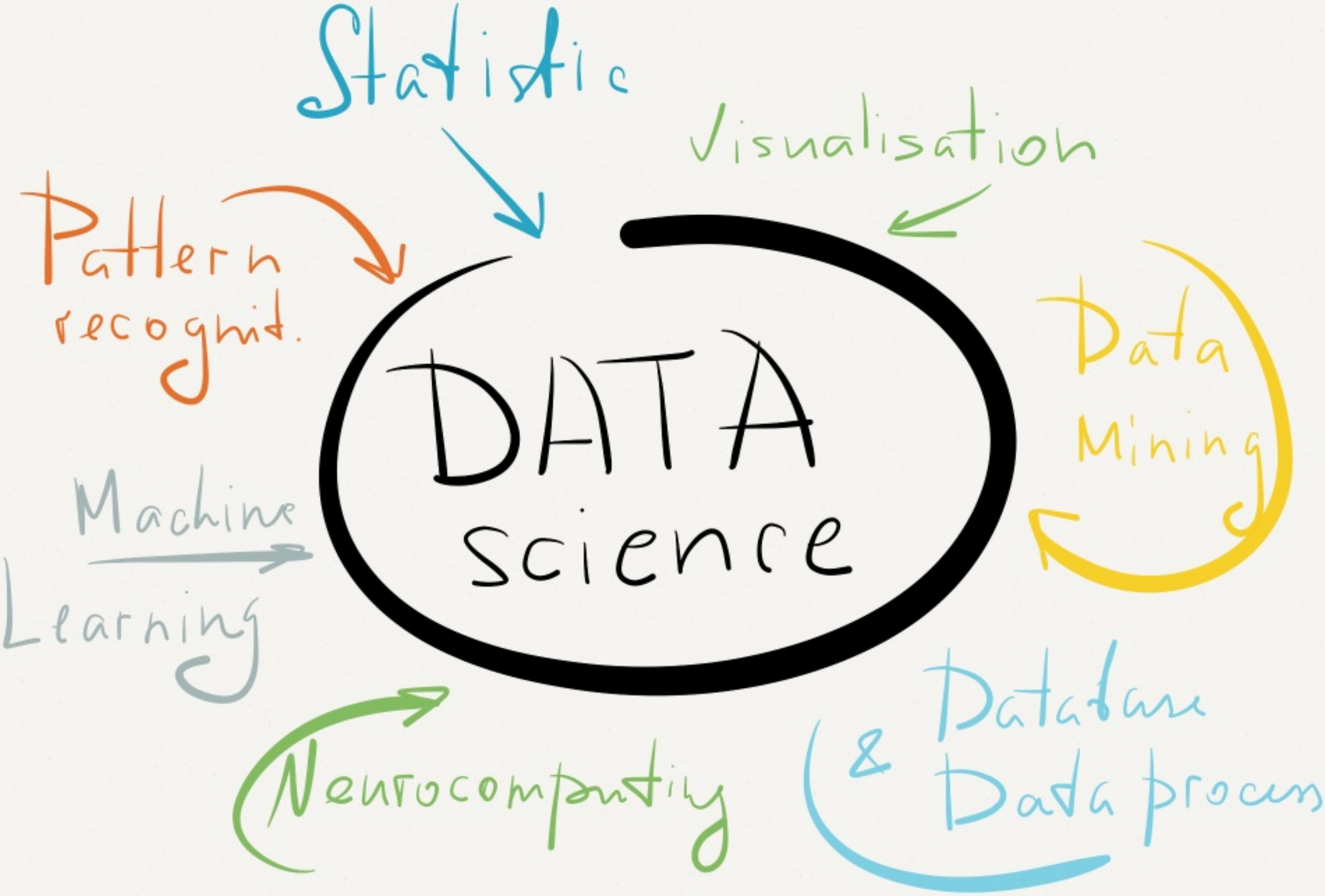
1

MOTIVAÇÃO E APRESENTAÇÃO DA DISCIPLINA

Profa. Raquel C. de Melo Minardi



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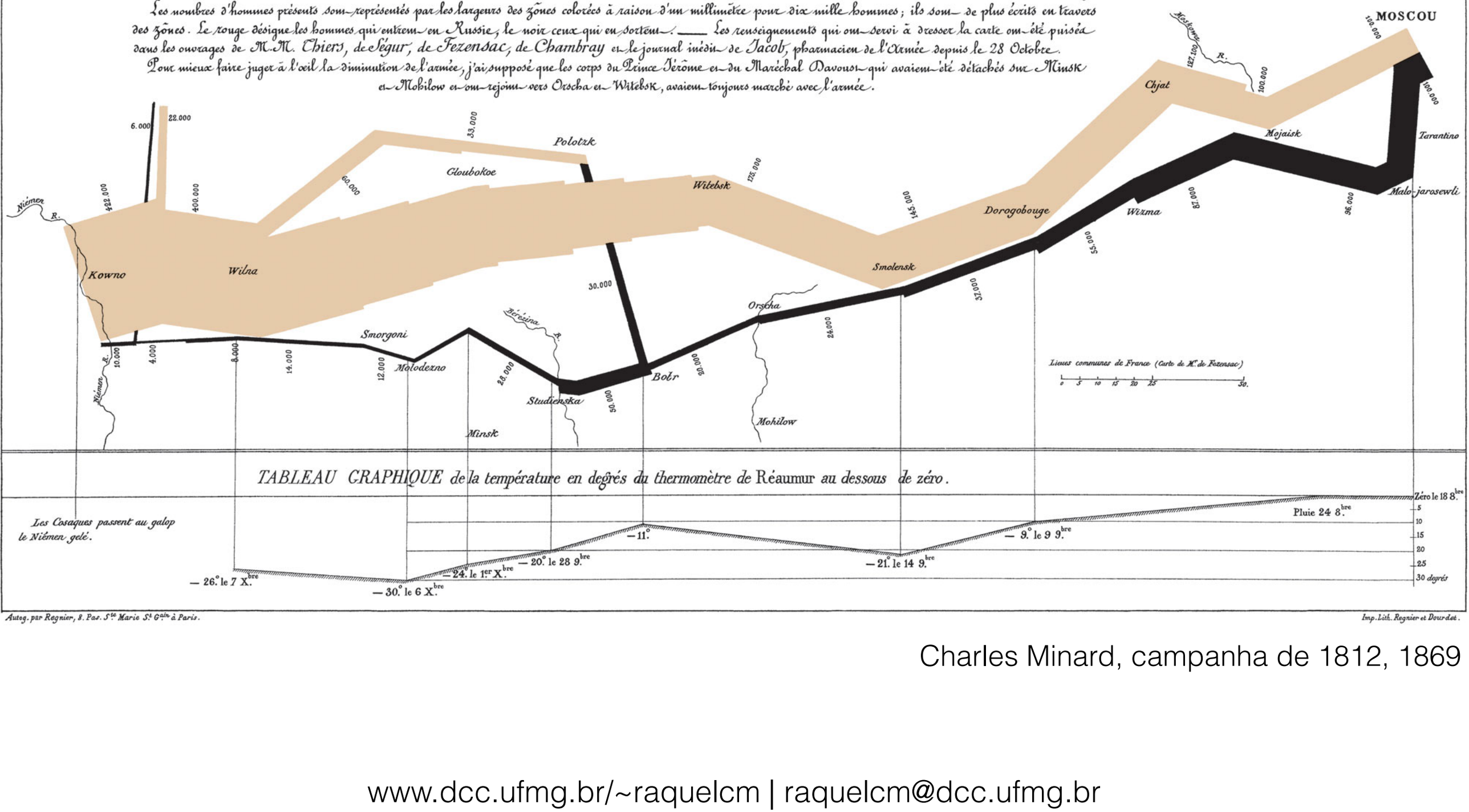
Carte Figurative des pertes successives en hommes de l'Armée Française dans la campagne de Russie 1812-1813.

Dressée par M. Minard, Inspecteur Général des Ponts et Chaussées en retraite.

Paris, le 20 Novembre 1869.

Les nombres d'hommes présents sont représentés par les largeurs des zônes colorées à raison d'un millimètre pour dix mille hommes ; ils sont de plus écrits en travers des zônes. Le rouge désigne les hommes qui entrent en Russie, le noir ceux qui en sortent. — Les renseignements qui ont servi à dresser la carte ont été puisés dans les ouvrages de M.M. Thiers, de Ségur, de Fezensac, de Chambray et le journal inédit de Jacob, pharmacien de l'Armée depuis le 28 Octobre.

Pour mieux faire juger à l'œil la diminution de l'armée, j'ai supposé que les corps du Prince Jérôme et du Maréchal Davoust qui avaient été détachés sur Minsk et Mobilow en ont rejoint vers Orscha et Witebsk, avaient toujours marché avec l'armée.



Autog. par Regnier, 8. Pas. Ste Marie St Gain à Paris.

Imp. Lith. Regnier et Dourdet.

Charles Minard, campanha de 1812, 1869

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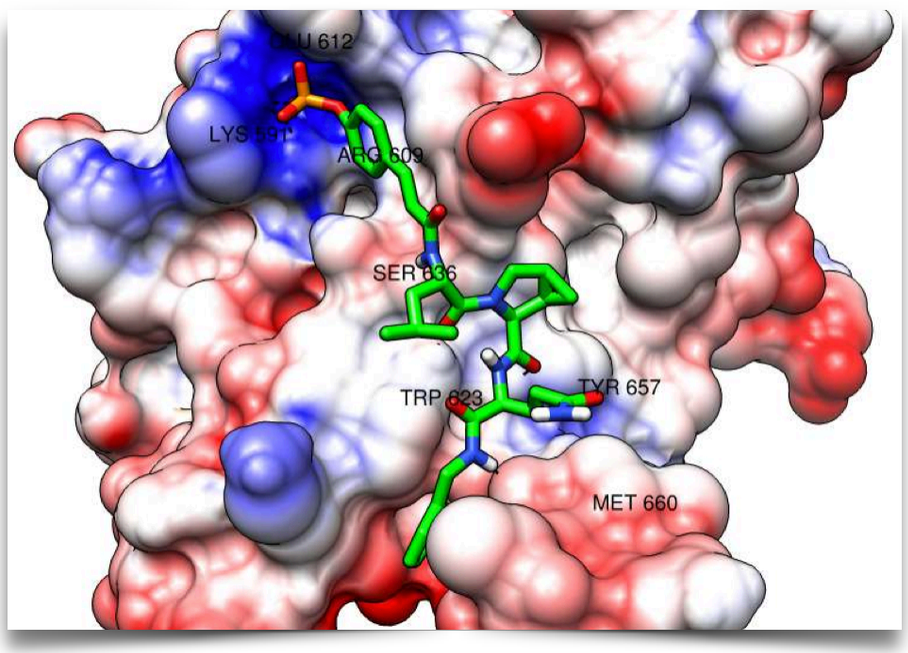
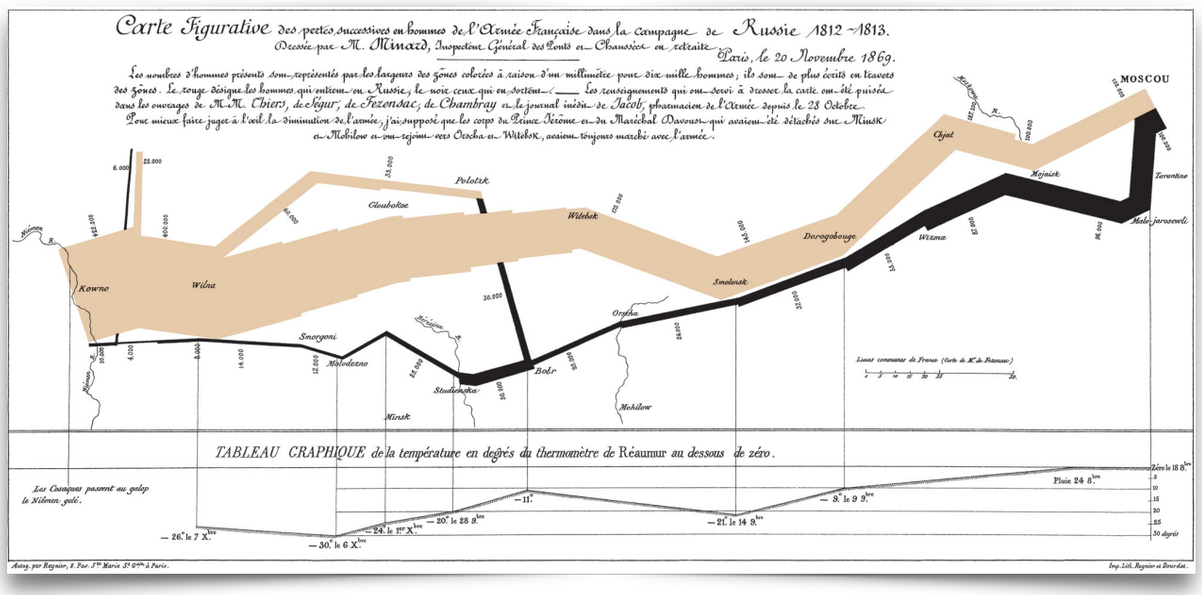
O que é **visualização de dados**?

É um “termo guarda-chuva” que envolve a **visualização de informação** e a **visualização científica**

A **visualização científica** ilustra objetos que tem um correspondente físico



A **visualização de informação** (ou de dados) representa objetos mais abstratos



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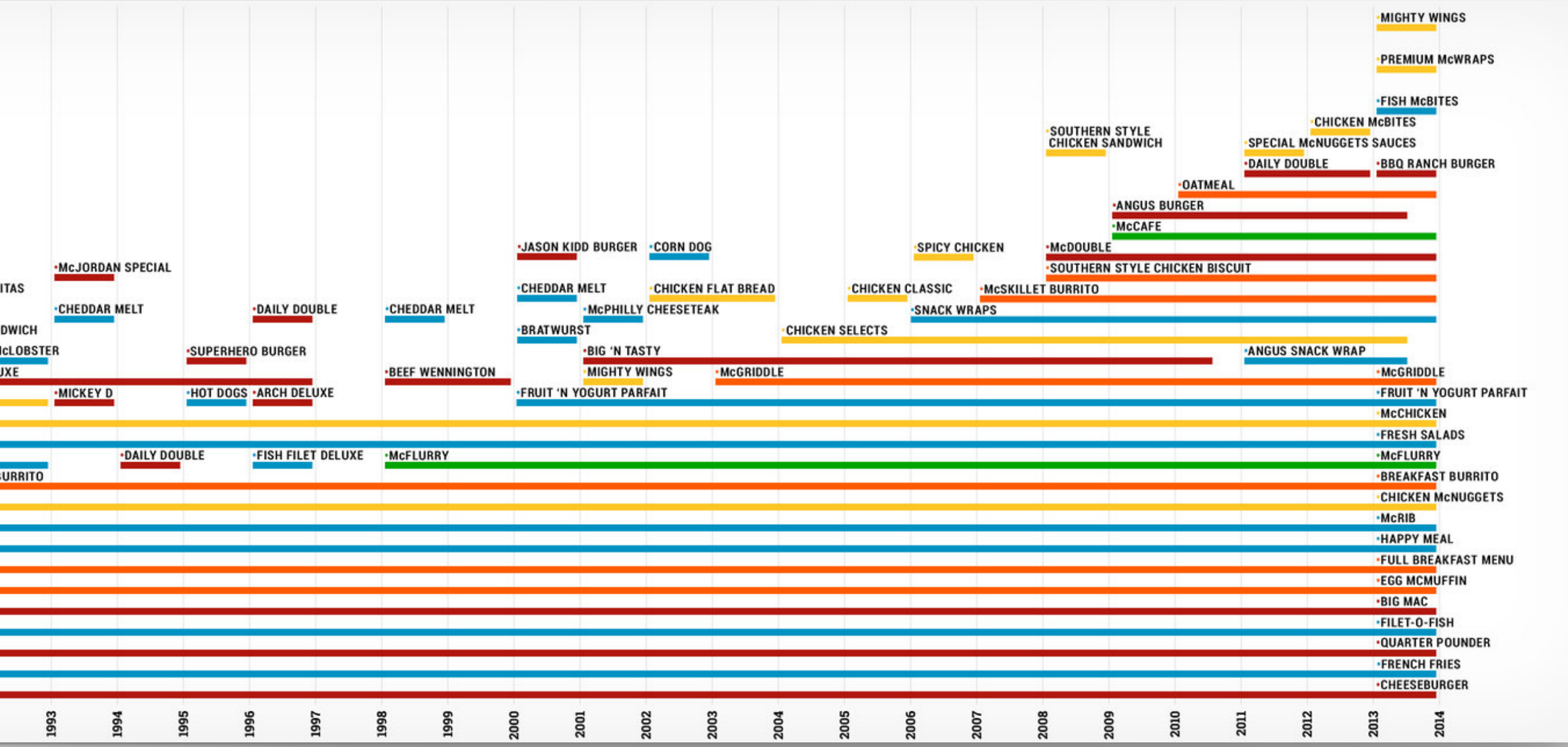
McCafé
blended
Real Fruit Smoothies 210-350 Cal. 0.00 0.00 0.00
mango pineapple | strawberry banana | wild berry
Frappé 450-680 Cal. 0.00 0.00 0.00
mocha | caramel
espresso & chocolate with whole or nonfat milk
Mocha 240-400 Cal. 0.00 0.00 0.00
Caramel Mocha 200-360 Cal. 0.00 0.00 0.00
Iced Mocha 230-390 Cal. 0.00 0.00 0.00
Iced Caramel Mocha 200-380 Cal. 0.00 0.00 0.00
Latte 80-330 Cal. 0.00 0.00 0.00
Iced Latte 40-230 Cal. 0.00 0.00 0.00
Hot Chocolate 250-460 Cal. 0.00 0.00 0.00
brewed
Premium Roast Coffee 0 Cal. 0.00 0.00 0.00
Iced Coffee 90-280 Cal. 0.00 0.00
made with cream
choose a flavor
caramel | hazelnut | vanilla | sugar-free vanilla
a la carte only
LIMITED TIME
new FRAPPÉ CHOCOLATE CHIP
0.00 sm. 0.00 med.
150 Cal. 210 Cal. 310 Cal. Soft Drink 0.00 0.00 0.00
160 Cal. 240 Cal. 350 Cal. Iced Tea 0 Cal. 0.00 0.00 0.00
000 Cal. 000 Cal. 000 Cal. Orange Juice 150 | 190 | 280 Cal. 0.00 0.00 0.00
000 Cal. 000 Cal. 000 Cal. Milk low-fat white 100 Cal. | fat free chocolate 130 Cal. 0.00
000 Cal. 000 Cal. 000 Cal. Dasani Bottled Water 0 Cal. 0.00
0 Cal. 0 Cal. 0 Cal.
Chocolate Shake 710 Cal. 0.00
Oreo McFlurry 340 Cal. 0.00
Hot Fudge Sundae 330 Cal. 0.00
Chocolate Chip Cookies 160 Cal. ea. 0.00 0.00
sweet treats
McCafé Shakes
chocolate | vanilla | strawberry
530-570 Cal. 0.00
670-710 Cal. 0.00
820-870 Cal. 0.00
McFlurry
340-430 Cal. 0.00
510-650 Cal. 0.00
Sundae 280-340 Cal. 0.00
hot fudge
Soft Baked Cookies 0.00
chocolate chip 150-160 Cal. ea. 0.00
Pies 250 Cal. ea. 0.00
apple 0.00
Cone vanilla 170 Cal. 0.00


extra value menu
20 PC. CHICKEN McNUGGETS
0.00
extra value menu
new DAILY DOUBLE
0.00 med. meal
0.00 sandwich
extra value menu
Daily Double 440 Cal. 0.00
20 Pc. Chicken McNuggets serves 2 470 Cal. ea. 0.00
Angus Snack Wrap 390-430 Cal. 0.00
deluxe | bacon & cheese | mushroom & swiss
Chicken Snack Wrap 230-350 Cal. 0.00
grilled or crispy | chipotle bbq | honey mustard | ranch
Double Cheeseburger 440 Cal. 0.00
Iced Coffee med. 90-200 Cal. 0.00
McFlurry snack size 340-430 Cal. 0.00
Local Option
Local Option
fries
230 Cal. 380 Cal. 500 Cal.
0.00 0.00 0.00
dollar menu $1
each a la carte only
lunch & dinner
McDouble 390 Cal.
Parfait made with low-fat yogurt 150 Cal.
Sweet Tea lg. 280 Cal.
Cookies 150-160 Cal. ea.
Side Salad 20 Cal.
Cone 170 Cal.
Local Option
Local Option
breakfast available during breakfast hours only
Sausage Burrito 300 Cal.
Sausage McMuffin 370 Cal.
Sausage Biscuit 430 Cal.
Hash Browns 150 Cal. ea.
Coffee sm. 0 Cal.
Local Option


