Interactive Visualization

JSC 370: Data Science II

What is interactive visualization?

- Interactive visualization involves the creation and sharing of graphical representations of data, model, or results that allow a user to directly manipulate and explore

- Some example products and packages in R:
    - Interactive plots (`plotly`)
    - Interactive maps (`plotly`, `leaflet`)
    - Interactive tables (`DT`)
    - Dashboards (`flexdashboard`)
    - Interactive applications (`shiny`)
    - Websites (Static using `R Markdown`, `blogdown`, `Hugo`, `Jeckyll`)

What is interactive visualization?

Interactivity allows users to engage with data / models in a way that static visuals cannot. Features of interactivity include:

- Identify, isolate, and visualize information for extended periods of time
- Zoom in and out
- Highlight relevant information
- Get more information
- Filter
- Animate
- Change parameters

Why use interactive visualization?

Interactive visualization helps with both the exploration and communication parts of the data science process

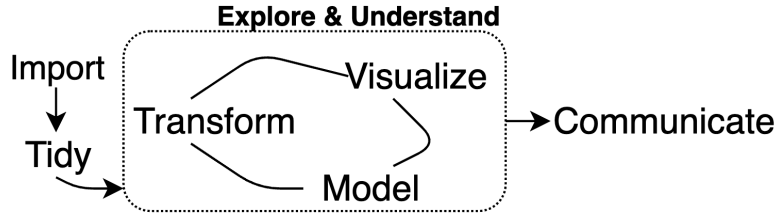


Diagram from: *R for Data Science* (Grolemund & Wickham 2016)

Where interactive visualization fits in to the data science workflow

Interactive Visualization for EDA

Interactive graphics are well suited to aid the exploration of high-dimensional or otherwise complex data. Interacting with information in a visual way helps to enable insights that wouldn't be easy or even possible with static graphics, for reasons including:

Interactive Visualization for EDA

(1.) Investigate faster: In a true exploratory setting, you have to make lots of visualizations, and investigate lots of follow-up questions, before stumbling across something truly valuable. Interactive visualization can aid in the sense-making process by searching for information quickly without fully specified questions (Unwin and Hofmann 1999)

Interactive Visualization for EDA

(2.) Identifying relationships or structure that would otherwise go missing
(J. W. Tukey and Fisherkeller 1973)

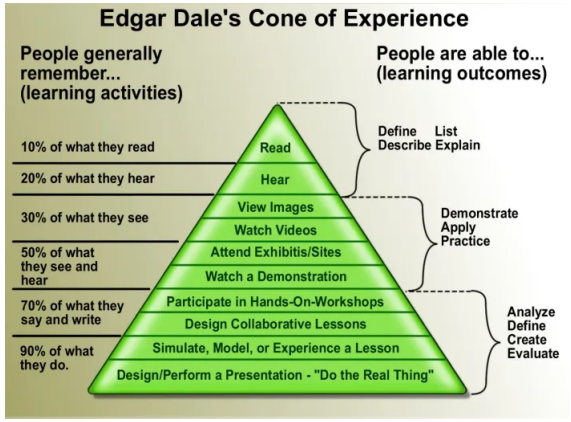
Interactive Visualization for EDA

(3.) Understand or diagnose problems with data, models, or algorithms (Wickham, Cook, and Hofmann 2015)

Interactive visualization for communication

Interactive graphics are well suited to communicating high-dimensional or otherwise complex data. Interacting with information in a visual way may help communicating data, models, and results for reasons including:

(1) Engagement with information has been shown to improve the ability to retain information



Edgar Dale's Cone of Learning

Interactive visualization for communication

(2) Automate and efficiently share multiple dimensions of data/models /findings or complex analysis tasks

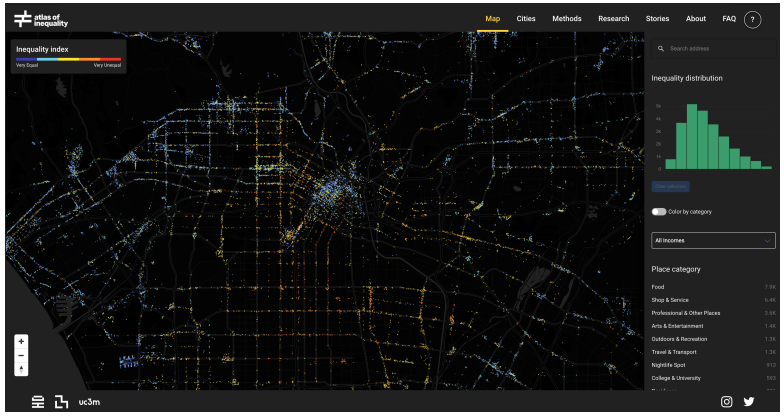
(3) Help users to better understand, and make decisions on, data/models /findings

