



Using R Markdown & the Tidyverse to Create Reproducible Research

Justin Post

Overview & R Markdown

Justin Post

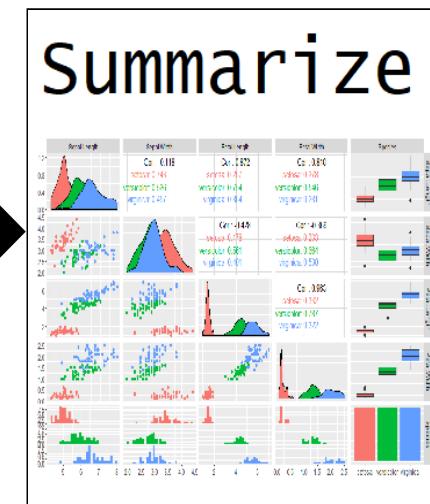
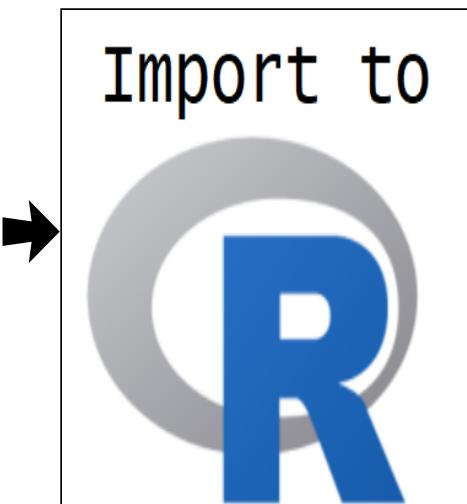
What is this course about?

Basic use of R for reading, manipulating, and summarizing data. With a focus on reproducibility!

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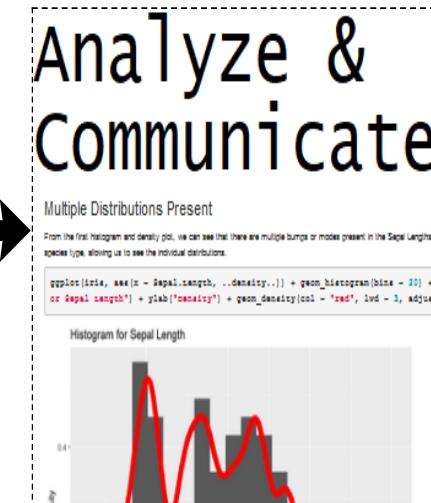
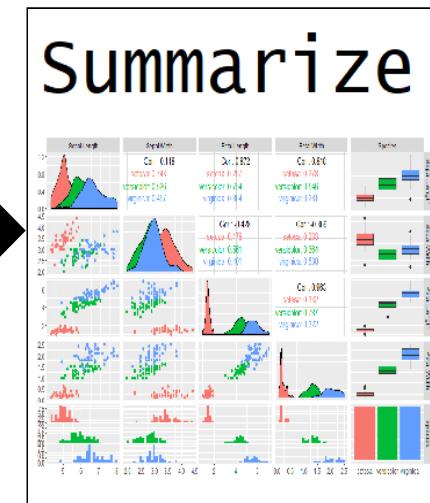
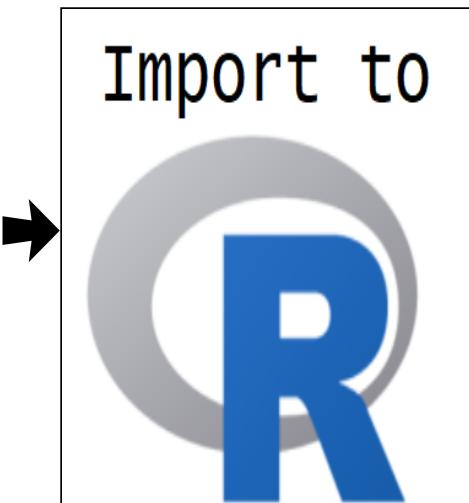
```
temp conc time percent
-1 -1 -1 45.9
1 -1 -1 60.6
-1 1 -1 57.5
1 1 1 Raw Data
-1
1 -1 1 58
-1 1 1 58.8
1 1 1 52.4
```



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```
temp conc time percent
-1 -1 -1 45.9
1 -1 -1 60.6
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-1
1 -1 1 58
-1 1 1 58.8
1 1 1 52.4
```



Start with an example!

First Part of Course

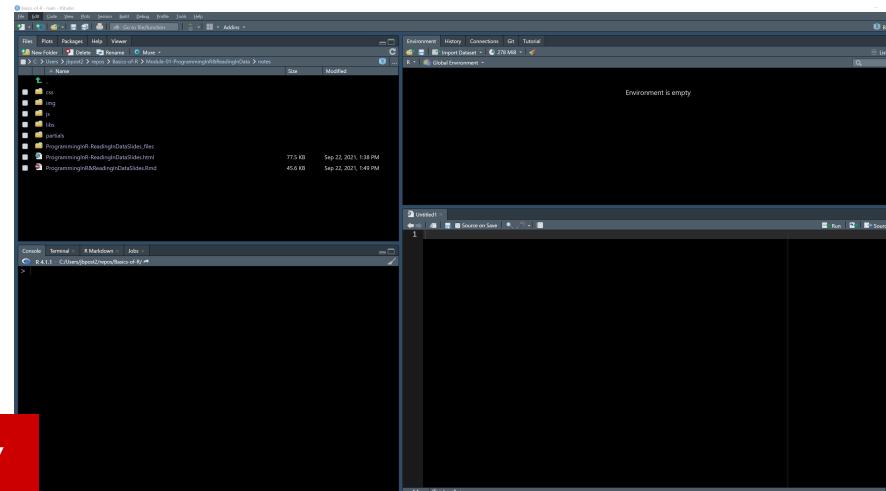


- Learn basics of R Markdown for literate programming
- Understand how R stores data
- Read external data into R

RStudio IDE

In RStudio, four main locations (easy to customize!)

- Console (& Terminal)
- Files/Plots/Packages/Help
- Environment (& Connections/Git)
- Scripting and Viewing Window



Console

- Type code directly into the **console** for evaluation

```
#simple math operations
# <-- is a comment - code not evaluated
3 + 7

## [1] 10

10 * exp(3) #exp is exponential function

## [1] 200.8554

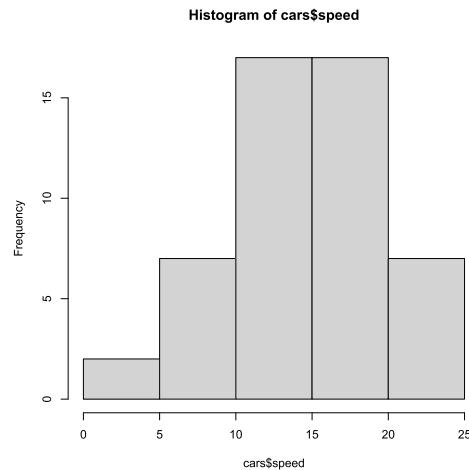
log(pi^2) #log is natural log by default

## [1] 2.28946
```

```
mean(cars$speed)
```

```
## [1] 15.4
```

```
hist(cars$speed)
```

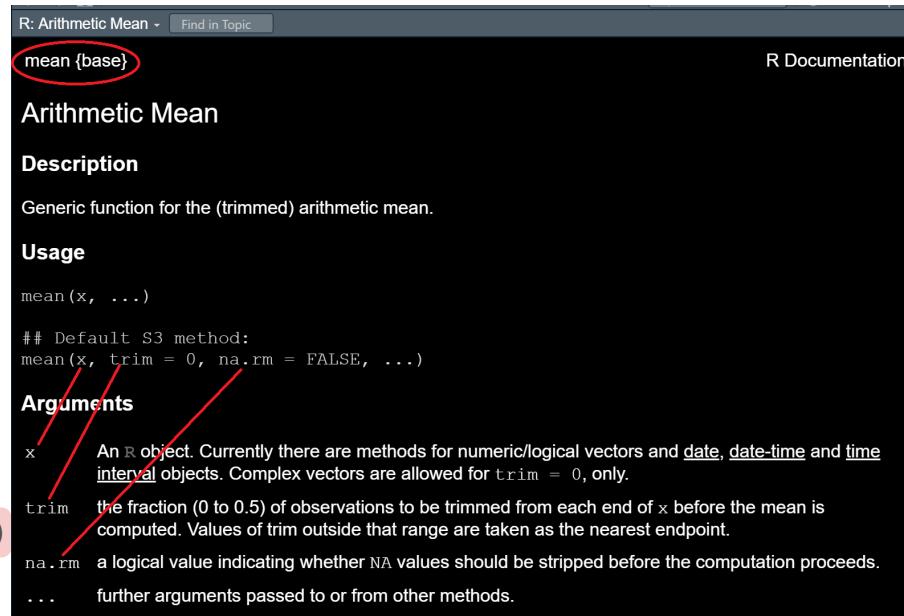


Files/Plots/Packages/Help

- Files (navigate through files)
- Created plots stored in `Plots` tab
 - Cycle through past plots
 - Easily save
- Packages (update and install)
- Documentation within RStudio via `help(...)`
 - Ex: `help(seq)`

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 - Ex: **help(seq)**

Value

If `trim` is zero (the default), the arithmetic mean of the values in `x` is computed ~~as a numeric or complex vector of length one. If `x` is not logical (coerced to numeric), numeric (including integer) or complex, `NA_real_` is returned, with a warning.~~

If `trim` is non-zero, a symmetrically trimmed mean is computed with a fraction of `trim` observations deleted from each end before the mean is computed.

References

Becker, R. A., Chambers, J. M. and Wilks, A. R. (1988) *The New S Language*. Wadsworth & Brooks/Cole.

See Also

`weighted.mean`, `mean.POSIXct`, `colMeans` for row and column means.

Examples

```
x <- c(0:10, 50)
xm <- mean(x)
c(xm, mean(x, trim = 0.10))
```

[Package `base` version 4.1.2 Index]

Environment

- We store **data/info/function/etc.** in R objects
- Create an R object via `<-` (recommended) or `=`

```
#save for later
avg <- (5 + 7 + 6) / 3
#call avg object
avg

## [1] 6

#strings (text) can be saved as well
words <- c("Hello there!", "How are you?")
words

## [1] "Hello there!" "How are you?"
```

Environment

- Built-in objects exist like `letters` and `cars` don't show automatically

```
letters
```

```
## [1] "a" "b" "c" "d" "e" "f" "g" "h" "i" "j" "k" "l" "m" "n" "o" "p" "q" "r" "s"  
## [20] "t" "u" "v" "w" "x" "y" "z"
```

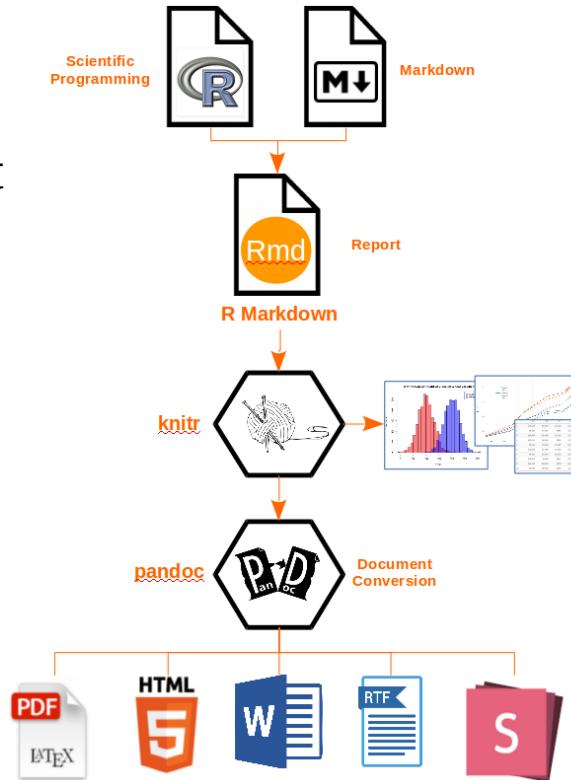
```
head(cars, n = 3)
```

```
##   speed dist  
## 1     4    2  
## 2     4   10  
## 3     7    4
```

- `data()` shows available built-in data sets

Scripting and Viewing Window

- Usually want to keep code for later use!
- Traditionally code in a 'script' and save script
 - Instead we'll use R Markdown
 - A file with extension `.Rmd`
- Let's start with R Markdown!



<http://applied-r.com/>

Documenting with Markdown

Designed to be used in three ways ([R for Data Science](#))

- Communicating to decision makers (focus on conclusions not code)
- Collaborating with other data scientists (including future you!)
- As environment to do data science (documents what you did and what you were thinking)

Markdown Languages

- May have heard of HTML (HyperText Mark-up Language)
 - Write plain text with *tags* that the browser interprets and renders

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- R Markdown is a specific markup language
 - Easier syntax
 - Not as powerful
- Any plain text file can be used (.Rmd extension associates it with R Studio)

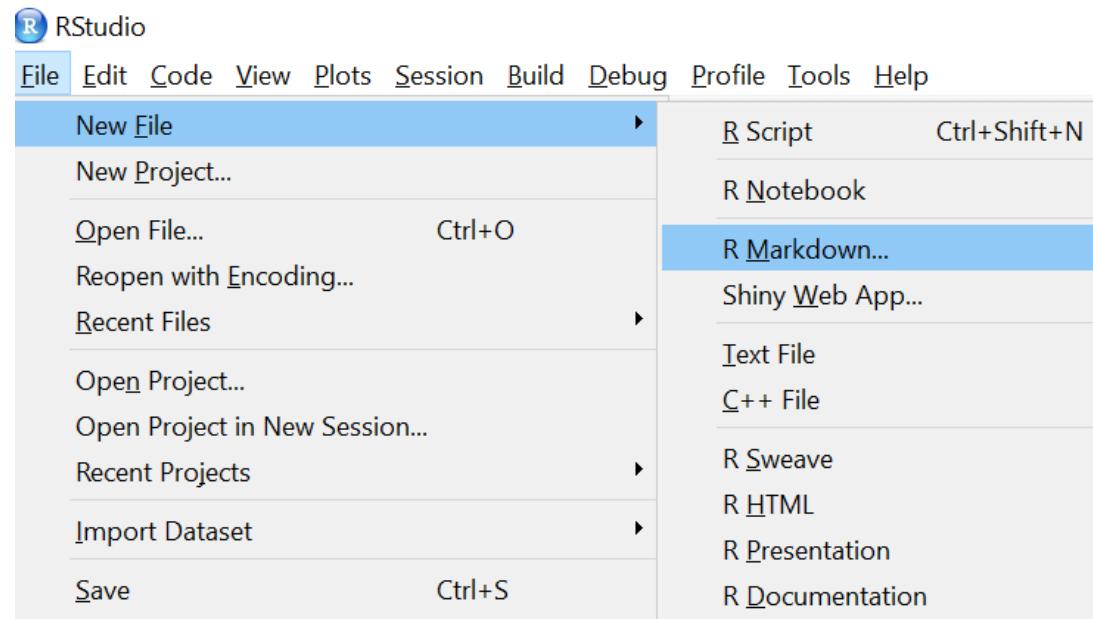
Markdown Languages

- May have heard of HTML (HyperText Mark-up Language)
 - Write plain text with *tags* that the browser interprets and renders
- R Markdown is a specific markup language
 - Easier syntax
 - Not as powerful
- Any plain text file can be used (`.Rmd` extension associates it with R Studio)
- Easy to create many types of documents in R Markdown!



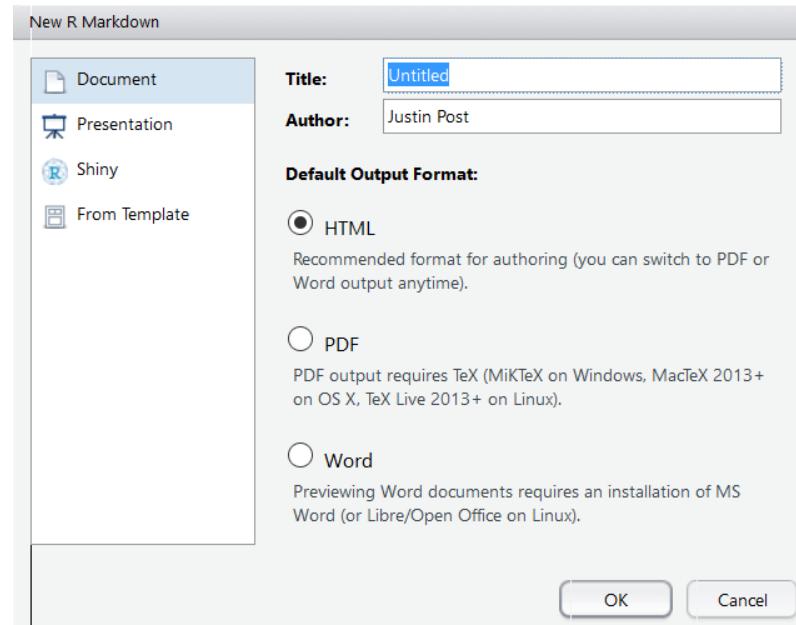
Creating an R Markdown Document

- R Studio makes it easy!



Choosing the Output Type

- Many commonly used document types can be created



.Rmd Files

R Markdown files (.Rmd) contain three important types of content:

1. (Optional) YAML header surrounded by ---s
 - Defines meta data about the document
2. Chunks of R code
 - Code that may evaluate and produce output when *knitting* the document
3. Text mixed with simple text formatting instructions (R Markdown syntax)

YAML Header

- Defines settings for the creation process

```
---
```

```
title: "Untitled"
author: "First Last"
date: "xxxx"
output: html_document
---
```

- CTRL/CMD + Shift + k or the **Knit** button creates a document via this info
- [Great examples of options here](#)

Creating PDF Output

Change the `output` to `pdf_document`

- If you have a `Tex` engine on their computer (such as `MikTex`), good to go
- If not, easiest to do the following first:
 1. Install the `tinytex` package
 2. Run `library(tinytex)`
 3. Run `install_tinytex()`
 4. Restart R

Markdown Syntax

- `# R Markdown` → First level header
- `## Next` → Second level header

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- `<http://rmarkdown.rstudio.com>` → A hyperlink: <http://rmarkdown.rstudio.com>
- `[Cheat Sheet link](https://www.rstudio.com/wp-content/uploads/2015/03/rmarkdown-reference.pdf)` → [Cheat Sheet link](https://www.rstudio.com/wp-content/uploads/2015/03/rmarkdown-reference.pdf)

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- `**Knit**` or `__Knit__` → Bold font (**Knit**)
- `*italic*` or `_italic_` → Italic font (*italic*)
- `*__both__*` → Bold and italic (**both**)

Markdown Syntax

- Can do lists (be careful with spaces & returns)
 - Indent sub lists four spaces

```
- unordered list
- item 2
  + sub-item 1
  + sub-item 2
```

```
1. ordered list
2. item 2
  a. sub-item 1
  b. sub-item 2
```

- See the cheatsheet [here](#) or [here](#)

- unordered list
- item 2
 - sub-item 1
 - sub-item 2

- 1. ordered list
- 2. item 2
 - a. sub-item 1
 - b. sub-item 2

Code Chunks

```
```{r ggplot,eval=FALSE}
select(iris, Sepal.Width)
ggplot(iris, aes(x = Sepal.Width, y = Sepal.Length)) +
geom_point()
```

# Code Chunks

```
```{r ggplot,eval=FALSE}
select(iris, Sepal.Width)
ggplot(iris, aes(x = Sepal.Width, y = Sepal.Length)) +
geom_point()
```

- Start code chunk by typing out the syntax or with CTRL/CMD + Alt/Option + I
- Can execute code in RStudio as you are writing
- Code is executed sequentially when document is created

Code Chunks

```
```{r ggplot, eval=FALSE}
select(iris, Sepal.Width)
ggplot(iris, aes(x = Sepal.Width, y = Sepal.Length)) +
 geom_point()
```

Can specify behavior of each code chunks via **global** or **local** chunk options:

- Hide/show code: `echo = FALSE/TRUE`
- `eval = TRUE/FALSE`
- Eval, not show code or output: `include = TRUE/FALSE`
- `message = TRUE/FALSE` and `warning = TRUE/FALSE`

# Code Chunks

```
```{r ggplot, eval=FALSE}
select(iris, Sepal.Width)
ggplot(iris, aes(x = Sepal.Width, y = Sepal.Length)) +
geom_point()
```

Global chunk options:

- Usually have a **setup** code chunk (with `include = FALSE`)
- Defines global behavior for all chunks

Ex: `opts_chunk$set(echo = FALSE, eval = TRUE, warning = FALSE)`

Code Chunks

```
knitr::include_graphics("img/chunk.png")
```

Using chunks is generally the best way to include an image.

Code chunk options often used

- `fig.align = 'center'`
- `out.width = "500px"`
- `echo = FALSE`

Inline R Code

R code can be evaluated inline!

- Begin with a single back-tick followed by `r`
- End with another back-tick

Ex: Iris has `r length(iris[,1])` observations → Iris has 150 observations

Recap!

- R Markdown allows for easily reproducible analyses and documenting of thought processes
 - YAML header
 - Plain text with R Markdown syntax
 - Code chunks
- [Cheat Sheet link](#) great for getting started
- Everything you could want to know about R Markdown in [R Markdown: The Definitive Guide](#)

Let's Practice

- Take the raw text [here](#)
- Create the HTML output [here](#)

Guidance:

- Create a new .Rmd file and replace its test with the raw text (copy/paste)
- Knit the document as is to start
- Add headers (the `dplyr`, `ggplot2`, `readr`, and `tidyverse` sections are second level headers), reknit
- [Update YAML header](#) to add code folding, reknit
- Update the global chunk options (`echo`, `eval` should be `TRUE`, `message` should be `FALSE`), reknit
- Modify local chunk options on the images to suppress code, reknit
- [Add in markdown syntax](#) (links, code font, etc.), reknit
- [Add tabssets](#), reknit

Data Storage in R

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R Objects and Classes

- Create an R object via `<-` (recommended) or `=`
 - allocates memory to object

```
vec <- c(1, 4, 10)
vec
## [1] 1 4 10
```

R Objects and Classes

- Create an R object via `<-` (recommended) or `=`
 - allocates memory to object

```
vec <- c(1, 4, 10)
vec
## [1] 1 4 10

fit <- lm(dist ~ speed, data = cars)
fit

##
## Call:
## lm(formula = dist ~ speed, data = cars)
##
## Coefficients:
## (Intercept)      speed
## -17.579        3.932
```

Investigating Objects

Many functions to help understand an R Object

- `str()`
- compactly displays the internal structure of an R object

```
str(cars)

## 'data.frame':   50 obs. of  2 variables:
## $ speed: num  4 4 7 7 8 9 10 10 10 11 ...
## $ dist : num  2 10 4 22 16 10 18 26 34 17 ...

str(vec)

