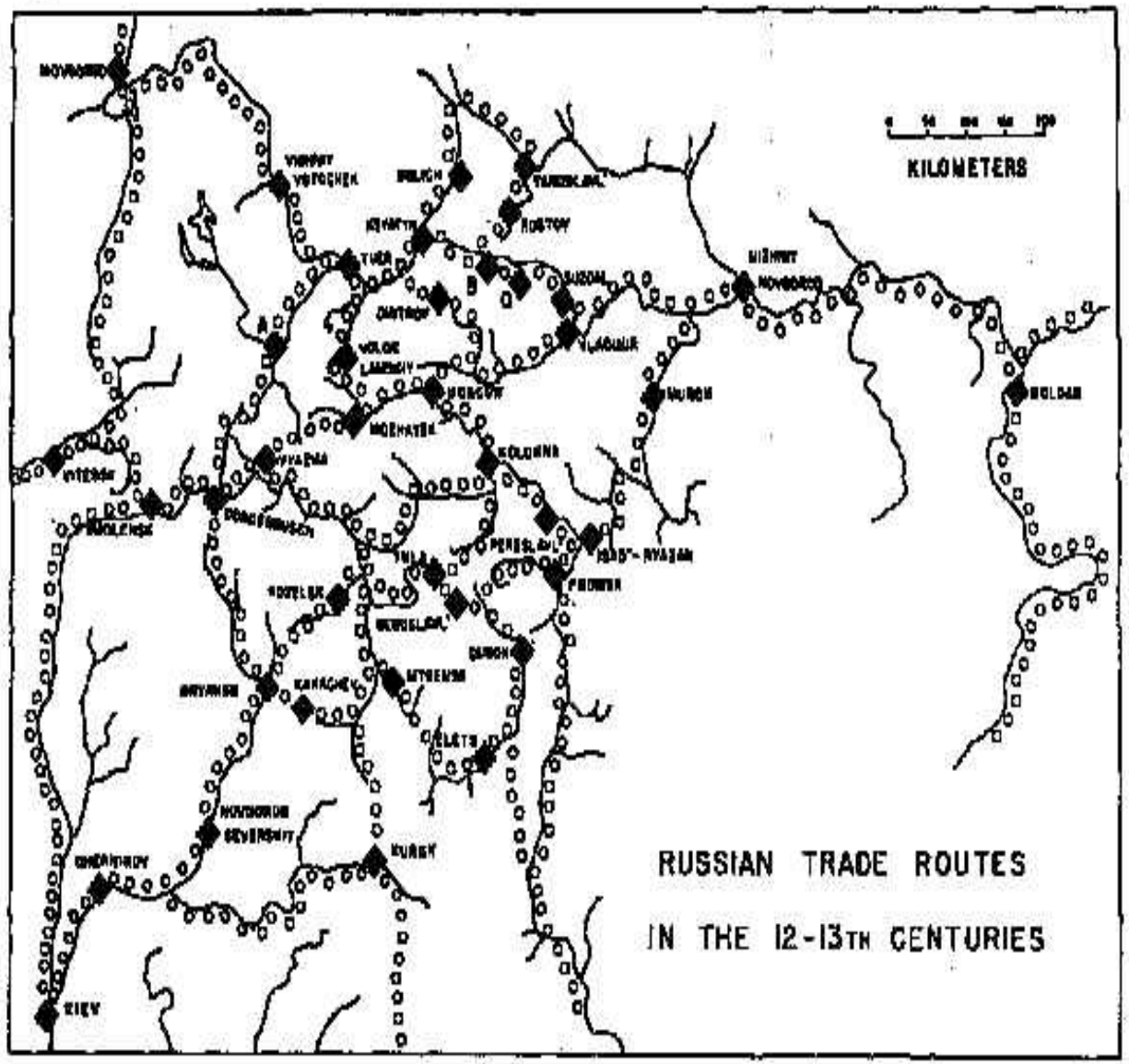
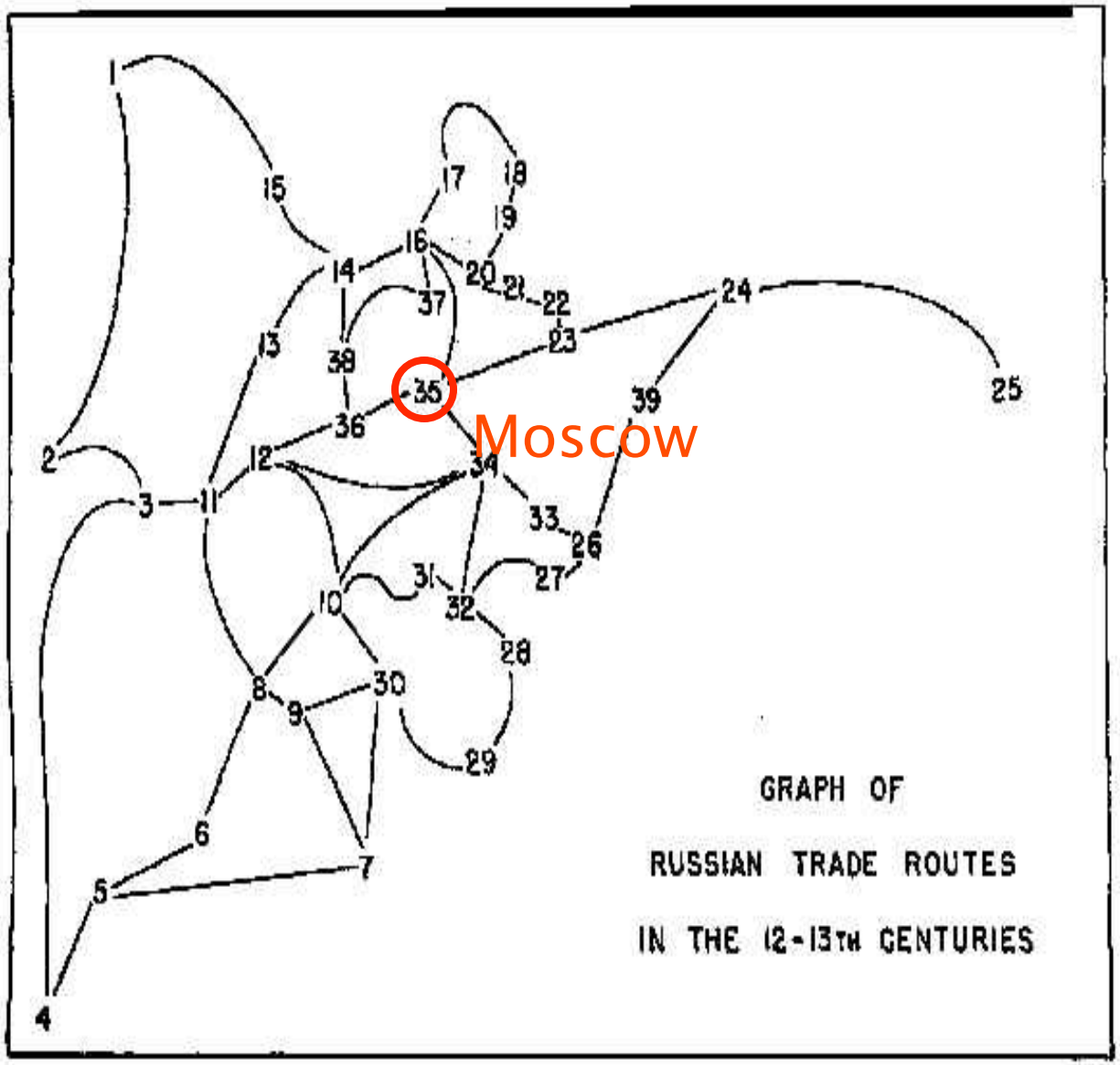
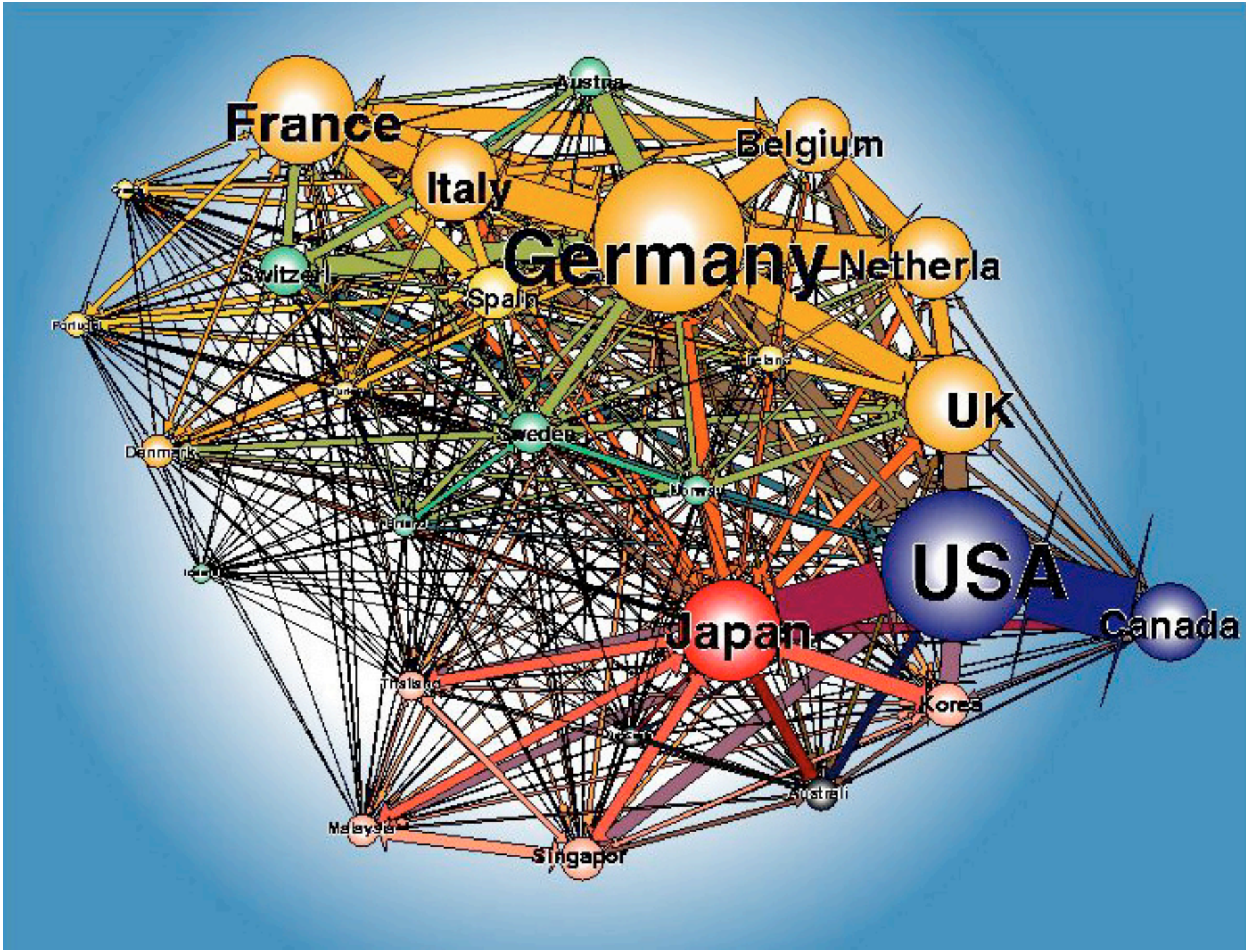
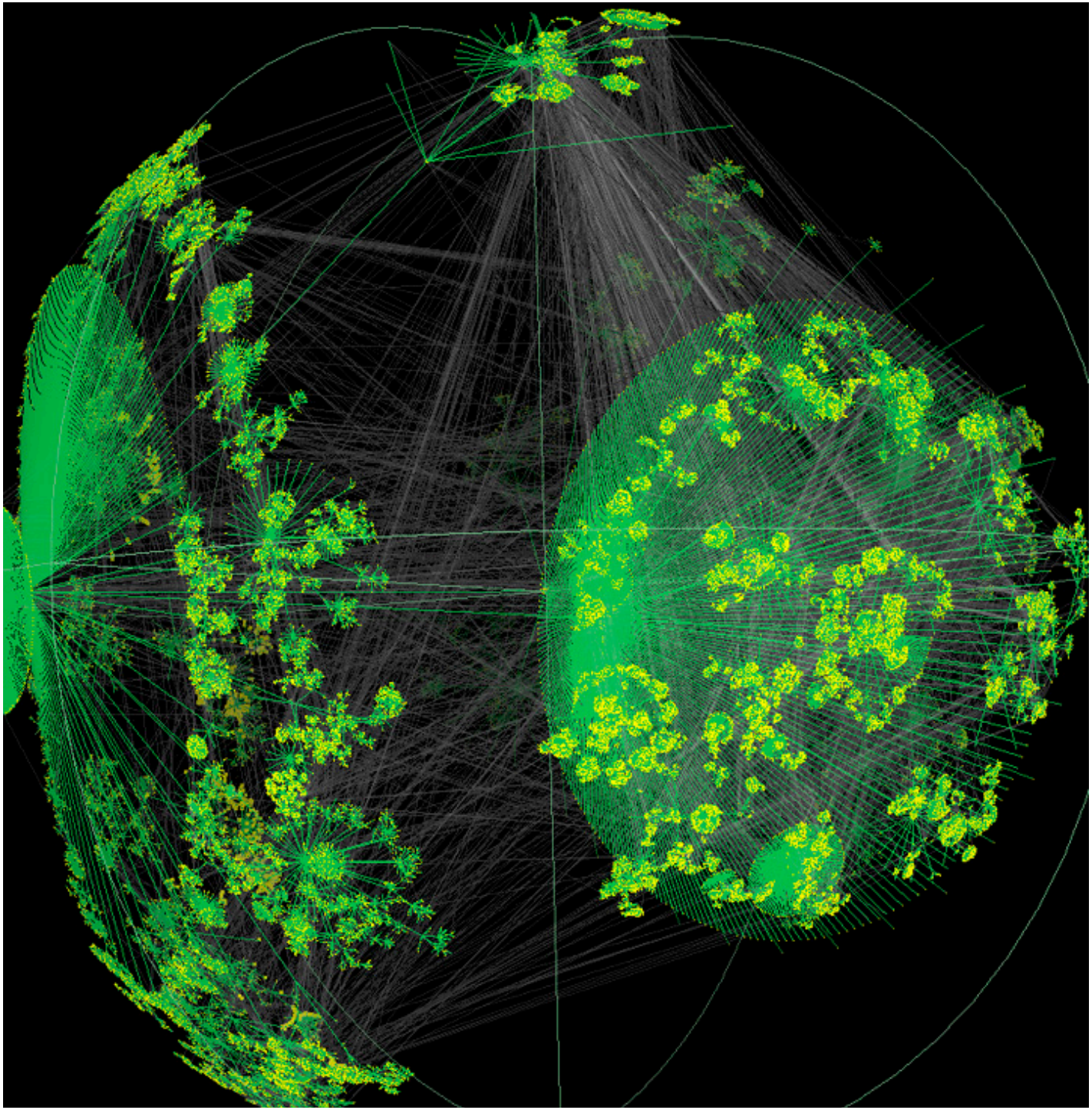


Figure 2. *Graph of Russian trade routes in the 12th - 13th centuries.*



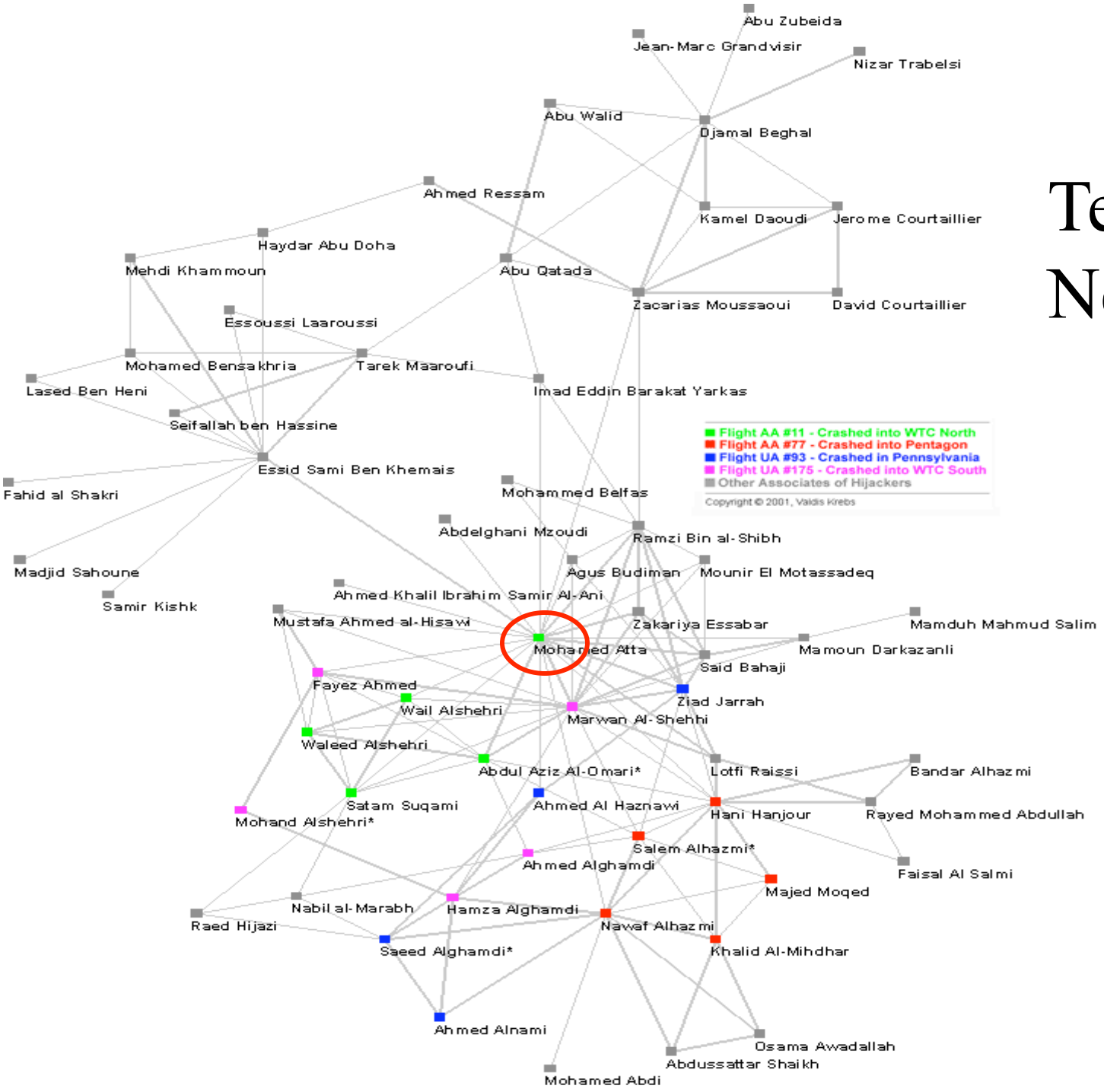
Connection Array			Short-Path	
Actual	**Percentage**	**Place**	**Actual**	**Rank**
2652	0.51	Novgorod	176	35
3574	0.68	Vitebsk	172	32
9521	1.82	Smolensk	148	17.50
5303	1.01	Kiev	173	33
8691	1.66	Chernikov	181	36
10181	1.95	Novgorod Severskiy	162	28
14703	2.81	Kursk	160	26
26898	5.15	Bryansk	130	9
18662	3.57	Karachev	157	22.50
41022	7.85	Kozclsk	116	4
24001	4.59	Dorogobusch	121	7
36292	6.94	Vyarma	113	3
11282	2.16	"A"	132	11
14843	2.84	Tver	128	8
5184	0.99	Vishniy Totochck	158	24
19451	3.72	Ksyatyn	118	5.50
6883	1.32	Uglich	152	20
3114	0.60	Yaroslavi'	184	38
3415	0.65	Rostov	182	37
8150	1.56	"B"	148	17.50
3711	0.71	"C"	174	34
4249	0.81	Suzdal	163	29
10344	1.98	Vladimir	133	12
4518	0.86	Nizhniy Novgorod	161	27
1394	0.27	Bolgar (Kazan)	198	39
7101	1.36	Isad'-Ryazan	156	21
8135	1.56	Pronsk	159	25
8671	1.66	Dubok	157	22.50
9248	1.77	Elets	170	30
23936	4.58	M tsensk	141	15
17717	3.39	Tula	145	16
21015	4.02	Dedoslavi'	131	10
13414	2.57	Pereslavj'	134	13
39478	7.55	Kolomna	104	1
26663	5.10	Moscow	107	2
22016	4.21	Mozhaysk	118	5.50
9954	1.90	Dmitrov	151	19
13681	2.62	Volok Lamskiy	138	14
3515	0.67	Murom	171	31


France
Austria
Belgium
Italy
Germany
Netherla
Switzerl
Spain
Portugal
Ireland
UK
Sweden
Denmark
Norway
Finland
USA
Iceland
Japan
Canada
Thailand
Korea
Australi
Malaysia
Singapor

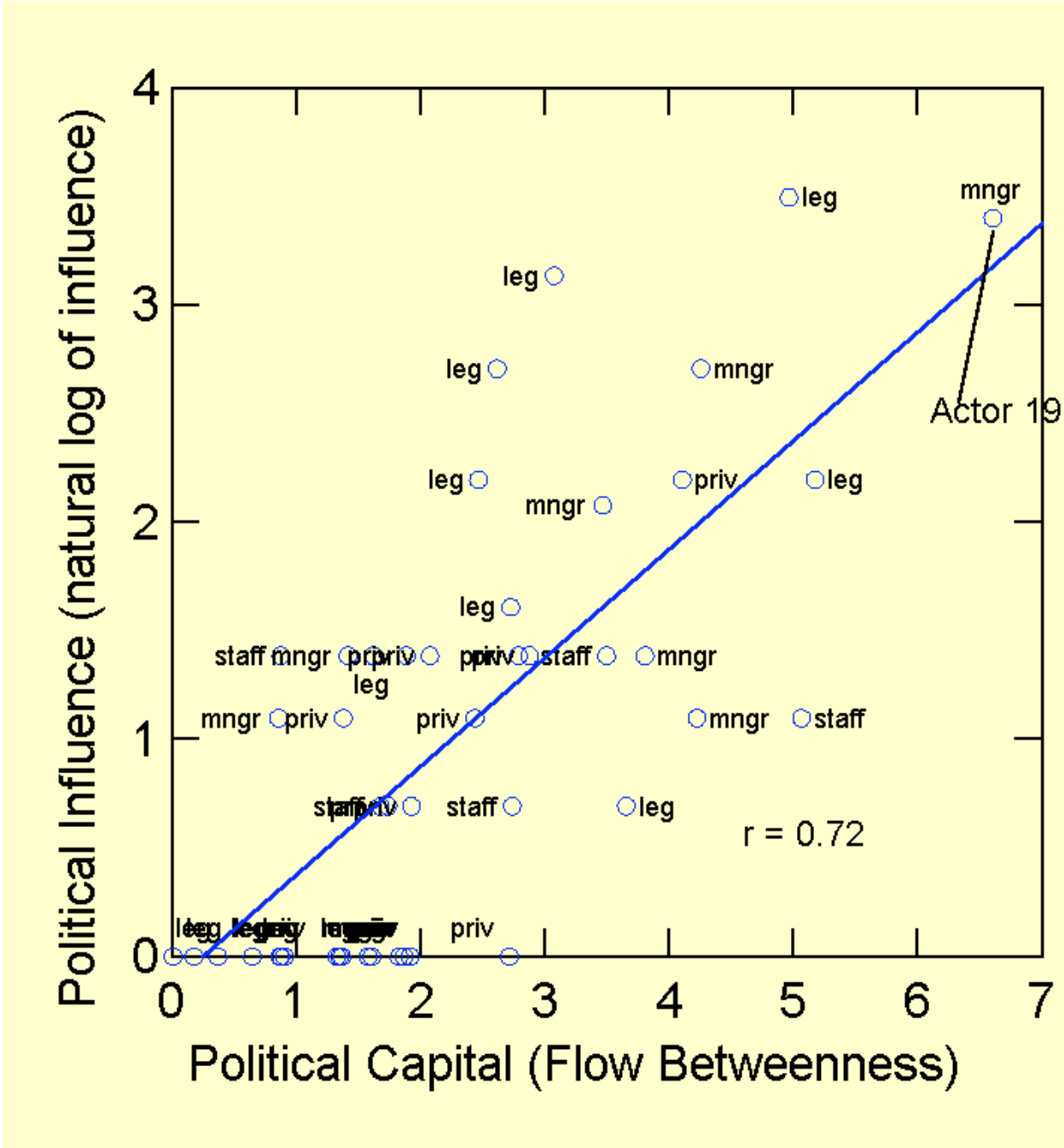


Network Topology of the Internet

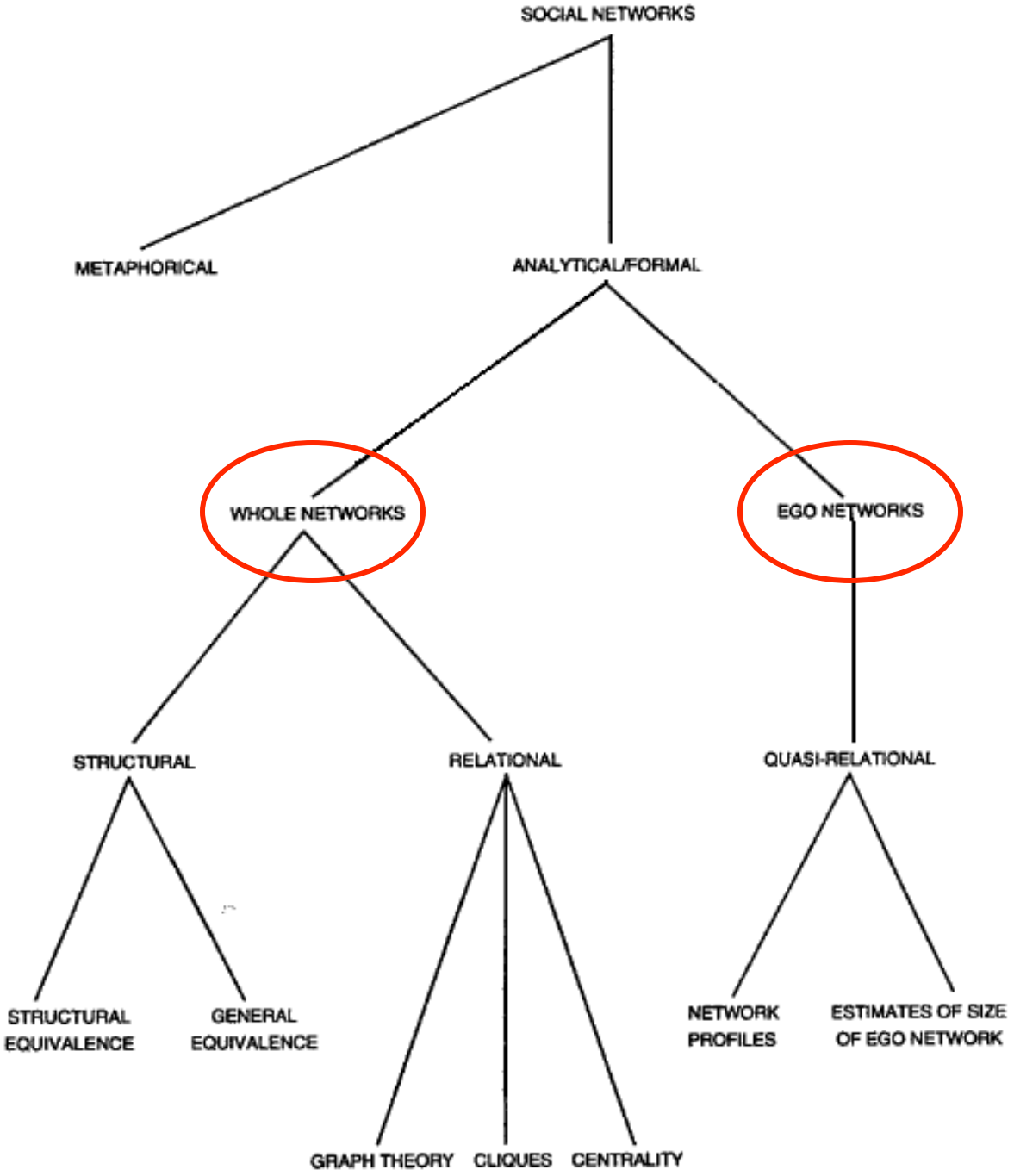
Terrorist Network



- “Well of course ‘Actor 19’; he was probably the major player. He had a lot of help, but he was the major player. Without him providing the ***political capital*** I don’t think it would ever have happened.”(Actor 27, an important lobbyist)


Political Influence (natural log of influence)
Political Capital (Flow Betweenness)
Actor 19
r = 0.72
0
1
2
3
4
5
6
7
leg
mngr
priv
staff

Politics is one social context in which the term ‘capital’, in the form of political capital, is used in every day political discourse.

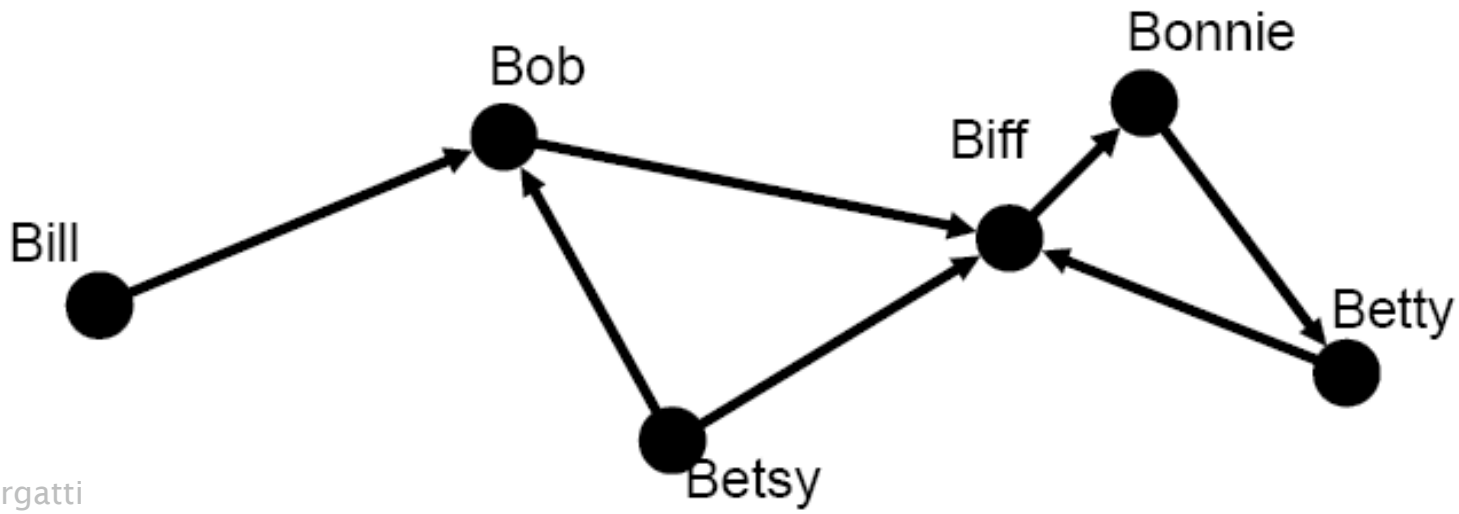

SOCIAL NETWORKS
METAPHORICAL
ANALYTICAL/FORMAL
WHOLE NETWORKS
EGO NETWORKS
STRUCTURAL
RELATIONAL
QUASI-RELATIONAL
STRUCTURAL EQUIVALENCE
GENERAL EQUIVALENCE
GRAPH THEORY
CLIQUES
CENTRALITY
NETWORK PROFILES
ESTIMATES OF SIZE OF EGO NETWORK

Network Science: What's Involved?

- DATA
  - Network Data (Interaction, Advice)
  - Non-Network Data (Nonstructural Attributes)
- Theory (The Substance)
  - Describe
  - Explain
  - Predict
- Measures (e.g., Centrality, Clustering Coefficient)
  - Structural Features at Various Levels (Individual Actor, Group, Society)
- Models (The Formalization and Validation of The Theory)
  - Cross-sectional (ERGM, MCMC)
  - Dynamic (SIENA)

What is a Network?

