# Gov 50: 6. Causality

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# 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

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- **Fundamental problem of causal inference**:
    - Can never observe counterfactuals, must be inferred.

# Political canvassing study

POLITICAL SCIENCE

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

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- Can canvassers change minds about topics like transgender rights?

Credit: Fabrice Florian via Flickr

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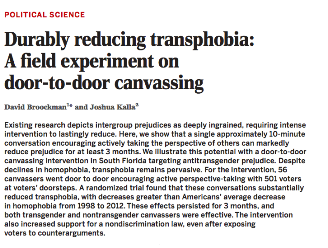

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- Experimental setting:
  - Randomly assign canvassers to have a conversation about transgender right or a conversation about recycling.

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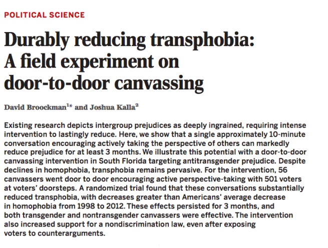

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- Experimental setting:
  - Randomly assign canvassers to have a conversation about transgender right or a conversation about recycling.
  - Trans rights conversations focused on "perspective taking"
- Outcome of interest: support for trans rights 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 |

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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**:

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

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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)

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|---|---|---|
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becomes...

| $i$ | $T_i$ | $Y_i$ |
|---|---|---|
| Respondent 1 | 0 | 0 |
| Respondent 2 | 1 | 1 |

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# Potential outcomes

| $i$ | $T_i$ | $Y_i$ | $Y_i(1)$ | $Y_i(0)$ |
|---|---|---|---|---|
| Respondent 1 | 0 | 0 | ??? | 0 |
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  - 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!

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- 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?

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- 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.

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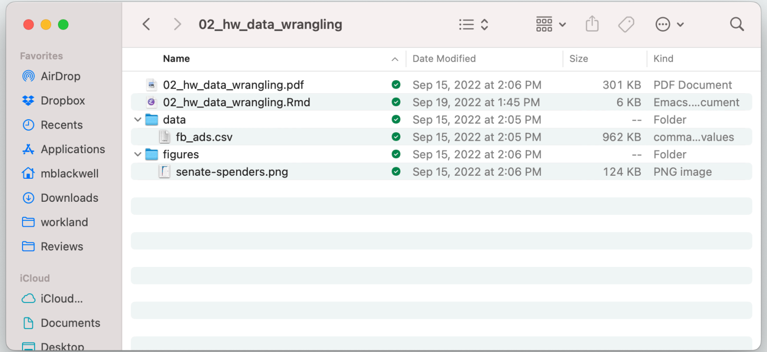
- **Selection Bias:** $Y_i(1) \neq Y_j(1)$
- Those who take treatment may be different that those who take control.
- How can we correct for that?

# 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

```r
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

```r
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:

```r
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
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## # 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:

```r
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
```