An Introduction to Social Network Analysis

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Slides: http://tinyurl.com/spsp-sna
Paper: http://tinyurl.com/sna-paper

Workshop Overview

Three Parts

I. What *is* a social network?

II. How do we find and collect data on social networks?

III. How do we analyze social network data?

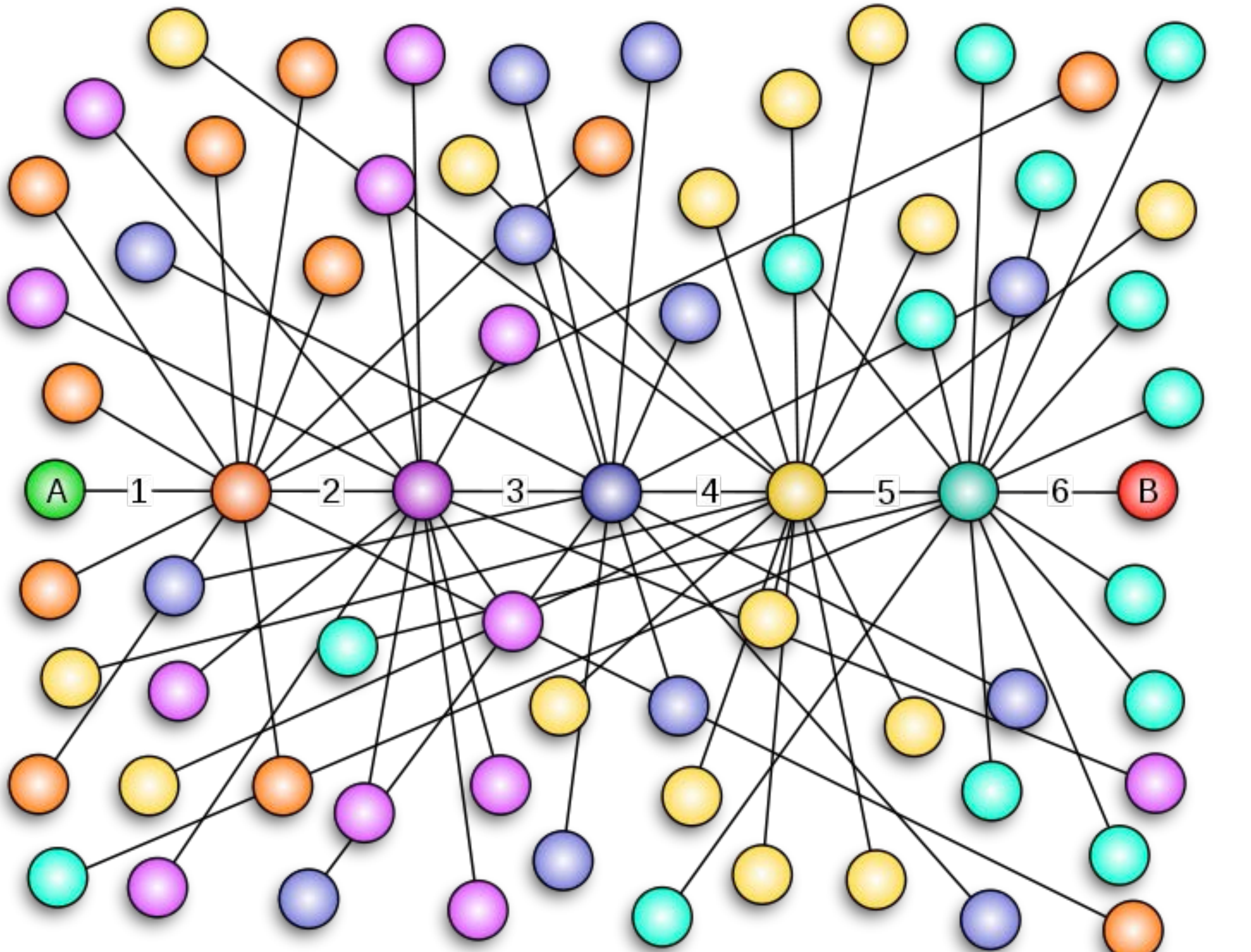
Part I:

What *Is* a Social Network?

Kevin Bacon

6 Degrees of Kevin Bacon

Small-World Experiment



Small-World Experiment

- What is the average path length from one person to another in the U.S.?
- For example, how many steps exist between you and Barak Obama (or a randomly chosen person somewhere)?
- Average length is about 5.5 to 6 links.
- "Six Degrees of Separation"
- Is changing with online social networks

Small-World Experiment

- But it's no longer just six degrees; it's changing with online social networks.

Year	Distance	
2008	5.28	
2011	4.74	
2016	3.57	
Distances as reported in Feb 2016 [38]		

Online Social Networks

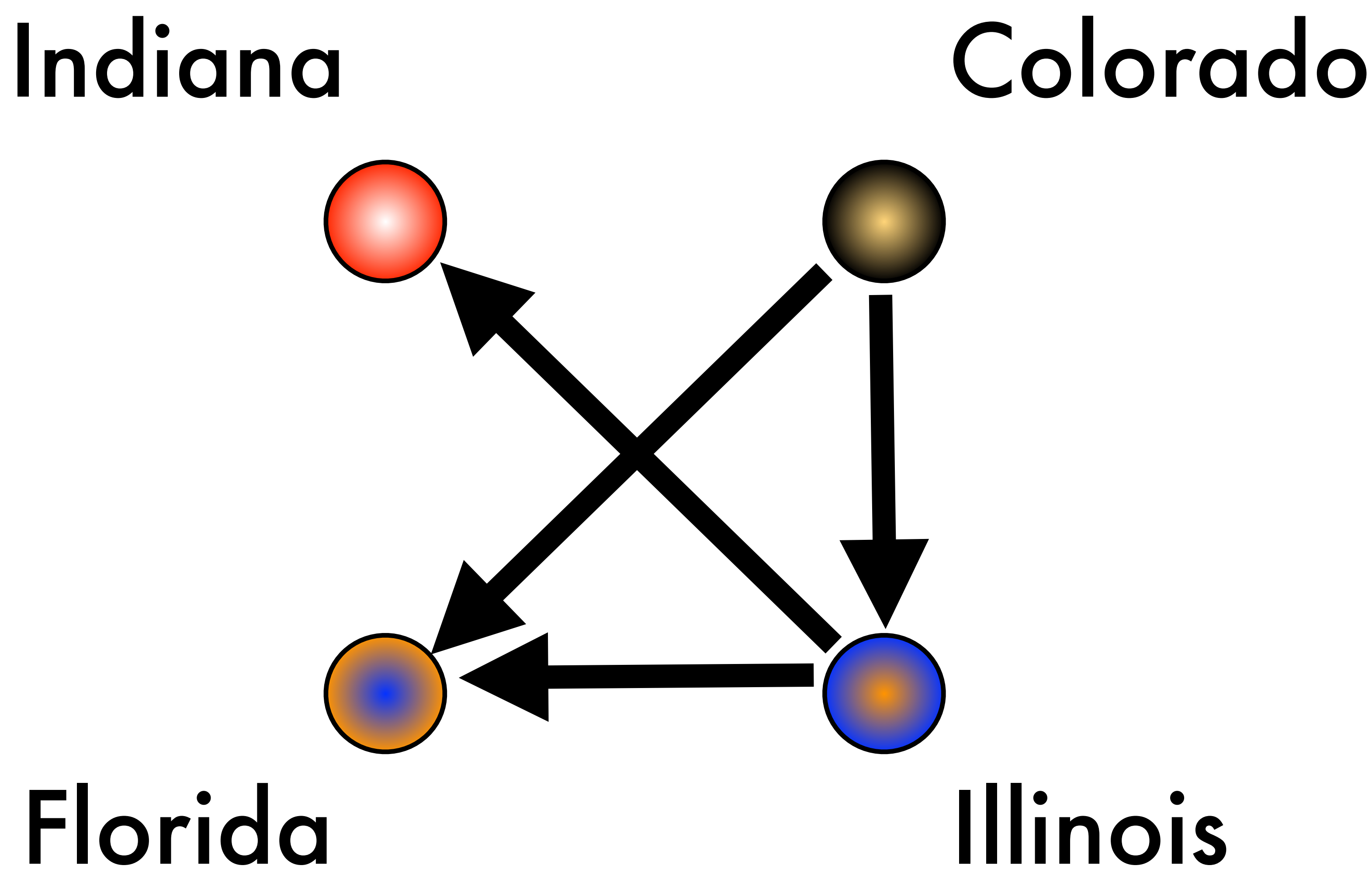
- Online social networks are everywhere!
  - Friendster
  - MySpace
  - Facebook
  - Google+
  - LinkedIn
  - Twitter
  - Instagram

What *Is* a Social Network?

- A social network is a representation of nodes and the relationships between individual nodes (i.e., ties, links, paths).
- *Nodes* can be people, schools, corporations, states, countries, events, places, films, bands, groups, etc.
- *Ties* can be (dis)liking, friendship, acquaintance, co-authorship, citation, debt/credit, spatial relationships, common attendance, agreement, etc.

What *Is* a Social Network?

- *Nodes*: Individual universities
- *Ties*: Hiring relations; who hires whom



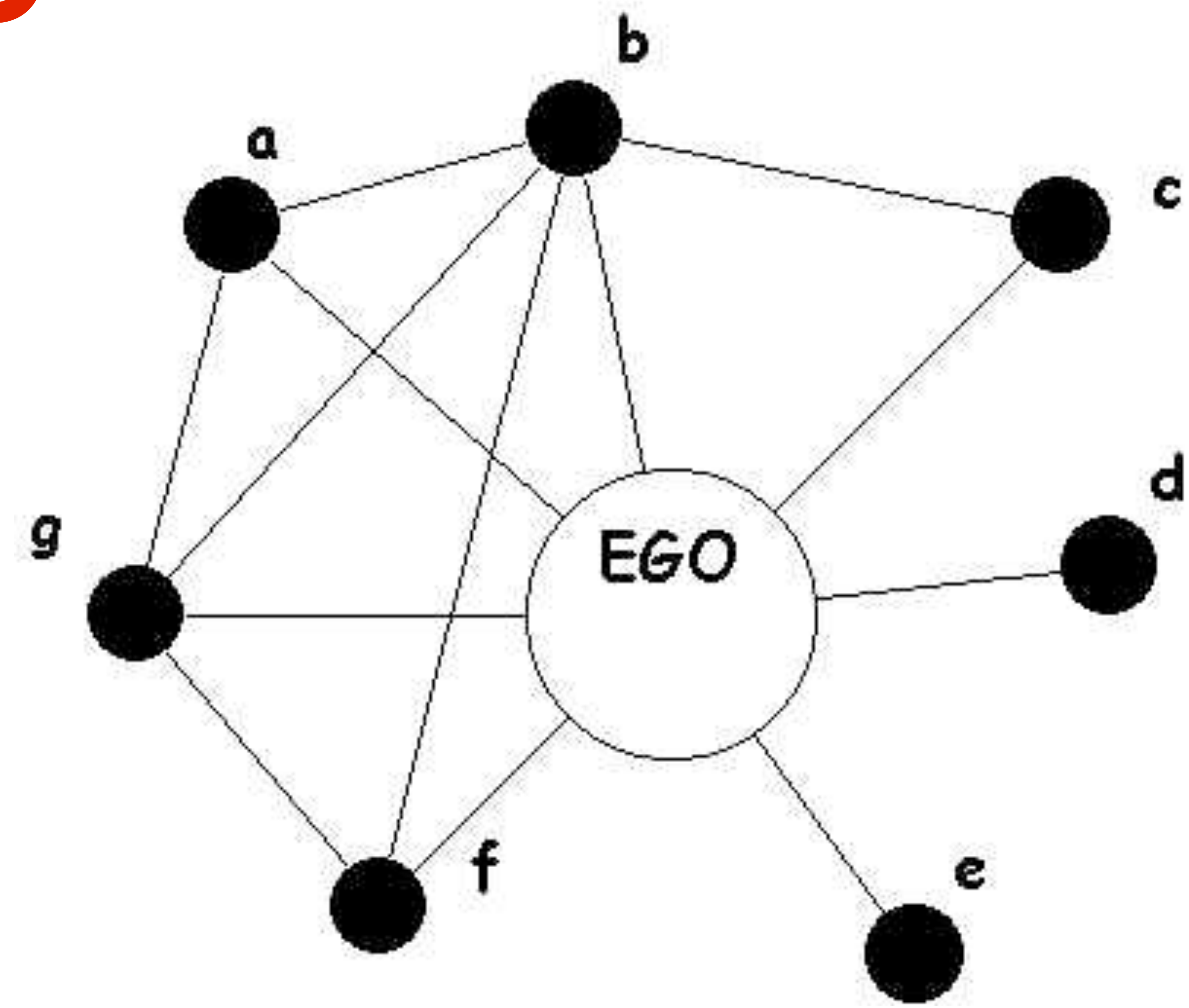
Types of Social Networks

- Egocentric vs. Sociocentric
- One-Mode vs. Two-Mode Networks
- Directed vs. Bidirectional (Non-Directed) Ties
- Valued vs. Binary (Non-Valued) Ties

Ego- vs. Sociocentric

- Egocentric or “Personal” Networks
  - Who do you know?
    - How well do you know them?
  - Do those people know each other?
    - How well do they know each other?
  - Everyone knows you, the ego
    - “Star” network, with ego at center

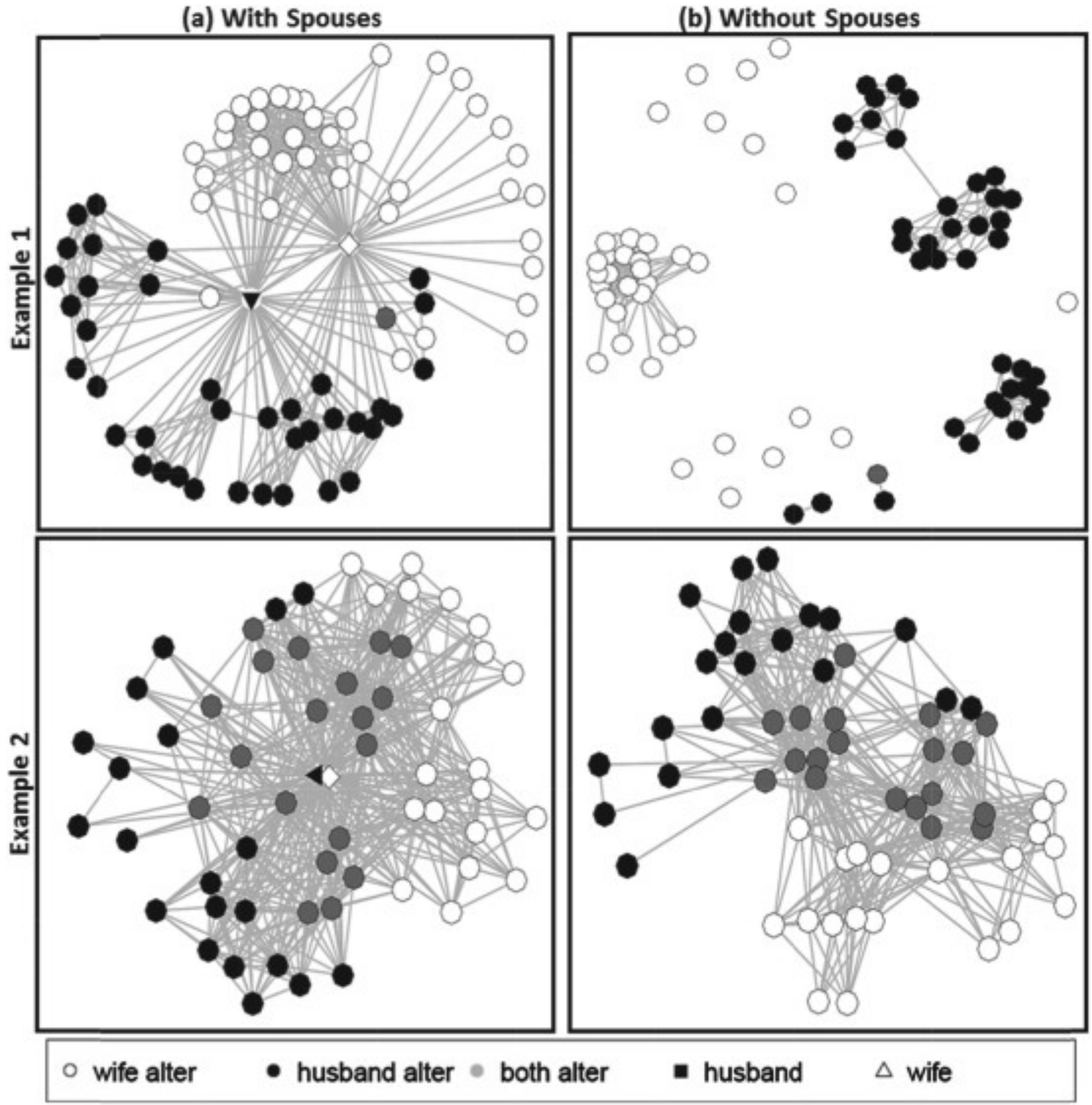
An Egocentric Network



- Ego knows everyone (by definition).
- Person A knows B and G (and ego).
- Persons D and E know only ego.

An Egocentric Network

- Egocentric networks are ideal for studying people's social support networks.
- Researchers are often interested in how dense people's ego networks are.
- Some programs: <u>EgoNet</u>, <u>E-Net</u>
- New research focusing on overlap among couples' ego networks (duocentric networks), and how that relates to relationship outcomes.

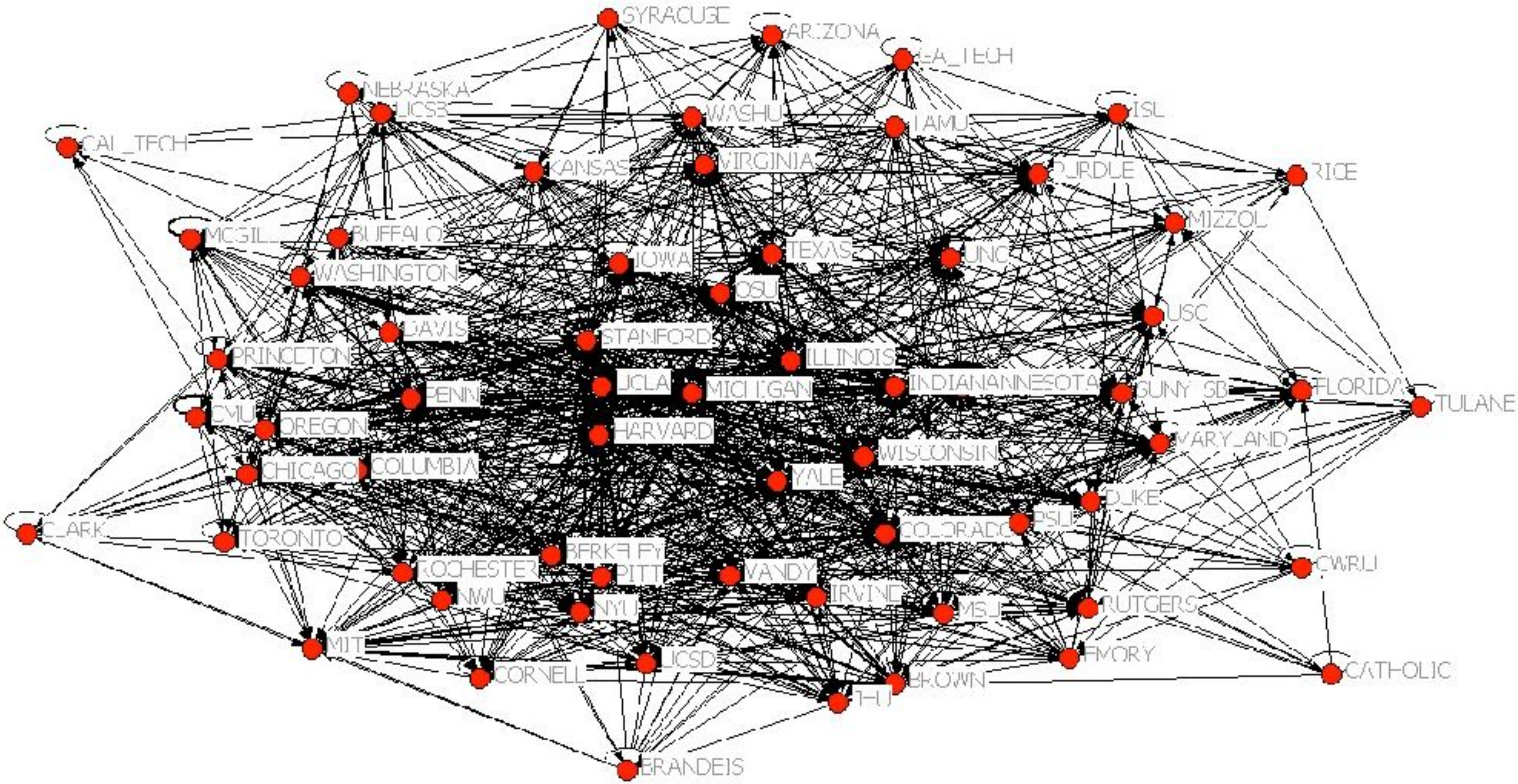


(a) With Spouses
(b) Without Spouses
Example 1
Example 2
wife alter
husband alter
both alter
husband
wife

Ego- vs. Sociocentric

- Sociocentric or “Whole” Networks
  - Network bound/defined by something other than you/self/ego. For example:
    - Everyone on Facebook, Twitter, etc.
    - Everyone in your home department
    - Everyone attending SPSP/workshop
  - Do all these people know each other?
    - How *well* do they know each other?

A Sociocentric Network



Who Hires Whom in AAU Psychology Depts.

<u>Association of American Universities</u>

1- vs. 2-Mode Networks

- Most social networks are "one-mode."
- In an association matrix, the row labels are the same as the column labels; the matrix is square.

Liking	Alex	Brandy	Cecilia
Alex	–	1	0
Brandy	1	–	$\boxed{0}$
Cecilia	0	$\boxed{1}$	–

1- vs. 2-Mode Networks

- Some social networks are "two-mode."
- In an association matrix, the row labels are different from the column labels; the matrix is often rectangular.

<u>Present</u>	Jan.	Feb.	March	April
Alex	1	1	0	1
Brandy	1	1	0	1
Cecilia	0	0	1	1

1- vs. 2-Mode Networks

- We can analyze two-mode data as one-mode data by collapsing one dimension,
- We can have a social network of either *people* (how are people linked by events) or *events* (which events are linked by people).

<u>Present</u>	Jan.	Feb.	March	April
Alex	1	1	0	1
Brandy	1	1	0	1
Cecilia	0	0	1	1

Present	Jan.	Feb.	March	April
Alex	1	1	0	1
Brandy	1	1	0	1
Cecilia	0	0	1	1

Collapsing across *events*...

Present	Alex	Brandy	Cecilia
Alex	–	3	1
Brandy	3	–	1
Cecilia	1	1	–

Present	Jan.	Feb.	March	April
Alex	1	1	0	1
Brandy	1	1	0	1
Cecilia	0	0	1	1

Collapsing across *people*...

Present	Jan.	Feb.	March	April
Jan.	–	2	0	2
Feb.	2	–	0	2
March	0	0	–	1
April	2	2	1	–

Some 2-Mode Examples

- People and events (e.g., meetings)
- People and places
- Supreme court justices (people) and their decisions (events)
- People and survey items (clustering)
- People in movies (IMDb, Kevin Bacon)
- People in bands
- Characters appearing in common episodes or chapters (*Game of Thrones*)

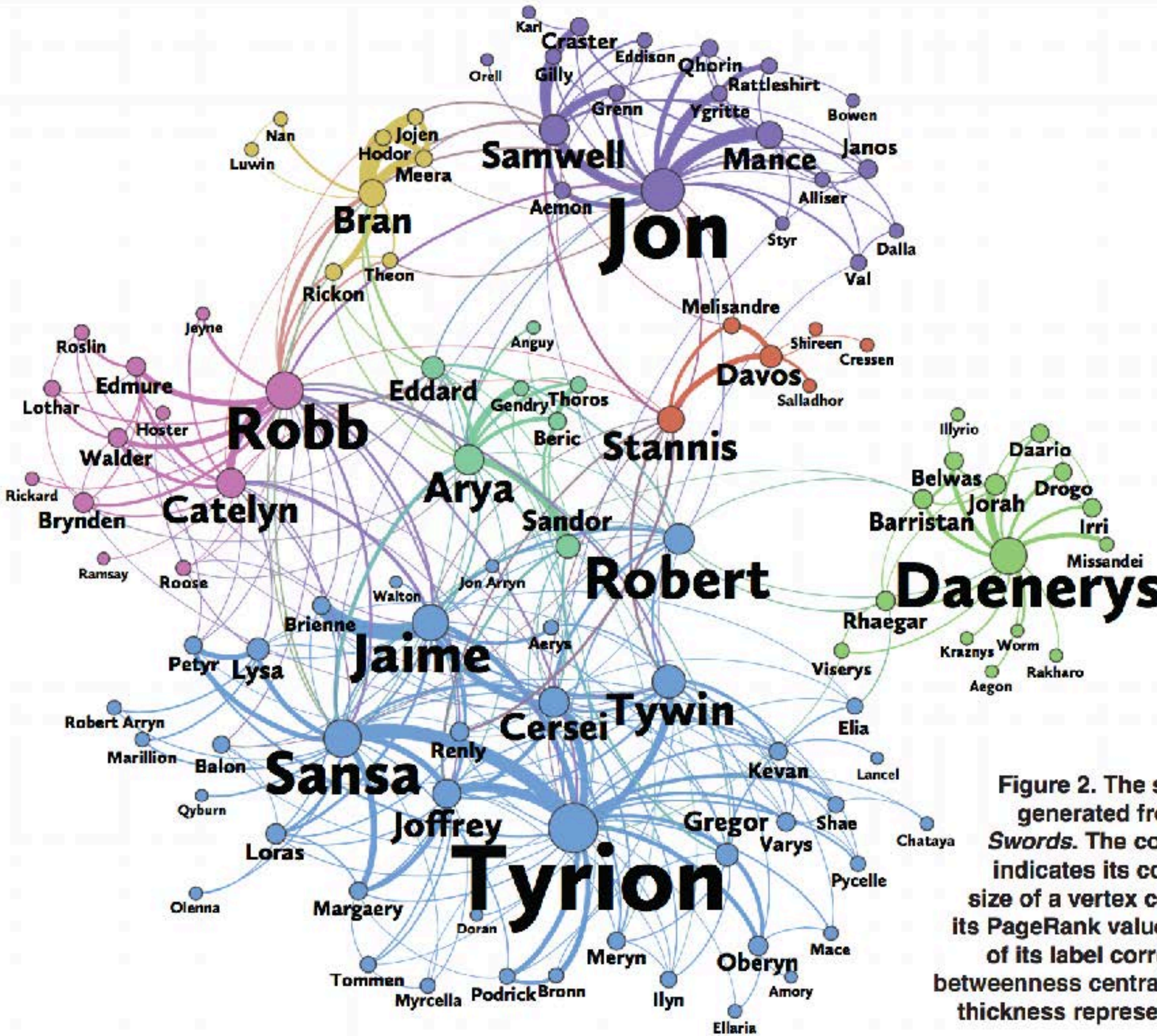


Figure 2. The social network generated from *A Storm of Swords*. The color of a vertex indicates its community. The size of a vertex corresponds to its PageRank value, and the size of its label corresponds to its betweenness centrality. An edge's thickness represents its weight.

- Note: Collapsing asymmetric two-mode data produce symmetric one-mode data.

Present	Jan.	Feb.	March	April
Alex	1	1	0	1
Brandy	1	1	0	1
Cecilia	0	0	1	1

Collapsing across *people*...

Present	Jan.	Feb.	March	April
Jan.	–	2	0	2
Feb.	2	–	0	2
March	0	0	–	1
April	2	2	1	–

Directed/non-directed Ties

- Social networks may be either *directed* (symmetric about the matrix diagonal) or *non-directed* (asymmetric...diagonal).
- A *liking* matrix will often have directed, unreciprocated, asymmetric ties.

<u>Liking</u>	Alex	Brandy	Cecilia
Alex	–	1	0
Brandy	1	–	0
Cecilia	0	1	–

Directed/non-directed Ties

- An *acquaintance* matrix will have non-directed, reciprocated, symmetric ties.
- Example: Facebook data produce non-directed, reciprocated, symmetric ties.

Liking	Alex	Brandy	Cecilia
Alex	–	1	0
Brandy	1	–	1
Cecilia	0	1	–

Valued vs. non-valued Ties

- Most social networks have *non-valued* or *dichotomous* ties, using only 1s and 0s.
- Either a person knows, likes, is friends with another person or not.

Liking	Alex	Brandy	Cecilia
Alex	–	1	0
Brandy	1	–	0
Cecilia	0	1	–

Valued vs. non-valued Ties

- Some social networks have *valued* ties, using ordinal, ratio, or continuous data.
- We might ask *how much* a person knows, likes, or is friends with another.

Liking	Alex	Brandy	Cecilia
Alex	–	3	0
Brandy	2	–	0
Cecilia	0	1	–

0 = don’t know, 1 = know, 2 = friends, 3 = BFFs

Valued Ties: Examples

- Survey data of friendship strength
- Some egocentric data
- Networks of debt and credit
- Trade networks using economic data

- Note: Collapsing *dichotomous* two-mode data can produce *valued* one-mode data.

<u>Present</u>	Jan.	Feb.	March	April
Alex	1	1	0	1
Brandy	1	1	0	1
Cecilia	0	0	1	1

Collapsing across *people*...

<u>Present</u>	Jan.	Feb.	March	April
Jan.	–	2	0	2
Feb.	2	–	0	2
March	0	0	–	1
April	2	2	1	–

- Note: *Some* social network metrics only work with *dichotomous* data, so this..

<u>Present</u>	Jan.	Feb.	March	April
Jan.	–	2	0	2
Feb.	2	–	0	2
March	0	0	–	1
April	2	2	1	–

Becomes this...

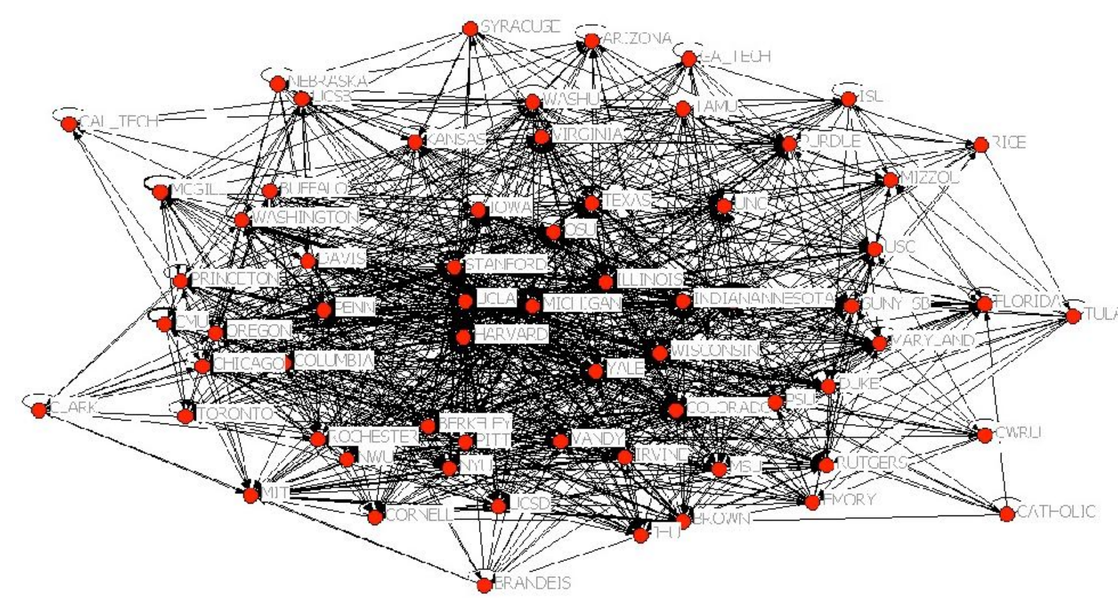
<u>Present</u>	Jan.	Feb.	March	April
Jan.	–	1	0	1
Feb.	1	–	0	1
March	0	0	–	1
April	1	1	1	–

Assumptions of Social Networks

- Defining Network Space or Scope
- Networks as Units of Analysis

Network Space or Scope

- Both ego- and sociocentric researchers should define their network space or scope prior to data collection.
  - Egocentric: How many people? 25?
  - Sociocentric: Network boundary?
    - All Psych. Depts. in the world?
    - U.S. Psych. Depts.?
    - "Research-I" Depts.?
    - AAU Depts.?



