New Approaches to Collecting Data From a Respondent-Driven Sample

Session: Computational Demography, Machine Learning, and Algorithmic Bias

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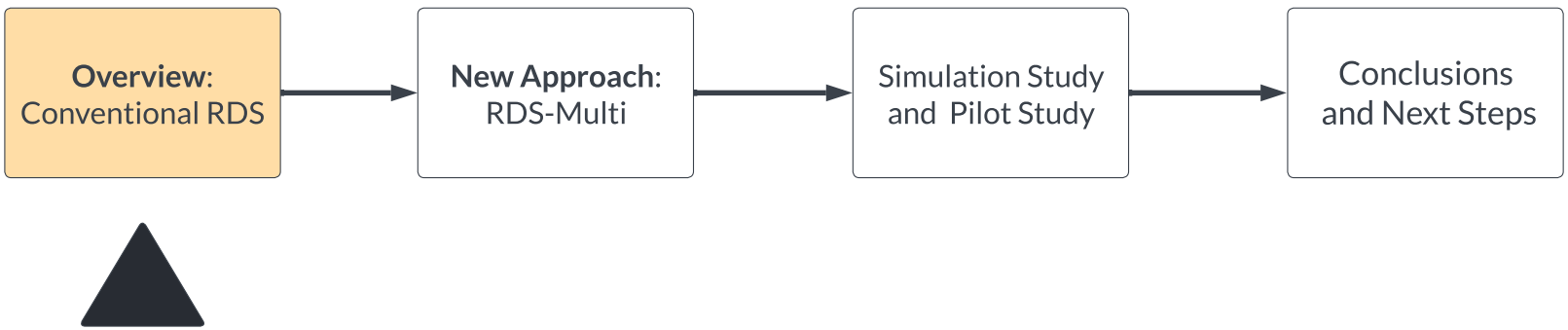
- **Hidden populations:** populations that are hard-to-reach, often due to engaging in stigmatized or illegal behavior (persons who inject drug, commercial sex workers, etc.)
- **RDS Key insight:** Members of a hidden population are often socially connected to each other – and can recruit each other to be interviewed

Presentation Roadmap

- **Goal**: Introduce RDS-Multi, a new approach to collecting data from a respondent-driven sample



Respondent-Driven Sampling – Overview

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2. Seeds recruit other members of the hidden population to be interviewed
3. After being interviewed, respondents recruit next wave of respondents

