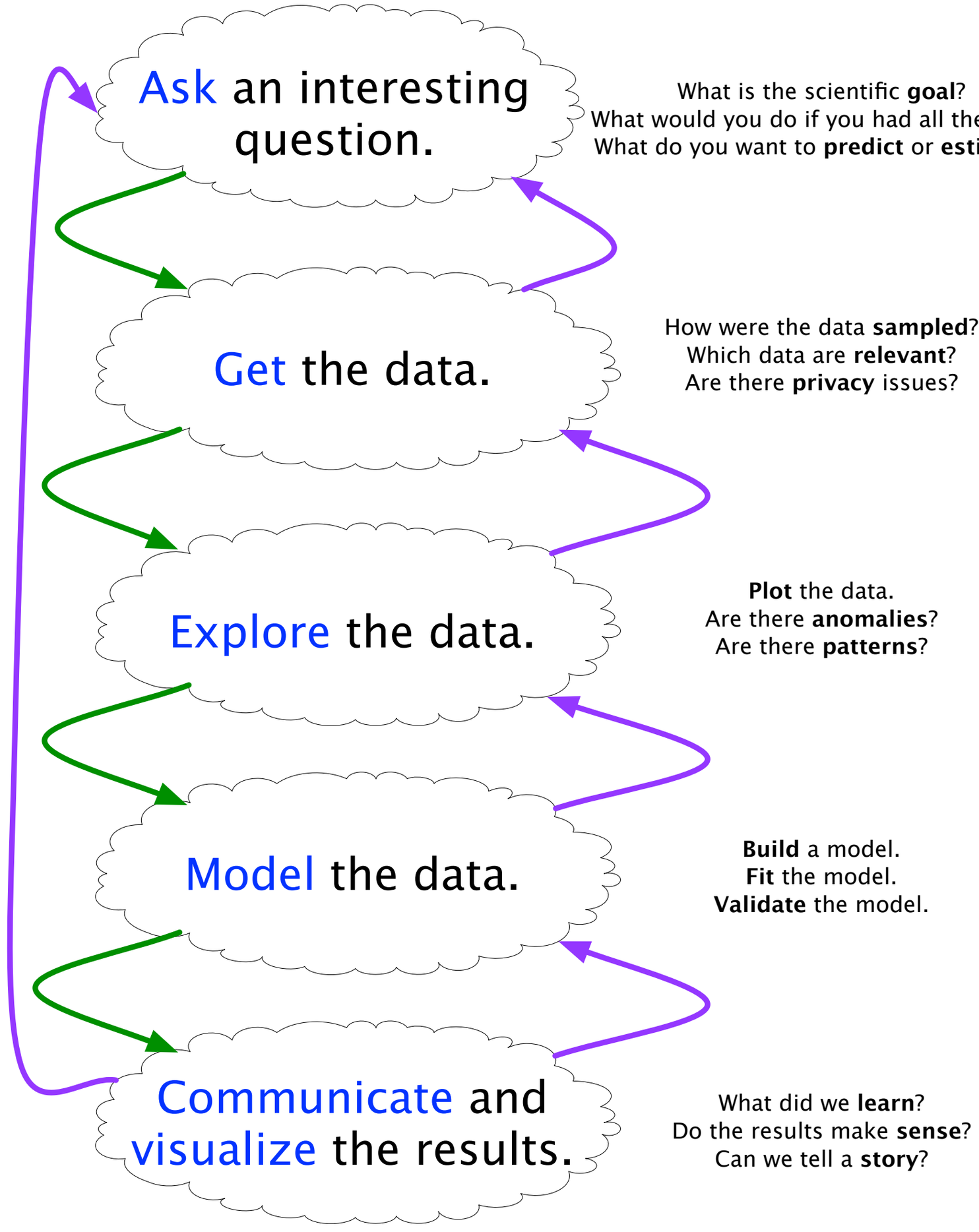
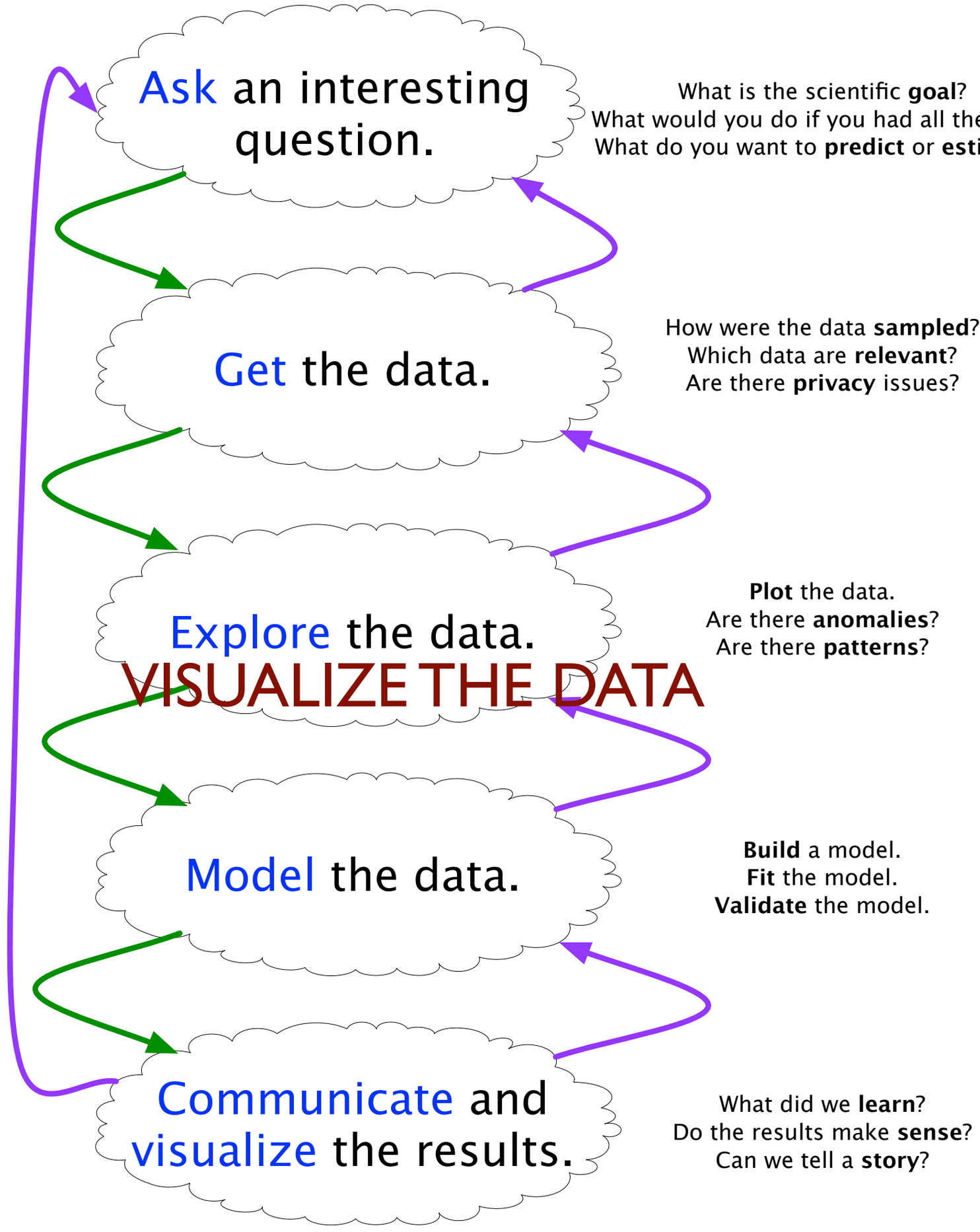
CS 109a: Data Science
Effective Exploratory Data Analysis and Visualization

Pavlos Protopapas, Kevin Rader, Rahul Dave, Margo Levine


Ask an interesting question.
What is the scientific **goal**?
What would you do if you had all the **data**?
What do you want to **predict** or **estimate**?
Get the data.
How were the data **sampled**?
Which data are **relevant**?
Are there **privacy** issues?
Explore the data.
Plot the data.
Are there **anomalies**?
Are there **patterns**?
Model the data.
Build a model.
Fit the model.
Validate the model.
Communicate and visualize the results.
What did we **learn**?
Do the results make **sense**?
Can we tell a **story**?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How were the data **sampled**?
Which data are **relevant**?
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Explore the data.
VISUALIZE THE DATA
Plot the data.
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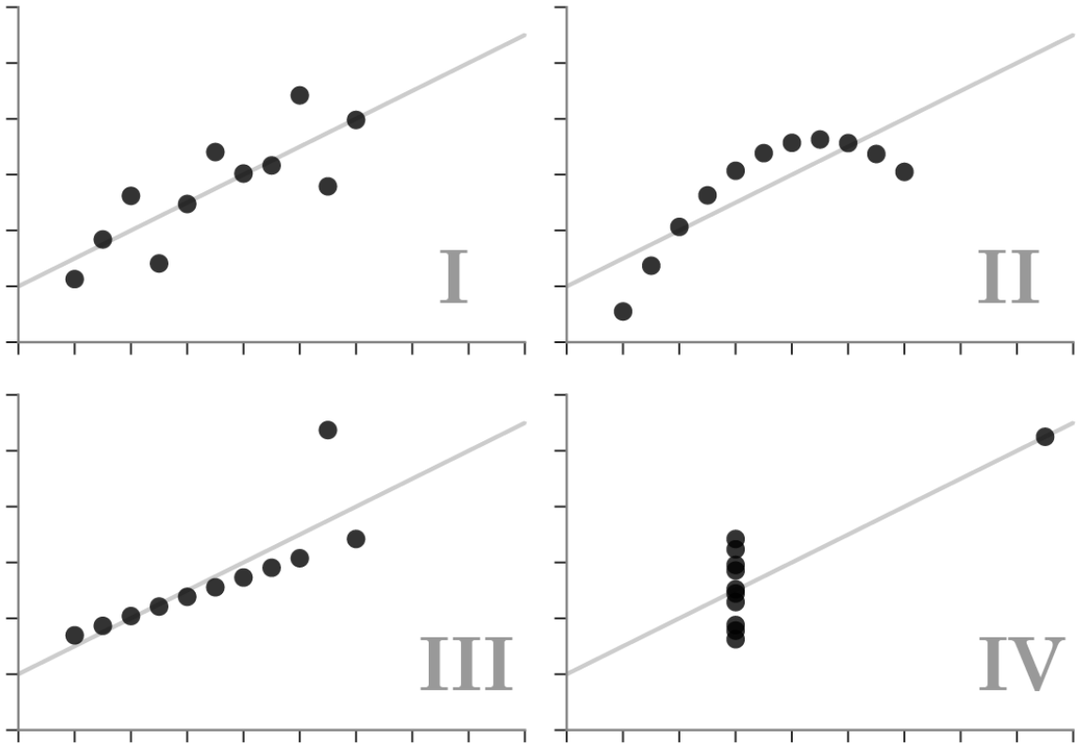
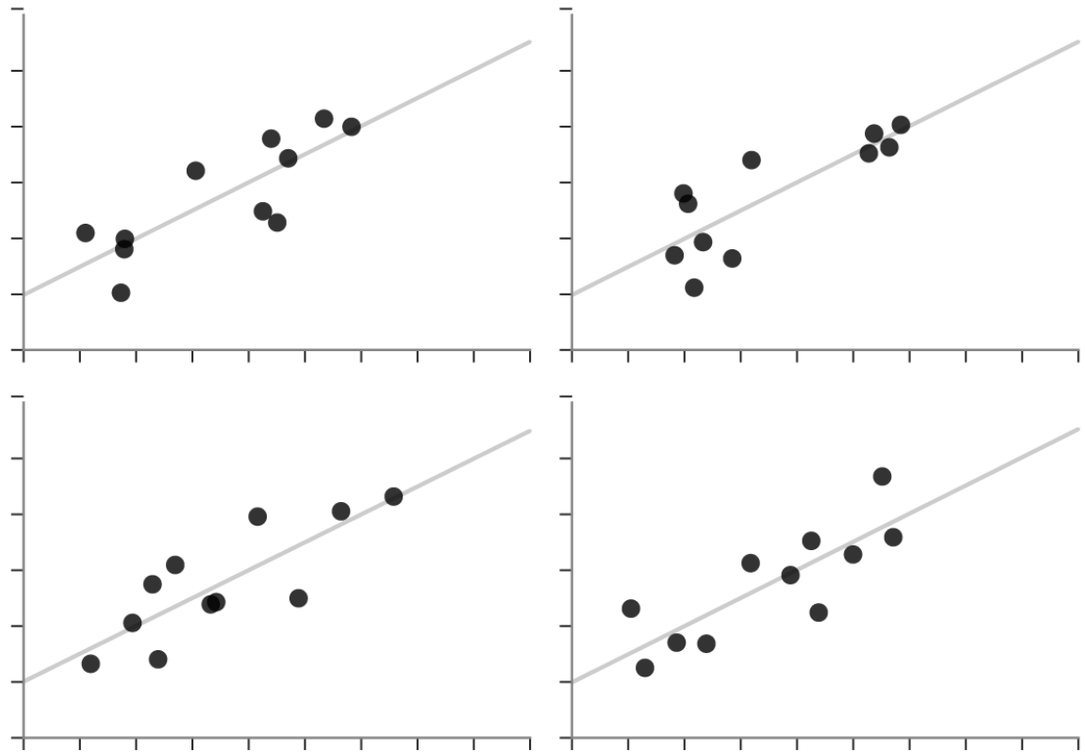
Anscombe's Quartet

Each dataset has the same summary statistics (mean, standard deviation, correlation), and the datasets are *clearly different*, and *visually distinct*.



Unstructured Quartet

Each dataset here also has the same summary statistics. However, they are not *clearly different* or *visually distinct*.



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

https://www.autodeskresearch.com/publications/samestats

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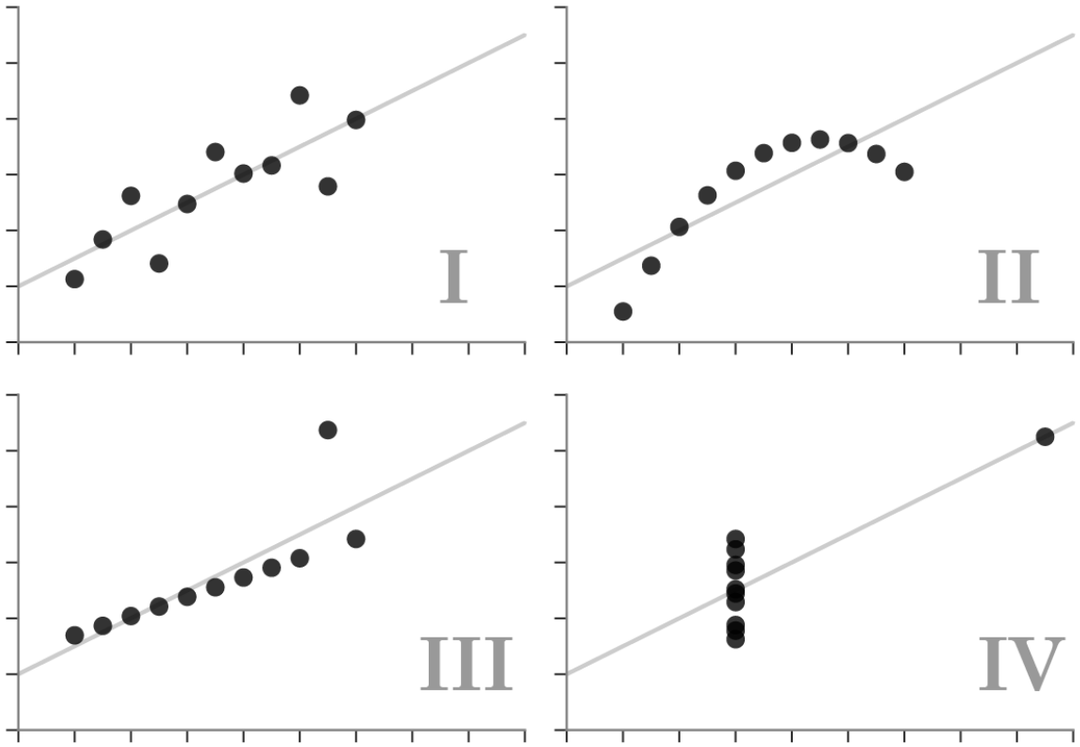

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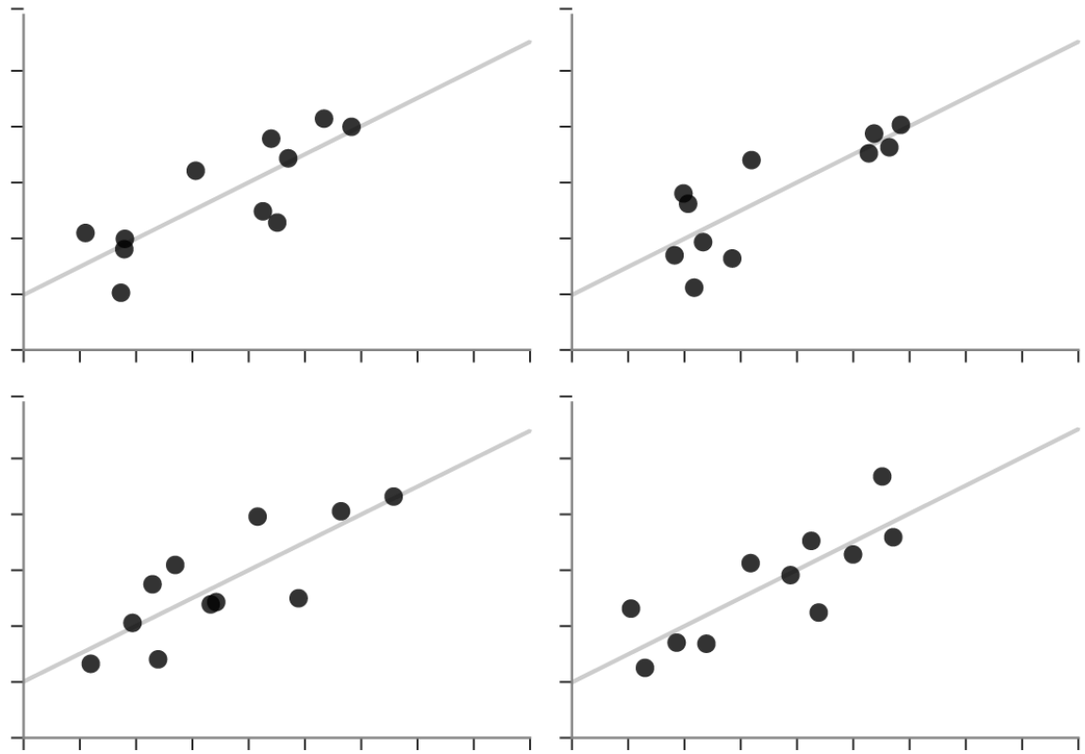

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Example: Antibiotics

Will Burtin, 1951

Data

Table 1: Burtin's data.

Bacteria	Antibiotic			Gram Staining
	Penicillin	Streptomycin	Neomycin	
Aerobacter *aerogenes*	870	1	1.6	negative
Brucella *abortus*	1	2	0.02	negative
Brucella *anthracis*	0.001	0.01	0.007	positive
Diplococcus *pneumoniae*	0.005	11	10	positive
Escherichia *coli*	100	0.4	0.1	negative
Klebsiella *pneumoniae*	850	1.2	1	negative
Mycobacterium *tuberculosis*	800	5	2	negative
Proteus *vulgaris*	3	0.1	0.1	negative
Pseudomonas *aeruginosa*	850	2	0.4	negative
Salmonella (Eberthella) *typhosa*	1	0.4	0.008	negative
Salmonella *schottmuelleri*	10	0.8	0.09	negative
Staphylococcus *albus*	0.007	0.1	0.001	positive
Staphylococcus *aureus*	0.03	0.03	0.001	positive
Streptococcus *fecalis*	1	1	0.1	positive
Streptococcus *hemolyticus*	0.001	14	10	positive
Streptococcus *viridans*	0.005	10	40	positive

Data

Genus, *Species*

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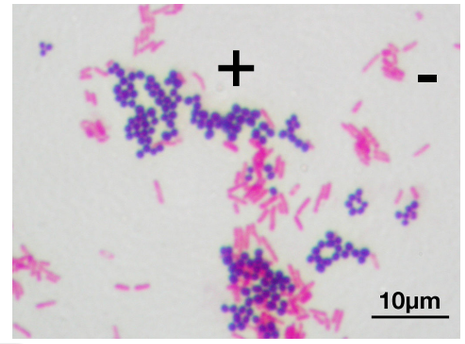

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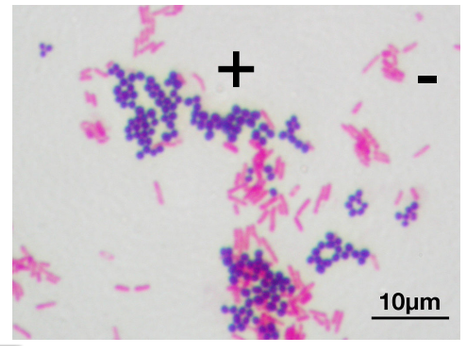

Genus, *Species*

Min. Inhibitory Concentration [ml/g]

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What Questions?

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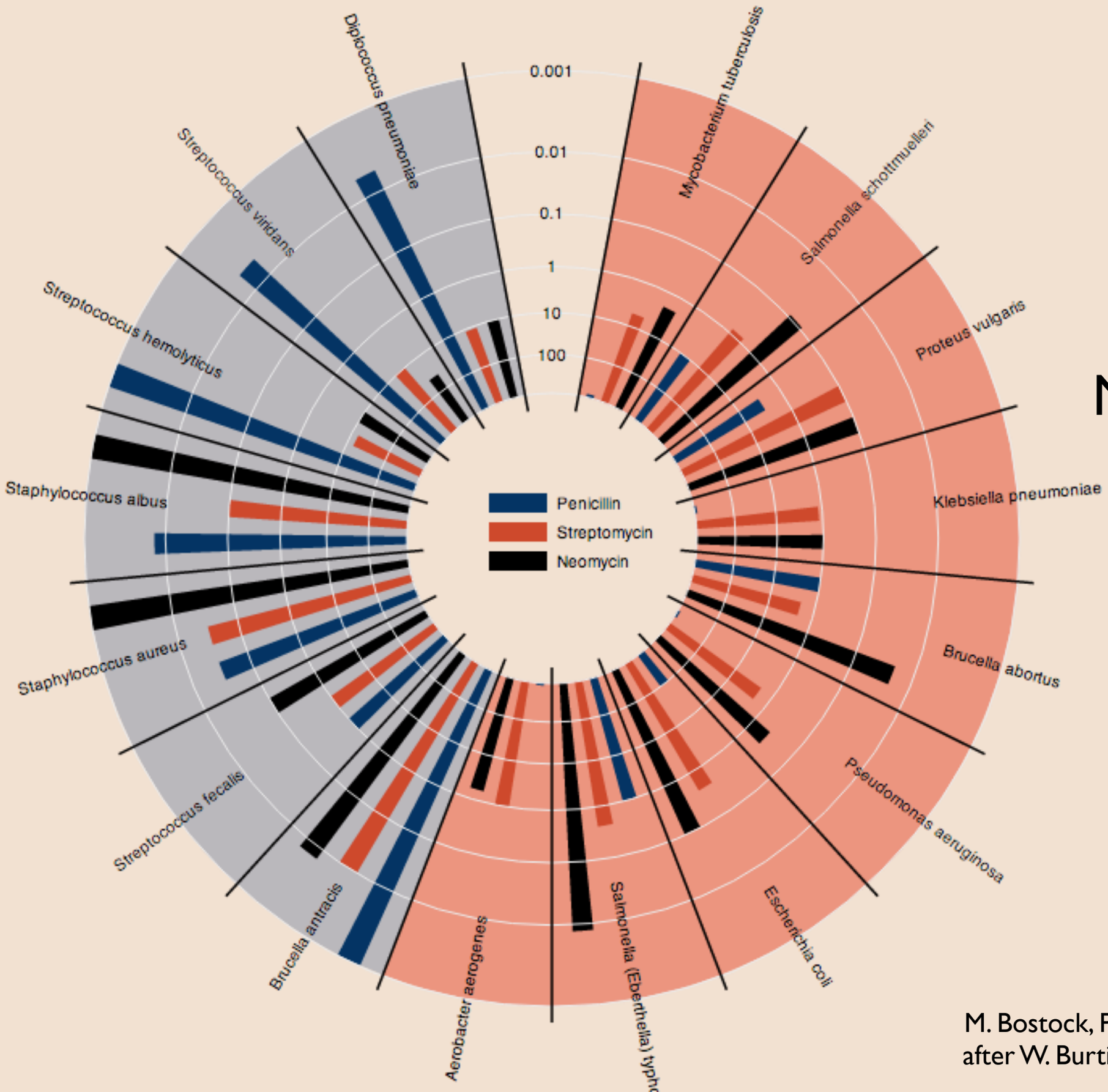
Gram Positive



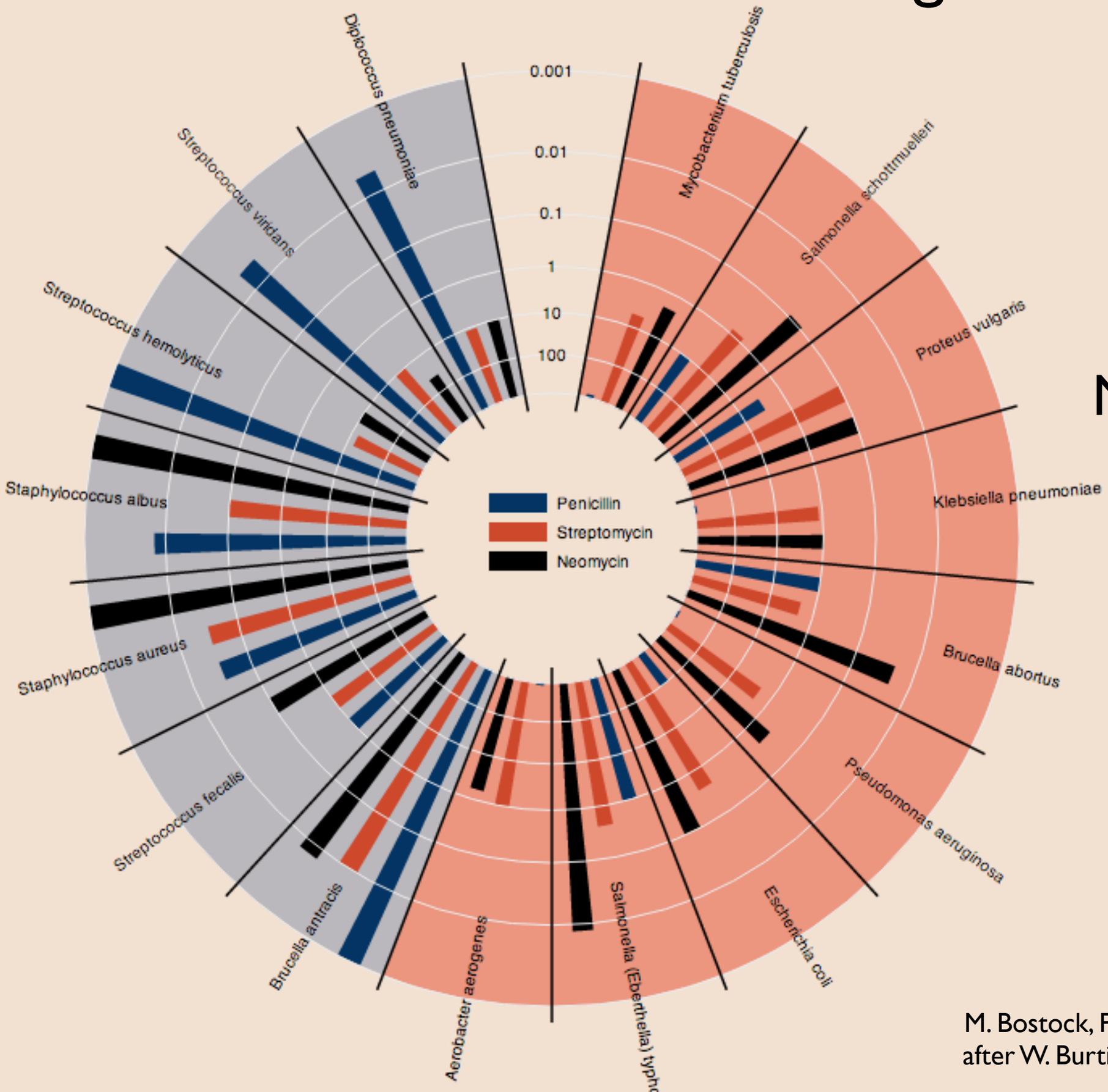
Gram Negative

M. Bostock, Protovis after W. Burtin, 1951

How effective are the drugs?

Gram Positive

Gram Negative



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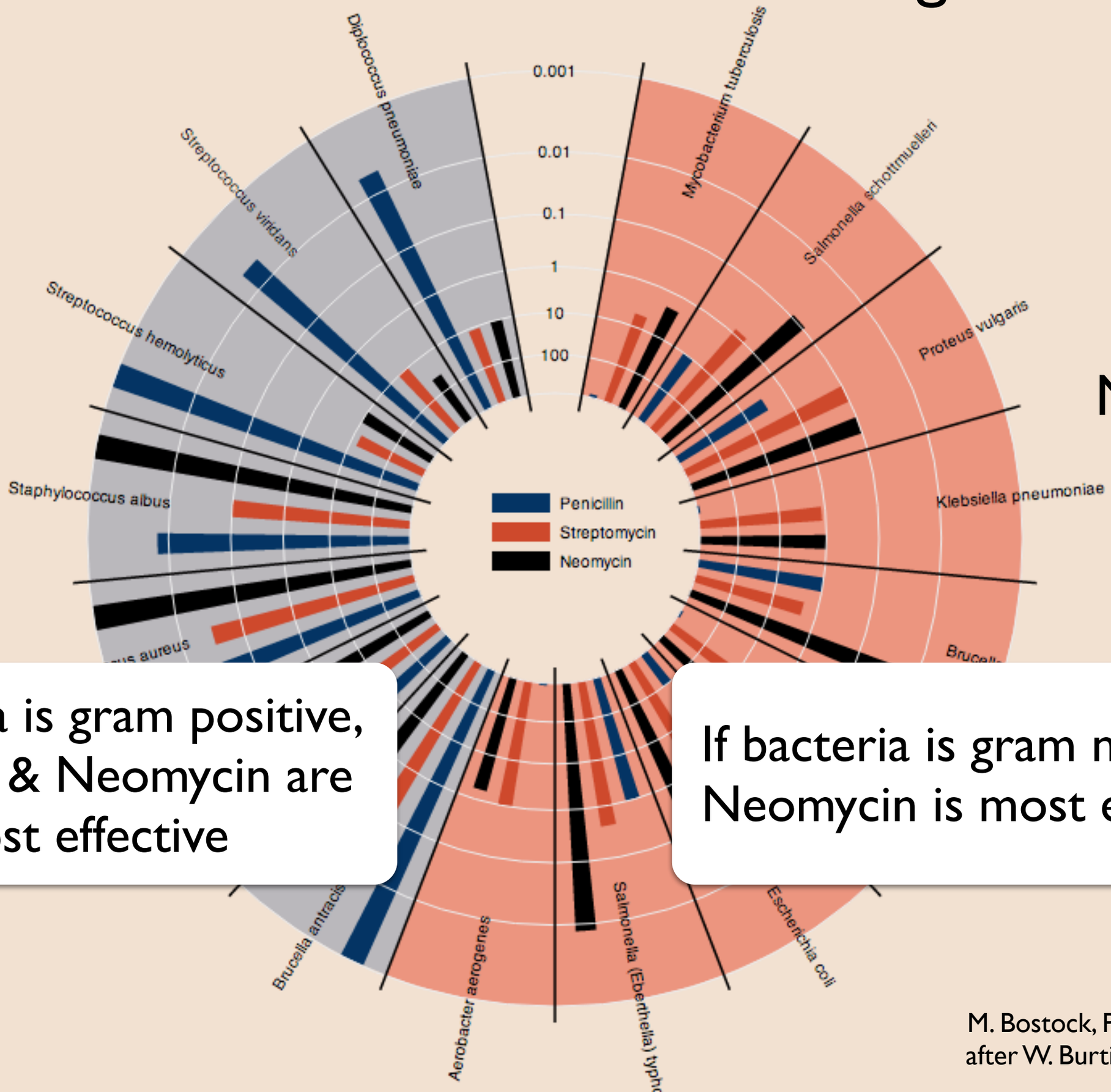
Gram Positive

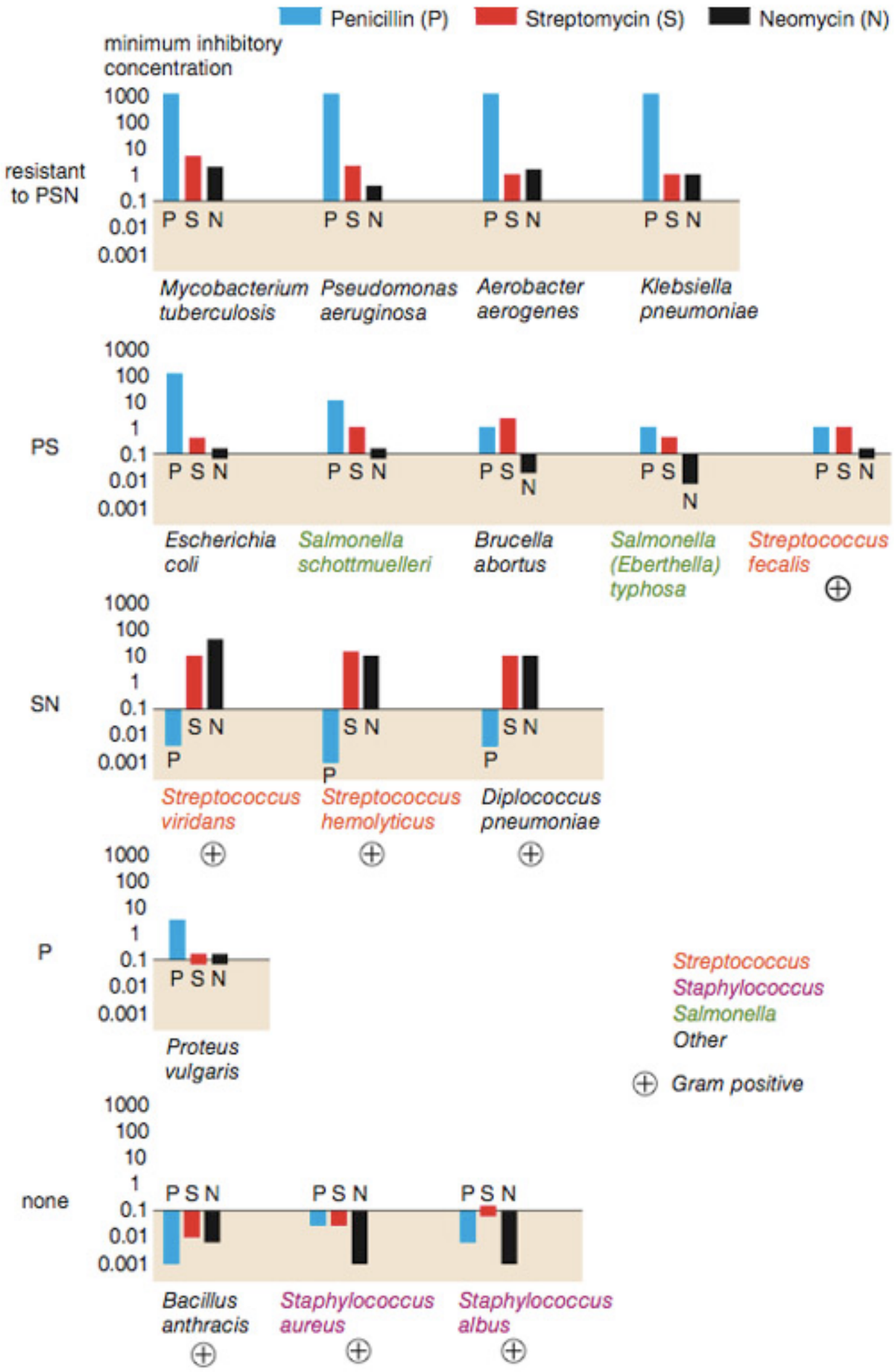
Gram Negative



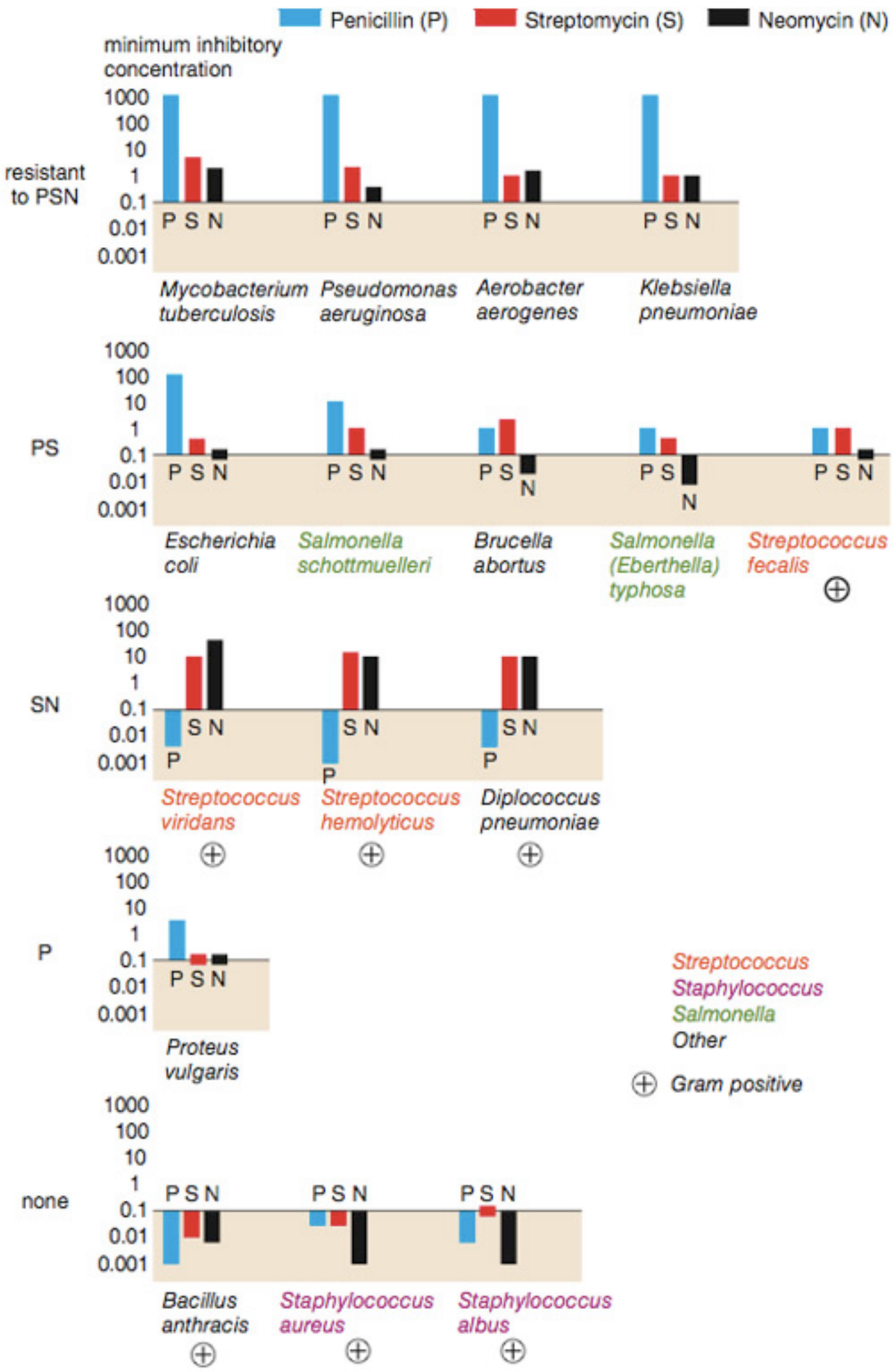
If bacteria is gram positive, Penicillin & Neomycin are most effective

If bacteria is gram negative, Neomycin is most effective

M. Bostock, Protovis after W. Burtin, 1951



Wainer & Lysen, "That's funny..."
American Scientist, 2009
Adapted from Brian Schmotzer



How do the bacteria compare?

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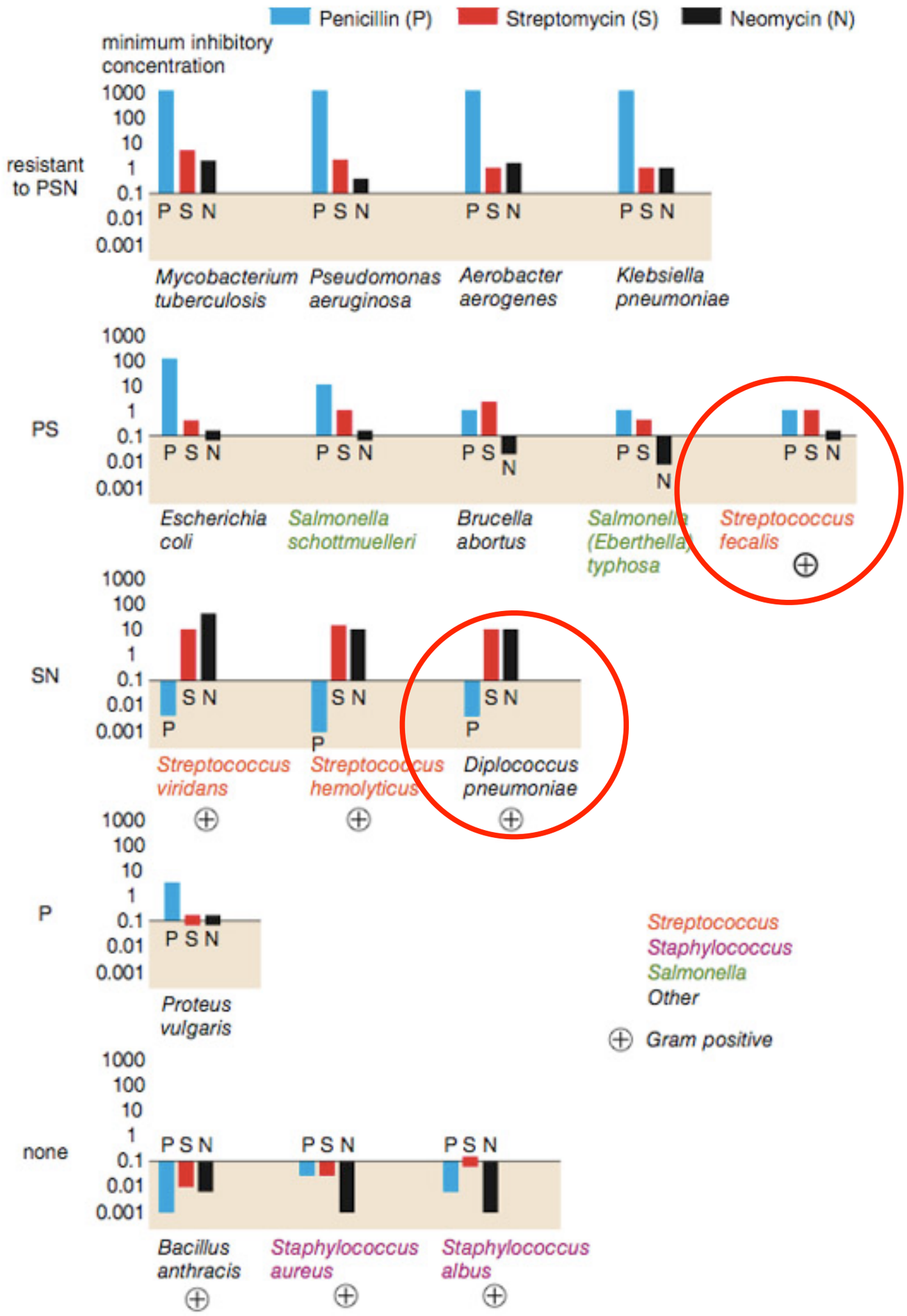

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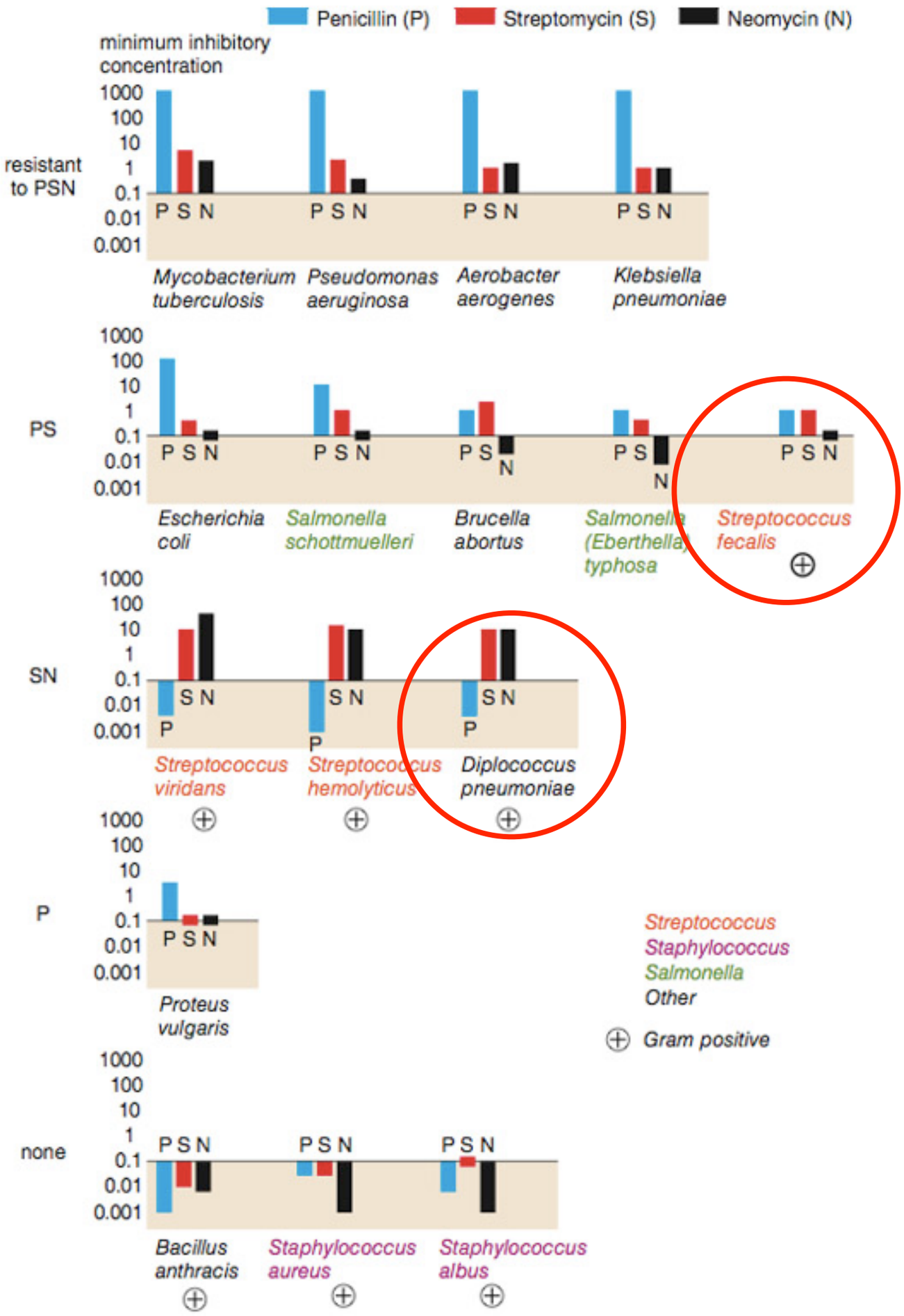

How do the bacteria compare?

Not a streptococcus!
(realized ~30 years later)

Really a streptococcus!
(realized ~20 years later)

Wainer & Lysen, "That's funny..."
American Scientist, 2009
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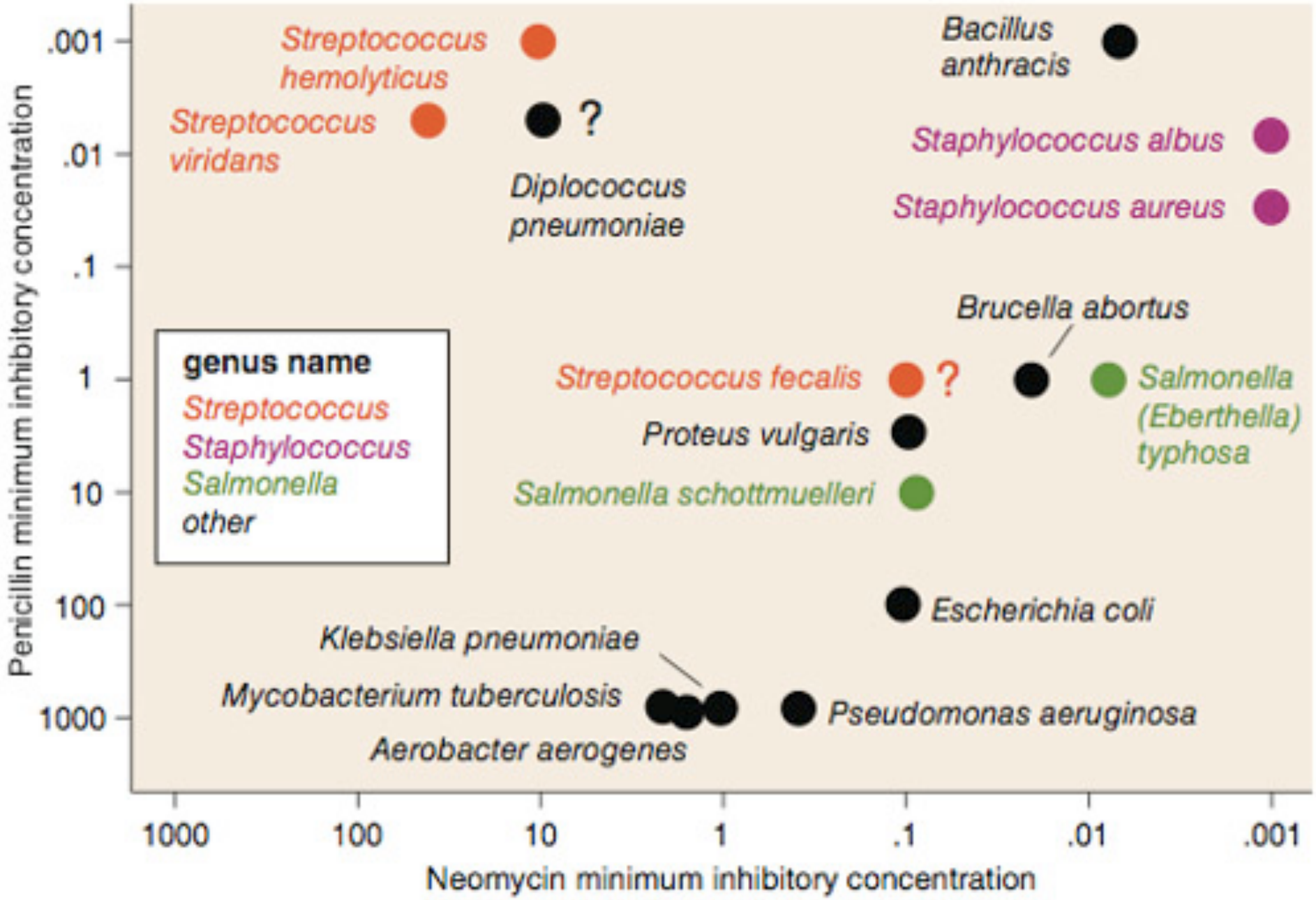
How do the bacteria compare?



