Visualization for scientific communication

GSTP Retreat 2023

Matthew Kay
Assistant Professor
Computer Science & Communication Studies
Northwestern University

A little bit about me

BS and MS in CS (Fine Art minor) @ U of Waterloo
PhD in CSE @ U of Washington
Assistant Professor @ U of Michigan
Assistant Professor @ Northwestern

Work draws upon HCI, visualization, design, statistics…

Matthew Kay

Uncertainty visualization

Usable tools for data scientists

Visualization literacy and misinformation

Collective


Fumeng Yang


Xiaoying Pu


Mandi Cai


Lily Ge


Charles Cui


Alireza Karduni

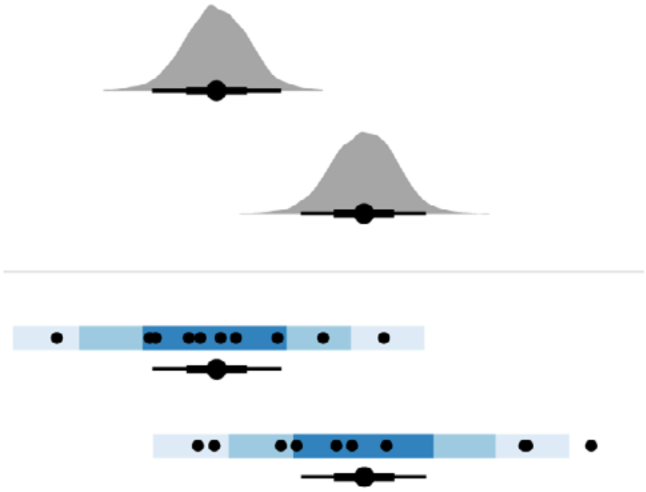

Brian Hall

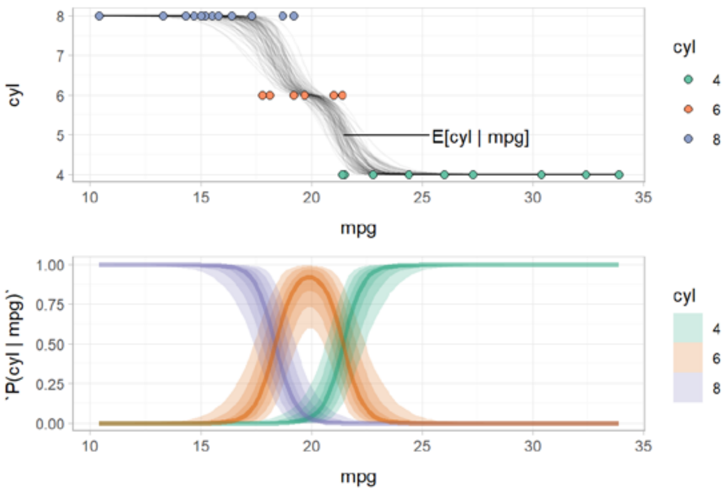

Abhraneel Sarma

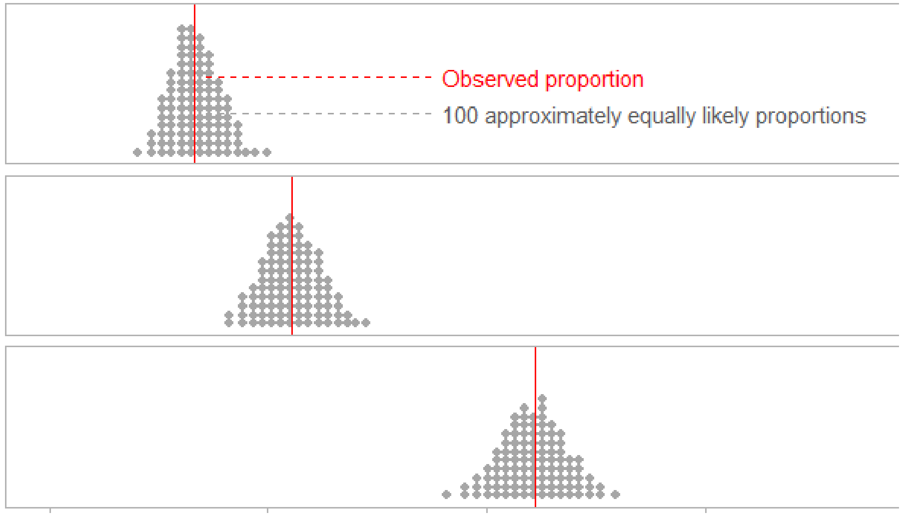

Taewook Kim

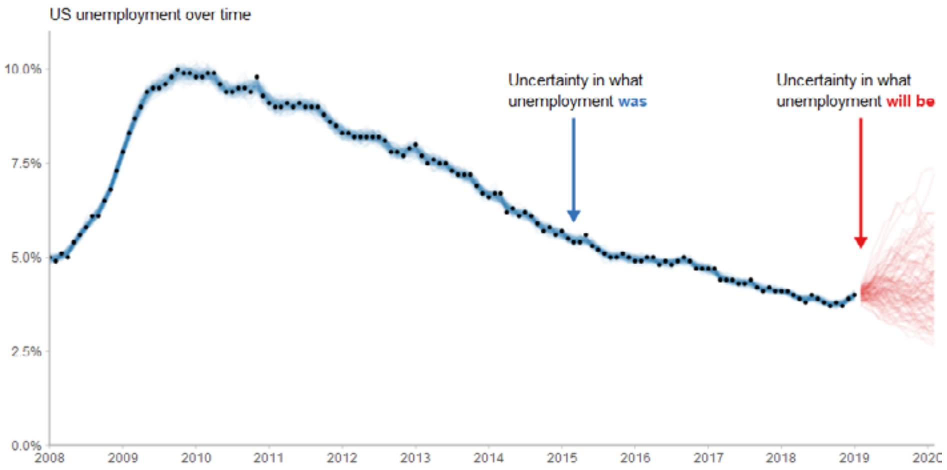

Maryam Hedayati

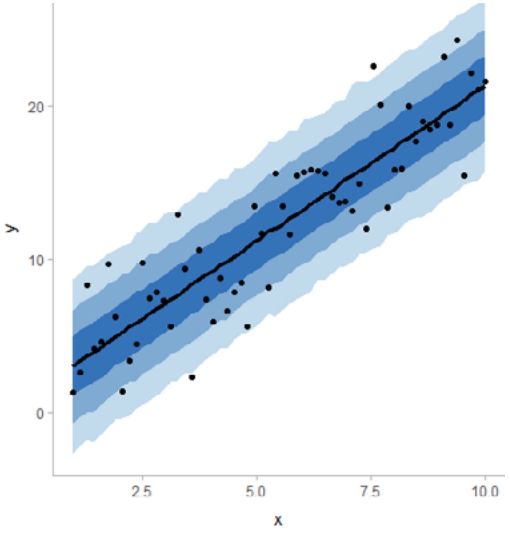

Sheng Long





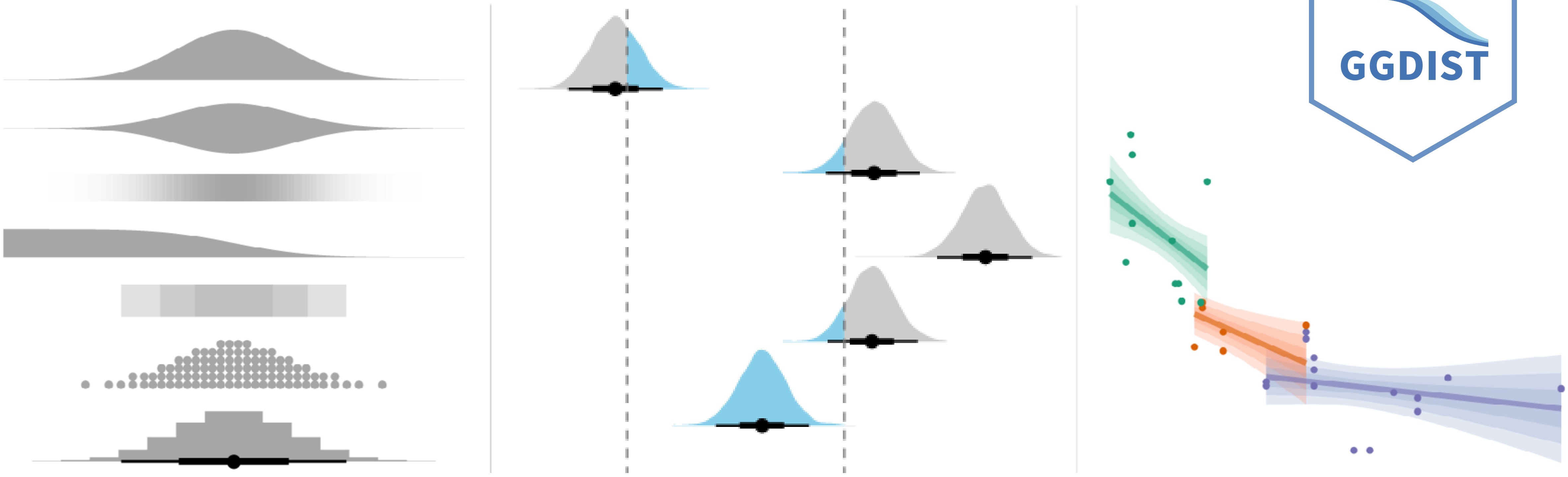






http://mjskay.github.io/tidybayes/

https://github.com/mjskay/uncertainty-examples



GGDIST

http://mjskay.github.io/ggdist/

Today

This morning

Introduce basics of visualization design

Do some design / sketching

This afternoon

Special topics (Uncertainty?)

More design / sketching

Interrupt me!

Introduce yourselves

Research area, interest in vis, ...

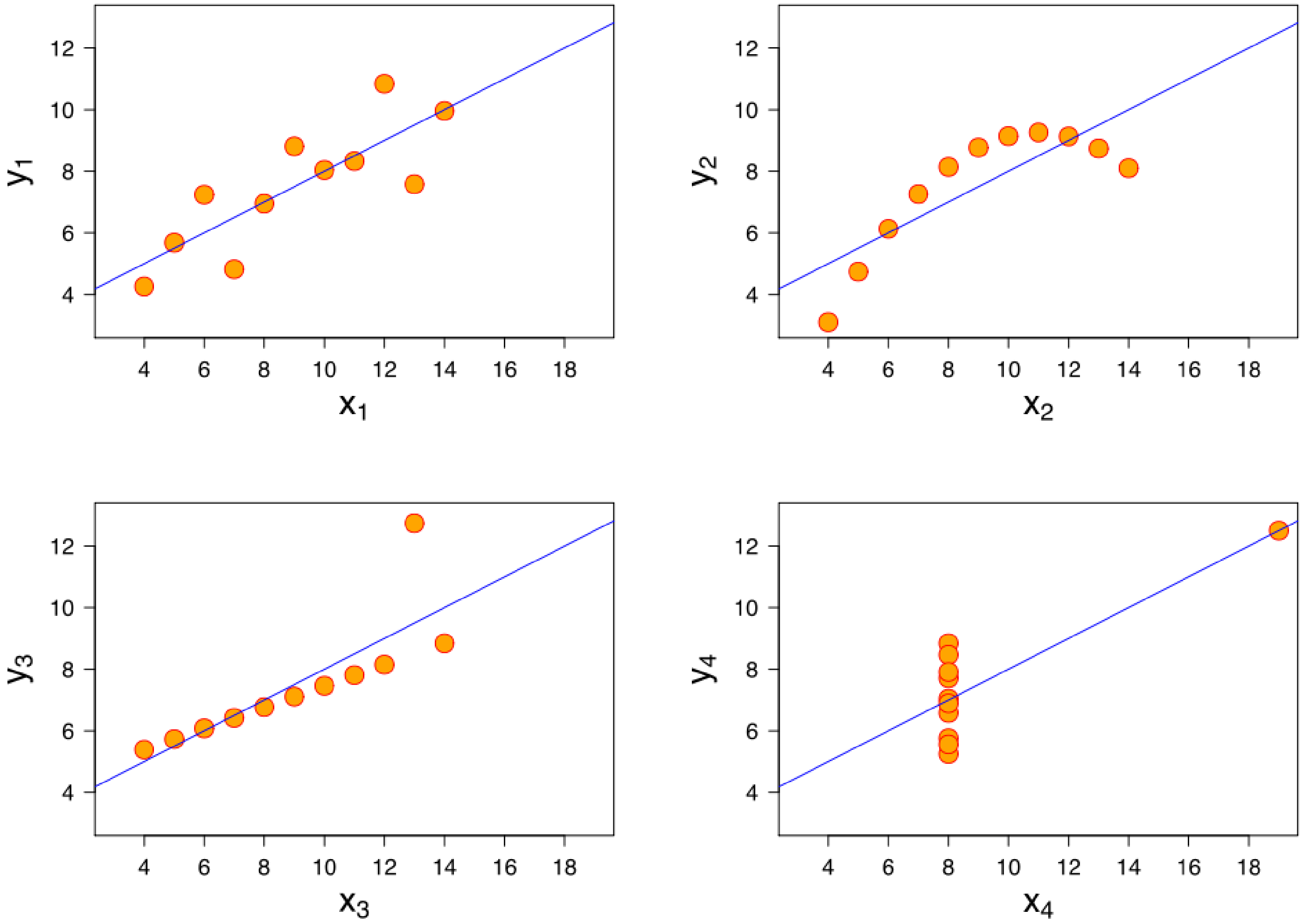
Why visualize in scientific communication?

Anscombe's quartet

I		II		III		IV	
x	y	x	y	x	y	x	y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

4 datasets, same means, variances, correlation

Anscombe's quartet



Visualize to see patterns you wouldn’t otherwise

Visualize to see patterns you wouldn’t otherwise

A mixed-design ANOVA with sex of face (male, female) as a within-subjects factor and self-rated attractiveness (low, average, high) and oral contraceptive use (true, false) as between-subjects factors revealed a main effect of sex of face, $F(1, 1276) = 1372$, $p < .001$, $\eta_p^2 = .52$. This was qualified by interactions between sex of face and SRA, $F(2, 1276) = 6.90$, $p = .001$, $\eta_p^2 = .011$, and between sex of face and oral contraceptive use, $F(1, 1276) = 5.02$, $p = .025$, $\eta_p^2 = .004$. The predicted interaction among sex of face, SRA and oral contraceptive use was not significant, $F(2, 1276) = 0.06$, $p = .94$, $\eta_p^2 < .001$. All other main effects and interactions were non-significant and irrelevant to our hypotheses, all $F \leq 0.94$, $p \geq .39$, $\eta_p^2 \leq .001$.

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Text to table

Table 7
Stevens et al. 2006, table 2: Determinants of authoritarian aggression

Variable	Coefficient (Standard Error)
Constant	.41 (.93)
Countries	
Argentina	1.31 (.33)**B,M
Chile	.93 (.32)**B,M
Colombia	1.46 (.32)**B,M
Mexico	.07 (.32)A,CH,CO,V
Venezuela	.96 (.37)**B,M
Threat	
Retrospective egocentric economic perceptions	.20 (.13)
Prospective egocentric economic perceptions	.22 (.12)#
Retrospective sociotropic economic perceptions	−.21 (.12)#
Prospective sociotropic economic perceptions	−.32 (.12)*
Ideological distance from president	−.27 (.07)**
Ideology	
Ideology	.23 (.07)**
Individual Differences	
Age	.00 (.01)
Female	−.03 (.21)
Education	.13 (.14)
Academic Sector	.15 (.29)
Business Sector	.31 (.25)
Government Sector	−.10 (.27)
R^2	.15
Adjusted R^2	.12
N	500

**$p < .01$, *$p < .05$, #$p < .10$ (twotailed)

[A]Coefficient is significantly different from Argentina's at $p < .05$;

[B]Coefficient is significantly different from Brazil's at $p < .05$;

[CH]Coefficient is significantly different from Chile's at $p < .05$;

[CO]Coefficient is significantly different from Colombia's at $p < .05$;

[M]Coefficient is significantly different from Mexico's at $p < .05$;

[V]Coefficient is significantly different from Venezuela's at $p < .05$.

Text to table to graph

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Stevens et al. 2006, table 2: Determinants of authoritarian aggression

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^{M}Coefficient is significantly different from Mexico's at $p < .05$;

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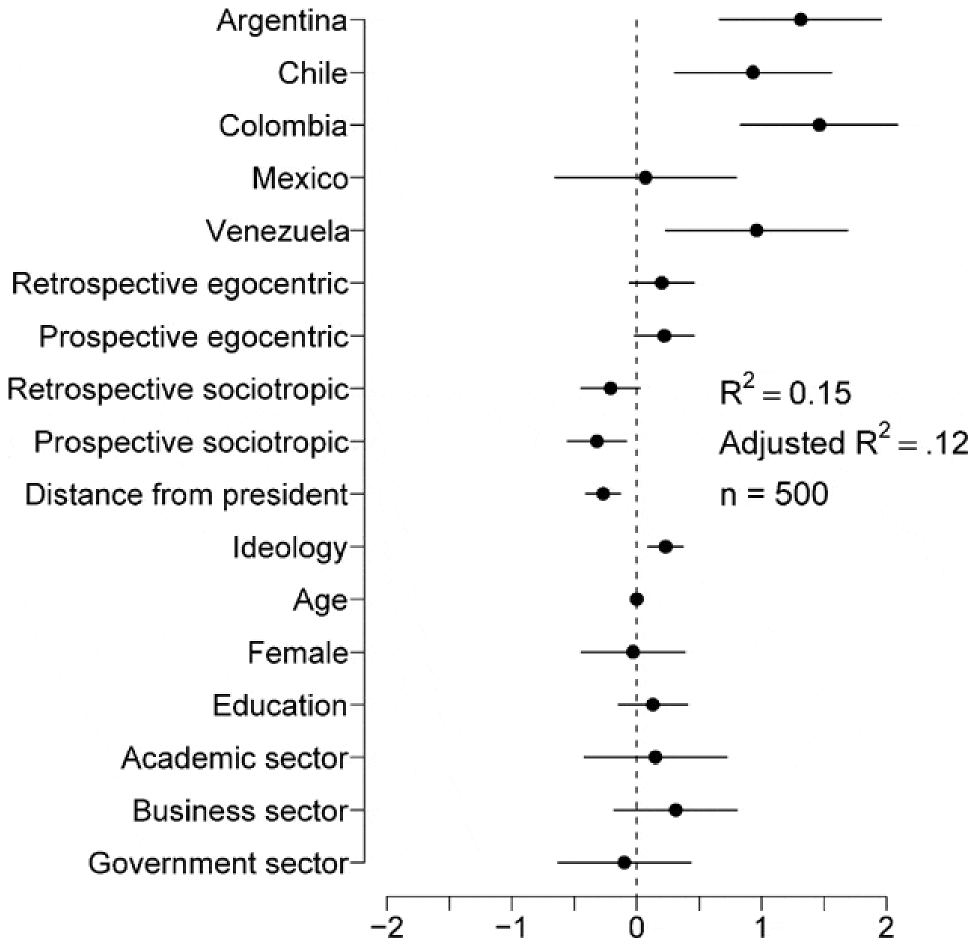

[Jonathan P Kastellec and Eduardo L Leoni. 2007. Using Graphs Instead of Tables in Political Science. Perspectives on politics 5, 4: 755–771]

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Government Sector	−.10 (.27)
R^2	.15
Adjusted R^2	.12
N	500

**$p < .01$, *$p < .05$, #$p < .10$ (twotailed)

ACoefficient is significantly different from Argentina's at $p < .05$;

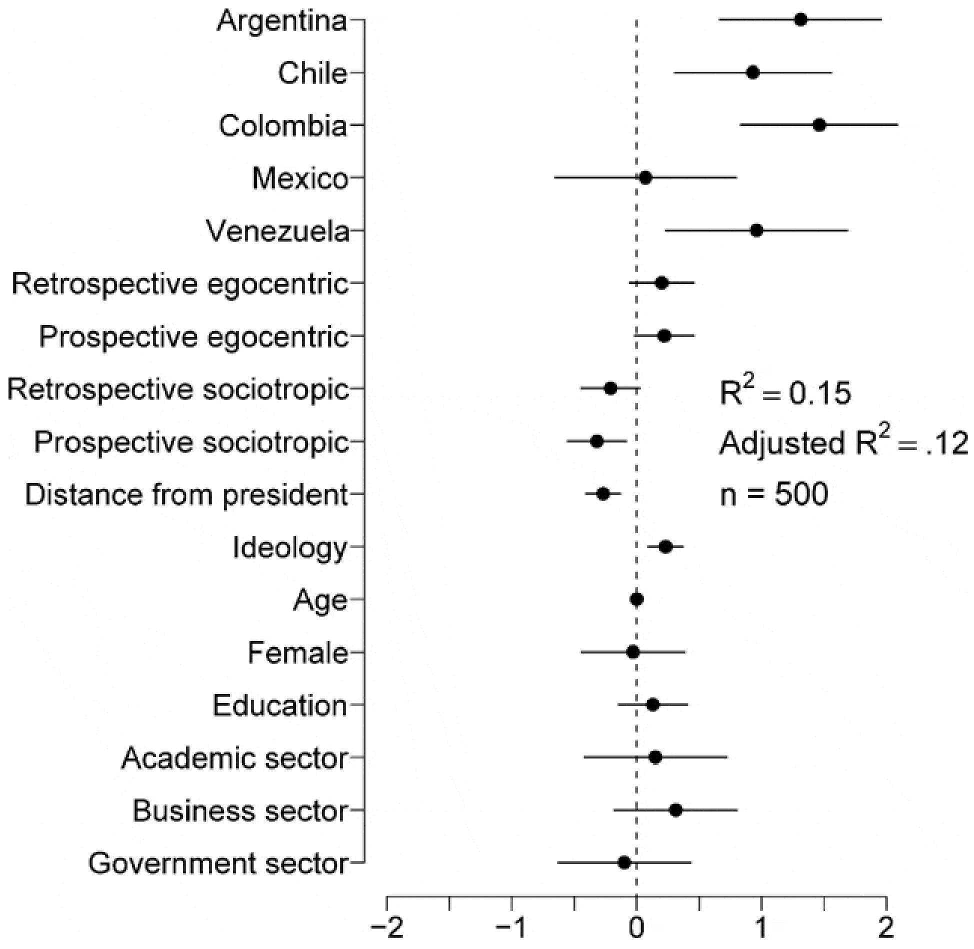
BCoefficient is significantly different from Brazil's at $p < .05$;

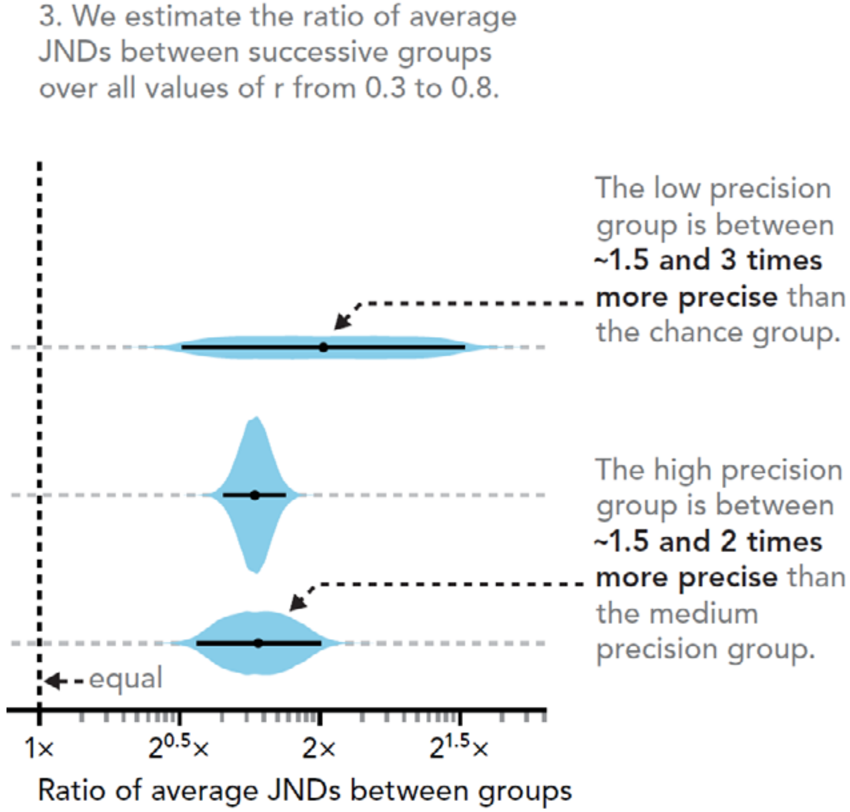
CHCoefficient is significantly different from Chile's at $p < .05$;

COCoefficient is significantly different from Colombia's at $p < .05$;

MCoefficient is significantly different from Mexico's at $p < .05$;

VCoefficient is significantly different from Venezuela's at $p < .05$.





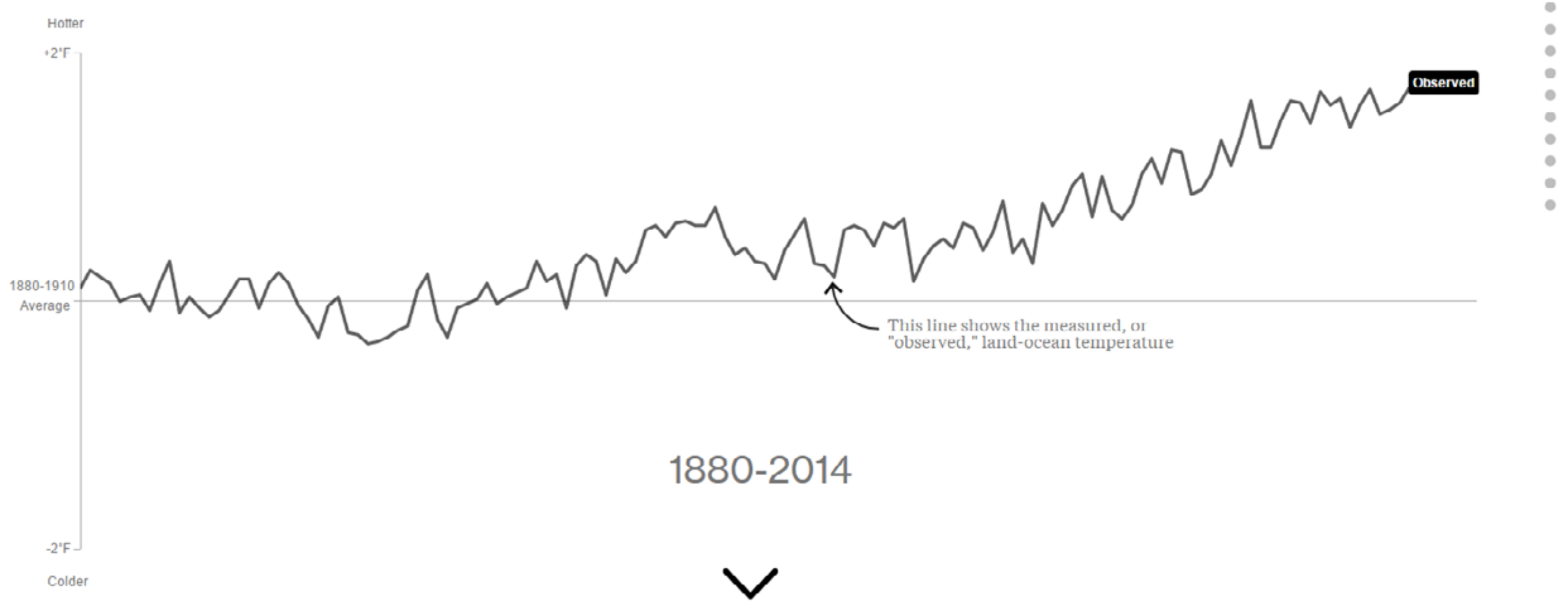
[Jonathan P Kastellec and Eduardo L Leoni. 2007. Using Graphs Instead of Tables in Political Science. Perspectives on politics 5, 4: 755–771]

Visualize for persuasion

What's Really Warming the World?

By Eric Roston and Blacki Migliozzi | June 24, 2015

Skeptics of manmade climate change offer various natural causes to explain why the Earth has warmed 1.4 degrees Fahrenheit since 1880. But can these account for the planet's rising temperature? Scroll down to see show how much different factors, both natural and industrial, contribute to global warming, based on findings from NASA's Goddard Institute for Space Studies.



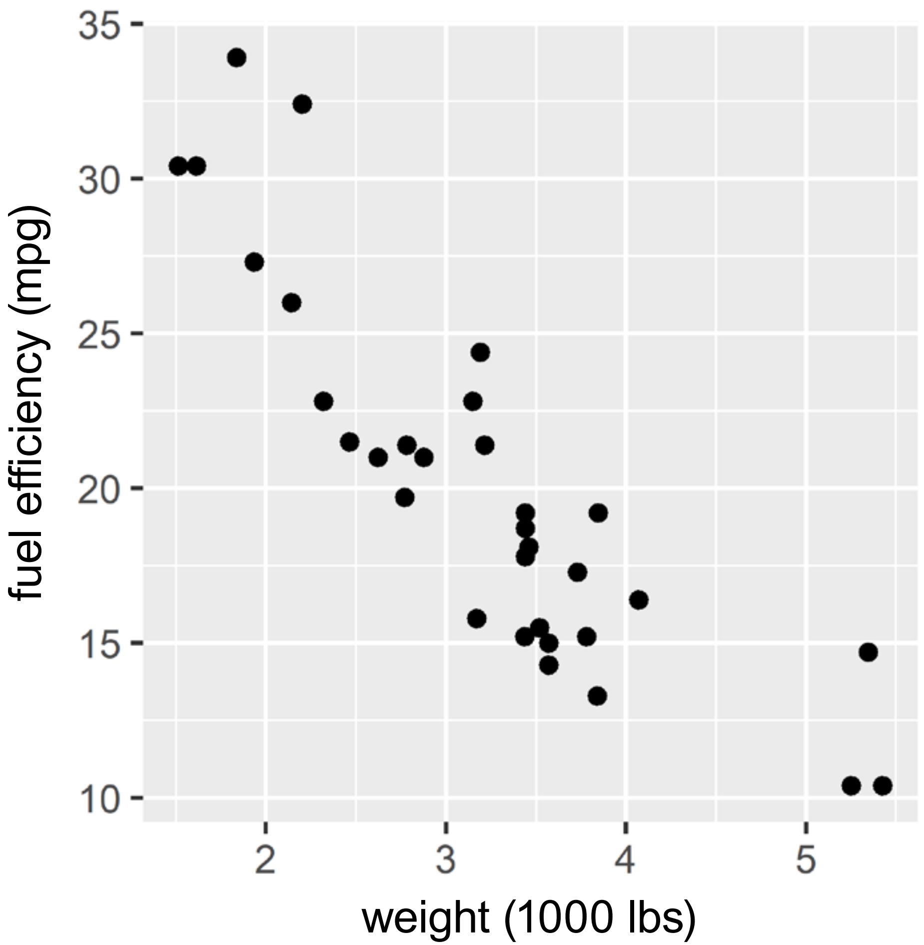
[https://www.bloomberg.com/graphics/2015-whats-warming-the-world/]

Evolution of bacteria

https://vimeo.com/180908160

How do we turn data into visualizations?

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0
Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0
Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0
Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0
Merc 280	19.2	6	167.6	123	3.92	3.440	18.30	1	0
Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0
Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0
Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0
Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0
Cadillac Fleetwood	10.4	8	472.0	205	2.93	5.250	17.98	0	0
Lincoln Continental	10.4	8	460.0	215	3.00	5.424	17.82	0	0
Chrysler Imperial	14.7	8	440.0	230	3.23	5.345	17.42	0	0
Fiat 128	32.4	4	78.7	66	4.08	2.200	19.47	1	1
Honda Civic	30.4	4	75.7	52	4.93	1.615	18.52	1	1
Toyota Corolla	33.9	4	71.1	65	4.22	1.835	19.90	1	1
Toyota Corona	21.5	4	120.1	97	3.70	2.465	20.01	1	0
Dodge Challenger	15.5	8	318.0	150	2.76	3.520	16.87	0	0
AMC Javelin	15.2	8	304.0	150	3.15	3.435	17.30	0	0
Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0
Pontiac Firebird	19.2	8	400.0	175	3.08	3.845	17.05	0	0
Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1



	mpg	cyl	disp	hp	drat	wt	qsec	vs	am
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1
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Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0
Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0
Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0
Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0
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Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0
Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0
Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0
Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0
Cadillac Fleetwood	10.4	8	472.0	205	2.93	5.250	17.98	0	0
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Fiat 128	32.4	4	78.7	66	4.08	2.200	19.47	1	1
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Dodge Challenger	15.5	8	318.0	150	2.76	3.520	16.87	0	0
AMC Javelin	15.2	8	304.0	150	3.15	3.435	17.30	0	0
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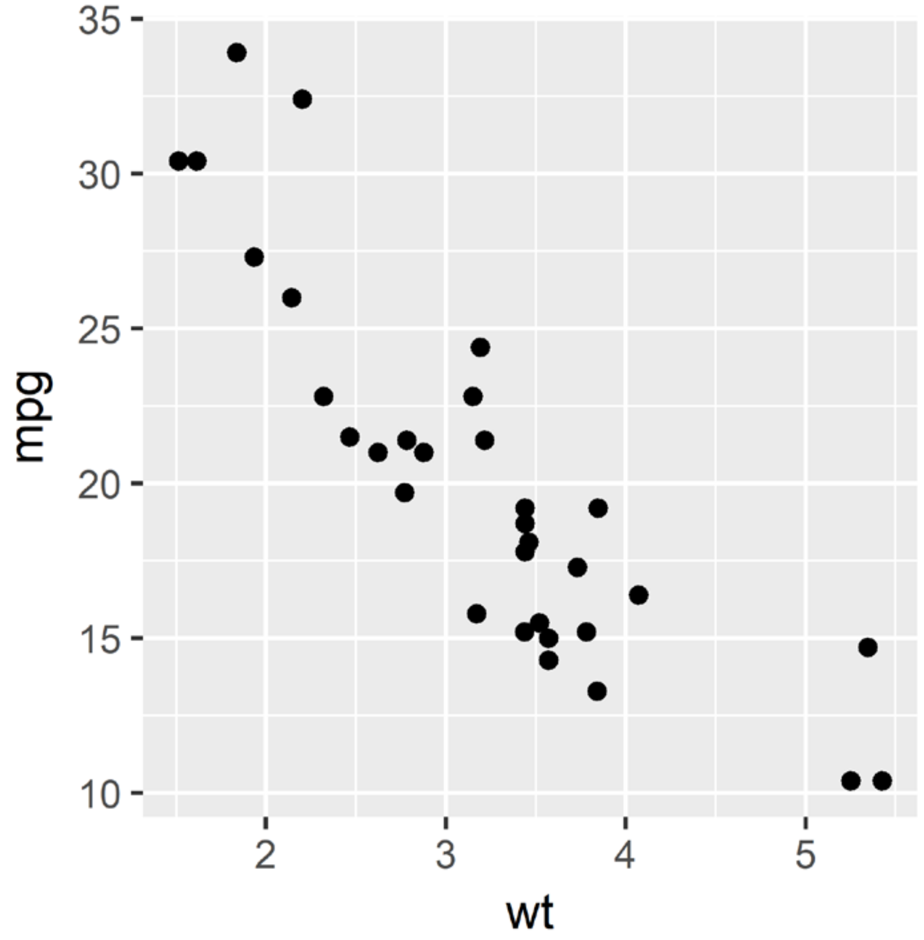


Let's systematize "turning data into a vis"

data -> ??? -> marks on the screen (or paper)

Let's systematize "turning data into a vis"

data -> ??? -> marks on the screen (or paper)

??? = some vis API
= some way of thinking about vis systematically

Let's systematize "turning data into a vis"

data -> ??? -> marks on the screen (or paper)

??? = New function for every chart type:

```
scatter_plot(data, ...)
bar_chart(data, ...)
...
```

Let's systematize "turning data into a vis"

data -> ??? -> marks on the screen (or paper)

??? = New function for every chart type:

scatter_plot(data, ...)
bar_chart(data, ...)
...
Every new chart is a new adventure!
Too many specs! — Too high level!

Let's systematize "turning data into a vis"

data -> ??? -> marks on the screen (or paper)

??? = ~~New function for every chart type~~

= Low-level drawing functions

draw_point(...)

draw_rectangle(...)

Let's systematize "turning data into a vis"

data -> ??? -> marks on the screen (or paper)

??? = ~~New function for every chart type~~
= Low-level drawing functions
draw_point(...)
draw_rectangle(...)

Too low level!