Units of Analysis

- Single Ego- or Sociocentric Network
  - Individual nodes are units of analysis
- Multiple Ego- or Sociocentric Networks
  - Either nodes or networks can be units of analysis (similar to persons in groups).
  - Can use a mixed- or multilevel model approach: Nodes nested within networks.
  - Examples: Liking data from 30 classes, Egocentric data from 100 people, etc.

Part II:

Finding and Collecting Social Network Data

Finding and Collecting Social Network Data

- Survey Methods
- Behavioral Methods
- Web/Online Methods
- Archival Methods

Survey Methods

- Sociocentric or Whole Networks
  - Simply ask the all group members who knows, likes, is friends with whom.
  - Can be valued or dichotomous ties
    - Roster/checklist method
    - Free recall or memory method
    - Nomination method (name 5 friends)

Roster/Checklist Method

Aleksandra's checklist:

Name	Closeness
Aleksandra	–
Brynna	1
Chelsea	0
Dominique	0
Eunice	3
Fernando	2

Brynna's checklist:

Name	Closeness
Aleksandra	1
Brynna	–
Chelsea	0
Dominique	1
Eunice	3
Fernando	0

0 = don't know, 1 = know, 2 = friends, 3 = BFFs

Roster/Checklist Method

Aleksandra's checklist: Multiple measures

Name	Closeness*	Coauthor	Cited
Aleksandra	–	–	8
Brynna	1	0	0
Chelsea	0	0	1
Dominique	0	0	0
Eunice	3	1	0
Fernando	2	2	4

*0 = don't know, 1 = know, 2 = friends, 3 = BFFs

Free Recall or Memory

- "Please list all the people you know in this group or organization."
  - Optional: "Indicate how *well* you know each of the people you listed using the following 3-point scale..."

1. Pat – 1
2. Sam – 3
3. Jim – 1
4. Frank – 2

Nomination Method

- "Please list your five best friends in this class."
- "Please list the five people you work with the most in this organization."

1. __________
2. __________
3. __________
4. __________
5. __________

Nomination Method

- Often used in egocentric network data collection with caps of 15, 20, or 25 nodes.
- "Name 25 of your friends."
- "Now indicate which friends know each other friend. Does Person A know person B? Does person A know Person C?" And so on...
- More nodes = exponentially more ties/time.
  - Ties = [nodes x (nodes - 1)] ÷ 2
  - 15 nodes =105 ties; 25 nodes = 300 ties

Behavioral Methods

- Observe and record actual behavior in field or laboratory settings.
- Record small-group interactions.
  - Code who touches, looks at, interrupts, or speaks/listens to whom for each person.
- Examine who cites whom in a journal.
- Record trade or kin networks in the field.
- Record who wishes to contact whom at speed-dating events. Also: Sex networks.

Two-Mode Sexual Network: Sexual Relations among 39 People (18 Men, 21 Women), Their Degree Centrality, and Bar Patronage

	Men																		
Women	m012	m013	m016	***m017***	m019	m025	m026	m201	m202	m203	m204	m206	m207	m208	m209	m210	m526	m551	**Degree**
f009	1	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	**4**
f010	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	**1**
f011	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	1	**5**
f012	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	**1**
f014	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f015	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	**2**
f017	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	**1**
f019	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	**3**
f020	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	**3**
f022	0	0	1	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1	**7**
f033	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f034	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f035	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f038	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f201	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
f202	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f307	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	**1**
f336	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f514	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	**1**
f533	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
f900	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	**1**
Degree	**3**	**1**	**5**	**7**	**1**	**1**	**2**	**2**	**2**	**2**	**1**	**2**	**2**	**1**	**1**	**1**	**4**	**2**	—

Note. **Boldface**: degree centrality scores for men (bottom) and women (right). ***Boldface italics***: person regularly attended a local bar. Source: De, Singh, Wong, Yacoub, and Jolly (2004, p. 283, Figure 1).

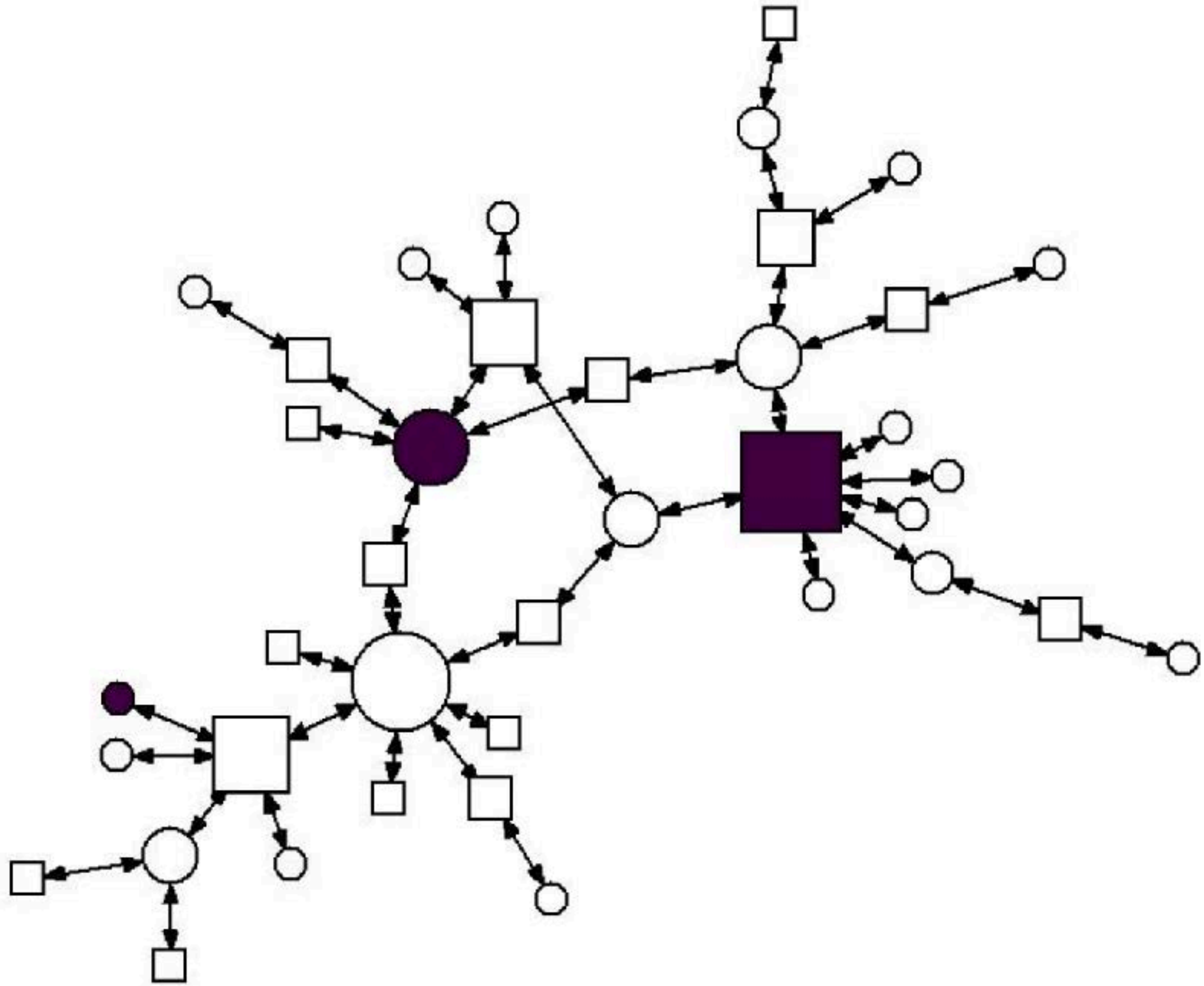
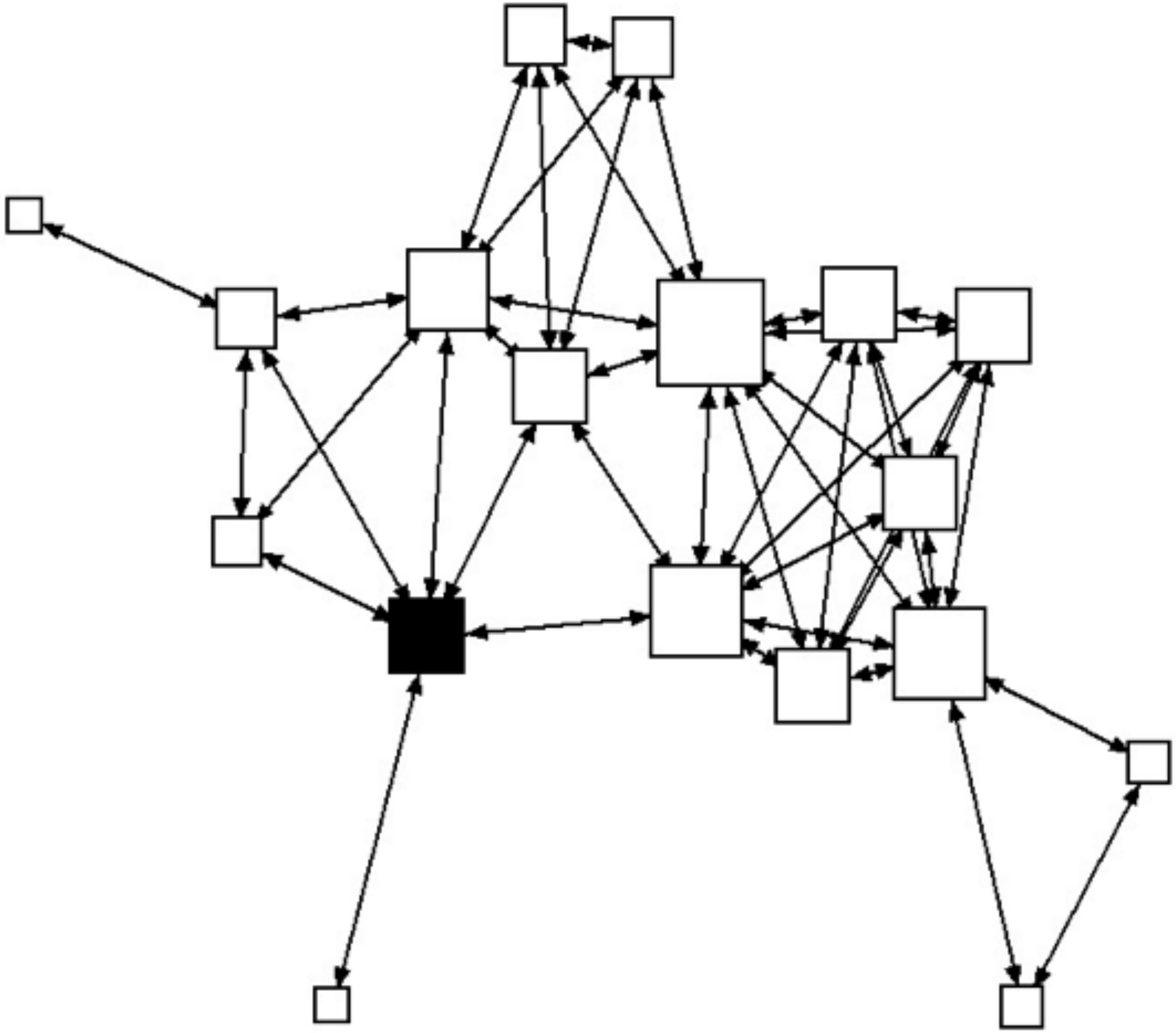


Figure 4. Sexual network sociogram of heterosexual pairings among 18 men (squares) and 21 women (circles) in Alberta, Canada (Table 3). Node size shows degree centrality. Black nodes show people who attended the same bar. Source: De, Singh, Wong, Yacoub, and Jolly (2004).

Two-Mode Sexual Network Collapsed into a One-Mode Network among 18 Men Linked by 21 Women with Whom They Have Had Sex

	m012	m013	m016	***m017***	m019	m025	m026	m201	m202	m203	m204	m206	m207	m208	m209	m210	m526	m551
m012	**3**	1	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0
m013	1	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
m016	0	0	**5**	0	1	1	0	0	0	0	0	1	1	1	1	1	0	1
m017	1	0	0	**7**	0	0	1	1	1	0	0	1	0	0	0	0	1	0
m019	0	0	1	0	**1**	0	0	0	0	0	0	0	0	0	0	1	0	0
m025	0	0	1	0	0	**1**	0	0	0	0	0	1	1	1	1	0	0	1
m026	0	0	0	1	0	0	**2**	0	0	0	0	0	0	0	0	0	0	0
m201	1	0	0	1	0	0	0	**2**	1	0	0	0	0	0	0	0	0	0
m202	1	0	0	1	0	0	0	1	**2**	1	1	0	0	0	0	0	1	1
m203	0	0	0	0	0	0	0	0	1	**2**	1	0	0	0	0	0	1	1
m204	0	0	0	0	0	0	0	0	1	1	**1**	0	0	0	0	0	1	1
m206	0	0	1	1	0	1	0	0	0	0	0	**2**	1	1	1	0	1	1
m207	0	0	1	0	0	1	0	0	0	0	0	1	**2**	1	1	0	0	1
m208	0	0	1	0	0	1	0	0	0	0	0	1	1	**1**	1	0	0	1
m209	0	0	1	0	0	1	0	0	0	0	0	1	1	1	**1**	0	0	1
m210	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	**1**	0	0
m526	0	0	0	1	0	0	0	0	1	1	1	1	0	0	0	0	**4**	1
m551	0	0	1	0	0	1	0	0	1	1	1	1	1	1	1	0	1	**2**

Note. **Boldface**: degree centrality scores for men (diagonal). ***Boldface italics***: man regularly attended a local bar.
Source: De, Singh, Wong, Yacoub, and Jolly (2004, p. 283, Figure 1).

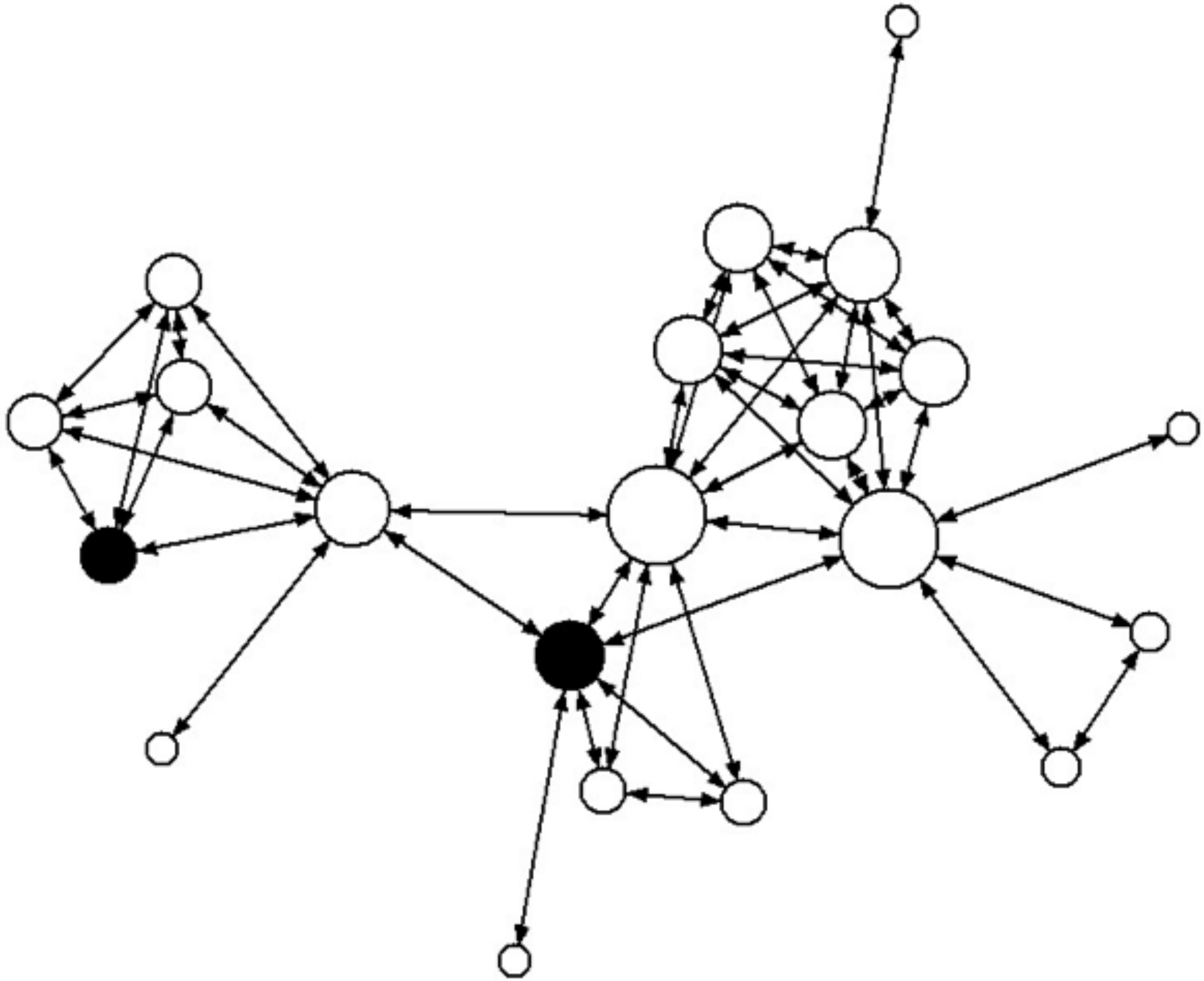


Sexual network among 18 men linked by women.
Node sizes reflect degree centrality.
Black nodes show people who attended same bar.

Two-Mode Sexual Network Collapsed into a One-Mode Network among 21 Women Linked by 18 Men with Whom They Have Had Sex

	f009	f010	***f011***	f012	***f014***	f015	f017	f019	f020	f022	f033	f034	f035	f038	f201	f202	f307	f336	f514	f533	f900
f009	**4**	0	1	0	0	1	0	1	0	0	1	1	1	0	1	1	1	1	0	0	0
f010	0	**1**	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
f011	1	0	**5**	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	1	0	1
f012	0	0	0	**1**	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
f014	0	0	0	0	**1**	0	0	0	1	1	0	0	0	1	0	0	0	0	0	1	0
f015	1	1	0	0	0	**2**	0	1	0	0	1	1	1	0	0	0	0	1	0	0	0
f017	0	0	1	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
f019	1	0	1	0	0	1	0	**3**	0	1	1	1	1	0	0	0	0	1	1	0	1
f020	0	0	0	0	1	0	0	0	**3**	1	0	0	0	1	0	0	0	0	0	1	0
f022	0	0	1	1	1	0	0	1	1	**7**	0	0	0	1	0	0	0	0	0	1	0
f033	1	0	0	0	0	1	0	1	0	0	**1**	1	1	0	0	0	0	1	0	0	0
f034	1	0	0	0	0	1	0	1	0	0	1	**1**	1	0	0	0	0	1	0	0	0
f035	1	0	0	0	0	1	0	1	0	0	1	1	**1**	0	0	0	0	1	0	0	0
f038	0	0	0	0	1	0	0	0	1	1	0	0	0	**1**	0	0	0	0	0	1	0
f201	1	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**	1	0	0	0	0	0
f202	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**1**	0	0	0	0	0
f307	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0
f336	1	0	0	0	0	1	0	1	0	0	1	1	1	0	0	0	0	**1**	0	0	0
f514	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	**1**	0	0
f533	0	0	0	0	1	0	0	0	1	1	0	0	0	1	0	0	0	0	0	**1**	0
f900	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	**1**

Note. **Boldface**: degree centrality scores for women (diagonal). ***Boldface italics***: woman regularly attended a local bar.
Source: De, Singh, Wong, Yacoub, and Jolly (2004, p. 283, Figure 1).



Sexual network among 21 women linked by men.
Node sizes reflect degree centrality.
Black nodes show people who attended same bar.

Web/Online Methods

- Collect your own survey data on the Web.
- Collect data from existing online social network sites or ask <u>scientists who have access to these data</u> (10^3 to 10^6 of nodes).
- Record data from academic department websites to see who hires whom.
- Download data from existing academic databases to examine citation and/or coauthorship networks in a field or journal.

Archival Methods

- Archival data can yield social networks
- Corporate or institutional board members
- An increasing amount of archival data, both old and new, is available on the Web.
- The lines separating survey, behavioral, online, and archival data collection methods are gradually disappearing (e.g., IMDb).
- 18 women attending 14 events (Davis et al., 1941)
- <u>Medici influence, 1400–1434</u> (Pagdett & Ansell, 1993)

Arranged Intermarriages among 16 Florentine Families (1394–1434) and Their Wealth (1427)

	Family																	Wealth[a]	
	Family	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Degree	Lira	Log
1.	Acciaiuol	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	10	4.00
2.	Albizzi	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	3	36	4.56
3.	Barbadori	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	2	55	4.74
4.	Bischeri	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	3	44	4.64
5.	Castellan	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	3	20	4.30
6.	Ginori	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	32	4.51
7.	Guadagni	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	1	4	8	3.90
8.	Lambertes	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	42	4.62
9.	Medici	1	1	1	0	0	0	0	0	0	0	0	0	1	1	0	1	6	103	5.05
10.	Pazzi	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	48	4.68
11.	Peruzzi	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	3	49	4.69
12.	Pucci	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	3.48
13.	Ridolfi	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	3	27	4.43
14.	Salviati	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	2	10	4.00
15.	Strozzi	0	0	0	1	1	0	0	0	0	0	1	0	1	0	0	0	4	146	5.16
16.	Tornabuon	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	3	48	4.68

Note. [a]Family net wealth in 1427 in thousands of Lira ("Lira") or $\log_{10}$(Lira) ("Log").
Sources: Breiger and Pattison (1986); Kent (1978); Padgett and Ansell (1993).

Marriage Network Data

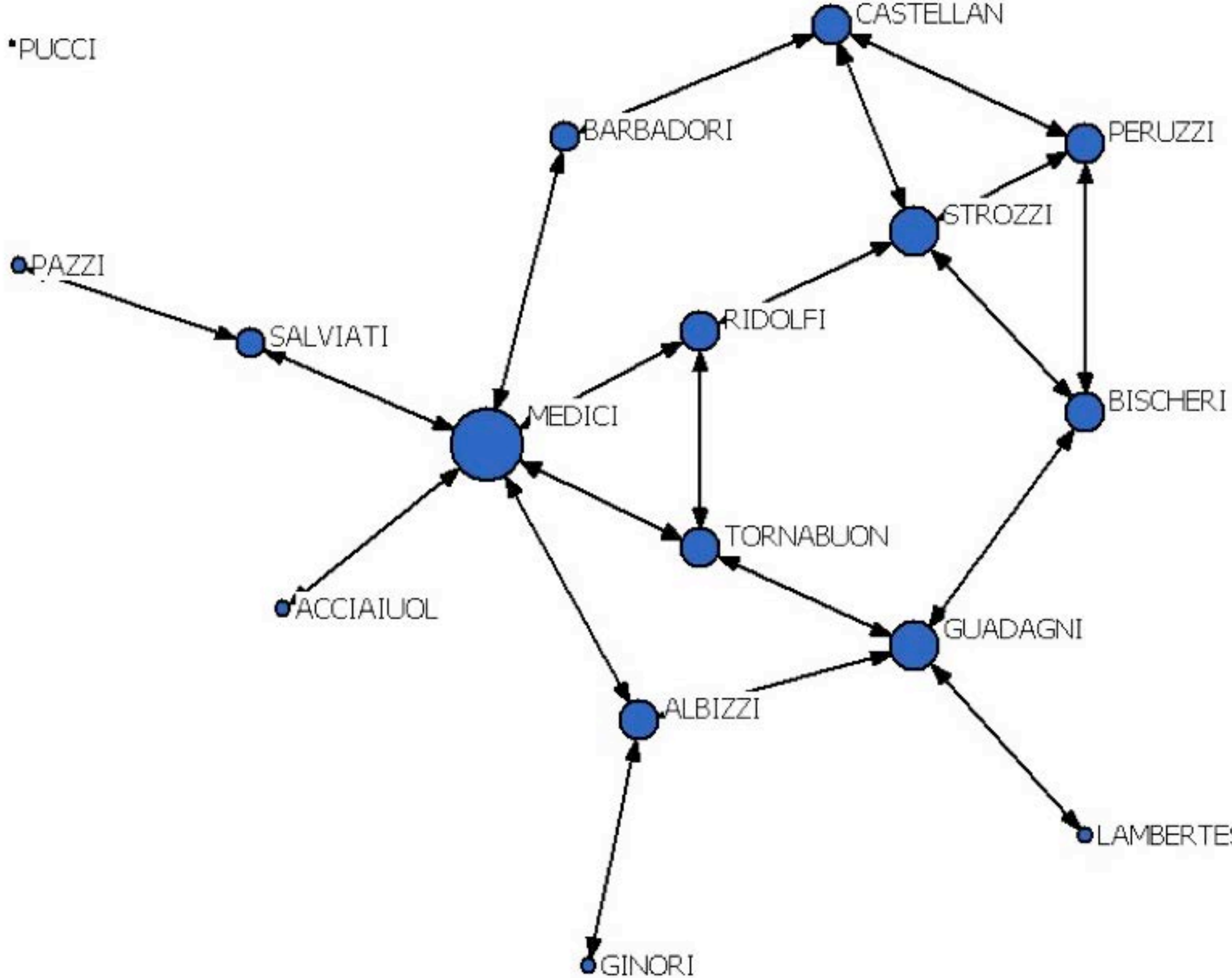
	Family	1	2	3	4	5	6	7	8	9
1.	Acciaiuol	0	0	0	0	0	0	0	0	1
2.	Albizzi	0	0	0	0	0	1	1	0	1
3.	Barbadori	0	0	0	0	1	0	0	0	1
4.	Bischeri	0	0	0	0	0	0	1	0	0
5.	Castellan	0	0	1	0	0	0	0	0	0
6.	Ginori	0	1	0	0	0	0	0	0	0
7.	Guadagni	0	1	0	1	0	0	0	1	0
8.	Lambertes	0	0	0	0	0	0	1	0	0
9.	Medici	1	1	1	0	0	0	0	0	0

Attribute (Wealth) Data

Arranged Intermarriages among 16 Florentine Families (1394–1434) and Their Wealth (1427)

	Family																	Wealth[a]	
Family	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Degree	Lira	Log
1. Acciaiuol	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	10	4.00
2. Albizzi	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	3	36	4.56
3. Barbadori	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	2	55	4.74
4. Bischeri	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	3	44	4.64
5. Castellan	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	3	20	4.30
6. Ginori	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	32	4.51
7. Guadagni	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	1	4	8	3.90
8. Lambertes	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	42	4.62
9. Medici	1	1	1	0	0	0	0	0	0	0	0	0	1	1	0	1	6	103	5.05
10. Pazzi	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	48	4.68
11. Peruzzi	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	3	49	4.69
12. Pucci	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	3.48
13. Ridolfi	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	3	27	4.43
14. Salviati	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	2	10	4.00
15. Strozzi	0	0	0	1	1	0	0	0	0	0	1	0	1	0	0	0	4	146	5.16
16. Tornabuon	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	3	48	4.68

Note. [a]Family net wealth in 1427 in thousands of Lira ("Lira") or $\log_{10}$(Lira) ("Log").
Sources: Breiger and Pattison (1986); Kent (1978); Padgett and Ansell (1993).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CASTELLAN
BARBADORI
PERUZZI
STROZZI
PAZZI
RIDOLFI
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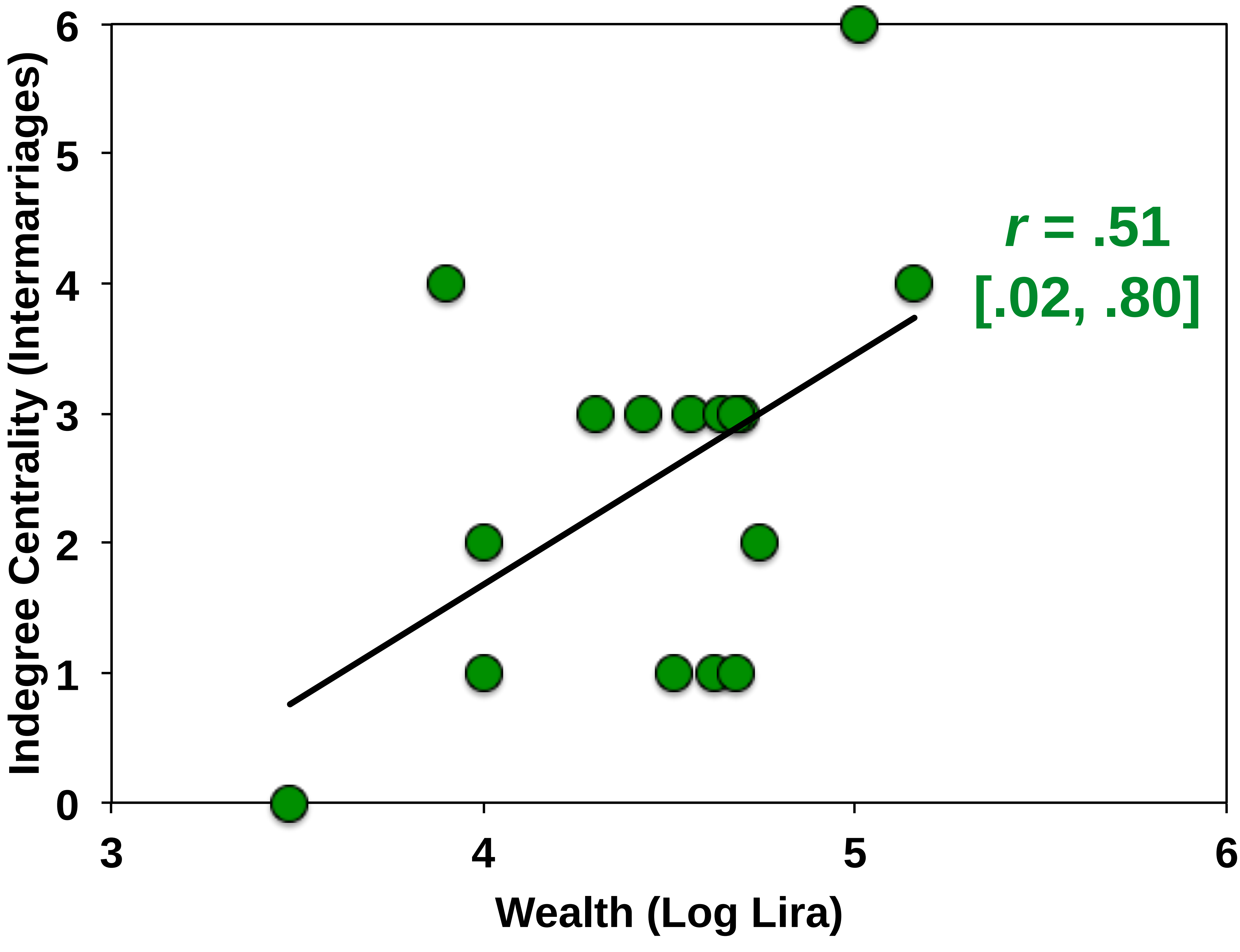
ACCIAIUOL
GUADAGNI
ALBIZZI
LAMBERTES
GINORI


r = .51
[.02, .80]
Indegree Centrality (Intermarriages)
Wealth (Log Lira)
0
1
2
3
4
5
6
3
4
5
6

Archival Research Examples

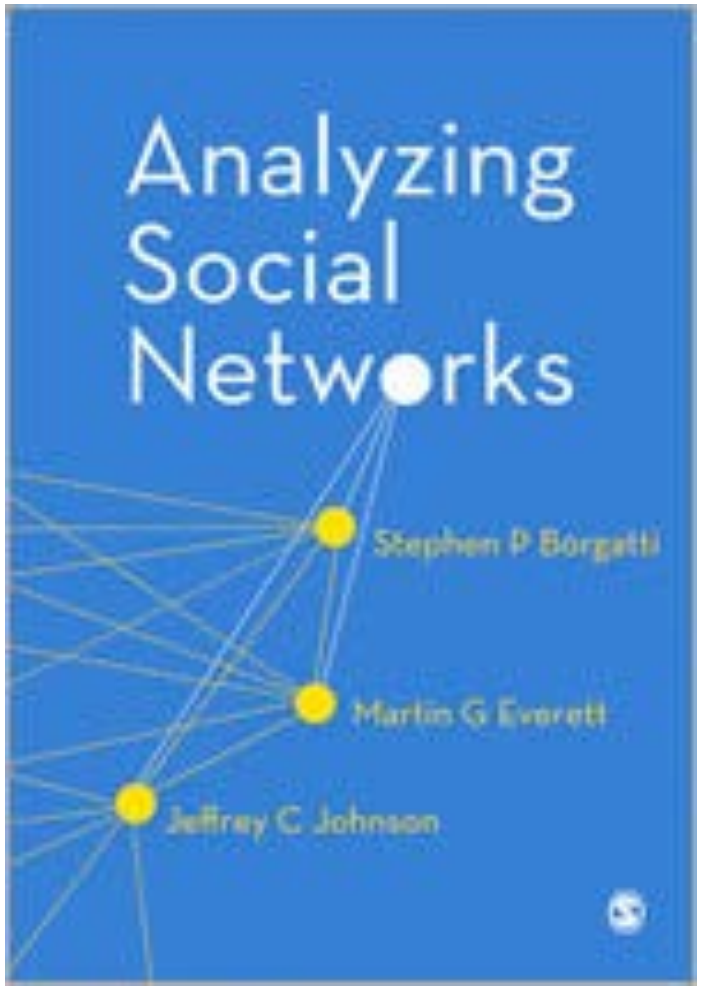
- MyPersonality Data: Facebook ego networks and "Big Five" personality traits (survey/archival/online).
- U.S. Supreme Court decisions, 1994–2005: Is Justice Kennedy a "clique broker"? (behavioral/archival/online).
    - Two-mode network: Justices by decisions
- Sovereign debt/lending among countries (behavioral/archival/online).