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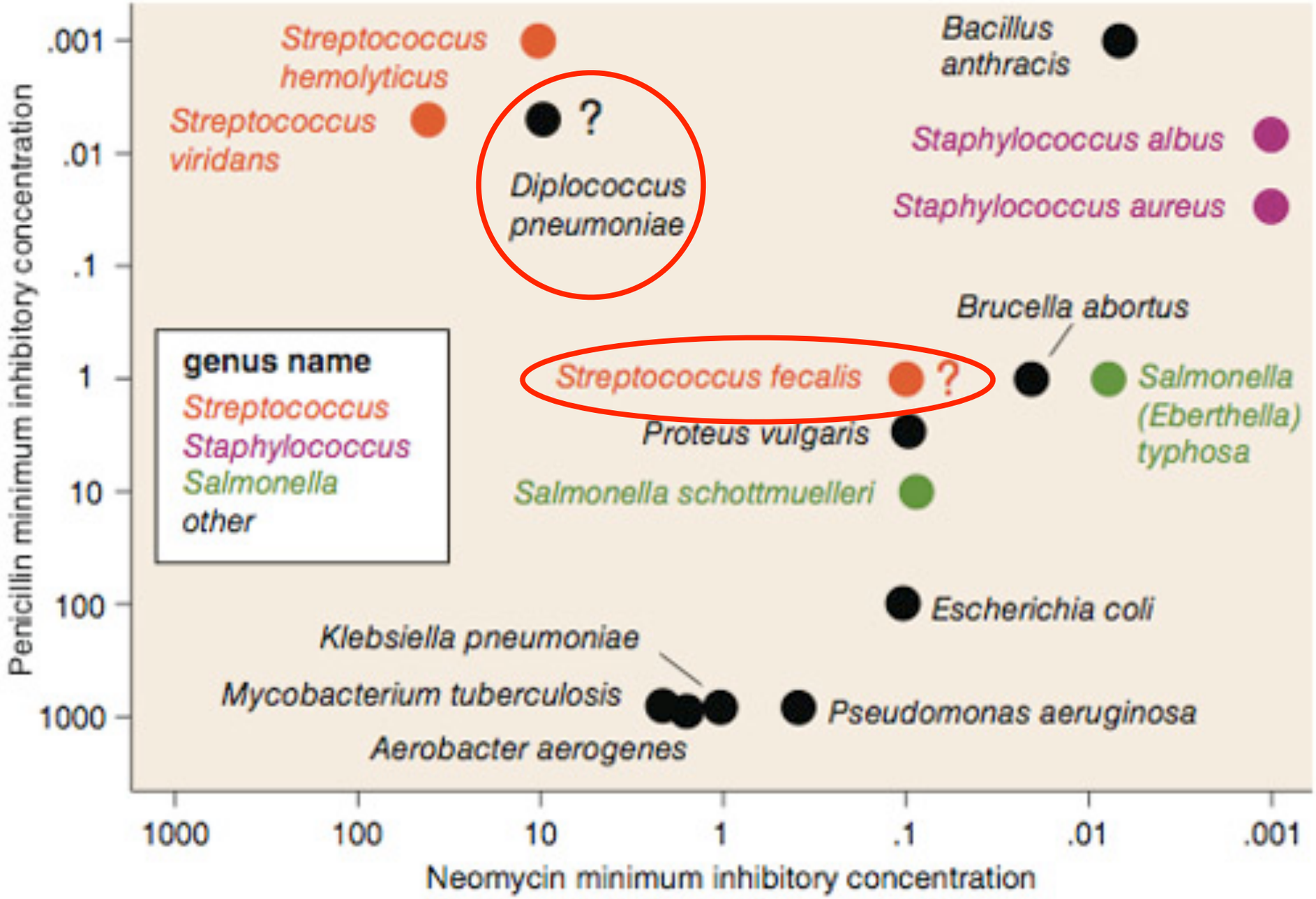

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American Scientist, 2009

Exploratory Data Analysis

"The greatest value of a picture is when it forces us to notice what we never expected to see."

John Tukey

Visualization Goals

Communicate (Explanatory)

Present data and ideas

Explain and inform

Provide evidence and support

Influence and persuade

Analyze (Exploratory)

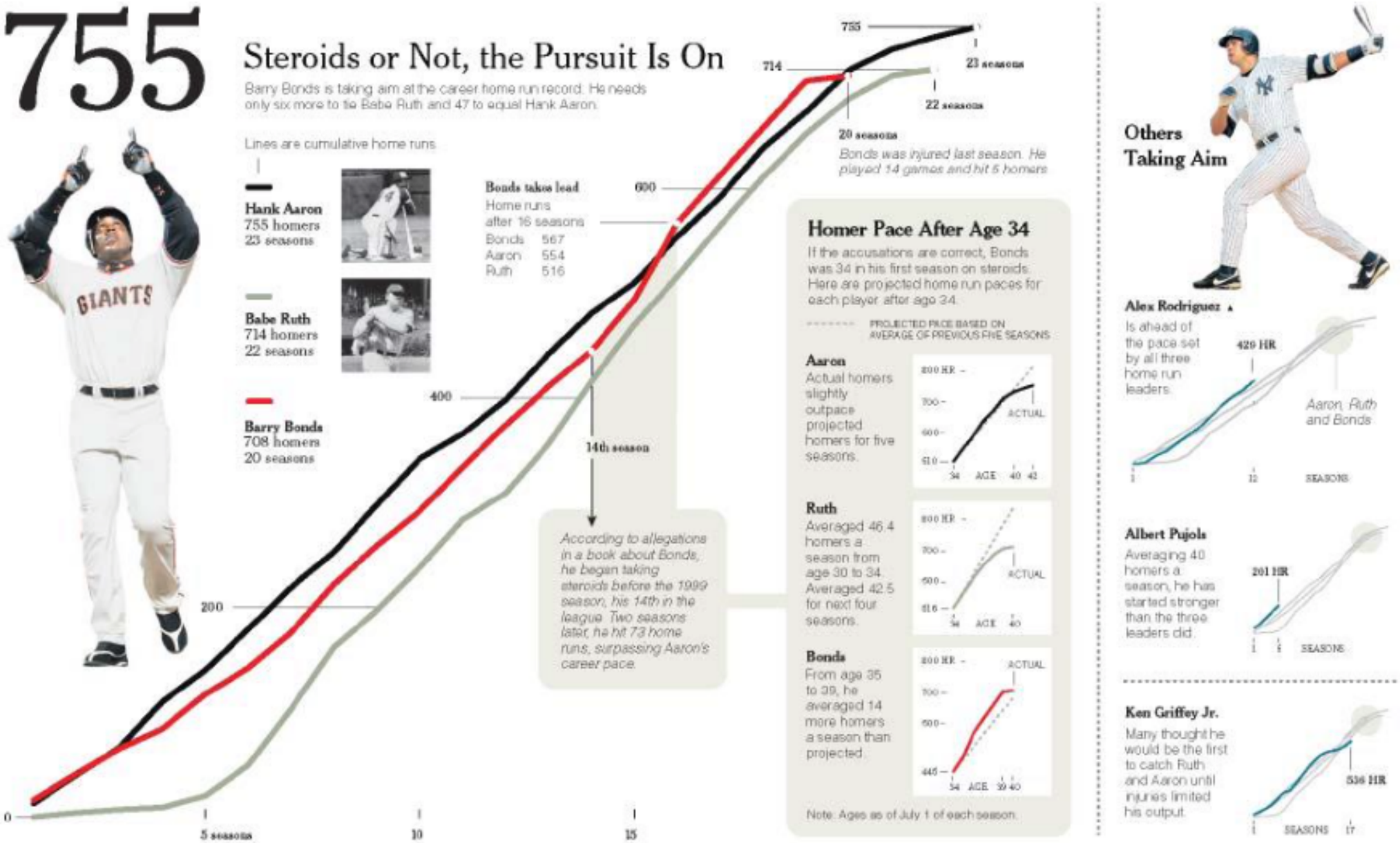
Explore the data

Assess a situation

Determine how to proceed

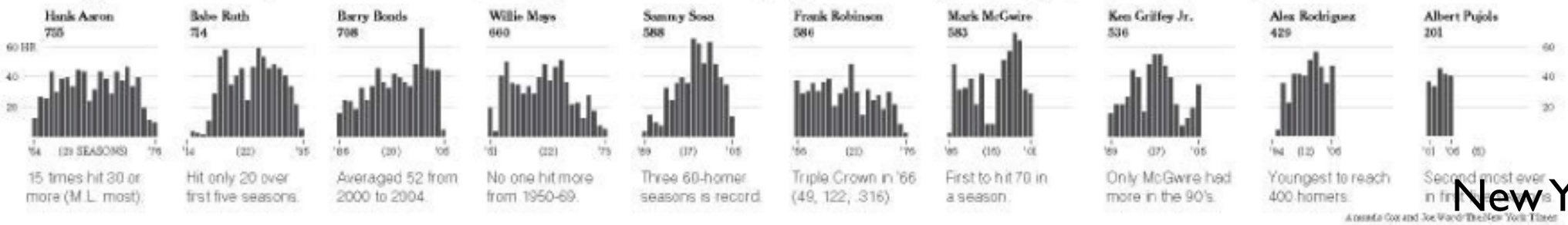
Decide what to do

Communicate



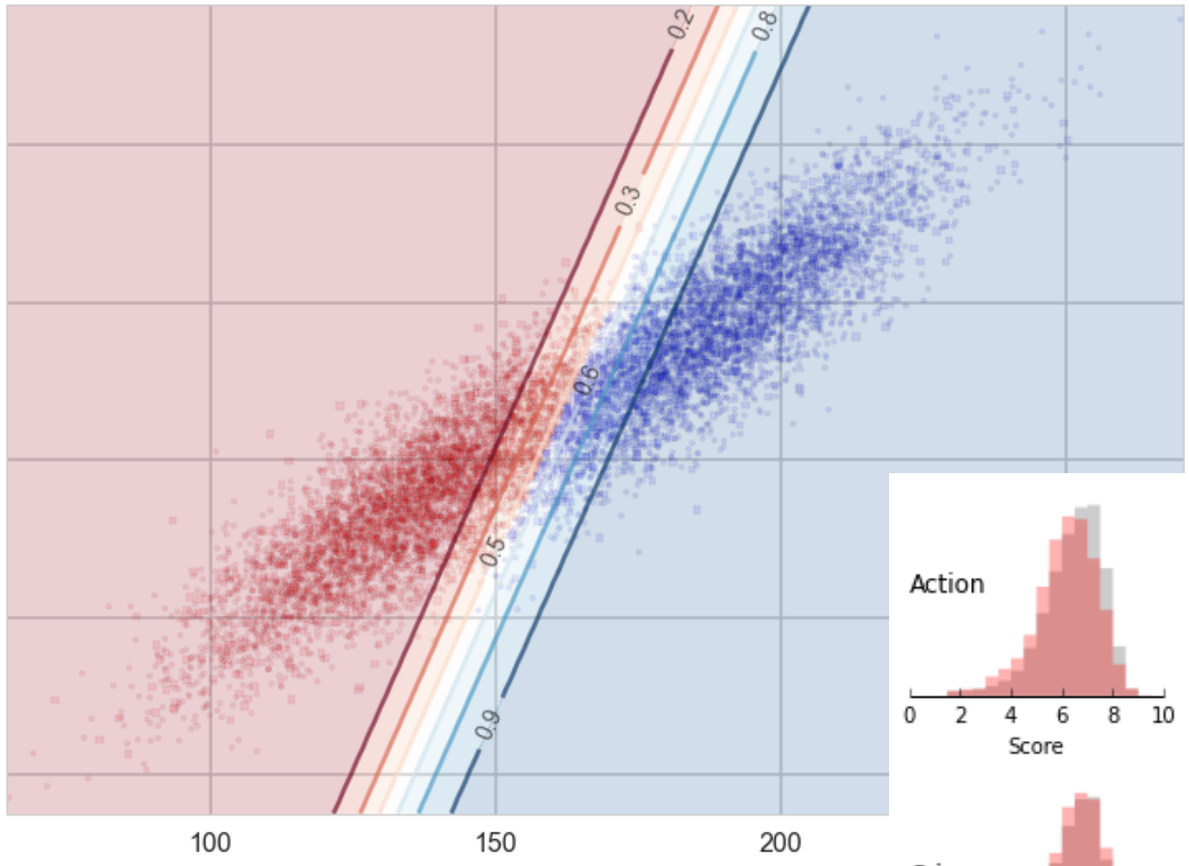
Differing Paths to the Top of the Charts

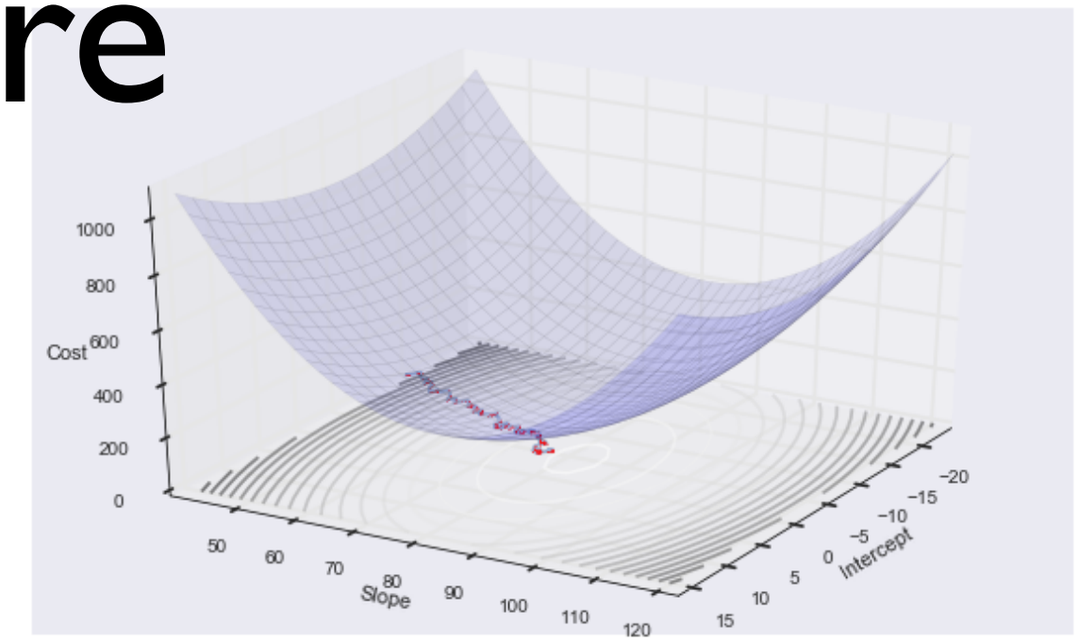
The top seven players on the career home run list, along with a look at Griffey (12th), Rodriguez (37th) and Pujols (tied 257th)

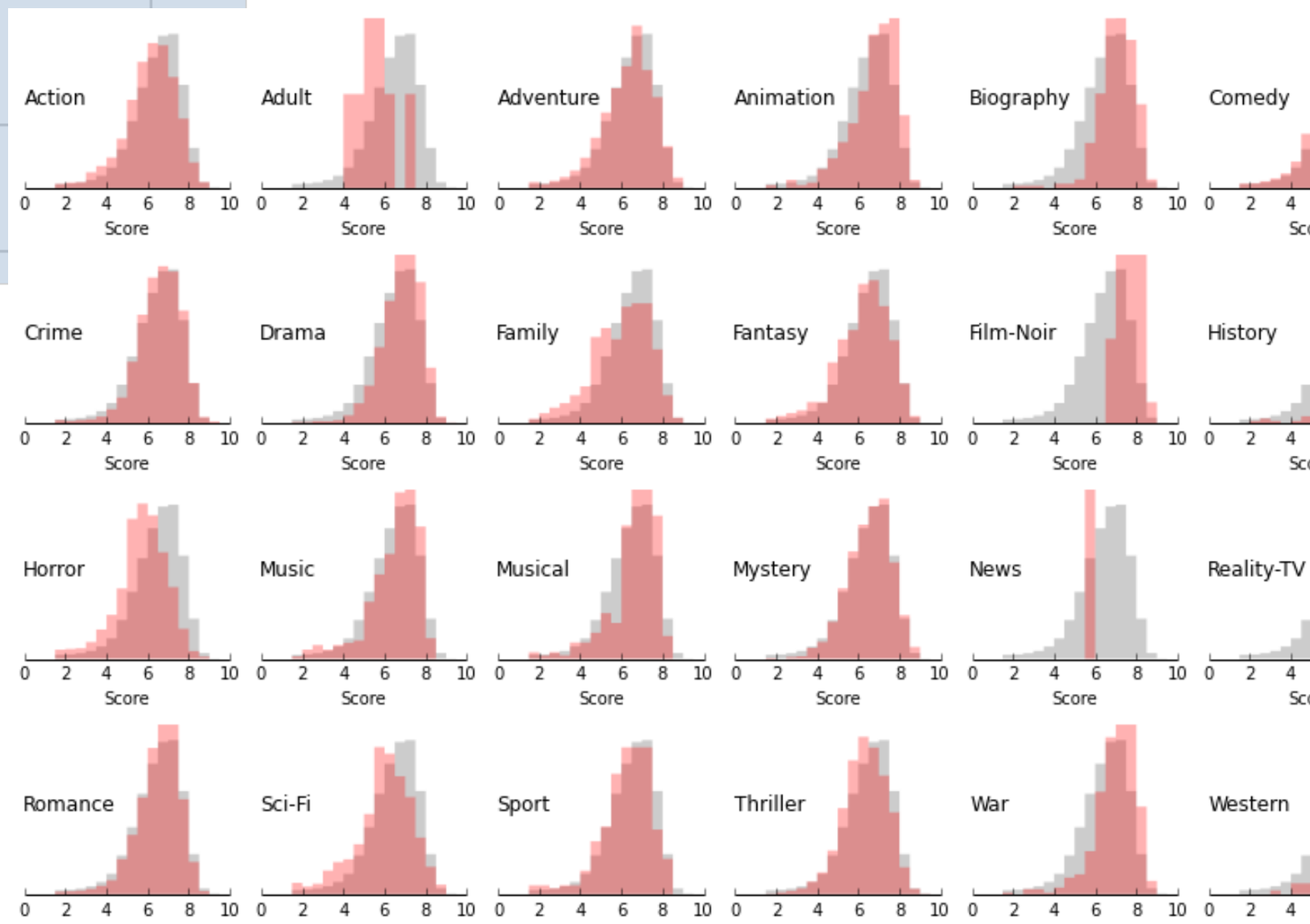


New York Times

Explore


0.2
0.3
0.5
0.6
0.8
0.9
75
70
65
60
55
100
150
200


Cost
1000
800
600
400
200
0
50
60
70
80
90
100
110
120
Slope
15
10
5
0
−5
−10
−15
−20
Intercept


Action
Adult
Adventure
Animation
Biography
Comedy
Crime
Drama
Family
Fantasy
Film-Noir
History
Horror
Music
Musical
Mystery
News
Reality-TV
Romance
Sci-Fi
Sport
Thriller
War
Western
0 2 4 6 8 10
Score

EDA Workflow

1. **Build** a DataFrame from the data (ideally, put all data in this object)
2. **Clean** the DataFrame. It should have the following properties
    - Each row describes a single object
    - Each column describes a property of that object
    - Columns are numeric whenever appropriate
    - Columns contain atomic properties that cannot be further decomposed
3. Explore **global properties**. Use histograms, scatter plots, and aggregation functions to summarize the data.
4. Explore **group properties**. Use groupby and small multiples to compare subsets of the data.

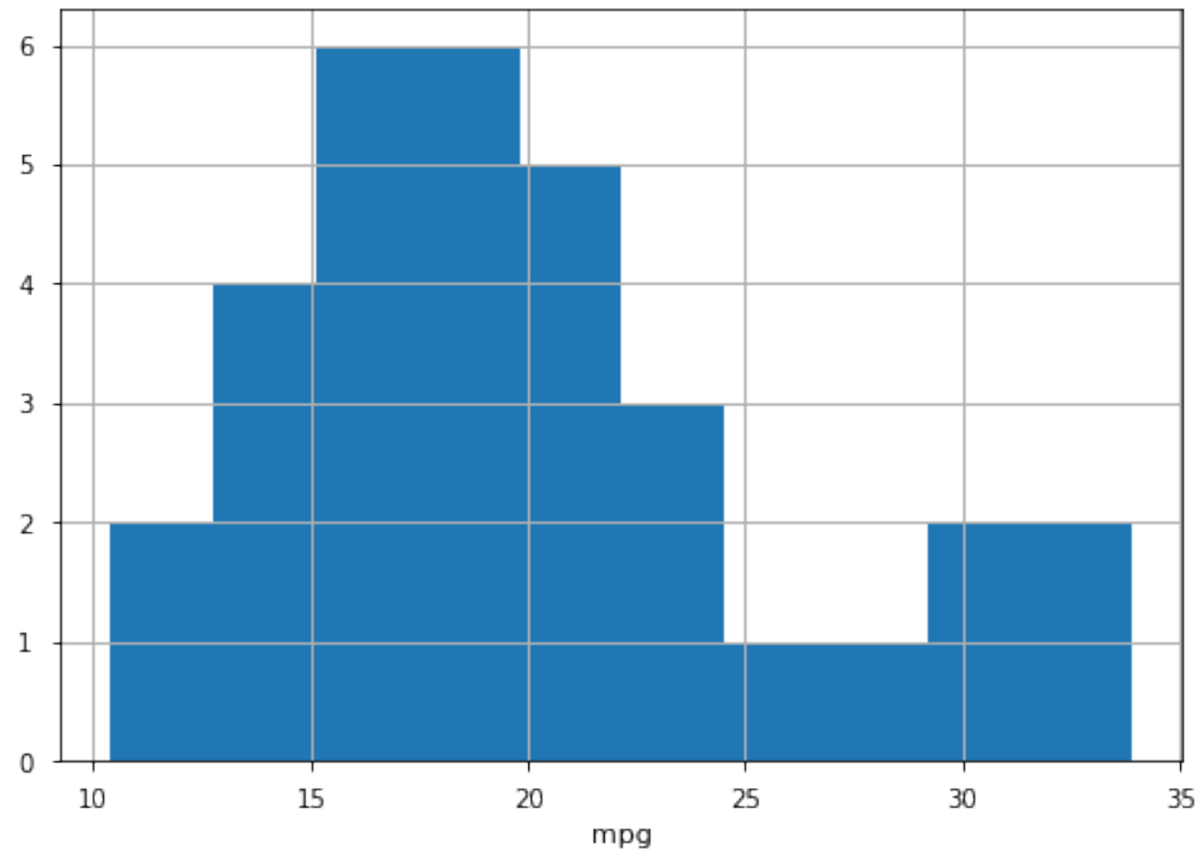
Viz options

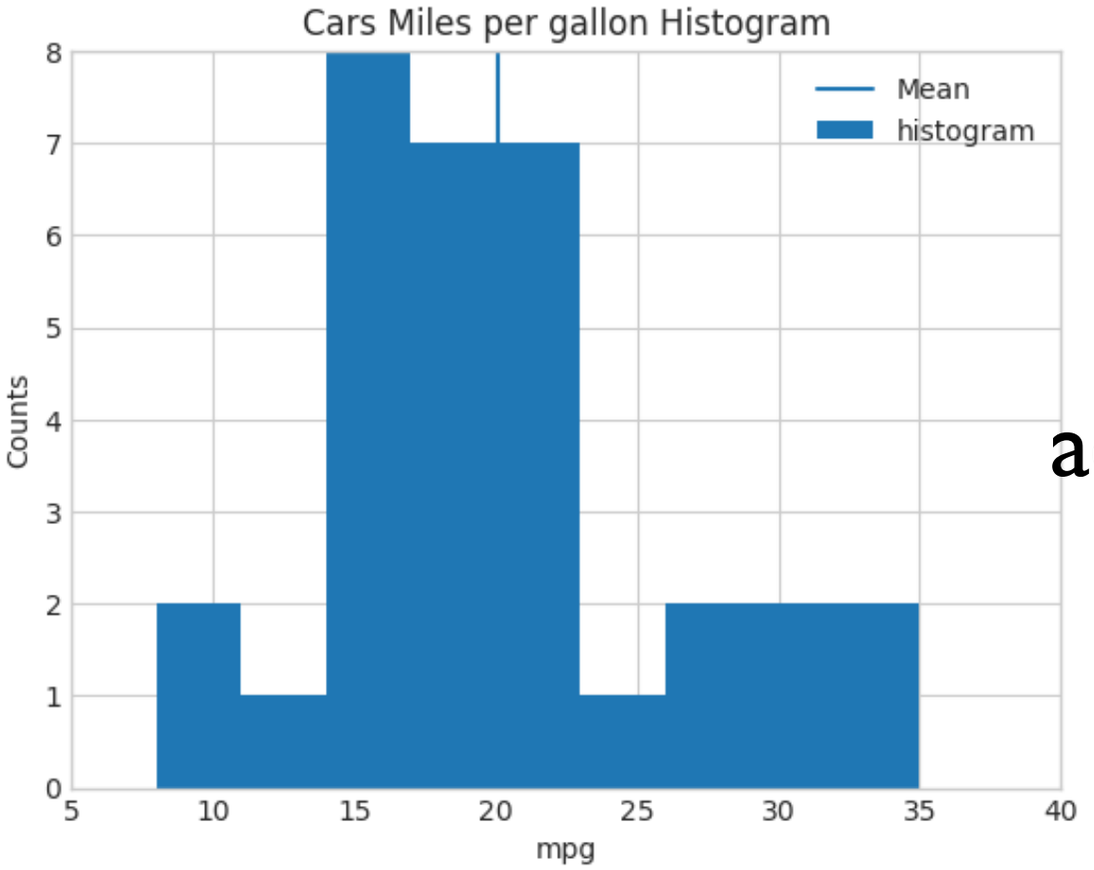
- Pandas Visualization module
- Matplotlib
- Seaborn
- Above 3 are inter-mixable
- Be lazy (to an extent…)
- Other options: Bokeh, Vega, Vincent, Altair

Cars Dataset

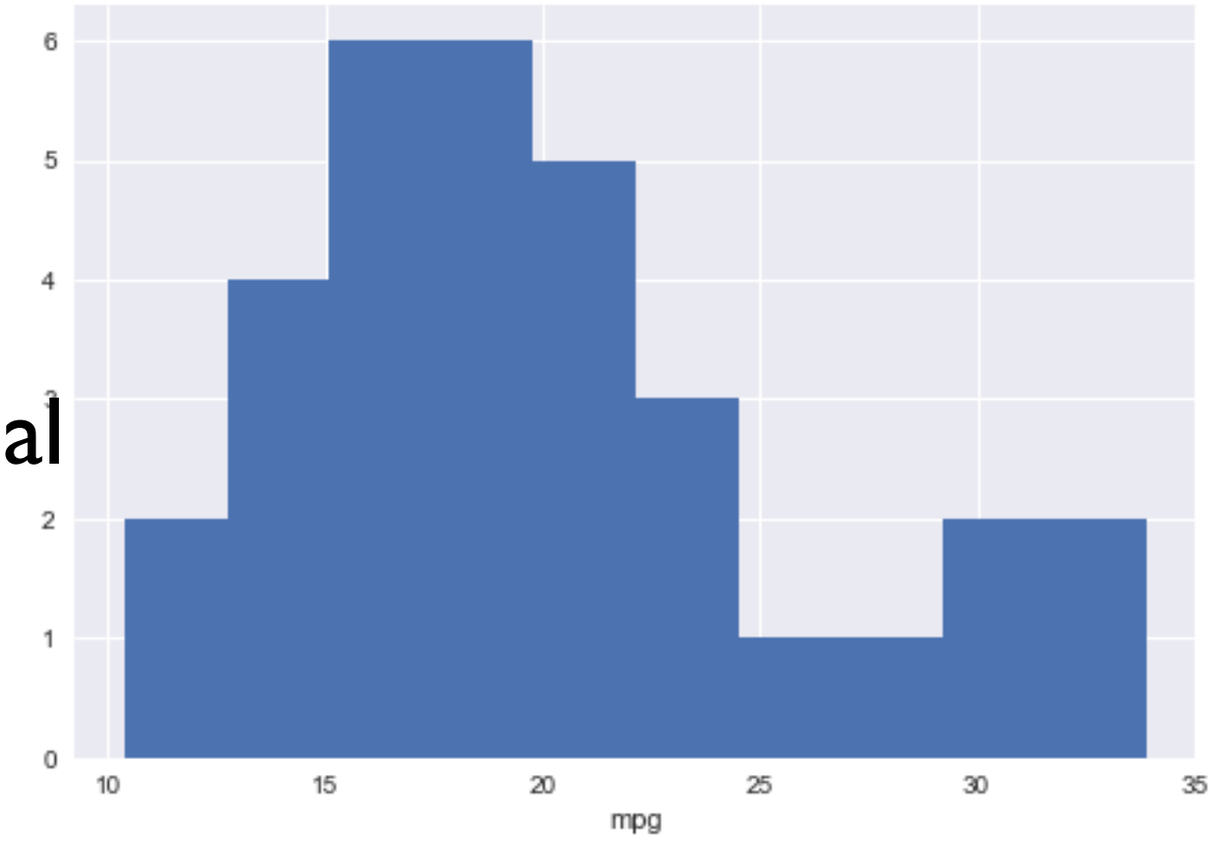
	name	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb	maker
0	Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4	Mazda
1	Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4	Mazda
2	Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1	Datsun
3	Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1	Hornet
4	Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2	Hornet

Basic Pandas/matplotlib

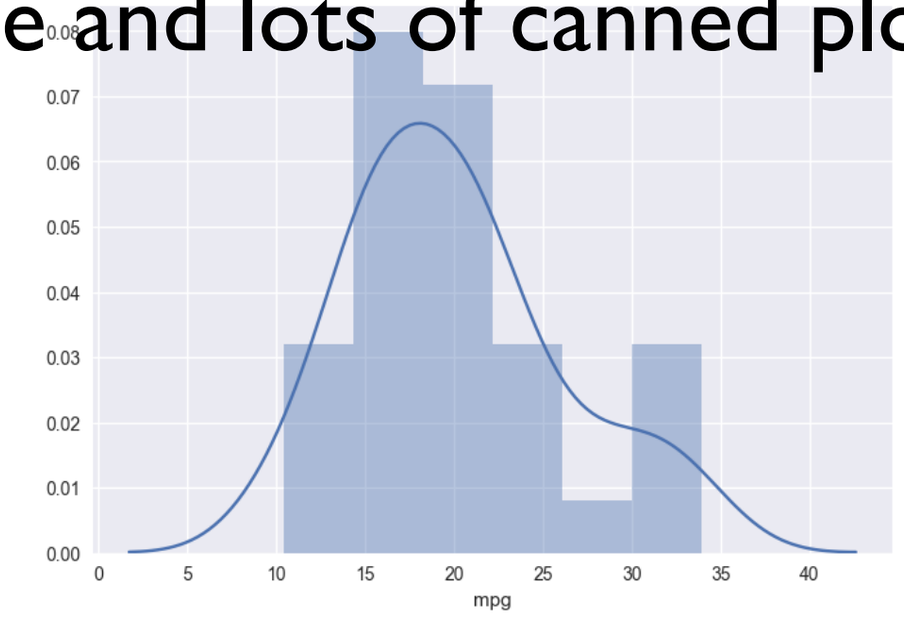




Can set limits, tick styles, scales, add lines, annotations, titles, legends

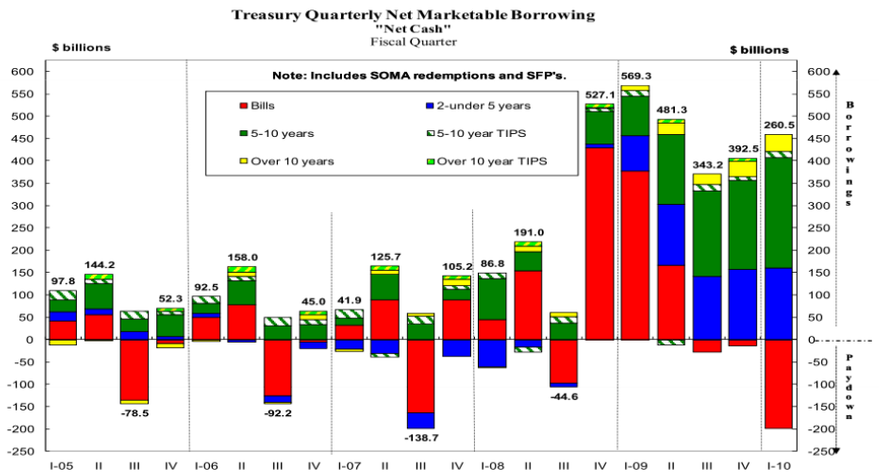


Seaborn provides a different visual style and lots of canned plots.



Effective Visualizations

Not Effective…



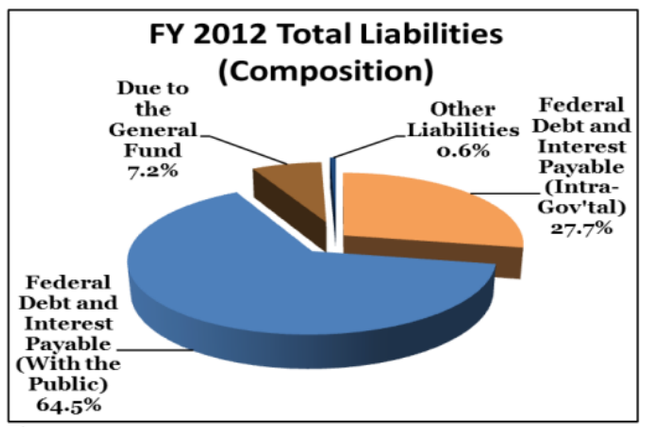
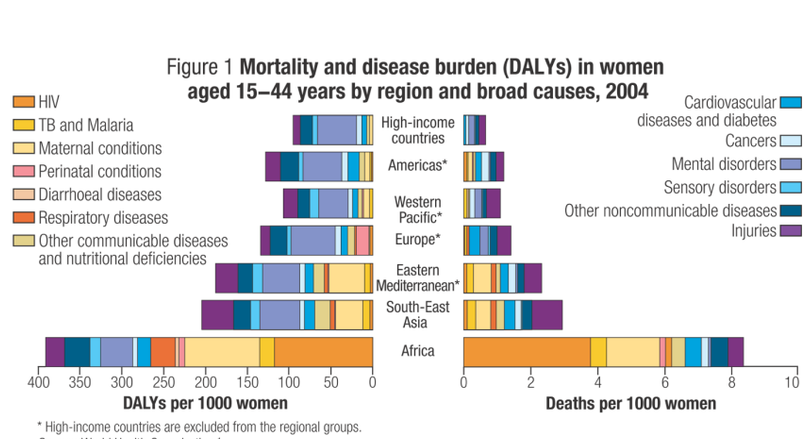
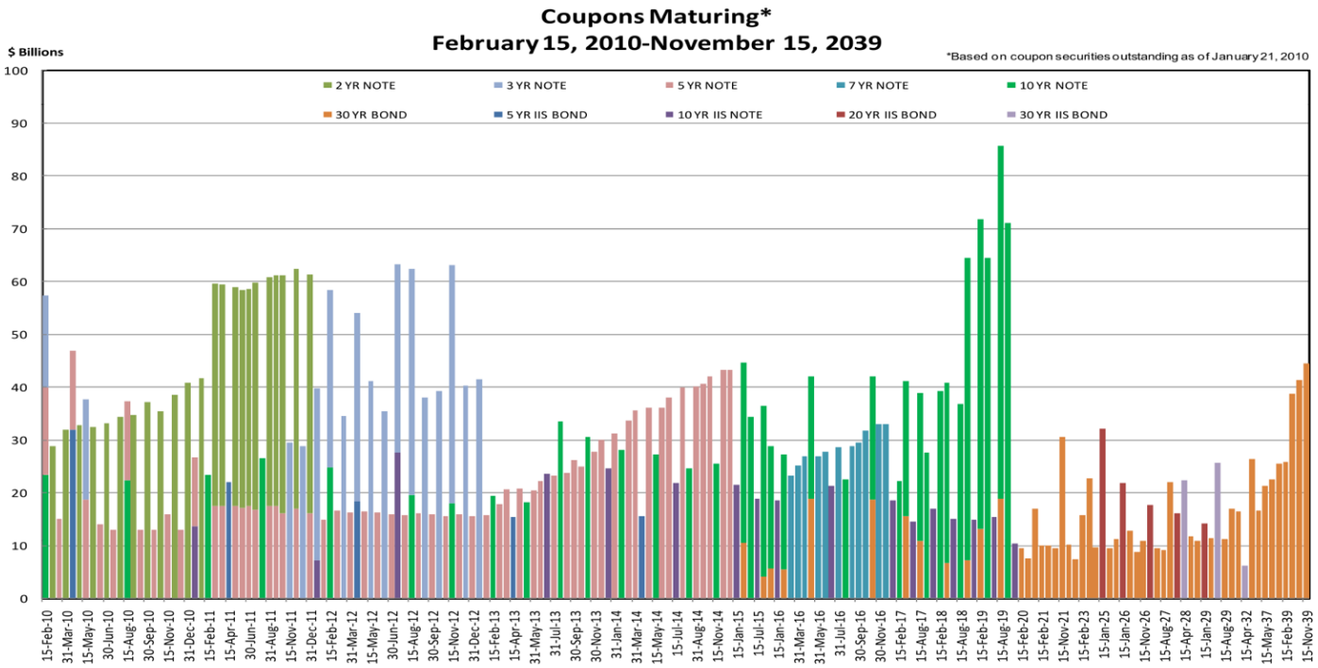


Figure 10





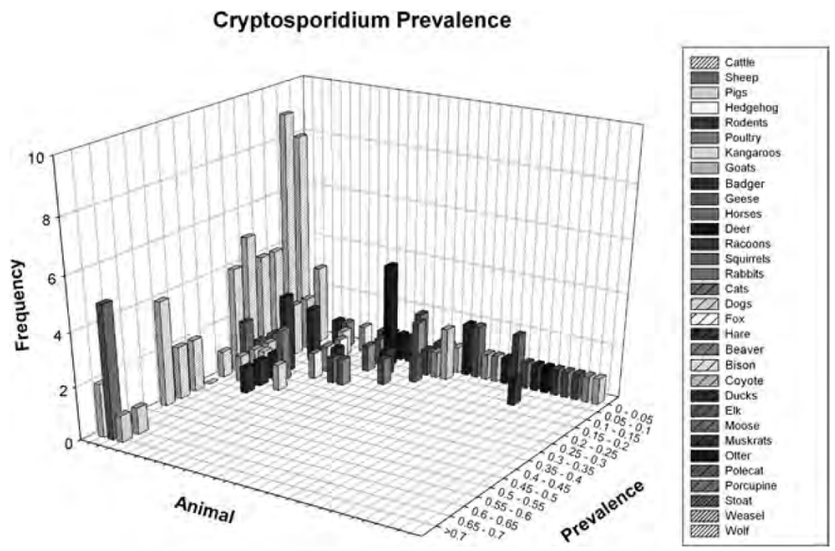


Figure 5.2 Mean prevalence rates of *Cryptosporidium* oocysts by animal species.

Sources: US Treasury and WHO reports

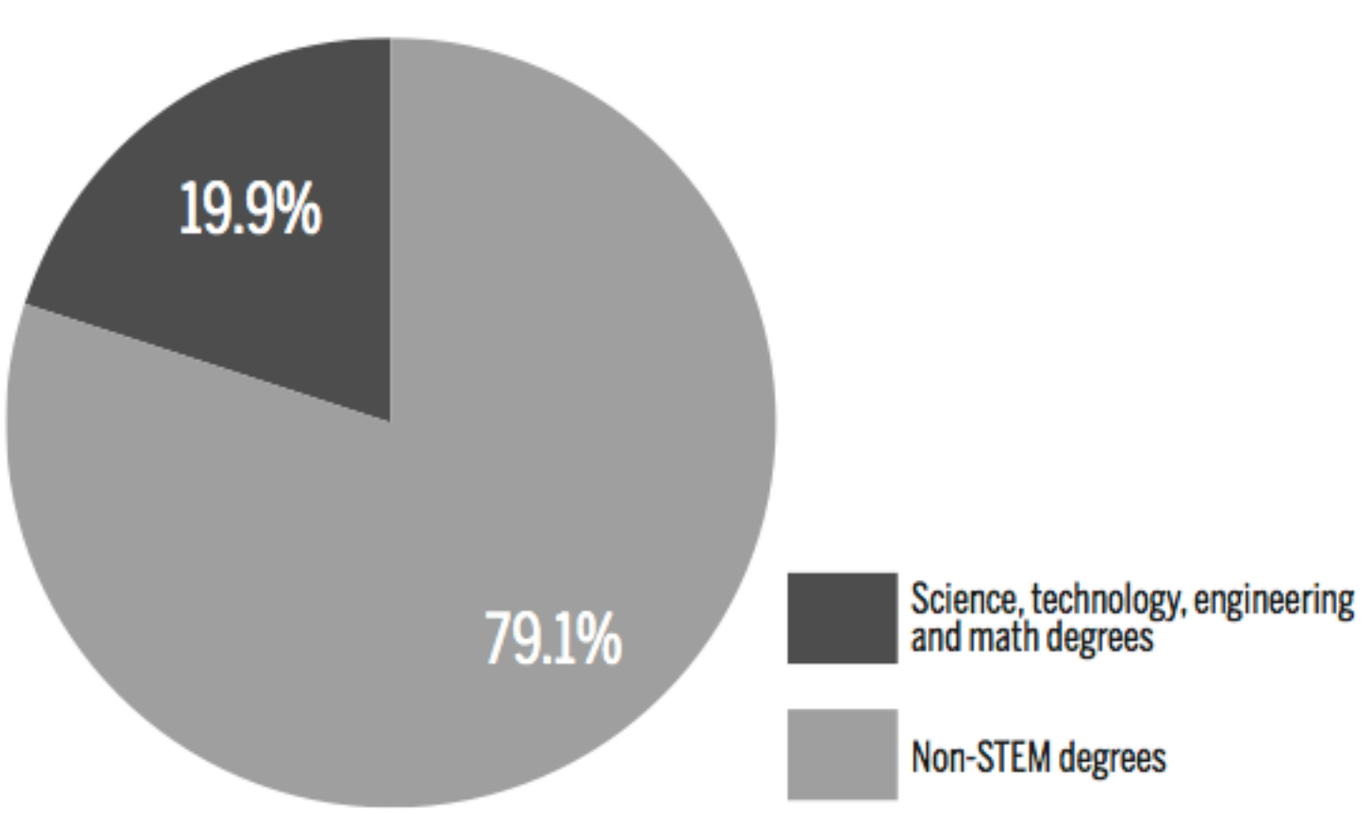
Effective EDA Viz

1. Have graphical integrity
2. Keep it simple
3. Use the right display
4. Use color sensibly

1. Graphical Integrity

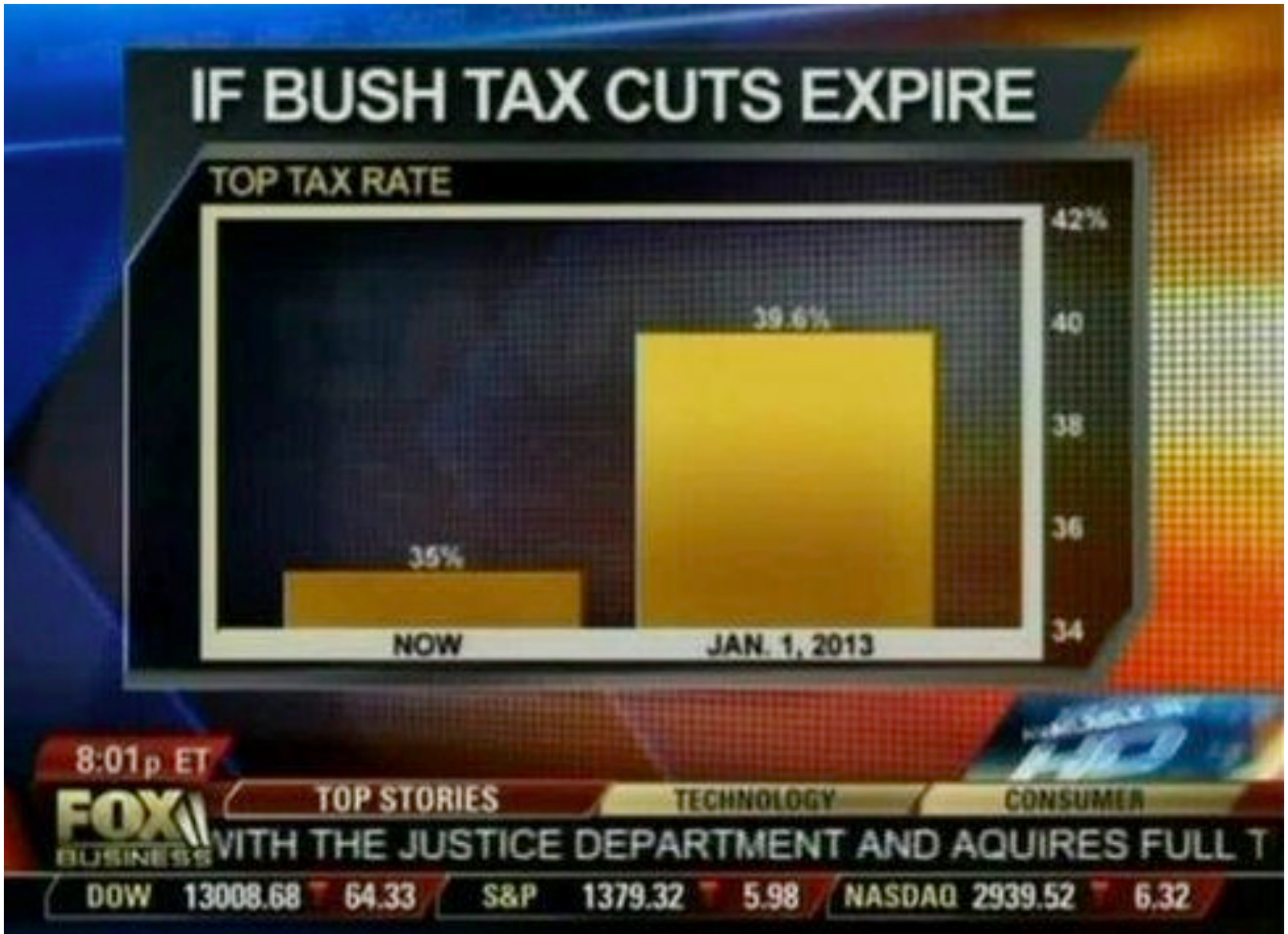
Yale Daily News | THE OLDEST COLLEGE DAILY ESTABLISHED 1878