EpiModel Shiny app for COVID testing at universities

Interactive visualization for communication

(4) Tell a more interesting or engaging story, presenting multiple viewpoints of data

(5) Allow users to focus on the aspects most important to them, making the user more likely to understand, learn from, remember and appreciate the data



MIT Media Lab Atlas of Inequality

Two Classes on Interactive Visualization in Data Science

Today:

- Creating interactive graphs with plotly for R package and tables with DataTable

Next Week:

- Create a website using RStudio and GitHub Pages
- Share your interactive graphics
- Survey other options for sharing interactive graphics (Shiny apps, dashboards)

What is Plotly?

- Plotly is an open source library for creating and sharing interactive graphics

- It is powered by the JavaScript graphing library plotly.js and is designed on principles of adding layers

- Plotly can work with several programming languages and applications including R, JavaScript, Python, Matlab, and Excel.

- Plotly for R graphics are based on the `htmlwidgets` framework, which allows them to work seamlessly inside of larger Rmarkdown documents, inside shiny apps,RStudio,Jupyter, the R prompt, and more.

`plot_ly()` vs. `ggplotly()`

- There are two main ways to create a plotly object:
  - Transforming a `ggplot2` object (via `ggplotly()`) into a plotly object
  - Directly initializing a plotly object with `plot_ly()`/`plot_geo()`/`plot_mapbox()`. This provides a 'direct' interface to plotly.js with some additional abstractions to help reduce typing
- Both approaches are powered by plotly.js so many of the same concepts and tools that you learn for one interface can be reused in the other

`plot_ly()` function

- The `plot_ly()` function has numerous arguments that are unique to the R package (e.g., `color`, `stroke`, `span`, `symbol`, `linetype`, etc.) and make it easier to encode data variables as visual properties (e.g., color). By default, these arguments map values of a data variable to a visual range defined by the plural form of the argument

- (almost) every function anticipates a plotly object as input to its first argument and returns a modified version of that plotly object

`plot_ly()` function

- The `layout()` function, which modifies layout components of the plotly object, anticipates a plotly object in its first argument and its other arguments add and/or modify various layout components of that object (e.g., the title)

`plot_ly()` function

- A family of `add_*()` functions (e.g., `add_histogram()`, `add_lines()`, `add_trace()`, etc.) define how to render data into geometric objects by adding a graphical layer to a plot. Layers can be included to add:
    - data
    - aesthetic mappings (e.g., assigning `clarity` to `color`)
    - geometric representation (e.g., rectangles, circles, etc.)
    - statistical transformations (e.g., sum, mean, etc.)
    - positional adjustments (e.g., dodge, stack, etc.)

ggplotly()

- We also have the option of working with the `ggplotly()` function from the plotly package, which can translate ggplot2 to plotly.

- The essence of this is very straightforward:

```
p <- ggplot(*) + geom_*()
ggplotly(p)
```

- This functionality can be really helpful for quickly adding interactivity to your existing ggplot2 workflow. `ggplotly()` provides advantages to `plot_ly()` in particular when it comes to exploring statistical summaries across groups. The ability to quickly generate statistical summaries across groups and map to an interactive plot works for basically any geom (e.g., `geom_boxplot()`, `geom_histogram()`, `geom_density()`, etc.)

Install Plotly

```
if(!require(plotly)) install.packages("plotly", repos = "http://cran.us.r-project.org")
library(plotly)
```

Load data for examples

For examples today we will be using COVID data direct downloaded from the New York Times GitHub repository: https://raw.githubusercontent.com/nytimes/covid-19-data/master/us-states.csv These data provide COVID cases (confirmed infections) and deaths by each US state and each date

Load data for examples

We have preprocessed the data for this presentation and added variables to `"input_data/coronavirus_states.csv"`

- `population` of each state
- `new_cases`: daily change in cases
- `new_deaths`: daily change in deaths
- `per100k`: cases per 100,000 population
- `deathsper100k`: deaths per 100,000 population
- `naive_CFR`: naive Case Fatality Rate (CFR) = deaths / cases, for each state on each date

In the lab we will preprocess these data together.