Part III:

Analyzing Social Network Data

Social Network Programs

- Collecting/Analyzing Egocentric Data
  - EgoNet (also as an R package)
- Analyzing Ego-/Sociocentric Data
  - UCINet
    - *Analyzing Social Networks*
  - ORA
  - R: "sna" within the "statnet" meta-package



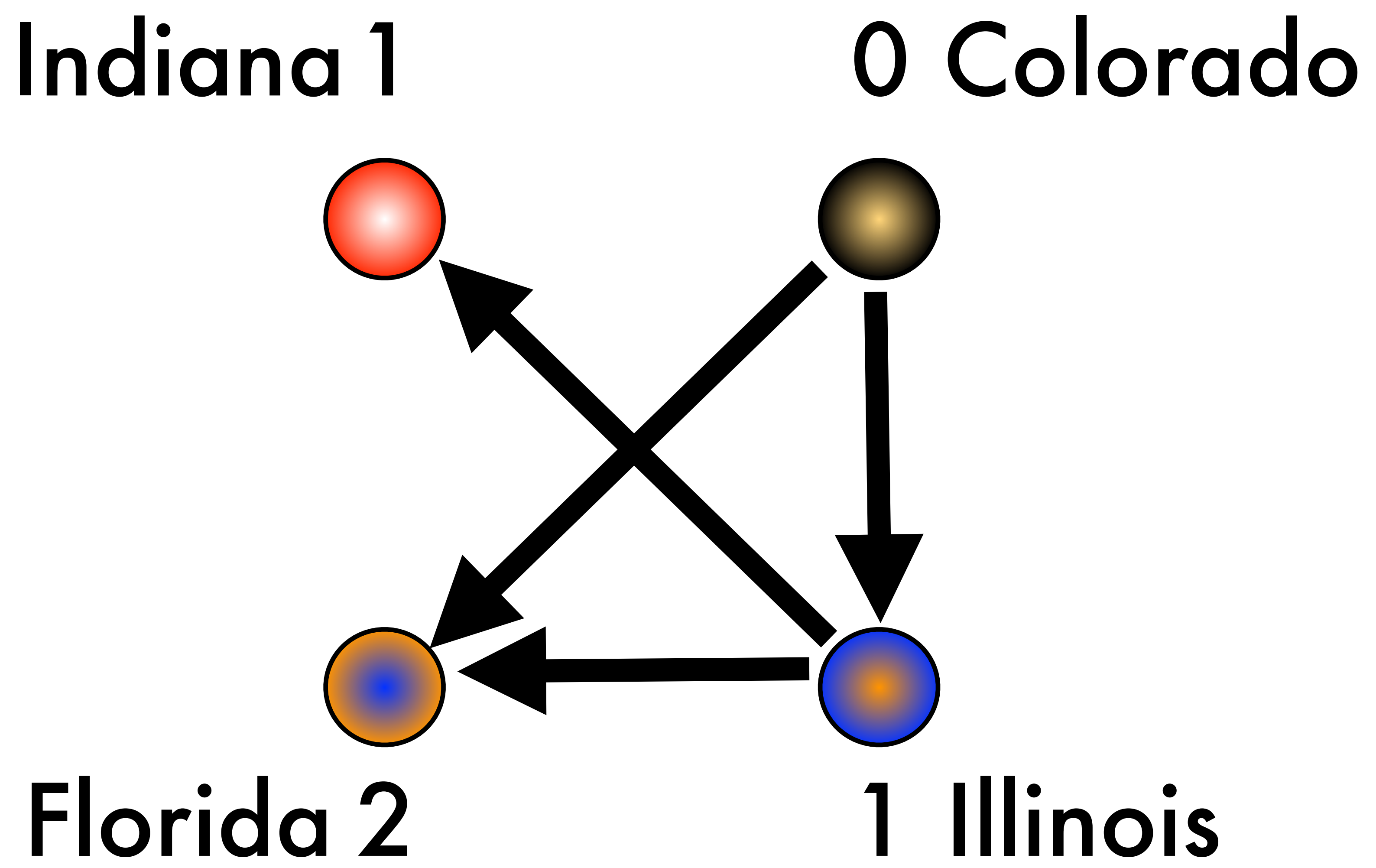
Some SNA Measures

- SNA software can generate useful measures
- Network level
  - Density (number of ties out of possible ties)
  - Number of components (separate groups)
- Node level
  - Centrality – influence/importance measure
    - Indegee, Outdegree, Betweeness, etc.

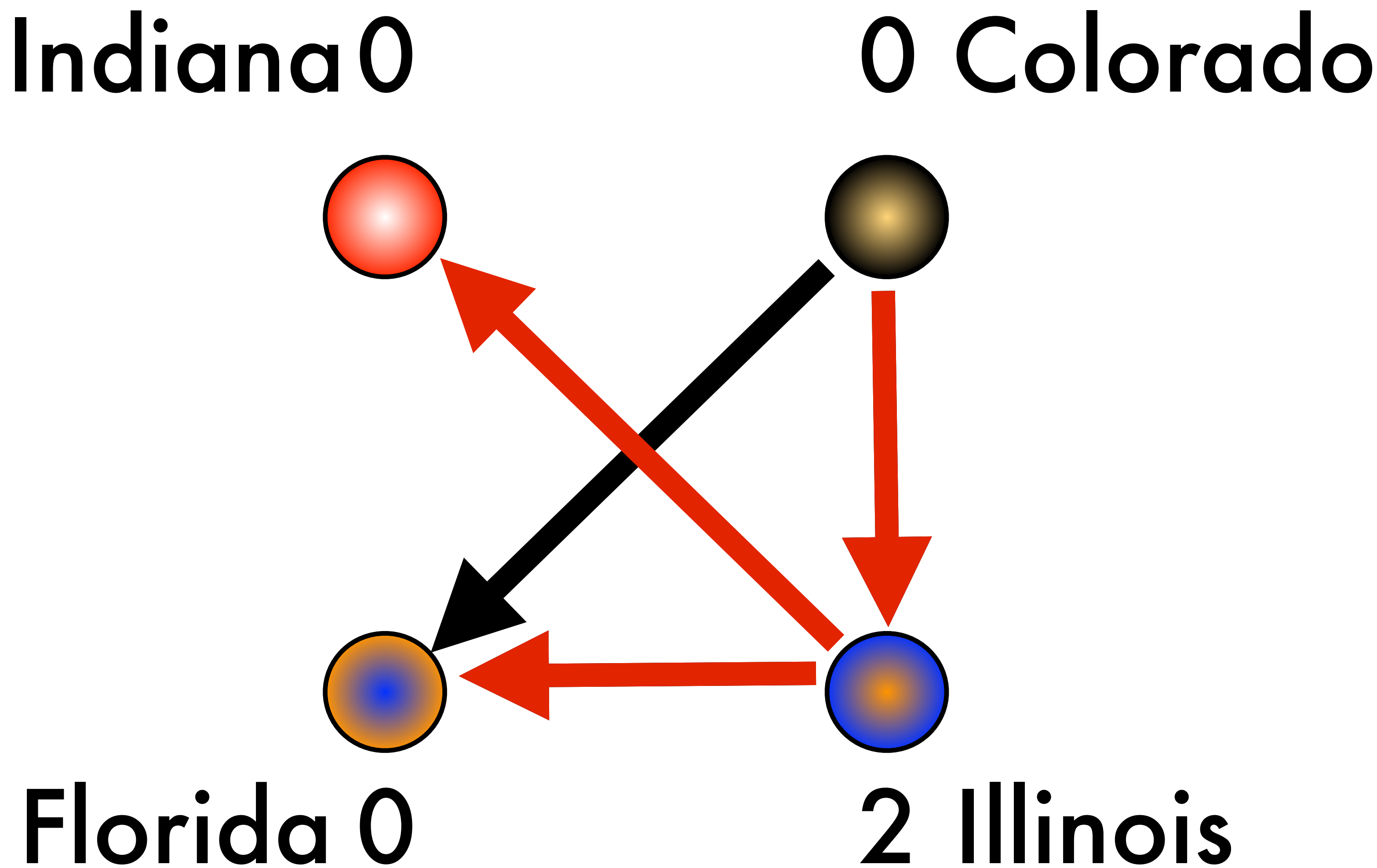
SNA Metrics Example

- *Nodes*: Individual universities
- *Ties*: Hiring relations; who hires whom
- *Centrality*: Measures of importance and influence in a social network.
  - *In-degree*: Number of PhDs from one university hired by other universities.
  - *Betweenness*: Number of hiring paths that pass through a university.

In-Degree Centrality

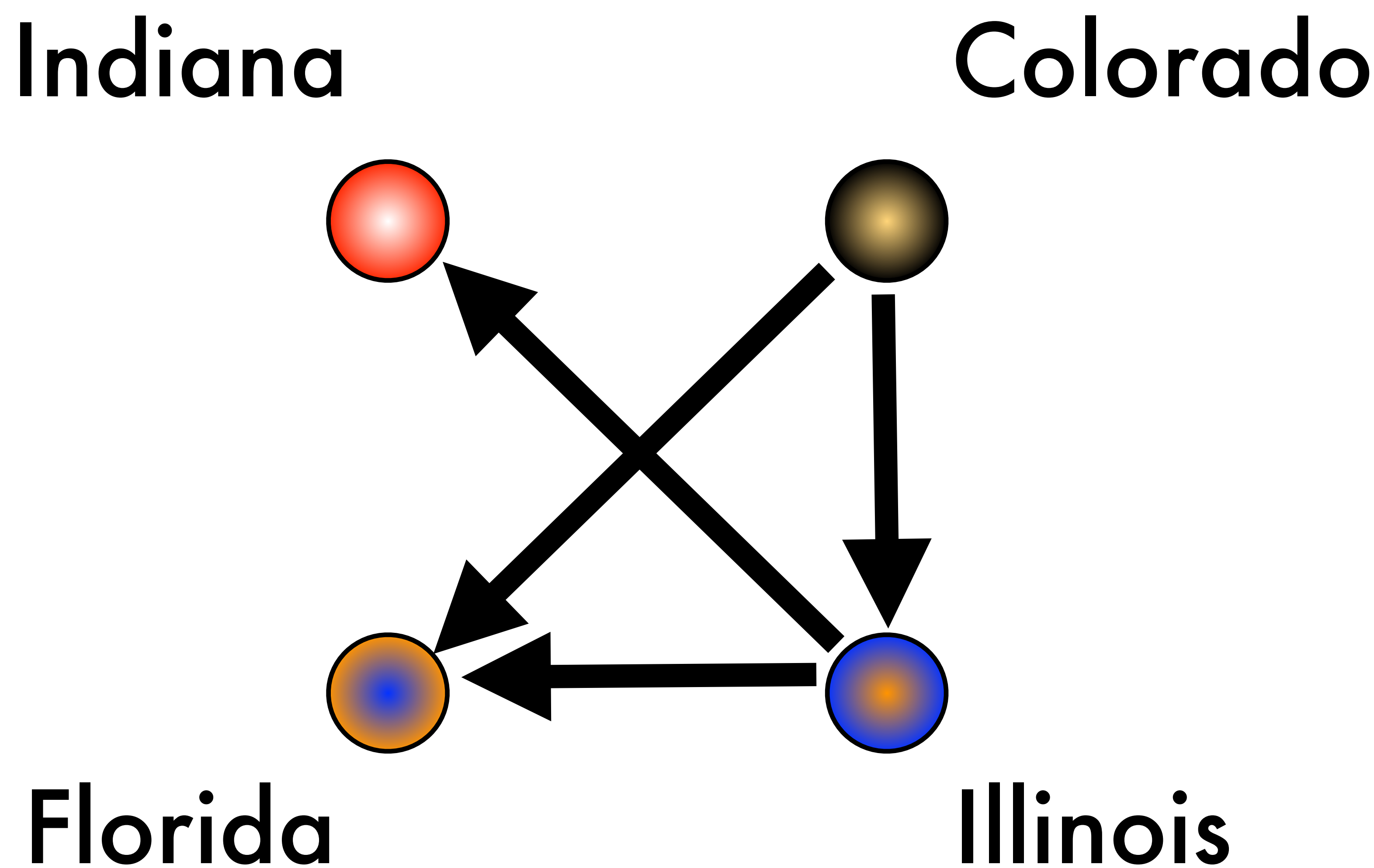


Betweenness Centrality



Network Density

Ties ÷ Number of Possible Ties = Density



If *non*-directed: 4 ÷ {[4 x (4 - 1)] ÷ 2} = 0.67

If directed: 4 ÷ [4 x (4 - 1)] = 0.33

...*and* if allowing reflexive ties: 4 ÷ (4 x 4) = 0.25

Empirical Examples from My Research

- Hiring Networks in Academic Psychology
- Classroom Friendships and Aggression
- Co-author Networks and Citation Counts
- Popularity and Sexual Behavior in Social Fraternities and Sororities
- Classroom Friendships and Attachment

Example 1:
Hiring Networks in Academic Psychology

Psychology Hiring Example

- American Association of Universities (AAU)
  - 63 current or former members
  - "Research I"; produce 52% of U.S. PhDs
- Info. obtained from Psych. Dept. websites
  - 1,936 professors; 36% women, 64% men
    - Current and PhD-conferring universities
    - PhD year: 1,600 of 1,936 (83%)
    - Range: 1946–2011; M = 1986, SD = 15

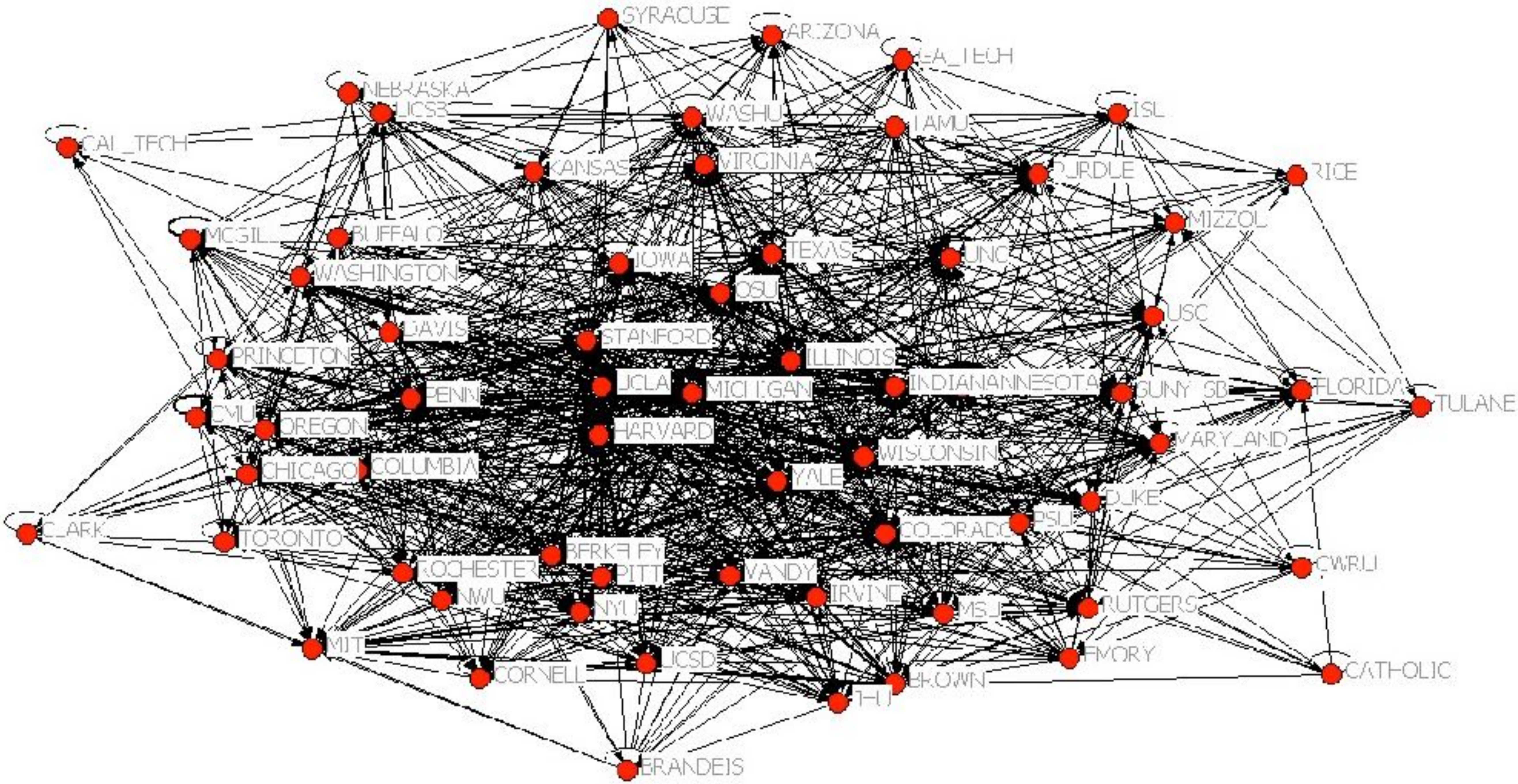
Validation Criteria

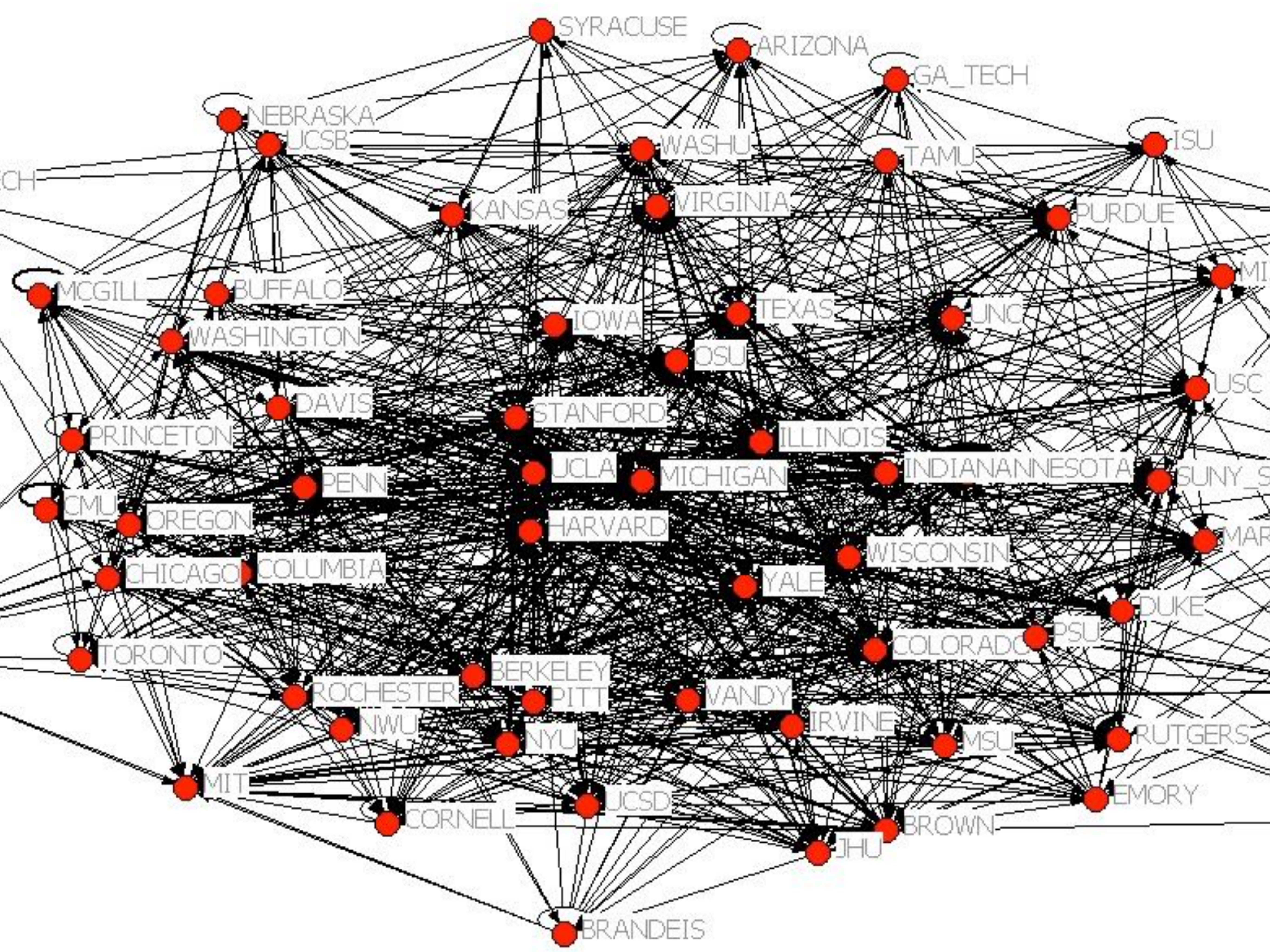
- Psychology department level
- Productivity data
  - National Research Council (NRC) score
- Prestige data (peer-rated)
  - U.S. News & World Report ranking score

Network Space

- Only examined inter-AAU psychology hires
- Excluded non-AAU universities and hires
- 1,936 ties (hires) among 65 nodes (AAU)

AAU Hiring Network





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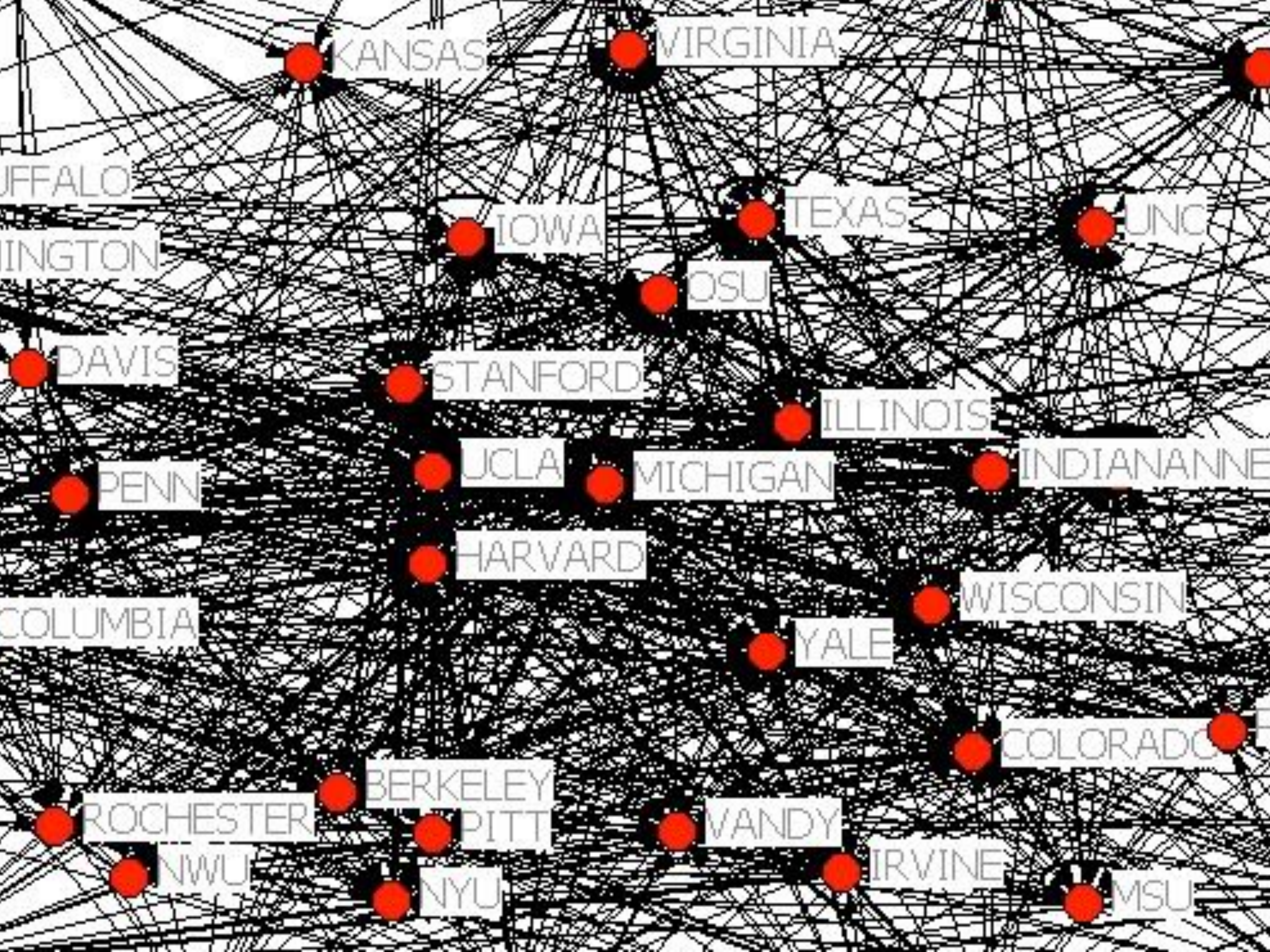
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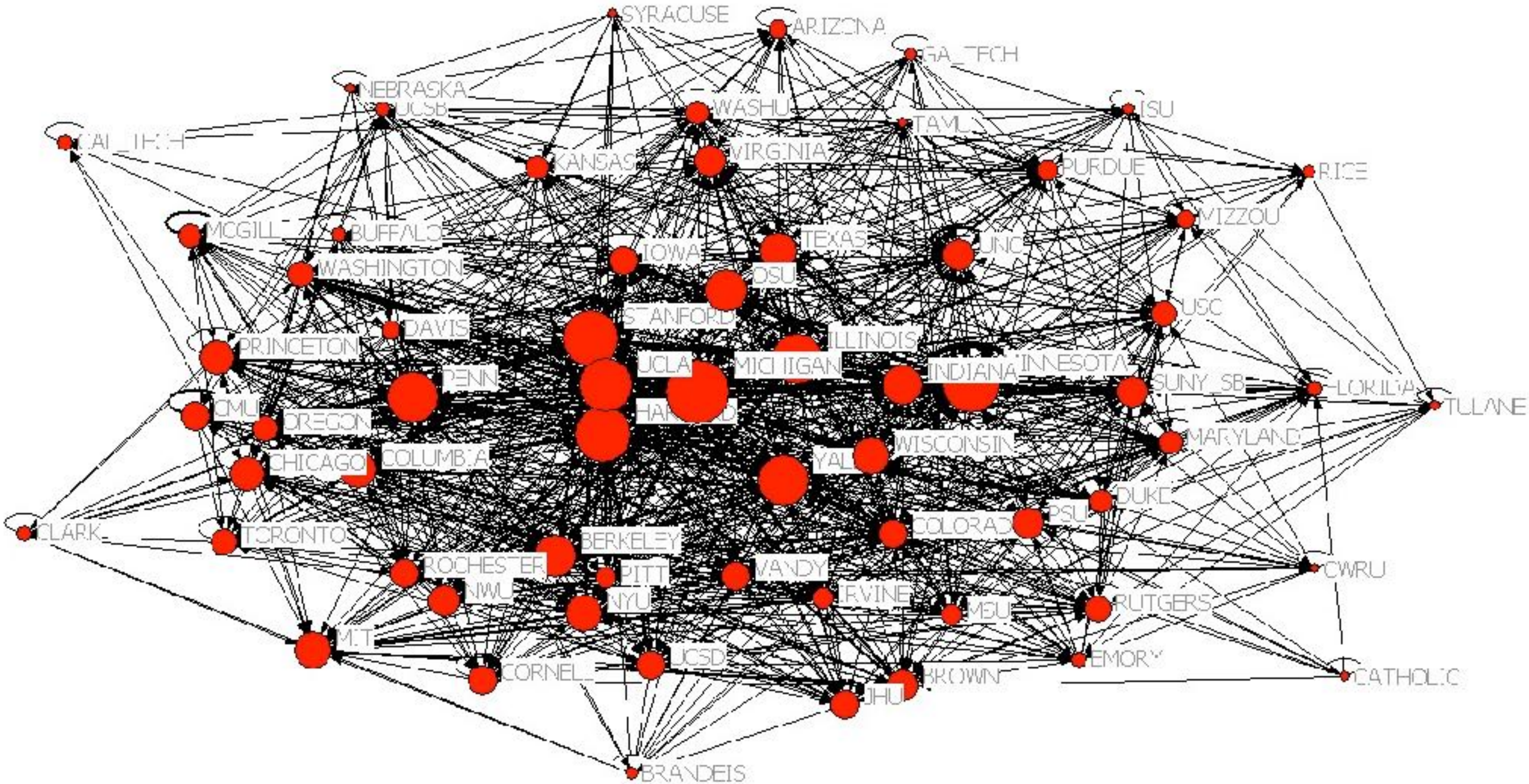
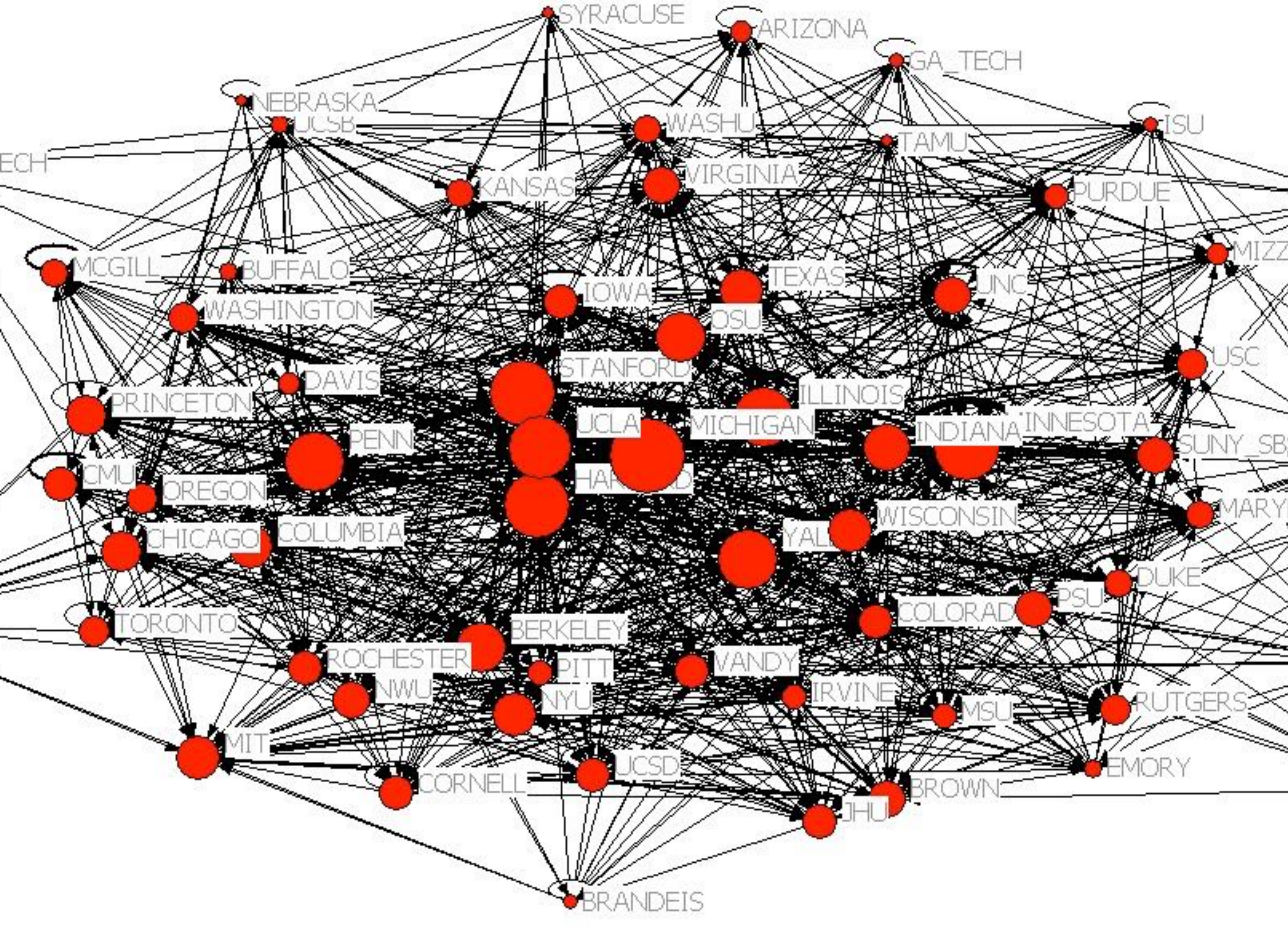
MSU

