R MIEF Skills Workshop

Session 1

January 12, 2026

Introduction

Purpose | Learning R

Purpose of this course: Put you on the right track to use R for data or policy analysis.

- As data work has become near-ubiquitous in the research/policy world, so have basic tasks like aggregating, analyzing, summarizing, and visualizing data.
- **The vast majority** of research assistant/analyst (RA) work consists of cleaning and constructing datasets for analysis
- **Entry-level RA positions rarely require complex econometric/regression skills**

Introduction

Purpose | Learning R

You should think of learning R like learning a language.

- Taking a six-hour course won't make you proficient in it
- If you don't practice it, you'll forget it
- Solution — **Find ways to use R in your life, either personally or professionally**

Why R?

Jobs | Beautiful Tables | Beautiful Graphs | Beautiful Maps

- Many entry-level research jobs in policy, economic, development, or political science institutions now expect quantitative work using Stata, R, or Python
- Coding skills make you more valuable in any position — data adds value to nearly every kind of research!

Why R?

Jobs | **Beautiful Tables** | Beautiful Graphs | Beautiful Maps

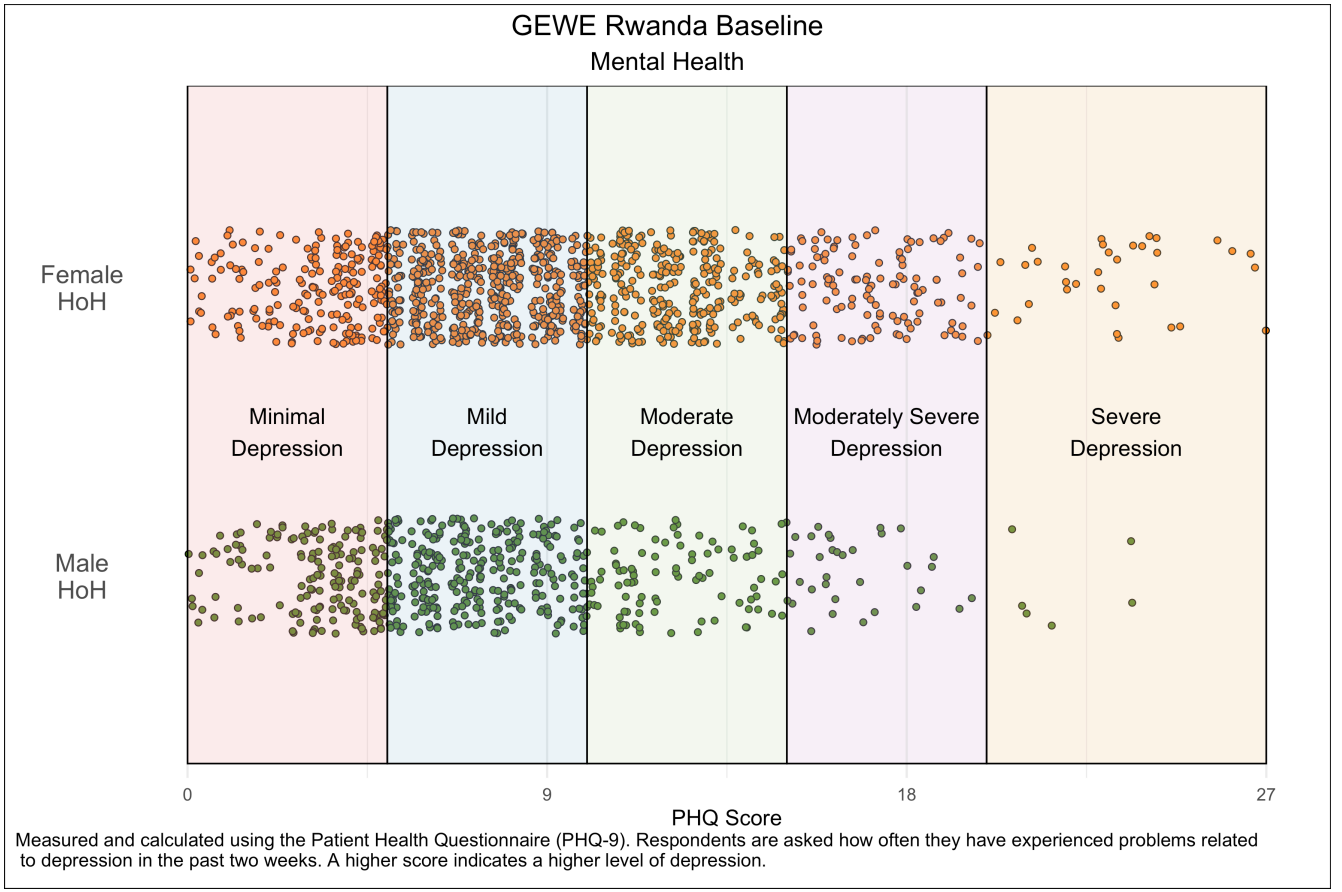
2021 Expected vs. Actual Fantasy Points

Top 40 Running Backs

Player	Team	Expected FP	Expected FP Rank	Actual FP	Actual FP Rank
Jonathan Taylor	IND	301.20	RB 1	324.20	RB 1
Najee Harris	PIT	292.67	RB 2	228.10	RB 4
Joe Mixon	CIN	251.89	RB 3	254.80	RB 3
Leonard Fournette	TB	232.12	RB 4	221.10	RB 5
Ezekiel Elliott	DAL	225.03	RB 5	214.76	RB 6
Austin Ekeler	LAC	217.88	RB 6	263.90	RB 2
Antonio Gibson	WAS	216.49	RB 7	186.70	RB 11

Why R?

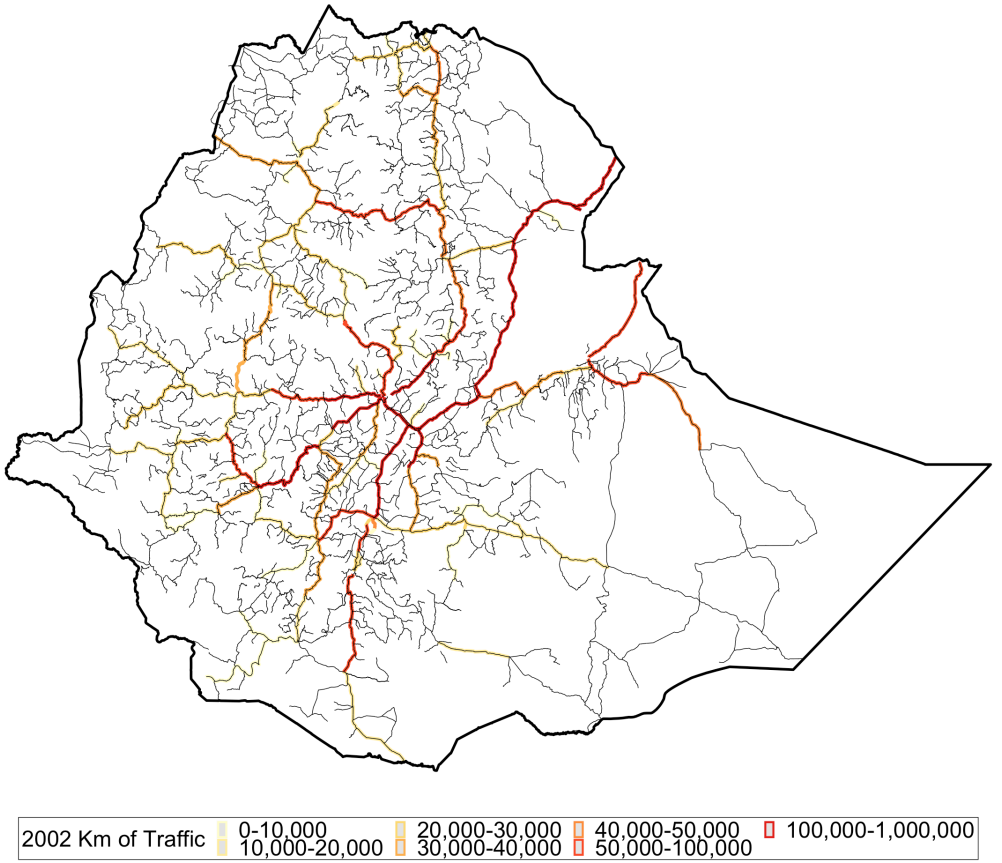
Jobs | Beautiful Tables | **Beautiful Graphs** | Beautiful Maps