Load data for examples

```
# import data

cv_states = read.csv("/Users/meredith/Dropbox/Courses/JSC370/slides/11-interactive-viz1/input_data/coronavirus_st

# format the date
cv_states$date = as.Date(cv_states$date, format="%Y-%m-%d")

# create most recent day data frame
cv_states_today = subset(cv_states, date==max(cv_states$date))

dim(cv_states)
```

```
## [1] 13104    15
```

Load data for examples

Inspect the data

```
summary(cv_states)
```

```
##     state                date                 fips           cases        
##  Length:13104       Min.   :2020-01-21   Min.   : 1.00   Min.   :     1  
##  Class :character   1st Qu.:2020-05-01   1st Qu.:17.00   1st Qu.:  2089  
##  Mode  :character   Median :2020-06-29   Median :31.00   Median : 16764  
##                     Mean   :2020-06-28   Mean   :31.87   Mean   : 62365  
##                     3rd Qu.:2020-08-28   3rd Qu.:46.00   3rd Qu.: 70786  
##                     Max.   :2020-10-26   Max.   :78.00   Max.   :916562  
##      deaths           population         new_cases         new_deaths      
##  Min.   :    0.00   Min.   :   56882   Min.   :    0.0   Min.   :   0.00  
##  1st Qu.:   51.75   1st Qu.: 1360301   1st Qu.:   45.0   1st Qu.:   0.00  
##  Median :  453.50   Median : 3831074   Median :  264.0   Median :   4.00  
##  Mean   : 2158.38   Mean   : 5882962   Mean   :  670.6   Mean   :  17.26  
##  3rd Qu.: 2057.00   3rd Qu.: 6547629   3rd Qu.:  770.0   3rd Qu.:  15.00  
##  Max.   :33073.00   Max.   :37253956   Max.   :22276.0   Max.   :1877.00  
##  days_since_death10 days_since_case100    per100k          newper100k      
##  Min.   :  0.00     Min.   :  0.00     Min.   :   0.0   Min.   :  0.00  
##  1st Qu.: 22.00     1st Qu.: 36.00     1st Qu.: 125.2   1st Qu.:  2.50  
##  Median : 83.00     Median : 96.00     Median : 623.4   Median :  7.10  
##  Mean   : 87.37     Mean   : 98.12     Mean   : 954.1   Mean   : 11.28  
##  3rd Qu.:146.00     3rd Qu.:158.00     3rd Qu.:1563.9   3rd Qu.: 15.30  
##  Max.   :237.00     Max.   :233.00     Max.   :5686.4   Max.   :220.40  
##  deathsper100k    newdeathsper100k    naive_CFR       
##  Min.   :  0.00   Min.   : 0.0000   Min.   : 0.000  
```

Basic Scatterplot

Let's start with a scatterplot of population-normalized (`per100k`) deaths vs. cases on the most recent date from dataframe `cv_states_today`

- Specify a scatterplot by `type = "scatter"` and `mode = 'markers'`

- Notice how the arguments for the `x` and `y` variables as specified as formulas, with the tilde operator (~)

- Use `color` to specify an additional data dimension (factor or continuous), and map each level of the dimension to a different color (factor or continuous)

- `colors` is used to specify the range of colors

Basic Scatterplot

- Scatterplot of deaths vs. cases population-normalized (`per100k`)

