

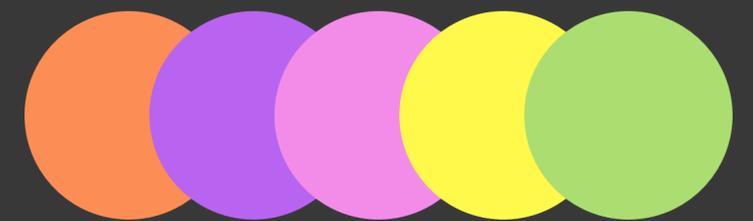
Jeff Tao



2/4/2026

CIS 7000: Foundations & Frontiers of HCI

# Data Visualization





[speculative.tech](http://speculative.tech)

# Jeff Tao

CIS PhD Student (3rd year)

Current Research: Data-oriented tools for debugging code, ML-based query optimization

Previously: MS Thesis @ Columbia

Thesis topic: *An Execution Engine for Physical Visualization Design*

Pre-previously: 5 years senior software engineer @ MongoDB, Microsoft

# Why Study Vis?



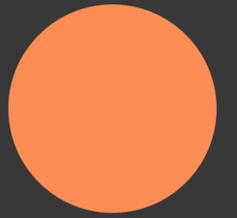
## Microcosm of HCI

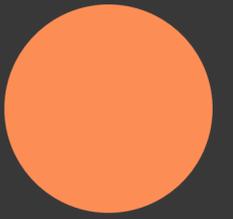
- Perception
- Cognition
- Systems
  - Languages/Formalisms
  - Data transformation
  - Novel interactions/encodings
- Interaction
- Emotion/Affect
- Design conventions
- Art
- Conceptual Frameworks (taxonomies, design dimensions)
- Experimental Design/Evaluation
- Tasks/Workflows
- Context of Use (science, journalism, business analytics, public health, data science)
- Users (scientists, journalists, programmers, data scientists, novices)

# Why Study Vis?

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# Why Visualize?

# Your Brain is Good at Pattern Recognition

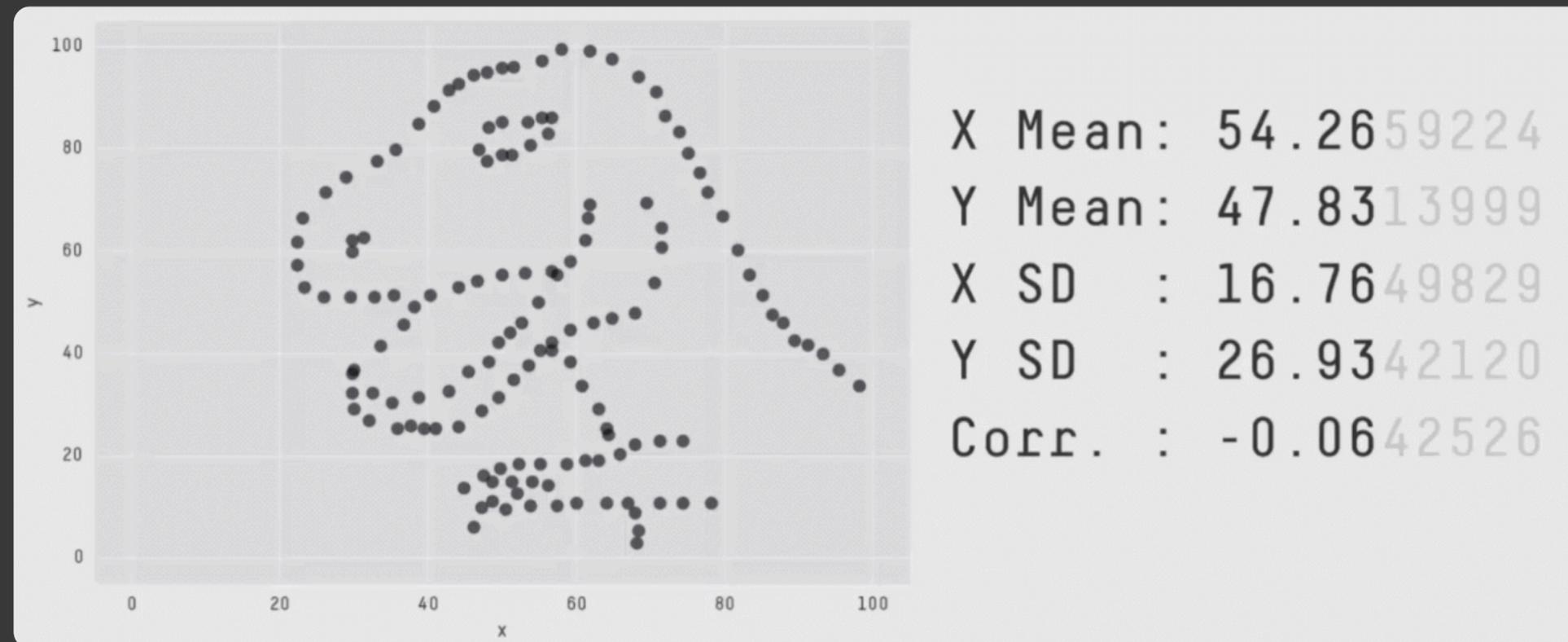
```
[10] :  
      x      y  
0  55.3846  97.1795  
1  51.5385  96.0256  
2  46.1538  94.4872  
3  42.8205  91.4103  
4  40.7692  88.3333  
...      ...      ...  
137 39.4872  25.3846  
138 91.2821  41.5385  
139 50.0000  95.7692  
140 47.9487  95.0000  
141 44.1026  92.6923
```

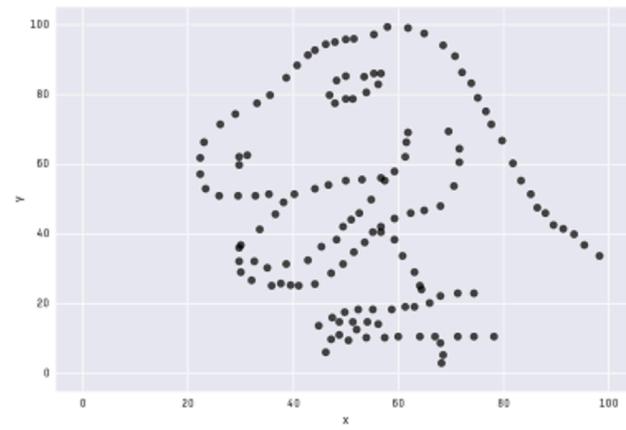
142 rows × 2 columns

# Your Brain is Good at Pattern Recognition

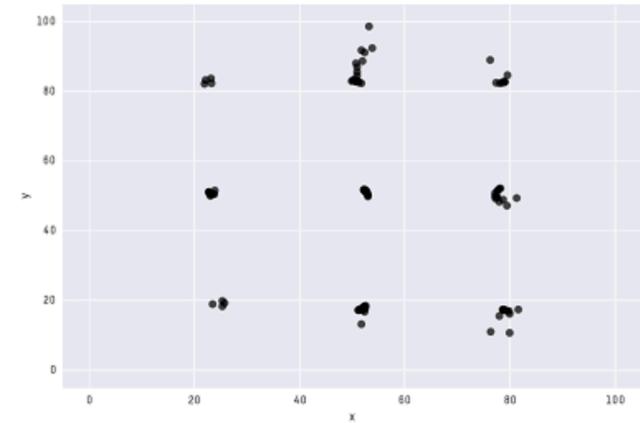
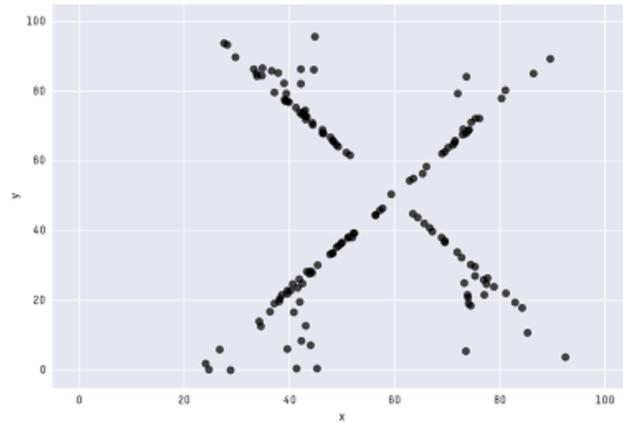
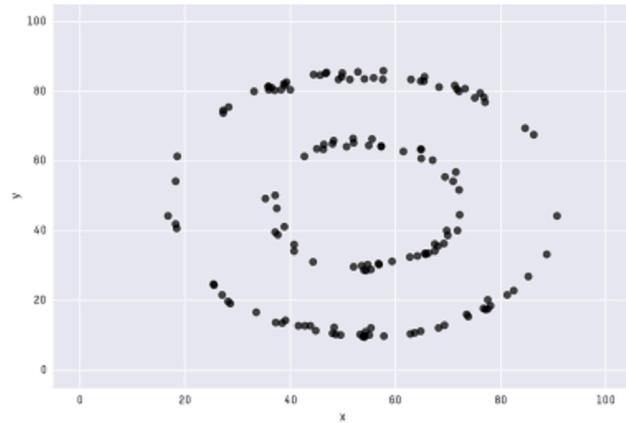
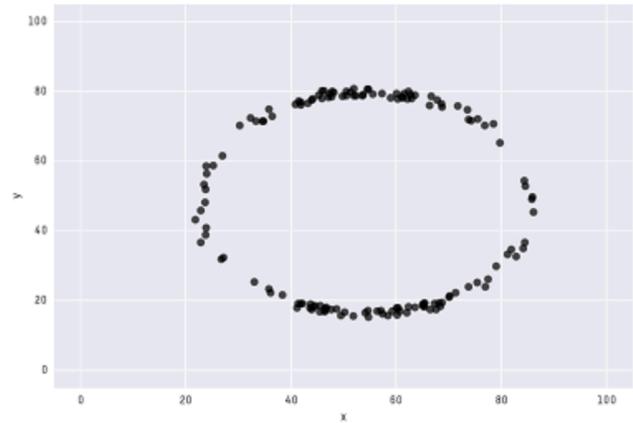
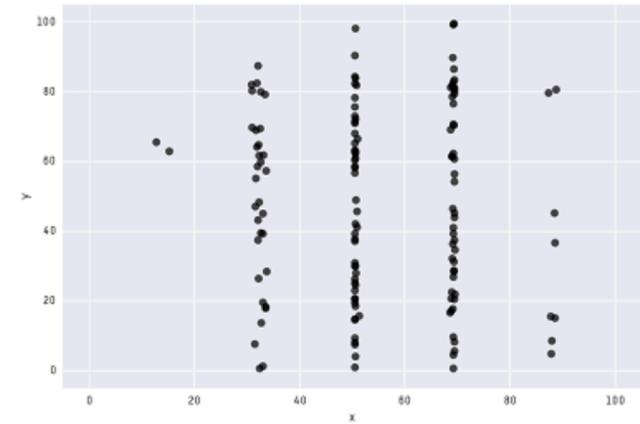
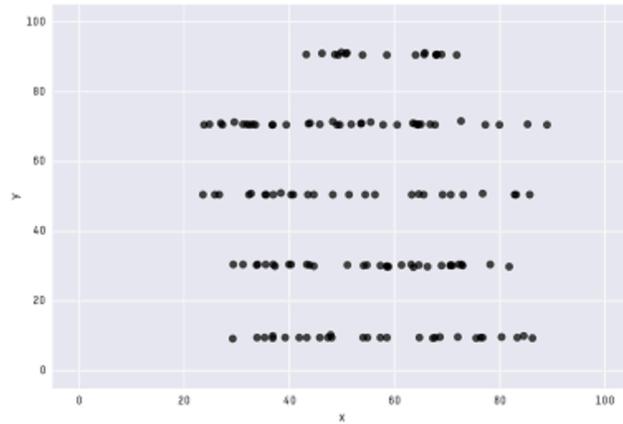
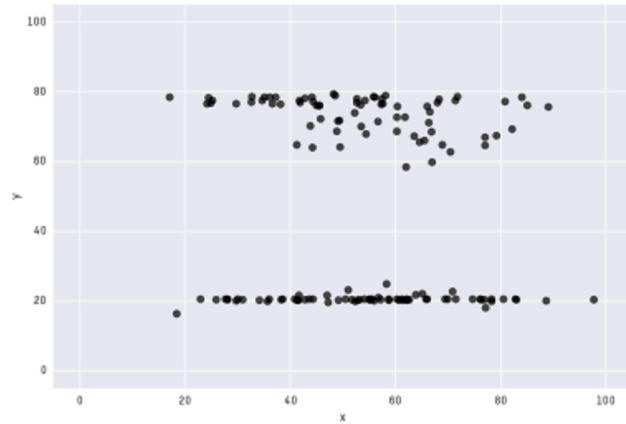
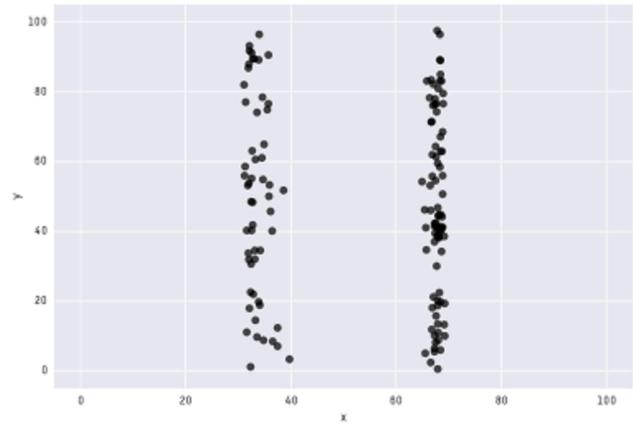
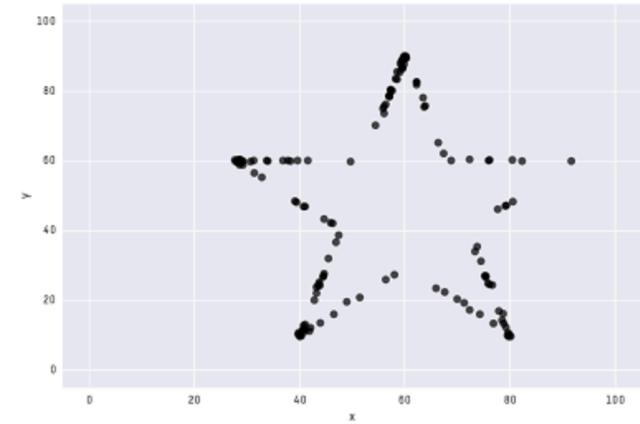
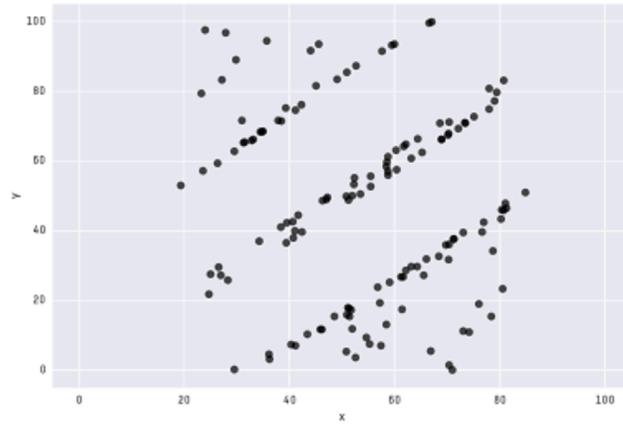
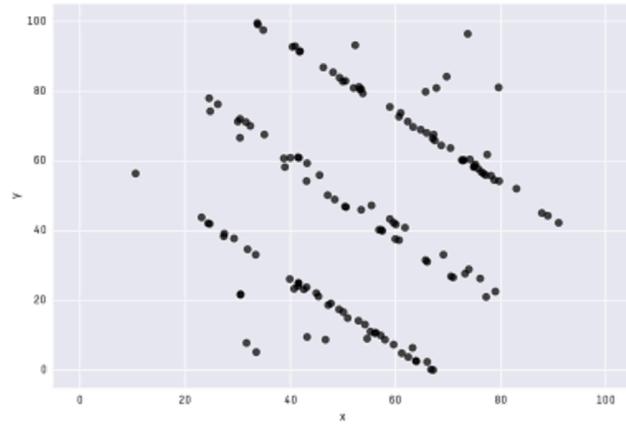
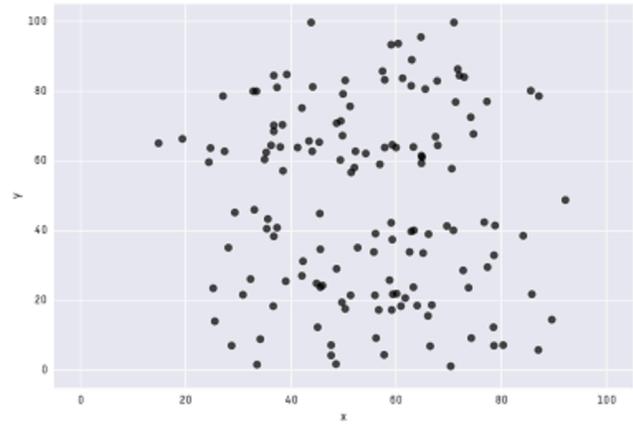
```
X Mean: 54.2659224  
Y Mean: 47.8313999  
X SD   : 16.7649829  
Y SD   : 26.9342120  
Corr.  : -0.0642526
```

# Your Brain is Good at Pattern Recognition

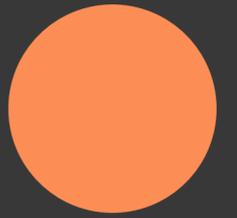




X Mean: 54.26  
Y Mean: 47.83  
X SD : 16.76  
Y SD : 26.93  
Corr. : -0.06



# Use Cases



## To Explore

Your brain is really good at noticing visual patterns!

Use your eyes helps you discover interesting things.

## To Debug

“What changed about the data after I ran this code?”

Visual summaries help you decide if the data align with your expectations.

## To Present

Help *other people* understand what you found in the data.

Tell a *story* about data while letting the viewer verify it.

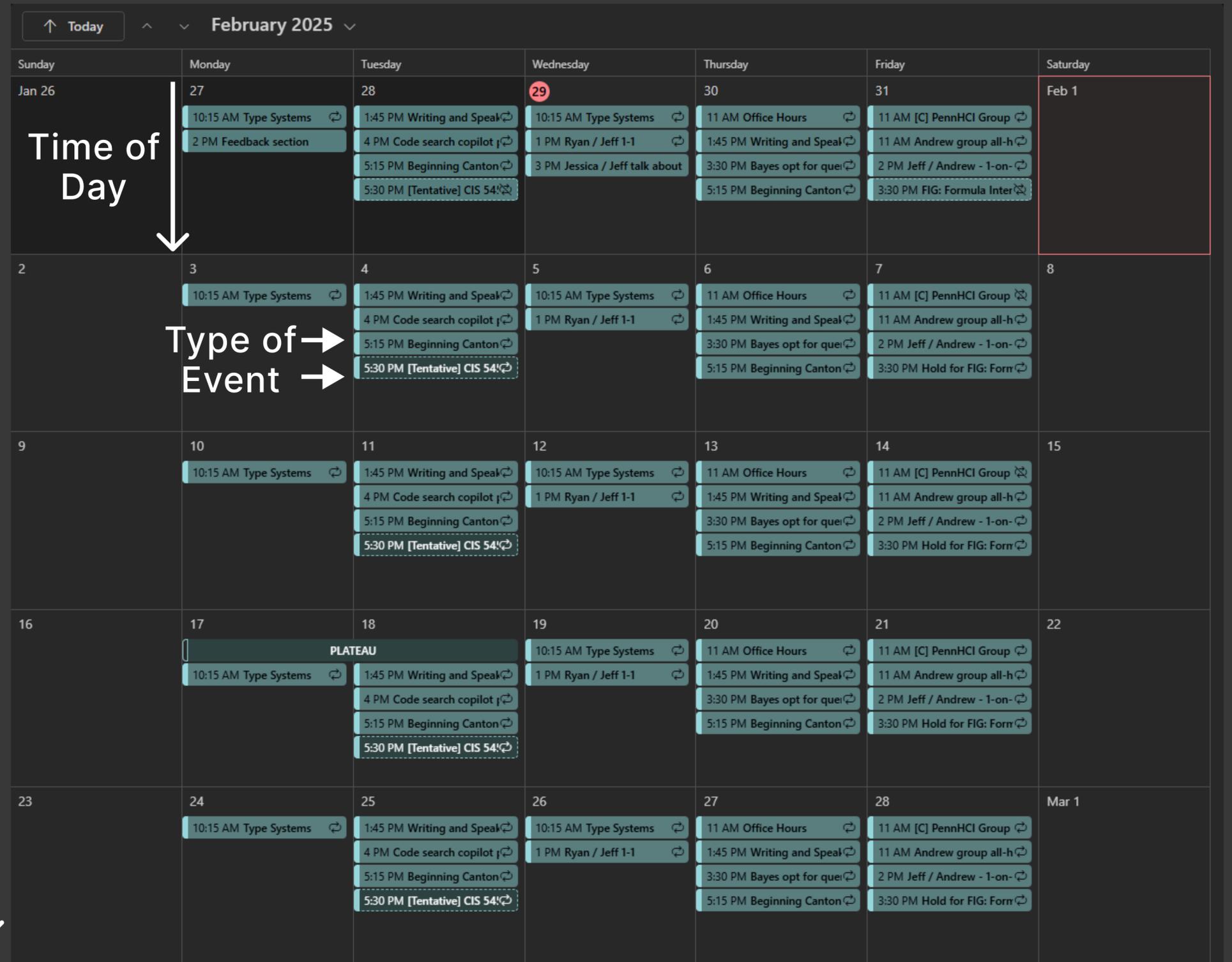
# Visualizations Are Everywhere!

↑ Today ^ v February 2025 v

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Jan 26	27 10:15 AM Type Systems ↻ 2 PM Feedback section	28 1:45 PM Writing and Speak ↻ 4 PM Code search copilot ↻ 5:15 PM Beginning Canton ↻ 5:30 PM [Tentative] CIS 54 ↻	29 10:15 AM Type Systems ↻ 1 PM Ryan / Jeff 1-1 ↻ 3 PM Jessica / Jeff talk about	30 11 AM Office Hours ↻ 1:45 PM Writing and Speak ↻ 3:30 PM Bayes opt for que ↻ 5:15 PM Beginning Canton ↻	31 11 AM [C] PennHCI Group ↻ 11 AM Andrew group all-h ↻ 2 PM Jeff / Andrew - 1-on- ↻ 3:30 PM FIG: Formula Inter ↻	Feb 1
2	3 10:15 AM Type Systems ↻	4 1:45 PM Writing and Speak ↻ 4 PM Code search copilot ↻ 5:15 PM Beginning Canton ↻ 5:30 PM [Tentative] CIS 54 ↻	5 10:15 AM Type Systems ↻ 1 PM Ryan / Jeff 1-1 ↻	6 11 AM Office Hours ↻ 1:45 PM Writing and Speak ↻ 3:30 PM Bayes opt for que ↻ 5:15 PM Beginning Canton ↻	7 11 AM [C] PennHCI Group ↻ 11 AM Andrew group all-h ↻ 2 PM Jeff / Andrew - 1-on- ↻ 3:30 PM Hold for FIG: Forn ↻	8
9	10 10:15 AM Type Systems ↻	11 1:45 PM Writing and Speak ↻ 4 PM Code search copilot ↻ 5:15 PM Beginning Canton ↻ 5:30 PM [Tentative] CIS 54 ↻	12 10:15 AM Type Systems ↻ 1 PM Ryan / Jeff 1-1 ↻	13 11 AM Office Hours ↻ 1:45 PM Writing and Speak ↻ 3:30 PM Bayes opt for que ↻ 5:15 PM Beginning Canton ↻	14 11 AM [C] PennHCI Group ↻ 11 AM Andrew group all-h ↻ 2 PM Jeff / Andrew - 1-on- ↻ 3:30 PM Hold for FIG: Forn ↻	15
16	17 PLATEAU 10:15 AM Type Systems ↻	18 1:45 PM Writing and Speak ↻ 4 PM Code search copilot ↻ 5:15 PM Beginning Canton ↻ 5:30 PM [Tentative] CIS 54 ↻	19 10:15 AM Type Systems ↻ 1 PM Ryan / Jeff 1-1 ↻	20 11 AM Office Hours ↻ 1:45 PM Writing and Speak ↻ 3:30 PM Bayes opt for que ↻ 5:15 PM Beginning Canton ↻	21 11 AM [C] PennHCI Group ↻ 11 AM Andrew group all-h ↻ 2 PM Jeff / Andrew - 1-on- ↻ 3:30 PM Hold for FIG: Forn ↻	22
23	24 10:15 AM Type Systems ↻	25 1:45 PM Writing and Speak ↻ 4 PM Code search copilot ↻ 5:15 PM Beginning Canton ↻ 5:30 PM [Tentative] CIS 54 ↻	26 10:15 AM Type Systems ↻ 1 PM Ryan / Jeff 1-1 ↻	27 11 AM Office Hours ↻ 1:45 PM Writing and Speak ↻ 3:30 PM Bayes opt for que ↻ 5:15 PM Beginning Canton ↻	28 11 AM [C] PennHCI Group ↻ 11 AM Andrew group all-h ↻ 2 PM Jeff / Andrew - 1-on- ↻ 3:30 PM Hold for FIG: Forn ↻	Mar 1

# Visualizations Are Everywhere!

Week of Month



Day of Week

# Visualizations Are Everywhere!

↑ Today ^ February 2025 v

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Jan 26	27 10:15 AM Type Systems 2 PM Feedback section	28 1:45 PM Writing and Speak 4 PM Code search copilot 5:15 PM Beginning Canton 5:30 PM [Tentative] CIS 54	29 10:15 AM Type Systems 1 PM Ryan / Jeff 1-1 3 PM Jessica / Jeff talk about	30 11 AM Office Hours 1:45 PM Writing and Speak 3:30 PM Bayes opt for que 5:15 PM Beginning Canton	31 11 AM [C] PennHCI Group 11 AM Andrew group all-h 2 PM Jeff / Andrew - 1-on- 3:30 PM FIG: Formula Inter	Feb 1
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# Visualizations Are Everywhere!

**Today** Wed, Jan 29 ☀️ 51° / 29°

10:15 AM 1h 30m ● Type Systems  
📍 Towne 327

1:00 PM 1h ● Ryan / Jeff 1-1  
👤 rcmarcus@seas.upenn.edu  
📍 Towne 219C or Online

3:00 PM 30m ● Jessica / Jeff talk about proof assistants  
👤 jwshi@seas.upenn.edu

**Tomorrow** Thu, Jan 30 ☀️ 42° / 33°

11:00 AM 2h 🏢 Office Hours

1:45 PM 1h 30m ● Writing and Speaking with Style

3:30 PM 1h ● Bayes opt for query optimization  
👤 Levine 460  
👥 J H N R

5:15 PM 1h 30m ● Beginning Cantonese II

**Fri, Jan 31** ☁️ 48° / 37°

11:00 AM 1h 🧑‍🤝🧑 [C] PennHCI Group Meeting  
👤 PH E P S F +10  
📍 <https://upenn.zoom.us/j/91976100977?p...>

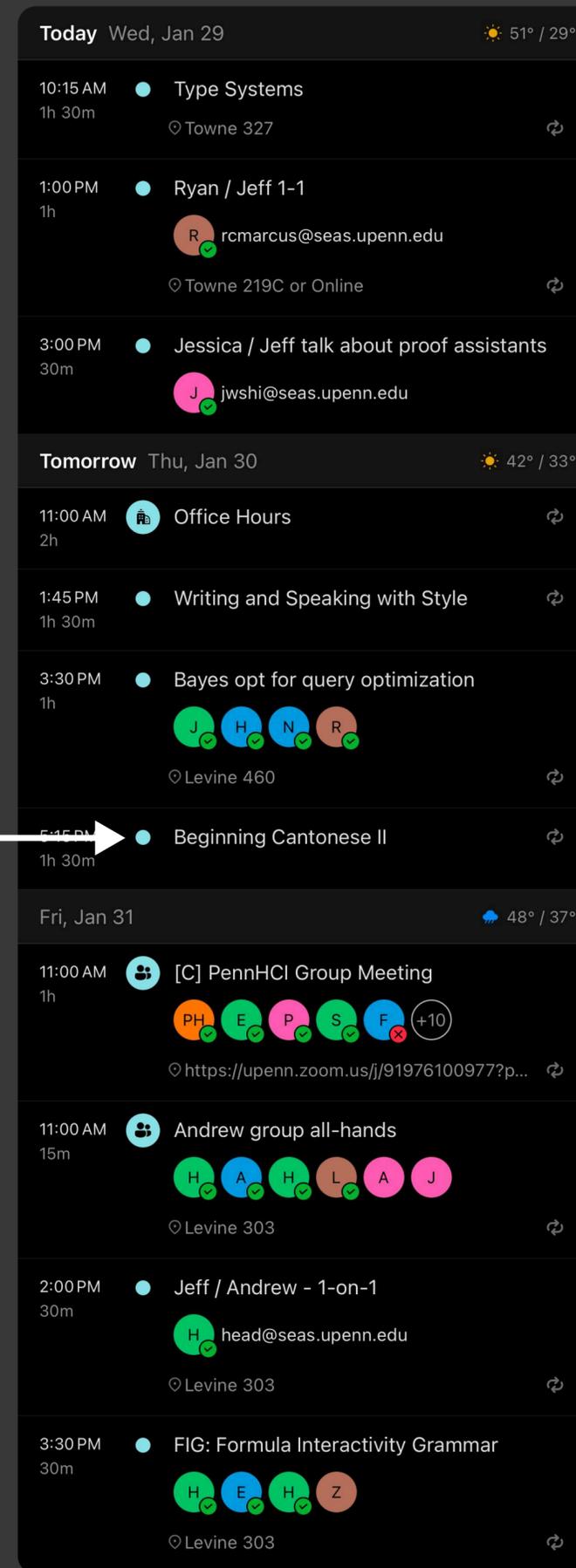
11:00 AM 15m 🧑‍🤝🧑 Andrew group all-hands  
👤 H A H L A J  
📍 Levine 303

2:00 PM 30m ● Jeff / Andrew - 1-on-1  
👤 head@seas.upenn.edu  
📍 Levine 303

3:30 PM 30m ● FIG: Formula Interactivity Grammar  
👤 H E H Z  
📍 Levine 303

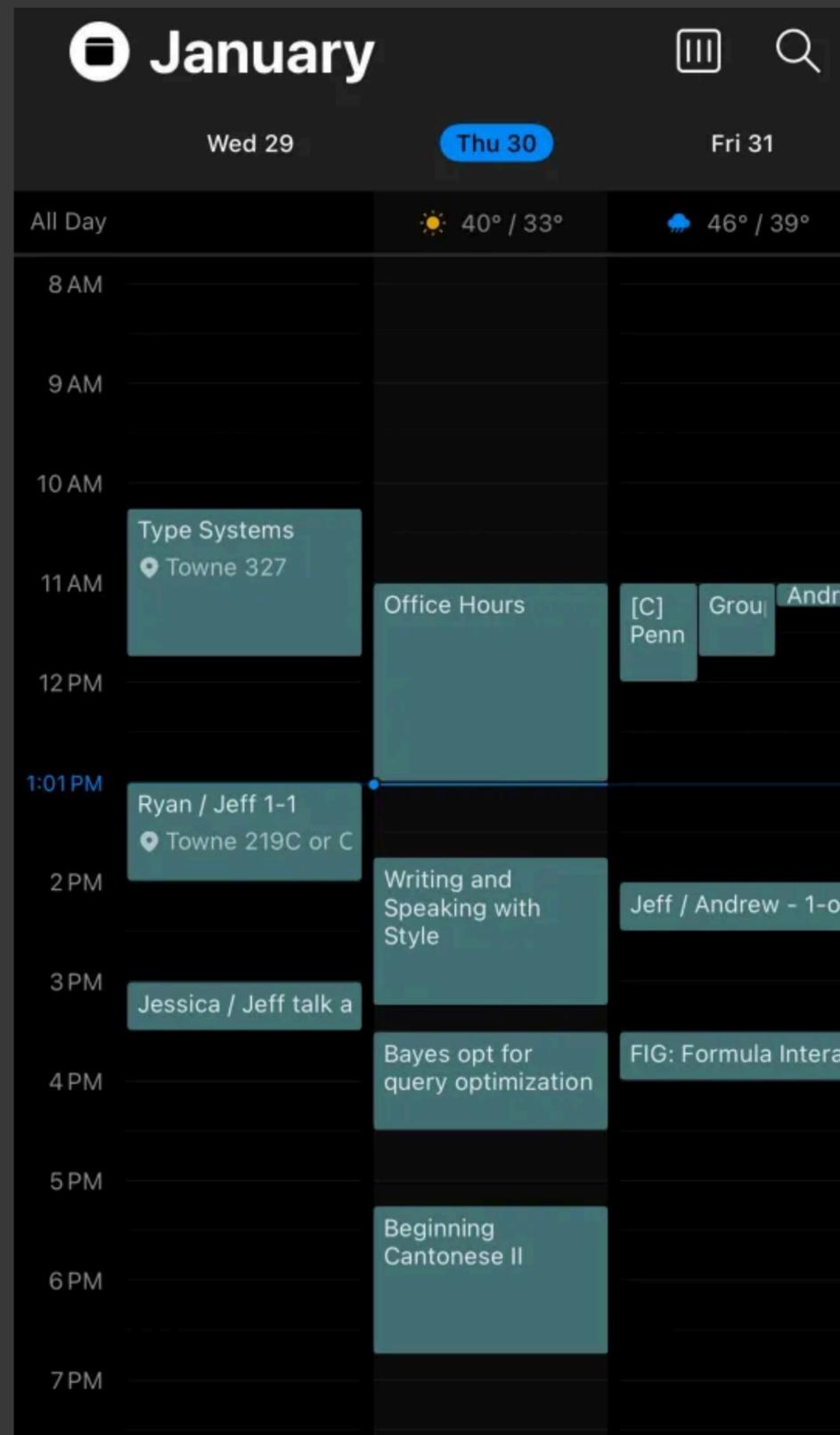
# Visualizations Are Everywhere!

Calendar category →



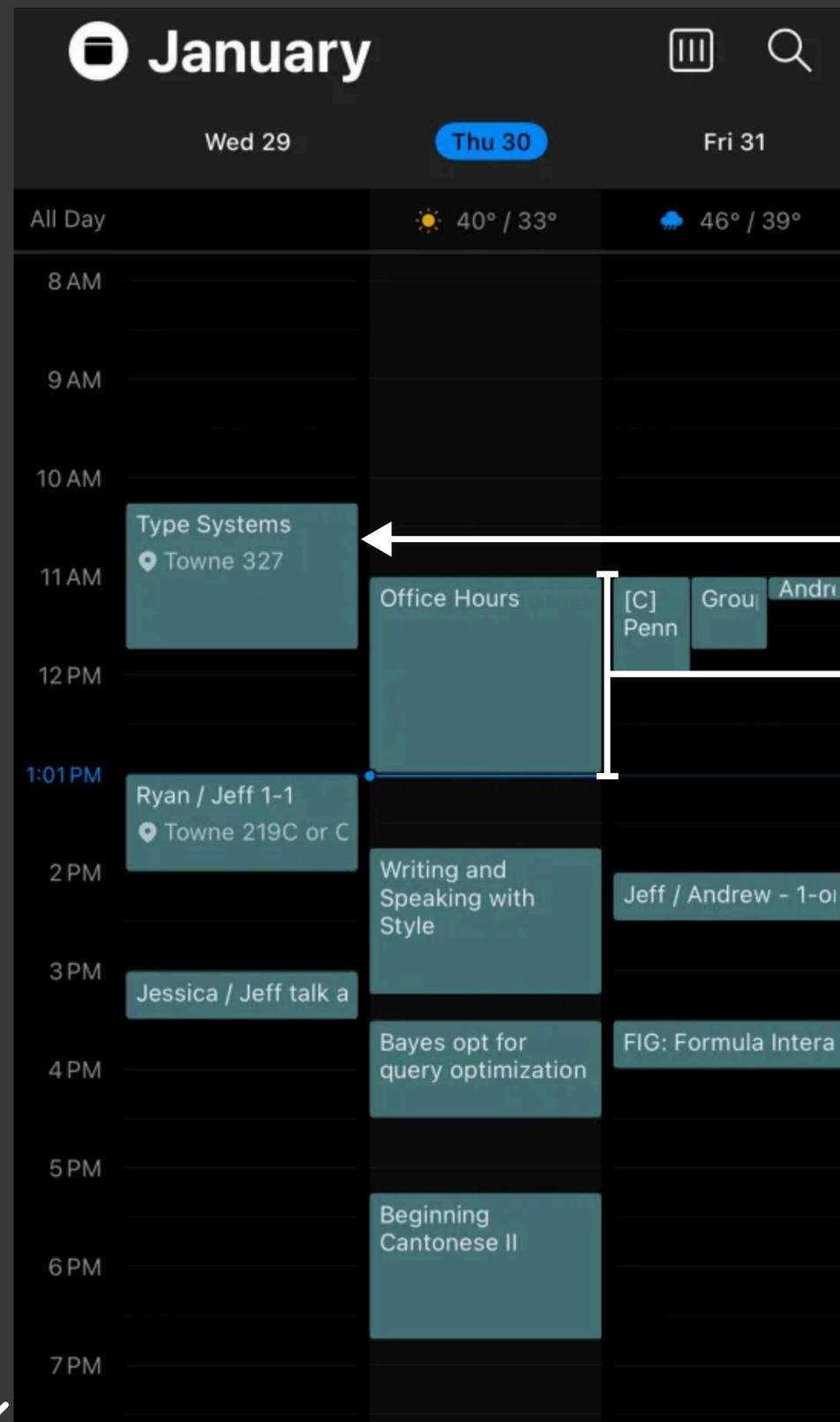
Time ↓

# Visualizations Are Everywhere!



# Visualizations Are Everywhere!

Time

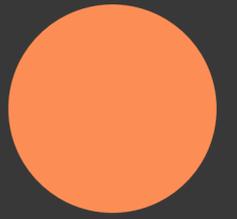


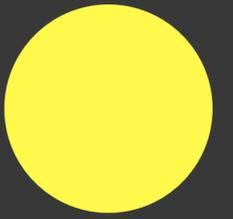
Calendar category

Length of time

Day of week

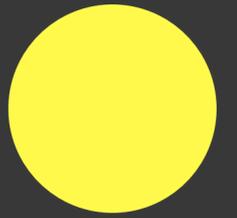
Visualization leverages  
your *perception* and  
*pattern recognition* to  
help explain data.





