The **gap-closing estimand**

Slides at
ianlundberg.org

Software at
ilundberg.github.io/gapclosing

A causal approach to study **interventions** that **close disparities** across social categories

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Paper in *Sociological Methods and Research*. Replication code on Dataverse. R package `gapclosing` on CRAN.
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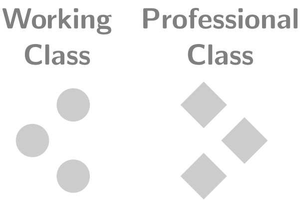

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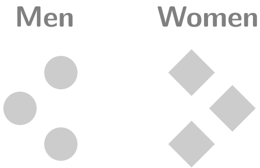

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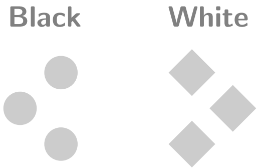

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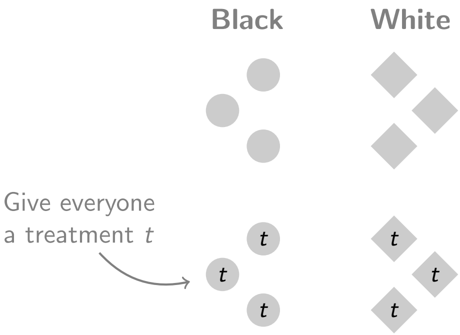

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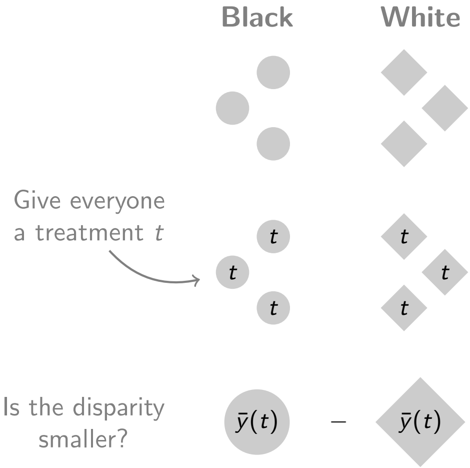

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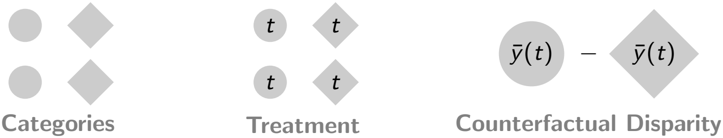
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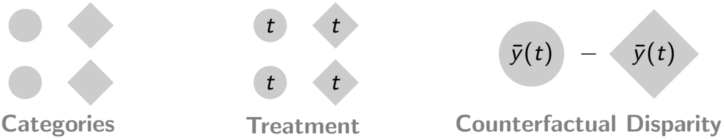
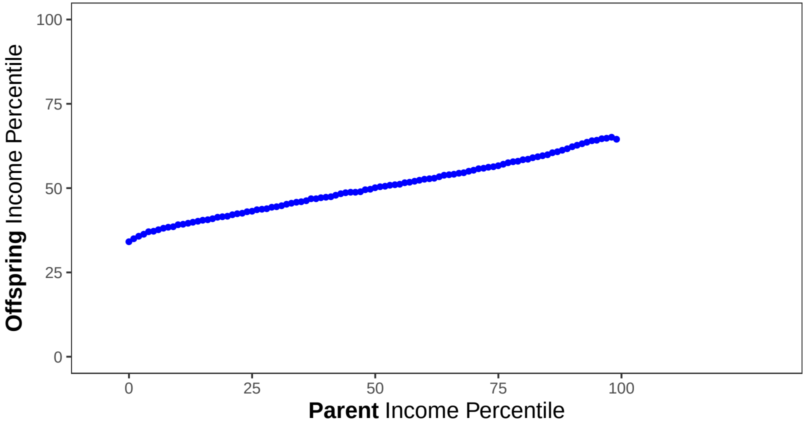
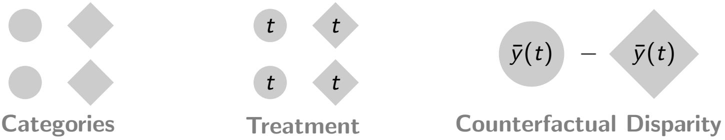
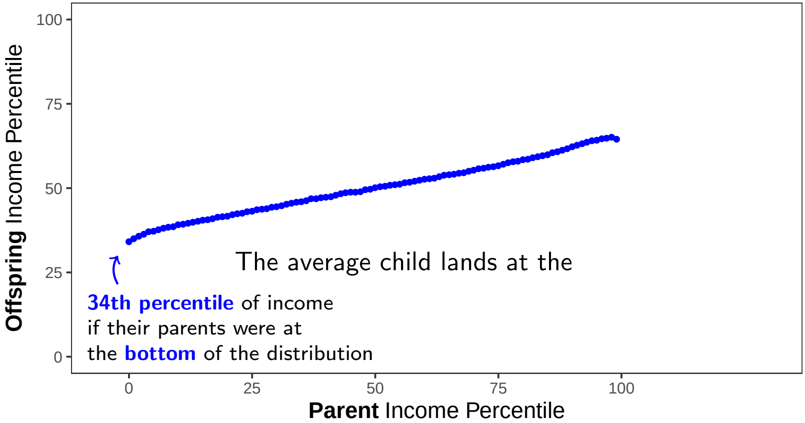
t
$\bar{y}(t)$ − $\bar{y}(t)$
Categories
Treatment
Counterfactual Disparity





Chetty et al. 2017





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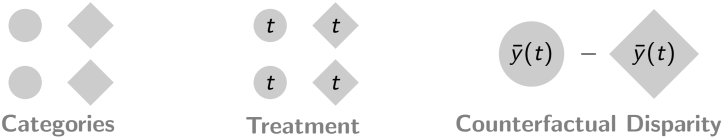

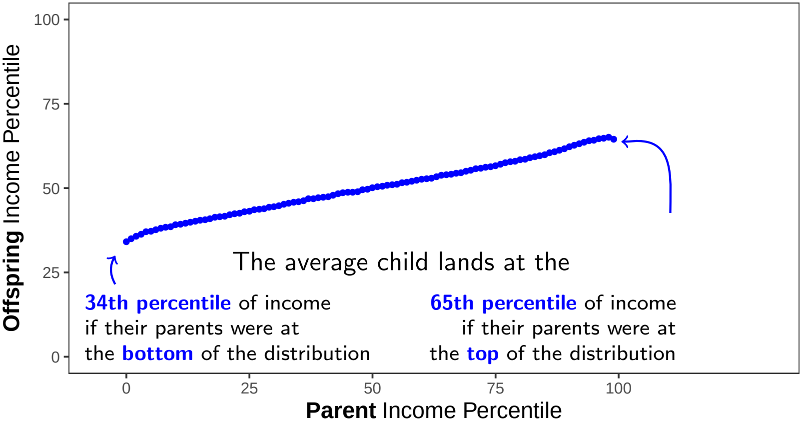

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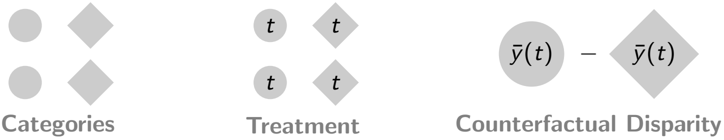