- A set of dyadic ties, all of the same type, among a set of actors
- Actors can be persons, organizations …
- A tie is an instance of a social relation



From Borgatti

Relations Among Persons

- Kinship
  - mother of, wife of
- Other role-based
  - boss of, teacher of
  - friend of
- Cognitive/perceptual
  - knows
  - aware of what they know
- Affective
  - likes, trusts
- Interactions
  - give advice, talks to, fights with
  - sex / drugs with
- Affiliations
  - belong to same clubs
  - is physically near

Note: Content matters!
Each relation yields a different structure & has different effects

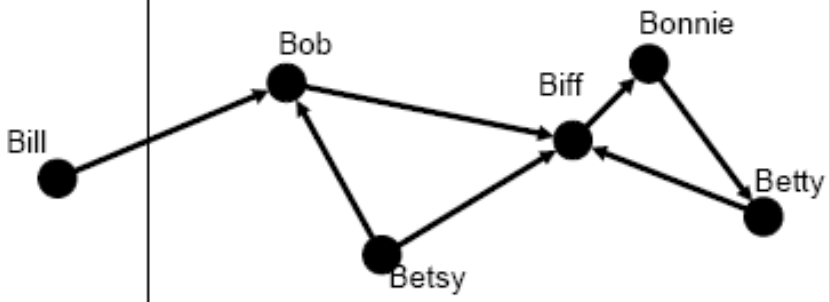
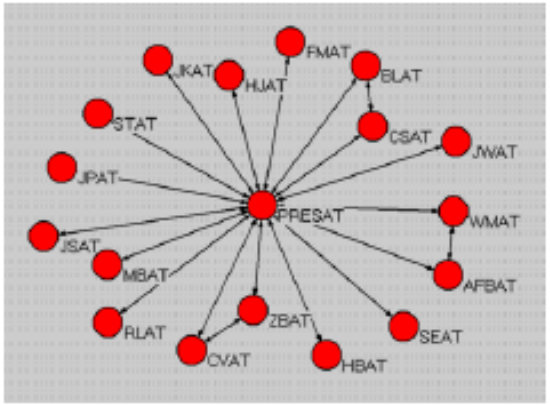
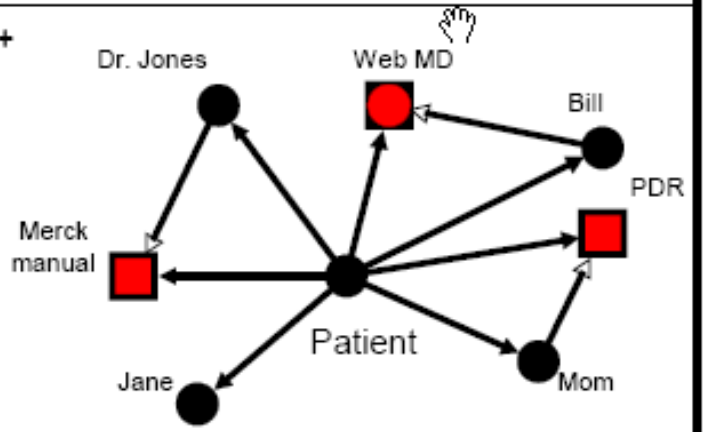
From Borgatti

Relations Among Organizations

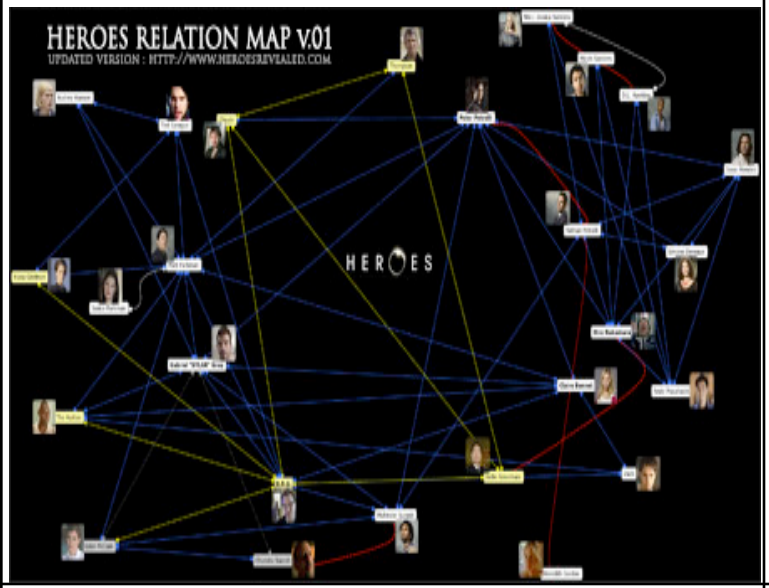
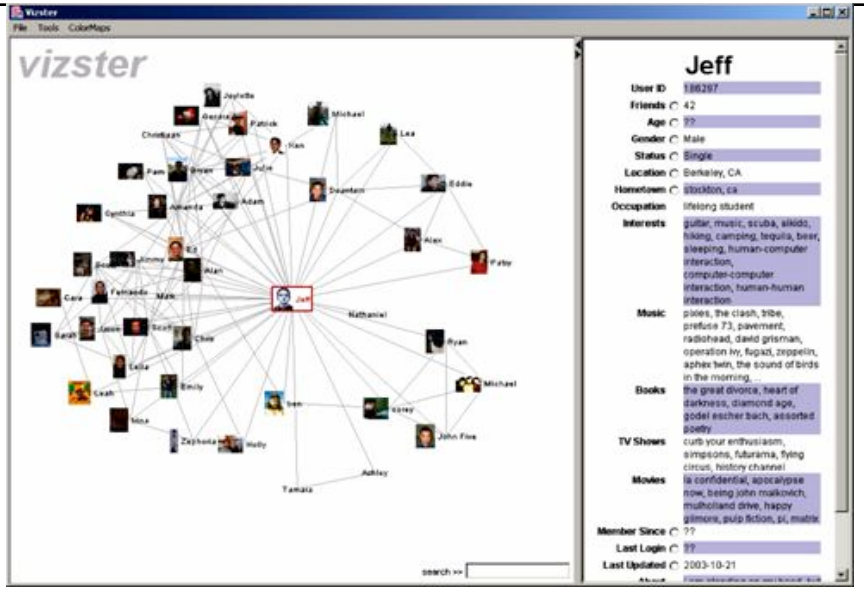
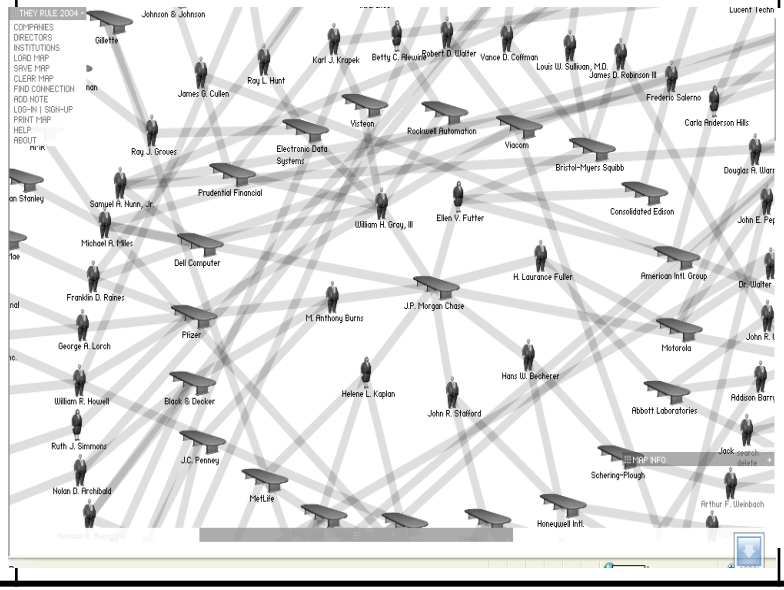
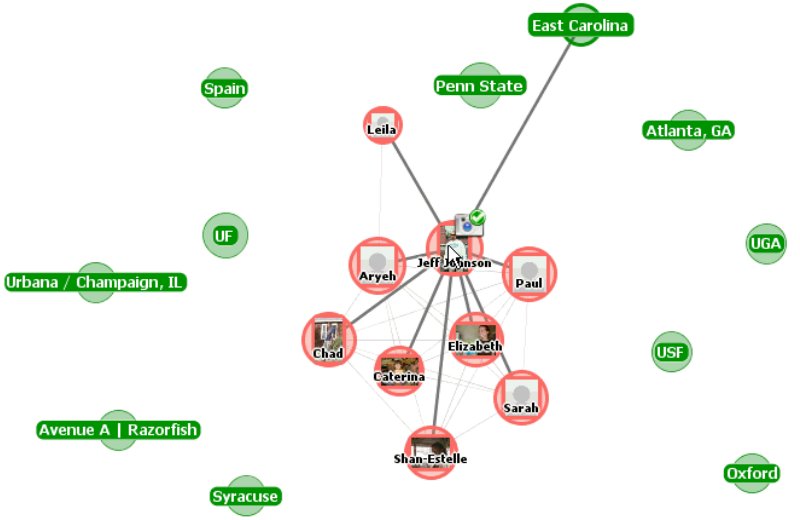
- As corporate entities
  - Buy from / sell to, leases to, outsources to
  - Owns shares of, subsidiary of
  - Joint ventures, cooperate sales agreements, alliances
  - Regulates
- Via their members
  - Personnel flows
  - Interlocking directorates
  - Personal friendships
  - Co-memberships

From Borgatti

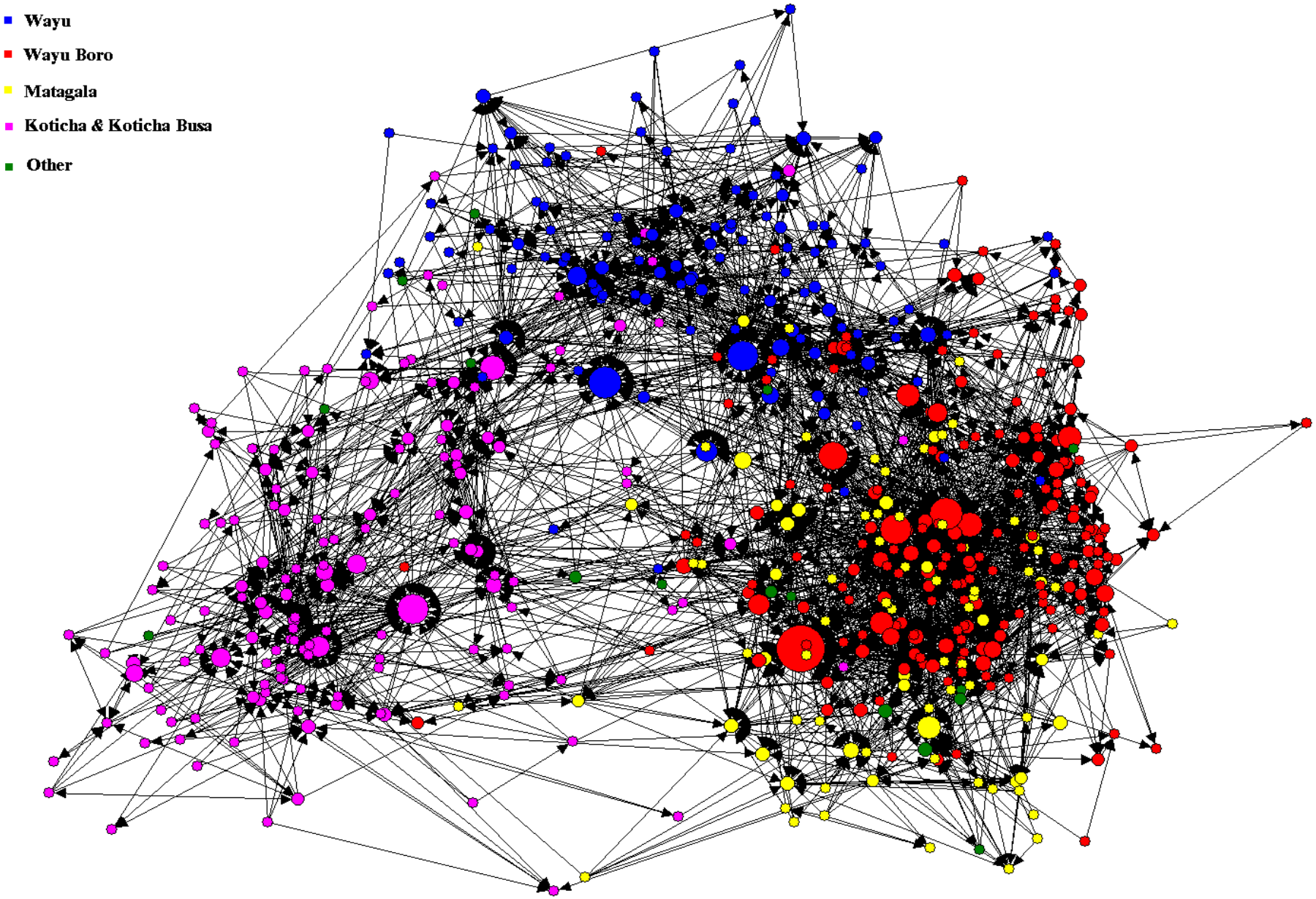
Kinds of Network Data

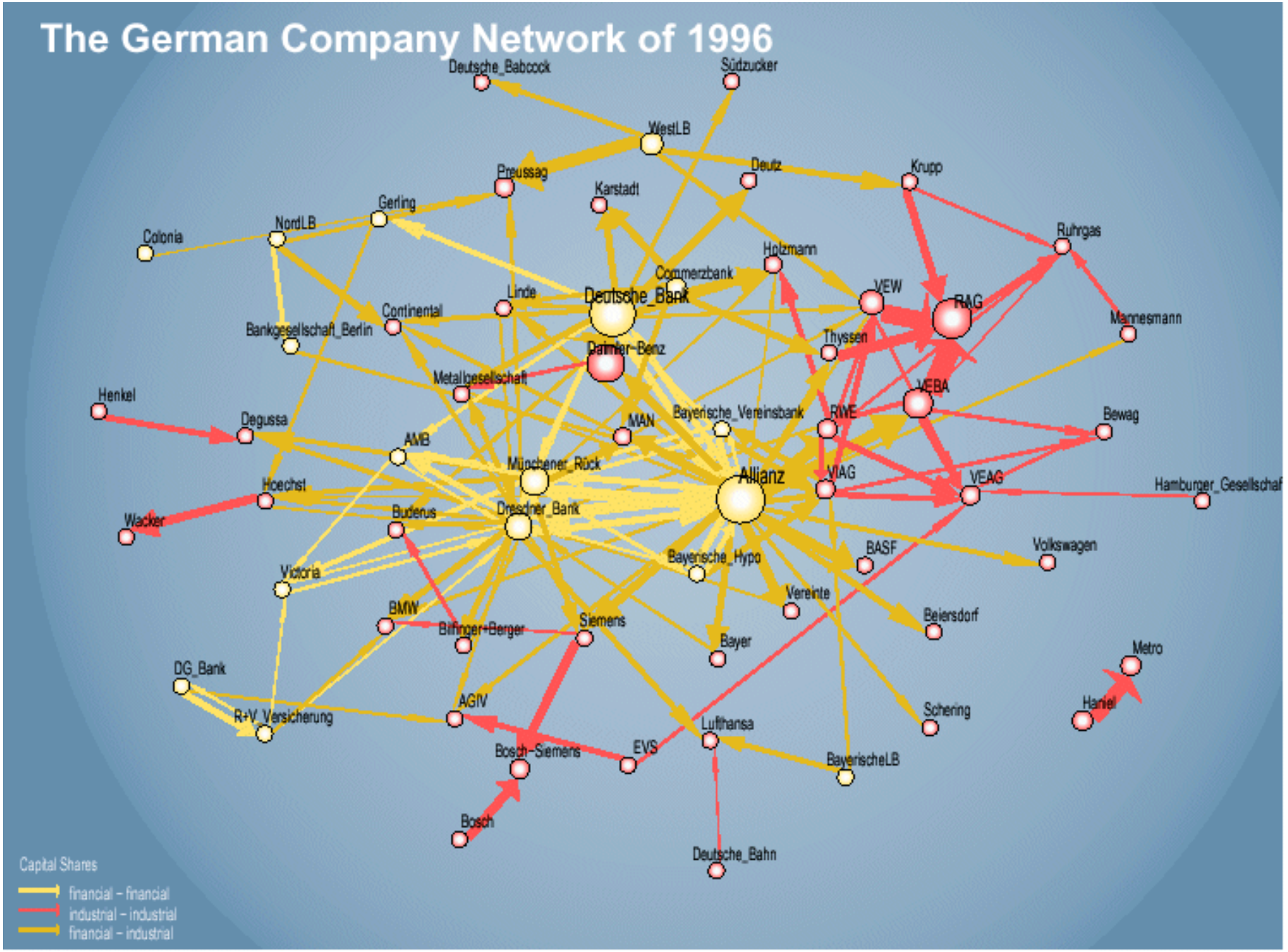
	Complete	Ego
1-mode	++++ 	++++ 
2-mode	** 	+ 

From Borgatti

	Complete	Ego
1-Mode		
2-Mode		

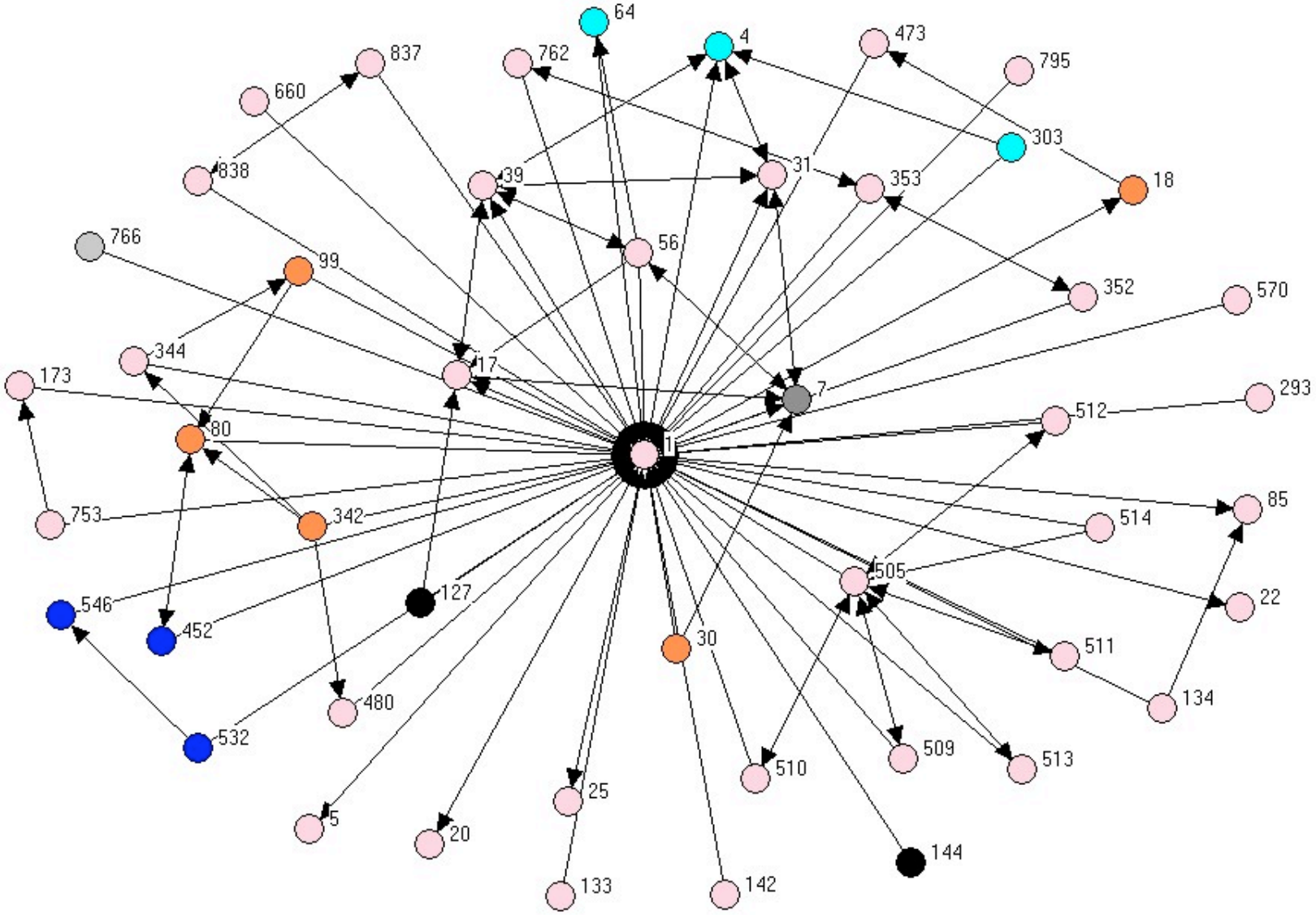
1-mode complete network


Wayu
Wayu Boro
Matagala
Koticha & Koticha Busa
Other

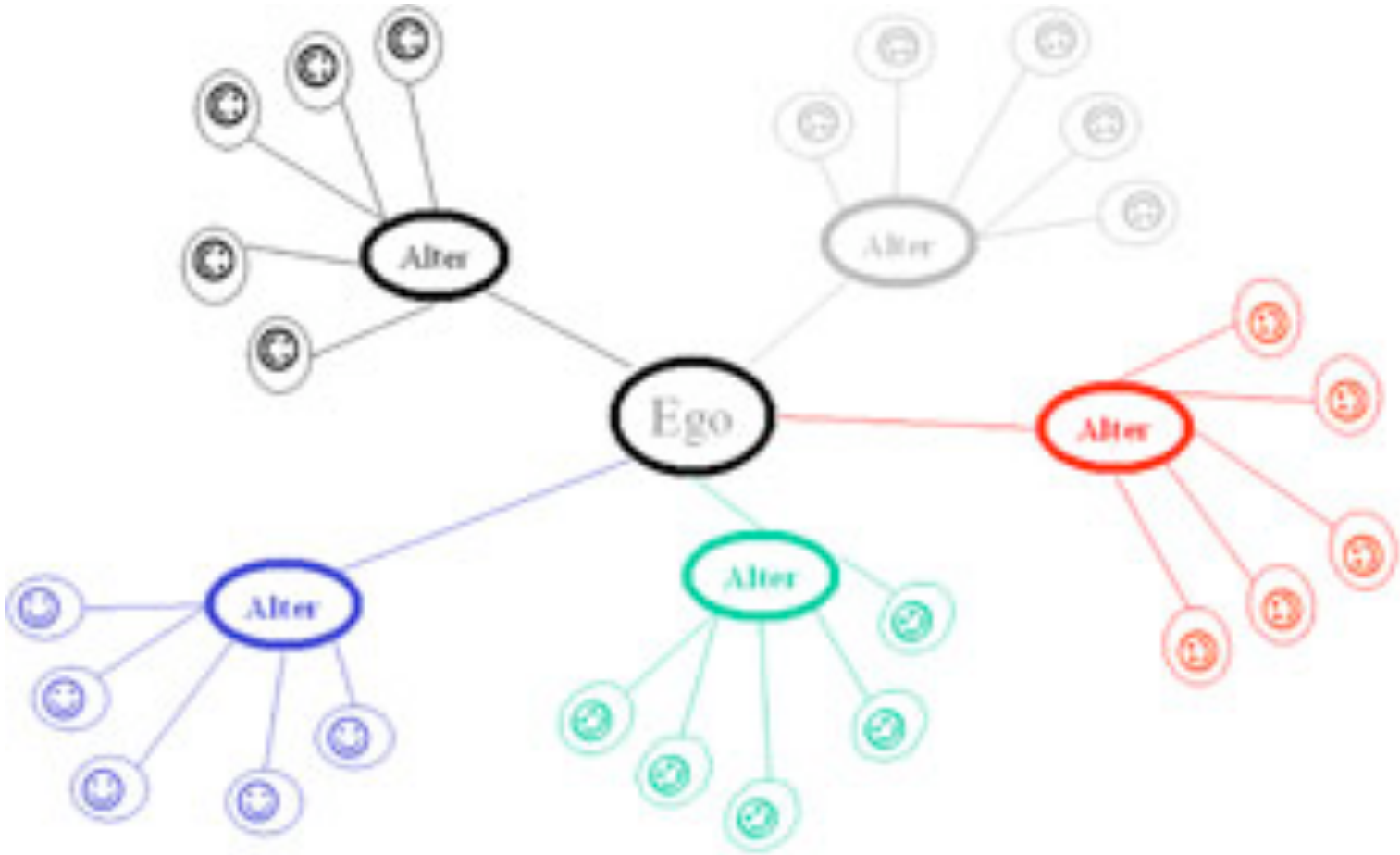

The German Company Network of 1996
Deutsche_Babcock
Südzucker
WestLB
Preussag
Deutz
Krupp
Karstadt
Gerling
NordLB
Colonia
Ruhrgas
Holzmann
Commerzbank
Linde
Deutsche_Bank
VEW
RAG
Continental
Mannesmann
Bankgesellschaft_Berlin
Thyssen
Daimler-Benz
Metallgesellschaft
VEBA
Henkel
Degussa
Bayerische_Vereinsbank
RWE
Bewag
MAN
AMB
Münchener_Rück
Allianz
VIAG
VEAG
Hamburger_Gesellschaf
Hoechst
Wacker
Buderus
Dresdner_Bank
BASF
Volkswagen
Bayerische_Hypo
Victoria
Vereinte
BMW
Beiersdorf
Bilfinger+Berger
Siemens
Bayer
Metro
DG_Bank
Haniel
AGIV
Schering
R+V_Versicherung
Lufthansa
Bosch-Siemens
EVS
BayerischeLB
Bosch
Deutsche_Bahn
Capital Shares
financial – financial
industrial – industrial
financial – industrial

