13. Inverse Probability Weighting

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Cornell Info 6751: Causal Inference in Observational Settings
Fall 2022

4 Oct 2022

Learning goals for today

At the end of class, you will be able to:

1. Trace inverse probability weighting to survey sampling
2. Apply the Horvitz-Thompson estimator for causal inference
3. Recognize the bias-variance tradeoff of trimmed weights
4. Estimate the ATE, ATT, and ATC by weighting

Inverse probability weighting: Sampling

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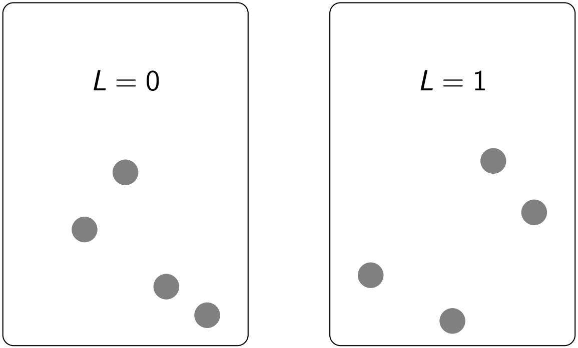

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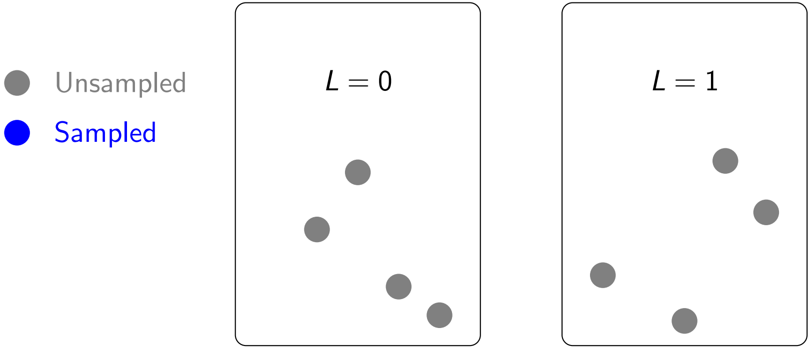

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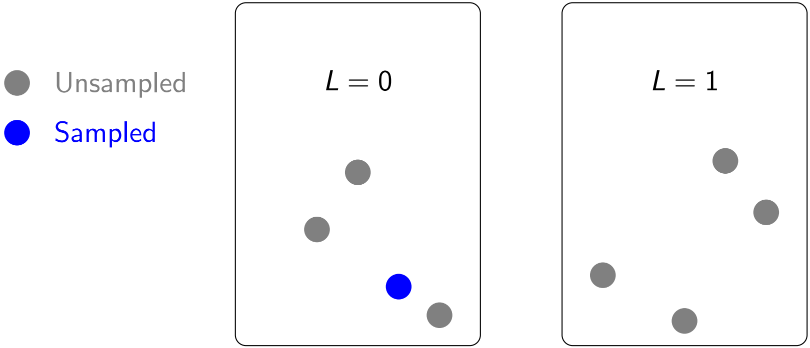

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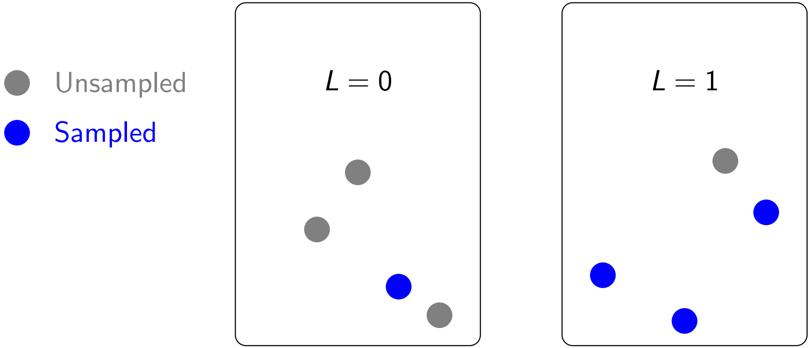

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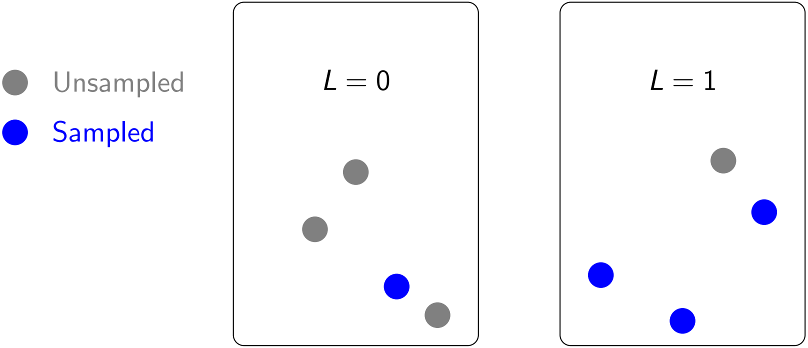

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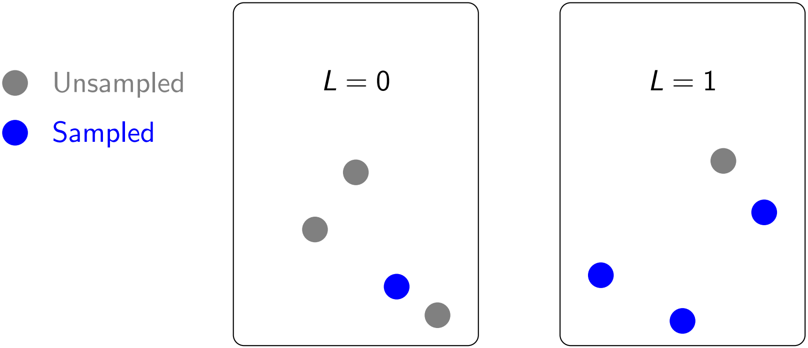

