Day 3

Let’s get some lunch

Austin Cutler
FSU

Agenda

- In today's class, we're going to go over the following:
  - The first homework assignment
  - User created functions
  - `If` statements
  - The `sandwich` package for robust standard errors
  - More plotting practice

Homework check in

User created functions

The `function()` function

- There are some instances where in R, there isn't a preexisting package that has a function we need
- This can happen if we have a very niche task to complete
- Fortunately, we can use `function()` to make our own functions in R

`function()`al form

- `function()` is incredibly flexible
- In the parentheses [`()`], we put in whatever arguments we're going to give the function, and then in the brackets (`{}`) we put what we're actually doing with the function
- We can create conditional functions using the `if` function and `else` as well
- Here is an example of a very simple user created function:

```
1  add_two <- function(x){
2    x+2
3  }
4
5  add_two(2)
```

```
[1] 4
```

Functions Practice

- Individually, do the following:

1. Simulate data from the normal distribution with 1000 observations, name this vector x
2. Write a function to by hand take the mean of a variable
3. Once you have the mean from your own function, use the built in mean function to check your work

Functions for Complex Calculations

- User made functions can have as many arguments as you want, and use as many other functions as you want within them
- Here is an example of a generic function:

```
generic <- function(argument1, argument2, argument3) {
## we can comment in here freely to describe each step of our code

output <- mean(argument1) - sd(argument2) + argument1*argument3

return(output)
}
```

Functions for Calculations

- We can even make user created functions for complex methods, such as SE estimation using the KTW method
- Let's look at problem 2 from Homework 1, first we'll load in the data and fit our model

```
1 library(tidyverse)
2
3 #note that I'm reading the data in directly from the Dropbox link
4 read_rds('https://www.dropbox.com/scl/fi/z3u93qlx19dw77tr6ss9b/pes_cleaned_
5   filter(!is.na(out_feel)) -> data
6
7 fit <- lm(out_feel ~ tr, data = data)
```

Functions for KTW

- If you have multiple models that you're trying to fit, it would be very beneficial to write a function to estimate KTW confidence intervals rather than doing it by hand each time

```r
#Notice how I set some values in the function, that gives it a default of .
ktw <- function(mod,n_sim = 1000, ci_lvl = .95, tails = 'two'){
  mvtnorm::rmvnorm(n_sim,coef(mod),vcov(mod)) -> draws

  if(tails == 'two'){
  apply(draws, 2, quantile, probs = c((1-ci_lvl)/2,ci_lvl+(1-ci_lvl)/2)) ->
  }
  else
    apply(draws, 2, quantile, probs = c(1-ci_lvl,ci_lvl)) -> ci

  return(ci)
}
```

KTW EX

- Let's look at the summary statistics for our model

```
1  summary(fit)
```

```
Call:
lm(formula = out_feel ~ tr, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-13.741 -12.941  -9.741   5.907  87.059

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  12.9415     1.0363  12.488   <2e-16 ***
trpolicy      0.7991     1.4618   0.547    0.585
trpartisan    0.6059     1.4780   0.410    0.682
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

- Let's use our new function to get KTW confidence intervals

```r
ktw(fit)
```

```
      (Intercept)  trpolicy trpartisan
2.5%     10.89584 -1.972749  -2.350846
97.5%    15.13101  3.899124   3.323305
```

KTW EX

- We can improve this function even further, however
- While the data provided is useful, it still requires cleaning after the fact
- We can modify the original function to make improve the data we get back from the function

```
ktw <- function(mod,n_sim = 1000, ci_lvl = .95, tails = 'two'){
  mvtnorm::rmvnorm(n_sim,coef(mod),vcov(mod)) -> draws

  if(tails == 'two'){
  apply(draws, 2, quantile, probs = c((1-ci_lvl)/2,ci_lvl+(1-ci_lvl)/2)) ->
  }
  else
    apply(draws, 2, quantile, probs = c(1-ci_lvl,ci_lvl)) -> ci

  as.data.frame(ci) %>%
    pivot_longer(cols =  1:ncol(.),
                 names_to = 'coef') %>%
    mutate(qi = rep(c('lower','upper'), each = 3)) %>%
    pivot_wider(names_from = qi, values_from = value) -> ci

```

