Reporting data results #2

Example data

Example data

This week, we'll be using some example data from NOAA's Storm Events Database.

Go to https://www1.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/ and download the bulk storm details data for 2017, in the file that starts "StormEvents_details" and includes "d2017".

Move this into a good directory for your current working directory and read it in using `read_csv` from the `readr` package.

Example data

This data lists major weather-related storm events during 2017.

For each event, it includes information like the start and end dates, where it happened, associated deaths, injuries, and property damage, and some other characteristics.

Example data

```r
colnames(storms_2017)
```

```
##  [1] "BEGIN_YEARMONTH"    "BEGIN_DAY"          "BEGIN_TIME"
##  [4] "END_YEARMONTH"      "END_DAY"            "END_TIME"
##  [7] "EPISODE_ID"         "EVENT_ID"           "STATE"
## [10] "STATE_FIPS"         "YEAR"               "MONTH_NAME"
## [13] "EVENT_TYPE"         "CZ_TYPE"            "CZ_FIPS"
## [16] "CZ_NAME"            "WFO"                "BEGIN_DATE_TIME"
## [19] "CZ_TIMEZONE"        "END_DATE_TIME"      "INJURIES_DIRECT"
## [22] "INJURIES_INDIRECT"  "DEATHS_DIRECT"      "DEATHS_INDIRECT"
## [25] "DAMAGE_PROPERTY"    "DAMAGE_CROPS"       "SOURCE"
## [28] "MAGNITUDE"          "MAGNITUDE_TYPE"     "FLOOD_CAUSE"
## [31] "CATEGORY"           "TOR_F_SCALE"        "TOR_LENGTH"
## [34] "TOR_WIDTH"          "TOR_OTHER_WFO"      "TOR_OTHER_CZ_STATE"
## [37] "TOR_OTHER_CZ_FIPS"  "TOR_OTHER_CZ_NAME"  "BEGIN_RANGE"
## [40] "BEGIN_AZIMUTH"      "BEGIN_LOCATION"     "END_RANGE"
## [43] "END_AZIMUTH"        "END_LOCATION"       "BEGIN_LAT"
## [46] "BEGIN_LON"          "END_LAT"            "END_LON"
## [49] "EPISODE_NARRATIVE"  "EVENT_NARRATIVE"    "DATA_SOURCE"
```

Example data

Each row is a separate **event**. However, often several events are grouped together within the same **episode**.

```r
storms_2017 %>% nrow()
```

```
## [1] 56989
```

```r
storms_2017 %>%
  select(EVENT_ID) %>%
  distinct() %>%
  nrow()
```

```
## [1] 56989
```

```r
storms_2017 %>%
  select(EPISODE_ID) %>%
  distinct() %>%
  nrow()
```

```
## [1] 8964
```

Example data

Some of the event types are listed by their county ID (FIPS code) ("C"), but some are listed by a forecast zone ID ("Z"). Which ID is used is given in the column CZ_TYPE:

```
storms_2017 %>%
  group_by(CZ_TYPE) %>%
  count()
```

```
## # A tibble: 3 x 2
## # Groups:   CZ_TYPE [3]
##   CZ_TYPE     n
##   <chr>   <int>
## 1 2          17
## 2 C       36933
## 3 Z       20039
```

Example data

For the first in-course exercise, you will clean up this data a bit for us to use in the rest of the class.

- Download and read in the data
- Limit the dataframe to: the beginning and ending dates and times, the episode ID, the event ID, the state name and FIPS, the "CZ" name, type, and FIPS, the event type, the source, and the begining latitude and longitude and ending latitude and longitude
- Convert the beginning and ending dates to a "date-time" class (there should be one column for the beginning date-time and one for the ending date-time)
- Change state and county names to title case (e.g., "New Jersey" instead of "NEW JERSEY")
- Limit to the events listed by county FIPS (`CZ_TYPE` of "C") and then remove the `CZ_TYPE` column
- Pad the state and county FIPS with a "0" at the beginning (hint: there's a function in `stringr` to do this) and then unite the two columns to make one `fips` column with the 5-digit county FIPS code
- Change all the column names to lower case (you may want to try the `rename_all` function for this)

Example data

```r
storms_2017 %>%
  slice(1:3)
```

```
## # A tibble: 3 x 13
##   begin_date_time     end_date_time       episode_id event_id state fips
##   <dttm>              <dttm>                   <dbl>    <dbl> <chr> <chr>
## 1 2017-04-06 15:09:00 2017-04-06 15:09:00     113355   678791 New ~ 34015
## 2 2017-04-06 09:30:00 2017-04-06 09:40:00     113459   679228 Flor~ 12071
## 3 2017-04-05 17:49:00 2017-04-05 17:53:00     113448   679268 Ohio  39057
## # ... with 7 more variables: event_type <chr>, cz_name <chr>, source <chr>,
## #   begin_lat <dbl>, begin_lon <dbl>, end_lat <dbl>, end_lon <dbl>
```

State data

There is data that comes with R on U.S. states. Use that to create a dataframe with the state name, area, and region:

```
data("state")
us_state_info <- tibble(state = state.name,
                        area = state.area,
                        region = state.region)
```

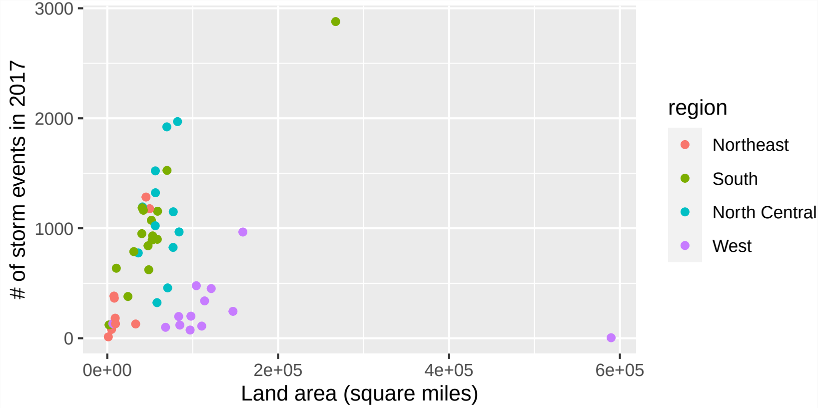
Example data

Create a dataframe with the number of events per state in 2017. Merge in the state information dataframe you just created. Remove any states that are not in the state information dataframe.

```
state_storms <- storms_2017 %>%
  group_by(state) %>%
  count() %>%
  ungroup() %>%
  right_join(us_state_info, by = "state")
```

Example data

Ultimately, in this group exercise, you will create a plot of state land area versus the number of storm events in the state:



In-course exercise

We'll now take a break to do the first part of the in-course exercise.

`ggplot2` extras and extensions

`ggplot2` extensions

The `ggplot2` framework is set up so that others can create packages that "extend" the system, creating functions that can be added on as layers to a ggplot object.

Some of the types of extensions available include:

- More themes
- Useful additions (things that you may be able to do without the package, but that the package makes easier)
- Tools for plotting different types of data

Where to find `ggplot2` extensions

There is a gallery with links to `ggplot2` extensions at
https://exts.ggplot2.tidyverse.org/gallery/.

This list may not be exhaustive—there may be other extensions on CRAN or on GitHub that the package maintainer did not submit for this gallery.