LIMITED TIME
new SPICY CHICKEN McBITES
POP'EM WHILE THEY'RE HOT!
0.00 regular size meal
Choose your FAVORITES UNDER 400 CALORIES
400 calories or under each
390 McDouble
380 Medium Fries
380 Chicken Sandwich Ranch BLT (grilled)
380 Filet-O-Fish
350 Crispy Chicken Ranch Snack Wrap
340 OREO McFlurry (snack size)
300 calories or under each
300 Egg McMuffin
290 Southwest Salad (grilled chicken, excludes dressing)
290 Fruit & Maple Oatmeal
280 6 pc. McNuggets
260 Strawberry Banana Real Fruit Smoothie (med.)
240 Caramel Mocha (med.) nonfat milk
230 Small Fries
200 calories or under each
200 Iced Coffee (med.)
170 Vanilla Cone
150 Parfait
150 Hash Browns
130 Chocolate Milk Fat Free
100 calories or under each
100 Milk 1% Low-Fat
90 Latte (sm.) nonfat milk
20 Side Salad (excludes dressing)
fruit & oatmeal
Fruit & Maple Oatmeal 290 Cal. 0.00
Fruit & Walnuts 210 Cal. 0.00
happy meal
includes apple slices & kids fries
4 Pc. Chicken McNuggets 305 Cal. 0.00
Hamburger 365 Cal. 0.00
Cheeseburger 415 Cal. 0.00
mighty kids meal includes apple slices & small fries
6 Pc. Chicken McNuggets 525 Cal. 0.00
McDouble 635 Cal. 0.00
add McNuggets Sauces 30-110 Cal. ea.
choose a drink for your meal additional charges may apply
1% Low-Fat White Milk +100 Cal. Kids Soft Drink +0-120 Cal.
Fat Free Chocolate Milk +130 Cal. Small Soft Drink +0-160 Cal.
100% Apple Juice +100 Cal. Mighty Kids Meal only
Julius by paul frank.


pairfection!
extra value meals include medium fries and soft drink large fries and soft drink +, add 120-230 Cal.
1 Big Mac 0.00 0.00 meal 550 Cal. 930-1170 Cal.
2 Quarter Pounder with cheese 0.00 0.00 meal 520 Cal. 900-1140 Cal.
3 Double Quarter Pounder with cheese 0.00 0.00 meal 750 Cal. 1130-1370 Cal.
4 2 Cheeseburgers 0.00 0.00 meal 600 Cal. 980-1220 Cal.
5 Ranch BLT grilled | crispy 0.00 0.00 meal 380 | 540 Cal. 760-1000 | 920-1160 Cal.
6 Club grilled | crispy 0.00 0.00 meal 460 | 620 Cal. 840-1080 | 1000-1240 Cal.
7 Classic grilled | crispy 0.00 0.00 meal 350 | 510 Cal. 730-970 | 890-1130 Cal.
8 Southern Style Chicken 0.00 0.00 meal 420 Cal. 800-1040 Cal.
9 Chicken Selects sauces 30-110 Cal. 0.00 3 pc. 0.00 3 pc. meal 380 Cal. 760-1000 Cal.
10 10 Pc. Chicken McNuggets sauces 30-110 Cal. 0.00 0.00 meal 470 Cal. 850-1090 Cal.
11 Filet-O-Fish 0.00 0.00 meal 380 Cal. 760-1000 Cal.
12 Angus Deluxe 0.00 0.00 meal 750 Cal. 1130-1370 Cal.
13 Angus Bacon & Cheese 0.00 0.00 meal 790 Cal. 1170-1410 Cal.
14 Angus Mushroom & Swiss 0.00 0.00 meal 770 Cal. 1150-1390 Cal.
salads
grilled | crispy chicken
Southwest 0.00 290 | 450 Cal.
Bacon Ranch 0.00 230 | 390 Cal.
Caesar 0.00 190 | 350 Cal.
salad dressings 35-190 Cal.
*calorie counts do not include dressing



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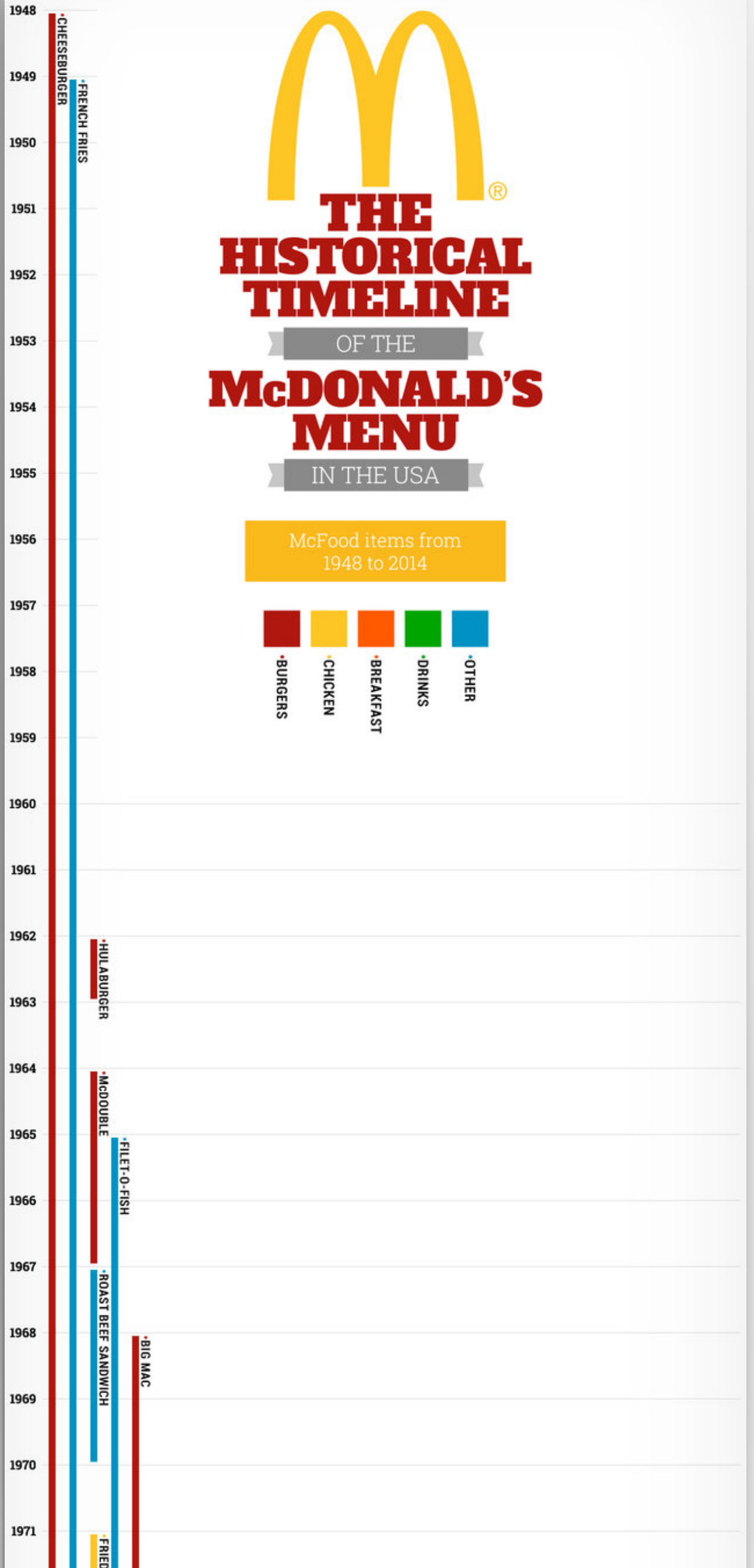

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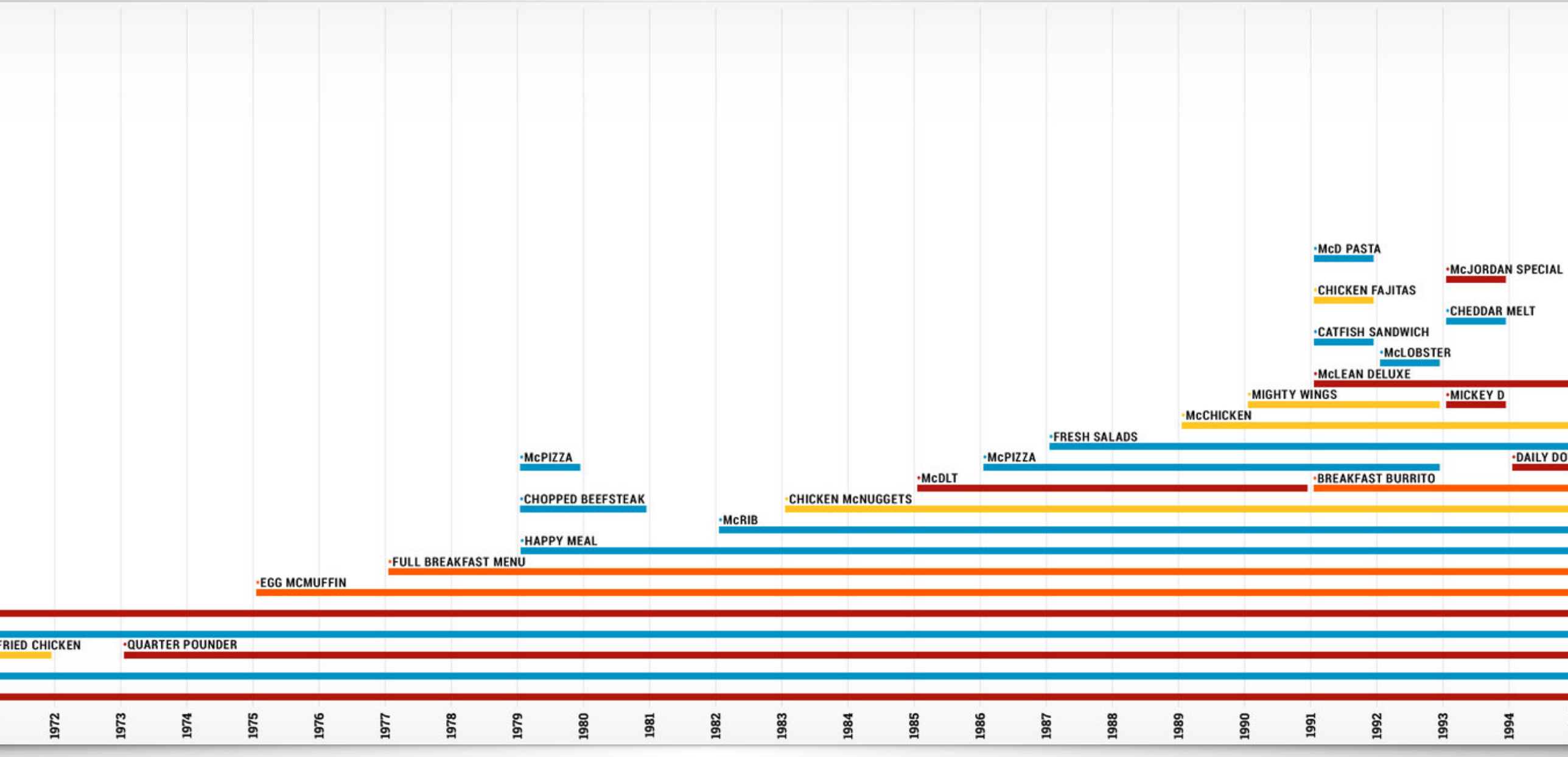

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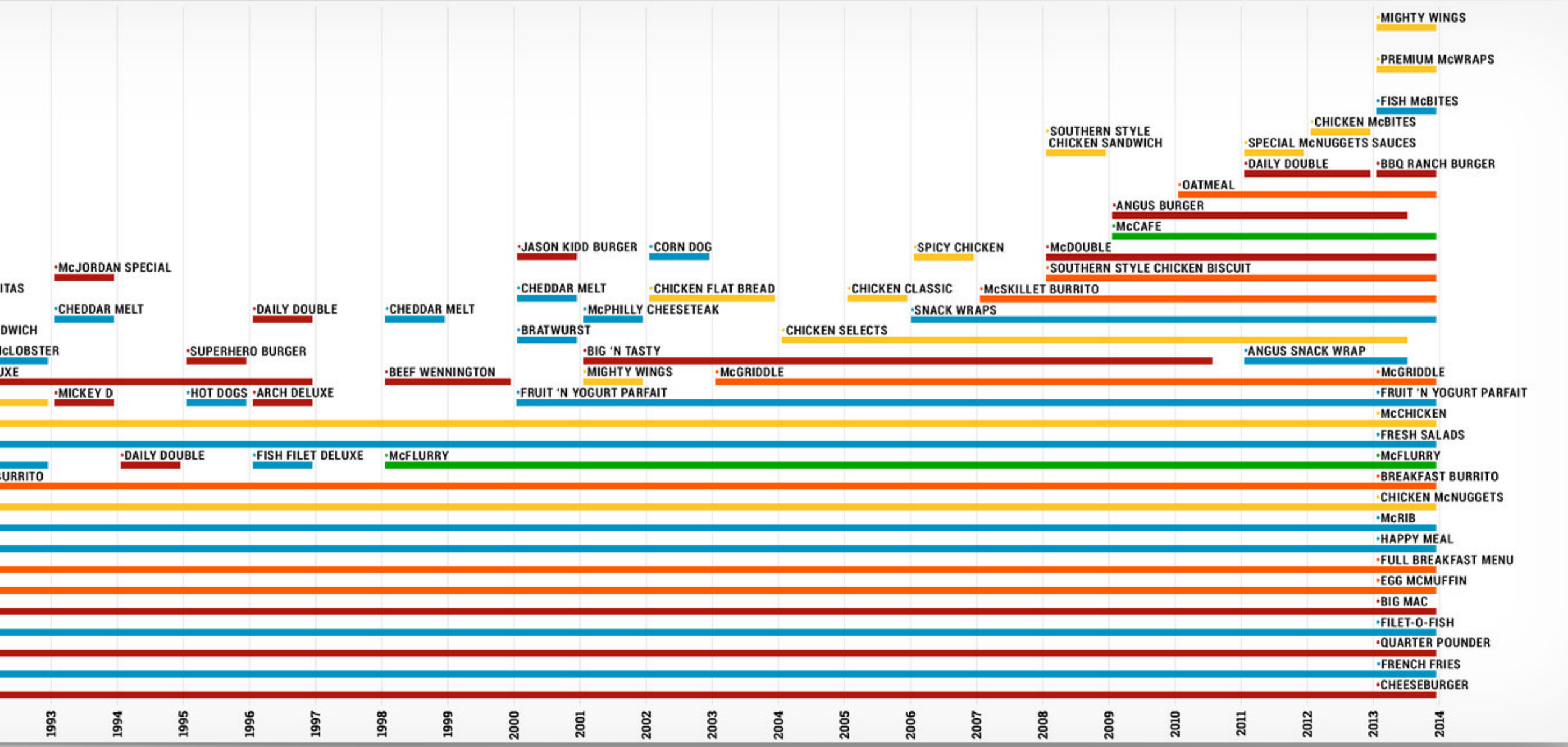

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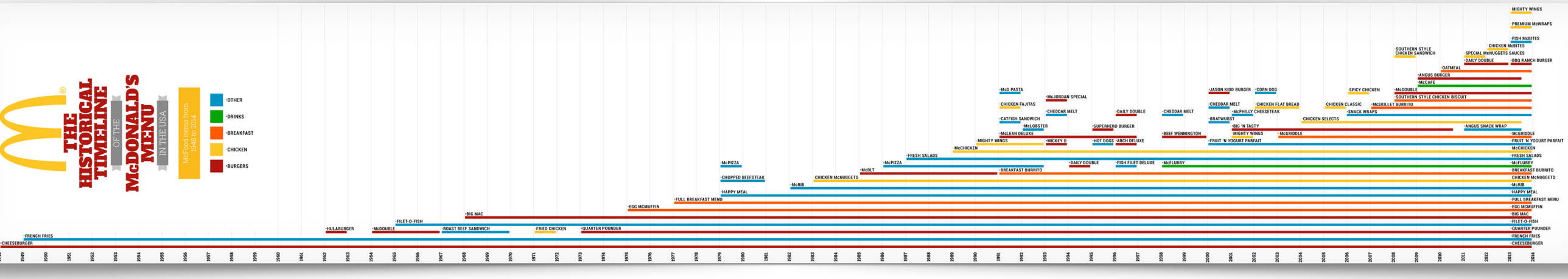

Essa é uma **técnica de visualização** chamada *timeline* ou linha do tempo

Ela ilustra um **relacionamento quantitativo** intrínseco aos dados que é denominado **série temporal**

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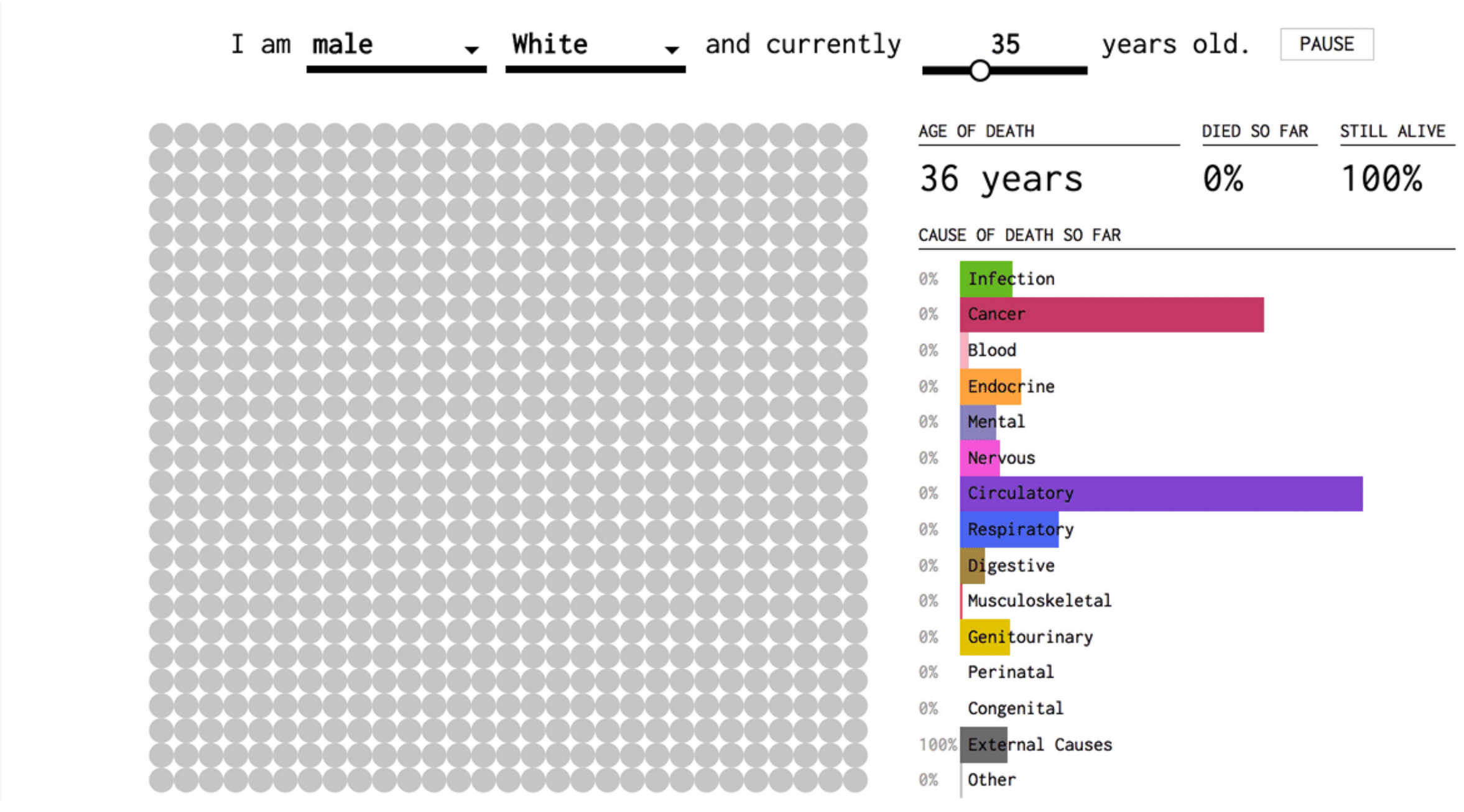
A **análise quantitativa** envolve relacionamentos entre valores que, por sua vez, envolve a busca por **padrões visuais** nos dados e o uso de **técnicas** de análise particulares

Os principais tipos de relacionamentos são:

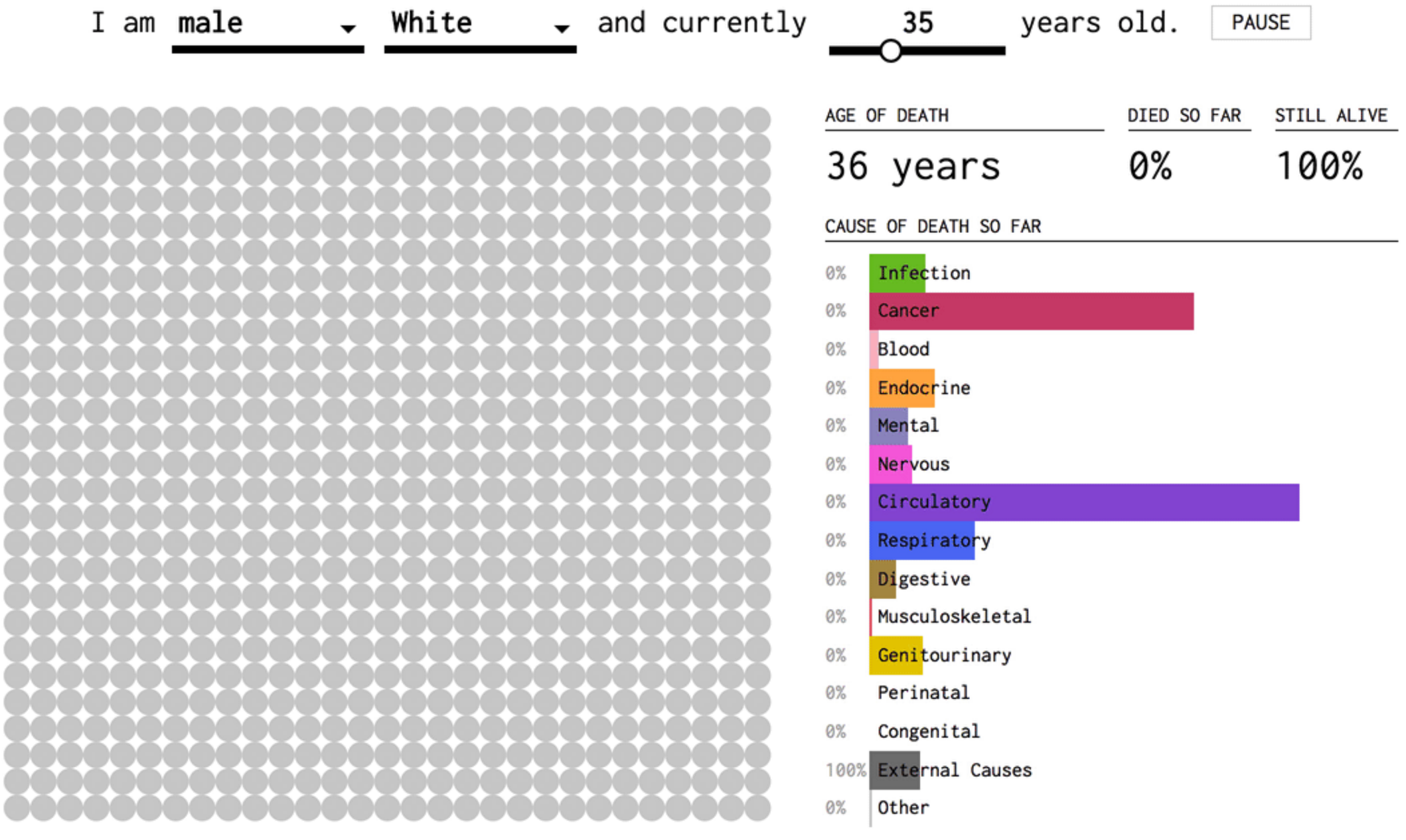
- Séries temporais
- Ranking
- Parte-todo
- Desvio
- Distribuição
- Correlação
- Multivariados

Essa visualização é uma composição entre um diagrama e um **histograma** que representa o relacionamento quantitativo **parte-todo**



Nathan Yau

O que você é capaz de **aprender ou descobrir** através dessa visualização?