In-Degree Centrality

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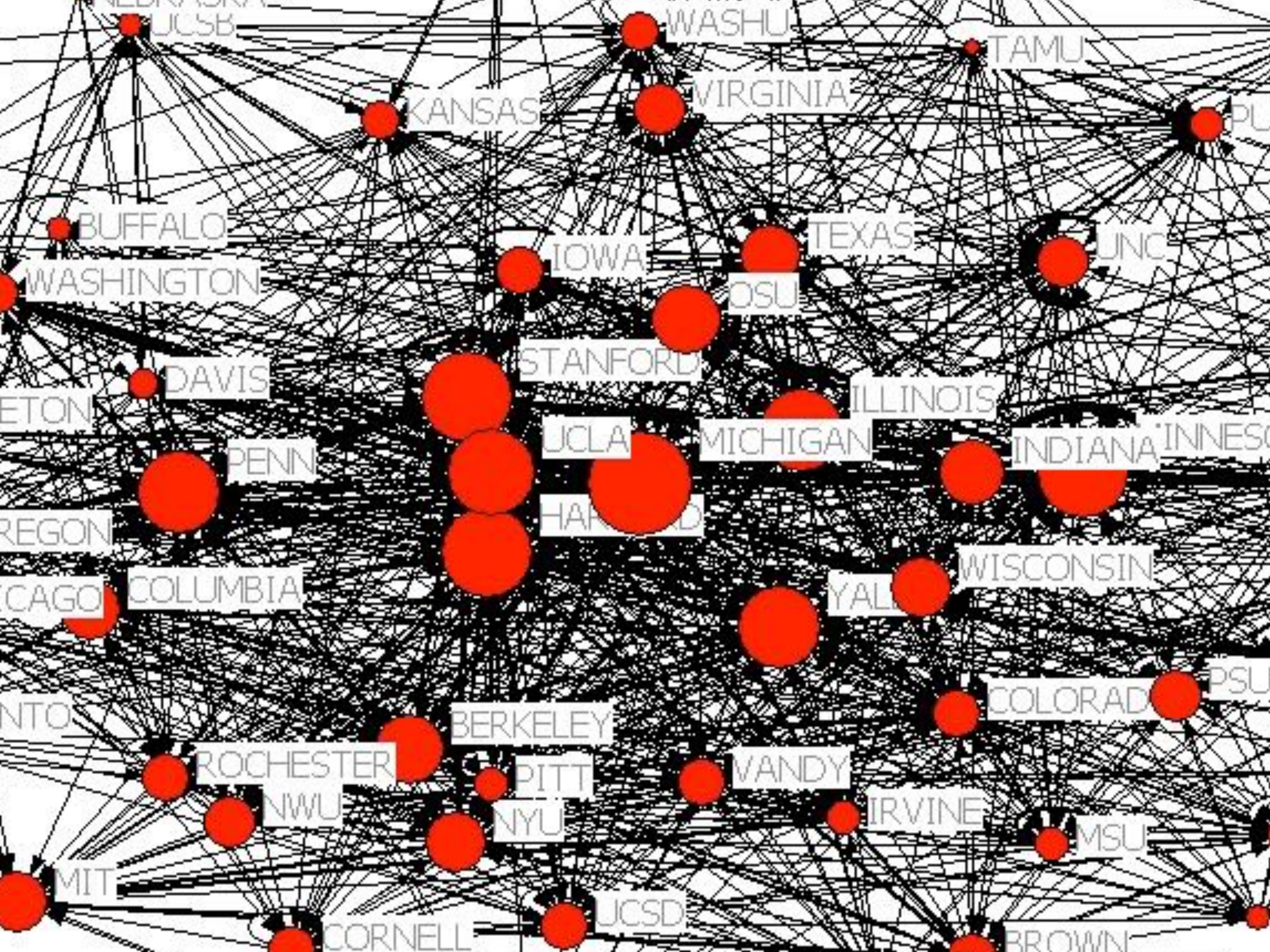

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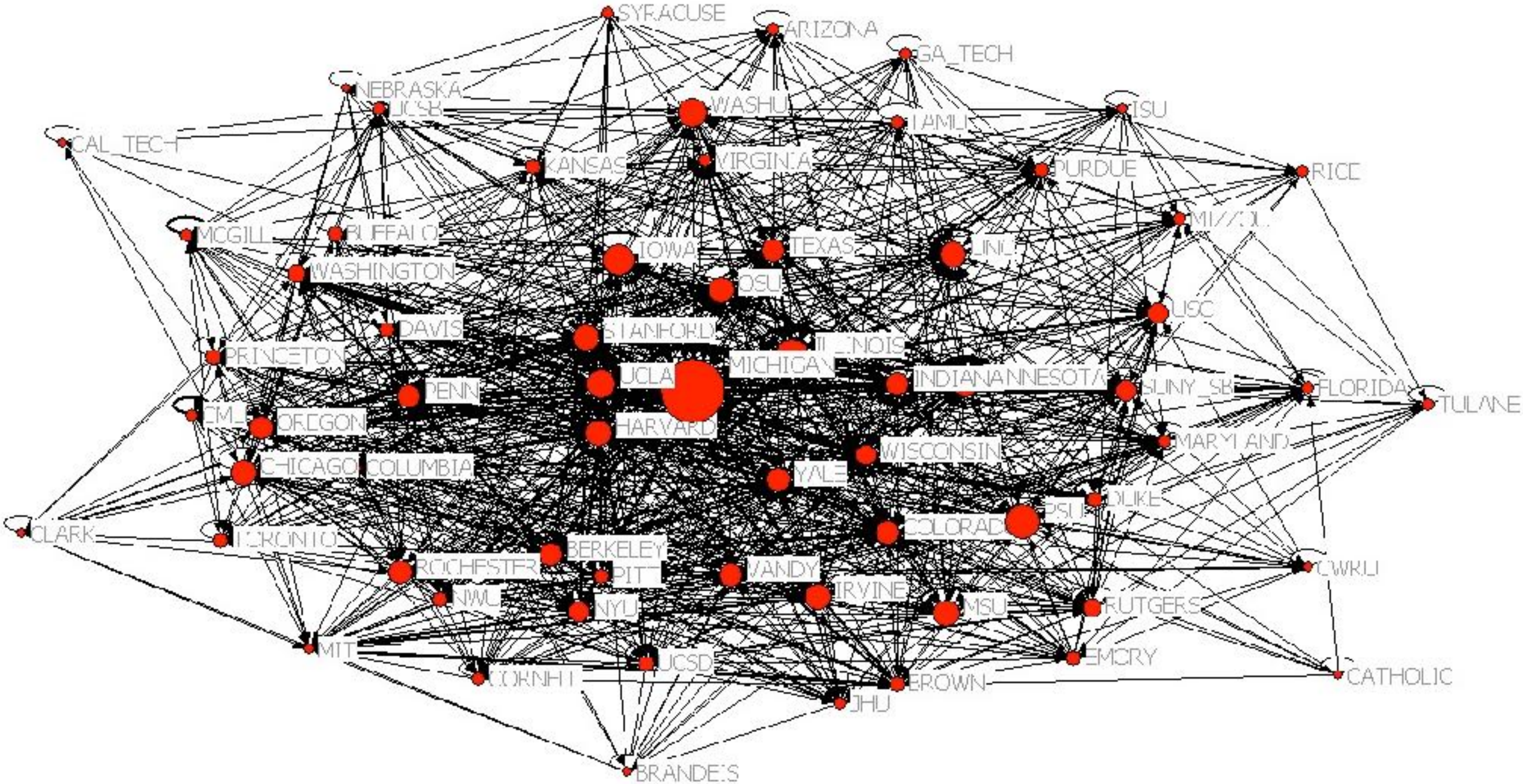
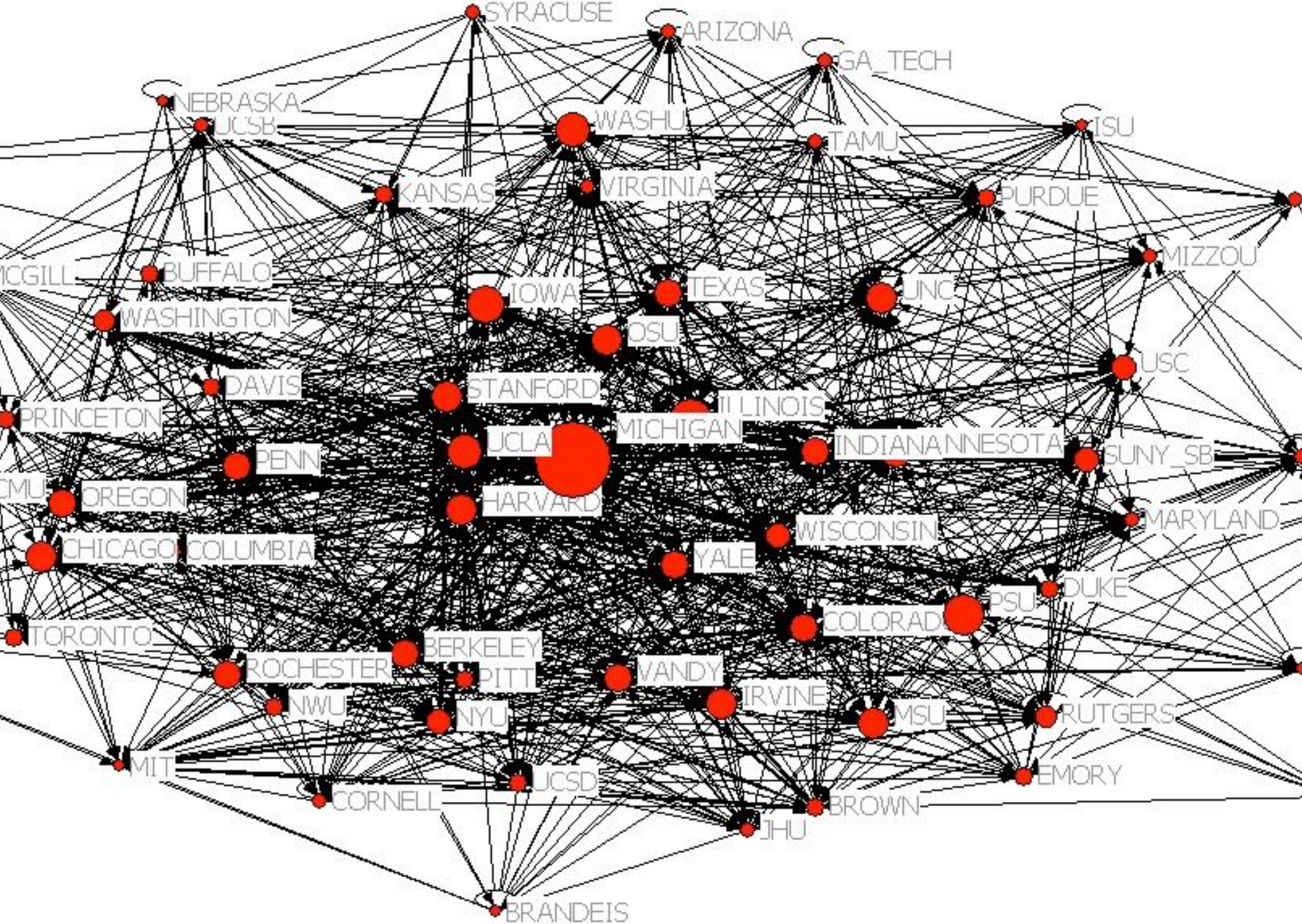
Betweenness Centrality





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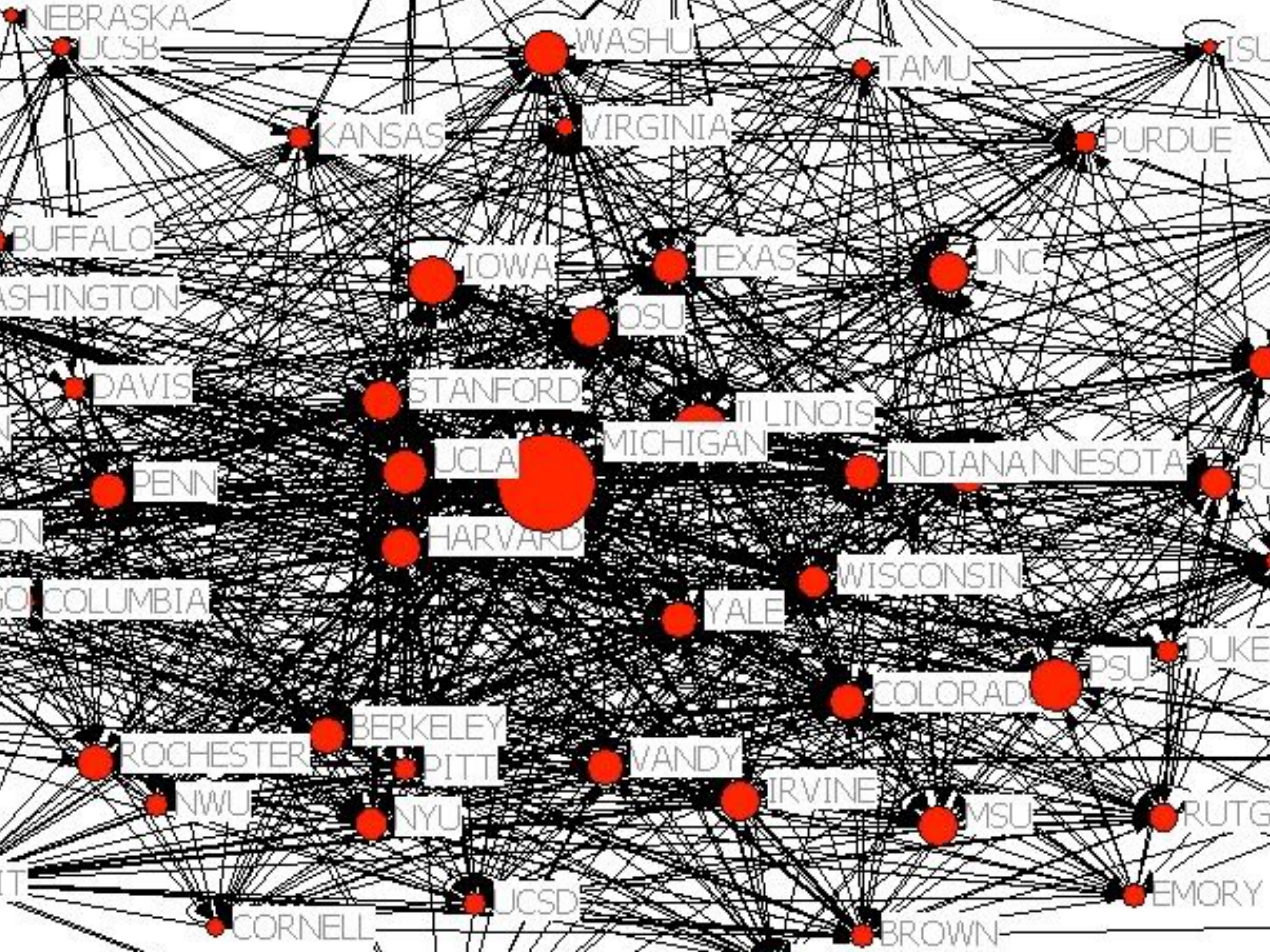
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UCSD
EMORY
CORNELL
BROWN

Network Centrality and Department Productivity & Prestige

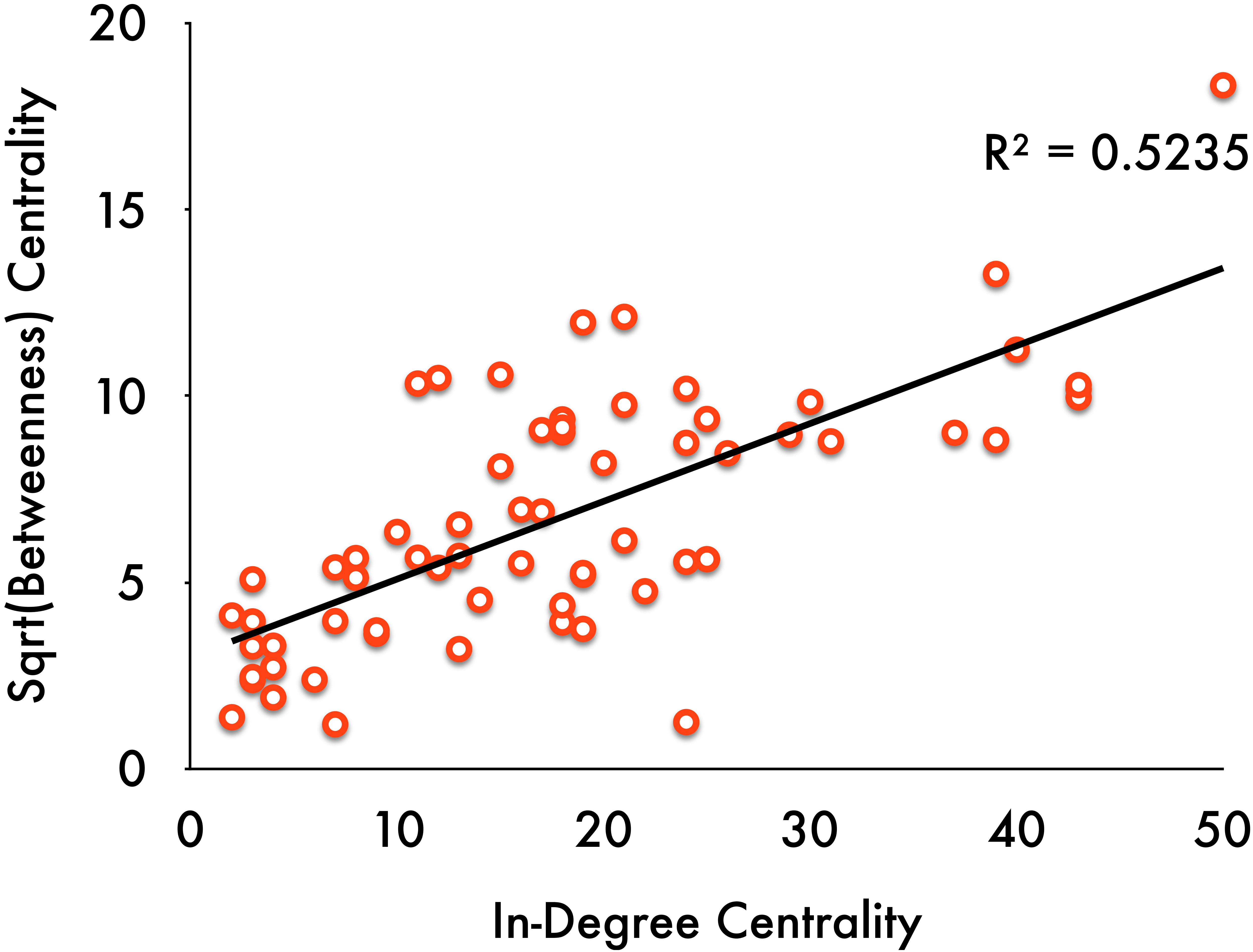
Variable	*M*	*SD*	1	2	3
1. In-Degree	17.91	11.77			
2. Betweenness$^{1/2}$	6.73	3.39	0.72		
3. NRC score	60.2	6.25	0.88	0.65	
4. USNews score	3.85	0.5	0.86	0.62	0.89

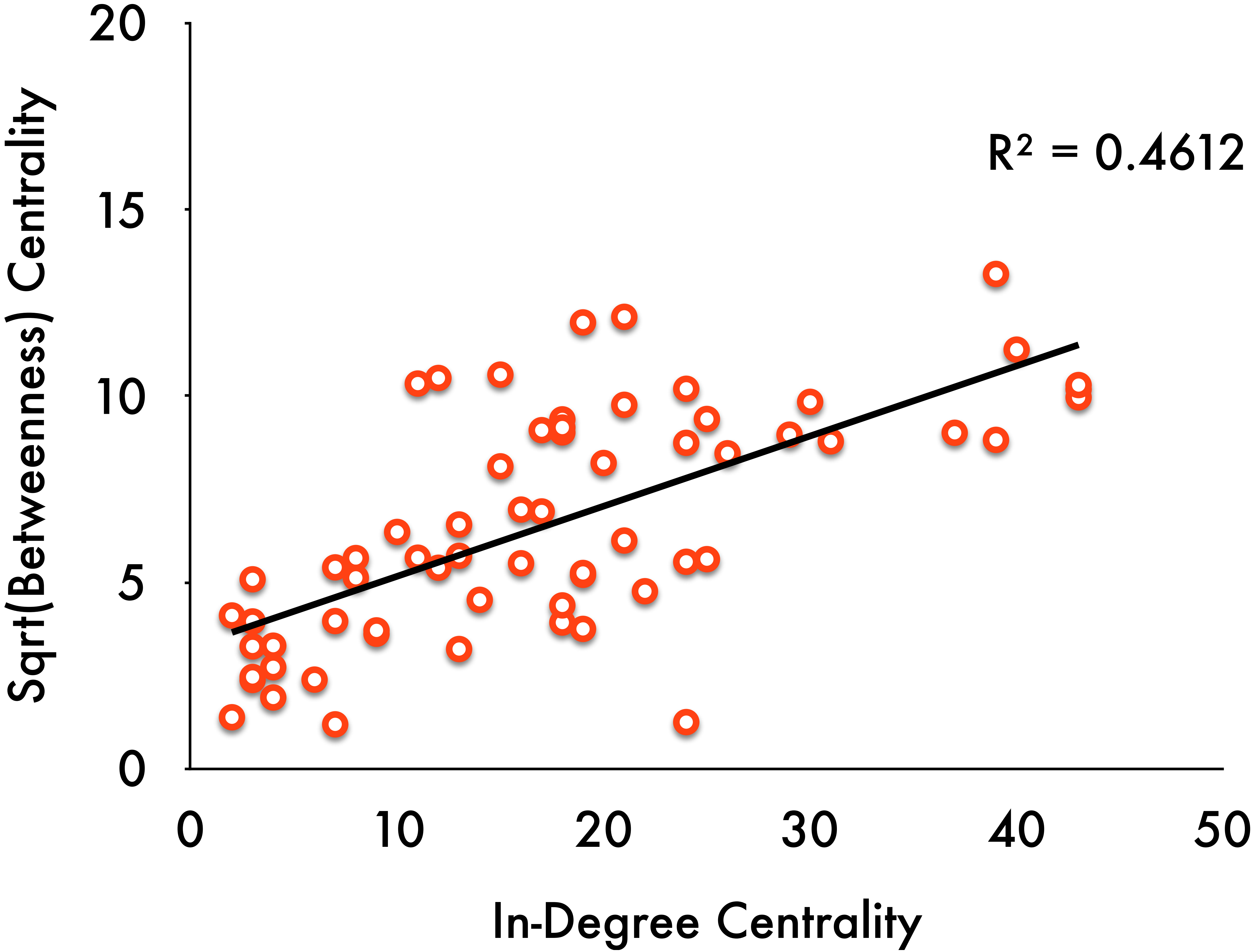
*N*s = 60–65. All *p*s < .001.

Network Centrality and Department Productivity & Prestige

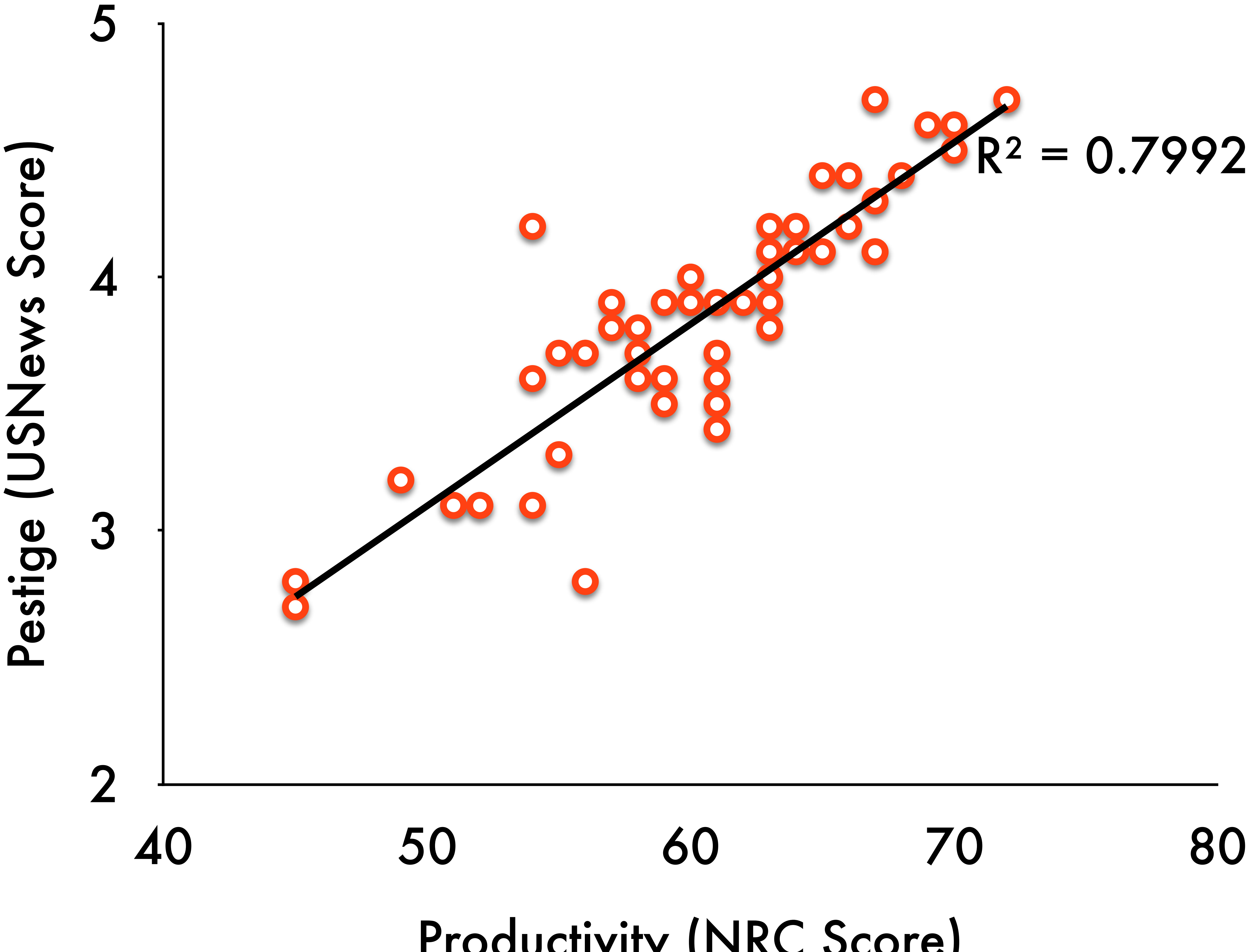
Variable	*M*	*SD*	1	2	3
1. In-Degree	17.91	11.77			
2. Betweenness$^{1/2}$	6.73	3.39	0.72		
3. NRC score	60.2	6.25	0.88	0.65	
4. USNews score	3.85	0.5	0.86	0.62	0.89

*N*s = 60–65. All *p*s < .001.