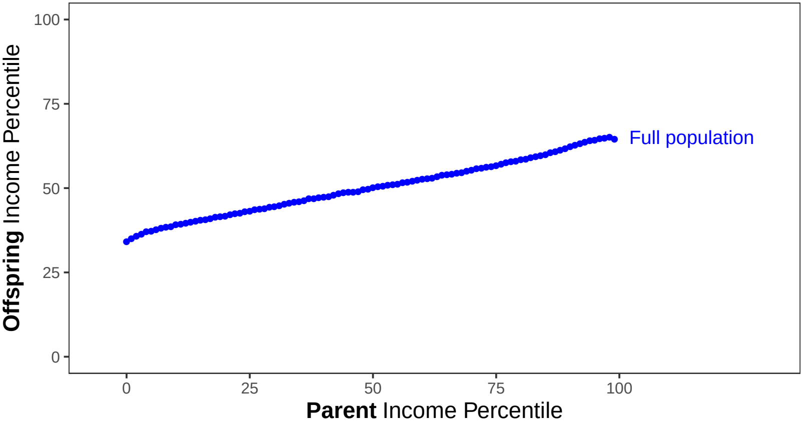

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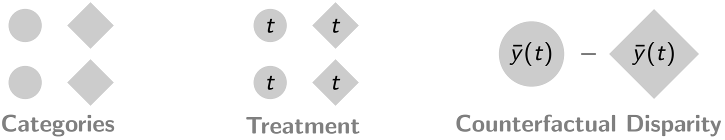

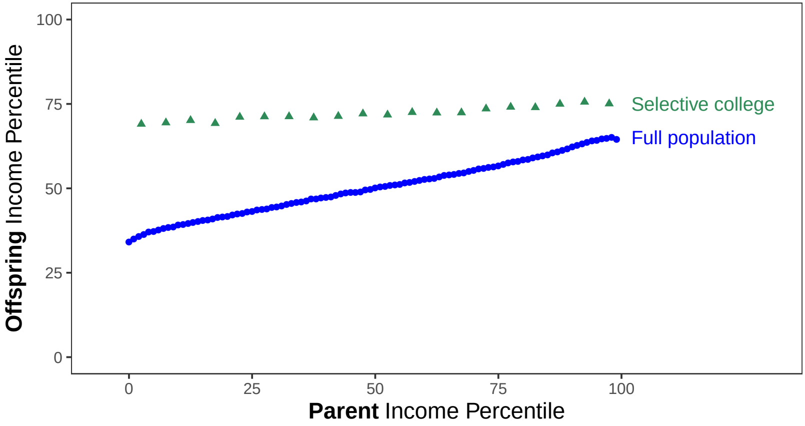

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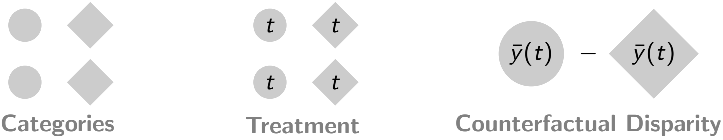

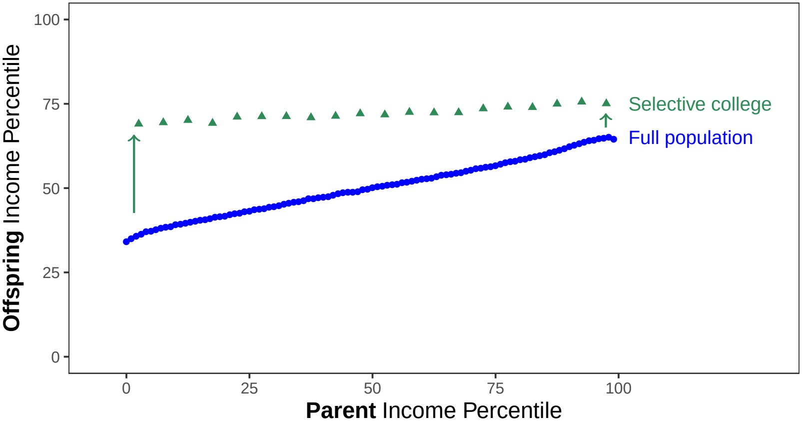

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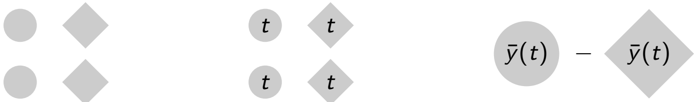
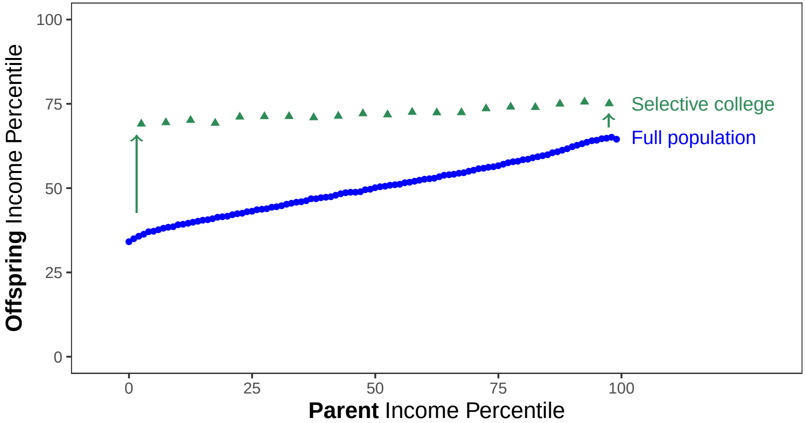


Categories Parent Income

Treatment Selective College

Counterfactual Disparity Offspring Income



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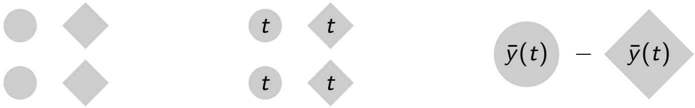
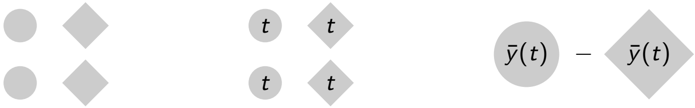


Categories Treatment Counterfactual Disparity

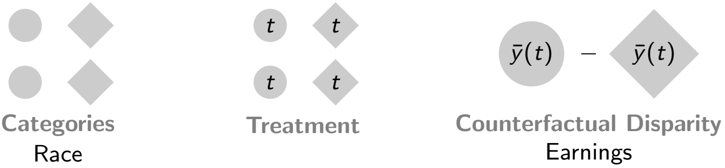


Categories **Treatment** **Counterfactual Disparity**

Race

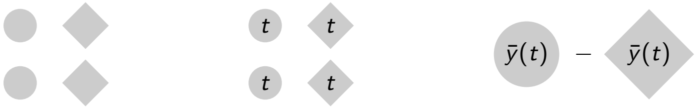
The difference in earnings
between blacks and whites

— Western 2006:12



The difference in earnings
between blacks and whites
would be reduced only by about 3 percent
if the incarceration rate were zero

— Western 2006:12



Categories
Race

Treatment
Incarceration

Counterfactual Disparity
Earnings

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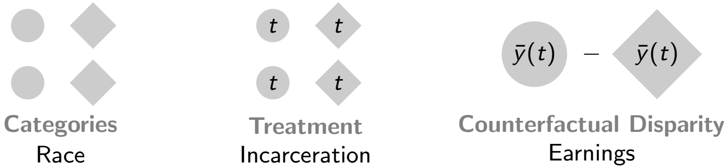

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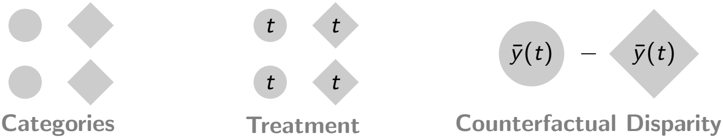

We often want to know
if **intervening** on a treatment variable
would close gaps

