Identifying Positive and Negative Ties in Social Networks Through Triangulated Data

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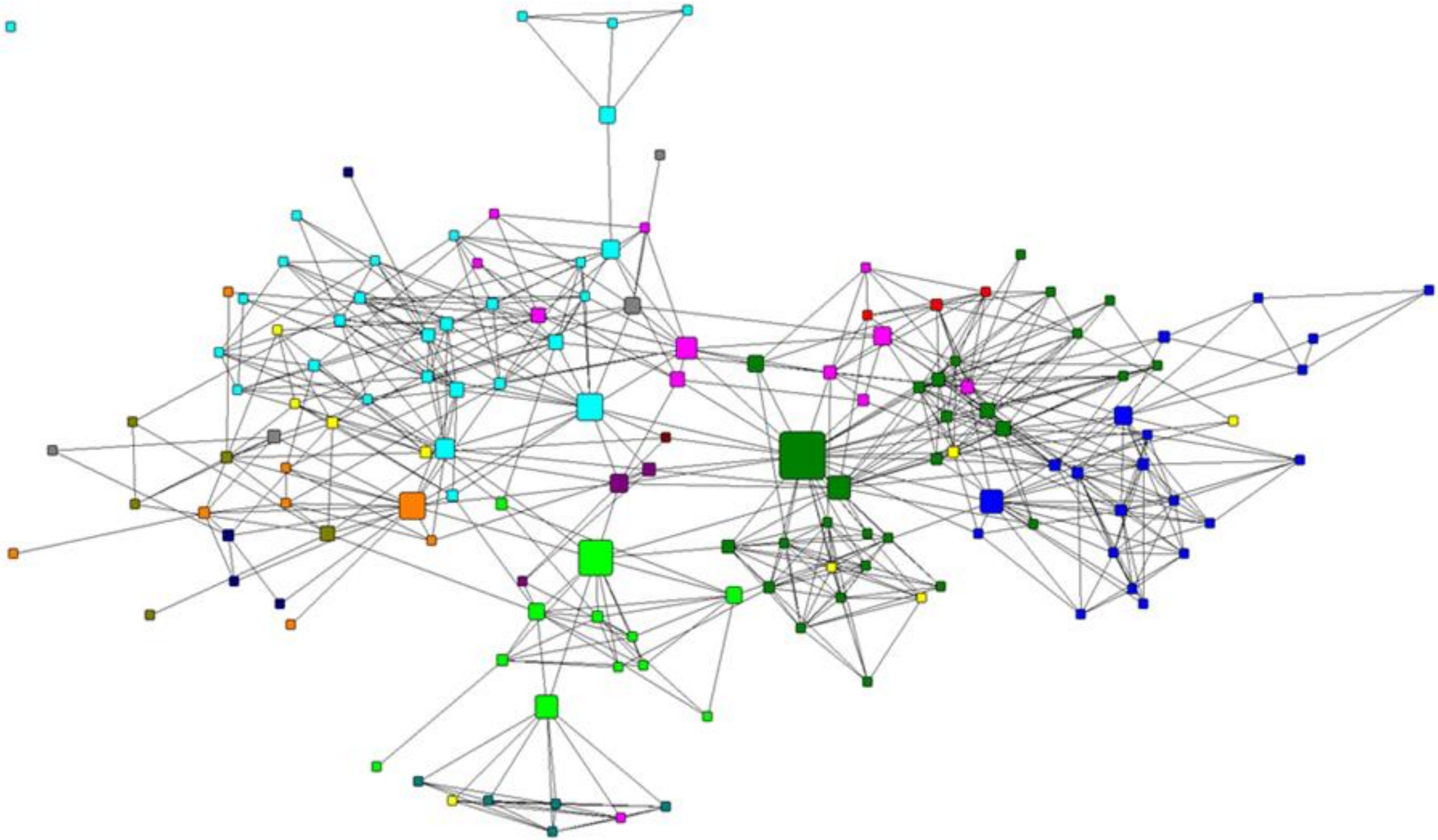
Network Perspective: Incorporating Negative Ties

*Communication Network: Every Day



“Please indicate how often you communicate with each colleague regarding matters that concern work.”