## num [1:3] 1 4 10
```

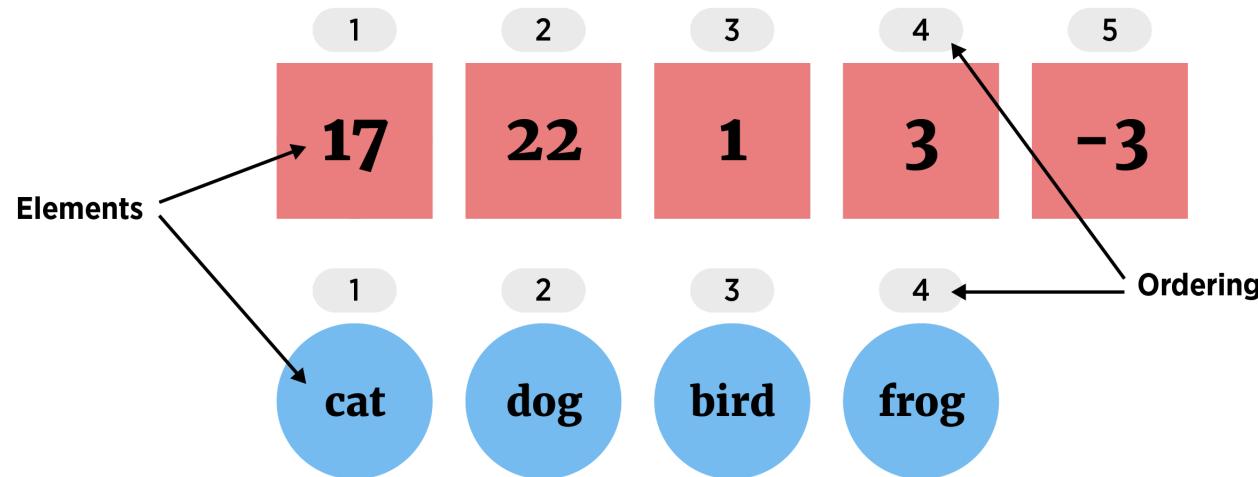
Data Objects

- Understand data structures first: Five major types
 - **Atomic Vector (1d)**
 - Matrix (2d)
 - Array (nd)
 - **Data Frame (2d)**
 - List (1d)

Dimension	Homogeneous	Heterogeneous
1d	Atomic Vector	List
2d	Matrix	Data Frame
nd	Array	

Vector

(Atomic) Vector (1D group of elements with an ordering)



- Elements must be same 'type'
 - numeric, character, or logical

Vector

(Atomic) Vector (1D group of elements with an ordering)

- Create with `c()` function ('combine')

```
#vectors (1 dimensional) objects
x <- c(17, 22, 1, 3, -3)
y <- c("cat", "dog", "bird", "frog")
x
## [1] 17 22  1  3 -3
y
## [1] "cat"  "dog"  "bird" "frog"
```

Vector

- Many **functions** output a numeric vector

```
v <- seq(from = 1, to = 5, length = 5)
#same result with different inputs:
v <- seq(from = 1, to = 5, by = 1)
```

```
v
```

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

```
str(v)
```

```
## num [1:5] 1 2 3 4 5
```

:

to Create a Sequence

1:20

```
## [1] 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
```

- R does element-wise math on vectors

1:20/20

```
## [1] 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40 0.45 0.50 0.55 0.60 0.65 0.70 0.75  
## [16] 0.80 0.85 0.90 0.95 1.00
```

1:20 + 1

```
## [1] 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21
```

Slicing Vectors

- Return elements using square brackets `[]`

```
letters #built-in vector  
## [1] "a" "b" "c" "d" "e" "f" "g" "h" "i" "j" "k" "l" "m" "n" "o" "p" "q" "r" "s"  
## [20] "t" "u" "v" "w" "x" "y" "z"  
letters[1] #R starts counting at 1!  
## [1] "a"  
letters[26]  
## [1] "z"
```

Slicing Vectors

- Return elements using square brackets `[]`
- Can 'feed' in a vector of indices to `[]`

```
letters[1:4]
## [1] "a" "b" "c" "d"

letters[c(5, 10, 15, 20, 25)]
## [1] "e" "j" "o" "t" "y"

x <- c(1, 2, 5)
letters[x]

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

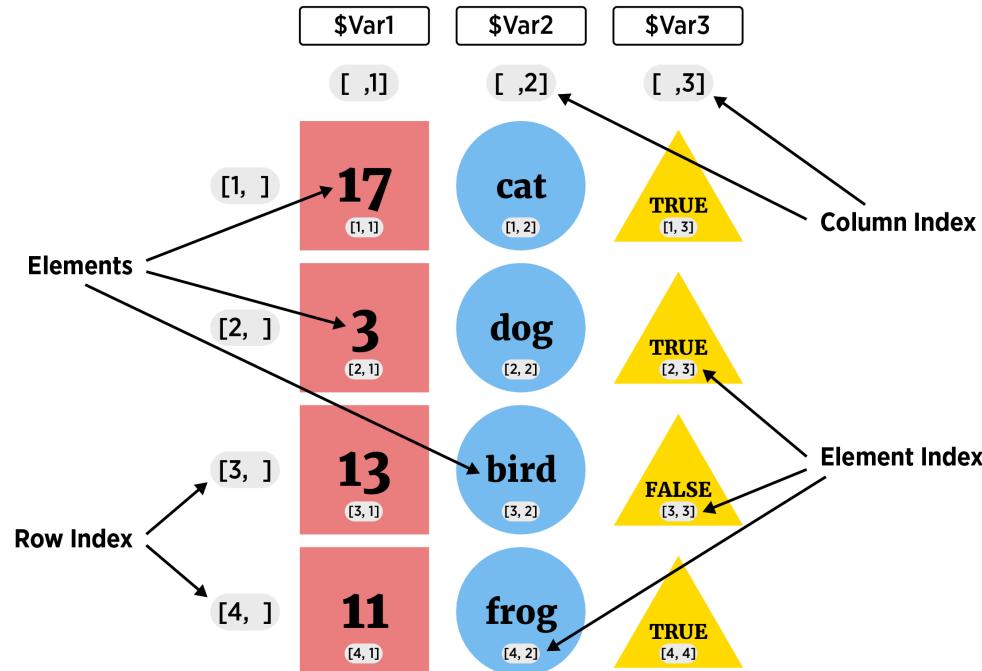
Slicing Vectors

- Return elements using square brackets `[]`
- Can 'feed' in a vector of indices to `[]`
- Use negative indices to return without

```
letters[-(1:4)]  
## [1] "e" "f" "g" "h" "i" "j" "k" "l" "m" "n" "o" "p" "q" "r" "s" "t" "u" "v" "w"  
## [20] "x" "y" "z"  
  
x <- c(1, 2, 5)  
letters[-x]  
## [1] "c" "d" "f" "g" "h" "i" "j" "k" "l" "m" "n" "o" "p" "q" "r" "s" "t" "u" "v"  
## [20] "w" "x" "y" "z"
```

Building Blocks for Data Frames

- Columns of a data frame are vectors



Data Frame

Data Frame (2D data structure)

- Collection (list) of **vectors** of the same *length*
- Create with `data.frame()` function

```
x <- c("a", "b", "c", "d", "e", "f")
y <- c(1, 3, 4, -1, 5, 6)
z <- 10:15
myDF <- data.frame(x, y, z)
myDF
```

```
##   x  y  z
## 1 a  1 10
## 2 b  3 11
## 3 c  4 12
## 4 d -1 13
## 5 e  5 14
## 6 f  6 15
```

Data Frame

Data Frame (2D data structure)

- Collection (list) of **vectors** of the same *length*
- Create with `data.frame()` function

```
myDF <- data.frame(char = x, data1 = y, data2 = z)  
myDF
```

```
##   char data1 data2  
## 1   a     1    10  
## 2   b     3    11  
## 3   c     4    12  
## 4   d    -1    13  
## 5   e     5    14  
## 6   f     6    15
```

- `char`, `data1`, and `data2` become the variable names for the data frame

Slicing a Data Frame

- Use square brackets with a comma [,]
 - Index rows (prior to the comma) then columns (after the comma)

```
myDF
```

```
##   char data1 data2
## 1   a     1    10
## 2   b     3    11
## 3   c     4    12
## 4   d    -1    13
## 5   e     5    14
## 6   f     6    15
```

```
myDF[c(2, 4), ]
```

```
##   char data1 data2
## 2   b     3    11
## 4   d    -1    13
```

```
myDF[, 1]
```

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

```
myDF[2, ]
```

```
##   char data1 data2
## 2   b     3    11
```

```
myDF[2, 1]
```

```
## [1] "b"
```

Slicing a Data Frame

- Can use columns names to subset

```
myDF[ , c("char", "data1")]
```

```
##   char data1
## 1     a     1
## 2     b     3
## 3     c     4
## 4     d    -1
## 5     e     5
## 6     f     6
```

Slicing a Data Frame

- Dollar sign allows easy access to a single column!

```
myDF$char  
## [1] "a" "b" "c" "d" "e" "f"  
  
myDF$data1  
## [1] 1 3 4 -1 5 6
```

Slicing a Data Frame

- Dollar sign allows easy access to a single column!
- Most used method for accessing a single variable
- RStudio fills in options.
 - Type `mydf$`
 - If no choices - hit tab
 - Hit tab again to choose

Recap!

Data Frame (2D data structure)

- Collection (list) of **vectors** of the same *length*
- Create with `data.frame()` function
- Access with `[,]` or `$`
- Perfect for most data sets!
- Most functions that read 2D data store it as a `data frame` (or `tibble` - a special data frame covered shortly)

Let's Practice

We'll add to our `.Rmd` file from the previous activity

- Download the prompts to add to our markdown document [here](#)

Guidance:

- Copy and paste the text from above into the bottom of the document, reknit
- Add to the code chunks, evaluating in the notebook
- Reknit occasionally to check the output

The tidyverse

Justin Post

Where Do Our Objects & Functions Come From?

Dimension	Homogeneous	Heterogeneous
1d	Atomic Vector	List
2d	Matrix	Data Frame
nd	Array	

Basic access via

- Atomic vectors - `x[]`
- Data Frames - `x[,]` or `x$name`
- Lists - `x[]`, `x[[]]`, or `x$name`

Where Do Our Objects & Functions Come From?

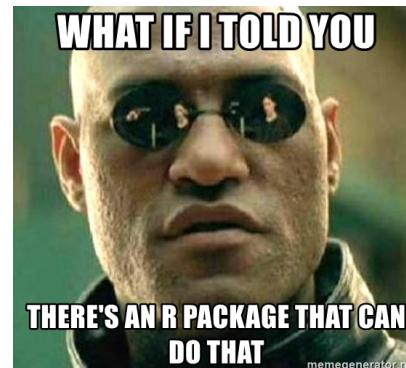
When you open R a few packages are loaded

- R package:
 - Collection of functions/objects/datasets/etc.

Where Do Our Objects & Functions Come From?

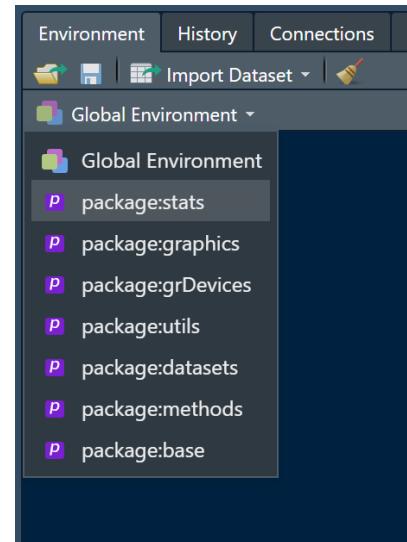
When you open R a few packages are loaded

- R package:
 - Collection of functions/objects/datasets/etc.
- Packages exist to do almost anything
 - [List of CRAN](#) approved packages
 - Plenty of other packages on places like GitHub



Where Do Our Objects & Functions Come From?

- Packages loaded automatically



- `base` package has `c()`, `data.frame()`, `list()`, ...

Base R vs Tidyverse

- Everything done so far uses Base R

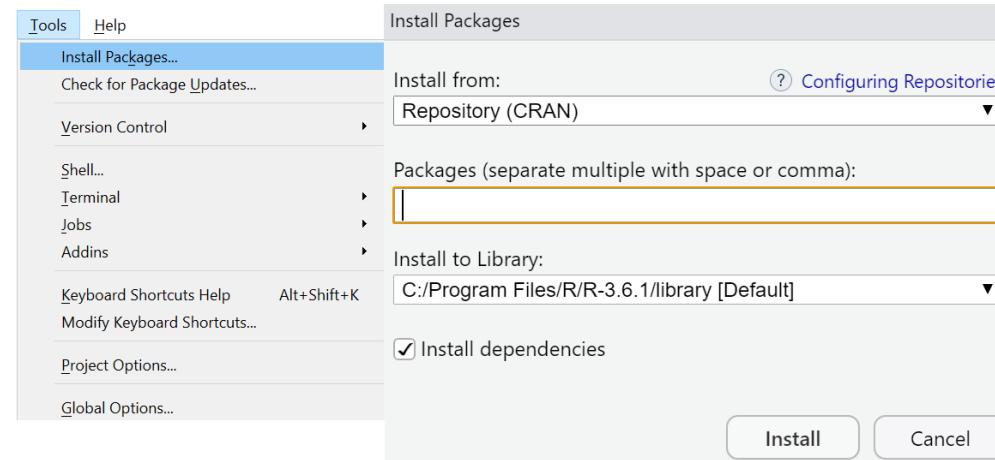
Coherent and opinionated framework for common data tasks:

- TidyVerse
 - data importing (`readr`, `readxl`, `haven`, `DBI`)
 - data manipulation (`dplyr`, `tidyverse`)
 - plotting (sort of) (`ggplot2`)
 - ...

Installing an R Package

- First time using a package
 - Must **install package** (download files to your computer)
 - Can use code, menus, or Packages tab

```
install.packages("dplyr")
```



Accessing a Package in Your R Session

- Only install once!
- **Each session:** read in package using `library()` or `require()`

```
library("dplyr")
```

Accessing a Package in Your R Session

- Only install once!
- **Each session:** read in package using `library()` or `require()`

```
library("dplyr")
```

- See everything from that package:

```
ls("package:dplyr")
```

## [1] "%>%"	"across"	"add_count"
## [4] "add_count_"	"add_row"	"add_rownames"
## [7] "add_tally"	"add_tally_"	"all_equal"
## [10] "all_of"	"all_vars"	"anti_join"
## [13] "any_of"	"any_vars"	"arrange"
## [16] "arrange_"	"arrange_all"	"arrange_at"
## [19] "arrange_if"	"as.tbl"	"as_data_frame"
## [22] "as_label"	"as_tibble"	"auto_copy"
## [25] "band_instruments"	"band_instruments2"	"band_members"
## [28] "bench_tbls"	"between"	"bind_cols"
## [31] "bind_rows"	"c_across"	"case_when"
## [34] "bind_tf"	"check_dbplyr"	"coalesce"
## [37] "bind_tf2"	"collect"	"combine"
## [40] "bind_tf3"	"compare_tbls"	"compare_tbls2"
## [43] "bind_tf4"	"contains"	"copy_to"

Calling From a Library

- Call functions without loading full library with `::`
- If not specified, most recently loaded package takes precedent

```
#stats::filter(...) calls time-series function from stats package  
dplyr::filter(iris, Species == "virginica")
```

```
##   Sepal.Length Sepal.Width Petal.Length Petal.Width   Species  
## 1          6.3         3.3          6.0          2.5 virginica  
## 2          5.8         2.7          5.1          1.9 virginica  
## 3          7.1         3.0          5.9          2.1 virginica  
## 4          6.3         2.9          5.6          1.8 virginica  
## 5          6.5         3.0          5.8          2.2 virginica  
## 6          7.6         3.0          6.6          2.1 virginica  
## 7          4.9         2.5          4.5          1.7 virginica  
## 8          7.3         2.9          6.3          1.8 virginica  
## 9          6.7         2.5          5.8          1.8 virginica  
## 10         7.2         3.6          6.1          2.5 virginica  
## 11         6.5         3.2          5.1          2.0 virginica  
## 12         6.4         2.7          5.3          1.9 virginica  
## 13         6.8         3.0          5.5          2.1 virginica  
## 14         5.7         2.5          5.0          2.0 virginica  
## 15         5.8         2.8          5.1          2.4 virginica  
## 16         6.0         3.0          5.3          2.3 virginica  
## 17         5.9         3.0          5.5          1.8 virginica  
## 18         6.7         3.0          5.5          2.2 virginica  
## 19         6.9         3.1          5.1          2.3 virginica
```

Reading Raw Data Into R

- Read in **raw** data using the `tidyverse` via `readr`, `readxl`, `haven`, and `DBI`

Reading Raw Data Into R

- Read in **raw** data using the `tidyverse` via `readr`, `readxl`, `haven`, and `DBI`

Plan:

- Read 'clean' delimited data
- Read Excel data
- See an example of connecting to a database

Reading Delimited Data

`baseR utils` package and `tidyverse readr` package function and purpose:

Type of Delimiter	<code>utils</code> Function	<code>readr</code> Function
Comma	<code>read.csv()</code>	<code>read_csv()</code>
Semicolon (<code>,</code> for decimal)	<code>read.csv2()</code>	<code>read_csv2()</code>
Tab	<code>read.delim()</code>	<code>read_tsv()</code>
General	<code>read.table(sep = "")</code>	<code>read_delim()</code>
White Space	<code>read.table(sep = "")</code>	<code>read_table()</code>

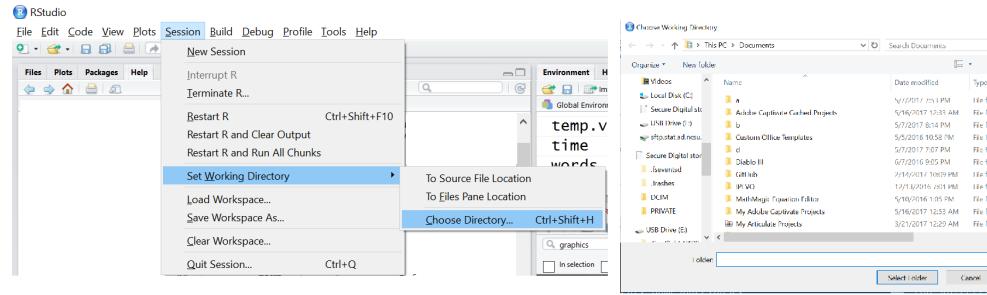
Working Directory

- Let's read in the '**neuralgia.csv**' file
 - *csv* implies comma separated value (sometimes semi-colon)
- By default, R looks in the **working directory** for the file

```
getwd()  
## [1] "C:/Users/jbpost2/repos/R4Reproducibility/slides"
```

Working Directory

- Can change *working directory* via code or menus



```
setwd("C:/Users/jbpost2/repos/R4Reproducibility/datasets")
#or
setwd("C:\\\\Users\\\\jbpost2\\\\repos\\\\R4Reproducibility\\\\datasets")
```

Reading a .csv File

Common arguments to `read_csv()`:

```
read_csv(  
  file,  
  col_names = TRUE,  
  na = c("", "NA"),  
  skip = 0,  
  col_types = NULL,  
  guess_max = min(1000, n_max),  
)
```

Reading a .csv File

With `neuralgia.csv` file in the working directory:

```
neuralgiaData <- read_csv("neuralgia.csv")  
  
neuralgiaData  
  
## # A tibble: 60 × 5  
##   Treatment Sex     Age Duration Pain  
##   <chr>      <chr> <dbl>    <dbl> <chr>  
## 1 P          F       68        1 No  
## 2 B          M       74       16 No  
## 3 P          F       67       30 No  
## 4 P          M       66       26 Yes  
## 5 B          F       67       28 No  
## # ... with 55 more rows
```

Reading a .csv File

- Use full local path

```
neuralgiaData <- read_csv("C:/Users/jbpost2/repos/R4Reproducibility/slides/data/neuralgia.csv")
```

Reading a .csv File

- Use full local path

```
neuralgiaData <- read_csv("C:/Users/jbpost2/repos/R4Reproducibility/slides/data/neuralgia.csv")
```

- R can pull from URLs as well!

```
neuralgiaData <- read_csv("https://www4.stat.ncsu.edu/~online/datasets/neuralgia.csv")  
neuralgiaData
```

```
## # A tibble: 60 x 5  
##   Treatment Sex     Age Duration Pain  
##   <chr>      <chr> <dbl>    <dbl> <chr>  
## 1 P          F       68        1 No  
## 2 B          M       74        16 No  
## 3 P          F       67        30 No  
## 4 P          M       66        26 Yes  
## 5 B          F       67        28 No  
## # ... with 55 more rows
```

tibbles

What kind of object does `read_csv()` create?

```
class(neuralgiaData)
## [1] "spec_tbl_df" "tbl_df"       "tbl"          "data.frame"

str(neuralgiaData)

## #> spec_tbl_df [60 x 5] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
## #>   $ Treatment: chr [1:60] "P" "B" "P" "P" ...
## #>   $ Sex      : chr [1:60] "F" "M" "F" "M" ...
## #>   $ Age      : num [1:60] 68 74 67 66 67 77 71 72 76 71 ...
## #>   $ Duration : num [1:60] 1 16 30 26 28 16 12 50 9 17 ...
## #>   $ Pain     : chr [1:60] "No" "No" "No" "Yes" ...
## #> - attr(*, "spec")=
## #>   .. cols(
## #>     ..   Treatment = col_character(),
## #>     ..   Sex = col_character(),
## #>     ..   Age = col_double(),
## #>     ..   Duration = col_double(),
## #>     ..   Pain = col_character()
## #>     .. )
## #> - attr(*, "problems")=<externalptr>
```

tibbles

- `tibbles` are the main object the tidyverse works with

tibbles

- `tibbles` are the main object the tidyverse works with
 - Fancy printing!
 - Checking column type is a basic data validation step

```
neuralgiaData  
## # A tibble: 60 × 5  
##   Treatment Sex     Age Duration Pain  
##   <chr>      <chr> <dbl>    <dbl> <chr>  
## 1 P          F        68       1   No  
## 2 B          M        74      16   No  
## 3 P          F        67      30   No  
## 4 P          M        66      26 Yes  
## 5 B          F        67      28   No  
## # ... with 55 more rows
```

- Behavior slightly different than a standard data frame. No simplification!

tibbles

- tibbles do not simplify

```
neuralgiaData[ ,1]  
  
## # A tibble: 60 x 1  
##   Treatment  
##   <chr>  
## 1 P  
## 2 B  
## 3 P  
## 4 P  
## 5 B  
## # ... with 55 more rows
```

```
neuralgiaData2 <- as.data.frame(neuralgiaData)  
neuralgiaData2[ ,1]  
  
## [1] "P"  "B"  "P"  "P"  "B"  "B"  "A"  "B"  "B"  "A"  "A"  "A"  "B"  "A"  "P"  "A"  "P"  
## [20] "B"  "B"  "A"  "A"  "B"  "P"  "B"  "B"  "P"  "P"  "A"  "A"  "B"  "B"  "B"  "A"  "P"  
## [39] "B"  "P"  "P"  "P"  "A"  "B"  "A"  "P"  "P"  "A"  "B"  "P"  "P"  "P"  "B"  "A"  "P"  
## [58] "A"  "B"  "A"
```

tibbles

- Use either `dplyr::pull()` or `$` to return a vector

```
pull(neuralgiaData, Treatment) #or pull(neuralgiaData, 1)

## [1] "P"  "B"  "P"  "P"  "B"  "B"  "A"  "B"  "B"  "A"  "A"  "A"  "B"  "A"  "P"  "A"  "P"  "A"  "P"
## [20] "B"  "B"  "A"  "A"  "B"  "P"  "B"  "B"  "P"  "P"  "A"  "A"  "B"  "B"  "B"  "A"  "P"  "B"
## [39] "B"  "P"  "P"  "P"  "A"  "B"  "A"  "P"  "P"  "A"  "B"  "P"  "P"  "P"  "B"  "A"  "P"  "A"  "P"
## [58] "A"  "B"  "A"

neuralgiaData$Treatment

## [1] "P"  "B"  "P"  "P"  "B"  "B"  "A"  "B"  "B"  "A"  "A"  "A"  "B"  "A"  "P"  "A"  "P"  "A"  "P"
## [20] "B"  "B"  "A"  "A"  "B"  "P"  "B"  "B"  "P"  "P"  "A"  "A"  "B"  "B"  "B"  "A"  "P"  "B"
## [39] "B"  "P"  "P"  "P"  "A"  "B"  "A"  "P"  "P"  "A"  "B"  "P"  "P"  "P"  "B"  "A"  "P"  "A"  "P"
## [58] "A"  "B"  "A"
```

Reading Delimited Data with `readr`

- Reading *clean* delimited data pretty easy with the tidyverse!

