

**(quiz)**

**(laptops)**

# Design

SI 649 W20: Information visualization

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University of Michigan

Portions of slides adapted from Eytan Adar

# This week

Lecture

Design

Lab

Group project proposal critiques

**Reminder: Last Altair lab due next week**

The extra week is because **web stuff is annoying**

Use the time!

# Remaining labs...

...are design labs, largely **in-class**.

From here on out, **sit with your project group** in lab

# Design!

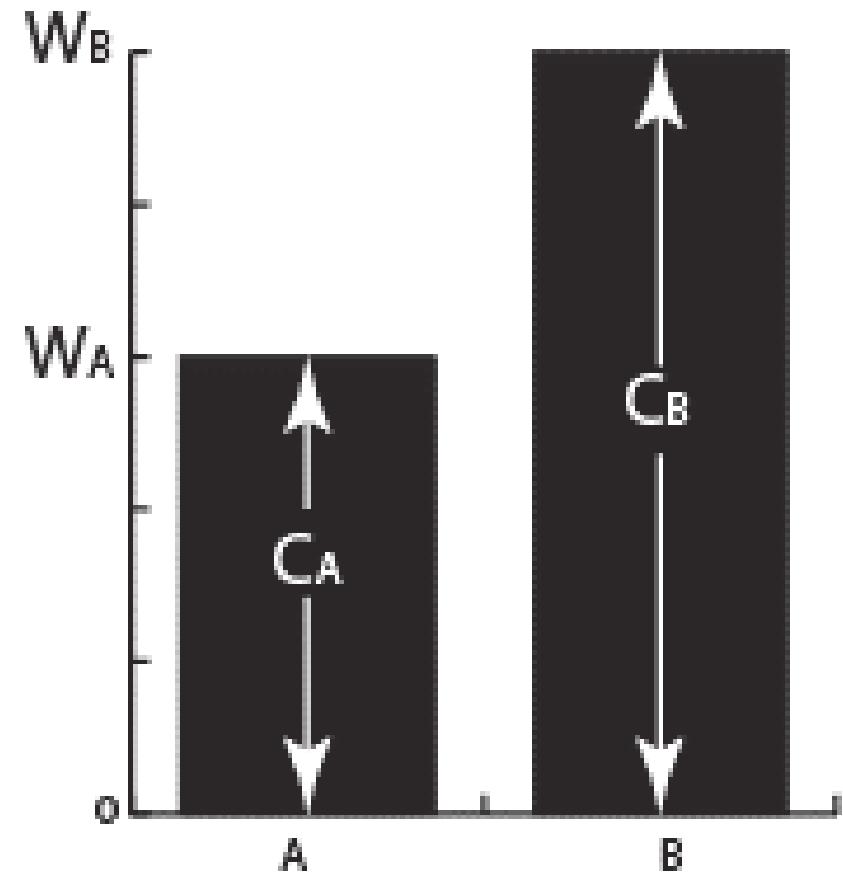
Let's talk Tufte for a bit:  
**lie factors** and **data-ink ratios**

# Lie factor =

size of effect in graphic  
size of effect in data

Don't overthink this:  
usually **you want it to be  $\approx 1$**

Connects back to **effectiveness**



# Lie factor (quiz)

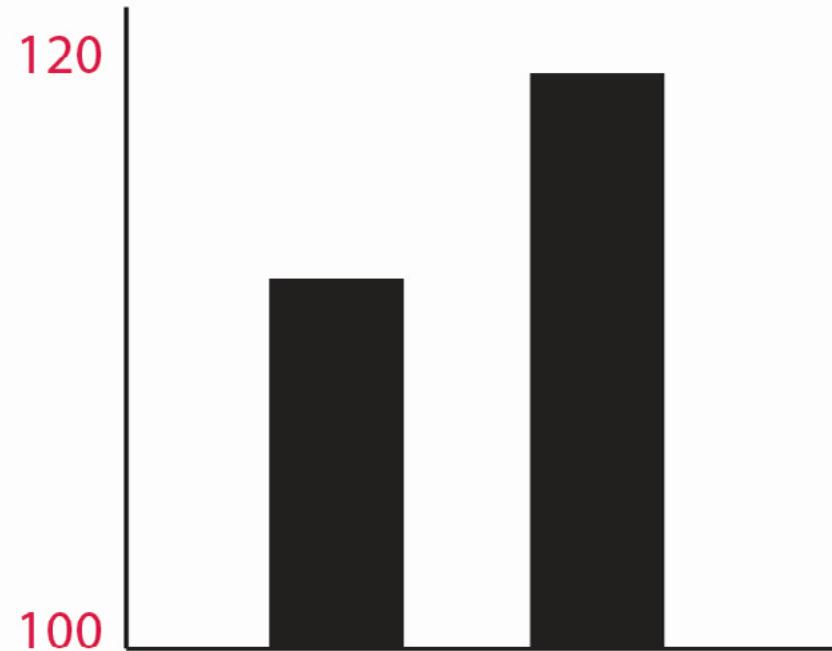


CHART A

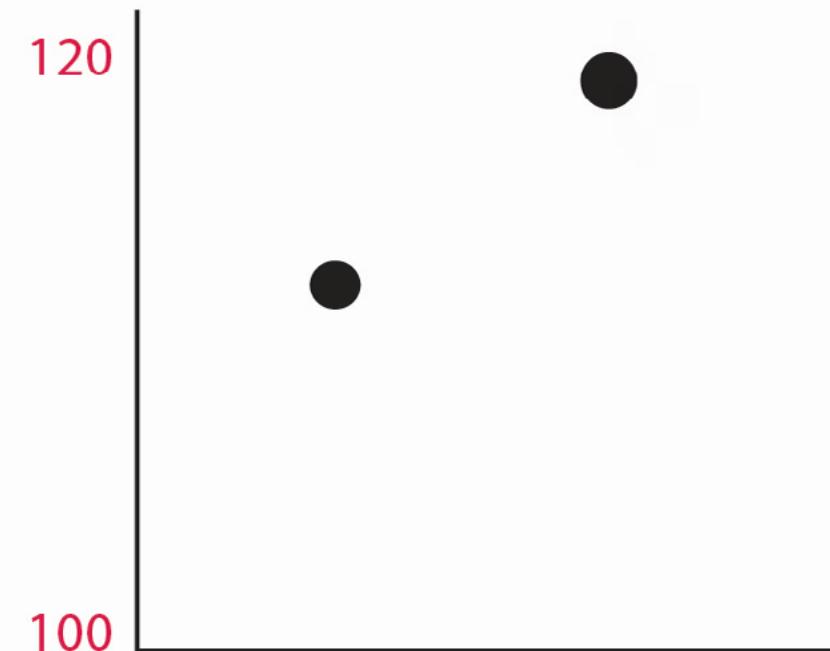
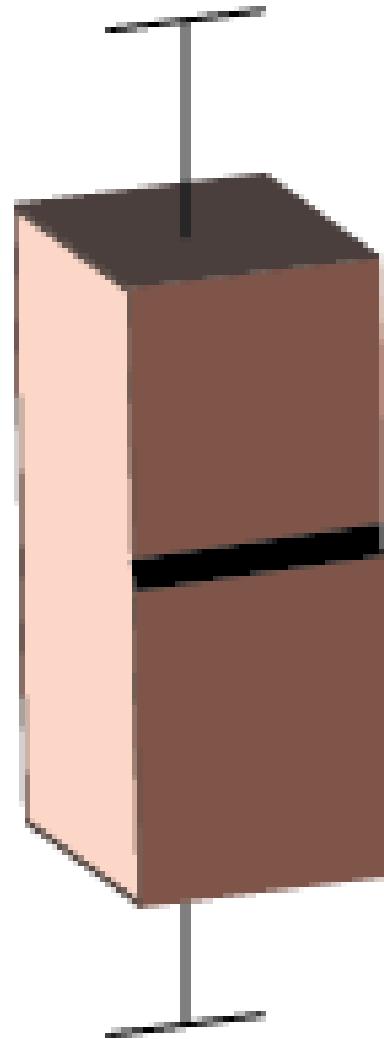


CHART B

# Data-ink ratio

**Group activity:** maximize the data-ink ratio of this 3d boxplot. E.g.:

1. Remove redundant / non-data ink
2. Refine the design
3. Repeat



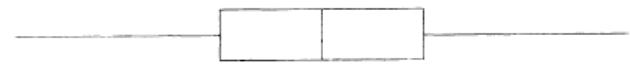
# Data-ink ratio: boxplots and mid-gap plots

These have been tested:

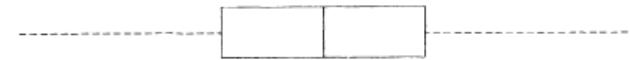
The boxplot and lineplot led  
to more accurate estimates

[<http://dx.doi.org/10.3102/10769986016001001>]

Panel 1: Box-and-whisker plot



Panel 2: Schematic plot



Panel 3: Line plot



Panel 4: Mid-gap plot



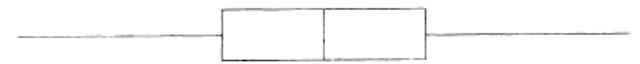
# Data-ink ratio: boxplots and mid-gap plots

Limited expressiveness,  
Tufte-esque or otherwise

Many other, usually better, options  
for visualizing distributions...

