Bringing It All Together feat. Basic Models

Lesson

R Code

- We are going to use (the tiniest portion of) our final new package today `tidymodels`, as well as `estimatr` to fit a different kind of regression, and a couple of packages to make pretty regression output tables

```
install.packages(c("tidymodels", "estimatr", "stargazer", "gtsummary"))
```

- First off, let me say I am not a stats professor nor is this not a stats lesson
  - Some of you have taken years of stats classes, while others are yet to take any.
  - The purpose of this lesson is meant to focus how everything we have learned this semester comes together when we begin to work with some simple models
- That said, it may still be a lot of information for those less familiar with stats.
  - Fear not, there is no expectation to use of any this in your final assignment, nor is there an assignment for this lesson (optional final project drafts are due Sunday)!
  - If this lesson starts to go beyond your comfort level, that's completely fine! Try your best to follow along, and maybe revisit this lesson once you're a little further along your stats journey

Data Preparation

- Before we can run any kind of models, we need to make sure our data is prepared
- This involves using skills from our data wrangling lessons such as
  - Data Wrangling I
    - Handling missing data
    - Making sure our data is the right format (`numeric`, `factor`, `character`, etc.)
    - Performing basic calculations (e.g., percentages, differences, etc.)
  - Data Wrangling II
    - Joining multiple data sets together
    - Pivoting data wider and/or longer
  - Data Wrangling III
    - Cleaning up text data
    - Transforming dates into
  - Data Wrangling IV
    - Performing any of the above tasks `across()` multiple columns
    - `coalesce()`-ing multiple columns into one variable

- For the purpose of today's lesson, we are going to focus on two of these tasks, dealing with missing data, and making sure our data is in the right format

Handling Missing Data

- When modeling, by default, R will simply drop any rows that have an `NA` in any variable you are modeling on (this is a little different to the cautious R we ran into in Data Wrangling I)
  - In real world applications, you need to think carefully about how you handle these…
    - Should I impute the missing data? If so, using what method?
    - Should I use this variable at all if it's missing for a bunch of observations?
  - For this lesson, however, we are just going to drop `NA` values so we can focus on the main content
- The below code uses the combines the logic we use for making `NA`s in Data Wrangling I with the ability to work across multiple columns in Data Wrangling IV
  - First, we read our data and `select()` the columns we want to use

```
data <- read_csv("data/hsls-small.csv") |>
      select(stu_id, x1sex, x1race, x1txmtscor, x1paredu, x1ses, x1poverty185,
x1paredexpct)
```

```
Rows: 23503 Columns: 16
── Column specification ────────────────────────────────────────────────────────
Delimiter: ","
dbl (16): stu_id, x1sex, x1race, x1stdob, x1txmtscor, x1paredu, x1hhnumber, ...

ℹ Use `spec()` to retrieve the full column specification for this data.
ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
-   Second we use a combination of `!,` `filter(),` and `if_any()` to say, to
say
    -   "If a row..."
        -   "has a -8 or -9"
            -   `.fns = ~ . %in% c(-8, -9)`
        -   "in any columns"
            -   `.cols = everything()`
        -   "do NOT keep it"
            -   `filter(!)`
```

```
data <- data |>
      filter(! if_any(.cols = everything(),
                      .fns = ~ . %in% c(-8, -9)))
```

Making Sure Our Data is the Right Format

- In our Data Viz I and Data Viz II lessons, we saw that for R to accurately plot categorical variables, we had to convert them into `factor()`s
  - The same is true for using categorical variables in models
    - Those more familiar with stats may know that you have to "dummy code" categorical variables as 0 and 1 with one category serving as the "reference level" and all other categories getting their own binary variable
  - The wonderful thing is that R handles that all for us if we tell it to treat the variable as a `factor()`
- The below code combines the logic of turning variables into a `factor()` from Data Viz I with working across multiple columns for Data Wrangling IV to sat
  - "Modify"
    - `mutate()`
  - "Each of these columns"
    - `across(.cols = c(stu_id, x1sex, x1race, x1paredu, x1poverty185)`
  - "Into a factor"
    - `.fns = ~ factor(.)`

```
data <- data |>
  mutate(across(.cols = c(stu_id, x1sex, x1race, x1paredu, x1poverty185),
                .fns = ~ factor(.)))
```