Type of Delimiter	<code>readr</code> Function
Comma	<code>read_csv()</code>
Semicolon (, for decimal)	<code>read_csv2()</code>
Tab	<code>read_tsv()</code>
General	<code>read_delim()</code>
White Space	<code>read_table()</code>

- Let's read in the 'chemical.txt' file (space delimited) with `read_table()`
- Common arguments to `read_table()` are the same as `read_csv()`

Reading Space Delimited Data

- Let's read in the 'chemical.txt' file (space delimited) with `read_table()`

```
read_table("https://www4.stat.ncsu.edu/~online/datasets/chemical.txt")  
  
## # A tibble: 19 x 4  
##   temp conc time percent  
##   <dbl> <dbl> <dbl>    <dbl>  
## 1 -1    -1    -1     45.9  
## 2 1     -1    -1     60.6  
## 3 -1    1     -1     57.5  
## 4 1     1     -1     58.6  
## 5 -1    -1     1     53.3  
## 6 1     -1     1     58  
## 7 -1    1     1     58.8  
## 8 1     1     1     52.4  
## 9 -2    0     0     46.9  
## 10 2    0     0     55.4  
## 11 0    -2    0     55  
## 12 0    2     0     57.5  
## 13 0    0    -2     56.3  
## 14 0    0     2     58.9  
## 15 0    0     0     56.9  
## 16 2    -3    0     61.1  
## 17 2    -3    0     62.9
```

Reading Tab Delimited Data

- Let's read in the 'crabs.txt' file (tab delimited) with `read_tsv()`

```
read_tsv("https://www4.stat.ncsu.edu/~online/datasets/crabs.txt")  
  
## # A tibble: 173 x 6  
##   color spine width satell weight     y  
##   <dbl> <dbl> <dbl>  <dbl>  <dbl> <dbl>  
## 1     3     3  28.3      8    3050     1  
## 2     4     3  22.5      0    1550     0  
## 3     2     1  26.0      9    2300     1  
## 4     4     3  24.8      0    2100     0  
## 5     4     3  26.0      4    2600     1  
## # ... with 168 more rows
```

Reading Generic Delimited Data

- Let's read in the '**umps2012.txt**' file ('>' delimited) with `read_delim()`
 - `read_delim()` requires a `delim` argument

Reading Generic Delimited Data

- Let's read in the '**umps2012.txt**' file ('>' delimited) with `read_delim()`
 - `read_delim()` requires a `delim` argument
- In **umps2012.txt** data file, no column names provided!
 - Use `col_names` argument: Either TRUE, FALSE or a character vector of column names.
 - When specifying a character vector, `read_delim()` automatically starts reading first row of data

Reading Generic Delimited Data

- Let's read in the 'umps2012.txt' file ('>' delimited) with `read_delim()`

```
read_delim("https://www4.stat.ncsu.edu/~online/datasets/umps2012.txt",
            delim = ">",
            col_names = c("Year", "Month", "Day", "Home", "Away", "HPUmpire"))

## # A tibble: 2,359 x 6
##   Year Month Day Home Away HPUmpire
##   <dbl> <dbl> <dbl> <chr> <chr> <chr>
## 1 2012     4    12 MIN   LAA D.J. Reyburn
## 2 2012     4    12 SD    ARI Marty Foster
## 3 2012     4    12 WSH   CIN Mike Everitt
## 4 2012     4    12 PHI   MIA Jeff Nelson
## 5 2012     4    12 CHC   MIL Fieldin Culbreth
## # ... with 2,354 more rows
```

Reading Fixed Field & Tricky Non-Standard Data

- `read_fwf()`
 - reads in raw data where entries are very structured
- `read_file()`
 - reads an entire file into a single string
- `read_lines()`
 - reads a file into a character vector with one element per line
- Usually parse the last two with `regular expressions` :(

Recap!

Type of Delimiter	readr Function
Comma	read_csv()
Semicolon (, for decimal)	read_csv2()
Tab	read_tsv()
General	read_delim()
White Space	read_table()

Common arguments: `file,`

```
  col_names = TRUE,  
  na = c("", "NA"),  
  skip = 0,  
  col_types = NULL,  
  guess_max = min(1000, n_max),
```

Excel Data



Excel data refers to a `.xls` or `.xlsx` file

- `readxl` package does not load with `tidyverse` but is part of it!

Excel Data



Excel data refers to a `.xls` or `.xlsx` file

- `readxl` package does not load with `tidyverse` but is part of it!
- `read_excel()` function can read both types of excel data files
 - Can't pull from web though!
- Read in `censusEd.xlsx`

read_excel()

```
#install package if necessary  
library(readxl)
```

read_excel()

```
#install package if necessary
library(readxl)
#reads first sheet by default
edData <- read_excel("censusEd.xlsx")
```

edData

```
## # A tibble: 3,198 x 42
##   Area_name    STCOU EDU010187F EDU010187D EDU010187N1 EDU010187N2 EDU010188F
##   <chr>        <chr>     <dbl>      <dbl>      <chr>      <chr>      <dbl>
## 1 UNITED STATES 00000         0  40024299  0000       0000          0
## 2 ALABAMA        01000         0   733735  0000       0000          0
## 3 Autauga, AL    01001         0    6829  0000       0000          0
## 4 Baldwin, AL    01003         0   16417  0000       0000          0
## 5 Barbour, AL    01005         0   5071  0000       0000          0
## # ... with 3,193 more rows, and 35 more variables: EDU010188D <dbl>,
## #   EDU010188N1 <chr>, EDU010188N2 <chr>, EDU010189F <dbl>, EDU010189D <dbl>,
## #   EDU010189N1 <chr>, EDU010189N2 <chr>, EDU010190F <dbl>, EDU010190D <dbl>,
## #   EDU010190N1 <chr>, EDU010190N2 <chr>, EDU010191F <dbl>, EDU010191D <dbl>,
## #   EDU010191N1 <chr>, EDU010191N2 <chr>, EDU010192F <dbl>, EDU010192D <dbl>,
## #   EDU010192N1 <chr>, EDU010192N2 <chr>, EDU010193F <dbl>, EDU010193D <dbl>,
## #   EDU010193N1 <chr>, EDU010193N2 <chr>, EDU010194F <dbl>, ...
```

Dealing with Excel Sheets

- Can look at sheets available with `excel_sheets()`

```
excel_sheets("censusEd.xlsx")  
## [1] "EDU01A" "EDU01B" "EDU01C" "EDU01D" "EDU01E" "EDU01F" "EDU01G" "EDU01H"  
## [9] "EDU01I" "EDU01J"
```

- Specify sheet with name or integers (or `NULL` for 1st) using `sheet =`

```
read_excel("censusEd.xlsx", sheet = "EDU01D")  
## # A tibble: 3,198 x 42  
##   Area_name    STCOU EDU264190F EDU264190D EDU264190N1 EDU264190N2 EDU280190F  
##   <chr>        <chr>     <dbl>      <dbl>      <chr>        <chr>      <dbl>  
## 1 UNITED STATES 00000         0     4187099  0000       0000          0  
## 2 ALABAMA       01000         0      57284  0000       0000          0  
## 3 Autauga, AL   01001         0       604  0000       0000          0  
## 4 Baldwin, AL   01003         0      1761  0000       0000          0  
## 5 Barbour, AL   01005         0       466  0000       0000          0  
## # ... with 3,193 more rows, and 35 more variables: EDU280190D <dbl>,  
## #   EDU280190N1 <chr>, EDU280190N2 <chr>, EDU282190F <dbl>, EDU282190D <dbl>,  
## #   EDU282190N1 <chr>, EDU282190N2 <chr>, EDU284190F <dbl>, EDU284190D <dbl>,  
## #   EDU284190N1 <chr>, EDU284190N2 <chr>, EDU299190F <dbl>, EDU299190D <dbl>,  
## #   90N2 <chr>, EDU300200F <dbl>, EDU300200D <dbl>, 00N2 <chr>, EDU310200F <dbl>, EDU310200D <dbl>,  
## #   00N2 <chr>, EDU312200F <dbl>, ...
```

SAS Data



SAS data refers to a `.sas7bdat` file

- `haven` package does not load with `tidyverse` but is part of it!

SAS Data



SAS data refers to a `.sas7bdat` file

- `haven` package does not load with `tidyverse` but is part of it!
- `read_sas()` basically just needs the path to the SAS data set
- Read in `smoke2003.sas7bdat`

read_sas()

```
#install if necessary  
library(haven)
```

read_sas()

```
#install if necessary
library(haven)
smokeData <- read_sas("https://www4.stat.ncsu.edu/~online/datasets/smoke2003.sas7bdat")
smokeData

## # A tibble: 443 x 54
##   SEQN SDDSRVYR RIDSTATR RIDEXMON RIAGENDR RIDAGEYR RIDAGEMN RIDAGEEX RIDRETH1
##   <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
## 1 21010      3       2       2       2      52     633     634      3
## 2 21012      3       2       2       1      63     765     766      4
## 3 21048      3       2       1       2      42     504     504      1
## 4 21084      3       2       1       2      57     692     693      3
## 5 21093      3       2       1       2      64     778     778      2
## # ... with 438 more rows, and 45 more variables: RIDRETH2 <dbl>,
## #   DMQMILIT <dbl>, DMDBORN <dbl>, DMDCITZN <dbl>, DMDYRSUS <dbl>,
## #   DMDEDUC3 <dbl>, DMDEDUC2 <dbl>, DMDEDUC <dbl>, DMDSCHOL <dbl>,
## #   DMDMARTL <dbl>, DMDHHSIZ <dbl>, INDHHINC <dbl>, INDFMINC <dbl>,
## #   INDFMPIR <dbl>, RIDEXPRG <dbl>, DMDHRGND <dbl>, DMDHRAGE <dbl>,
## #   DMDHRBRN <dbl>, DMDHREDU <dbl>, DMDHRMAR <dbl>, DMDHSEDU <dbl>,
## #   SIALANG <dbl>, SIAPROXY <dbl>, SIAINTRP <dbl>, FIALANG <dbl>, ...
```

- `haven` can also read SPSS data and others

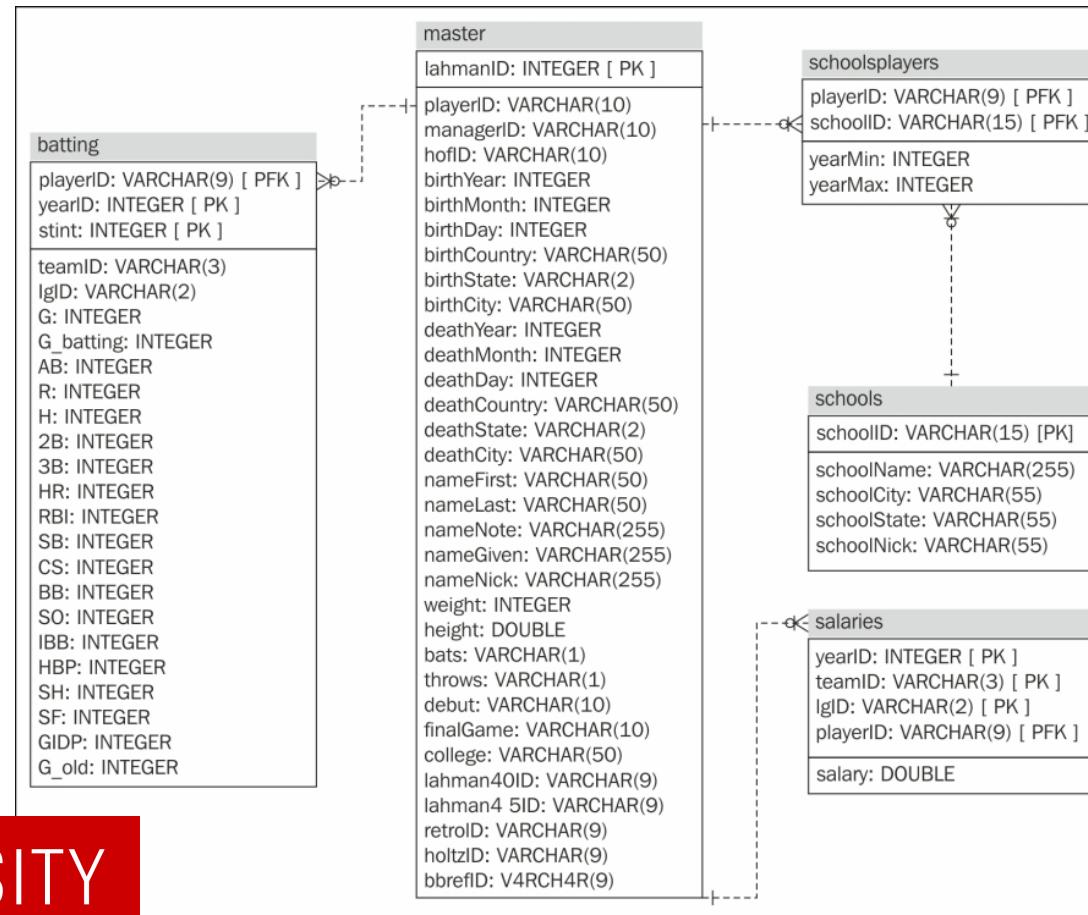
Other Data Sources

JSON - JavaScript Object Notation

- Used widely across the internet and databases
- Can represent usual 2D data or heirarchical data
- `tidyjson` package

Other Data Sources

Databases - Collection of data, often many related 2D tables



Databases - Common flow in R

1. Connect to the database with `DBI::dbConnect()`

- Need appropriate R package for database backend. Ex:
 - `RSQLite::SQLite()` for RSQLite
 - `RMySQL::MySQL()` for RMySQL

```
con <- DBI::dbConnect(  
  RMySQL::MySQL(),  
  host = "hostname.website",  
  user = "username",  
  password = rstudioapi::askForPassword("DB password"))  
)
```

Databases - Common flow in R

1. Connect to the database with `DBI::dbConnect()`
 - Need appropriate R package for database backend
2. Use `tbl()` to reference a table in the database

```
tbl(con, "name_of_table")
```

Databases - Common flow in R

1. Connect to the database with `DBI::dbConnect()`
 - Need appropriate R package for database backend
2. Use `tbl()` to reference a table in the database
3. Query the database with `SQL` or `dplyr/dbplyr`

Databases - Common flow in R

1. Connect to the database with `DBI::dbConnect()`
 - Need appropriate R package for database backend
2. Use `tbl()` to reference a table in the database
3. Query the database with `SQL` or `dplyr/dbplyr`
4. Disconnect from database with `dbDisconnect()`

More about [R Studio and Databases](#)

Connect to chinook Database

- chinook database is a commonly used intro database
 - sqlite backend

```
library(DBI)
con <- dbConnect(
  RSQLite::SQLite(),
  "data/chinook.db"
)
dbListTables(con)

## [1] "albums"          "artists"         "customers"        "employees"
## [5] "genres"          "invoice_items"   "invoices"         "media_types"
## [9] "playlist_track" "playlists"        "sqlite_sequence" "sqlite_stat1"
## [13] "tracks"
```

Connect to chinook Database

- chinook database is a commonly used intro database

```
dbGetQuery(con, "SELECT * FROM invoices") %>%
  collect() %>%
  as_tibble()

## # A tibble: 412 x 9
##   InvoiceId CustomerId InvoiceDate      BillingAddress BillingCity BillingState
##       <int>      <int> <chr>          <chr>        <chr>        <chr>
## 1         1          2 2009-01-01 00:00~ Theodor-Heuss~ Stuttgart <NA>
## 2         2          4 2009-01-02 00:00~ Ullevålsveien~ Oslo      <NA>
## 3         3          8 2009-01-03 00:00~ Grétrystraat ~ Brussels <NA>
## 4         4         14 2009-01-06 00:00~ 8210 111 ST NW Edmonton AB
## 5         5         23 2009-01-11 00:00~ 69 Salem Stre~ Boston    MA
## # ... with 407 more rows, and 3 more variables: BillingCountry <chr>,
## #   BillingPostalCode <chr>, Total <dbl>
```

Big Recap!

Dimension	Homogeneous	Heterogeneous
1d	Atomic Vector	List
2d	Matrix	Data Frame
nd	Array	

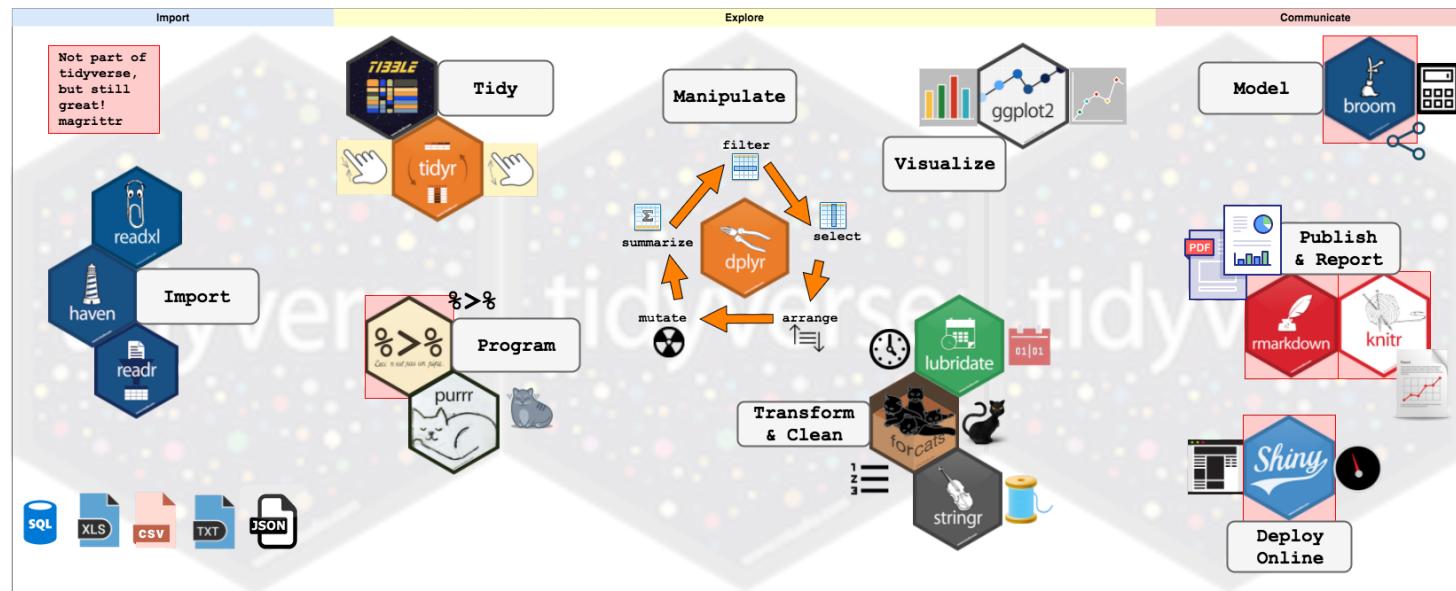
Basic access via

- Atomic vectors - `x[]`
- Data Frames - `x[,]` or `x$name`
- Lists - `x[]`, `x[[]]`, or `x$name`

Big Recap!