Sqrt(Betweenness) Centrality
In-Degree Centrality
R² = 0.5235
0
5
10
15
20
0
10
20
30
40
50



R² = 0.4612
Sqrt(Betweenness) Centrality
In-Degree Centrality
0
5
10
15
20
0
10
20
30
40
50

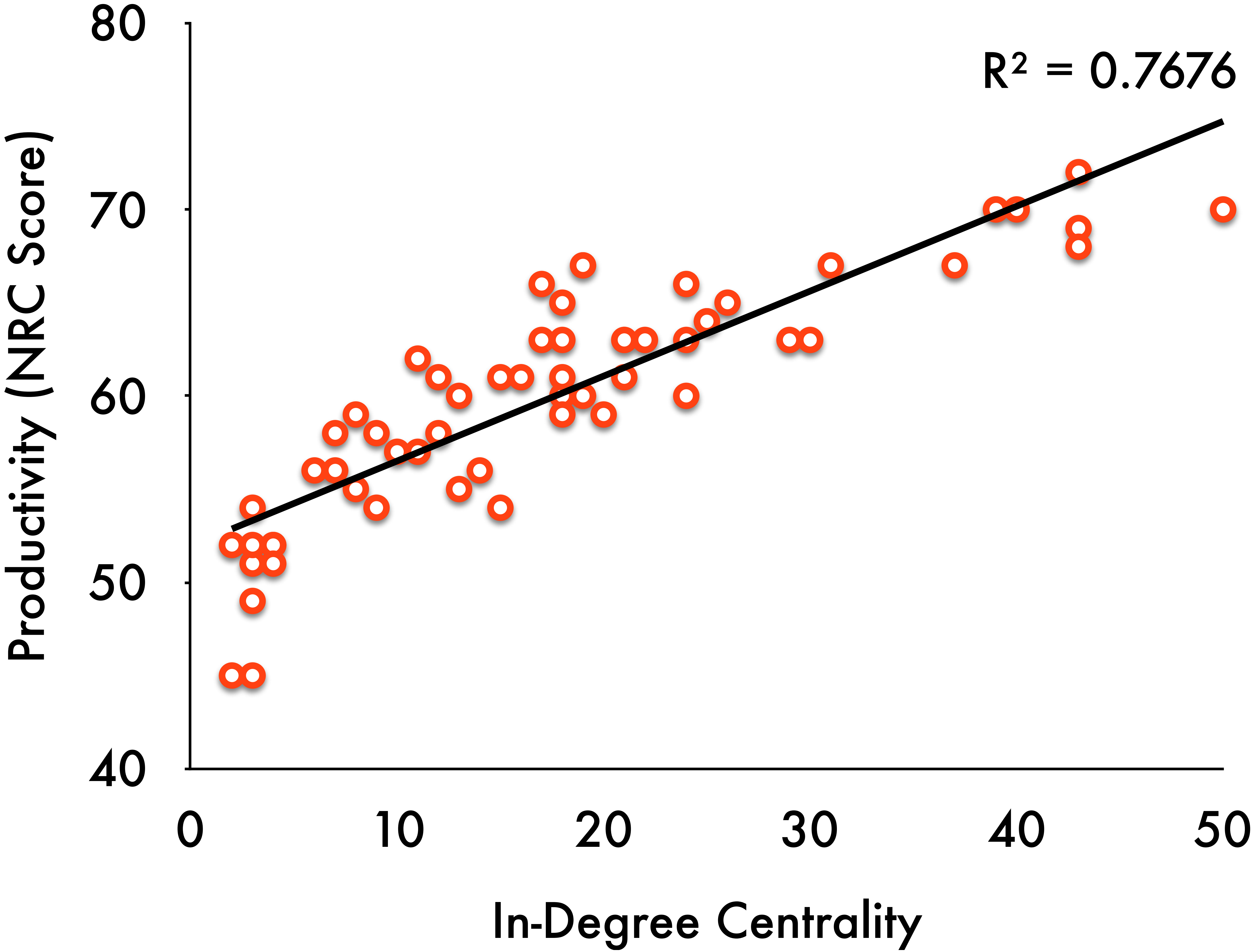


5
4
3
2
40
50
60
70
80
Pestige (USNews Score)
Productivity (NRC Score)
R² = 0.7992

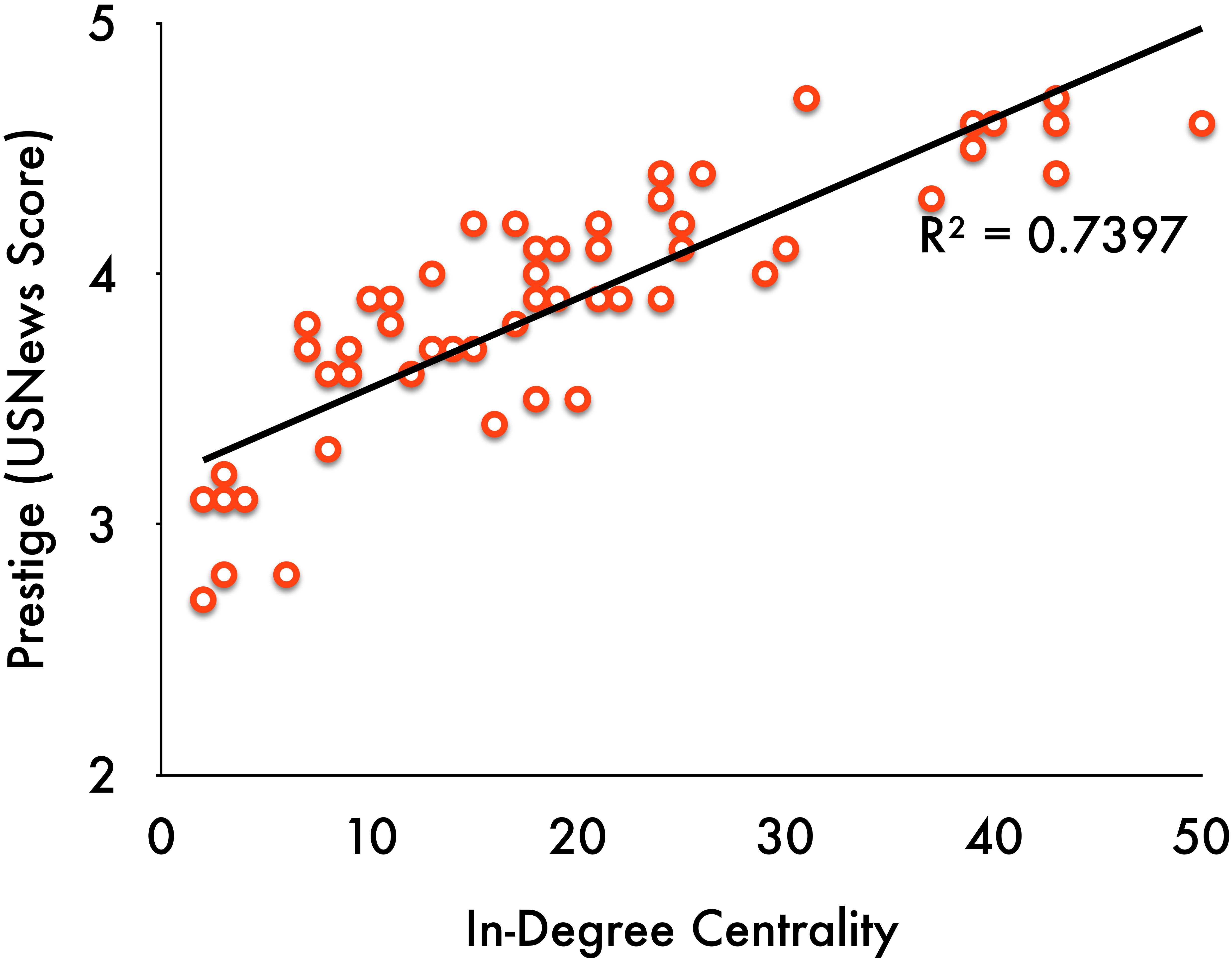
Network Centrality and Department Productivity & Prestige

Variable	*M*	*SD*	1	2	3
1. In-Degree	17.91	11.77			
2. Betweenness½	6.73	3.39	0.72		
3. NRC score	60.2	6.25	0.88	0.65	
4. USNews score	3.85	0.5	0.86	0.62	0.89

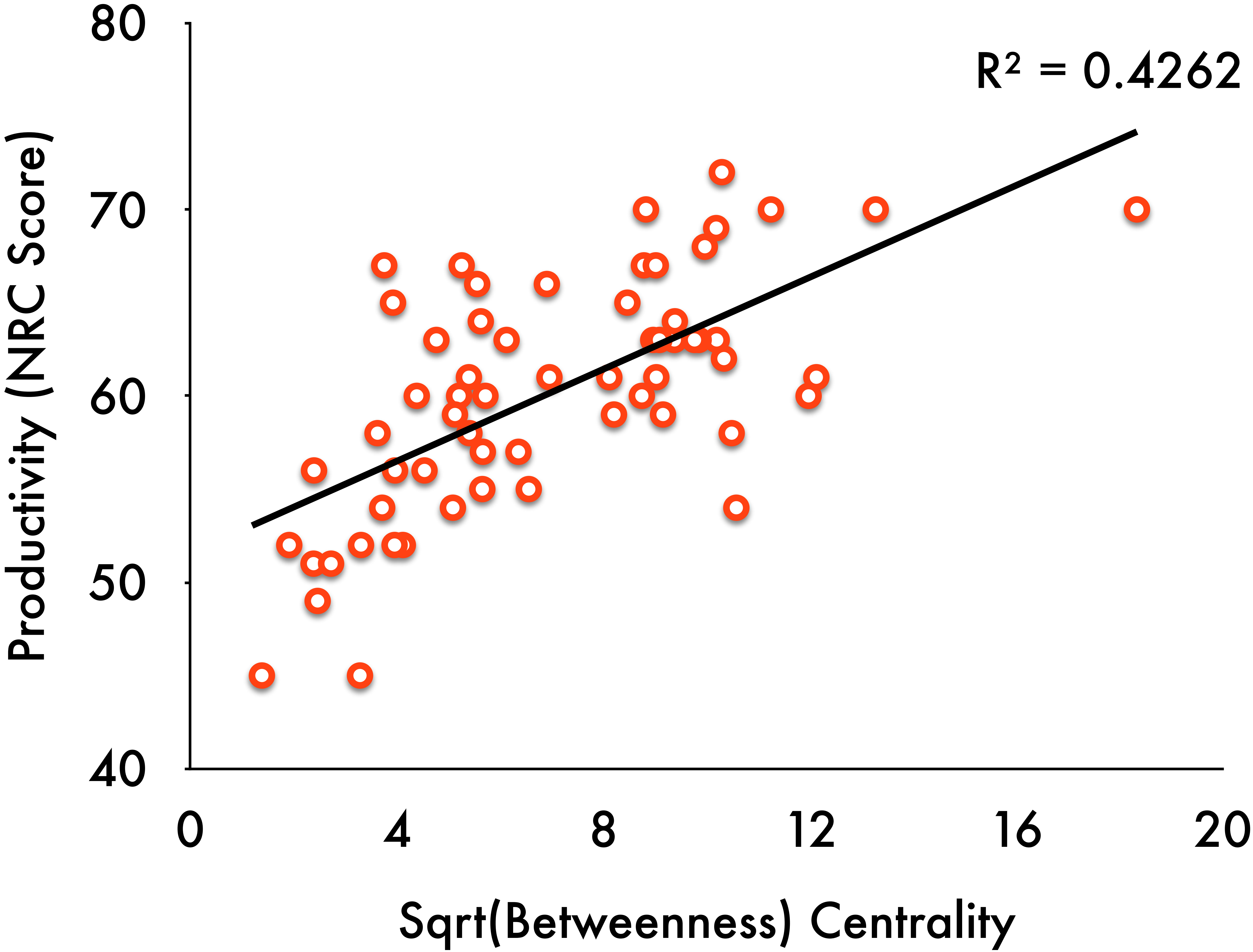
*N*s = 60–65. All *p*s < .001.



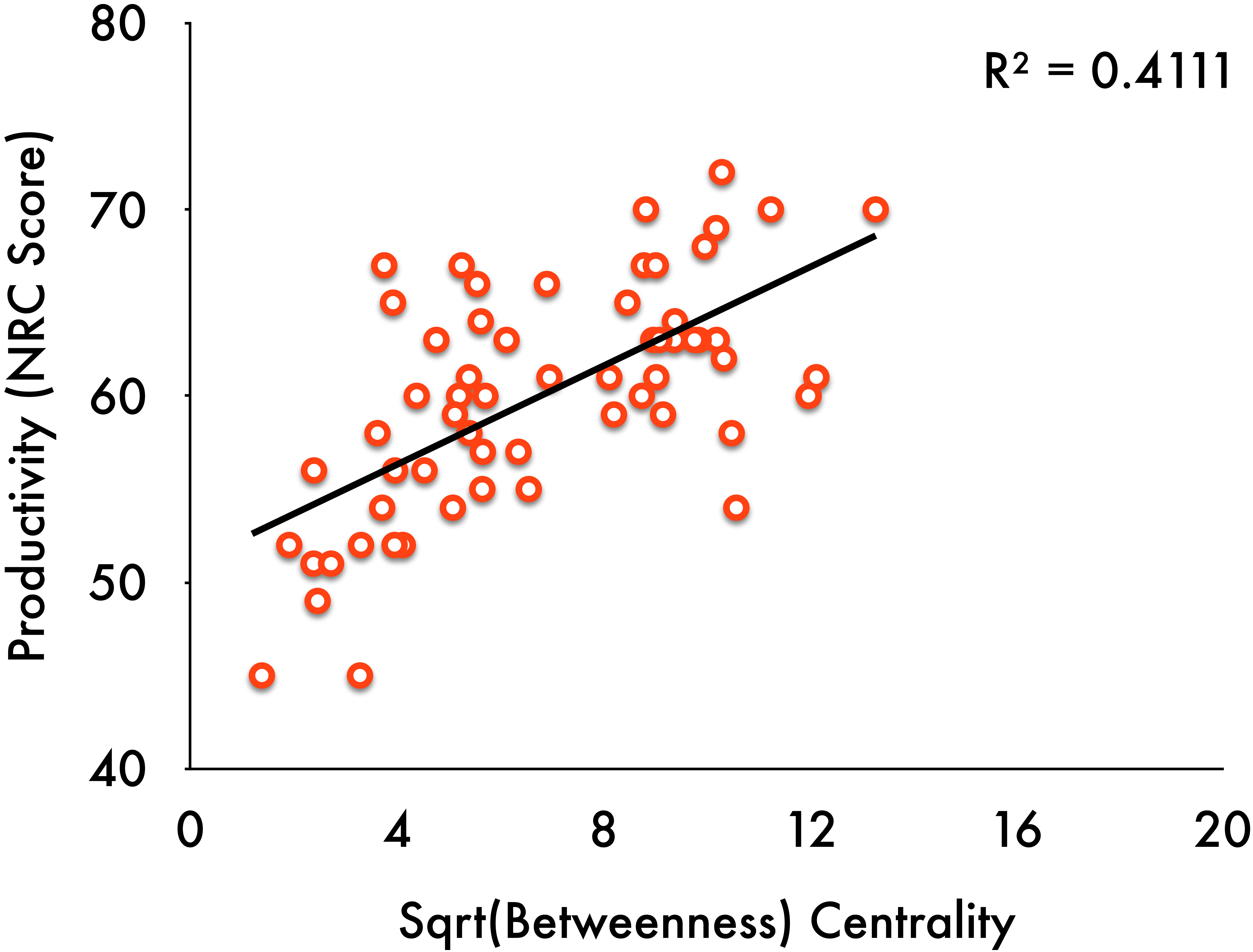
80
70
60
50
40
0
10
20
30
40
50
Productivity (NRC Score)
In-Degree Centrality
R² = 0.7676



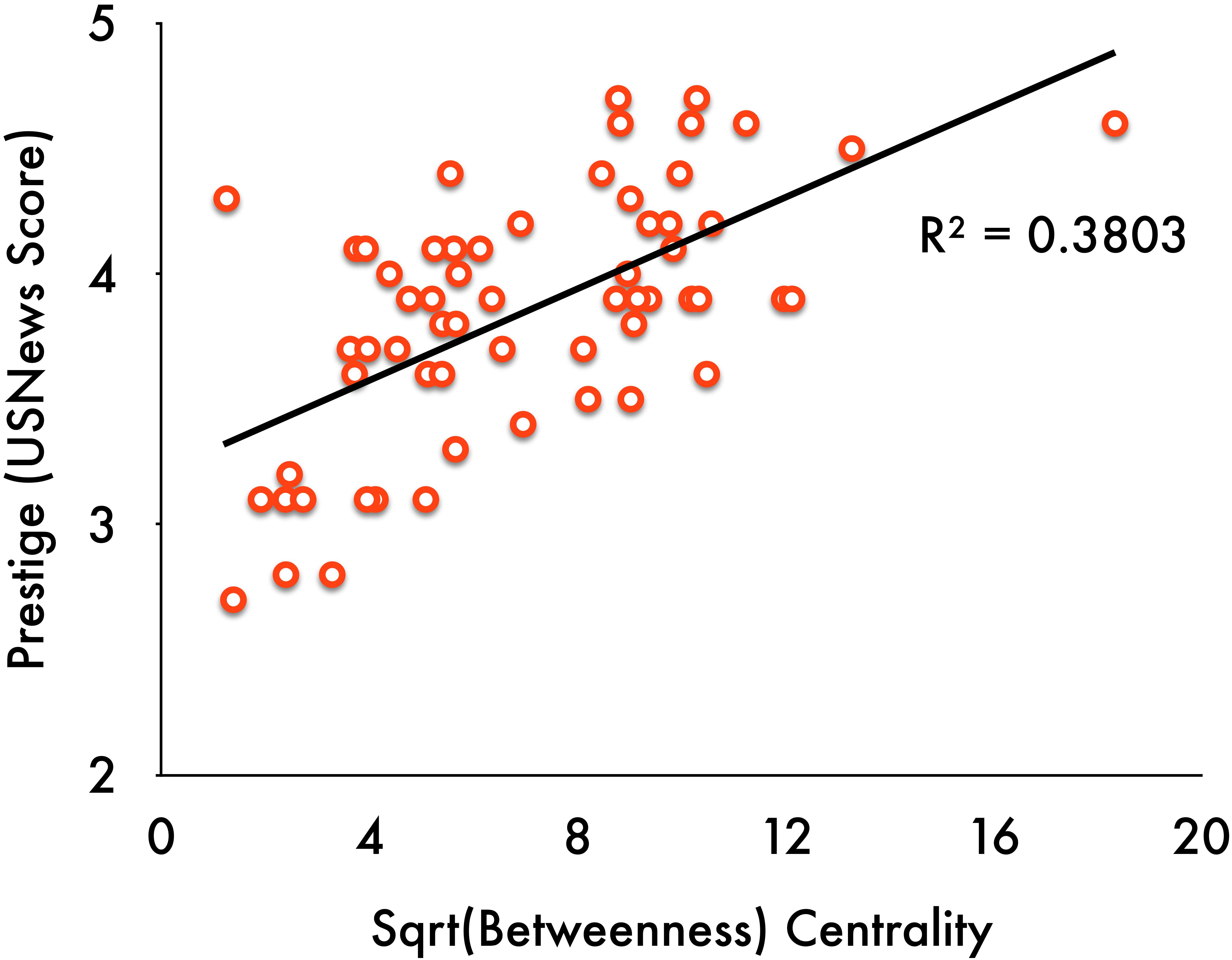
Prestige (USNews Score)
5
4
3
2
0
10
20
30
40
50
In-Degree Centrality
R^2 = 0.7397

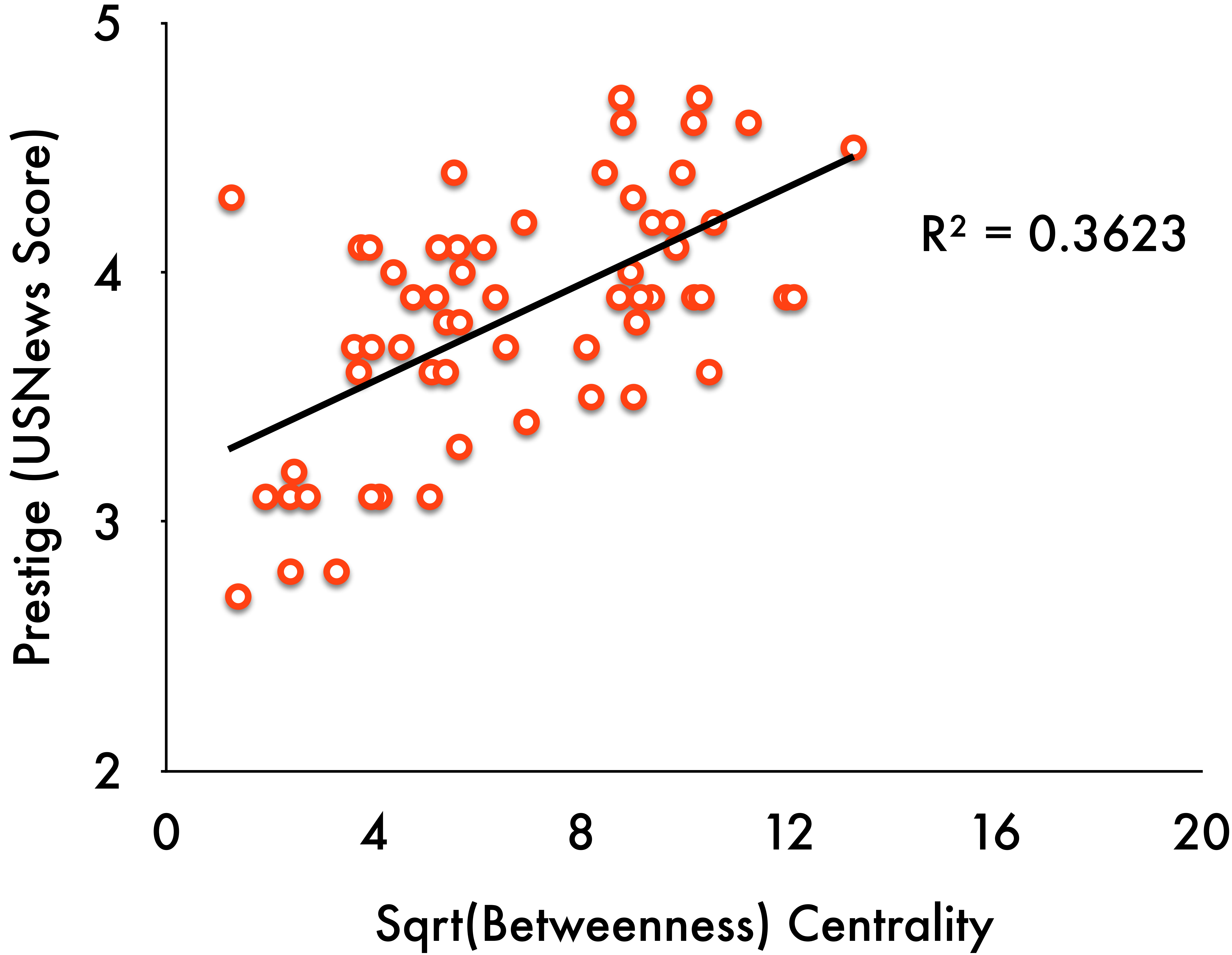


R² = 0.4262
Productivity (NRC Score)
80
70
60
50
40
0
4
8
12
16
20
Sqrt(Betweenness) Centrality



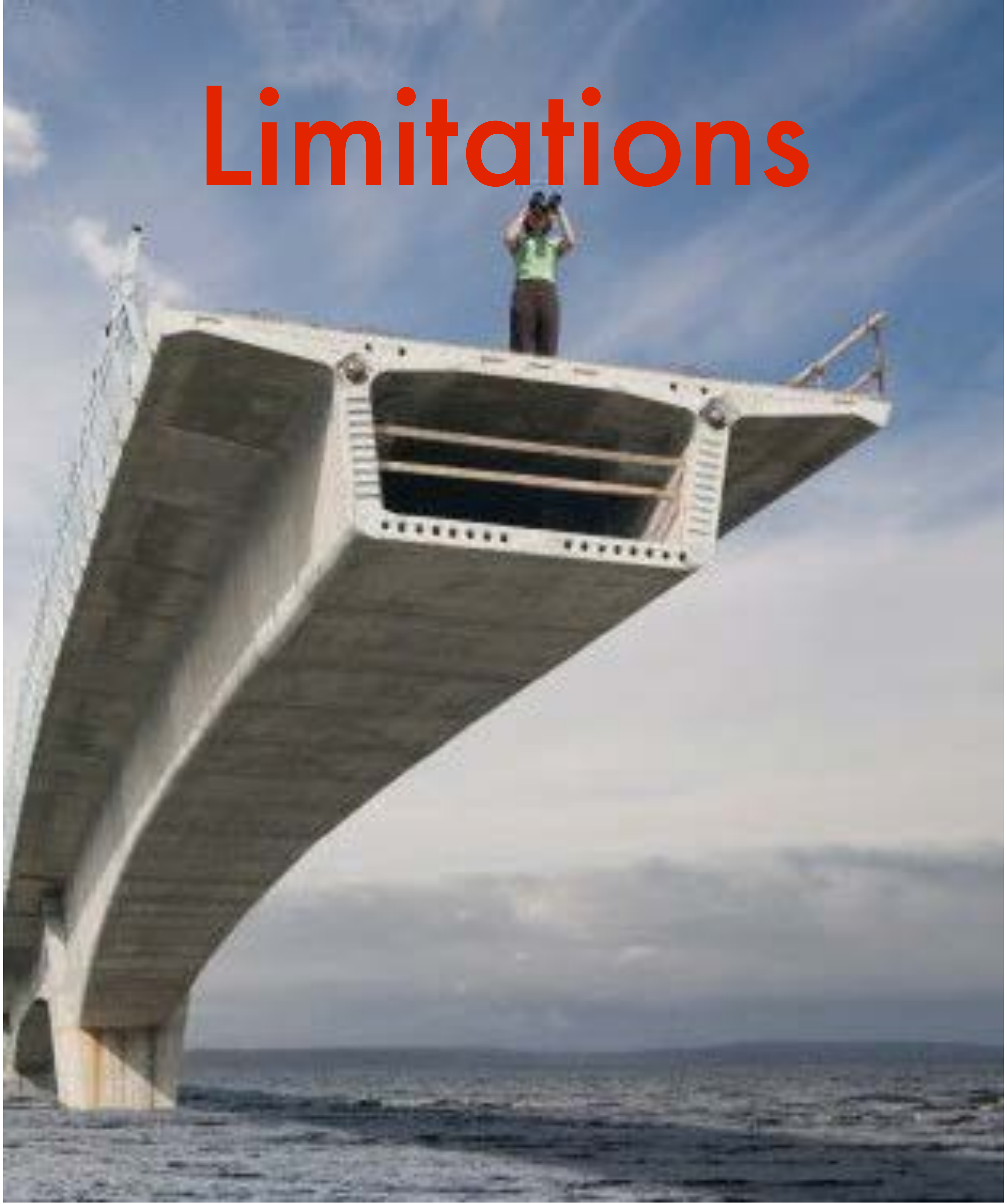
80
70
60
50
40
Productivity (NRC Score)
R² = 0.4111
0
4
8
12
16
20
Sqrt(Betweenness) Centrality


5
4
3
2
0
4
8
12
16
20
Prestige (USNews Score)
Sqrt(Betweenness) Centrality
R² = 0.3803



Prestige (USNews Score)
5
4
3
2
0
4
8
12
16
20
Sqrt(Betweenness) Centrality
$R^2 = 0.3623$

Limitations



Limitations

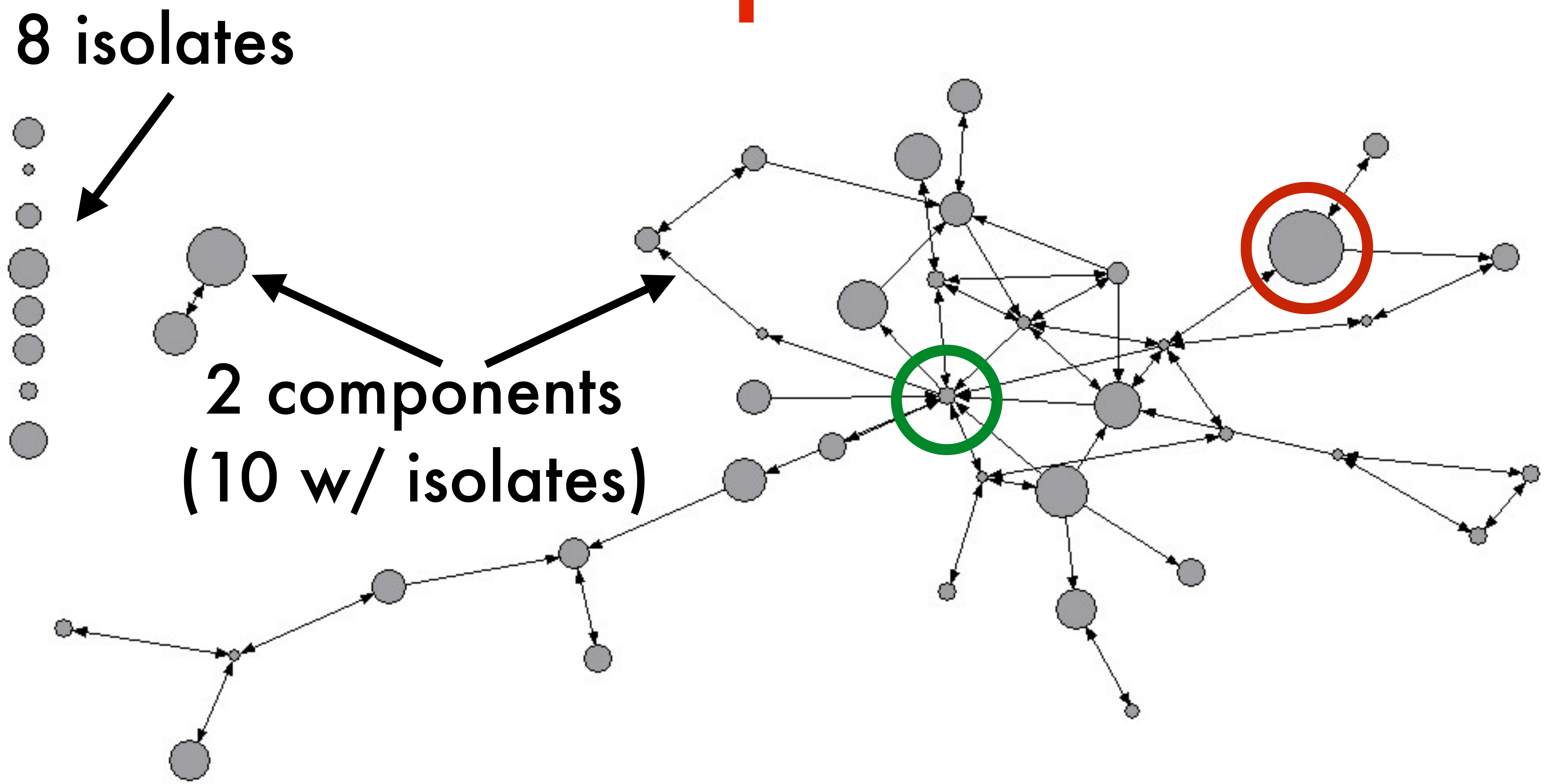
- Sample depends on accuracy of websites
- Limited in scope to AAU institutions
  - But where do we stop? Research I or II? International? Business schools?
- Does not account for hires/positions held in between PhD and current position
- Future research should expand network scope and intermediate hires/positions

Example 2:
Classroom Friendships and Aggression

Friendship and Aggression

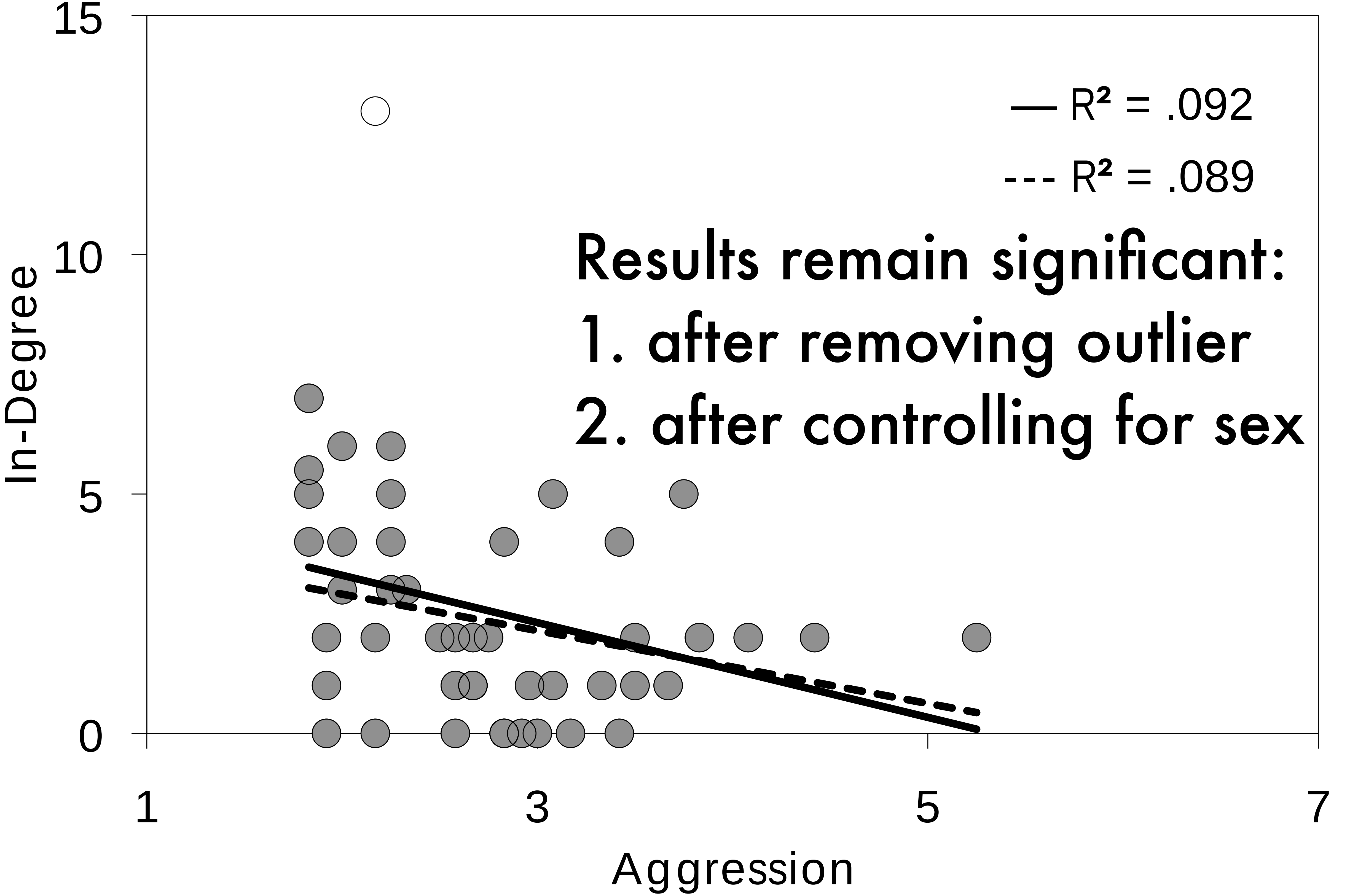
- 46 undergraduates in a psychology class
  - 14 men, 32 women
- Asked about friendships at end of semester:
  - 1=acquaintance, 2=friend, 3=close friend
- Focussed on in-degree (i.e., popularity)
- Completed the Brief Aggression Questionnaire.
  - Subscales: Physical Aggression, Verbal Aggression, Anger, and Hostility.
- Are more aggressive students liked less?

