Data Wrangling and Types

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Math 241

Week 4 | Spring 2026

Announcements

- Welcome to the newly admitted students!
- Course Interest Form

04:00

Week 4 Goals

Mon Lecture

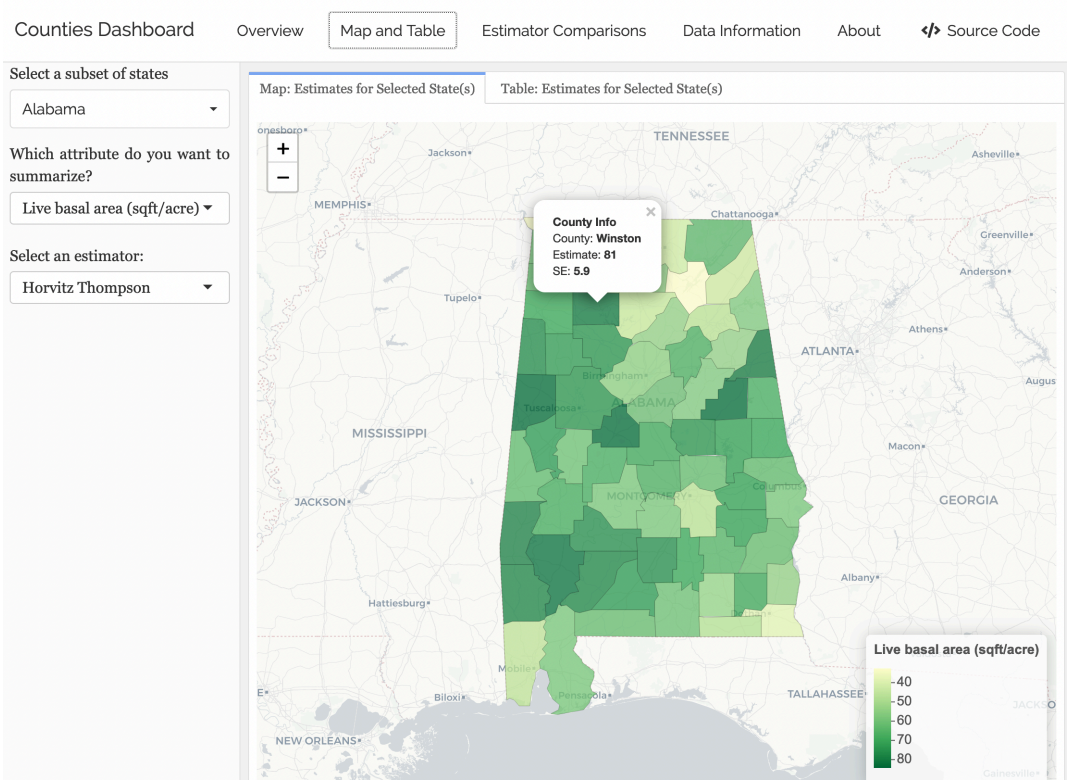
- Different types of data in R
  - atomic and generic vectors
  - subsetting objects
- Talk more about logical statements
- More practice with `dplyr` verbs and data wrangling

Wed Lecture

- Joining multiple data frames
- “Tidy” data
- Reshaping data frames

Looking Ahead to Project 1

Goal: Create interactive dashboards with `shinydashboard` and `flexdashboard`.



- Link to example dashboard

What We Need First

- Need a robust understanding of wrangling data frames.
- Need to explore more **data objects** in R.
- Need to learn how to interact with and wrangle these **data objects**.

`dplyr` review

Data: Census 2000 (from `openintro`)

```r
library(openintro)
data(census)
census %>% head(n = 5)
```

```
# A tibble: 5 × 8
  census_year state_fips_code total_family_income   age sex    race_general
        <int> <fct>                          <int> <int> <fct>  <fct>
1        2000 Florida                        14550    44 Male   Two major races
2        2000 Florida                        22800    20 Female White
3        2000 Florida                            0    20 Male   Black
4        2000 Florida                        23000     6 Female White
5        2000 Florida                        48000    55 Male   White
# ℹ 2 more variables: marital_status <fct>, total_personal_income <int>
```

select()