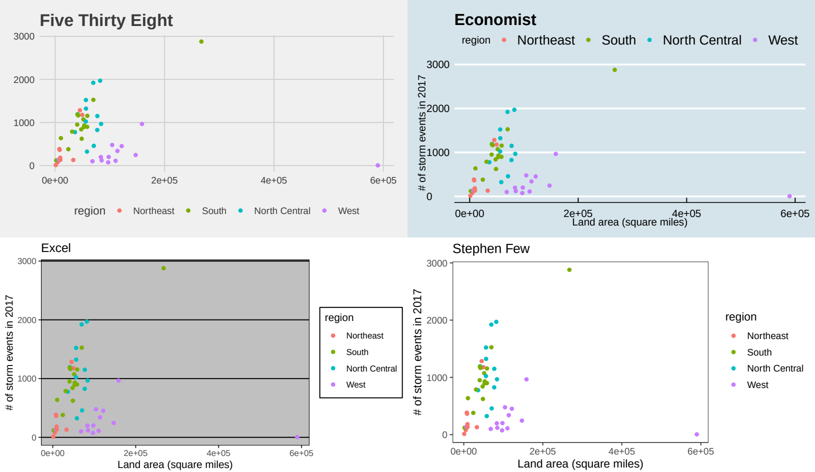
`ggplot2` extensions: Themes

You have already played around a lot with using `ggplot` themes to change how your graphs look.

Several people have created packages with additional themes:

- `ggthemes`
- `ggthemr`
- `ggtech`
- `ggsci`

Some ggthemes themes



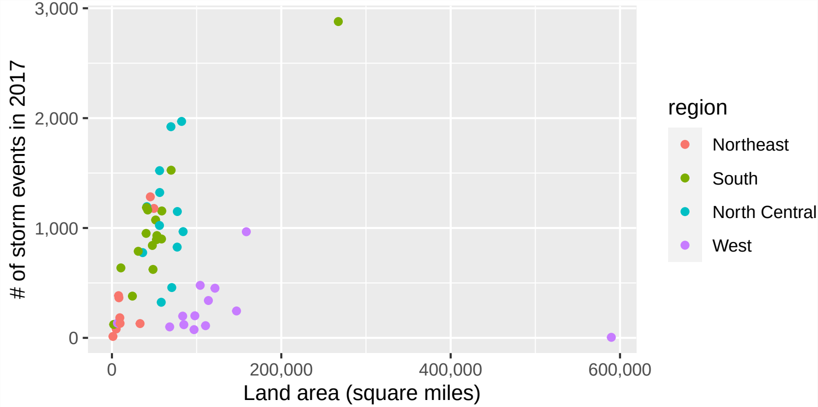
`scales` package

The `scales` package gives you a few more options for labeling with your `ggplot` scales. For example, if you wanted to change the notation for the axes in the plot of state area versus number of storm events, you could use the `scales` package to add commas to the numeric axis values.

For the rest of these slides, I've saved the `ggplot` object with out plot to the object named `storm_plot`, so we don't have to repeat that code every time.

scales package

```r
library(scales)
storm_plot +
  scale_x_continuous(labels = comma) +
  scale_y_continuous(labels = comma)
```



`scales` package

The `scales` package also includes labeling functions for:

- dollars (`labels = dollar`)
- percent (`labels = percent`)

`viridis` package

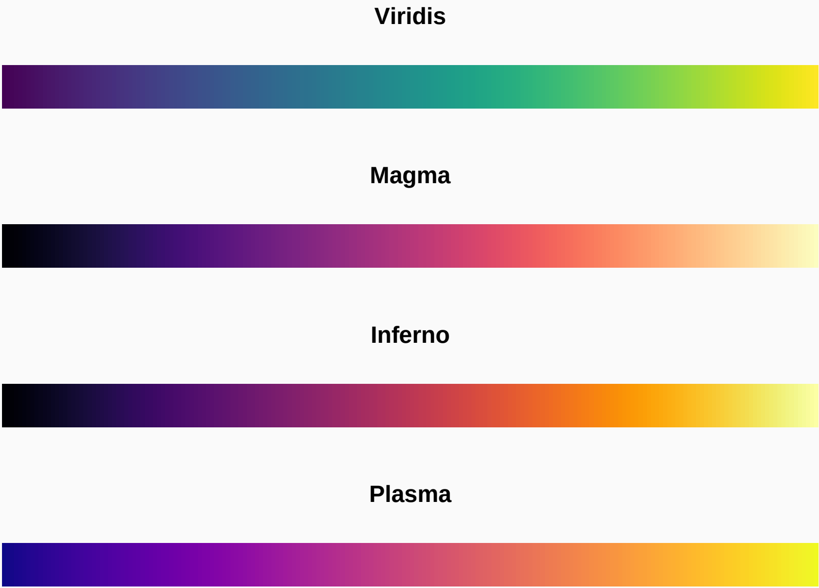
The `viridis` package can be used to change to a better color scale (see https://www.youtube.com/watch?v=xAoljeRJ3lU&feature=youtu.be for more on this color scale).

From the `viridis` helpfile:

> *"This color map is designed in such a way that it will analytically be perfectly perceptually-uniform, both in regular form and also when converted to black-and-white. It is also designed to be perceived by readers with the most common form of color blindness."*

Also see the `viridis` package introduction vignette: https://cran.r-project.org/web/packages/viridis/vignettes/intro-to-viridis.html

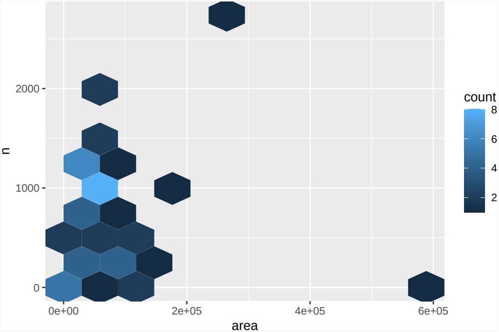
viridis package



viridis package

For example, here is a hexagonal heatmap showing the two-dimensional distribution of state land area versus number of reported storm events:

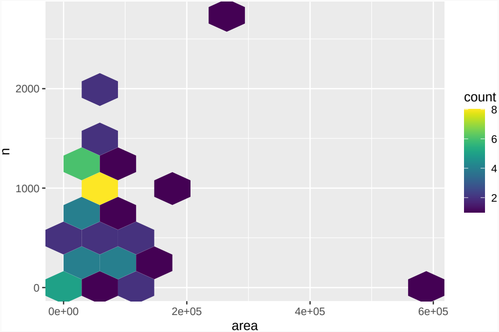
```
state_storms %>%
  ggplot(aes(x = area, y = n)) +
  geom_hex(bins = 10)
```



viridis package

Change to a viridis color scale with `scale_fill_viridis`:

```
library(viridis)
state_storms %>%
  ggplot(aes(x = area, y = n)) +
  geom_hex(bins = 10) +
  scale_fill_viridis()
```