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Each counts for: $w_i = \dfrac{1}{\pi_i} = 4$ $\qquad$ $w_i = \dfrac{1}{\pi_i} = \dfrac{4}{3}$

The Horvitz-Thompson estimator for a population mean:

$$\hat{\mathrm{E}}(Y) = \frac{1}{N} \sum_{i:S_i=1} \frac{Y_i}{\pi_i}$$

where N is the population size and
π_i is the known probability of sampling

Inverse probability weighting: Conditional randomizaton

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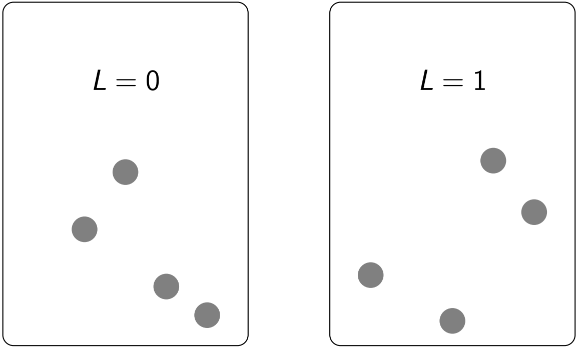

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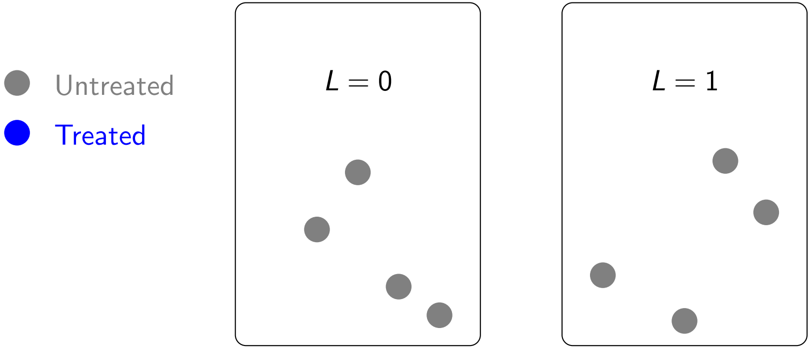

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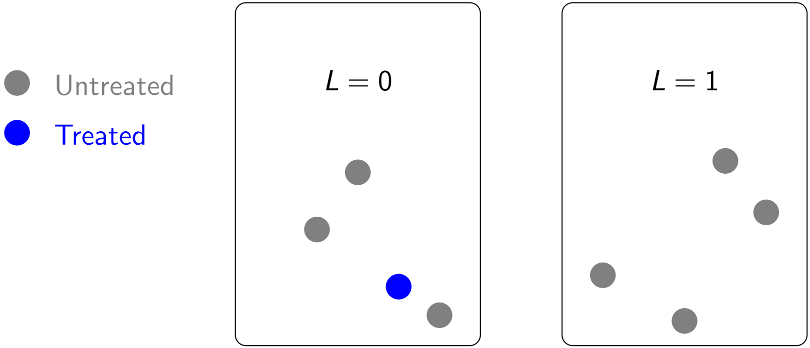

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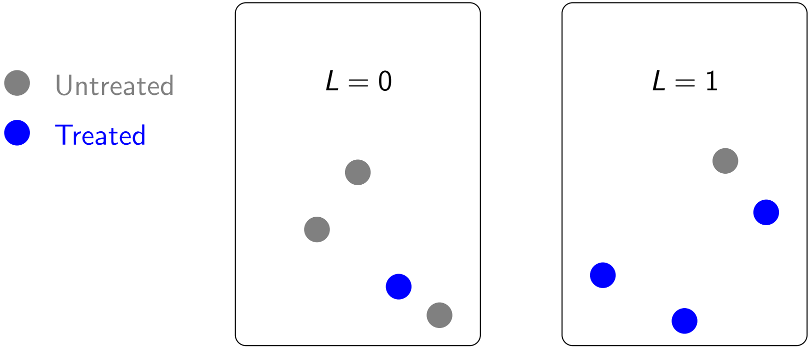

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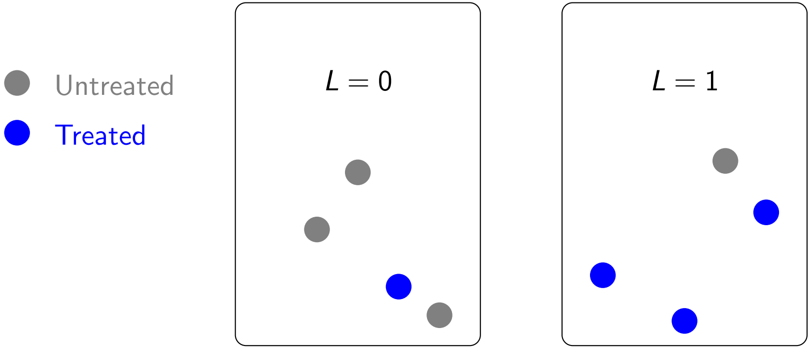

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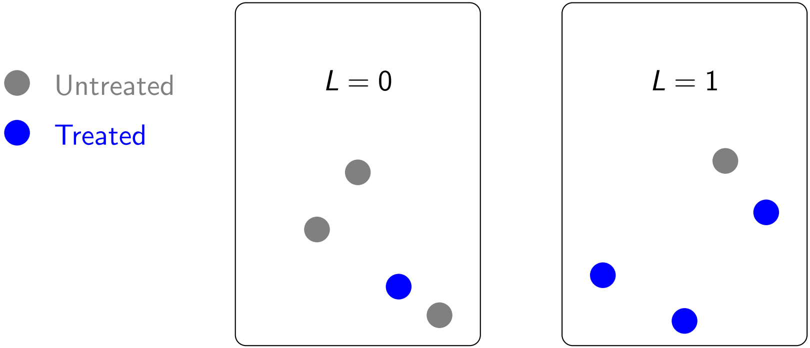

