Lecture 22: Network scale-up method to study groups most at-risk for HIV

Matthew J. Salganik

Sociology 204: Social Networks Princeton University

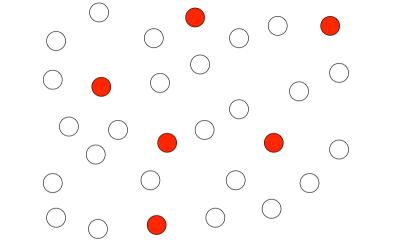
1/2 Network scale-up method, methods

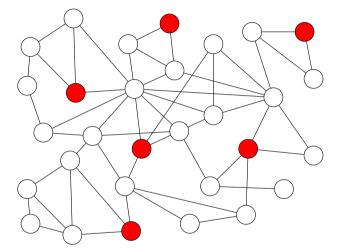


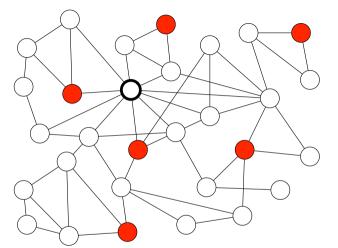
Network scale-up method

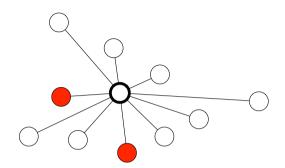


Basic insight from Bernard et al. (1989)





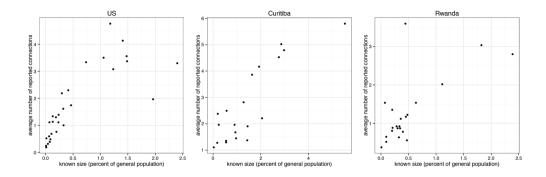




$$\hat{N}_H = \frac{2}{10} \times 30 = 6$$

- ► Requires a random sample from the entire population
- Respondents are asked:
- How many people do you know who are drug injectors?
 - How many women do you know that have given birth in the last 12 months?
 How many people do you know who are middle school teachers?
 - ...
 - ► How many people do you know named Michael?

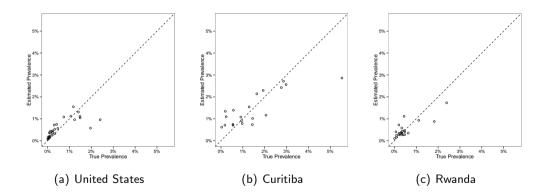
"Know" typically defined: you know them and they know you and have you been in contact with them over the past two years



On average, these answers are not crazy.

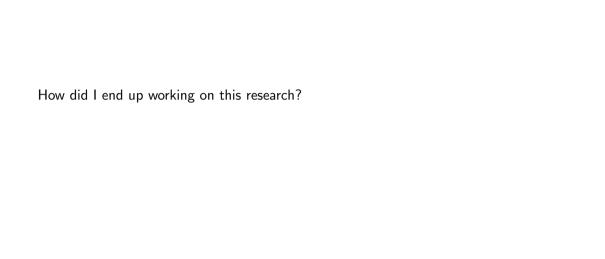
Other size estimation methods are problematic, and scale-up method has many nice properties:

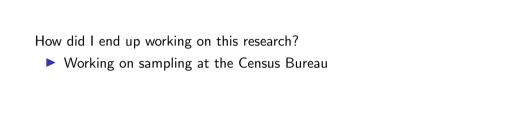
- ▶ Requires a random sample of the general population, not specific contact with the hard-to-reach population
- ► Can be added as a module (5-10 minutes) in any existing survey
- ► Can estimate many target populations in a single survey
- ► Can be applied at the city-level, sub-national-level, or national-level
- Statistical methods are improvable
- ▶ Partially self-validating because it uses groups of known size

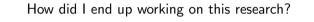


But, basic scale-up also has problems. I will focus on insights about basic scale-up that
we discovered from developing the generalized scale-up.