Causal decomposition analysis

Causal decomposition analysis

Unadjusted

$$Y = \beta(\texttt{Black}) + \epsilon$$

Adjusted

$$Y = \gamma(\texttt{Black}) + \vec{X}'\vec{\eta} + \delta$$

Causal decomposition analysis

Unadjusted	Adjusted
$Y = \beta(\texttt{Black}) + \epsilon$	$Y = \gamma(\texttt{Black}) + \vec{X}'\vec{\eta} + \delta$

Effect of race

Causal decomposition analysis

Unadjusted	Adjusted
$Y = \beta(\texttt{Black}) + \epsilon$	$Y = \gamma(\texttt{Black}) + \vec{X}'\vec{\eta} + \delta$

× Effect of race

Vanderweele & Robinson 2014

Causal decomposition analysis

Unadjusted	Adjusted
$Y = \beta(\texttt{Black}) + \epsilon$	$Y = \gamma(\texttt{Black}) + \vec{X}'\vec{\eta} + \delta$

- × Effect of race
- ✓ Disparity after intervention on $\vec{X}$

Vanderweele & Robinson 2014

Causal decomposition analysis

Unadjusted	Adjusted
$Y = \beta(\texttt{Black}) + \epsilon$	$Y = \gamma(\texttt{Black}) + \vec{X}'\vec{\eta} + \delta$

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Vanderweele & Robinson 2014

Choice of intervention targets

Jackson & Vanderweele 2018

Causal decomposition analysis

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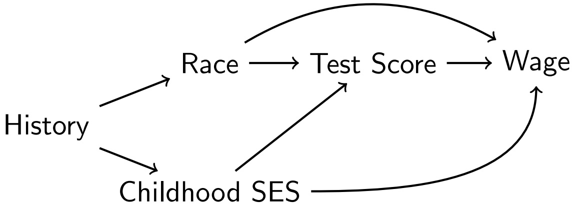

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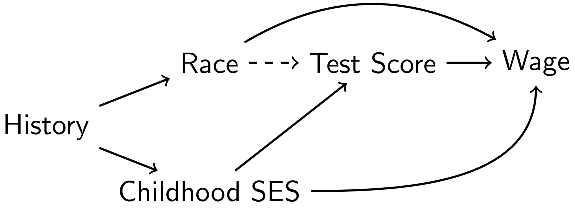

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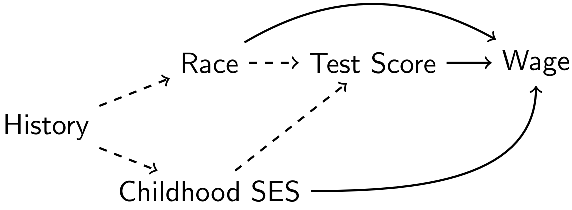

Causal decomposition analysis

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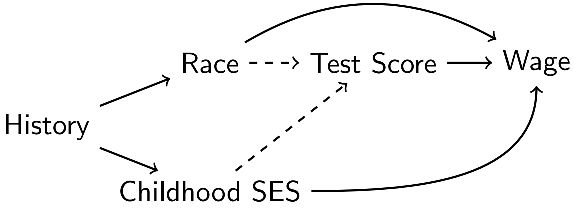
Choice of intervention targets

Jackson & Vanderweele 2018



Causal decomposition analysis

Unadjusted

$$Y = \beta(\texttt{Black}) + \epsilon$$

Adjusted

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- × Effect of race
- ✓ Disparity after intervention on $\vec{X}$

Vanderweele & Robinson 2014

Choice of intervention targets

Jackson & Vanderweele 2018

Equity: What should we equalize?

Jackson 2021

Causal decomposition analysis

Unadjusted	Adjusted
$Y = \beta(\texttt{Black}) + \epsilon$	$Y = \gamma(\texttt{Black}) + \vec{X}'\vec{\eta} + \delta$

× Effect of race

✓ Disparity after intervention on $\vec{X}$

Vanderweele & Robinson 2014

Choice of intervention targets

Jackson & Vanderweele 2018

Equity: What should we equalize?

Jackson 2021

Systems may adapt to maintain inequity

Jackson & Arah 2020

Causal decomposition analysis

Unadjusted

$$Y = \beta(\texttt{Black}) + \epsilon$$

Adjusted

$$Y = \gamma(\texttt{Black}) + \vec{X}'\vec{\eta} + \delta$$

× Effect of race
✓ Disparity after intervention on $\vec{X}$ — Vanderweele & Robinson 2014

Choice of intervention targets — Jackson & Vanderweele 2018

Equity: What should we equalize? — Jackson 2021

Systems may adapt to maintain inequity — Jackson & Arah 2020

Present paper — Lundberg 2022
— Local intervention interpretation
— Doubly robust estimator
— Software

How this works

1. Define an intervention
2. Make causal assumptions
3. Estimate

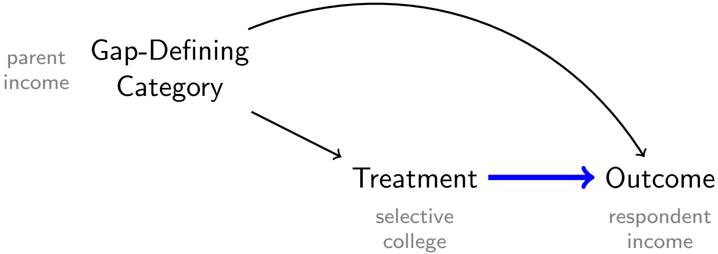
Define an intervention

Define an intervention

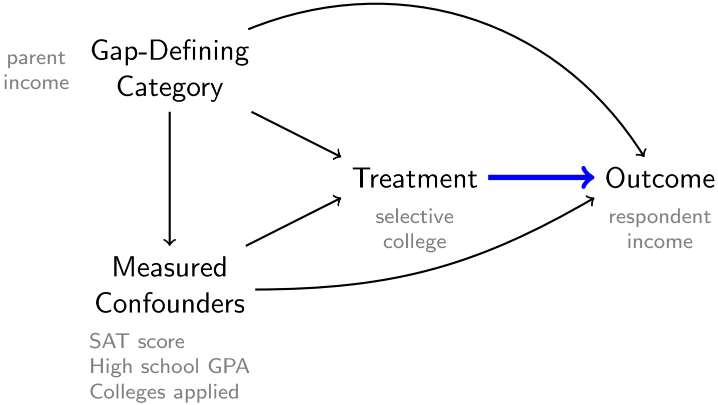
Using the Chetty et al. 2017 example,

What gap in respondent incomes would remain
across categories of parent income
if we intervened to send people to selective colleges?

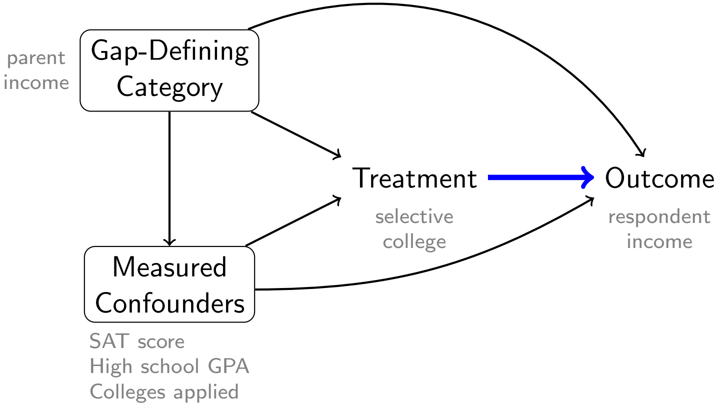
Make causal assumptions


parent
income
Gap-Defining
Category
Treatment
Outcome
selective
college
respondent
income