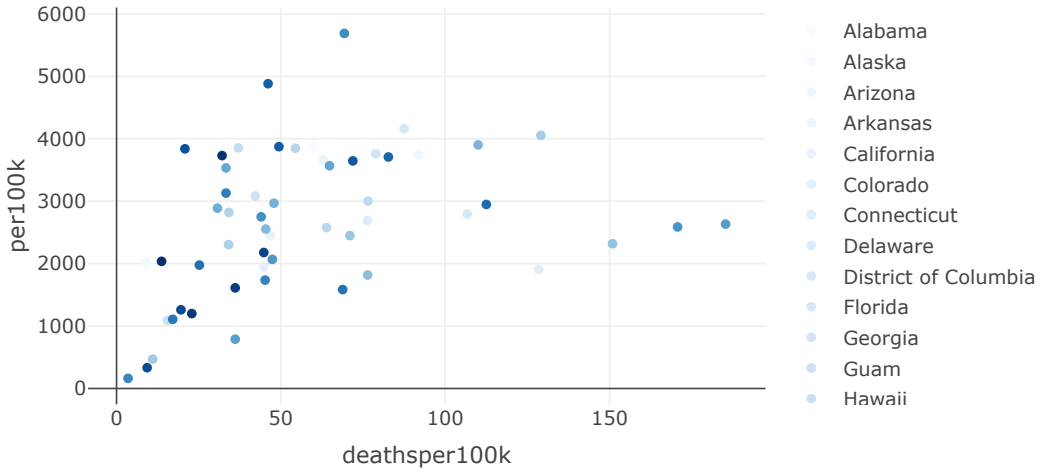
- plotly allows us to hover and see the exact (x, y) values of each point

- Notice the automatic `tooltip` that appears when your mouse hovers over each point

- Double click any item in legend to isolate that point in the plot

Basic Scatterplot

```
cv_states_today %>%
          plot_ly(x = ~deathsper100k, y = ~per100k,
                  type = 'scatter',
                  mode = 'markers',
                  color = ~state,
                  colors = "Blues")
```



Scatterplot: size

- You can add an additional dimension by adjusting the `size` of each point (also with ~ operator)
    - Specify the limits of the size through `sizes`
    - `sizemode` specifies `'area'` or `'diameter'`
- Here we specify size as mapped to each state's `naive_CFR`

```
cv_states_today %>%
           plot_ly(x = ~deathsper100k, y = ~per100k,
                   type = 'scatter',
                   mode = 'markers',
                   color = ~state,
                   size = ~naive_CFR,
                   sizes = c(5, 70),
                   marker = list(sizemode='diameter', opacity=0.5))
```

Scatterplot: size

The closer to the bottom right corner of the plot, the higher the CFR, and the larger the point's circle.

Specifying hover information

- You can specify what info will appear when hovering using `hoverinfo` through the `text` argument (also with ~ operator)
    - Multiple variables can be included upon hover
    - Create new lines between variables in `hoverinfo` using `sep = "<br>"`
- Let's add `per100k`, `deathsper100k`, and `naive_CFR` to the hover info:

```
cv_states_today %>%
  plot_ly(x = ~deathsper100k, y = ~per100k,
          type = 'scatter', mode = 'markers', color = ~state,
          size = ~naive_CFR, sizes = c(5, 70), marker = list(sizemode='diameter', opacity=0.5),
          hoverinfo = 'text',
          text = ~paste( paste(state, ":", sep=""),
                         paste(" Cases per 100k: ", per100k, sep="") ,
                         paste(" Deaths per 100k: ", deathsper100k, sep=""),
                         paste(" CFR (%): ", naive_CFR,sep=""),
```

Specifying hover information

We can now clearly understand the information being shown in the `tooltip`

Layout

- Specify chart labels through `layout()`

- `hovermode = "compare"` allows comparing multiple points (default is `"closest"`)

```
cv_states_today %>%
  plot_ly(x = ~deathsper100k, y = ~per100k,
          type = 'scatter', mode = 'markers', color = ~state,
          size = ~naive_CFR, sizes = c(5, 70), marker = list(sizemode='diameter', opacity=0.5),
          hoverinfo = 'text',
          text = ~paste( paste(state, ":", sep=""), paste(" Cases per 100k: ", per100k, sep="") , paste(" Deaths |
                         deathsper100k, sep=""), paste(" CFR (%): ", naive_CFR,sep=""), sep = "<br>")) %>%
  layout(title = "Cases, Deaths, and Naive Case Fatality Rate for US States",
                  yaxis = list(title = "Cases"), xaxis = list(title = "Deaths"),
         hovermode = "compare")
```