*Nodes sized by bridging position—larger nodes bridge unconnected people and groups to a greater degree

All that is social is not positive

- As people interact with each other, emnity and conflict can develop
- The study of negative relationships from a network perspective is still lacking

Negative relationship: Definition

- An enduring, recurring set of negative judgments, feelings, and behavioral intentions toward another person (a negative person schema)

Source: Labianca, G., & Brass, D. J. (2006). Exploring the social ledger: Negative relationships and negative asymmetry in social networks in organizations. *Academy of Management Review*, *31*, 596-614.

Why study negative relationships?

- Compared to positive or neutral relationships, negative relationships are relatively rare
  - Average of about 5% of total relationships at work (e.g., Baldwin, et al., 1997; Gersick, et al., 2000; Labianca, et al., 1998)
  - By comparison, friends are about 20% of total relationships

Rare doesn’t mean unimportant

- But the rarity of negative ties makes them very powerful in explaining attitudes, behaviors, and outcomes

Negative asymmetry

- Rarity leads to asymmetry (Skowronski & Carlston, 1989)
- Negative events:
  - elicit greater physiological, affective, cognitive, and behavioral activity
  - lead to more cognitive analysis than neutral or positive events (Taylor, 1991)
- Negative interactions:
  - have a disproportionately greater effect on life satisfaction, mood, illness, and stress (e.g., Rook, 1984; Pagel, Erdly, & Becker, 1987)

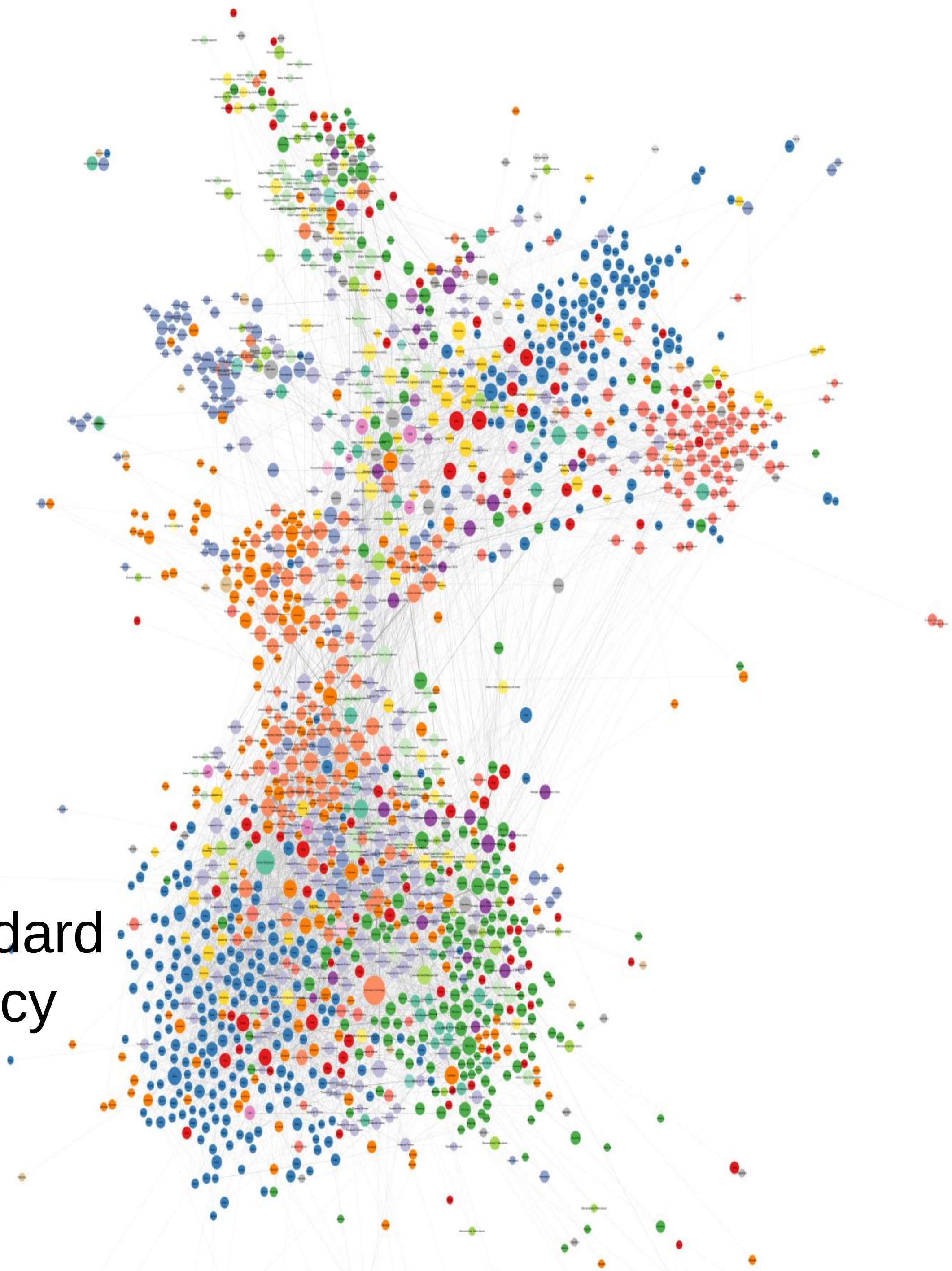
Collecting negative tie data: Example whole network survey

