Intro to Base R iterations

And Lab 1

Daniel Anderson

Week 2

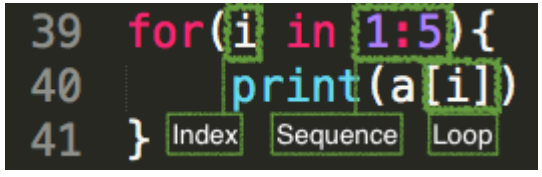
Agenda

- For loops
- Apply family of loops
  - `lapply()`
  - `sapply()`
  - `vapply()`
  - `apply()` (briefly)

Learning objectives

- Understand the basics of what it means to loop through a vector
- Begin to recognize use cases
- Be able to apply basic `for` loops and write their equivalents with `lapply`.

Basic overview: `for` loops




```
a <- letters[1:26]
a
```

```
##  [1] "a" "b" "c" "d" "e" "f" "g" "h" "i" "j" "k" "l" "m" "n" "o" "p" "q"
```

```
for(i in 1:5){
    print(a[i])
}
```

```
## [1] "a"
## [1] "b"
## [1] "c"
## [1] "d"
## [1] "e"
```

Note these are five different character scalars (atomic vectors of length one). It is NOT a single vector.

Creating indexes

- You will commonly see code like

```
for(i in 1:nrow(df))
```

- Instead, preference `seq_along()` or `seq_len()`.

Examples

```
x <- c(3, 2.6, 8)
seq_along(x)
```

```
## [1] 1 2 3
```

```
seq_len(length(x))
```

```
## [1] 1 2 3
```

seq_*

- `seq_along()` will create an index from 1 to the length of the vector
- `seq_len()` takes a single positive integer argument, and creates an index from 1 to that integer

Why are these preferable?

Avoid the `1:0` problem

```
means <- c()
out <- rep(NA, length(means))

for (i in 1:length(means)) {
  out[i] <- rnorm(10, means[i])
}
```

```
## Error in rnorm(10, means[i]): invalid arguments
```

`seq_*` version

```
means <- c()
out <- rep(NA, length(means))

for (i in seq_along(means)) {
  out[i] <- rnorm(10, means[i])
}
```

Basically, the loop is just not executed.

Another basic example

Simulate tossing a coin, record results

- For a single toss

```
sample(c("Heads", "Tails"), 1)
```

```
## [1] "Heads"
```

- For multiple tosses, first allocate a vector with `length` equal to the number of iterations

```
result <- rep(NA, 10)
result
```

```
##  [1] NA NA NA NA NA NA NA NA NA NA
```

- Next, run the trial n times, storing the result in your pre–allocated vector.

```
for(i in seq_along(result)) {
    result[i] <- sample(c("Heads", "Tails"), 1)
}
result
```

```
##  [1] "Tails" "Heads" "Tails" "Heads" "Tails" "Tails" "Tails" "Heads" "Ta
```

Growing vectors

- **Always** pre–allocate a vector for storage before running a `for` loop.
- Contrary to some opinions you may see out there, `for` loops are not actually slower than `lapply`, etc., provided the `for` loop is written well
- This primarily means not growing a vector

Example

100,000 coin flips by growing a vector

```
library(tictoc)

set.seed(1)
tic()
not_allocated <- sample(c("Heads", "Tails"), 1)
for(i in seq_len(1e5 - 1)) {
    not_allocated <- c(
      not_allocated,
      sample(c("Heads", "Tails"), 1)
     )

}
toc()
```

```
## 50.637 sec elapsed
```

same *exact* thing with pre–allocated vector

```
set.seed(1)
tic()
allocated <- rep(NA, 1e5)
for(i in seq_len(1e5)) {
    allocated[i] <- sample(c("Heads", "Tails"), 1)
}
toc()
```

```
## 0.855 sec elapsed
```

Result

- The result is the same, regardless of the approach (notice I forced the random number generator to start at the same place in both samples)

```
identical(not_allocated, allocated)
```

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

- Speed is obviously not identical

You try

Base R comes with `letters` and `LETTERS`

- Make an alphabet of upper/lower case. For example, create "Aa" with `paste0(LETTERS[1], letters[1])`
- Write a `for` loop for all letters

03:00

Answer

```
alphabet <- rep(NA, length(letters))

for(i in seq_along(alphabet)) {
    alphabet[i] <- paste0(LETTERS[i], letters[i])
}
alphabet
```

```
##  [1] "Aa" "Bb" "Cc" "Dd" "Ee" "Ff" "Gg" "Hh" "Ii" "Jj" "Kk" "Ll" "Mm" "N
## [22] "Vv" "Ww" "Xx" "Yy" "Zz"
```

Another example

- Say we wanted to simulate 100 cases from random normal distribution, where we varied the standard deviation in increments of 0.2, ranging from 1 to 5
- Hopefully this is a relatable example, but if not, that's okay – focus on the process.
- First, specify a vector standard deviations

```
increments <- seq(1, 5, by = 0.2)
```

- Next, allocate a vector. There are many ways I could store this result (data frame, matrix, list). I'll do it in a list.

```
simulated <- vector("list", length(increments))
```

Look at our vector

```
str(simulated)
```

```
## List of 21
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
##  $ : NULL
```

Write `for` loop

```
for(i in seq_along(simulated)) {
    simulated[[i]] <- rnorm(100, 0, increments[i])
    # note use of `[[` above
}
```

Now look at our vector

```
str(simulated)
```

```
## List of 21
##  $ : num [1:100] -2.387 0.405 -1.599 -0.285 0.288 ...
##  $ : num [1:100] 0.298 0.433 -1.021 1.384 -0.323 ...
##  $ : num [1:100] 0.893 -1.799 -0.819 -1.11 -2.198 ...
##  $ : num [1:100] -0.332 1.067 -0.823 2.899 1.863 ...
##  $ : num [1:100] -2.568 -0.672 -0.244 -1.645 2.221 ...
##  $ : num [1:100] 2.4 -1.95 1.13 3.05 3.56 ...
##  $ : num [1:100] -2.978 0.798 2.212 2.15 -2.197 ...
##  $ : num [1:100] -0.211 -1.768 3.35 2.06 0.213 ...
##  $ : num [1:100] 0.718 -4.029 -1.093 0.417 -3.952 ...
##  $ : num [1:100] 0.632 3.084 -2.62 -1.282 -2.965 ...
##  $ : num [1:100] 2.1759 -0.4681 1.6349 -0.0809 -0.7611 ...
##  $ : num [1:100] 1.236 3.055 -2.575 -0.868 4.369 ...
##  $ : num [1:100] 0.7795 -1.0125 -6.465 0.0926 1.8629 ...
```

