



WhatWorks

TO PREVENT VIOLENCE

A Global Programme To Prevent
Violence Against Women and Girls

Prevalence and risk factors for gender based violence among class 6 learners in the informal settlements of Nairobi, Kenya: baseline analysis from the IMpower & SoS cluster randomized controlled trial

Michael Baiocchi, Rina Friedberg, Mary Amuyunza, Gabriel Oguda,
Dorothy Otieno, Amit Pasupathy, and Clea Sarnquist



WhatWorks

TO PREVENT VIOLENCE

A Global Programme To Prevent
Violence Against Women and Girls

the teams

BY MANY HANDS



the organizations



NO MEANS NO
WORLDWIDE

the organizations



NO MEANS NO
WORLDWIDE

the organizations



NO MEANS NO
WORLDWIDE

the Kenyan intervention team



stakeholders: schools and MoE





WhatWorks

TO PREVENT VIOLENCE

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the intervention

BY MANY MEANS







the intervention: girls program

Four pathways:

- Empowerment,
- Situational awareness,
- Verbal skills, and
- Physical self-defense skills.













the intervention: boys program

Three pathways:

- Healthy gender norms
- Positive masculinity
- Bystander intervention (limited)







WhatWorks

TO PREVENT VIOLENCE

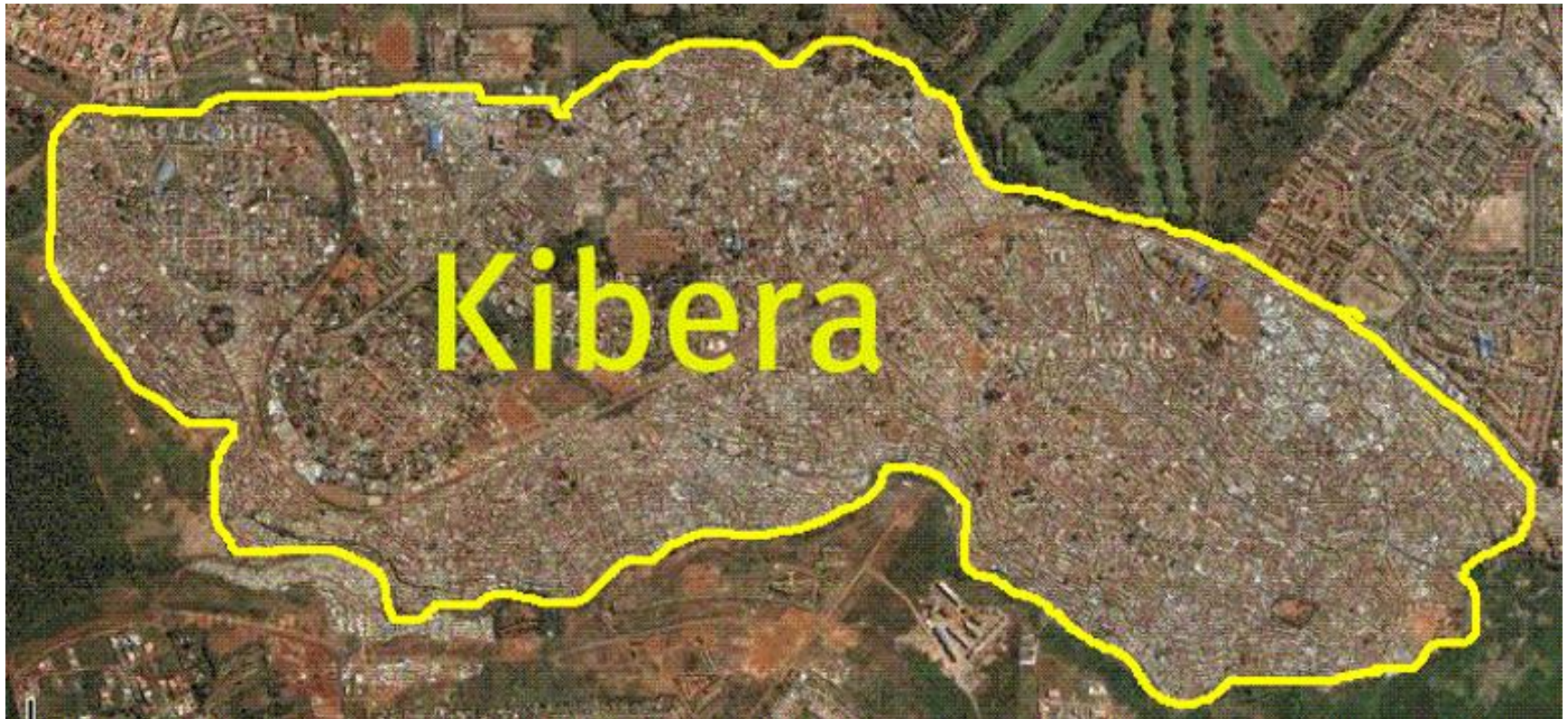
A Global Programme To Prevent
Violence Against Women and Girls

the study

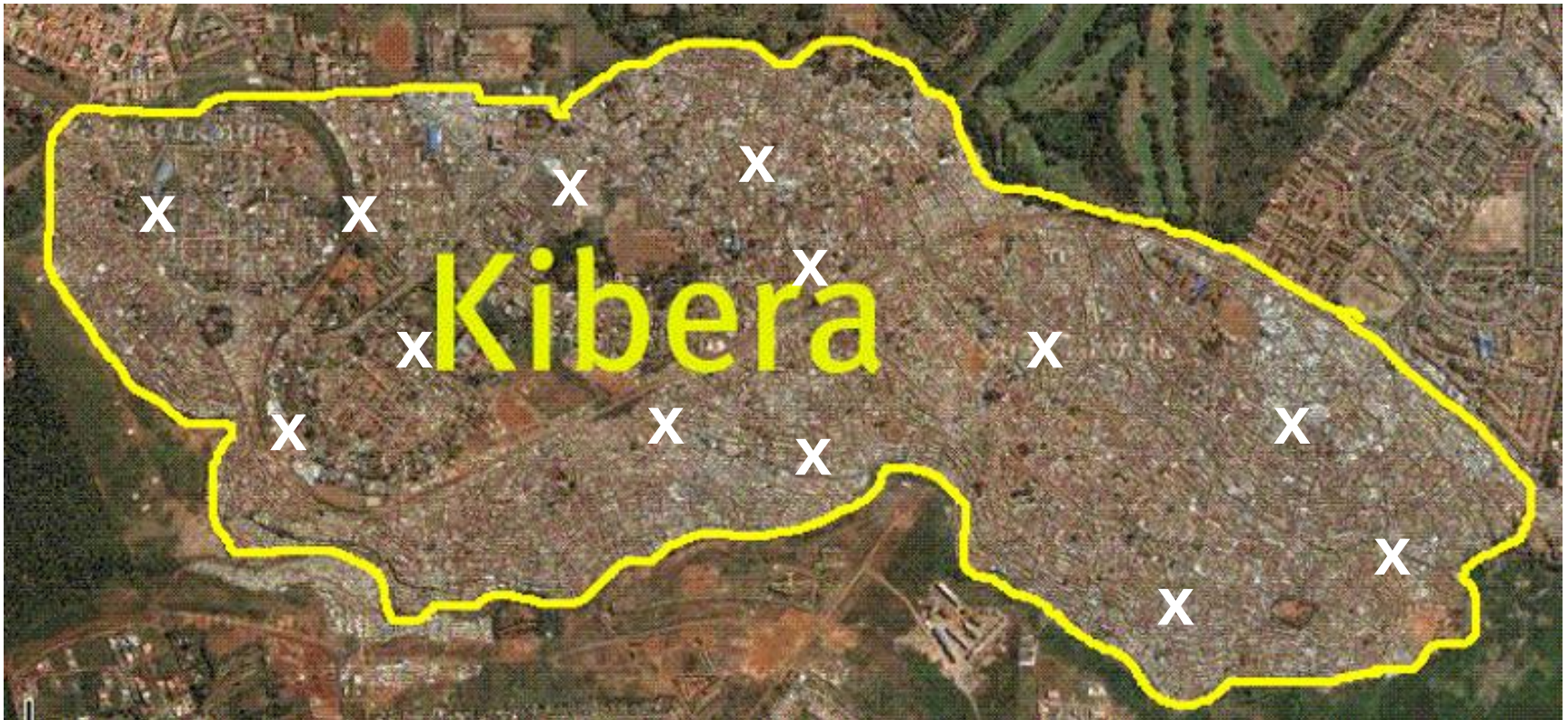
RANDOMIZED TRIAL



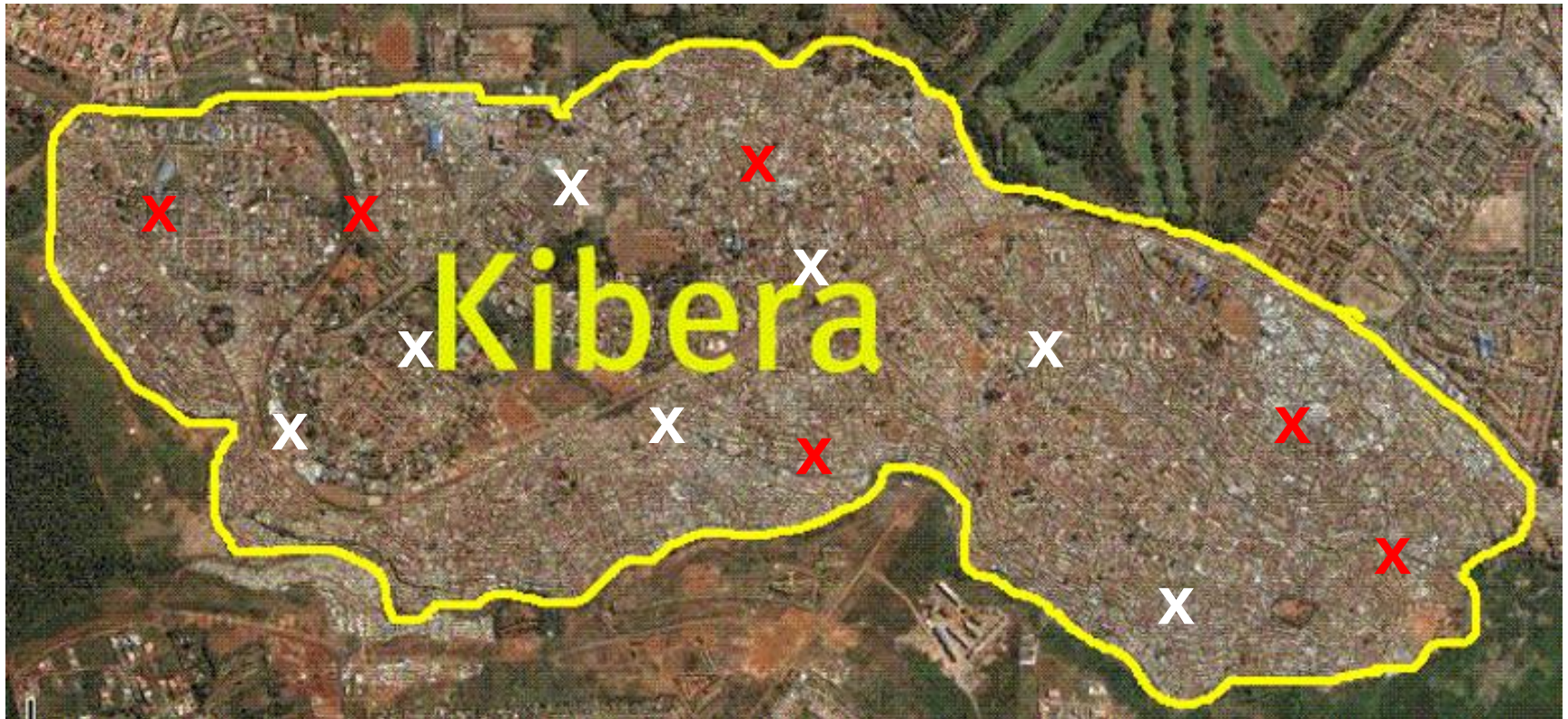
informal settlements



informal settlements



informal settlements



the study

Completed baseline data collection

- Quantitative data:
 - › ~4,000 girls surveys
 - › ~1,000 boys surveys

the study

Completed baseline data collection

- Quantitative data:
 - › ~4,000 girls surveys
 - › ~1,000 boys surveys
- Qualitative data
 - › 20 girls qualitative interviews
 - › 11 boys qualitative interviews





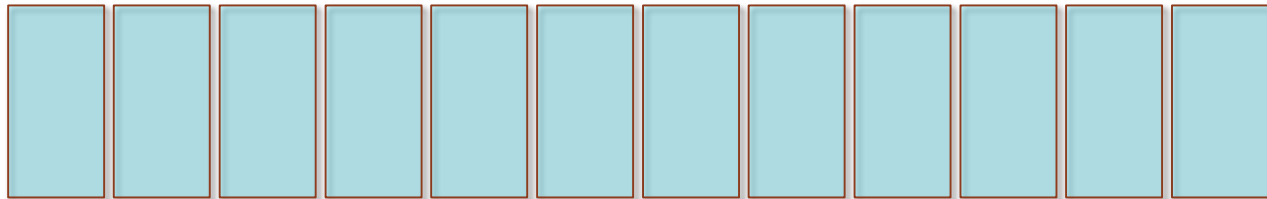
the study: timeline

the study: timeline

2016

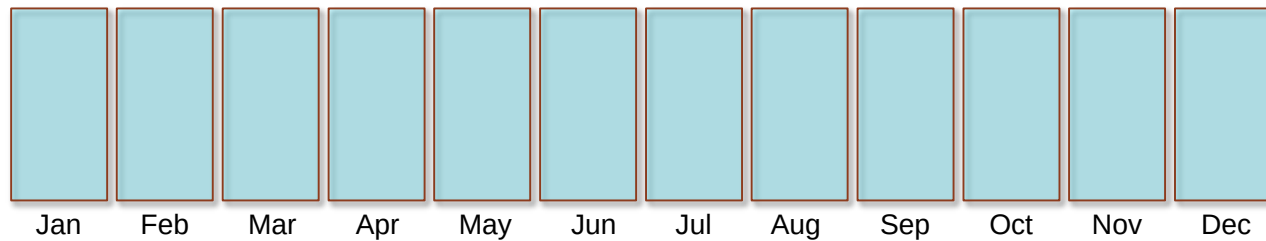
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2016

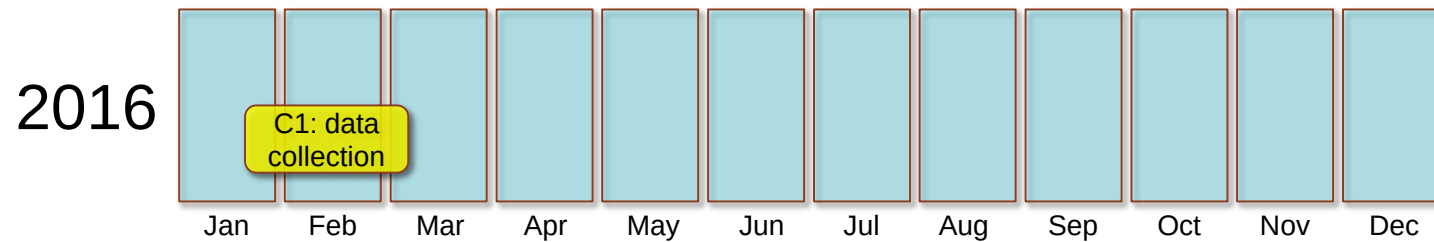


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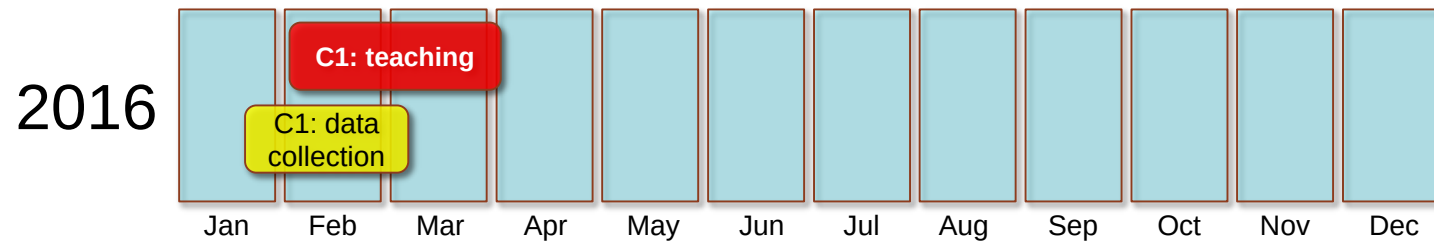
2016