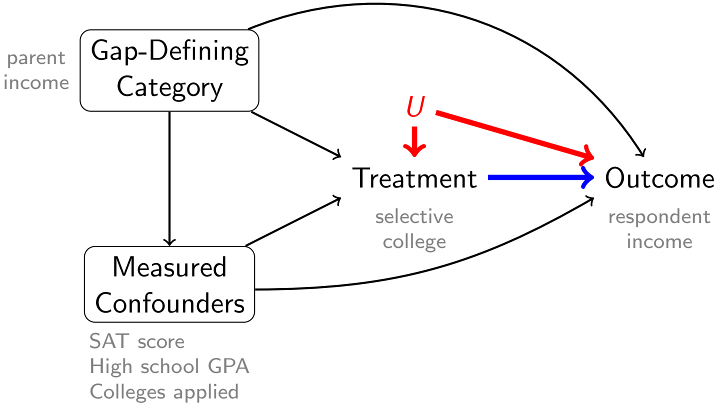
Pearl 2009


parent
income
Gap-Defining
Category
Treatment
Outcome
selective
college
respondent
income
Measured
Confounders
SAT score
High school GPA
Colleges applied

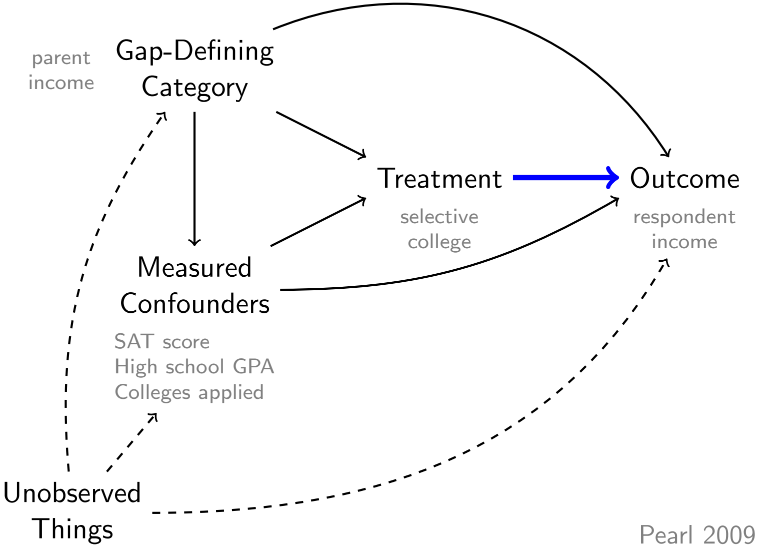
Pearl 2009


Gap-Defining Category
parent income
Treatment
selective college
Outcome
respondent income
Measured Confounders
SAT score
High school GPA
Colleges applied

Pearl 2009


Gap-Defining Category
parent income
U
Treatment
selective college
Outcome
respondent income
Measured Confounders
SAT score
High school GPA
Colleges applied

Pearl 2009


parent income
Gap-Defining Category
Treatment
selective college
Outcome
respondent income
Measured Confounders
SAT score
High school GPA
Colleges applied
Unobserved Things
Pearl 2009

Estimate

		Outcome under treatment	Outcome under control
People in category 1	Person 1	?	Y_1
	Person 2	Y_2	?
	Person 3	Y_3	?
People in category 2	Person 4	?	Y_4
	Person 5	Y_5	?
	Person 6	?	Y_6

		Outcome under treatment	Outcome under control
People in category 1	Person 1	?	Y_1
	Person 2	Y_2	?
	Person 3	Y_3	?
People in category 2	Person 4	?	Y_4
	Person 5	Y_5	?
	Person 6	?	Y_6

Learn a prediction function

		Outcome under treatment	Outcome under control
People in category 1	Person 1	?	Y_1
	Person 2	Y_2	?
	Person 3	Y_3	?
People in category 2	Person 4	?	Y_4
	Person 5	Y_5	?
	Person 6	?	Y_6

Learn a prediction function

		Outcome under treatment	Outcome under control
People in category 1	Person 1	?	Y_1
	Person 2	Y_2	?
	Person 3	Y_3	?
People in category 2	Person 4	?	Y_4
	Person 5	Y_5	?
	Person 6	?	Y_6

Predict the whole table

		Outcome under treatment	Outcome under control
People in category 1	Person 1	$\hat{Y}_1(1)$	$\hat{Y}_1(0)$
	Person 2	$\hat{Y}_2(1)$	$\hat{Y}_2(0)$
	Person 3	$\hat{Y}_3(1)$	$\hat{Y}_3(0)$
People in category 2	Person 4	$\hat{Y}_4(1)$	$\hat{Y}_4(0)$
	Person 5	$\hat{Y}_5(1)$	$\hat{Y}_5(0)$
	Person 6	$\hat{Y}_6(1)$	$\hat{Y}_6(0)$

Robins 1986
Hahn 1998

Learn a prediction function

		Outcome under treatment	Outcome under control
People in category 1	Person 1	?	Y_1
	Person 2	Y_2	?
	Person 3	Y_3	?
People in category 2	Person 4	?	Y_4
	Person 5	Y_5	?
	Person 6	?	Y_6

Predict the whole table

		Outcome under treatment	Outcome under control
People in category 1	Person 1	$\hat{Y}_1(1)$	$\hat{Y}_1(0)$
	Person 2	$\hat{Y}_2(1)$	$\hat{Y}_2(0)$
	Person 3	$\hat{Y}_3(1)$	$\hat{Y}_3(0)$
People in category 2	Person 4	$\hat{Y}_4(1)$	$\hat{Y}_4(0)$
	Person 5	$\hat{Y}_5(1)$	$\hat{Y}_5(0)$
	Person 6	$\hat{Y}_6(1)$	$\hat{Y}_6(0)$

Robins 1986
Hahn 1998

Learn a prediction function

		Outcome under treatment	Outcome under control
People in category 1	Person 1	?	Y_1
	Person 2	Y_2	?
	Person 3	Y_3	?
People in category 2	Person 4	?	Y_4
	Person 5	Y_5	?
	Person 6	?	Y_6

Predict the whole table

		Outcome under treatment	Outcome under control
People in category 1	Person 1	$\hat{Y}_1(1)$	$\hat{Y}_1(0)$
	Person 2	$\hat{Y}_2(1)$	$\hat{Y}_2(0)$
	Person 3	$\hat{Y}_3(1)$	$\hat{Y}_3(0)$
People in category 2	Person 4	$\hat{Y}_4(1)$	$\hat{Y}_4(0)$
	Person 5	$\hat{Y}_5(1)$	$\hat{Y}_5(0)$
	Person 6	$\hat{Y}_6(1)$	$\hat{Y}_6(0)$

Problem: Optimization for the wrong task

Learn a prediction function

		Outcome under treatment	Outcome under control
People in category 1	Person 1	?	Y_1
	Person 2	Y_2	?
	Person 3	Y_3	?
People in category 2	Person 4	?	Y_4
	Person 5	Y_5	?
	Person 6	?	Y_6

Predict the whole table

		Outcome under treatment	Outcome under control
People in category 1	Person 1	$\hat{Y}_1(1)$	$\hat{Y}_1(0)$
	Person 2	$\hat{Y}_2(1)$	$\hat{Y}_2(0)$
	Person 3	$\hat{Y}_3(1)$	$\hat{Y}_3(0)$
People in category 2	Person 4	$\hat{Y}_4(1)$	$\hat{Y}_4(0)$
	Person 5	$\hat{Y}_5(1)$	$\hat{Y}_5(0)$
	Person 6	$\hat{Y}_6(1)$	$\hat{Y}_6(0)$

Problem: Optimization for the wrong task

Prediction error over **observed** cases

Learn a prediction function

		Outcome under treatment	Outcome under control
People in category 1	Person 1	?	Y_1
	Person 2	Y_2	?
	Person 3	Y_3	?
People in category 2	Person 4	?	Y_4
	Person 5	Y_5	?
	Person 6	?	Y_6

