# Big Data and Economics

## The Empirical Workflow and Clean Code

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Bates College | EC/DCS 368

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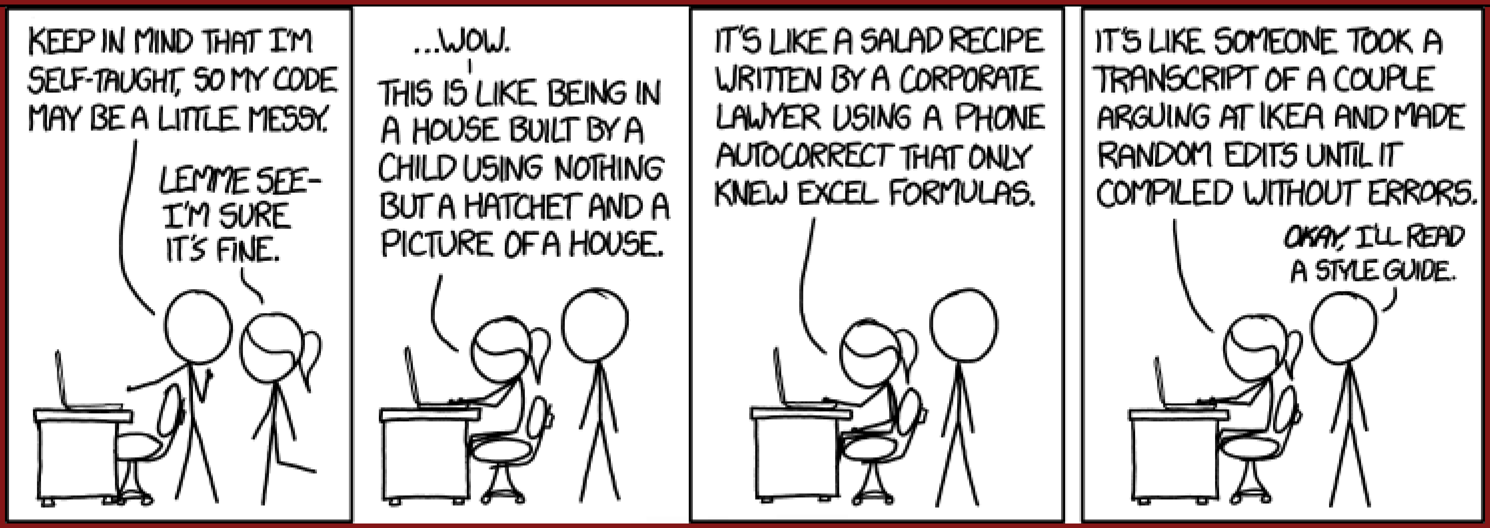
# Prologue




Source: xkcd

# Forgot to mention

- **Office Hours:**
  - My office hours are 9am-10am on Tuesdays and 3pm-4pm on Wednesdays
  - My office is 276 Pettengill
  - I'm also available by appointment on Zoom
- **Problem Set 0:** due on Sunday, September 17th at 11:59pm

# Attribution

- Today's material comes from these sources:

1. Clean Code by Tyler Ransom

2. *Code and Data for the Social Sciences: A Practitioner's Guide*, by Gentzkow and Shapiro

3. Causal Inference and Research Design by Scott Cunningham

4. Jenny Bryan's UseR 2018 keynote address

Also a small contribution from here and other sundry internet pages

# Jargon

- There is a jargon in this class that won't make sense at first, I'll try to flag it as it comes
  - If I don't flag a term, look it up on ChatGPT
  - If it still doesn't make sense, ask me -- could be I'm using it idiosyncratically
- Here's a few terms:
  - **Local machine:** Your personal (or any) computer that isn't a server accessed via the internet
  - **Version Control:** Keep track of different iterations of a project/code
  - **Repository:** The location on GitHub of all project files and (commented) file revision history
  - **GUI:** A Graphical User Interface -- what you're used to pointing and clicking to navigate a computer and execute programs
  - **Command line:** Removes the "graphical" from GUI, instead you type all commands to navigate a computer and execute programs
    - R operates via the Command line, RStudio is a GUI
    - On Mac, this is called Terminal
    - Windows has Powershell, but it Powershell uses quite user-unfriendly commands
    - If you installed Git for Windows, you got *Git Bash*, which uses Bash (Linux) commands
    - You can also install Windows Subsystem for Linux to run Linux on a Windows machine

# Clean Code

# Reducing empirical chaos

## Sad story

- Once upon a time there was a boy who was writing a job market paper on unemployment insurance during the pandemic
- This boy presented the findings a half dozen times, spoke to the media some, and generally thought he had cool results
- Several people suggested he look at a handful of other outcome series and try changing his analysis unit frequency from monthly to weekly
- He also knew that he needed to restrict his sample to reduce noise

# The horror!

- But then after making these changes and re-running his code that took two days, his new sample dropped by 50 percent!
- He was, understandably, terrified.
- The young boy spent a week looking for the fix weeding through six different versions of the .do, .R, .dta, .csv, .sh, .py files with suffixes like *_v1* and *_test* and *_test2* and *_final_I_swear* and *_okay_i_lied*
- Finally he discovered the phrase:

```
df %>% filter(insample_new==0)
```

**instead of**

```
df %>% filter(insample_new==1)
```

- The boy was very frustrated and decided to work on these slides while re-running his code.

