Toward Evaluation of Disseminated Effects of HIV Prevention Interventions Among Networks of People who Inject Drugs

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# Outline





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### Definition

#### Implementation Science

Translation and scale-up of research evidence into practice (Madon et al., 2007; Padian et al., 2011)

- Natural clustering by social network or community
- Biological and social influence in networks
- Understanding this influence can inform public health practice and policy

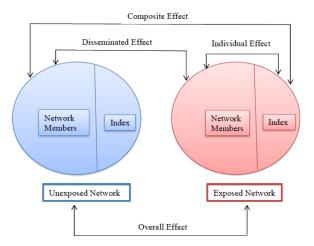
# Causal Inference

- A Potential Outcome (i.e., Counterfactual)
  - Y(0): Response that would have been seen if (possibly contrary to fact) the participant were not exposed
  - Y(1): Response that would have been seen if (possibly contrary to fact) the participant were exposed
- Assumptions: Consistency, No Interference, Positivity, Exchangeability (Cole and Frangakis, 2009; Rubin, 1980)
- With associations, we can predict the future. With causation, we can change the future.

### Two-stage Randomized Design

- One approach to conduct causal inference with interference or dissemination is to use two-stage randomized design (Halloran and Struchiner (1991), Hudgens and Halloran (2008)).
- In this design, networks/communities are randomly assigned to an allocation strategy of exposure (or coverage of exposure) at the first stage, then, in the second stage, individuals in a community are randomly exposed according to the coverage assigned in the first stage.
- **Coverage** of exposure is defined as the proportion of subjects who are exposed in a certain community.

# Cluster-Randomized Trial



Adapted from Halloran and Struchiner (1991, 1995).

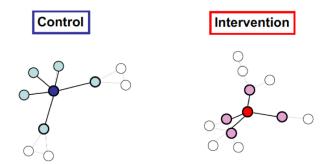
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Introduction

### Network-Based Study



Adapted from Benjamin-Chung, et al. (2017).

- Connections: Shared HIV risk (injection or sexual)
- Index shaded blue or red nodes
- Nearest neighbors outlined nodes

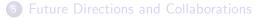
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### Study Motivation

- Injection drug use increases HIV risk through sharing equipment (e.g. syringes, needles, etc.) and often correlates with risky sexual behaviors
- PWIDs are not only at high risk of HIV infection, but also face unique barriers along the HIV treatment cascade (Ghosh et al., 2017)

#### Primary Motivation

PWIDs are embedded in HIV/AIDS risk network and such network structure can support and sustain **positive behavioral change** via interventions that leverage network structure.

# Motivating Example

#### The Social Factors and HIV Risk Study (SFHR)

- Sociometric network study conducted between 1991 and 1993 in Bushwick, Brooklyn, New York among *street-recruited injection drug users*
- Investigated how HIV/AIDS infection spread through shared sexual and injection risk behaviors.
- 767 participants along with 3,162 dyadic relationships (i.e. a connection b/w two people).
- Connections were shared risk behaviors (i.e. inject drug together and/or having sexual intercourse) within 30 days before the interview.

full network

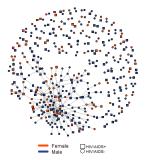
### Goal of the Study

- To assess attitudes toward HIV/AIDS risk among PWIDs and their effect on health-seeking behaviors.
- Used **causal inference methods** under the presence of *dissemination or spillover effects* in an observational study.
- Exposures were (1) health beliefs and (2) blame attributes of each participants.
- Outcomes were (1) receipt of study-based HIV testing result and (2) a recent medical visit within the past year.

Motivation

### SFHR PWIDs Network for Analysis

SFHR PWIDs Network



A network (or graph) G is defined as a collection of vertices (or nodes) (V) and edges (or links)(E), G = (V, E). Here, G is the SFHR PWIDs network.

Figure 1: SFHR PWIDs Network for Analysis. There are 402 vertices and 403 edges. Motivation

## SFHR PWIDs Network for Analysis

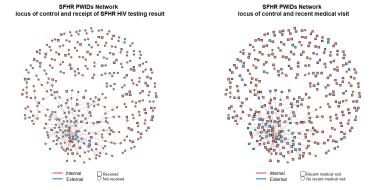


Figure 2: The Social Factors and HIV Risk Study PWIDs' network for the analysis. Locus of control and receipt of HIV testing result (Left) and recent medical encounter (Right).