List/data frame

- Remember, if all the vectors of our list are the same length, it can be transformed into a data frame.
- First, let's provide meaningful names

```
names(simulated) <- paste0("sd_", increments)
str(simulated)
```

```
## List of 21
##  $ sd_1  : num [1:100] -2.387 0.405 -1.599 -0.285 0.288 ...
##  $ sd_1.2: num [1:100] 0.298 0.433 -1.021 1.384 -0.323 ...
##  $ sd_1.4: num [1:100] 0.893 -1.799 -0.819 -1.11 -2.198 ...
##  $ sd_1.6: num [1:100] -0.332 1.067 -0.823 2.899 1.863 ...
##  $ sd_1.8: num [1:100] -2.568 -0.672 -0.244 -1.645 2.221 ...
##  $ sd_2  : num [1:100] 2.4 -1.95 1.13 3.05 3.56 ...
##  $ sd_2.2: num [1:100] -2.978 0.798 2.212 2.15 -2.197 ...
##  $ sd_2.4: num [1:100] -0.211 -1.768 3.35 2.06 0.213 ...
##  $ sd_2.6: num [1:100] 0.718 -4.029 -1.093 0.417 -3.952 ...
##  $ sd_2.8: num [1:100] 0.632 3.084 -2.62 -1.282 -2.965 ...
##  $ sd_3  : num [1:100] 2.1759 -0.4681 1.6349 -0.0809 -0.7611 ...
##  $ sd_3.2: num [1:100] 1.236 3.055 -2.575 -0.868 4.369 ...
##  $ sd_3.4: num [1:100] 0.7795 -1.0125 -6.465 0.0926 1.8629 ...
##  $ sd_3.6: num [1:100] 3.466 -1.245 0.496 3.67 -2.207 ...
```

Convert to df

```
sim_d <- data.frame(simulated)
head(sim_d)
```

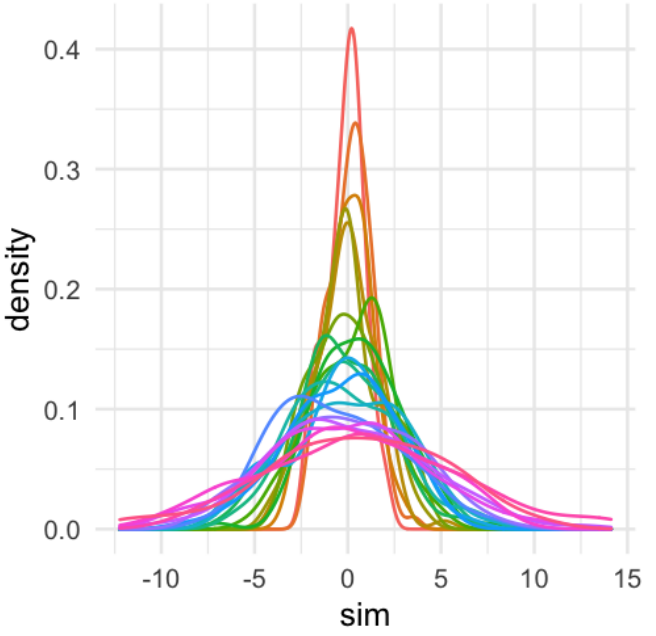
```
##         sd_1     sd_1.2     sd_1.4     sd_1.6     sd_1.8       sd_2      sd_2.8
## 1 -2.3872613  0.2979273  0.8930471 -0.3319310 -2.5676229  2.3954045 -2.9 0.6321448
## 2  0.4051212  0.4329239 -1.7989656  1.0673114 -0.6722755 -1.9542566  0.7 3.0843027
## 3 -1.5992856 -1.0209222 -0.8192303 -0.8232251 -0.2435614  1.1309855  2.2 -2.6196216
## 4 -0.2847246  1.3838266 -1.1097486  2.8991565 -1.6445420  3.0545722  2.1 -1.2824915
## 5  0.2881735 -0.3233308 -2.1982580  1.8633398  2.2213515  3.5578607 -2.1 -2.9646399
## 6  0.1175257 -0.4150724  0.6353818  0.7142314 -0.5219616 -0.8029945  0.1 4.5420524
##         sd_3     sd_3.2      sd_3.4     sd_3.6     sd_3.8     sd_4.6     sd_4.8
## 1 2.17589282  1.2362364  0.77947966  3.4658329 -2.7119876  2 2.4479578  0.6723229
## 2 -0.46812673  3.0554725 -1.01245886 -1.2451870 -4.2104097  6 -1.4721622 -4.7240885
## 3  1.63492841 -2.5751022 -6.46499466  0.4960868 -3.6861183 -3 4.4111688  3.3779921
## 4 -0.08085208 -0.8678742  0.09259855  3.6701383 -0.7277885  4 2.3400425 -1.8110032
## 5 -0.76111234  4.3687915  1.86290325 -2.2067855 -0.1416683  4 -0.3461786 10.3301558
## 6  3.53122922 -2.4194781 -1.14660593 -1.7557261 -2.2110984  4 4.7260451  0.4489877
##         sd_5
## 1  -3.464762
## 2   2.825094
## 3 -11.486532
## 4  -1.857547
## 5   7.544994
## 6   2.956989
```

tidyverse

- One of the *best* things about the tidyverse is that it often does the looping for you

```
library(tidyverse)
pd <- sim_d %>%
    pivot_longer(
      everything(),
      names_to = "sd",
      values_to = "sim",
      names_prefix = "sd_",
      names_ptypes = list(
        sd = factor()
      )
    )

ggplot(pd, aes(sim)) +
 geom_density(
   aes(color = sd)
 ) +
 guides(color = "none")
```



> Of course, someone has to write loops. It doesn't have to be you. --- Jenny Bryan