CHART YALE GRADUATES' MAJORS, CLASS OF 2011

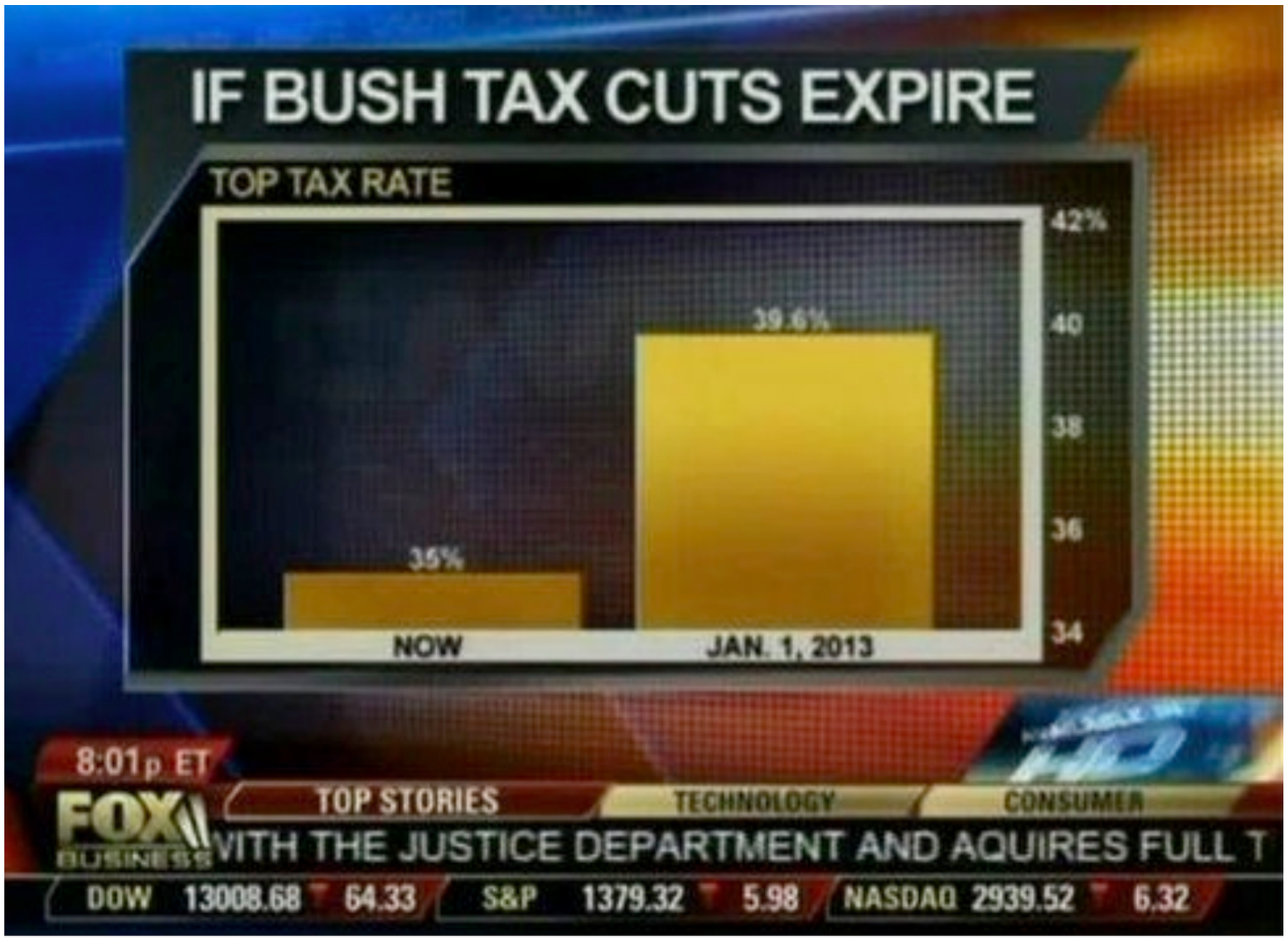


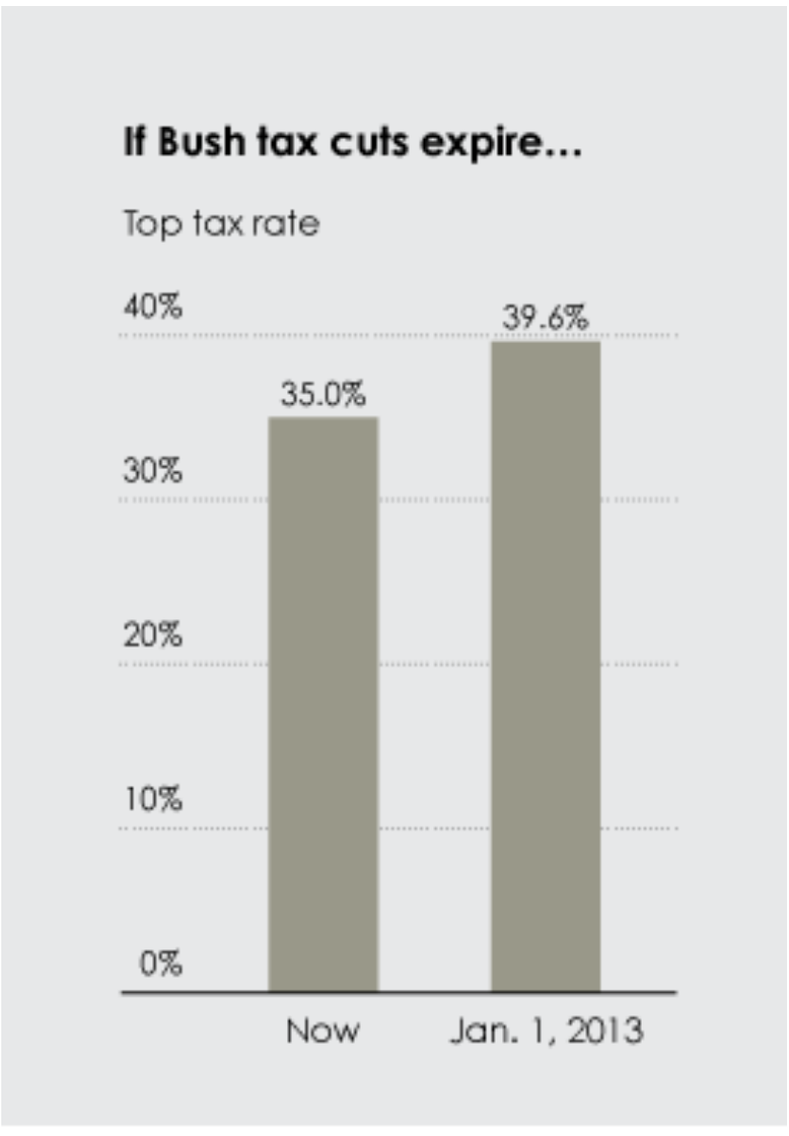
September 13, 2011

Graphical Integrity



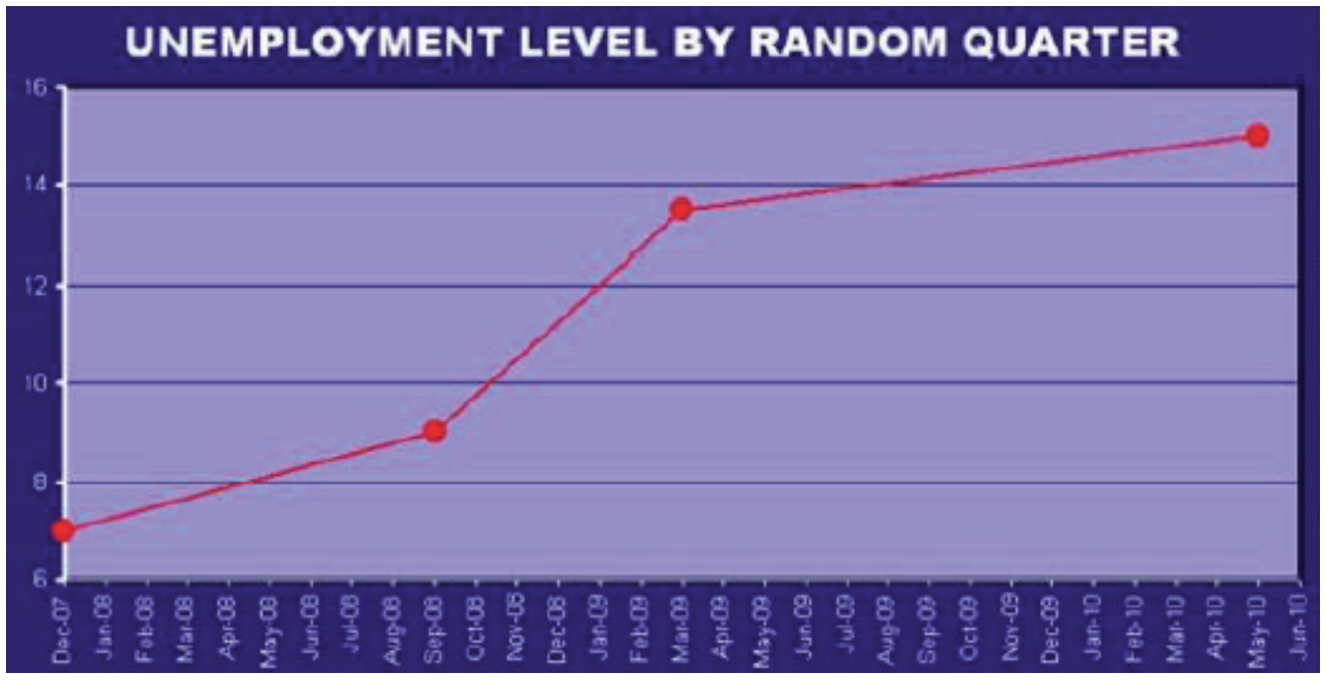
Scale Distortions





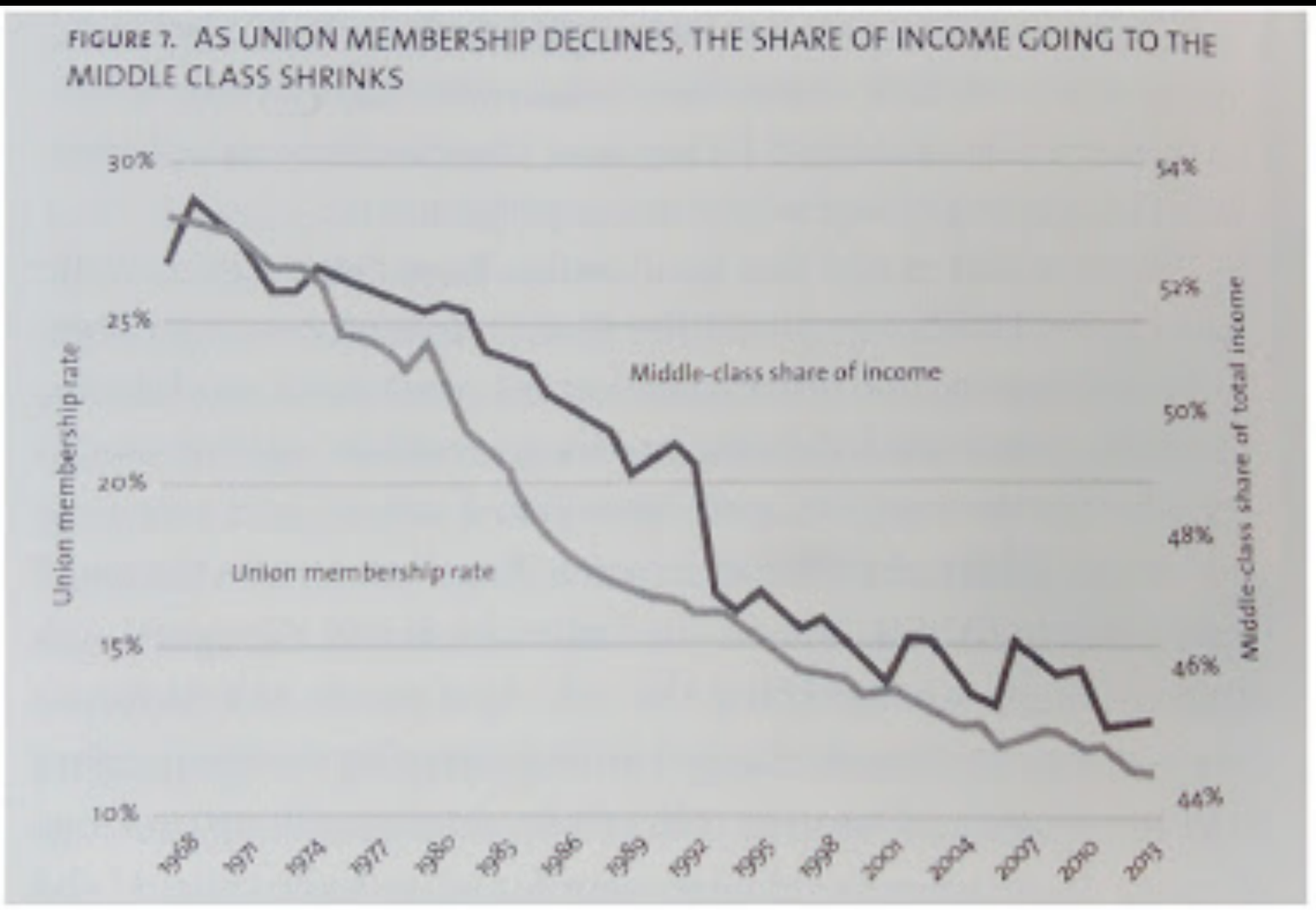

JOB LOSS BY QUARTER
15 MIL
13.5 MIL
9 MIL
7 MIL
DEC '07
SEPT '08
MARCH '09
JUNE '10
FOX NEWS .COM
SOURCE: BLS
AMERICA'S NEWSROOM

Scale Distortions

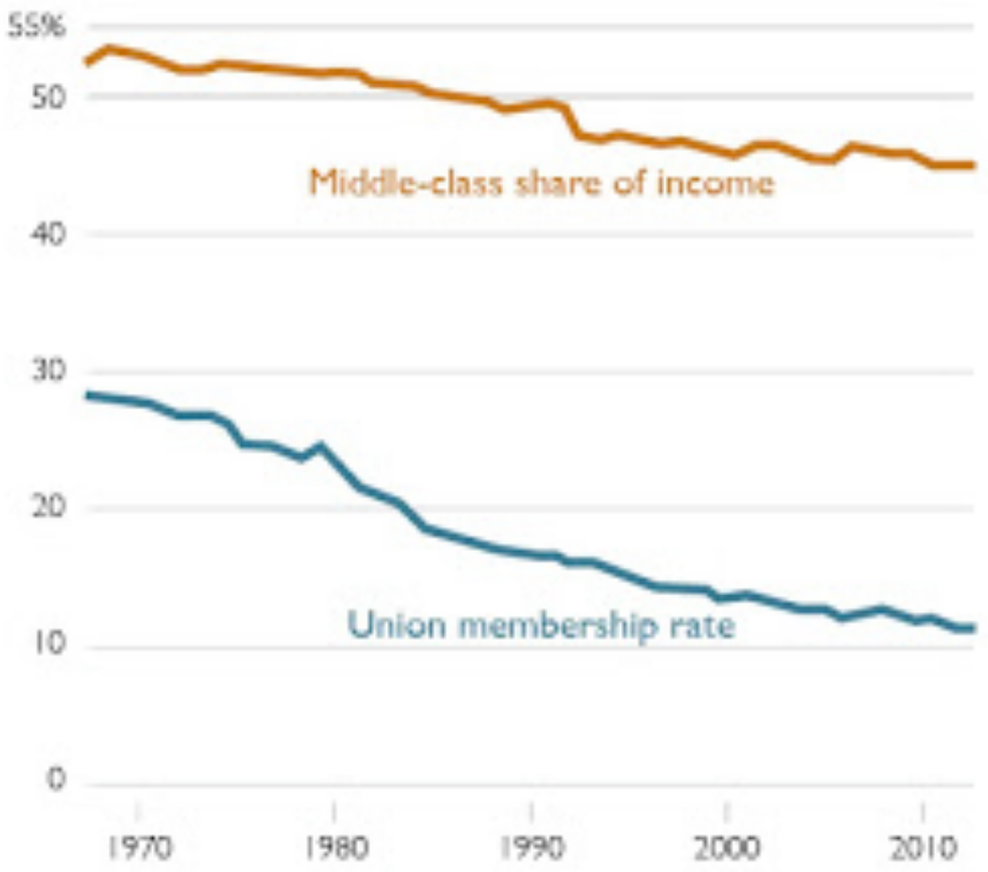


"Double the axes, double the mischief"

(Quote from Gary Smith's *Standard Deviations*)



NEW VERSION



Graphic from Robert Reich's *Saving Capitalism*

http://www.thefunctionalart.com/2015/10/double-axes-double-mischief.html

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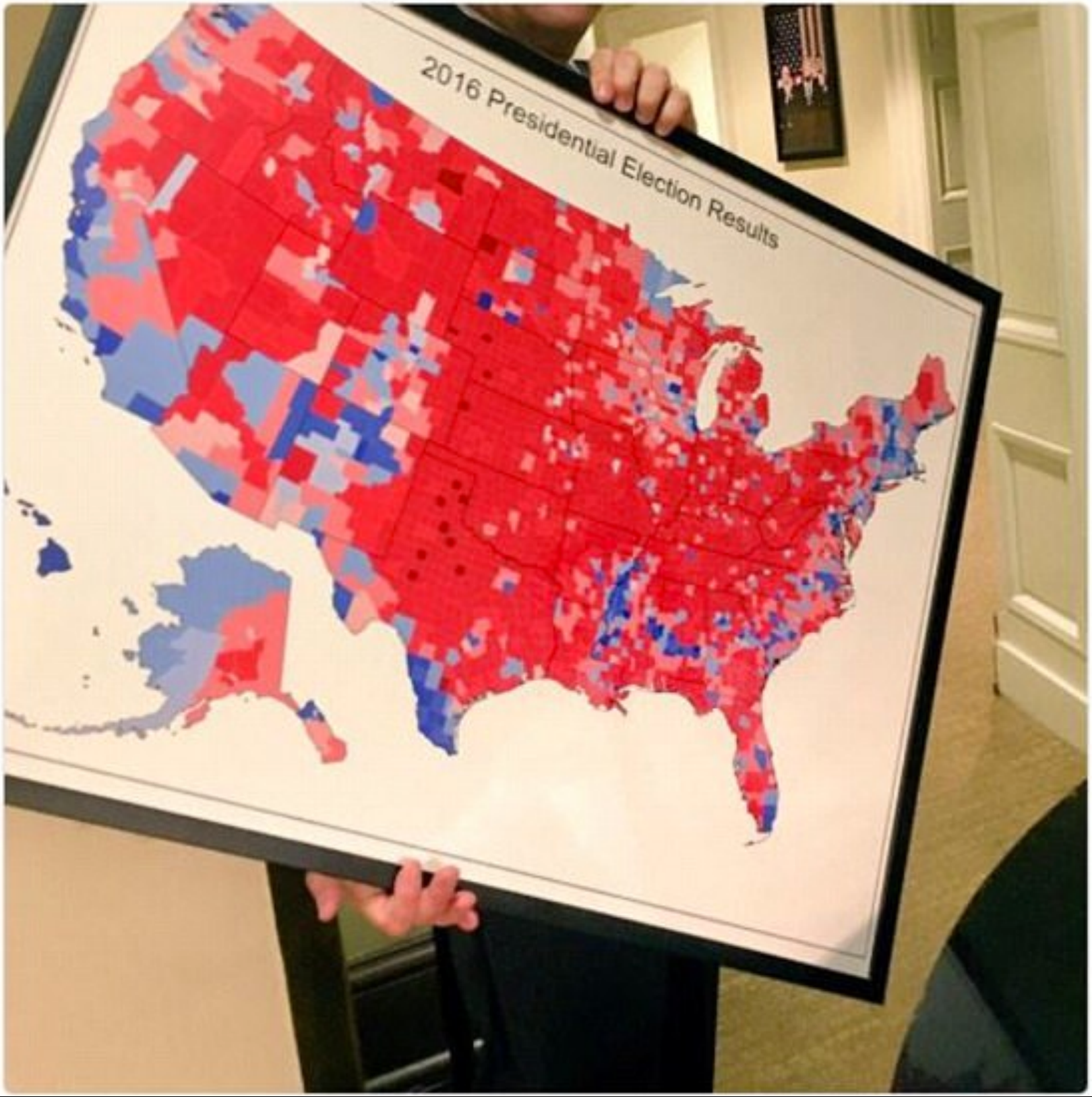
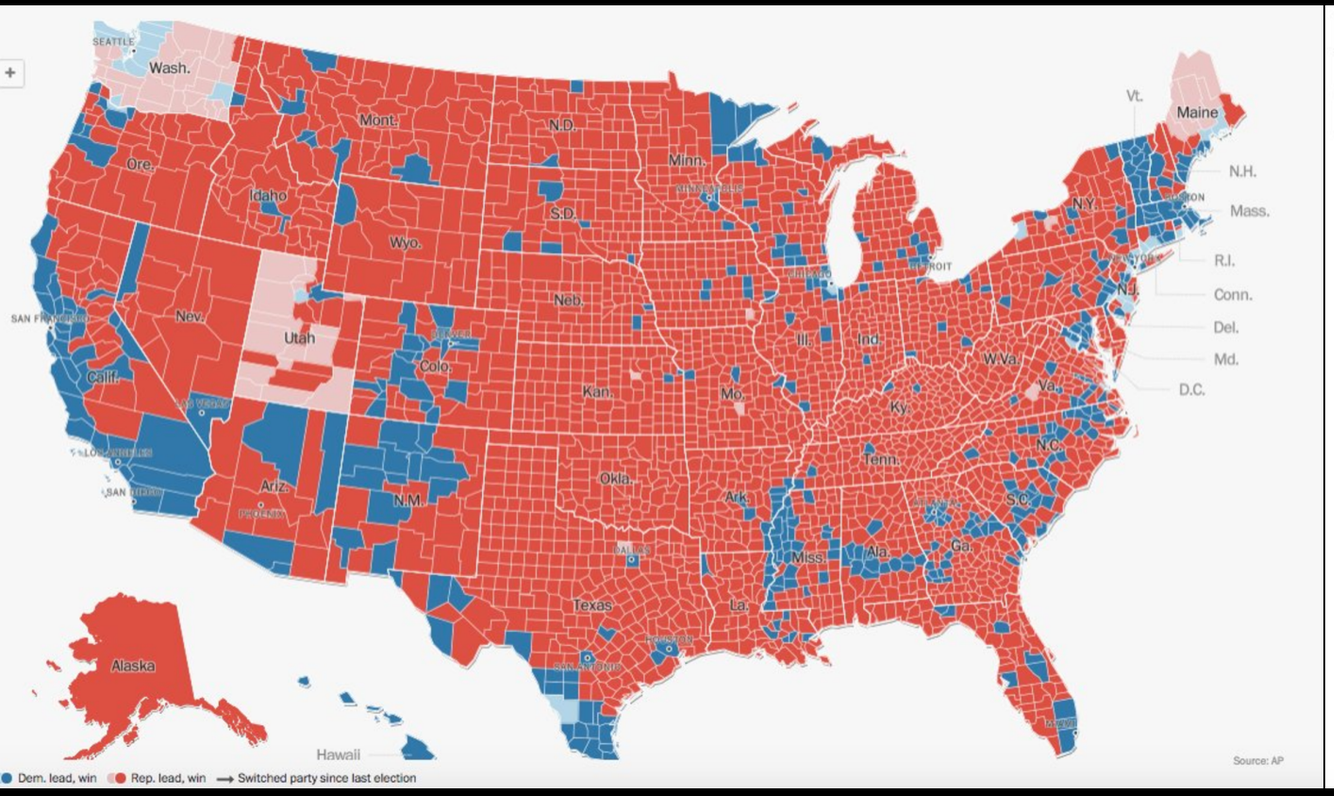
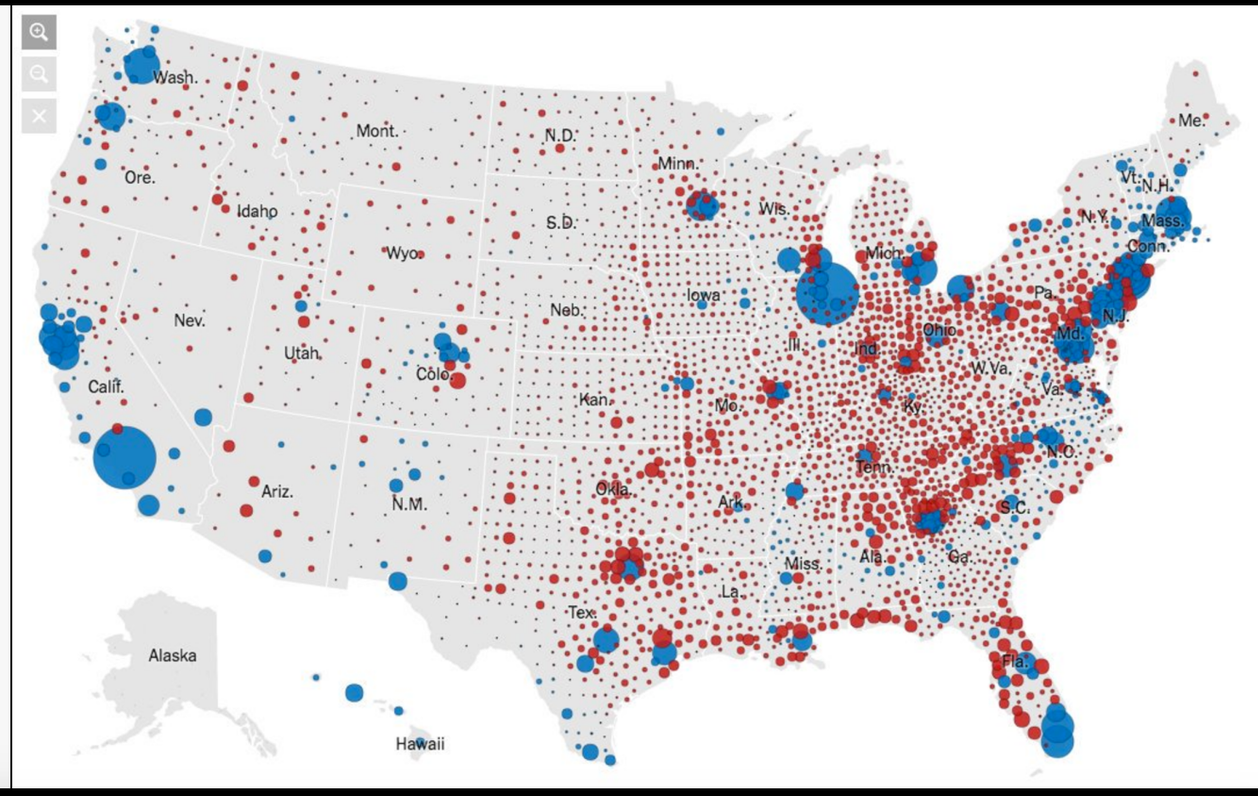
Be Proportional

Trey Yingst @TreyYingst · May 11

Spotted: A map to be hung somewhere in the West Wing







US Presidential Election 2016

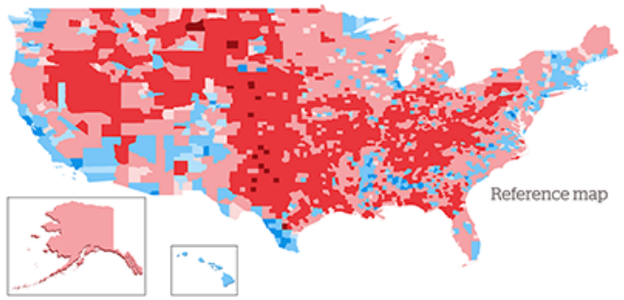
Results mapped at county level showing the candidate with the largest vote share in each area

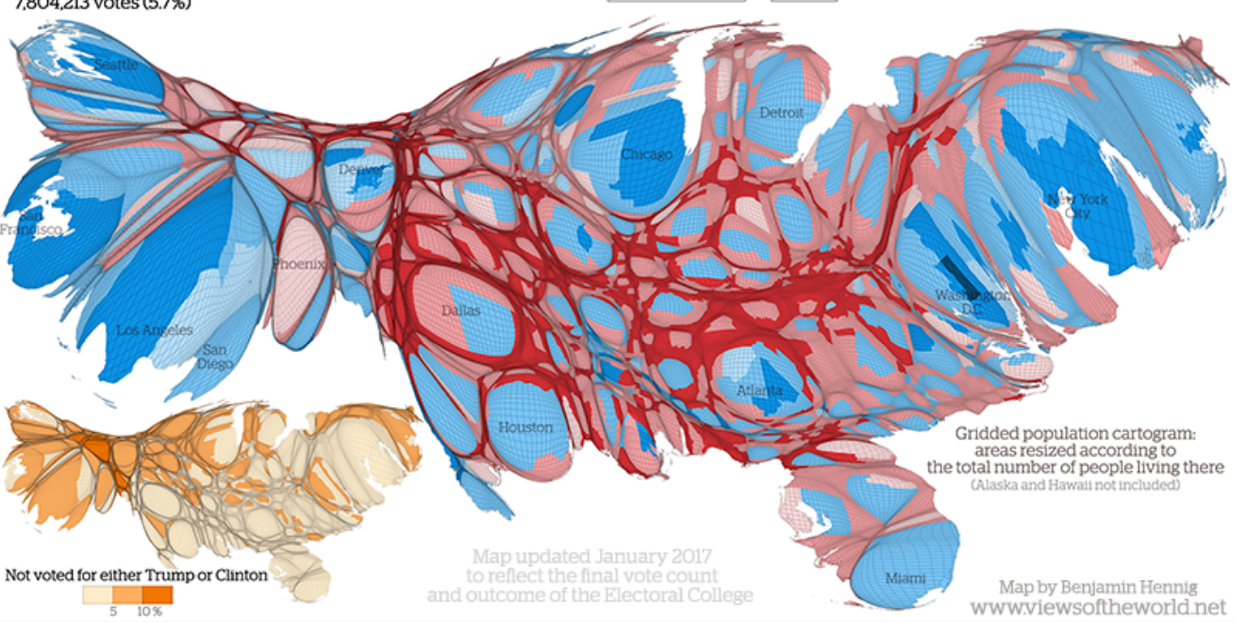
Overall result:

Trump
62,979,636 votes (46.1%)
306 electoral votes
(received 304 in the Electoral College)

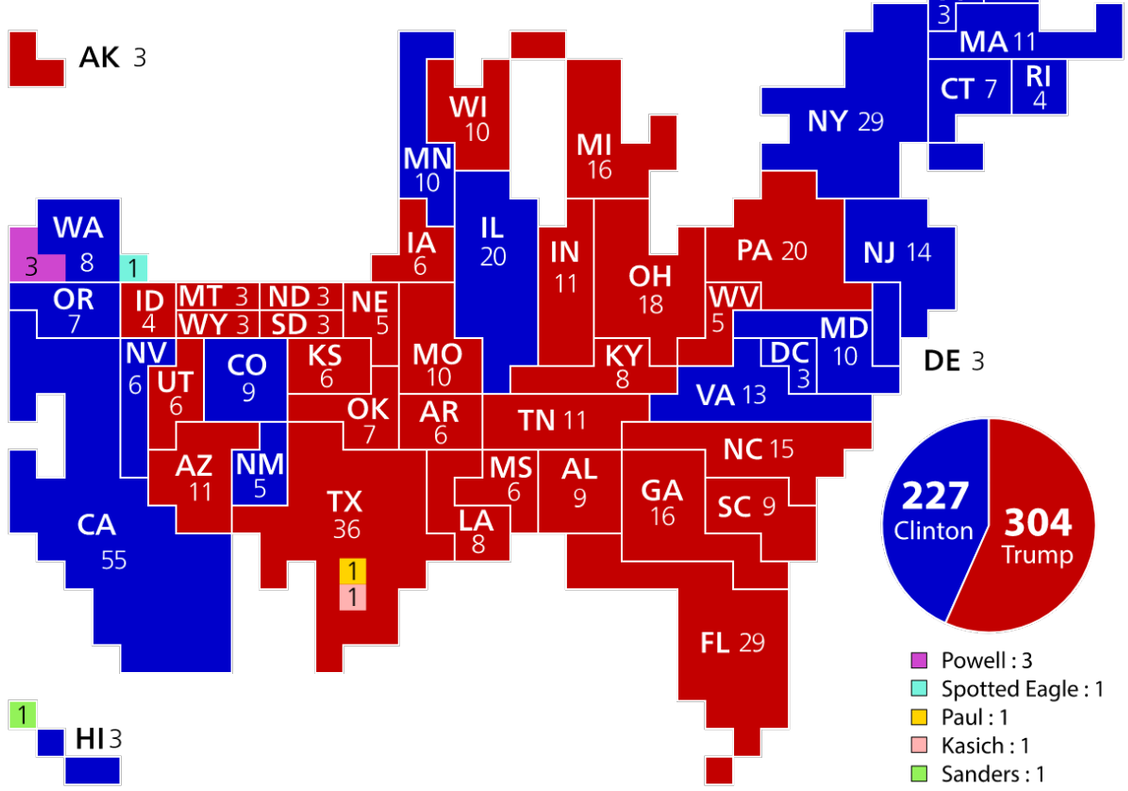
Clinton
65,844,610 votes (48.2%)
232 electoral votes
(received 227 in the Electoral College)

Other candidates
7,804,213 votes (5.7%)





2016 Electoral Vote



Include Uncertainty

Note: The cone contains the probable path of the storm center but does not show the size of the storm. Hazardous conditions can occur outside of the cone.

MO
KY
WV
VA
TN
NC
AR
SC
GA
MS
AL
LA
FL
Bermuda
Bahamas
Cuba
Haiti
Dominican Rep.
Puerto Rico
Jamaica
Belize

35N
30N
25N
20N
95W
90W
85W
80W
75W
70W
65W
60W

2 AM Sun
2 AM Sat
2 AM Mon
2 AM Fri
2 AM Thu
8 AM Wed

H
M

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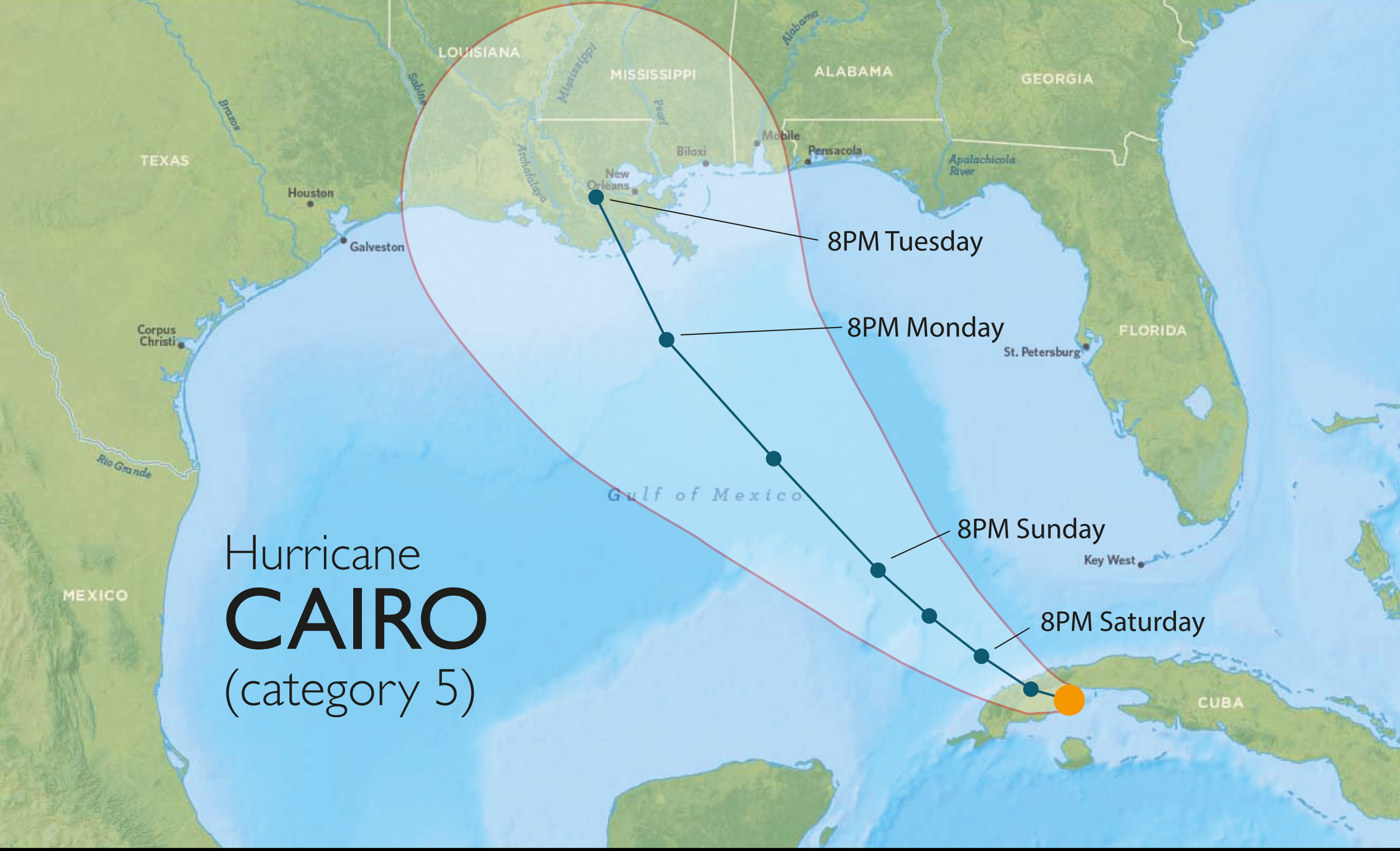

What you show

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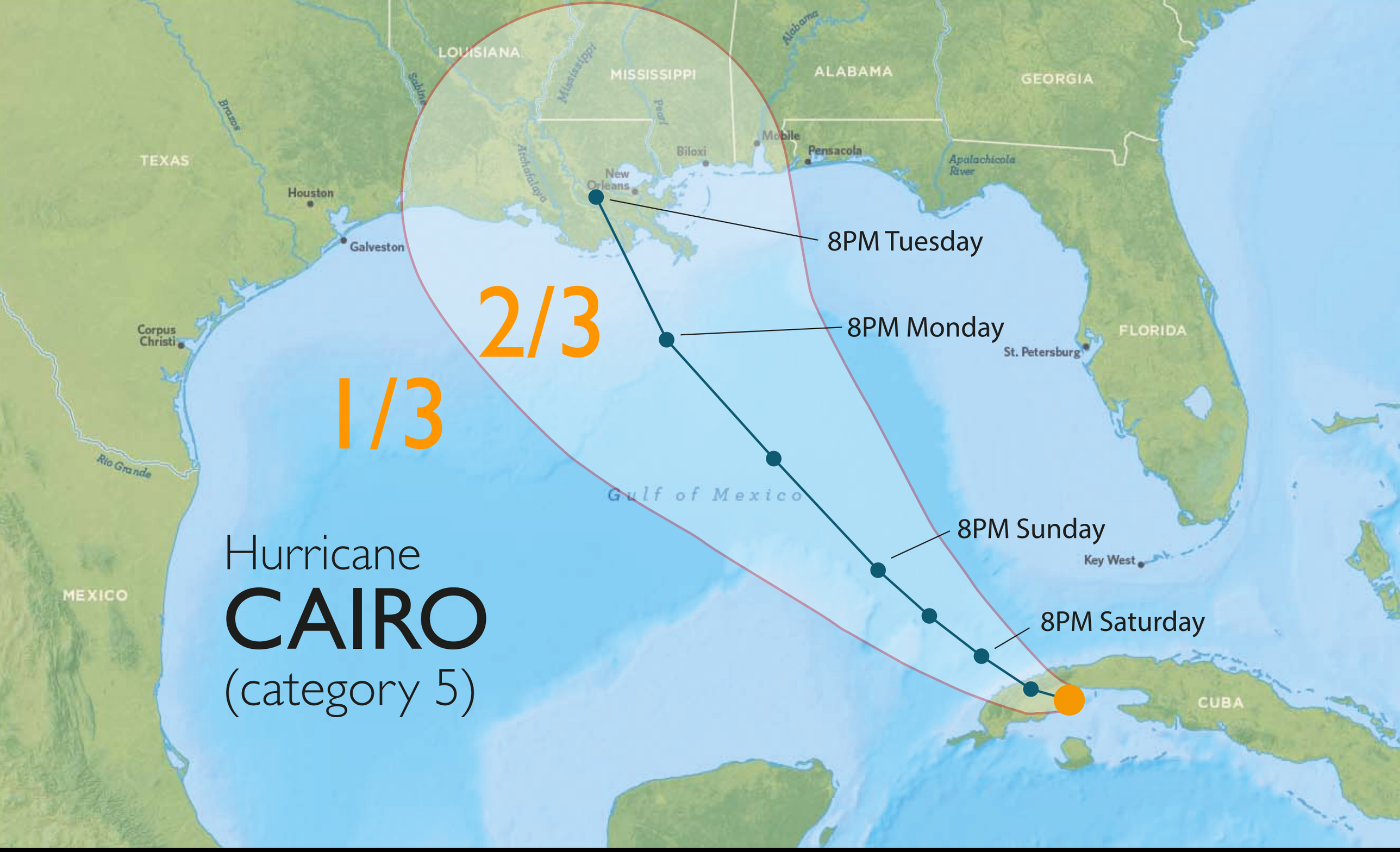

What non-scientists are not aware of (cone is just 66% probability)

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What we could be showing instead

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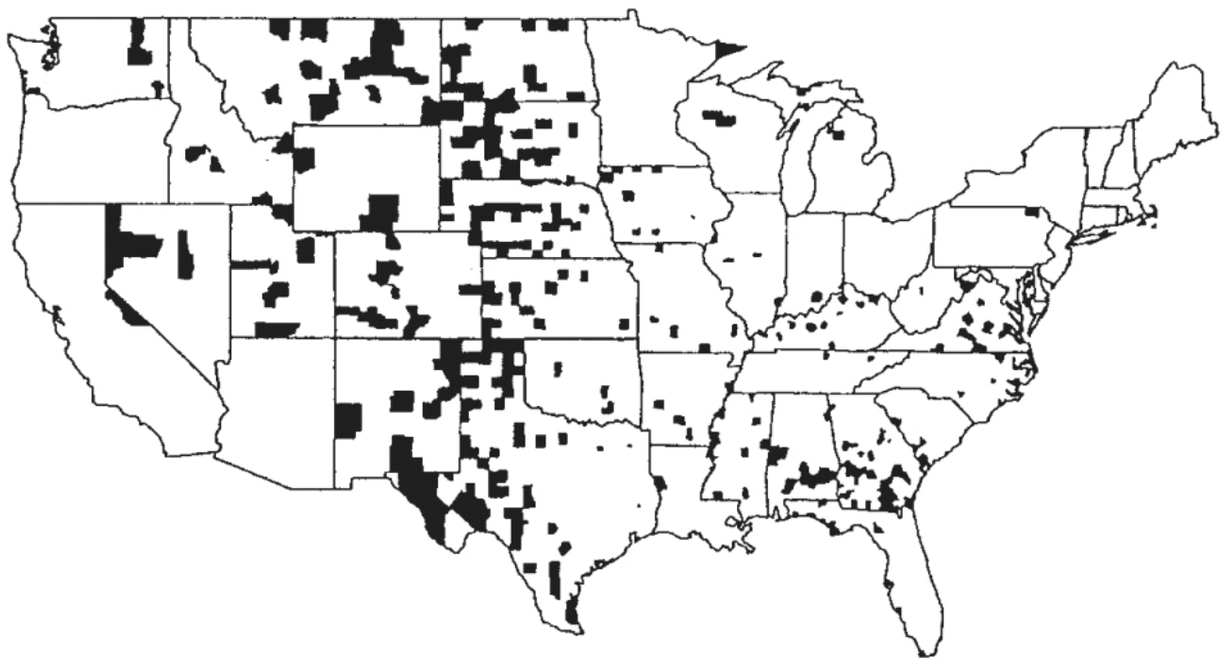
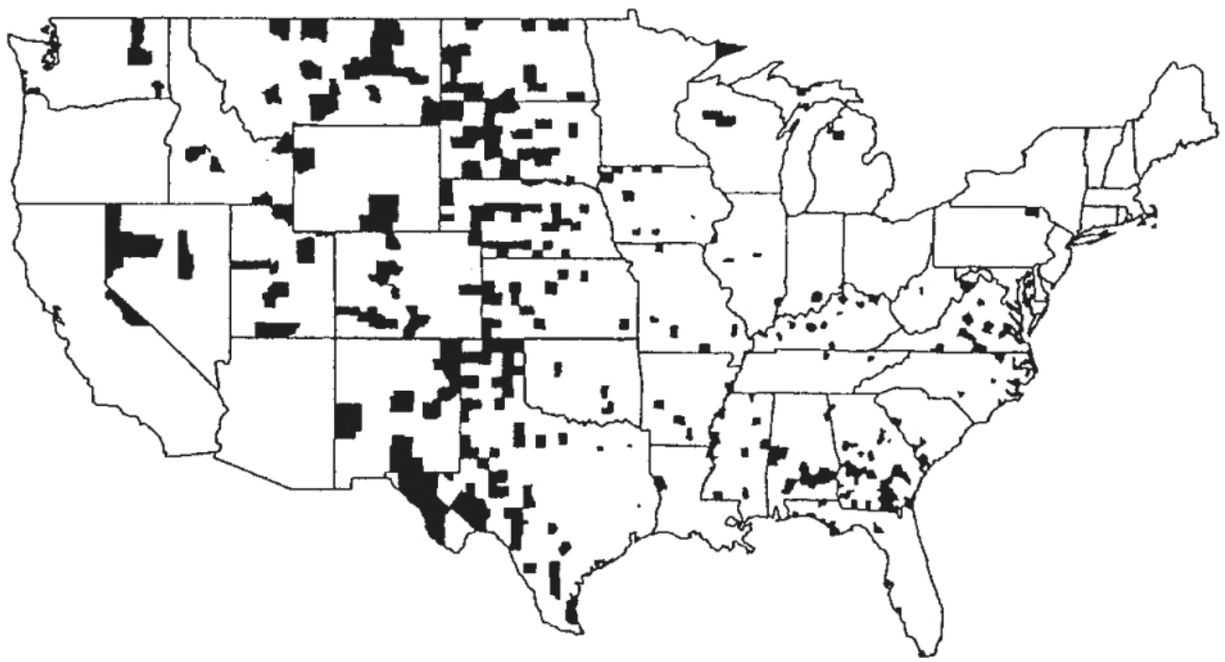
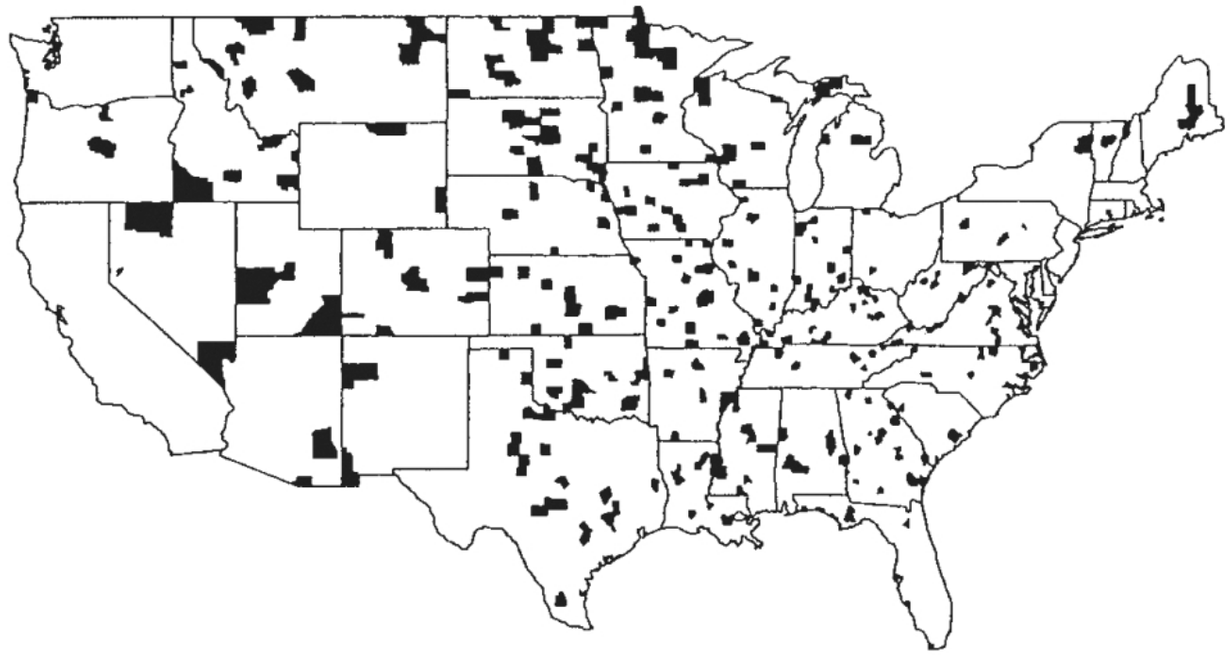
Plot all your data



Counties with the LOWEST kidney cancer death rates (1980-1989)



Counties with the LOWEST kidney cancer death rates (1980-1989)



Counties with the HIGHEST kidney cancer death rates (1980-1989)

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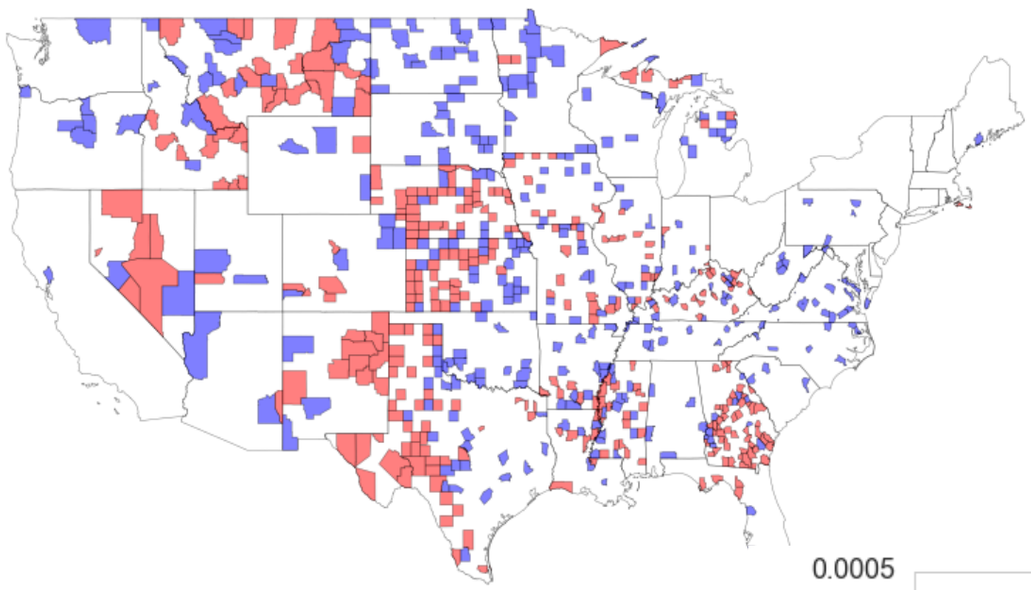

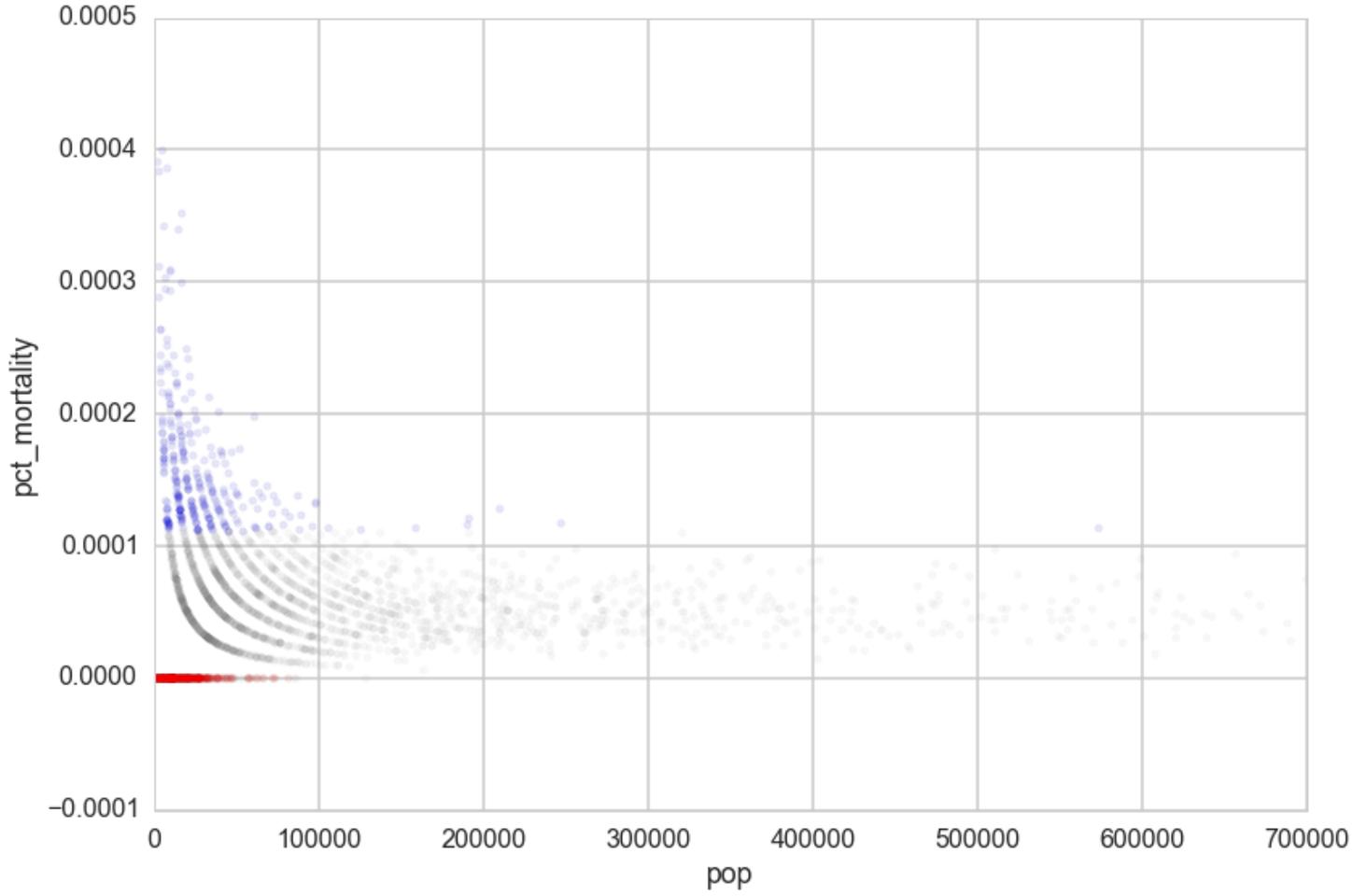
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−0.0001
pct_mortality
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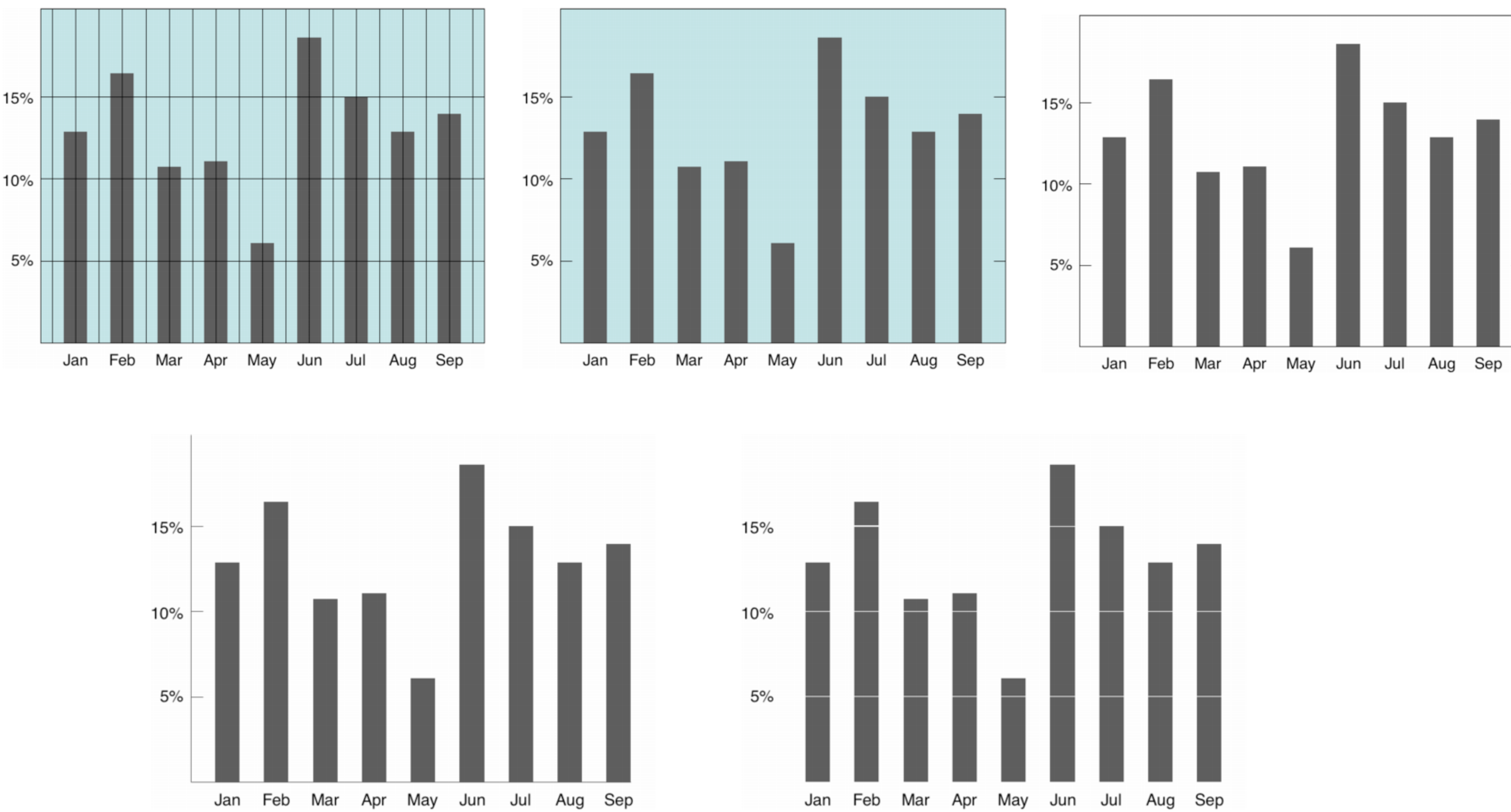
100000
200000
300000
400000
500000
600000
700000
pop

