Managing Data in R

KEL - Quantitative Methods

Housekeeping

- You need some data for this class (assignment one)
- If you still do not have data, and do not have a plan to acquire data (e.g. chatting with your advisor, surfing dryad, using some from a cool paper you recently read), we need to speak about your options ASAP.
- Please email me klangwig@vt.edu if you are worried about this.
- **I need your github username turned in before next class**

Assignment Reminder

- Please turn in your GitHub name and the paragraph about your data on canvas.
  - There is a text entry box to do this under the "assignments" tab. (You don't need to send me an email or a canvas message.)

Goals

You should be able to

- read data into R
- understand and control how R represents those data
  - numbers, characters, factors, missing values
- examine the data visually, numerically, textually, etc.

Getting Started with Data

- Save files as .csv
- IMPORTANT – saving an excel file as a CSV means that you will lose some data
- For example, if you used excel to calculate a formula, the formula will be gone as R will just store this as plain text
- DON'T USE EXCEL TO DO CALCULATIONS – JUST ADD THIS TO YOUR CODE IN R
- Use smart column names. R can't handle spaces in your column names, so get rid of those. Also don't use a bunch of capitals unnecessarily because it slows down your coding. e.g. use "species" not "Species"

Making your excel file

- Excel files should have a list of column names at the top only and variable values
- Your excel file should not look like your field data sheet

What is wrong with this entry?

	A	B	C	D	E
1	Site	Neda Mine	Date	1/13/18	State
2					
3	sample id	section	species		
4	1	A	pesu		
5	2	A	pesu		
6	3	B	mylu		
7					
8					
9					
10					

Corrected entry

	A	B	C
1	sample id	section	species
2	1	A	pesu
3	2	A	pesu
4	3	B	mylu
5			

Representations

Numeric and character types are fairly straightforward, and you rarely have to worry about when and whether R represents things as integers or *floating point*.

You do need to know about **factors**, and to be aware when your variables are being treated as such. See lecture 1 for more about factors.

Date reminder

Working with dates can be a bit frustrating because as time units get larger, they become more variable. For example, at what day does the 75th percentile of the month fall?

An important note – macs and windows machines often handle dates differently and the default is different in excel.

One a mac the default is mo/day/two digit year – e.g. 01/13/18 is January 13, 2018, but on a PC the default is "01/13/2018". This can result in some frustration between people sharing scripts!

Missing values

When you input data, you need to be aware of `NA` (“not available”). Your read function has an option called `na.strings` which you can use to communicate between R and your CSV files, for example. You need to know that

- use `is.na()` to test for `NA` values, `na.omit()` to drop them, and the optional `na.rm` argument in some functions (`mean`, `sum`, `median` . . .)
- in the tidyverse, you can use `drop_na()` to remove `NA`

Changing representations

- R has a big suite of functions for creating, testing and changing representations.

-These have names like `factor()`, `as.numeric()` and `is.character()`.

Examination

You should think creatively, and early on, about how to check your data. Is it internally consistent? Are there extreme outliers? Are there typos? Are there certain values that really mean something else?

An American Airlines memo about fuel reporting from the 1980s complained of multiple cases of:

- Reported departure fuel greater than aircraft capacity
- Reported departure fuel less than minimum required for trip
- Reported arrival fuel greater than reported departure fuel

You should think about what you can test, and what you can fix if it's broken.

Things to fix in excel

- naming inconsistencies (see maple example last lecture)
- column name issues (spaces)
- use excel's find and replace and filter function to find these

Visualizing data with graphs

Graphical approaches are really useful for data cleaning; we will discuss this more later on.