ID Number From Roster	How frequently do you communicate with this person?					How do you generally feel about this person?					Would you go to this person for personal advice? *(including family situations, relationships with non-church members, or church members in non-professional setting)*					Would you go to this person for professional advice? *(including relationships with other clergy, church members in course of duties, or other job-related duties)*					Check if this minister has provided material support to you or your church *(e.g., financial support, staff support, member referrals, guest preaching)*
	Once/ year	Several times/year	Once/ month	Once/ week	Daily or more	Dislike a lot	Dislike a little	Neutral	Like a little	Like a lot	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Check if applicable
# RM1	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	
# 9999	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	

Moving beyond surveys

- While surveys are useful for small organizations where we can use the roster method (less than 200 people)…
- …we are increasingly interested in understanding negative ties in larger organizations

M&A Context
April 2013
1500 professionals



Each person is represented by a single dot.

Lines between two people indicate email communication between them.

Size indicates the centrality of a person.

- GPD
- Legal
- Sales
- Other
- GPE&S
- Logistics
- Sourcing
- Marketing
- Operations
- Accounting
- Manufacturing
- Exec. Committee
- Customer Service
- Human Resources
- Corporate Finance
- Direct to Consumer
- Information Technology

Data

- All email data among the 1,500+ professionals from the date the merger closed for the following 15 months (4 terabytes of data)
  - Includes all content, all meetings, all attachments
- Two waves of survey data across all employees (June 2013 and June 2014)
  - Merger-related constructs (e.g., merger-related commitment)
  - Organizational identification
  - Organizational attachment
  - Individual characteristics, including personality
  - Interdepartmental collaboration
- Turnover, employee performance, salary, promotions, future promotability
- Note: No negative tie data via network survey

