R for Excel Users

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Contents

Chapter 1

Welcome

Excel is a widely used and powerful tool for working with data. As automation, reproducibility, collaboration, and frequent reporting become increasingly expected in data analysis, a good option for Excel users is to extend their workflows with R. Integrating R into data analysis with Excel can bridge the technical gap between collaborators using either software. R enables use of existing tools built for specific tasks and overcomes some limitations that arise when working with large datasets or repeated analyses. This course is for Excel users who want to add or integrate R and RStudio into their existing data analysis toolkit. Participants will get hands-on experience working with data across R, Excel, and Google Sheets, focusing on: data import and export, basic wrangling, visualization, and reporting with RMarkdown. Throughout, we will emphasize conventions and best practices for working reproducibly and collaboratively with data, including naming conventions, documentation, organization, all while "keeping the raw data raw". Whether you are working in Excel and want to get started in R, already working in R and want tools for working more seamlessly with collaborators who use Excel, or whether you are new to data analysis entirely, this is the course for you!

If you answer yes to these questions, this course is for you!

- Are you an Excel user who wants to expand your data analysis toolset with R?
- Do you want to bridge analyses between Excel and R, whether working independently or to more easily collaborate with others who use Excel or R?
- Are you new to data analysis, and looking for a good place to get started?

1.1 Prerequisites

Before the training, please make sure you have done the following:

1. Download and install **up-to-date versions** of:
   - R: https://cloud.r-project.org
   - RStudio: http://www.rstudio.com/download
2. Install the Tidyverse

3. Get comfortable: if you're not in a physical workshop, be set up with two screens if possible. You will be following along in RStudio on your own computer while also watching a virtual training or following this tutorial on your own.

Chapter 2

Overview

TODO: shorten so it's just the overview (ie cut the Rscripts)

2.1 Summary (a few sentences)

2.2 Objectives (more detailed, bulletpoints?)

- working with data that are not your own.

2.3 Resources

R is not only a language, it is an active community of developers, users, and educators (often these traits are in each person). This workshop and book based on many excellent materials created by other members in the R community, who share their work freely to help others learn. Using community materials is how WE learned R, and each chapter of the book will have Resources listed for further reading into the topics we discuss. And, when there is no better way to explain something (ahem Jenny Bryan), we will quote or reference that work directly.

- What They Forgot to Teach You About R — Jenny Bryan & Jim Hester
- Stat545 — Jenny Bryan & Stat545 TAs
- Where do Things Live in R? REX Analytics
-

2.4 Overview

Welcome.

This workshop you will learn hands-on how to begin to interoperate between Excel and R.

A main theme throughout is to produce analyses people can understand and build from — including Future You. Not so brittle/sensitive to minor changes.

We will learn and reinforce X main things all at the same time: coding with best practices (R/RStudio), how this relates to operations in Excel, Z. This training will teach these all together to reinforce skills and best practices, and get you comfortable with a workflow that you can use in your own projects.

2.4.1 What to expect

This is going to be a fun workshop.

The plan is to expose you to X that you can have confidence using in your work. You'll be working hands-on and doing the same things on your own computer as we do live on up on the screen. We're going to go through a lot in these two days and it's less important that you remember it all. More importantly, you'll have experience with it and confidence that you can do it. The main thing to take away is that there *are* good ways to work between R and Excel; we will teach you to expect that so you can find what you need and use it! A theme throughout is that tools exist and are being developed by real, and extraordinarily nice, people to meet you where you are and help you do what you need to do. If you expect and appreciate that, you will be more efficient in doing your awesome science.

You are all welcome here, please be respectful of one another. You are encouraged to help each other.

Everyone in this workshop is coming from a different place with different experiences and expectations. But everyone will learn something new here, because there is so much innovation in the data science world. Instructors and helpers learn something new every time, from each other and from your questions. If you are already familiar with some of this material, focus on how we teach, and how you might teach it to others. Use these workshop materials not only as a reference in the future but also for talking points so you can communicate the importance of these tools to your communities. A big part of this training is not only for you to learn these skills, but for you to also teach others and increase the value and practice of open data science in science as a whole.

2.4.2 What you'll learn

TODO: dev

- Motivation is to bridge and/or get out of excel
- We're not going to replicate all of your fancy things in R,
- We use Excel to look at data that we're reading into R
- Spreadsheets are great; blend data entry with analyses and we're going to try to help you think about them a bit more distinctively.
- Most important collaborator is future you, and future us

An important theme for this workshop is being deliberate about your analyses and setting things up in a way that will make your analytical life better downstream in the current task, and better when Future You or Future Us revisit it in the future (i.e. avoiding: what happens next? What does this name mean?)

This graphic by Hadley Wickham and Garrett Grolemund in their book R for Data Science is simple but incredibly powerful:

You may not have ever thought about analysis in such discrete steps: I certainly hadn't before seeing this. That is partly because in Excel, it can be easy to blend these steps together. We are going to keep them separate, and talk about why. The first step is Import: and implicit in this as a first step is that the data is stored elsewhere and is not manipulated directly, which **keeps the raw data raw**.

We will be focusing on:

- **Import**: `readr`, `readxl` to read raw data stored in CSV or Excel files directly into R
- **Tidy**: `tidyr` to (re)organize rows of data into unique values
- **Transform**: `dplyr` to "wrangle" data based on subsetting by rows or columns, sorting and joining
- **Visualize**: `ggplot2` static plots, using grammar of graphics principles
- **Communicate**
  - `writexl` to export intermediate and final data
  - GitHub File Upload and Issues for online publishing and collaboration

2.4.3 Emphasizing collaboration

TODO: rewrite/update (from OHI book):

Collaborating efficiently has historically been really hard to do. It's only been the last 20 years or so that we've moved beyond mailing things with the postal service. Being able to email and get feedback on files through track changes was a huge step forward, but it comes with a lot of bookkeeping and reproduciblity issues (did I send that report based on `analysis_final_final.xls` or `analysis_final_usethisone.xls`?). But now, open tools make it much easier to collaborate.

Working with collaborators in mind is critical for reproducibility. And, your most important collaborator is Future You. This training will introduce best practices using open tools, so that collaboration will become second nature to you!

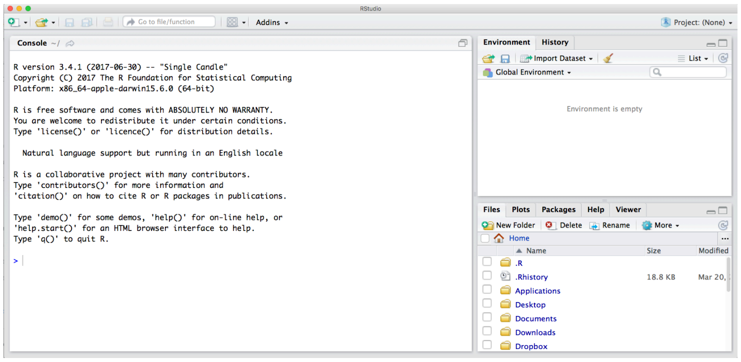
2.4.4 By the end of the course...

By the end of this course you'll produce this report that you can reproduce, which means... Introduce the problem we will solve. Eg: (just an idea maybe time-series is not a great idea) SMALL PROBLEM. (4 mins) Show data files, We will discuss our analysis plan (only enough to motivate!) Create a report, that looks great.

2.5 RStudio Orientation

Open RStudio for the first time.

Launch RStudio/R.



```
R version 3.4.1 (2017-06-30) -- "Single Candle"
Copyright (C) 2017 The R Foundation for Statistical Computing
Platform: x86_64-apple-darwin15.6.0 (64-bit)

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

  Natural language support but running in an English locale

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> 
```

Name	Size	Modified
.R		
.Rhistory	18.8 KB	Mar 20,
Applications		
Desktop		
Documents		
Downloads		
Dropbox		

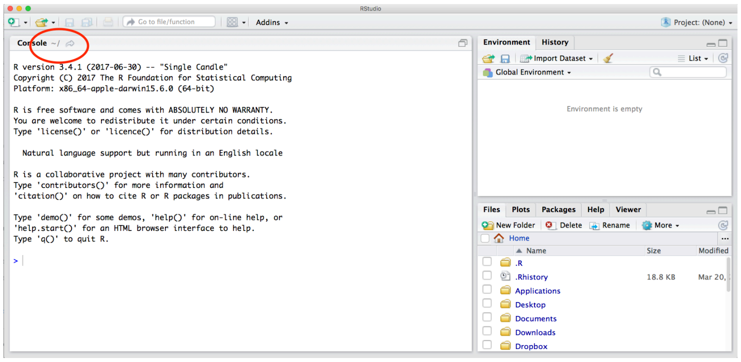
Notice the default panes:

- Console (entire left)
- Environment/History (tabbed in upper right)
- Files/Plots/Packages/Help (tabbed in lower right)

FYI: you can change the default location of the panes, among many other things: Customizing RStudio.

An important first question: **where are we?**

If you've have opened RStudio for the first time, you'll be in your Home directory. This is noted by the `~/` at the top of the console. You can see too that the Files pane in the lower right shows what is in the Home directory where you are. You can navigate around within that Files pane and explore, but note that you won't change where you are: even as you click through you'll still be Home: `~/`.



```
R version 3.4.1 (2017-06-30) -- "Single Candle"
Copyright (C) 2017 The R Foundation for Statistical Computing
Platform: x86_64-apple-darwin15.6.0 (64-bit)

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'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> 
```

Name	Size	Modified
.R		
.Rhistory	18.8 KB	Mar 20,
Applications		
Desktop		
Documents		
Downloads		
Dropbox		

2.5.1 RStudio Projects

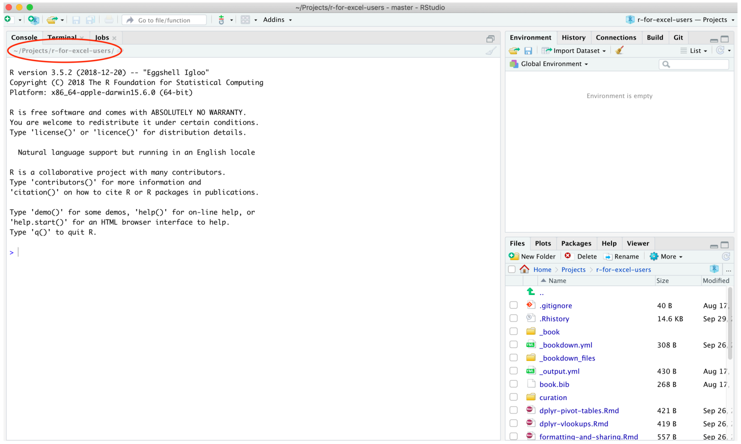
Create a new Project called 'r-for-excel-users'. File > New Project… > New Directory > New Project. Give your Project a name browse to a place to keep it. And then click to Create Project!

What is a Project? It is a way to organize all of the relevant things you need for an analysis in the same place. This means data, code, figures, notes, etc.

Why does this matter? Keeping everything you need for your analysis together makes it less brittle and more portable — across people, time, and computers.

Working directory = no file path/broken path issues. Notice that a folder now appears wherever you saved this project with the same name, and it contains a .Rproj file.

Now that we have our Project, here is an important question: where are we? Now we are in our Project. Everything we do will by default be saved here so we can be nice and organized.



```
R version 3.5.2 (2018-12-20) -- "Eggshell Igloo"
Copyright (C) 2018 The R Foundation for Statistical Computing
Platform: x86_64-apple-darwin15.6.0 (64-bit)

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
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Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> 
```

Name	Size	Modified
..		
.gitignore	40 B	Aug 17,
.Rhistory	14.6 KB	Sep 29,
_book		
_bookdown.yml	308 B	Sep 26,
_bookdown_files		
_output.yml	430 B	Aug 17,
book.bib	268 B	Aug 17,
curation		
dplyr-pivot-tables.Rmd	421 B	Sep 26,
dplyr-vlookups.Rmd	419 B	Sep 26,
formatting-and-sharing.Rmd	557 B	Sep 26,

2.5.2 R Console

Watch me work in the Console.

I can do math:

```
52*40
365/12
```

TODO: refine

But like Excel, the power comes not from doing small operations by hand (like 8*22.3), it's by being able to operate on whole suites of numbers and datasets. In Excel, data are stored in the spreadsheet. In R, they are stored in dataframes, and named as variables.