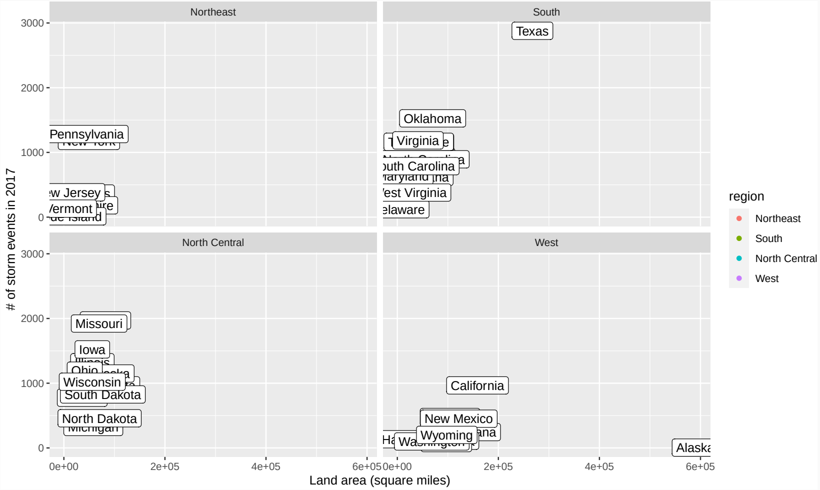
`ggplot2` extensions: Useful additions

- Highlighting interesting points
- “Repelling” text labels
- Arranging plots

ggplot2 extensions: repelling text labels

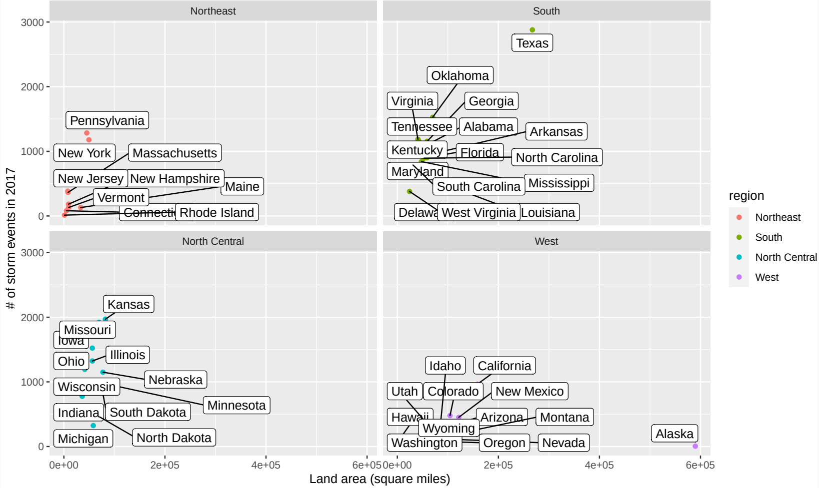
When you add labels to points on a plot, they often overlap:

```r
storm_plot + facet_wrap(~ region) +
  geom_label(aes(label = state))
```



ggplot2 extensions: repelling text labels

```r
library(ggrepel)
storm_plot + facet_wrap(~ region) +
  geom_label_repel(aes(label = state))
```

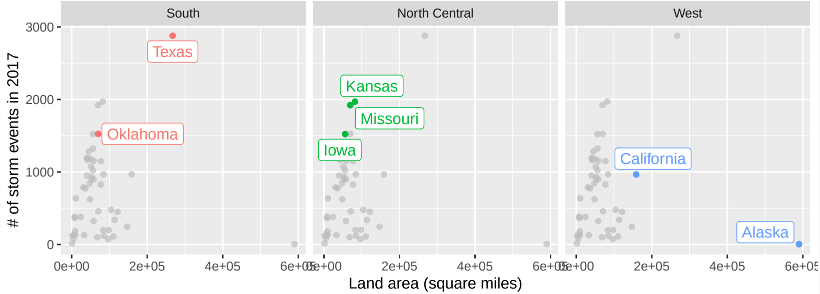


gghighlight package

It may be too much to label every point. Instead, you may just want to highlight notable point.

You can use the gghighlight package to do that.

```r
library(gghighlight)
storm_plot + facet_wrap(~ region) +
  gghighlight(area > 150000 | n > 1500, label_key = state)
```



ggplot2 extensions: Arranging plots

You may have multiple related plots you want to have as multiple panels of a single figure.

There are a few packages that help with this. One very good one is `patchwork`.

You need to install this from GitHub:

```
devtools::install_github("thomasp85/patchwork")
```

Find out more: https://github.com/thomasp85/patchwork#patchwork

Say we want to plot seasonal patterns in events in the five counties with the highest number of events in 2017. We can use dplyr to figure out these counties:

```
top_counties <- storms_2017 %>%
  group_by(fips, state, cz_name) %>%
  count() %>%
  ungroup() %>%
  top_n(5, wt = n)
```

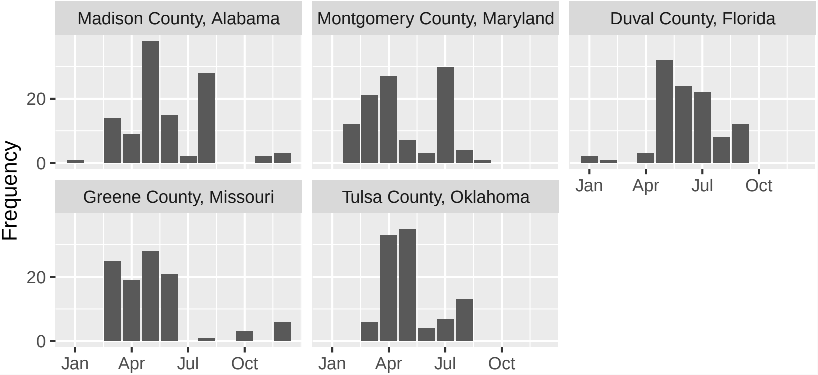
ggplot2 extensions: Arranging plots

Then create a plot with the time patterns:

```
library(forcats)
top_counties_month <- storms_2017 %>%
  semi_join(top_counties, by = "fips") %>%
  mutate(month = month(begin_date_time),
         county = paste(cz_name, " County, ", state, sep = "")) %>%
  count(county, month) %>%
  ggplot(aes(x = month, y = n)) +
  geom_bar(stat = "identity") +
  facet_wrap(~ fct_reorder(county, n, .fun = sum, .desc = TRUE), nrow = 2) +
  scale_x_continuous(name = "", breaks = c(1, 4, 7, 10),
                     labels = c("Jan", "Apr", "Jul", "Oct")) +
  scale_y_continuous(name = "Frequency", breaks = c(0, 20))
```

Here's this plot:

```
top_counties_month
```

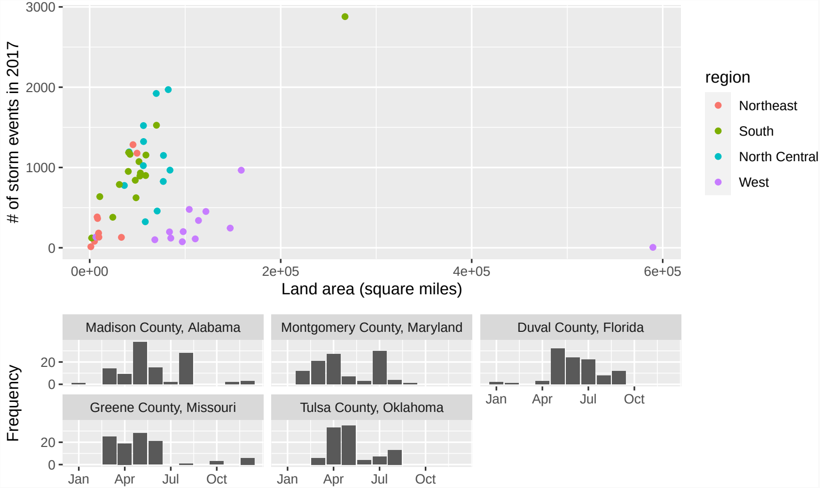


ggplot2 extensions: Arranging plots

Now that you have two ggplot objects (storm_plot and top_counties_month), you can use patchwork to put them together:

```
library(patchwork)
storm_plot +
  top_counties_month +
  plot_layout(ncol = 1, heights = c(2, 1))
```