RDS Recruitment Trees

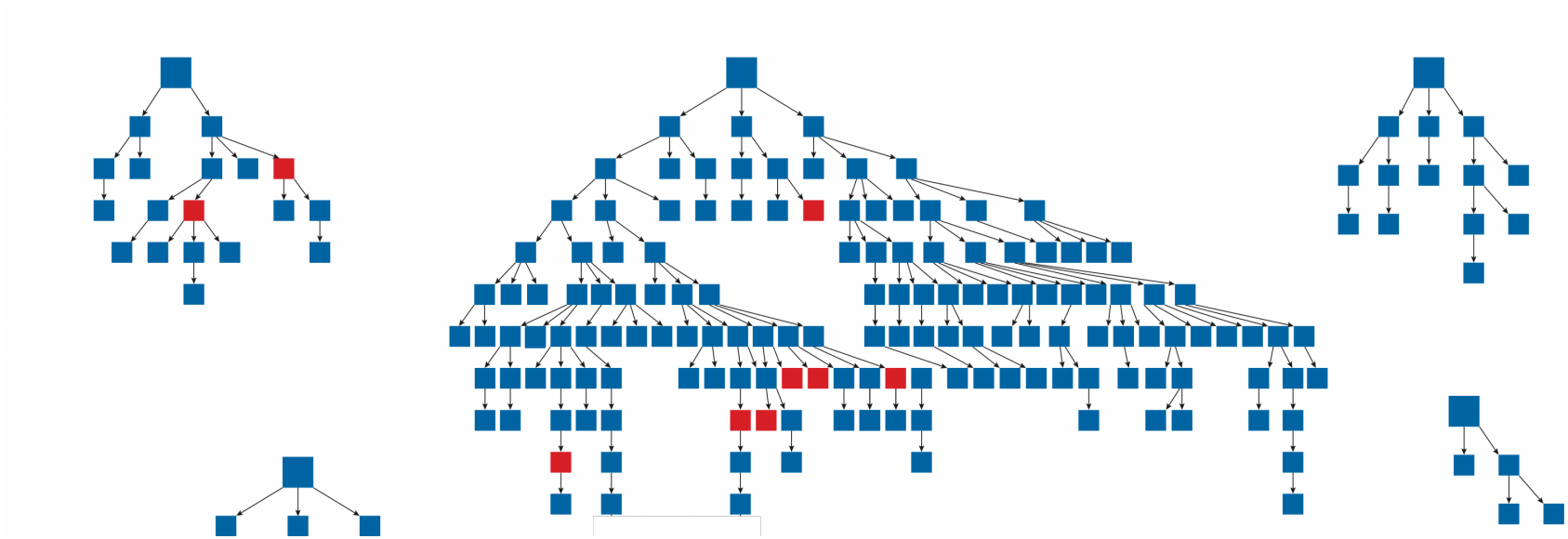

Figure: Recruitment tree plots from Gile et al. (2015)

When Conventional RDS Doesn't Work Well . . .

- **Low Connectivity:** Members of a hidden population don't know other members of hidden population to recruit
- **High Clustering**: Bottlenecks due to extreme homophily make it difficult for RDS to fully traverse network

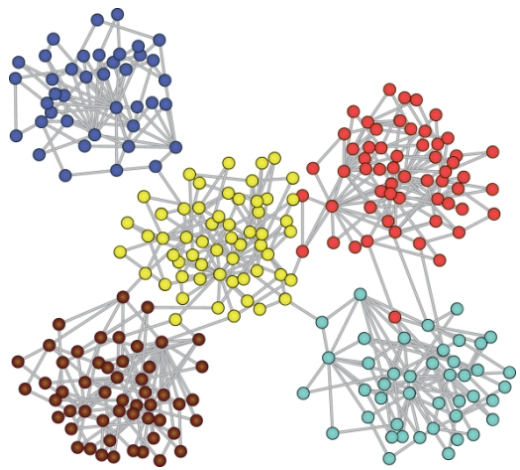

Figure: Clustered Social Network

What Do We Do When RDS Doesn't Work Well?

- Improve statistical methods for analyzing RDS data

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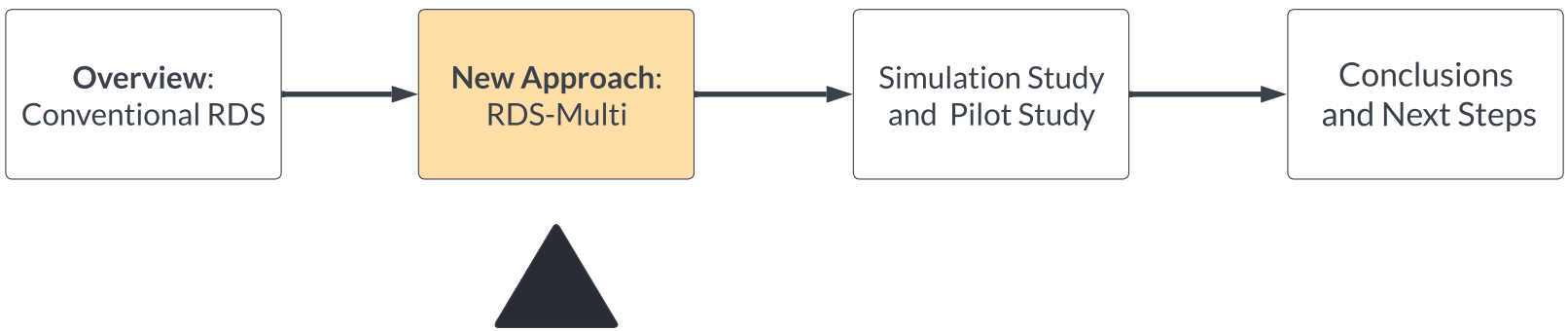
- **Change data collection procedure to give more favorable underlying network structure**

RDS-Multi: Roadmap



Motivating Example

- RDS Study: What is the proportion of people experiencing homelessness in the San Francisco Bay Area are fully vaccinated for COVID-19?