- With that, our data is ready for some basic analysis!
  - Note: In most real-world projects your data preparation will be much more thorough, usually taking up the vast majority of the lines of code in your entire project, this is just the bare minimum to have to models run

t-tests with `t.test()`

- One of the first inferential statistical tests you will have learned (or will learn) is the t-test
  - For those unfamiliar, the basic concept of a t-test if variance between two groups (i.e., the difference between treatment and control) is greater than the variance within those groups (i.e., random variance between people within the same group)
    - If that between-group-variance is great enough compared to the within-group-variance, the t-test will be "statistically significant"
      - This means we are (most often) 95% confident that the there is a genuine difference between the groups

- There are also a handful of statistical assumptions we have to satisfy, which are beyond our scope here, but hopefully the general concept will hope those of you yet to take your stats foundations follow along

```
t.test(x1txmtscor ~ x1sex, data = data)
```

```

	Welch Two Sample t-test

data:  x1txmtscor by x1sex
t = 0.38555, df = 16321, p-value = 0.6998
alternative hypothesis: true difference in means between group 1 and group 2 is
not equal to 0
95 percent confidence interval:
 -0.2455338  0.3657777
sample estimates:
mean in group 1 mean in group 2
       52.14309        52.08297
```

- Luckily, the code for `t.test()` is actually very simple (as is the case for regression too)
  - The first argument is a `forumla`, which for a t-test is just `outcome ~ group` where group must only have 2 levels
    - In this case, we are looking at math score as our outcome and sex as our group
  - The second argument is `data =` which we supply our prepared data frame
    - Note: the pipe `|>` doesn't play as nicely with models as it does other commands it's usually easier to just specify `data =` in a new line (don't pipe anything in)
  - This code simply prints out our `t.test()` result
    - As our p-value is above 0.05, our result is not significant
      - This indicates there is not a significant difference between male and female math scores in our sample

Regression with `lm()`

- The problem with t-tests for our research, is that they don't provide any ability to control for external variables
  - They work great in experimental setting with random-treatment-assignment, but in the messy world of educational research, that's rarely what we have
- What we far more commonly use is a regression (or more advanced methods that build off regression) which allows use to control for other variables
- The basic premise of regression very much builds off the logic of t-tests, testing if the variance associated with our treatment variable is great enough compared to a) residual/random variance and b) variance associated with our control variables, to say with confidence that there is a significant difference associated with our treatment

- Overall, this looks relatively similar to our code above, with three main differences

1. We use `lm()` (which stands for linear model) instead of `t.test()`
2. Instead of our formula just being `x1txmtscor ~ x1sex` we have added `+ x1poverty185 + x1paredu` to "control" for these variables
3. We assigned `<-` our `lm()` results to an object rather than just spitting them out

- That's because the `summary()` function is much more useful for `lm()` objects, plus, we are going to explore the `lm()` object more in the next steps

```r
regression <- lm(x1txmtscor ~ x1sex + x1poverty185 + x1paredu, data = data)
summary(regression)
```

```

Call:
lm(formula = x1txmtscor ~ x1sex + x1poverty185 + x1paredu, data = data)

Residuals:
    Min      1Q  Median      3Q     Max 
-32.748  -5.715   0.160   6.136  30.413 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)    49.0485     0.3379 145.139  < 2e-16 ***
x1sex2         -0.0412     0.1429  -0.288    0.773    
x1poverty1851  -3.0224     0.1729 -17.483  < 2e-16 ***
x1paredu2       1.3419     0.3234   4.149 3.36e-05 ***
x1paredu3       2.4834     0.3584   6.929 4.38e-12 ***
x1paredu4       6.1227     0.3507  17.460  < 2e-16 ***
x1paredu5       8.1726     0.3814  21.426  < 2e-16 ***
x1paredu7      10.7669     0.4294  25.074  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.161 on 16421 degrees of freedom
Multiple R-squared:  0.1605,	Adjusted R-squared:  0.1601 
F-statistic: 448.4 on 7 and 16421 DF,  p-value: < 2.2e-16
```

- Our results show that, sex still had no significant association with math scores, but, our control variables of poverty and parental education seem to have some very strong associations

Quick Question

- You may notice we actually have more variables in the regression table than we put in, why? What do they represent?