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#### Data Pre-processing

Table 1: Questions about Health Beliefs in SFHR (5-point Likert Scale)

Questions related to belief (BLF)

- Q1. It is my own behavior which determines whether I get AIDS or not.
- Q2. No matter what I do, if I'm going to get AIDS, I will get AIDS.
- Q3. I'm in control of whether or not I get AIDS.
- Q6. Getting AIDS is largely a matter of bad luck.
- Q7. No matter what I do, I'm likely to get AIDS.
- Q8. If I take the right actions, I can avoid getting AIDS.
- Q10. No matter what I do, I'm unlikely to get AIDS.

Questions related to blame (BLM)

- Q4. My family have a lot to do with whether I get AIDS.
- Q5. If I get AIDS, I'm not to blame.
- Q9. If I get AIDS, it is because of the society we live in.

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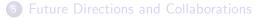
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#### **Causal Parameters**

Direct effect : 
$$\overline{DE}(\alpha) = \overline{Y}(a = 0; \alpha) - \overline{Y}(a = 1; \alpha)$$

$$\textit{Indirect effect}: \quad \overline{\textit{IE}}(\alpha, \alpha') = \overline{\textit{Y}}(\textit{a} = \textit{0}; \alpha) - \overline{\textit{Y}}(\textit{a} = \textit{0}; \alpha')$$

$$\textit{Total effect}: \quad \overline{\textit{TE}}(\alpha, \alpha') = \overline{\textit{Y}}(\textit{a} = \textit{0}; \alpha) - \overline{\textit{Y}}(\textit{a} = \textit{1}; \alpha')$$

$$\begin{array}{ll} \textit{Overall effect}: & \overline{\textit{OE}}(\alpha, \alpha') = \overline{\textit{Y}}(\alpha) - \overline{\textit{Y}}(\alpha') \\ \\ & \text{coverage: } \alpha < \alpha' \end{array}$$

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# Causal Inference with Observational Study Data

• Inverse probability weighting (IPW) method to adjust for confounding in an observational study (Tchetgen and VanderWeele, 2012)

#### APPROACH

- 1. Split the SFHR network into smaller subnetworks/ communities of PWIDs.
- Calculate group-level propensity score (i.e., probability of having specific attitude toward HIV/AIDS risk) for each subnetwork based on individual-level covariates of sex, race, education, age and their pairwise interactions.
- 3. Use the inverse of propensity scores as weights to compute IPW estimators of potential outcomes.

Image: A 1 → A

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#### Assumptions

- Partial interference: Allow interference within a subnetwork/community, but not between subnetworks.
- (2) **Stratified interference**: Individual's potential outcome is dependent only on own exposure and the proportion of exposed in the community.
- (3) Bernoulli individual group allocation strategy: The distribution of exposure selection mechanism A is assumed to be a Bernoulli distribution and used to define the potential outcomes Y<sup>a</sup>.
- (4) No homophily: Assume there is no latent variables related to health-seeking behavior with which an individual has a tie with another individual who has the similar characteristics.
- (5) Well-defined interventions: Locus of control is a well defined exposure and there is no other version of locus of control in the study.
- (6) Positivity: Probability of exposure is positive given each level of covariates.
- (7) **Conditional exchangeability**: Assume that conditioning on a set of covariates is sufficient to control confounding.

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# **Community Detection**

- **Community**: A set of vertices densely connected, with only sparser tie to vertices that belong to other groups or communities.
- Hierarchical clustering: Common methods for community detection where the closest or most similar vertices are combined to form communities with a measure of similarity or connection strength between vertices based on the network structure.
- As the measure of similarity, we use **modularity** (Kolaczyk, 2009; Newman, 2006)

#### Modularity

**Modularity** is defined as following:

- Assume there are  $C = \{C_1, C_2, \cdots, C_K\}$  candidate of K communities in an observed network G.
- We also define  $f_{ij} = f_{ij}(C)$  as the fraction of edges in the original network that connect vertices in cluster *i* with vertices in cluster *j*,  $i \neq j$ .
- Given this,

$$mod(C) = \sum_{k=1}^{K} [f_{kk}(C) - f_{kk}^*]^2,$$
 (1)

where  $f_{kk}$  is the fraction of edges which connect vertices within the same cluster k in G, and  $f_{kk}^*$  is the expected value of  $f_{kk}$  under some model of random edge assignment.

