Entering and cleaning data #3

Odds and ends

Groups for homework #5

- Group 1: Jessy, Kyle, Alyssa, Devin
- Group 2: Kayla, Kathleen, Amanda
- Group 3: Grant, Aeriel, Rebecca
- Group 4: Anastasia, Camron, Nichole
- Group 5: Randy, Ana, Amy

Group projects

Potential ideas:

- Predicting if trapped mosquitoes test positive for West Nile virus
- Investigating temporal and spatial patterns in human West Nile cases within a state (and link to Census data and / or climate information)
- Explore 'omics data for West Nile virus (https://omics-lhv.org/data/)
- Genomic epidemiology of West Nile virus in California (https://github.com/andersen-lab/west-nile)
- Patterns in papers about West Nile virus

“Products”

Each group will need to generate:

1. The code for their piece of the project (we’ll use GitHub to collaborate).
2. A brief report (4 to 5 pages) describing how the group tackled their problem, what pieces were particularly challenging and how they tackled those, what they would do differently if they started fresh, and what interesting things they found in this set of data. Each group must submit a draft of this the last Wednesday of class and submit the final version on the day of presentations.
3. A presentation (12 minutes maximum) that covers the same material as the report. The groups will present these during finals week, in the time period scheduled for a final exam for our course.

Pulling online data

APIs

API: "Application Program Interface"

An API provides the rules for software applications to interact. In the case of open data APIs, they provide the rules you need to know to write R code to request and pull data from the organization's web server into your R session.

Often, an API can help you avoid downloading all available data, and instead only download the subset you need.

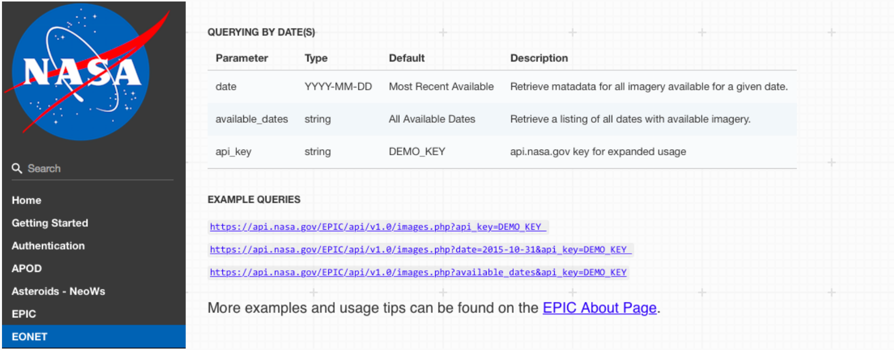
APIs

Strategy for using APIs from R:

- Figure out the API rules for HTTP requests
- Write R code to create a request in the proper format
- Send the request using GET or POST HTTP methods
- Once you get back data from the request, parse it into an easier-to-use format if necessary

API documentation

Start by reading any documentation available for the API. This will often give information on what data is available and how to put together requests.



NASA

Search

Home

Getting Started

Authentication

APOD

Asteroids - NeoWs

EPIC

EONET

QUERYING BY DATE(S)

Parameter	Type	Default	Description
date	YYYY-MM-DD	Most Recent Available	Retrieve matadata for all imagery available for a given date.
available_dates	string	All Available Dates	Retrieve a listing of all dates with available imagery.
api_key	string	DEMO_KEY	api.nasa.gov key for expanded usage

EXAMPLE QUERIES

https://api.nasa.gov/EPIC/api/v1.0/images.php?api_key=DEMO_KEY

https://api.nasa.gov/EPIC/api/v1.0/images.php?date=2015-10-31&api_key=DEMO_KEY

https://api.nasa.gov/EPIC/api/v1.0/images.php?available_dates&api_key=DEMO_KEY

More examples and usage tips can be found on the EPIC About Page.

Source: https://api.nasa.gov/api.html#EONET

API key

Many organizations will require you to get an API key and use this key in each of your API requests. This key allows the organization to control API access, including enforcing rate limits per user. API rate limits restrict how often you can request data (e.g., an hourly limit of 1,000 requests per user for NASA APIs).

You should keep this key private. In particular, make sure you do not include it in code that is posted to GitHub.

Example– `riem` package

The `riem` package, developed by Maelle Salmon and an ROpenSci package, is an excellent and straightforward example of how you can use R to pull open data through a web API.

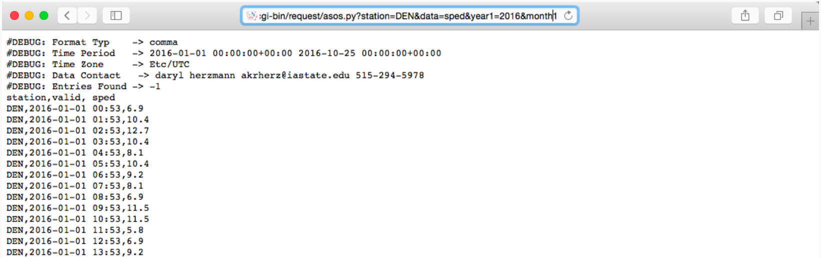
This package allows you to pull weather data from airports around the world directly from the Iowa Environmental Mesonet.

Example– `riem` package

To get a certain set of weather data from the Iowa Environmental Mesonet, you can send an HTTP request specifying a base URL, "https://mesonet.agron.iastate.edu/cgi-bin/request/asos.py/", as well as some parameters describing the subset of dataset you want (e.g., date ranges, weather variables, output format).

