Data Visualization

Getting Fancy: Drawing Maps

Ciara Zogheib

Data Sciences Institute, University of Toronto

In today's class, we will...

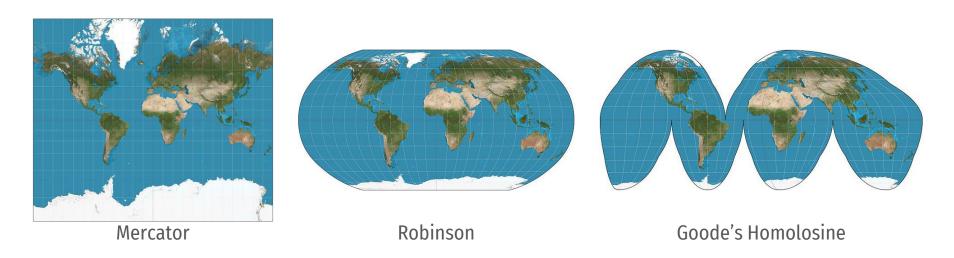
- Develop basic understanding of elements of maps
- Work through practice code from Chapter 7 (*Drawing Maps*) of Healy,
 K. (2018). Data Visualization: A Practical Introduction. Princeton
 University Press. This code will let us
 - Map choropleths with R
 - Explore alternate ways of grouping spatial data
 - Interrogate whether our data are truly spatial

Data visualization with maps: 101

Maps and projections

- A map is "a representation usually on a flat surface of the whole or a part of an area"
- In order to display positions on the curved, 3-dimensional surface of the earth in a flat, 2-dimensional representation, our position data has to be transformed
- This transformation is called a projection
- The projection of a map impacts the map's appearance (and therefore the conclusions that viewers will form)

Maps and projections - Example



Types of maps

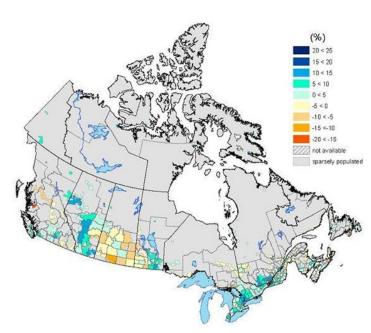
- Reference map → shows the locations, boundaries, and names of geographic areas and features
 - For example, the maps used to navigate on a road trip
- Thematic map → shows the "spatial distribution of one or more specific data themes for selected geographic areas"
 - For example, population density in each province, or percentage of college graduates in a neighbourhood
- When we visualize spatial data, we make thematic maps

Types of maps



Reference map showing topography of Canada

(Atlas of America, 2022)



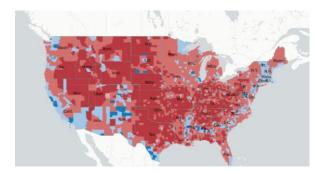
Thematic map showing population growth in Canada

(Statistics Canada, 2006)

Thematic maps



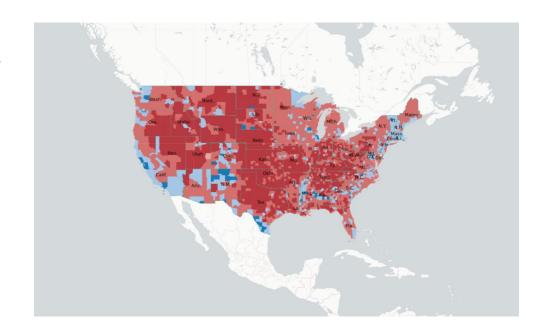




Point map Heat map Choropleth

Choropleths

- "Show geographical regions colored, shaded, or graded according to some variable"
- Often made using
 Geographical Information
 System (GIS) tools, but can
 be made using ggplot in R



Map state- and province-level data

- To explore making choropleth maps in ggplot, we will again use our
 2016 election dataset from the socviz library
- We will start by viewing random rows from a subset of our dataset:

- Recall: we have been working with spatial data throughout Module the class - it can be represented non-spatially!
- We can create dotplots of the point margins of our election data, faceted by census region, using methods we have learned so far.

