### Matching Lab

#### INFO/STSCI/ILRST 3900: Causal Inference

4 Oct 2023

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### Agenda

- ► Reminders/Announcements
- ► Icebreaker: Matching Lecture Review
- Matching with Multiple Covariates Overview
- R Demonstration
- ► Your turn (get ahead on the HW!)

### Icebreaker: Matching Lecture Review

In groups of 2-4, you will be assigned one of the questions below. Your task is to explain and answer the assigned question. Have one person in your group ready to share what you discuss with the whole class.

- 1. What is the difference between the ATE and the ATT, and what is the challenge in estimating the ATT?
- 2. Explain what matching is and how we use it to estimate causal effects (like the ATT).
- 3. What is the difference between caliper versus no caliper matching, and what changes in the estimand when we use calipers?
- 4. What is 1 : 1 matching versus k : 1 matching? Explain the bias-variance trade off.
- 5. What is matching with replacement and without replacement? Explain the bias-variance trade off.
- 6. What is greedy versus optimal matching and what trade off should be considered there?





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- Estimate E(Y<sup>a=0</sup> | A = 1) with a group of untreated units, *M*, which has a similar distribution of Age and Education to the treated group



Age



 ${} \quad = \quad \square \quad \flat$ 



#### Which untreated unit should be the match?

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Define a way to measure "distance" between two individuals as a single number



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- Match individuals in the same way as before using that distance!





Manhattan distance:

Euclidean distance:



• Manhattan distance:  $d(i,j) = \sum_{p} |L_{pi} - L_{pj}|$ 

Euclidean distance:



- Manhattan distance:  $d(i,j) = \sum_{p} |L_{pi} L_{pj}|$ 
  - d(Treated, Untreated 1) = 3 + 4 = 7
  - $d(\text{Treated}, \text{Untreated } 2) = 6 + 0 = 6 \checkmark$
- Euclidean distance:



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• Euclidean distance: 
$$d(i,j) = \sqrt{\sum_{p} (L_{pi} - L_{pj})^2}$$



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- Euclidean distance:  $d(i,j) = \sqrt{\sum_{p} (L_{pi} L_{pj})^2}$ 
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- It depends on the distance metric!

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Motivated by two principles

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We should care about a correlation-corrected distance

$$d(i,j) = \sqrt{\left(ec{L}_i - ec{L}_j
ight)^T \Sigma^{-1} \left(ec{L}_i - ec{L}_j
ight)}$$

where  $\Sigma = V(\vec{L})$ , the variance-covariance matrix of L

### Let's try this out in R!