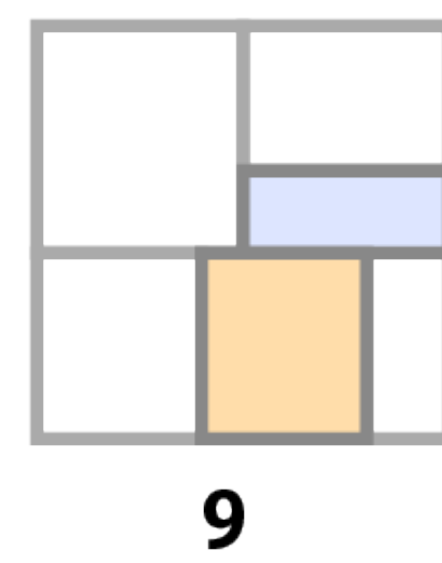
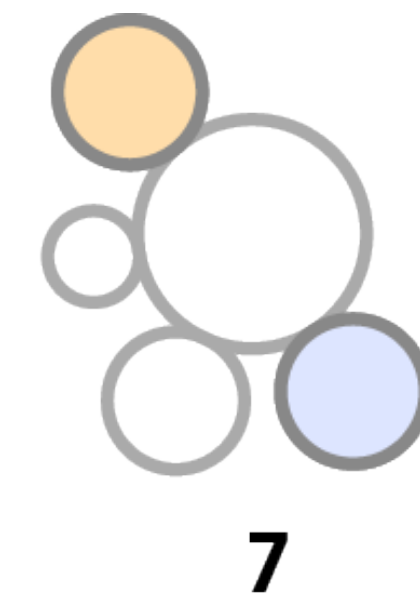
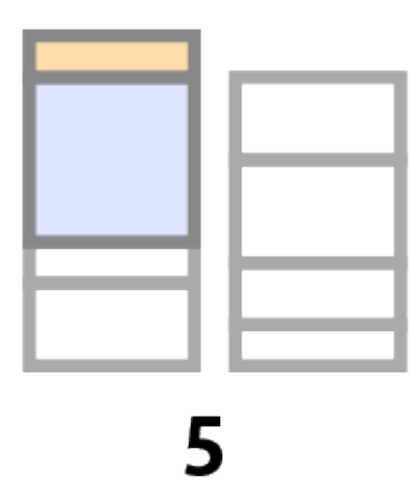
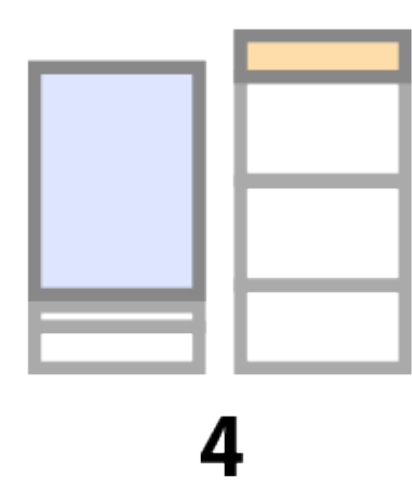
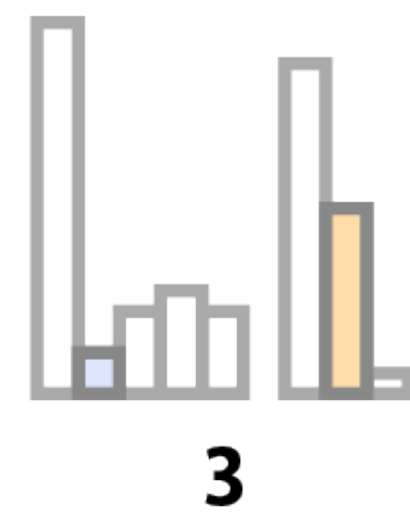
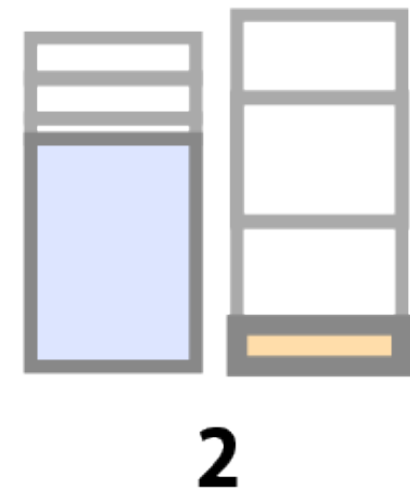
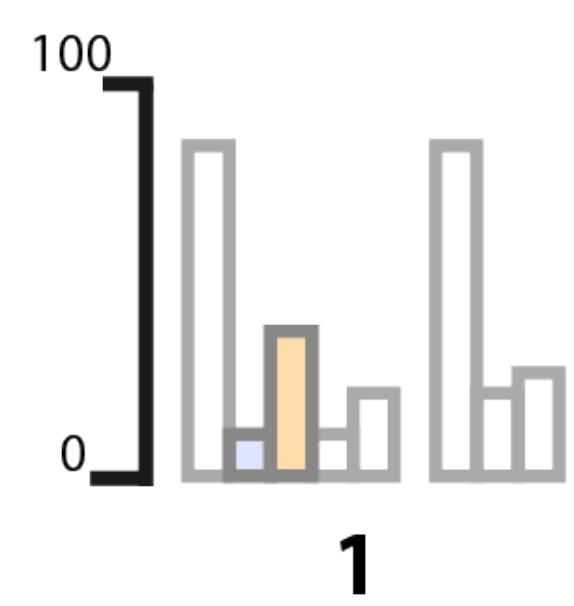




Position

Length

Angle

**Circular
Area**

Rectangular Areas

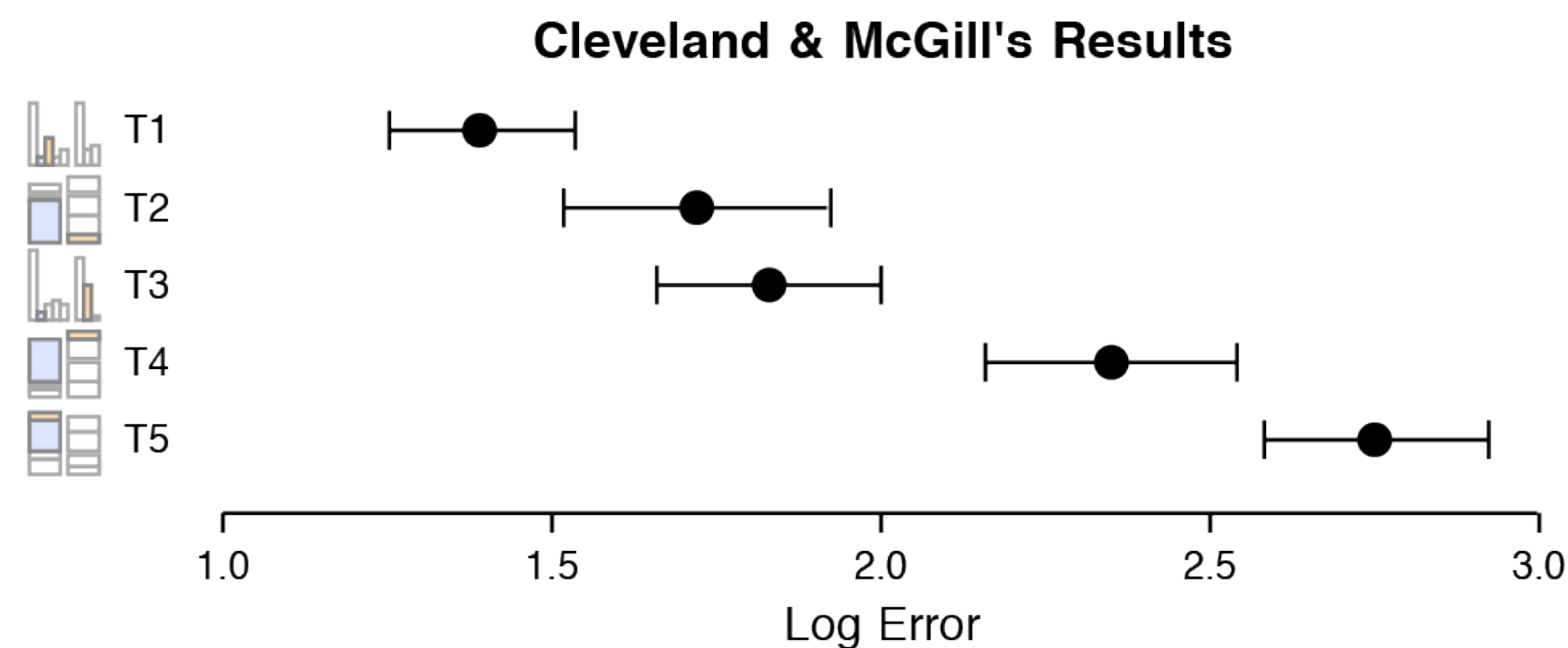
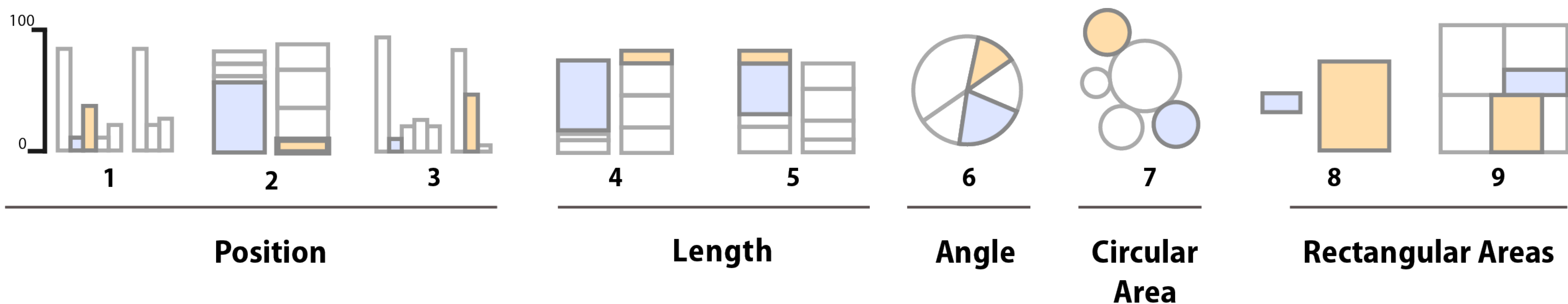
Last week

- Visualization in three phases: three “how” questions to ask
 1. ***How*** humans ***perceive*** graphical information
 2. ***How*** human perception means you should ***design*** your graphics
 3. ***How***, practically, you ***draw*** your graphics with software

Human Perceptual Efficiencies and Inefficiencies

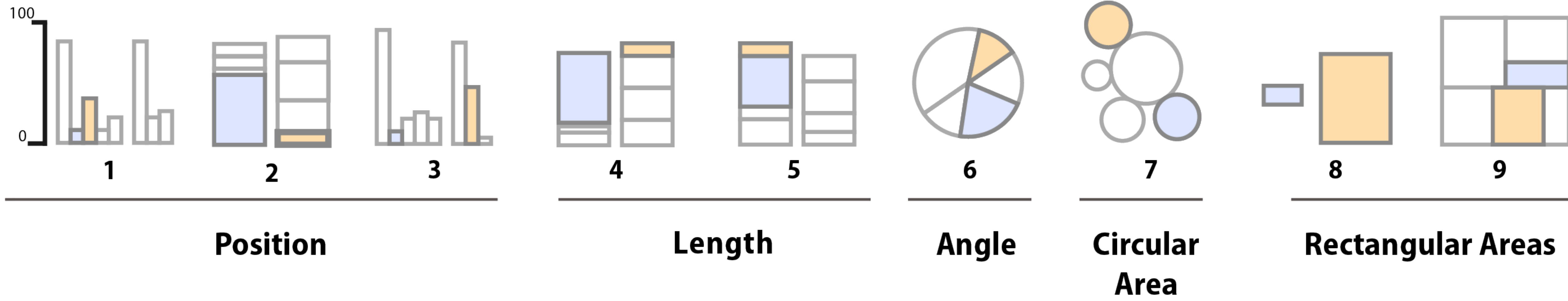
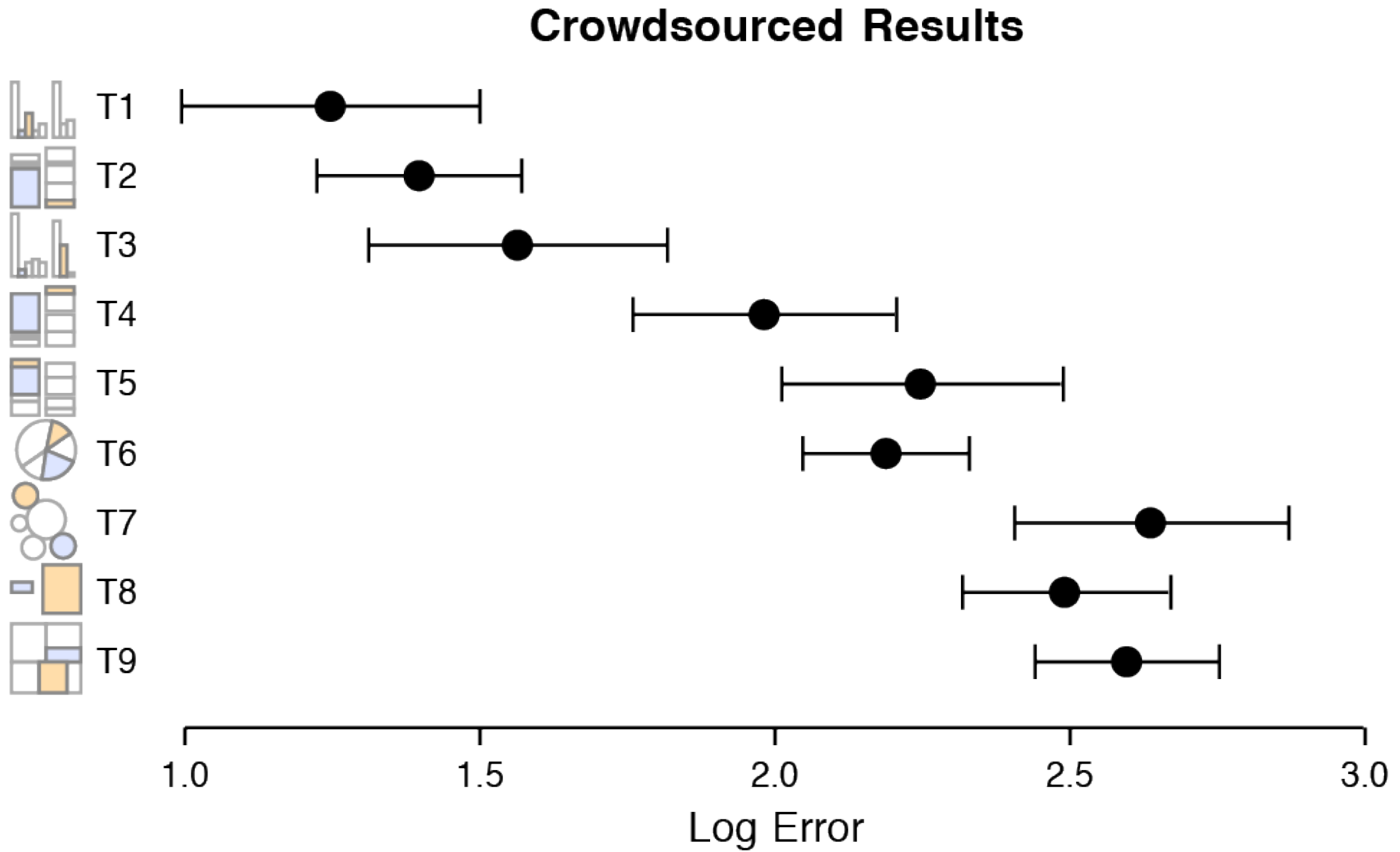
Ease and efficacy of perceptual tasks

- Another representation (Healy, 2019)



Replicated

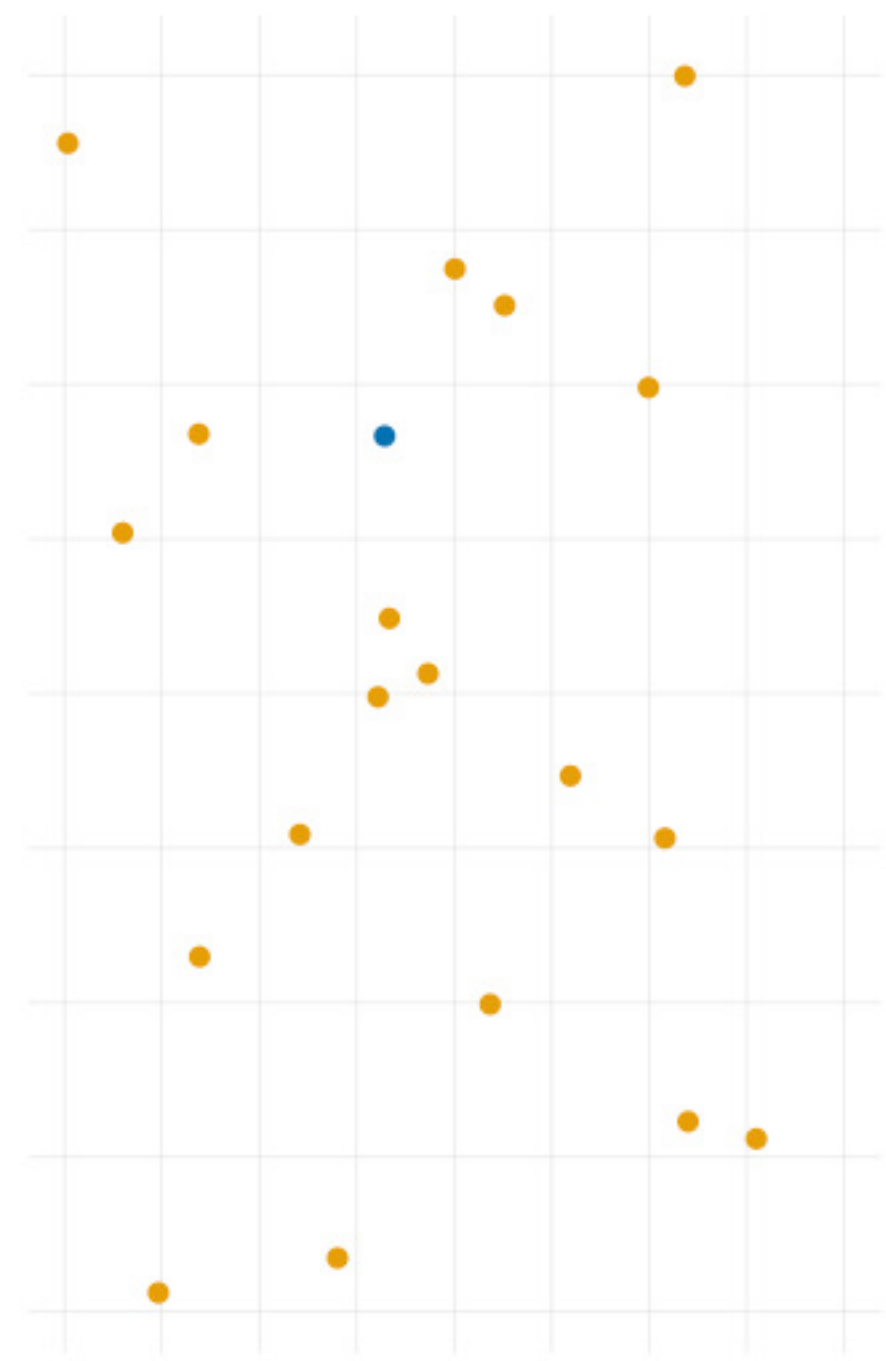
- Heer and Bostock (2010)
- Note the continued strength, especially, of position on a scale



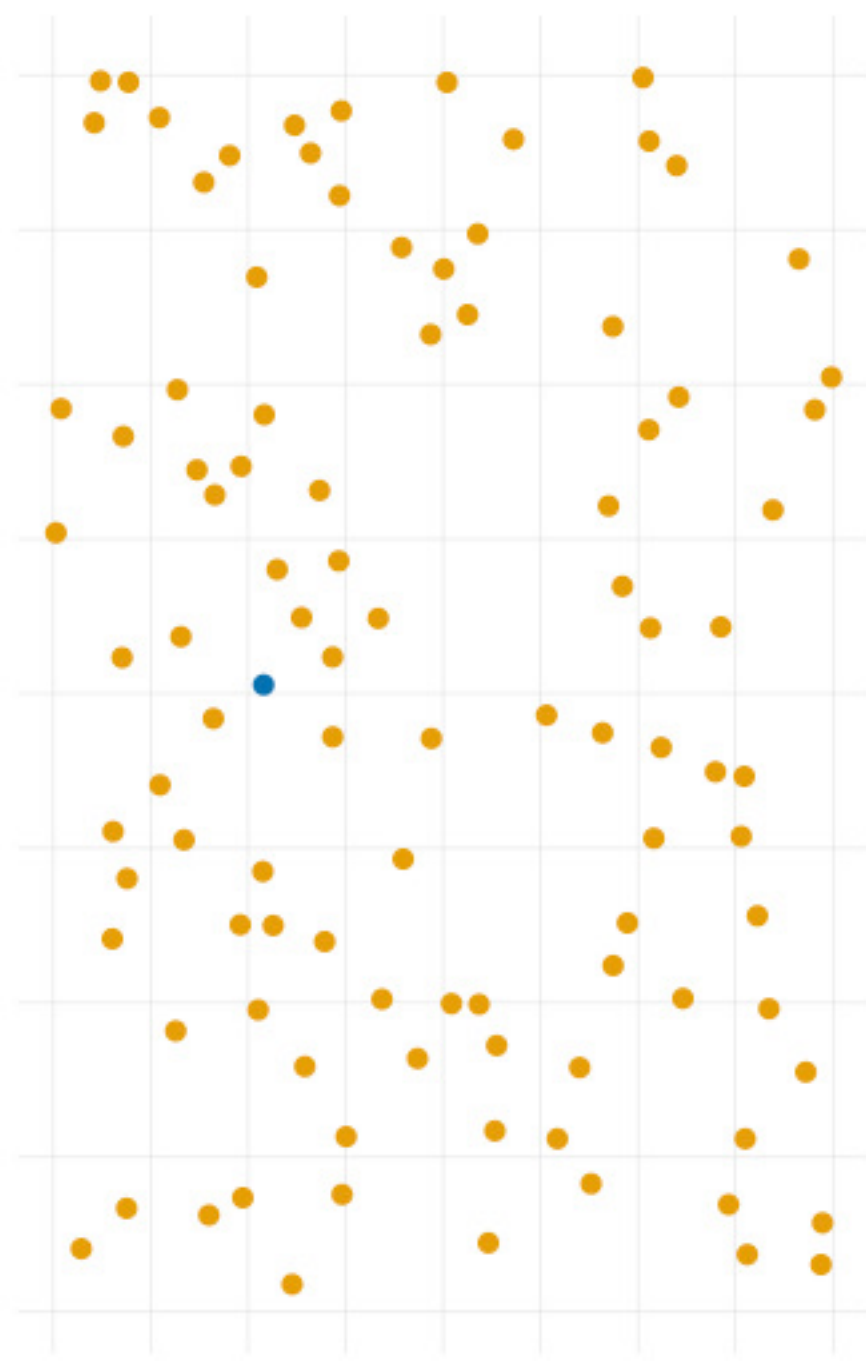
Drawing attention (Healy, 2019)

- While color and shape is *not* always effective for conveying scale
 - They can be useful for drawing attention to points, but mind cognitive capacities