Use `select()` to grab only the variables/columns we want

```
census %>%
  select(census_year, age, sex, marital_status)
```

```
# A tibble: 500 × 4
   census_year   age sex    marital_status
         <int> <int> <fct>  <fct>
 1        2000    44 Male   Married/spouse present
 2        2000    20 Female Never married/single
 3        2000    20 Male   Never married/single
 4        2000     6 Female Never married/single
 5        2000    55 Male   Married/spouse present
 6        2000    43 Female Married/spouse present
 7        2000    60 Female Married/spouse present
 8        2000    47 Female Married/spouse present
 9        2000    54 Female Married/spouse present
10        2000    58 Female Widowed
# ℹ 490 more rows
```

select()

Or you can add **minus signs** to *delete* columns from the dataset.

```
census %>%
  select(-census_year, -age, -sex, -marital_status)
```

```
# A tibble: 500 × 4
   state_fips_code total_family_income race_general    total_personal_income
   <fct>                         <int> <fct>                          <int>
 1 Florida                       14550 Two major races                    0
 2 Florida                       22800 White                          13000
 3 Florida                           0 Black                          20000
 4 Florida                       23000 White                             NA
 5 Florida                       48000 White                          36000
 6 Florida                       74000 White                          27000
 7 Florida                       23000 White                          11800
 8 Florida                       74000 White                          48000
 9 Florida                       60000 Black                          40000
10 Florida                       14600 White                          14600
# ℹ 490 more rows
```

mutate()

`mutate()` can add new columns that are functions of existing columns:

```
census %>%
  mutate(age_decade = (age %/% 10)) %>%
  select(census_year, state_fips_code, total_family_income, age, age_decade)
```

```
# A tibble: 500 × 5
   census_year state_fips_code total_family_income   age age_decade
         <int> <fct>                          <int> <int>      <dbl>
 1        2000 Florida                        14550    44          4
 2        2000 Florida                        22800    20          2
 3        2000 Florida                            0    20          2
 4        2000 Florida                        23000     6          0
 5        2000 Florida                        48000    55          5
 6        2000 Florida                        74000    43          4
 7        2000 Florida                        23000    60          6
 8        2000 Florida                        74000    47          4
 9        2000 Florida                        60000    54          5
10        2000 Florida                        14600    58          5
# ℹ 490 more rows
```

- New operator: `%/%` does integer division

filter()

`filter()` only keeps rows/observations that match certain criteria

```
census %>%
  filter(age < 25, sex == 'Female')
```

```
# A tibble: 80 × 8
   census_year state_fips_code total_family_income   age sex    race_general
         <int> <fct>                          <int> <int> <fct>  <fct>
 1        2000 Florida                        22800    20 Female White
 2        2000 Florida                        23000     6 Female White
 3        2000 Florida                       103700     8 Female White
 4        2000 Florida                        70700    17 Female White
 5        2000 Florida                       118100    18 Female White
 6        2000 New York                       68020     2 Female Chinese
 7        2000 New York                       50400    21 Female White
 8        2000 New York                       65000     1 Female White
 9        2000 New York                       62900    17 Female Black
10        2000 New York                      168200     6 Female White
# ℹ 70 more rows
```

arrange()

`arrange()` sorts the rows by a certain variable (or set of variables)

```
1 census %>%
2   arrange(age)
```

```
# A tibble: 500 × 8
   census_year state_fips_code total_family_income   age sex    race_general
         <int> <fct>                          <int> <int> <fct>  <fct>
 1        2000 Texas                           9200     0 Male   Black
 2        2000 Florida                        48000     1 Male   White
 3        2000 New York                       13000     1 Male   White
 4        2000 New York                       65000     1 Female White
 5        2000 Michigan                       57400     1 Female White
 6        2000 Pennsylvania                   27150     1 Male   White
 7        2000 Florida                        50090     2 Male   White
 8        2000 Florida                         6000     2 Male   White
 9        2000 New York                       68020     2 Female Chinese
10        2000 New York                       17000     2 Male   Two major races
# ℹ 490 more rows
```

arrange()

Can do **descending order** too with the `desc()` function!

```
census %>%
  arrange(desc(age))
```

```
# A tibble: 500 × 8
   census_year state_fips_code total_family_income   age sex    race_general
         <int> <fct>                          <int> <int> <fct>  <fct>
 1        2000 Louisiana                       8100    93 Female White
 2        2000 Illinois                          NA    87 Female White
 3        2000 West Virginia                      0    87 Male   White
 4        2000 Delaware                       46200    85 Female White
 5        2000 Indiana                         8000    85 Male   Black
 6        2000 New York                       15570    83 Male   White
 7        2000 New York                        8800    82 Female White
 8        2000 Massachusetts                  34300    82 Female White
 9        2000 New York                       55000    81 Male   White
10        2000 Minnesota                          0    81 Female White
# ℹ 490 more rows
```

arrange()

