Network Mechanisms and Network Structures

Searching for Mechanisms

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MSc in Business Analytics, 2022/23

Outline

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Network Theories across the Various Weeks of SMM638

Network theory	**2**	**3**	**4**	**5**	**6**	**7**	**9**	**10**
Value creation		•	•					
Coordination				•				
Network change					•	•	•	•
Contagion						•		•

Groups of Network Theories

Underlying model	**Social capital**	**Social homogeneity**
Network flow	Capitalization (value creation)	Contagion
Network architecture	Coordination	Adaptation (network change)

Source is [5, page 47]

Networks as Social Capital: Capitalization and Coordination

How do the capitalization and coordination perspectives differ?

	Capitalization	**Coordination**
Level of analysis	Individual nodes/groups of nodes — aka, the trees in the forest	The network as a whole — aka, the forest
Key tenet	(Information exchange) Networks bring resources to individual nodes	The organization and functioning of organizations/markets depend on the characteristics of its underlying (information exchange) network
Sample problem	What is the best network position for a node or a group of nodes with a given objective function (e.g., innovativeness)?	What is the best reporting structure for an organization with certain characteristics (e.g., a start-up in a high-tech industry)?

Market Coordination and Network Structure

Price fixing conspiracies in the heavy electrical equipment industry

THE SOCIAL ORGANIZATION OF CONSPIRACY: ILLEGAL NETWORKS IN THE HEAVY ELECTRICAL EQUIPMENT INDUSTRY*

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We analyze the social organization of three well-known price-fixing conspiracies in the heavy electrical equipment industry. Although aspects of collusion have been studied by industrial organization economists and organizational criminologists, the organization of conspiracies has remained virtually unexplored. Using archival data, we reconstruct the actual communication networks involved in conspiracies in switchgear, transformers, and turbines. We find that the structure of illegal networks is driven primarily by the need to maximize concealment, rather than the need to maximize efficiency. However, network structure is also contingent on information-processing requirements imposed by product and market characteristics. Our individual-level model predicts verdict (guilt or innocence), sentence, and fine as functions of personal centrality in the illegal network, network structure, management level, and company size.

"People of the same trade seldom meet together but the conversation ends in a conspiracy against the public, or in some diversion to raise prices."

—*Adam Smith,* Wealth of Nations

"The fact that secrets do not remain guarded forever is the weakness of the secret society."

—*Georg Simmel,* The Secret Society

(Pfeffer 1987; Pfeffer and Salancik 1978; Burt 1983), direct manipulation of market ties (Baker 1990), and embeddeding business decisions in social relationships (Granovetter 1985). These market-restricting tactics are legal, but business organizations also indulge in practices proscribed by law that flagrantly subvert the market mechanism.

We analyze the social organization of a prevalent illegal corporate practice—price-fixing.

Source is [1]

Key features of the case

- **Scope of the business case**: the case deals with the organization of three well-known price-fixing conspiracies in the heavy electrical equipment industry
- **Relationship under investigation**: the information exchange network among the individuals involved in the price-fixing conspiracy
- **Outcomes of interest**:
  - Coordination among the conspirators
  - Concealment of the conspiracy

Market Coordination and Network Structure

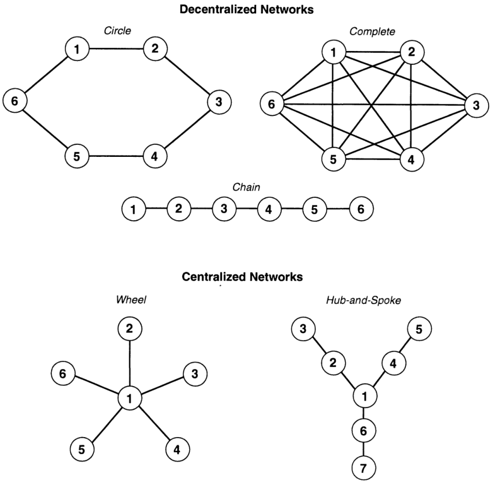
Network structure promoting concealment

Proposition 1

The need for secrecy leads conspirators to conceal their activities by creating sparse and decentralized networks.