```
16    return(ci)
17  }
```

KTW EX

```
1 ktw(fit)
```

```
# A tibble: 3 × 3
  coef        lower upper
  <chr>       <dbl> <dbl>
1 (Intercept) 10.8  15.1
2 trpolicy    -2.38  3.53
3 trpartisan  -2.29  3.65
```

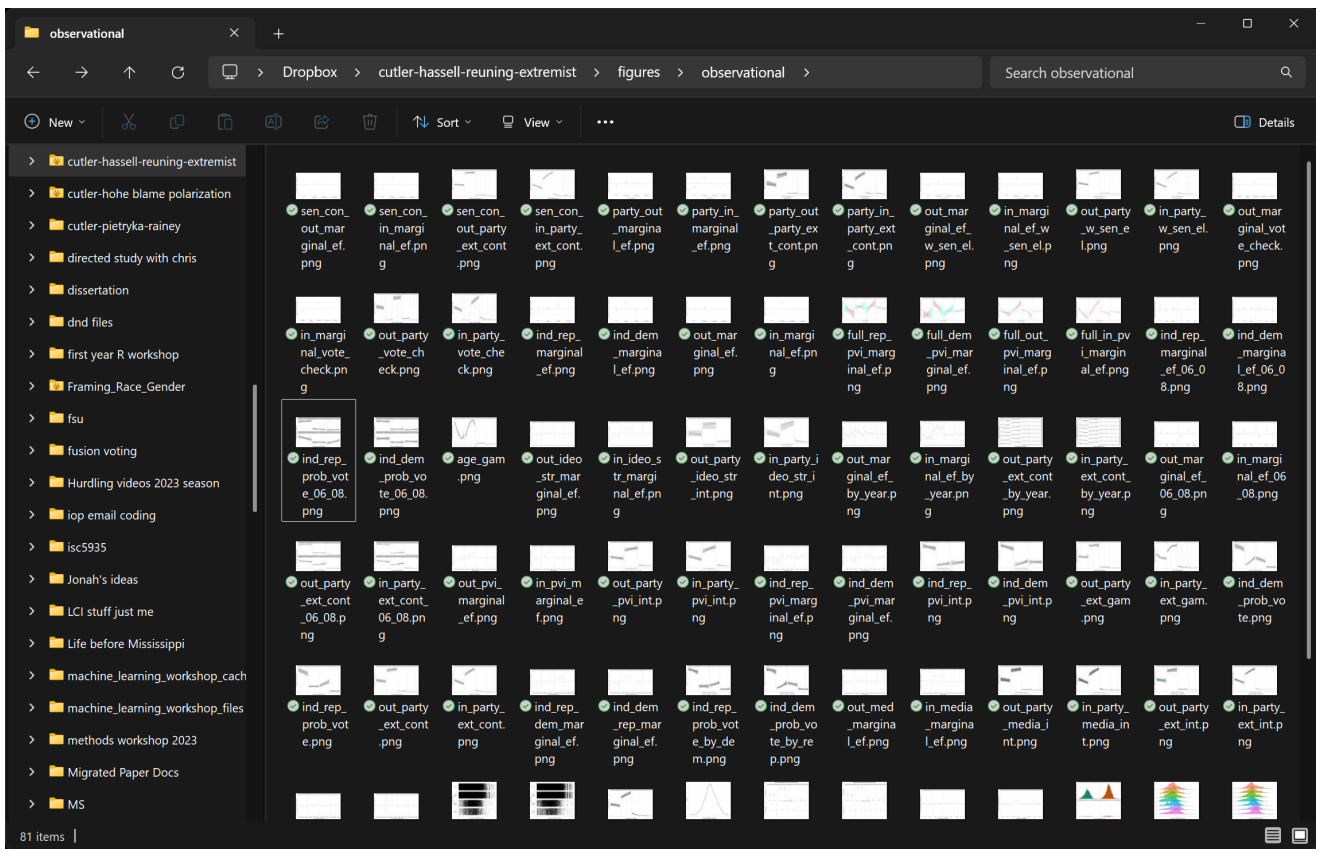
- Please note that this function isn't 100% perfect
- In particular, the code for one-tailed tests only does a positive one-tailed test
- If we wanted, we could further expand this function to distinguish between positive and negative one-tailed tests

Practice Writing Functions

- Write a function called `hand_beta()` that will give you the by hand regression coefficients for the model from the previous example
- Create a vector that has values that range from 60 to 100, and 100 observations; name this vector *a*. Create a custom function called `letter_grade()` that converts these numbers into a letter grade. Combine both vectors into a table.
- Make a new object, x, and make it follow a normal distribution with a mean of 10 and standard deviation of 5, and 1000 observations. Create a function called `normalize()` that normalizes this variable (i.e., make it have a mean of 0 and standard deviation of 1). Compare the values produced from your function to the values produced from the base R function, `scale()`
- Make a function called `summary_stats()` that returns a list of summary statistics, the mean, median, variance, and standard deviation. Apply this function to x, y, and a new variable z that follows a beta distribution (use the function `rbeta()`, and set shape1 to 20 and shape2 to 5)
- Write a function called `list_ext()` to extract items from a list. Store the results from the previous examples in a single list, and try to extract them with your new function.

Functions to Help with graphs

- Another area where user made functions can be useful is making figures
- Hypothetically, let's say you were working on a paper for publication and the figures required two distinct aesthetics



Custom Themes