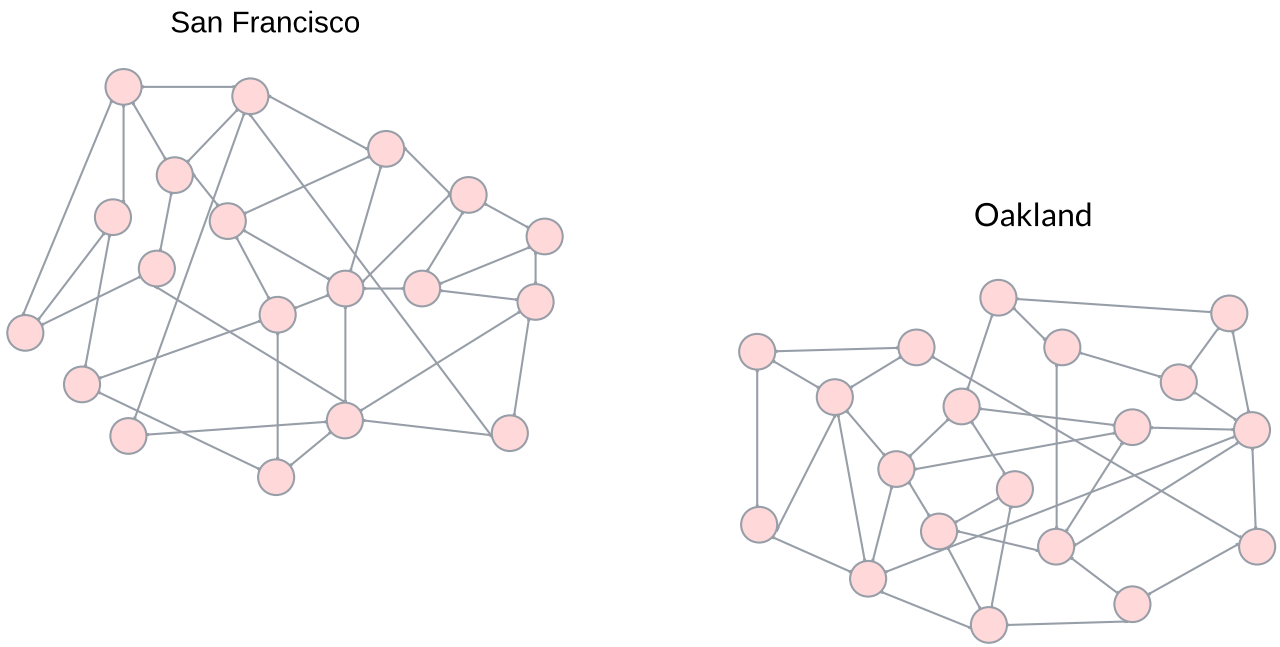


Figure: Bottlenecks between San Francisco and Oakland

New Approach: RDS-Multi

- New referral method: hidden population members refer other hidden population members or **social referents**, people highly connected to – but not in – the hidden population.
- For example:
  - **Hidden population:** People experiencing homelessness in the Bay area
  - **Social Referents**: Social workers specializing in homeless outreach services