Argument for Proposition 1

Decentralization or ‘compartmental insulation’ limits exposure, making it difficult to uncover an entire network, particularly its leader



Source [1, page 849]

Market Coordination and Network Structure

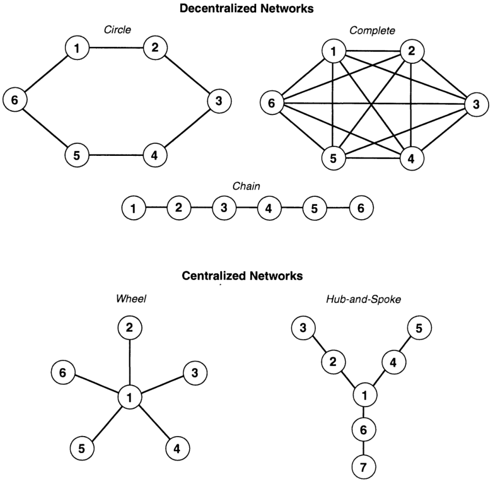
Network structure promoting coordination

Proposition 2

The conspiracies with low information-processing requirements — switchgear and transformers — exhibit centralized communication networks. The conspiracy with high information-processing requirements — turbines — should exhibit decentralized communication networks

Argument for Proposition 2

Experimental research on small groups has found that simple, routine, unambiguous tasks are performed more efficiently in centralized structures, while difficult, complex, ambiguous tasks are performed more efficiently in decentralized structures.



Source [1, page 849]

Market Coordination and Network Structure

Which is the best network structure to achieve coordination in the price-fixing conspiracy?

Organization Objective	Information-Processing Requirement: High	Information-Processing Requirement: Low
Concealment	Decentralized networks	Decentralized networks
Coordination	Decentralized networks	Centralized networks

Figure 1. Concealment Versus Coordination: Theoretical Expectations

Source [1, page 845]

Market Coordination and Network Structure

Results

Table 1. Network Characteristics and Outcomes for Three Price-Fixing Conspiracies

Network Characteristic and Outcome	Conspiracy: Switchgear	Transformers	Turbines
Network Characteristic			
Size (number of participants)	33	21	24
Density	23.3	32.4	35.5
Nieminen graph centralization (degree)	41.7	36.1	51.4
Freeman graph centralization (betweenness)	21.3	17.6	24.2
Sabidussi graph centralization (farness)	39.0	37.4	60.8
Outcome			
Percent guilty	66.7	52.4	16.7***
Recommended sentence (in months)	1.43	2.64	1.25
Imposed sentence (in months)	.57	.82	.75
Time served (in months)	.10	.18	.25
Recommended fine (in dollars)	$2.33	$2.95	$5.25***
Imposed fine (in dollars)	$2.17	$2.91	$4.50*

* $p < .05$ *** $p < .001$ (one-way ANOVA)

Note: All outcomes except verdict are averages based on guilty verdicts.

Source [1, page 851]

Table 2. Logistic Coefficients for Regression of Verdict on Personal Attributes and Network Variables: Participants in Three Price-Fixing Conspiracies

Independent Variable	Model 1
Constant	-3.834* (1.890)
General Electric (1 = GE; 0 = otherwise)	-.561 (.769)
Westinghouse (1 = Westinghouse; 0 = otherwise)	-.060 (.875)
Turbines conspiracy (1 = turbines; 0 = switchgear or transformers)	-3.416* (1.471)
Top executive (1 = top executive; 0 = otherwise)	.281 (.753)
Middle manager (1 = middle manager; 0 = otherwise)	1.643† (.927)
Turbines conspiracy × top executive	4.020* (2.019)
Degree centrality	.381** (.138)
Betweenness centrality	.002 (.021)
Farness centrality	.020 (.019)
Number of participants	69

† $p < .05$ (one-tailed test)

* $p < .05$ ** $p < .01$ (two-tailed test)

Note: Numbers in parentheses are standard errors. This model correctly classifies 86.5 percent of those found guilty and 78.1 percent of those found not guilty. Overall, the model correcly classifies 82.6 percent.

Source [1, page 852]

Time for the Ragu Sauce Simulation Game!

Ragu Sauce Simulation Game

Goal

Teams of seven members are asked to write on a piece of paper the recipe for the authentic Italian ragu sauce without using the Internet and without asking to 'externals.'

Setup

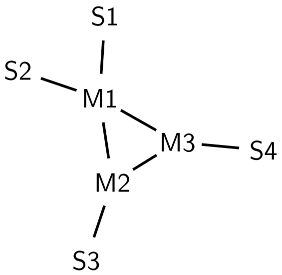
- A team has seven members, a.k.a., nodes
- The information on how to make the sauce is dispersed across four 'source' nodes
  - Two members know sub-sets of ingredients
  - Two members know sub-sets of cooking steps
- The 'manager' nodes — who do not have any specific information on ingredients and cooking steps — are required to collect and synthesize the information from the 'source' nodes

Ragu Sauce Simulation Game

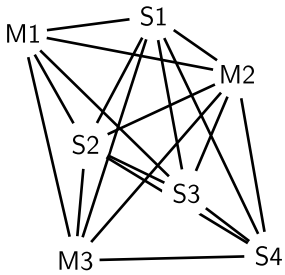
Experimental manipulation

Two teams are supposed to achieve the goal presented in the previous frame. The only difference between the two teams in the network structure. Team **A** has a centralized reporting structure; team **B** has a decentralized reporting structure.