Friendship Network

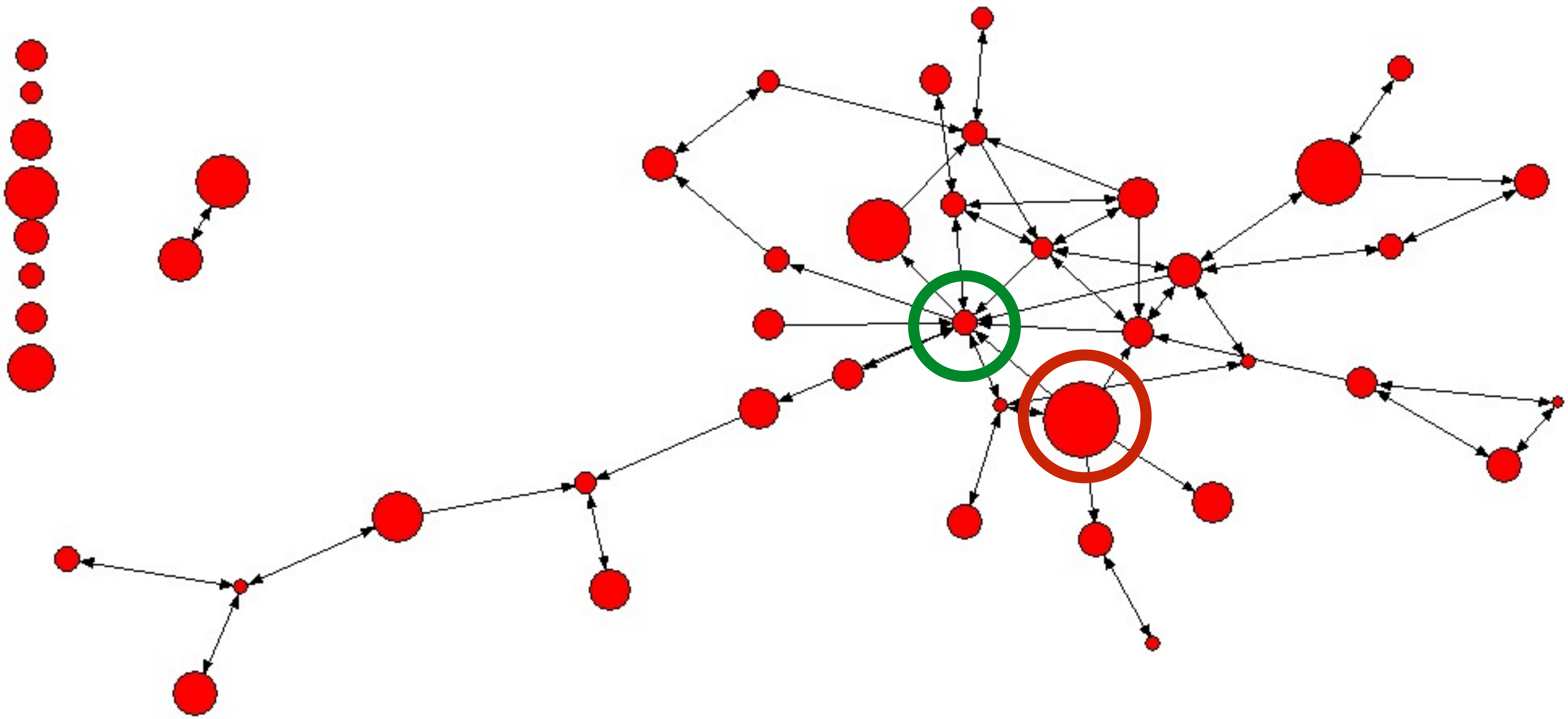


Node Size: Aggression

In-Degree and Aggression

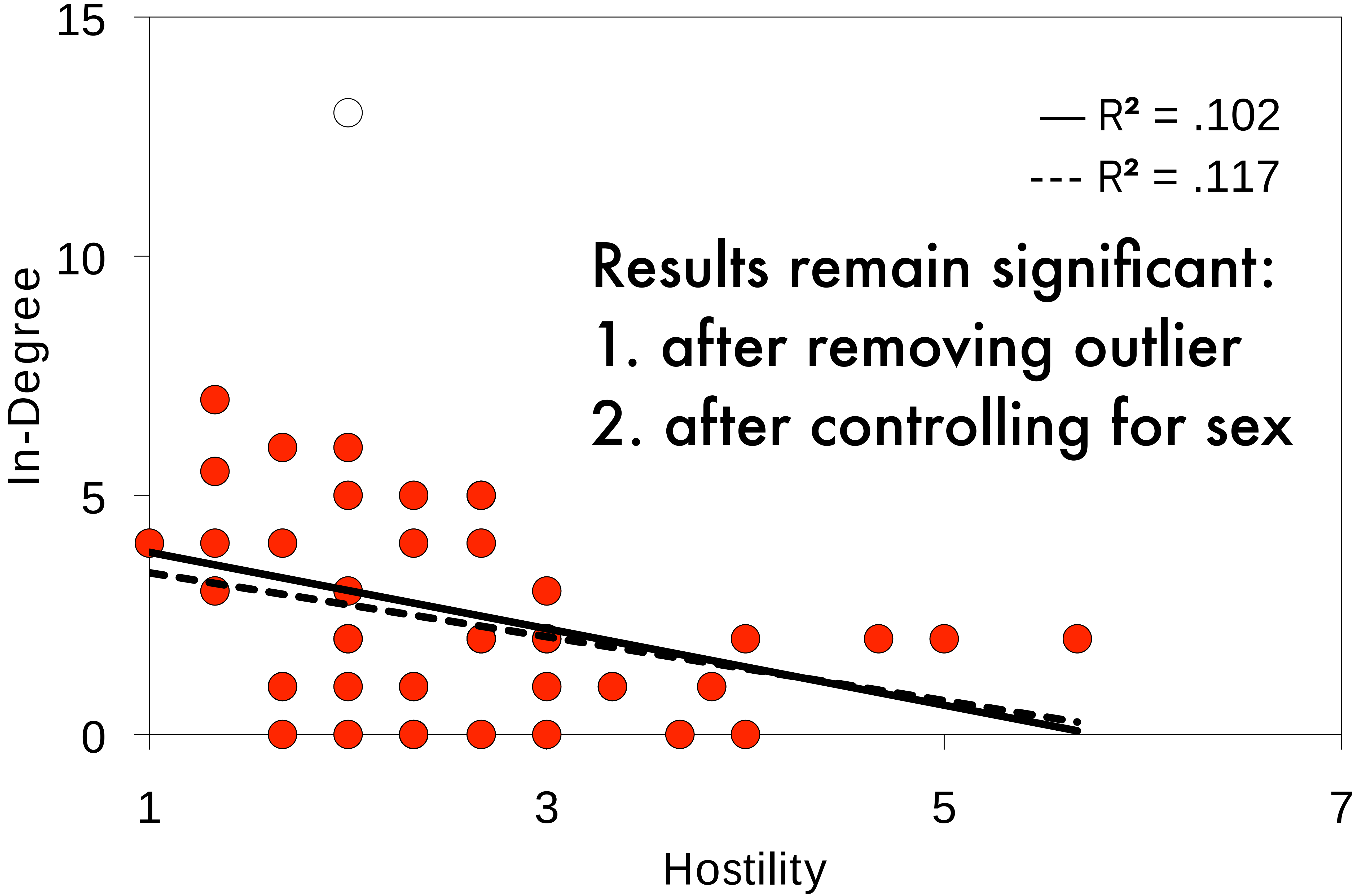


Friendship Network



Node Size: Hostility

In-Degree and Hostility

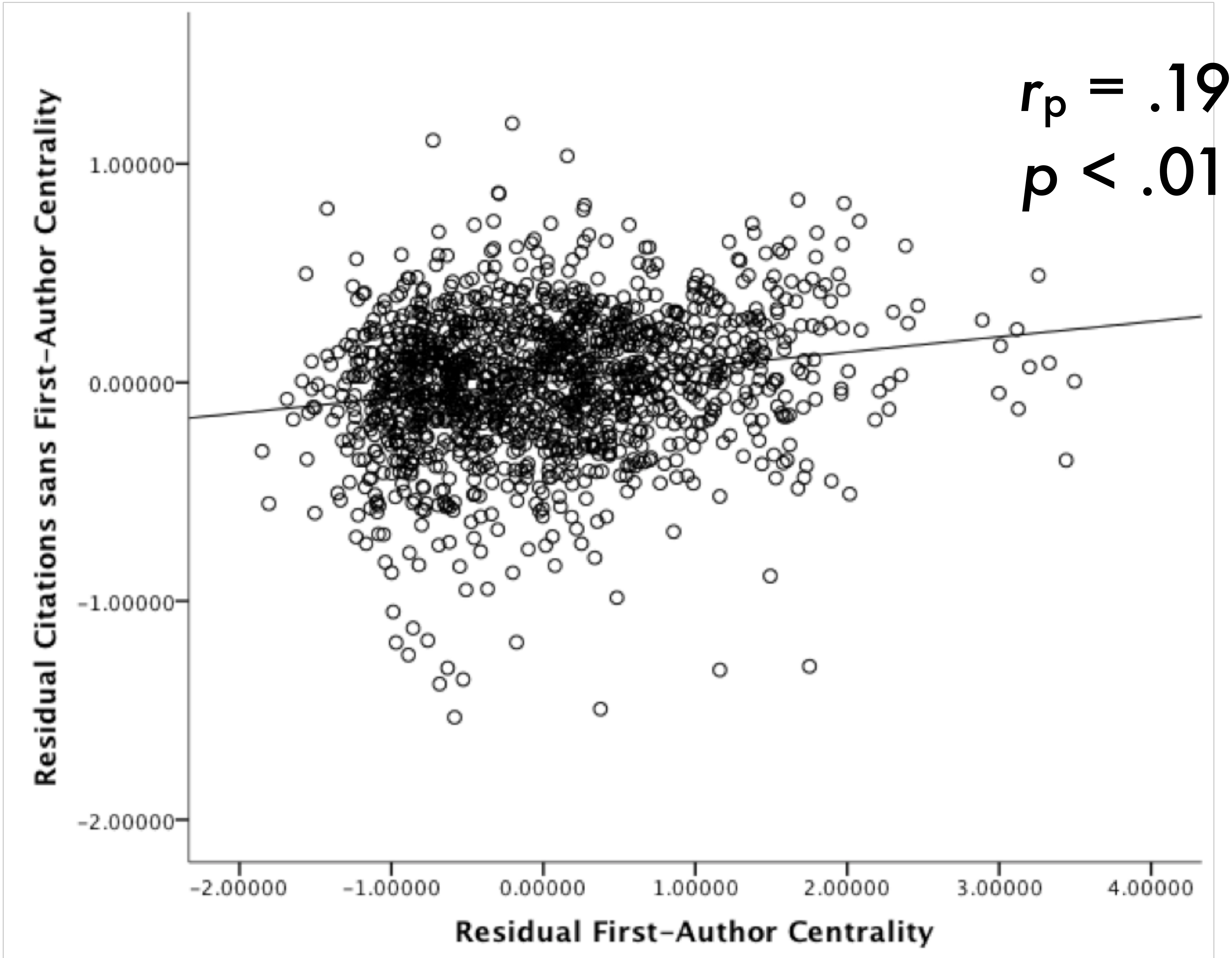


Example 3:
Coauthor Networks and Citation Counts

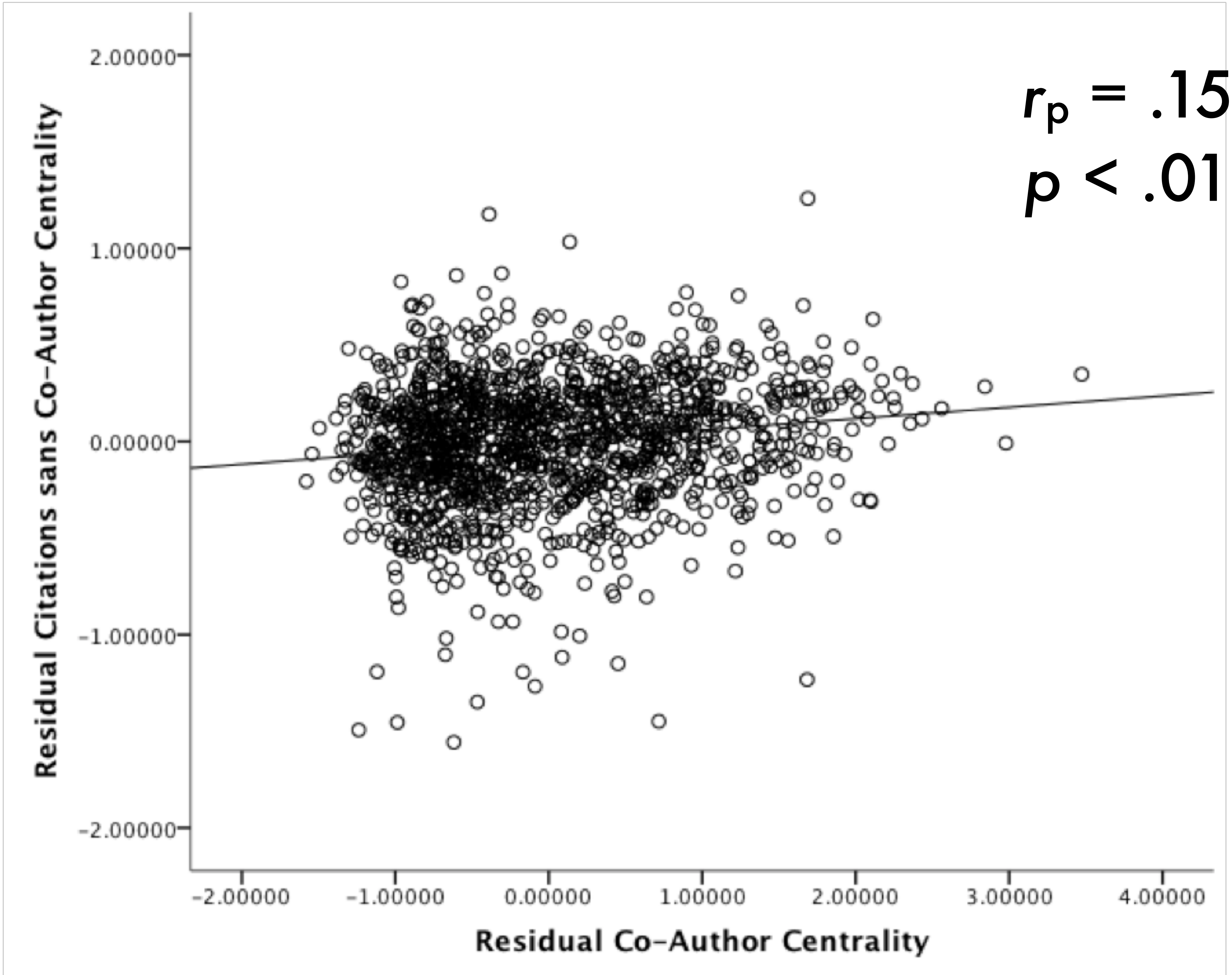
Author Centrality & Citation

- Examined 1,770 articles published in *J. Pers. & Soc. Psych.* (*JPSP*), 1995–2005
- Assessed co-authorship networks (who's published with whom)
- Standardized and averaged log in-degree and log betweenness centrality (r = .73)
- Correlated composite centrality with log citation counts per article.
- Are more central authors cited more often?

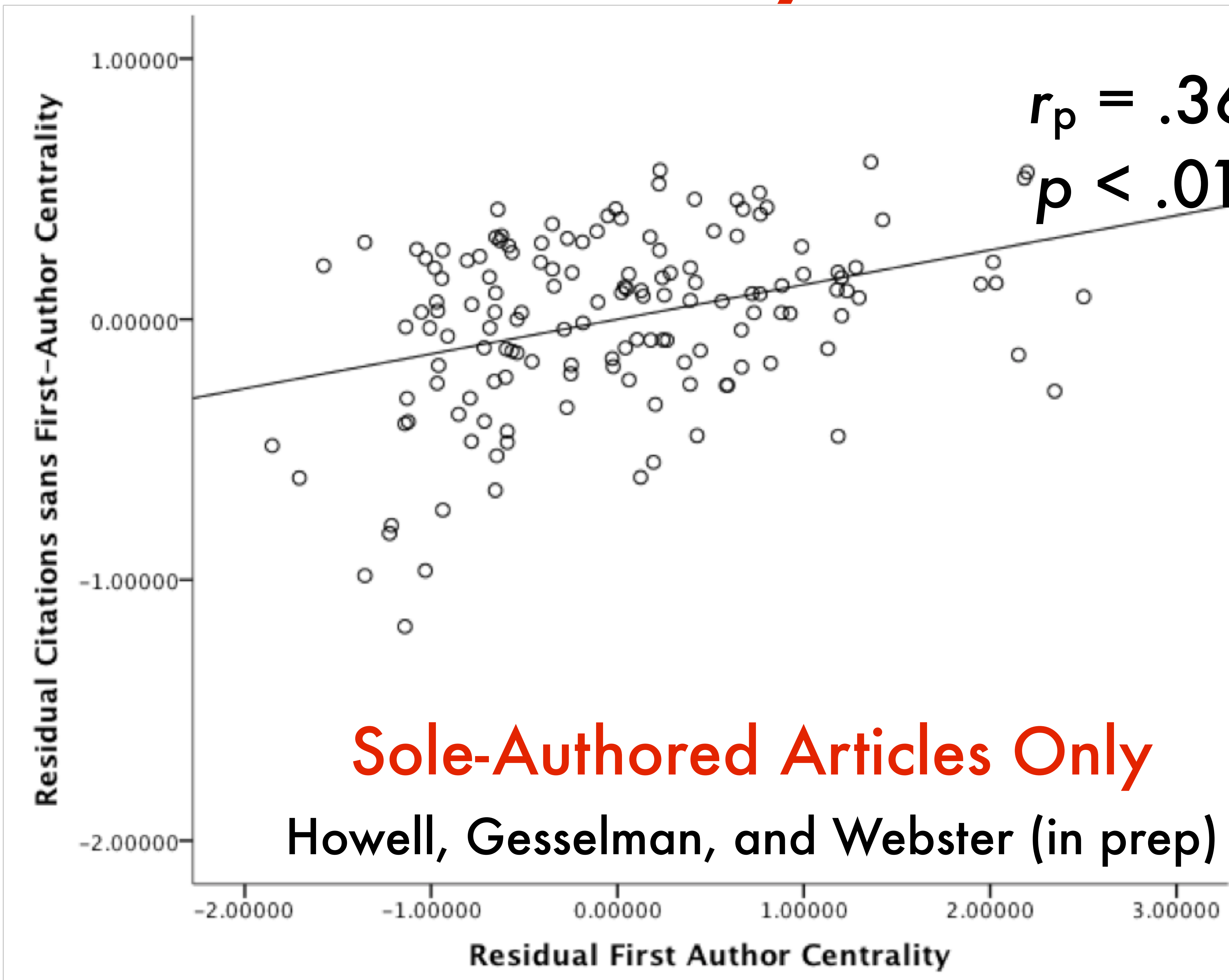
1st-author centrality & citations



Co-author centrality & citations



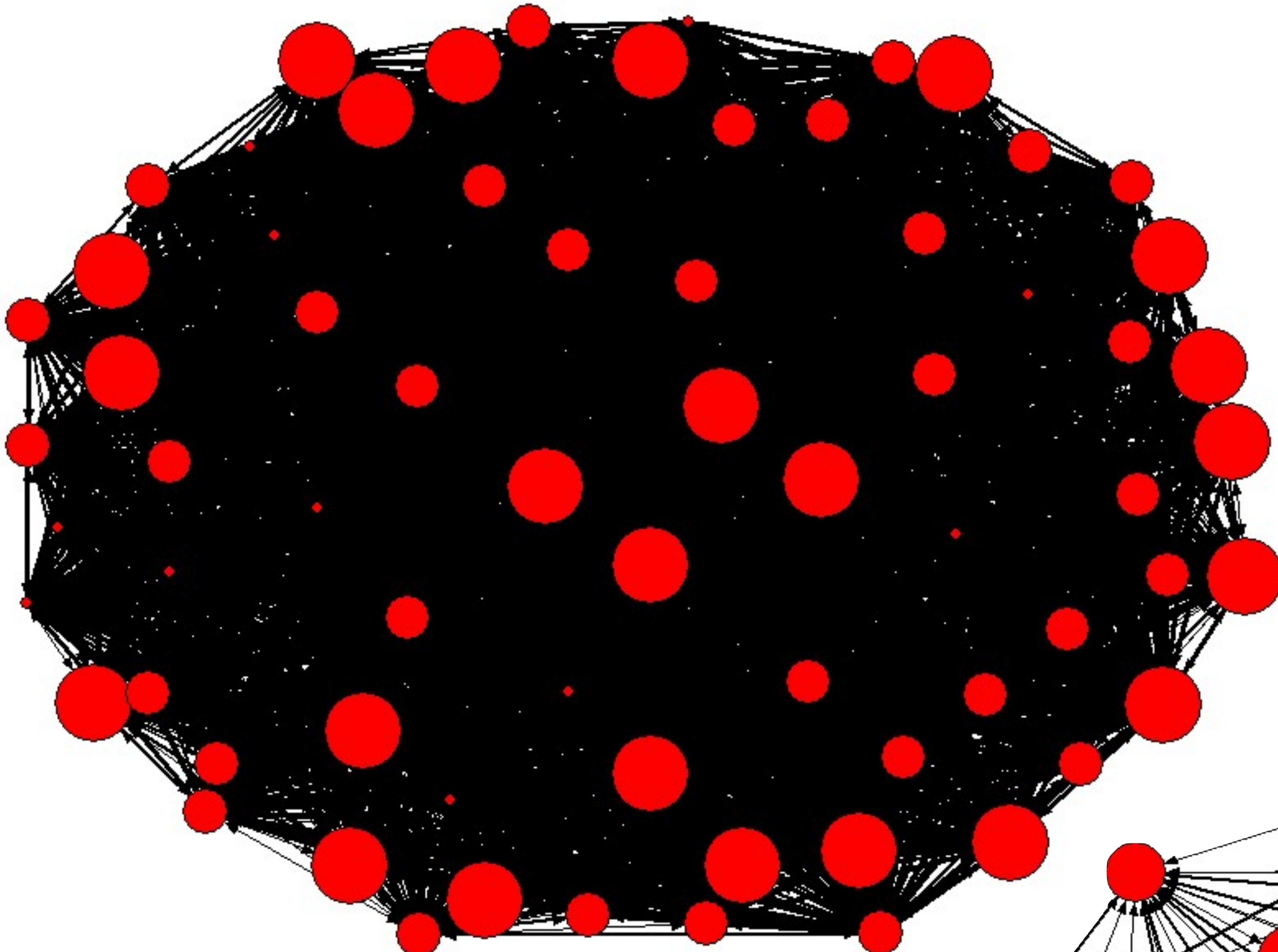
1st-author centrality & citations



Example 4:
Popularity and Sexual Behavior in Social Fraternities and Sororities

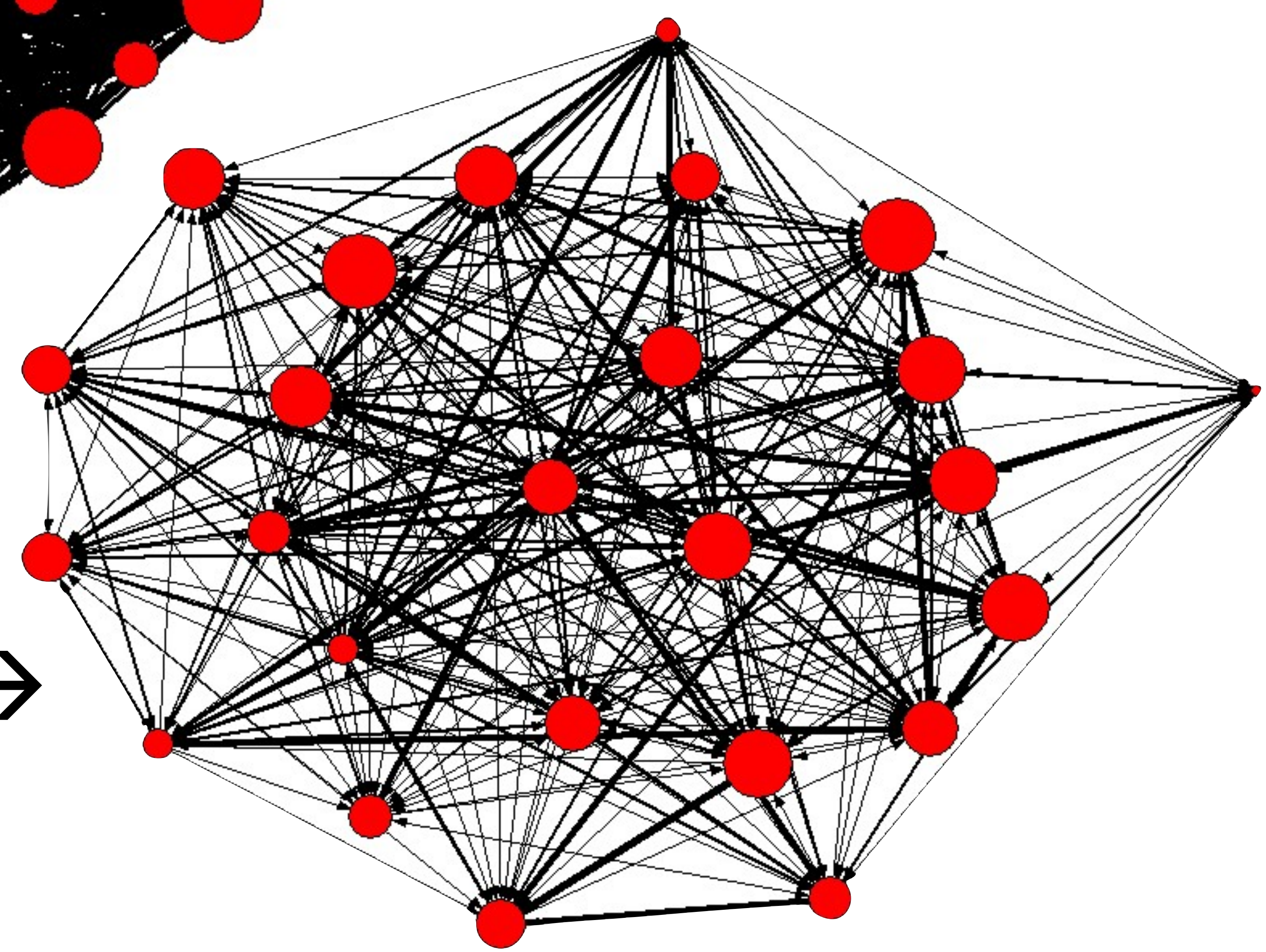
Popularity & Sex Behavior

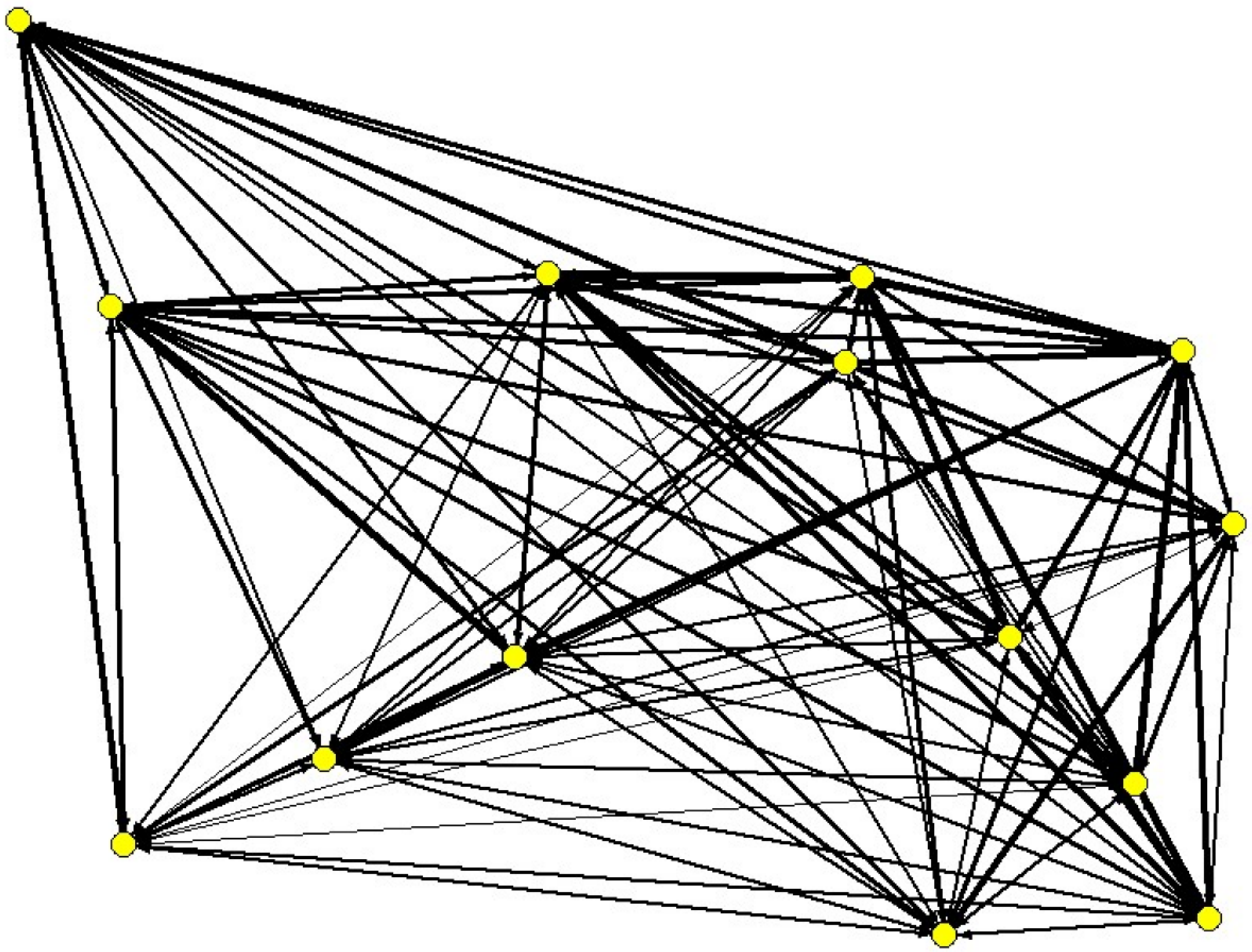
- 3 fraternities, 2 sororities (*N* = 222)
- Friendship networks at three time points across the semester
- Social network analyses of change in friendship indegree across time (T1, T2, T3)
- Change in indegree (popularity) moderated the relationship betwen T1 and T3 socio-sexual behavior (e.g., one-night stands)
- Measured Greek identity and sociosexuality



