Gov 50: 6. Causality

Matthew Blackwell

Harvard University

Roadmap

1. What is causality?

2. Data importing

3. Logicals

1/ What is causality?

Two roads diverged in a yellow wood,
And sorry I could not travel both
And be one traveler, long I stood
And looked down one as far as I could
To where it bent in the undergrowth;

What is a causal effect?

factual vs. counterfactual

- Does increasing the minimum wage increase the unemployment rate?
  - Unemployment rate went up after the minimum wage increased
  - Would it have gone up if the minimum wage increase not occurred?
- Does having girls affect a judge's rulings in court?
  - A judge with a daughter gave a pro-choice ruling.
  - Would they have done that if had a son instead?
- **Fundamental problem of causal inference**:
  - Can never observe counterfactuals, must be inferred.

Political canvassing study

POLITICAL SCIENCE

Durably reducing transphobia: A field experiment on door-to-door canvassing

David Broockman[1]* and Joshua Kalla[2]

Existing research depicts intergroup prejudices as deeply ingrained, requiring intense intervention to lastingly reduce. Here, we show that a single approximately 10-minute conversation encouraging actively taking the perspective of others can markedly reduce prejudice for at least 3 months. We illustrate this potential with a door-to-door canvassing intervention in South Florida targeting antitransgender prejudice. Despite declines in homophobia, transphobia remains pervasive. For the intervention, 56 canvassers went door to door encouraging active perspective-taking with 501 voters at voters' doorsteps. A randomized trial found that these conversations substantially reduced transphobia, with decreases greater than Americans' average decrease in homophobia from 1998 to 2012. These effects persisted for 3 months, and both transgender and nontransgender canvassers were effective. The intervention also increased support for a nondiscrimination law, even after exposing voters to counterarguments.

- Can canvassers change minds about topics like transgender rights?
- Experimental setting:
    - Randomly assign canvassers to have a conversation about transgender right or a conversation about recycling.
    - Trans rights conversations focused on “perspective taking”
- Outcome of interest: support for trans rights policies.

Credit: Fabrice Florian via Flickr

A tale of two respondents

	Conversation Script	Support for Nondiscrimination Law
Respondent 1	Recycling	No
Respondent 2	Trans rights	Yes

Did the second respondent support the law **because** of the perspective-taking conversation?

Translating into math

Useful to have **compact** notation for referring to **treatment variable**:

$$T_i = \begin{cases} 1 & \text{if respondent } i \text{ had trans rights conversation} \\ 0 & \text{if respondent } i \text{ had recycling conversation} \end{cases}$$

Similar notation for the **outcome variable**:

$$Y_i = \begin{cases} 1 & \text{if respondent } i \text{ supports trans nondiscrimination laws} \\ 0 & \text{if respondent } i \text{ doesn't support nondiscrimination laws} \end{cases}$$

i is a placeholder to refer to a generic unit/respondent: Y_{42} is the outcome for the 42nd unit.

A tale of two respondents (redux)

	Conversation Script	Support for Nondiscrimination Law
Respondent 1	Recycling	No
Respondent 2	Trans rights	Yes

becomes...

i	T_i	Y_i
Respondent 1	0	0
Respondent 2	1	1

Causal effects & counterfactuals

- What does "T_i causes Y_i" mean? $\rightsquigarrow$ **counterfactuals**, "what if"
- Would respondent change their support based on the conversation?
- Two **potential outcomes**:
  - $Y_i(1)$: would respondent *i* support ND laws if they had trans rights script?
  - $Y_i(0)$: would respondent *i* support ND laws if they had recycling script?
- **Causal effect**: $Y_i(1) - Y_i(0)$
  - $Y_i(1) - Y_i(0) = 0 \rightsquigarrow$ script has no effect on policy views
  - $Y_i(1) - Y_i(0) = -1 \rightsquigarrow$ trans rights script lower support for laws
  - $Y_i(1) - Y_i(0) = +1 \rightsquigarrow$ trans rights script increases support for laws

Potential outcomes

i	T_i	Y_i	$Y_i(1)$	$Y_i(0)$
Respondent 1	0	0	???	0
Respondent 2	1	1	1	???

- **Fundamental problem of causal inference**:
  - We only observe one of the two potential outcomes.
  - Observe $Y_i = Y_i(1)$ if $T_i = 1$ or $Y_i = Y_i(0)$ if $T_i = 0$
- To infer causal effect, we need to infer the missing counterfactuals!

Potential outcomes vs possible outcomes

- **Potential outcomes** are all about counterfactuals:
    - What outcome would we see if I received treatment?
- Different from the **possible values of the outcome**
    - the “vote” variable can take on a 0 or a 1.