Measured and calculated using the Patient Health Questionnaire (PHQ-9). Respondents are asked how often they have experienced problems related to depression in the past two weeks. A higher score indicates a higher level of depression.

Why R?

Jobs | Beautiful Tables | Beautiful Graphs | **Beautiful Maps**



Today

- Learn how to:
    - Think as a coder
    - Identify the basic components of data analysis
    - Set up your environment to use R and RStudio
    - Identify and address basic errors in your R setup
- Be introduced to:
    - The R coding language
    - The building blocks of coding in R: scalars, vectors, lists, and data frames
    - Creating a scatter plot, density plot, and bar chart using the `ggplot2` package
    - Creating flexible and easy-to-read tables of any dataset using the `gt` package
    - Creating simple academic-standard regression output tables using the `stargazer` package

Think As A Coder

Recipe Analogy

- Your data are your ingredients
- Your script is your recipe
- Your output is your... cake? Whatever you're making

What this means:

- **Make sure you have all of the ingredients you need.**
- **Follow every step of the recipe — you can't skip any steps!**
- If you mess up somewhere, you have to start from scratch to make sure that you get the correct outcome.

Identify the Basic Components of Data Analysis

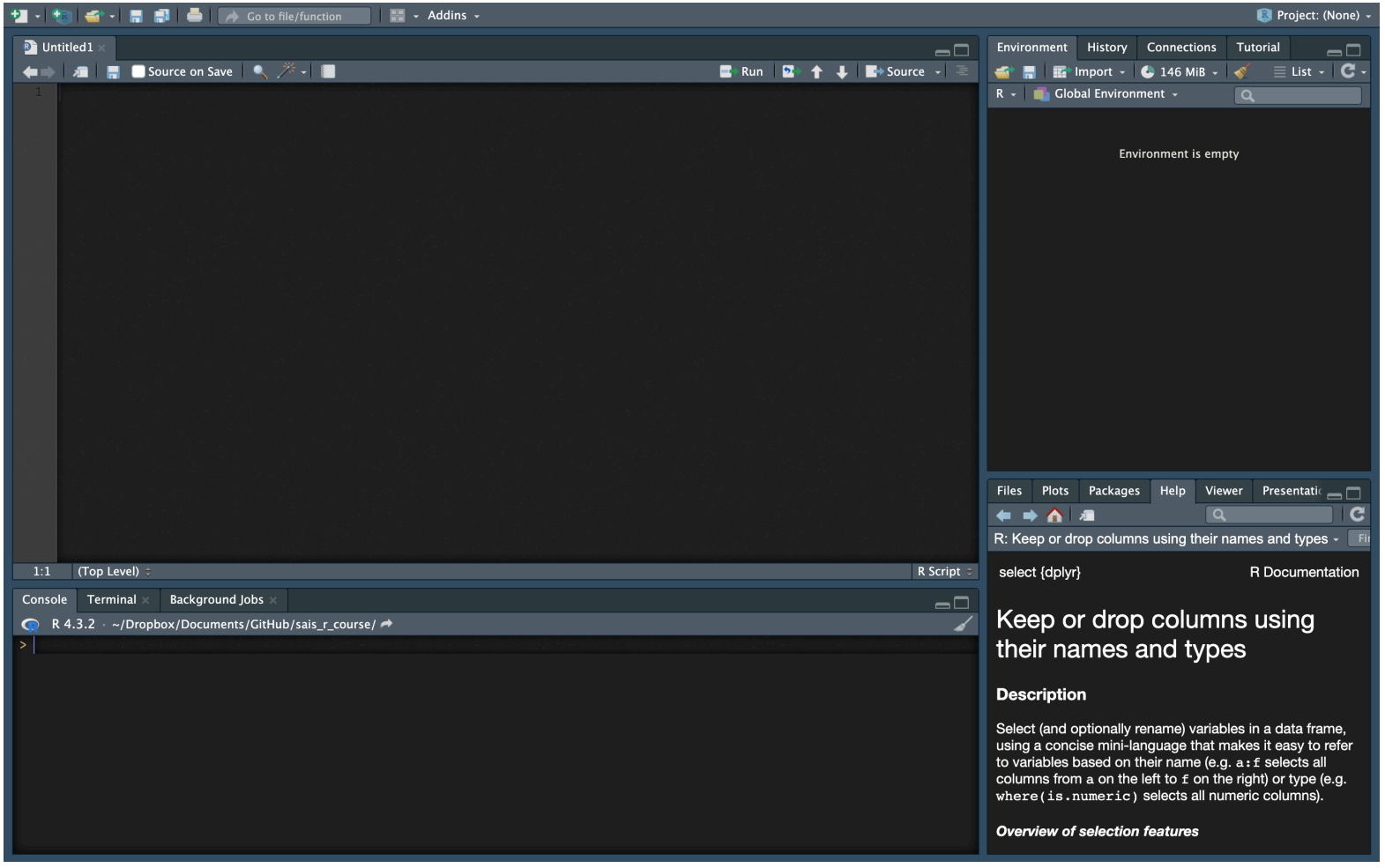
Three main components to your data analysis:

- Data
- Code
- Outputs

Questions to ask:

- Where is the file stored?
- In which format is the file?
- How easy is it for you/other people to access it?
- Is it intuitive for you to navigate to the file?

Your RStudio Environment



R Basics

Scalars | Vectors | More Vectors | Selecting Vector Elements

This is a scalar:

```
a ← 2
```

It's an object (a) with a single value (2). Notice that we assign the value 2 to a using an arrow ←.

R Basics

These are vectors:

```
vector ← c(1, 2, 5)
vector
```

```
## [1] 1 2 5
```

```
vector ← 2:6
vector
```

```
## [1] 2 3 4 5 6
```

R Basics

These are more vectors:

```
vector ← seq(2, 3, by = 0.5)
vector
```

```
## [1] 2.0 2.5 3.0
```

Vectors take multiple values. Notice that vectors have a specific **order**: `c(1, 2)` is not the same as `c(2, 1)`.