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# IPW estimation: Group-Level Propensity Score

Group-level propensity score can be calculated by adjusting for individual-level covariates among those in the community.

$$f_{A_i|X_i}(A_i|X_i;\theta_x,\theta_s) = \int \prod_{j=1}^{n_i} h_{ij}(b_i;\theta_x)^{A_{ij}} \{1 - h_{ij}(b_i;\theta_x)\}^{1-A_{ij}} f_b(b_i;\theta_s) db_i$$

where

 $h_{ij}(b_i; \theta_x) = Pr(a_{ij} = 1 | X_{ij}, b_i, \theta_x) = logit^{-1}(X_{ij}\theta_x + b_i)$  is a propensity score for *j*th individual in community *i* and  $f_b(\cdot; \theta_s)$  is the density of community specific random effect and assume  $b_i \sim N(0, \theta_s)$ .

#### IPW estimation: IPW estimator

#### IPW estimator for group-level potential outcome:

$$\hat{Y}_{i}^{ipw}(\boldsymbol{a},\alpha) = \frac{\sum_{j=1}^{n_{i}} \pi_{i}(A_{i,-j};\alpha) I(A_{ij}=\boldsymbol{a}) Y_{ij}}{n_{i} f_{A_{i}|X_{i}}(A_{i}|X_{i};\hat{\theta})}$$
(2)

Marginal potential outcome:

$$\hat{Y}_i^{ipw}(\alpha) = \frac{\sum_{j=1}^{n_i} \pi_i(A_i; \alpha) Y_{ij}}{n_i f_{A_i|X_i}(A_i|X_i; \hat{\theta})}$$
(3)

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#### Population-level IPW estimators

$$\widehat{DE}(\alpha) = \hat{Y}^{ipw}(a = 0; \alpha) - \hat{Y}^{ipw}(a = 1; \alpha)$$

$$\widehat{\mathit{lE}}(lpha,lpha')=\hat{Y}^{\mathit{ipw}}(\mathit{a}=\mathsf{0};lpha)-\hat{Y}^{\mathit{ipw}}(\mathit{a}=\mathsf{0};lpha')$$

$$\widehat{\mathsf{TE}}(\alpha,\alpha') = \hat{Y}^{ipw}(\mathbf{a} = 0; \alpha) - \hat{Y}^{ipw}(\mathbf{a} = 1; \alpha')$$

$$\widehat{\textit{OE}}(lpha, lpha') = \hat{Y}^{\textit{ipw}}(lpha) - \hat{Y}^{\textit{ipw}}(lpha')$$
  
coverage:  $lpha < lpha'$ 

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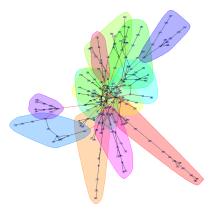


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#### Modularity-based Community Detection

85 connected components and one of them forms the giant component that include 199 participants. In total, **96 communities** in the SFHR network for analysis.



# Descriptive Statistics (1)

# Table 2: The Relationship between Locus of Control andHealth-Seeking Behaviors

	Odds Ratio (95% CI)					
	Giant	Not Giant	Total			
Received 1.94 (0.55, 6.85) Not received		1.64 (0.59, 4.57)	1.87 (0.85, 4.11)			
Recent medical visit No recent medi- cal visit	1.32 (0.49, 3.56)	0.88 (0.28, 2.72)	1.07 (0.51, 2.24)			

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# Descriptive Statistics (2)

Table 3: The Relationship between Blame and Health-Seeking Behaviors

	Odds Ratio (95% CI)					
	Giant	Not Giant	Total			
Received Not received	1.35 (0.56, 3.29)	1.00 (0.52, 1.98)	1.15 (0.68, 1.96)			
Recent medical visit No recent medi- cal visit	1.09 (0.47, 2.55)	0.89 (0.39, 1.99)	0.96 (0.54, 1.74)			

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Results

# Observed Distribution of Locus and Blame Coverages

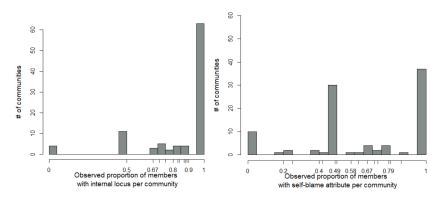


Figure 3: Observed coverages of subjects with internal locus (left) and subjects with self-blame (right).