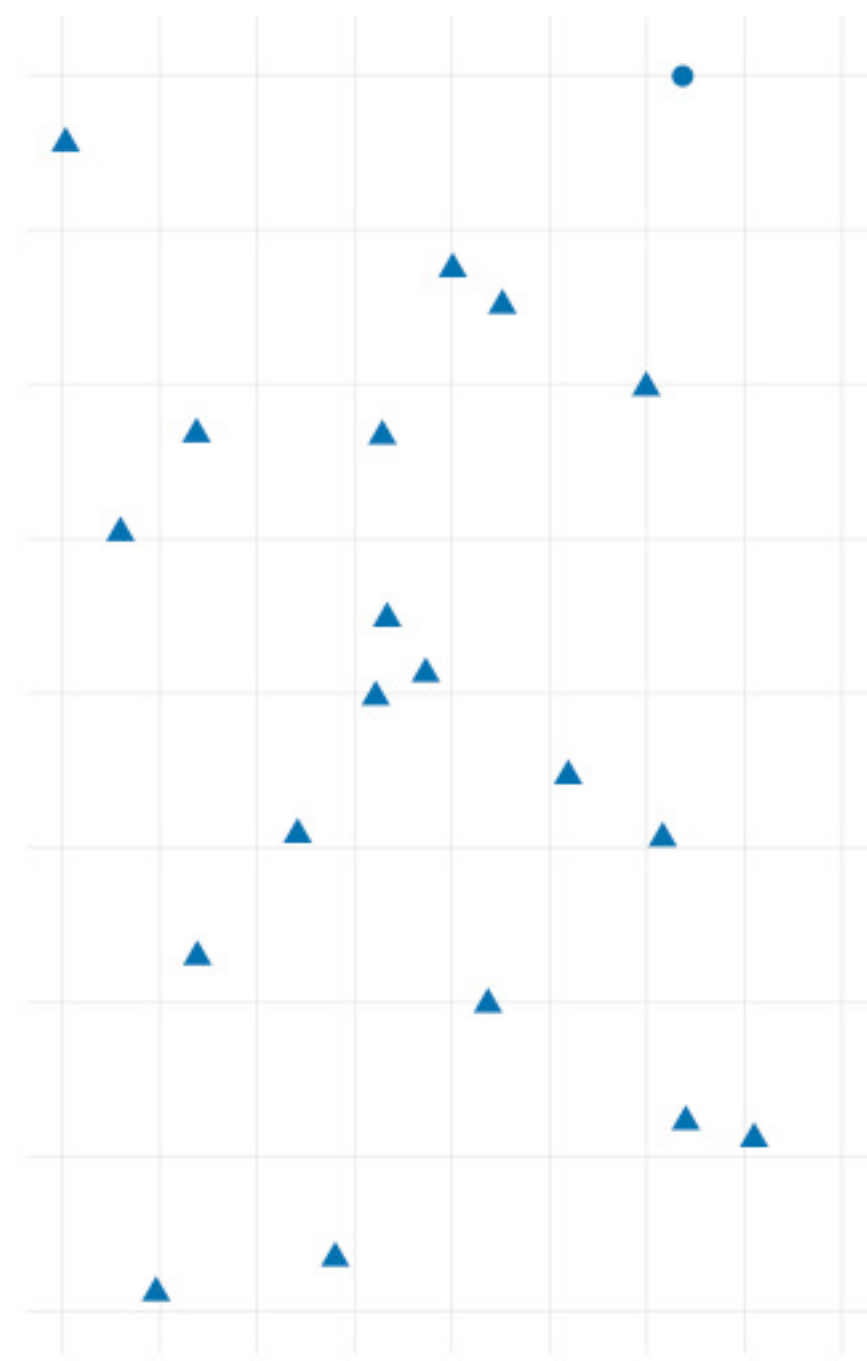
Color Only, N=20



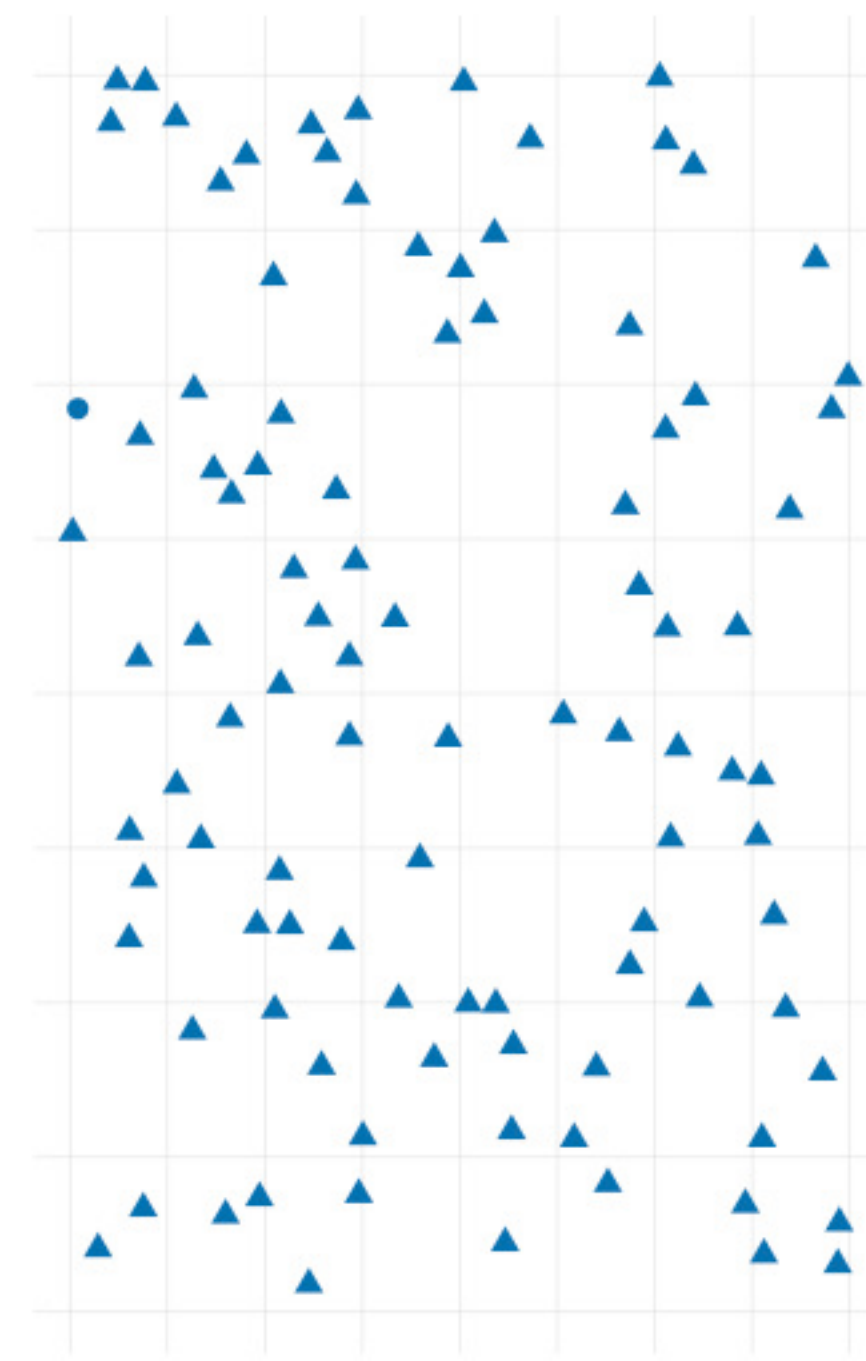
Color Only, N=100



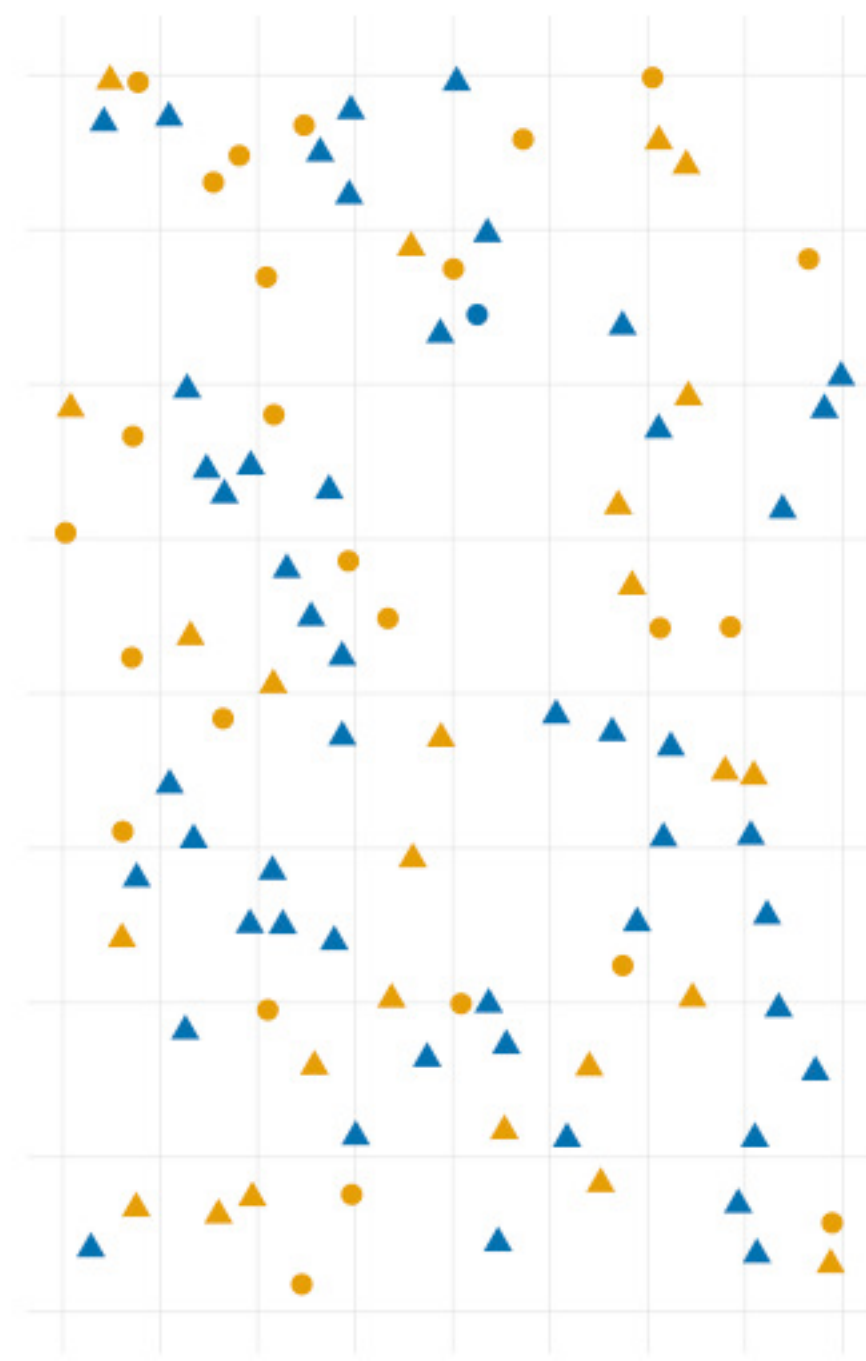
Shape Only, N=20



Shape Only, N=100



Color & Shape, N=100



What makes a graphic good and bad?

“Graphical excellence is the well-designed presentation of interesting data—a matter of substance, of statistics, and of design ... [It] consists of complex ideas communicated with clarity, precision, and efficiency. ... [It] is that which gives to the viewer the greatest number of ideas in the shortest time with the least ink in the smallest space ... [It] is nearly always multivariate ... And graphical excellence requires telling the truth about the data.”

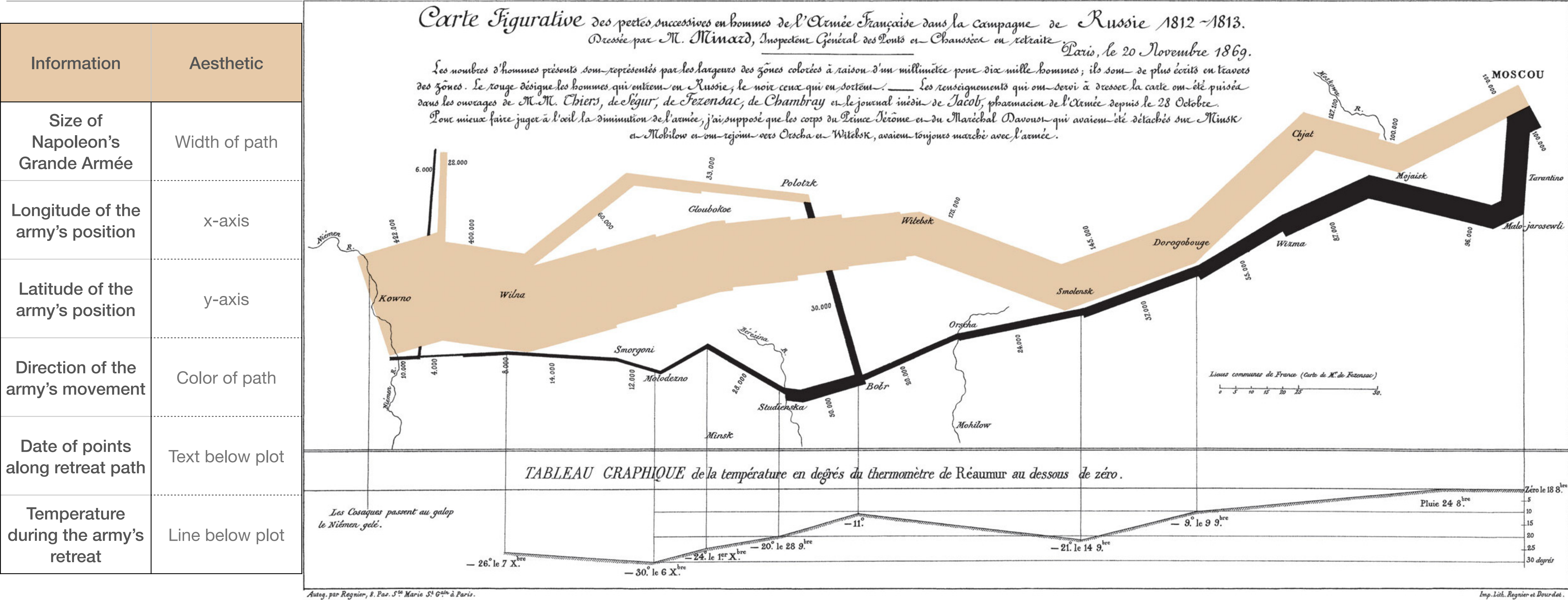
– Edward Tufte (1983) p. 51

as quoted in Healy (2019)

Clarifying

- Healy (2019). Three varieties of badness:
 - **Aesthetic** - a graph that is tasteless or inconsistent
 - **Substantive** - there is a problem with the data being presented
 - **Perceptual** - a graph can be “confusing or misleading because of how people perceive and process what they are looking at”
- **Chartjunk**
- **Data-Ink Ratio**

Minard's Napoleon



Complicating the story

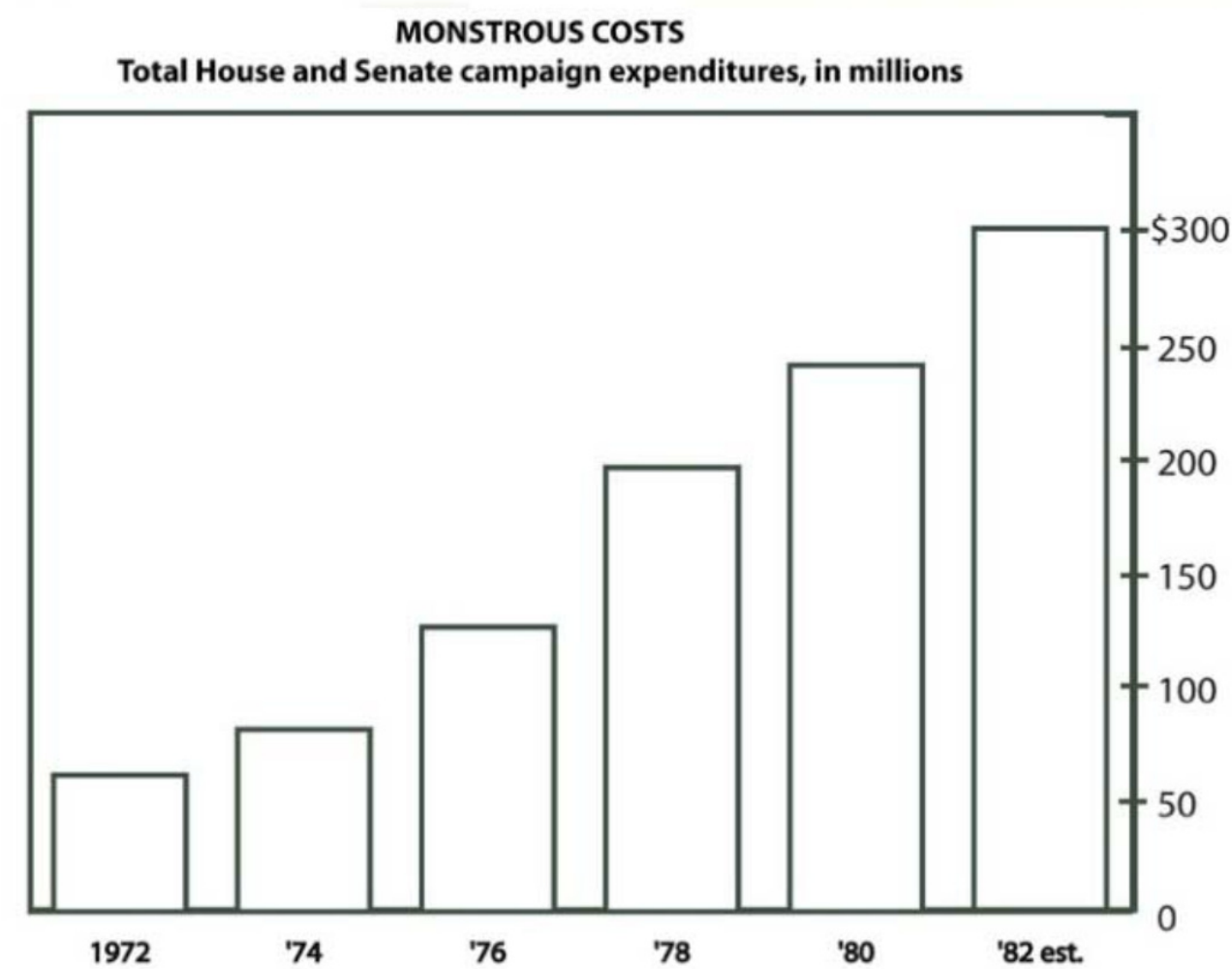
- A figure that breaks all the rules



(Bateman (2010); image: Nigel Holmes)