To get you started here are just a few:

- `hist`: will make a histogram plot

Example

```
batdat=read.csv("/Users/klangwig/Desktop/VT/teaching/quant

head(batdat)
```

```
##       swab_id gd        gdL swab_type state          site
## 1 KL15WI0002  1 0.00007560       BAT    WI HORSESHOE BAY
## 2 KL15WI0003  1 0.47879100       BAT    WI HORSESHOE BAY
## 3 KL15WI0004  0         NA       BAT    WI HORSESHOE BAY
## 4 KL15WI0005  1 0.00000551       BAT    WI HORSESHOE BAY
## 5 KL15WI0006  1 0.00003560       BAT    WI HORSESHOE BAY
## 6 KL15WI0007  1 0.00003160       BAT    WI HORSESHOE BAY
##   country count
## 1    u.s.     3
## 2    u.s.  1110
## 3    u.s.  1110
## 4    u.s.  1110
## 5    u.s.  1110
## 6    u.s.  1110
```

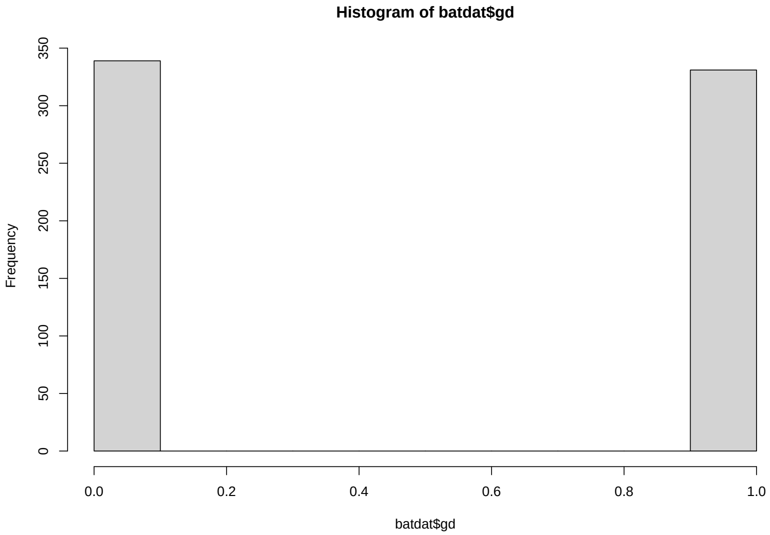
Example Cont.

```
unique(batdat$species)
```

```
## [1] "MYSE"      "MYLU"      "PESU"      "EPFU"      "SUB
```

Example Cont.

```
hist(batdat$gd)
```



Some other useful tools

- `dim`: gives the dimensions of the dataframe
- `str`: gives the structure of each variable
- `glimpse`: a dyplr function, that allows for preview as much of each column as possible
- `head`: get the first 6 rows
- `tail`: get the last 6 rows

Some other useful base R tools

- `aggregate`: creating summary dfs using various functions on a set of variables
- `match`: match a value from one dataframe into another df given a common column. Only the value you want to copy is matched.
- `merge`: merge two dataframes together based on some common columns, all columns are merged.
- Note `merge` is made more versatile by the `join` functions in tidyverse

Example with bat data

```
batdat=read.csv("/Users/klangwig/Desktop/VT/teaching/quant
head(batdat)
```

```
##      swab_id gd          gdL swab_type state          site
## 1 KL15WI0002  1 0.00007560       BAT    WI HORSESHOE BAY
## 2 KL15WI0003  1 0.47879100       BAT    WI HORSESHOE BAY
## 3 KL15WI0004  0         NA       BAT    WI HORSESHOE BAY
## 4 KL15WI0005  1 0.00000551       BAT    WI HORSESHOE BAY
## 5 KL15WI0006  1 0.00003560       BAT    WI HORSESHOE BAY
## 6 KL15WI0007  1 0.00003160       BAT    WI HORSESHOE BAY
##   country count
## 1    u.s.     3
## 2    u.s.  1110
## 3    u.s.  1110
## 4    u.s.  1110
## 5    u.s.  1110
## 6    u.s.  1110
```

Here, we will use aggregate

```
batcounts<-aggregate(count~species+site+date,data=batdat, F
#make a df of bat counts
head(batcounts)
```

```
##   species           site     date count
## 1    MYLU       ST. JOHN 11/20/15    87
## 2    MYLU HORSESHOE BAY  11/7/15   646
## 3    MYSE HORSESHOE BAY  11/7/15     1
## 4    MYLU    BEAR CREEK  11/9/15   116
## 5    MYSE    BEAR CREEK  11/9/15     7
## 6    PESU    BEAR CREEK  11/9/15    50
```