`tidyverse` - nice ecosystem of packages with similar behavior and syntax

- `readr`, `haven`, `readxl` all read the data into a tibble
- Good defaults that do the work for you



Let's Practice

We'll add to our `.Rmd` file from the previous activity

- Download the prompts to add to our markdown document [here](#)

Guidance:

- Copy and paste the text from above into the bottom of the document, reknit
- Add to the code chunks, evaluating in the notebook
- Reknit occasionally to check the output

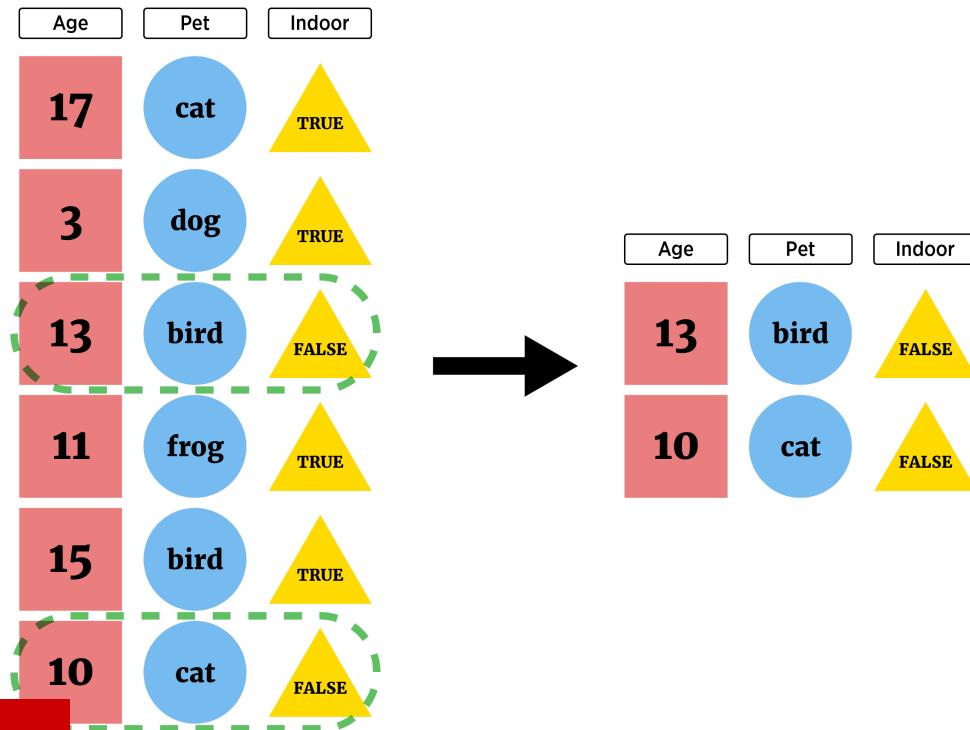
Data Manipulations with dplyr

Justin Post

Data Manipulation Ideas

We may want to subset our full data set or create new variables (columns)

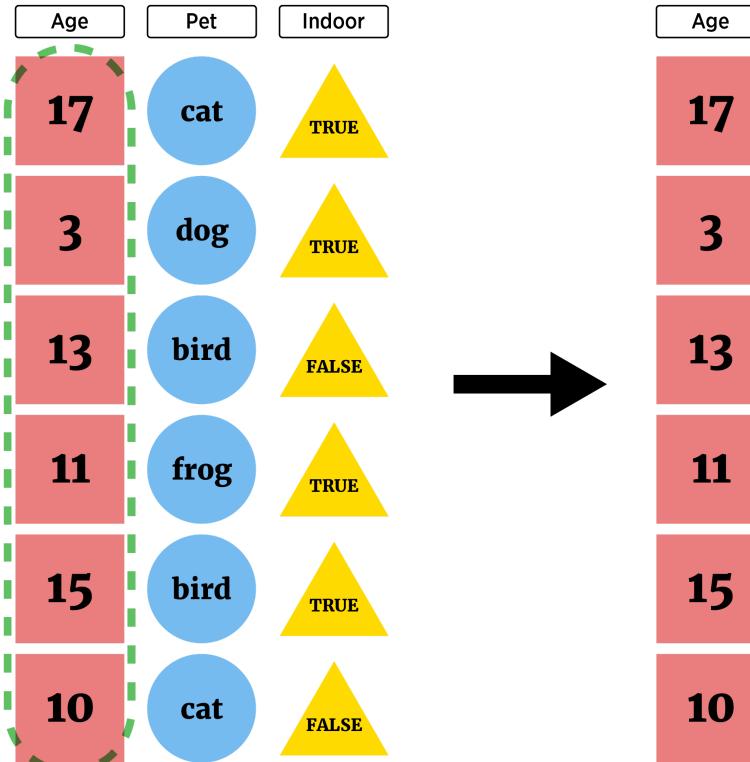
- Grab only certain types of observations (**filter** rows)



Data Manipulation Ideas

We may want to subset our full data set or create new variables (columns)

- Look at only certain variables (**select** columns)



Data Manipulation Ideas

We may want to subset our full data set or create new variables (columns)

- Create new variables (**mutate** columns)

The diagram illustrates a data manipulation process. On the left, there is a 6-row dataset with three columns: Age (red boxes), Pet (blue circles), and Indoor (yellow triangles). The data is as follows:

Age	Pet	Indoor
17	cat	TRUE
3	dog	TRUE
13	bird	FALSE
11	frog	TRUE
15	bird	TRUE
10	cat	FALSE

An arrow points from this dataset to the right, indicating transformation. On the right, the resulting dataset has four columns: Age (red boxes), Pet (blue circles), Indoor (yellow triangles), and AgeType (blue circles). The new AgeType column classifies the animals based on their age:

Age	Pet	Indoor	AgeType
17	cat	TRUE	old
3	dog	TRUE	young
13	bird	FALSE	young
11	frog	TRUE	old
15	bird	TRUE	young
10	cat	FALSE	old

tidyverse

`tidyverse` provides a coherent ecosystem for these tasks via the `dplyr` package! [Cheat Sheet](#)

- Functions take in a `tibble` (special data frames)
- Functions output a `tibble`
- All functions have similar syntax!
`function(tibble, actions, ...)`
- Chaining makes for readable code: `tibble %>% function(actions)`

dplyr

- Commonly used functions:
 - `as_tibble()` - convert data frame to one with better printing

dplyr

- Commonly used functions:
 - `as_tibble()` - convert data frame to one with better printing
 - `filter()` - subset **rows**
 - `arrange()` - reorder **rows**

dplyr

- Commonly used functions:
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 - `rename()` - rename **columns**
 - `mutate()` - add newly created **column**

dplyr

- Commonly used functions:
 - `as_tibble()` - convert data frame to one with better printing
 - `filter()` - subset **rows**
 - `arrange()` - reorder **rows**
 - `select()` - subset **columns**
 - `rename()` - rename **columns**
 - `mutate()` - add newly created **column**
 - `group_by()` - group **rows** by a variable or variables
 - `if_else()` - conditional execution of code

as_tibble() - A Tidy Data Frame

Want to work on `tibbles`, not just `data frames`

- `as_tibble()` - converts a data frame to one with better printing and no simplification

```
#install.packages("Lahman")
library(Lahman)
head(Batting, n = 4) #look at just first 4 observations

##   playerID yearID stint teamID lgID   G   AB   R   H  X2B  X3B  HR RBI SB CS BB SO
## 1 abercda01  1871     1    TR0   NA  1   4   0   0   0   0   0   0   0   0   0   0   0
## 2 addybo01   1871     1    RC1   NA 25 118  30  32   6   0   0  13   8   1   4   0
## 3 allisar01  1871     1    CL1   NA 29 137  28  40   4   5   0  19   3   1   2   5
## 4 allisdo01  1871     1    WS3   NA 27 133  28  44  10   2   2  27   1   1   0   2
##   IBB HBP SH SF GIDP
## 1   NA  NA  NA  NA   0
## 2   NA  NA  NA  NA   0
## 3   NA  NA  NA  NA   1
## 4   NA  NA  NA  NA   0
```

as_tibble() - A Tidy Data Frame

- Can 'wrap' a standard R data frame to convert it to a `tibble`

```
myBatting <- as_tibble(Batting)
myBatting

## # A tibble: 108,789 x 22
##   playerID  yearID stint teamID lgID     G    AB     R     H    X2B    X3B    HR
##   <chr>      <int> <int> <fct>  <fct> <int> <int> <int> <int> <int> <int>
## 1 abercda01  1871     1 TRO     NA     1     4     0     0     0     0     0
## 2 addybo01   1871     1 RC1     NA    25    118    30    32     6     0     0
## 3 allisar01  1871     1 CL1     NA    29    137    28    40     4     5     0
## 4 allisdo01  1871     1 WS3     NA    27    133    28    44    10     2     2
## 5 ansonca01  1871     1 RC1     NA    25    120    29    39    11     3     0
## # ... with 108,784 more rows, and 10 more variables: RBI <int>, SB <int>,
## #   CS <int>, BB <int>, SO <int>, IBB <int>, HBP <int>, SH <int>, SF <int>,
## #   GIDP <int>
```

Filtering Rows Requires Logical Conditions

- **logical statement** - comparison that resolves as `TRUE` or `FALSE`

```
"hi" == " hi" #== is comparison
```

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

```
"hi" == "hi"
```

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

```
4 >= 1
```

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

```
4 != 1
```

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

```
sqrt(3)^2 == 3
```

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

```
dplyr::near(sqrt(3)^2, 3)
```

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

Filtering Rows Requires Logical Conditions

- **logical statement** - comparison that resolves as `TRUE` or `FALSE`

```
#use of is. functions
is.numeric("Word")
## [1] FALSE

is.numeric(10)
## [1] TRUE
```

```
is.character("10")
## [1] TRUE

is.na(c(1:2, NA, 3))
## [1] FALSE FALSE TRUE FALSE

is.matrix(c("hello", "world"))
## [1] FALSE
```

Filtering Rows

- Concept:
 - Feed an *indexing* vector of TRUE/FALSE values
 - R returns elements where TRUE

```
myBatting$G > 20 #vector indicating Games > 20
```

```
## [1] FALSE TRUE TRUE TRUE TRUE FALSE FALSE TRUE FALSE FALSE TRUE FALSE
## [13] FALSE FALSE FALSE TRUE FALSE FALSE FALSE FALSE TRUE TRUE TRUE FALSE
## [25] FALSE FALSE TRUE FALSE FALSE TRUE TRUE FALSE FALSE TRUE TRUE FALSE
## [37] TRUE TRUE TRUE FALSE TRUE TRUE FALSE FALSE TRUE FALSE TRUE FALSE
## [49] TRUE TRUE FALSE TRUE TRUE TRUE FALSE TRUE TRUE FALSE FALSE FALSE
## [61] TRUE FALSE TRUE FALSE FALSE TRUE TRUE TRUE FALSE TRUE TRUE FALSE
## [73] TRUE TRUE TRUE TRUE TRUE TRUE FALSE FALSE TRUE TRUE TRUE FALSE
## [85] TRUE TRUE TRUE FALSE FALSE FALSE TRUE TRUE FALSE TRUE FALSE TRUE
## [97] TRUE FALSE TRUE TRUE FALSE TRUE TRUE FALSE TRUE TRUE TRUE FALSE
## [109] FALSE TRUE TRUE FALSE TRUE TRUE TRUE FALSE TRUE FALSE FALSE TRUE
## [121] FALSE TRUE FALSE TRUE TRUE FALSE FALSE FALSE FALSE TRUE TRUE
## [133] TRUE FALSE FALSE FALSE TRUE FALSE TRUE FALSE FALSE TRUE FALSE TRUE
## [145] FALSE FALSE TRUE FALSE FALSE FALSE TRUE FALSE TRUE TRUE TRUE TRUE
## [157] FALSE FALSE TRUE TRUE FALSE TRUE TRUE FALSE FALSE FALSE FALSE TRUE
## [169] FALSE TRUE FALSE FALSE FALSE FALSE FALSE FALSE TRUE TRUE FALSE TRUE
## [181] FALSE TRUE FALSE TRUE FALSE TRUE FALSE FALSE TRUE FALSE FALSE FALSE
## [193] FALSE FALSE FALSE FALSE FALSE FALSE FALSE TRUE FALSE TRUE FALSE FALSE
## [241] FALSE TRUE TRUE FALSE FALSE FALSE FALSE TRUE FALSE TRUE FALSE TRUE
## [253] FALSE TRUE TRUE FALSE TRUE FALSE FALSE TRUE FALSE TRUE FALSE TRUE
```

filter() - Subset Rows

- Return observations where myBatting\$G is greater than 20

```
filter(myBatting, G > 20)

## # A tibble: 70,926 x 22
##   playerID  yearID stint teamID lgID     G    AB     R     H    X2B    X3B    HR
##   <chr>      <int> <int> <fct> <fct> <int> <int> <int> <int> <int> <int> <int>
## 1 addybo01    1871     1 RC1    NA    25   118    30    32     6     0     0
## 2 allisar01    1871     1 CL1    NA    29   137    28    40     4     5     0
## 3 allisdo01    1871     1 WS3    NA    27   133    28    44    10     2     2
## 4 ansonca01    1871     1 RC1    NA    25   120    29    39    11     3     0
## 5 barnero01    1871     1 BS1    NA    31   157    66    63    10     9     0
## # ... with 70,921 more rows, and 10 more variables: RBI <int>, SB <int>,
## #   CS <int>, BB <int>, SO <int>, IBB <int>, HBP <int>, SH <int>, SF <int>,
## #   GIDP <int>
```

Compound Logical Operators

- `&` 'and'
- `|` 'or'

Operator	A,B both true	A true, B false	A,B both false
and	TRUE	FALSE	FALSE
or	TRUE	TRUE	FALSE

Logical statements

- Condition on those that played more than 20 games and played in 2015

```
(myBatting$G > 20) & (myBatting$yearID == 2015)
```

```
## [1] FALSE  
## [13] FALSE  
## [25] FALSE  
## [37] FALSE  
## [49] FALSE  
## [61] FALSE  
## [73] FALSE  
## [85] FALSE  
## [97] FALSE  
## [109] FALSE  
## [121] FALSE  
## [133] FALSE  
## [145] FALSE  
## [157] FALSE  
## [169] FALSE  
## [181] FALSE  
## [193] FALSE  
## [205] FALSE  
## [217] FALSE  
## [229] FALSE  
## [241] FALSE  
## [253] FALSE  
## [265] FALSE  
## [277] FALSE FALSE
```

filter() - Subset Rows

- Pull out those that played more than 20 games and played in 2015

```
filter(myBatting, (G > 20) & (yearID == 2015))

## # A tibble: 949 x 22
##   playerID  yearID stint teamID lgID     G    AB     R     H    X2B    X3B    HR
##   <chr>      <int> <int> <fct>  <fct> <int> <int> <int> <int> <int> <int>
## 1 aardsda01  2015     1 ATL    NL     33     1     0     0     0     0     0
## 2 abadfe01  2015     1 OAK    AL     62     0     0     0     0     0     0
## 3 abreuj02  2015     1 CHA    AL    154    613    88    178    34     3    30
## 4 ackledu01 2015     1 SEA    AL     85    186    22    40     8     1     6
## 5 ackledu01 2015     2 NYA    AL     23     52     6    15     3     2     4
## # ... with 944 more rows, and 10 more variables: RBI <int>, SB <int>, CS <int>,
## #   BB <int>, SO <int>, IBB <int>, HBP <int>, SH <int>, SF <int>, GIDP <int>
```

filter() - Subset Rows

- `%in%` to choose any observations matching a vector

```
filter(myBatting, teamID %in% c("ATL", "PIT", "WSH"))

## # A tibble: 7,236 x 22
##   playerID  yearID stint teamID lgID     G    AB     R     H    X2B    X3B    HR
##   <chr>      <int> <int> <fct> <fct> <int> <int> <int> <int> <int> <int>
## 1 barklsa01  1887     1 PIT    NL     89    340    44    76    10     4     1
## 2 beeched01  1887     1 PIT    NL     41    169    15    41     8     0     2
## 3 bishobi01  1887     1 PIT    NL      3     9     0     0     0     0     0
## 4 brownto01  1887     1 PIT    NL     47    192    30    47     3     4     0
## 5 carrofr01  1887     1 PIT    NL    102    421    71   138     24    15     6
## # ... with 7,231 more rows, and 10 more variables: RBI <int>, SB <int>,
## #   CS <int>, BB <int>, SO <int>, IBB <int>, HBP <int>, SH <int>, SF <int>,
## #   GIDP <int>
```

arrange() - Reorder Rows

- Other major observation (row) manipulation is to reorder the observations (rows)

```
arrange(myBatting, teamID)

## # A tibble: 108,789 x 22
##   playerID  yearID stint teamID lgID     G    AB     R     H    X2B    X3B    HR
##   <chr>      <int> <fct> <fct> <int> <int> <int> <int> <int> <int> <int>
## 1 berrych01  1884    1 ALT   UA     7    25     2     6     0     0     0
## 2 brownji01  1884    1 ALT   UA    21    88    12    22     2     2     1
## 3 carropa01  1884    1 ALT   UA    11    49     4    13     1     0     0
## 4 connojo01  1884    1 ALT   UA     3    11     0     1     0     0     0
## 5 crosscl01  1884    1 ALT   UA     2     7     1     4     1     0     0
## # ... with 108,784 more rows, and 10 more variables: RBI <int>, SB <int>,
## #   CS <int>, BB <int>, SO <int>, IBB <int>, HBP <int>, SH <int>, SF <int>,
## #   GIDP <int>
```

arrange() - Reorder Rows

- Can obtain a secondary arrangement

```
arrange(myBatting, teamID, G)

## # A tibble: 108,789 x 22
##   playerID  yearID stint teamID lgID     G    AB     R     H    X2B    X3B    HR
##   <chr>      <int> <int> <fct> <fct> <int> <int> <int> <int> <int> <int>
## 1 daisege01  1884     1 ALT    UA     1     4     0     0     0     0     0
## 2 crosscl01  1884     1 ALT    UA     2     7     1     4     1     0     0
## 3 manloch01  1884     1 ALT    UA     2     7     1     3     0     0     0
## 4 connojo01  1884     1 ALT    UA     3    11     0     1     0     0     0
## 5 shafff01   1884     1 ALT    UA     6    19     1     3     0     0     0
## # ... with 108,784 more rows, and 10 more variables: RBI <int>, SB <int>,
## #   CS <int>, BB <int>, SO <int>, IBB <int>, HBP <int>, SH <int>, SF <int>,
## #   GIDP <int>
```

arrange() - Reorder Rows

- Can reorder descending on a variable

```
arrange(myBatting, teamID, desc(G))

## # A tibble: 108,789 x 22
##   playerID  yearID stint teamID lgID     G    AB     R     H    X2B    X3B    HR
##   <chr>      <int> <fct> <fct> <int> <int> <int> <int> <int> <int> <int>
## 1 smithge01  1884    1 ALT   UA     25  108    9   34     8     1     0
## 2 harrifr01  1884    1 ALT   UA     24   95   10   25     2     1     0
## 3 doughch01  1884    1 ALT   UA     23   85     6   22     5     0     0
## 4 murphjo01  1884    1 ALT   UA     23   94   10   14     1     0     0
## 5 brownji01  1884    1 ALT   UA     21   88   12   22     2     2     1
## # ... with 108,784 more rows, and 10 more variables: RBI <int>, SB <int>,
## #   CS <int>, BB <int>, SO <int>, IBB <int>, HBP <int>, SH <int>, SF <int>,
## #   GIDP <int>
```

Recap!

- `dplyr` allows for easy row manipulations
 - `as_tibble()`
 - `filter()`
 - `arrange()`
- `dplyr` and `tidyverse` Cheat Sheet

select() - Subset Columns

- To return a single (probably simplified) column:

- `dplyr::pull()`
- `$`
- `[,]`

select() - Subset Columns

- To return a single (probably simplified) column:

- `dplyr::pull()`
- `$`
- `[,]`

```
library(Lahman)
library(dplyr)
myBatting <- as_tibble(Batting)
pull(Batting, X2B)
```

```
## [1] 0 6 4 10 11 2 0 10 1 2 1 0 0 0 9 3 0 0 1 0 2 3 4 0
## [25] 2 2 8 3 0 8 7 0 1 5 7 0 6 3 8 0 5 6 3 1 9 1 3 1 3 1
## [49] 9 3 0 4 6 3 4 3 4 5 1 1 1 1 10 1 3 8 7 7 3 8 3 0
## [73] 4 0 9 9 4 6 0 0 2 2 5 0 10 5 6 0 1 0 7 7 0 7 3 5
## [97] 6 2 10 5 0 4 3 1 7 7 6 2 0 6 10 7 5 5 3 3 2 4 0 4
## [121] 2 10 0 1 28 1 0 1 1 2 11 4 3 0 0 3 5 4 6 3 0 7 0 3
## [145] 0 0 7 1 7 0 4 1 3 9 10 4 0 1 20 3 3 10 13 1 0 0 1 11
## [169] 2 1 0 3 1 0 0 2 9 17 0 4 3 15 0 12 0 10 1 3 5 1 1 1
## [193] 0 0 0 1 0 0 8 1 7 0 0 9 5 0 0 2 1 2 3 6 5 3 0 0
## [217] 3 9 6 10 10 0 0 14 0 0 1 0 5 0 5 0 1 2 15 0 13 0 0 3
## [241] 0 7 10 2 0 5 2 2 12 0 5 1 0 6 1 0 2 4 7 1 2 0 1 11
## [337] 0 0 0 13 0 5 11 4 1 3 7 0 8 7 5 14 20 2 4 1 21 9 6 0
## [338] 0 2 18 10 2 0 9 5 5 5 4 2 0 13 0 1 3
## [339] 9 0 0 6 4 5 1 5 6 4 2 1 0 0 0 0 0
## [340] 13 0 1 3
## [341] 21 9 6 0
```

select() - Subset Columns

- `select()` function has same syntax as other `dplyr` functions:

```
function(tibble, actions, ...)
```

select() - Subset Columns

- `select()` function has same syntax as other `dplyr` functions:

```
function(tibble, actions, ...)
```

```
  select(myBatting, X2B)

## # A tibble: 108,789 x 1
##       X2B
##   <int>
## 1     0
## 2     6
## 3     4
## 4    10
## 5    11
## # ... with 108,784 more rows
```

select() - Subset Columns

- `select()` function has same syntax as other `dplyr` functions:

```
function(tibble, actions, ...)
```

```
  select(myBatting, playerID, X2B)

## # A tibble: 108,789 x 2
##   playerID    X2B
##   <chr>     <int>
## 1 abercda01     0
## 2 addybo01      6
## 3 allisar01      4
## 4 allisdo01     10
## 5 ansonca01     11
## # ... with 108,784 more rows
```

Piping or Chaining

- When applying multiple functions, reading the code can be difficult!

```
arrange(select(filter(myBatting, teamID == "PIT"), playerID, G, X2B), desc(X2B))

## # A tibble: 4,920 x 3
##   playerID      G   X2B
##   <chr>     <int> <int>
## 1 wanerpa01    154    62
## 2 wanerpa01    148    53
## 3 sanchfr01    157    53
## 4 wanerpa01    152    50
## 5 comorad01    152    47
## # ... with 4,915 more rows
```

Piping or Chaining

- Piping or Chaining with `%>%` operator helps make code more readable

```
myBatting %>%
  filter(teamID == "PIT") %>%
  select(playerID, G, X2B) %>%
  arrange(desc(X2B))
```

```
## # A tibble: 4,920 x 3
##   playerID      G   X2B
##   <chr>     <int> <int>
## 1 wanerpa01    154    62
## 2 wanerpa01    148    53
## 3 sanchfr01    157    53
## 4 wanerpa01    152    50
## 5 comorad01    152    47
## # ... with 4,915 more rows
```

- Read `%>%` as 'then'

Piping or Chaining

- Generically, `%>%` does the following

`x %>% f(y)` turns into `f(x, y)`

`x %>% f(y) %>% g(z)` turns into `g(f(x, y), z)`

Piping or Chaining

- Generically, `%>%` does the following

`x %>% f(y)` turns into `f(x, y)`

`x %>% f(y) %>% g(z)` turns into `g(f(x, y), z)`

- As `tidyverse` function generally have the same syntax:

```
function(tibble, actions, ...)
```

and they usually return a tibble, they all work great together!

