

# YData: Introduction to Data Science



Class 18: Maps and Intro to Statistical Inference

# Overview

Very quick review of interactive heatmaps

Mapping continued

If there is time

- Introduction to Statistical Inference

# Reminder: class project

The final project is a **6-10 page** Jupyter notebook report where you analyze your own data to address a question that you find interesting

- A project template Jupyter notebooks is on Canvas

A **polished** draft of the project is due on April 9<sup>th</sup>

Focus on giving insight into some interesting questions

- You do not need to use all methods discussed in the class



# Very quick review of Interactive visualizations

Interactive visualizations are useful for exploring data to find trends

We discussed several interactive visualization we can make with plotly:

```
import plotly.express as px
```

```
px.scatter(data_frame = , x = , y = , size = , color = , hover_name = )
```

```
px.line(data_frame = , x = , y = , color = , hover_name = , line_shape = )
```

```
px.sunburst(data_frame = , path = , values = , color = )
```

```
px.treemap(data_frame = , path = , values = , color = )
```

```
px.imshow(df2) # heatmap
```

# Pivot Tables and heatmaps

Pivot tables aggregate values based on two grouping variables, and create a table where:

- The columns are the levels of one variable
- The rows are the levels of the other variable

```
df2 = df.pivot_table(index = "col1", columns = "col2",  
                      values = "col3", aggfunc = "mean")
```

Once we have a 2D table, we can visualize it using:

- `px.imshow(df2)` # create a heatmap using plotly
- `sns.heatmap(df2)` # create a heatmap using seaborn

**Grouping:** `df.groupby(["col1" col2])`.

		col1	col2	
		Flavor	Color	count
	bubblegum		pink	1
	chocolate		dark brown	2
	chocolate		light brown	1
	strawberry		pink	2

**Pivot Table:** `df.pivot_table()`

		col1		
col2	Color	bubblegum	chocolate	strawberry
	dark brown	0	2	0
	light brown	0	1	0
	pink	1	0	2

# Pivot Tables and heatmaps


If we want to create a pivot table without aggregating data, we can use the `.pivot()` method

- rather than `.pivot_table()` method

```
df2 = df.pivot(index = "col1", columns = "col2",  
               values = "col3")
```

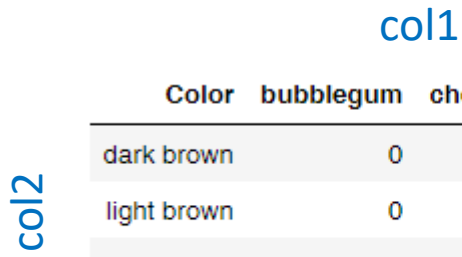
Note: there needs to be one value for each combination of "col1" x "col2" levels.

Grouping: `df.groupby(["col1" col2])`.



Flavor	Color	count
bubblegum	pink	1
chocolate	dark brown	2
chocolate	light brown	1
strawberry	pink	2

Pivot Table: `df.pivot_table()`



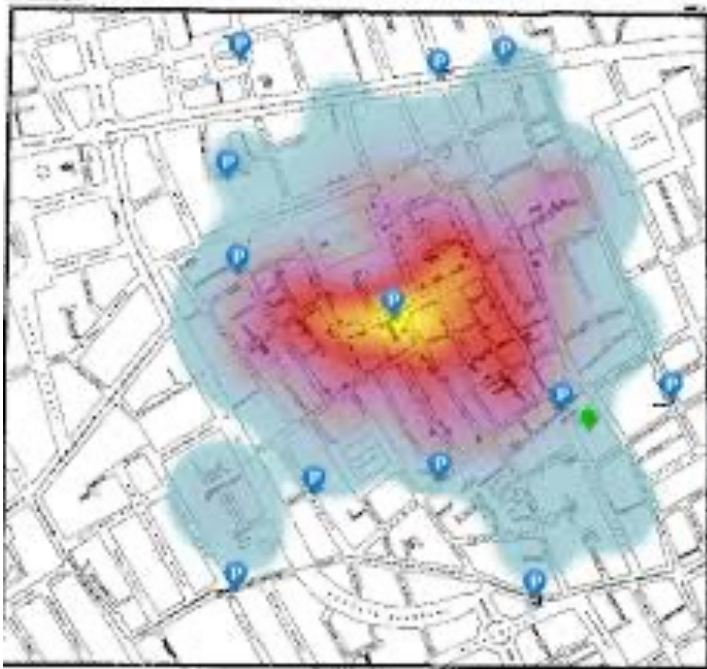
	col1			
	Color	bubblegum	chocolate	strawberry
col2	dark brown	0	2	0
	light brown	0	1	0
	pink	1	0	2

Let's explore this in Jupyter!