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### Causal Inference: IPW estimation - Model 1

Table 4: Estimated risk differences (RDs) with 95% Cls of locus of control (external vs. internal) on likelihood of receiving HIV test results in SFHR (coverage of internal)

		Unadjusted		Adjusted	I with interactions
Effect	Coverage $(\alpha, \alpha')$	RD	95% CI	RD	95% CI
Direct	(50%, 50%)	-0.148	(-0.230, -0.065)	-0.160	(-0.265, -0.055)
Direct	(70%, 70%)	-0.142	(-0.246, -0.038)	-0.162	(-0.268, -0.055)
Direct	(99%, 99%)	-0.101	(-0.258, 0.056)	-0.130	(-0.268, 0.008)
Indirect	(50%, 70%)	-0.041	(-0.071, -0.012)	-0.031	(-0.054, -0.008)
Indirect	(50%, 99%)	-0.070	(-0.156, 0.019)	-0.062	(-0.123, 0.000)
Indirect	(70%, 99%)	-0.029	(-0.098, 0.040)	-0.030	(-0.072, 0.011)
Total	(50%, 70%)	-0.183	(-0.271, -0.096)	-0.193	(-0.286, -0.100)
Total	(50%, 99%)	-0.172	(-0.278, -0.066)	-0.192	(-0.291, -0.093)
Total	(70%, 99%)	-0.130	(-0.254, -0.006)	-0.161	(-0.272, -0.049)
Overall	(50%, 70%)	-0.067	(-0.096, -0.038)	-0.065	(-0.089, -0.041)
Overall	(50%, 99%)	-0.097	(-0.183, -0.010)	-0.111	(-0.190, -0.032)
Overall	(70%, 99%)	-0.030	(-0.095, 0.035)	-0.046	(-0.105, 0.013)

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### Associations with Recent Medical Visit - Model 2

Table 5: Estimated risk differences (RDs) with 95% Cls of locus of control (external vs. internal) on likelihood of a recent medical visit in SFHR (coverage of internal)

		Unadjusted		Adjusted	d with interactions
Effect	Coverage $(\alpha, \alpha')$	RD	95% CI	RD	95% CI
Direct	(50%, 50%)	0.211	(-0.286, 0.708)	0.090	(-0.271, 0.451)
Direct	(70%, 70%)	0.003	(-0.296, 0.301)	-0.111	(-0.346, 0.123)
Direct	(99%, 99%)	-0.227	(-0.463, 0.009)	-0.280	(-0.470, -0.089)
Indirect	(50%, 70%)	-0.001	(-0.260, 0.257)	-0.008	(-0.181, 0.165)
Indirect	(50%, 99%)	0.208	(-0.298, 0.715)	0.077	(-0.311, 0.464)
Indirect	(70%, 99%)	0.210	(-0.063, 0.482)	0.085	(-0.136, 0.305)
Total	(50%, 70%)	0.001	(-0.537, 0.539)	-0.119	(-0.496, 0.258)
Total	(50%, 99%)	-0.019	(-0.491, 0.453)	-0.203	(-0.559, 0.153)
Total	(70%, 99%)	-0.017	(-0.255, 0.220)	-0.195	(-0.409, 0.018)
Overall	(50%, 70%)	-0.105	(-0.316, 0.106)	-0.131	(-0.265, 0.003)
Overall	(50%, 99%)	-0.122	(-0.358, 0.114)	-0.246	(-0.430, -0.061)
Overall	(70%, 99%)	-0.017	(-0.082, 0.048)	-0.114	(-0.181, -0.047)

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### Causal Inference: IPW estimation - Model 3

Table 6: Estimated risk differences (RDs) with 95%Cls of blame (others vs. self) on likelihood of receiving HIV testing results in SFHR (coverage of self-blame).