- That's correct, they represent the different levels of our `factor()`-ed categorical variables

Creating Pretty Regression Output Tables

- Running regressions in R is all well and good, but the output you see here isn't exactly "publication ready"
- There are multiple ways of creating regression (and other model) output tables, each with their own pros and cons
  - Here, we will go over three of the most common methods

`stargazer` Package

- One of the most common packages for getting "publication ready" regression tables is `stargazer`
- I personally find these tables a little inflexible, but it's very common in the world of R, so it's worth covering here
- The code is very simple, at minimum, provide the regression model you fitted, and the type of table you want
  - We are using "html" here so it formats for the website, you could use "text" or "latex", I don't think there's currently support for typst though

```
stargazer(regression, type = "latex")
```

% Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com % Date and time: Tue, Apr 09, 2024 - 23:06:26

- This would be rendered more professionally in a pdf Quarto document rather than this website, but you see what it would look like
- Note: If you give a full data frame to `stargazer()` it will also create a descriptive statistics table

`gtsummary` Package

- Personally, I find the `gtsummary` package (which is built on the `gt` tables package) much more like what I want
  - If I'm going to use a package to create my tables, this is my prefered option
  - `tbl_regression()` creates a pretty great table when you just provide the regression model
    - One thing I particularly like is how `gtsummary` handles factors, I think it makes the it super-duper clear

```
tbl_regression(regression)
```

Characteristic	Beta	95% CI[1]	p-value
x1sex			
1	—	—	
2	−0.04	−0.32, 0.24	0.8
x1poverty185			
0	—	—	
1	−3.0	−3.4, −2.7	<0.001
x1paredu			
1	—	—	
2	1.3	0.71, 2.0	<0.001
3	2.5	1.8, 3.2	<0.001
4	6.1	5.4, 6.8	<0.001
5	8.2	7.4, 8.9	<0.001
7	11	9.9, 12	<0.001
[1] CI = Confidence Interval			

- With a couple of extra lines to handle variable labels and add significance stars, we can get something that looks pretty great
  - Reminder from Intro to Quarto: To get captions and table numbers if we are using Quarto, we use the "chunk options" to cross reference them, not manually adding them to the table code
    - You see more about that on the Quarto guide for cross referencing
    - To get the table to appear like this, I labeled the chunk `{r tbl-gtsummary}` and added `#| tbl-cap: "Regression Table Using gtsummary"` as the first line

```
tbl_regression(regression,
               label = list(x1sex ~ "Sex",
                            x1poverty185 ~ "Below Poverty Line",
                            x1paredu ~ "Parental Education")) |>
  add_significance_stars(hide_ci = FALSE)
```

Table 1: Regression Table Using gtsummary

Characteristic	Beta[1]	SE[2]	95% CI[2]
Sex			
1	—	—	—
2	−0.04	0.143	−0.32, 0.24
Below Poverty Line			
0	—	—	—
1	−3.0***	0.173	−3.4, −2.7
Parental Education			
1	—	—	—
2	1.3***	0.323	0.71, 2.0
3	2.5***	0.358	1.8, 3.2
4	6.1***	0.351	5.4, 6.8
5	8.2***	0.381	7.4, 8.9
7	11***	0.429	9.9, 12
[1] *p<0.05; **p<0.01; ***p<0.001			
[2] SE = Standard Error, CI = Confidence Interval			

- Note: You can also create matching descriptive statistics tables using the `tbl_summary()` function
- If you like `gtsummary` tables and want to learn more, check out
  - `gtsummary` documentation
  - `gt` documentation

"Homemade" Regression Tables with `kable()`

- While a little more work, we can also create our own table using the default `summary()` and `kable()` like we saw in Intro to Quarto for descriptive tables
- You might want to do this to specifically format a table in a way `gtsummary` doesn't allow, or, to match some other tables you already created with `kable`
- First things first, let's save the `summary()` output to a new object

```
summary_object <- summary(regression)
```