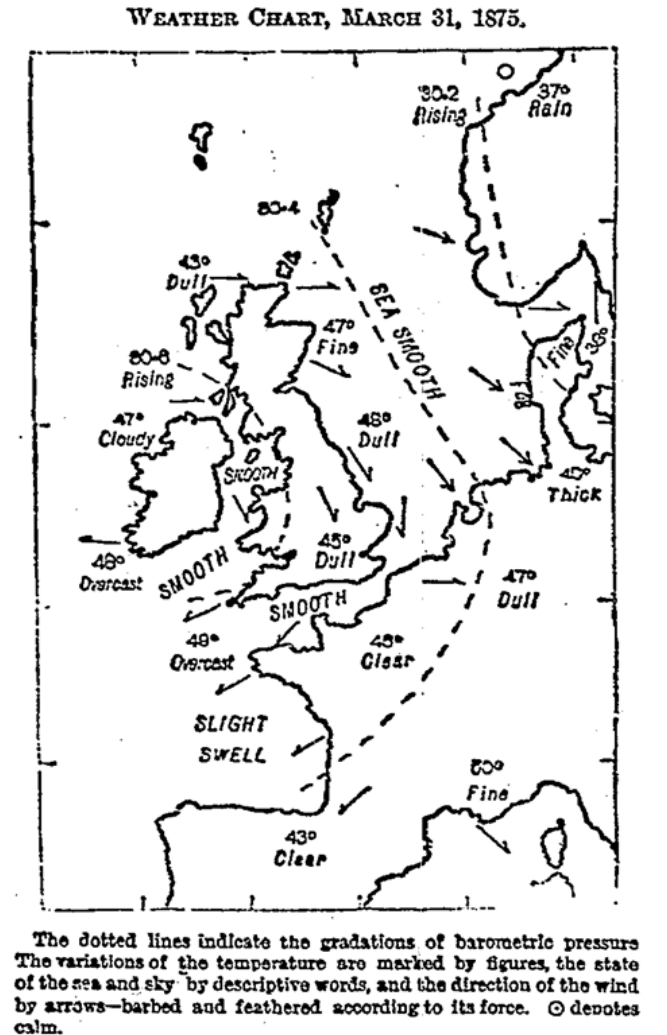
Maps

# Maps

Visualizing data on a map can be a powerful way to see spatial trends



John Snow's ghost map (1854)



Galton's first weather map (1875)



# geopandas

To create maps in Python we will use the geopandas package

- `import` geopandas `as` gpd

The key object of interest is the geopandas DataFrame

- It is the same as a regular data frame but it has an extra column called "geometry" that contains geospatial shape features
  - The geometry column as "Shapely" objects used to represent geometric shapes

	key_comb_drvr	geometry
0	M11551	POINT (117.525391 34.008926)
1	M17307	POINT (86.51248 30.474344)
2	M19584	POINT (89.537415 37.157627)
3	M21761	POINT (117.526871 34.00647)
4	M22374	POINT (117.525345 34.008915)
5	U01997A	POINT (84.80533 33.719654)
6	U153601	POINT (78.24838 39.986454)
7	U159393	POINT (98.49438499999999 40.801544)
8	U722222	POINT (84.23309 33.9386)
9	U723030	POINT (83.86456 34.08479)
10	U723333	POINT (85.67151 42.83093)
11	U753333	POINT (117.498535 34.069157)
12	U760505	POINT (90.61252 41.456993)

# geopandas

We can read in data as a geopandas DataFrame using

- `map = gpd.read_file('my_file.geojson')`

We can plot maps using the `gpd.plot()` function

Let's explore this in Jupyter!

# Coordinate reference systems

A coordinate reference system (CRS) is a framework used to precisely measure locations on the surface of the Earth as coordinates

The goal of any coordinate reference system is to create a common reference frame in which locations can be measured precisely as coordinates, so that any recipient can identify the same location that was originally intended.

- Needed for aligning different layers on maps

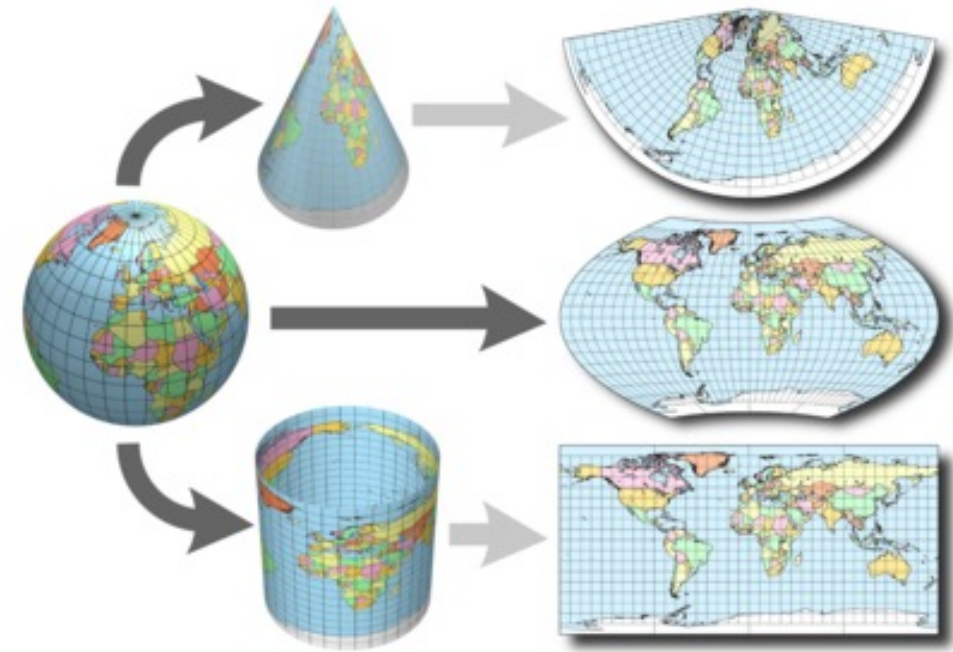


# Map projections

Since the earth is a 3D structure, coordinate systems have to project their data onto a 2D maps

Different projects preserve different properties

- **Mercator projection** keeps angles intact
  - Useful for navigation
- **Eckert IV projection** keeps the size of land areas intact



Let's explore this in Jupyter!

