A Précis of Key Types of Social Network Analyses and Recent Applications Involving Physician Networks

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Geisel Medical School at Dartmouth
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Acknowledgements

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Outline

1. Introduction to social networks and social network analyses
   • Three key general types of problems in networks

2. Example 1: Accounting for variation in whether use of implantable cardiac defibrillators (ICDs) is within guidelines

3. Example 2: Modeling the inter-hospital diffusion in adoption of capability to implant ICDs
A social network consists of one or more sets of actors—also known as “units,” “nodes,” or “vertices”—together with the possibly directed relationships or social ties among them.
Components of a social network

• **Actors:**
  - Individual persons (e.g., patients or clinicians)
  - Organizations (e.g., hospitals)
  - Health states (e.g., diseases)
  - Work products (e.g., academic papers)

• **Social ties:**
  - Communication
  - Influence
  - Trust or affect (e.g., friendship)
  - Affiliations (e.g., co-authors)

• **Attributes:**
  - Actors, relationships, or both
Layers of Networks in Medicine

Barabási (New England Journal of Medicine 2007)
Spread of Obesity in Framingham Heart Study (Christakis and Fowler, 2007)
Social network of physicians in a Boston health clinic

Spring embedder algorithm determines positions of actors (Fruchterman and Reingold 1991)

Network of Hospitals in Two Adjourning Health Referral Regions (Moen et al, 2015)

Gary, IN (181) – blue
South Bend, IN (187) – green

**Edges:** Thickness reflects # cardiovascular disease patients treated at both hospitals by at least one physician
Biological network
(genes as nodes, shared proteins reflect edges)

Gene network

Adapted from: Goh, Cusick, Valle, Childs, Vidal & Barabási (PNAS 2007)
Human Disease Network
(health phenotypes as nodes; edges reflect shared genes)

Adapted from: Goh, Cusick, Valle, Childs, Vidal & Barabási (PNAS 2007)
Three “Important” Types of Social Network Problems

I. Do features of social networks correlate with health outcome variables of interest?
   - Multiple networks
   - Example: do network characteristics of a health care organization and the network positions of providers caring for a patient within the system correlate with utilization, quality and cost of care?

II. Do physicians influence one another, leading to diffusion of medical ideas/habits/practices?
   - Example: diffusion of use of medical treatments across physicians
   - Long history of work (Coleman, 1957, 1966)

III. What factors affect the structure of a network and the formation/dissolution of relationships?
   - Examples: similarity of personal characteristics or institutional training (homophily), reinforcement of relationships (e.g., triadic closure)
Theoretical framework and scope of ongoing network research at Dartmouth

Care utilization
Clinical guideline adherence
Diffusion/Adoption of new treatments/technologies

Physician network  Patient outcome

Communication
Coordination
Influence
Referral

Detection and diagnosis
Treatment strategy
Disease management

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• Use network science and social network statistical methods to determine whether physician networks and network positions of physicians or hospitals within them are determinants of health outcome variables.

• For each network or actor within, generate summary measures of their features that are used as predictors of health utilization variables.

Example of Problem Type I: Multiple Networks
# Measurement of the **physician network**

<table>
<thead>
<tr>
<th>Method</th>
<th>Pros</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Survey</td>
<td>Direct measure</td>
<td>Time intensive</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Generalizability issues</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Health topic-specific</td>
</tr>
<tr>
<td>RFID tags</td>
<td>Direct measure (interaction/contact)</td>
<td>Participation decline over study period</td>
</tr>
<tr>
<td></td>
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<td>Extensive staff commitment</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Battery life issues</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Generalizability issues</td>
</tr>
<tr>
<td>Administrative data on patient-sharing</td>
<td>Inclusive of all physicians</td>
<td>Indirect measure of relationship</td>
</tr>
<tr>
<td></td>
<td>Data already exist</td>
<td></td>
</tr>
</tbody>
</table>
Measurement of the network of physician professional ties from claims data

Patients’ medical visits during a period of time:

Patient – physician complexities
- Multiple encounters
- Different medical reasons for encounters
- Varying importance of encounters

