


# Discovery, Diagnosis, and Design of Team Networks

Lovegety



**SNIF: Social Networking in Fur**  
Group: Noah Fields, Jonathan Gips, Philip Liang, Arnaud Pilpré

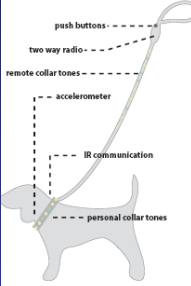


**What**  
We present a system that allows pet owners to interact through their pets' social networks. Inexpensive, unobtrusive hardware can be affixed to pet collars and paraphernalia in order to augment pet-to-pet, pet-to-owner, and owner-to-owner interactions. SNIF devices aggregate pertinent environmental, social and individual information that can be broadcast or addressed to other participating community members.

**Why**  
Pets already function as social devices. Walking a dog in the park can lead to conversations that one might not otherwise have. Pets function as active icebreakers that will go up to anyone without any notion of social inhibition. Furthermore, pet-owners love buying products for their pets: sweaters, leashes, collars, toys, dishes, and beds. These items provide a set of rich interactions that can be brought into the digital world.

**How**  
The SNIF system kit includes a leash and collar as well as membership in the online community. SNIF collars contain an LED display, an IR transceiver, and various sensors such as accelerometers and digital thermometers. They function as output devices that display personalized "collar tones" when the pet comes in proximity to another pet. They serve as input devices that sense activity levels, micro-climate conditions, and other pets' presence. The online community portion of SNIF allows pet-owners to set privacy preferences, communicate with other pet owners, arrange pet outings, and customize the ambient information that their SNIF leashes display.

**Extensions**  
Pet toys that serve as tangible interfaces for the pet. Degrees of separation between pets that changes as they interact. Remote monitoring of pet's activity. Local RF detection to display degrees of separation from the other pets in the vicinity.

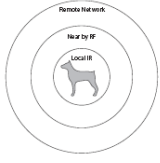


**1. leashup**  
By connecting the leash to the collar, you signal the network that you are about to head out to play.

**2. walk**  
While you stroll on your walk, your collar keeps an aware log for you.

**3. sniff**  
When you discover another dog, your collar displays a unique sequence of flashing lights. When you see your collar tones, that friend's collar tone flashes on his collar.

**4. friend!**  
When you are back at your house, you can keep an eye on your computer. When one of your pals goes out to play, that collar tone is displayed on your leash.



**Noshir Contractor**

*Jane S. & William J. White Professor of Behavioral Sciences*

Professor of Ind. Engg & Mgmt Sciences, McCormick School of Engineering

Professor of Communication Studies, School of Communication &

Professor of Management & Organizations, Kellogg School of Management,

Director, Science of Networks in Communities (SONIC) Research Laboratory

nosh@northwestern.edu



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# Aphorisms about Networks

## ■ Social Networks:

◆ Its not what you know, its **who** you know.

## ■ Cognitive Social Networks:

◆ Its not who you know, its **who they think** you know.

## ■ Knowledge Networks:

◆ Its not who you know, its **what they think** you know.



# Cognitive Knowledge Networks

It's not  
who you know.

It's what  
who you know  
knows.

There's research. And then there's research written by the world's top analysts and strategists. The leading industry authorities on everything from F2B and healthcare to investing in the Pacific Rim. Bottom line? The only people who should be guiding your investment decisions are the people who are truly "in the know." Who measure success one investor at a time. Move your money. Get well connected.

*Well Connected* | MORGAN STANLEY  
DEAN WITTER

[msd.com](http://msd.com)

\*Source: Institutional Investor, December 1999

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# Multidimensional Networks in Team Science

## Multiple types of Nodes and Multiple Types of Relationships



# The Hubble telescope: \$2.5 billion



*Source: David Lazer*



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# CERN particle accelerator: \$1 billion/year



*Source: David Lazer*

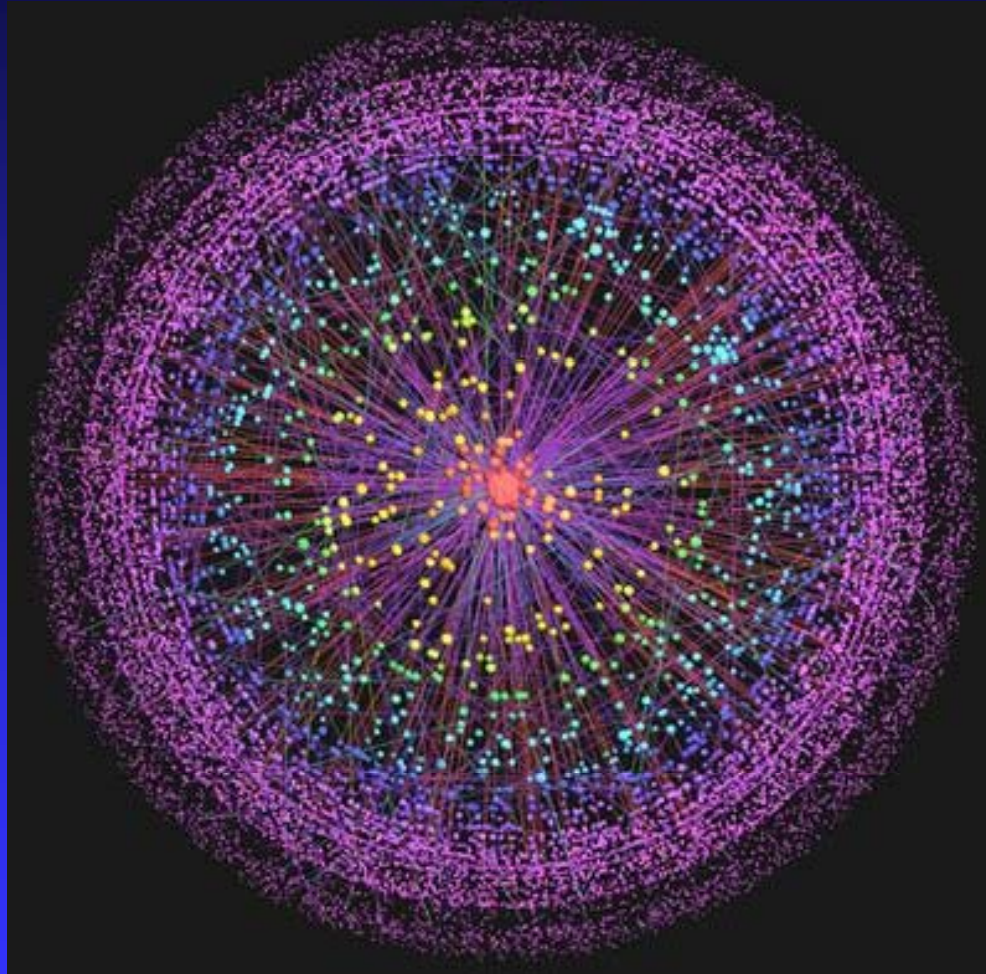
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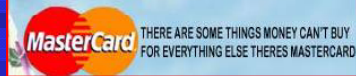


