Welcome!

An overview of the course & intro to data types

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Week 1

Agenda

- Getting on the same page
- Syllabus
- Intro to data types

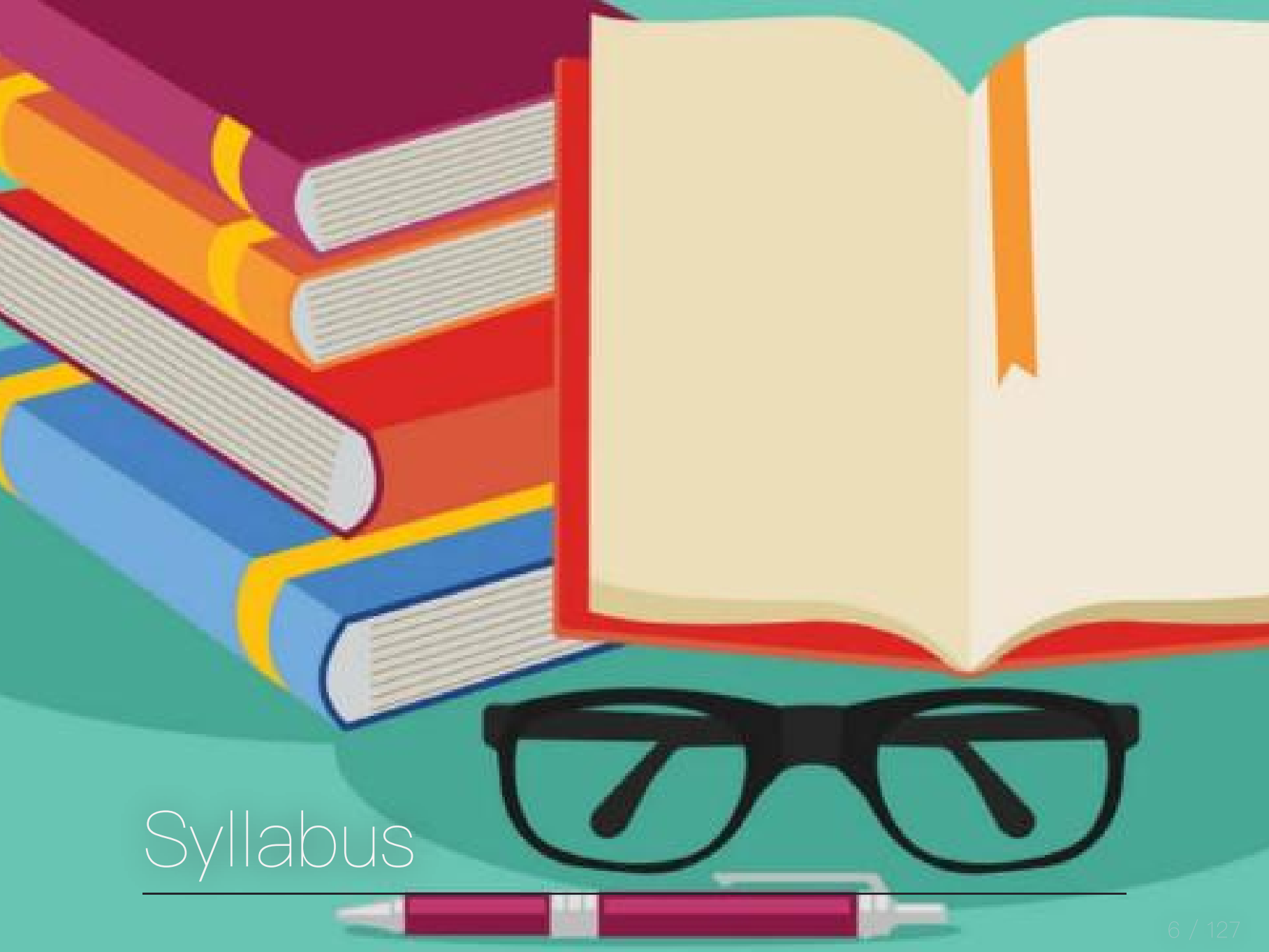
Getting on the same page

Introduce yourself!

- We mostly know each other, but it's always good to hear from each other.
- Tell us why you're taking the class
- What's one fun thing you've done recently outside of school stuff?
- What pronouns would you like us to use for you in this class?

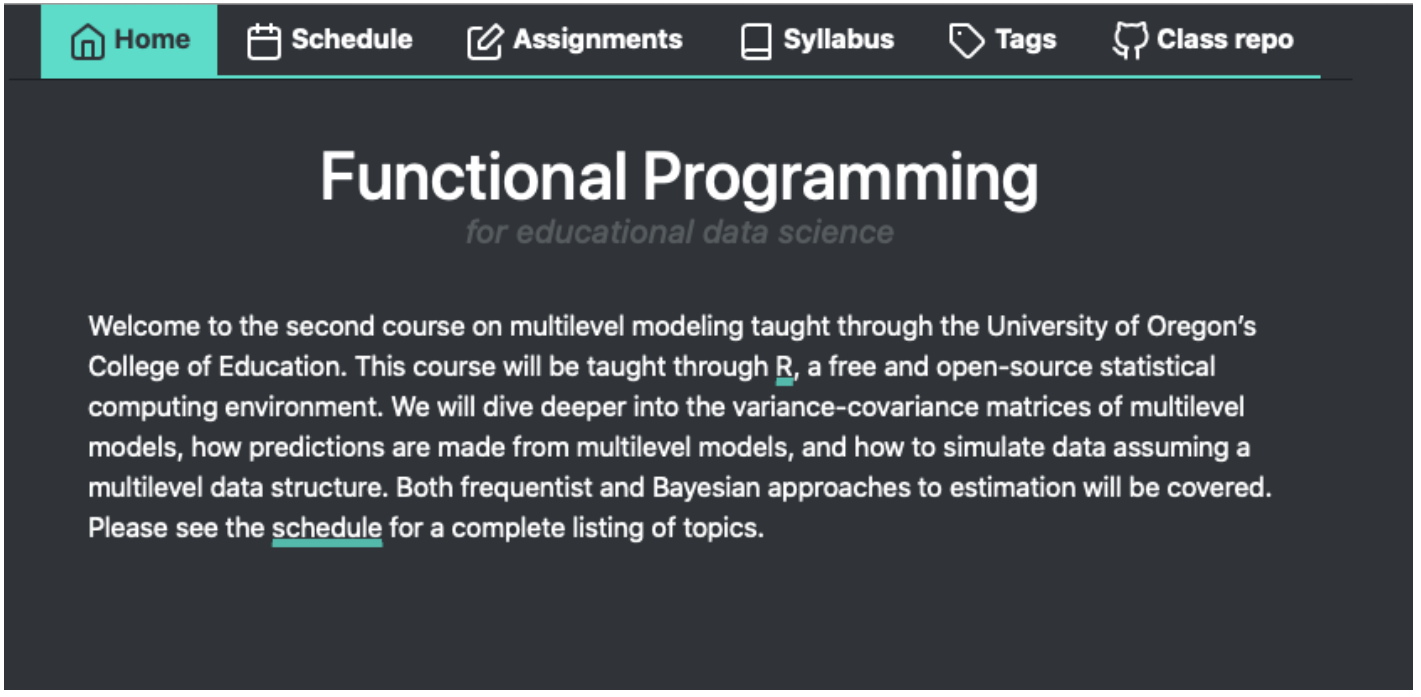
This term for me

- Full–time employed with Abl starting next week.
- This is my only UO responsibilities
- Doesn't mean I'm less committed to you
- Does mean time is going to be tricky
    - Friday afternoons will be best for meetings – can do evenings too if needed.