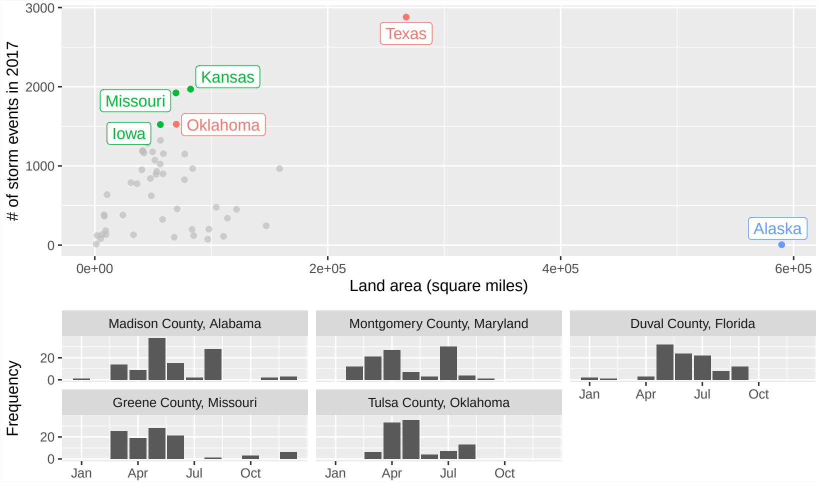
ggplot2 extensions: Arranging plots



A slightly fancier version:

```
(storm_plot + theme(legend.position = "top") +
    gghighlight(n > 1500 | area > 200000,
                label_key = state)) +
  top_counties_month +
  plot_layout(ncol = 1, heights = c(2, 1))
```

ggplot2 extensions: Arranging plots



`ggplot2` extensions: Arranging plots

Other packages for arranging `ggplot` objects:

- `gridExtra`
- `cowplot`

In-course exercise

We'll take a break now to do the second part of the in-course exercise.

Heat maps

Heat maps are helpful for exploring the measurements for many variables, including how similar they are, by showing small boxes of color.

In `ggplot2`, there is a `geom_tile` that is useful for creating heatmaps.

Heat maps

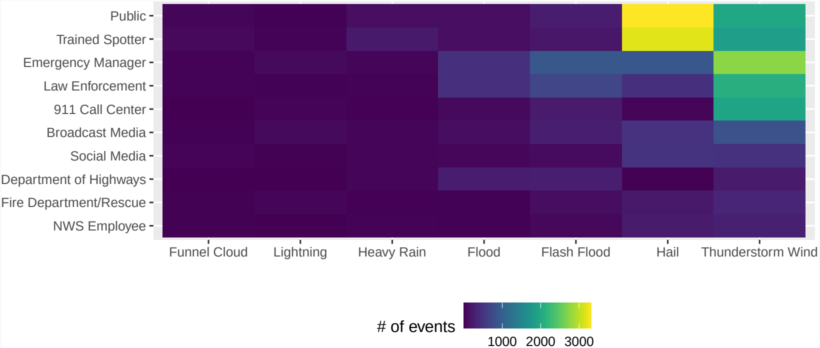
For example, we might want to look at how many events of each type were reported by each type of source. First, we can summarize the data to get this data:

```
type_by_source <- storms_2017 %>%
  filter(event_type %in% c("Thunderstorm Wind", "Heavy Rain",
                           "Funnel Cloud", "Flash Flood",
                           "Flood", "Hail", "Lightning")) %>%
  filter(source %in% c("911 Call Center", "Broadcast Media",
                       "Department of Highways",
                       "Emergency Manager", "Fire Department/Rescue",
                       "Law Enforcement", "NWS Employee", "Public",
                       "Social Media", "Trained Spotter")) %>%
  group_by(event_type, source) %>% count() %>% ungroup()
type_by_source %>% slice(1:3)
```

```
## # A tibble: 3 x 3
##   event_type  source                     n
##   <chr>       <chr>                  <int>
## 1 Flash Flood 911 Call Center          238
## 2 Flash Flood Broadcast Media          268
## 3 Flash Flood Department of Highways   276
```

Heat maps

```
library(viridis); library(forcats)
ggplot(type_by_source,
       aes(x = fct_reorder(event_type, n, .fun = sum),
           y = fct_reorder(source, n, .fun =  sum))) +
  geom_tile(aes(fill = n)) +
  scale_fill_viridis() +
  labs(x = "", y = "", fill = "# of events") +
  theme(legend.position = "bottom")
```

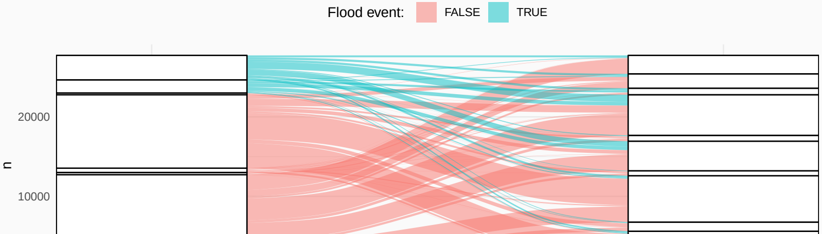


Alluvial plots

The package `ggalluvial` allows you to make **alluvial plots**.

```
library(ggalluvial)
ggplot(data = type_by_source,
       aes(axis1 = event_type, axis2 = source, y = n)) +
  scale_x_discrete(limits = c("Type", "Source"), expand = c(.1, .05)) +
  geom_alluvium(aes(fill = event_type %in% c("Flash Flood", "Flood"))) +
  theme_minimal() + geom_stratum() +
  geom_text(stat = "stratum", label.strata = TRUE) +
  theme(legend.position = "top") + labs(fill = "Flood event: ")
```

```
## Warning: Computation failed in `stat_stratum()`:
## The parameter `label.strata` is defunct.
## use `aes(label = after_stat(stratum))`.
```



`ggridges` package

The `ggridges` package lets you plot the distribution of several levels of a factor across another variable.