# The Web: priceless\*



\* *Apologies to MasterCard*

**PRICELESS**



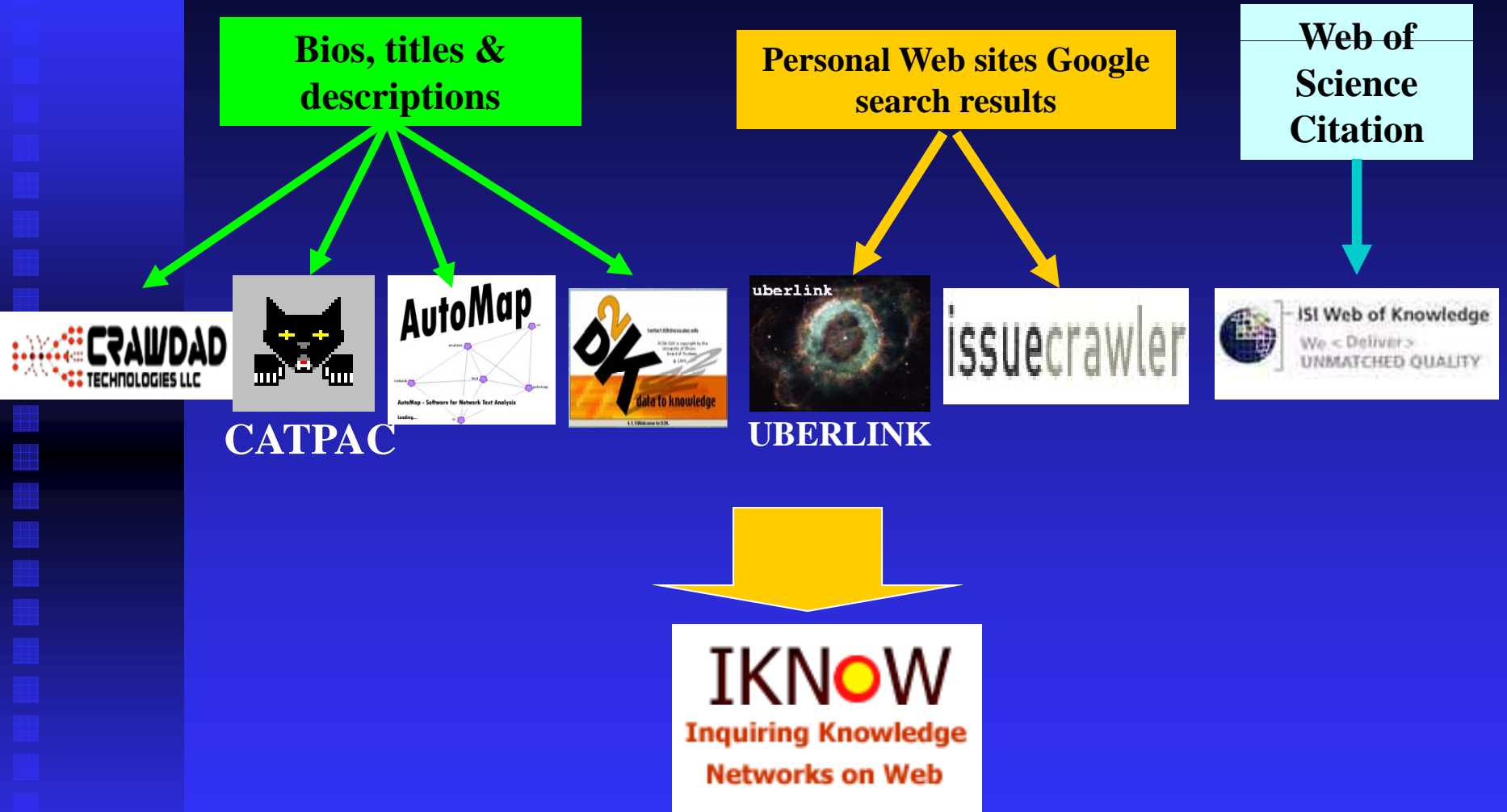
*Source: David Lazer*

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# Digital Harvesting of Relational Metadata



## CI-KNOW Analyses and Visualizations



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SOCIAL SCIENCE

# Computational Social Science

David Lazer,<sup>1</sup> Alex Pentland,<sup>2</sup> Lada Adamic,<sup>3</sup> Sinan Aral,<sup>2,4</sup> Albert-László Barabási,<sup>5</sup> Devon Brewer,<sup>6</sup> Nicholas Christakis,<sup>1</sup> Noshir Contractor,<sup>7</sup> James Fowler,<sup>8</sup> Myron Gutmann,<sup>3</sup> Tony Jebara,<sup>9</sup> Gary King,<sup>1</sup> Michael Macy,<sup>10</sup> Deb Roy,<sup>2</sup> Marshall Van Alstyne<sup>2,11</sup>

We live life in the network. We check our e-mails regularly, make mobile phone calls from almost any location, swipe transit cards to use public transportation, and make purchases with credit cards. Our movements in public places may be captured by video cameras, and our medical records stored as digital files. We may post blog entries accessible to anyone, or maintain friendships through online social networks. Each of these transactions leaves digital traces that can be compiled into comprehensive pictures of both individual and group behavior, with the potential to transform our understanding of our lives, organizations, and societies.

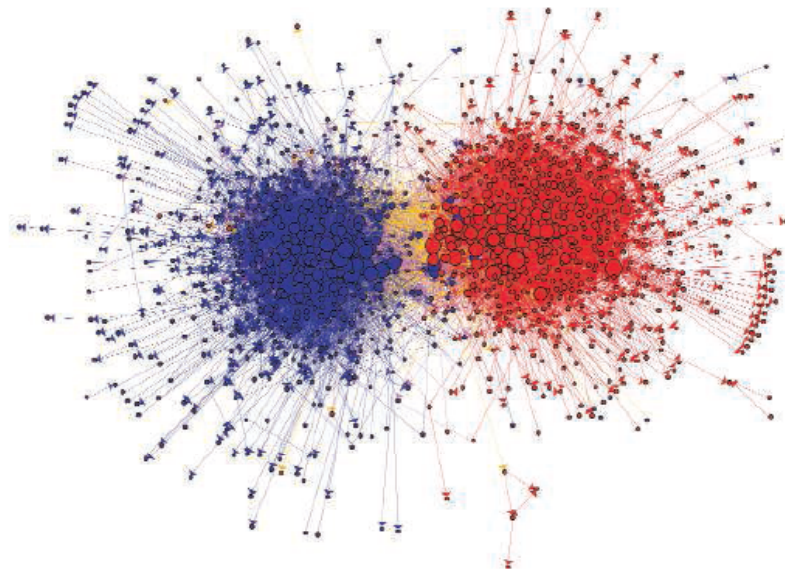
The capacity to collect and analyze massive amounts of data has transformed such fields as biology and physics. But the emergence of a data-driven “computational social science” has been much slower. Leading journals in economics, sociology, and political science show little evidence of this field. But computational social science is occurring—in Internet companies such as Google and Yahoo, and in govern-

ment agencies such as the U.S. National Security Agency. Computational social science could become the exclusive domain of private companies and government agencies. Alternatively, there might emerge a privileged set of academic researchers presiding over private data from which they produce papers that cannot be

A field is emerging that leverages the capacity to collect and analyze data at a scale that may reveal patterns of individual and group behaviors.

critiqued or replicated. Neither scenario will serve the long-term public interest of accumulating, verifying, and disseminating knowledge.

What value might a computational social science—based in an open academic environment—offer society, by enhancing understanding of individuals and collectives? What are the



**Data from the blogosphere.** Shown is a link structure within a community of political blogs (from 2004), where red nodes indicate conservative blogs, and blue liberal. Orange links go from liberal to conservative, and purple ones from conservative to liberal. The size of each blog reflects the number of other blogs that link to it. [Reproduced from (8) with permission from the Association for Computing Machinery]

<sup>1</sup>Harvard University, Cambridge, MA, USA. <sup>2</sup>Massachusetts Institute of Technology, Cambridge, MA, USA. <sup>3</sup>University of Michigan, Ann Arbor, MI, USA. <sup>4</sup>New York University, New York, NY, USA. <sup>5</sup>Northeastern University, Boston, MA, USA. <sup>6</sup>Interdisciplinary Scientific Research, Seattle, WA, USA. <sup>7</sup>Northwestern University, Evanston, IL, USA. <sup>8</sup>University of California—San Diego, La Jolla, CA, USA. <sup>9</sup>Columbia University, New York, NY, USA. <sup>10</sup>Cornell University, Ithaca, NY, USA. <sup>11</sup>Boston University, Boston, MA, USA. E-mail: david\_lazer@harvard.edu. Complete affiliations are listed in the supporting online material.