We can make identical dataframes for loads

```
batdat$lgdL=log10(batdat$gdL)#log the amount of fungus
batloads<-aggregate(lgdL~species+site+date,data=batdat, FUN
head(batloads)
```

```
##     species           site     date      lgdL
## 1      MYLU       ST. JOHN 11/20/15 -3.702218
## 2      MYLU HORSESHOE BAY  11/7/15 -3.181897
## 3      MYSE HORSESHOE BAY  11/7/15 -2.568128
## 4      MYLU HORSESHOE BAY  2/27/15 -3.629430
## 5      MYSE HORSESHOE BAY  2/27/15 -4.021487
## 6 SUBSTRATE HORSESHOE BAY  2/27/15 -4.406571
```

We can "match" the loads column into our count df

```
batloads$unique.row.id = paste(batloads$species,batloads$si
batcounts$unique.row.id = paste(batcounts$species,batcounts
#dataframe you are bringing to first, and the one you match
batloads$count = batcounts$count[match(batloads$unique.row.
head(batloads)
```

```
##     species           site     date      lgdL
## 1      MYLU       ST. JOHN 11/20/15 -3.702218          MY
## 2      MYLU HORSESHOE BAY  11/7/15 -3.181897      MYLU H
## 3      MYSE HORSESHOE BAY  11/7/15 -2.568128      MYSE H
## 4      MYLU HORSESHOE BAY  2/27/15 -3.629430      MYLU H
## 5      MYSE HORSESHOE BAY  2/27/15 -4.021487      MYSE H
## 6 SUBSTRATE HORSESHOE BAY  2/27/15 -4.406571 SUBSTRATE H
##   count
## 1    87
## 2   646
## 3     1
## 4  1110
## 5     3
```

Alternatively, we can merge dataframes together for wide format

```
batwide=merge(batloads,batcounts,by=c("site","date"))
#merge df together by site and date
head(batwide)
```

```
##          site    date species.x      lgdL                ur
## 1 BEAR CREEK 3/10/17      MYLU -1.404181      MYLU BEAR
## 2 BEAR CREEK 3/10/17      MYLU -1.404181      MYLU BEAR
## 3 BEAR CREEK 3/10/17      PESU -1.784292      PESU BEAR
## 4 BEAR CREEK 3/10/17      PESU -1.784292      PESU BEAR
## 5 BEAR CREEK 3/10/17 SUBSTRATE -4.127488 SUBSTRATE BEAR
## 6 BEAR CREEK 3/10/17 SUBSTRATE -4.127488 SUBSTRATE BEAR
##   species.y count.y          unique.row.id.y
## 1      MYLU      38 MYLU BEAR CREEK 3/10/17
## 2      PESU      22 PESU BEAR CREEK 3/10/17
## 3      MYLU      38 MYLU BEAR CREEK 3/10/17
## 4      PESU      22 PESU BEAR CREEK 3/10/17
## 5      MYLU      38 MYLU BEAR CREEK 3/10/17
```

How do you clean data?

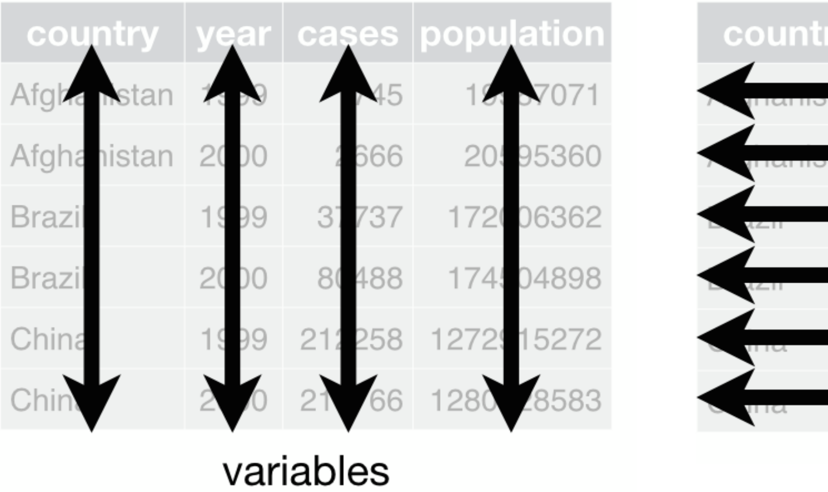
What R functions do you know that are useful for examination?
What are your strategies?