Ego Network Analysis

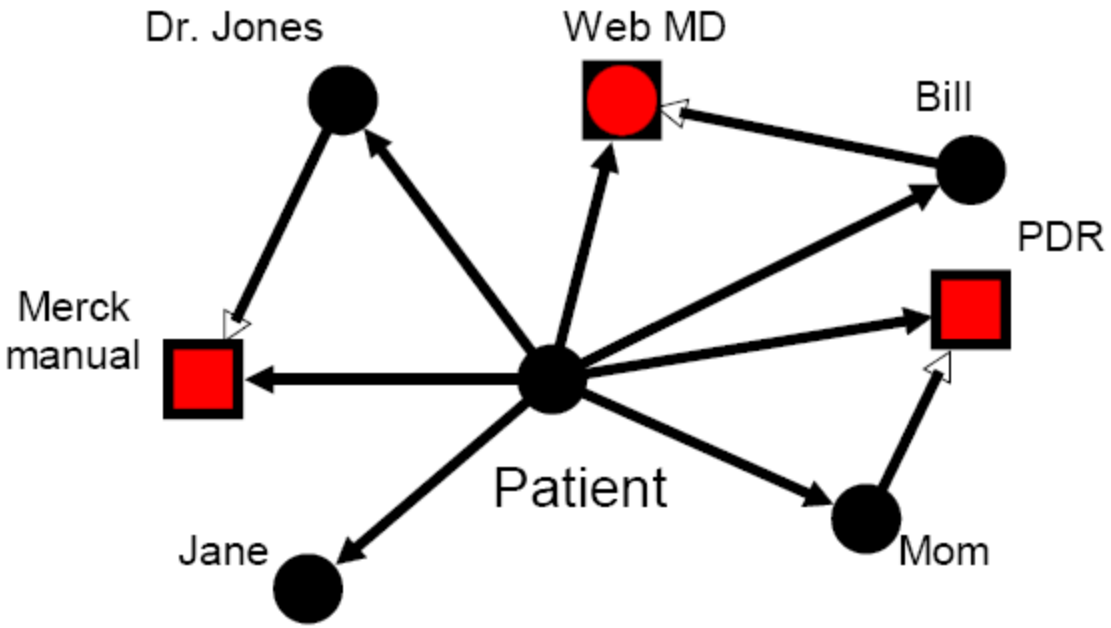
1-mode ego network



Osama Financial Sources and Sinks

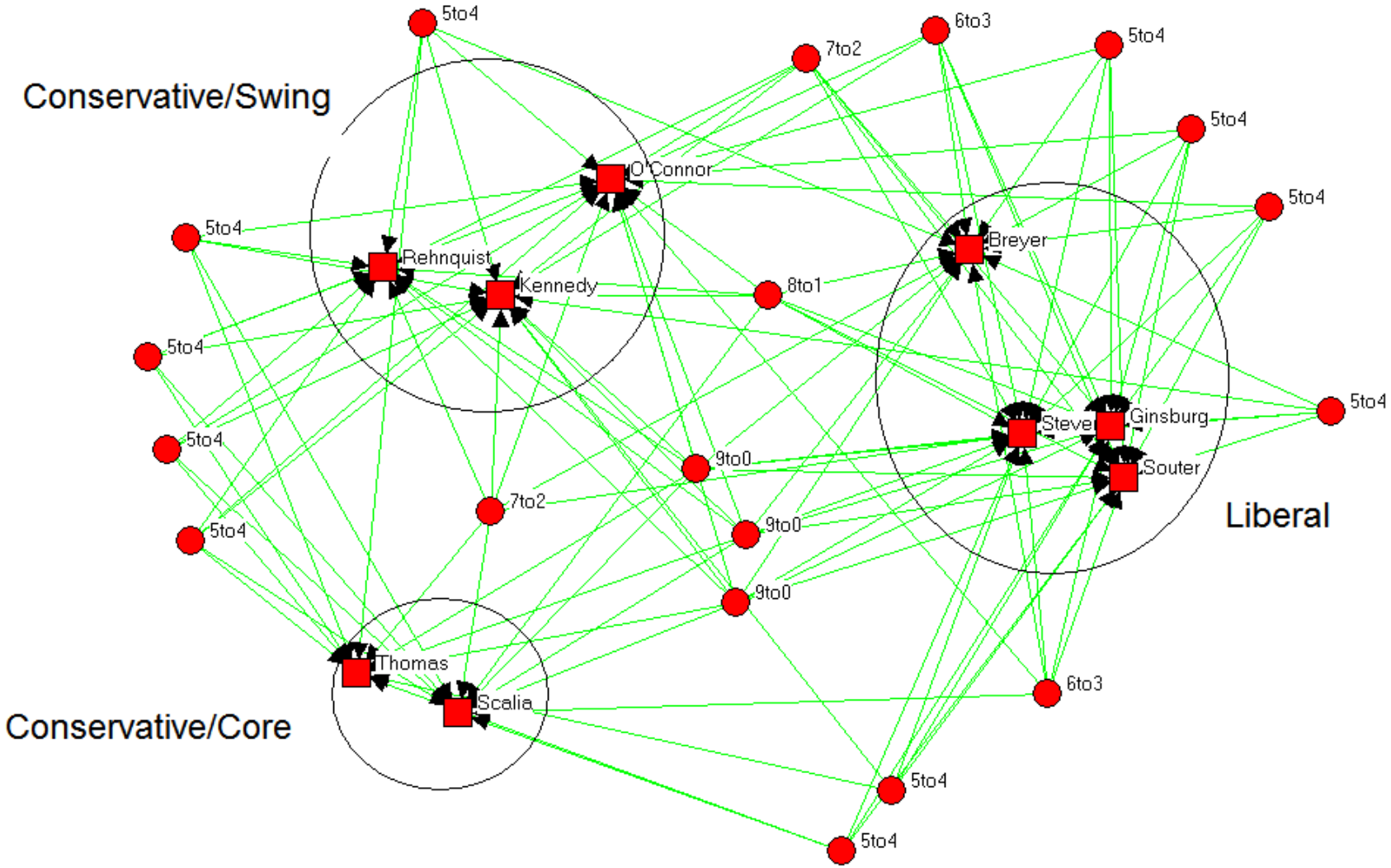

Alter
Alter
Ego
Alter
Alter
Alter

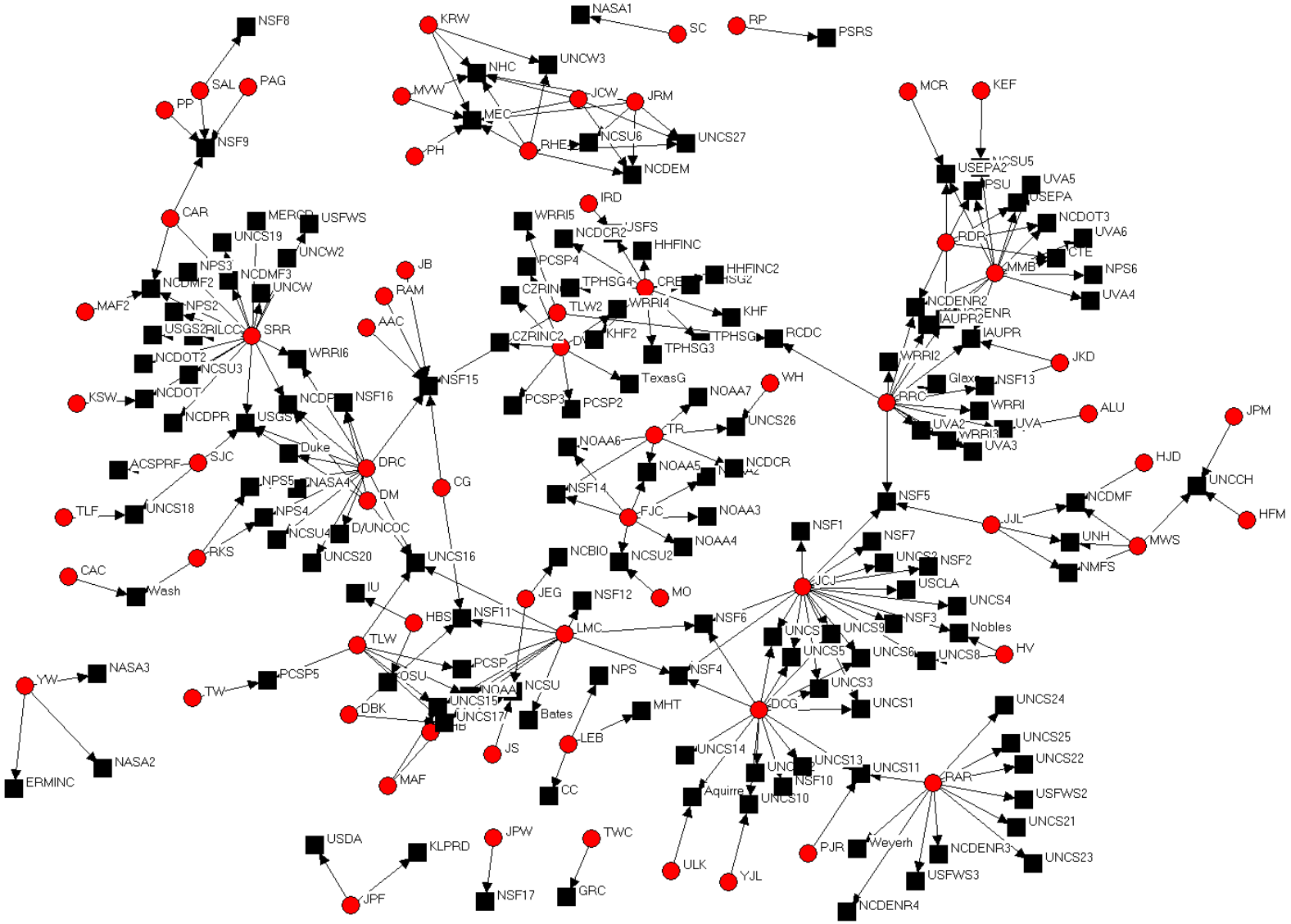
2-mode Ego Network

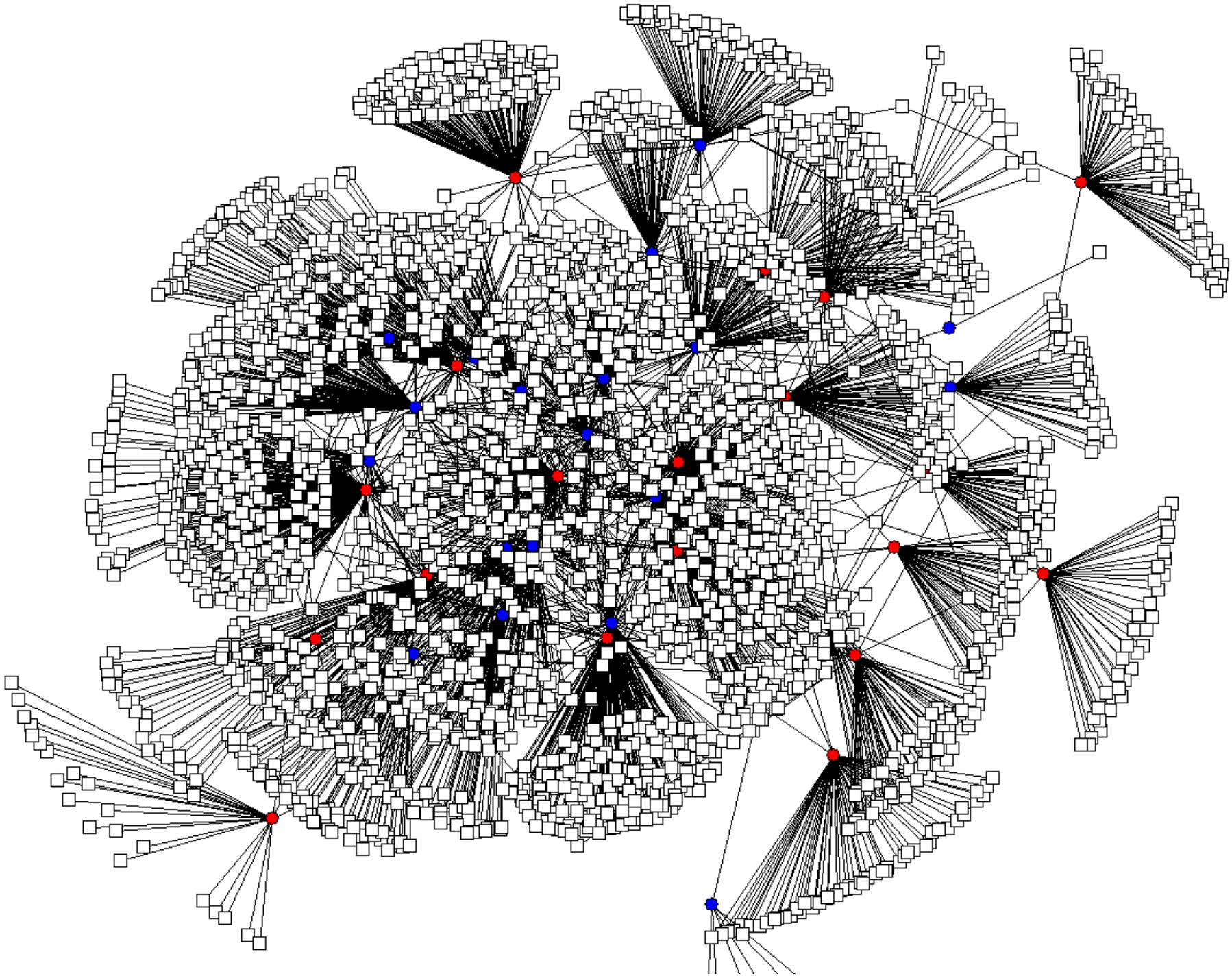


From Borgatti

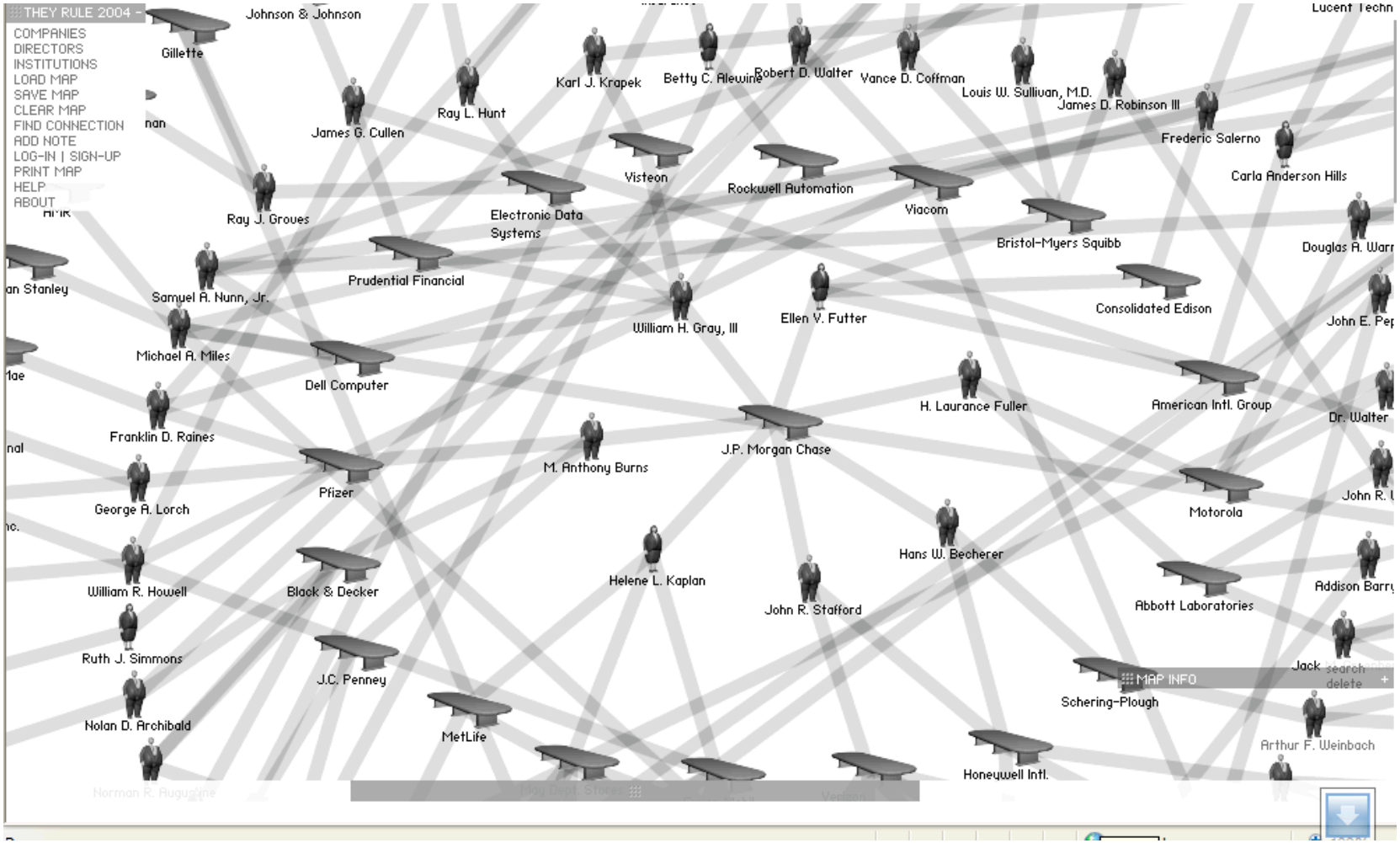
2-mode complete network

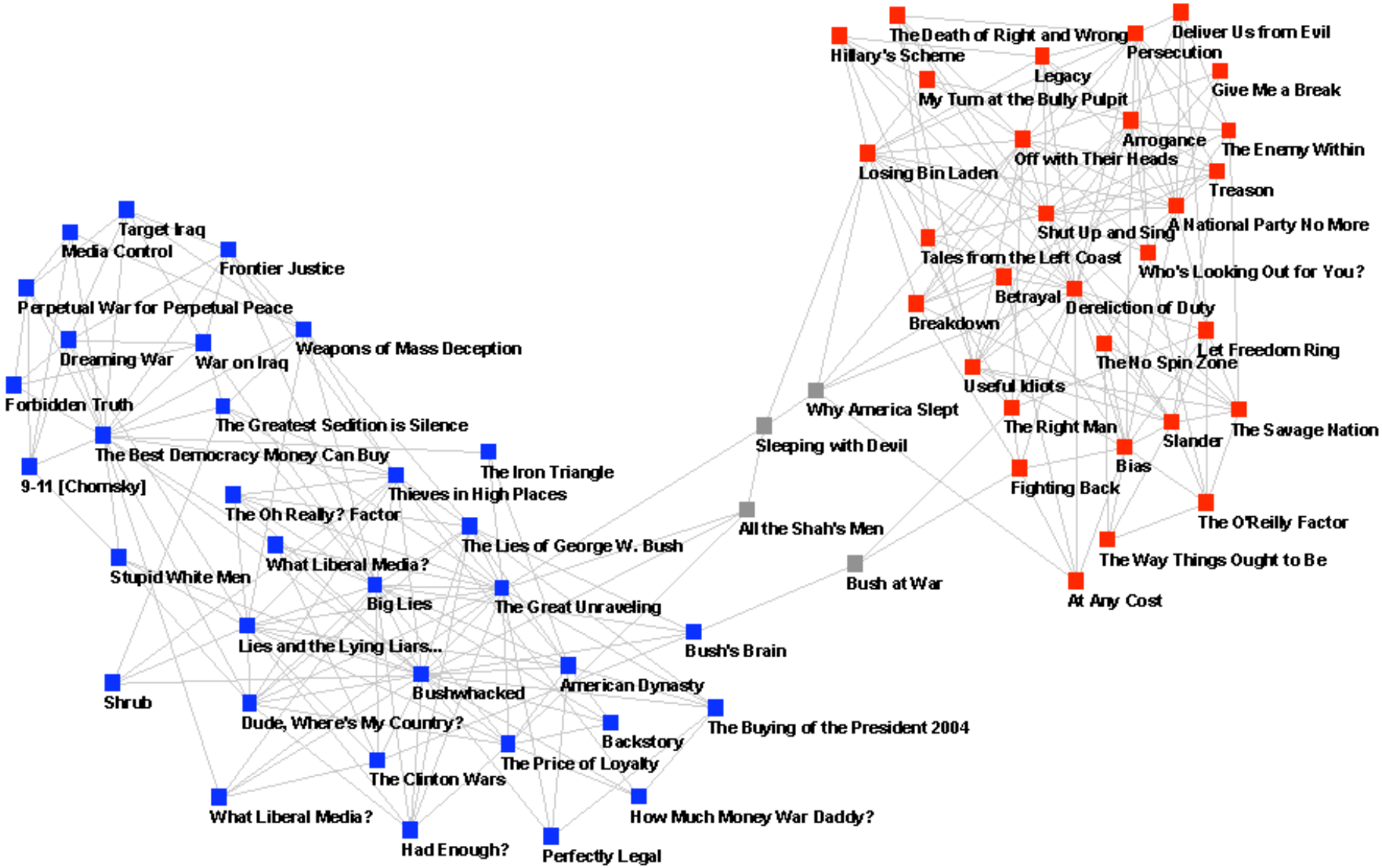

Conservative/Swing
Liberal
Conservative/Core
5to4
7to2
6to3
5to4
5to4
O'Connor
5to4
5to4
Rehnquist
Breyer
Kennedy
8to1
5to4
5to4
Steven
Ginsburg
9to0
Souter
5to4
7to2
9to0
5to4
9to0
Thomas
6to3
Scalia
5to4
5to4


NSF8
SAL
PAG
PP
NSF9
CAR
MERCD
USFWS
UNCS19
UNCW2
NPS3
NCDMF2
NCDMF3
UNCW
MAF2
NPS2
USGS2
RILCC
SRR
NCDOT2
NCSU3
WRRI6
KSW
NCDOT
NCDPR
USGS
NCDP
NSF16
ACSPRF
SJC
Duke
DRC
TLF
UNCS18
NPS5
NASA4
DM
NPS4
NCSU4
D/UNCOC
UNCS20
RKS
CAC
Wash
KRW
NASA1
SC
RP
PSRS
UNCW3
NHC
MVW
JCW
JRM
MEC
NCSU6
UNCS27
PH
RHE
NCDEM
JB
RAM
AAC
NSF15
CG
UNCS16
IRD
WRRI5
NCDCR2
USFS
HHFINC
PCSP4
HHFINC2
CZRINC
TPHSG4
CRE
TLW2
WRRI4
KHF
CZRINC2
KHF2
TPHSG3
TPHSG
RCDC
TexasG
PCSP3
PCSP2
WH
NOAA7
UNCS26
TR
NOAA6
NOAA5
NCDCR
NSF14
FJC
NOAA3
NOAA4
NCSU2
NCBIO
MO
JEG
NSF12
IU
HBS
NSF11
LMC
TLW
PCSP5
TW
PCSP
COSU
NOAA
NCSU
UNCS15
UNCS17
Bates
DBK
JS
MAF
NPS
MHT
LEB
CC
NSF4
NSF6
MCR
KEF
USEPA2
NCSU5
PSU
UVA5
USEPA
NCDOT3
UVA6
RDR
CTE
MMB
NPS6
UVA4
NCDENR2
NCDENR
IAUPR2
IAUPR
JKD
WRRI2
Glex
NSF13
RRC
WRRI
ALU
UVA2
UVA
WRRI3
UVA3
JPM
HJD
UNCCH
HFM
NCDMF
JJL
UNH
MWS
NMFS
NSF5
NSF1
NSF7
UNCS2
NSF2
JCJ
USCLA
UNCS4
NSF3
Nobles
UNCS7
UNCS9
UNCS5
UNCS6
UNCS8
HV
UNCS3
DCG
UNCS1
UNCS24
UNCS25
UNCS22
UNCS14
UNCS13
UNCS11
RAR
USFWS2
Aquirre
NSF10
UNCS10
UNCS21
PJR
Weyerh
NCDENR3
UNCS23
USFWS3
NCDENR4
ULK
YJL
USDA
KLPRD
JPW
TWC
JPF
NSF17
GRC
YW
NASA3
NASA2
ERMINC



Fortune 500 Boards
Overlapping Directorates




The Death of Right and Wrong
Deliver Us from Evil
Hillary's Scheme
Persecution
Legacy
Give Me a Break
My Turn at the Bully Pulpit
Arrogance
The Enemy Within
Off with Their Heads
Losing Bin Laden
Treason
A National Party No More
Shut Up and Sing
Tales from the Left Coast
Who's Looking Out for You?
Betrayal
Dereliction of Duty
Breakdown
Let Freedom Ring
The No Spin Zone
Useful Idiots
Why America Slept
The Right Man
Slander
The Savage Nation
Sleeping with Devil
Bias
Fighting Back
The O'Reilly Factor
All the Shah's Men
The Way Things Ought to Be
Bush at War
At Any Cost
Target Iraq
Media Control
Frontier Justice
Perpetual War for Perpetual Peace
Weapons of Mass Deception
Dreaming War
War on Iraq
Forbidden Truth
The Greatest Sedition is Silence
The Best Democracy Money Can Buy
The Iron Triangle
9-11 [Chomsky]
Thieves in High Places
The Oh Really? Factor
The Lies of George W. Bush
What Liberal Media?
Stupid White Men
Big Lies
The Great Unraveling
Lies and the Lying Liars...
Bush's Brain
Shrub
Bushwhacked
American Dynasty
Dude, Where's My Country?
The Buying of the President 2004
Backstory
The Price of Loyalty
The Clinton Wars
What Liberal Media?
How Much Money War Daddy?
Had Enough?
Perfectly Legal

The Network Perspective

- Relations vs. Attributes
  - Individual characteristics only half the story
  - People influence each other, ideas & materials flow
  - Predicting adoption of innovation
  - Interdependence vs atomistic essentialism
- Structure vs. Composition
  - It's not just the elements of a system, but how they are put together
  - non-reductionist, holistic, systemic

From Borgatti

Levels of Focus

- Macro--attributes and characteristics of the whole network
- Micro--attributes and characteristics of the individual node and subgroup
- These characteristics have important implications

Macro

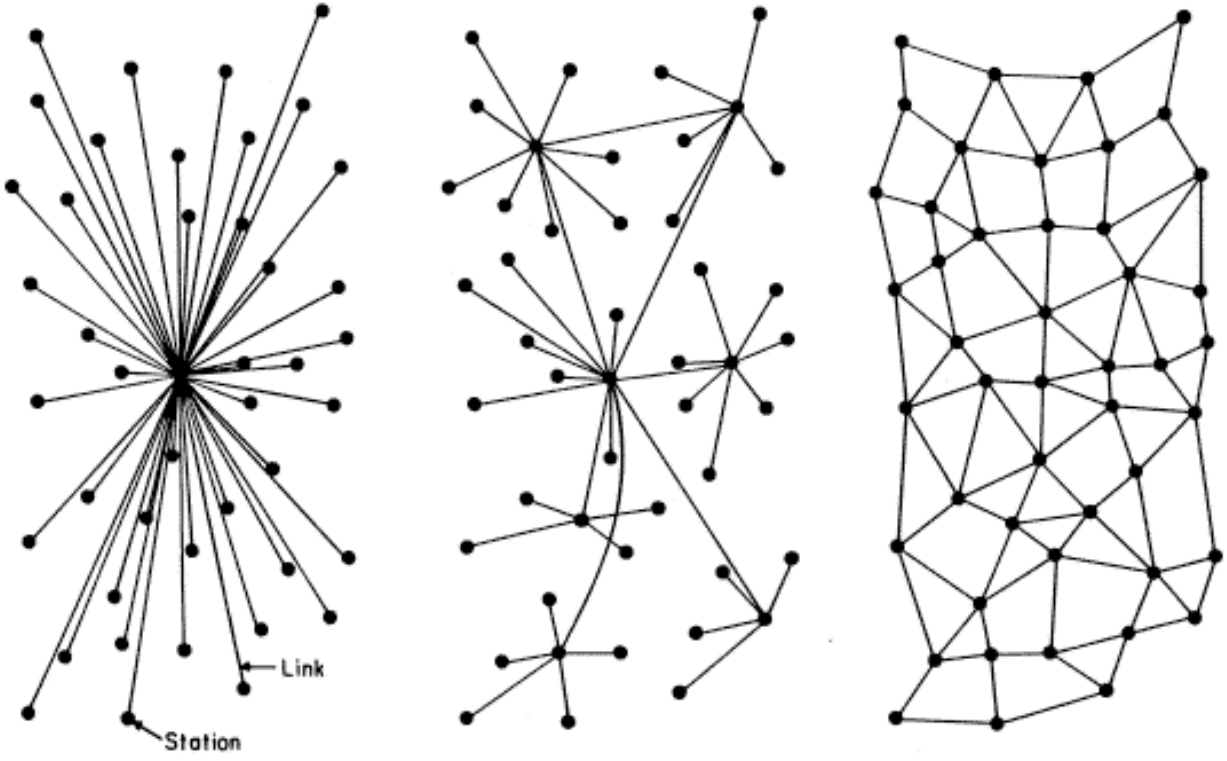
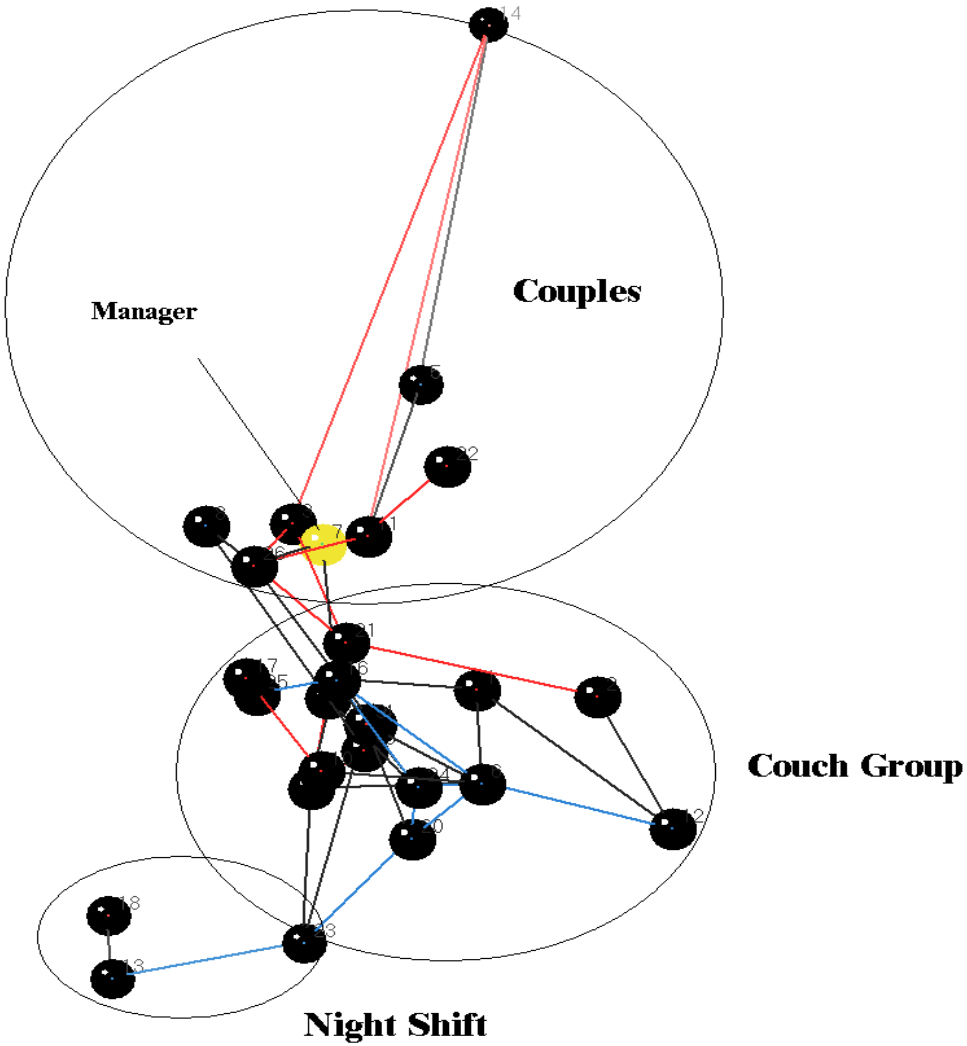
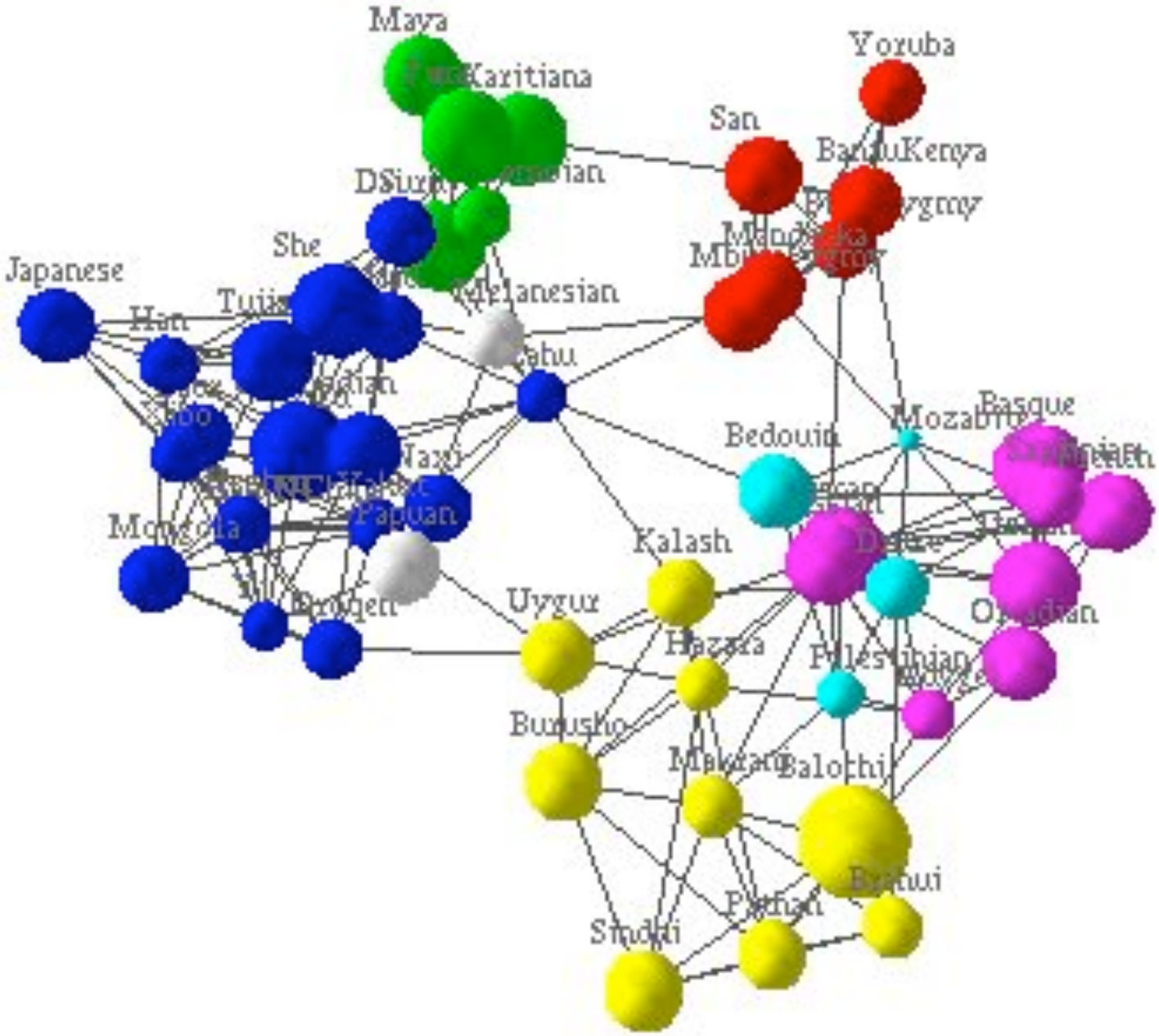


FIG. 1 — Centralized, Decentralized and Distributed Networks

Micro

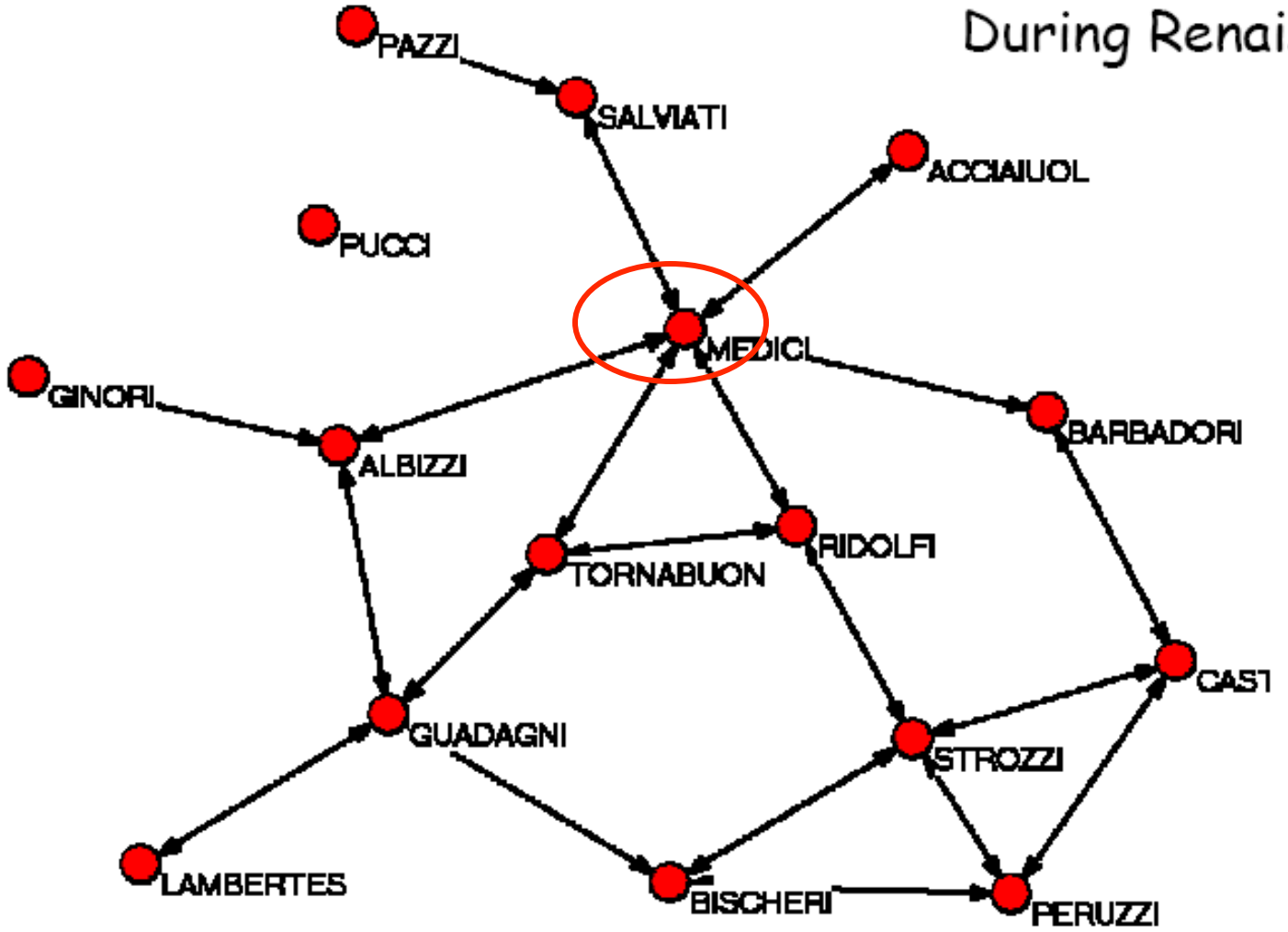



Maya
Karitiana
Yoruba
San
Japanese
She
Melanesian
Bedouin
Basque
Kalash
Uygur
Hazara
Palestinian
Burusho
Balochi
Brahui
Pathan
Sindhi

Example of a Network

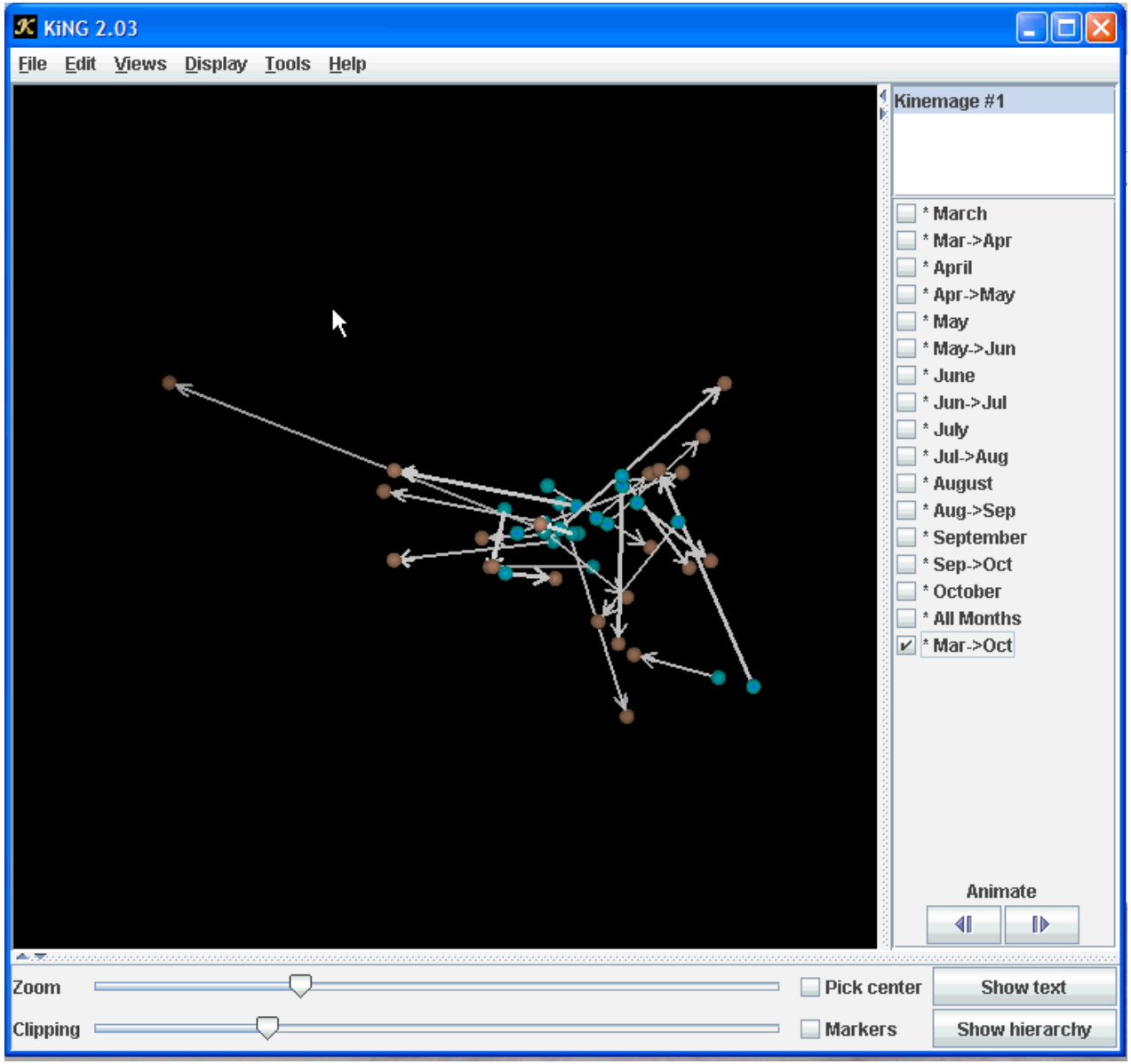
Marriage Ties Among Florentine Families

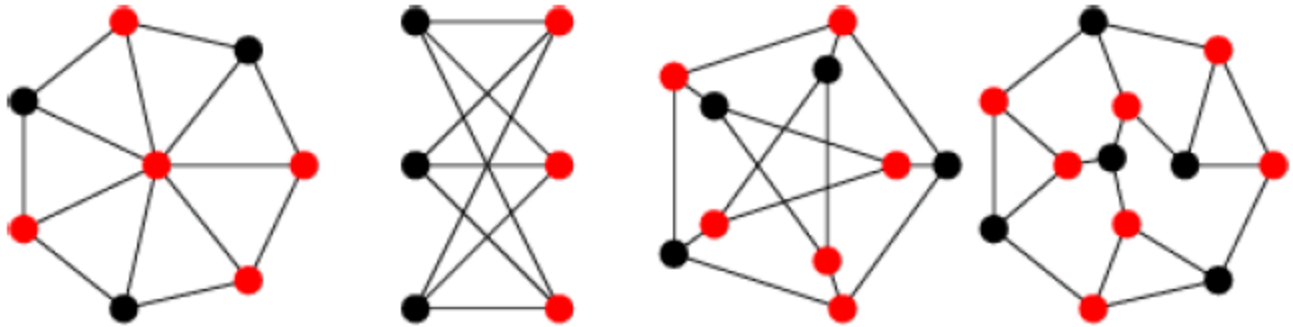
During Renaissance times



Data compiled by John Padgett

Dynamic Networks

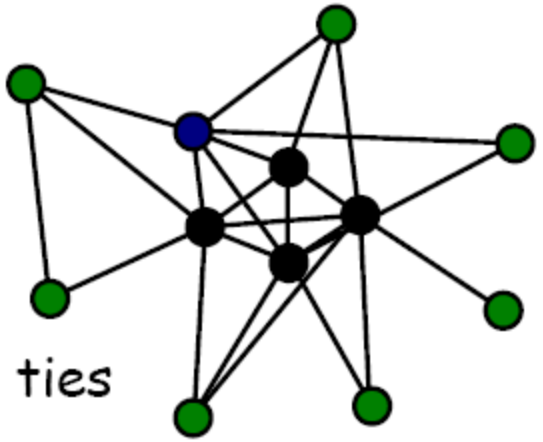


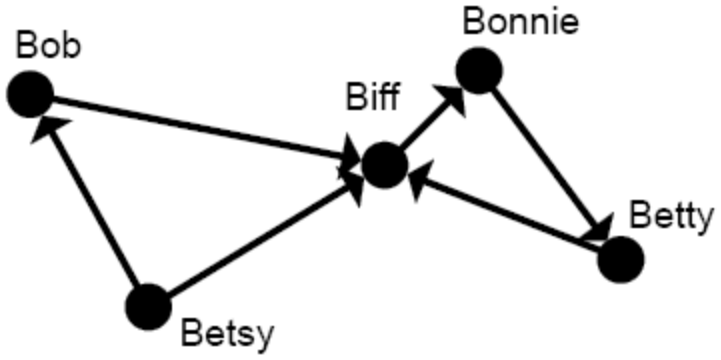


Graph Theoretic Concepts

Directed vs undirected ties

- Undirected relations
  - Attended meeting with
  - Communicates daily with
- Directed relations
  - Lent money to
- Logically vs empirically directed ties
  - Empirically, even un-directed relations can be non-symmetric due to measurement error

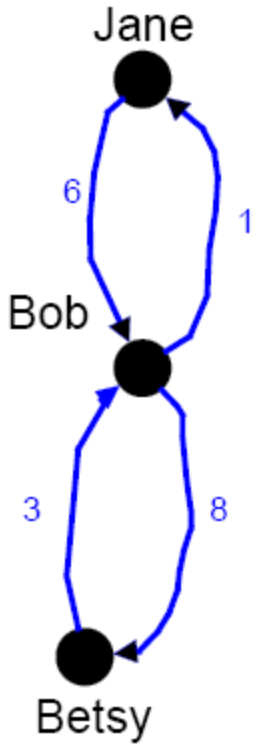




From Borgatti

Strength of Tie

- We can attach values to ties, representing quantitative attributes
  - Strength of relationship
  - Information capacity of tie
  - Rates of flow or traffic across tie
  - Distances between nodes
  - Probabilities of passing on information
  - Frequency of interaction