How to  
Visualize?

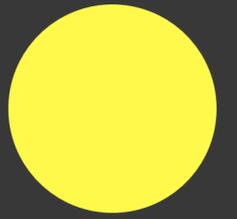
# What Type of Data?



Your data has a *type*.

Each visualization pattern only works with certain types of data.

# Nominal/Categorical



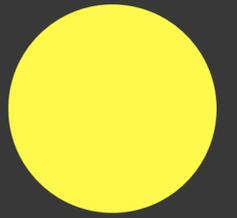
Can only compare equal/non-equal

- States, Countries
- Type of Student (undergrad, masters, phd)
- Basically anything that isn't written with numbers
- Could be hierarchical (country → state → city)

# Ordinal

Having an order

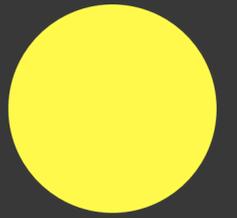
- Olympic medals
- Likert scales (strongly disagree  $\leftrightarrow$  strongly agree)
- Level of education



# Quantitative

Inherently numeric, you can do math to it

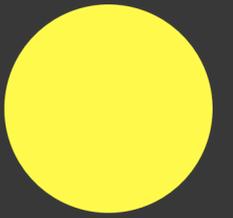
- \$ of Revenue
- # of customers
- Intervals
- Ratios



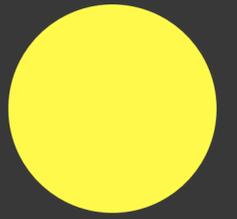
# Temporal

Having to do with dates/time

- Year/Month/Day
- Fiscal quarter
- School year
- Ranges/Duration

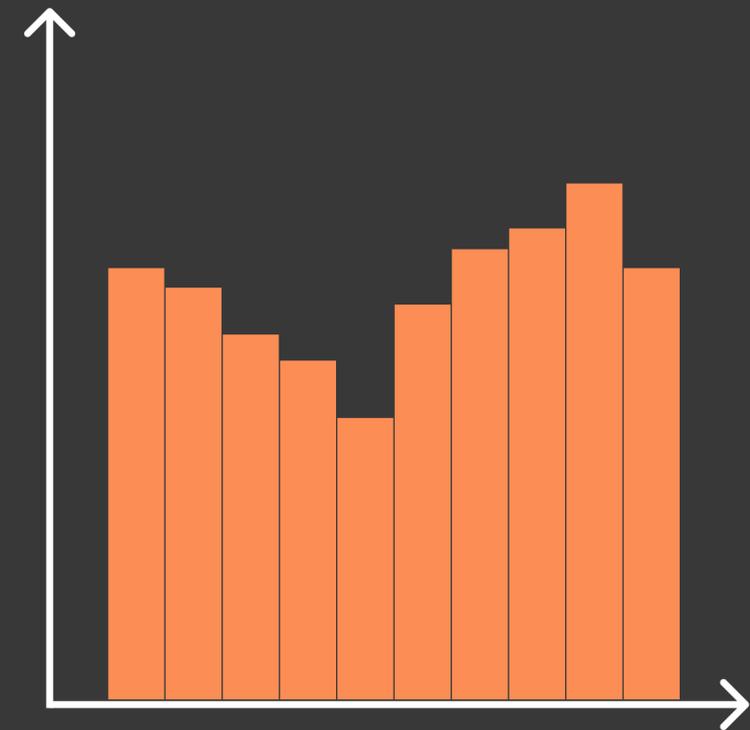
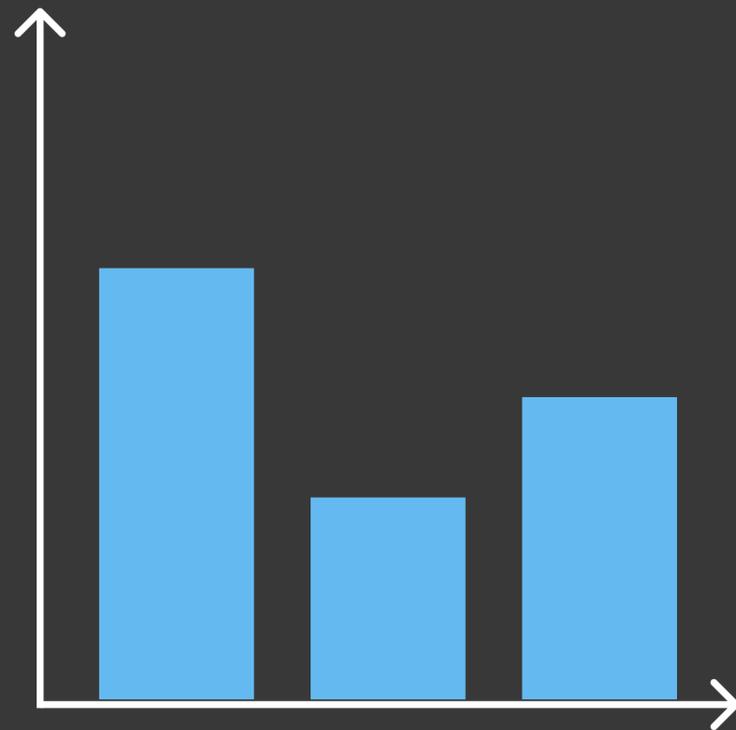


# Marks

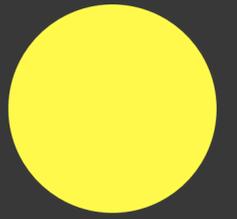


Graphical shapes that represents some part of the data

Bars: Compare Position, Length

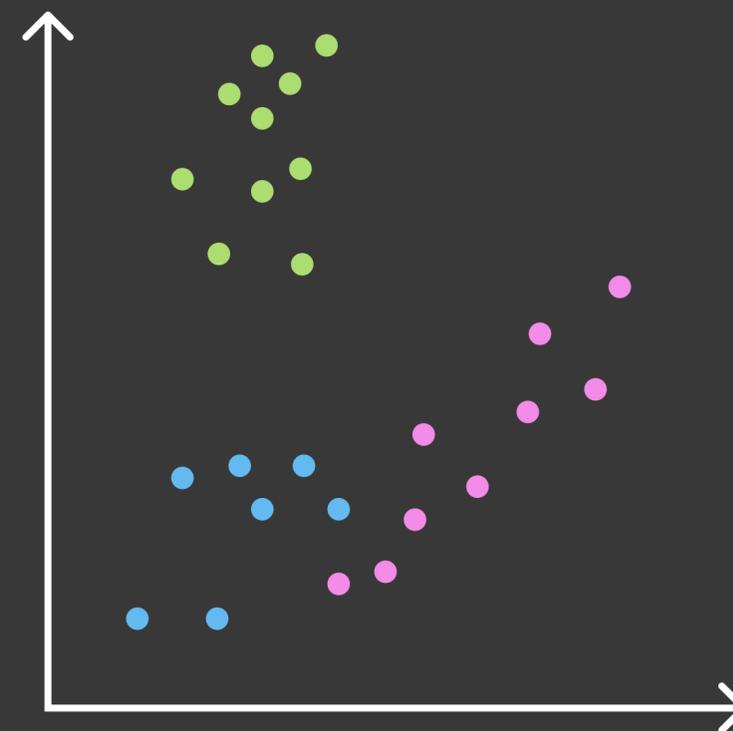
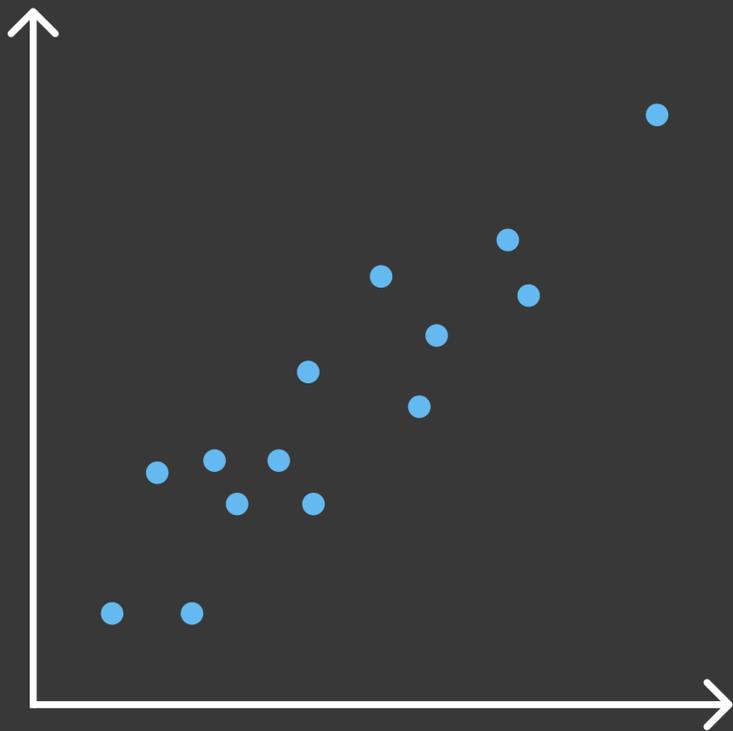


# Marks



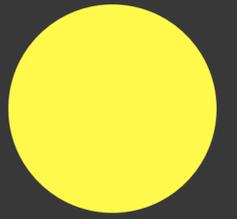
Graphical shapes that represents some part of the data

Points: Compare Position

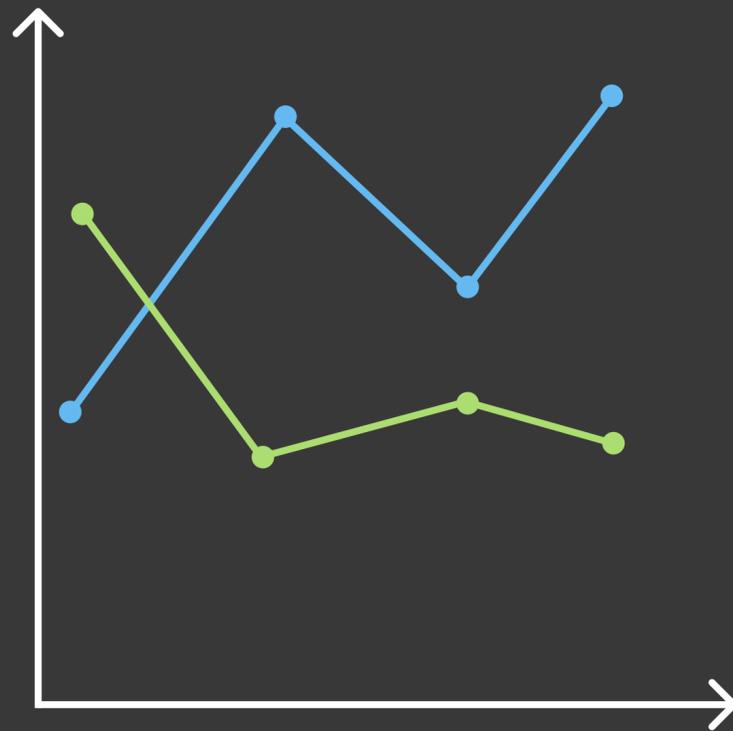


# Marks

Graphical shapes that represents some part of the data

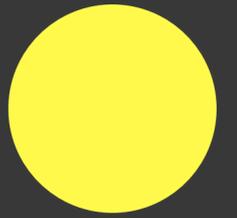


Lines: Compare Position, Length

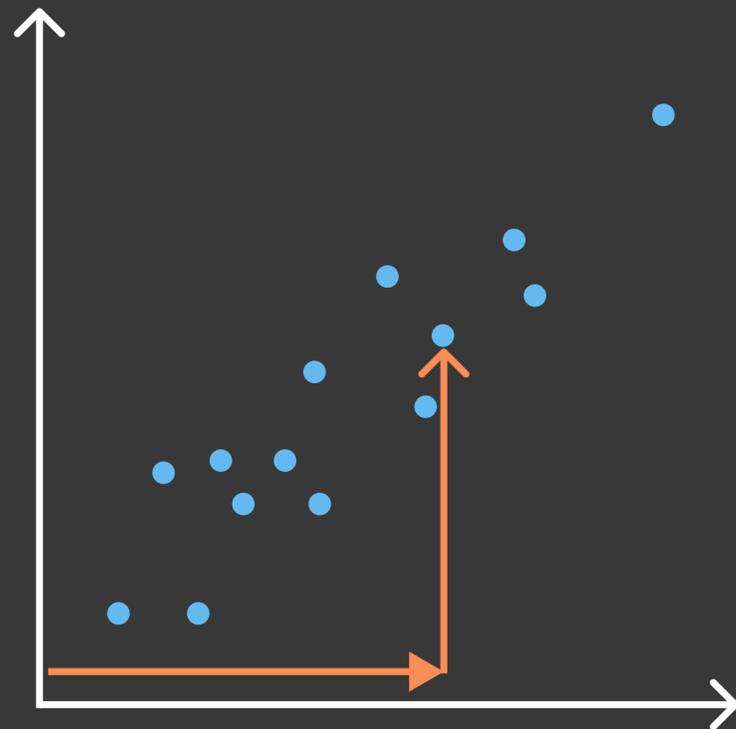


# Encodings

How data maps to perceptual “channels”

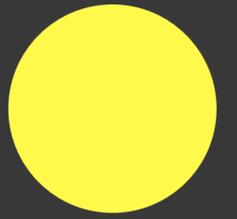


Position: Quantitative, Categorical

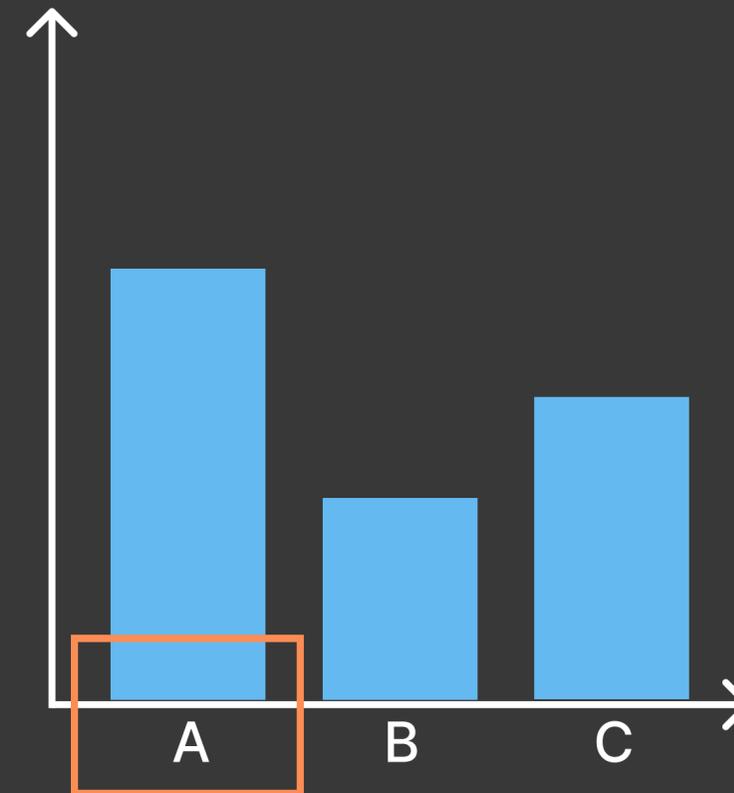
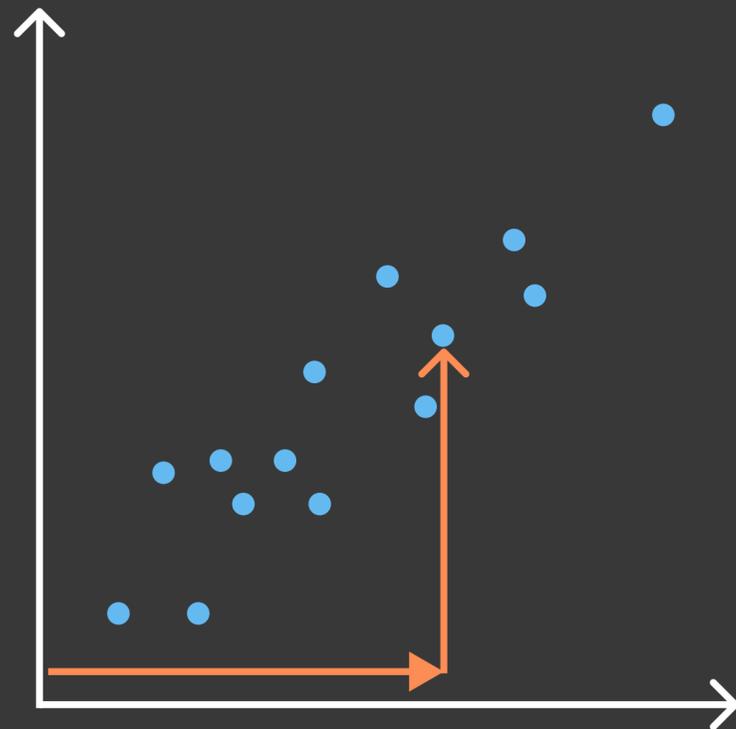


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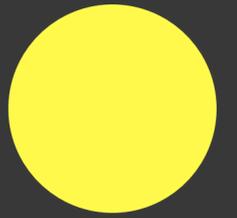


Position: Quantitative, Categorical

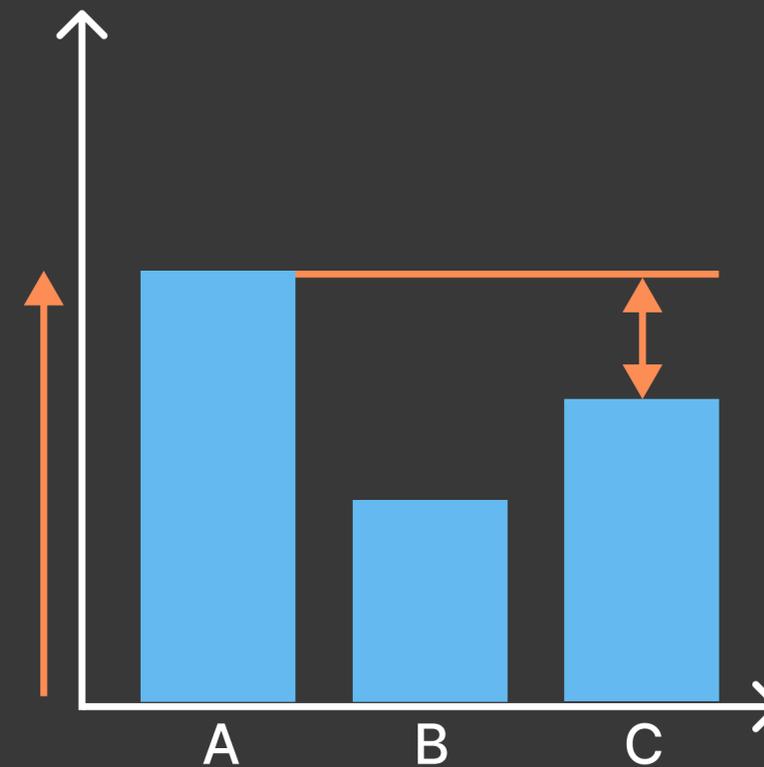


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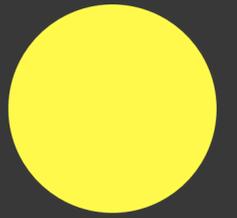


Length: Quantitative

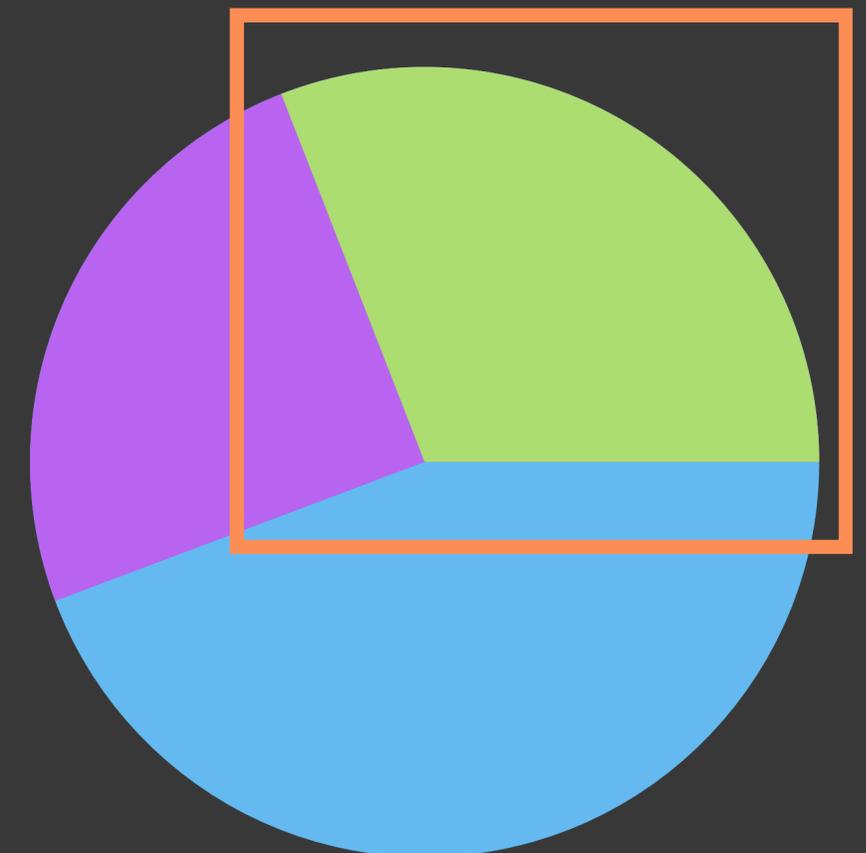
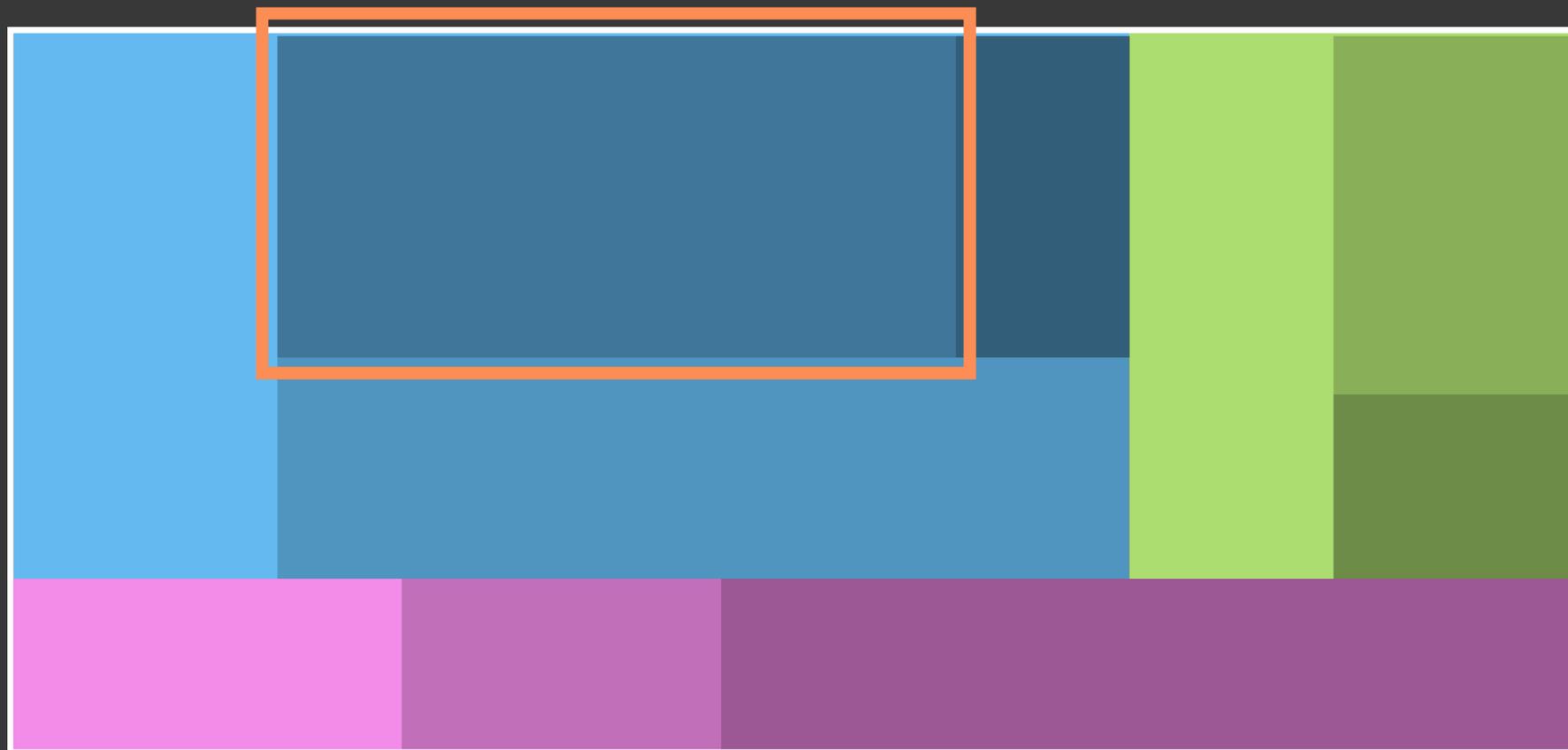


# Encodings

How data maps to perceptual “channels”

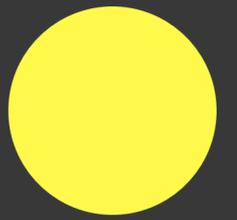


Area: Quantitative

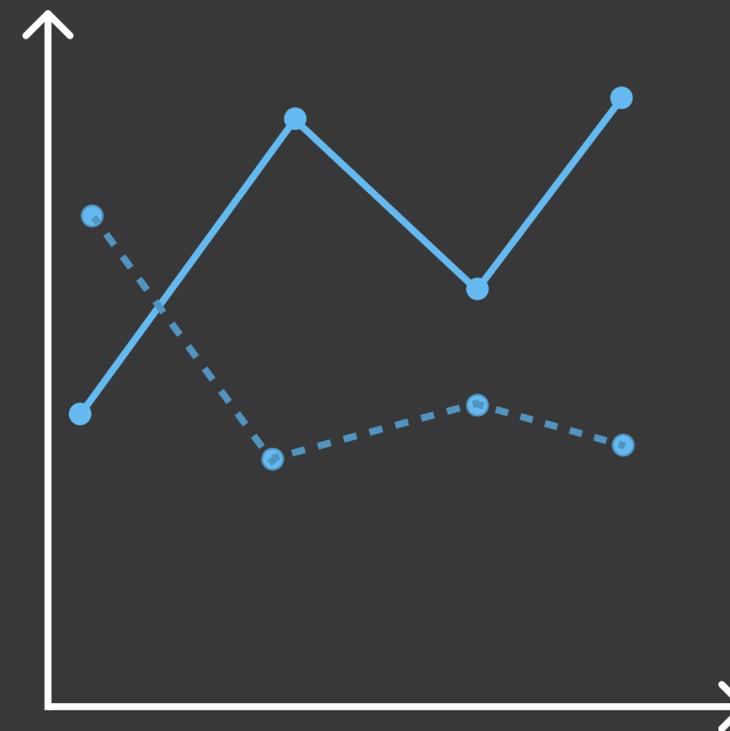
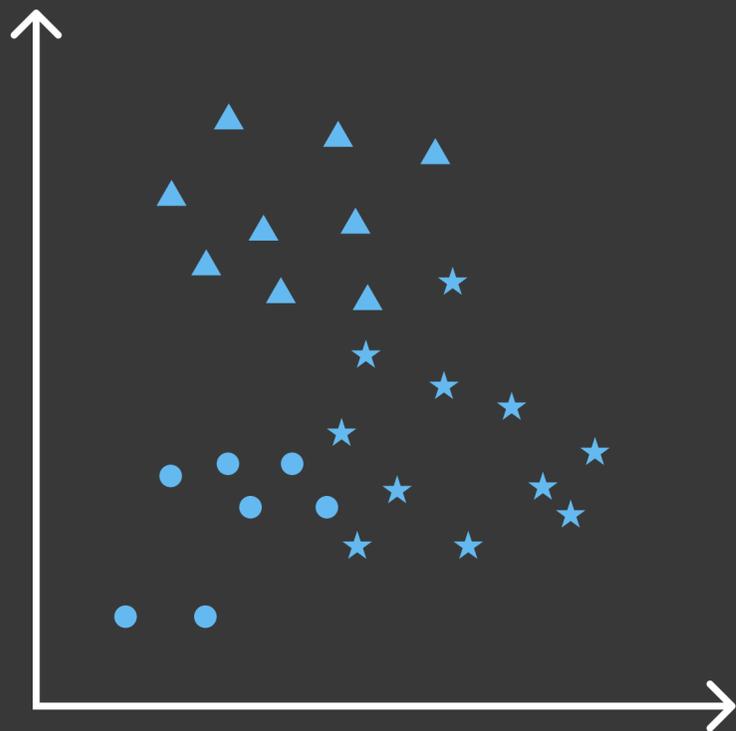


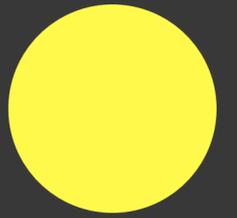
# Encodings

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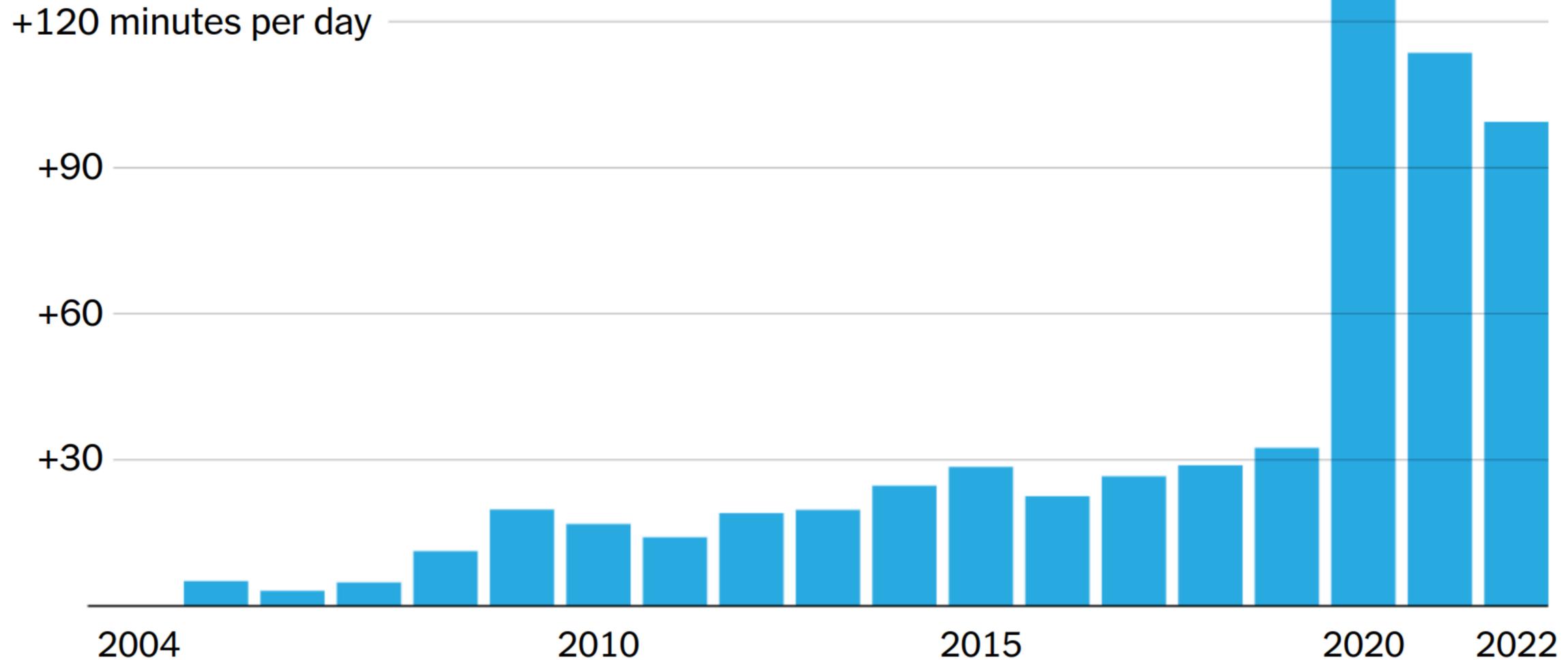


Shape, Style: Categorical





## Change since 2003 in average time spent at home

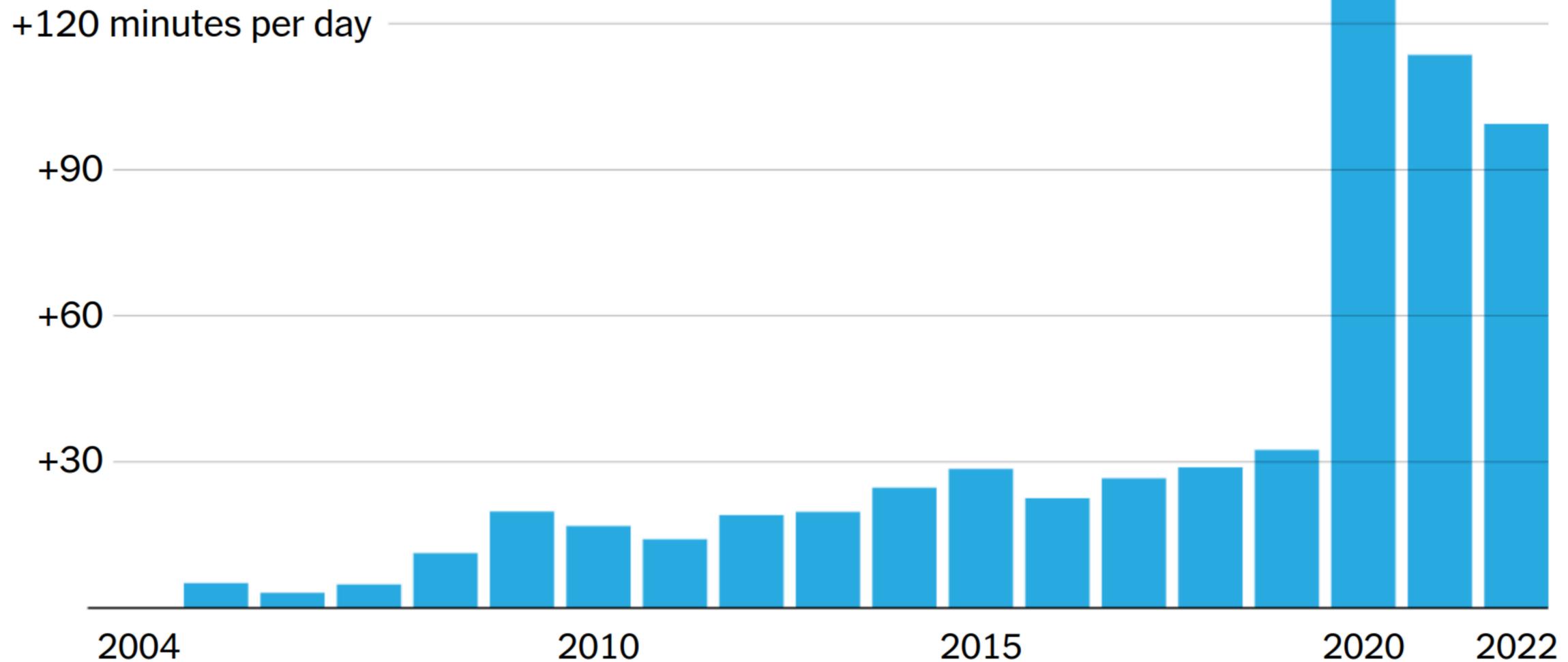


Among U.S. adults • Source: Analysis of the U.S. Census Bureau's American Time Use Survey by Patrick Sharkey, Princeton University • The New York Times

# Anatomy of a Chart

Source: NYT

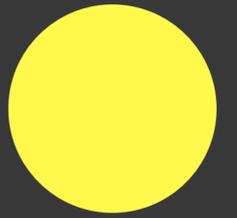
Title → **Change since 2003 in average time spent at home**



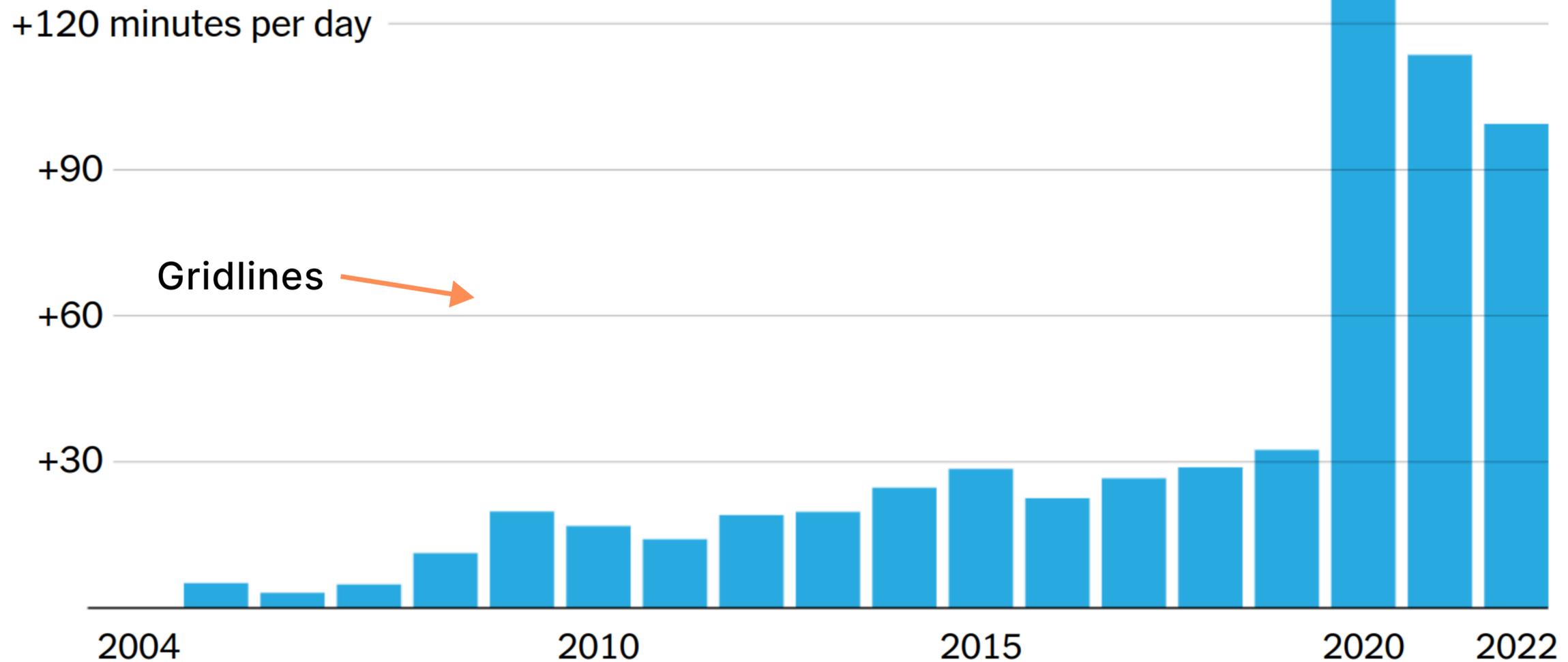
Among U.S. adults • Source: Analysis of the U.S. Census Bureau's American Time Use Survey by Patrick Sharkey, Princeton University • The New York Times