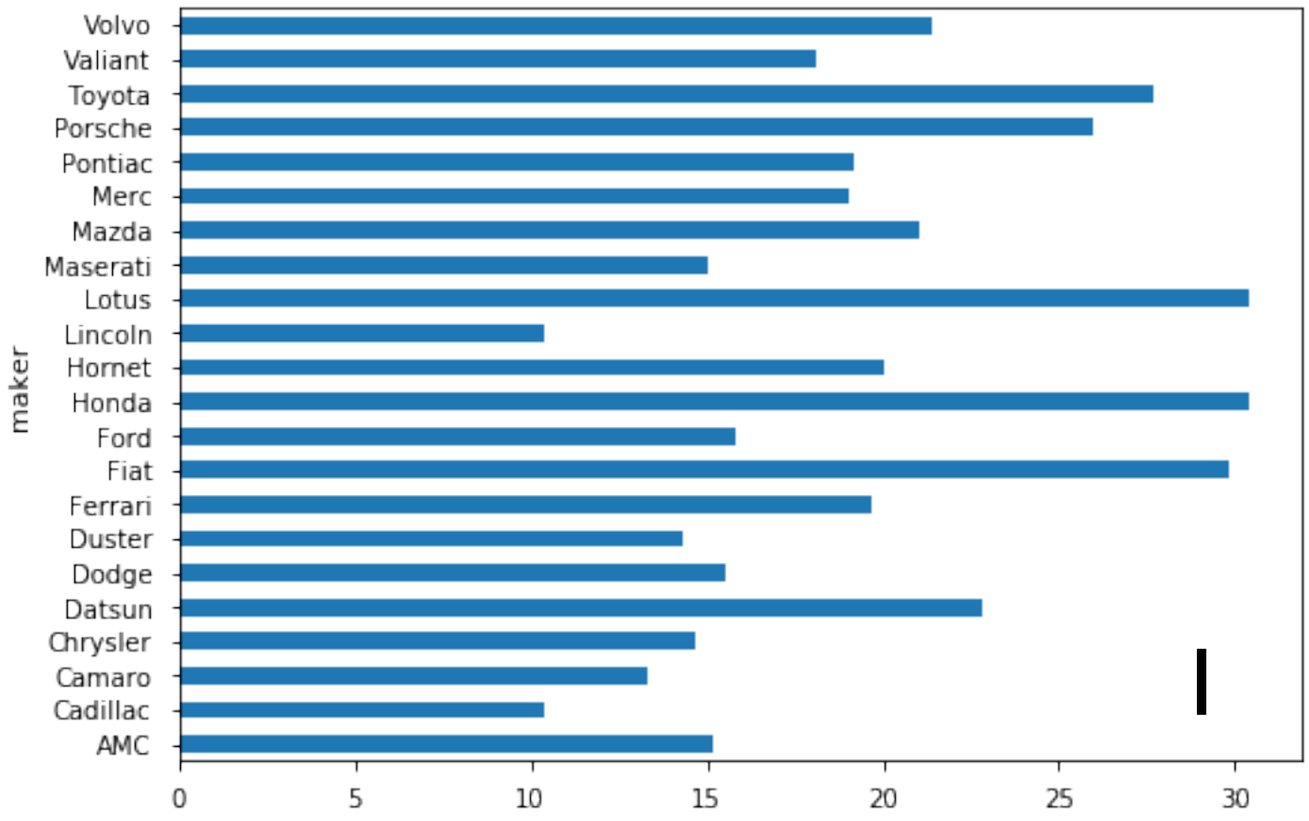
2. Keep It Simple

Avoid Chartjunk

Extraneous visual elements that distract from the message



ongoing, Tim Brey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Toyota
Porsche
Pontiac
Merc
Mazda
Maserati
Lotus
Lincoln
Hornet
Honda
Ford
Fiat
Ferrari
Duster
Dodge
Datsun
Chrysler
Camaro
Cadillac
AMC
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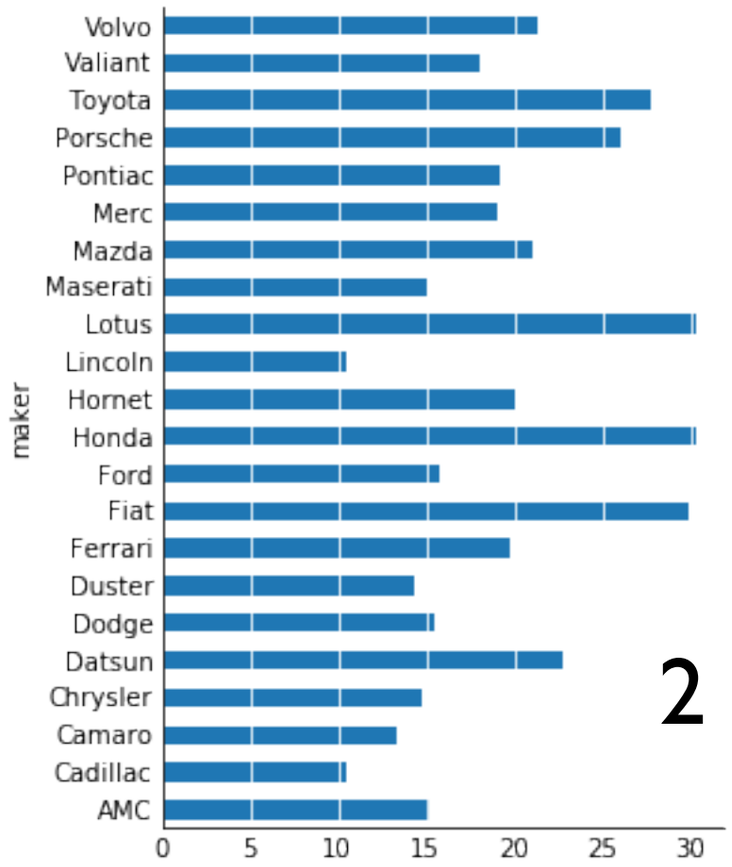
30
1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Volvo
Valiant
Toyota
Porsche
Pontiac
Merc
Mazda
Maserati
Lotus
Lincoln
Hornet
Honda
Ford
Fiat
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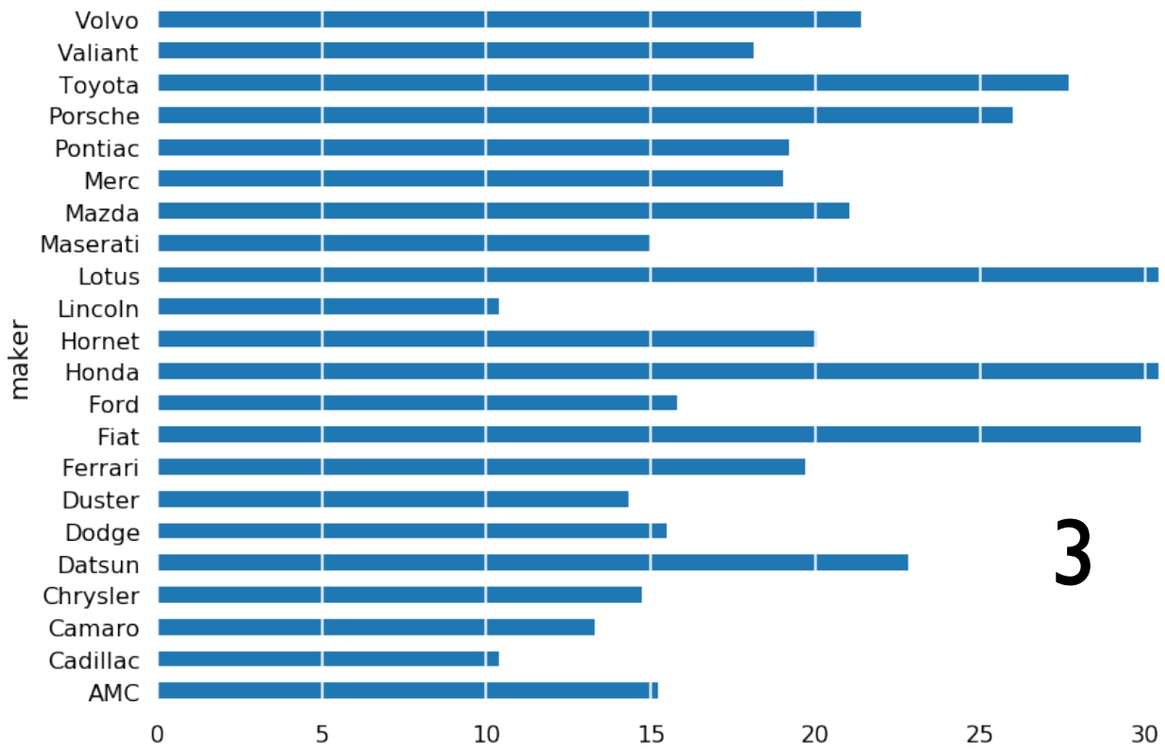
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Toyota
Porsche
Pontiac
Merc
Mazda
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Lincoln
Hornet
Honda
Ford
Fiat
Ferrari
Duster
Dodge
Datsun
Chrysler
Camaro
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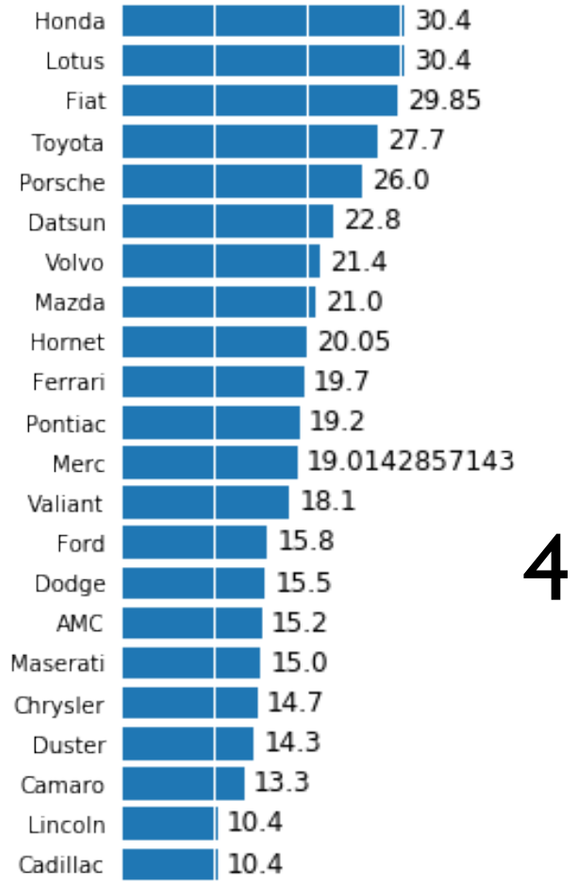
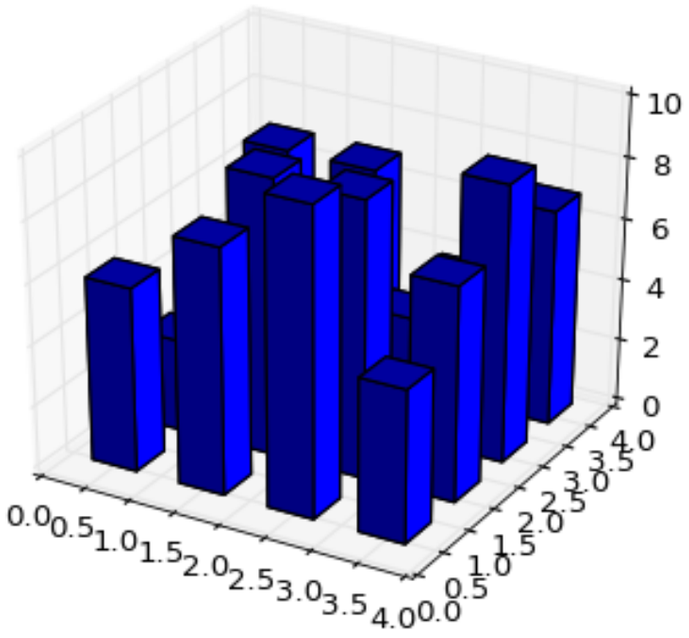
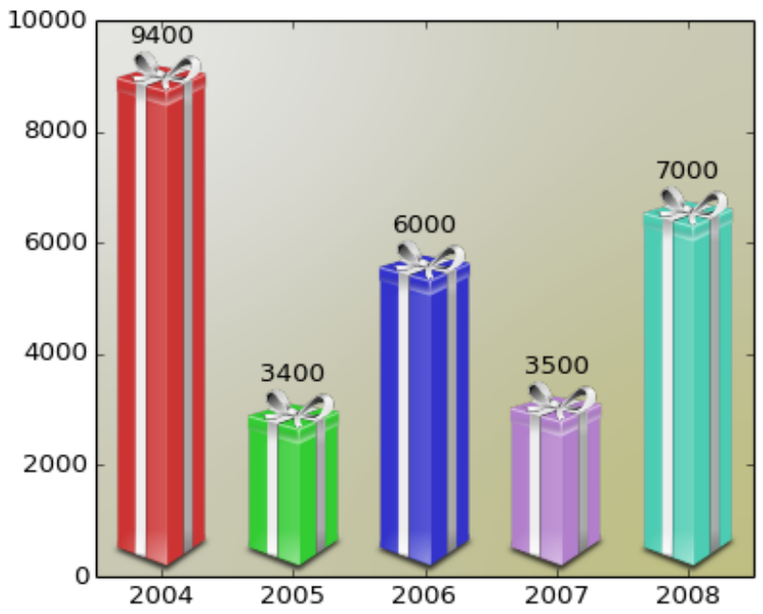
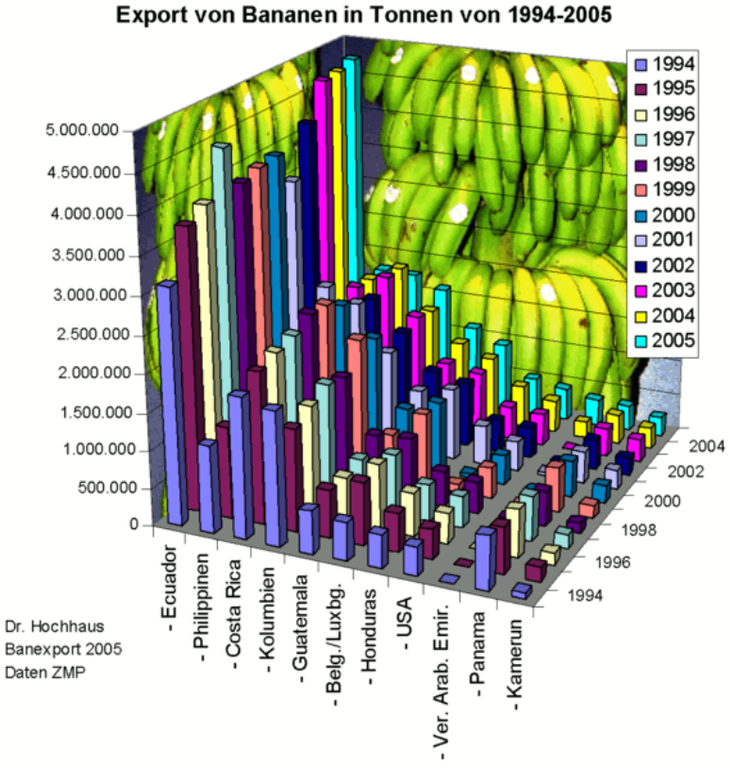

Honda 30.4
Lotus 30.4
Fiat 29.85
Toyota 27.7
Porsche 26.0
Datsun 22.8
Volvo 21.4
Mazda 21.0
Hornet 20.05
Ferrari 19.7
Pontiac 19.2
Merc 19.0142857143
Valiant 18.1
Ford 15.8
Dodge 15.5
AMC 15.2
Maserati 15.0
Chrysler 14.7
Duster 14.3
Camaro 13.3
Lincoln 10.4
Cadillac 10.4
4

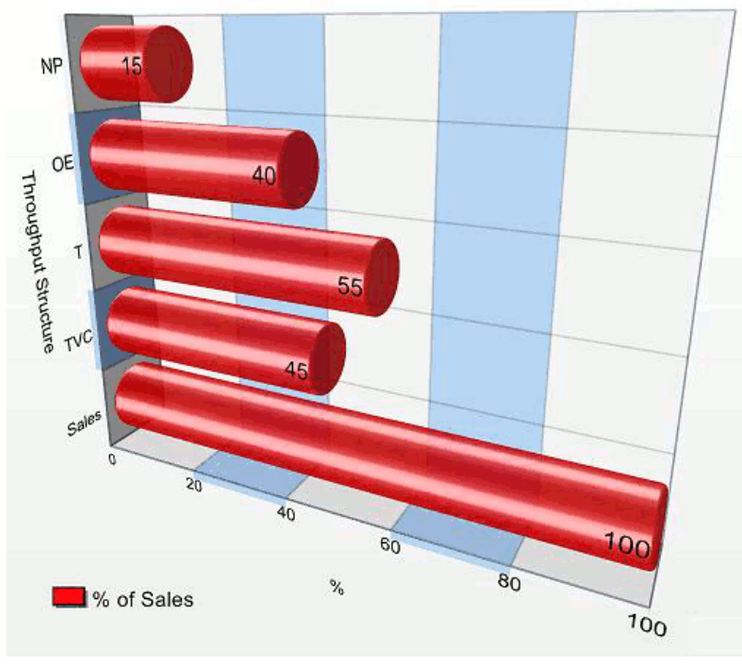
Don’t!





matplotlib gallery

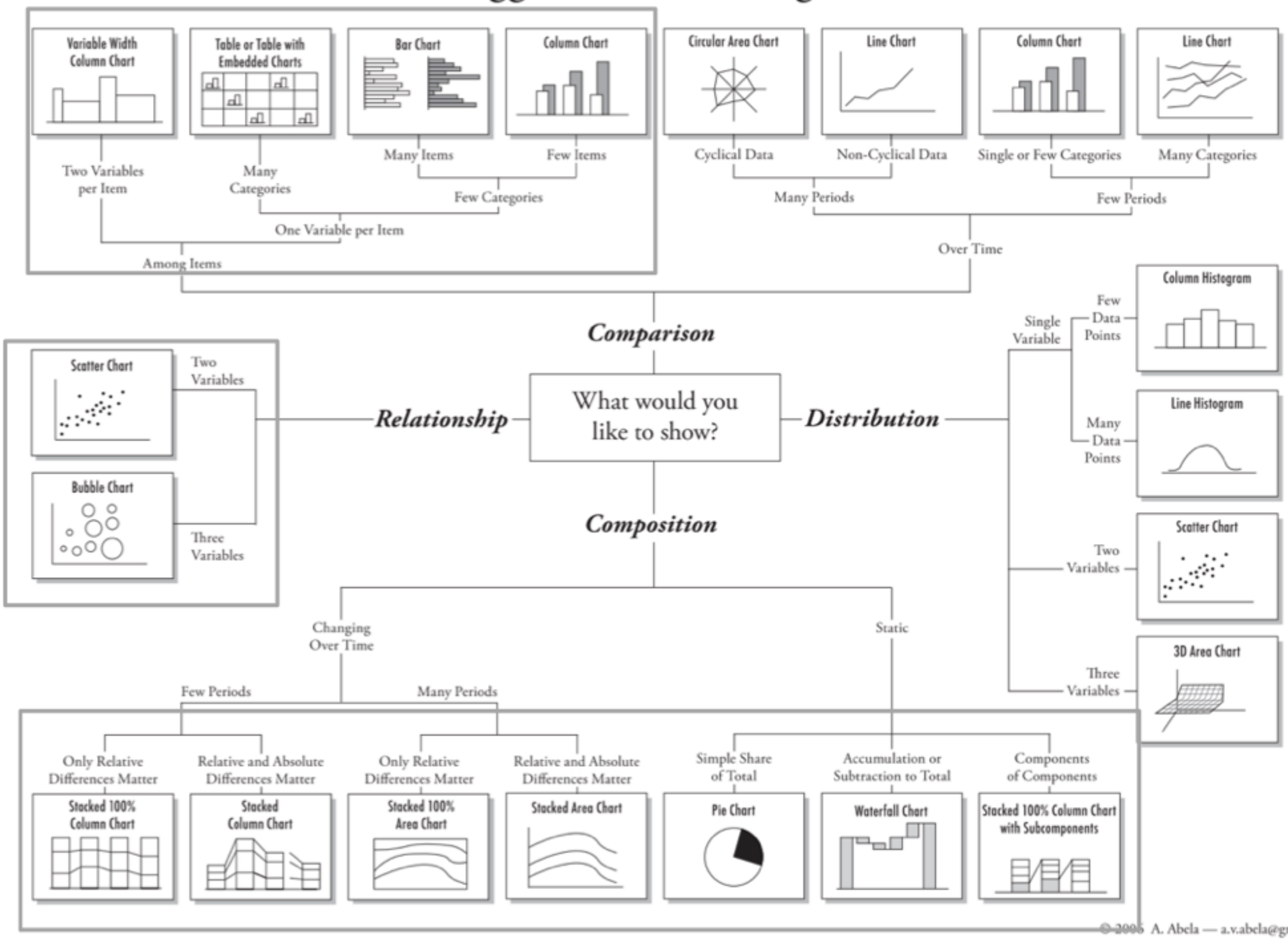




Excel Charts Blog

3. Use The Right Display

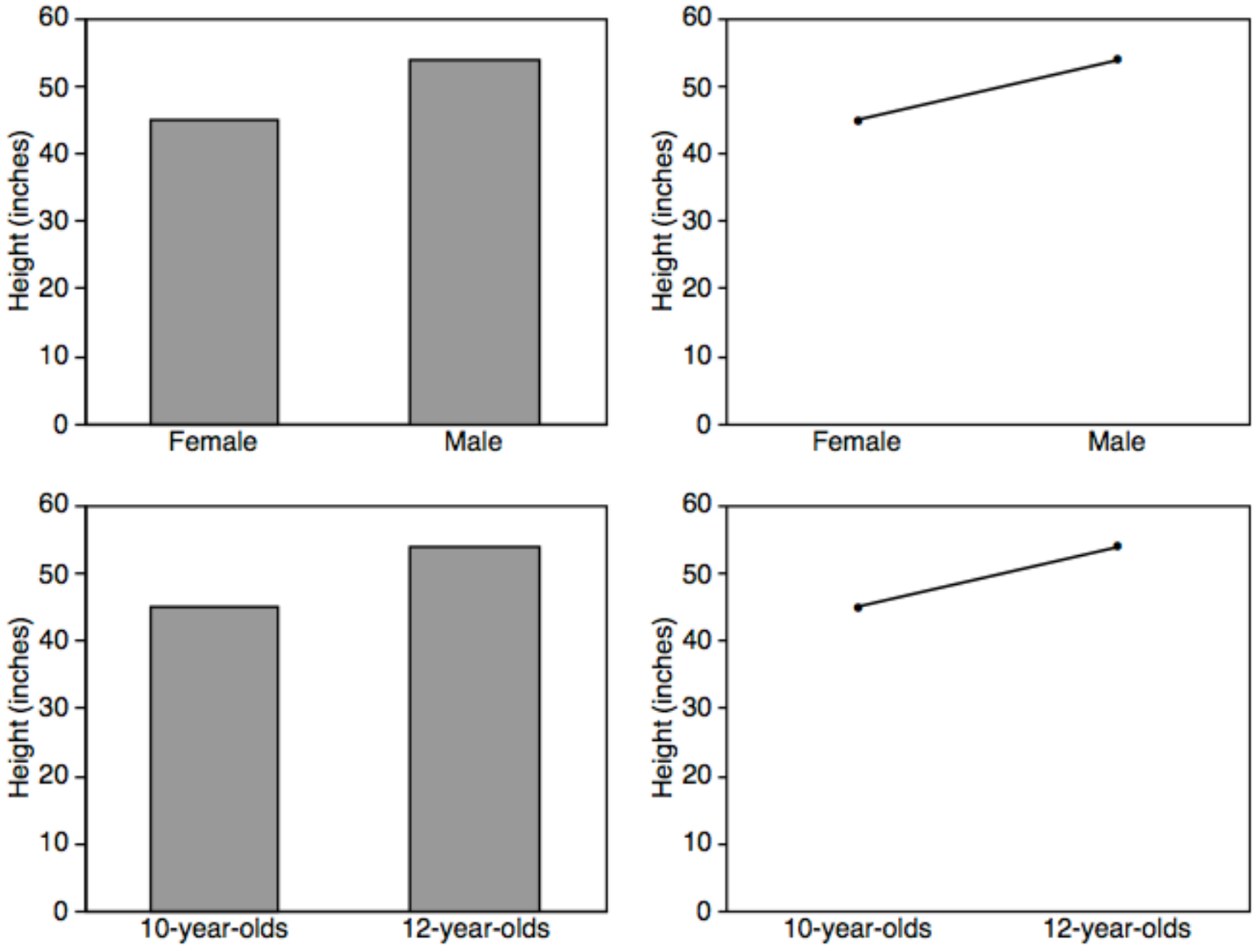
Chart Suggestions—A Thought-Starter



http://extremepresentation.typepad.com/blog/files/choosing_a_good_chart.pdf

Comparisons

Bars vs. Lines

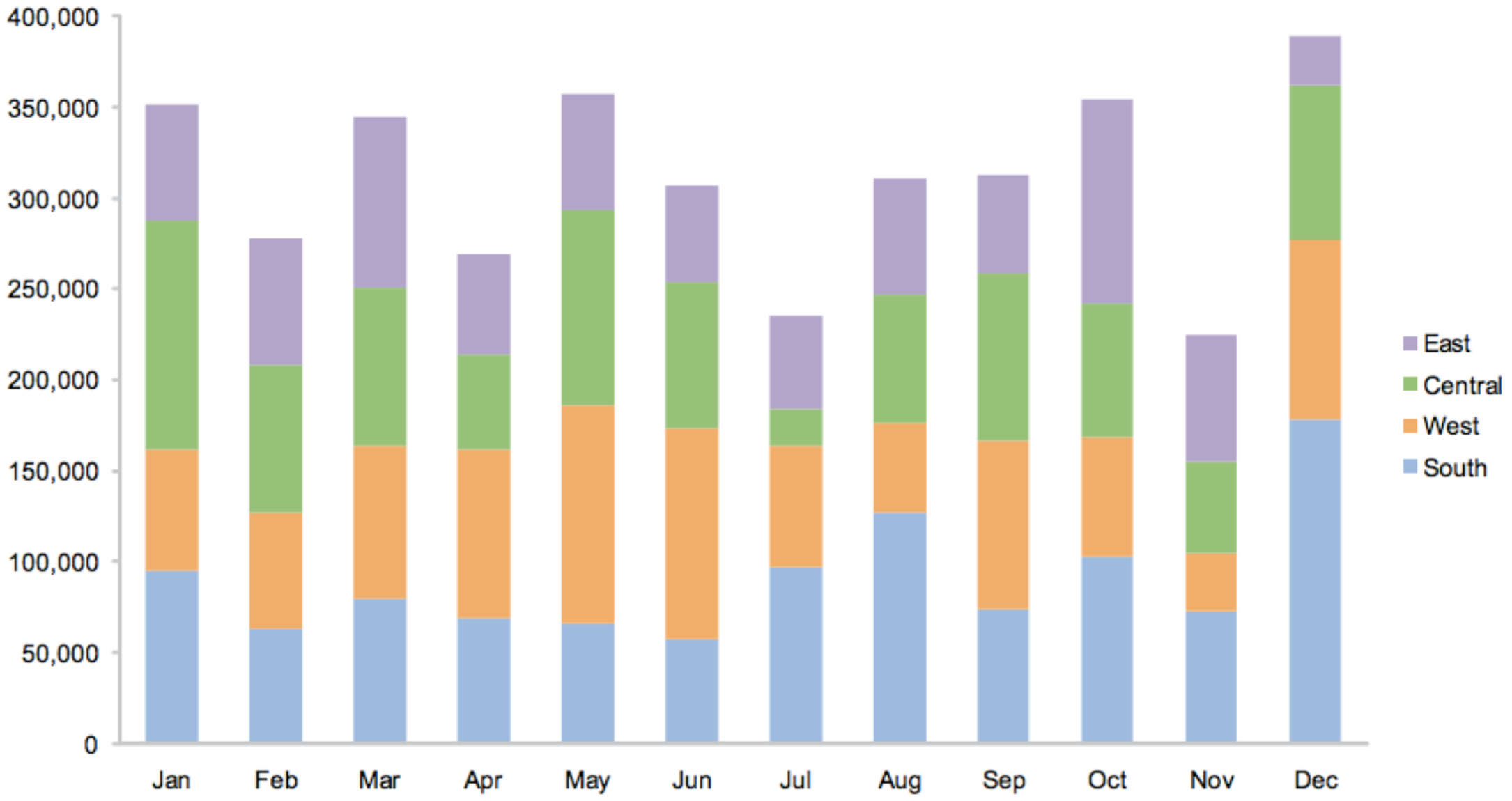


Zacks 1999

Proportions

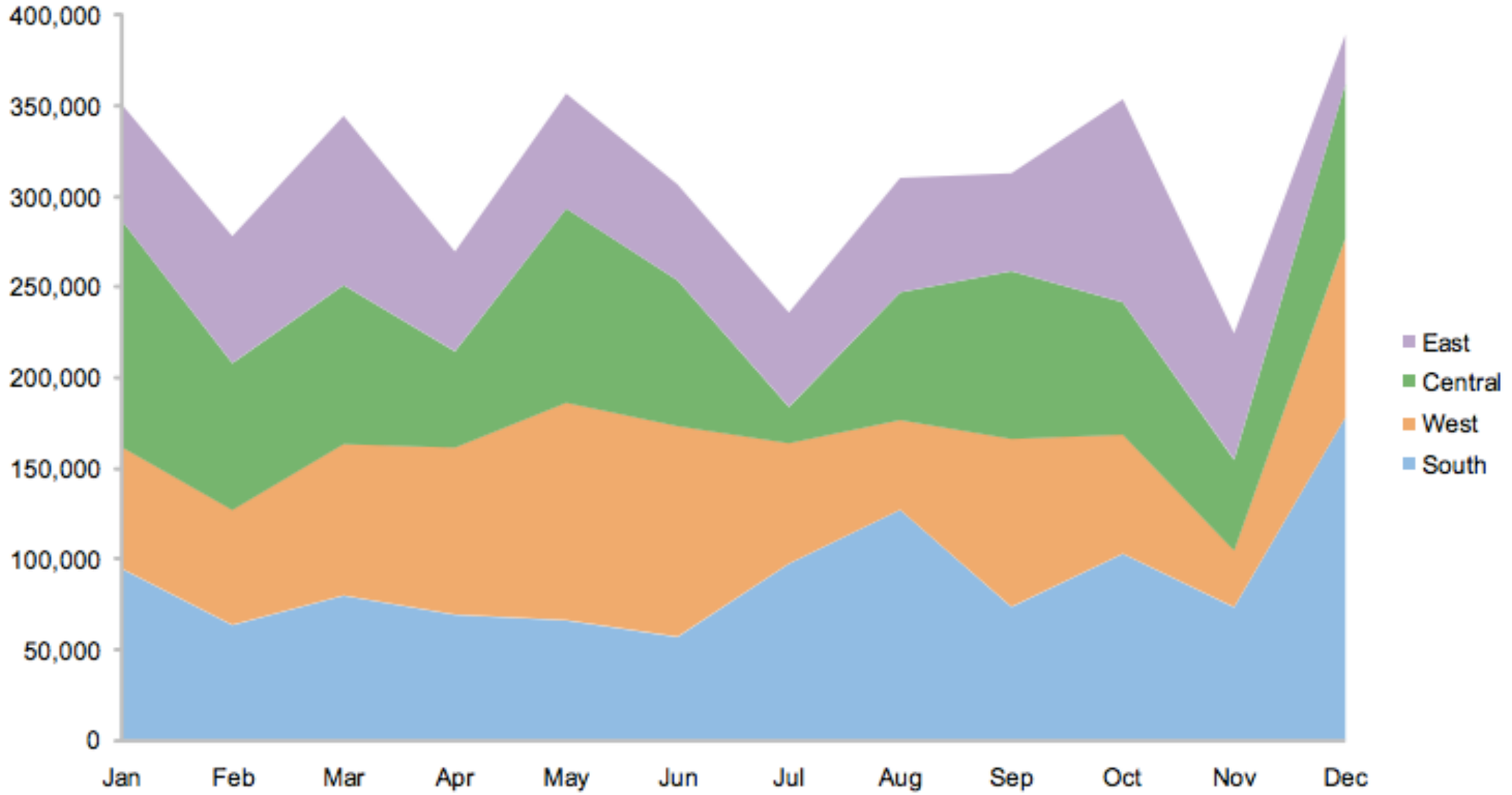
Pie Charts

Stacked Bar Chart



S. Few

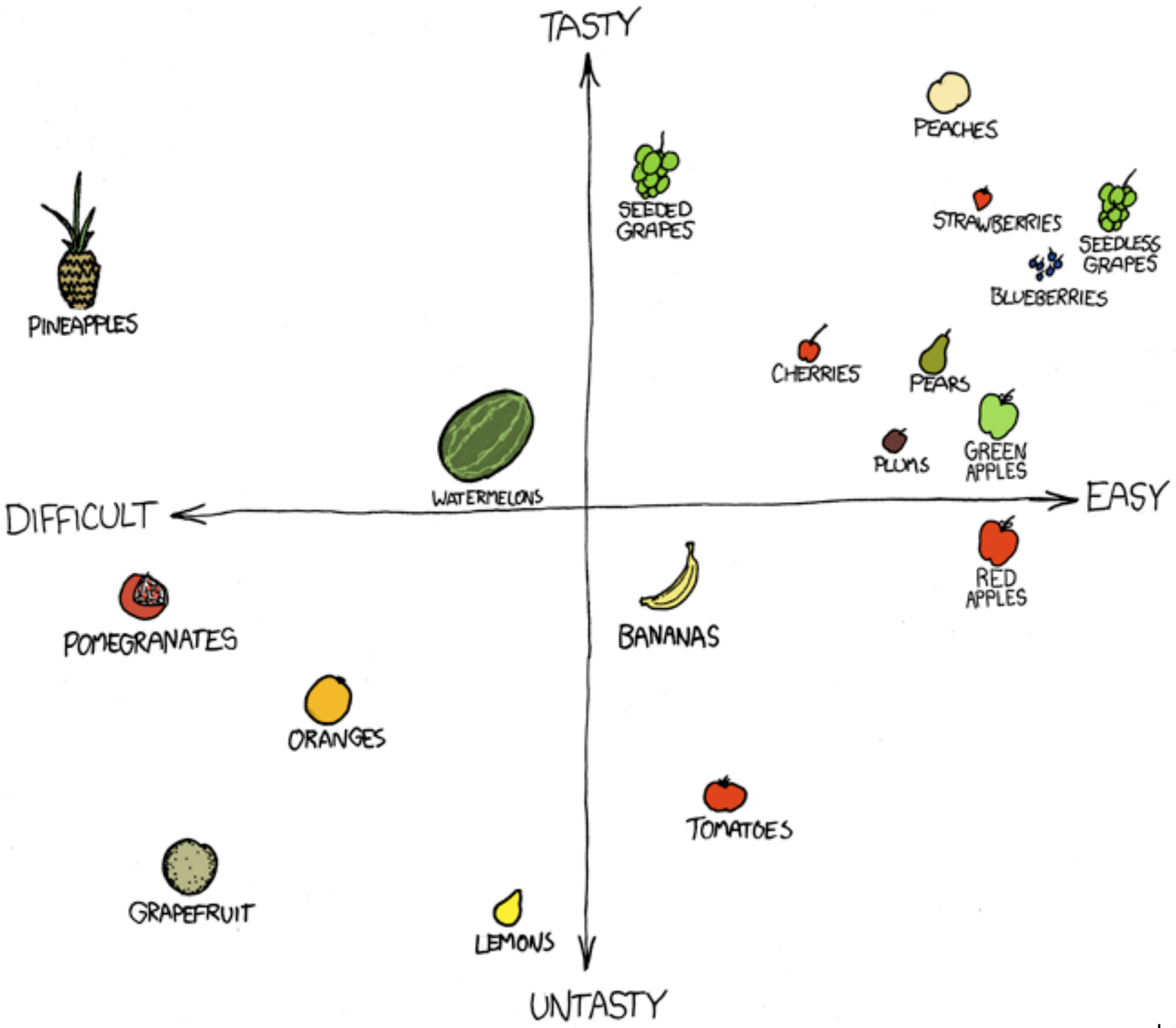
Stacked Area Chart



S. Few

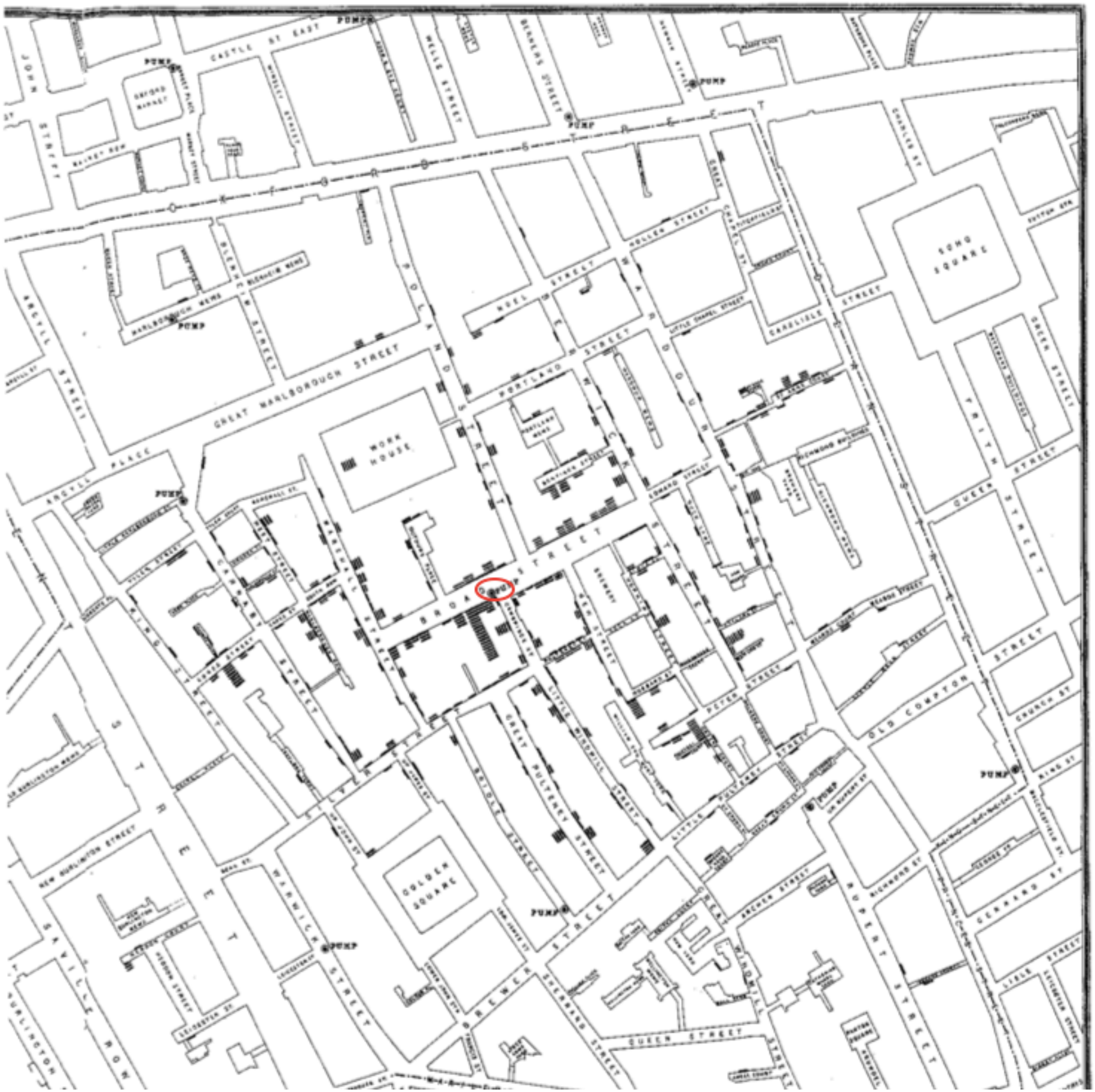
Correlations

Scatterplots



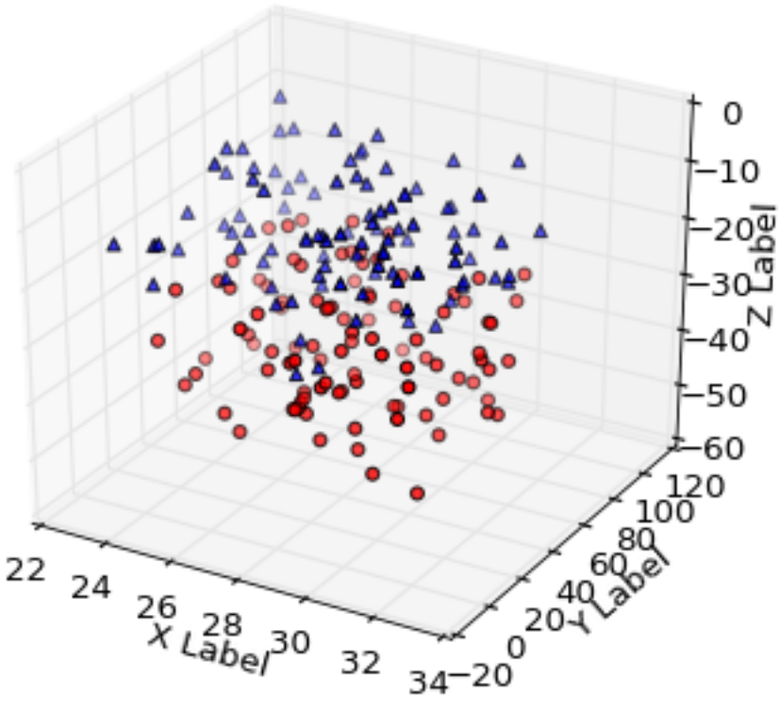
http://xkcd.com/388/

London Cholera Epidemic



From Edward Tufte, Visual and Statistical Thinking

Don’t!