		Unadjusted		Adjusted	l with interactions
Effect	Coverage $(\alpha, \alpha')$	RD	95%CI	RD	95%CI
Direct	(50%, 50%)	-0.043	(-0.164, 0.079)	-0.045	(-0.159, 0.069)
Direct	(70%, 70%)	-0.035	(-0.159, 0.088)	-0.034	(-0.154, 0.085)
Direct	(99%, 99%)	-0.077	(-0.250, 0.096)	-0.065	(-0.230, 0.100)
Indirect	(50%, 70%)	-0.002	(-0.047, 0.044)	-0.001	(-0.043, 0.041)
Indirect	(50%, 99%)	0.034	(-0.077, 0.145)	0.034	(-0.066, 0.134)
Indirect	(70%, 99%)	0.036	(-0.037, 0.109)	0.035	(-0.032, 0.102)
Total	(50%, 70%)	-0.037	(-0.164, 0.090)	-0.035	(-0.154, 0.083)
Total	(50%, 99%)	-0.043	(-0.200, 0.115)	-0.031	(-0.175, 0.113)
Total	(70%, 99%)	-0.041	(-0.197, 0.115)	-0.030	(-0.176, 0.116)
Overall	(50%, 70%)	-0.005	(-0.048, 0.038)	-0.003	(-0.042, 0.036)
Overall	(50%, 99%)	-0.021	(-0.135, 0.094)	-0.008	(-0.113, 0.097)
Overall	(70%, 99%)	-0.015	(-0.095, 0.064)	-0.005	(-0.079, 0.068)

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### Associations with Recent Medical Visit - Model 4

Table 7: Estimated risk differences (RDs) with 95%Cls of blame (others vs. self) on likelihood of reporting a recent medical encounter within the past year (coverage of self-blame)

		Unadjusted		Adjusted	l with interactions
Effect	Coverage $(\alpha, \alpha')$	RD	95%CI	RD	95%CI
Direct	(50%, 50%)	0.017	(-0.141, 0.175)	0.002	(-0.156, 0.160)
Direct	(70%, 70%)	-0.054	(-0.205, 0.096)	-0.076	(-0.213, 0.060)
Direct	(99%, 99%)	-0.209	(-0.467, 0.050)	-0.269	(-0.527, -0.011)
Indirect	(50%, 70%)	0.076	(-0.001, 0.153)	0.086	(-0.014, 0.186)
Indirect	(50%, 99%)	0.238	(0.053, 0.423)	0.272	(0.072, 0.472)
Indirect	(70%, 99%)	0.162	(0.019, 0.305)	0.186	( 0.038, 0.335)
Total	(50%, 70%)	0.022	(-0.099, 0.143)	0.009	(-0.126, 0.144)
Total	(50%, 99%)	0.029	(-0.159, 0.218)	0.003	(-0.214, 0.219)
Total	(70%, 99%)	-0.047	(-0.263, 0.170)	-0.083	(-0.299, 0.133)
Overall	(50%, 70%)	0.029	(-0.022, 0.081)	0.031	(-0.054, 0.117)
Overall	(50%, 99%)	0.023	(-0.119, 0.164)	0.005	(-0.178, 0.187)
Overall	(70%, 99%)	-0.007	(-0.148, 0.134)	-0.027	(-0.183, 0.130)

## Discussion

- Additional benefit to reporting internal locus beyond being around those who have internal for likelihood of receipt of HIV test result
- Among those with external locus, having more community members with internal increased likelihood of receipt of HIV test
- Protective overall association of internal locus with recent medical visit and additional benefit for those with internal among 99% coverage networks
- Attitudes are an important determinant of health-seeking behavior among PWIDs
- Future interventions could consider this influence in the network to increase and sustain impact

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Results

# Original PWIDs Network in SFHR

Full Network

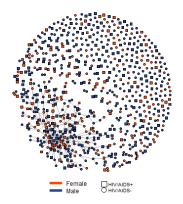


Figure 4: Full Network.

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