Base R Method

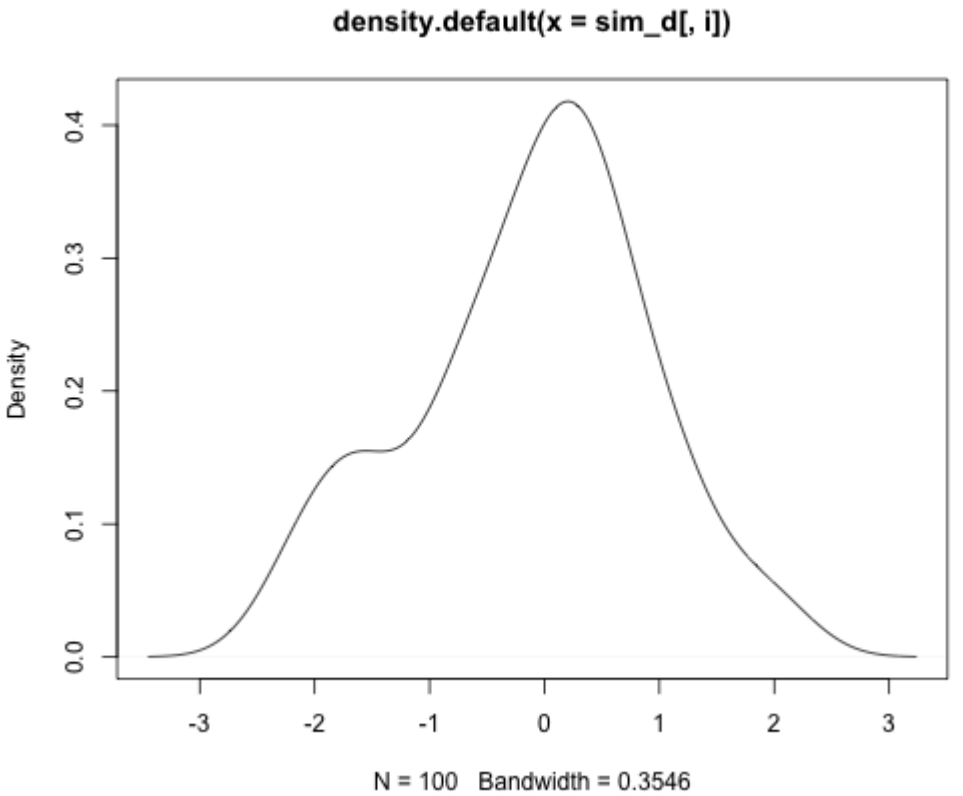
- Calculate all the densities

```
densities <- vector("list", length(sim_d))
for(i in seq_along(densities)) {
    densities[[i]] <- density(sim_d[ ,i])
}
str(densities)
```

```
## List of 21
##  $ :List of 7
##   ..$ x         : num [1:512] -3.45 -3.44 -3.42 -3.41 -3.4 ...
##   ..$ y         : num [1:512] 0.000173 0.000195 0.000219 0.000245 0.00027
##   ..$ bw        : num 0.355
##   ..$ n         : int 100
##   ..$ call      : language density.default(x = sim_d[, i])
##   ..$ data.name: chr "sim_d[, i]"
##   ..$ has.na    : logi FALSE
##   ..- attr(*, "class")= chr "density"
##  $ :List of 7
##   ..$ x         : num [1:512] -3.39 -3.38 -3.36 -3.35 -3.33 ...
##   ..$ y         : num [1:512] 0.000261 0.000296 0.000334 0.000377 0.00042
##   ..$ bw        : num 0.405
##   ..$ n         : int 100
##   ..$ call      : language density.default(x = sim_d[, i])
```

- Next, plot the first density

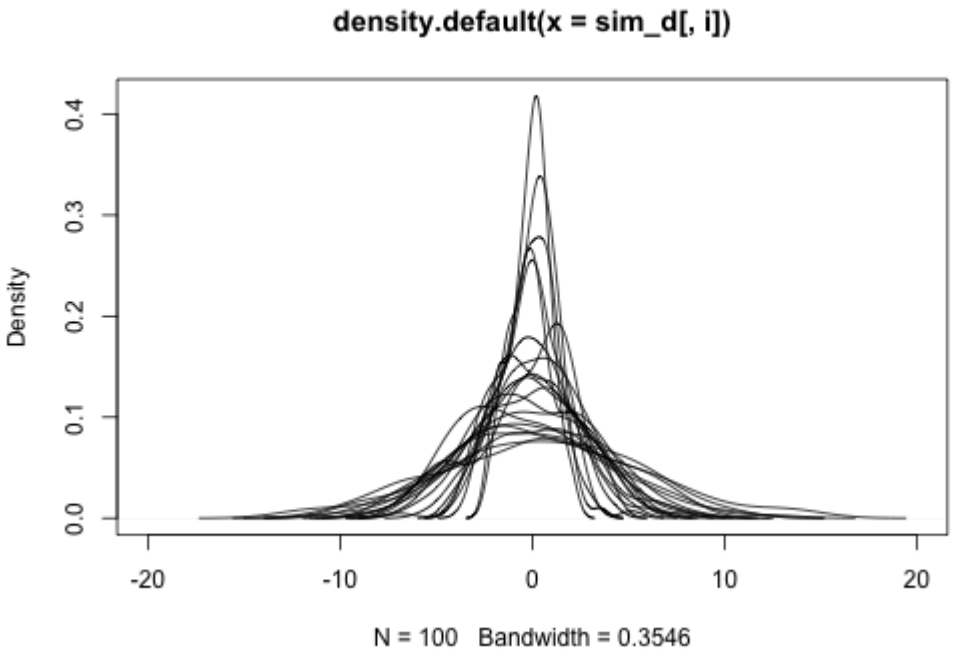
```
plot(densities[[1]])
```



- Finally, loop through all the other densities

```
plot(densities[[1]], xlim = c(-20, 20))

for(i in seq(2, length(densities))) {
    lines(x = densities[[i]]$x,
          y = densities[[i]]$y)
}
```



Skipping iterations

- On the prior slide, I set the index to skip over the first by using `seq(2, length(densities))`
- Alternatively, the loop could have been written like this

```
plot(densities[[1]], xlim = c(-20, 20))

for(i in seq_along(densities)) {
    if(i == 1) next
    lines(x = densities[[i]]$x,
          y = densities[[i]]$y)
}
```

Breaking loops

- Similarly, if a condition is met, you may want to break out of the loop

```
set.seed(1)

rand_unif <- vector("double", 10)

for(i in seq_along(rand_unif)) {
    rand_unif[i] <- runif(1, 0, 10)
    if(any(rand_unif > 5)) {
        break
    }
}

rand_unif
```

```
##  [1] 2.655087 3.721239 5.728534 0.000000 0.000000 0.000000 0.000000 0.00
```

*apply

`lapply`

- One of numerous *functionals* in R
- A functional "takes a function as an input and returns a vector as output" (adv–r, Chpt 9)
- `lapply` will **always** return a list

Revisiting our simulation with $n = 10$

Our `for` loop version

```
increments <- seq(1, 5, by = 0.2)

simulated <- vector("list", length(increments))

for(i in seq_along(simulated)) {
    simulated[[i]] <- rnorm(10, 0, increments[i])
}

simulated
```

```
## [[1]]
##  [1]  1.329799263  1.272429321  0.414641434 -1.539950042 -0.928567035 -0
##  [9]  0.763593461 -0.799009249
##
## [[2]]
##  [1] -1.3771884 -0.3473539 -0.3590581 -0.4938130  0.3026681 -1.0703054
## [10]  0.4528748
##
## [[3]]
##  [1]  0.18667091  1.12586531 -0.07994948  0.70505116  1.52007711 -0.9673
```