Let's systematize "turning data into a vis"

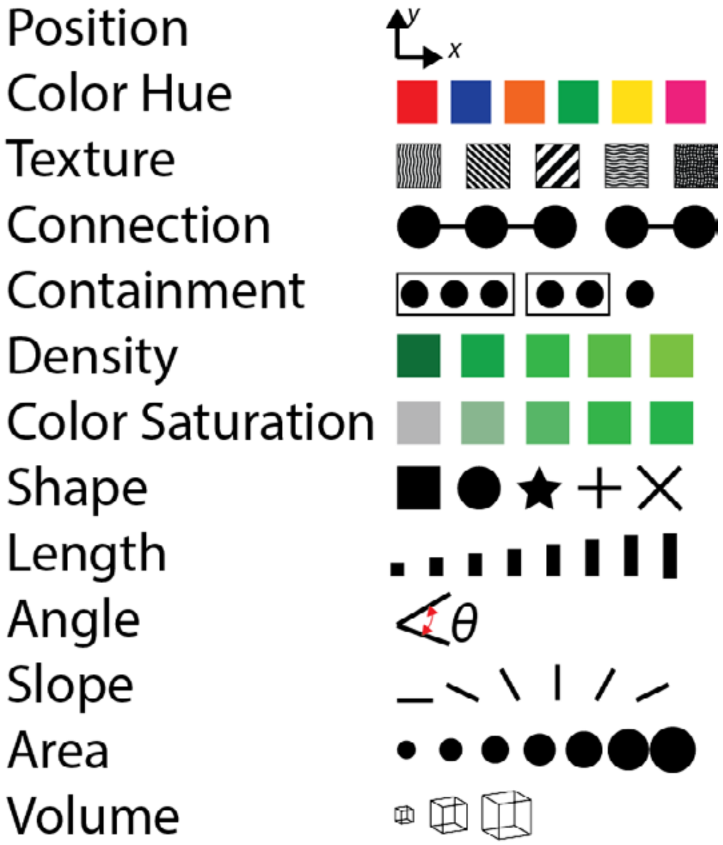
data -> ??? -> marks on the screen (or paper)

??? = ~~New function for every chart type~~
= ~~Low-level drawing functions~~
= Grammar of graphics

Encode data with visual channels
Display encodings with marks

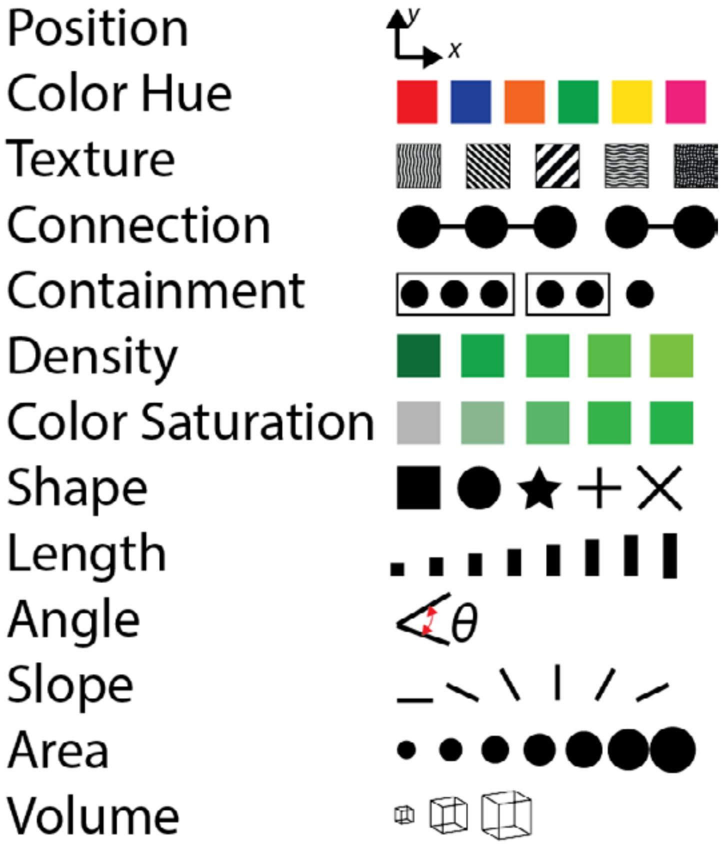
Visual channels

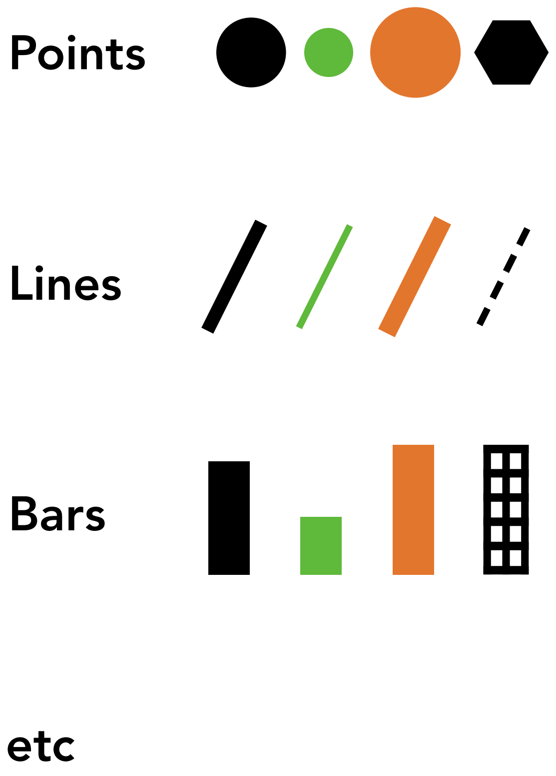
(ggplot “aesthetics”)



Visual channels --------> Marks

(ggplot "aesthetics") (ggplot "geometries")





Grammar of graphics

Codifies data types, encodings/channels, marks

Maps data -> channels -> marks

Makes visualization specification straightforward

Undergirds ggplot, Tableau, Vega-Lite, Altair,...
(terms may vary)

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am
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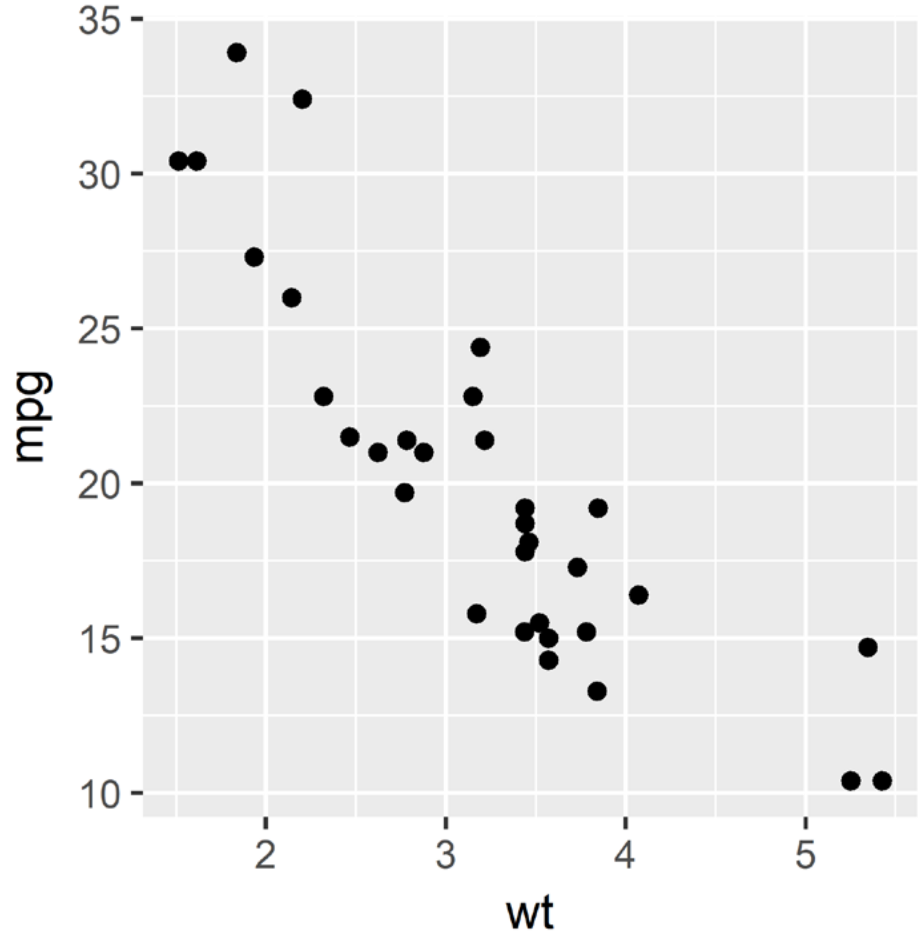
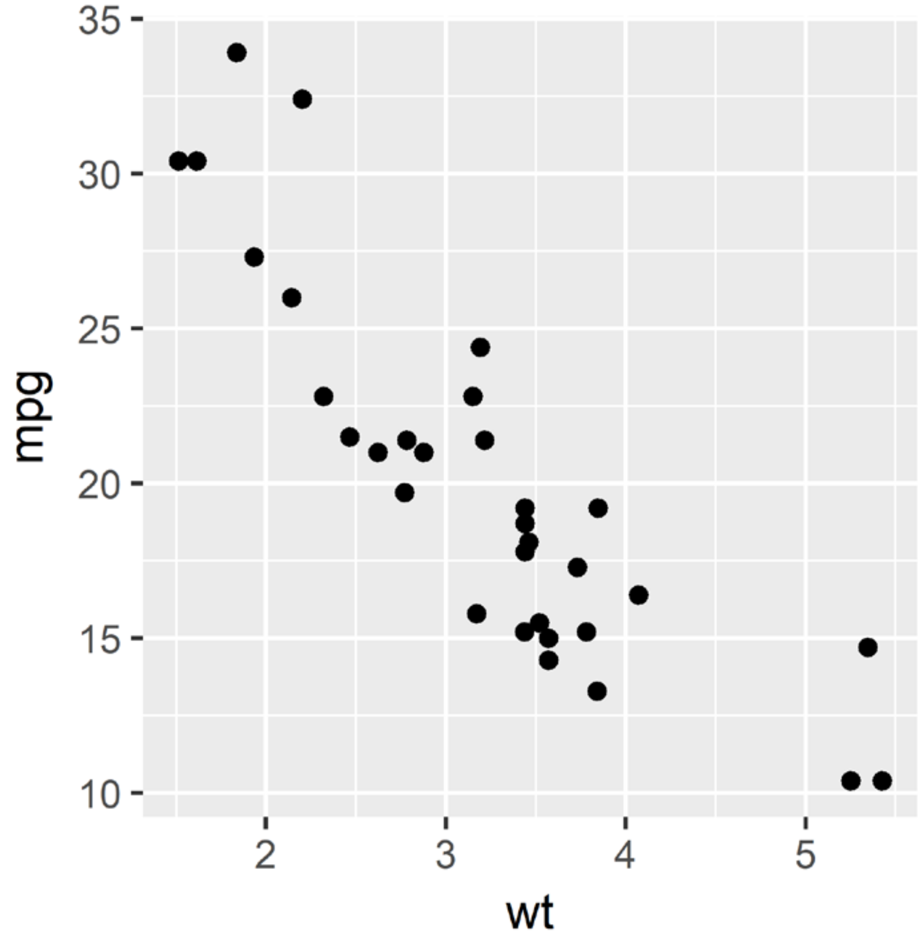


Grammar of graphics

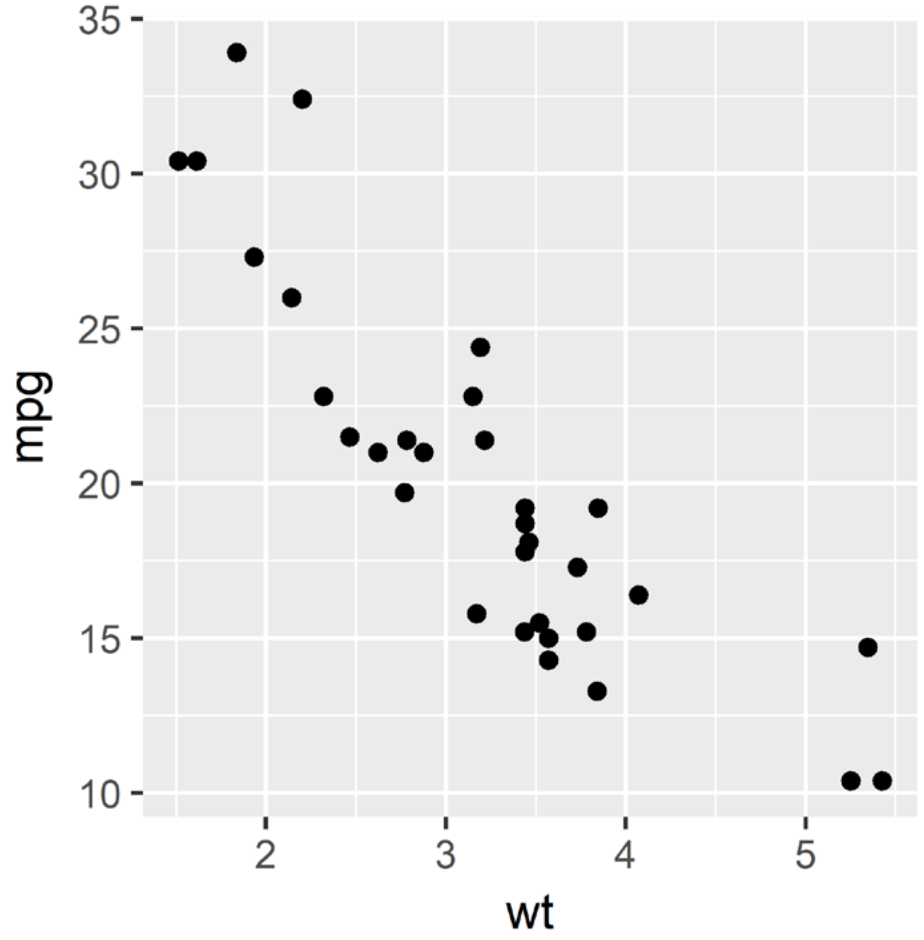
(data types, channels, marks)



Grammar of graphics

(data types, channels, marks)

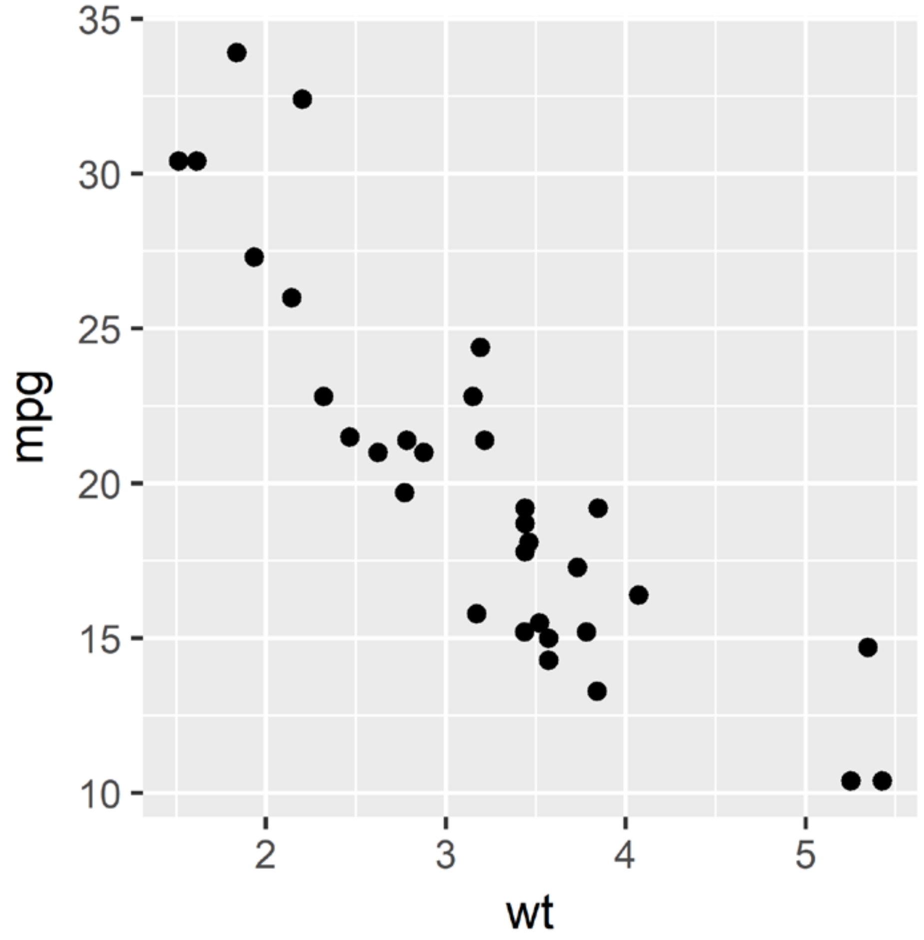
mpg: numeric
wt: numeric



Grammar of graphics

(data types, channels, marks)

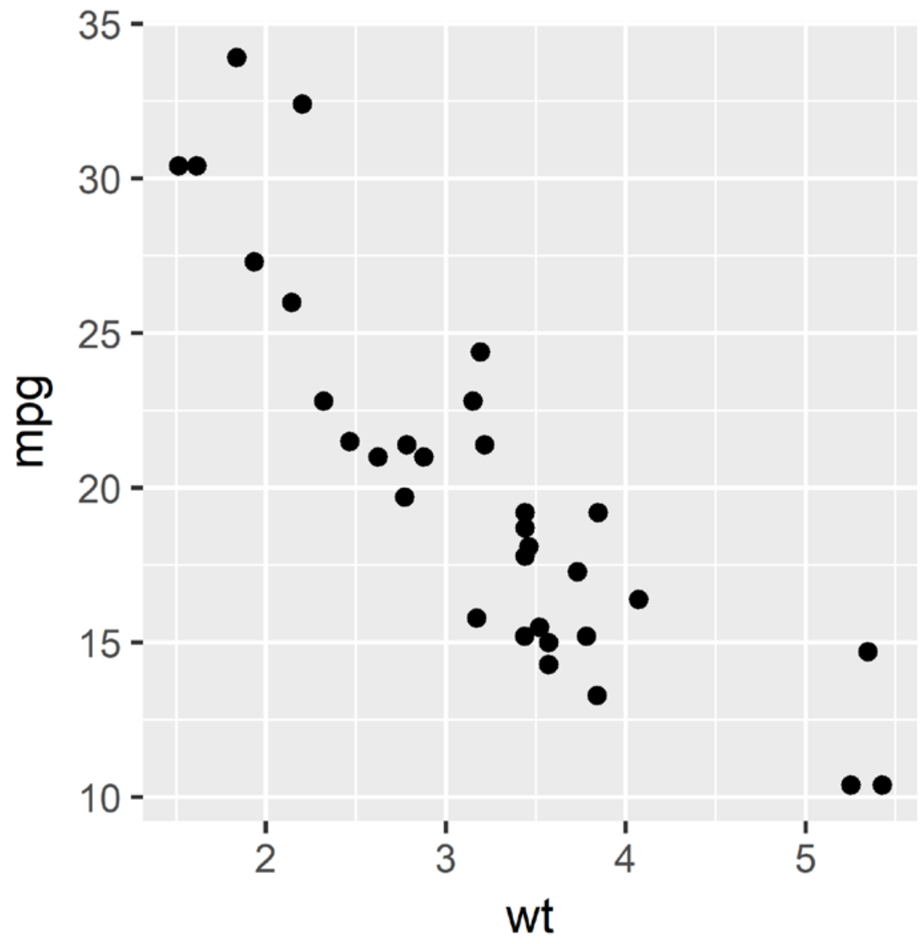
mpg: numeric
wt: numeric
wt -> x position
mpg -> y position



Grammar of graphics

(data types, channels, marks)

mpg: numeric
wt: numeric
wt -> x position
mpg -> y position
mark: point



Grammar of graphics

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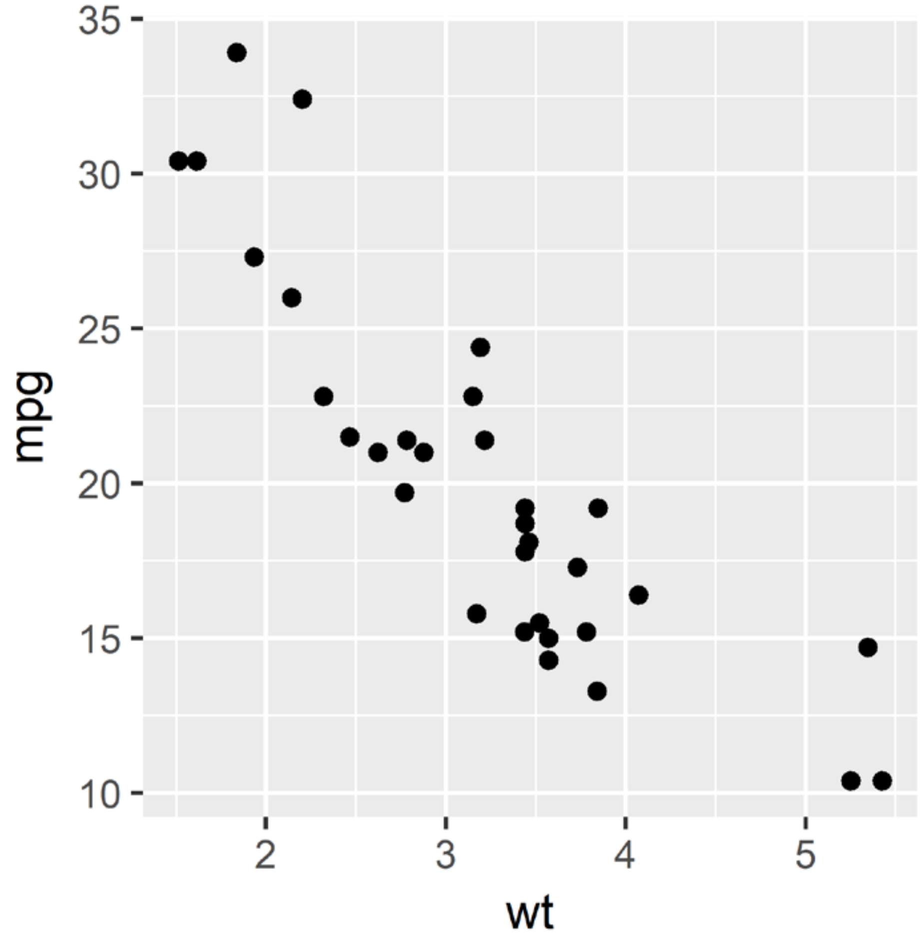


Grammar of graphics

(data types, channels, marks)

mpg: numeric

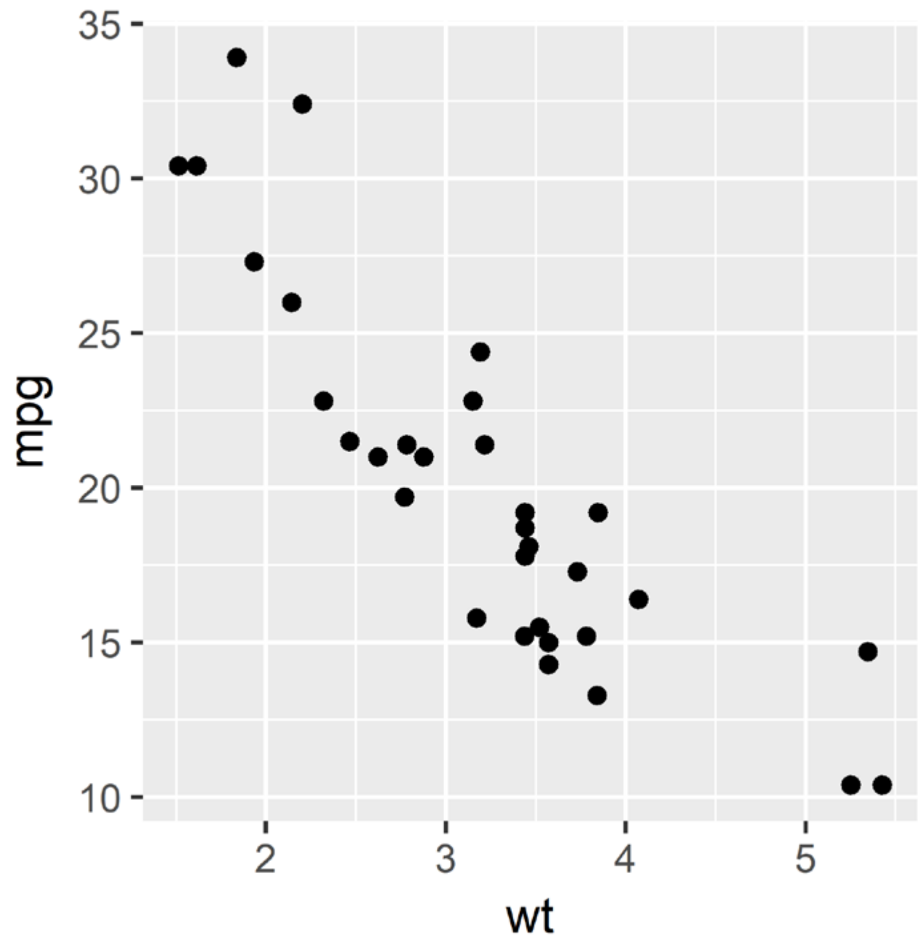
wt: numeric

manual: nominal

wt -> x position

mpg -> y position

mark: point

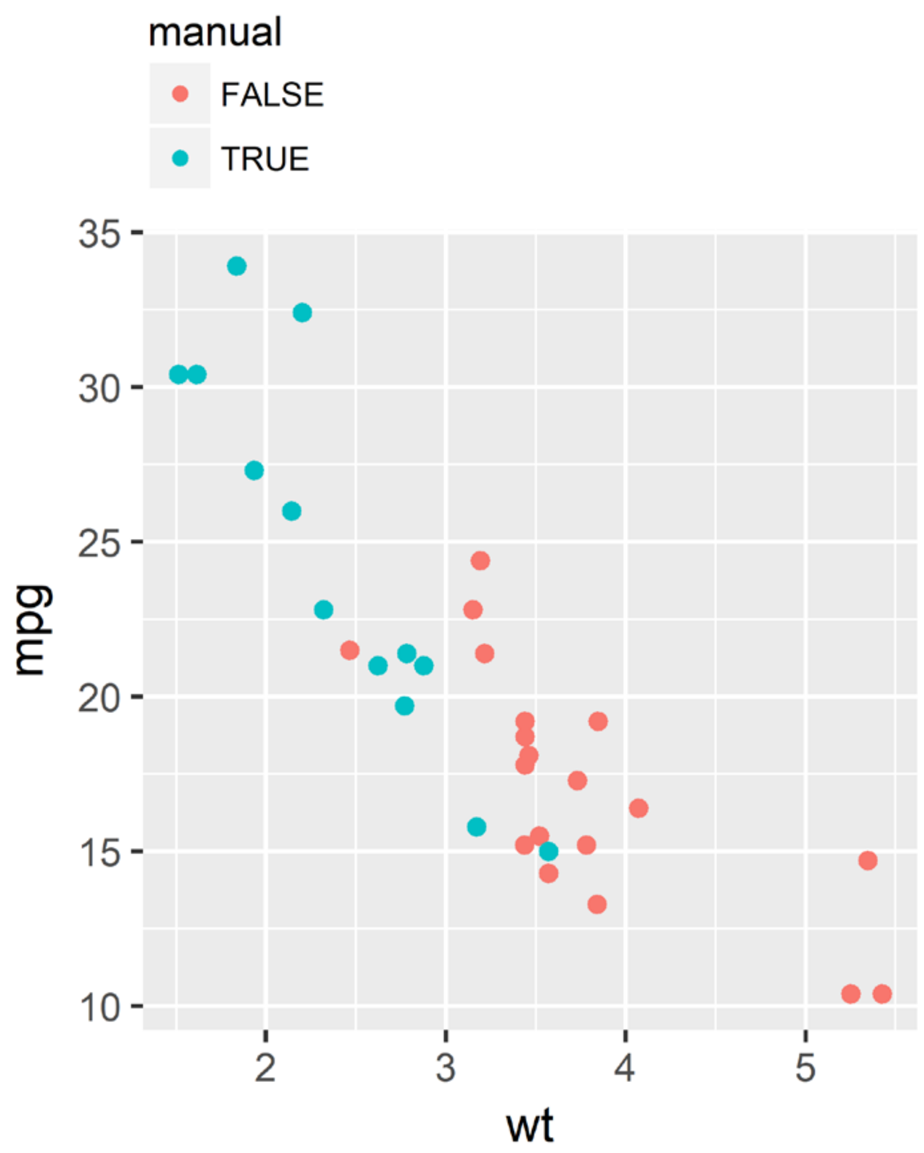


Grammar of graphics

(data types, channels, marks)

mpg: numeric
wt: numeric
manual: nominal
wt -> x position
mpg -> y position
manual -> color

mark: point



Grammar of graphics

(data types, channels, marks)

mpg: numeric

wt: numeric

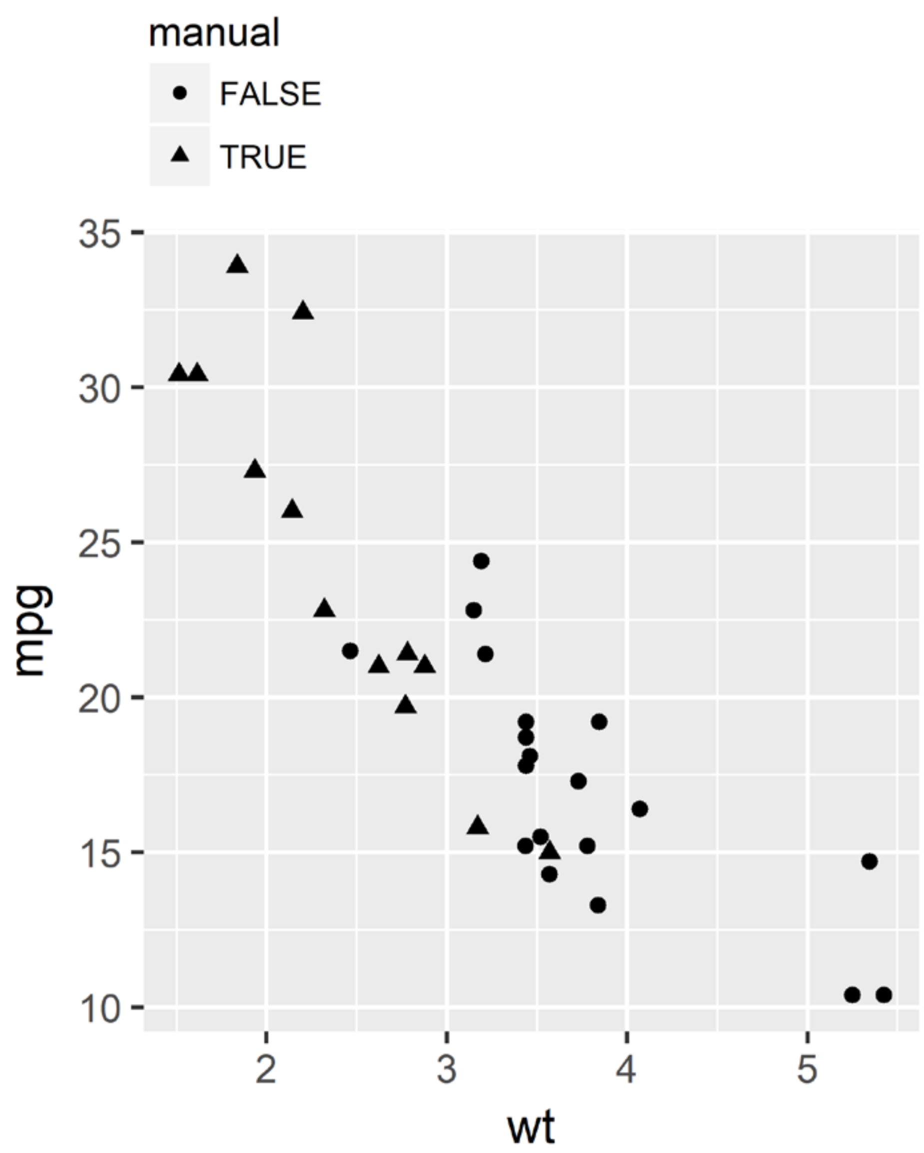
manual: nominal

wt -> x position

mpg -> y position

manual -> shape

mark: point



Grammar of graphics

(data types, channels, marks)

mpg: numeric
wt: numeric
manual: nominal
wt -> x position
mpg -> y position
manual -> color
manual -> shape
mark: point

Grammar of graphics

(data types, channels, marks)

mpg: numeric
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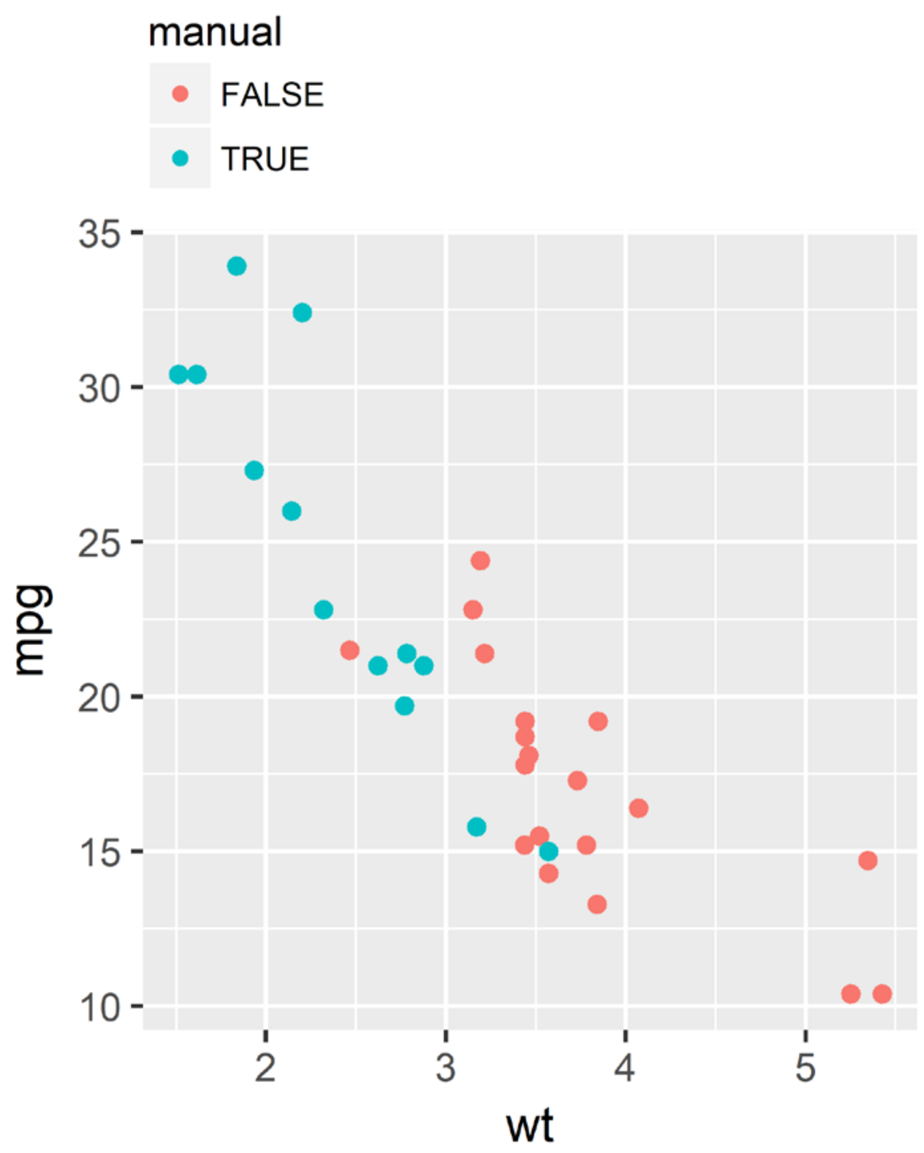


Why is the grammar of graphics useful?