Syllabus

Course Website(s)



Course learning objectives

- Understand and be able to describe the differences in R's data structures and when each is most appropriate for a given task
- Explore `purrr::map` and its variants, how they relate to base R functions, and why the {purrr} variants are often preferable.
- Work with lists and list columns using `purrr::nest` and `purrr:unnest`
- Understand how `dplyr::rowwise()` can help you avoid some of the above

Course learning objectives

- Convert repetitive tasks into functions
- Understand elements of good functions, and things to avoid
- Write effective and clear functions with the mantra of "Don't Repeat Yourself"

This Week's learning objectives

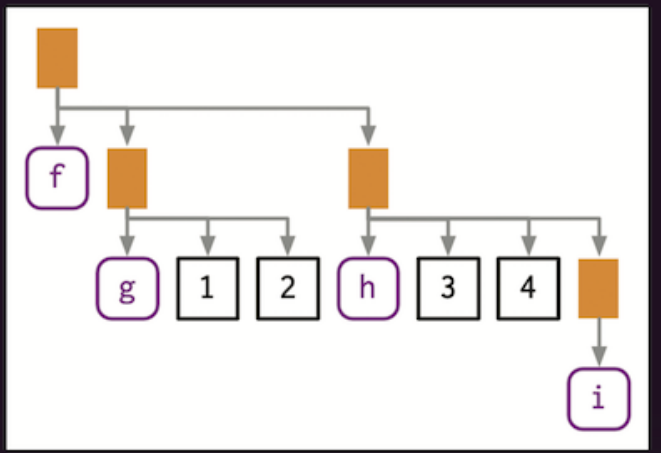
- Understand the requirements of the course
- Understand the requirements of the final project
- Understand the fundamental difference between lists and atomic vectors
- Understand how atomic vectors are coerced, implicitly or explicitly
- Understand various ways to subset vectors, and how subsetting differs for lists
- Understand attributes and how to set/modify

Textbooks

The R Series

Advanced R

Second Edition



Hadley Wickham

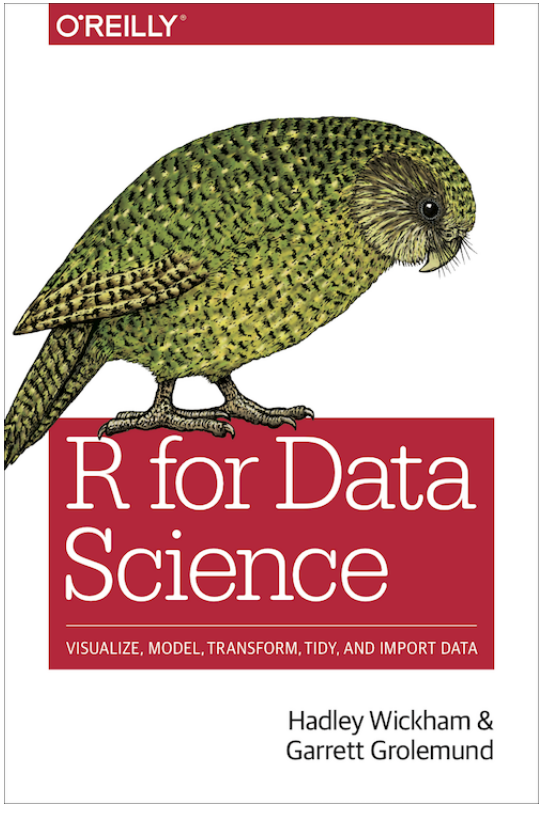
CRC Press
Taylor & Francis Group
A CHAPMAN & HALL BOOK

Link

Other books (also free)

Bryan

Wickham & Grolemund



Structure of the course

- First 5 weeks – mostly iteration
    - Data types
    - Base R iterations
    - {purrr}
    - Batch processes and working with list columns
    - Parallel iterations (and a few extras)
- Second 5 weeks – Writing functions and shiny
    - Writing functions 1–3
    - Shiny 1–3

Labs

15%

3 @ 10 points each

Two labs on iteration and one on functions.

If possible – please try to be in–class on Lab days. I understand this is not always possible, but it helps me help you.

Lab	Date Assigned	Date Due	Topic
1	Mon, April 04	Mon, April 11	Subsetting lists and base R `for()` loops
2	Mon, April 11	Mon, April 18	Multiple models and API calls with **{purrr}**
3	Mon, May 09	Mon, May 16	Create and apply functions

Midterm

70 points total (35%)

Two parts:

- Small quiz on canvas to demonstrate knowledge (4/22; 10 points)
    - Identifying bugs in code
    - Multiple choice/fill–in the blank questions
    - Free response
- Take–home portion to demonstrate ability to write the correct code (assigned 4/22; 60 points)
    - Write loops to solve problems

Take home midterm

- Group project: 3–5 people
- Shared GitHub repo
- Divide it up to ease the workload, then just check each other's work

Already posted!

Final Project

100 points total (60%)

5 parts

Component	Due	Points	Percentage of final grade
Groups finalized	04–04–22	0	0
Outline	04–18–22	5	2.5
Draft data script	05–16–22	10	5
Peer Review	05–23–22	15	7.5
Final Product	06–06–22	70	35

What is it?

Two basic options

Data Product

Similar to first class

- Brief research manuscript (can be APA or not, I don't really care 🤷)
- Shiny app
- Dashboard
    - Probably unlikely to work well though, unless you make it a shiny dashboard
- Blog post
- For the ambitious – a documented R package

Tutorial

- Probably best done through a blog post or series of blog posts
- Approach as if you're teaching others about the content I'll ask you to cover
- BONUS: You can actually release the blog post(s) and may get some traffic 🎉👏🥳


Make it your own

What you have to have

- Everything on GitHub
- Publicly available dataset
- Team of 2–5

What you have to cover

Unfortunately, this still is a class assignment. I have to be able to evaluate that you can actually apply the content within a messy, real–world setting.

The grading criteria (which follow) may force you into some use cases that are a bit artificial. This is okay.

Grading criteria

- No code is used repetitively (no more than twice) 10 points
- More than one variant of `purrr::map` is used 5 points
- At least one {purrr} function outside the basic `map` family (`walk_*`, `reduce`, `modify_*`, etc.) 5 points
- At least one instance of parallel iteration (e.g., `map2_*`, `pmap_*`) 5 points
- At least one use case of `purrr::nest %>% mutate()` 5 points

Grading criteria

- At least two custom functions 20 points; 10 points each
    - Each function must do exactly one thing
    - The functions **may** replicate the behavior of a base function – as noted above this is about practicing the skills you learn in class
- Code is fully reproducible and housed on GitHub 10 points
- No obvious errors in chosen output format 5 points
- Deployed on the web and shareable through a link 5 points

Outline

Due 4/18/21

Four components:

- Description of data source (must be publicly available)
- Purpose (tutorial or substantive)
- Chosen format
- Lingering questions
    - How can I help?

Please include all components – including the question(s) section!