Can arrange by multiple variables too:

```
1 census %>%
2   arrange(age, sex)
```

```
# A tibble: 500 × 8
   census_year state_fips_code total_family_income   age sex    race_general
         <int> <fct>                          <int> <int> <fct>  <fct>
 1        2000 Texas                           9200     0 Male   Black
 2        2000 New York                       65000     1 Female White
 3        2000 Michigan                       57400     1 Female White
 4        2000 Florida                        48000     1 Male   White
 5        2000 New York                       13000     1 Male   White
 6        2000 Pennsylvania                   27150     1 Male   White
 7        2000 New York                       68020     2 Female Chinese
 8        2000 Maryland                       95500     2 Female White
 9        2000 Oregon                          9300     2 Female White
10        2000 Michigan                       20340     2 Female White
# ℹ 490 more rows
```

summarize()

`summarize()` computes summary statistics and collapses data into row(s) that show those summary statistics

```
census %>%
  summarize(mean_income = mean(total_family_income, na.rm = TRUE),
            sd_income = sd(total_family_income, na.rm = TRUE),
            size = n())
```

```
# A tibble: 1 × 3
  mean_income sd_income  size
        <dbl>     <dbl> <int>
1      57411.    70732.   500
```

- Can compute multiple measures

`group_by()` + `summarize()`

Add `group_by()` to `summarize()` to calculate summary statistics *by specified grouping variable(s)*

```
census %>%
  group_by(state_fips_code) %>%
  summarize(mean_income = mean(total_family_income, na.rm = TRUE),
            sd_income = sd(total_family_income, na.rm = TRUE),
            size = n()) %>%
  filter(size > 10) %>%
  arrange(mean_income)
```

```
# A tibble: 14 × 4
   state_fips_code mean_income sd_income  size
   <fct>                 <dbl>     <dbl> <int>
 1 Washington           20079.    12980.    11
 2 Louisiana            34899.    42097.    12
 3 Ohio                 40748.    26796.    23
 4 Indiana              46738.    32291.    17
 5 Florida              46848.    31787.    39
 6 Pennsylvania         51685     44823.    26
 7 Illinois             55972.    42426.    21
 8 New York             57064.    44793.    43
 9 Texas                58240.    72468.    37
10 Michigan             59160     27403.    14
11 Massachusetts        59506.    38984.    12
```

Tip: `count()`

`count()` is a short-cut for `group_by()` + `summarize(n())`

```
census %>%
  group_by(sex) %>%
  summarize(n())
```

```
# A tibble: 2 × 2
  sex    `n()`
  <fct>  <int>
1 Female   232
2 Male     268
```

```
census %>% count(sex)
```

```
# A tibble: 2 × 2
  sex        n
  <fct>  <int>
1 Female   232
2 Male     268
```

`group_by()` + `mutate()`

Adding `group_by()` allows functions (e.g., `sum()`) to operate on variables *by specified grouping variable(s)*

Let's start with this summary dataset:

```
1 temp <- census %>%
2   count(marital_status, sex)
3 temp
```

```
# A tibble: 12 × 3
   marital_status         sex        n
   <fct>                  <fct>  <int>
 1 Divorced               Female    21
 2 Divorced               Male      17
 3 Married/spouse absent  Female     5
 4 Married/spouse absent  Male       9
 5 Married/spouse present Female    92
 6 Married/spouse present Male     100
 7 Never married/single   Female    93
 8 Never married/single   Male     129
 9 Separated              Female     1
10 Separated              Male       2
11 Widowed                Female    20
```

group_by() + mutate()

```
1 temp %>%
2   mutate(p = n / sum(n))
```

```
# A tibble: 12 × 4
   marital_status         sex        n     p
   <fct>                  <fct>  <int> <dbl>
 1 Divorced               Female    21 0.042
 2 Divorced               Male      17 0.034
 3 Married/spouse absent  Female     5 0.01
 4 Married/spouse absent  Male       9 0.018
 5 Married/spouse present Female    92 0.184
 6 Married/spouse present Male     100 0.2
 7 Never married/single   Female    93 0.186
 8 Never married/single   Male     129 0.258
 9 Separated              Female     1 0.002
10 Separated              Male       2 0.004
11 Widowed                Female    20 0.04
```

Q: What is the denominator for the proportions in the new p variable?