Increase network connectivity

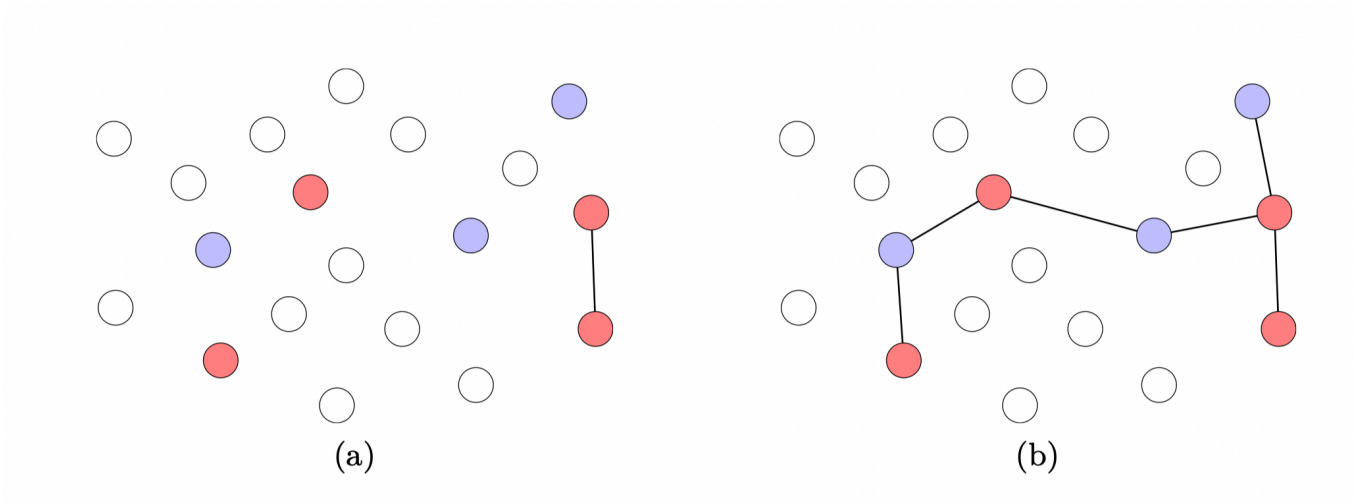
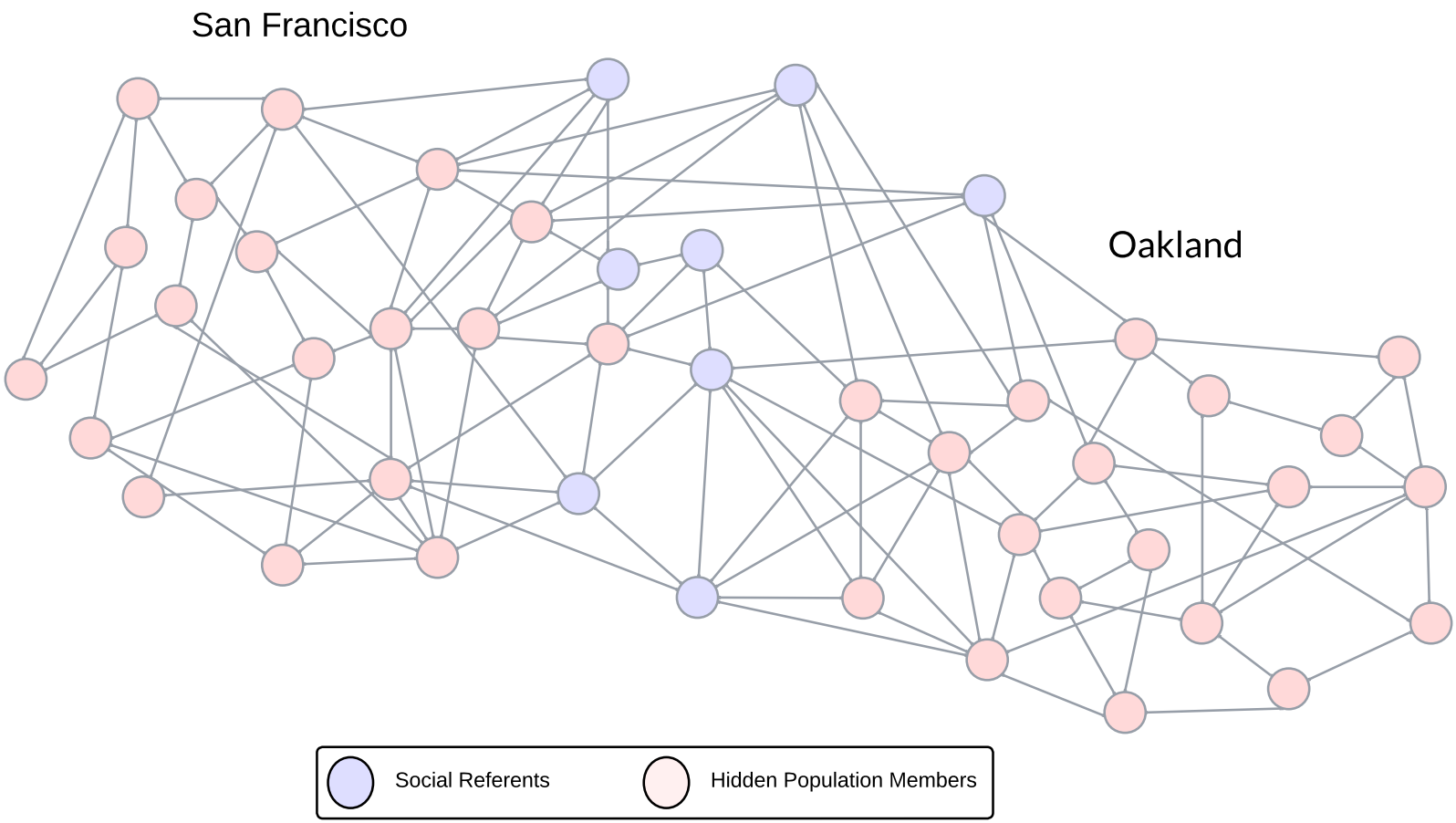