(Hint: may be helpful for Individual Assignment)

Panel 1: Box-and-whisker plot



Panel 2: Schematic plot

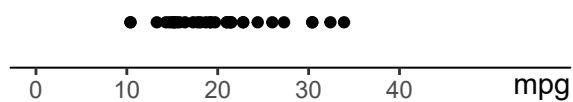


Panel 3: Line plot

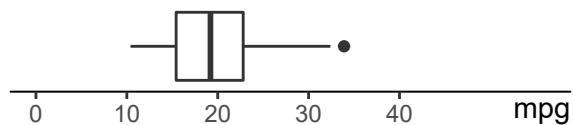


Panel 4: Mid-gap plot

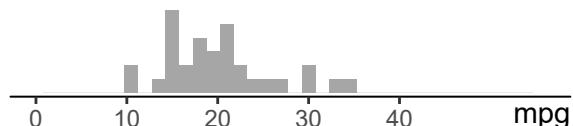




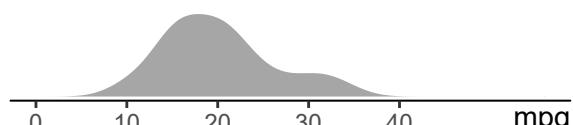
Raw data



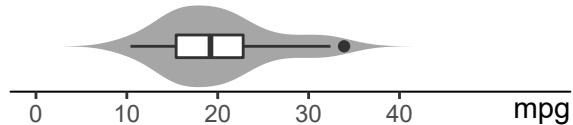
Boxplot



Histogram

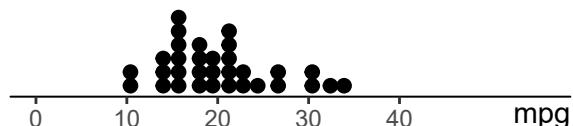


Density plot



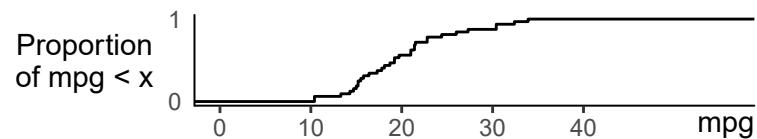
Violin plot

(or similar: “bean plot”)



(Wilkinson) dotplot

(or similar: “beeswarm”)



Cumulative distribution function (CDF)

# **Is the data-ink ratio a good design guideline?**

# Is the data-ink ratio a good design guideline?

It is **sensitive** but not **specific**  
(lots of false positives, hard to tell when to stop)

Better to rely on principles like **effectiveness** and  
**avoiding ambiguity**

The data-ink ratio is better thought of as a minimalist aesthetic guideline that you should feel free to disagree with (I often do!)

Tufte is a minimalist...





Okay okay,  
Lie factors should be about 1,  
Don't take data-ink ratios too seriously,  
What **should** I do?

# 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

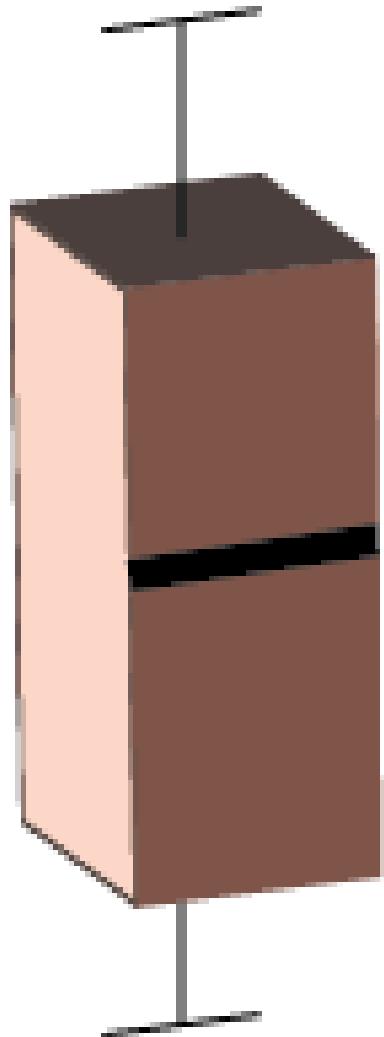
\* These guidelines are drawn largely from my experience + personal preferences + the literature. Design is messy, these are not perfect, others will disagree with me, etc. *Caveat emptor.*

# **1. (Match effectiveness with importance)**

(see also, Perception lecture)

## 2. Avoid ambiguity

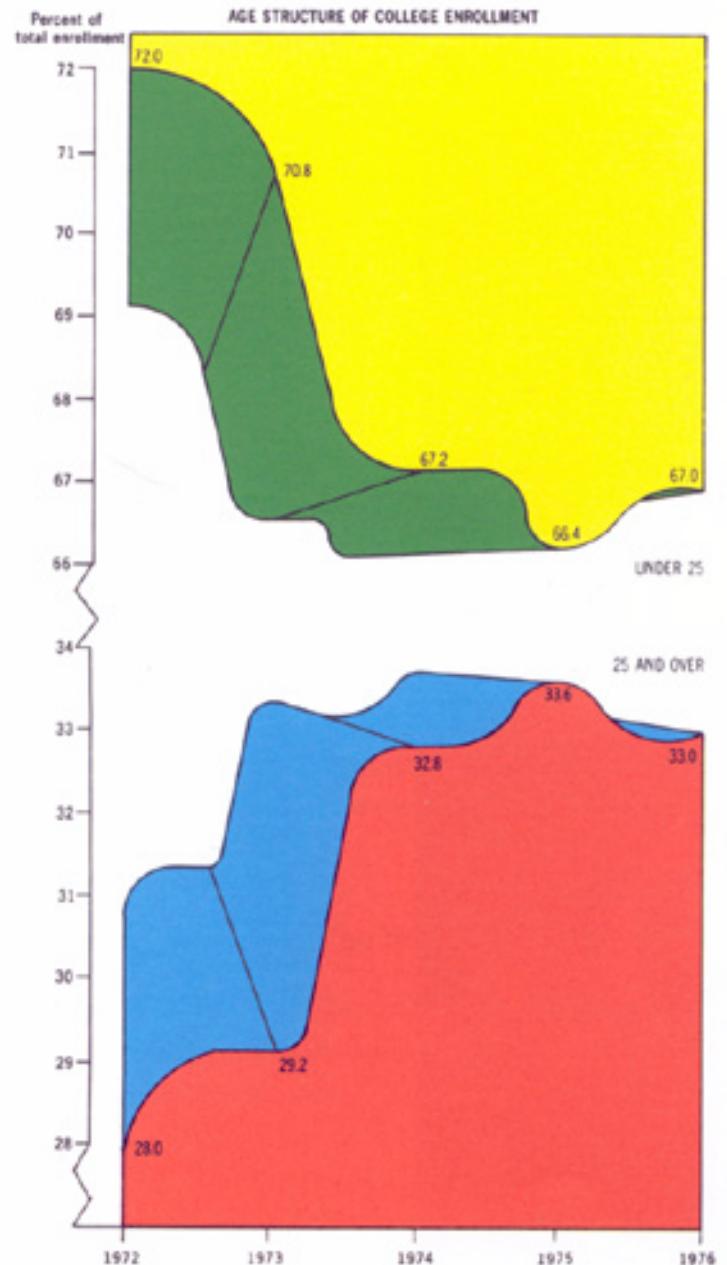
Most of the **correct** changes you make due to the data-ink ratio amount to this



## 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

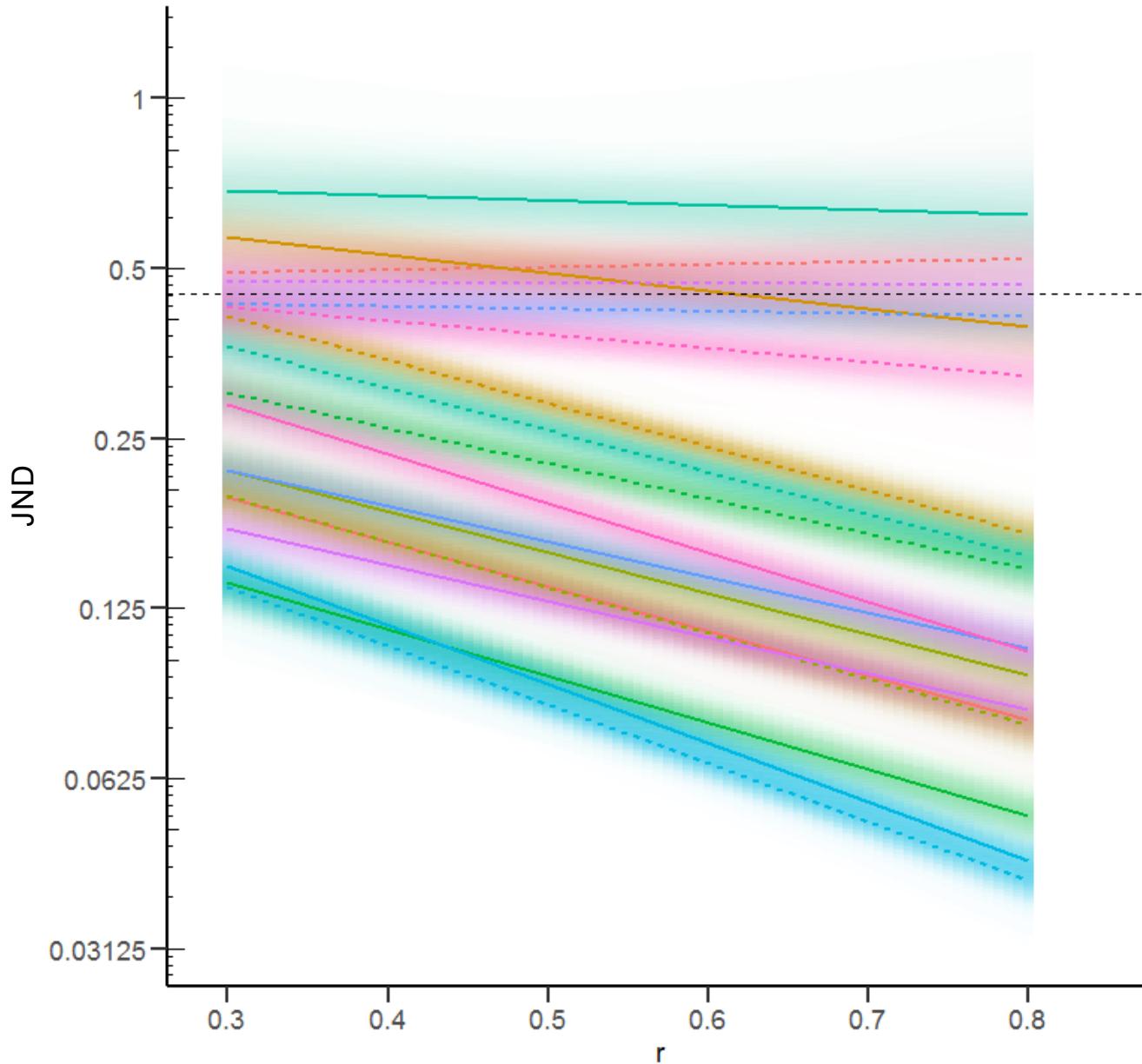
Yes:

Thing



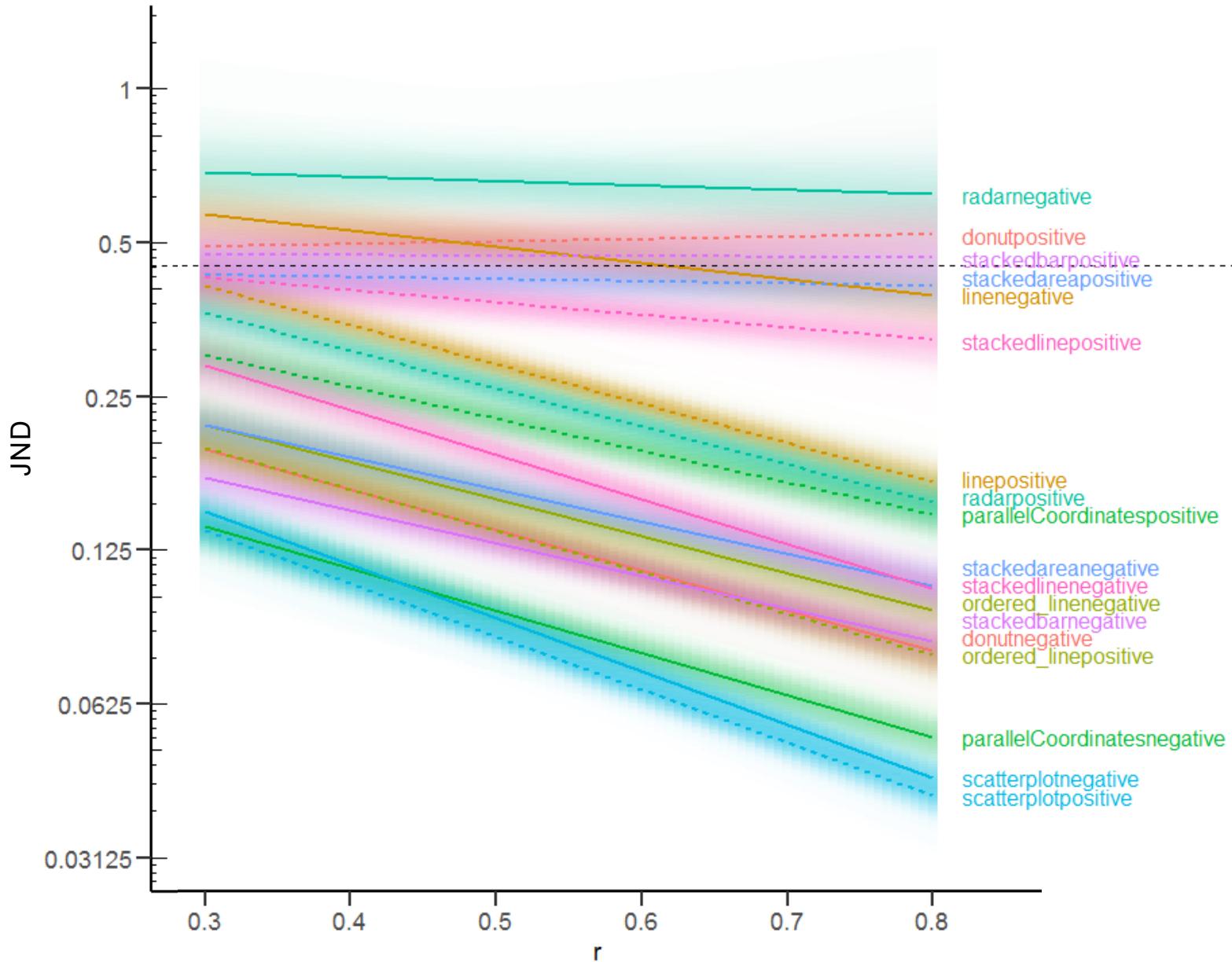
Information I need  
to understand thing

# No

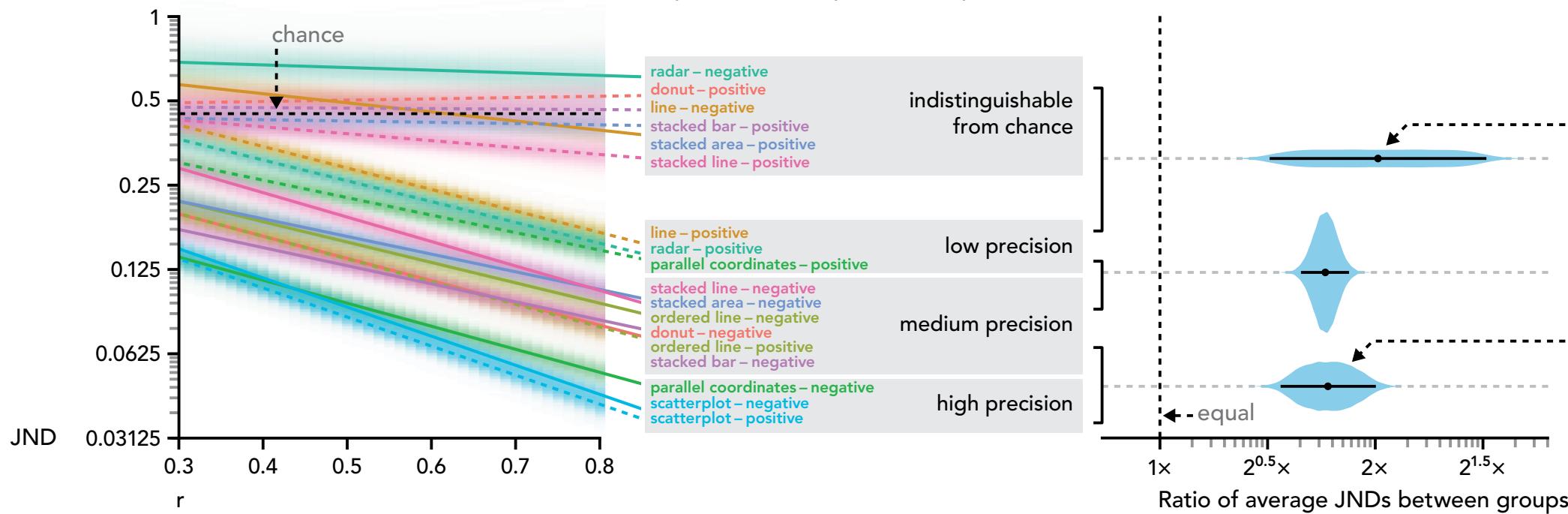


- sign**
- negative
  - positive
- vis**
- donut
  - line
  - ordered\_line
  - parallelCoordinates
  - radar
  - scatterplot
  - stackedarea
  - stackedbar
  - stackedline