R Basics

Scalars | Vectors | More Vectors | Selecting Vector Elements

```r
## By Position
x[4]       # Fourth element
x[-4]      # Everything but the fourth element
x[2:4]     # Elements two to four
x[-(2:4)]  # Everything but elements two to four
x[c(1, 5)] # Elements one and five
```

```r
# By Value
x[x == 10]           # Elements which are equal to 10
x[x < 0]             # Elements that are less than zero
x[x %in% c(1, 2, 5)] # Elements in the set 1, 2, 5
```

R Basics

Lists | Some Classes | Data Frames | Assignment vs. Printing

This is a list:

```
y ← list("a", 1, "b")
```

Lists are different from vectors in one key manner: **they can take objects of different classes**. Vectors can only take objects of the same class.

R Basics

Here are some classes in R:

```
a ← "a"     # Character
b ← 1       # Integer
c ← 1.2     # Numeric
d ← 1 + 2i  # Complex
e ← TRUE    # Logical
```

R Basics

This is a data frame:

```
df ← data.frame(
    first_name = c("Mark", "Mary", "July"),
    last_name  = c("Smith", "John", "Sanchez"),
    age        = c(21, 34, 55)
)
```

At their core, data frames are just a group of named vectors of the same length. In practice, we visualize data frames as **tables** where each vector is a **column**, or variable, and each group of nth elements of the vectors is a **row**, or observation.

R Basics

KEY — We can classify the code we write in our script into two general categories:

1- Assignment code. We are **assigning** a value to an object:

```
a ← 2
```

2- Printing code. We are **printing** an object's value:

```
a
```

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

```
print(a)
```

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

Only 2- results in something appearing in your console. When you assign a value to an object, nothing prints in the console.

R Basics

NOTE — R works in a manner that allows to write a specific function over multiple lines. This is called a **code chunk**.

This:

```
a ← mean(c(seq(1, 4, by = 0.5)))

a
```

```
## [1] 2.5
```

Is the same as this:

```
a ← mean(
    c(
        seq(1, 4, by = 0.5)
    )
)

a
```

```
## [1] 2.5
```

R Basics

Functions | Packages

Like in mathematics, a function is an expression or rule that takes an input, or *argument*, and returns an *output*. A function is any `f` such that `f(x) = y`.

In R, functions take the following form:

```
# The function is called
sum_function ← function(x, y) { # x and y are the function's arguments
    x + y # Within the brackets {}, we define the function's output
}

sum_function(2, 3)
```

```
## [1] 5
```

The vast majority of using R is done using functions, either included with R or written by external users. For instance, to find the sum of 2 and 3, we can use the "base R" function `sum()`.

R Basics

Functions | Packages

A package is a bundle of functions created by external users. They innovate and, in many cases, improve upon base R functions. Most work in R is done using functions from external packages.

We will look at how to install and load packages shortly. Examples of commonly-used packages are `dplyr`, `tidyr`, `stringr`, `ggplot2`, and `data.table`.

R Basics

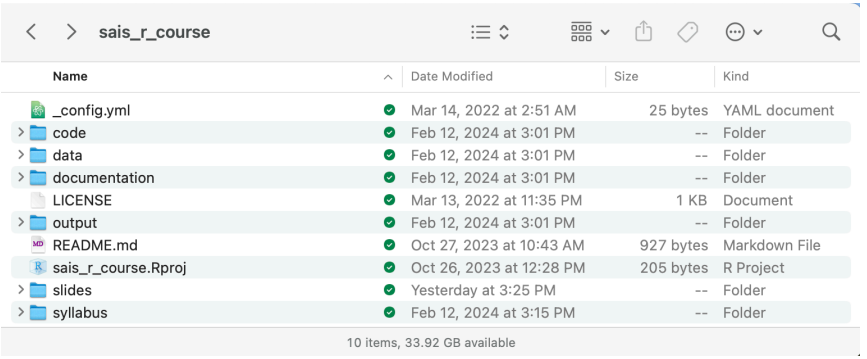
You can click anywhere in the code chunk and click "run" or Cmd+Enter (Mac)/Ctrl+Enter (Windows), and the whole chunk will run.

KEY — If you only select a portion of the code chunk and run that, then R will identify the chunk as unfinished and refuse to let you do anything else until you've "completed" it.

Coding Set Up

Setting Up Your RStudio Environment

Setting Up Your Data Structure | Setting Up Your Script



- code
- data
  - raw
  - intermediate
- output
- documentation (Optional)
- slides (Optional)

Setting Up Your RStudio Environment

Setting Up Your Data Structure | **Setting Up Your Script**

Defining your code's purpose — What are its inputs? What are its outputs?

```
## Programming for Professional Research Using R -- Session 1

### Session Description

  # Basic R Use - Introduction to R and RStudio, How to import/export data
  # Using Basic Tidyverse Functions - how to subset, mutate, summarize, and reshape data
  # Using R in a Collaborative Setting - Introduction to downloading and publishing data using
  # GitHub
```

Set up your packages — Which user-created functions do you plan to use?

```
## 1. Setup ----

  ### Packages Random

# NOTE -- Unlike using library(), the 'pacman::p_load()' function installs the package if it is
# already not present in the user's R environment.

if(!require(pacman)) install.packages("pacman")

pacman::p_load(tidyverse, data.table, janitor, usethis)
```

Import your data — Which data frames do you need to fulfill the script's purpose?

```
## 2. Import Data ----

# This is session 1 so we're going to import the data from Dropbox:

if(!(file.exists("data/final/wvs_values_norms_data.csv"))) { # Checks whether the data has been
                                                             # downloaded already
    usethis::use_zip(
        "https://www.dropbox.com/scl/fo/vnxjbqyq1g9z368coh1vq/h?rlkey=zc66o2ll7613b5e9ipp915ynk6dl=1"
    )

}

norms_values_data <- data.table::fread( # Other options are base R's read.csv() and data.table::fread()
    "data/final/wvs_values_norms_data.csv", na.strings = ""
)
```

Installing Packages

Packages are groups of user-created functions that help us accomplish tasks that would be harder/impossible using base R functions.

Easy

```
install.packages("tidyverse")
library(tidyverse)
```

Better

The `pacman` package installs packages if they aren't installed yet, loads them otherwise

```
if(!require(pacman)) install.packages("pacman")
pacman::p_load(tidyverse)
```

Setting up File Paths

File paths help R identify where the files you want to use are located.

You want your code to be **reproducible** and **easy to use by other people**

Simple solution: Create an `.rproj` file that people can open to access your R environment

Better solution:

```
# Set User (this allows us to use fixed file paths but to adapt them
# for multiple possible users)
      # 1 - Marc-Andrea Fiorina
      # 2 - Enter here if needed

user ← 1

if(user == 1) {
    # Absolute file path
    main_filepath ← "/Users/marc-andreafiorina/Dropbox/SAIS R Course/"
}

# Notice the relative file paths
data_filepath ← paste0(main_filepath, "data/")
```

Importing Data

Easiest file type to import into R is a .csv file. But you can also import .xlsx, .dta (Stata), etc.