R stores data in variables, and you give them names. This is a big difference with Excel, where you usually identify data by by its location on the grid, like `$A1:D$20`. (You can do this with Excel by naming ranges of cells, but most people don't do this.)

Data can be a variety of formats, like numeric and text.

Let's have a look at some data in R. R has several built-in data sets that we can look at and work with.

One of these datasets is called `mtcars`. If I write this in the Console, it will print the data in the console.

```
mtcars
```

I can also use RStudio's Viewer to see this in a more familiar-looking format:

```
View(mtcars)
```

This opens the fourth pane of the RStudio IDE; when you work in R you will have all four panes open so this will become a very comforting setup for you.

> The basic R data structure is a vector. You can think of a vector like a column in an Excel spreadsheet with the limitation that all the data in that vector must be of the same type. If it is a character vector, every element must be a character; if it is a logical vector, every element must be TRUE or FALSE; if it's numeric you can trust that every element is a number. There's no such constraint in Excel: you might have a column which has a bunch of numbers, but then some explanatory test intermingled with the numbers. This isn't allowed in R. - https://blog.shotwell.ca/posts/r_for_excel_users/

In the Viewer I can do things like filter or sort. This does not do anything to the actual data, it just changes how you are viewing the data. So even as I explore it, I am not editing or manipulating the data.

Like Excel, some of the biggest power in R is that there are built-in functions that you can use in your analyses (and, as we'll see, R users can easily create and share functions, and it is this open source developer and contributor community that makes R so awesome).

So let's look into some of these functions. In Excel, there is a "SUM" function to calculate a total. Let's expect that there is the same in R. I will type this into the Console:

```
?sum
```

A few important things to note:

1. R is case-sensitive. So "sum" is a completely different thing to "Sum" or "SUM". And this is true for the names of functions, data sets, variable names, and data itself ("blue" vs "Blue").

2. RStudio has an autocomplete feature that can help you find the function you're looking for. In many cases it pops up as you type, but you can always type the tab key (above your caps lock key) to prompt the autocomplete. And, bonus: this feature can help you with the case-sensitivity mentioned above: If I start typing "?SU" and press tab, it will show me all options starting with those two letters, regardless of capitalization (although it will start with the capital S options).

OK but what does typing `?sum` actually *do*?

When I press enter/return, it will open up a help page in the bottom right pane. Help pages vary in detail I find some easier to digest than others. But they all have the same structure, which is helpful to know. The help page tells the name of the package in the top left, and broken down into sections:

- Description: An extended description of what the function does.
- Usage: The arguments of the function and their default values.

- Arguments: An explanation of the data each argument is expecting.
- Details: Any important details to be aware of.
- Value: The data the function returns.
- See Also: Any related functions you might find useful.
- Examples: Some examples for how to use the function.

When I look at a help page, I start with the description, which might be too in-the-weeds for the level of understanding I need at the offset. For the `sum` page, it is pretty straight-forward and lets me know that yup, this is the function I want.

I next look at the usage and arguments, which give me a more concrete view into what the function does. This syntax looks a bit cryptic but what it means is that you use it by writing sum, and then passing whatever you want to it in terms of data: that is what the "…" means. And the "na.rm=FALSE" means that by default, it will not remove NAs (I read this as: "remove NAs? FALSE!")

Then, I usually scroll down to the bottom to the examples. This is where I can actually see how the function is used, and I can also paste those examples into the Console to see their output. Best way to learn what the function actually does is seeing it in action. Let's try:

```
sum(1:5)
```

So this is calculating the sum of the numbers from 1 and 5; that is what that `1:5` syntax means in this case. We can check it with the next example:

```
sum(1, 2, 3, 4, 5)
```

Awesome. Let's try this on our `mtcars` data

```
sum(mtcars)
```

Alright. What is this number? It is the sum of ALL of the data in the mtcars dataset. Maybe in some analysis this would be a useful operation, but I would worry about the way your data is set up and your analyses if this is ever something you'd want to do. More likely, you'd want to take the sum of a specific column. In R, you can do that with the `$` operator.

Let's say we want to calculate the total number of gears that all these cars have:

```
sum(mtcars$gear)
```

2.6 Deep thought

How would you do this in Excel? The calculations are usually the same shape as the data. In other words if you want to multiply 20 numbers stored in cells A1:An by 2, you will need 20 calculations: =A1 * 2, =A2 * 2, …., =An * 2.

OK so now that we've got a little bit of a feel for R and RStudio, let's do something much more interesting and really start feeling its power.

2.7 R Scripts

OK so working in the Console is great for quick things, but it gets messy. Keeping track at what I've done and trying to build upon it would be a nightmare.

Instead of working in the Console, we can be more organized by writing analyses in a script. This is a really powerful way to work in R. *TODO dev more* Scripts are a written record of the analyses you do, unlike Excel. And they can be re-run easily…

In this script, we're going to make our first figure in R. Let's all do this together.

File > New File > R Script.

This is a blank slate for us to write our code; but there are some good practices we can start off with. Let's add a useful header to the top of it. For example, at a minimum:

```
# --------------------------------
# A descriptive title
# Your name
# Contact information
# Date
# --------------------------------
```

And then let's save it, naming it something like "my_first_figure.R". Let's get into good habits now with this filename: no spaces! Use underscores `_` or dashes `-` or no space at all.

Since we're working in or Project, this script is now nicely saved in our Project. You can see our `.R` show up in our Files pane on the bottom right.

Let's attach a package. Since you've already installed tidyverse,

```
# Attach the tidyverse
library(tidyverse)
```

What is the tidyverse? *TODO* - ggplot2

Let's look at one of the datasets that is built into the ggplot2 package. Type this into your R script:

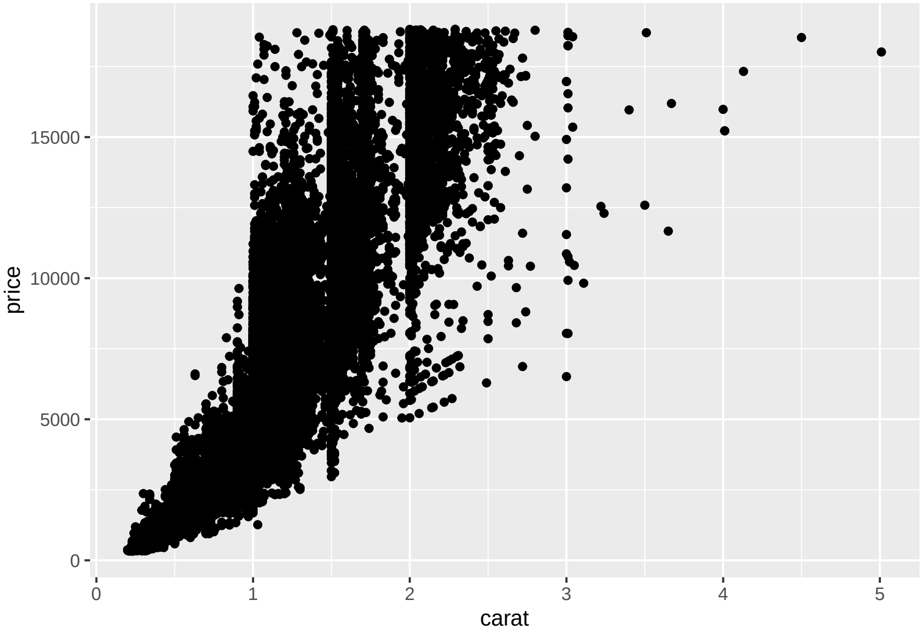
```
View(diamonds)
```

So this is not immediately executed like when we were typing in the Console. That's because an R script is really just a text file that doesn't do anything on its own; you need to tell R to execute it. You do that in a few ways (let's do each of them):

1. copy-paste this line into the console.
2. click Run (with green arrow at the top-right of your script) to run the line where your cursor is or any highlighted selection
3. click Source (top right of your script) to run the whole script.

Now let's plot it. Type this or copy-paste and then we'll discuss:

```
ggplot(diamonds, aes(x = carat, y = price)) +
  geom_point()
```



2.7.1 Deep thought: Error messages are your friends

As Jenny Bryan says:

> Implicit contract with the computer / scripting language: Computer will do tedious computation for you. In return, you will be completely precise in your instructions. Typos matter. Case matters. Pay attention to how you type.

Remember that this is a language, not unsimilar to English! There are times you aren't understood – it's going to happen. There are different ways this can happen. Sometimes you'll get an error. This is like someone saying 'What?' or 'Pardon'? Error messages can also be more useful, like when they say 'I didn't understand what you said, I was expecting you to say blah'. That is a great type of error message. Error messages are your friend. Google them (copy-and-paste!) to figure out what they mean.

And also know that there are errors that can creep in more subtly, when you are giving information that is understood, but not in the way you meant. Like if I am telling a story about suspenders that my British friend hears but silently interprets in a very different way (true story). This can leave me thinking I've gotten something across that the listener (or R) might silently interpreted very differently. And as I continue telling my story you get more and more confused… Clear communication is critical when you code: write clean, well documented code and check your work as you go to minimize these circumstances!

2.8 Don't save the workspace

2.9 Deep thought: keep the raw data raw.

Discussing using Excel for variables.

Horror Stories! Economist etc. –

Mine: genetics example doesn't hit home as much as Durham bike accidents where age groups are converted to dates just by opening the bloody csv in excel

2.10 Activity 1

2.11 Activity 2

2.12 Efficiency Tips

2.13 Troubleshooting

Here are some additional things we didn't have time to discuss:

2.13.1 I entered a command and nothing's happening

It may be because you didn't complete a command: is there a little `+` in your console? R is saying that it is waiting for you to finish. In the example below, I need to close that parenthesis.

```
> x <- seq(1, 10
+
```

Chapter 3

RMarkdown

TODO: move count and uncount to the pivot table summary statistics chapter

3.1 Summary (a few sentences)

Here we'll learn RMarkdown, which helps you tell a story with your data analysis because you can write text alongside the code.

3.2 Objectives (more detailed, bulletpoints?)

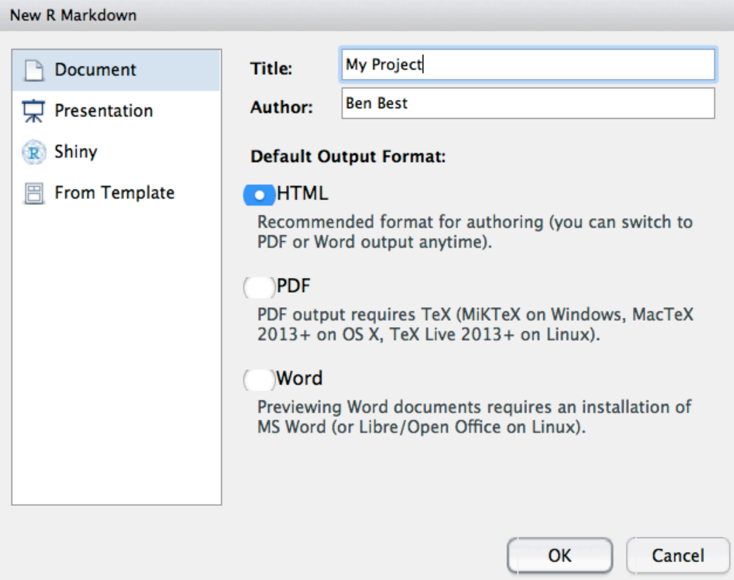
3.3 Resources

3.4 Intro to RMarkdown

TODO (write out): Intro, knitting How it's different from R Script (which we just created) How in-line figures are awesome (no copy-pasting from excel to word) Reproducibility is important (this might be new to some people). Reproducible research/self-contained Rmd files: read in data at the top. Read_csv.

An RMarkdown file will allow us to weave markdown text with chunks of R code to be evaluated and output content like tables and plots.

File -> New File -> RMarkdown… -> Document of output format HTML, OK.



New R Markdown

Title: My Project

Author: Ben Best

Default Output Format:

● HTML
Recommended format for authoring (you can switch to PDF or Word output anytime).

○ PDF
PDF output requires TeX (MiKTeX on Windows, MacTeX 2013+ on OS X, TeX Live 2013+ on Linux).