September 2013

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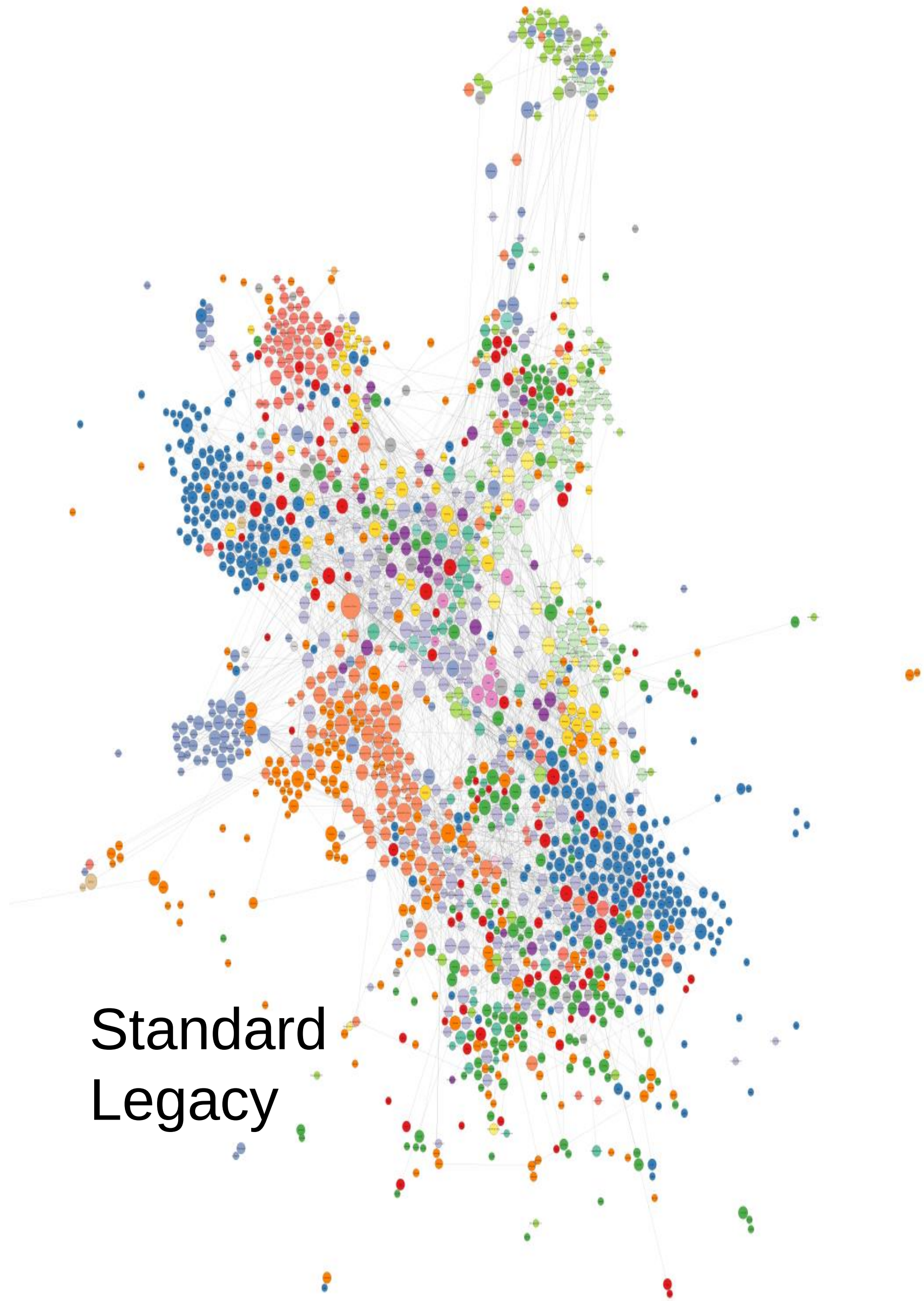
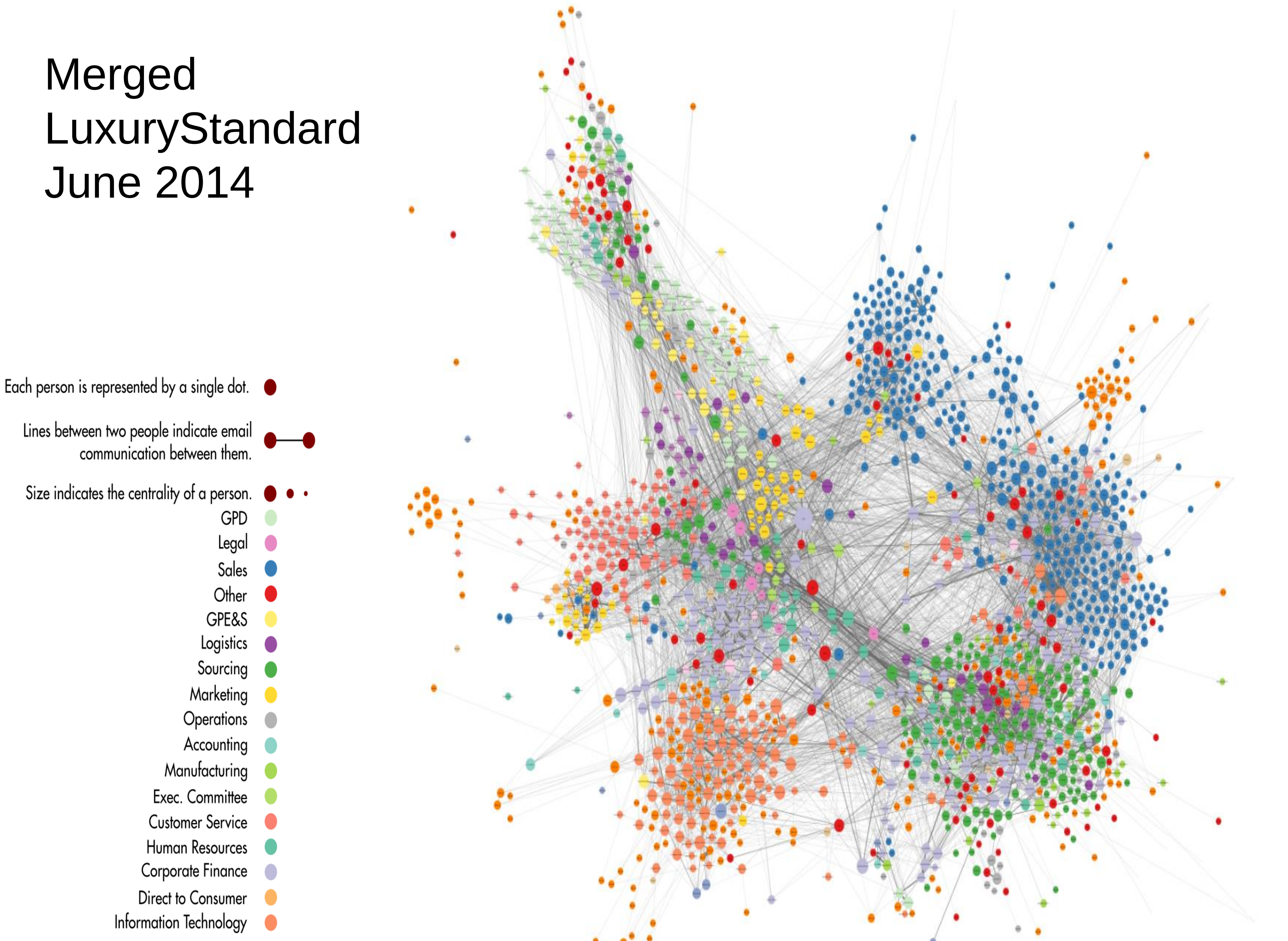