group_by() + mutate()

```
1 temp %>%
2   group_by(marital_status) %>% # added this!
3   mutate(p = n / sum(n))
```

```
# A tibble: 12 × 4
# Groups:   marital_status [6]
   marital_status         sex        n     p
   <fct>                  <fct>  <int> <dbl>
 1 Divorced               Female    21 0.553
 2 Divorced               Male      17 0.447
 3 Married/spouse absent  Female     5 0.357
 4 Married/spouse absent  Male       9 0.643
 5 Married/spouse present Female    92 0.479
 6 Married/spouse present Male     100 0.521
 7 Never married/single   Female    93 0.419
 8 Never married/single   Male     129 0.581
 9 Separated              Female     1 0.333
10 Separated              Male       2 0.667
```

Q: *Now* what is the denominator for the proportions in the new p variable?

Now: type of data objects

Math 241 R Data Objects So Far:

Data frames:

```
1 crash_data <- read_csv("data/pdx_crash_2018_page1.csv")
2 class(crash_data)
```

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

(Atomic) Vectors:

```
1 pretty_colors <- c("steelblue", "seagreen", "goldenrod")
2 class(pretty_colors)
```

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

```
1 size <- 3
2 class(size)
```

```
[1] "numeric"
```

- The last two are both examples of what are called **atomic vectors**.

R Objects: Vectors

- **Vectors** are the fundamental building blocks of data in R.
  - Each column in a data frame is an atomic vector!
  - Come in 2 flavors!
- **Flavor 1: Atomic vectors**
  - Homogeneous collections of the same type.
  - Confusingly, people usually just call these *vectors*.
- **Flavor 2: Generic vectors**
  - Heterogeneous collections of any type of R objects.
  - Commonly called *lists*.

Deep Dive into (atomic) vectors

- Let's explore the common types and how to interact with them.
- This will allow us to use vectors to **do useful things**,
- Understand logical statements and `dplyr` more robustly, and
- **debug our code** more effectively!

Flavors of Atomic Vectors

Logical: TRUEs and FALSEs

```
1 happy <- c(TRUE, FALSE, TRUE, TRUE)
2 class(happy)
```

```
[1] "logical"
```

Numeric: Integers, real numbers (double-precision floating point numbers)

```
1 x <- c(1, 4, 5)
2 class(x)
```

```
[1] "numeric"
```

```
1 x <- c(1L, 4L, 5L)
2 class(x)
```

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

Character: Strings (contains 1 or more characters)

```
1 animals <- c("mountain goat", "lemur", "capybara")
2 class(animals)
```

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

Factors: Strings with order

```
1 animals <- as.factor(animals)
2 class(animals)
```

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

Factors versus Characters

Character: Strings (contains 1 or more characters)

```
animals <- c("mountain goat", "lemur", "capybara")
class(animals)
```

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

```
typeof(animals)
```

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

```
str(animals)
```

```
 chr [1:3] "mountain goat" "lemur" "capybara"
```

Factors: Strings with order

```
animals <- as.factor(animals)
class(animals)
```

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

```
typeof(animals)
```

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

```
str(animals)
```

```
 Factor w/ 3 levels "capybara","lemur",..: 3 2 1
```

What?!

- If you want to read more about this rabbit hole, go here.

Concatenation

Atomic vectors are created and combined with `c()`.

```
1 x <- 5
2 x
```

```
[1] 5
```

```
1 y <- c(4, 1, 7)
2 y
```

```
[1] 4 1 7
```

```
1 z <- c(y, x, c(20))
2 z
```

```
[1]  4  1  7  5 20
```

```
1 quick <- c(2:5, 13)
2 quick
```

```
[1]  2  3  4  5 13
```

Checking Type

```
1 is.logical(c(FALSE, TRUE))
```

```
[1] TRUE
```

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

```
[1] FALSE
```

```
1 is.factor(c("mountain goat", "lemur", "capybara"))
```

```
[1] FALSE
```

```
1 is.character(c("mountain goat", "lemur", "capybara"))
```

```
[1] TRUE
```

Checking Type

```
1 is.integer(1)
```

```
[1] FALSE
```

```
1 is.double(1)
```

```
[1] TRUE
```

```
1 is.numeric(1)
```

```
[1] TRUE
```

```
1 is.atomic(1)
```

```
[1] TRUE
```

```
1 is.integer(1L)
```

```
[1] TRUE
```

```
1 is.double(1L)
```

```
[1] FALSE
```

```
1 is.numeric(1L)
```

```
[1] TRUE
```

```
1 is.atomic(1L)
```

```
[1] TRUE
```