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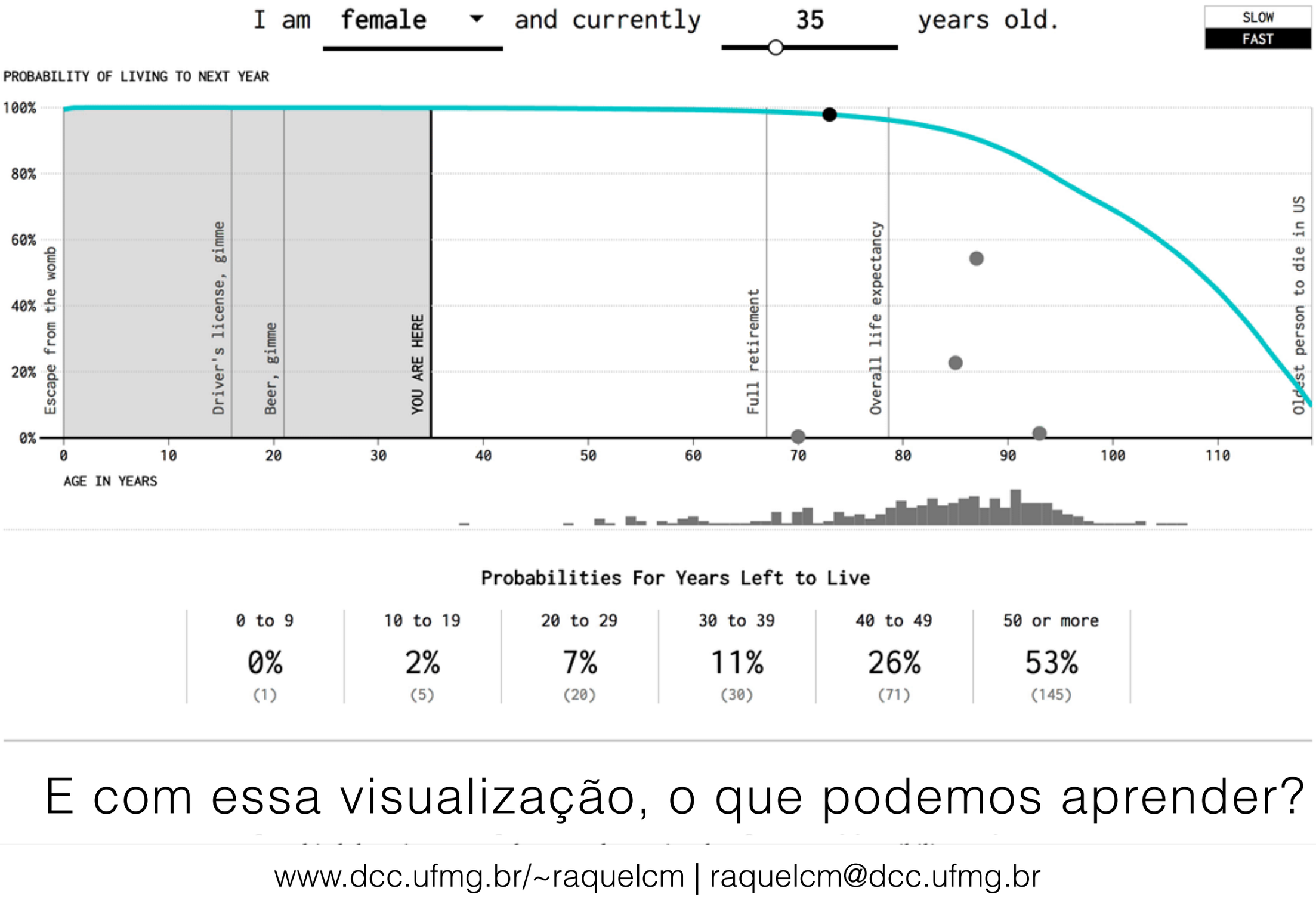
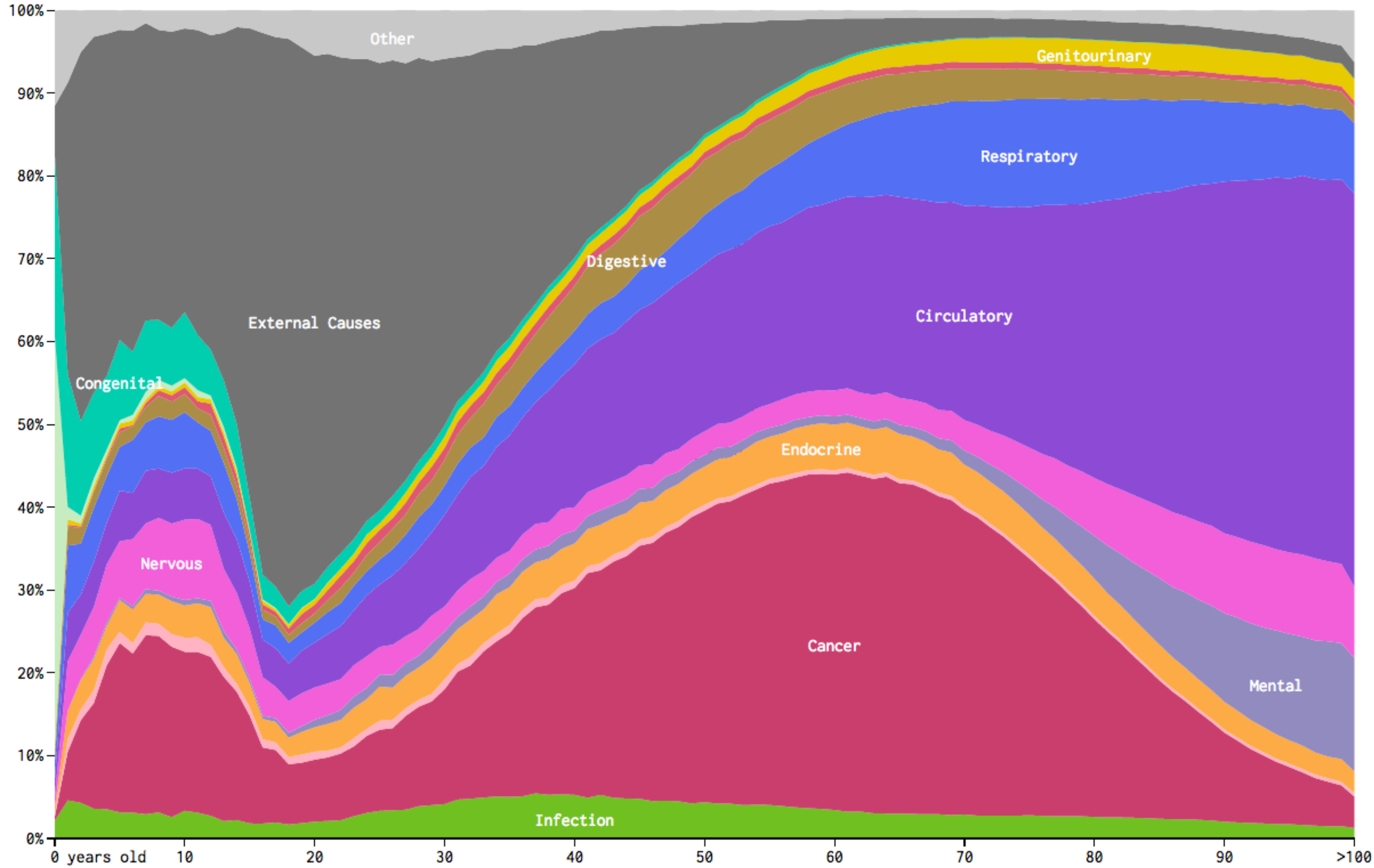
Essa visualização é um **gráfico de linhas** que representa o relacionamento quantitativo **distribuição**



E com essa visualização, o que podemos aprender?

Female | Male | American Indian or Alaska Native | Asian or Pacific Islander | Black or African American | White



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Essa visualização também é uma **série temporal** e a técnica é o **gráfico de áreas empilhadas**

Note que esse tipo de visualização traz mais **densidade de informação**, tem maior **potencial analítico** e nos permite **aprender mais**

*"Over history, **visual abstractions** have been developed to **aid thinking**...*

*What information visualization is really about is external cognition, that is, **how resources outside the mind can be used to boost the cognitive capabilities of the mind.**"*

-Stuart Card

in Visualization: Perception for Design

Visualizações só serão **efetivas** se operarem sobre princípios que **respeitem como a percepção visual e a cognição funcionam**.

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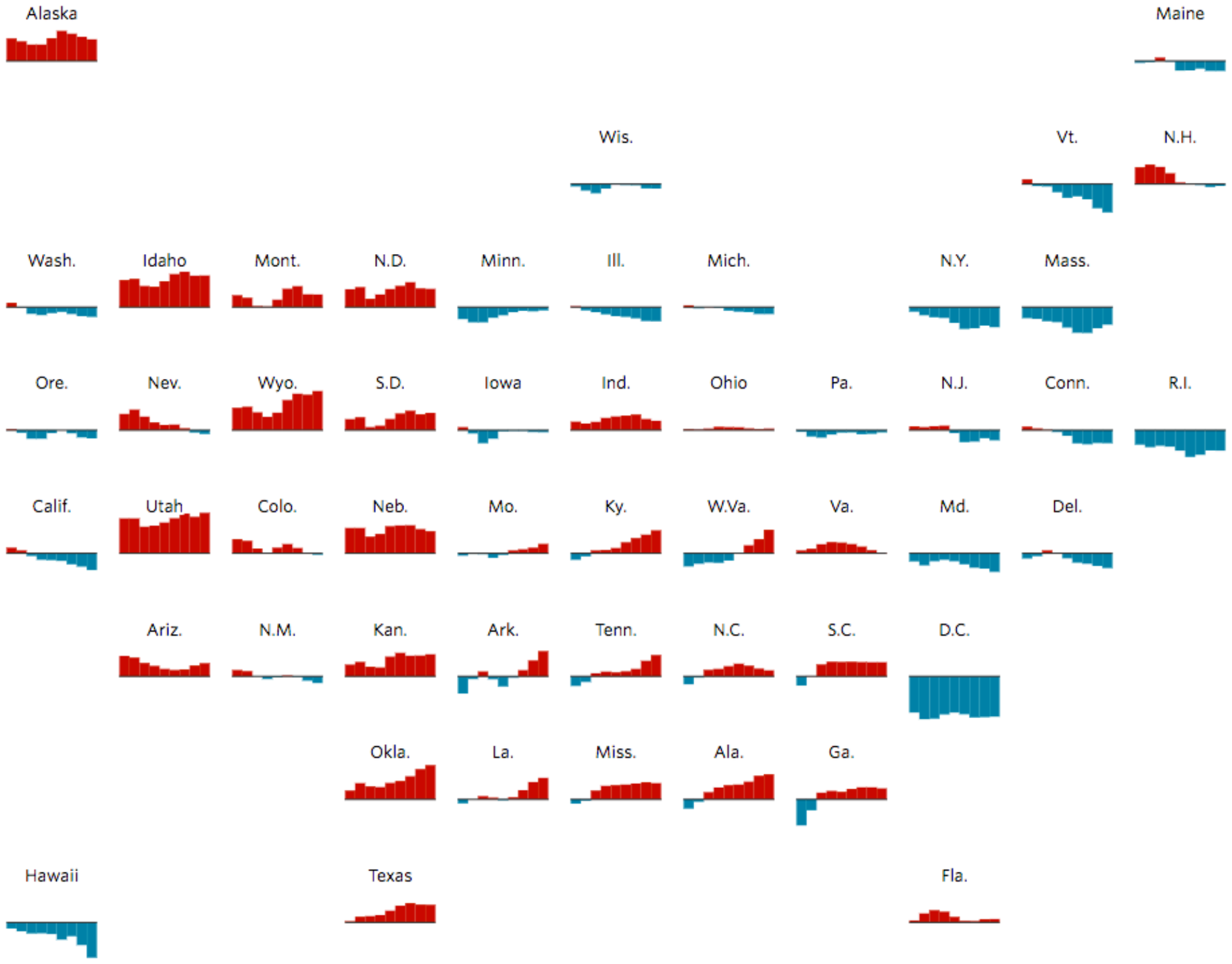
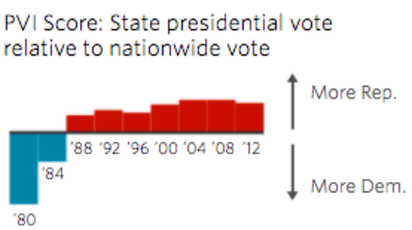
A Field Guide to Red and Blue America





Note: Charts based on the partisan voting index (PVI), which measures how each state voted in the presidential election relative to the nation as a whole, on a rolling two-election average. Washington, D.C., is charted on a different scale due to its strong Democratic lean.

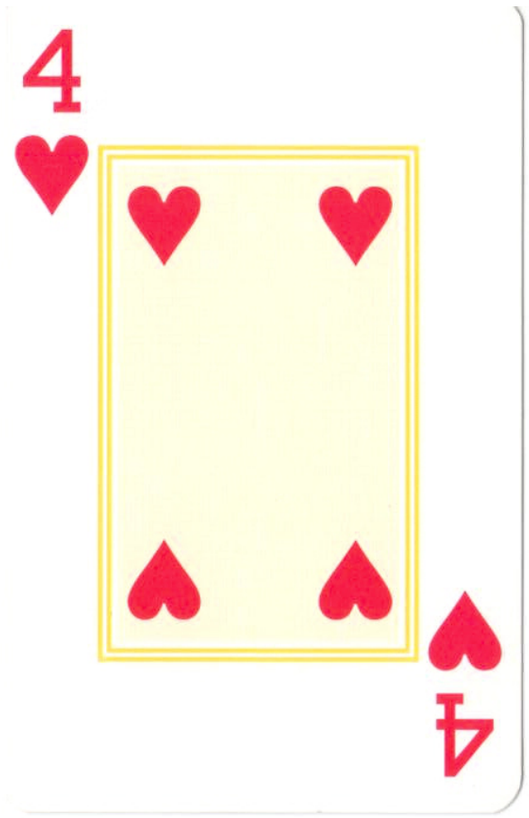
Randy Yeip,
Stuart A. Thompson
e Will Welch

Esse gráfico usa o padrão visual denominado **pequenos múltiplos** (Edward Tufte) para compor um diagrama composto por **histogramas** que retratam **séries temporais**

O diagrama é organizado usando uma posição relacionada à posição geográfica

O que essa organização nos permite aprender?

Por que essa visualização potencializa nossas capacidades de cognição?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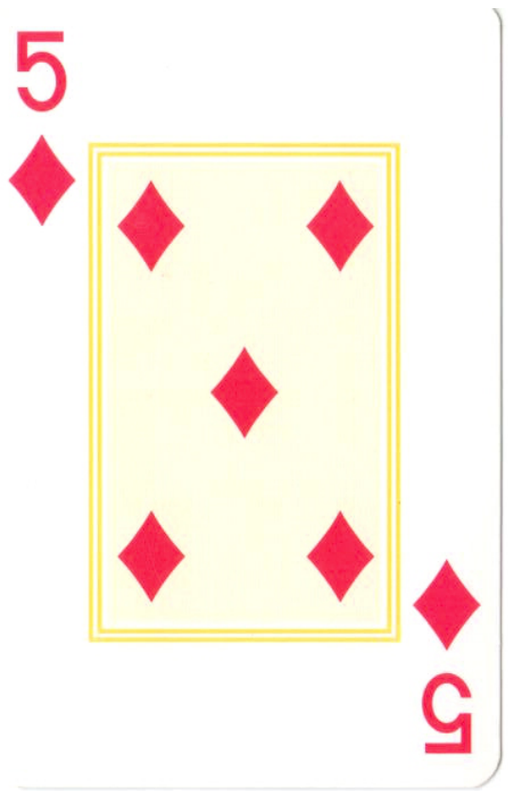
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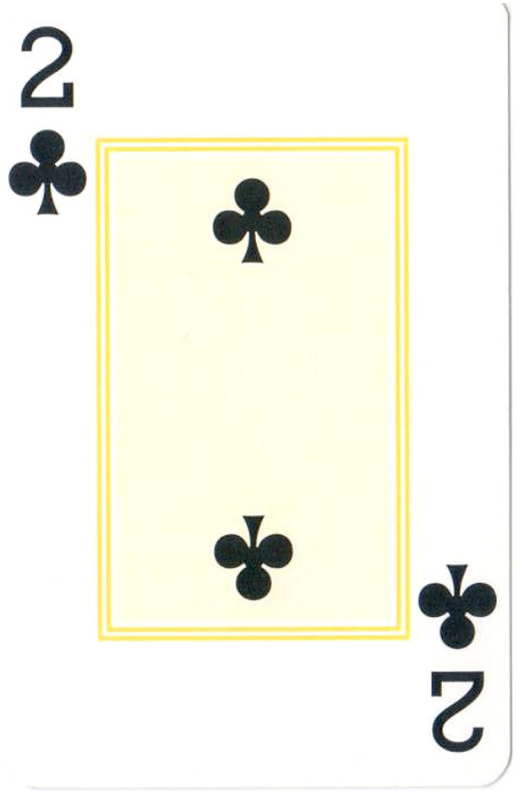
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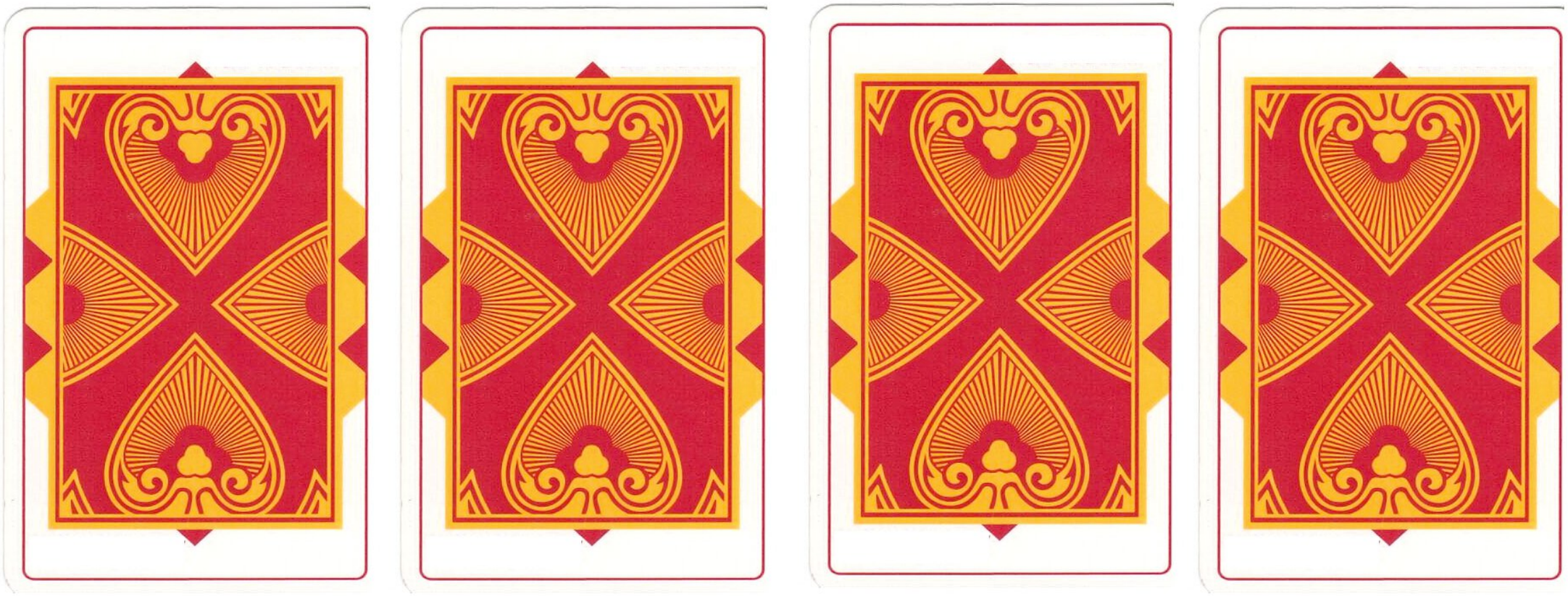