# WHAT YOUR FAVORITE MAP PROJECTION SAYS ABOUT YOU

## MERCATOR



YOU'RE NOT REALLY INTO MAPS.

## VAN DER GRINTEN



YOU'RE NOT A COMPLICATED PERSON. YOU LOVE THE MERCATOR PROJECTION; YOU JUST WISH IT WEREN'T SQUARE. THE EARTH'S NOT A SQUARE, IT'S A CIRCLE. YOU LIKE CIRCLES. TODAY IS GONNA BE A GOOD DAY!

## HOBBO-DYER



YOU WANT TO AVOID CULTURAL IMPERIALISM, BUT YOU'VE HEARD BAD THINGS ABOUT GAIL-PETERS. YOU'RE CONFLICT-AVERSE AND BUY ORGANIC. YOU USE A RECENTLY-INVENTED SET OF GENDER-NEUTRAL PRONOUNS AND THINK THAT WHAT THE WORLD NEEDS IS A REVOLUTION IN CONSCIOUSNESS.

## PLATE CARREE (EQUIRECTANGULAR)



YOU THINK THIS ONE IS FINE. YOU LIKE HOW X AND Y MAP TO LATITUDE AND LONGITUDE. THE OTHER PROJECTIONS OVERCOMPLICATE THINGS. YOU WANT ME TO STOP ASKING ABOUT MAPS SO YOU CAN ENJOY DINNER.

## ROBINSON



YOU HAVE A COMFORTABLE PAIR OF RUNNING SHOES THAT YOU WEAR EVERYWHERE. YOU LIKE COFFEE AND ENJOY THE BEATLES. YOU THINK THE ROBINSON IS THE BEST-LOOKING PROJECTION, HANDS DOWN.

## DYMAXION



YOU LIKE ISAAC ASIMOV, XML, AND SHOES WITH TOES. YOU THINK THE SEAGRAY GOT A BAD RAP. YOU OWN 3D GOGGLES, WHICH YOU USE TO VIEW ROTATING MODELS OF BETTER 3D GOGGLES. YOU TYPE IN DVDRMK.

## A GLOBE!



YES, YOU'RE VERY CLEVER.

## WATERMAN BUTTERFLY



REALLY? YOU KNOW THE WATERMAN? HAVE YOU SEEN THE 1909 CAHILL MAP ITS BASED— ... YOU HAVE A FRAMED REPRODUCTION AT HOME?! WHOA ... LISTEN, FORGET THESE QUESTIONS. ARE YOU DOING ANYTHING TONIGHT?

## WINKEL-TRIPLE



NATIONAL GEOGRAPHIC ADOPTED THE WINKEL-TRIPLE IN 1998, BUT YOU'VE BEEN A WAT FAN SINCE LONG BEFORE 'NAT'GEO' SHOWED UP. YOU'RE WORRIED IT'S GETTING PLAYED OUT, AND ARE THINKING OF SWITCHING TO THE KAVRANSKY. YOU ONCE LEFT A PARTY IN DISGUST WHEN A GUEST SHOWED UP WEARING SHOES WITH TOES. YOUR FAVORITE MUSICAL GENRE IS "POST-".

## GOODE HOMOLOGINE



THEY SAY MAPPING THE EARTH ON A 2D SURFACE IS LIKE FLATTENING AN ORANGE PEEL, WHICH SEEMS EASY ENOUGH TO YOU. YOU LIKE EASY SOLUTIONS. YOU THINK WE WOULDN'T HAVE SO MANY PROBLEMS IF WE'D JUST ELECT *ADORABLE* PEOPLE TO CONGRESS INSTEAD OF POLITICIANS. YOU THINK AIRLINES SHOULD JUST BUY RODO FROM THE RESTAURANTS NEAR THE GATES AND SERVE *PIAT* ON BOARD. YOU CHANGE YOUR OILS OIL, BUT SECRETLY WONDER IF YOU REALLY *NEED* TO.

## PEIRCE QUINCUNCIAL



YOU THINK THAT WHEN WE LOOK AT A MAP, WHAT WE REALLY SEE IS OURSELVES. PETER YOU FIRST SAW *INCEPTION*, YOU SAT SILENT IN THE THEATER FOR SIX HOURS. IT BREAKS YOU OUT TO REALIZE THAT EVERYONE AROUND YOU HAS A SKELETON INSIDE THEM. YOU *HAVE* REALLY LOOKED AT YOUR HANDS.

## GAIL-PETERS



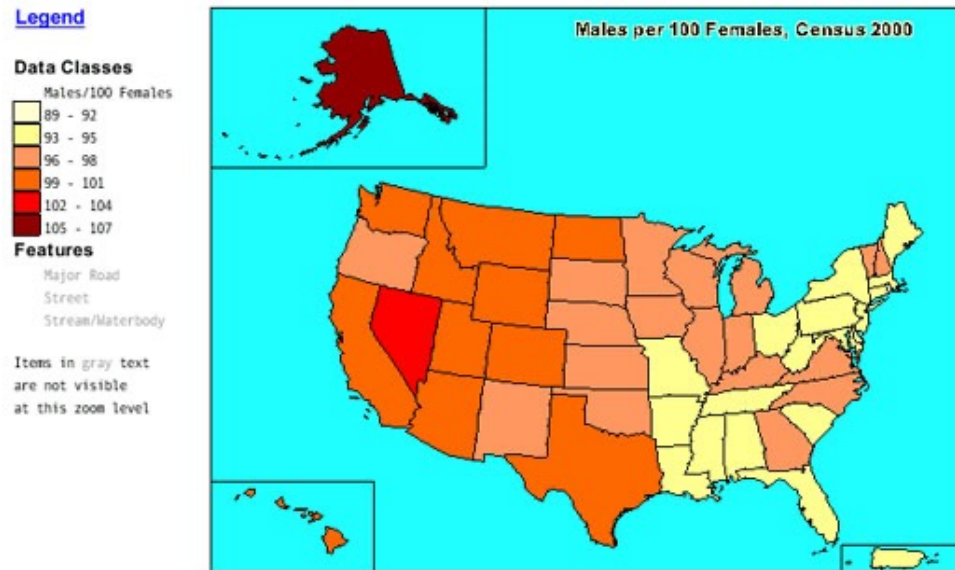
I HATE YOU.