From Borgatti

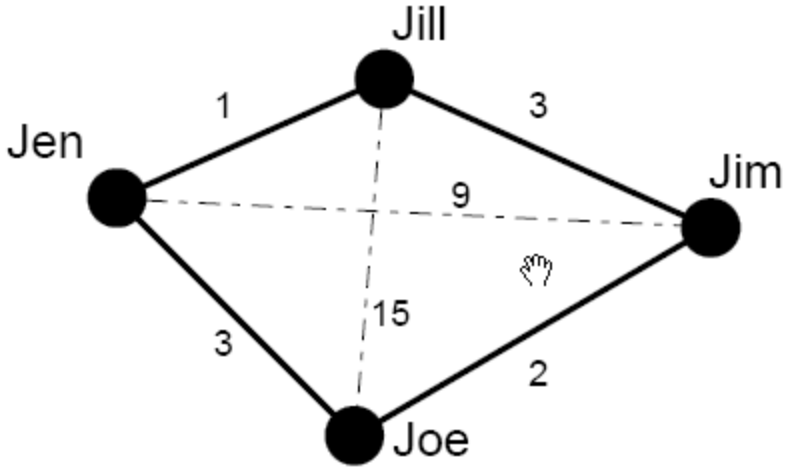
Adjacency Matrices

Friendship

	Jim	Jill	Jen	Joe
Jim	-	1	0	1
Jill	1	-	1	0
Jen	0	1	-	1
Joe	1	0	1	-

Proximity

	Jim	Jill	Jen	Joe
Jim	-	3	9	2
Jill	3	-	1	15
Jen	9	1	-	3
Joe	2	15	3	-



From Borgatti

Data Formats

Dl n = 5 Format = fullmatrix Labels embedded Data:	Dl n = 5 Format = nodelist Labels embedded Data:	Dl n = 5 Format = edgelist Labels embedded Data:
	Billy jill john jim jane Jill billy bob bertha Dick jane Jim bob billy brenda	Billy jill Billy john 6.3 Dick jane Jim bob 2.5

	billy	john	jill	mary
billy	0	1	0	0
john	1	0	1	0
jill	0	0	0	1
mary	1	0	1	0

(Values optional)

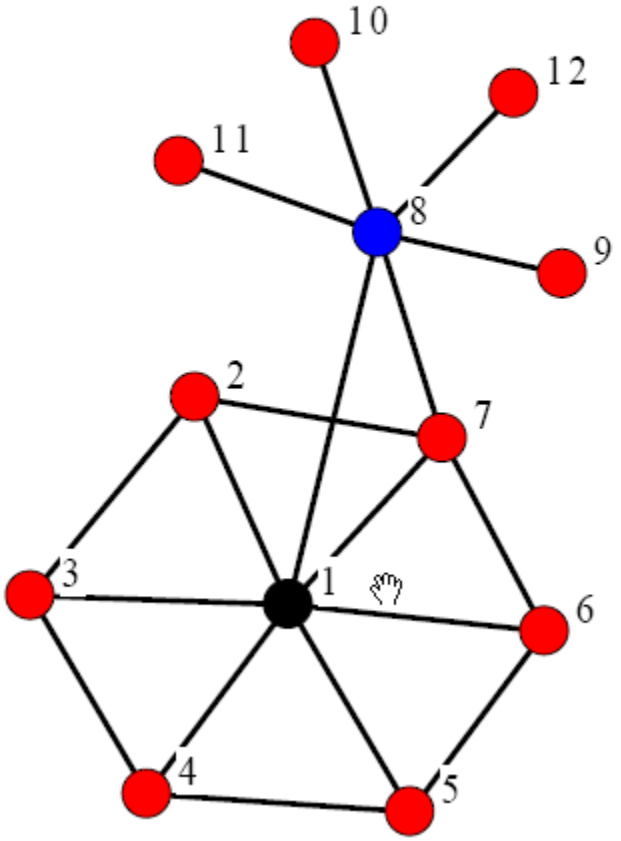
(No values possible)

(Values optional – assigned 1 if omitted)

From Borgatti

Length & Distance

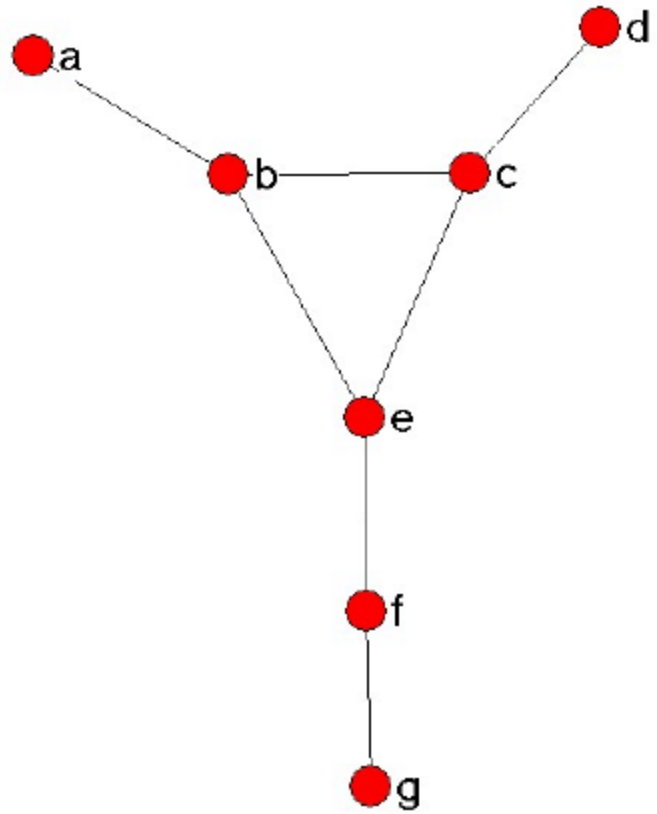
- Length of a path is number of links
- Distance between two nodes is length of shortest path (aka geodesic)



From Borgatti

Geodesic Distance Matrix

	a	b	c	d	e	f	g
a	0	1	2	3	2	3	4
b	1	0	1	2	1	2	3
c	2	1	0	1	1	2	3
d	3	2	1	0	2	3	4
e	2	1	1	2	0	1	2
f	3	2	2	3	1	0	1
g	4	3	3	4	2	1	0



From Borgatti

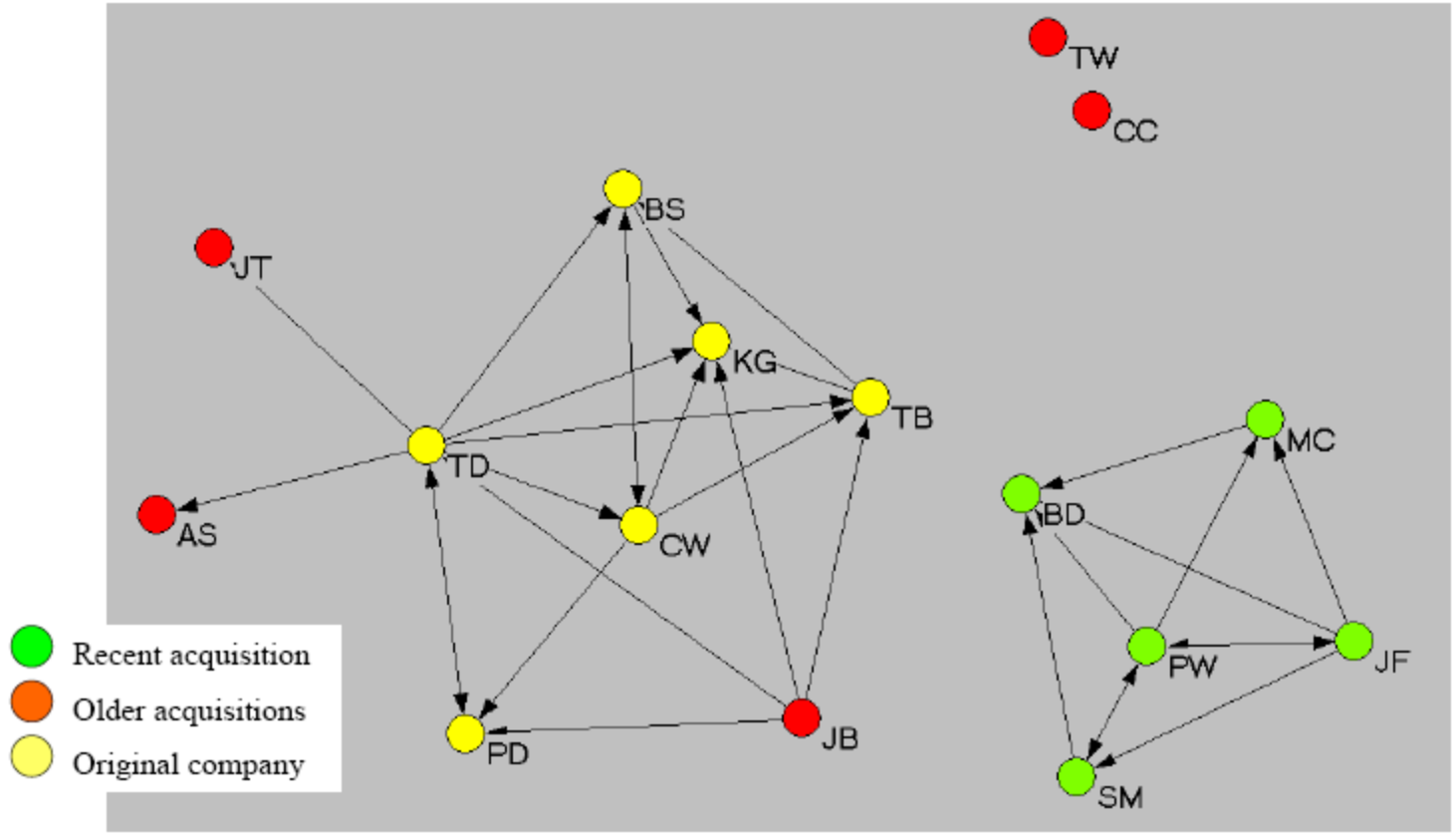
Components

- Maximal sets of nodes in which every node can reach every other by some path (no matter how long)
- A connected graph has just one component

Relations form different networks. Components don't.

A network with 4 components

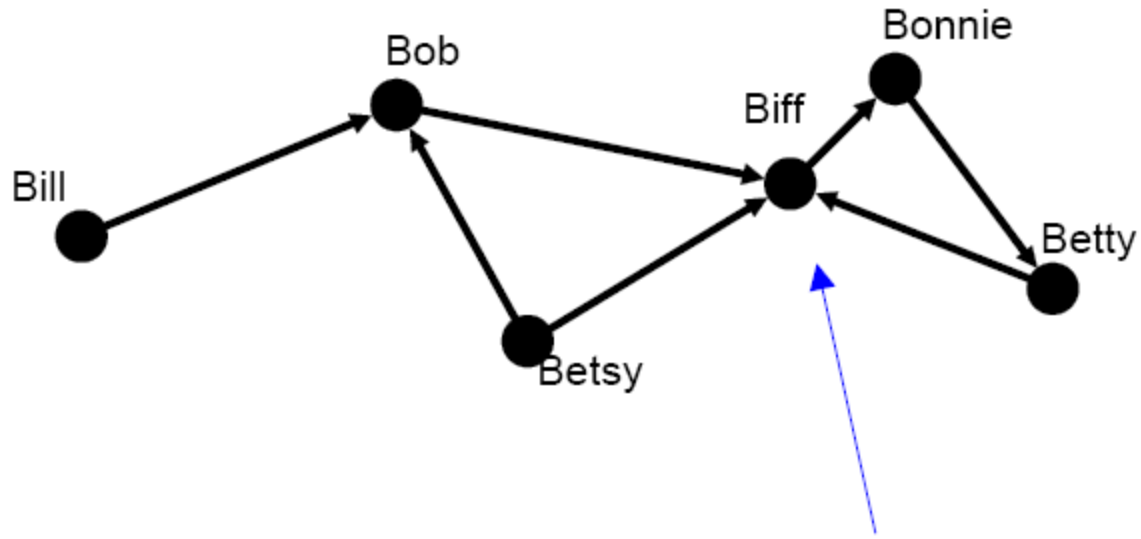
Who you go to so that you can say 'I ran it by ____, and she says ...'



Data drawn from Cross, Borgatti & Parker 2001.

Cutpoints

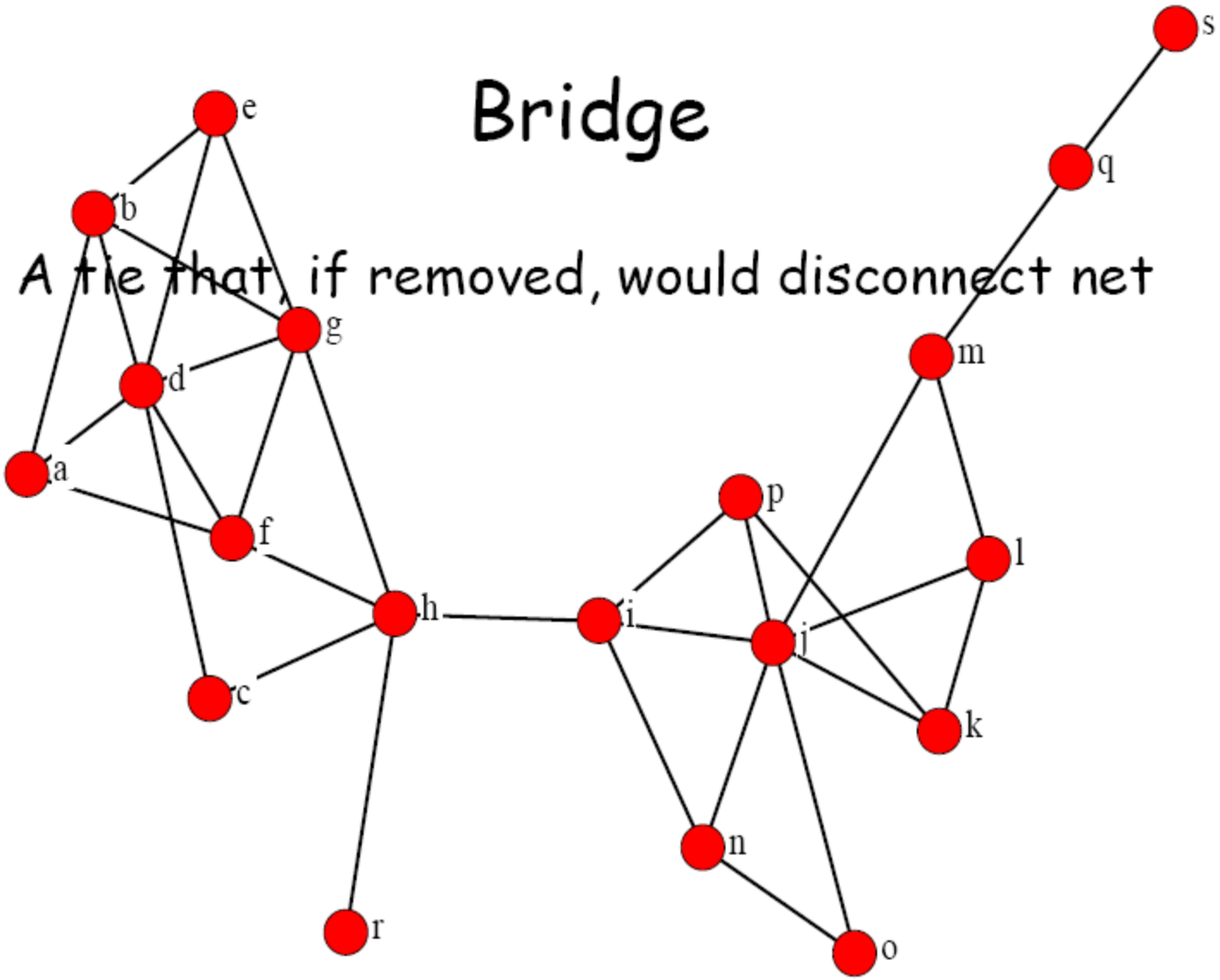
- Nodes which, if deleted, would disconnect net



From Borgatti

Bridge

- A tie that, if removed, would disconnect net

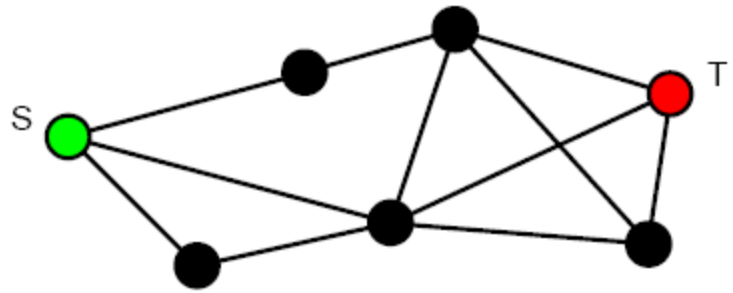


From Borgatti

Network Cohesion

Connectivity

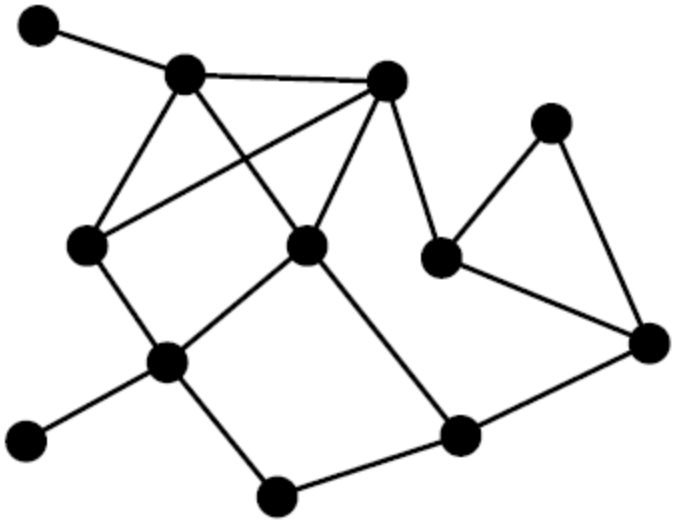
- Line connectivity λ is the minimum number of lines that must be removed to disconnect network
- Node connectivity κ is minimum number of nodes that must be removed to disconnect network



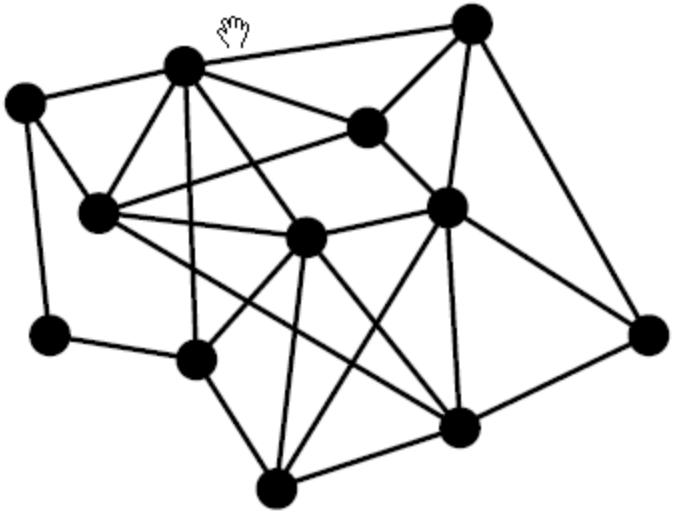
From Borgatti

Density

- Number of ties, expressed as percentage of the number of ordered/unordered pairs



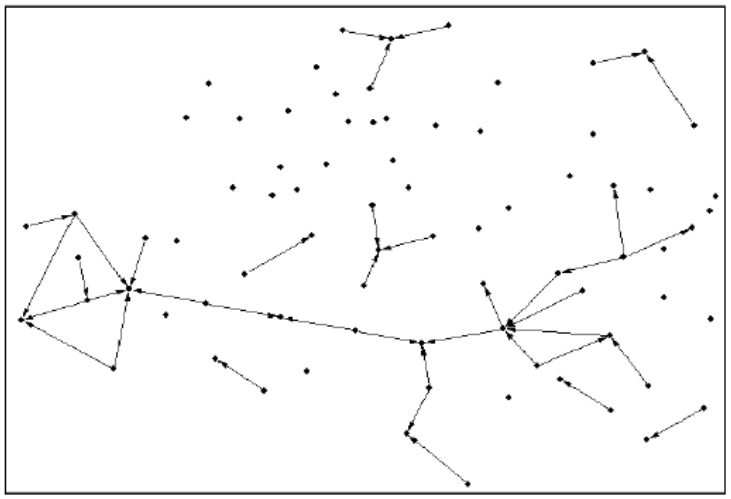
Low Density (25%)
Avg. Dist. = 2.27



High Density (39%)
Avg. Dist. = 1.76

From Borgatti

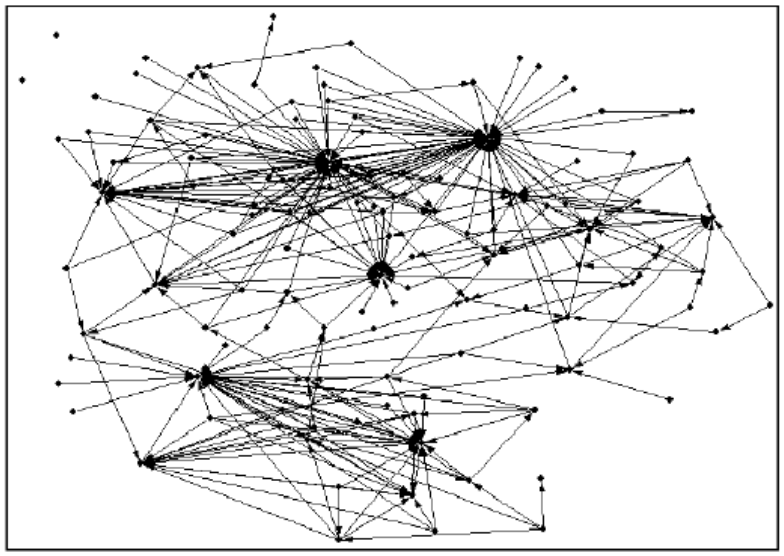
Help With the Rice Harvest



Village 1

Data from

Help With the Rice Harvest



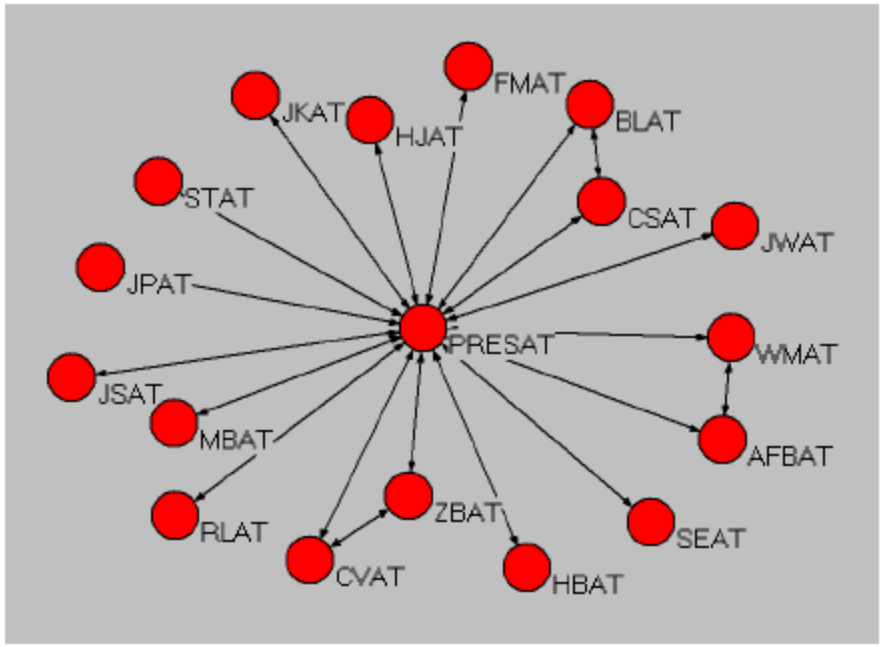
Village 2

Which village is more likely to survive?

Data from Entwistle et al

Centralization

- Degree to which network revolves around a single node

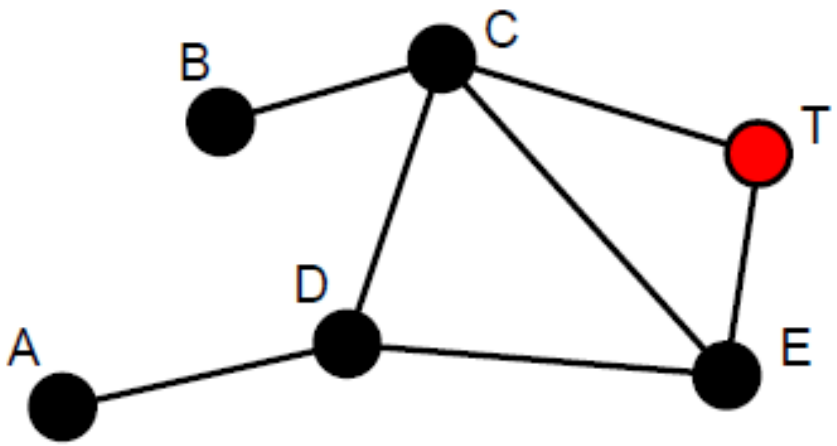


Carter admin.
Year 1

From Borgatti

Transitivity

- Proportion of triples with 3 ties as a proportion of triples with 2 or more ties
  - Aka the clustering coefficient

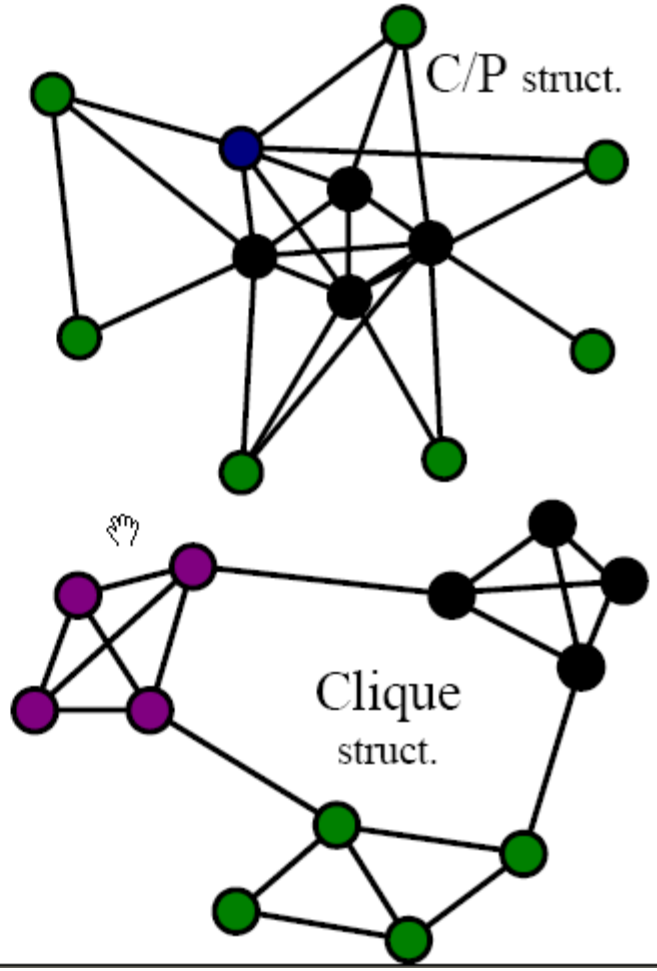


cc = 2/6 = 33%

{C,T,E} is a transitive triple, but {B,C,D} is not

Core/Periphery Structures

- Does the network consist of a single group (a core) together with hangers-on (a periphery), or
- are there multiple subgroups, each with their own peripheries?



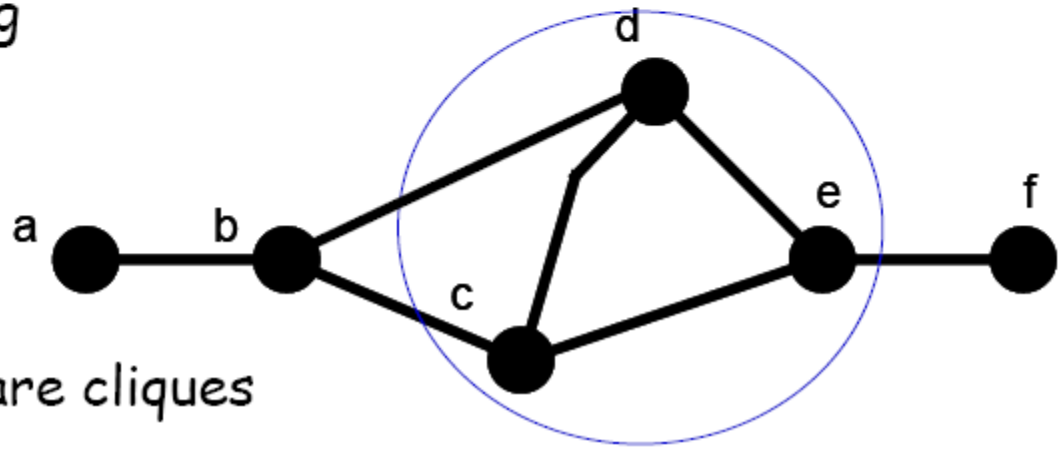
From Borgatti

Graph-Theoretic Concepts

- Structural definitions of groups
  - Clique
  - N-clique, n-clan, n-club
  - K-core, K-plexes
  - Ls-set, Lambda sets
  - Factions

Clique

- Maximal set of actors in which every actors is connected to every other
- Properties
  - Maximum density (1.0)
  - Minimum distances (avg = 1)
  - overlapping

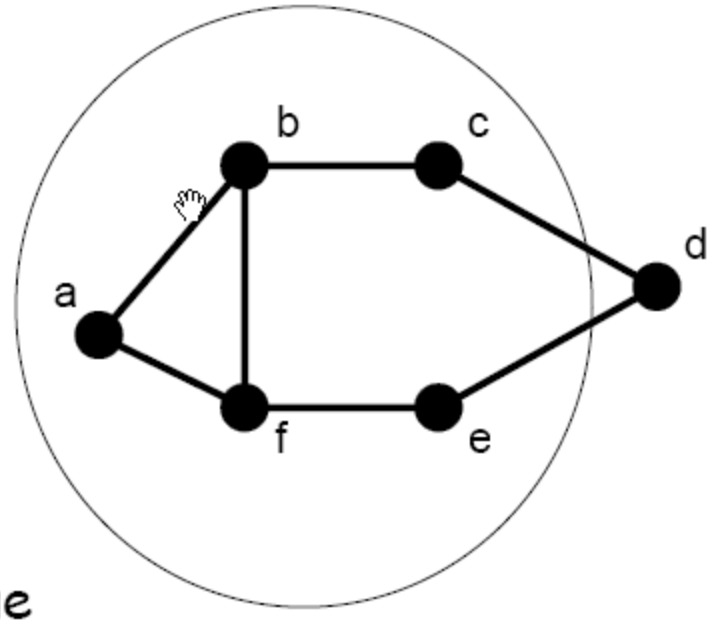


{c,d,e} & {b,c,d} are cliques

From Borgatti

N-Clique

- A set of nodes that are within distance n of each other
- Relaxes distance aspect of clique concept
  - 1-clique is just a clique



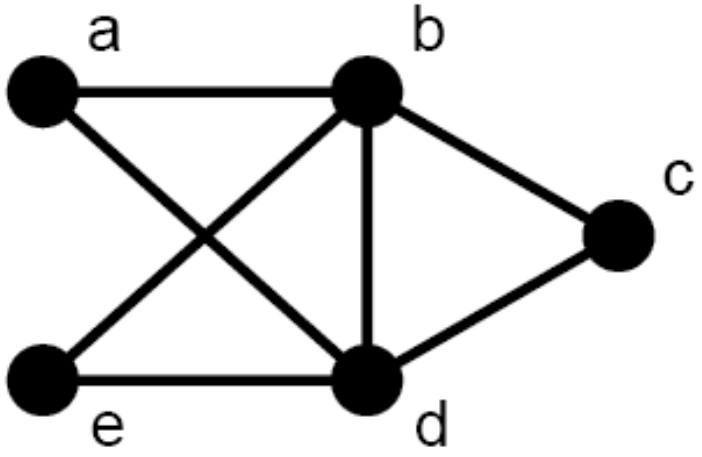
{a,b,c,e,f} is a 2-clique

From Borgatti

K-Plex

A set of n nodes in which every node has a tie to at least n-k others in the set

- In a 1-plex, every node is connected to all but one others in the set – i.e., is a clique



{a,b,d,e} is a 2-plex: each node tied to 4-2 others in set.

Is {a,b,c,d,e} a 2-plex?

