How to Analyze RDS Data? —A Simple Guide

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Intro to RDSAnalyst PART ONE

PART ONE: Intro to RDSAnalyst •

What is it?

- Base: a R package named "RDS" (Cran)
- Built in Java for a user-friendly graphical interface software
- No need to write code by yourself
- Analyze RDS data for sample and population estimations, testing, CIs, sensitivity analysis

Installation

- http://wiki.stat.ucla.edu/hpmrg/index.php/RDS_Analyst_Install
- Windows and Mac

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What you need in data? PART TWO

PART TWO: What you need in data

- File Format:
- RDS Object: *.rdsobj, *.rdsat
- R Object: *.robj
- Others: *.csv, *.txt, *.sav, *.xpt, *bdf, *.dta, *.sys, *.syd, *.arff, *.rec, *.mtp, *.s3
- Required Variables in Coupon Format Data:
- Subject ID
- Seed Indicator: 0 is No, 1 is Yes
- Subject's Coupon ID
- Each Coupon ID Given to Subject to Recruit Others
- Network Size: each subject's self-reported degree (number of associations in such population)
- Variables of Interest: demographic info, such as age, race, job, HIV status, education
- Required Variables in Recruiter ID Format Data:
- Subject ID
- Seed Indicator: 0 is No, 1 is Yes
- Recruiter ID: subject ID of the recruiter for each respondent
- Network Size: each subject's self-reported degree (number of associations in such population)
- Variables of Interest: demographic info, such as age, race, job, HIV status, education

Logic: find the path of one subject connected to other

Several Estimators PART THREE

PART THREE: Several estimators

RDS I

- S-H Estimator
- Based Markov chain assumption
- Equating the number of crossrelations between pairs of subpopulations of interest

RDS II

- V-H Estimator
- Estimating inclusion probabilities of sampled units
- Sampling process as random walk

HCG

- Homophily Configuration Graph Estimator
- Based on configuration graph network model
- Added homophily
- Without replacement sampling

We use estimator to estimate population from sample

RDS I (DS)

- Data smoothed version of RDS I
- Averaging over all pairs of groups (averaging degrees in group)

Gile's SS

- Successive Sampling Estimator
- Based on configuration graph network model
- Estimating inclusion probabilities of sampled units
- Without replacement sampling

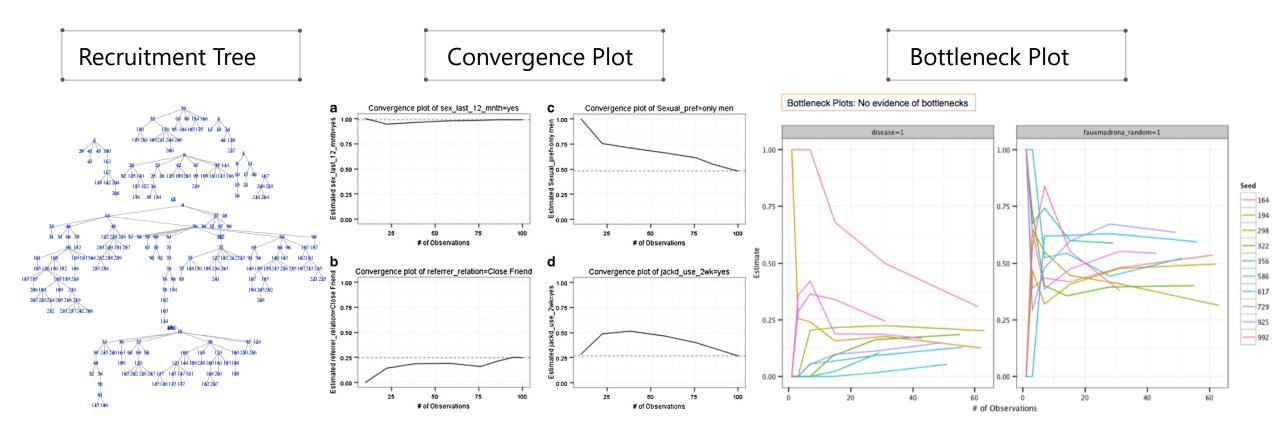
PART THREE: Several estimators

How to choose?