How can we figure out counterfactuals?

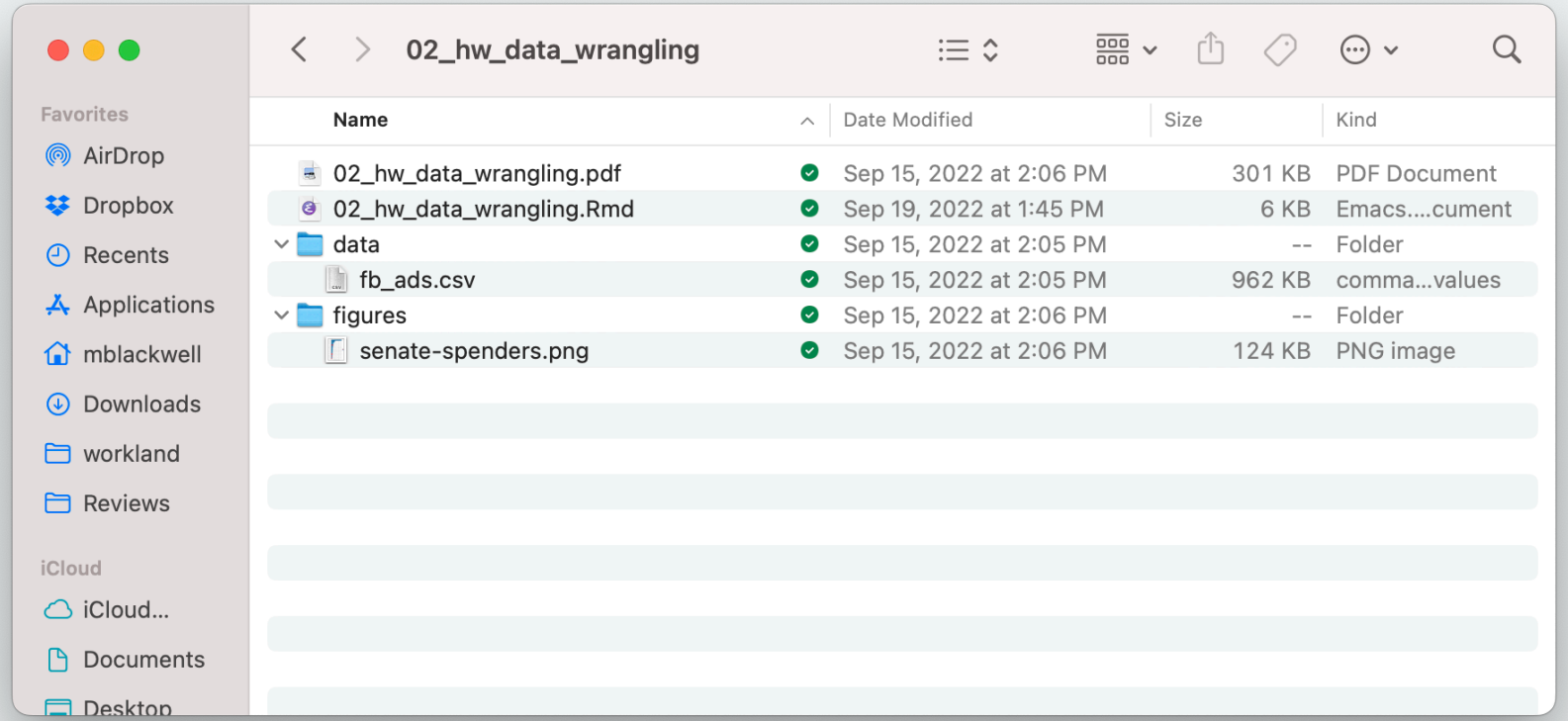
- Find a similar unit! $\rightsquigarrow$ **matching**
  - Mill's method of difference
- Does respondent support law because of the trans rights script?
  - $\rightsquigarrow$ find a identical respondent who got the recycling script.
- NJ increased the minimum wage. Causal effect on unemployment?
  - $\rightsquigarrow$ find a state similar to NJ that didn't increase minimum wage.

Imperfect matches

- The problem: imperfect matches!
- Say we match i (treated) and j (control)
- **Selection Bias:** $Y_i(1) \neq Y_j(1)$
- Those who take treatment may be different that those who take control.
- How can we correct for that?

2/ Data importing

Organizing your project



Keep your workspace clean. Directories help organize. Future you will thank present you.