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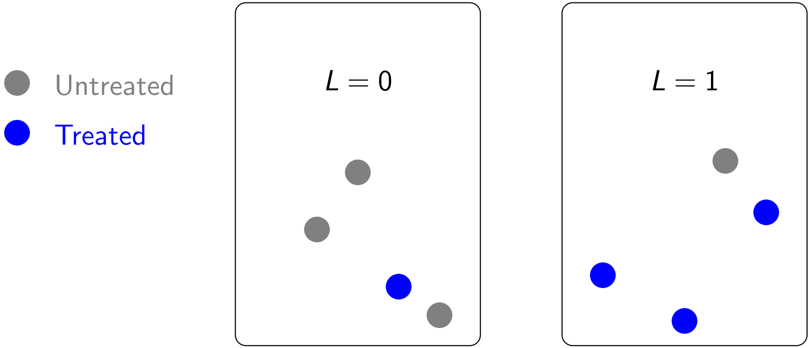

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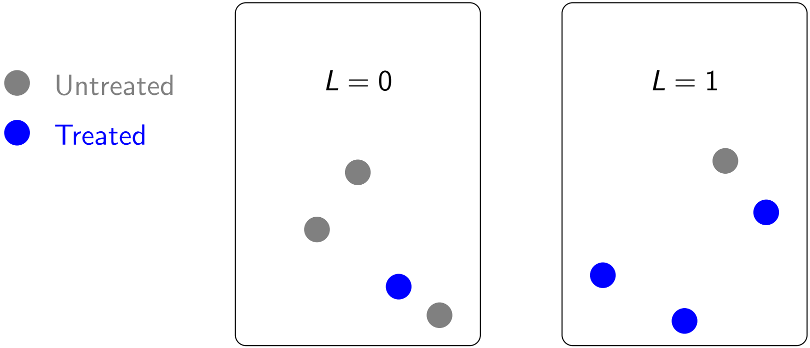

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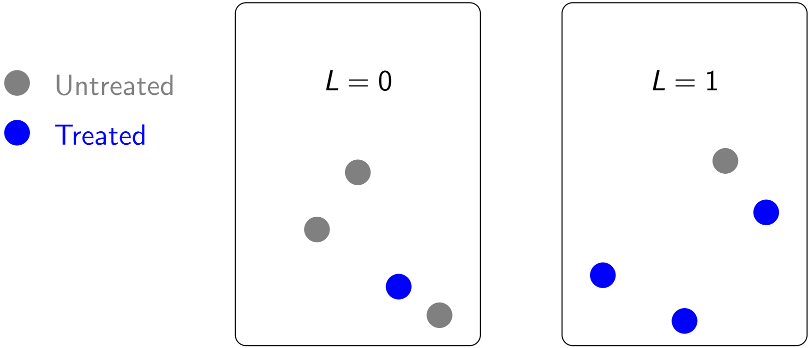

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Inverse probability weighted (IPW) estimator
for the average treatment effect (ATE)

$$\mathrm{E}(Y^1) - \mathrm{E}(Y^0) = \frac{1}{N} \sum_{i:A_i=1} \frac{Y_i}{\pi_i} - \frac{1}{N} \sum_{i:A_i=0} \frac{Y_i}{\pi_i}$$

where $\pi_i = \mathrm{P}(A = a_i \mid \vec{L} = \vec{\ell}_i)$
is the probability of the observed treatment given confounders

Inverse probability weighting: Mathematical proof[1]

[1] Hernán & Robins Technical Point 2.3

Inverse probability weighting: Mathematical proof[1]

$$\mathrm{E}\left(\frac{\mathbb{I}(A = a)}{\mathrm{P}(A = a \mid \vec{L})} Y\right) \tag{1}$$

$$= \mathrm{E}(Y^a) \tag{6}$$

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$$=\mathrm{E}\left(\mathrm{E}\left[\frac{\mathbb{I}(A=a)}{\mathrm{P}(A=a\mid\vec{L})}Y^a\mid\vec{L}\right]\right) \qquad \text{iterated expectation} \tag{3}$$

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Inverse probability weighting: Mathematical proof[1]

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\begin{aligned}
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Inverse probability weighting: Observational studies

In an experiment, we control treatment assignment.
We know the dashed edge does not exist.
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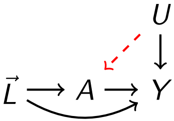

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Otherwise all estimators (including IPW) are the same.

Inverse probability weighting: Nonparametric procedure

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$$\hat{\text{E}}(Y^a) = \frac{1}{N} \sum_{i:A_i=a} \frac{Y_i}{\hat{\pi}_i}$$

Inverse probability weighting: Parametric procedure[2]

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$$\hat{\pi}_i = \begin{cases} \text{logit}^{-1}\left(\hat{\alpha} + \hat{\vec{\gamma}}\vec{L}\right) & \text{if } A_i = 1 \\ 1 - \text{logit}^{-1}\left(\hat{\alpha} + \hat{\vec{\gamma}}\vec{L}\right) & \text{if } A_i = 0 \end{cases}$$

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3. Apply an IPW estimator

$$\hat{\text{E}}(Y^a) = \frac{1}{N} \sum_{i:A_i=a} \frac{Y_i}{\hat{\pi}_i} \qquad \text{(Horvitz-Thompson)}$$

or

$$\hat{\text{E}}(Y^a) = \frac{1}{\sum_{i:A_i=a} \frac{1}{\hat{\pi}_i}} \sum_{i:A_i=a} \frac{Y_i}{\hat{\pi}_i} \qquad \text{(Hajek)}$$