1. Easier to specify many charts, combinations

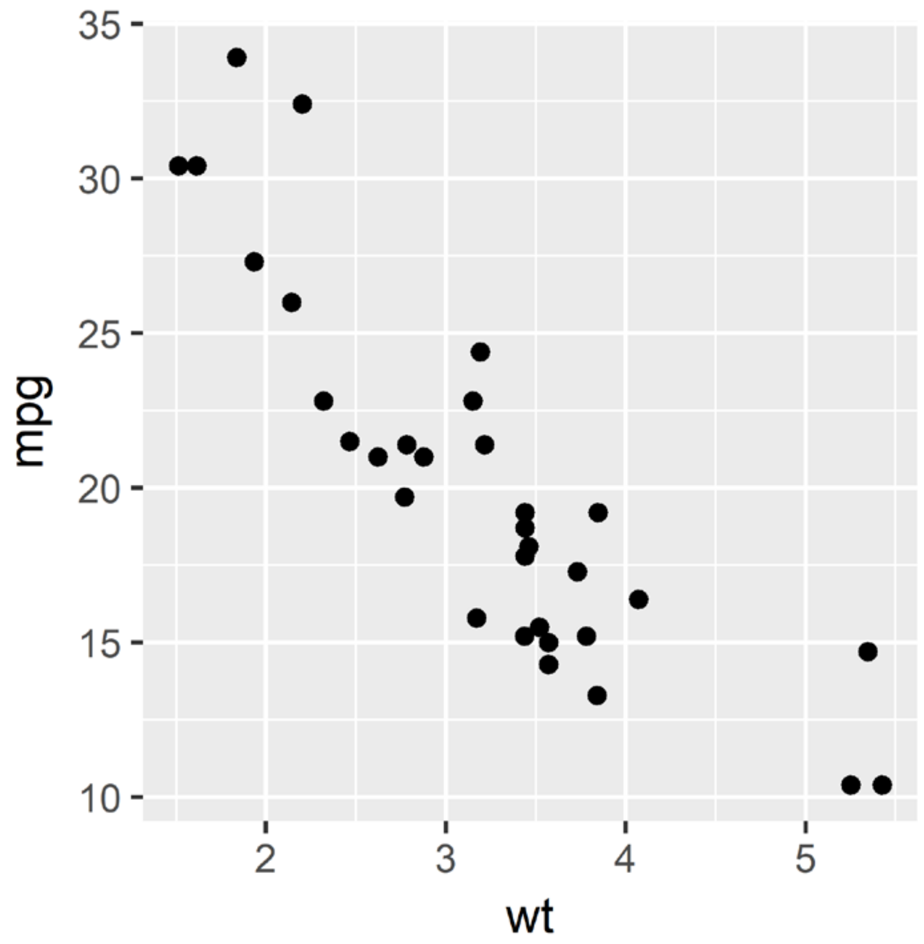
2. Helps you design/evaluate charts systematically

1. Easier to specify many charts, combinations

mpg: numeric
wt: numeric

wt -> x position
mpg -> y position

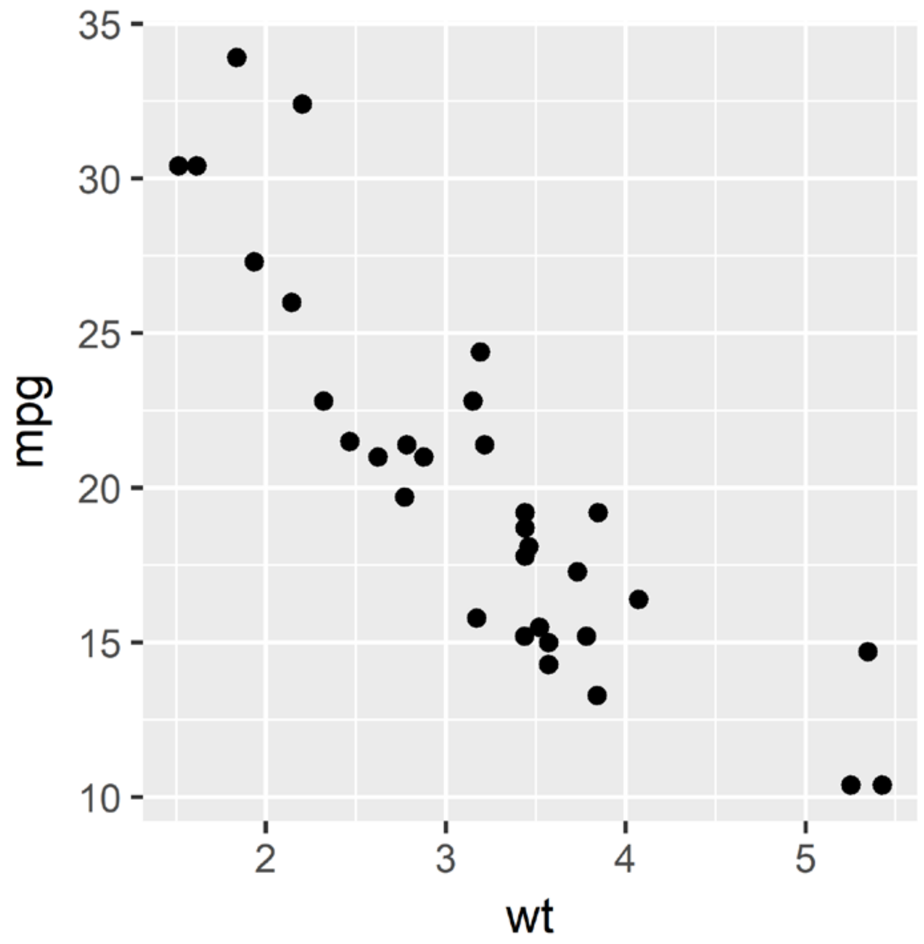
mark: point



1. Easier to **specify** many charts, combinations

Not:

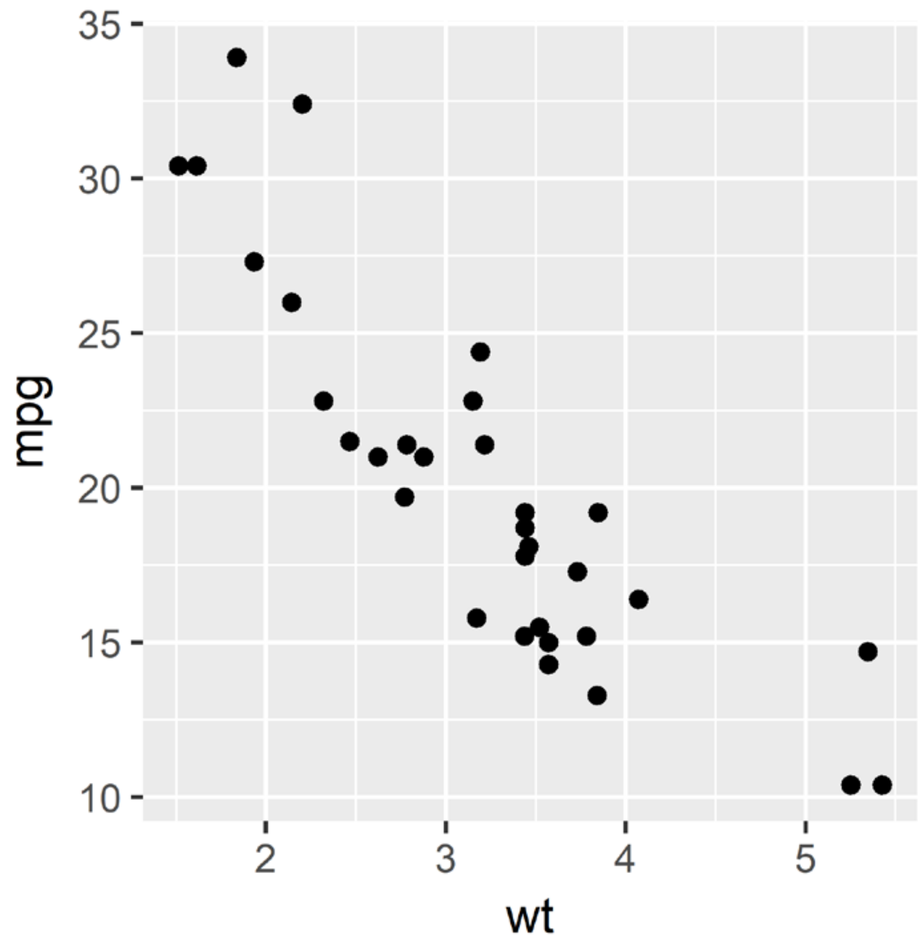
```
some_big_function_to_make_scatterplots(
   my_data,
   a_bunch_of_options
)
```



1. Easier to specify many charts, combinations

Not:

```
some_function_to_draw_grid()
some_function_to_draw_axes()
for (row in data) {
   draw_point(data[i]["x"], ...)
}
  ...
```

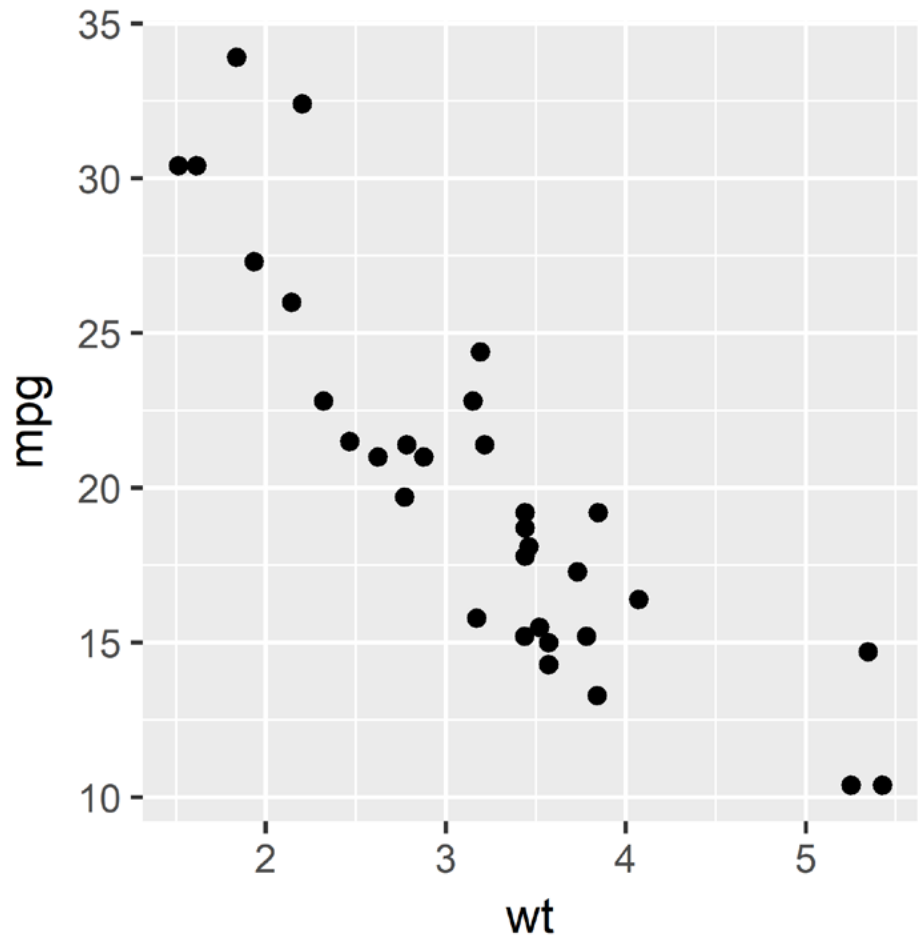


1. Easier to specify many charts, combinations

e.g., in ggplot

(data, channels, marks):

```
ggplot(mtcars, aes(
    x = wt,
    y = mpg
  )) +
  geom_point()
```



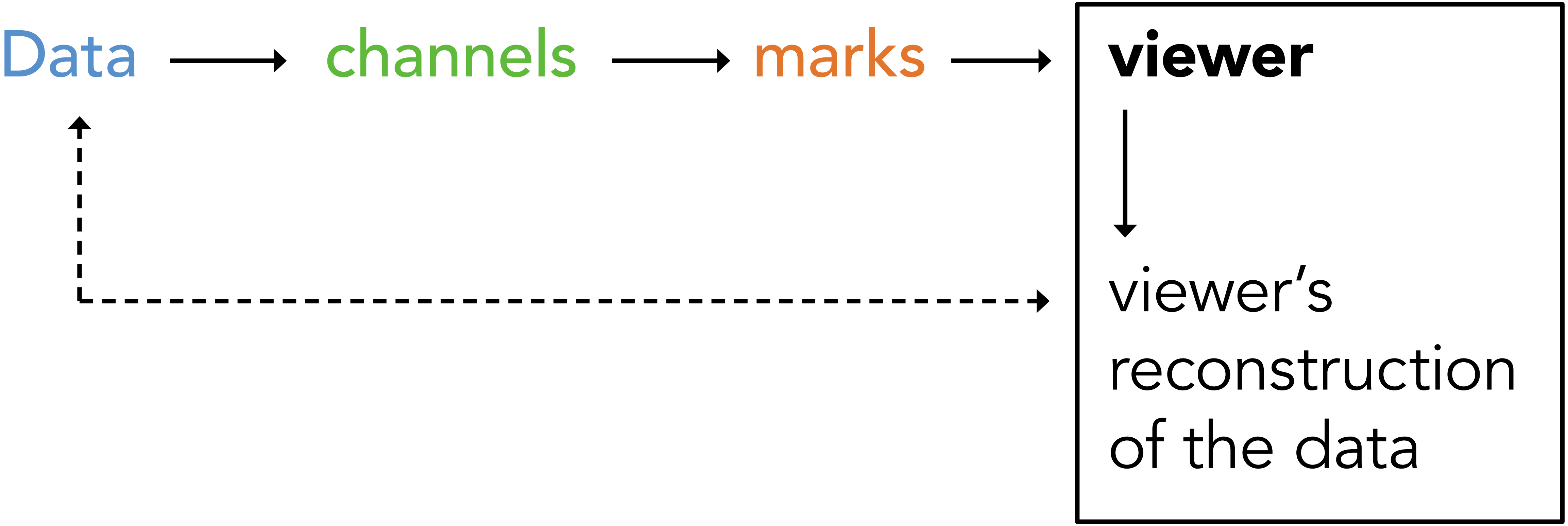
2. Helps you design charts systematically

Data → channels → marks → **viewer**

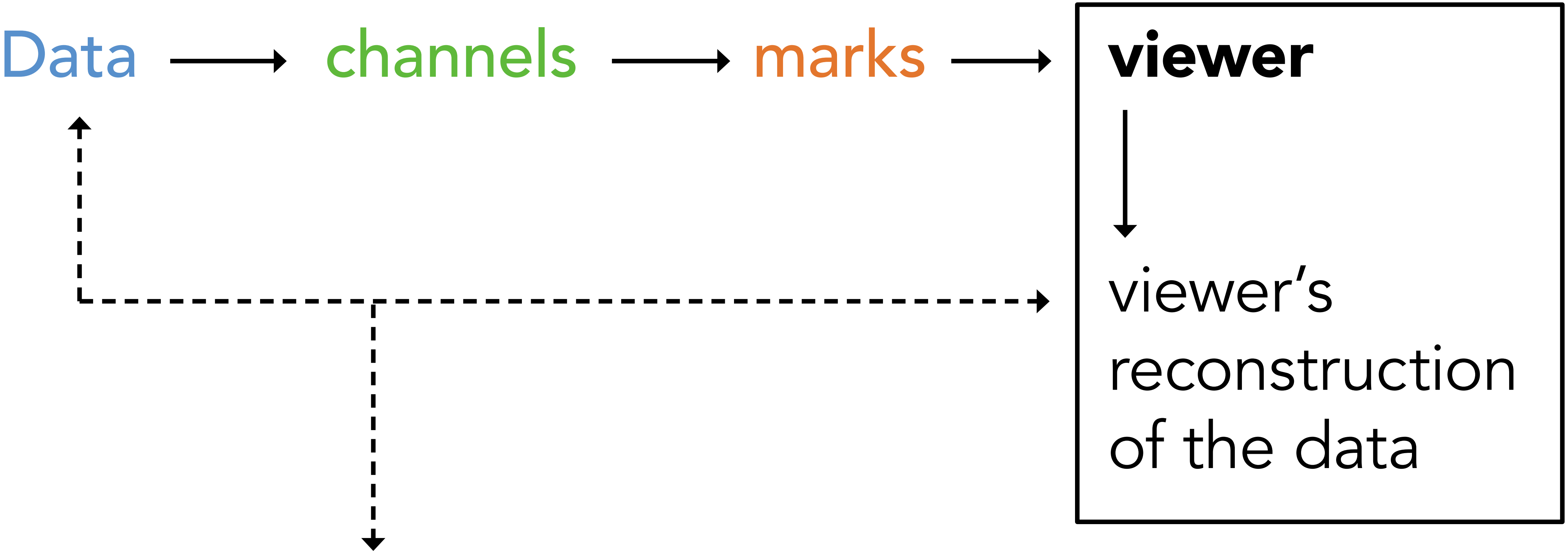
↓

viewer's reconstruction of the data

2. Helps you design charts systematically



2. Helps you **design** charts systematically



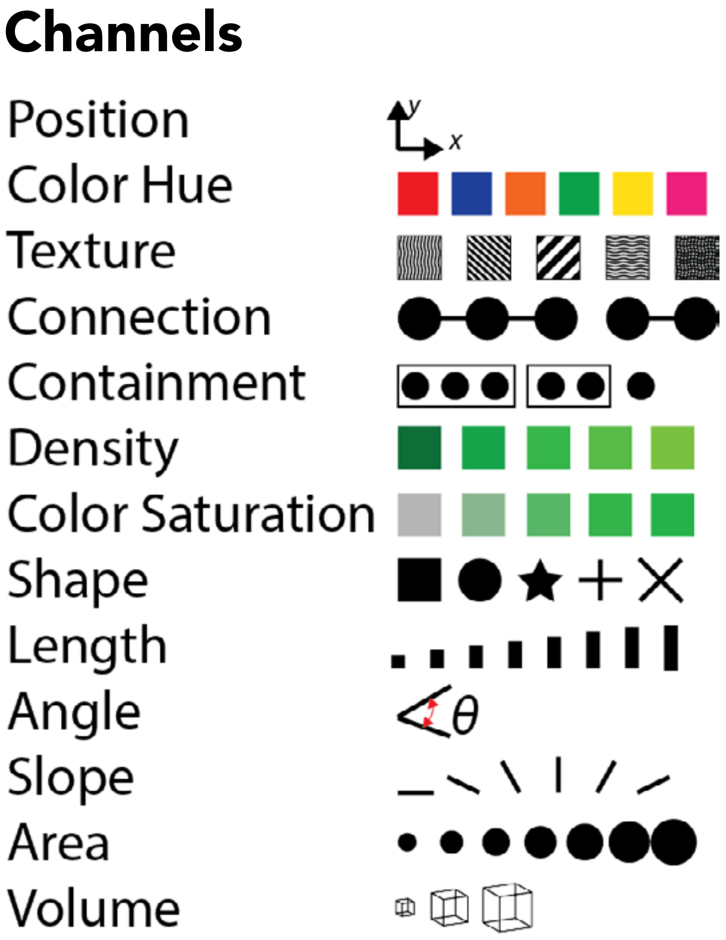
How well do these match, given the channel used?

2. Helps you **design** charts systematically

E.g.,

*How accurately do people perceive **position**?*

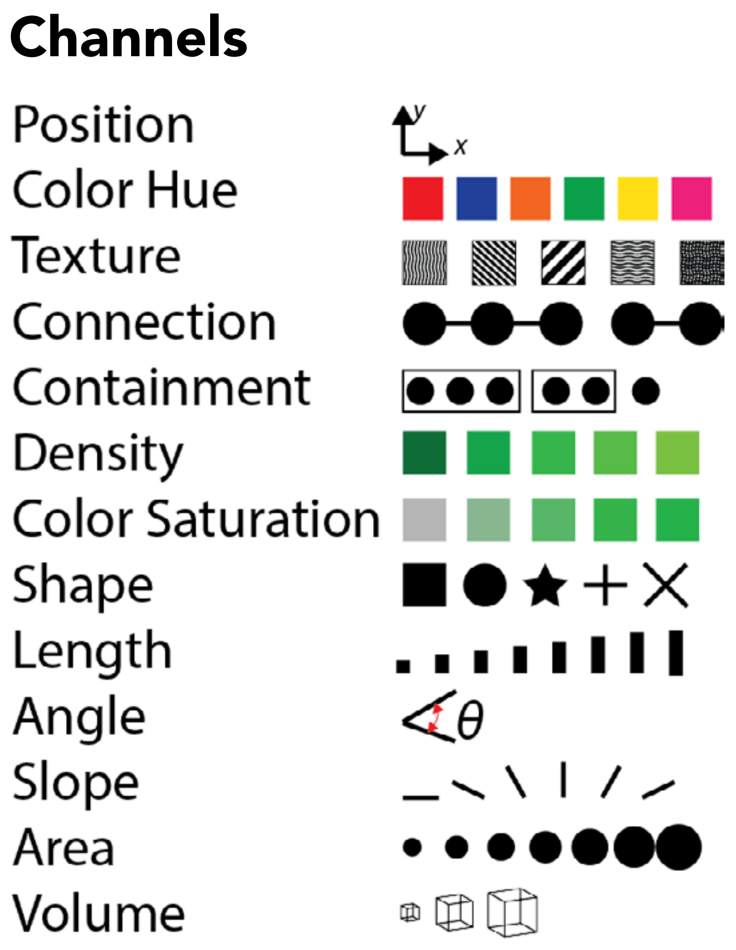
*How accurately do people perceive **area**?*



2. Helps you design charts systematically

E.g.,

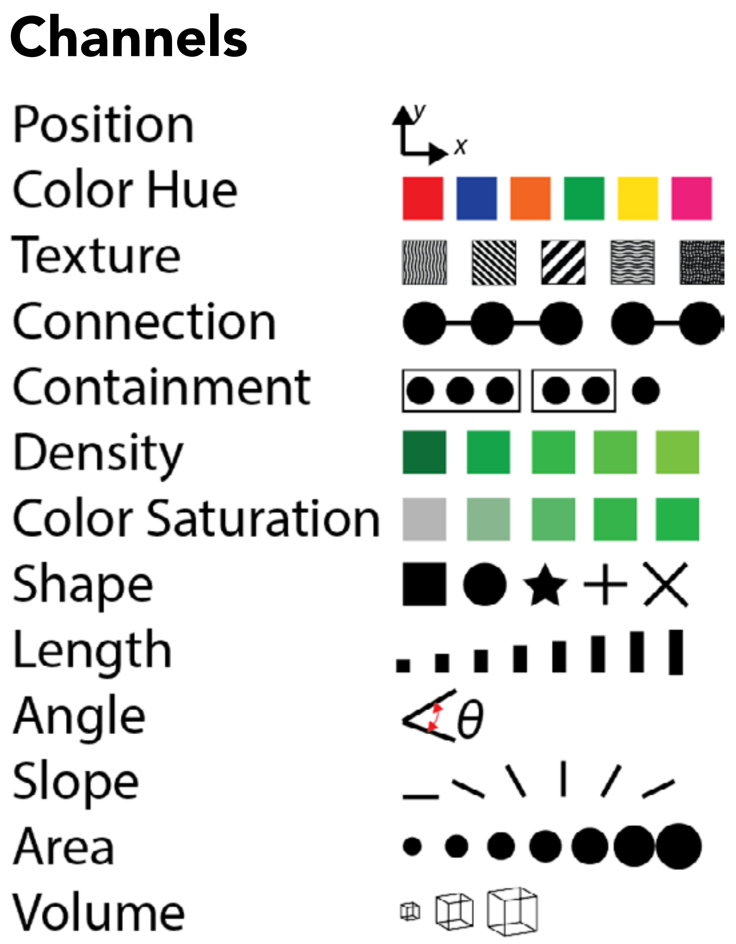
How accurately do people perceive position for quantitative data?
...for ordered data?
...for nominal data?
etc.



2. Helps you **design** charts systematically

E.g.,

*What **channel** is best for*
***quantitative** data?*
*...for **ordered** data?*
*...for **nominal** data?*
etc.



Encodings help us judge chart effectiveness

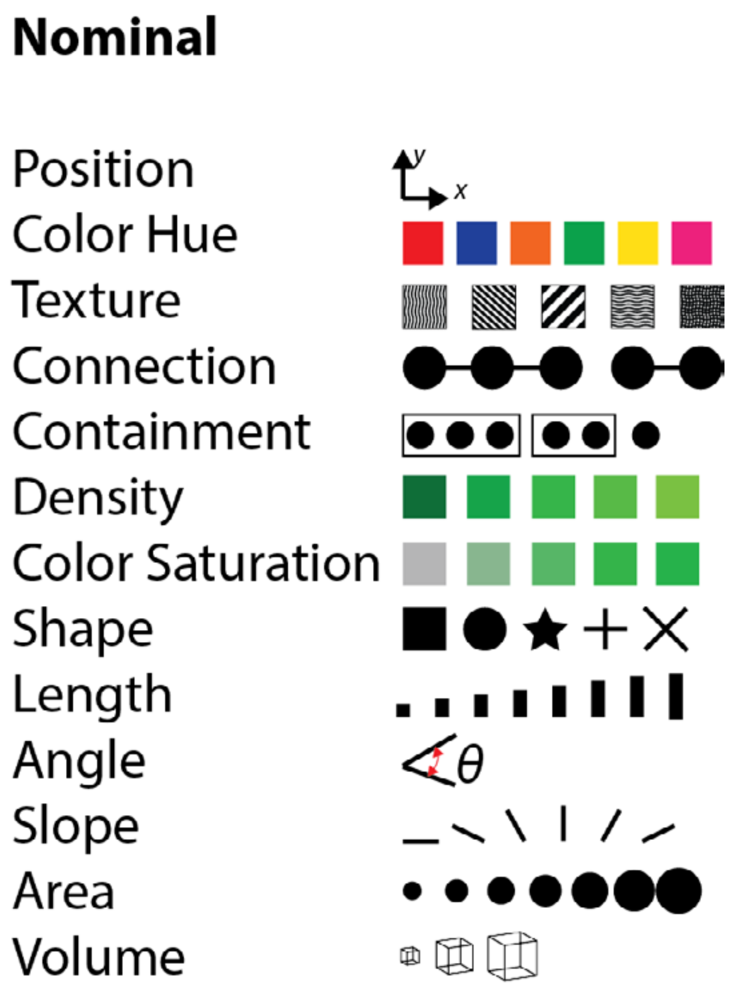
E.g.,

What channel is best for quantitative data?

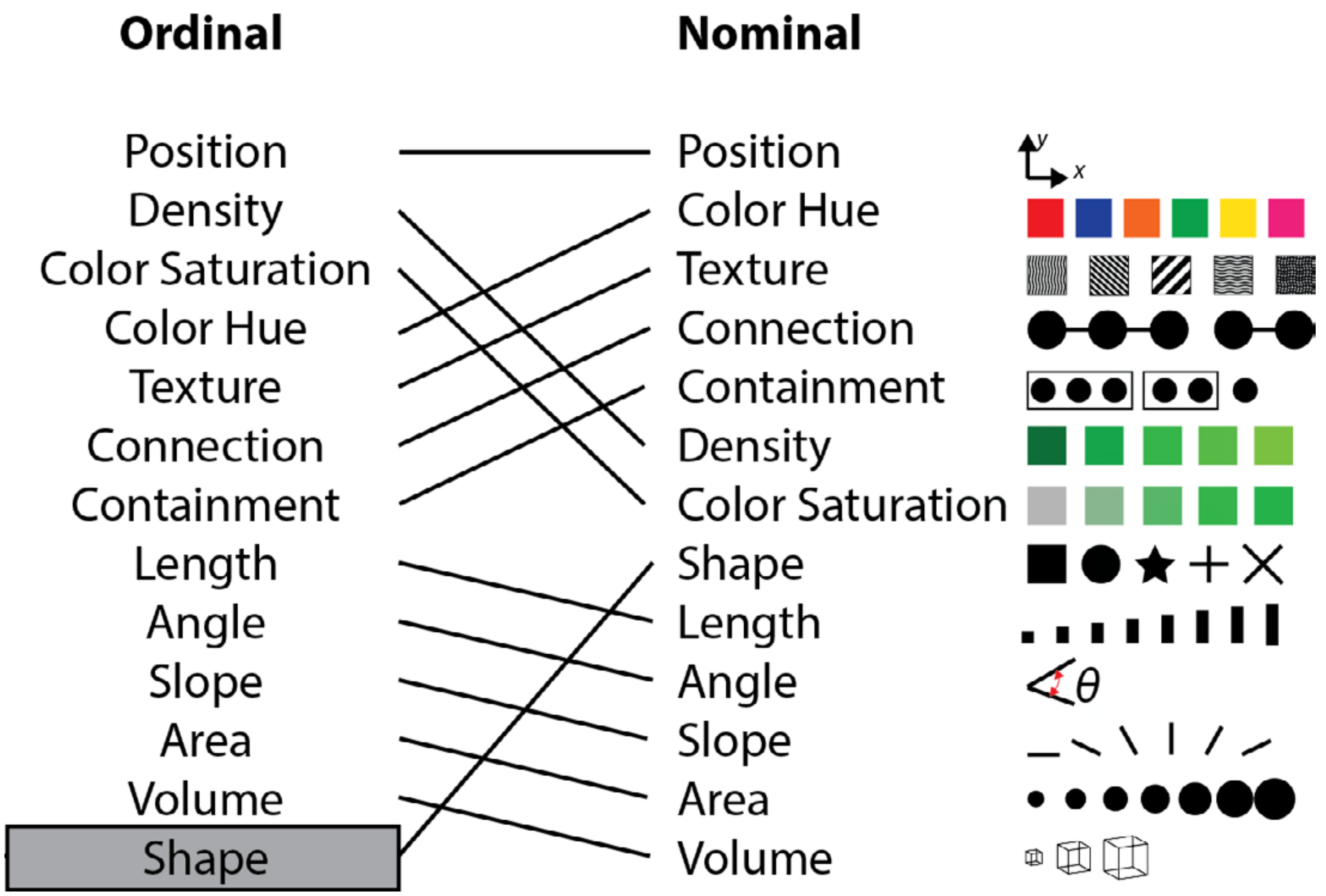
...for ordered data?

...for nominal data?

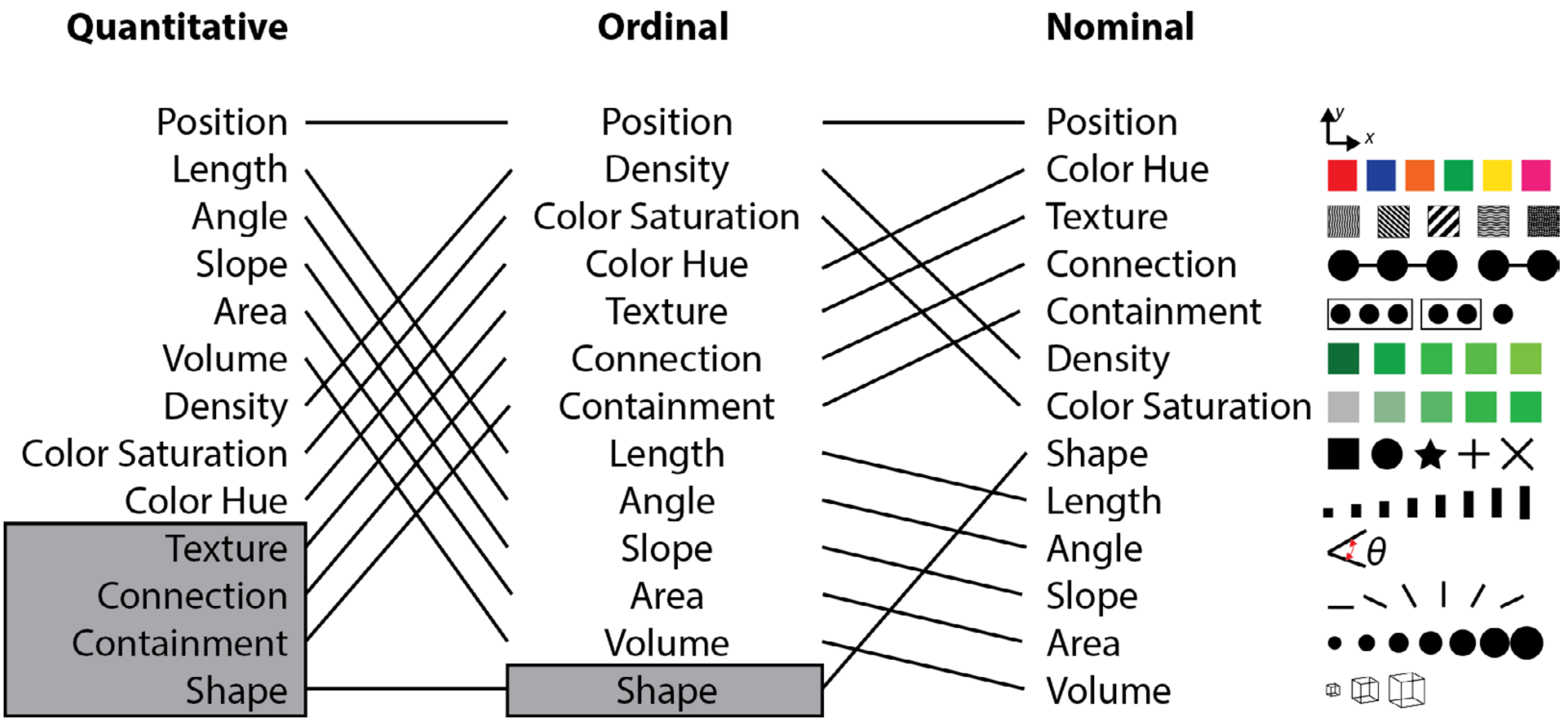
etc.



Encodings help us judge chart effectiveness



Encodings help us judge chart effectiveness



How good is a visual channel / encoding?

Length encoding:

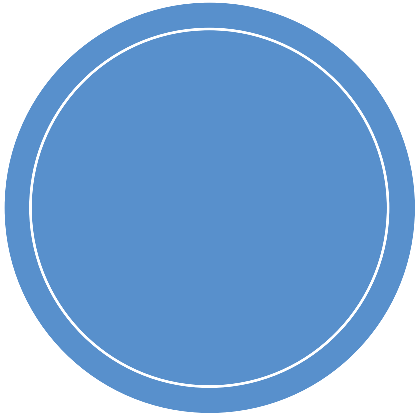
How good is a visual channel / encoding?

Length encoding:

How good is a visual channel / encoding?

Length encoding:

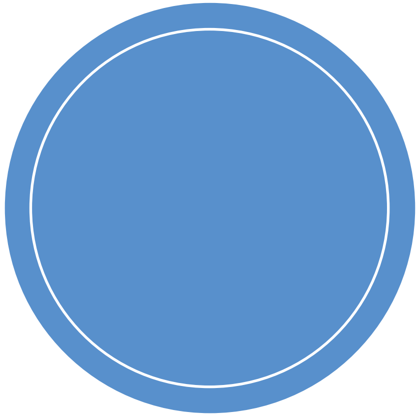
Area encoding:

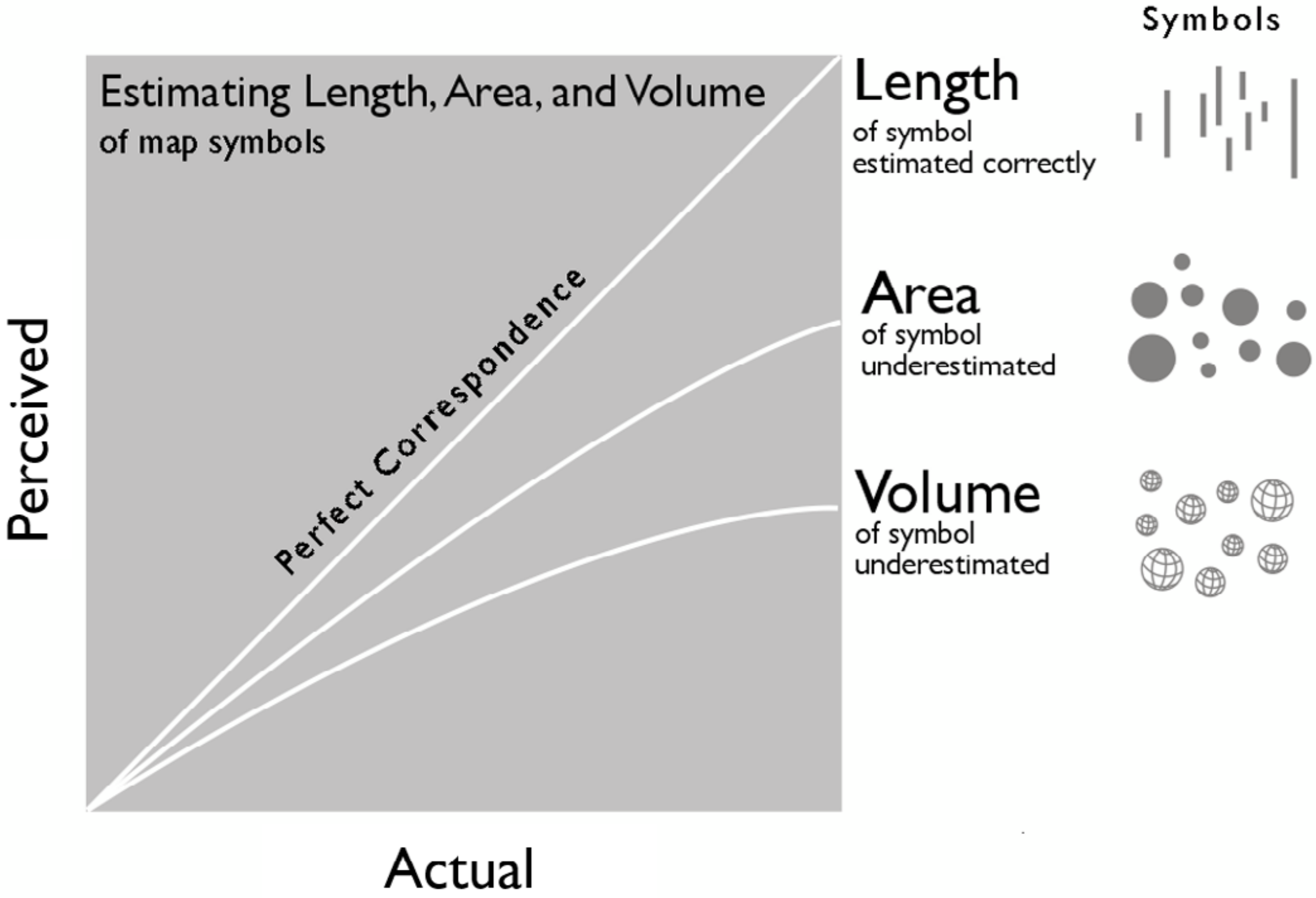


How good is a visual channel / encoding?