The `lapply` version

```
increments <- seq(1, 5, by = 0.2)
sim_l <- lapply(increments, function(sd) rnorm(10, 0, sd))
sim_l
```

```
## [[1]]
##  [1] -1.06620017 -0.23845635  1.49522344  1.17215855 -1.45770721  0.0950
##  [9]  1.40856336 -0.54176036
##
## [[2]]
##  [1]  0.33439767 -0.23276729  1.89138982 -1.77065716 -0.17352985 -1.1438
##  [9] -1.81739641 -0.07404891
##
## [[3]]
##  [1] -0.2061791  2.1582303 -1.3745979  0.6952094  2.3757270 -0.3650308 -
## [10] -1.4189555
##
## [[4]]
##  [1]  2.583603577  0.009027176 -4.647838497 -1.771463710  2.476107092 -1
##  [9] -2.554748823  0.785547796
##
## [[5]]
##  [1]  0.7588861  3.3730270  1.8621258  0.1472586 -0.1485428  1.0909322 -
## [10]  0.9907080
##
## [[6]]
```

Some more examples

Loop through a data frame

- Remember – a data frame is a list. We can loop through it easily

```
library(palmerpenguins)
lapply(penguins, is.double)
```

```
## $species
## [1] FALSE
##
## $island
## [1] FALSE
##
## $bill_length_mm
## [1] TRUE
##
## $bill_depth_mm
## [1] TRUE
##
## $flipper_length_mm
## [1] FALSE
```

```
lapply(mtcars, mean)
```

```
## $mpg
## [1] 20.09062
##
## $cyl
## [1] 6.1875
##
## $disp
## [1] 230.7219
##
## $hp
## [1] 146.6875
##
## $drat
## [1] 3.596563
##
## $wt
## [1] 3.21725
##
## $qsec
## [1] 17.84875
##
## $vs
## [1] 0.4375
##
## $am
## [1] 0.40625
##
## $gear
```

Add a condition

```
lapply(penguins, function(x) {
    if(is.numeric(x)) {
        mean(x, na.rm = TRUE)
    }
})
```

```
## $species
## NULL
##
## $island
## NULL
##
## $bill_length_mm
## [1] 43.92193
##
## $bill_depth_mm
## [1] 17.15117
##
## $flipper_length_mm
## [1] 200.9152
##
## $body_mass_g
## [1] 4201.754
##
## $sex
```

Add a second condition

```
lapply(penguins, function(x) {
    if(is.numeric(x)) {
      return(mean(x, na.rm = TRUE))
    }
    else if(is.character(x) | is.factor(x)) {
      return(table(x))
  }
})
```

```
## $species
## x
##    Adelie Chinstrap    Gentoo
##       152        68       124
##
## $island
## x
##    Biscoe     Dream Torgersen
##       168       124        52
##
## $bill_length_mm
## [1] 43.92193
##
## $bill_depth_mm
## [1] 17.15117
##
```

Passing arguments

There's missing data, so this won't work

```
head(airquality)
```

```
##   Ozone Solar.R Wind Temp Month Day
## 1    41     190  7.4   67     5   1
## 2    36     118  8.0   72     5   2
## 3    12     149 12.6   74     5   3
## 4    18     313 11.5   62     5   4
## 5    NA      NA 14.3   56     5   5
## 6    28      NA 14.9   66     5   6
```

```
lapply(airquality, mean)
```

```
## $Ozone
## [1] NA
##
## $Solar.R
## [1] NA
##
## $Wind
## [1] 9.957516
##
```

But this will.

```
lapply(airquality, mean, na.rm = TRUE)
```

```
## $Ozone
## [1] 42.12931
##
## $Solar.R
## [1] 185.9315
##
## $Wind
## [1] 9.957516
##
## $Temp
## [1] 77.88235
##
## $Month
## [1] 6.993464
##
## $Day
## [1] 15.80392
```

Alternative notation

The prior code could also be written like this

```
lapply(airquality, function(x) mean(x, na.rm = TRUE))
```

```
## $Ozone
## [1] 42.12931
##
## $Solar.R
## [1] 185.9315
##
## $Wind
## [1] 9.957516
##
## $Temp
## [1] 77.88235
##
## $Month
## [1] 6.993464
##
## $Day
## [1] 15.80392
```

Simulation again

```
lapply(seq(1, 5, 0.2), rnorm, n = 10, mean = 0)
```

```
## [[1]]
##  [1] -0.02516264 -0.16367334  0.37005975 -0.38082454  0.65295237  2.0613
##  [9] -0.72275312 -0.62916466
##
## [[2]]
##  [1] -2.1794473 -0.3111469  0.4015587 -1.7126011  2.3263539 -0.9114363 -
## [10]  1.9155850
##
## [[3]]
##  [1]  1.7884237  1.1045592  0.6460515 -0.6132968 -2.1109298 -3.1121246 -
## [10]  1.0198842
##
## [[4]]
##  [1] -1.4154959 -2.4615063 -1.6710007 -2.7490179  1.2860121 -2.4028595 -
## [10]  3.0302573
##
## [[5]]
##  [1] -3.1684074  1.6641842 -1.0017759 -0.3250514  2.6053925 -1.0928366
## [10]  2.5391869
##
## [[6]]
##  [1] -0.4491476 -0.4249910  1.3927569  1.8303650 -1.8467486  2.2937465 -
## [10] -0.2909816
##
```