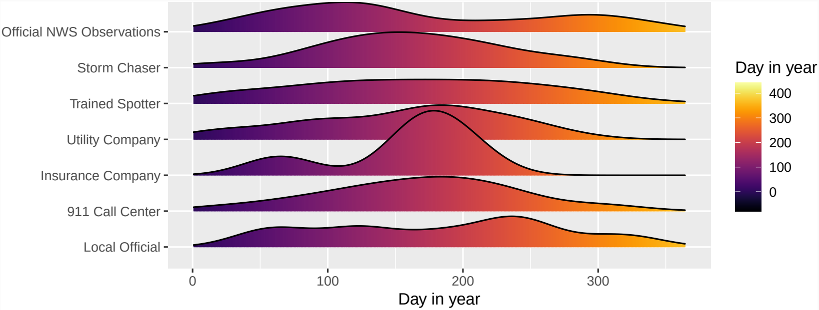
ggridges package

Create a dataframe with the timing versus the source of the storm:

```
library(ggridges)
library(forcats)
storms_by_yday <- storms_2017 %>%
  filter(source %in% c("River/Stream Gages", "Insurance Company",
                       "Airline Pilot", "Trained Spotter",
                       "Storm Chaser", "Local Official",
                       "Official NWS Observations", "Utility Company",
                       "PostOffice", "911 Call Center")) %>%
  mutate(yday = yday(begin_date_time)) %>%
  group_by(yday, source) %>%
  count() %>%
  ungroup()
```

ggridges package

```
library(viridis)
ggplot(storms_by_yday, aes(x = yday,
                           y = fct_reorder(source, yday,
                                           .fun = median, .desc = TRUE),
                           fill = ..x..)) +
  geom_density_ridges_gradient() +
  scale_fill_viridis(name = "Day in year", option = "B") +
  xlim(c(0, 365)) +
  labs(x = "Day in year", y = "")
```



Odds and ends

Before next week's class, be sure to do the following:

- Register for GitHub: https://github.com
- Download and install git: https://git-scm.com

Mapping in the tidyverse

Simple features

`sf` objects: "Simple features"

- R framework that is in active development
- There will likely be changes in the near future
- Plays very well with tidyverse functions, including `dplyr` and `ggplot2` tools

```
library(sf)
```

Simple features

To show simple features, we'll pull in the Colorado county boundaries from the U.S. Census.

To do this, we'll use the `tigris` package, which accesses the U.S. Census API. It allows you to pull geographic data for U.S. counties, states, tracts, voting districts, roads, rails, and a number of other geographies.

To learn more about the `tigris` package, check out this article: https://journal.r-project.org/archive/2016/RJ-2016-043/index.html

Simple features

With `tigris`, you can read in data for county boundaries using the `counties` function.

We'll use the option `class = "sf"` to read these spatial dataframes in as `sf` objects.

```
library(tigris)
co_counties <- counties(state = "CO", cb = TRUE, class = "sf")
```

```
class(co_counties)
```

```
## [1] "sf"         "data.frame"
```

Simple features

You can think of an `sf` object as a dataframe, but with one special column called `geometry`.

```
co_counties %>%
  slice(1:3)
```

```
## Simple feature collection with 3 features and 9 fields
## geometry type:  MULTIPOLYGON
## dimension:      XY
## bbox:           xmin: -109.0603 ymin: 37.28912 xmax: -104.3511 ymax: 41.0034
## geographic CRS: NAD83
##   STATEFP COUNTYFP COUNTYNS       AFFGEOID GEOID     NAME LSAD      ALAND
## 1      08      077 00198154 0500000US08077 08077     Mesa   06 8621849401
## 2      08      107 00198169 0500000US08107 08107    Routt   06 6117602807
## 3      08      055 00198143 0500000US08055 08055 Huerfano   06 4120756304
##     AWATER                       geometry
## 1 31490395 MULTIPOLYGON (((-109.0603 3...
## 2 15831744 MULTIPOLYGON (((-107.4426 4...
## 3  5792101 MULTIPOLYGON (((-105.5013 3...
```

Simple features

The `geometry` column has a special class (sfc):

```
class(co_counties$geometry)
```

```
## [1] "sfc_MULTIPOLYGON" "sfc"
```

Simple features

You'll notice there's some extra stuff up at the top, too:

- **Geometry type**: Points, polygons, lines
- **Dimension**: Often two-dimensional, but can go up to four (if you have, for example, time for each measurement and some measure of measurement error / uncertainty)
- **Bounding box (bbox)**: The x- and y-range of the data included
- **EPSG**: The EPSG Geodetic Parameter Dataset code for the Coordinate Reference Systems
- **Projection (proj4string)**: How the data is currently projected, includes projection ("+proj") and datum ("+datum")

Simple features

You can pull some of this information out of the `geometry` column. For example, you can pull out the coordinates of the bounding box:

```
st_bbox(co_counties$geometry)      # For all counties
```

```
##       xmin       ymin       xmax       ymax
## -109.06025   36.99243 -102.04152   41.00344
```

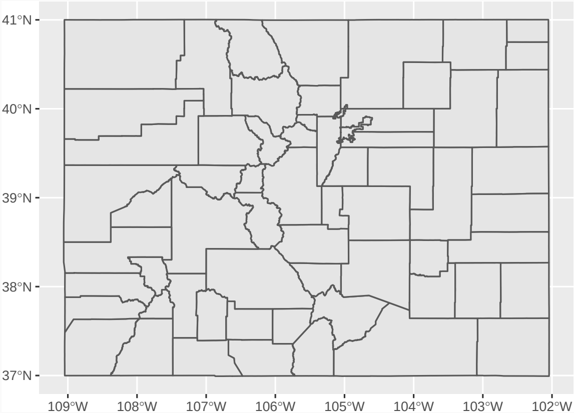
```
st_bbox(co_counties$geometry[1]) # Just for first county
```

```
##       xmin       ymin       xmax       ymax
## -109.06025   38.49999 -107.37748   39.36671
```

Simple features

You can add sf objects to ggplot objects using geom_sf:

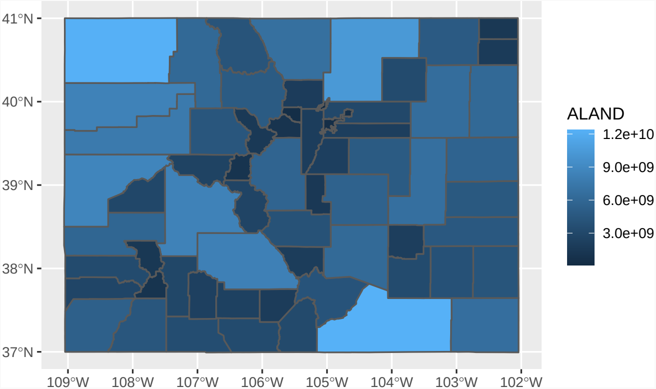
```
library(ggplot2)
ggplot() +
  geom_sf(data = co_counties)
```



Simple features

You can map one of the columns in the sf object to the fill aesthetic to make a **choropleth**:

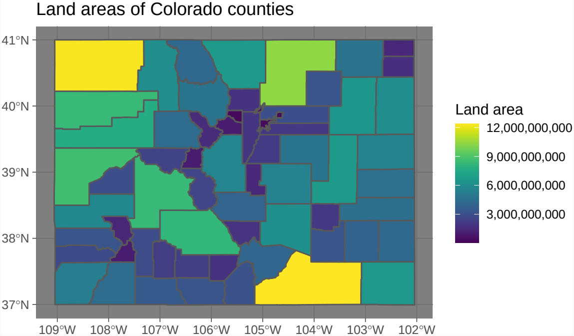
```
ggplot() +
  geom_sf(data = co_counties, aes(fill = ALAND))
```



Simple features

You can use all your usual ggplot tricks with this:

```
ggplot() +
  geom_sf(data = co_counties, aes(fill = ALAND)) +
  scale_fill_viridis(name = "Land area", label = comma) +
  ggtitle("Land areas of Colorado counties") +
  theme_dark()
```



Simple features

Because simple features are a special type of dataframe, you can also use a lot of `dplyr` tricks.