Complicating the story

- A figure that breaks all the rules
- And a cleaner version

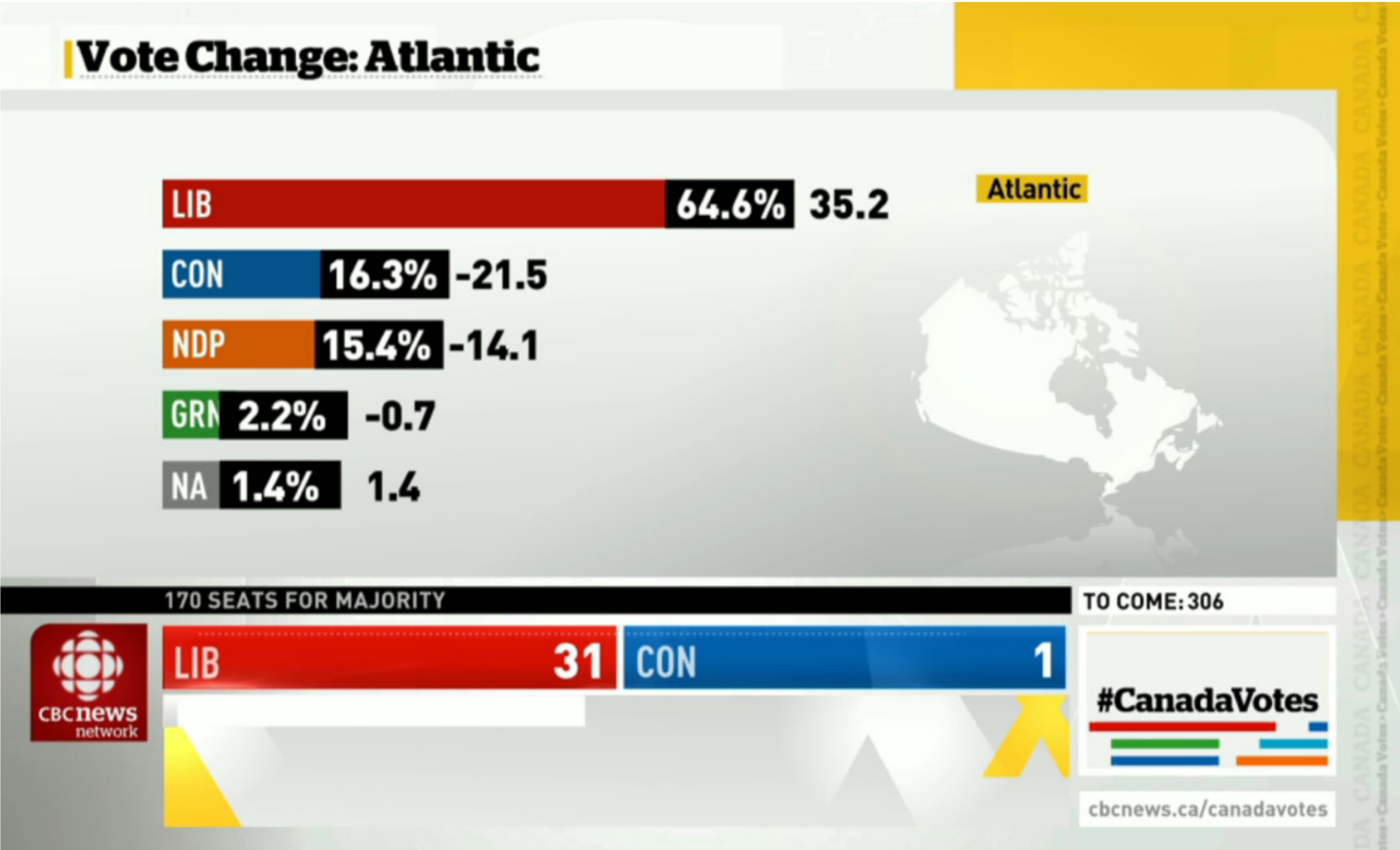


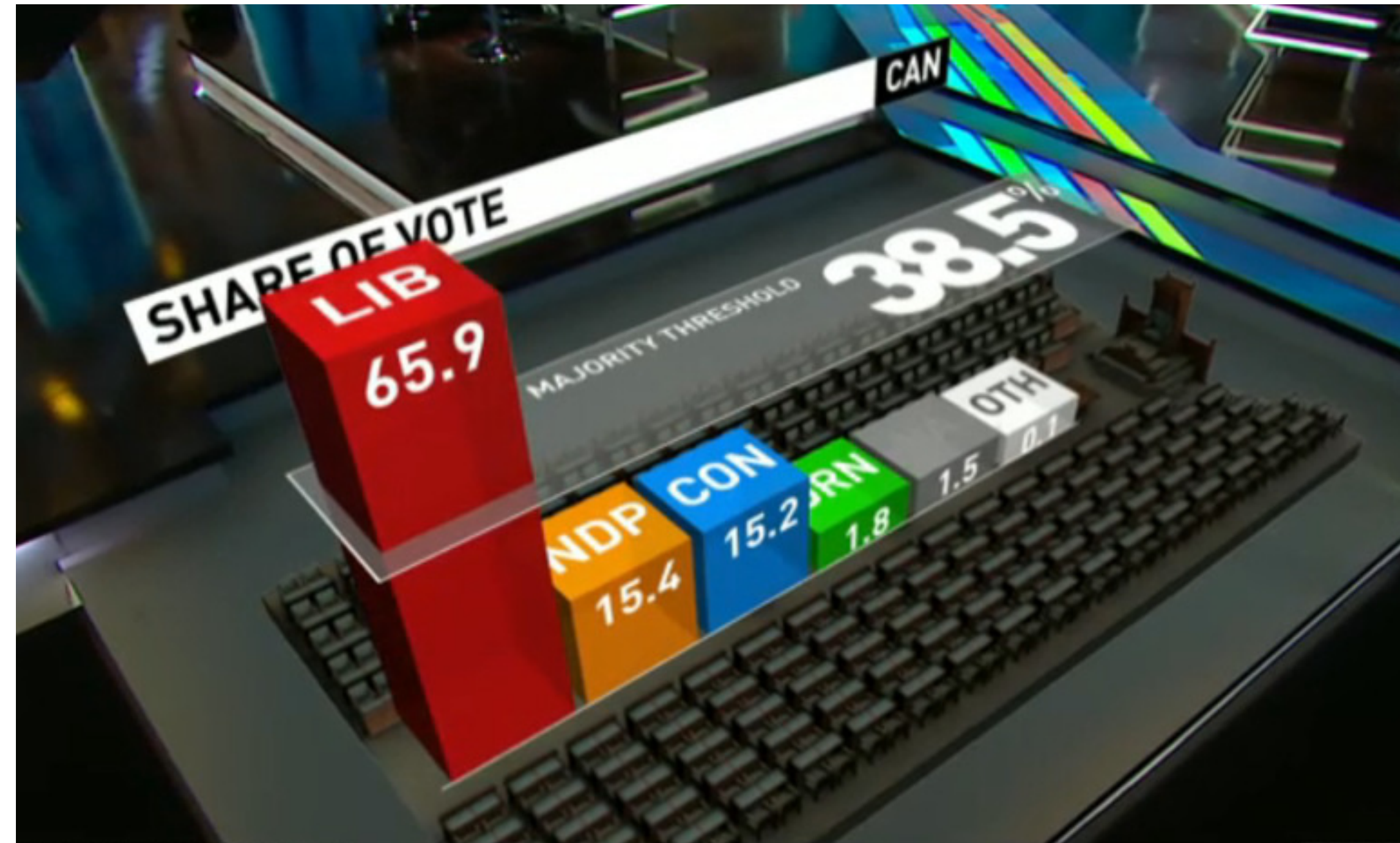
- Yet the original is more memorable



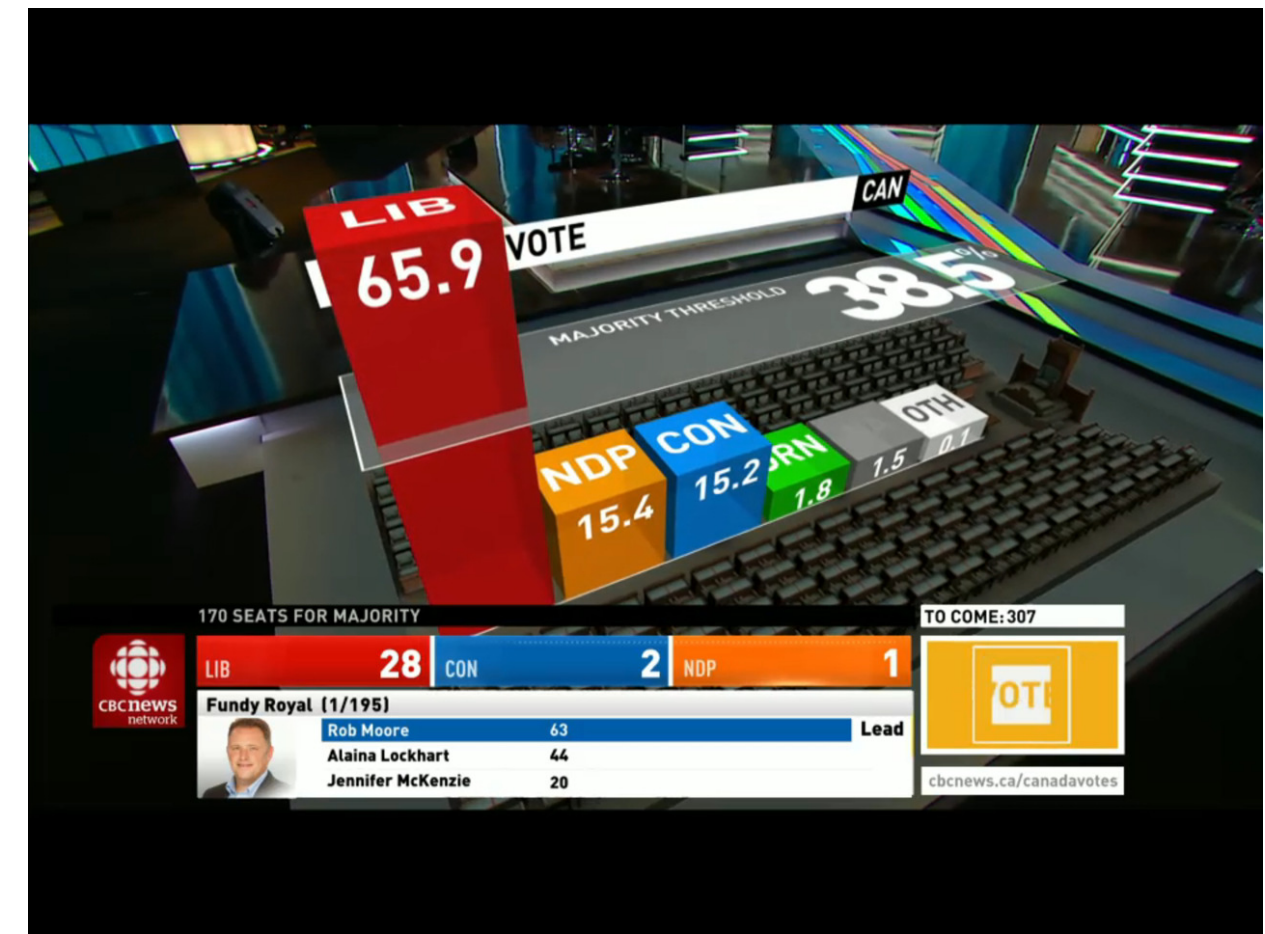
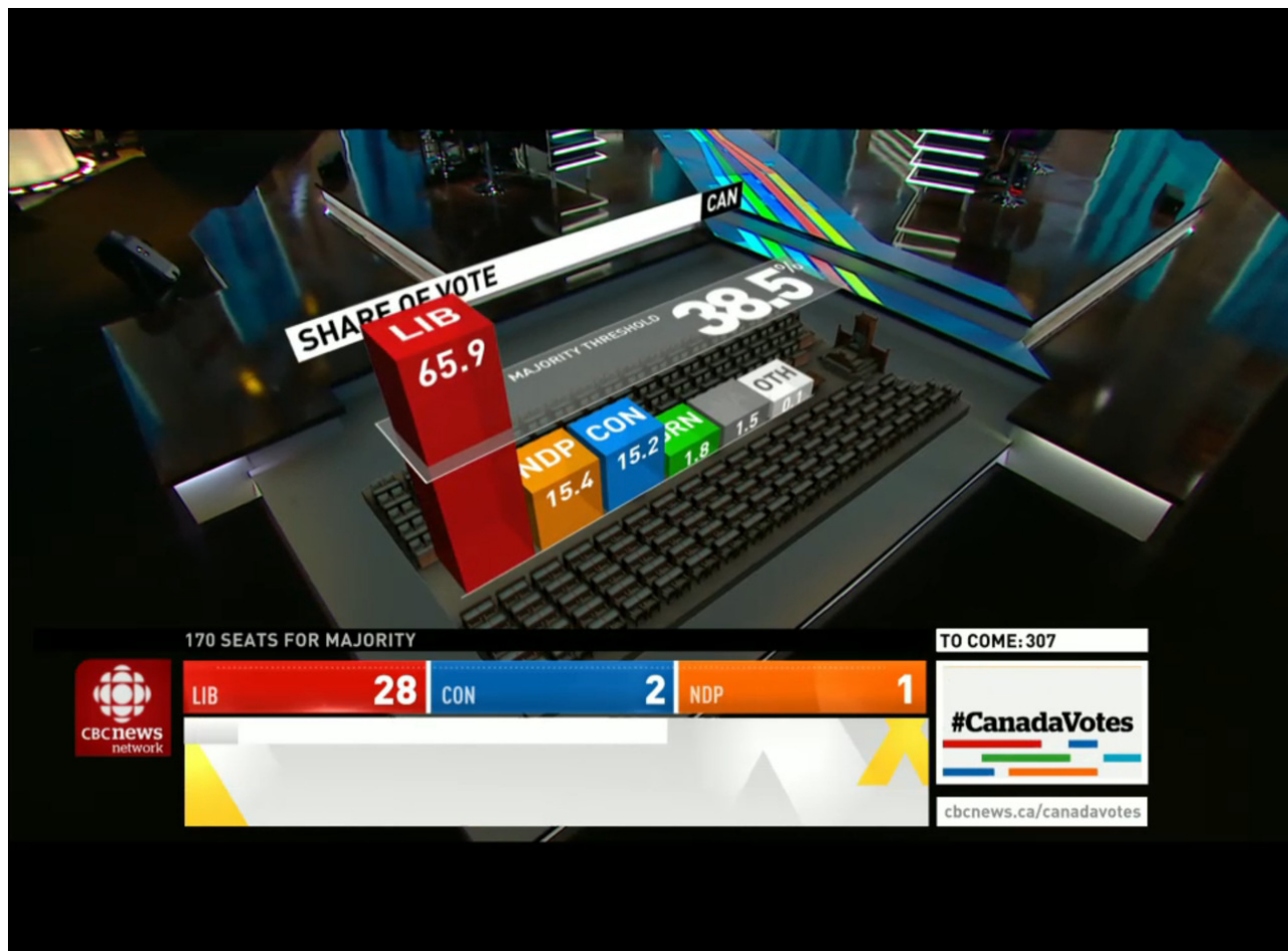
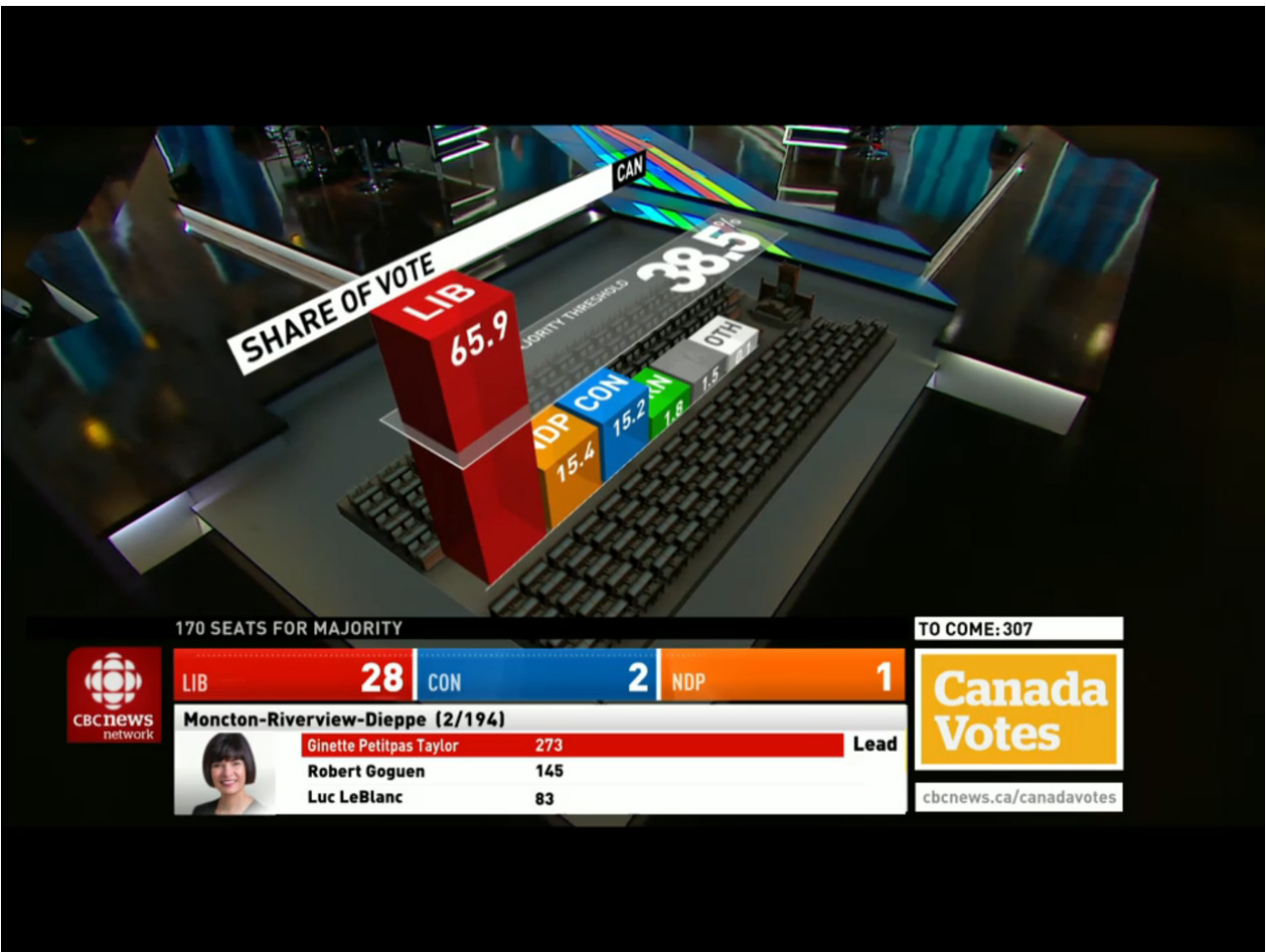
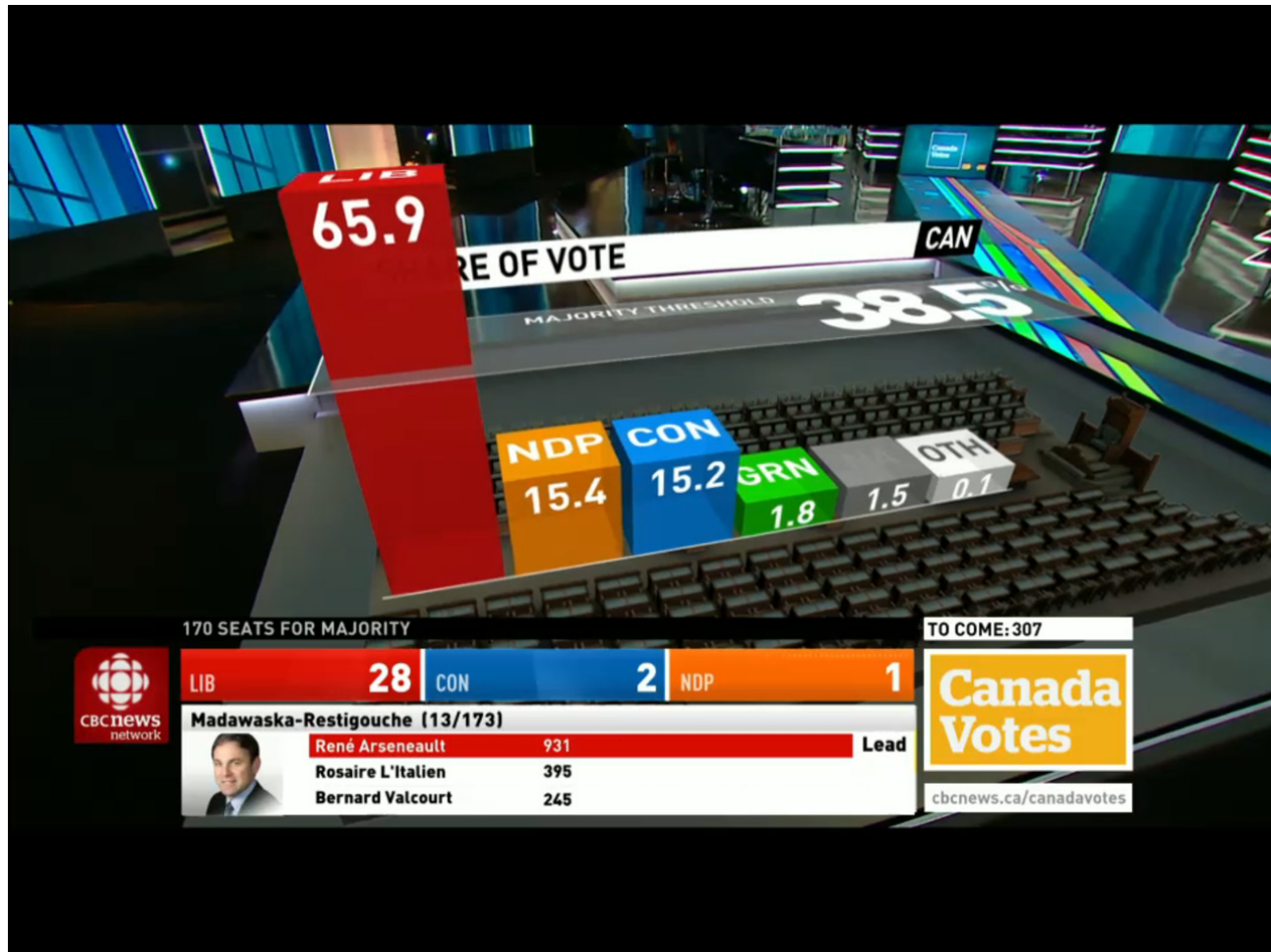
Bad Graphics

We also talked about some heinous graphics . . . how about some more?

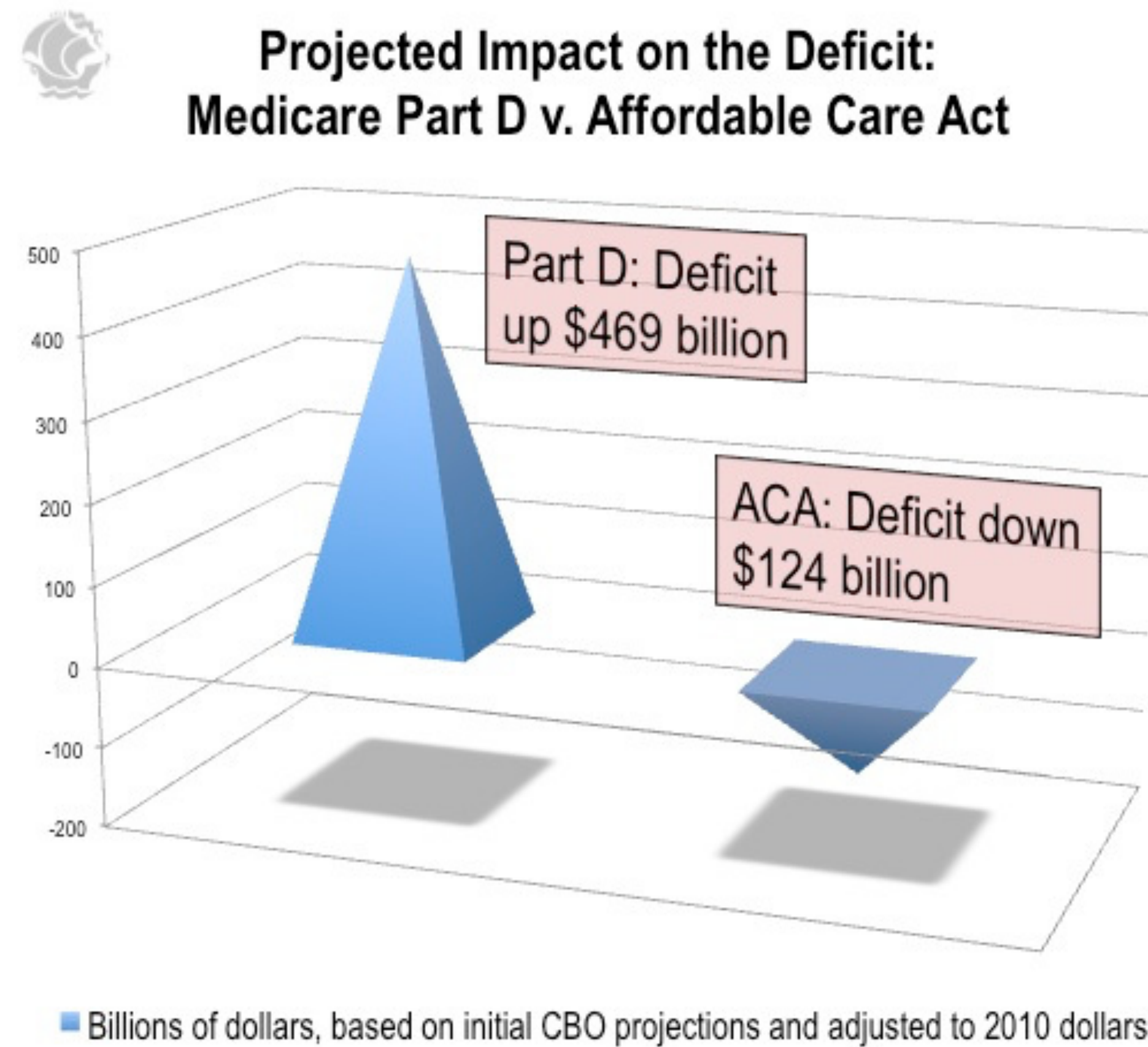




this thing MOVED! and zoomed. and stuff.