Predict the whole table

		Outcome under treatment	Outcome under control
People in category 1	Person 1	$\hat{Y}_1(1)$	$\hat{Y}_1(0)$
	Person 2	$\hat{Y}_2(1)$	$\hat{Y}_2(0)$
	Person 3	$\hat{Y}_3(1)$	$\hat{Y}_3(0)$
People in category 2	Person 4	$\hat{Y}_4(1)$	$\hat{Y}_4(0)$
	Person 5	$\hat{Y}_5(1)$	$\hat{Y}_5(0)$
	Person 6	$\hat{Y}_6(1)$	$\hat{Y}_6(0)$

Problem: Optimization for the wrong task

Prediction error over **observed** cases

vs

Prediction error over **all** cases

Solution: Reweight errors to approximate the correct task

Solution: Reweight errors to approximate the correct task

		Prediction under treatment
People in category 1	Person 1	$\hat{Y}_1(1)$
	Person 2	$\hat{Y}_2(1)$
	Person 3	$\hat{Y}_3(1)$
People in category 2	Person 4	$\hat{Y}_4(1)$
	Person 5	$\hat{Y}_5(1)$
	Person 6	$\hat{Y}_6(1)$

Solution: Reweight errors to approximate the correct task

		Prediction under treatment	Outcome under treatment
People in category 1	Person 1	$\hat{Y}_1(1)$	?
	Person 2	$\hat{Y}_2(1)$	Y_2
	Person 3	$\hat{Y}_3(1)$	Y_3
People in category 2	Person 4	$\hat{Y}_4(1)$	?
	Person 5	$\hat{Y}_5(1)$	Y_5
	Person 6	$\hat{Y}_6(1)$	?

Solution: Reweight errors to approximate the correct task

		Prediction under treatment	Outcome under treatment	Error
People in category 1	Person 1	$\hat{Y}_1(1)$	?	?
	Person 2	$\hat{Y}_2(1)$	Y_2	$\hat{Y}_2(1) - Y_2$
	Person 3	$\hat{Y}_3(1)$	Y_3	$\hat{Y}_3(1) - Y_3$
People in category 2	Person 4	$\hat{Y}_4(1)$	?	?
	Person 5	$\hat{Y}_5(1)$	Y_5	$\hat{Y}_5(1) - Y_5$
	Person 6	$\hat{Y}_6(1)$	?	?

Solution: Reweight errors to approximate the correct task

		Prediction under treatment	Outcome under treatment	Error	Weight on error
People in category 1	Person 1	$\hat{Y}_1(1)$	?	?	
	Person 2	$\hat{Y}_2(1)$	Y_2	$\hat{Y}_2(1) - Y_2$	3 / 2
	Person 3	$\hat{Y}_3(1)$	Y_3	$\hat{Y}_3(1) - Y_3$	3 / 2
People in category 2	Person 4	$\hat{Y}_4(1)$	?	?	
	Person 5	$\hat{Y}_5(1)$	Y_5	$\hat{Y}_5(1) - Y_5$	3
	Person 6	$\hat{Y}_6(1)$	?	?	

Solution: Reweight errors to approximate the correct task

Estimated bias: Mean($\hat{Y}_i - Y_i$) with inverse probability of treatment weights

		Prediction under treatment	Outcome under treatment	Error	Weight on error
People in category 1	Person 1	$\hat{Y}_1(1)$	?	?	
	Person 2	$\hat{Y}_2(1)$	Y_2	$\hat{Y}_2(1) - Y_2$	3 / 2
	Person 3	$\hat{Y}_3(1)$	Y_3	$\hat{Y}_3(1) - Y_3$	3 / 2
People in category 2	Person 4	$\hat{Y}_4(1)$	?	?	
	Person 5	$\hat{Y}_5(1)$	Y_5	$\hat{Y}_5(1) - Y_5$	3
	Person 6	$\hat{Y}_6(1)$	?	?	

Solution: Reweight errors to approximate the correct task

Estimated bias: Mean($\hat{Y}_i - Y_i$) with inverse probability of treatment weights

New Estimate: (Original Estimate) $-$ (Estimated Bias)

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Doubly
Robust
Estimation

Robins, Rotnitzky, & Zhao 1994
Bang & Robins 2005

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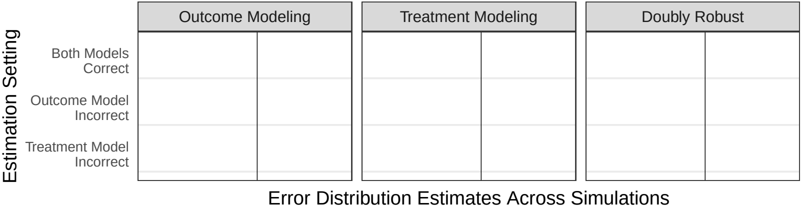

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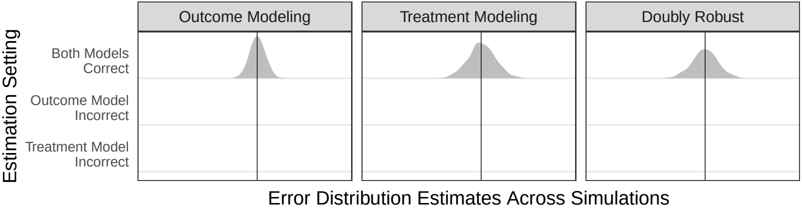

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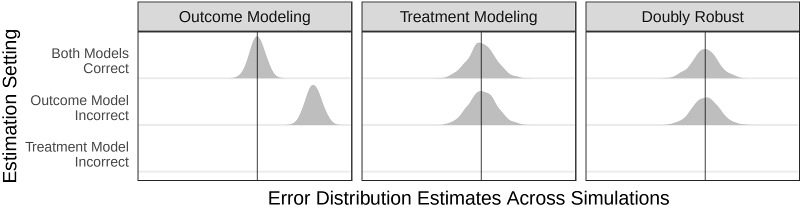

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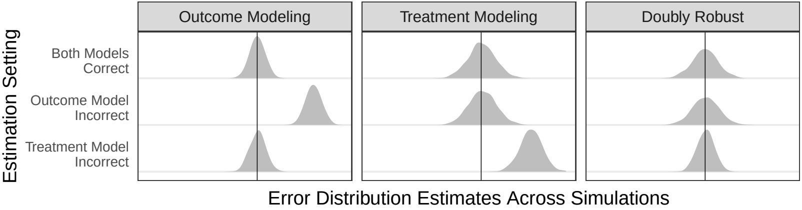

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Even better:

Chernozhukov et al. 2018
Bickel 1982

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New Estimate: (Original Estimate) − (Estimated Bias)

Doubly Robust Estimation

Even better:

— Learn $\hat{Y}_i$ in sample A

— Estimate bias in sample B

Chernozhukov et al. 2018
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Solution: Reweight errors to approximate the correct task

Estimated bias: Mean($\hat{Y}_i - Y_i$) with inverse probability of treatment weights

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Doubly Robust Estimation

Even better:

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— Cross fit: Swap roles and average

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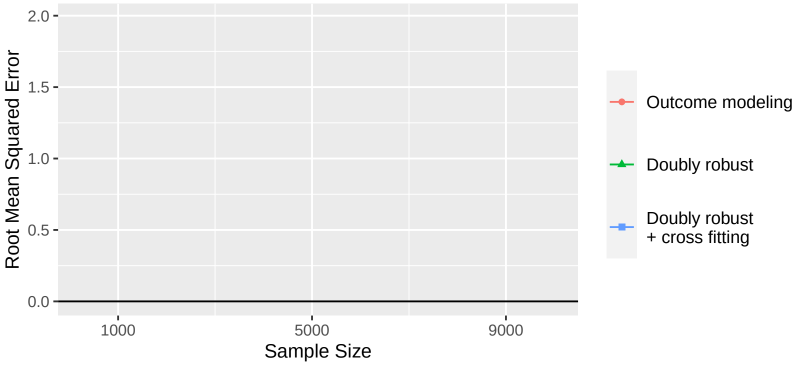