# Maps

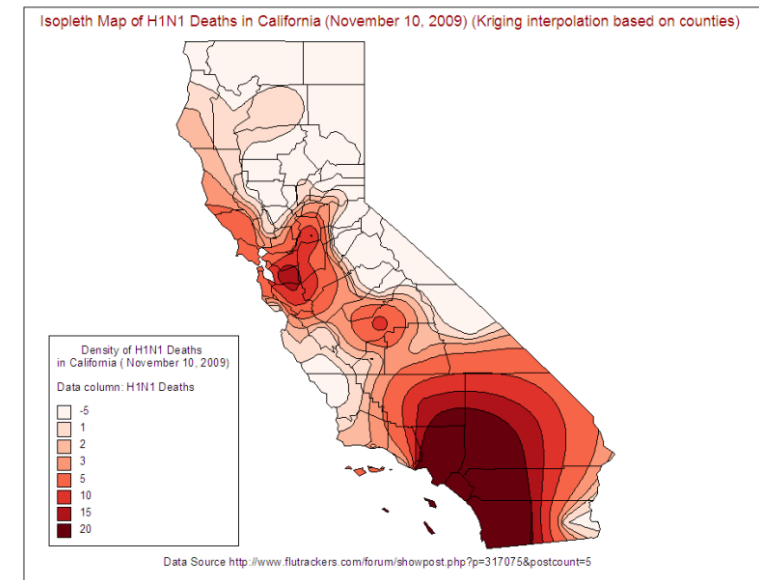
**Choropleth maps:** shades/colors in predefined areas based on properties of a variable

**Isopleth maps:** creates regions based on constant values

Choropleth map



Isopleth map



# Choropleth maps

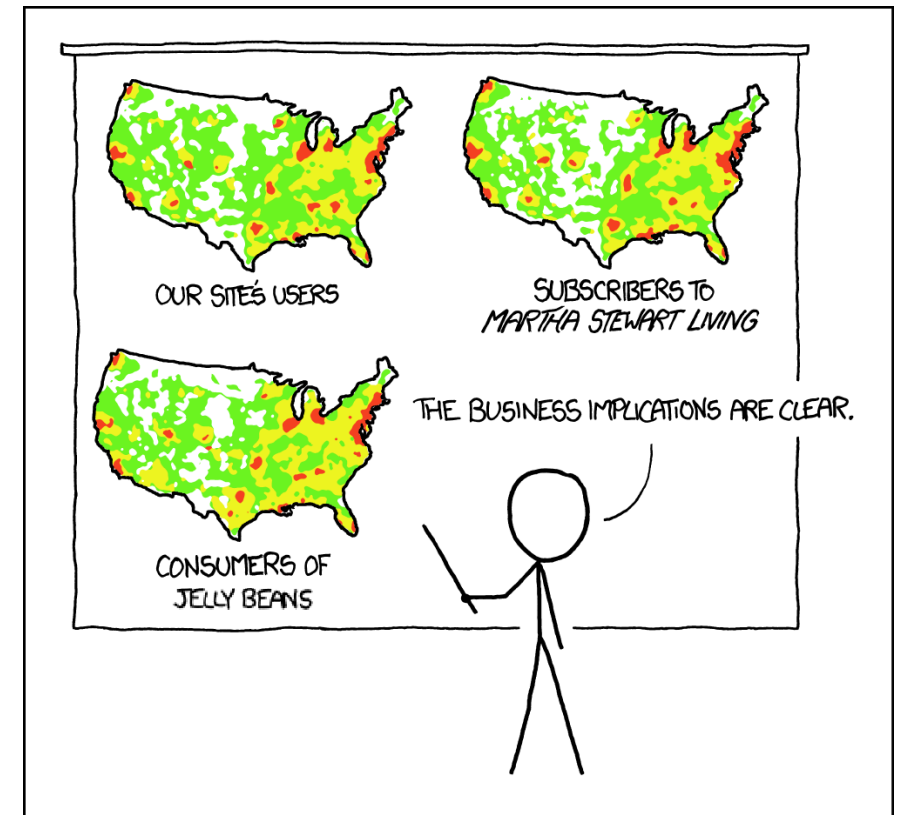
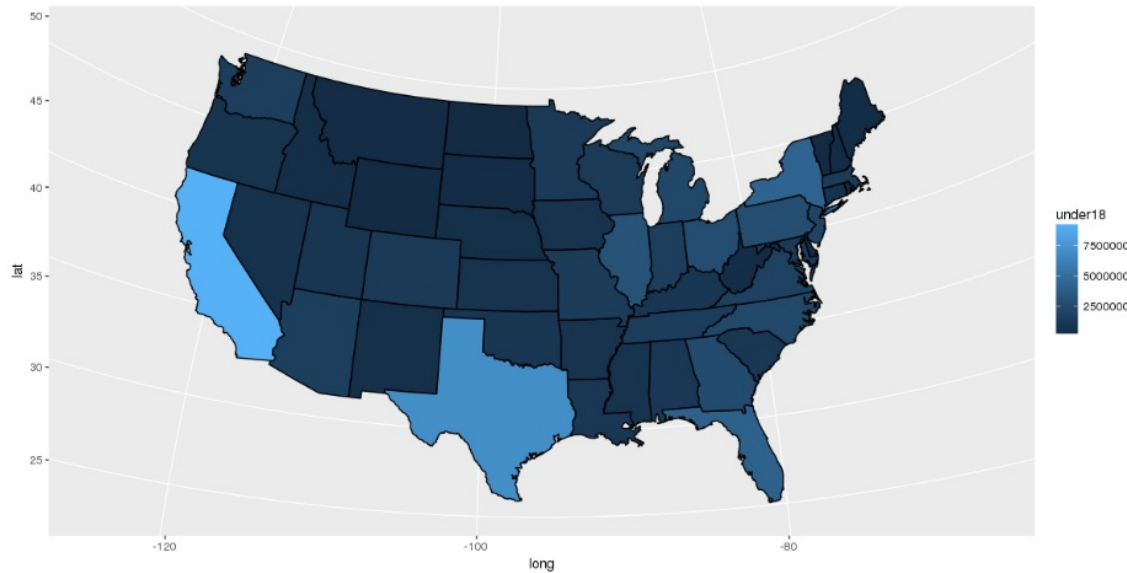
We can create choropleth maps using geopandas by joining region information on to a geopandas DataFrame that has a map