From Borgatti

Factions

- A set of mutually exclusive groups of actors such that density of ties within group is greater than density of ties between groups

	a	b	c	d	e	f	g
a	-	1	1	0	0	1	0
b	1	-	1	1	0	0	1
c	0	1	-	1	1	0	0
d	1	0	1	-	0	0	0
e	0	0	0	0	-	1	1
f	0	0	0	0	1	-	1
g	0	1	0	0	1	0	-

Density within group: 14/18 = .78
Density between groups: 4/24 = .17

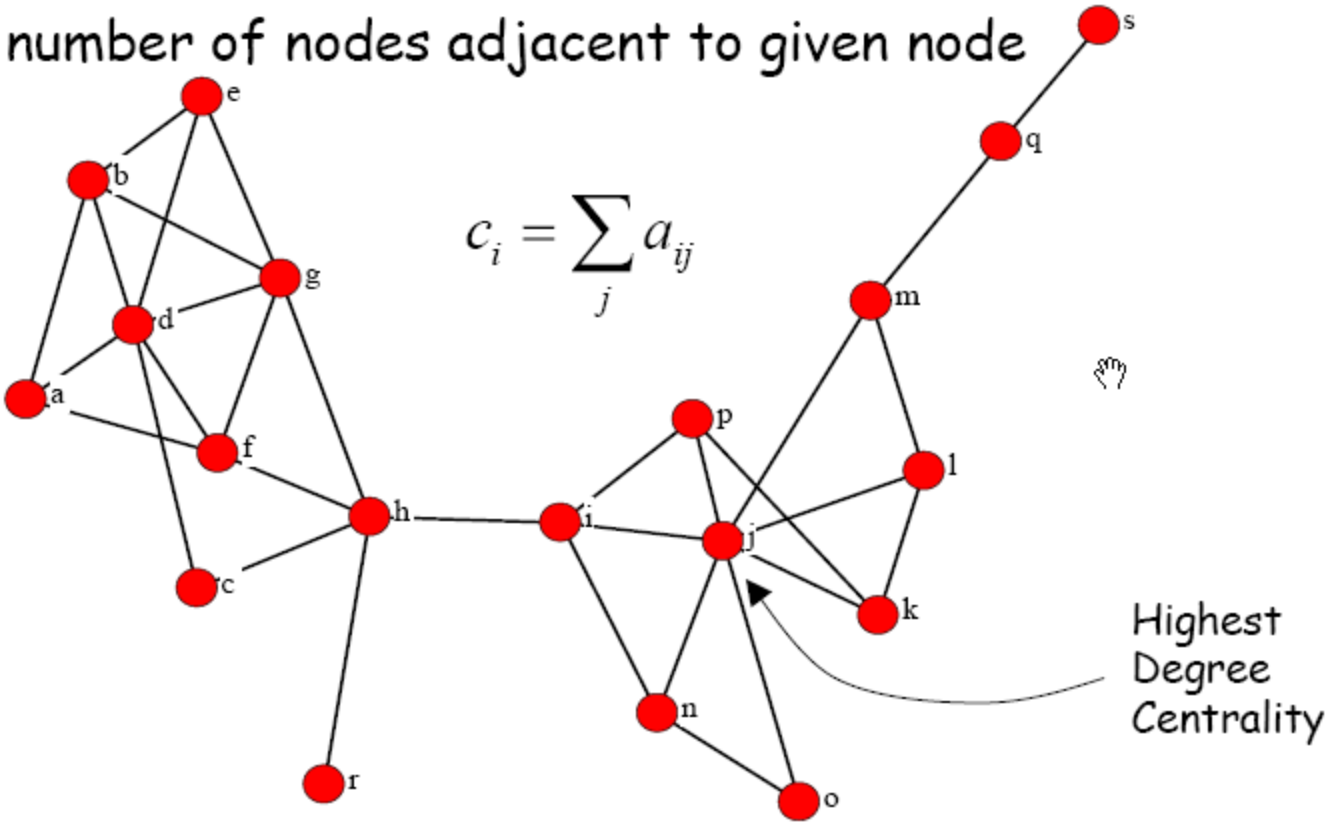
From Borgatti

Centrality

- Path-based
  - Degree
  - Closeness
  - Betweenness
  - Flow betweenness
  - Redundancy/constraint
- Walk-based
  - Eigenvector
  - Bonacich Power
  - Katz
  - Hubbell

Degree Centrality

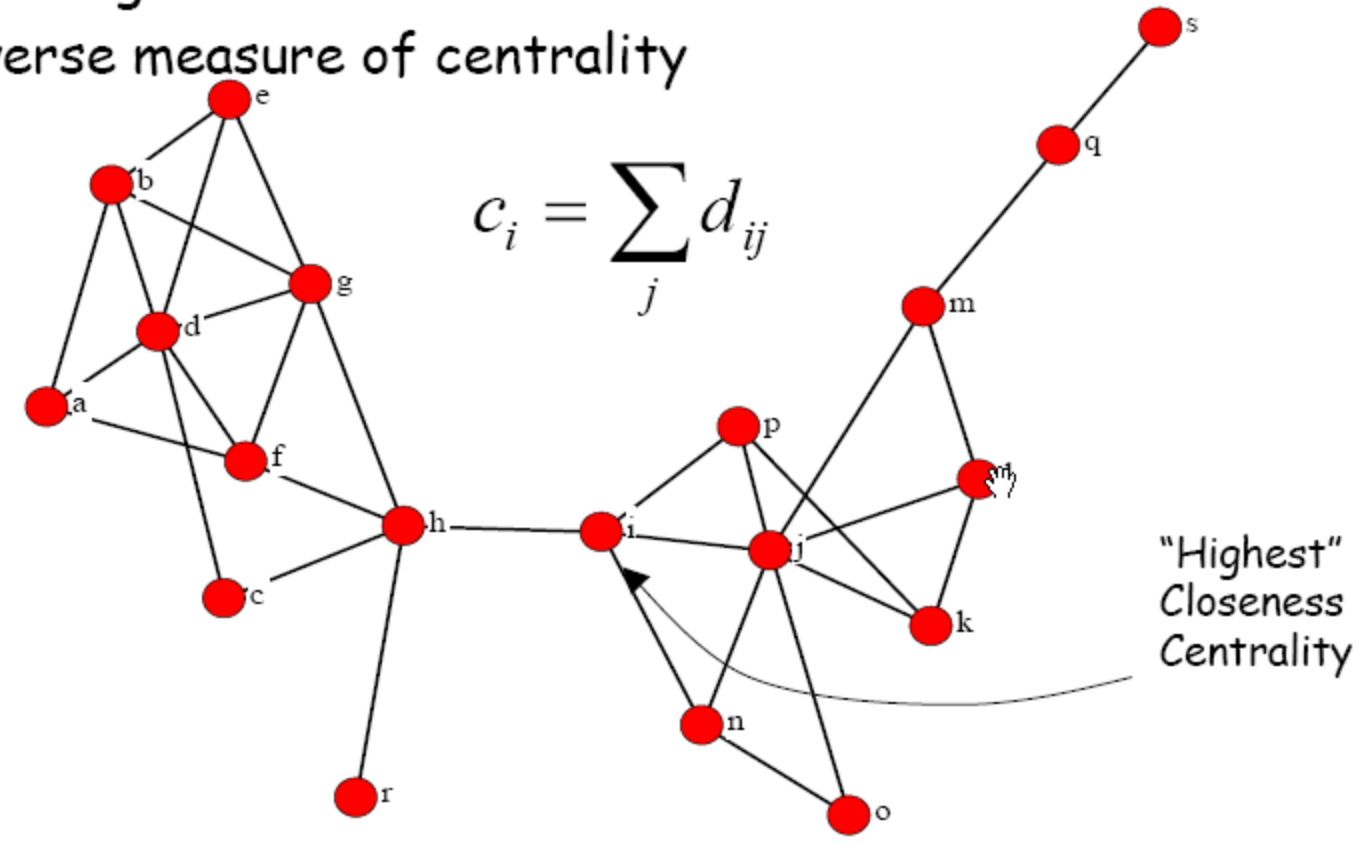
- The number of nodes adjacent to given node



From Borgatti

Closeness Centrality

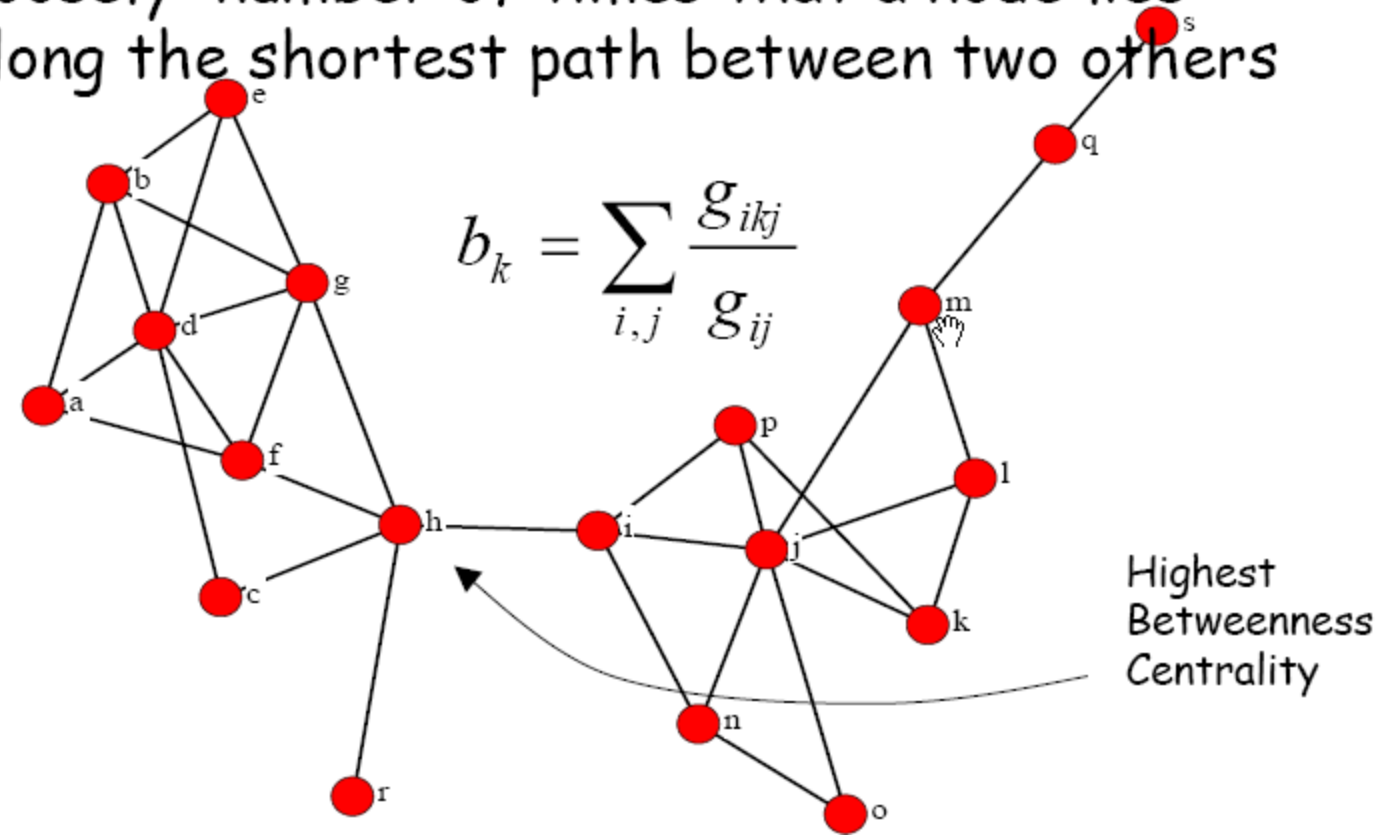
- Sum of geodesic distances to all other nodes
- Inverse measure of centrality



From Borgatti

Betweenness Centrality

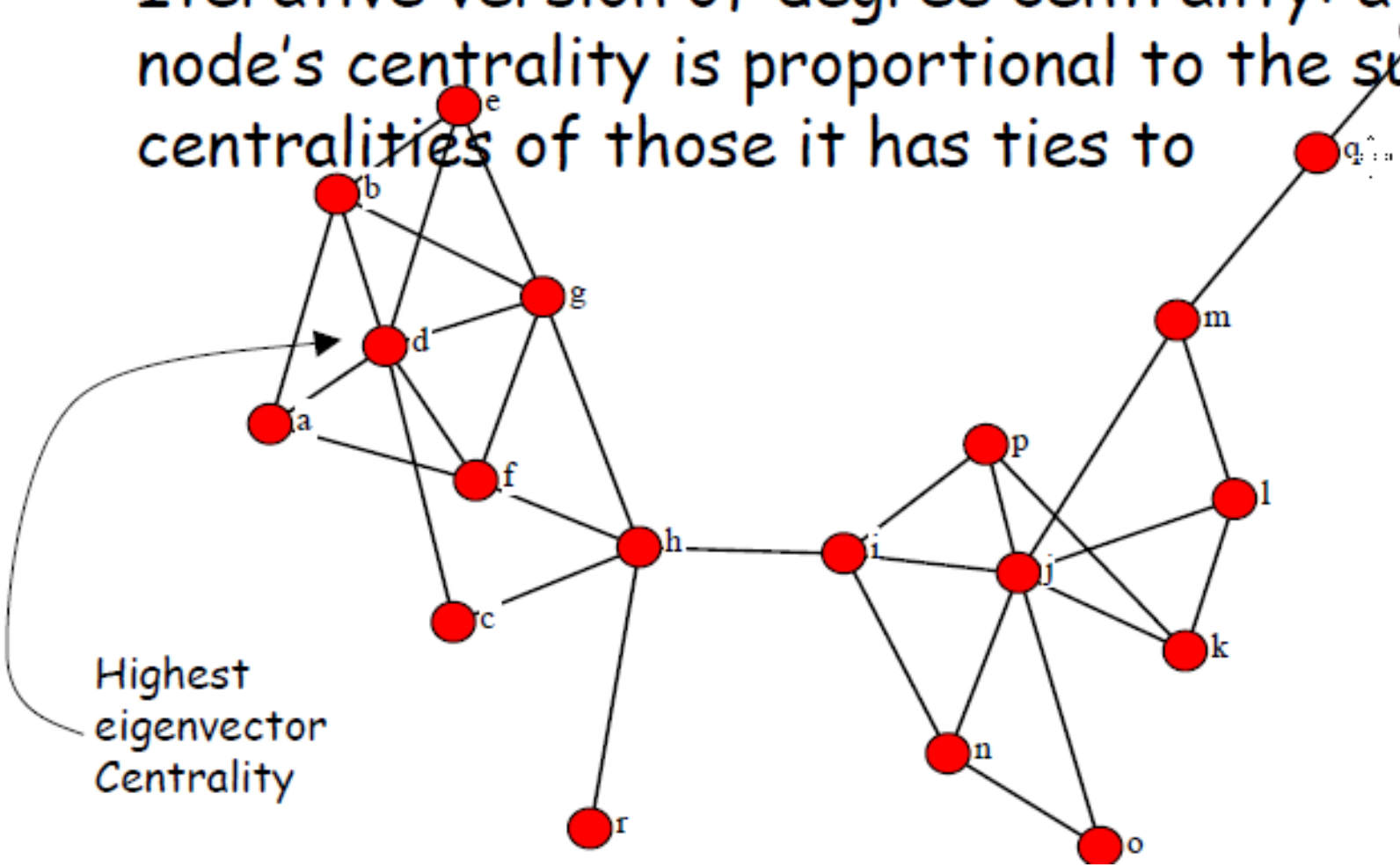
- Loosely: number of times that a node lies along the shortest path between two others



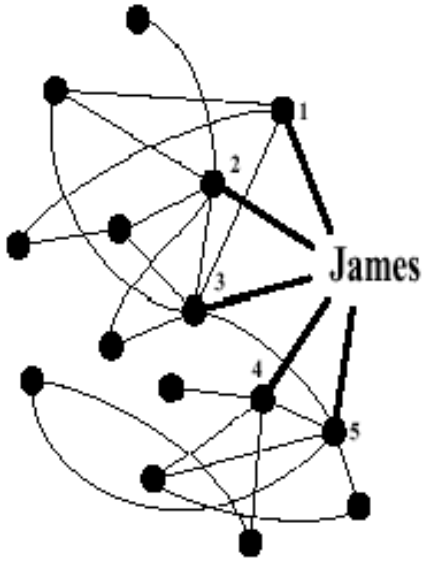
From Borgatti

Eigenvector Centrality

- Iterative version of degree centrality: a node's centrality is proportional to the sum of centralities of those it has ties to

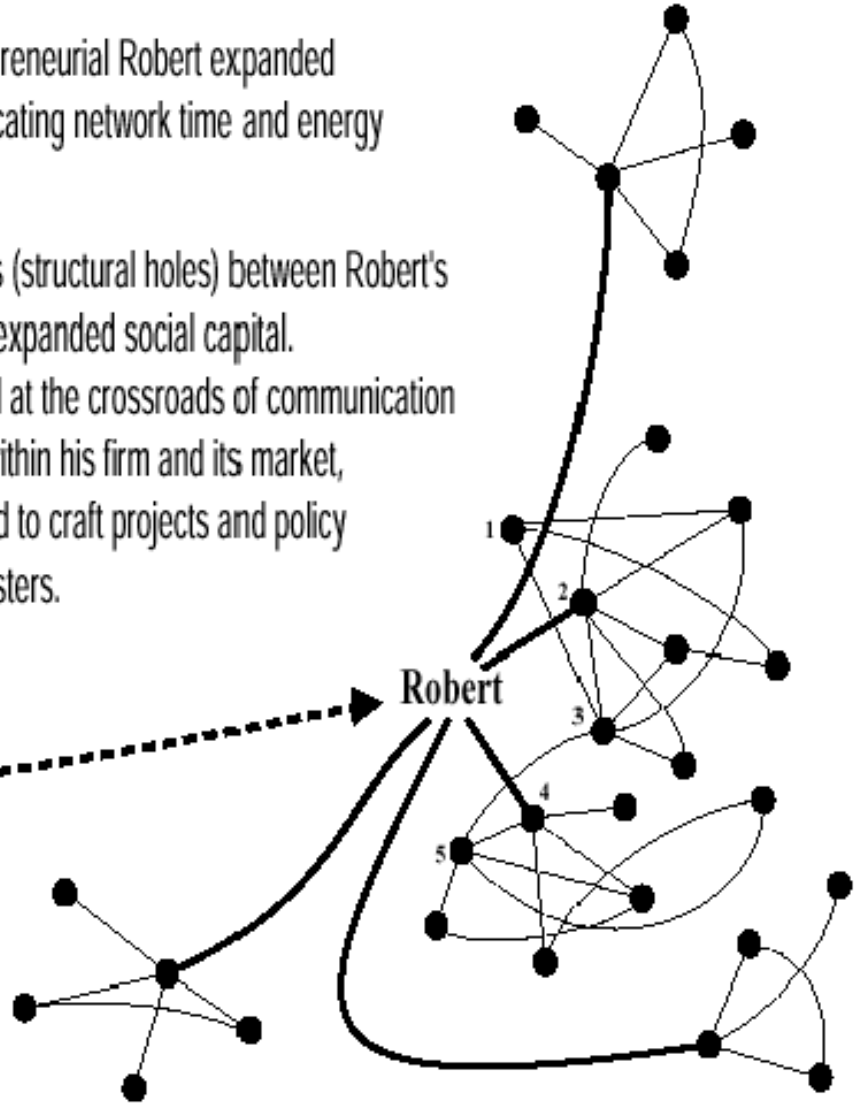


Structural Holes



Robert took over James' job. Entrepreneurial Robert expanded the social capital of the job by reallocating network time and energy to more diverse contacts.

It is the weak connections (structural holes) between Robert's contacts that provide his expanded social capital. Robert is more positioned at the crossroads of communication between social clusters within his firm and its market, and so is better positioned to craft projects and policy that add value across clusters.

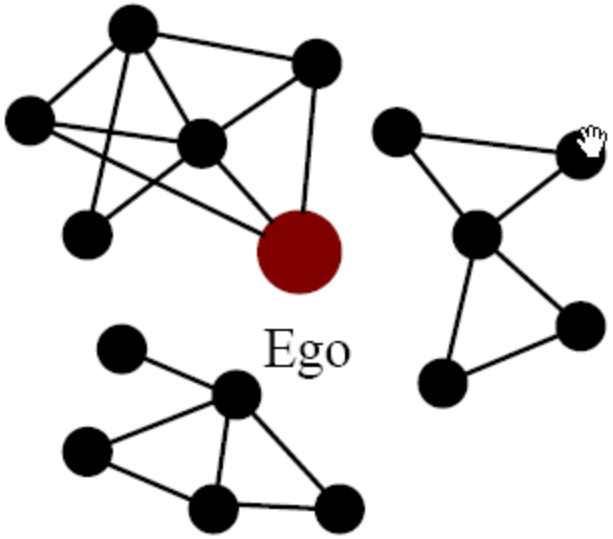


Research shows that people like Robert, better positioned for entrepreneurial opportunity, are the key to integrating across functions and across the people of increasingly diverse backgrounds in today's flatter organizations. In research comparisons between managers like James and Robert, it is the people like Robert who get promoted faster, earn higher compensation, receive better performance evaluations, and perform more successfully on teams.

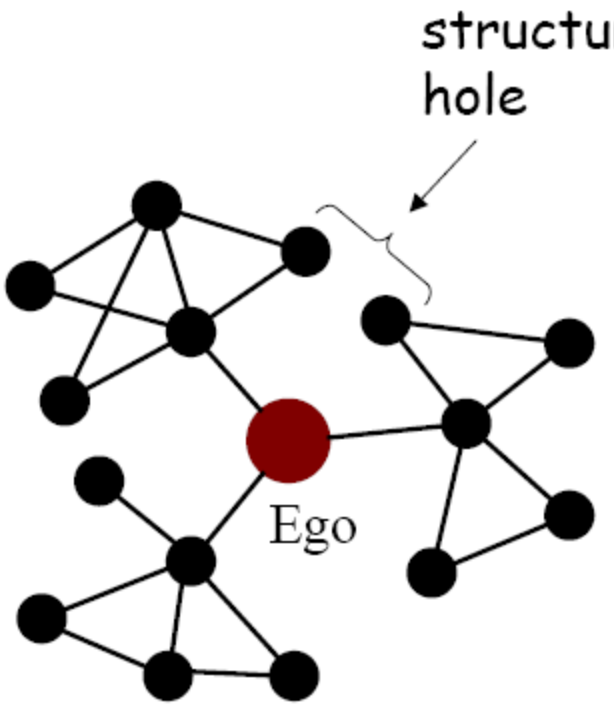
Slide from Ron Burt

Structural Holes

- "cheap" betweenness



Few structural holes



Many structural holes:
- power, info, freedom

From Borgatti

Simplistic View of Social Capital:

Social Capital Should Get You Something

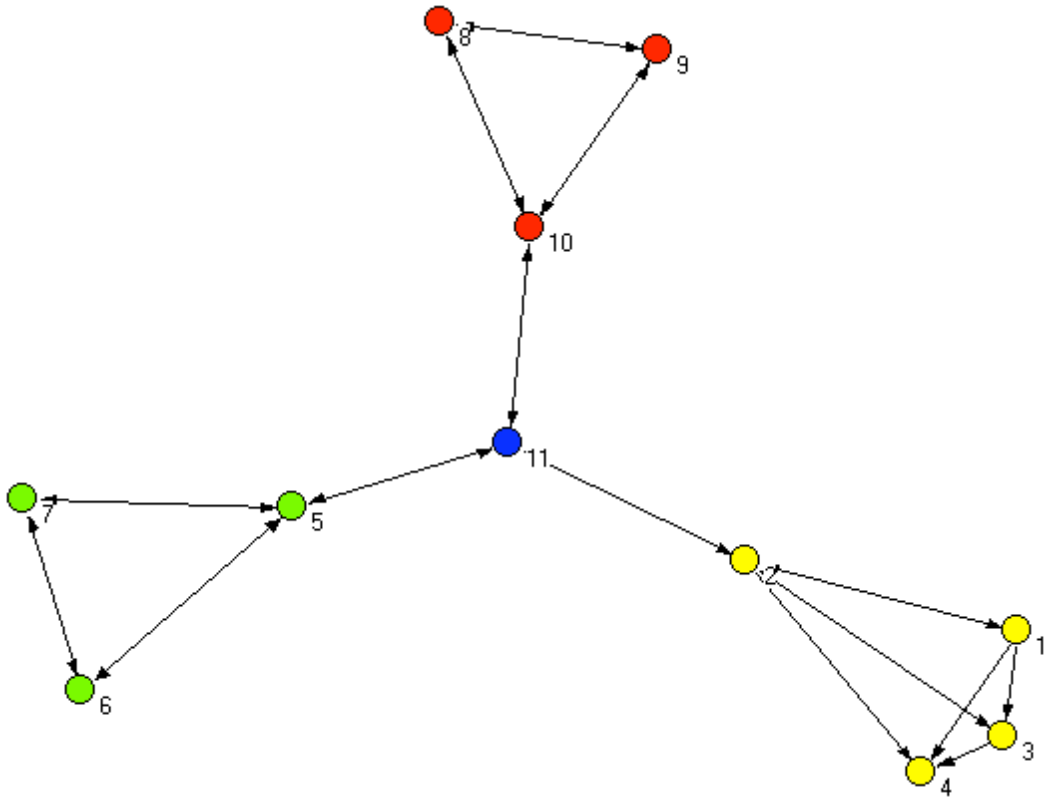
- Opportunity (Burt, Lin and Others)
- Power, influence, money, advancement, access, advantage, etc.
- Protection (Coleman, Portes, and others[e.g., World Bank and Putnam])
- Security, insurance, protection from out-group conflicts, sharing, trust, money, etc.

Features of Networks

- **Social Capital as Opportunity(Focus: individual)**
- Low density, low redundancy, extensive, complex
- Leads to control (e.g., information), entrepreneurial opportunities, etc.
- Flexibility at the expense of risk

- **Social Capital as Security (Focus: Group)**
- High density, cohesion, and redundancy, simple
- Leads to protection, cooperation, and sense of belonging (e.g., results in poverty alleviation, sustainable development, lower crime, higher educational achievement), but involves obligations and restrictive norms
- Certainty at the expense of constraint and obligations

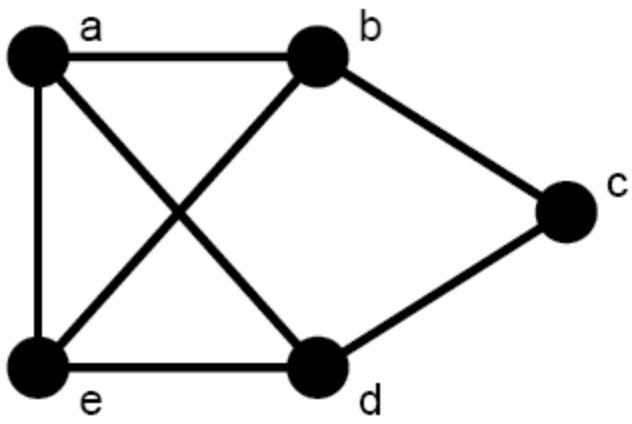
Network Example



Structural Similarity

Network Neighborhoods

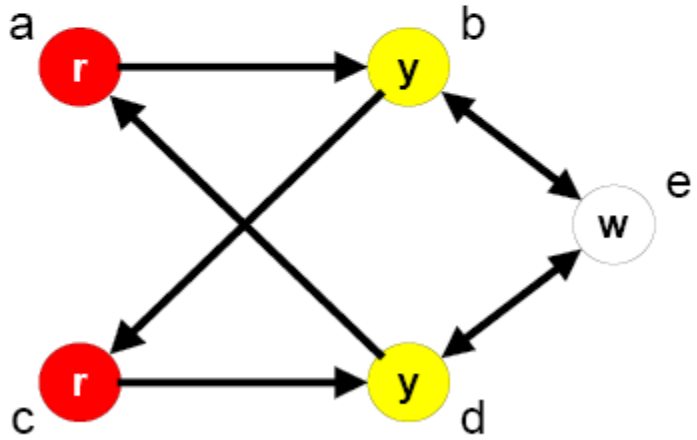
- An actor's neighborhood is the set of actors they are connected to
- For directed networks:
  - In-neighborhood
    - Actors sending ties to focal actor
  - Out-neighborhood
    - Set of actors receiving ties from focal actor



From Borgatti

Structural Equivalence

- Actors are structurally equivalent to the extent they have the same in-neighborhoods and out-neighborhoods



Structurally equivalent nodes are colored the same

From Borgatti

Structural Equivalence

- Structurally indistinguishable
  - Same degree, centrality, belong to same number of cliques, etc.
  - Only the label on the node can distinguish it from those equiv to it.
  - Perfectly substitutable: same contacts, resources
- Face the same social environment
  - Similar forces affecting them
- Captures notions like niche
- Location or position
  - You are your friends

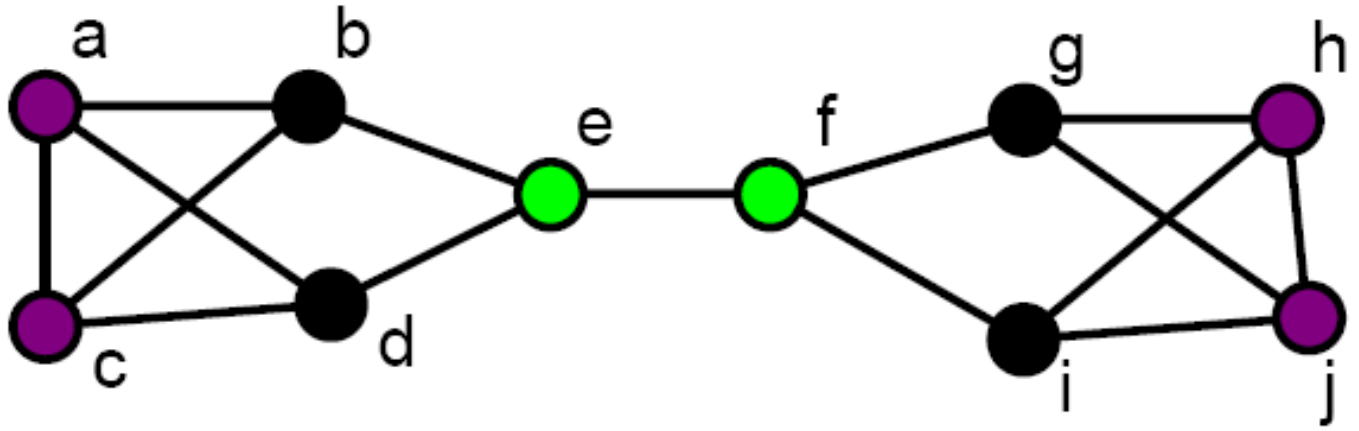
BlockModeling

	a	b	c	d	e	f	g	h	i	j
a				1	1	1				
b				1	1	1				
c				1	1	1				
d	1	1	1				1	1	1	1
e	1	1	1					1	1	1
f	1	1	1				1	1	1	1
g	1	1	1	1	1	1	1	1	1	1
h	1	1	1	1	1	1	1	1	1	1
i	1	1	1	1	1	1	1	1	1	1
j	1	1	1	1	1	1	1	1	1	1

From Borgatti

Regular Equivalence

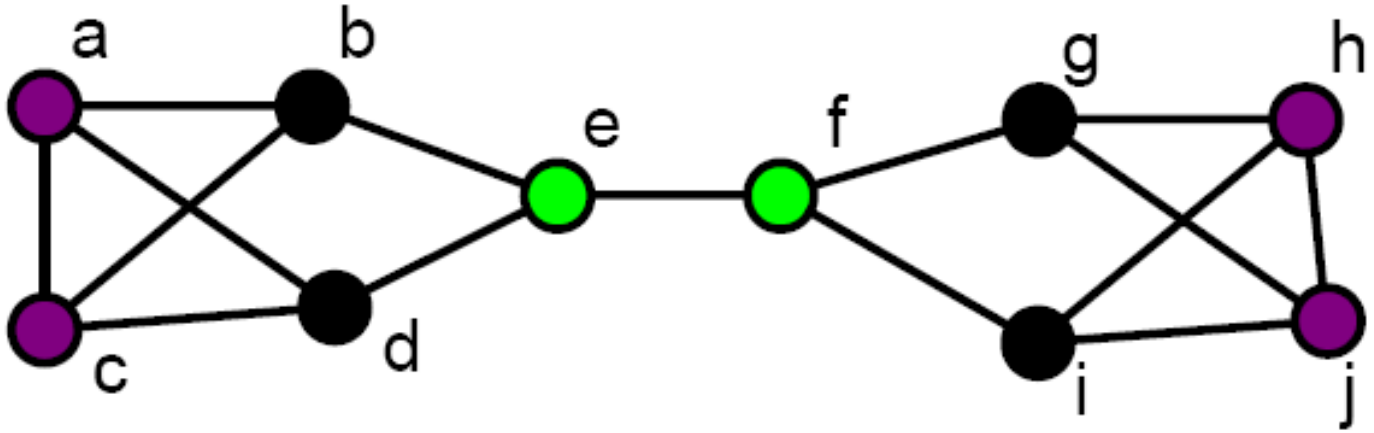
- B and D are structurally equivalent but what B and G?
  - E on left has mirror-image counterpart F
- Structural equivalence is to equality what regular equivalence is analogy



From Borgatti

Regular Equivalence

- Two actors are regularly equivalent if they are connected to equivalent others
  - Not necessarily same others
  - Not necessarily in same quantity



From Borgatti

Regular Equivalence

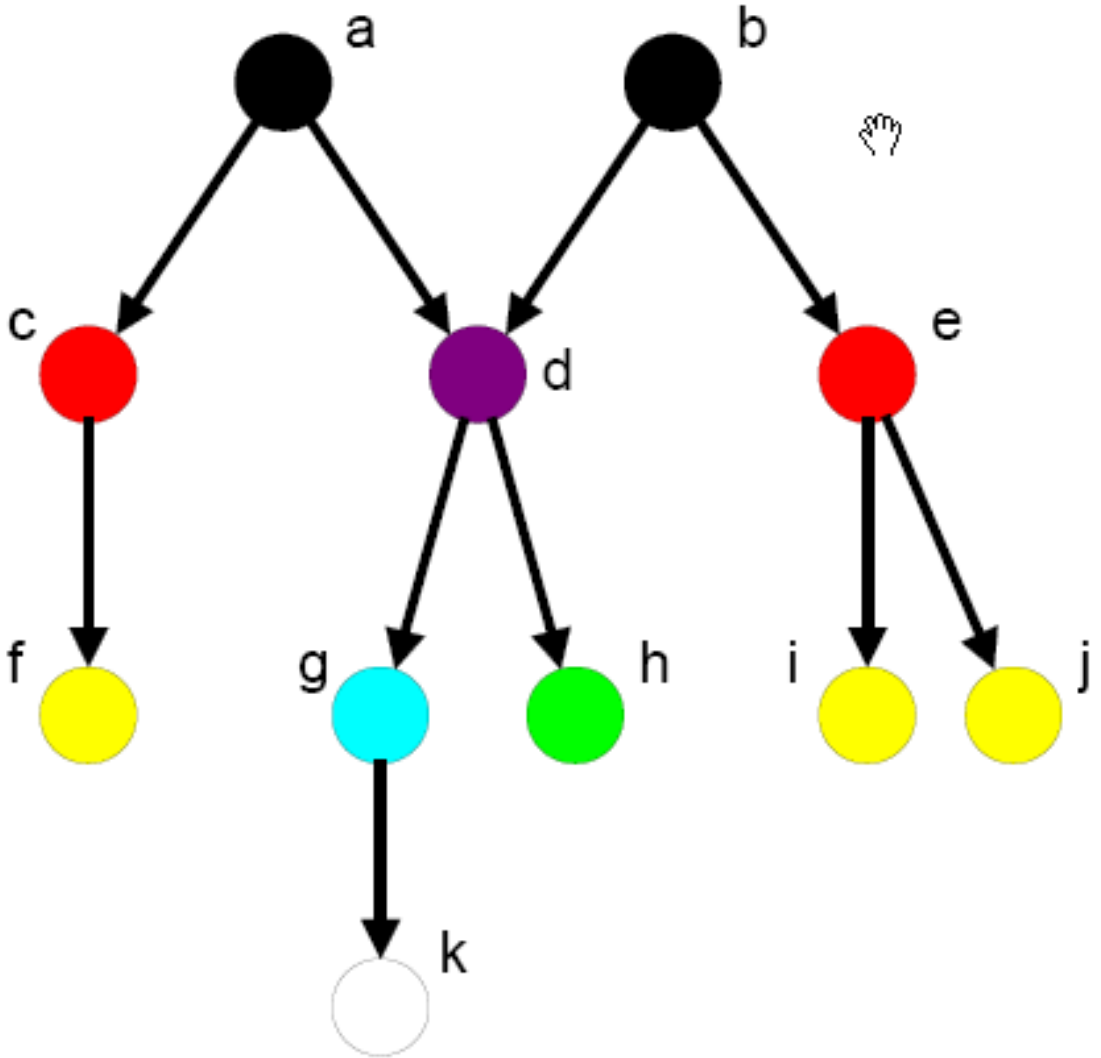
- Captures notion of role counterpart
  - Two doctors equivalent because they have same kinds of relations with same kinds of others, such giving advice to patients, giving orders to nurses, receiving products from vendors, etc.
  - Works when when roles are emergent – unnamed
- Captures position in hierarchies well