Draft

Due 5/16/21, before class

- Expected to still be a work in progress
    - This means some of your code may be rough and/or incomplete. However:
- Direction should be obvious
- Most, if not all, grading elements should be present
- Provided to your peers so they can learn from you as much as you can learn from their feedback

Peer Review

- Exact same process we've used before
- If, during your peer review, you find grading elements not present, definitely note them

Utilizing GitHub (required)

- You'll be assigned two groups to review
- Fork their repo
- Embed comments, suggest changes to their code
    - Please do both of these
- Submit a PR
    - Summarize your overall review in the PR

Grading

200 points total

- 3 labs at 10 points each (30 points; 15%)
- Midterm in–class (10 points; 5%)
- Midterm take–home (60 points; 30%)
- Final Project (100 points; 50%)
    - Outline (5 points; 2.5%)
    - Draft (10 points; 5%)
    - Peer review (15 points; 7.5%)
    - Product (70 points; 35%)

Grading

Lower percent	Lower point range	Grade	Upper point range	Upper percent
0.970+	(194 pts or more)	A+		
0.930	(186 pts)	A	(193 pts)	0.969
0.900	(180 pts)	A–	(185 pts)	0.929
0.870	(174 pts)	B+	(179 pts)	0.899
0.830	(166 pts)	B	(173 pts)	0.869
0.800	(160 pts)	B–	(165 pts)	0.829
0.770	(154 pts)	C+	(159 pts)	0.799
0.730	(146 pts)	C	(153 pts)	0.769
0.700	(140 pts)	C–	(145 pts)	0.739
		F	(139 pts or less)	0.699


COMMUNICATION

Break

05:00

Basic data types

Vectors

05:00

Pop quiz

Discuss in small breakout groups

- What are the four basic types of atomic vectors?
- What function creates a vector?
- **T**/**F**: A list (an R list) is not a vector.
- What is the fundamental difference between a matrix and a data frame?
- What does *coercion* mean, and when does it come into play?

Vector types

4 basic types

Note there are two others (complex and raw), but we almost never care about them.

- Integer
- Double
- Logical
- Character

Integer and double vectors are both numeric.

Creating vectors

Vectors are created with `c`. Below are examples of each of the four main types of vectors.

```
# L explicitly an integer, not double
integer <- c(5L, 7L, 3L, 94L)
double <- c(3.27, 8.41, Inf, -Inf)
logical <- c(TRUE, TRUE, TRUE, FALSE, TRUE, FALSE, FALSE)
character <- c("red", "orange", "yellow", "green", "blue",
               "violet", "rainbow")
```

Coercion

- Vectors **must** be of the same type.
- If you try to mix types, implicit coercion will occur
- Implicit coercion defaults to the most flexible type
    - which is... ?

```
c(7L, 3.25)
```

```
## [1] 7.00 3.25
```

```
c(3.24, TRUE, "April")
```

```
## [1] "3.24"  "TRUE"  "April"
```

```
c(TRUE, 5)
```

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

Explicit coercion

- You can alternatively define the coercion to occur

```
as.integer(c(7L, 3.25))
```

```
## [1] 7 3
```

```
as.logical(c(3.24, TRUE, "April"))
```

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

```
as.character(c(TRUE, 5)) # still maybe a bit unexpected?
```

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

Checking types

- Use `typeof` to verify the type of vector

```
typeof(c(7L, 3.25))
```

```
## [1] "double"
```

```
typeof(as.integer(c(7L, 3.25)))
```

```
## [1] "integer"
```

Coercing to logical

```
as.logical(c(0, 1, 1, 0))
```

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

Any number that is not zero gets coerced to FALSE

```
as.logical(c(0, 5L, 7.4, -1.6, 0))
```

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

Wait... why the NA here?

```
as.logical(c(3.24, TRUE, "April"))
```

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

Piping

- Although traditionally used within the tidyverse (not what we're doing here), it can still be useful. The following are equivalent

```
library(magrittr)

typeof(as.integer(c(7L, 3.25)))
```

```
## [1] "integer"
```

```
c(7L, 3.25) %>%
  as.integer() %>%
  typeof()
```

```
## [1] "integer"
```

Don't actually need magrittr

Base pipe! |>

This is a bigger topic than I want to get into here, but for reference...

```
c(7L, 3.25) |>
  as.integer() |>
  typeof()
```

```
## [1] "integer"
```

Pop quiz

Without actually running the code, predict which type each of the following will coerce to.

```
c(1.25, TRUE, 4L)
c(1L, FALSE)
c(7L, 6.23, "eight")
c(TRUE, 1L, 0L, "False")
```

01:00

Answers

```
typeof(c(1.25, TRUE, 4L))
```

```
## [1] "double"
```

```
typeof(c(1L, FALSE))
```

```
## [1] "integer"
```

```
typeof(c(7L, 6.23, "eight"))
```

```
## [1] "character"
```

```
typeof(c(TRUE, 1L, 0L, "False"))
```

```
## [1] "character"
```

Lists

- Lists are vectors, but not *atomic* vectors
- Fundamental difference – each element can be a different type

```
list("a", 7L, 3.25, TRUE)
```

```
## [[1]]
## [1] "a"
##
## [[2]]
## [1] 7
##
## [[3]]
## [1] 3.25
##
## [[4]]
## [1] TRUE
```

Lists

- Each element of the list is another vector, possibly atomic, possibly not
- The prior example included all *scalar* vectors
- Lists do not require all elements to be the same length

```
list(
  c("a", "b", "c"),
  rnorm(5),
  c(7L, 2L),
  c(TRUE, TRUE, FALSE, TRUE)
)
```

```
## [[1]]
## [1] "a" "b" "c"
##
## [[2]]
## [1] -0.2693514 -0.3909654  1.3487070
##
## [[3]]
## [1] 7 2
##
## [[4]]
## [1]  TRUE  TRUE FALSE  TRUE
```

Summary

- Atomic vectors must all be the same type
    - implicit coercion occurs if not (and you haven't specified the coercion explicitly)
- Lists are also vectors, but not atomic vectors
    - Each element can be of a different type and length
    - Incredibly flexible, but often a little more difficult to get the hang of

Challenge

Work with a partner

One of you share your screen:

- Create four atomic vectors, one for each of the fundamental types
- Combine two or more of the vectors. Predict the implicit coercion of each.
- Apply explicit coercions, and predict the output for each.

(basically quiz each other)

05:00

Attributes

Attributes

- What are attributes?
    - metadata... what's metadata?
    - Data about the data

Other data types

Atomic vectors by themselves make up only a small fraction of the total number of data types in R

What are some other data types?

- Data frames
- Matrices & arrays
- Factors
- Dates

Remember, atomic vectors are the atoms of R. Many other data structures are built from atomic vectors.

- We use attributes to create other data types from atomic vectors

Attributes

Common

- Names
- Dimensions

Less common

- Arbitrary metadata

Examples

Please follow along!