# Projects Investigating Social Drivers for Teams

## Science Applications

CI-Scope: Understanding & Enabling CI in Virtual Communities (*NSF*)

NUCATS: Clinical & Translational Science (*NIH*)

VOSS: *NanoHub* (*NSF*)

TSEEN: Tobacco Surveillance Evaluation & Epidemiology Network (*NSF, NIH, CDC*)

## *Business Applications*

PackEdge Community of Practice (*P&G*)

*Kraft Design Teams*

## Core Research

Socio-technical Drivers for Understanding & Enabling Teams

## Societal Justice Applications

Mapping Climate Change Networks In Low Income Communities (*City of Chicago*)

Mapping Digital Media and Learning Networks (*MacArthur Foundation*)

## Entertainment Applications

Second Life (*NSF, Army Research Institute, Linden Labs*)

*EverQuest II* (*NSF, Army Research Institute, Linden Labs*)



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# The Assembly of Task-oriented Groups

Yun Huang, Mengxiao Zhu, Jing Wang, Brian Keegan & Noshir Contractor,  
Northwestern University

Nishith Pathak  
University of Minnesota

Cuihua Shen, Dmitri Williams  
University of Southern California



*Supported by NSF IIS-0729505, Army Research Institute (W91WAW-08-C-0106), and Sony Online Entertainment*



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# Using Digital Traces to Understand Team Assembly

- Massively-multiplayer online games (MMOGs) have over 45 million users worldwide and over \$3 billion in revenue in 2008
- What does social behavior in online worlds tell us about the “real” world and vice versa?
  - ◆ Online games exhibit features that map onto real world processes:
    - ✦ Social networks, economics, groups, communication, conflict, expertise, leadership, crime, innovation, epidemics, etc.
  - ◆ Online games already capture the signatures of these behaviors in huge databases, just waiting to be analyzed





# Hypotheses

## ■ Team formation mechanisms

H1: Players who have low combat ability are more likely to participate in teams than those who have high combat ability. (*Self-interest*)

H2: Players are more likely to join the same set of players multiple times. (*Reduce Coordination cost*)

H3a: Players are more likely to join teams of high expertise diversity. (*Transactive Memory*)

H3b: Players are more likely to join teams in which they can provide unique expertise. (*Transactive Memory*)




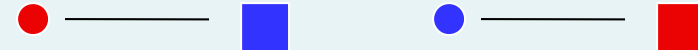
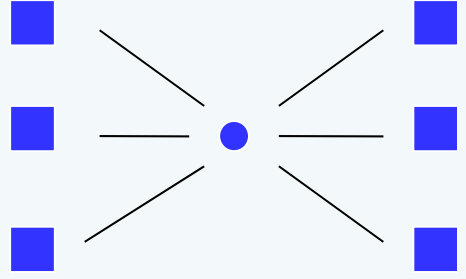
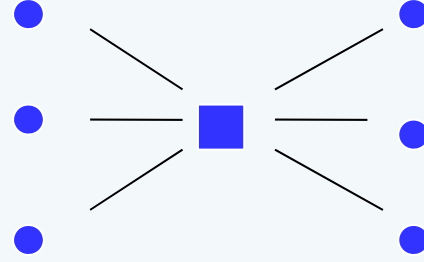
# Hypotheses (cont.)

## ■ Group outcome

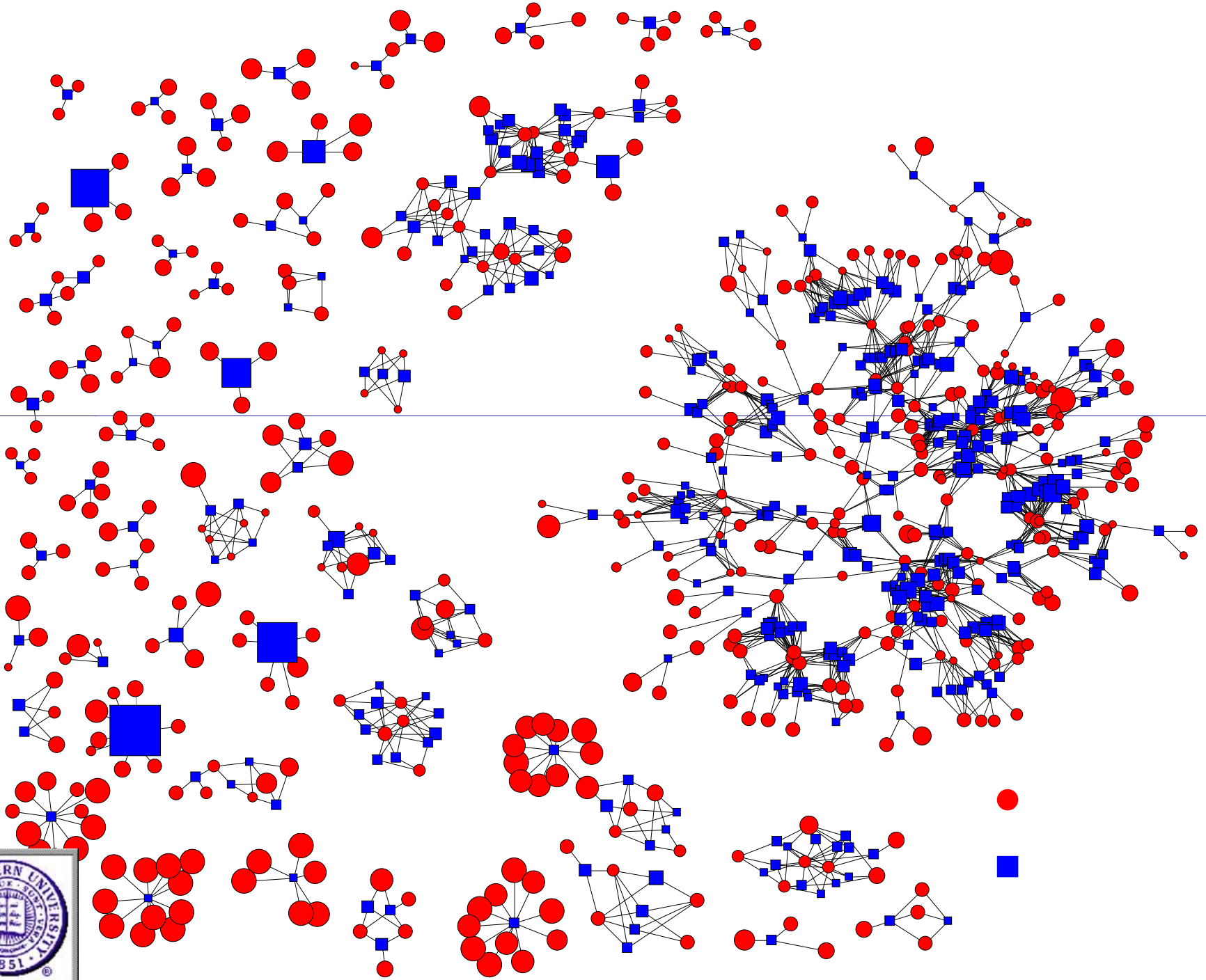
- ◆ H4: Teams with many players are more likely to have member death. (*Higher Coordination cost*)
- ◆ H5: Teams with many players tend to have higher performance. (*Mutual interest*)
- ◆ H6: Teams with many players have shorter duration. (*Higher Coordination Cost*)