# Anatomy of a Chart

Source: NYT



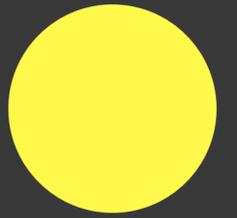
Title → **Change since 2003 in average time spent at home**

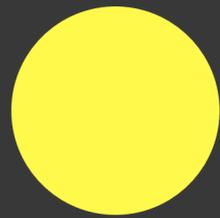


Among U.S. adults • Source: Analysis of the U.S. Census Bureau's American Time Use Survey by Patrick Sharkey, Princeton University • The New York Times

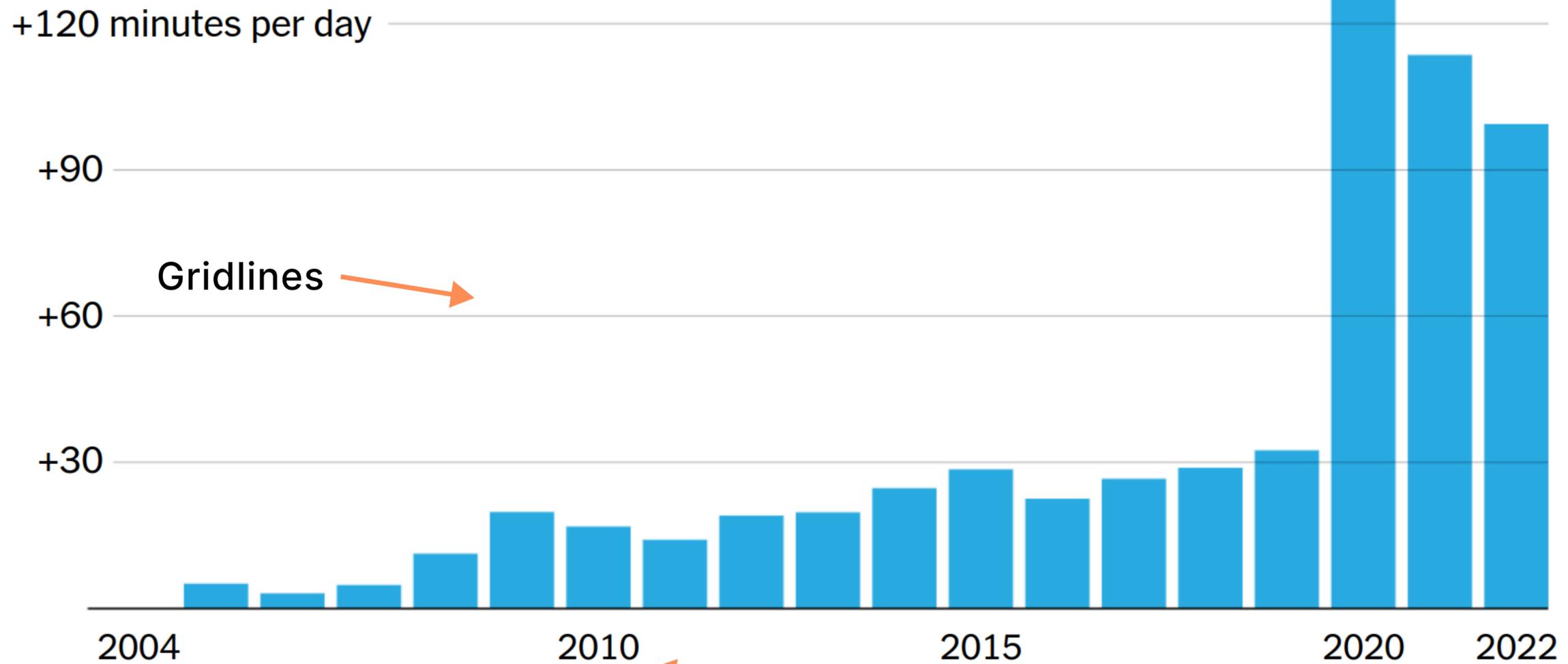
# Anatomy of a Chart

Source: NYT





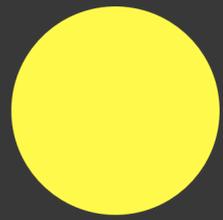
Title → **Change since 2003 in average time spent at home**



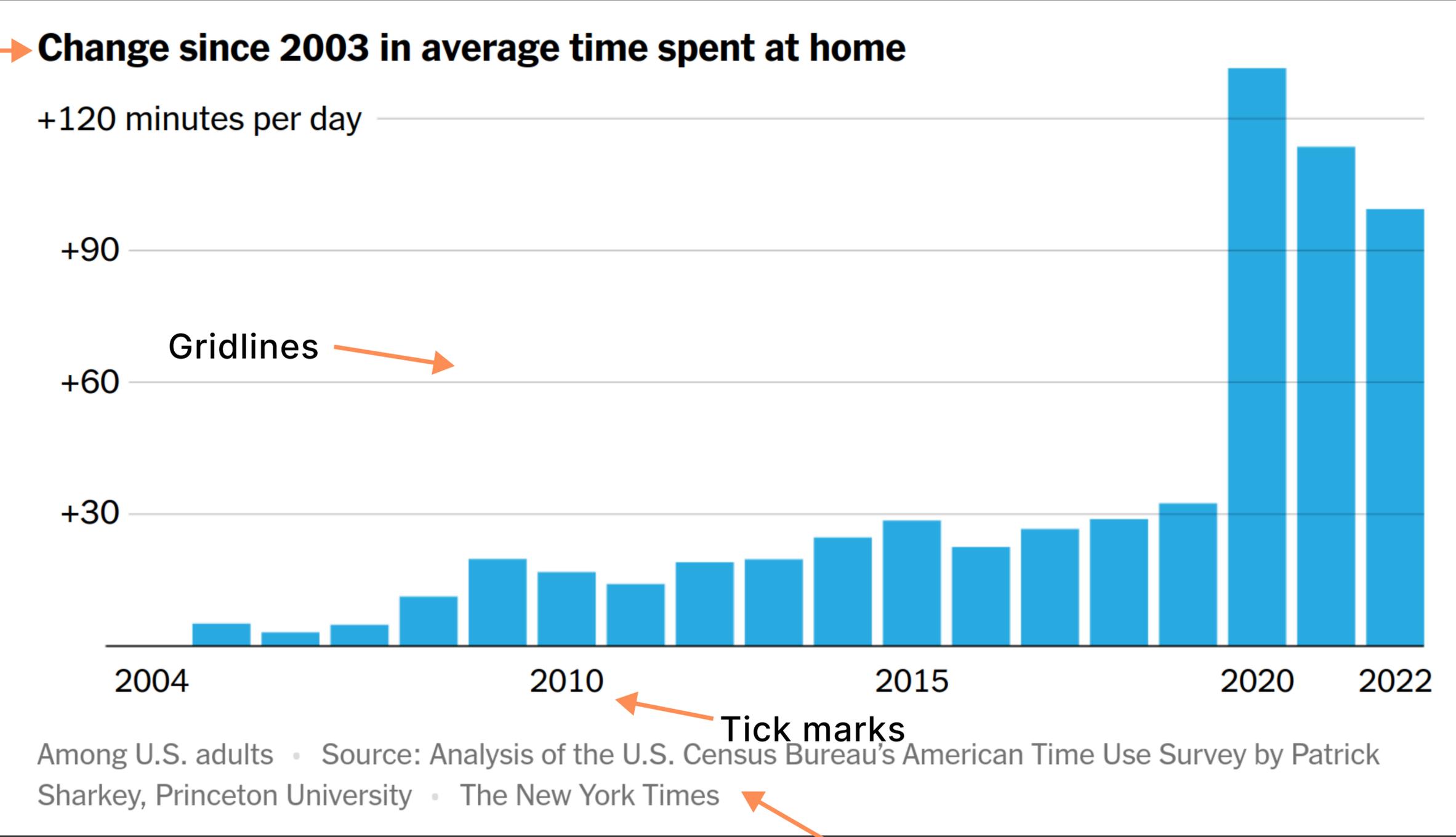
Among U.S. adults • Source: Analysis of the U.S. Census Bureau's American Time Use Survey by Patrick Sharkey, Princeton University • The New York Times

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Among U.S. adults • Source: Analysis of the U.S. Census Bureau's American Time Use Survey by Patrick Sharkey, Princeton University • The New York Times

# Anatomy of a Chart

Source: NYT

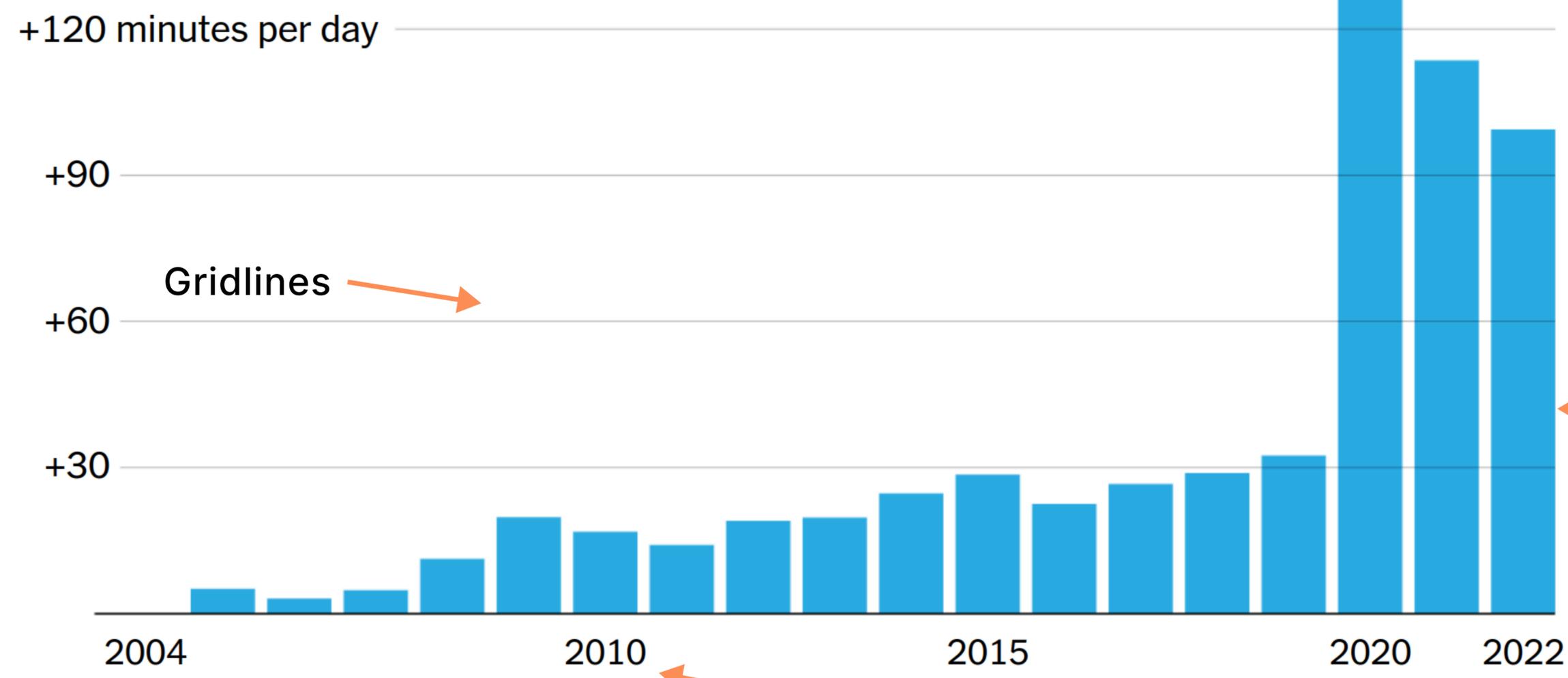
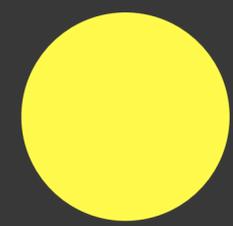
Title

Gridlines

Tick marks

Caption

Title → **Change since 2003 in average time spent at home**



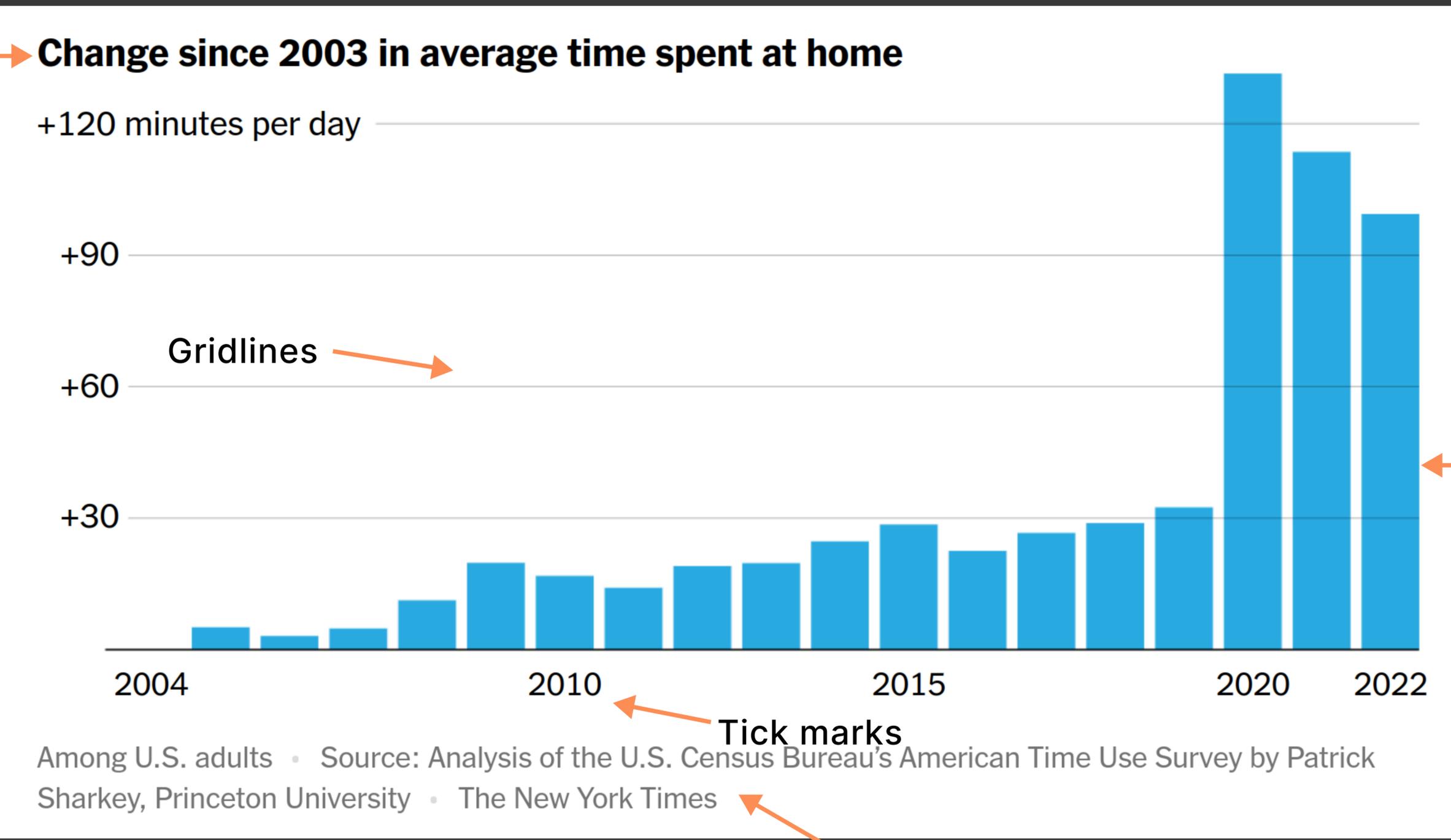
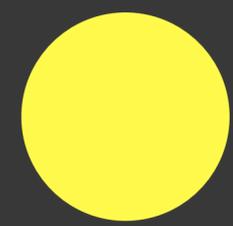
Among U.S. adults • Source: Analysis of the U.S. Census Bureau's American Time Use Survey by Patrick Sharkey, Princeton University • The New York Times

# Anatomy of a Chart

Source: NYT

→ Caption

Title → **Change since 2003 in average time spent at home**



+120 minutes per day

+90

+60

+30

Gridlines →

Bars Marks →

2004

2010

2015

2020

2022

Tick marks →

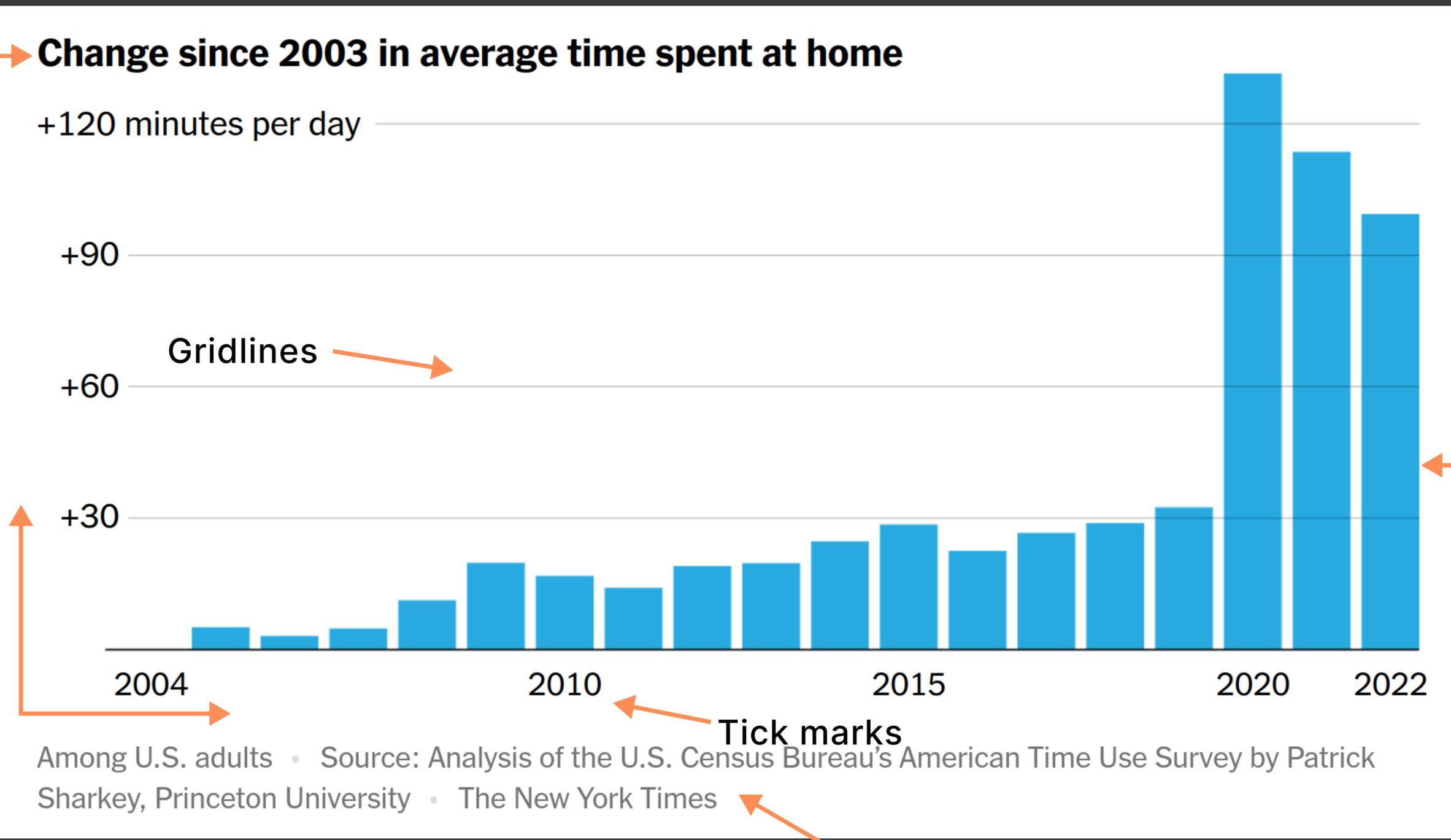
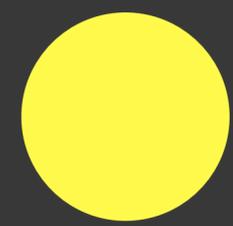
Among U.S. adults • Source: Analysis of the U.S. Census Bureau's American Time Use Survey by Patrick Sharkey, Princeton University • The New York Times

Caption →

# Anatomy of a Chart

Source: NYT

Title → **Change since 2003 in average time spent at home**



→ **Bars  
Marks**

← **Tick marks**

Among U.S. adults • Source: Analysis of the U.S. Census Bureau's American Time Use Survey by Patrick Sharkey, Princeton University • The New York Times

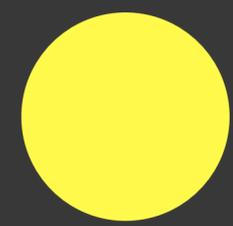
← **Caption**

# Anatomy of a Chart

Source: NYT

Title

**Change since 2003 in average time spent at home**



+120 minutes per day

+90

Gridlines

+60

+30

Bars  
Marks

Axes  
Encodings

2004

2010

2015

2020

2022

Tick marks

Among U.S. adults • Source: Analysis of the U.S. Census Bureau's American Time Use Survey by Patrick Sharkey, Princeton University • The New York Times

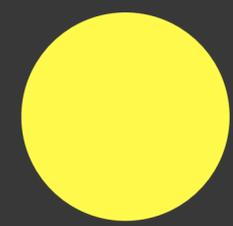
Caption

# Anatomy of a Chart

Source: NYT

Title

**Change since 2003 in average time spent at home**



+120 minutes per day

+90

Gridlines

+60

+30

Bars  
Marks

Axes  
Encodings

2004

2010

2015

2020

2022

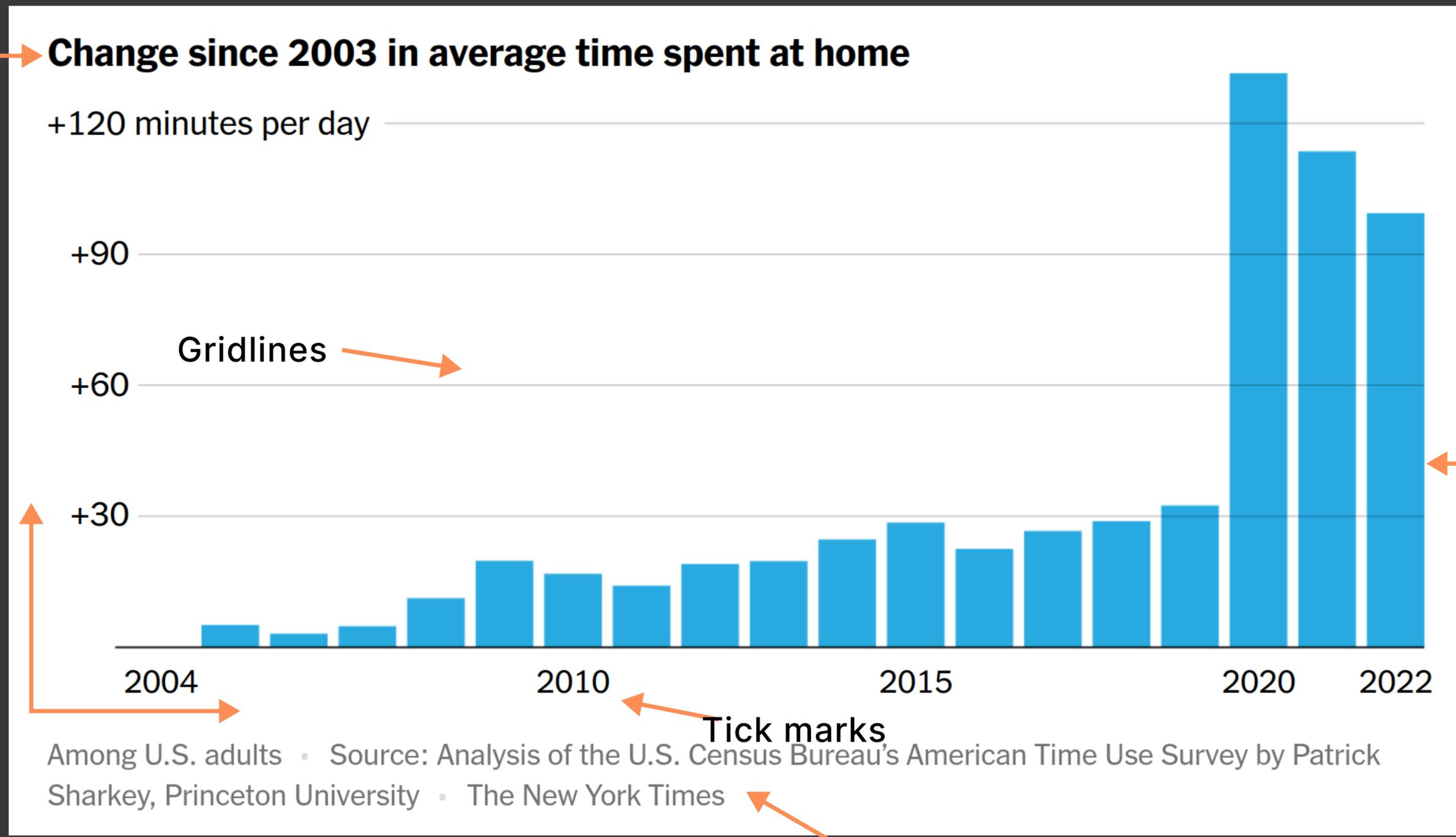
Tick marks

Among U.S. adults • Source: Analysis of the U.S. Census Bureau's American Time Use Survey by Patrick Sharkey, Princeton University • The New York Times

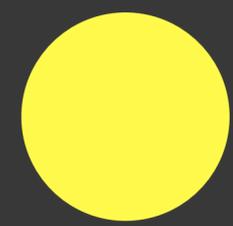
Caption

# Anatomy of a Chart

Source: NYT



Title → **Change since 2003 in average time spent at home**



+120 minutes per day

+90

Gridlines →

+60

+30

← Bars Marks

Axes Encodings

2004 →

2010 ←

← Tick marks

2015

2020

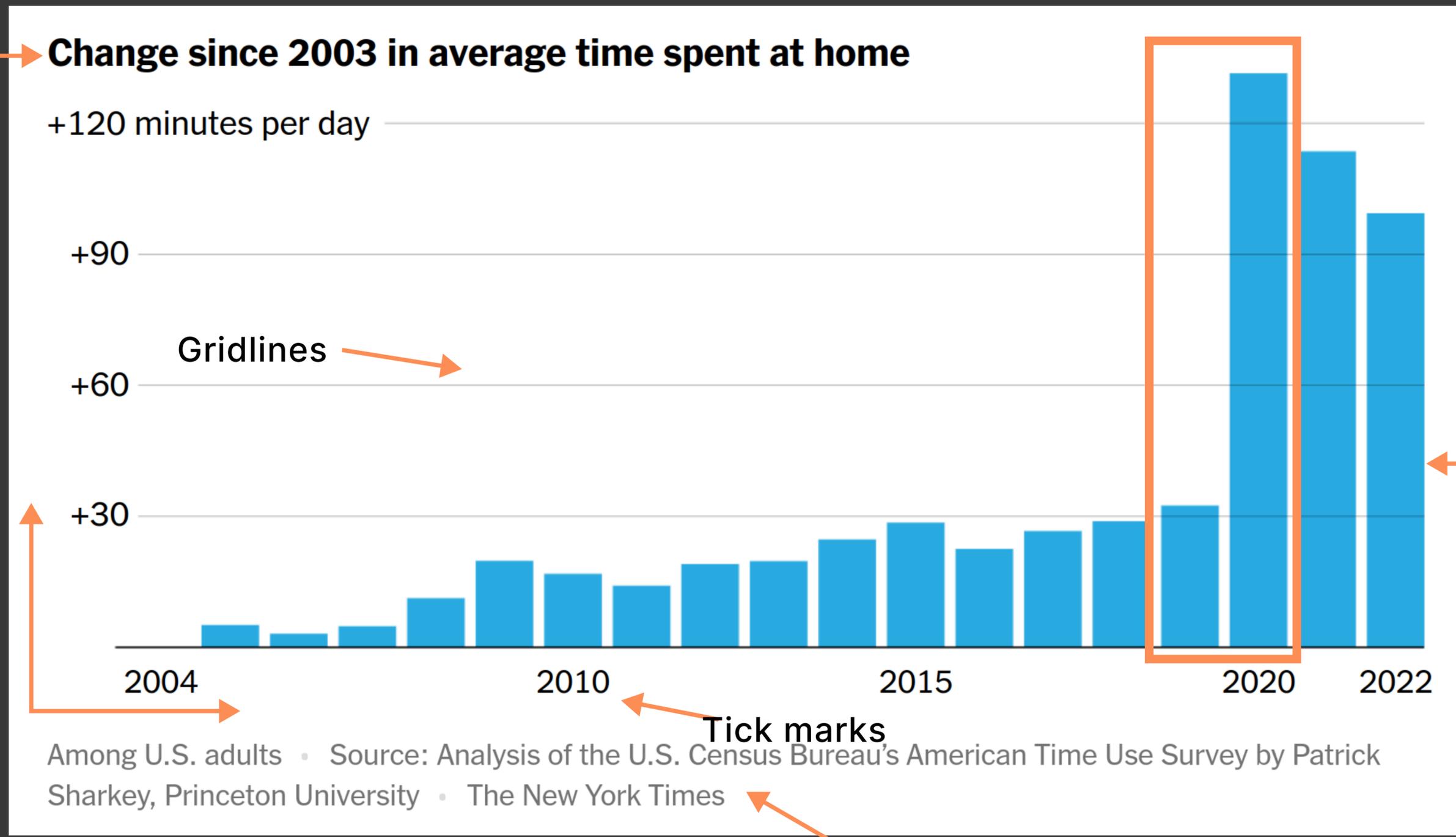
2022

Among U.S. adults • Source: Analysis of the U.S. Census Bureau's American Time Use Survey by Patrick Sharkey, Princeton University • The New York Times

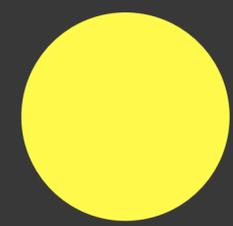
← Caption

# Anatomy of a Chart

Source: NYT



Title → **Change since 2003 in average time spent at home**



+120 minutes per day

+90

+60

+30

Gridlines →

**Salient Features**

→ **Bars  
Marks**

→ **Axes  
Encodings**

2004

2010

2015

2020

2022

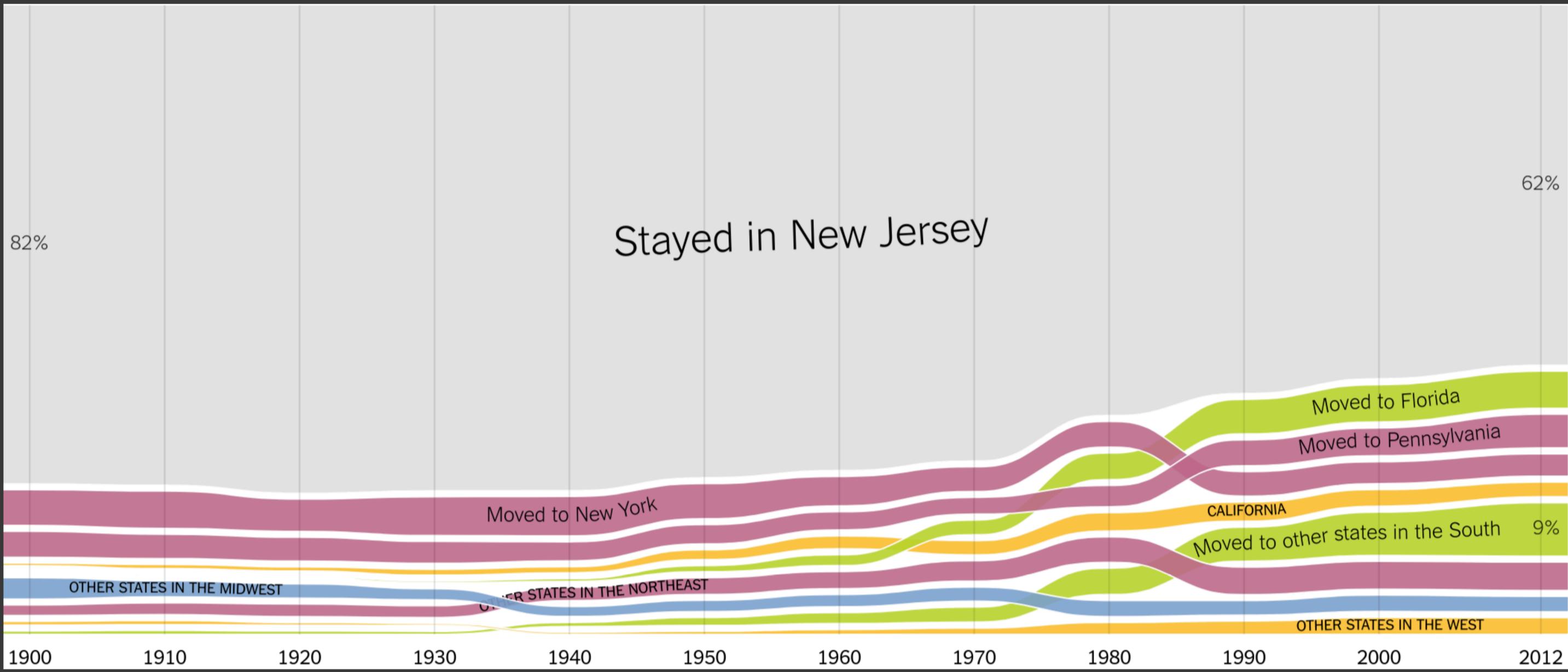
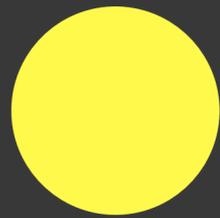
← **Tick marks**

Among U.S. adults • Source: Analysis of the U.S. Census Bureau's American Time Use Survey by Patrick Sharkey, Princeton University • The New York Times