Once you know the rules for the names and possible values of these parameters (more on that below), you can submit an HTTP GET request using the `GET` function from the `httr` package.

Example– `riem` package




```
#DEBUG: Format Typ    -> comma
#DEBUG: Time Period   -> 2016-01-01 00:00:00+00:00 2016-10-25 00:00:00+00:00
#DEBUG: Time Zone     -> Etc/UTC
#DEBUG: Data Contact   -> daryl herzmann akrherz@iastate.edu 515-294-5978
#DEBUG: Entries Found -> -1
station,valid, sped
DEN,2016-01-01 00:53,6.9
DEN,2016-01-01 01:53,10.4
DEN,2016-01-01 02:53,12.7
DEN,2016-01-01 03:53,10.4
DEN,2016-01-01 04:53,8.1
DEN,2016-01-01 05:53,10.4
DEN,2016-01-01 06:53,9.2
DEN,2016-01-01 07:53,8.1
DEN,2016-01-01 08:53,6.9
DEN,2016-01-01 09:53,11.5
DEN,2016-01-01 10:53,11.5
DEN,2016-01-01 11:53,5.8
DEN,2016-01-01 12:53,6.9
DEN,2016-01-01 13:53,9.2
```

https://mesonet.agron.iastate.edu/cgi-bin/request/asos.py?station=DEN&data=sknt&year1=2016&month1=6&day1=1&year2=2016&month2=6&day2=30&tz=America%2FDenver&format=comma&latlon=no&direct=no&report_type=1&report_type=2

Using `httr` to get data from a webpage

When you are making an HTTP request using the `GET` or `POST` functions from the `httr` package, you can include the key-value pairs for any query parameters as a list object in the `query` argurment of the function.

```
library(httr)
meso_url <- paste0("https://mesonet.agron.iastate.edu/",
                   "cgi-bin/request/asos.py/")
denver <- GET(url = meso_url,
              query = list(station = "DEN", data = "sped",
                           year1 = "2016", month1 = "6",
                           day1 = "1", year2 = "2016",
                           month2 = "6", day2 = "30",
                           tz = "America/Denver",
                           format = "comma"))
```

Using `httr` to get data from a webpage

The `GET` call will return a special type of list object with elements that include the url you queried and the content of the page at that url:

```
str(denver, max.level = 1, list.len = 6)
```

```
## List of 10
##  $ url        : chr "https://mesonet.agron.iastate.edu/cgi-bi
##  $ status_code: int 200
##  $ headers    :List of 6
##   ..- attr(*, "class")= chr [1:2] "insensitive" "list"
##  $ all_headers:List of 1
##  $ cookies    :'data.frame': 0 obs. of  7 variables:
##  $ content    : raw [1:230654] 23 44 45 42 ...
##   [list output truncated]
##  - attr(*, "class")= chr "response"
```

Using `httr` to get data from a webpage

The `httr` package includes functions to pull out elements of this list object, including:

- `headers`: Pull out the header information
- `content`: Pull out the content returned from the page
- `status_code`: Pull out the status code from the `GET` request (e.g., 200: okay; 404: not found)

Note: For some fun examples of 404 pages, see https://www.creativebloq.com/web-design/best-404-pages-812505

Using `httr` to get data from a webpage

You can use `content` from `httr` to retrieve the contents of the HTTP request we made. For this particular web data, the requested data is a comma-separated file, so you can convert it to a dataframe with `read_csv`:

```
denver %>% content() %>%
  read_csv(skip = 5, na = "M") %>%
  slice(1:3)
```

```
## # A tibble: 3 x 3
##   station valid                sped
##   <chr>   <dttm>              <dbl>
## 1 DEN     2016-06-01 01:00:00   6.9
## 2 DEN     2016-06-01 01:05:00   6.9
## 3 DEN     2016-06-01 01:10:00   6.9
```

Example– riem package

The `riem` package wraps up this whole process, so you can call a single function to get in the data you want from the API:

```
library(riem)
denver_2 <- riem_measures(station = "DEN",
                          date_start = "2016-06-01",
                          date_end = "2016-06-30")
denver_2 %>% slice(1:3)
```

```
## # A tibble: 3 x 24
##   station valid                 lon   lat  tmpf  dwpf  relh  drct  sknt
##   <chr>   <dttm>              <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 DEN     2016-06-01 00:00:00 -105.  39.8    NA    NA    NA    70     7
## 2 DEN     2016-06-01 00:05:00 -105.  39.8    NA    NA    NA    80     8
## 3 DEN     2016-06-01 00:10:00 -105.  39.8    NA    NA    NA    80     9
## # ... with 15 more variables: p01i <dbl>, alti <dbl>, mslp <dbl>,
## #   vsby <dbl>, gust <dbl>, skyc1 <chr>, skyc2 <chr>, skyc3 <chr>,
## #   skyc4 <chr>, skyl1 <dbl>, skyl2 <dbl>, skyl3 <dbl>, skyl4 <dbl>,
## #   wxcodes <chr>, metar <chr>
```