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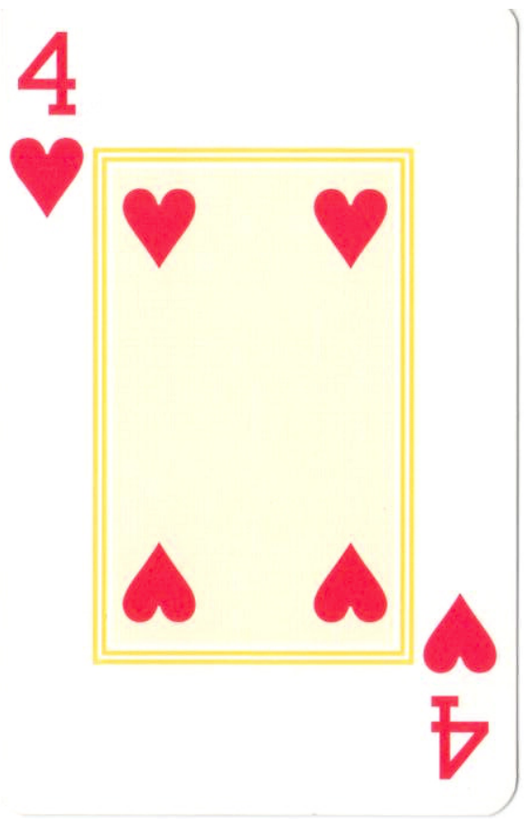

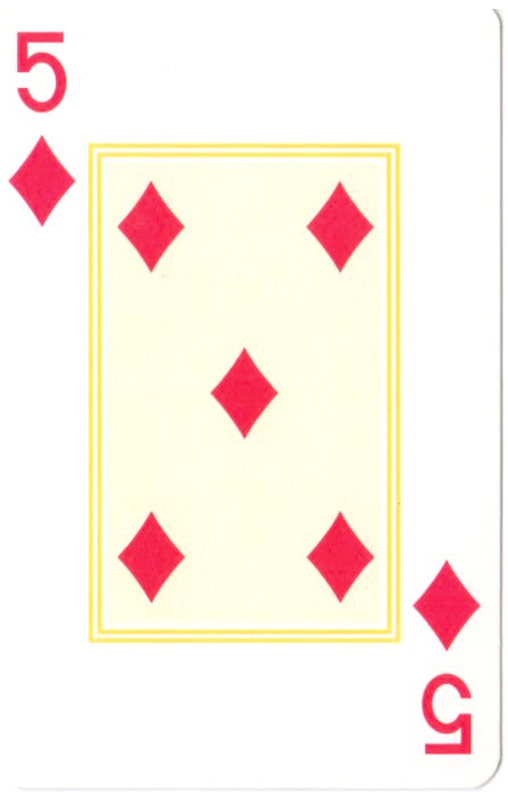

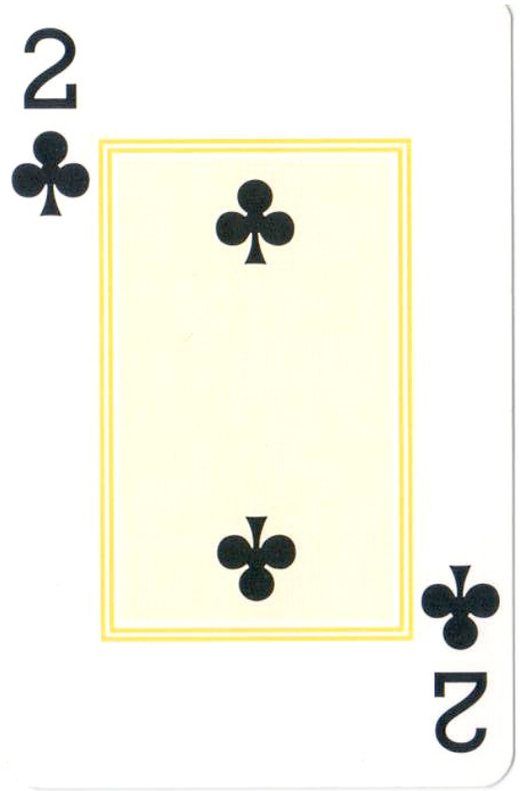

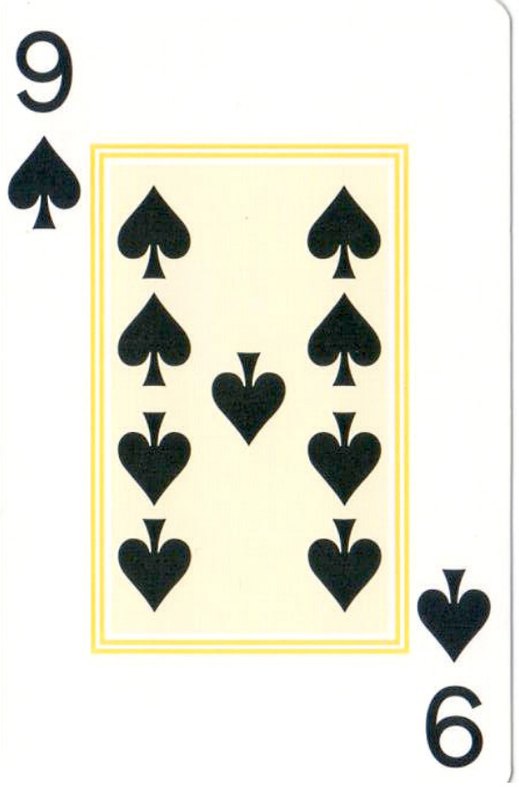

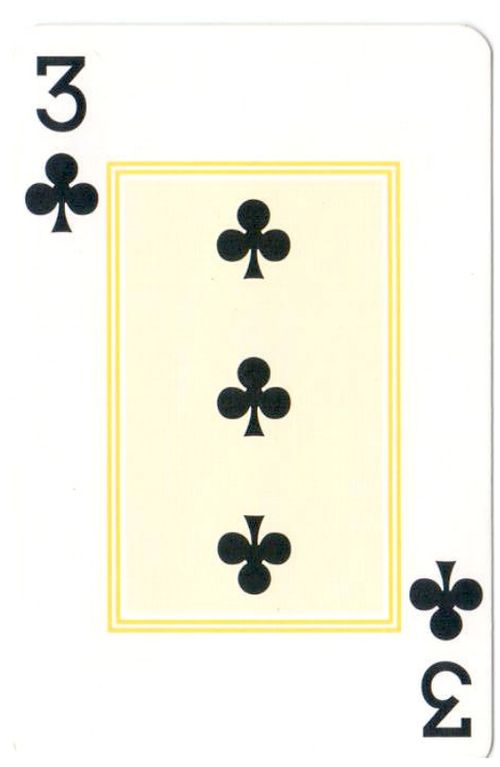

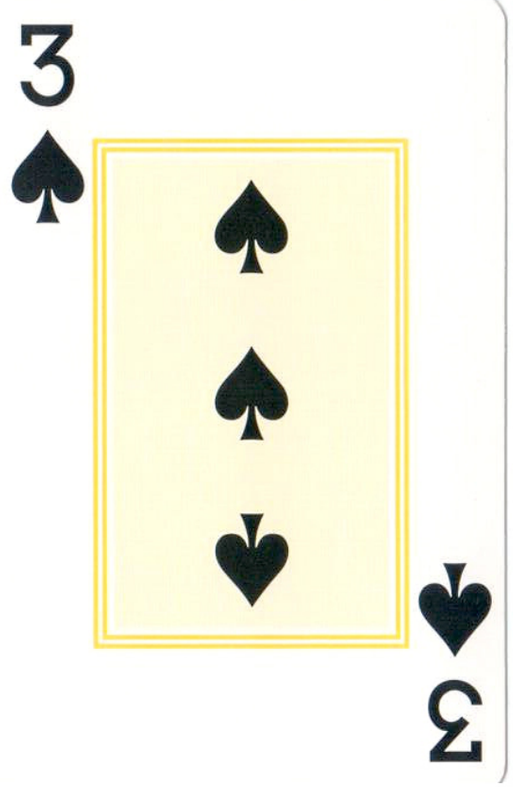

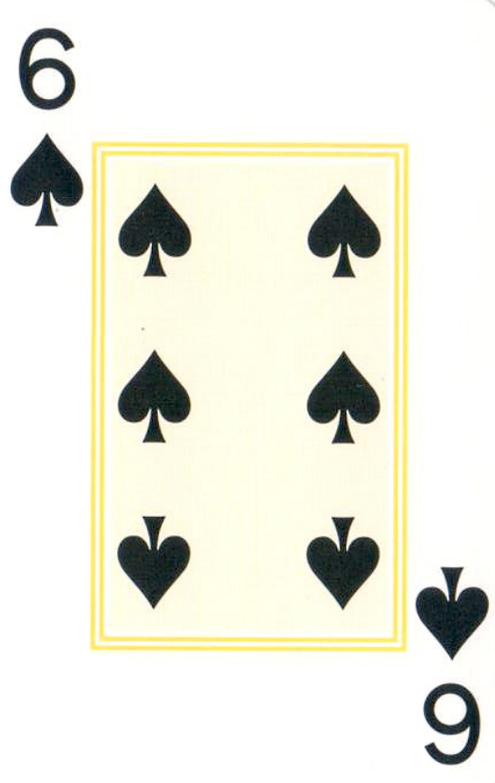

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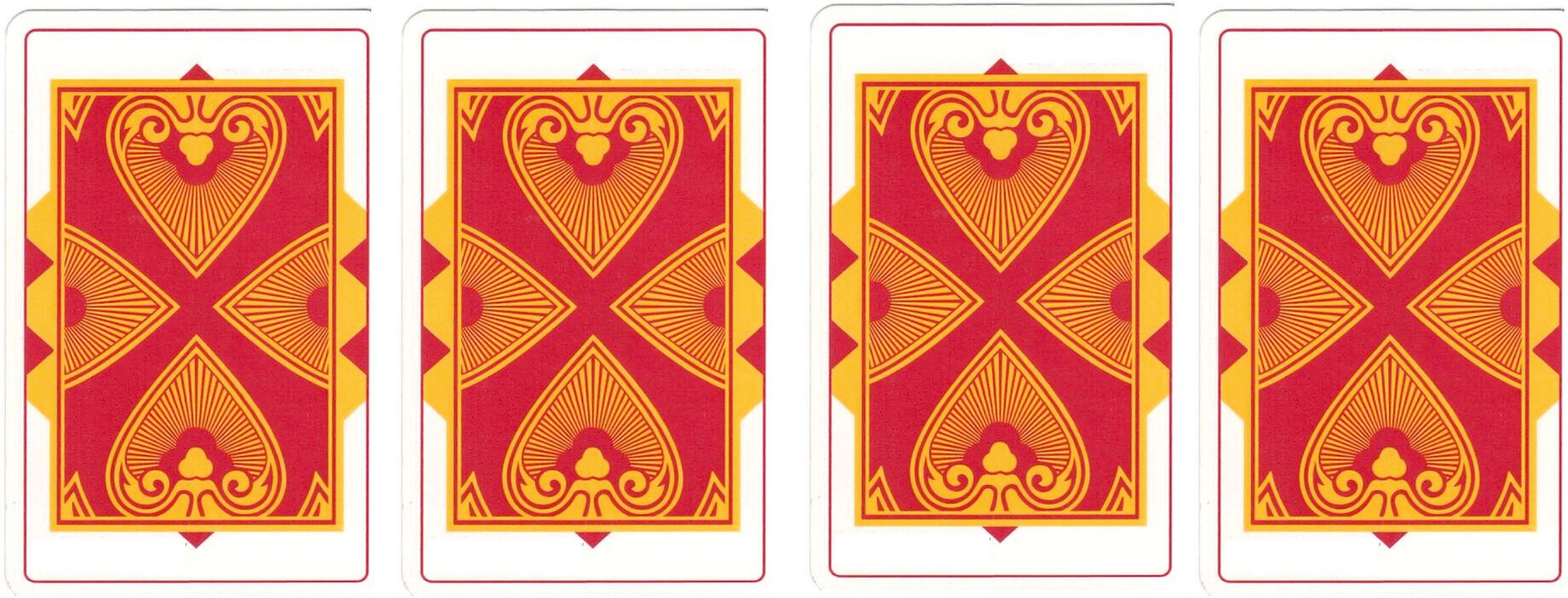

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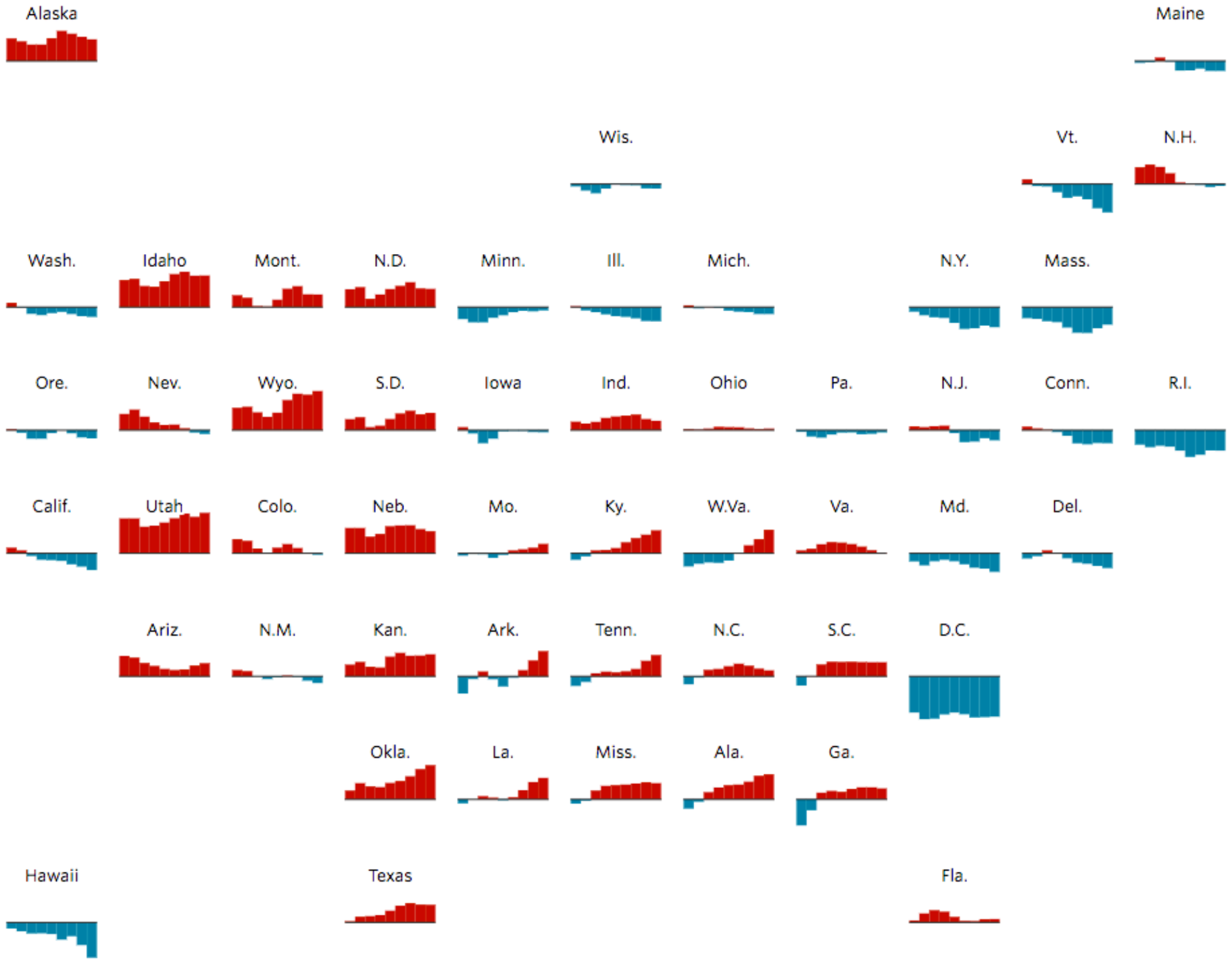
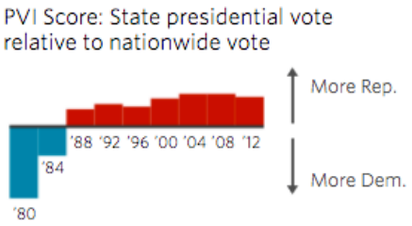
A **memória** tem **papel fundamental** na cognição, mas nossa memória de trabalho é **extremamente limitada**

A Field Guide to Red and Blue America

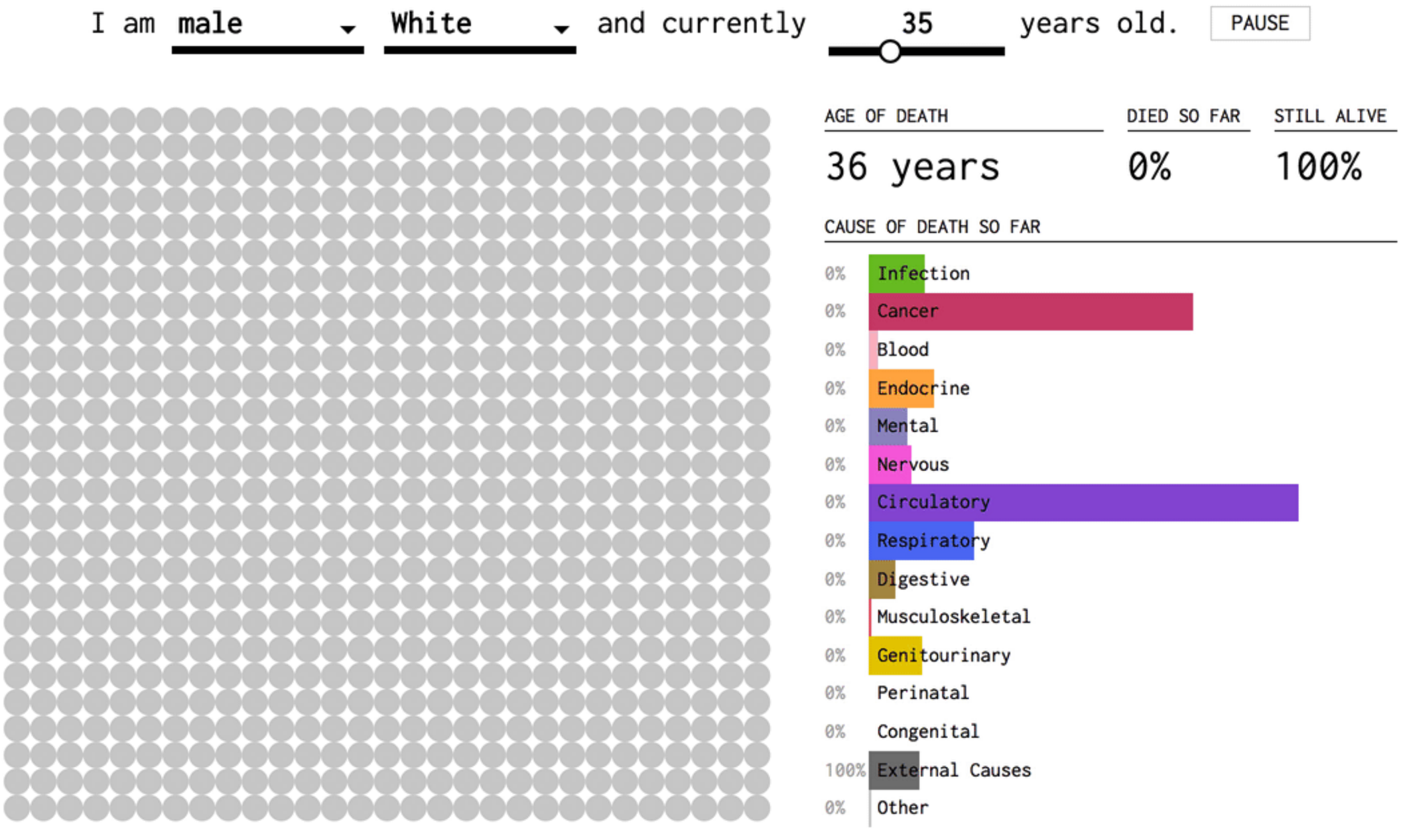




Note: Charts based on the partisan voting index (PVI), which measures how each state voted in the presidential election relative to the nation as a whole, on a rolling two-election average. Washington, D.C., is charted on a different scale due to its strong Democratic lean.