Figure: New referral method can improve underlying network structure

Decrease clustering and bottlenecks



Conventional RDS: Volz & Heckathorn Point Estimator

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$$\mu_{VH} = \frac{\sum_{i=1}^{n} \frac{z_i}{d_i}}{\sum_{i=1}^{n} \frac{1}{d_i}}$$

where d_i is respondent i's degree and z_i is a binary covariate

RDS-Multi: Adapted Volz & Heckathorn Point Estimator

Adapt Volz-Heckathorn estimator to account for the new referral pattern:

$$\widehat{\mu}'_{VH} = \frac{\sum_{i \in s' \cap H} \frac{q_i}{d_{i,R}}}{\sum_{i \in s' \cap H} \frac{1}{d_{i,R}}},$$

where

- z_i is a binary covariate
- $s' \cap H$ is the subset of the sample that consists of hidden population members;
- and $d_{i,R}$ is the number of connections between i and the set R of social referents.

Variance Estimator

Estimating uncertainty in respondent-driven sampling using a tree bootstrap method

Aaron J. Baraff, Tyler H. McCormick, and Adrian E. Raftery

+ See all authors and affiliations

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https://doi.org/10.1073/pnas.1617258113

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Variance Estimator – Tree Bootstrap

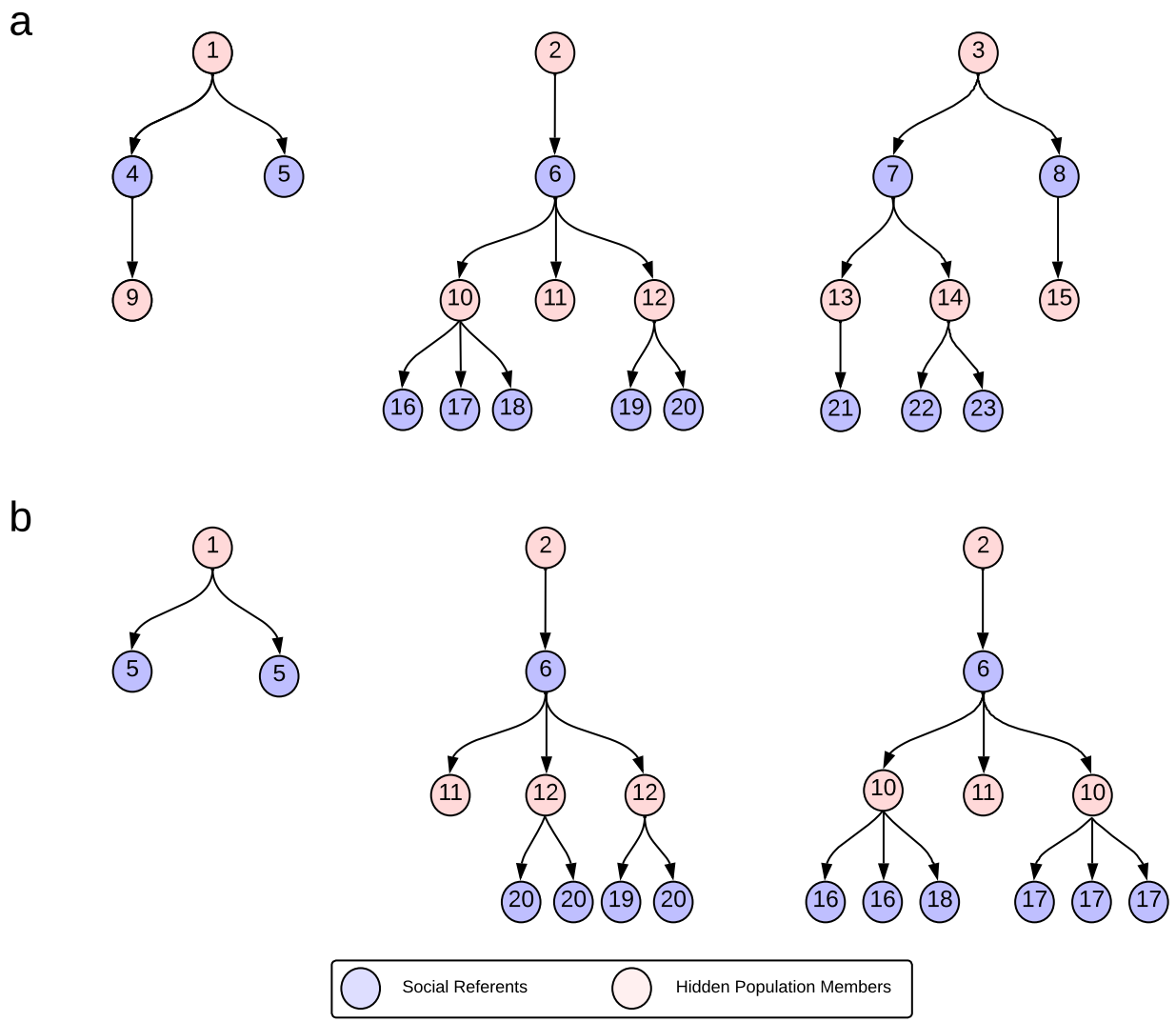


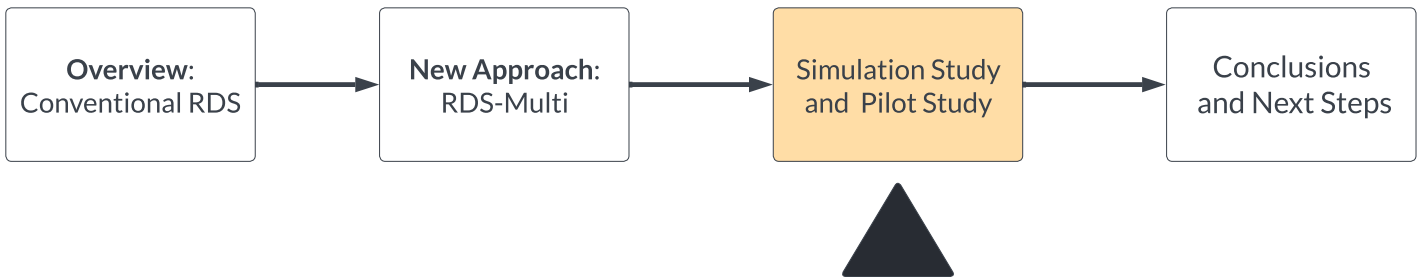
Figure: Adapted Tree Bootstrap Estimator (Baraff, McCormick and Raftery, 2016)

RDS-Multi: Key Considerations

1. Population of interest is the hidden population – we'll drop all social referents, resulting in a smaller effective sample size (or will need to conduct more interviews)