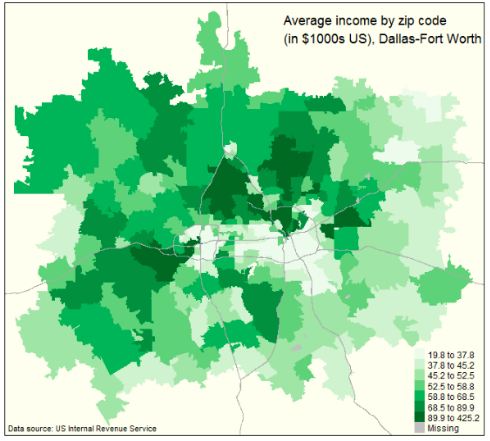
Example R API wrappers

`tigris` package

- Location boundaries
  - States
  - Counties
  - Blocks
  - Tracks
  - School districts
  - Congressional districts
- Roads
  - Primary roads
  - Primary and secondary roads
- Water
  - Area-water
  - Linear-water
  - Coastline
- Other
  - Landmarks
  - Military

tigris package

Example from: Kyle Walker. 2016. "tigris: An R Package to Access and Work with Geographic Data from the US Census Bureau". The R Journal.



US Census packages

A number of other R packages also help you access and use data from the U.S. Census:

- `acs`: Download, manipulate, and present American Community Survey and Decennial data from the US Census (see "Working with the American Community Survey in R: A Guide to Using the acs Package", a book available free online through the CSU library)
- `USABoundaries`: Historical and contemporary boundaries of the United States of America
- `idbr`: R interface to the US Census Bureau International Data Base API (e.g., populations of other countries)

rOpenSci

rOpenSci (https://ropensci.org):

> *"At rOpenSci we are creating packages that allow access to data repositories through the R statistical programming environment that is already a familiar part of the workflow of many scientists. Our tools not only facilitate drawing data into an environment where it can readily be manipulated, but also one in which those analyses and methods can be easily shared, replicated, and extended by other researchers."*

rOpenSci

rOpenSci collects a number of packages for tapping into open data for research: https://ropensci.org/packages

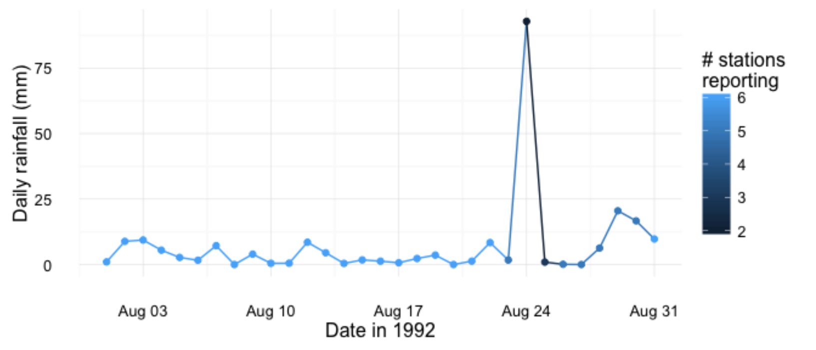
Some examples (all descriptions from rOpenSci):

- `AntWeb`: Access data from the world's largest ant database
- `chromer`: Interact with the chromosome counts database (CCDB)
- `gender`: Encodes gender based on names and dates of birth
- `musemeta`: R Client for Scraping Museum Metadata, including The Metropolitan Museum of Art, the Canadian Science & Technology Museum Corporation, the National Gallery of Art, and the Getty Museum, and more to come.
- `rusda`: Interface to some USDA databases
- `webchem`: Retrieve chemical information from many sources. Currently includes: Chemical Identifier Resolver, ChemSpider, PubChem, and Chemical Translation Service.

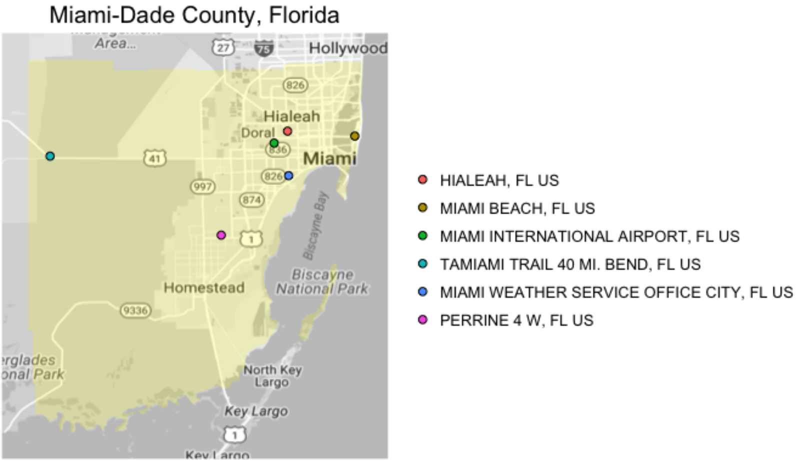
"Access climate data from NOAA, including temperature and precipitation, as well as sea ice cover data, and extreme weather events"

- Buoy data from the National Buoy Data Center
- Historical Observing Metadata Repository (HOMR))— climate station metadata
- National Climatic Data Center weather station data
- Sea ice data
- International Best Track Archive for Climate Stewardship (IBTrACS)— tropical cyclone tracking data
- Severe Weather Data Inventory (SWDI)

The `countyweather` package wraps the `rnoaa` package to let you pull and aggregate weather at the county level in the U.S. For example, you can pull all data from Miami during Hurricane Andrew:



When you pull the data for a county, the package also maps the contributing weather stations:



USGS-R Packages

USGS has a very nice collection of R packages that wrap USGS open data APIs: https://owi.usgs.gov/R/

> *"USGS-R is a community of support for users of the R scientific programming language. USGS-R resources include R training materials, R tools for the retrieval and analysis of USGS data, and support for a growing group of USGS-R developers."*

USGS R Packages

USGS R packages include:

- `dataRetrieval`: Obtain water quality sample data, streamflow data, and metadata directly from either the USGS or EPA
- `EGRET`: Analysis of long-term changes in water quality and streamflow, including the water-quality method Weighted Regressions on Time, Discharge, and Season (WRTDS)
- `laketemps`: Lake temperature data package for Global Lake Temperature Collaboration Project
- `lakeattributes`: Common useful lake attribute data
- `soilmoisturetools`: Tools for soil moisture data retrieval and visualization

Other R API wrappers

Here are some examples of other R packages that faciliate use of an API for open data:

- `twitteR`: Twitter
- `Quandl`: Quandl (financial data)
- `RGoogleAnalytics`: Google Analytics
- `WDI`, `wbstats`: World Bank
- `GuardianR`, `rdian`: The Guardian Media Group
- `blsAPI`: Bureau of Labor Statistics
- `rtimes`: New York Times

R and APIs

Find out more about writing API packages with this vignette for the httr package: https://cran.r-project.org/web/packages/httr/vignettes/api-packages.html.

This document includes advice on error handling within R code that accesses data through an open API.

In-course exercise

We'll take a break now to do the first part of the In-Course Exercise.

Cleaning very messy data

Hurricane tracking data

One version of Atlantic basin hurricane tracks is available here:
https://www.nhc.noaa.gov/data/hurdat/hurdat2-1851-2017-050118.txt.
The data is not in a classic delimited format:

```
AL011851,            UNNAMED,     14,
18510625, 0000,  , HU, 28.0N,  94.8W,  80, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510625, 0600,  , HU, 28.0N,  95.4W,  80, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510625, 1200,  , HU, 28.0N,  96.0W,  80, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510625, 1800,  , HU, 28.1N,  96.5W,  80, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510625, 2100, L, HU, 28.2N,  96.8W,  80, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510626, 0000,  , HU, 28.2N,  97.0W,  70, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510626, 0600,  , TS, 28.3N,  97.6W,  60, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510626, 1200,  , TS, 28.4N,  98.3W,  60, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510626, 1800,  , TS, 28.6N,  98.9W,  50, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510627, 0000,  , TS, 29.0N,  99.4W,  50, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510627, 0600,  , TS, 29.5N,  99.8W,  40, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510627, 1200,  , TS, 30.0N, 100.0W,  40, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510627, 1800,  , TS, 30.5N, 100.1W,  40, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510628, 0000,  , TS, 31.0N, 100.2W,  40, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
AL021851,            UNNAMED,      1,
18510705, 1200,  , HU, 22.2N,  97.6W,  80, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
AL031851,            UNNAMED,      1,
18510710, 1200,  , TS, 12.0N,  60.0W,  50, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
AL041851,            UNNAMED,     49,
18510816, 0000,  , TS, 13.4N,  48.0W,  40, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510816, 0600,  , TS, 13.7N,  49.5W,  40, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510816, 1200,  , TS, 14.0N,  51.0W,  50, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510816, 1800,  , TS, 14.4N,  52.8W,  50, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510817, 0000,  , TS, 14.9N,  54.6W,  60, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
18510817, 0600,  , TS, 15.4N,  56.5W,  60, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999, -999,
```

Hurricane tracking data

This data is formatted in the following way:

- Data for many storms are included in one file.
- Data for a storm starts with a shorter line, with values for the storm ID, name, and number of observations for the storm. These values are comma separated.
- Observations for each storm are longer lines. There are multiple observations for each storm, where each observation gives values like the location and maximum winds for the storm at that time.

Hurricane tracking data

Strategy for reading in very messy data:

1. Read in all lines individually.
2. Use regular expressions to split each line into the elements you'd like to use to fill columns.
3. Write functions and / or `map` calls to process lines and use the contents to fill a data frame.
4. Once you have the data in a data frame, do any remaining cleaning to create a data frame that is easy to use to answer research questions.

Hurricane tracking data

Because the data is not nicely formatted, you can't use `read_csv` or similar functions to read it in.

However, the `read_lines` function from `readr` allows you to read a text file in one line at a time. You can then write code and functions to parse the file one line at a time, to turn it into a dataframe you can use.

Note: Base R has `readLines`, which is very similar.

Hurricane tracking data

The `read_lines` function from `readr` will read in lines from a text file directly, without trying to separate into columns. You can use the `n_max` argument to specify the number of lines to read it.