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Two solutions

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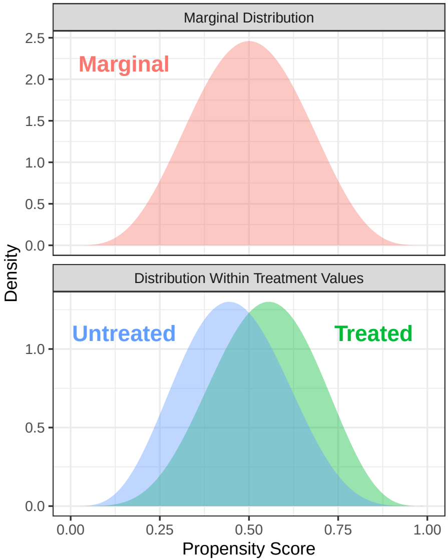
Both solutions accept bias in order to reduce variance

Accepting bias to reduce variance: Trimming



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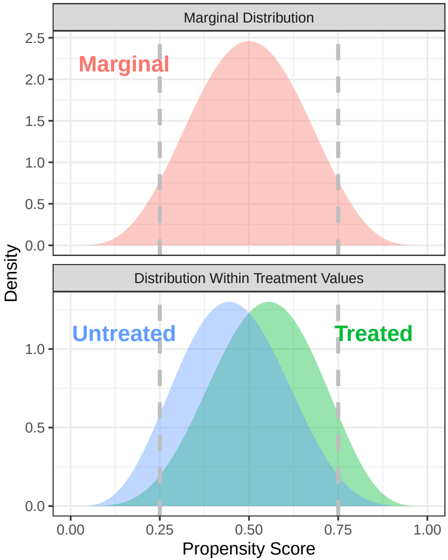

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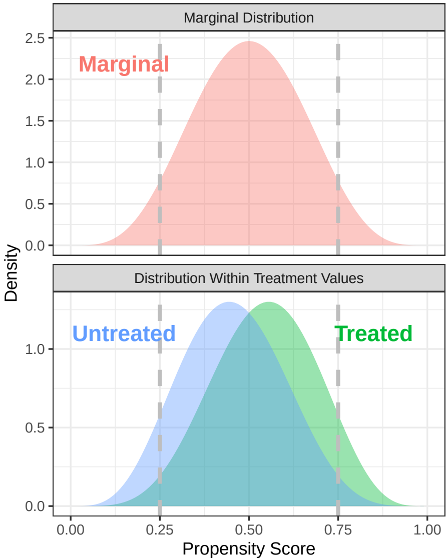

Drop units with extreme weights

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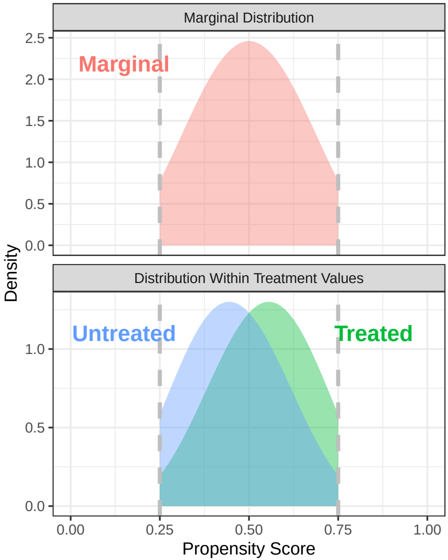

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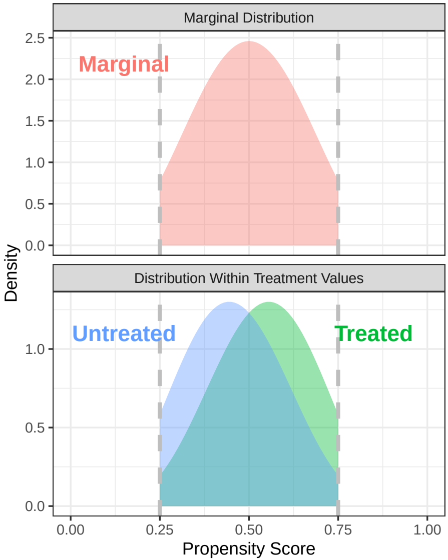
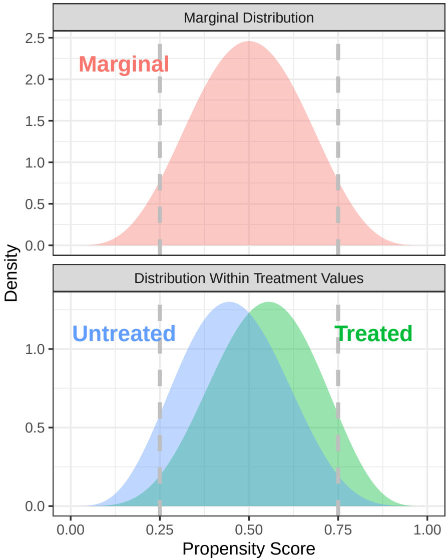


Drop units with extreme weights

Changes target population — Biased for full population

Accepting bias to reduce variance: Weight truncation



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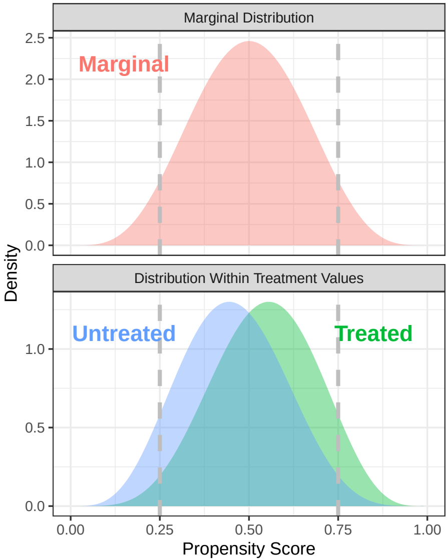