# Yes

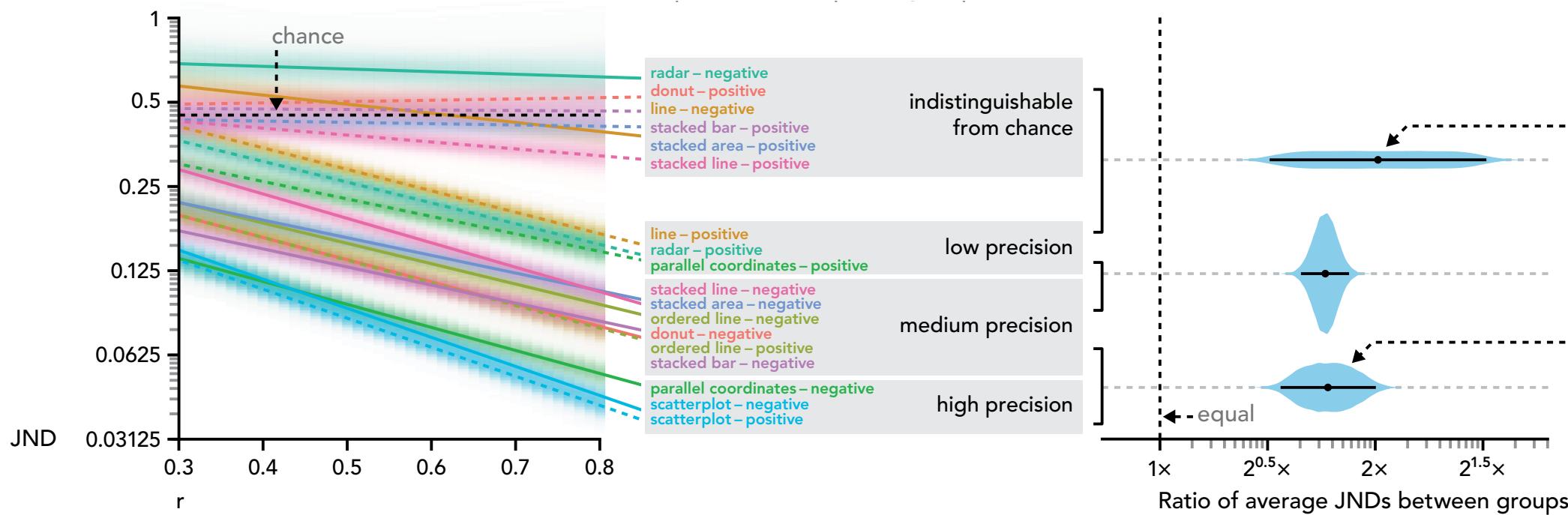


# No



The left panel shows the Bayesian censored log-linear model, which gives us a posterior probability distribution over the mean  $\log(\text{JND})$  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 successive 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.

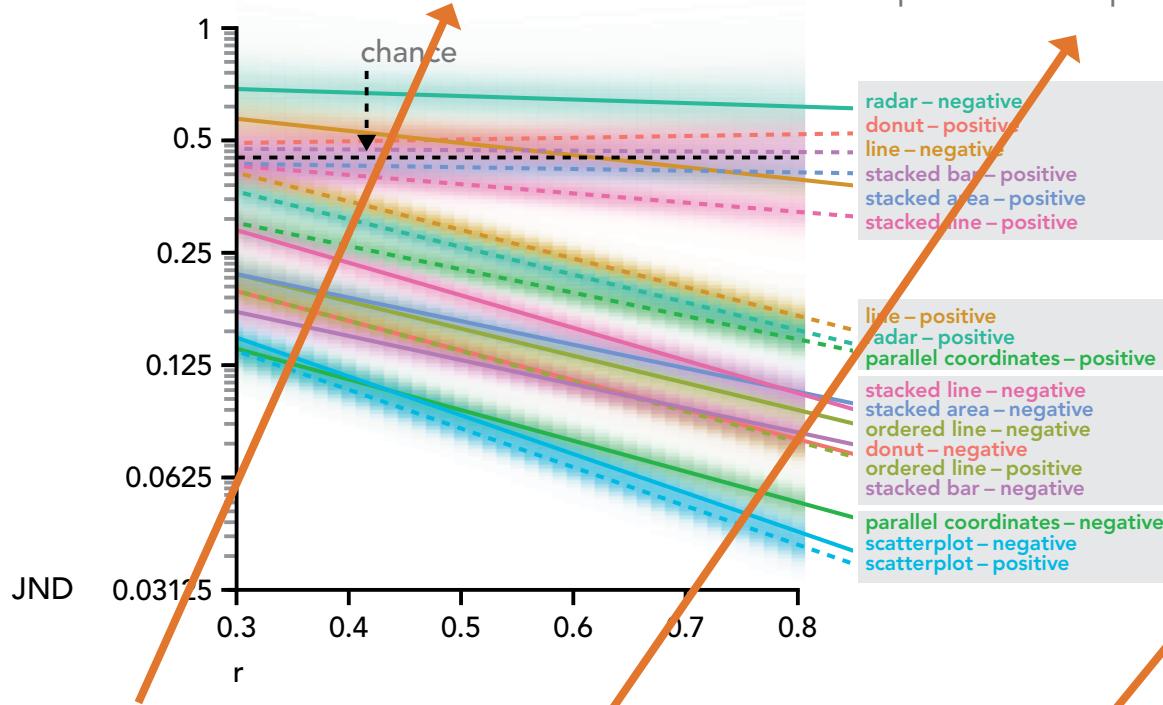
# No



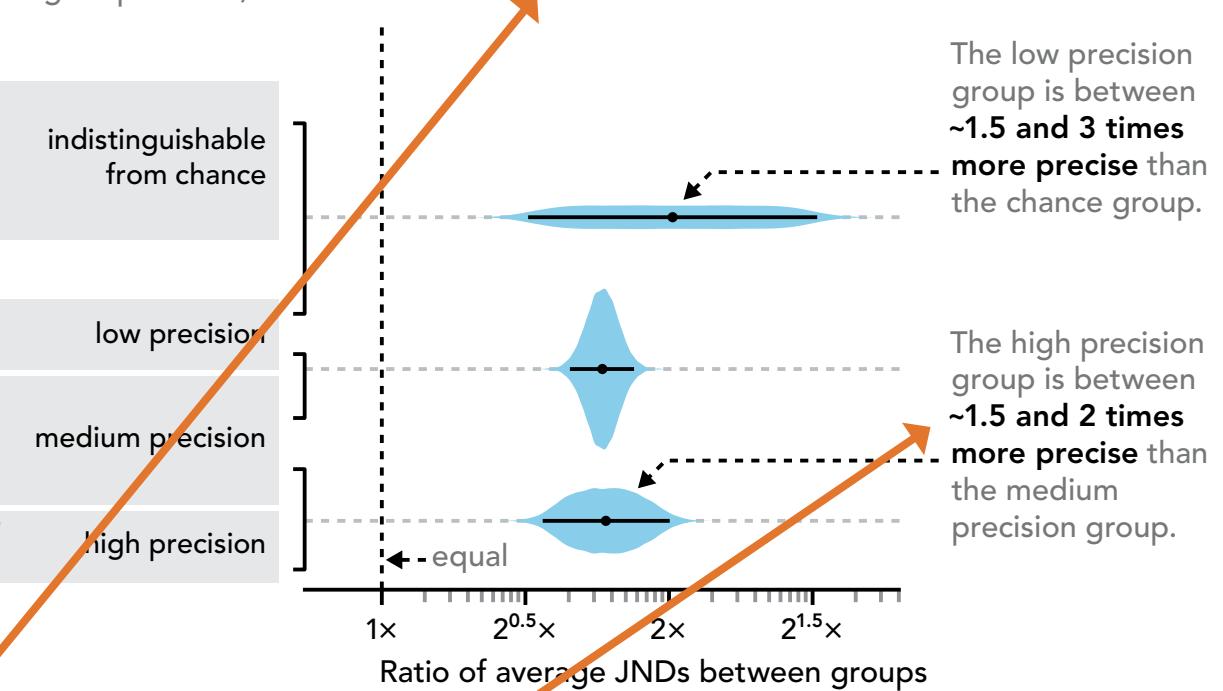
The left panel shows the Bayesian censored log linear model, which gives us a posterior probability distribution over the mean  $\log(JND)$  for each value of  $r$ . In the center panel we rank and group visualizations based on how precise estimations of correlations are with them (lower expected JND implies higher precision). In the right panel we estimate the ratio of average JNDs between successive 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.

# 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)



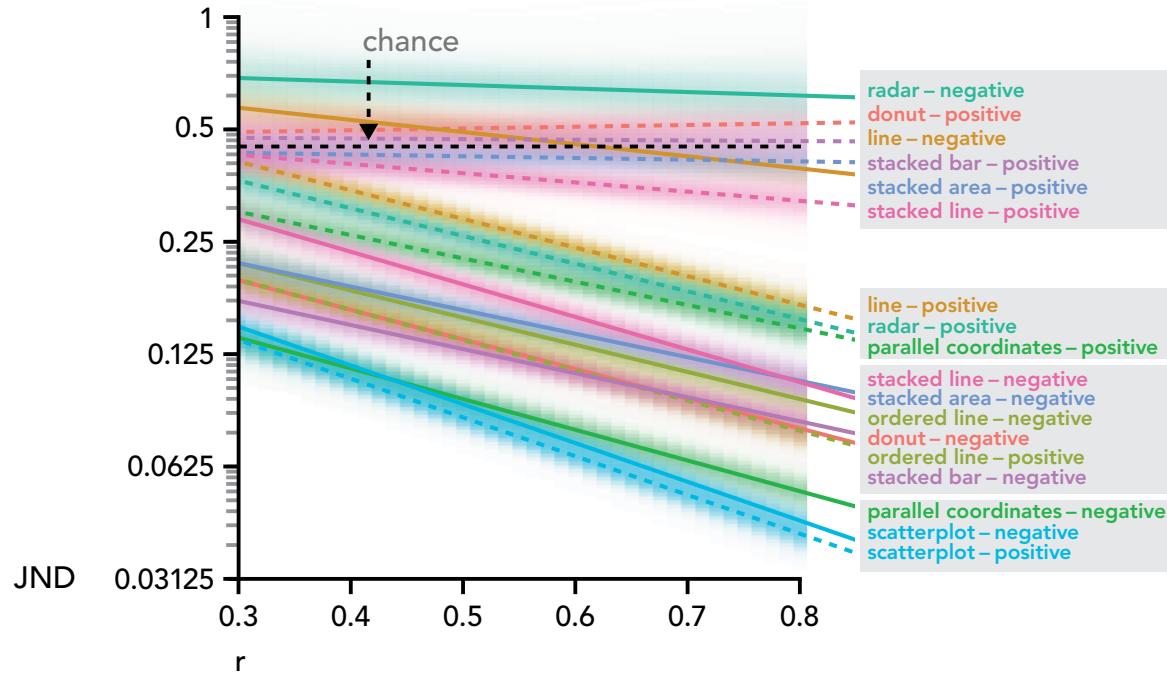
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The low precision group is between **~1.5 and 3 times more precise** than the chance group.

