R mini-course: week 2

NORC, Academic Research Centers

http://lefft.xyz/r_minicourse

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housekeeping

agenda for the day:

- prep for next week
- week1 exercises
- quick R Studio tips + tricks
- looking at some real datasets
- packages
- reading ("loading/importing") and writing ("saving/exporting") data
- common operations for data cleaning and transformation
- writing pipe-chains via `magrittr::`'s forward pipe `%>%` (**if time**)
- writing your own functions (**if time**)

all materials on the course website:

http://lefft.xyz/r_minicourse

prep for next week

for next week: everyone obtain a dataset and send it to me!

(see sec 0 of week2 notes for details + some tips)

week1 exercises

a couple R Studio tips + tricks

1. multiple cursors in find+replace
2. "import dataset" functionality

multiple cursors

multiple cursors

multiple cursors

1. working with real data

iris and mtcars

```r
head(iris, n=5)
```

```
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1          5.1         3.5          1.4         0.2  setosa
## 2          4.9         3.0          1.4         0.2  setosa
## 3          4.7         3.2          1.3         0.2  setosa
## 4          4.6         3.1          1.5         0.2  setosa
## 5          5.0         3.6          1.4         0.2  setosa
```

```r
head(mtcars, n=5)
```

```
##                    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
```

We can just introduce a variable and assign a built-in dataset to it:

```
tim_mtcars <- mtcars
```

Let's check out what the columns are:

```
str(tim_mtcars)
```

```
## 'data.frame':    32 obs. of  11 variables:
##  $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
##  $ cyl : num  6 6 4 6 8 6 8 4 4 6 ...
##  $ disp: num  160 160 108 258 360 ...
##  $ hp  : num  110 110 93 110 175 105 245 62 95 123 ...
##  $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
##  $ wt  : num  2.62 2.88 2.32 3.21 3.44 ...
##  $ qsec: num  16.5 17 18.6 19.4 17 ...
##  $ vs  : num  0 0 1 1 0 1 0 1 1 1 ...
##  $ am  : num  1 1 1 0 0 0 0 0 0 0 ...
##  $ gear: num  4 4 4 3 3 3 3 4 4 4 ...
##  $ carb: num  4 4 1 1 2 1 4 2 2 4 ...
```

`mtcars` column info

- `mtcars$mpg` – miles per gallon
- `mtcars$cyl` – number of cylinders
- `mtcars$disp` – displacement (in^3)
- `mtcars$hp` – gross horsepower
- `mtcars$drat` – rear axle ratio
- `mtcars$wt` – weight (1000lb)
- `mtcars$qsec` – 1/4 mile time
- `mtcars$vs` – V/S (V- versus Straight block, I think)
- `mtcars$am` – automatic or manual transmission
- `mtcars$gear` – number of gears
- `mtcars$carb` – number of carburetors

row names :/

```
rownames(tim_mtcars)
```

```
##  [1] "Mazda RX4"           "Mazda RX4 Wag"       "Datsun 710"         
##  [4] "Hornet 4 Drive"      "Hornet Sportabout"   "Valiant"            
##  [7] "Duster 360"          "Merc 240D"           "Merc 230"           
## [10] "Merc 280"            "Merc 280C"           "Merc 450SE"         
## [13] "Merc 450SL"          "Merc 450SLC"         "Cadillac Fleetwood" 
## [16] "Lincoln Continental" "Chrysler Imperial"   "Fiat 128"           
## [19] "Honda Civic"         "Toyota Corolla"      "Toyota Corona"      
## [22] "Dodge Challenger"    "AMC Javelin"         "Camaro Z28"         
## [25] "Pontiac Firebird"    "Fiat X1-9"           "Porsche 914-2"      
## [28] "Lotus Europa"        "Ford Pantera L"      "Ferrari Dino"       
## [31] "Maserati Bora"       "Volvo 142E"
```

since **`rownames(tim_mtcars)`** is a character vector, we can just move it to a column and then delete the rownames.

```
tim_mtcars$make_model <- rownames(tim_mtcars)
rownames(tim_mtcars) <- NULL
```

missing values

Do we have any missing values?

```
# one way to check would be:
sum(is.na(tim_mtcars$mpg))
```

```
## [1] 0
```

```
sum(is.na(tim_mtcars$cyl))
```

```
## [1] 0
```

```
sum(is.na(tim_mtcars$disp))
```

```
## [1] 0
```

```
# ...
```

missing values

```
# a quicker way to check:
colSums(is.na(tim_mtcars))
```

```
##        mpg        cyl       disp         hp       drat         wt
##          0          0          0          0          0          0
##       qsec         vs         am       gear       carb make_model
##          0          0          0          0          0          0
```

```
# aaand make sure there aren't NA's that accidentally became characters
# (note "NA" is not the same as NA)
colSums(tim_mtcars=="NA")
```

```
##        mpg        cyl       disp         hp       drat         wt
##          0          0          0          0          0          0
##       qsec         vs         am       gear       carb make_model
##          0          0          0          0          0          0
```

2. a brief but necessary detour: packages!

If you are using a particular package for the first time, you will have to install it, which is done with `install.packages("<package name>")` (note quotes around the name). Everyone should install the following packages for the class:

```
# install.packages("dplyr")
# install.packages("reshape2")
# install.packages("ggplot2")
```

After a package is installed, you can "load" it (i.e. make its functions available for use) with `library("<packagename>")`. For this course, we'll use the following packages (maybe more too).

```
# don't worry if you get some output here that you don't expect!
# some packages send you messages when you load them. no need for concern.
library("dplyr")
library("reshape2")
library("ggplot2")
```

You can see your **library** – a list of your installed packages – by saying `library()`, *without* an argument. You can see which packages are currently **attached** ("loaded") with `search()`, again with no argument.

```
# see installed packages (will be different for everyone)
# library()

# see packages available *in current session*
search()
```

```
##  [1] ".GlobalEnv"        "package:ggplot2"   "package:reshape2"
##  [4] "package:dplyr"     "package:stats"     "package:graphics"
##  [7] "package:grDevices" "package:utils"     "package:datasets"
## [10] "package:methods"   "Autoloads"         "package:base"
```

note: R Studio has lots of point-and-click tools to deal with package management and data import. Look at the [R Studio IDE cheatsheet]() on the course page for details.

3. the outside world (or: reading and writing external files)

3.1 read from a url

Here's a cool word-frequency dataset:

```r
# link to url of a word frequency dataset
link <- "http://lefft.xyz/r_minicourse/datasets/top5k-word-frequency-dot-info.csv"
# read in the dataset with defaults (header=TRUE, sep=",")
words <- read.csv(link)
# look at the first few rows
head(words, n=5)
```

```
##   Rank Word PartOfSpeech Frequency Dispersion
## 1    1  the            a  22038615       0.98
## 2    2   be            v  12545825       0.97
## 3    3  and            c  10741073       0.99
## 4    4   of            i  10343885       0.97
## 5    5    a            a  10144200       0.98
```

3.2 read from a local file

Here's a government education dataset I found here.

```
# i saved it to a local folder, so I can read it in like this
edu_data <- read.csv("datasets/university/postscndryunivsrvy2013dirinfo.csv")
head(edu_data[, 1:10], n=5)
```

```
##   UNITID                                    INSTNM
## 1 100654            Alabama A & M University
## 2 100663 University of Alabama at Birmingham
## 3 100690                  Amridge University
## 4 100706 University of Alabama in Huntsville
## 5 100724            Alabama State University
##                               ADDR       CITY STABBR        ZIP FIPS OBEREG
## 1           4900 Meridian Street     Normal     AL      35762    1      5
## 2 Administration Bldg Suite 1070 Birmingham     AL 35294-0110    1      5
## 3                 1200 Taylor Rd Montgomery     AL 36117-3553    1      5
## 4                301 Sparkman Dr Huntsville     AL      35899    1      5
## 5           915 S Jackson Street Montgomery     AL 36104-0271    1      5
##                 CHFNM  CHFTITLE
```

3.3 reading different file types

excel .xls format:

```
library("readxl")
# an example of reading xls datasets
crime1 <- read_xls("datasets/crime/Crime2016EXCEL/noncampusarrest131415.xls")
crime2 <- read_xls("datasets/crime/Crime2016EXCEL/noncampuscrime131415.xls")

# see how many rows + columns each one has
dim(crime1); dim(crime2)
```

```
## [1] 11306    24
```

```
## [1] 11306    46
```

stata .dta format:

```
# an example of reading a stata dta file (note we need the haven:: package)
library("haven")
election_data <- read_dta("datasets/election/bes_f2f_original_v3.0.dta")

# notice that objects read from stata maintain some of their
# idiosyncratic internal structure -- e.g. you can see the survey items
# "embedded" inside the header fields in the R Studio spreadsheet view
head(election_data, n=5)
```

```
## # A tibble: 5 x 476
##   finalserialno serial wt_sel_wt wt_combined_main_capped wt_combined_main
##           <dbl>  <dbl>     <dbl>                   <dbl>            <dbl>
## 1         10102   2915  0.568195                0.594137         0.594137
## 2         10104   2505  1.136390                1.188274         1.188274
## 3         10107    876  1.136390                0.970153         0.970153
## 4         10109    875  1.136390                0.996799         0.996799
## 5         10202   3034  1.136390                0.968325         0.968325
## # ... with 471 more variables: wt_combined_CSES <dbl>, A1 <chr>,
## #   a02 <dbl+lbl>, a03 <dbl+lbl>, m02_1 <dbl+lbl>, m02_2 <dbl+lbl>,
```

extracting column info from .dta input:

```
# how many columns are there
numcols <- ncol(election_data)
# create an empty container to catch the column info text
election_data_colinfo <- rep(NA, times=numcols)
# for every number x between 1 and however many columns election_data has:
for (x in 1:numcols){
  # to the x'th element of
  election_data_colinfo[x] <- attributes(election_data[[x]])$label
}
# now make a df w each row as the name and description of an election_data col
election_dictionary <- data.frame(
  colname  = names(election_data),
  colinfo  = election_data_colinfo
)
```

we end up with a "data dictionary"

```r
# check out the first 20 -- not bad, eh?
head(election_dictionary, n=3)
```

```
##         colname                              colinfo
## 1 finalserialno                  Final Serial Number
## 2        serial             Respondent Serial Number
## 3     wt_sel_wt Selection weight (including capping)
```

3.4 simulating data

If we don't have actual data on a topic but still want to explore it quantitatively, a good option is to use randomly (but systematically) **simulate** some data.

```
# what's the probability that two of the people here have the same bday?!
# here's one strategy we could use:
# get a vector of days of the year
days <- seq(as.Date("2017-01-01"), as.Date("2017-12-31"), "days")
# define a df with 11 people, randomly assigning birthdays
birthday <- data.frame(
  # create 11 "people"
  person = paste0("person_", 1:11),
  # sample from days with replacement to assign birthdays
  bday   = sample(days, size=11, replace=TRUE)
)
# write a statement that'll be true iff two ppl have the same bday
length(unique(birthday$bday)) < nrow(birthday)
```

```
## [1] TRUE
```

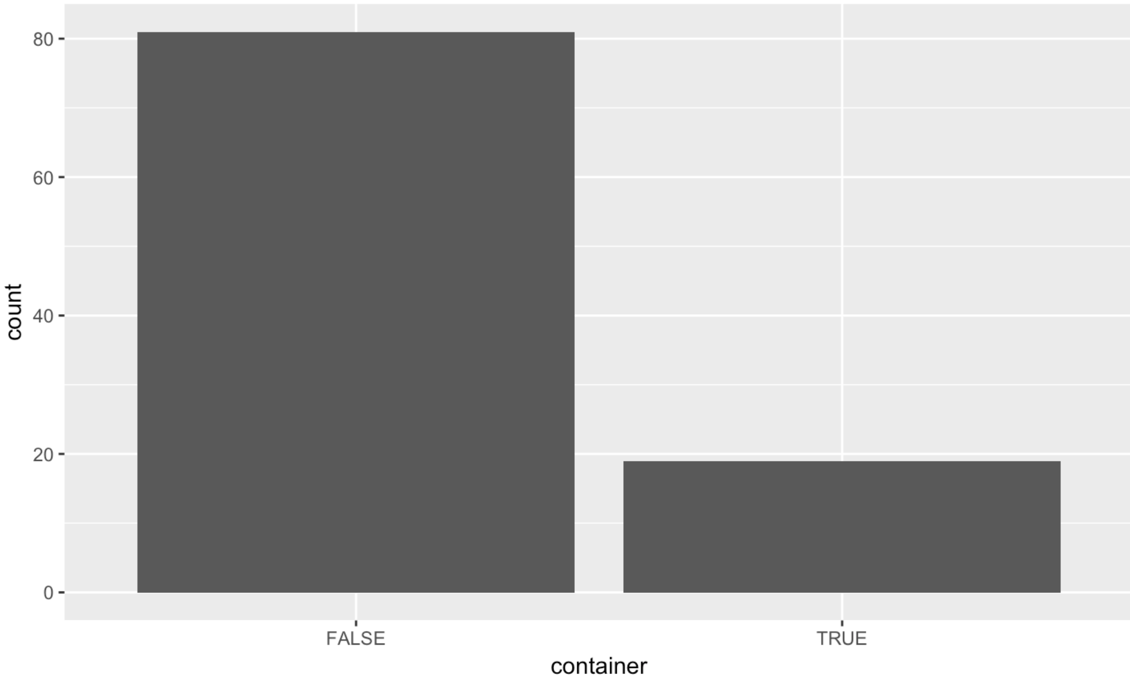
more on birthdays

here's a simple simulation, based on the strategy in the previous slide

```r
# define some parameters
numsims <- 100
numppl  <- 11
# make a container to hold the simulation results
container <- rep(NA, times=numsims)
# loop over 1,2,...,numsims and generate numppl-many birthdays
for (x in 1:numsims){
  dat <- sample(days, size=numppl, replace=TRUE)
  # for each iteration, assign TRUE to the container element if we have a match
  container[x] <- length(unique(dat)) < length(dat)
}
# now get the proportion of sims where there's a common bday
sum(container==TRUE) / length(container)
```

```
## [1] 0.19
```

```r
# make a quick plot to see the results
ggplot2::qplot(container)
```



3.5 cleaning up a dataset and then writing (saving) it

Say we want to introduce info about the region of the manufacturer of each make/model in the `mtcars` dataset. One approach:

- first, list all the manufacturers in the dataset, organizing them by where the maker is from.
- second, make a data frame consisting of all the unique manufacterers (`mfr`), and the regions associated with them.

```
### step 1

mfr_NA   <- c("Hornet", "Valiant", "Duster")             # unknown  manufacturer
mfr_asia <- c("Mazda", "Datsun", "Honda", "Toyota")      # asian    manufacturer
mfr_usa  <- c("Cadillac","Lincoln","Chrysler","Dodge", # american manufacturer
              "AMC","Chevrolet","Pontiac","Ford")        # european manufacturer
mfr_euro <- c("Mercedes", "Fiat", "Porsche", "Lotus",
              "Ferrari", "Maserati", "Volvo")
```

A good way to represent this information would be as a data frame with two columns: one listing the manufacturer, and the other listing the region.

```
### step 2

# make a data frame assigning regions to car types
car_regions <- data.frame(
  # the mfr_* vectors strung together
  make   = c(mfr_NA, mfr_asia, mfr_usa, mfr_euro),
  # assign regions to manufacturers, based on the mfr_* vectors and 'make'
  # the idea is to repeat the label for each value in the corresponding vector
  region = c(rep(NA,    length(mfr_NA)),   rep("asia", length(mfr_asia)),
             rep("usa", length(mfr_usa)),  rep("euro", length(mfr_euro))),
  # since we know we'll be joining this with another df, don't use factors
  stringsAsFactors=FALSE
)
```

```
print(car_regions)
```

```
##         make region
## 1     Hornet   <NA>
## 2    Valiant   <NA>
## 3     Duster   <NA>
## 4      Mazda   asia
## 5     Datsun   asia
## 6      Honda   asia
## 7     Toyota   asia
## 8   Cadillac    usa
## 9    Lincoln    usa
## 10  Chrysler    usa
## 11     Dodge    usa
## 12       AMC    usa
## 13 Chevrolet    usa
## 14   Pontiac    usa
## 15      Ford    usa
## 16  Mercedes   euro
## 17      Fiat   euro
## 18   Porsche   euro
```

let's recode `gear` as a category, instead of a number

```
# make a "lookup table" that associates values of gear with the labels we want
gear_lookup <- c(three=3, four=4, five=5)

# now combine names(), match(), and [] to recode the values how we want them
mtcars$gear <- names(gear_lookup[match(mtcars$gear, gear_lookup)])
```

note: since we manipulated `mtcars`, now it shows up in the environment pane in R Studio :)

some realistic data-cleaning operations (**many ways to skin a cat!**)

```r
# the variable 'mtcars_clean' will hold the result of piping mtcars
# into the chain mutate() %>% select() %>% rename()
mtcars_clean <- mtcars %>%
  mutate(
    car       = row.names(mtcars),                          # create 'car' column
    qsec      = round(qsec),                                # round qm time
    mpg       = round(mpg),                                 # round mpg
    wt        = wt * 1000,                                  # get weight in lbs
    am        = ifelse(am==0, "manual", "auto"),            # code as char
    musclecar = cyl >= 6 & hp > 200 & qsec < 16             # define a muscle car
  ) %>%
  select(
    car, am, gear, musclecar, cyl,
    hp, qsec, gear, wt, mpg
  ) %>%
  rename(
    horsepower=hp, cylinders=cyl, qm_time=qsec,
    num_gears=gear, lbs=wt, transmission=am
  )
```

now the dataset is cleaned up to our liking and now we want to use the cleaned up vesion as our official version of record (or share it with ppl)

```
# write as .csv (the default strategy)
write.csv(mtcars_clean, file="mtcars_clean.csv", row.names=FALSE)

# write as .rda (a compressed R data file -- can include multiple objects)
save(mtcars_clean, file="mtcars_clean.rda")
```

you can export to excel format, including multiple sheets

```r
# you'll get a message w instructions for installing some suggested packages --
# i recommend following them
library("rio")

# export to sheets of an Excel workbook
export(list(mtcars = mtcars, iris = iris), "multi.xlsx")
```

4. 99 problems!

see the notes for discussion of common problems/errors/pitfalls that will inevitably arise when you are learning how to read and write datasets from different sources and in different formats

5. now let's play with some data!

here's our cleaned up version of `mtcars`, which we saved as `mtcars_clean.csv`

```
# read it in
dat <- read.csv("mtcars_clean.csv")

knitr::kable(head(dat, 5))
```

car	transmission	num_gears	musclecar	cylinders	horsepower	qm_time	lbs	mpg
Mazda RX4	auto	four	FALSE	6	110	16	2620	21
Mazda RX4 Wag	auto	four	FALSE	6	110	17	2875	21
Datsun 710	auto	four	FALSE	4	93	19	2320	23
Hornet 4 Drive	manual	three	FALSE	6	110	19	3215	21
Hornet Sportabout	manual	three	FALSE	8	175	17	3440	19

now let's manipulate it in a bunch of ways.

what should we do?!

some ideas:

- aggregation
- subsetting
- grouping vars (dplyr)
- summary statistics
- contingency tables
- diagnostic plots
- modeling…

if time 1: pipe-chains

Most R commands consist of a function applied to one or more arguments (potentially assigning the result to a variable). In the case where there's only one argument, it can be nice to use the forward pipe operator `%>%`. This is part of a family of similar operators defined in the `magrittr::` package, and is made use of heavily in modern `dplyr::` data processing workflows.

It's not as scary as it looks: `x %>% f()` is equivalent to `f(x)`. What's nice about this is that you can make "pipe-chains" when you want to apply a sequence of functions to a single object (`dplyr::`'s functions are designed for exactly this). Forward pipe-chains have the following shape:

```
x %>% f() %>% g() %>% h() %>% z()
```

which is equivalent to:

```
z(h(g(f(x))))
```

assuming we want to save the result of `x` applied to `f()` through `z()`, we can just assign the whole chain to a variable. Here's a little example where given the schema above, `x` is `chars`, and `f()` and `g()` are `unique()` and `length()`.

```
chars <- sample(letters, size=20, replace=TRUE)

# we could write
numUnique <- length(unique(chars))
numUnique
```

```
## [1] 16
```

```
# or equivalently:
numUnique <- chars %>% unique() %>% length()
numUnique
```

```
## [1] 16
```

if time 2: writing functions

the more you use R, the more things you'll realize you could be doing in a way more efficient manner.

Learning to write your own functions is a crucial step in learning any programming language, including R.

```r
thing1 <- factor(rep(1:3, 5), labels=c("catA", "catB", "catC"))
thing2 <- factor(rep(4:6, 5), labels=c("catA", "catB", "catC"))
thing3 <- factor(rep(3:5, 5), labels=c("catA", "catB", "catC"))
thing4 <- factor(rep(2:4, 5), labels=c("catA", "catB", "catC"))
thing5 <- factor(rep(3:1, 5), labels=c("catA", "catB", "catC"))
```

question: how to get all the things coded as character?

one solution:

```
thing1 <- as.character(thing1)
thing2 <- as.character(thing2)
# ...
```

more compact (in the long run at least!), function-based solution

```
# a quick function to save us keystrokes
ac <- function(x){as.character(x)}

thing1 <- ac(thing1)
thing2 <- ac(thing2)
# ...
```

another example:

```
# saves us even more keystrokes
lu <- function(x){
  length(unique(x))
}

lu(thing1)
```

```
## [1] 3
```

```
length(unique(thing1))
```

```
## [1] 3
```

So what can writing functions do for you?

```
# define analysis routine
custom_summary <- function(df, group_col, measure_col){
  require("dplyr"); require("ggplot2")

  df <- data.frame(group_col=df[[group_col]], measure_col=df[[measure_col]])

  out_table <- df %>% group_by(group_col) %>% summarize(
    avg = mean(measure_col, na.rm=TRUE),
    sd  = sd(measure_col, na.rm=TRUE)     # ... more calculations
  ) %>% data.frame()

  out_plot <- ggplot(out_table, aes(x=group_col, y=avg)) +
    geom_bar(stat="identity") +
    geom_errorbar(aes(ymin=avg-sd, ymax=avg+sd, width=.25)) +
    labs(x=group_col, y=paste0("mean of ", measure_col, ", +/- sd"),
         title=paste0("average ", measure_col, " by ", group_col))

  out <- list(table=out_table, plot=out_plot)
  return(out)
}
```

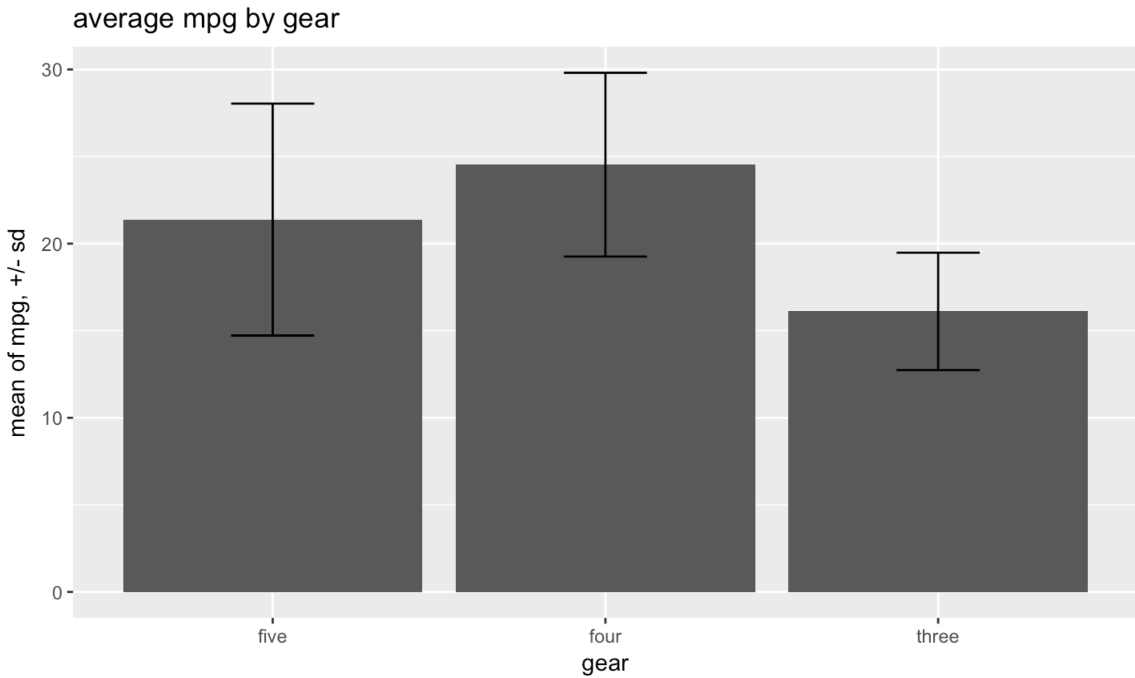
We can apply `custom_summary()` to `mtcars` in a number of ways. Summarize `mtcars$mpg` for each value of `mtcars$gear` using `custom_summary()`, and assign the result to the variable `mpg_by_gear`.

```
mpg_by_gear <- custom_summary(df=mtcars, group_col="gear", measure_col="mpg")
```

```r
# print a table
knitr::kable(mpg_by_gear$table)
```

group_col	avg	sd
five	21.38000	6.658979
four	24.53333	5.276764
three	16.10667	3.371618

```r
# display the plot
mpg_by_gear$plot
```



then rinse and repeat on whatever combo of dataset and variables you want!

(some combinations make more sense than others…)

next week…

- we look through everyone's datasets and discuss any issues that came up
- wide- vs long-format data, reshaping data, the concept of "tidy data"
- visualizing a dataset as a class (type-along)
- visualizing your own dataset with base graphics and `ggplot2::`