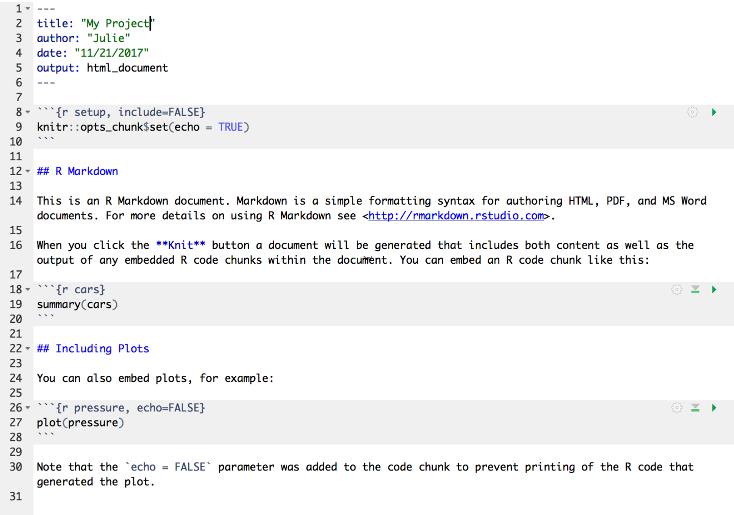
○ Word
Previewing Word documents requires an installation of MS Word (or Libre/Open Office on Linux).

You can give it a Title like “My Analysis”. Then click OK.

OK, first off: by opening a file, we are seeing the 4th pane of the RStudio console, which is essentially a text editor. This lets us organize our files within RStudio instead of having a bunch of different windows open.

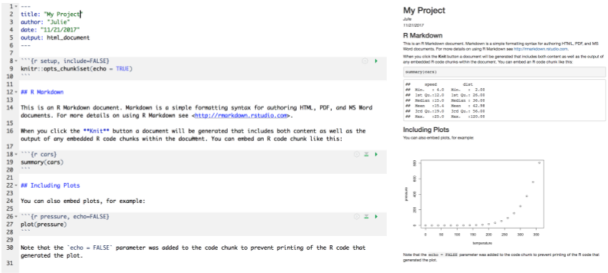
Let’s have a look at this file — it’s not blank; there is some initial text is already provided for you. Notice a few things about it:

- There are white and grey sections. R code is in grey sections, and other text is in white.



~~~
---
title: "My Project"
author: "Julie"
date: "11/21/2017"
output: html_document
---

```{r setup, include=FALSE}
knitr::opts_chunk$set(echo = TRUE)
```

## R Markdown

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word
documents. For more details on using R Markdown see <http://rmarkdown.rstudio.com>.

When you click the **Knit** button a document will be generated that includes both content as well as the
output of any embedded R code chunks within the document. You can embed an R code chunk like this:

```{r cars}
summary(cars)
```

## Including Plots

You can also embed plots, for example:

```{r pressure, echo=FALSE}
plot(pressure)
```

Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that
generated the plot.

~~~

Let's go ahead and "Knit HTML" by clicking the blue yarn at the top of the RMarkdown file.



```
1  ---
2  title: "My Project"
3  author: "Julie"
4  date: "11/21/2017"
5  output: html_document
6  ---
7
8  ```{r setup, include=FALSE}
9  knitr::opts_chunk$set(echo = TRUE)
10 ```
11
12 ## R Markdown
13
14 This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word
   documents. For more details on using R Markdown see <http://rmarkdown.rstudio.com>.
15
16 When you click the **Knit** button a document will be generated that includes both content as well as the
   output of any embedded R code chunks within the document. You can embed an R code chunk like this:
17
18 ```{r cars}
19 summary(cars)
20 ```
21
22 ## Including Plots
23
24 You can also embed plots, for example:
25
26 ```{r pressure, echo=FALSE}
27 plot(pressure)
28 ```
29
30 Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that
   generated the plot.
31
```

My Project

Julie

11/21/2017

R Markdown

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see http://rmarkdown.rstudio.com.

When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

```
summary(cars)
```

```
##      speed           dist       
##  Min.   : 4.0   Min.   :  2.00  
##  1st Qu.:12.0   1st Qu.: 26.00  
##  Median :15.0   Median : 36.00  
##  Mean   :15.4   Mean   : 42.98  
##  3rd Qu.:19.0   3rd Qu.: 56.00  
##  Max.   :25.0   Max.   :120.00  
```

Including Plots

You can also embed plots, for example:

Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.

What do you notice between the two? So much of learning to code is looking for patterns.

Notice how the grey **R code chunks** are surrounded by 3 backticks and `{r LABEL}`. These are evaluated and return the output text in the case of `summary(cars)` and the output plot in the case of `plot(pressure)`.

Notice how the code `plot(pressure)` is not shown in the HTML output because of the R code chunk option `echo=FALSE`.

The hashtag (#) at lines 12 and 22 cause the following text to be displayed larger and in bold.

This RMarkdown file has 2 different languages within it: **R** and **Markdown**.

We don't know that much R yet, but you can see that we are taking a summary of some data called 'cars', and then plotting. We will focus on R for the rest of the workshop, but for the rest of this morning let's focus on the second language.

The second language is Markdown. This is a formatting language for plain text, and there are only about 15 rules to know.

Notice the syntax for:

- **headers** get rendered at multiple levels: `#`, `##`
- **bold**: `**word**`

There are some good cheatsheets to get you started, and here is one built into RStudio: Go to Help > Markdown Quick Reference

Important: note that the hashtag `#` is used differently in Markdown and in R:

- in R, a hashtag indicates a comment that will not be evaluated. You can use as many as you want: `#` is equivalent to `######`. It's a matter of style. I use two `##` to indicate a comment so that it's clearer what is a comment versus what I don't want to run at the moment.
- in Markdown, a hashtag indicates a level of a header. And the number you use matters: `#` is a "level one header", meaning the biggest font and

the top of the hierarchy. ### is a level three header, and will show up nested below the # and ## headers.

If this seems confusing, take comfort in the fact that you are already used to using #s differently in real life: it can mean "number" or "pound" or hashtags on social media.

Learn more: http://rmarkdown.rstudio.com/

3.4.1 Activity

1. In Markdown write some italic text, make a numbered list, and add a few subheaders. Use the Markdown Quick Reference (in the menu bar: Help > Markdown Quick Reference).
2. Reknit your html file.

3.4.2 Code chunks

OK. Now let's practice with some of those commands that we were working on this morning.

Create a new chunk in your RMarkdown first in one of these ways:

- click "Insert > R" at the top of the editor pane
- type by hand "'{r} "'
- if you haven't deleted a chunk that came with the new file, edit that one

Now, let's write some R code.

```
x <- seq(1:15)
```

Now, hitting return does not execute this command; remember, it's a text file in the text editor, it's not associated with the R engine. To execute it, we need to get what we typed in the the R chunk (the grey R code) down into the console. How do we do it? There are several ways (let's do each of them):

1. copy-paste this line into the console.
2. select the line (or simply put the cursor there), and click 'Run'. This is available from
   a. the bar above the file (green arrow)
   b. the menu bar: Code > Run Selected Line(s)
   c. keyboard shortcut: command-return
3. click the green arrow at the right of the code chunk

3.4.3 Activity

> Add a few more commands to your file from this morning. Execute them by trying the three ways above. Then, knit your R Markdown file, which will also save the Rmd by default.

3.5 Create a Rmd for our fish analysis

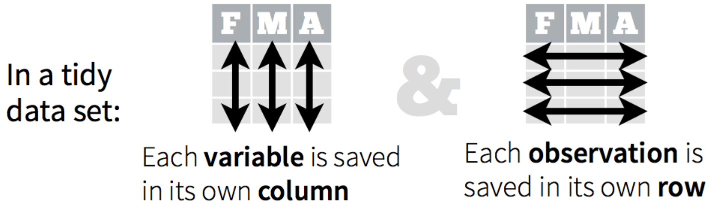
OK now let's open a new RMarkdown file and begin some analyses.

- read in
- View()

fish_counts are what we call Tidy Data.

3.6 Tidy data

Tidy data has a simple convention: put variables in the columns and observations in the rows.


In a tidy data set:
F M A
Each **variable** is saved in its own **column**
&
F M A
Each **observation** is saved in its own **row**

Uncount this data so that we can use it with pivot tables

TODO: Explore data: summaries/data table Uncount and count Why would you ever want to uncount? You don't want to assume how future you will want to use this data How easy is it to get these counts by different groupings Simplest ggplot (introduced in readxl chapter)

3.7 Activity

1. knit!

3.8 Fun facts (quirky things) - making a note of these wherever possible for interest (little "Did you know?" sections)

3.9 Interludes (deep thoughts/openscapes)

3.10 Interludes (deep thoughts/openscapes)

Comments! Organization (spacing, subsections, vertical structure, indentation, etc.)! Well-named variables! Also, well-named operations so analyses (select(data, columnname)) instead of data[1:6,5] and excel equivalent. (Ex with strings) Not so brittle/sensitive to minor changes.

3.10.1 RMarkdown video (1-minute)

Let's watch this to demonstrate all the amazing things you can now do:

What is RMarkdown?

3.11 Efficiency Tips

Chapter 4

GitHub

Setup GitHub GitHub Scrap plans for publishing and issues: setup version control and practice like OHI data-science-training. Practice committing the README and .gitignore Copy our rproj into this repo and push

4.1 Summary (a few sentences)

4.2 Objectives

-

4.3 Resources

4.4 Lessons

4.4.1 Reading

4.5 Fun facts (quirky things) - making a note of these wherever possible for interest (little “Did you know?” sections)

4.6 Interludes (deep thoughts/openscapes)

4.7 Our Turn Your Turn 1

4.8 Our Turn Your Turn 2

4.9 Efficiency Tips

Chapter 5

`readxl`

5.1 Summary

Check this, may need to be a block quote: The **readxl** package makes it easy to import tabular data from Excel spreadsheets (.xls or .xlsx files) and includes several options for cleaning data during import. **readxl** has no external dependencies and functions on any operating system, making it an OS- and user-friendly package that simplifies getting your data from Excel into R.

5.2 Objectives

- Use `readr::read_csv()` to read in a comma separated value (CSV) file
- Use `readxl::read_excel()` to read in an Excel worksheet from a workbook
- Replace a specific string/value in a spreadsheet with with `NA`
- Skip *n* rows when importing an Excel worksheet
- Use `readxl::read_excel()` to read in parts of a worksheet (by cell range)
- Specify column names when importing Excel data
- Read and combine data from multiple Excel worksheets into a single df using `purrr::map_df()`
- Write data using `readr::write_csv()` or `writexl::write_excel()`
- Workflows with `readxl`: considerations, limitations, reproducibility

5.3 Resources

- https://readxl.tidyverse.org/

- readxl Workflows article (from tidyverse.org)

5.4 Lesson

5.4.1 Lesson prep: get data files into your working directory

In Session 1, we introduced how and why R Projects are great for reproducibility, because our self-contained working directory will be the **first** place R looks for files.

You downloaded four files for this workshop:

- fish_counts_curated.csv
- invert_counts_curated.xlsx
- kelp_counts_curated.xlsx
- substrate_cover_curated.xlsx

Copy and paste those files into the ‘r-and-excel’ folder on your computer. Notice that now these files are in your working directory when you go back to that Project in RStudio (check the ‘Files’ tab). That means they’re going to be in the first place R will look when you ask it to find a file to read in.

5.4.2 Create a new .R script, attach the `tidyverse`, `readxl` and `writexl` packages

In your RforExcelUsers project in RStudio, open a new .R script and add a useful header to the top of it. For example, at a minimum:

```
# --------------------------------
# A descriptive title
# Summary of what this script is for
# Your name
# Contact information
# --------------------------------

# Other things you might include: required packages or datasets, relevant links (e.g.
```

In this lesson, we’ll read in a CSV file with the `readr::read_csv()` function, so we need to have the `readr` package attached. Since it’s part of the `tidyverse`, we’ll go ahead and attach the `tidyverse` package below our script header using `library(package_name)`. It’s a good idea to attach all necessary packages near the top of a script, so we’ll also attach the `readxl` packages here.

```
# Attach the tidyverse, readxl and writexl packages:
library(tidyverse)
library(readxl)
library(writexl)
```

Now, all of the packages and functions within the `tidyverse` and `readxl`, including `readr::read_csv()` and `readxl::read_excel()`, are available for use.

5.4.3 Use `readr::read_csv()` to read in data from a CSV file

There are many types of files containing data that you might want to work with in R. A common one is a comma separated value (CSV) file, which contains values with each column entry separated by a comma delimiter. CSVs can be opened, viewed, and worked with in Excel just like an .xls or .xlsx file - but let's learn how to get data directly from a CSV into R where we can work with it more reproducibly.