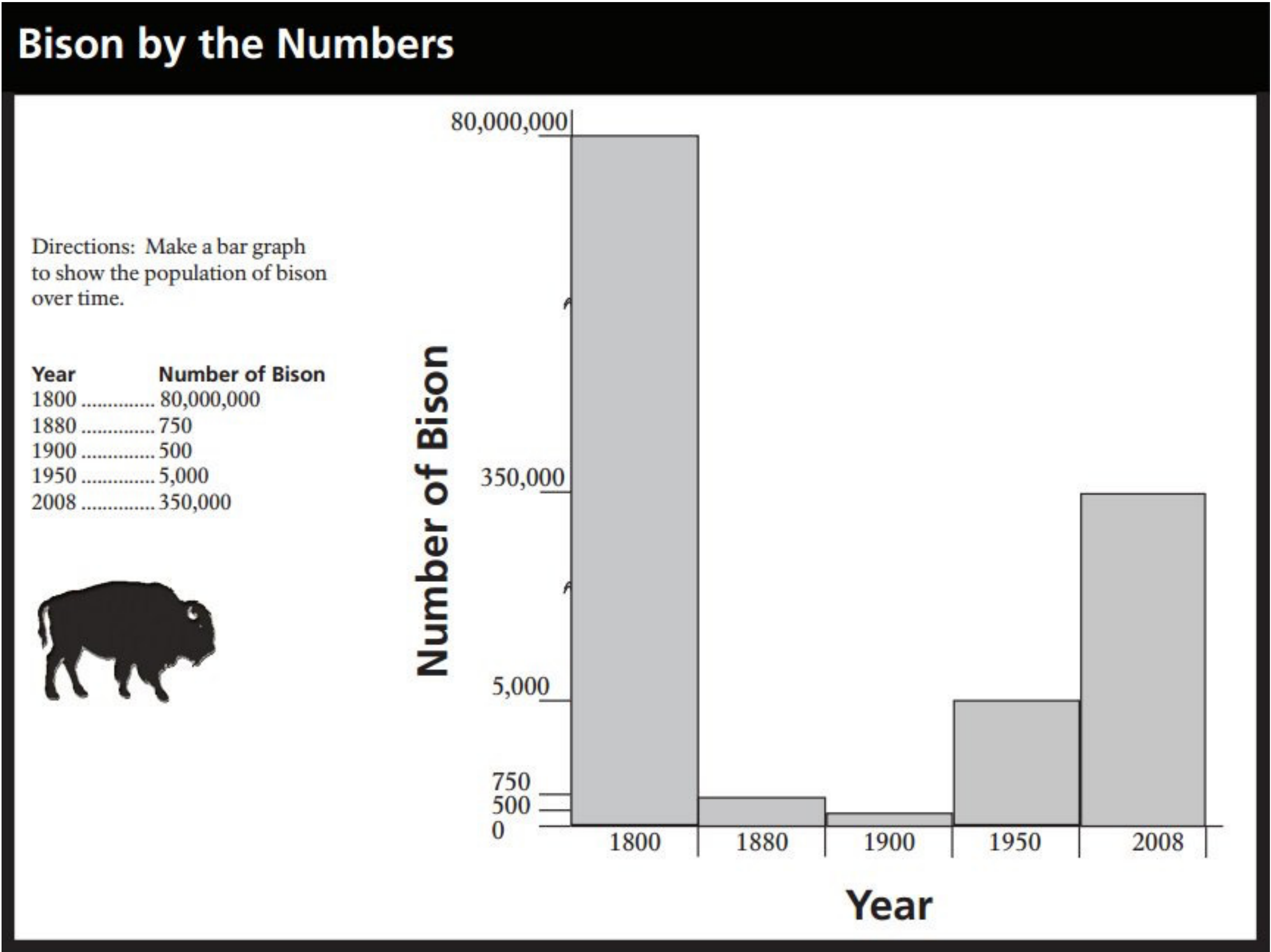


More bad graphics

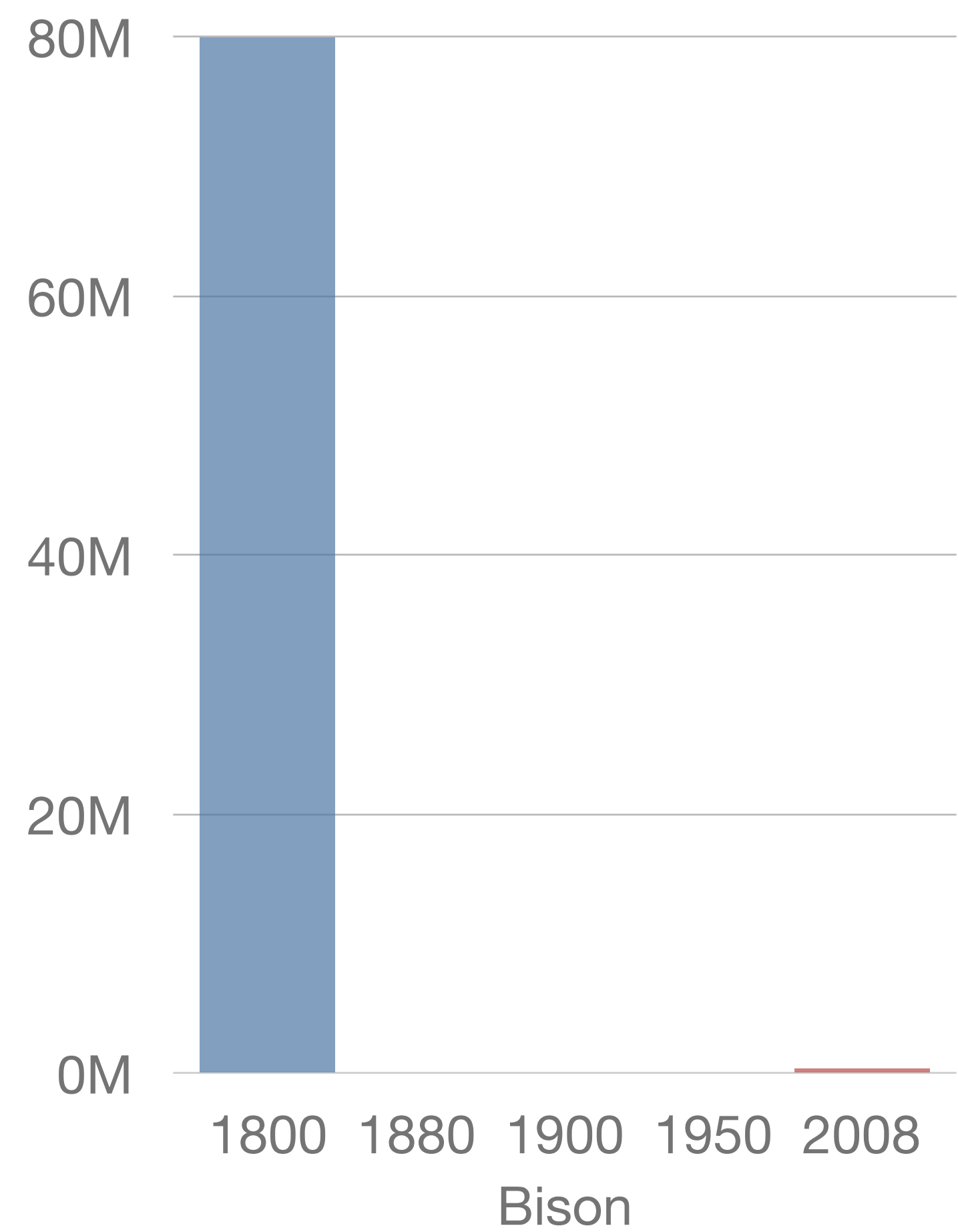


Graphic by the New Republic

More bad graphics



A *less* terrible bison graph

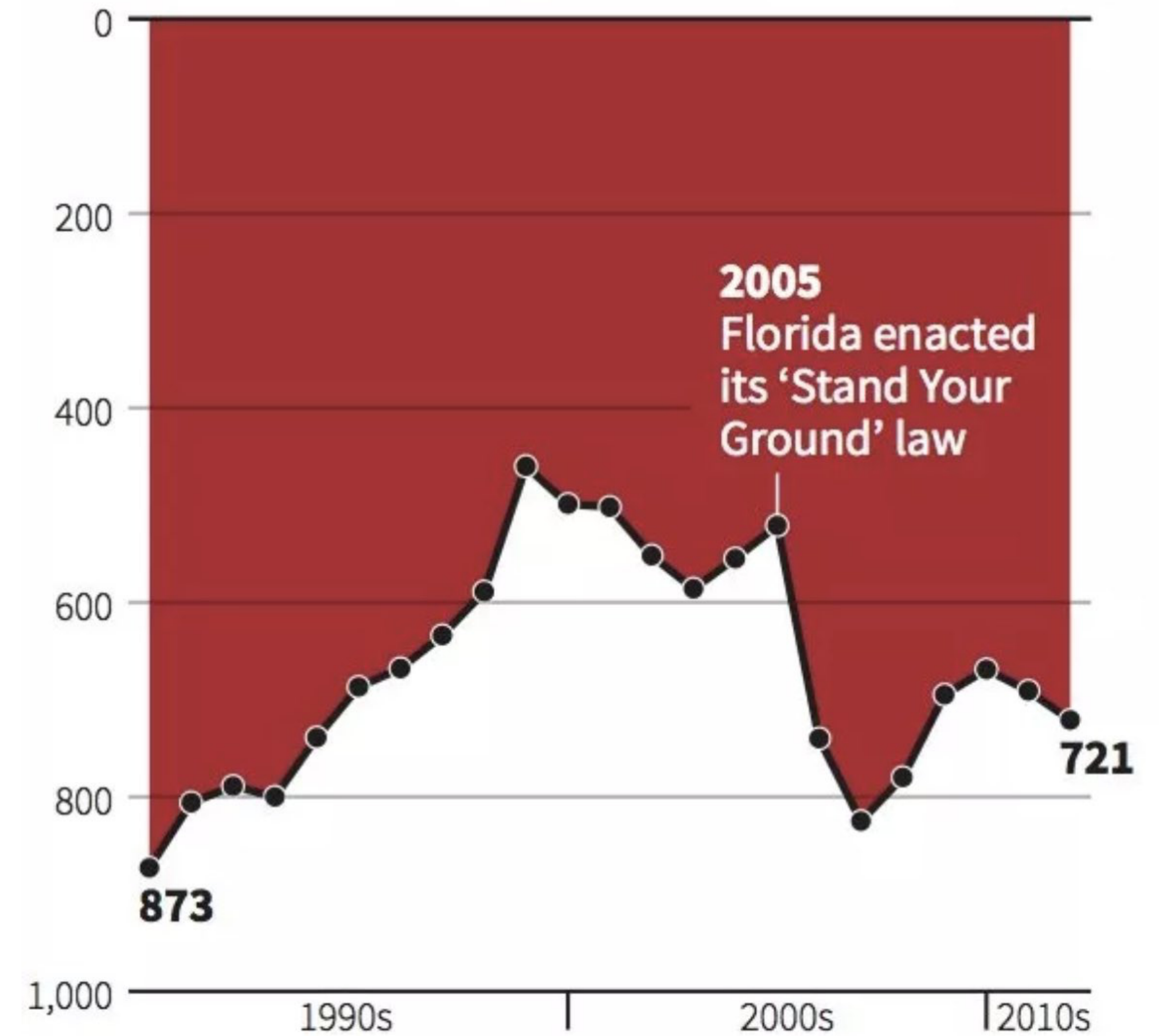


Humans are quite bad
at understanding how
large big numbers
really are

More bad graphics

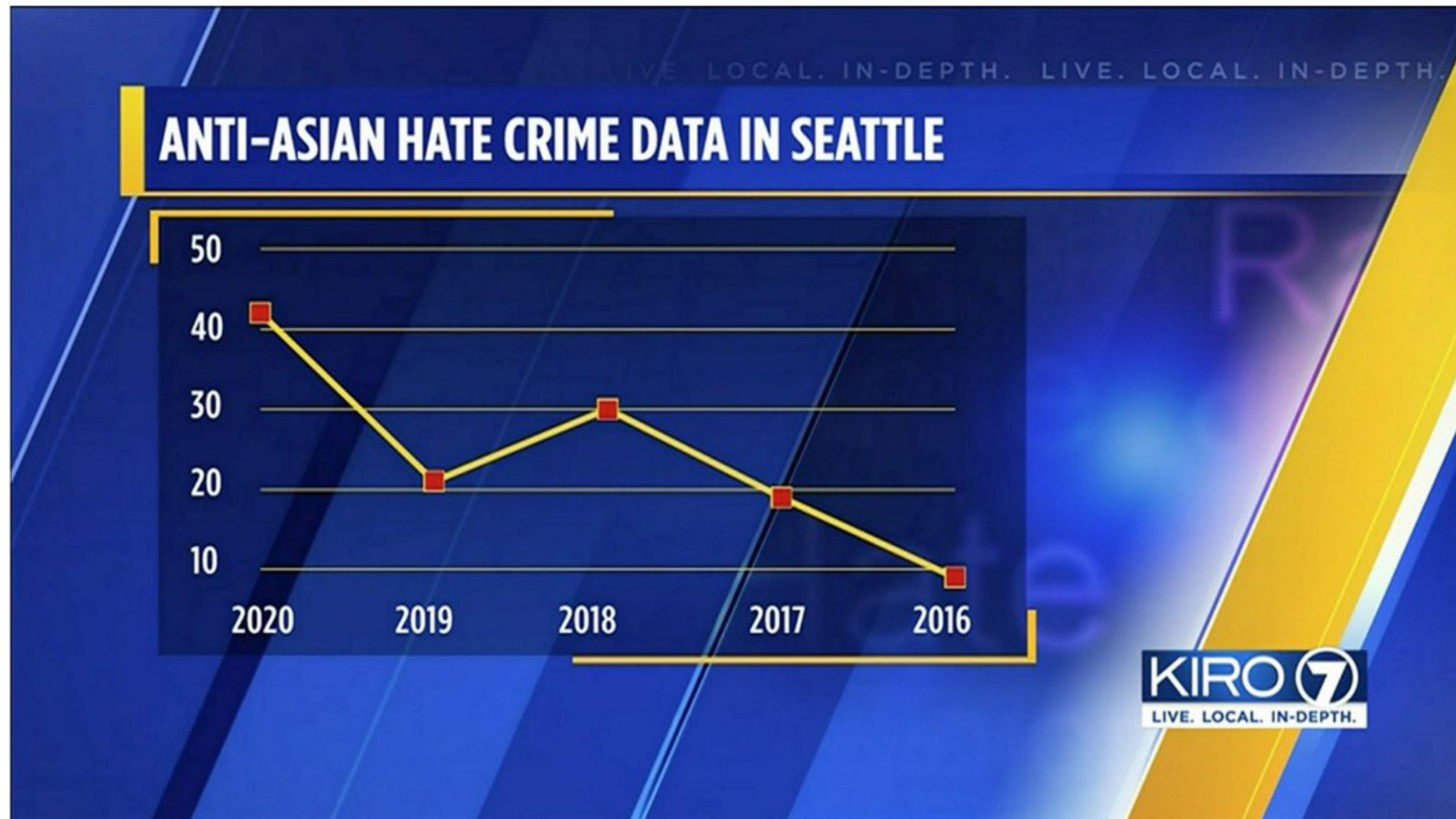
Gun deaths in Florida

Number of murders committed using firearms



Source: Florida Department of Law Enforcement

More bad graphics



VIDEO: Anti-Asian hate crimes continue in Seattle and across U.S.

COVID yielded new terrible opportunities for terrible graphics

The perfect storm of opportunity - new data and emerging new data tools

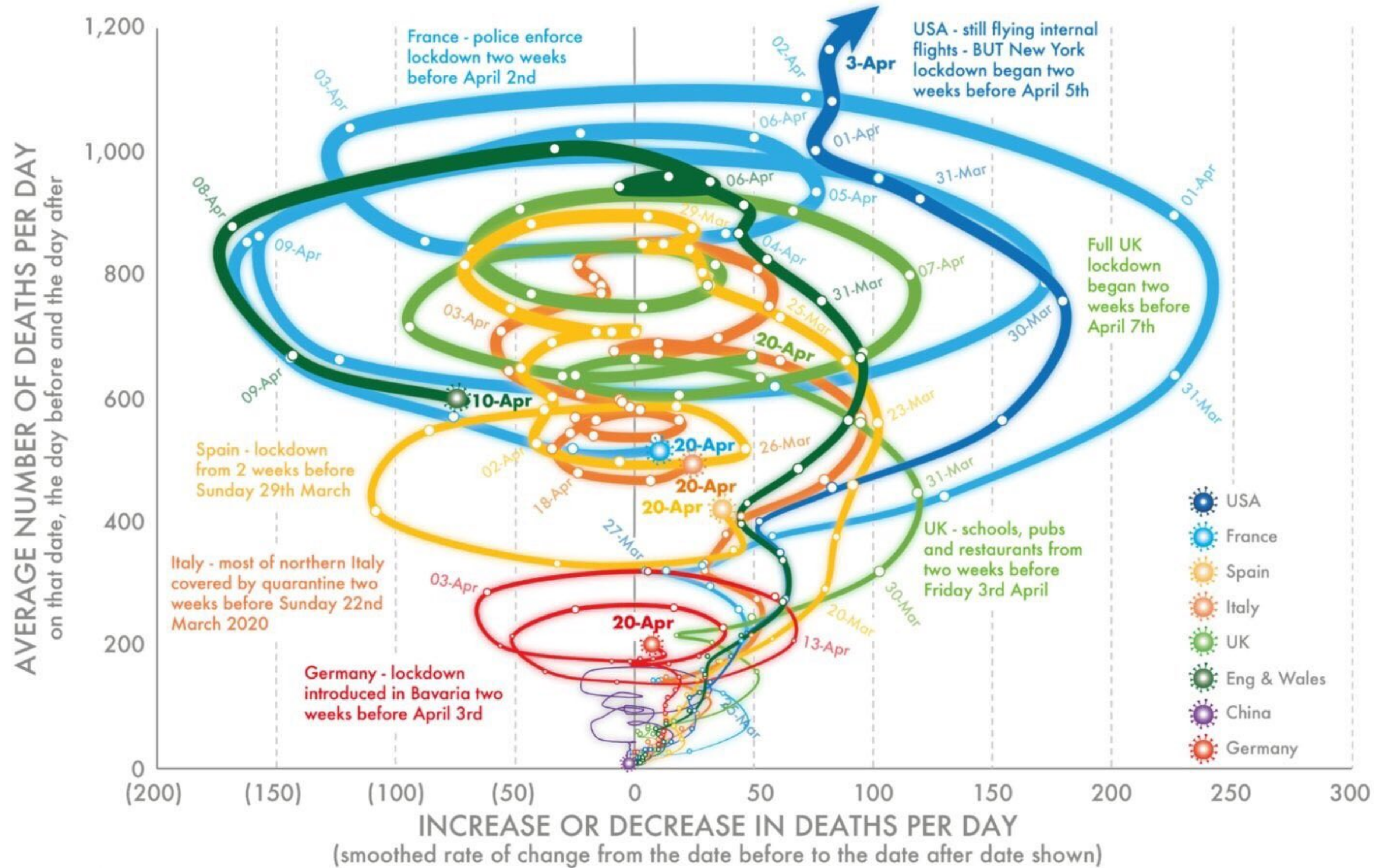
CORONAVIRUS

FLORIDA CONFIRMED CASES

COVID-19



SOURCE: FLORIDA DEPT. OF HEALTH

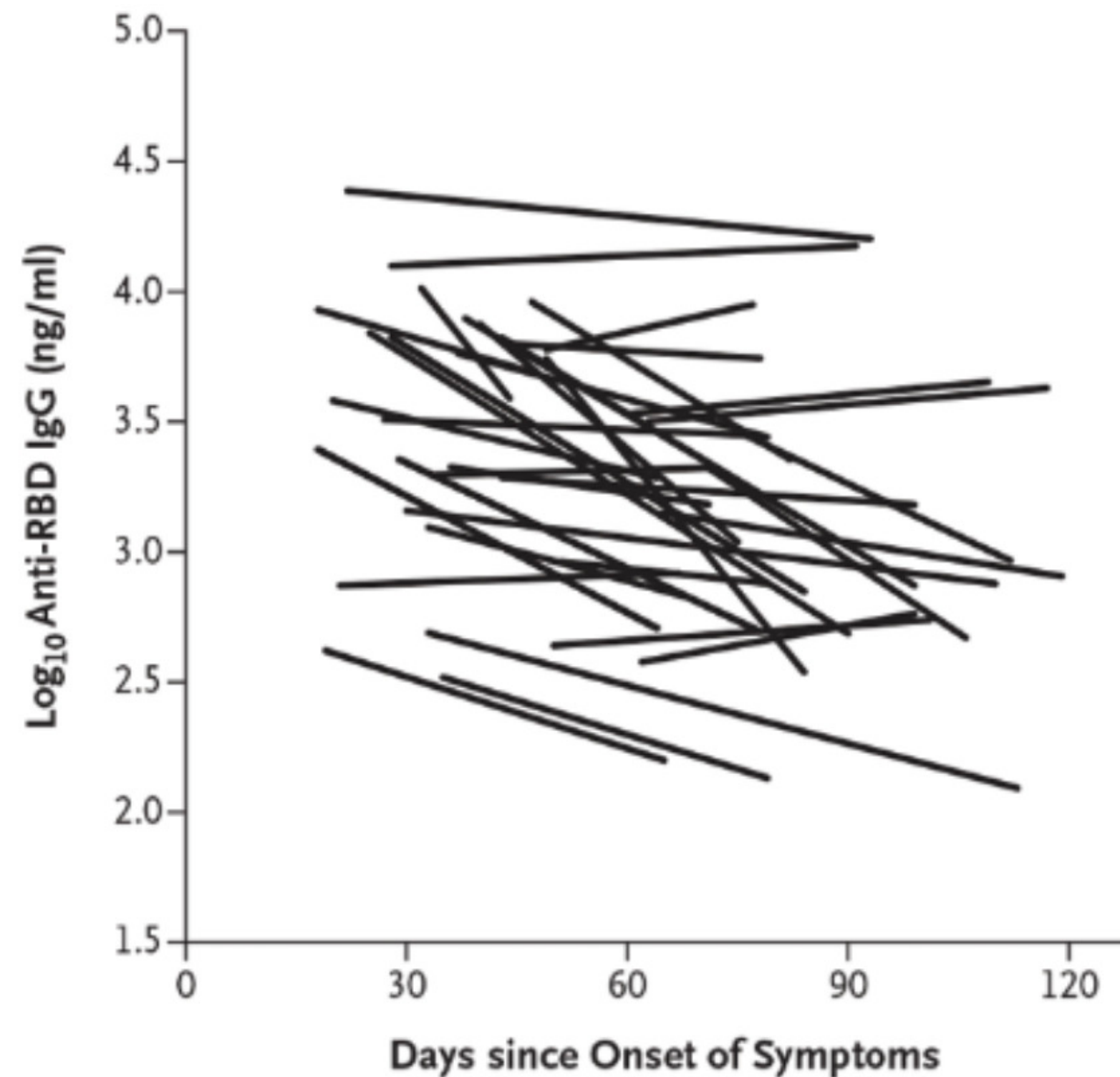




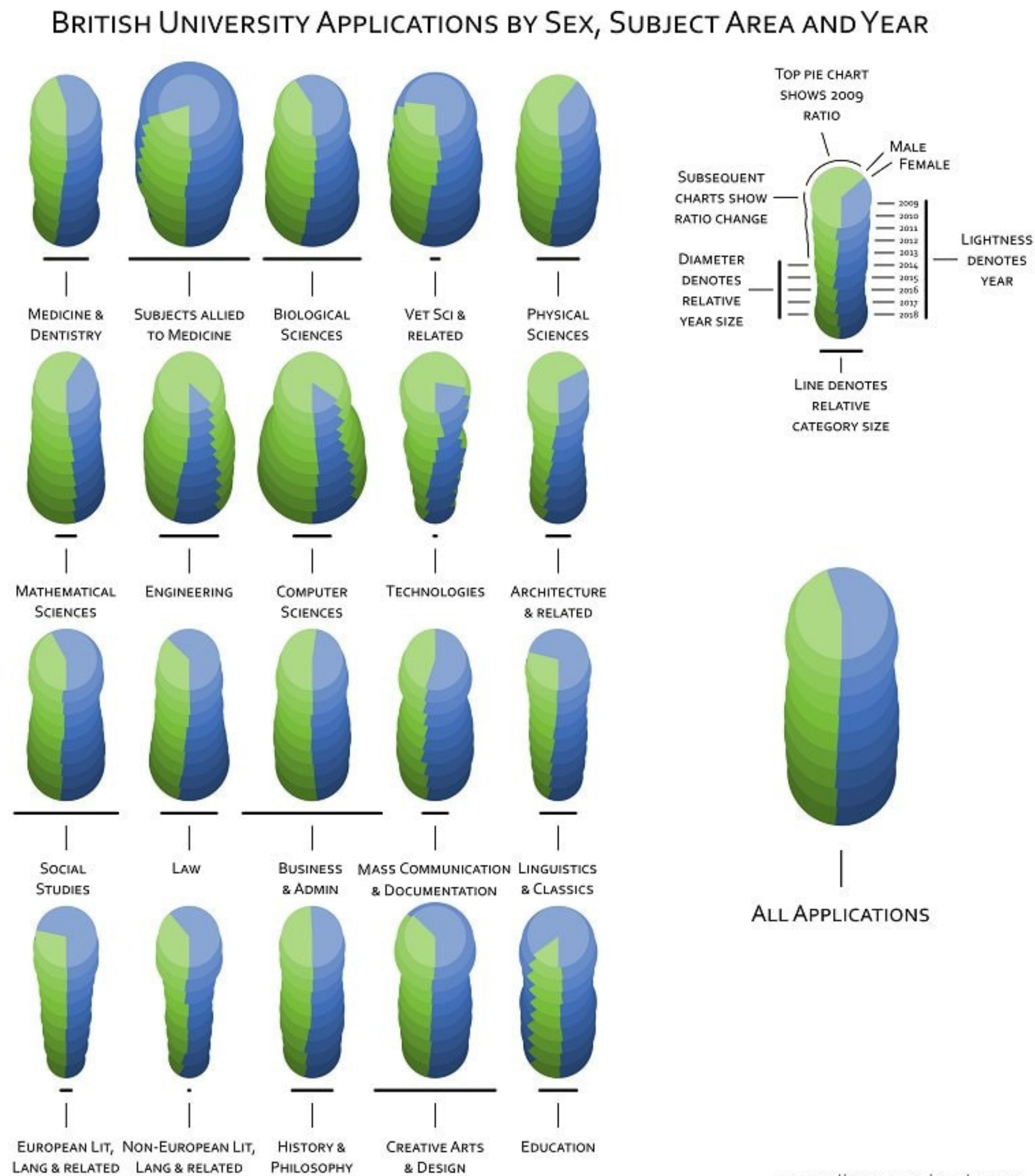
NEJM
@NEJM



Correspondence: Rapid Decay of Anti-SARS-CoV-2 Antibodies in Persons with Mild Covid-19 [#COVID19](#) [#SARSCoV2](#)

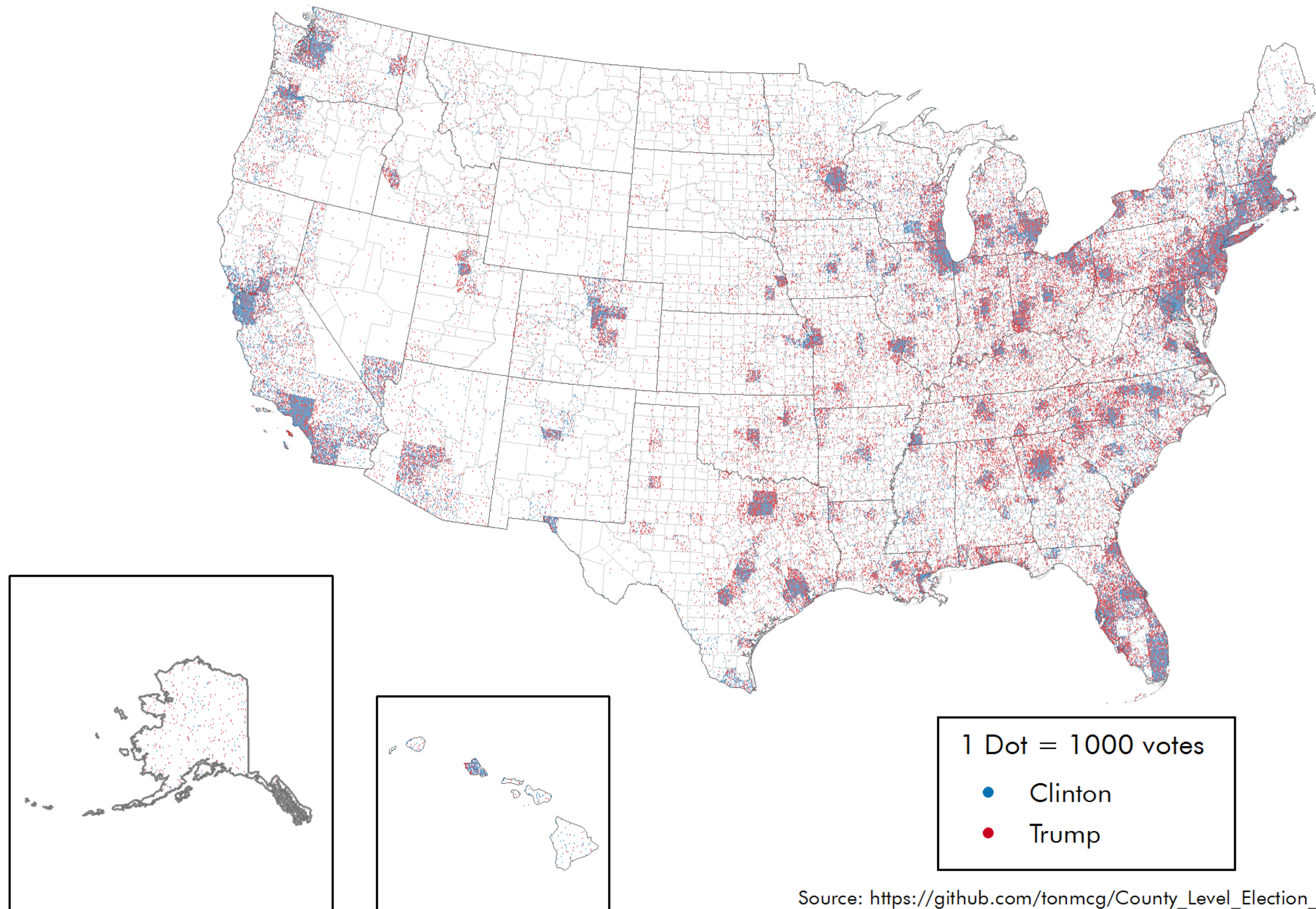


Aggressively Bad



How about some good graphics?

