## Why model?

# Cornell STSCI / INFO / ILRST 3900 <br> Fall 2023 <br> causal3900.github.io 

26 Sep 2023

## Arc of the course

We began by asking causal questions

- Defining counterfactuals

Then we discussed causal assumptions

- Exchangeability and experiments
- Consistency and positivity
- Directed Acyclic Graphs


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5 weeks

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## 5 weeks

0 statistical models

## Learning goals for today

At the end of class, you will be able to

- explain the curse of dimensionality
- recognize the possible futility of nonparametric estimation


## Motivating a research question ${ }^{1}$

Income inequality across households depends on

1. inequality across individuals
2. how individuals pool into households

A college degree affects (1) and (2)

[^0]
## Research question

To what degree does finishing college increase the probability of having a spouse who finished college?

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Data. National Longitudinal Survey of Youth 1997

- Probability sample of U.S. non-institutional civilian youth age 12-16 on Dec 311996
- Surveyed annually 1997-2011, then biennially
- $n=8,984$


## Data access

To access these data, first

- set your working directory where you will be working
- download two supporting files from us

1. nlsy97. NLSY97 is a tagset file containing the variable names
2. prepare_nlsy97. R is an R script to prepare the data

## Data access

Now go to the data distributor

1. Register with the survey
2. Log in to the NLS Investigator
3. Choose the NLSY97 study
4. Upload the tagset nlsy97. NLSY97 that you downloaded from us
5. In the Investigator, download the data. Type to change the file name from default to nlsy97
6. Unzip the file. Drag nlsy97. dat into the folder you will work in
7. In your R console, run the line of code below
this will take about 30 seconds to run

- you will need these R packages: tidyverse and Amelia
source("prepare_nlsy97.R")
In the future, you can now load the data with
d <- readRDS("d.RDS")


## Register with the survey

## NLS Investigator



Password must be 8 characters or more and contain at least one numeric and one non numeric character. In addition the password must not be based on username.I agree to the NLS Investigator Privacy Policy.

[^1]Register

## Choose the NLSY97 study

## NLS Investigator

Select the study you want to work with:
NLSY97 (National Longitudinal Survey of Youth 1997) $\vee$
Select a substudy:
NLSY97 1997-2019 (rounds 1-19) $\vee$
Released November 01, 2021

## Upload our tagset

Choose Tagsets

## Upload Tagset (from PC):

Choose File No file chosen
Upload

## Download the data

## Choose Tagsets

Customize your advanced download:Create Download of DataTagset (list of selected variables)
SAS® control file (includes the datafile of selected variables)SPSS® control file (includes the datafile of selected variables)STATA® dictionary file of selected variables

$R ®$ Source code (includes the datafile of selected variables)Codebook of selected variablesShort Description FileComma-delimited datafile of selected variables (to be read in Excel, etc.) Column headers -- Use OReference Number OQuestion Name (does not guarantee uniqueness)Create Frequency / TableApply Universe Restrictors (How to use Universe Restrictors)Notify me by email when download is complete.
Filename: nlsy97
Filename must only con alpha, numeric,
hyphen or underscore c
Download


## Run our code

This code prepares the data file (one time, takes about 30 seconds) source("prepare_NLSY97.R")

This code loads the prepared data (after the above, very fast) d <- readRDS("d.RDS")

## Research question

To what degree does finishing college increase the probability of having a spouse who finished college?

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To what degree does finishing college increase the probability of having a spouse who finished college?

Treatment $A$ : Finished BA by age 25

- Outcome $Y$ : Spouse or partner at age 30-40 holds a BA
- 0 if no spouse or partner, or partner with no BA
- 1 if spouse or partner holds a BA


## Research question

To what degree does finishing college increase the probability of having a spouse who finished college?

Treatment $A$ : Finished BA by age 25

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To what degree does finishing college increase the probability of having a spouse who finished college?

