Intermediate Social Network Theory

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From Description to Theory

- We have developed a **vocabulary for describing networks**.
- **Common patterns?**
- **What *processes* underlay observed structure?**
- **Structure ⇔ outcomes?**
Identifying A Relational Theory
Why Do We Care?

- What is your theory a theory of?
- Do you really need a network representation?
- Adding degree centrality to a regression – **NOT** a relational theory.
- **Occam’s Razor** – the simplest explanation is best.
Positional Theories

Definition 1: A *positional theory* is a theory about how the positions of nodes in a network affect their individual or group level outcomes, or how their positions in the network change over time.
Positional Theories

- People with more friends have more social capital.

- People with more sexual partners are more likely to have HIV.

- Senators with more connections are more powerful.

- Network centrality is related to some outcome (degree, betweenness, closeness).
Definition 2: A relational theory concerns the structure of the connections between nodes in which the state of a node is related to ties that do not involve that node.
Relational Theories

- Small world networks are fault tolerant.
- Friendship networks between school children are race and gender homophilous.
- The international economic sanctions network is intransitive.
- Women are excluded from the ‘locus of control’ in organizations.
Building Blocks
The Network

Nodes and Edges
Transitivity and Reciprocity

Transitivity — Clustering

Reciprocity — Collaboration, Stability
Preferential Attachment

Popularity – Power, Path Dependence

Sociality – Economies of Scale
Ill-Defined Concepts
What is Hierarchy?
Hierarchy

- Physicists say it is a wide tree.
- Is it defined on “positions” or structure?
- **Width and Depth.**
- Is hierarchy a useful concept?
Compartmentalization

http://arxiv.org/abs/1407.2854
Levels of Analysis
Levels of Analysis

- The **systems level** concerns characteristics of the entire network.

- The **group level** concerns differences and similarities in the network structure within, between and across groups.

- The **node level** concerns the patterns connections by individual nodes.
Levels of Analysis
Example: Information Diffusion

Efficiency

Fault Tolerance
Specifying A Relational Theory
A Rule of Three: Researchers should subset (through matching or experimental design) their data until a regression with only three (at most) covariates explains the data.

What about in the relational context?

A Relational Rule of Three: A relational theory should seek to explain the observed network structure at all three levels of analysis, and should be parsimonious.
Parsimony vs. Completeness
A Note on Observational Data

- How do we measure network properties?
- We count:

![Diagram of Triangle and Two-Star Network Structures]
Multicolinearity and Omitted Variable Bias

- **Multicolinearity** – a motivation for A.R.T.

  - If counts are too highly correlated – inflated standard errors, sign switching.

- **Omitted Variable Bias**

  - Multicolinearity will exacerbate, leading to biased estimates.
The Exponential Random Graph Model

- Let $Y$ be a $n$-node network
- An ERGM is specified as:

\[ P(Y, \theta) = \frac{\exp\{\theta'h(Y)\}}{\sum_{\text{all } Y^* \in \mathcal{Y}} \exp\{\theta'h(Y^*)\}} \]

- $\theta$ is a parameter vector
- $h(Y)$ is a vector of statistics on the network
- Object of inference: the probability of $Y$ among all possible permutations of $Y$ given the network statistics.
Null Model: High Correlation

Nodes in Network

Correlations

out2star
in2star
c triads
recip
edgeweight
Solution?

- Develop A Strong Theory!
  - Theory is highly parsimonious + complete – no theoretical problem.

- Nuance vs. Interpretability

- In practice network models are tricky, may not be able to estimate.
Example – Beyond “Gravity” in International Trade


- Yearly data on international trade flows from the UN Commodity Trade Statistics Database (1980-2001)

- What is our Theory?
(Generalized) ERGM Results

Sociality – (Exporters)  Popularity – (Importers)

Reciprocity  Transitivity
Unidentified Models
The Latent Space Model

Under the latent space model, the log odds of a tie between two nodes $i$ and $j$ is defined as:

$$
\eta_{i,j} = \text{log odds}(y_{i,j} = 1|z_i, z_j, x_{i,j}, \alpha, \beta) \\
= \alpha + \beta' x_{i,j} - |z_i - z_j|
$$

- $\alpha$ is an intercept term
- $\beta$ is a vector of dyad specific covariate effects
- $|z_i - z_j|$ is the euclidean distance between nodes
Example: Gender Mixing

Trace Plot of Log Likelihoods

Geweke Statistic: 3.42

Mixing Parameter Estimates

0 500 1000 1500
−1950 −1940 −1930 −1920 −1910

Cluster: 1 Fraction of Edges: 0.505
Number of Emails Represented: 439 of 518

Darker edges indicate more communication

Male
Female
How Do We Interpret?