Operations by group

Mimic dplyr::group_by

```
by_cyl <- split(mtcars, mtcars$cyl)
str(by_cyl)
```

```
## List of 3
##  $ 4:'data.frame':    11 obs. of  11 variables:
##   ..$ mpg : num [1:11] 22.8 24.4 22.8 32.4 30.4 33.9 21.5 27.3 26 30.4 .
##   ..$ cyl : num [1:11] 4 4 4 4 4 4 4 4 4 4 ...
##   ..$ disp: num [1:11] 108 146.7 140.8 78.7 75.7 ...
##   ..$ hp  : num [1:11] 93 62 95 66 52 65 97 66 91 113 ...
##   ..$ drat: num [1:11] 3.85 3.69 3.92 4.08 4.93 4.22 3.7 4.08 4.43 3.77
##   ..$ wt  : num [1:11] 2.32 3.19 3.15 2.2 1.61 ...
##   ..$ qsec: num [1:11] 18.6 20 22.9 19.5 18.5 ...
##   ..$ vs  : num [1:11] 1 1 1 1 1 1 1 1 0 1 ...
##   ..$ am  : num [1:11] 1 0 0 1 1 1 0 1 1 1 ...
##   ..$ gear: num [1:11] 4 4 4 4 4 4 3 4 5 5 ...
##   ..$ carb: num [1:11] 1 2 2 1 2 1 1 1 2 2 ...
##  $ 6:'data.frame':    7 obs. of  11 variables:
##   ..$ mpg : num [1:7] 21 21 21.4 18.1 19.2 17.8 19.7
##   ..$ cyl : num [1:7] 6 6 6 6 6 6 6
##   ..$ disp: num [1:7] 160 160 258 225 168 ...
##   ..$ hp  : num [1:7] 110 110 110 105 123 123 175
##   ..$ drat: num [1:7] 3.9 3.9 3.08 2.76 3.92 3.92 3.62
##   ..$ wt  : num [1:7] 2.62 2.88 3.21 3.46 3.44 ...
##   ..$ qsec: num [1:7] 16.5 17 19.4 20.2 18.3 ...
##   ..$ vs  : num [1:7] 0 0 1 1 1 1 0
```

```
lapply(by_cyl, function(x) mean(x$mpg))
```

```
## $`4`
## [1] 26.66364
##
## $`6`
## [1] 19.74286
##
## $`8`
## [1] 15.1
```

Your turn

Try splitting the penguins dataset by species and calculating the average `bill_length_mm`

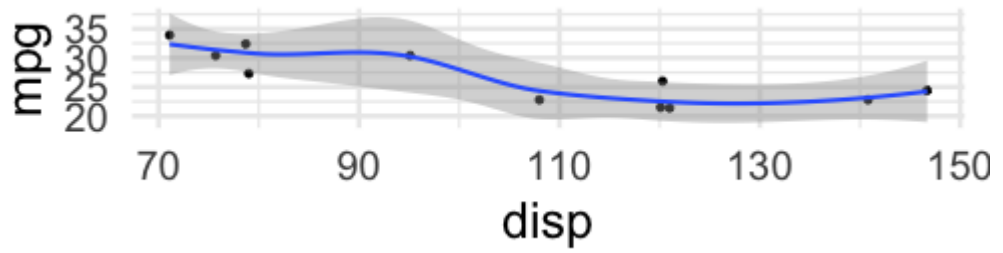
04:00

[demo]

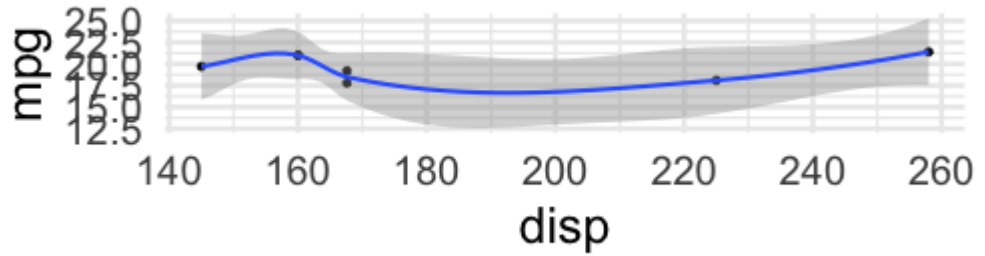
Produce separate plots

```
lapply(by_cyl, function(x) {
    ggplot(x, aes(disp, mpg)) +
        geom_point() +
        geom_smooth()
})
```

```
## $`4`
```


mpg
35
30
25
20
70
90
110
130
150
disp

```
##
## $`6`
```


mpg
25.0
22.5
20.0
17.5
15.0
12.5
140
160
180
200
220
240
260
disp

```
##
## $`8`
```

Your turn

Produce separate plots of the relation between `bill_length_mm` and `body_mass_g`

04:00

Saving

- You can extend this example further by saving the plot outputs to an object, then looping through that object to save the plots to disk.
- Using functionals, this would require parallel iterations, which we'll cover later (need to loop through plots and a file name)
- Could extend it fairly easily with a `for` loop

Saving w/ `for` loop

Save plots to an object (list)

```
plots <- lapply(by_cyl, function(x) {
    ggplot(x, aes(disp, mpg)) +
        geom_point() +
        geom_smooth()
})
```

Specify file names/directory

```
#dir.create(here::here("plots"))
filenames <- here::here(
  "plots",
  paste0("cyl", names(by_cyl), ".png")
)
filenames
```

```
## [1] "/Users/daniel/Teaching/data_sci_specialization/2021-22/c3-fp-2022/p
## [2] "/Users/daniel/Teaching/data_sci_specialization/2021-22/c3-fp-2022/p
## [3] "/Users/daniel/Teaching/data_sci_specialization/2021-22/c3-fp-2022/p
```

Saving

```
for(i in seq_along(plots)) {
    ggsave(filenames[i], # single bracket
           plots[[i]], # double bracket
           device = "png",
           width = 6.5,
           height = 8)
}
```

You try!

04:00

More than one groups

Let's say we wanted to create a plot of bill length vs bill depth by for each combination of species/island.

Just split by both! Pass both variables as a `list()`.

```
splt2 <- split(
  penguins,
  list(penguins$species, penguins$island)
)
```

Inspect it

```
splt2
```

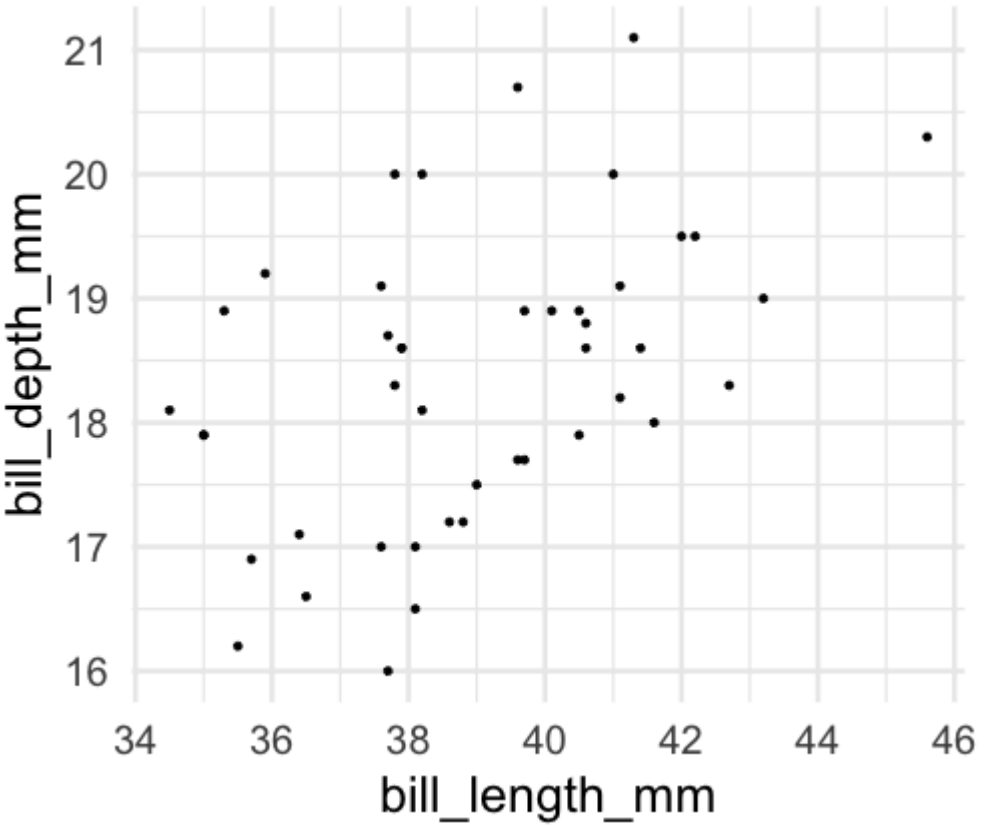
```
## $Adelie.Biscoe
## # A tibble: 44 × 8
##    species island bill_length_mm bill_depth_mm flipper_length_mm body_ma
##    <fct>   <fct>           <dbl>         <dbl>             <int>       <
##  1 Adelie  Biscoe           37.8          18.3               174
##  2 Adelie  Biscoe           37.7          18.7               180
##  3 Adelie  Biscoe           35.9          19.2               189
##  4 Adelie  Biscoe           38.2          18.1               185
##  5 Adelie  Biscoe           38.8          17.2               180
##  6 Adelie  Biscoe           35.3          18.9               187
##  7 Adelie  Biscoe           40.6          18.6               183
##  8 Adelie  Biscoe           40.5          17.9               187
##  9 Adelie  Biscoe           37.9          18.6               172
## 10 Adelie  Biscoe           40.5          18.9               180
## # … with 34 more rows
##
## $Chinstrap.Biscoe
## # A tibble: 0 × 8
## # … with 8 variables: species <fct>, island <fct>, bill_length_mm <dbl>,
## #   flipper_length_mm <int>, body_mass_g <int>, sex <fct>, year <int>
##
## $Gentoo.Biscoe
## # A tibble: 124 × 8
##    species island bill_length_mm bill_depth_mm flipper_length_mm body_ma
```

Create plots

```
plots2 <- lapply(splt2, function(x) {
  ggplot(x, aes(bill_length_mm, bill_depth_mm)) +
    geom_point()
})
```

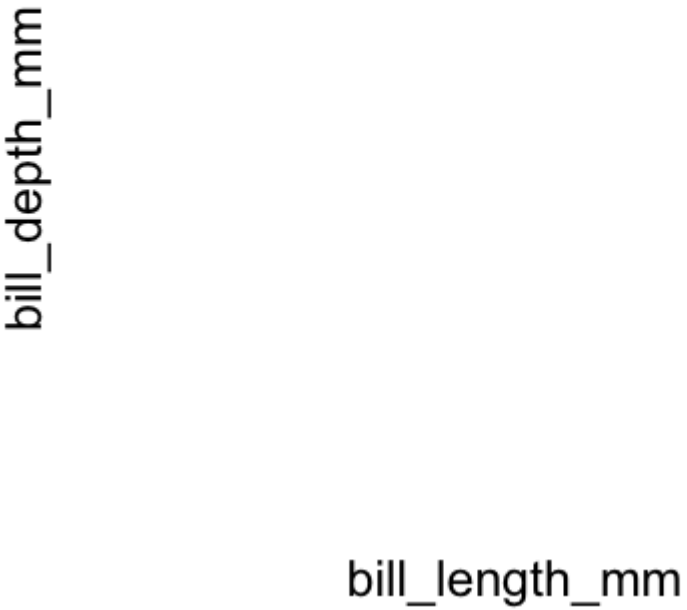
First few

```
plots2[[1]]
```



First few

```
plots2[[2]]
```



First few

```
plots2[[3]]
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```

Uh oh

Let's get rid of our empty plots – how? Ideas?

Create a logical vector that checks the number of rows.

We'll do this in a moment.

Variants of `lapply`

- `sapply`
  - Will try to **s**implify the output, if possible. Otherwise it will return a list.
  - Fine for interactive work, but I strongly recommend against it if writing a function (difficult to predict the output)
- `vapply`
  - Strict – you specify the output
  - Use if writing functions (or just always stick with `lapply`), or consider jumping to `{purrr}` (next week)

Examples

Our simulation

```
sim_s <- sapply(seq(1, 5, by = 0.2), function(x) {
  rnorm(10, 0, x)
})
class(sim_s)
```

```
## [1] "matrix" "array"
```

```
dim(sim_s)
```

```
## [1] 10 21
```

```
sim_s
```

```
##                [,1]        [,2]       [,3]       [,4]        [,5]        [
##  [1,] -2.939773695 -0.38696441 -2.0067288 -0.6857975  0.26119194 -2.6882
##  [2,]  0.002415809 -1.60656089 -1.4772590 -1.0498872 -4.39616038 -3.0463
##  [3,]  0.509665571  0.82578723 -1.0263566  1.5350309  1.04457363 -0.8439
##  [4,] -1.084720001  0.08553678  0.2952702  2.4896842  1.17909360  2.7218
##  [5,]  0.704832977  2.62770283 -1.3984890 -1.6652743 -0.54811591  3.5075
```

```
sapply(penguins, is.double)
```

```
##           species            island    bill_length_mm     bill_depth_mm
##             FALSE             FALSE              TRUE              TRUE
##               sex              year
##             FALSE             FALSE
```

- Now that it's a vector we can easily use it for subsetting

```
head(penguins)
```

```
## # A tibble: 6 × 8
##   species island    bill_length_mm bill_depth_mm flipper_length_mm body_
##   <fct>   <fct>              <dbl>         <dbl>             <int>
## 1 Adelie  Torgersen           39.1          18.7               181
## 2 Adelie  Torgersen           39.5          17.4               186
## 3 Adelie  Torgersen           40.3          18                 195
## 4 Adelie  Torgersen           NA            NA                  NA
## 5 Adelie  Torgersen           36.7          19.3               193
## 6 Adelie  Torgersen           39.3          20.6               190
```