Physician – physician complexities
- Multiple overlapping patients
- Different patient medical conditions
- Different level of care requirements across patients

Overlap suggests professional relationship between A and B
Construction of network from Medicare claims

Patients with relevant condition/status

Physician (color denotes hospital)

Adjacency matrix of weighted edges between physicians (shared patients)

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
<td>3</td>
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<td>B</td>
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<td>1</td>
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<tr>
<td>C</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>D</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Sum 2x2 quadrants to get network with hospitals as nodes
Hospital-Level Social Network in 2011
(Only Top 25% Degree Hospitals Shown)

Node size corresponds to hospital’s degree
Edge thickness reflects shared patient care

Prepared by Erika Moen
Networks of Physicians in 4 Health Referral Regions (Landon et al 2012, JAMA)

Points are physicians
- Color = hospital affiliation
- Lines are connections with ≥10 shared patients

A

B

C

D

PCP
- Medical Specialist
- Surgical Specialist
- Other Specialist

James O'Malley, Ph.D.
Social network of physicians in a Boston health clinic

Spring embedder algorithm determines positions of actors (Fruchterman and Reingold 1991)

Density – number of edges divided by the maximum possible number of edges

= Degree averaged across nodes

Hospital density and variation in care

• Hospitals with a higher density of physician ties have higher costs and more intensive care (Barnett et al, 2012)
Centralization – the extent to which there is a subgroup of highly central actors in the network

Hospital centralization and variation in care: We have found greater centralization associated with greater utilization
Centralization – the extent to which there is a subgroup of highly central actors in the network

High centralization
Low centralization

Network centralization

Hospital centralization and variation in care: We have found greater centralization associated with greater utilization

Network positional summarization examples

Clustering coefficient

Fraction of connections among neighbors of given actor (e.g., physician). In this example Clust. Coef. = 4/10

Betweenness centrality

Fraction of geodesic (shortest) paths between other actors (e.g., physicians) that pass through given actor; bigger = more central actor

Hospitals with high centrality of primary care physicians have lower costs and care intensity (Barnett et al, 2012)
Transitivity ("A friend of a friend is a friend")

- Sociologists → Triads are an important building block of society
- Triadic clustering is a special form of clustering
- Undirected network: the count of triangles is the basis of transitivity
- Directed network:
  - $4^3 = 64$ states of a triad
  - 16 triad groups that are non-isomorphic; embody multiple sociological constructs
  - The **transitive triad** (shown above for actor A) is perhaps of greatest interest
ICDs use electrical pulses or shocks to control potentially life-threatening ventricular arrhythmias in patients with heart failure.

Surgery is primarily performed by electrophysiologists, cardiologists, and thoracic surgeons.

Disagreement on appropriateness; therapeutic benefit versus quality of life.

Benefits depend on patient characteristics.

High cost of device.
ICD therapy guidelines

Clinical Guidelines ≠ Clinical Practice

1. Ejection fraction ≤35%
2. Patient’s symptoms are NYHA Class II or III
3. At least 40 days post myocardial infarction

A retrospective cohort study found that 22.5% of patients who received ICD therapy do not meet clinical guidelines.

(Al-Khatib et al. JAMA, 2011)
Example 1: Guideline consistency of ICD utilization

**Question**: Are the within-hospital network importance of the implanting surgeon or the importance of the referring or implanting hospitals in the US hospital network associated with ICD guideline consistency?

- Network importance measured by degree (but lots of alternatives)
- Outcome measures overuse, but not underuse, of ICD therapy
- Research focuses on patients at hospitals not equipped to perform ICDs as care more likely to be dependent on between-hospital ties for referral
Outcome data development is distinct from development of physician and hospital networks.
Hierarchical model with network positional measures of 3 sources of clinical influence as predictors