←Time 1

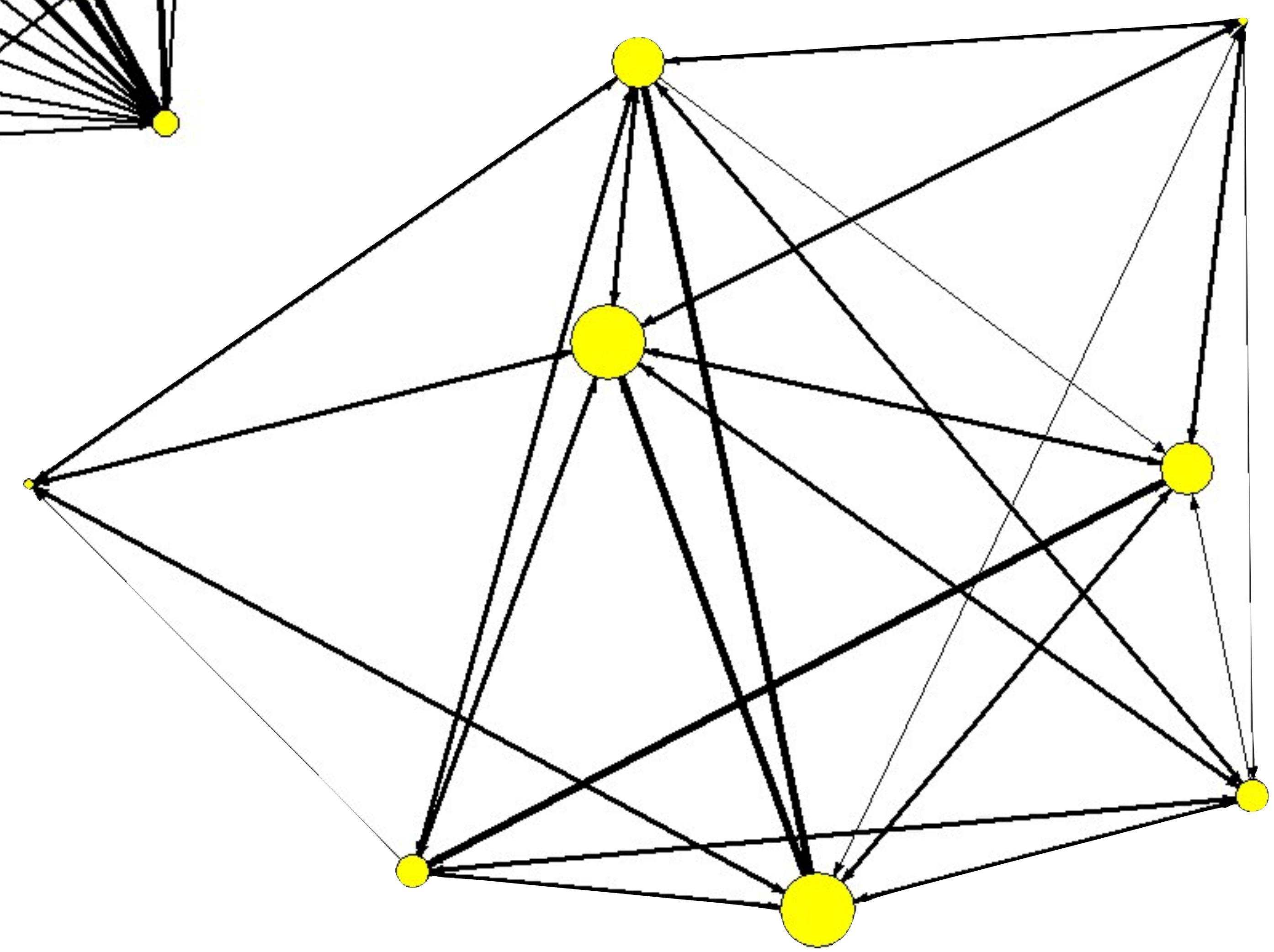
Change over Time →

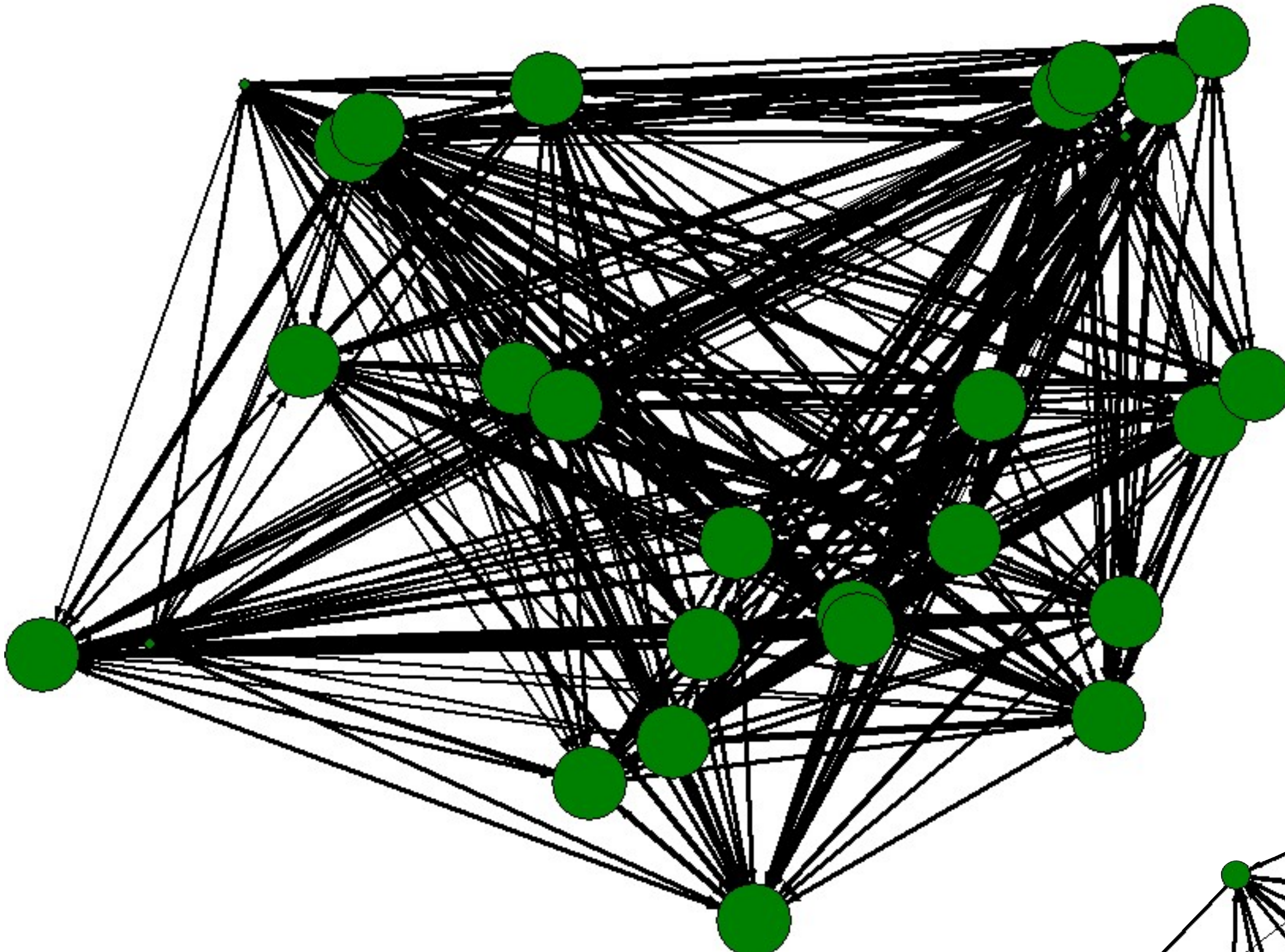




←Time 1

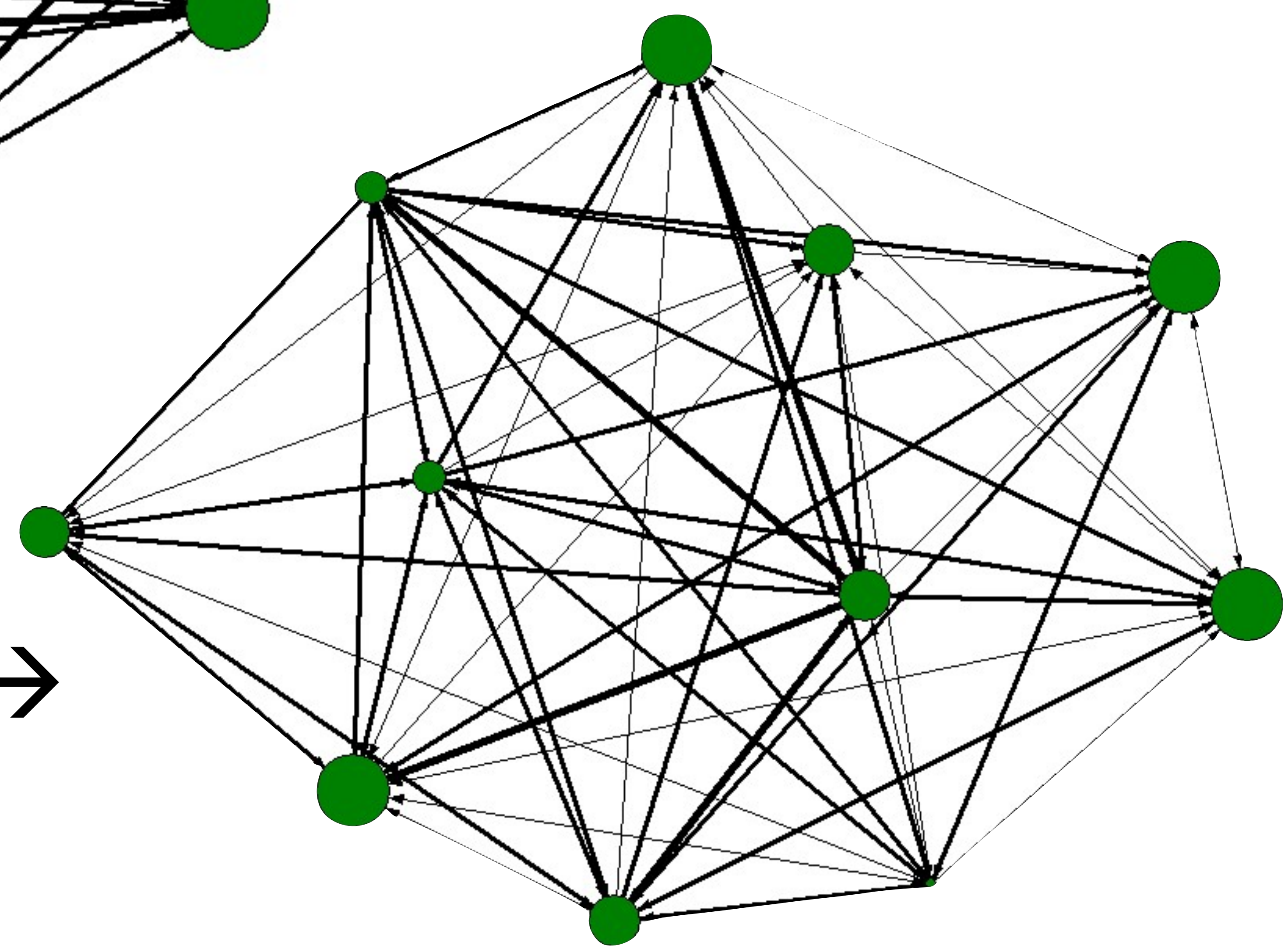
Change over Time →

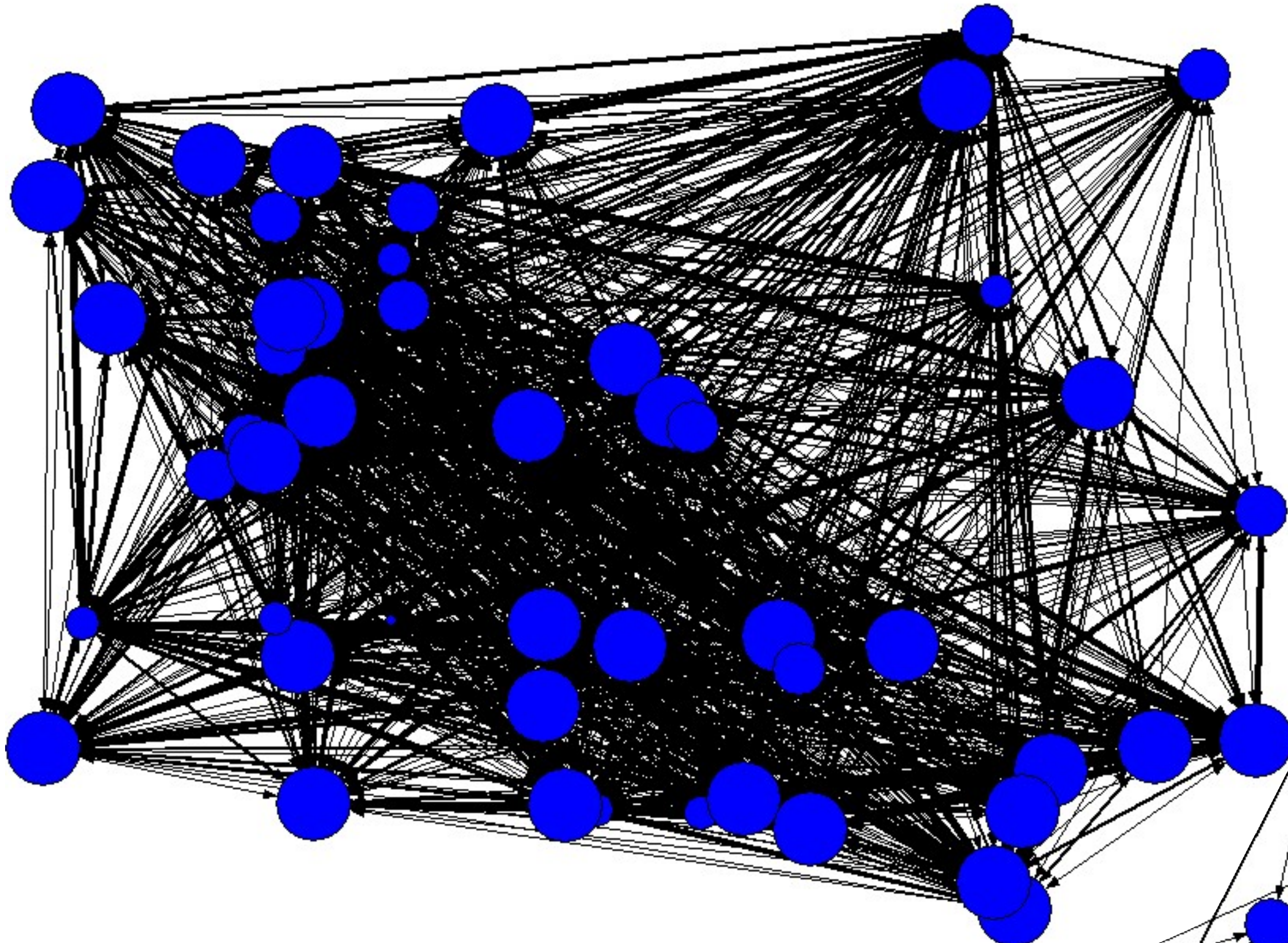




←Time 1

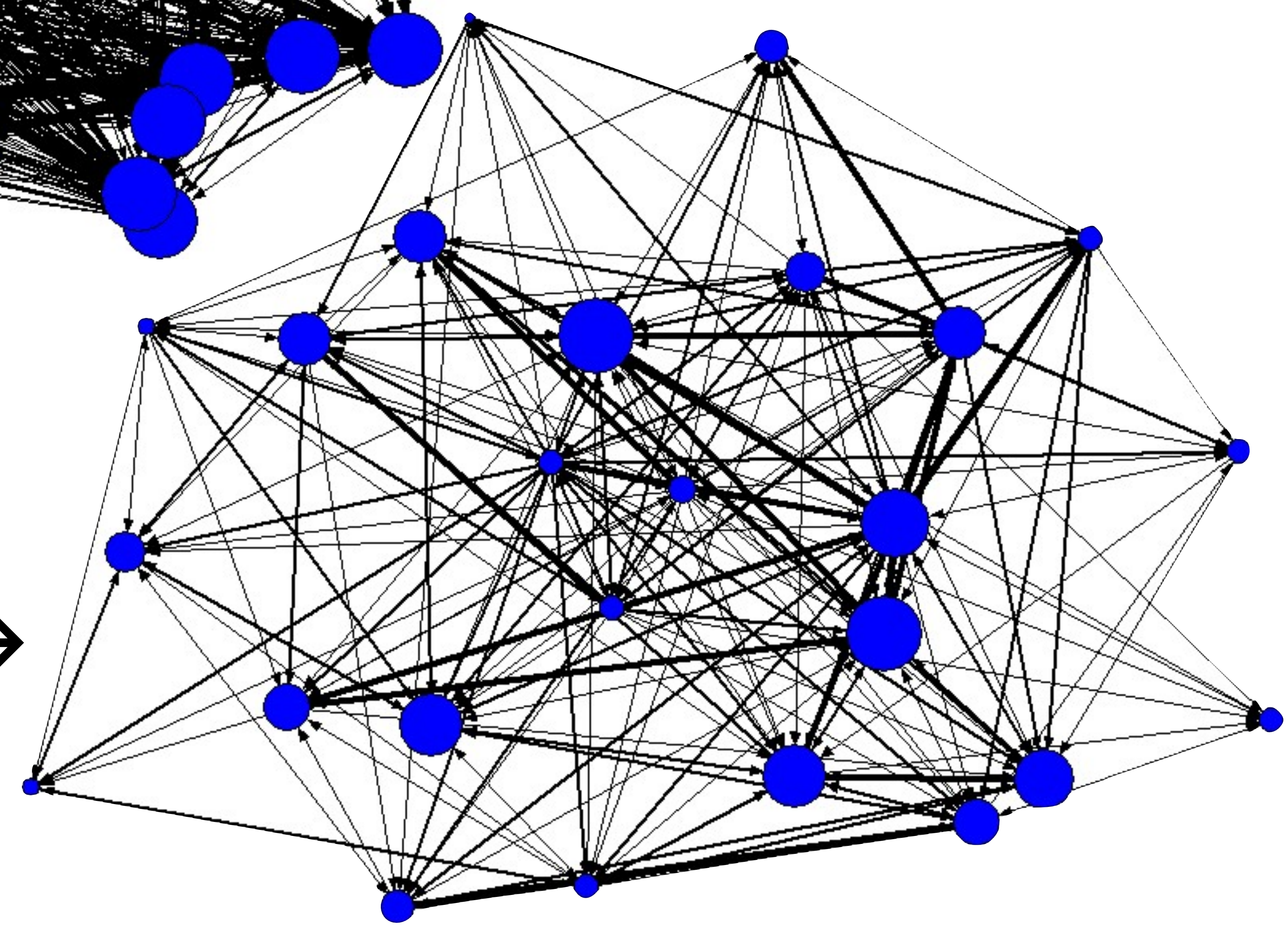
Change over Time →

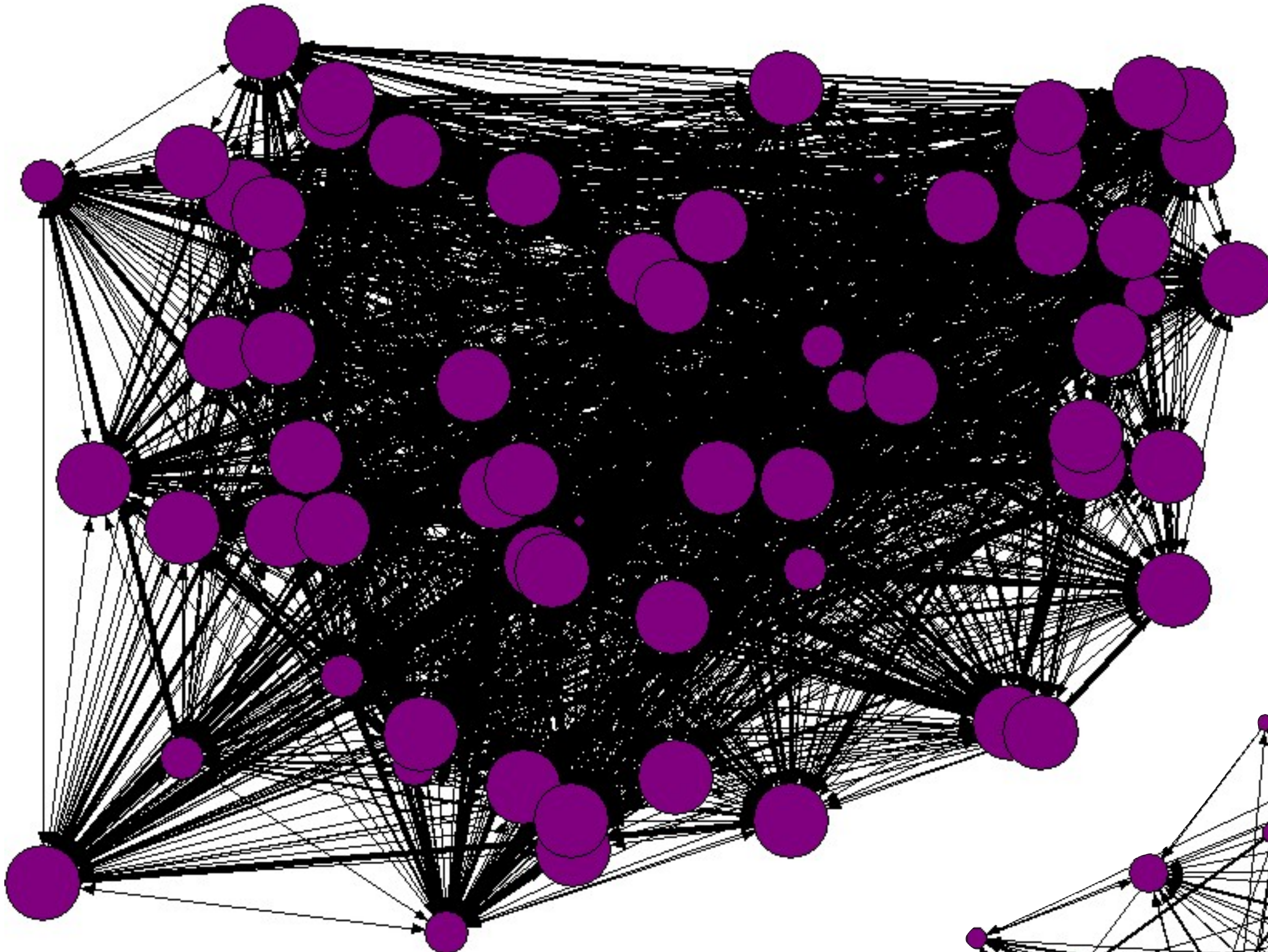




←Time 1

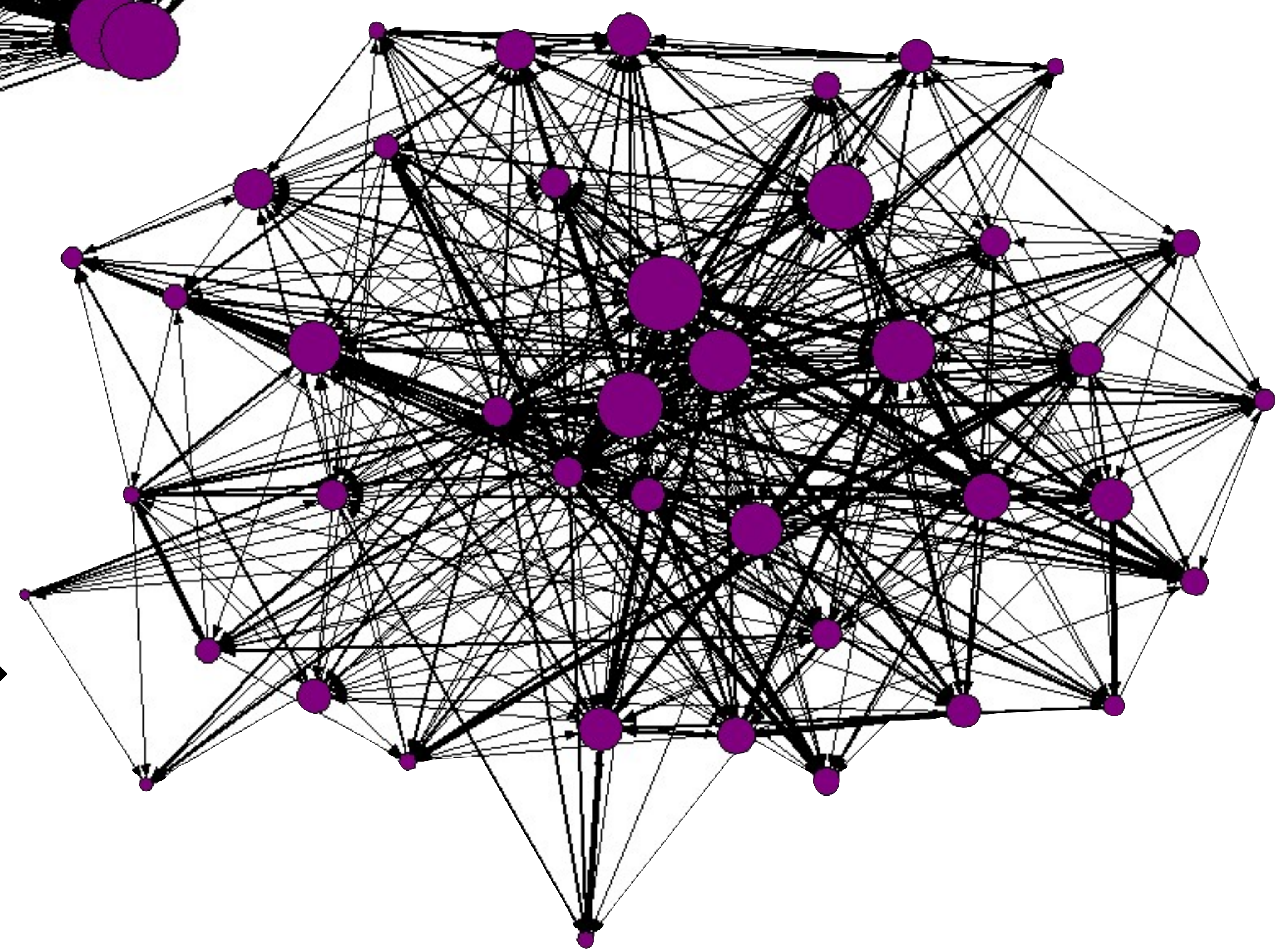
Change over Time →



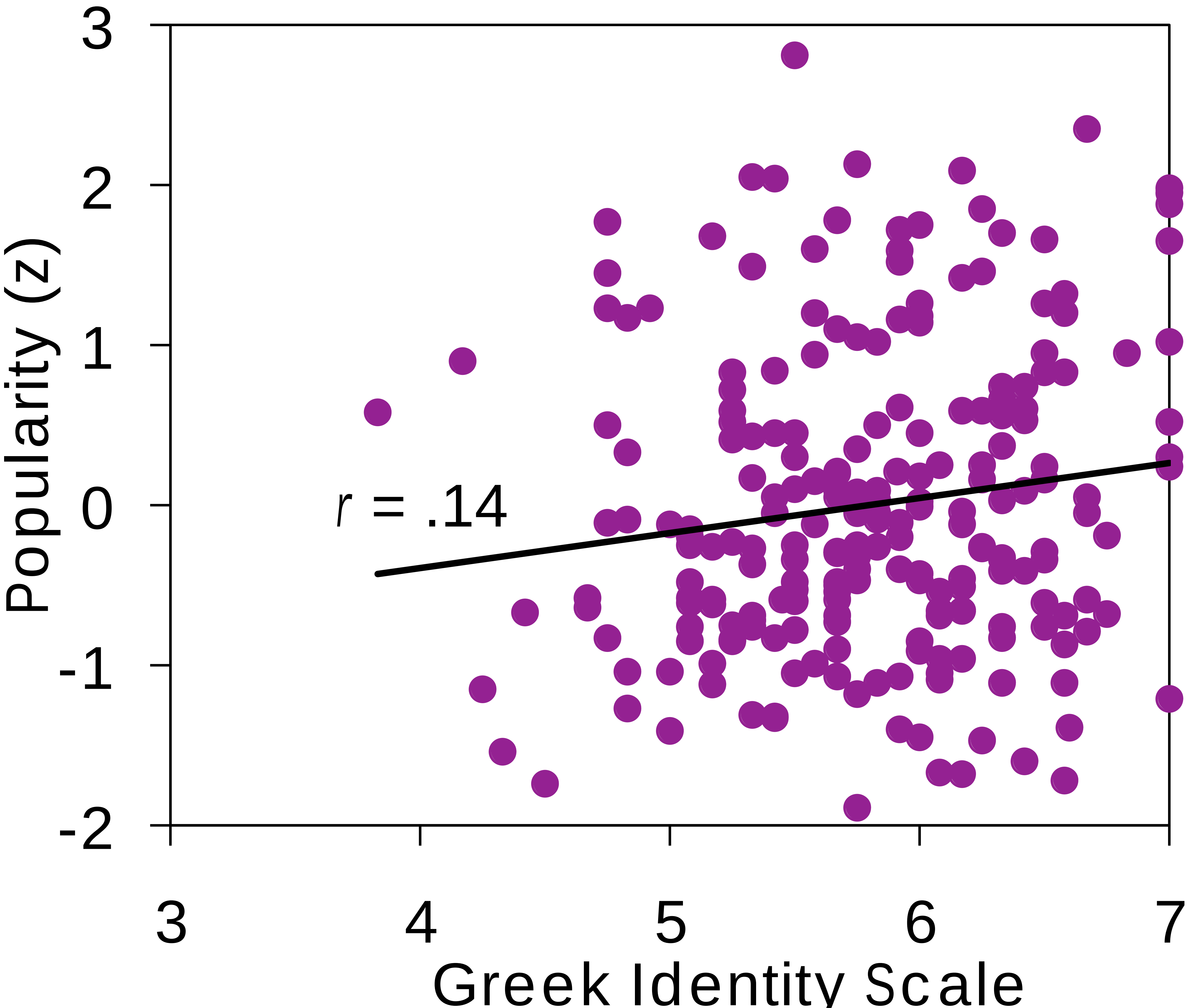


←Time 1

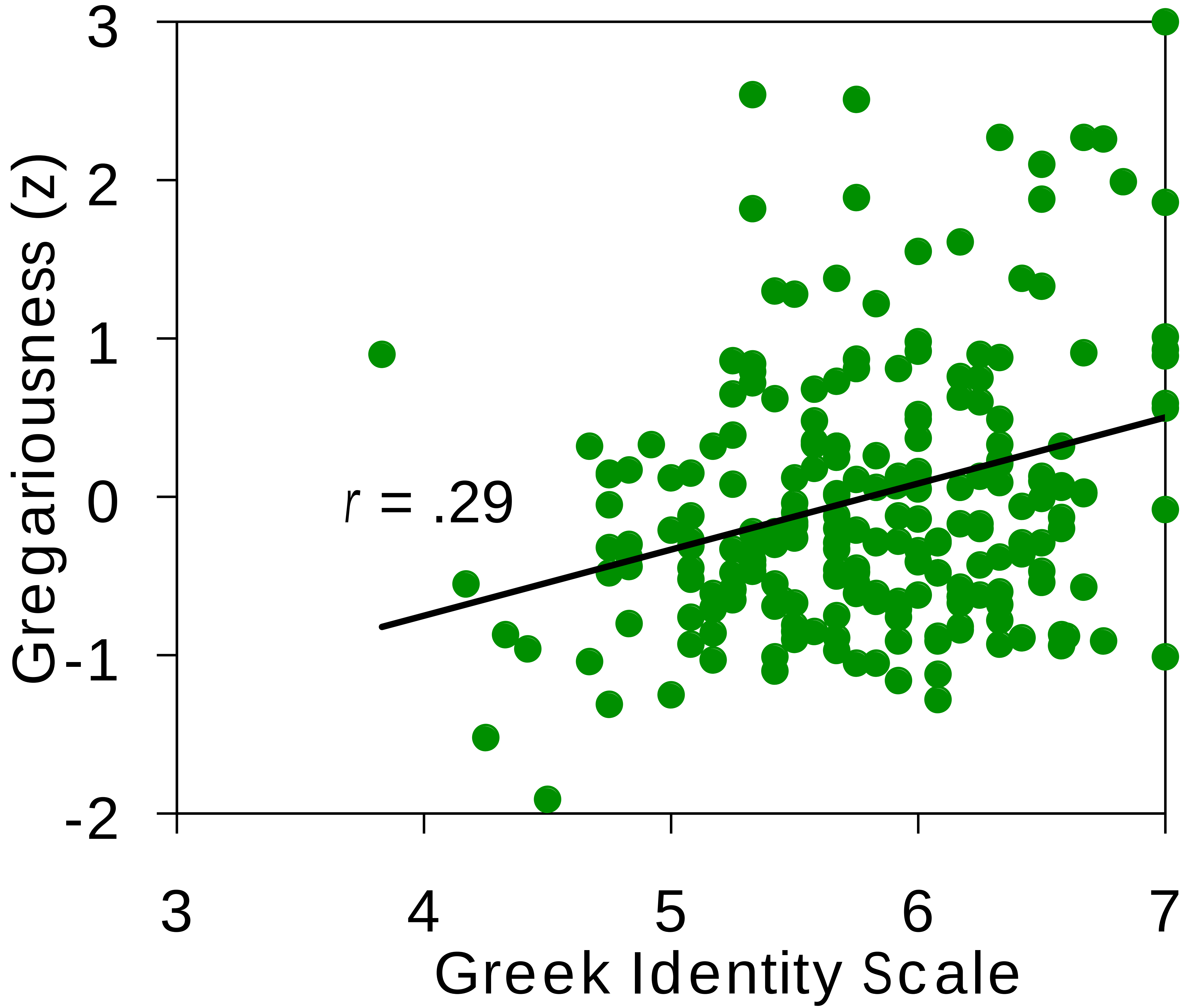
Change over Time →



Greek Identity Scale Items ($\alpha = .65$)
It is likely that I will vote for members of my [fraternity/sorority] when they run for office in the student government.
It is important to me that my [fraternity/sorority] is the best.
I see myself as a supporter of my [fraternity/sorority].
My friends support my [fraternity/sorority].
I often try to persuade other to join my [fraternity/sorority].
I regularly attend events sponsored by my [fraternity/sorority].
I often publicly display my support for my [fraternity/sorority] through hats, key rings, clothing, and/or other items.
I often decorate my car with stickers, flags, magnets, license plate frames and/or other items promoting my [fraternity/sorority].
I see myself as belonging to the same group as other members of my [fraternity/sorority].
It is likely that I will vote for members of my [fraternity/sorority] when they run for homecoming king or queen.
I am proud to be a member of my [fraternity/sorority].
My closest friends are also members of my [fraternity/sorority].