Tidy(ing) data

Hadley Wickham has defined a concept of tidy data, and has introduced the `tidyverse` package.

- Each variable is in a column
- Each observation is in a row
- "Long" rather than "wide" form
- Sometimes duplicates data
- Statistical modeling tools and graphical tools (especially the **ggplot2** package) in R work best with long form

An example of tidy data



Learning about the tidyverse

- https://www.tidyverse.org

Putting your data in tidy format

- Discerning what is a variable can be hard when making data files
- For example, species in my bat dataset is usually a single variable
- I usually also include a “count” column (the number of individuals at a site)
- But what if I wanted to test the effect of the count of one species (e.g.MYSE) on another?

Example with bat count data

```
batcounts<-aggregate(count~species+site+date,data=batdat,
head(batcounts)
```

```
##   species           site     date count
## 1    MYLU       ST. JOHN 11/20/15    87
## 2    MYLU HORSESHOE BAY  11/7/15   646
## 3    MYSE HORSESHOE BAY  11/7/15     1
## 4    MYLU     BEAR CREEK  11/9/15   116
## 5    MYSE     BEAR CREEK  11/9/15     7
## 6    PESU     BEAR CREEK  11/9/15    50
```

Testing the effect of one species on another

- What if I wanted to test how the count of MYSE influenced counts of MYLU? I need to MYSE to be a variable

Pivoting

- Here is a link to vignette: https://tidyr.tidyverse.org/articles/pivot.html
- Using `pivot_wider()` and `pivot_longer()` we can specify how the metadata stored become data variables
- This has replaced `spread` and `gather`

Let's 'pivot' (make wider)

```
library(tidyr)
batcounts.wide<- batcounts %>% #this says - make a new df c
  pivot_wider(names_from = species, values_from = count)
##make columns for each of the values in the species colum
```

What does our new df look like?

```
head(batcounts.wide)
```

```
## # A tibble: 6 x 6
##   site          date      MYLU  MYSE  PESU  EPFU
##   <chr>         <chr>    <dbl> <dbl> <dbl> <dbl>
## 1 ST. JOHN      11/20/15    87    NA    NA    NA
## 2 HORSESHOE BAY 11/7/15    646     1    NA    NA
## 3 BEAR CREEK    11/9/15    116     7    50    NA
## 4 HORSESHOE BAY 2/27/15   1110     3     2    NA
## 5 HORSESHOE BAY 3/1/17      10    NA    10    NA
## 6 BEAR CREEK    3/10/17     38    NA    22    NA
```

Here's another example using "pivot"

Look at some example data that comes with the tidyr package:

```
fish_encounters
```

```
## # A tibble: 114 x 3
##    fish  station  seen
##    <fct> <fct>   <int>
##  1 4842  Release     1
##  2 4842  I80_1       1
##  3 4842  Lisbon      1
##  4 4842  Rstr        1
##  5 4842  Base_TD     1
##  6 4842  BCE         1
##  7 4842  BCW         1
##  8 4842  BCE2        1
##  9 4842  BCW2        1
## 10 4842  MAE         1
## # ... with 104 more rows
```

Pivot_wider

Using `pivot_wider()`

```
fish_encounters %>%
  pivot_wider(names_from = station, values_from = seen)
```

```
## # A tibble: 19 x 12
##    fish  Release I80_1 Lisbon  Rstr Base_TD   BCE   BCW
##    <fct>   <int> <int>  <int> <int>   <int> <int> <int>
##  1 4842        1     1      1     1       1     1     1
##  2 4843        1     1      1     1       1     1     1
##  3 4844        1     1      1     1       1     1     1
##  4 4845        1     1      1     1       1    NA    NA
##  5 4847        1     1      1    NA      NA    NA    NA
##  6 4848        1     1      1     1      NA    NA    NA
##  7 4849        1     1     NA    NA      NA    NA    NA
##  8 4850        1     1     NA     1       1     1     1
##  9 4851        1     1     NA    NA      NA    NA    NA
## 10 4854        1     1     NA    NA      NA    NA    NA
## 11 4855        1     1      1     1       1    NA    NA
```