Type Coercion

- R will often change the type of a vector with no warning.
- Usually it makes the smart choice.

```r
y <- c(4, 1, 7)
class(y)
```

```
[1] "numeric"
```

```r
z <- c(y, "cat")
class(z)
```

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

```r
z
```

```
[1] "4"   "1"   "7"   "cat"
```

```r
z <- c(y, 3L)
class(z)
```

```
[1] "numeric"
```

```r
z
```

```
[1] 4 1 7 3
```

```r
a <- c(FALSE, 4)
class(a)
```

```
[1] "numeric"
```

```r
a
```

```
[1] 0 4
```

```r
b <- c(NA, 4)
class(b)
```

```
[1] "numeric"
```

```r
b
```

```
[1] NA  4
```

Operator Coercion

- Functions and operators (like +, −, ∗, etc.) will often try to convert a vector to an appropriate type.
- Once we are writing our own functions, we will consider building in tests to ensure the user provided the correct type.

```
1L + 3.1415
```

```
[1] 4.1415
```

```
log(TRUE)
```

```
[1] 0
```

```
sum(c(FALSE, TRUE, TRUE))
```

```
[1] 2
```

```
TRUE & FALSE
```

```
[1] FALSE
```

```
TRUE | FALSE
```

```
[1] TRUE
```

```
TRUE & 7
```

```
[1] TRUE
```

```
FALSE | !7
```

```
[1] FALSE
```

Changing Type

- We can also explicitly change the type, for example:

```
1 as.logical(c(0, 6.4, 1))
```

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

```
1 as.character(c(FALSE, TRUE, TRUE))
```

```
[1] "FALSE" "TRUE"  "TRUE"
```

```
1 as.integer(pi)
```

```
[1] 3
```

```
1 as.numeric(c(FALSE, TRUE, TRUE))
```

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

```
1 as.double(c("01", "02", "03"))
```

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

```
1 as.double(c("one", "two", "three"))
```

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

Vectorized

- R is built to work with vectors.
- Many operations are **vectorized**: will happen component-wise when given a vector as input.

```r
y <- c(4, 1, 7)
y + 4
```

```
[1]  8  5 11
```

```r
y * 2
```

```
[1]  8  2 14
```

```r
x <- c(-4, 0, 2)
y + x
```

```
[1] 0 1 9
```

```r
rnorm(n = 3, mean = c(-5, 0, 5))
```

```
[1] -4.954060 -1.526970  3.411176
```

Vectorized: Caution

- We need to be careful with vectorization!

```
my_pets <- data.frame(
  name = c("Dude", "Pickle", "Kyle", "Nubs"),
  type = c("dog", "cat", "cat", "cat"),
  age = c(8, 6, 4, NA),
  birthplace = c("Washington", NA, "Utah", NA)
)
my_pets
```

```
   name type age birthplace
1   Dude  dog   8 Washington
2 Pickle  cat   6       <NA>
3   Kyle  cat   4       Utah
4   Nubs  cat  NA       <NA>
```

Want the rows where name is either Dude or Kyle.

```
library(tidyverse)
my_pets %>%
  filter(name == c("Dude", "Kyle"))
```

```
  name type age birthplace
1 Dude  dog   8 Washington
```

- What happened?

Recycling

- R recycles vectors if they are not the necessary length.
  - Notice we got NO error but that wasn't what we wanted.

```
1 library(tidyverse)
2 my_pets %>%
3   filter(name %in% c("Dude", "Kyle"))
```

```
  name type age birthplace
1 Dude  dog   8 Washington
2 Kyle  cat   4       Utah
```

Indexing a Vector

```r
x <- c(4, 6, 9)
x[1]
```

```
[1] 4
```

```r
x[-1]
```

```
[1] 6 9
```

```r
x[c(2, 4)]
```

```
[1]  6 NA
```

```r
a <- c(2, 4)
x[a]
```

```
[1]  6 NA
```

So what about generic vectors/lists?

- Recall they are heterogeneous collections of any type of R objects.