	RDS I	RDS I (DS)	RDS II	SS	HCG
Don't pop size	V	V	V	×	×
Large sampling fraction	Biased	Biased	Biased		▽
Don't know recruitment time	▽	V	V		×
Shorter waves	Biased	Biased	Biased		▼
Higher homophily	Somewhat Biased	Somewhat Biased	Biased	Biased	V
Biased seeds	Somewhat Biased	Somewhat Biased	Biased	Somewhat biased	▽
Highly differential activity	×	×	×		▽
Continuous variable	×	×	▼		~

Diagnosis PART FOUR

PART FOUR: Diagnosis



Seeds, waves, network

Whether results are converging to constant value and when how many samples

Homophily: the ratio of number of recruits that have the same disease status as their recruiter to the number we would expect by chance

Whether the population of interest contains distinct sub-communities that could bias the RDS estimate

Differential activity: compare the (weighted) average network size of two classes of the population

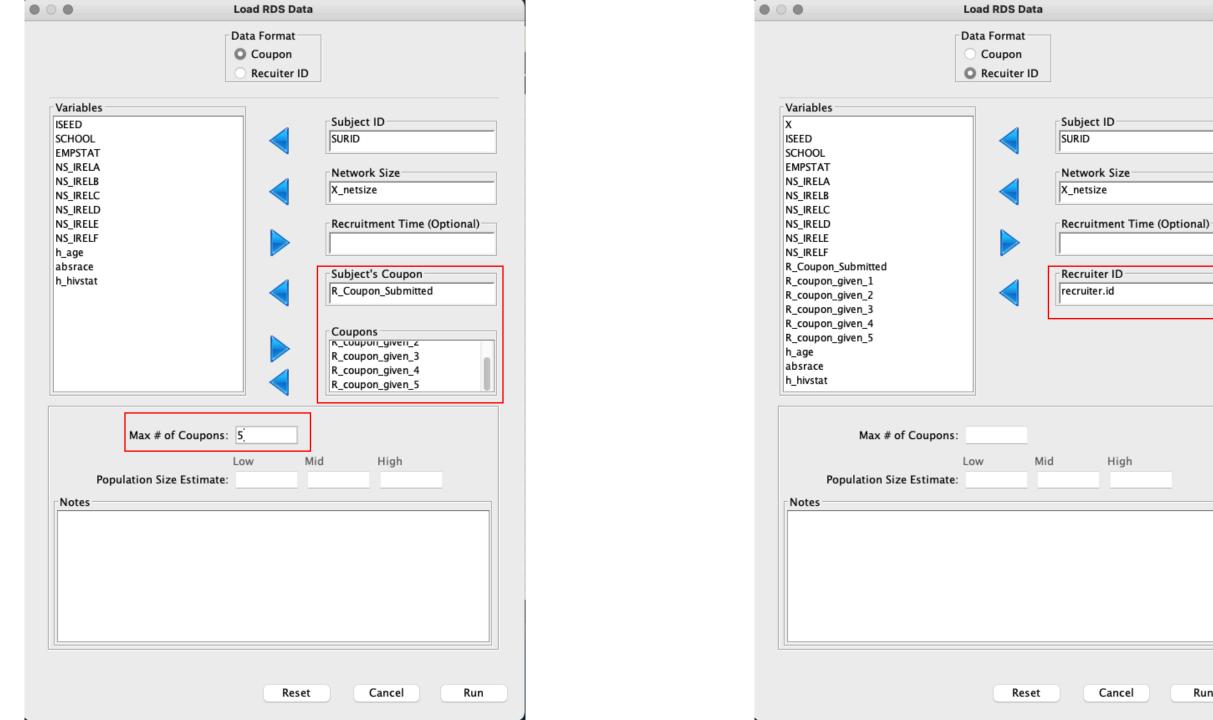
A Real Example PART FIVE

Check your data

Assume: population size is 5000; Sample size: 524; Sampling fraction is small; No continuous variable; Waves > 10; Lower homophily;

Α	В	С	D	E	F	G	н	1	J	K	L	М	N
SURID	ISEED	SCHOOL	EMPSTAT	R_Coupon_Submitted	R_coupon_given_1	R_coupon_given_	R_coupon_giv	R_coupon_g	R_coupon_gi	_netsize	h_age	absrace	h_hivstat
1	1	. 3	7	-1	1001	1002	1003	1004	1005	17	3	5	3
2	1	. 1	. 7	-1	-1	-1	-1	-1	-1	47	2	7	3
3	1	. 2	. 8	-1	1017	1018	1019	1020	1021	40	1	5	3
4	1	. 2	7	-1	1022	1023	1024	1025	1026	60	1	7	3
5	1	. 3	6	-1	1027	1028	1029	1030	1031	110	2	7	3
6	1	. 3	7	-1	1517	1518	1519	1520	1521	25	3	5	3
7	1	. 3	7	-1	1526	1527	1528	1529	1530	23	2	5	3
8	1	. 3	7	-1	1533	1534	1535	1536	1537	50	3	5	3
9	1	. 3	1	-1	1538	1539	1540	1541	1542	7	3	5	3
10	1	. 3	2	-1	1601	1602	1603	1604	1605	15	3	5	3
11	1	. 4	7	-1	1853	1854	1855	1856	1857	7	3	5	3
												-	





Run

Deleted because of confidentiality

Reference PART SIX

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THANK YOU FOR LISTENING