- Can be used with functions outside the tidyverse if this structure works!

select() - Subset Columns

- Great functionality for choosing variables
 - All columns between

```
#all columns between
myBatting %>%
  select(X2B:HR)

## # A tibble: 108,789 x 3
##   X2B   X3B   HR
##   <int> <int> <int>
## 1     0     0     0
## 2     6     0     0
## 3     4     5     0
## 4    10     2     2
## 5    11     3     0
## # ... with 108,784 more rows
```

select() - Subset Columns

- Great functionality for choosing variables
 - All columns containing

```
myBatting %>%  
  select(contains("X"))  
  
## # A tibble: 108,789 x 2  
##   X2B   X3B  
##   <int> <int>  
## 1     0     0  
## 2     6     0  
## 3     4     5  
## 4    10     2  
## 5    11     3  
## # ... with 108,784 more rows
```

select() - Subset Columns

- Great functionality for choosing variables
 - All columns starting with

```
myBatting %>%  
  select(starts_with("X"))
```

```
## # A tibble: 108,789 x 2  
##   X2B   X3B  
##   <int> <int>  
## 1     0     0  
## 2     6     0  
## 3     4     5  
## 4    10     2  
## 5    11     3  
## # ... with 108,784 more rows
```

select() - Subset Columns

- Great functionality for choosing variables
 - Combinations of operators

```
myBatting %>%  
  select(starts_with("X"), ends_with("ID"), G)  
  
## # A tibble: 108,789 x 7  
##   X2B    X3B playerID  yearID teamID lgID      G  
##   <int> <int> <chr>     <int> <fct>  <fct> <int>  
## 1     0     0 abercda01  1871  TR0    NA      1  
## 2     6     0 addybo01  1871  RC1    NA     25  
## 3     4     5 allisar01  1871  CL1    NA     29  
## 4    10     2 allisdo01  1871  WS3    NA     27  
## 5    11     3 ansonca01  1871  RC1    NA     25  
## # ... with 108,784 more rows
```

select() - Subset Columns

- Can reorder variables with `everything()`

```
myBatting %>%  
  select(playerID, HR, everything())  
  
## # A tibble: 108,789 x 22  
##   playerID     HR yearID stint teamID lgID      G    AB     R     H    X2B    X3B  
##   <chr>     <int> <int> <int> <fct> <fct> <int> <int> <int> <int> <int> <int>  
## 1 abercda01     0    1871     1 TRO    NA     1     4     0     0     0     0  
## 2 addybo01      0    1871     1 RC1    NA    25    118    30    32     6     0  
## 3 allisar01     0    1871     1 CL1    NA    29    137    28    40     4     5  
## 4 allisdo01     2    1871     1 WS3    NA    27    133    28    44    10     2  
## 5 ansonca01     0    1871     1 RC1    NA    25    120    29    39    11     3  
## # ... with 108,784 more rows, and 10 more variables: RBI <int>, SB <int>,  
## #   CS <int>, BB <int>, SO <int>, IBB <int>, HBP <int>, SH <int>, SF <int>,  
## #   GIDP <int>
```

rename() - Rename Columns

- Easy to rename multiple columns (variables) at once

```
myBatting %>%  
  select(starts_with("X"), ends_with("ID"), G) %>%  
  rename("Doubles" = X2B, "Triples" = X3B)  
  
## # A tibble: 108,789 x 7  
##   Doubles Triples playerID yearID teamID lgID      G  
##   <int>    <int> <chr>     <int> <fct> <fct> <int>  
## 1       0       0 abercda01  1871  TR0    NA      1  
## 2       6       0 addybo01  1871  RC1    NA     25  
## 3       4       5 allisar01  1871  CL1    NA     29  
## 4      10       2 allisdo01  1871  WS3    NA     27  
## 5      11       3 ansonca01  1871  RC1    NA     25  
## # ... with 108,784 more rows
```

Recap!

- `dplyr` allows for easy column manipulations
 - `select()`
 - `rename()`
- Pipe or Chain with `%>%`

Creating New Variables

- Consider a data set on movie ratings

```
library(fivethirtyeight)
fandango

## # A tibble: 146 x 23
##   film      year rottentomatoes rottentomatoes_~ metacritic metacritic_user    imdb
##   <chr>     <dbl>        <int>           <int>       <int>       <dbl> <dbl>
## 1 Avenge~  2015         74            86          66        7.1    7.8
## 2 Cinder~  2015         85            80          67        7.5    7.1
## 3 Ant-Man  2015         80            90          64        8.1    7.8
## 4 Do You~  2015         18            84          22        4.7    5.4
## 5 Hot Tu~  2015         14            28          29        3.4    5.1
## # ... with 141 more rows, and 16 more variables: fandango_stars <dbl>,
## #   fandango_ratingvalue <dbl>, rt_norm <dbl>, rt_user_norm <dbl>,
## #   metacritic_norm <dbl>, metacritic_user_nom <dbl>, imdb_norm <dbl>,
## #   rt_norm_round <dbl>, rt_user_norm_round <dbl>, metacritic_norm_round <dbl>,
## #   metacritic_user_norm_round <dbl>, imdb_norm_round <dbl>,
## #   metacritic_user_vote_count <int>, imdb_user_vote_count <int>,
## #   fandango_votes <int>, fandango_difference <dbl>
```

mutate() - Create New Column(s)

- Add newly created column(s) to current data frame (doesn't overwrite the data frame)

```
mutate(data, newVarName = functionOfData, newVarName2 = functionOfData, ...)
```

```
fandango %>%
  mutate(avgRotten = (rottentomatoes + rottentomatoes_user)/2)

## # A tibble: 146 x 24
##   film      year  rottentomatoes rottentomatoes_~ metacritic metacritic_user    imdb
##   <chr>     <dbl>        <int>           <int>       <int>       <dbl> <dbl>
## 1 Avenge~  2015          74            86         66        7.1    7.8
## 2 Cinder~  2015          85            80         67        7.5    7.1
## 3 Ant-Man  2015          80            90         64        8.1    7.8
## 4 Do You~ 2015          18            84         22        4.7    5.4
## 5 Hot Tu~  2015          14            28         29        3.4    5.1
## # ... with 141 more rows, and 17 more variables: fandango_stars <dbl>,
## #   fandango_ratingvalue <dbl>, rt_norm <dbl>, rt_user_norm <dbl>,
## #   metacritic_norm <dbl>, metacritic_user_nom <dbl>, imdb_norm <dbl>,
## #   rt_norm_round <dbl>, rt_user_norm_round <dbl>, metacritic_norm_round <dbl>,
## #   metacritic_user_norm_round <dbl>, imdb_norm_round <dbl>,
## #   metacritic_user_vote_count <int>, imdb_user_vote_count <int>,
## #   fandango_votes <int>, fandango_difference <dbl>, avgRotten <dbl>
```

mutate() - Create New Column(s)

- Reorder columns so we can see it!

```
fandango %>%  
  mutate(avgRotten = (rottentomatoes + rottentomatoes_user)/2) %>%  
  select(film, year, avgRotten, everything())  
  
## # A tibble: 146 x 24  
##   film              year  avgRotten rottentomatoes rottentomatoes_~ metacritic  
##   <chr>             <dbl>     <dbl>        <int>          <int>      <int>  
## 1 Avengers: Age of U~  2015       80            74            86         66  
## 2 Cinderella           2015     82.5           85            80         67  
## 3 Ant-Man              2015       85            80            90         64  
## 4 Do You Believe?     2015       51            18            84         22  
## 5 Hot Tub Time Machi~  2015       21            14            28         29  
## # ... with 141 more rows, and 18 more variables: metacritic_user <dbl>,  
## #     imdb <dbl>, fandango_stars <dbl>, fandango_ratingvalue <dbl>,  
## #     rt_norm <dbl>, rt_user_norm <dbl>, metacritic_norm <dbl>,  
## #     metacritic_user_nom <dbl>, imdb_norm <dbl>, rt_norm_round <dbl>,  
## #     rt_user_norm_round <dbl>, metacritic_norm_round <dbl>,  
## #     metacritic_user_norm_round <dbl>, imdb_norm_round <dbl>,  
## #     metacritic_user_vote_count <int>, imdb_user_vote_count <int>, ...
```

mutate() - Create New Column(s)

- Add more than one variable

```
fandango %>%  
  mutate(avgRotten = (rottentomatoes + rottentomatoes_user)/2,  
        avgMeta = (metacritic_norm + metacritic_user_nom)/2) %>%  
  select(film, year, avgRotten, avgMeta, everything())  
  
## # A tibble: 146 x 25  
##   film      year avgRotten avgMeta rottentomatoes rottentomatoes_~ metacritic  
##   <chr>     <dbl>    <dbl>    <dbl>       <int>       <int>       <int>  
## 1 Avengers: ~ 2015      80     3.42         74          86          66  
## 2 Cinderella 2015     82.5    3.55         85          80          67  
## 3 Ant-Man    2015      85     3.62         80          90          64  
## 4 Do You Bel~ 2015      51     1.72         18          84          22  
## 5 Hot Tub Ti~ 2015      21     1.58         14          28          29  
## # ... with 141 more rows, and 18 more variables: metacritic_user <dbl>,  
## #   imdb <dbl>, fandango_stars <dbl>, fandango_ratingvalue <dbl>,  
## #   rt_norm <dbl>, rt_user_norm <dbl>, metacritic_norm <dbl>,  
## #   metacritic_user_nom <dbl>, imdb_norm <dbl>, rt_norm_round <dbl>,  
## #   rt_user_norm_round <dbl>, metacritic_norm_round <dbl>,  
## #   metacritic_user_norm_round <dbl>, imdb_norm_round <dbl>,  
## #   metacritic_user_vote_count <int>, imdb_user_vote_count <int>, ...
```

mutate() - Create New Column(s)

mutate() can use some statistical functions

```
fandango %>%  
  select(rottentomatoes) %>%  
  mutate(avg = mean(rottentomatoes), sd = sd(rottentomatoes))  
  
## # A tibble: 146 x 3  
##   rottentomatoes     avg      sd  
##       <int>    <dbl>   <dbl>  
## 1          74    60.8   30.2  
## 2          85    60.8   30.2  
## 3          80    60.8   30.2  
## 4          18    60.8   30.2  
## 5          14    60.8   30.2  
## # ... with 141 more rows
```

mutate() & group_by() - Create New Column(s)

mutate() can use some statistical functions

- group_by() to create summaries for groups

```
fandango %>%  
  select(year, rottentomatoes) %>%  
  group_by(year) %>%  
  mutate(avg = mean(rottentomatoes), sd = sd(rottentomatoes))  
  
## # A tibble: 146 x 4  
## # Groups:   year [2]  
##   year  rottentomatoes    avg     sd  
##   <dbl>      <int> <dbl> <dbl>  
## 1 2015          74  58.4  30.3  
## 2 2015          85  58.4  30.3  
## 3 2015          80  58.4  30.3  
## 4 2015          18  58.4  30.3  
## 5 2015          14  58.4  30.3  
## # ... with 141 more rows
```

mutate() & group_by() - Create New Column(s)

- `across(.cols, .funs)` for multiple columns/summaries at once

```
fandango %>%  
  select(year, rottentomatoes, metacritic) %>%  
  group_by(year) %>%  
  mutate(across(c(rottentomatoes, metacritic), list(avg = mean, SD = sd)))
```

```
## # A tibble: 146 x 7  
## # Groups:   year [2]  
##   year  rottentomatoes  metacritic  rottentomatoes_avg  rottentomatoes_SD  
##   <dbl>      <int>      <int>          <dbl>            <dbl>  
## 1 2015        74         66          58.4            30.3  
## 2 2015        85         67          58.4            30.3  
## 3 2015        80         64          58.4            30.3  
## 4 2015        18         22          58.4            30.3  
## 5 2015        14         29          58.4            30.3  
## # ... with 141 more rows, and 2 more variables: metacritic_avg <dbl>,  
## #   metacritic_SD <dbl>
```

mutate() & group_by() - Create New Column(s)

- `across(.cols, .funs)` for multiple columns/summaries at once

```
fandango %>%  
  select(year, ends_with("user")) %>%  
  group_by(year) %>%  
  mutate(across(ends_with("user"), list(trim_mean = mean), trim = 0.2))  
  
## # A tibble: 146 x 5  
## # Groups: year [2]  
##   year rottentomatoes_user metacritic_user rottentomatoes_use~ metacritic_user~  
##   <dbl>        <int>       <dbl>           <dbl>          <dbl>  
## 1 2015         86          7.1            64.9          6.63  
## 2 2015         80          7.5            64.9          6.63  
## 3 2015         90          8.1            64.9          6.63  
## 4 2015         84          4.7            64.9          6.63  
## 5 2015         28          3.4            64.9          6.63  
## # ... with 141 more rows
```

Conditional Execution

- Often want to execute statements conditionally to create a variable

`dplyr::if_else()` - *vectorized* conditional execution. Syntax:

- `if_else(condition, true, false)`
- `condition` is a vector of TRUE/FALSE
- `true` is what to do when TRUE occurs
- `false` is what to do when FALSE occurs

Returns a vector

Conditional Execution

- Consider built-in data set `airquality`
 - daily air quality measurements in New York
 - from May (Day 1) to September (Day 153) in 1973

```
myAirquality <- as_tibble(airquality)
myAirquality

## # A tibble: 153 x 6
##   Ozone Solar.R  Wind  Temp Month Day
##   <int>    <int> <dbl> <int> <int> <int>
## 1     41      190   7.4    67     5     1
## 2     36      118    8      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
## # ... with 148 more rows
```

Conditional Execution

Want to code a wind category variable

- high wind days ($15\text{mph} \leq \text{wind}$)
- windy days ($10\text{mph} \leq \text{wind} < 15\text{mph}$)
- lightwind days ($6\text{mph} \leq \text{wind} < 10\text{mph}$)
- calm days ($\text{wind} \leq 6\text{mph}$)

if_else()

```
if_else(myAirquality$Wind >= 15, "HighWind",
       if_else(myAirquality$Wind >= 10, "Windy",
              if_else(myAirquality$Wind >= 6, "LightWind", "Calm")))

## [1] "LightWind" "LightWind" "Windy"      "Windy"      "Windy"      "Windy"
## [7] "LightWind" "Windy"      "HighWind"    "LightWind"   "LightWind"   "LightWind"
## [13] "LightWind" "Windy"      "Windy"      "Windy"      "Windy"      "HighWind"
## [19] "Windy"     "LightWind"   "LightWind"   "HighWind"   "LightWind"   "Windy"
## [25] "HighWind"   "Windy"      "LightWind"   "Windy"      "Windy"      "Calm"
## [31] "LightWind"  "LightWind"   "LightWind"   "HighWind"   "LightWind"   "LightWind"
## [37] "Windy"     "LightWind"   "LightWind"   "Windy"      "Windy"      "Windy"
## [43] "LightWind"  "LightWind"   "Windy"      "Windy"      "Windy"      "HighWind"
## [49] "LightWind"  "Windy"      "Windy"      "LightWind"   "Calm"       "Calm"
## [55] "LightWind"  "LightWind"   "LightWind"   "Windy"      "Windy"      "Windy"
## [61] "LightWind"  "Calm"       "LightWind"   "LightWind"   "Windy"      "Calm"
## [67] "Windy"     "Calm"       "LightWind"   "Calm"       "LightWind"   "LightWind"
## [73] "Windy"     "Windy"      "Windy"      "Windy"      "LightWind"   "Windy"
## [79] "LightWind"  "Calm"       "Windy"      "LightWind"   "LightWind"   "Windy"
## [85] "LightWind"  "LightWind"   "LightWind"   "Windy"      "LightWind"   "LightWind"
## [91] "LightWind"  "LightWind"   "LightWind"   "Windy"      "LightWind"   "LightWind"
## [97] "LightWind"  "Calm"       "Calm"       "Windy"      "LightWind"   "LightWind"
## [103] "Windy"     "Windy"      "Windy"      "LightWind"   "Windy"      "Windy"
## [109] "LightWind"  "LightWind"   "Windy"      "Windy"      "HighWind"   "Windy"
## [115] "Windy"     "LightWind"   "Calm"       "LightWind"   "Calm"       "LightWind"
## [121] "Calm"      "LightWind"   "LightWind"   "LightWind"   "LightWind"   "Calm"
## [127] "HighWind"   "Windy"      "Windy"      "Windy"      "Windy"      "Windy"
## [133] "HighWind"   "LightWind"   "Windy"      "Windy"      "Windy"      "Windy"
## [139] "Windy"     "Windy"      "LightWind"   "Windy"      "LightWind"   "Windy"
```

if_else() with mutate()

```
myAirquality <- myAirquality %>%
  mutate(Status = if_else(Wind >= 15, "HighWind",
                         if_else(Wind >= 10, "Windy",
                                if_else(Wind >= 6, "LightWind", "Calm"))))

myAirquality

## # A tibble: 153 x 7
##   Ozone Solar.R Wind  Temp Month Day Status
##   <int>    <int> <dbl> <int> <int> <chr>
## 1     41      190   7.4    67     5 1 LightWind
## 2     36      118    8     72     5 2 LightWind
## 3     12      149  12.6    74     5 3 Windy
## 4     18      313  11.5    62     5 4 Windy
## 5     NA       NA  14.3    56     5 5 Windy
## # ... with 148 more rows
```

Recap!

- `mutate()` - add newly created **column(s)** to current data frame
- Can use `group_by()` with `mutate()` to add common summary statistics
- Use `if_else()` to do conditional creation
- `dplyr` and `tidyverse` Cheat Sheet

Let's Practice

We'll add to our `.Rmd` file from the previous activity

- Download the prompts to add to our markdown document [here](#)

Guidance:

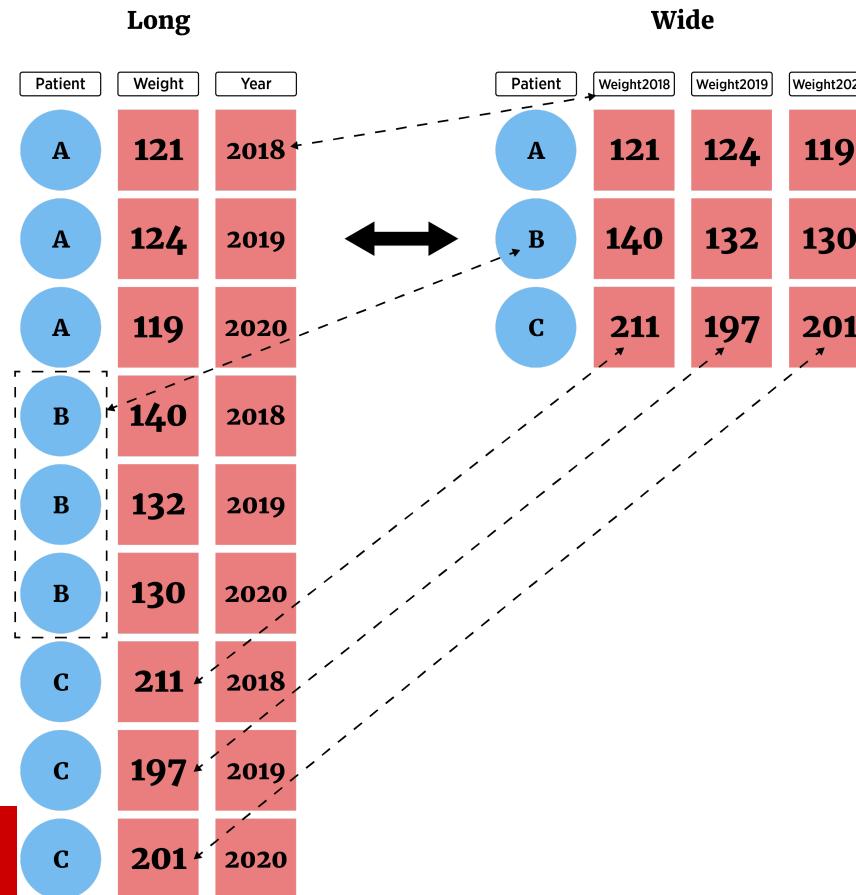
- Copy and paste the text from above into the bottom of the document, reknit
- Add to the code chunks, evaluating in the notebook
- Reknit occasionally to check the output

Reshaping Data with `tidyverse`

Justin Post

Reshaping Data

Long vs Wide format data



tidyverse Package

Easily allows for two very important actions

- `pivot_longer()` - lengthens data by increasing the number of rows and decreasing the number of columns
 - Most important as analysis methods often prefer this form
- `pivot_wider()` - widens data by increasing the number of columns and decreasing the number of rows

tidyverse Package

- Data in 'Wide' form

```
tempsData <- read_table(file = "https://www4.stat.ncsu.edu/~online/datasets/cityTemps.txt")
tempsData

## # A tibble: 6 x 8
##   city      sun    mon    tue    wed    thr    fri    sat
##   <chr>   <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>
## 1 atlanta    81    87    83    79    88    91    94
## 2 baltimore   73    75    70    78    73    75    79
## 3 charlotte   82    80    75    82    83    88    93
## 4 denver      72    71    67    68    72    71    58
## 5 ellington   51    42    47    52    55    56    59
## 6 frankfort   70    70    72    70    74    74    79
```

Reshaping Data

```
## # A tibble: 6 x 8
##   city      sun    mon    tue    wed    thr    fri    sat
##   <chr>   <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>
## 1 atlanta     81     87     83     79     88     91     94
## 2 baltimore    73     75     70     78     73     75     79
## 3 charlotte    82     80     75     82     83     88     93
## 4 denver       72     71     67     68     72     71     58
## 5 ellington    51     42     47     52     55     56     59
## 6 frankfort    70     70     72     70     74     74     79
```

- Switch to 'Long' form with `pivot_longer()`
 - `cols` = columns to pivot to longer format (`cols = 2:8`)
 - `names_to` = new name(s) for columns created (`names_to = "day"`)
 - `values_to` = new name(s) for data values (`values_to = "temp"`)

Reshaping Data

- Switch to 'Long' form with `pivot_longer()`
 - `cols` = columns to pivot to longer format (`cols = 2:8`)
 - `names_to` = new name(s) for columns created (`names_to = "day"`)
 - `values_to` = new name(s) for data values (`values_to = "temp"`)

```
tempsData %>% pivot_longer(cols = 2:8, names_to = "day", values_to = "temp")
```

```
## # A tibble: 42 x 3
##   city    day    temp
##   <chr>   <chr> <dbl>
## 1 atlanta sun     81
## 2 atlanta mon     87
## 3 atlanta tue     83
## 4 atlanta wed     79
## 5 atlanta thr     88
## # ... with 37 more rows
```

Reshaping Data

- Switch to 'Long' form with `pivot_longer()`
- Can provide columns in many ways!

```
newTempsData <- tempsData %>%
  pivot_longer(cols = sun:sat, names_to = "day", values_to = "temp")
newTempsData

## # A tibble: 42 x 3
##   city    day    temp
##   <chr>   <chr> <dbl>
## 1 atlanta sun     81
## 2 atlanta mon     87
## 3 atlanta tue     83
## 4 atlanta wed     79
## 5 atlanta thr     88
## # ... with 37 more rows
```

Reshaping Data

- Switch to 'Wide' form with `pivot_wider()`
 - `names_from` = column(s) to get the names used in the output columns (`names_from = "day"`)
 - `values_from` = column(s) to get the cell values from (`values_from = "temp"`)

```
newTempsData %>%
  pivot_wider(names_from = "day", values_from = "temp")

## # A tibble: 6 x 8
##   city      sun    mon    tue    wed    thr    fri    sat
##   <chr>    <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>
## 1 atlanta    81    87    83    79    88    91    94
## 2 baltimore   73    75    70    78    73    75    79
## 3 charlotte   82    80    75    82    83    88    93
## 4 denver      72    71    67    68    72    71    58
## 5 ellington   51    42    47    52    55    56    59
## 6 frankfort   70    70    72    70    74    74    79
```

Big Recap!