- Patient-level logistic regression
- $i = \text{HRR}, j = \text{provider}, k = \text{patient}$
- Five types of network variables
- Lag network-based predictors by a year

\[
\text{logit}(E[\text{InGuide}_{ijk} | \theta_i, \delta_{ij}]) = \beta_0 + \beta_1 \text{Covariates}_{ijk} + \beta_2 \text{ProvPos}_{ij} + \beta_3 \text{ReferralHospPos}_i + \beta_4 \text{ReferralHospStructure}_i + \beta_5 \text{SurgeryHospPos}_i + \beta_6 \text{SurgeryHospStructure}_i + \theta_i + \delta_{ij}
\]

where $\theta_i \sim \text{Normal}(0, \sigma^2)$ and $\delta_{ij} \sim \text{Normal}(0, \tau^2)$
## Results: ICD implanting physician

<table>
<thead>
<tr>
<th></th>
<th>Concurrent year analyses</th>
<th>Lagged year analyses</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Odds ratio (95% CI)</td>
<td>p-value</td>
</tr>
<tr>
<td>ICD implanter (physician)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Betweenness centrality</td>
<td>0.81 (0.18, 3.65)</td>
<td>0.785</td>
</tr>
<tr>
<td>Cardiologist</td>
<td>1.77 (1.37, 2.29)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Clinical trial count</td>
<td>0.99 (0.95, 1.04)</td>
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<tr>
<td>Publication count category</td>
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<tr>
<td>None</td>
<td>referent</td>
<td></td>
</tr>
<tr>
<td>Low (1-24)</td>
<td>1.05 (0.91, 1.22)</td>
<td>0.495</td>
</tr>
<tr>
<td>High (&gt;25)</td>
<td>1.09 (0.89, 1.33)</td>
<td>0.408</td>
</tr>
</tbody>
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### Results: Patient’s referring hospital

<table>
<thead>
<tr>
<th></th>
<th>Concurrent year analyses</th>
<th>Lagged year analyses</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Odds ratio</td>
<td>p-value</td>
</tr>
<tr>
<td></td>
<td>(95% CI)</td>
<td></td>
</tr>
<tr>
<td>Referring hospital</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degree</td>
<td>0.49 (0.25, 0.96)</td>
<td>0.037</td>
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<tr>
<td>Betweenness centrality</td>
<td>1.14 (1.00, 1.30)</td>
<td>0.056</td>
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<tr>
<td>Urbanicity</td>
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</tr>
<tr>
<td>Urban</td>
<td>referent</td>
<td></td>
</tr>
<tr>
<td>Large town</td>
<td>1.00 (0.85, 1.16)</td>
<td>0.961</td>
</tr>
<tr>
<td>Small town</td>
<td>0.92 (0.76, 1.11)</td>
<td>0.359</td>
</tr>
<tr>
<td>Teaching status</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Teaching</td>
<td>0.84 (0.62, 1.13)</td>
<td>0.245</td>
</tr>
</tbody>
</table>

## Results: ICD surgery hospital

<table>
<thead>
<tr>
<th></th>
<th>Concurrent year analyses</th>
<th></th>
<th>Lagged year analyses</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Odds ratio (95% CI)</td>
<td>p-value</td>
<td>Odds ratio (95% CI)</td>
<td>p-value</td>
</tr>
<tr>
<td>ICD surgery hospital</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degree</td>
<td>1.61 (0.98, 2.64)</td>
<td>0.059</td>
<td>1.67 (0.97, 2.89)</td>
<td>0.064</td>
</tr>
<tr>
<td>Betweenness centrality</td>
<td>0.94 (0.89, 1.00)</td>
<td>0.067</td>
<td>0.93 (0.87, 1.00)</td>
<td>0.049</td>
</tr>
<tr>
<td>Urbanicity</td>
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<td></td>
</tr>
<tr>
<td>Urban</td>
<td>referent</td>
<td></td>
<td>referent</td>
<td></td>
</tr>
<tr>
<td>Large town</td>
<td>1.08 (0.76, 1.55)</td>
<td>0.660</td>
<td>1.07 (0.71, 1.60)</td>
<td>0.756</td>
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<tr>
<td>Small town</td>
<td>1.44 (0.37, 5.67)</td>
<td>0.602</td>
<td>1.24 (0.30, 5.08)</td>
<td>0.764</td>
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<tr>
<td>Teaching status</td>
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<td></td>
</tr>
<tr>
<td>Teaching</td>
<td>1.06 (0.88, 1.28)</td>
<td>0.567</td>
<td>1.05 (0.85, 1.30)</td>
<td>0.644</td>
</tr>
</tbody>
</table>