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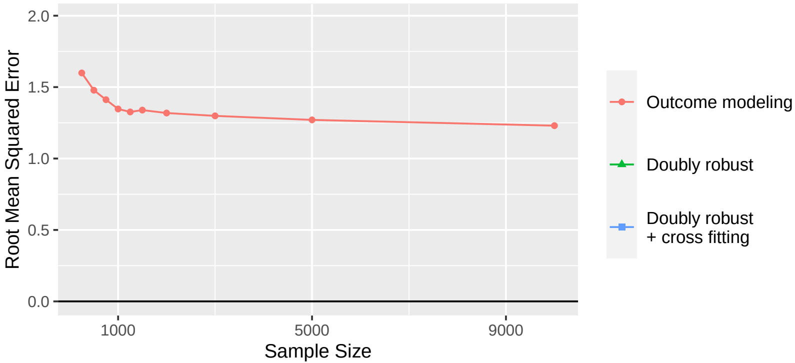

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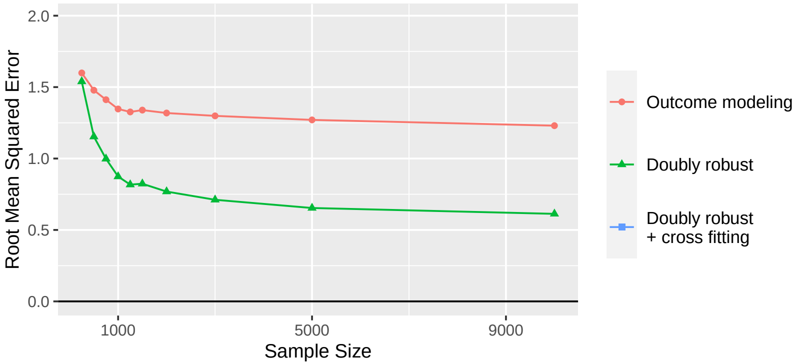

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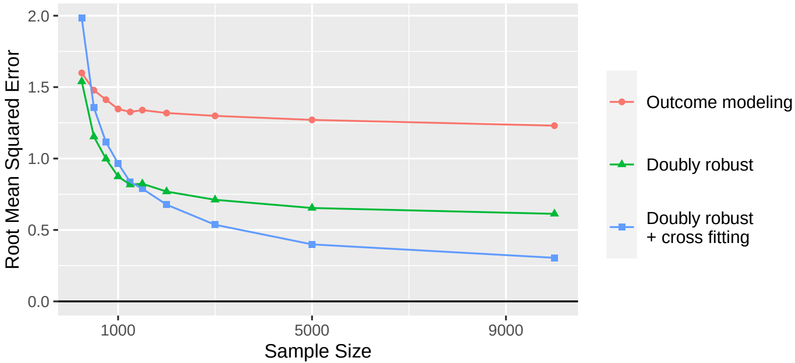

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Double Machine Learning

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Double Machine Learning

So complicated!

gapclosing

An R package to estimate gap closing estimands. Install this package with the command `devtools::install_github("ilundberg/gapclosing")`.

```
estimate <- gapclosing(
  data = simulated_data,
  outcome_formula = formula(outcome ~ category + confounder),
  treatment_formula = formula(treatment ~ category + confounder),
  category_name = "category",
  counterfactual_assignments = 1,
  outcome_algorithm = "ranger",
  treatment_algorithm = "ranger",
  sample_split = "cross_fit",
  se = T
)
```

```
       description estimate   se ci.min ci.max
       Factual gap     2.14 0.40   1.36    2.9
 Counterfactual gap     0.67 0.44  -0.19    1.5
```

How should one interpret results?

Interpret with respect to a **target trial** (Hernán & Robins 2016)

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1. Sample $\mathcal{S}$ from the population

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1. Sample $\mathcal{S}$ from the population
2. Assign treatment $T = 1$ to $\mathcal{S}$

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1. Sample $\mathcal{S}$ from the population
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3. Observe the disparity
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Interpret with respect to a **target trial** (Hernán & Robins 2016)

1. Sample $\mathcal{S}$ from the population
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Goal: Expected result over hypothetical samples $\mathcal{S}$

Interpret with respect to a **target trial** (Hernán & Robins 2016)

Local intervention

1. Sample $\mathcal{S}$ from the population
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1. Take the entire population $\mathcal{P}$

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Global intervention

1. Take the entire population $\mathcal{P}$
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Goal: Result of this procedure

Interpret with respect to a **target trial** (Hernán & Robins 2016)

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1. Sample $\mathcal{S}$ from the population
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Difficulty: Causal inference

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Difficulty: Causal inference
Equilibrium dynamics

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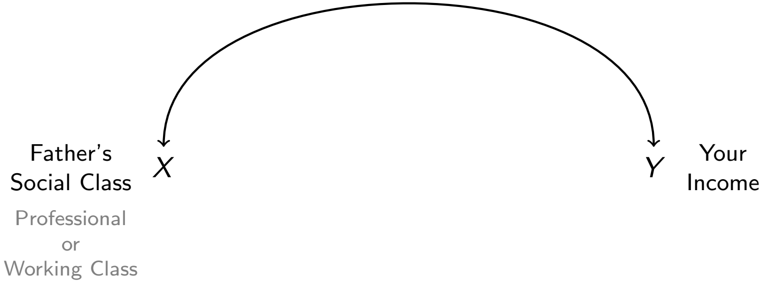
Empirical Examples

Empirical Example 1: Economic Mobility



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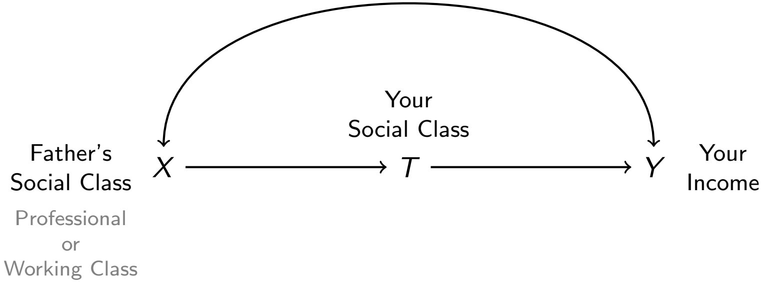

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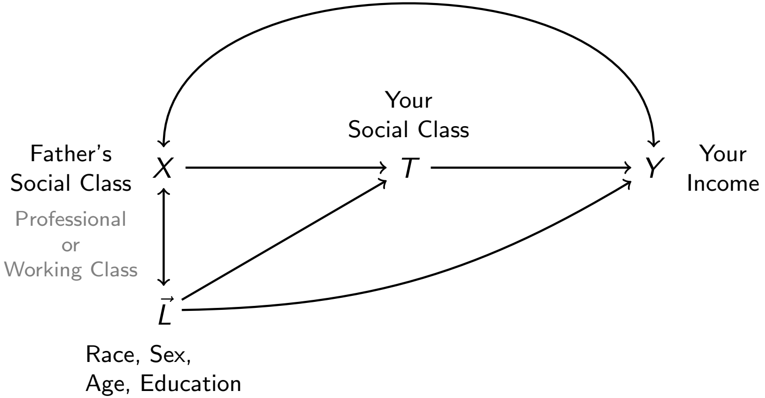