We can then use the `gpd.plot(column = )` method to visualize the map

Let's explore this in Jupyter!



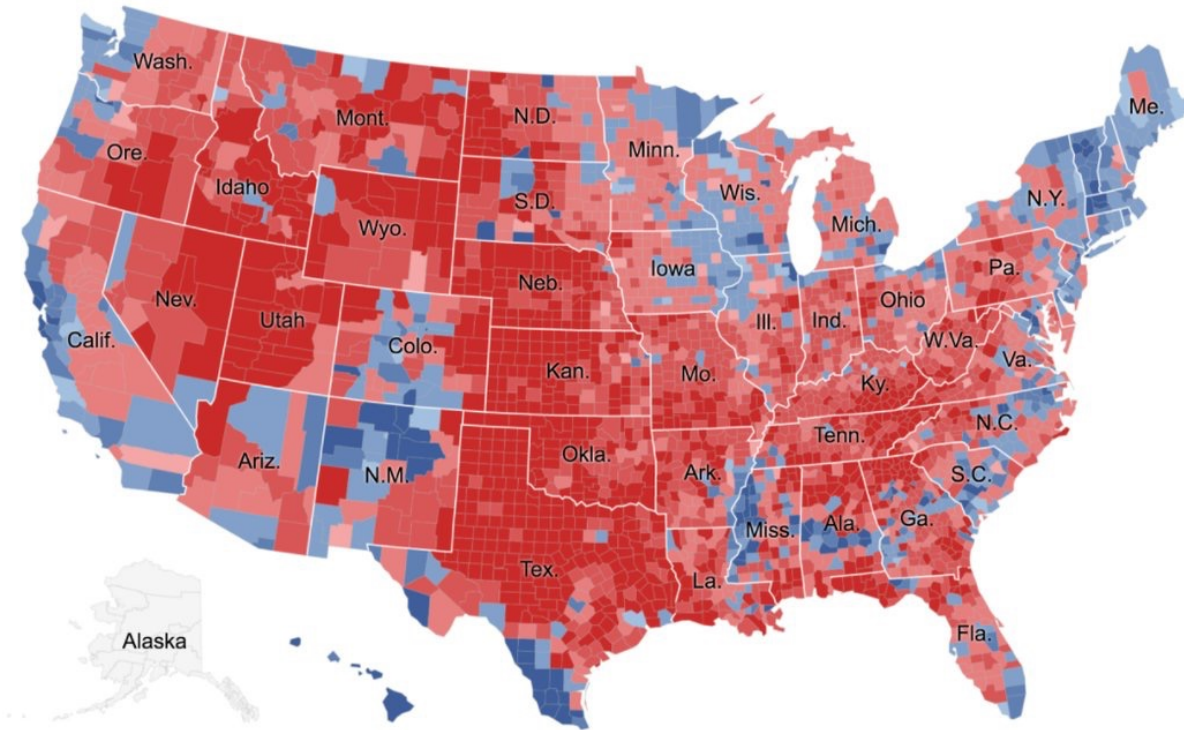
# Pet Peeve #208



PET PEEVE #208:  
GEOGRAPHIC PROFILE MAPS WHICH ARE  
BASICALLY JUST POPULATION MAPS



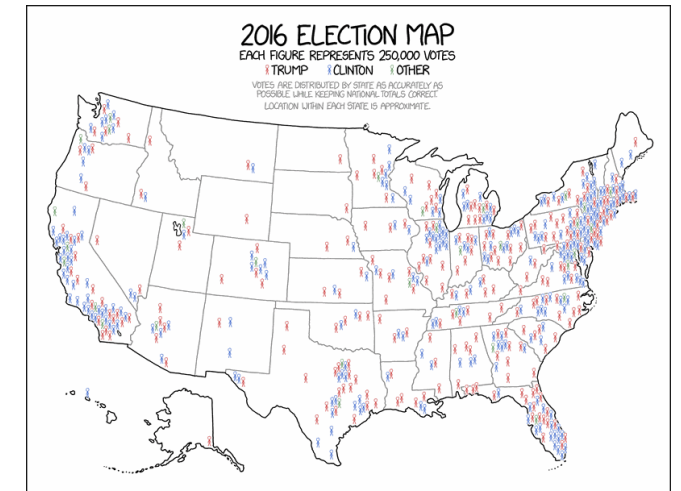
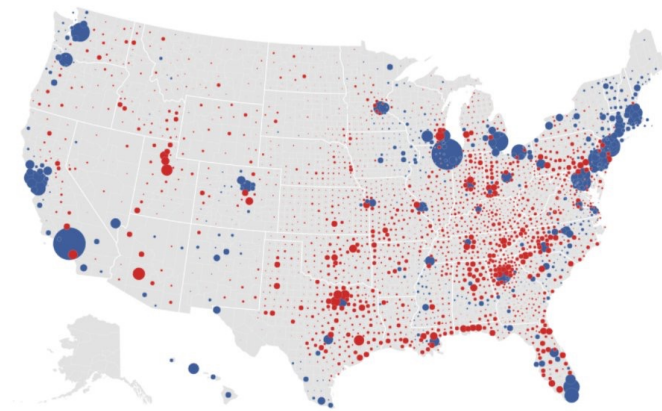
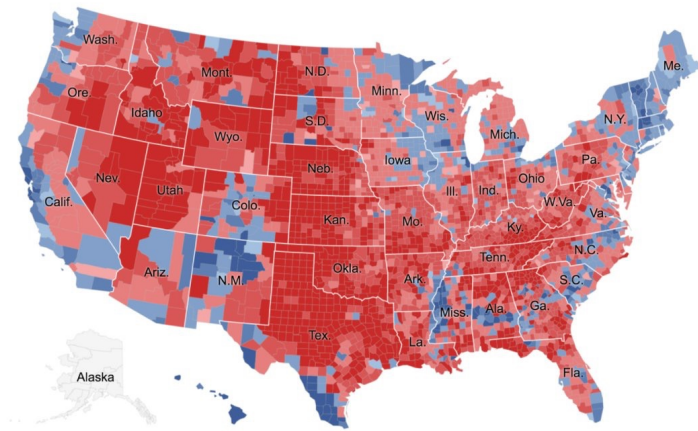
# Question: in what way could this map be misleading?



Darker red: county had higher % Trump vote

Darker blue: county had higher % Clinton vote

# Choropleth maps can be misleading



Looks like most of the country  