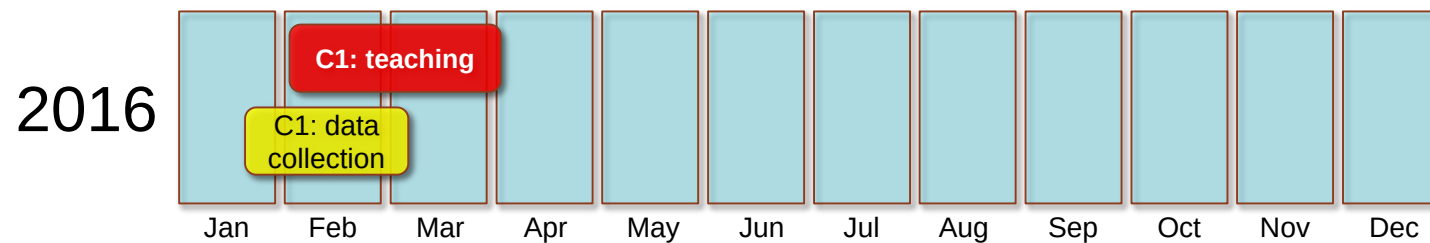
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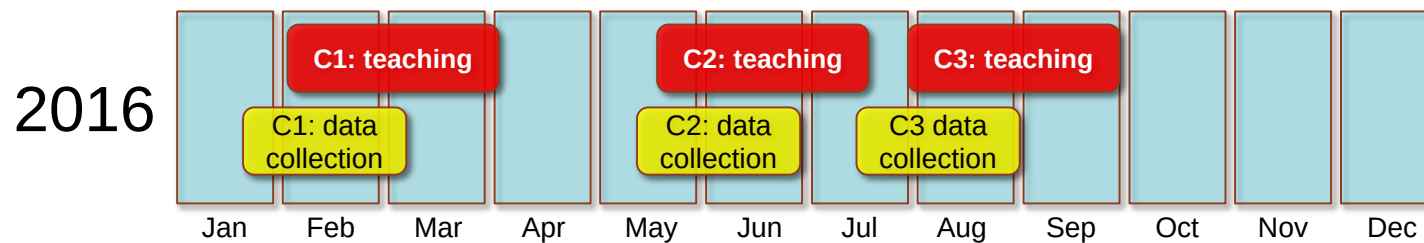


the study: timeline



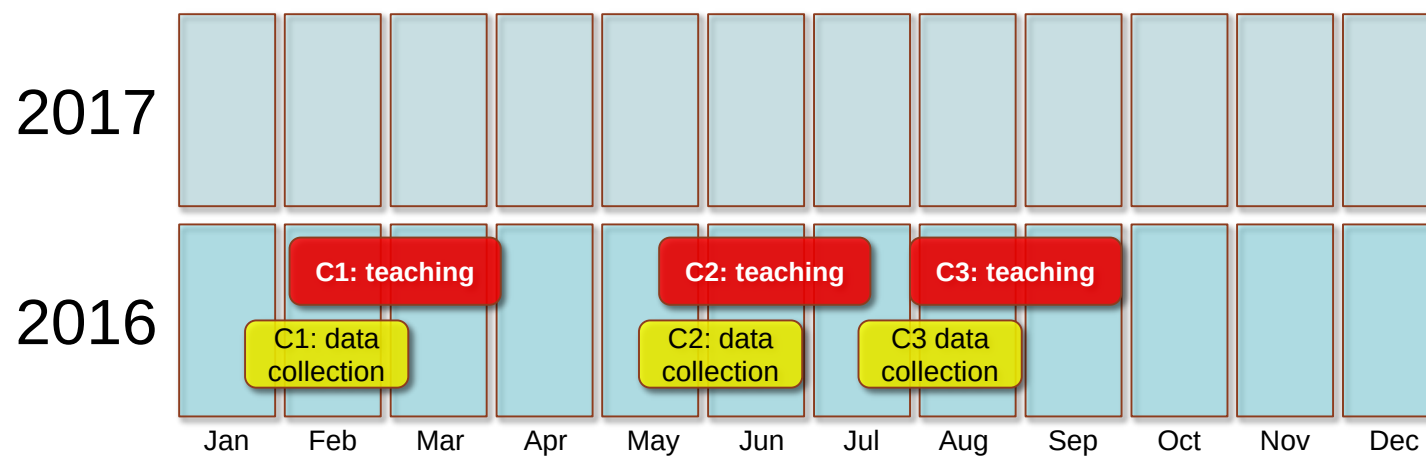
Three cohorts, each with $\cong 30$ schools.

the study: timeline



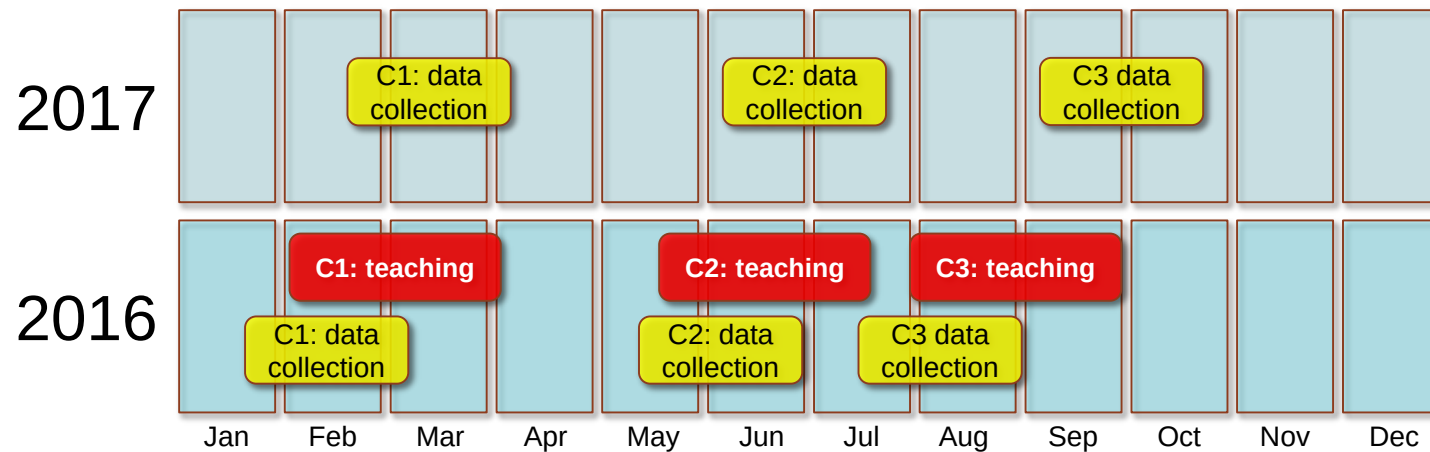
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the study: timeline



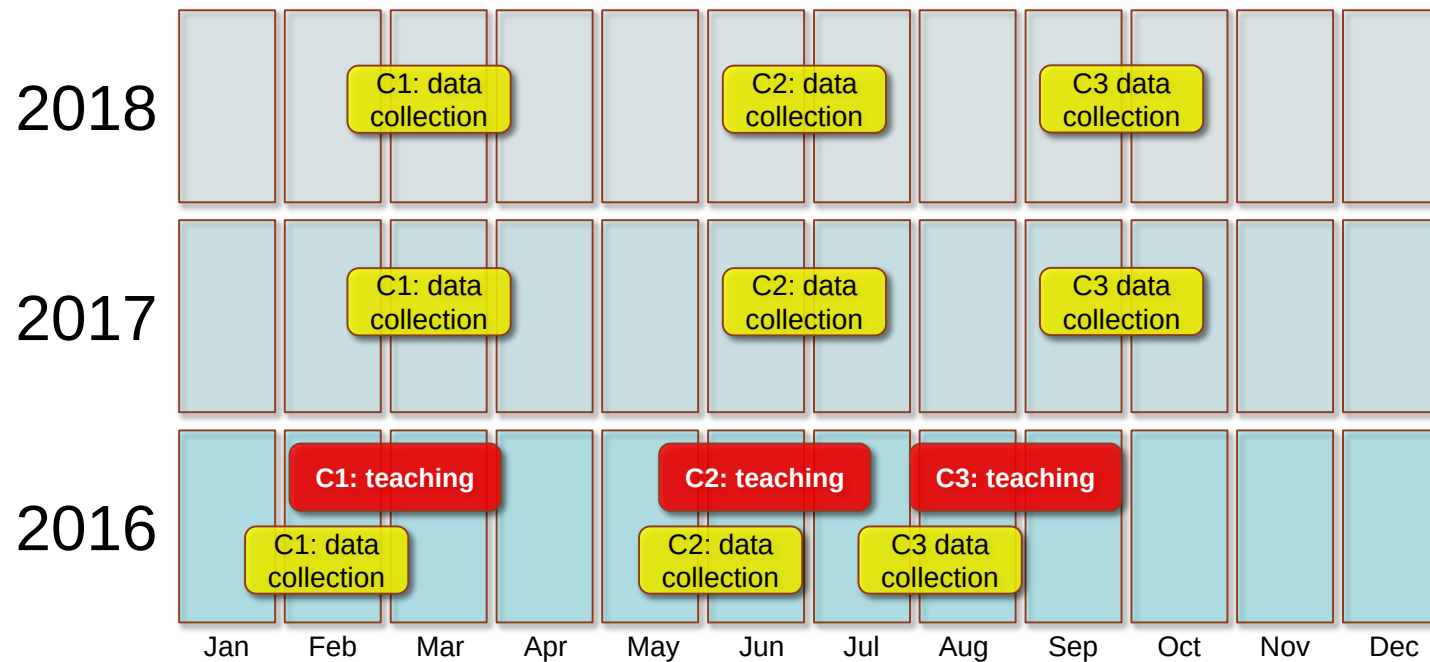
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the study: timeline



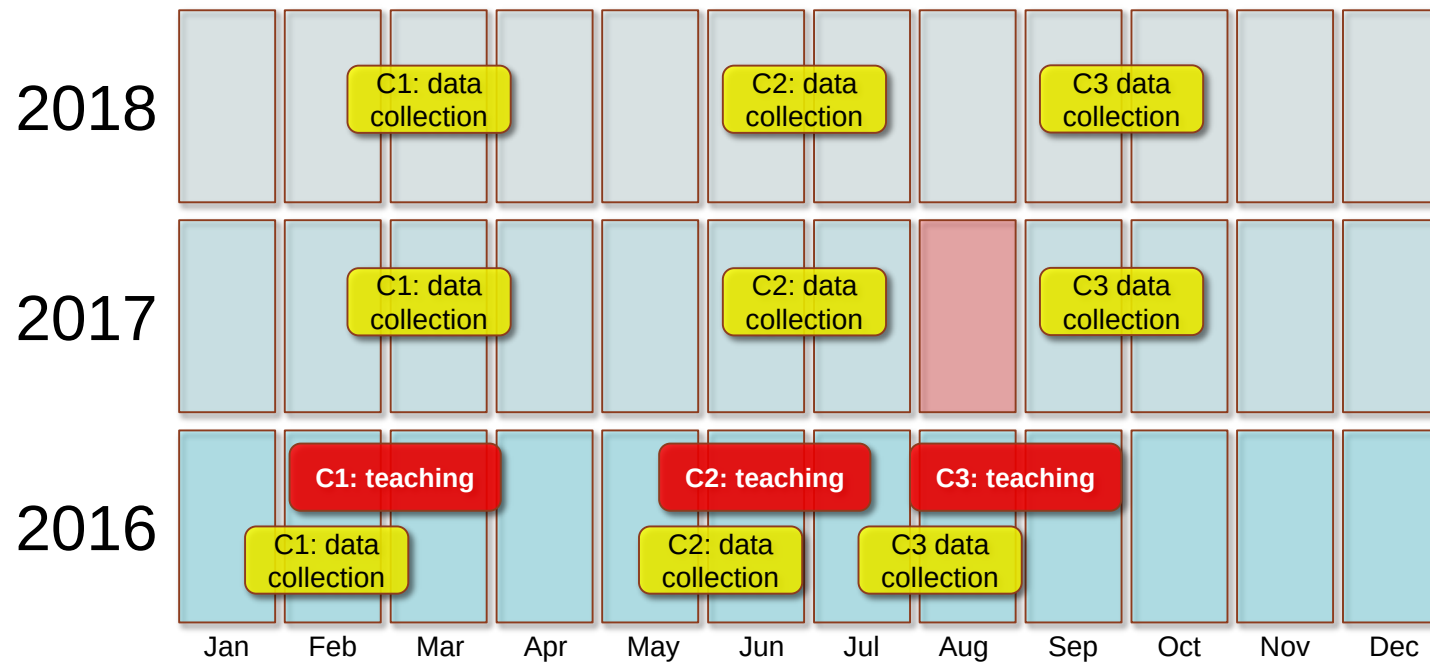
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the study: timeline



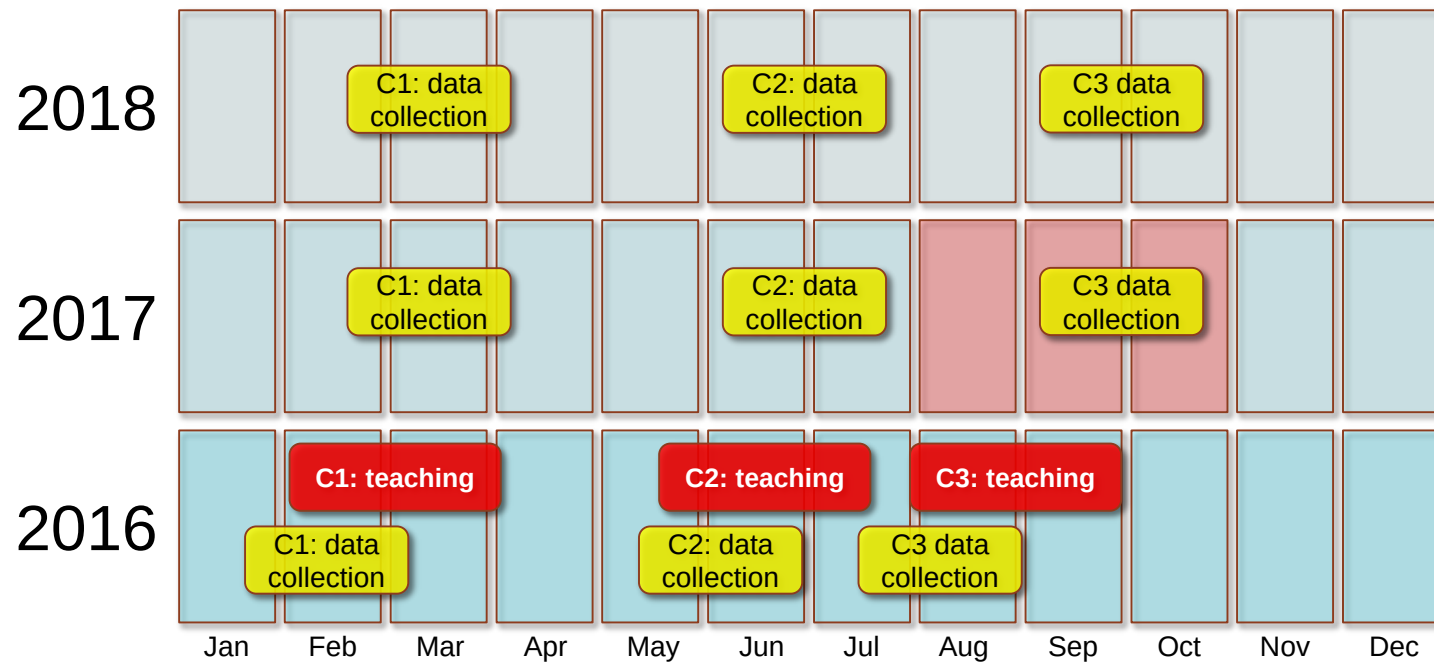
Three cohorts, each with ≈ 30 schools.

the study: timeline



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the study: timeline



Three cohorts, each with ≈ 30 schools.

comparison group: standard of care

Kenyan Ministry of Education curriculum

- Life-skills class covering: hygiene, sexual health, finances, etc.
- Part of national requirement, but taught by NMNW trainers to ensure consistency.

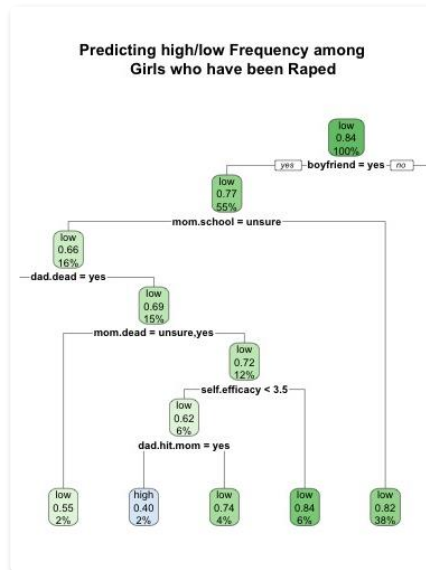


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the baseline

PRELIMINARY FINDINGS



baseline: randomization table

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	A	B
Total Schools	57	53
Total Girls	2086	2045
Relationships ¹	0.21 (0.20, 0.23)	0.22 (0.20, 0.23)
Rape	0.11 (0.10, 0.12)	0.11 (0.09, 0.12)
Partner rape	0.06 (0.04, 0.08)	0.04 (0.03, 0.06)
All IPV ²	0.17 (0.14, 0.20)	0.16 (0.13, 0.19)