Layout

3D Scatterplot

- Can add a 3rd dimension using `type = 'scatter3d'` (make sure to specify the dimension as `z`)

```
cv_states_today %>%
  plot_ly(x = ~deathsper100k, y = ~per100k, z = ~population,
          type = 'scatter3d', mode = 'markers', color = ~state,
          size = ~naive_CFR, sizes = c(5, 70), marker = list(sizemode='diameter', opacity=0.5),
          hoverinfo = 'text',
          text = ~paste( paste(state, ":", sep=""), paste(" Cases per 100k: ", per100k, sep="") , paste(" Deaths |
                         deathsper100k, sep=""), paste(" CFR (%): ", naive_CFR,sep=""), sep = "<br>")) %>%
  layout(title = "Cases, Deaths, and Naive Case Fatality Rate for US States",
                  yaxis = list(title = "Cases"), xaxis = list(title = "Deaths"),
         hovermode = "compare")
```

3D Scatterplot

Scatterplot with `ggplotly()`

- You can create a scatterplot with the `ggplotly()` function in 1 additional line of code

- The advantage of `ggplotly()` is that it allows taking advantage of the geom `geom_smooth()` to see the pattern in the scatter

```
library(ggplot2)
p <- ggplot(cv_states_today, aes(x=deathsper100k, y=per100k, size=naive_CFR)) + geom_point() + geom_smooth()
ggplotly(p)
```

Scatterplot with `ggplotly()`

`geom_smooth()` helps us to see there is not a clear correlation between cases and deaths relative to population across the states. Note that the

Annotations

- You can add annotations to your interactive plot

Annotations

Line graph

- Specify a line plot using `type = "scatter"` and `mode = "lines"`

- Be sure to specify the feature (column in the data) that distinguishes the lines (normally through `color`)

```
cv_states %>% filter(population>7500000) %>%
plot_ly(x = ~date, y = ~deaths, color = ~state, type = "scatter", mode = "lines",
        hoverinfo = 'text',
        text = ~paste( paste("Date: ", date, sep=""), paste(state, ":", sep=""), paste(" Deaths (total): ", deaths
                       paste(" Deaths per 100k: ", deathsper100k, sep=""), sep = "<br>"))
```

Line graph

Line graph

Deaths stabilized for New York and New Jersey around the time they started to rise for California, Texas, and Florida.

It helps to be able to see the exact values for each date upon hover.

Line graph: `ggplotly()`

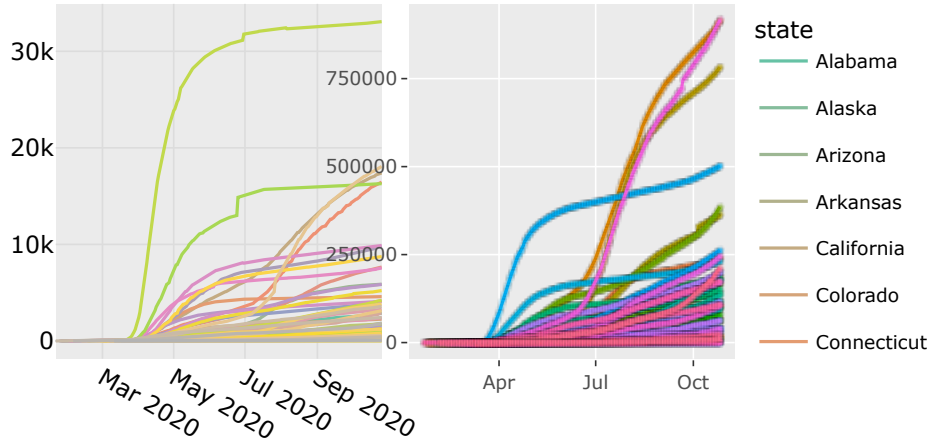
- Simply pass a `ggplot` object to `ggplotly()` to create an interactive version

- `subplot()` can be used to join arrange multiple plots -- works similarly to `grid.arrange()` function from the gridExtra package

    - Compare the automatic `tooltip` results for both plots

```
g1 = plot_ly(cv_states, x = ~date, y = ~deaths, color = ~state, type = "scatter", mode = "lines")
g2 = ggplot(cv_states, aes(x = date, y = cases, color = state)) + geom_line() + geom_point(size = .5, alpha = 0.5)
g2_plotly <- ggplotly(g2)
subplot(g1, g2_plotly)
```