Personal background







and Doug Heckathorn was working on respondent-driven sampling

▶ Working on sampling at the Census Bureau

▶ When I began grad school I knew about sampling and was interested in networks

- How did I end up working on this research?
- Working on sampling at the Census Bureau
- ► When I began grad school I knew about sampling and was interested in networks
- and Doug Heckathorn was working on respondent-driven sampling
- Respondent-driven sampling lead to the network scale-up method

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Modeling

counting with multiplicity

Rwanda (this lecture)

Empirical

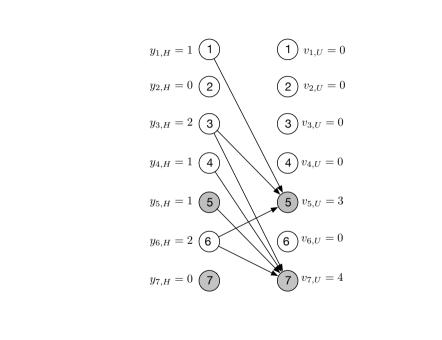
Brazil (next lecture)

If $y_{i,k} \sim Bin(d_i, N_k/N)$, then maximum likelihood estimator is

$$\hat{N}_{H} = \frac{\sum_{i} y_{i,H}}{\sum_{i} \hat{d}_{i}} \times N$$

- $ightharpoonup \hat{N}_H$: number of people in the hidden population
- \triangleright $y_{i,H}$: number of people in hidden population known by person i
- $ightharpoonup \hat{d}_i$: estimated number of people known by person i
- ▶ *N*: number of people in the population

See Killworth et al., (1998)





total out-reports = total in-reports

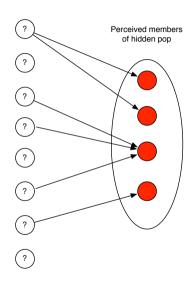
total out-reports = size of hidden pop \times

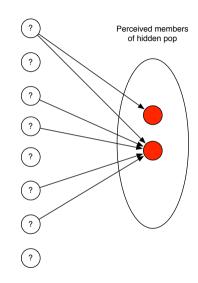
in-reports per member of hidden pop

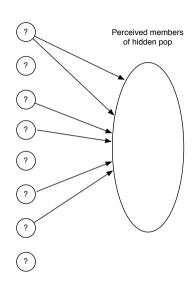
total out-reports = total in-reports

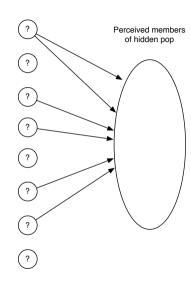
total out-reports = size of hidden pop
$$\times$$
 in-reports per member of hidden pop

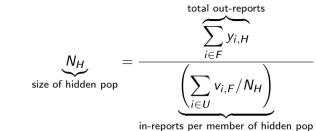
$$\mbox{size of hidden pop} = \frac{\mbox{total out-reports}}{\mbox{in-reports per member of hidden pop}}$$











$$\underbrace{N_H}_{\text{size of hidden pop}} = \underbrace{\frac{\displaystyle\sum_{i \in F} y_{i,H}}{\displaystyle\sum_{i \in U} v_{i,F}/N_H}}_{\text{in-reports per member of hidden pop}}$$

If there are no false positives,

$$N_{H} = \frac{\sum_{i \in F} y_{i,H}}{\left(\sum_{i \in H} v_{i,F}/N_{H}\right)}$$
avg visible degree of hidden pop

Generalized scale-up identity

$$\underbrace{N_{H}}_{\text{size of hidden pop}} = \underbrace{\frac{\sum\limits_{i \in F} y_{i,H}}{\sum\limits_{i \in H} v_{i,F}/N_{H}}}_{\text{avg visible degree of hidden pop}}$$

Basic scale-up estimator

$$\hat{N}_{H} = \frac{\sum_{i \in s_{F}} y_{i,H}}{\sum_{i \in s_{F}} \hat{d}_{i}} \times N$$

Generalized scale-up identity

$$N_{H} = \frac{\sum_{i \in F} y_{i,H}}{\left(\sum_{i \in H} v_{i,F}/N_{H}\right)}$$
avg visible degree of hidden pop