- See **all** attributes associated with a give object with `attributes`

```
library(palmerpenguins)
attributes(penguins[1:50, ]) # limiting rows just for slides
```

```
## $names
## [1] "species"           "island"            "bill_length_mm"    "bill_de
## [6] "body_mass_g"       "sex"               "year"
##
## $row.names
##  [1]  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 2
## [36] 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50
##
## $class
## [1] "tbl_df"     "tbl"        "data.frame"
```

```
head(penguins)
```

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

Get specific attribute

- Access just a single attribute by naming it within `attr`

```
attr(penguins, "class")
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

```
attr(penguins, "names")
```

```
## [1] "species"           "island"            "bill_length_mm"    "bill_de
## [6] "body_mass_g"       "sex"               "year"
```

Note – this is not generally how you would pull these attributes. Rather, you would use `class()` and `names()`.

Be specific

- Note in the prior slides, I'm asking for attributes on the entire data frame.
- Is that what I want?... maybe. But the individual vectors may have attributes as well

```
attributes(penguins$species)
```

```
## $levels
## [1] "Big one"    "Little one" "Funny one"
##
## $class
## [1] "factor"
```

```
attributes(penguins$bill_length_mm)
```

```
## NULL
```

Set attributes

- Just redefine them within `attr`

```
attr(penguins$species, "levels") <- c("Big one",
                                      "Little one",
                                      "Funny one")

head(penguins)
```

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

Note – you would generally not define levels this way either, but it is a general method for modifying attributes.

Dimensions

- Let's create a matrix (please do it with me)

```
m <- matrix(1:6, ncol = 2)
m
```

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

- Notice how the matrix fills
- Check out the attributes

```
attributes(m)
```

```
## $dim
## [1] 3 2
```

Modify the attributes

- Let's change it to a 2 x 3 matrix, instead of 3 x 2 (you try first)

```
attr(m, "dim") <- c(2, 3)
m
```

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

- is this the result you expected?

Alternative creation

- Create an atomic vector, assign a dimension attribute

```
v <- 1:6
v
```

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

```
attr(v, "dim") <- c(3, 2)
v
```

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

Aside

- What if we wanted it to fill by row?

```
matrix(6:13,
       ncol = 2,
       byrow = TRUE)
```

```
##      [,1] [,2]
## [1,]    6    7
## [2,]    8    9
## [3,]   10   11
## [4,]   12   13
```

```
vect <- 6:13
dim(vect) <- c(2, 4)
vect
```

```
##      [,1] [,2] [,3] [,4]
## [1,]    6    8   10   12
## [2,]    7    9   11   13
```

```
t(vect)
```

```
##      [,1] [,2]
## [1,]    6    7
## [2,]    8    9
## [3,]   10   11
## [4,]   12   13
```

Names

- The following (this slide and the next) are equivalent

```
dim_names <- list(
    c("the first", "second", "III"),
    c("index", "value")
  )

attr(v, "dimnames") <- dim_names

v
```

```
##           index value
## the first     1     4
## second        2     5
## III           3     6
```

Names

```
v2 <- 1:6
attr(v2, "dim") <- c(3, 2)
rownames(v2) <- c("the first", "second", "III")
colnames(v2) <- c("index", "value")
v2
```

```
##           index value
## the first     1     4
## second        2     5
## III           3     6
```

Arbitrary metadata

```
attr(v, "matrix_mean") <- mean(v)
v
```

```
##           index value
## the first     1     4
## second        2     5
## III           3     6
## attr(,"matrix_mean")
## [1] 3.5
```

```
attr(v, "matrix_mean")
```

```
## [1] 3.5
```

- Note that *anything* can be stored as an attribute (including matrices or data frames, etc.)

Why would we do this?

This is a short example that is based on a real example

- Imagine we're accessing a database that has many years of data
- The tables in the database are the same, but the values (of course) differ
- We might want to return the data, but store the year as an attribute

This example is overly complicated for the first day, but it will give you an idea of what we're building toward.

Made up db

I'm using a list to mimic a database

```
db <- list(
  data.frame(
    color = c("red", "orange", "green"),
    transparency = c(0.80, 0.65, 0.93)
  ),
  data.frame(
    color = c("blue", "pink", "cyan"),
    transparency = c(0.40, 0.35, 0.87)
  )
)
```

```
db
```

```
## [[1]]
##    color transparency
## 1    red         0.80
## 2 orange         0.65
## 3  green         0.93
##
## [[2]]
##   color transparency
## 1  blue         0.40
## 2  pink         0.35
## 3  cyan         0.87
```

Write a function

Let's write a function that grabs one of these tables. If it's "1920" we'll grab the first one, otherwise we'll grab the second one.

```
pull_color_data <- function(year) {
  to_pull <- if(year == "1920") {
    out <- db[[1]]
  } else {
    out <- db[[2]]
  }
  out
}
```

Does it work?

```
pull_color_data(1920)
```

```
##    color transparency
## 1    red         0.80
## 2 orange         0.65
## 3  green         0.93
```

```
pull_color_data(2021)
```

```
##   color transparency
## 1  blue         0.40
## 2  pink         0.35
## 3  cyan         0.87
```

```
pull_color_data(2122)
```

```
##   color transparency
## 1  blue         0.40
## 2  pink         0.35
## 3  cyan         0.87
```

Yes!

Build a second function

Let's say we want to make a second function that does something with the previous output.

BUT

What we do with it is going to depend on the data frame we get back.

We need to know the year.

Modify our original function to store the year as an attribute!

Notice we redefine the attributes so we're including all the prior attributes it already had.

```
pull_color_data <- function(year) {
  to_pull <- if(year == "1920") {
    out <- db[[1]]
  } else {
    out <- db[[2]]
  }
  attributes(out) <- c(
    attributes(out),
    db = year
  )
  out
}
```

Try

```
pull_color_data(1920)
```

```
##    color transparency
## 1    red         0.80
## 2 orange         0.65
## 3  green         0.93
```

```
attr(pull_color_data(2021), "db")
```

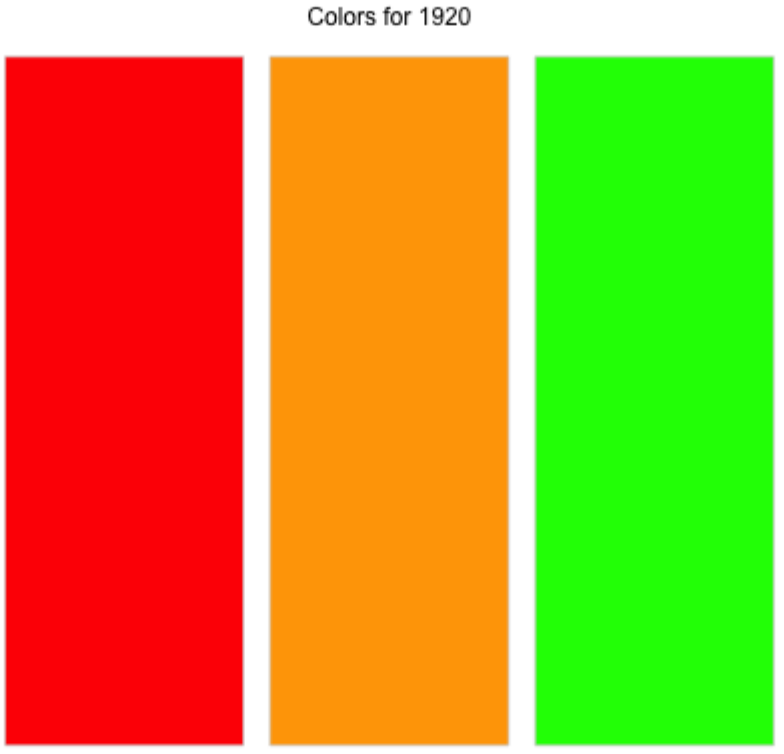
```
## [1] 2021
```

Build our second function

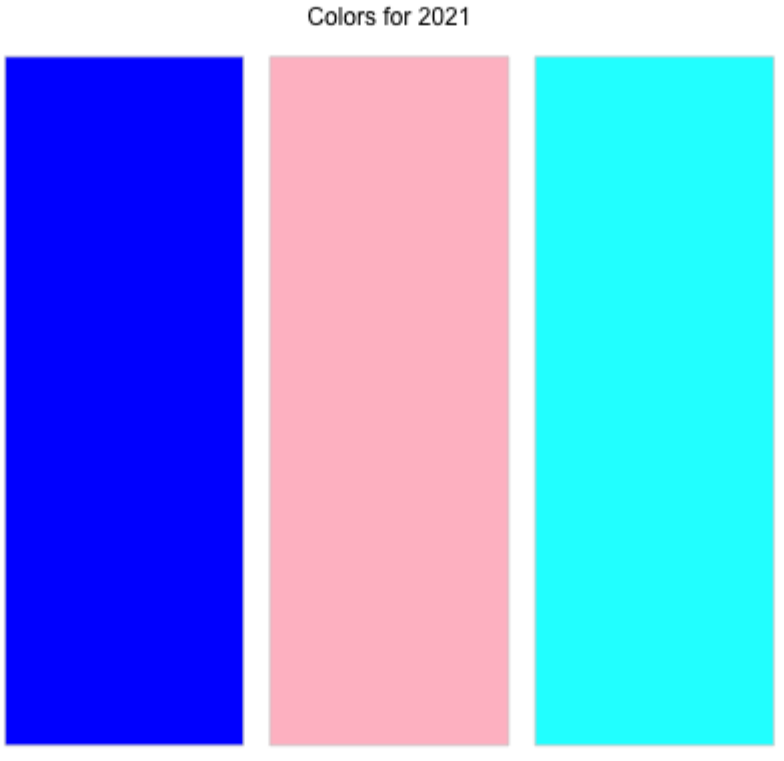
Now, we can make our second function, and have it do something different depending on the data that is passed to it.