Blockmodel View

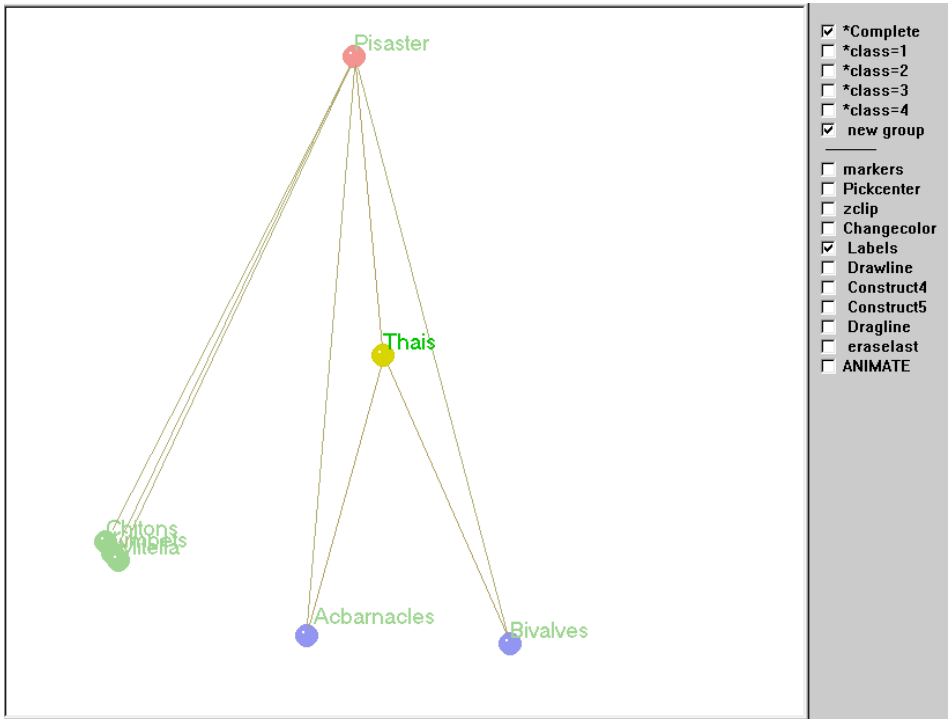
	a	b	c	d	e	f	g	h	i	j
a	0	0	0	0	1	0	0	0	0	0
b	0	0	0	1	0	0	0	0	0	0
c	0	0	0	1	1	1	0	0	0	0
d	0	1	0	0	0	0	1	0	0	0
e	0	1	1	0	0	0	0	1	0	0
f	1	0	0	0	0	0	0	0	1	1
g	1	1	0	0	0	1	1	0	0	1
h	1	0	1	0	1	0	0	1	0	1
i	0	1	1	1	1	0	1	0	1	1
j	1	0	1	0	0	1	1	0	1	1

From Borgatti

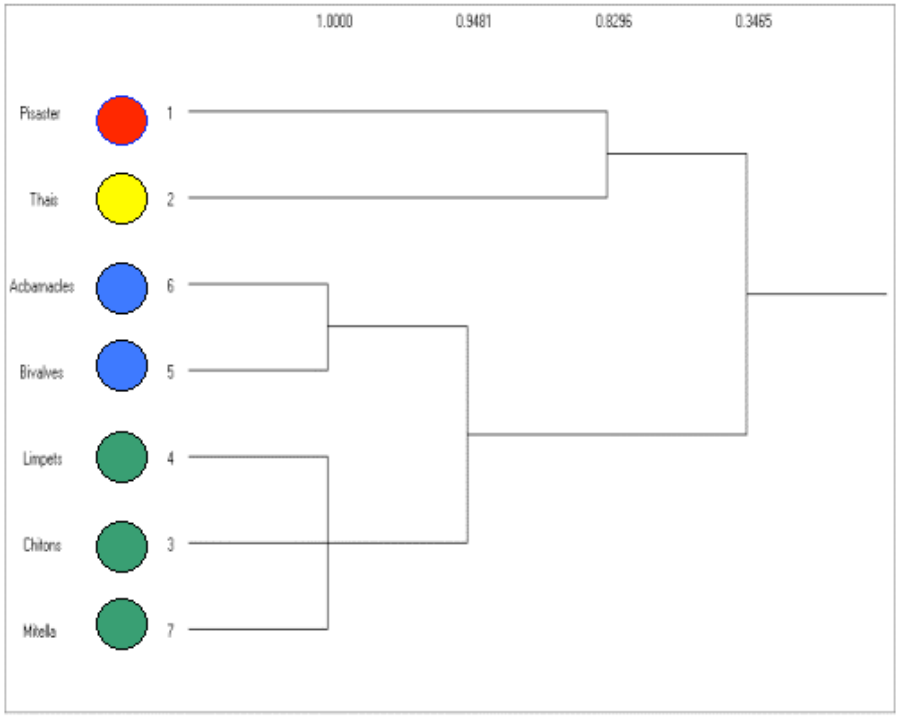
Hierarchical Position



From Borgatti



California Inter-tidal Food Web



Categorizing SN Concepts

	Whole network	Subsets	Individual actors
Connection	Cohesion Density; avg dist; centralization	Groups Cliques; n-clique; k-plex	Centrality Degree; closeness; betweenness; Struct holes
Similarity		Structural & regular equiv classes	

From Borgatti

Cognitive Social Networks

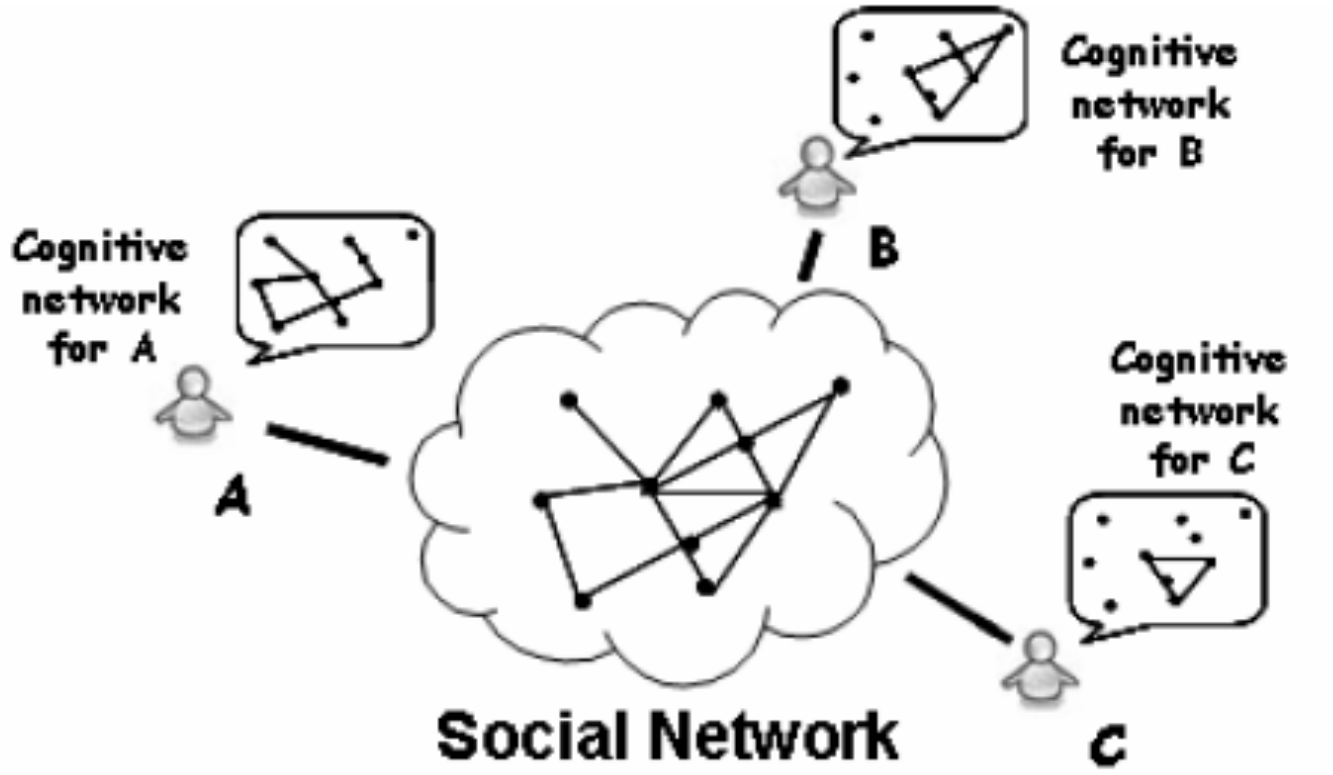
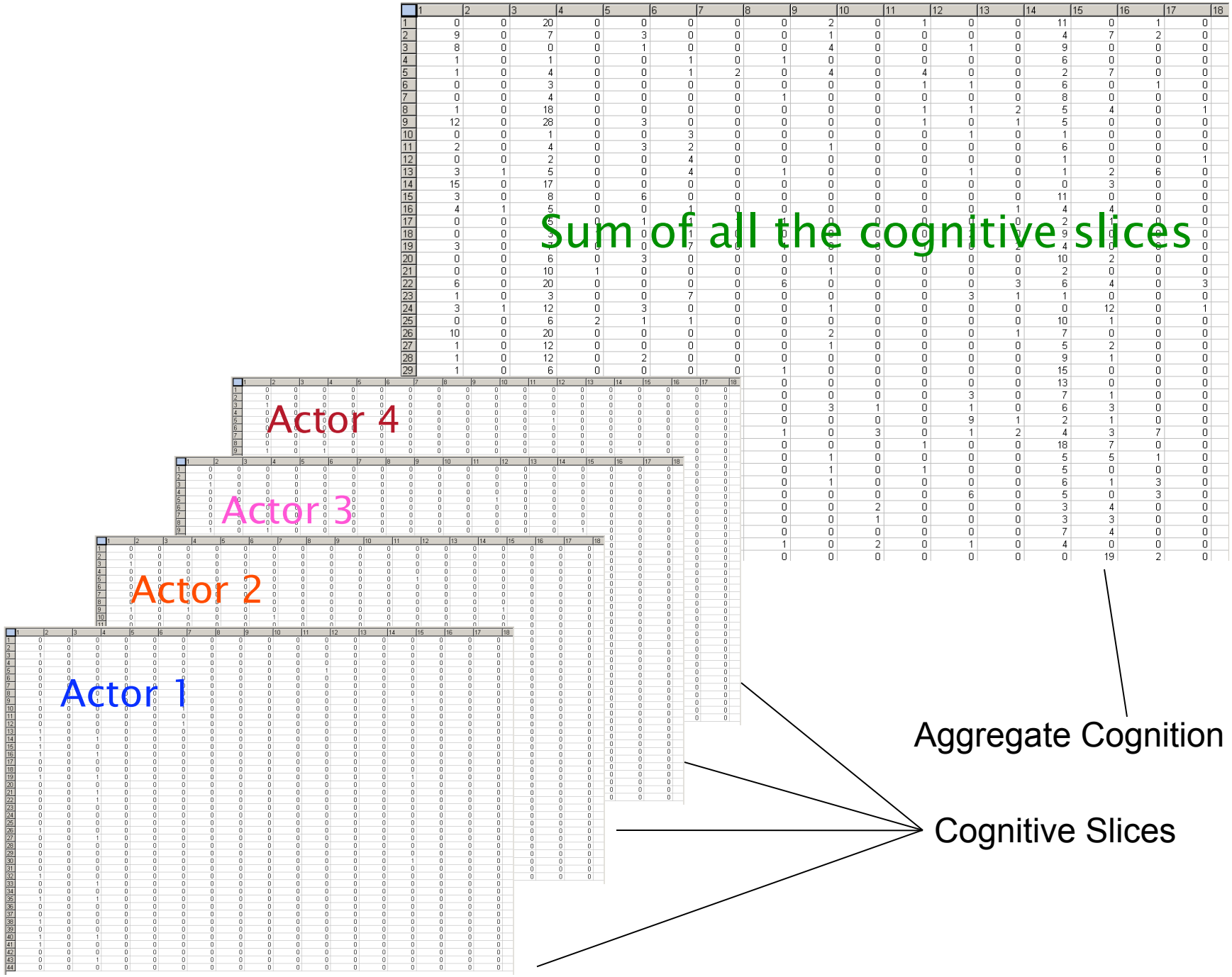


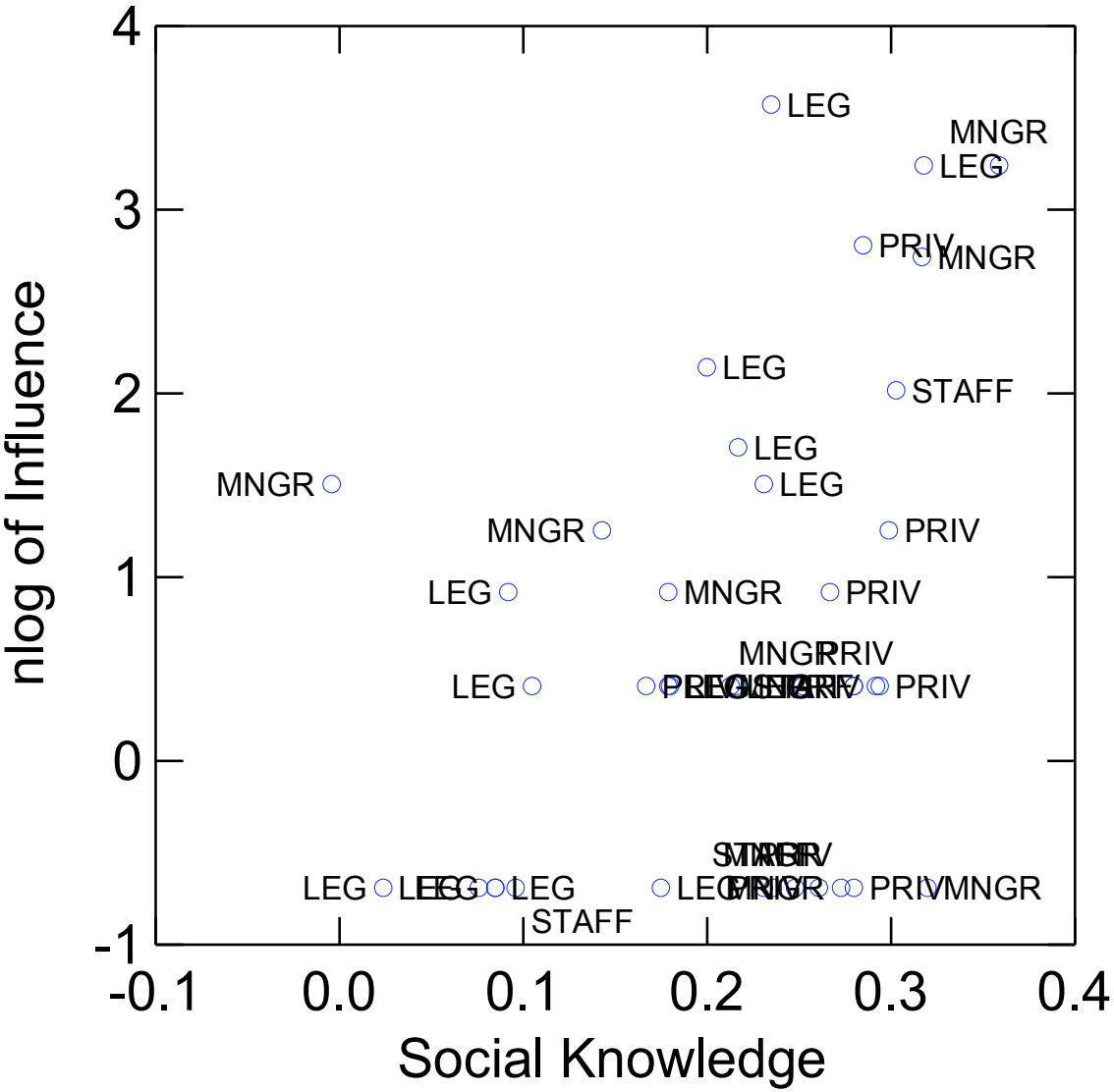
Figure 1. Illustration of a Socio-cognitive network


Sum of all the cognitive slices
Actor 4
Actor 3
Actor 2
Actor 1
Aggregate Cognition
Cognitive Slices

Features of Cognitive Social Networks

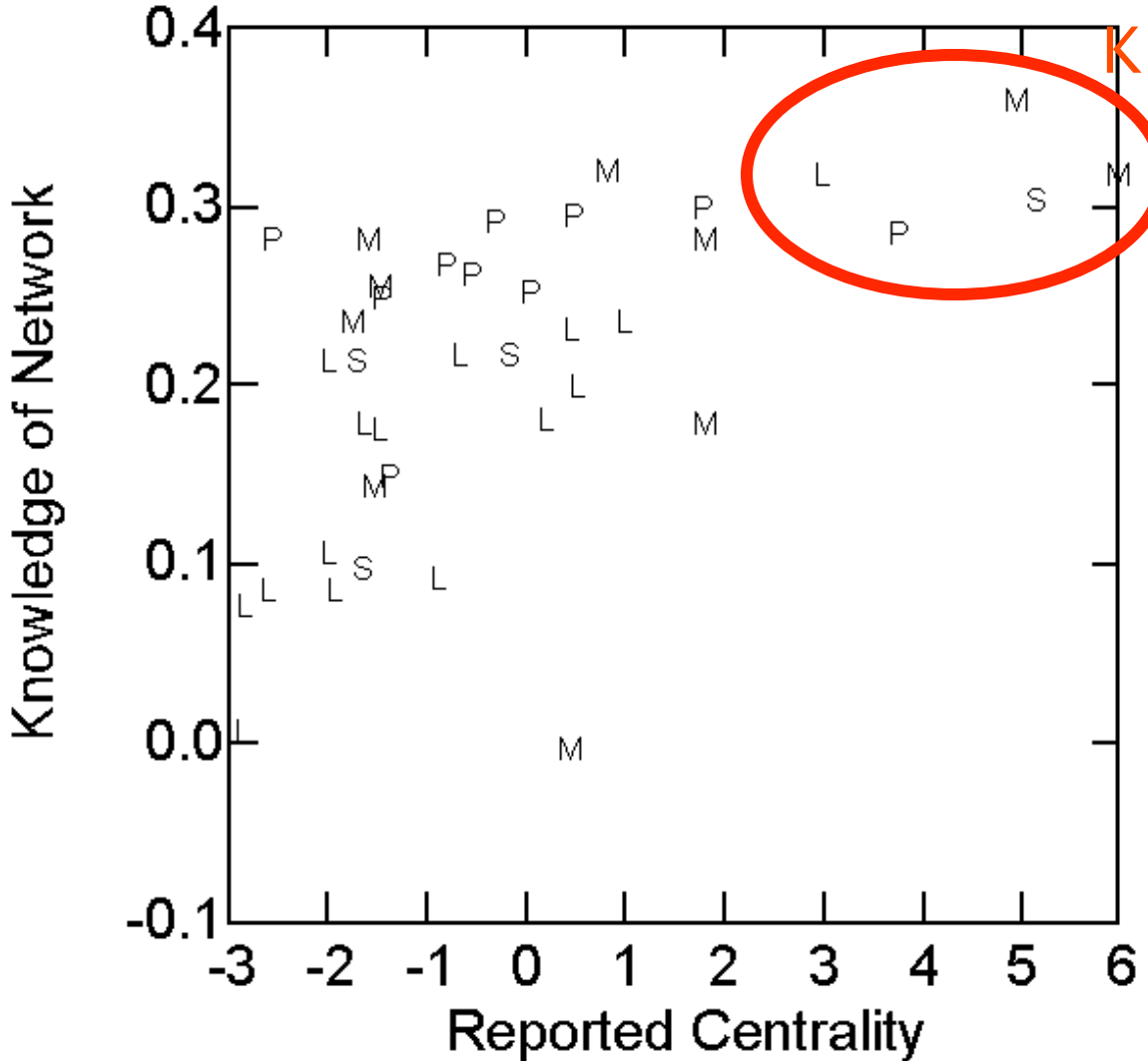
- Individual cognitive slices vary in accuracy
- More active (and powerful) actors tend to have the most accurate understanding of the network
- Aggregations of individual cognitive nets tend to produce a more valid picture of the true network
- The more slices the better
- Can construct a reasonably accurate network from a few aggregated cognitive slices (particularly if obtained from active and powerful actors)

Relationship between power and knowledge



Relationship between activity and knowledge

High Activity and High Knowledge



Measuring Knowledge

- Use of QAP for correlating matrices

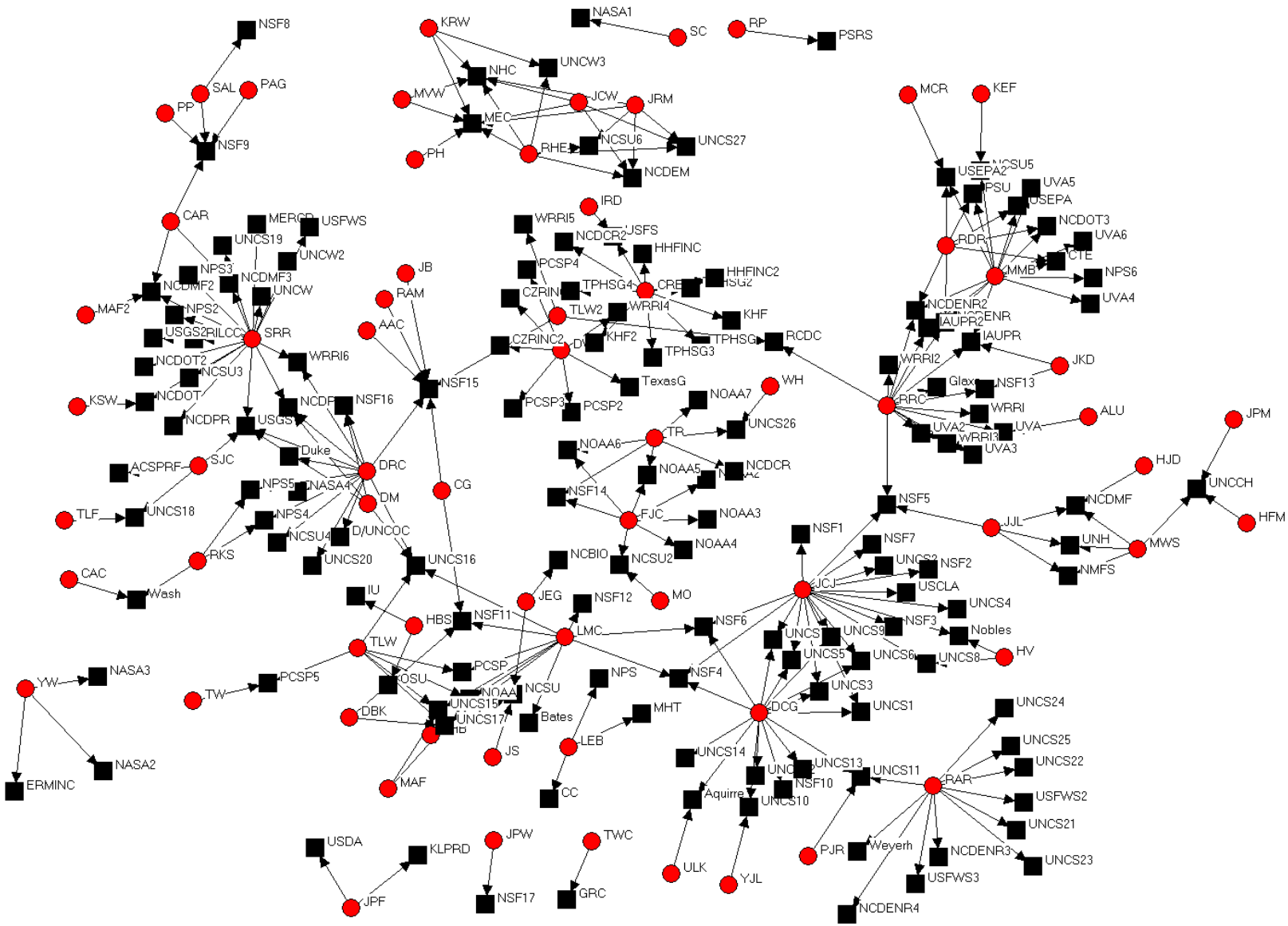
2-Mode Social Networks and Affiliation Networks

- Advantages
  - Can construct from observations
  - Can construct from reports of behavior
  - Can construct from secondary source materials
  - Can often be used as a proxy for 1-mode relational networks

The Structure of Coastal Research at ECU
The Extent of Interdisciplinary Research

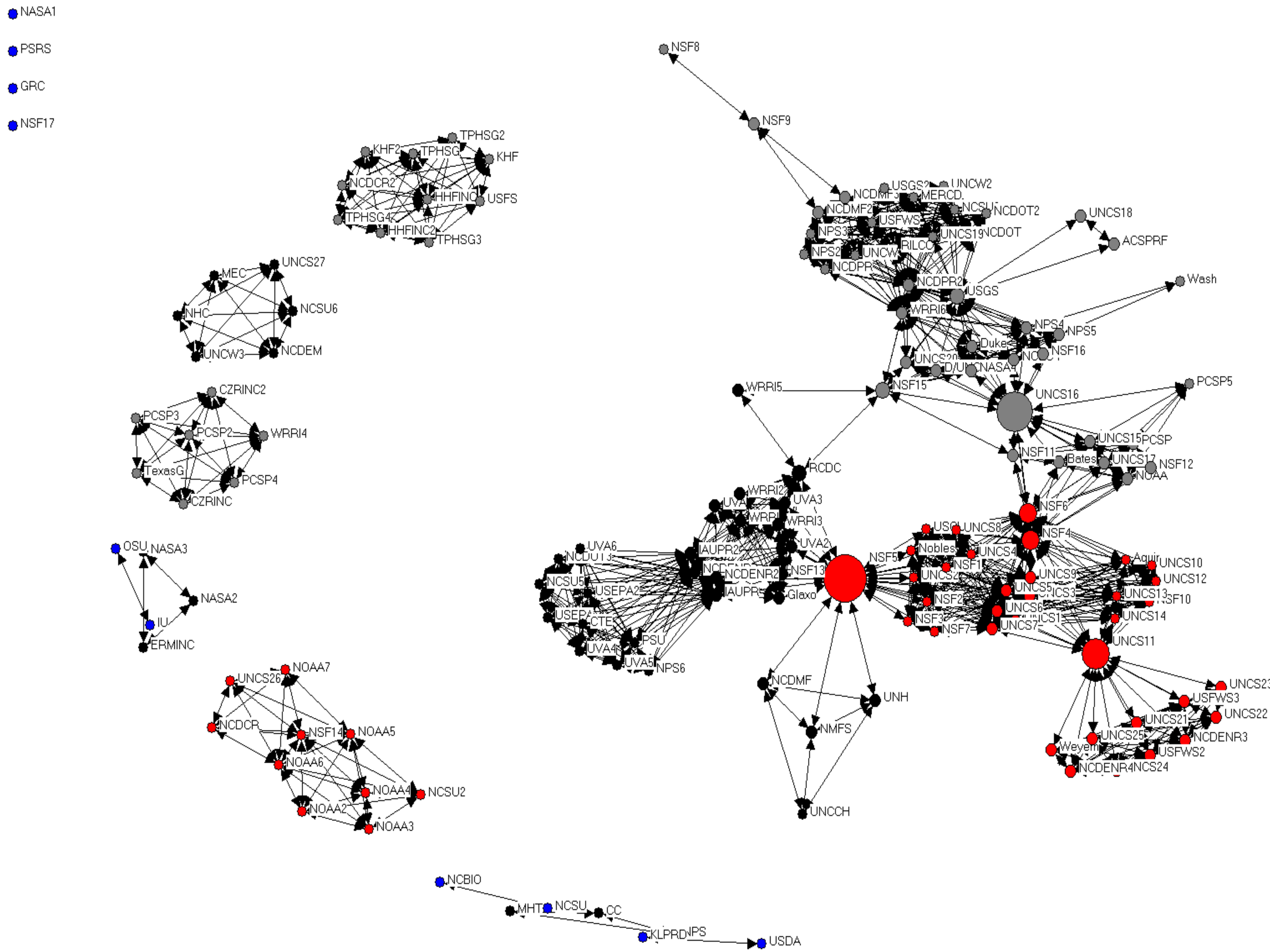
- The network of investigators by funded research (past 10 years)
- Relationships among projects vis-à-vis investigators
- Analysis of key projects
- Relationships among investigators vis-à-vis projects
- Analysis of key investigators
- Factors facilitating interdisciplinary coastal research

The Network of Investigators by Projects


NSF8
SAL
PAG
PP
NSF9
CAR
MERCD
USFWS
UNCS19
UNCW2
NPS3
NCDMF2
NCDMF3
UNCW
MAF2
NPS2
USGS2RILCC
SRR
NCDOT2
NCSU3
WRRI6
KSW
NCDOT
NCDPR
USGS
NCDP
NSF16
ACSPRF
SJC
Duke
DRC
NPS5
NASA4
DM
TLF
UNCS18
NPS4
NCSU4
D/UNCOC
UNCS20
RKS
CAC
Wash
KRW
NASA1
SC
RP
PSRS
UNCW3
NHC
MVW
JCW
JRM
MEC
PH
RHE
NCSU6
UNCS27
NCDEM
IRD
WRRI5
NCDCR2
JSFS
HHFINC
PCSP4
HHFINC2
CZRIN
TPHSG4
CRE
TLW2
WRRI4
KHF
CZRINC2
KHF2
TPHSG
RCDC
TPHSG3
TexasG
PCSP3
PCSP2
JB
RAM
AAC
NSF15
CG
NOAA7
WH
UNCS26
TR
NOAA6
NOAA5
NCDCR
NSF14
FJC
NOAA3
NOAA4
NCSU2
MO
NCBIO
JEG
NSF12
IU
HBS
NSF11
TLW
LMC
PCSP
OSU
NOAA
NCSU
UNCS15
UNCS17
Bates
DBK
JS
MAF
NPS
MHT
LEB
CC
NSF4
NSF6
MCR
KEF
USEPA2
NCSU5
PSU
UVA5
USEPA
NCDOT3
RDR
UVA6
CTE
MMB
NPS6
UVA4
NCDENR2
IAUPR2
IAUPR
JKD
WRRI2
Glax
NSF13
WRRI
ALU
UVA2
UVA
WRRI3
UVA3
NSF5
JJL
JPM
HJD
UNCCH
NCDMF
HFM
UNH
MWS
NMFS
NSF1
NSF7
UNCS2
NSF2
JCJ
USCLA
UNCS4
NSF3
Nobles
UNCS9
UNCS5
UNCS6
UNCS8
HV
UNCS3
UNCS1
DCG
UNCS24
UNCS25
UNCS22
USFWS2
UNCS21
UNCS23
PAR
UNCS11
UNCS13
NSF10
UNCS10
UNCS14
Aquirre
PJR
Weyerh
NCDENR3
USFWS3
NCDENR4
ULK
YJL
YW
NASA3
NASA2
ERMINC
TW
PCSP5
USDA
KLPRD
JPF
JPW
NSF17
TWC
GRC

Project Affiliation Networks and the Identification of Key Projects

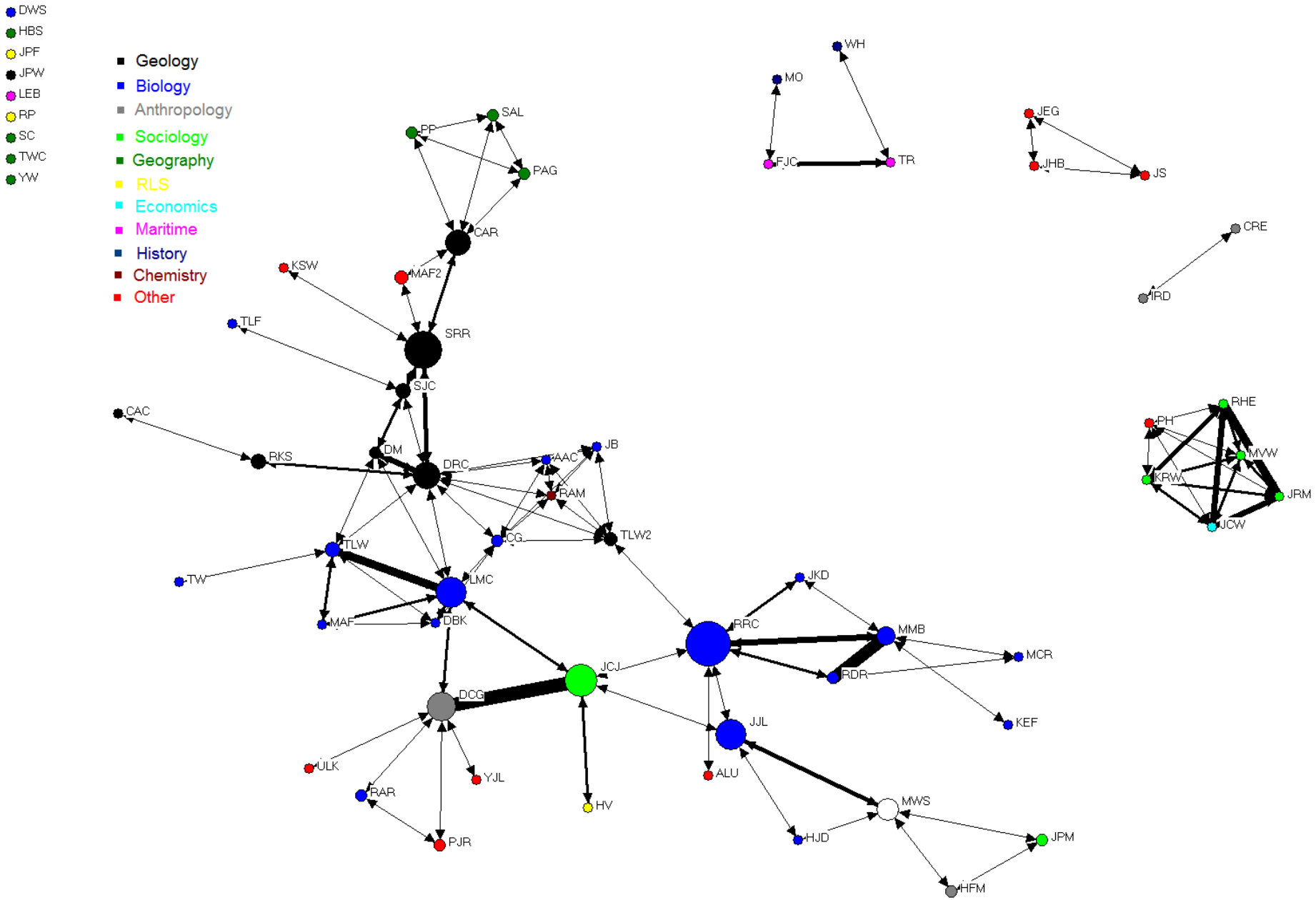
Find the projects that, if removed,
would maximize the number of
network components