The connectedness of hospitals involved in the referral was associated with guideline adherence

- Patients were more likely to meet guidelines if:
  - Their assigned hospital had fewer connections to other hospitals
  - Their ICD surgery hospital had more connections

Regionalization of specialized ICD services may promote adherence to guidelines

- If referring hospitals have fewer connections (enforcing existing information/referral paths) this could lead to more efficient relationships, improved communication/learning, and thus increased adherence to guidelines
Visualization of “Regionalization”

- Referring hospitals have fewer connections!!!
Many other network measures at multiple levels of aggregation!

- 306 HRRs
  - Density
  - Centralization
  - Degree Assortativity
  - Unipartite Average Clustering
  - Bipartite Average Clustering
  - Number of Physicians
  - ICD-related metrics
    - Total number of ICDs
    - Proportion of evidence-based ICDs

- ~4,000 Hospitals
  - Density
  - Centralization
  - Degree Assortativity
  - Unipartite Average Clustering
  - Bipartite Average Clustering
  - Number of Physicians
  - ICD-related metrics
    - Total number of ICDs
    - Proportion of evidence-based ICDs

- >300,000 Physicians
  - Degree
  - Betweenness Centrality
  - Closeness Centrality
  - Eigenvector Centrality
  - Clustering Coefficient
Problem type 2: Social influence analysis

- **Network defines predictors**
  - Do physicians or hospitals influence one another (``social influence'')
  - Example, adoption of a new medical technology

- **Endogenous peer effects**
  - Does the behavior of peer physician or hospital affect the focal physician’s or hospital’s behavior?

* $Y, X = Y_{peer}, X_{peer}$

Exogenous peer effects Does the treatment received by my peers affect my outcome (above and beyond my treatment)?
Interest in studying peer effects in networks

The Spread of Obesity in a Large Social Network Over 32 Years

Nicholas A. Christakis, M.D., Ph.D., M.P.H., and James H. Fowler, Ph.D.

They used a unique and controversial identification strategy!
Why Estimate Peer Effects?

1. Justify budget-limited interventions to stop spread of bad practices in ICD utilization
   • Intervene (e.g., educate) a fraction of physicians or hospitals
   • Ideally, target hospitals strategically positioned to have the greatest influence on other hospitals

2. Evaluate full effect of an intervention
   • Peer effects measure extent that end up intervening on the untreated
   • Account for spillover effects (Sobel 2006)
   • “Collateral effects” (Christakis 2004)
Micro-level ("Peer-Effect") Diffusion: focal physician behavior regressed on that of their peers

- **Example 1**: Physician peer-to-peer influence of ICD utilization over time
  - **Peer effects**: core, elementary form of diffusion
  - Is there evidence of hospital-hospital influence on ICD capability adoption
  - If so, is modified by structural position in network?
    → Justify selecting certain physicians for limited-budget interventions
  - O’Malley, Moen, Bynum, Austin, Skinner (submitted)

- **Example 2**: Peer effect of another physician’s patient having an adverse reaction following a colonoscopy *(beyond effect of adverse reactions within own patient cohort)*
  - With Keating, Landon, and Onnela (Submitted)
  - Not discussed today
Regression of ICD equipped status

- Let $y_{it}$ denote ICD status ($1 = \text{equipped}, 0 = \text{not-equipped}$) at time $t$
- Key predictor is the prior year weighted average of $y_{it}$ over the peer hospitals of hospital $i$
- We used the network strength (number of shared patients) of the edges between the hospitals as weights, $W$
- Thus, model has the form
  \[
  y_{it} \mid y_{i(t-1)} = j \sim \text{Bernoulli}(p_{it}(j))
  \]
  where \(\text{logit}(p_{it}(j)) = \theta_{ij} + \beta_{1j} x_{i(t-1)} + \beta_{2j} [W_{t-1}Y_{t-1}]_i\)
  and $\theta_{ij} \sim \text{Normal}(\beta_{0j}, \tau_{j}^2)$ is a random effect for hospital and $x$ is a vector of control predictors
Regression of ICD equipped status: Add Network Positional Variables and geographic control