Basic scale-up estimator

$$\underbrace{\hat{N}_{H}}_{\text{est size of hidden pop}} = \underbrace{\frac{\displaystyle\sum_{i \in s_{F}} y_{i,H}}{\displaystyle\sum_{i \in s_{F}} \hat{d}_{i,U}/N}}_{\text{avg degree of pop}}$$

Counting with multiplicity approach:

- ▶ no assumptions about the underlying social network
- extends naturally to incomplete social awareness
- extends naturally to incomplete frames
- extends naturally to complex sample designs

$$N_{H} = \underbrace{\left(\frac{y_{F,H}}{\bar{d}_{U,F}}\right)}_{} \times \underbrace{\frac{1}{\bar{d}_{F,F}/\bar{d}_{U,F}}}_{} \times \underbrace{\frac{1}{\bar{d}_{H,F}/\bar{d}_{F,F}}}_{} \times \underbrace{\frac{1}{\bar{v}_{H,F}/\bar{d}_{H,F}}}_{} = \underbrace{\left(\frac{y_{F,H}}{\bar{v}_{H,F}}\right)}_{}.$$

$$N_H =$$

$$N_H = 1$$

basic

scale-up

frame ratio

 ϕ_F

degree ratio

adjustment factors

generalized

scale-up

true positive rate

 τ_F

Frame ratio: Less a focus for us. As a first approximation, sampling frame is adults

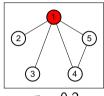
you don't want to include kids in any of the reports

Degree ratio: If the hidden population has smaller network sizes than the general
population, the size of the hidden population will be underestimated. Likewise, if the

hidden population will be overestimated.

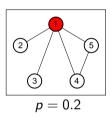
hidden population has larger network sizes than the general population, the size of the

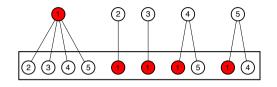
Set of egos can be different from set of alters.



p = 0.2

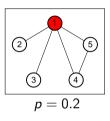
Set of egos can be different from set of alters.

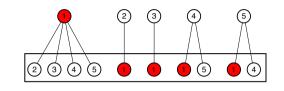




 $p_{alter} = 0.4$

Set of egos can be different from set of alters.





$$p_{alter} = 0.4$$

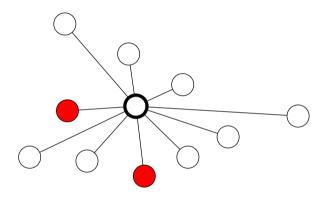
$$p_{alter} = p imes rac{ ext{avg. degree (hidden pop.)}}{ ext{avg. degree (general pop.)}} = p \delta$$

Estimates will be biased by a factor of δ_F ("degree ratio")

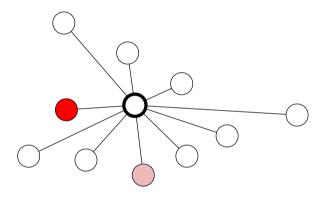
True positive rate: If people are connected to people in the hidden population but not

aware of it, the size of the hidden population will be underestimated

How might imperfect knowledge impact scale-up estimates? Ego is not aware of everything about all of their alters.



How might imperfect knowledge impact scale-up estimates? Ego is not aware of everything about all of their alters.



Estimates will be biased by a factor of τ_F ("true positive rate") More about this in next lecture

$$N_H = \bigcup$$

 $N_{H} = \underbrace{\left(\frac{y_{F,H}}{\bar{d}_{U,F}}\right)} \times \underbrace{\frac{1}{\bar{d}_{F,F}/\bar{d}_{U,F}}} \times \underbrace{\frac{1}{\bar{d}_{H,F}/\bar{d}_{F,F}}} \times \underbrace{\frac{1}{\bar{v}_{H,F}/\bar{d}_{H,F}}} = \underbrace{\left(\frac{y_{F,H}}{\bar{v}_{H,F}}\right)}_{\bar{v}_{H,F}}.$ basic frame ratio degree ratio

true positive rate scale-up ϕ_F τ_F

adjustment factors

generalized

scale-up

From a talk I gave at a UNAIDS workshop

Generalized scale-up approach

- simple estimators (just addition, subtraction, multiplication, and division)
- handles incomplete social awareness
- no assumptions about the underlying social network
- handles incomplete frames
- handles complex sample designs

and could still be very wrong in practice!