0
−10
−20
−30
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Z Label
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80
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40
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Y Label
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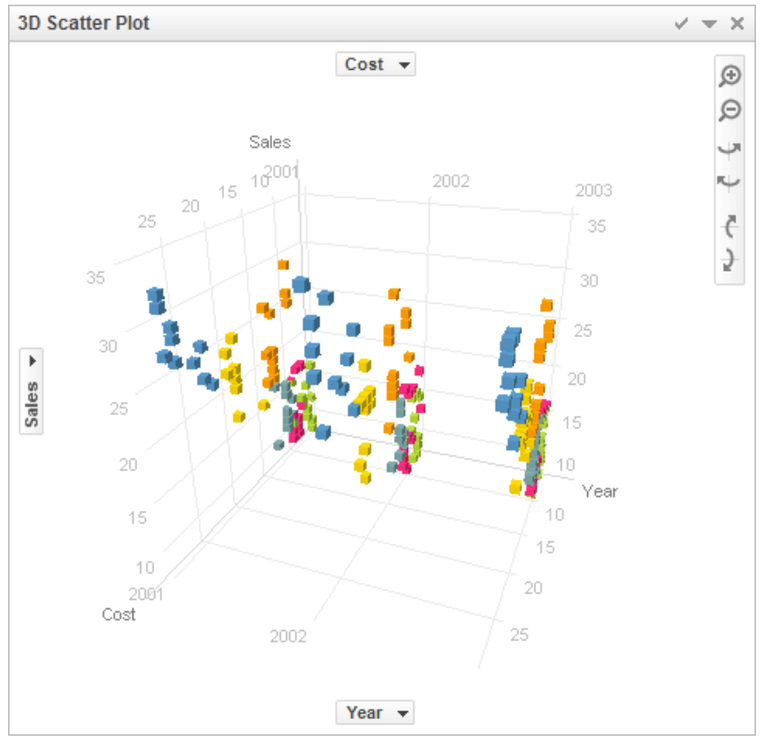
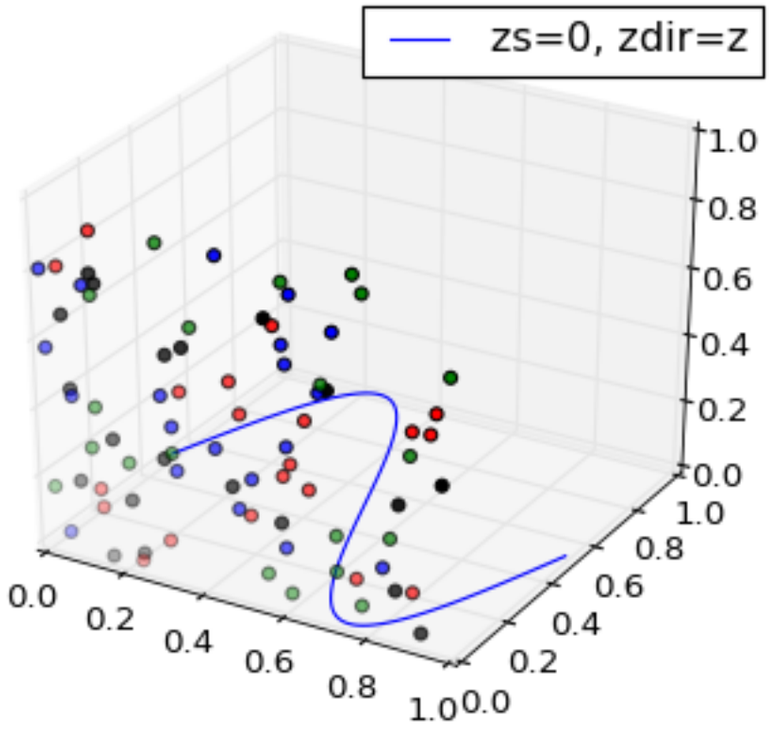
28
30
32
34
−20
X Label


3D Scatter Plot
Cost
Sales
2001
2002
2003
Year
Sales
Cost
Year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1.0
0.8
0.6
0.4
0.2
0.0

Trends

Apple Inc. (AAPL) - NasdaqGS

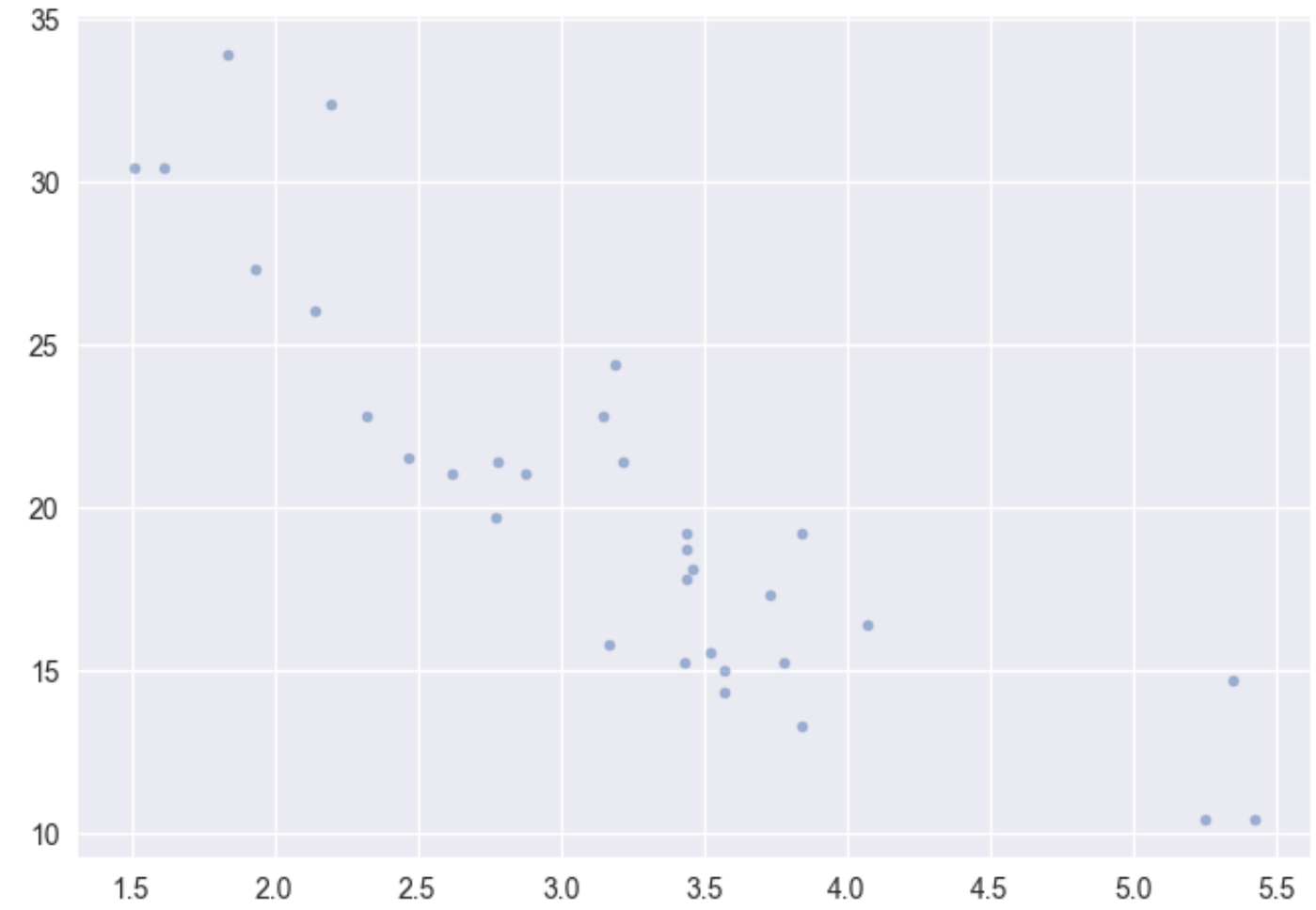
Add to Portfolio | Like 6k

601.10 ↑15.53(2.65%) 4:00PM EDT | After Hours: **604.60** ↑3.50 (0.58%) 7:15PM EDT - Nasdaq Real Time Price

Enter name(s) or symbol(s) | GET CHART | COMPARE | EVENTS | TECHNICAL INDICATORS | CHART SETTINGS | RESET

Basic Chart | Full Screen | Print | Share | Send Feedback

Yahoo! Finance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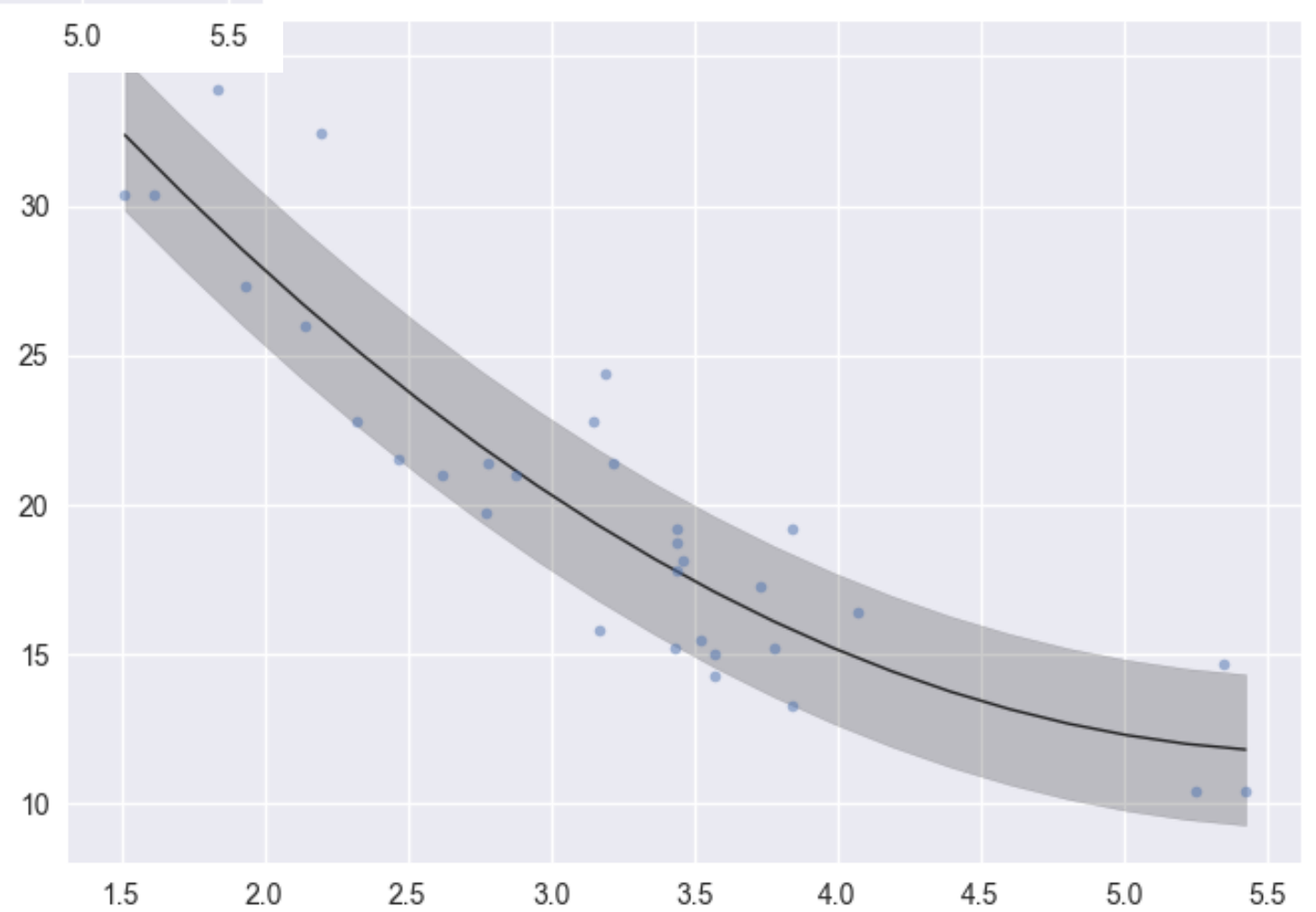
5.5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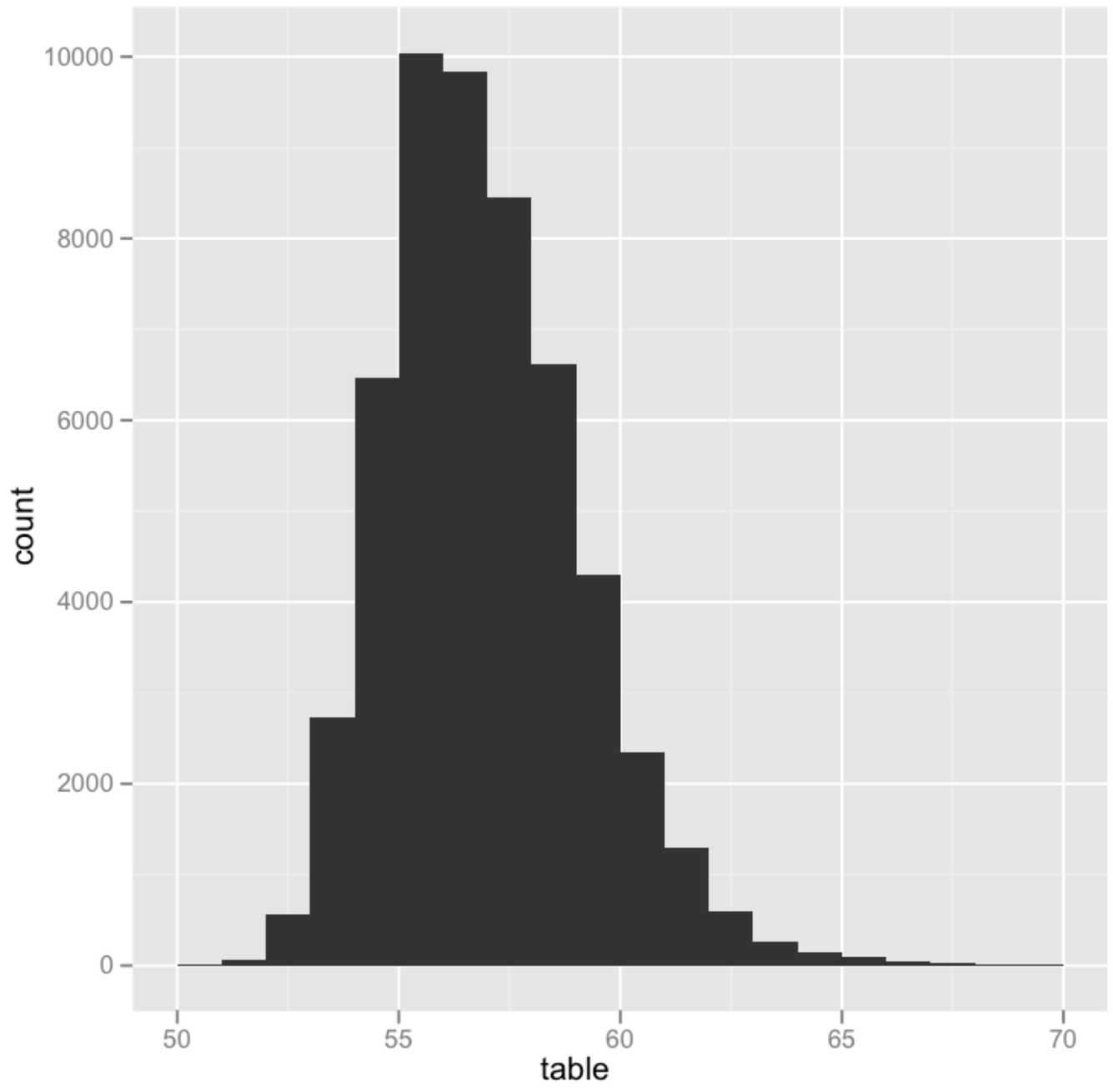
4.5
5.0
5.5

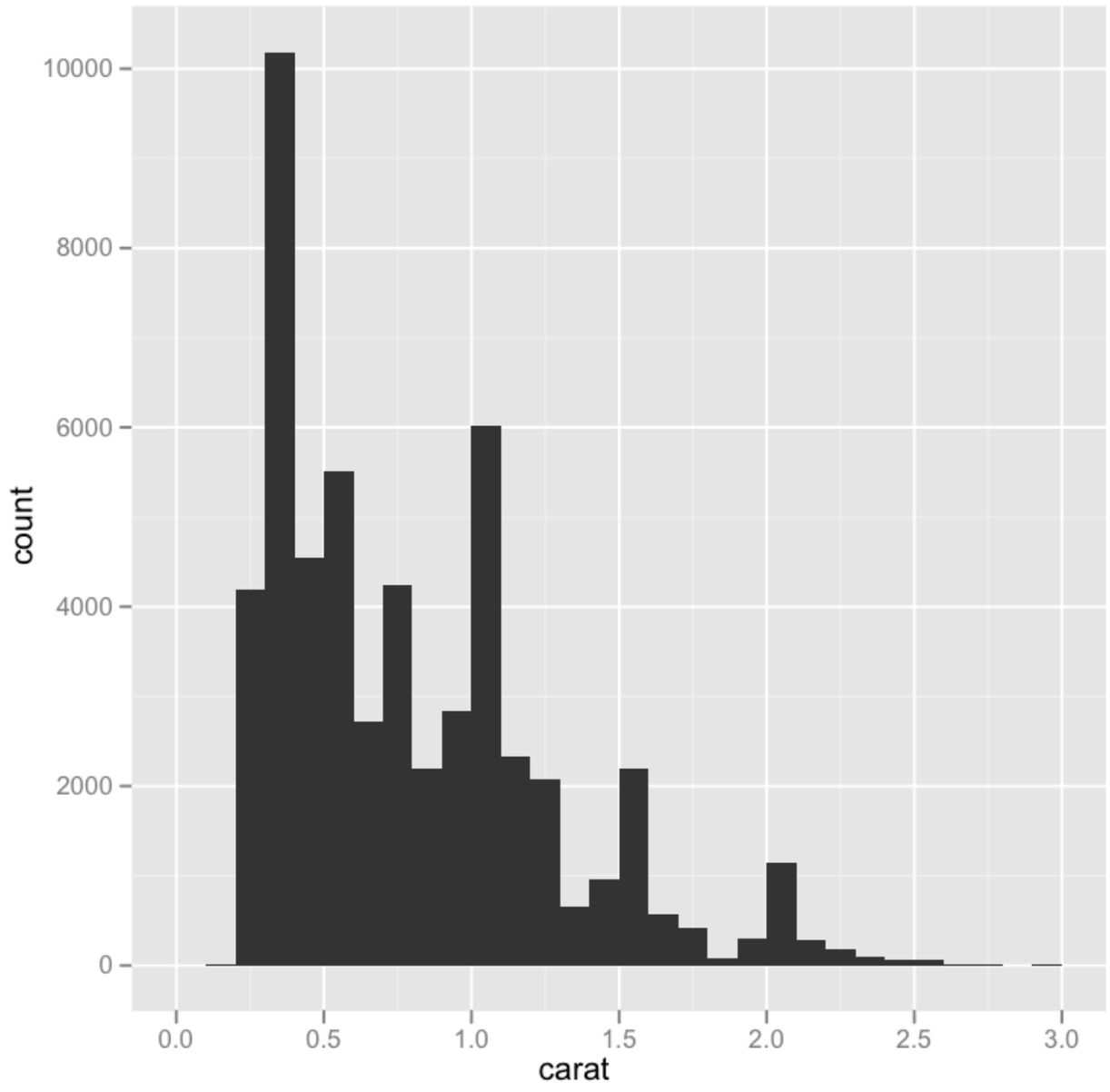
Distributions

Histogram



ggplot2

Bin Width



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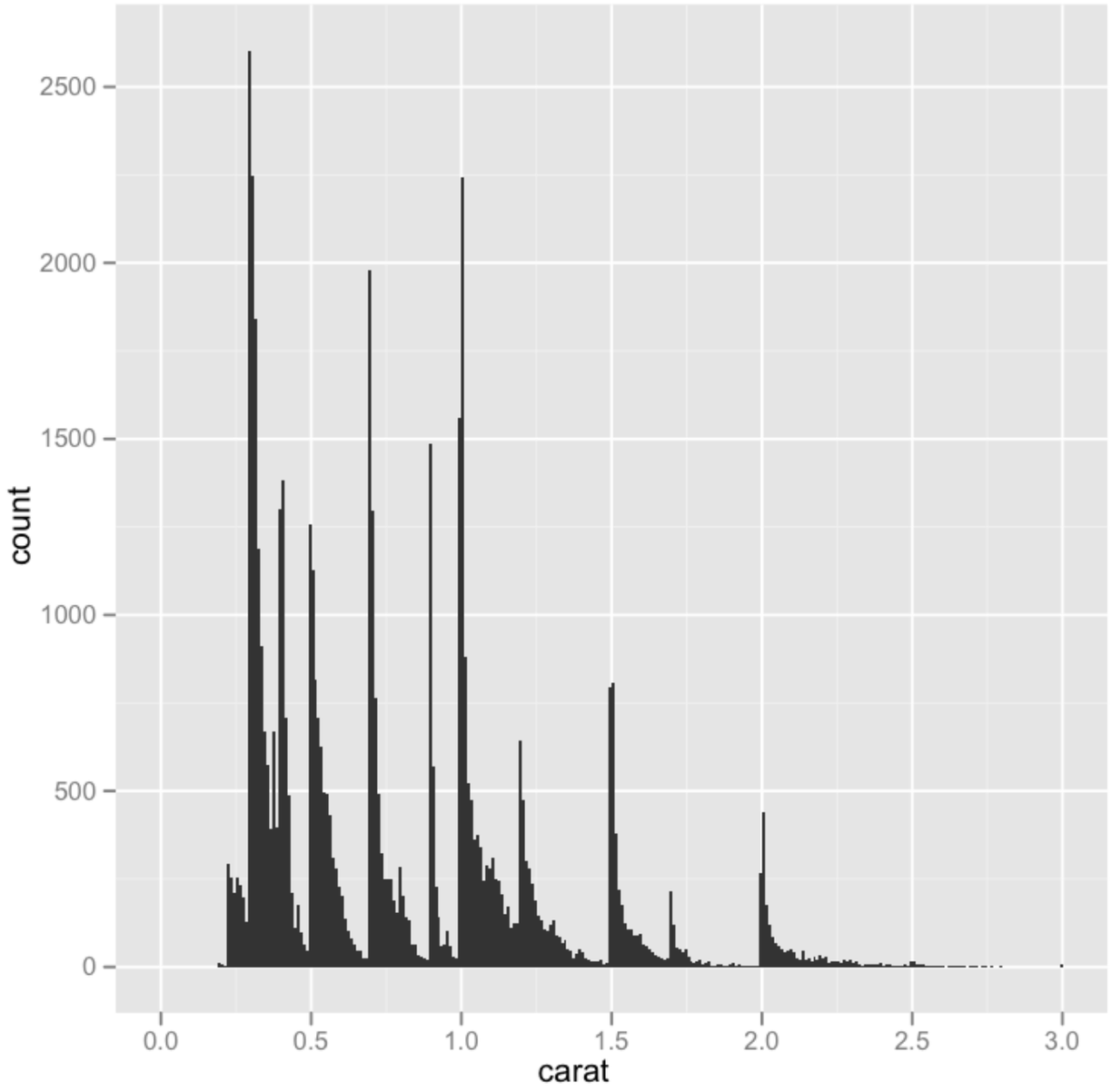

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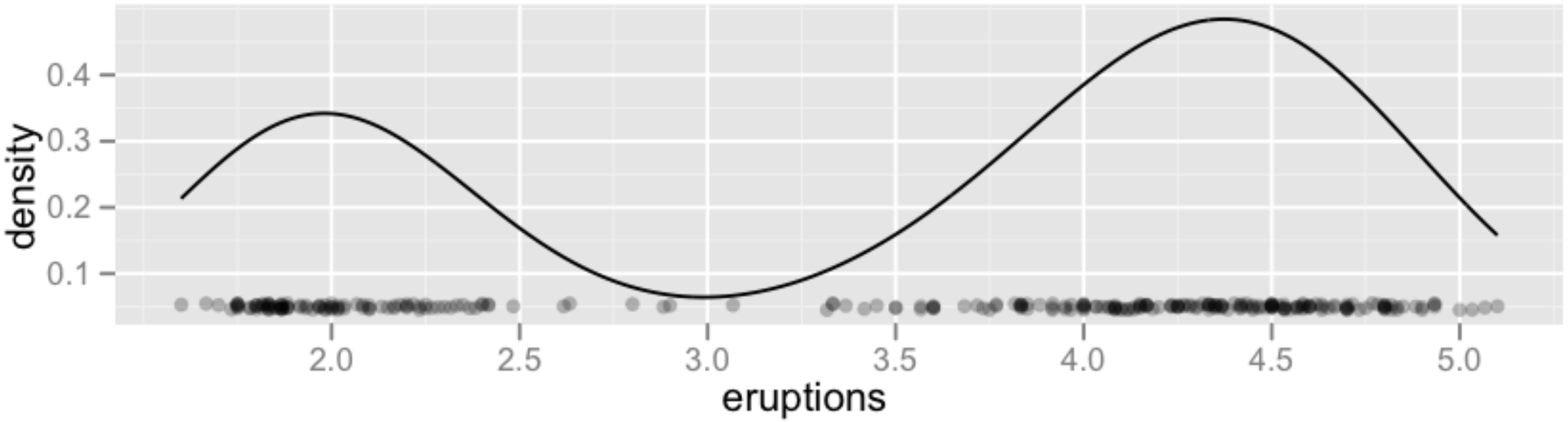
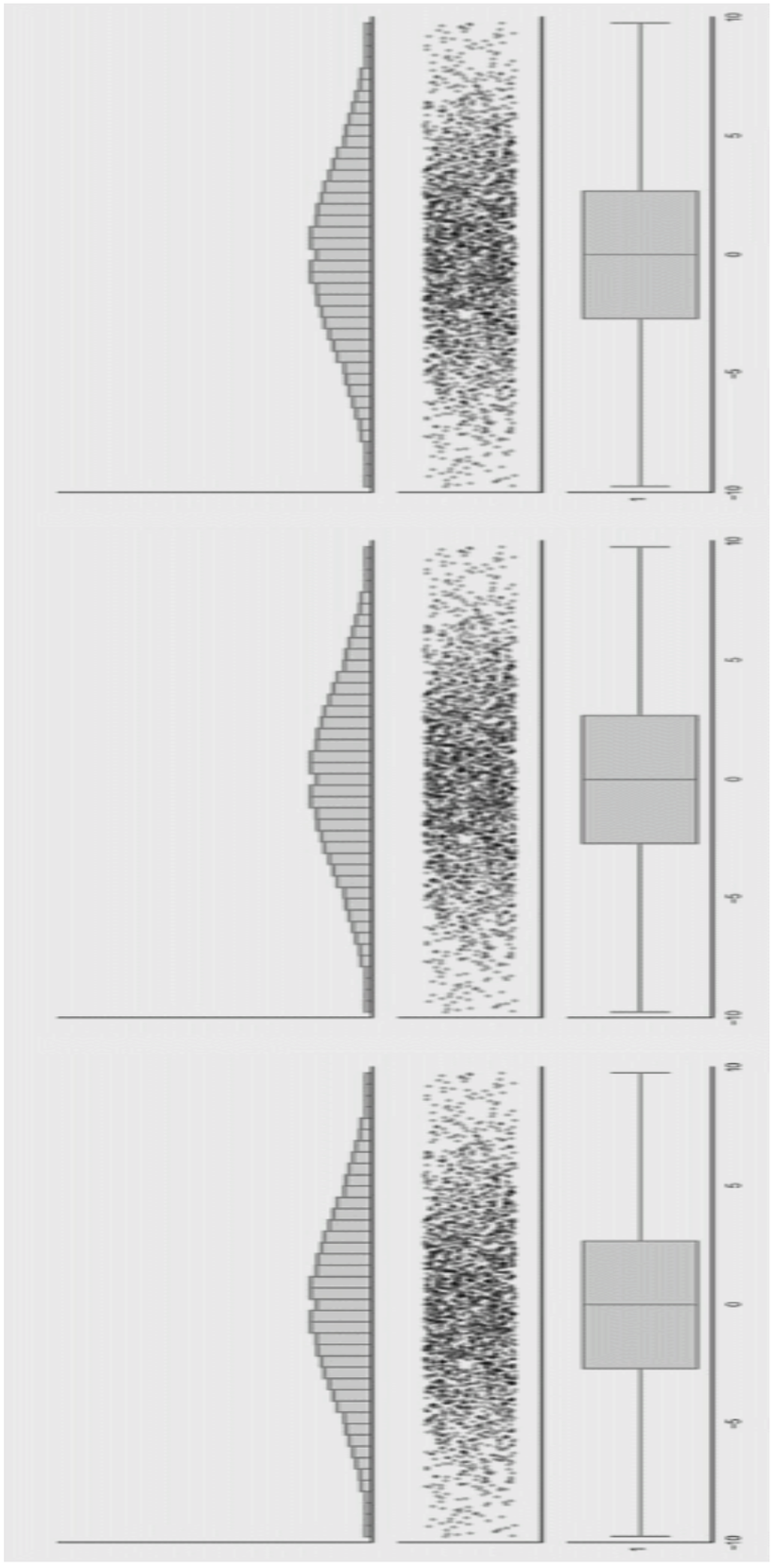
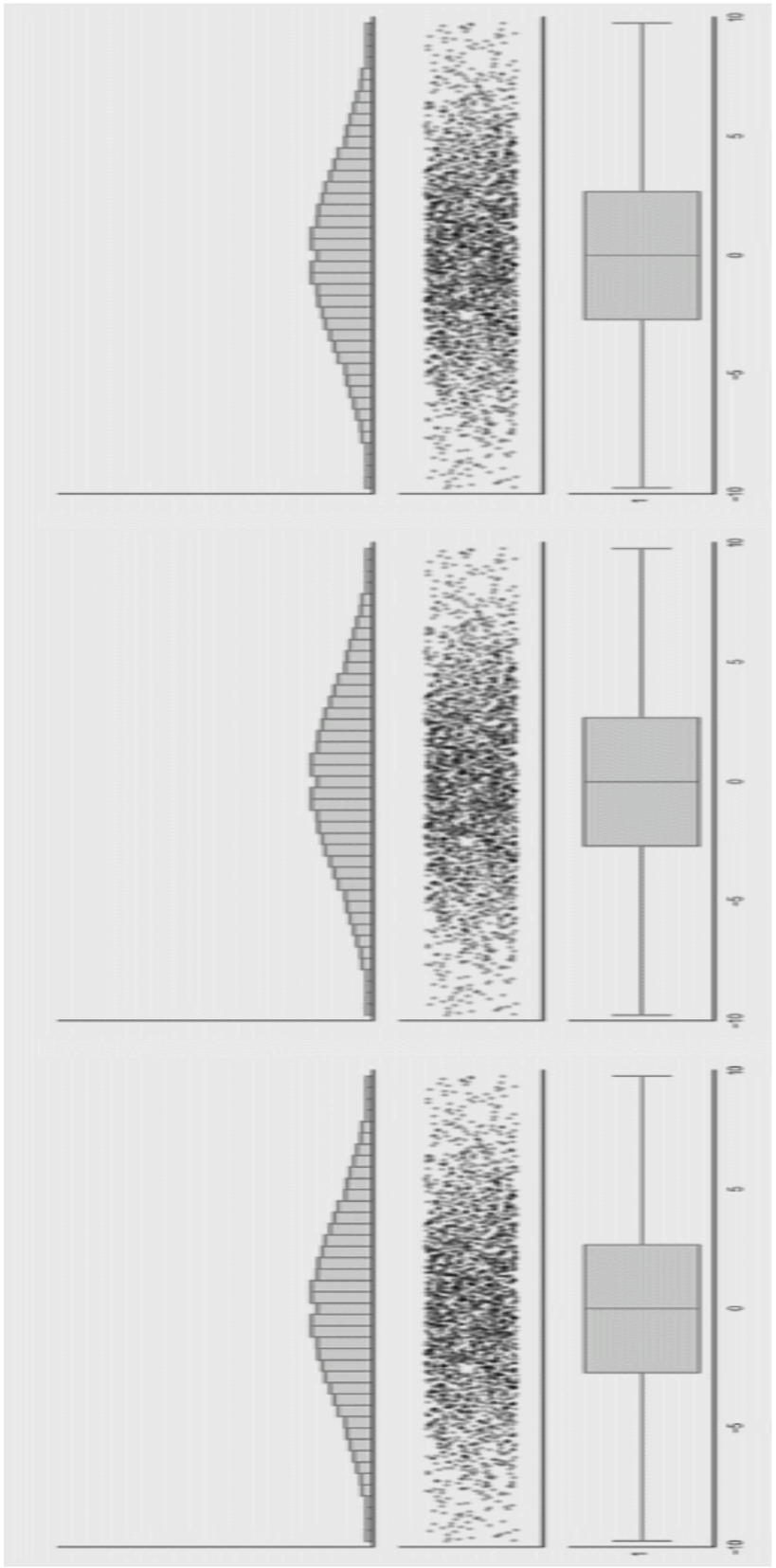
Density Plots



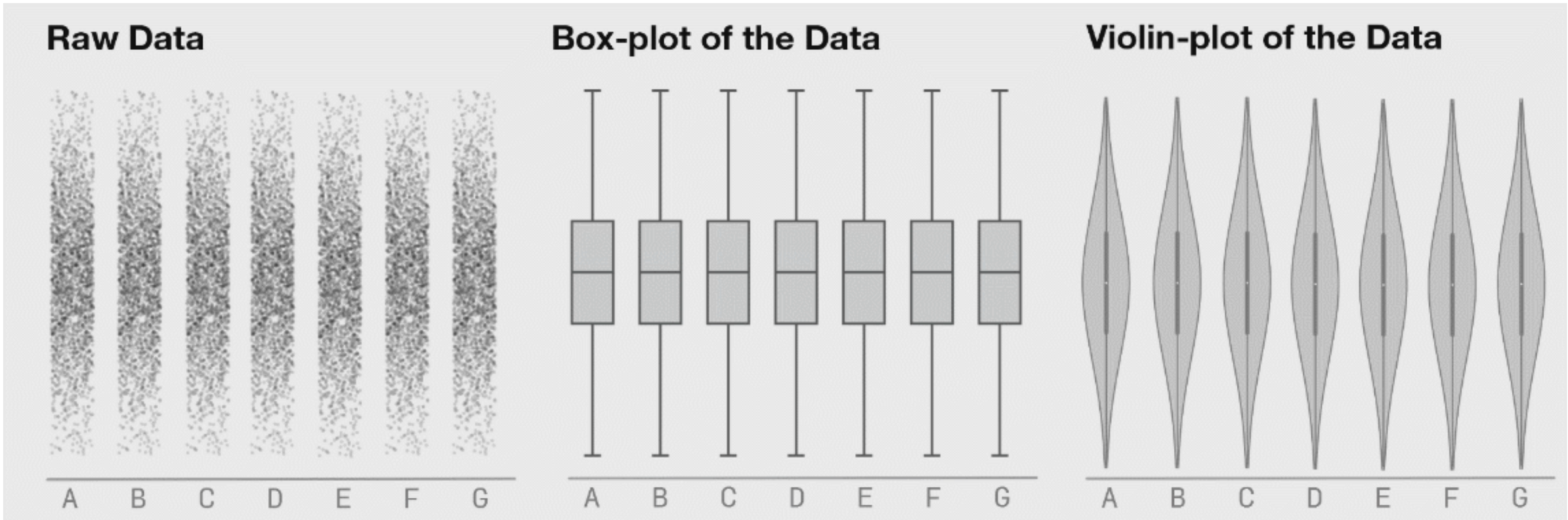


https://
www.autodeskresearch.com/
publications/samestats



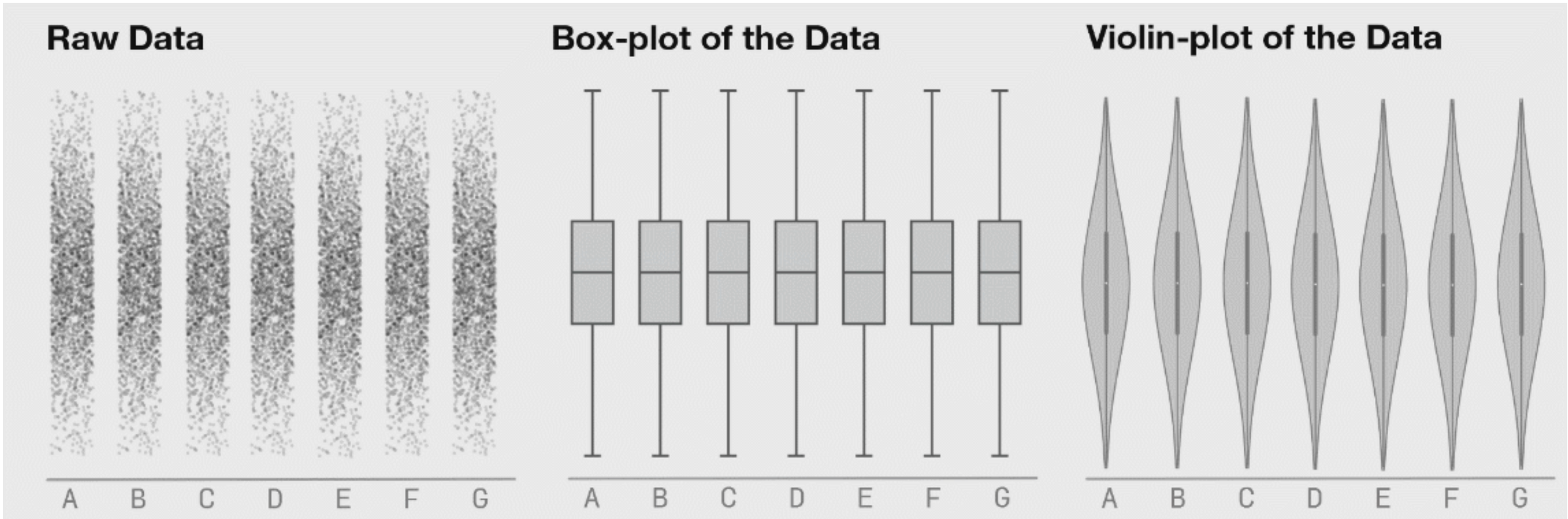
same box plot but diff distributions (animation)

https://
www.autodeskresearch.com/
publications/samestats



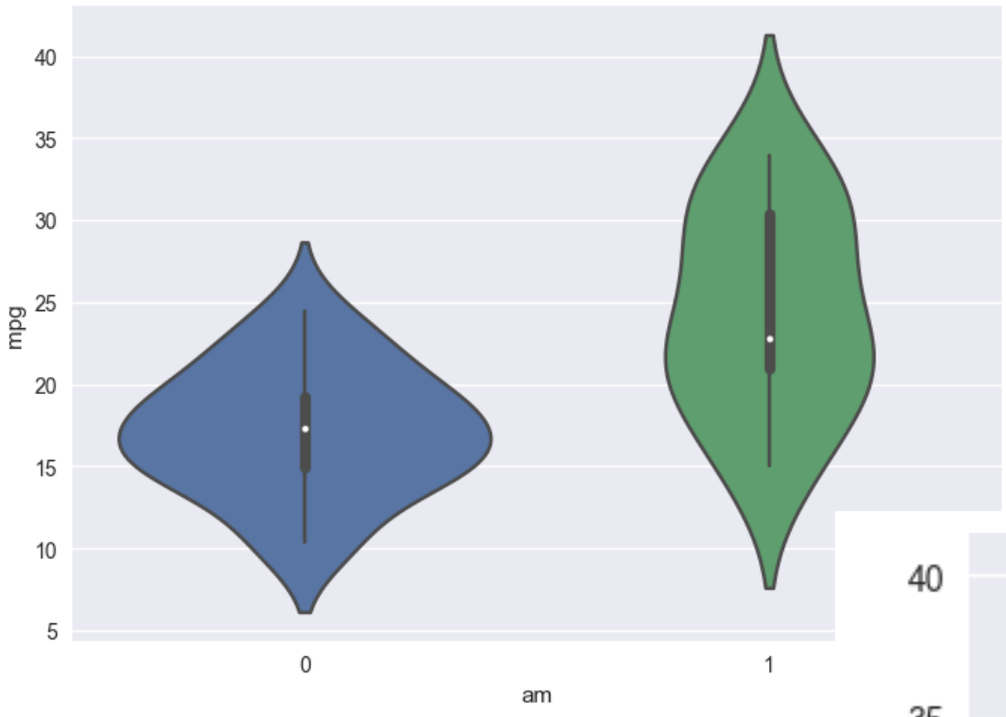
2 sided kernel density plot

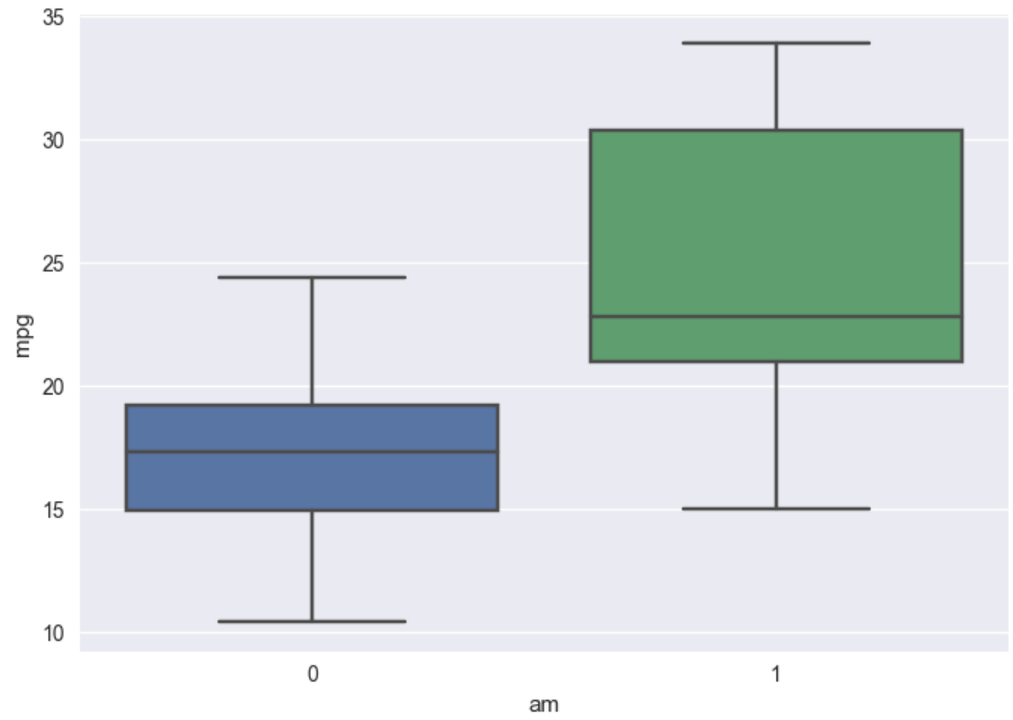
https://www.autodeskresearch.com/publications/samestats



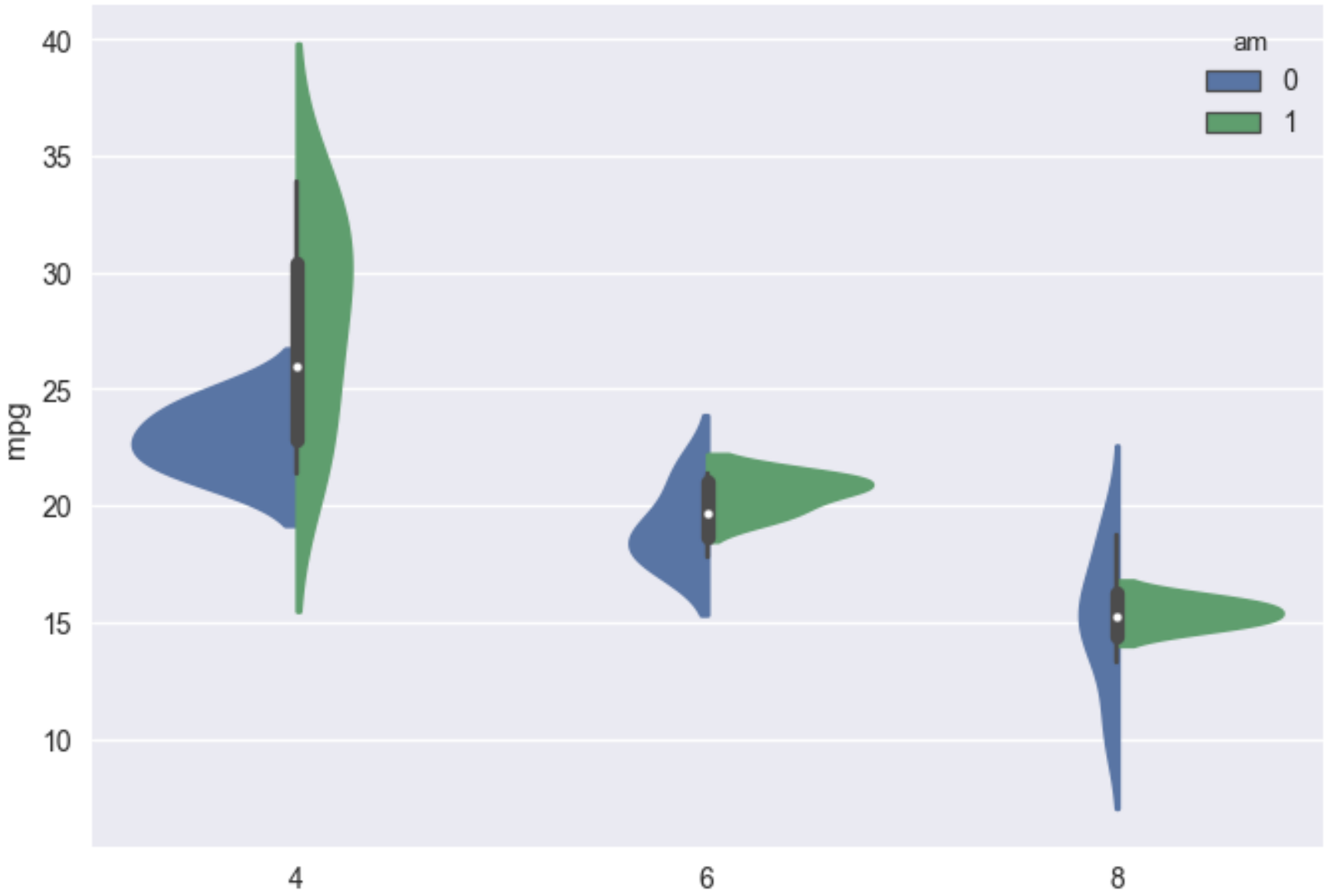
https://www.autodeskresearch.com/publications/samestats

GROUP



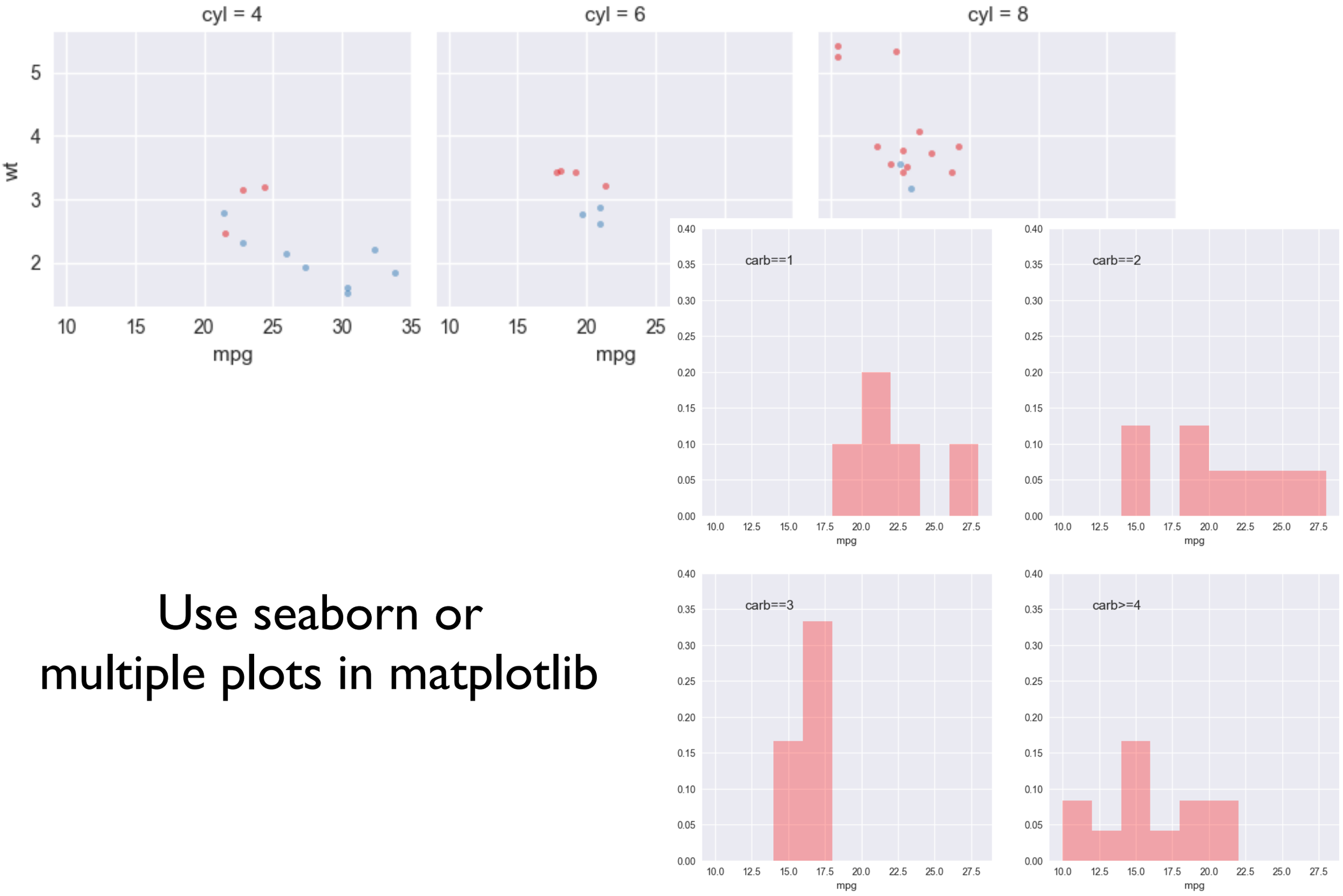


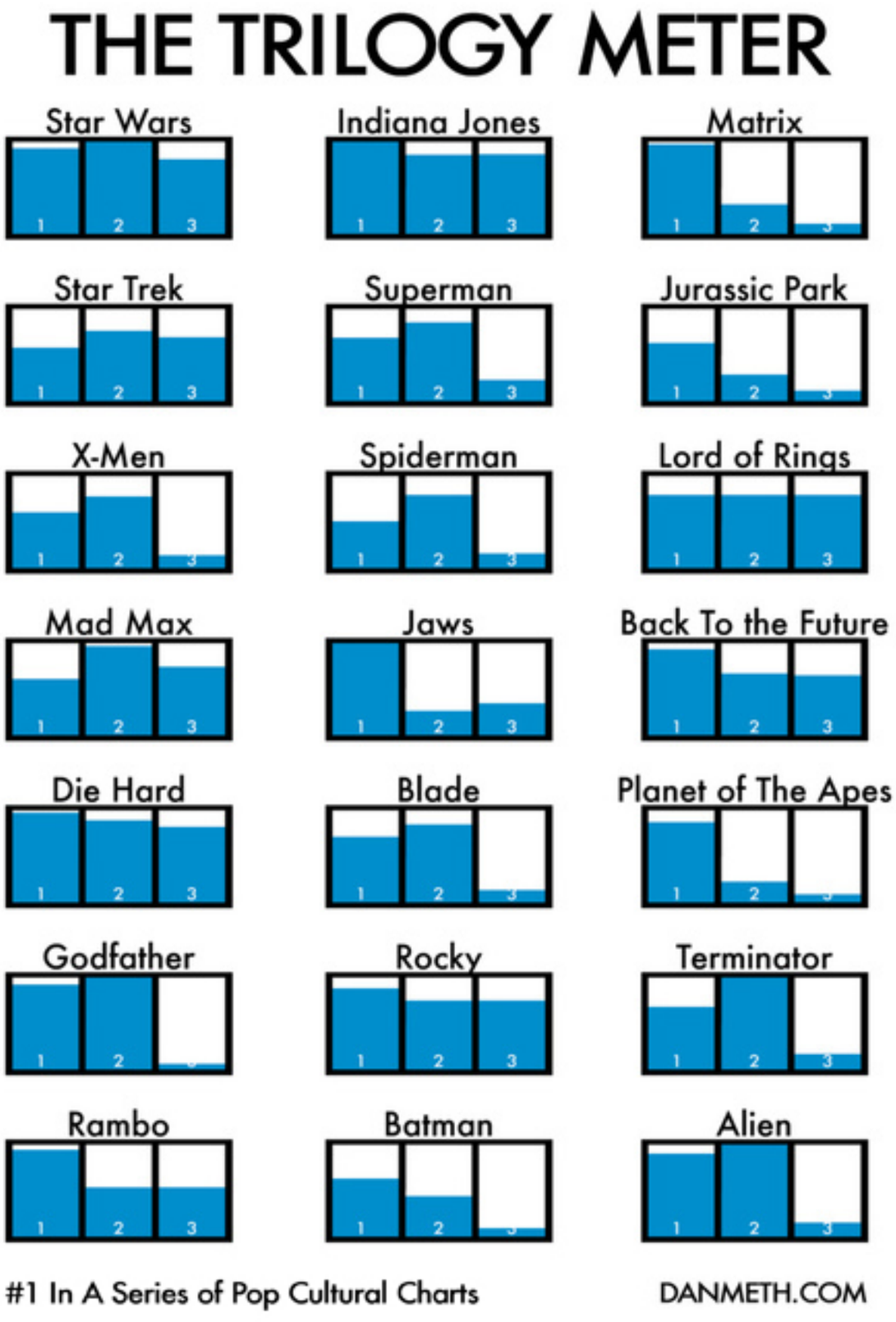
getting complex…



Faceting and Small Multiples

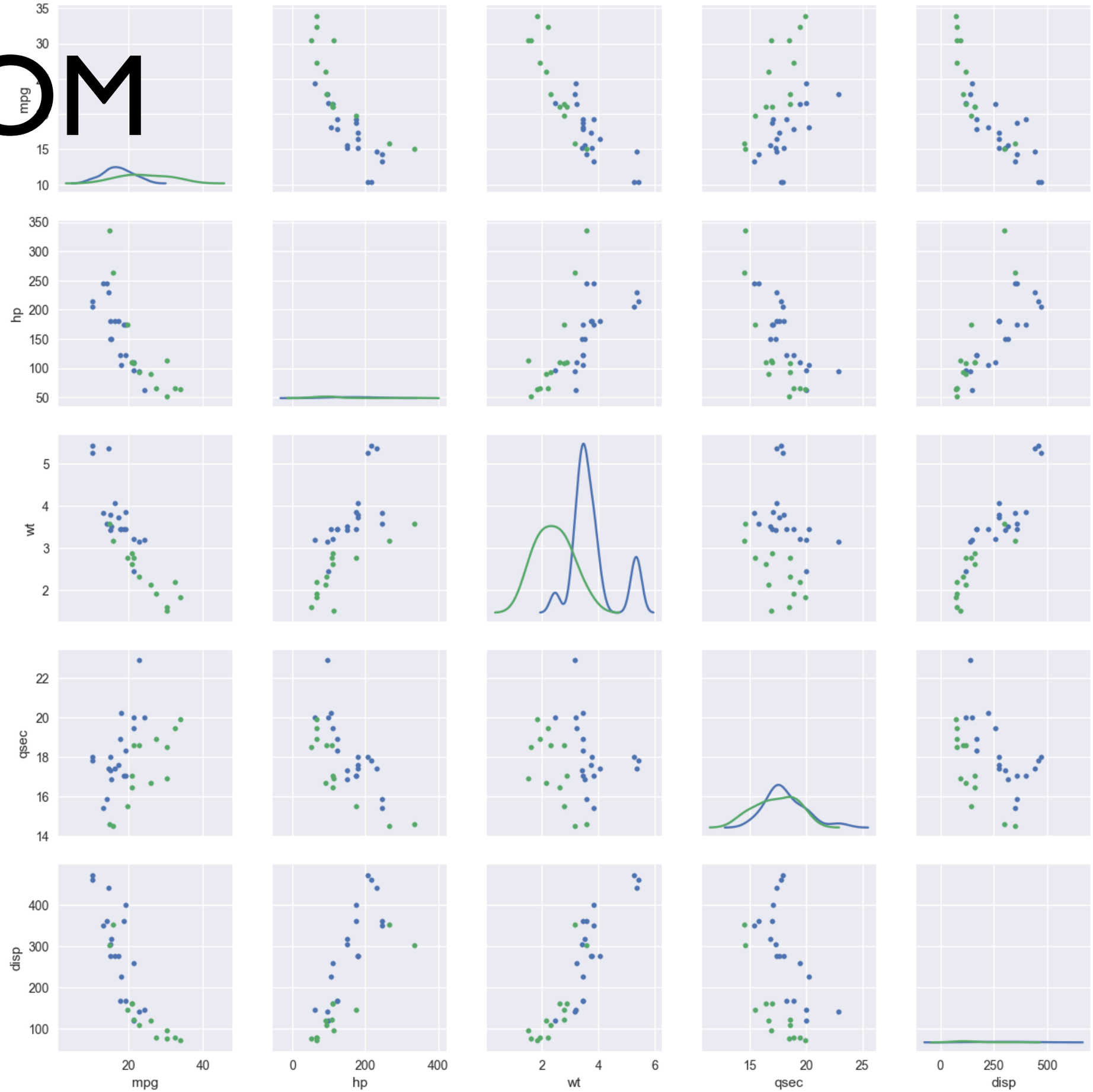
Use seaborn or
multiple plots in matplotlib





Small multiples

SPLOM


mpg
hp
wt
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30
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100
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5
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20
18
16
14
400
300
200
100
20
40
0
200
400
2
4
6
15
20
25
0
250
500

Design Exercise

Hands-On Exercise

How do you feel about doing science?