Team A.
Centralized reporting structure



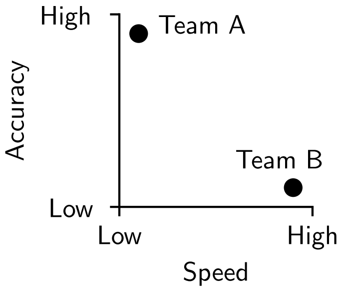
Team B.
Decentralized reporting structure



Ragu Sauce Simulation Game

Main results

Speed Vs. accuracy in decision making



Notes. — Team A is slower in processing information, but less likely to make mistakes. Team B is faster in processing information, but more likely to make mistakes.

Fluid Vs. rigid task partitioning

- In team A, there is a clear the distinction of roles and responsibilities: manager nodes are responsible for the gathering and integration of dispersed information; source nodes are supposed to share their private information but do not take part in the integration phase
- In team B, the distinction of roles is not visible — potentially, everybody does everything

Ragu Sauce Simulation Game

Generalizable insights

Proposition 3

The characteristic of a reporting network — present in any organization — affects the way in which information is gathered, integrated, and used to make decisions.

Ragu Sauce Simulation Game

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Corollario to Proposition 3

The centralization of a reporting network is a key attribute shaping the decision-making process.

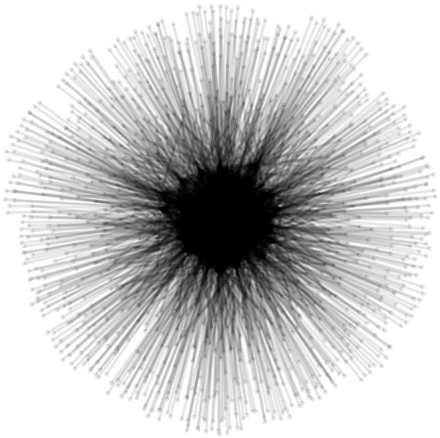
How Do We Measure Network Centralization?

- First-thing-first: centralization is a network-level property — that is, it regards the 'forest' not the 'trees' of a network
- The paper on illicit networks uses the following measures of graph centralization, Freemans's graph centrality index [3] , defined as $\sum_{i=1}^{g}[C_A(n^*) - C_A(n_i)]$, where $C_A(n^*)$ is the largest centrality index across the g actors in the network and $C_A(n_i)$ is the centrality index of the i-th actor in the network
- For an overview of graph-centrality measures, see for example [2] and [6, pages 176-177]

!! Be aware that NetworkX does not implement any centralization measure !!

The Trees Mask the Forest Behind a Network

A graph with $N = 2,000$ and $\langle k \rangle = 502.598$

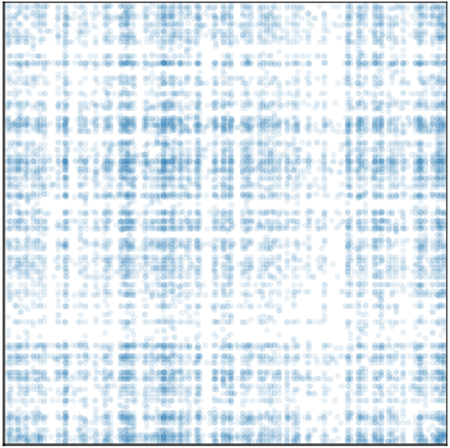


Leading question

- Can you see any type of position in this network visualization?
- That is, can you see specific types of nodes occupying a certain position in the network?

The Trees Mask the Forest Behind a Network

A graph with $N = 2,000$ and $\langle k \rangle = 502.598$



Leading question

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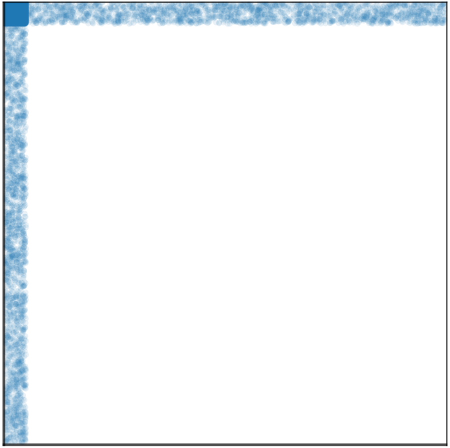