The high precision group is between **~1.5 and 2 times more precise** than the medium precision group.

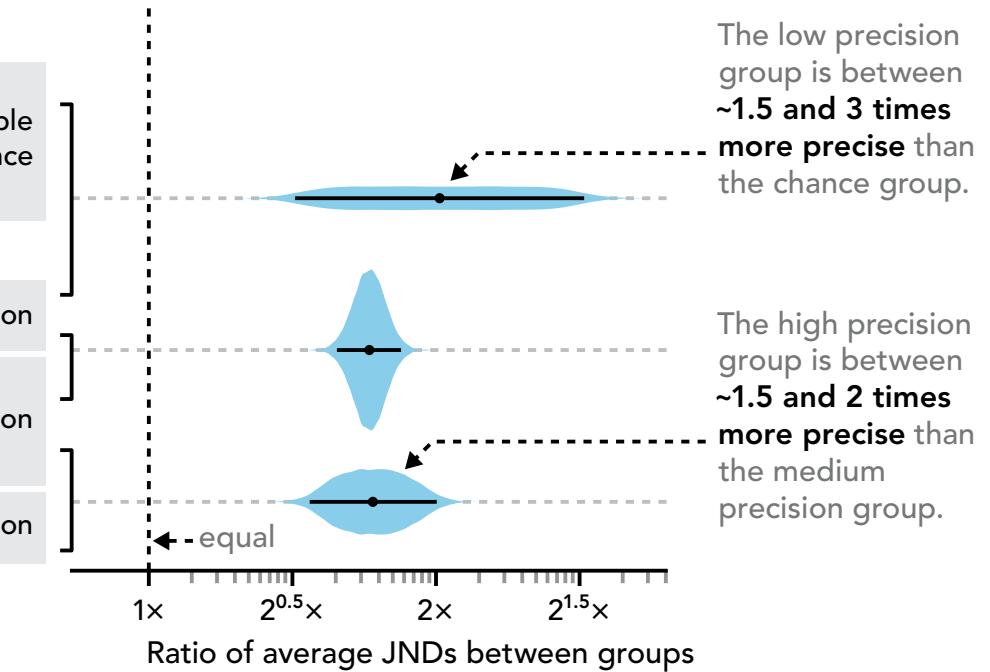
# Yes

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.



### **3. Locality is king / eyes beat memory**

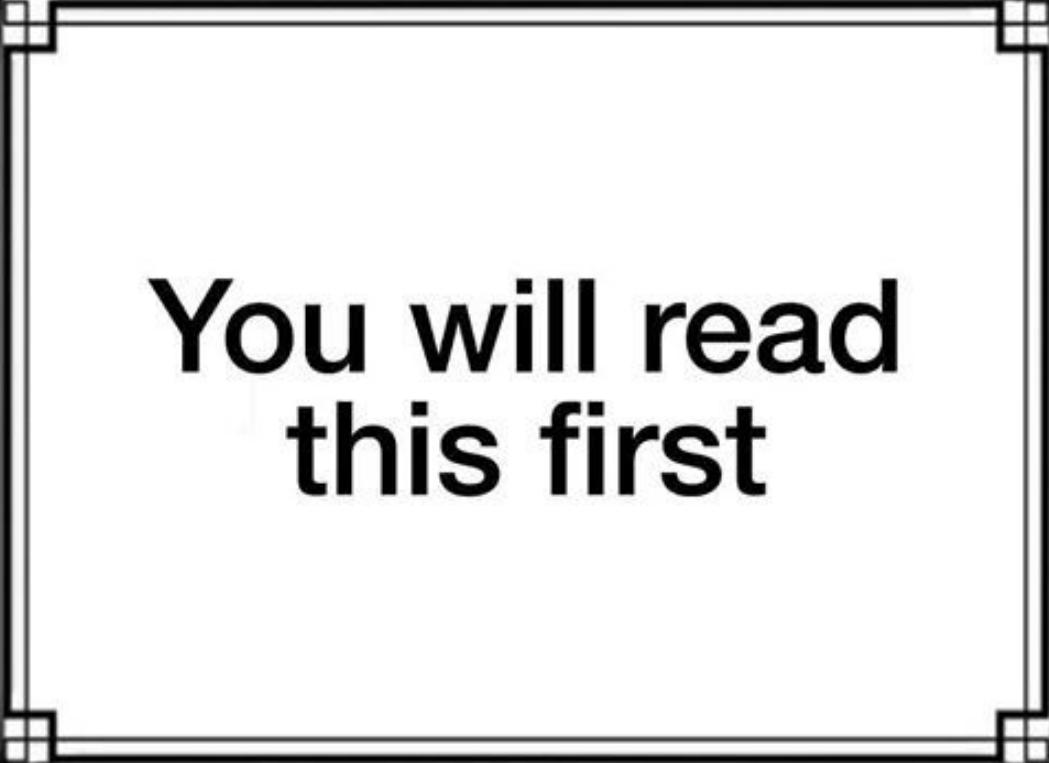
Implies **animation / interaction can make things worse**  
(though they are often useful)

E.g.: If the comparison you want is in a tooltip, you have to remember values to make comparisons

**Count lookups!**

# **4. Establish viewing order**

And you will read this at the end



You will read  
this first

And then you will read this

Then this one

## 4. Establish viewing order

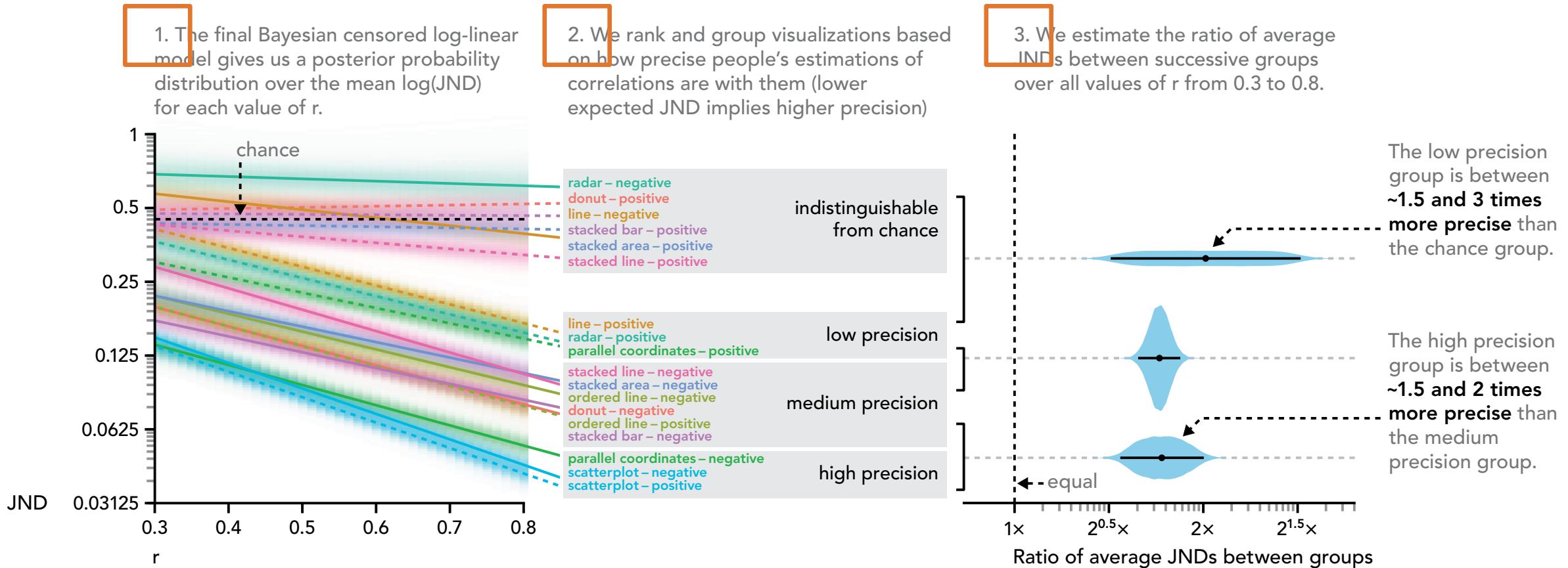
Know where your audience will look first, second.

Remember salience from perception.