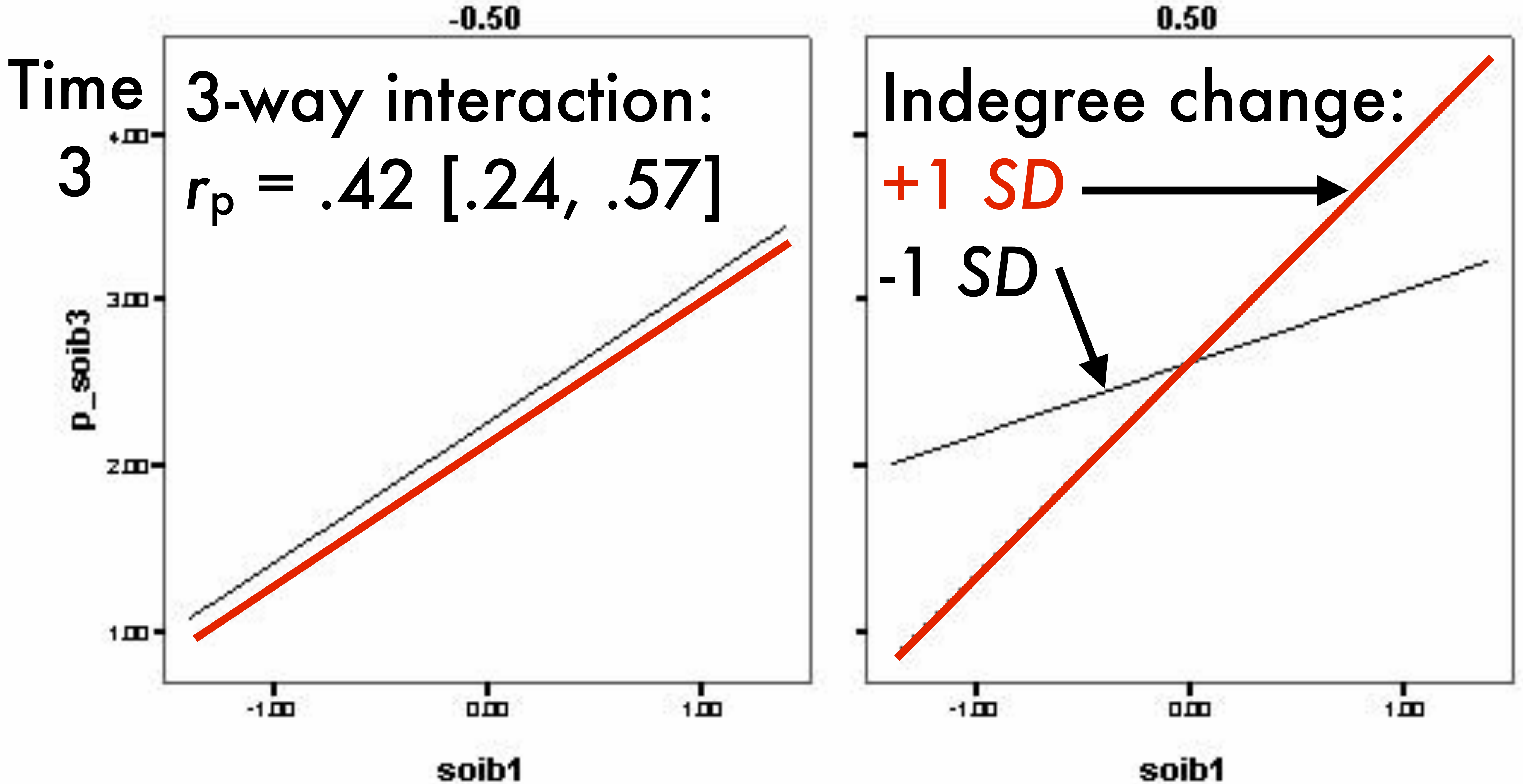
Popularity (z)
3
2
1
0
-1
-2
r = .14
3
4
5
6
7
Greek Identity Scale


r = .29
Gregariousness (z)
Greek Identity Scale
3
2
1
0
-1
-2
3
4
5
6
7

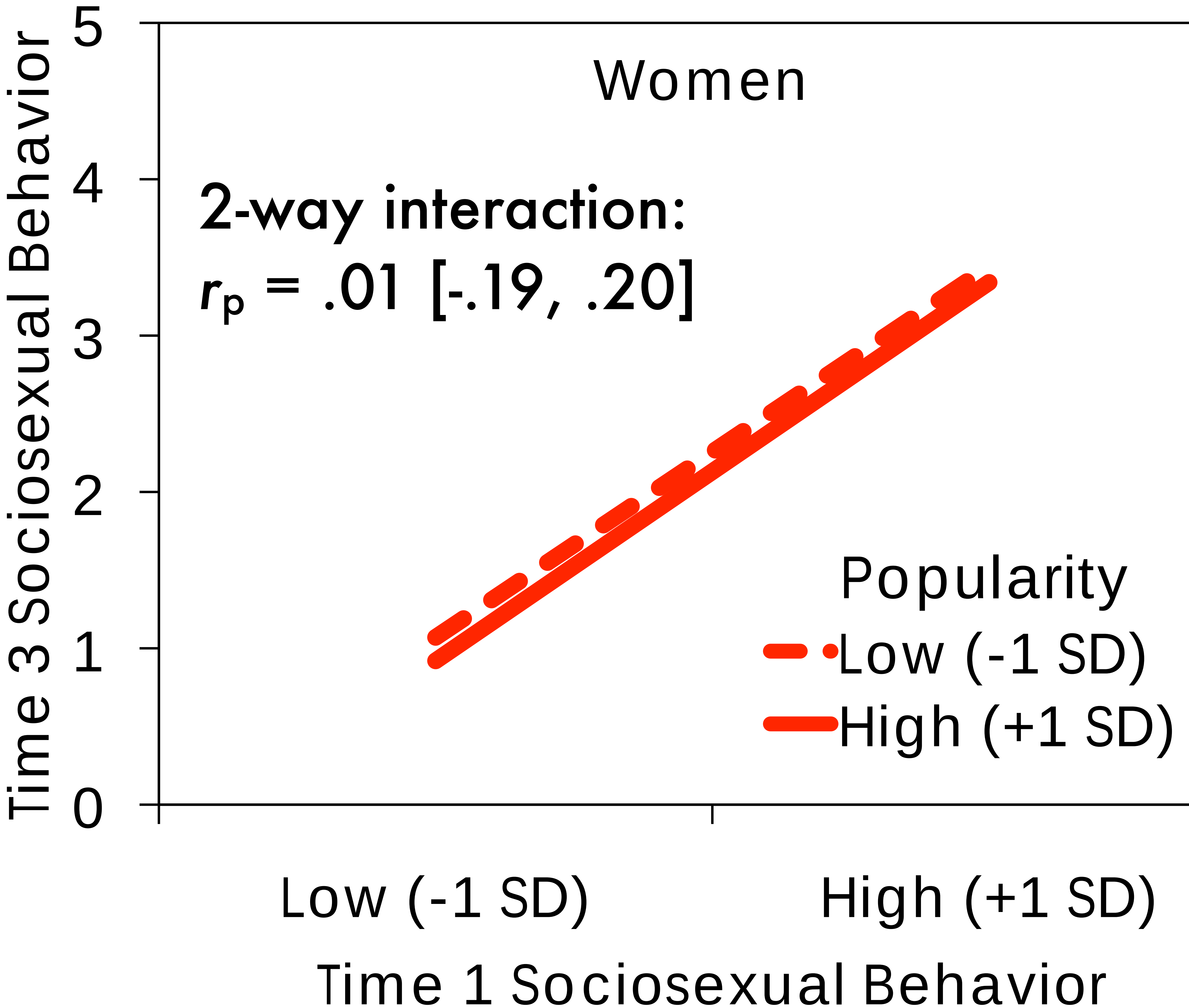
Sociosexual Orientation Inventory ($\alpha = .89$)
With how many different partners have you had sex (sexual intercourse) within the past year?
How many partners do you foresee yourself having sex with during the next five years?
With how many different partners have you had sex on one and only one occasion?
How often do you fantasize about having sex with someone other than your current partner?
Sex without love is okay.
I can imagine myself being comfortable and enjoying “casual” sex with different partners.
I would have to be close to someone before I could feel comfortable having sex with him or her. [reversed]

Popularity & Sex Behavior

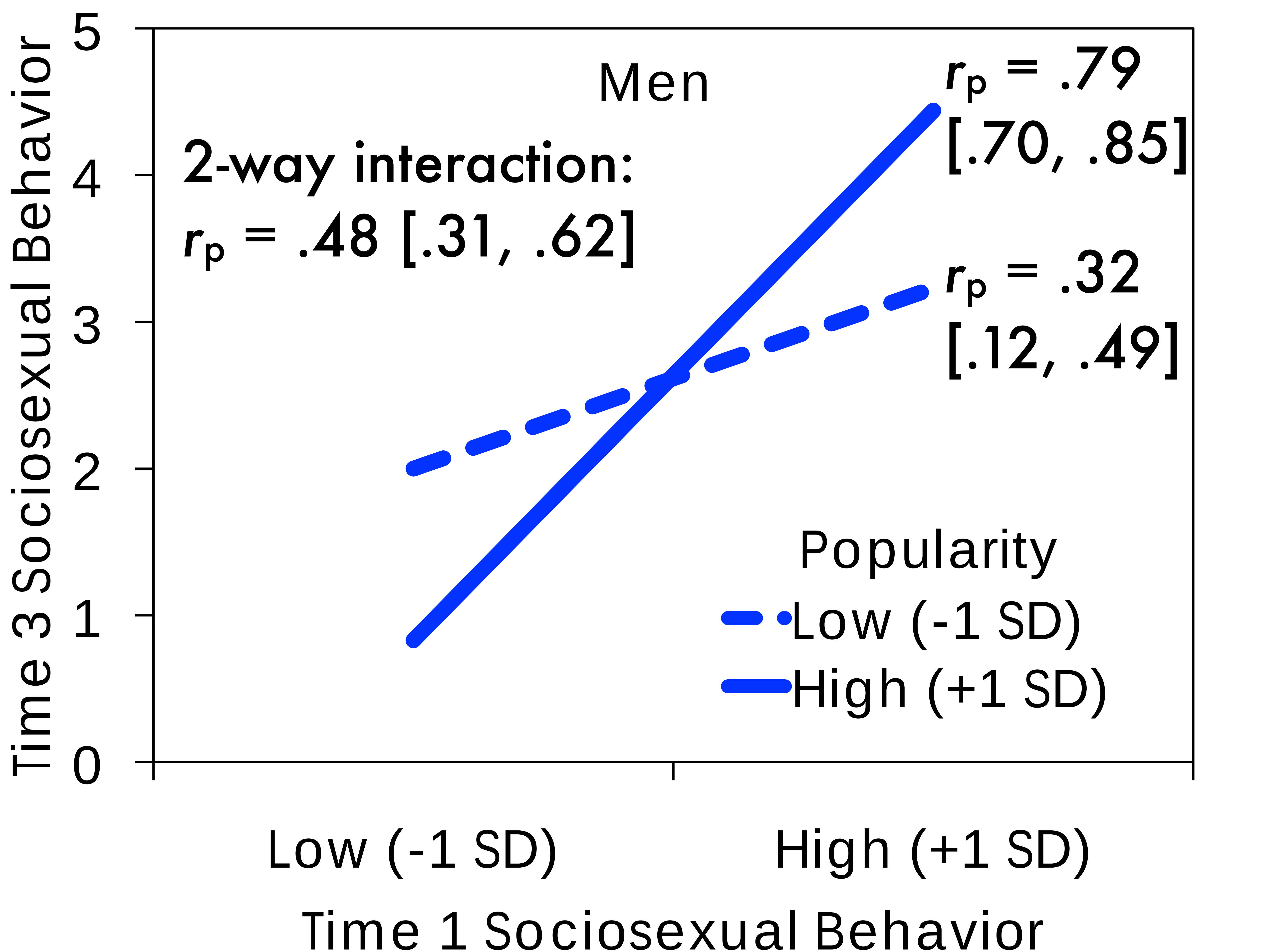
Women (Sororities) Men (Fraternities)



Time 1 Sociosexual Behavior



Women
2-way interaction:
r_p = .01 [-.19, .20]
Popularity
Low (-1 SD)
High (+1 SD)
Time 3 Sociosexual Behavior
0
1
2
3
4
5
Low (-1 SD)
High (+1 SD)
Time 1 Sociosexual Behavior


Men
2-way interaction:
r_p = .48 [.31, .62]
r_p = .79 [.70, .85]
r_p = .32 [.12, .49]
Popularity
Low (-1 SD)
High (+1 SD)
Time 3 Sociosexual Behavior
0
1
2
3
4
5
Low (-1 SD)
High (+1 SD)
Time 1 Sociosexual Behavior

Conclusions

- Greek Identity positively related to popularity and gregariousness at Time 1.
- Change in sociosexual behavior (having more sex partners) related to increased popularity in fraternities, but not sororities.
- Supports a sexual double-standard explanation.
- Future direction: Model bidirectional causality between popularity and sexual behavior in men.

Example 5:
Classroom Friendship and Attachment

Friendship and Attachment

- 2 college psychology classes (*N*s = 44, 57)
- Completed friendship networks (valued)
- Completed Big Five personality traits
- Completed attachment measures: Anxious and avoidant dimensions (Fraley et al., 2000)
- Measured network popularity with indegree (log eigenvector) centrality
- Are more avoidant people less likely to be nominated as close friends by others?

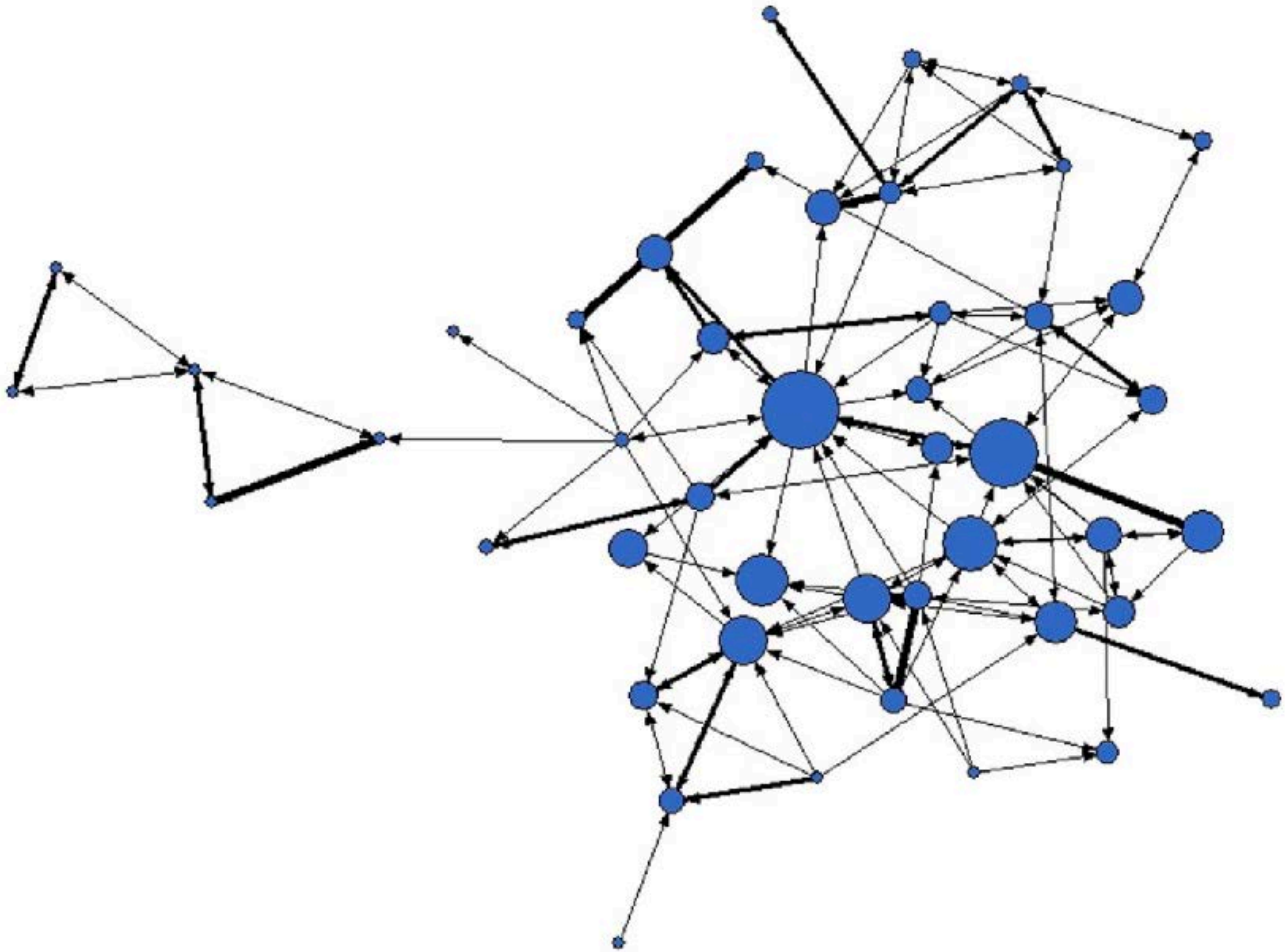


Fig. 2. Sociogram (social network) of 44 undergraduates enrolled in an evolutionary psychology class, omitting two isolates (unconnected nodes). Tie thickness reflects friendship strength (0 = *don't know the person*, 1 = *acquaintance*, 2 = *friend*, 3 = *close friend*). Node size reflects raw eigenvector indegree centrality (a measure of popularity).

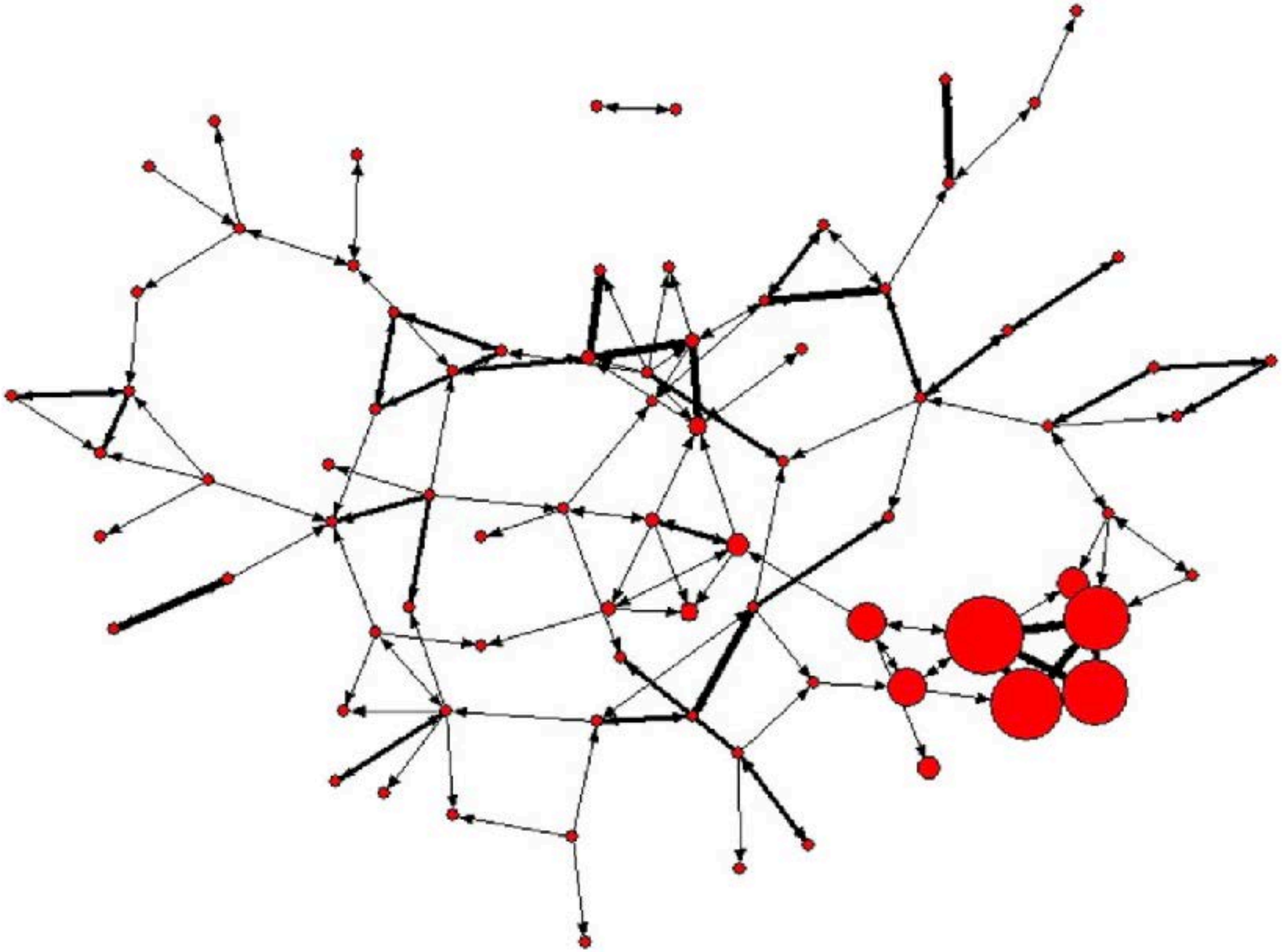


Fig. 3. Sociogram (social network) of 67 undergraduates enrolled in a social psychology class, omitting eight isolates (unconnected nodes). Tie thickness reflects friendship strength (0 = *don't know the person*, 1 = *acquaintance*, 2 = *friend*, 3 = *close friend*). Node size reflects raw eigenvector indegree centrality (a measure of popularity).

Friendship and Attachment

Table 2. Indegree (log eigenvector) as functions of trait personality and attachment.

Variable	Study 1				Study 2			
	b	$t(36)$	p	r_p	b	$t(59)$	p	r_p
Extraversion	0.083	3.15	.003	.46	-0.002	-0.12	.905	-.02
Agreeableness	-0.027	-0.68	.498	-.11	-0.028	-0.93	.357	-.12
Conscientiousness	-0.040	-1.46	.153	-.24	-0.031	-1.03	.308	-.13
Neuroticism	0.093	2.24	.031	.35	-0.021	-0.80	.426	-.10
Openness	0.095	2.42	.021	.37	0.042	1.53	.131	.20
Anxious attachment	0.002	0.07	.945	.01	0.042	2.40	.020	.30
Avoidant attachment	**-0.039**	**-1.99**	**.054**	**-.31**	**-0.035**	**-2.16**	**.035**	**-.27**

Webster, Gesselman, and Crosier (2016)

Variable	Studies 1 and 2 ($N = 111$)			
	b	$t(95)$	$p \leq$	r_p [95% CI]
Extraversion	0.040	2.39	.019	.24 [.04, .42]
Agreeableness	−0.027	−1.10	.273	−.11 [−.30, .09]
Conscientiousness	−0.036	−1.74	.086	−.18 [−.37, .02]
Neuroticism	0.036	1.46	.148	.15 [−.05, .34]
Openness	0.068	2.84	.005	.28 [.08, .46]
Anxious attachment	0.022	1.49	.139	.15 [−.05, .34]
Avoidant attachment	−0.037	−2.89	.005	−.28 [−.46, −.08]
Study	−0.131	−4.73	.001	−.44 [−.59, −.26]
Study × extraversion	−0.086	−2.54	.013	−.25 [−.43, −.05]
Study × agreeableness	−0.001	−0.02	.982	−.00 [−.20, .20]
Study × conscientiousness	0.008	0.20	.838	.02 [−.18, .22]
Study × neuroticism	−0.114	−2.31	.023	−.23 [−.41, −.03]
Study × openness	−0.053	−1.11	.270	−.11 [−.30, .09]
Study × anxious attachment	0.040	1.38	.171	.14 [−.06, .33]
Study × avoidant attachment	0.005	0.19	.852	.02 [−.18, .22]

Let’s Think of SNA Projects!

- A social network of attendees at this workshop (e.g., who knows whom, who’s published together)?
- What are some of your research projects that might benefit from SNA methods?
- What are some problems and obstacles to using SNA methods in your own research?

Acknowledgements

- Adam Dzedzy and Christopher McCarty (University of Florida)
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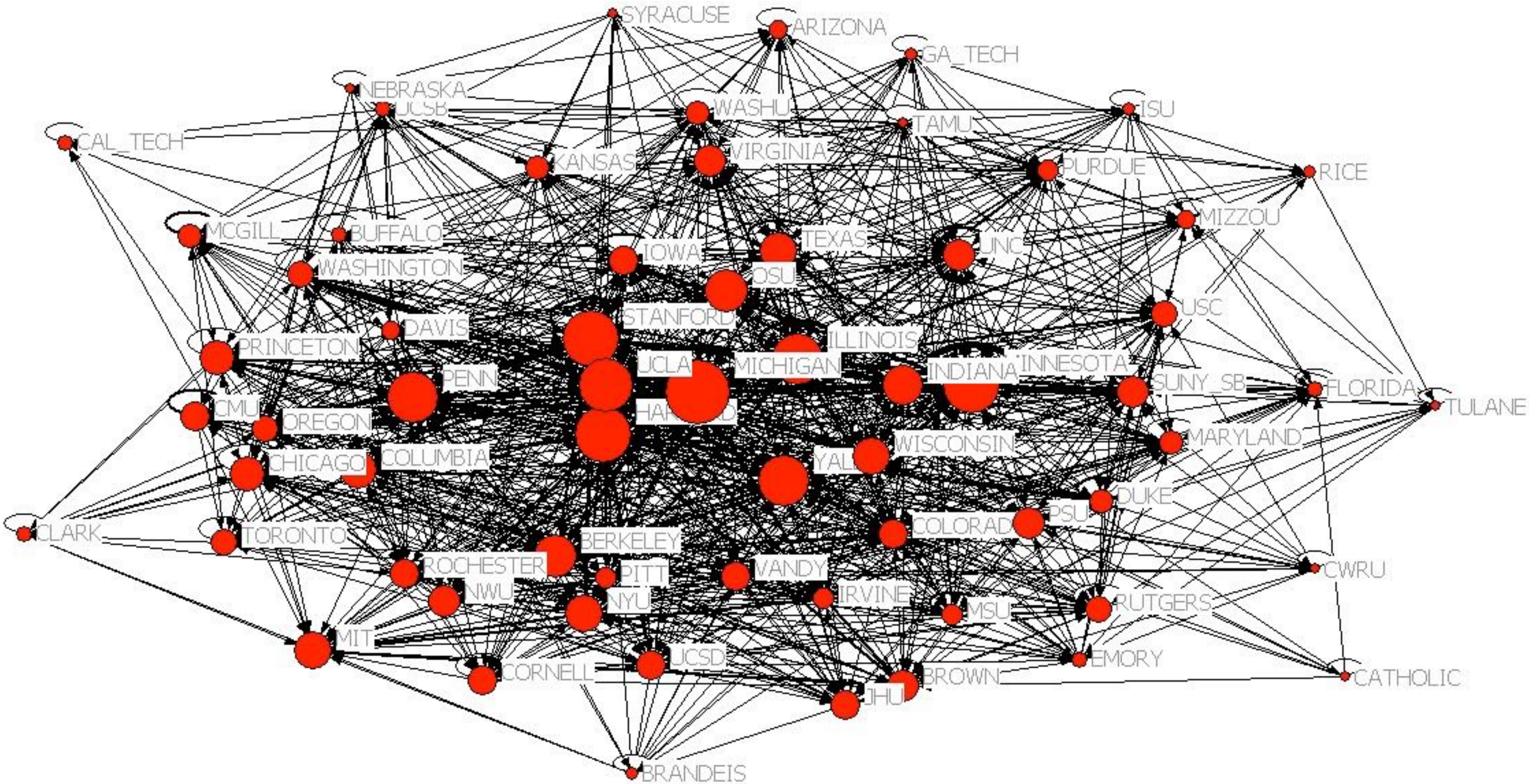
- Rosanna Guadagno (University of Texas at Dallas)
- Patrick Ewell (Kenyon College)
- Carrie Veronica Smith (University of Mississippi)

Thank You!



Questions?