For example, to read in three lines from the hurricane tracking data, you can run:

```
tracks_url <- paste0("http://www.nhc.noaa.gov/data/hurdat/",
                     "hurdat2-1851-2017-050118.txt")
hurr_tracks <- read_lines(tracks_url, n_max = 3)
hurr_tracks
```

```
## [1] "AL011851,            UNNAMED,     14,"
## [2] "18510625, 0000,  , HU, 28.0N,  94.8W,  80, -999, -999, -
## [3] "18510625, 0600,  , HU, 28.0N,  95.4W,  80, -999, -999, -
```

Hurricane tracking data

The data has been read in as a vector, rather than a dataframe:

```
class(hurr_tracks)
```

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

```
length(hurr_tracks)
```

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

```
hurr_tracks[1]
```

```
## [1] "AL011851,            UNNAMED,     14,"
```

Hurricane tracking data

You can use regular expressions to break each line up. For example, you can use `str_split` from the `stringr` package to break the first line of the hurricane track data into its three separate components:

```
library(stringr)
str_split(hurr_tracks[1], pattern = ",")
```

```
## [[1]]
## [1] "AL011851"            "            UNNAMED" "     14"
## [4] ""
```

Hurricane tracking data

You can use this to create a list where each element of the list has the split-up version of a line of the original data. First, read in all of the data:

```
tracks_url <- paste0("http://www.nhc.noaa.gov/data/hurdat/",
                     "hurdat2-1851-2017-050118.txt")
hurr_tracks <- read_lines(tracks_url)
length(hurr_tracks)
```

```
## [1] 52151
```

Hurricane tracking data

Next, use map with str_split to split each line of the data at the commas:

```
library(purrr)
hurr_tracks <- map(hurr_tracks, str_split,
                   pattern = ",", simplify = TRUE)
hurr_tracks[[1]]
```

```
##      [,1]       [,2]                  [,3]      [,4]
## [1,] "AL011851" "            UNNAMED" "     14" ""
```

```
hurr_tracks[[2]][1:2]
```

```
## [1] "18510625" " 0000"
```

Hurricane tracking data

Next, you want to split this list into two lists, one with the shorter "meta-data" lines and one with the longer "observation" lines. You can use `map_int` to create a vector with the length of each line. You will later use this to identify which lines are short or long.

```
hurr_lengths <- map_int(hurr_tracks, length)
hurr_lengths[1:17]
```

```
##  [1]  4 21 21 21 21 21 21 21 21 21 21 21 21 21 21  4 21
```

```
unique(hurr_lengths)
```

```
## [1]  4 21
```

Hurricane tracking data

You can use bracket indexing to split the `hurr_tracks` into two lists: one with the shorter lines that start each observation (`hurr_meta`) and one with the storm observations (`hurr_obs`). Use bracket indexing with the `hurr_lengths` vector you just created to make that split.

```
hurr_meta <- hurr_tracks[hurr_lengths == 4]
hurr_obs <- hurr_tracks[hurr_lengths == 21]
```

Hurricane tracking data

```
hurr_meta[1:3]
```

```
## [[1]]
##      [,1]       [,2]                  [,3]      [,4]
## [1,] "AL011851" "            UNNAMED" "     14" ""
##
## [[2]]
##      [,1]       [,2]                  [,3]      [,4]
## [1,] "AL021851" "            UNNAMED" "      1" ""
##
## [[3]]
##      [,1]       [,2]                  [,3]      [,4]
## [1,] "AL031851" "            UNNAMED" "      1" ""
```

Hurricane tracking data

```r
hurr_obs[1:2]
```

```
## [[1]]
##      [,1]       [,2]    [,3] [,4]  [,5]     [,6]       [,7]
## [1,] "18510625" " 0000" "  " " HU" " 28.0N" "  94.8W" "  80"
##      [,9]    [,10]   [,11]   [,12]   [,13]   [,14]   [,15]
## [1,] " -999" " -999" " -999" " -999" " -999" " -999" " -999"
##      [,17]   [,18]   [,19]   [,20]   [,21]
## [1,] " -999" " -999" " -999" " -999" ""
##
## [[2]]
##      [,1]       [,2]    [,3] [,4]  [,5]     [,6]       [,7]
## [1,] "18510625" " 0600" "  " " HU" " 28.0N" "  95.4W" "  80"
##      [,9]    [,10]   [,11]   [,12]   [,13]   [,14]   [,15]
## [1,] " -999" " -999" " -999" " -999" " -999" " -999" " -999"
##      [,17]   [,18]   [,19]   [,20]   [,21]
## [1,] " -999" " -999" " -999" " -999" ""
```

Hurricane tracking data

Now, you can use `bind_rows` from `dplyr` to change the list of metadata into a dataframe. (You first need to use `as_tibble` with `map` to convert all elements of the list from matrices to dataframes.)

```
library(dplyr); library(tibble)
hurr_meta <- hurr_meta %>%
  map(as_tibble) %>%
  bind_rows()
hurr_meta %>% slice(1:3)
```

```
## # A tibble: 3 x 4
##   V1       V2                          V3         V4
##   <chr>    <chr>                       <chr>      <chr>
## 1 AL011851 "            UNNAMED" "     14" ""
## 2 AL021851 "            UNNAMED" "      1" ""
## 3 AL031851 "            UNNAMED" "      1" ""
```

Hurricane tracking data

You can clean up the data a bit more.

- First, the fourth column doesn't have any non-missing values, so you can get rid of it:

```
unique(hurr_meta$V4)
```

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

- Second, the second and third columns include a lot of leading whitespace:

```
hurr_meta$V2[1:2]
```

```
## [1] "                 UNNAMED" "                 UNNAMED"
```

- Last, we want to name the columns.