Fill in 0's

```
fish_encounters %>%
  pivot_wider(
    names_from = station,
    values_from = seen,
    values_fill = list(seen = 0)
  )
```

```
## # A tibble: 19 x 12
##    fish  Release I80_1 Lisbon  Rstr Base_TD   BCE   BCW
##    <fct>   <int> <int>  <int> <int>   <int> <int> <int>
##  1 4842        1     1      1     1       1     1     1
##  2 4843        1     1      1     1       1     1     1
##  3 4844        1     1      1     1       1     1     1
##  4 4845        1     1      1     1       1     0     0
##  5 4847        1     1      1     0       0     0     0
##  6 4848        1     1      1     1       0     0     0
##  7 4849        1     1      0     0       0     0     0
##  8 4850        1     1      0     1       1     1     1
##  9 4851        1     1      0     0       0     0     0
```

Making a dataframe long (e.g. tidy)

Let's look at an example of an untidy dataframe.

```
head(relig_income)
```

```
## # A tibble: 6 x 11
##   religion  `<$10k` `$10-20k` `$20-30k` `$30-40k` `$40-5
##   <chr>       <dbl>     <dbl>     <dbl>     <dbl>     <d
## 1 Agnostic       27        34        60        81
## 2 Atheist        12        27        37        52
## 3 Buddhist       27        21        30        34
## 4 Catholic      418       617       732       670
## 5 Don’t kn~      15        14        15        11
## 6 Evangeli~     575       869      1064       982
## # ... with 3 more variables: $100-150k <dbl>, >150k <dbl
## #   Don't know/refused <dbl>
```

Make a row for the number of individuals for each religion by income category

```
relig_income %>%
  pivot_longer(-religion, names_to = "income", values_to =
```

```
## # A tibble: 180 x 3
##    religion  income             count
##    <chr>     <chr>              <dbl>
##  1 Agnostic  <$10k                 27
##  2 Agnostic  $10-20k               34
##  3 Agnostic  $20-30k               60
##  4 Agnostic  $30-40k               81
##  5 Agnostic  $40-50k               76
##  6 Agnostic  $50-75k              137
##  7 Agnostic  $75-100k             122
##  8 Agnostic  $100-150k            109
##  9 Agnostic  >150k                 84
## 10 Agnostic  Don't know/refused    96
## # ... with 170 more rows
```

Another example using temporal data:

The billboard dataset has a row for every week and the rank of that song

```
billboard
```

```
## # A tibble: 317 x 79
##    artist   track   date.entered   wk1   wk2   wk3   wk4
##    <chr>    <chr>   <date>       <dbl> <dbl> <dbl> <dbl>
##  1 2 Pac    Baby D~ 2000-02-26      87    82    72    77
##  2 2Ge+her  The Ha~ 2000-09-02      91    87    92    NA
##  3 3 Doors~ Krypto~ 2000-04-08      81    70    68    67
##  4 3 Doors~ Loser   2000-10-21      76    76    72    69
##  5 504 Boyz Wobble~ 2000-04-15      57    34    25    17
##  6 98^0     Give M~ 2000-08-19      51    39    34    26
##  7 A*Teens  Dancin~ 2000-07-08      97    97    96    95
##  8 Aaliyah  I Don'~ 2000-01-29      84    62    51    41
##  9 Aaliyah  Try Ag~ 2000-03-18      59    53    38    28
## 10 Adams, ~ Open M~ 2000-08-26      76    76    74    69
## # ... with 307 more rows, and 68 more variables: wk9 <db
```

We want week to be temporal data, but it has letters in it

- We want names to be a variable called "week" and the values to be a variable called "rank"
- We want to remove NAs because not all songs stay on the charts for 76 weeks