The CSV we'll read in here is called "fish_counts_curated.csv", and contains observations for "the abundance and size of fish species as part of SBCLTER's kelp forest monitoring program to track long-term patterns in species abundance and diversity" from the Santa Barbara Channel Long Term Ecological Research program.

Source: Reed D. 2018. SBC LTER: Reef: Kelp Forest Community Dynamics: Fish abundance. Environmental Data Initiative. https://doi.org/10.6073/pasta/dbd1d5f0b225d903371ce89b09ee7379. Dataset accessed 9/26/2019.

Read in the "fish_counts_curated.csv" file `read_csv("file_name.csv")`, and store it in R as an object called *fish_counts*:

```
fish_counts <- read_csv("fish_counts_curated.csv")
```

Notice that the name of the stored object (here, *fish_counts*) will show up in our Environment tab in RStudio.

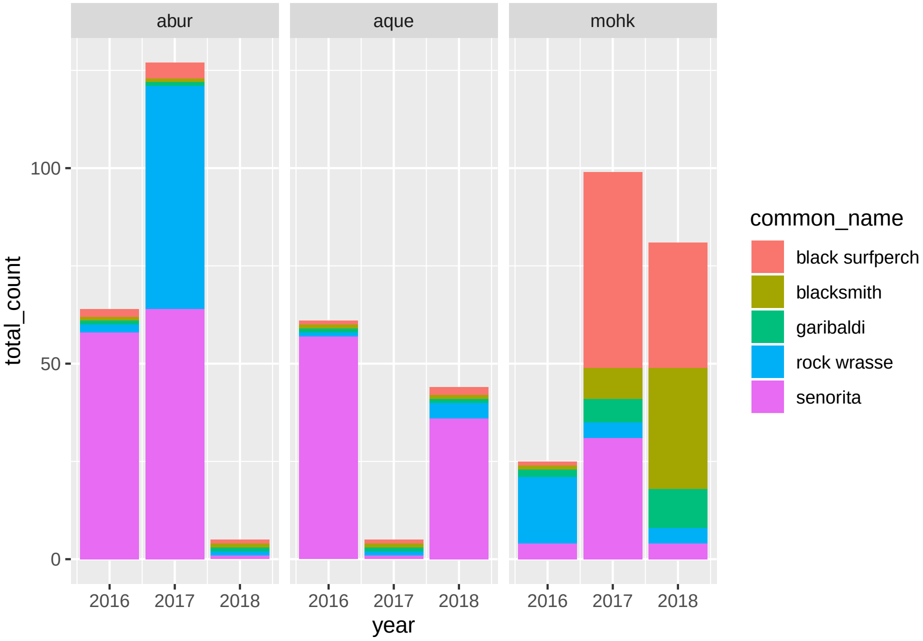
Click on the object in the Environment, and R will automatically run the `View()` function for you to pull up your data in a separate viewing tab. Now we can look at it in the spreadsheet format we're used to.

Here are a few other functions for quickly exploring imported data:

- `summary()`: summary of class, dimensions, `NA` values, etc.
- `names()`: variable names (column headers)
- `ls()`: list all objects in environment
- `head()`: Show the first x rows (default is 6 lines)
- `tail()`: Show the last x rows (default is 6 lines)

Now let's make a simple plot of some fish counts with `ggplot2`.

```
ggplot(fish_counts, aes(x = year, y = total_count)) +
  geom_col(aes(fill = common_name)) +
  facet_wrap(~site)
```



Now that we have our fish counts data ready to work with in R, let's get the substrate cover and kelp data (both .xlsx files). In the following sections, we'll learn that we can use `readxl::read_excel()` to read in Excel files directly.

5.4.4 Use `readxl::read_excel()` to read in a single Excel worksheet

First, take a look at *substrate_cover_curated.xlsx* in Excel, which contains a single worksheet with substrate type and percent cover observations at different sampling locations in the Santa Barbara Channel.

A few things to notice:

- The file contains a single worksheet
- There are multiple rows containing text information up top
- Where observations were not recorded, there exists '-9999'

Let's go ahead and read in the data. If the file is in our working directory, we can read in a single worksheet .xlsx file using `readxl::read_excel("file_name.xlsx")`. *Note: readxl::read_excel() works for both .xlsx and .xls types.*

Like this:

```
substrate_cover <- read_excel("substrate_cover_curated.xlsx")
```

Tada? Not quite.

Click on the object name (*substrate_cover*) in the Environment to view the data in a new tab. A few things aren't ideal:

```
substrate_cover
```

```
## # A tibble: 23,942 x 9
##    `Substrate cover data~ ...2  ...3   ...4  ...5   ...6  ...7  ...8  ...9 
##    <chr>                  <chr> <chr>  <chr> <chr>  <chr> <chr> <chr> <chr>
##  1 Source: https://porta~ <NA>  <NA>   <NA>  <NA>   <NA>  <NA>  <NA>  <NA> 
##  2 Accessed: 9/28/2019    <NA>  <NA>   <NA>  <NA>   <NA>  <NA>  <NA>  <NA> 
##  3 <NA>                   <NA>  <NA>   <NA>  <NA>   <NA>  <NA>  <NA>  <NA> 
##  4 year                   month date   site  trans~ quad  side  subs~ perc~
##  5 -9999                  -9999 -9999  carp  1      20    i     b     -9999
##  6 2000                   9     -9999  carp  1      20    o     b     -9999
##  7 2000                   9     9/8/00 carp  1      20    i     b     100  
##  8 2000                   9     9/8/00 carp  1      20    o     b     100  
##  9 2000                   9     9/8/00 carp  1      40    i     b     100  
## 10 2000                   9     9/8/00 carp  1      40    o     b     100  
## # ... with 23,932 more rows
```

- The top row of text has automatically become the (messy) column headers
- There are multiple descriptive rows before we actually get to the data
- There are -9999s that we want R to understand NA instead

We can deal with those issues by adding arguments within `read_excel()`. Include argument `skip = n` to skip the first 'n' rows when importing data, and `na = "this"` to replace "this" with NA when importing:

```
substrate_cover <- read_excel("curation/substrate_cover_curated.xlsx, skip = 4, na = "-9999")
```

```
substrate_cover
```

```
## # A tibble: 23,938 x 9
##    year  month date  site  transect quad  side  substrate_type
##    <chr> <chr> <chr> <chr> <chr>    <chr> <chr> <chr>         
##  1 <NA>  <NA>  <NA>  carp  1        20    i     b             
##  2 2000  9     <NA>  carp  1        20    o     b             
##  3 2000  9     9/8/~ carp  1        20    i     b             
##  4 2000  9     9/8/~ carp  1        20    o     b             
##  5 2000  9     9/8/~ carp  1        40    i     b             
##  6 2000  9     9/8/~ carp  1        40    o     b             
##  7 2000  9     9/8/~ carp  2        20    i     b             
##  8 2000  9     9/8/~ carp  2        20    o     b             
##  9 2000  9     9/8/~ carp  2        40    i     b             
## 10 2000  9     9/8/~ carp  2        40    o     b             
## # ... with 23,928 more rows, and 1 more variable: percent_cover <chr>
```

Check out *substrate_cover*, and see that the first row *after* the 4 skipped are the column names, and all -9999s have been updated to `NA`. Hooray!

5.4.5 Use `readxl::read_excel()` to read in only *part* of an Excel worksheet

We always advocate for leaving the raw data raw, and writing a complete script containing all steps of data wrangling & transformation. But in *some* situations (be careful), you may want to specify a range of cells to read in from an Excel worksheet.

You can specify a range of cells to read in using the `range =` argument in `read_excel()`. For example, if I want to read in the rectangle from D12:I15 in *substrate_cover_curated.xlsx* - only observations for Carpenteria Beach (Transect 2) in September 2000 - I can use:

```
carp_cover_2000 <- readxl::read_excel("substrate_cover_curated.xlsx", range = "D12:I15
```

But yuck. Look at *carp_cover_2000* and you'll notice that the first row *of that range* is automatically made the column headers. To keep all rows within a range and **add your own column names**, add a `col_names =` argument:

```
carp_cover_2000 <- readxl::read_excel("substrate_cover_curated.xlsx", range = "D12:I15
```

```
carp_cover_2000
```

```
## # A tibble: 4 x 6
##   site_name transect quad  plot_side type  coverage
##   <chr>     <chr>    <chr> <chr>     <chr> <chr>
## 1 carp      2        20    i         b     90
## 2 carp      2        20    o         b     80
## 3 carp      2        40    i         b     80
## 4 carp      2        40    o         b     85
```

So far we've read in a single CSV file using `readr::read_csv()`, and an Excel file containing a single worksheet with `readxl::read_excel()`. Now let's read in data from an Excel workbook with multiple worksheets.

5.4.6 Use `readxl::read_excel()` to read in selected worksheets from a workbook

Now, we'll read in the kelp fronds data from file *kelp_counts_curated.xlsx*. If you open the Excel workbook, you'll see that it contains multiple worksheets with giant kelp observations in the Santa Barbara Channel during July 2016, 2017, and 2018, with data collected at each *site* in a separate worksheet.

To read in a single Excel worksheet from a workbook we'll again use `readxl::read_excel("file_name.xlsx")`, but we'll need to let R know which worksheet to get.

Let's read in the kelp data just like we did above, as an object called *kelp_counts*.

```
kelp_counts <- readxl::read_excel("kelp_counts_curated.xlsx")
```

You might be thinking, "Hooray, I got all of my Excel workbook data!" But remember to always look at your data - you will see that actually only the first worksheet was read in. The default in `readxl::read_excel()` is to read in the **first worksheet** in a multi-sheet Excel workbook.

To check the worksheet names in an Excel workbook, use `readxl::excel_sheets()`:

```
readxl::excel_sheets("kelp_counts_curated.xlsx")
```

If we want to read in data from a worksheet other than the first one in an Excel workbook, we can specify the correct worksheet by name or position by adding the `sheet` argument.

Let's read in data from the worksheet named *golb* (Goleta Beach) in the *kelp_counts_curated.xlsx* workbook:

```
kelp_golb <- readxl::read_excel("kelp_counts_curated.xlsx", sheet = "golb")
```

Note that you can also specify a worksheet by position: since *golb* is the 6th worksheet in the workbook, we could also use the following:

```
kelp_golb <- readxl::read_excel("kelp_counts_curated.xlsx", sheet = 6)
```

```
kelp_golb
```

```
## # A tibble: 3 x 4
##   year  month site  total_fronds
##   <chr> <chr> <chr>        <dbl>
## 1 2016  7     golb          2557
## 2 2017  7     golb          1575
## 3 2018  7     golb          1629
```

5.4.7 Read in and combine data from multiple worksheets into a data frame simultaneously with `purrr::map_df()`

So far, we've read in entire Excel worksheets and pieces of a worksheet. What if we have a workbook (like *kelp_counts_curated.xlsx*) that contains worksheets that contain observations for the same variables, in the same organization? Then we may want to read in data from *all* worksheets, and combine them into a single data frame.

We'll use `purrr::map_df()` to loop through all the worksheets in a workbook, reading them in & putting them together into a single df in the process.

The steps we'll go through in the code below are:

- Set a pathway so that R knows where to look for an Excel workbook
- Get the names of all worksheets in that workbook with `excel_sheets()`
- Set names of a vector with `set_names()`
- Read in all worksheets, and put them together into a single data frame with `purrr::map_df()`

QUESTION: Have they learned the pipe operator at this point?