- Assumptions can be put into four broad categories
 - sampling
 - social network structure
 - ► reporting
 - survey construction

Results for non-sampling assumptions have this form:

Estimator	Imperfect assumptions	Effective estimand
$\widehat{\bar{d}}_{F,F}$ (Result B.3)	(i) $\widehat{N}_{\mathcal{A}} = c_1 N_{\mathcal{A}}$	$rac{c_2 \ c_3}{c_1} \ ar{d}_{F,F}$
	(ii) $ar{d}_{\mathcal{A},F} = c_2 \; ar{d}_{F,F}$	
	(iii) $y_{F,\mathcal{A}} = c_3 \ d_{F,\mathcal{A}}$	

Estimator	Imperfect assumptions	Effective estimand
$\hat{\bar{d}}_{F,F}$ (Result B.3)	(i) $\widehat{N}_A = c_1 N_A$	$\frac{c_2 \ c_3}{c_1} \ \bar{d}_{F,F}$
	(ii) $\bar{d}_{A,F} = c_2 \; \bar{d}_{F,F}$	
	(iii) $y_{F,A} = c_3 d_{F,A}$	
$\hat{d}_{U,F}$ (Result B.4)	(i) $\widehat{N}_A = c_1 N_A$	$\frac{c_2 \ c_3}{c_1} \ \bar{d}_{U,F}$
	(ii) $\bar{d}_{A,F} = c_2 \; \bar{d}_{U,F}$	
	(iii) $y_{F,A} = c_3 d_{F,A}$	
$\widehat{\phi}_F$ (Result B.6)	(i) $\hat{d}_{F,F} \leadsto c_1 \ \bar{d}_{F,F}$	$\frac{c_1}{c_2} \phi_F$
	(ii) $\hat{d}_{U,F} \leadsto c_2 \ \bar{d}_{U,F}$	
$\widehat{\overline{v}}_{H,F}$ (Result C.2)	(i) $\widehat{N}_{A\cap F} = c_1 \ N_{A\cap F}$	$\frac{c_3 \cdot c_2}{c_1} \cdot \bar{v}_{H,F}$
	(ii) $\tilde{v}_{H,A\cap F} = c_2 \ v_{H,A\cap F}$	
	(iii) $\frac{v_{H,A\cap F}}{N_{A\cap F}}=c_3 \frac{v_{H,F}}{N_F}$	
$\hat{\delta}_F$ (Result C.6)	(i) $\hat{\bar{d}}_{H,F} \leadsto c_1 \ \bar{d}_{H,F}$	$\frac{c_1}{c_2}$ δ_F
	(ii) $\hat{d}_{F,F} \leadsto c_2 \ \bar{d}_{F,F}$	
$\hat{\tau}_F$ (Result C.7)	(i) $\widehat{v}_{H,F} \leadsto c_1 \ \overline{v}_{H,F}$	$\frac{c_1}{c_2} \tau_F$
	(ii) $\hat{d}_{H,F} \leadsto c_2 \ \bar{d}_{H,F}$	
\widehat{N}_H (Result C.8)	(i) $\hat{\bar{v}}_{H,F} \leadsto c_1 \; \bar{v}_{H,F}$	$\frac{1}{c_1} N_H$
\widehat{N}_H (Result C.10)	(i) $\hat{\bar{d}}_{F,F} \leadsto c_1 \ \bar{d}_{F,F}$	$\frac{1}{c_1} \frac{1}{c_2} \frac{1}{c_3} N_H$
	(ii) $\hat{\delta}_F \leadsto c_2 \delta_F$	
	(iii) $\hat{\tau}_F \leadsto c_3 \tau_F$	



Fails when:

- adjustment factors not measured
- adjustment factors measured poorly
- reporting not consistent with awareness
- variance estimation fails

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Modeling

counting with multiplicity

Rwanda (this lecture)

Empirical

Brazil (next lecture)