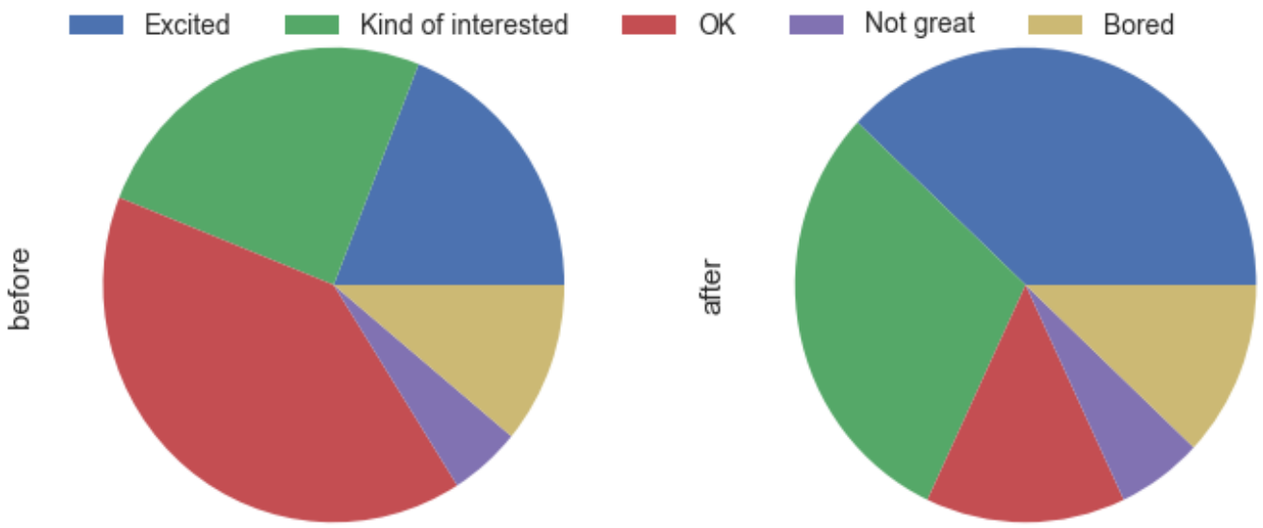
Table

Interest	Before	After
Excited	19	38
Kind of interested	25	30
OK	40	14
Not great	5	6
Bored	11	12

Data courtesy of Cole Nussbaumer

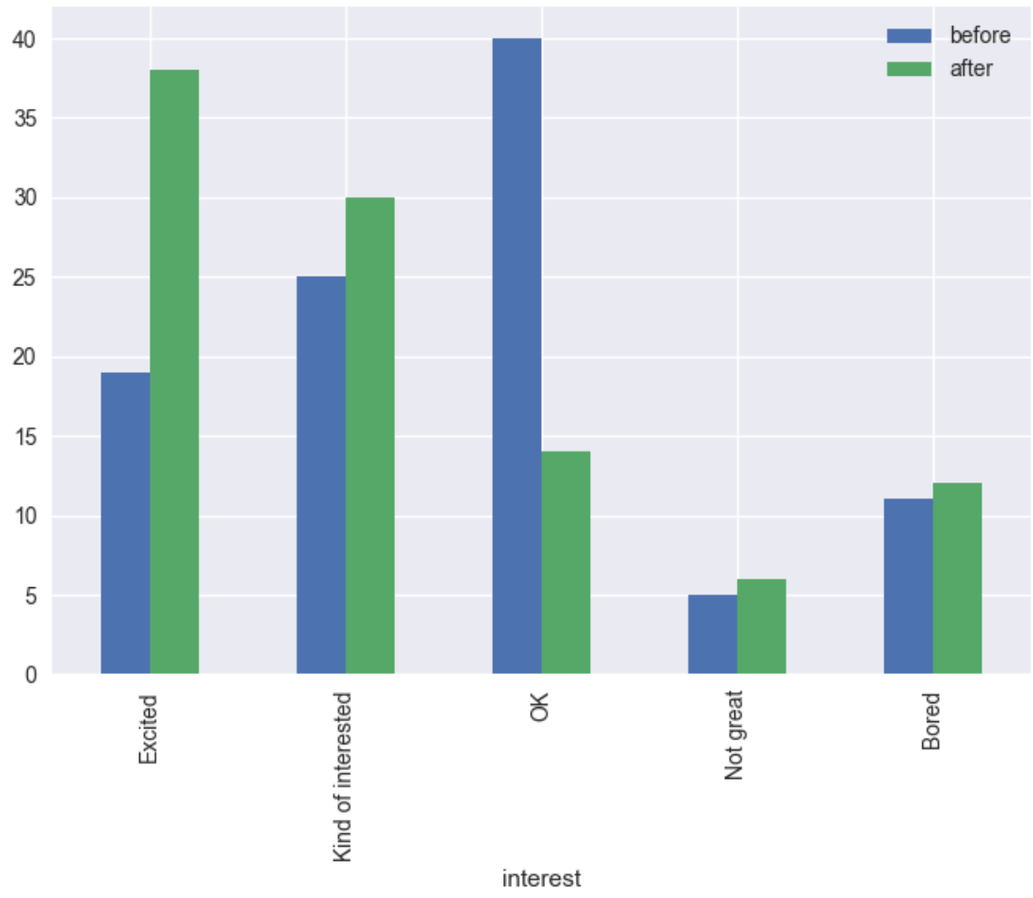
Come up with multiple visualizations.

Pen and Paper Only.

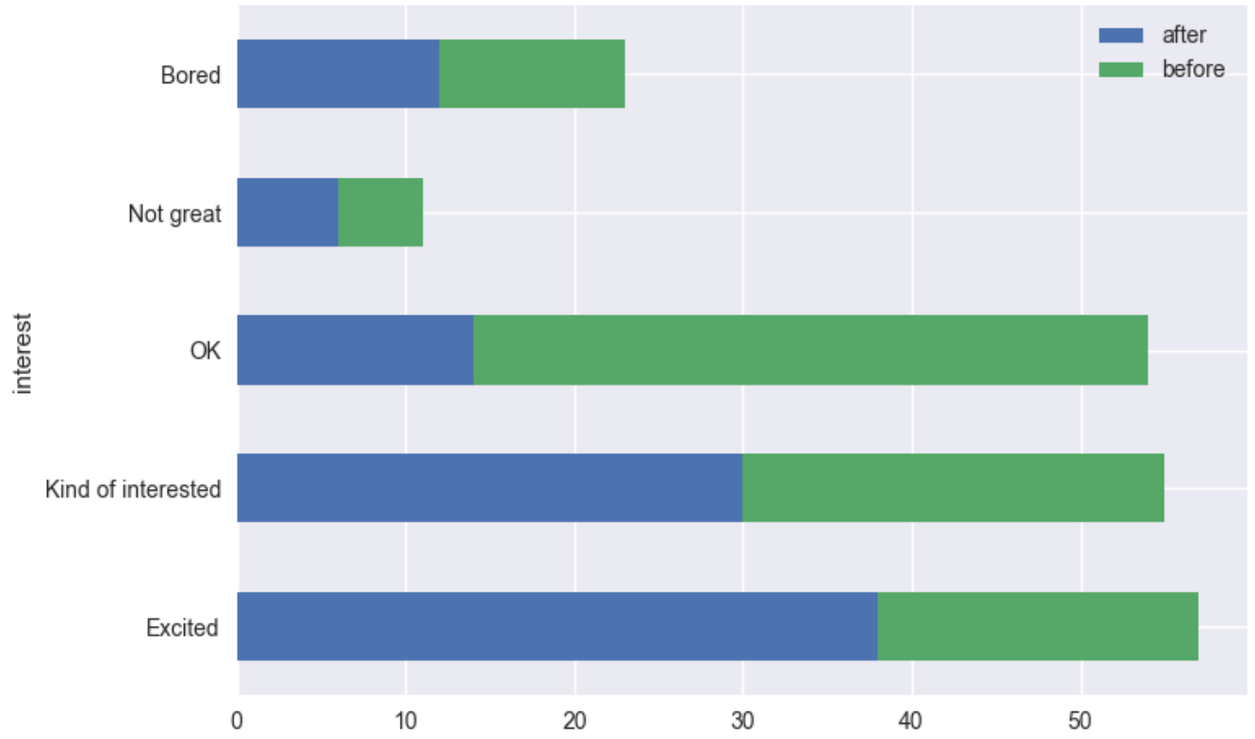


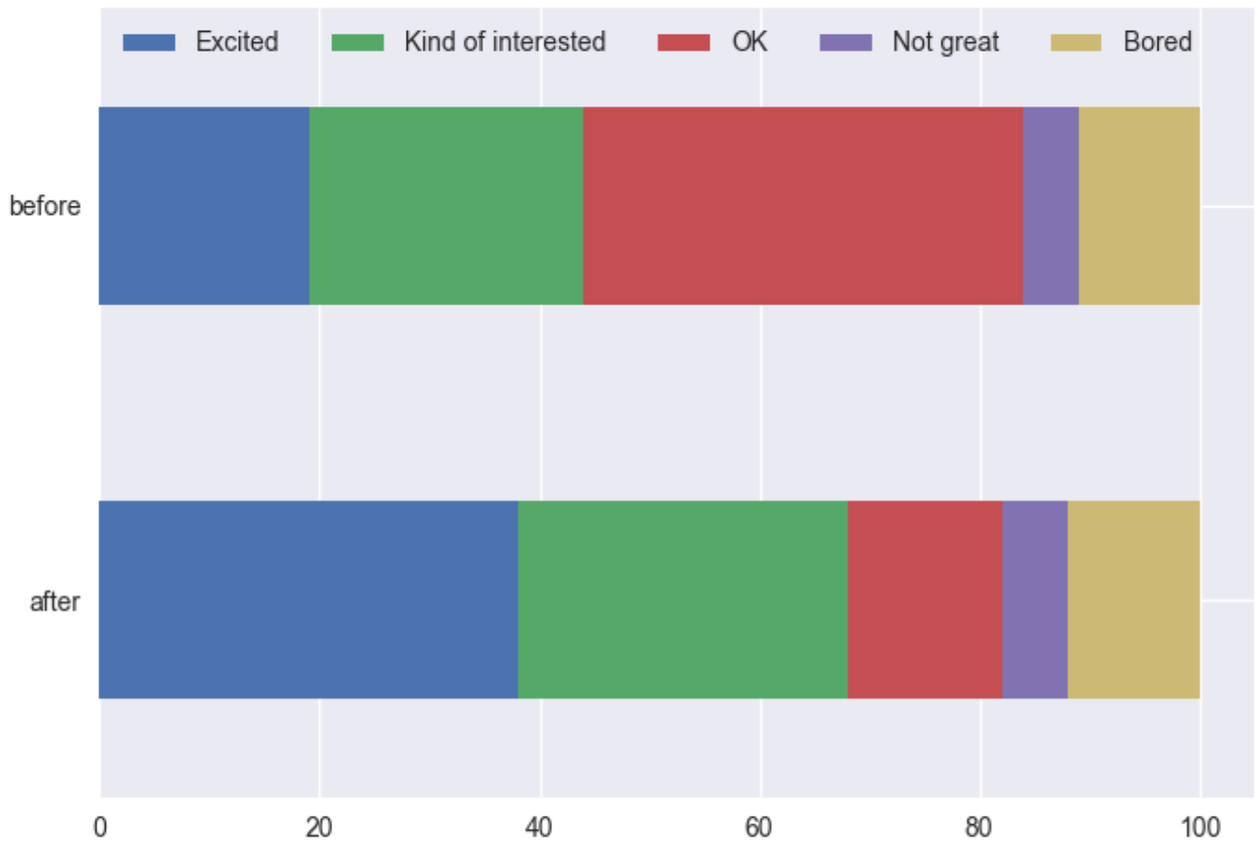
Pie

Side by side bar



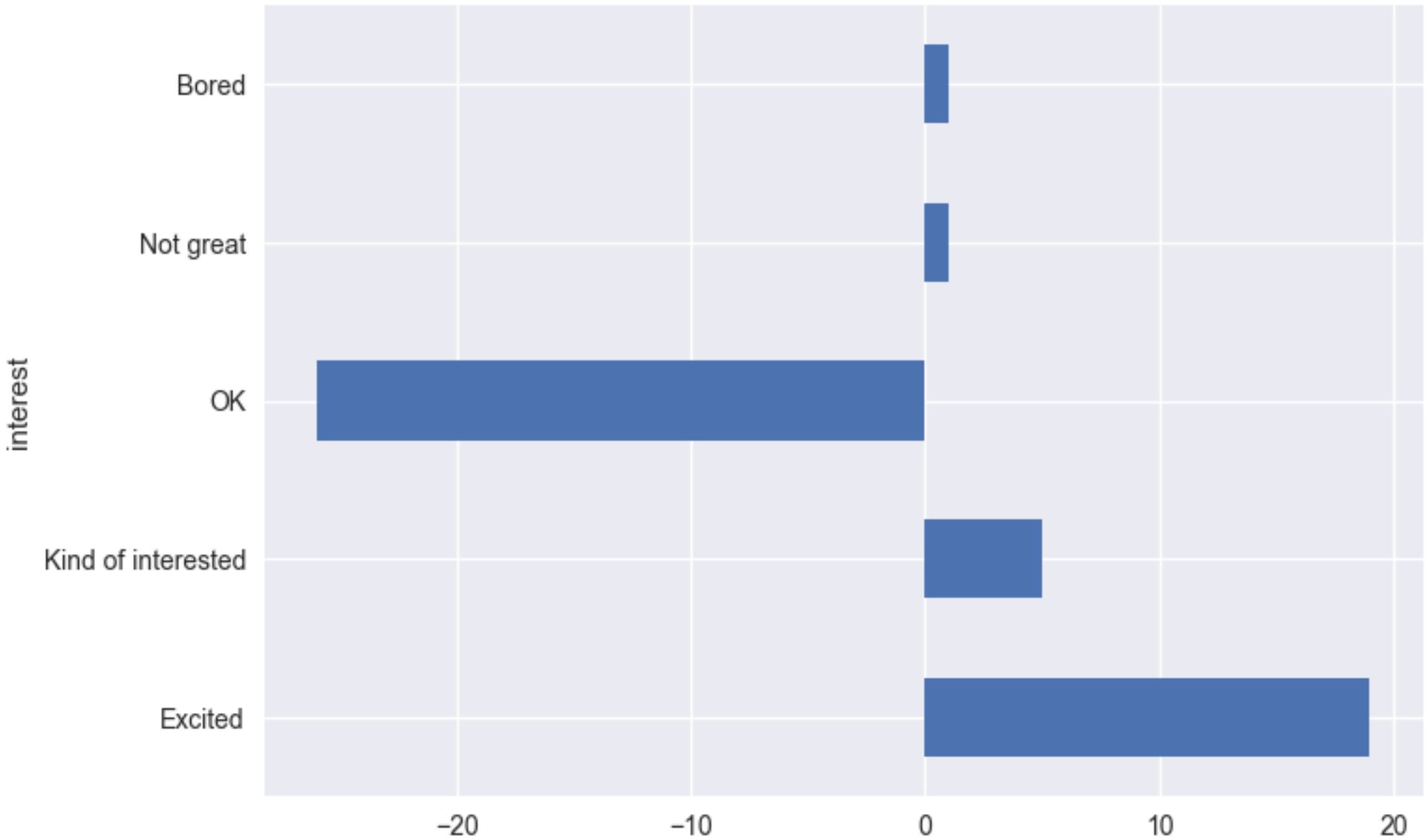
Stacked bar, not very useful



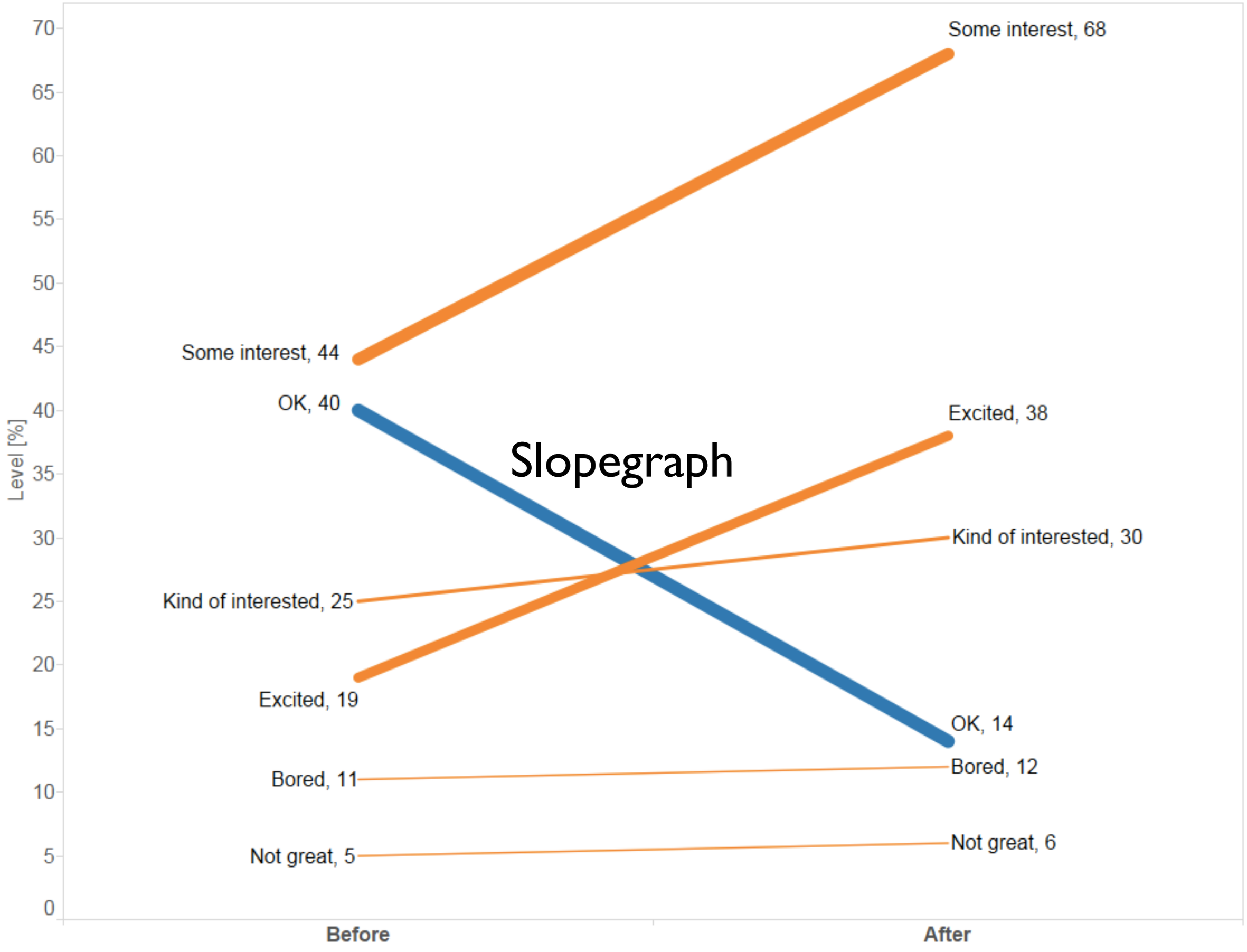


Data Transposed Bar Chart

Difference Bar Chart



How do you feel about doing science?

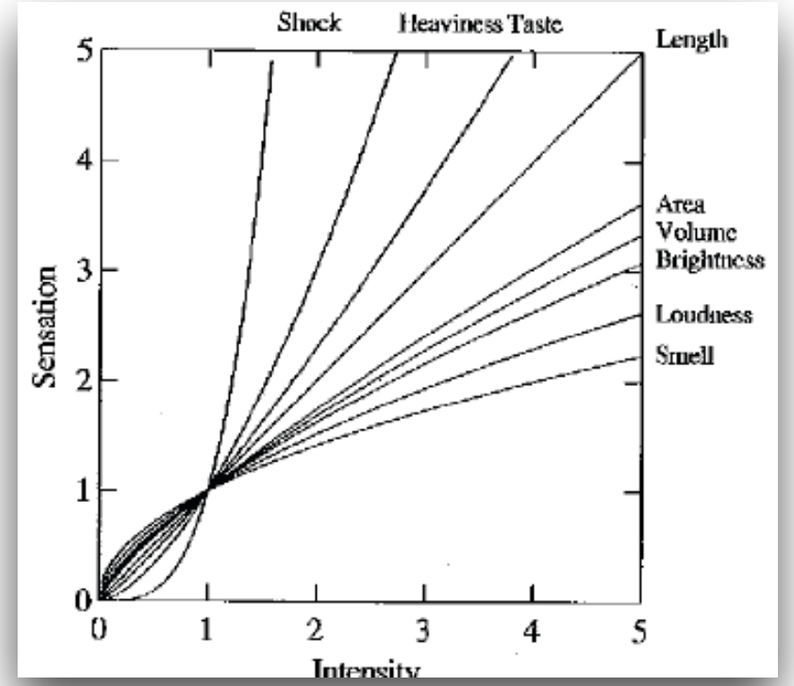


After the pilot program,

68%

of kids expressed interest towards science,
compared to 44% going into the program.

Perceptual Effectiveness



Stephen's Power Law, 1961

	Nominal	Ordinal	Quantitative
Position	✔	✔	✔
Size	✔	✔	~
(Grey)Value	✔	✔	~
Texture	✔	~	✖
Color	✔	✖	✖
Orientation	✔	✖	✖
Shape	✔	✖	✖

✔ = Good
~ = OK
✖ = Bad

J. Bertin, 1967

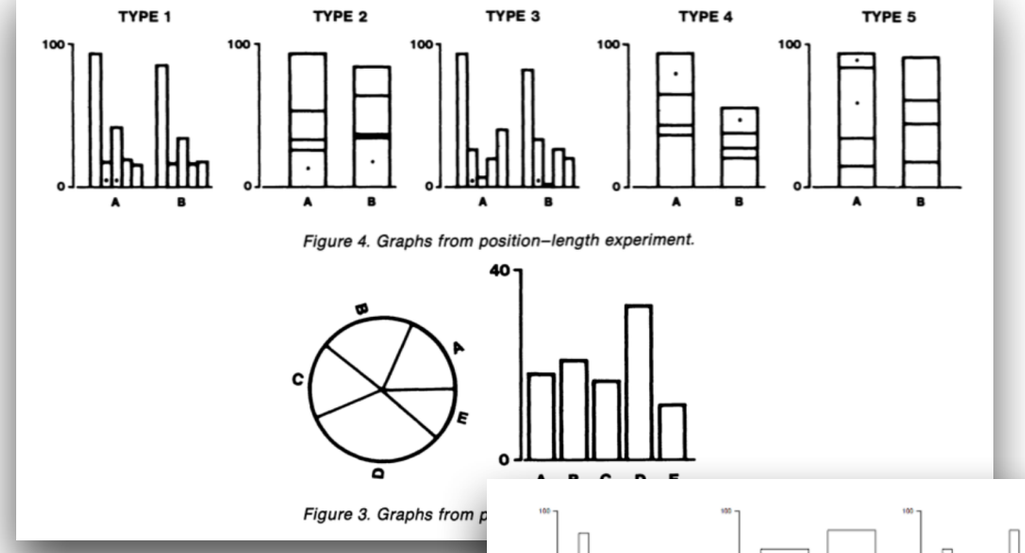
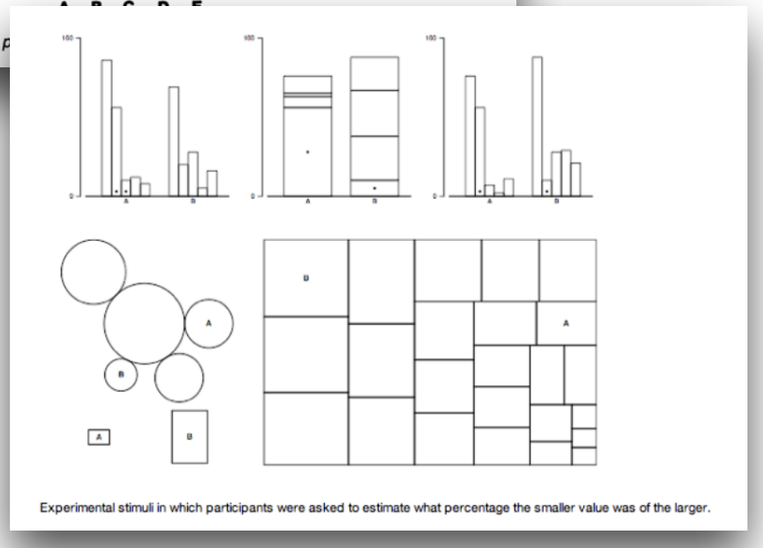


Figure 4. Graphs from position–length experiment.

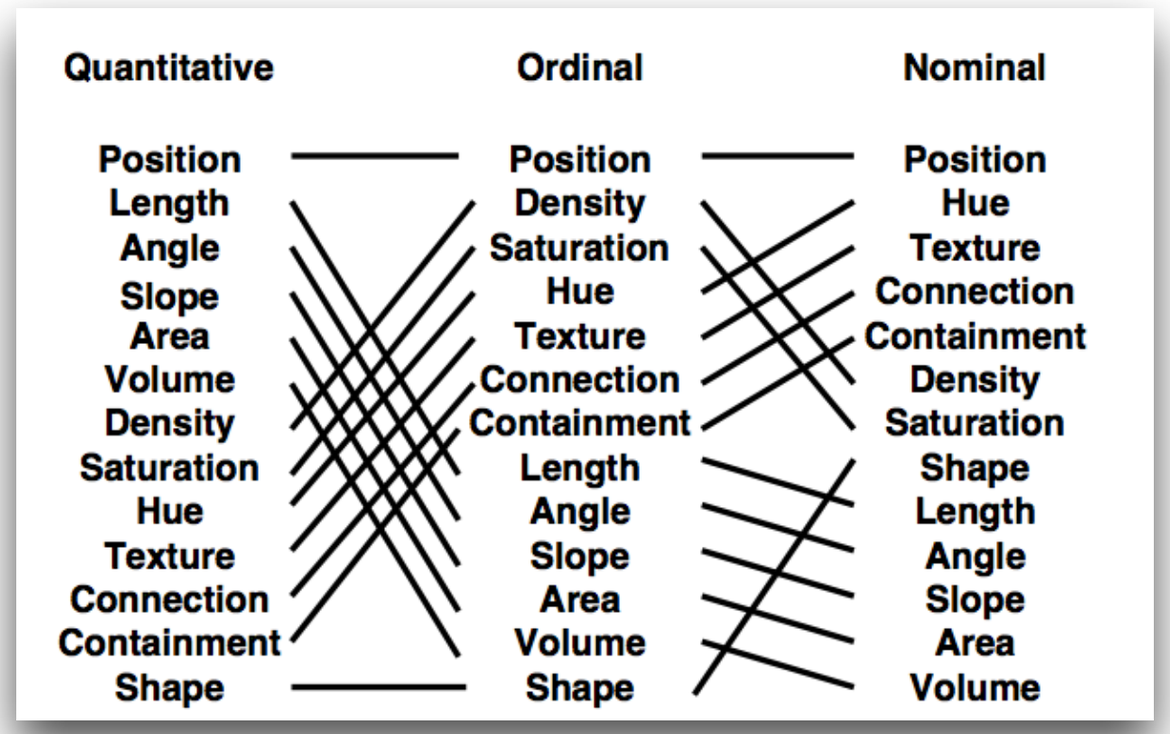
Figure 3. Graphs from p

Cleveland / McGill, 1984



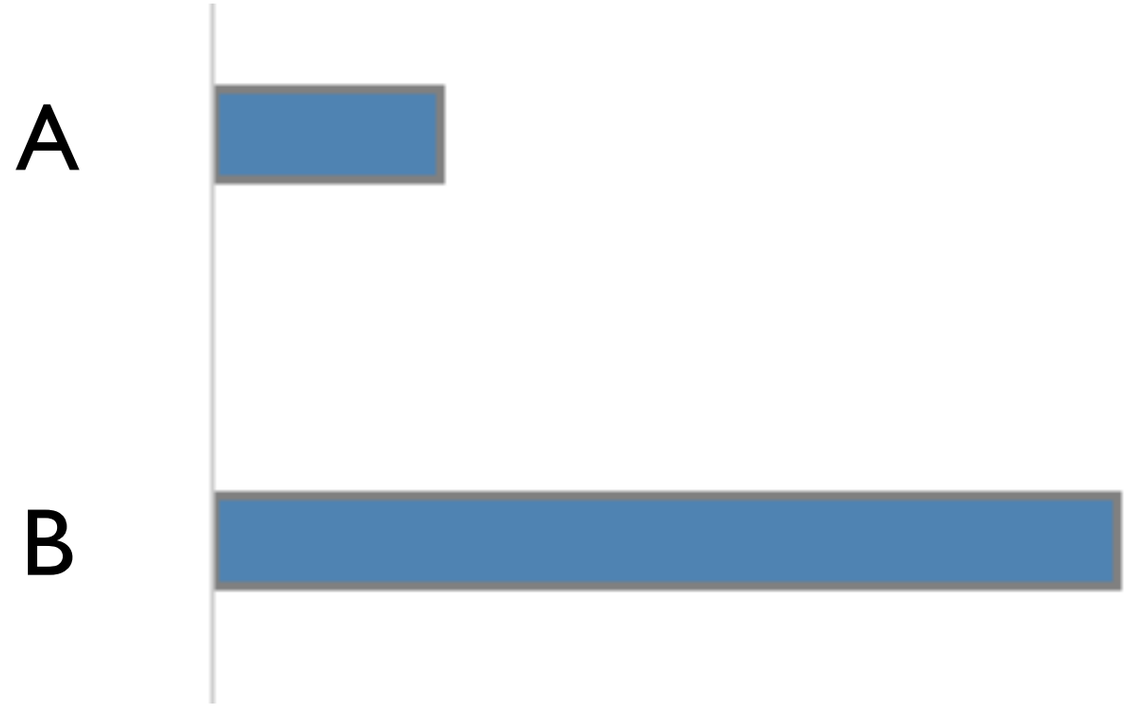
Experimental stimuli in which participants were asked to estimate what percentage the smaller value was of the larger.

Heer / Bostock, 2010

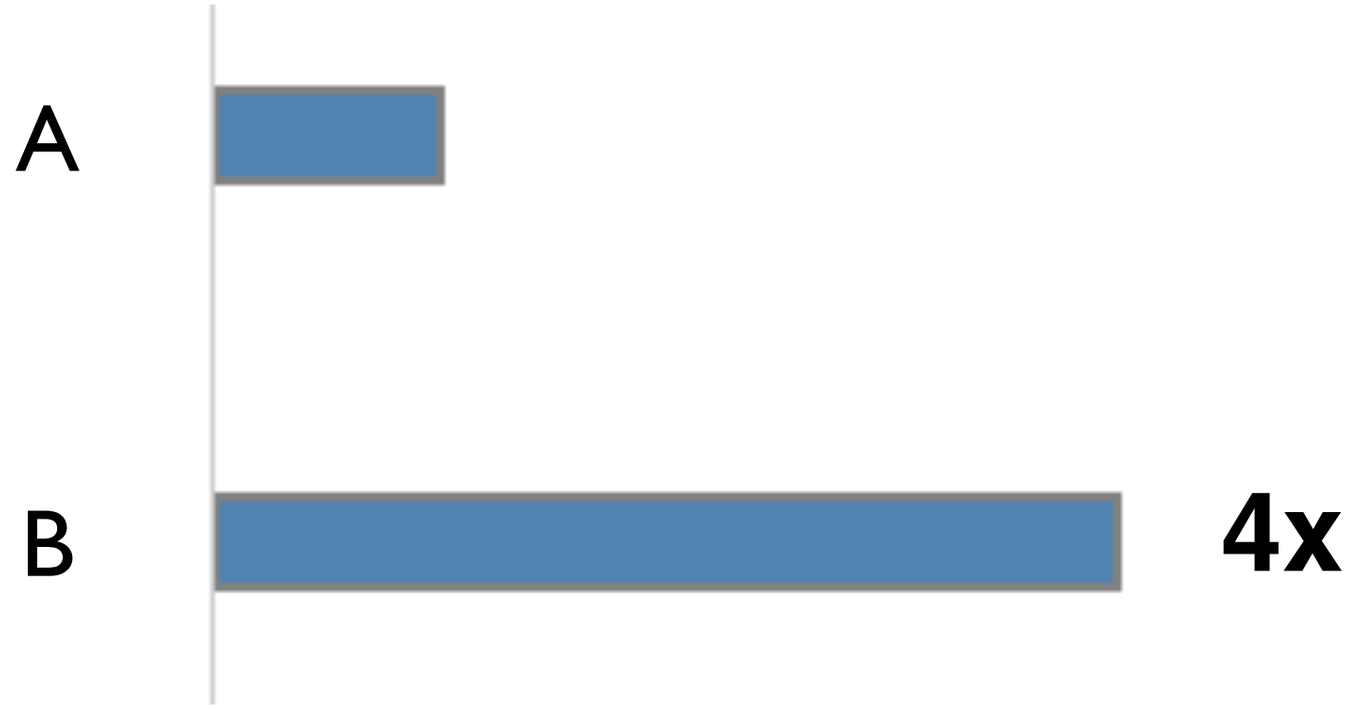


J. Mackinlay, 1986

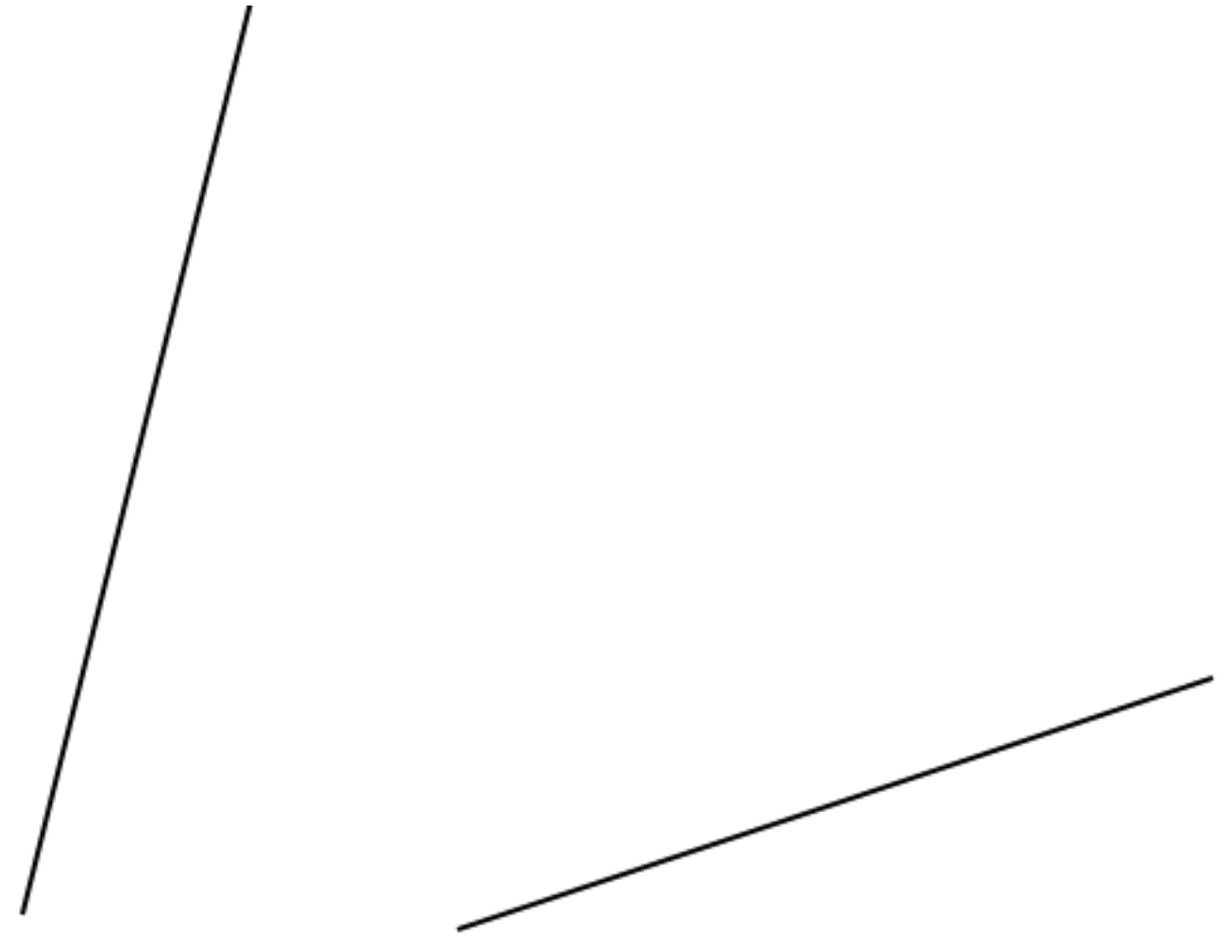
How much longer?



How much longer?



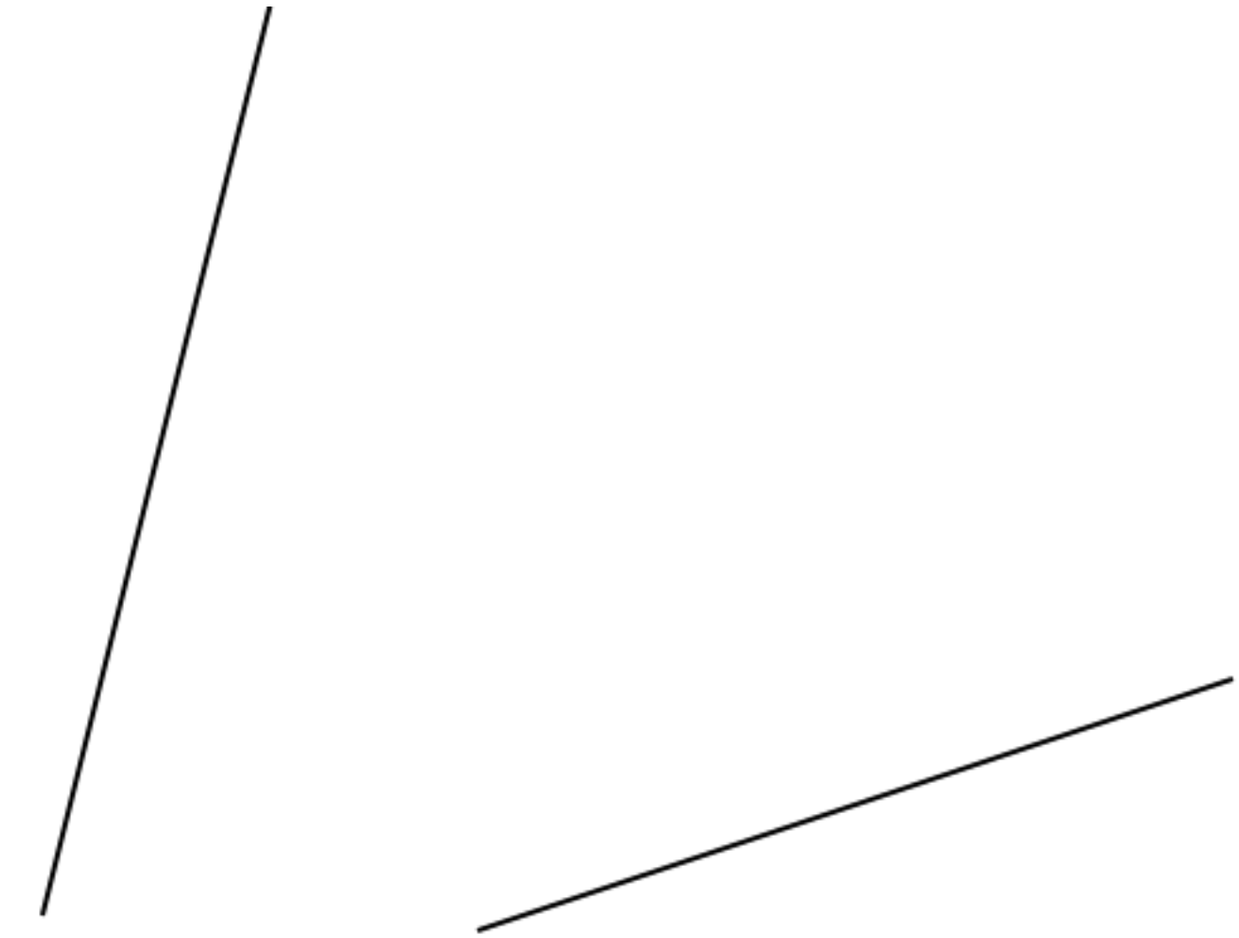
How much steeper slope?



A

B

How much steeper slope?

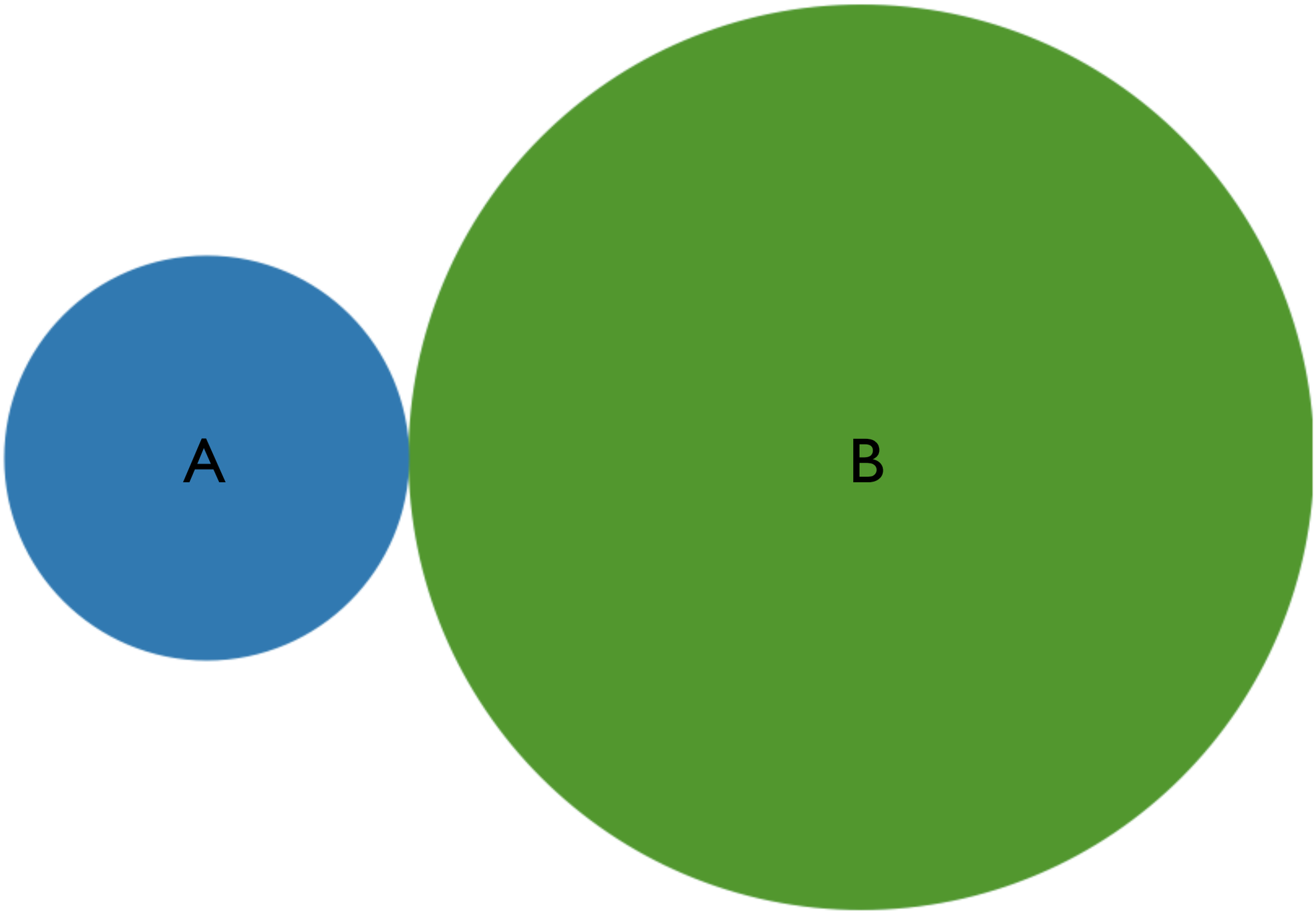


A

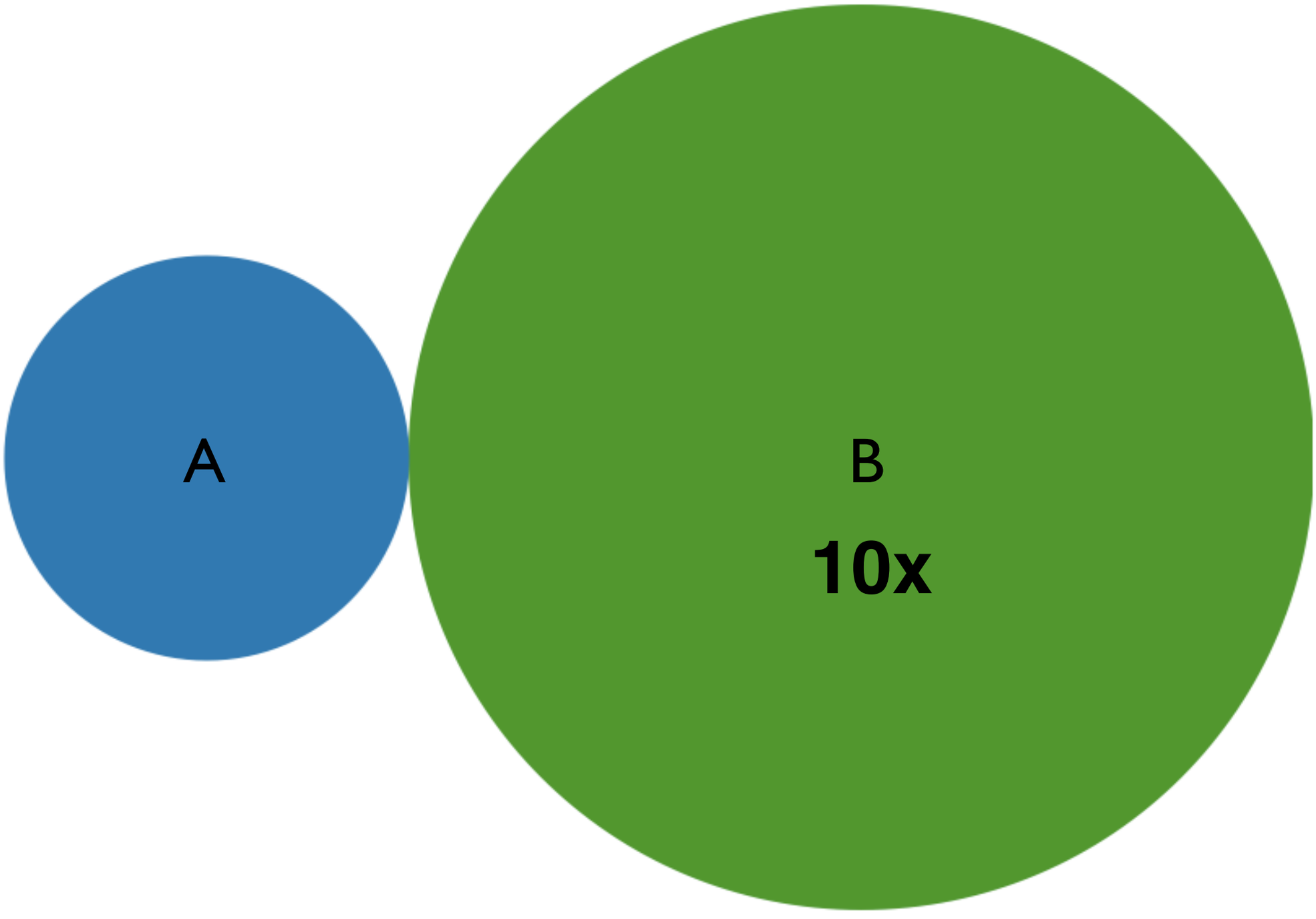
B

4x

How much larger area?



How much larger area?



How much darker?

A

B

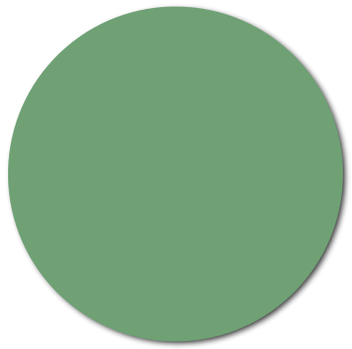
How much darker?

A

B

2x

How much bigger value?



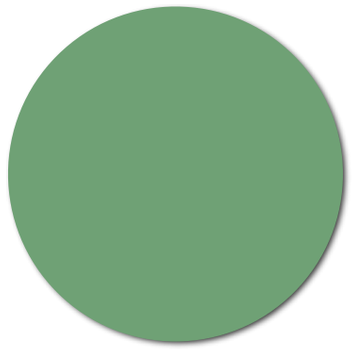
A

B

2

16

How much bigger value?