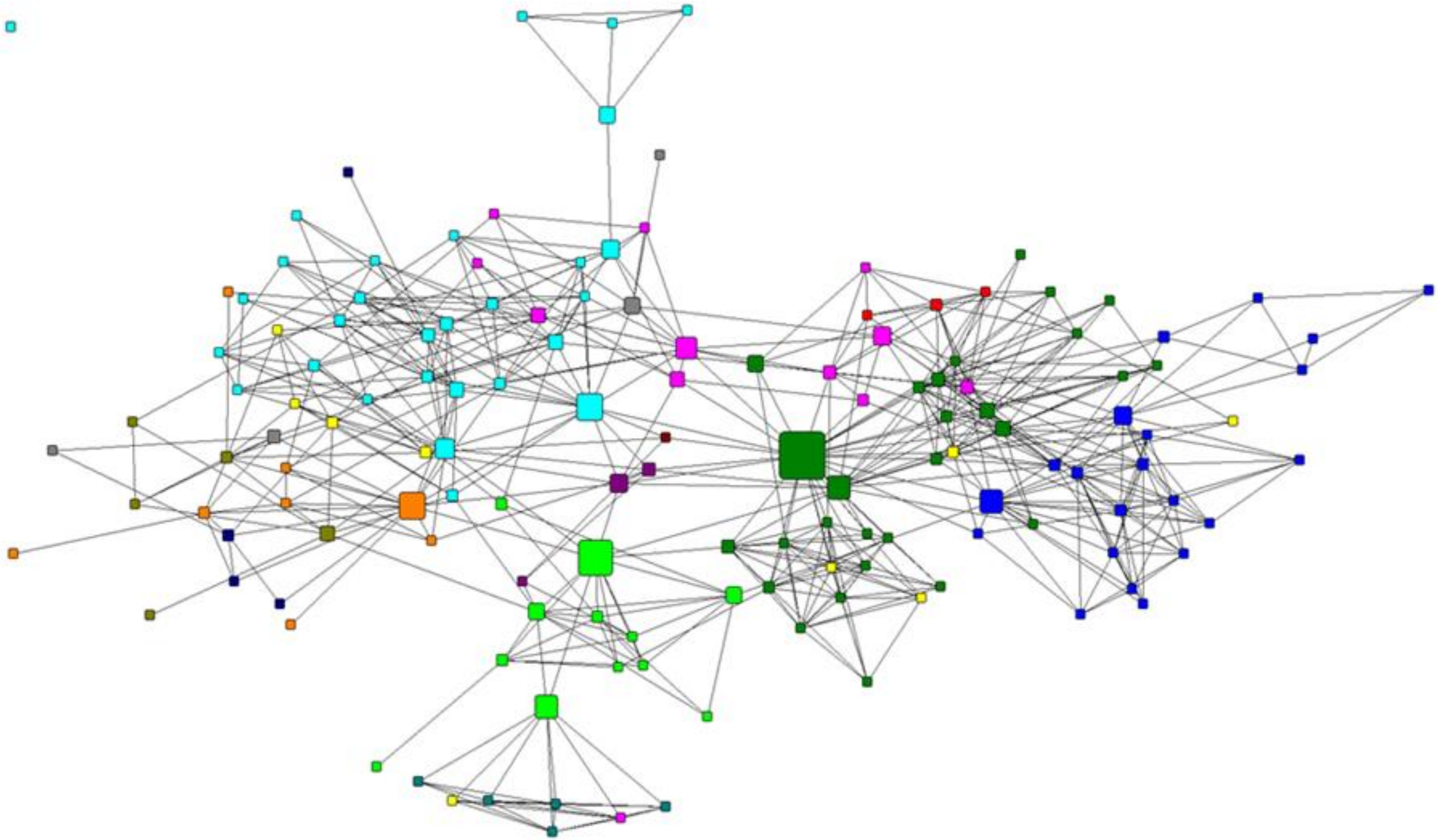
Merged LuxuryStandard June 2014



Moving beyond surveys

- We do know through the smaller survey where respondents were reporting negative ties just before the merger for 150+ of the professionals

*Communication Network: Every Day



"Please indicate how often you communicate with each colleague regarding matters that concern work."

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Moving beyond surveys

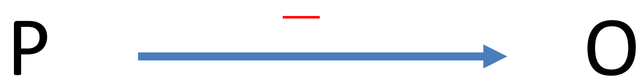
- We do know through the smaller survey where respondents were reporting negative ties just before the merger for 150+ of the professionals
- We can use a combination of data to identify the negative ties we already know about and to infer the other negative ties
- We also have 4.5 years of qualitative observation and interviews with participants identifying where conflict is occurring within the organization

Preliminary approach

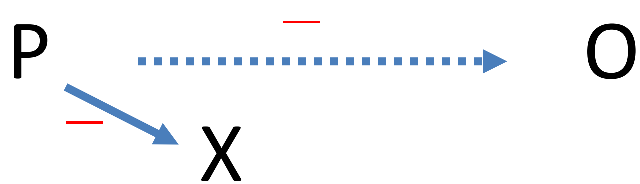
- Use the small dataset as a training subset for the model
- Extract topics from the email content using probabilistic topic modeling
  - e.g., Latent Dirichlet Allocation (LDA)
- Create a dyad-by-topic matrix
- Trained a random forest model to predict the negative ties on the training set
- Used that model to infer negative ties in the rest of the organization

Major challenges

- Unlike simple sentiment analysis where you know that a person is rating an object (e.g., rating a product or reacting to a tweet)…



- …a person is unlikely to send a negative email to their adversary, but rather to a third party complaining about the adversary, not necessarily by name



Major challenges

- Greater need to be able to identify positive and negative ties in large databases from organizations in closer to real time
- Rely on a combination of attitudinal, behavioral, content, and network data to infer the location of negative ties

Applications

Why identify negative ties?

- Understand where the social faultlines are within the organization
  - People at top of organization as well as outsiders often have no idea where the conflicts are in the organization
  - Can create a dashboard for conflict
- Provide insights into the distribution of power in networks from a power dependence theory perspective

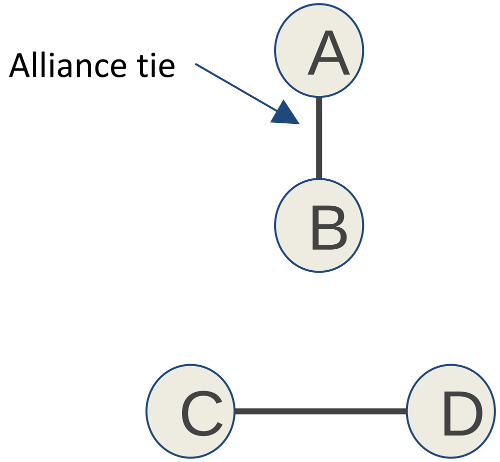
Power Dependence

A has power over B to the extent that A can get B to do something B normally wouldn't.