Lists

Think of these as the **most general** way to store things.

```
groceries <- list()
groceries$new_seasons <- c("apples", "goat cheese", "pizza slice")
groceries$safeway <- c("black beans", "tortillas")
groceries$peoples_food_coop <- c("squash", "tea", "fresh greens")
groceries$budget <- data.frame(stores = c("new_seasons", "safeway", "peoples_food_coop"),
                               fund = c(100, 25, 200))
class(groceries)
```

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

Lists

Notice the nested structure

```
1 groceries
```

```
$new_seasons
[1] "apples"      "goat cheese" "pizza slice"

$safeway
[1] "black beans" "tortillas"

$peoples_food_coop
[1] "squash"       "tea"          "fresh greens"

$budget
             stores fund
1       new_seasons  100
2           safeway   25
3 peoples_food_coop  200
```

```r
holidays <- c("Valentine's", "President's")
feb <- list(groceries = groceries, holidays = holidays)
feb
```

```
$groceries
$groceries$new_seasons
[1] "apples"      "goat cheese" "pizza slice"

$groceries$safeway
[1] "black beans" "tortillas"

$groceries$peoples_food_coop
[1] "squash"       "tea"          "fresh greens"

$groceries$budget
             stores fund
1       new_seasons  100
2           safeway   25
```

Indexing lists

Distinguishing between [ ] and [[]]

```
thing1 <- feb$groceries[3]
thing1
```

```
$peoples_food_coop
[1] "squash"       "tea"          "fresh greens"
```

```
class(thing1)
```

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

```
thing2 <- feb$groceries[[3]]
thing2
```

```
[1] "squash"       "tea"          "fresh greens"
```

```
class(thing2)
```

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

[ ] versus [[ ]]

x is a list: the pepper shaker containing packets of pepper.

`[ ]` versus `[[ ]]`

`x[1]` is a pepper shaker containing the first packet of pepper.

[ ] versus [[ ]]

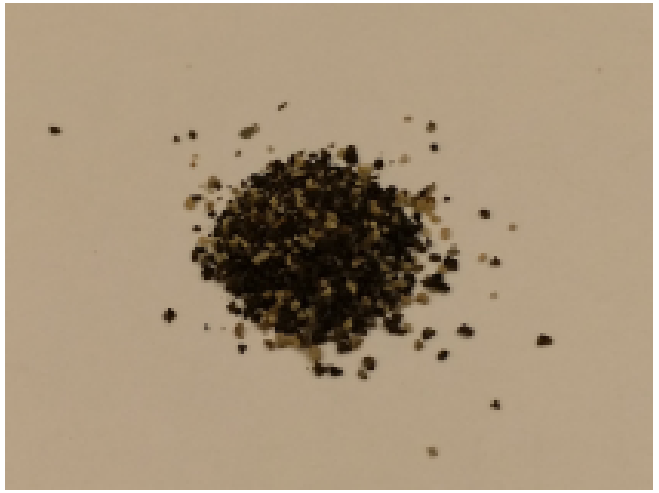
x[2] is what?

[ ] versus [[ ]]

x[[1]] is what?

[ ] versus [[ ]]

`x[[1]][[1]]` is what?



Data Frames

Let's relate `list()`s to our favorite R object: `data.frame()`s!

- `data.frame()`s are `list()`s.
- Each variable of a `data.frame`() is an atomic `vector()`.
- The `vector()`s all have the same length but not necessary the same class.

Data Frames

```
1 my_pets
```

```
   name type age birthplace
1   Dude  dog   8 Washington
2 Pickle  cat   6       <NA>
3   Kyle  cat   4       Utah
4   Nubs  cat  NA       <NA>
```

```
1 my_pets$name
```

```
[1] "Dude"   "Pickle" "Kyle"   "Nubs"
```

Data Frames

```
1 str(my_pets[1])
```

```
'data.frame':   4 obs. of  1 variable:
 $ name: chr  "Dude" "Pickle" "Kyle" "Nubs"
```

```
1 str(my_pets[[1]])
```

```
 chr [1:4] "Dude" "Pickle" "Kyle" "Nubs"
```

```
1 my_pets[1, 2]
```

```
[1] "dog"
```

```
1 my_pets[1, ]
```

```
  name type age birthplace
1 Dude  dog   8 Washington
```

Thoughts about R data objects

- We can create and interact with (atomic) **vectors** and **lists** (generic vectors).
- When writing and debugging code, it is a good idea to check the `class()` of an object.
- R will sometimes change the type of an object without telling us (but based on our actions).
- **Vectorization** makes R code speedy but also can cause you to do something you didn't mean to do.
- While we will primarily interact with `vector()`s and `data.frame()`s, we will sometimes need `list()`s.

Next time

- Joining, reshaping, and tidying data!

Next Week

- Spatial data in R