- We will do this more below, but if you click on the object `summary_object` in the Environment (top right) you can see all the different pieces of information it holds

1. We are most interested in `coefficients`, if you click on the right hand side of that row, you will see the code `summary_object[["coefficients"]]` auto-populate

- Tip: This works for most objects like this

2. We then turn that into as data frame with `as.data.frame()`
3. Add a new column that contains the correct significance stars using `case_when()`
4. Pipe all that into `kable()` with updated column names and rounded numbers
5. Similarly to above, we add table numbers and captions using Quarto cross referencing

- `{r tbl-manual}`
- `#| tbl-cap: "Regression Table Using Kable"`

```
summary_object[["coefficients"]] |>
  as.data.frame() |>
  mutate(sig = case_when(`Pr(>|t|)` < 0.001 ~ "***",
                         `Pr(>|t|)` < 0.01 ~ "**",
                         `Pr(>|t|)` < 0.05 ~ "*",
                         TRUE ~ "")) |>
  kable(col.names = c("estimate", "s.e.", "t", "p", ""),
        digits = 3)
```

Table 2: Regression Table Using Kable

	estimate	s.e.	t	p	
(Intercept)	49.049	0.338	145.139	0.000	***
x1sex2	−0.041	0.143	−0.288	0.773	
x1poverty1851	−3.022	0.173	−17.483	0.000	***
x1paredu2	1.342	0.323	4.149	0.000	***
x1paredu3	2.483	0.358	6.929	0.000	***
x1paredu4	6.123	0.351	17.460	0.000	***
x1paredu5	8.173	0.381	21.426	0.000	***
x1paredu7	10.767	0.429	25.074	0.000	***

- There are other ways as well, but between these three options, you should be able to get what you want!

Predictions with `lm()`

- When you fit a regression model in R, there is a lot more saved than you see with `summary()`
- Since we have our `lm()` object saved as `lm_sex`, let's start by taking a look inside it by clicking on the object in our environment (top right) panel

- Confusing, right?
  - Most statistical models look something like this, it's basically a collection of lists and tables containing different information about the model
- There are functions such as `summary()` that are great at pulling out the most commonly needed information without having to go manually digging through the model object, but sometimes, it can be useful to know it's there
- Another great function is `predict()` which extracts estimated values of the outcome variable based on the predictor variables (some other models use `fitted()` for the same purpose)
  - For those more familiar with stats, you'll know predicted values are often compared against the true values to see how strong the model is
- To start, let's save a full set of predictions to a new columns in our data frame

```
data <- data |>
  mutate(prediction = predict(regression))

data
```

```
# A tibble: 16,429 × 9
   stu_id x1sex x1race x1txmtscor x1paredu   x1ses x1poverty185 x1paredexpct
   <fct>  <fct> <fct>       <dbl> <fct>      <dbl> <fct>               <dbl>
 1 10001  1     8            59.4 5         1.56   0                       6
 2 10002  2     8            47.7 3        -0.370  1                       6
 3 10003  2     3            64.2 7         1.27   0                      10
 4 10004  2     8            49.3 4         0.550  0                      10
 5 10005  1     8            62.6 4         0.150  0                      10
 6 10006  2     8            58.1 3         1.06   0                       8
 7 10007  2     8            49.5 2        -0.43   0                      11
 8 10008  1     8            54.6 7         1.51   0                       6
 9 10009  1     8            53.2 2        -0.310  0                      11
10 10010  2     8            63.8 3         0.0451 0                       6
# ℹ 16,419 more rows
# ℹ 1 more variable: prediction <dbl>
```

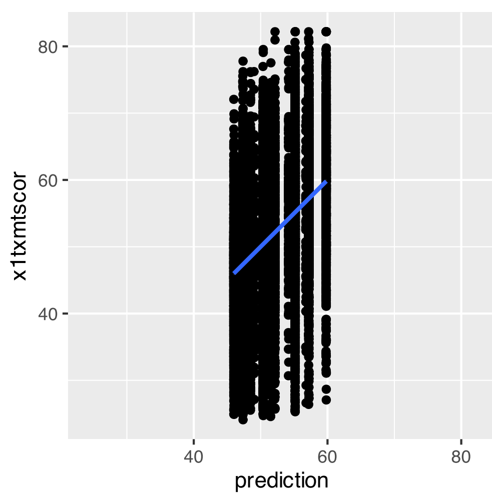
- Next, we can compare these to our actual results using a simple plot (no formatting) from Data Viz I
  - The only new thing we add here is `coord_obs_pred()` which is from the `tidymodels` package
    - This fixes the axes so that the predictions and observed values are plotted on the same scale