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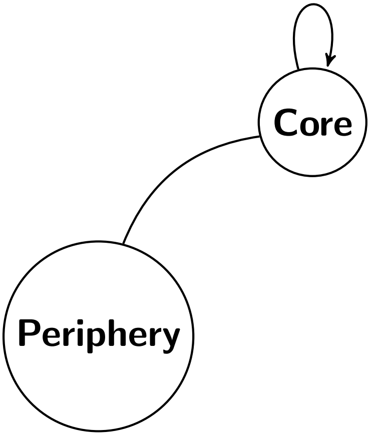
Blockmodeling: The Nuts and Bolts

- The procedure through which an adjacency matrix's rows and columns are permuted to reveal a hidden structure (if any) is called **block-modeling** [4]
- By scrutinizing the outcome of a block-modeling procedure, one can identify the presence of types of nodes in the network — oftentimes called 'positions' — as well as the relationship between them.
- Furthermore, block modeling allows creating a stripped-down representation of a real-world network can — known as reduced form network



Notes. — The reduced-form network representation of a core-periphery network.

Problem Set/Homework

Create the adjacency matrix behind the reporting network of a multi-unit organization with the following attributes

- Ten units
- One manager by unit
- Five middle managers by unit reporting to the unit manager
- Ten employees reporting to each middle manager

Then

- Visualize the adjacency matrix of the network
- Visualize the network
- Get the centralization index of the network

Outline

Why do Network Mechanisms Matter?

1. Network mechanisms can explain why networks look how they look!
2. If we know the network mechanisms, we can predict the evolution of a network. E.g.,
   - Who will pay attention to which market offers
   - Who will date whom
   - Who will adopt or reject whom's opinion

What Are We Trying to Achieve in Sessions 6 and 7?

Network theory	**2**	**3**	**4**	**5**	**6**	**7**	**9**	**10**
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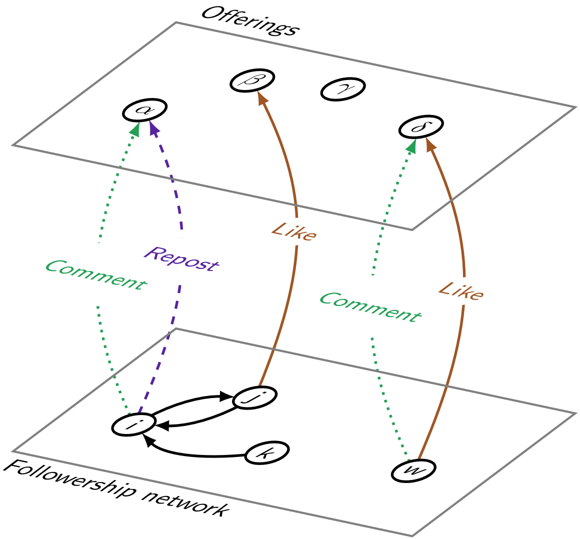
Network change					•	•	•	•
Contagion						•		•

- In today's session, we will try to discover the mixture of network mechanisms accounting for Soundcloud's network structure
- In the next session, we will learn how to quantify a key network mechanism and will connect it to the problem of contagion (critically important to explain offering popularity in markets)

A Real-World Example: The Soundcloud Networks



Some key general points emerging from the analysis of the Soundcloud example:

- The same pair of nodes can be connected because of multiple relationships (i.e., 'like,' 'repost,' 'comment')
- The nodes of a network may have the same type (e.g., 'following') or different types (e.g., 'like')
- Analytically separated networks may be correlated (e.g., one tends to like her/his followings' likes)

References

[1] Wayne E Baker and Robert R Faulkner. “The Social Organization of Conspiracy: Illegal Networks in the Heavy Electrical Equipment Industry”. In: *American Sociological Review* 58.6 (1993), p. 837.

[2] Stephen P Borgatti and Martin G Everett. “A Graph-Theoretic Perspective on Centrality”. In: *Social networks* 28.4 (2006), pp. 466–484.

[3] Linton C Freeman. “Centrality in Social Networks: Conceptual Clarification”. In: *Social networks* 1.3 (1979), pp. 215–239.

[4] Tiago P Peixoto. “Efficient Monte Carlo and Greedy Heuristic for the Inference of Stochastic Block Models”. In: *Physical Review E* 89.1 (2014), p. 012804.

[5] John Scott and Peter J Carrington. *The SAGE Handbook of Social Network Analysis*. SAGE publications, 2011.

[6] Stanley Wasserman, Katherine Faust, et al. “Social Network Analysis: Methods and Applications”. In: (1994).