`read_csv` to load CSV files

`read_csv` will import a csv file and create a tibble:

```
library(tidyverse)
resume <- read_csv("data/resume.csv")
resume
```

```
## # A tibble: 4,870 x 4
##    firstname sex    race   call
##    <chr>     <chr>  <chr> <dbl>
##  1 Allison   female white     0
##  2 Kristen   female white     0
##  3 Lakisha   female black     0
##  4 Latonya   female black     0
##  5 Carrie    female white     0
##  6 Jay       male   white     0
##  7 Jill      female white     0
##  8 Kenya     female black     0
##  9 Latonya   female black     0
## 10 Tyrone    male   black     0
## # i 4,860 more rows
```

3/ Logicals

News data, redux

```
library(gov50data)
news <- na.omit(news)
news
```

```
## # A tibble: 2,560 x 10
##    callsign affiliation date       weekday  ideology
##    <chr>    <chr>       <date>     <ord>       <dbl>
##  1 KECI     NBC         2017-06-07 Wed      0.0655
##  2 KPAX     CBS         2017-06-07 Wed      0.0853
##  3 KRBC     NBC         2017-06-07 Wed      0.0183
##  4 KTAB     CBS         2017-06-07 Wed      0.0850
##  5 KTMF     ABC         2017-06-07 Wed      0.0842
##  6 KTXS     ABC         2017-06-07 Wed     -0.000488
##  7 KAEF     ABC         2017-06-08 Thu      0.0426
##  8 KBVU     FOX         2017-06-08 Thu     -0.0860
##  9 KECI     NBC         2017-06-08 Thu      0.0902
## 10 KPAX     CBS         2017-06-08 Thu      0.0668
## # i 2,550 more rows
## # i 5 more variables: national_politics <dbl>,
## #   local_politics <dbl>, sinclair2017 <dbl>, post <dbl>,
## #   month <ord>
```

Creating logical vectors

You can create logical vectors using mutate. We can use the `.keep = "used"` here to only show the variables used in this mutate call:

```
news |>
  mutate(
    right_leaning = ideology > 0,
    fall = month == "Sep" | month == "Oct" | month == "Nov",
    .keep = "used"
  )
```

```
## # A tibble: 2,560 x 4
##     ideology month right_leaning fall
##        <dbl> <ord> <lgl>         <lgl>
##  1  0.0655   Jun   TRUE          FALSE
##  2  0.0853   Jun   TRUE          FALSE
##  3  0.0183   Jun   TRUE          FALSE
##  4  0.0850   Jun   TRUE          FALSE
##  5  0.0842   Jun   TRUE          FALSE
##  6 -0.000488 Jun   FALSE         FALSE
##  7  0.0426   Jun   TRUE          FALSE
##  8 -0.0860   Jun   FALSE         FALSE
##  9  0.0902   Jun   TRUE          FALSE
```

Using the logical variables to filter

```
news |>
  mutate(
    right_leaning = ideology > 0,
    fall = month == "Sep" | month == "Oct" | month == "Nov"
  ) |>
  filter(right_leaning & fall)
```

```
## # A tibble: 1,050 x 12
##    callsign affiliation date       weekday ideology
##    <chr>    <chr>       <date>     <ord>      <dbl>
##  1 KBZK     CBS         2017-09-01 Fri       0.121
##  2 KHSL     CBS         2017-09-01 Fri       0.0564
##  3 KNVN     NBC         2017-09-01 Fri       0.0564
##  4 KRCR     ABC         2017-09-01 Fri       0.324
##  5 WCTI     ABC         2017-09-01 Fri       0.0649
##  6 WCYB     NBC         2017-09-01 Fri       0.0613
##  7 WEMT     FOX         2017-09-01 Fri       0.187
##  8 WITN     NBC         2017-09-01 Fri       0.0297
##  9 WJHL     CBS         2017-09-01 Fri       0.151
## 10 WNCT     CBS         2017-09-01 Fri       0.186
## # i 1,040 more rows
## # i 7 more variables: national_politics <dbl>,
```

Using ! for not

To get the left-leaning fall broadcasts, negate the `right_leaning` logical:

```
news |>
  mutate(
    right_leaning = ideology > 0,
    fall = month == "Sep" | month == "Oct" | month == "Nov"
  ) |>
  filter(!right_leaning & fall)
```

```
## # A tibble: 167 x 12
##    callsign affiliation date       weekday ideology
##    <chr>    <chr>       <date>     <ord>      <dbl>
##  1 KRBC     NBC         2017-09-01 Fri     -0.0387
##  2 KTVM     NBC         2017-09-01 Fri     -0.302
##  3 WCTI     ABC         2017-09-04 Mon     -0.00694
##  4 WEMT     FOX         2017-09-04 Mon     -0.0140
##  5 KECI     NBC         2017-09-05 Tue     -0.0294
##  6 KRCR     ABC         2017-09-05 Tue     -0.0113
##  7 KTMF     ABC         2017-09-05 Tue     -0.105
##  8 KTXS     ABC         2017-09-05 Tue     -0.0286
##  9 KWYB     ABC         2017-09-05 Tue     -0.0462
## 10 WCTI     ABC         2017-09-05 Tue     -0.0313
```