Quick Excercise

- Try removing the final line `coord_obs_pred()` and see what happens. Which plot do you think is better?

```
ggplot(data,
       aes(x = prediction,
           y = x1txmtscor)) +
  geom_point() +
  geom_smooth(method = "lm") +
  coord_obs_pred()
```

```
`geom_smooth()` using formula = 'y ~ x'
```



(Easier) Quick Question

- What do we think about our model? Does it look like it's doing a great job of predicting? Why/why not?

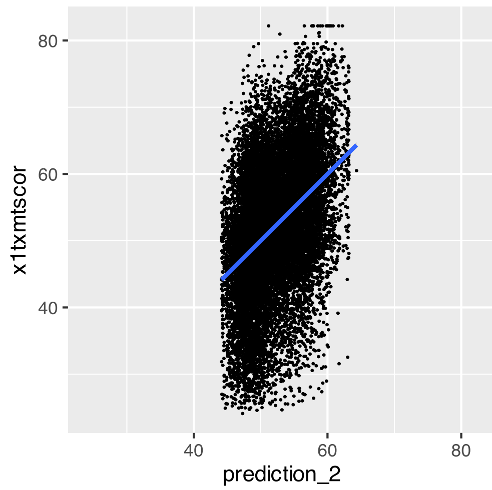
(Harder) Quick Question

- You'll notice our plot looks kind of clumped together, why do you think that it? What about the model would lead to that?

(Not So) Quick (Group) Excercise

- Given what we just discussed, can we change one of the variables we are using in the model to make it less "clumpy" but caputre the same information?

```
`geom_smooth()` using formula = 'y ~ x'
```



Quick Question

- Does that look better? What else is odd about our predictions?

- We can also use `predict()` to estimate potential outcome values for new students who don't have the outcome for
- This is a common way you evaluate machine learning models
- If you think you're model is a really good predictor (which ours is not) you may feel comfortable using something like this to help your office predict student outcomes/identify students in need of additional help
- To demonstrate this, we are first going to split out 10% of our data using `slice_sample()` and drop the math score from it

```
data_outcome_unknown <- data |>
  slice_sample(prop = 0.1) |>
  select(-x1txmtscor)
```

- Then, we can use `anti_join()` which is basically the opposite of the joins we used in Data Wrangling II
  - It looks for every row in x that isn't in y and keeps those

```
data_outcome_known <-  anti_join(x = data, y = data_outcome_unknown, by
= "stu_id")
```

- Now, we can fit one more `lm()` using our data we "know" the outcome for

```
regression_3 <- lm(x1txmtscor ~ x1sex + x1ses + x1paredu, data
= data_outcome_known)
```

- Finally, we can `predict()` outcomes for the data we "don't know" the outcome for
  - We add the `regression_3` we just fitted as the model, same as before
  - But we also add `newdata = data_outcome_unknown` to say predict the outcome for this new data, instead of extract the predictions the model originally made

```
data_outcome_unknown <- data_outcome_unknown |>
  mutate(prediction_3 = predict(regression_3, newdata = data_outcome_unknown))
```

- Lastly, let's see how similar our predictions we made using our model without the outcome were to those made when the outcome was known for everyone using `cor()` to get the correlation

```
cor(data_outcome_unknown$prediction_2, data_outcome_unknown$prediction_3)
```

```
[1] 0.9998948
```

- Pretty close!