Which actor in this network is in the most powerful position?

If we examine only the positive (alliance) ties, each actor has the same number of ties (one)

But why examine alliances in isolation from adversaries?

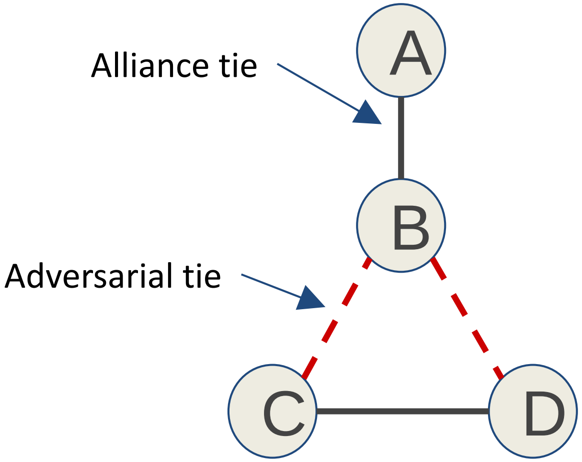


Power Dependence

Allies and adversaries are inextricably linked

The reason we take on allies is to counter adversaries

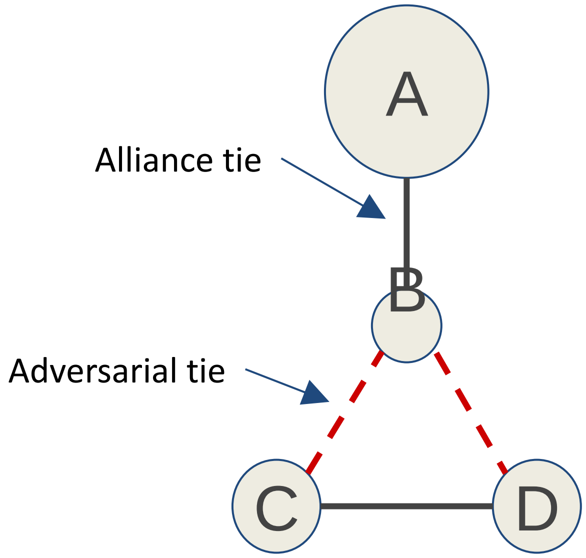
Taking on an ally has costs (e.g., autonomy, resources)



Power Dependence

From a power dependence perspective **A** has the most power.

A has a weak dependent **B** who has two allied adversaries, **C** and **D**.

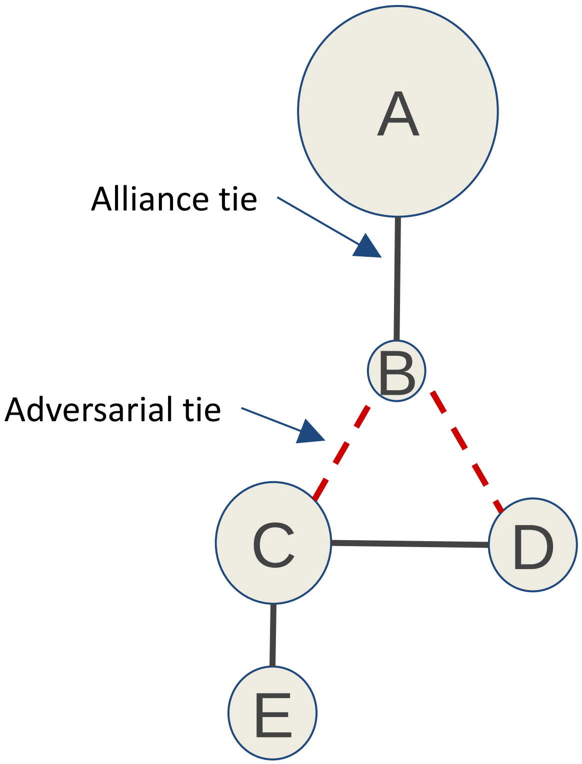


Power Dependence

If **C** gains a new dependent, he becomes more powerful.