```
head( penguins[ ,sapply(penguins, is.double)] )
```

```
## # A tibble: 6 × 2
##   bill_length_mm bill_depth_mm
##            <dbl>         <dbl>
## 1           39.1          18.7
## 2           39.5          17.4
## 3           40.3          18
## 4           NA            NA
## 5           36.7          19.3
## 6           39.3          20.6
```

Challenge

Can you make return the opposite? In other words – all those that are *not* double?

02:00

```
head( penguins[ ,!sapply(penguins, is.double)] )
```

```
## # A tibble: 6 × 6
##   species island    flipper_length_mm body_mass_g sex     year
##   <fct>   <fct>                 <int>       <int> <fct>  <int>
## 1 Adelie  Torgersen               181        3750 male    2007
## 2 Adelie  Torgersen               186        3800 female  2007
## 3 Adelie  Torgersen               195        3250 female  2007
## 4 Adelie  Torgersen                NA          NA <NA>    2007
## 5 Adelie  Torgersen               193        3450 female  2007
## 6 Adelie  Torgersen               190        3650 male    2007
```

Clean up our plots

Can you recreate the plots while omitting the empty ones now?

Try!

03:00

Remove zero–row dfs

```
# check if n rows > 0
keep <- sapply(splt2, function(x) nrow(x) > 0)
keep
```

```
##       Adelie.Biscoe    Chinstrap.Biscoe       Gentoo.Biscoe        Adeli
##                TRUE               FALSE                TRUE
##       Gentoo.Dream    Adelie.Torgersen Chinstrap.Torgersen    Gentoo.To
##              FALSE                TRUE               FALSE
```

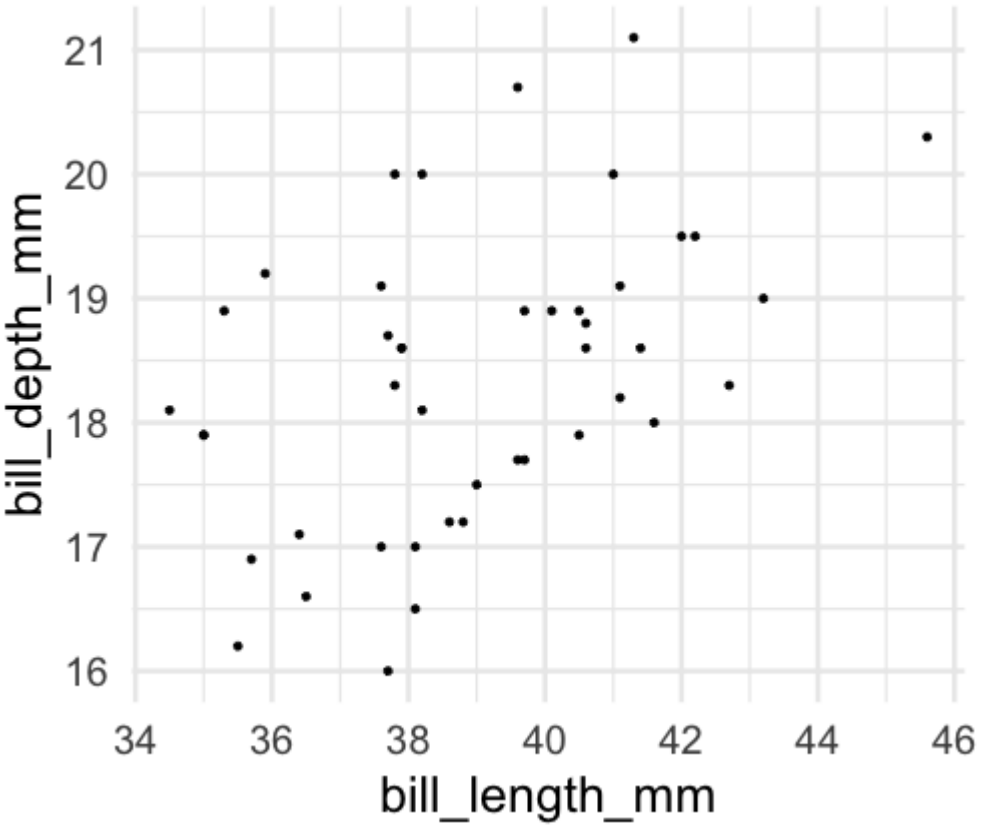
```
# Use this to subset the list
splt3 <- splt2[keep]
```

Recreate plots

```
plots3 <- lapply(splt3, function(x) {
  ggplot(x, aes(bill_length_mm, bill_depth_mm)) +
    geom_point()
})
```

First few

```
plots3[[1]]
```



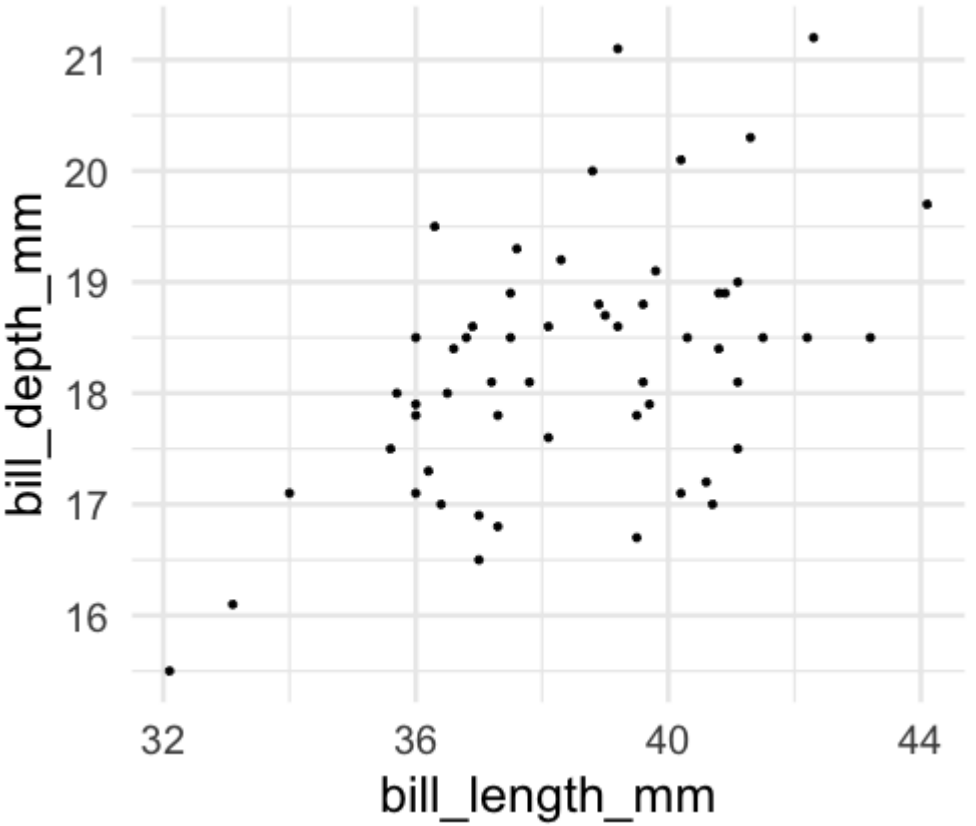
First few

```
plots3[[2]]
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```

First few

```
plots3[[3]]
```



vapply

- As you can probably see, simplifying can be *really* helpful for interactive work.