Table 1: Covariate balance between treatment and control schools. Note relationships (1) tracks whether a girl has had a boyfriend; all IPV (2) tracks physical, verbal, and sexual intimate partner violence

baseline: randomization table

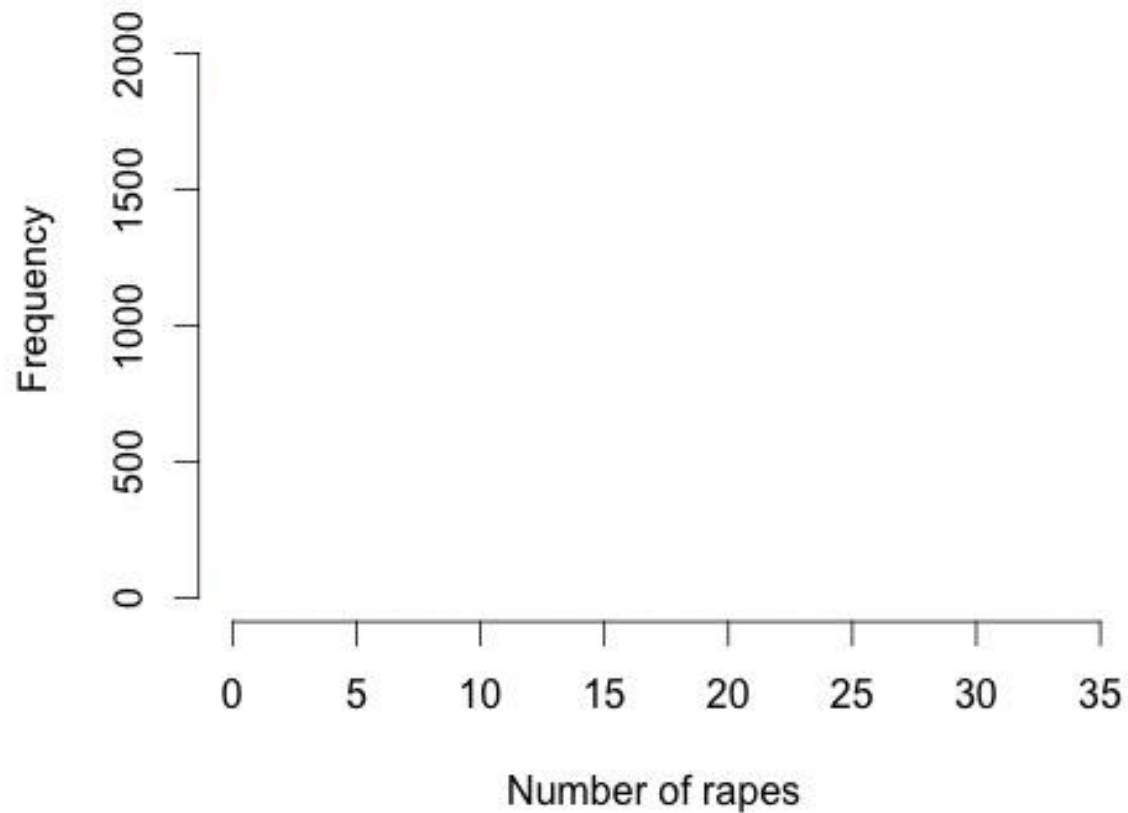
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baseline: distribution of counts

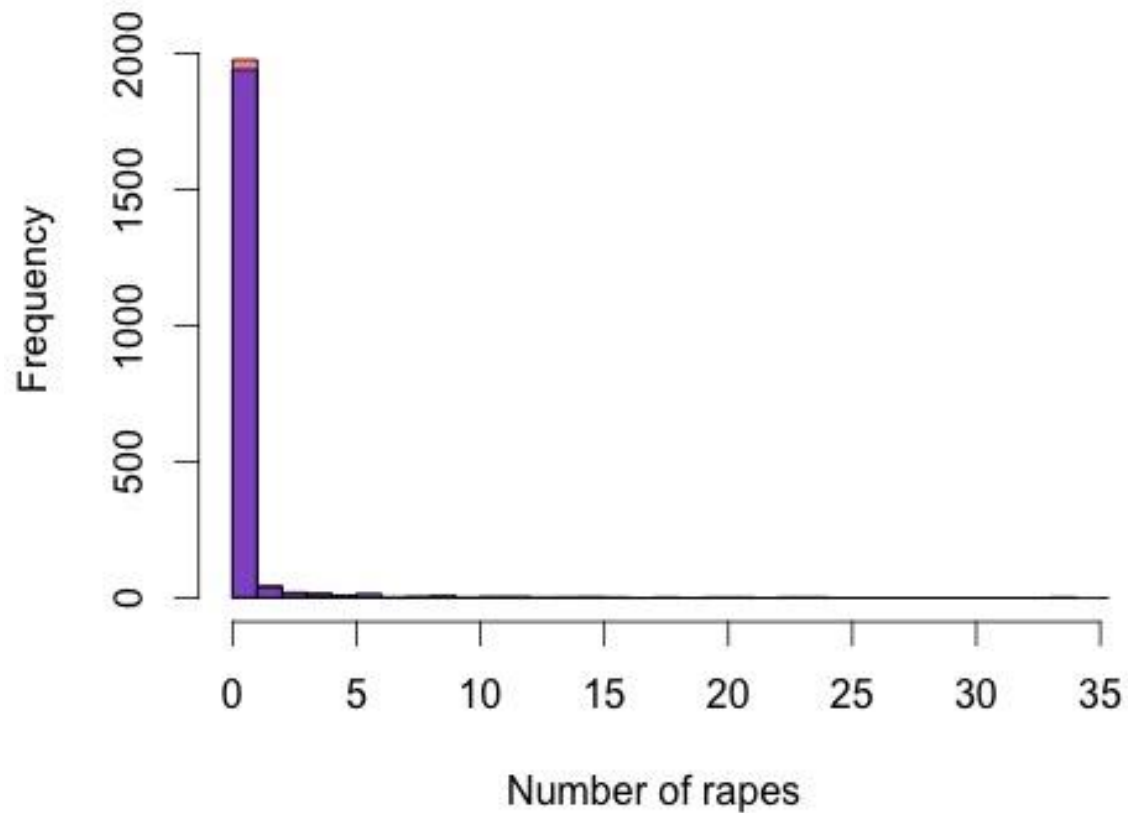
baseline: distribution of counts

Number of rapes among all girls

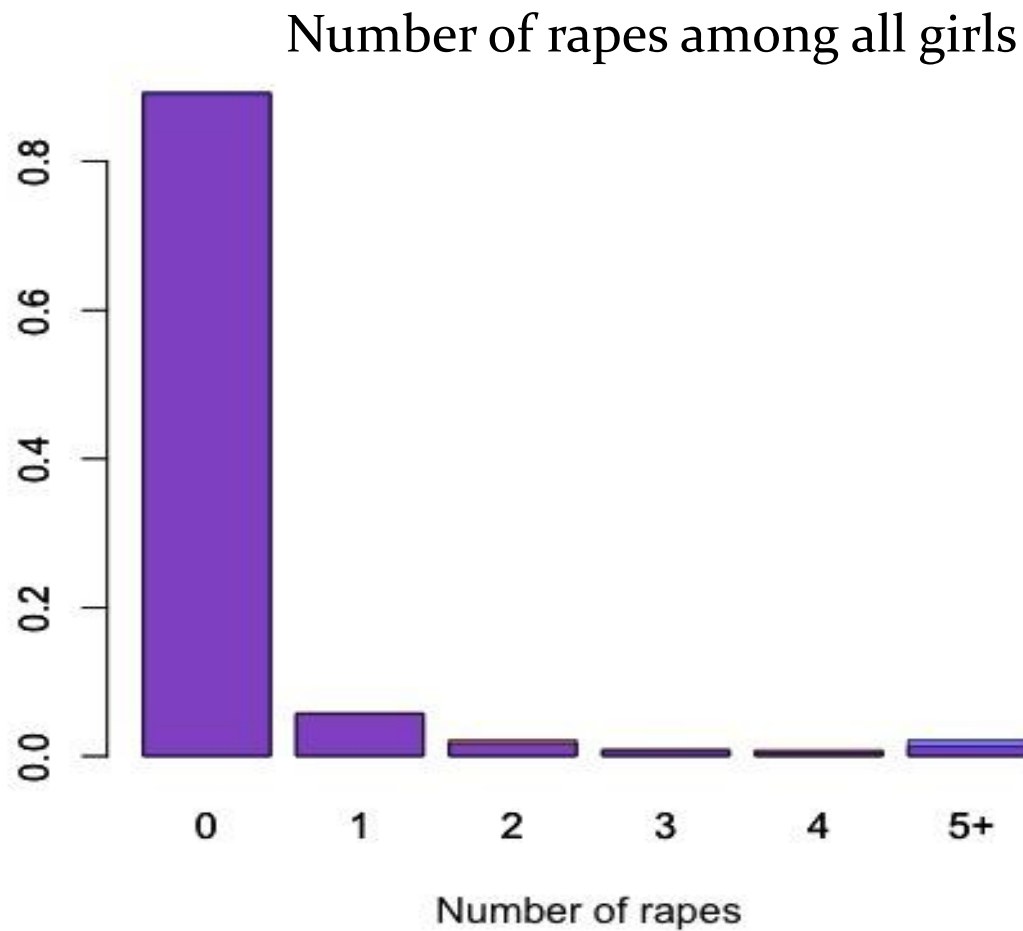


baseline: distribution of counts

Number of rapes among all girls



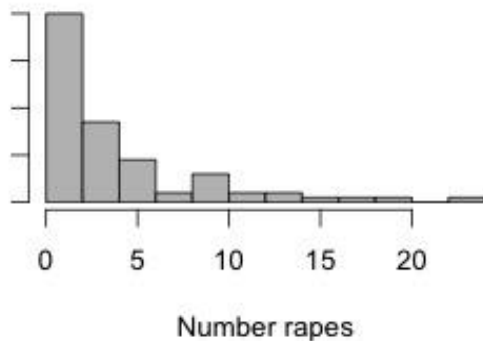
baseline: distribution of counts



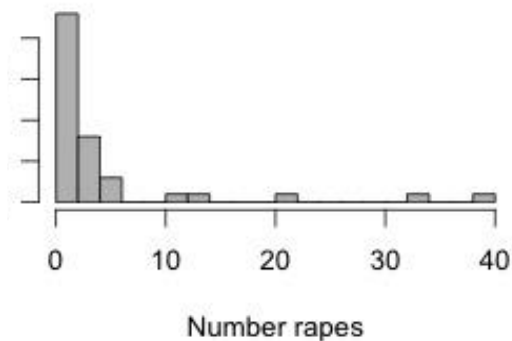
baseline: distribution of counts by perpetrators

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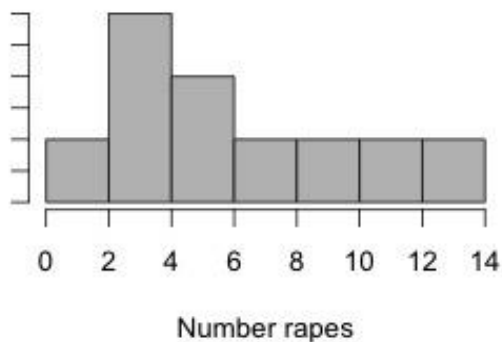
Boyfriend



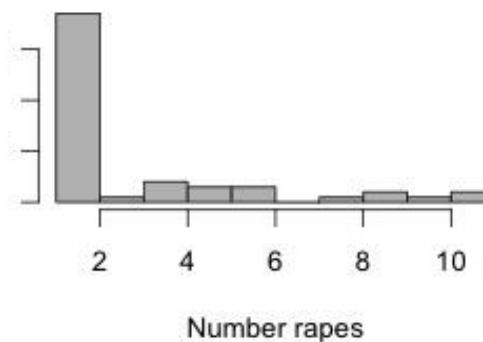
Relative



Authority Figure



Stranger



baseline: predictive models

baseline: predictive models

Two types of models:

baseline: predictive models

Two types of models:

- Individual level models

baseline: predictive models

Two types of models:

- Individual level models
- School level models

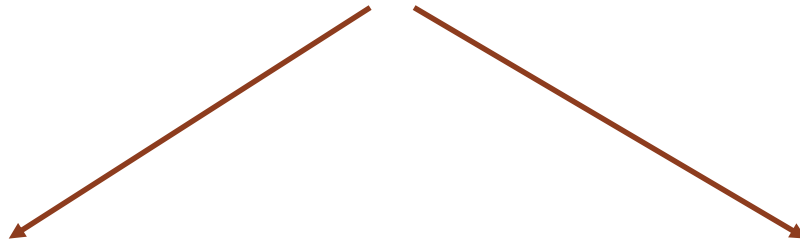
baseline: individual models

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What kind of girls are at risk?

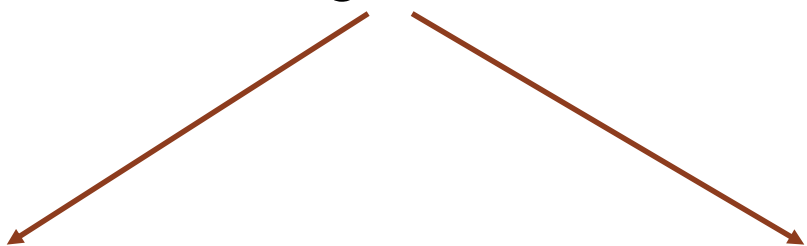
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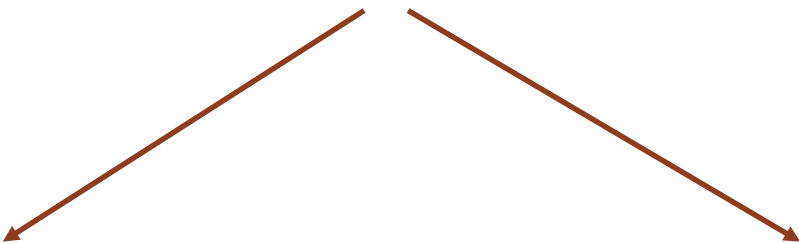
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None vs. >1

baseline: individual models

What kind of girls are at risk?



None vs. >1

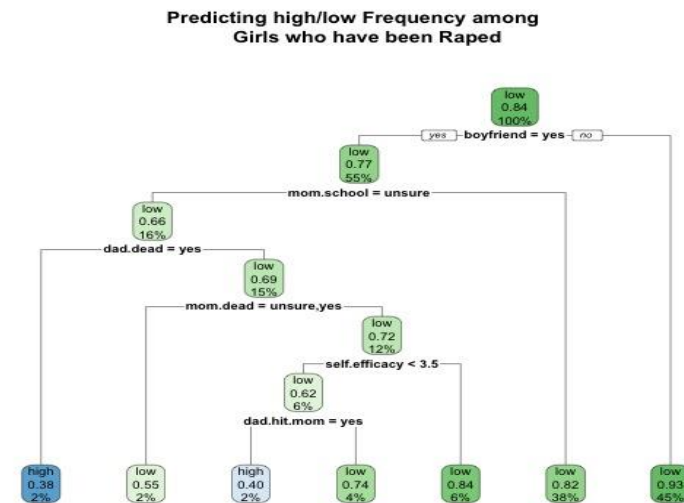
<4 vs. >5

baseline: individual models

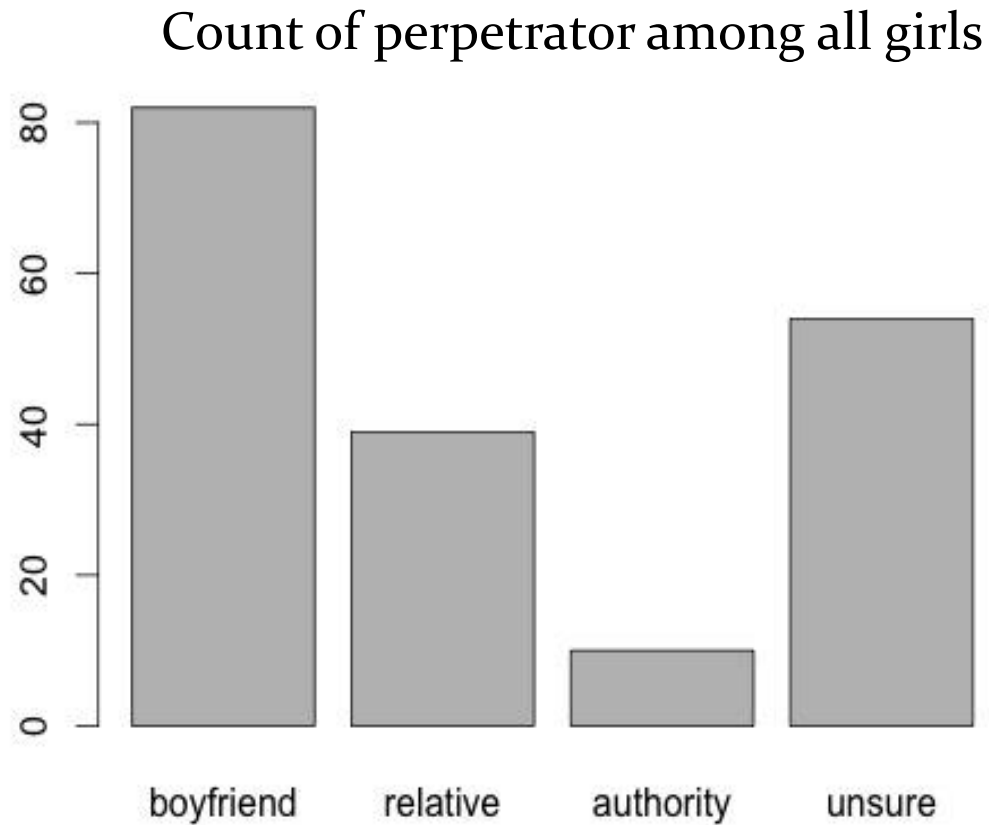
What kind of girls are at risk?