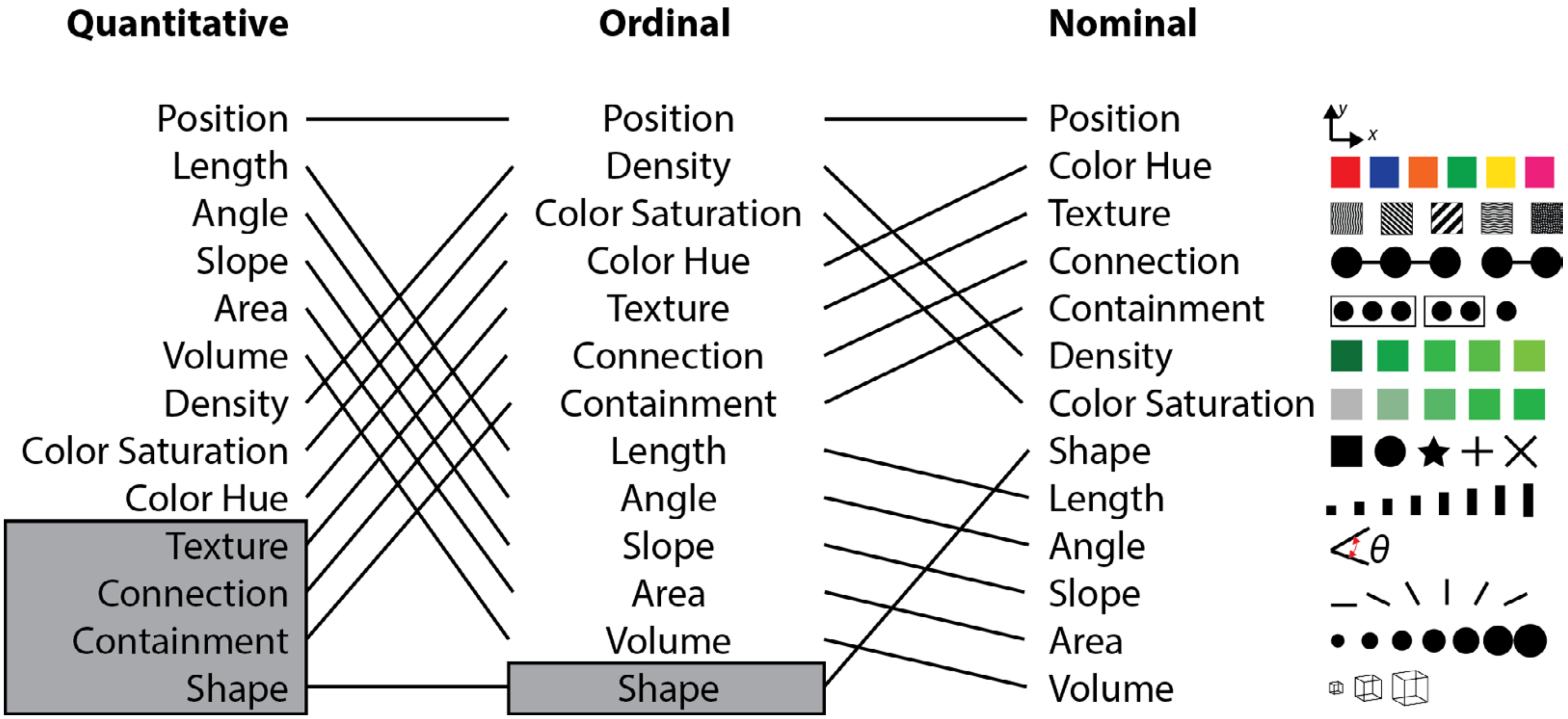
Length encoding:

Area encoding:



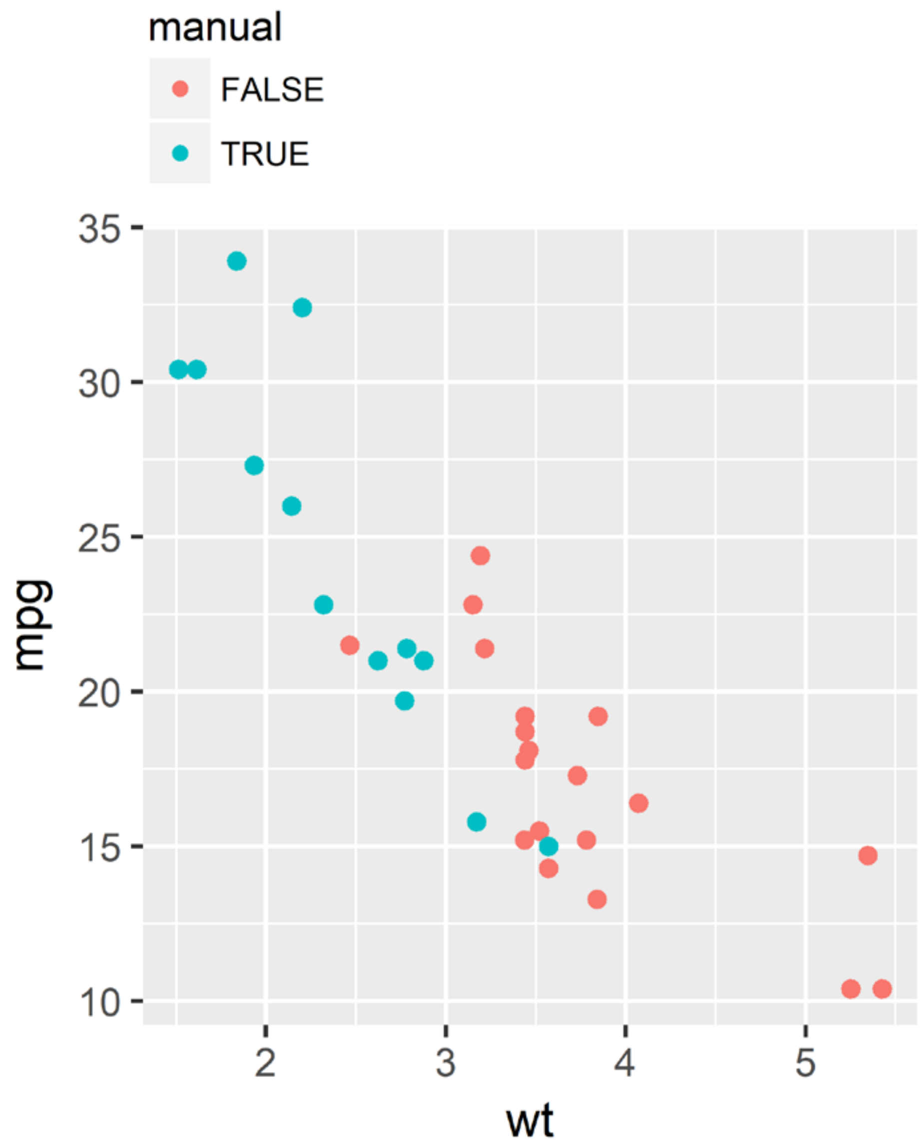


Pick one, cross it off...



Pick one, cross it off...

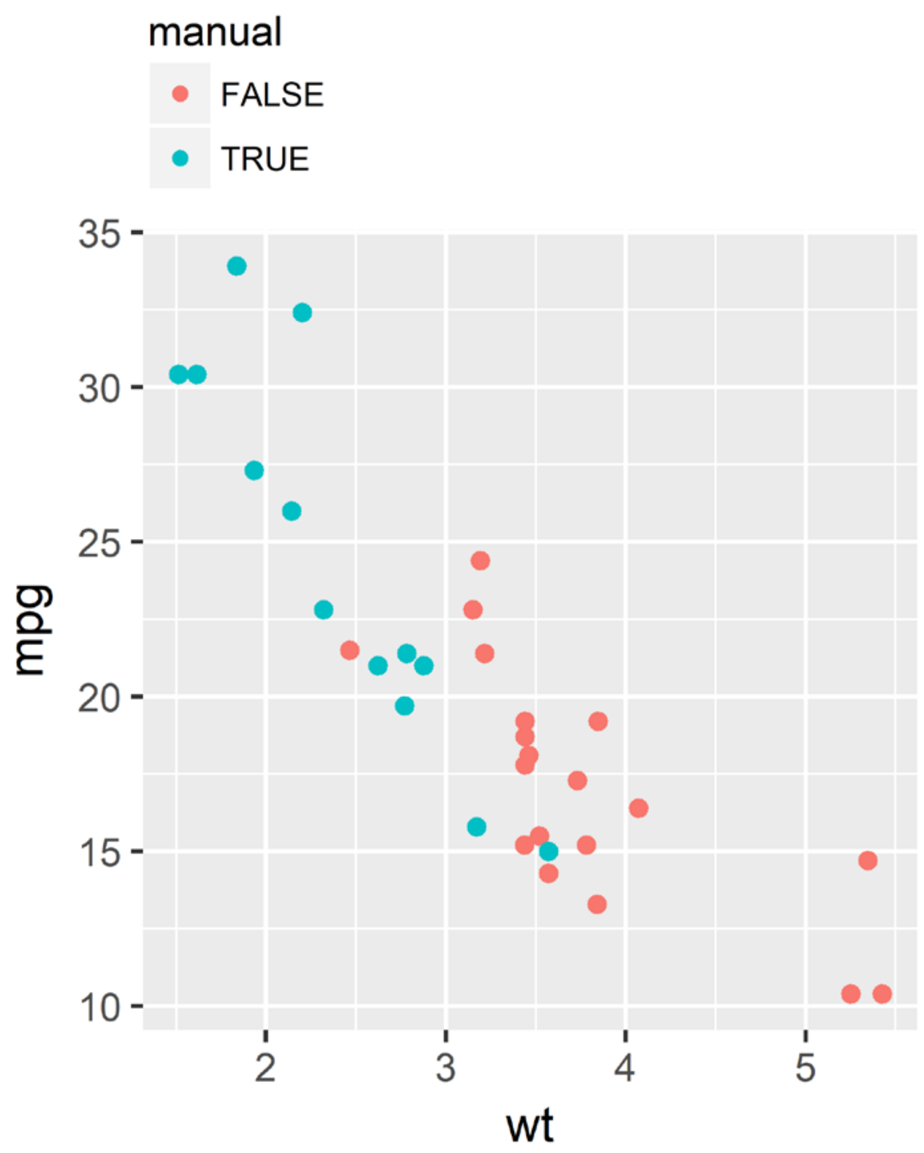
Quantitative	Nominal
Position	Position
Length	Color Hue
Angle	Texture
Slope	Connection
Area	Containment
Volume	Density
Density	Color Saturation
Color Saturation	Shape
Color Hue	Length
Texture	Angle
Connection	Slope
Containment	Area
Shape	Volume



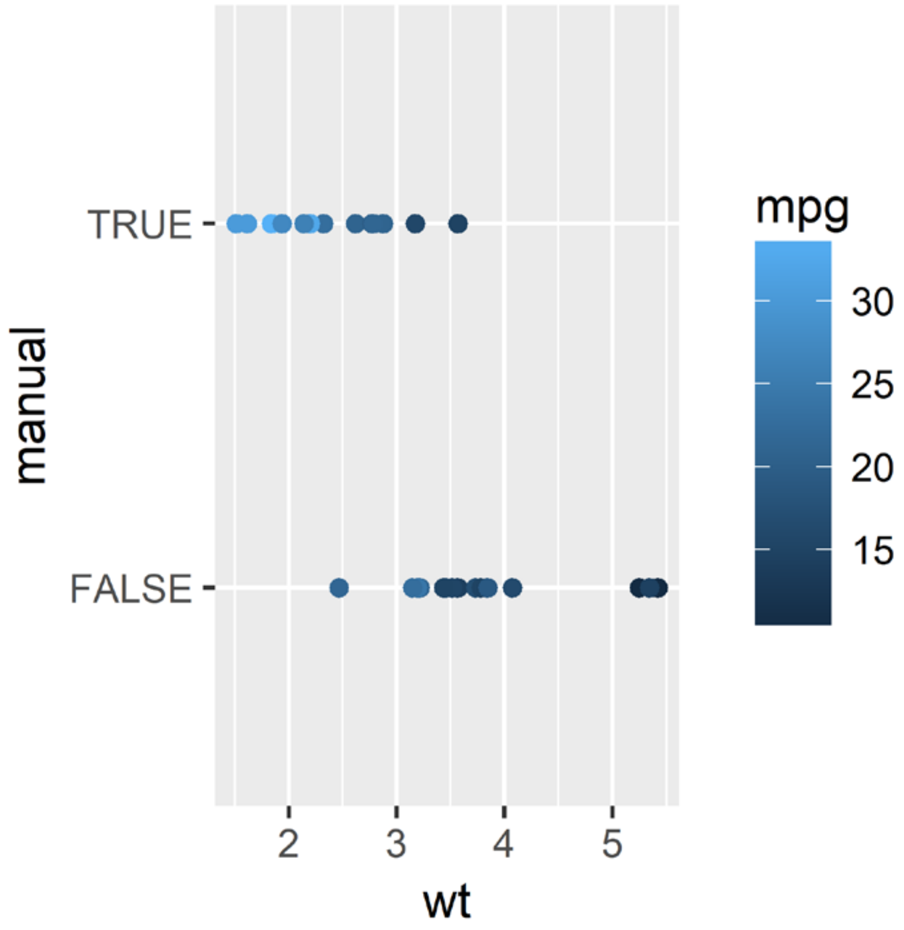
Effectiveness

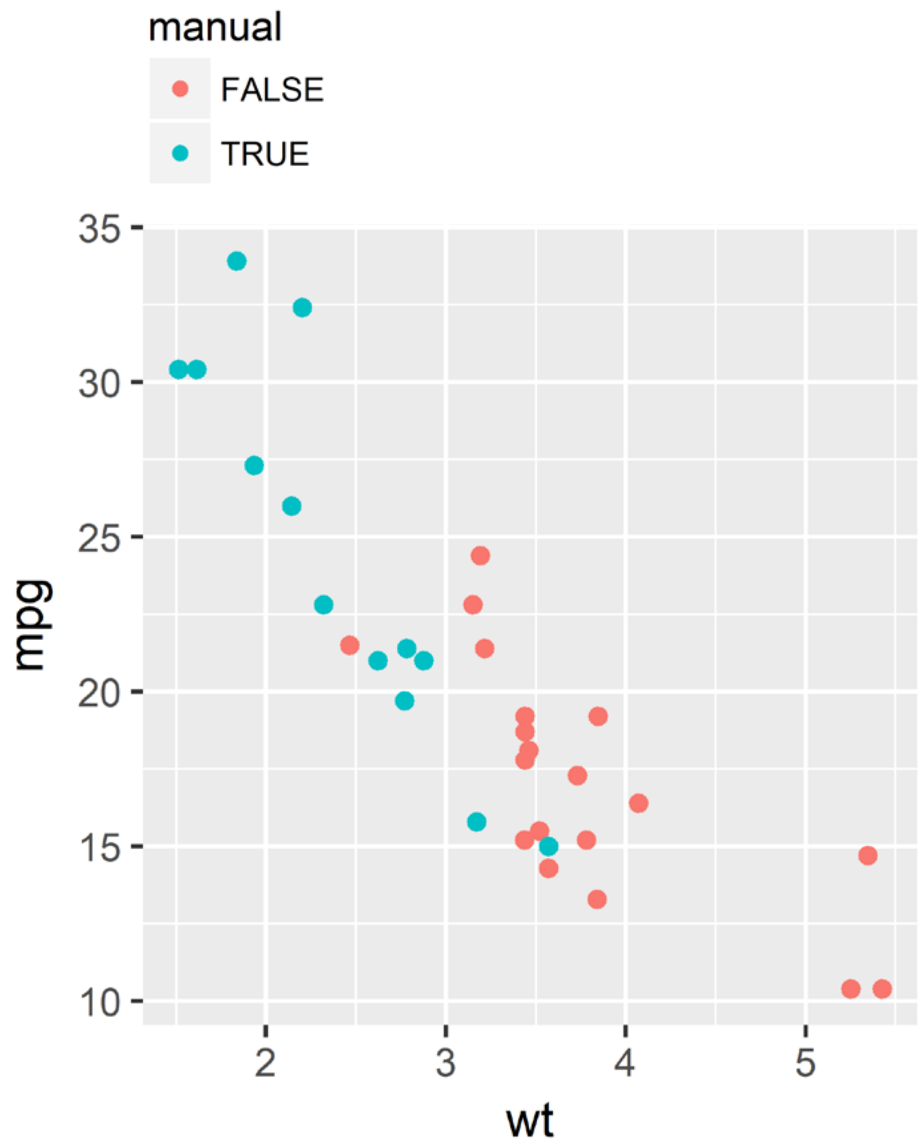
This chart works because it uses accurate channels (ones with low estimation error).

This is an important (but not the only!) aspect of effectiveness.

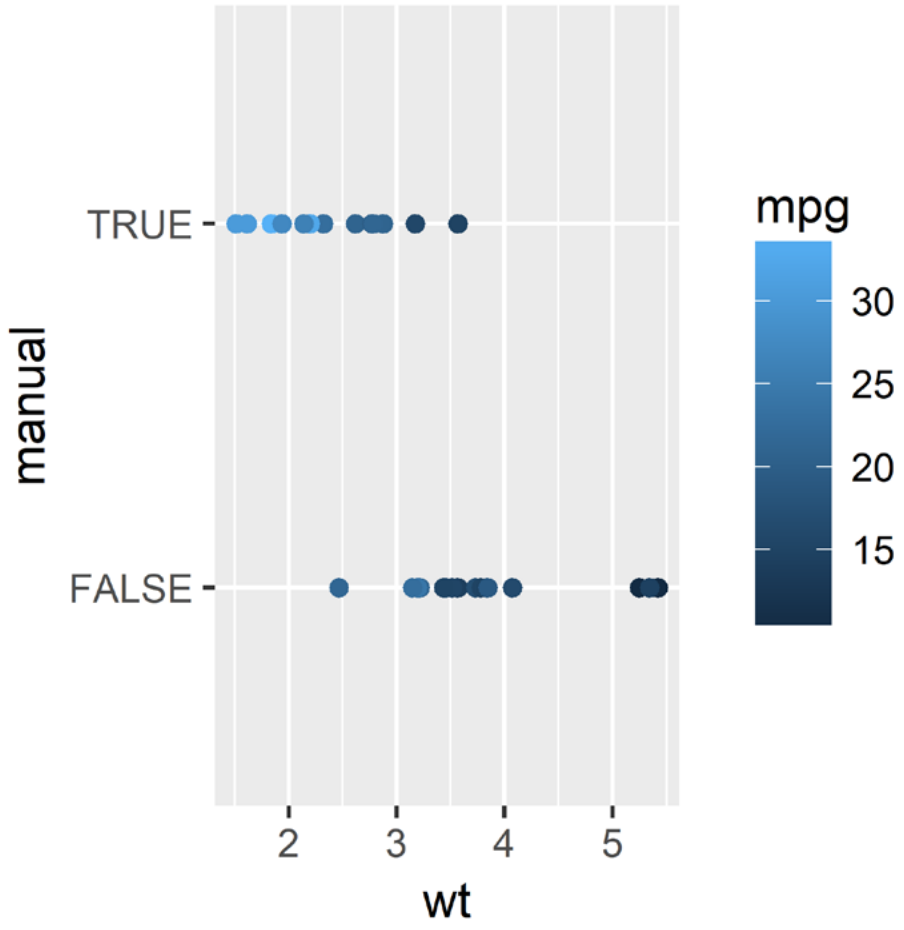


What about this?





What about this?



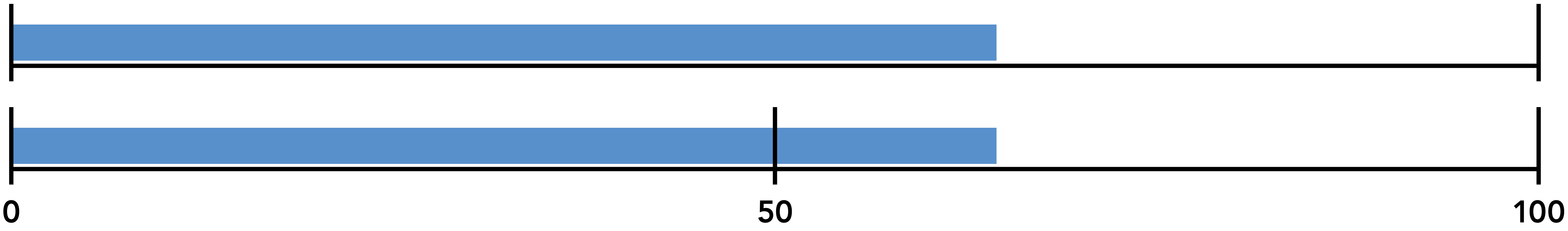
Quantitative

Position
Length
Angle
Slope
Area
Volume
Density
Color Saturation
Color Hue
Texture
Connection
Containment
Shape

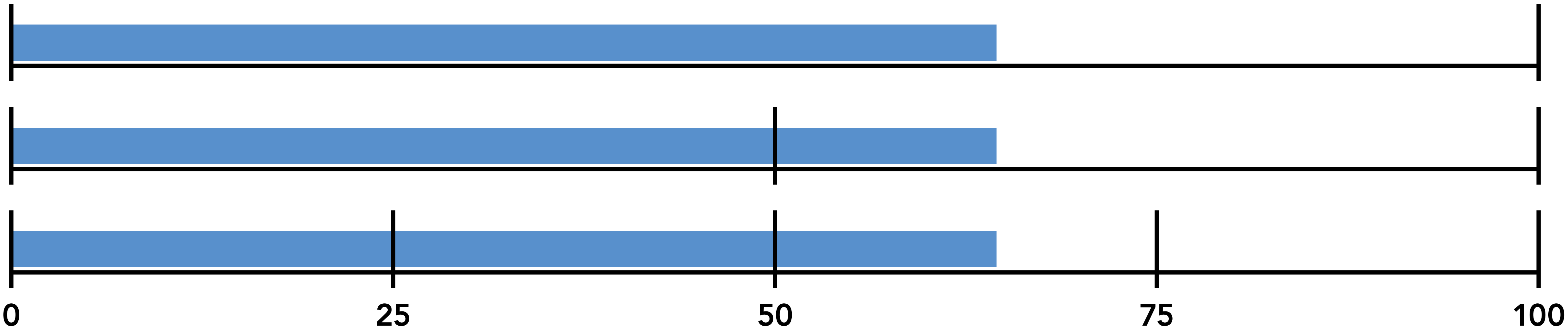
Other insights from perception

Reference lines can help...

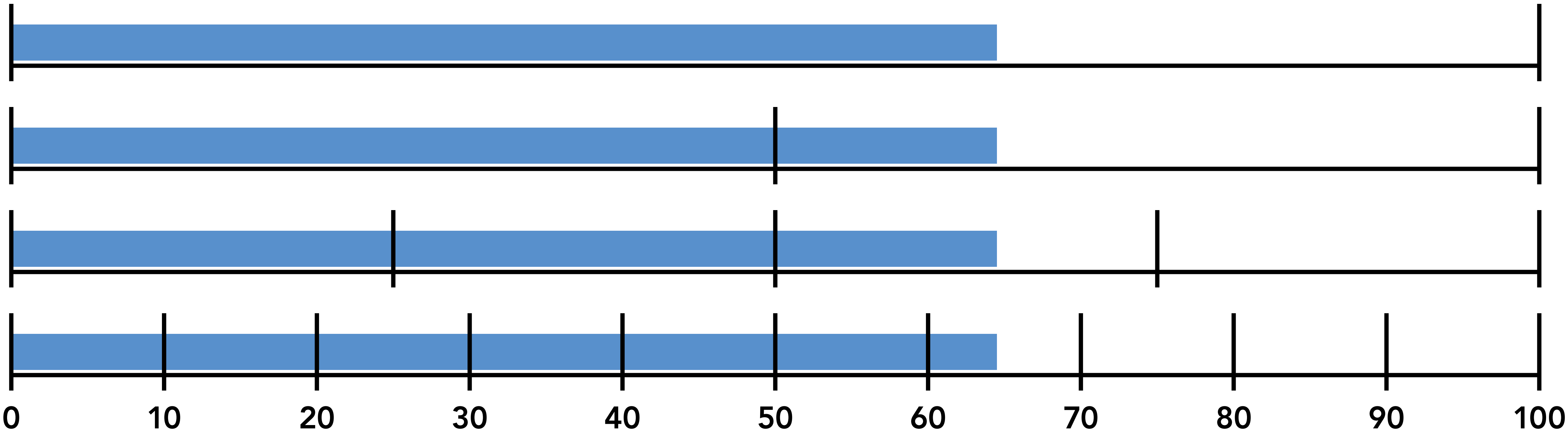
Reference lines can help...



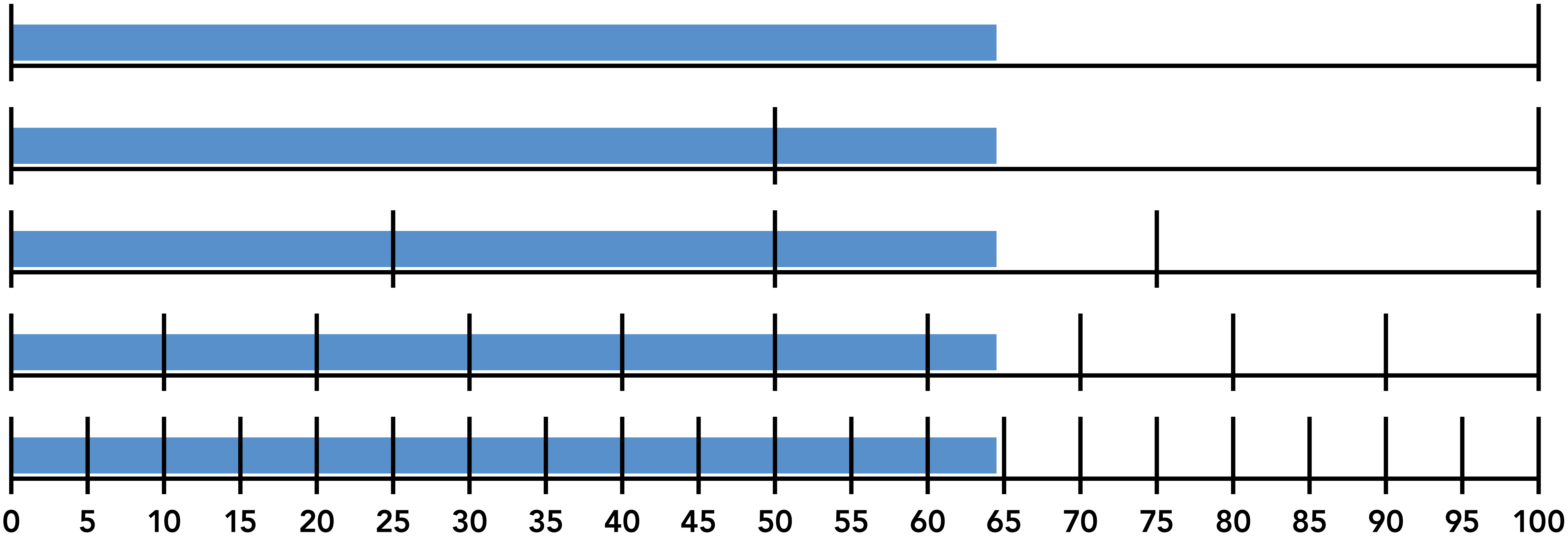
Reference lines can help...



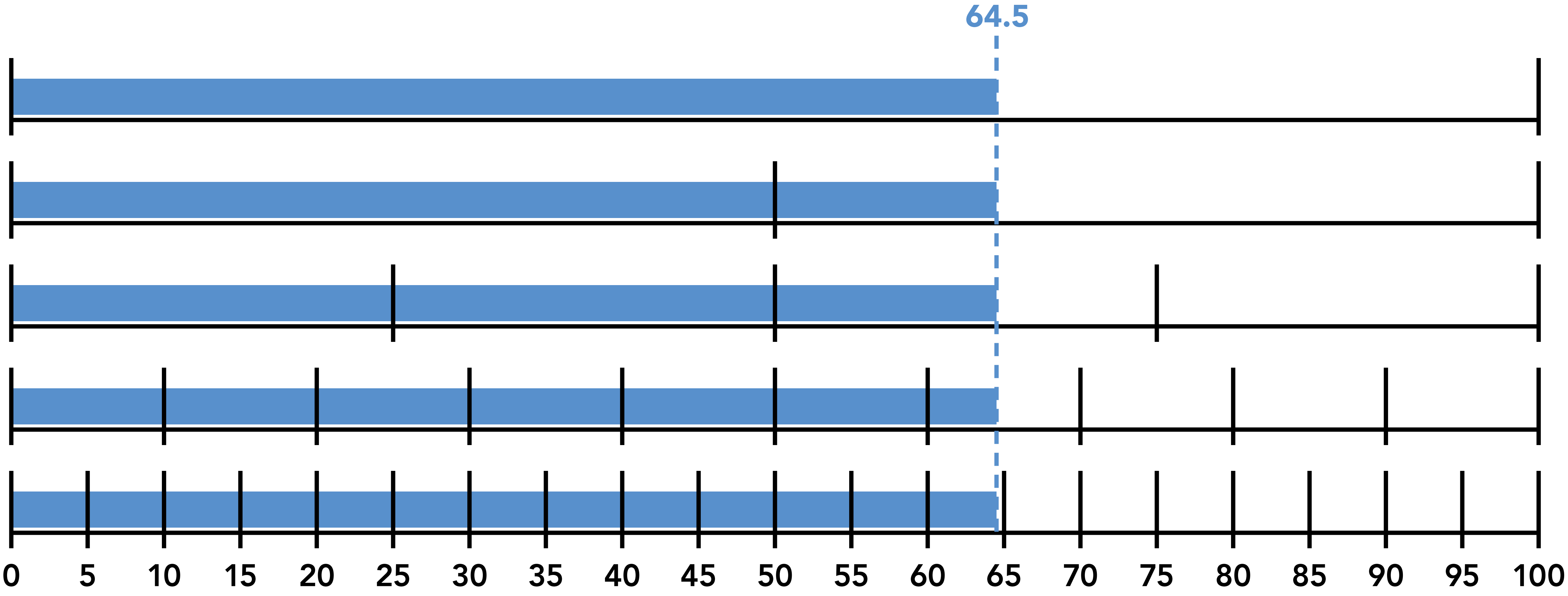
Reference lines can help...



Reference lines can help...



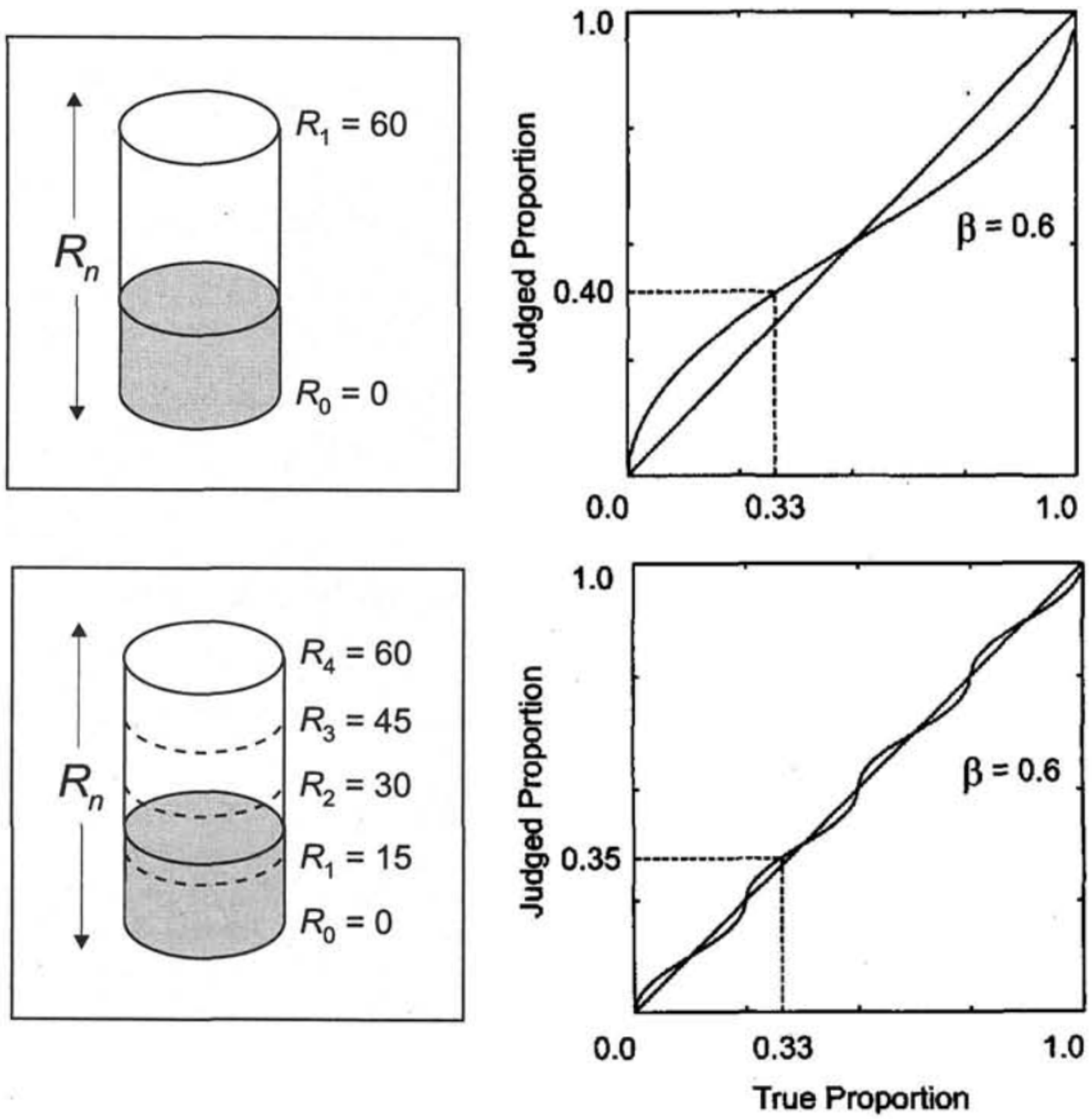
Reference lines can help...