Billboard

```
billboard %>%
  pivot_longer(
    cols = starts_with("wk"),
    names_to = "week",
    names_prefix = "wk",
    values_to = "rank",
    values_drop_na = TRUE
  )
```

```
## # A tibble: 5,307 x 5
##    artist  track                   date.entered week   r
##    <chr>   <chr>                   <date>       <chr> <c
##  1 2 Pac   Baby Don't Cry (Keep... 2000-02-26   1
##  2 2 Pac   Baby Don't Cry (Keep... 2000-02-26   2
##  3 2 Pac   Baby Don't Cry (Keep... 2000-02-26   3
##  4 2 Pac   Baby Don't Cry (Keep... 2000-02-26   4
##  5 2 Pac   Baby Don't Cry (Keep... 2000-02-26   5
##  6 2 Pac   Baby Don't Cry (Keep... 2000-02-26   6
```

Changing something to an integer

- We want to turn week into an integer so we can easily determine how long a song was on the charts

```
billboard %>%
  pivot_longer (
    cols = starts_with("wk"),
    names_to = "week",
    names_prefix = "wk",
    values_to = "rank",
    values_drop_na = TRUE
)
```

```
## # A tibble: 5,307 x 5
##    artist  track                   date.entered week   r
##    <chr>   <chr>                   <date>       <chr> <c
##  1 2 Pac   Baby Don't Cry (Keep... 2000-02-26   1
##  2 2 Pac   Baby Don't Cry (Keep... 2000-02-26   2
##  3 2 Pac   Baby Don't Cry (Keep... 2000-02-26   3
##  4 2 Pac   Baby Don't Cry (Keep... 2000-02-26   4
```

So how do we create tidy datasets?

- Make your data as tidy as possible
- Learn to manipulate data in R and hardcode these changes into your scripts
- There is no perfect method - each dataset is unique
- Manipulating data in R is hard, sometimes harder than excel. But learning to do it SO worth it because you will save hours of time for each project you do.

Tools

base R

- `reshape`: wide-to-long and vice versa
- `merge`: join data frames
- `ave`: compute averages by group
- `subset`, `[`-indexing: select obs and vars
- `transform`: modify variables and create new ones
- `aggregate`: split-apply-summarize
- `sort`

The tidyverse

- `pivot_longer`, `pivot_wider`
- `mutate`: add a column
- `select`: select columns
- `filter`: select rows
- `group_by`: group then do something (usually mutate or summarise)
- `summarise`: make a summary table
- `arrange`: sort
- `left_join`: merge see other `join` options

Group by, Mutate, and Summarise

- `group_by` is my favorite tidyverse command which has cut my need to write loops in half
- `group_by` allows you to do calculations on groups of things, for example, by species or year

First load the package

```
library(tidyverse)
```

```
## -- Attaching packages ---------------------------------

## v ggplot2 3.3.5     v dplyr   1.0.7
## v tibble  3.1.6     v stringr 1.4.0
## v readr   2.1.1     v forcats 0.5.1
## v purrr   0.3.4

## -- Conflicts ------------------------------------------
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

Group by species

```
batdat$lgdL = log10(batdat$gdL)
batdat %>%
  group_by(species) %>%
    summarise(mean.fungal.loads=mean(lgdL,na.rm=TRUE))
```

```
## # A tibble: 5 x 2
##   species   mean.fungal.loads
##   <chr>                 <dbl>
## 1 EPFU                  -3.64
## 2 MYLU                  -3.03
## 3 MYSE                  -3.69
## 4 PESU                  -2.04
## 5 SUBSTRATE             -4.11
```

Summarise versus Mutate

- `summarise` creates a new dataframe
- `mutate` does a calculation where it add a new column to your existing dataframe

```
batdat_with_sample_size = batdat %>%
  #create a new dataframe  called batdat_with_sample_size
    group_by(site,species,date) %>%
  #you can group_by multiple things
    mutate(sample.size=n())
#this adds a column to the dataframe
```

What does our dataframe look like now?