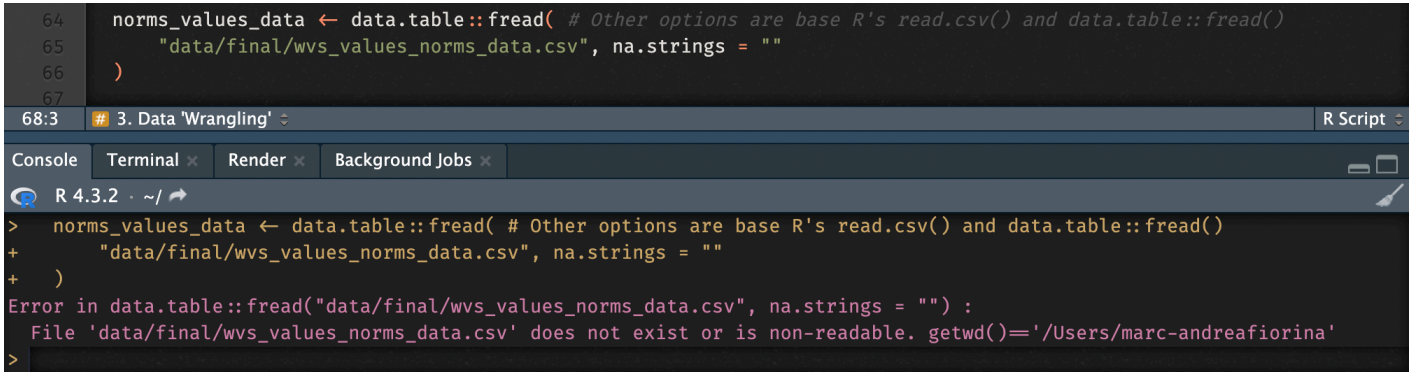
- Easy → `read.csv()`
- Harder (faster) → `data.table::fread()`

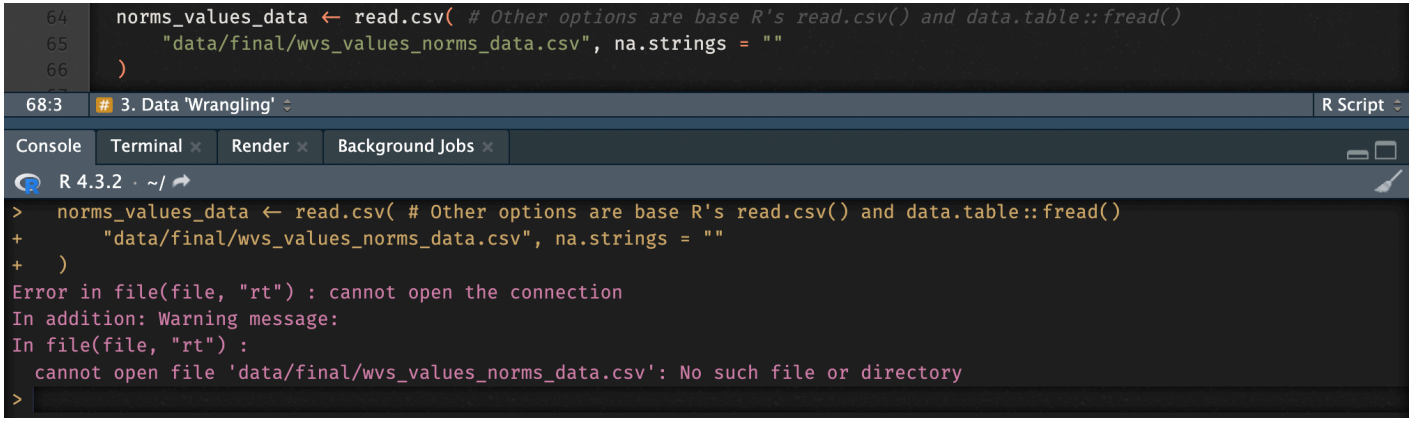
```
norms_values_data ← data.table::fread(
    "raw/wvs_values_norms_data.csv",
    na.strings = ""
)
```

Note the construction of the "harder" method, with the " `::` ". This is used to refer to the package from which the function originates. The structure is `package::function()`.

Basic Issues in RStudio

Data Not Loading





Basic Issues in RStudio

Data Not Loading

Check:

- Working directory — `getwd()` or check the top of the RStudio console.
- File path — are there any typos? Is your file where you expect it to be?

Solutions:

- If you were provided with an `.Rproj` file alongside your script, make sure that you opened the project.
- Modify the working directory using `setwd()` or correct the file path if need be!

Basic Issues in RStudio

Function Not Found

Basic Issues in RStudio

Function Not Found

Check:

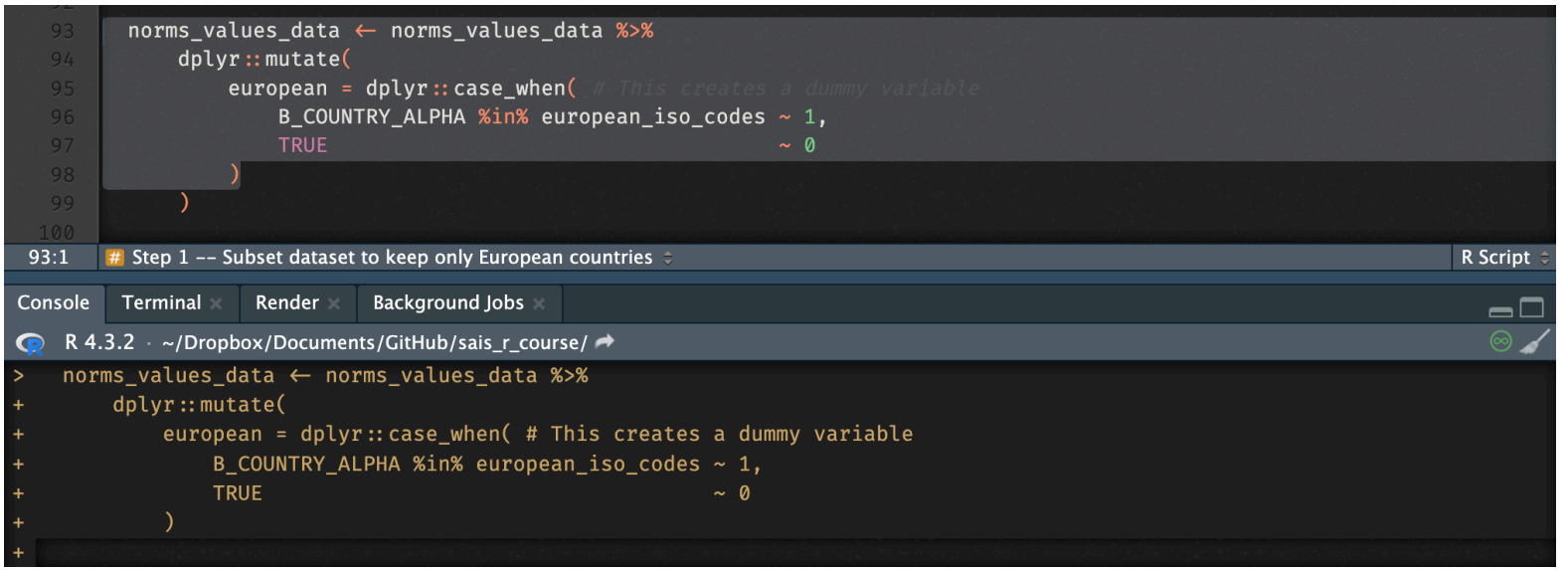
- From which package the function comes. You can do this using `?? FUNCTION NAME` (e.g. `?? tabyl`) or through a Google search.
- That the package is (1) installed in your environment and (2) loaded. Having the package installed isn't sufficient!

Solutions:

- If the package isn't installed, use `install.packages("tabyl")`. If the package isn't loaded, use `library(tabyl)` or `pacman::p_load(tabyl)`.