```
print_colors <- function(color_data) {
  title <- paste0("Colors for ", attr(color_data, "db"))
  colorspace::swatchplot(color_data$color)
  mtext(title) # base plotting function
}
```

```
pull_color_data(1920) %>%
  print_colors()
```



```
pull_color_data(2021) %>%
  print_colors()
```



Another example

Fit a multilevel model and pull the variance–covariance matrix

```
m <- lme4::lmer(Reaction ~ 1 + Days + (1 + Days|Subject),
                data = lme4::sleepstudy)

lme4::VarCorr(m)$Subject
```

```
##             (Intercept)      Days
## (Intercept)  612.100158  9.604409
## Days           9.604409 35.071714
## attr(,"stddev")
## (Intercept)         Days
##   24.740658    5.922138
## attr(,"correlation")
##             (Intercept)       Days
## (Intercept)  1.00000000 0.06555124
## Days         0.06555124 1.00000000
```

Matrices vs Data frames

Usually we want to work with data frames because they represent our data better.

Sometimes a matrix is more efficient because you can operate on the **entire** matrix at once.

```
set.seed(42)
m <- matrix(rnorm(100, 200, 10), ncol = 10)
m
```

```
##           [,1]     [,2]     [,3]     [,4]     [,5]     [,6]     [,7]
##  [1,] 213.7096 213.0487 196.9336 204.5545 202.0600 203.2193 196.3277 189
##  [2,] 194.3530 222.8665 182.1869 207.0484 196.3894 192.1616 201.8523 199
##  [3,] 203.6313 186.1114 198.2808 210.3510 207.5816 215.7573 205.8182 206
##  [4,] 206.3286 197.2121 212.1467 193.9107 192.7330 206.4290 213.9974 190
##  [5,] 204.0427 198.6668 218.9519 205.0496 186.3172 200.8976 192.7271 194
##  [6,] 198.9388 206.3595 195.6953 182.8299 204.3282 202.7655 213.0254 205
##  [7,] 215.1152 197.1575 197.4273 192.1554 191.8861 206.7929 203.3585 207
##  [8,] 199.0534 173.4354 182.3684 191.4909 214.4410 200.8983 210.3851 204
##  [9,] 220.1842 175.5953 204.6010 175.8579 195.6855 170.0691 209.2073 191
## [10,] 199.3729 213.2011 193.6001 200.3612 206.5565 202.8488 207.2088 189
```

```
sum(m)
```

```
## [1] 20032.51
```

```
mean(m)
```

```
## [1] 200.3251
```

```
rowSums(m)
```

```
##  [1] 2048.470 1993.774 2041.155 2025.924 1978.173 2007.265 1998.086 1960
```

```
colSums(m)
```

```
##  [1] 2054.730 1983.654 1982.192 1963.610 1997.978 2001.839 2053.908 1978
```

```
# standardize the matrix
z <- (m - mean(m)) / sd(m)
```

```
z
```

```
##              [,1]       [,2]       [,3]        [,4]       [,5]        [,
##  [1,]  1.28528802  1.2218239 -0.3256841  0.40613865  0.1665940  0.277916
##  [2,] -0.57349498  2.1646089 -1.7417882  0.64562157 -0.3779416 -0.783932
##  [3,]  0.31748345 -1.3649263 -0.1963133  0.96277141  0.6968297  1.481924
##  [4,]  0.57650528 -0.2989403  1.1352110 -0.61596668 -0.7290676  0.586143
##  [5,]  0.35698951 -0.1592501  1.7887033  0.45367758 -1.3451640  0.054972
##  [6,] -0.13313334  0.5794704 -0.4445968 -1.68004206  0.3844054  0.234344
##  [7,]  1.42026916 -0.3041875 -0.2782756 -0.78452812 -0.8103926  0.621087
##  [8,] -0.12212321 -2.5821792 -1.7243635 -0.84833774  1.3555260  0.055041
##  [9,]  1.90703954 -2.3747685  0.4106013 -2.34955213 -0.4455350 -2.905444
## [10,] -0.09144695  1.2364622 -0.6458013  0.00346451  0.5983857  0.242345
##             [,10]
##  [1,]  1.30560568
##  [2,] -0.48848642
##  [3,]  0.59329679
##  [4,]  1.30463971
##  [5,] -1.09789797
##  [6,] -0.85783015
##  [7,] -1.11801576
##  [8,] -1.43248556
##  [9,]  0.04558258
## [10,]  0.59603916
```

Stripping attributes

- Many operations will strip attributes (which makes storing important things in them a bit precarious)

```
v
```

```
##             index value
## the first       1     4
## second          2     5
## III             3     6
## attr(,"matrix_mean")
## [1] 3.5
```

```
rowSums(v)
```

```
## the first    second       III
##         5         7         9
```

```
attributes(rowSums(v))
```

```
## $names
## [1] "the first" "second"    "III"
```

- Generally `names` are maintained
- Sometimes, `dim` is maintained, sometimes not
- All else is stripped

More on `names`

- The `names` attribute corresponds to the individual elements within a vector

```
names(v)
```

```
## NULL
```

```
names(v) <- letters[1:6]
v
```

```
##           index value
## the first     1     4
## second        2     5
## III           3     6
## attr(,"matrix_mean")
## [1] 3.5
## attr(,"names")
## [1] "a" "b" "c" "d" "e" "f"
```

- Perhaps more straightforward

```
v3a <- c(a = 5, b = 7, c = 12)
v3a
```

```
##  a  b  c
##  5  7 12
```

```
names(v3a)
```

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

```
attributes(v3a)
```

```
## $names
## [1] "a" "b" "c"
```

Alternatives

```
v3b <- c(5, 7, 12)
names(v3b) <- c("a", "b", "c")
v3b
```

```
##  a  b  c
##  5  7 12
```

```
v3c <- setNames(c(5, 7, 12), c("a", "b", "c"))
v3c
```

```
##  a  b  c
##  5  7 12
```

- Note that `names` is **not** the same thing as `colnames`, but, somewhat confusingly, both work to rename the variables (columns) of a data frame. We'll talk more about why this is momentarily.

Why names might be helpful