None vs. >1

<4 vs. >5



baseline: boyfriends



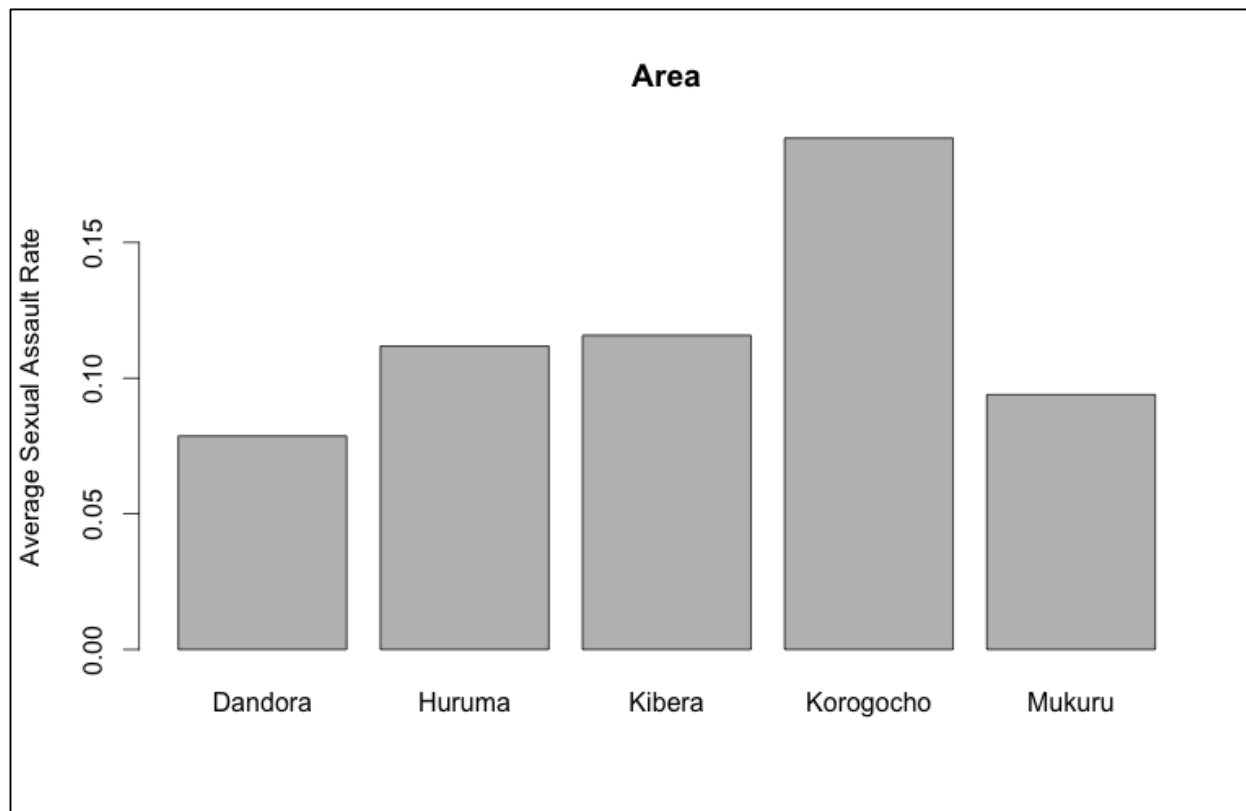
baseline: school level

baseline: school level

Which schools should we reach out to first?

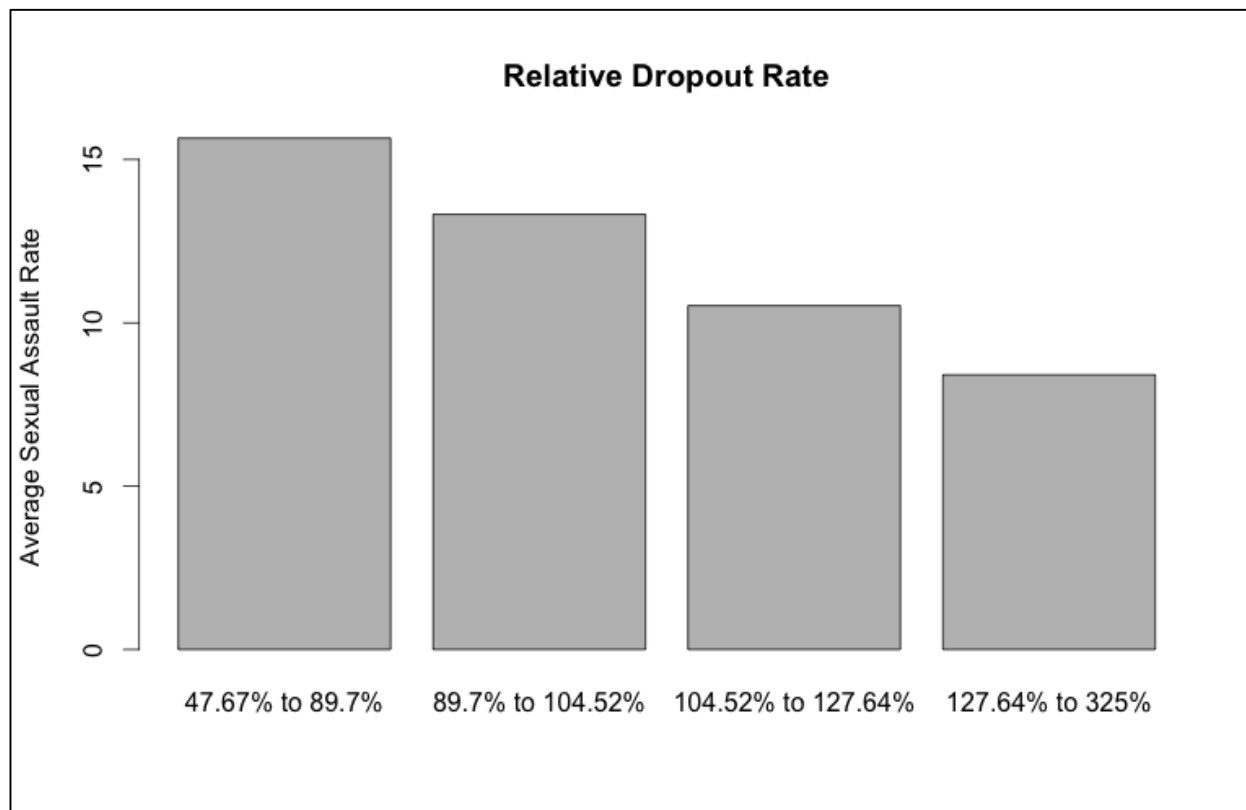
baseline: school level

Which schools should we reach out to first?



baseline: school level

Which schools should we reach out to first?