```
theme_a <- function(){
 theme_light()+
            theme(legend.position = 'bottom',
                  legend.text = element_text(size = 20),
                  legend.title = element_text(size = 22),
                  panel.grid = element_line(linetype = 2,
                                            color = alpha('lightgray',.6)),
                  axis.title = element_text(size = 20),
                  axis.text  = element_text(size = 15))
}

theme_b <- function(){
  theme_light()+
            theme(legend.position = 'bottom',
                  legend.text = element_text(size = 15),
                  legend.title = element_text(size = 10),
                  panel.grid = element_line(linetype = 2,
                                            color = alpha('lightgray',.6)),
```

Repetitive Figures

```
make_coef_plot <- function(data){
  data %>%
  ggplot(aes(x = median, y = fct_rev(policy_id),
             color = fct_rev(v_party), shape = fct_rev(v_party)))+
  geom_pointrange(aes(xmin = low, xmax = high),
                  position = position_dodge(.5), size = .75)+
  geom_vline(aes(xintercept = 0), linetype = 2)+
  annotate('label', x = .486, y = 10.35, color = '#ff6666',
           label = 'Party is Not Given')+
  annotate('label', x = .145, y = 9.65, color = 'gray65',
           label = 'Out-party')+
  annotate('label', x = .08, y = 10.2, color = 'gray55',
           label = 'In-party')+
  #facet_wrap(vars(v_party))+
  labs(x = "Effect of Race on Probability of Expecting Vignette to Adopt Ow
       y = 'Policy', color = 'Vignette Party')+
  xlim(-.3,.6)+
  scale_y_discrete(labels = label_wrap_gen(16))+
```

Sandwich

Sandwich

- The sandwich package is used to estimate robust standard errors
- Robust standard errors can be estimated for all types of models including clustered models, panel data, longitudinal data, etc.