Since **B**'s adversary is more powerful, **B** is less powerful.

Since **A**'s dependent ally is now less powerful, **A** becomes even more powerful.



Political Independence Index

Iterates over the edges in the network.

i - edge distance from subject node. Edges directly incident on the node are at distance 0.
K - the maximum edge distance from the subject node.
M - maximum degree of any node in the network
P(i) - number of positive edges at distance *i*
N(i) - number of negative edges at distance *i*

β - attenuation factor. Attenuates the influence of edges at a large distance from the subject node.

$$\sum_{i=0}^{K} \beta^{i}[P(i)^{x} - N(i)^{x}]$$

$$x \leq \frac{\ln(2) - \ln(|\beta|)}{\ln(M)}$$

Smith, J. M., Halgin, D. S., Kidwell-Lopez, V., Labianca, G., Brass, D. J., & Borgatti, S. P. (2014). Power in politically charged networks. *Social Networks*, *36*, 162-176.

International relations context

Table 6
Cross-sectional time series analysis with fixed effects predicting change in military personnel, 1946–2000.

	Model 1	Model 2
Node attributes		
Military expenditures	6.21** (0.001)	6.19** (0.001)
Total population	–0.04 (0.001)	–0.02 (0.001)
Iron and steel production	1.81[t] (0.001)	1.74[t] (0.001)
Primary energy consumption	–10.35** (0.001)	–10.36* (0.001)
Contiguous allies	1.25 (1.05)	1.71[t] (1.08)
Non-contiguous allies	–1.86[t] (0.20)	–1.72[t] (0.20)
Contiguous threats	–0.13 (1.05)	–0.83 (1.11)
Non-contiguous threats	–2.07* (0.61)	–2.41* (0.61)
Political Independence Index		–2.02* (1.31)

Source: Smith, J. M., Halgin, D. S., Kidwell-Lopez, V., Labianca, G., Brass, D. J., & Borgatti, S. P. (2014). Power in politically charged networks. *Social Networks*, *36*, 162-176.

Sample 1 results (healthcare setting)

		Model 1				Model 2				Model 3			
	Variable	B		Std. Error		B		Std. Error		B		Std. Error	
Involuntary Exit	Female	1.49		1.11		1.29		1.19		1.62		1.41	
	Supervisor	0.83		0.59		0.50		1.01		0.43		0.63	
	Tenure with Firm	0.12	*	0.05		0.08		0.08		0.11	+	0.06	
	Performance	-2.16	**	0.64		-1.77	**	0.56		-1.41	*	0.6	
	Size of Positive Tie Network					-0.14	*	0.06		-0.05		0.03	
	Size of Negative Tie Network					0.57	*	0.23		0.11		0.16	
	Negative Tie to Supervisor					-0.07		0.18		0.18	*	0.08	
	Political Independence Index									-2.77	**	0.69	
	Intercept	2.71		2.28		2.84		3.03		3.87		4.41	

Sample 2 results (consulting setting)

		Model 1				Model 2				Model 3			
	Variable	B		Std. Error		B		Std. Error		B		Std. Error	
Involuntary Exit	Female	0.47		0.38		0.57		0.44		0.59		0.44	
	Supervisor	1.00	*	0.51		2.04	**	0.82		2.19	**	0.70	
	Tenure with Firm	-0.12		0.09		-0.18	**	0.06		-0.19	**	0.06	
	USA Location	0.23		0.37		0.65		0.45		0.63		0.52	
	Performance	-1.06	*	0.44		-0.49		0.49		-0.53		0.46	
	Size of Positive Tie Network					-0.01		0.02		0.01		0.02	
	Size of Negative Tie Network					0.17	**	0.06		0.09		0.06	
	Negative Tie to Supervisor					0.89	*	0.37		0.96	*	0.42	
	Political Independence Index									-0.72	*	0.35	
	Intercept	3.15		1.46		0.83		1.68		1.18		1.60	

Conclusion

- Identifying negative ties in large social networks is an important endeavor
- We need to develop ways to find negative ties and monitor them over time

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