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impact model

INTERMEDIATE EFFECTS

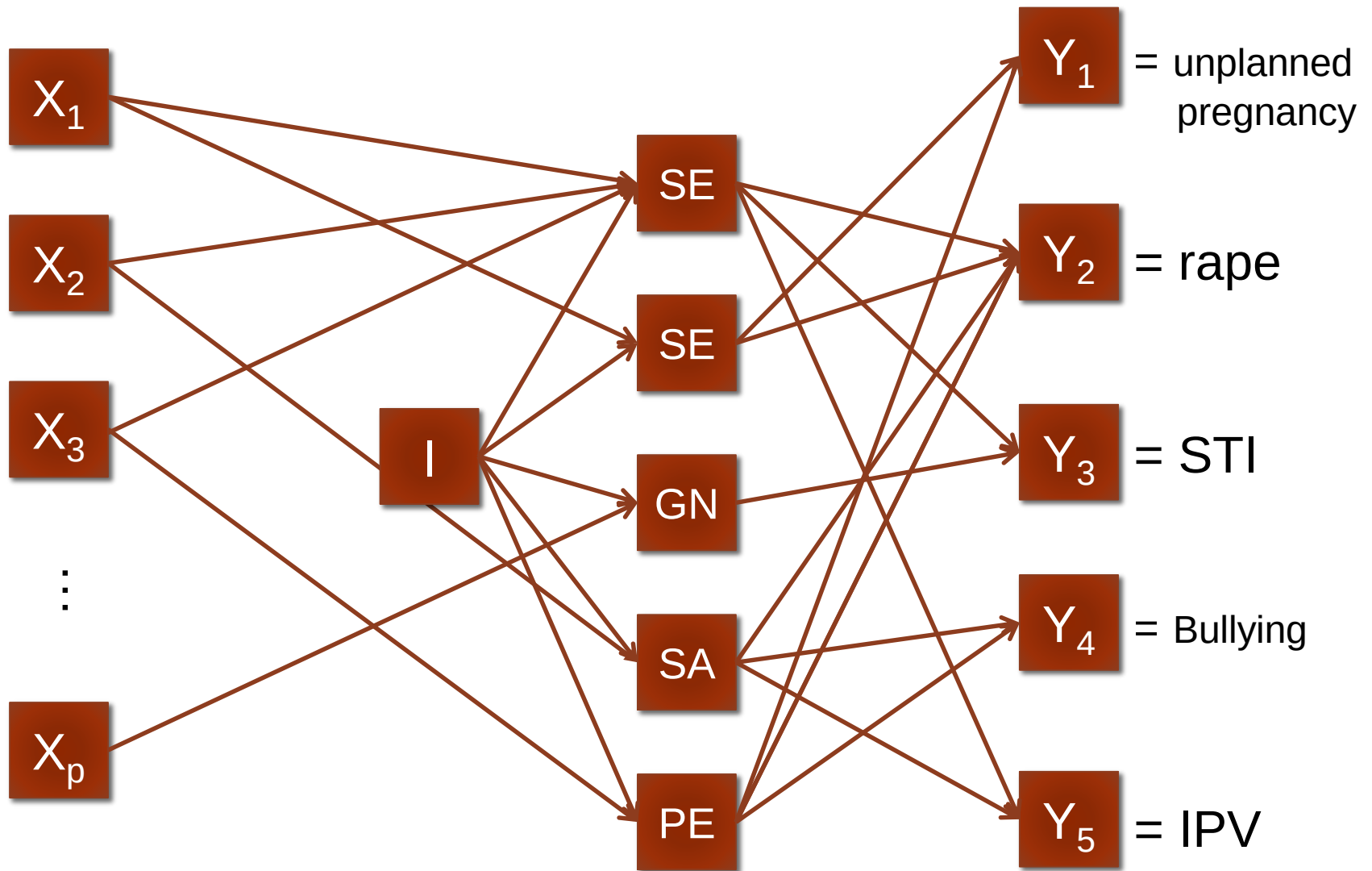




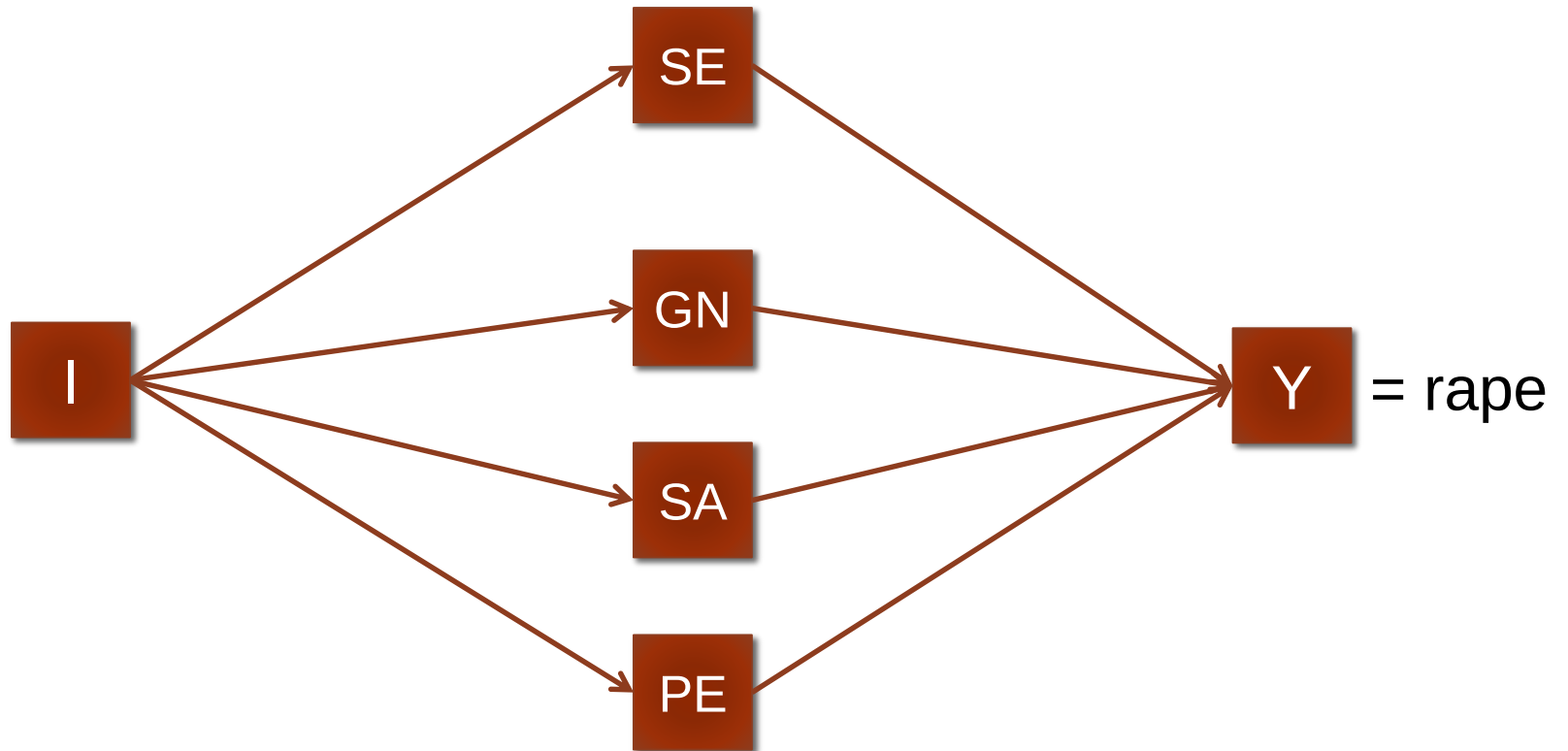




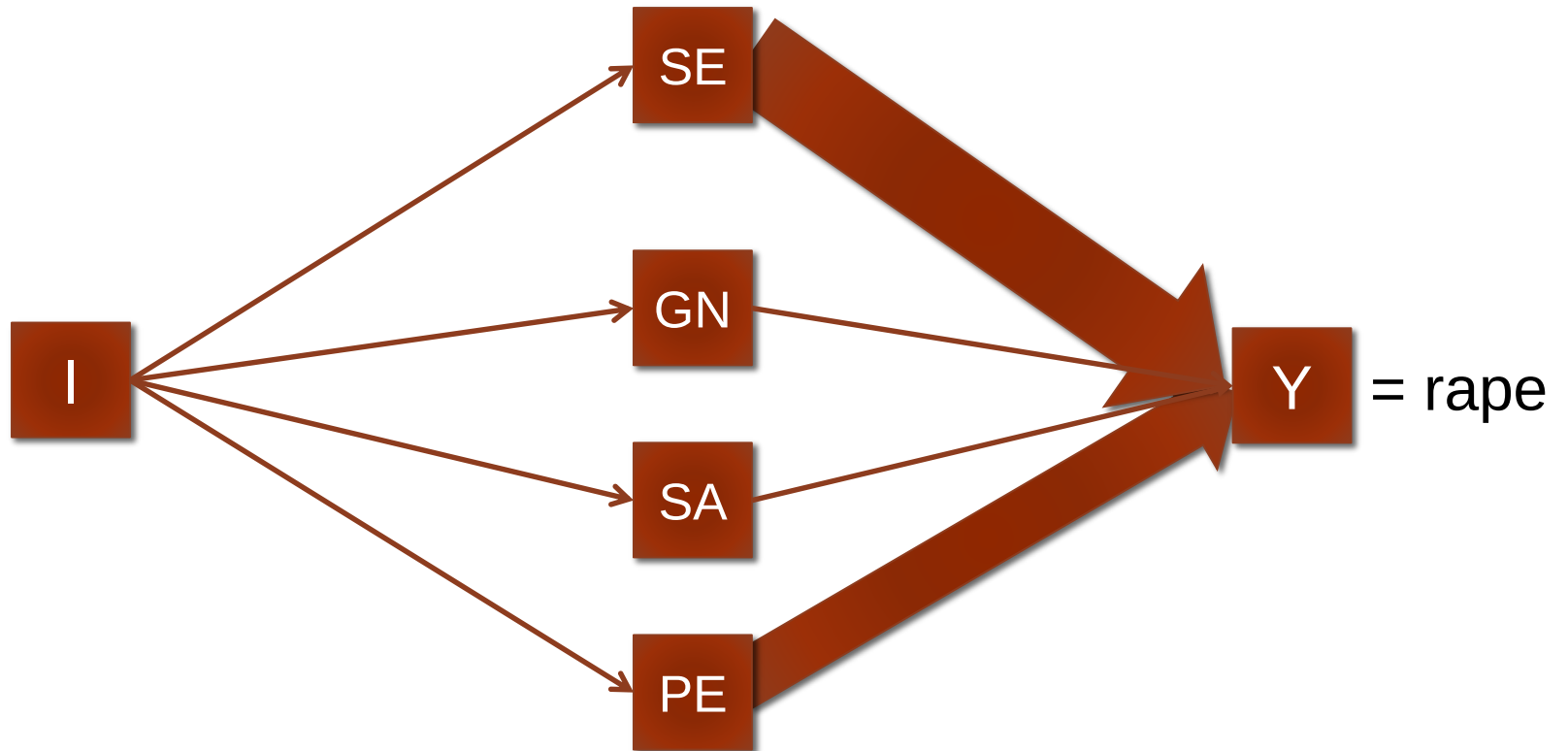
Complete Model



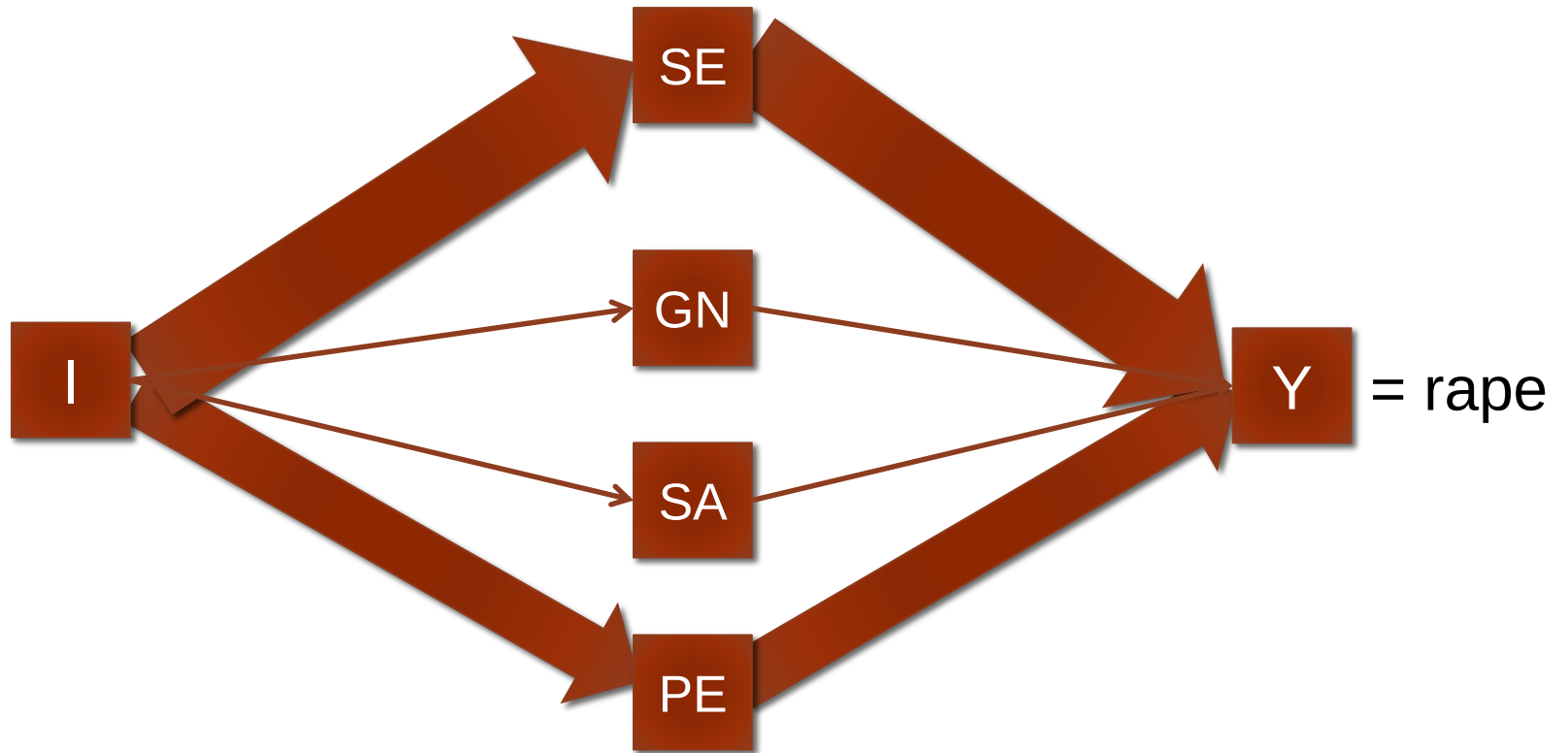
Reduced Model



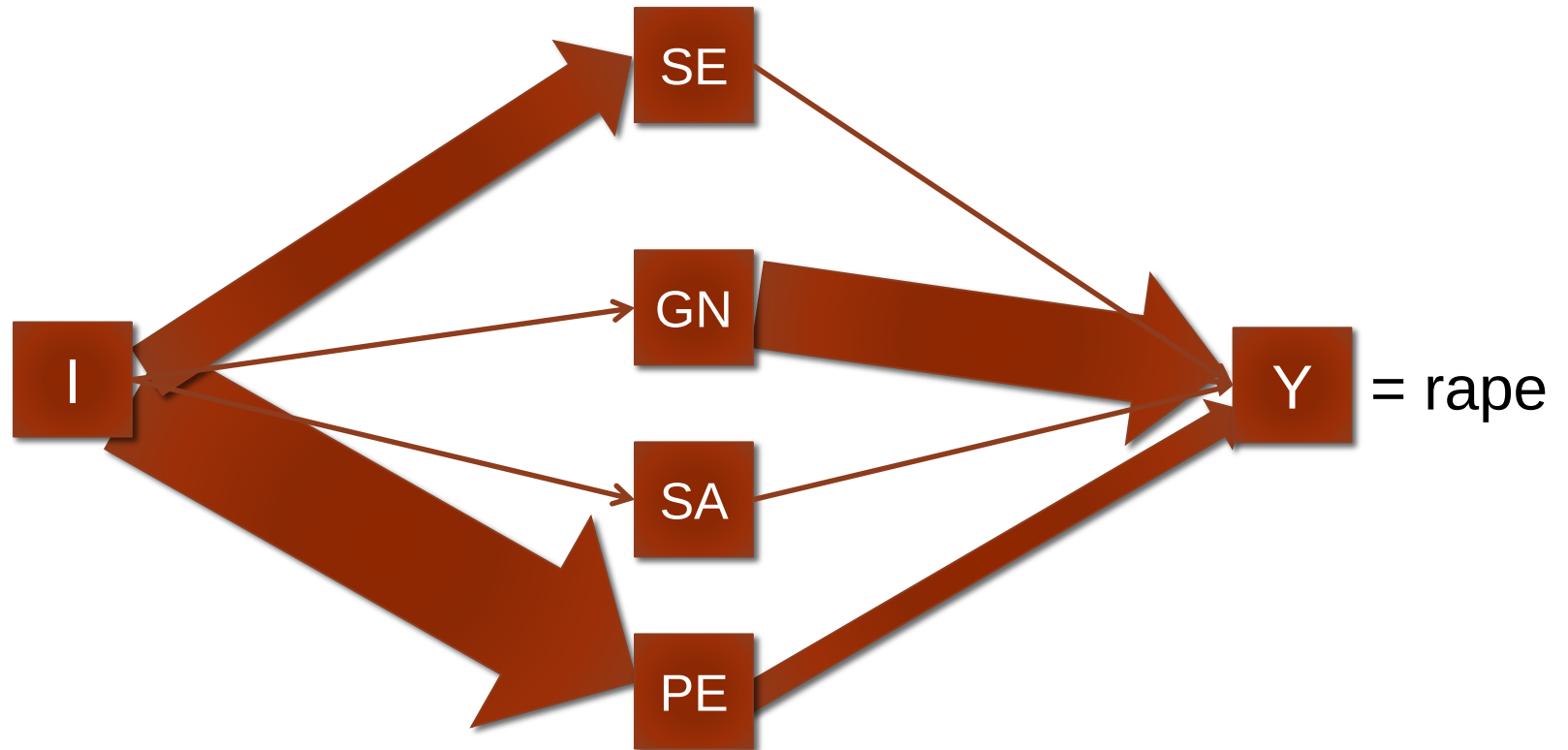
Reduced Model



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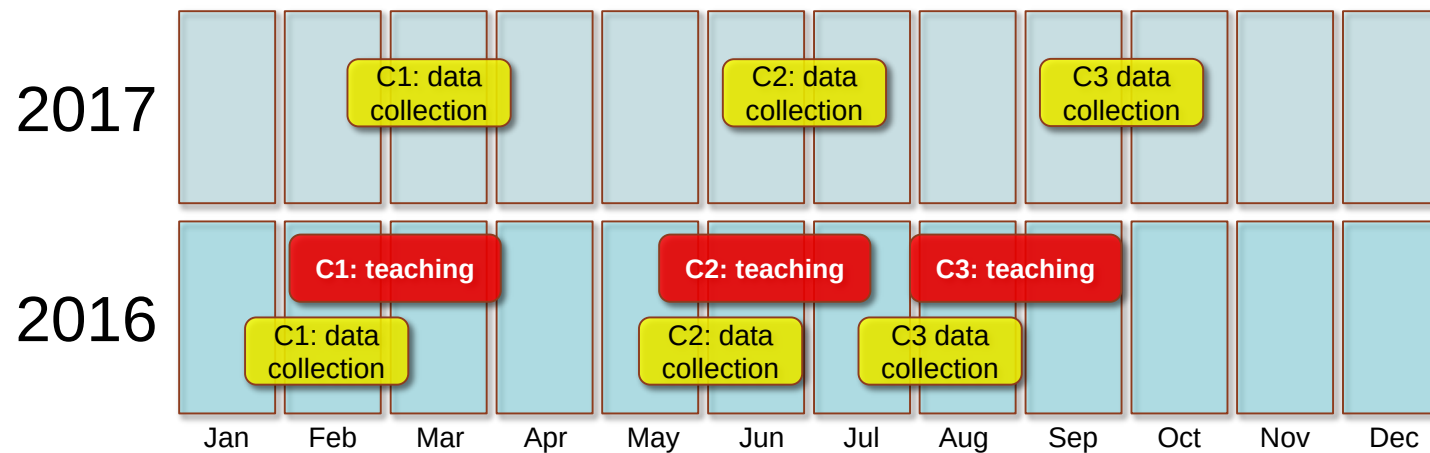


Reduced Model

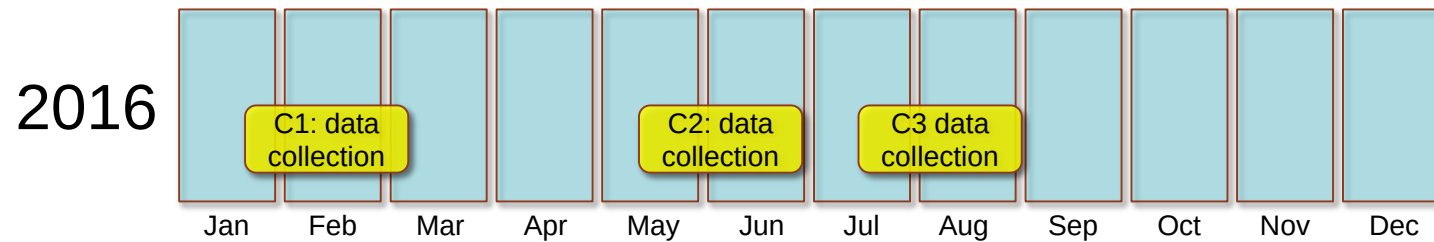


baseline: principal stratification modeling

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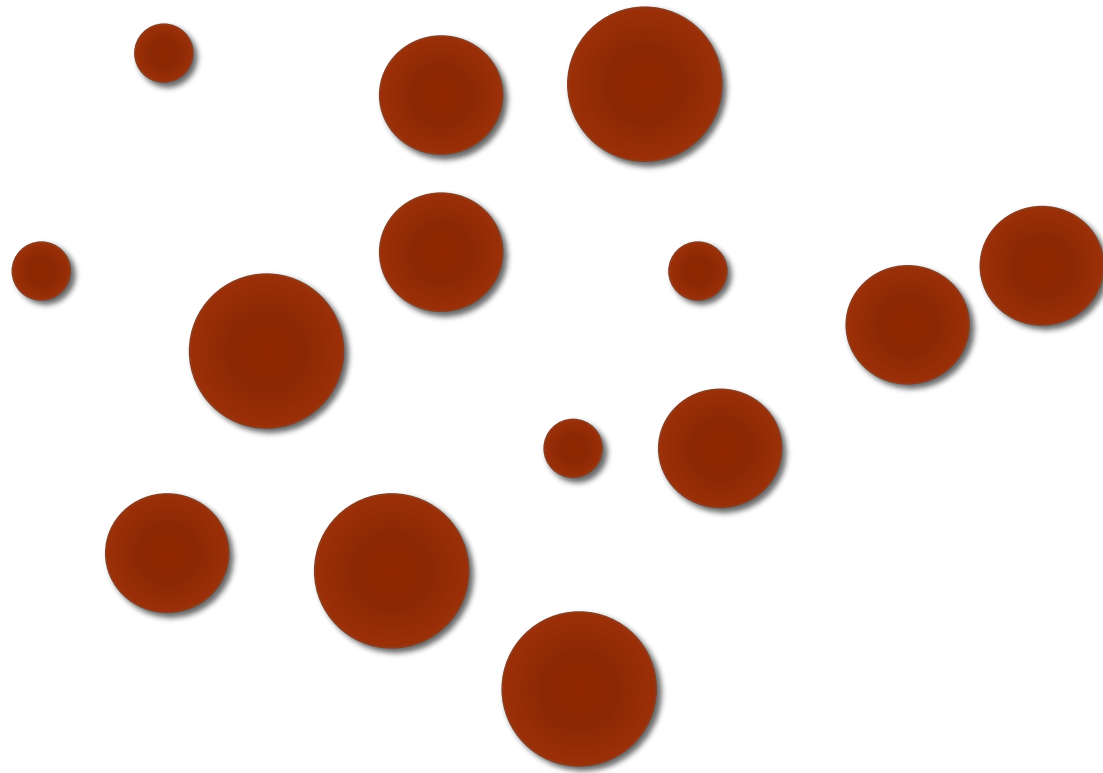


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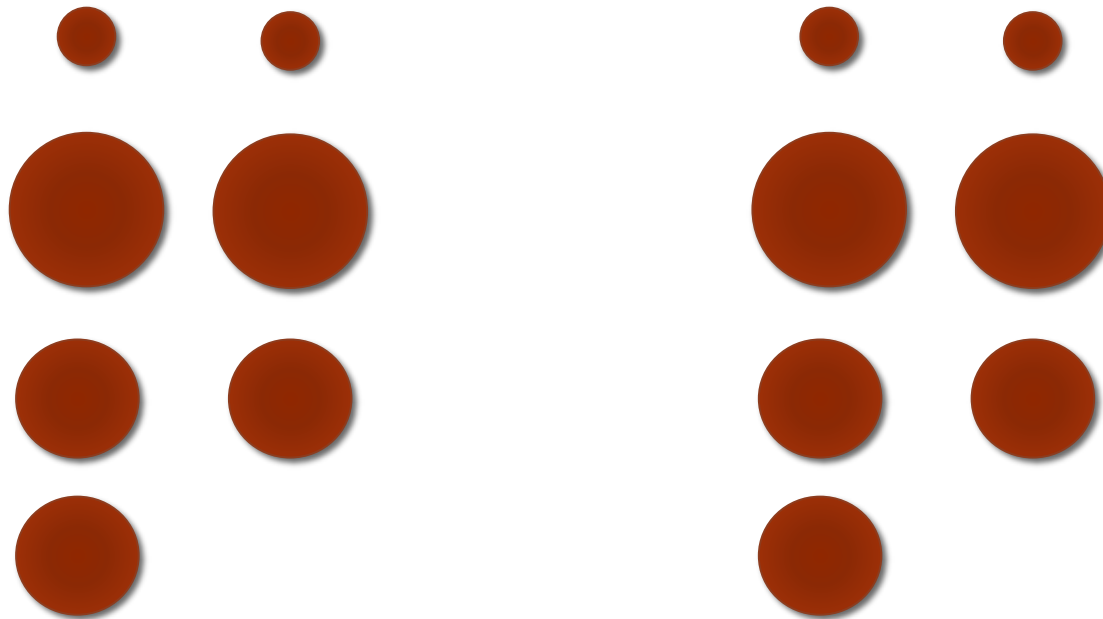


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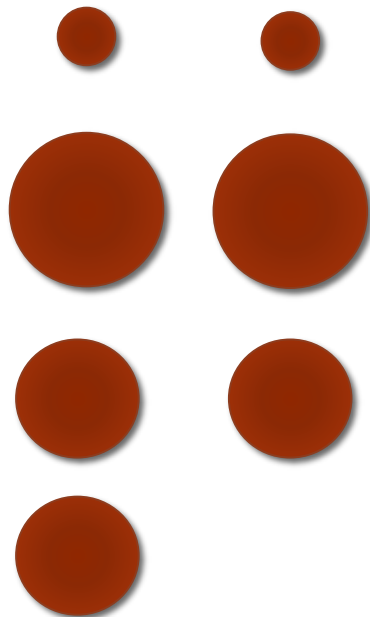