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

# 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



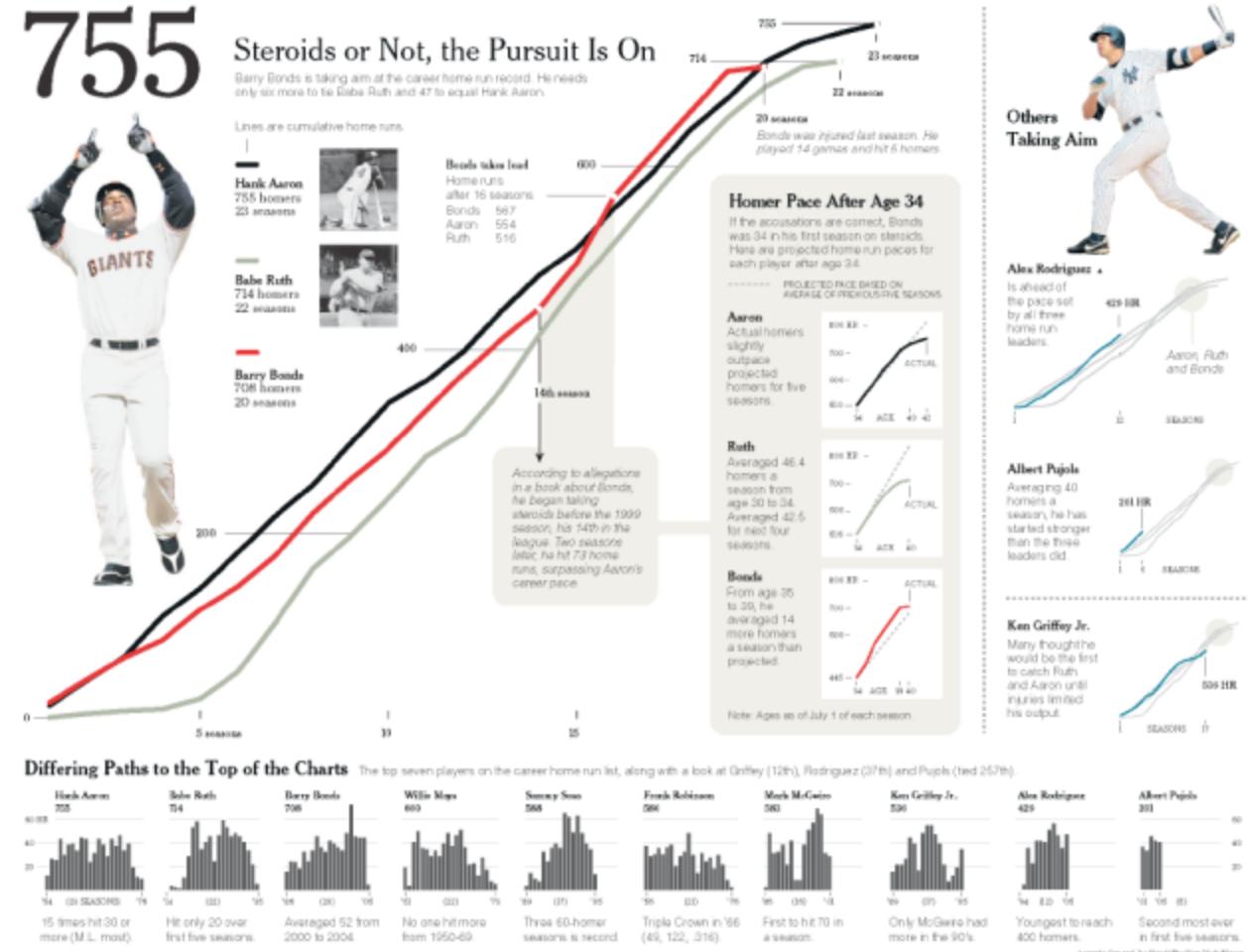
You will read  
this first

And then you will read this

Then this one

# 4. Establish viewing order

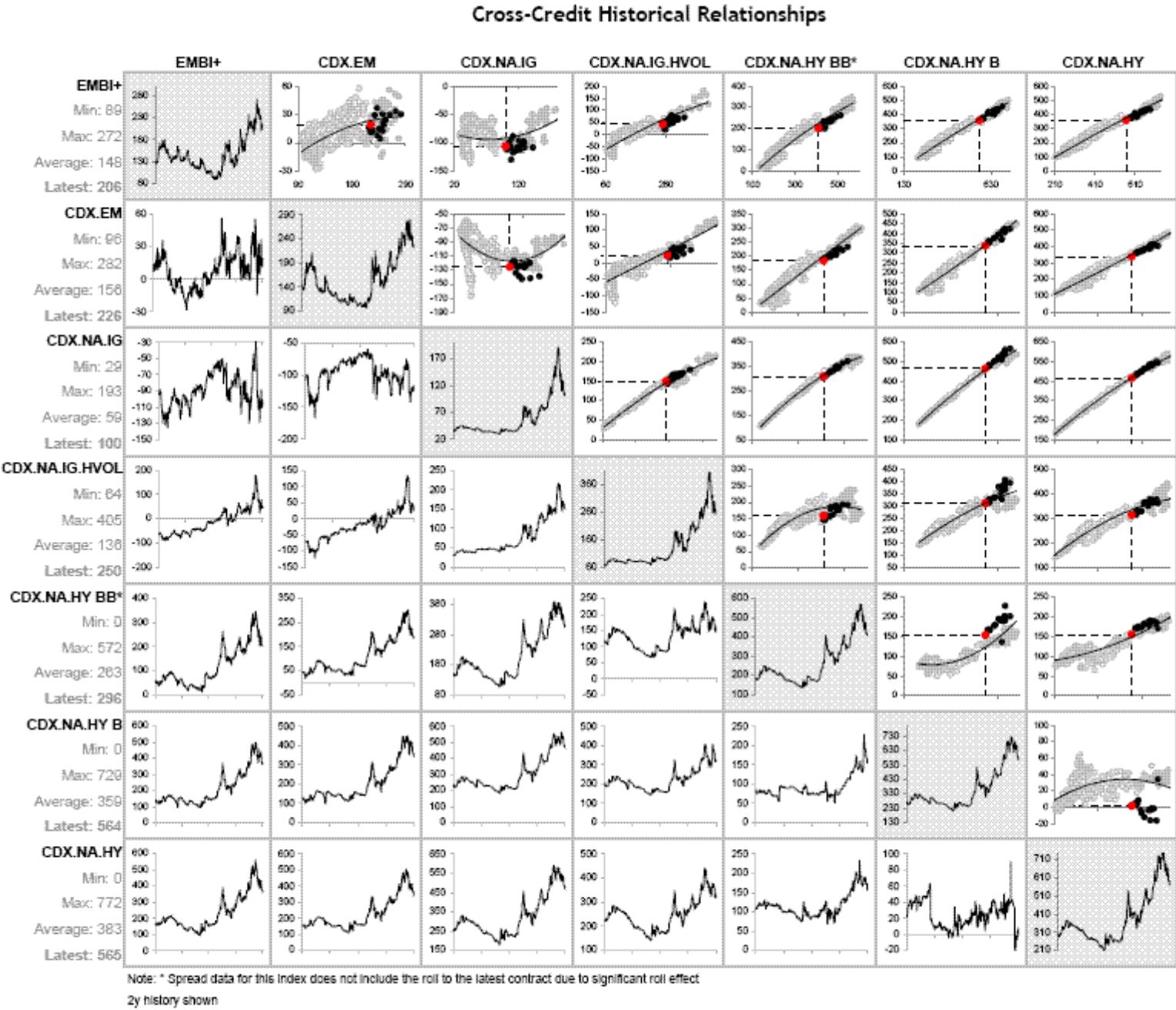
Or more complex,  
relying on **salience**,  
other visual cues,  
viewer expectations  
(maybe)



# 5. Layer, layer, layer, layer

Design for reading  
at different levels  
of detail

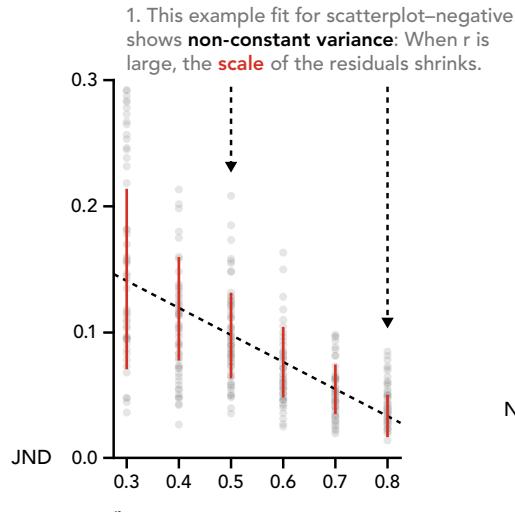
Pre-attentive  
attributes help



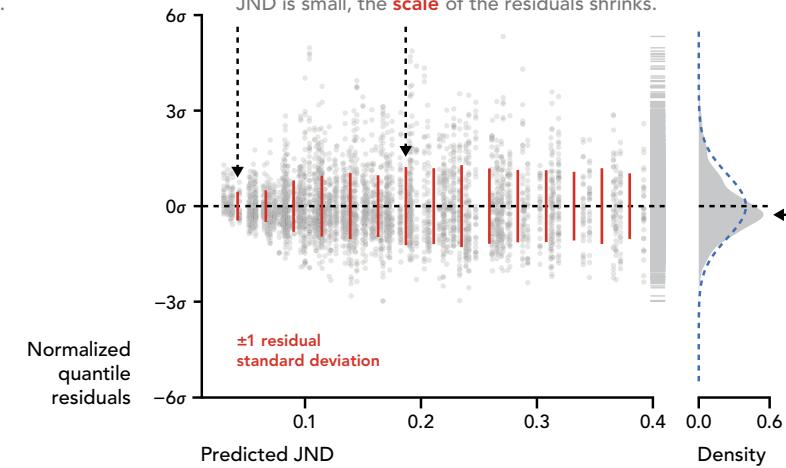
# 6. When in doubt, grid

And get  
synchronized  
axes as a bonus

## A. LINEAR MODEL

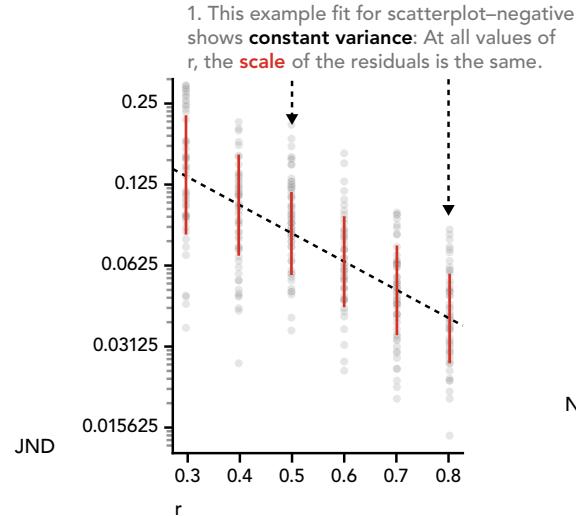


2. The combined fit for all visualizations also shows **non-constant variance**: When the predicted JND is small, the **scale** of the residuals shrinks.