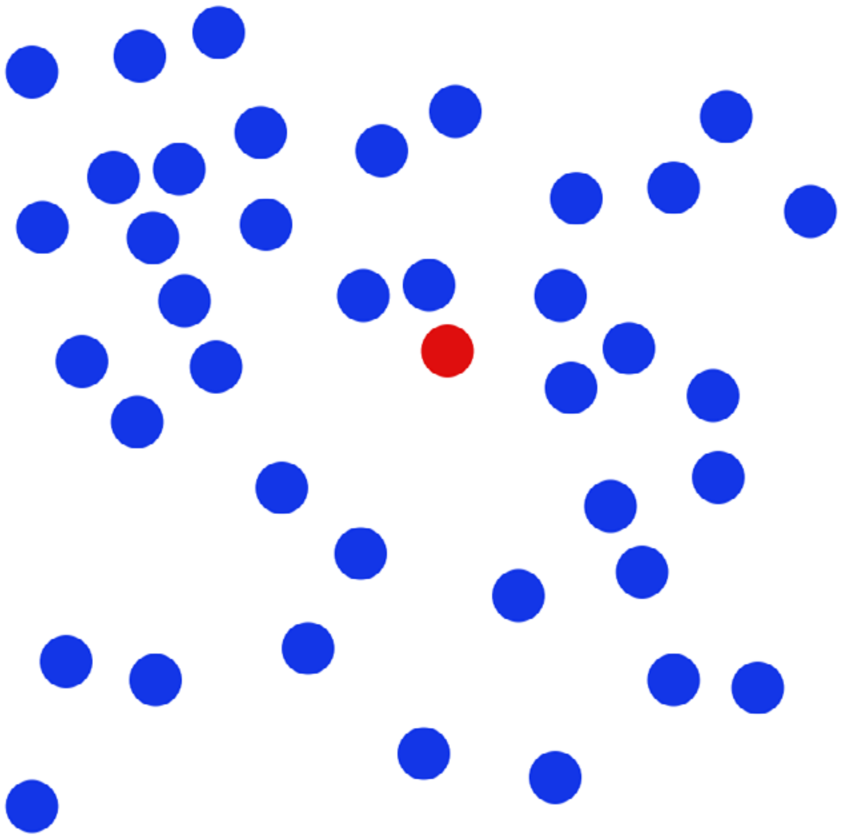
Reference lines

Induce bias...

...but can be used to decrease error

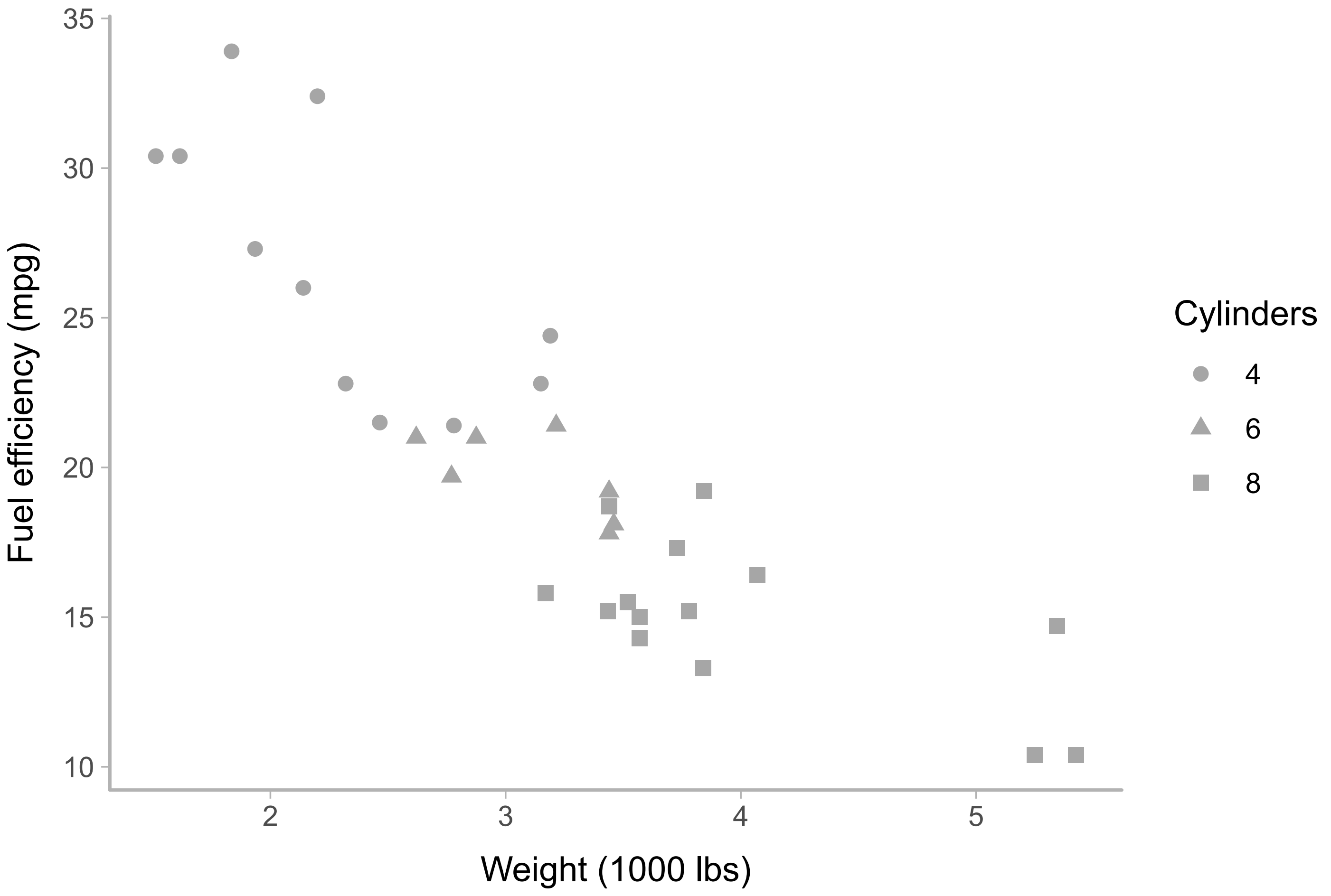


Popout and preattentiveness



https://www.csc2.ncsu.edu/faculty/healey/PP/

Popout and preattentiveness

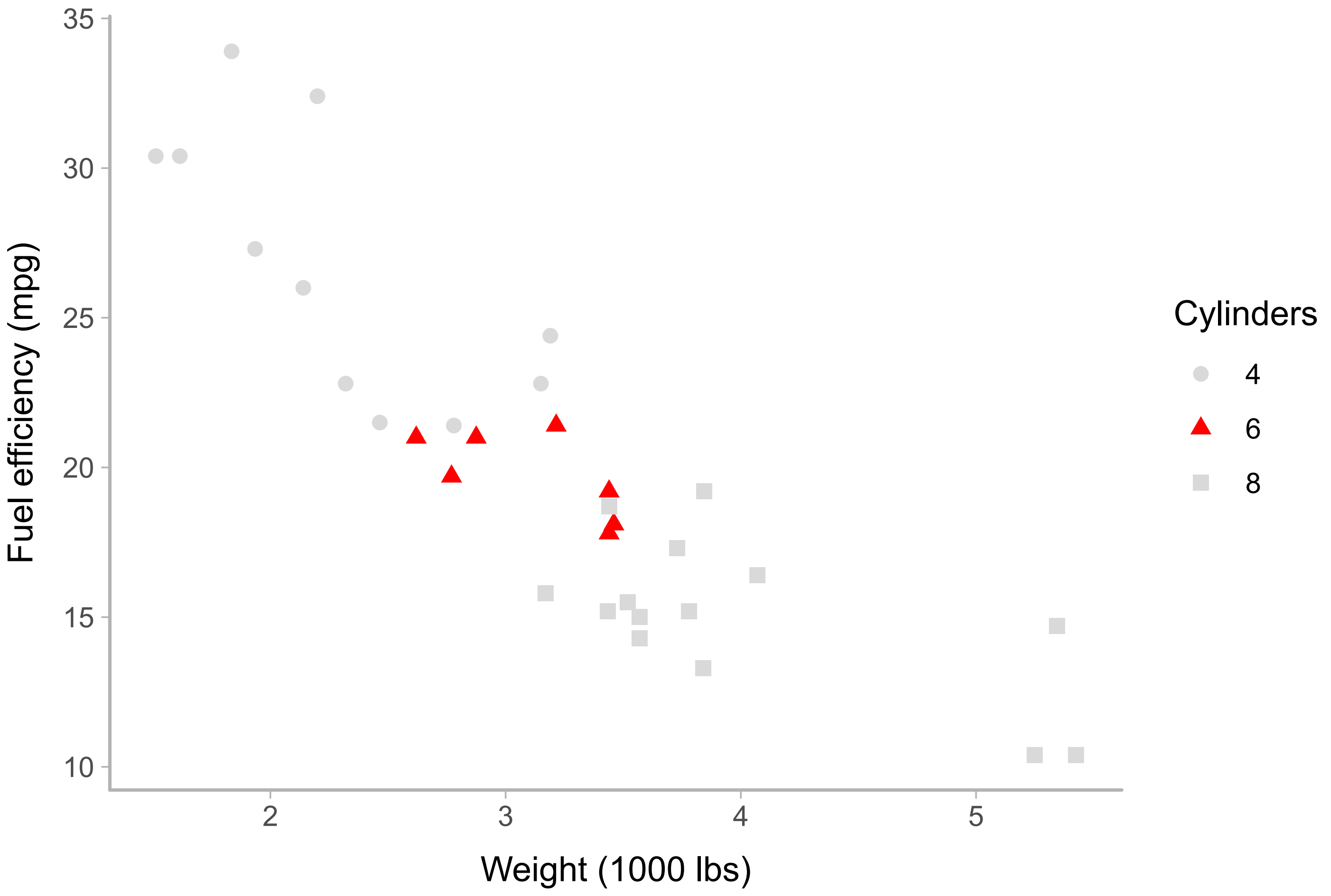


Preattentiveness
-> popout
-> layering

What do people see first?

What can people see separately?

Popout and preattentiveness

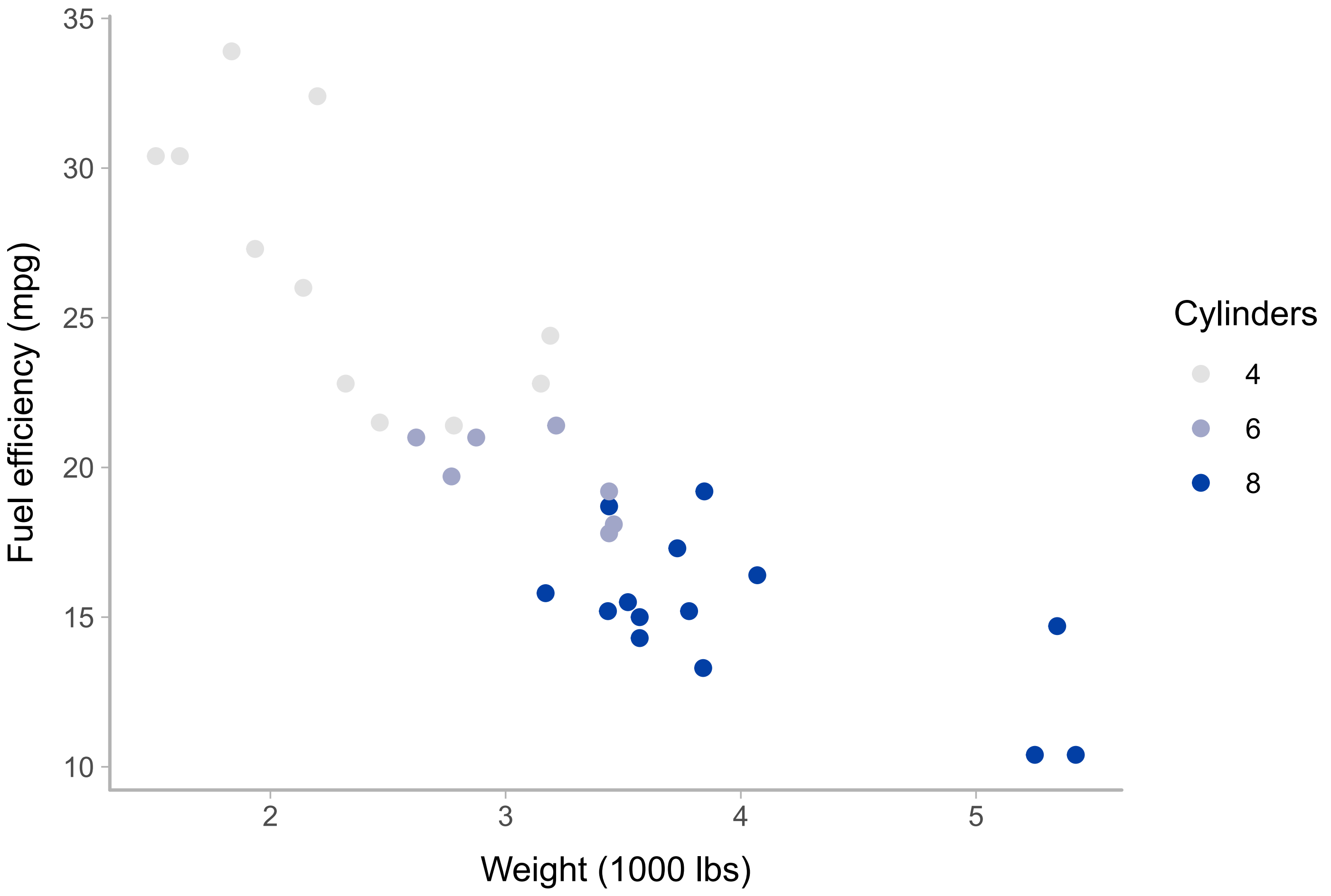


Preattentiveness
-> popout
-> layering

What do people see first?

What can people see separately?

Popout and preattentiveness



Preattentiveness

-> popout

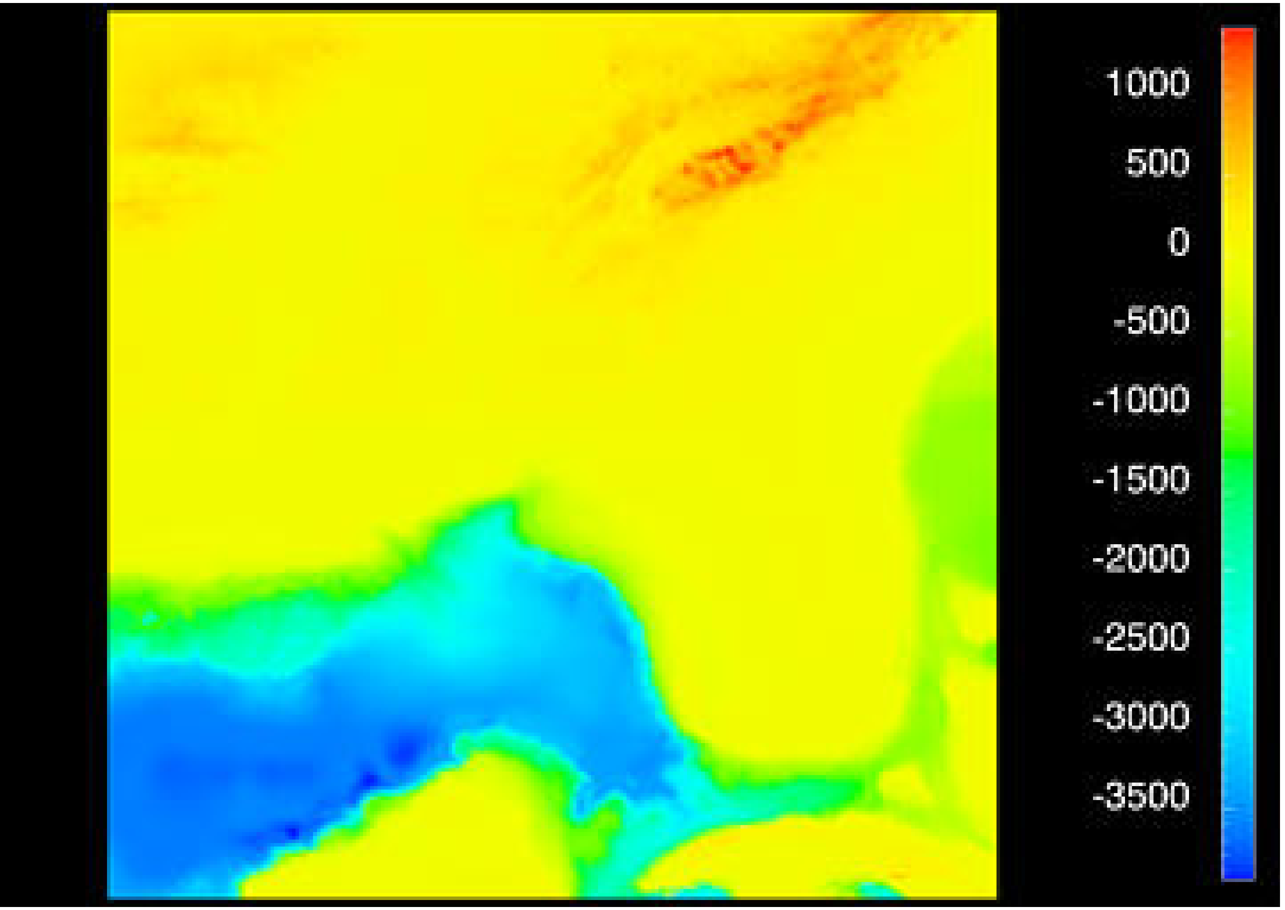
-> layering

What do people see first?

What can people see separately?

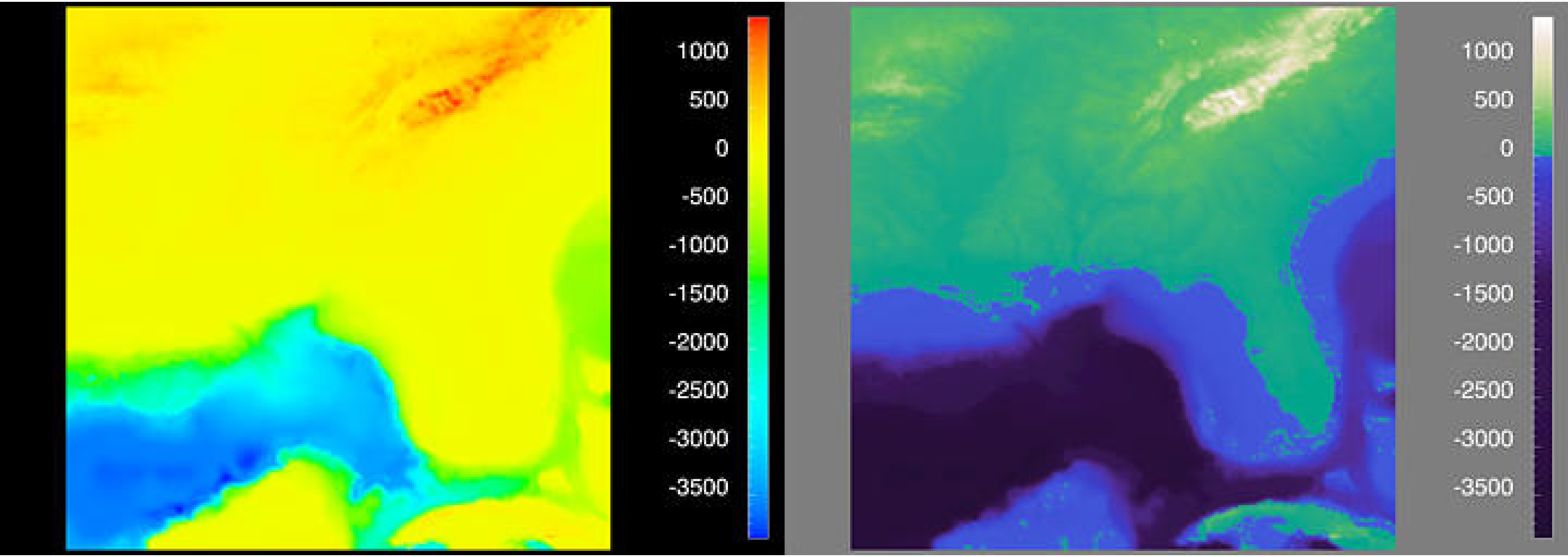
Color

Sequential / diverging data



[http://www.research.ibm.com/people/l/lloydt/color/color.HTM]

Sequential / diverging data

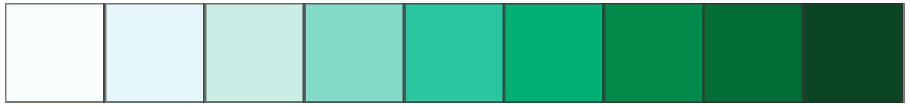


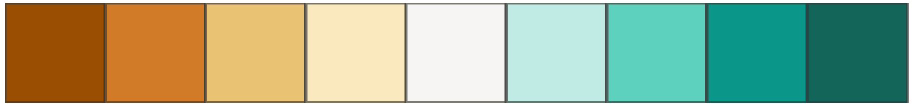
[http://www.research.ibm.com/people/l/lloydt/color/color.HTM]

Sequential / diverging scales

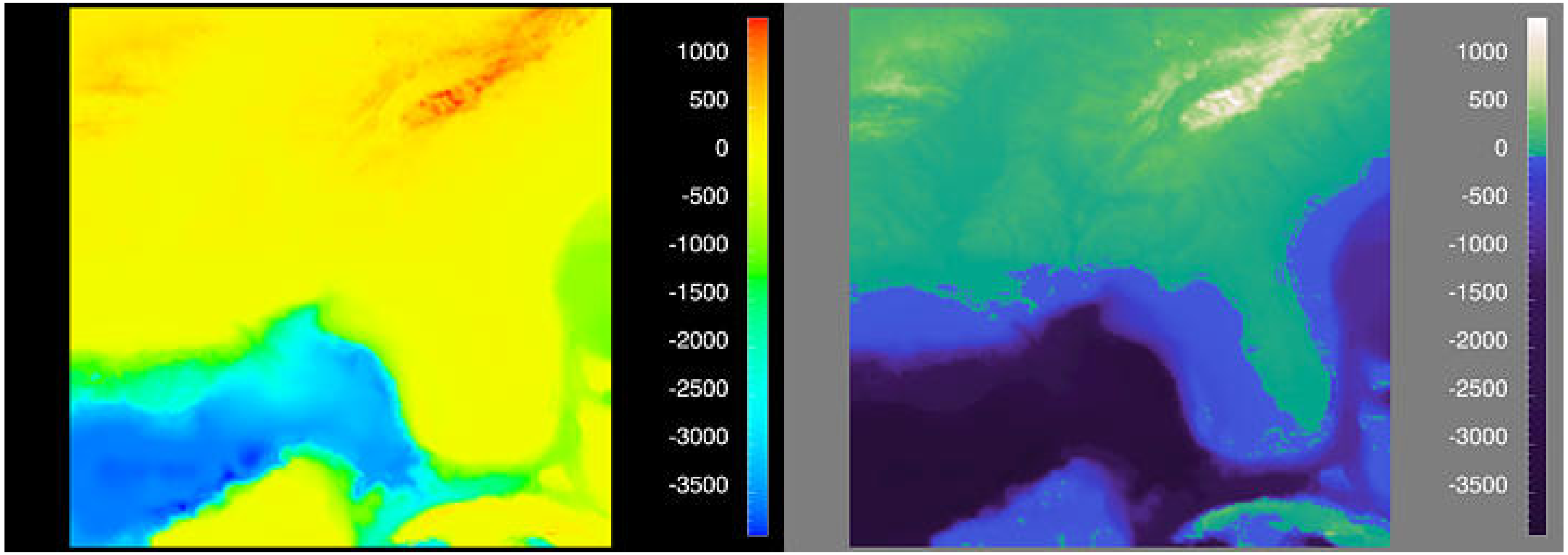
Ordered / quantitative data may be sequential or diverging

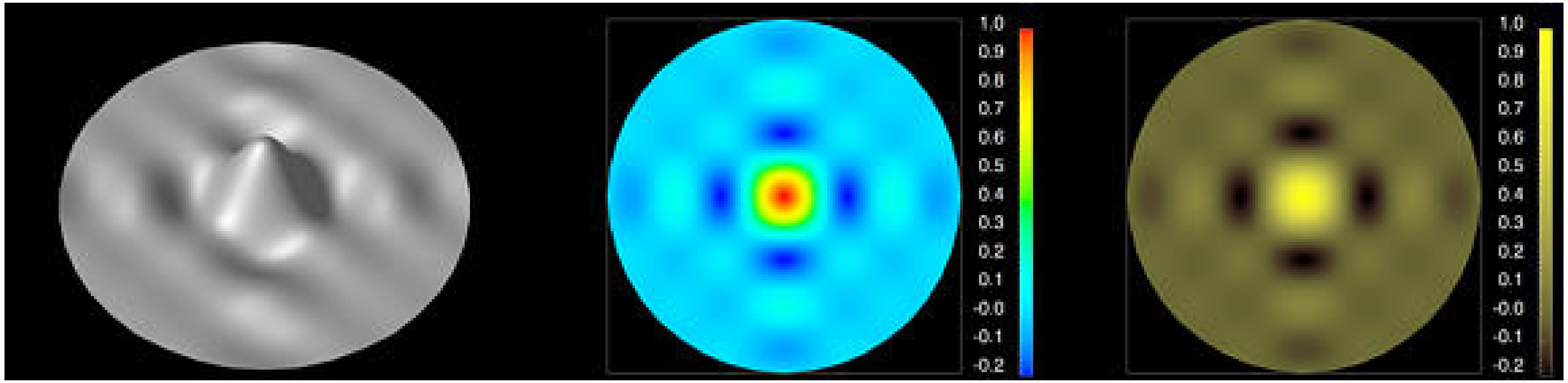
This impacts encoding choice, for example:

Sequential color scale: 

Diverging color scale: 

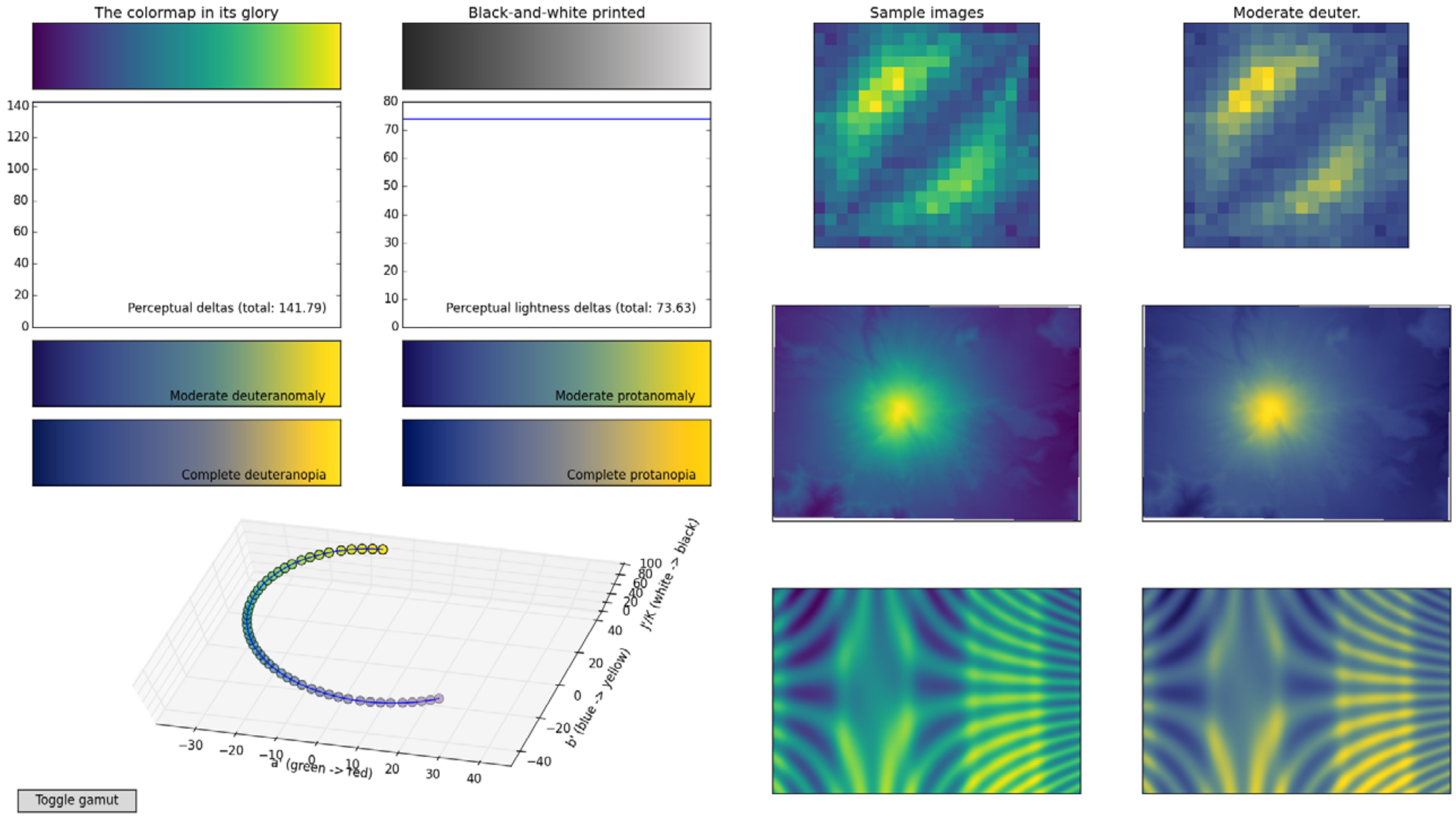
Prefer perceptually uniform colormaps





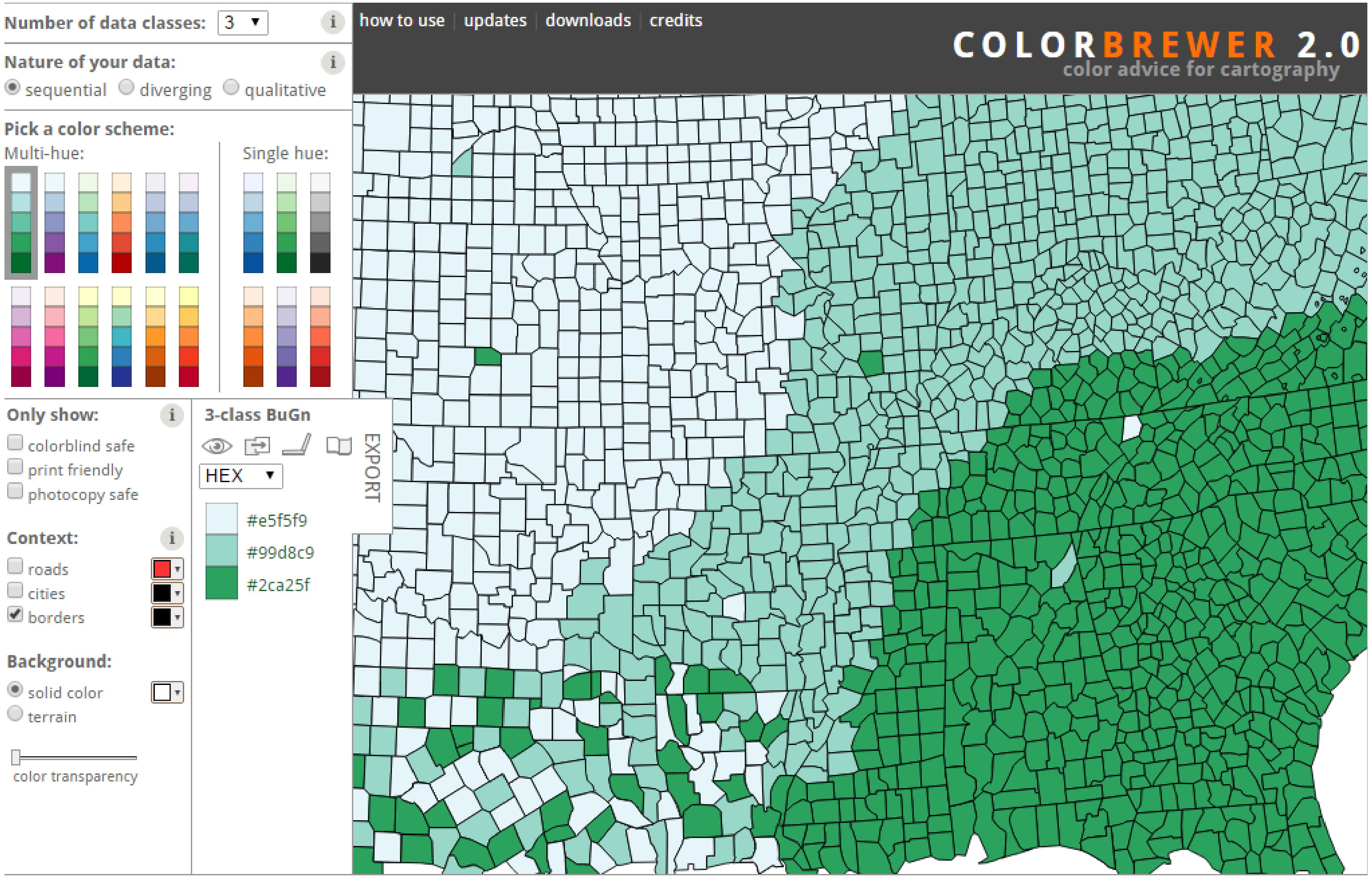
[Bernice E Rogowitz and Lloyd A Treinish. 1993. Why Should Engineers and Scientists Be Worried About Color? IBM Thomas J. Watson Research Center. Retrieved May 11, 2013 from http://www.research.ibm.com/people/l/lloydt/color/color.HTM]

For continuous color maps, Viridis (and co)…



[http://bids.github.io/colormap]

For discrete colormaps, Color Brewer…



[http://colorbrewer2.org]

For more, hclwizard / colorspace R package

Palette Creator

»Design your own color palette based on HCL principles.«

Deficiency Emulator

»Do your figures work for viewers with color vision deficiencies?«

Color Picker

»Select and export colors using the HCL color space.«

HCL Color Space

The **hclwizard** provides tools for manipulating and assessing colors and palettes based on the underlying ***colorspace*** software (available in **R** and **Python**). It leverages the HCL color space: a color model that is based on human color perception and thus makes it easy to choose good color palettes by varying three color properties: Hue (= type of color, dominant wavelength) - Chroma (= colorfulness) - Luminance (= brightness). As shown in the color swatches below each property can be varied while keeping the other two properties fixed.

Hue **Chroma** **Luminance**

Color Palettes

For color coding data visualizations it is crucial to choose a palette that appropriately captures the underlying information. Three types

[http://hclwizard.org/]

Grammar of graphics + Perception
helps us design more effective charts

Grammar of Graphics + Perception

Think in data types, channels, and marks.

Helps you specify and design charts using perceptually effective channels.

Consider sequential / diverging nature of data.

Questions so far?