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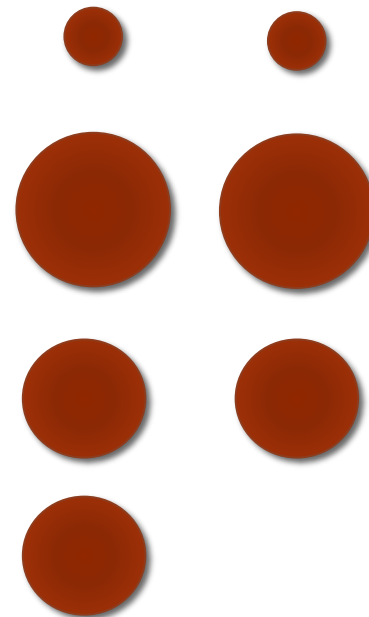


baseline: principal stratification modeling

Treatment

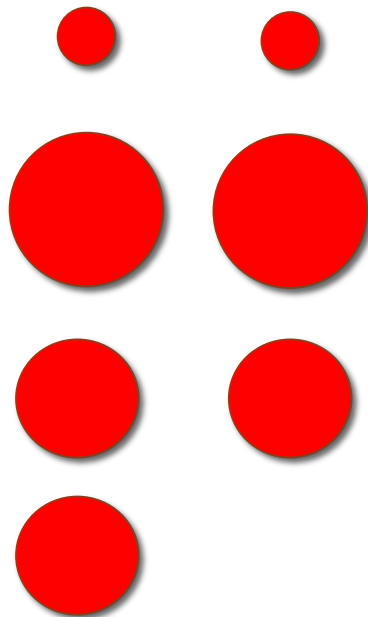


Control

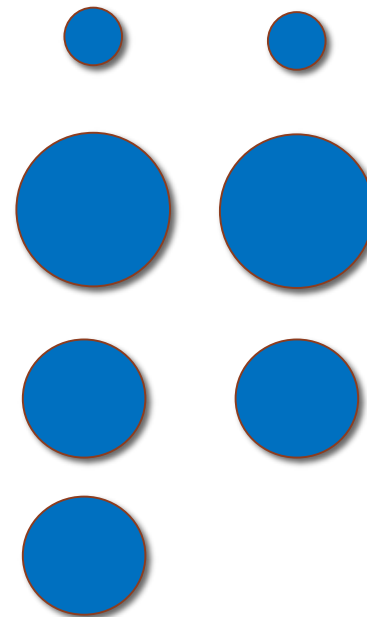


baseline: principal stratification modeling

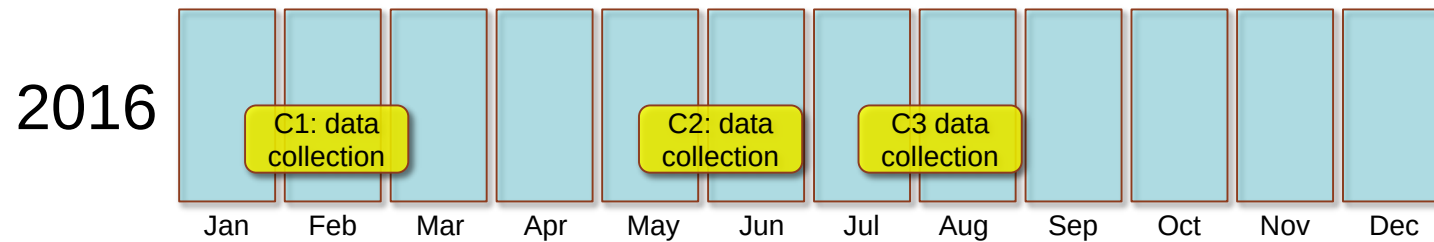
Treatment



Control

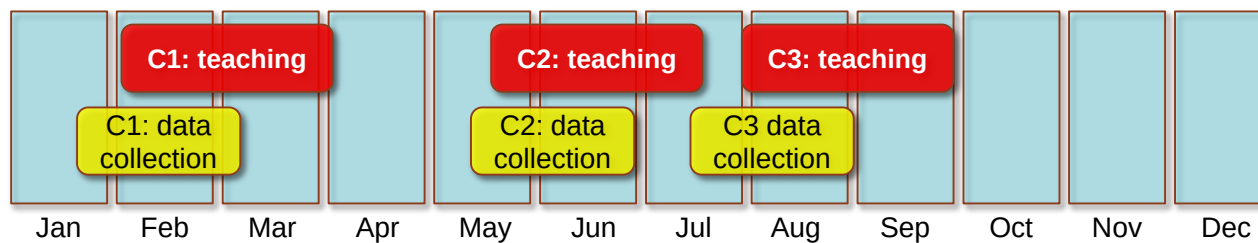


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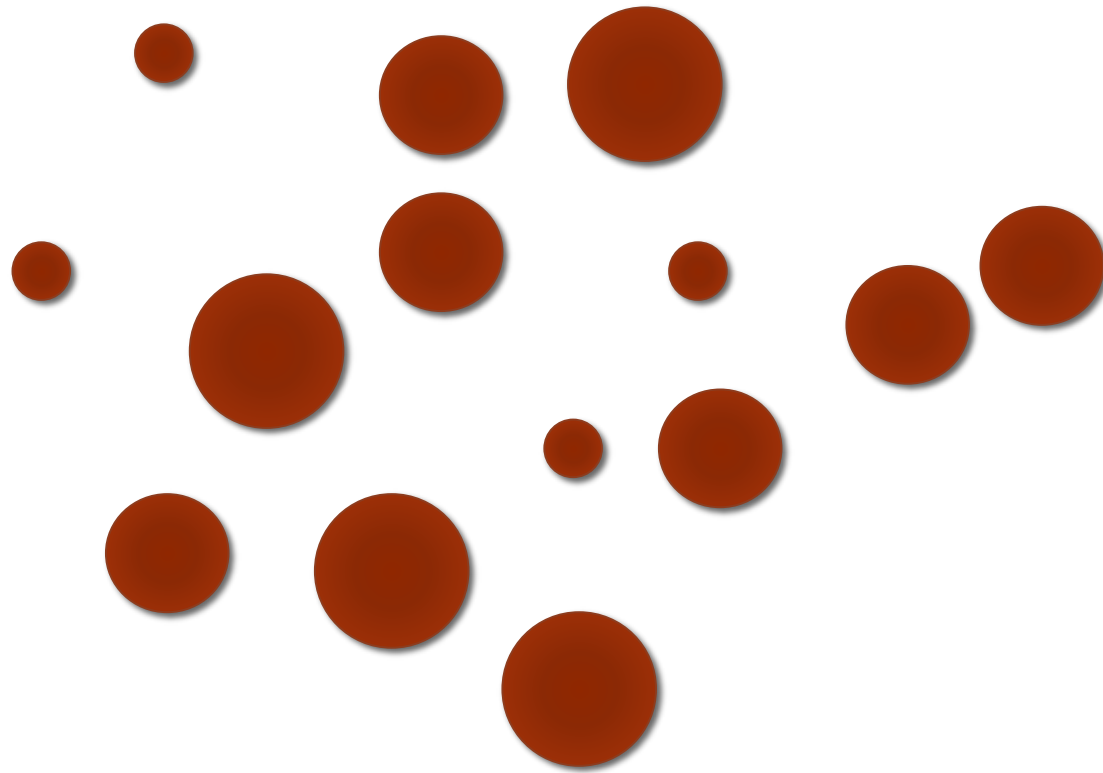


baseline: principal stratification modeling

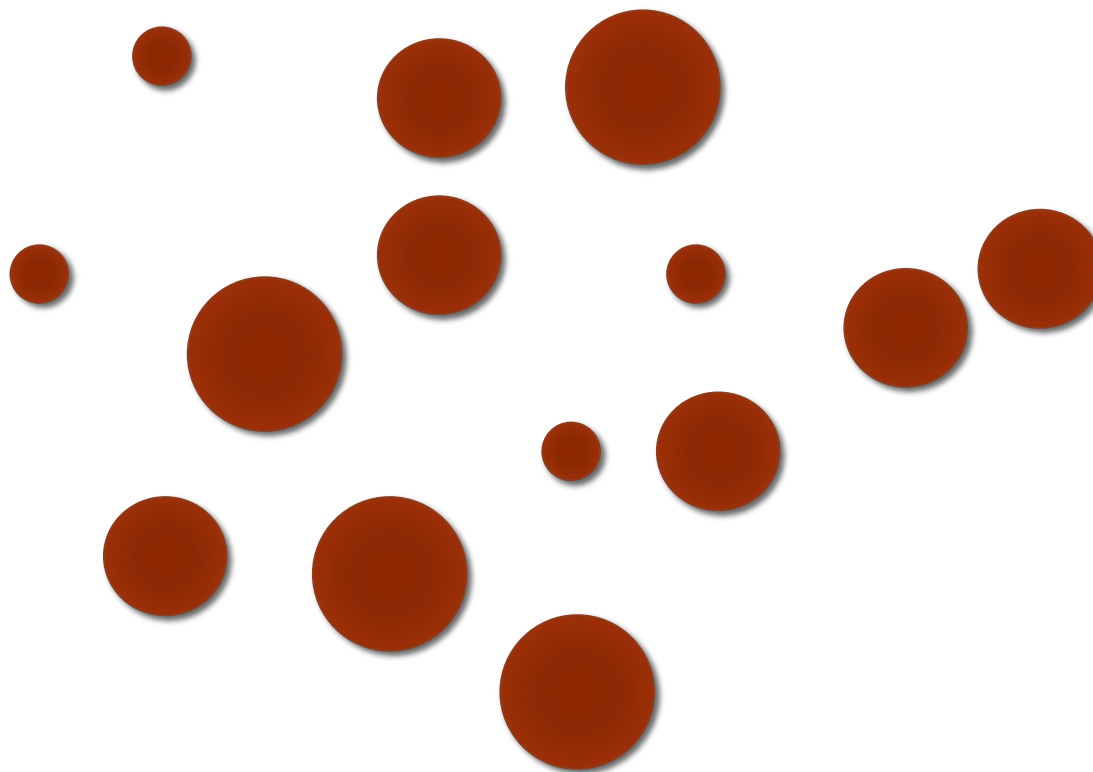
2016



baseline: principal stratification modeling

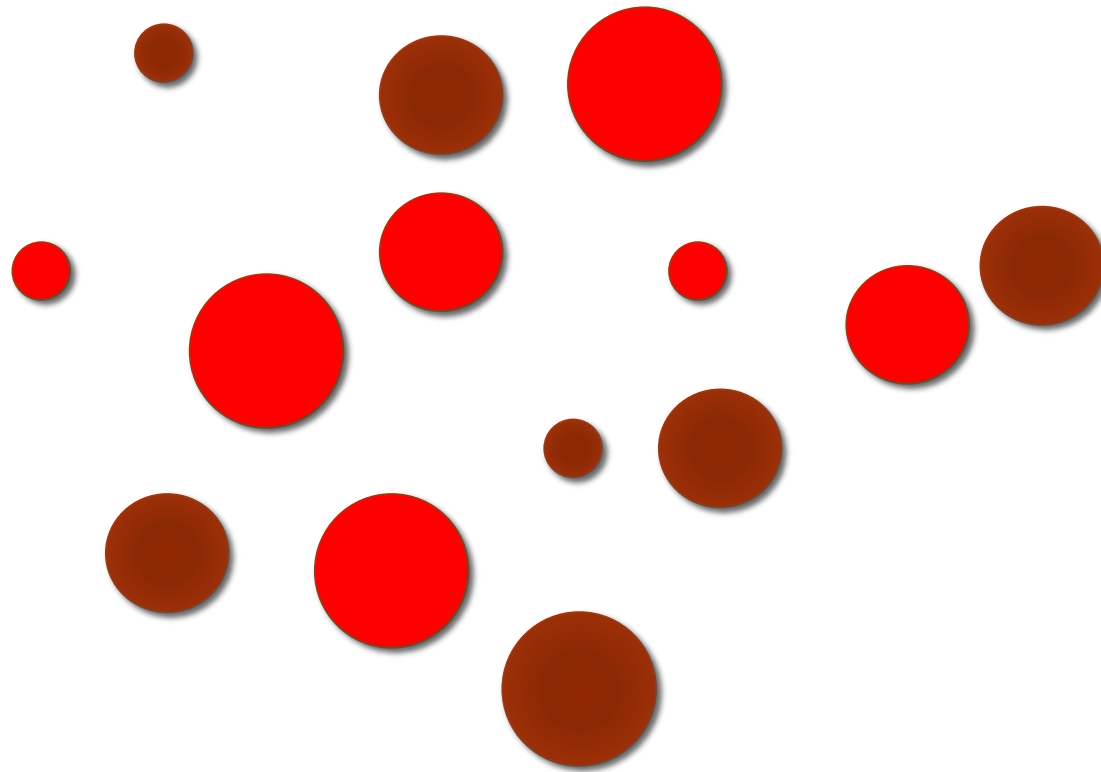


baseline: principal stratification modeling



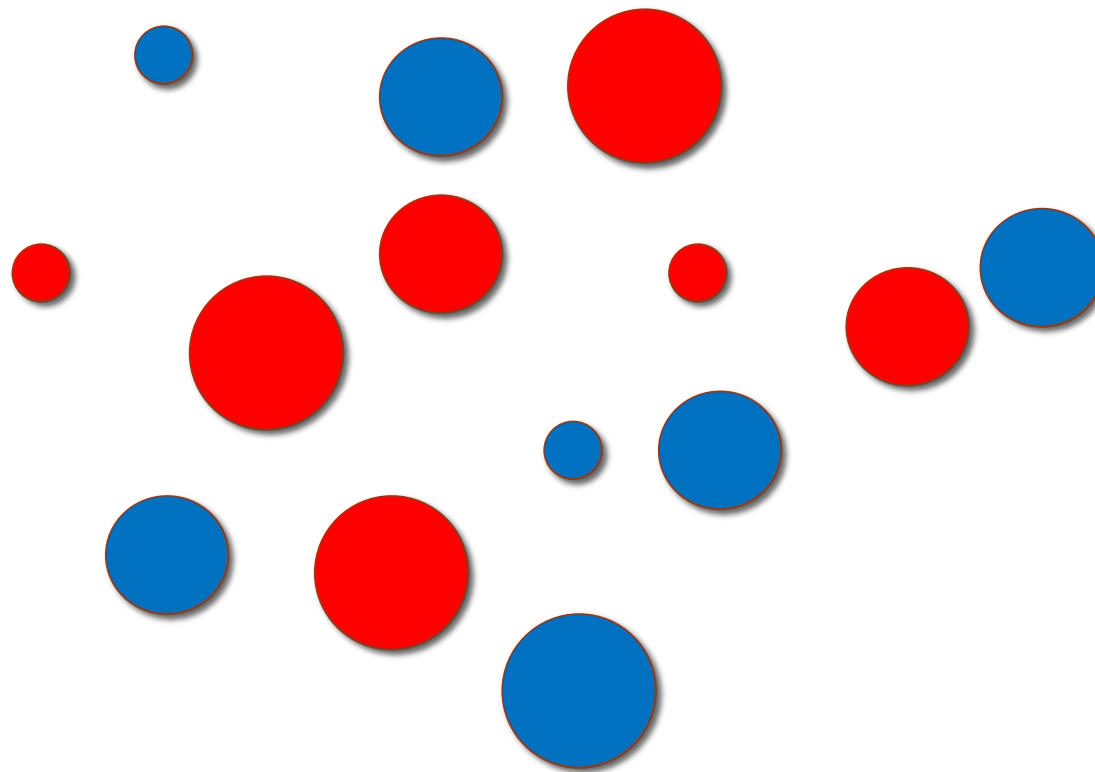
Example: impact of no male guardian?

baseline: principal stratification modeling



Example: impact of no male guardian?

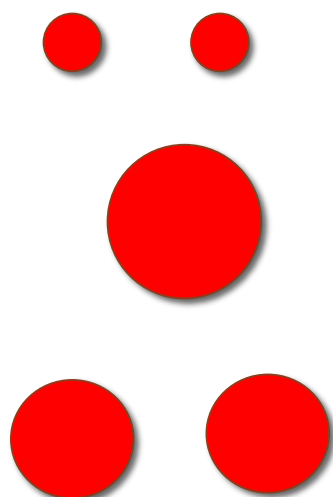
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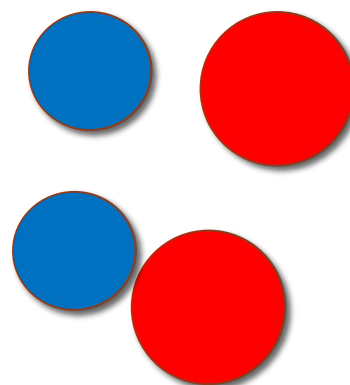
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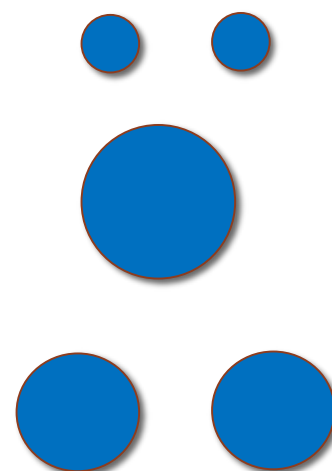
Matched-exposed



Unmatched



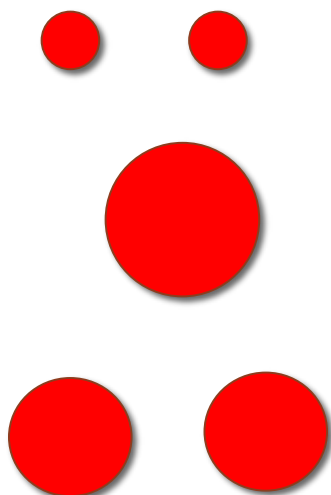
Matched-unexposed



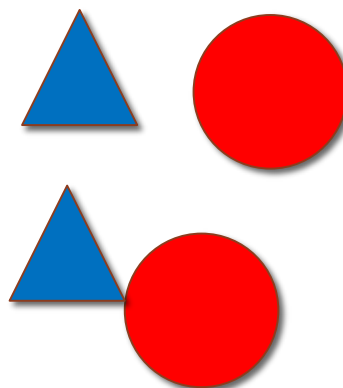
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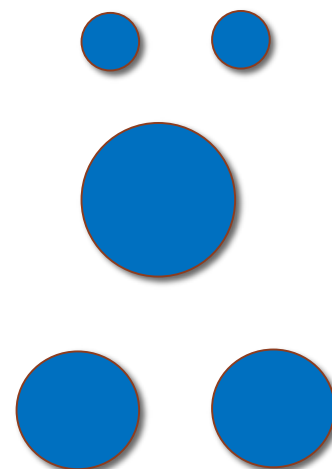
Matched-exposed



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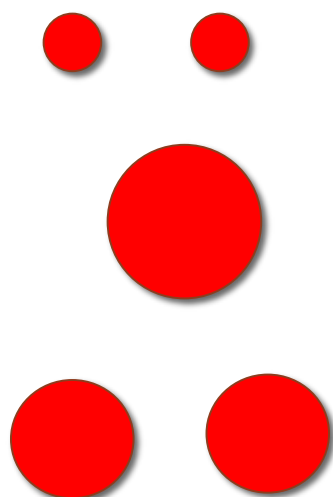
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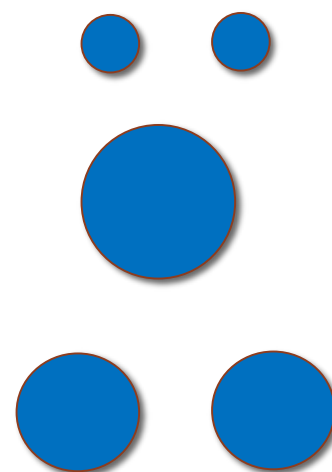
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baseline: principal stratification modeling