Line graph: `ggplotly()`



Specifying text with `ggplotly()`

```
g1 = ggplot(cv_states, aes(x = date, y = cases, color = state,
                           text=paste( paste("Date: ", date, sep=""), paste(state, ":", sep=""), paste(" Cases (t
g2<-ggplotly(g1, tooltip = "text")
widgetframe::frameWidget(g2, width = '85%')
```

Specifying text with `ggplotly()`

- You can specify the tooltip text in the `ggplot()` or `ggplotly()` prompt, but note that the `ggplotly()` prompt only accepts text in `" "`

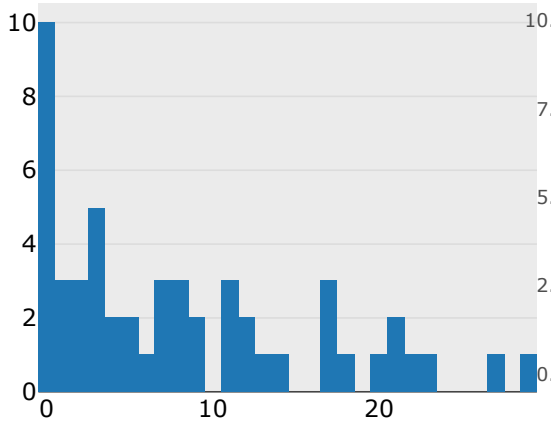
Histograms

- For `plot_ly()` use the `type = "histogram"` argument
- Note that `list()` is used to input keys with multiple values (e.g. `xbins`)

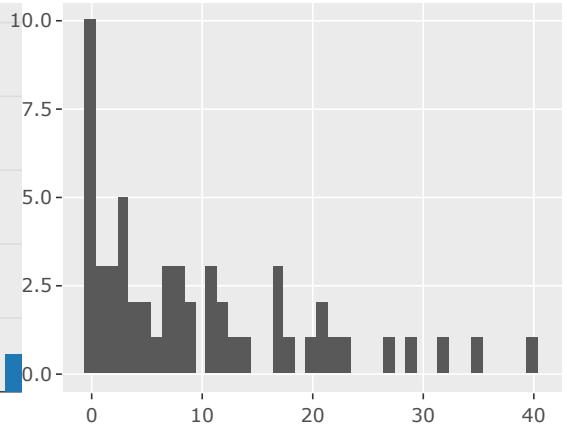
```
g1 <- cv_states_today %>%
  plot_ly(x = ~new_deaths, type = "histogram", xbins = list(size = 1, end=30 ))
g2 <- cv_states_today %>% ggplot( aes(x=new_deaths)) + geom_histogram(binwidth=1)
g2_plotly <- ggplotly(g2)
subplot(g1, g2_plotly)
```

Histograms

`plot_ly()`



`ggplotly()`



Heatmap

- Heatmaps are useful for displaying three dimensional data in two dimensions, using color for the third dimension.

- To create a heatmap from a dataframe we first have to create a matrix out of the three dimensions we want to include. We can do this using the `pivot_wider()` function from tidyr (there are many other options)

    - Here we are choosing `date`, `state`, and `newdeathsper100k` to show in our heatmap

```
library(tidyr)
cv_states_mat <- cv_states %>% select(state, date, newdeathsper100k) %>% filter(date>"2020-03-31") %>% filter(new
cv_states_mat2 <- as.data.frame(pivot_wider(cv_states_mat, names_from = state, values_from = newdeathsper100k))
rownames(cv_states_mat2) <- cv_states_mat2$date
cv_states_mat2$date <- NULL
head(cv_states_mat2)
```

Heatmap

- We can then create a heatmap from the matrix by using the `type = "heatmap"` argument

- If you want the x and y axes to show specify that with `x=colnames(data), y=rownames(data)`

- You can hide or show scale using `showscale=T/F`

```
library(tidyr)
cv_states_mat <- cv_states %>% select(state, date, newdeathsper100k) %>% filter(date>"2020-03-31") %>% filter(new
cv_states_mat2 <- as.data.frame(pivot_wider(cv_states_mat, names_from = state, values_from = newdeathsper100k))
rownames(cv_states_mat2) <- cv_states_mat2$date
cv_states_mat2$date <- NULL
data <- as.matrix(cv_states_mat2)

plot_ly(x=colnames(data), y=rownames(data),
             z=~data,
             type="heatmap",
             showscale=T)
```

Heatmap

We can see when new deaths started to rise and fall for each state. No other state approached the values seen in NY. The hover info conveniently allows us to inspect the exact date and number of new deaths.