voted republican

# Statistical Inference

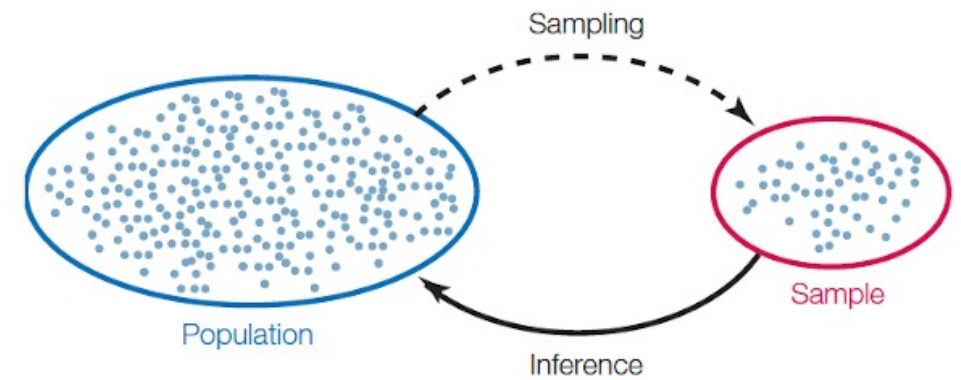
# Inference

**Statistical Inference:** Making conclusions about a population based on data in a random sample

This usually involves using data in a sample to estimate the value of a **fixed** unknown number

Example:

- Estimating the average height of all humans on Earth from a random sample of 1,000 humans
  - Our estimate will vary from sample to sample



# Terminology

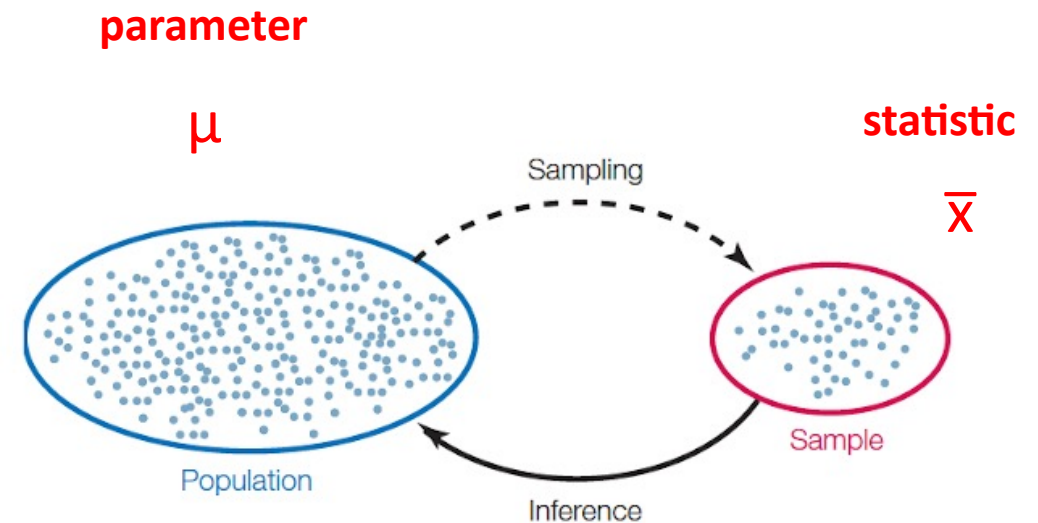
A **parameter** is number associated with the population