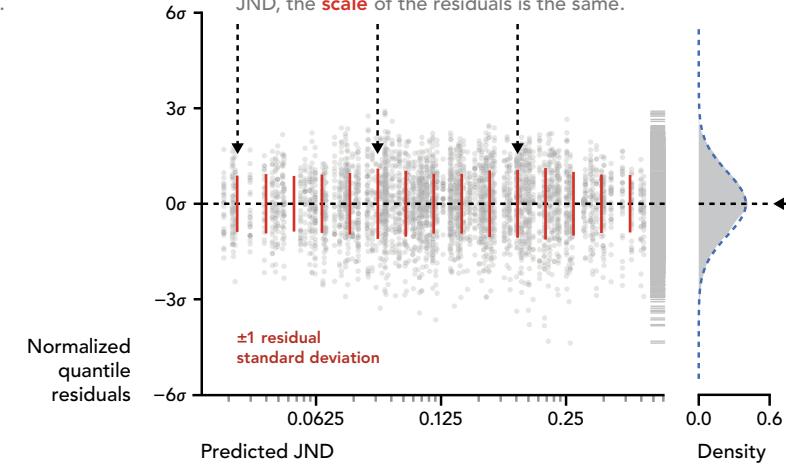


3. The distribution of the residuals is **skewed** compared to the **Normal distribution** assumed by the model.

## B. LOG-LINEAR MODEL



2. The combined fit for all visualizations also shows **constant variance**: At all values of predicted JND, the **scale** of the residuals is the same.



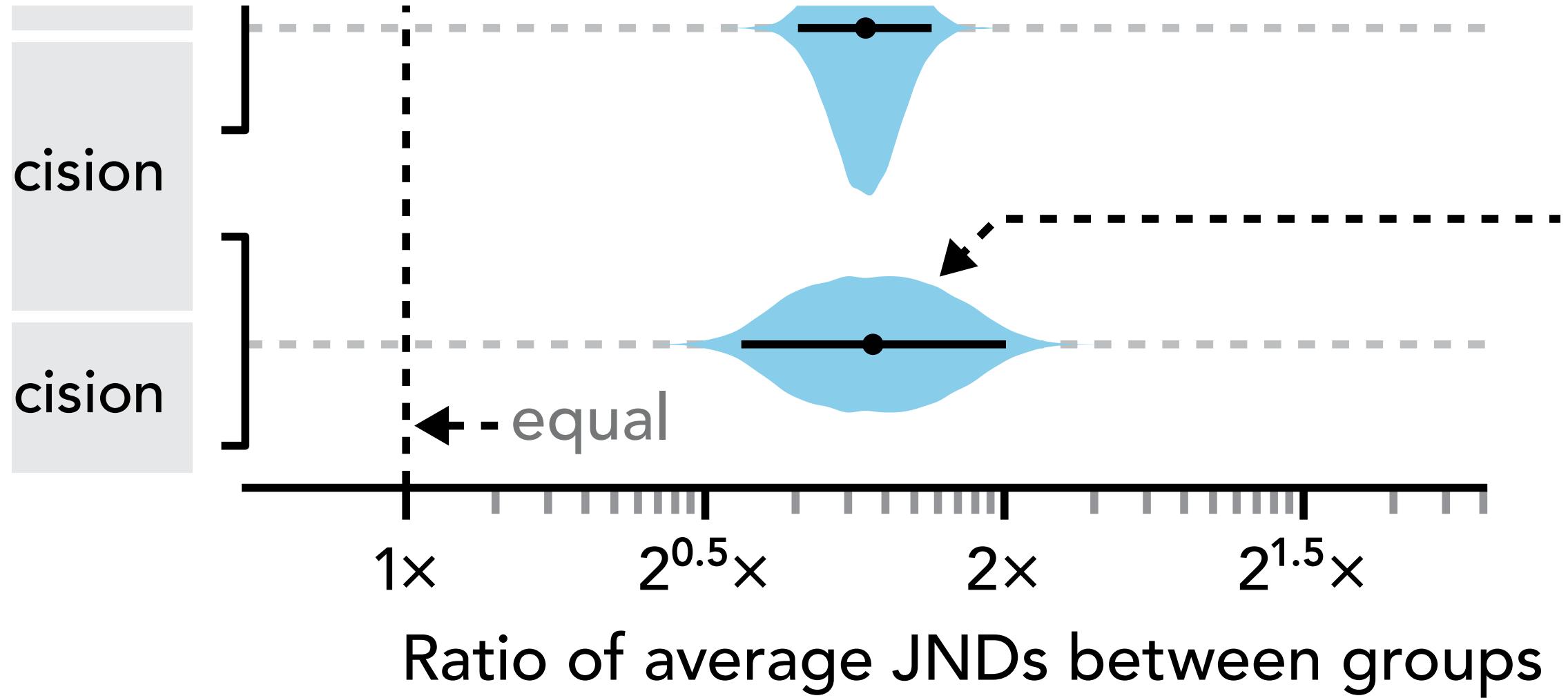
3. The distribution of the residuals more closely matches the **Normal distribution** assumed by the model.

## **7. Treat visual attributes like adjectives**

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

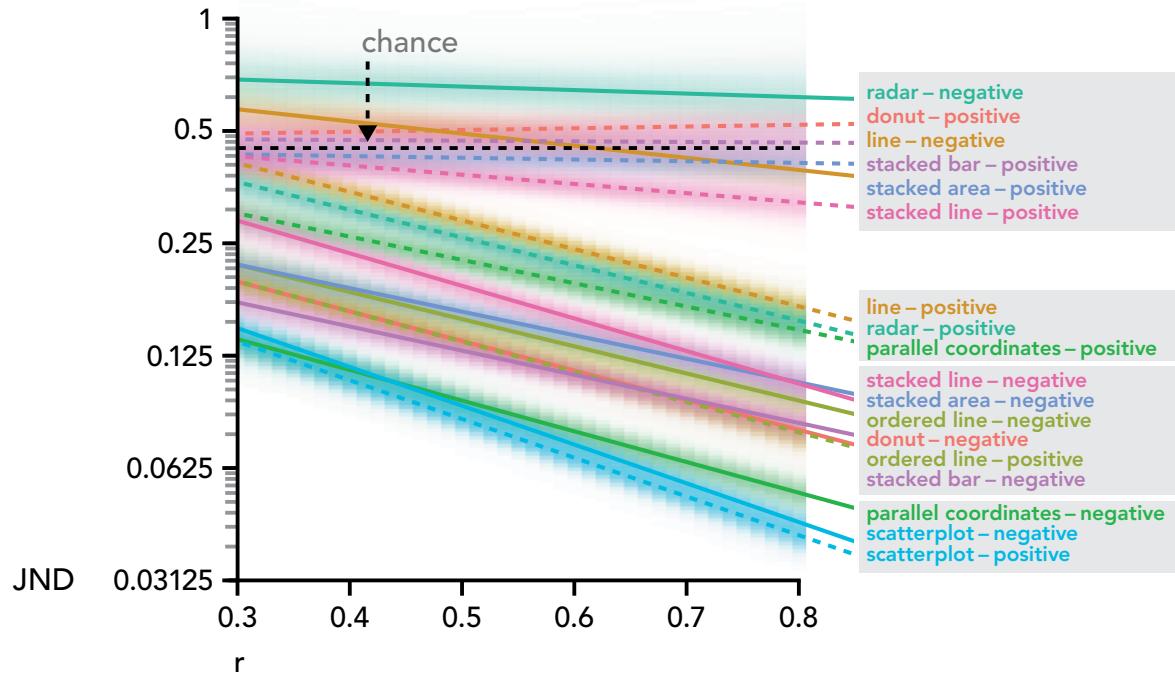
*The very tall building is very extremely tall.*