Activity

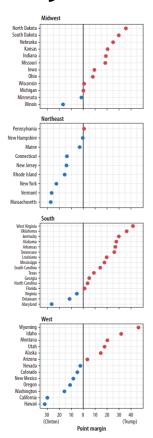
- The next slide contains code (also available in <u>Healy (2018)</u>) for creating a faceted dotplot of 2016 U.S. election data by census region
- Recall: we discussed how commenting code helps to ensure reproducibility and understanding of what choices were made
- Comment the following code so that a new viewer could understand what is being accomplished with each step
- Hint: it can be helpful to run the code piecewise (one step at a time) to see what each step adds/changes!

Activity

```
party colors <- c("#2E74C0", "#CB454A")</pre>
p0 <- ggplot(data = subset(election, st %nin% "DC"), mapping = aes(x =
r points, y = reorder(state, r points), color = party))
p1 <- p0 + geom vline(xintercept = 0, color = "gray30") +
 geom point(size = 2)
p2 <- p1 + scale color manual (values = party colors)
40), labels = c("30\n (Clinton)", "20", "10", "0", "10", "20", "30",
"40\n(Trump)"))
p3 + facet wrap(~ census, ncol=1, scales="free y") +
 guides(color=FALSE) + labs(x = "Point Margin", y = "") +
 theme (axis.text=element text(size=8))
```

(Healy, 2018)

Activity - Result



```
party colors <- c("#2E74C0", "#CB454A")</pre>
p0 <- ggplot(data = subset(election, st %nin% "DC"), mapping
= aes(x = r points, y = r eorder(state, r points), color =
party))
p1 <- p0 + geom vline(xintercept = 0, color = "gray30") +
  geom point(size = 2)
p2 <- p1 + scale color manual (values = party colors)
p3 \leftarrow p2 + scale x continuous (breaks = c(-30, -20, -10, 0,
10, 20, 30, 40), labels = c("30\n (Clinton)", "20", "10", "0", "10", "20", "30", "40\n (Trump)"))
p3 + facet wrap(~ census, ncol=1, scales="free y") +
  quides(color=FALSE) + labs(x = "Point Margin", y = "") +
  theme(axis.text=element text(size=8))
```

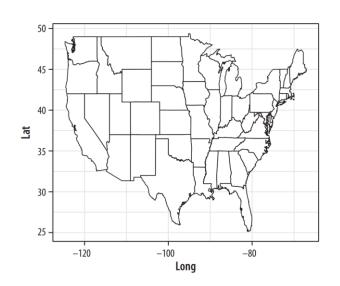
- Now we want to create the map on which we will plot our data
- As with any other ggplot, we need a dataframe with our information inside - in this case, that information will give R instructions for making a map
- The maps package contains predrawn map data

```
install.packages("maps")
library(maps)
us_states <- map_data("state")
head(us_states)</pre>
```

• Our us_states dataframe gives R the instructions for drawing lines in the shape of a map of the United States using geom_polygon()

```
p <- ggplot(data =
us_states, mapping = aes(x =
long, y = lat, group =
group))

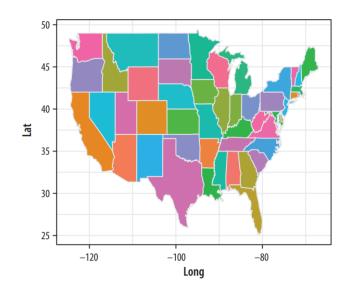
p + geom_polygon(fill =
"white", color = "black")</pre>
```



 By mapping the fill aesthetic to region and changing the colour of our lines, we can adjust the appearance of our blank map

