R Coding Demonstration Week 11: Hypothesis Tests (Tidy)

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Gov 51 (Harvard)

- Today we're going to cover some tools for exploring bivariate relationships.
- We'll use the data from the Broockman & Kalla (2016) transphobia study.
- Basic summary of experiment:
 - Randomly assigned door-to-door canvassers to two conditions
 - Conditions: perspective-taking script (treatment) or recycling script (placebo)
 - Follow up surveys at 3 days, 3 weeks, 6 weeks, and 3 months.

library(tidyverse)

phobia <- read.csv("data/transphobia_all.csv")</pre>

| Variable Name | Description |
|----------------|---|
| age | Age of the respondent in years |
| female | 1=respondent marked "Female" on voter registration, 0 otherwise |
| voted_gen_14 | 1 if respondent voted in the 2014 general election |
| voted_gen_12 | 1 if respondent voted in the 2012 general election |
| treat_ind | 1 if respondent was assigned to treatment, 0 for control |
| racename | character name of racial identity indicated on voter file |
| democrat | 1 if respondent is a registered Democrat |
| therm_trans_t0 | 0-100 feeling therm. about transgender people at baseline |
| therm_trans_tX | 0-100 feeling therm. about transgender people in Wave X after |
| | treatment |
| therm_obama_t0 | 0-100 feeling therm. about Barack Obama at baseline |
| therm_obama_tX | 0-100 feeling therm. about Barack Obama in Wave X after treatment |

Permutation tests

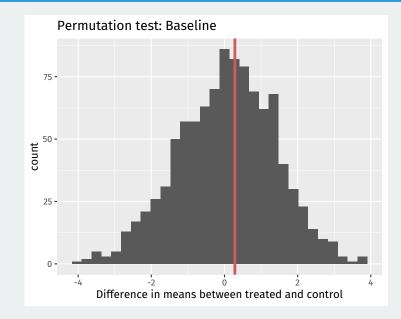
- A common way to conduct inference in an experiment is called a **permutation test**.
 - Null hypothesis of no treatment effect: $H_0: Y_i(1) = Y_i(0)$
 - Doesn't matter if we flip treatment for someone.
 - But different allocation of treatment will lead to different estimated ATEs by random chance.
- Permutation test:
 - 1. Calculate observed difference in means.
 - 2. Randomly shuffle treatment indicator across units.
 - 3. Calculate difference in means of shuffled data.
 - 4. Repeat 2-3 many times and compare observed effect to this distribution.
- Shuffled distribution = reference distribution.
 - p-value: what proportion of effects would we see if treatment had no effect?

Conduct a permutation test for the "effect" of treatment on baseline thermometer scores for transgender people. Show a histogram of the reference distribution and plot a line that indicates where the observed difference in means is.

Answer 1

```
n sims <- 1000
n obs <- nrow(phobia)</pre>
trans t0 test <- rep(NA, times = n sims)</pre>
treated <- phobia %>% filter(treat_ind == 1)
control <- phobia %>% filter(treat ind == 0)
trans_t0_est <- mean(treated$therm_trans t0) -</pre>
 mean(phobia$therm trans t0)
for (i in 1:n sims) {
  phobia <- phobia %>% mutate(
    shuff_treat = sample(treat_ind)
  shuff treated <- phobia %>% filter(shuff treat == 1)
  shuff control <- phobia %>% filter(shuff treat == 0)
  trans_t0_test[i] <- mean(shuff_treated$therm_trans_t0) -</pre>
    mean(shuff control$therm trans t0)
ggplot(mapping = aes(x = trans_t0_test)) + geom_histogram() +
  labs(title = "Permutation test: Baseline",
    x = "Difference in means between treated and control") +
  geom vline(xintercept = trans t0 est, size = 1.3, col = "indianred")
```

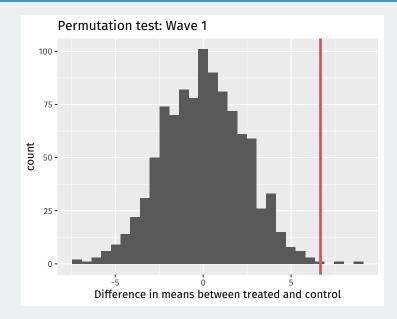
Answer 1 (plot)



Conduct a permutation test for the effect of treatment on thermometer scores for transgender people in wave 1 (therm_trans_t1). Note that there are missing values in wave 1, so be sure to drop those from your analyses.

```
trans_t1_test <- rep(NA, times = n_sims)</pre>
trans_t1 est <- mean(treated$therm_trans_t1, na.rm = TRUE) -</pre>
 mean(control$therm trans t1. na.rm = TRUE)
for (i in 1:n sims) {
 phobia <- phobia %>% mutate(
    shuff treat = sample(treat ind)
  shuff treated <- phobia %>% filter(shuff treat == 1)
  shuff control <- phobia %>% filter(shuff_treat == 0)
  trans t1 test[i] <- mean(shuff treated$therm trans t1. na.rm = TRUE) -</pre>
    mean(shuff_control$therm_trans_t1, na.rm = TRUE)
ggplot(mapping = aes(x = trans t1 test)) + geom histogram() +
 labs(title = "Permutation test: Wave 1",
    x = "Difference in means between treated and control") +
 geom vline(xintercept = trans t1 est, size = 1.3, col = "indianred")
```

Answer 2 (plot)



For the baseline thermometer score permutation test, calculate the one-sided and two-sided p-values for the estimated effect.

one-sided
mean(trans_t0_test > trans_t0_est)

[1] 0.44

two-sided
mean(trans_t0_test > trans_t0_est) + mean(trans_t0_test < -trans_t0_est</pre>

[1] 0.823

For the wave 1 thermometer score permutation test, calculate the one-sided and two-sided p-values for the estimated effect.

one-sided
mean(trans_t1_test > trans_t1_est)

[1] 0.002

two-sided
mean(trans_t1_test > trans_t1_est) + mean(trans_t1_test < -trans_t1_est</pre>

[1] 0.005

Conduct a t-test of the difference in average baseline thermometer scores between the treated and control group with the following null hypothesis:

$$\cdot \ H_0: \mu_T - \mu_C = 0$$

where μ_T is the population mean of the potential outcomes under treatment. What are some differences between this null and the null hypothesis from the permutation test?

t.test(treated\$therm_trans_t0, control\$therm_trans_t0)

```
##
## Welch Two Sample t-test
##
## data: treated$therm_trans_t0 and control$therm_trans_t0
## t = 0.4, df = 1820, p-value = 0.7
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -2.12 3.26
## sample estimates:
## mean of x mean of y
## 53.6 53.0
```

Conduct a t-test of the difference in average wave 1 thermometer scores between the treated and control group.

t.test(treated\$therm_trans_t1, phobia\$therm_trans_t1)

```
##
## Welch Two Sample t-test
##
## data: treated$therm_trans_t1 and phobia$therm_trans_t1
## t = 2, df = 533, p-value = 0.1
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.758 7.656
## sample estimates:
## mean of x mean of y
## 60.7 57.3
```