A

B

4x

2

16

Most Efficient

Position

Length

Slope

Angle

Area

Intensity

Color

Shape

Least Efficient

C. Mulbrandon
VisualizingEconomics.com

Most Efficient

Position

Length

Slope

Angle

Quantitative

Area

Intensity

Ordered

Least Efficient

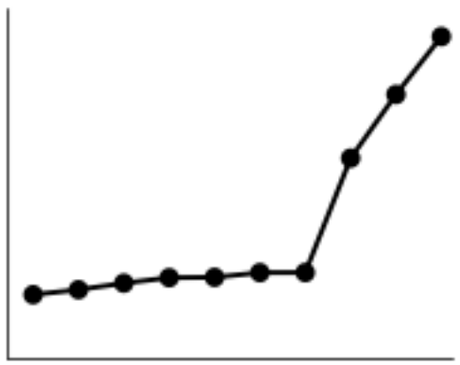
Color

Shape

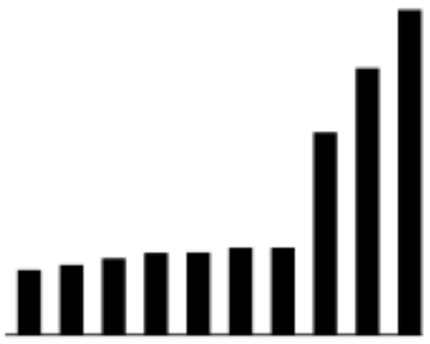
Categories

C. Mulbrandon
VisualizingEconomics.com

Most Effective

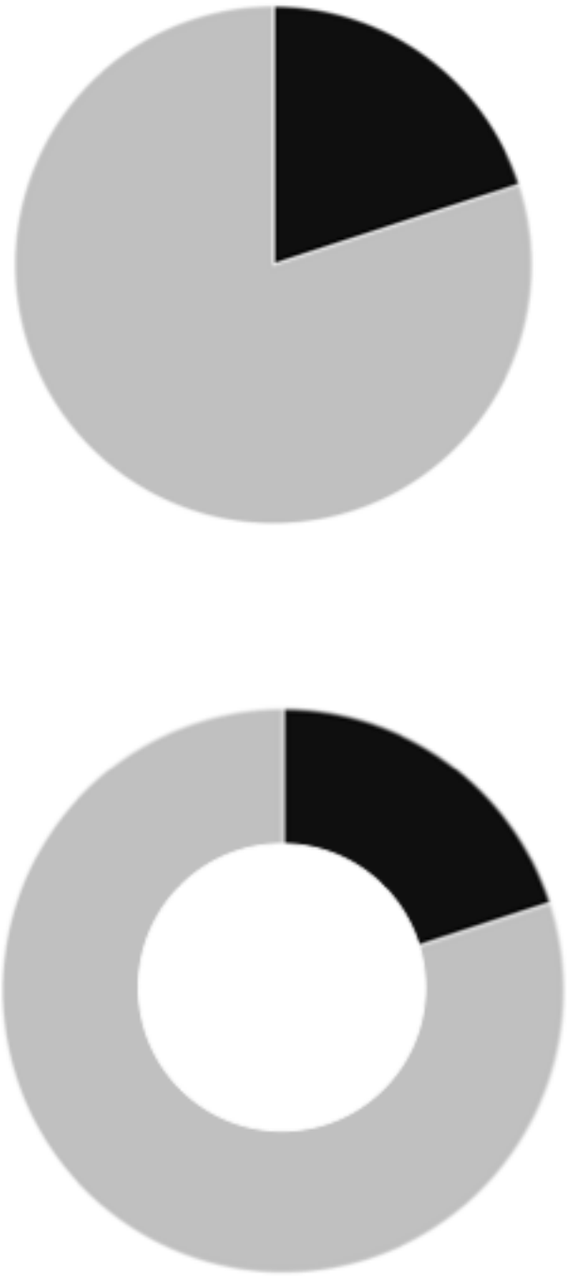


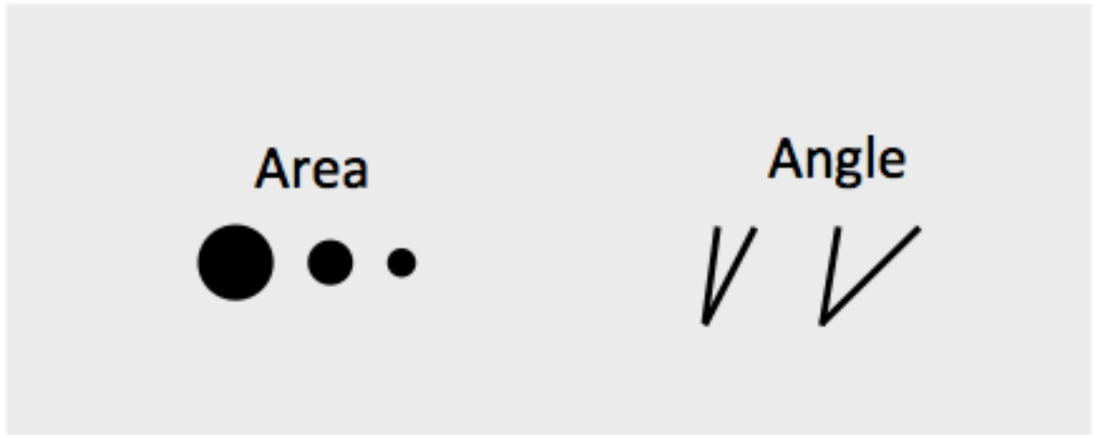
Position



Length

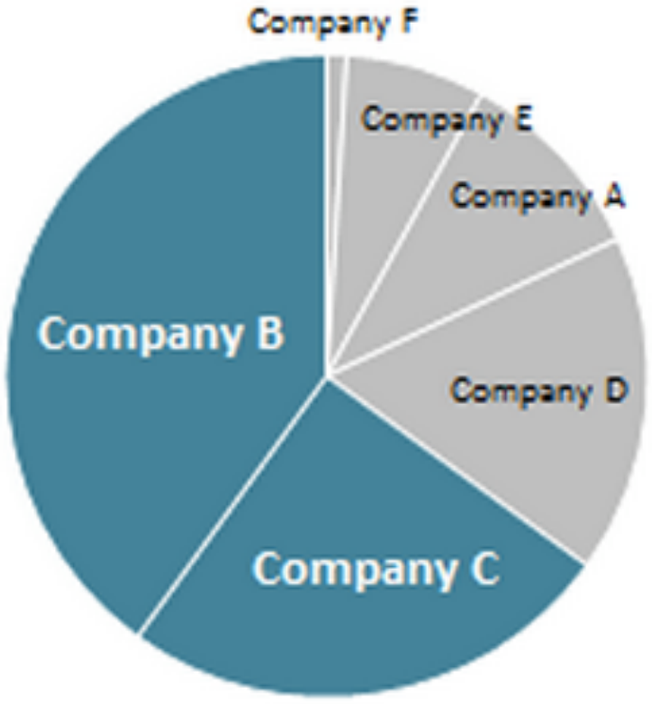
Less Effective

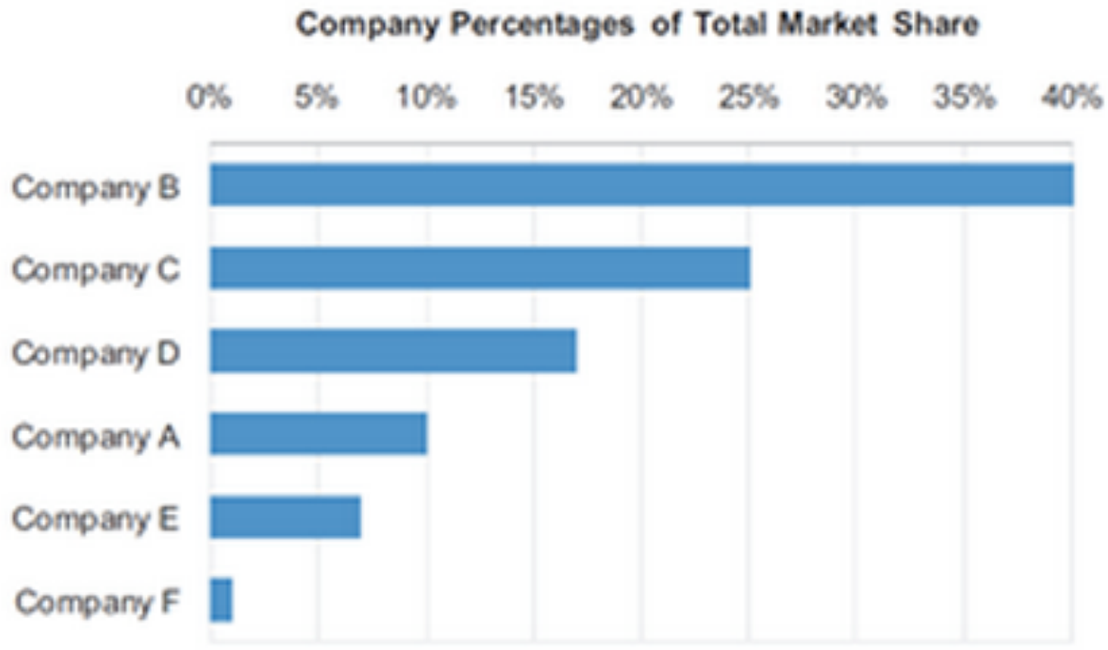




Pie vs. Bar Charts

65% of the market is controlled by companies B and C





Least Effective

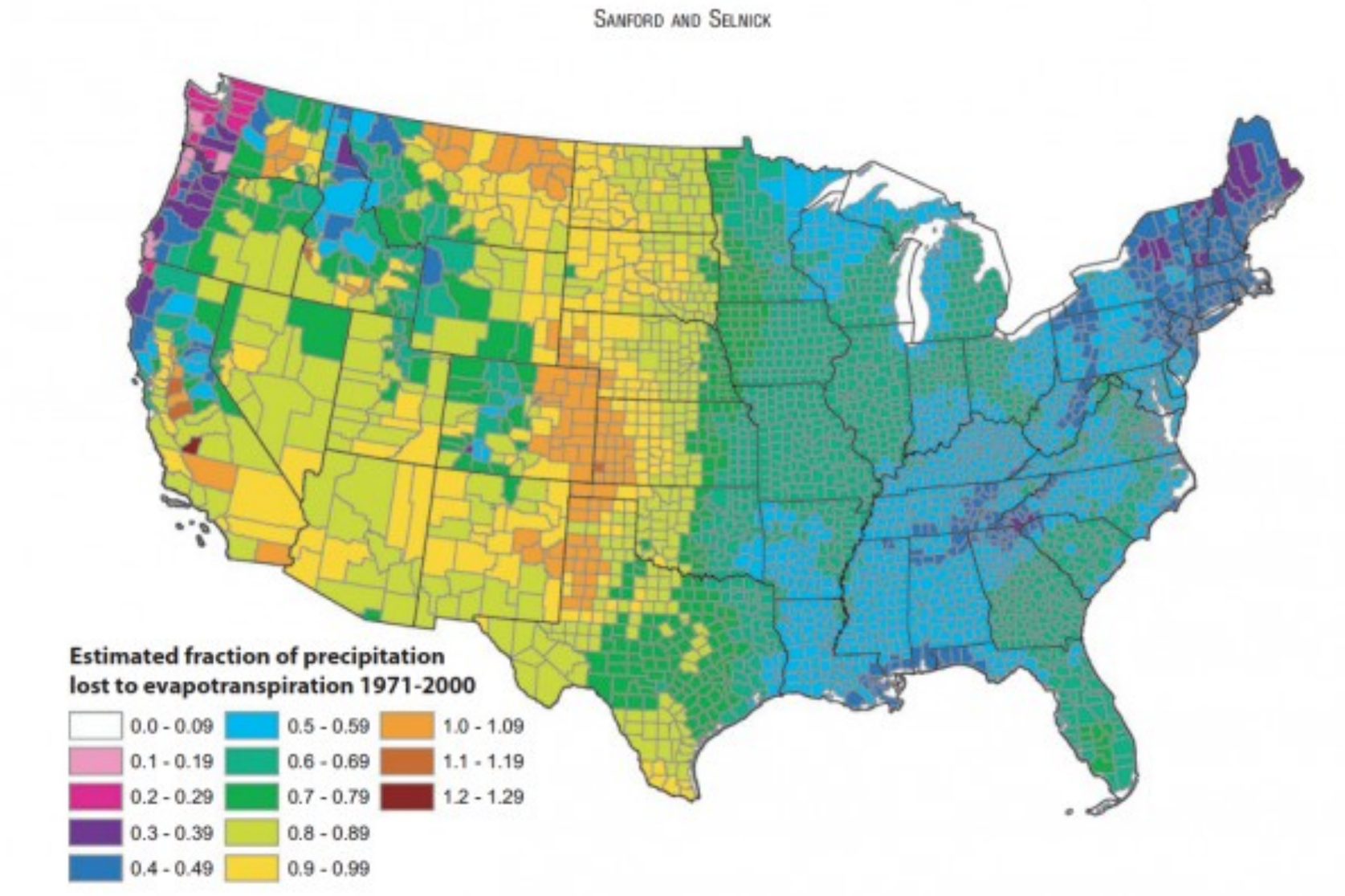
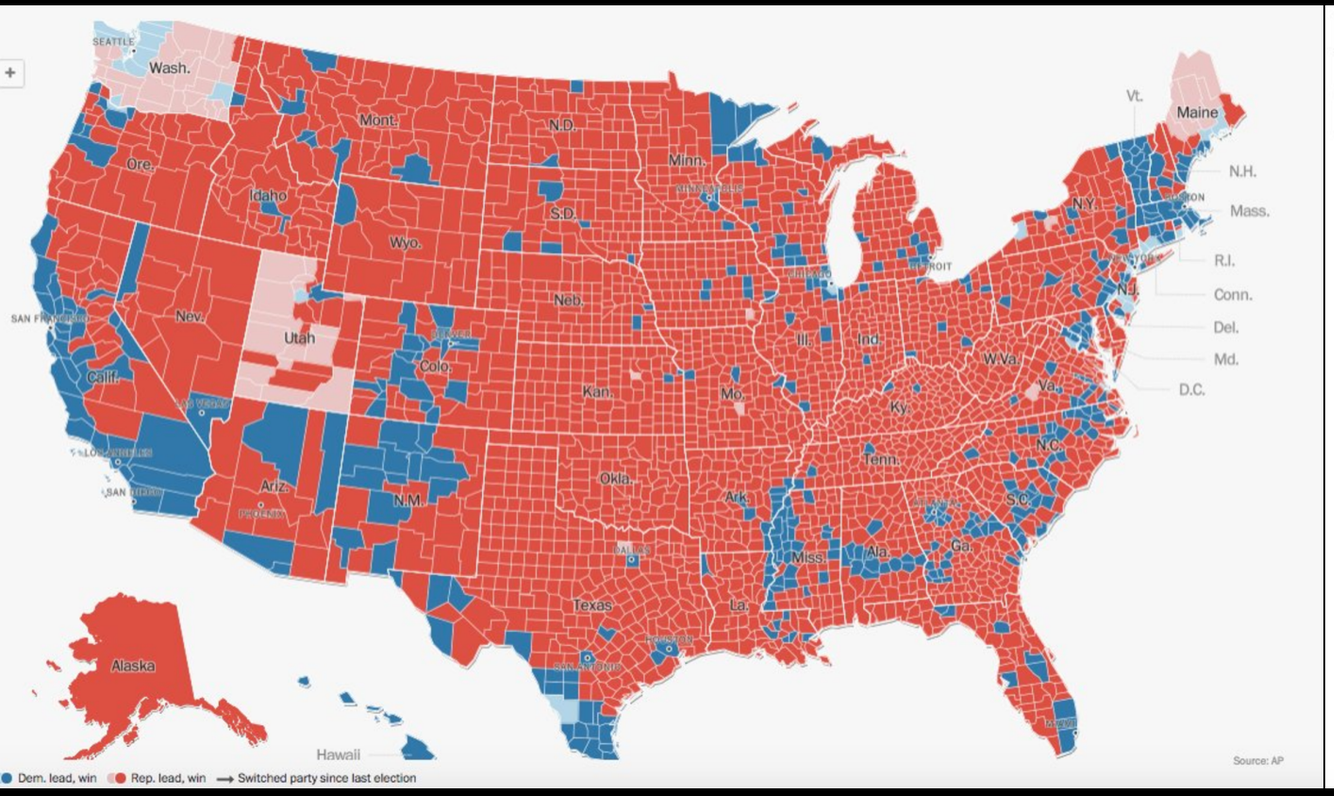
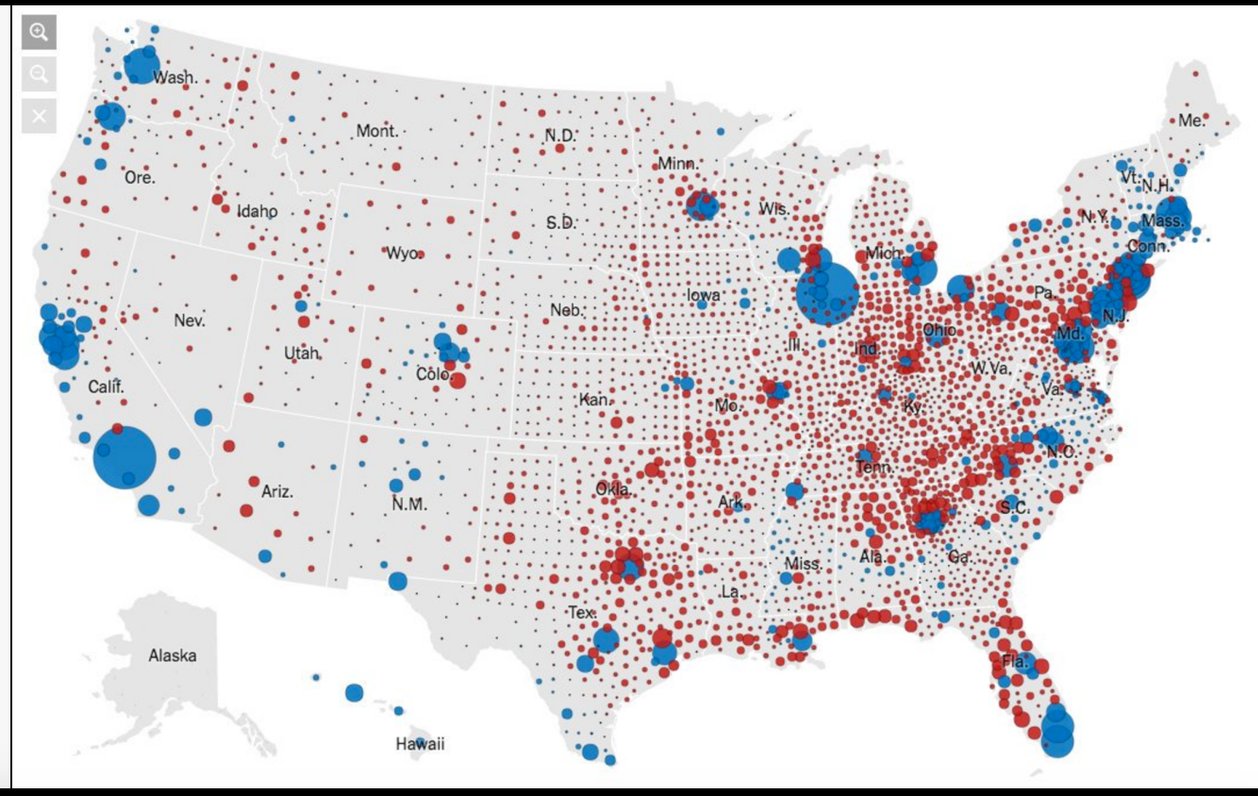


FIGURE 13. Estimated Mean Annual Ratio of Actual Evapotranspiration (ET) to Precipitation (P) for the Conterminous U.S. for the Period 1971-2000. Estimates are based on the regression equation in Table 1 that includes land cover. Calculations of ET/P were made first at the 800-m resolution of the PRISM climate data. The mean values for the counties (shown) were then calculated by averaging the 800-m values within each county. Areas with fractions >1 are agricultural counties that either import surface water or mine deep groundwater.

Cliff Mass





US Presidential Election 2016

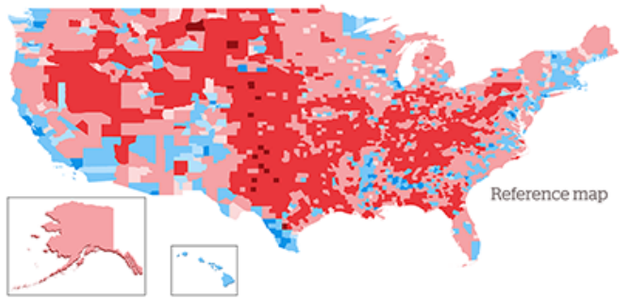
Results mapped at county level showing the candidate with the largest vote share in each area

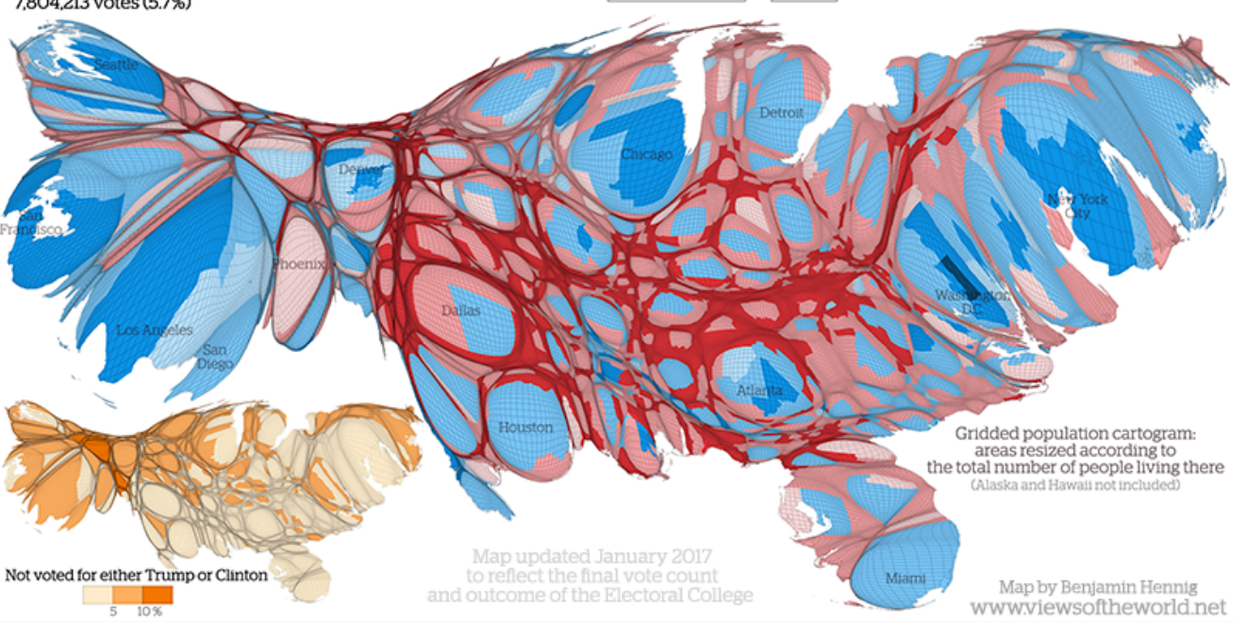
Overall result:

Trump
62,979,636 votes (46.1%)
306 electoral votes
(received 304 in the Electoral College)

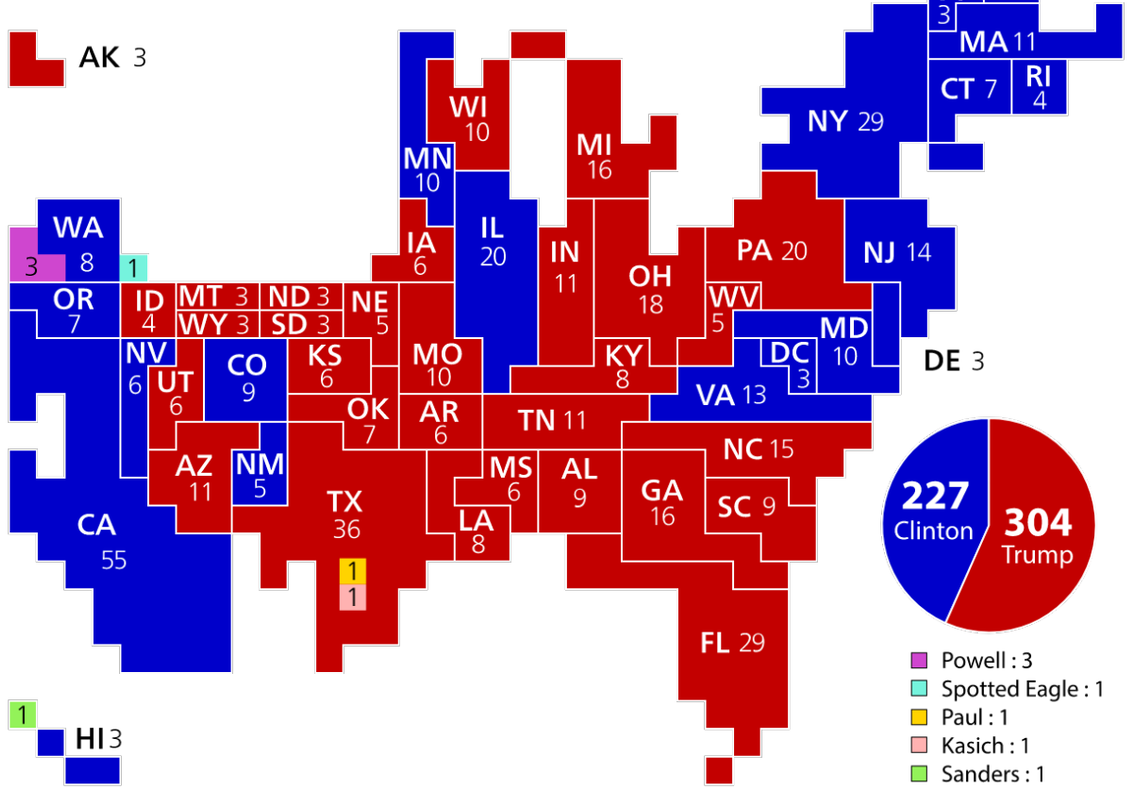
Clinton
65,844,610 votes (48.2%)
232 electoral votes
(received 227 in the Electoral College)

Other candidates
7,804,213 votes (5.7%)



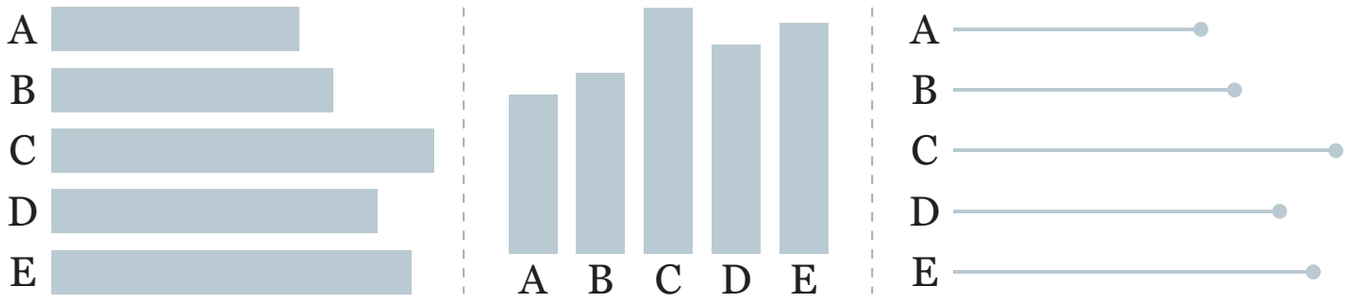


2016 Electoral Vote

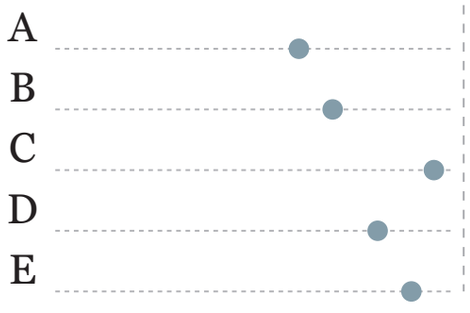


Data visualization and visual encoding

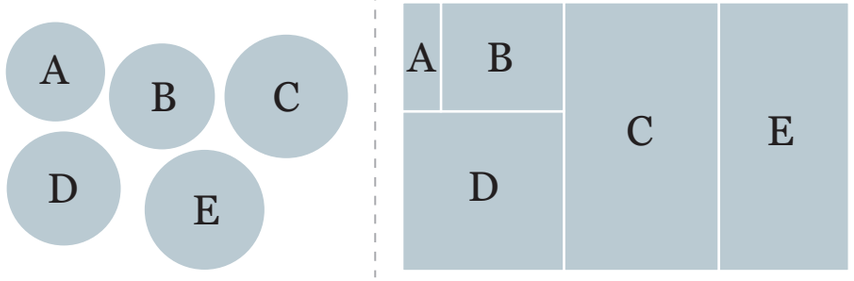
Length or height



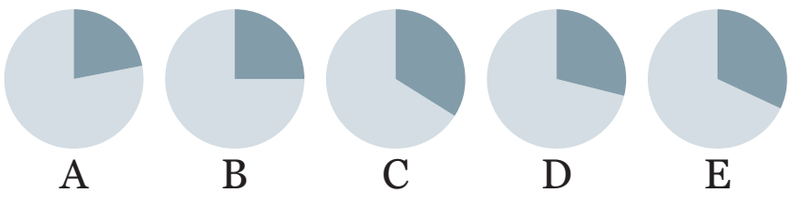
Position



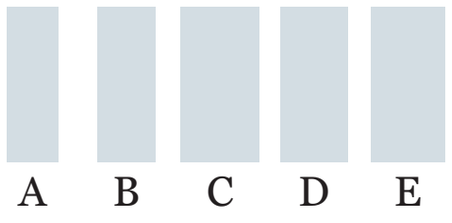
Area



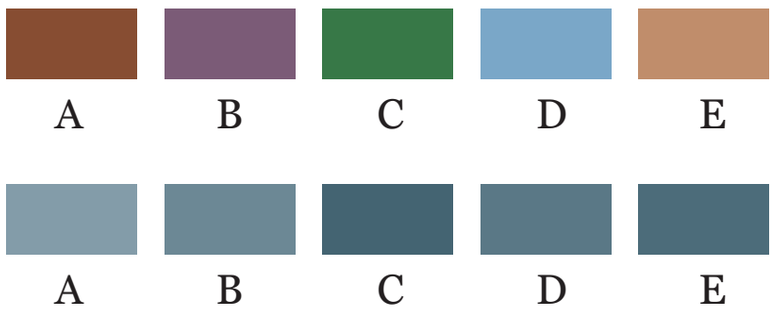
Angle/area



Line weight



Hue and shade



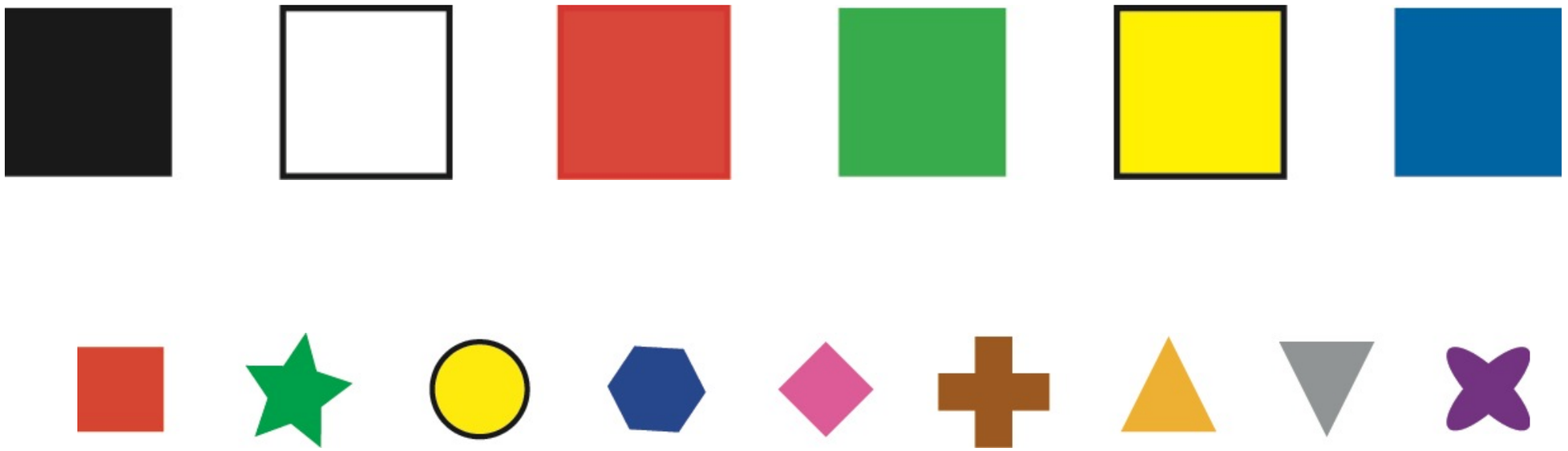
Figures represented in all these graphics: 22%, 25%, 34%, 29%, 32%

Alberto Cairo • University of Miami • www.thefunctionalart.com • Twitter: @albertocairo

4. Use Color Strategically

Colors for Categories

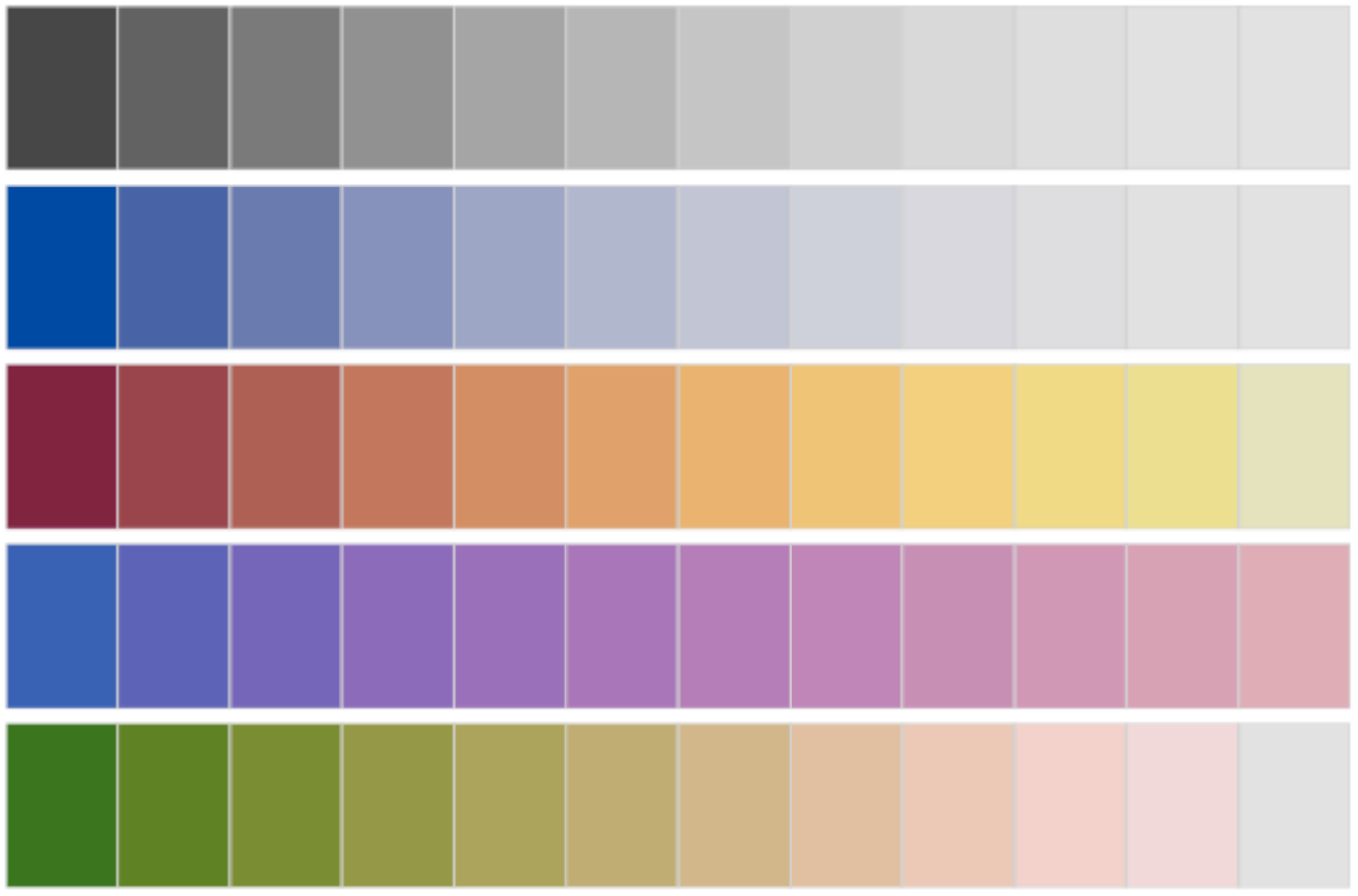
Do not use more than 5-8 colors at once



Ware, "Information Visualization"

Colors for Ordinal Data

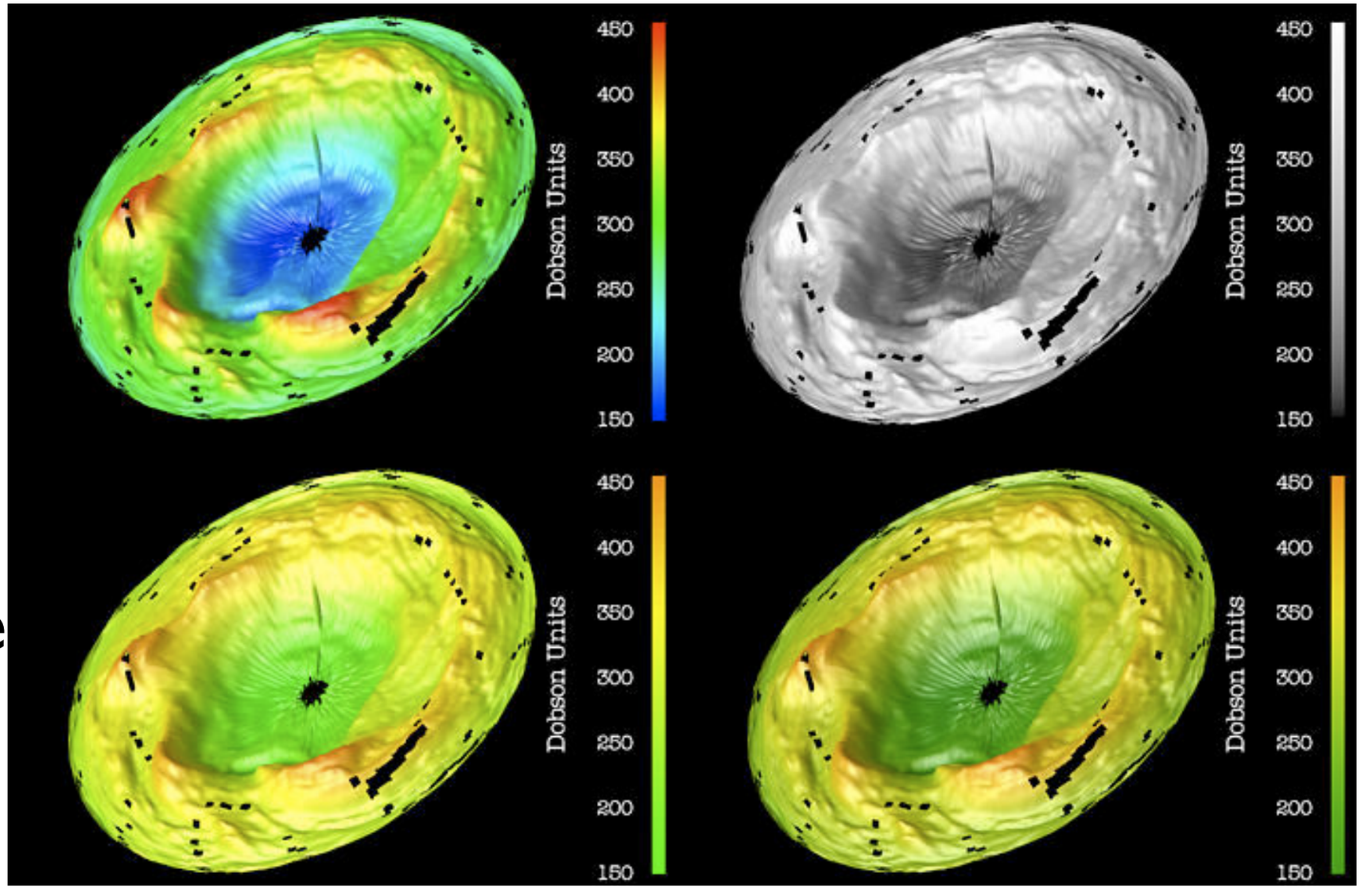
Vary luminance and saturation



Zeilis et al, 2009, "Escaping RGBland: Selecting Colors for Statistical Graphics"

Colors for Quantitative Data

Hue (Rainbow)

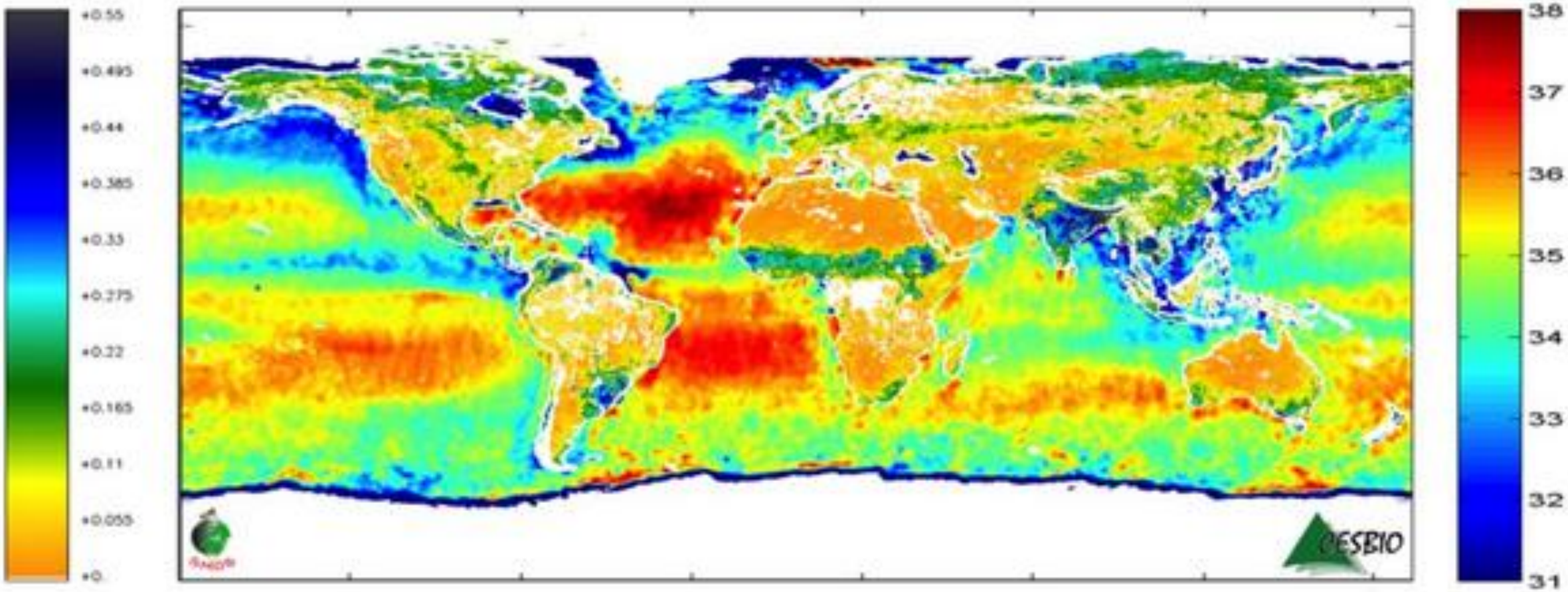


Luminance

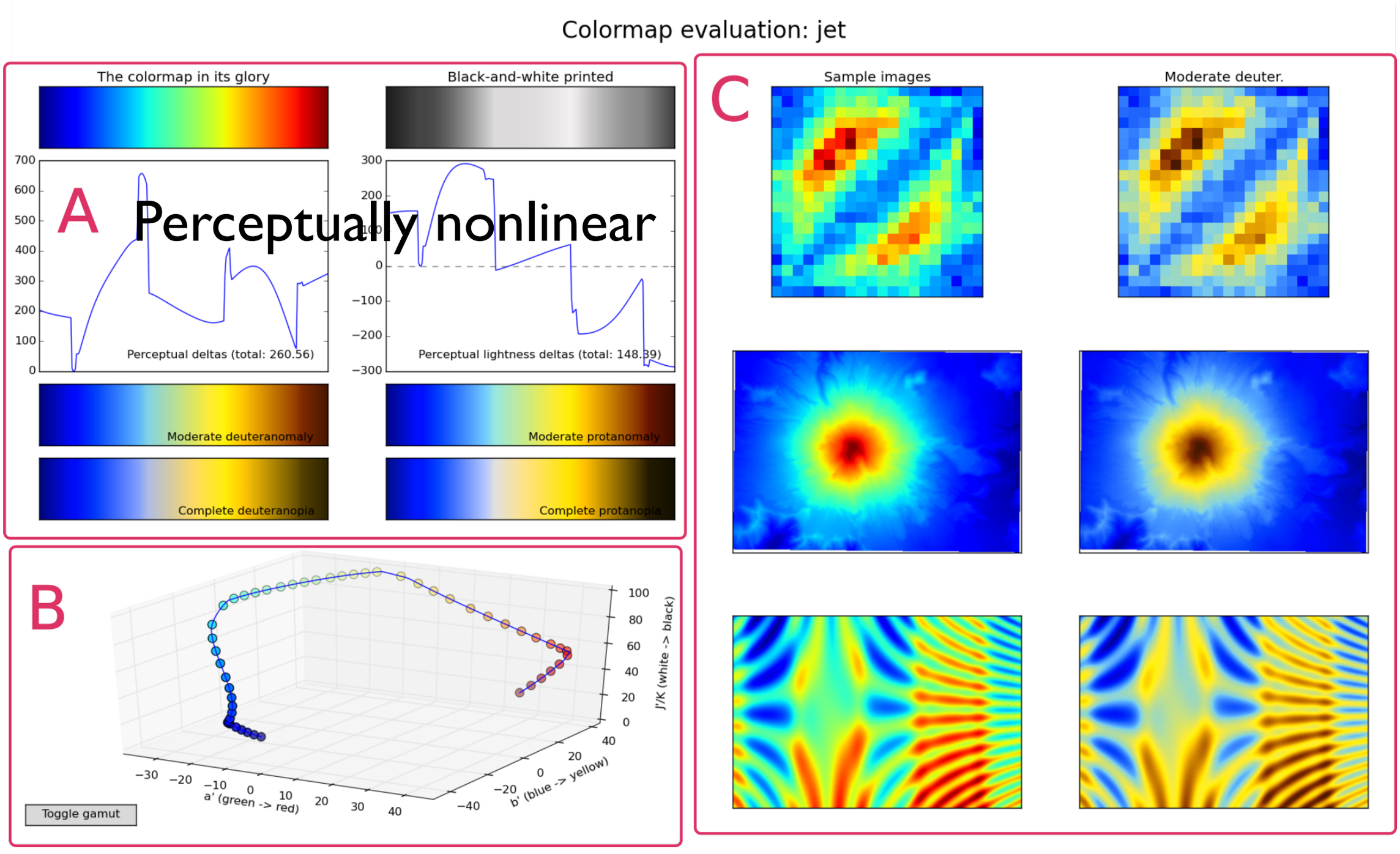
Luminance & Hue

Rogowitz and Treinish, Why should engineers and scientists be worried about color?

Rainbow Colormap



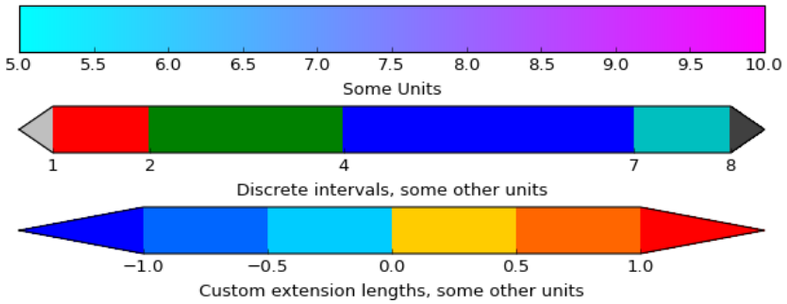
Rainbow Colormap

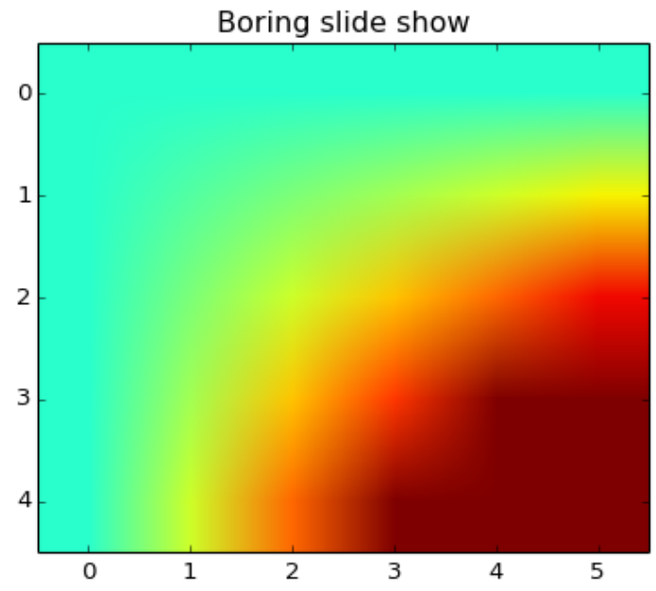


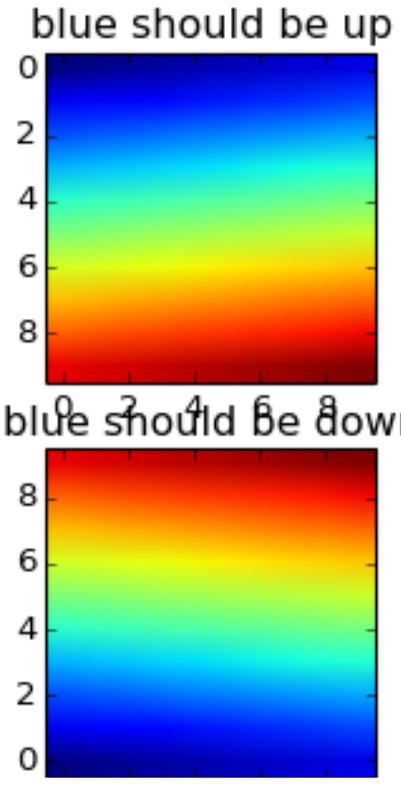
Perceptually nonlinear

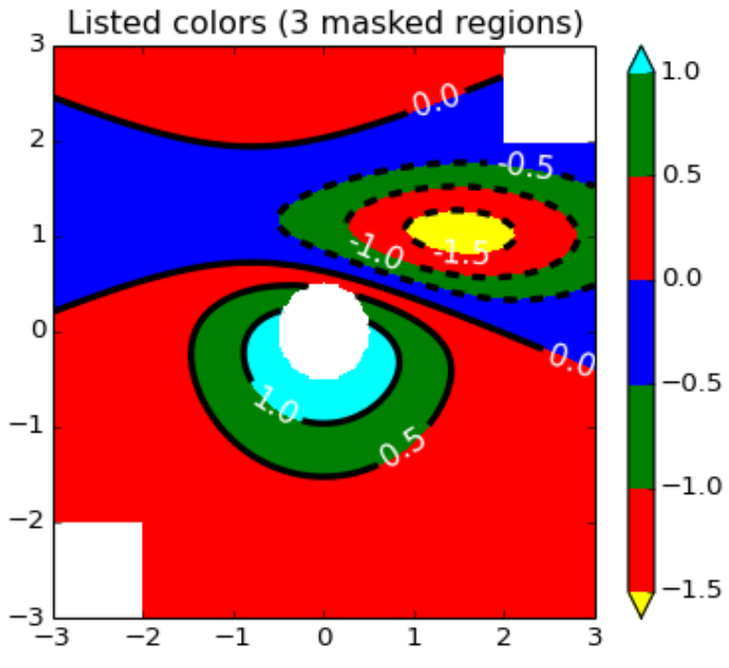
R. Simmon

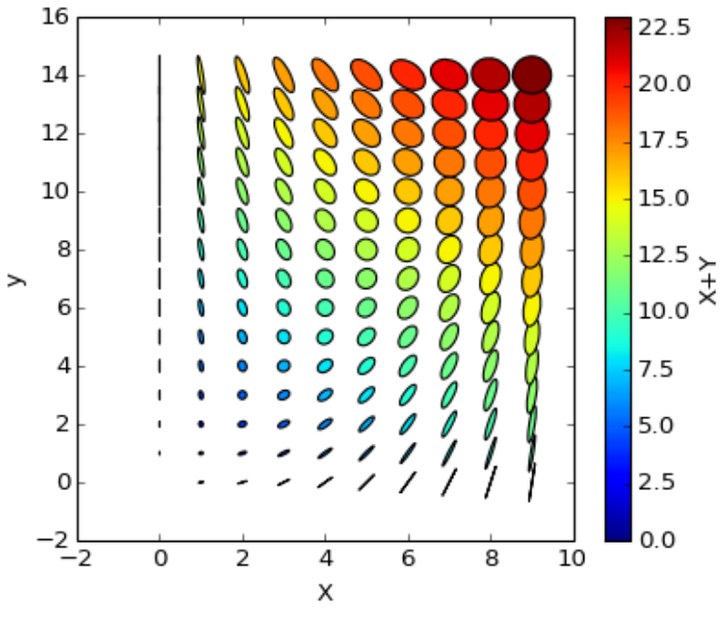
Avoid Rainbow Colors!