- `dplyr` and `tidyverse` packages
 - Convert to tibble: `as_tibble()`
 - Row manipulations: `arrange()`, `filter()`
 - Column manipulations: `select()`, `rename()`, `mutate()`, `group_by()`, `if_else()`
 - Reshape data: `pivot_wider()`, `pivot_longer()`

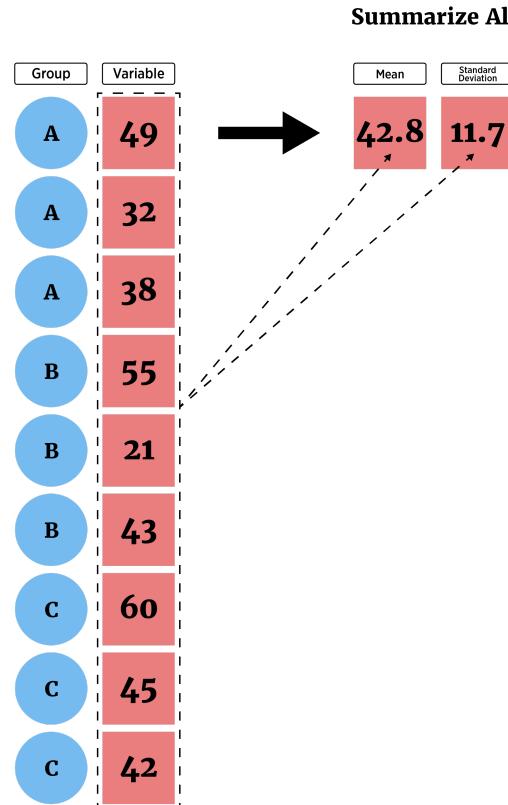
EDA: Numeric Summaries

Justin Post

Making Sense of Data

Goal: Understand types of data and their distributions

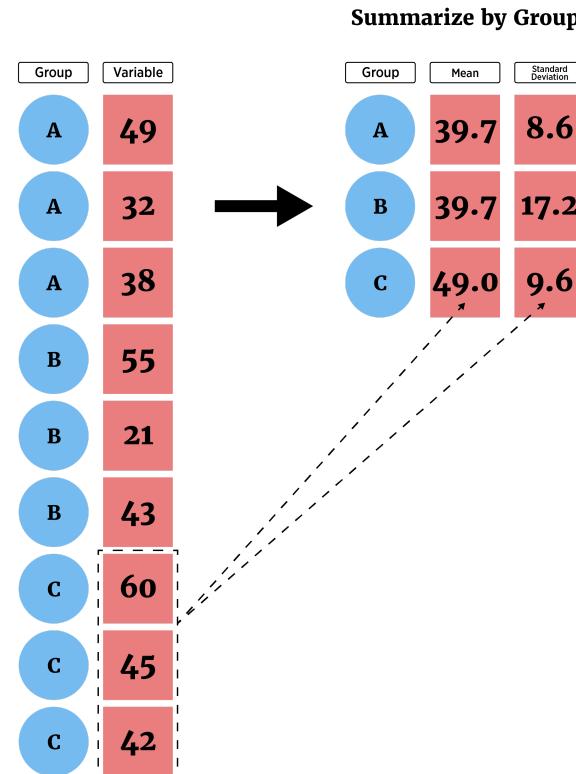
- Numerical summaries



Making Sense of Data

Goal: Understand types of data and their distributions

- Numerical summaries (across subgroups)



Making Sense of Data

Goal: Understand types of data and their distributions

- Numerical summaries (across subgroups)
 - Contingency Tables
 - Mean/Median
 - Standard Deviation/Variance/IQR
 - Quantiles/Percentiles

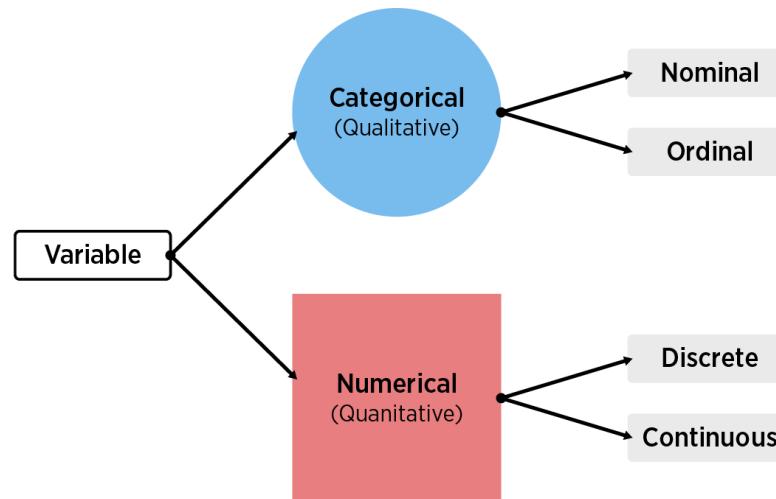
Making Sense of Data

Goal: Understand types of data and their distributions

- Numerical summaries (across subgroups)
 - Contingency Tables
 - Mean/Median
 - Standard Deviation/Variance/IQR
 - Quantiles/Percentiles
- Graphical summaries (across subgroups)
 - Bar plots
 - Histograms
 - Box plots
 - Scatter plots

Types of Data

- How to summarize data depends on the type of data
 - Categorical (Qualitative) variable - entries are a label or attribute
 - Numeric (Quantitative) variable - entries are a numerical value where math can be performed



Categorical Data

Goal: Describe the **distribution** of the variable

- Distribution = pattern and frequency with which you observe a variable
- Categorical variable - entries are a label or attribute

Categorical Data

Goal: Describe the **distribution** of the variable

- Distribution = pattern and frequency with which you observe a variable
- Categorical variable - entries are a label or attribute
 - Describe the relative frequency (or count) for each category
 - Can be done with `group_by()` and `summarize()` from `dplyr` (easier with base R `table()`)

Contingency tables

- Consider data on titanic passengers in `titanic.csv`

```
titanicData <- read_csv("https://www4.stat.ncsu.edu/~online/datasets/titanic.csv")
titanicData

## # A tibble: 1,310 x 14
##   pclass survived name      sex    age sibsp parch ticket  fare cabin embarked
##   <dbl>     <dbl> <chr>    <chr> <dbl> <dbl> <dbl> <chr>  <dbl> <chr> <chr>
## 1     1       1 Allen, M~ fema~ 29        0      0 24160  211. B5      S
## 2     1       1 Allison,~ male   0.917     1      2 113781 152. C22     ~ S
## 3     1       0 Allison,~ fema~ 2          1      2 113781 152. C22     ~ S
## 4     1       0 Allison,~ male   30         1      2 113781 152. C22     ~ S
## 5     1       0 Allison,~ fema~ 25         1      2 113781 152. C22     ~ S
## # ... with 1,305 more rows, and 3 more variables: boat <chr>, body <dbl>,
## #   home.dest <chr>
```

Contingency tables

- Create a **one-way contingency table** for the `embarked` variable and for the `survived` variable

```
titanicData %>%  
  group_by(embarked) %>%  
  summarize(counts = n())  
  
## # A tibble: 4 x 2  
##   embarked counts  
##   <chr>     <int>  
## 1 C          270  
## 2 Q          123  
## 3 S          914  
## 4 <NA>        3
```

```
titanicData %>%  
  group_by(survived) %>%  
  summarize(counts = n())  
  
## # A tibble: 3 x 2  
##   survived counts  
##   <dbl>    <int>  
## 1 0          809  
## 2 1          500  
## 3 NA         1
```

Two-way contingency tables

- Create **two-way contingency tables** for pairs of categorical variables

```
titanicData %>%
  group_by(embarked, survived) %>%
  summarize(counts = n())

## # A tibble: 8 x 3
## # Groups:   embarked [4]
##   embarked survived counts
##   <chr>     <dbl>  <int>
## 1 C           0     120
## 2 C           1     150
## 3 Q           0      79
## 4 Q           1      44
## 5 S           0     610
## 6 S           1     304
## 7 <NA>        1      2
## 8 <NA>       NA      1
```

Two-way contingency tables

- Create **two-way contingency tables** for pairs of categorical variables

```
titanicData %>%  
  group_by(embarked, survived) %>%  
  summarize(counts = n())  
  
## # A tibble: 8 x 3  
## # Groups:   embarked [4]  
##   embarked survived counts  
##   <chr>     <dbl>   <int>  
## 1 C           0     120  
## 2 C           1     150  
## 3 Q           0      79  
## 4 Q           1      44  
## 5 S           0     610  
## 6 S           1     304  
## 7 <NA>        1      2  
## 8 <NA>        NA     1
```

```
titanicData %>%  
  group_by(embarked, survived) %>%  
  summarize(counts = n()) %>%  
  pivot_wider(values_from = counts, names_from = embarked)  
  
## # A tibble: 3 x 5  
##   survived     C     Q     S `NA`  
##   <dbl>   <int> <int> <int> <int>  
## 1       0     120     79    610     NA  
## 2       1     150     44    304      2  
## 3     NA     NA     NA     NA      1
```

Two-way contingency tables

- Let's drop the NA values first

```
titanicData %>%  
  drop_na(embarked, survived) %>%  
  group_by(embarked, survived) %>%  
  summarize(counts = n())  
  
## # A tibble: 6 x 3  
## # Groups:   embarked [3]  
##   embarked survived counts  
##   <chr>     <dbl>  <int>  
## 1 C          0     120  
## 2 C          1     150  
## 3 Q          0      79  
## 4 Q          1      44  
## 5 S          0     610  
## 6 S          1     304
```

```
titanicData %>%  
  drop_na(embarked, survived) %>%  
  group_by(embarked, survived) %>%  
  summarize(counts = n()) %>%  
  pivot_wider(values_from = counts, names_from = embarked)  
  
## # A tibble: 2 x 4  
##   survived    C     Q     S  
##   <dbl> <int> <int> <int>  
## 1       0    120     79    610  
## 2       1    150     44    304
```

Numeric Data

Goal: Describe the **distribution** of the variable

- Distribution = pattern and frequency with which you observe a variable
- Numeric variable - entries are a numerical value where math can be performed

Numeric Data

Goal: Describe the **distribution** of the variable

- Distribution = pattern and frequency with which you observe a variable
- Numeric variable - entries are a numerical value where math can be performed

For a single numeric variable, describe the distribution via

- Shape: Histogram, Density plot, ...
- Measures of center: Mean, Median, ...
- Measures of spread: Variance, Standard Deviation, Quartiles, IQR, ...

Measures of Center

Mean & Median

```
mean(titanicData$fare, na.rm = TRUE)  
## [1] 33.29548  
  
median(titanicData$fare, na.rm = TRUE)  
## [1] 14.4542  
  
titanicData %>%  
  summarize(fareMean = mean(fare, na.rm = TRUE),  
            fareMedian = median(fare, na.rm = TRUE))  
  
## # A tibble: 1 x 2  
##   fareMean fareMedian  
##     <dbl>      <dbl>  
## 1     33.3      14.5
```

```
mean(titanicData$age, na.rm = TRUE)  
## [1] 29.88113  
  
median(titanicData$age, na.rm = TRUE)  
## [1] 28  
  
titanicData %>%  
  summarize(ageMean = mean(age, na.rm = TRUE),  
            ageMedian = median(age, na.rm = TRUE))  
  
## # A tibble: 1 x 2  
##   ageMean ageMedian  
##     <dbl>      <dbl>  
## 1     29.9      28
```

Measures of Spread

Standard Deviation, Quantiles, & IQR

```
titanicData %>%  
  summarize(fareMean = mean(fare, na.rm = TRUE),  
            fareMedian = median(fare, na.rm = TRUE),  
            fareSD = sd(fare, na.rm = TRUE),  
            fareIQR = IQR(fare, na.rm = TRUE),  
            fareQ1 = quantile(fare, probs = c(0.25), na.rm = TRUE))  
  
## # A tibble: 1 x 5  
##   fareMean fareMedian fareSD fareIQR fareQ1  
##     <dbl>      <dbl>    <dbl>    <dbl>    <dbl>  
## 1     33.3      14.5    51.8    23.4     7.90
```

Measures of Spread

Standard Deviation, Quantiles, & IQR

```
titanicData %>%  
  summarize(fareQuantiles = quantile(fare, probs = c(0.1, 0.25, 0.5, 0.75, 0.9), na.rm = TRUE),  
            q = c(0.1, 0.25, 0.5, 0.75, 0.9))  
  
## # A tibble: 5 x 2  
##   fareQuantiles     q  
##       <dbl> <dbl>  
## 1        7.57  0.1  
## 2        7.90  0.25  
## 3       14.5   0.5  
## 4      31.3   0.75  
## 5      78.1   0.9
```

Measures of Linear Relationship

For two numeric variables we can find Covariance & Correlation

```
titanicData %>%  
  summarize(covar = cov(fare, age, use = "complete.obs"),  
            corr = cor(fare, age, use = "complete.obs"))  
  
## # A tibble: 1 x 2  
##   covar    corr  
##   <dbl> <dbl>  
## 1 143. 0.179
```

Summaries Across Groups

Usually want summaries for different **subgroups of data**

- Ex: Get similar fare summaries for each *survival status*

Idea:

- Use `dplyr::group_by()` to associate groups with the tibble
- Use `dplyr::summarize()` to create basic summaries for each subgroup

Summaries Across Groups

- Ex: Get similar fare summaries for each *survival status*

```
titanicData %>%
  group_by(survived) %>%
  summarise(avg = mean(fare, na.rm = TRUE),
            med = median(fare, na.rm = TRUE),
            var = var(fare, na.rm = TRUE))

## # A tibble: 3 x 4
##   survived     avg     med     var
##       <dbl>    <dbl>    <dbl>    <dbl>
## 1        0    23.4    10.5 1166.
## 2        1    49.4    26.0 4713.
## 3      NA    NaN     NA     NA
```

Summaries Across Groups

- Remove NA class for survived

```
titanicData %>%
  drop_na(survived) %>%
  group_by(survived) %>%
    summarise(avg = mean(fare, na.rm = TRUE),
              med = median(fare, na.rm = TRUE),
              var = var(fare, na.rm = TRUE))

## # A tibble: 2 x 4
##   survived   avg   med   var
##       <dbl> <dbl> <dbl> <dbl>
## 1        0  23.4  10.5 1166.
## 2        1  49.4  26   4713.
```

Summaries Across Groups

- Ex: Get similar fare summaries for each *survival status* and *embarked value*

```
titanicData %>%  
  drop_na(survived, embarked) %>%  
  group_by(survived, embarked) %>%  
    summarise(avg = mean(fare, na.rm = TRUE),  
              med = median(fare, na.rm = TRUE),  
              var = var(fare, na.rm = TRUE))  
  
## # A tibble: 6 x 5  
## # Groups:   survived [2]  
##   survived   embarked     avg     med     var  
##   <dbl> <chr>     <dbl> <dbl> <dbl>  
## 1       0   C         40.3  15.0  3198.  
## 2       0   Q         11.6  7.75  119.  
## 3       0   S         21.5  11.5  829.  
## 4       1   C         80.0  55.4  9534.  
## 5       1   Q         13.8  7.75  306.  
## 6       1   S         39.2  25.9  2271.
```

Summarizing across groups

`dplyr::across()` allows for applying a summarization to multiple columns easily!

```
titanicData %>%  
  drop_na(survived) %>%  
  group_by(survived) %>%  
    summarise(across(.fns = mean, .cols = c(age, fare), na.rm = TRUE))  
  
## # A tibble: 2 x 3  
##   survived     age   fare  
##       <dbl> <dbl> <dbl>  
## 1        0  30.5  23.4  
## 2        1  28.9  49.4
```

Summarizing across groups

`dplyr::across()` allows for applying a summarization to multiple columns easily!

```
titanicData %>%
  drop_na(survived) %>%
  group_by(survived) %>%
  summarise(across(.fns = mean, .cols = where(is.double), na.rm = TRUE))

## # A tibble: 2 x 7
##   survived pclass    age sibsp parch  fare body
##   <dbl>     <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1       0     30.5 0.522 0.329  23.4  161.
## 2       1     28.9 0.462 0.476  49.4   NaN
```

Recap!

- Must understand the type of data you have
- Goal: Describe the distribution
- Numerical summaries: use `summarize()`
 - Contingency Tables: `n()`
 - Mean/Median: `mean()`, `median()`
 - Standard Deviation/Variance/IQR: `sd()`, `var()`, `IQR()`
 - Quantiles/Percentiles: `quantile()`
- Across subgroups with `dplyr::group_by()`,
- Multiple columns/functions with `dplyr::across()`

Let's Practice

We'll add to our `.Rmd` file from the previous activity

- Download the prompts to add to our markdown document [here](#)

Guidance:

- Copy and paste the text from above into the bottom of the document, reknit
- Add to the code chunks, evaluating in the notebook
- Reknit occasionally to check the output

ggplot2

Justin Post

Graphical Summaries in R

Three major systems for plotting:

- Base R (built-in functions)
- `lattice`
- `ggplot2` (sort of part of the tidyverse)

Great `ggplot2` reference book here!

ggplot2 Plotting

ggplot2 basics ([Cheat Sheet](#))

- `ggplot(data = data_frame)` creates a plot instance
- Add "layers" to the plot (`geom` or `stat` layers)
 - Creates a visualization of the data

ggplot2 Plotting

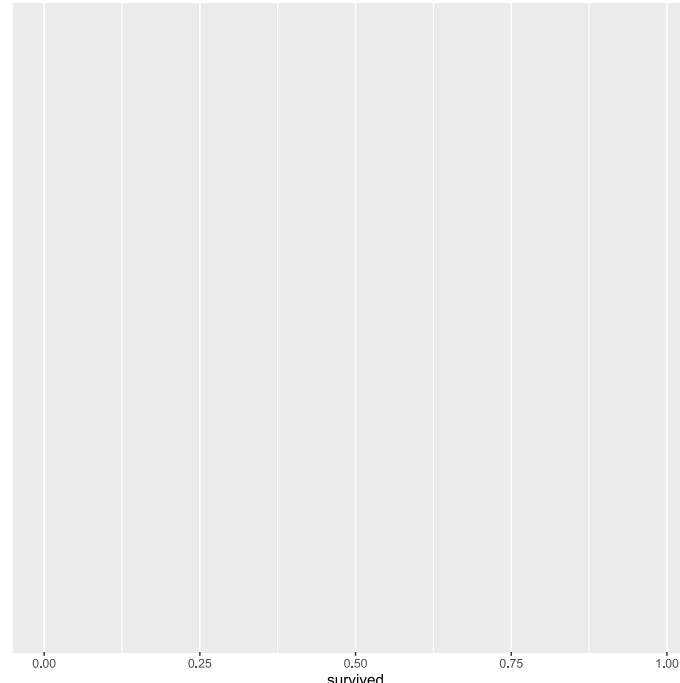
ggplot2 basics ([Cheat Sheet](#))

- `ggplot(data = data_frame)` creates a plot instance
- Add "layers" to the plot (`geom` or `stat` layers)
 - Creates a visualization of the data
- Modify layer "mapping" args (usually with `aes()`)
 - Map variables to attributes of the plot
 - Ex: size, color, x variable, y variable
- Improve by adding title layers, faceting, etc.

ggplot2 Barplots

- Barplots via `ggplot() + geom_bar()`
- Across x-axis we want our categories - specify with `aes(x = ...)`

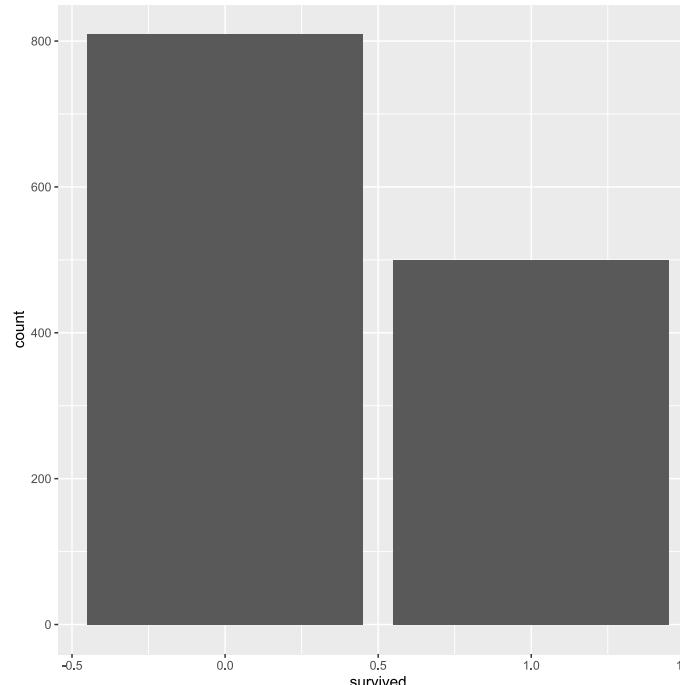
```
ggplot(data = titanicData, aes(x = survived))
```



ggplot2 Barplots

- Barplots via `ggplot() + geom_bar()`
- Must add `geom` (or `stat`) layer!

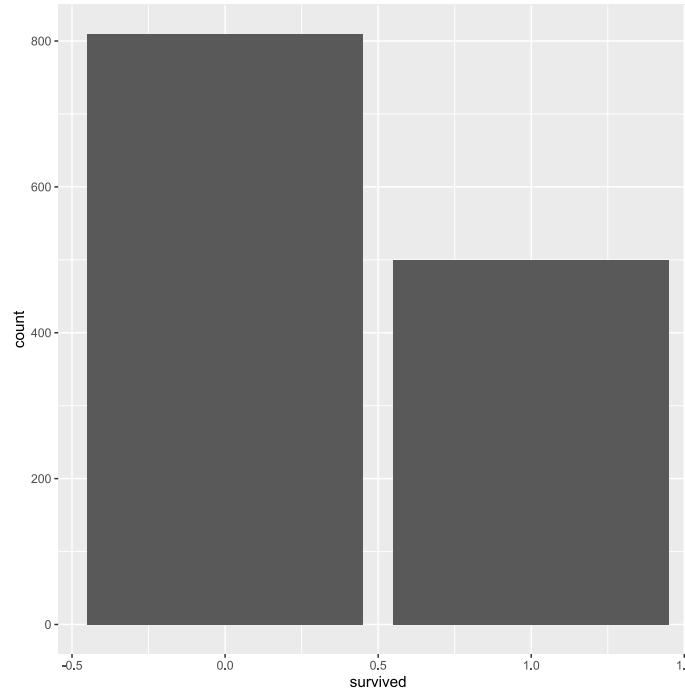
```
ggplot(data = titanicData, aes(x = survived)) + geom_bar()
```



ggplot2 Barplots

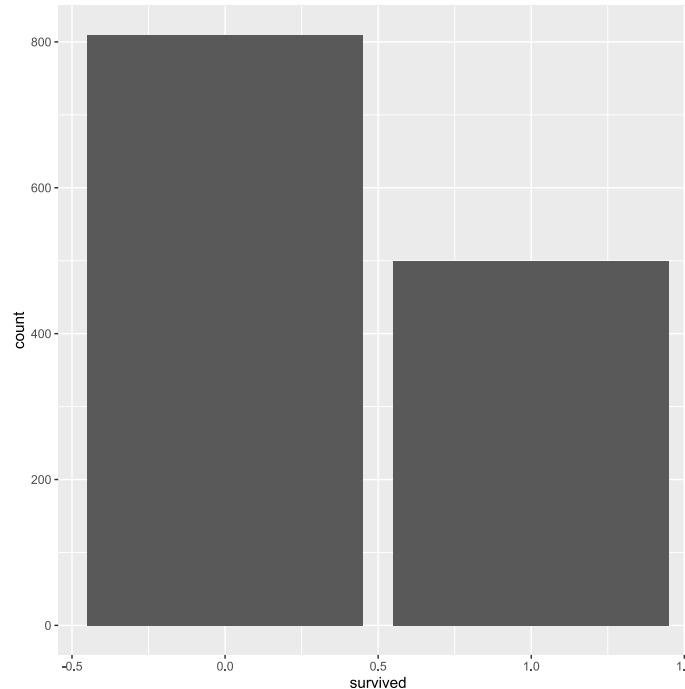
- Generally: Save base object with **global** `aes()` assignments, then add layers

```
g <- ggplot(data = titanicData, aes(x = survived))  
g + geom_bar()
```



Better Labeling Needed

- `survived` data values create a sub-optimal plot!