Hurricane tracking data

```r
hurr_meta <- hurr_meta %>%
  select(-V4) %>%
  rename(storm_id = V1, storm_name = V2, n_obs = V3) %>%
  mutate(storm_name = str_trim(storm_name),
         n_obs = as.numeric(n_obs))
hurr_meta %>% slice(1:3)
```

```
## # A tibble: 3 x 3
##   storm_id storm_name n_obs
##   <chr>    <chr>      <dbl>
## 1 AL011851 UNNAMED       14
## 2 AL021851 UNNAMED        1
## 3 AL031851 UNNAMED        1
```

Hurricane tracking data

Now you can do the same idea with the hurricane observations. First, we'll want to add storm identifiers to that data. The "meta" data includes storm ids and the number of observations per storm. We can take advantage of that to make a `storm_id` vector that will line up with the storm observations.

```
storm_id <- rep(hurr_meta$storm_id, times = hurr_meta$n_obs)
head(storm_id, 3)
```

```
## [1] "AL011851" "AL011851" "AL011851"
```

```
length(storm_id)
```

```
## [1] 50303
```

```
length(hurr_obs)
```

```
## [1] 50303
```

Hurricane tracking data

```
hurr_obs <- hurr_obs %>%
  map(as_tibble) %>%
  bind_rows() %>%
  mutate(storm_id = storm_id)
hurr_obs %>% select(V1:V2, V5:V6, storm_id) %>% slice(1:3)
```

```
## # A tibble: 3 x 5
##   V1       V2      V5       V6         storm_id
##   <chr>    <chr>   <chr>    <chr>      <chr>
## 1 18510625 " 0000" " 28.0N" "  94.8W" AL011851
## 2 18510625 " 0600" " 28.0N" "  95.4W" AL011851
## 3 18510625 " 1200" " 28.0N" "  96.0W" AL011851
```

In-course exercise

We'll take a break now to do the next part of the In-Course Exercise.

Setting up for Homework #5

Get together with your group for Homework #5, and you will be setting up your GitHub repository to use for that project:

1. Select one person in your group to "host" the repository.
2. You may use that person's Homework 4 repository (just create new documents for Homework 5), or you may create a new repository just for Homework 5. If you create a new repository, go through all the steps we took for Homework 4 to create a local R Project, put it under git version control, and connect it to a remote GitHub repository. This only needs to be done for the person "hosting" the repository.
3. Once one person in your group has the GitHub repository you'll all use, that person should go to GitHub and make the other group members collaborators. Within the GitHub repository, go to the "Settings" tab and go to "Collaborators". You should be able to find and add other GitHub members. Once you do, your other group members should get email invitations.

(More on next slide)

Setting up for Homework #5

4. For the other group members, accept your email invitation to collaborate on the repository. Now you can "clone" this repository to your own computer, to have a local version to work on. Open a command line, use `cd` to change into the directory where you'd like to save the R project, and then use:

```
git clone git@github.com:geanders/ex_repo.git
```

But replace `geanders` with the GitHub handle for your group member who is hosting the account and `ex_repo` with the repository name for your GitHub repository for the project.

Setting up for Homework #5

5. Now have one of your group members create an RMarkdown document to use for your homework write-up. That person should create that document on their local version of the repository, save their changes, commit them, and then push them to GitHub. Check online to make sure it went through. Everyone else in the group should then “pull” (use the down arrow in your “Git” box in RStudio) to pull that change to their local version of the repository.
6. Now explore resolving commit conflicts. Have two members of your group open the RMarkdown document and change the “author” input in the YAML of the document to include their own name. They both should save and commit this change locally. Have one of the two push the change to GitHub. The second person should then pull the latest version of the repo from GitHub. There will be commit conflicts (you’ll see a filled box for the file in the GitHub page). Open that file and look for the section that starts with “<<<<”. Look at the two versions given for that part of the document, decide what you want as the final version, clean up the “<<<”, “===”, and “>>>” lines, and then commit and push the changes.

Setting up for Homework #5

7. Talk with your group members about how you'd like to share the work for the homework. Go to the "Issues" page for the GitHub repository and create some Issues for the tasks your group will need to do. Try using the `@` notation to reference other people in your group in the message (e.g., `@geanders` would reference me and send me an email about the Issue message).
8. Create one practice Issue that's something like "Test closing an issue with commit". Then have one group member make some change on their local version of the project, commit that change with the message "Close #[x]", where [x] is the number of the test Issue you opened, and then push the changes. Go online to GitHub and you should see that that Issue is now "Closed".

Working with network data

Network data

Networks are made up of **nodes** and **edges**. We'll start with a very simple example: a network of the groups for an in-course exercise.

For this network, the students in the class will be the nodes. The edges of this network will be the connections of students working together. I ran our group assignments one and used the results to set up a dataframe with these edges.

Network data

For each row, it has columns for "from" and "to". Since this network is *undirected*, it doesn't matter what order the students are included in these two columns. I've also added a column for "group" to say which group the students were in.

```
## # A tibble: 5 x 3
##   from   to     group
##   <chr>  <chr>  <dbl>
## 1 Amy    Camron     1
## 2 Amy    Ana        1
## 3 Camron Ana        1
## 4 Kayla  Katy       2
## 5 Grant  Amanda     3
```

Network data

The new `tidygraph` package allows you to work easy with network data in a tidyverse framework. As an engine, it uses much of the functionality from a very powerful package for network data called `igraph`.

You can use the `as_tbl_graph` function to create an R object that can be used for pipelines based on `tidygraph`.

```
library(tidygraph)
groups_network <- as_tbl_graph(class_groups_1,
                                directed = FALSE)
class(groups_network)
```

```
## [1] "tbl_graph" "igraph"
```

Network data

This object includes slots for both nodes and edges for the network data. It might not initially look like a “tidy” dataframe, but in fact it combines two separate tidy dataframes (for edges and nodes), and it allows you to create pipelines to work with either or both similarly to classic tidyverse manipulations.