3D Surface

You can also create a 3D surface out of the matrix using `type = "surface"`

```
plot_ly(x=colnames(cv_states_mat2), y=rownames(cv_states_mat2),
             z=~cv_states_mat2,
             type="surface",
             showscale=F)
```

Choropleth Maps: Setup

Choropleth maps illustrate data across geographic areas by shading regions with different colors. Choropleth maps are easy to make with Plotly though they require more setup compared to other Plotly graphics.

Making choropleth maps requires two main types of input:

- Geometry information: This can be supplied using:
    - GeoJSON file where each feature has either an id field or some identifying value in properties
    - or a built-in geometry within plot_ly: US states and world countries
- A list of values indexed by feature identifier

Choropleth Maps: Setup

- Let's focus on interactively mapping the feature `naive_CFR` to each of the US states, including their boundaries

- To use the USA States geometry, set `locationmode='USA-states'` and provide locations as two-letter state abbreviations

- Our `cv_states` identifies states by their long names, so we need to transpose to their abbreviations first

```
cv_CFR <- cv_states_today %>% select(state, naive_CFR) # select data

# Get state abbreviations and map to state names
library(dplyr)
st_crosswalk <- tibble(state = state.name) %>%
   bind_cols(tibble(abb = state.abb)) %>%
   bind_rows(tibble(state = "District of Columbia", abb = "DC"))
cv_CFR2 <- left_join(cv_CFR, st_crosswalk, by = "state")
cv_CFR2$state.name <- cv_CFR2$state
cv_CFR2$state <- cv_CFR2$abb
```

Choropleth Maps: Setup

- Hover text can be specified within the data frame (this is true for any `plot_ly()` object)

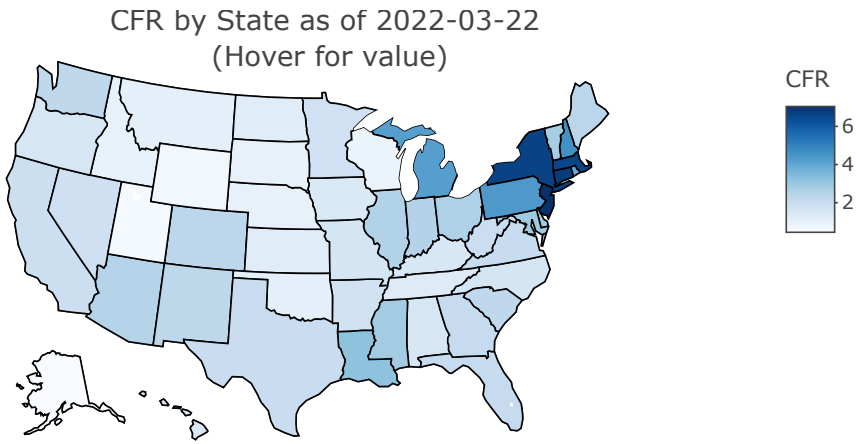
```
# Create hover text
cv_CFR2$hover <- with(cv_CFR, paste(state.name, '<br>', "CFR:", naive_CFR))

# Set up mapping details
set_map_details <- list(
  scope = 'usa',
  projection = list(type = 'albers usa'),
  showlakes = TRUE,
  lakecolor = toRGB('white')
)
```

Choropleth Maps: Mapping

- Recall: To use the USA States geometry, set `locationmode='USA-states'`
- Specify the map projection details inside `layout()`

```
# Create the map
fig <- plot_geo(cv_CFR2, locationmode = 'USA-states') %>%
  add_trace(
    z = ~naive_CFR, text = ~hover, locations = ~state,
    color = ~naive_CFR, colors = 'Blues'
  )
fig <- fig %>% colorbar(title = "CFR")
fig <- fig %>% layout(
    title = paste('CFR by State as of', Sys.Date(), '<br>(Hover for value)'),
    geo = set_map_details
  )
```

Choropleth Maps: Mapping



The northeast was hit hard with high CFRs. It would be interesting to see this map at different time points.

A note on interactive mapping

- There are in fact 4 different ways to render interactive maps with plotly: `plot_geo()`, `plot_ly()`, `plot_mapbox()`, and via ggplot2's `geom_sf()`.