- Full model interacts the weighted average $WY$ with hospital $i$’s network strength
- Model given by: $logit(p_{it}(j))$
  
  $$
  = \theta_{ij} + \beta_{1j} x_{i(t-1)} + \beta_{2j}[W_{t-1}Y_{t-1}]_i + \beta_{3j}[G_{t-1}Y_{t-1}]_i \\
  + (\beta_{4j}[W_{t-1}Y_{t-1}]_i + \beta_{5j}[G_{t-1}Y_{t-1}]_i)d_{i(t-1)}
  $$

  where $d_{i(t-1)}$ is the network weighted degree (strength) of physician $i$ at time $t-1$

- $G$ is a weight matrix based on geodesic distances
- In future work, we may add additional ego and peer variables for number of implants and referrals to account for inertia and the extent of the implanting or referring

4/20/2018
ICD Adoption of Equipped Status

ICD Adoption: 306 hrrs, 3720 hospitals, 12716 observations

<table>
<thead>
<tr>
<th>Term</th>
<th>Estimate</th>
<th>z-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag network strength</td>
<td>-1.593</td>
<td>-2.67</td>
<td>0.008</td>
</tr>
<tr>
<td>Lag peer equipped</td>
<td>-0.391</td>
<td>-1.29</td>
<td>0.198</td>
</tr>
<tr>
<td>Lag peer equipped*network strength</td>
<td>2.295</td>
<td>2.81</td>
<td>0.005</td>
</tr>
<tr>
<td>Lag peer referral</td>
<td>0.268</td>
<td>0.58</td>
<td>0.564</td>
</tr>
<tr>
<td>Lag peer implant</td>
<td>-0.146</td>
<td>-0.58</td>
<td>0.561</td>
</tr>
<tr>
<td>Lag geographic equipped</td>
<td>22.750</td>
<td>4.67</td>
<td>0.000</td>
</tr>
<tr>
<td>Lag geographic referral</td>
<td>-0.607</td>
<td>-4.30</td>
<td>0.000</td>
</tr>
<tr>
<td>Lag geographic implant</td>
<td>-0.059</td>
<td>-1.27</td>
<td>0.204</td>
</tr>
<tr>
<td>Var(hospital, HRR)</td>
<td>1.15 +/- 1.07, 0.49 +/- 0.70</td>
<td></td>
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</tr>
</tbody>
</table>

A non-capable hospital with strong connections to peer hospitals who have the capability to implant ICDs is more likely to acquire the capability to implant ICDs
### ICD De-adoption: 305 hrrs, 1410 hospitals, 4418 observations

<table>
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<tr>
<th>Term</th>
<th>Estimate</th>
<th>z-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag network strength</td>
<td>-1.670</td>
<td>-3.01</td>
<td>0.003</td>
</tr>
<tr>
<td>Lag peer equipped</td>
<td>-1.456</td>
<td>-3.27</td>
<td>0.001</td>
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<tr>
<td>Lag peer equipped*network strength</td>
<td>2.216</td>
<td>2.75</td>
<td>0.006</td>
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<tr>
<td>Lag peer referral</td>
<td>-0.055</td>
<td>-0.07</td>
<td>0.943</td>
</tr>
<tr>
<td>Lag peer implant</td>
<td>-0.322</td>
<td>-1.14</td>
<td>0.254</td>
</tr>
<tr>
<td>Lag geographic equipped</td>
<td>-4.753</td>
<td>-1.15</td>
<td>0.248</td>
</tr>
<tr>
<td>Lag geographic referral</td>
<td>-0.042</td>
<td>-0.29</td>
<td>0.773</td>
</tr>
<tr>
<td>Lag geographic implant</td>
<td>-0.029</td>
<td>-0.78</td>
<td>0.433</td>
</tr>
<tr>
<td>Var(hospital, HRR)</td>
<td>0.84 +/- 0.92, 0.00 +/- 0.00</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