Randy Yeip,
Stuart A. Thompson e
Will Welch

É devido à limitação da nossa memória que animações não são tão efetivas no processo analítico



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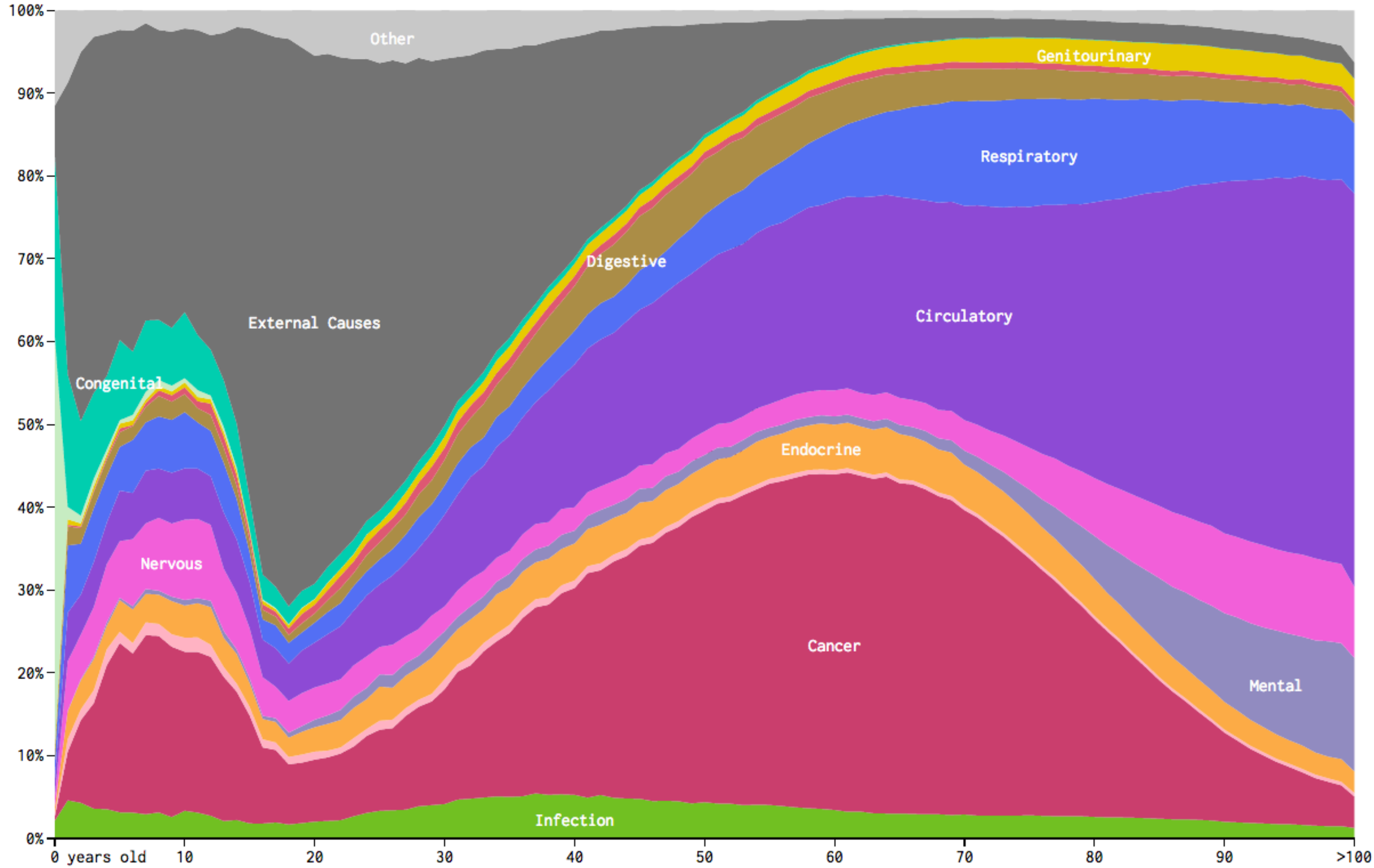

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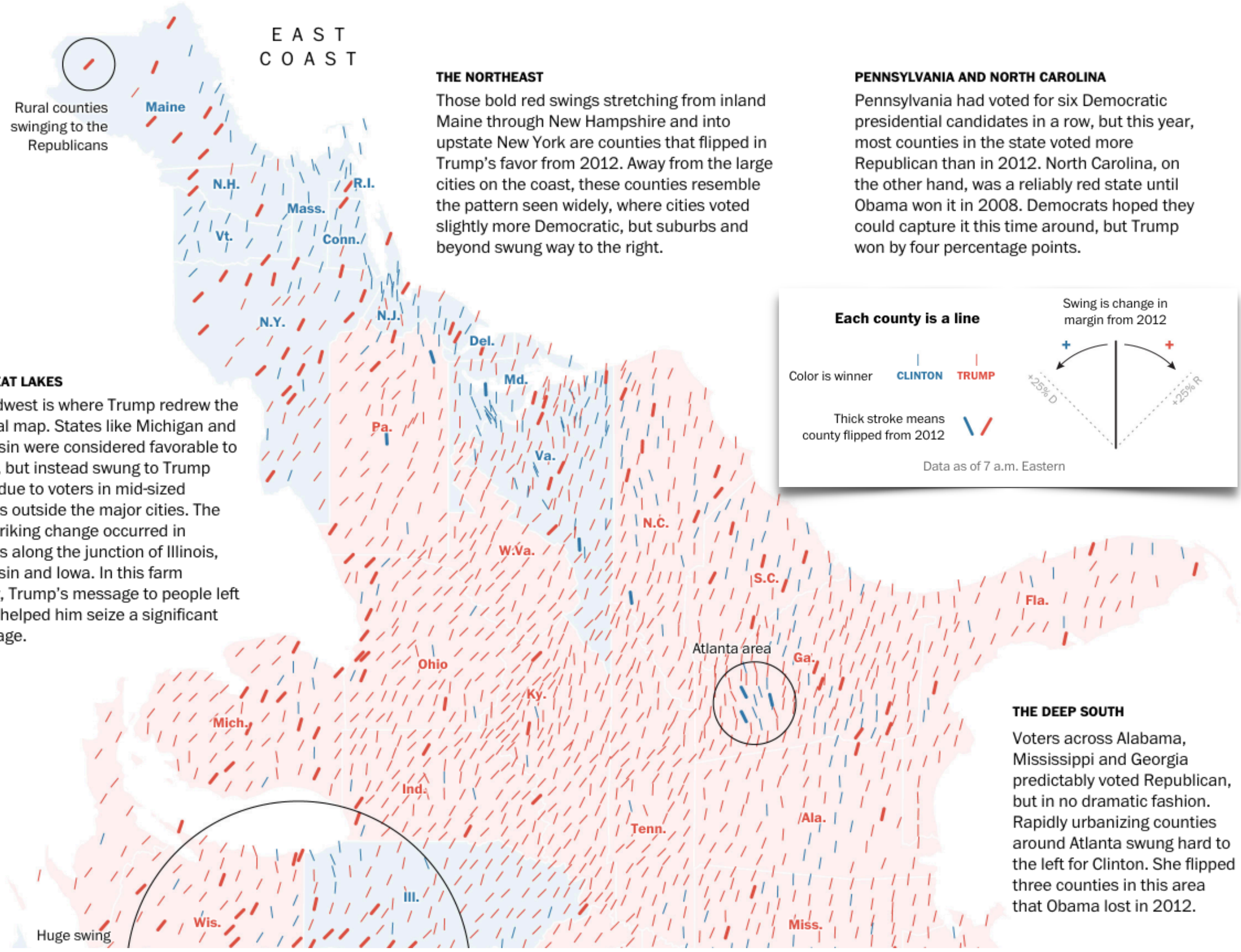


THE NORTHEAST

Those bold red swings stretching from inland Maine through New Hampshire and into upstate New York are counties that flipped in Trump's favor from 2012. Away from the large cities on the coast, these counties resemble the pattern seen widely, where cities voted slightly more Democratic, but suburbs and beyond swung way to the right.

PENNSYLVANIA AND NORTH CAROLINA

Pennsylvania had voted for six Democratic presidential candidates in a row, but this year, most counties in the state voted more Republican than in 2012. North Carolina, on the other hand, was a reliably red state until Obama won it in 2008. Democrats hoped they could capture it this time around, but Trump won by four percentage points.

THE GREAT LAKES

The Midwest is where Trump redrew the electoral map. States like Michigan and Wisconsin were considered favorable to Clinton, but instead swung to Trump mostly due to voters in mid-sized counties outside the major cities. The most striking change occurred in counties along the junction of Illinois, Wisconsin and Iowa. In this farm country, Trump's message to people left behind helped him seize a significant advantage.

THE DEEP SOUTH

Voters across Alabama, Mississippi and Georgia predictably voted Republican, but in no dramatic fashion. Rapidly urbanizing counties around Atlanta swung hard to the left for Clinton. She flipped three counties in this area that Obama lost in 2012.

Princípio da densidade de dados de Tufte

Data Density in Graphical Practice

The numbers that go into a graphic can be organized into a data matrix of observations by variables. Taking into account the size of the graphic in relation to the amount of data displayed yields the *data density*:

$$\text{data density of a graphic} = \frac{\text{number of entries in data matrix}}{\text{area of data graphic}}$$

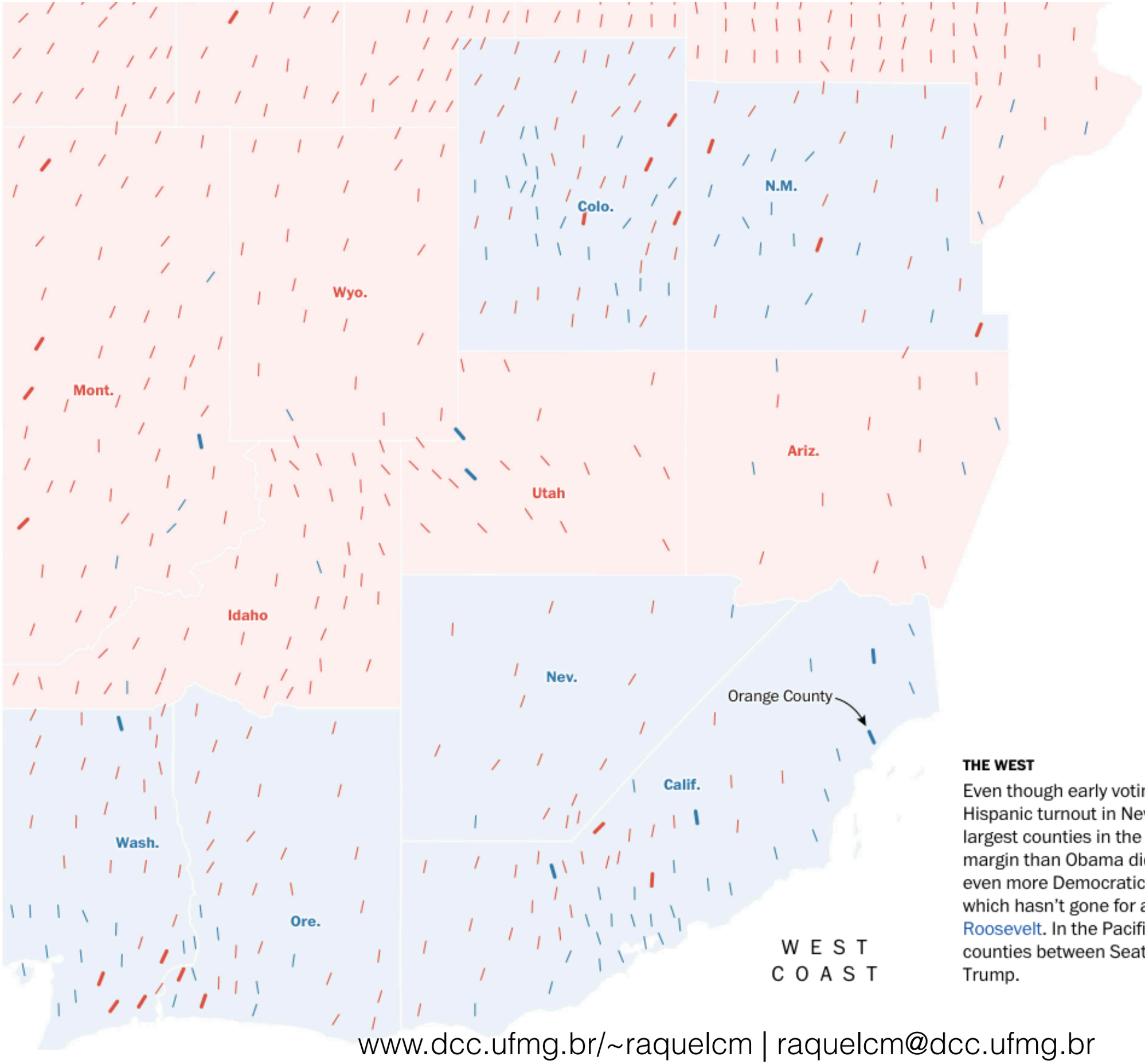
Data matrices and data densities vary enormously in practice. At one extreme, this overwrought display (originally printed in five colors) presents a data matrix of four entries, the names and the numbers for the two bars on the right. The left bar is merely the total of the other two. The graph covers 26.5 square inches (171 square centimeters), resulting in a data density of .15 numbers per square inch (.02 numbers per square centimeter), which is thin indeed.

Data-rich designs give a context and credibility to statistical evidence. Low-information designs are suspect: what is left out, what is hidden, why are we shown so little? High-density graphics help us to compare parts of the data by displaying much information within the view of the eye: we look at one page at a time and the more on the page, the more effective and comparative our eye can be.[5] The principle, then, is:

> Maximize data density and the size of the data matrix, within reason.

High-information graphics must be designed with special care. As the volume of data increases, data measures must shrink (smaller dots for scatters, thinner lines for busy time-series). The clutter of

Edward Tufte
Visual display of quantitative information



ALONG THE BORDER

People closest to where Trump said he would build a wall consistently voted against him, all the way from the Gulf of Mexico to the Pacific Ocean.

UTAH

The reason you're seeing counties in Utah swinging has a simple answer: Evan McMullin. The three-way contest with the independent conservative candidate in this state reduced the Republican margin, even though Clinton wasn't competitive.

THE WEST

Even though early voting suggested a historic Hispanic turnout in Nevada, Clinton won the two largest counties in the state by a slightly slimmer margin than Obama did in 2012. California became even more Democratic: Clinton won Orange County, which hasn't gone for a Democrat since Franklin Roosevelt. In the Pacific Northwest, a pocket of rural counties between Seattle and Portland swung toward Trump.

EAST COAST

Maine
Boston
N.H.
R.I.
Mass.
Vt.
Conn.
New York City
Philadelphia
N.Y.
N.J.
Del.
Md.
Rochester
Buffalo
Pa.
Va.
Raleigh
N.C.
Charlotte
Cleveland
W.Va.
S.C.
Detroit
Columbus
Orlando
South Florida
Fla.
Tampa
Flint
Ohio
Cincinnati
Ga.
Atlanta
Ky.
Mich.
Grand Rapids
Indianapolis
Louisville
Chicago
Ind.
Nashville
Tenn.
Ala.
Milwaukee
Madison
Wis.
Ill.
St. Louis
Memphis
Miss.
New Orleans

THE NORTHEAST

To no one's surprise, Clinton won decisively in the Northeast Corridor. Those cities provided huge margins for her from Boston to Washington. Trump's most notable big-city win was in Suffolk County on Long Island. While Trump didn't win in the most urban counties, he held a significant edge in suburban counties.

THE URBAN-RURAL DIVIDE

Nationwide, Clinton won the urban core overwhelmingly, but Trump won 75 percent or more of everything else from suburbs to rural counties.

Each county is a triangle

Color is winner — CLINTON — TRUMP

Thick stroke is county won in a landslide (50%+)

Height is total votes cast

Width is margin in net votes

Data as of 7 a.m. Eastern

THE GREAT LAKES

Clinton's large wins in Midwestern cities like Cleveland and Detroit weren't enough to offset the Trump margins from many more smaller cities and counties. For example, Clinton won seven of Ohio's 88 counties. She lost the area around Dayton, a medium-sized city that voted for Obama in 2012.

FLORIDA

Clinton held her own in Democratic strongholds in South Florida and Orlando, but Trump flipped St. Petersburg by a slim margin. Trump pulled away with large wins up and down both coasts in areas growing with retirees.

Colorado Springs
Denver
Colo.
N.M.
Albuquerque
El Paso
Wyo.
Mont.
Salt Lake City
Utah
Phoenix
Tucson
Ariz.
Missoula
Idaho
Boise
Las Vegas
Nev.
San Diego
Los Angeles
Spokane
Reno
Calif.
Seattle
Wash.
Sacramento
Portland
Ore.
Bay Area

WEST COAST

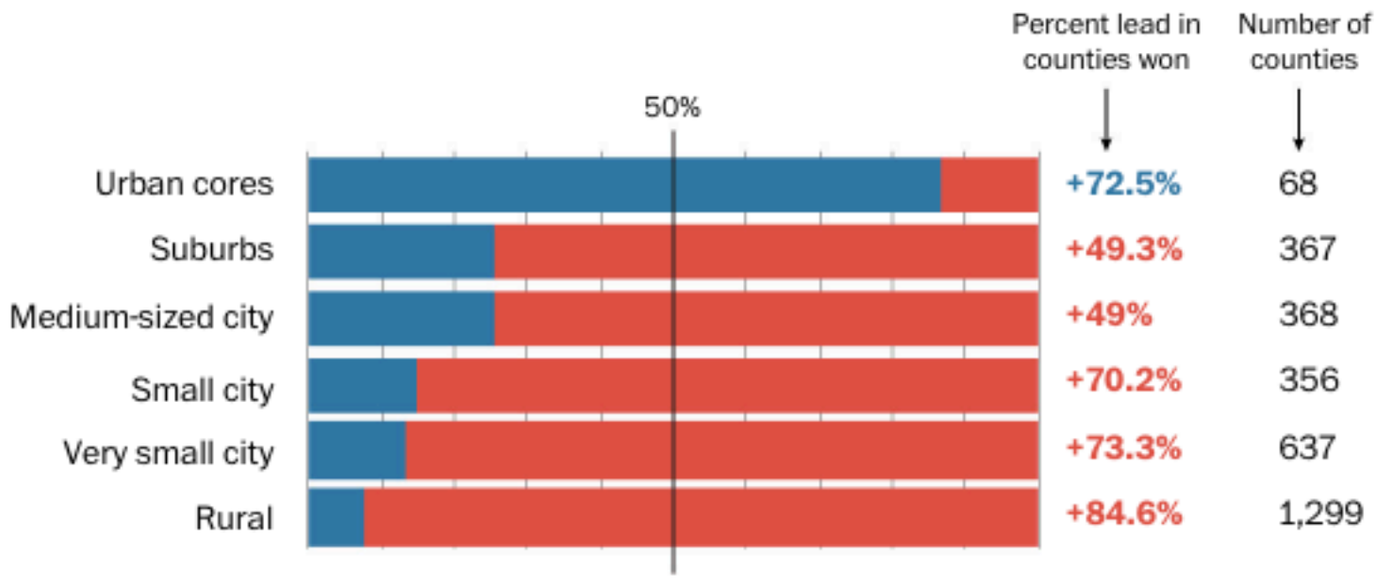
TEXAS AND THE PLAINS

Compared to Trump's wins in the South, his margins in rural counties in the Great Plains were much higher, consistently winning by more than 50 percentage points. These counties are tiny, but combined, they handed him easy wins through the region.

THE SOUTHWEST

Maricopa County bucks the trend of urban areas voting for Democrats. Like Romney in 2012, Trump narrowly carried the county, netting him by far his largest single county win. The county includes the urban voters in Phoenix but even more conservative suburban voters.

Geography proves to be a crucial determining factor of how people vote. The urban classification of the counties reveals the parties' startling extremes.



Clinton won almost 90 percent of urban cores, while Trump won the vast majority – between 75 and 90 percent – of suburbs, small cities and rural areas. Though these latter geographies are more sparsely populated, they were home to the majority of voters this election.

Nesse curso, vamos entender porque esse tipo de visualização, apesar de **complexa** e **densa** é **eficaz**

Entender o funcionamento dos sistemas de **percepção** e **cognição** humanos será fundamental para nos ajudar a projetar visualizações eficazes

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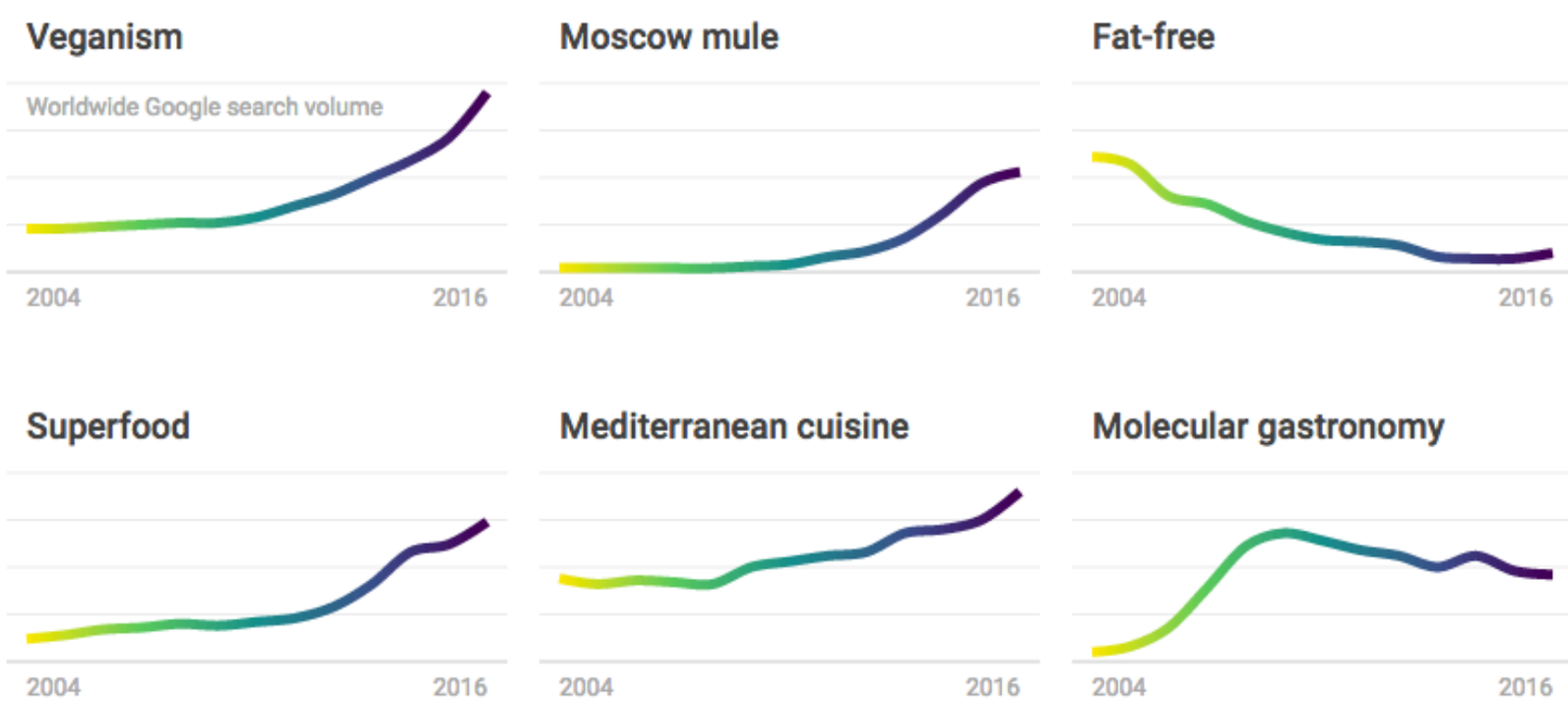
How do we search for food? Google search interest can reveal key food trends over the years.