```
v
```

```
##           index value
## the first     1     4
## second        2     5
## III           3     6
## attr(,"matrix_mean")
## [1] 3.5
## attr(,"names")
## [1] "a" "b" "c" "d" "e" "f"
```

```
v["b"]
```

```
## b
## 2
```

```
v["e"]
```

```
## e
## 5
```

Implementation of factors

```
fct <- factor(c("a", "a", "b", "c"))
typeof(fct)
```

```
## [1] "integer"
```

```
attributes(fct)
```

```
## $levels
## [1] "a" "b" "c"
##
## $class
## [1] "factor"
```

```
str(fct)
```

```
##  Factor w/ 3 levels "a","b","c": 1 1 2 3
```

More manually

```
# First create integer vector
int <- c(1L, 1L, 2L, 3L, 1L, 3L)

# assign some levels
attr(int, "levels") <- c("red", "green", "blue")

# change the class to a factor
class(int) <- "factor"

int
```

```
## [1] red   red   green blue  red   blue
## Levels: red green blue
```

This can make things tricky

```
age <- factor(sample(c("baby", 1:10), 100, replace = TRUE))
str(age)
```

```
##  Factor w/ 11 levels "1","10","2","3",..: 8 1 9 2 1 1 2 10 9 6 ...
```

```
age
```

```
##   [1] 7    1    8    10   1    1    10   9    8    5    4    9    baby b
##  [21] 5    9    10   3    9    baby 10   10   3    3    3    10   baby 8
##  [41] 1    7    2    4    baby 2    4    7    5    6    9    6    8    8
##  [61] 8    5    7    baby 5    10   8    5    9    5    5    3    6    5
##  [81] 5    baby baby 10   1    6    1    9    9    3    3    6    baby 1
## Levels: 1 10 2 3 4 5 6 7 8 9 baby
```

What if we wanted to convert this to numeric?

```
data.frame(age) %>%
  count(age) %>%
  mutate(age_numeric = as.numeric(age)) %>%
  select(starts_with("age"), n)
```

```
##      age age_numeric  n
## 1      1           1  9
## 2     10           2 10
## 3      2           3  5
## 4      3           4 10
## 5      4           5  9
## 6      5           6 11
## 7      6           7  5
## 8      7           8  4
## 9      8           9 11
## 10     9          10 11
## 11 baby          11 15
```

These are the integers associated with the factor levels, so `as.numeric()` will not give us the results we want.

Fix

First convert to character, then to numeric (you can ignore the warning in this case)

```
data.frame(age) %>%
  mutate(
    age_chr = as.character(age),
    age_num = ifelse(age_chr == "baby", 0, as.numeric(age_chr))
  ) %>%
  count(age, age_chr, age_num)
```

```
##      age age_chr age_num  n
## 1      1       1       1  9
## 2     10      10      10 10
## 3      2       2       2  5
## 4      3       3       3 10
## 5      4       4       4  9
## 6      5       5       5 11
## 7      6       6       6  5
## 8      7       7       7  4
## 9      8       8       8 11
## 10     9       9       9 11
## 11 baby    baby       0 15
```

Implementation of dates

```
date <- Sys.Date()
typeof(date)
```

```
## [1] "double"
```

```
attributes(date)
```

```
## $class
## [1] "Date"
```

```
attributes(date) <- NULL
date
```

```
## [1] 19054
```

- This number represents the days passed since January 1, 1970, known as the Unix epoch.

A bit more on classes

Why do these all print different things?

```
summary(mtcars[, 1:2])
```

```
##       mpg              cyl
##  Min.   :10.40   Min.   :4.000
##  1st Qu.:15.43   1st Qu.:4.000
##  Median :19.20   Median :6.000
##  Mean   :20.09   Mean   :6.188
##  3rd Qu.:22.80   3rd Qu.:8.000
##  Max.   :33.90   Max.   :8.000
```

```
summary(gss_cat$marital)
```

```
##     No answer Never married
##            17          5416
```

```
m <- lm(mpg ~ cyl, mtcars)
summary(m)
```

```
##
## Call:
## lm(formula = mpg ~ cyl, data = mtcars
##
## Residuals:
##     Min      1Q  Median      3Q     M
## -4.9814 -2.1185  0.2217  1.0717  7.51
##
## Coefficients:
##             Estimate Std. Error t val
## (Intercept)  37.8846     2.0738   18.
## cyl          -2.8758     0.3224   -8.
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.
##
## Residual standard error: 3.206 on 30
## Multiple R-squared:  0.7262,    Adjus
## F-statistic: 79.56 on 1 and 30 DF,  p
```

Separated Divorced Widowed
743 3383 1807

What are the classes?

```
class(mtcars[, 1:2])
```

```
## [1] "data.frame"
```

```
class(gss_cat$marital)
```

```
## [1] "factor"
```

```
class(m)
```

```
## [1] "lm"
```

S3 methods

When you call `summary()`, it looks for a method (function) for that specific class.

`summary(mtcars[, 1:2])` becomes
`summary.data.frame(mtcars[, 1:2])`

`summary(gss_cat$marital)` becomes
`summary.factor(gss_cat$marital)`

`summary(m)` becomes `summary.lm(m)`

Naming function

Because S3 is so common in R, I recommend against including dots in function names.

`summary.data.frame()` is less clear than it would be if it were `summary.data_frame()`

Classes and methods is not something I'm going to expect you to have a deep knowledge on, but I want you to be aware of it.

Missing values

- Missing values breed missing values

```
NA > 5
```

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

```
NA * 7
```

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

- What about this one?

```
NA == NA
```

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

It is correct because there's no reason to presume that one missing value is or is not equal to another missing value.

When missing values don't propagate

```
NA | TRUE
```

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

```
x <- c(NA, 3, NA, 5)
any(x > 4)
```

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

How to test missingness?

- We've already seen the following doesn't work

```
x == NA
```

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

- Instead, use `is.na`

```
is.na(x)
```

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

Lists

Lists

- Lists are vectors, but not *atomic* vectors
- Fundamental difference – each element can be a different type

```
list("a", 7L, 3.25, TRUE)
```

```
## [[1]]
## [1] "a"
##
## [[2]]
## [1] 7
##
## [[3]]
## [1] 3.25
##
## [[4]]
## [1] TRUE
```

Lists

- Technically, each element of the list is a vector, possibly atomic
- The prior example included all *scalars*, which are vectors of length 1.
- Lists do not require all elements to be the same length

```
l <- list(
  c("a", "b", "c"),
  rnorm(5),
  c(7L, 2L),
  c(TRUE, TRUE, FALSE, TRUE)
)
l
```

```
## [[1]]
## [1] "a" "b" "c"
##
## [[2]]
## [1]  0.19253010 -0.97561601 -0.060921
##
## [[3]]
## [1] 7 2
##
## [[4]]
## [1]  TRUE  TRUE FALSE  TRUE
```

Check the list

```
typeof(l)
```

```
## [1] "list"
```

```
attributes(l)
```

```
## NULL
```

```
str(l)
```

```
## List of 4
##  $ : chr [1:3] "a" "b" "c"
##  $ : num [1:5] 0.1925 -0.9756 -0.0609 1.6597 -0.074
##  $ : int [1:2] 7 2
##  $ : logi [1:4] TRUE TRUE FALSE TRUE
```

Data frames as lists

- A data frame is just a special case of a list, where all the elements are of the same length.