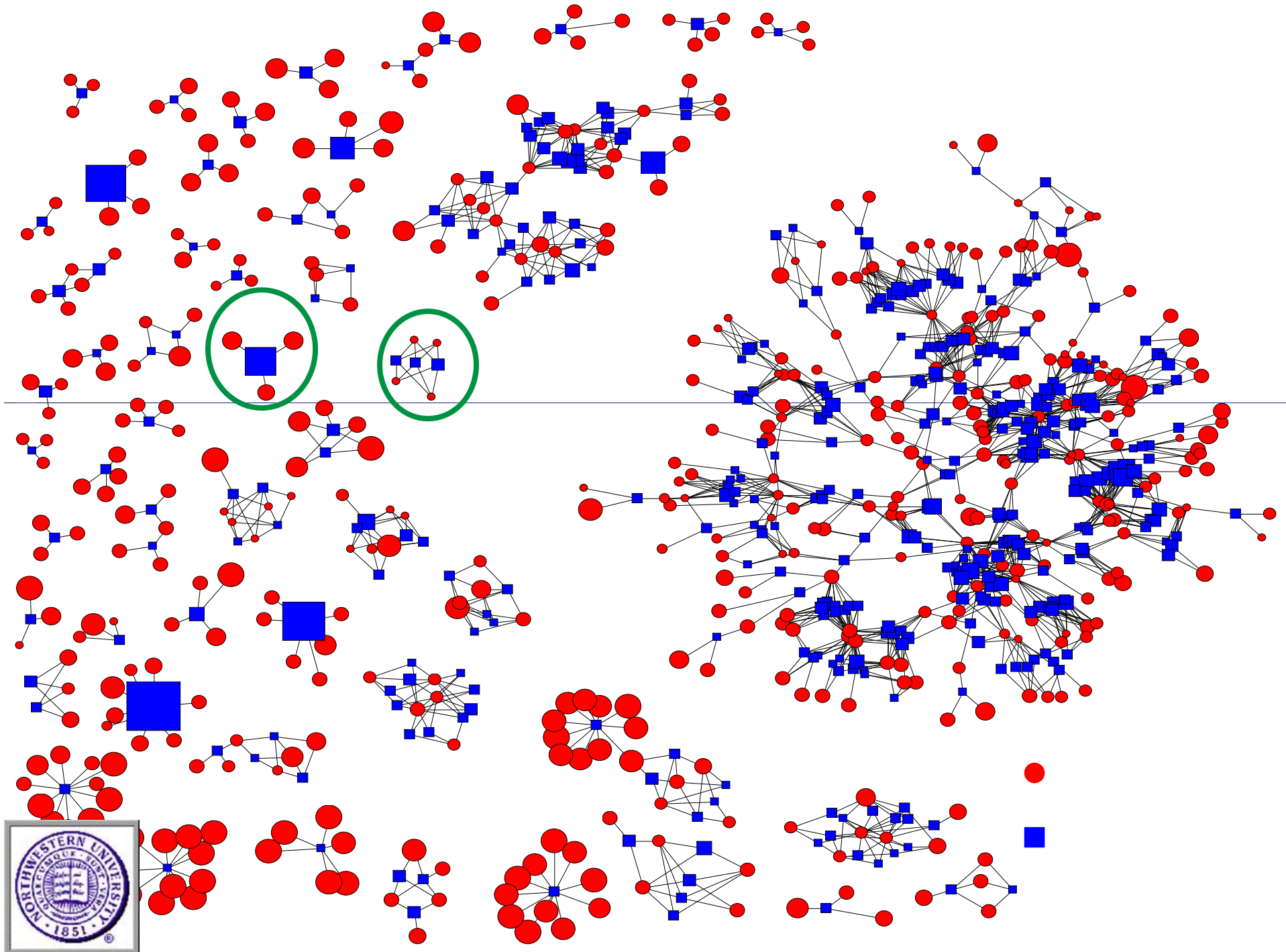
# Team Formation Structures

|   |   |
|---|---|
| <p>Team membership</p>   | <p>Selective team membership</p>   |
| <p>Membership in multiple teams</p>   | <p>Teams with many members</p>    |
| <p>Notes:</p> <ul style="list-style-type: none"> <li>● Characters whose attributes are <u>not</u> taken into consideration</li> <li>● Characters whose attributes are taken into consideration</li> </ul> | <p>—— Team membership</p> <ul style="list-style-type: none"> <li>■ Teams whose attributes are <u>not</u> taken into consideration</li> <li>■ Teams whose attributes are taken into consideration</li> </ul> |









# Descriptive Statistics for the Zones

- In the whole dataset, there are 2,774 characters, 3,547 group events; 15,152 group membership links.
- divide it into 11 zones based on the game map

| Zone # | Zone Name           | # of char | # of group | Median Level | Mean Group Size |
|--------|---------------------|-----------|------------|--------------|-----------------|
| 1      | Thundering Steppes  | 639       | 591        | 29           | 4.15            |
| 2      | Kingdom of Sky      | 625       | 436        | 65           | 4.80            |
| 3      | The Enchanted Lands | 530       | 537        | 38           | 4.48            |
| 4      | Desert of Flames    | 499       | 518        | 53           | 4.36            |
| 5      | Antonica            | 465       | 396        | 21           | 4.04            |
| 6      | Commonlands         | 380       | 315        | 24           | 4.01            |
| 7      | Nektulos Forest     | 287       | 161        | 36           | 3.92            |
| 8      | Feerrott            | 269       | 206        | 45           | 4.45            |
| 9      | Everfrost           | 211       | 165        | 45           | 4.36            |
| 10     | Lavastorm           | 198       | 141        | 49           | 4.51            |
| 11     | Zek                 | 170       | 81         | 40           | 3.95            |



# Results: Antonica as An Example

| Findings   | Coefficient  |
|--|--|
| Low level players are more likely to join groups.<br>(H1: Supported)   | <b>-0.01*</b>  |
| Players are more likely to join the same set of players for multiple times. (H2: Not supported)  | -0.11  |
| Players are more likely to join groups of high expertise diversity. (H3a: Supported)   | <b>4.24*</b>   |
| Players are more likely to join groups in which they can provide unique expertise (H3b: Partially supported)<br>Supported for priests but the other character classes do not show such a tendency. | <b>-1.27* (Priest)</b><br>0.03 (Mage)<br>-0.07 (Scout) |
| Groups of larger size are more likely to have member death. (H4: Supported)  | <b>0.60*</b>   |

Notes:

\* indicate twice of standard deviation

**Green** indicates results supporting the hypotheses; **black** indicates non-significant results; **red** indicates results in the opposite direction.



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# Results: Antonica as An Example

| Findings  | Coefficient                                     |
|---|---|
| Groups with many players gain higher performance.<br>(H5: Supported)                        | 0.005*  |
| Groups with many players have shorter duration.<br>(H6: Supported)                          | -0.33*  |
| Players are active in joining groups.   | 5.00*   |
| Players tend to join multiple groups (or group events).                                     | 0.79*   |
| Combat groups tend to be small.   | -7.44*  |
| Compared to fighters, priests are more likely to join a group, but mages or scouts are not. | 0.92* (priest)<br>-0.05 (mage)<br>0.004 (scout) |

**Notes:** \* indicate twice of standard deviation

**Green** indicates results supporting the hypotheses;

**Black** indicates non-significant results;

**Red** indicates results in the opposite direction.



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# Results Summary

- Players are active in joining groups, especially those at lower levels.
- Players are more likely to join the groups that 1) have higher expertise diversity and 2) to which they can provide unique expertise (especially for priest and mage).
- Groups with more members tend to 1) have higher performance, 2) last a shorter time, and 3) be more likely to have member death during the combat.
- Players tend to join multiple groups, and most groups are of small size.



# Projects Investigating Social Drivers for Teams

## Science Applications

**CI-Scope: Understanding & Enabling CI in Virtual Communities (NSF)**

**NUCATS: Clinical & Translational Science (NIH)**

**VOSS: NanoHub (NSF)**

**TSEEN: Tobacco Surveillance Evaluation & Epidemiology Network (NSF, NIH, CDC)**

## Business Applications

**PackEdge Community of Practice (P&G)**

**Kraft Design Teams**

### Core Research

Socio-technical Drivers for Understanding & Enabling Teams

## Societal Justice Applications

**Mapping Climate Change Networks In Low Income Communities (City of Chicago)**

**Mapping Digital Media and Learning Networks (MacArthur Foundation)**

## Entertainment Applications

**Second Life (NSF, Army Research Institute, Linden Labs)**

**EverQuest II (NSF, Army Research Institute, Linden Labs)**



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# The Impacts of Co-authorship Networks and Citation Networks in “Team Science”\*

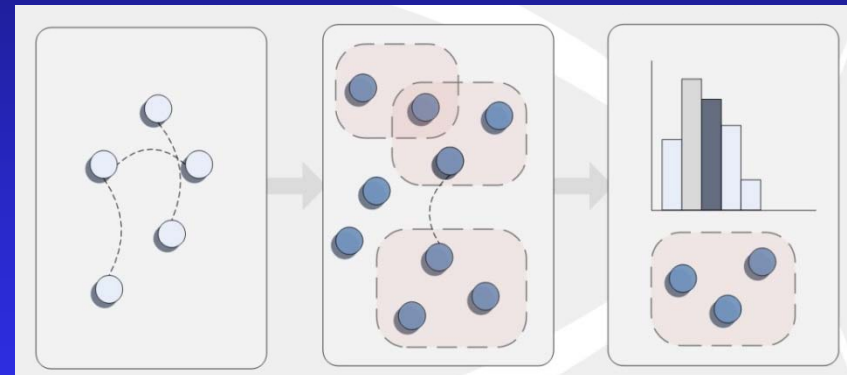
By Meikuan Huang, Jordan Liu, Annie Wang, & Noshir Contractor

- **“Group-staffing riddle”** (Huber & Lewis, 2010):

How to assembly a group to obtain both

- (1) high productivity based on diversity of expertise and cognitive models &
- (2) smooth coordination and communication among group members with shared cognitive models

- Our goal: To discover how prior co-authorship and citation network configurations influence team formation and success in scientific research groups.