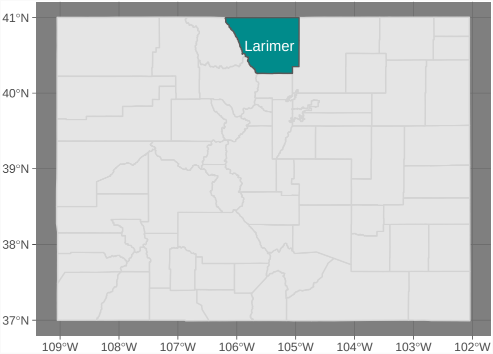
For example, you could pull out just Larimer County, CO:

```
larimer <- co_counties %>%
  filter(NAME == "Larimer")
larimer
```

```
## Simple feature collection with 1 feature and 9 fields
## geometry type:  MULTIPOLYGON
## dimension:      XY
## bbox:           xmin: -106.1954 ymin: 40.25788 xmax: -104.9431 ymax: 40.9982
## geographic CRS: NAD83
##   STATEFP COUNTYFP COUNTYNS       AFFGEOID GEOID    NAME LSAD      ALAND
## 1      08      069 00198150 0500000US08069 08069 Larimer   06 6723025059
##     AWATER                       geometry
## 1 99007869 MULTIPOLYGON (((-106.1954 4...
```

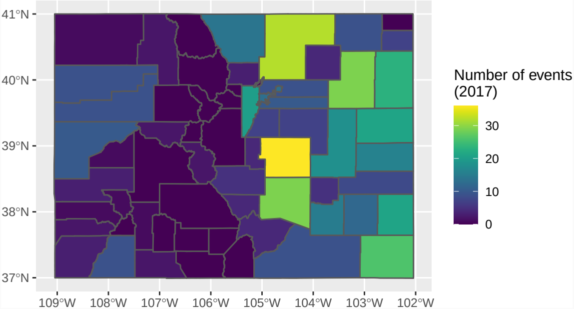
Simple features

```r
ggplot() +
  geom_sf(data = co_counties, color = "lightgray") +
  geom_sf(data = larimer, fill = "darkcyan") +
  geom_sf_text(data = larimer, aes(label = NAME),
               color = "white") +
  theme_dark() + labs(x = "", y = "")
```



Simple features

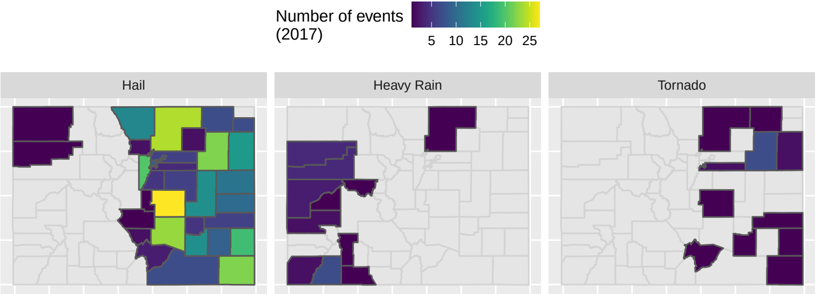
This operability with tidyverse functions means that you should now be able to figure out how to create a map of the number of events listed in the NOAA Storm Events database (of those listed by county) for each county in Colorado:



In-course exercise

We'll now take a break for the next part of the in-course exercise. For this, create the map shown on the previous slide.

If you have time, try this one, too. It shows the number of three certain types of events by county. If a county had no events, it's shown in gray (as having a missing value when you count up the events that did happen).



Simple features

```r
co_event_counts <- storms_2017 %>%
  filter(state == "Colorado") %>%
  group_by(fips) %>%
  count() %>%
  ungroup()

co_county_events <- co_counties %>%
  mutate(fips = paste(STATEFP, COUNTYFP, sep = "")) %>%
  full_join(co_event_counts, by = "fips") %>%
  mutate(n = ifelse(!is.na(n), n, 0))

ggplot() +
  geom_sf(data = co_county_events, aes(fill = n)) +
  scale_fill_viridis(name = "Number of events\n(2017)")
```

Simple features

```r
co_event_counts <- storms_2017 %>%
  filter(state == "Colorado") %>%
  filter(event_type %in% c("Tornado", "Heavy Rain", "Hail")) %>%
  group_by(fips, event_type) %>%
  count() %>%
  ungroup()

co_county_events <- co_counties %>%
  mutate(fips = paste(STATEFP, COUNTYFP, sep = "")) %>%
  right_join(co_event_counts, by = "fips")

ggplot() +
  geom_sf(data = co_counties, color = "lightgray") +
  geom_sf(data = co_county_events, aes(fill = n)) +
  scale_fill_viridis(name = "Number of events\n(2017)") +
  theme(legend.position = "top") +
  facet_wrap(~ event_type, ncol = 3) +
  theme(axis.line = element_blank(),
        axis.text = element_blank(),
        axis.ticks = element_blank())
```

State boundaries

The `tigris` package allows you to pull state boundaries, as well, but on some computers mapping these seems to take a really long time.

Instead, for now I recommend that you pull the state boundaries using base R's `maps` package and convert that to an `sf` object:

```
library(maps)
us_states <- map("state", plot = FALSE, fill = TRUE) %>%
  st_as_sf()
```

State boundaries

You can see these borders include an ID column that you can use to join by state:

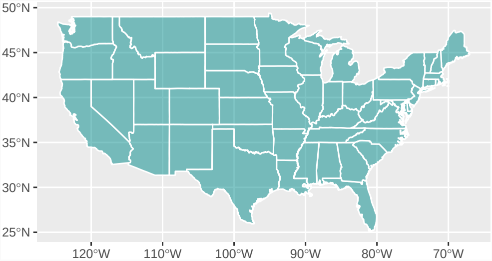
```
head(us_states)
```

```
## Simple feature collection with 6 features and 1 field
## geometry type:  MULTIPOLYGON
## dimension:      XY
## bbox:           xmin: -124.3834 ymin: 30.24071 xmax: -71.78015 ymax: 42.0493
## geographic CRS: WGS 84
##            ID                           geom
## 1     alabama MULTIPOLYGON (((-87.46201 3...
## 2     arizona MULTIPOLYGON (((-114.6374 3...
## 3    arkansas MULTIPOLYGON (((-94.05103 3...
## 4  california MULTIPOLYGON (((-120.006 42...
## 5    colorado MULTIPOLYGON (((-102.0552 4...
## 6 connecticut MULTIPOLYGON (((-73.49902 4...
```

State boundaries

As with other `sf` objects, you can map these state boundaries using `ggplot`:

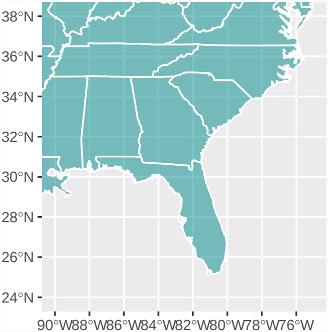
```
ggplot() +
  geom_sf(data = us_states, color = "white",
          fill = "darkcyan", alpha = 0.5)
```



State boundaries

As a note, you can use `xlim` and `ylim` with these plots, but remember that the x-axis is longitude in degrees West, which are negative:

```
ggplot() +
  geom_sf(data = us_states, color = "white",
          fill = "darkcyan", alpha = 0.5) +
  xlim(c(-90, -75)) + ylim(c(24, 38))
```



Basics of creating an `sf` object

You can create an `sf` object from a regular dataframe.