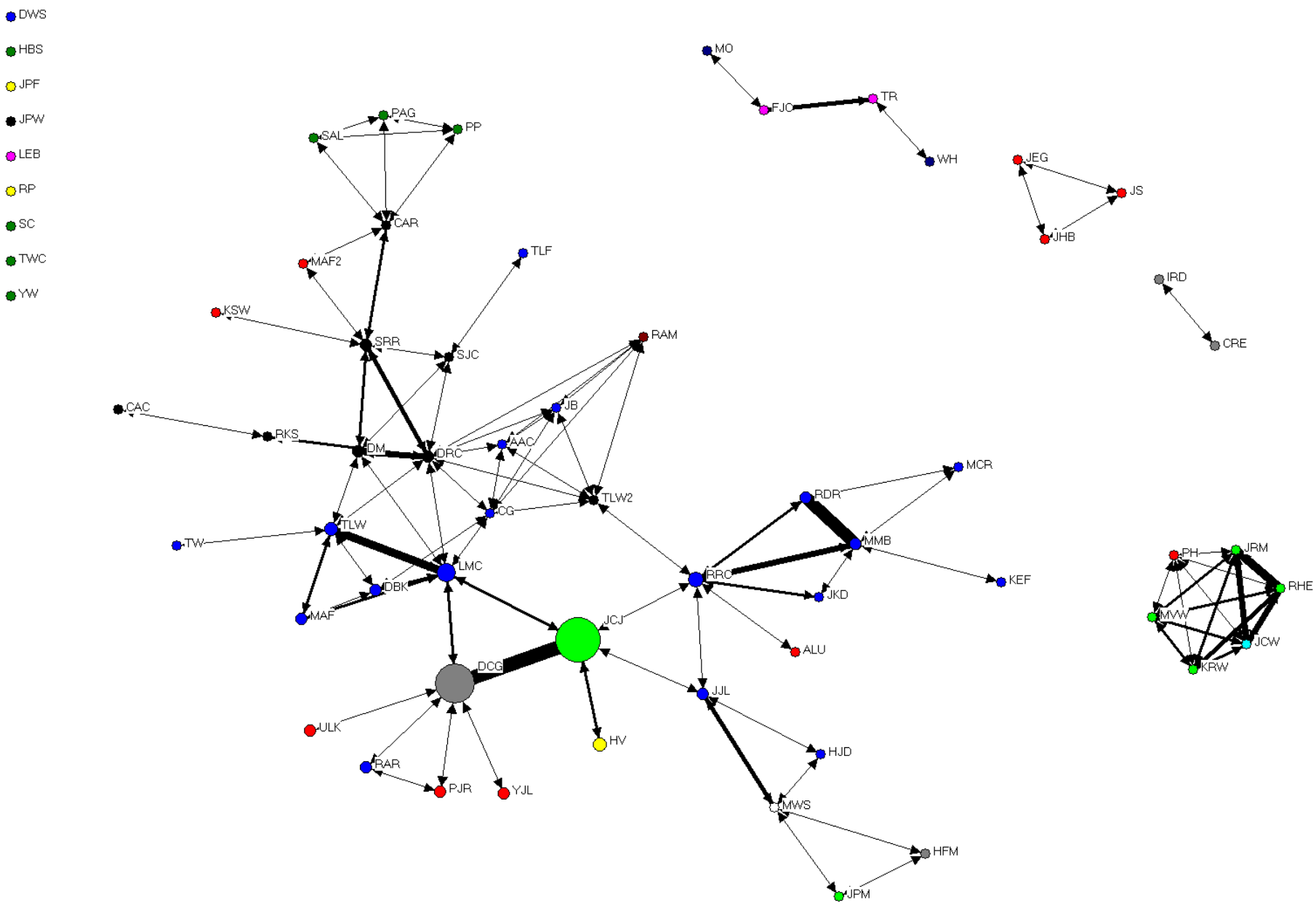


NASA1
PSRS
GRC
NSF17
NSF8
NSF9
UNCS18
ACSPRF
Wash
TPHSG2
KHF2
TPHSG
KHF
NCDCR2
HHFINC
USFS
TPHSG4
HHFINC2
TPHSG3
UNCS27
MEC
NCSU6
NHC
UNCW3
NCDEM
CZRINC2
PCSP3
PCSP2
WRRI4
TexasG
PCSP4
CZRINC
OSU
NASA3
NASA2
IU
ERMINC
NOAA7
UNCS26
NCDCR
NSF14
NOAA5
NOAA6
NOAA4
NCSU2
NOAA2
NOAA3
NCBIO
MHT
NCSU
CC
KLPRD
NPS
USDA
UNCW2
NCDOT2
NCDOT
UNCS19
USFWS
NCDPR2
USGS
WRRI6
NPS4
NPS5
Duke
NSF16
NSF15
WRRI5
PCSP5
UNCS16
UNCS15
PCSP
NSF11
Bates
UNCS17
NSF12
NOAA
RCDC
WRRI2
UVA3
WRRI3
UVA2
UVA6
NCSU5
USEPA2
NCDENR2
NSF13
Glaxo
CTE
PSU
UVA4
UVA5
NPS6
NSF5
NSF6
NSF4
UNCS8
Nobles
UNCS4
UNCS9
UNCS10
UNCS12
UNCS13
NSF10
UNCS14
UNCS11
NSF2
NSF3
NSF7
UNCS6
UNCS7
NCDMF
UNH
NMFS
UNCCH
UNCS23
USFWS3
UNCS22
UNCS21
UNCS25
NCDENR3
USFWS2
NCDENR4

Investigator Affiliation Networks and the Identification of Key Investigators

Find the investigators that, if removed, would maximize the number of network components


DWS
HBS
JPF
JPW
LEB
RP
SC
TWC
YW
Geology
Biology
Anthropology
Sociology
Geography
RLS
Economics
Maritime
History
Chemistry
Other
WH
MO
FJC
TR
JEG
JHB
JS
CRE
IRD
SAL
PP
PAG
CAR
KSW
MAF2
TLF
SRR
SJC
CAC
RKS
DM
DRC
AAC
JB
RAM
TLW
CG
TLW2
TW
LMC
MAF
DBK
JKD
RRC
MMB
MCR
RDR
KEF
JCJ
DCG
JJL
ULK
YJL
RAR
HV
ALU
PJR
HJD
MWS
JPM
HFM
RHE
PH
MVW
KRW
JRM
JCW


DWS
HBS
JPF
JPW
LEB
RP
SC
TWC
YW
MO
FJC
TR
WH
JEG
JS
JHB
IRD
CRE
PAG
SAL
PP
CAR
MAF2
TLF
KSW
SRR
SJC
RAM
CAC
JB
RKS
DM
DRC
AAC
TLW2
CG
MCR
RDR
MMB
KEF
TLW
TW
LMC
DBK
MAF
JCJ
RRC
JKD
ALU
DCG
JJL
ULK
HV
HJD
RAR
PJR
YJL
MWS
HFM
JPM
PH
JRM
RHE
MVW
JCW
KRW

Summary

- Lack of a robust interdisciplinary research network at ECU
- Primary nature of interdisciplinary research is within natural sciences
- The limited amount of social and natural interdisciplinary research was facilitated by the spatial proximity of the investigators

Network Visualization of the IMDB

Do the Top Liberal and Conservative Hollywood Actors/Producers/Writers/ Directors Collaborate?

Identifying Liberal and Conservative Actors: But Isn't All of Hollywood Liberal?

- Not according to Celebpolitics.com a conservative Hollywood watch group.

WHAT IS A POLITICAL MOVIE RATING?

Are you tired of Hollywood's outspoken elite making ignorant political statements? Do you boycott all Barbra Streisand or Alec Baldwin movies? Then political movie ratings are for you!

Political Movie Ratings Explained
We at CelebPolitics.com have cataloged actors' political statements and campaign contributions. Based upon this data, we have created a system that rates movies on a "Conservative Friendly" scale based upon the movies' actors. We tell you whether to see the movie at theaters, wait for it to come to video, or never see it at all!

Before you go to the theaters, log onto CelebPolitics.com to check the movie's political rating, so that your money does not go into the pockets of outspoken liberals.

Ratings Calculations
Both movies and actors begin with a conservative-friendly rating of zero, indicating neutrality, which is then modified up or down based upon:

1. Political statements, and
2. Campaign contributions

Negative ratings indicate that the actor is liberal (or that the movie stars liberal actors), while positive ratings indicate that the actor is conservative (or that the movie stars conservative actors). Large positive numbers indicate strong conservatism, while large negative numbers indicate strong liberalism.

Movie ratings are simply the sum of the ratings of the actors appearing in the movie.

Boycott Liberal Hollywood!

Exercise your right to be informed! Stop going to movies starring liberal actors, so that your money stops going into their liberal pockets.

headlines

Rates Movies and Actors as to a conservative/liberal index

- How the index is calculated:

(-1)(# of liberal quotes) + (-1)(liberal donations / $10,000) + (5)(# of conservative quotes) + (3)(conservative donations / $5,000)

Our Formulas

1. **Actor's Overall Rating:** Each actor's Overall Rating is calculated as follows: (-1)(# of liberal quotes) + (-1)(liberal donations / $10,000) + (5)(# of conservative quotes) + (3)(conservative donations / $5,000). In other words, actors receive one negative point for each liberal quote made and for each $10,000 of liberal campaign donations made (with an upper limit of 50 for campaign donations).
2. **Movie's Overall Rating:** A movie's Overall Rating is the sum of the overall ratings of the actors who appear in the movie.

Example of Actor Overall Rating - Barbra Streisand

To give you a better idea of how we calculate the Overall Ratings, let's take an example - Barbra Streisand. Each actor - even Barbra - starts with a rating of zero, indicating neutrality, which is then modified up or down based upon political statements and campaign contributions.

Barbra's calculation: First, we count the number of liberal statements she has made. As of 01/29/06, we had recorded ten such statements, so that takes her rating from zero to -10.

Next, we take her overall liberal campaign contributions ($498,075) and divide by 10,000. This gives us -50 (we always round up). We add -50 to -10, and Barbra's Overall Rating is now -60. Because she has made no conservative-friendly statements or campaign contributions, she receives no offsetting (positive) points.

BARBRA STREISAND - *WACKO LIBERAL NUTCASE*

View All Political Statements | View All Movies

Wacko Liberal Nutcase

Barbra Streisand At a Glance		
Conservative-Friendly Rating:	-60	Ratings FAQ
Liberal Campaign Contributions	$498,075	
Conservative Campaign Contributions:	$0	

CelebPolitics.com says: Barbra Streisand has a conservative-friendly rating of -60, making Barbra a Wacko Liberal Nutcase. To learn more about how CelebPolitics.com arrived at these ratings, or what the ratings mean, please visit our Ratings FAQ.

Barbra Streisand's Political Statements Barbra Streisand's Movies

Barbra Streisand 's Political Statements

Barbra Streisand's highest level of education is graduating from high school. Because of this education, Barbra Streisand felt qualified to make the following statements about politics:

Streisand Blows Smoke

"We have a president who stole the presidency through family ties, arrogance and intimidation, employing Republican operatives to exercise the tactics of voter fraud by disenfranchising thousands of blacks, elderly Jews and other minorities."

http://www.dead.net/special_events/images/barbra.html

Uh-oh Barbra's Freightened!

"I find George Bush and Dick Cheney frightening, Donald Rumsfeld and John Ashcroft frightening..."

http://www.drudgereport.com/strei2.htm

BEN STEIN - *CONSERVATIVE*

View All Political Statements | View All Movies

Conservative

Ben Stein At a Glance		
Conservative-Friendly Rating:	27	Ratings FAQ
Liberal Campaign Contributions	$0	
Conservative Campaign Contributions:	$40,550	

CelebPolitics.com says: Ben Stein has a conservative-friendly rating of 27, making Ben a Conservative. To learn more about how CelebPolitics.com arrived at these ratings, or what the ratings mean, please visit our Ratings FAQ.

Ben Stein's Political Statements Ben Stein's Movies

Ben Stein 's Political Statements

Ben Stein's highest level of education is graduating from Columbia University with honors in economics, and Yale Law School. Because of this education, Ben Stein felt qualified to make the following statements about politics:

Are you aware of a political statement by Ben Stein not listed here? Please let us know.

Ben Stein 's Movies

Ben Stein has appeared in, directed, produced, or been otherwise involved in the following movies:

A Smile Like Yours
Casper
Casper: A Spirited Beginning
Dave
Dennis the Menace
Easy Wheels
Ferris Bueller's Day Off
Ghostbusters II
Honeymoon in Vegas
House Arrest
Miami Rhapsody
My Girl 2
North
Osmosis Jones
Planes, Trains & Automobiles
Soapdish
Son of the Mask
The Day My Parents Ran Away
The Mask
The Wild Life

TOP 25 MOST LIBERAL ACTORS

Below is the updated CelebPolitics.com Top 25 Most Liberal Actors. Be sure also to check out the Top 25 Most Conservative Actors!

Actor's Overall Rating is calculated as follows: (-1)(# of liberal quotes) + (-1)(liberal donations / $10,000) + (5)(# of conservative quotes) + (3)(conservative donations / $5,000). For more, visit our Ratings FAQ.

Rank	Actor Name	Money to Liberals	Money to Conservatives	This Actor is:	Conservative Friendly Rating
1	Streisand, Barbra	$498,075	$0	Wacko Liberal Nutcase	-60
2	Douglas, Michael	$492,750	$0	Wacko Liberal Nutcase	-52
3	Katzenberg, Jeffrey	$1,255,130	$0	Wacko Liberal Nutcase	-50
4	Lear, Norman	$845,645	$0	Wacko Liberal Nutcase	-50
5	Reiner, Rob	$456,811	$0	Wacko Liberal Nutcase	-48
6	Pollack, Sydney	$242,531	$0	Wacko Liberal Nutcase	-25
7	Thomas, Marlo	$236,100	$0	Wacko Liberal Nutcase	-24
8	Fonda, Jane	$194,546	$0	Wacko Liberal Nutcase	-23
9	Chase, Chevy	$162,075	$0	Wacko Liberal Nutcase	-22
10	Newman, Paul	$190,500	$0	Wacko Liberal Nutcase	-21
11	Baldwin, Alec	$108,502	$0	Wacko Liberal Nutcase	-19
12	Garofalo, Janeane	$5,738	$0	Wacko Liberal Nutcase	-19
13	Woodward, Joanne	$172,050	$0	Wacko Liberal Nutcase	-18
14	Burrows, James	$167,130	$0	Wacko Liberal Nutcase	-17
15	Hoffman, Dustin	$139,250	$0	Wacko Liberal Nutcase	-16
16	Moore, Michael	$4,500	$0	Wacko Liberal Nutcase	-16
17	Williams, Robin	$103,500	$0	Wacko Liberal Nutcase	-16
18	Clooney, George	$10,000	$0	Wacko Liberal Nutcase	-14
19	Penn, Sean	$2,000	$0	Wacko Liberal Nutcase	-14
20	Sarandon, Susan	$31,894	$0	Wacko Liberal Nutcase	-14
21	Springer, Jerry	$138,500	$0	Wacko Liberal Nutcase	-14
22	Thomas, Heather	$131,914	$0	Wacko Liberal Nutcase	-14
23	Asner, Ed	$33,075	$0	Wacko Liberal Nutcase	-12
24	Norton, Edward	$72,500	$0	Wacko Liberal Nutcase	-12
T-25	Devito, Danny	$100,750	$0	Wacko Liberal Nutcase	-11
T-25	Robbins, Tim	$10,510	$0	Wacko Liberal Nutcase	-11

Honorable Mentions: Brooks, James | Danson, Ted | Midler, Bette | O'Donnell, Rosie | Sheen, Martin | Brinkley, Christie | David, Larry | Gere, Richard | Glover, Danny | Lange, Jessica | Stone, Oliver | Whitford, Bradley | DeNiro, Robert | Dreyfuss, Richard | Hawke, Ethan | Beatty, Warren | Bergen, Candice | Harrelson, Woody | Hawn, Goldie | Redford, Robert | Spacey, Kevin

TOP 25 MOST CONSERVATIVE ACTORS

Below is the updated CelebPolitics.com Top 25 Most Conservative Actors. Be sure also to check out the Top 25 Most Liberal Actors!

Actor's Overall Rating is calculated as follows: (-1)(# of liberal quotes) + (-1)(liberal donations / $10,000) + (5)(# of conservative quotes) + (3)(conservative donations / $5,000). For more, visit our Ratings FAQ.

Rank	Actor Name	Money to Liberals	Money to Conservatives	This Actor is:	Conservative Friendly Rating
1	Stein, Ben	$0	$40,550	Conservative	27
2	Norris, Chuck	$0	$32,225	Conservative	21
3	Stallone, Sylvester	$0	$33,800	Conservative	21
4	Boone, Pat	$0	$27,605	Conservative	18
5	Newton, Wayne	$0	$27,250	Conservative	18
6	Grammer, Kelsey	$0	$10,000	Conservative	16
7	Schwarzenegger, Arnold	$0	$13,250	Conservative	14
8	Heston, Charlton	$0	$8,750	Conservative	11
9	Selleck, Tom	$0	$6,500	Conservative	11
10	Caviezel, James	$0	$0	Conservative	10
11	Russell, Kurt	$0	$0	Conservative	10
12	Carey, Drew	$0	$3,000	Conservative	8
13	Danza, Tony	$0	$1,000	Conservative	8
14	Duvall, Robert	$0	$1,000	Conservative	8
15	Eastwood, Clint	$0	$250	Conservative	8
16	Hopper, Dennis	$0	$2,000	Conservative	8
17	Locklear, Heather	$0	$1,000	Conservative	8
18	Torn, Rip	$0	$2,000	Conservative	8
19	Woods, James	$0	$500	Conservative	8
20	Baldwin, Stephen	$0	$0	Conservative	5
21	Boyle, Lara Flynn	$0	$0	Conservative	5
22	Derek, Bo	$0	$0	Conservative	5
23	Gellar, Sarah Michelle	$0	$0	Conservative	5
24	Gibson, Mel	$0	$0	Conservative	5
25	Harmon, Angie	$0	$0	Conservative	5

Honorable Mentions: Dwayne "The Rock" Johnson; Freddie Prinze Jr.; Adam Sandler; Ron Silver; Fred Thompson; Vince Vaughn; Bob Barker; Ernes Borgnine; Jule Bowen; Dean Cain; Shannen Doherty.

TOP 100 MOST LIBERAL MOVIES

Below is the updated CelebPolitics.com Top 100 Most Liberal Movies. Be sure also to check out the Top 100 Most Conservative Mc

We do not rate movies based on content, as that would require actually seeing movies that we suggest people boycott. A mo sum of the actor overall ratings who appear in the movie. An Actor's Overall Ratings is calculated as follows: (-1)(# of liberal quot donations / $10,000) + (5)(# of conservative quotes) + (3)(conservative donations / $5,000). For more, visit our Ratings FAQ.

Rank	Movie Name	Money to Liberals	Money to Conservatives	This Movie is:	Conservative Friendly Rating
1	The American President	$1,009,061	$2,000	Toxic Liberal Waste	-118
2	The Princess Bride	$1,306,856	$0	Toxic Liberal Waste	-100
3	Meet the Fockers	$729,675	$0	Toxic Liberal Waste	-86
4	The War of the Roses	$718,750	$0	Toxic Liberal Waste	-77
5	Wall Street	$531,100	$0	Toxic Liberal Waste	-70
6	One Flew Over the Cuckoo's Nest	$617,500	$0	Toxic Liberal Waste	-68
7	Romancing the Stone	$626,000	$0	Toxic Liberal Waste	-67
8	Tell Them Who You Are	$687,296	$2,000	Toxic Liberal Waste	-67
9	The Jewel of the Nile	$626,000	$0	Toxic Liberal Waste	-67
10	The Game	$494,750	$0	Toxic Liberal Waste	-66
11	The Mirror Has Two Faces	$529,625	$0	Toxic Liberal Waste	-66
12	EdTV	$489,561	$2,000	Toxic Liberal Waste	-64
13	The Prince of Tides	$523,225	$0	Toxic Liberal Waste	-63
14	The In-Laws	$558,900	$0	Toxic Liberal Waste	-62
15	A Few Good Men	$533,811	$0	Toxic Liberal Waste	-61
16	A Perfect Murder	$503,450	$0	Toxic Liberal Waste	-61
17	Sleepless in Seattle	$547,311	$0	Toxic Liberal Waste	-61
18	Throw Momma From the Train	$557,561	$0	Toxic Liberal Waste	-60
19	Face/Off	$492,750	$0	Toxic Liberal Waste	-58
20	Flatliners	$506,750	$0	Toxic Liberal Waste	-58

TOP 100 MOST CONSERVATIVE MOVIES

Below is the updated CelebPolitics.com Top 100 Most Conservative Movies. Be sure also to check out the Top 100 Most Liberal Mov

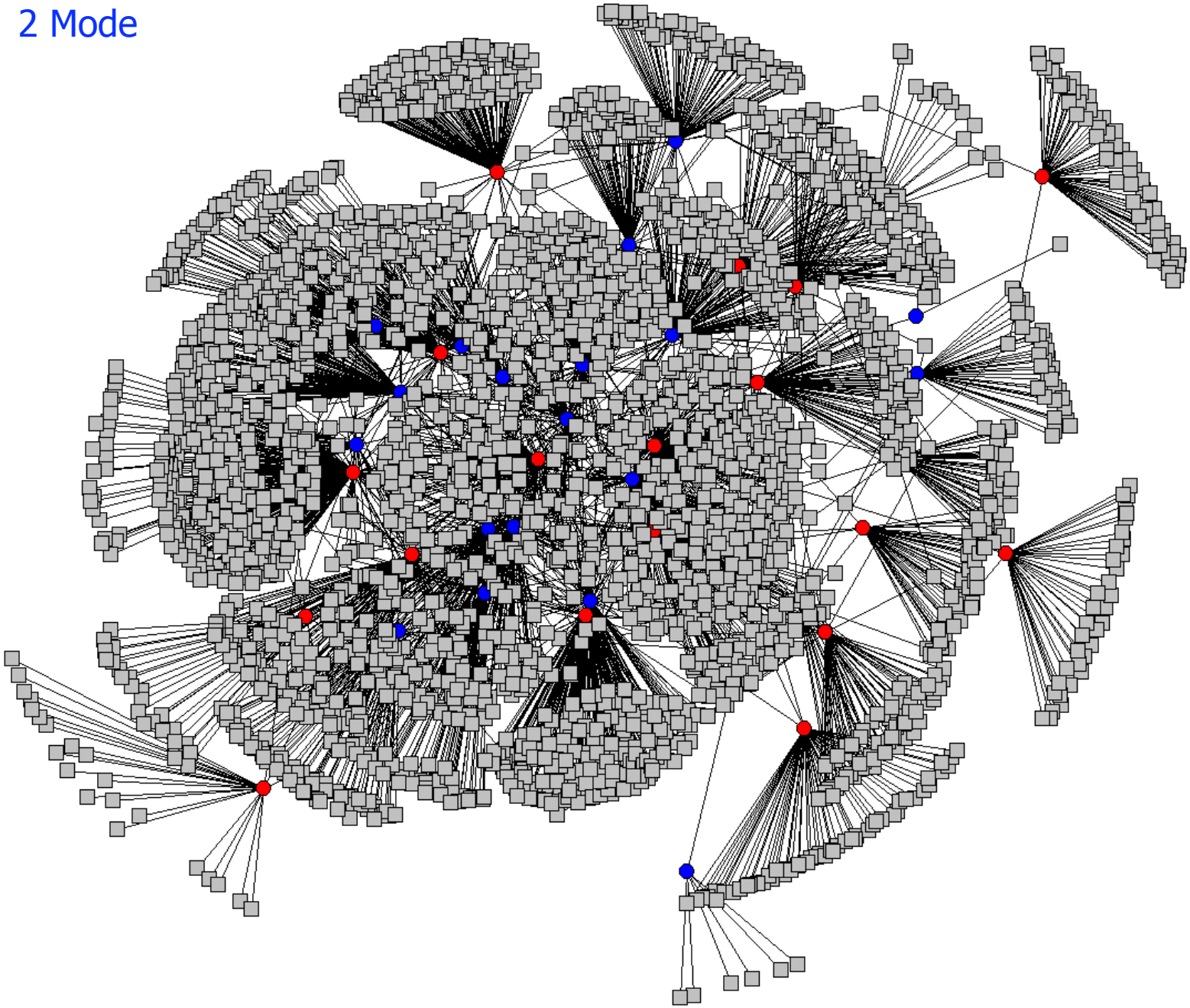
We do not rate movies based on content, as that would require actually seeing movies that we suggest people boycott. A mov sum of the actor overall ratings who appear in the movie. An Actor's Overall Ratings is calculated as follows: (-1)(# of liberal quote donations / $10,000) + (5)(# of conservative quotes) + (3)(conservative donations / $5,000). For more, visit our Ratings FAQ.

Rank	Movie Name	Money to Liberals	Money to Conservatives	This Movie is:	Conservative Friendly Rating
1	Dave	$30,850	$53,800	Conservative	33
2	Dodgeball: A True Underdog Story	$4,500	$34,225	Conservative	33
3	Tango & Cash	$0	$33,800	Conservative	31
4	The Greatest Story Ever Told	$0	$36,355	Conservative	29
5	A Smile Like Yours	$0	$40,550	Conservative	27
6	Casper	$0	$40,550	Conservative	27
7	Casper: A Spirited Beginning	$0	$40,550	Conservative	27
8	Dennis the Menace	$0	$40,550	Conservative	27
9	Easy Wheels	$0	$40,550	Conservative	27
10	Ferris Bueller's Day Off	$0	$40,550	Conservative	27
11	Ghostbusters II	$0	$40,550	Conservative	27
12	Planes, Trains & Automobiles	$0	$40,550	Conservative	27
13	Son of the Mask	$0	$40,550	Conservative	27
14	The Wild Life	$0	$40,550	Conservative	27
15	Silent Rage	$0	$32,225	Conservative	26
16	The Mask	$0	$40,550	Conservative	26
17	Miami Rhapsody	$9,000	$40,550	Conservative	25
18	The Day My Parents Ran Away	$12,000	$40,550	Conservative	25
19	Down Periscope	$0	$12,000	Conservative	24
20	Honeymoon in Vegas	$14,250	$40,550	Conservative	24

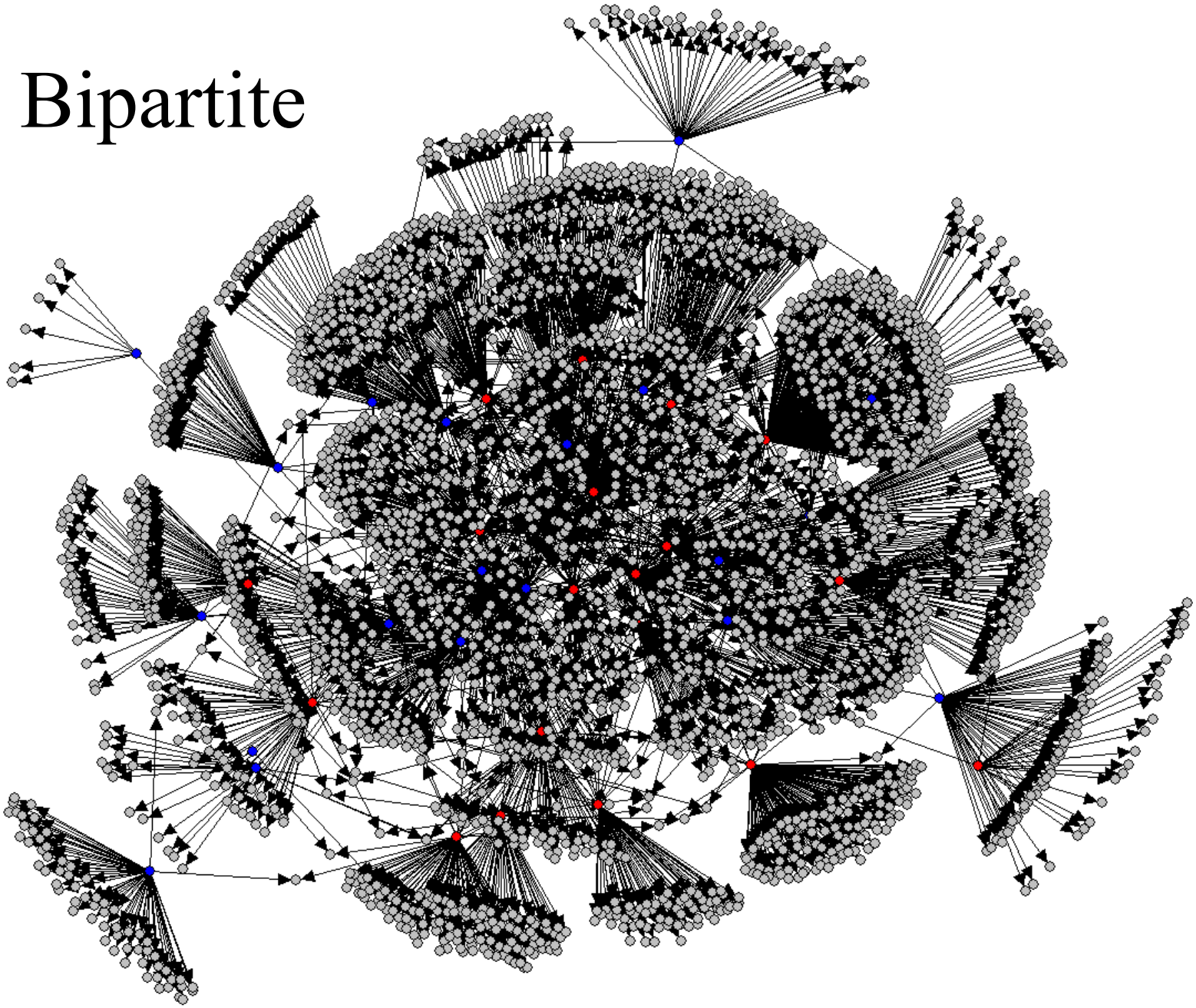
Look at the Extent to Which the Top 20 Actors from Each Persuasion Interact Through Various Venues

- Created a 2-mode matrix consisting of the 40 actors by venues which yielded a 40 x 2818 matrix.
- Also Bipartite 2858 x 2858

2 Mode



Bipartite



Graph Has Problems Showing Underlying Overlaps

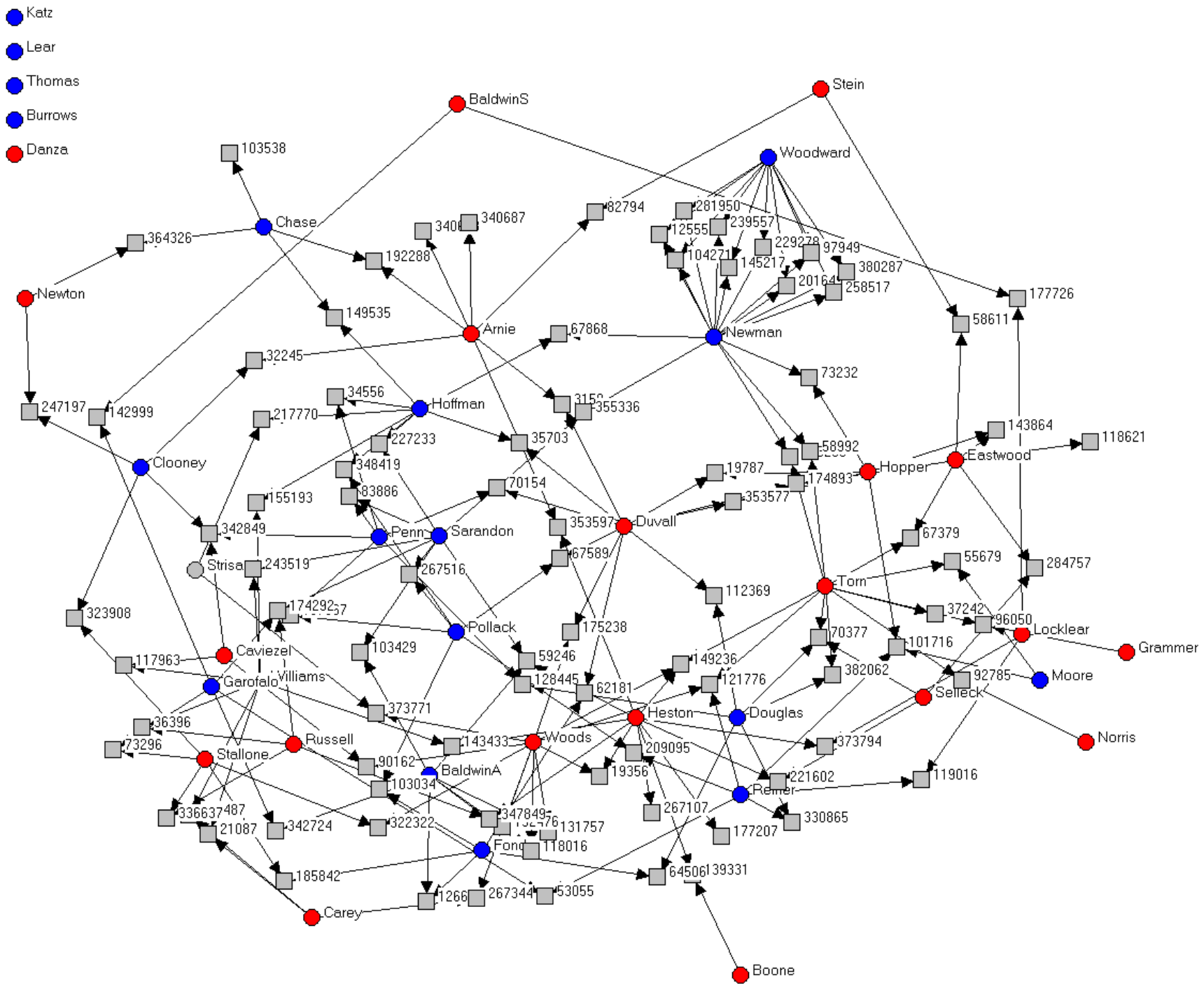
Large number of nodes with degree 1

Large number of events that reflect little about project collaborations (e.g., Academy Award Shows, Music Award Shows, Documentaries)

182445	12		182445 "Kennedy Center Honors: A Celebration of the Performing Arts, The" [1-*]
425079	10		425079 ""TV Land Moguls"" [1-*]
3208	8		3208 "70th Annual Academy Awards, The" [1-*]
418963	8		418963 "Retrosexual: The 80's" [1-*]
3084	7		3084 "63rd Annual Academy Awards, The" [1-*]
3241	7		3241 "75th Annual Academy Awards, The" [1-*]
3243	7		3243 "76th Annual Academy Awards, The" [1-*]
14375	7		14375 "America: A Tribute to Heroes" [1-*]
282938	7		282938 "Rated 'R': Republicans in Hollywood" [1-*]
910	6		910 "101 Most Unforgettable SNL Moments" [1-*]
1768	6		1768 "2000 Blockbuster Entertainment Awards" [1-*]
2995	6		2995 "59th Annual Academy Awards, The" [1-*]
3090	6		3090 "64th Annual Academy Awards, The" [1-*]
3110	6		3110 "67th Annual Academy Awards, The" [1-*]
3227	6		3227 "72nd Annual Academy Awards, The" [1-*]
60313	6		60313 "Century of Cinema, A" [1-*]
306821	6		306821 "Sex at 24 Frames Per Second" [1-*]
372923	6		372923 "Warner Bros. 75th Anniversary: No Guts, No Glory" [1-*]
401328	6		401328 "Directors, The" [1-*]
2972	5		2972 "55th Annual Academy Awards, The" [1-*]
2993	5		2993 "58th Annual Academy Awards, The" [1-*]
3072	5		3072 "60th Annual Academy Awards, The" [1-*]
3095	5		3095 "65th Annual Academy Awards, The" [1-*]
7980	5		7980 "AFI's 100 Years... 100 Movies" [1-*]
7986	5		7986 "AFI's 100 Years... 100 Stars" [1-*]
122473	5		122473 "Forever Hollywood" [1-*]

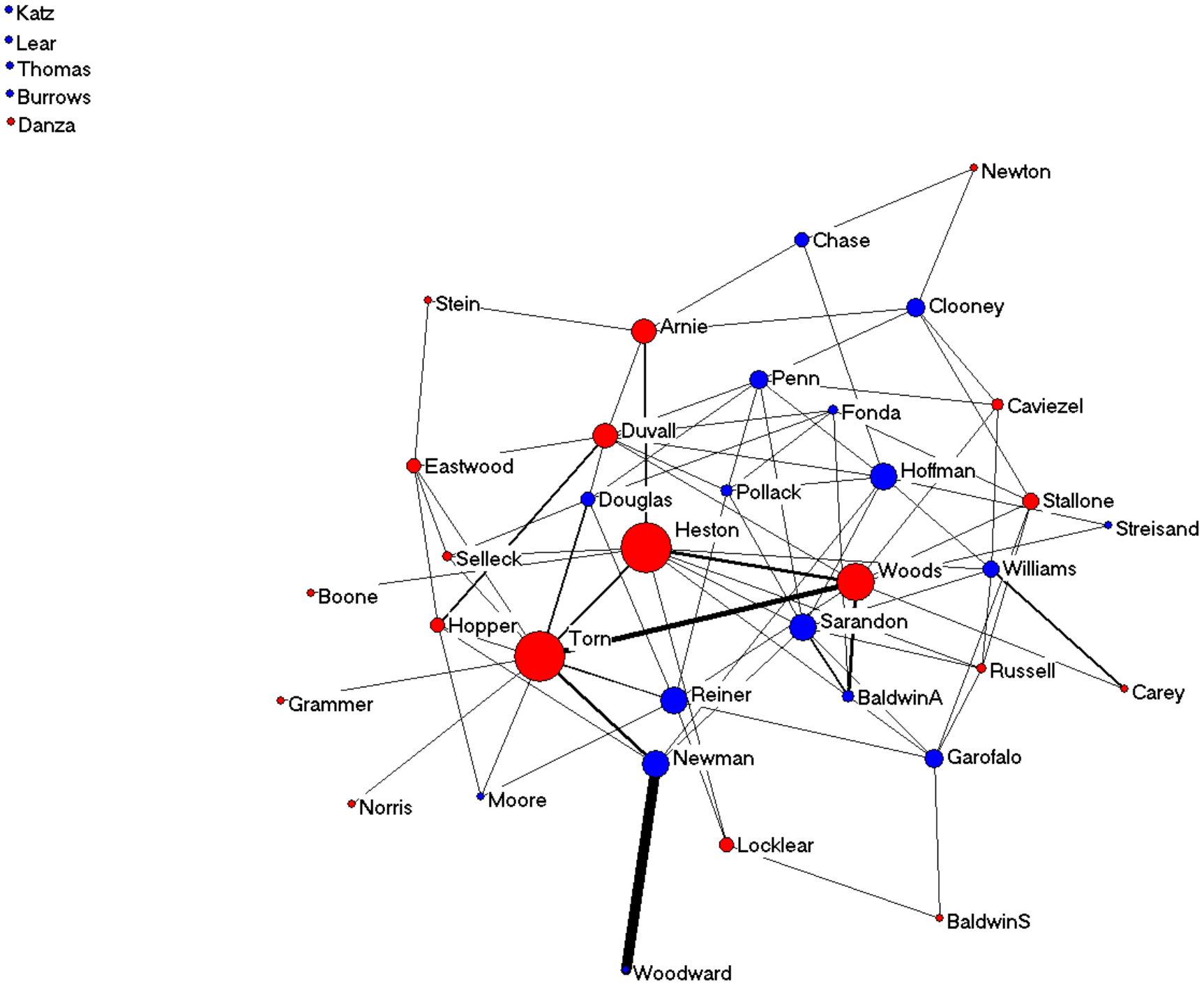
Reduce to Meaningful Venues-- Movies

- Included only movies (no documentaries or TV of any form)
- 40 x 96 Matrix


Katz
Lear
Thomas
Burrows
Danza
BaldwinS
Stein
103538
Woodward
Chase
364326
340687
82794
281950
12555
239557
229278
97949
104271
145217
380287
20164
258517
192288
177726
Newton
149535
Arnie
67868
Newman
58611
32245
73232
247197
142999
34556
Hoffman
355336
143864
118621
217770
227233
35703
58992
Eastwood
Clooney
348419
19787
Hopper
174893
83886
70154
353577
155193
353597
Duvall
342849
Penn
Sarandon
67379
Strisa
243519
267516
67589
55679
284757
112369
Torn
323908
174292
37242
96050
Locklear
Grammer
Pollack
175238
70377
101716
117963
Caviezel
103429
59246
149236
382062
92785
Moore
Garofalo
Villiams
128445
62181
121776
Selleck
373771
Heston
Douglas
36396
Norris
Russell
143433
Woods
373794
73296
Stallone
90162
209095
BaldwinA
19356
221602
119016
103034
Reiner
336637
487
267107
330865
21087
342724
322322
131757
177207
Fond
118016
185842
64506
139331
1266
267344
53055
Carey
Boone

Not very Informative: What about Overlaps?