← **Caption**

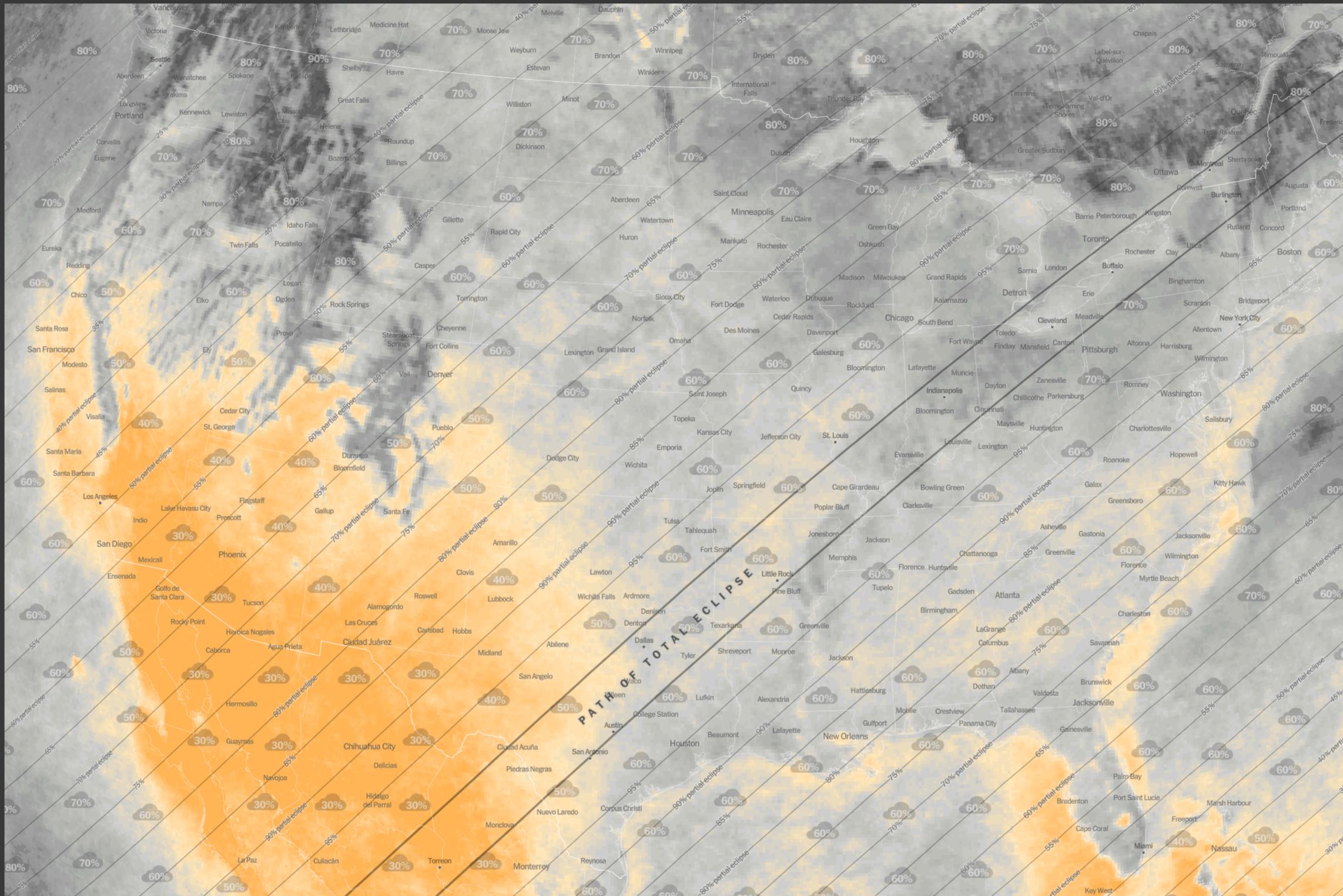
# Anatomy of a Chart

Source: NYT



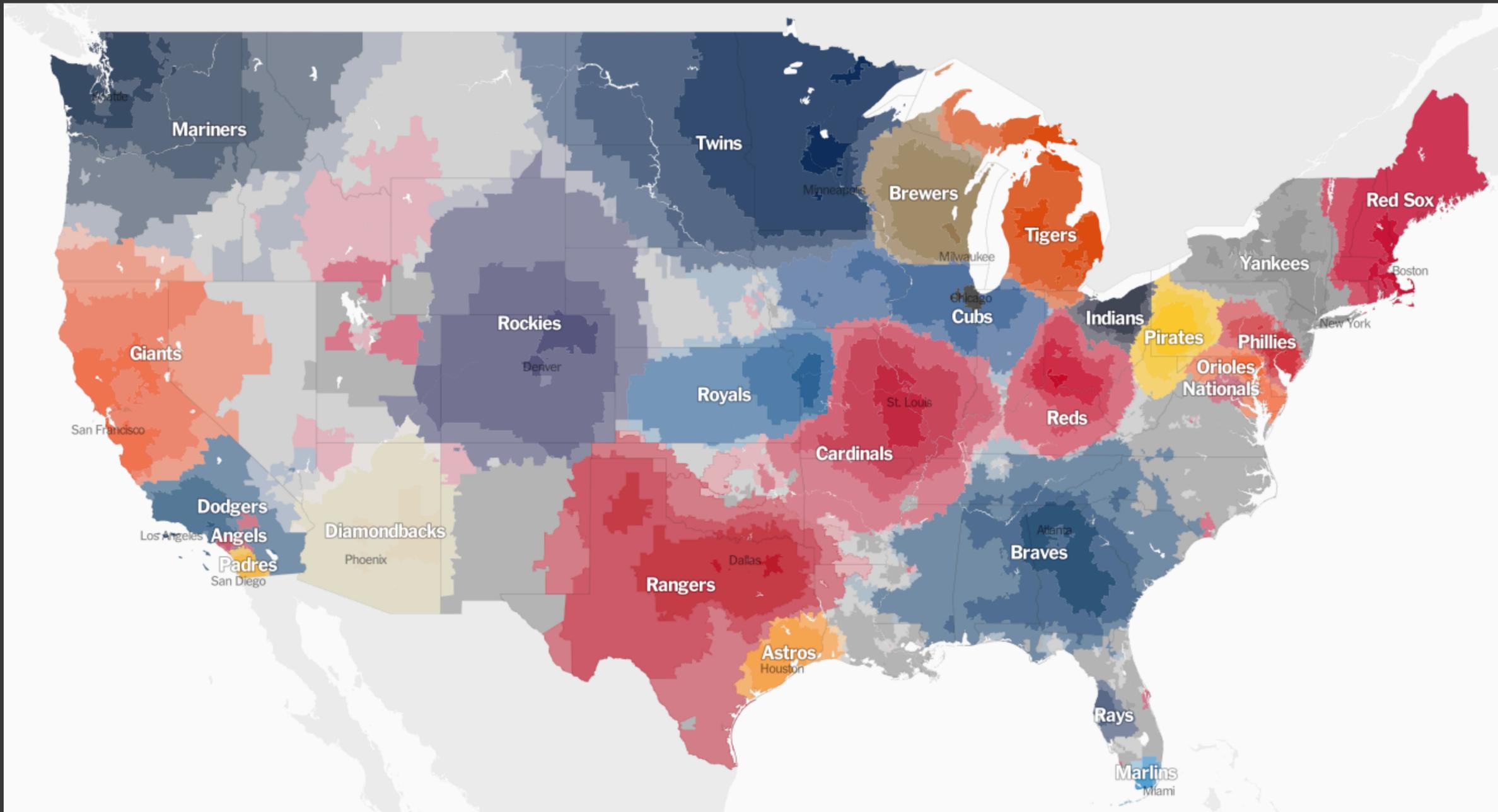
Color: Categorical

Source: NYT



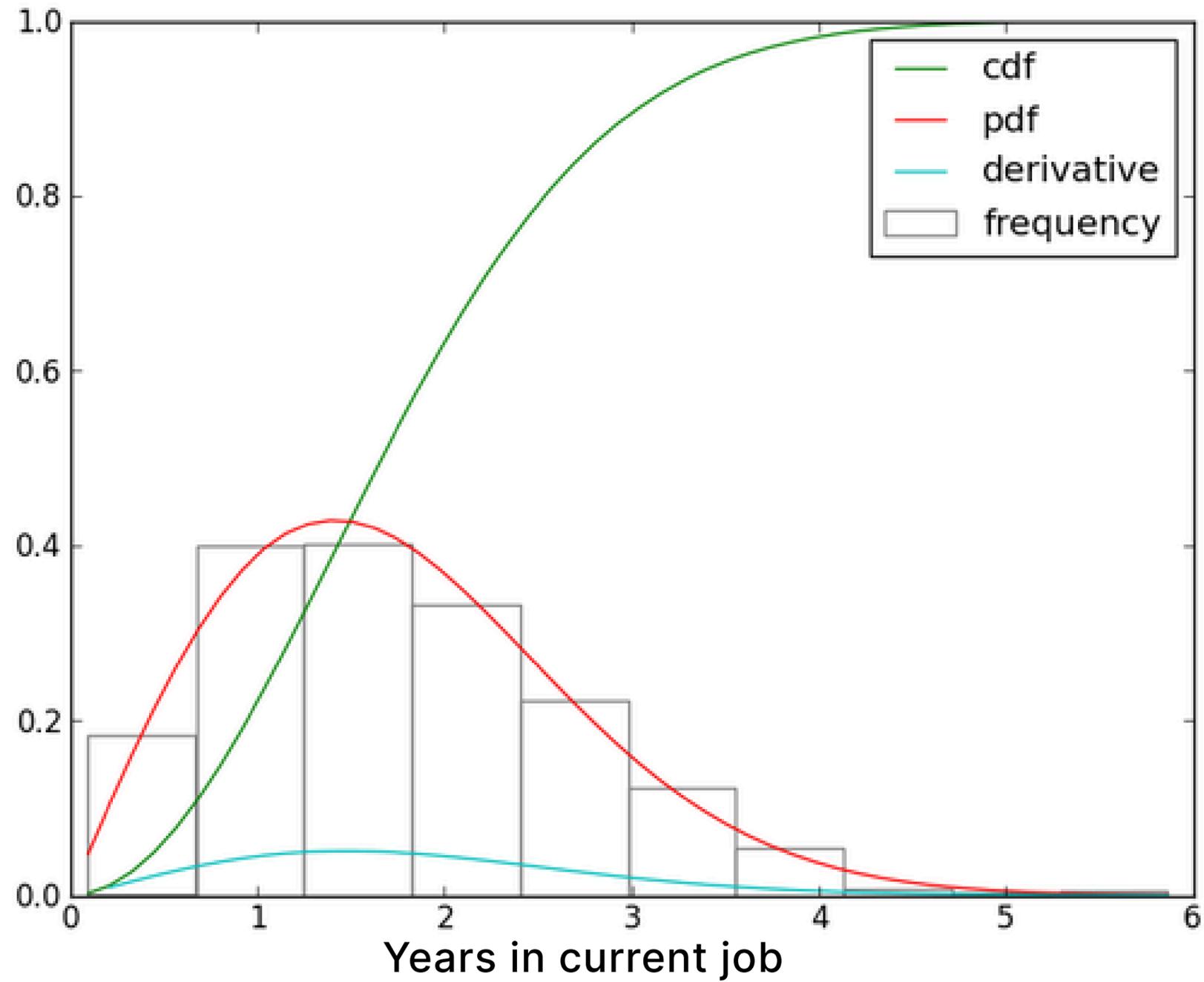
Color: Quantitative

Source: NYT



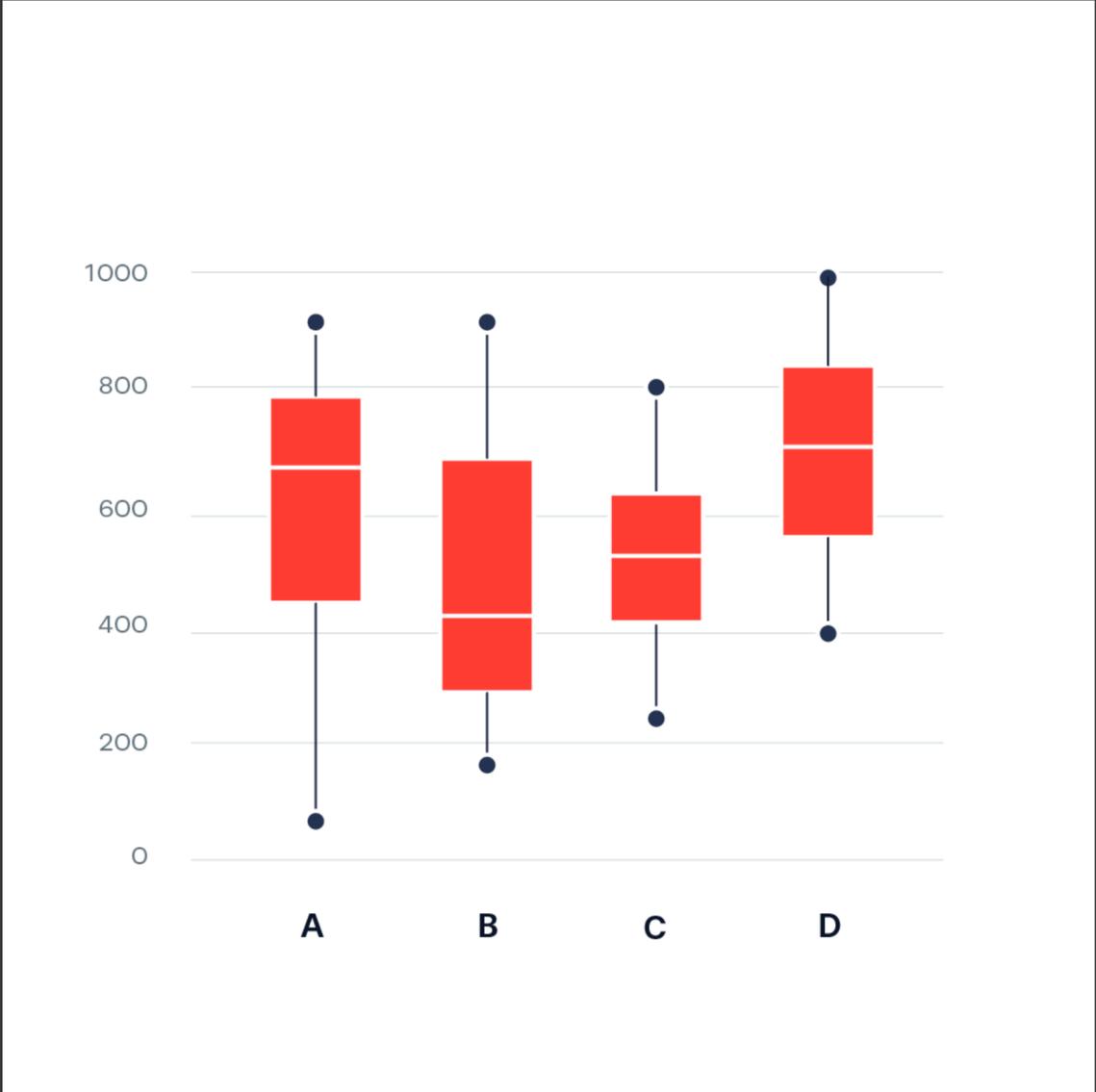
Color: Both?

Source: NYT



# Visualizing Distributions

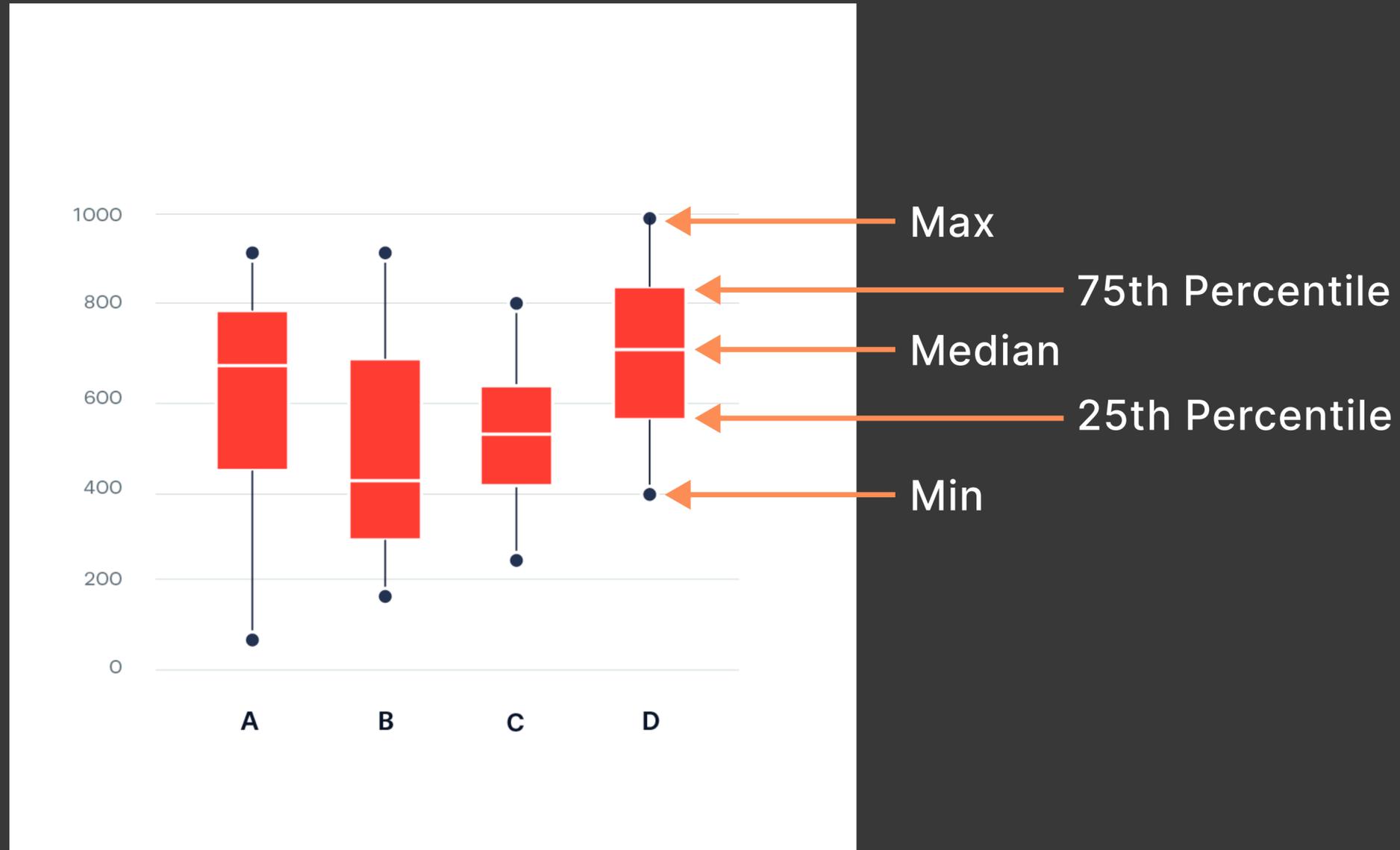
Source



Box Plot

# Visualizing Distributions

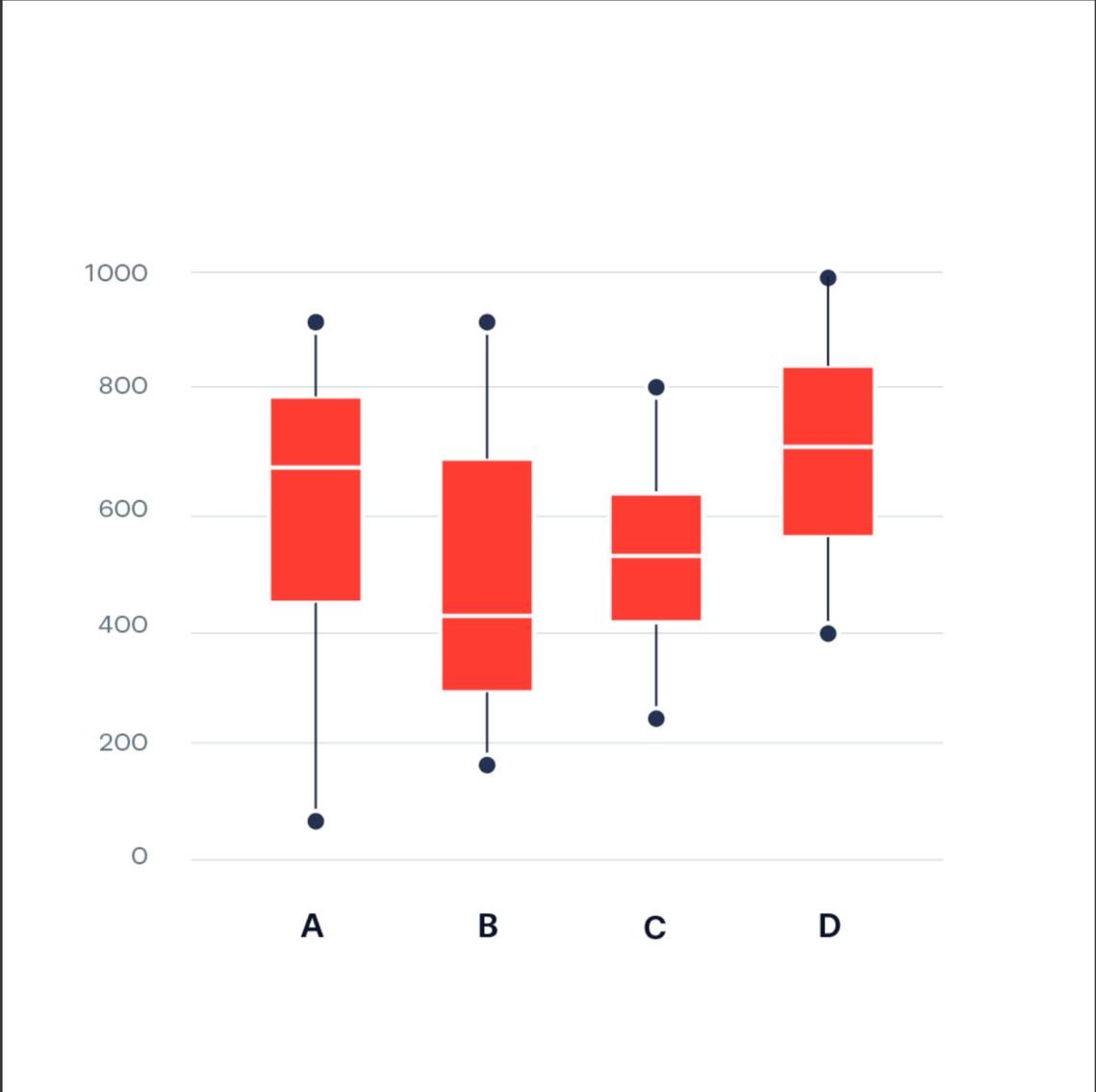
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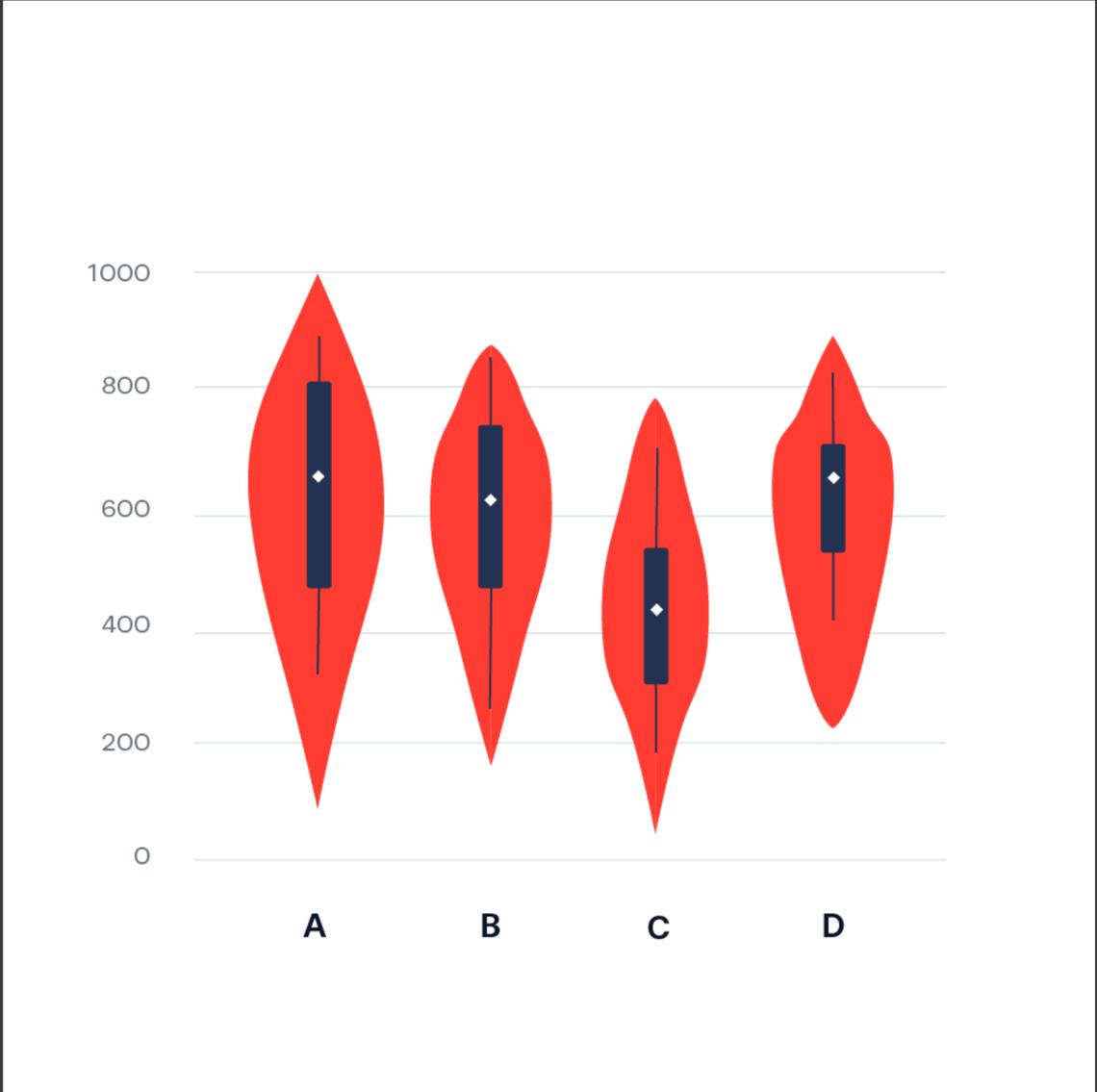
Box Plot