Basic Issues in RStudio

Code Not Running



Basic Issues in RStudio

Code Not Running

Check:

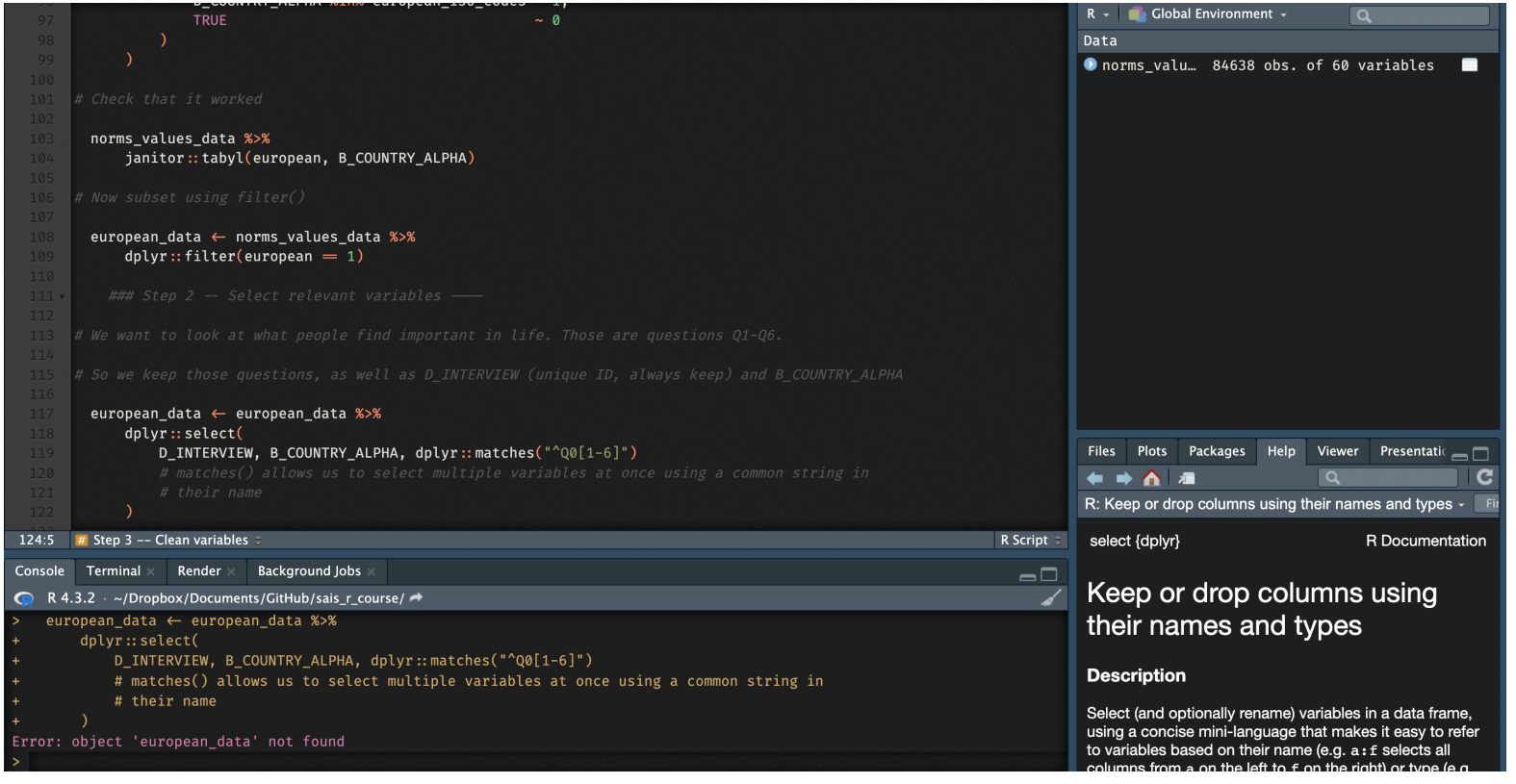
- That you didn't miss a parenthesis ( )) or bracket (}) in your code! This is the most common reason.
- If you missed it, the console will show a + at the start of the console line instead of the expected >.

Solutions:

- Type gibberish and/or the missing parenthesis/bracket until the > reappears. More likely, you'll have to rerun the code chunk to make sure it works!

Basic Issues in RStudio

Object Not Found



Basic Issues in RStudio

Object Not Found

Check:

- Whether the object exists in your environment. More likely than not, you either misspelt the name of the object, or you skipped the code that creates it (remember that a script is like a recipe and steps can't be skipped!).

Solutions:

- Backtrack in your code and run the chunk that creates the object.
- If a typo is at fault, correct the typo.

Practical Exercise

Using the World Values Survey Dataset

World Values Survey

Background

"The survey, which started in 1981, seeks to use the most rigorous, high-quality research designs in each country. The WVS consists of nationally representative surveys conducted in almost 100 countries which contain almost 90 percent of the world's population, using a common questionnaire. [...] WVS seeks to help scientists and policy makers understand changes in the beliefs, values and motivations of people throughout the world."

Survey Contents

- Social values, attitudes & stereotypes
- Societal well-being
- Social capital, trust and organizational membership
- Economic values
- Corruption
- Migration
- Post-materialist index
- Science & technology
- Religious values
- Security
- Ethical values & norms
- Political interest and political participation
- Political culture and political regimes
- Demography

Today's practical component

1— Download the World Values Survey (Wave 7) at this link: https://www.worldvaluessurvey.org/WVSDocumentationWV7.jsp

2— Set up your data analysis folder. Make sure that it contains the following folders:

- data
  - raw
  - intermediate
- code
- output
- documentation

3— Place the data and documentation files that you find appropriate for your analysis in the corresponding folders.

4— Open RStudio and click on "New Project" in the "File" dropdown menu. Navigate to your data folder and select it.

Today's practical component

5— Set up your R Script. It should have the following components:

- Package setup. For now, have the script load the `dplyr`, `data.table`, and `skimr` packages.
- Data import. Import your data into the script using `read.csv()` or `fread()`. Remember to give your data frame an intuitive name!

6— Test your R Script. Type and run the following line in your code: `skim([[DATASETNAME]])`.
Replace [[DATASETNAME]] with the name you gave your dataset. If this works without issue, you're free to take a break!

BREAK

Data Visualization — Descriptive Statistics — Plots

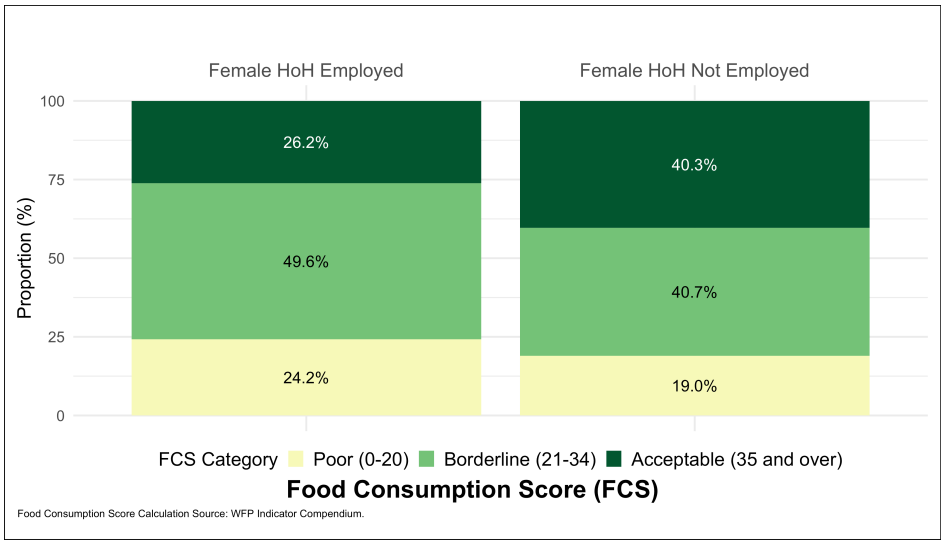
Descriptive Stats Plots

`ggplot2` is the gold standard in data visualization in data work. It's one of the main reason that people use R over other programming languages.