- How this is done is by changing how we get the variance covariance matrix that is used to estimate standard errors
- More information about the package and it's uses can be found here.

Using `Sandwich`

- There are several use cases for the `sandwich` package that apply to political science work
- We can use `sandwich` to estimate heteroskedastic robust standard errors with `vcovHC()`
- Or to get clustered-robust standard errors with `vcovCL()`
- We can even use the sandwich package to get bootstrapped standard errors with `vcovBS()`
  - We can also add clusters to our bootstrap if needed

Using `Sandwich`

- The general process for using these different approaches is the same
- We want to use the function from sandwich to estimate whatever variance-covariance matrix is needed
- We then will use the `coeftest()` function from the `lmtest` package to get the standard errors for based on the estimation strategy we intend on using

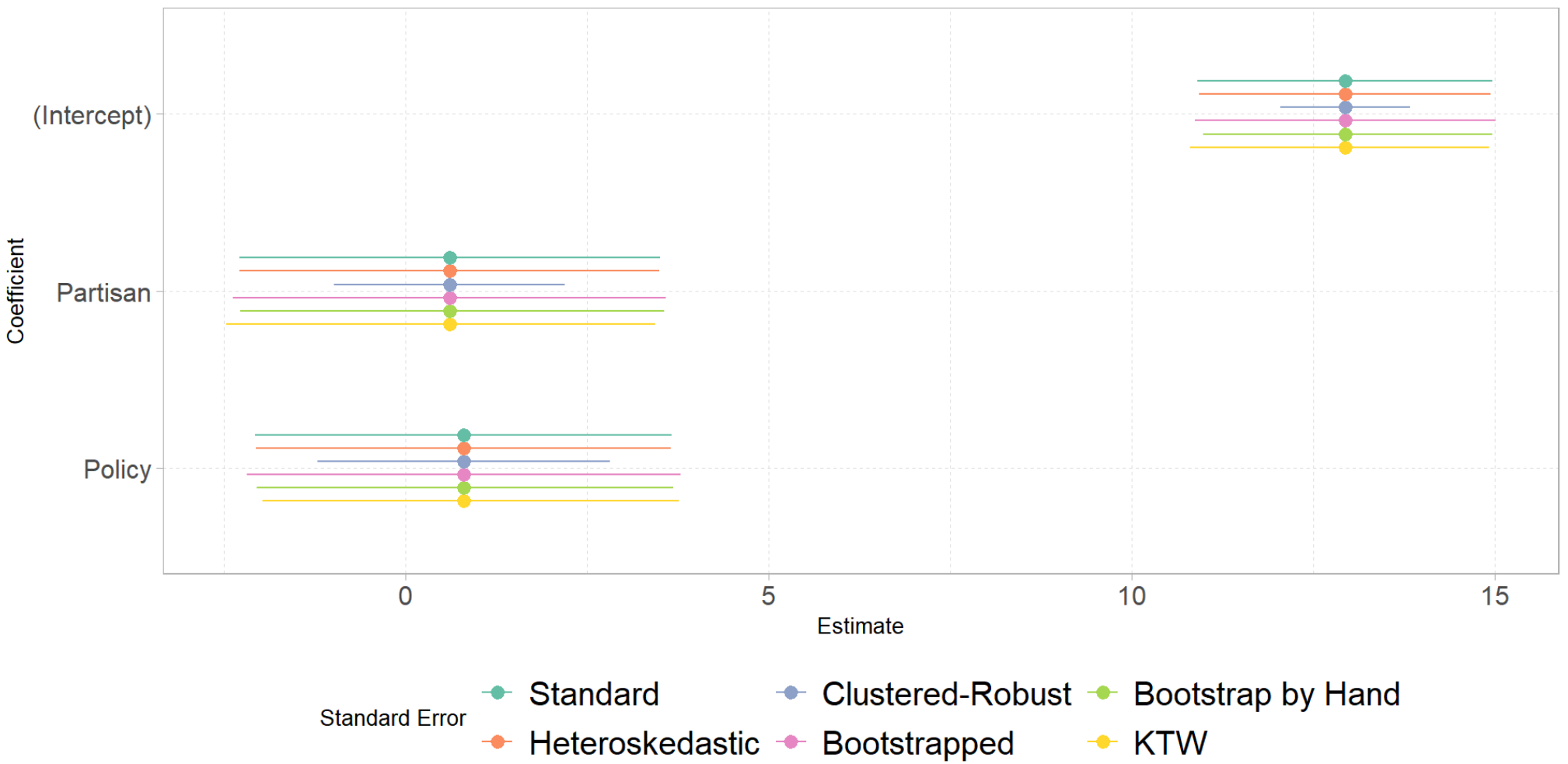
```
#getting clustered standard errors

new_vcov <- sandwich::vcovCL(model)

fit_clustered <- lmtest::coeftest(model, vcov = new_vcov)
```

Practice with `sandwich`

- Using the model from the homework, compare the normal standard errors to heteroskedastic robust standard errors, clustered-robust standard errors, and bootstrapped standard errors
- When clustering, cluster the standard errors by 3-point partisanship (really just Republicans and Democrats since pure Independents won't be included in the model, this variable is called `pid1`)
- Which method produced the largest standard error? Which one produced the smallest?
- Bonus: make a plot showing the regression coefficients with each type of confidence interval

Plot

- Code


(Intercept)
Partisan
Policy
Coefficient
0
5
10
15
Estimate
Standard Error
Standard
Heteroskedastic
Clustered-Robust
Bootstrapped
Bootstrap by Hand
KTW