```
head(batdat_with_sample_size[c(1,6,7,8,12,13)])
```

```
## # A tibble: 6 x 6
## # Groups:   site, species, date [2]
##   swab_id    site           date    species   lgdL sample
##   <chr>      <chr>          <chr>   <chr>    <dbl>
## 1 KL15WI0002 HORSESHOE BAY 2/27/15 MYSE    -4.12
## 2 KL15WI0003 HORSESHOE BAY 2/27/15 MYLU    -0.320
## 3 KL15WI0004 HORSESHOE BAY 2/27/15 MYLU    NA
## 4 KL15WI0005 HORSESHOE BAY 2/27/15 MYLU    -5.26
## 5 KL15WI0006 HORSESHOE BAY 2/27/15 MYLU    -4.45
## 6 KL15WI0007 HORSESHOE BAY 2/27/15 MYLU    -4.50
```

```
#this is just showing a few columns for effect
```

Managing Pipelines in R

- Pipelines are ways of carefully recording and systematizing the steps you take to work with your data
- The idea is that you should be able to delete any results of computer calculations and be able to quickly re-do them
- Ideally your project will depend on:
  - Some data files
  - Some scripts
  - Something that tells you how these things go together (RMarkdown is helpful for this), at minimum a README file

Advantages of this approach

- Clarity: we aren't confused about the 600 pages of information stored with our projects
- Reproducibility: we can always re-do something we did
- Flexibility : we can use different data and re-create the same thing

Spreadsheets

- Spreadsheets are a useful tool for working with R
- `read.csv` and `write.csv` are very useful commands for working with spreadsheets
- when using `write.csv` use `row.names=F` to avoid line numbers
- Importantly, spreadsheets are for storing data, NOT FOR MANIPULATING DATA
  - Your goal should be to take data from a spreadsheet and manipulate it entirely using scripts.
  - Avoid spreadsheet addiction: http://www.burns-stat.com/documents/tutorials/spreadsheet-addiction/
  - The jist is: friends don't let friends use excel for statistics.

Database

- Your spreadsheet is a database (just because it isn't stored in microsoft access doesn't mean it isn't!)
- "small" databases are usually considered to be fewer than 1000 observations of 10-20 vars
- "medium" databases are about 1000 to 100,000 observations of about 10-50 vars. These are most helpful with data handling packages.
- "large" means millions of observations and potentially 1000s of variables. These may need to be stored in an external application.

Working in Github

- Git is version control system, with the original purpose of allowing groups to work collaboratively on software projects
- Git manages the evolution of a set of files - called a repository
- A repository is essentially a folder where you store your stuff
- Version control works a bit like “Track Changes” in word, Git will track the changes we make to our code so we can return to previous versions
- It also allows collaboration so I can look at your code and make changes - a bit like a more complicated version of Google Docs

Will this hurt?

- Maybe!
- But, I think this important enough that we NEED exposure to this. This is the future!

But I only code alone!

- You need to carefully document your steps if the only person you are sharing code with is the future version of yourself
- In addition, most journals require publicly available data and code - open code is the norm, not the exception.
- Using Git has gotten easier. We used to have to use command line to communicate with Git, but now we can just use RStudio!

Terminology

- repository: A directory or storage space where your projects can live. Sometimes GitHub users shorten this to "repo." (If you're cool like that.) It is usually a local folder on your computer. You can keep code files, text files, image files, you name it, inside a repository.
- commit: This is the command that gives Git its power. When you commit, you are taking a "snapshot" of your repository at that point in time, giving you a checkpoint to which you can reevaluate or restore your project to any previous state.When you first start "commiting", it is important to remember this is taking the picture, not SENDING the picture. (Sending is called "pushing")

Terminology cont.

- branch: How do multiple people work on a project at the same time without Git getting them confused? Usually, they “branch off” of the main project with their own versions full of changes they themselves have made. After they’re done, it’s time to “merge” that branch back with the “master,” the main directory of the project. Because we’ll be working within our own repos, we don’t need to worry too much about branching but is good to know for future.
- push: This is how you upload your file to GitHub. Remember, you need to both commit and push for your file to be sent to GitHub.

Sending your files to our class repository

- We have an "organization" account for our class
- Normally, we would have to pay for private repositories, but I emailed github and they are giving us UNLIMITED private repositories. That's pretty awesome.
- Why should we want things open-source? Why not?

Installing Git

- Please try to start this before our next class.
- Here is a link:
  http://happygitwithr.com/install-git.html#install-git
- Please follow instructions to get started with git.
- Try to install git in the most scientific way possible - if one way doesn't work, try the next, and google your mistakes!