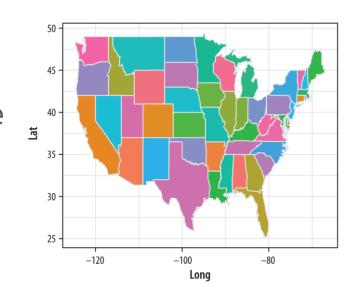
```
p <- ggplot(data = us_states,
aes(x = long, y = lat, group =
group, fill = region))

p + geom_polygon(color =
"gray90", linewidth = 0.1) +
guides(fill = FALSE)</pre>
```



Changing our map projection

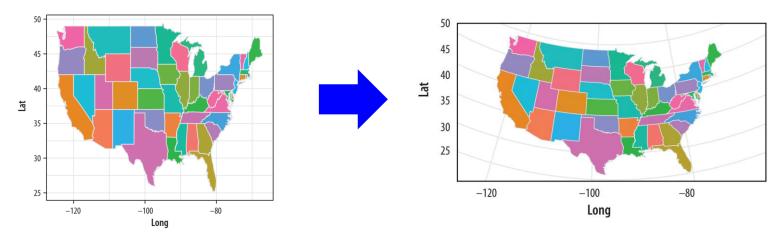
- By default, our map is plotted using the Mercator projection
- If we want our visualization to look more like typical maps of the United States, we can add two latitude parameters to transform our data to an Albers projection



Changing our map projection

```
p <- ggplot(data = us_states, mapping = aes(x = long, y = lat, group
= group, fill = region))

p + geom_polygon(color = "gray90", size = 0.1) +
coord_map(projection = "albers", lat0 = 39, lat1 = 45) + guides(fill
= FALSE)</pre>
```



Adding data to our map

- The next step is to add our election data to our map visual
- To do this, we need to merge our map dataframe and our election dataframe
- It is very important to ensure that the variable we use to merge our datasets matches (that is, same case and no missing values), otherwise the polygons of our map visual will not join properly

```
election$region <- tolower(election$state)
us_states_elec <- left_join(us_states, election, by = 'region')</pre>
```

Adding data to our map

Now that all of our data are in a single dataframe
 (us_states_elec), we can plot statewise election data on a map

```
p0 <- ggplot(data = us_states_elec, mapping = aes(x = long, y = lat, group = group, fill = party))

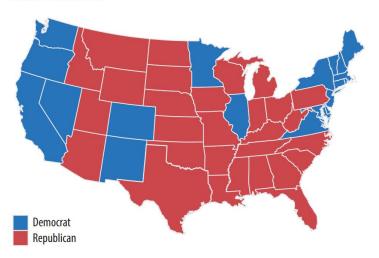
p1 <- p0 + geom_polygon(color = "gray90", size = 0.1) +
    coord_map(projection = "albers", lat0 = 39, lat1 = 45)

p2 <- p1 + scale_fill_manual(values = party_colors) +
    labs(title = "Election Results 2016", fill = NULL)

p2 + theme_map()</pre>
```

Adding data to our map - Result





```
p0 <- ggplot(data = us_states_elec, mapping = aes(x = long, y = lat, group = group, fill = party))

p1 <- p0 + geom_polygon(color = "gray90", size = 0.1) + coord_map(projection = "albers", lat0 = 39, lat1 = 45)

p2 <- p1 + scale_fill_manual(values = party_colors) + labs(title = "Election Results 2016", fill = NULL)

p2 + theme_map()
```

Questioning our choropleths

- Our choropleth map shows voting results spatially (by state), but is it the best way to communicate our data?
- Could other factors be influencing the trends we see on our map?