\*Funded by NIH/NCRR grant for Northwestern University Clinical and Translational Sciences Institute (NU-CATS) (2008-2013).

# Theoretical Background

## (1) Transactive memory (TM)

- Shared cognitive models or directories of “who knows what” among group members (Hollingshead, 1997, 1998; Wegner, 1995).
- A key TM dimension: Sharedness of knowledge at the group level, or the extent to which all members have similar perceptions of each other’s task responsibilities and expertise level in different knowledge areas (Brandon & Hollingshead, 2004; Huber & Lewis, 2010)

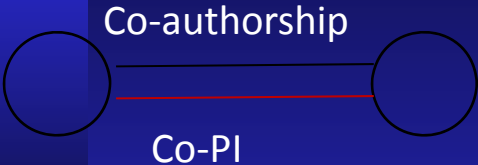
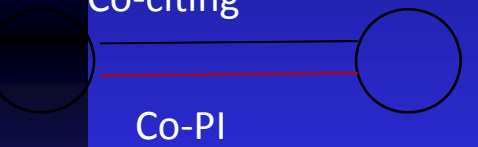
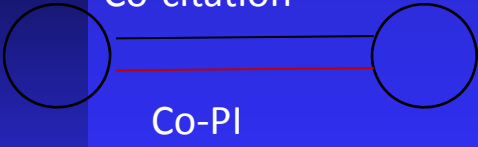
## (2) Prior collaboration

- People are likely to prefer partners with whom they are already familiar from prior work on joint projects (Hinds, Carley, Krackhardt, & Wholey, 2000)

## (3) Homophily

- The tendency of individuals to interact more with those to whom they are more similar (Ibarra, 1992; McPherson & Smith-Lovin, 1987)
- Reasons: Ease of communication, shared understandings and comfort (Carley, 2002).

# Hypotheses & Analysis

|    |   |  |
|----|---|--|
| H1 |    | Researchers tend to collaborate on proposal teams with those with whom they have a co-authorship relationship. |
| H2 |    | Researchers tend to collaborate on proposal teams with those with whom they have a citation relationship.      |
| H3 |  | Researchers who cite similar publications are more likely to collaborate on proposal teams.                    |

## Analysis:

- ERGM models (Exponential Random Graph Modeling) (Frank & Strauss, 1986; Robins & Pattison, 2005; Wasserman & Pattison, 1996)
- PNet (Wang, Robins, & Pattison, 2006).

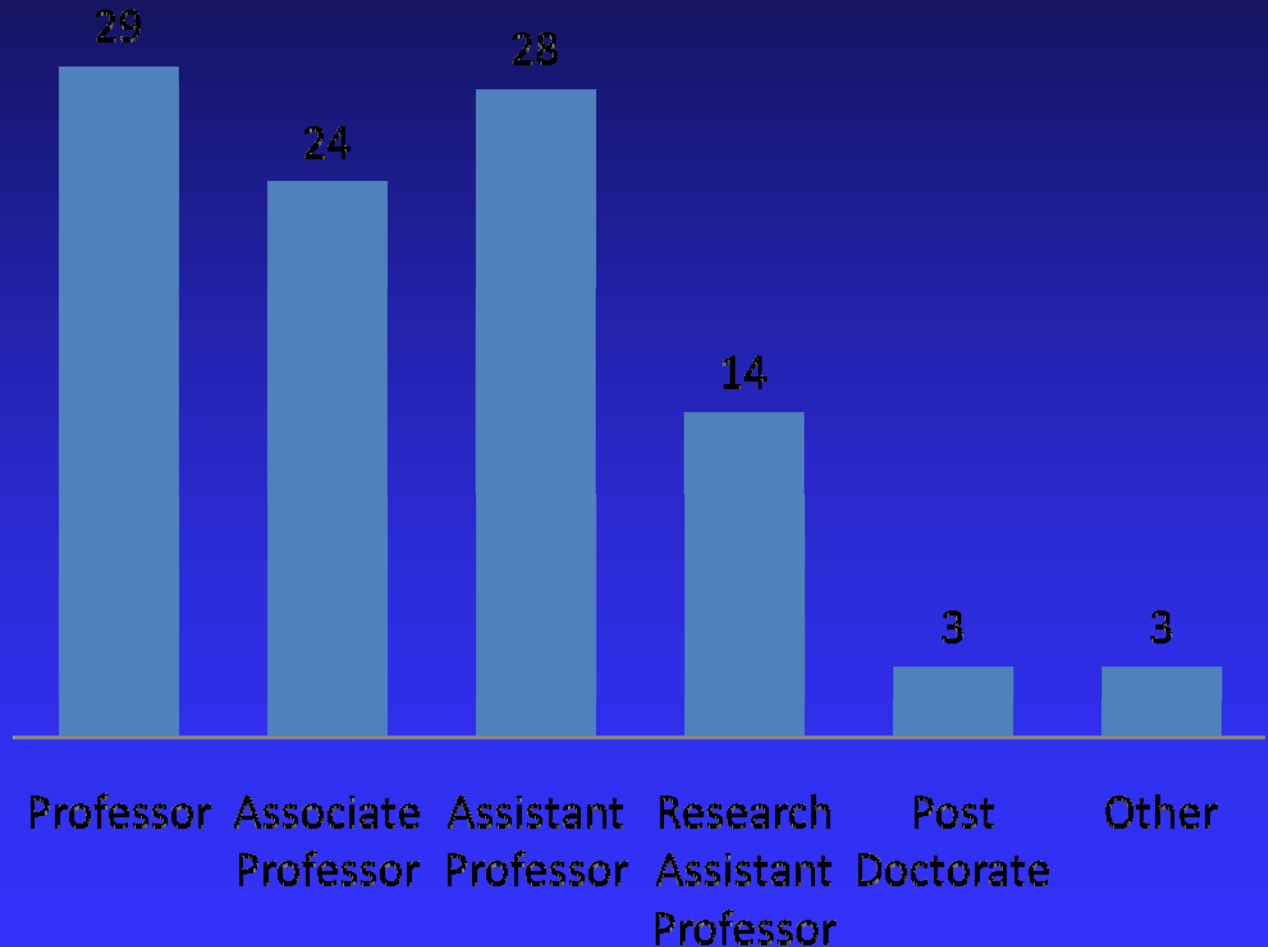


# Data

- 60 Proposals
- 117 applicants, with 60 PIs and 57 Co-PIs, totally
- 37 departments in total

# Tenure Distribution

- 29 Professors
- 24 Associate Professors
- 28 Assistant Professors
- 14 Research Assistant Professors
- 3 Post Docs
- 3 Others: student, research scientist, adjunct assistant professor
- 101 in data