- e.g., population mean  $\mu$
- e.g., average height of all humans

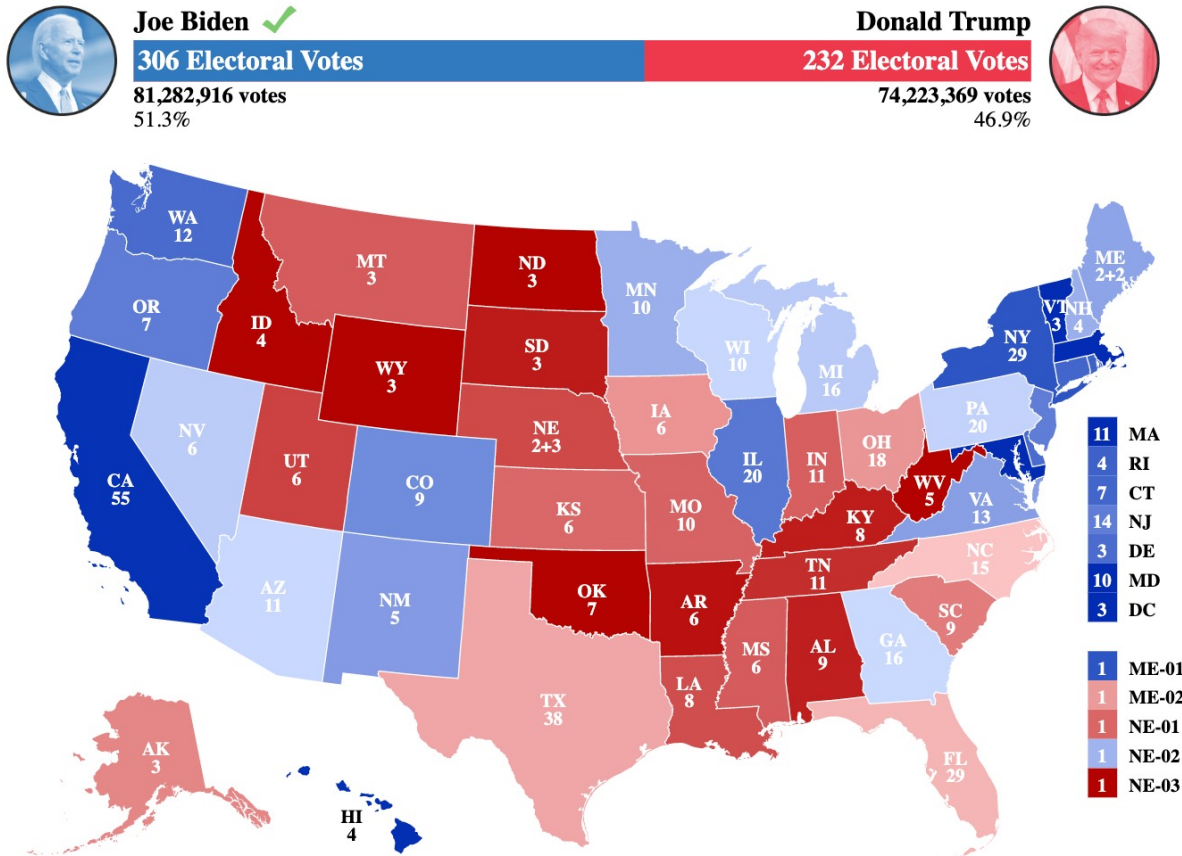
A **statistic** is number calculated from the sample

- e.g., sample mean  $\bar{x}$
- e.g., average height of 1,000 people in our sample