Alternate choropleths

Population size and demographics

- State-level maps like the one that we have created are useful and easy to read, but they can insinuate a geographical explanation where none exists
- Voting data (like our example) are heavily influenced by population density

 We will plot U.S. population density at the county level, using a premade county map dataframe and county information dataframe, both from the socviz library

```
county_map |>
  sample_n(5)

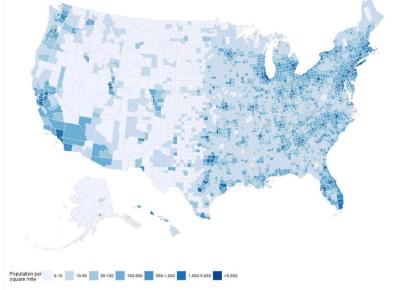
county_data |>
  select(id, name, state, pop_dens) |>
  sample_n(5)
```

Now we can merge our county_map and county_data dataframes
 on the shared id column

```
county_full <- left_join(county_map, county_data, by = "id")</pre>
```

 Our new dataframe contains (among other variables) longitude and latitude data for our map, population density in people per square mile, and county information

```
p <- ggplot(data = county full,</pre>
           mapping = aes(x = long, y = lat, fill = pop dens, group =
group))
p1 <- p + geom polygon(color = "gray90", size = 0.05) + coord equal()
p2 <- p1 + scale fill brewer(palette="Blues",
                             labels = c("0-10", "10-50", "50-100", "100-
500", "500-1,000", "1,000-5,000", ">5,000"))
p2 + labs(fill = "Population per\nsquare mile") +
  theme map() +
  guides(fill = guide legend(nrow = 1)) +
  theme(legend.position = "bottom")
```

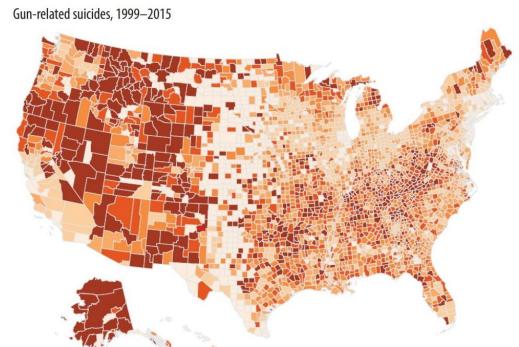


```
p <- ggplot(data = county_full, mapping = aes(x = long, y = lat, fill = pop_dens, group = group))
p1 <- p + geom_polygon(color = "gray90", size = 0.05) + coord_equal()
p2 <- p1 + scale_fill_brewer(palette="Blues", labels = c("0-10", "10-50", "50-100", "100-500", "500-1,000", "1,000-5,000", ">5,000"))
p2 + labs(fill = "Population per\nsquare mile") + theme_map() + guides(fill = guide_legend(nrow = 1)) + theme(legend.position = "bottom")
```

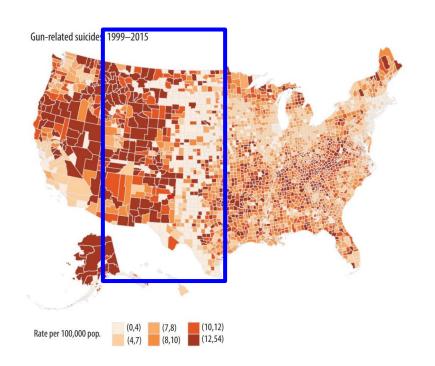
Why is it important to consider things like population density when we visualize data with thematic maps?

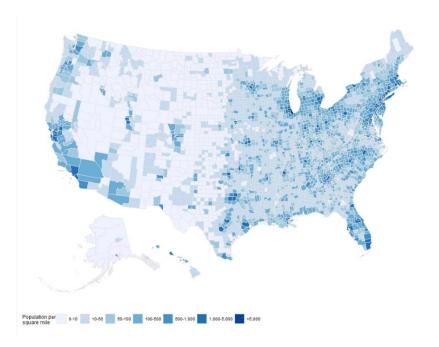
Map - Gun-related suicides in the United States

Rate per 100,000 pop.