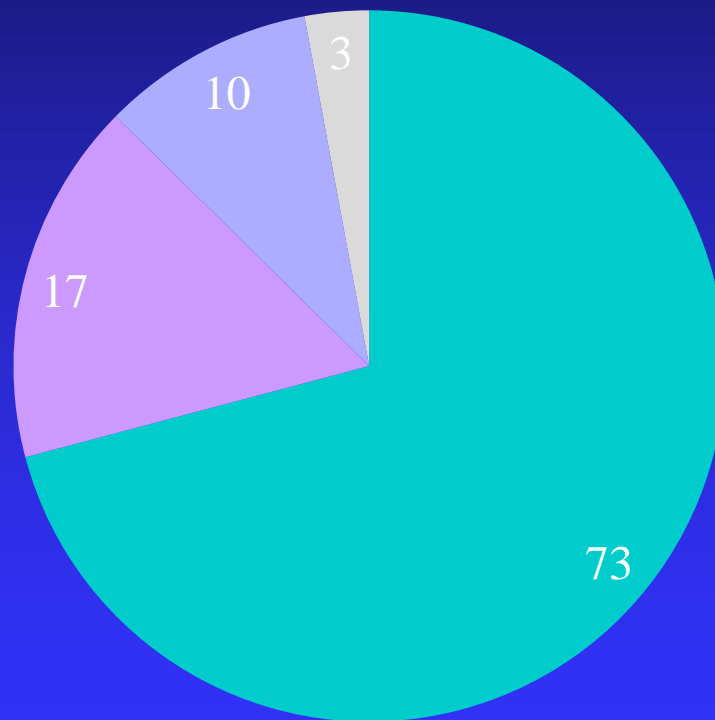


# Departments

| Department                           | Number of applicants in the department |
|--------------------------------------|--|
| Physical Medicine and Rehabilitation | 9                                      |
| Surgery                              | 8                                      |
| Biomedical Engineering *             | 6                                      |
| Cardiology                           | 6                                      |
| Pediatrics                           | 5                                      |
| Chemistry *                          | 4                                      |
| Hematology Oncology                  | 4                                      |
| Infectious Disease                   | 4                                      |
| Molecular Pharmacology               | 4                                      |
| All others                           | 3 or less                              |

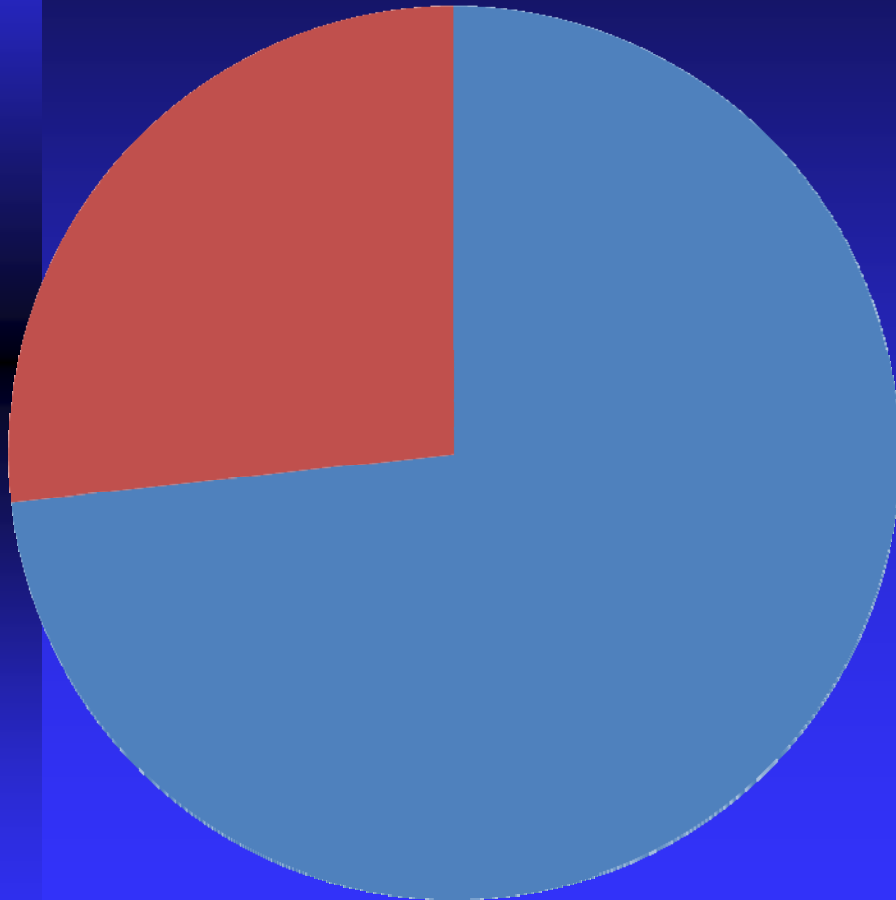
\* Indicates that the department is outside the medical school.

# Applicant Distribution Across Schools



- School of Medicine
- School of Engineering
- College of Arts & Sciences
- School of Communication