From the rise and fall of recipes over diets and drinks to cooking trends and regional cuisines.



http://rhythm-of-food.net/

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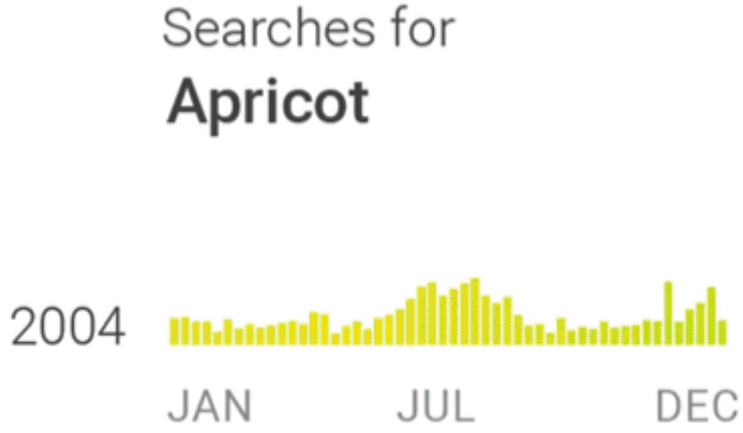
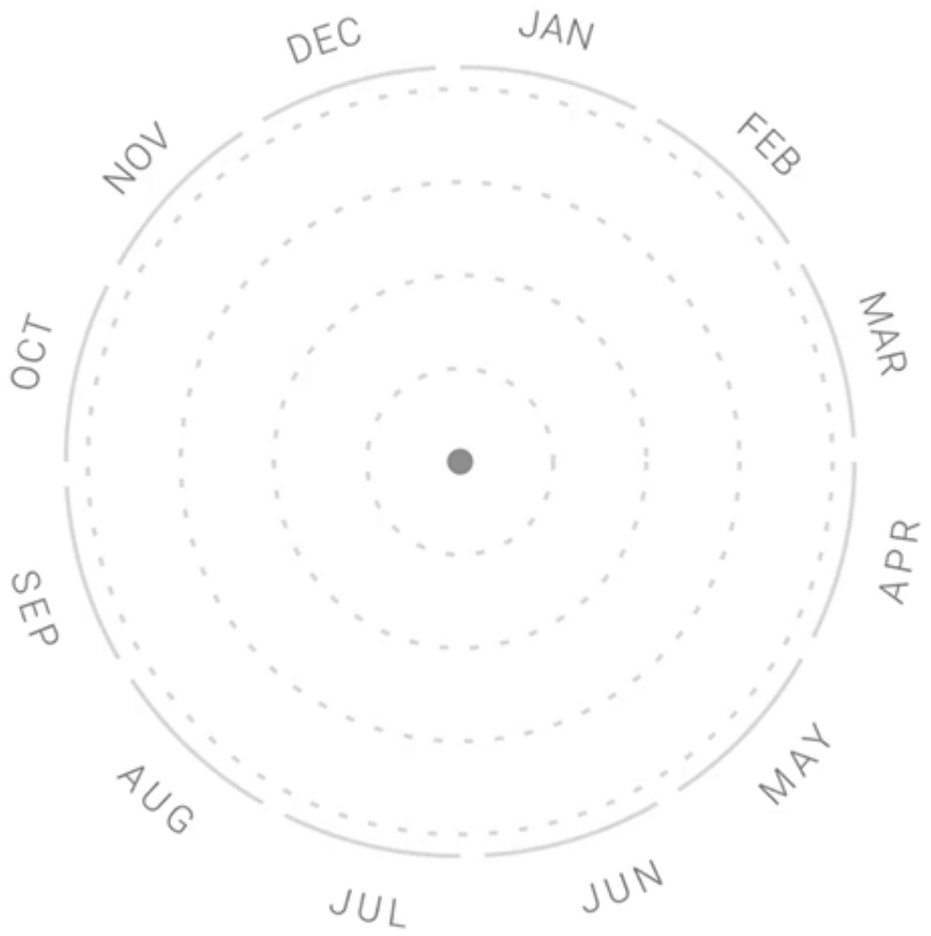
But it turns out that we can learn even more from analyzing search patterns.

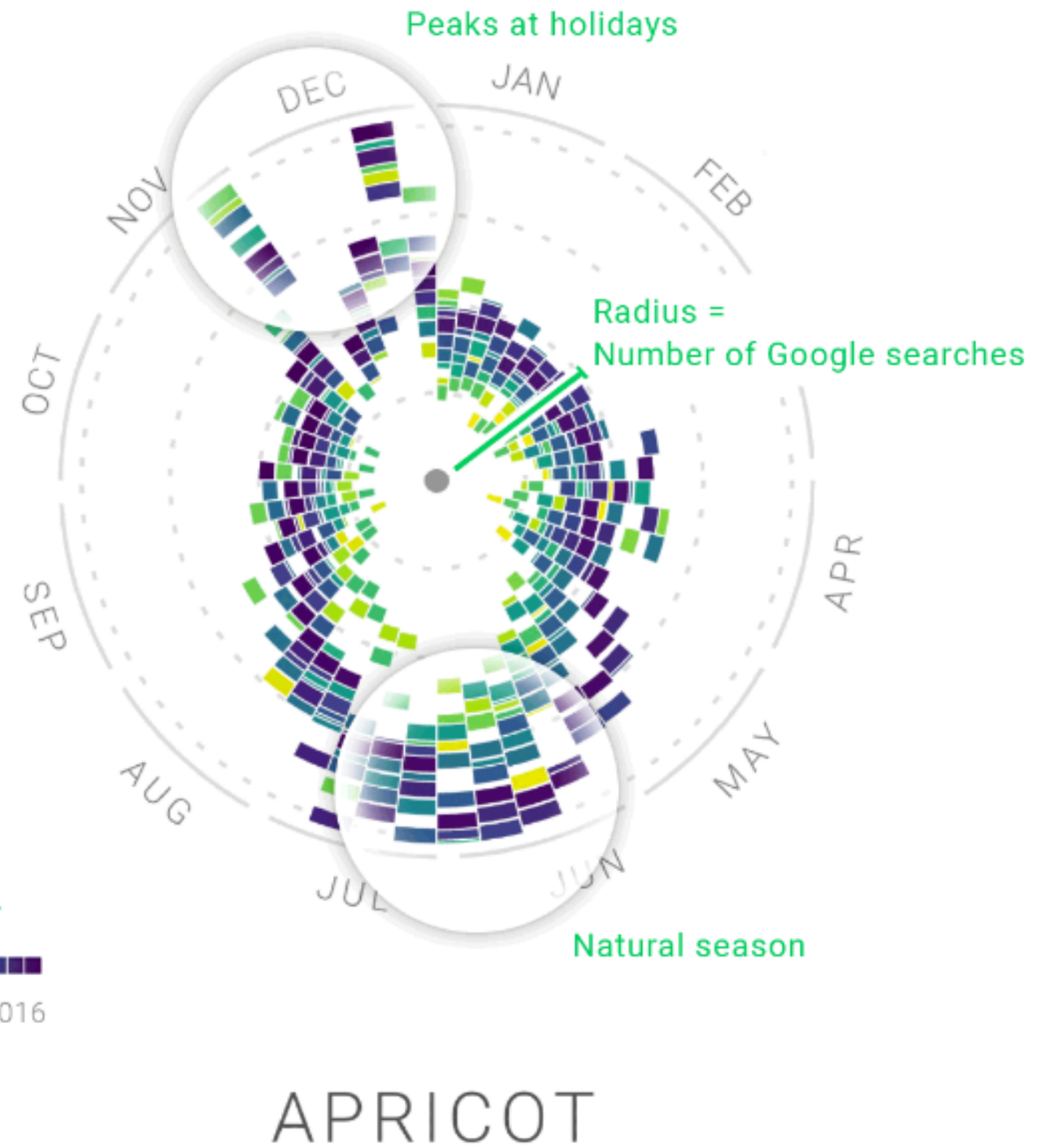
We collected weekly Google Trends data for hundreds of dishes and ingredients, over twelve years



and plotted the results on a **year clock**



to investigate the seasons and
rhythm of food around the world.



APRICOT

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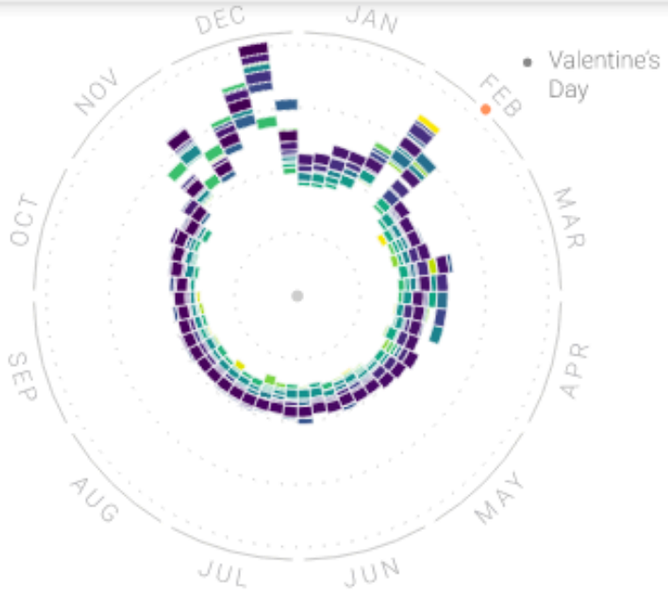
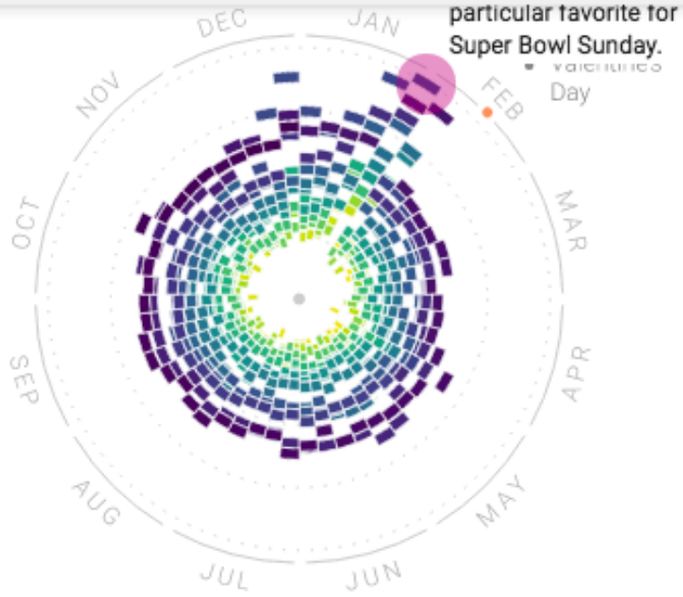
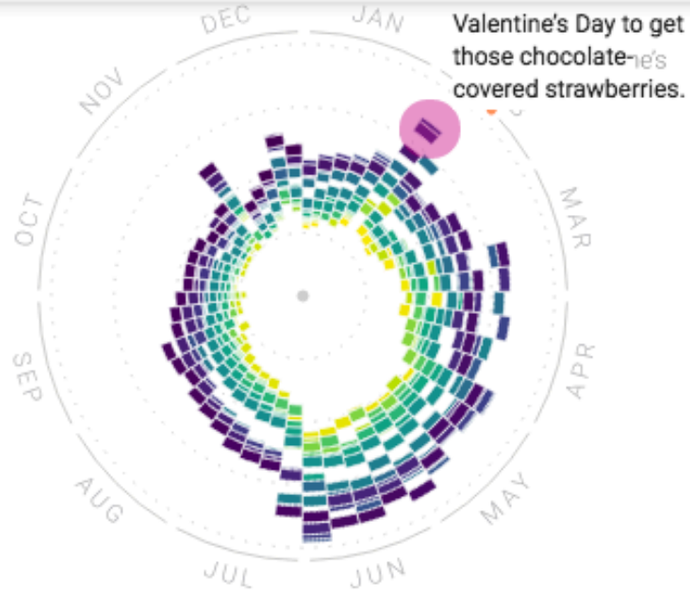
January | **February** | March | April | May | June | July | August | September | October | November | December



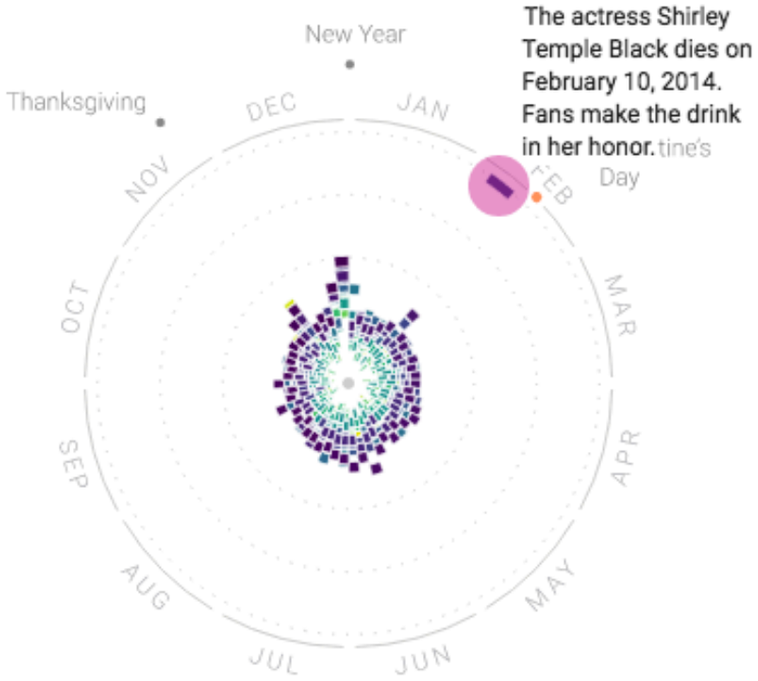
CHOCOLATE



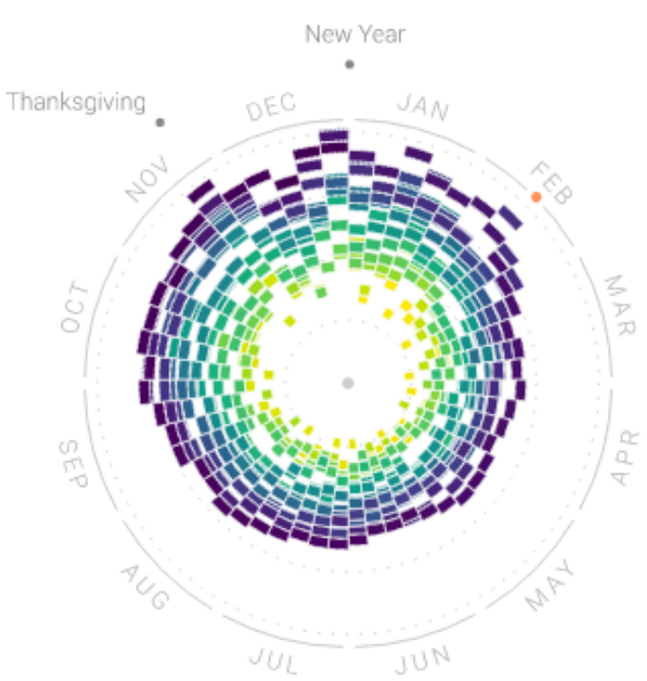
NACHOS



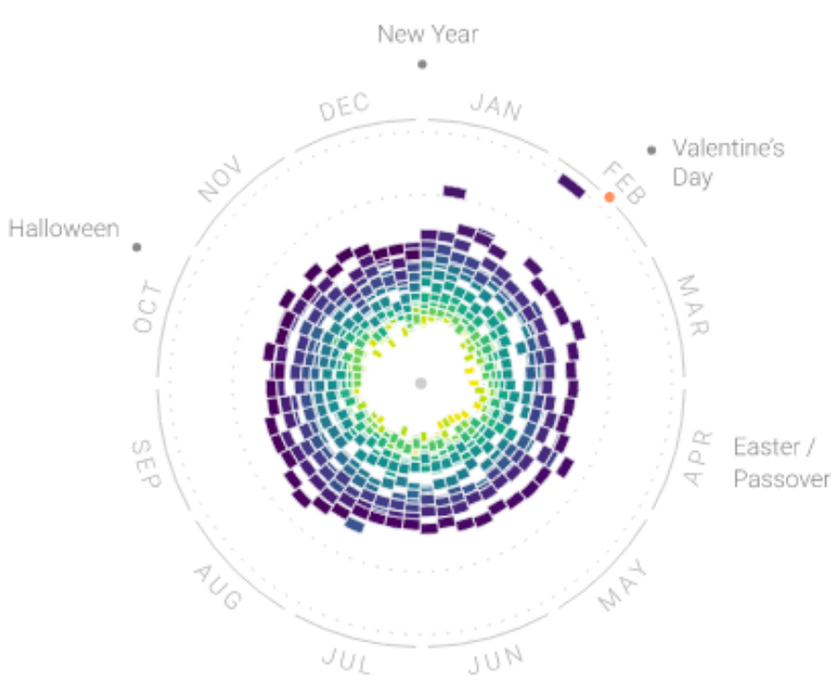
STRAWBERRY



SHIRLEY TEMPLE



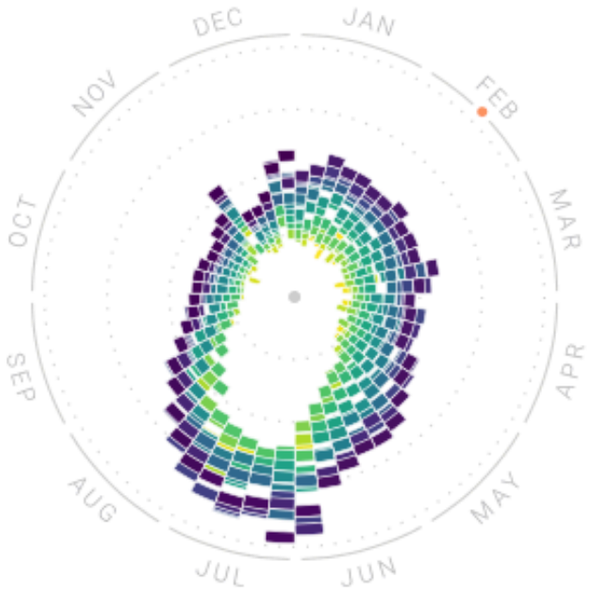
DUMPLING



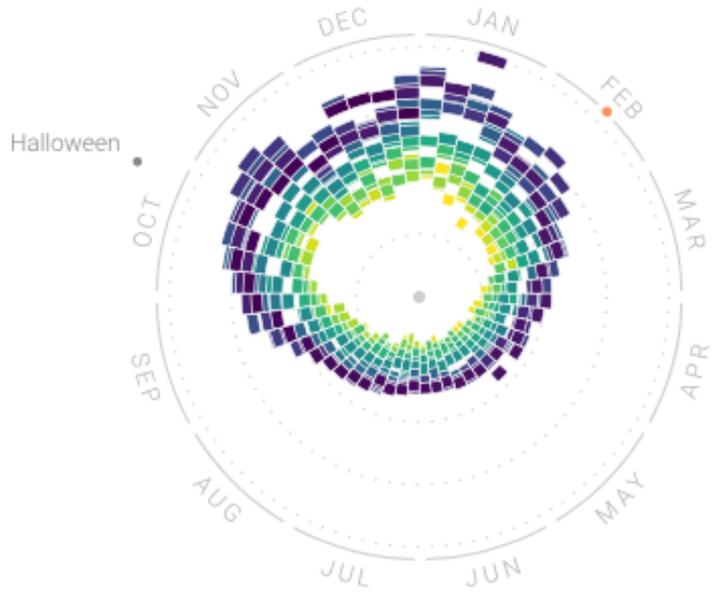
BURRITO

What are the most common patterns?