Overlap Among Actors via Movies


Katz
Lear
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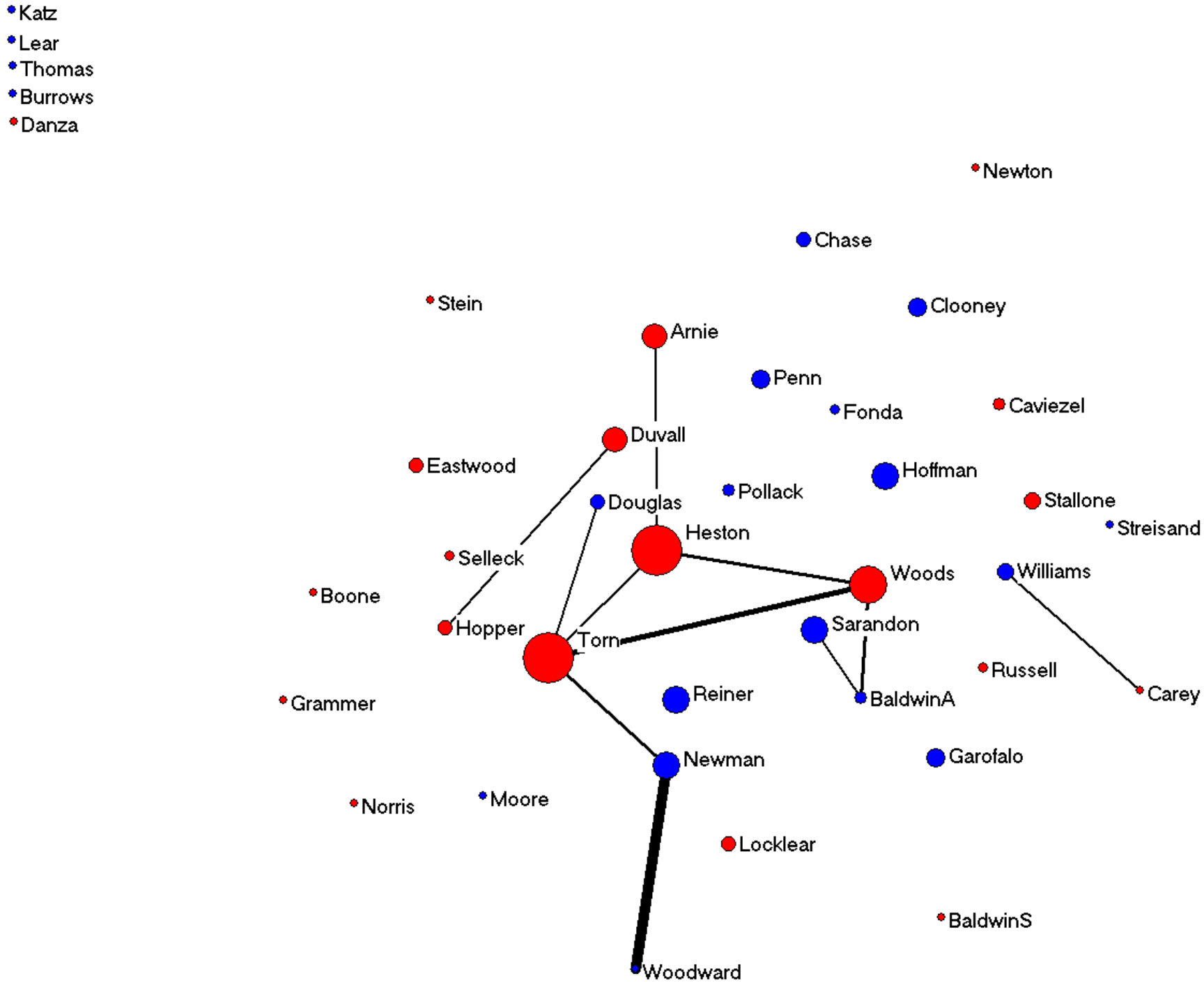
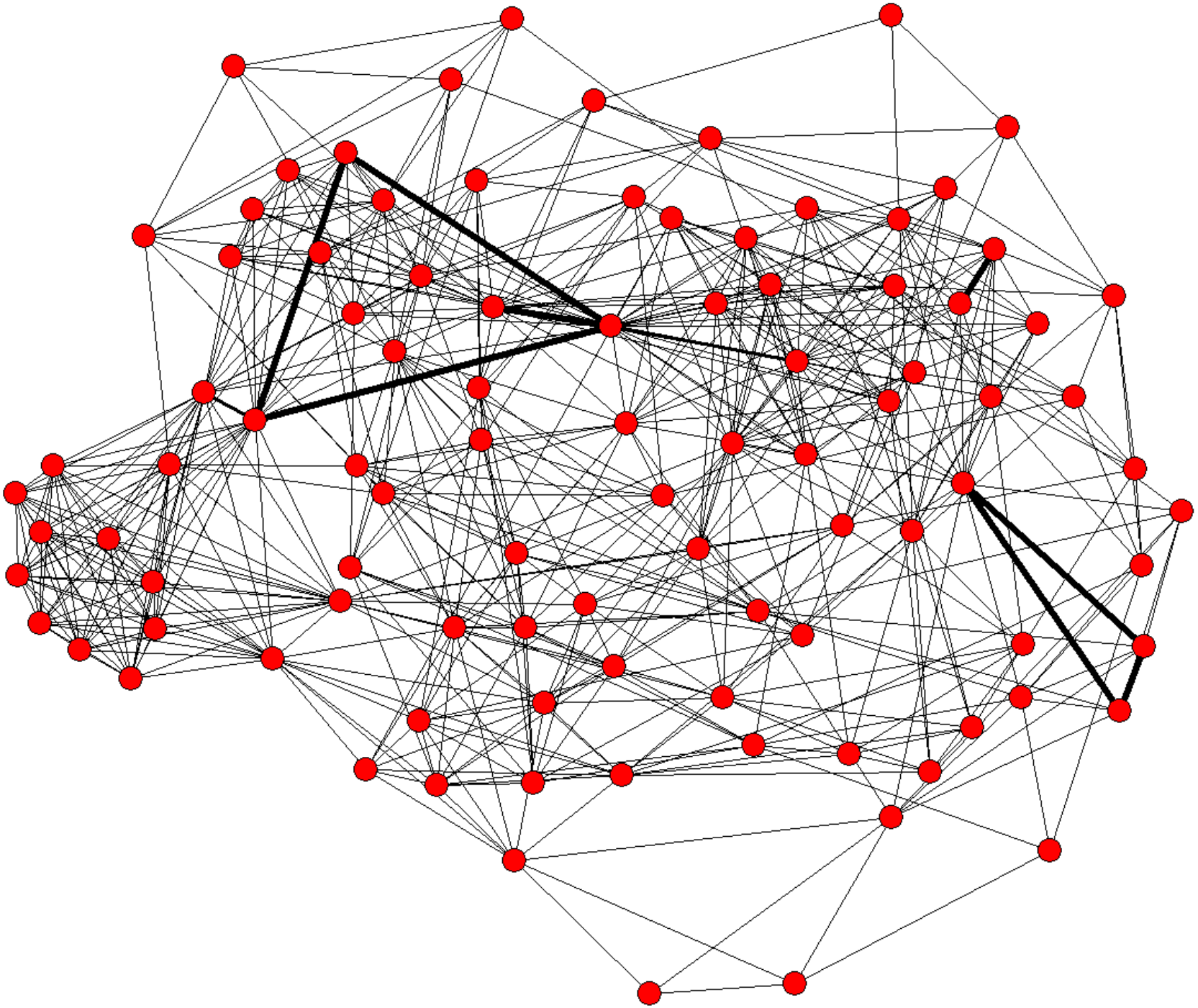
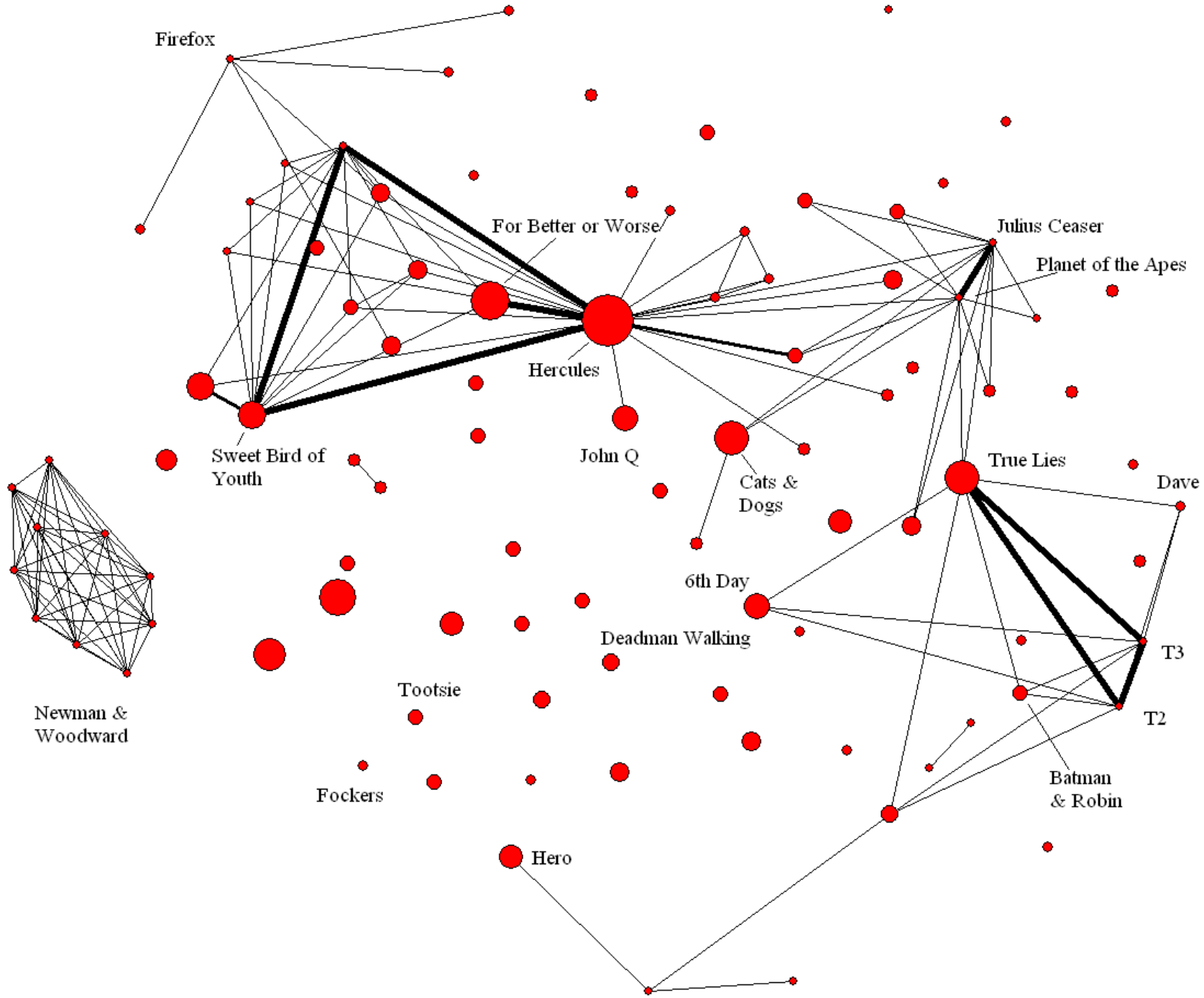
Burrows
Danza
Newton
Chase
Stein
Arnie
Clooney
Penn
Caviezel
Fonda
Duvall
Eastwood
Hoffman
Pollack
Douglas
Stallone
Streisand
Heston
Selleck
Woods
Williams
Boone
Hopper
Torn
Sarandon
Russell
Carey
Grammer
Reiner
BaldwinA
Garofalo
Newman
Norris
Moore
Locklear
BaldwinS
Woodward

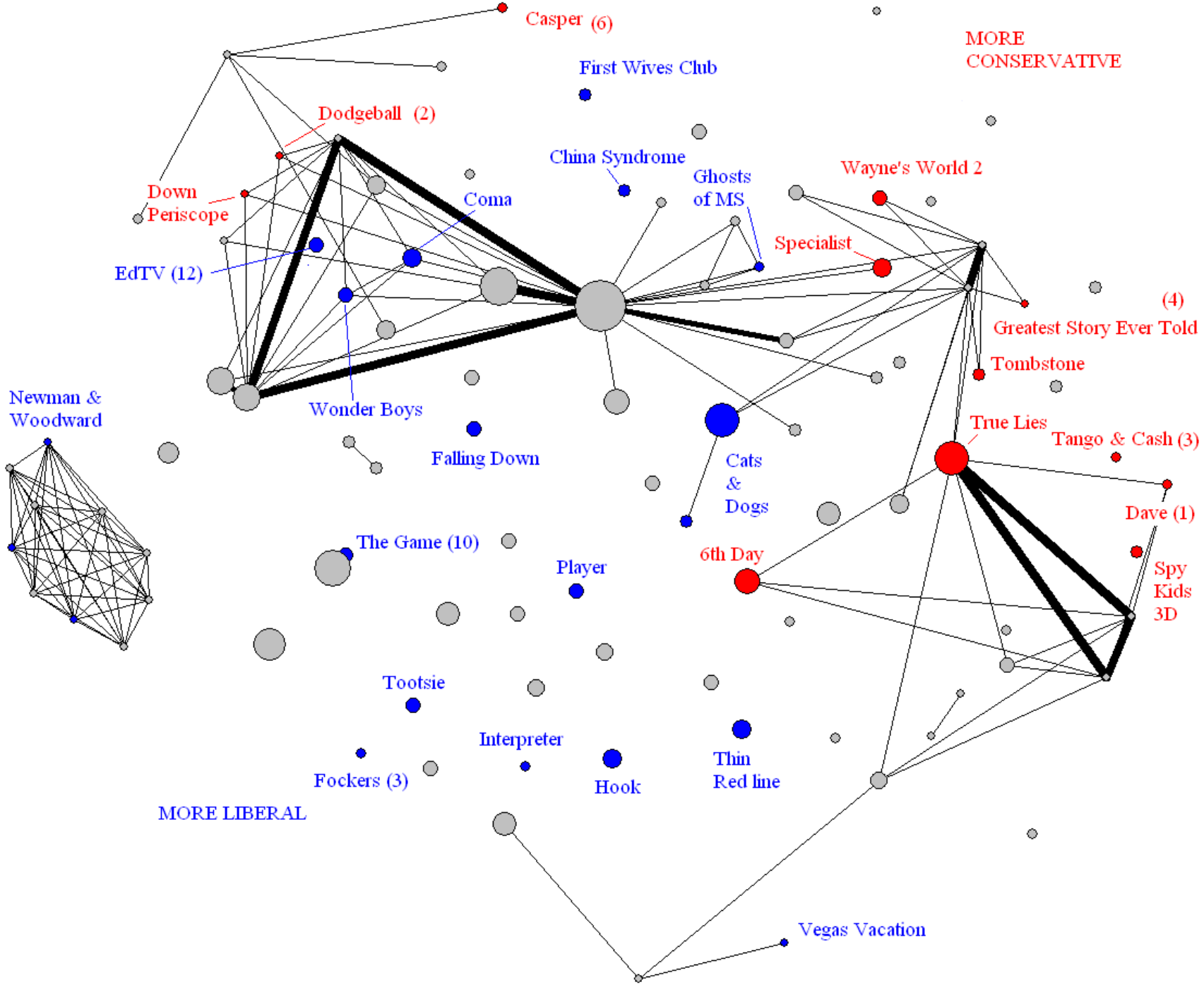

Katz
Lear
Thomas
Burrows
Danza
Newton
Chase
Stein
Clooney
Arnie
Penn
Fonda
Caviezel
Duvall
Eastwood
Hoffman
Pollack
Douglas
Stallone
Streisand
Heston
Selleck
Woods
Williams
Boone
Hopper
Torn
Sarandon
Russell
Carey
Grammer
Reiner
BaldwinA
Newman
Garofalo
Norris
Moore
Locklear
BaldwinS
Woodward

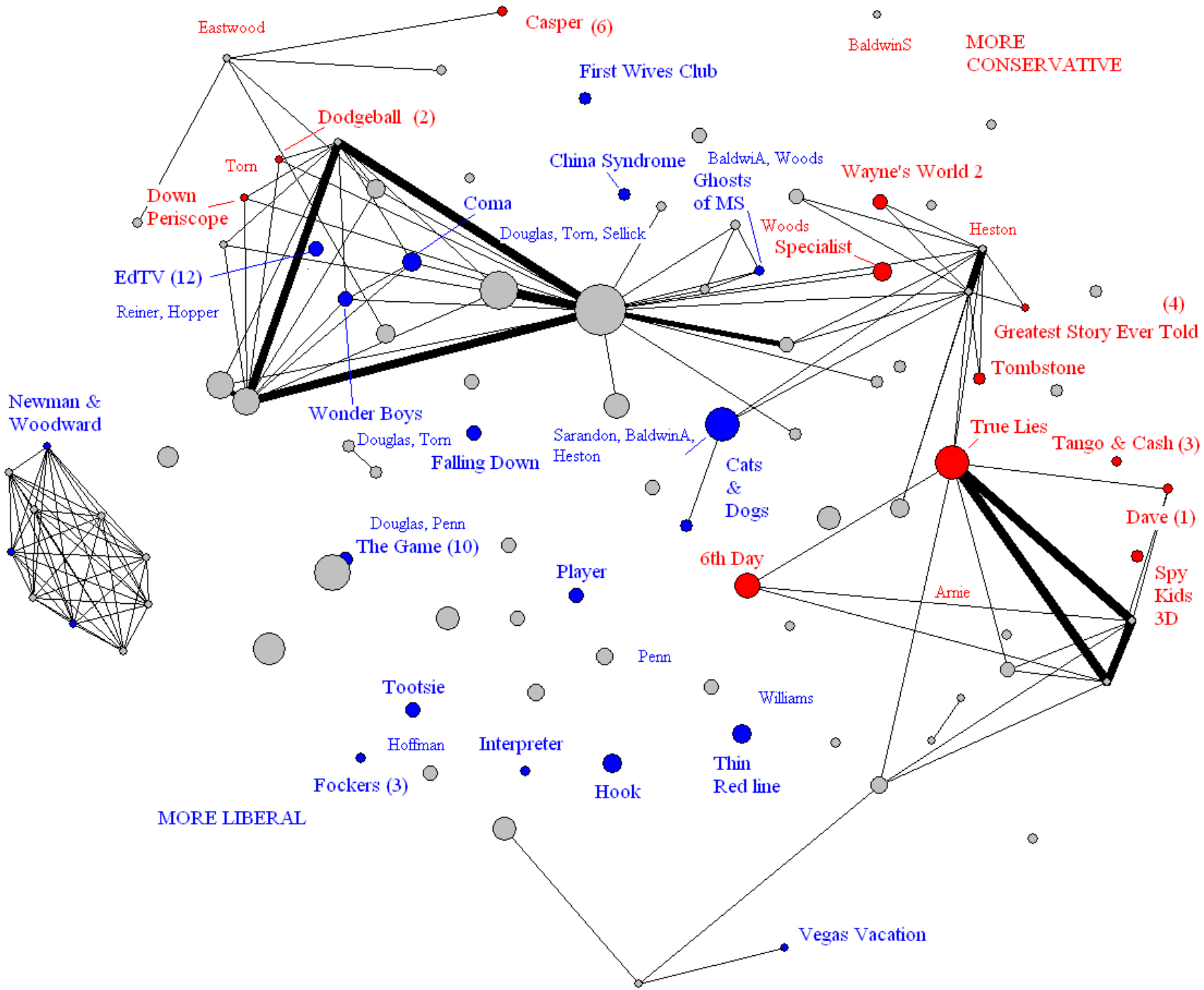
Overlap Among Movies via Actors

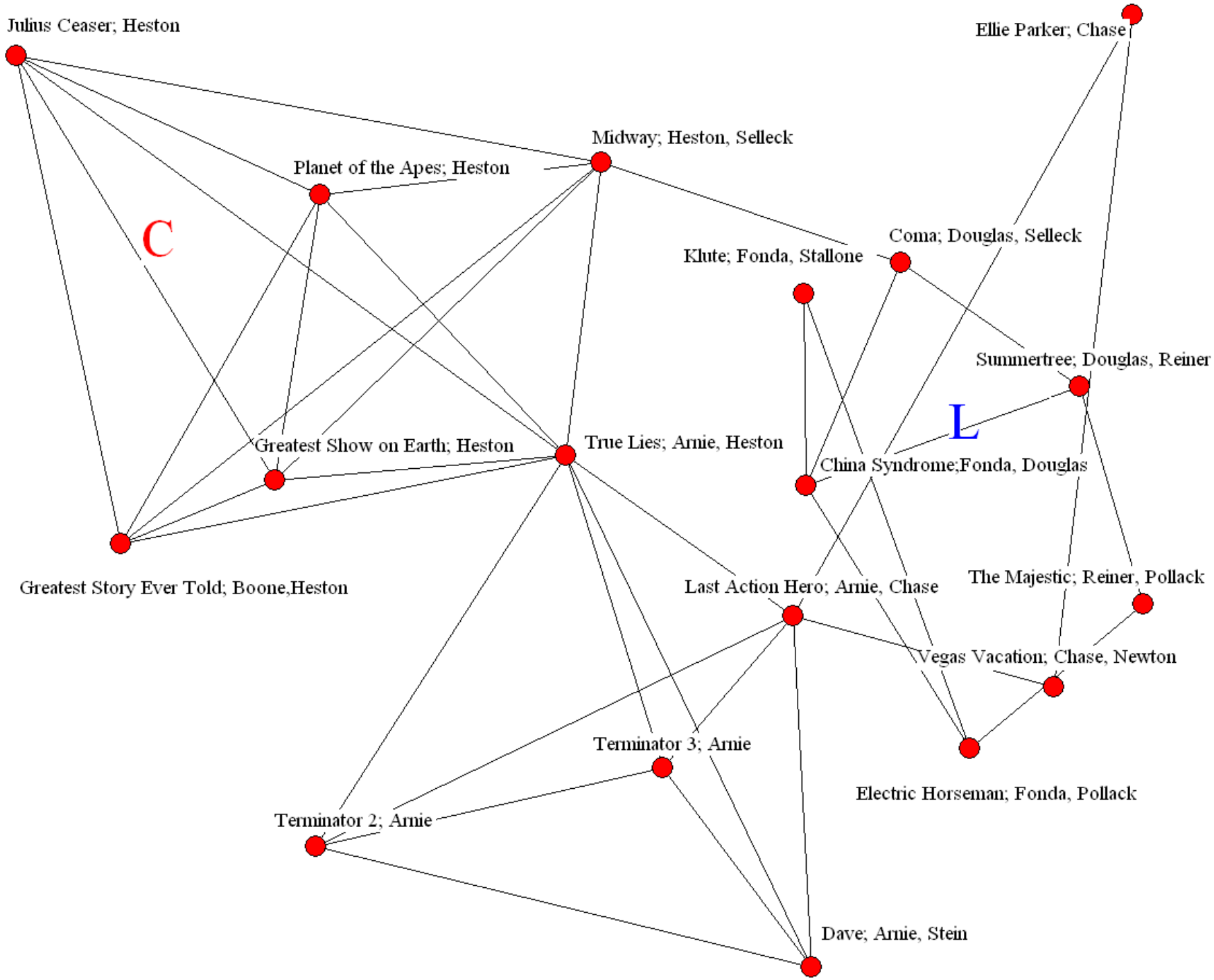


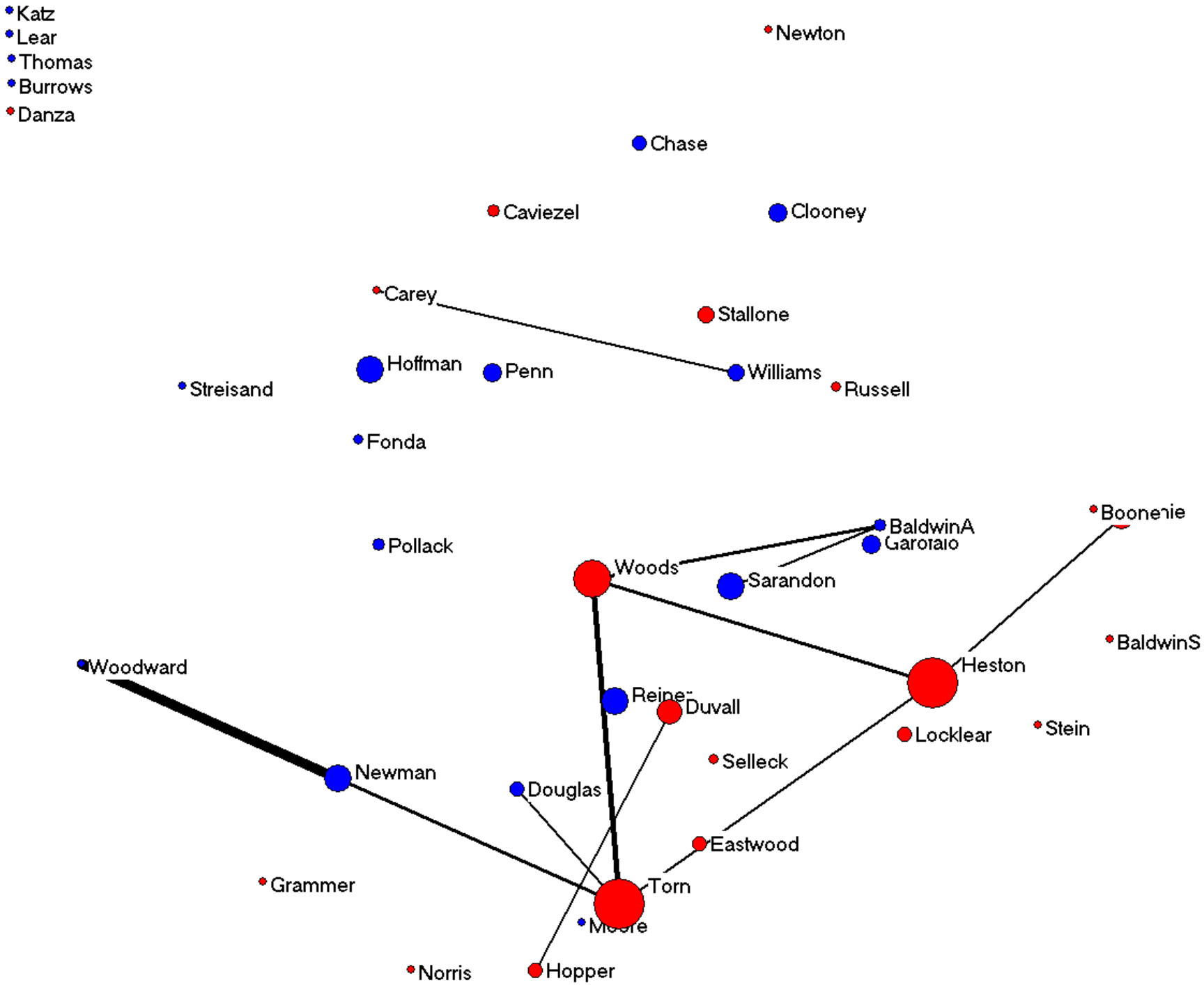

Firefox
For Better or Worse
Julius Ceaser
Planet of the Apes
Hercules
Sweet Bird of Youth
John Q
Cats & Dogs
True Lies
Dave
6th Day
Deadman Walking
T3
T2
Tootsie
Newman & Woodward
Batman & Robin
Fockers
Hero

Top 100 Liberal & Conservative Movies


Casper (6)
MORE
CONSERVATIVE
First Wives Club
Dodgeball (2)
China Syndrome
Ghosts
of MS
Wayne's World 2
Down
Periscope
Coma
Specialist
EdTV (12)
(4)
Greatest Story Ever Told
Tombstone
Newman &
Woodward
Wonder Boys
True Lies
Tango & Cash (3)
Falling Down
Cats
&
Dogs
Dave (1)
The Game (10)
6th Day
Player
Spy
Kids
3D
Tootsie
Interpreter
Thin
Red line
Fockers (3)
Hook
MORE LIBERAL
Vegas Vacation


Eastwood
Casper (6)
BaldwinS
MORE
CONSERVATIVE
First Wives Club
Dodgeball (2)
Torn
China Syndrome
BaldwiA, Woods
Ghosts
of MS
Wayne's World 2
Down
Periscope
Coma
Douglas, Torn, Sellick
Woods
Heston
Specialist
EdTV (12)
Reiner, Hopper
(4)
Greatest Story Ever Told
Tombstone
Newman &
Woodward
Wonder Boys
Douglas, Torn
Falling Down
Sarandon, BaldwinA,
Heston
True Lies
Tango & Cash (3)
Cats
&
Dogs
Douglas, Penn
The Game (10)
Dave (1)
6th Day
Player
Arnie
Spy
Kids
3D
Penn
Tootsie
Williams
Hoffman
Interpreter
Thin
Red line
Fockers (3)
Hook
MORE LIBERAL
Vegas Vacation


Julius Ceaser; Heston
Ellie Parker; Chase
Midway; Heston, Selleck
Planet of the Apes; Heston
C
Coma; Douglas, Selleck
Klute; Fonda, Stallone
Summertree; Douglas, Reiner
L
Greatest Show on Earth; Heston
True Lies; Arnie, Heston
China Syndrome;Fonda, Douglas
Greatest Story Ever Told; Boone,Heston
The Majestic; Reiner, Pollack
Last Action Hero; Arnie, Chase
Vegas Vacation; Chase, Newton
Terminator 3; Arnie
Electric Horseman; Fonda, Pollack
Terminator 2; Arnie
Dave; Arnie, Stein


Katz
Lear
Thomas
Burrows
Danza
Newton
Chase
Caviezel
Clooney
Carey
Stallone
Hoffman
Penn
Williams
Russell
Streisand
Fonda
Pollack
BaldwinA
Woods
Sarandon
Heston
BaldwinS
Woodward
Duvall
Locklear
Stein
Selleck
Newman
Douglas
Eastwood
Grammer
Torn
Hopper
Norris

Mage Visualization

Conclusions

- It looks like Rip Torn and to some extent James Woods will work with almost any wacko liberal nutcase!

Network Visualization

- Much of the work conducted in both the social and ecological sciences concerns a search for patterns and regularities in data
- Use of visualizations to aid in discovering these patterns and regularities

Factors to Consider in Displaying the Properties of Network Nodes and Arcs

- Node properties
- Arc properties
- Reducing Complexity

Node Properties

- Nodal color, shape, label, or nodal geometric distortions (e.g., ratios) are all examples of possible ways for conveying information of either a nominal or numerical kind.
- Some work has suggested that no more than six colors should be used in any computer graph (Derefeldt and Marmolin 1981) although others have suggested the maximum may be more like nine (Smallman and Boynton 1990).
- Care should be exercised in the selection and number of attributes to be explored.

Color

- Color can be used to represent the nominal properties of nodes in terms of such things as gender, membership in groups, political party affiliation, guild membership, etc.
- Any qualitative property of the node can be represented by color.
- **The Culture of Color in Conveying Information.**
- Another important aspect is color brightness or saturation.

Symbol Size and Shape

- A quantitative property of a node can be reflected in the its size relative to other nodes.
- A qualitative property of a node can be reflected in the shape of nodes.

Relationships or Flows (Arcs)

- Arc color and or thickness can be varied to reveal qualitative or quantitative properties of flows, relations, or connections. Additionally arrows can be varied in placement and size to symbolize arc properties.

Reducing Complexity: Groupings of Nodes and/or Arcs

- Many networks are complex, involving large numbers of both nodes and arcs.
- Groups of nodes can be turned on and off by button and groups of arcs, possibly in combination with nodes, can also be turned on and off in order to reveal both connections within and between clusters of nodes.

Spatial Considerations