Not As Red As You Think: 2016 Presidential Election Results By County Vote Tally



Source: https://github.com/tonmcg/County_Level_Election_Results_12-16
igotcharts.com | twitter: @igotcharts

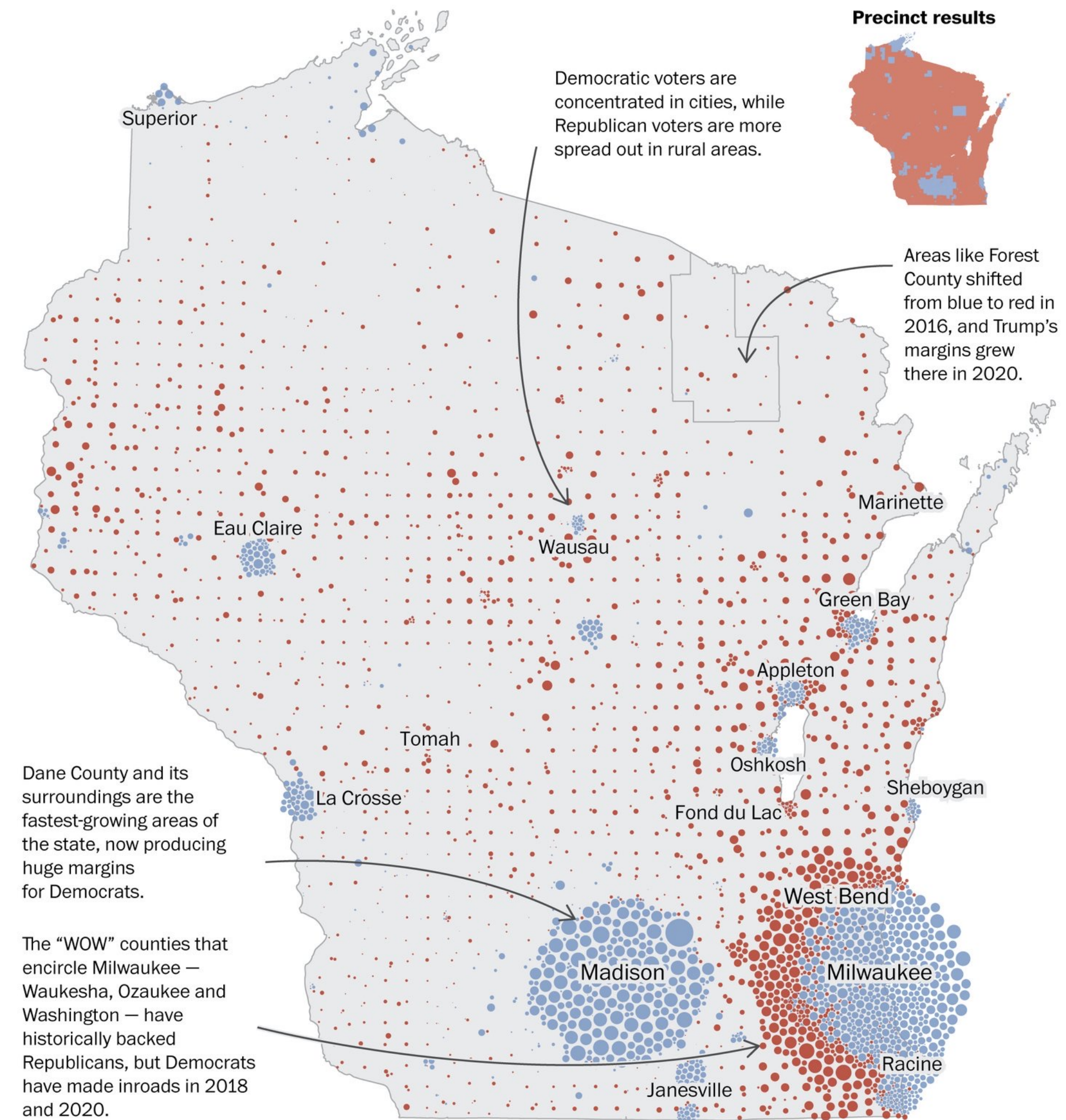
More *good* graphics

How Wisconsin voted in the 2020 presidential election

Narrow margins have defined recent presidential elections in Wisconsin. Biden won by just 20,682 votes out of 3.3 million cast. Four years earlier, Trump had bested Hillary Clinton by only 22,748 of almost 3 million votes cast.

Circle sizes are scaled according to the vote margin between **Biden** and **Trump** in each precinct.

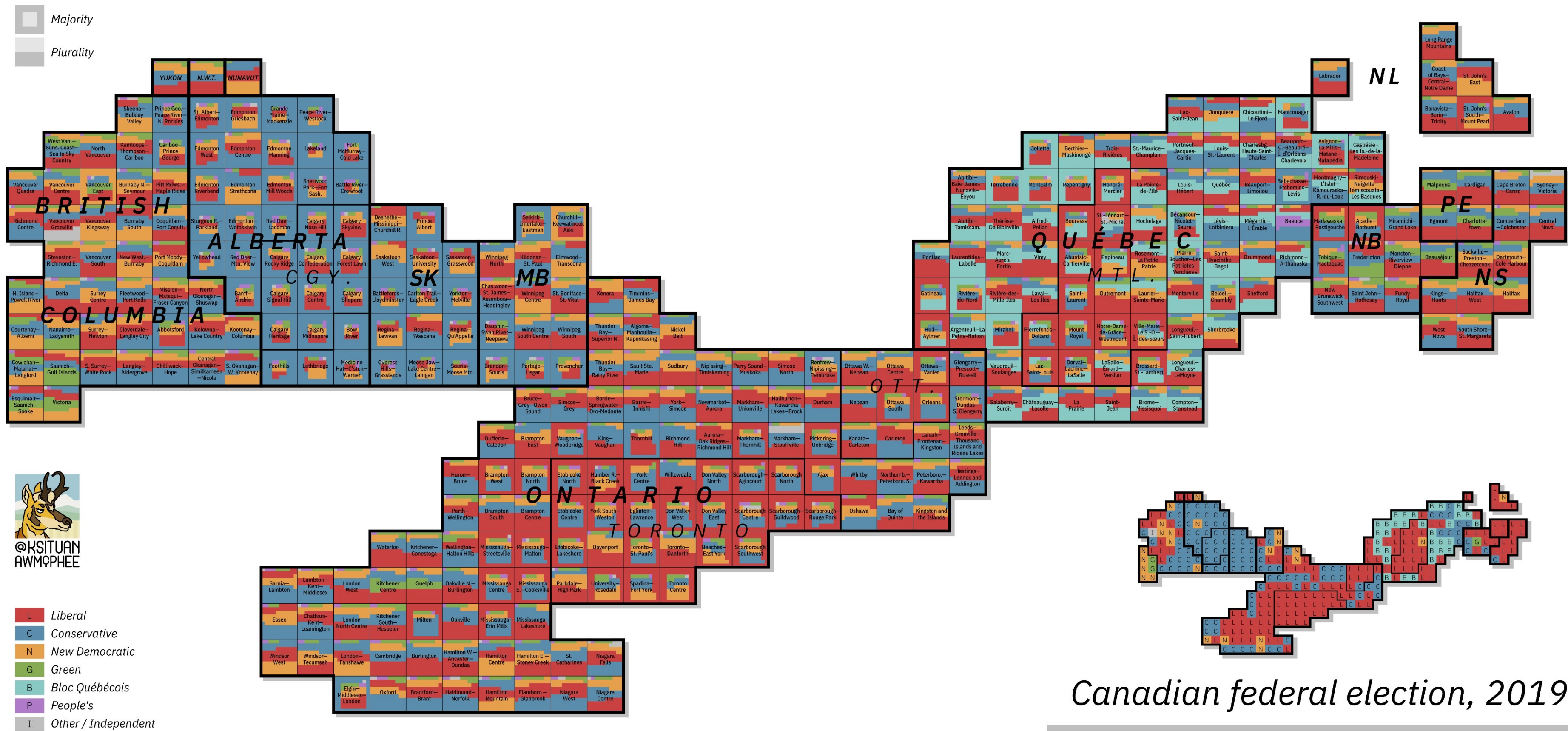
• +100 ○ +1,000 ○ +5,000 ○ +10,000 votes

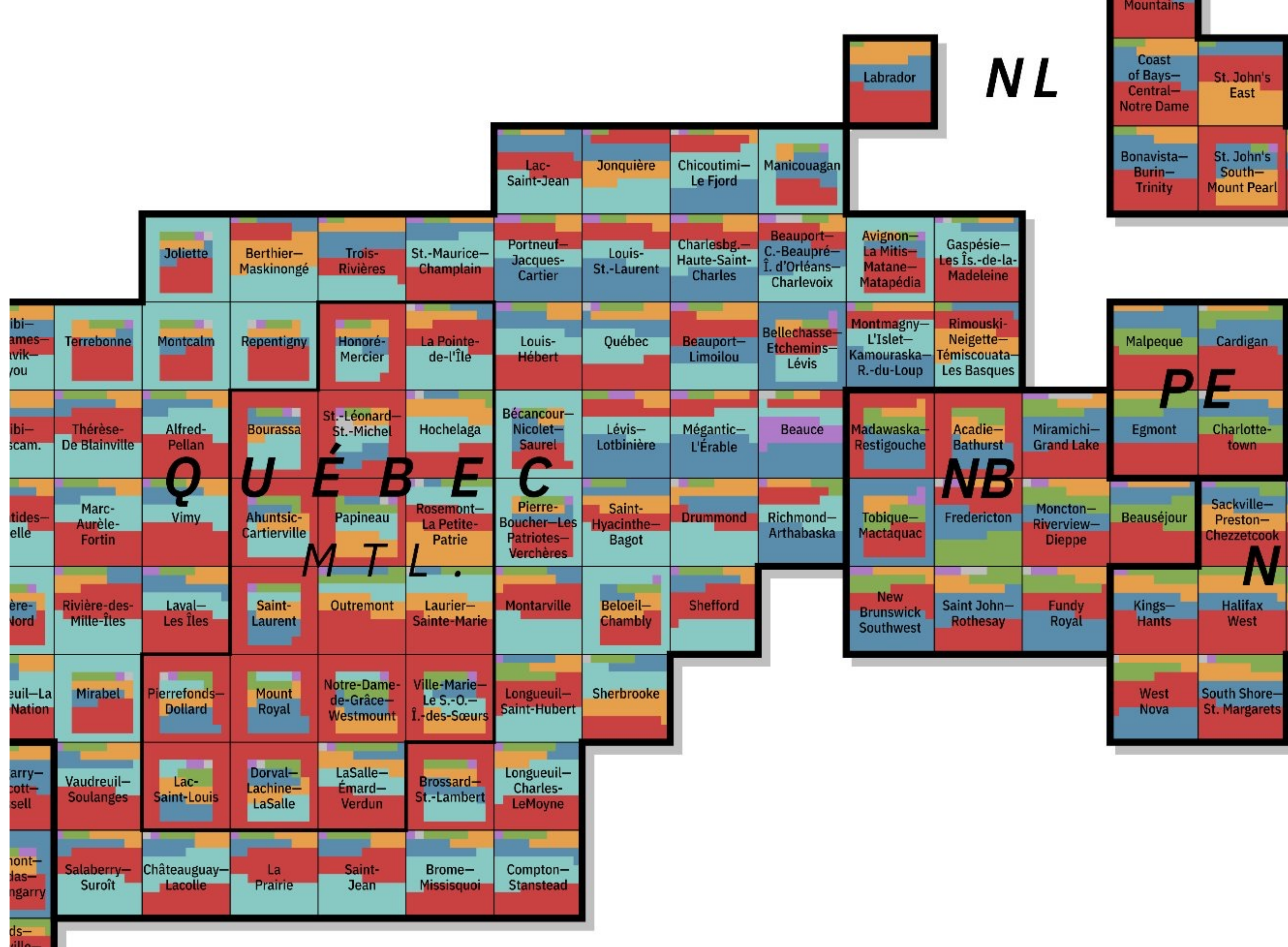


Note: Circles are clustered in areas with many precincts, so locations are approximate.

Source: Decision Desk HQ

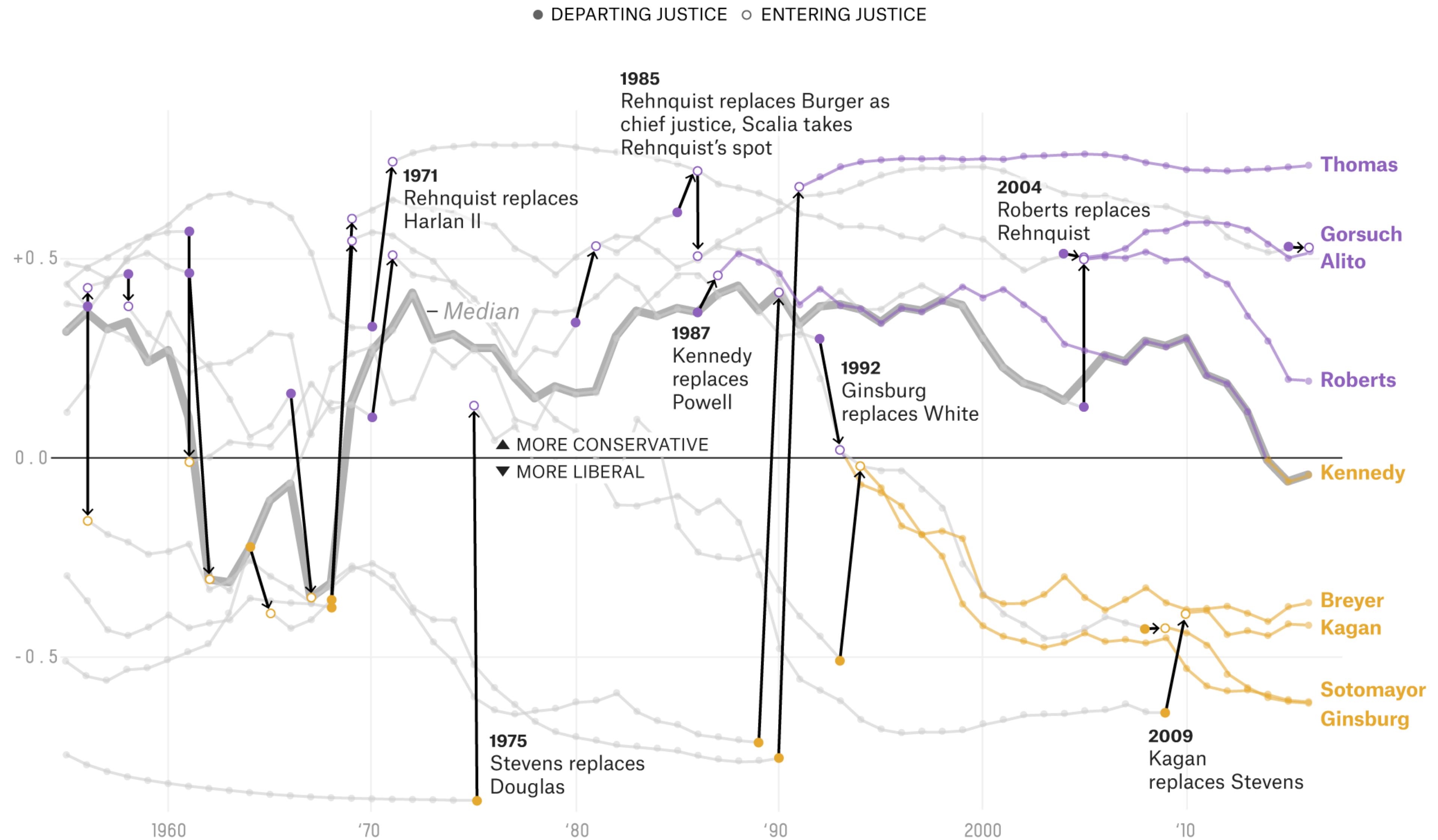
ADRIÁN BLANCO AND SHELLY TAN/THE WASHINGTON POST





Supreme Court departures and replacements

Supreme Court justices from 1955-2016 by their ideological leanings, based on their Judicial Common Space scores



Years refer to Supreme Court terms, which run from October to September.