Expect the question: Why do I need to use read_excel() instead of just giving it the file path (as below)?

```
kelp_path <- "kelp_counts_curated.xlsx"

kelp_all_sites <- kelp_path %>%
  excel_sheets() %>%
  set_names() %>%
  purrr::map_df(read_excel, kelp_path)
```

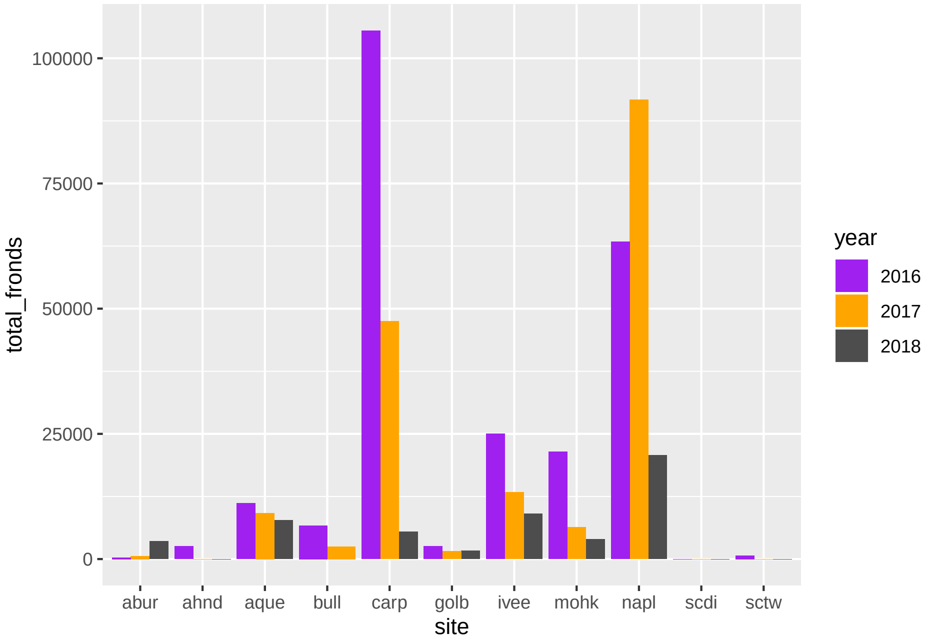
Check out *kelp_all_sites*, and notice that now the data from all 11 sites is now collected into a single data frame:

```
kelp_all_sites
```

```
## # A tibble: 32 x 4
##    year  month site  total_fronds
##    <chr> <chr> <chr>        <dbl>
##  1 2016  7     abur           307
##  2 2017  7     abur           604
##  3 2018  7     abur          3532
##  4 2016  7     ahnd          2572
##  5 2017  7     ahnd            16
##  6 2018  7     ahnd            16
##  7 2016  7     aque         11152
##  8 2017  7     aque          9194
##  9 2018  7     aque          7754
## 10 2016  7     bull          6706
## # ... with 22 more rows
```

Awesome! Let's make a graph with ggplot2:

```
ggplot(kelp_all_sites, aes(x = site, y = total_fronds)) +
  geom_col(aes(fill = year), position = "dodge") +
  scale_fill_manual(values = c("purple","orange","gray30"))
```



5.4.8 Save data frames as .csv or .xlsx with `readr::write_csv()` or `writexl::write_xlsx()`

There are a number of reasons you might want to save (/export) data in a data frame as a .csv or Excel worksheet, including:

- To cache raw data within your project
- To store copies of intermediate data frames
- To convert your data back to a format that your coworkers/clients/colleagues will be able to use it more easily

Use `readr::write_csv(object, "file_name.csv")` to write a data frame to a CSV, or `writexl::write_xlsx(object, "file_name.xlsx")` to similarly export as a .xlsx (or .xls) worksheet.

In the previous step, we combined all of our kelp frond observations into a single data frame. Wouldn't it make sense to store a copy?

As a CSV:

```
readr::write_csv(kelp_all_sites, "kelp_all_sites.csv")
```

A cool thing about `readr::read_csv()` is that it just quietly *works* without wrecking anything else you do in a sequence, so it's great to add at the end of a piped sequence.

For example, if I want to read in the 'ivee' worksheet from kelp_counts_curated.xlsx, select only columns 'year' and 'total_fronds', then write that new subset to a .csv file, I can pipe all the way through:

```
kelp_ivee <- readxl::read_excel("kelp_counts_curated.xlsx", sheet = "ivee") %>%
  select(year, total_fronds) %>%
  write_csv("kelp_ivee.csv")
```

Now I've created *kelp_ivee.csv*, but the object *kelp_ivee* also exists for me to use in R.

If needed, I can also export a data frame as an Excel (.xlsx) worksheet:

```
writexl::write_xlsx(kelp_all_sites, "kelp_all_sites.xlsx")
```

5.5 Fun facts ideas:

- Did you know that Clippy shows up to help you in the documentation for ?writexl::write_xlsx()?
- The name of the `purrr` package? Why map?

5.6 Interludes (deep thoughts/openscapes)

- Workflow/reproducibility/readxl workflows article
- Respecting the tools people are working with already (e.g. don't make your Excel using co-workers hate you)

5.7 Activity: Import some invertebrates!

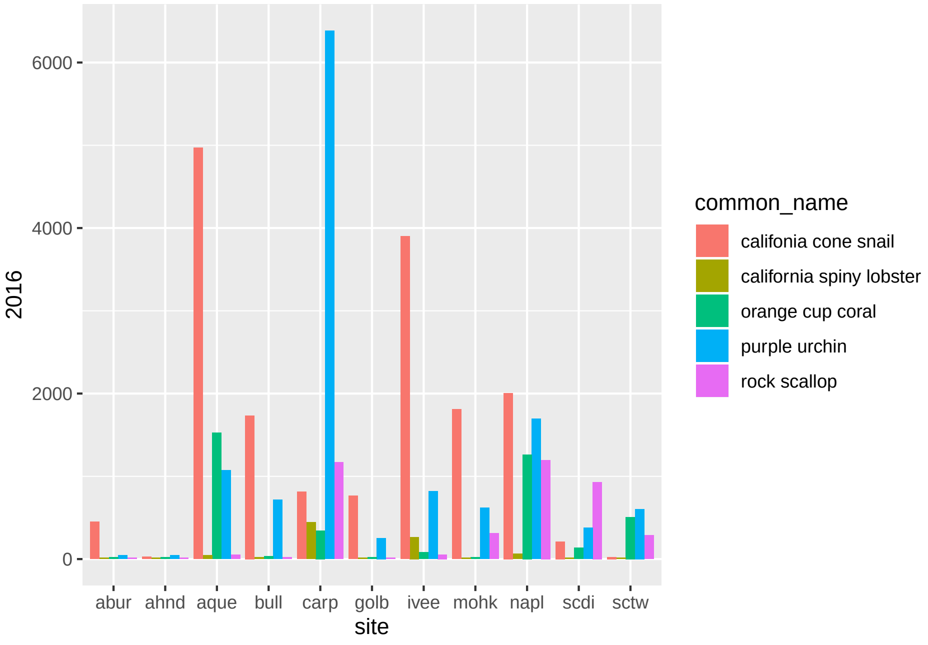
There's one dataset we haven't imported or explored yet: invertebrate counts for 5 popular invertebrates (California cone snail, California spiny lobster, orange cup coral, purple urchin and rock scallops) at 11 sites in the Santa Barbara Channel. Take a look at the *invert_counts_curated.xlsx* data by opening it in Excel

- Read in the *invert_counts_curated.xlsx* worksheet as object 'inverts_july', only retaining **site**, **common_name**, and **2016** and setting the existing first row in the worksheet as to column headers upon import
- Explore the imported data frame using View, names, head, tail, etc.
- Write 'inverts_july' to a CSV file in your working directory called "inverts_july.csv"
- Create a basic graph of invert counts in 2016 (y-axis) by site (x-axis), with each species indicated by a different fill color

  - **Note:** If your column name is a number (not great) you'll probably want to rename it…but in the meantime, to call it as a variable make sure you put single or double quotes around it (e.g. `'2016'` or `"2016"`) so that R recognizes it's a variable and not a value

```
# Importing only 'site' through '2016' columns:
inverts_july <- readxl::read_excel("curation/invert_counts_curated.xlsx", range = "B1:D56")

# Do some basic exploring (why might we want to do this in the Console instead?):
#View(inverts_july)
names(inverts_july)
head(inverts_july)
tail(inverts_july)
ls()

# Make a gg-graph plot:
inverts_graph <- ggplot(inverts_july, aes(x = site, y = `2016`)) +
  geom_col(aes(fill = common_name),
           position = "dodge")
```

```
inverts_graph
```



5.8 Efficiency Tips

- Add an assignment arrow in script/code chunk (<-): Alt + minus (-)
- Undo shortcut: Command + Z
- Redo shortcut: Command + Shift + Z

5.9 Deep thoughts

- Economist article about gene > dates issue in Excel
- Mine: data frame of bike casualities in NC, column names are age ranges but some of them import as dates
- Excel makes some wrong assumptions and doesn't give you a heads up about its decision making

Chapter 6

ggplot2

Plots are awesome! You've read in data, now we plot!

6.1 Summary (a few sentences)

6.2 Objectives

6.3 Resources

6.4 Lessons

6.4.1 Reading

6.5 Fun facts (quirky things) - making a note of these wherever possible for interest (little "Did you know?" sections)

6.6 Interludes (deep thoughts/openscapes)

6.7 Our Turn Your Turn 1

6.8 Our Turn Your Turn 2

6.9 Efficiency Tips

Chapter 7

`dplyr` and Pivot Tables

TODO: use lobster data Count and uncount, summary statistics Use uncounted lobster data summarize(mean, sd, n) with uncounted fish data (stdev in excel?) DT, kable if time, could we show count vs n but if you want to get other statistics

7.1 Summary (a few sentences)

First of two chapters on data wrangling, here focused on pivot tables.

7.2 Objectives (more detailed, bulletpoints?)

In R, we can use dplyr for pivot tables by using 2 main verbs in combination: `group_by` and `summarize`, and that's where we'll start. Then, we will learn 2 critical verbs that are powerful for data wrangling: `mutate` and `select`.

We will also continue to emphasize reproducibility in all our analyses.

7.3 Resources

- dplyr.tidyverse.org
- R for Data Science: Transform Chapter

7.4 Introduction / our analytical plan

We are going to continue with our analysis with the fish-counts data. So far, our RMarkdown has the following in the "setup" chunk:

```
## attach libraries
library(tidyverse)

## read in data
fish_counts <- read_csv("fish_counts_curated.csv")
```

And we have explored the data by looking at some summary statistics and making a simple plot. Now, we are going to learn how to wrangle data in R, using the `dplyr` package which is included in the `tidyverse`. In this session, we'll focus on the functions in `dplyr` that operate like pivot tables.

This is because what we want to do with our fish_counts data is XXXXX.

7.5 What are pivot tables?

TODO:

- what they are
- what they allow you to do

Let's talk about how this looks like in R.

7.6 `dplyr` overview

`dplyr` is a grammar of data manipulation that provides a consistent set of verbs that help you solve the most common data manipulation challenges. These common verbs are:

- **`filter()`**: pick observations by their values
- **`select()`**: pick variables by their names
- **`mutate()`**: create new variables with functions of existing variables
- **`summarise()`**: collapse many values down to a single summary
- **`arrange()`**: reorder the rows

These can all be used in conjunction with `group_by()` which changes the scope of each function from operating on the entire dataset to operating on it group-by-group. These six functions provide the verbs for a language of data manipulation.

All verbs work similarly:

1. The first argument is a data frame.
2. The subsequent arguments describe what to do with the data frame. You can refer to columns in the data frame directly without using `$`.
3. The result is a new data frame.

Together these properties make it easy to chain together multiple simple steps to achieve a complex result using the pipe operator `%>%`.

I love thinking of these `dplyr` verbs and the pipe operator `%>%` as telling a story. When I see `%>%` I think "and then":

```
data %>%          # start with data, and then
  group_by() %>%  # group by a variable, and then
  mutate() %>%    # mutate to add a new column, and then
  select()        # select specific columns
```

7.7 pivot tables: `group_by() %>% summarize()`

In R, we can create the functionality of pivot tables by using 2 main `dplyr` verbs in combination: `group_by` and `summarize`.

Say it with me: "pivot tables are group_by and then summarize". And just like pivot tables, you have flexibility with how you are going to summarize. For example, we can calculate an average, or a total.

Let's try this on our `fish_counts` data. Let's summarize this data by calculating the the total number of fish by type, which in our dataframe is called `common_name`. We'll use the pipe operator `%>%`

```
fish_counts %>%
  group_by(common_name) %>%
  summarize(total_fish = sum(total_count)) # within summarize, we name a new column and calculate
```

```
## # A tibble: 5 x 2
##   common_name     total_fish
##   <chr>                <dbl>
## 1 black surfperch         94
## 2 blacksmith              46
## 3 garibaldi               24
## 4 rock wrasse             91
## 5 senorita               256
```

This returns output summarizing the total_fish for each fish. There are way more senorita fish than any other kind!

Notice how together, group_by and summarize collapse the amount of information we see. We lose the other columns that aren't involved here; we no longer have `year`, `common_name`, or `total_count`. This is also what you would expect from a pivot table.