Truncate values of extreme weights

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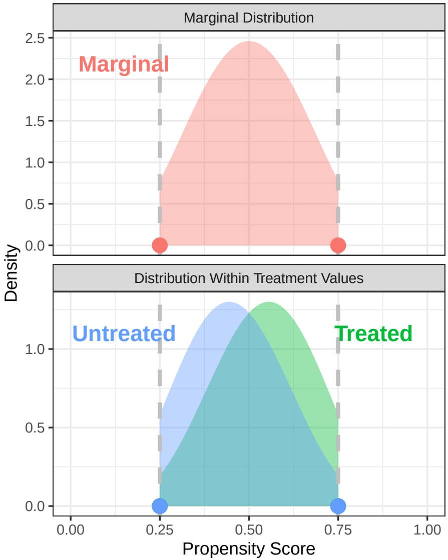

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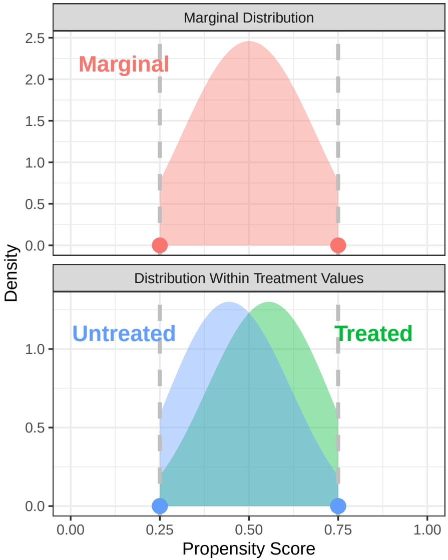

Truncate values of extreme weights

Biased: Ignores some confounding

Weighting for the ATE, ATT, ATC

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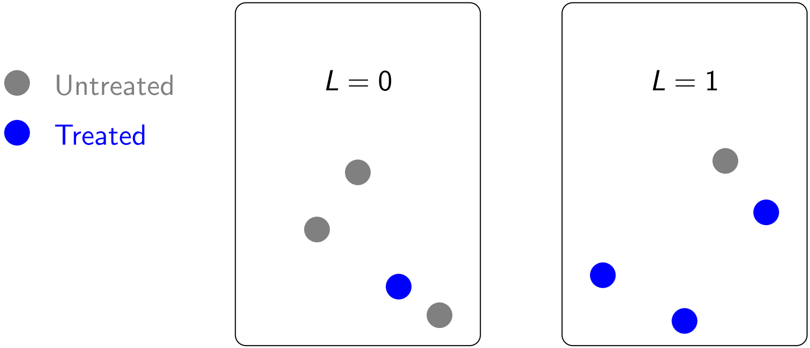

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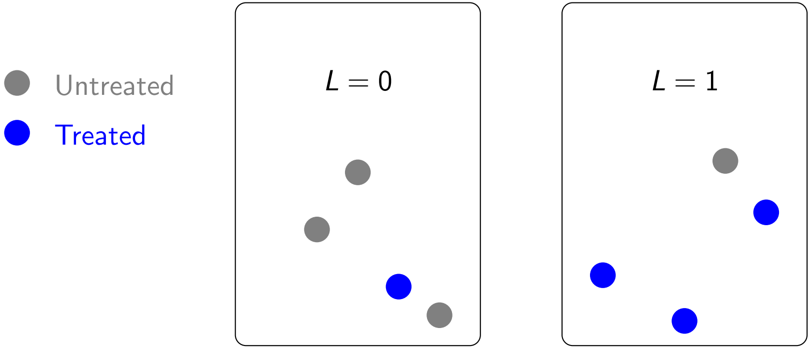
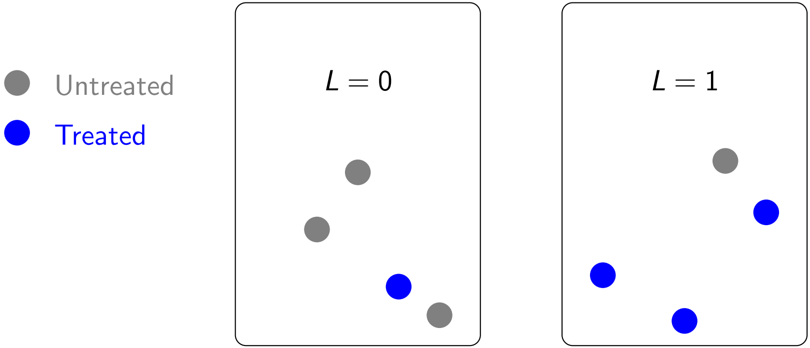


For ATE:

$w_i = \frac{1}{\mathrm{P}(A=a_i|L=\ell_i)}$

Weighting for the ATE, ATT, ATC

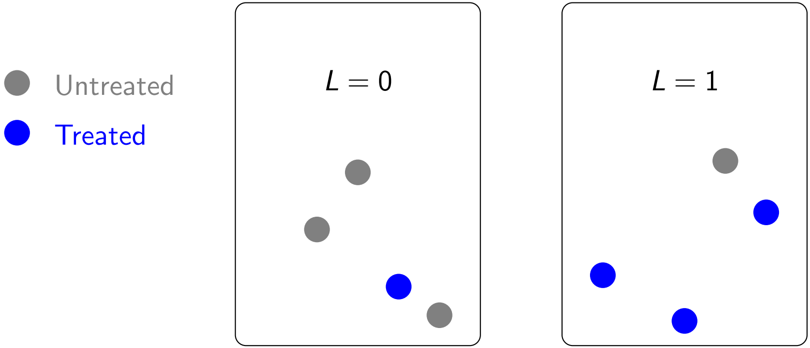


$$\frac{1}{3/4} = \frac{4}{3}$$

For ATE:

$w_i = \frac{1}{\text{P}(A=a_i|L=\ell_i)}$

Weighting for the ATE, ATT, ATC



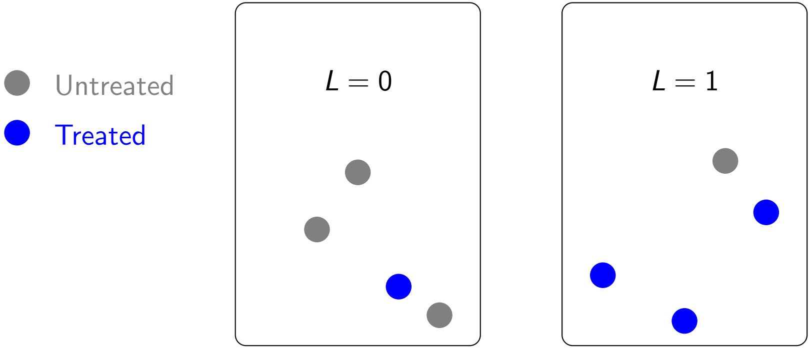
For ATE:

$w_i = \frac{1}{\mathrm{P}(A{=}a_i | L{=}\ell_i)}$

$$\frac{1}{3/4} = \frac{4}{3}$$

$$\frac{1}{1/4} = \frac{4}{1}$$

Weighting for the ATE, ATT, ATC



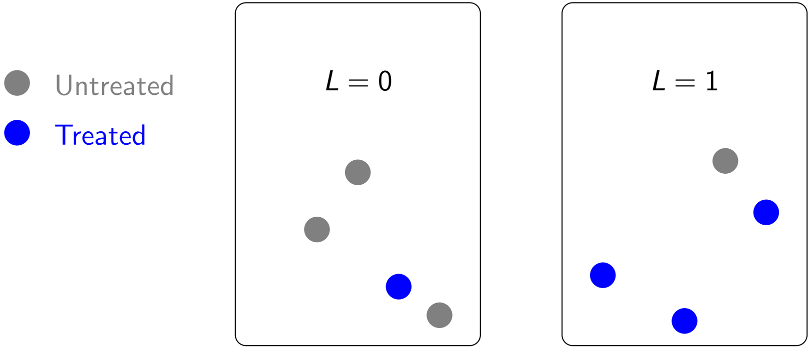
For ATE:

$w_i = \frac{1}{\mathrm{P}(A=a_i|L=\ell_i)}$

$$\frac{1}{3/4} = \frac{4}{3} \qquad \frac{1}{1/4} = \frac{4}{1}$$

$$\frac{1}{1/4} = \frac{4}{1}$$

Weighting for the ATE, ATT, ATC

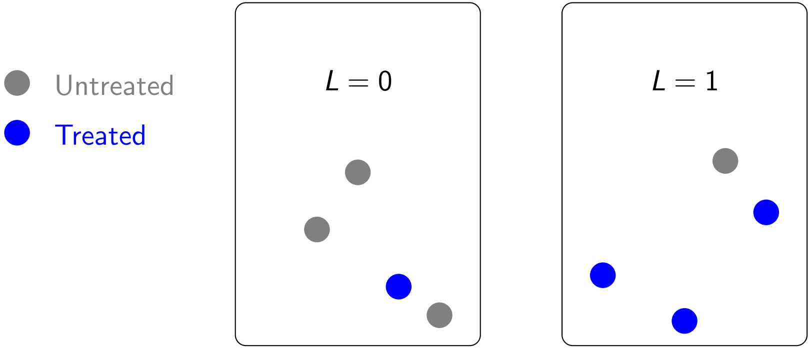


For ATE:

$w_i = \frac{1}{\text{P}(A=a_i|L=\ell_i)}$

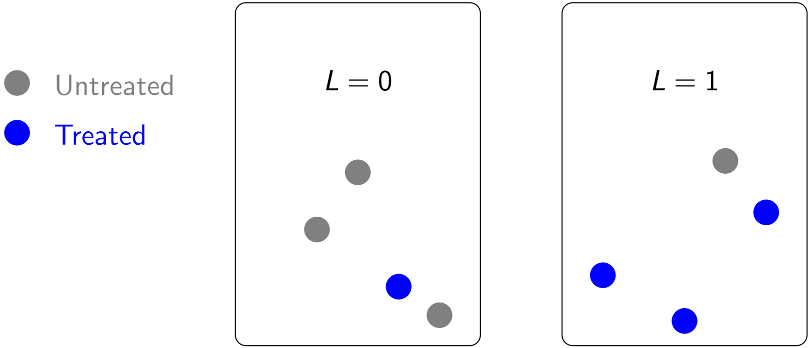
$L = 0$	$L = 1$
$\frac{1}{3/4} = \frac{4}{3}$	$\frac{1}{1/4} = \frac{4}{1}$
$\frac{1}{1/4} = \frac{4}{1}$	$\frac{1}{3/4} = \frac{4}{3}$

Weighting for the ATE, ATT, ATC



For ATT?

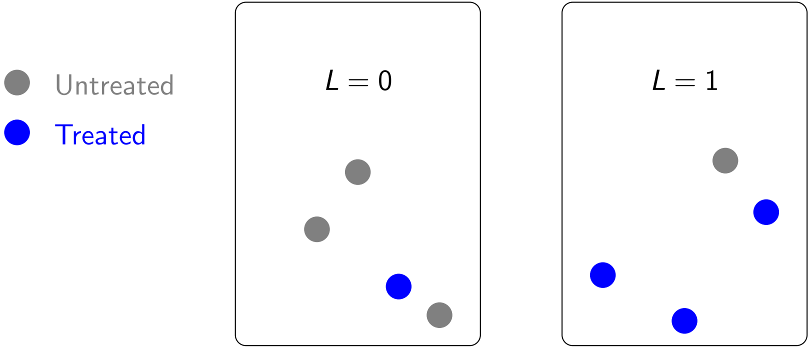
Weighting for the ATE, ATT, ATC



$$\frac{1}{3}$$

For ATT?