- Women are more likely to email women given network structure.
- Women are on the periphery in the network – less likely to communicate.
- Intercept and spread of latent positions
- Class of models is only weakly identified through an informative prior.
Relational Processes
Relational Processes

- Why does the network look the way it does?
- How will the network grow?
- How relatively important are different processes shaping the network?
- Many processes can lead to same observed structure.
In hierarchical structures, one country stands at the center of the system, and other states are on the periphery. Hence influence is unevenly distributed between a central hegemon and everyone else. In flat structures, no country is substantially more central than another. Hence influence is more evenly balanced between countries. Thus hierarchical and flat network topologies generate the same distributions of influence that existing IR structure-based models emphasize. [p.137]

Oatley et al. (2013). The Political Economy of Global Finance: A Network Model. *PS.*
By What Process?

“Hierarchical” (Star)  “Flat” (Tree)
A Relational Theory of Global Finance

- **Hierarchy:** *Fitness with Preferential Attachment (FPA)* – (authors actually suggest this as the process)

- Degree centrality not important – **position** is.

- **Flat:** *Erdos-Renyi random graph model*

- If we think of financial crises as diffusion processes then Hierarchical structure is better.
Specified Process

Preferential Attachment

Random
Influence and Homophily

- One of the big areas of research in network dynamics.

- Is smoking passed on to friends or do people who smoke just hang out with smokers?

- Hard to distinguish, can use experiments.

Yahoo Go!

launched in July 2007 (Yahoo! Go) (Fig. 2A), and

(iii) precise

attribute and dynamic behavioral data on users' demographics, geographic location, mobile device type and usage, and per-day page views of different types of content (e.g., sports, weather, news, finance, and photo sharing) from desktop, mobile, and Go platforms. Much of these data, such as mobile device usage and page views of different types of content, provide fine-grained proxies for individuals' tastes and preferences. The complete set of covariates includes 40 time-varying and 6 time-invariant individual and network characteristics. Taken together, the sampled users of the IM network registered 11022 page views and sent 3.9 billion messages over 89.3 million distinct relationships. For details about the service, the data, and descriptive statistics see the Data section of the SI.

Evidence of Assortative Mixing and Temporal Clustering

We observe strong evidence of both assortative mixing and temporal clustering in Go adoption. At the end of the 5-month period, adopters have a 5-fold higher percentage of adopters in their local networks ($t_{\text{stat}} = 100.12, p < 0.001$; $k.s._{\text{stat}} = 0.06, p < 0.001$) and receive a 5-fold higher percentage of messages from adopters than nonadopters ($t_{\text{stat}} = 88.30, p < 0.001$; $k.s._{\text{stat}} = 0.17, p < 0.001$). Both the number and percentage of one's local network who have adopted are highly predictive of one's propensity to adopt (Logistic: $\beta = 0.153, p < 0.001$; $\% = 1.268, p < 0.001$), and to adopt earlier (Hazard Rate: $\beta = 0.10, p < 0.001$; $\% = 0.003, p < 0.001$). The likelihood of adoption increases dramatically with the number of adopter friends (Fig. 2C), and correspondingly, adopters are more likely to have more adopter friends (Fig. 2B), mirroring prior evidence on product adoption in networks (29).

Adoption decisions among friends also cluster in time. We randomly reassigned all Go adoption times (while maintaining the adoption frequency distribution over time) and compared observed dyadic differences in adoption times among friends to differences among friends with randomly reassigned adoption times, a procedure known as the ''shuffle test'' of social influence (25). Compared with these randomly reassigned adoption times, friends are between 100% and 500% more likely to adopt within 2 days of each other, after which the temporal interdependence of adoption among friends disappears (Fig. 1D).

Evidence of assortative mixing and temporal clustering may suggest peer influence in Go adoption, but is by no means conclusive. Demographic, behavioral, and preference similarities could simultaneously drive friendship and adoption, creating assortative mixing. Such homophily could also explain the temporal clustering.

Fig. 1. Diffusion of Yahoo! Go over time. (A–C and D–F) Two subgraphs of the Yahoo! IM network colored by adoption states on July 4 (the Go launch date), August 10, and October 29, 2007. For animations of the diffusion of Yahoo! Go over time see Movies S1 and S2.
Influence and homophily effects in Go adoption. (A) Influence (solid line) and homophily (dashed line) per day, showing the influence of adoption on other users. (B) Cumulative influence over time. (C–E) Treatment effects are displayed when the average strength of ego’s ties to adopters (measured by the volume of IM message traffic) is greater than and less than the median under random and propensity score matching (C); the clustering coefficient in the network around ego is greater than and less than the median (D); and ego’s page views of news content are greater than and less than the median (E).
Participation Time!