# Gender Distribution

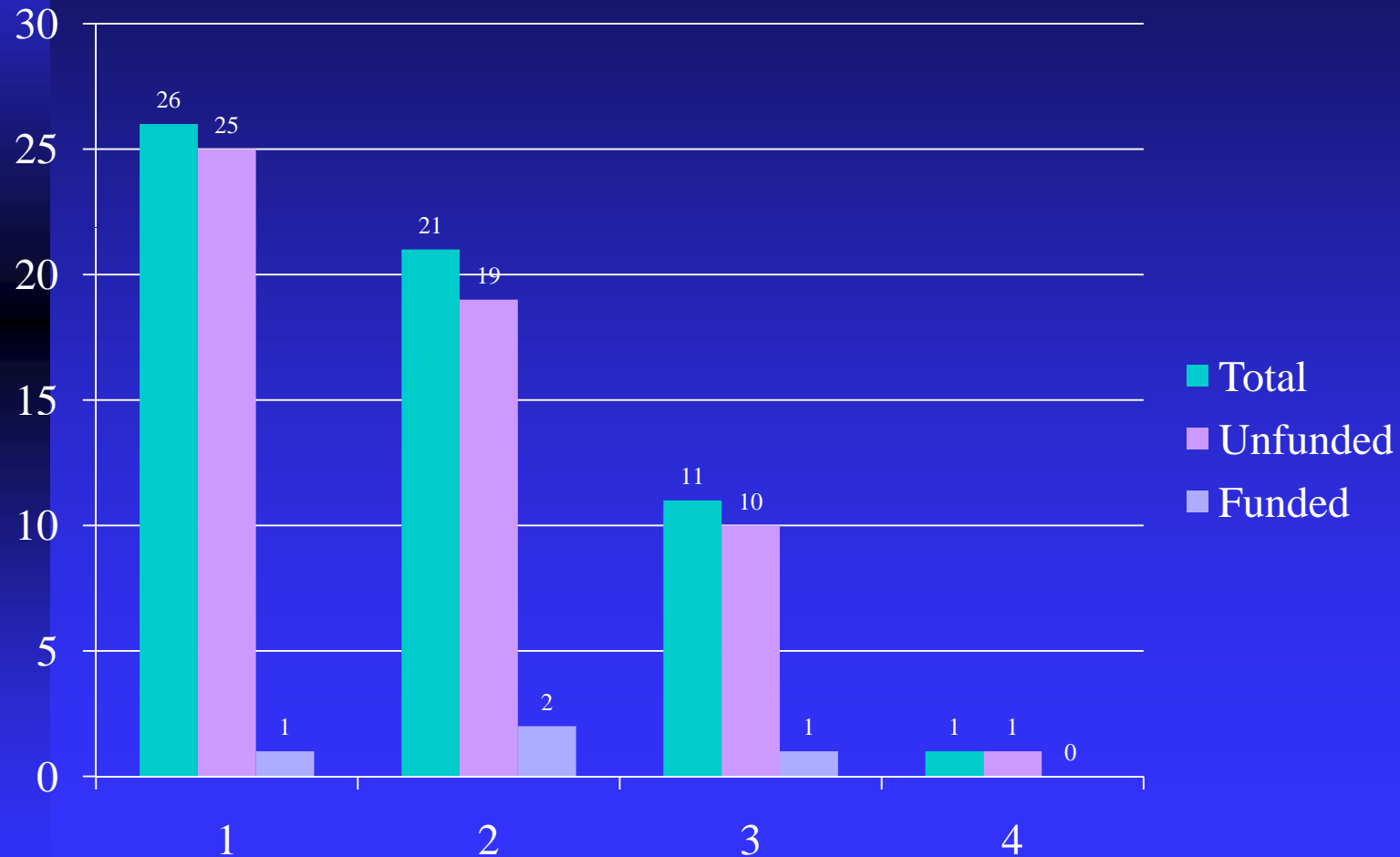


**74** males (72%)

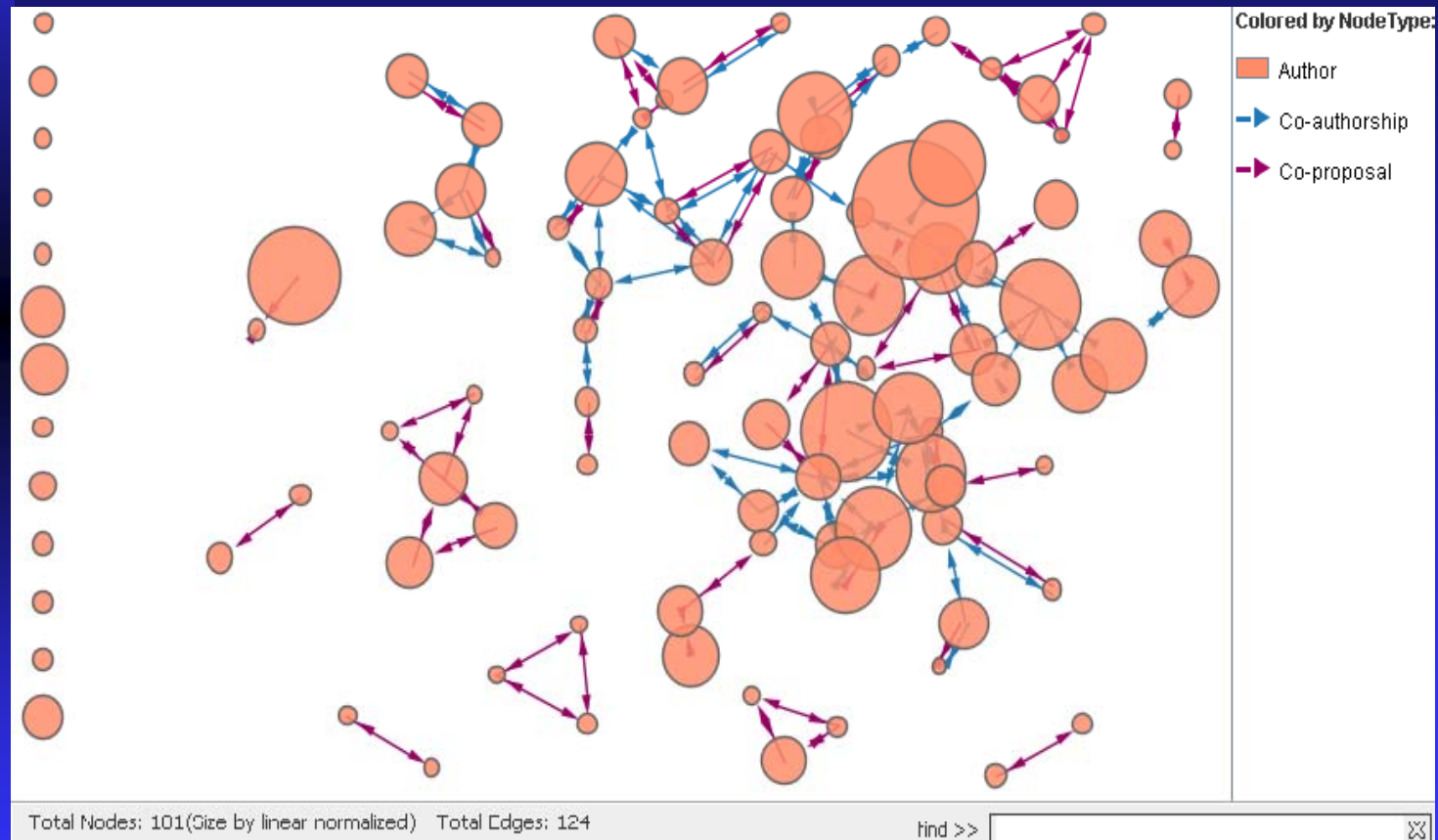
**27** females (28%)