- Can fix with additional layers but it is easier to change the variable used for plotting!

Factors

- `survived` is read as a numeric variable (truly it is categorical)

```
titanicData
```

```
## # A tibble: 1,310 x 14
##   pclass survived name      sex    age sibsp parch ticket fare cabin embarked
##   <dbl>     <dbl> <chr>    <chr> <dbl> <dbl> <dbl> <chr> <dbl> <chr> <chr>
## 1     1       1 Allen, M~ fema~ 29      0     0 24160  211. B5    S
## 2     1       1 Allison,~ male   0.917    1     2 113781 152. C22   ~ S
## 3     1       0 Allison,~ fema~ 2        1     2 113781 152. C22   ~ S
## 4     1       0 Allison,~ male   30      1     2 113781 152. C22   ~ S
## 5     1       0 Allison,~ fema~ 25      1     2 113781 152. C22   ~ S
## # ... with 1,305 more rows, and 3 more variables: boat <chr>, body <dbl>,
## #   home.dest <chr>
```

- Can create a new version that is a `factor` - works well with `ggplot()`

Factors

Factor - special class of vector with a `levels` attribute

- Levels define all possible values for that variable
 - Great for variable like `Day` (Monday, Tuesday, ..., Sunday)
 - Not great for variable like `Name` where new values may come up

Factors

- Create a new factor version of survived

```
titanicData <- titanicData %>% mutate(mySurvived = as.factor(survived))
str(titanicData$mySurvived)

## Factor w/ 2 levels "0","1": 2 2 1 1 1 2 2 1 2 1 ...
levels(titanicData$mySurvived)

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

- Useful if you want to create better labels (or change the ordering)

```
levels(titanicData$mySurvived) <- c("Died", "Survived")
levels(titanicData$mySurvived)

## [1] "Died"      "Survived"
```

Prepare our Data

- Let's convert another categorical variable to a factor for better plotting

```
titanicData <- titanicData %>% mutate(myEmbarked = as.factor(embarked))  
levels(titanicData$myEmbarked) <- c("Cherbourg", "Queenstown", "Southampton")
```

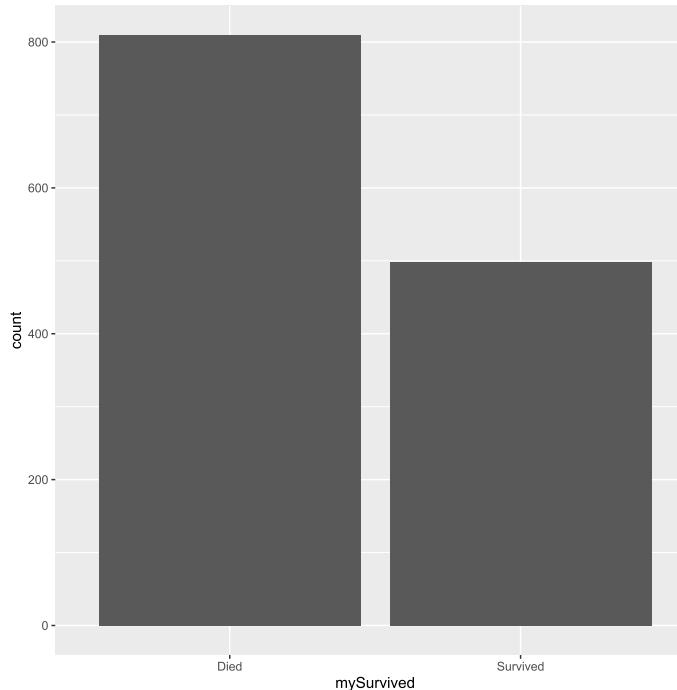
- Let's drop any rows with missing values for any of these variables

```
titanicData <- titanicData %>% drop_na(mySurvived, sex, myEmbarked)
```

Better Labels!

- Same barplot using the factor version of the variable: `mySurvived`

```
g <- ggplot(data = titanicData, aes(x = mySurvived))  
g + geom_bar()
```



aes() Arguments

- `aes()` defines visual properties of objects in the plot
- Map variables in the data frame to plot elements
 - `x = , y = , size = , shape = , color = , alpha = , ...`
- **Cheat Sheet** gives most common properties for a given `geom`

aes() Arguments for Barplots

- `aes()` defines visual properties of objects in the plot
- Map variables in the data frame to plot elements

`x = , y = , size = , shape = , color = , alpha = , ...`

- **Cheat Sheet** gives most common properties for a given `geom`

`d + geom_bar()`

`x, alpha, color, fill, linetype, size, weight`

aes() Arguments for Barplots

- **Stacked barplot** created by via `fill` aesthetic
- Automatic assignment of colors and creation of legends for `aes` elements (except group)

```
g <- ggplot(data = titanicData, aes(x = mySurvived, fill = myEmbarked))  
g + geom_bar()
```

ggplot2 Global vs Local Aesthetics

`data` and `aes` can be set in two ways;

- 'globally' (for all layers) via the `aes()` function in the `ggplot()` call
- 'locally' (for just that layer) via the `geom` or `stat` layer's `aes()`

ggplot2 Global vs Local Aesthetics

`data` and `aes` can be set in two ways;

- 'globally' (for all layers) via the `aes()` function in the `ggplot()` call
- 'locally' (for just that layer) via the `geom` or `stat` layer's `aes()`

```
#global  
ggplot(data = titanicData, aes(x = mySurvived, fill = myEmbarked)) + geom_bar()
```

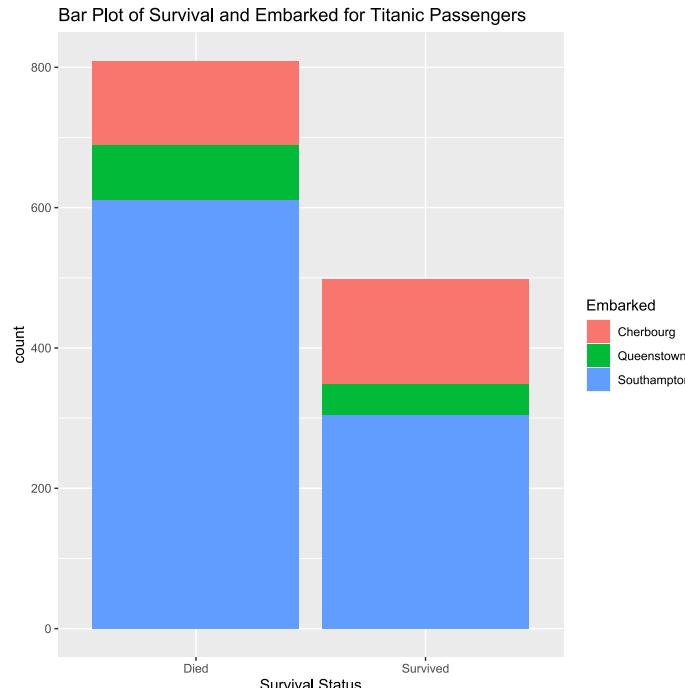
```
#some local, some global  
ggplot(data = titanicData, aes(fill = myEmbarked)) + geom_bar(aes(x = mySurvived))
```

```
#all local  
ggplot() + geom_bar(data = titanicData, aes(x = mySurvived, fill = myEmbarked))
```

ggplot2 Barplots

- Improve our plot by adding a `labs` layer

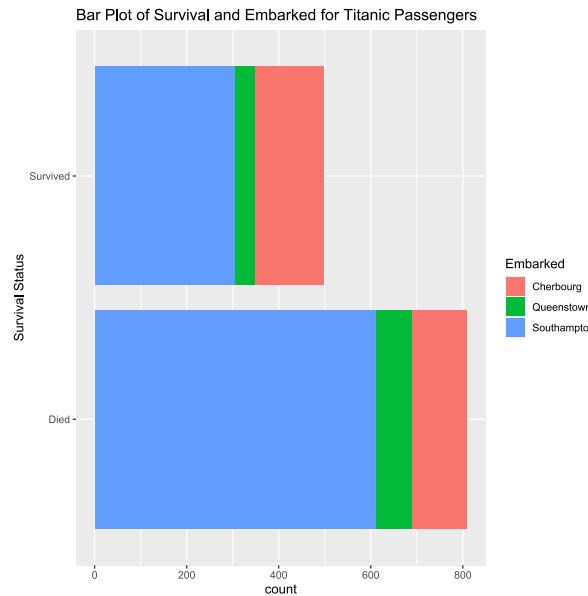
```
g <- ggplot(titanicData)
g + geom_bar(aes(x = mySurvived, fill = myEmbarked)) +
  labs(x = "Survival Status", title = "Bar Plot of Survival and Embarked for Titanic Passengers",
       fill = "Embarked")
```



ggplot2 Horizontal Barplots

- Easy to rotate a plot with `coord_flip()`

```
g <- ggplot(titanicData)
g + geom_bar(aes(x = mySurvived, fill = myEmbarked)) +
  labs(x = "Survival Status", title = "Bar Plot of Survival and Embarked for Titanic Passengers",
       fill = "Embarked") +
  coord_flip()
```



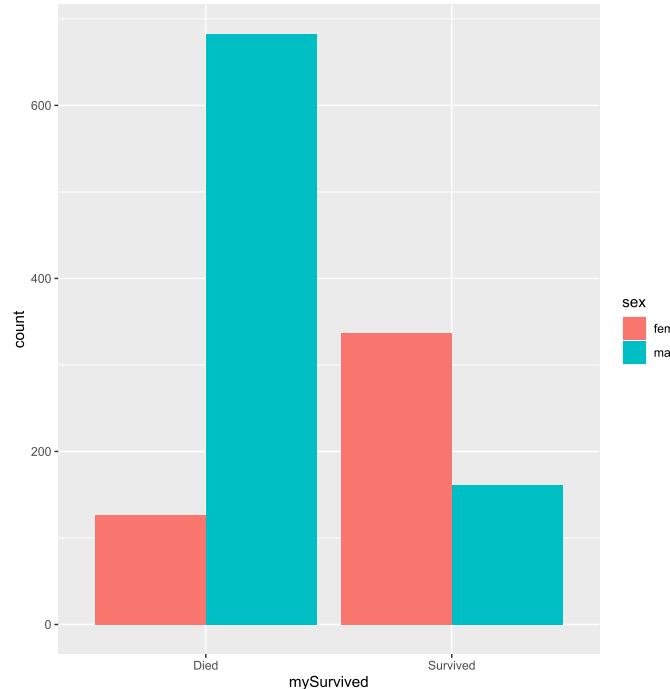
ggplot2 Side-By-Side Barplots

- **Side-by-side barplot** created via the `position` aesthetic
 - `dodge` for side-by-side bar plot
 - `jitter` for continuous data with many points at same values
 - `fill` stacks bars and standardises each stack to have constant height
 - `stack` stacks bars on top of each other

ggplot2 Side-By-Side Barplots

- **Side-by-side barplot** created by via `position` aesthetic

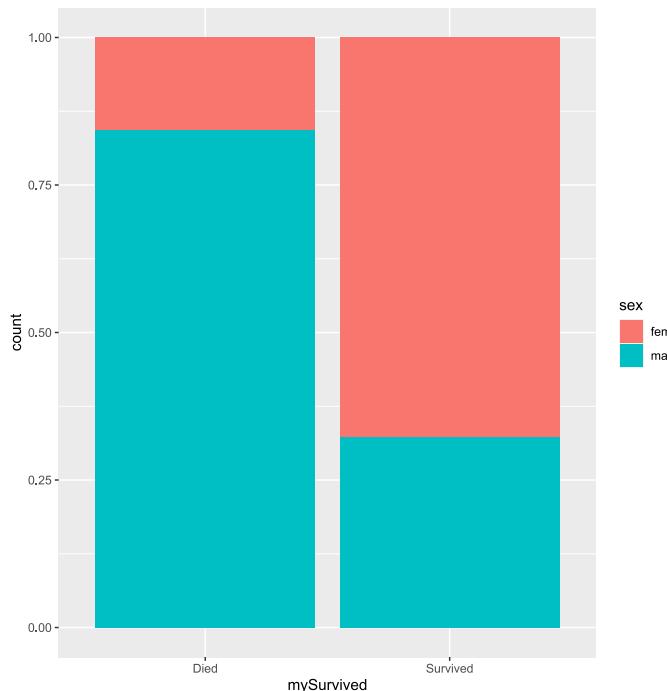
```
g <- ggplot(data = titanicData, aes(x = mySurvived, fill = sex))  
g + geom_bar(position = "dodge")
```



ggplot2 Filled Barplots

- `position = fill` stacks bars and standardizes each stack to have constant height (especially useful with equal group sizes)

```
g <- ggplot(data = titanicData, aes(x = mySurvived, fill = sex))  
g + geom_bar(position = "fill")
```



Recap!

General `ggplot2` things:

- Create base plot with `ggplot()`
- Add `geom` layer
- Can set local or global `aes()` (mappings of variables to attributes of the plot)
- Modify titles, labels, etc. by adding more layers
- `position` argument can change style of plot

ggplot2 Smoothed Histogram

- **Kernel Smoother** - Smoothed version of a histogram
- Common `aes` values (from cheat sheet):

```
c + geom_density(kernel = "gaussian")
```

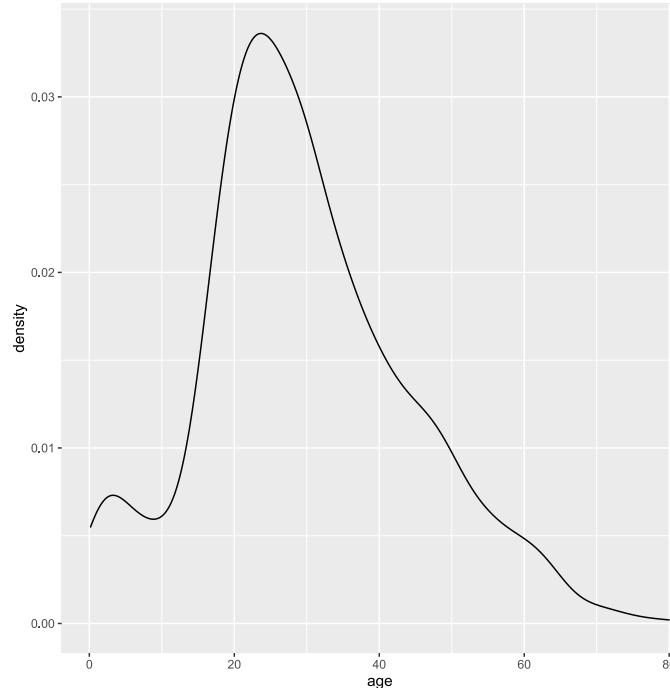
```
x, y, alpha, color, fill, group, linetype, size, weight
```

- Only `x =` is really needed

ggplot2 Smoothed Histogram

- **Kernel Smoother** - Smoothed version of a histogram

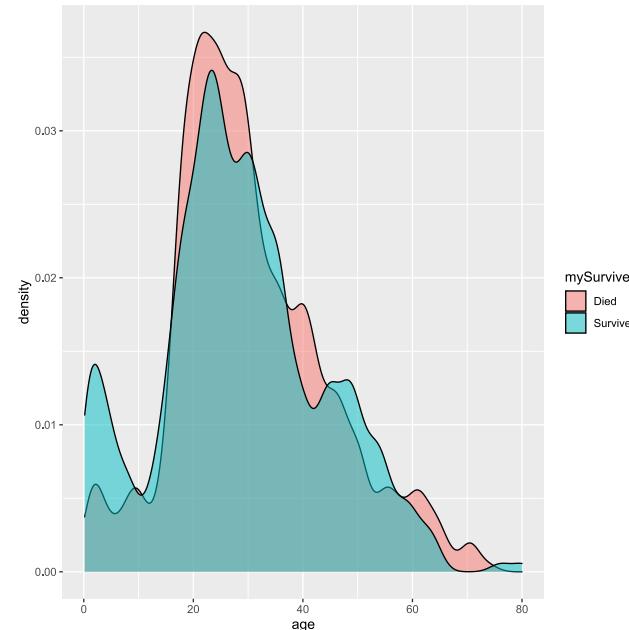
```
g <- ggplot(titanicData, aes(x = age))  
g + geom_density()
```



ggplot2 Smoothed Histogram

- **Kernel Smoother** - Smoothed version of a histogram
- **fill** a useful aesthetic!

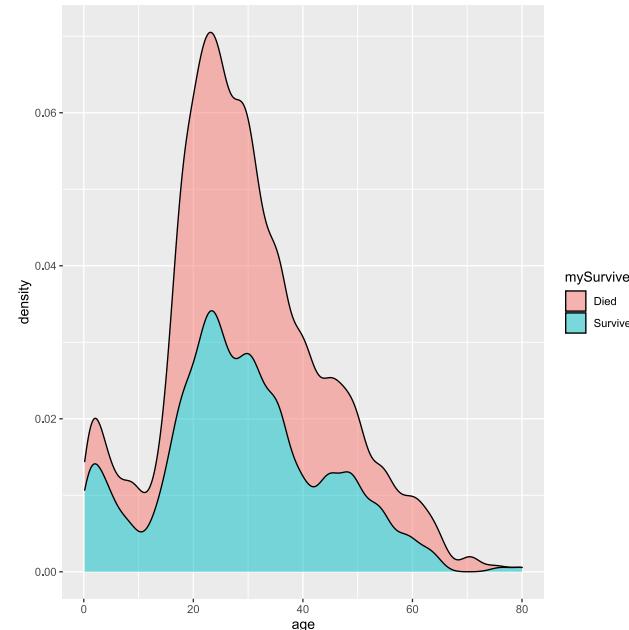
```
g <- ggplot(titanicData, aes(x = age))
g + geom_density(adjust = 0.5, alpha = 0.5, aes(fill = mySurvived))
```



ggplot2 Smoothed Histogram

- **Kernel Smoother** - Smoothed version of a histogram
- Recall `position` choices of `dodge`, `jitter`, `fill`, and `stack`

```
g <- ggplot(titanicData, aes(x = age))
g + geom_density(adjust = 0.5, alpha = 0.5, position = "stack", aes(fill = mySurvived))
```



ggplot2 Boxplots

- **Boxplot** - Provides the five number summary in a graph
- Common `aes` values (from cheat sheet):

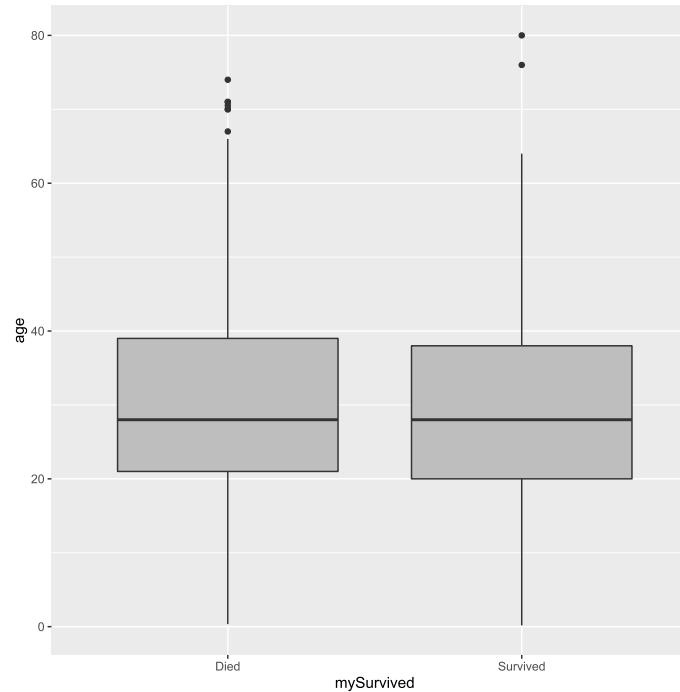
```
f + geom_boxplot()
```

```
x, y, lower, middle, upper, ymax, ymin, alpha, color, fill, group, linetype, shape,  
size, weight
```

- Only `x =`, `y =` are really needed

ggplot2 Boxplots

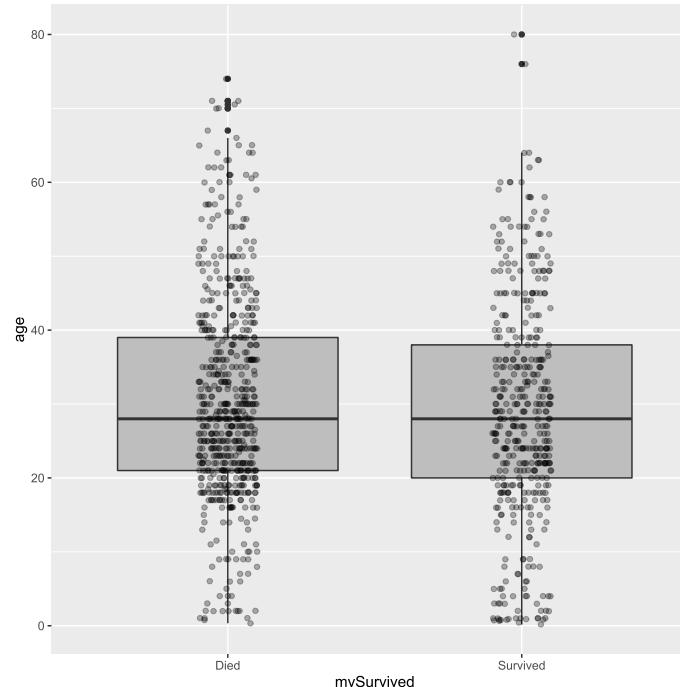
```
g <- ggplot(titanicData, aes(x = mySurvived, y = age))
g + geom_boxplot(fill = "grey")
```



ggplot2 Boxplots with Points

- Can add data points (jittered) to see shape of data better (or use violin plot)

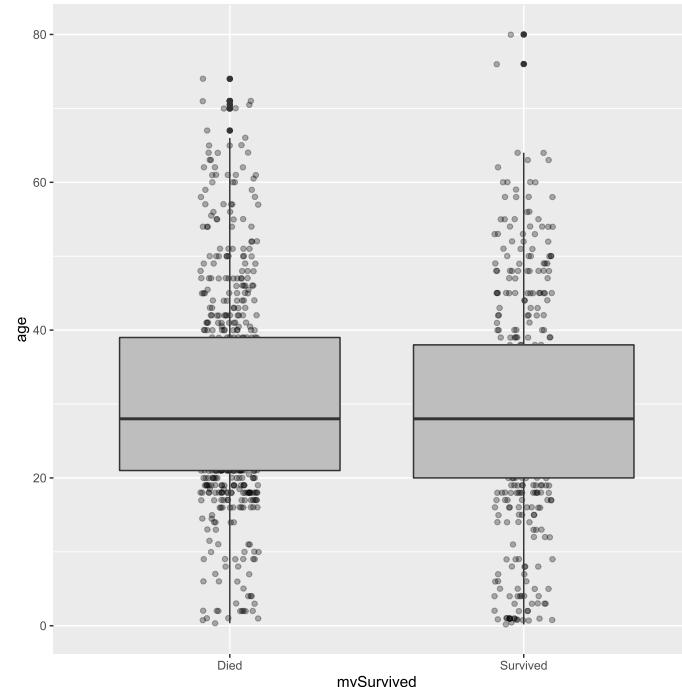
```
g <- ggplot(titanicData, aes(x = mySurvived, y = age))
g + geom_boxplot(fill = "grey") +
  geom_jitter(width = 0.1, alpha = 0.3)
```



ggplot2 Boxplots with Points

- Order of layers important!

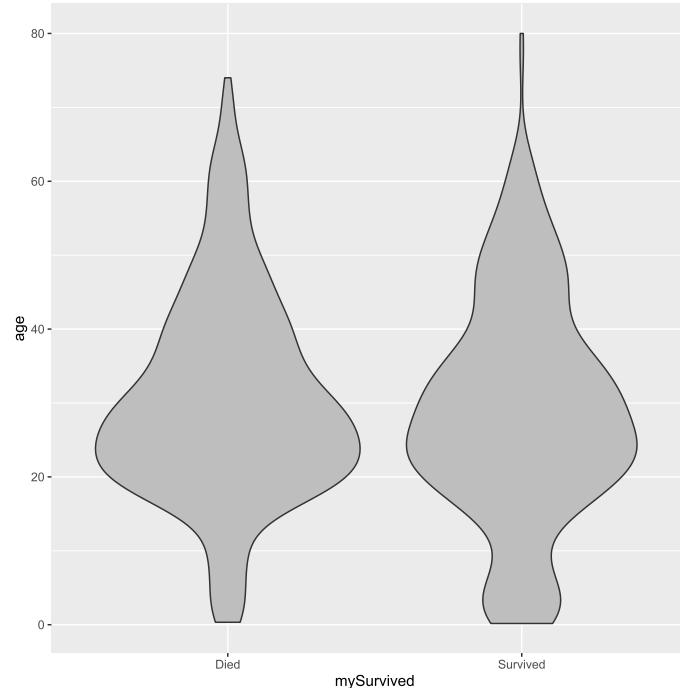
```
g <- ggplot(titanicData, aes(x = mySurvived, y = age))
g + geom_jitter(width = 0.1, alpha = 0.3) +
  geom_boxplot(fill = "grey")
```



ggplot2 Violin Plots

- Violin plot similar to boxplot