Comparing maps

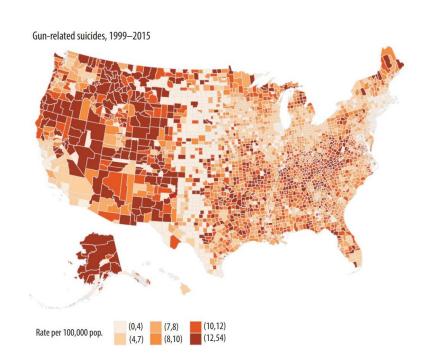


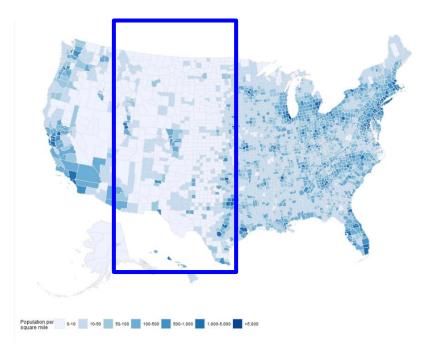


Gun-related suicides

Population density

Comparing maps





Gun-related suicides

Population density

Maps need context

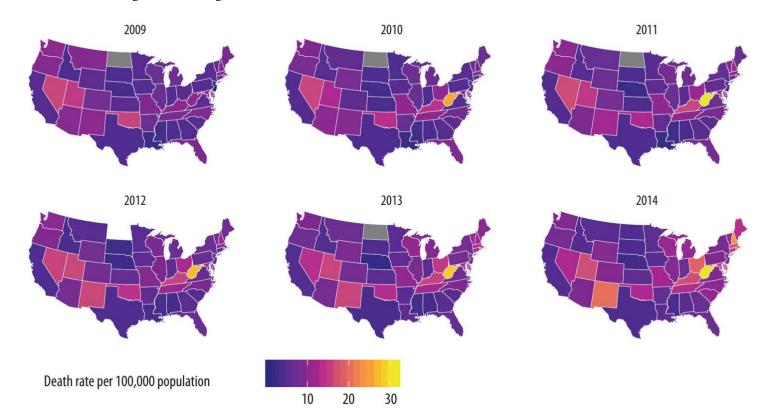
- If there are fewer than ten firearm-related suicides in a county per year, the CDC will report them as 'suppressed' so that individuals cannot be identified
- Imagine a situation with 10 such deaths in a county with only 100,000 inhabitants. We know that the number is between 0 and 10, so we could put it in our 0-10 (lowest suicide rate) bin on our map
- But 12 such deaths in the same county would put it in the highest suicide rate bin

Maps need context

- Differences in reporting and choices made while binning our data can produce misleading and mistaken spatial data visualizations
- It is worth exploring underlying population and demographic data before relying on choropleths to find trends

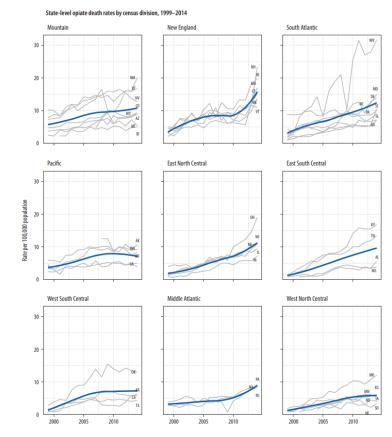
Are our data really spatial?

When are maps helpful?



When are maps helpful?

- The same data as the previous slide, visualized as a faceted time series by census region
- This version of the data lets us see change over time, and emphasizes differing trajectories of states within regions



Spatial for convenience

- Often (especially with public data), data are collected at the level of provinces, states, or some geographic area, or rates for these groups
 - For convenience and practicality
 - To protect individual privacy
- As data scientists, we need to "take care not to commit a kind of fallacy of misplaced concreteness that mistakes the unit of observation for the thing of real substantive or theoretical interest"
- That is, data being plotted on a map does not necessarily mean that location is a factor affecting those data



Next...

- Dynamic Data Visualization
- What is the difference between static and dynamic data visualization? When should we use each?
- What are some tools for making dynamic data visualizations?