```
l_df <- list(
  a = c("red", "blue"),
  b = rnorm(2),
  c = c(7L, 2L),
  d = c(TRUE, FALSE)
)
l_df
```

```
## $a
## [1] "red"  "blue"
##
## $b
## [1] 0.3921062 2.0518441
##
## $c
## [1] 7 2
##
## $d
## [1]  TRUE FALSE
```

```
data.frame(l_df)
```

```
##      a         b c     d
## 1  red 0.3921062 7  TRUE
## 2 blue 2.0518441 2 FALSE
```

Subsetting Lists

A nested list

Lists are often complicated objects. Let's create a somewhat complicated one

```
x <- c(a = 3, b = 5, c = 7)
l <- list(
  x = x,
  x2 = c(x, x),
  x3 = list(
    vect = x,
    squared = x^2,
    cubed = x^3)
)
```

Subsetting lists

Multiple methods

- Most common: `$`, `[`, and `[[`

```
l[1]
```

```
## $x
## a b c
## 3 5 7
```

```
typeof(l[1])
```

```
## [1] "list"
```

```
l[[1]]
```

```
## a b c
## 3 5 7
```

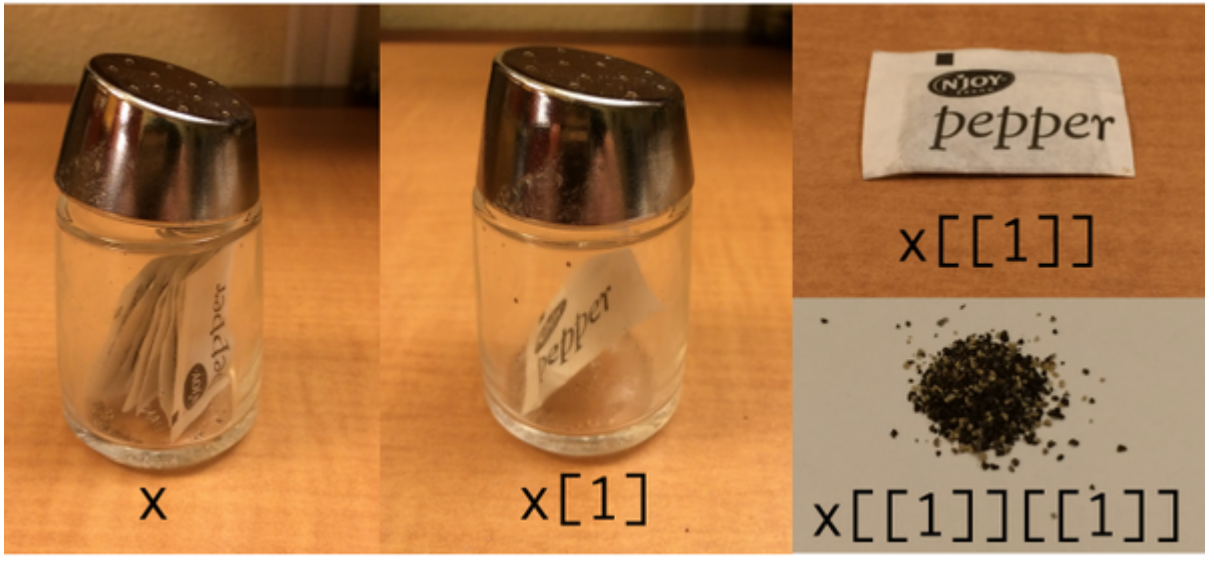
```
typeof(l[[1]])
```

```
## [1] "double"
```

```
l[[1]]["c"]
```

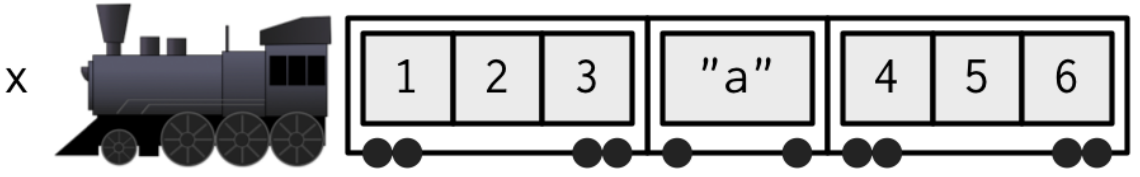
```
## c
## 7
```

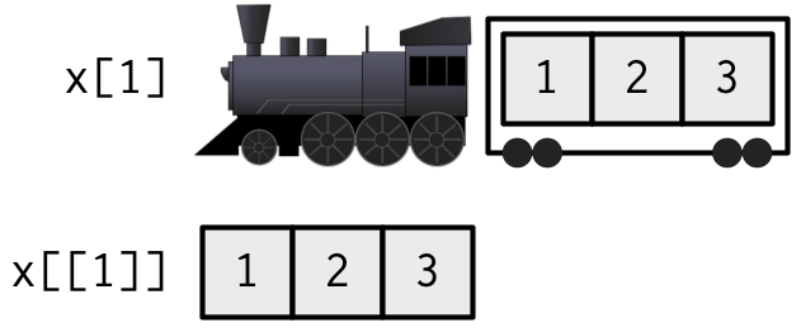
Which bracket to use?

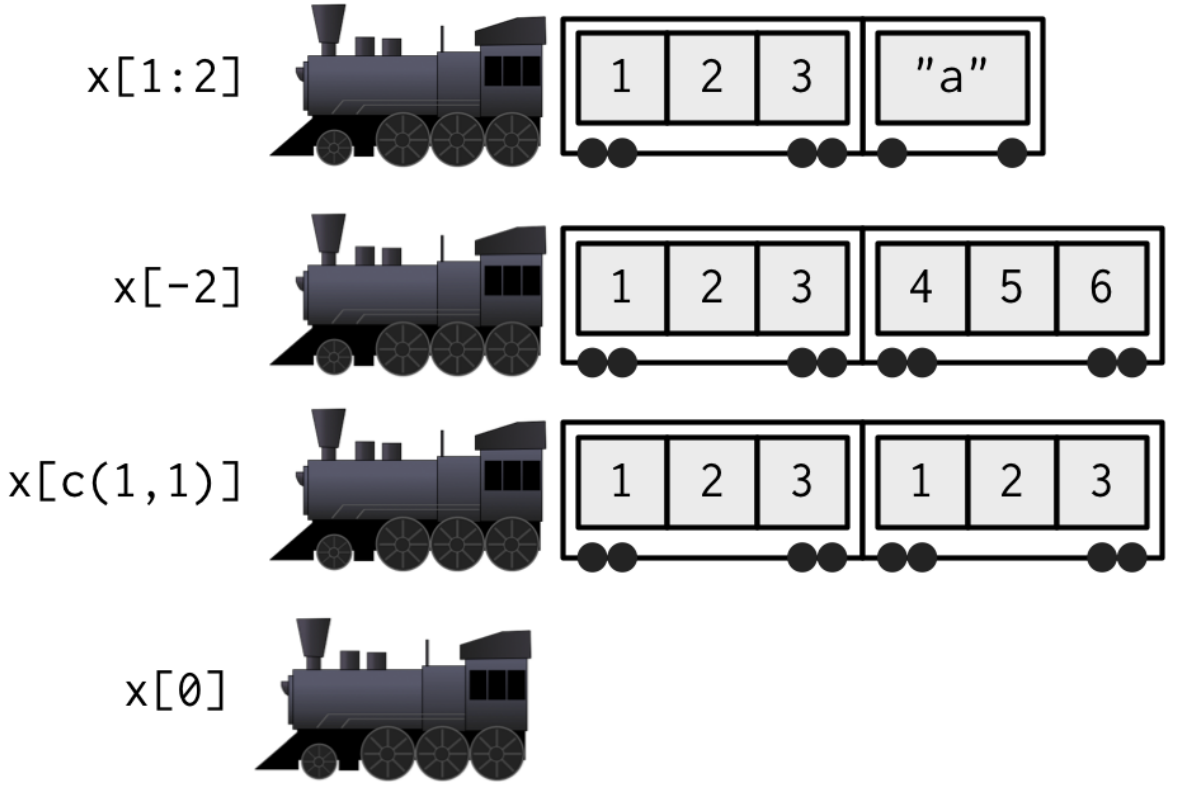


From r4DS

Another analogy




x[1]
1
2
3
x[[1]]
1
2
3



From Advanced–R

Named list

- Because the elements of the list are named, we can also use `$`, just like with a data frame (which is a list)