An ICD capable hospital with strong connections to peer hospitals who have the capability to implant ICDs is more likely to remain ICD capable.
Causality Concerns

• **Homophily**: “Birds of a feather flock together”
  • Individuals with similar behaviors more likely to become friends
  • Physicians who train together have similar treatment preferences and more likely to subsequently work together?
  • Tie-dissolution due to diverging viewpoints or attitudes over time

• **Unmeasured common causes**
  • Unknown peer physicians
  • Regional activities (e.g., marketing campaign)
  • Exposure to marketing or the same supplier of free medical products
Social influence analysis causal challenges

• Overlapping groups of individuals yield the predictor(s) of individuals’ outcomes!
  • Reflection problem (Manski, 1993)
• Statistical analysis challenging if seek causal claim when network not formed at random!
  • Complicated simultaneous equations model can be used but makes strong assumptions
• Longitudinal data helps with identification of causal effects
  • Reverse causality, simultaneity, …
  • Avoids reliance on strong parametric assumptions

Problem Type 3: Analysis of network structure

“Extra Material”

- Observed network is the outcome
- Often only observe network once (cross-sectional data)
  - Longitudinal data now becoming more common
- Are global network properties explained by local configurations or sub-networks?
  - Closed dyads: reciprocity
  - Closed triads: transitivity, 3-cycles, …
- Are individuals with particular characteristics more likely to form ties (homophily, assortative mixing, social selection)?
- Do (latent) communities underlie the network?
- Non-standard and challenging statistical analyses required!
Why Model Relationships?

- Recipe for manipulating the influences to which an individual is exposed
  - Determine factors that reinforce relationships
- Find optimal position in the network to identify actors for which intervention will have maximal impact
  - Optimize interventions on physicians, hospitals, health systems, regions
- Gain insight in how to manipulate health organization into more favorable forms
  - Identify key elements of network structure of the best Accountable Care Organization (ACO) and replicate them!
Some Key Sociological Relationships

Homophily

\[ \text{dist}(x_i, x_j) = \text{small} \]

\[ \text{I} \quad \text{---} \quad \text{J} \]

Tie more likely

\[ \text{dist}(x_i, x_j) = \text{big} \]

\[ \text{I} \quad \text{---} \quad \text{J} \]

Tie less likely

Triadic Closure (Transitivity)

\[ \text{K} \quad \text{---} \quad \text{I} \quad \text{---} \quad \text{J} \]

I,J tie leads to closure

\[ \text{K} \quad \text{---} \quad \text{I} \quad \text{---} \quad \text{J} \]

I,J tie does not lead to closure
Simple Example: Estimate effects of physician homophily on the relationships between physicians within a hospital

Exponential family random graph model (ERGM) of hospital network:

<table>
<thead>
<tr>
<th>Term</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Edge (overall density of ties)</td>
<td>-0.4238</td>
</tr>
<tr>
<td>Homophily by specialty</td>
<td></td>
</tr>
<tr>
<td>Cardiology</td>
<td>3.42</td>
</tr>
<tr>
<td>Family Practice</td>
<td>-1.39</td>
</tr>
<tr>
<td>Internal Medicine</td>
<td>0.20</td>
</tr>
</tbody>
</table>

*ICD Provider

Change in log-odds of the tie if the physicians are both cardiologists compared to if they have different specialties, conditional on the rest of the network
• Assuming dyadic independence (as in prior slide) allows model for the network to be generated from the model for the dyad
  • Allows logistic regression estimation to be used!
• Dependence between dyads arises whenever the state of one dyad depends on the state of another dyad over and above actor-specific effects
  • Triadic dependence: an edge is more (or less) likely to form if its actors have a common third actor
  • Cannot multiply probability distributions of dyads to generate model for the network!
→ Forced to model whole network simultaneously!
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