You just need to specify:

1. The coordinate information (which columns are longitudes and latitudes)
2. The Coordinate Reference System (CRS) (how to translate your coordinates to places in the world)

For the CRS, if you are mapping the new `sf` object with other, existing `sf` objects, make sure that you use the same CRS for all `sf` objects.

Coordinate reference system

Spatial objects can have different Coordinate Reference Systems (CRSs). CRSs can be *geographic* (e.g., WGS84, for longitude-latitude data) or *projected* (e.g., UTM, NADS83).

There is a website that lists projection strings and can be useful in setting projection information or re-projecting data:
http://www.spatialreference.org

Here is an excellent resource on projections and maps in R from Melanie Frazier: https://www.nceas.ucsb.edu/~frazier/RSpatialGuides/OverviewCoordinateReferenceSystems.pdf

Basics of creating an `sf` object

Let's look at floods in Colorado. First, clean up the data:

```
co_floods <- storms_2017 %>%
  filter(state == "Colorado" &
           event_type %in% c("Flood", "Flash Flood")) %>%
  select(begin_date_time, event_id, begin_lat:end_lon) %>%
  gather(key = "key", value = "value",
         -begin_date_time, -event_id) %>%
  separate(key, c("time", "key")) %>%
  spread(key = key, value = value)
```

Basics of creating an sf object

There are now two rows per event, one with the starting location and one with the ending location:

```
co_floods %>%
  slice(1:5)
```

```
## # A tibble: 5 x 5
##   begin_date_time     event_id time    lat   lon
##   <dttm>                 <dbl> <chr> <dbl> <dbl>
## 1 2017-05-08 16:00:00   693374 begin  40.3 -105.
## 2 2017-05-08 16:00:00   693374 end    40.5 -104.
## 3 2017-05-10 15:00:00   686479 begin  38.1 -105.
## 4 2017-05-10 15:00:00   686479 end    38.1 -105.
## 5 2017-05-10 15:20:00   686480 begin  38.2 -105.
```

Basics of creating an sf object

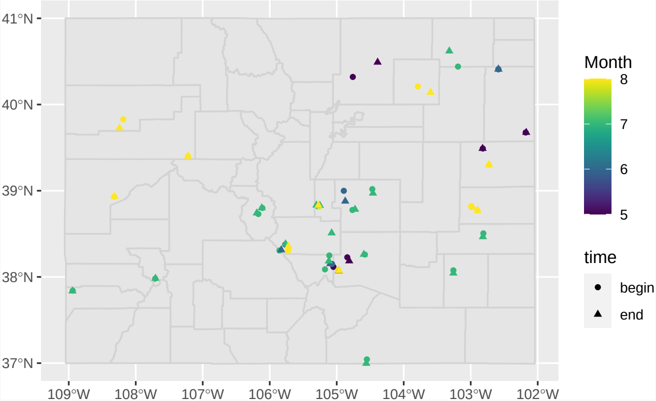
Change to an sf object by saying which columns are the coordinates and setting a CRS:

```
co_floods <- st_as_sf(co_floods, coords = c("lon", "lat")) %>%
  st_set_crs(4269)
co_floods %>% slice(1:3)
```

```
## Simple feature collection with 3 features and 3 fields
## geometry type:  POINT
## dimension:      XY
## bbox:           xmin: -105.0496 ymin: 38.1167 xmax: -104.39 ymax: 40
## geographic CRS: NAD83
## # A tibble: 3 x 4
##   begin_date_time     event_id time              geometry
##   <dttm>                 <dbl> <chr>          <POINT [°]>
## 1 2017-05-08 16:00:00   693374 begin     (-104.76 40.32)
## 2 2017-05-08 16:00:00   693374 end       (-104.39 40.49)
## 3 2017-05-10 15:00:00   686479 begin (-105.0496 38.1167)
```

Basics of creating an sf object

```
ggplot() +
  geom_sf(data = co_counties, color = "lightgray") +
  geom_sf(data = co_floods, aes(color = month(begin_date_time),
                                 shape = time)) +
  scale_color_viridis(name = "Month")
```



Changing from points to lines

If you want to show lines instead of points, group by the appropriate ID and then summarize within each event to get a line:

```
co_floods <- co_floods %>%
  group_by(event_id) %>%
  summarize(month = month(first(begin_date_time)),
            do_union = FALSE) %>%
  st_cast("LINESTRING")
```

```
## `summarise()` ungrouping output (override with `.groups` argu
```

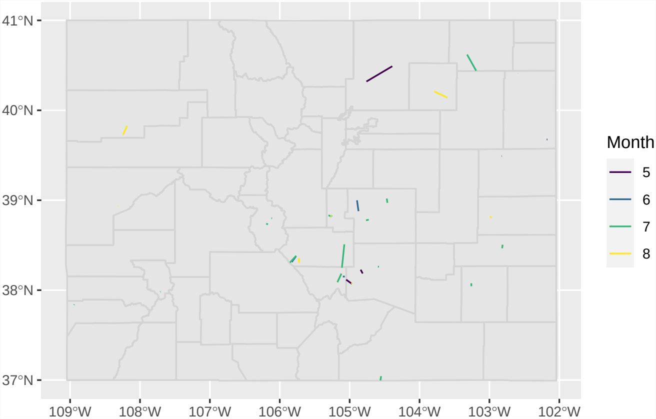
Changing from points to lines

```
head(co_floods)
```

```
## Simple feature collection with 6 features and 2 fields
## geometry type:  LINESTRING
## dimension:      XY
## bbox:           xmin: -105.8286 ymin: 38.0708 xmax: -104.39 y
## geographic CRS: NAD83
## # A tibble: 6 x 3
##   event_id month                                     geometry
##      <dbl> <dbl>                              <LINESTRING [°]>
## 1   686479     5 (-105.0496 38.1167, -104.9687 38.0708)
## 2   686480     5 (-104.8425 38.2275, -104.8137 38.1854)
## 3   693306     6  (-104.8947 38.999, -104.8734 38.8783)
## 4   693374     5          (-104.76 40.32, -104.39 40.49)
## 5   693444     6 (-105.7688 38.3753, -105.8286 38.3127)
## 6   693449     6     (-105.07 38.15, -105.0973 38.1524)
```

Changing from points to lines

```r
ggplot() +
  geom_sf(data = co_counties, color = "lightgray") +
  geom_sf(data = co_floods,
          aes(color = factor(month), fill = factor(month))) +
  scale_fill_viridis(name = "Month", discrete = TRUE) +
  scale_color_viridis(name = "Month", discrete = TRUE)
```



Reading from GIS files

You can also create `sf` objects by reading in data from files you would normally use for GIS.

For example, you can read in an `sf` object from a shapefile, which is a format often used for GIS in which a collection of several files jointly store geographic data. The files making up a shapefile can include:

- ".shp": The coordinates defining the shape of each geographic object. For a point, this would be a single coordinate (e.g., latitude and longitude). For lines and polygons, there will be multiple coordinates per geographic object.
- ".prf": Information on the projection of the data (how to get from the coordinates to a place in the world).
- ".dbf": Data that goes along with each geographical object. For example, earlier we looked at data on counties, and one thing measured for each county was its land area. Characteristics like that would be included in the ".dbf" file in a shapefile.

Reading from GIS files

Often, with geographic data, you will be given the option to downloaded a compressed file (e.g., a zipped file). When you unzip the folder, it will include a number of files in these types of formats (".shp", "prf", ".dbf", etc.).