Question: What if you *don't* group_by first? Let's try it and discuss what's going on.

```
fish_counts %>%
  summarize(total_fish = sum(total_count))
```

```
## # A tibble: 1 x 1
##   total_fish
##        <dbl>
## 1        511
```

So if we don't `group_by` first, we will get a single summary statistic (total in this case) for the whole dataset. Useful in some cases for sure. But being able to do it so easily by group can be very powerful.

Let's now check the `fish_counts` variable.

```
View(fish_counts)
```

We see that we haven't changed any of our original data that was stored in this variable. But maybe we do want to save this summary as a variable so we can refer to it or even include it in further analyses. So let's add a variable assignment to that first line:

```
common_name_summary <- fish_counts %>%
  group_by(common_name) %>%
  summarize(total_fish = sum(total_count))
```

Now let's summarize by site. We will assign it to a variable called `site_summary`. How do we do that? Let's do it together:

```
site_summary <- fish_counts %>%
  group_by(site) %>%
  summarize(total_fish = sum(total_count))
```

Great. It can be useful to summarize by both site and year, so that we can learn a little more about how things change over time across sites. And, awesomely, we are able to `group_by` more than one variable. Let's do this together, and assign this to a new variable called `site_year_summary`:

```
site_year_summary <- fish_counts %>%
  group_by(site, year) %>%
  summarize(total_fish = sum(total_count))

site_year_summary
```

```
## # A tibble: 9 x 3
## # Groups:   site [3]
##   site   year total_fish
##   <chr> <dbl>      <dbl>
## 1 abur   2016         64
## 2 abur   2017        127
## 3 abur   2018          5
## 4 aque   2016         61
## 5 aque   2017          5
## 6 aque   2018         44
## 7 mohk   2016         25
## 8 mohk   2017         99
## 9 mohk   2018         81
```

OK, so this is awesome. We can see the total counts for each site by year, and have this saved here in a nice variable.

We will revisit this in a moment, but now let's move on to our next `dplyr` verb.

7.8 mutate()

We use the `mutate()` function to add columns to a data frame. This is one of the most common things that I do in Excel: you need to name the new column, and then you can fill it with new values. From the help pages, we learn that unlike `summarize()`, `mutate()` preserves the number of rows of the input. Additionally, new variables overwrite existing variables of the same name.

Let's say we need to add a column that indicates that these observations were made by SCUBA diving. To do this, first we tell R we want to add a new column using the `mutate()` function. Then, we tell it the name of the column we want, let's call it `observation_type`. Then, we tell it the value we want in the cells: let's say `"SCUBA"`. We need to put SCUBA in quotes:

```
fish_counts %>%
  mutate(observation_type = "SCUBA")
```

```
## # A tibble: 45 x 5
##     year site  common_name     total_count observation_type
##    <dbl> <chr> <chr>                 <dbl> <chr>
##  1  2016 abur  black surfperch           2 SCUBA
##  2  2016 abur  blacksmith                1 SCUBA
##  3  2016 abur  garibaldi                 1 SCUBA
##  4  2016 abur  rock wrasse               2 SCUBA
##  5  2016 abur  senorita                 58 SCUBA
##  6  2016 aque  black surfperch           1 SCUBA
##  7  2016 aque  blacksmith                1 SCUBA
##  8  2016 aque  garibaldi                 1 SCUBA
##  9  2016 aque  rock wrasse               1 SCUBA
## 10  2016 aque  senorita                   57 SCUBA
## # ... with 35 more rows
```

Notice that when you just give one value like “SCUBA”, mutate will repeat this value for you; it’s the equivalent in Excel to when you grab the bottom right corner of a cell and drag down.

Let’s try a calculation. Let’s calculate the total count for the whole data site as we did above. We add a new column named `total_fish`:

```
fish_counts %>%
  mutate(total_fish = sum(total_count))
```

```
## # A tibble: 45 x 5
##     year site  common_name     total_count total_fish
##    <dbl> <chr> <chr>                 <dbl>      <dbl>
##  1  2016 abur  black surfperch           2        511
##  2  2016 abur  blacksmith                1        511
##  3  2016 abur  garibaldi                 1        511
##  4  2016 abur  rock wrasse               2        511
##  5  2016 abur  senorita                 58        511
##  6  2016 aque  black surfperch           1        511
##  7  2016 aque  blacksmith                1        511
##  8  2016 aque  garibaldi                 1        511
##  9  2016 aque  rock wrasse               1        511
## 10  2016 aque  senorita                 57        511
## # ... with 35 more rows
```

And notice that this was the same calculated value as when we did this with summarize, but here it is repeated for every row instead of being collapsed.

7.8.1 Activity

Take 3 minutes to add a new column to the data frame; discuss with your neighbor for ideas!

7.8.2 `group_by() %>% mutate()`

So there are many things you could add to a new column; but let’s focus on how powerful mutate can be in combination with `group_by`. So just like we were just doing `group_by() %>% summarize()`, we can do `group_by() %>% mutate()`.

Let’s add a new column named `siteyear_counts`, and we will calculated after grouping by site and year. Let’s have a look at it first, and then we will assign it as a variable in a moment.

```
fish_counts %>%
  group_by(site, year) %>%
  mutate(siteyear_counts = sum(total_count))
```

```
## # A tibble: 45 x 5
## # Groups:   site, year [9]
##     year site  common_name     total_count siteyear_counts
##    <dbl> <chr> <chr>                 <dbl>           <dbl>
##  1  2016 abur  black surfperch           2              64
##  2  2016 abur  blacksmith                1              64
##  3  2016 abur  garibaldi                 1              64
##  4  2016 abur  rock wrasse               2              64
##  5  2016 abur  senorita                 58              64
##  6  2016 aque  black surfperch           1              61
##  7  2016 aque  blacksmith                1              61
##  8  2016 aque  garibaldi                 1              61
##  9  2016 aque  rock wrasse               1              61
## 10  2016 aque  senorita                 57              61
## # ... with 35 more rows
```

We now have an additional column in our dataframe called `siteyear_counts`. And again, if we recall from our `site_year_summary` above, it has calculated the same information. But instead of collapsing our dataframe, we retain all of the information from the other columns, and the `siteyear_counts` column will have values that are repeated.

7.9 mutate() vs summarize()

Why would you use `mutate` instead of `summarize`? Why would you ever want to have that `siteyear_counts` column with values repeated like we just did? Why wouldn't you always do `group_by() %>% summarize()` rather than `group_by() %>% mutate()`? The truth is, there is no one way to do anything in R, but there are ways to make your analyses have fewer steps or read more nicely. Let's explore this by doing a bit of analysis.

Let's say we want to calculate the percentage of fish type at each site. This means we are going to do a calculation using both the raw and summary data. And we're going to do it in 2 ways, first using `group_by() %>% summarize()` and then `group_by() %>% mutate()`.

Let's start off doing this as a `group_by() %>% mutate()`.

```
fish_percs <- fish_counts %>%
  group_by(site, year) %>%
  mutate(siteyear_counts = sum(total_count)) %>%
  mutate(perc_fish = total_count/siteyear_counts*100)
```

When I'm doing analyses, I like `group_by() %>% mutate()` because I can build out the logic step-by-step and actually look at it as it builds. It's both comforting and good for error-checks; I can do what we call "spot checks" of calculating a few values by hand to make sure it's working. This would also be relatively easy for someone else to follow.

(Again here we can see that senorita fish really dominate each site-year combination).

If we wanted to do this with `group_by() %>% summarize()` we would need a few more steps. We can write it up as pseudo-code:

```
## first calculate fish siteyear_counts
x <- fish_counts %>%
  group_by(site, year) %>%
  summarize(siteyear_counts = sum(total_count))

## then somehow join or merge that information to the fish_counts data
x %>%
  mutate(perc_fish = total_count/siteyear_counts*100)
```

In order to calculate the percentages with the appropriate values, we need to somehow join the summarized data back to the fish_counts. This actually requires a few more dplyr verbs: filter and *_join; we will do this tomorrow!

count column (would have to uncount first)

7.10 Deep thoughts

Highly recommended read: Broman & Woo: Data organization in spreadsheets. Practical tips to make spreadsheets less error-prone, easier for computers to process, easier to share

Great opening line: "Spreadsheets, for all of their mundane rectangularness, have been the subject of angst and controversy for decades."

7.11 Efficiency Tips

arrow keys with shift, option, command

Chapter 8

Dplyr and vlookups

8.1 Summary

In previous sessions, we've learned to do some basic wrangling and find summary information with functions in the `dplyr` package, which exists within the `tidyverse`. We've used:

TODO: Check these to make sure what we do in 1 - 4!

- `dplyr::count()` and `dplyr::uncount()` to get counts of observations for groupings we specify (or the reverse!)
- `dplyr::mutate()`: **add** a new column, while keeping the existing ones
- `dplyr::group_by()`: let R know that **groups** exist within the dataset, by variable(s)
- `dplyr::summarize()`: calculate a value (that you specify) for each group, then report each group's value in a table

In Session 5, we'll expand our data wrangling toolkit using:

- `dplyr::filter()` to conditionally subset our data by **rows**, and
- `dplyr::*_join()` functions to merge data frames together

The combination of `dplyr::filter()` and `dplyr::*_join()` - to return rows satisfying a condition we specify, and merging data frames by like variables - is analogous to the useful VLOOKUP function in Excel.

8.2 Objectives

- Continue building R Markdown skills
- Return **rows** that satisfy variable conditions using `dplyr::filter()`

- Use `dplyr::full_join()`, `dplyr::left_join()`, and `dplyr::inner_join()` to merge data frames by matching variables, with different endpoints in mind
- Use `dplyr::anti_join()` to find things that **do not** exist in both data frames
- Understand the similarities between `dplyr::filter()` + `dplyr::*_join()` and Excel's VLOOKUP function

8.3 Resources

- `dplyr::filter()` documentation from tidyverse.org
- `dplyr::join()` documentation from tidyverse.org
- Chapters 5 and 13 in *R for Data Science* by Garrett Grolemund and Hadley Wickham

8.4 Lessons

Session 5 set-up: TODO

- Create a new .Rmd within the r-and-excel directory (project) you created in Session 1
- Add some descriptive text
- Add new code chunks to:
  - Attach packages
  - Read in the necessary data

In this session we'll use the **fish_counts_curated.csv** and **invert_counts_curated.xlsx** files, and the first worksheet from **kelp_counts_curated.xlsx**.

```
# Attach packages:
library(tidyverse)
library(readxl)

# Read in data:
invert_counts <- read_excel("invert_counts_curated.xlsx")
fish_counts <- read_csv("fish_counts_curated.csv")
kelp_counts_abur <- read_excel("kelp_counts_curated.xlsx")
```

Remember to always explore the data you've read in using functions like `View()`, `names()`, `summary()`, `head()` and `tail()` to ensure that the data you *think* you read in is *actually* the data you read in.

Now, let's use `dplyr::filter()` to decide which observations (rows) we'll keep or exclude in new subsets, similar to using Excel's VLOOKUP function.

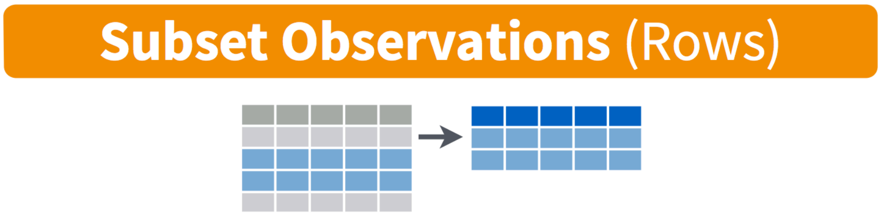


Figure 8.1: dplyr::filter()

8.4.1 `dplyr::filter()` to conditionally subset by rows

Use `dplyr::filter()` to let R know which **rows** you want to keep or exclude, based whether or not their contents match conditions that you set for one or more variables.

Some examples in words that might inspire you to use `dplyr::filter()`:

- "I only want to keep rows where the temperature is greater than 90°F."
- "I want to keep all observations **except** those where the tree type is listed as **unknown**."
- "I want to make a new subset with only data for mountain lions (the species variable) in California (the state variable)."

When we use `dplyr::filter()`, we need to let R know a couple of things:

- What data frame we're filtering from
- What condition(s) we want observations to **match** and/or **not match** in order to keep them in the new subset

Follow along with the examples below to learn some common ways to use `dplyr::filter()`.