Bivariate Graphics

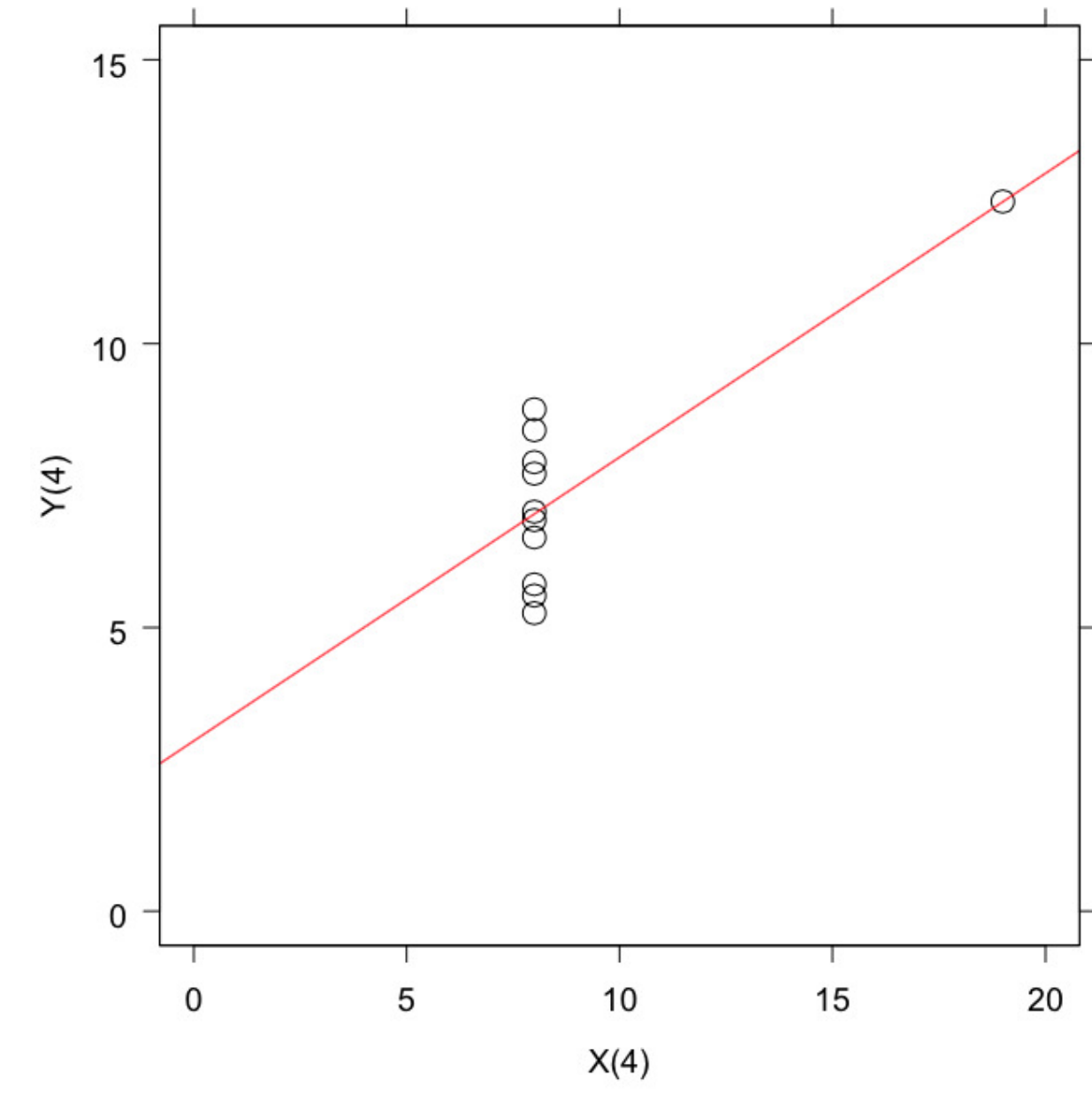
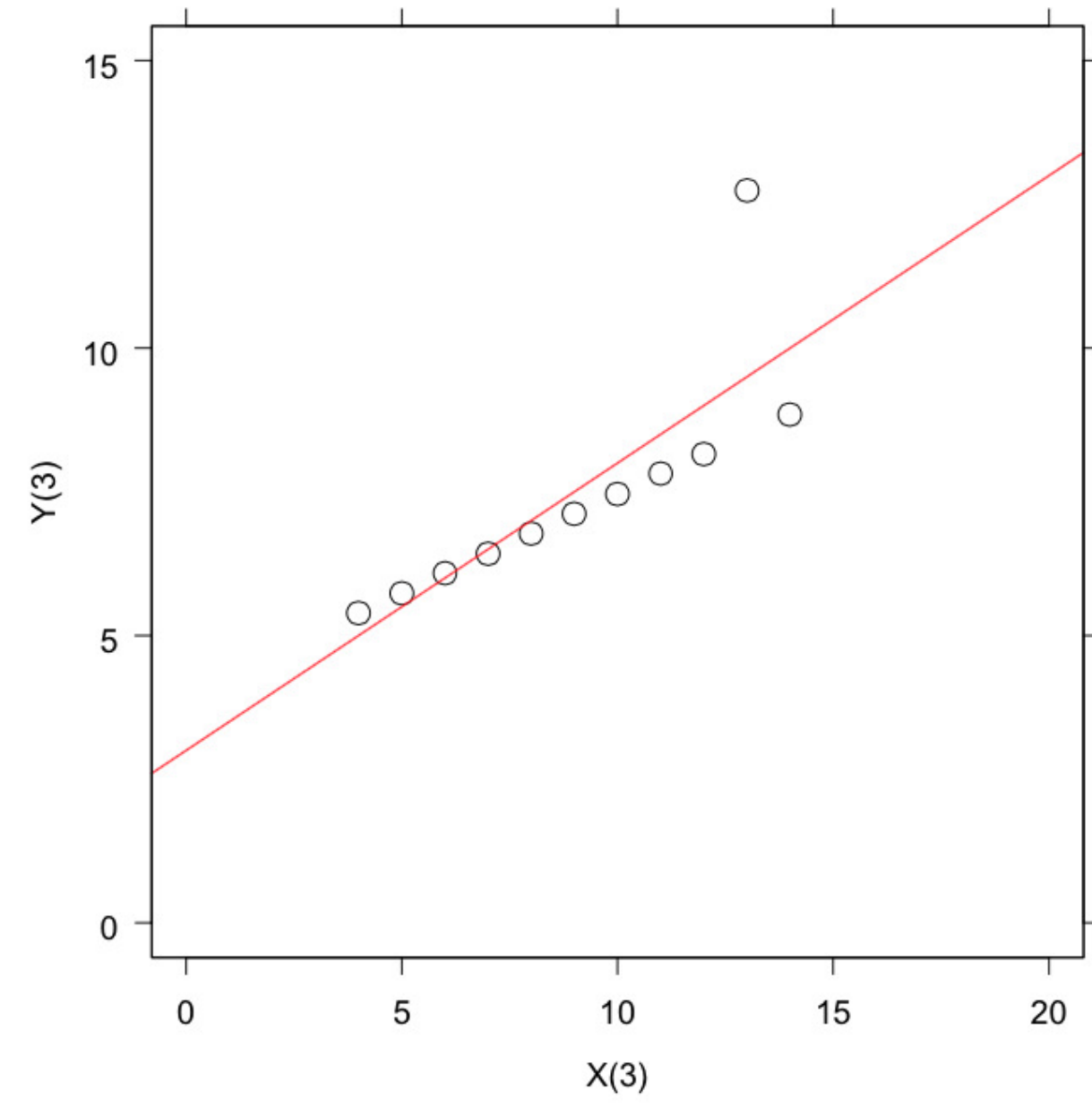
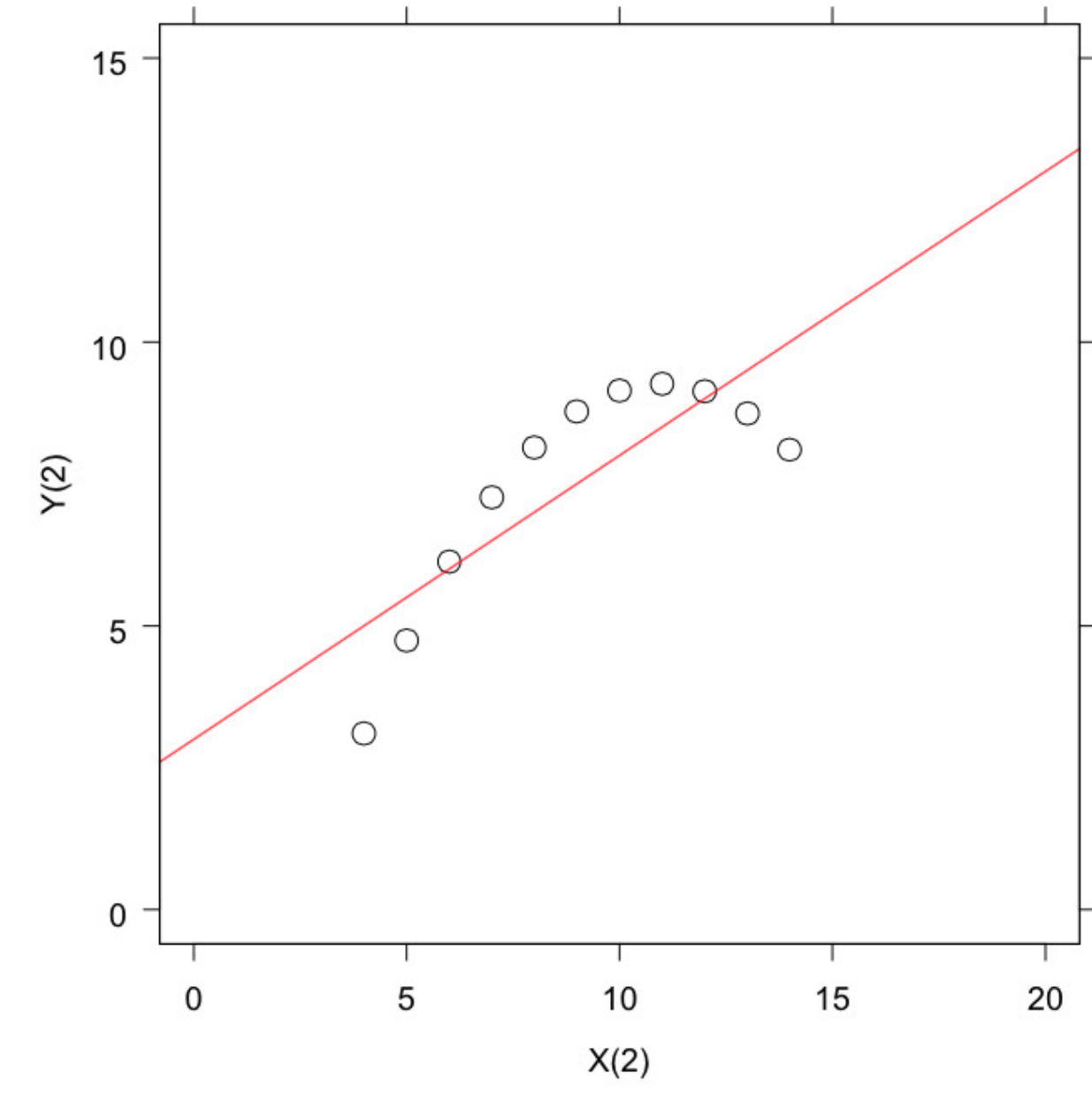
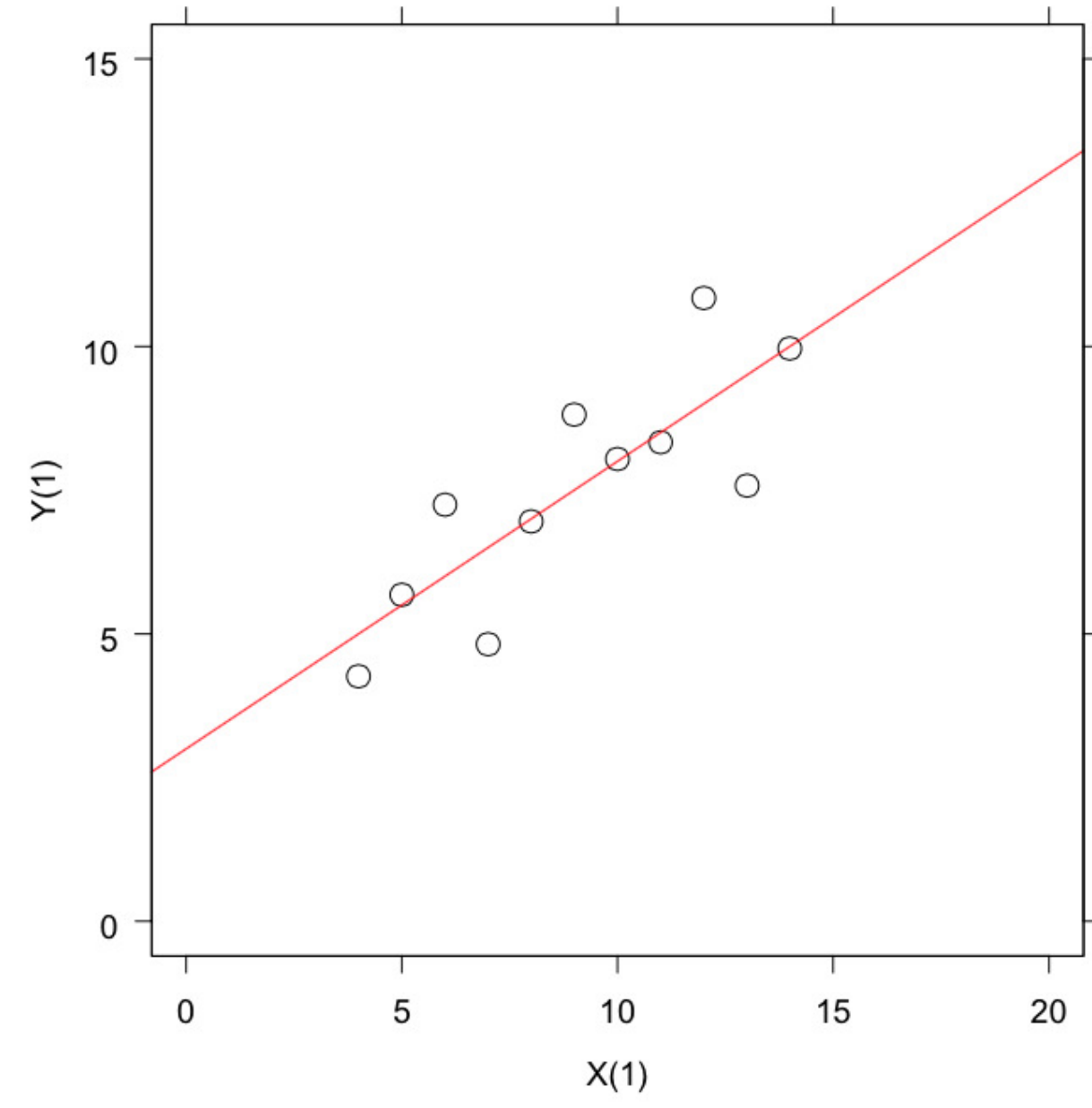
- Last time: looked at univariate graphics, and a number of different ways to examine univariate graphics
 - Now we're back!
- First . . . why should we care about bivariate graphics?
 - To convince you . . .

Equivalent OLS Estimates

- $Y_i = 3.00 + .5X_i + e_i$
- $R^2 = .67$
- Standard Errors: (1.12) and (0.12)

*the critical statistics for each regression are **identical***

X_1	Y_1	X_2	Y_2	X_3	Y_3	X_4	Y_4
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



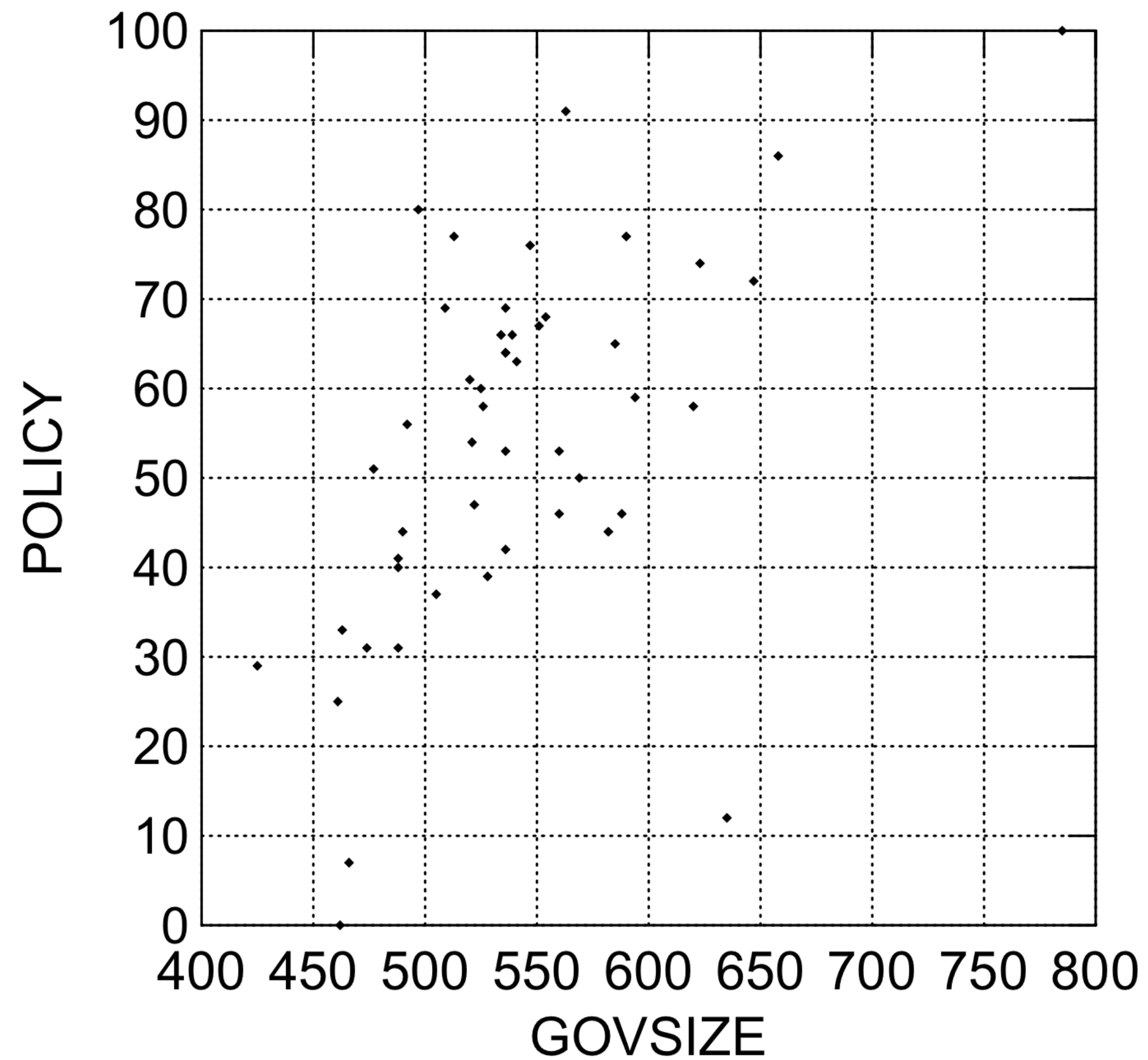
Aw, shucks. Silly OLS.

- These datasets, despite what the OLS regressions tell us, are not remotely identical.
 - *You should be starting to get suspicious of unexamined OLS estimates ...*
- Graphics can help us diagnose many significant issues with OLS stemming from nonlinearity, non spherical error terms, and outliers
- And bivariate graphics can even help us with truly nonlinear data!

So, how are we going to do this?

- Guidelines for bivariate graphs follow same conventions as univariate graphics.
 - Keep graphs clean and simple, and focus on your data.
 - Follow cognitive guidelines and rules as before; eliminate clutter, think about the **data-ink ratio**.
- Like univariate graphs, bivariate graphs have a dominant citizen - the **scatterplot**. Like histograms, scatterplots can be drawn well . . . or poorly.

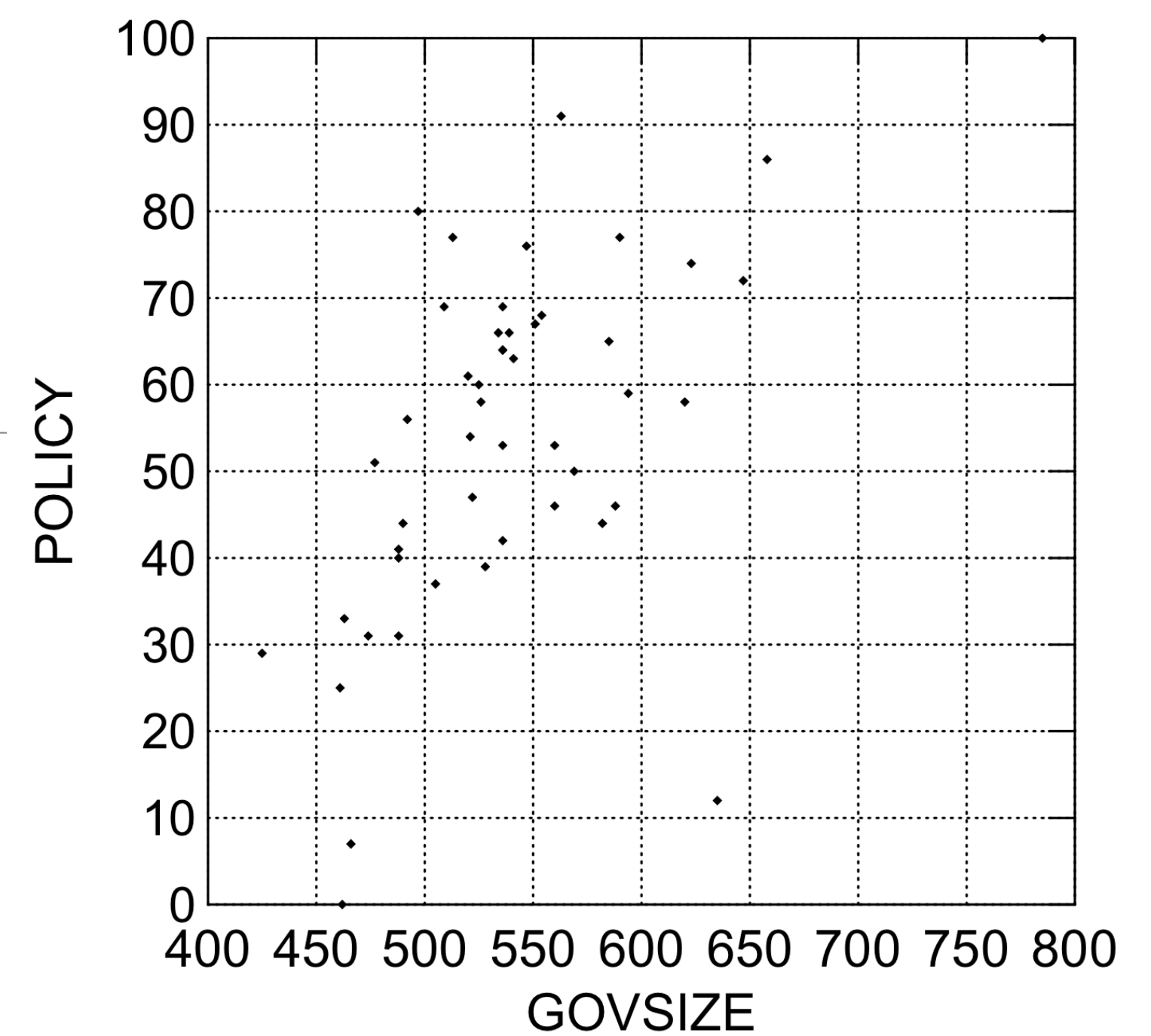
An ugly scatterplot



*Aggressively
difficult to see
properly*

Why is it so ugly?

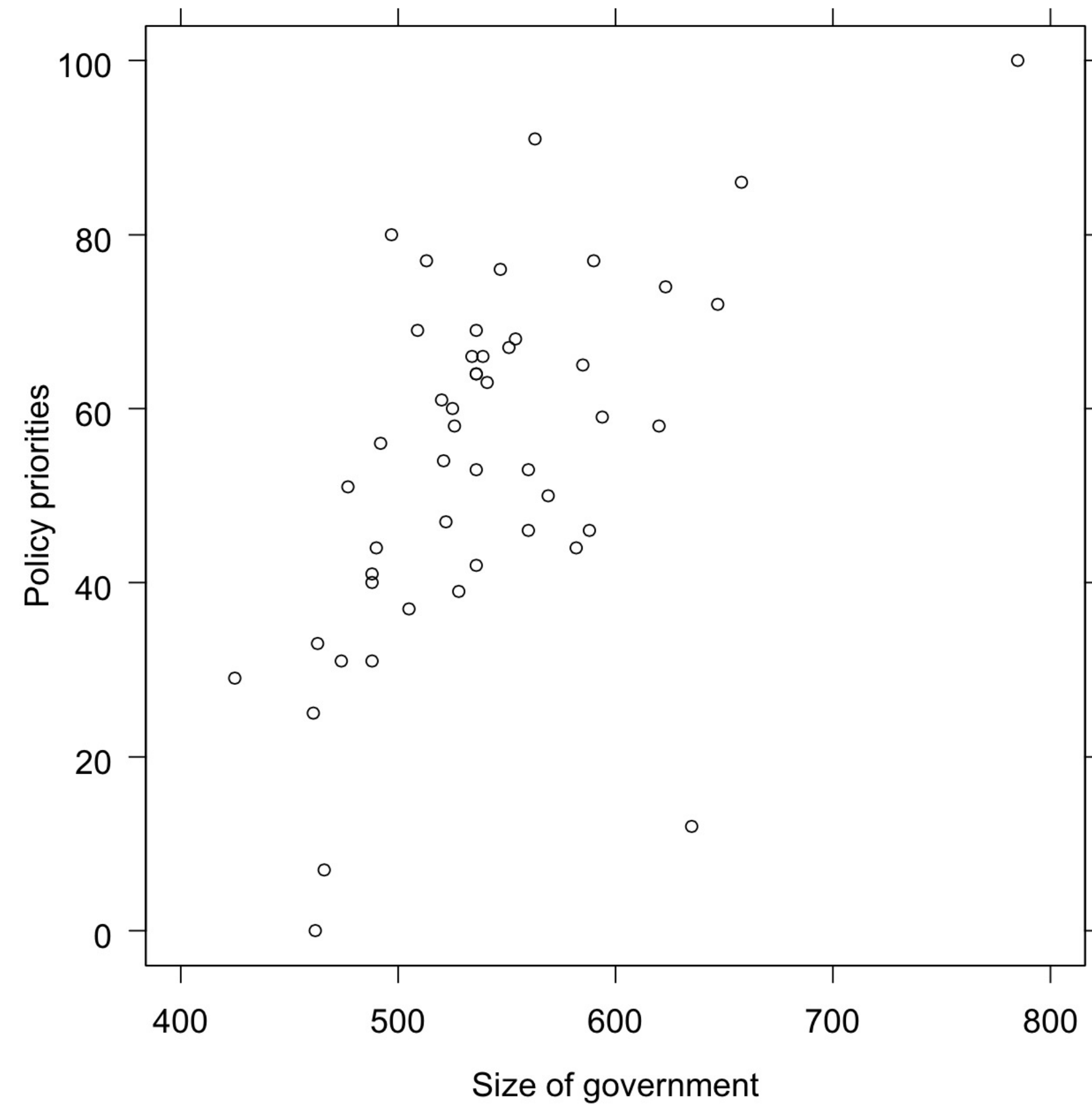
- Doesn't follow the rules!
 - Why all those gridlines?
 - Why so many so many ticks?
 - Origin labels jammed together
 - LABELS ANGRY! YELLING AT YOU! SHORTENED TOO! FOR NO GOOD REASON!
 - Where are those data points again? Can you squint and see them?
 - What is this even a graph of? Curling policy?
- *Data-ink ratio is poor*



How do I make not-ugly graphs?

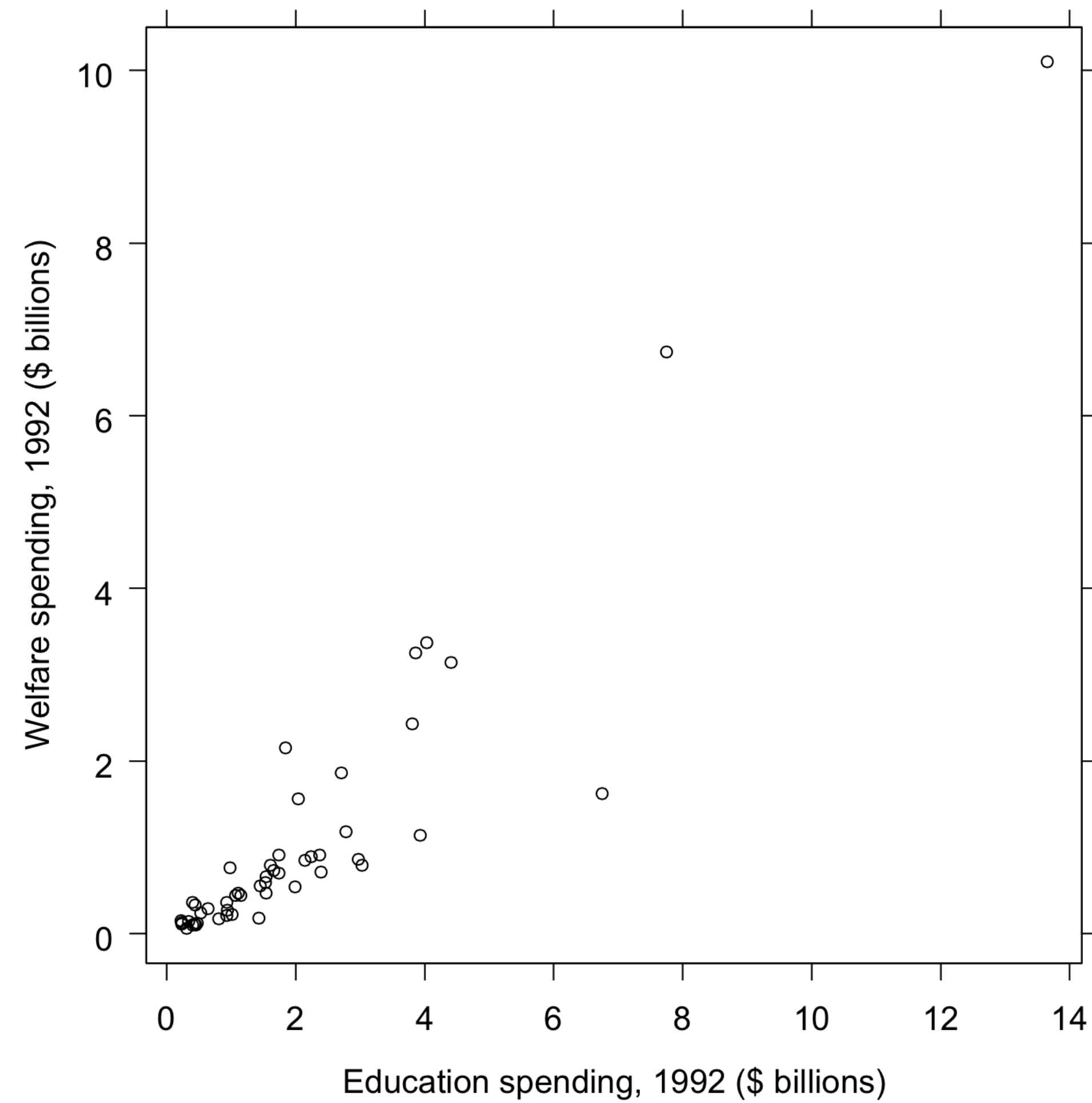
- Use axes to enclose the plot region
- Clear axis labels
- Rectangular grid lines within the plot region are unnecessary
- Plotting symbols should be visually prominent (data!)
- Tick marks point outward, not inward over the plot region
- Few tick marks on each axis
- Data rectangle should be slightly smaller than the scale rectangle
- When (and if) necessary, transform data values so plotted points fill up the data rectangle more fully
- Labels should be written in plain language

A not as ugly scatterplot

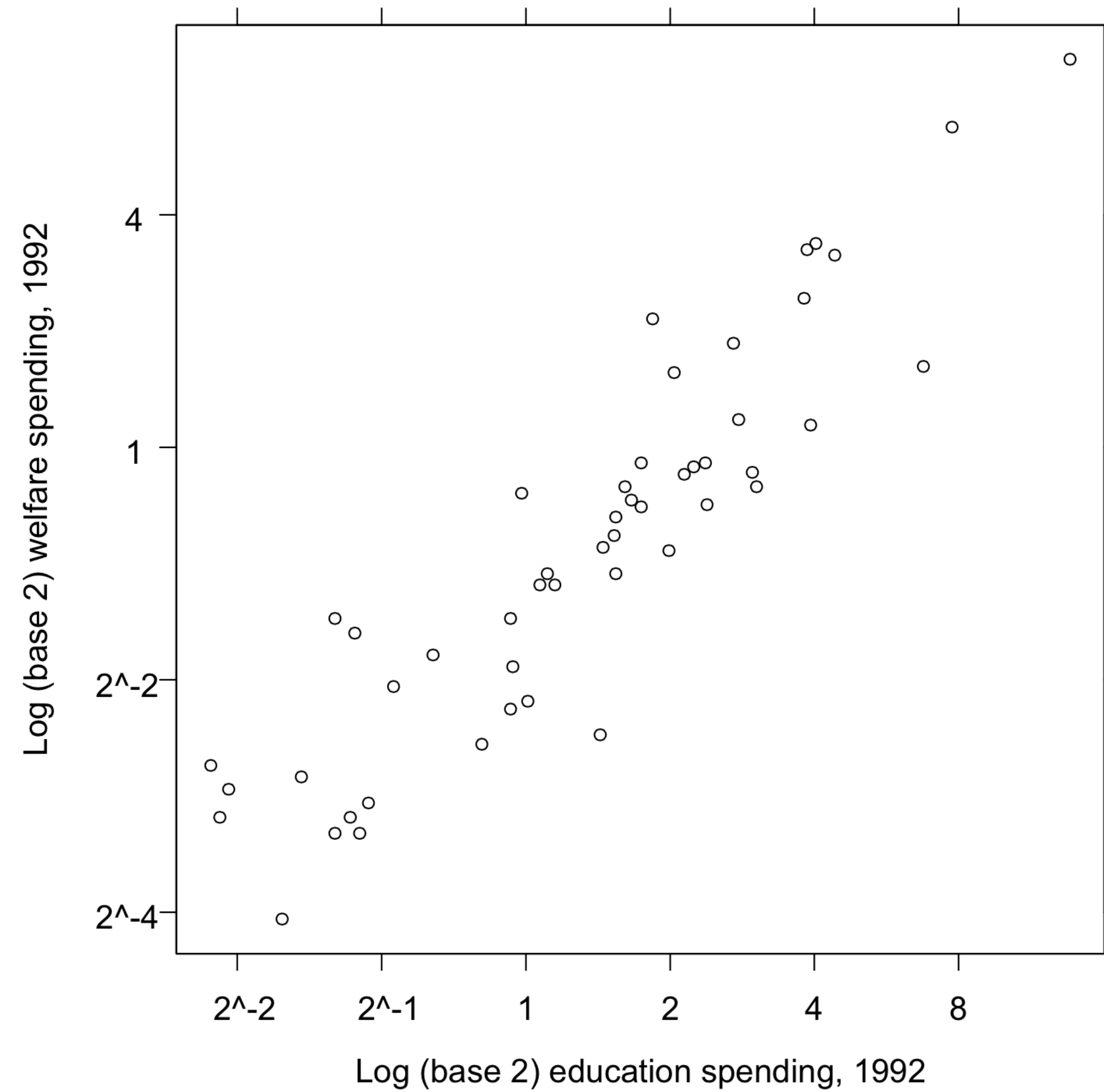
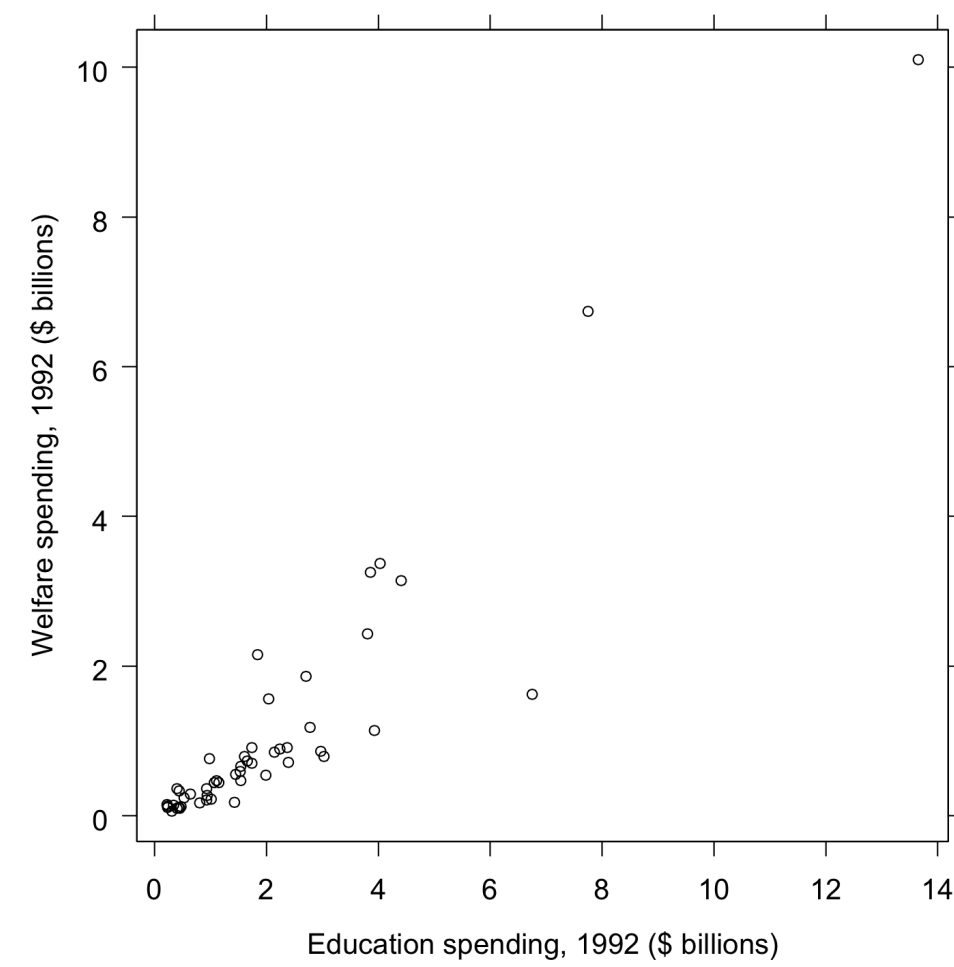


Ahhh . . .

Transforming variables



Transforming variables

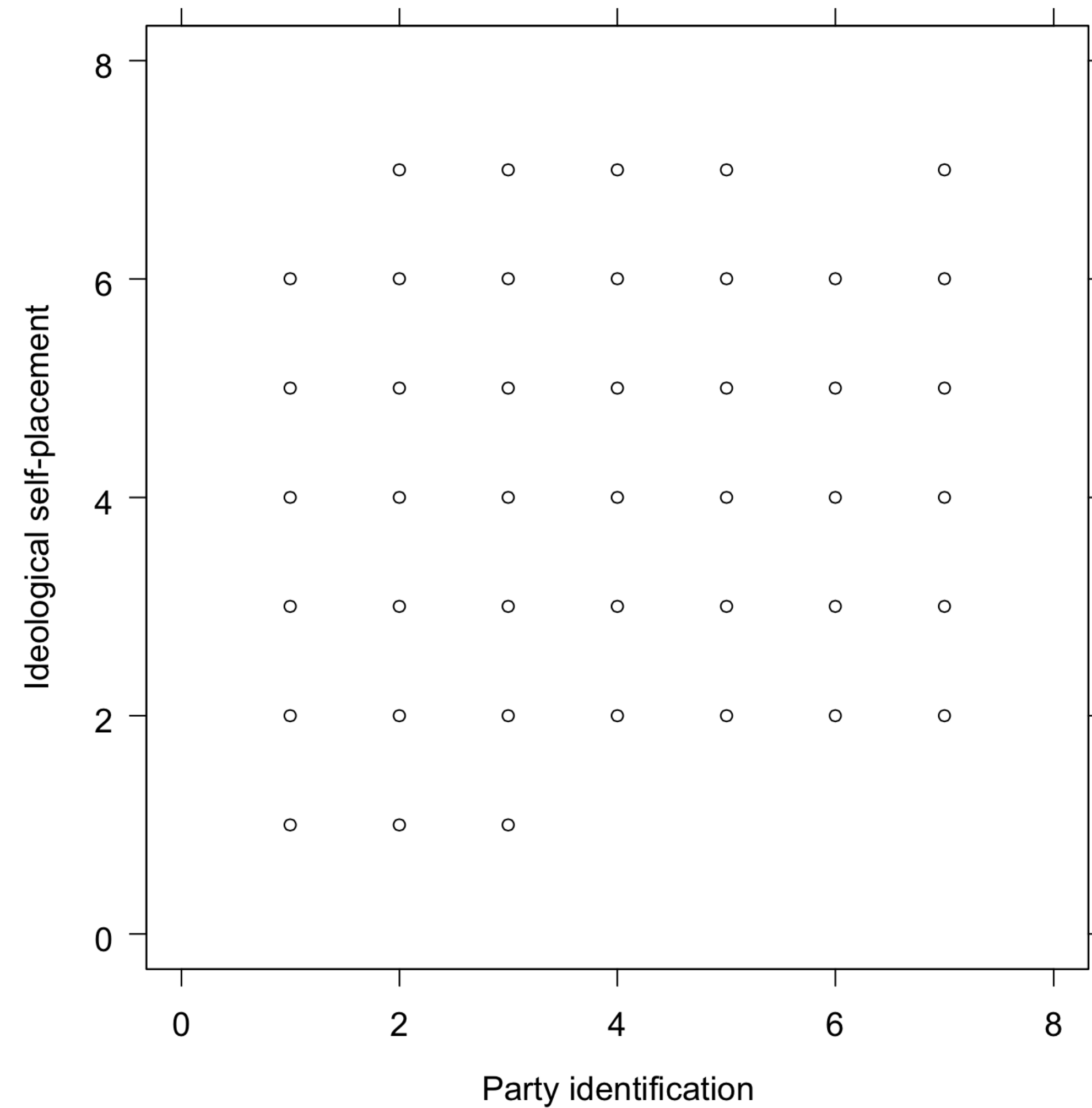


Enhancements

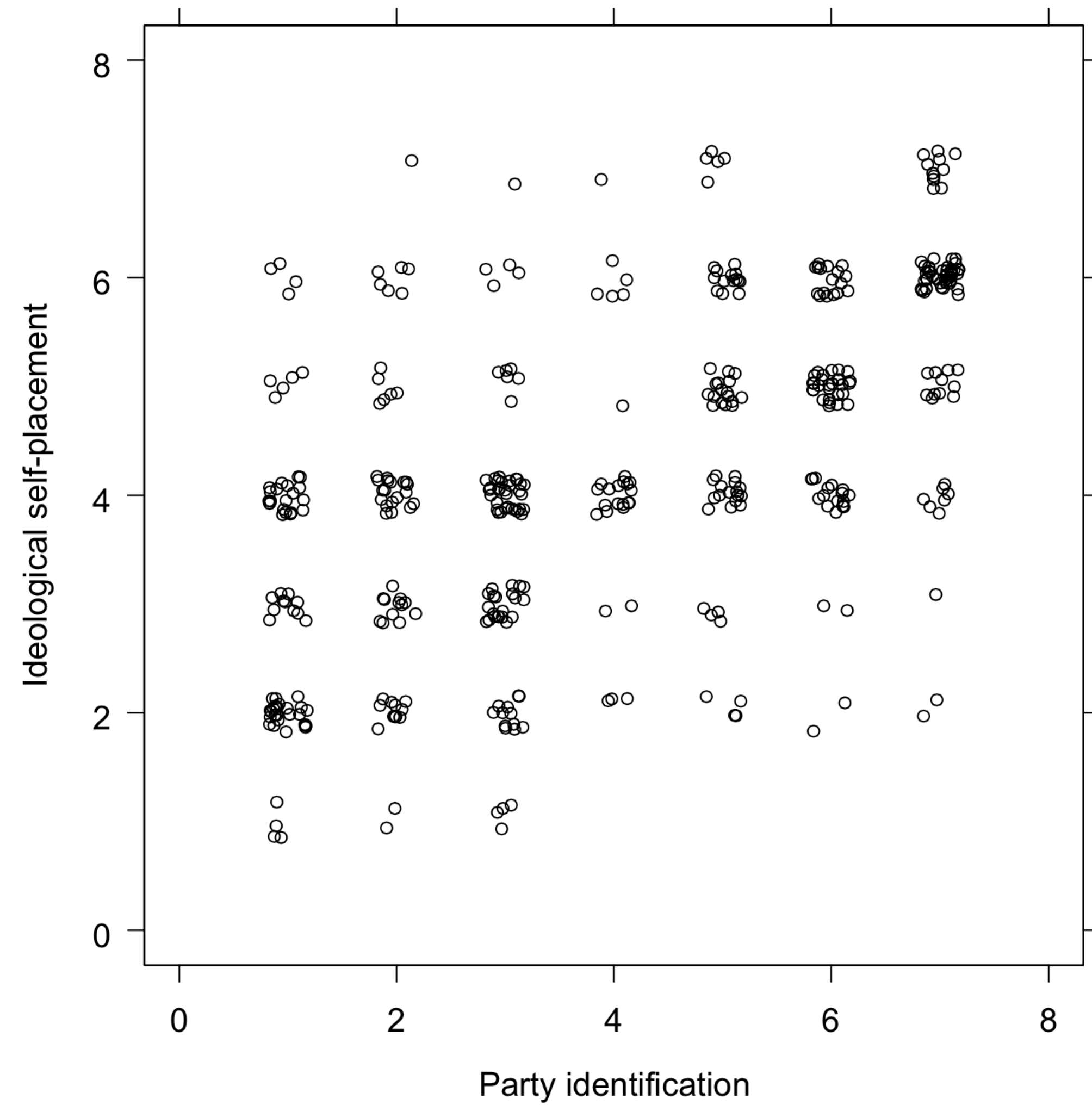
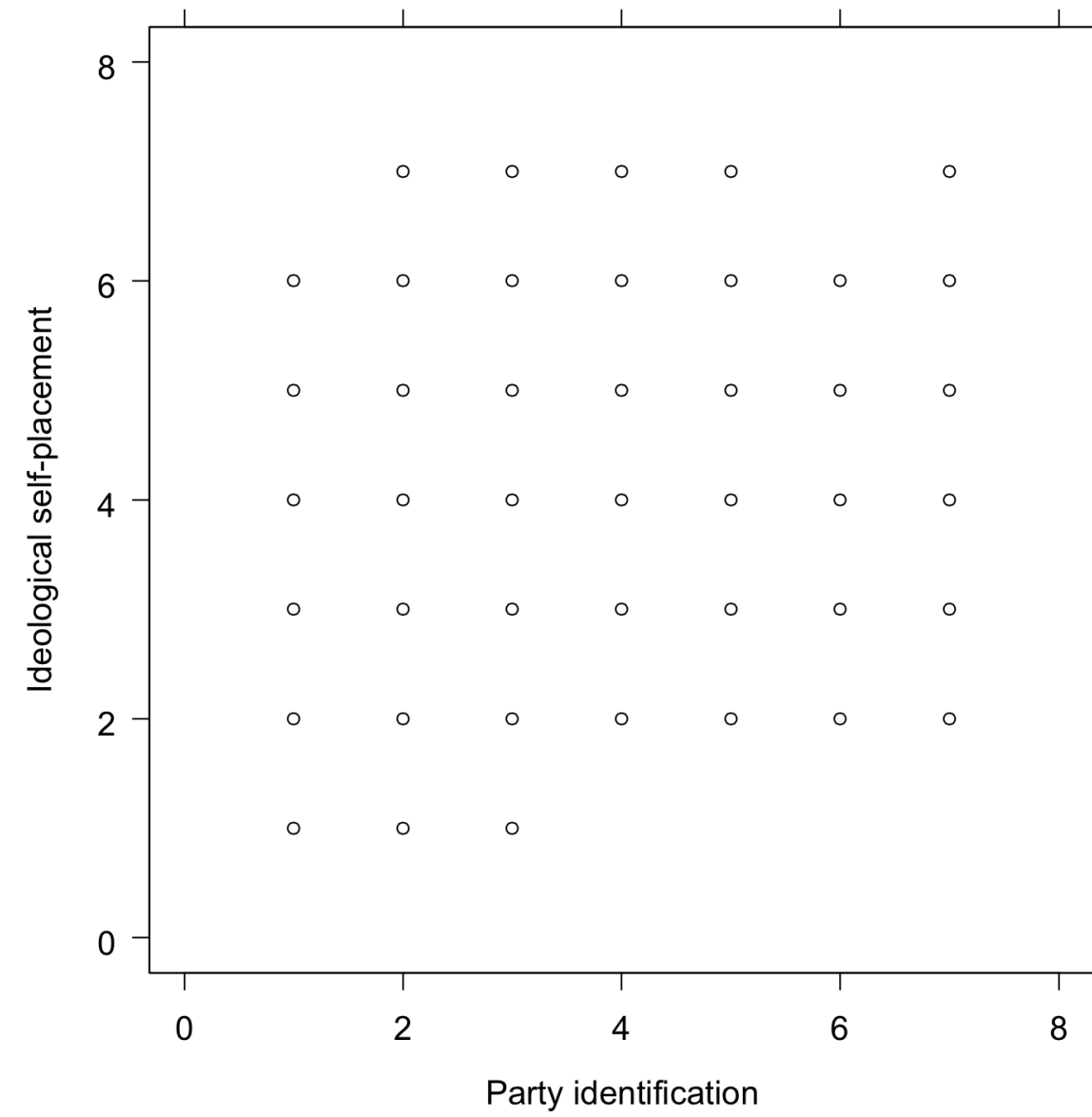
- How else can we make better looking, more informative scatterplots?
 - Jitter data to prevent overplotting and deal appropriately with repeated data points
 - Marginal displays of univariate information (box plots!)
 - Label data points (but use sparingly - data-ink ratio)

Jittering

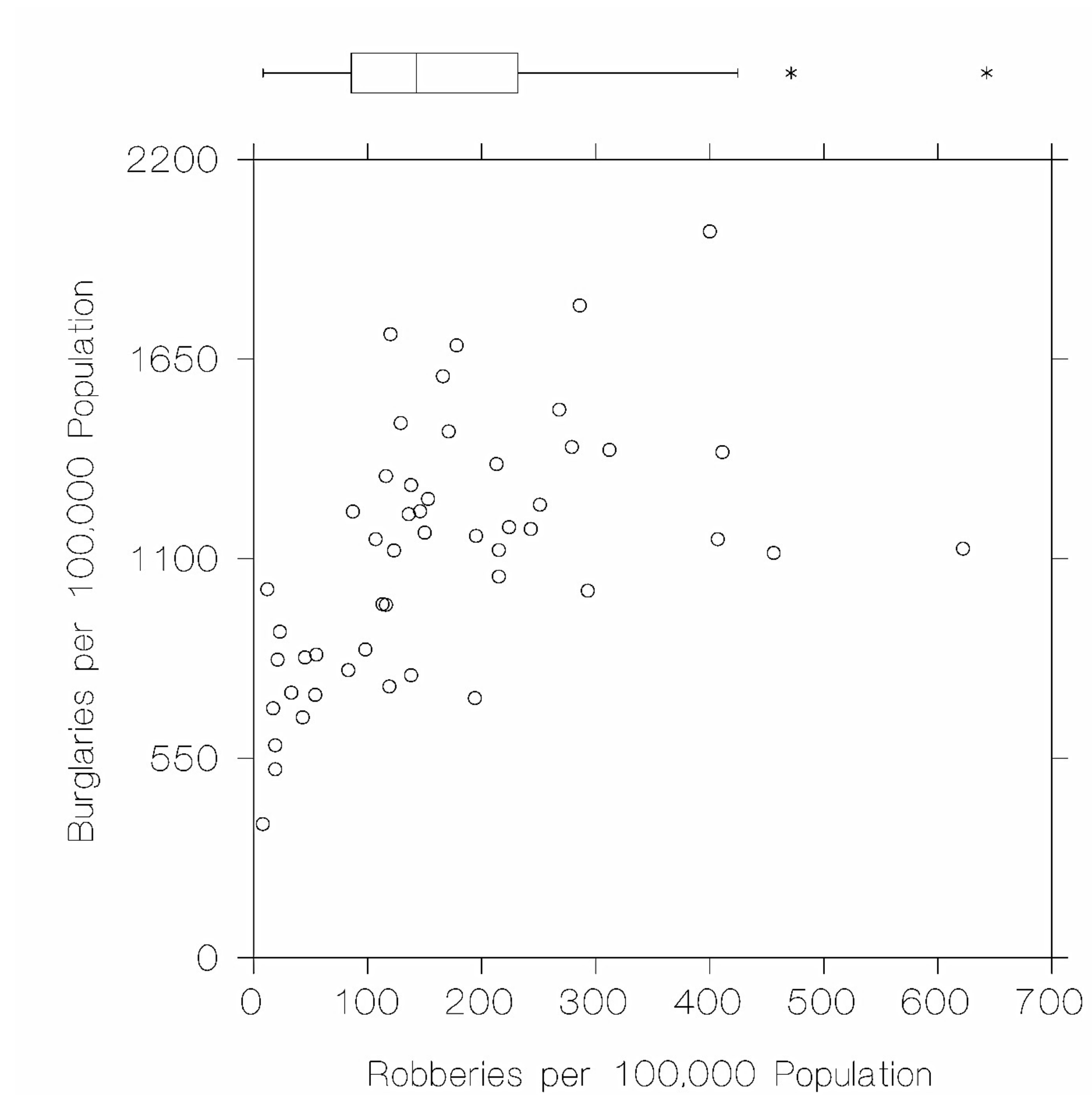
- What's going on in this figure?