# Visualizing Distributions

Source: DVP



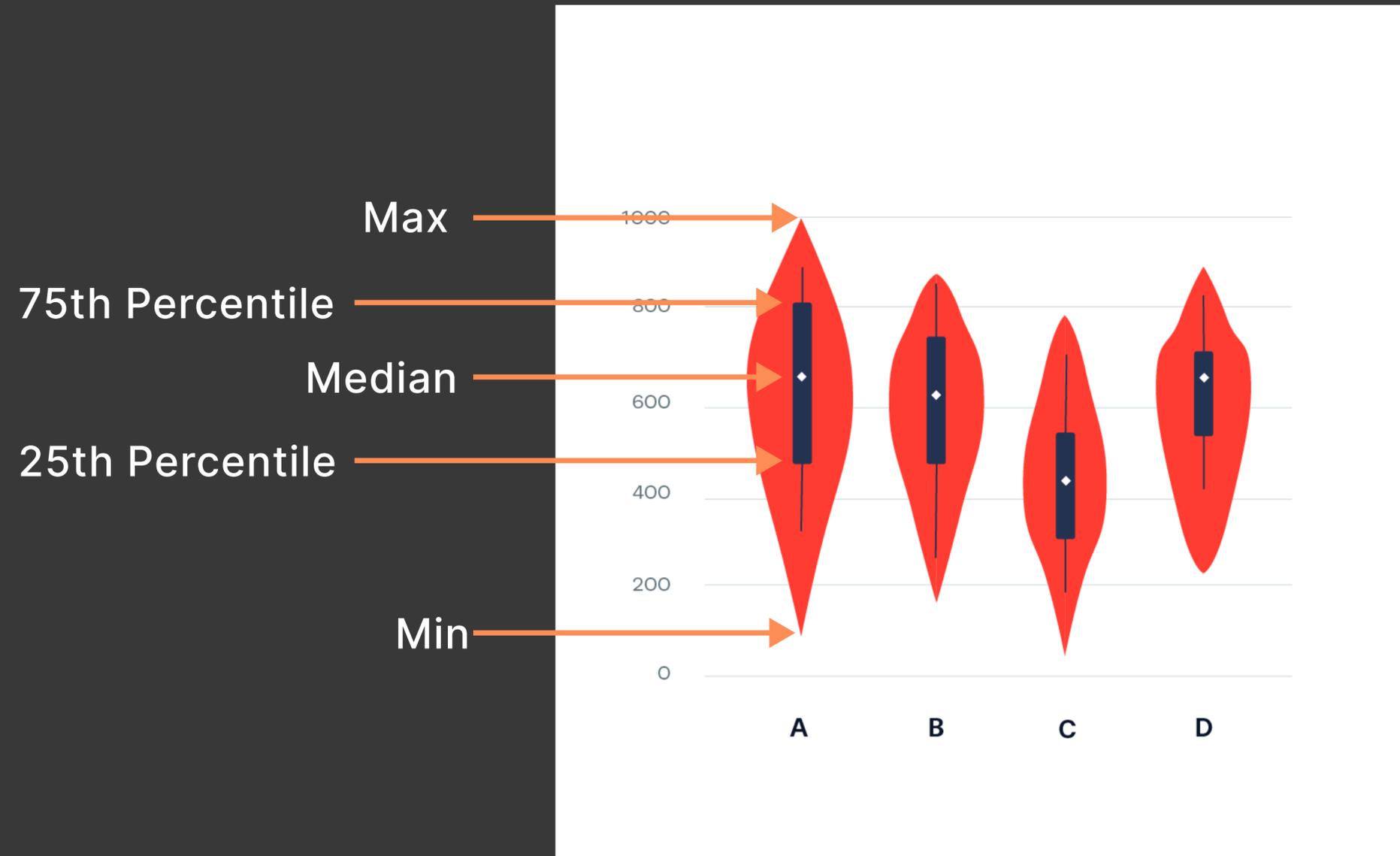
Box Plot



Violin Plot

# Visualizing Distributions

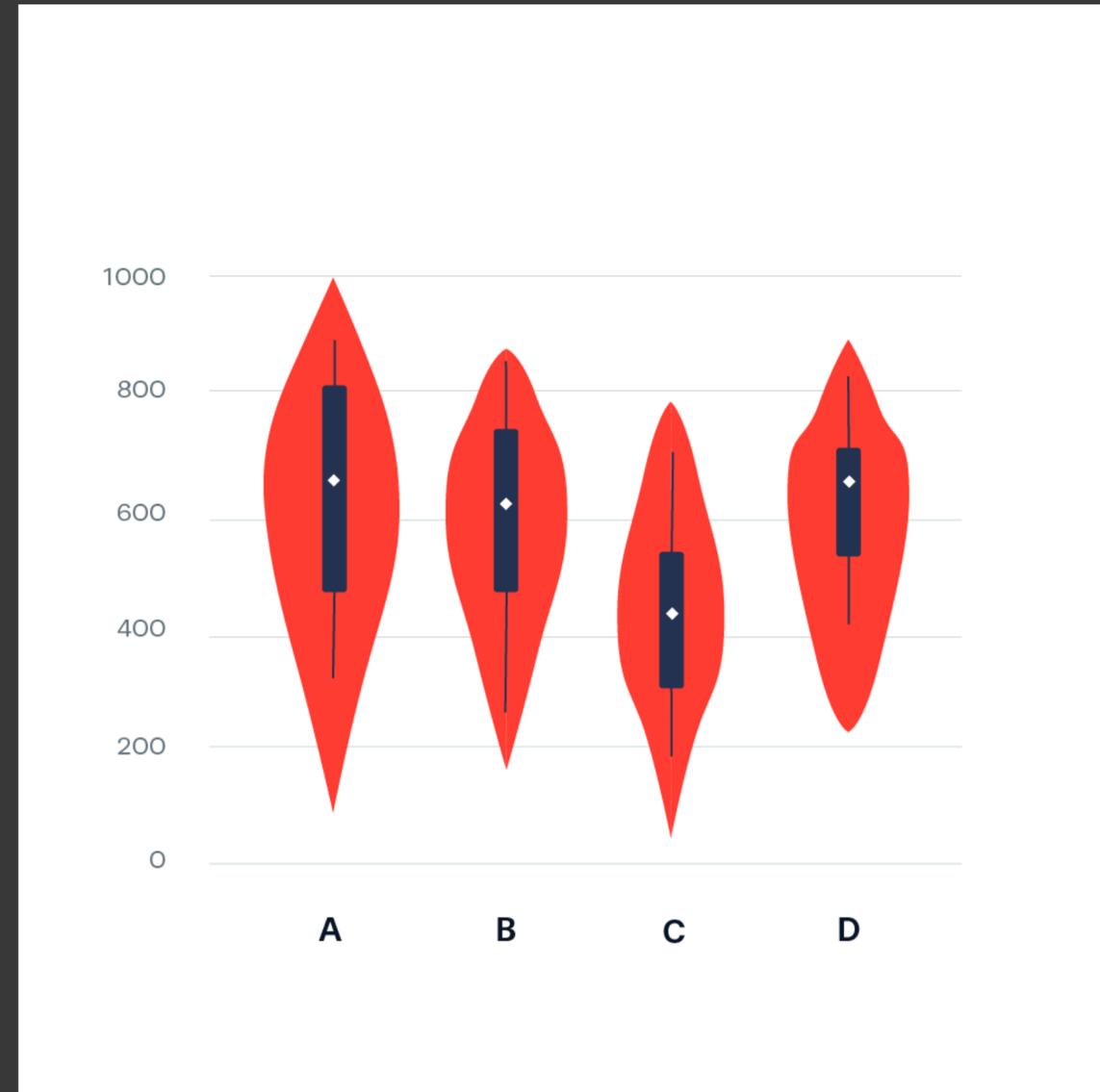
Source: DVP



Violin Plot

# Visualizing Distributions

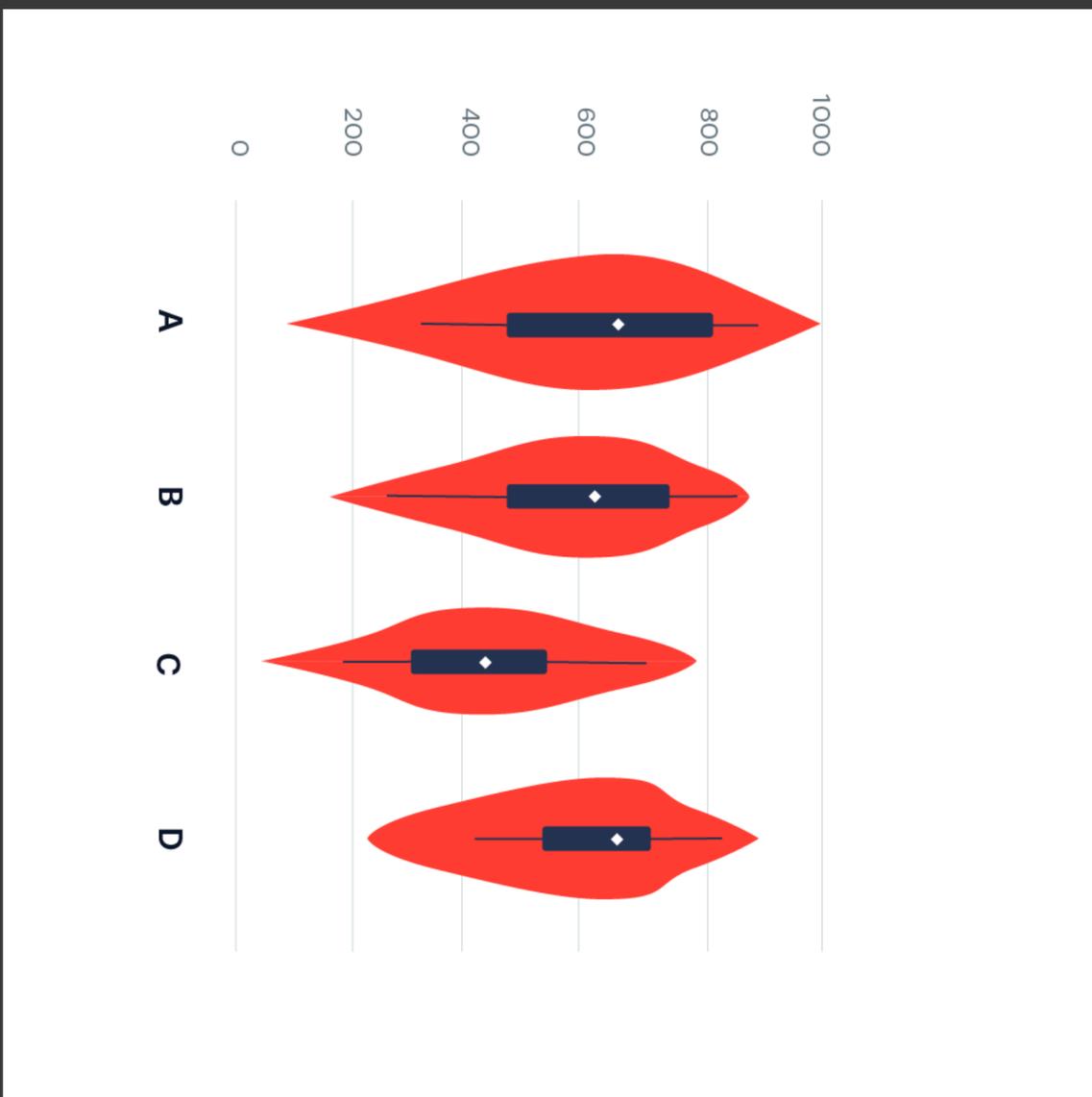
Source: DVP



Violin Plot

# Visualizing Distributions

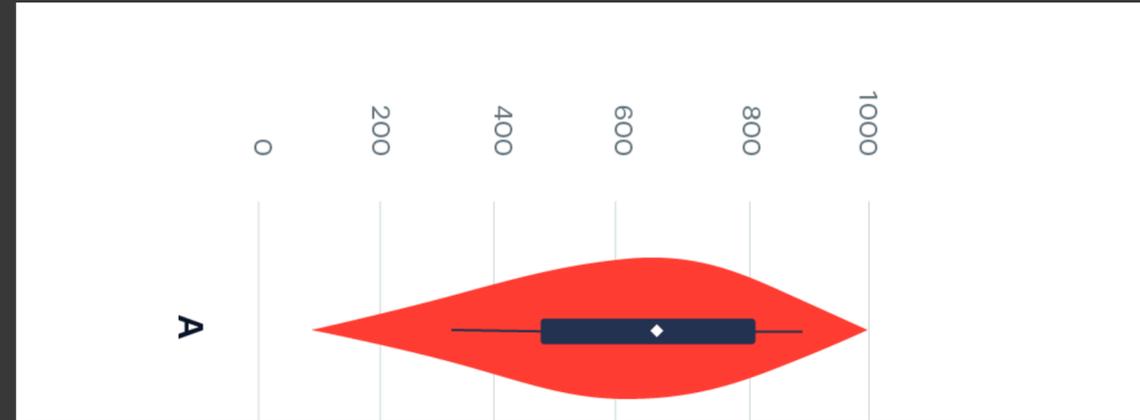
Source: DVP



Violin Plot

# Visualizing Distributions

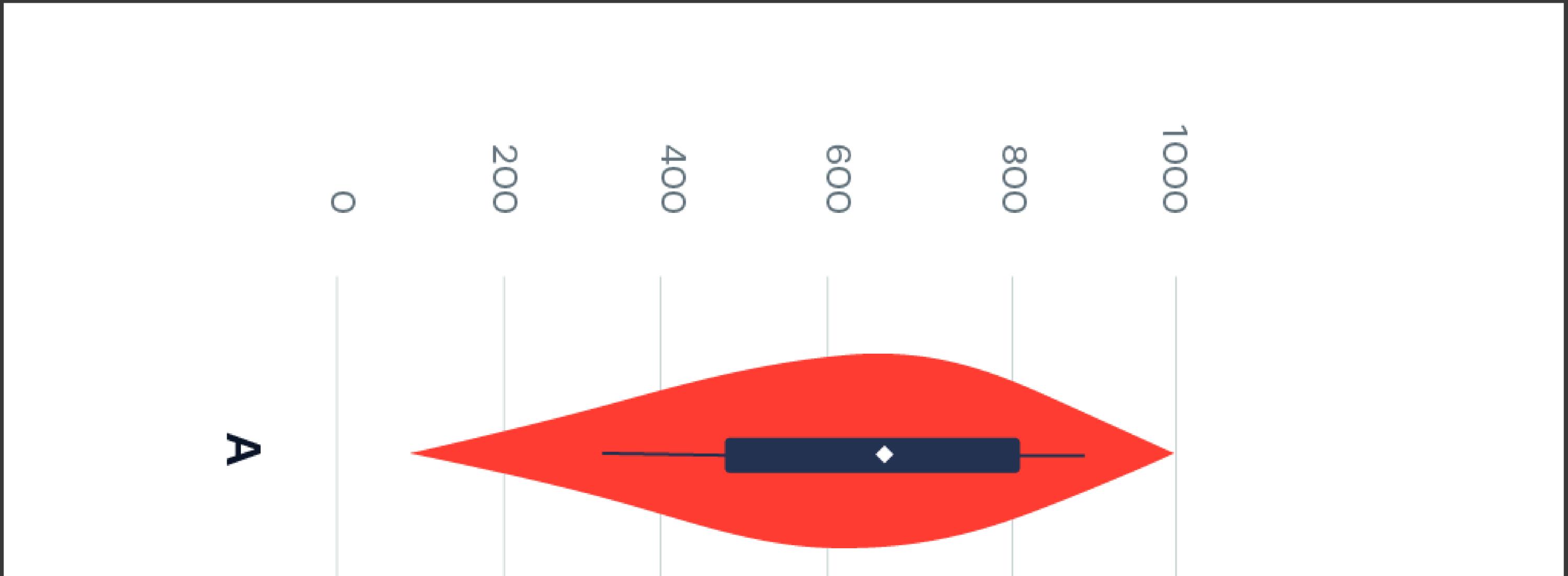
Source: DVP



Violin Plot

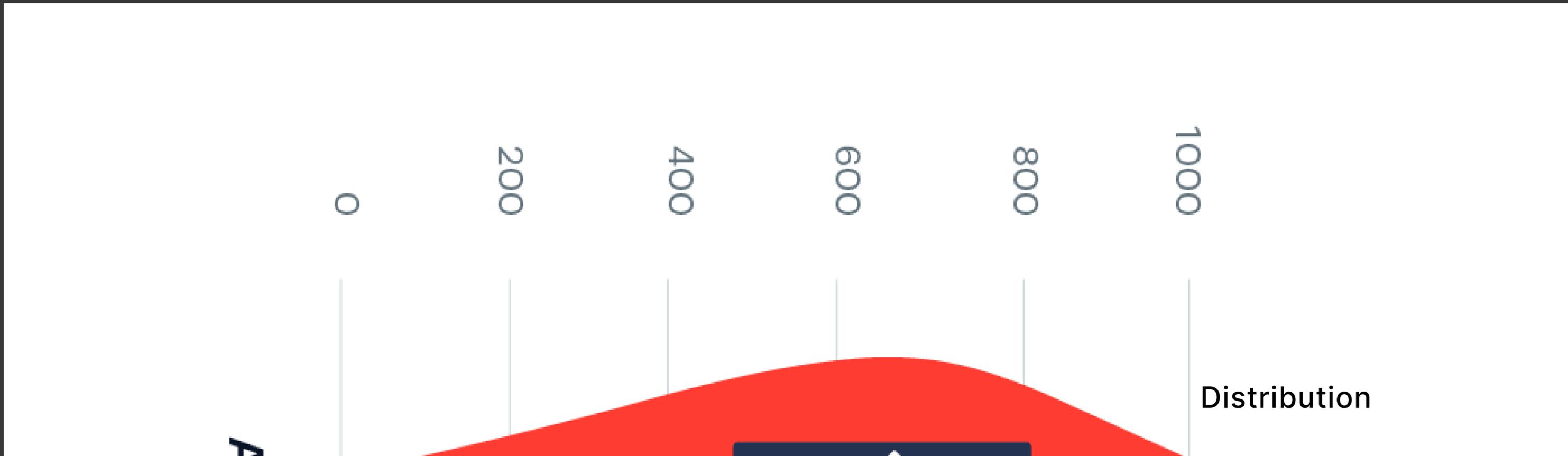
# Visualizing Distributions

Source: DVP



# Visualizing Distributions

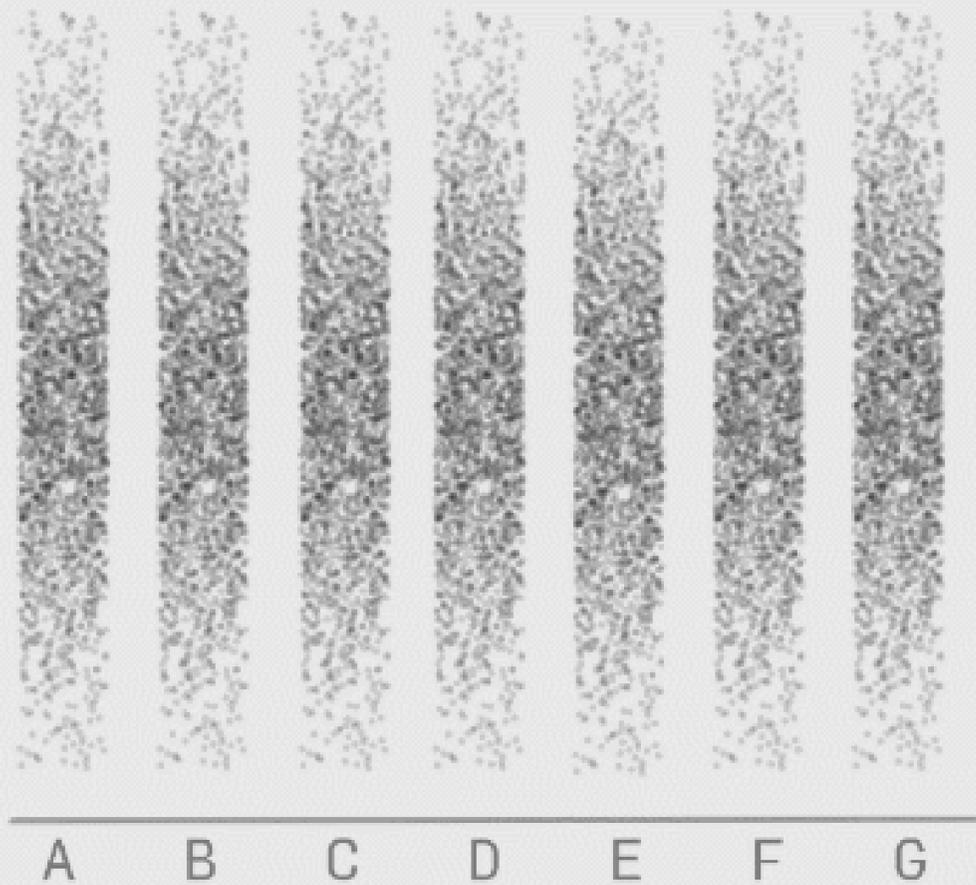
Source: [DVP](#)



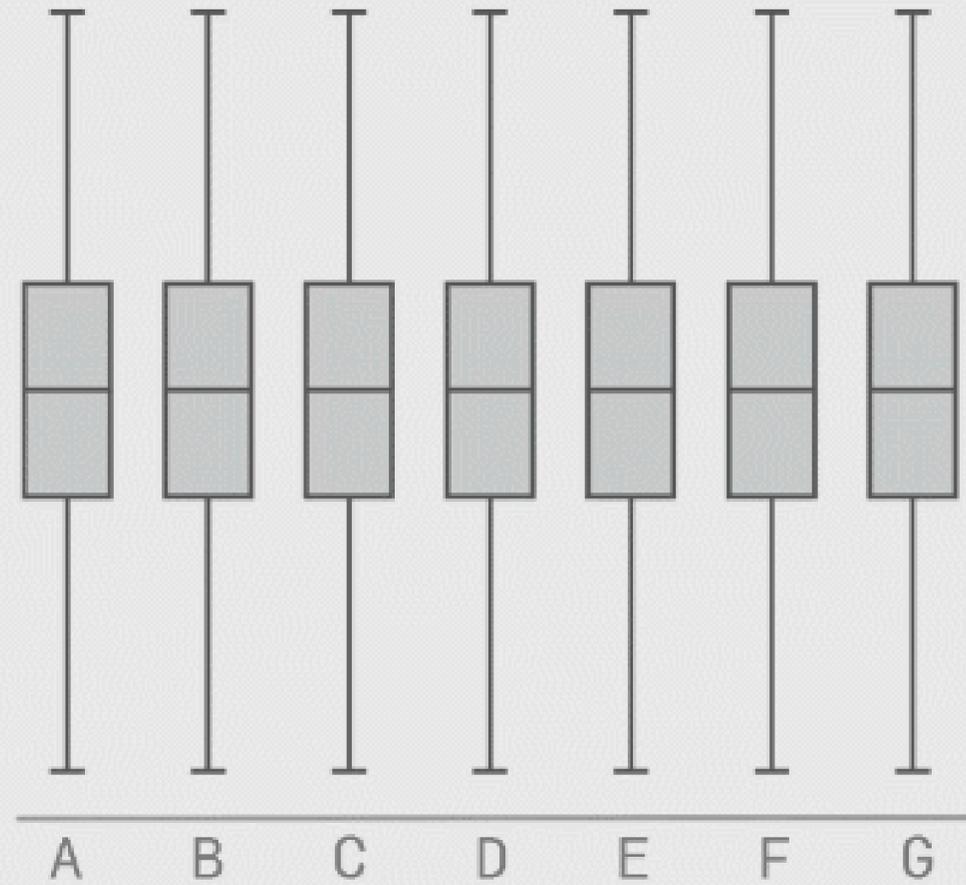
# Visualizing Distributions

Source: DVP

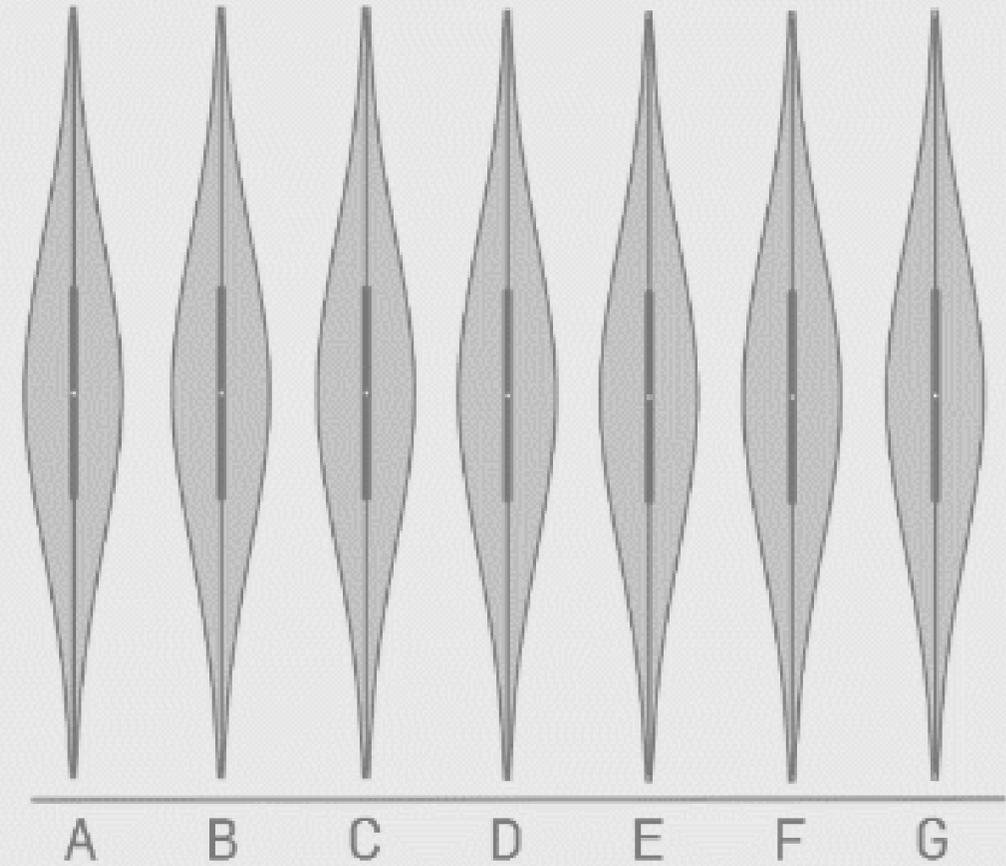
**Raw Data**

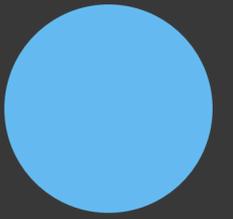


**Box-plot of the Data**



**Violin-plot of the Data**

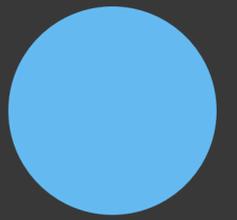




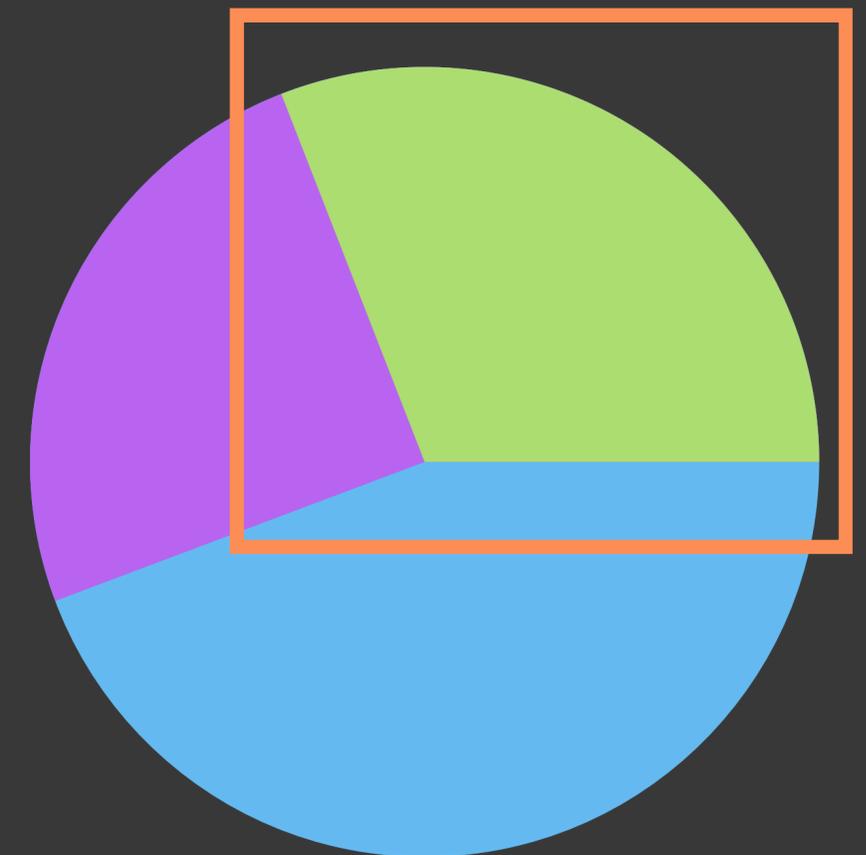
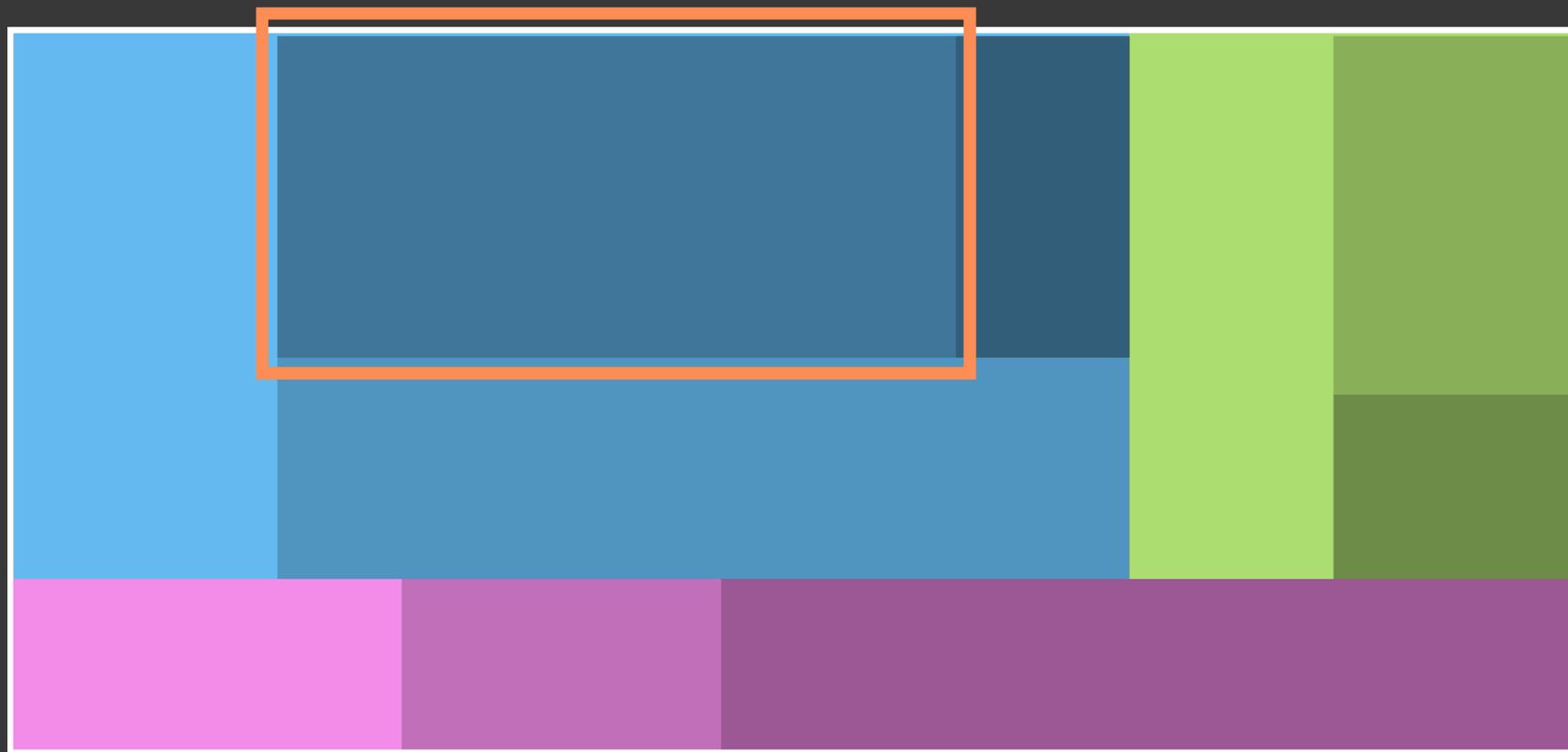
# Perception & Comparison

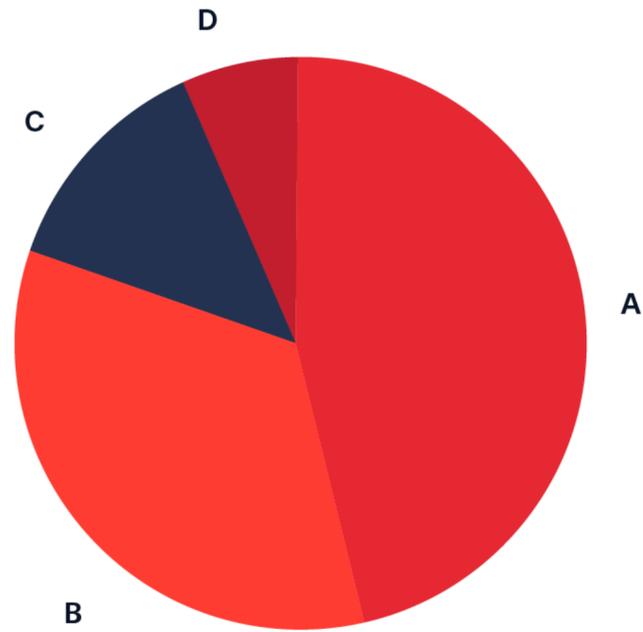
# Encodings

How data maps to perceptual “channels”



Area: Quantitative

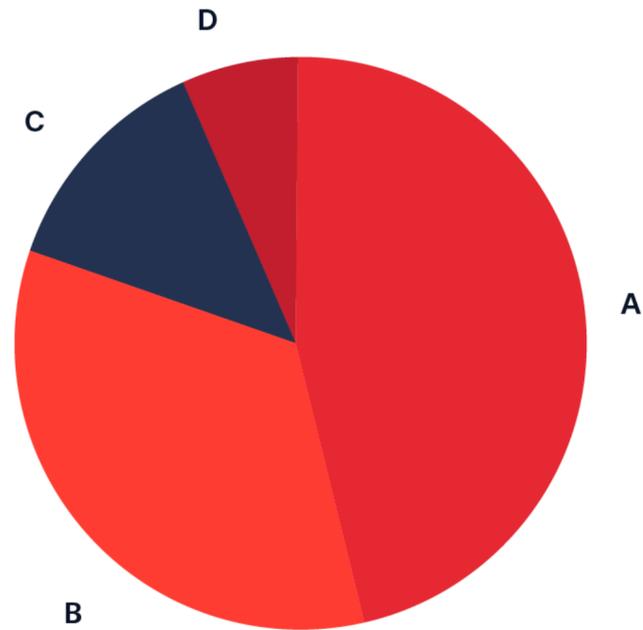




## No Pie Charts!

The eye tends to perceive *area* instead of *angle*, making large segments look much larger than small segments.

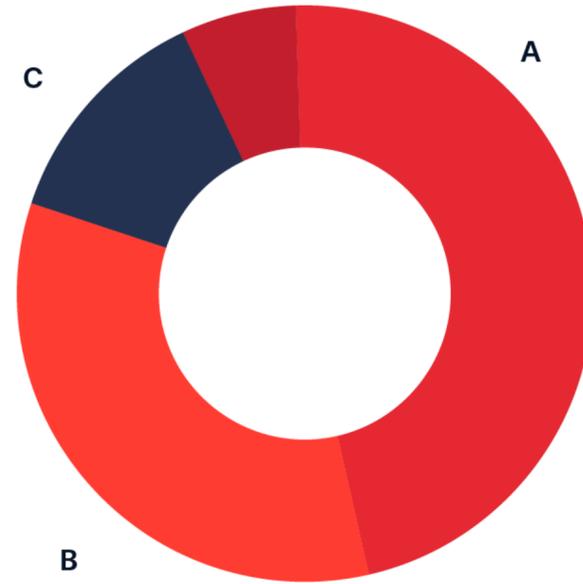
Source: DVP



## No Pie Charts!

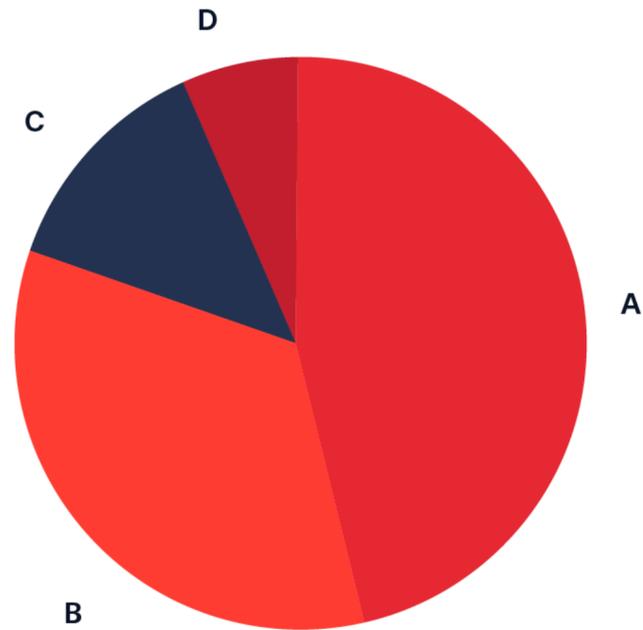
The eye tends to perceive *area* instead of *angle*, making large segments look much larger than small segments.

Source: DVP



## Donut Chart

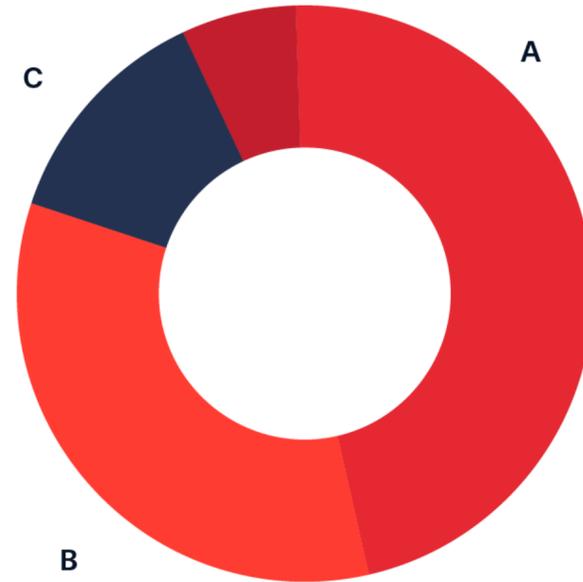
Encourages viewer to perceive *angle* instead of *area*.



## No Pie Charts!

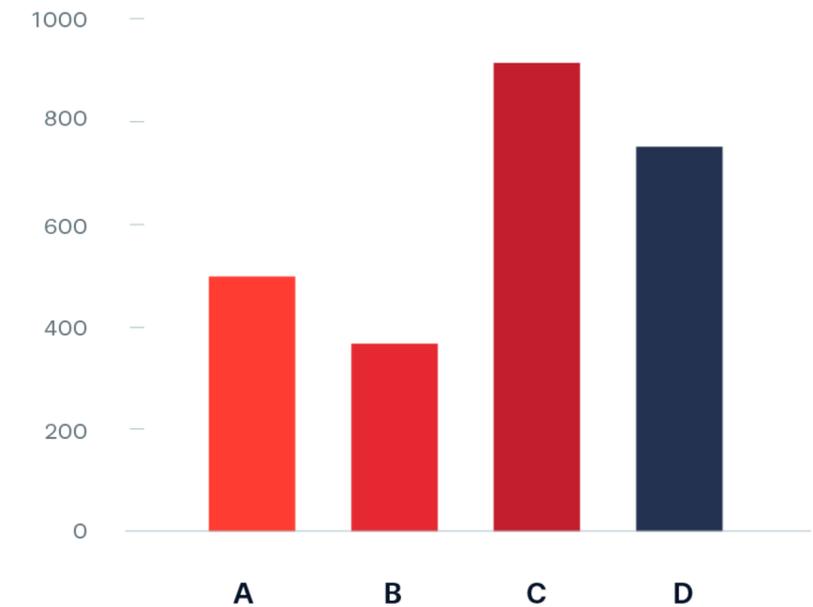
The eye tends to perceive *area* instead of *angle*, making large segments look much larger than small segments.

Source: DVP



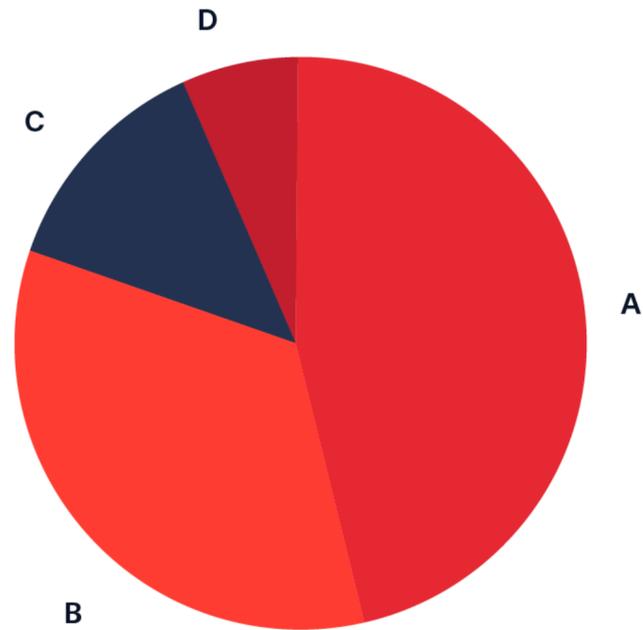
## Donut Chart

Encourages viewer to perceive *angle* instead of *area*.



## Bar Chart

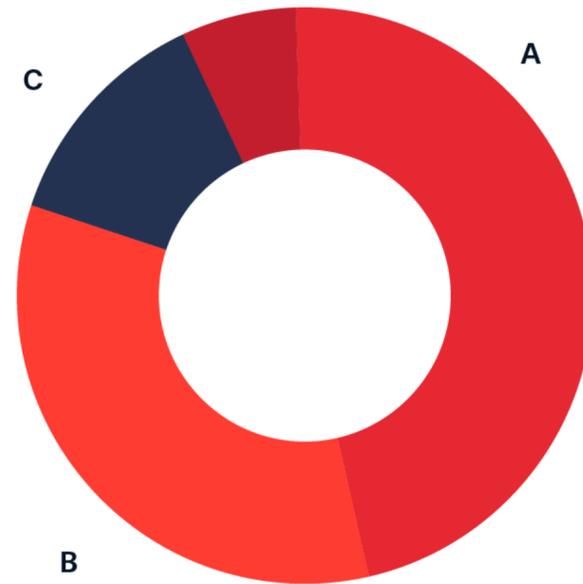
Like a donut chart, but not bendy! Your eye is good at comparing straight lengths!



## No Pie Charts!

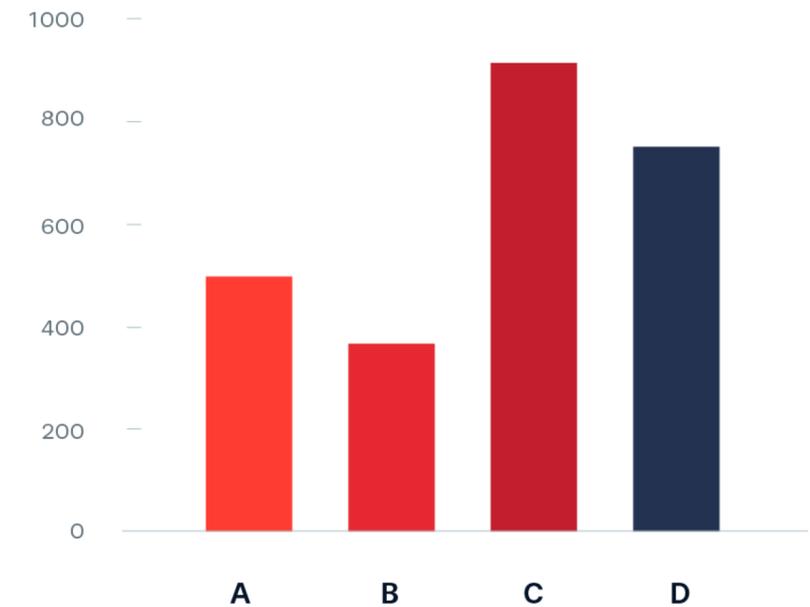
The eye tends to perceive *area* instead of *angle*, making large segments look much larger than small segments.

Source: DVP



## Donut Chart

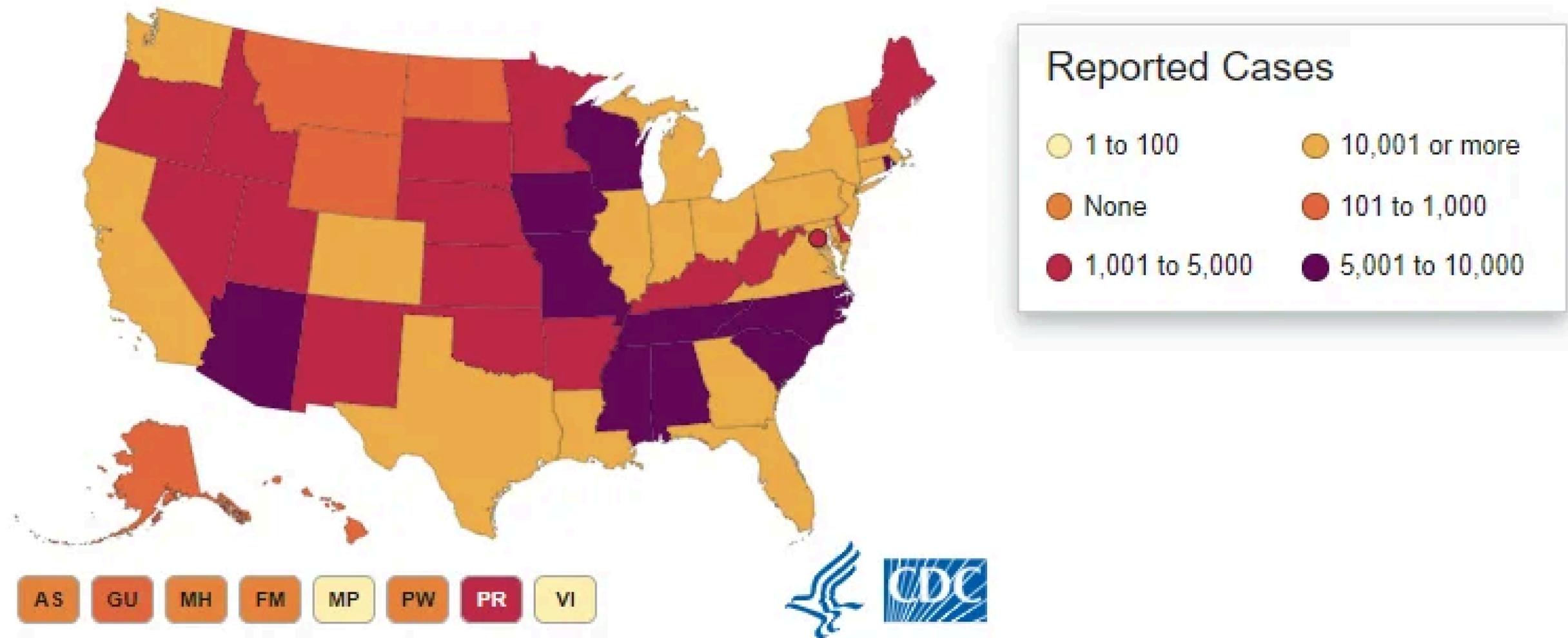
Encourages viewer to perceive *angle* instead of *area*.



## Bar Chart

Like a donut chart, but not bendy! Your eye is good at comparing straight lengths!

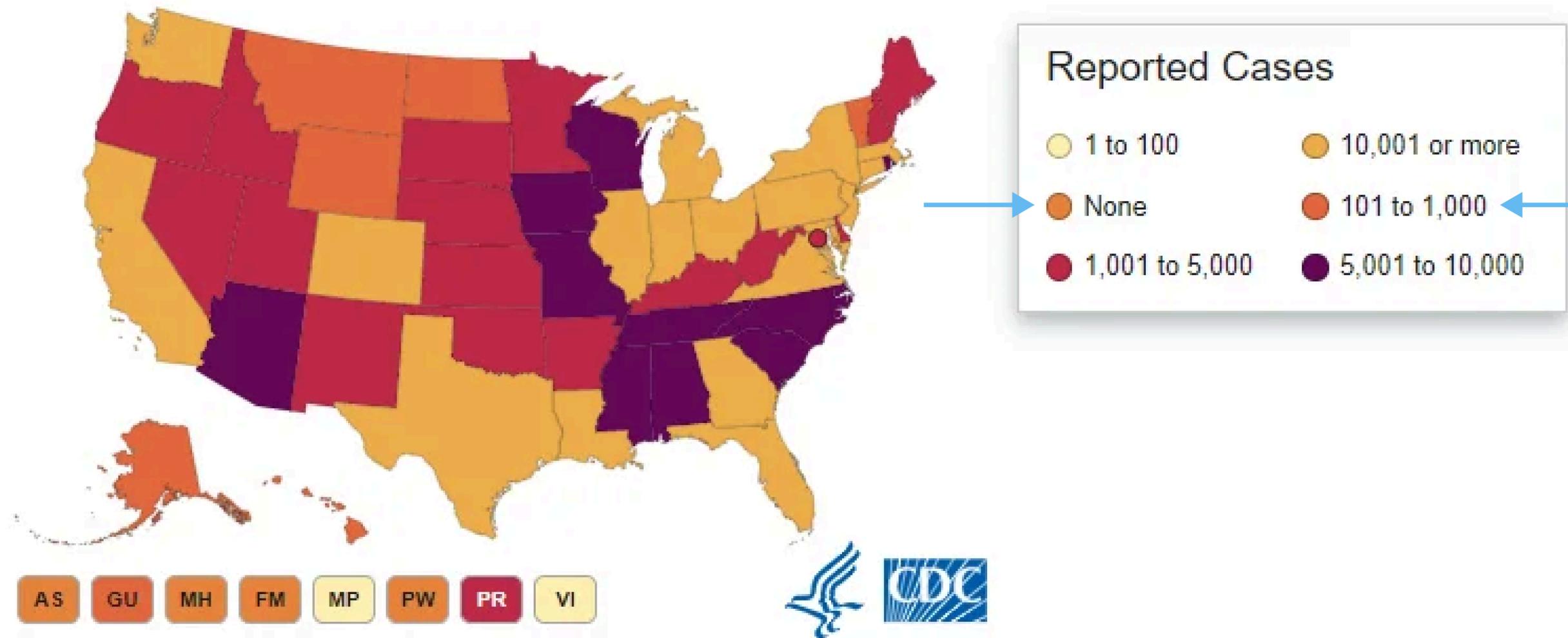
18 states report more than 10,000 cases of COVID-19.