Sometimes, that single folder will include multiple files from each extension. For example, it might have several files that end with ".shp". In this case, you have multiple **layers** of geographic information you can read in.

Reading in from GIS files

We've been looking at data on storms from NOAA for 2017. As an example, let's try to pair that data up with some from the National Hurricane Center for the same year.

The National Hurricane Center allows you to access a variety of GIS data through the webpage https://www.nhc.noaa.gov/gis/?text.

Let's pull some data on Hurricane Harvey in 2017 and map it with information from the NOAA Storm Events database.

Reading in from GIS files

On https://www.nhc.noaa.gov/gis/?text, go to the section called "Preliminary Best Track". Select the year 2017. Then select "Hurricane Harvey" and download "al092017_best_track.zip".

Depending on your computer, you may then need to unzip this file (many computers will unzip it automatically). Base R has a function called `unzip` that can help with this.

You'll then have a folder with a number of different files in it. Move this folder somewhere that is convenient for the working directory you use for class. For example, I moved it into the "data" subdirectory of the working directory I use for the class.

Reading in from GIS files

You can use `list.files` to see all the files in this unzipped folder:

```
list.files("../data/al092017_best_track/")
```

```
##  [1] "al092017_lin.dbf"           "al092017_lin.prj"
##  [3] "al092017_lin.shp"           "al092017_lin.shp.xml"
##  [5] "al092017_lin.shx"           "al092017_pts.dbf"
##  [7] "al092017_pts.prj"           "al092017_pts.shp"
##  [9] "al092017_pts.shp.xml"       "al092017_pts.shx"
## [11] "al092017_radii.dbf"         "al092017_radii.prj"
## [13] "al092017_radii.shp"         "al092017_radii.shp.xml"
## [15] "al092017_radii.shx"         "al092017_windswath.dbf"
## [17] "al092017_windswath.prj"     "al092017_windswath.shp"
## [19] "al092017_windswath.shp.xml" "al092017_windswath.shx"
```

Reading from GIS files

You can use `st_layers` to find out the available layers in a shapefile directory:

```
st_layers("../data/al092017_best_track/")
```

```
## Driver: ESRI Shapefile
## Available layers:
##            layer_name geometry_type features fields
## 1 al092017_windswath       Polygon        4      6
## 2     al092017_radii       Polygon       61      9
## 3       al092017_lin   Line String       17      3
## 4       al092017_pts         Point       74     15
```

Reading from GIS files

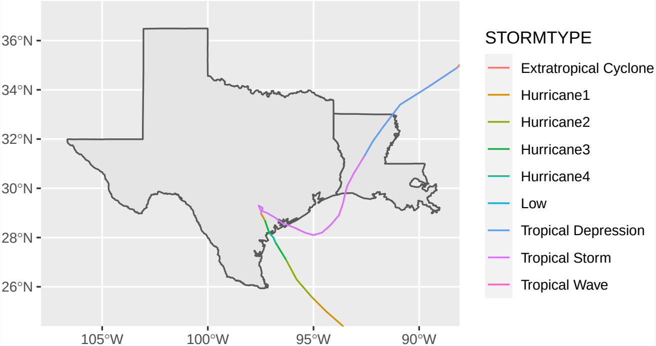
Once you know which layer you want, you can use `read_sf` to read it in as an `sf` object:

```
harvey_track <- read_sf("../data/al092017_best_track/",
                        layer = "al092017_lin")
head(harvey_track)
```

```
## Simple feature collection with 6 features and 3 fields
## geometry type:  LINESTRING
## dimension:      XY
## bbox:           xmin: -92.3 ymin: 13 xmax: -45.8 ymax: 21.4
## geographic CRS: Unknown datum based upon the Authalic Sphere
## # A tibble: 6 x 4
##   STORMNUM STORMTYPE         SS
##      <dbl> <chr>          <int>
## 1        9 Low                0 (-45.8 13.7, -47.4 13.7, -49
## 2        9 Tropical Depr~     0                         (-52 13.4,
## 3        9 Tropical Storm     0 (-55 13, -56.6 13, -58.4 13,
```

Reading from GIS files

```r
ggplot() +
  geom_sf(data = filter(us_states, ID %in% c("texas", "louisiana
  geom_sf(data = harvey_track, aes(color = STORMTYPE)) +
  xlim(c(-107, -89)) + ylim(c(25, 37))
```



Reading from GIS files

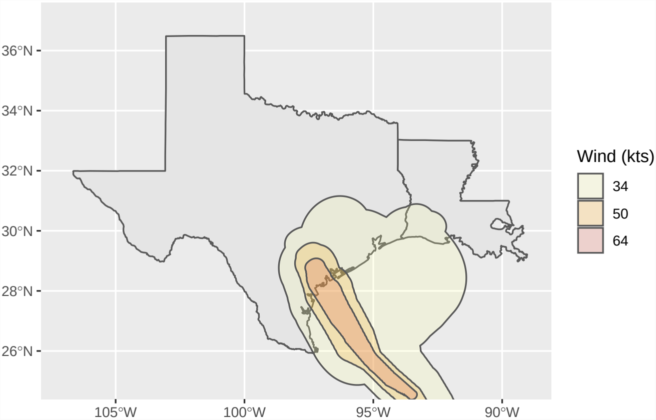
You can read in other layers:

```
harvey_windswath <- read_sf("../data/al092017_best_track/",
                            layer = "al092017_windswath")
head(harvey_windswath)
```

```
## Simple feature collection with 4 features and 6 fields
## geometry type:  POLYGON
## dimension:      XY
## bbox:           xmin: -98.66872 ymin: 12.94564 xmax: -54.58527 ymax: 31.1589
## geographic CRS: Unknown datum based upon the Authalic Sphere
## # A tibble: 4 x 7
##   RADII STORMID  BASIN STORMNUM STARTDTG ENDDTG                           geom
##   <dbl> <chr>    <chr>    <dbl> <chr>    <chr>                       <POLYGON
## 1    34 al092017 AL           9 2017081~ 20170~ ((-65.68199 14.50528, -65.66
## 2    34 al092017 AL           9 2017082~ 20170~ ((-96.22456 31.15752, -96.17
## 3    50 al092017 AL           9 2017082~ 20170~ ((-97.32707 29.60604, -97.31
## 4    64 al092017 AL           9 2017082~ 20170~ ((-97.20689 29.08475, -97.19
```

Reading from GIS files

```
ggplot() +
  geom_sf(data = filter(us_states, ID %in% c("texas", "louisiana"))) +
  geom_sf(data = harvey_windswath,
          aes(fill = factor(RADII)), alpha = 0.2) +
  xlim(c(-107, -89)) + ylim(c(25, 37)) +
  scale_fill_viridis(name = "Wind (kts)", discrete = TRUE,
                     option = "B", begin = 0.6, direction = -1)
```



Reading from GIS files

The `read_sf` function is very powerful and can read in data from lots of different formats.

See Section 2 of the `sf` manual (https://cran.r-project.org/web/packages/sf/vignettes/sf2.html) for more on this function.

More on spatial data with R

You can find (much, much) more on working with spatial data in R online:

- **R Spatial**: http://rspatial.org/index.html
- **Geocomputation with R**: https://geocompr.robinlovelace.net

In-course exercise

For the in-course exercise, see if you can put everything we've talked about together to create this map: