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

```
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**.

```
nrow(storms_2017)
```

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

```
length(unique(storms_2017$EVENT_ID))
```

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

```
length(unique(storms_2017$EPISODE_ID))
```

```
## [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:

```
summary(factor(storms_2017$CZ_TYPE))
```

```
##      2     C     Z
##     17 36933 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>                   <int>    <int> <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 <- data_frame(state = state.name,
                            area = state.area,
                            region = state.region)
```

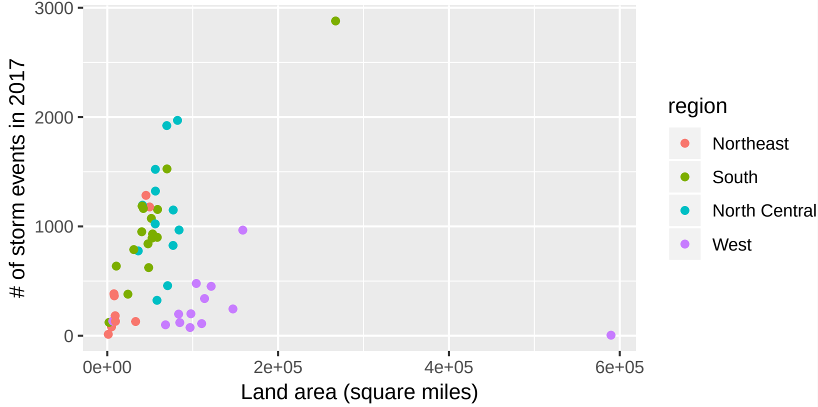
Example data

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

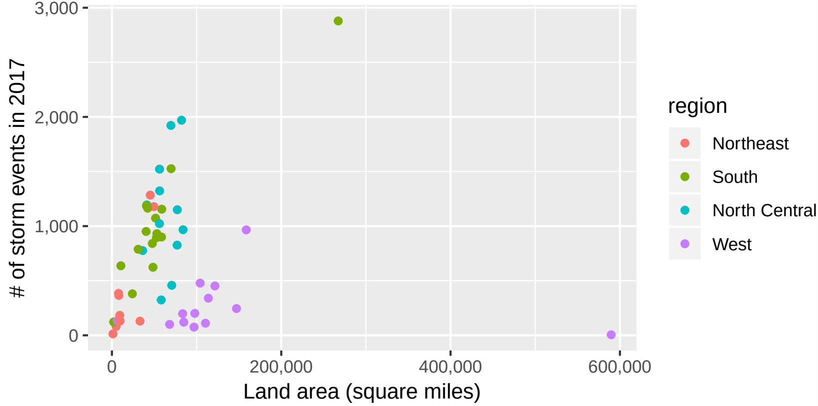
`scales` package

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

```
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`)

`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://www.ggplot2-exts.org.

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.

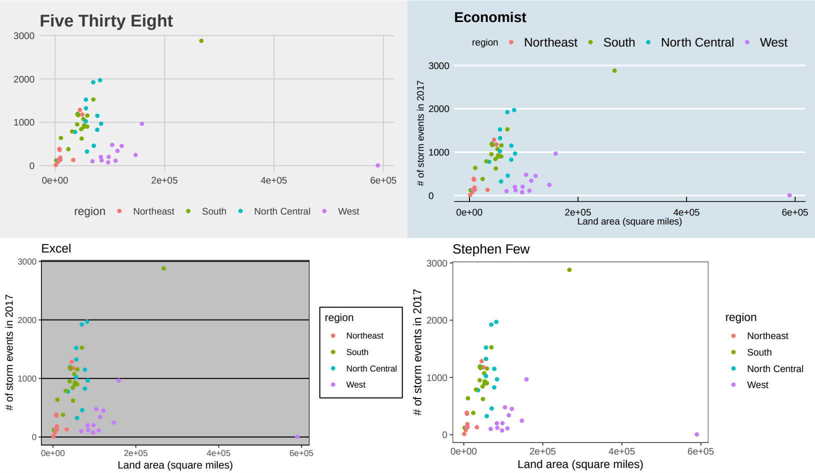
`ggplot2` extensions: Themes

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



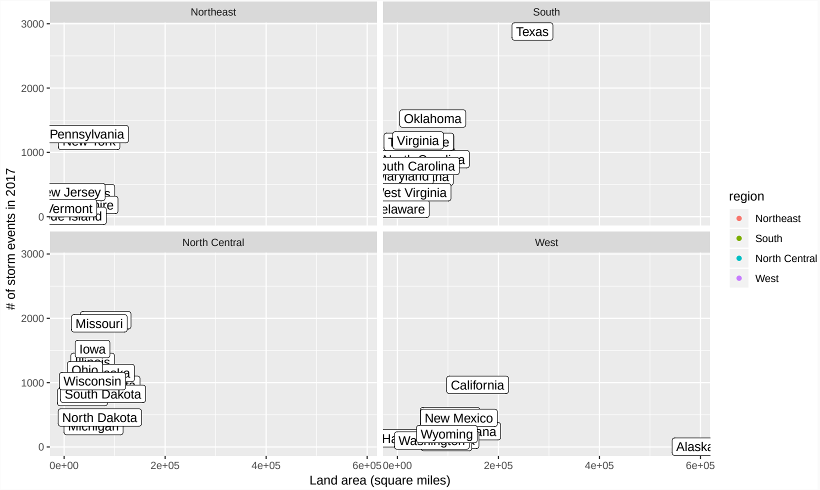
`ggplot2` extensions: Useful additions

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

ggplot2 extensions: repelling text labels

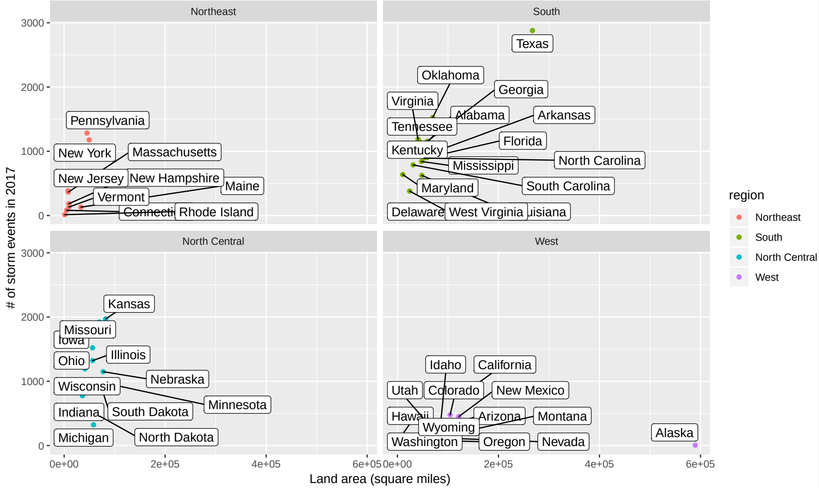
When you add labels to points on a plot, they often overlap:

```
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))
```

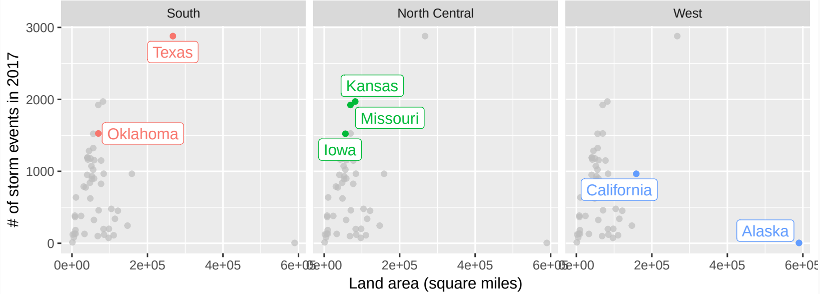


gghighlight package

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.

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



gghighlight package

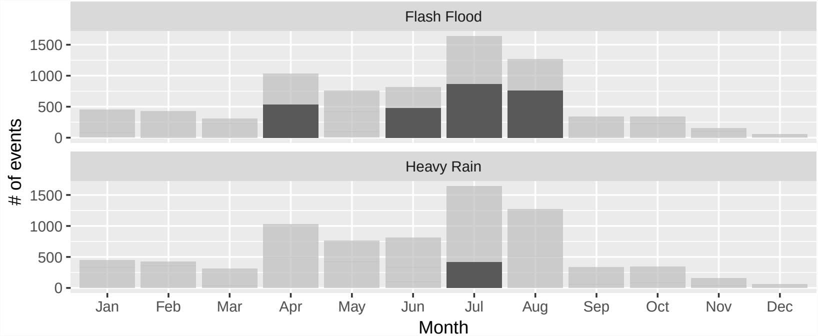
The gghighlight package also works for things like histograms. For example, you could create a dataset with the count by day-of-year of certain types of events:

```
storms_by_month <- storms_2017 %>%
  filter(event_type %in% c("Flood", "Flash Flood", "Heavy Rain")) %>%
  mutate(month = month(begin_date_time, label = TRUE)) %>%
  group_by(month, event_type) %>%
  count() %>%
  ungroup()
storms_by_month %>%
  slice(1:4)
```

```
## # A tibble: 4 x 3
##   month event_type      n
##   <ord> <chr>       <int>
## 1 Jan   Flash Flood   113
## 2 Jan   Flood         255
## 3 Jan   Heavy Rain     80
## 4 Feb   Flash Flood    65
```

gghighlight package

```
ggplot(storms_by_month, aes(x = month, y = n, group = event_type)) +
  geom_bar(stat = "identity") +
  labs(x = "Month", y = "# of events") +
  gghighlight(max(n) > 400, label_key = event_type) +
  facet_wrap(~ event_type, ncol = 1)
```



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

ggplot2 extensions: Arranging plots

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

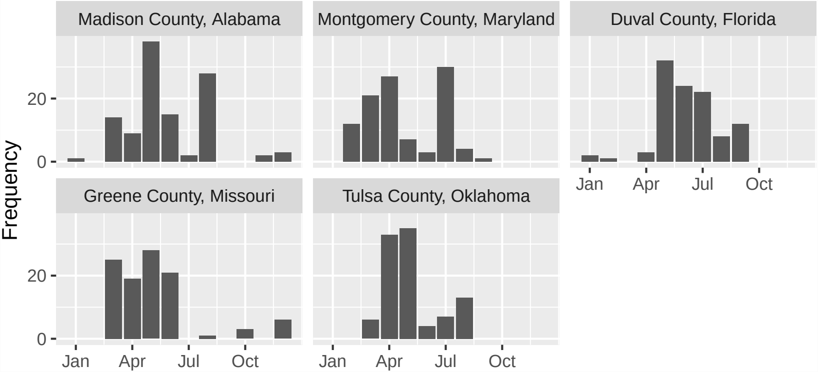
Then create a plot with the time patterns:

```
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))
```

ggplot2 extensions: Arranging plots

Here's this plot:

```
top_counties_month
```

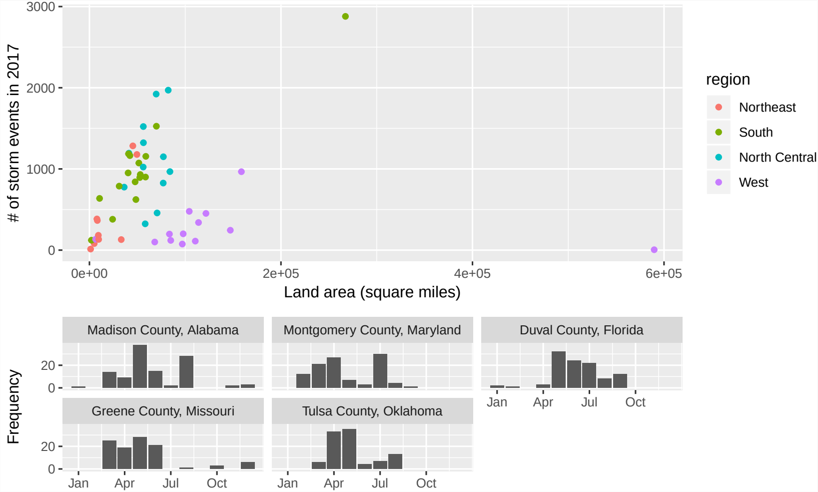


ggplot2 extensions: Arranging plots

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))
```

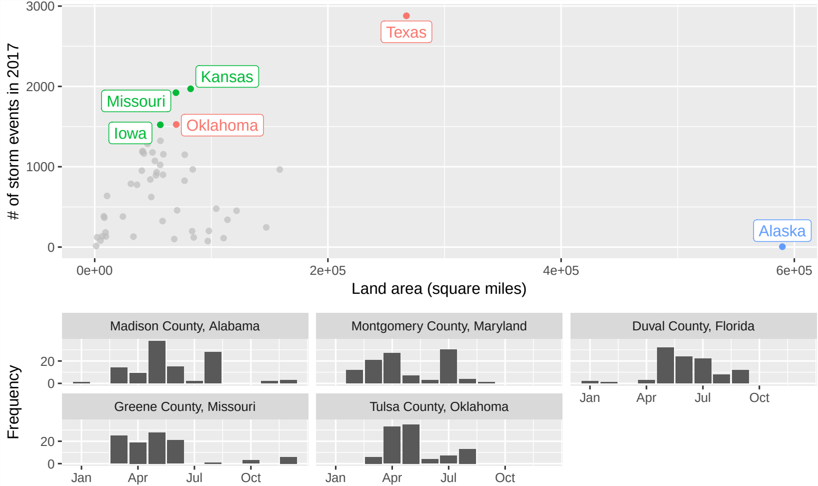
ggplot2 extensions: Arranging plots



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

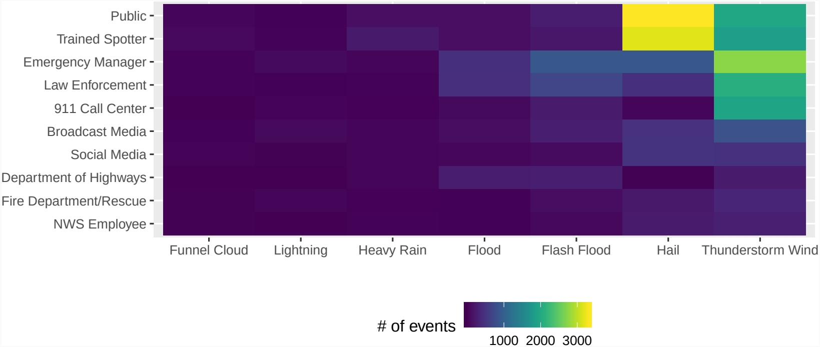
For example, we might want to look at how many events of each type were reported by each type of source. First, we can summarize the data to get this data:

```
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

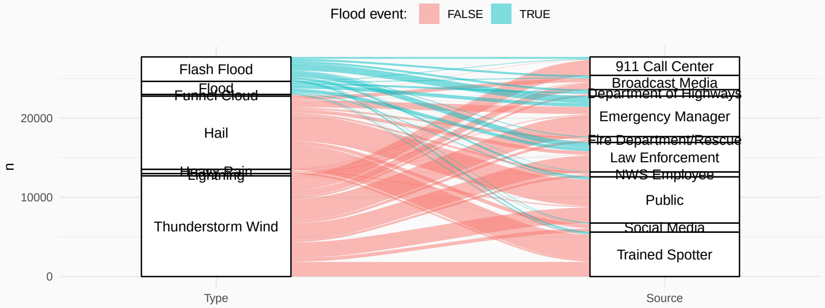
```r
library(viridis); library(forcats)
ggplot(type_by_source,
       aes(x = fct_reorder(event_type, n, .fun = sum),
           y = fct_reorder(source, n, .fun =  sum))) +
  geom_tile(aes(fill = n)) +
  scale_fill_viridis() +
  labs(x = "", y = "", fill = "# of events") +
  theme(legend.position = "bottom")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



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: ")
```



`ggridges` package

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

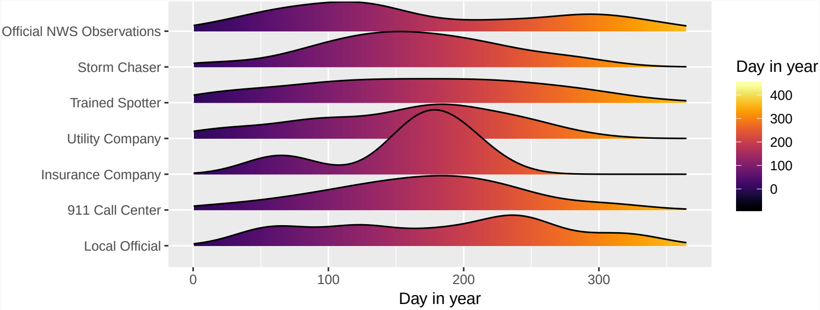
ggridges package

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 = "")
```



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 Census API. 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)
```

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: 36.99243 xmax: -102.0415 ymax: 41.0034
## epsg (SRID):    4269
## proj4string:    +proj=longlat +datum=NAD83 +no_defs
##   STATEFP COUNTYFP COUNTYNS       AFFGEOID GEOID     NAME LSAD      ALAND
## 1      08      023 00198127 0500000US08023 08023 Costilla   06 3179452292
## 2      08      037 00198134 0500000US08037 08037    Eagle   06 4362874882
## 3      08      043 00198137 0500000US08043 08043  Fremont   06 3970664556
##     AWATER                       geometry
## 1  8828906 MULTIPOLYGON (((-105.7714 3...
## 2 18849997 MULTIPOLYGON (((-107.1137 3...
## 3  2235368 MULTIPOLYGON (((-106.0123 3...
```

Simple features

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

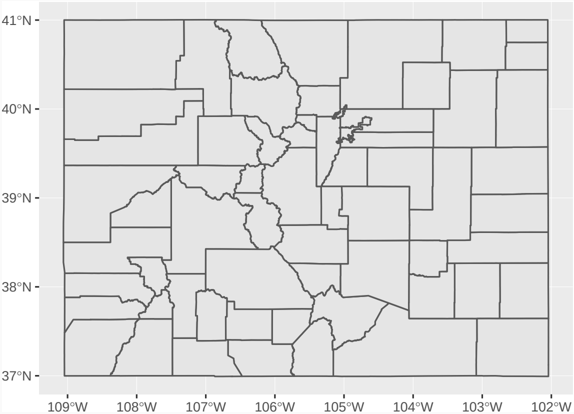
```
class(co_counties$geometry)
```

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

Simple features

You can add `sf` objects to `ggplot` objects using `geom_sf`:

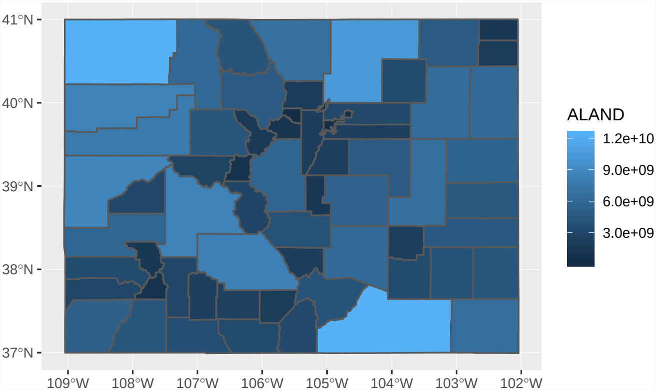
```
library(ggplot2)
ggplot() +
  geom_sf(data = co_counties)
```



Simple features

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

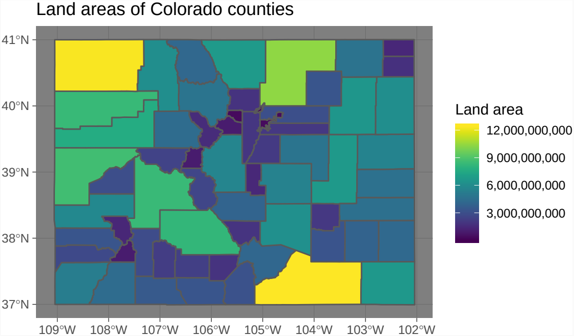
```
ggplot() +
  geom_sf(data = co_counties, aes(fill = ALAND))
```



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:

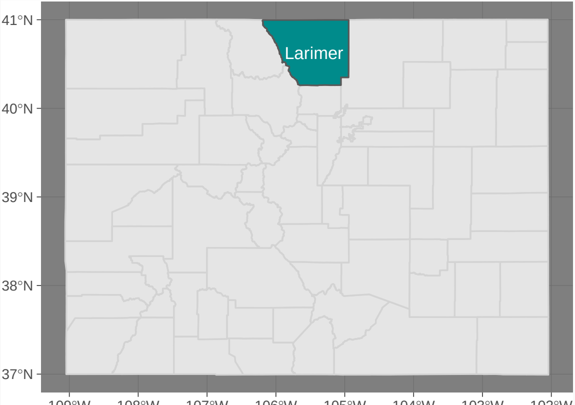
```
larimer <- co_counties %>%
  filter(NAME == "Larimer")
larimer
```

```
## Simple feature collection with 1 feature and 9 fields
## geometry type:  MULTIPOLYGON
## dimension:      XY
## bbox:           xmin: -106.1954 ymin: 40.25788 xmax: -104.943
## epsg (SRID):    4269
## proj4string:    +proj=longlat +datum=NAD83 +no_defs
##   STATEFP COUNTYFP COUNTYNS       AFFGEOID GEOID    NAME LSAD
## 1      08      069 00198150 0500000US08069 08069 Larimer   06
##     AWATER                       geometry
## 1 97955155 MULTIPOLYGON (((-106.1954 4...
```