A statistic can be used as an estimate of a parameter



# Example: The 2020 US Presidential Election



According to The Cook Political Report, the voting outcome in Georgia was

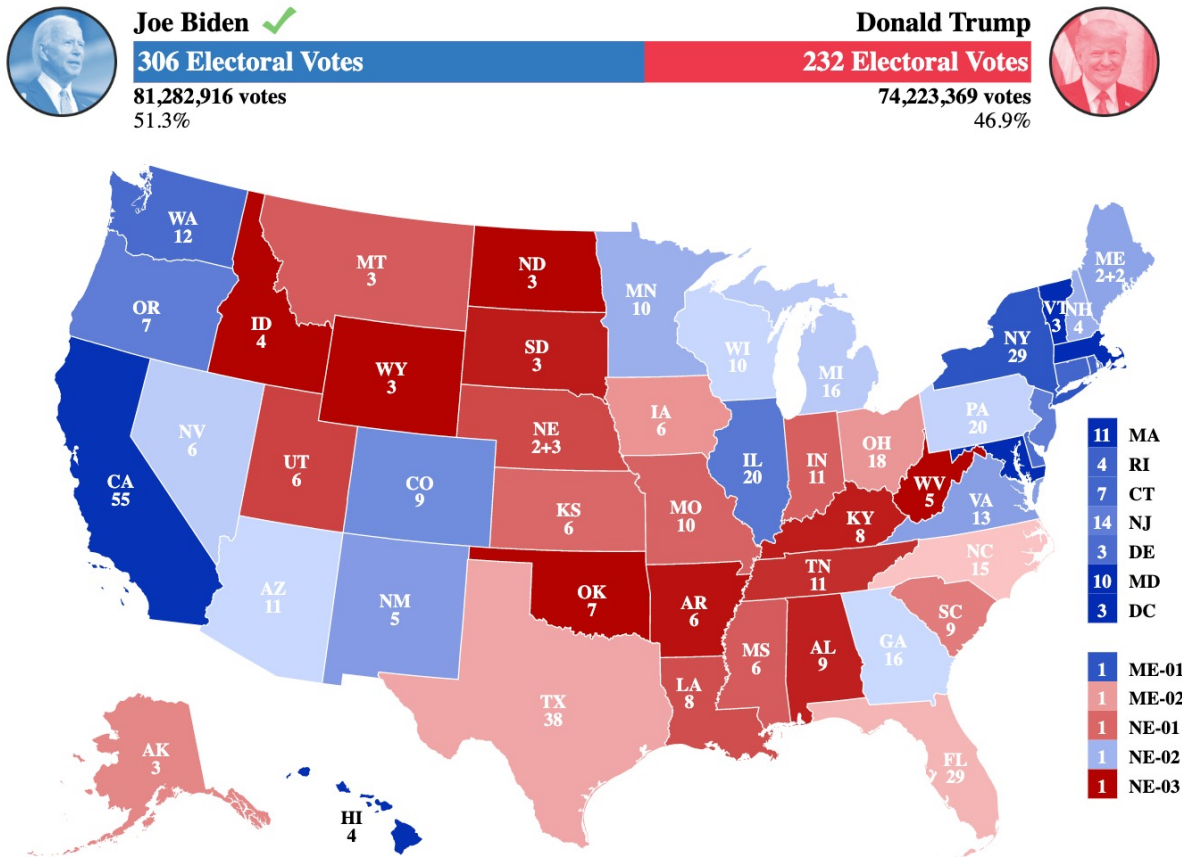
- Trump = 2,461,854
- Biden = 2,473,633

We can denote the proportion of the vote that Biden got using  $\pi_{\text{Biden}}$

- Q: what is the value of  $\pi_{\text{Biden}}$  ?



# Example: The 2020 US Presidential Election



If 1,000 voters were randomly sampled, we could denote the proportion in the sample that voted for Biden using:  $\hat{p}_{\text{Biden}}$

Would we expect  $\hat{p}_{\text{Biden}}$  to be equal to  $\pi_{\text{Biden}}$ ?

If we repeated the process of sampling another 1,000 random voters, would we expect to get the same  $\hat{p}_{\text{Biden}}$ ?

Let's explore this in Jupyter!

# Probability distribution of a statistic

Values of a statistic vary because random samples vary

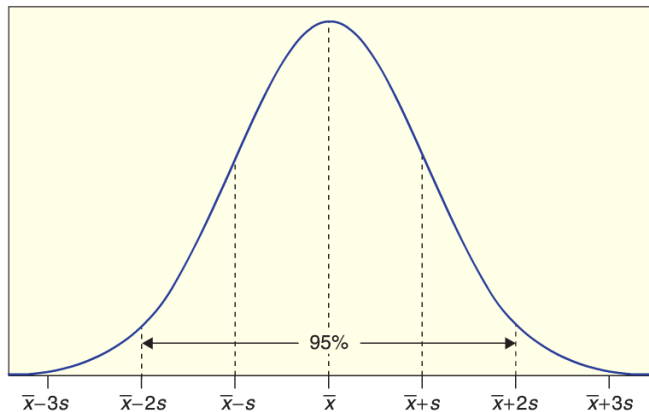
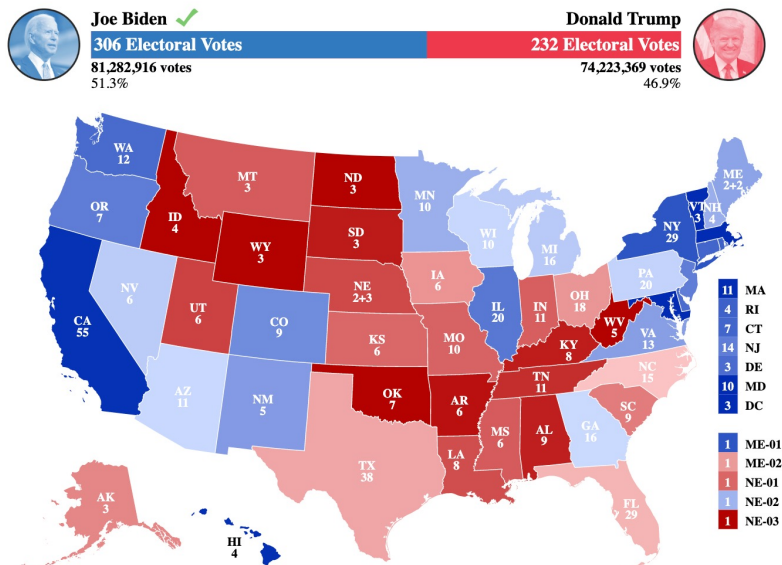
A **sampling distribution** is a probability distribution of *statistics*

- All possible values of the statistic and all the corresponding probabilities
- We can approximate a sampling distribution by a simulated statistics



$\pi$ Biden

n = 1,000



## Sampling distribution!



$\hat{p}_{\text{Biden}}$



$\hat{p}_{\text{Biden}}$



$\hat{p}_{\text{Biden}}$

## Let's explore this in Jupyter!