2. We need a sufficiently large and well-connected set of social referent nodes

RDS–Multi: Roadmap



Simulation Study

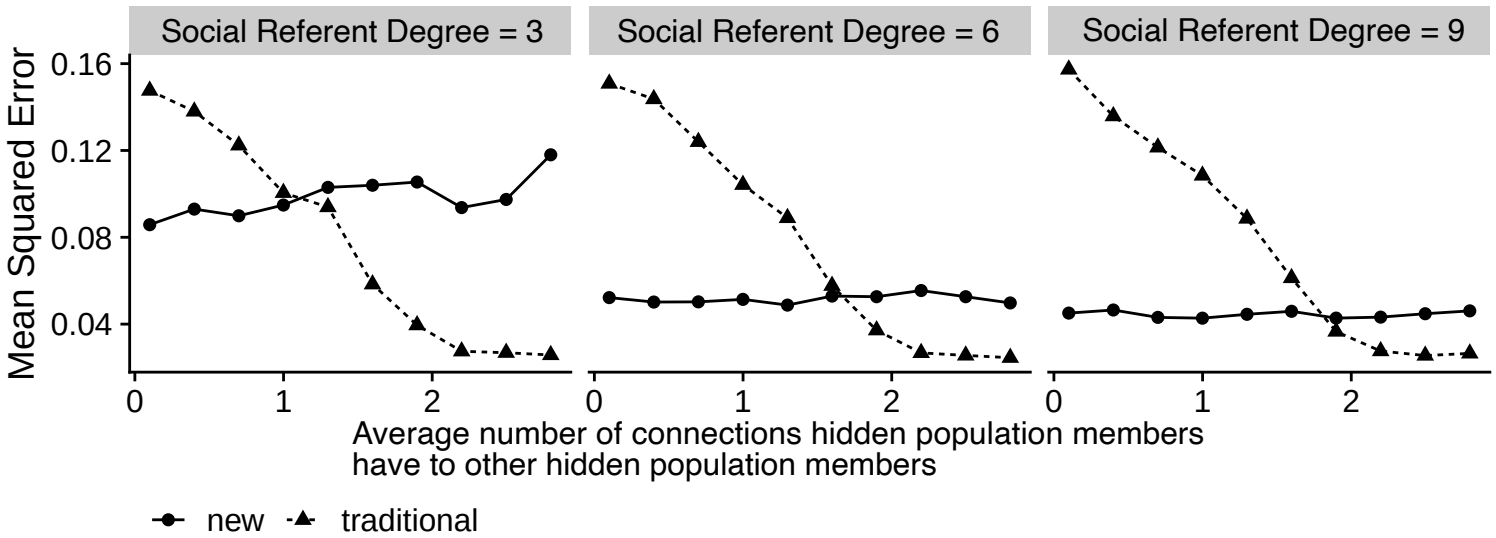


Figure: When connectivity is low, RDS-Multi performs better than the conventional RDS

Note: Sample sizes = 500, including social referents

Pilot Study in Kaya, Burkina Faso

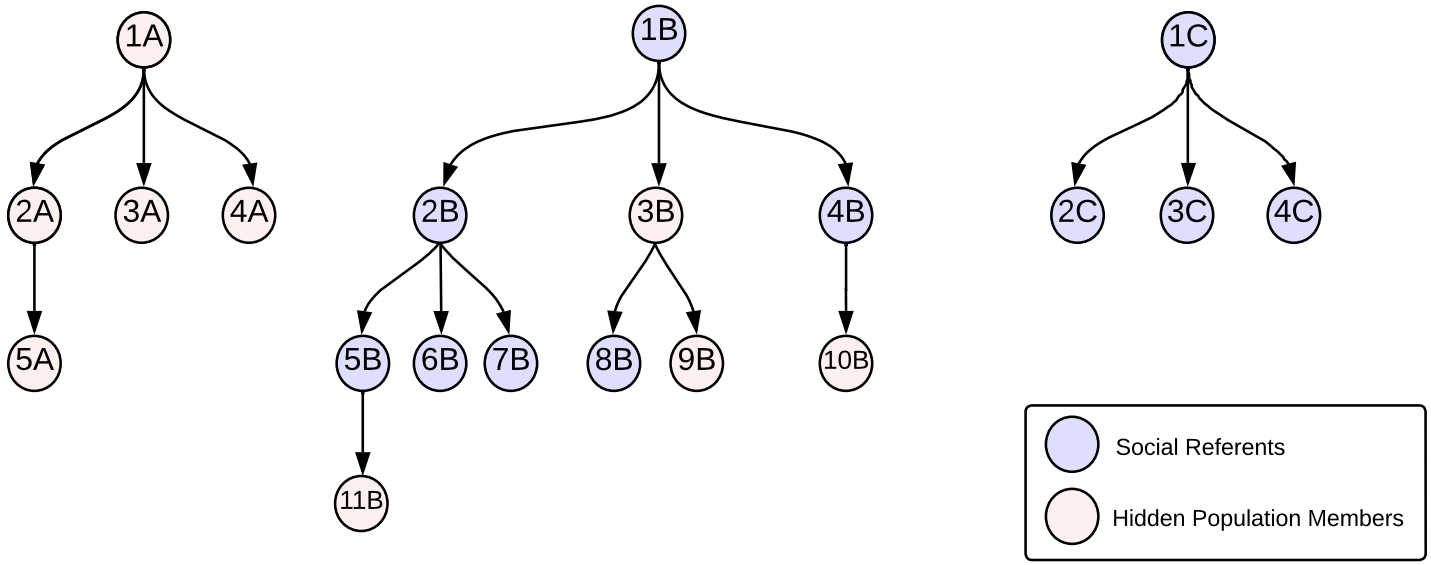
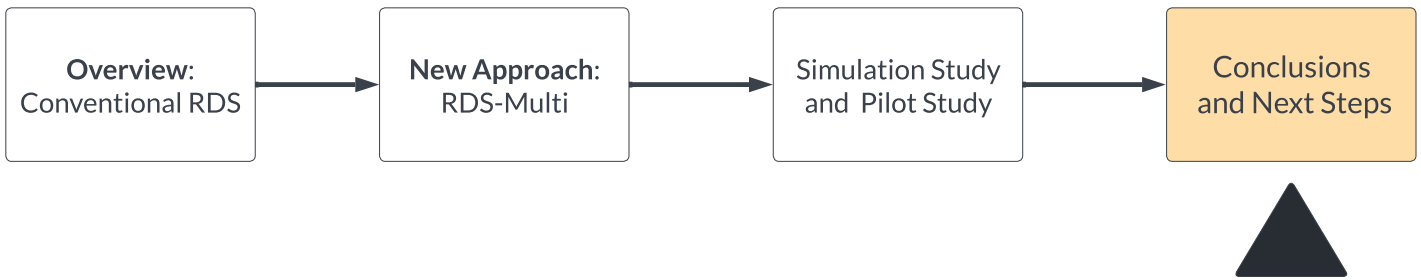


Figure: RDS-Multi recruitment trees from pilot study[1]

[1] Zan, Owolabi, Baguiya, Oduor, Bangha, Kim and Rossier (2022)

RDS–Multi: Roadmap



Conclusion

- RDS-Multi is a novel approach to collecting RDS data using **social referents**
- **Key advantages:**
  - Enables RDS for weakly connected hidden populations
  - Enables RDS for highly clustered networks
- **Key consideration:** RDS-Multi requires the availability of a sufficiently large and well-connected set of **social referents**

Next Steps

- More formal mathematical and empirical understanding of the trade-offs between RDS and RDS-Multi
- More empirical evidence from real world RDS-Multi studies

Thank You

- Questions?

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References

Baraff, Aaron J., Tyler H. McCormick and Adrian E. Raftery. 2016. "Estimating Uncertainty in Respondent-Driven Sampling Using a Tree Bootstrap Method." *Proceedings of the National Academy of Sciences* 113(51):14668–14673.

Zan, Moussa L., Onikepe Owolabi, Adama Baguiya, Clement Oduor, Martin Bangha, Caron Kim and Clémentine Rossier. 2022. "Using Respondent Driven Sampling to Measure Abortion Safety in Restrictive Contexts: Results from Kaya (Burkina Faso) and Nairobi (Kenya).".