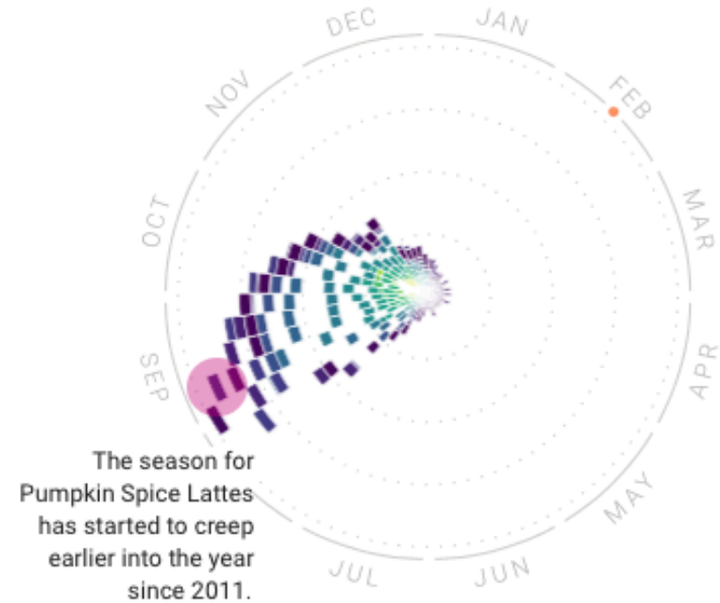
Some items fade in and out of a natural season.



BLUEBERRY



STEW



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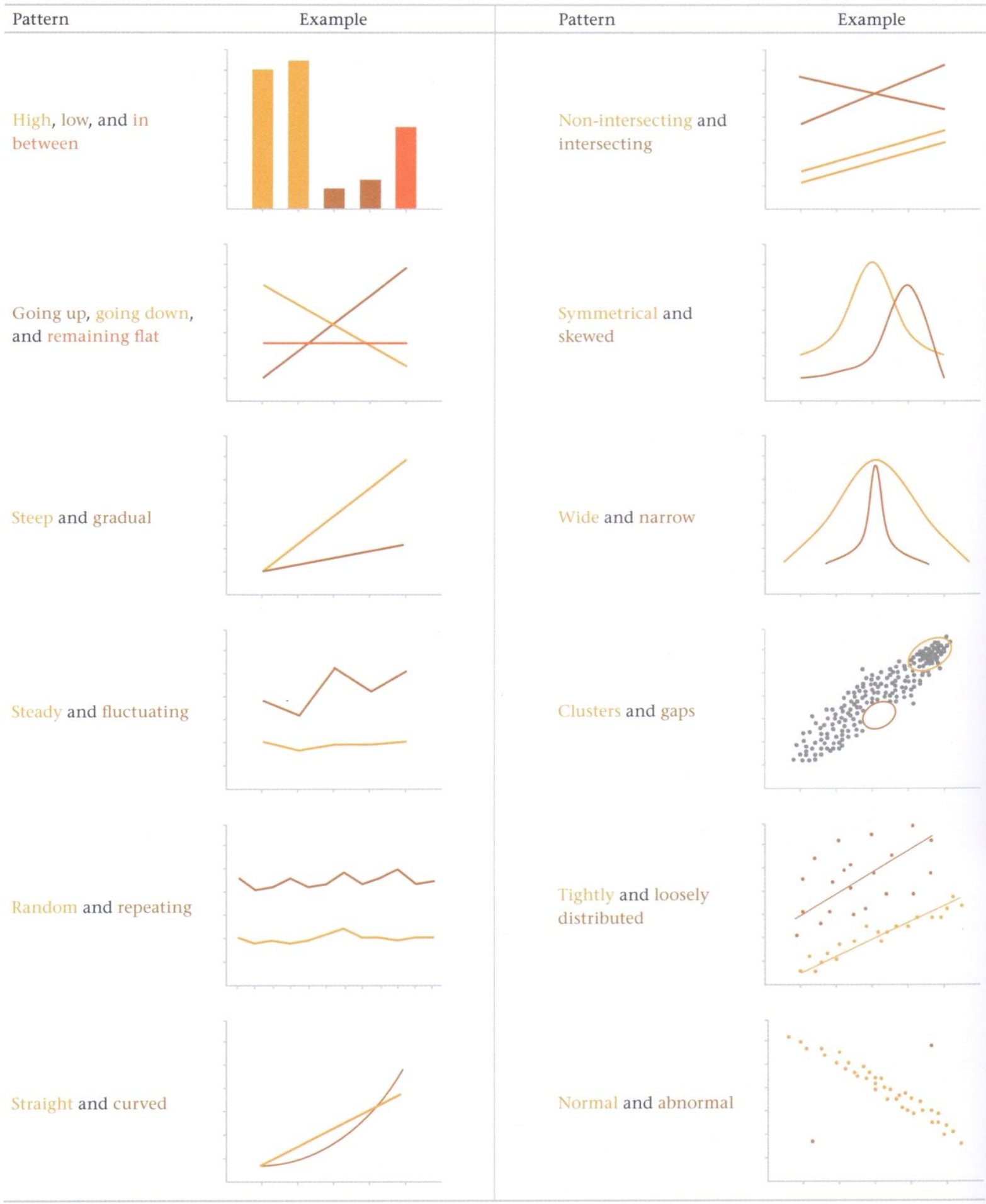
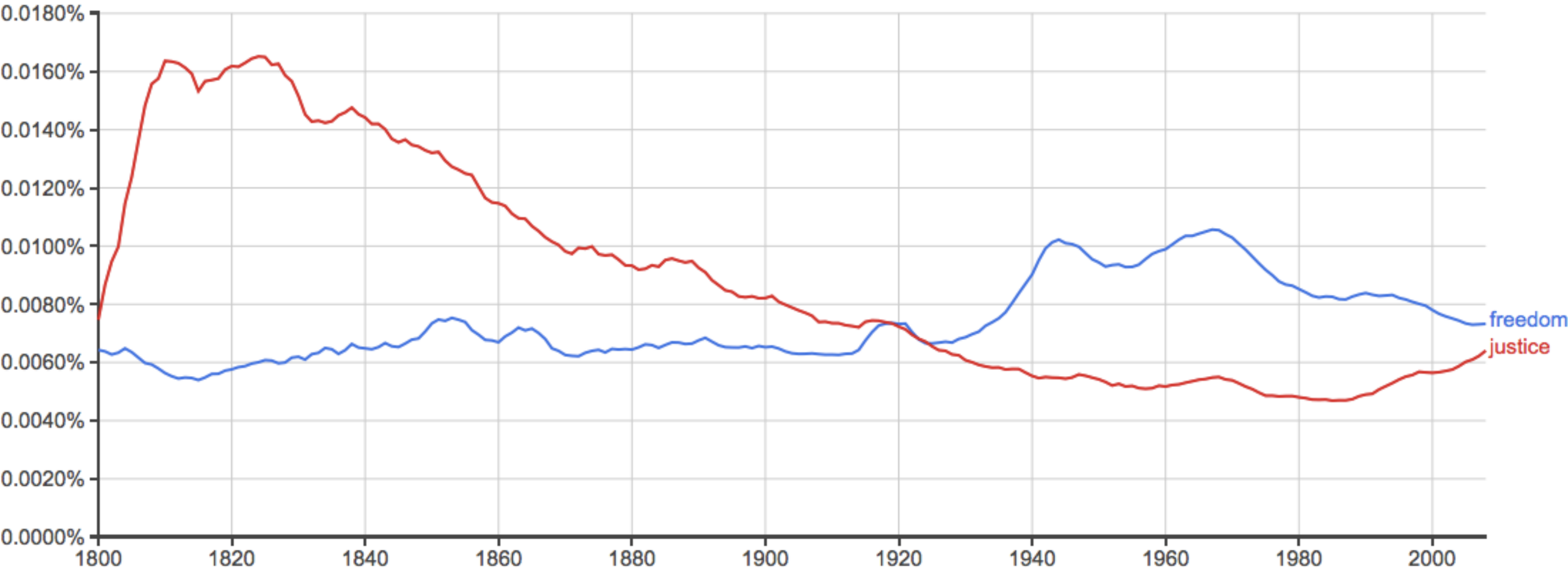
Padrões visuais

Como padrões visuais particulares podem ser úteis em determinados problemas?

Quais as técnicas capazes de evidenciar certos tipos de padrões mais efetivamente?

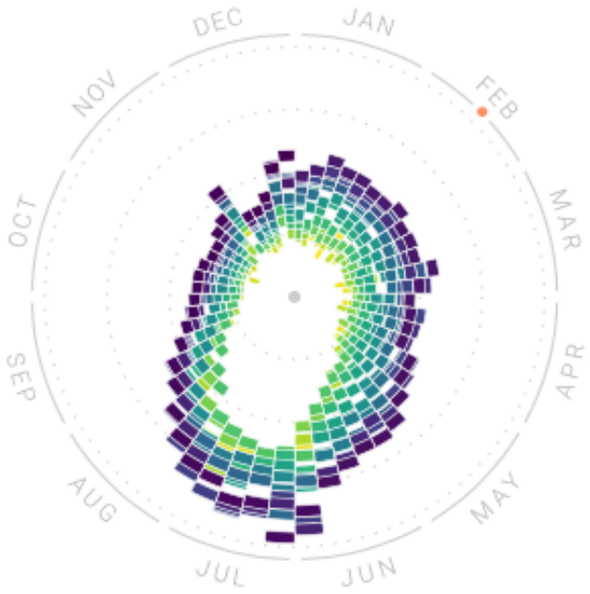




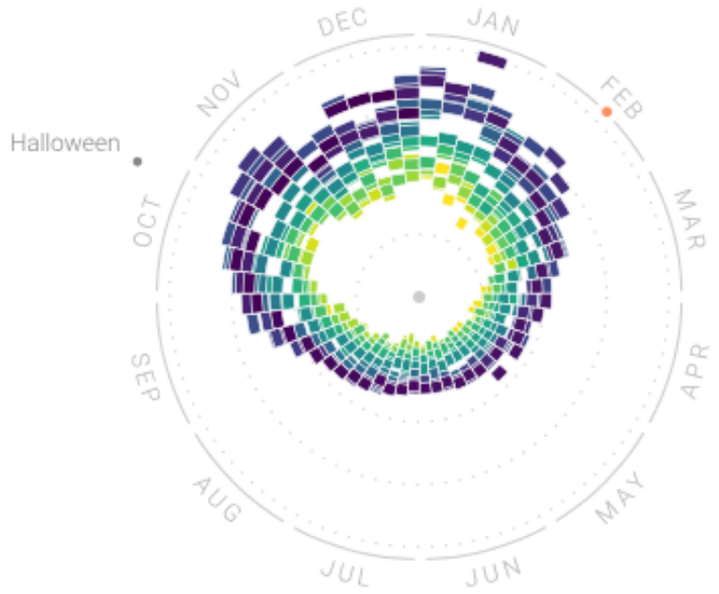
Google NGram Viewer

What are the most common patterns?

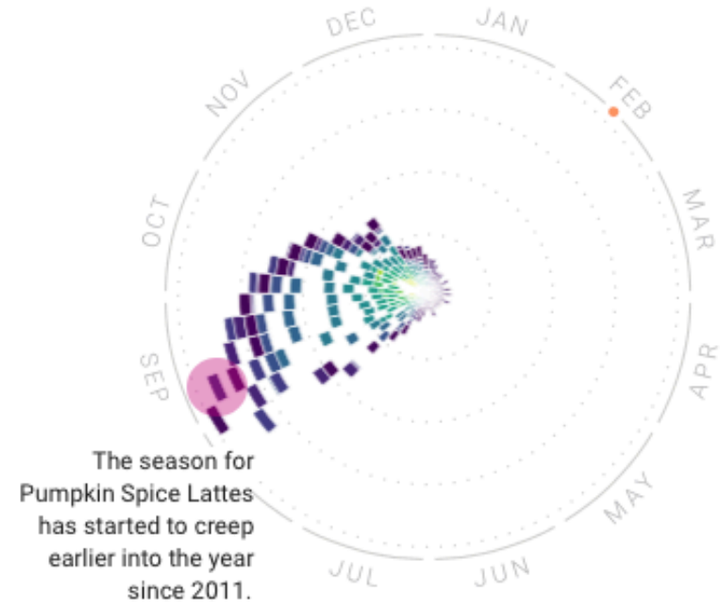
Some items fade in and out of a natural season.



BLUEBERRY



STEW



PUMPKIN SPICE LATTE

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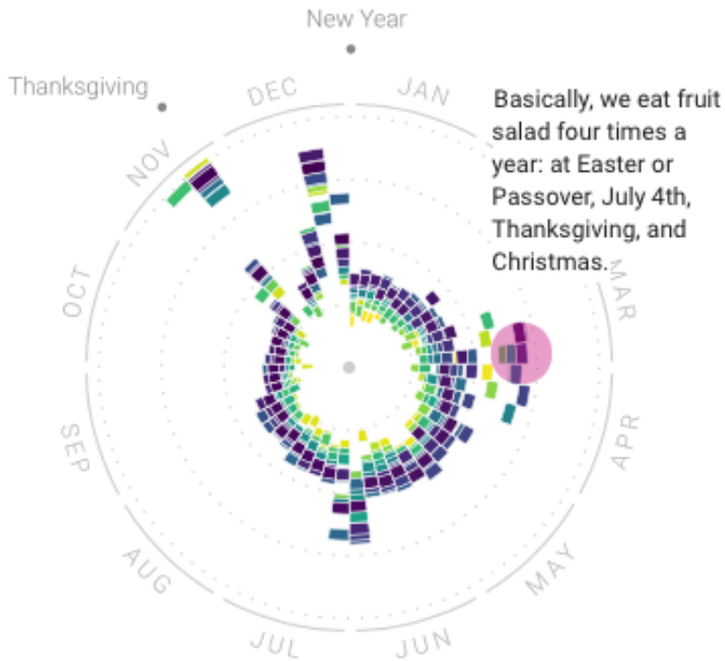
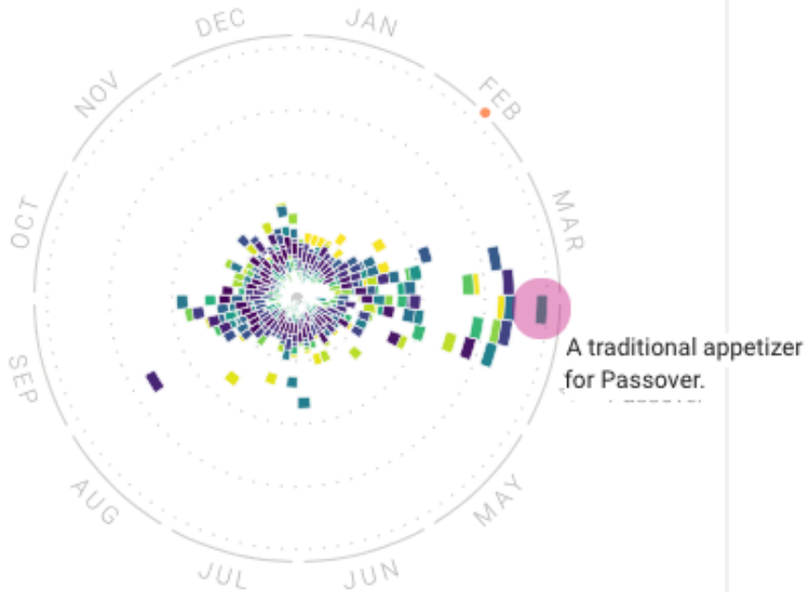
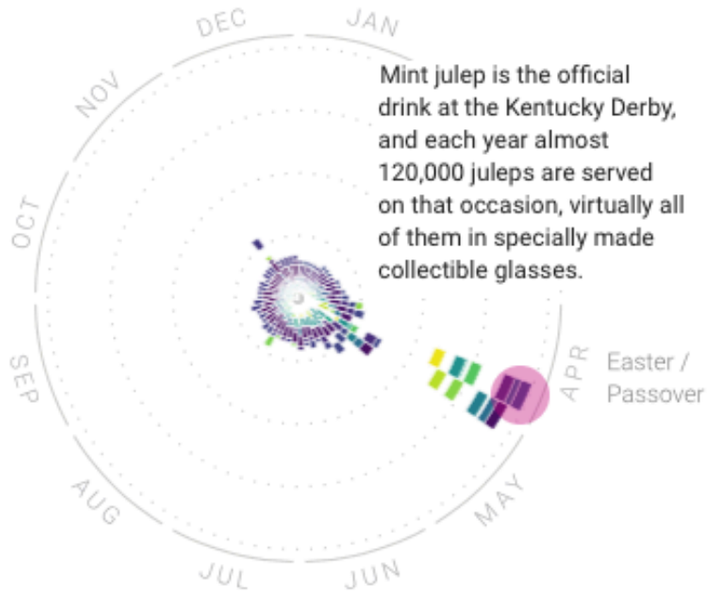
Others peak at holidays and special events.



FRUIT SALAD



GEFILTE FISH



MINT JULEP

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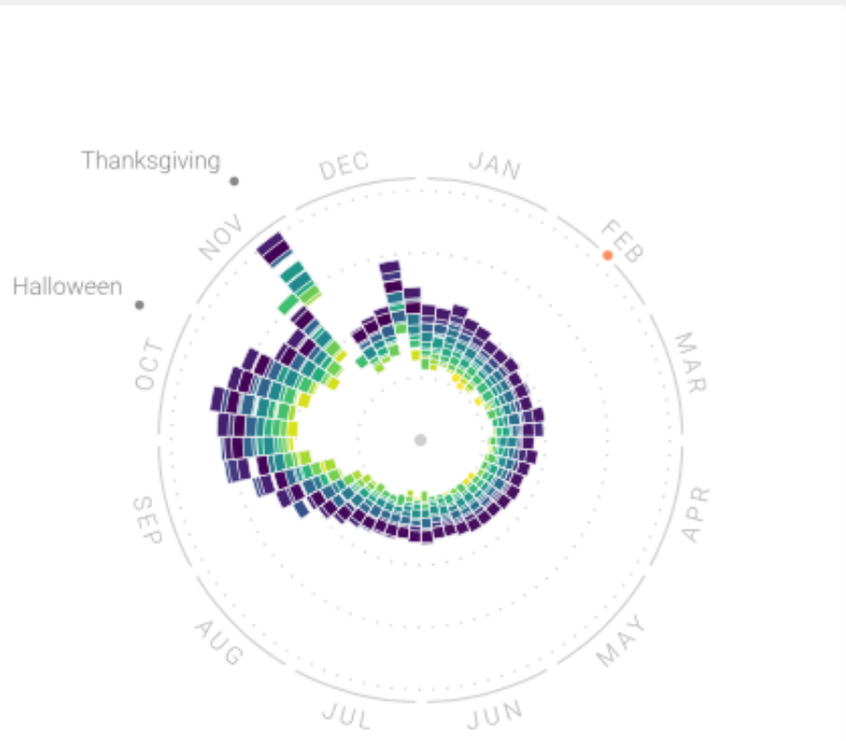
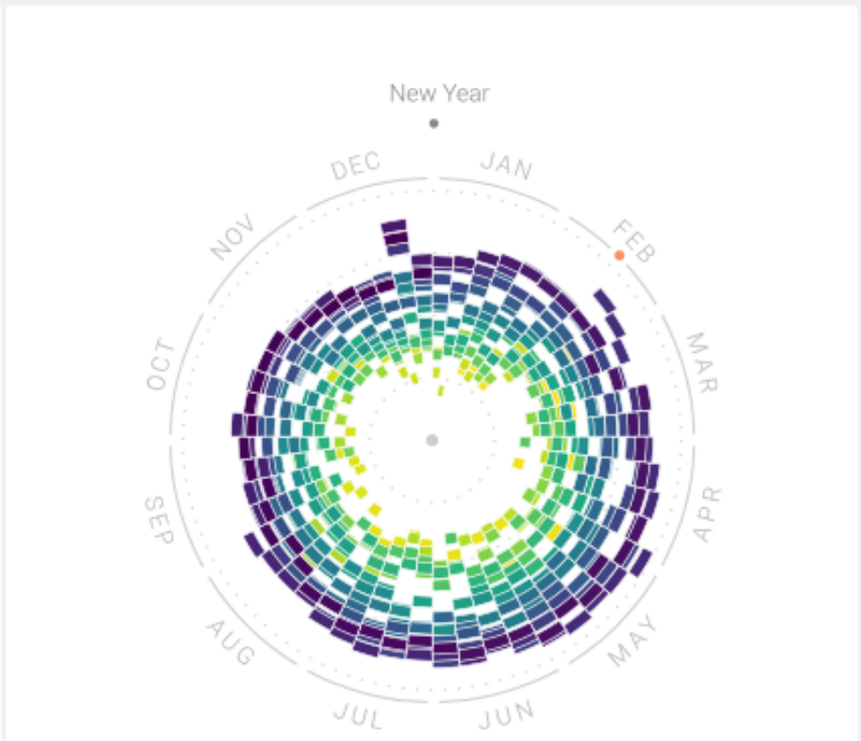
Of course, seasonality varies across the world, too!