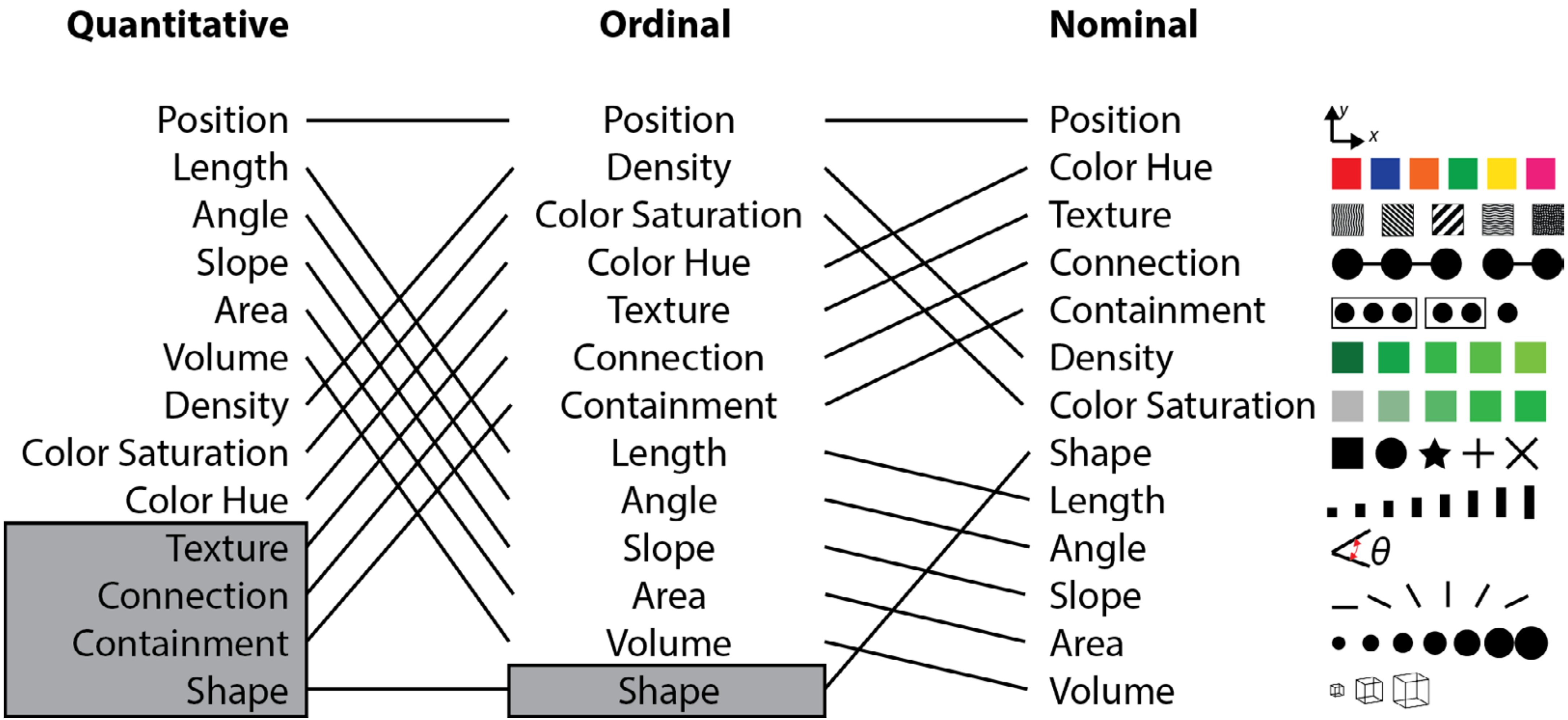
Design guidelines

Some rough design guidelines*

1. Match effectiveness with importance
2. Avoid ambiguity
3. Locality is king / eyes beat memory
4. Establish viewing order
5. Layer, layer, layer
6. When in doubt, grid
7. Treat visual attributes like adjectives

* These guidelines are drawn largely from my experience + personal preferences + the literature. Design is messy, these are not perfect, others will disagree with me, etc. *Caveat emptor.*

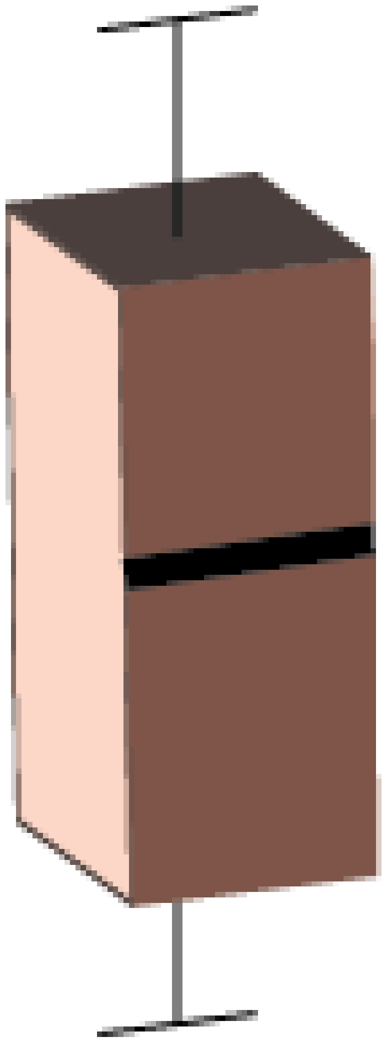
1. Match effectiveness with importance



2. Avoid ambiguity

Does the 3D mean anything here?

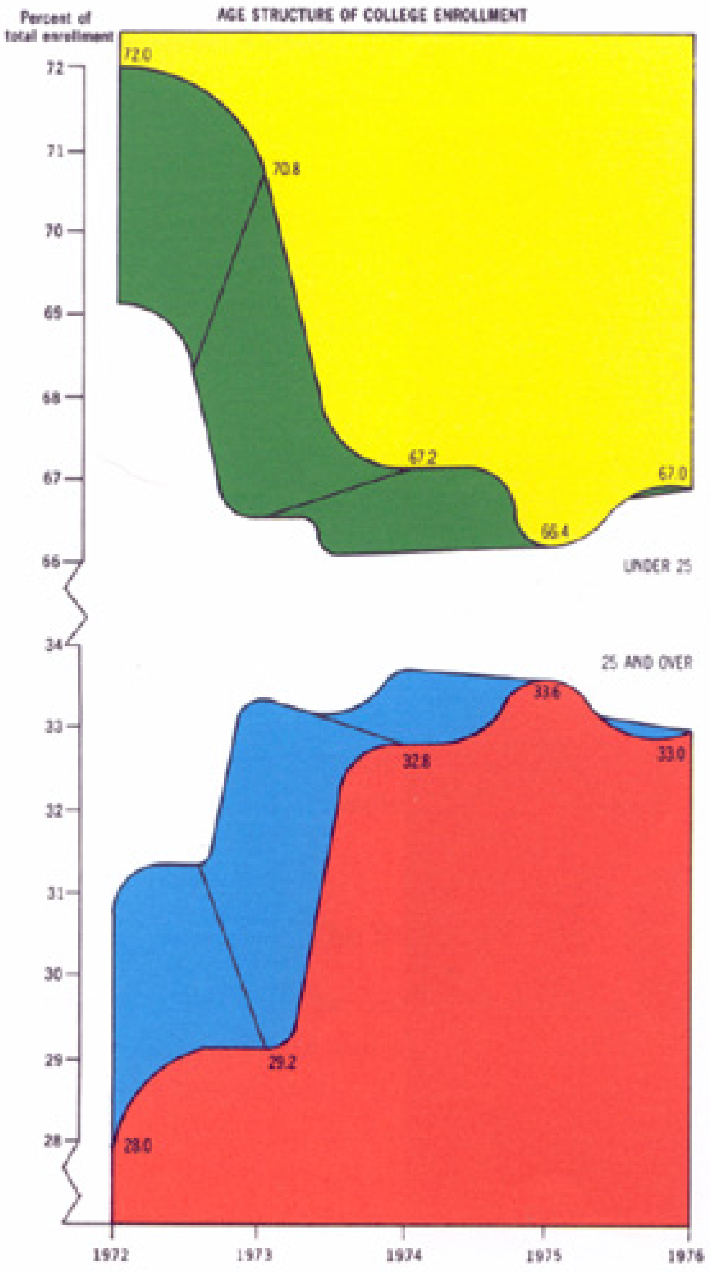
(Hint: No)



2. Avoid ambiguity

Marks should not have multiple reasonable interpretations

If it looks like it could come from data, it should come from data



3. Locality is king / eyes beat memory

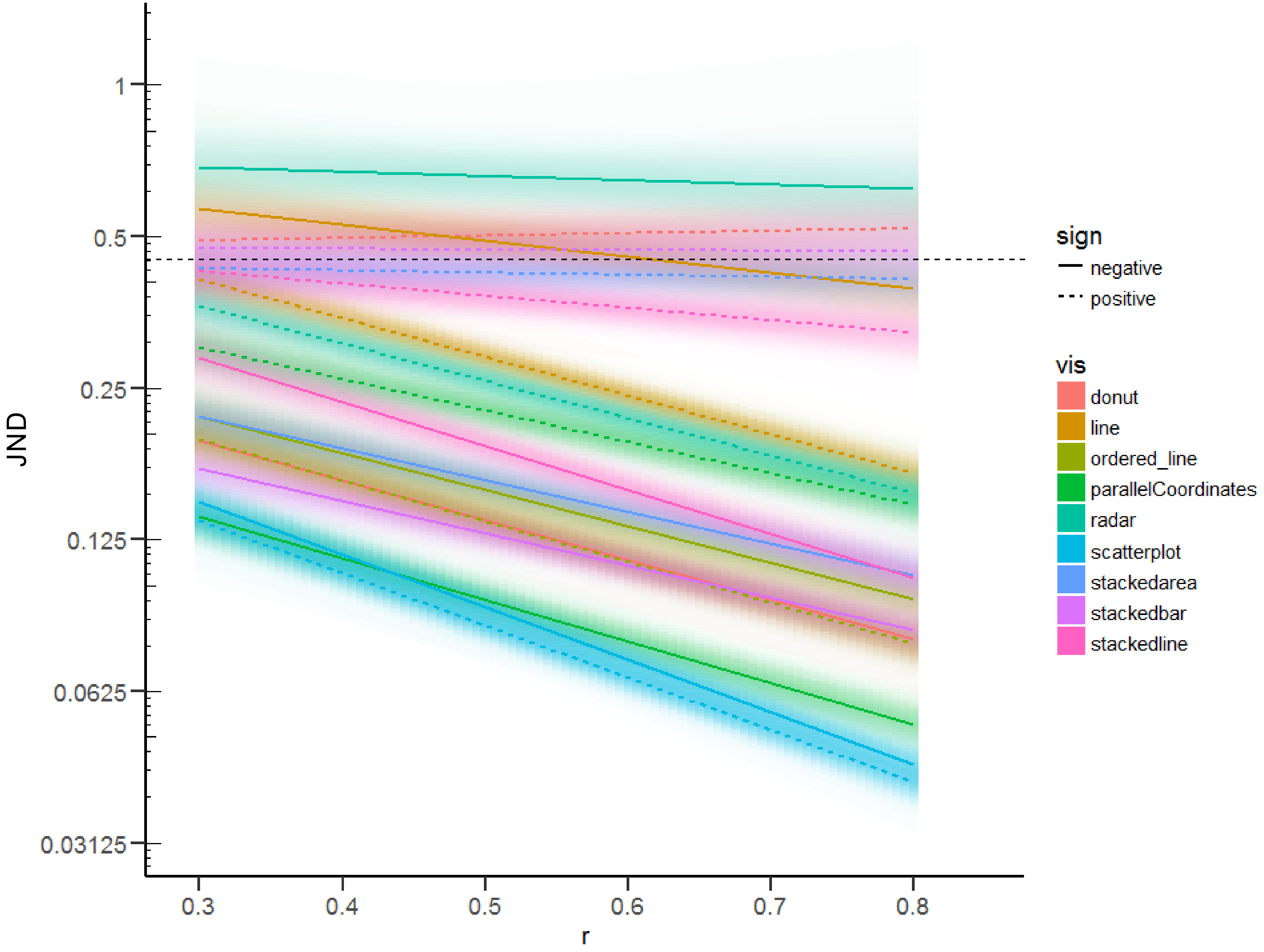
No:

Thing ⟷ Information I need to understand thing

Yes:

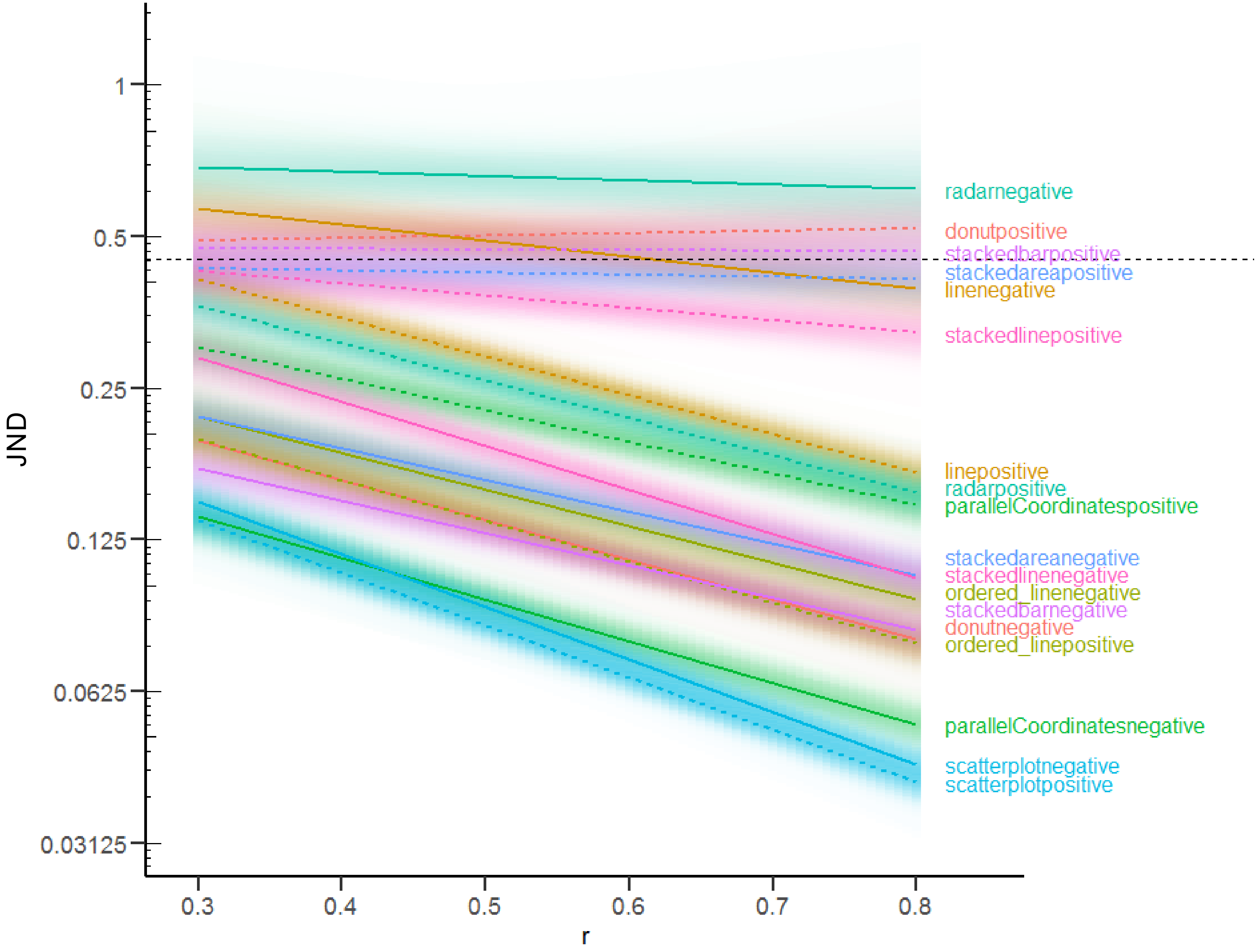
Thing ↔ Information I need to understand thing

No



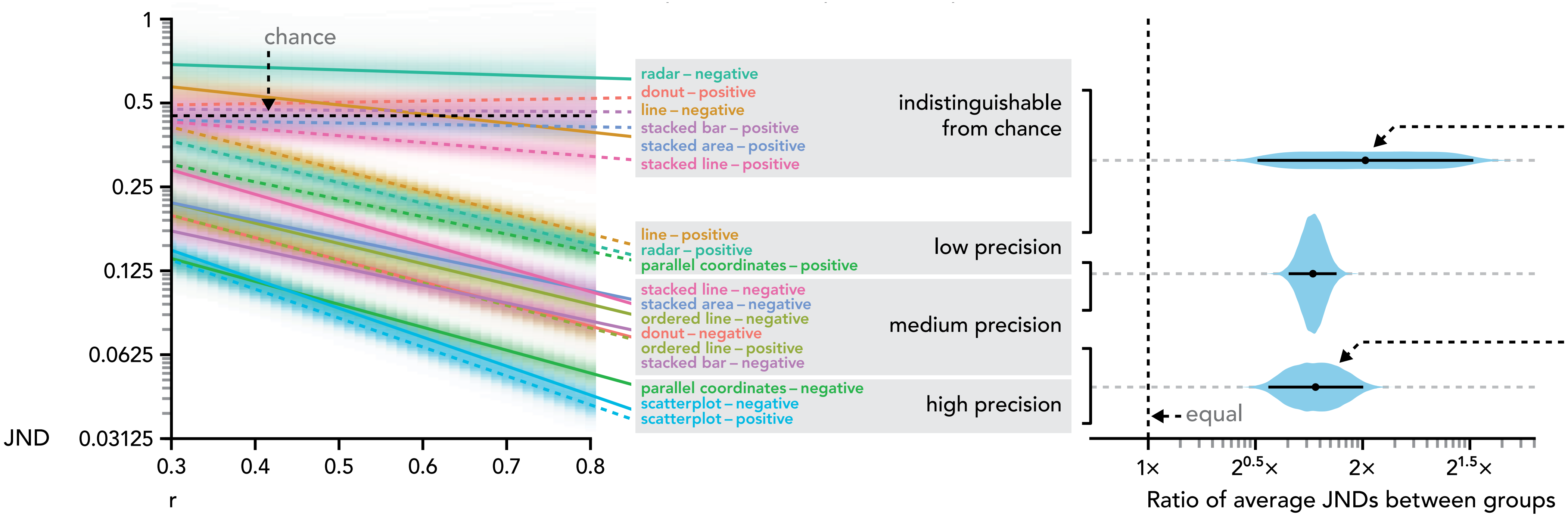
JND
1
0.5
0.25
0.125
0.0625
0.03125
0.3
0.4
0.5
0.6
0.7
0.8
r
sign
negative
positive
vis
donut
line
ordered_line
parallelCoordinates
radar
scatterplot
stackedarea
stackedbar
stackedline

Yes



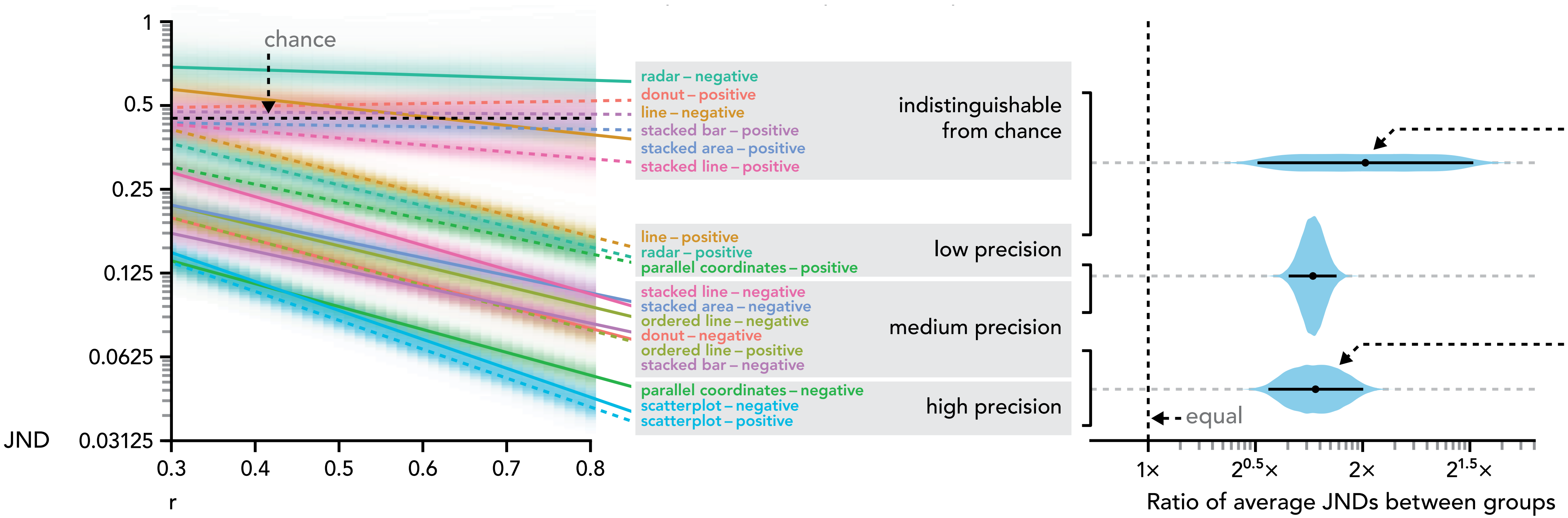
JND
r
1
0.5
0.25
0.125
0.0625
0.03125
0.3
0.4
0.5
0.6
0.7
0.8
radarnegative
donutpositive
stackedbarpositive
stackedareapositive
linenegative
stackedlinepositive
linepositive
radarpositive
parallelCoordinatespositive
stackedareanegative
stackedlinenegative
ordered_linenegative
stackedbarnegative
donutnegative
ordered_linepositive
parallelCoordinatesnegative
scatterplotnegative
scatterplotpositive

No



The left panel shows the Bayesian censored log-linear model, which gives us a posterior probability distribution over the mean log(JND) for each value of r. In the center panel we rank and group visualizations based on how precise estimations of correlations are with them (lower expected JND implies higher precision). In the right panel we estimate the ratio of average JNDs between succesive groups over all values of r from 0.3 to 0.8. The low precision group is between ~1.5 and 3 times more precise than the chance group. The high precision group is between ~1.5 and 2 times more precise than the medium precision group.

No



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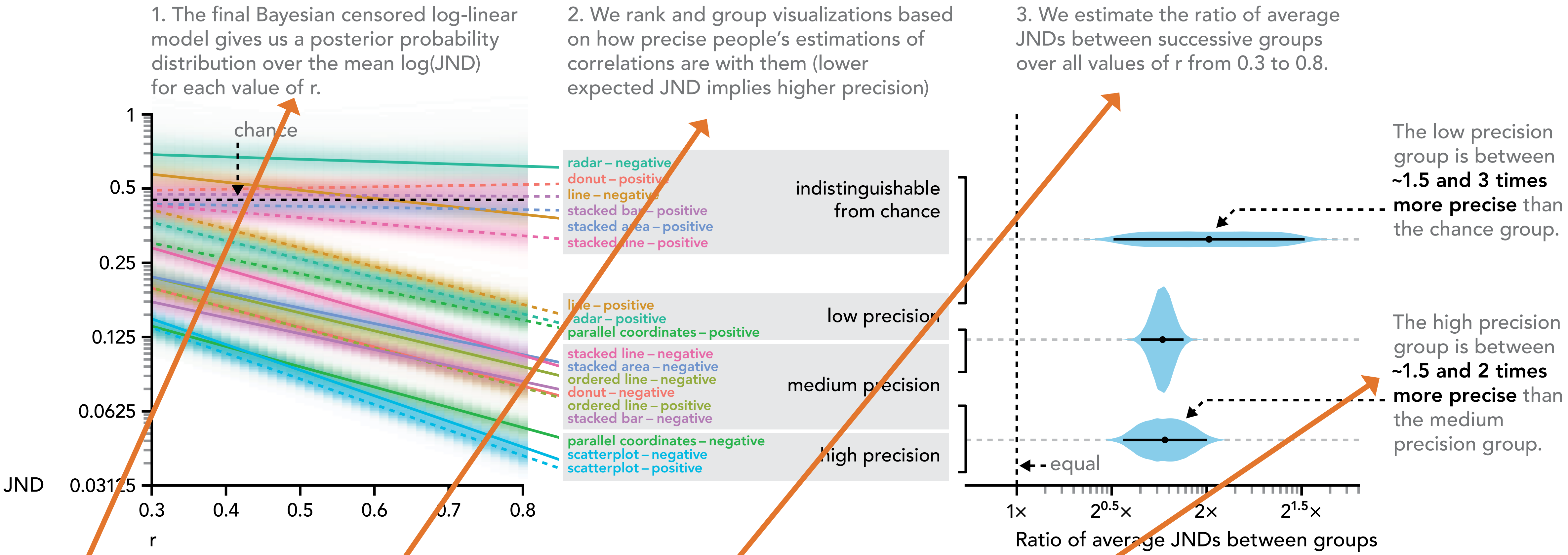
Yes



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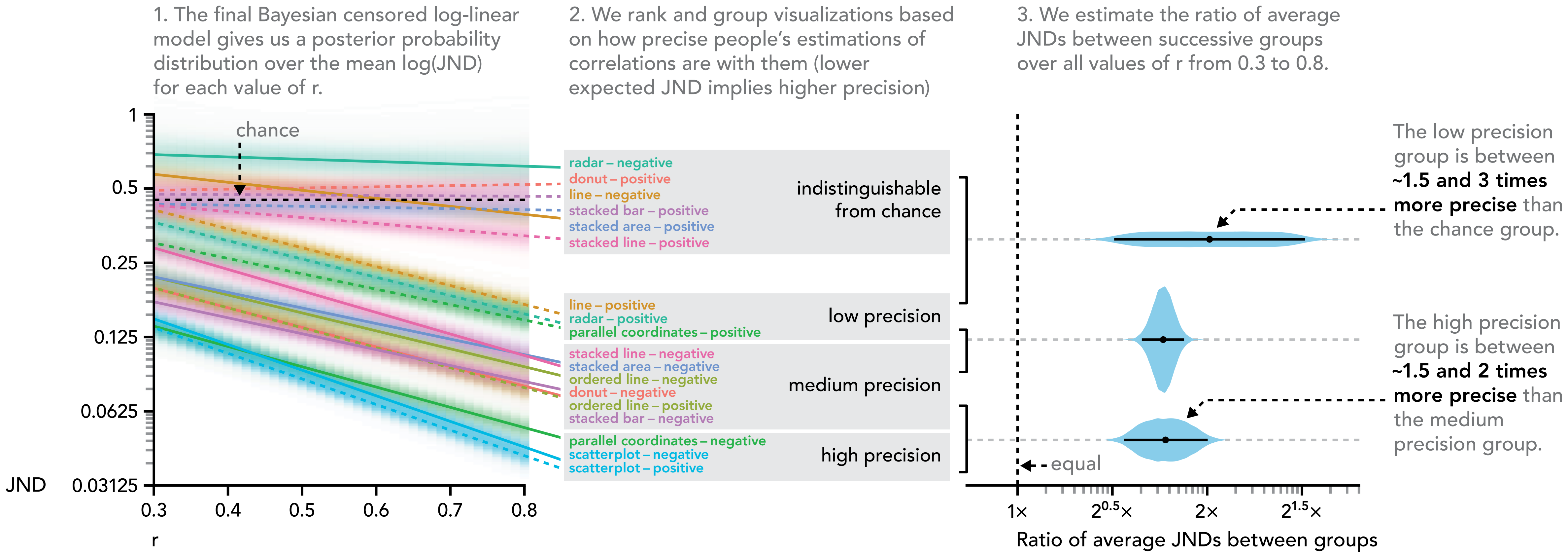
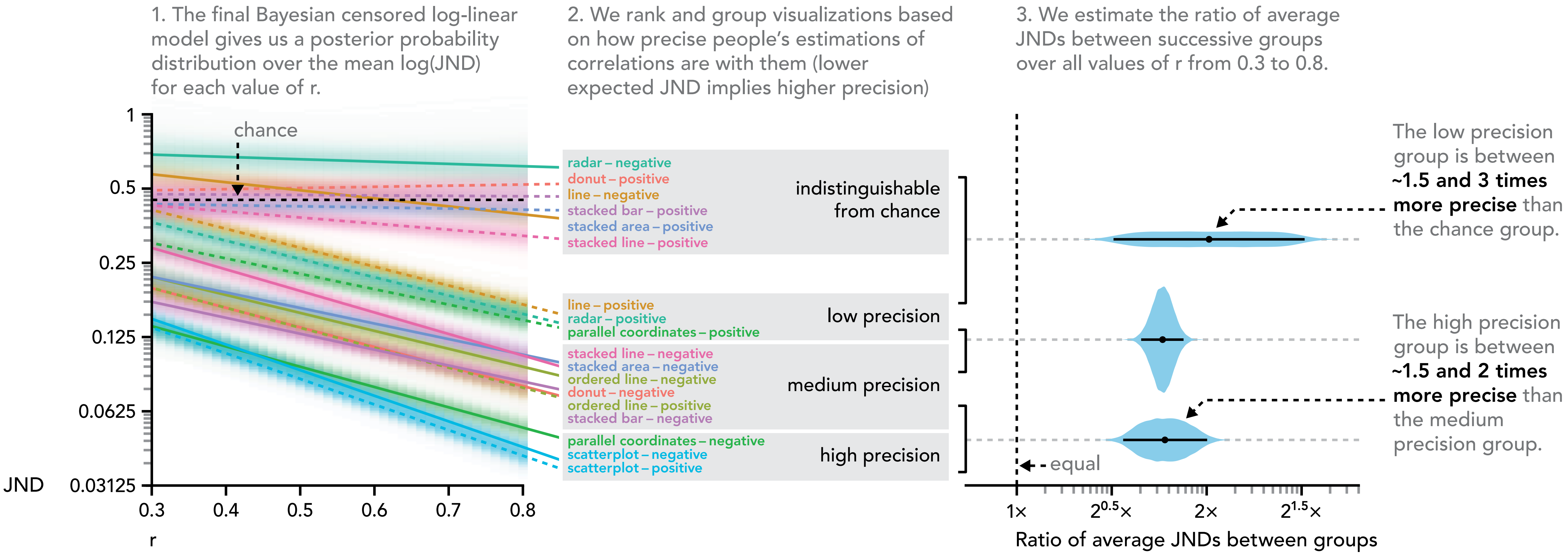
Yes

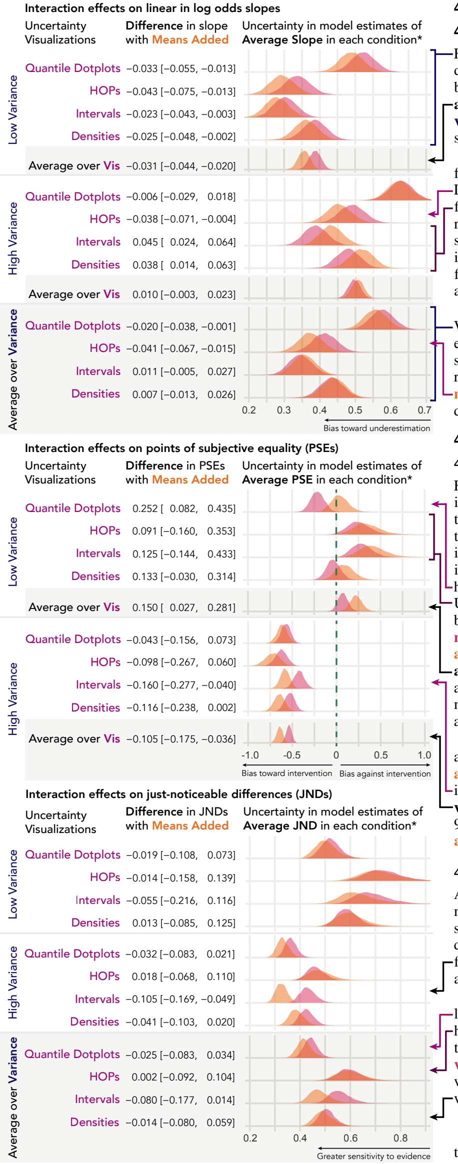


1. The final Bayesian censored log-linear model gives us a posterior probability distribution over the mean log(JND) for each value of r.
2. We rank and group visualizations based on how precise people's estimations of correlations are with them (lower expected JND implies higher precision)
3. We estimate the ratio of average JNDs between successive groups over all values of r from 0.3 to 0.8.
chance
1
0.5
0.25
0.125
0.0625
0.03125
JND
0.3
0.4
0.5
0.6
0.7
0.8
r
radar – negative
donut – positive
line – negative
stacked bar – positive
stacked area – positive
stacked line – positive
indistinguishable from chance
line – positive
radar – positive
parallel coordinates – positive
low precision
stacked line – negative
stacked area – negative
ordered line – negative
donut – negative
ordered line – positive
stacked bar – negative
medium precision
parallel coordinates – negative
scatterplot – negative
scatterplot – positive
high precision
equal
1×
$2^{0.5}$×
2×
$2^{1.5}$×
Ratio of average JNDs between groups
The low precision group is between **~1.5 and 3 times more precise** than the chance group.
The high precision group is between **~1.5 and 2 times more precise** than the medium precision group.

Yes



Count lookups!



4 Results

4.1 Probability of Superiority Judgments

For each uncertainty visualization, **adding means** at **low variance** decreases LLO slopes. Recall that a slope of one corresponds to no bias, and a slope less than one indicates underestimation. When we **average over uncertainty visualizations**, **adding means** at **low variance** reduces LLO slopes for the average user, indicating a very small 0.8 percentage points increase in probability estimation error.

At **high variance**, the effect of **adding means** changes directions for different uncertainty visualizations. **Adding means** decreases LLO slopes for **HOPs**, whereas **adding means** increases LLO slopes for **intervals and densities**. Because differences in LLO slopes represent changes in the exponent of a power law relationship, these slope differences of similar magnitude indicate a very small increase in probability of superiority estimation error of 0.3 percentage points for HOPs and small reductions in error of about 1.5 and 1.0 percentage points for intervals and densities, respectively.

Users of all uncertainty visualizations underestimate effect size. When we **average over variance**, users show an average estimation error of 8.6, 14.0, 14.8, and 12.4 percentage points in probability of superiority units for quantile dotplots, HOPs, intervals, and densities, respectively, each **without means**. In this marginalization, **adding means** only has a reliable impact on LLO slopes for **HOPs**, but the difference is practically negligible.

4.2 Intervention Decisions

4.2.1 Points of Subjective Equality

For each uncertainty visualization, **adding means** at **low variance** increases PSEs. This results in different effects depending on whether the visualization with **no means** has a PSE below or above utility-optimal. Recall that a PSE of zero is utility-optimal, a negative PSE indicates intervening too often, and a positive PSE indicates not intervening often enough. Users of **quantile dotplots** with **no means** have negative PSEs which become unbiased when we **add means**. Users of **HOPs and intervals** with **no means** have positive PSEs, biases which increase when we **add means**. Users of **densities** with **no means** have PSEs near zero and become more biased when we **add means**. Only the effect for quantile dotplots is reliable. When we **average over uncertainty visualizations**, at **low variance** the average user may have a PSE 0.6 percentage points above utility-optimal with **no means**, and **adding means** increases this mild bias by about 1.7 percentage points in terms of the probability of winning.

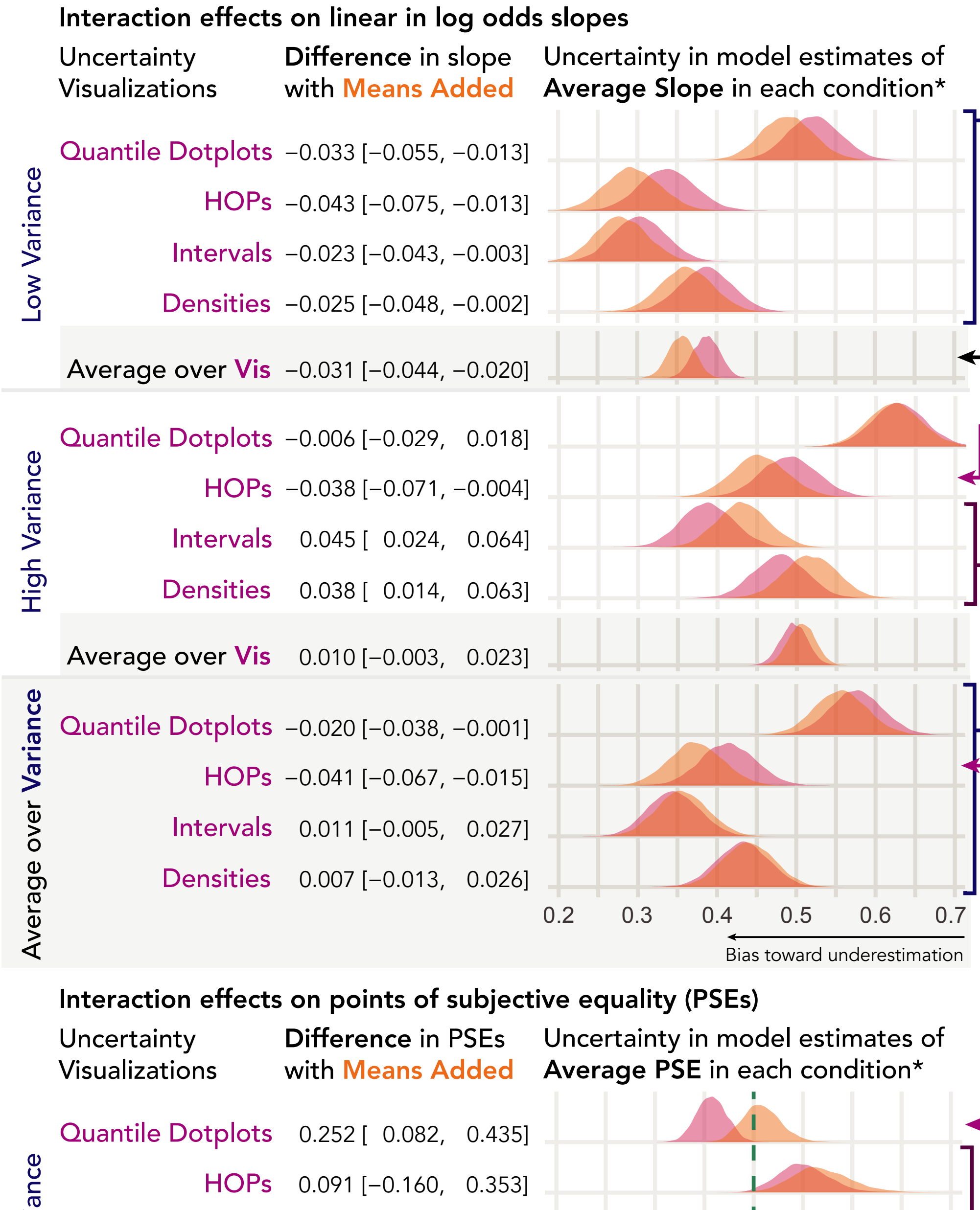
At **high variance**, **adding means** decreases PSEs. Since PSEs for all uncertainty visualizations with **no means** are below optimal, **adding means** increases biases in all conditions, however, the effect is only reliable for **intervals**. When we **average over uncertainty visualizations**, at **high variance** the average user has a negative PSE 9.5 percentage points below utility-optimal with **no means**, and **adding means** increases this bias by about 2.1 percentage points.