- `plotly` is a general purpose visualization library and doesn't offer most fully featured geo-spatial visualization toolkit. If you run into limitations with plotly's mapping functionality there are many other tools for interactive geospatial visualization in R, including: leaflet, mapview, mapedit, tmap, and mapdeck.

Interactive tables

The `DT` package creates an interactive DataTable html widget out of a dataframe in 1 line of code

```
library(DT)
cv_california <- cv_states %>% filter(state=="California") %>% select(date,cases,deaths,new_cases,new_deaths,naiv
datatable(cv_california)
```

Note that you can interactively reorder the values by clicking on the arrows at the top of each column, or search for specific values

Interactive tables

Show 10 entries Search:

	date	cases	deaths	new_cases	new_deaths	naive_CFR
1	2020-01-25	1	0	1	0	0
2	2020-01-26	2	0	1	0	0
3	2020-01-27	2	0	0	0	0
4	2020-01-28	2	0	0	0	0
5	2020-01-29	2	0	0	0	0
6	2020-01-30	2	0	0	0	0
7	2020-01-31	3	0	1	0	0
8	2020-02-01	3	0	0	0	0

Publishing views

Both `plot_ly()` and `ggplotly()` objects and be computed directly as part of an R Markdown file, which means they will show up on a website you create using R Markdown and GitHub pages.

You can also share your visualizations on https://plot.ly/ by making an account on their site

But you may want to save and embed the interactive HTML file, or save a static image based on the plot

Saving and embedding HTML

Any widget made from any htmlwidgets package (e.g., plotly, leaflet, DT, etc.) can be saved as a standalone HTML file via the `htmlwidgets::saveWidget()` function. By default, it produces a completely self-contained HTML file, meaning that all the necessary JavaScript and CSS dependency files are bundled inside the HTML file.

If you want to embed numerous widgets in a larger HTML document, save all the dependency files externally into a single directory. You can do this by setting `selfcontained = FALSE` and specifying a fixed `libdir` in `saveWidget()`:

```
library(htmlwidgets)
p <- plot_ly(x = rnorm(100))
saveWidget(p, "p1.html", selfcontained = F, libdir = "lib")
saveWidget(p, "p2.html", selfcontained = F, libdir = "lib")
```

Saving a static image

- With code (convenient if you need to output many static images): Any plotly object can be saved as a static image via the `orca()` function.

- From a browser (convenient if you want to manually post-process an image): By default, the 'download plot' icon in the modebar will download to PNG and use the `height` and `width` of the plot, but these defaults can be altered via the plot's configuration, e.g.

```
plot_ly() %>%
  config(
    toImageButtonOptions = list(
      format = "svg",
      filename = "myplot",
      width = 600,
      height = 700
    )
  )
```

Takeaways

Hopefully in this class you have learned:

- How to create plots with plotly package using either `plot_ly()` calls or `ggplotly()` applied to a ggplot2 workflow -Other interactive options -- maps (multiple options), tables (DataTable)

- To appreciate how interactive visualization can help to explore data in ways static graphics cannot

- Get an idea of the multitude of options available to you

- Get inspired to create engaging, effective data visualizations and tell stories with your data and findings!

Avoid pitfals

- Don’t overcomplicate!
- Only use when adding value!
- Some examples of bad practices: (link)
- And just hilariously bad examples: (link)

More Resources

`Plotly`

- Plolty R Reference
- The Plotly R API
- The Plotly R Package on GitHub
- The Plotly R Cheatsheet
- "Plotly for R" book by Carson Sievert

More Resources

`shiny` and dashboards

- The `Shiny` Website

- R Markdown: The Definitive Guide, Chapter 5: Dashboards (Layout, Components, Shiny)

More Resources

Website development in rmarkdown

- Tutorial: Creating websites in R, Emily C. Zabor
- Creating websites with R Markdown: advanced website creation with `blogdown`, `Hugo`, `Jeckyll`

More Resources

Data visualization best practices

- Data Visualization: A Practical Introduction, Kieran Healy
- Fundamentals of Data Visualization, Claus O. Wilke

References

- "Plotly for R" book by Carson Sievert

- Coursera course on Developing Data Products, Johns Hopkins Data Science Lab: (GitHub repo for all course materials) materials)

- Plolty R Reference