Treatment $A$ : Finished BA by age 25

- Outcome $Y$ : Spouse or partner at age 30-40 holds a BA
- 0 if no spouse or partner, or partner with no BA
- 1 if spouse or partner holds a BA


Adjustment procedure

1) Estimate within subgroups defined by $\{\operatorname{sex}\}$
2) Aggregate over the subgroups

## Data

```
d %>%
    select(sex, a, y) %>%
    print(n = 8)
# A tibble: 7,771 x 3
    sex a y
    <chr> <chr> <lgl>
1 Female college FALSE
2 Male no_college FALSE
3 Female no_college FALSE
4 \text { Male no_college TRUE}
5 Female no_college FALSE
6 ~ M a l e ~ n o - c o l l e g e ~ F A L S E ~
7 Female college FALSE
8 Male college TRUE
# i 7,763 more rows
```


## 1) Estimate in subgroups

```
ybar_in_subgroups <- d %>%
    # Group by confounders and treatment
    group_by(sex, a) %>%
    # Summarize mean outcomes and nber of cases
    summarize(ybar = mean(y),
            n = n(),
            .groups = "drop") %>%
    print()
# A tibble: 4 x 4
    sex a ybar n
    <chr> <chr> <dbl> <int>
1 Female college 0.467 896
2 Female no_college 0.102 2953
3 Male college 0.614 637
4 Male no_college 0.174 3285
```


## 1) Estimate in subgroups

| \# A tibble: $4 \times 4$ |  |  |  |
| :--- | :--- | ---: | ---: |
|  | sex a | ybar | $n$ |
|  | <chr> | <chr> | <dbl> |
| <int> |  |  |  |
| 1 | Female college | 0.467 | 896 |
| 2 Female | no_college | 0.102 | 2953 |
| 3 Male college | 0.614 | 637 |  |
| 4 Male | no_college | 0.174 | 3285 |

## 1) Estimate in subgroups

```
# A tibble: 4 x 4
    sex a ybar ren
1 Female college 0.467 896
2 Female no_college 0.102 2953
3 Male college 0.614 637
4 Male no_college 0.174 3285
pivoted <- ybar_in_subgroups %>%
    pivot_wider(names_from = a,
    values_from = c("ybar","n")) %>%
    print()
# A tibble: 2 x 5
    sex ybar_college ybar_no_college n_college n_no_college
    <chr> <dbl> <dbl> <int> <int>
1 Female 0.467 0.102 896 2953
2 Male 0.614 0.174 637 3285
```


## 1) Estimate in subgroups



## 1) Estimate in subgroups

```
# A tibble: 2 x 5
    sex ybar_college ybar_no_college n_college n_no_college
    <chr> <dbl> <dbl> <int> <int>
1 Female 0.467 0.102 896 2953
2 Male 0.614 0.174 637 3285
cate <- pivoted %>%
    mutate(conditional_effect = ybar_college - ybar_no_college,
    n_in_stratum = n_college + n_no_college) %>%
    select(sex, conditional_effect, n_in_stratum) %>%
    print()
# A tibble: 2 x 3
    sex conditional_effect n_in_stratum
    <chr> <dbl> <int>
1 Female 0.365 3849
2 Male
    0.440 3922
```


## 2) Aggregate over subgroups

```
# A tibble: 2 x 3
    sex conditional_effect n_in_stratum
    <chr> <dbl> <int>
1 Female 0.365 3849
2 Male
0.440
    3922
```


## 2) Aggregate over subgroups

```
# A tibble: 2 x 3
    sex conditional_effect n_in_stratum
    <chr> <dbl> <int>
1 Female 0.365 3849
2 Male 0.440 3922
cate %>%
    summarize(population_average_effect = weighted.mean(
        conditional_effect,
        w = n_in_stratum
    ))
# A tibble: 1 x 1
    population_average_effect
        <dbl>
1
    0.403
```


## Recap: Intuition



Female
Male

## Recap: In code

```
d %>%
    # Group by confounders and treatment
    group_by(sex, a) %>%
    # Estimate within subgroups
    summarize(ybar = mean(y),
        n = n(),
            .groups = "drop") %>%
    pivot_wider(names_from = a,
        values_from = c("ybar","n")) %>%
    mutate(conditional_effect = ybar_college - ybar_no_college,
        n_in_stratum = n_college + n_no_college) %>%
    # Aggregate over subgroups
    summarize(population_average_effect = weighted.mean(
        conditional_effect,
        w = n_in_stratum
    ))
# A tibble: 1 x 1
    population_average_effect
        <dbl>
1
        0.403
```


## Adjust for sex and race



## Adjust for sex and race



1) Estimate effects within subgroups defined by $\{$ sex, race $\}$
2) Aggregate over subgroups

## Adjust for sex and race

Hispanic

Female
Male

Female
Male

## Adjust for sex and race



## Adjust for sex, race, mom education



1) Estimate effects within subgroups defined by $\{$ race,sex, mom education $\}$
2) Aggregate over subgroups

## Adjust for sex, race, mom education



## Adjust for sex, race, mom education



## Adjust for sex, race, mom education, dad education



1) Estimate effects within subgroups defined by \{race,sex, mom education, dad education\}
2) Aggregate over subgroups

## Adjust for sex, race, mom education, dad education




| Non-Hispanic Non-Black |  |  |
| :---: | :---: | :---: |
| No College ${ }^{\text {a }}$ - No College | No dad | No mom |
|  | $<\mathrm{HS}$ | No mom |
|  | High school | No mom |
|  | Some college | No mom |
|  | College | No mom |
| No College $\quad$ No College | No dad | $<\mathrm{HS}$ |
| No College - No College | $<\mathrm{HS}$ | $<\mathrm{HS}$ |
| No College - ${ }^{\text {N }}$ Nocollege | High school | $<\mathrm{HS}$ |
|  | Some college | $<\mathrm{HS}$ |
| - - - - - CoClililepe - - - - - No College | College | $<\mathrm{HS}$ |
|  | No dad | High school |
|  | $<\mathrm{HS}$ | High school |
|  | High school | High school |
|  | Some college | High school |
|  | College | High school |
|  | No dad | Some college |
|  | $<\mathrm{HS}$ | Some college |
|  | High school | Some college |
|  | Some college | Some college |
|  | College | Some college |
|  | No dad | College |
|  | $<\mathrm{HS}$ | College |
|  | High school | College |
|  | Some college | College |
|  | College | College |

## Adjust for sex, race, mom education, dad education




| Non-Hispanic Non-Black |  |  |
| :---: | :---: | :---: |
| No College ${ }^{\text {a }}$ - No College | No dad | No mom |
| No Colege ${ }^{\text {N }}$ - No College | $<\mathrm{HS}$ | No mom |
|  | High school | No mom |
|  | Some college | No mom |
|  | College | No mom |
| No College $\quad[$ No College | No dad | $<\mathrm{HS}$ |
| No College - No College | $<\mathrm{HS}$ | $<\mathrm{HS}$ |
|  | High school | $<\mathrm{HS}$ |
|  | Some college | < HS |
| - - - - NoColiejee - - - - - No College | College | $<\mathrm{HS}$ |
|  | No dad | High school |
|  | $<\mathrm{HS}$ | High school |
|  | High school | High school |
|  | Some college | High school |
|  | College | High school |
|  | No dad | Some college |
|  | $<\mathrm{HS}$ | Some college |
|  | High school | Some college |
|  | Some college | Some college |
| - - - $\mathrm{NO}_{\text {college }}$ | College | Some college |
|  | No dad | College |
|  | $<\mathrm{HS}$ | College |
|  | High school | College |
| - - Colege | Some college | College |
|  | College | College |

## Curse of dimensionality: Unpopulated cells

| \# A tibble: 147 x 6 |  |  |  |  |  |
| :--- | :--- | :--- | :--- | ---: | ---: |
| sex race | mom_educ | dad_educ | n_college n_no_college |  |  |
|  | <chr> | <chr> | <fct> | <fct> | <int> |$\quad$| <int> |
| ---: | :--- | ---: |

## Curse of dimensionality



## 4.2\% of the sample

is in a subgroup with either 0 treated or 0 untreated units

## Curse of dimensionality



## Curse of dimensionality



## $100 \%$ of the sample

is in a subgroup with either 0 treated or 0 untreated units

## Learning goals for today

At the end of class, you will be able to

- explain the curse of dimensionality
- recognize the possible futility of nonparametric estimation

After class, you should

- read Hernán \& Robins Ch 11
- attend discussion: you will learn to use models!


[^0]:    ${ }^{1}$ Mare 1991, Schwartz 2013

[^1]:    * Required field