8.4.1.1 Filter rows by matching a single character string

Let's say we want to keep all observations from the fish_counts data frame where the common name is "garibaldi." Here, we need to tell R to only *keep rows* from the **fish_counts** data frame when the common name (**common_name** variable) exactly matches **garibaldi**. Use `==` to ask R to look for matching strings:

```
fish_gari <- dplyr::filter(fish_counts, common_name == "garibaldi")
```

Check out the **fish_gari** object to ensure that only *garibaldi* observations remain.

You could also do this using the pipe operator `%>%` (though for a single function, it doesn't save much effort or typing):

```
fish_gari <- fish_counts %>%
  dplyr::filter(common_name == "garibaldi")
```

8.4.1.2 Filter rows based on numeric conditions

Use expected operators (>, <, >=, <=, =) to set conditions for a numeric variable when filtering. For this example, we only want to retain observations when the **total_count** column value is >= 50:

```
fish_over50 <- dplyr::filter(fish_counts, total_count >= 50)
```

Or, using the pipe:

```
fish_over50 <- fish_counts %>%
  dplyr::filter(total_count >= 50)
```

TODO: show example of between and exact =

8.4.1.3 Filter to return rows that match *this* OR *that* OR *that*

What if we want to return a subset of the fish_counts df that contains *garibaldi*, *blacksmith* OR *black surfperch*?

There are several ways to write an "OR" statement for filtering, which will keep any observations that match Condition A *or* Condition B *or* Condition C. In this example, we will create a subset from **fish_counts** that only contains rows where the **common_name** is *garibaldi* or *blacksmith* or *black surfperch*.

Use `%in%` to ask R to look for *any matches* within a combined vector of strings:

```
fish_3sp <- fish_counts %>%
  dplyr::filter(common_name %in% c("garibaldi", "blacksmith", "black surfperch"))
```

Alternatively, you can indicate **OR** using the vertical line operator `|` to do the same thing (but you can see that it's more repetitive when looking for matches within the same variable):

```
fish_3sp <- fish_counts %>%
  dplyr::filter(common_name == "garibaldi" | common_name == "blacksmith" | common_name
```

8.4.1.4 Filter to return rows that match conditions for multiple variables

In the previous examples, we set filter conditions based on a single variable (e.g. common_name). What if we want to return observations that satisfy conditions for multiple variables?

For example: We want to create a subset that only returns rows from 'invert_counts' where the **site** is "abur" or "mohk" *and* the **common_name** is "purple urchin." In `dplyr::filter()`, add a comma (or ampersand, &) between arguments for multiple *AND* conditions:

```r
urchin_abur_mohk <- invert_counts %>%
  dplyr::filter(site %in% c("abur","mohk"), common_name == "purple urchin")
```

```r
head(urchin_abur_mohk)
```

```
## # A tibble: 2 x 6
##   month site  common_name   `2016` `2017` `2018`
##   <chr> <chr> <chr>          <dbl>  <dbl>  <dbl>
## 1 7     abur  purple urchin     48     48     48
## 2 7     mohk  purple urchin    620    505    323
```

Like most things in R, there are other ways to do the same thing. For example, you could do the same thing using `&` (instead of a comma) between "and" conditions:

```r
# Use the ampersand (&) to add another condition "and this must be true":

urchin_abur_mohk <- invert_counts %>%
  dplyr::filter(site %in% c("abur","mohk") & common_name == "purple urchin")
```

Or you could just do two filter steps in sequence:

```r
# Written as multiple filter steps:

urchin_abur_mohk <- invert_counts %>%
  dplyr::filter(site %in% c("abur", "mohk")) %>%
  dplyr::filter(common_name == "purple urchin")
```

8.4.1.5 Filter to return rows that *do not* match conditions

Sometimes we might want to exclude observations. Here, let's say we want to make a subset that contains all rows from **fish_counts** except those recorded at the Mohawk Reef site ("mohk" in the *site* variable).

We use `!=` to return observations that **do not match** a condition.

Like this:

```
fish_no_mohk <- fish_counts %>%
  dplyr::filter(site != "mohk")
```

This similarly works to exclude observations by a value.

For example, if we want to return all observations *except* those where the total fish count is 1, we use:

```
fish_more_one <- fish_counts %>%
  dplyr::filter(total_count != 1)
```

What if we want to exclude observations for multiple conditions? For example, here we want to return all rows where the fish species **is not** garibaldi **or** rock wrasse.

We can use `filter(!variable %in% c("apple", "orange"))` to return rows where the variable does **not** match "apple" or "orange". For our fish example, that looks like this:

```
fish_subset <- fish_counts %>%
  dplyr::filter(!common_name %in% c("garibaldi", "rock wrasse"))
```

Which then only returns observations for the other fish species in the dataset.

```
head(fish_subset)
```

```
## # A tibble: 6 x 4
##    year site  common_name     total_count
##   <dbl> <chr> <chr>                 <dbl>
## 1  2016 abur  black surfperch           2
## 2  2016 abur  blacksmith                1
## 3  2016 abur  senorita                 58
## 4  2016 aque  black surfperch           1
## 5  2016 aque  blacksmith                1
## 6  2016 aque  senorita                 57
```

8.4.1.6 Example: combining `filter()` with other functions using the pipe operator (`%>%`)

We can also use `dplyr::filter()` in combination with the functions we previously learned for wrangling. If we have multiple sequential steps to perform, we can string them together using the *pipe operator* (`%>%`).

Here, we'll start with the `invert_counts` data frame and create a subset that:

TODO: NOPE, can't do this, they don't learn `pivot_longer()` until the next section (tidying)

- Converts to long format with `pivot_longer()`

- Only keeps observations for rock scallops
- Calculates the total count of rock scallops by site only

```
# Counts of scallops by site (all years included):

scallop_count_by_site <- invert_counts %>%
  pivot_longer(cols = '2016':'2018',
               names_to = "year",
               values_to = "sp_count") %>%
  filter(common_name == "rock scallop") %>%
  group_by(site) %>%
  summarize(tot_count = sum(sp_count, na.rm = TRUE))
```

```
scallop_count_by_site
```

```
## # A tibble: 11 x 2
##    site  tot_count
##    <chr>     <dbl>
##  1 abur         48
##  2 ahnd         48
##  3 aque        152
##  4 bull         48
##  5 carp       2519
##  6 golb         48
##  7 ivee        169
##  8 mohk        346
##  9 napl       6416
## 10 scdi       2390
## 11 sctw       1259
```

8.4.1.7 Activity 1: using `filter()` in a wrangling sequence

Write a sequence of code (connected by the pipe operator, `%>%`), to complete the following and store the output as object `my_fish_wrangling`:

- Starting from the `fish_counts` data frame (stored earlier)
- Only keep observations from *Arroyo Burro* (site ‘abur’)
- Group by *common_name* (species)
- Find total fish counts (by species) across all years

8.4.2 Merging data frames with `dplyr::*_join()`

Excel’s `VLOOKUP` can also be used to merge data from separate tables or worksheets. Here, we’ll use the `dplyr::*_join()` functions to merge separate data frames in R.

There are a number of ways to merge data frames in R. We'll use `full_join()`, `left_join()`, and `inner_join()` in this session.

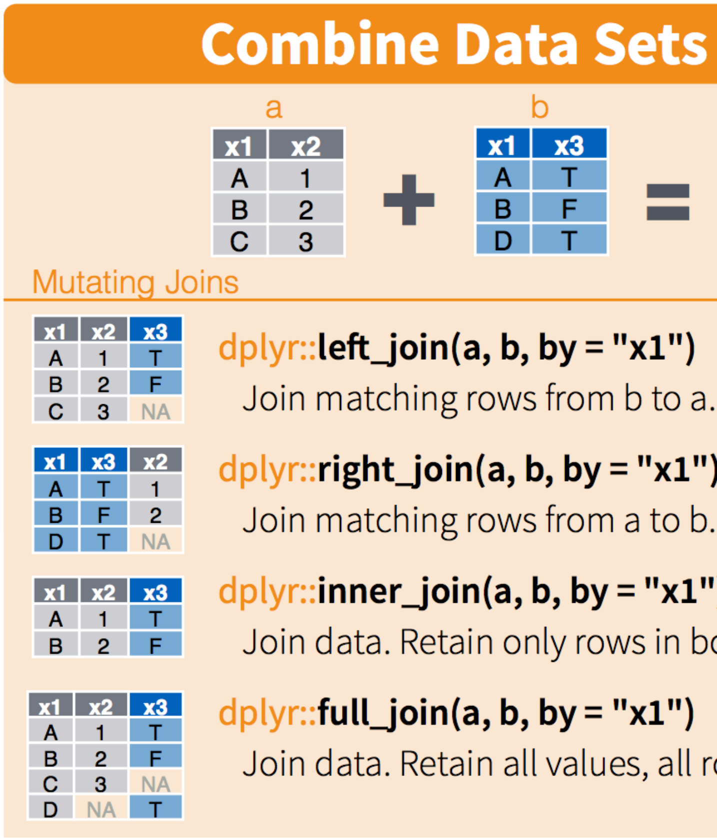
From R Documentation (`?join`):

- `dplyr::full_join()`: "returns all rows and all columns from both x and y. Where there are not matching values, returns NA for the one missing." Basically, nothing gets thrown out, even if a match doesn't exist - making `full_join()` the safest option for merging data frames. When in doubt, `full_join()`.

- `dplyr::left_join()`: "return all rows from x, and all columns from x and y. Rows in x with no match in y will have NA values in the new columns. If there are multiple matches between x and y, all combinations of the matches are returned."

- `dplyr::inner_join()`: "returns all rows from x where there are matching values in y, and all columns from x and y. If there are multiple matches between x and y, all combination of the matches are returned." This will drop observations that don't have a match between the merged data frames, which makes it a riskier merging option if you're not sure what you're trying to do.

Schematic (from RStudio data wrangling cheat sheet):



Combine Data Sets

a

x1	x2
A	1
B	2
C	3

+

b

x1	x3
A	T
B	F
D	T

=

Mutating Joins

x1	x2	x3
A	1	T
B	2	F
C	3	NA

dplyr::left_join(a, b, by = "x1")
Join matching rows from b to a.

x1	x3	x2
A	T	1
B	F	2
D	T	NA

dplyr::right_join(a, b, by = "x1")
Join matching rows from a to b.

x1	x2	x3
A	1	T
B	2	F

dplyr::inner_join(a, b, by = "x1"
Join data. Retain only rows in bo

x1	x2	x3
A	1	T
B	2	F
C	3	NA
D	NA	T

dplyr::full_join(a, b, by = "x1")
Join data. Retain all values, all r

To clarify what the different joins are doing, let's first make a subset of the *fish_counts* data frame that only contains observations from 2016 and 2017.

```
fish_2016_2017 <- fish_counts %>%
  filter(year == 2016 | year == 2017)
```

Take a look to ensure that only those years are included with `View(fish_2016_2017)`. Now, let's merge it with our kelp fronds data in different ways.

8.4.2.1 `dplyr::full_join()` to merge data frames, keeping everything

When we join data frames in R, we need to tell R a couple of things (and it does the hard joining work for us):

- Which data frames we want to merge together
- Which variables to merge by

Note: If there are **exactly matching** column names in the data frames you're merging, the `*_join()` functions will assume that you want to join by those columns. If there are *no* matching column names, you can specify which columns to join by manually. We'll do both here.

```
# Join the fish_counts and kelp_counts_abur together:
abur_kelp_join <- fish_2016_2017 %>%
  full_join(kelp_counts_abur) # Uh oh. An error message.
```

When we try to do that join, we get an error message: `Error: Can't join on 'year' x 'year' because of incompatible types (character / numeric)`

What's going on here? First, there's something fishy (ha) going on with the class of the *year* variable in `kelp_counts_abur`. Use the `class()` function to see how R understands that variable (remember, we use `$` to return a specific column from a data frame).

```
class(kelp_counts_abur$year)
```

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

So the variable is currently stored as a character. Why?

If we go back to the kelp_counts_curated.xlsx file, we'll see that the numbers in both the year and month column have been stored as *text*. There are several hints Excel gives us:

- Cells are left aligned, when values stored as numbers are right aligned
- The green triangles in the corner indicate some formatting
- The warning sign shows up when you click on one of the values with text formatting, and lets you know that the cell has been stored as text. We are given the option to reformat as numeric in Excel, but we'll do it here in R so we have a reproducible record of the change to the variable class.