Very simple syntax and allows you to add elements very easily.

You can use `ggplot2` to create any type of plot you can think of.

I've included a lot of links at the end of these slides to explore the possibilities of `ggplot2` further. Strongly recommend you use them or at least save them somewhere.



The Magic of `ggplot2`

Using `ggplot2` to create plots is great because the **structure** it sets up makes plot creation intuitive.

```
ggplot(data = <DATA>) +
  <GEOM_FUNCTION>(
     mapping = aes(<MAPPINGS>),
     stat = <STAT>,
     position = <POSITION>
  ) +
  <SCALE_FUNTION> +
  <FACET_FUNCTION> +
  <THEME_FUNCTION>
```

1. `Data`: The data that you want to visualize
2. `Layers`: geom_ and stat_ → The geometric shapes and statistical summaries representing the data
3. `Aesthetics`: aes() → Aesthetic mappings of the geometric and statistical objects
4. `Scales`: scale_ → Maps between the data and the aesthetic dimensions
5. `Facets`: facet_ → The arrangement of the data into a grid of plots
6. `Visual themes`: theme() and theme_ → The overall visual defaults of a plot

Scatter Plot — Step-by-Step

Dataset | Convert to Plot | Add Something

Start with a dataset you want to visualize

```
head(mtcars)
```

```
##                   mpg cyl disp  hp drat    wt  qsec vs am gear carb
## Mazda RX4         21.0   6  160 110 3.90 2.620 16.46  0  1    4    4
## Mazda RX4 Wag     21.0   6  160 110 3.90 2.875 17.02  0  1    4    4
## Datsun 710        22.8   4  108  93 3.85 2.320 18.61  1  1    4    1
## Hornet 4 Drive    21.4   6  258 110 3.08 3.215 19.44  1  0    3    1
## Hornet Sportabout 18.7   8  360 175 3.15 3.440 17.02  0  0    3    2
## Valiant           18.1   6  225 105 2.76 3.460 20.22  1  0    3    1
```

Scatter Plot — Step-by-Step

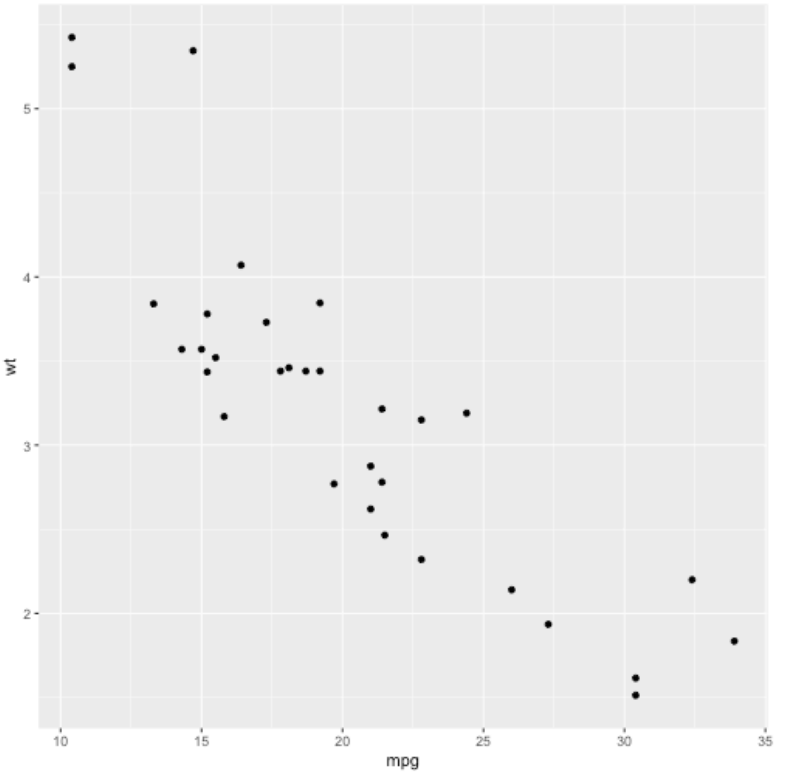
Dataset | Convert to Plot | Add Something

```
ggplot(mtcars)
```

Scatter Plot — Step-by-Step

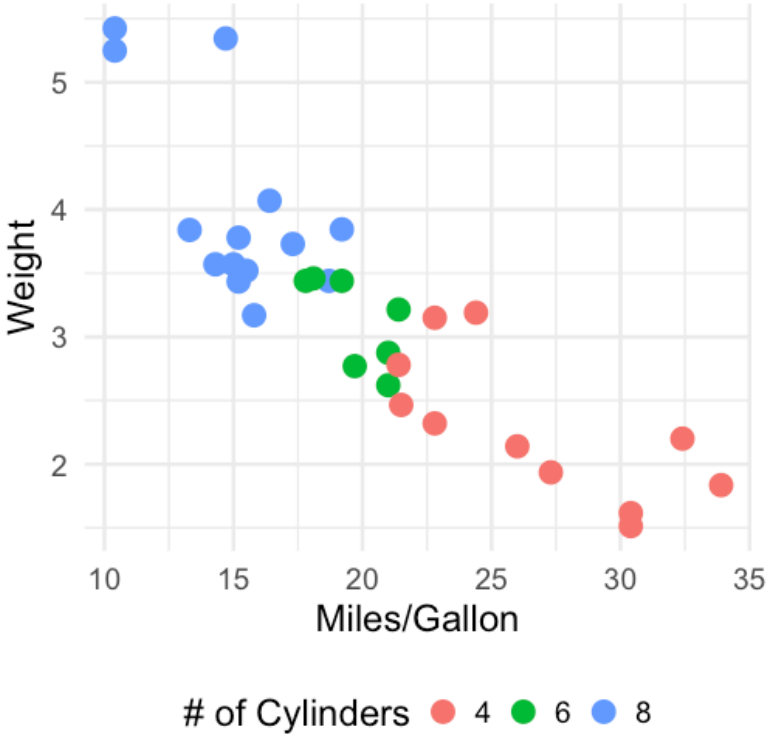
Dataset | Convert to Plot | Add Something

```
ggplot(mtcars) +
  geom_point(
    aes(x = mpg, y = wt)
  )
```



Scatter Plot — Make It Better

```
ggplot(mtcars) +
  geom_point(
    aes(
      x = mpg, y = wt,
      color = factor(cyl)
    ),
    size = 6
  ) +
  xlab("Miles/Gallon") +
  ylab("Weight") +
  scale_color_discrete(
    name = "# of Cylinders"
  ) +
  theme_minimal(base_size = 24) +
  theme(
    legend.position = "bottom"
  )
```