```
g <- ggplot(titanicData, aes(x = mySurvived, y = age))
g + geom_violin(fill = "grey")
```



ggplot2 Scatter Plots

Two numerical variables

- **Scatter Plot** - graphs points corresponding to each observation
- Common `aes` values (from cheat sheet):

`e + geom_point()`

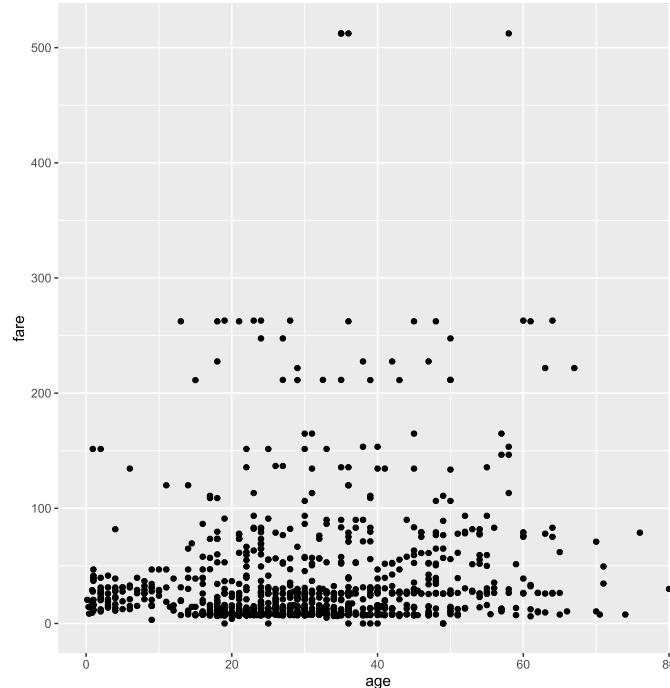
`x, y, alpha, color, fill, shape, size, stroke`

- Only `x =`, `y =` are really needed

ggplot2 Scatter Plots

- **Scatter Plot** - graphs points corresponding to each observation

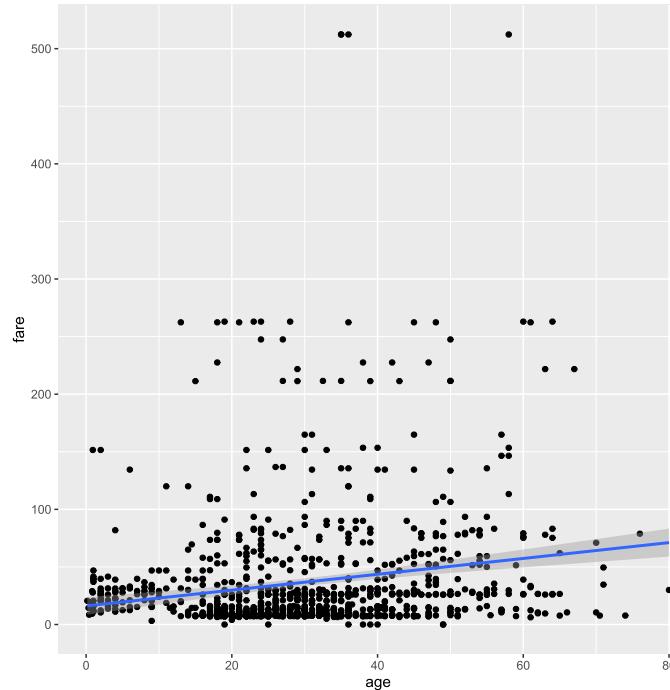
```
g <- ggplot(titanicData, aes(x = age, y = fare))  
g + geom_point()
```



ggplot2 Scatter Plots with Trend Line

- Add trend lines easily with `geom_smooth()`

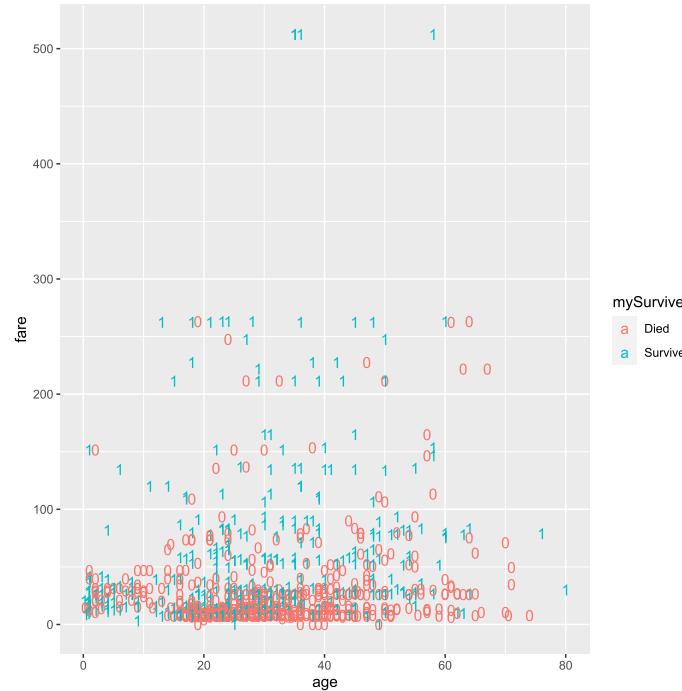
```
g <- ggplot(titanicData, aes(x = age, y = fare))  
g + geom_point() +  
  geom_smooth(method = lm)
```



ggplot2 Scatter Plots with Text Points

- Text for points with `geom_text`

```
g <- ggplot(titanicData, aes(x = age, y = fare))
g + geom_text(aes(label = survived, color = mySurvived))
```

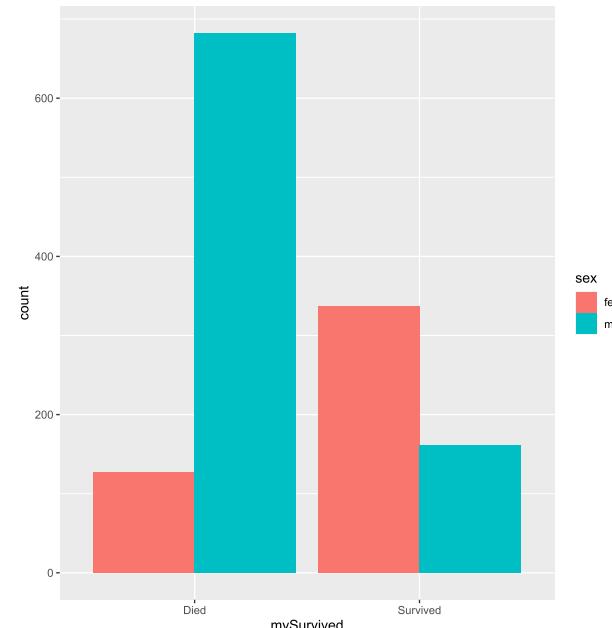


ggplot2 Faceting

Suppose we want to take one of our plots and produce similar plots across another variable!

How to create this plot across each `myEmbarked` category? Use **faceting**!

```
g <- ggplot(data = titanicData, aes(x = mySurvived, fill = sex))  
g + geom_bar(position = "dodge")
```



ggplot2 Faceting

`facet_wrap(~ var)` - creates a plot for each setting of `var`

- Can specify `nrow` and `ncol` or let R figure it out

ggplot2 Faceting

`facet_wrap(~ var)` - creates a plot for each setting of `var`

- Can specify `nrow` and `ncol` or let R figure it out

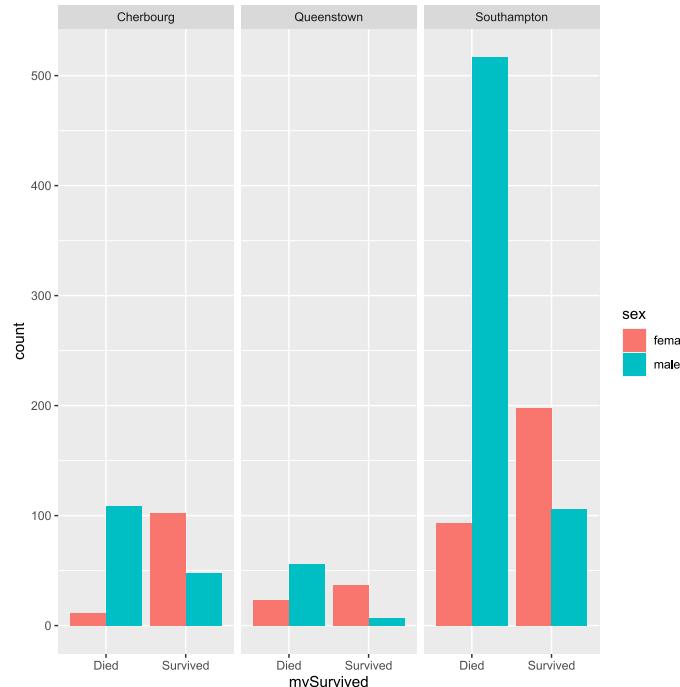
`facet_grid(var1 ~ var2)` - creates a plot for each combination of `var1` and `var2`

- `var1` values across rows
- `var2` values across columns
- Use `. ~ var2` or `var1 ~ .` to have only one row or column

ggplot2 Faceting

- `facet_wrap(~ var)` - creates a plot for each setting of `var`

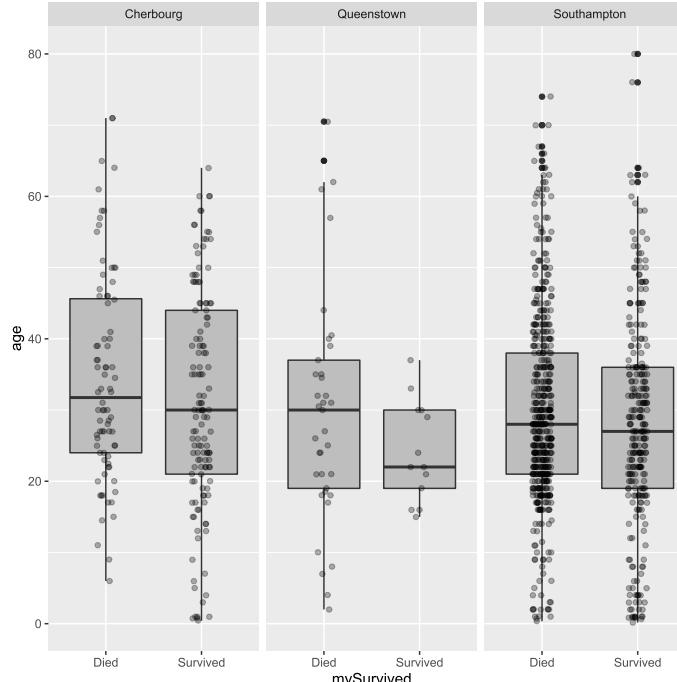
```
g <- ggplot(data = titanicData, aes(x = mySurvived, fill = sex))  
g + geom_bar(position = "dodge") +  
  facet_wrap(~ myEmbarked)
```



ggplot2 Faceting

- Faceting can be used with any `ggplot`

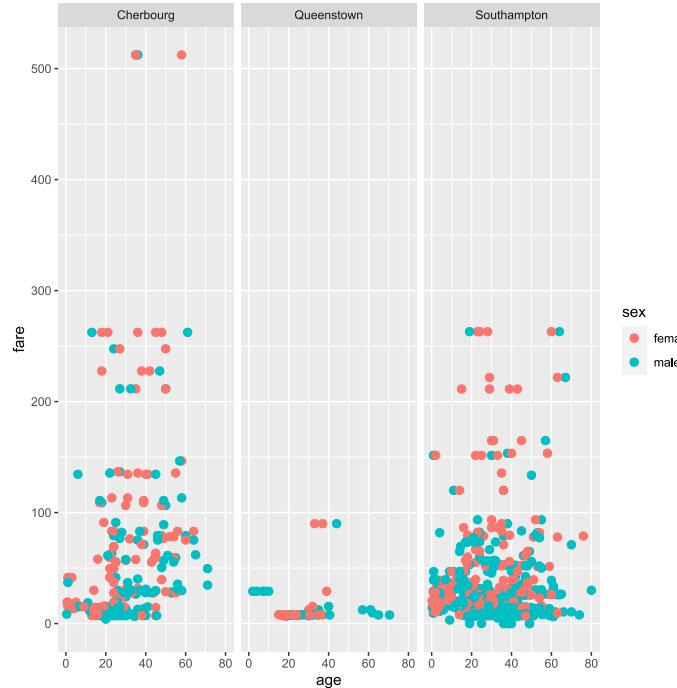
```
g <- ggplot(titanicData, aes(x = mySurvived, y = age))  
g + geom_boxplot(fill = "grey") +  
  geom_jitter(width = 0.1, alpha = 0.3) +  
  facet_wrap(~ myEmbarked)
```



ggplot2 Faceting

- Faceting can be used with any `ggplot`

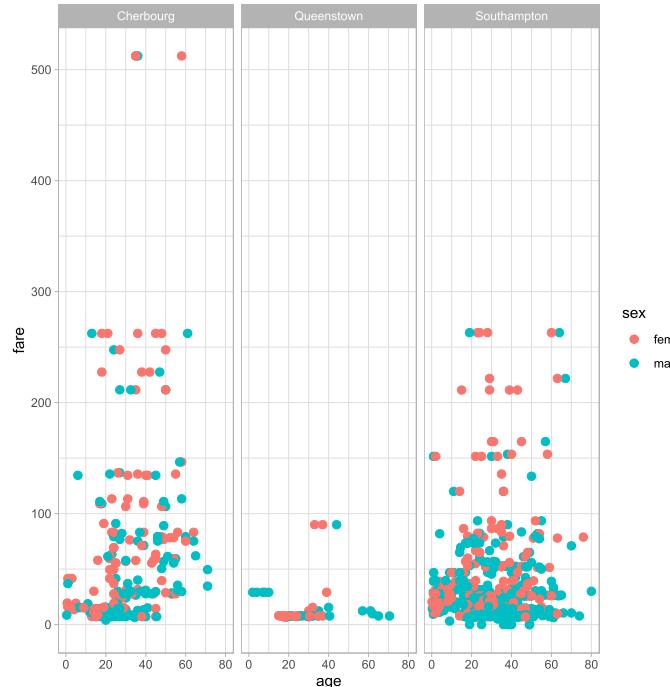
```
g <- ggplot(titanicData, aes(x = age, y = fare))  
g + geom_point(aes(color = sex), size = 2.5) +  
  facet_wrap(~ myEmbarked)
```



ggplot2 Themes

- Can easily change the general look of plots using themes

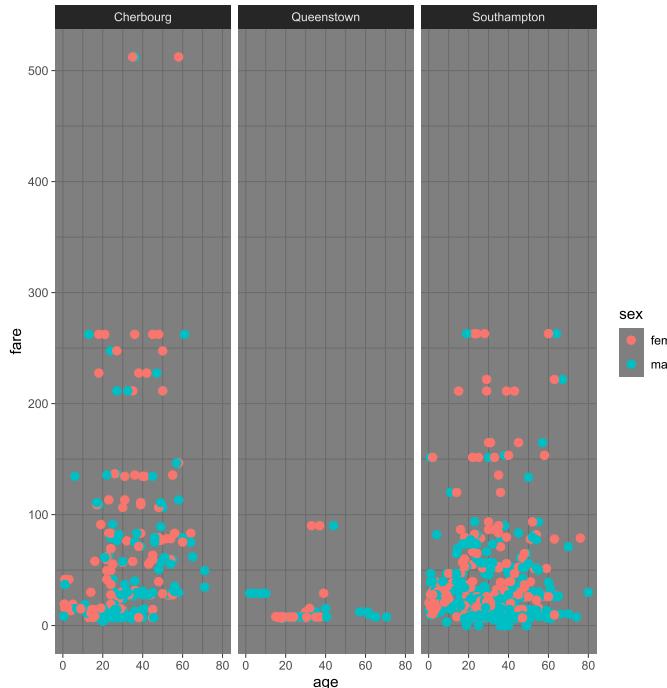
```
g <- ggplot(titanicData, aes(x = age, y = fare))  
g + geom_point(aes(color = sex), size = 2.5) +  
  facet_wrap(~ myEmbarked) +  
  theme_light()
```



ggplot2 Themes

- Can easily change the general look of plots using themes

```
g <- ggplot(titanicData, aes(x = age, y = fare))  
g + geom_point(aes(color = sex), size = 2.5) +  
  facet_wrap(~ myEmbarked) +  
  theme_dark()
```

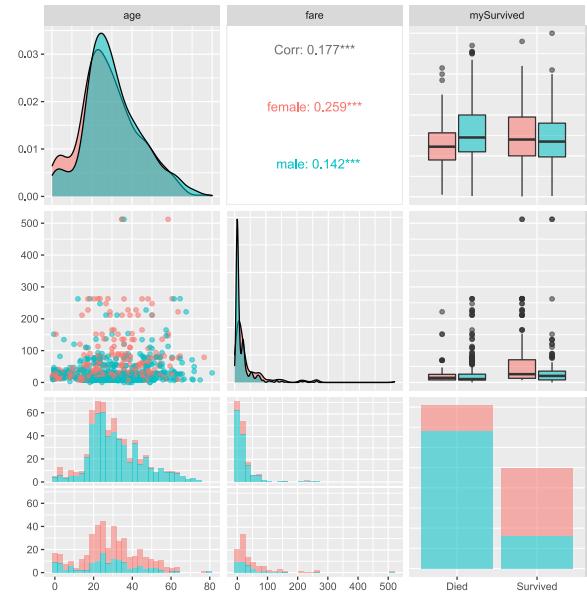


ggplot2 Extensions

Many extension packages that do nice things!

- `GGally` package has the `ggpairs()` function

```
library(GGally) #install if needed  
ggpairs(titanicData, aes(colour = sex, alpha = 0.4), columns = c("age", "fare", "mySurvived"))
```



ggplot2 Extensions

Over 100 registered extensions at <https://exts.ggplot2.tidyverse.org/>!

- `ggridge` package allows for the creation of gifs

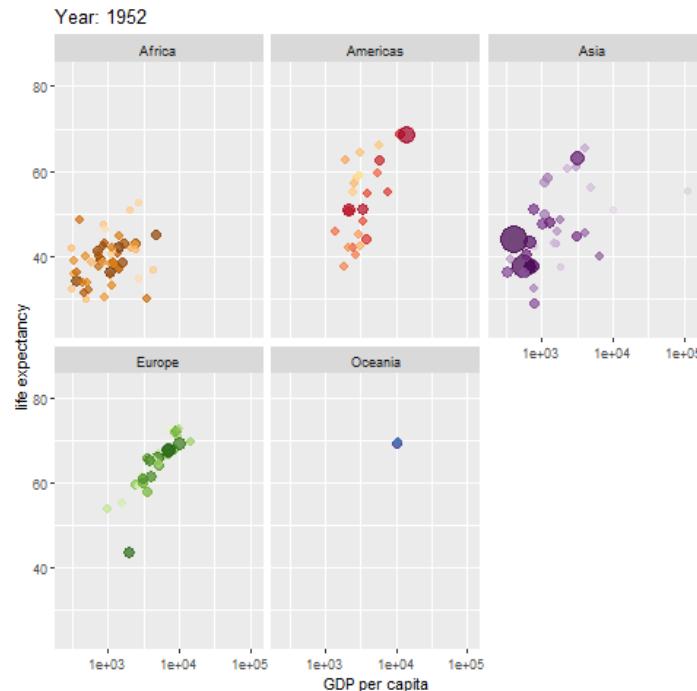
```
#install each if needed
library(gapminder)
library(ggridge)
library(gifski)

gif <- ggplot(gapminder, aes(gdpPercap, lifeExp, size = pop, colour = country)) +
  geom_point(alpha = 0.7, show.legend = FALSE) +
  scale_colour_manual(values = country_colors) +
  scale_size(range = c(2, 12)) +
  scale_x_log10() +
  facet_wrap(~continent) +
  # Here comes the ggridge specific bits
  labs(title = 'Year: {frame_time}', x = 'GDP per capita', y = 'life expectancy') +
  transition_time(year) +
  ease_aes('linear')
anim_save(filename = "img/myGif.gif", animation = gif, renderer = gifski_renderer())
```

ggplot2 Extensions

Over 100 registered extensions at [https://exts.ggplot2.tidyverse.org/!](https://exts.ggplot2.tidyverse.org/)

- `ggridge` package allows for the creation of gifs



Recap!

General `ggplot2` things:

- Can set local or global `aes()`
 - Generally, only need `aes()` if setting a mapping value that is dependent on the data
- Modify titles/labels by adding more layers
- Use either `stat` or `geom` layer
- Faceting (multiple plots) via `facet_grid()` or `facet_wrap()`
- `esquisse` is a great package for exploring `ggplot2`!

Let's Practice

We'll add to our `.Rmd` file from the previous activity

- Download the prompts to add to our markdown document [here](#)

Guidance:

- Copy and paste the text from above into the bottom of the document, reknit
- Add to the code chunks, evaluating in the notebook
- Reknit occasionally to check the output