Bad Color Encoding,  
Quantitative  $\Rightarrow$  Categorical (CDC, 2020)

Source

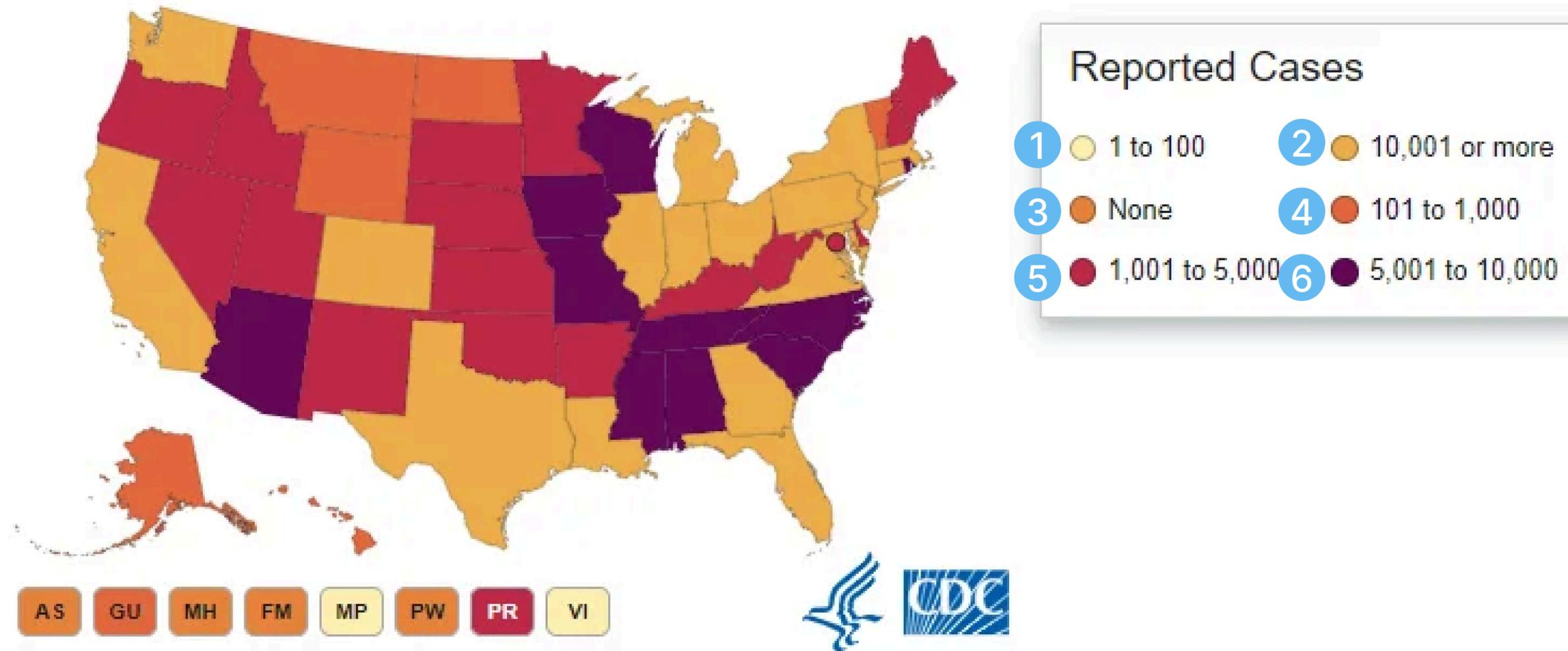
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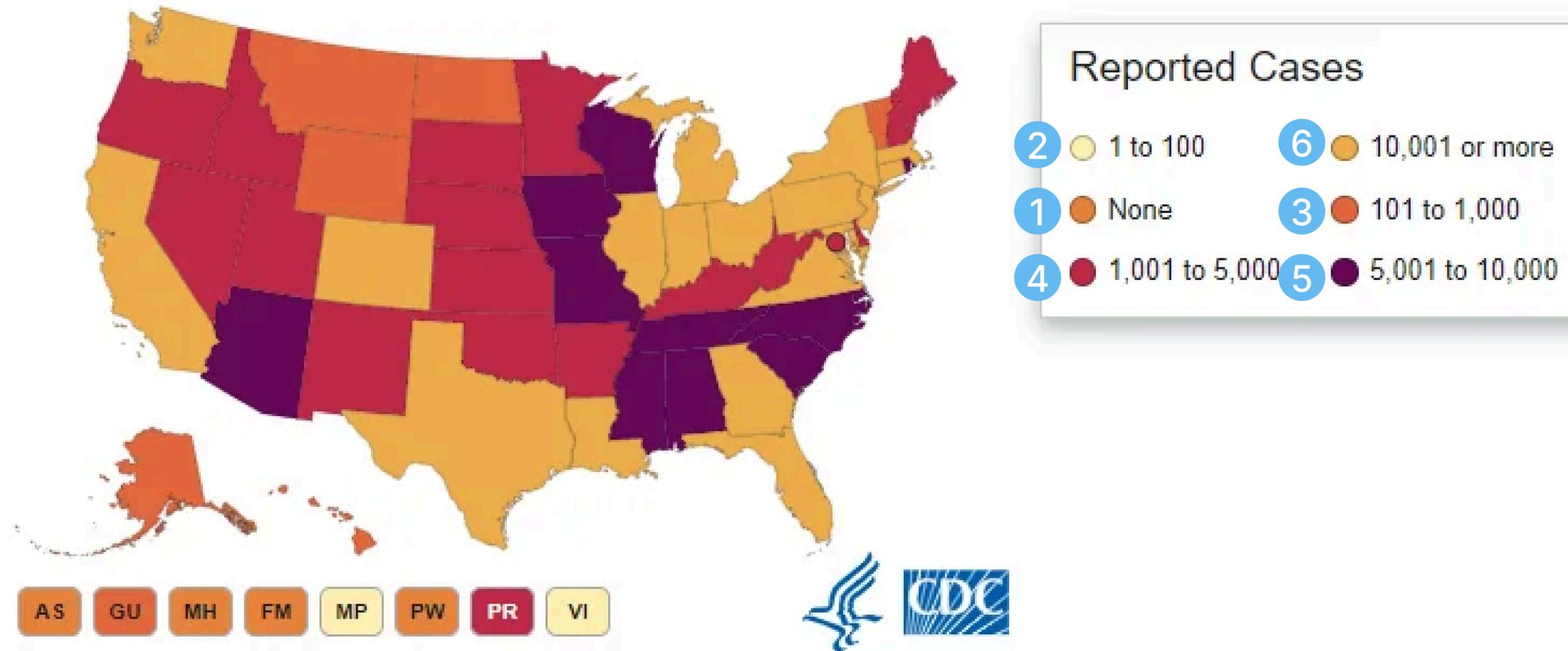
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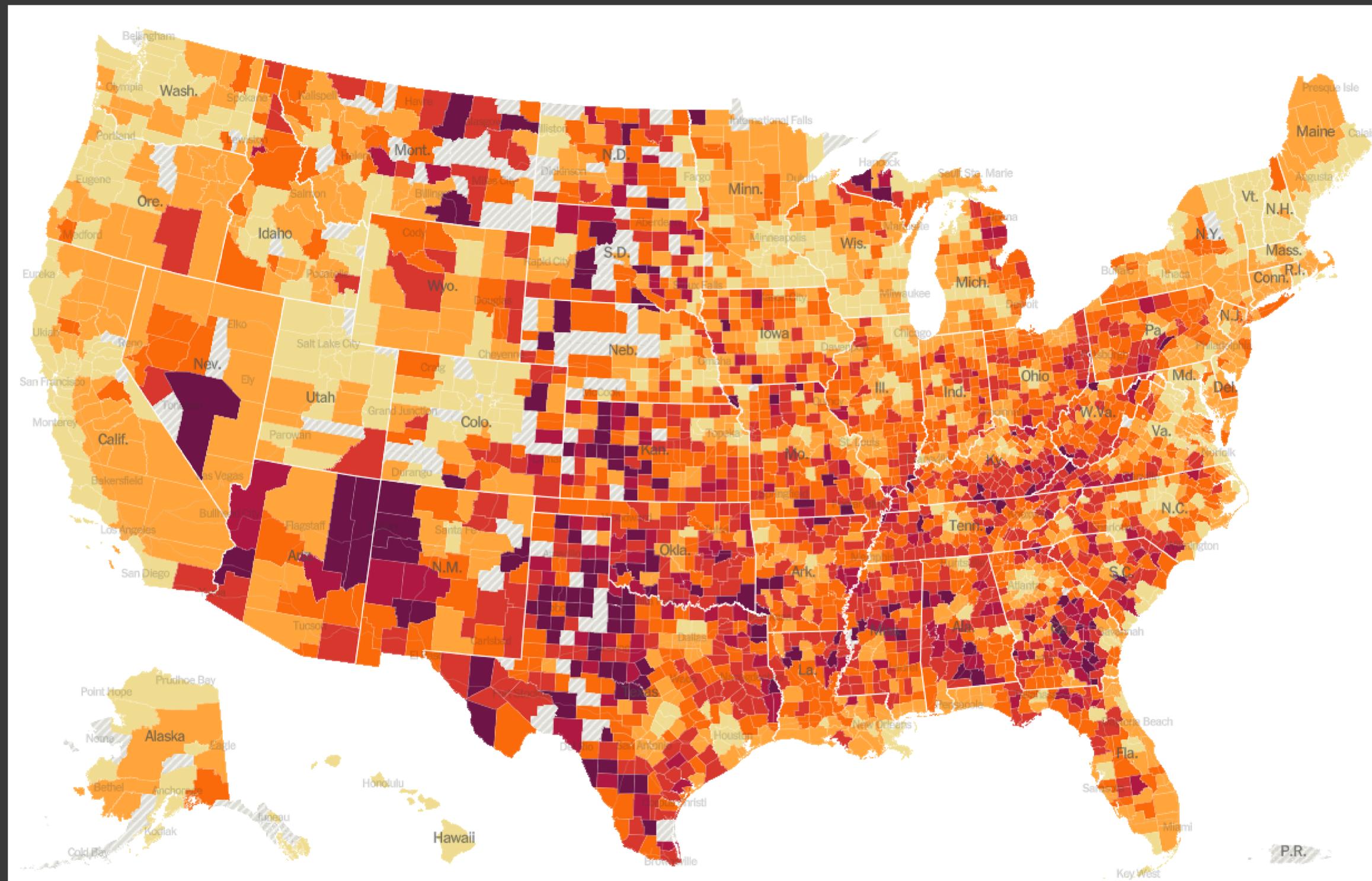
Source

18 states report more than 10,000 cases of COVID-19.



Bad Color Encoding,  
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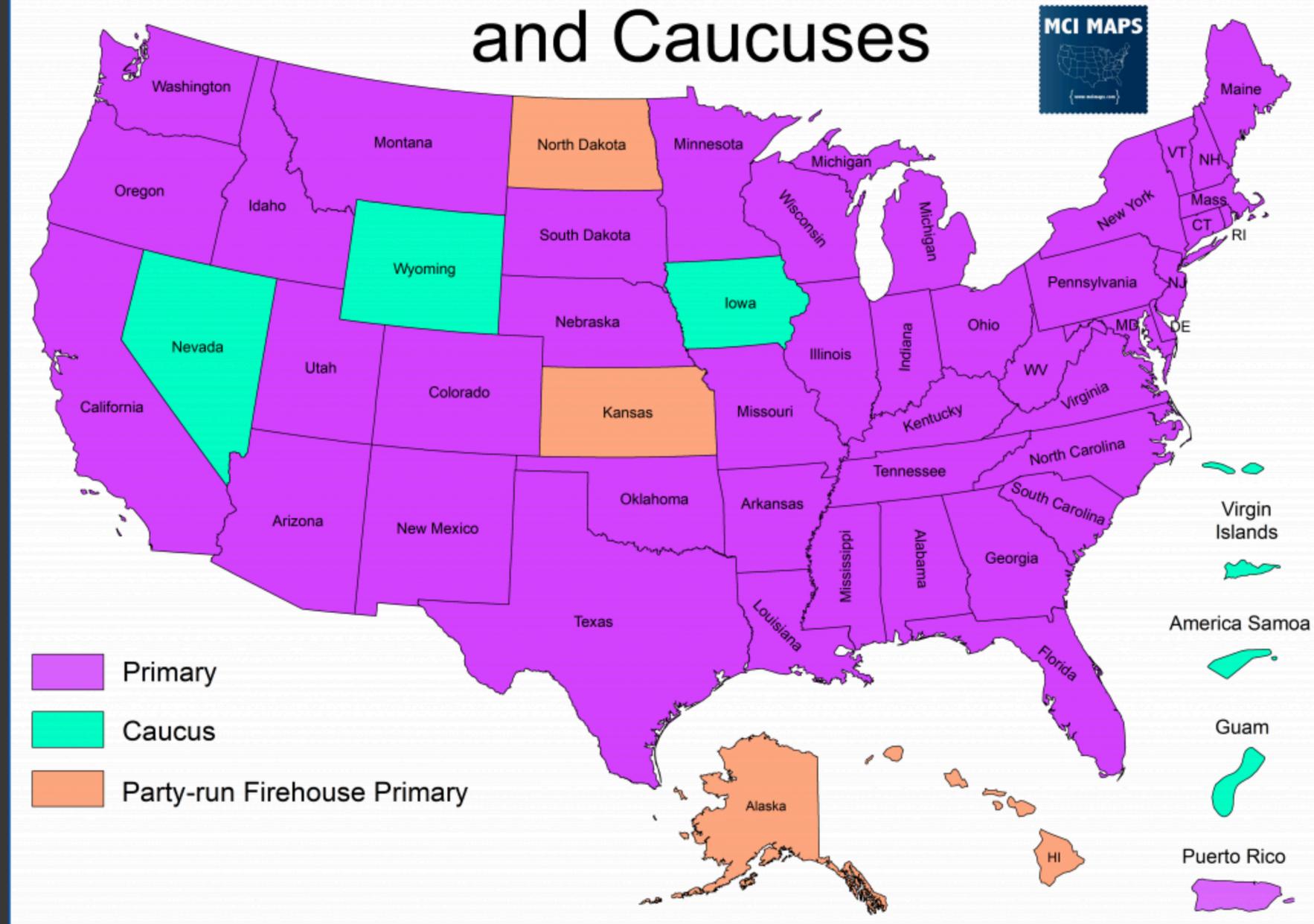
Source



# All-Time COVID Deaths (NYTimes, 2023)

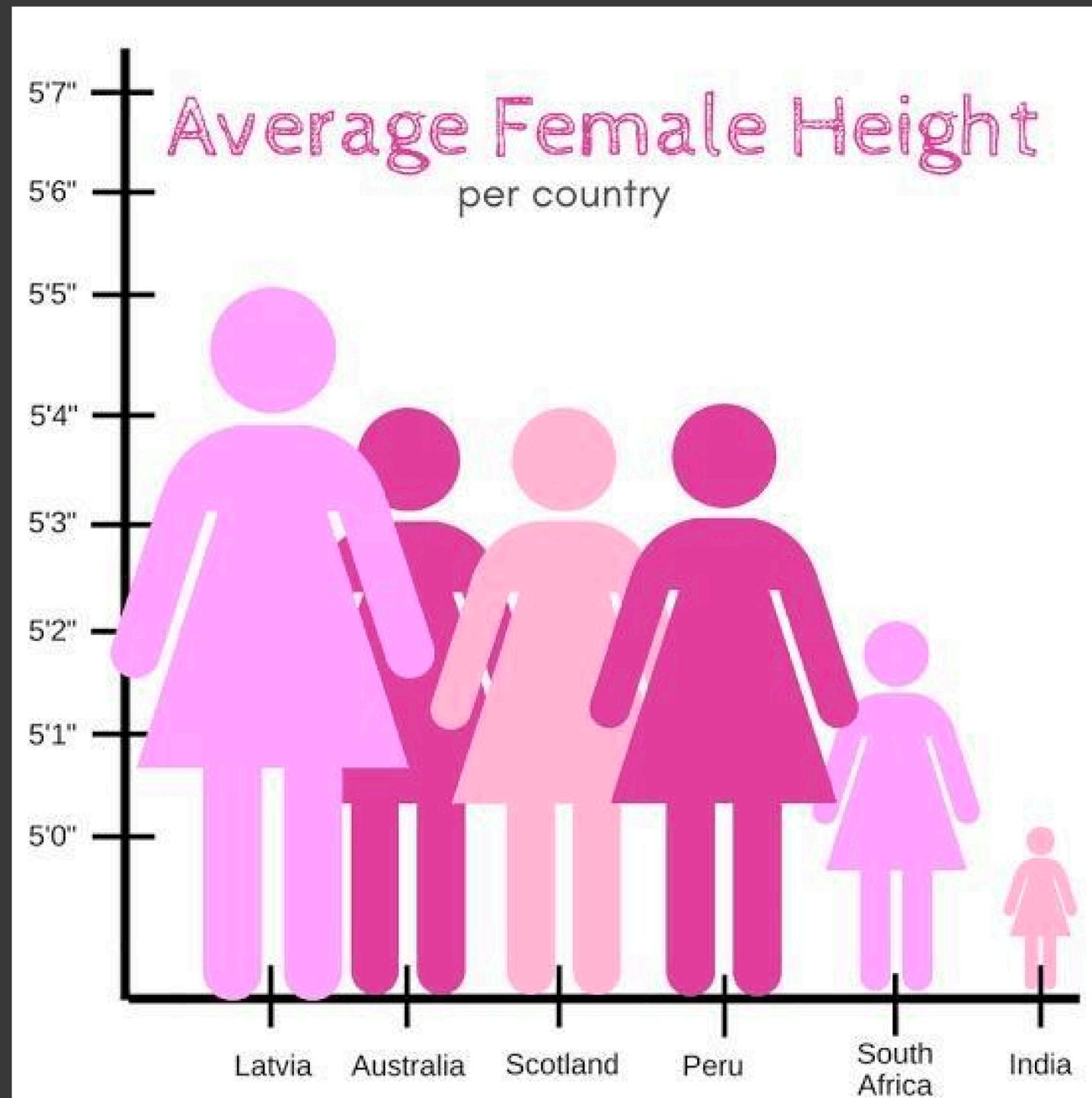
Source

# 2020 Democratic Primaries and Caucuses



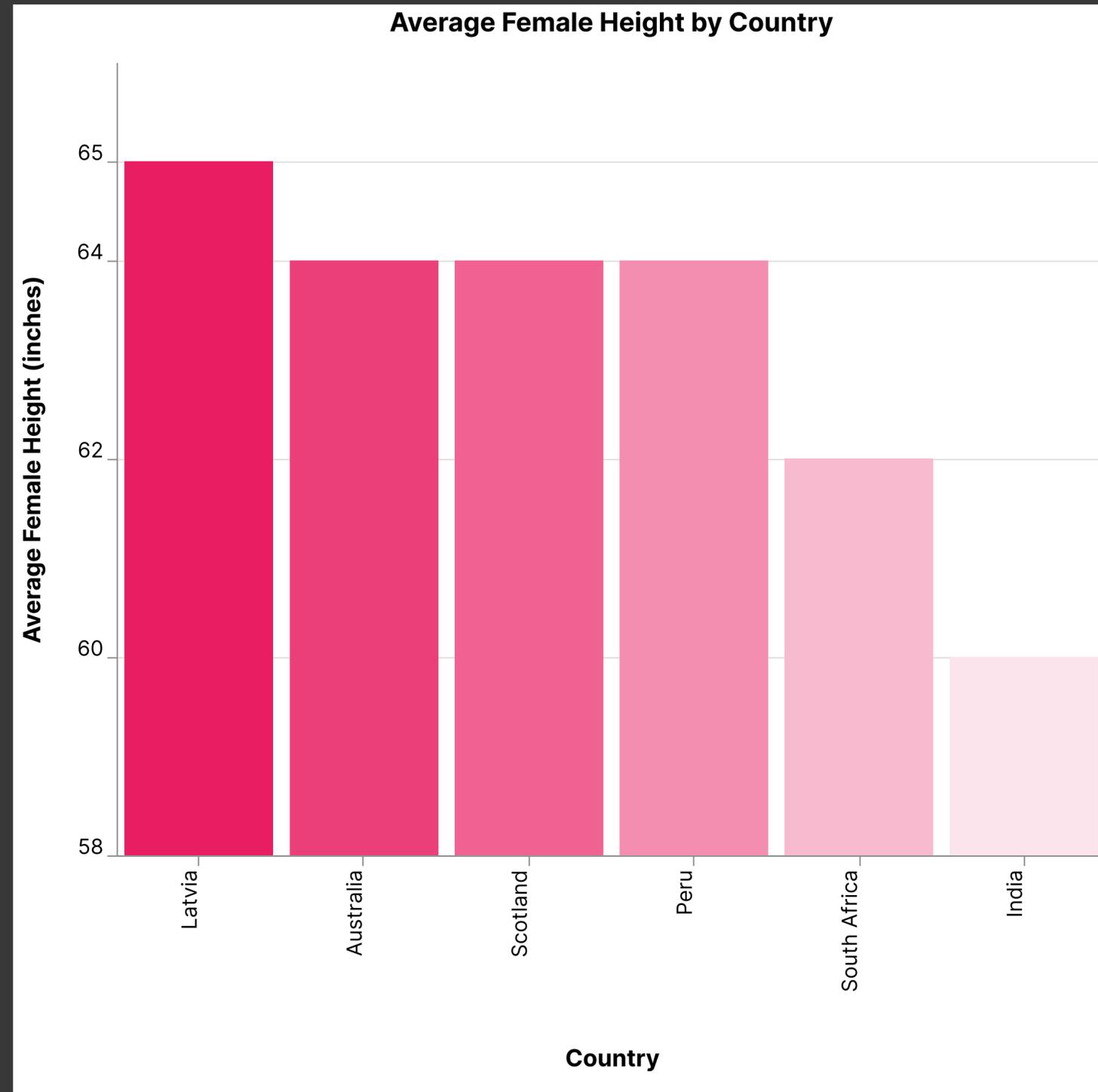
## Primaries vs. Caucuses (MCI Maps, 2020)

Source

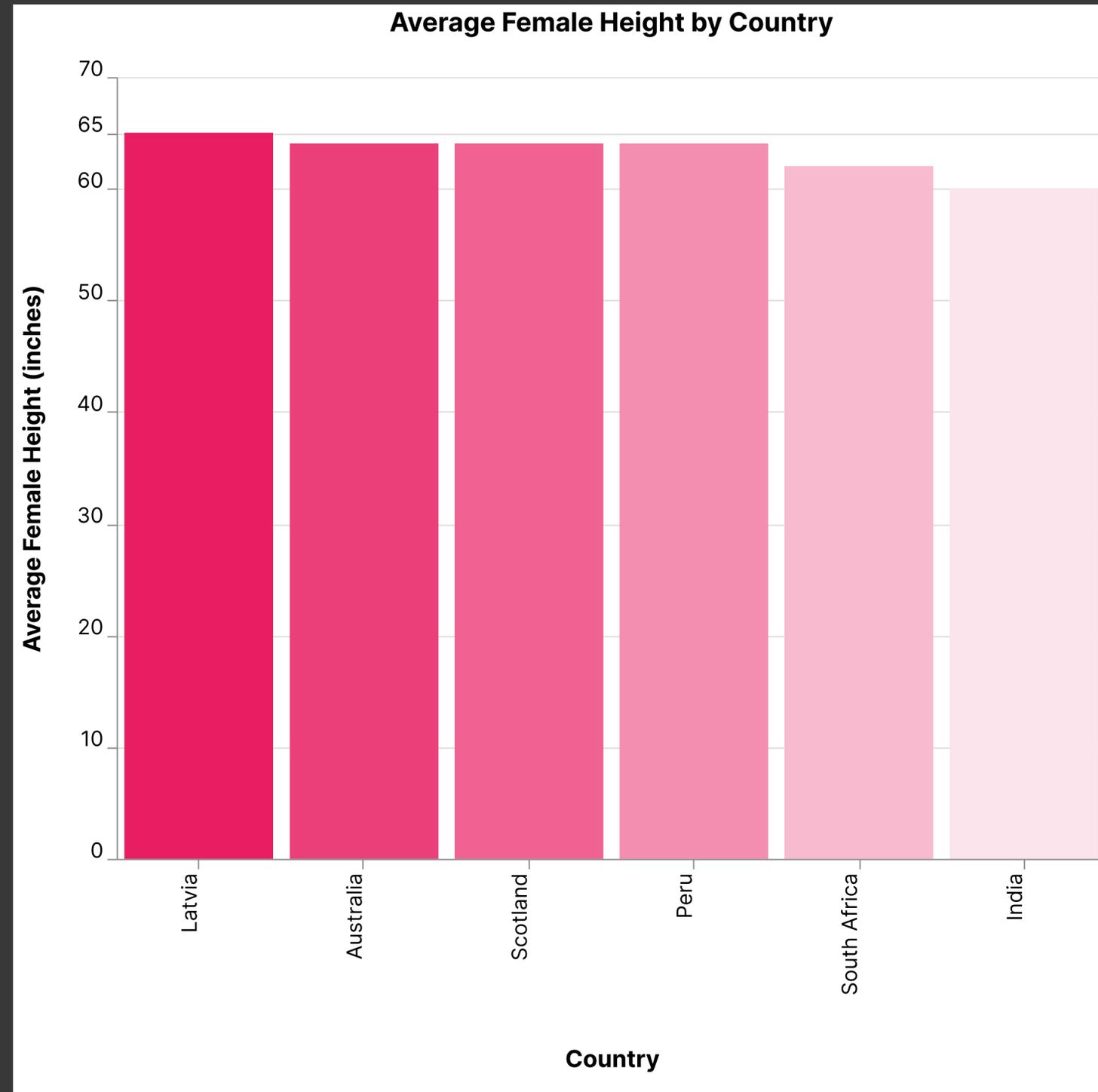


# Average Female Height

Source

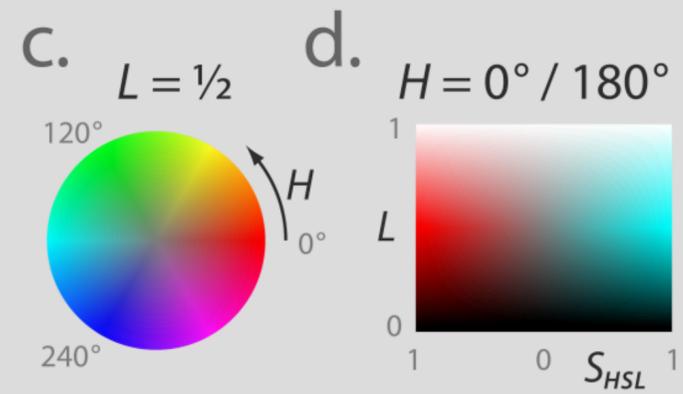
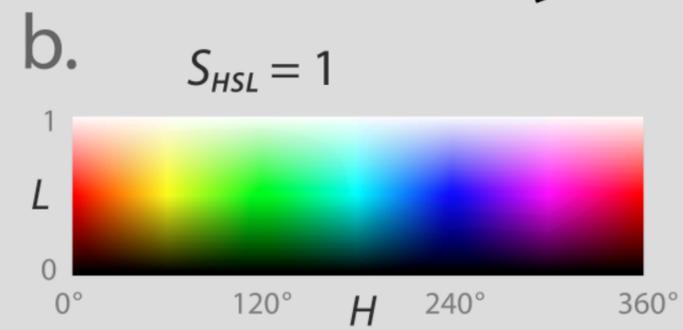
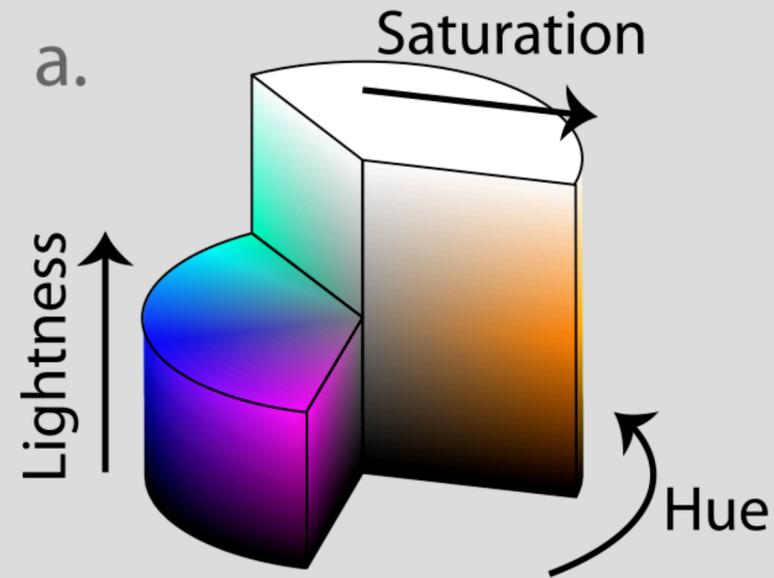


Average Female Height

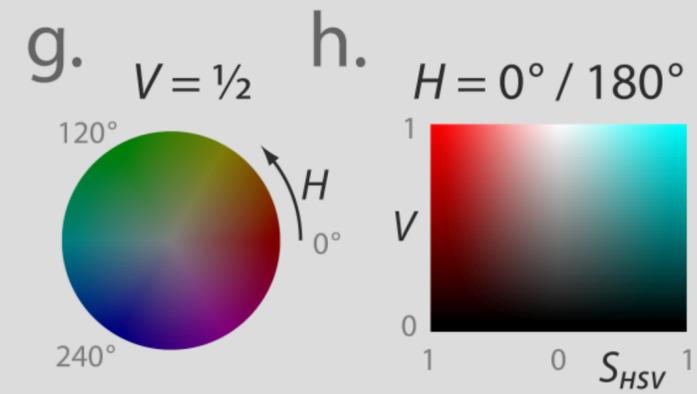
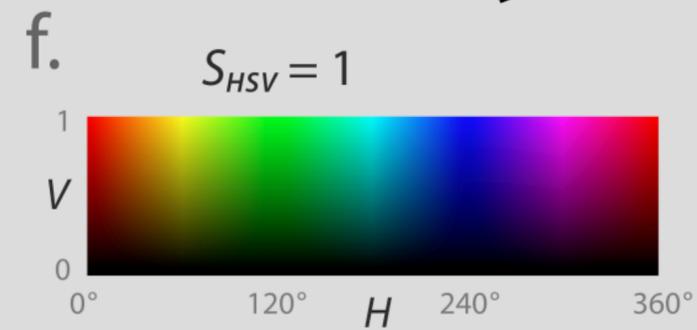
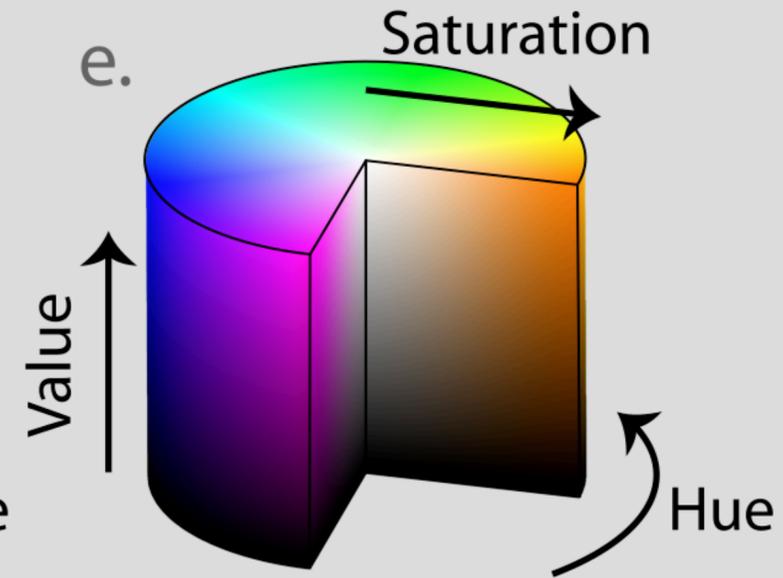


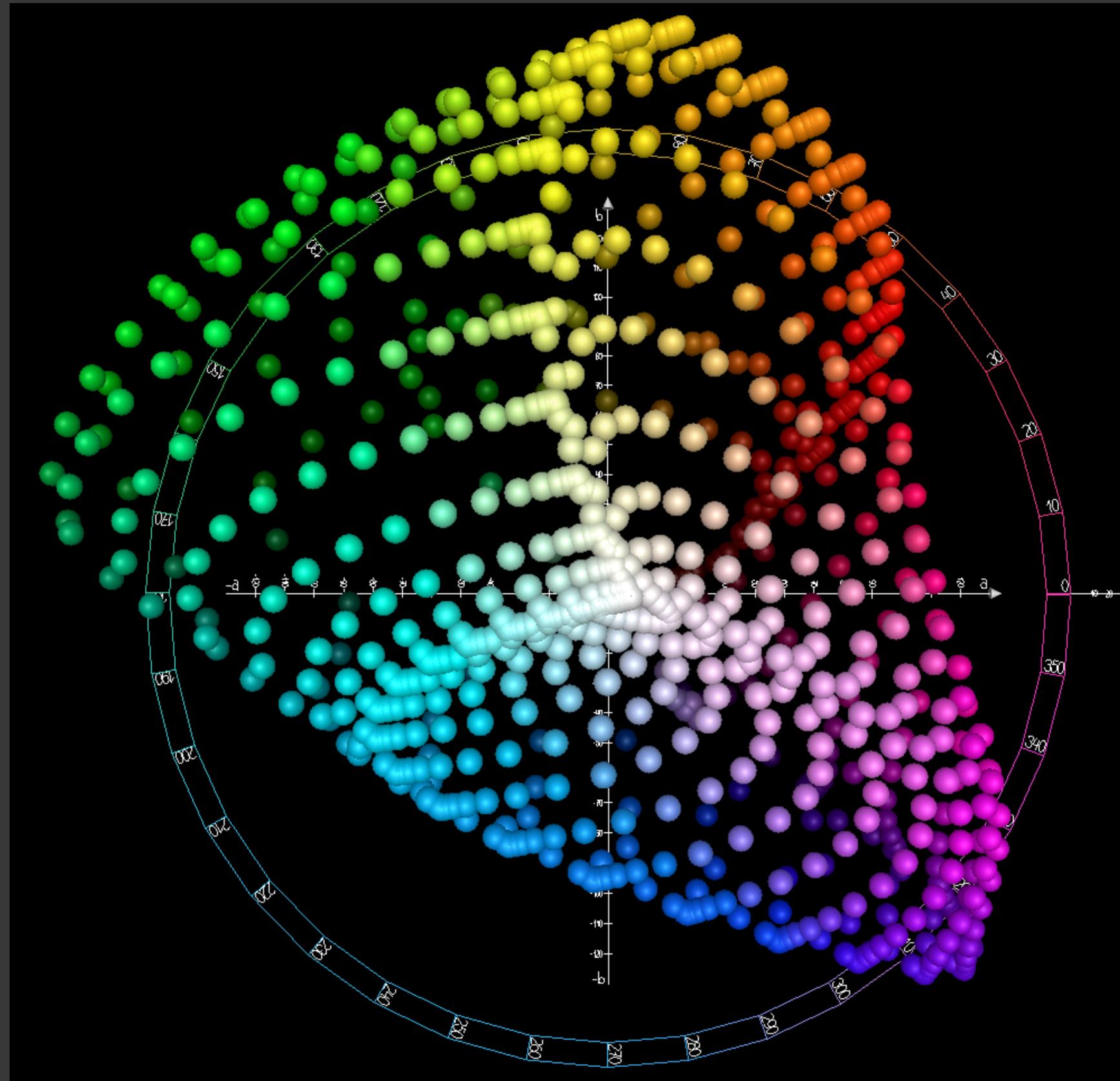
Average Female Height

# HSL

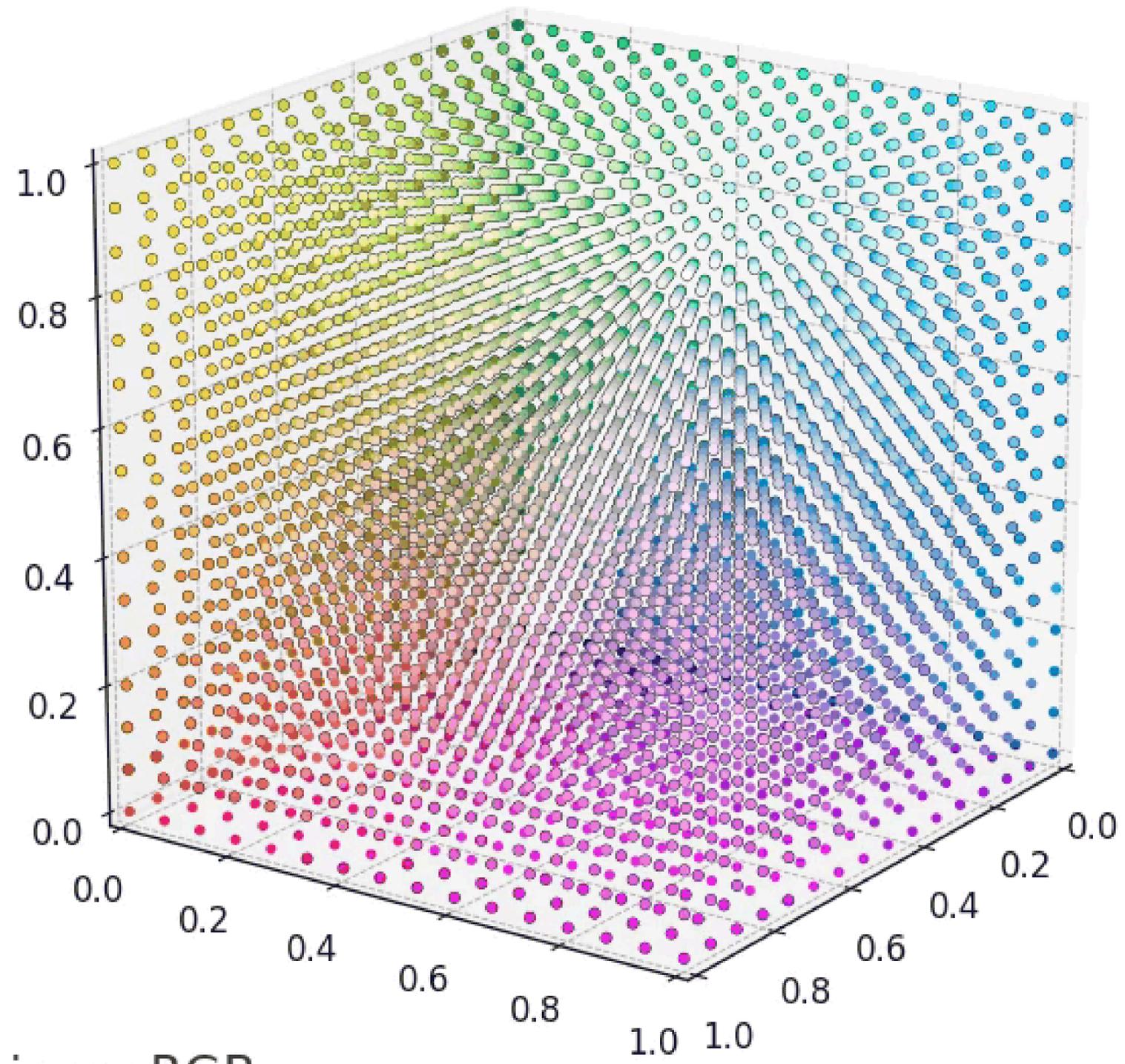


# HSV

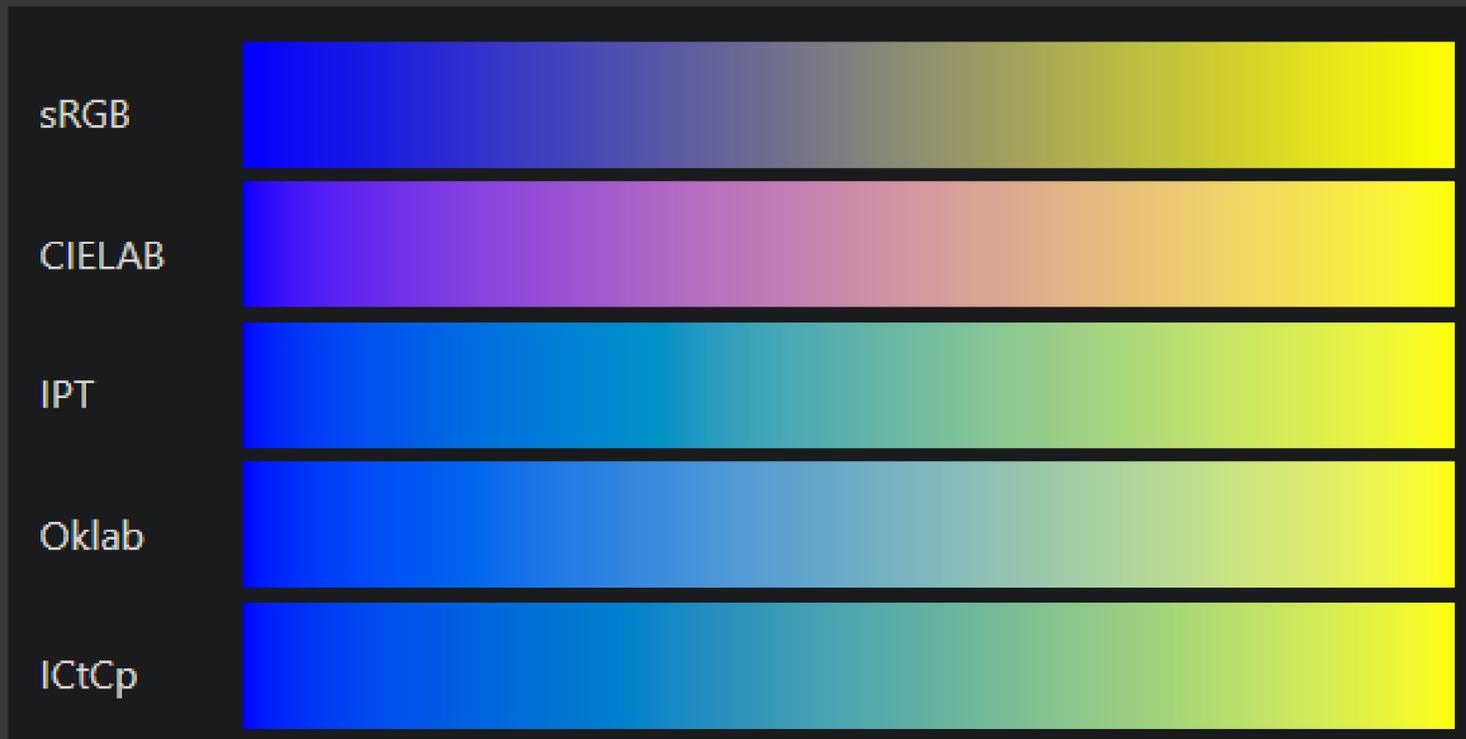




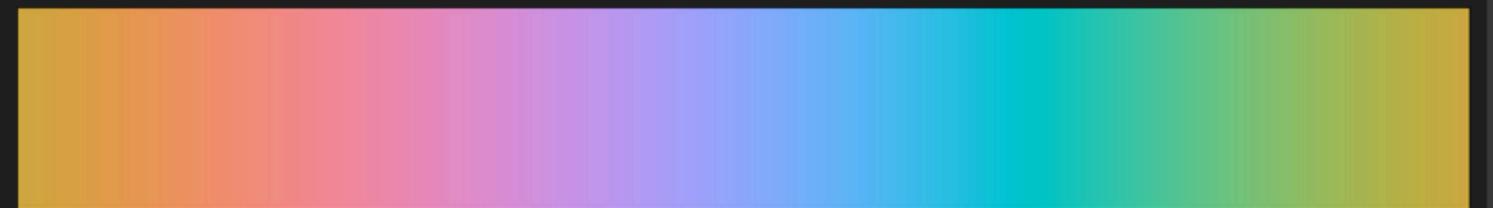
[Wikipedia](#)



Linear RGB



Here's an Oklab color gradient with varying hue and constant lightness and chroma.