Bar Plot — Step-by-Step

Dataset | Convert to Plot | Add Something | Fix Class Issue

Start with a dataset you want to visualize

```
mtcars_summary ← mtcars %>%
  group_by(cyl) %>%
  summarize(
    mpg = mean(mpg)
  ) %>%
  ungroup()

mtcars_summary
```

```
## # A tibble: 3 × 2
##     cyl   mpg
##   <dbl> <dbl>
## 1     4  26.7
## 2     6  19.7
## 3     8  15.1
```

Bar Plot — Step-by-Step

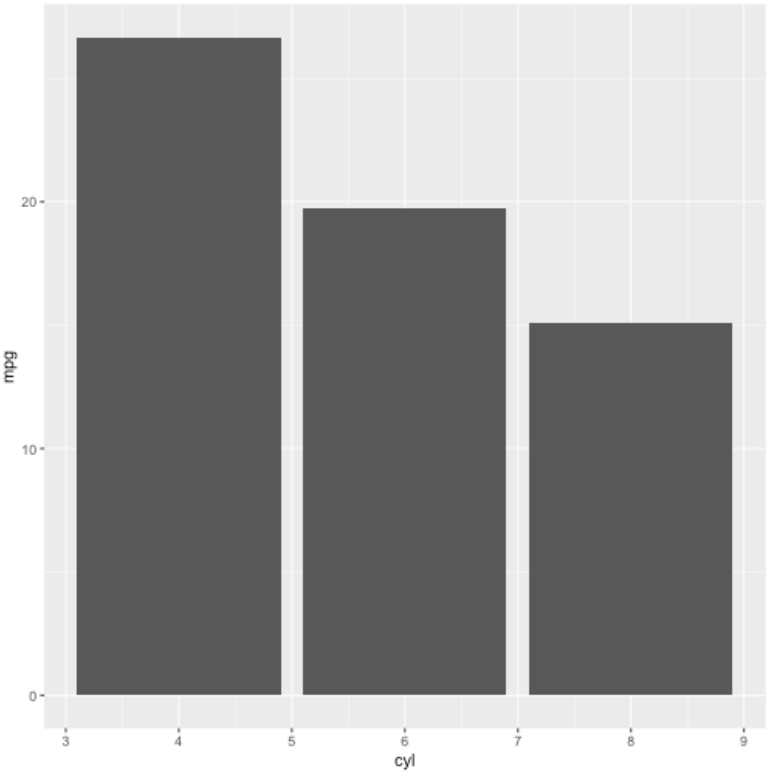
Dataset | Convert to Plot | Add Something | Fix Class Issue

```
ggplot(mtcars_summary)
```

Bar Plot — Step-by-Step

Dataset | Convert to Plot | **Add Something** | Fix Class Issue

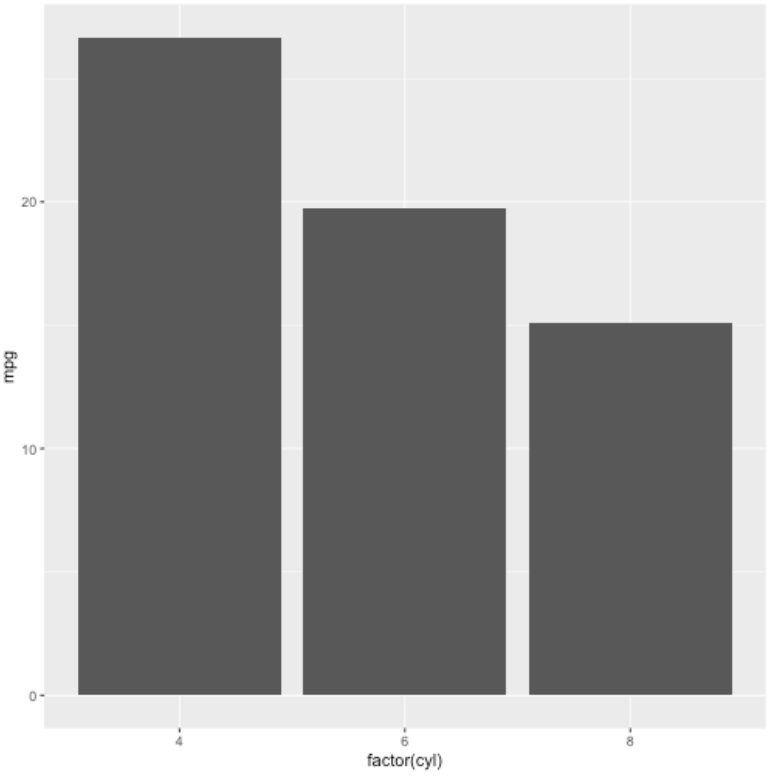
```
ggplot(mtcars_summary) +
  geom_col(
    aes(
      x = cyl,
      y = mpg
    )
  )
```



Bar Plot — Step-by-Step

Dataset | Convert to Plot | Add Something | **Fix Class Issue**

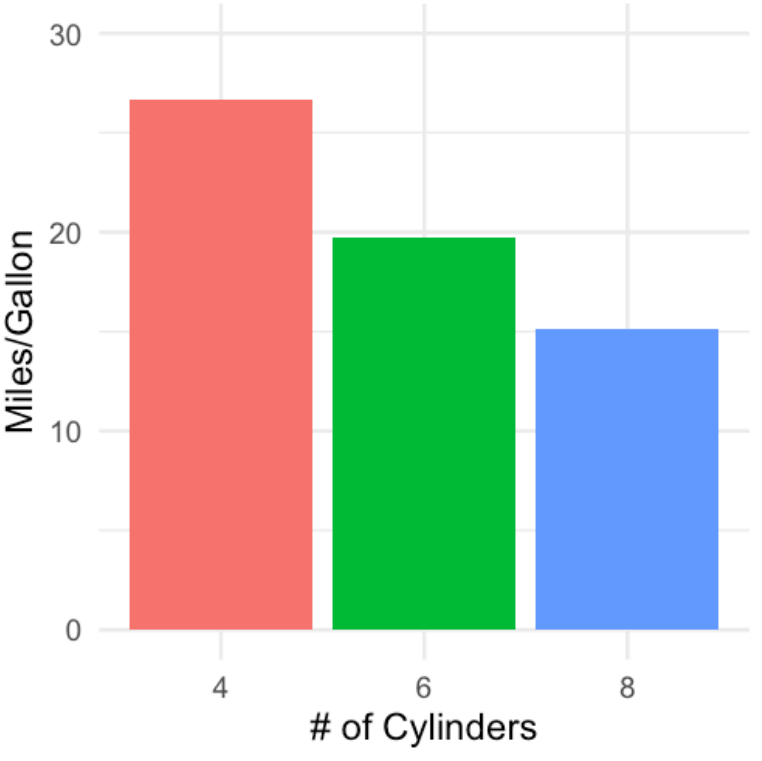
```
ggplot(mtcars_summary) +
  geom_col(
    aes(
      x = factor(cyl),
      y = mpg
    )
  )
```



`cyl` categorizes cars by number of cylinders. Although the values are numbers, it is a **categorical** variable. We communicate this to `ggplot()` using the `factor()` function.