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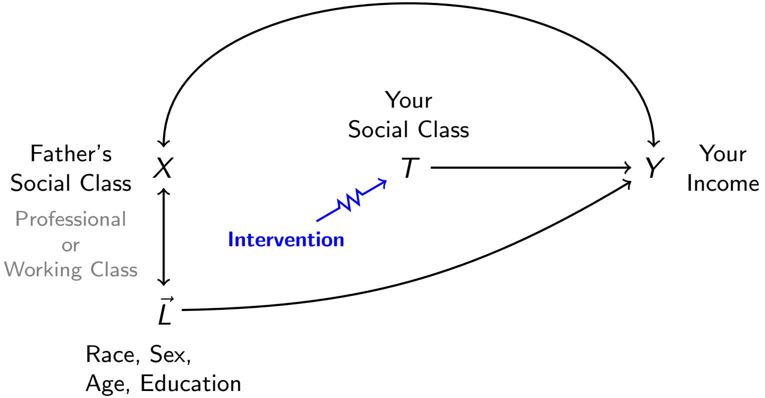

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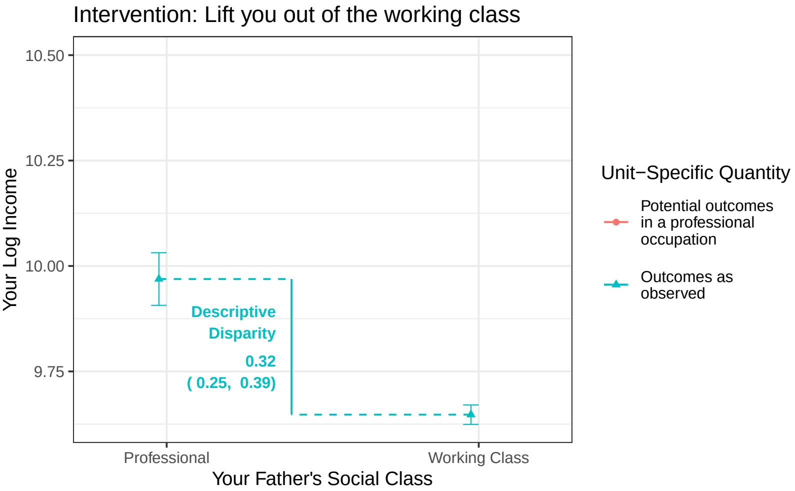

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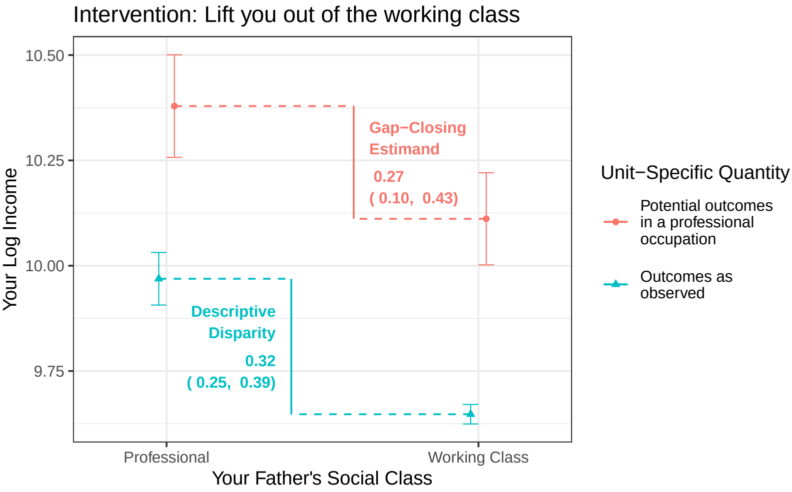

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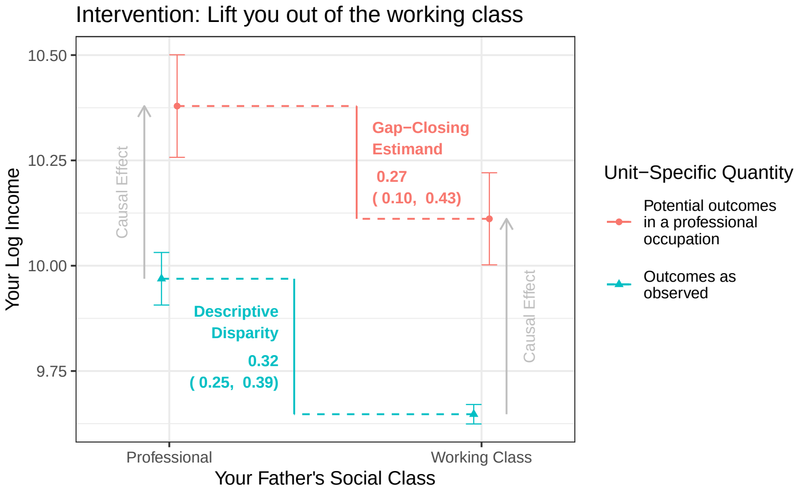
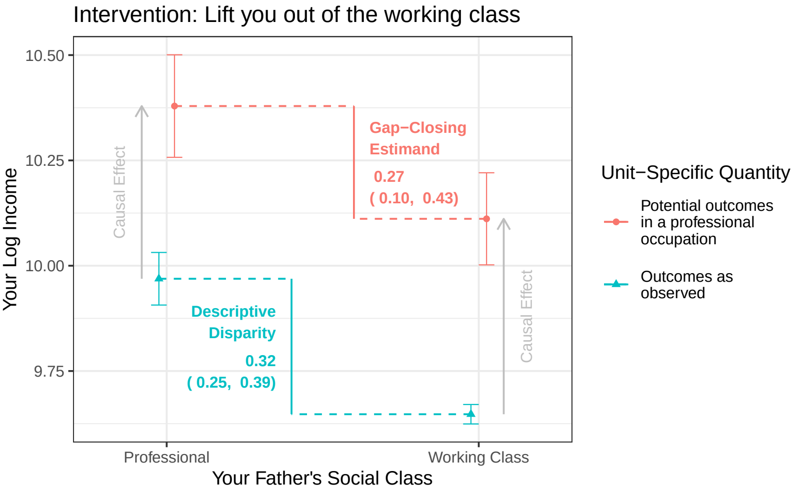
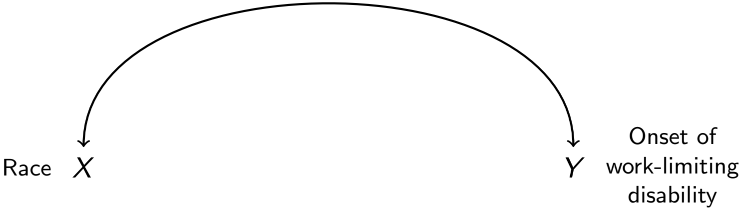


Empirical Example 1: Economic Mobility

`plot_two_categories()`



Empirical Example 2: Racial Disparities in Health



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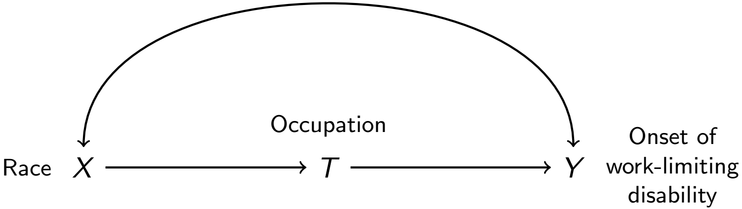