Checking Residuals

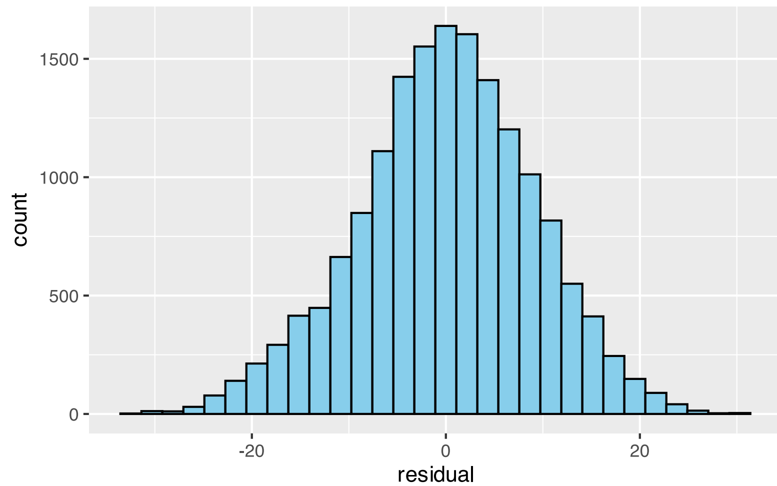
- Many of the assumptions relating to regression are tested by looking at the residuals
  - We aren't going to go over those assumptions, again, this is not a stats class
  - But it might be useful to see how to get them out of a model object
  - Let's start by viewing the lm object again (environment, top right panel), then clicking on the little white box on the right hand side of the screen for the row "residuals"
- That is a magic tip, if you ever want to get something specific out of a model object, often they'll be something you can click on to generate the code needed to access it in the console
  - For residuals, it is `regression_2[["residuals"]]`

```
data <- data |>
  mutate(residual = regression_2[["residuals"]])
```

- Now, again, not to get too deep into assumptions, but one of the key things to check is that your residuals have a normal distribution
  - So let's revisit some Data Visualization I content and make a simple `ggplot()` histogram to of them

```
ggplot(data) +
  geom_histogram(aes(x = residual),
                 color = "black",
                 fill = "skyblue")
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



- Wow, that is almost a perfect normal distribution!
  - Bonus points: can anyone remember/think of something about the variable `x1txmtscor` that made this result quite likely? Think about what *kind* of score it is

`formula()` Objects

- The second from last thing is really simple, but, it can be a time & error saver if you want to get more advanced like our final step
  - Above, we simply put our formula into the `t.test()` or `lm()` command
    - Instead, we can actually specify it as a formula object first, then call that object, which has two advantages

      1. If we run multiple tests with the same formula, we only have to change it once in our code for updates

      - Here, we will run both standard `lm()` and `lm_robust()` from the `estimatr` package

      2. If we want to run multiple tests in a loop like below, it makes that possible too

- To demonstrate this, we will fit the same model using standard `lm()` and `lm_robust()` which for those versed in stats, is one option we can use when we have a violation of heteroskedasticity

```
regression_formula <- formula(x1txmtscor ~ x1sex + x1ses + x1paredu)

regression_4 <- lm(regression_formula, data = data)
summary(regression_4)
```

```

Call:
lm(formula = regression_formula, data = data)

```

```
Residuals:
    Min      1Q  Median      3Q     Max 
-31.781  -5.703   0.180   6.129  30.996 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 50.82144    0.35585 142.819  < 2e-16 ***
x1sex2      -0.03767    0.14199  -0.265    0.791    
x1ses        3.77674    0.16341  23.112  < 2e-16 ***
x1paredu2   -0.04729    0.33298  -0.142    0.887    
x1paredu3   -0.15566    0.39027  -0.399    0.690    
x1paredu4    2.04812    0.42368   4.834 1.35e-06 ***
x1paredu5    2.57885    0.49454   5.215 1.86e-07 ***
x1paredu7    2.67655    0.60923   4.393 1.12e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.099 on 16421 degrees of freedom
Multiple R-squared:  0.1718,    Adjusted R-squared:  0.1714 
F-statistic: 486.5 on 7 and 16421 DF,  p-value: < 2.2e-16
```

```r
regression_robust <- lm_robust(regression_formula, data = data, se_type =
"stata")
summary(regression_robust)
```

```

Call:
lm_robust(formula = regression_formula, data = data, se_type = "stata")