# Number of Applicants in the Proposal

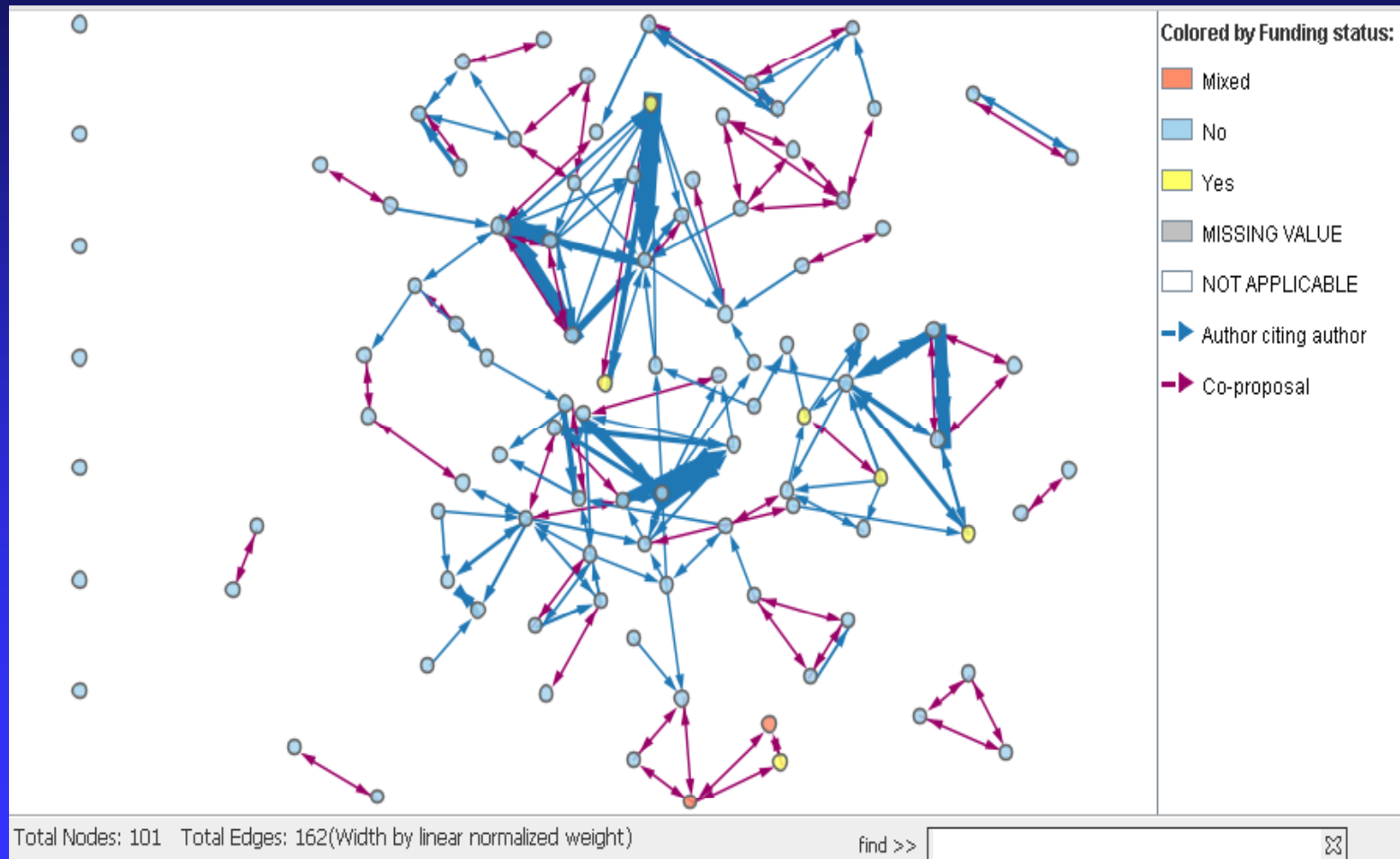


# H1: Co-proposal & Co-authorship Network

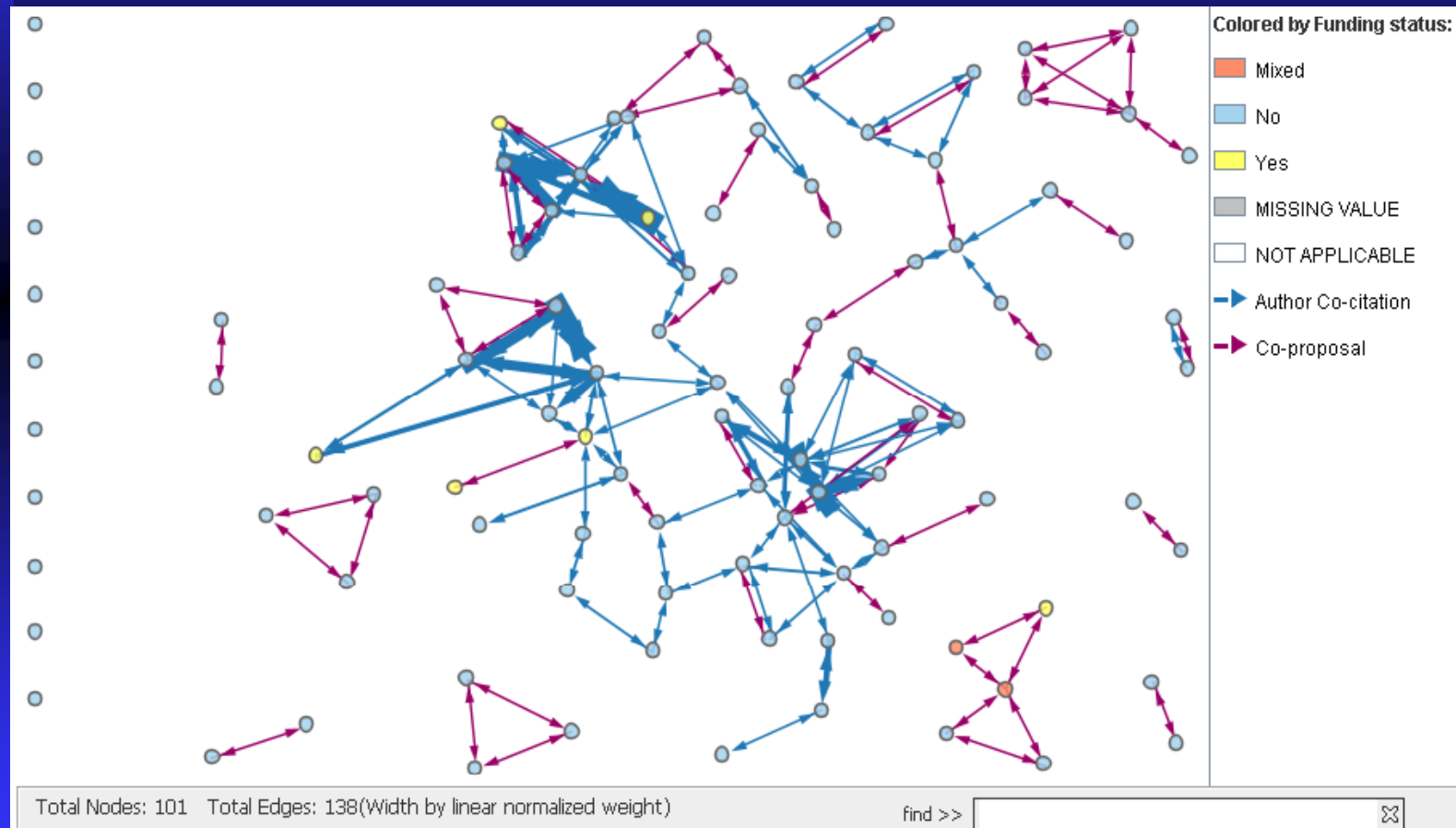


Node size indicates the # of publications

# H2: Co-proposal & co-citation network



# H3: Co-proposal & Citing network



|         | Analysis | Effects                                | Estimates | SD   |       |   |
|---------|----------|--|-----------|------|-------|---|
| Control | PNet     | Edge<br>(DV: co-proposal)              | -4.89     | 0.17 | -0.02 | * |
| Control | PNet     | 2-star (with co-citation as covariate) | -0.46     | 0.21 |       |   |
| Control | PNet     | 2-star (with citing as covariate)      | -0.45     | 0.21 |       |   |
| H1      | PNet     | coauthorship_edge                      | 3.67      | 0.32 | 0.04  | * |
| H2      | PNet     | citing_edge                            | 2.78      | 0.33 | -0.05 | * |
| H3      | PNet     | co-citation_edge                       | 2.96      | 0.37 | 0.03  | * |

Researchers are not likely to randomly form a project collaboration relationship with each other.

Researchers are more likely to have better familiarity of and collaborate again with those they share a collaboration history (co-authorship or citing each other).

Researchers are also more likely to collaborate with those who cited similar articles in their publications.



# Funded vs. Unfunded

| Effects            | Funded<br>(N = 8) |      | Unfunded<br>(N = 93) |       |
|--------------------|-------------------|------|----------------------|-------|
|                    | Estimates         | SD   | Estimates            | SD    |
| Edge (co-proposal) | -3.28             | 1.07 | -4.33                | 0.13  |
| Co-author          | 6.95              | 7.14 | 0.34                 | 1.06  |
| Cite one another   | 7.32              | 4.61 | -2.93                | 4.37  |
| Cite same sources  | 6.61              | 7.99 | -4.17                | 15.83 |

# 3D Strategy for Enabling Team Science

- **Discovery:** Effectively and efficiently foster network links from people to other people, knowledge, and artifacts (data sets/streams, analytic tools, visualization tools, documents, etc.)
  - ◆ *“If only NSF knew what NSF knows”.*
- **Diagnosis:** Assess the “health” of internal and external networks - in terms of scanning, absorptive capacity, diffusion, robustness, and vulnerability to external environment
- **Design:** Model or re-wire networks using social and organizational incentives (based on social network research) and network referral systems to enhance emergent and mature teams



# Design Examples: Mapping & Enabling Networks in ...

Tobacco Research: [TobIG Demo](#)

Computational Nanotechnology: [nanoHUB Demo](#)

Cyberinfrastructure: [CI-Scope Demo](#)

Oncofertility: [Onco-IKNOW](#)



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Networks in Communities

# Summary

- The Science of Team Science is well poised to make a quantum intellectual leap by facilitating collaboration that leverages recent advances in:
  - ◆ Theories about the social motivations for creating, maintaining, dissolving and re-creating network ties within teams
  - ◆ Developments in cyberinfrastructure and Web 2.0 that provide the technological capability to capture and analyze relational metadata needed to more effectively understand and enable teams.
  - ◆ Statistical techniques to make theoretically grounded team assembly recommendations that go beyond the Lovegely and SNIF
  - ◆ Petascale computational infrastructure to execute the statistical and optimization algorithms



# Acknowledgements



National Science Foundation  
WHERE DISCOVERIES BEGIN



National Cancer Institute

U.S. National Institutes of Health | [www.cancer.gov](http://www.cancer.gov)



MACARTHUR

The John D. and Catherine T. MacArthur Foundation

SONIC



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# Research Team @ SONIC



Yun Huang  
Post-doc



Annie Wang  
Post-doc



Mengxiao Zhu  
IEMS Doctoral candidate



David Huffaker  
SoC Doctoral candidate



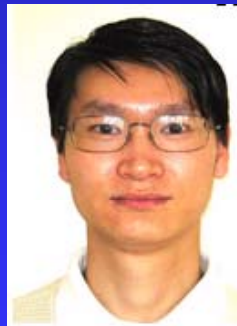
Brian Keegan  
Doctoral Candidate



Jingling Li  
Programmer



Jeffrey Treem  
Doctoral candidate



York Yao  
Programmer



Zack Johnson  
SoC Undergraduate