```
l$x2
```

```
## a b c a b c
## 3 5 7 3 5 7
```

```
l$x3
```

```
## $vect
## a b c
## 3 5 7
##
## $squared
##  a  b  c
##  9 25 49
##
## $cubed
##   a   b   c
##  27 125 343
```

Subsetting nested lists

- Multiple `$` if all named

```
l$x3$squared
```

```
##  a  b  c
##  9 25 49
```

- Note this doesn't work on named elements of an atomic vector, just the named elements of a list

```
l$x3$squared$b
```

```
## Error in l$x3$squared$b: $ operator is invalid for atomic vectors
```

But we could do something like...

```
l$x3$squared["b"]
```

```
##  b
## 25
```

Alternatives

- You can always use logical
- Indexing works too

```
l[c(TRUE, FALSE, TRUE)]
```

```
## $x
## a b c
## 3 5 7
##
## $x3
## $x3$vect
## a b c
## 3 5 7
##
## $x3$squared
##  a  b  c
##  9 25 49
##
## $x3$cubed
##   a   b   c
##  27 125 343
```

```
l[c(1, 3)]
```

```
## $x
## a b c
## 3 5 7
##
## $x3
## $x3$vect
## a b c
## 3 5 7
##
## $x3$squared
##  a  b  c
##  9 25 49
##
## $x3$cubed
##   a   b   c
##  27 125 343
```

Careful with your brackets

```
l[[c(TRUE, FALSE, FALSE)]]
```

```
## Error in l[[c(TRUE, FALSE, FALSE)]]: recursive indexing failed at level
```

- Why doesn't the above work?

Subsetting in multiple dimensions

- Generally we deal with 2d data frames
- If there are two dimensions, we separate the [subsetting with a comma

```
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
```

```
mtcars[3, 4]
```

```
## [1] 93
```

Empty indicators

- An empty indicator implies "all"

Select the entire fourth column

```
mtcars[ ,4]
```

```
##  [1] 110 110  93 110 175 105 245  62  95 123 123 180 180 180 205 215 230
## [27]  91 113 264 175 335 109
```

Select the entire 4th row

```
mtcars[4, ]
```

```
##                 mpg cyl disp  hp drat    wt  qsec vs am gear carb
## Hornet 4 Drive 21.4   6  258 110 3.08 3.215 19.44  1  0    3    1
```

Data types returned

- By default, each of the prior will return a vector, which itself can be subset

The following are equivalent

```
mtcars[4, c("mpg", "hp")]
```

```
##                 mpg  hp
## Hornet 4 Drive 21.4 110
```

```
mtcars[4, ][c("mpg", "hp")]
```

```
##                 mpg  hp
## Hornet 4 Drive 21.4 110
```

Return a data frame

- Often, you don't want the vector returned, but rather the modified data frame.
- Specify `drop = FALSE`

```
mtcars[ ,4]
```

```
##  [1] 110 110  93 110 175 105 245  62  95 123 123 180 180 180 205 215 230
## [27]  91 113 264 175 335 109
```

```
mtcars[ ,4, drop = FALSE]
```

```
##                     hp
## Mazda RX4          110
## Mazda RX4 Wag      110
## Datsun 710          93
## Hornet 4 Drive     110
## Hornet Sportabout  175
## Valiant            105
## Duster 360         245
## Merc 240D           62
```

tibbles

- Note dropping the data frame attribute is the default for a `data.frame` but NOT a `tibble`.

```
mtcars_tbl <- tibble::as_tibble(mtcars)
mtcars_tbl[ ,4]
```

```
## # A tibble: 32 × 1
##       hp
##    <dbl>
##  1   110
##  2   110
##  3    93
##  4   110
##  5   175
##  6   105
##  7   245
##  8    62
##  9    95
## 10   123
## # … with 22 more rows
```

You can override this

```
mtcars_tbl[ ,4, drop = TRUE]
```

```
##  [1] 110 110  93 110 175 105 245  62  95 123 123 180 180 180 205 215 230
## [27]  91 113 264 175 335 109
```

More than two dimensions

- Depending on your applications, you may not run into this much

```
array <- 1:12
dim(array) <- c(2, 3, 2)
array
```

```
## , , 1
##
##      [,1] [,2] [,3]
## [1,]    1    3    5
## [2,]    2    4    6
##
## , , 2
##
##      [,1] [,2] [,3]
## [1,]    7    9   11
## [2,]    8   10   12
```

Subset array

Select just the second matrix

```
array[ , ,2]
```

```
##      [,1] [,2] [,3]
## [1,]    7    9   11
## [2,]    8   10   12
```

Select first column of each matrix

```
array[ ,1, ]
```

```
##      [,1] [,2]
## [1,]    1    7
## [2,]    2    8
```

Back to lists

Why are they so useful?

- Much more flexible
- Often returned by functions, for example, `lm`

```
m <- lm(mpg ~ hp, mtcars)
str(m)
```

```
## List of 12
##  $ coefficients : Named num [1:2] 30.0989 -0.0682
##   ..- attr(*, "names")= chr [1:2] "(Intercept)" "hp"
##  $ residuals    : Named num [1:32] -1.594 -1.594 -0.954 -1.194 0.541 ...
##   ..- attr(*, "names")= chr [1:32] "Mazda RX4" "Mazda RX4 Wag" "Datsun 7
##  $ effects      : Named num [1:32] -113.65 -26.046 -0.556 -0.852 0.67 ..
##   ..- attr(*, "names")= chr [1:32] "(Intercept)" "hp" "" "" ...
##  $ rank         : int 2
##  $ fitted.values: Named num [1:32] 22.6 22.6 23.8 22.6 18.2 ...
##   ..- attr(*, "names")= chr [1:32] "Mazda RX4" "Mazda RX4 Wag" "Datsun 7
##  $ assign       : int [1:2] 0 1
##  $ qr           :List of 5
##   ..$ qr   : num [1:32, 1:2] -5.657 0.177 0.177 0.177 0.177 ...
```

Summary

- Atomic vectors must all be the same type
    - implicit coercion occurs if not (and you haven't specified the coercion explicitly)
- Lists are also vectors, but not atomic vectors
    - Each element can be of a different type and length
    - Incredibly flexible, but often a little more difficult to get the hang of, particularly with subsetting

Next time

Loops with base R