## (7b. Obey the pen)



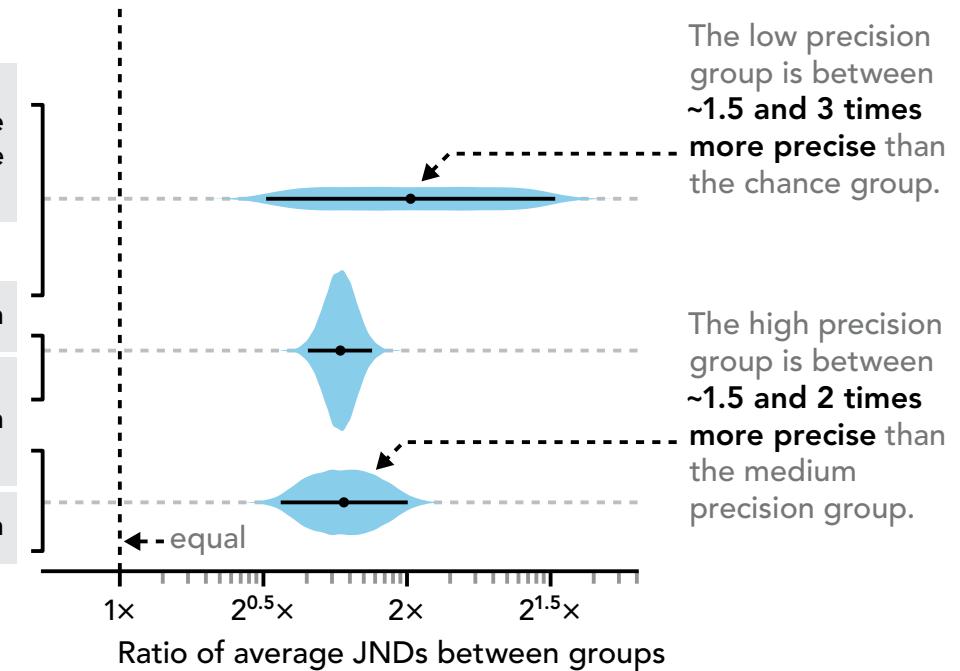
# (7b. Obey the pen)

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## (7b. Obey the pen)

Even visual texture is pleasing

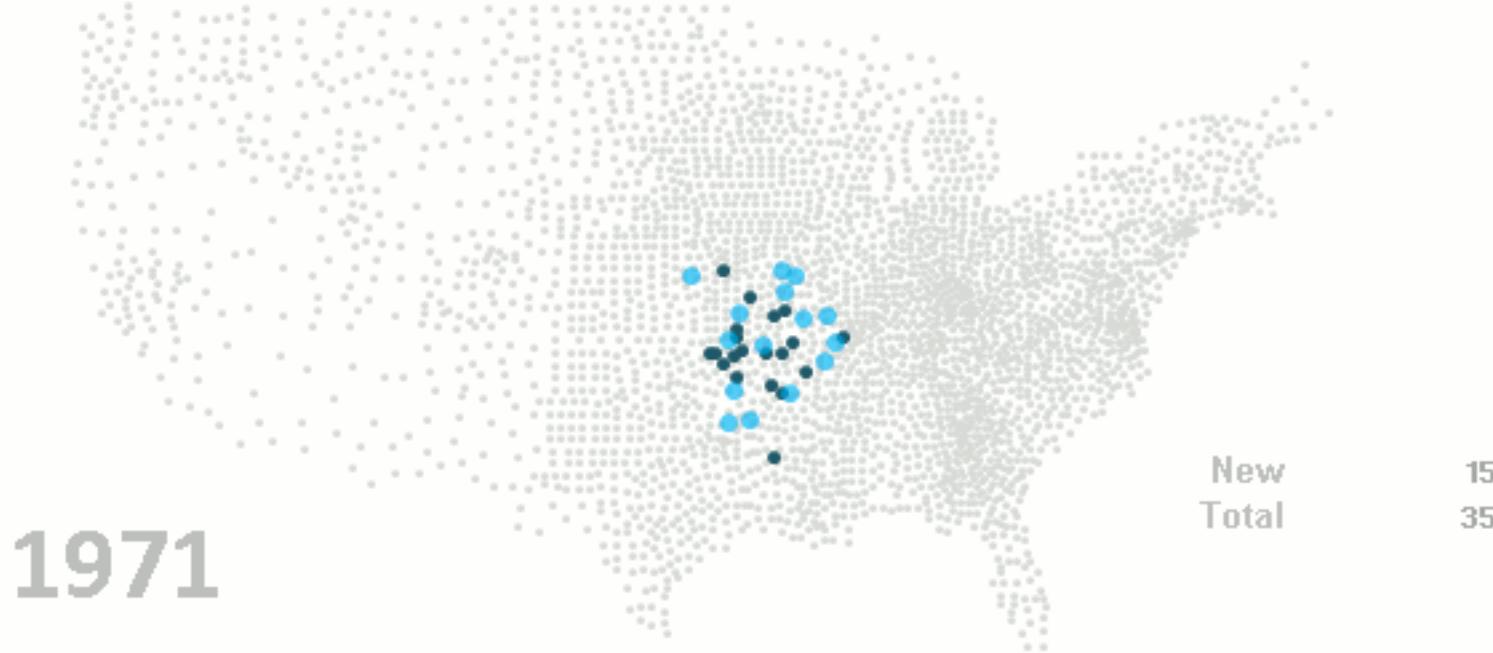
Also makes it easier to create **visual hierarchy** and call out something important when you need to

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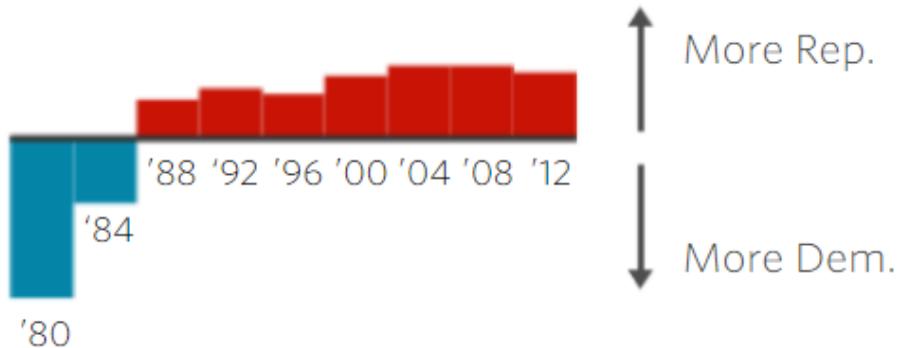
# Small multiples



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

# Small multiples

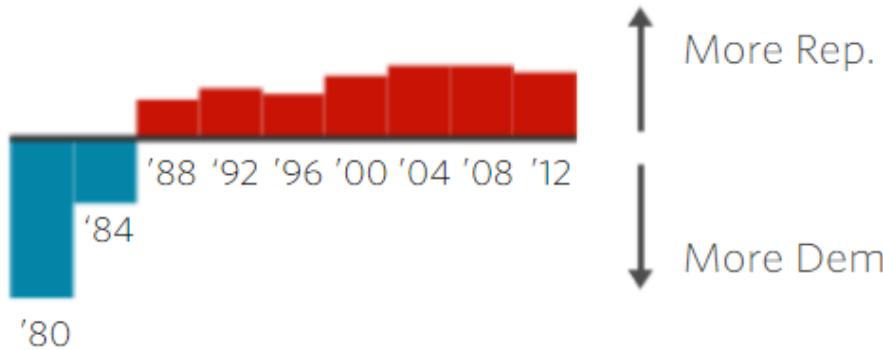
PVI Score: State presidential vote  
relative to nationwide vote



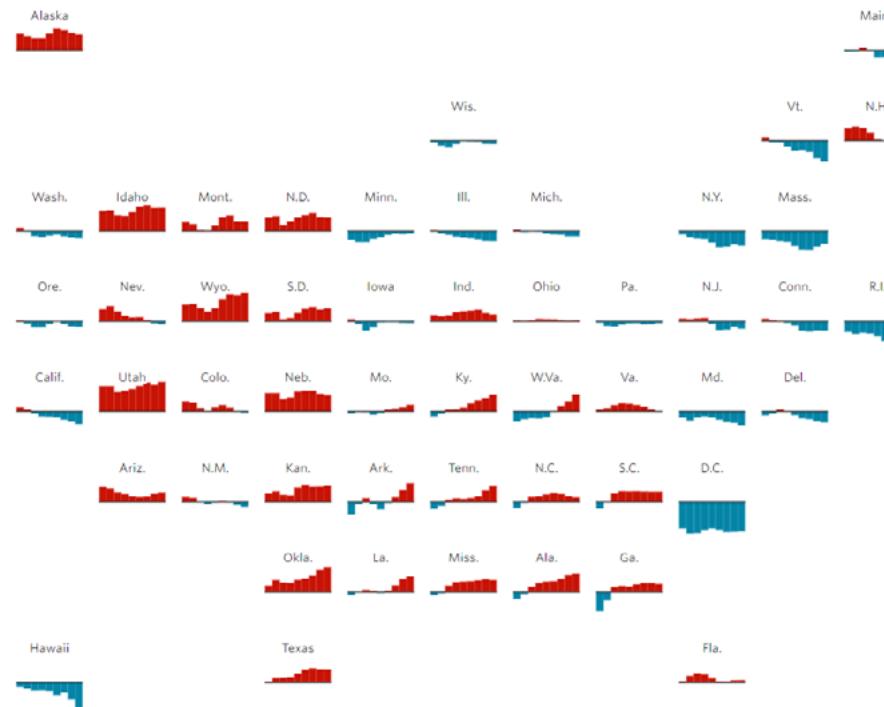
[<http://graphics.wsj.com/elections/2016/field-guide-red-blue-america/>]

# Small multiples

PVI Score: State presidential vote  
relative to nationwide vote



## A Field Guide to Red and Blue America



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