4.2.2 Just-Noticeable Differences

At **low and high variance**, the effects of **adding means** on JNDs are mostly unreliable. Recall that smaller JNDs indicate that a user is sensitive to smaller differences in effect size for the purpose of decision-making. **Adding means** only has a reliable effect on JNDs for **intervals** at **high variance**, where it reduces JNDs by 1.2 percentage points in terms of the probability of winning.

When we **average over variance**, **quantile dotplots with means** lead to the smallest JNDs, and users of **HOPs with** or **without means** have the largest JNDs, a difference of about 1 percentage point in terms of the probability of winning. Quantile dotplots **with** or **without means** have reliably smaller JNDs than other conditions, with the exception of unreliable differences between quantile dotplots with **no means** and **densities with** or **without means**.

*Probability densities of model estimates show posterior distributions of means conditional on the average participant.



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4. Establish viewing order

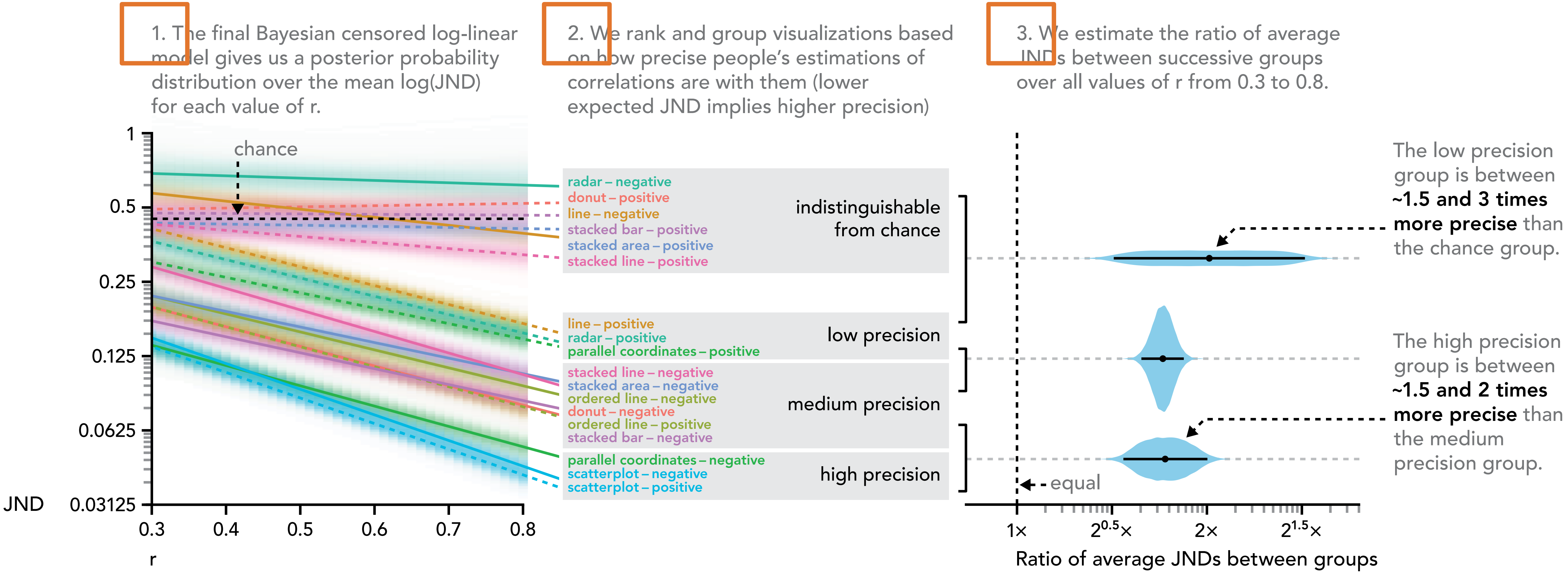
Know where your audience will look first, second.

Think like a movie director. Are you telling a story?

https://www.youtube.com/watch?v=v4seDVfgwOg

4. Establish viewing order

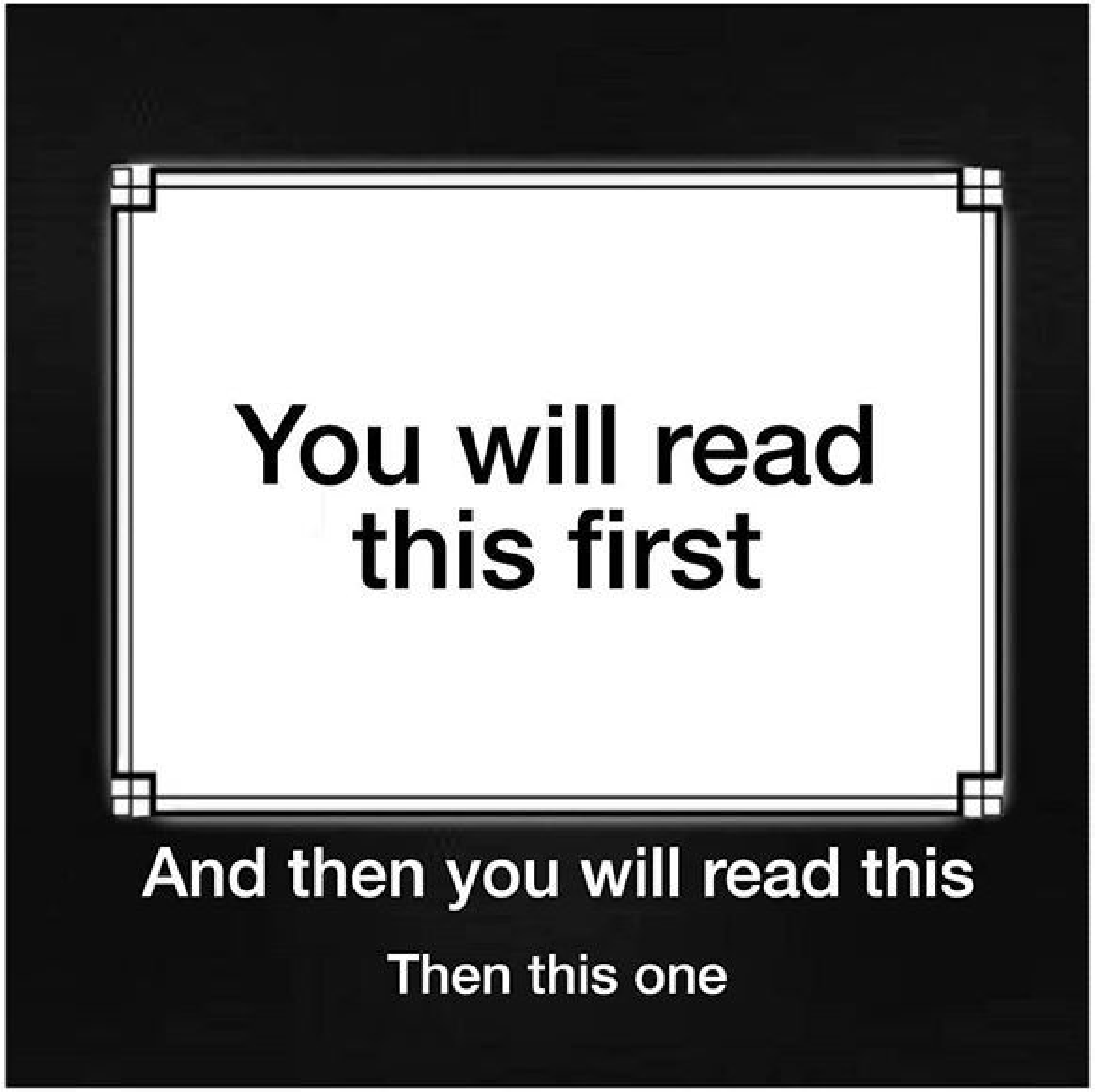
Can be as simple as some numbers…



4. Establish viewing order

Or more complex,
relying on salience,
other visual cues,
viewer expectations
(maybe) ...

And you will read this at the end



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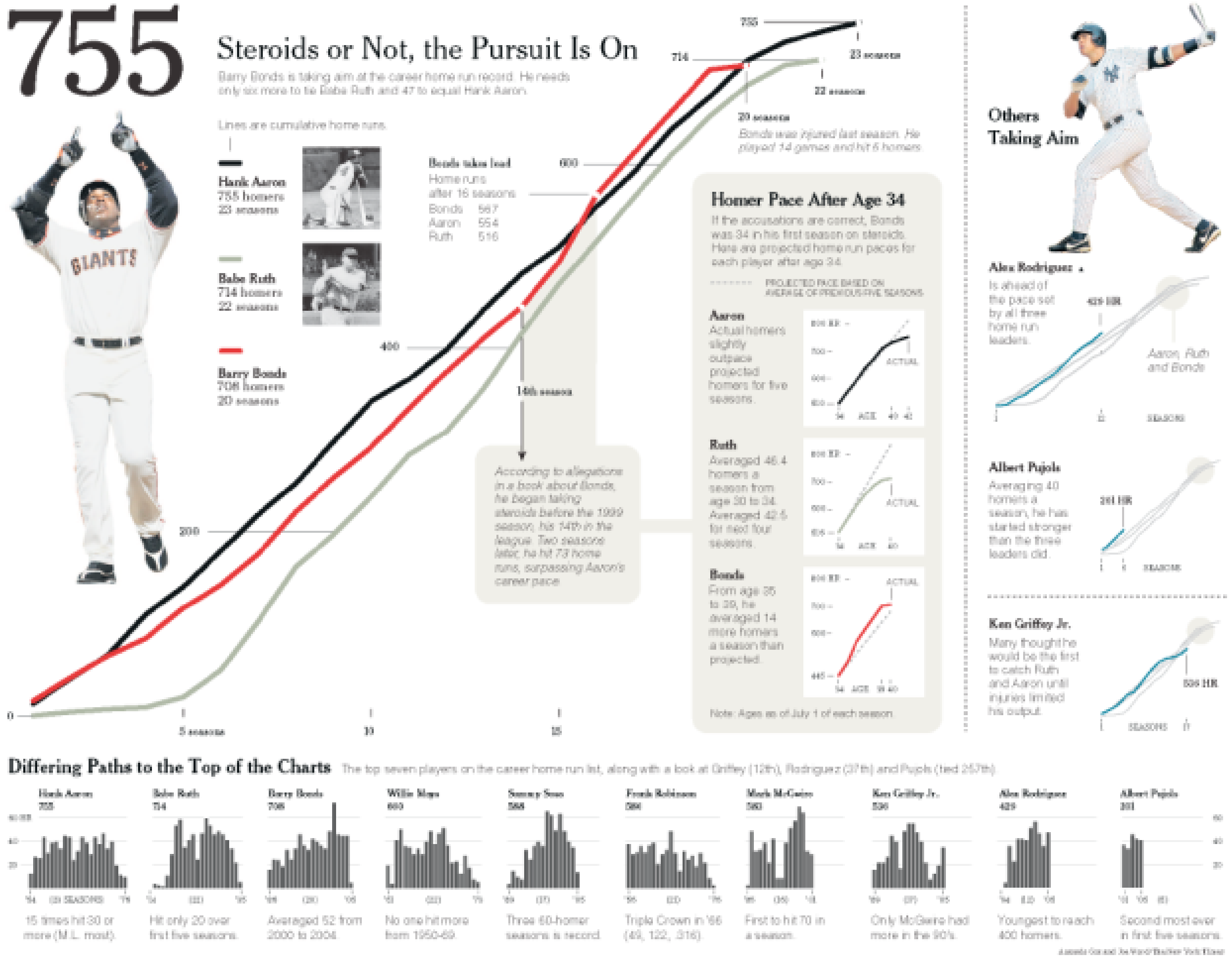
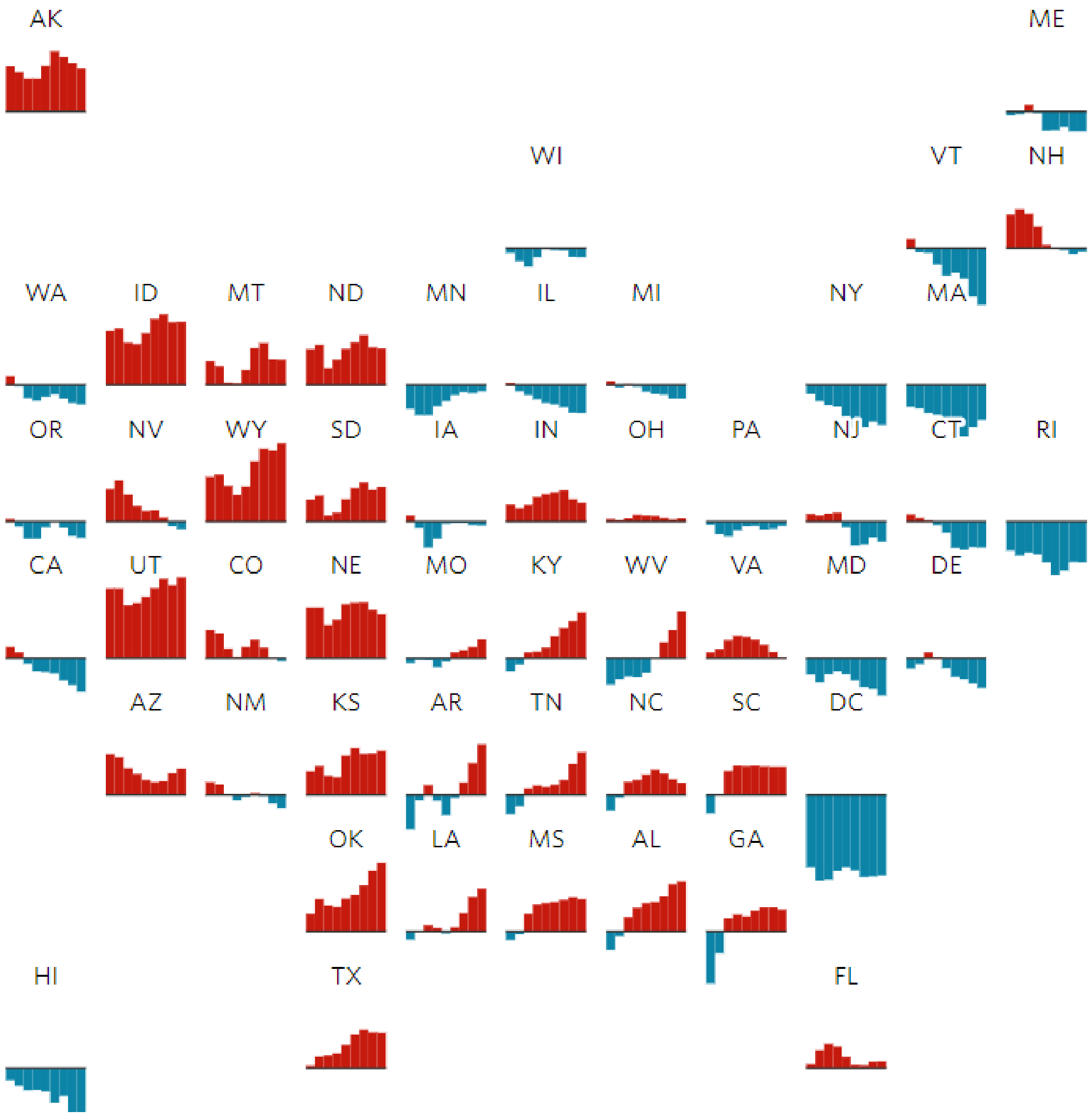


5. Layer, layer, layer

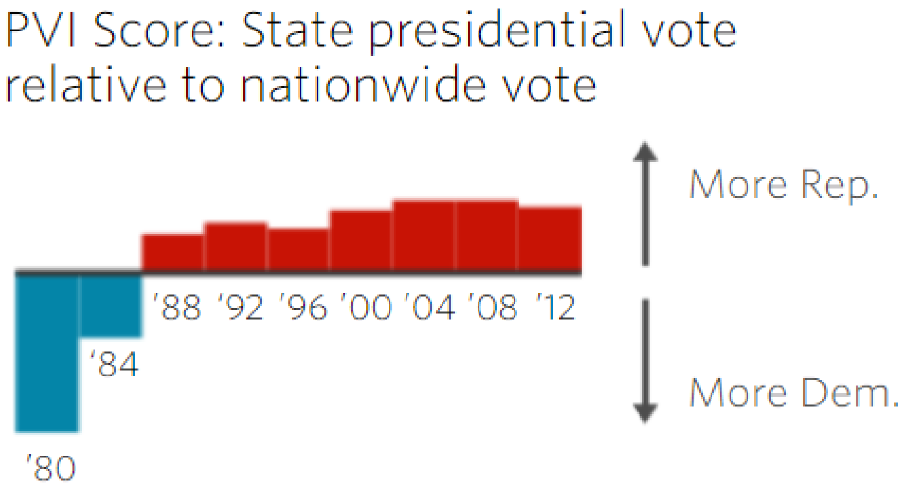
Design for micro-macro reading

Pre-attentive attributes help

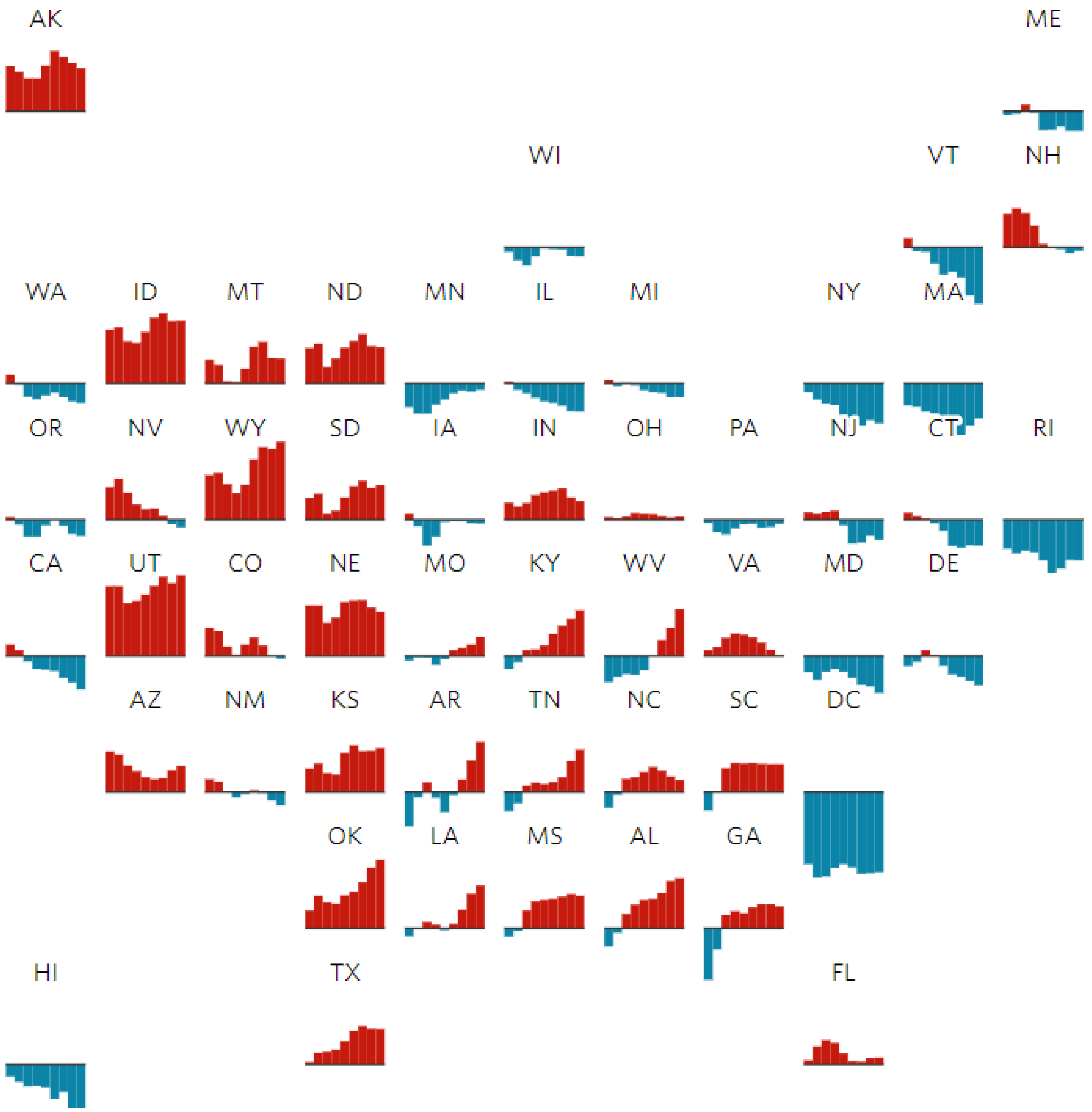
[http://graphics.wsj.com/elections/2016/field-guide-red-blue-america/]



5. Layer, layer, layer



[http://graphics.wsj.com/elections/2016/field-guide-red-blue-america/]

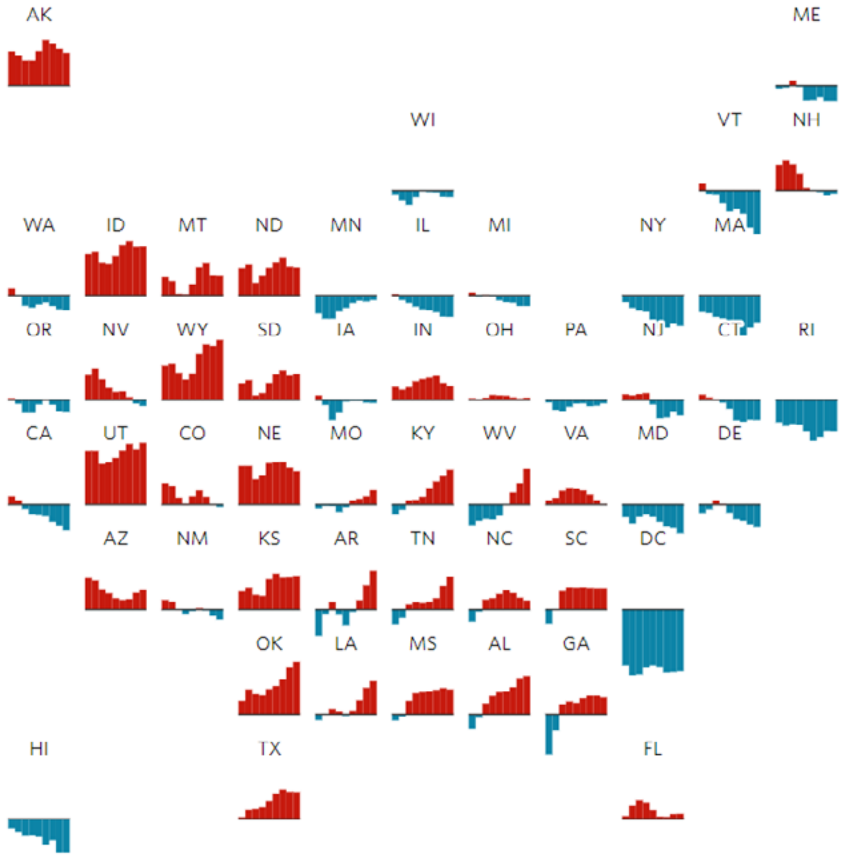


5. Layer, layer, layer

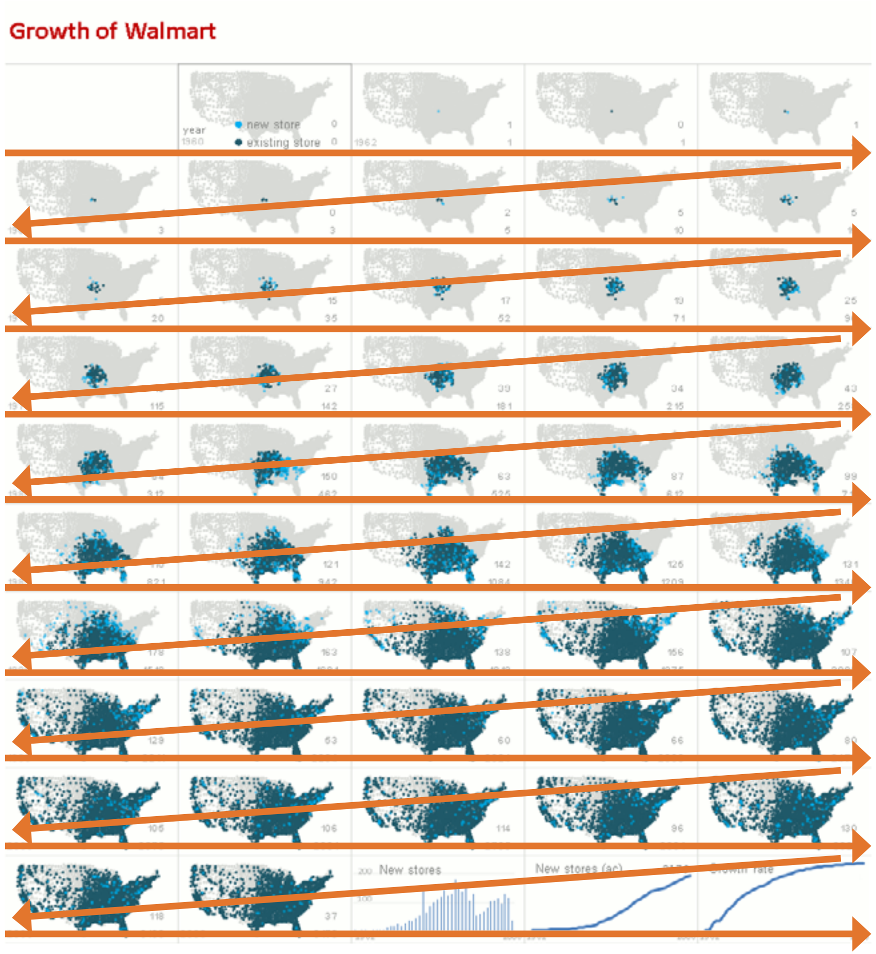
See also: poster design

Google *scientific poster* and see what comes up:
Now imagine reading them from 20 feet away

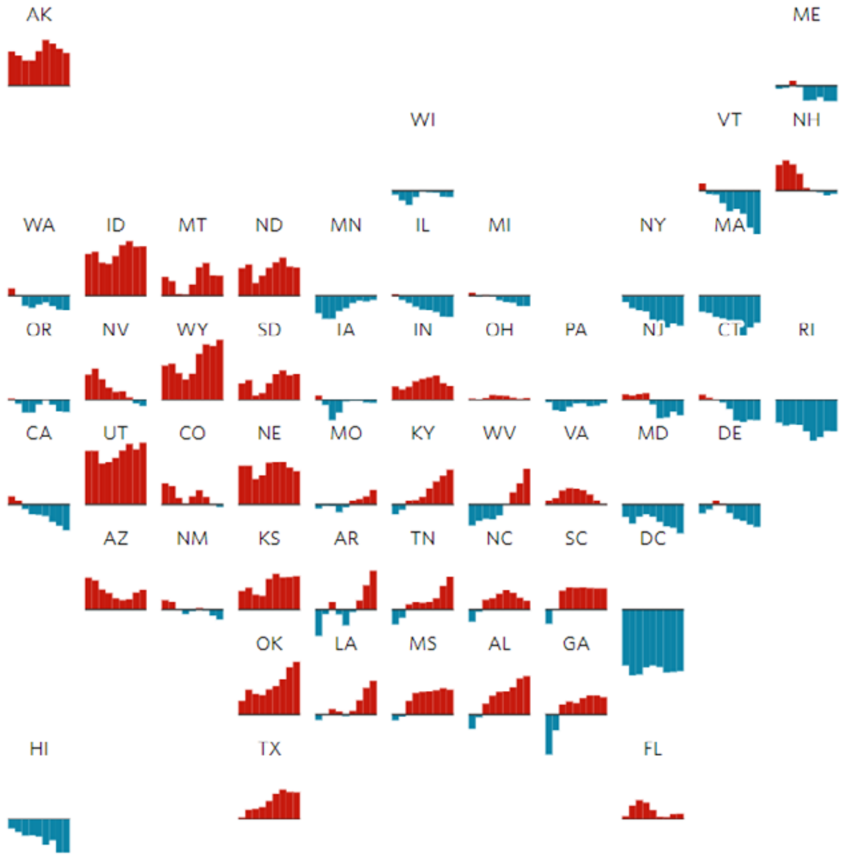
(small multiples)



(small multiples = double use of position)



year -> wrapped column (x position)



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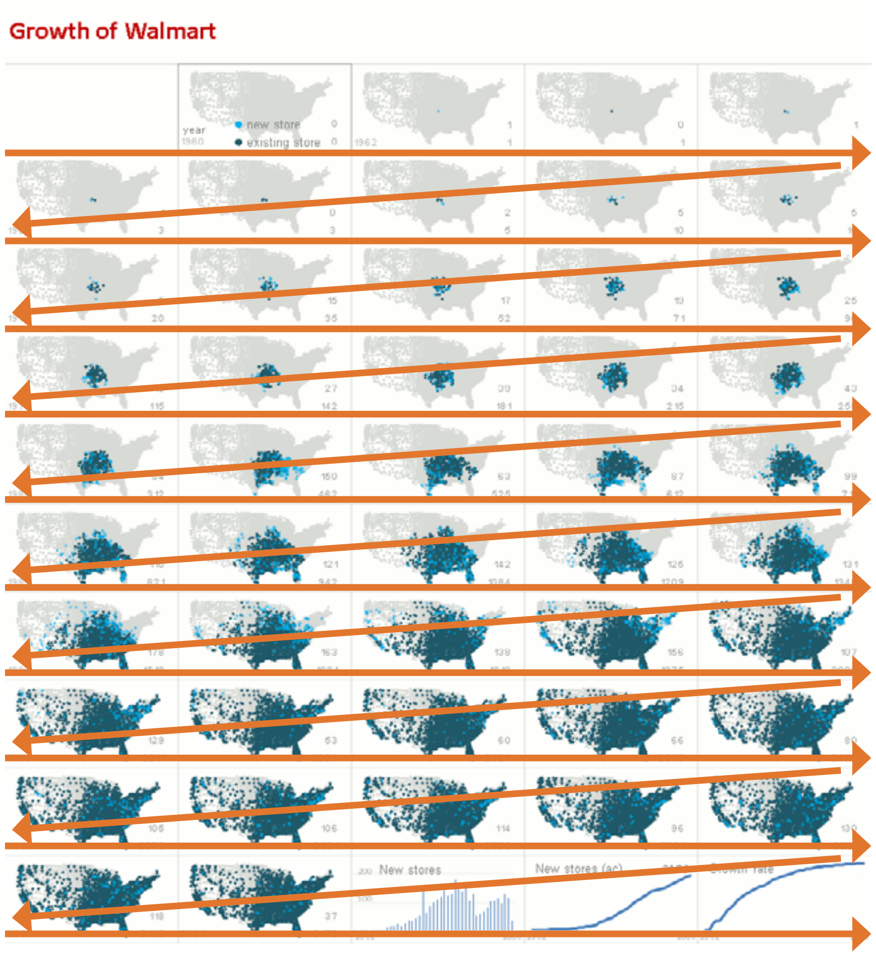
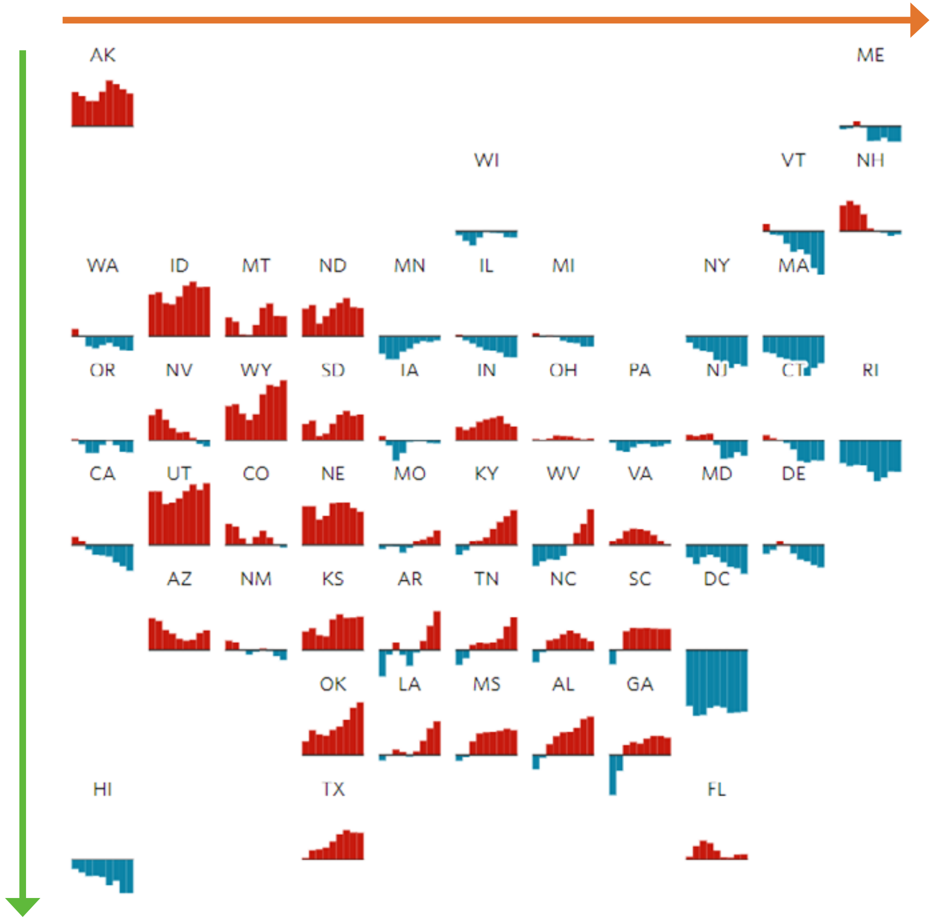


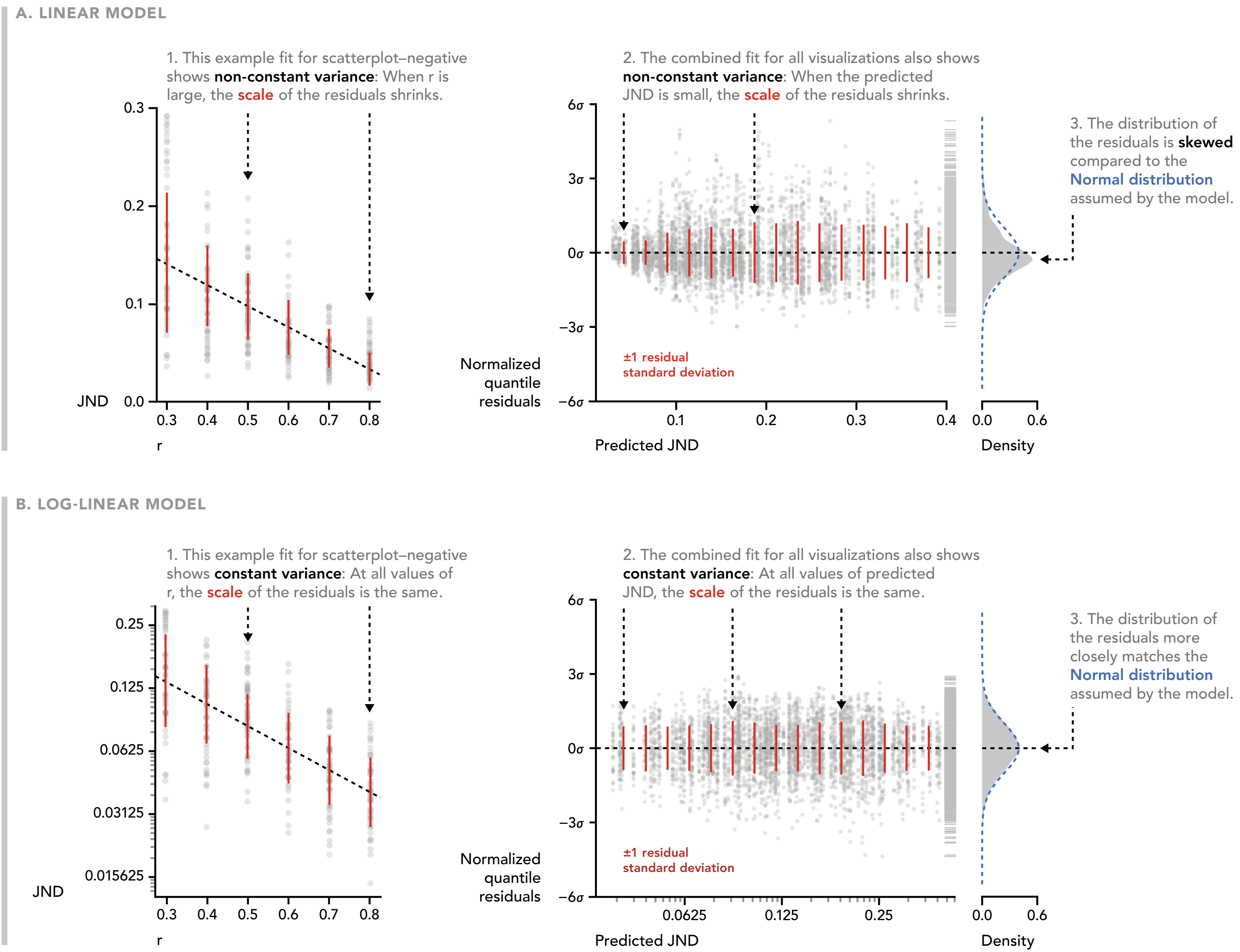
year -> wrapped column (x position)