Network data

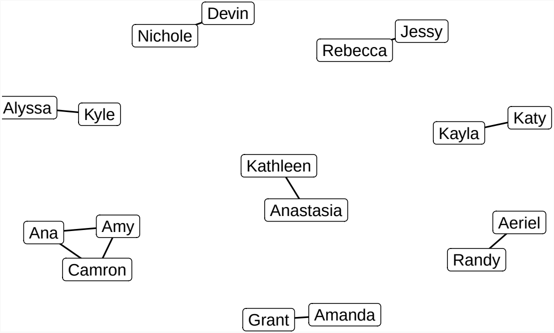
```r
groups_network %>%
  slice(1:3)
```

```
## # A tbl_graph: 3 nodes and 1 edges
## #
## # An undirected simple graph with 2 components
## #
## # Node Data: 3 x 1 (active)
##   name
##   <chr>
## 1 Amy
## 2 Camron
## 3 Kayla
## #
## # Edge Data: 1 x 3
##    from    to group
##   <int> <int> <dbl>
## 1     1     2     1
```

Network data

To plot the data, you can use the `ggraph` package, which behaves similarly to `ggplot2` for classical tidy data.

```
library(ggraph)
groups_network %>%
  ggraph() +
  geom_edge_link() +
  geom_node_label(aes(label = name)) +
  theme_graph()
```



Network data

You can use `dplyr` and other tidyverse functions to work with the `data`, just as you would with a tidy dataframe. You just need to "activate" either the edges or nodes, depending on which dataset you want to work with.

Network data

For example, say you want to have one column that specifies whether each person's name starts with A / K versus something else. You can add that column to the "nodes" part of the network data:

```
groups_network <- groups_network %>%
  activate(nodes) %>%
  mutate(a_or_k = str_sub(name, 1, 1) %in% c("A", "K"))
```

Network data

Here's is what the resulting data looks like:

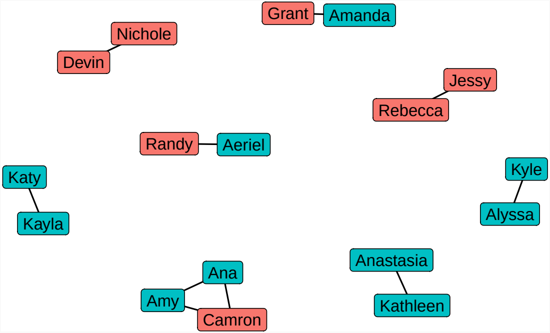
```
groups_network %>% slice(1:2)
```

```
## # A tbl_graph: 2 nodes and 1 edges
## #
## # An undirected simple graph with 1 component
## #
## # Node Data: 2 x 2 (active)
##   name   a_or_k
##   <chr>  <lgl>
## 1 Amy    TRUE
## 2 Camron FALSE
## #
## # Edge Data: 1 x 3
##    from    to group
##   <int> <int> <dbl>
## 1     1     2     1
```

Network data

You can use attributes of the "nodes" data when plotting, just like you can with regular plotting with ggplot2.

```
groups_network %>%
  ggraph() +
  geom_edge_link() +
  geom_node_label(aes(label = name, fill = a_or_k),
                  show.legend = FALSE) +
  theme_graph()
```



Network data

You can also manipulate one part of the network data (e.g., edges) while referencing the other part (e.g., nodes). For example, say you want to include, for each edge, whether it's a edge connecting two people who both have A / K names:

```
groups_network <- groups_network %>%
  activate(edges) %>%
  mutate(both_ak = .N()$a_or_k[from] == TRUE &
           .N()$a_or_k[to] == TRUE)
```

Notice that this code uses `.N()` to reference data in the "nodes" section while the "edges" are activated for the manipulation.

Network data

Here is what the resulting data looks like:

```r
groups_network %>% slice(1:2)
```

```
## # A tbl_graph: 17 nodes and 2 edges
## #
## # An undirected simple graph with 15 components
## #
## # Edge Data: 2 x 4 (active)
##    from    to group both_ak
##   <int> <int> <dbl> <lgl>
## 1     1     2     1 FALSE
## 2     1    10     1 TRUE
## #
## # Node Data: 17 x 2
##   name   a_or_k
##   <chr>  <lgl>
## 1 Amy    TRUE
## 2 Camron FALSE
## 3 Kayla  TRUE
## # ... with 14 more rows
```

Network data

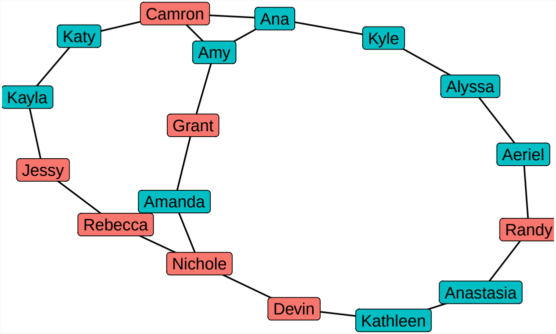
Now say I want to add in the group assignments for the next week, so we can start to see who's working together across the two class periods. I've generated another tidygraph object called `groups_network_2` that is very similar to the existing object, but with the second week's group assignments.