There are a number of ways to do this in R. We'll use `dplyr::mutate()` to overwrite the existing `year` column while coercing it to class *numeric* using the `as.numeric()` function.

```
# Coerce the class of 'year' to numeric
kelp_counts_abur <- kelp_counts_abur %>%
  mutate(year = as.numeric(year))
```

Now if we check the class of the *year* variable in `kelp_counts_abur`, we'll see that it has been coerced to 'numeric':

```
class(kelp_counts_abur$year)
```

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

Question: Isn't it bad practice to overwrite variables, instead of just making a new one? Great question, and usually the answer is yes. Here, we feel fine with "overwriting" the year column because we're not changing anything about what's contained within the column, we're only changing how

R understands it. Always use caution if overwriting variables, and if in doubt, add one instead!

OK, so now the class of *year* in the data frames we're joining is the same. Let's try that `full_join()` again:

```
abur_kelp_join <- fish_2016_2017 %>%
  full_join(kelp_counts_abur)
```

```
## Joining, by = c("year", "site")
```

First, notice that R tells us which sites it is joining by - in this case, *year* and *site* since those were the two matching variables in both data frames.

Now look at the merged data frame with `View(abur_kelp_join)`. A few things to notice about how `full_join()` has worked:

1. All columns that existed in **both data frames** still exist.
2. All observations are retained, even if they don't have a match. In this case, notice that for other sites (not 'abur') the observation for fish still exists, even though there was no corresponding kelp data to merge with it. The kelp frond data from 2018 is also returned, even though the fish counts dataset did not have 'year == 2018' in it.
3. The kelp frond data is joined to *all observations* where the joining variables (*year*, *site*) are a match, which is why it is repeated 5 times for each year (once for each fish species).

Because all data (observations & columns) are retained, `full_join()` is the safest option if you're unclear about how to merge data frames.

8.4.2.2 `dplyr::left_join()` to merge data frames, keeping everything in the 'x' data frame and only matches from the 'y' data frame

Now, we want to keep all observations in *fish_2016_2017*, and merge them with *kelp_counts_abur* while only keeping observations from *kelp_counts_abur* that match an observation within *fish_2016_2017*. So when we use `dplyr::left_join()`, any information on kelp counts from 2018 should be dropped.

```
fish_kelp_2016_2017 <- fish_2016_2017 %>%
  left_join(kelp_counts_abur)
```

```
## Joining, by = c("year", "site")
```

Notice when you look at `fish_kelp_2016_2017`, the 2018 data that **does** exist in `kelp_counts_abur` does **not** get joined to the `fish_2016_2017` data frame, because `left_join(df_a, df_b)` will only keep observations from `df_b` if they have a match in `df_a`!

8.4.2.3 dplyr::inner_join() to merge data frames, only keeping observations with a match in both

When we used `left_join(df_a, df_b)`, we kept all observations in `df_a` but *only observations from `df_b` that matched an entry in `df_a`* (in other words, some entries from `df_b` were excluded).

Use `inner_join()` if you know that you **only** want to retain observations when they match across **both data** frames. Caution: this is built to exclude any observations that don't match across data frames by joined variables - double check to make sure this is actually what you want to do!

For example, if we use `inner_join()` to merge fish_counts and kelp_counts_abur, then we are asking R to **only return observations where the joining variables (*year* and *site*) have matches in both data frames.** Let's see what the outcome is:

```
abur_kelp_inner_join <- fish_counts %>%
  inner_join(kelp_counts_abur)
```

```
## Joining, by = c("year", "site")
```

```
abur_kelp_inner_join
```

```
## # A tibble: 15 x 6
##     year site  common_name     total_count month total_fronds
##    <dbl> <chr> <chr>                 <dbl> <chr>        <dbl>
##  1  2016 abur  black surfperch           2 7              307
##  2  2016 abur  blacksmith                1 7              307
##  3  2016 abur  garibaldi                 1 7              307
##  4  2016 abur  rock wrasse               2 7              307
##  5  2016 abur  senorita                 58 7              307
##  6  2017 abur  black surfperch           4 7              604
##  7  2017 abur  blacksmith                1 7              604
##  8  2017 abur  garibaldi                 1 7              604
##  9  2017 abur  rock wrasse              57 7              604
## 10  2017 abur  senorita                 64 7              604
## 11  2018 abur  black surfperch           1 7             3532
## 12  2018 abur  blacksmith                1 7             3532
## 13  2018 abur  garibaldi                 1 7             3532
## 14  2018 abur  rock wrasse               1 7             3532
## 15  2018 abur  senorita                  1 7             3532
```

Here, we see that only observations where there is a match for *year* and *site* in both data frames are returned.

8.4.2.4 dplyr::*_join() in a sequence

We can also merge data frames as part of a sequence of wrangling steps.

As an example: Starting with the invert_counts data frame, we want to:

- First, use pivot_longer() to get year and counts each into a single column
- Convert the class of *year* to numeric (so it can join with another numeric year variable)
- Then, only keep observations for "california spiny lobster"
- Next, join the kelp_counts_abur to the resulting subset above, **only keeping observations that have a match in both data frames**

That might look like this:

```r
abur_lobster_kelp <- invert_counts %>%
  pivot_longer('2016':'2018', names_to = "year", values_to = "total_counts") %>%
  mutate(year = as.numeric(year)) %>%
  filter(common_name == "california spiny lobster") %>%
  dplyr::inner_join(kelp_counts_abur)
```

```
## Joining, by = c("month", "site", "year")
```

```r
abur_lobster_kelp
```

```
## # A tibble: 3 x 6
##   month site  common_name               year total_counts total_fronds
##   <chr> <chr> <chr>                    <dbl>        <dbl>        <dbl>
## 1 7     abur  california spiny lobster  2016           17          307
## 2 7     abur  california spiny lobster  2017           17          604
## 3 7     abur  california spiny lobster  2018           16         3532
```

8.4.2.5 Activity 2

Now let's combine what we've learned about piping, filtering and joining!

Complete the following as part of a single sequence (remember, check to see what you've produced after each step) to create a new data frame called my_fish_join:

- Start with fish_counts data frame
- Filter to only including observations for 2017 at Arroyo Burro
- Join the kelp_counts_abur data frame to the resulting subset using left_join()
- Add a new column that contains the 'fish per kelp fronds' density (total_count / total_fronds)

8.5 Fun / kind of scary facts

How is this similar to `VLOOKUP` in Excel? How does it differ?

From Microsoft Office Support, "use VLOOKUP when you need to find things in a table or a range by row."

So, both `filter()` and `VLOOKUP` look through your data frame (or spreadsheet, in Excel) to look for observations that match your conditions. But they also differ in important ways:

(1) By default `VLOOKUP` looks for and returns an observation for *approximate* matches (and you have to change the final argument to FALSE to look for an exact match). In contrast, by default `dplyr::filter()` will look for exact conditional matches.

(2) `VLOOKUP` will look for and return information from the *first observation* that matches (or approximately matches) a condition. `dplyr::filter()` will return all observations (rows) that exactly match a condition.

8.6 Interludes (deep thoughts/openscapes)

- Not overusing the pipe in really long sequences. What are other options? Why is that a concern? What are some ways to always know that what's happening in a sequence is what you EXPECT is happening in a sequence? tidylog, check intermediate data frames, sometimes write intermediate data frames, etc.
- The risk of partial joins (& a case for full_join + drop_na instead?)

8.7 Efficiency Tips

Chapter 9

Tidying

- After vlookups (filter & joins)
- Allison section Possibly return to uncount() if relevant to get a case_format thing pivot_longer(), pivot_wider(), separate(), unite() janitor::clean_names()

9.1 Better practices [needs a better name]

- How to be a nimble useR
- Modern useRs are nimble internet useRs
- No one gets out of cleaning chores in data science

9.2 Summary (a few sentences)

9.3 Objectives (more detailed, bulletpoints?)

- expect there is a better way, how and where to look (20 mins)
  - CRAN
  - Twitter #rstats
  - rOpenSci
  - RStudio
  - Example: how to Google.
- hands-on with janitor (30+ mins)
  - discovery and quality assurance
  - installing from GitHub
  - big payoff for little effort

- hands-on with another excel-useful example: skimr?

- reproducibility (20 mins)
  - it's important, scripted

9.4 Resources

- Wilson et al. 2014 "Good enough practices"

9.5 Lessons teaching for each objective..... (objectives, examples)

9.5.1 Expect there's a better way chat

- give time for them to google?

9.5.2 Janitor

janitor & other things that will make your life easier with limited effort Janitor: up till now the column names have been fine. Until now.

9.5.2.1 Our turn your turn

Walk through and example and leave our code up, and have you do it but clean another dataset. Work with a neighbor.

9.5.3 Example: How to Google

Pay attention to URLs, build github/rmarkdown savviness (ex: raw.githubusercontent.com)

- I read this blog: https://blog.revolutionanalytics.com/2018/08/how-to-use-r-with-excel.html
- I've never heard of click on `openxlsx`, what is it
- Takes me here https://www.rdocumentation.org/packages/openxlsx/versions/4.1.0.1, but I want more info. How recently was it worked on? Does it interface with tidyverse? Click on "news"
- Takes me here. https://raw.githubusercontent.com/awalker89/openxlsx/master/NEWS . Not useful. But from this URL, - I see the username so I can edit this url to be https://github.com/awalker89/openxlsx/

- 1st thing: most recent commit was a year ago. Can poke around more, are there issues open, are they taken care of? Etc. I will probably not pursue using this right now. But good to have learned about it.

9.6 Fun facts (quirky things) - making a note of these wherever possible for interest (little "Did you know?" sections)

9.7 Interludes (deep thoughts/openscapes)

9.8 Our Turn Your Turn 2

9.9 Efficiency Tips

- browser efficiency tips
  - Rmd/github anchors for urls
  - press command to open a new tab

Reproducibility is important (this might be new to some people) Example: run everything start to finish and then closing it all and trying to do again In excel Vs R If your computer shuts off are you nervous to close it? Recreate it "What they didn't forget to teach you about R" WTDF. uncool

Chapter 10

Synthesis

Allison section

10.1 Summary (a few sentences)

In this session, we'll put together the skills that we've learned so far to create a new document from scratch, and learn a few new ways to import and work with spreadsheet data along the way.

10.2 Objectives

- Read in data from a Google sheet with the `googlesheets4` package in R
-

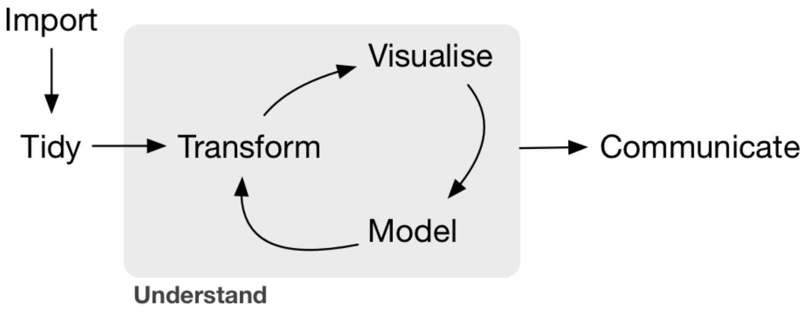


Figure 10.1: r4ds_drawing

10.3 Resources

- Googlesheets4 link

10.4 Lessons

Lesson set up:

- Log in to your GitHub account and create a new repository called `sea-creature-synthesis`
- Clone the repo to create a version controlled project (remember, copy & paste the URL from the GitHub Clone / Download)
- Copy and paste the `fish_counts_curated.csv` and `lobster_abundance.csv` into the project folder
- Create a new R Markdown document within your `sea-creature-synthesis` project
- Knit your .Rmd to html, saving as `sb_sea_creatures.Rmd`

10.4.1 Reading

- Read in lobster data with googlesheets4
- Join with another existing data frame (or 2?)
- Pivoting
- Transforming / subsetting
- Grouping & summarizing (for means, sd, count)
- Make a table
- Make a graph

Possible new things: complete()

10.5 Fun facts (quirky things) - making a note of these wherever possible for interest (little "Did you know?" sections)

10.6 Interludes (deep thoughts/openscapes)

10.7 Our Turn Your Turn 1

10.8 Our Turn Your Turn 2

10.9 Efficiency Tips