# What is Clean Code?

- **Clean Code:** Code that is easy to understand, easy to modify, and hence easy to debug
- Clean code saves you and your collaborators time

# Why clean code matters: Scientific

- Good science is based on careful observations
- Science progresses through iteratively testing hypotheses and making predictions
- Scientific progress is impeded if
    - mistaken previous results are erroneously given authority
    - previous hypothesis tests are not reproducible
    - previous methods and results are not transparent
- Thus, for science that involves computer code, clean code is a must

# Why clean code matters: Personal and

- You will always make a mistake while coding
- What makes good programmers great is their ability to quickly identify and correct mistakes
- Developing a habit of clean coding from the outset of your career will help you more quickly identify and correct mistakes
- It will save you a lot of stress in the long-run
- It will make your collaborative relationships more pleasant

# Why clean code is under-produced

- If clean code is so beneficial and important, why isn't there more of it?

1. **Competitive pressure** to produce research/products as quickly as possible
2. **End user** (journal editor, reviewer, reader, dean) **doesn't care what the code looks like**, just that the product works
3. In the moment, clean code **takes longer to produce** while seemingly conferring no benefit

# How does one produce clean code?

## Principles

# How does one produce clean code?

- Automation
- Version control
- Organization of data and software files
- Abstraction
- Documentation
- Time / task management
- Test-driven development (unit testing, profiling, refactoring)
- Pair programming

# Automation

- Gentzkow & Shapiro's two rules for automation:

1. Automate everything that can be automated

2. Write a single script that executes all code from beginning to end

- There are two reasons automation is so important
    - Reproducibility (helps with debugging and revisions)
    - Efficiency (having a code base saves you time in the future)
- A single script that shows the sequence of steps taken is the equivalent to "showing your work"

# Version control

- We've discussed Git and GitHub in a previous slide deck

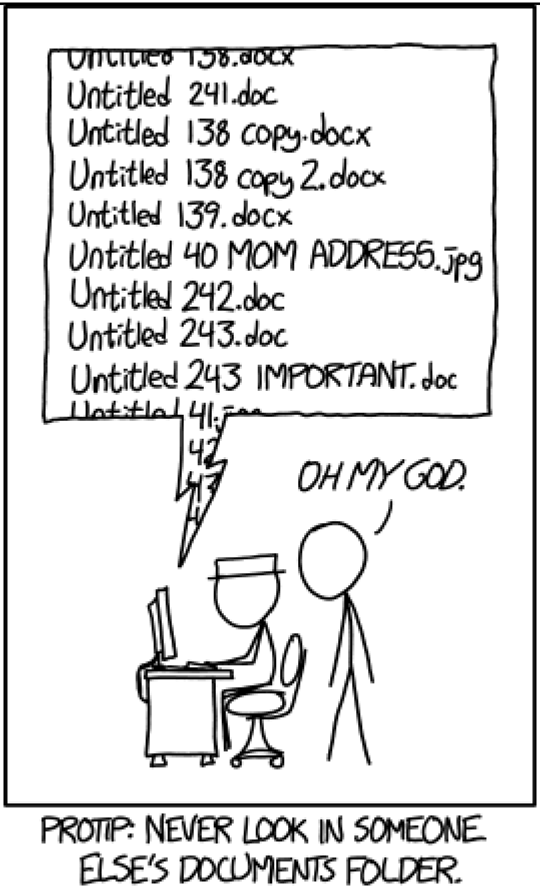
- Version control provides a principled way for you to easily undo changes, test out new specifications, and more

# File organization

1. Separate directories by function
2. Separate files into inputs and outputs
3. Make directories portable

- To see how professionals do this, check out the source code for R's dplyr package
  - There are separate directories for source code (`/src`), documentation (`/man`), code tests (`/test`), data (`/data`), examples (`/vignettes`), and more
- When you use version control, it forces you to make directories portable (otherwise a collaborator will not be able to run your code)
  - use **relative** file paths, not absolute file paths

# Don't be like this




Source: xkcd

# How I organize research projects

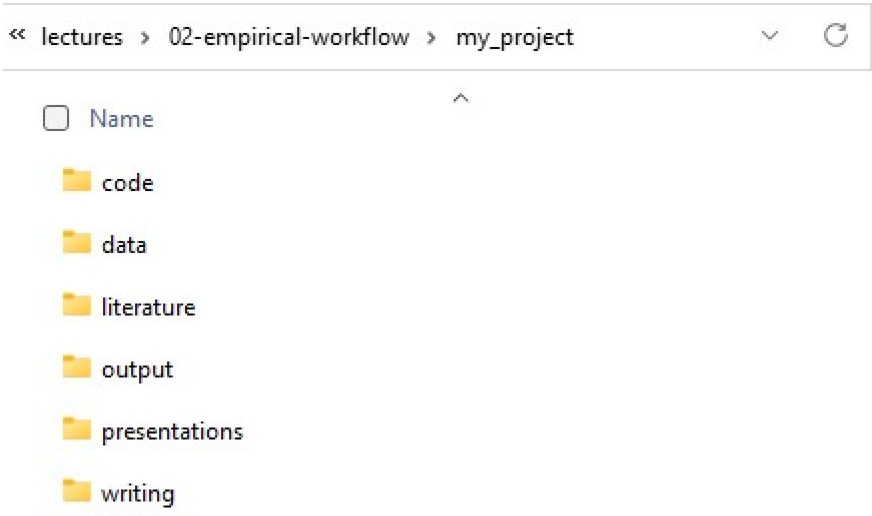
- I have a folder called (`my_project`)
- Within that folder I have subfolders:
    1. `data` for all data files a. `raw` for raw data files b. `clean` or `work` for cleaned data files c. `temp` for temporary data files
    2. `code` for all code files, and sometimes: a. `code/analysis` for code files that build/clean code a. `code/build` for code files that do analysis
    3. `output` for all output files a. `output/figures` for code files that make figures b. `output/tables` for code files that make tables
    4. `literature` or `articles` for all relevant literature
    5. `writing` for all writing files a. `writing/notes` for notes b. `writing/drafts` for drafts c. `writing/edits` for edits
    6. `presentations` for all presentations a. `presentations/slides` for slides b. `presentations/notes` for notes
- I'll further organize as needed
- See GitHub folder for this lecture as an example
    - I also include a script `make_directory.sh` that automates this process

# How I organize research projects

```
tree my_project
```

```
## my_project
## ├── code
## │   ├── analysis
## │   └── build
## ├── data
## │   ├── clean
## │   ├── raw
## │   │   └── my_data.csv
## │   └── temp
## ├── literature
## ├── output
## │   ├── figures
## │   └── tables
## ├── presentations
## │   ├── notes
## │   └── slides
## └── writing
##     ├── drafts
##     ├── edits
##     └── notes
##
## 18 directories, 1 file
```

# How I organize research projects




Source: My computer

# What is the value of directories?

- All of the files in a directory are related to each other
- Can reference a file within the `data/raw` folder, from the `code/build` folder, using a relative path: `../data/raw/my_data.csv`
  - `..` means "go up one directory", then down into `data/raw`
- Can save objects of strings of path directories to use later using the `paste()` function

```
my_project <- 'my_project'
data <- paste(my_project,'data',sep='/')
data_raw <- paste(data,'raw',sep='/')
data_clean <- paste(data,'clean',sep='/')
data_temp <- paste(data,'temp',sep='/')
code <- paste(my_project,'code',sep='/')
code_analysis <- paste(code,'analysis',sep='/')
code_build <- paste(code,'build',sep='/')

print(paste(data_raw,'my_data.csv',sep='/'))
```

```
## [1] "my_project/data/raw/my_data.csv"
```

```
read.csv(paste(data_raw,'my_data.csv',sep='/'))
```

```
##   this is my data
## 1    1  1  1    1
## 2    2  2  2    2
```

- This is a good way to make sure that your code is portable
- If you move your project to a different computer, you can just change the `my_project` variable and all the other paths will update automatically

# Alternative to all the pastes is here()

- Better yet is the here
  - `here()` will find the root directory of your project and then you can navigate from there

```
#install.packages('here')
library(here)
```

```
## here() starts at C:/Users/kgcsp/OneDrive/Documents/Education/Big Data/big-data-class-materials
```

```
here::i_am('my_project/code/build/.placeholder')
```

```
## here() starts at C:/Users/kgcsp/OneDrive/Documents/Education/Big Data/big-data-class-materials/lectures/02-empirical-workflow
```

```
here('data/raw','my_data.csv')
```

```
## [1] "C:/Users/kgcsp/OneDrive/Documents/Education/Big Data/big-data-class-materials/lectures/02-empirical-workflow/data/raw/my_data.csv"
```

- Can be less clunky than `paste()` and `sep='/'`

# How to write scripts

## Keep them modular

- Each script should do one thing and one thing only

- e.g. It takes an input in, it returns an output

    - Taking in a raw file and returning a cleaned version
    - Taking in two files and merging them
    - Taking in a cleaned file and returning a figure

## Have a main script that runs all scripts in order

- This is the script that you run to reproduce your results
- You will rarely run it all at once, but it will be a nice way to organize your thoughts
- This is a further benefit of a well-organized directory -- you can easily see what scripts you need to run in what order
- Use `source('rscript.R')` to run an external script

# Main script

```
#File: main.R
#By: Kyle Coombs
#What: Runs the project from start to finish in Python
#Date: 2023/09/12

#Install packages with housekeeping. Also put together paths.
source('housekeeping.R')
#User written functions can be sourced -- or you could write a package, your call
source(paste0(build,'clean_functions.R'))
source(paste0(analysis,'analysis_functions.R'))

#Import files
df1 <- read_csv(paste0(raw,'file1.csv'))
df2 <- read_parquet(paste0(raw,'file2.parquet'))
df3 <- read_dta(paste0(raw,'file3.dta'))

#Clean files
cleaned_df1  <- clean_df1(df1)
cleaned_df2  <- clean_df2(df2)
cleaned_df3  <- cf.clean_df3(df3)

#Merge files 1 to 2
merged_df1_df2 = merge(cleaned_df1, cleaned_df2, on=c('merge','vars'))

#Append file 1 to
append_df1_df2_df3 = rbind(merged_df1_df2, cleaned_df2)

#Analysis
sum_stats=summary_stats(append_df1_df2_df3,stats=c('mean','median','max'))
reg_results=basic_regression(append_df1_df2_df3)

#Tables will likely be made with a host of R packages
make_sum_figures(sum_stats)
make_figures(reg_results)
make_sum_tables(sum_stats)
make_tables(reg_results)
```

# Alternate master

```
#File: main.R
#By: Kyle Coombs
#What: Runs the project from start to finish in Python
#Date: 2023/09/12

#Install packages with housekeeping. Also put together paths.
source('housekeeping.R')
#User written functions can be sourced -- or you could write a package, your call
source(paste0(build,'clean_functions.R'))
source(paste0(analysis,'analysis_functions.R'))

#Import files
source(paste0(build,'import_census.R'))
source(paste0(build,'import_admin_data.R'))

#Clean files
source(paste0(build,'clean_census.R'))
source(paste0(build,'clean_admin_data.R'))

#Merge files 1 to 2
source(paste0(build,'merge_census_admin.R'))

#Analysis
source('analysis/summary_stats.R')
source('analysis/basic_regression.R')

#Tables will likely be made with a host of R packages
source('analysis/make_sum_figures.R')
source('analysis/make_reg_figures.R')
source('analysis/make_sum_tables.R')
source('analysis/make_reg_tables.R')
```

# Data organization

- The key idea is to practice **relational data base management**
- A relational database consists of many smaller data sets
- Each data set is tabular and has a unique, non-missing key
- Data sets "relate" to each other based on these keys
- You can implement these practices in any modern statistical analysis software (R, Stata, SAS, Python, Julia, SQL, ...)
- Gentzkow & Shapiro recommend not merging data sets until as far into your code pipeline as possible

# What problems would this create?

| county | state | cnty_pop | state_pop | region |
|---|---|---|---|---|
| 36037 | NY | 3817735 | 43320903 | 1 |
| 36038 | NY | 422999 | 43320903 | 1 |
| 36039 | NY | 324920 | . | 1 |
| 36040 | . | 143432 | 43320903 | 1 |
| . | NY | . | 43320903 | 1 |
| 37001 | VA | 3228290 | 7173000 | 3 |
| 37002 | VA | 449499 | 7173000 | 3 |
| 37003 | VA | 383888 | 7173000 | 4 |
| 37004 | VA | 483829 | 7173000 | 3 |

Source: Code and Data for the Social Sciences (p. 19)

# What's RDBM look like?

| county | state | population |
|---|---|---|
| 36037 | NY | 3817735 |
| 36038 | NY | 422999 |
| 36039 | NY | 324920 |
| 36040 | NY | 143432 |
| 37001 | VA | 3228290 |
| 37002 | VA | 449499 |
| 37003 | VA | 383888 |
| 37004 | VA | 483829 |

| state | population | region |
|---|---|---|
| NY | 43320903 | 1 |
| VA | 7173000 | 3 |

Source: Code and Data for the Social Sciences (p. 19)

# Abstraction

- What is abstraction? It means "reducing the complexity of something by hiding unnecessary details from the user"
- e.g. A dishwasher. All I need to know is how to put dirty dishes into the machine, and which button to press. I don't need to understand how the electrical wiring or plumbing work.
- In programming, abstraction is usually handled with functions
- Abstraction is usually a good thing
- But it can be taken to a harmful extreme: overly abstract code can be "impenetrable" which makes it difficult to modify or debug

# Rules for Abstraction

- Gentzkow & Shapiro give three rules for abstraction:

1. Abstract to eliminate redundancy
2. Abstract to improve clarity
3. Otherwise, don't abstract

# Abstract to eliminate redundancy

- Sometimes you might find yourself repeating lines of code with small modifications across the lines:

```
names ← c('one','two','three','four','five','one','two','three','four','five','one','two','three','four','five')

#Better
names_short ← c('one','two','three','four','five')
names_long ← c(names_short,names_short,names_short)

#Even better
name_repeater ← function(count,names_short=c('one','two','three','four','five')) {
    names_long ← rep(names_short, times = count)
    return(names_long)
}

print(names)
```

```
##  [1] "one"   "two"   "three" "four"  "five"  "one"   "two"   "three" "four"
## [10] "five"  "one"   "two"   "three" "four"  "five"
```

```
print(names_long)
```

```
##  [1] "one"   "two"   "three" "four"  "five"  "one"   "two"   "three" "four"
## [10] "five"  "one"   "two"   "three" "four"  "five"
```

```
print(name_repeater(3,names_short=names_short))
```

```
##  [1] "one"   "two"   "three" "four"  "five"  "one"   "two"   "three" "four"
## [10] "five"  "one"   "two"   "three" "four"  "five"
```

- Now if I need to make further changes to `name_repeater` I can do it once!

# Otherwise, don't abstract

- One could argue that the examples on the previous two slides are overly abstract
- OLS is a simple operation that only takes one line of code
- If we're only doing it once in our script, then it may not make sense to use the function version
- Similarly, it may not make sense to use the `name_repeater` function if I only need to use it to repeat five names three times
- This discussion points out that it can be difficult to know if one has reached the optimal level of abstraction
- As you're starting out programming, I would advise doing almost every inside of a function (i.e. err on the side of over-abstraction when starting out)

# Documentation

1. Don't write documentation you will not maintain

2. Code should be self-documenting

- Generally speaking, commented code is helpful
- However, sometimes it can be harmful if, e.g. code comments contain dynamic information
- It may not be helpful to have to rewrite comments every time you change the code
- Code can be "self-documenting" by leveraging abstraction: function arguments make it easier to understand what is a variable and what is a constant

# Documentation in R

- R has excellent built-in documentation called `Roxygen2`
- These make great documents above functions to increase readability
- Here's an example:

```
#' This is a sample function
#'
#' This function does something amazing.
#'
#' @param x A numeric input.
#' @return The result of the amazing operation.
#' @examples
#' amazing_function(5)
amazing_function <- function(x) {
  # function implementation
}
```

# Other documentation in R

- **R Help System:** access using `?function_name`
- **Package vignettes:** access using `vignette("vignette_name")`
- **Cheatsheets:** access at Posit Cheatsheets

# Time management

- Time management is key to writing clean code
- It is foolish to think that one can write clean code in a strained mental state
- Code written when you are groggy, overly anxious, or distracted will come back to bite you
- Schedule long blocks of time (1.5 hours - 3 hours) to work on coding where you eliminate distractions (email, social media, etc.)
- Stop coding when you feel that your focus or energy is dissipating

# Task management

- When collaborating on code, it is essential to not use email or Slack threads to discuss coding tasks
- Rather, use a task management system that has dedicated messages for a particular point of discussion (bug in the code, feature to develop, etc.)
- I use GitHub issues for all of my coding projects
- For my personal task management, I use Trello to take all tasks out of my email inbox and put them in Trello's task management system
- GitHub and Trello also have Kanban-style boards where you can easily visually track progress on tasks

# Workflow workflow workflow

## The Cunningham Empirical Workflow Conjecture

- The cause of most of your errors is **not** due to insufficient knowledge of syntax in your chosen programming language
- The cause of most of your errors is due to a poorly designed **Empirical Workflow**

# Empirical Workflow

- A workflow is a fixed set of routines you bind yourself to which when followed identifies the most common errors
  - Think of it as your morning routine: alarm goes off, go to wash up, make your coffee/tea, put pop tart in toaster, contemplate your existence in the universe until **ding**, eat pop tart repeat *ad infinitum*
- Finding the outlier errors is a different task; empirical workflows catch typical and common errors created by the modal data generating processes
- Empirical workflows follow a checklist

# Why do we use checklists?

- I got engaged in July am planning a wedding in Princeton for next July
- I also moved to New England in August and am still unpacking
    - Extra weird I live part-time in MA with my fiance
- I am teaching two upper-level electives
- I am trying to submit several papers to conferences/journals this year
- Each of these tasks gets a checklist:
    - Wedding: ☐ Finalize tent configuration

      ☐ Pick wedding colors
    - Unpacking: ☐ Put books on shelves

      ☐ Buy dresser
    - Big Data: ☐ Prep GitHub demo

      ☐ Create presentations repo
    - Public Economics: ☐ Update solutions for PS1

# To remember the obvious stuff you keep

- When I stop to think, I know I need to do everything on my checklists
- But then I forget when I move onto the next task
- Programming is the same, except you have an **empirical checklist**:
- The **empirical checklist**:
    - Covers the intermediate step between "getting the data" and "analyzing the data"
    - It largely focuses on ensuring data quality for the most common, easy to identify problems
    - It'll make you a better coauthor

# Simple data checks

- Simple, yet non-negotiable, programming commands and exercises to check for data errors

## Look at the data

- "Real eyes realize real lies" --Troy Ave via some dude from my high school
- This is a messy dataset of blood pressure adapted from work by Peter Higgins

```
bp <- read.csv('data/messier_bp.csv')
bp
```

```
##    STOP.Blood.Pressure.Study             X2        X3         X4        X5
## 1                       <NA>           <NA>      <NA>       <NA>      <NA>
## 2                     pat_id Month of birth Day birth Year birth      Race
## 3                          1             11        30       1967     White
```

## Check factor variables

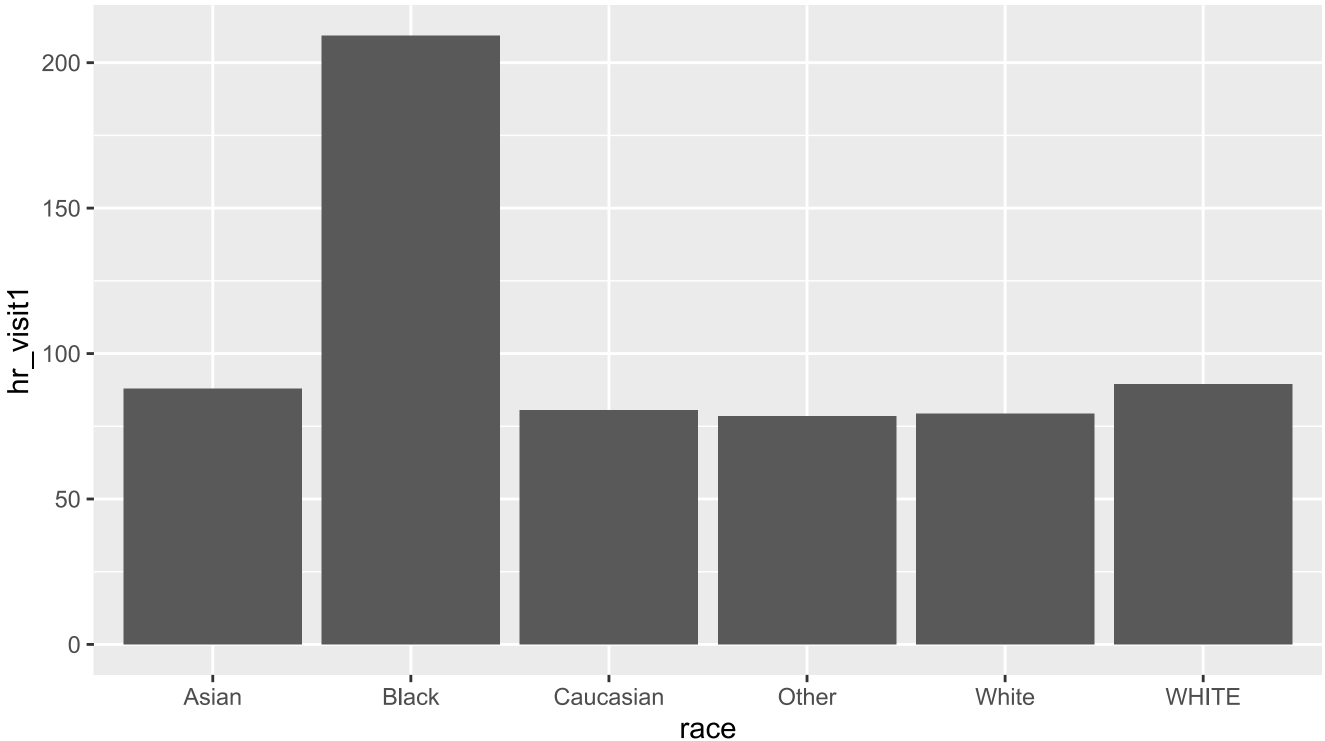
```
table(bp$race,bp$sex)
```

```
##
##              F Female M Male
##   Asian      0      1 0    1
##   Black      1      2 1    3
##   Caucasian  0      3 0    1
##   Other      0      1 0    1
##   White      0      2 0    2
```

# Before you summarize the data...

```
bp ← read_csv('data/messier_bp.csv',skip=4,
    col_names=c('pat_id','birth_month','birth_day','birth_year','race','sex','hispanic','bp_visit1','hr_visit1','bp_visit2','hr_visit

ggplot(data=bp,aes(y=hr_visit1,x=race)) + geom_bar(stat='summary',fun='mean')
```



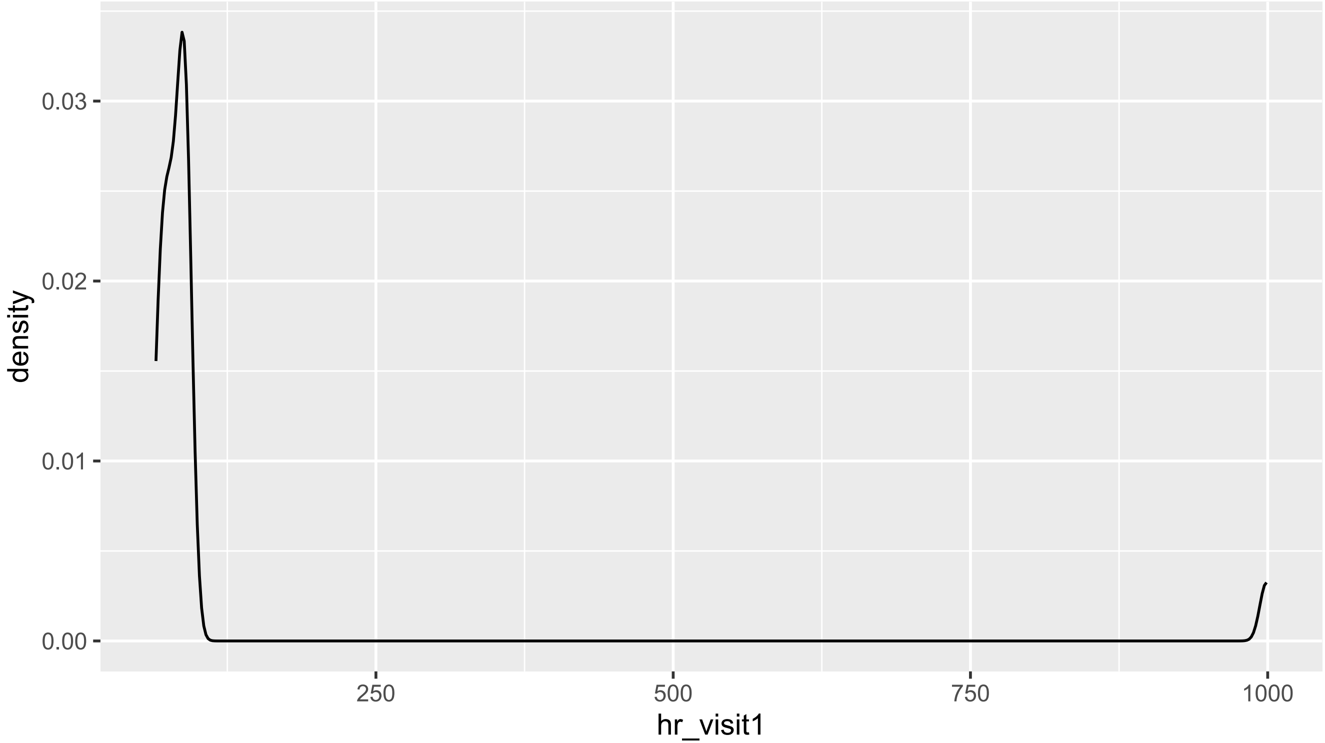

- Are Black people's heart rates really twice as high?

# Visualize the raw data

- Go beyond the eyeball and graph the data

```
# Get the first three rows of the data frame (or as many rows as needed)

#Make a density of the heart rate on visit 1:
ggplot(data=bp,aes(x=hr_visit1))+geom_density()
```

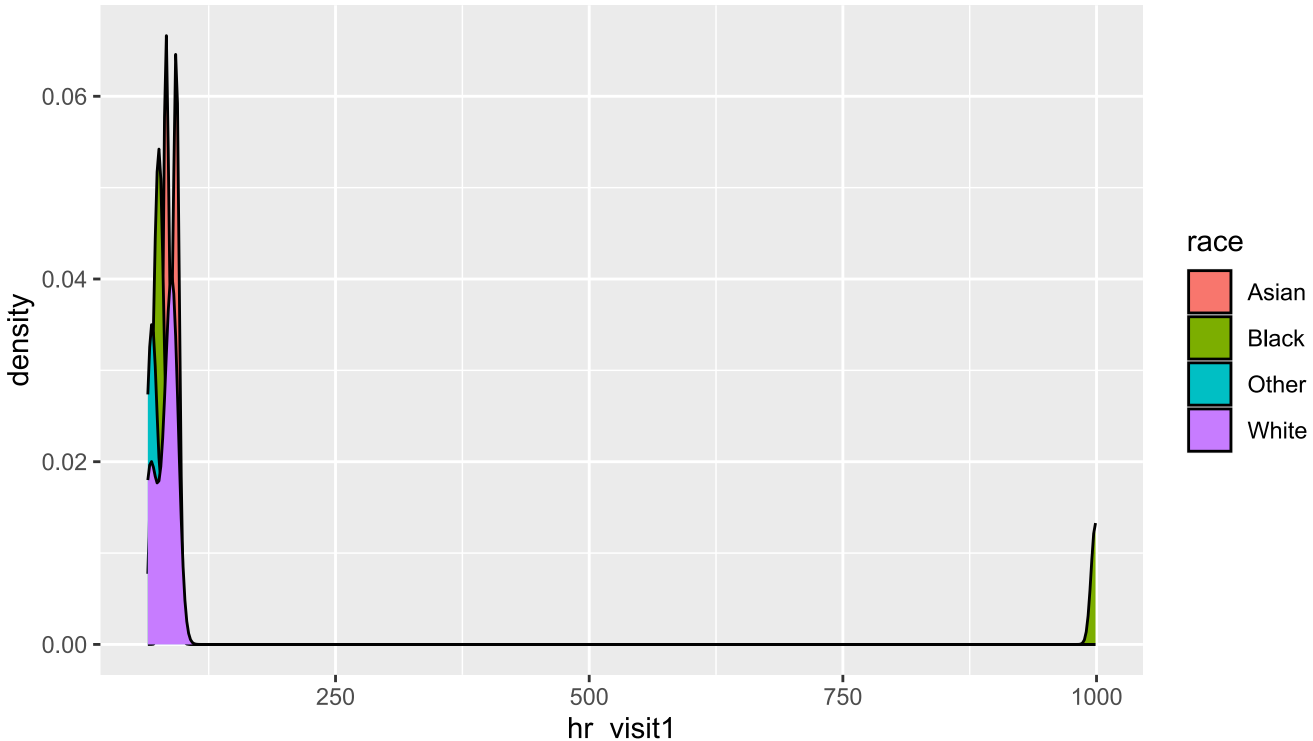



What might be going on here?

# Visualize by group

```
# Get the first three rows of the data frame (or as many rows as needed)

#Make a density of the heart rate on visit 1:
ggplot(data=bp %>% mutate(race=ifelse(race=='WHITE' | race=='Caucasian','White',race)),aes(x=hr_visit1,fill=race))+geom_density()
```




- Oh! I bet 999 means NA and a few Black patients have missing heart rates

# Other tricks:

- Check if the data are the right-size
- If you have a panel dataset is 50 states over 20 years, check if there are 1000 observations
- If not, find out why! Maybe there are 1020 because DC is (rightfully) included
- Search for outliers or oddities and work out possible explanations using:
    - Codebooks
    - Intuition
    - Emails to the source/creator of data

# Test-driven dev (unit testing, refactoring,

- The only way to know that your code works is to test it!
- Test-driven development (TDD) consists of a suite of tools for writing code that can be automatically tested
- **Unit testing** is nearly universally used in professional software development
- Unit testing is to software developers what washing hands is to surgeons

# Unit testing

- Unit tests are scripts that check that a piece of code does everything it is supposed to do
- When professionals write code, they also write unit tests for that code at the same time
- If code doesn't pass tests, then bugs are caught on the front end
- Test coverage determines how much of the code base is tested. High coverage rates are a must for unit testing to be useful.
- R's dplyr package shows that all unit tests are passing and that tests cover 88% of the code base
- testthat is a nice step-by-step guide for doing this in R

# Assertions

- Assert statements are extremely useful
- They exist in every langage
- In R it is called stopifnot()

```
x <- TRUE
stopifnot(x)

y <- FALSE
stopifnot(y)
```

```
## Error: y is not TRUE
```

# Minimal reproducible example (MRE)

- Sometimes you've made several changes to your code and suddenly it stops running
  - Was it the new `if` statement?
  - That sick new vectorized function to replace the `for` loop?
  - A stray typo?
- There's likely a ton of superfluous stuff in your code that is not relevant to the error
- Minimal reproducible examples (reprex), a concept from Stack Overflow, are a great way to isolate the error
  - Minimal: Use as little code as possible that still produces the same problem
  - Complete: Provide all parts someone else needs to reproduce your problem in the question itself
  - Reproducible: Test the code you're about to provide to make sure it reproduces the problem
- That means you should be able to copy and paste the code into R and run it yourself
  - Name all packages and data needed to reproduce error
  - Cut out irrelevant packages and data that are not relevant to the error
- Sometimes writing one will help you find the bug, sometimes it'll help a stranger find the bug in your code faster, and sometimes it'll identify a very real bug in the package itself

# Min Reprex

Example taken from RStudio community

```
library(ggplot2)

df <- data('iris') %>%
    mutate(Sepal.Length = Sepal.Length * 1000,
           Sepal.Width = Sepal.Width * 1000)
```

```
## Error in UseMethod("mutate"): no applicable method for 'mutate' applied to an object of class "character"
```

```
ggplot(data = df, x = Sepal.Length, y = Sepal.Width) +
    geom_point() +
    scale_x_log10() +
    theme_minimal() +
    labs(title = "Iris Sepal Width vs. Sepal Length",
         subtitle = "Log10 Scaled X Axis")
```

```
## Error in `ggplot()`:
## ! `data` cannot be a function.
## ℹ Have you misspelled the `data` argument in `ggplot()`
```

```
library(ggplot2)

df <- data.frame(stringsAsFactors = FALSE,
                 Sepal.Length = c(5.1, 4.9, 4.7, 4.6, 5),
                 Sepal.Width = c(3.5, 3, 3.2, 3.1, 3.6)
)
ggplot(data = df, x = Sepal.Length, y = Sepal.Width) +
    geom_point()
```

```
## Error in `geom_point()`:
## ! Problem while setting up geom.
## ℹ Error occurred in the 1st layer.
## Caused by error in `compute_geom_1()`:
```

# Refactoring

- Refactoring refers to the action of restructuring code without changing its external behavior or functionality. Think of it as "reorganizing"
- Example:

```
get_some_data <- function(config, outfile) {
  if (config_ok(config)) {
    if (can_write(outfile)) {
      if (can_open_network_connection(config)) {
        data <- parse_something_from_network()
        if(makes_sense(data)) {
          data <- beautify(data)
          write_it(data, outfile)
```

after refactoring becomes

```
get_some_data <- function(config, outfile) {
  if (config_bad(config)) {
    stop("Bad config")
  }

  if (!can_write(outfile)) {

    stop("Can't write outfile")
  }
```

- Nothing changed in the code except the number of characters in the function
- The new version may run faster, is more readable. The output is unchanged.
- Refactoring could also mean reducing the number of input arguments

# Profiling

- Profiling refers to checking the resource demands of your code
- How much processing time does your script take? How much memory?
- Clean code should be highly performant: it uses minimal computational resources
- Profiling and refactoring go hand in hand, along with unit testing, to ensure that code is maximally optimized
- Here is an intro guide to profiling in Julia using the `@time` macro

# Pair programming

- An essential part of clean code is reviewing code
- An excellent way to review code is to do so at the time of writing
- **Pair programming** involves sitting two programmers at one computer
- One programmer does the writing while the other reviews
- This is a great way to spot silly typos and other issues that would extend development time
- It's also a great way to quickly refactor code at the start
- **I strongly encourage you to do pair programming on problem sets in this course!**
    - (Sometimes I will require it)

# Appendix

# Textbooks: Smarter people than me

- Cunningham (2021) Causal Inference: The Mixtape (Also, free version on his website)
- Huntington-Klein (2022) The Effect
- Angrist and Pischke (2009) Mostly Harmless Econometrics (MHE)
- Morgan and Winship (2014) Counterfactuals and Causal Inference (MW)
- Sweigart (2019) Automate The Boring Stuff With Python

- The help documentation associated with your language (no really)
- Jesse Shapiro's "How to Present an Applied Micro Paper"
- Gentzkow and Shapiro's coding practices manual
- Ljubica "LJ" Ristovska's language agnostic guide to programming for economists
- Grant McDermott on Version Control using Github Link

- The help documentation associated with your language (no really)
- All languages: Stack Overflow, Stack Exchange
- Stata-specific (all hail Nick Cox): Statalist
- Cheatsheets: Stata, RStudio, Python
- Me: Sign up for office hours

- Just like learning a real language, no amount of talking today will teach you how to use any program.
    - You have to need to use it (immersion) to learn it.
    - Google is your dictionary.

# More complicated example of

```
set.seed(16)
prod1  = rnorm(1, 0, 1)*rnorm(1,4,6)
prod2  = rnorm(2, 0, 1)*rnorm(2,4,6)
prod3  = rnorm(3, 0, 1)*rnorm(3,4,6)
print(prod1)
```

```
## [1] 1.547257
```

```
print(prod2)
```

```
## [1] 11.934479 -1.717951
```

```
print(prod3)
```

```
## [1] -7.4831177  0.9587218  4.7882622
```

```
set.seed(16)
multiply = function(count,mean1=0,sd1=1,mean2=4,sd2=6) {
    prod = rnorm(count,mean1,sd1)*rnorm(count,mean2,sd2)
    return(prod)
}
prod1=multiply(1)
prod2=multiply(2)
prod3=multiply(3)

print(prod1)
```

```
## [1] 1.547257
```

# Note on seeds

- When randomizing in any language, you aren't really randomizing
- You're producing pseudo-random numbers that return in a deterministic ordered list
- If you set the seed, you can reproduce the same "random" numbers
- This is useful for debugging and sharing code
- Use `set.seed` in R

# Neat R functions to help reduce

```
set.seed(16)
list1 = list() # Make an empty list to save output in
for (i in 1:3) { # Indicate number of iterations with "i"
    list1[[i]] = multiply(i) # Save output in list for each iteration
}
list1
```

```
## [[1]]
## [1] 1.547257
##
## [[2]]
## [1] 11.934479 -1.717951
##
## [[3]]
## [1] -7.4831177  0.9587218  4.7882622
```

A better way to eliminate this redundancy is to use the `map` function:

```
set.seed(16)
map(1:3, multiply)
```

```
## [[1]]
## [1] 1.547257
##
## [[2]]
## [1] 11.934479 -1.717951
##
## [[3]]
## [1] -7.4831177  0.9587218  4.7882622
```

# Next lecture: Hidden Researcher Decisions