Kale | **Apple** | Asparagus



APPLE



APPLE (AUSTRALIA)

APPLE (RUSSIA)

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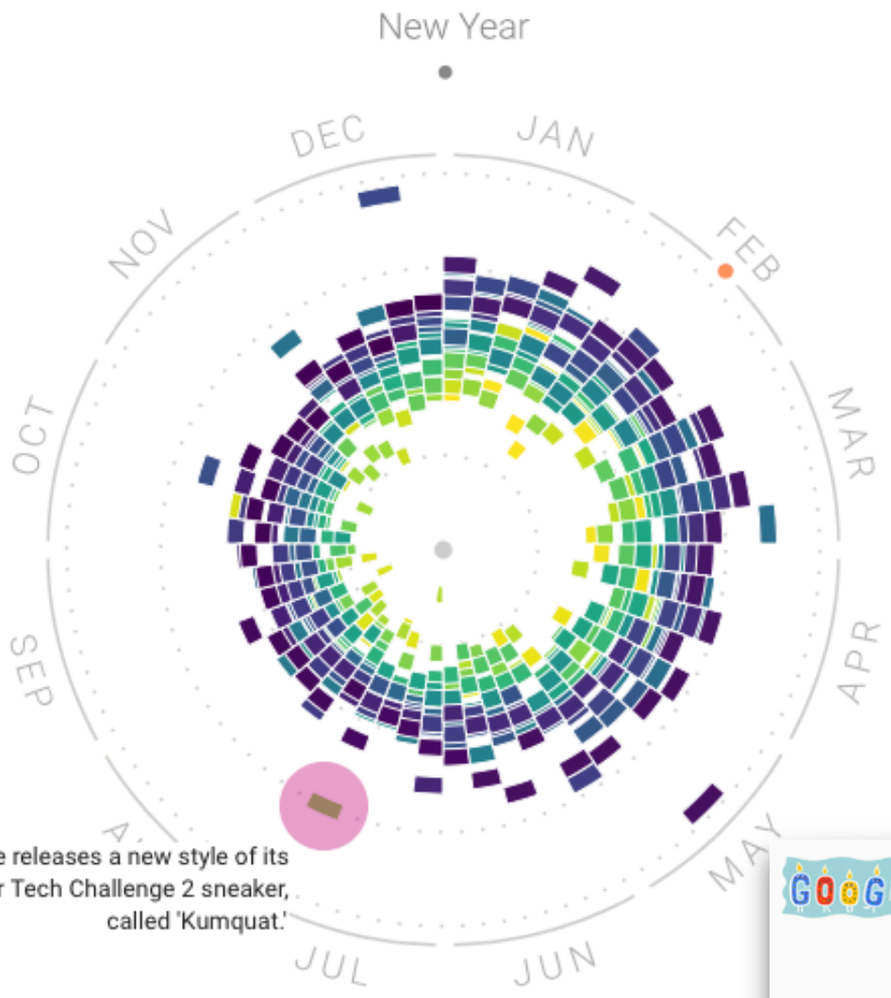


KUMQUAT

Fortunella

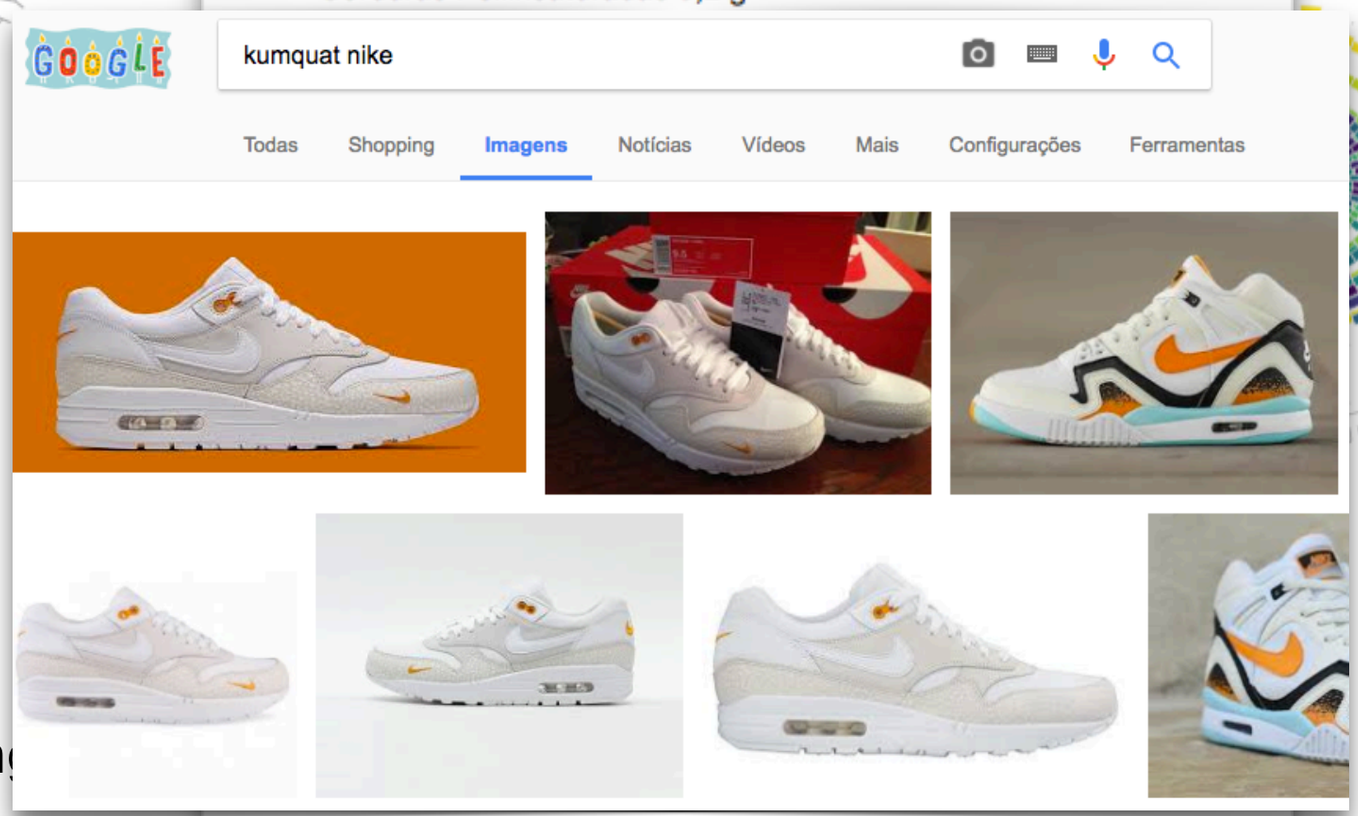
Fruto

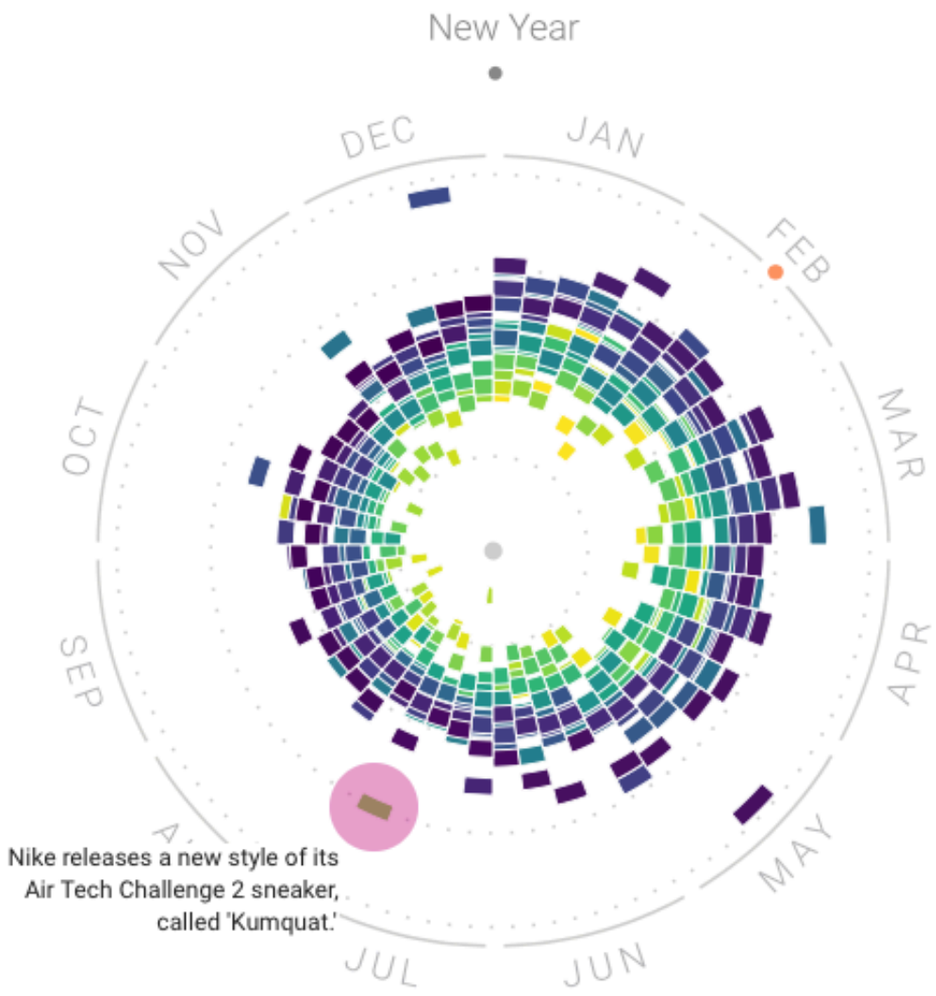
A Citrus japonica, conhecida pelos nomes comuns de quincã ou cunquate, ou ainda xinxim, é uma pequena fruta cítrica da família das rutáceas. Wikipédia

Informação Nutricional

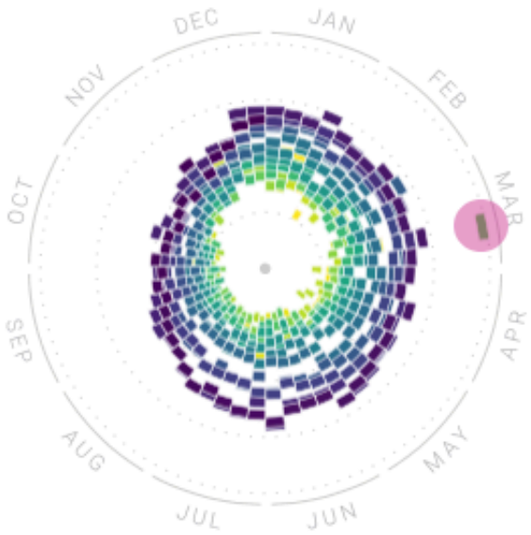
Laranjas kinkan

Quantidade por 100 gramas
Calorias 71
Gorduras Totais 0,9 g
Gorduras Saturadas 0,1 g
Gorduras Poliinsaturadas 0,2 g

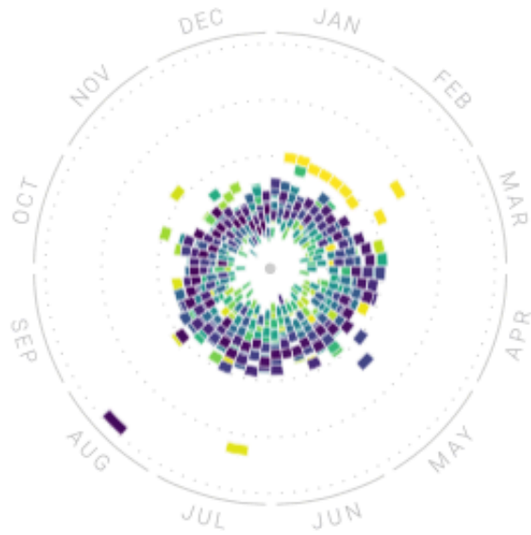




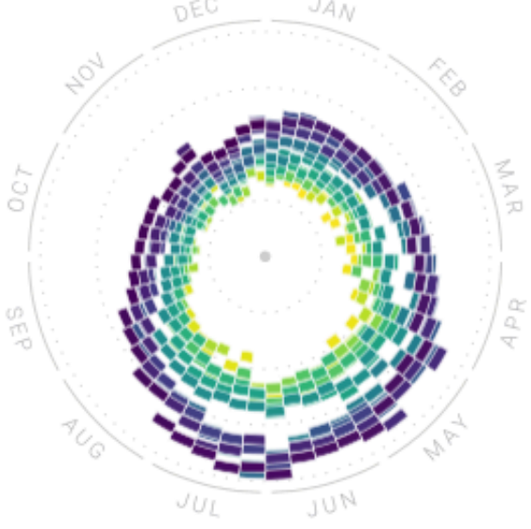
KUMQUAT



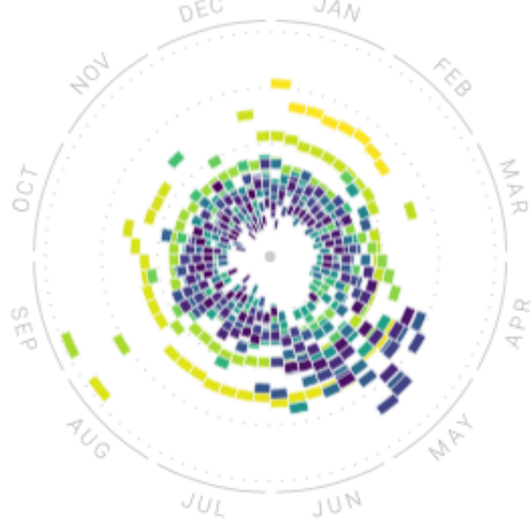
GRAPEFRUIT



FIG



MANGO



PLUM

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ALGUNS DOS OBJETIVOS DE UMA VISUALIZAÇÃO

- Identificar informações ocultas nos dados

- Identificar tendências

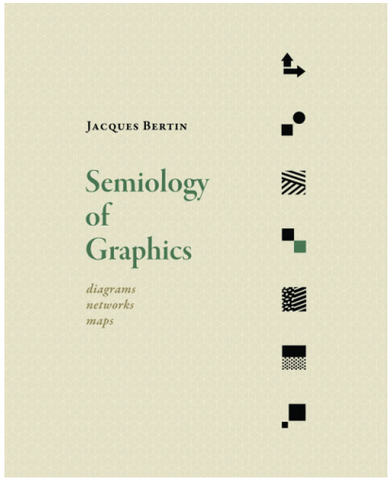
- Identificar exceções ou anomalias

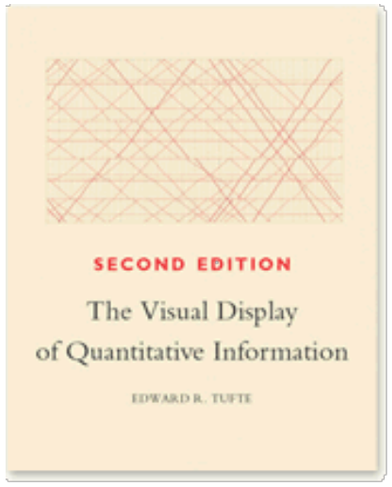
- Prever acontecimentos, dadas condições particulares, prevenindo problemas

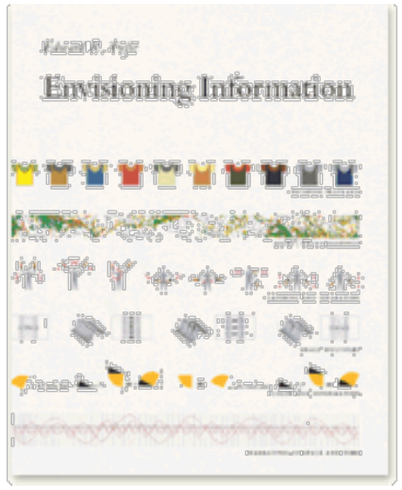
PARA QUE TIPO DE DADOS É INTERESSANTE

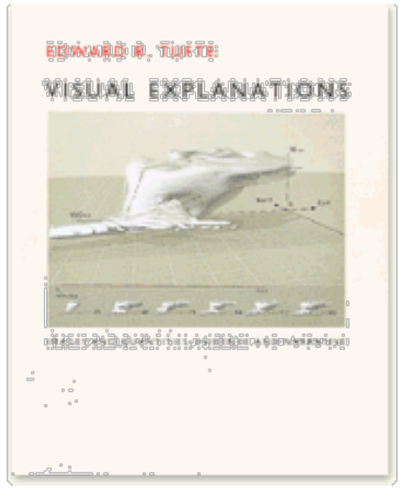
- Volume
- Histórico
- Consistente
- Multivariados
- Atômicos
- Limpos
- Claros
- Estruturados
- Ricamente segmentados
- De origem conhecida

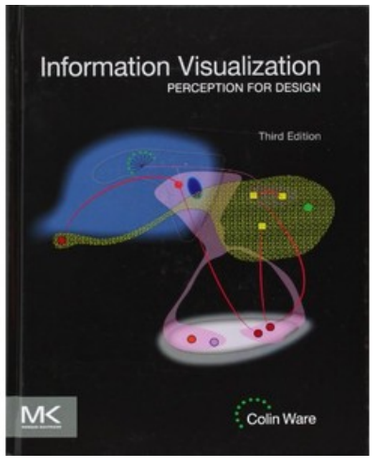
PRINCIPAIS REFERÊNCIAS

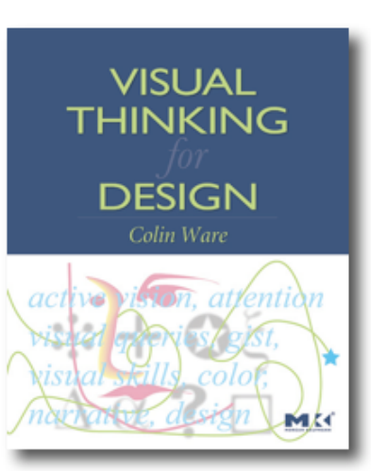


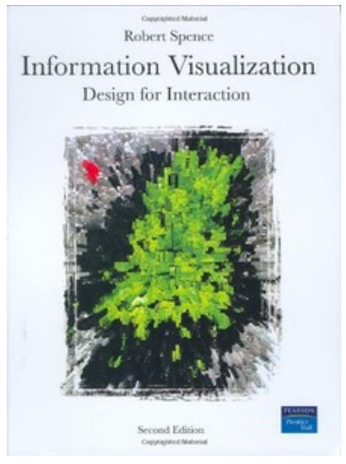


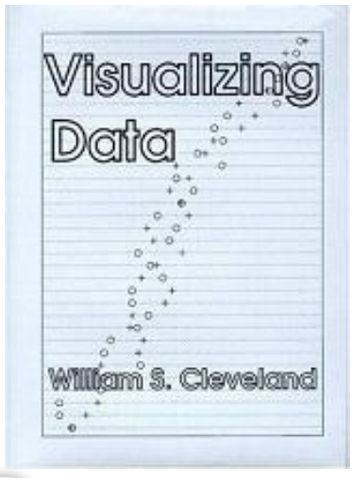


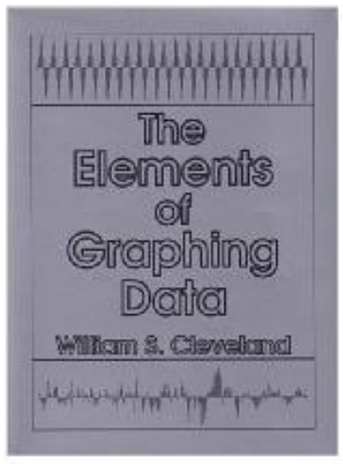


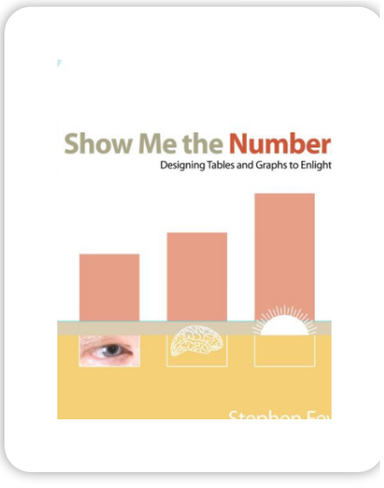


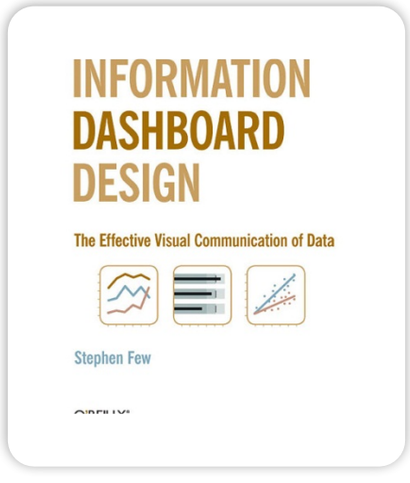


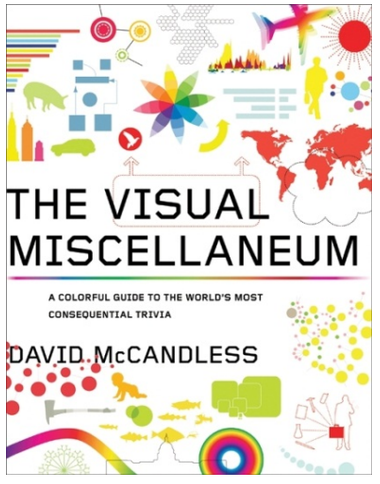


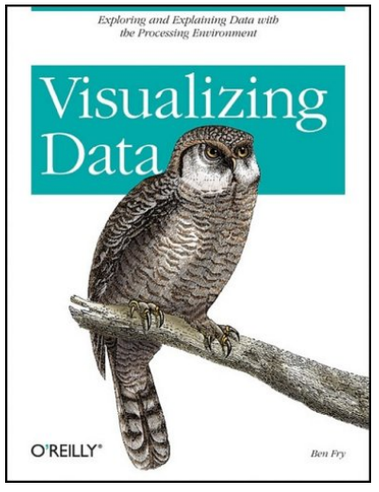












PUBLICAÇÕES ACADÊMICAS

- IEEE Transactions of Visualization and Computer Graphics
- VisWeek / InfoVis - IEEE Information Visualization Conference
- Mas há também o VAST / SciVis / etc

- IV - International Conference on Information Visualization
- Eurographics - IEEE VGTC Symposium of Visualization

POSSÍVEIS RESULTADOS

- Participação em competições
- Publicação de artigos
- Mostra / concurso de visualizações
- Outros