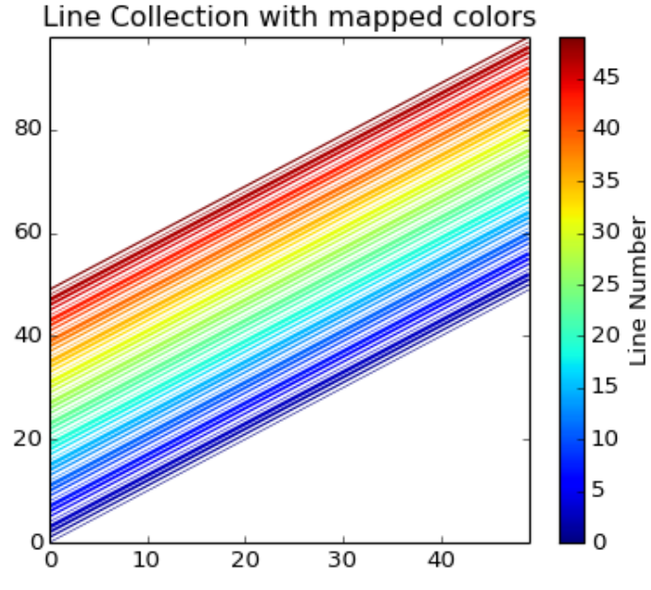








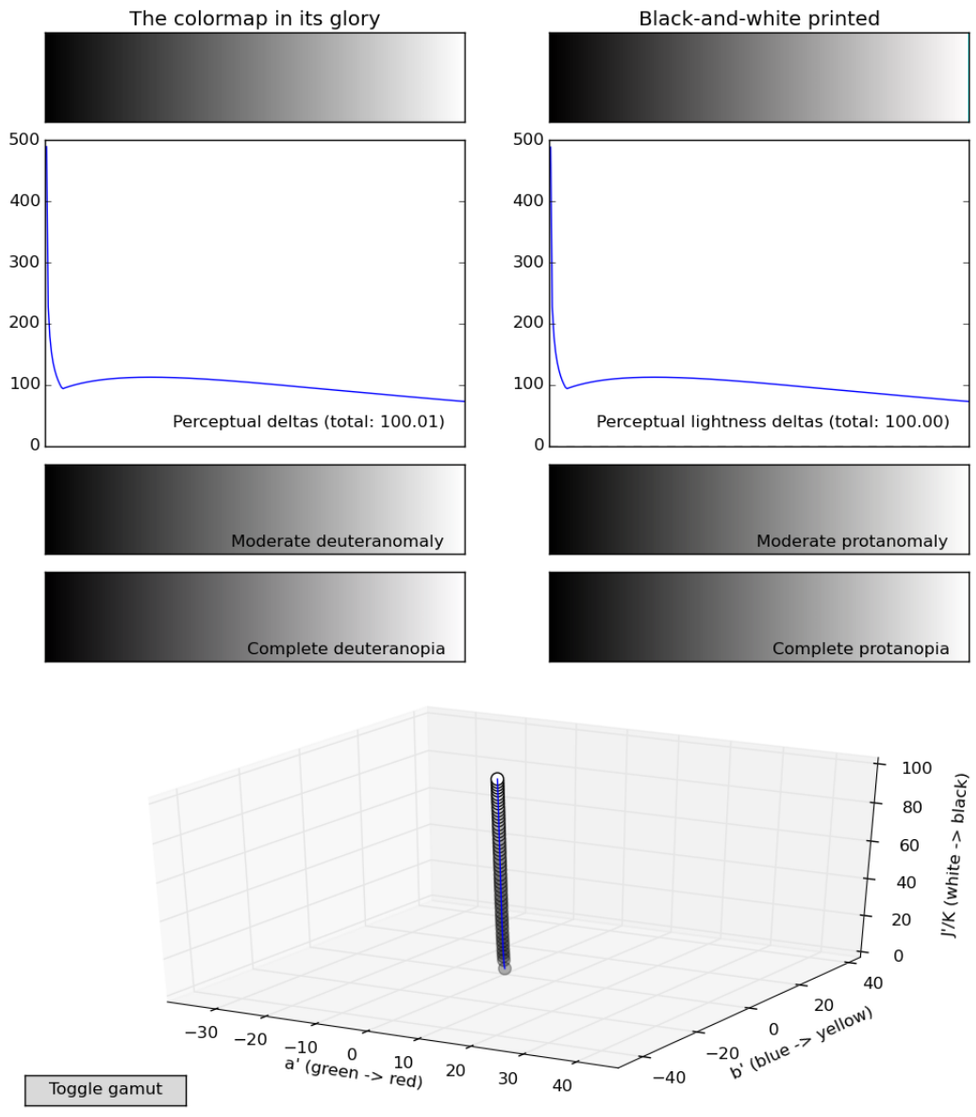


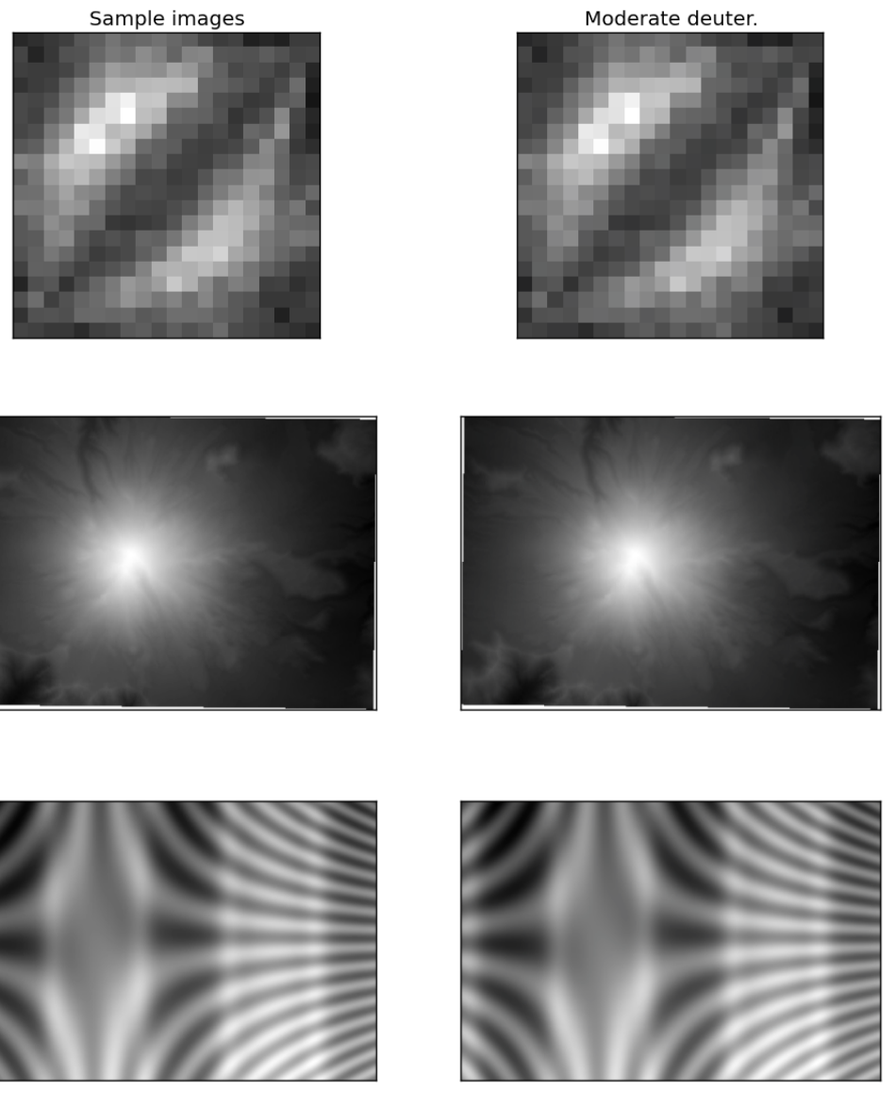


matplotlib gallery

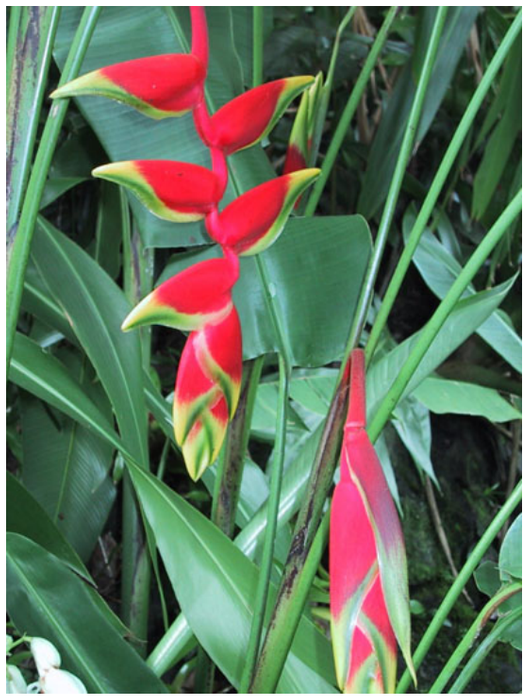
Gray

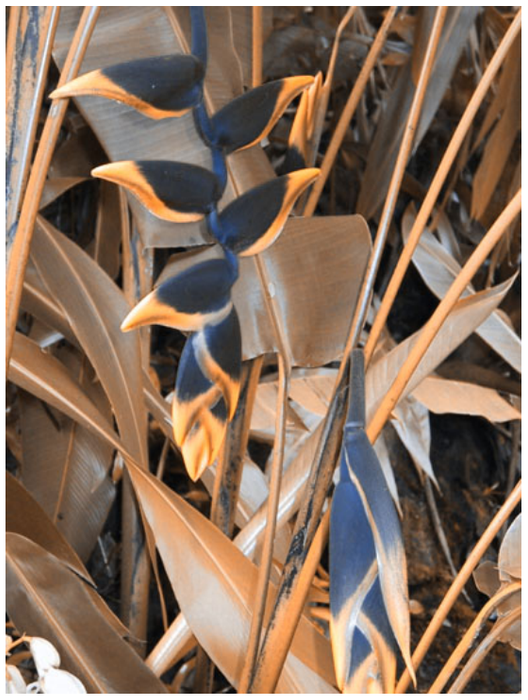
Colormap evaluation: gray



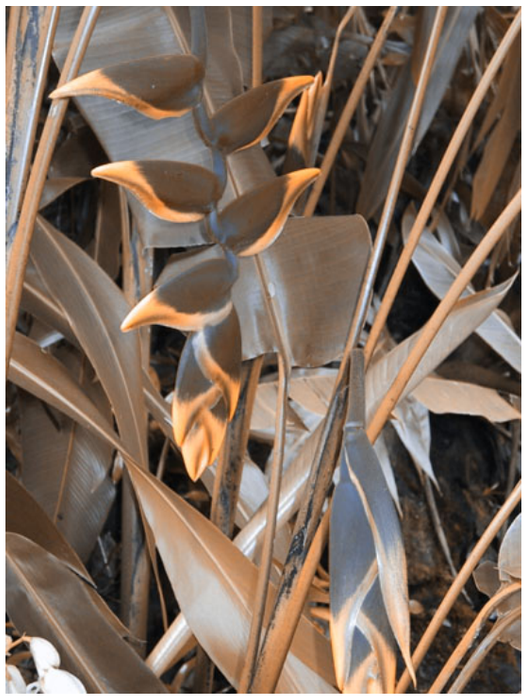


Color Blindness





Protanope



Deuteranope

Red / green deficiencies

Tritanope

Blue / Yellow deficiency

Based on slide from Stone

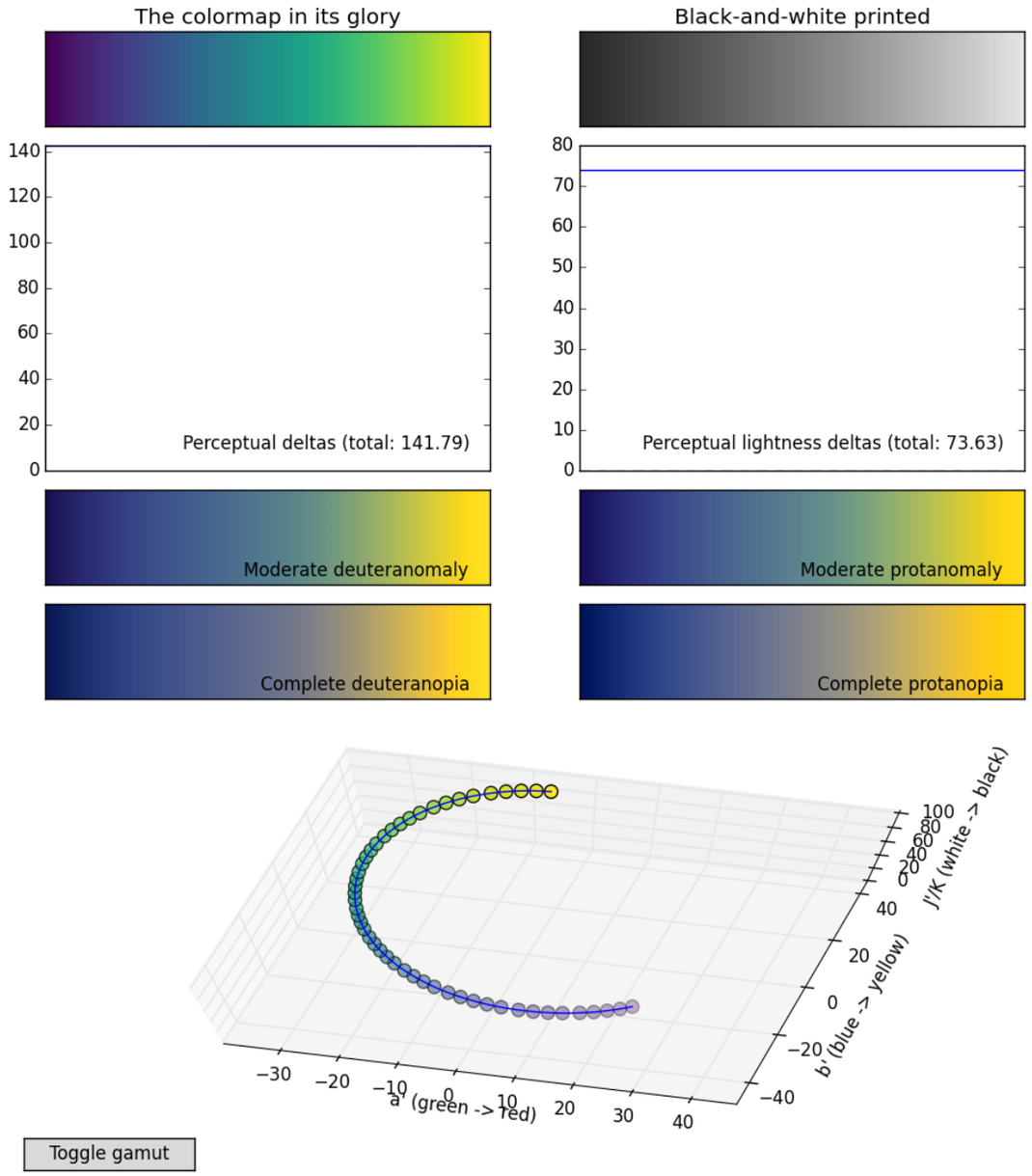
Color Blindness

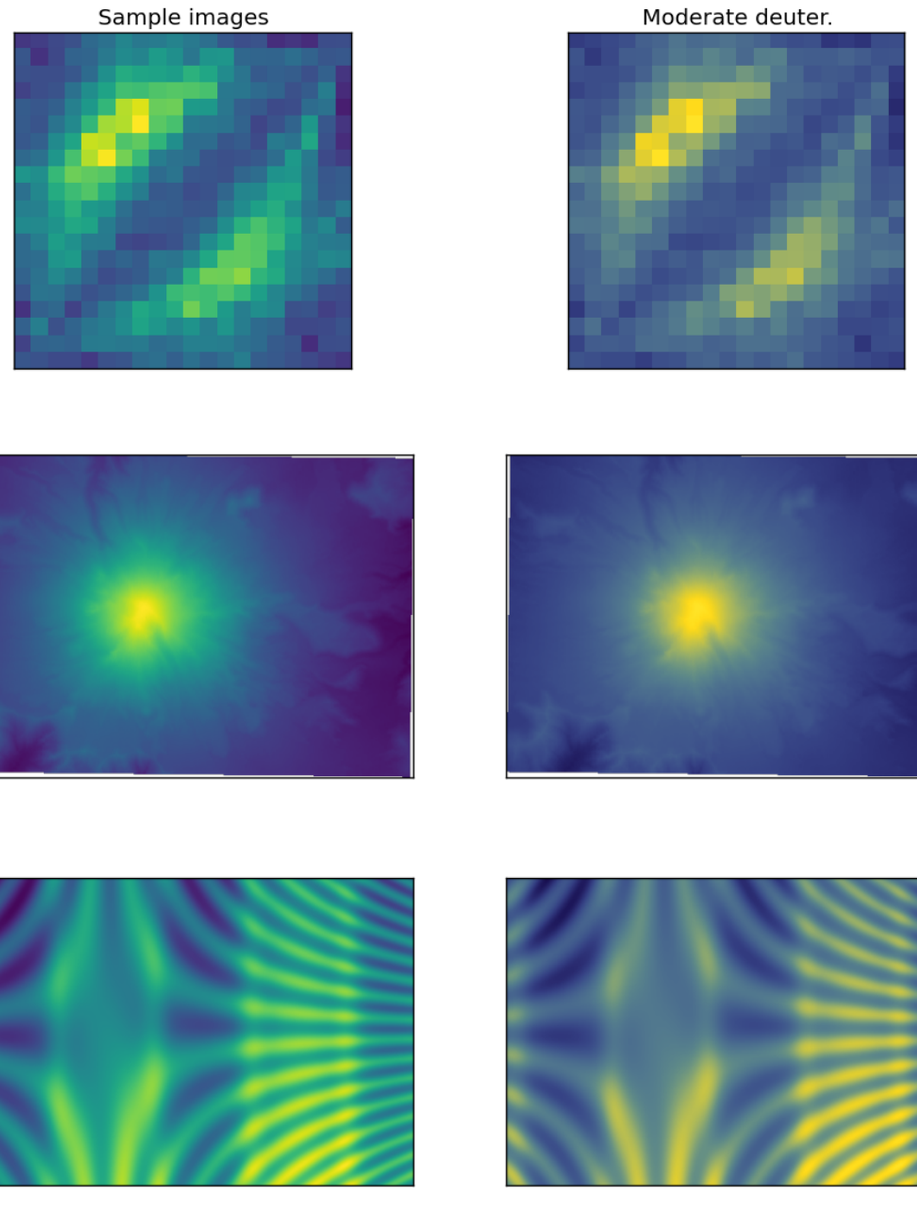
Normal | Protanope | Deuteranope | Lightness

Based on slide from Stone

Viridis

Colormap evaluation: option_d.py

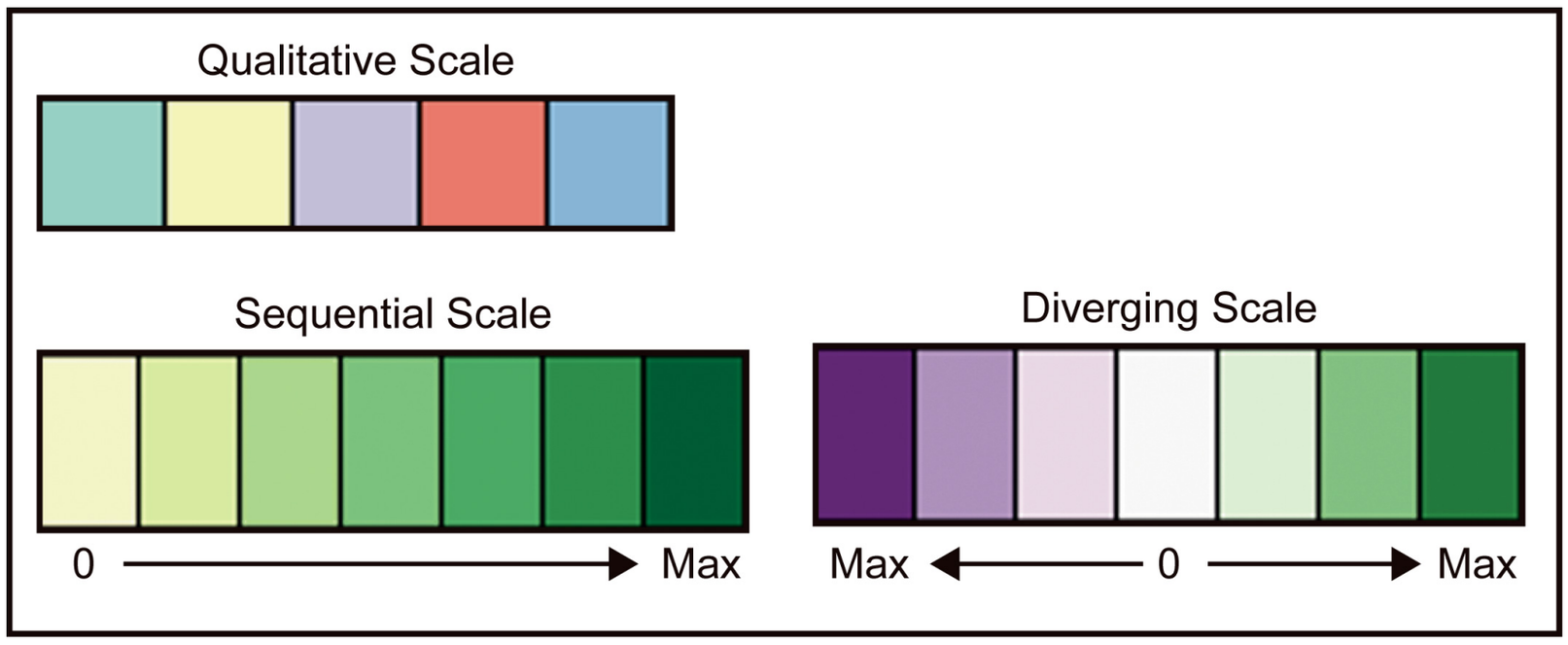




Color Brewer

Nominal

Ordinal



Cynthia Brewer, Color Use Guidelines for Data Representation

how to use | updates | credits

COLORBREWER 2.0

color advice for cartography

number of data classes on your map

3 | learn more >

the nature of your data

sequential | learn more >

pick a color scheme: GnBu

multihue | single hue

(optional) only show schemes that are:

- [x] colorblind safe
- [ ] print friendly
- [ ] photocopy-able

learn more >

pick a color system

224, 243, 219
168, 221, 181
67, 162, 202

(•) RGB ( ) CMYK ( ) HEX

adjust map context

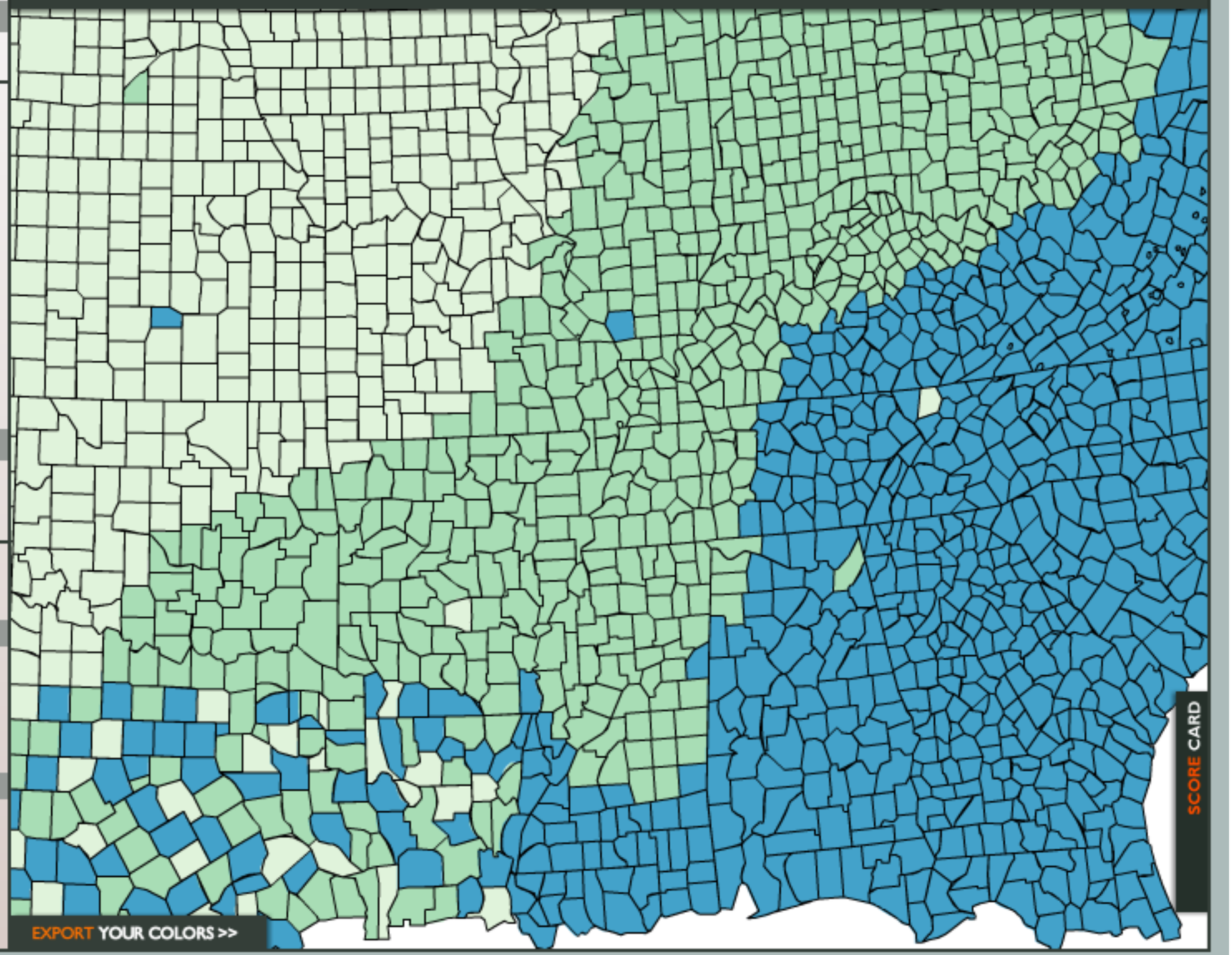
- [ ] roads
- [ ] cities
- [x] borders

select a background

(•) solid color
( ) terrain

color transparency

learn more >

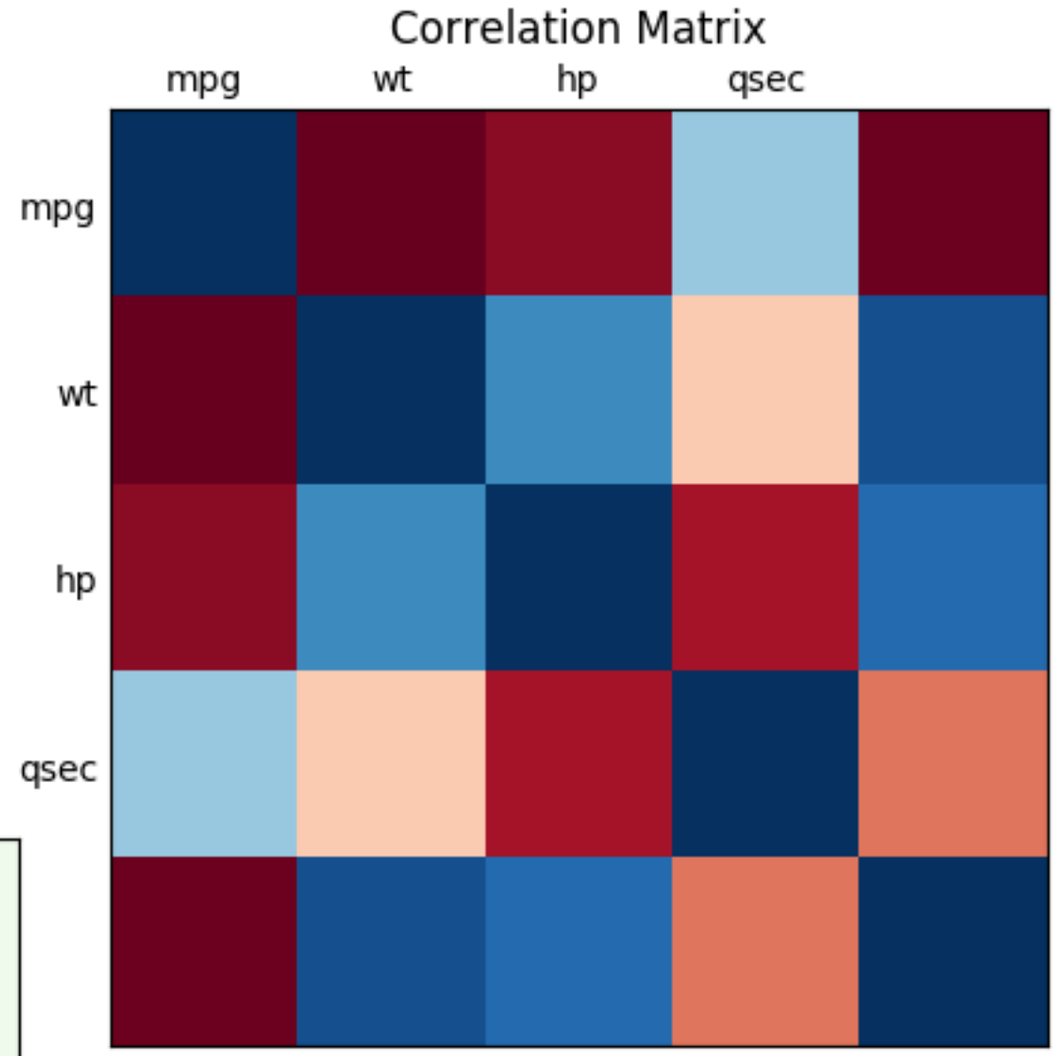


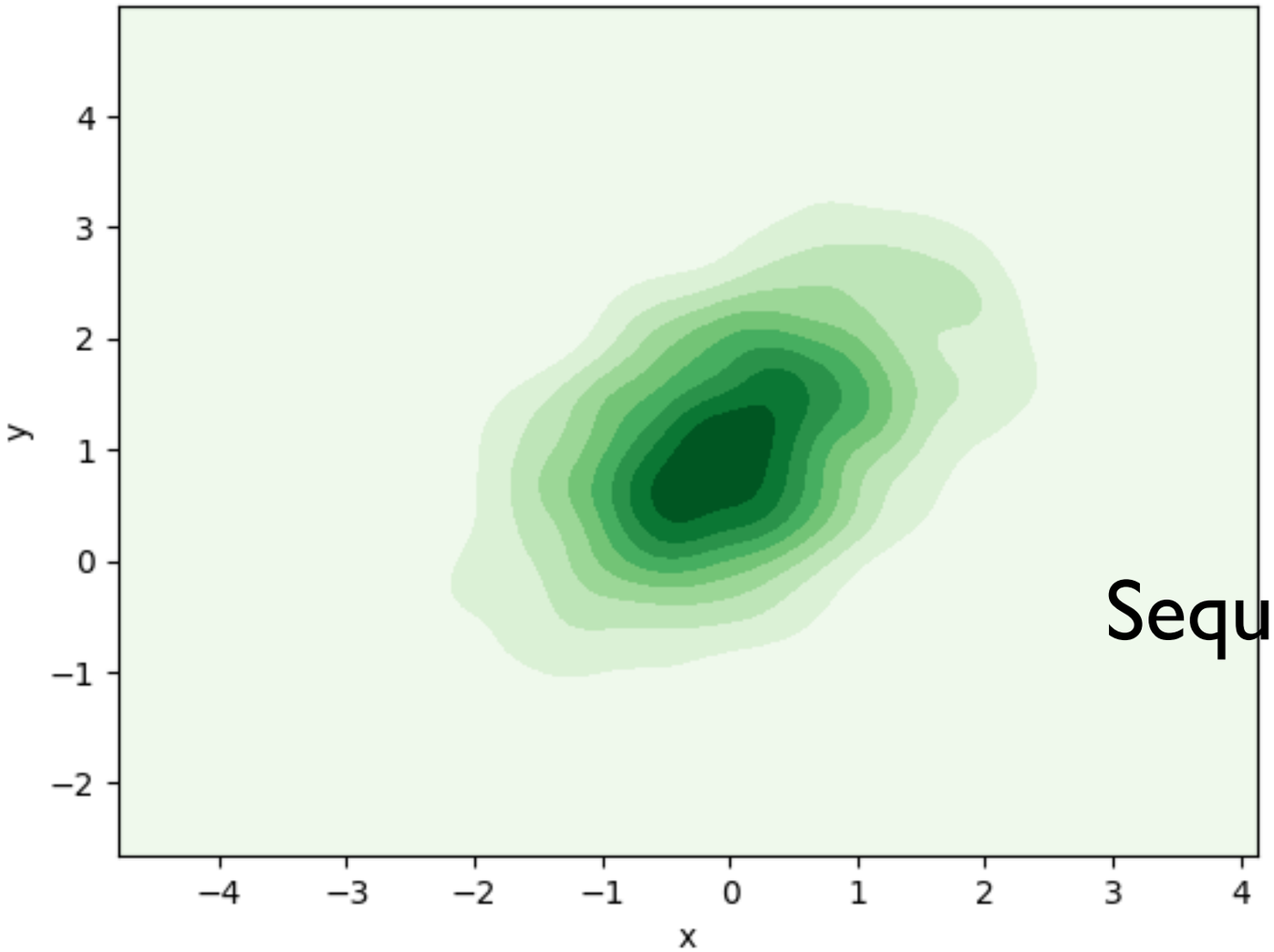
Support

Back to ColorBrewer 1.0

axm

Diverging Palette for Quantitative or Ordinal





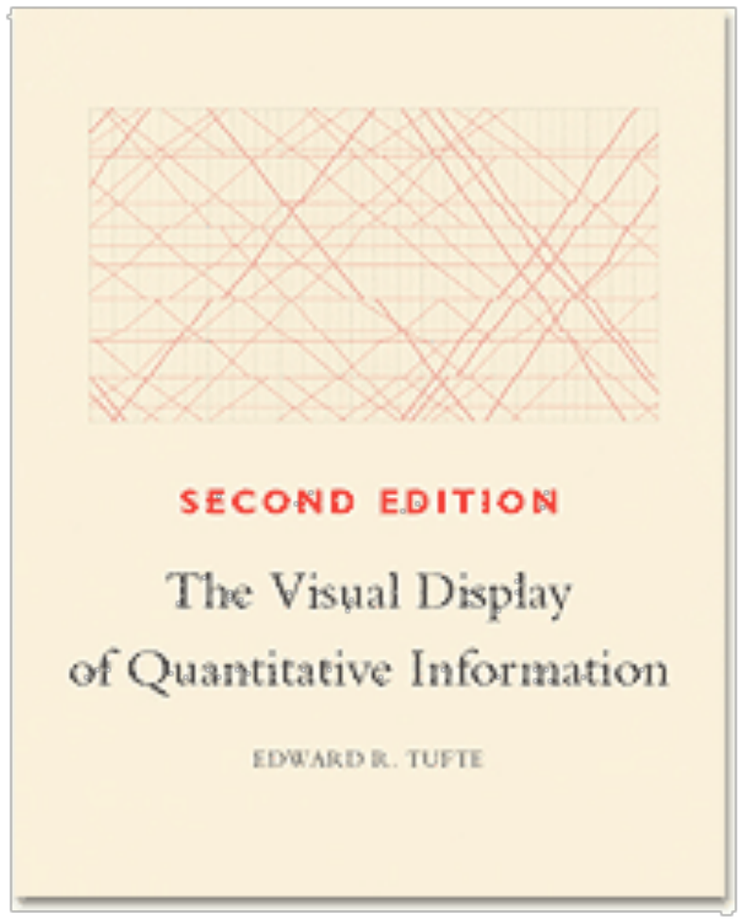
Sequential Palette for Densities

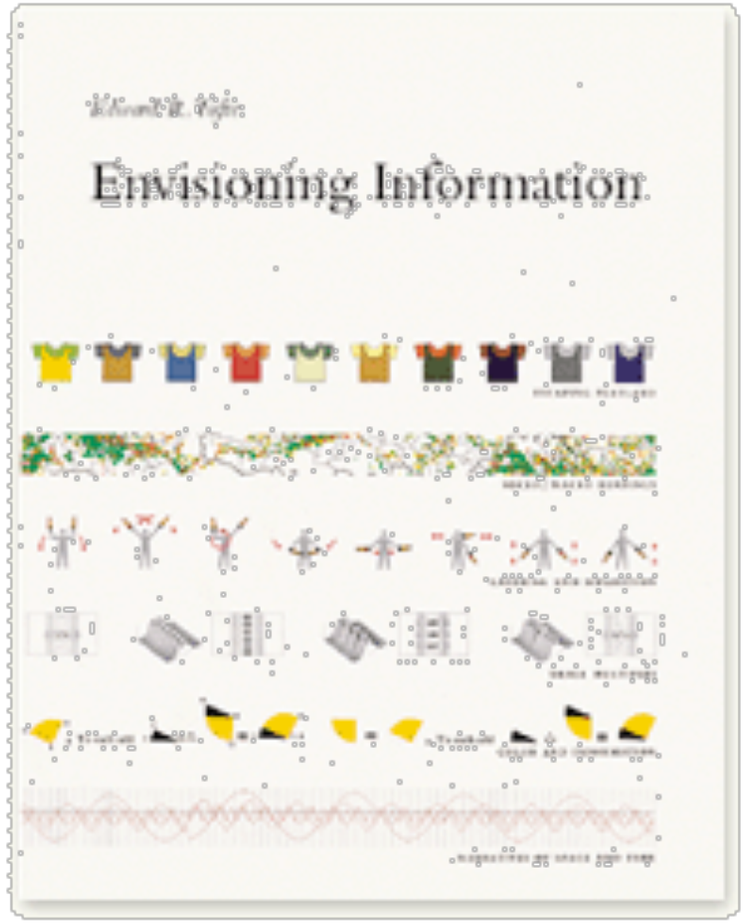
Effective Visualizations

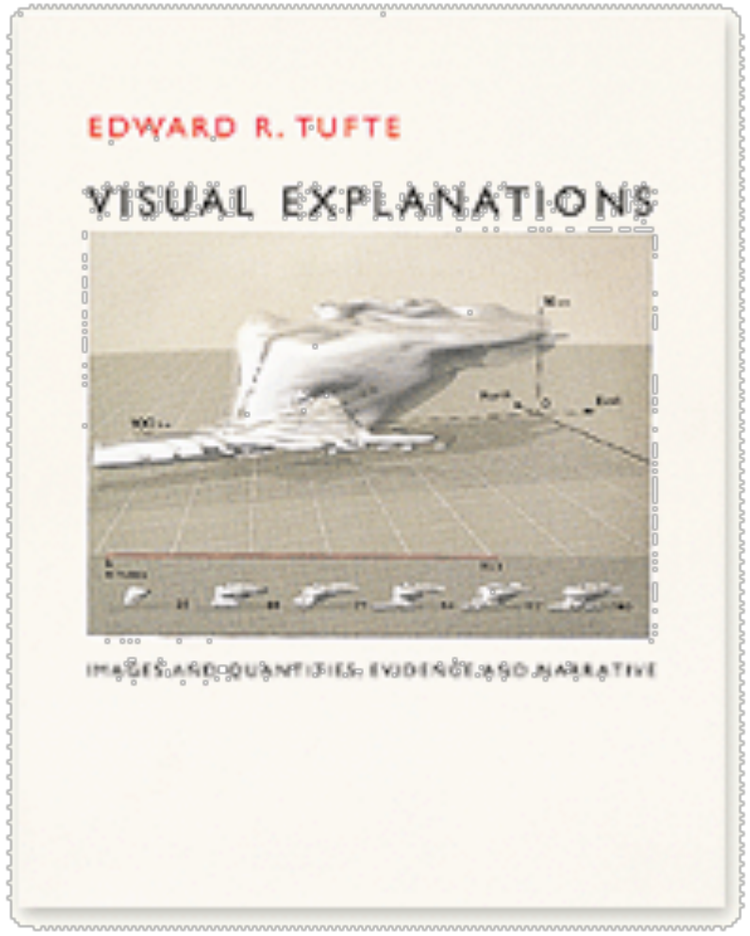
1. Have graphical integrity
2. Keep it simple
3. Use the right display
4. Use color strategically

Further Reading

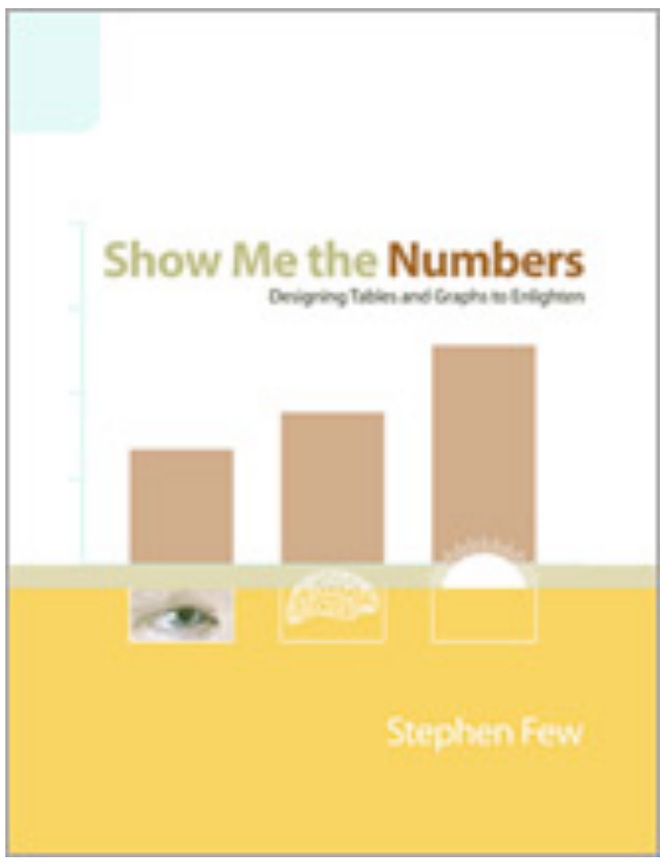
Edward Tufte

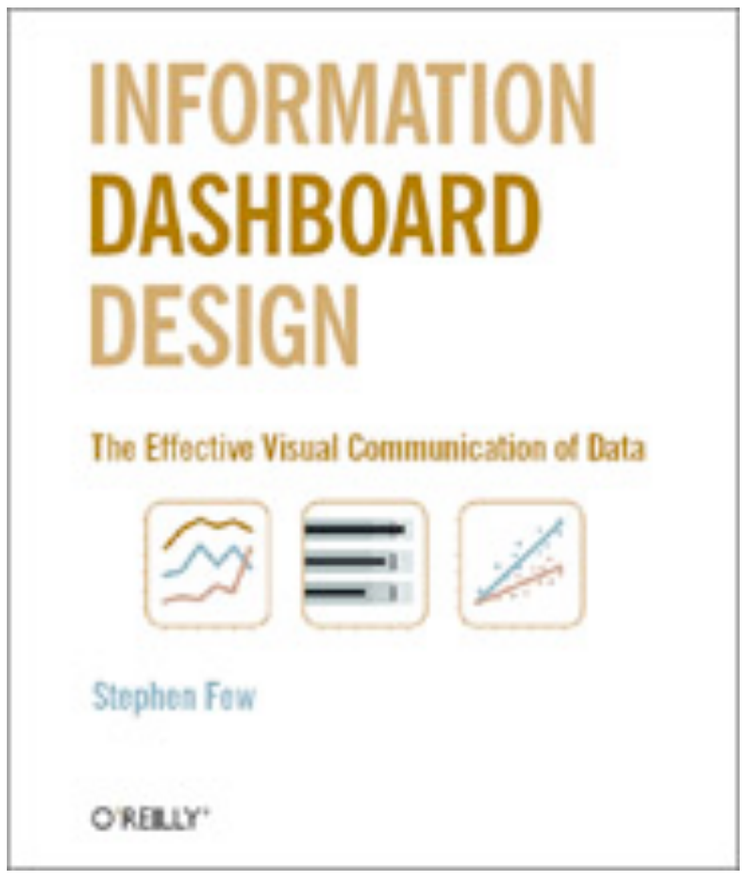




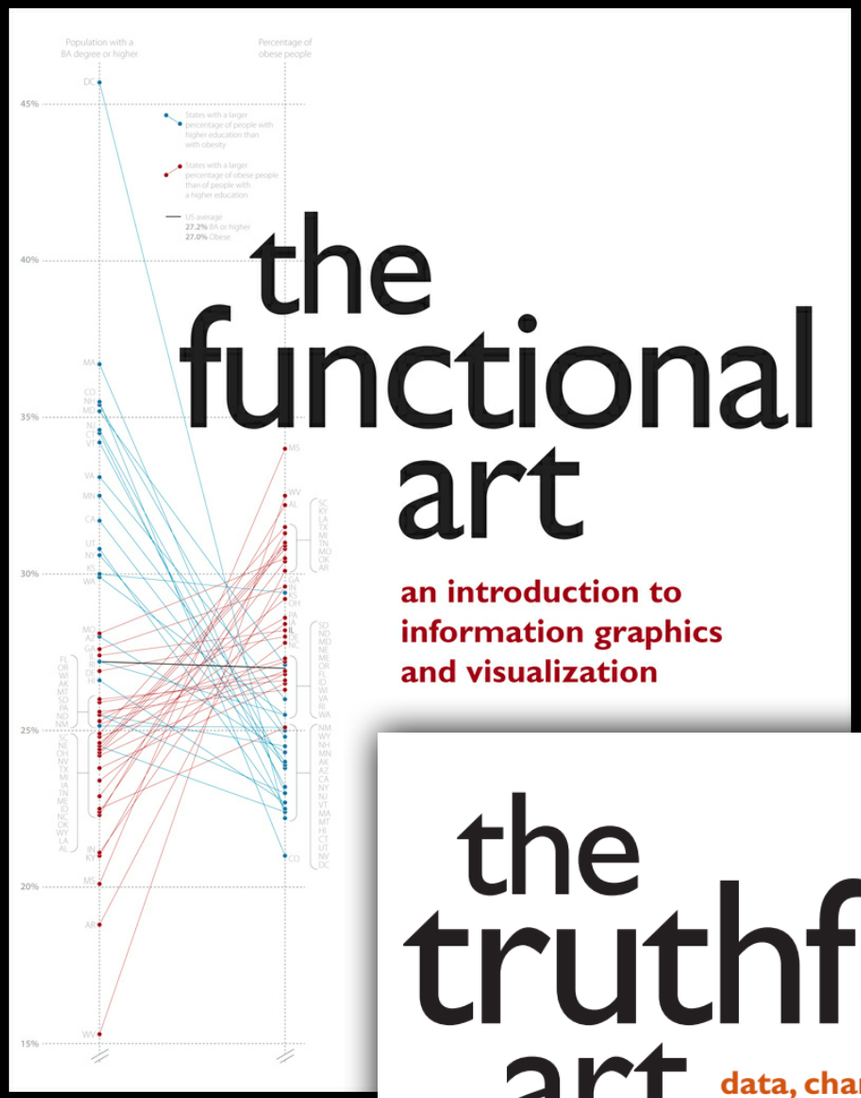


Stephen Few

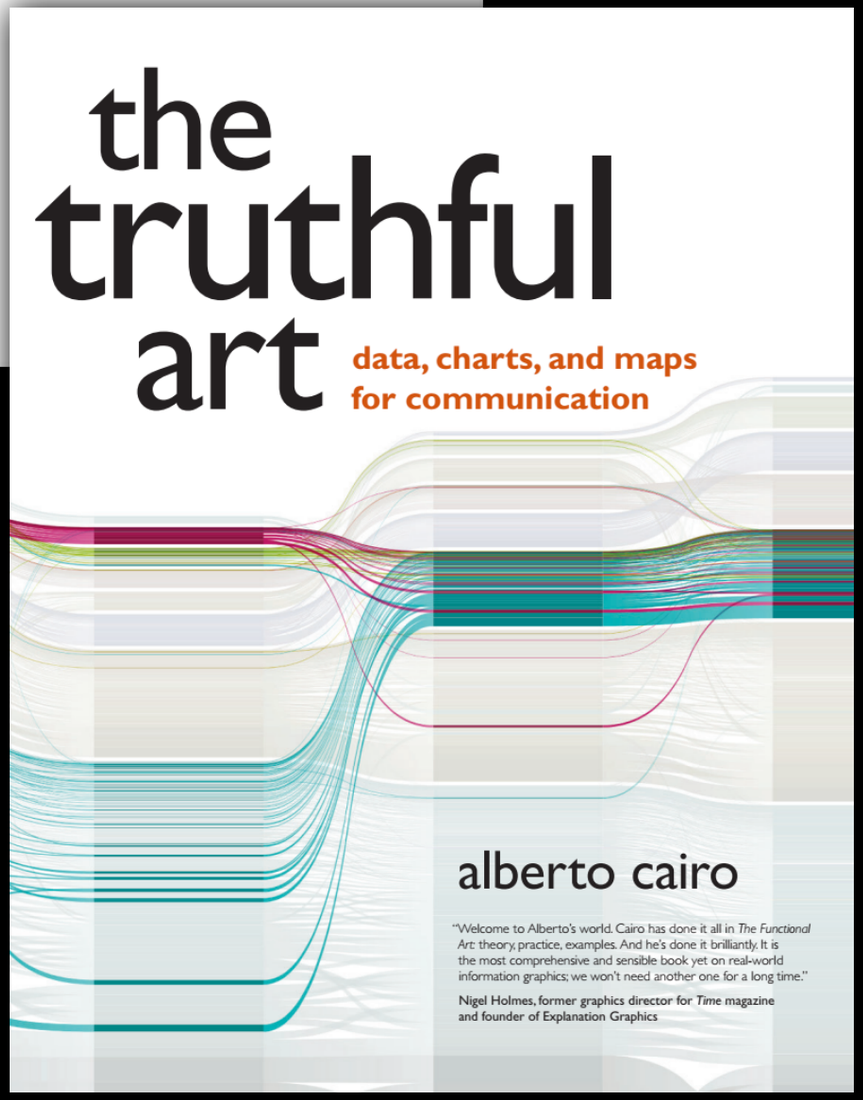

Show Me the Numbers
Designing Tables and Graphs to Enlighten
Stephen Few


INFORMATION
DASHBOARD
DESIGN
The Effective Visual Communication of Data
Stephen Few
O'REILLY


Now you see it
Stephen Few



2012



2016

I've always believed in the power of data visualization (the representation of information by means of charts, diagrams, maps, etc.) to enable understanding

Alberto Cairo • University of Miami • www.thefunctionalart.com • Twitter: @albertocairo