~longitude -> column (x position)
~latitude -> row (y position)

6. When in doubt, grid

And get synchronized axes as a bonus

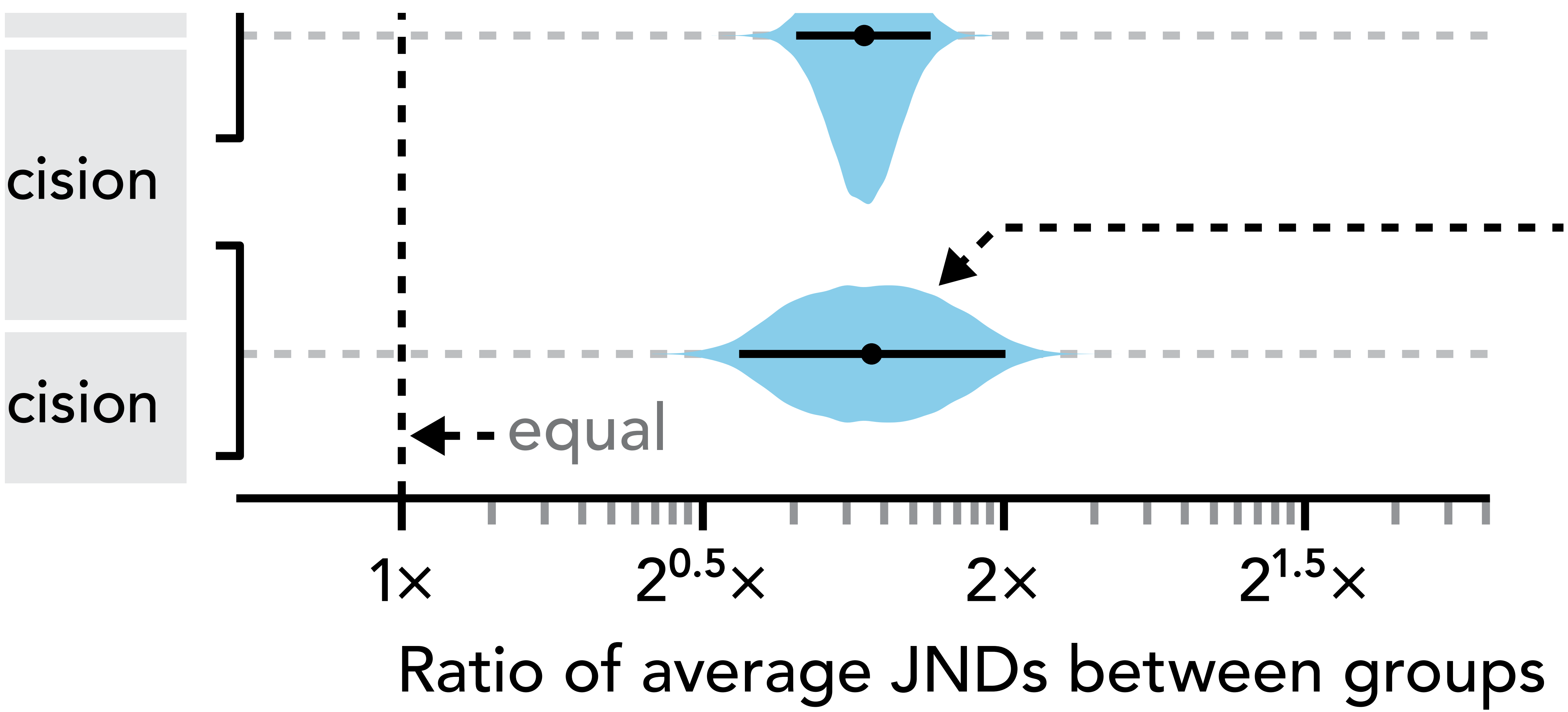


7. Treat visual attributes like adjectives

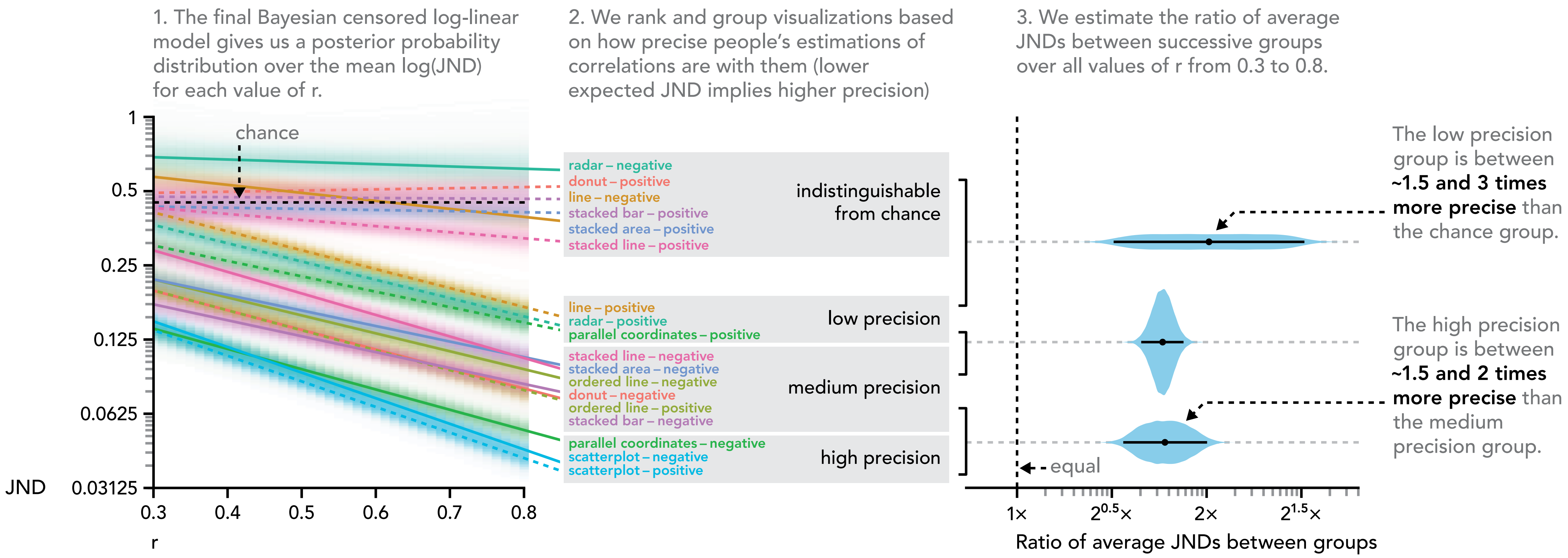
Don’t use three attributes (size, color, shape, …) to create emphasis where one or two will do.

The very tall building is very extremely tall.

(7b. Obey the pen)



(7b. Obey the pen)



(7b. Obey the pen)

Even visual texture is pleasing

Also makes it easier to create visual hierarchy and call out something important when you need to

Some rough design guidelines*

1. Match effectiveness with importance
2. Avoid ambiguity
3. Locality is king / eyes beat memory
4. Establish viewing order
5. Layer, layer, layer
6. When in doubt, grid
7. Treat visual attributes like adjectives

* These guidelines are drawn largely from my experience + personal preferences + the literature. Design is messy, these are not perfect, others will disagree with me, etc. *Caveat emptor.*

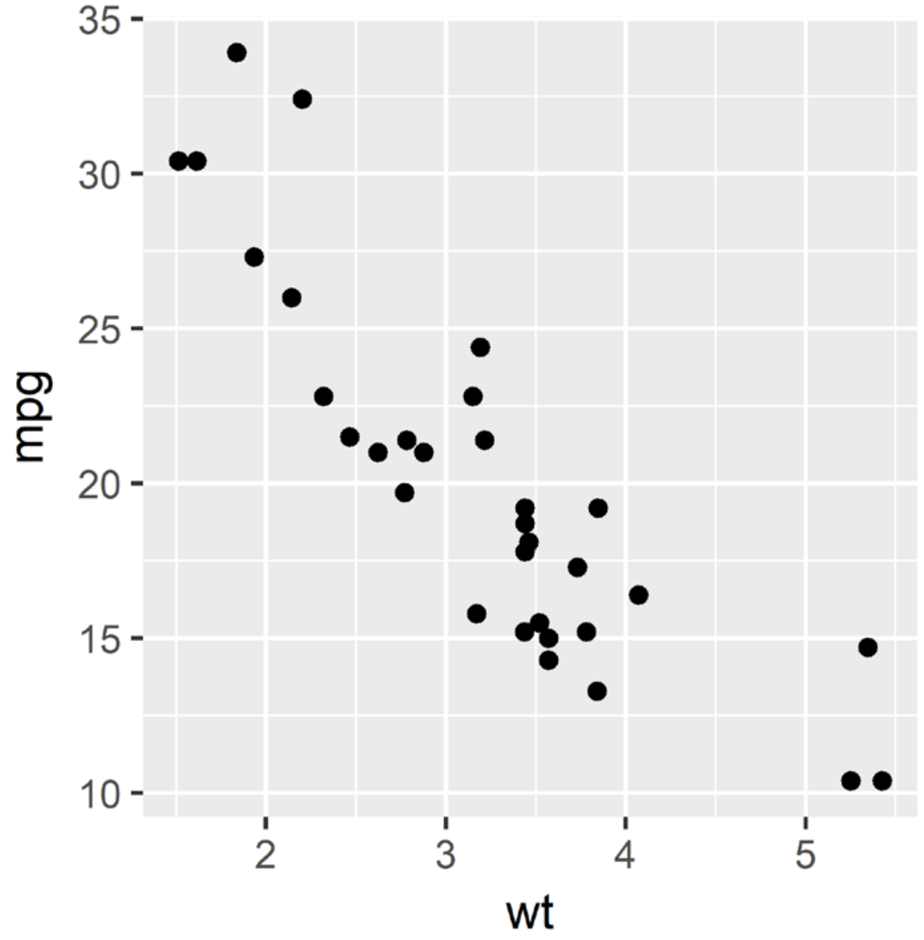
Questions?

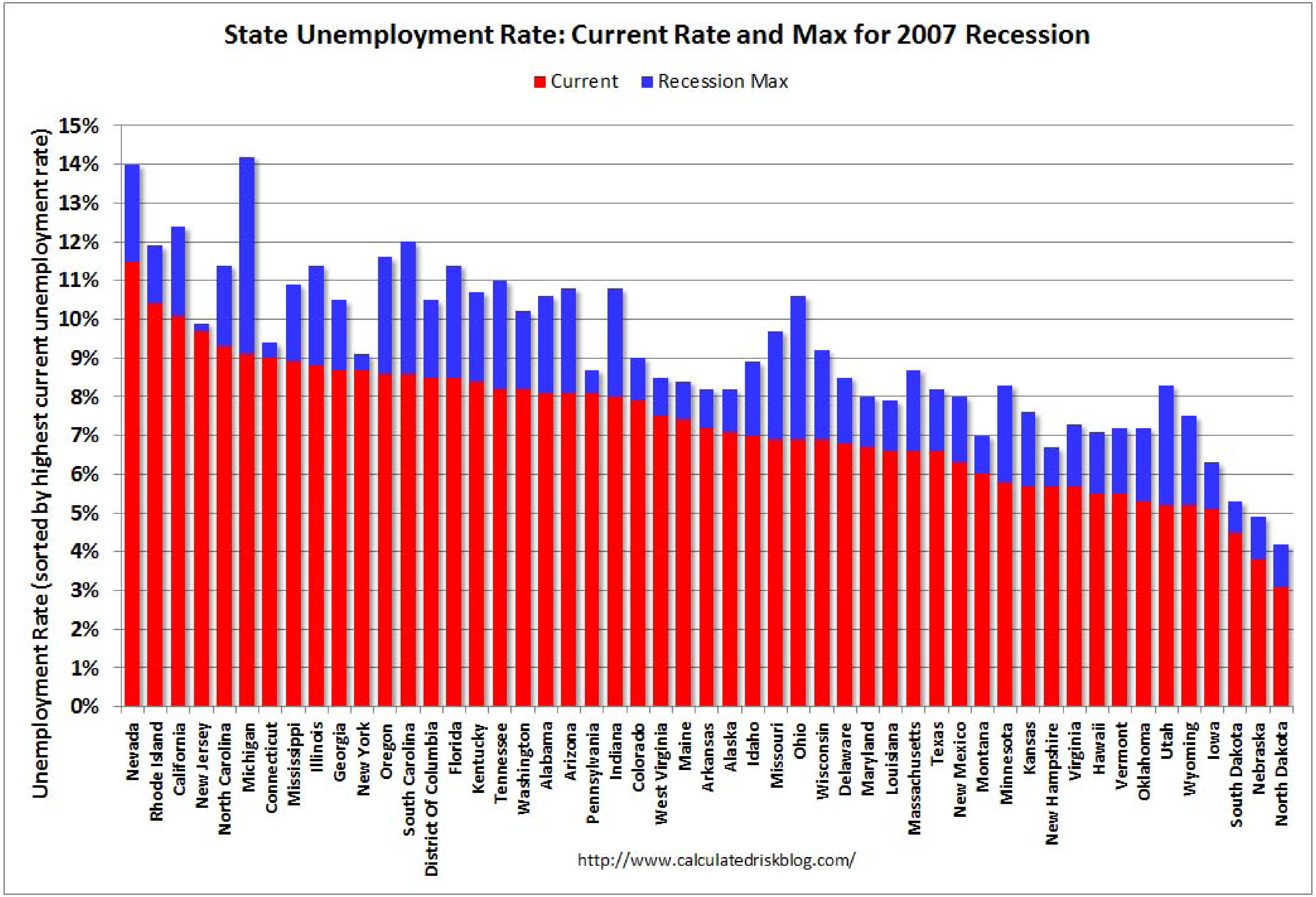
Examples / exercises

Grammar of graphics

(data types, channels, marks)

mpg: numeric
wt: numeric
wt -> x position
mpg -> y position
mark: point





Group activity

What are the variables / types?

Channels / encodings?

Marks?

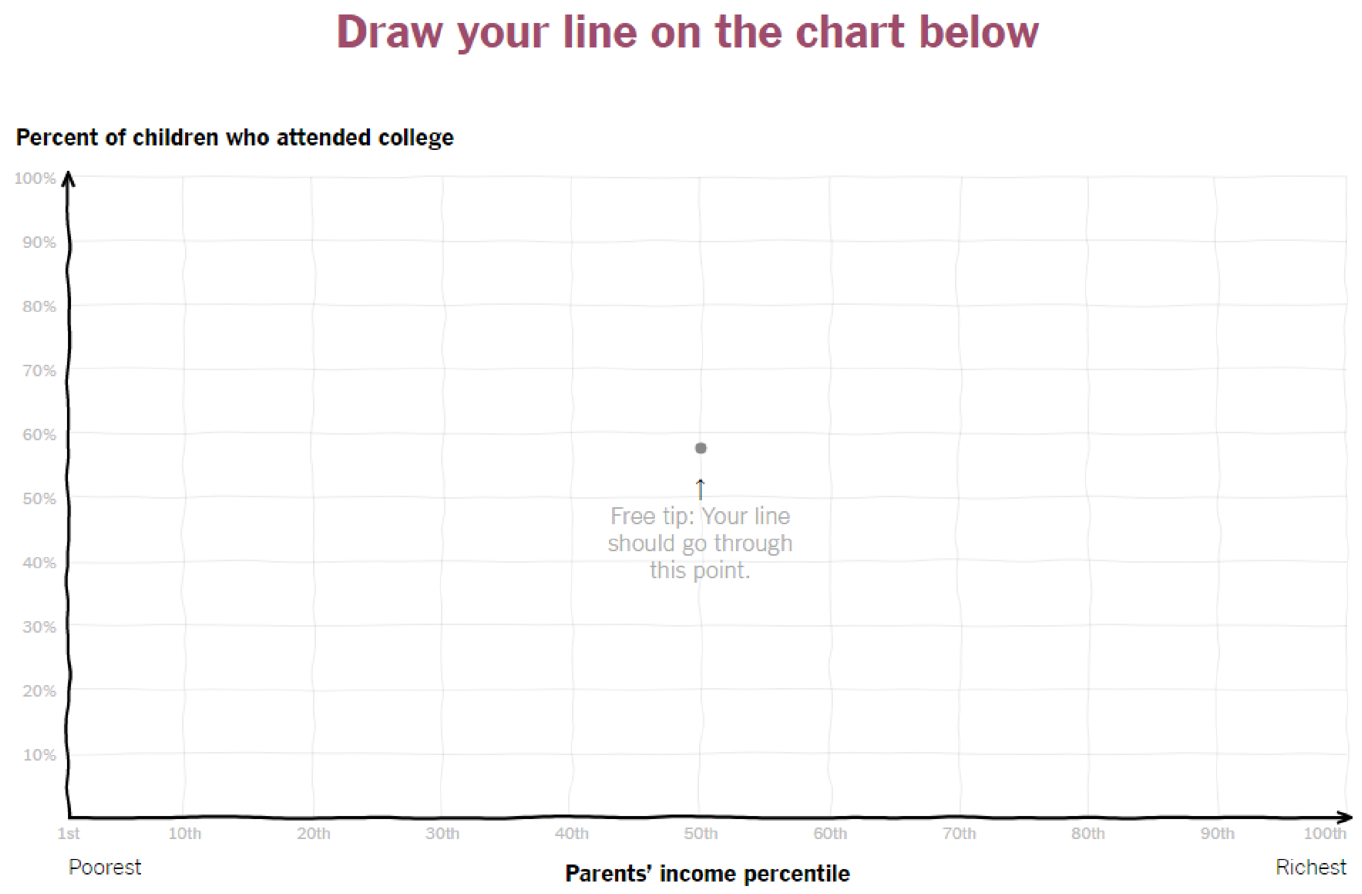
Is this effective?

Design / sketching

Quick intros: Name, what you plan to work on today

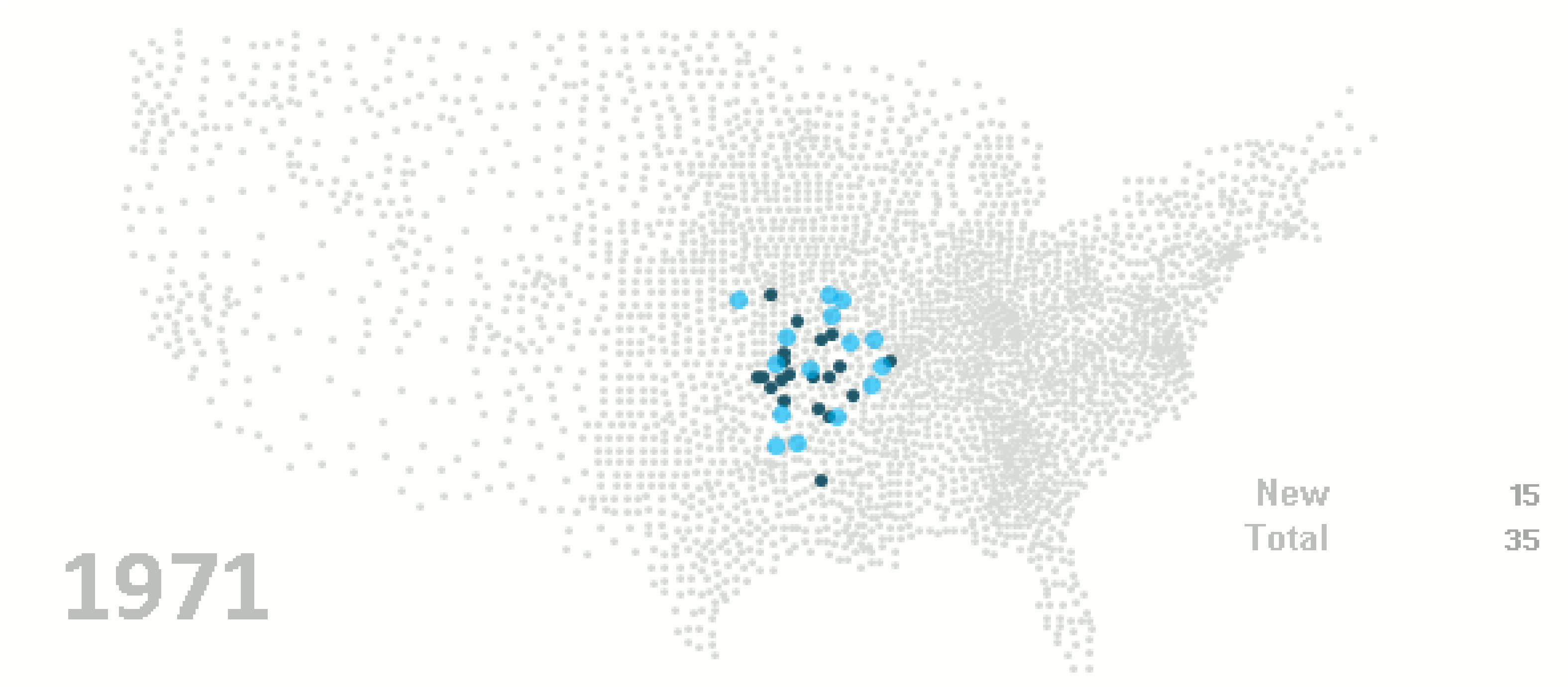
(could be on paper or computer, but I encourage you to try out sketching for part of today)

Prediction and memory

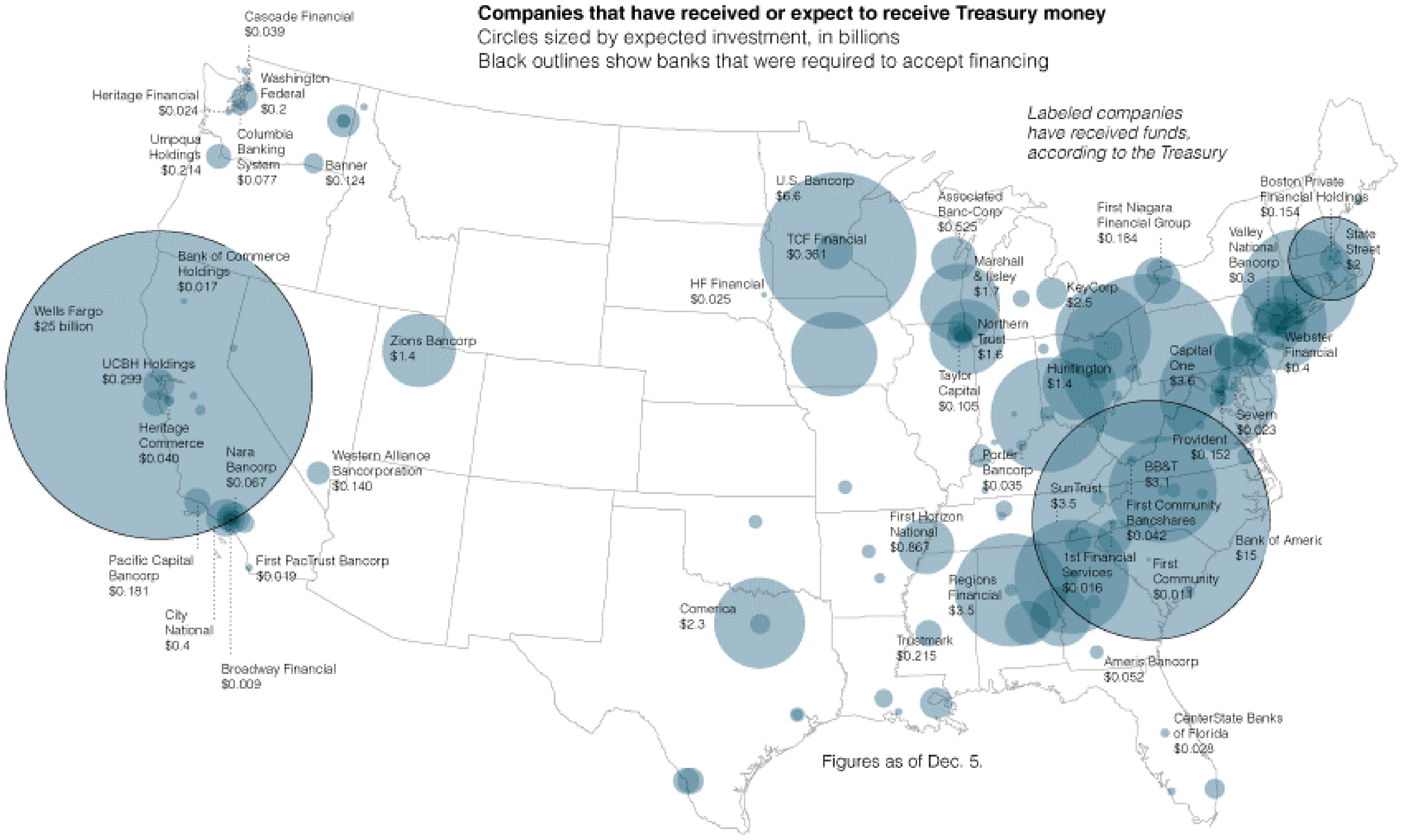


[https://nyti.ms/2jX8zue]

Small multiples



[https://excelcharts.com/animation-small-multiples-growth-walmart-excel-edition/]



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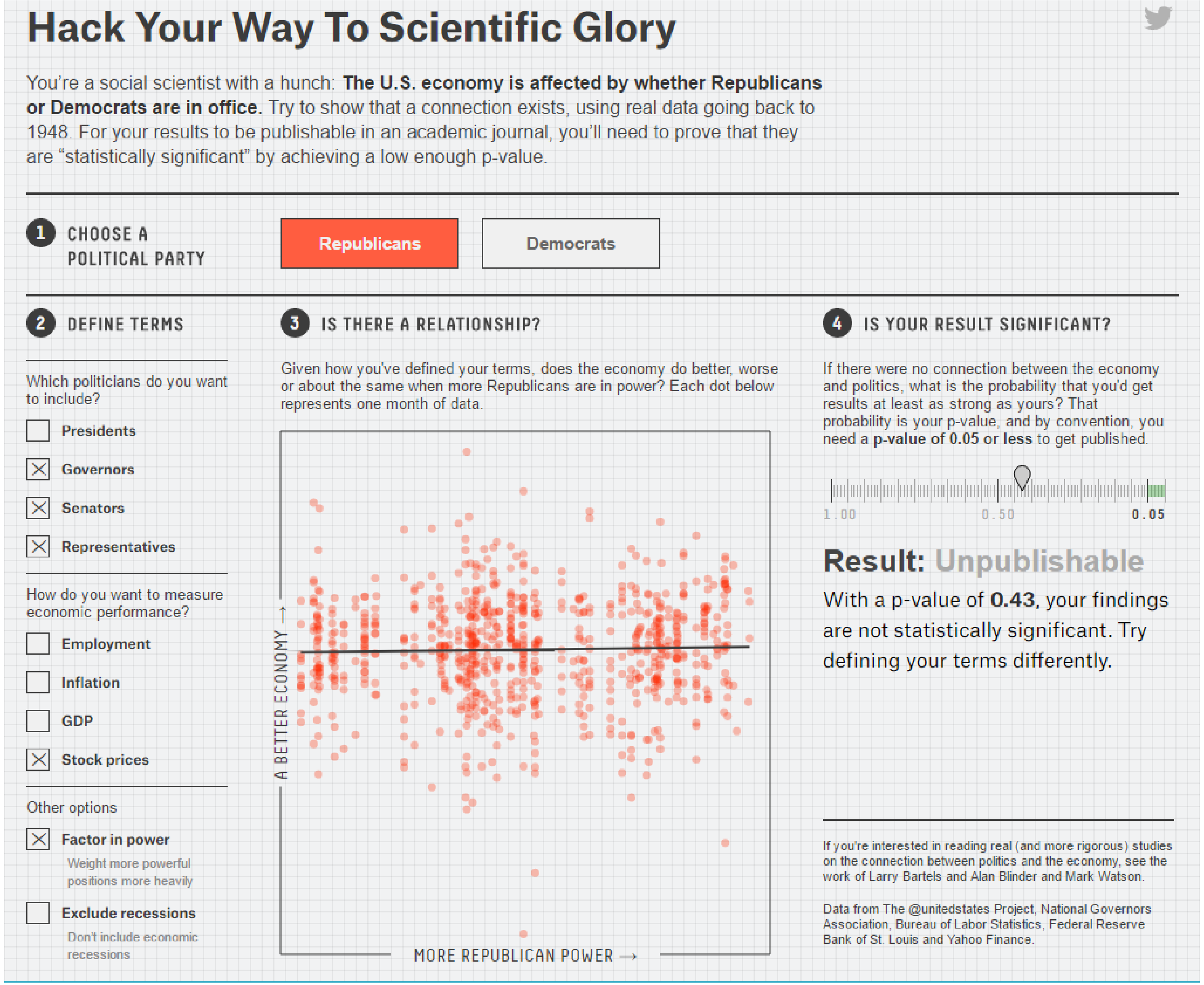
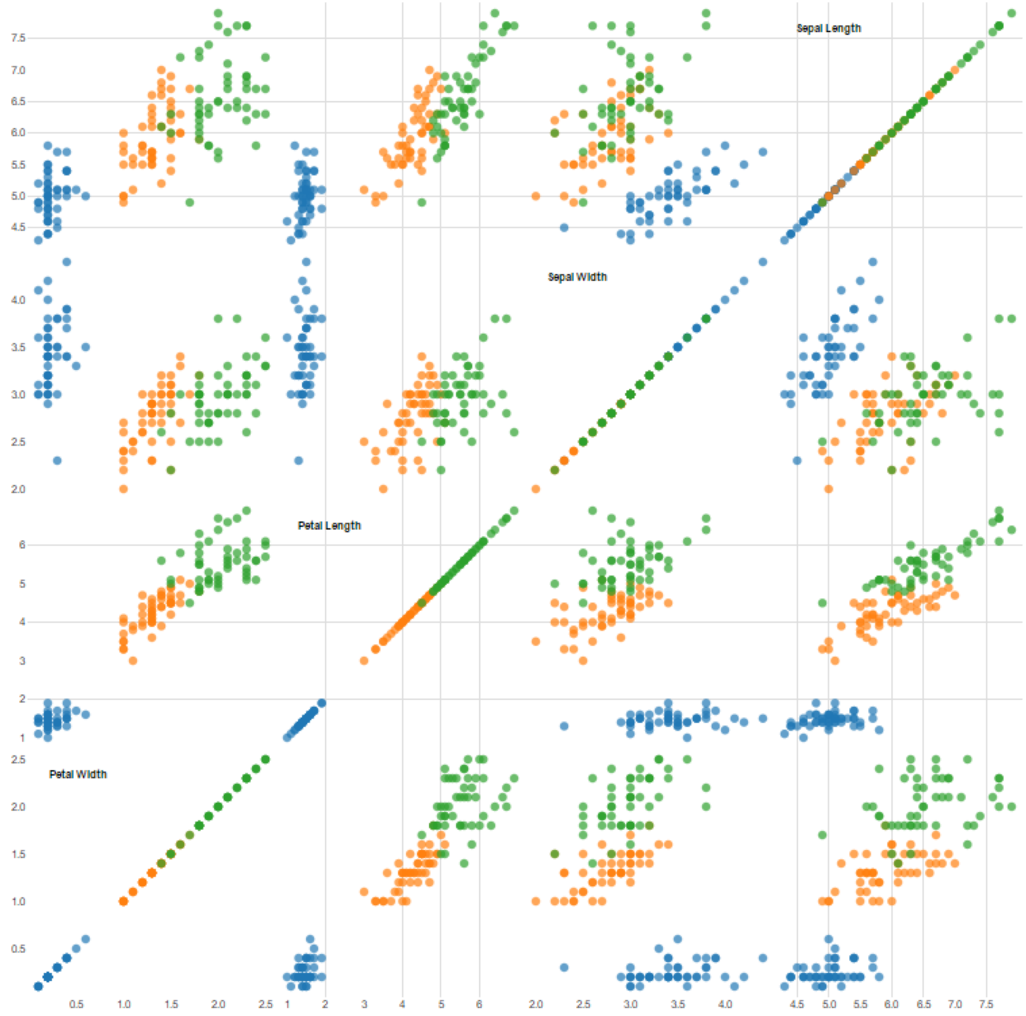


[https://fivethirtyeight.com/features/science-isnt-broken/]

SPLOM: Scatter plot matrix

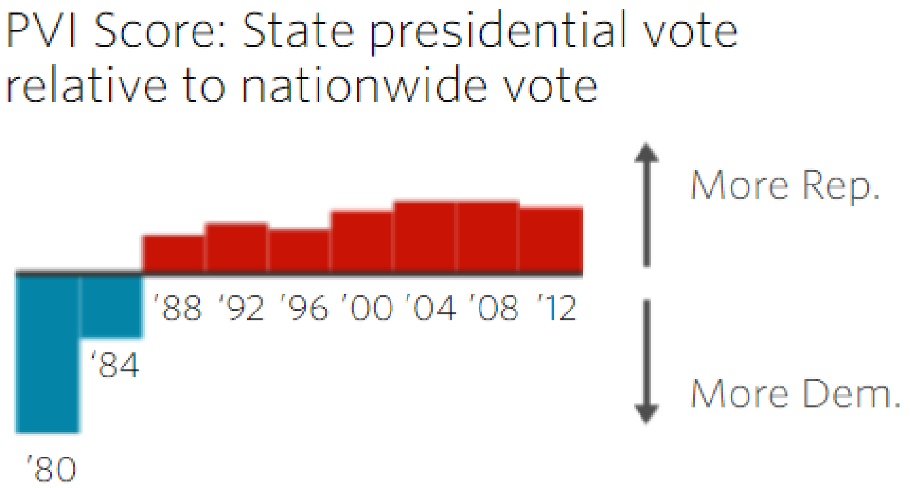


[https://bl.ocks.org/mbostock/4063663]

Hyberbolic trees

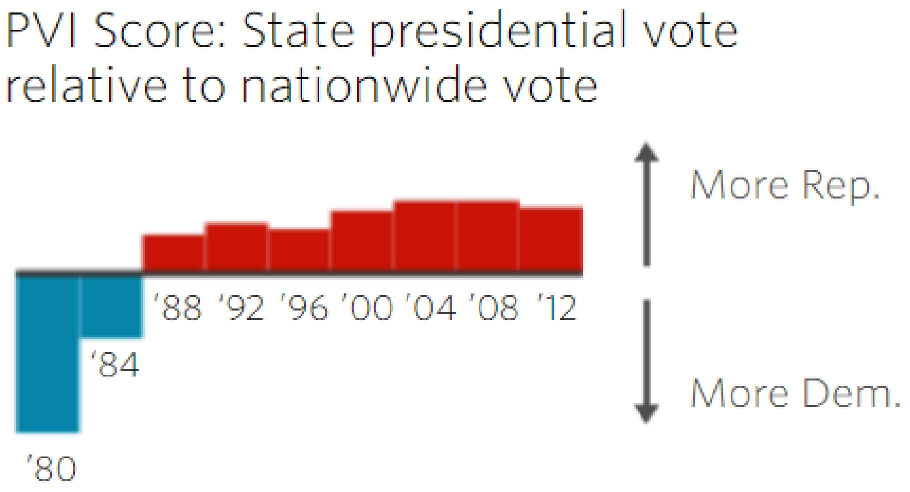
[https://youtu.be/fhbQy_NCwWI]

Small multiples



[http://graphics.wsj.com/elections/2016/field-guide-red-blue-america/]

Small multiples



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