Order of operations

Why doesn't this work:

```
news |>
  filter(month == "Sep" | "Oct")
```

```
## Error in `filter()`:
## i In argument: `month == "Sep" | "Oct"`.
## Caused by error in `month == "Sep" | "Oct"`:
## ! operations are possible only for numeric, logical or complex types
```

`month == "Sep"` evaluates first!

More subtle bugs

```
news |>
  mutate(
    month_num = as.numeric(month)
  ) |>
  filter(month_num == 9 | 10)
```

```
## # A tibble: 2,560 x 11
##    callsign affiliation date       weekday  ideology
##    <chr>    <chr>       <date>     <ord>       <dbl>
##  1 KECI     NBC         2017-06-07 Wed      0.0655
##  2 KPAX     CBS         2017-06-07 Wed      0.0853
##  3 KRBC     NBC         2017-06-07 Wed      0.0183
##  4 KTAB     CBS         2017-06-07 Wed      0.0850
##  5 KTMF     ABC         2017-06-07 Wed      0.0842
##  6 KTXS     ABC         2017-06-07 Wed     -0.000488
##  7 KAEF     ABC         2017-06-08 Thu      0.0426
##  8 KBVU     FOX         2017-06-08 Thu     -0.0860
##  9 KECI     NBC         2017-06-08 Thu      0.0902
## 10 KPAX     CBS         2017-06-08 Thu      0.0668
## # i 2,550 more rows
## # i 6 more variables: national_politics <dbl>,
## #   local_politics <dbl>, sinclair2017 <dbl>, post <dbl>,
```

`all` and `any`

`all()` tests if a vector is all TRUE and `any()` tests if any entry in a vector is true.

```
all(c(TRUE, TRUE, TRUE))
```

```
## [1] TRUE
```

```
all(c(TRUE, FALSE, FALSE))
```

```
## [1] FALSE
```

```
any(c(TRUE, FALSE, FALSE))
```

```
## [1] TRUE
```

```
any(c(FALSE, FALSE, FALSE))
```

```
## [1] FALSE
```

Grouped summaries with all/any

Can use these to summarize groups:

```
news |>
  group_by(callsign) |>
  summarize(
    any_liberal = any(ideology < 0),
    all_local = all(national_politics < local_politics)
  )
```

```
## # A tibble: 22 x 3
##    callsign any_liberal all_local
##    <chr>    <lgl>       <lgl>
##  1 KAEF     TRUE        FALSE
##  2 KBVU     TRUE        FALSE
##  3 KBZK     TRUE        FALSE
##  4 KCVU     TRUE        FALSE
##  5 KECI     TRUE        FALSE
##  6 KHSL     TRUE        FALSE
##  7 KNVN     TRUE        FALSE
##  8 KPAX     TRUE        FALSE
##  9 KRBC     TRUE        FALSE
## 10 KRCR     TRUE        FALSE
## # i 12 more rows
```

Converting logicals

When passed to `sum()` or `mean()`, TRUE is converted to 1 and FALSE is converted to 0.

```
sum(c(TRUE, FALSE, TRUE, FALSE))
```

```
## [1] 2
```

```
mean(c(TRUE, FALSE, TRUE, FALSE))
```

```
## [1] 0.5
```

Grouped logical summaries with sum/means

```
news |>
  group_by(callsign) |>
  summarize(
    prop_liberal = mean(ideology < 0),
    num_local_bigger = sum(national_politics < local_politics)
  )
```

```
## # A tibble: 22 x 3
##    callsign prop_liberal num_local_bigger
##    <chr>           <dbl>            <int>
##  1 KAEF           0.138               111
##  2 KBVU           0.143                31
##  3 KBZK           0.0526               11
##  4 KCVU           0.185                38
##  5 KECI           0.137                44
##  6 KHSL           0.132               127
##  7 KNVN           0.115               130
##  8 KPAX           0.0833               74
##  9 KRBC           0.196               103
## 10 KRCR           0.0992               99
## # i 12 more rows
```