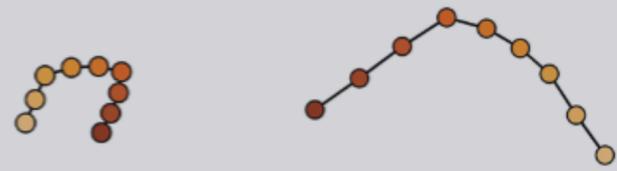


Compare this to a similar plot of a HSV color gradient with varying hue and constant value and saturation (HSV using the sRGB color space).



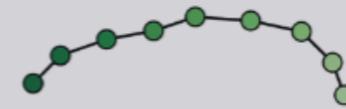
Source: [Björn Ottosson](#),  
[Raph Linus](#)

## Tableau



$a^* + b^*$

L + C



$a^* + b^*$

L + C

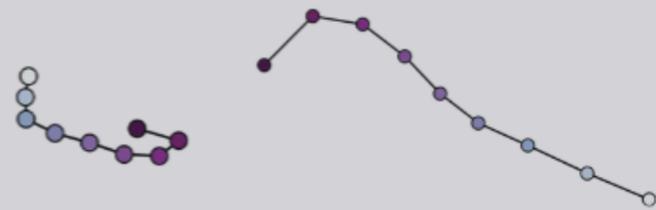


$a^* + b^*$

L + C



## ColorBrewer



$a^* + b^*$

L + C



$a^* + b^*$

L + C

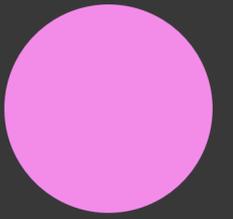


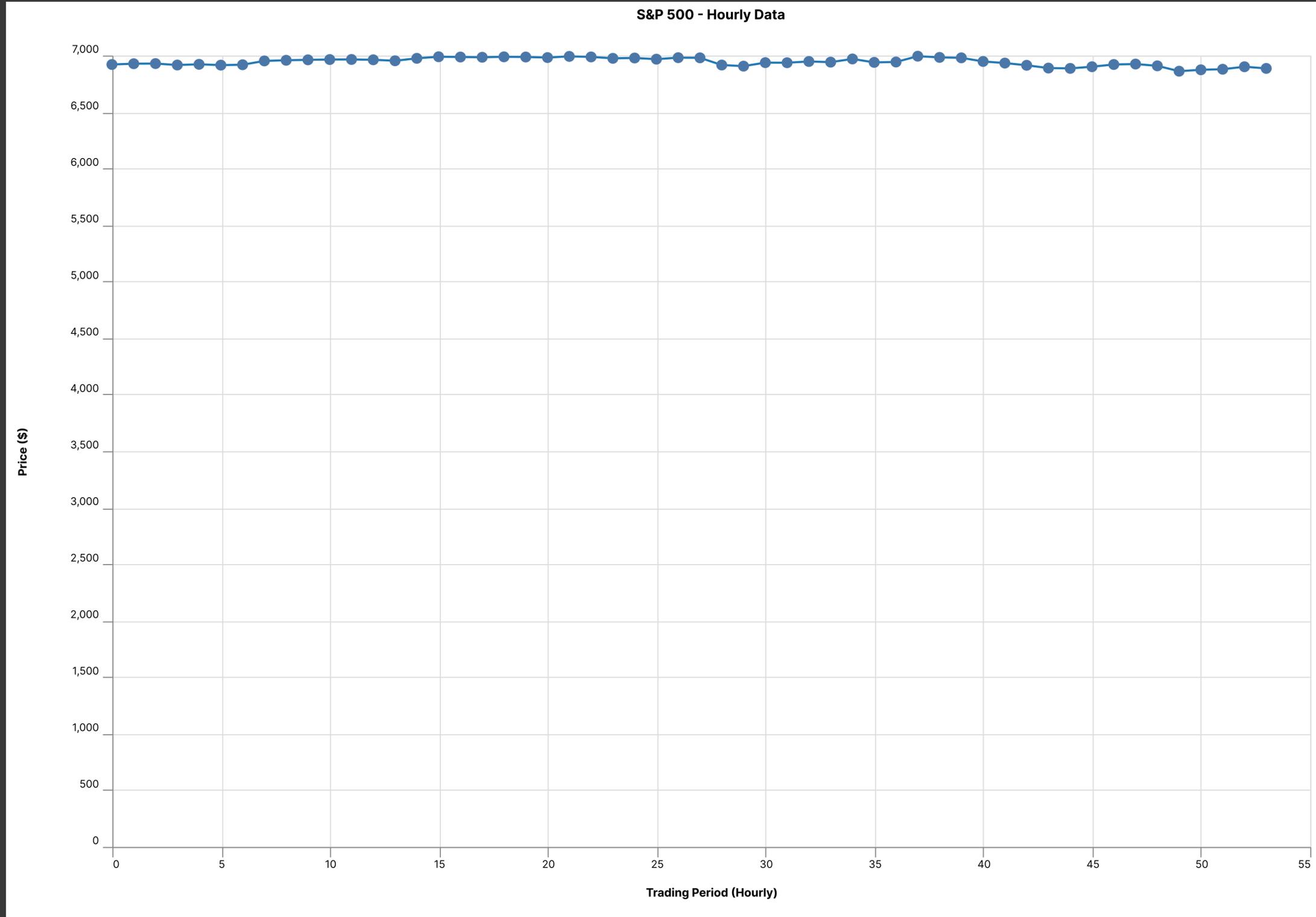
$a^* + b^*$

L + C



# Tasks





S&P 500

S&P 500 - Hourly Data



S&P 500

“Overview first, zoom and filter, then details on demand.”



— Bruce Shneiderman, “The Eyes Have It”

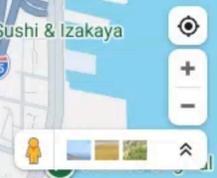
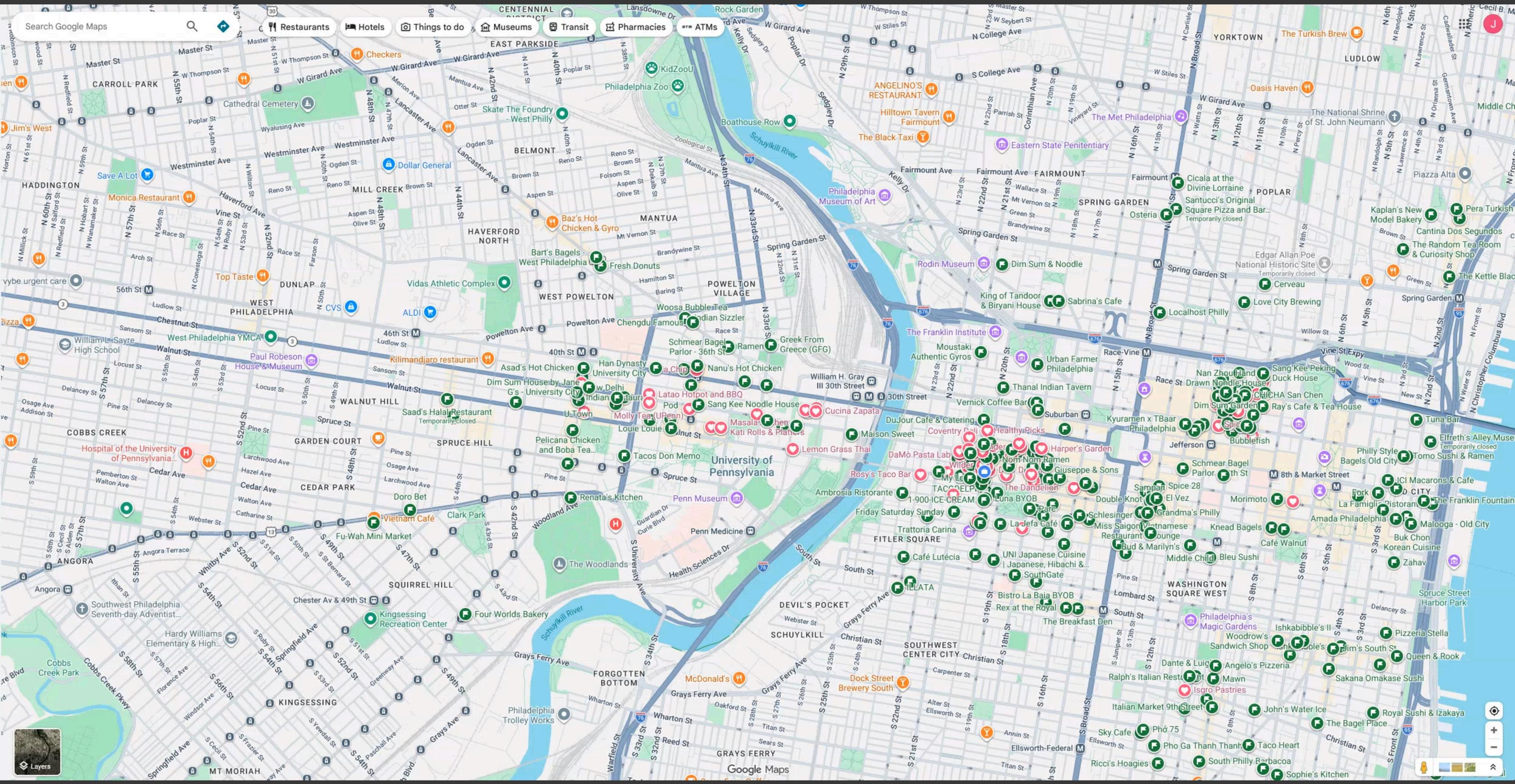
There are many visual design guidelines but the basic principle might be summarized as the Visual Information Seeking Mantra:

Overview first, zoom and filter, then details-on-demand  
Overview first, zoom and filter, then details-on-demand

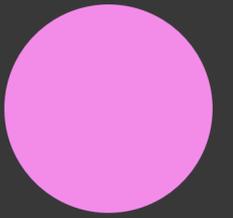
Each line represents one project in which I found myself rediscovering this principle and therefore wrote it down it as a reminder. It proved to be only a starting point in trying to characterize the multiple information-visualization innovations occurring at university, government, and industry research labs.

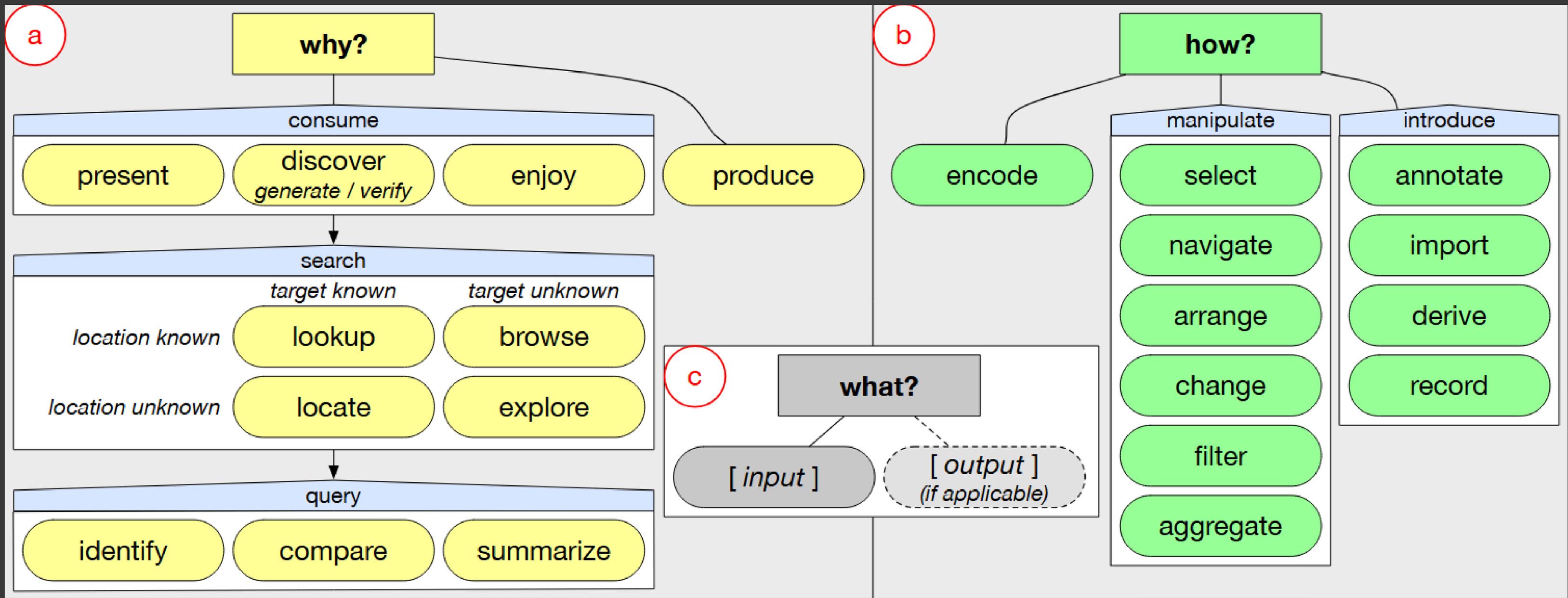
Search Google Maps

- Restaurants
- Hotels
- Things to do
- Museums
- Transit
- Pharmacies
- ATMs

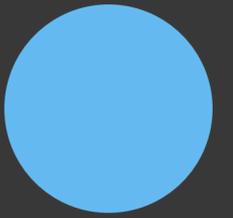


1. Overview
2. Zoom
3. Filter
4. Details on demand
5. Relate
6. History
7. Extract





# Affect & Salience



#ColombiaElige



GUSTAVO  
PETRO



FICO  
GUTIERREZ 19%



LA GRAN  
ENCUESTA

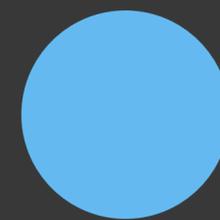
#ColombiaElige

YANHAAS

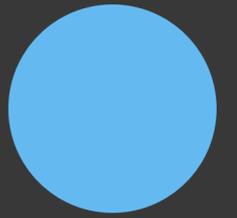


7 05 PM

# A Personal Tale



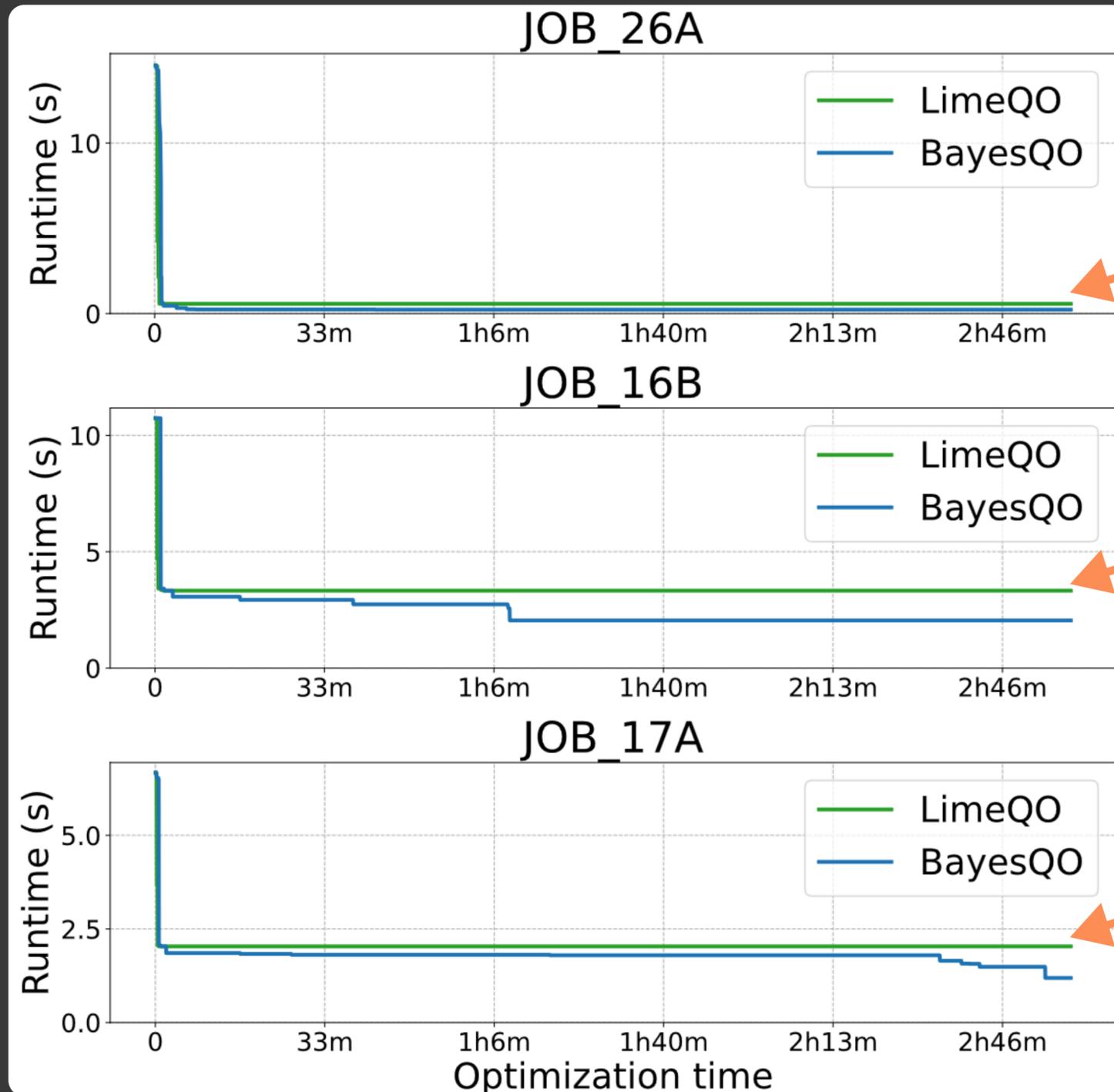
# Visualization is *narrative*



Visualization is a form of storytelling.

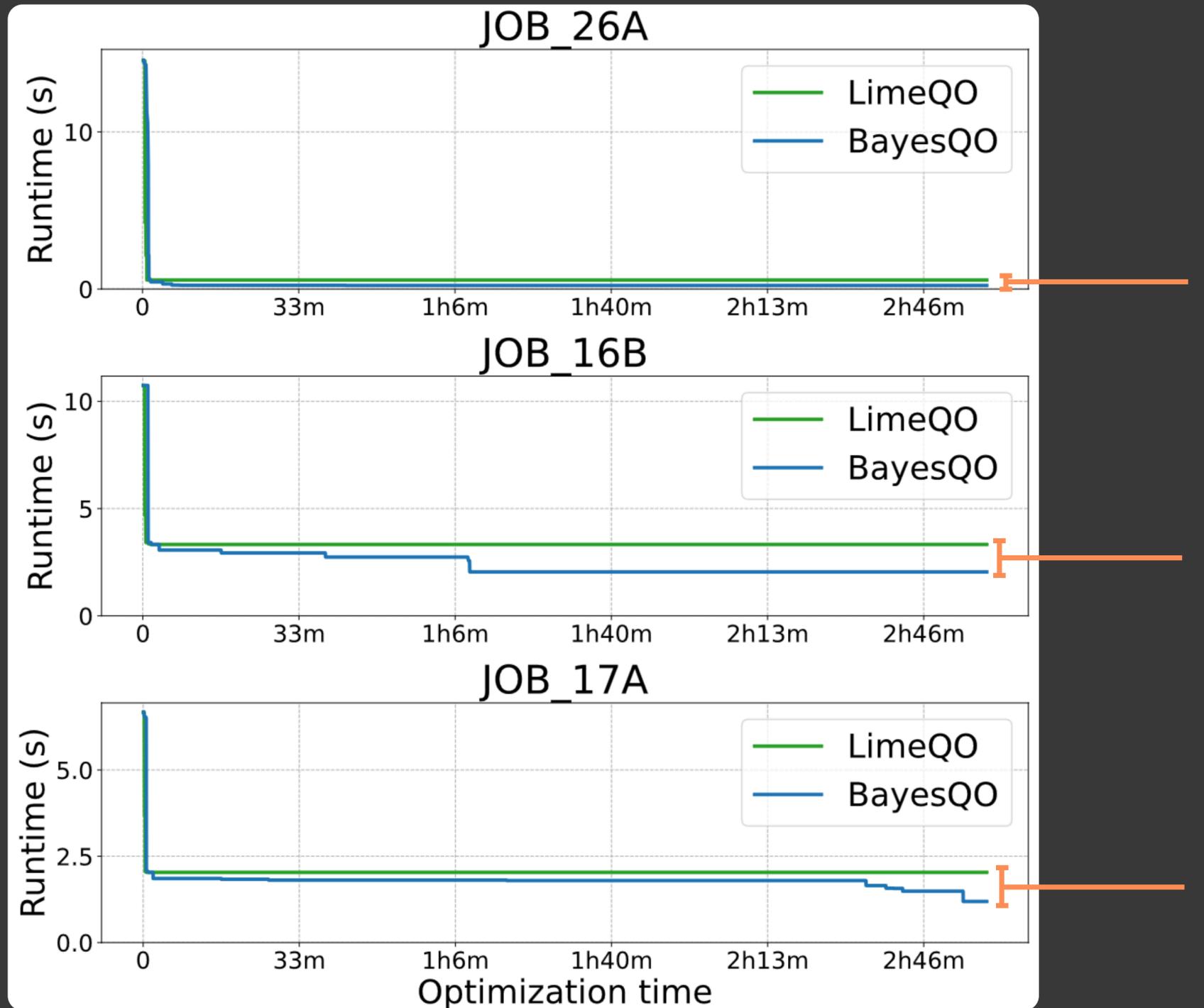
But what you intend and think is salient is not the same as what the viewer will think is salient!

# Case Study: My Own Research Paper



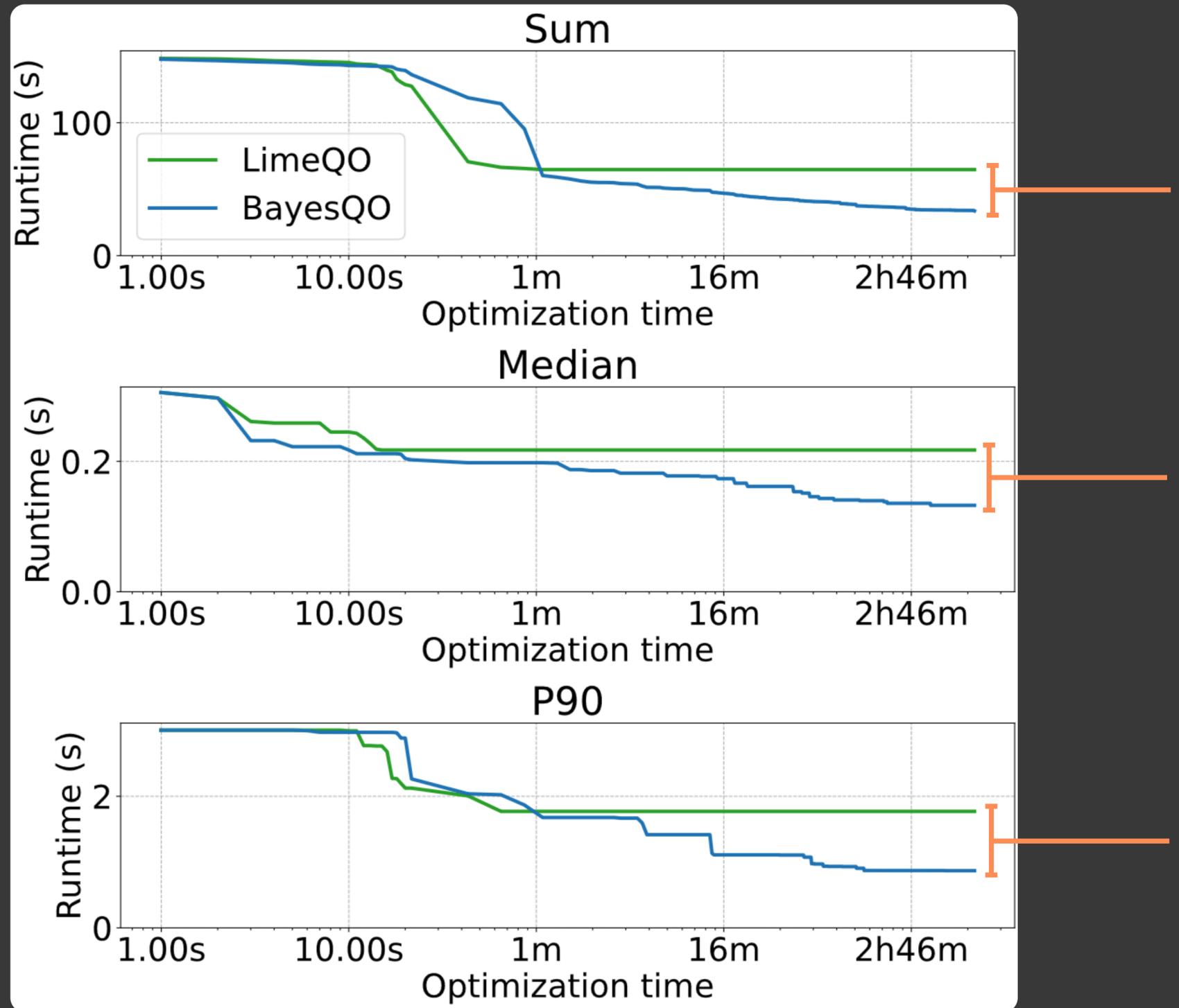
Us: "Look, the green line bottoms out and then doesn't get any better!"

# Case Study: My Own Research Paper



Them: "Wow, your method isn't that much better!"

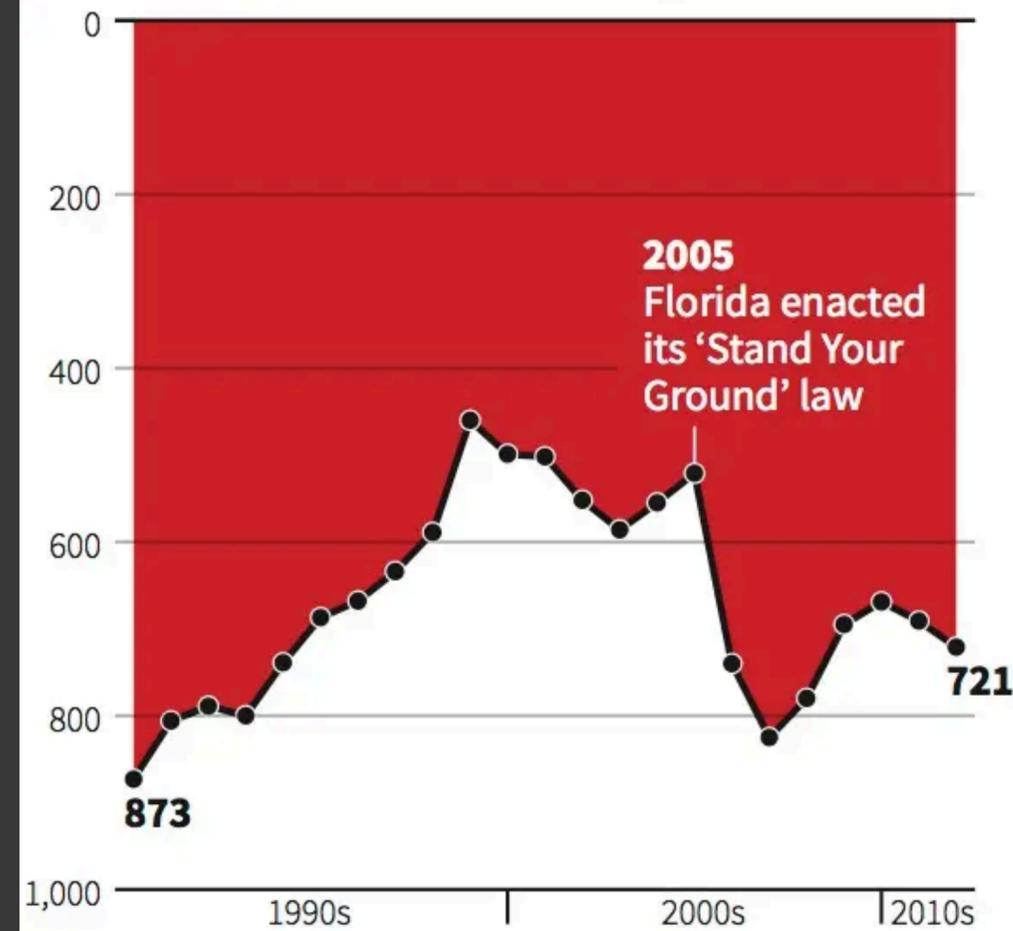
# Case Study: My Own Research Paper



Us: "Look, the gaps are bigger now!"

