Leveraging Social Networks to Understand Behavioral and Biological Pathways in Substance Abuse and Dependence

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Social networks and health

How do social networks influence and moderate biological and behavioral pathways in health?

- Decision-making
- Access to resources
- Behavior
- Recovery
- Phenotypic expression
Ongoing projects in behavior genetics...

Genetic risk for disinhibition

Substance misuse and dependence

SOCIAL NETWORKS

Low social regulation
Permissive social norms
Access to drugs/alcohol

Exhibit A

Exhibit B

New projects...

Doctor Shopping for Controlled Substances: Insights from Two-Mode Social Network Analysis

Collaborators:
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- Trish Freeman, Clinical Associate Professor, Univ. of Kentucky
- Adam Jonas, LINKS Center, Univ. of Kentucky
Prescription drug abuse

- Prescription drug abuse “epidemic”
  - Opioid abuse increased by 4,680% between 1996 and 2011 in the U.S.
  - Prevalence of prescription drug abuse exceeds that for all other illicit drugs combined, except marijuana
  - Mortality from drug overdose is among the nation’s leading preventable causes of death

Doctor shopping

Doctor shopping = obtaining controlled substances from multiple health care practitioners simultaneously, exceeding the recommended dosage (CDC, 2014)
Doctor shopping

- 12% of all prescriptions written for controlled substances
- Nearly 40% with prescription drug dependence obtain drugs through doctor shopping
- Indicator of escalating abuse, two-fold risk for fatal overdose
- Among most difficult drug seeking behaviors to identify and address

Existing gaps and limitations

- Poor measurement of doctor shopping
  - Usually “multiple provider episodes” (binary indicator) → Type I and Type II errors
  - Huge variation in measurement and estimates (ranging from 0.2% to 8%)
  - Difficult to identify doctor shopping and understand its etiology → impedes evaluation of prescription drug policies
Existing gaps and limitations

- Characteristics of patients involved
  - Doctor shopping used by a sub-group averse to illegal behavior
  - Women, older, higher SES, oral users
  - Harder to identify

- Two patterns that suggest SNA likely to provide insights:
  - Clustering: Physicians are systematically targeted on the basis of prescription behavior or other characteristics
  - Collusion: Knowledge of prescriber targets is shared amongst doctor shoppers
Social network analysis

Why SNA?

- Ideal when key mechanisms are relational processes or flow of resources or information between actors.
- SNA has been used to identify structural anomalies (e.g. fraud) in industry and financial markets, has not been applied to prescribing networks.

One mode versus two mode (affiliation) networks

- Standard one mode network
- Two mode affiliation network
- Weighted one mode affiliation network
What can be done with two mode SNA?

- Examine prescribers linked indirectly through co-visitation by the same doctor shoppers, and vice versa
  - Clustering?
  - Develop SNA measures of doctor shopping
  - Identify characteristics of central actors
  - Link to prescription drug outcomes

Data

- Deidentified patient health claims info from a large commercially insured population from 2007-2009
  - 15 million patients annually, with private insurance and Medicaid
  - Nationally-representative of the US with regard to gender (50% men), regional distribution, and age
Data

- Analysis sample = any patient who filled one or more opioid or benzodiazepine prescriptions and every clinician who prescribed to one of these patients

- 5,197,238 patients; 718,146 prescribers

Preliminary analyses

- A priori identification of doctor shopping (not deductive) = 4 prescriptions + 4 pharmacies criterion
- Only one mode weighted affiliation networks of clinicians
  - Degree centrality (# of ties to other clinicians through common doctor shopper)
  - Correlation of centrality to other measures
  - Visualization
Preliminary results

- 89,297 clinicians prescribed to at least one doctor shopper (12%)
- Mean degree centrality = 23.15
- Standard deviation = 61.48
- Range* = 0 – 995

*Most central prescriber in the network had been doctor shopped by 995 patients who also shopped another clinician in 1 year

Figure 1. Weighted one mode affiliation network of clinicians where degree centrality ≥ 4

Result is a large network of 7,288 doctors tied by 45,181 co-prescribing relationships.

About 76% of prescribers are connected in one main component that consists of 99.96% of all ties (Figure 1).

Node size = weighted degree centrality
Node color = Community
Line thickness = number of co-prescription ties

A strong ‘core’ of doctors and several subgroups clearly emerge.
Largest cluster forms a k-core of 19; is made up of 755 nodes (10.5%); accounts for 21,904 ties (48.8%)

Can see substantial co-prescribing in this figure between some communities, but not others.
23 communities
Node size = # clinicians
Line thickness = # of co-prescriptions

Figure 2. Ties between communities of clinicians in a large weighted one mode affiliation network

Table 1. Correlation between clinician degree centrality and aggregate patient characteristics

<table>
<thead>
<tr>
<th>Patient characteristics</th>
<th>Pearson’s r</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Severity of doctor shopping</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg # pharmacies</td>
<td>0.28</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Avg # prescriptions</td>
<td>0.21</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Avg # MPEs</td>
<td>0.43</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Avg # repeat visits</td>
<td>0.13</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Socio-demographics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% female</td>
<td>0.03</td>
<td>NS</td>
</tr>
<tr>
<td>% of patients on Medicaid</td>
<td>0.34</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Avg net worth</td>
<td>-0.08</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Avg age</td>
<td>-0.14</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Quantity prescribed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg # refills</td>
<td>-0.06</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Avg days of medication</td>
<td>-0.08</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Avg dose in mgs</td>
<td>-0.06</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>
Summary of findings

- There is substantial nonrandom clustering
  - Several very active communities (Drug rings? Pain clinics?) with ties to each other and to outside communities
  - Suggests that clinicians may be systematically targeted
  - Suggests collusion on the part of doctor shoppers and/or prescribers

Summary of findings

- Clinicians who are active in networks have significantly different patient populations
  - Involved in more serious drug abuse or diversion
  - Lower SES and younger
Summary of findings

- Clinicians who are more active prescribe lower quantities per patient
  - May be suspicious and want to reduce harm
  - May be complicit and want to maintain demand

Insights from SNA

- May be able to reduce errors of classification using SNA measures
  - Who patients target may be just as important for identifying doctor shopping as how many prescribers they visit
  - Improve ability to detect early signs of prescription drug abuse, behavior that is intermittent or less intense, but still problematic
Future directions

- Use SNA measures to establish doctor shopping criteria deductively
- Establish validity
  - Do SNA measures explain variance in drug abuse outcomes above and beyond MPEs?
  - Correlation with traditional criteria?
- Use social network informed criteria to examine characteristics of doctor shopping patients and their clinicians

THANK YOU!
Extra Slides

Ongoing projects in behavior genetics...

- Female, High risk genotype
- Male, High risk genotype
- Female, Low risk genotype
- Male, Low risk genotype

* n by group: Female, high-risk = 403; Female, low-risk = 873; Male, high-risk = 321; Male, low-risk = 684