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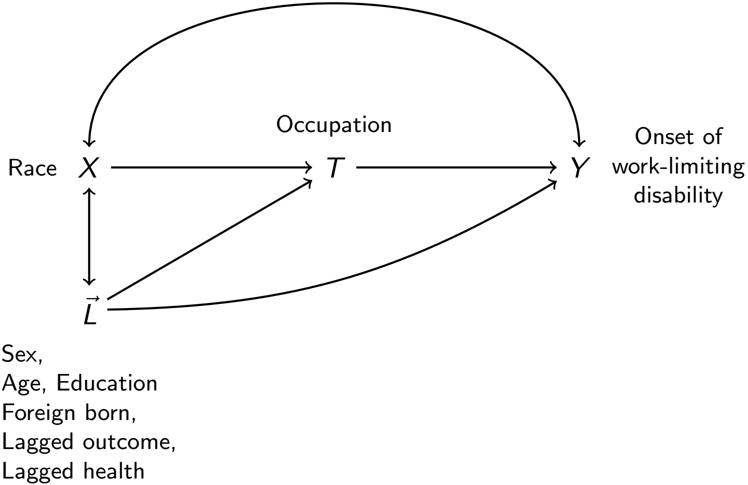

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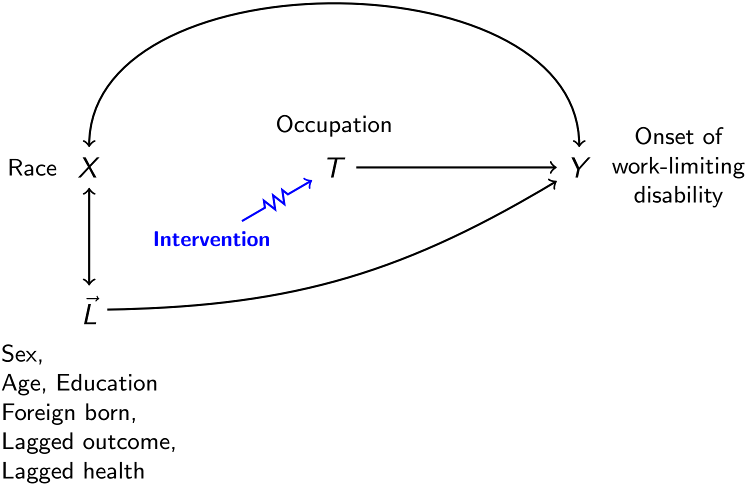

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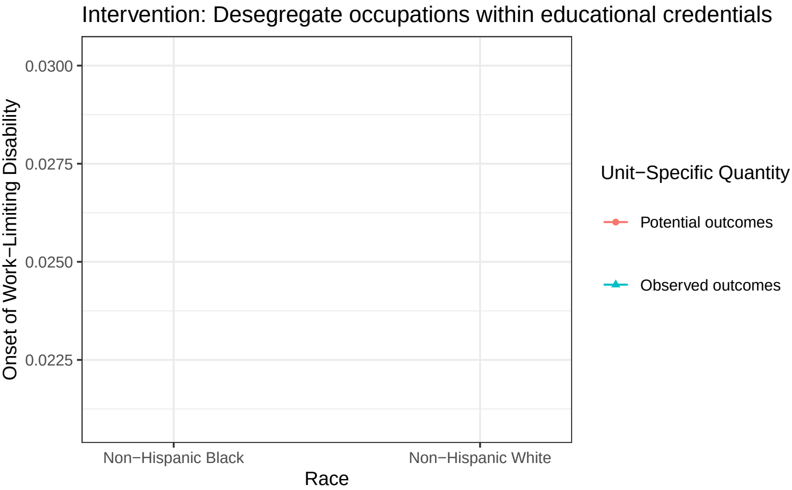

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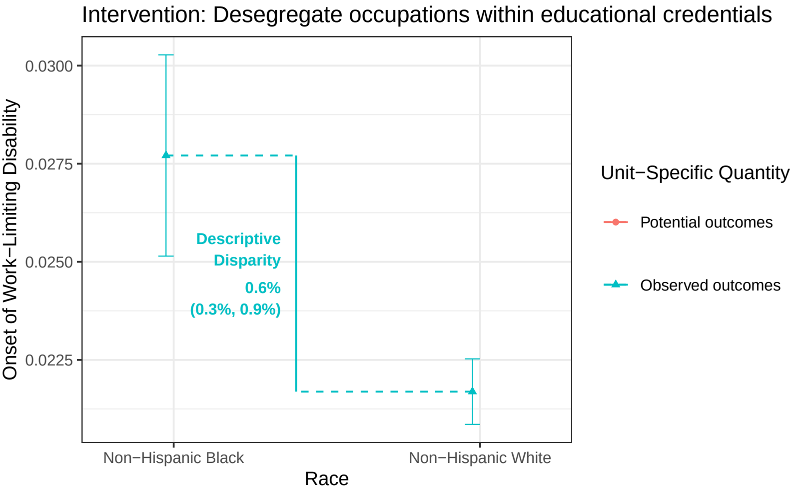

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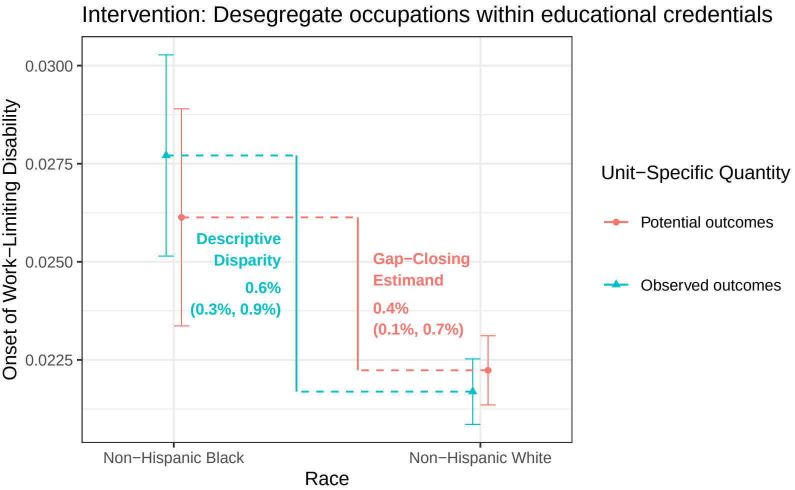

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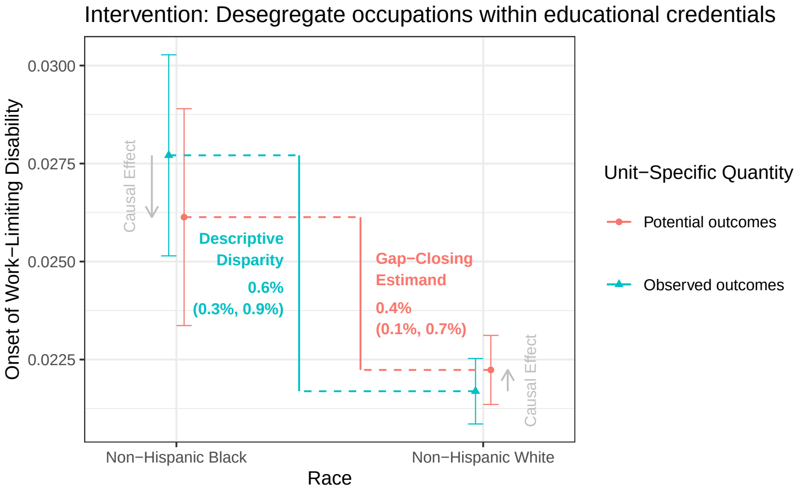

Discussion

Gap closing estimands

- Define the goal
  - two target populations
  - hypothetical intervention
- Make causal assumptions
  - draw a DAG
- Estimate
  - fit an outcome model
  - change the treatment
  - predict for everyone
  - average within the populations

Now try it!

ilundberg.github.io/gapclosing

Ian Lundberg
ianlundberg.org
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