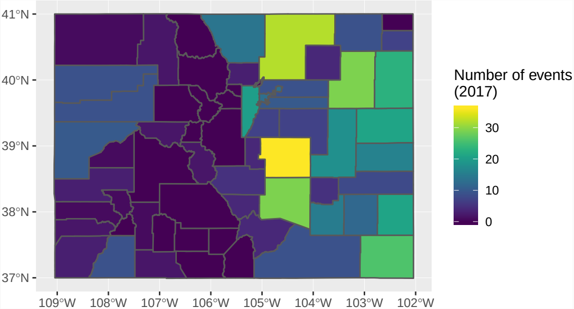
Simple features

Note: You may need the development version of ggplot2 for this to work.

```
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 = "")
```



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

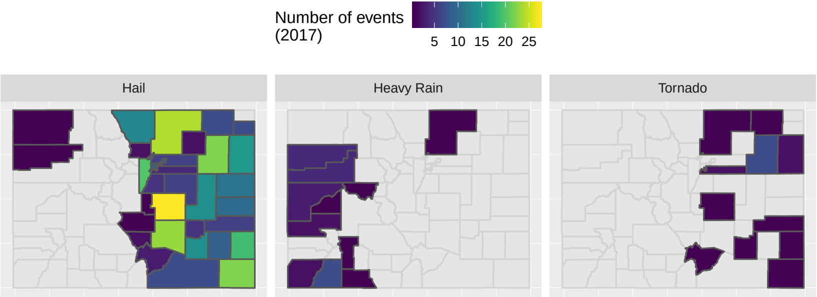


In-course exercise

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.

In-course exercise

If you have time, try this one, too:



Simple features

```
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

```
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())
```

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

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 CRS

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.

Basics of creating an sf object

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

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

Basics of creating an sf object

```r
co_tornados %>%
  slice(1:5)
```

```
## # A tibble: 5 x 5
##   begin_date_time     event_id time    lat   lon
##   <dttm>                 <int> <chr> <dbl> <dbl>
## 1 2017-04-12 15:13:00   686482 begin  38.0 -102.
## 2 2017-04-12 15:13:00   686482 end    38.0 -102.
## 3 2017-05-08 13:24:00   697290 begin  37.9 -105.
## 4 2017-05-08 13:24:00   697290 end    37.9 -105.
## 5 2017-05-09 17:11:00   686419 begin  38.5 -102.
```

Basics of creating an sf object

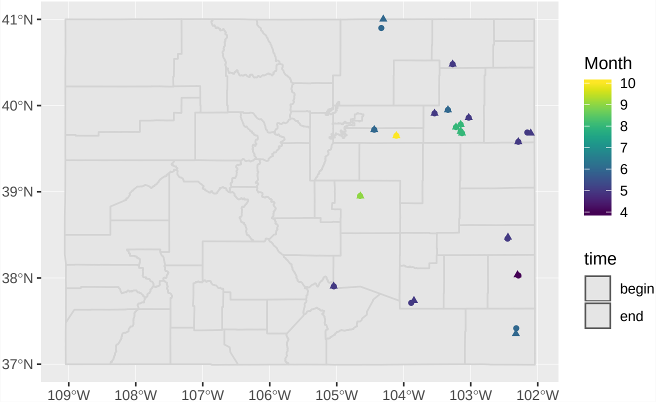
Change to an sf object:

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

```
## Simple feature collection with 3 features and 3 fields
## geometry type:  POINT
## dimension:      XY
## bbox:           xmin: -105.0459 ymin: 37.3536 xmax: -102.1044 ymax: 
## epsg (SRID):    4269
## proj4string:    +proj=longlat +ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +n
## # A tibble: 3 x 4
##   begin_date_time     event_id time               geometry
##   <dttm>                 <int> <chr>           <POINT [°]>
## 1 2017-04-12 15:13:00   686482 begin  (-102.2885 38.029)
## 2 2017-04-12 15:13:00   686482 end   (-102.3012 38.0363)
## 3 2017-05-08 13:24:00   697290 begin (-105.0433 37.9027)
```

Basics of creating an `sf` object

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



Basics of creating an sf object

If you want to show lines instead of points, group by the appropriate ID and then

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