BUT

- Not ideal for programmatic work – need to be able to reliably predict the output
- `vapply` solves this issue.

```r
vapply(mtcars, mean, FUN.VALUE = double(1))
```

```
##        mpg        cyl       disp         hp       drat         wt
##  20.090625   6.187500 230.721875 146.687500   3.596563   3.217250  17.84
##       gear       carb
##   3.687500   2.812500
```

```r
vapply(penguins, is.double, FUN.VALUE = character(1))
```

```
## Error in vapply(penguins, is.double, FUN.VALUE = character(1)): values m
##  but FUN(X[[1]]) result is type 'logical'
```

```r
vapply(penguins, is.double, FUN.VALUE = logical(1))
```

```
##           species            island    bill_length_mm     bill_depth_mm
##             FALSE             FALSE              TRUE              TRUE
##               sex              year
##             FALSE             FALSE
```

Coercion with `vapply`

- If it can coerce the vector without loss of information, it will

```
vapply(penguins, is.double, FUN.VALUE = double(1))
```

```
##           species            island    bill_length_mm     bill_depth_mm
##                 0                 0                 1                 1
##           sex               year
##                 0                 0
```

Count missing data

```
vapply(airquality, function(col) {
  sum(is.na(col))
  },
  FUN.VALUE = double(1)
)
```

```
##   Ozone Solar.R    Wind    Temp   Month     Day
##      37       7       0       0       0       0
```

`sapply` alternative

For interactive work, the code on the previous slide is maybe too much. Could be reduced to

```
sapply(airquality, function(col) sum(is.na(col)))
```

```
##   Ozone Solar.R    Wind    Temp   Month     Day
##      37       7       0       0       0       0
```

Summary

- `for` loops are incredibly flexible and there's nothing inherently "wrong" about them
    - Do require more text, and often repetitive text, which can lead to errors/bugs
    - The flexibility can actually be more of a curse than a blessing

Summary

- The `lapply` family of functions help put the focus on a given function, and what values are being looped through the function
    - `lapply` will always return a list
    - `sapply` will try to simplify, which is problematic for programming, but fine for interactive work
    - `vapply` is strict, and will only return the type specified

apply

Quickly

`apply(x, dimension, function, function_args)`

- `x` The thing to loop over (usually a matrix or data frame)
- `dimension`
  - `1` = apply the function to each row
  - `2` = apply the function to each column
  - `n` = apply to nth dimension of an array (rare for the work I do)

Rows example

```
people <- data.frame(
  first = c("Frederick", "Anna", "Julia"),
  last = c("Douglass", "Murray", "Griffiths")
)
people
```

```
##       first      last
## 1 Frederick  Douglass
## 2      Anna    Murray
## 3     Julia Griffiths
```

Suppose we wanted a new column that was the first and last name.

We might try this

```
people %>%
  mutate(full_name = paste(first, last, collapse = " "))
```

```
##       first      last                                          full_name
## 1 Frederick  Douglass Frederick Douglass Anna Murray Julia Griffiths
## 2      Anna    Murray Frederick Douglass Anna Murray Julia Griffiths
## 3     Julia Griffiths Frederick Douglass Anna Murray Julia Griffiths
```

... but it pastes together the full columns

Instead, do it by row

```
apply(people, 1, paste, collapse = " ")
```

```
## [1] "Frederick Douglass" "Anna Murray"        "Julia Griffiths"
```

Or within a `mutate()` call

```
people %>%
  mutate(full_name = apply(people, 1, paste, collapse = " "))
```

```
##       first      last          full_name
## 1 Frederick  Douglass Frederick Douglass
## 2      Anna    Murray        Anna Murray
## 3     Julia Griffiths    Julia Griffiths
```

Column example

Back to the airquality example – standardize all columns.

Notice it returns a matrix though, which is less than ideal.

```
apply(airquality, 2, function(x) {
  as.numeric(scale(x))
})
```

```
##                Ozone       Solar.R        Wind        Temp       Month
##   [1,] -0.03423409  0.0451761540 -0.72594816 -1.14971398 -1.40729432 -1.
##   [2,] -0.18580489 -0.7543048742 -0.55563883 -0.62146702 -1.40729432 -1.
##   [3,] -0.91334473 -0.4100838759  0.75006604 -0.41016823 -1.40729432 -1.
##   [4,] -0.73145977  1.4109562438  0.43783226 -1.67796094 -1.40729432 -1.
##   [5,]           NA            NA  1.23260914 -2.31185730 -1.40729432 -1.
##   [6,] -0.42831817            NA  1.40291847 -1.25536337 -1.40729432 -1.
##   [7,] -0.57988897  1.2555015994 -0.38532950 -1.36101276 -1.40729432 -0.
##   [8,] -0.70114561 -0.9652790344  1.09068470 -1.99490912 -1.40729432 -0.
##   [9,] -1.03460136 -1.8535912880  2.87893266 -1.78361034 -1.40729432 -0.
##  [10,]           NA  0.0895917667 -0.38532950 -0.93841519 -1.40729432 -0.
##  [11,] -1.06491552            NA -0.86787260 -0.41016823 -1.40729432 -0.
##  [12,] -0.79208809  0.7780337632 -0.07309573 -0.93841519 -1.40729432 -0.
##  [13,] -0.94365889  1.1555664709 -0.21502017 -1.25536337 -1.40729432 -0.
##  [14,] -0.85271641  0.9779040202  0.26752293 -1.04406459 -1.40729432 -0.
```

Last bit

There are other loops, like `tapply()`, but I tend to not use them much (instead just use `lapply(split(x)`).

All of this stuff takes practice, both to understand how it works and to start to see use cases

Careful not to get into too deep of nested loops – if you're nesting beyond two levels (and I honestly never go beyond one anymore) there's probably better ways to approach it.

Lab 1