Standard error type:  HC1 

Coefficients:
            Estimate Std. Error  t value   Pr(>|t|) CI Lower CI Upper    DF
(Intercept) 50.82144     0.3443 147.6058  0.000e+00  50.1466  51.4963 16421
x1sex2      -0.03767     0.1420  -0.2653  7.908e-01  -0.3160   0.2407 16421
x1ses        3.77674     0.1651  22.8741 5.068e-114   3.4531   4.1004 16421
x1paredu2   -0.04729     0.3196  -0.1479  8.824e-01  -0.6738   0.5792 16421
x1paredu3   -0.15566     0.3767  -0.4132  6.795e-01  -0.8941   0.5828 16421
x1paredu4    2.04812     0.4167   4.9150  8.963e-07   1.2313   2.8649 16421
x1paredu5    2.57885     0.4891   5.2725  1.363e-07   1.6201   3.5376 16421
x1paredu7    2.67655     0.6206   4.3130  1.620e-05   1.4601   3.8929 16421

Multiple R-squared:  0.1718 ,   Adjusted R-squared:  0.1714 
F-statistic: 490.1 on 7 and 16421 DF,  p-value: < 2.2e-16
```

Modeling Programatically with Loops

- Finally, we can also bring in content from Functions & Loops and fit regression models using loops
- This is kind of thing you might want to do if you are testing the same model on a set of outcomes

Quick Question

- Thinking back to that lesson, why might we want to go through the hassle of fitting regressions using loops? What are the advantages of using loops vs coding it all out separately?

- For example, we might be interested in modeling both a students math score and their parental education expectation
  1. we make a list containing our outcome variables (x1txmtscor and x1paredexpct)
  2. Use a `for()` loop to loop through these outcomes, which `paste()`s i (which takes on the name of each outcome variable) into the formula and then runs the model

```
outcomes <- c("x1txmtscor", "x1paredexpct")

for(i in outcomes) {

  print(i)

  loop_formula <- formula(paste0(i, "~ x1sex + x1ses + x1paredu"))

  loop_lm <- lm(loop_formula, data = data)

  print(summary(loop_lm))

}
```

```
[1] "x1txmtscor"

Call:
lm(formula = loop_formula, data = data)

Residuals:
    Min      1Q  Median      3Q     Max 
-31.781  -5.703   0.180   6.129  30.996 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 50.82144    0.35585 142.819  < 2e-16 ***
x1sex2      -0.03767    0.14199  -0.265    0.791    
x1ses        3.77674    0.16341  23.112  < 2e-16 ***
```

```
x1paredu2   -0.04729    0.33298  -0.142    0.887
x1paredu3   -0.15566    0.39027  -0.399    0.690
x1paredu4    2.04812    0.42368   4.834 1.35e-06 ***
x1paredu5    2.57885    0.49454   5.215 1.86e-07 ***
x1paredu7    2.67655    0.60923   4.393 1.12e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.099 on 16421 degrees of freedom
Multiple R-squared:  0.1718,    Adjusted R-squared:  0.1714
F-statistic: 486.5 on 7 and 16421 DF,  p-value: < 2.2e-16

[1] "x1paredexpct"

Call:
lm(formula = loop_formula, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-7.5279 -1.6021 -0.0548  2.2533  4.6503

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  7.17797    0.10020  71.638  < 2e-16 ***
x1sex2       0.47245    0.03998  11.817  < 2e-16 ***
x1ses        0.28497    0.04601   6.193 6.03e-10 ***
x1paredu2   -0.39488    0.09376  -4.212 2.55e-05 ***
x1paredu3   -0.28136    0.10989  -2.560   0.0105 *
x1paredu4   -0.07679    0.11930  -0.644   0.5198
x1paredu5    0.29117    0.13925   2.091   0.0365 *
x1paredu7    0.85235    0.17155   4.969 6.81e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.562 on 16421 degrees of freedom
Multiple R-squared:  0.04934,   Adjusted R-squared:  0.04894
F-statistic: 121.8 on 7 and 16421 DF,  p-value: < 2.2e-16
```

Assignment

No assignment for this week, optional drafts of your reproducible report are due Sunday!