Bar Plot — Make It Better

```
ggplot(mtcars_summary) +
  geom_col(
    aes(
      x    = factor(cyl),
      y    = mpg,
      fill = factor(cyl)
    )
  ) +
  xlab("# of Cylinders") +
  ylab("Miles/Gallon") +
  scale_y_continuous(
      limits = c(0, 30)
  ) +
  theme_minimal(base_size = 24) +
  theme(
    legend.position = "none"
  )
```



Plot Standards

1. Your plot should be **properly labeled**:
    - The plot should have a title describing its content
    - Axes should be labeled
    - Legend (if any) should have a title and labels
2. Your plot should be **properly formatted**:
    - Axis dimensions should be appropriate. What is appropriate varies depending on context, but usually you should aim to fill the plot space with data
    - Text size should be large enough for text to be legible
3. Your plot should be **self contained**. People should be able to understand your plot and its data without any other context or explanatory text. That means:
    - A caption note that includes data source and any important data construction notes
    - Title and subtitle that deliver the plot's *message*

Data Visualization — Descriptive Statistics — Tables

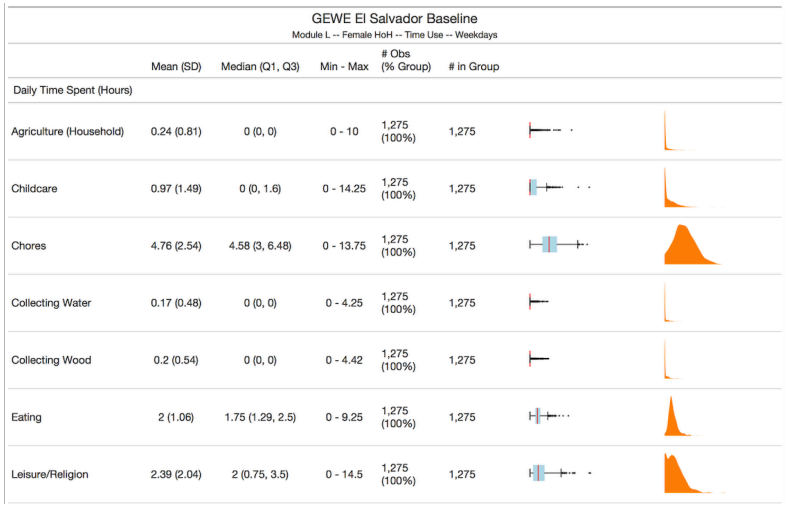
Descriptive Statistics Tables

Thankfully, not every RA position requires academic-standard tables or use of LateX.

It is still useful, however, to be able to communicate descriptive statistics about data.

There are countless R packages to help do this. Today, we're looking at the `gt` package. It's simple to use and it's very easy to create good-looking tables using it.

`gt` exports into .png, .pdf, or .html. You can add interactive elements, plots within columns.



GEWE El Salvador Baseline

Module L -- Female HoH -- Time Use -- Weekdays

	Mean (SD)	Median (Q1, Q3)	Min - Max	# Obs (% Group)	# in Group
Daily Time Spent (Hours)					
Agriculture (Household)	0.24 (0.81)	0 (0, 0)	0 - 10	1,275 (100%)	1,275
Childcare	0.97 (1.49)	0 (0, 1.6)	0 - 14.25	1,275 (100%)	1,275
Chores	4.76 (2.54)	4.58 (3, 6.48)	0 - 13.75	1,275 (100%)	1,275
Collecting Water	0.17 (0.48)	0 (0, 0)	0 - 4.25	1,275 (100%)	1,275
Collecting Wood	0.2 (0.54)	0 (0, 0)	0 - 4.42	1,275 (100%)	1,275
Eating	2 (1.06)	1.75 (1.29, 2.5)	0 - 9.25	1,275 (100%)	1,275
Leisure/Religion	2.39 (2.04)	2 (0.75, 3.5)	0 - 14.5	1,275 (100%)	1,275

Descriptive Statistics Table — Step-by-Step

We will mainly use the example in the script for this. To summarize, the steps are:

- Create a dataset you want to export
- Run the dataset through the `gt()` function to create a gt object
- Customize the table using functions from the `gt` package (see online for further things you can do). Examples of what you can do include:
    - Modify column names — `cols_label()`
    - Modify borders — `tab_style()`, `cell_borders()`
    - Add colors conditional on cell value — `data_color()`
    - Add title/subtitle — `tab_header()`
- Export the table using `gtsave()`

Data Visualization — Simple Regression Table

Regression Tables

Regression tables are very common in economic/policy analysis.

They're very simple to create using R and a software called **LateX** (pronounced latek).

Unless you're getting into academic research, you don't need to know how to properly use LateX. Just enough to:

- Export the LateX script from R
- Copy/paste it into a LateX-reading software, e.g. Overleaf
- Export the pdf or png to share

Predicted Consumption per Capita (2019 PPP USD)

	Any Treatment vs. Control	Women Working Treatment vs. Any Treatment
	(1)	(2)
Any Treatment	12.049**	12.155*
	(5.330)	(6.600)
Women Working Treatment		−0.222
		(8.463)
Baseline Control	0.249**	0.249**
	(0.101)	(0.101)
Constant	22.788***	22.791***
	(3.483)	(3.489)
Control Mean	27.91	27.91
Observations	761	761
R^2	0.028	0.028
Adjusted R^2	0.025	0.024
Residual Std. Error	44.983 (df = 758)	45.013 (df = 757)
F Statistic	10.925*** (df = 2; 758)	7.275*** (df = 3; 757)
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression Table — Step by Step

Run Regression in R | Convert to Exportable Table

```
# Simplest regression format in R

reg_example ← lm(
    outcome_variable ~ independent_variable + control_variables,
    data = dataset
)

# Observe results

reg_example %>% summary()
```

Regression Table — Step by Step

Run Regression in R | Convert to Exportable Table

Simply do one of these!

```
reg_example_ht ← reg_example %>%
    huxtable::huxreg()
```

OR

```
reg_example_sg ← reg_example %>%
    stargazer::stargazer() # Many options to make prettier
```

Regression Table — Step by Step

Export Huxtable Table | Export Stargazer Table

Some simple options for the Huxtable table:

```
huxtable::quick_latex(
    reg_example_ht,
    file = "filepath/filepath/filepath/reg_example_ht.tex"
)

huxtable::quick_pdf
    reg_example_ht,
    file = "filepath/filepath/filepath/reg_example_ht.pdf"
)

huxtable::quick_html(
    reg_example_ht,
    file = "filepath/filepath/filepath/reg_example_ht.html"
)
```

Regression Table — Step by Step

Export Huxtable Table | **Export Stargazer Table**

```
# You can export a LateX script using the 'writeLines' function

writeLines(
    reg_example_sg,
    "filepath/filepath/filepath/reg_example_sg.tex"
)
```

To visualize your table, the easiest solution is to:

- Create a free Overleaf account on overleaf.com
- Open a new document
- Copy/paste your .tex output in between the `begin{document}` and `end{document}` lines
- Click compile and then save!

You can also install the `tinytex` package and use `pdftolatex` to save a PDF file.

Wednesday

- Practice visualizations
- Learn how to wrangle data

Links

Thomas Mock, “A Gentle Introduction to Tidy Statistics in R” (blog post and video)

Hadley Wickham, Mine Çetinkaya-Rundel & Garrett Grolemund, R for Data Science (2e)

RStudio, RStudio Cheatsheets

Links

Tables

Marek Hlavac, “stargazer: beautiful LATEX, HTML and ASCII tables from R statistical output”

Thomas Mock, “gt - a (G)rammar of (T)ables”

Plots

Alicia Horsch, “A quick introduction to ggplot2”

RStudio, RStudio Cheatsheets