Matched-exposed



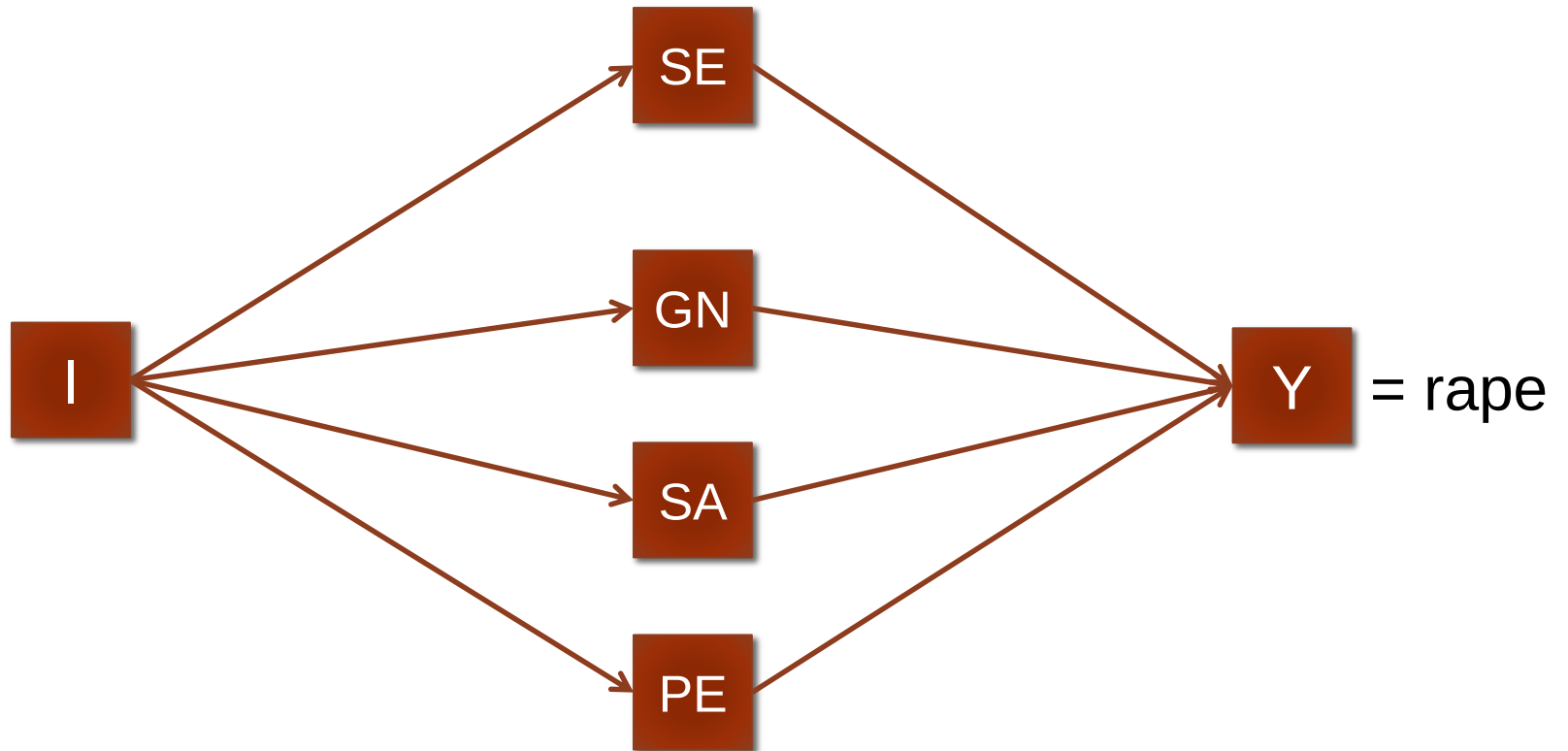
Matched-unexposed



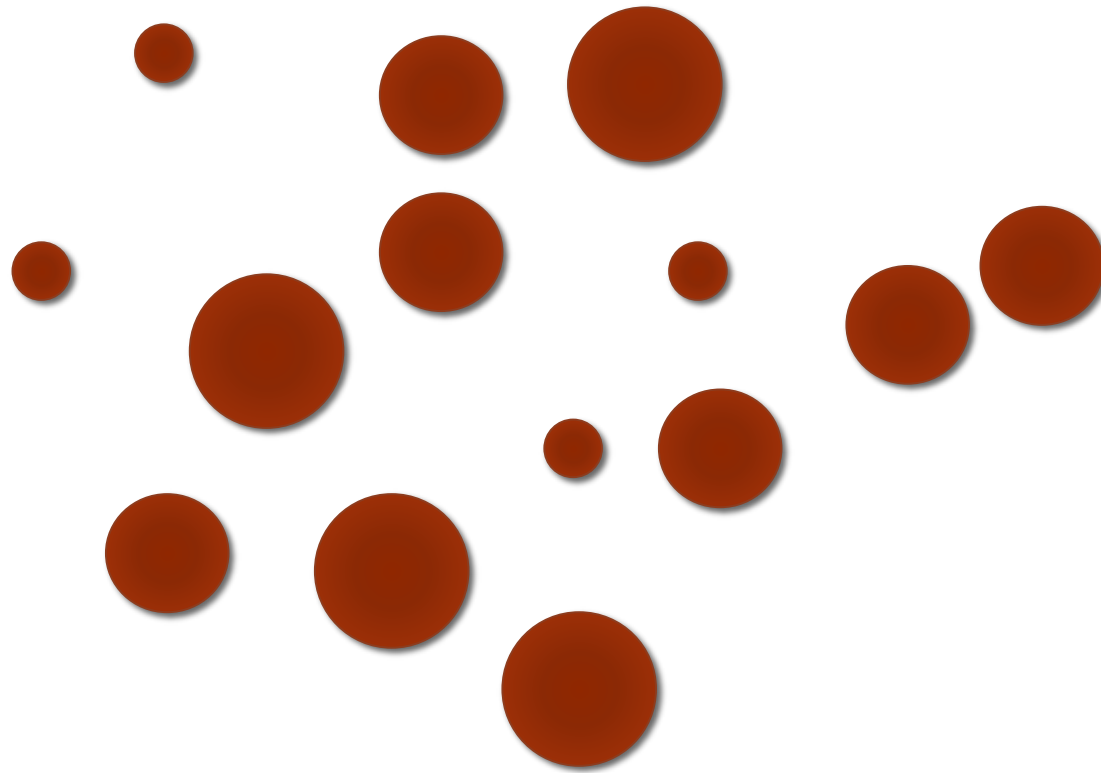
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baseline: principal stratification modeling

Reduced Model

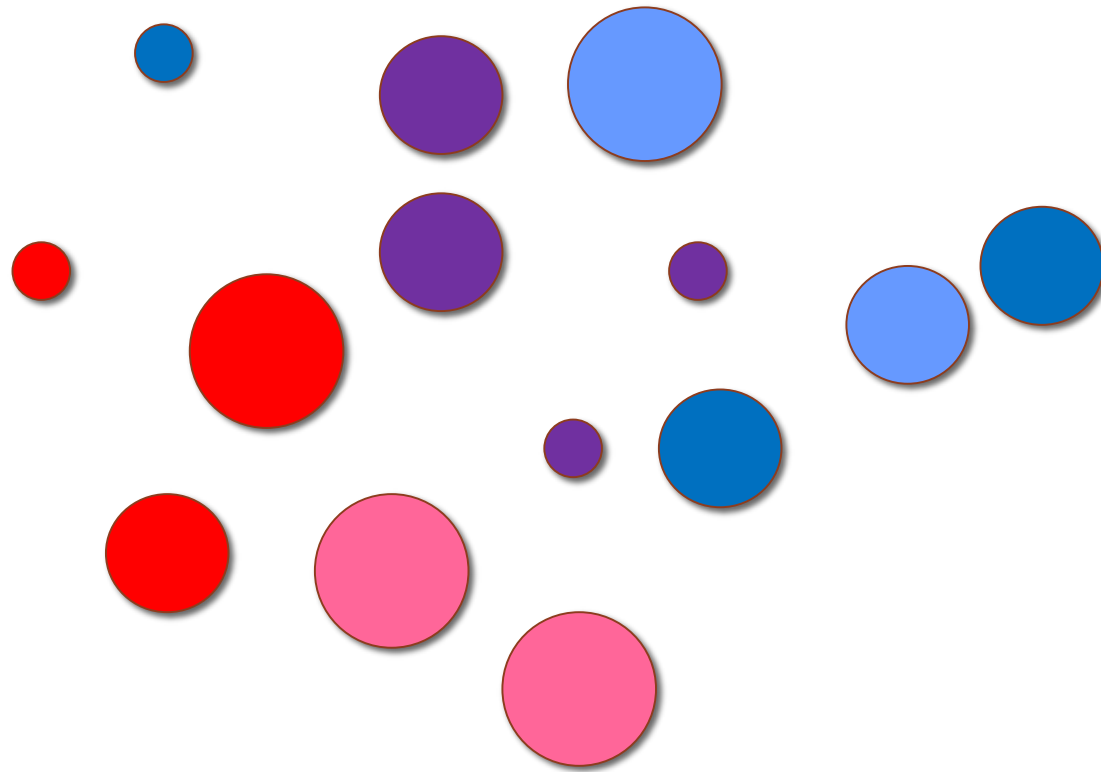


baseline: principal stratification modeling



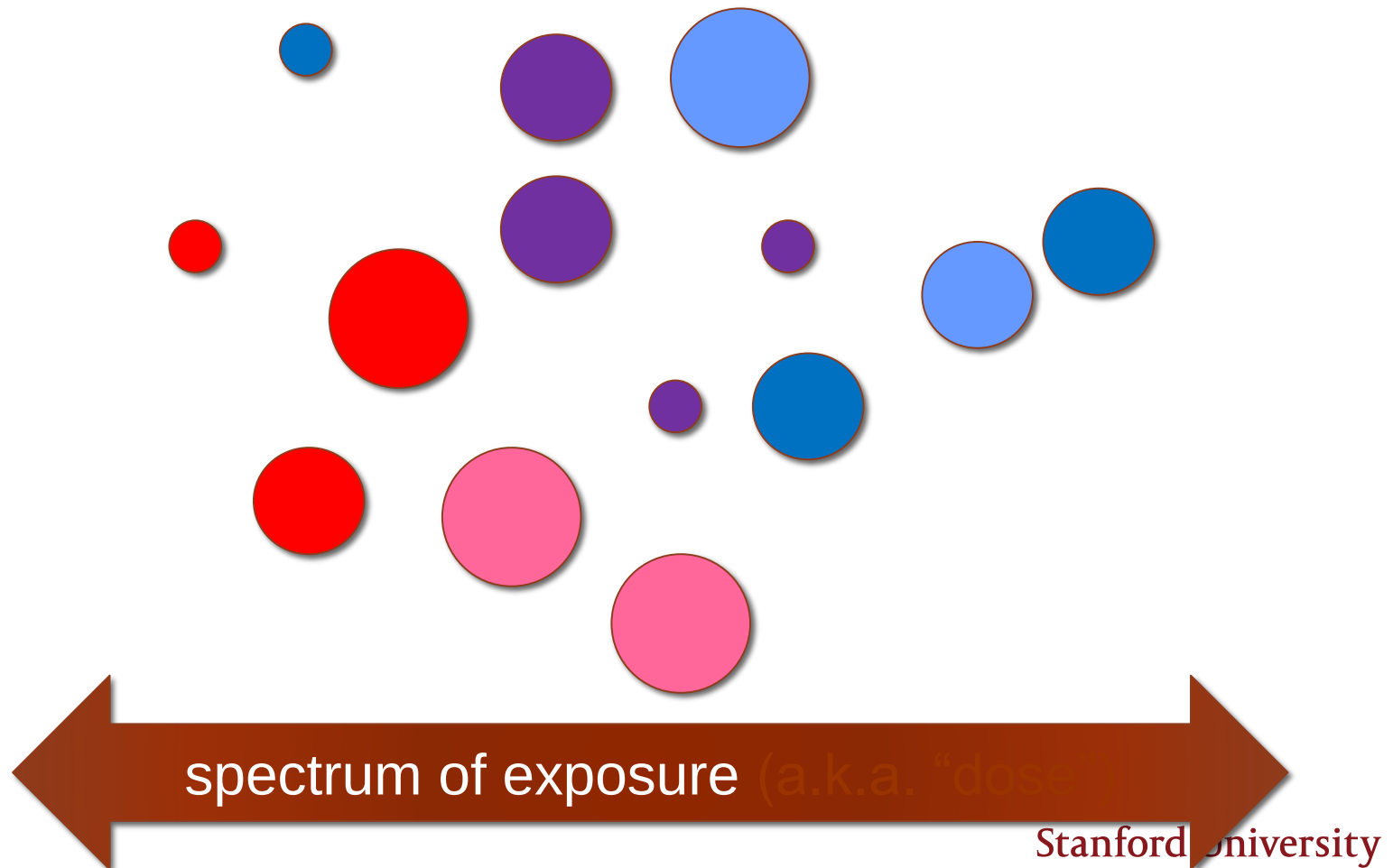
baseline: principal stratification modeling

Example: impact of self-efficacy on probability of rape.