# Gun deaths in Florida

Number of murders committed using firearms



Source: Florida Department of Law Enforcement

C. Chan 16/02/2014

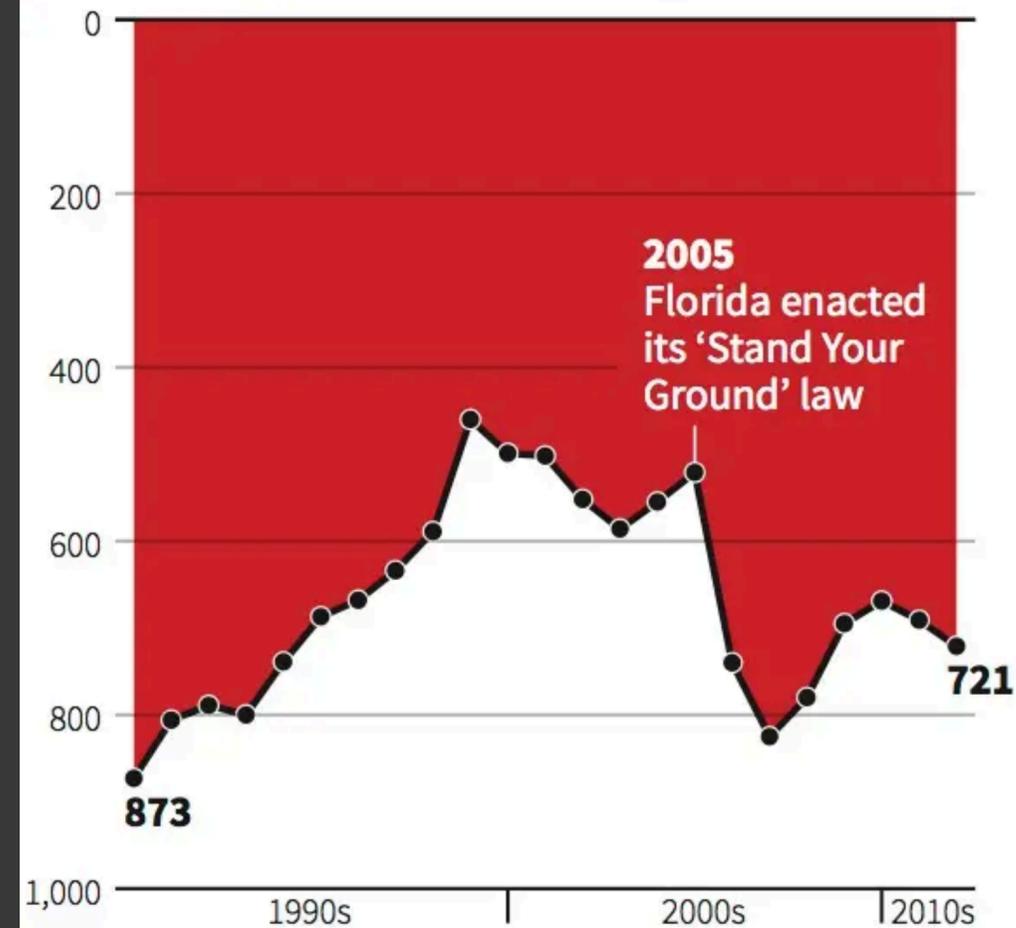
REUTERS

## Conventions? Affect? Art?

Source: Reuters

# Gun deaths in Florida

Number of murders committed using firearms

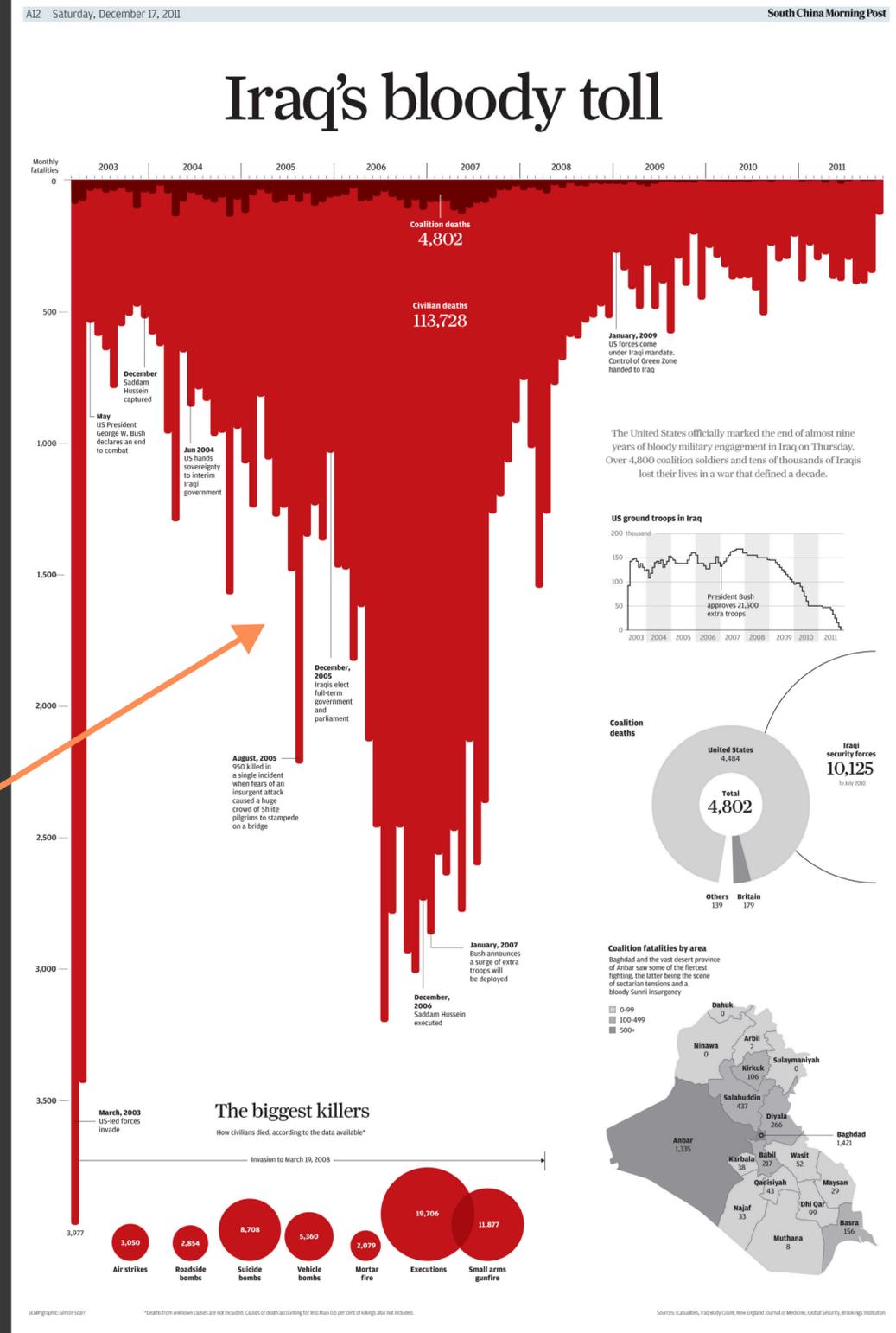


Source: Florida Department of Law Enforcement

C. Chan 16/02/2014



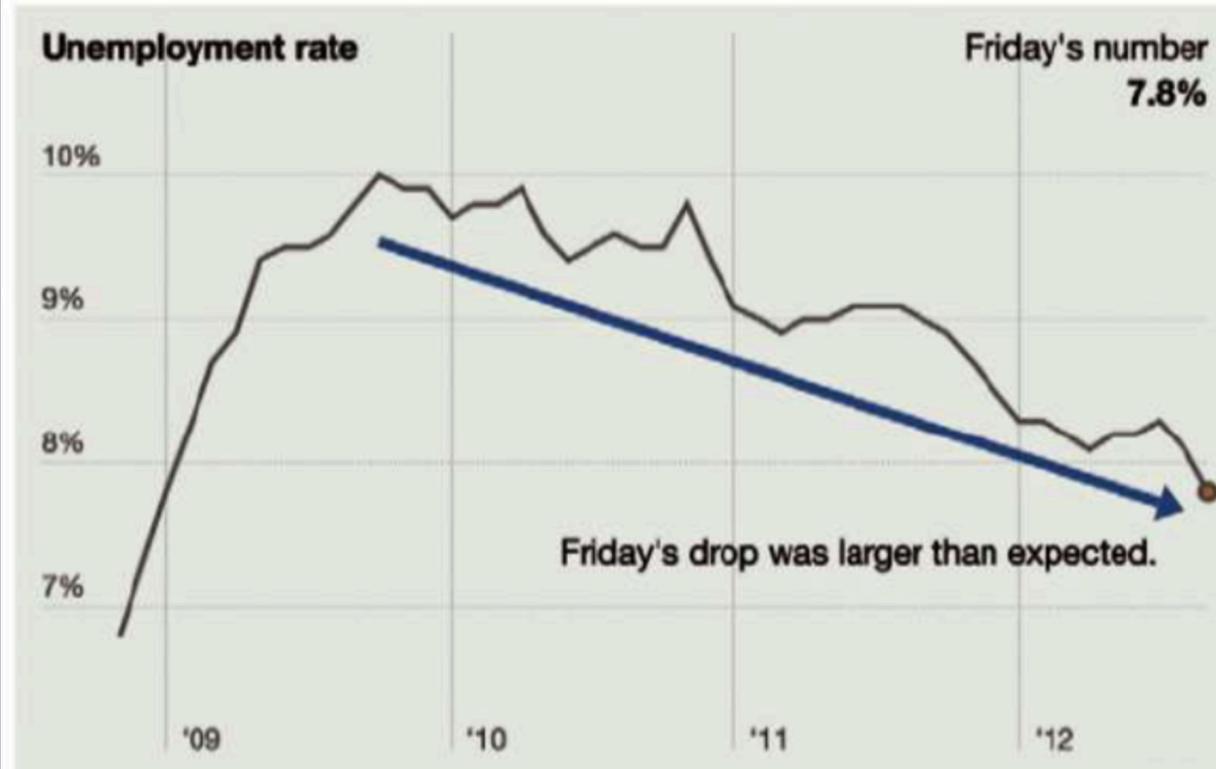
Won multiple awards!



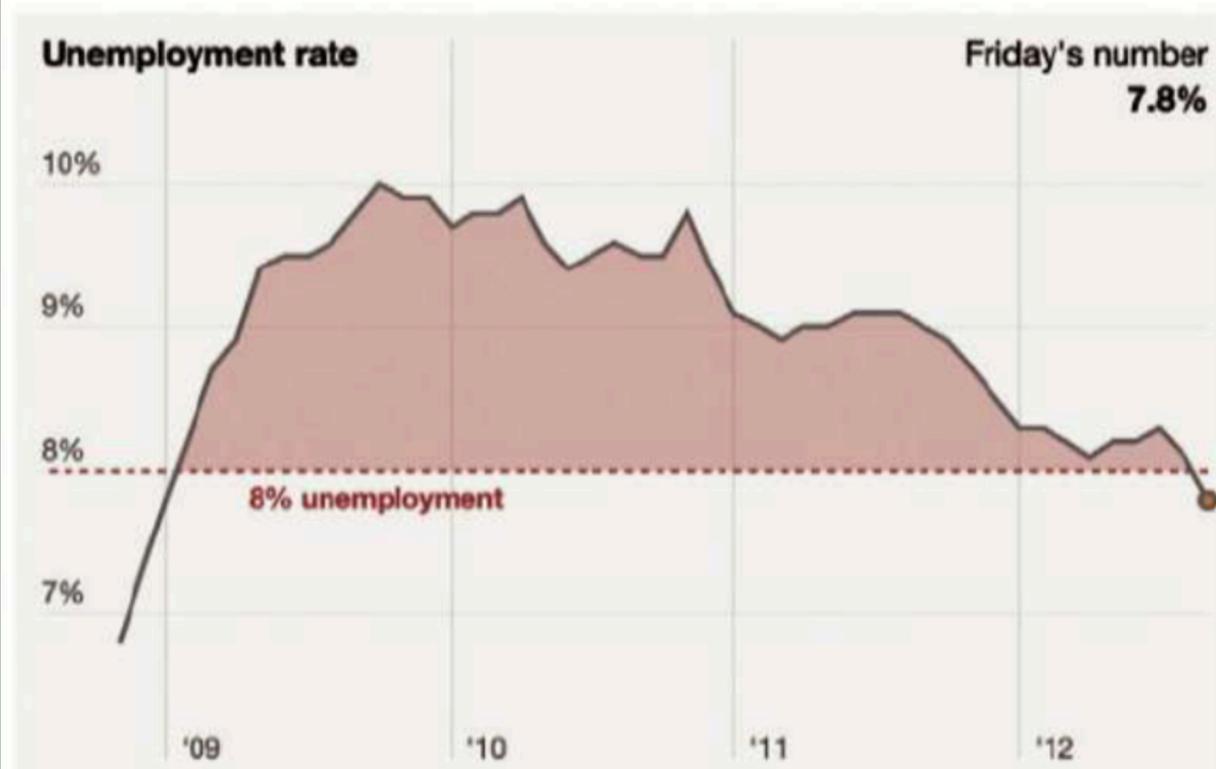
Conventions? Affect? Art?

Source: Reuters, SCMP

*The rate has fallen more than 2 points since its recent peak.*



*The rate was above 8 percent for 43 months.*



Source: Lan et al., VIS 2023

# U.S. GUN KILLINGS IN 2018

Source: Perisopic, 2018

Telling  
Stories Too  
Well





# Pareidolia

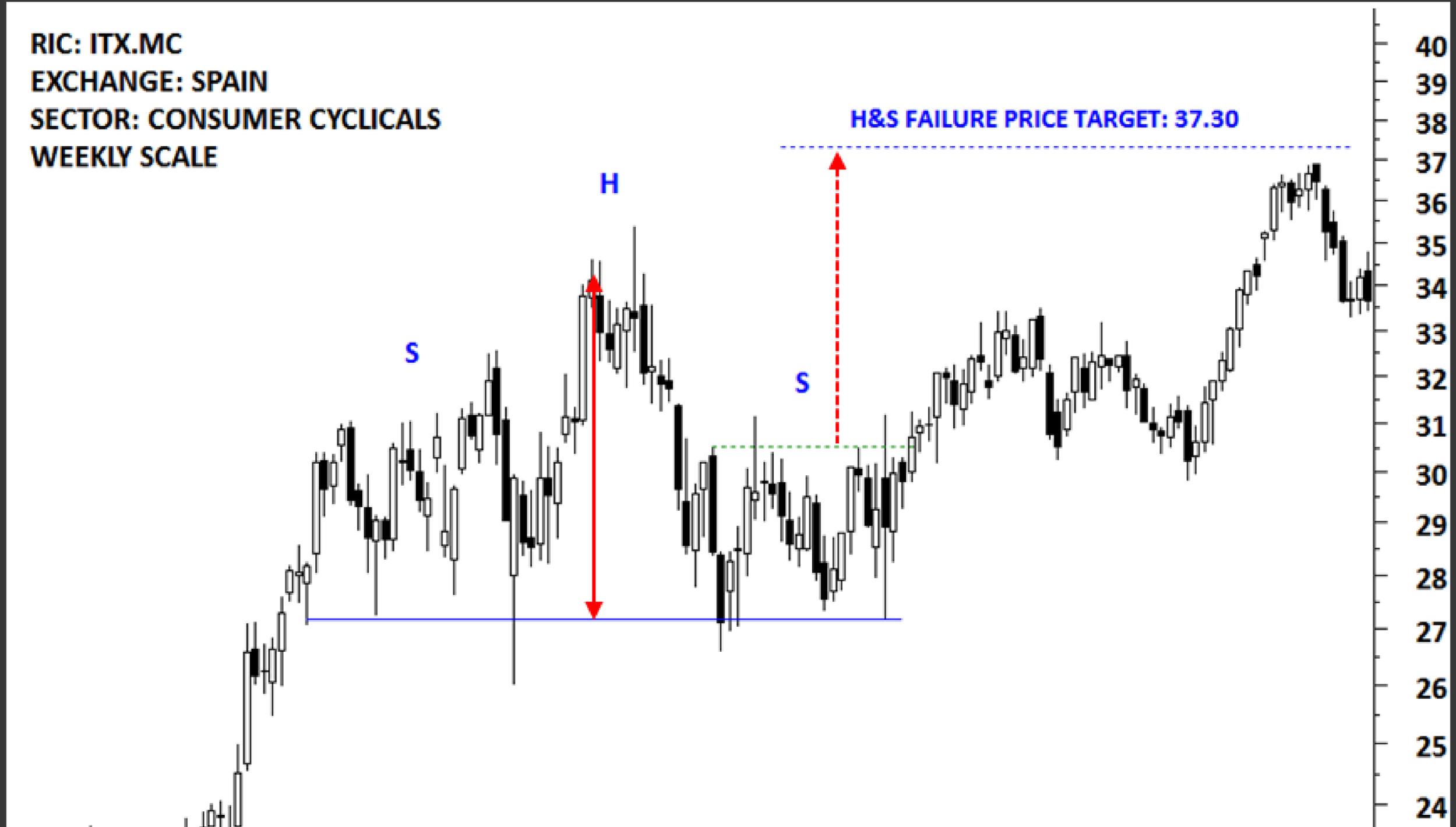
Source



# “Technical Analysis”

Source: [TrendSpider](#)

RIC: ITX.MC  
EXCHANGE: SPAIN  
SECTOR: CONSUMER CYCLICALS  
WEEKLY SCALE



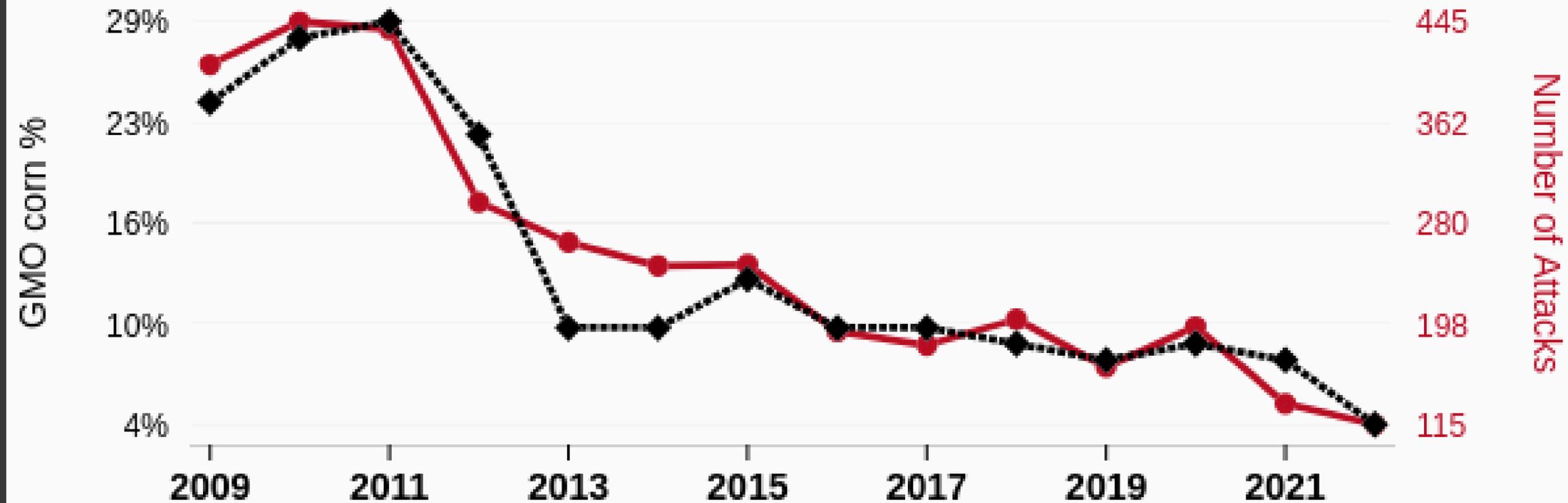
# “Technical Analysis”

Source: [TechCharts](#)

# GMO use in corn grown in Minnesota

correlates with

**Pirate attacks globally**



◆ Percent of all corn planted in Minnesota that is genetically modified to be herbicide-tolerant (HT), but not insect-resistant (Bt) · Source: USDA

● Global Pirate Attack Count · Source: Statista

2009-2022,  $r=0.956$ ,  $r^2=0.915$ ,  $p<0.01$  · [tylervigen.com/spurious/correlation/2052](http://tylervigen.com/spurious/correlation/2052)

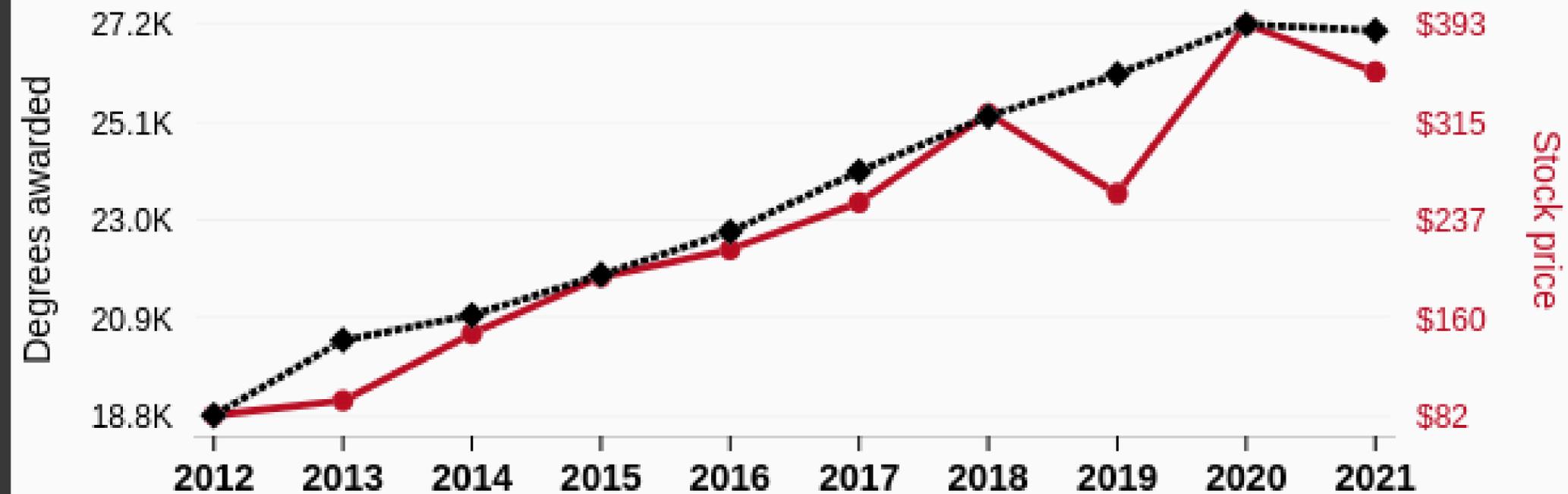
## Spurious Correlations

Source: [Spurious Correlations](http://SpuriousCorrelations.com)

# Bachelor's degrees awarded in Mathematics and statistics

correlates with

## Lockheed Martin's stock price (LMT)



◆ Bachelor's degrees conferred by postsecondary institutions, in field of study: Mathematics and statistics · Source: National Center for Education Statistics

● Opening price of Lockheed Martin (LMT) on the first trading day of the year · Source: LSEG Analytics (Refinitiv)

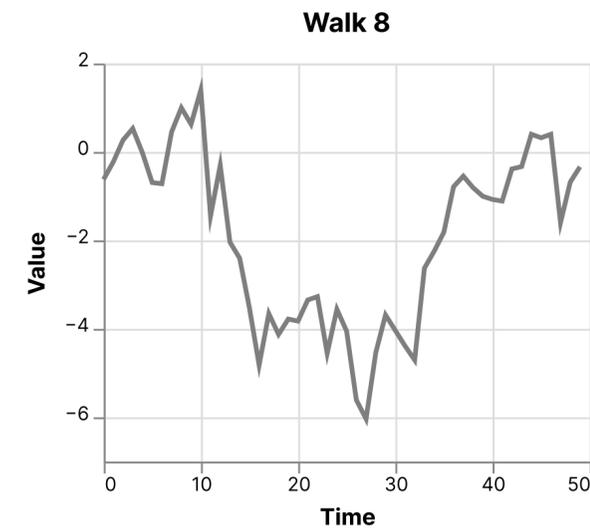
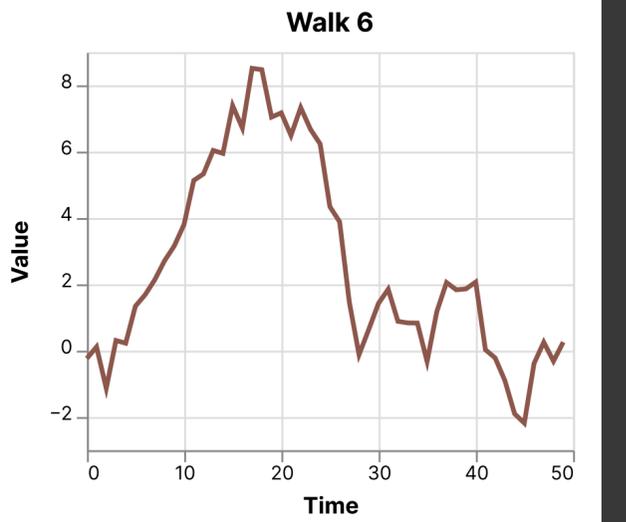
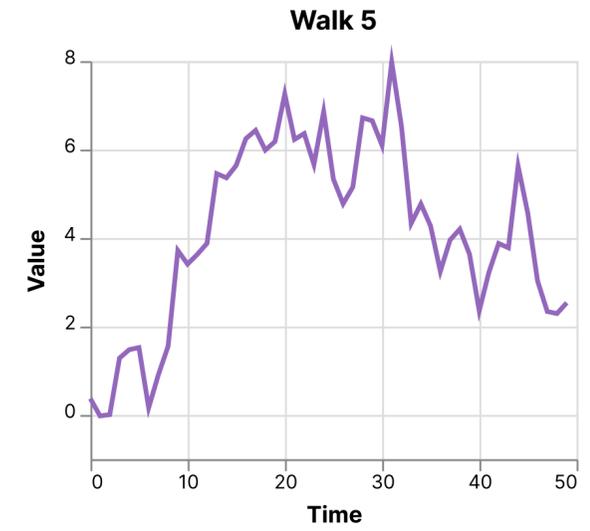
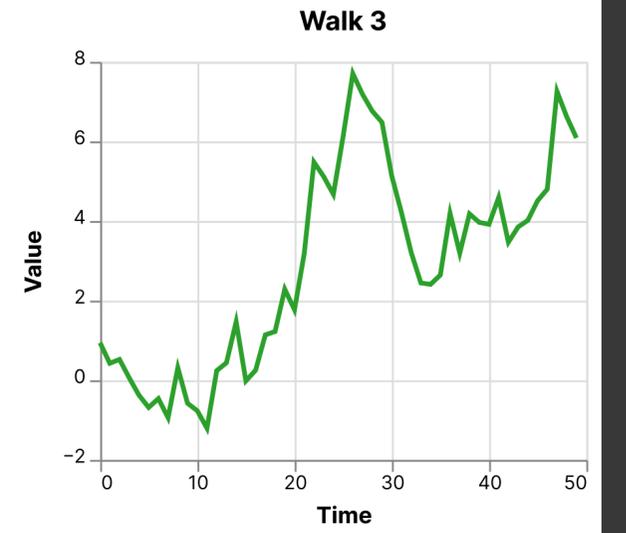
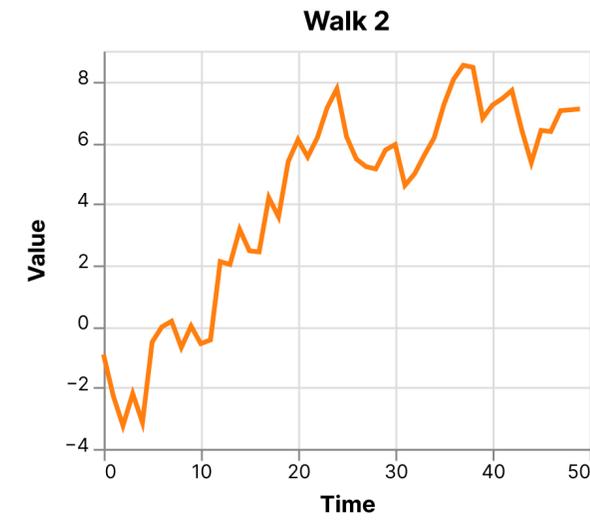
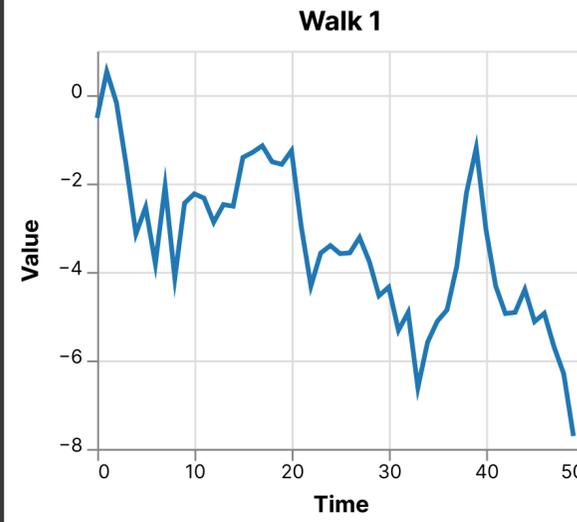
2012-2021,  $r=0.961$ ,  $r^2=0.924$ ,  $p<0.01$  · [tylervigen.com/spurious/correlation/1954](http://tylervigen.com/spurious/correlation/1954)

## Spurious Correlations

Source: [Spurious Correlations](http://SpuriousCorrelations.com)

# Multiple Comparisons

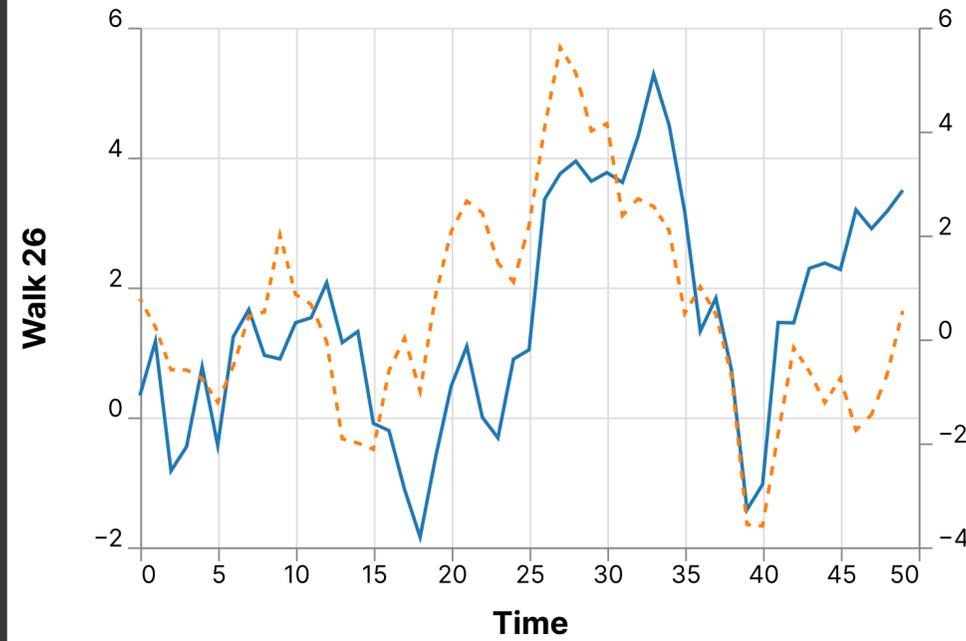
## Random Trends



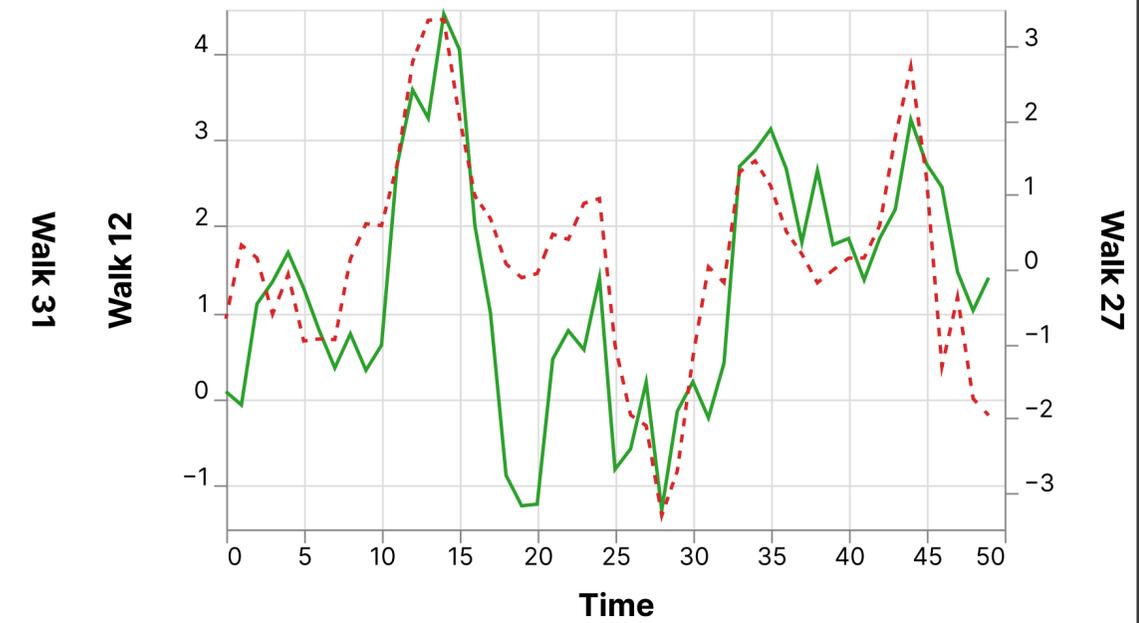
# Multiple Comparisons

## Most Correlated Pairs (positive correlations, based on de-trended data)

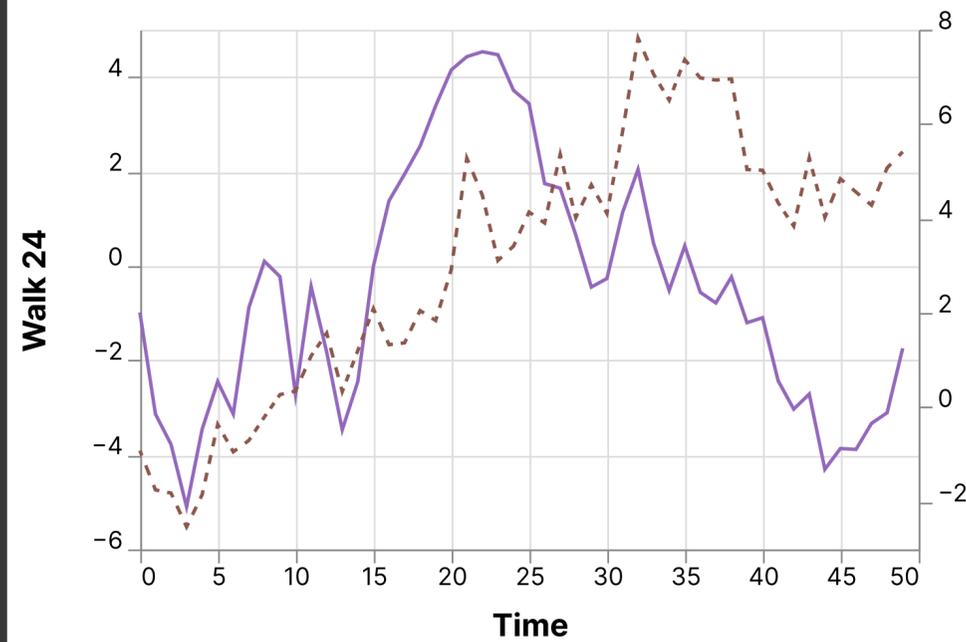
Most Correlated #1 ( $r=0.499$ ,  $p=0.0003$ )



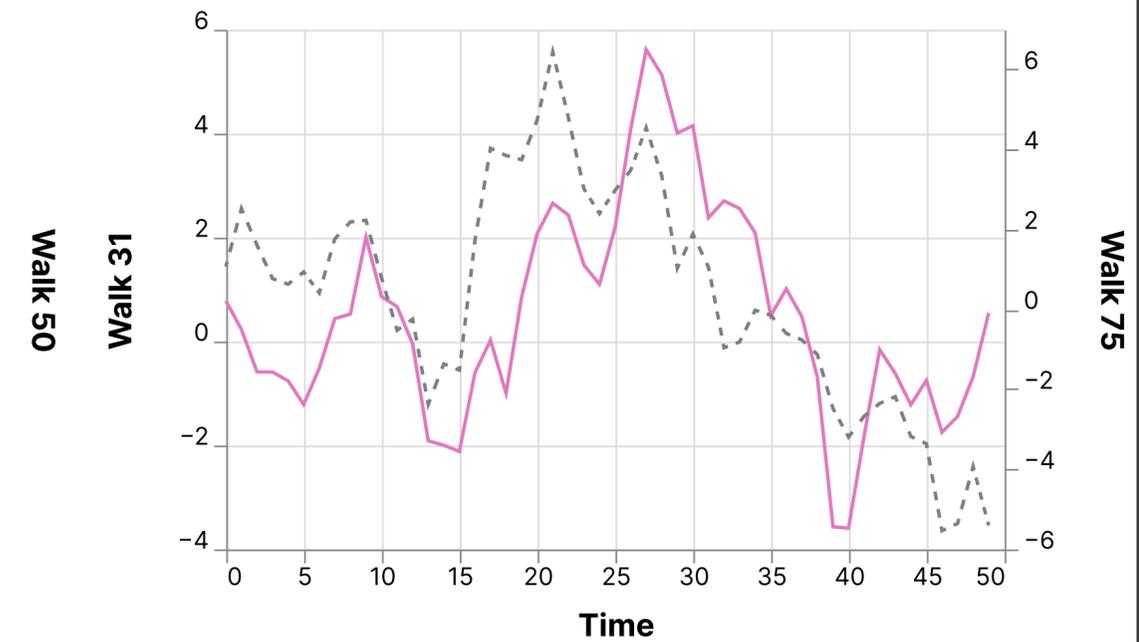
Most Correlated #2 ( $r=0.507$ ,  $p=0.0002$ )



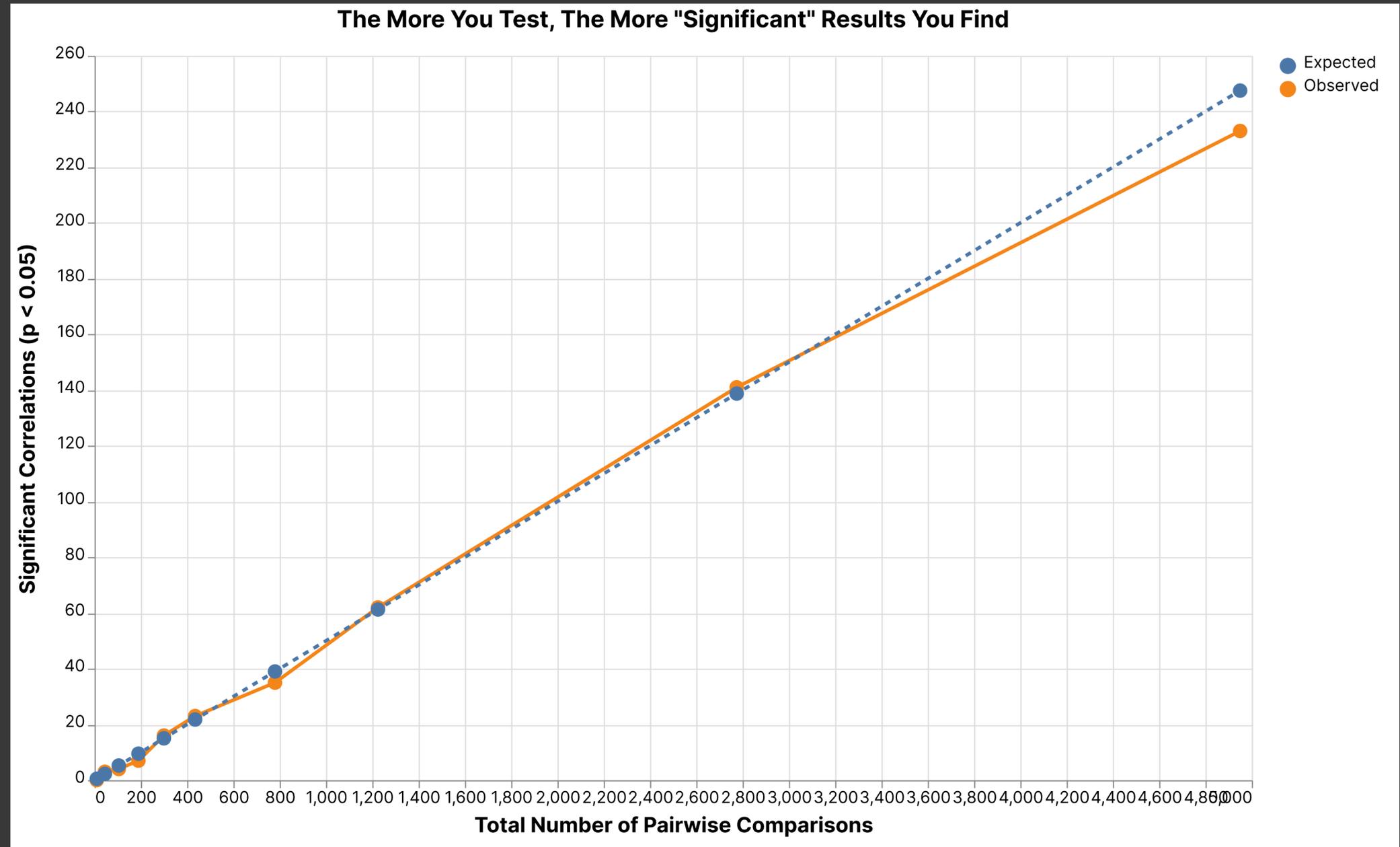
Most Correlated #3 ( $r=0.515$ ,  $p=0.0002$ )



Most Correlated #4 ( $r=0.522$ ,  $p=0.0001$ )

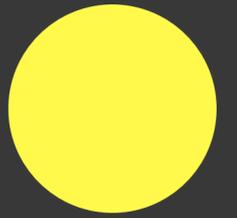


# Multiple Comparisons



If  $p = 0.05$ , then 5% of all comparisons I do will be significant, whether or not they make sense!

# Summary



- The basics: Data Types, Marks, Encodings
- We visualize data to take advantage of our *perception* and to make *cognition* easier
- Choosing the right encodings can be tricky and depends on *task*, context, and even the shape of the data itself
- Vis can be *affective*/emotional, and that doesn't make it fake
- But vis is so convincing that you can make yourself believe things that aren't true!