You can use the `graph_join` function to join these two network data objects together:

```
groups_network <- groups_network %>%
  graph_join(groups_network_2)
```

Network data

```
groups_network %>%
  ggraph() +
  geom_edge_link() +
  geom_node_label(aes(label = name, fill = a_or_k),
                  show.legend = FALSE) +
  theme_graph()
```



Network data

You can also use the network framework to explore connections in data, including different ways that the data is correlated.

To show this, I've pulled the NOAA Storm Events data for 2017. Difference events are collected in storm "episodes", and by using `include_ids`, I'll include the episode ID for each event.

```
library(noaastormevents)
events_2017 <- find_events(date_range = c("2017-01-01",
                                          "2017-12-31"),
                           include_ids = TRUE)
```

Storm events—Event types by episode

You can see that we have repeated episode IDs across some different events:

```
events_2017 %>%
  select(episode_id, event_type) %>%
  slice(1:8)
```

```
## # A tibble: 8 x 2
##   episode_id event_type
##        <int> <chr>
## 1     112776 Thunderstorm Wind
## 2     111732 Thunderstorm Wind
## 3     111732 Thunderstorm Wind
## 4     111732 Thunderstorm Wind
## 5     111731 Thunderstorm Wind
## 6     111732 Thunderstorm Wind
## 7     113022 Flash Flood
## 8     111731 Thunderstorm Wind
```

Storm events—Event types by episode

You can get the pairwise correlation between words using the `pairwise_cor` function from the `widyr` package. (For **much** more on this, see the wonderful "Tidytext" book.)

In this case, this will provide a measure of which event types (`item`) tend to show up together in the same episodes (`feature`).

Storm events—Event types by episode

```r
library(widyr)
event_type_cors <- events_2017 %>%
  pairwise_cor(item = event_type,
               feature = episode_id,
               sort = TRUE)
event_type_cors %>%
  slice(1:5)
```

```
## # A tibble: 5 x 3
##   item1             item2             correlation
##   <chr>             <chr>                   <dbl>
## 1 Tropical Storm    Storm Surge/Tide        0.532
## 2 Storm Surge/Tide  Tropical Storm          0.532
## 3 Hurricane         Storm Surge/Tide        0.481
## 4 Storm Surge/Tide  Hurricane               0.481
## 5 Hurricane         Tropical Storm          0.283
```

Storm events—Event types by episode

Now we can use the `as_tbl_graph` function from `tidygraph` to change this into network data. (We'll first filter the data, so we're only including pairings with higher correlation values.)

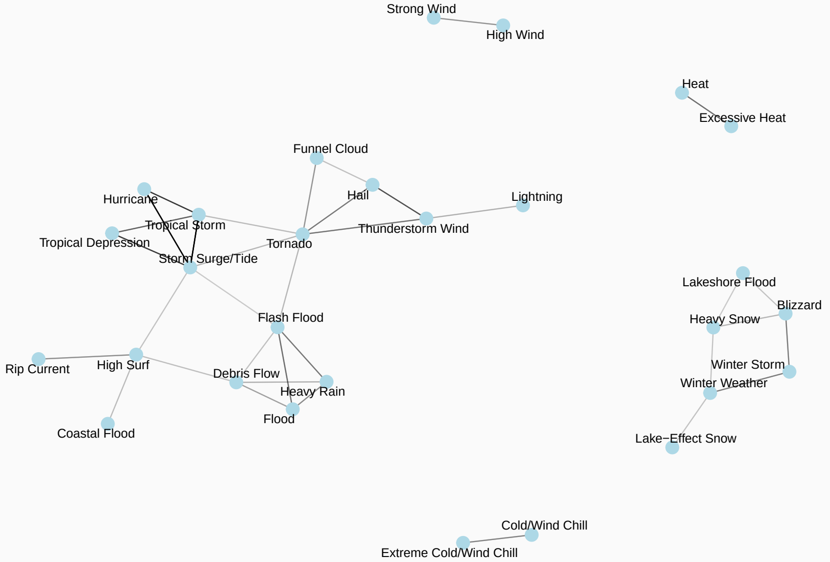
Then we can use `ggraph` to plot this relationships using a network framework.

Storm events—Event types by episode

```r
library(tidygraph)
library(ggraph)
cor_network <- event_type_cors %>%
  filter(correlation > .05) %>%
  as_tbl_graph() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(edge_alpha = correlation),
                 show.legend = FALSE) +
  geom_node_point(color = "lightblue", size = 5) +
  geom_node_text(aes(label = name), repel = TRUE) +
  theme_void()
```

Storm events—Event types by episode

```
cor_network
```



Groups for group project

- **Predicting if mosquitos have West Nile**: Kayla, Camron, Amy, Alyssa
- **Human epi. 1**: Kathleen, Randy, Nichole, Jessy
- **Human epi. 2**: Anastasia, Grant, Devin, Ana
- **’Omics**: Rebecca, Kyle, Aeriel, Amanda

Setting up for the group project

1. Take all the same steps as with Homework #5 to set up a repository for the group.
2. Start looking for datasets you can use. Start some Issues listing ideas you have (either datasets you might want to use or things you might want to include for your project). You can use Markdown notation for Issues, so try using that to include links to interesting datasets or other webpages for your ideas.
3. See if you can find a few academic papers on the topic your team is working on, so you can start to learn a bit about the state of the science in your area.