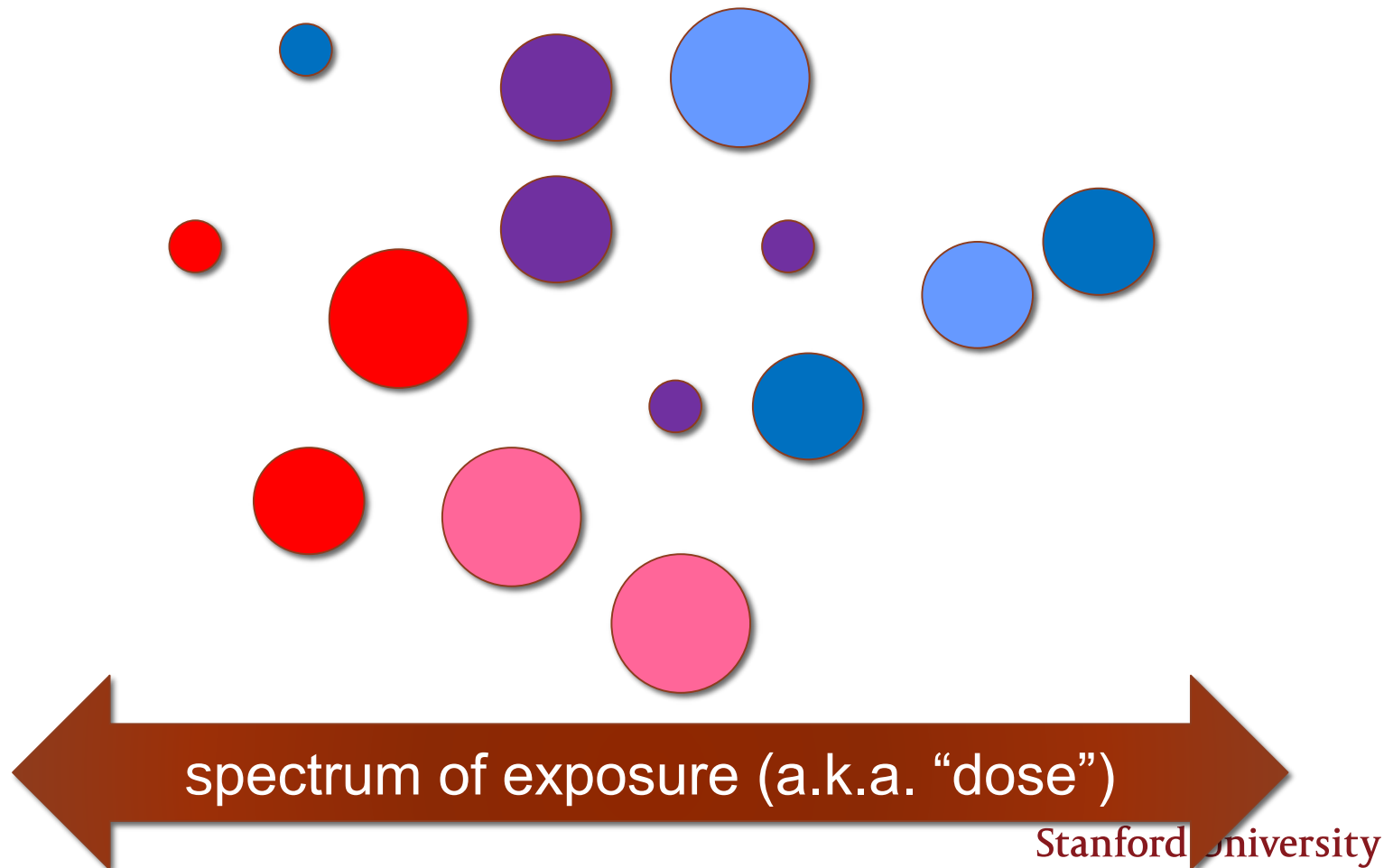
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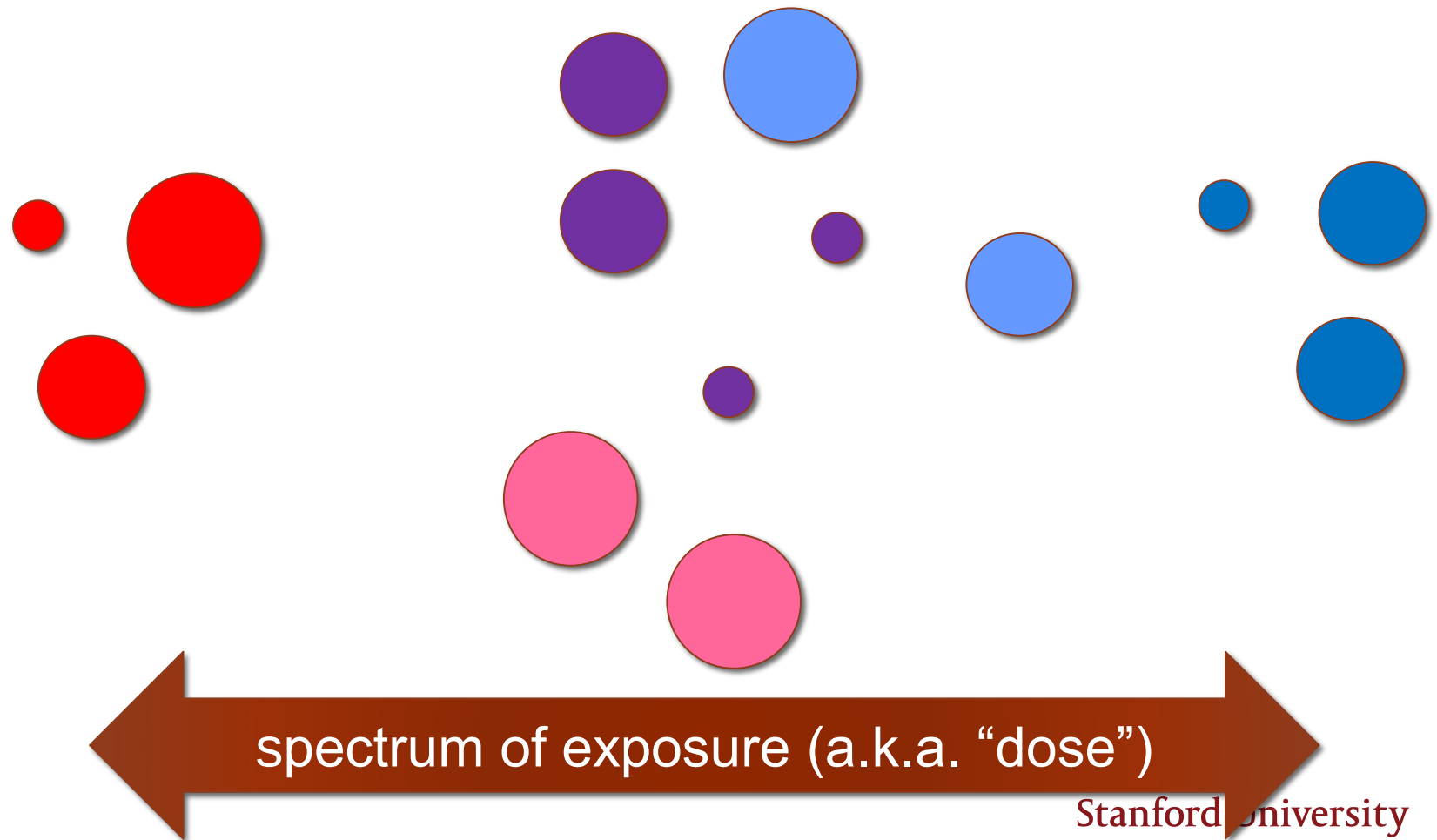
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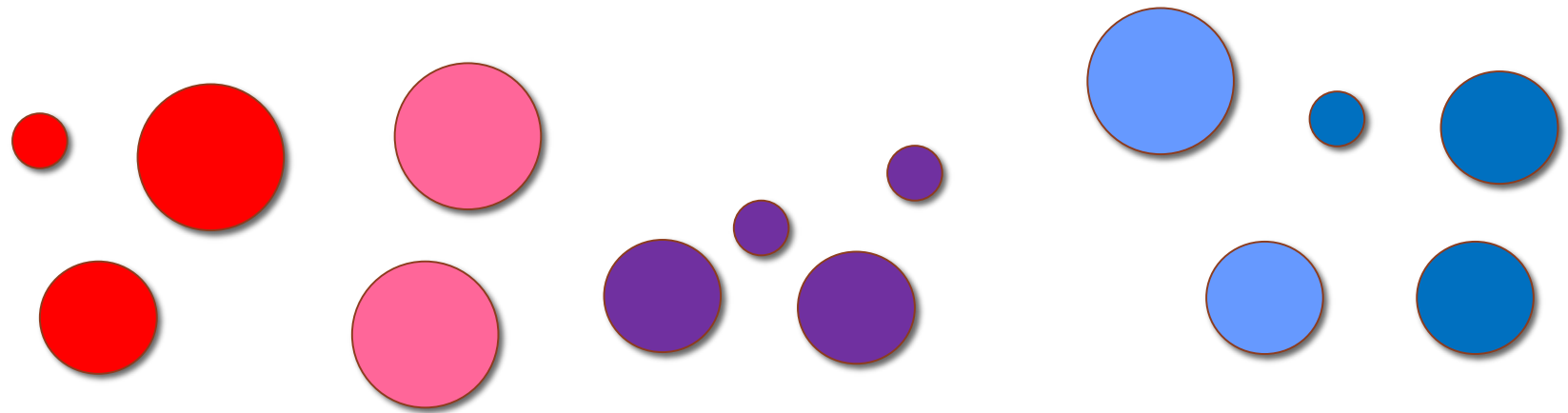
baseline: principal stratification modeling

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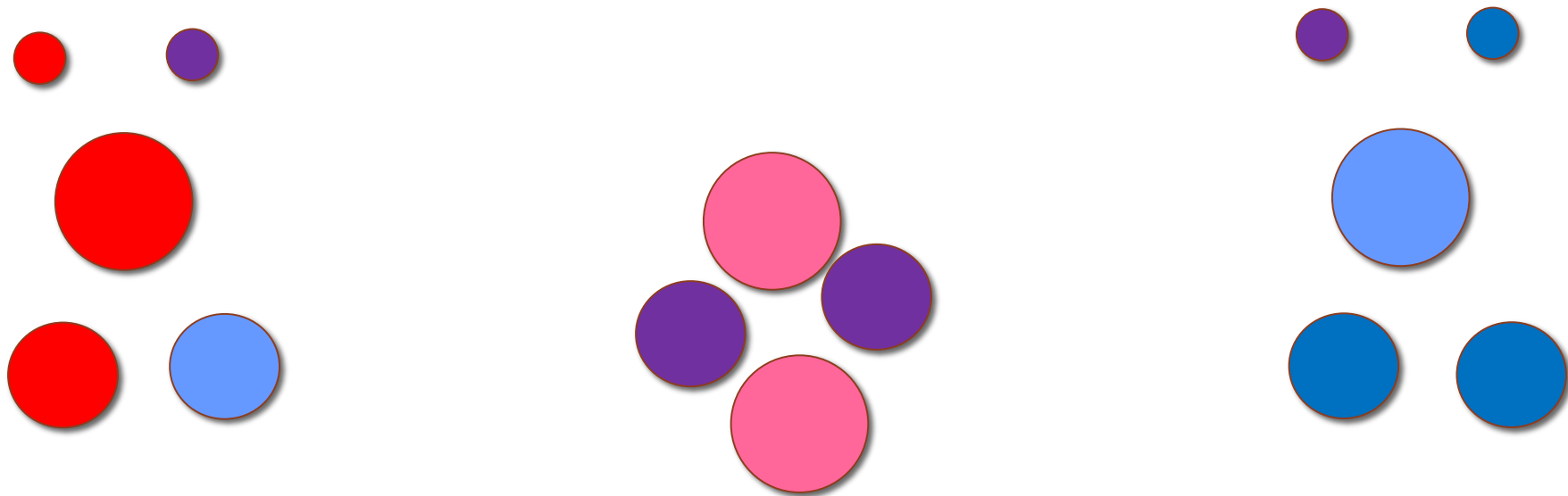
baseline: principal stratification modeling

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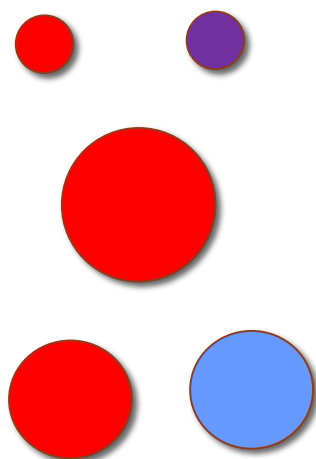
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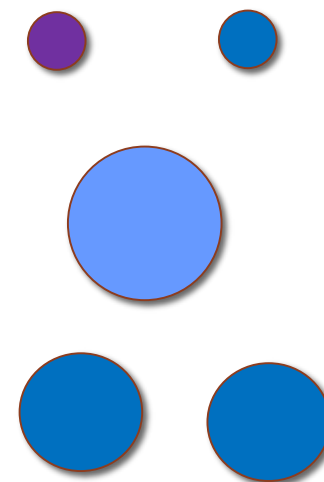
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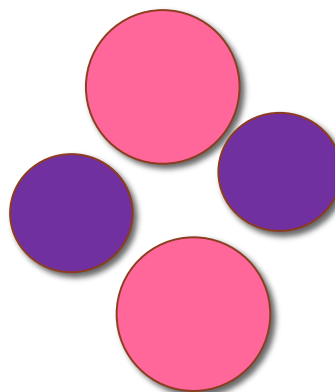
High-dose group



Low-dose group



Non-informative

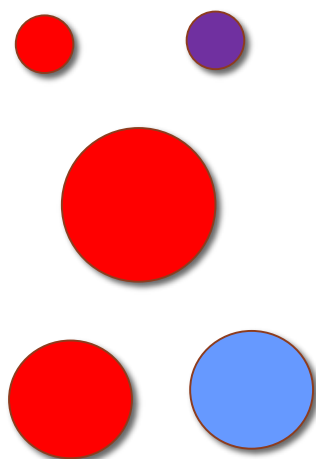


spectrum of exposure (a.k.a. “dose”)

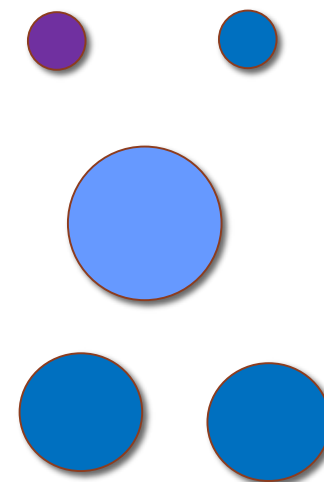
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Example: impact of self-efficacy on probability of rape.

High-dose group



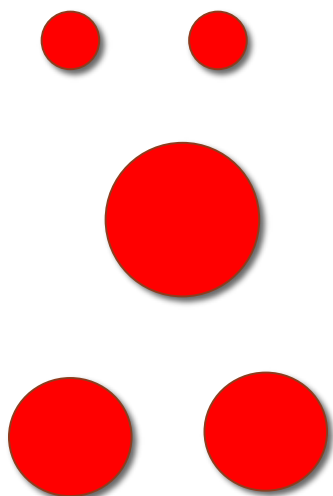
Low-dose group



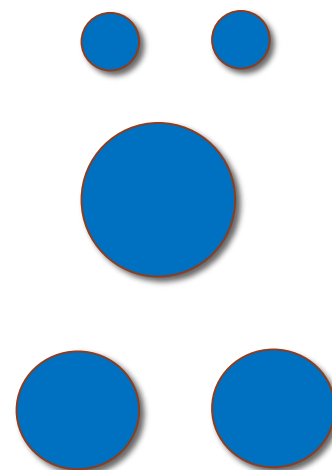
baseline: principal stratification modeling

Example: impact of no male guardian?

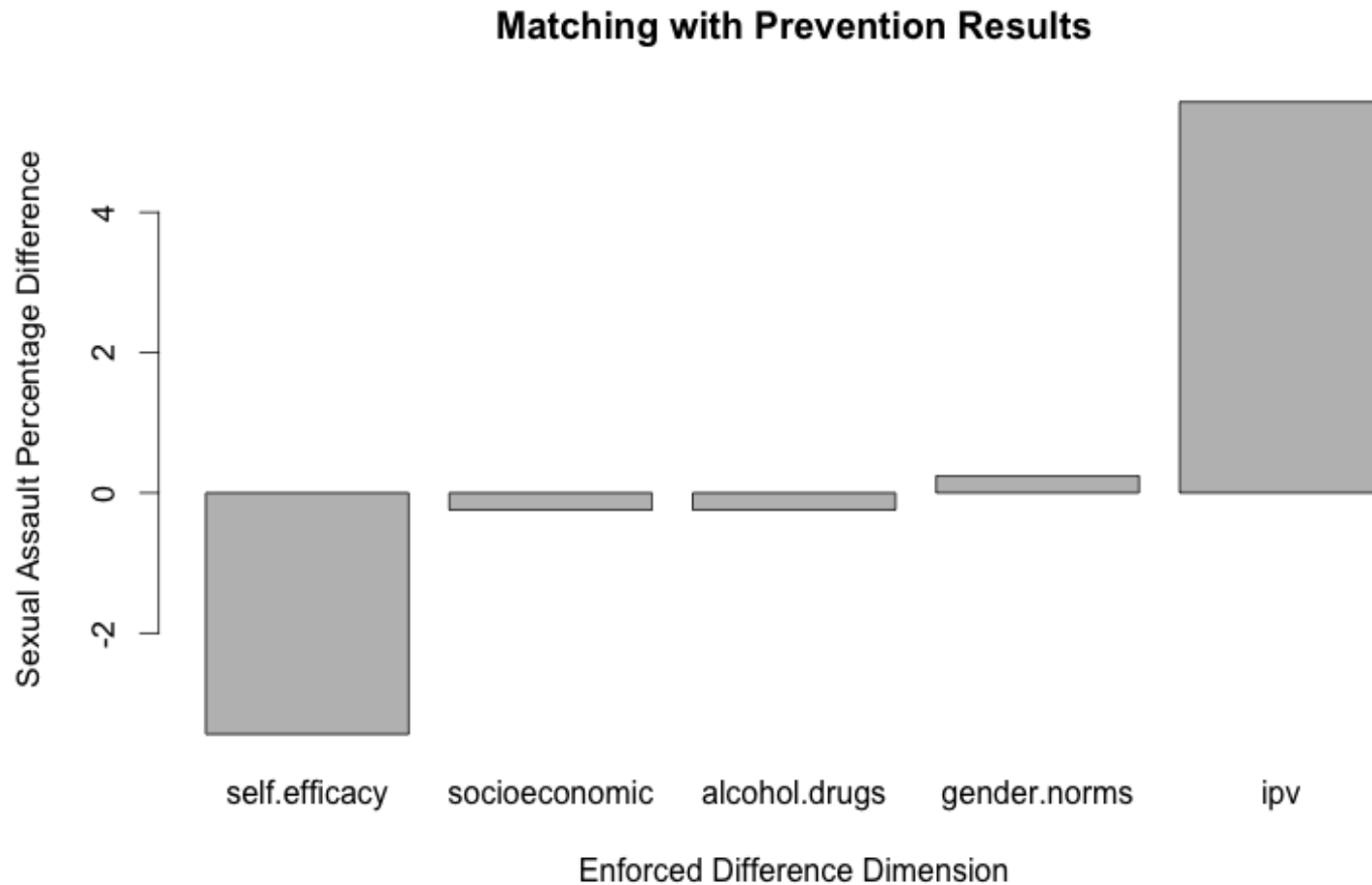
Matched-exposed



Matched-unexposed



baseline: principal stratification modeling




```
# Load the data
```

```
data <- read.csv("sample-dataset")  
head(data)
```

```
# Cast the data to a data frame.
```

```
df<- data.frame(data)
```

```
n <- nrow(df) # number of rows; here this is the total number of girls
```

Now we identify treatment and control schools. In our sample dataset, schools 1 and 2 are control schools, and schools 3 and 4 are treatment schools. In the real dataset, we similarly have a list of school IDs that correspond to each treatment and control. The `ifelse` command in R works as follows: `ifelse(statement, result if True, result if False)`. Also, note the expression `df$assignment` replaces the values of column assignment if they exist in dataframe `df`, and assigns them if they do not.

```
control<- 1:2
```

```
trt<- 3:4
```

```
df$assignment <- sapply(df$schoolid, function(id){ifelse(id%in%trt,1,0)})
```

```
# Isolate treatment and control rows.
```

```
treat.rows<- which(df$assignment == 1)
```

```
control.rows<- which(df$assignment == 0)
```

Once we have identified the students in treatment and control groups, we can begin to examine their demographics.

Exercise 1: find a command to print out the number of girls in school 3 (there are 107).

This will allow us to check that the covariates across the groups are balanced, a crucial part of our analysis. If we lack covariate balance, we will need to account for that when evaluating outcome differences between control and treatment groups.

Load the data

```
data <- read.csv("sample-dataset")  
head(data)
```

Cast the data to a data frame.

```
df<- data.frame(data)  
n <- nrow(df) # number of rows; here this is the total number of girls
```

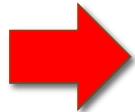
Now we identify treatment and control schools. In our sample dataset, schools 1 and 2 are control schools, and schools 3 and 4 are treatment schools. In the real dataset, we similarly have a list of school IDs that correspond to each treatment and control. The `ifelse` command in R works as follows: `ifelse(statement, result if True, result if False)`. Also, note the expression `df$assignment` replaces the values of column assignment if they exist in dataframe `df`, and assigns them if they do not.

```
control<- 1:2  
trt<- 3:4  
df$assignment <- sapply(df$schoolid, function(id){ifelse(id%in%trt,1,0)})
```

Isolate treatment and control rows.

```
treat.rows<- which(df$assignment == 1)  
control.rows<- which(df$assignment == 0)
```

Once we have identified the students in treatment and control groups, we can begin to examine their demographics.



Exercise 1: find a command to print out the number of girls in school 3 (there are 107).

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fin.

Thank you to:

DFID

SA-MRC

SPECTRUM

Stanford Population Health

Rosenkranz Family

Agency for Healthcare Research and Quality

Stanford Gender Based Violence Prevention Collaborative

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