Weighting for the ATE, ATT, ATC

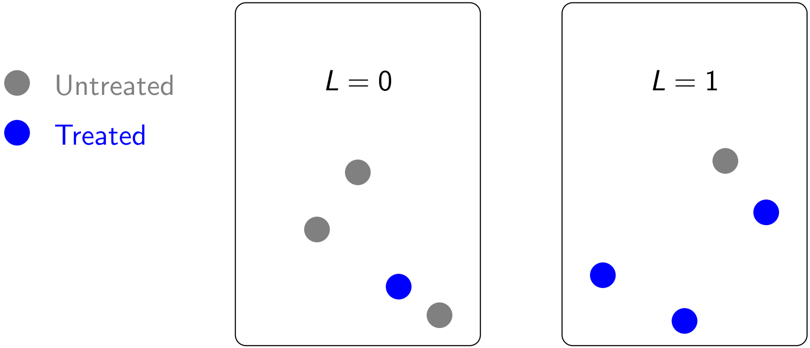


For ATT?

$\frac{1}{3}$

1

Weighting for the ATE, ATT, ATC

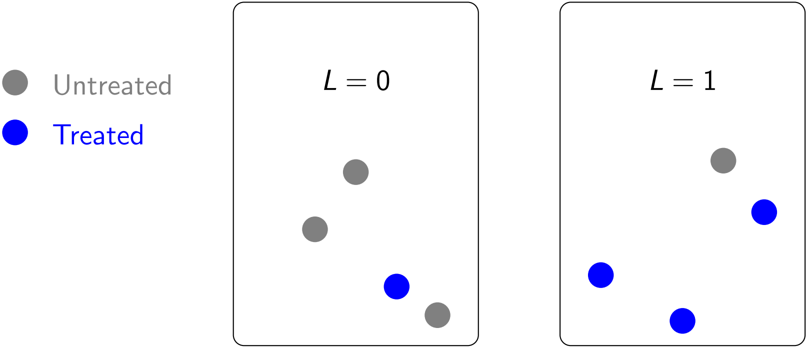


$\frac{1}{3}$ $\frac{3}{1}$

For ATT?

1

Weighting for the ATE, ATT, ATC

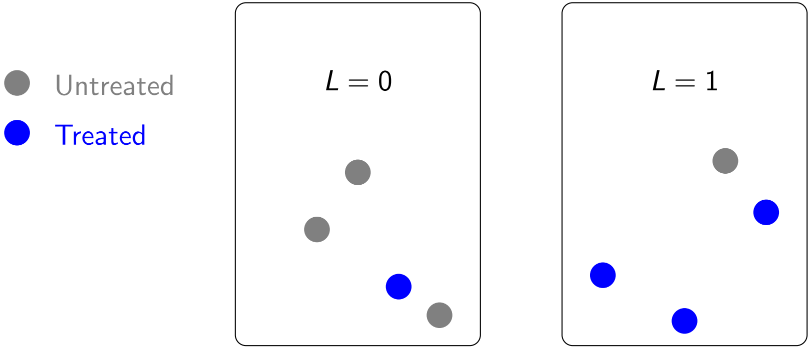


For ATT?

$\frac{1}{3}$ $\frac{3}{1}$

1 1

Weighting for the ATE, ATT, ATC

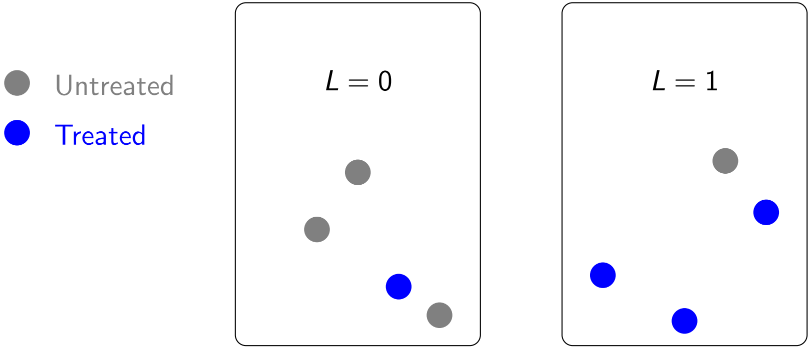


For ATT:
$w_i = \frac{P(A=1|L=\ell_i)}{P(A=a_i|L=\ell_i)}$

$\frac{1}{3}$ $\frac{3}{1}$

1 1

Weighting for the ATE, ATT, ATC

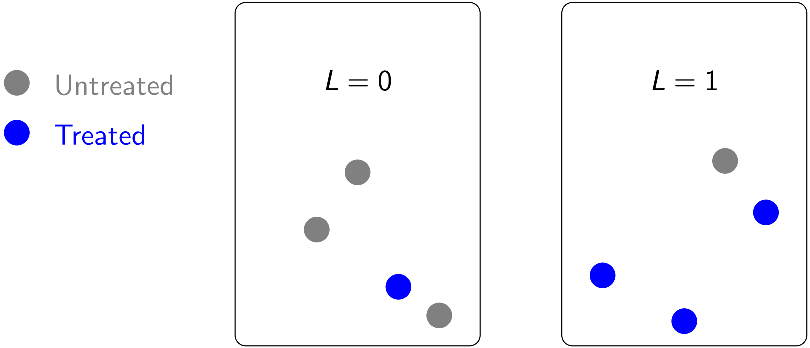


For ATT:
$w_i = \frac{P(A=1|L=\ell_i)}{P(A=a_i|L=\ell_i)}$

$L = 0$: $\frac{1/4}{3/4} = \frac{1}{3}$, $\frac{1/4}{1/4} = 1$

$L = 1$: $\frac{3/4}{1/4} = \frac{3}{1}$, $\frac{3/4}{3/4} = 1$

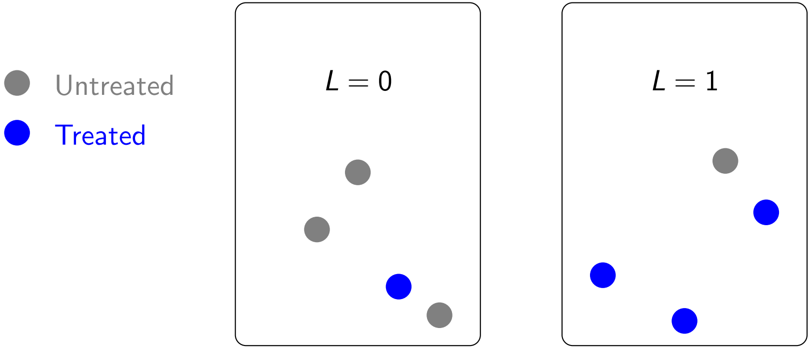
Weighting for the ATE, ATT, ATC



For ATC:

$w_i = \frac{\mathrm{P}(A{=}0 \mid L{=}\ell_i)}{\mathrm{P}(A{=}a_i \mid L{=}\ell_i)}$

Weighting for the ATE, ATT, ATC

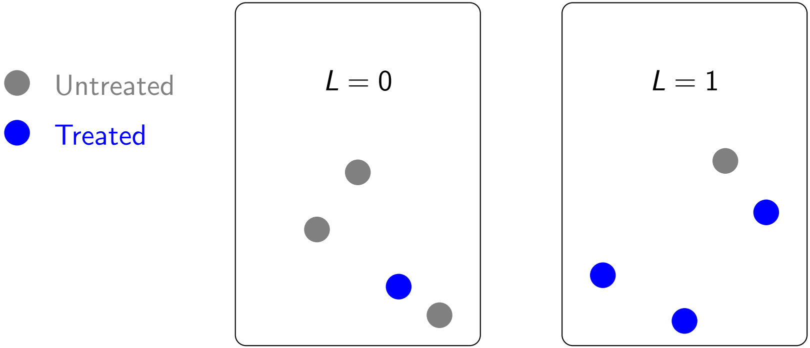


$$\frac{3/4}{3/4} = 1$$

For ATC:

$w_i = \frac{\text{P}(A=0|L=\ell_i)}{\text{P}(A=a_i|L=\ell_i)}$

Weighting for the ATE, ATT, ATC

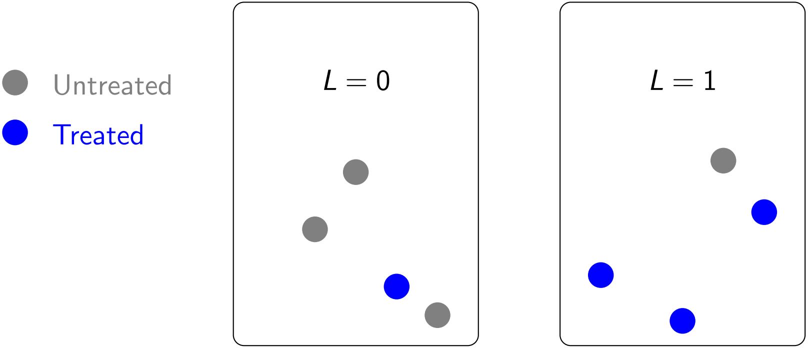


$$\frac{3/4}{3/4} = 1$$

For ATC:
$w_i = \frac{\mathrm{P}(A=0|L=\ell_i)}{\mathrm{P}(A=a_i|L=\ell_i)}$

$$\frac{3/4}{1/4} = 3$$

Weighting for the ATE, ATT, ATC



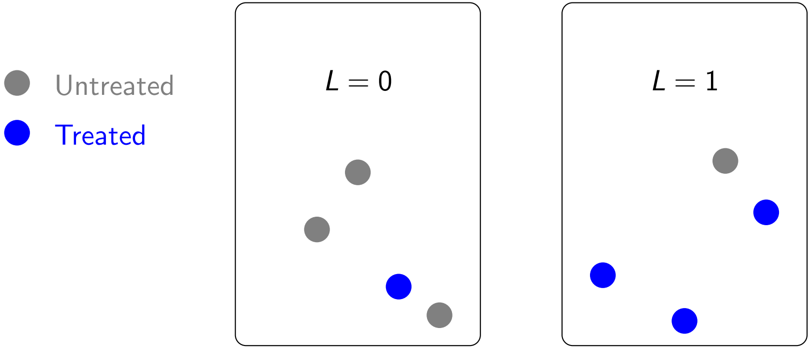
$$\frac{3/4}{3/4} = 1 \qquad \frac{1/4}{1/4} = 1$$

For ATC:

$$w_i = \frac{\mathrm{P}(A{=}0 \mid L{=}\ell_i)}{\mathrm{P}(A{=}a_i \mid L{=}\ell_i)}$$

$$\frac{3/4}{1/4} = 3$$

Weighting for the ATE, ATT, ATC



$L=0$: $\frac{3/4}{3/4} = 1$, $\frac{3/4}{1/4} = 3$

$L=1$: $\frac{1/4}{1/4} = 1$, $\frac{1/4}{3/4} = \frac{1}{3}$

For ATC:

$$w_i = \frac{\mathrm{P}(A=0 | L=\ell_i)}{\mathrm{P}(A=a_i | L=\ell_i)}$$

Weighting for the ATE, ATT, ATC

General formula:

$$w_i = \frac{\text{Size of target population in } \vec{L} = \vec{\ell}_i}{\text{Size of factual population in } \vec{L} = \vec{\ell}_i}$$

Intuition:

- Normalize the factual population across strata (denominator)
- Upweight to the counterfactual population (numerator)

Inverse probability weighting: Reading

Hernán & Robins

- 2.4
- 12.1–12.3

Learning goals for today

At the end of class, you will be able to:

1. Trace inverse probability weighting to survey sampling
2. Apply the Horvitz-Thompson estimator for causal inference
3. Recognize the bias-variance tradeoff of trimmed weights
4. Estimate the ATE, ATT, and ATC by weighting

Let me know what you are thinking

tinyurl.com/CausalQuestions

Office hours TTh 11am-12pm and at
calendly.com/ianlundberg/office-hours
Come say hi!