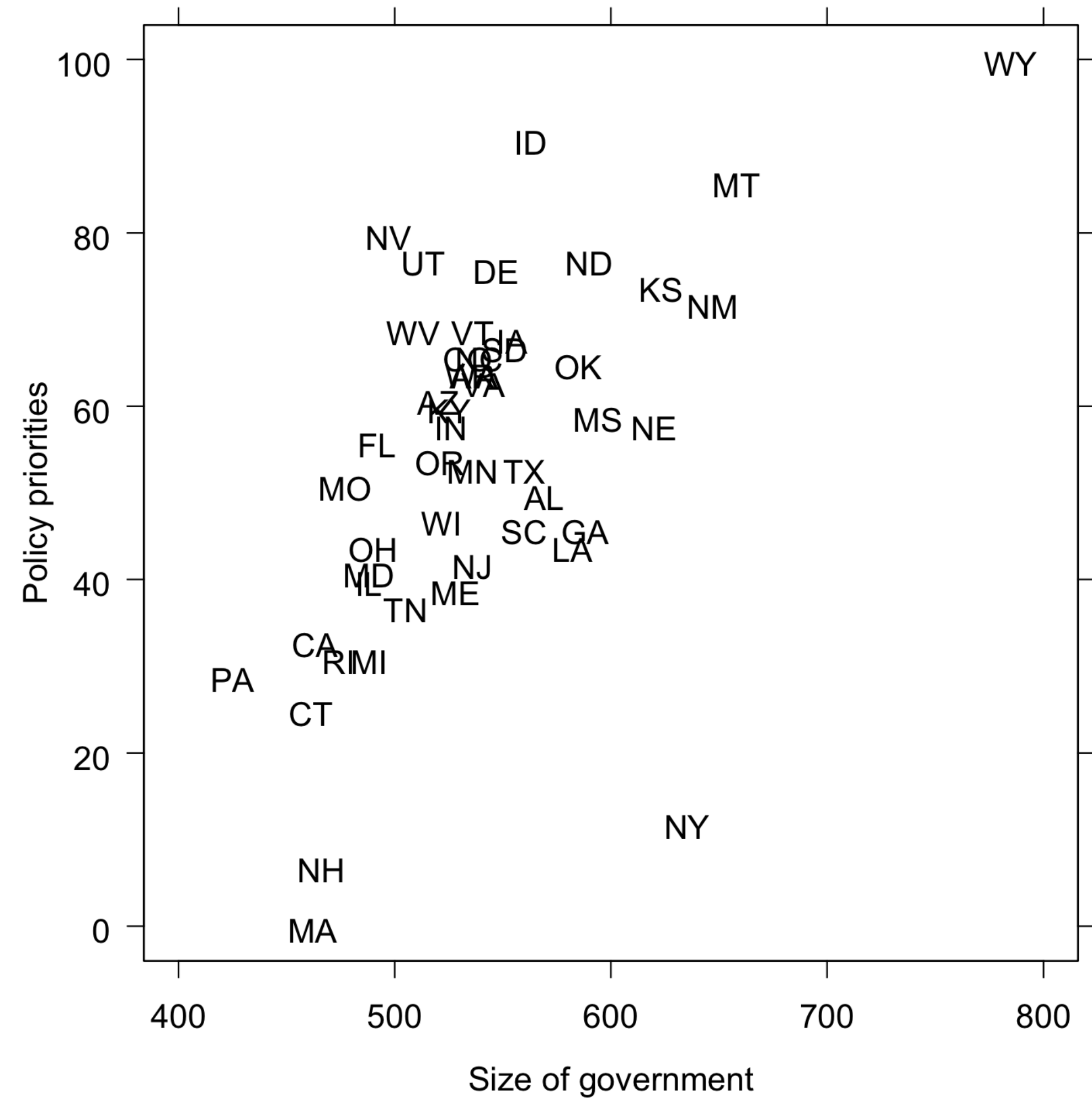
Jittering



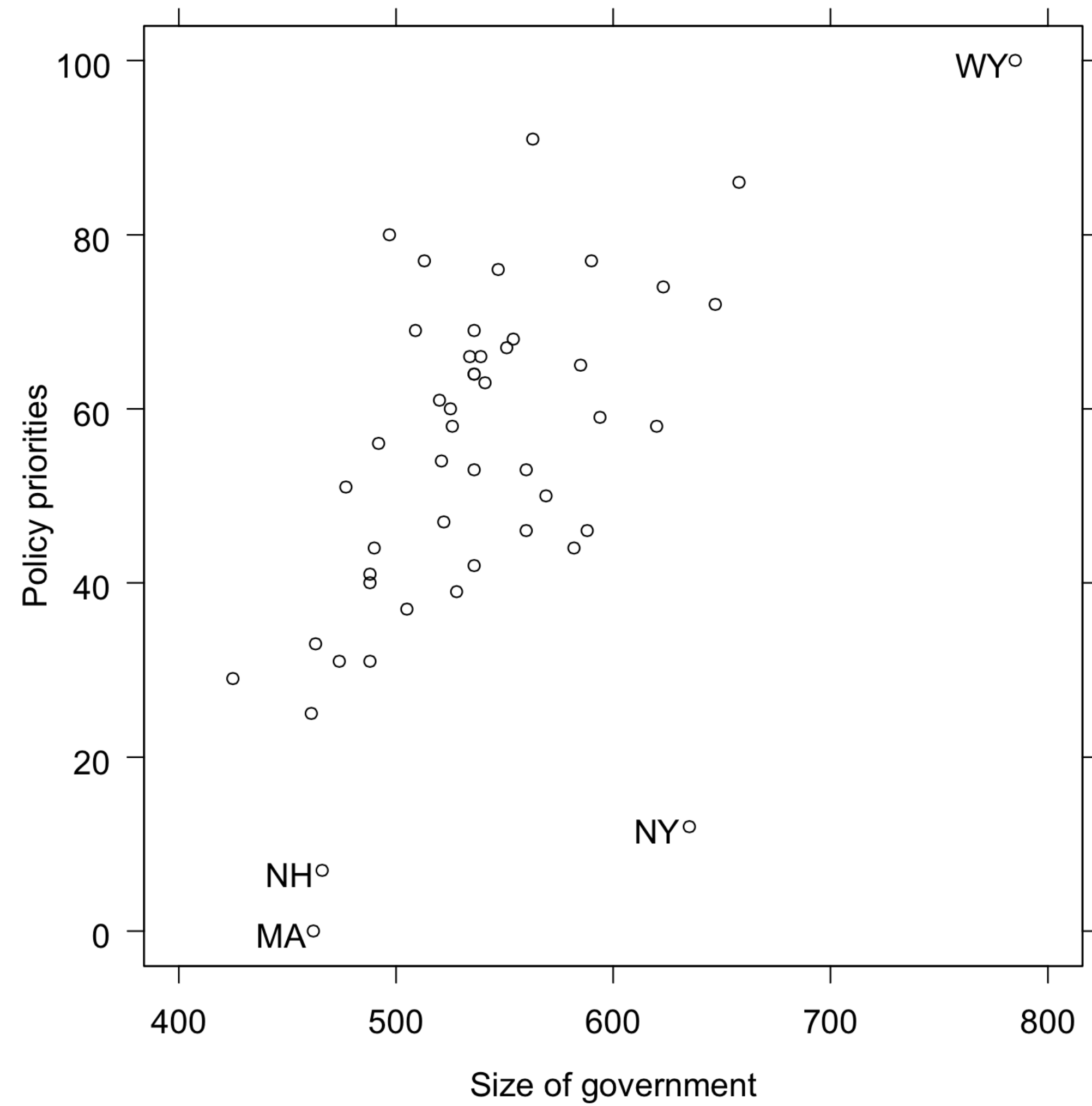
Univariate axes for clarity



A not super great use of point labels



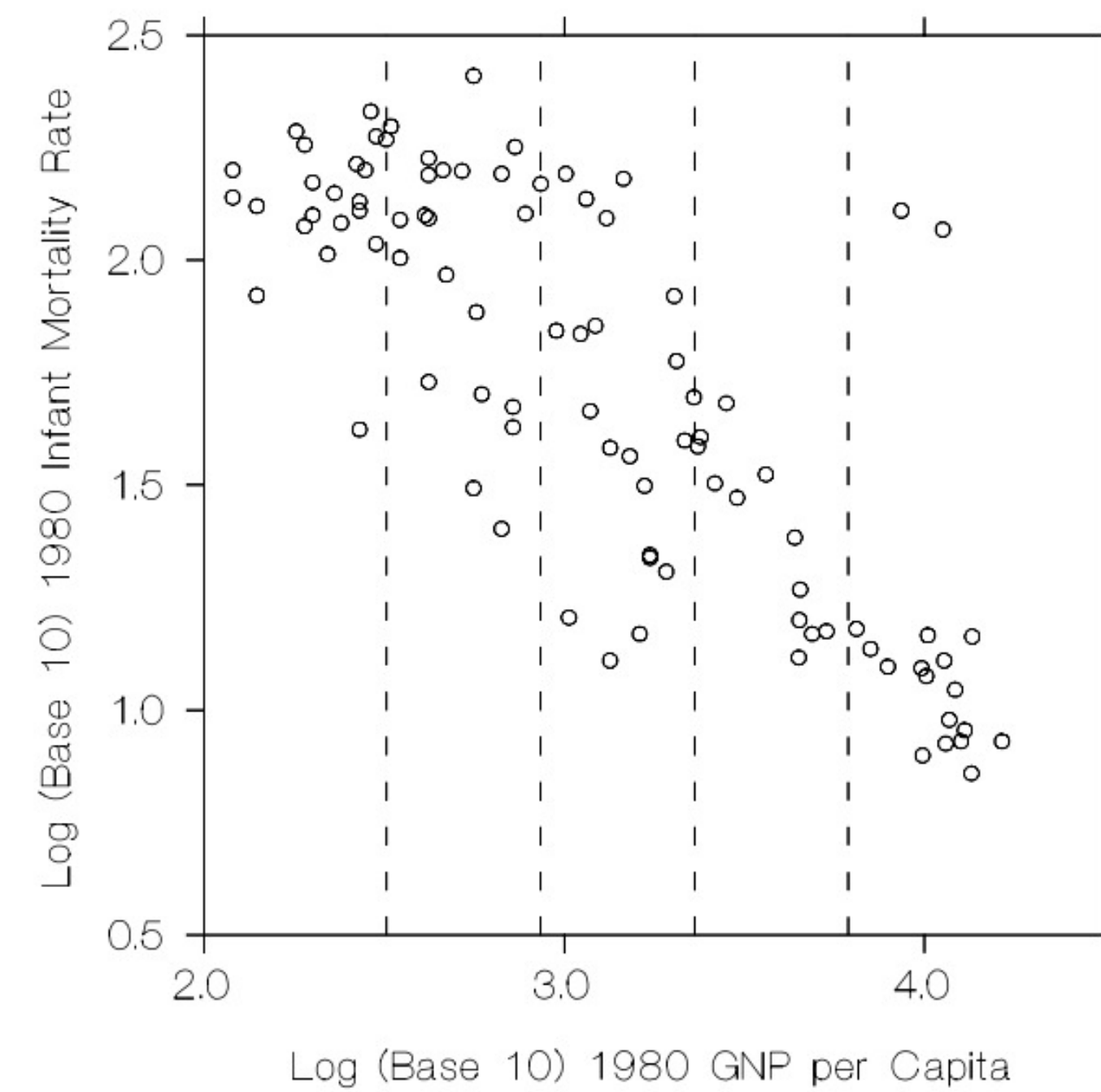
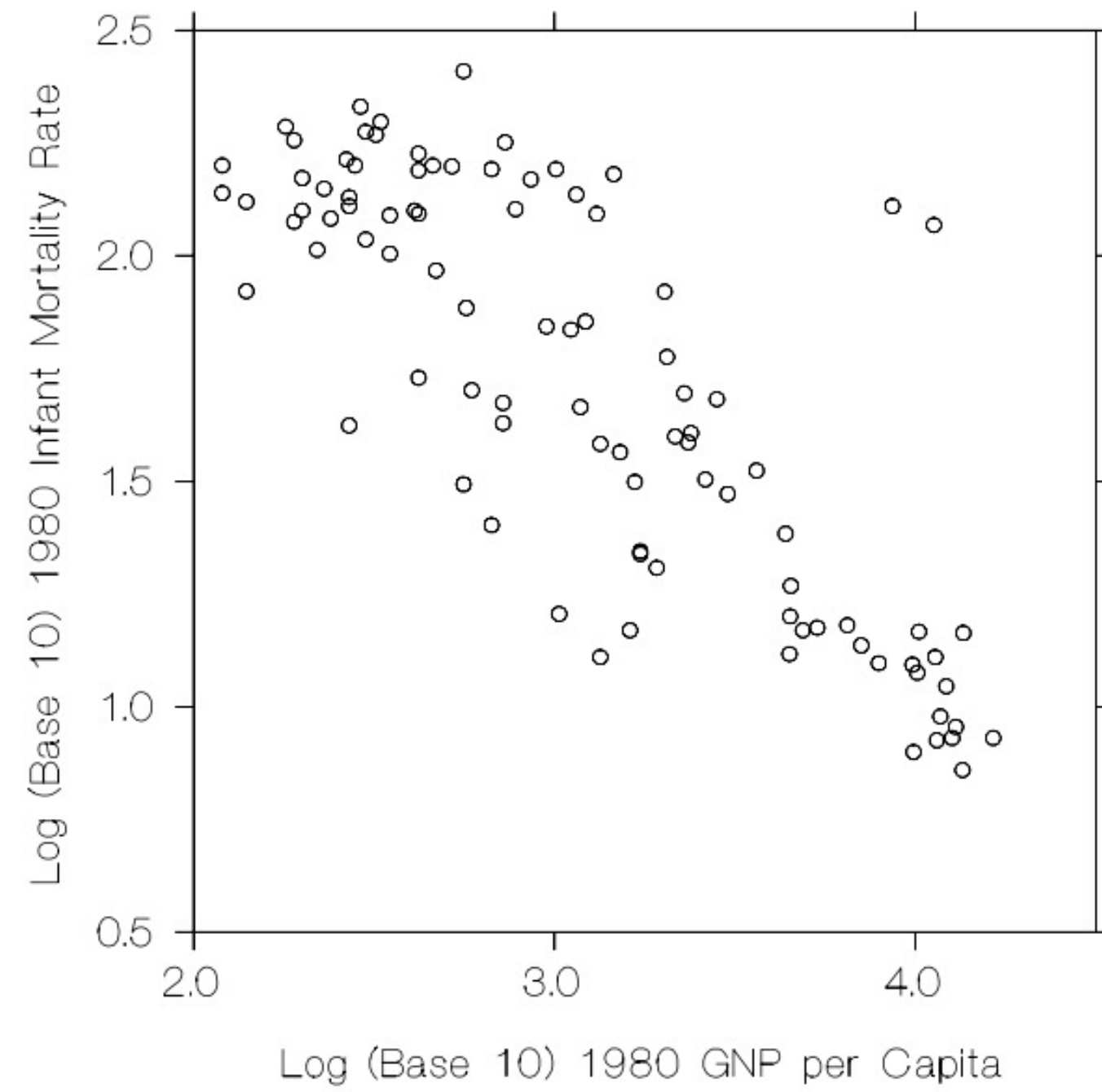
A better use of point labels



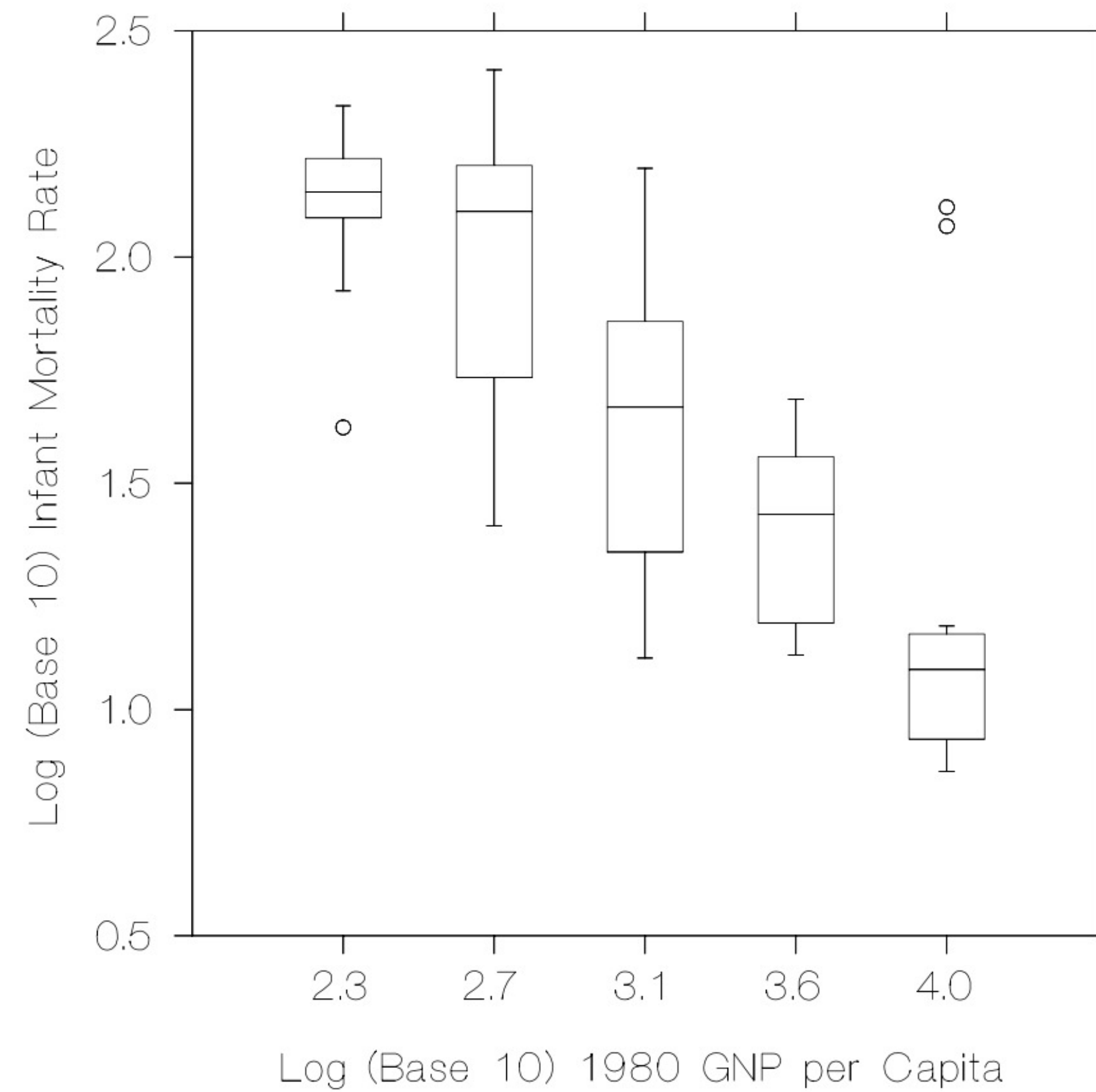
What else can we do?

- Primary point to visual displays of bivariate data is to better assess *functional dependence* - a fancy phrase for the kind of relationship existing between variables
- *Slice* a scatterplot with box plots (or something else) to give a better visual flow and abstract from individual data points
 - where you divide a plot region on the scatterplot into vertical “slices”, enabling nice visual displays
 - Can use univariate graphical displays in each slice
- Can allow for easier examination of relationships between variables

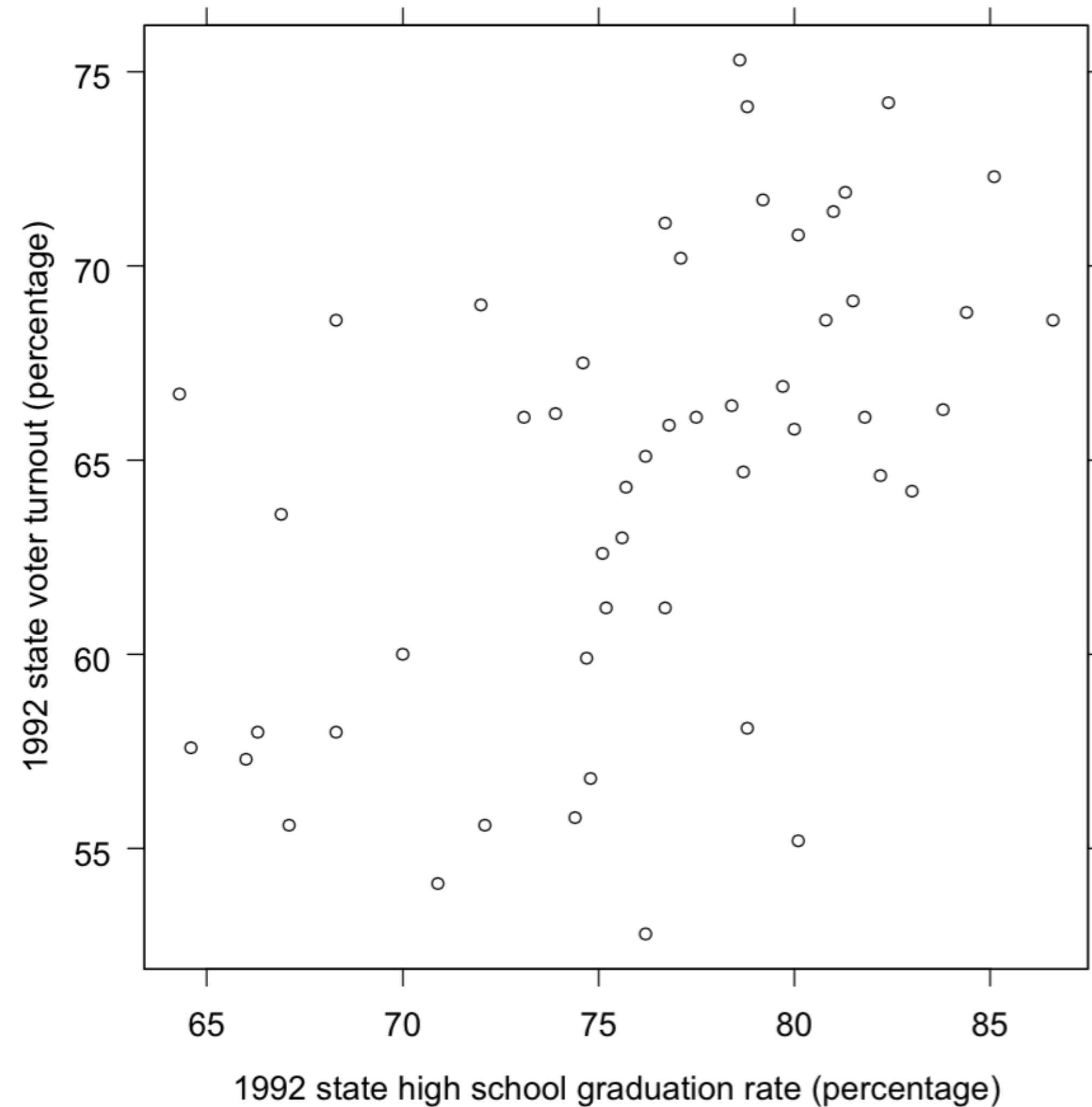
Slicing a scatterplot . . .



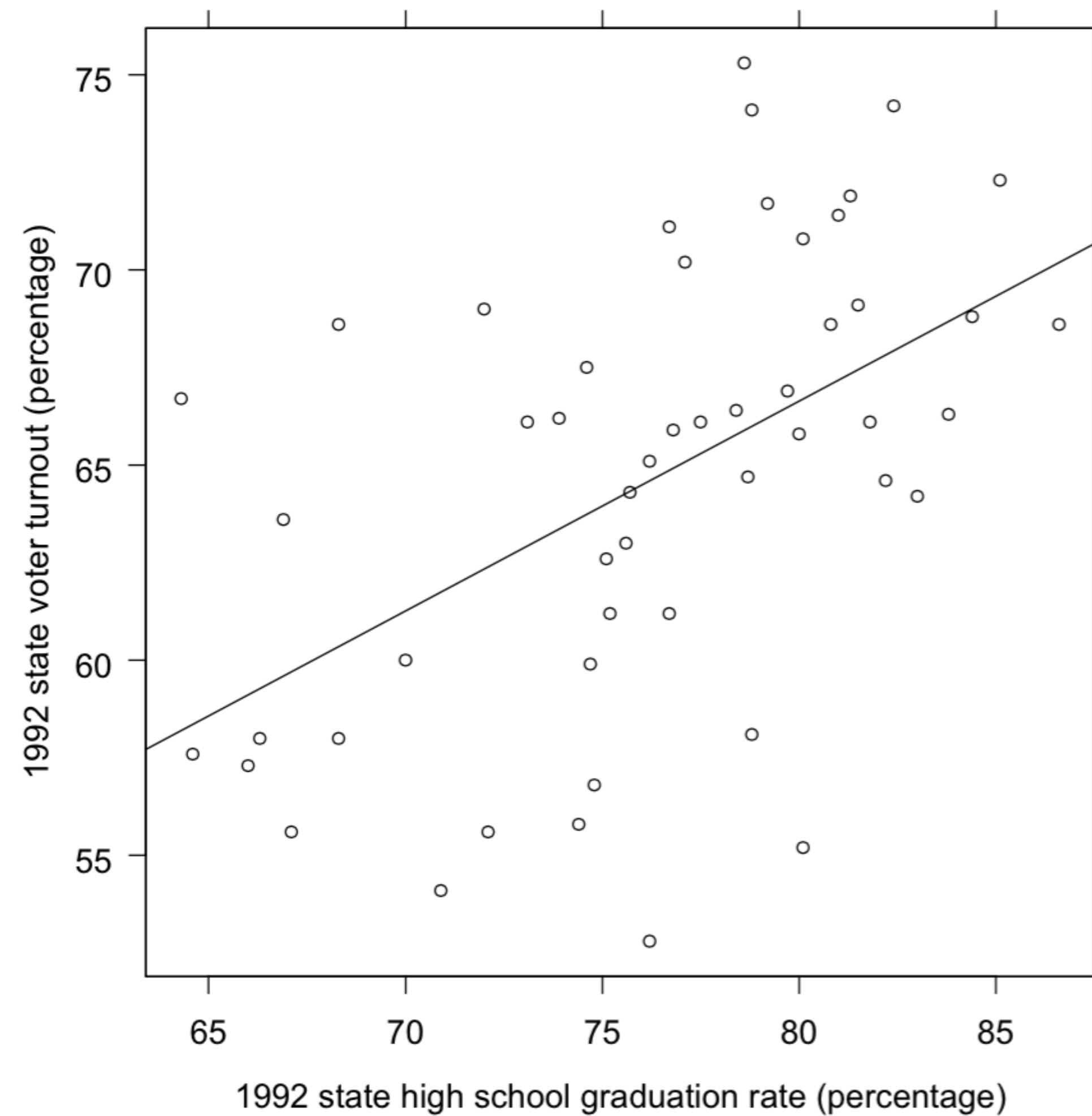
. . . and making box plots!



How can we clarify scatterplots with vague relationships?



OLS regression lines?



Doesn't,
perhaps,
capture
the data
well

OK, back to . . . (non)linearity

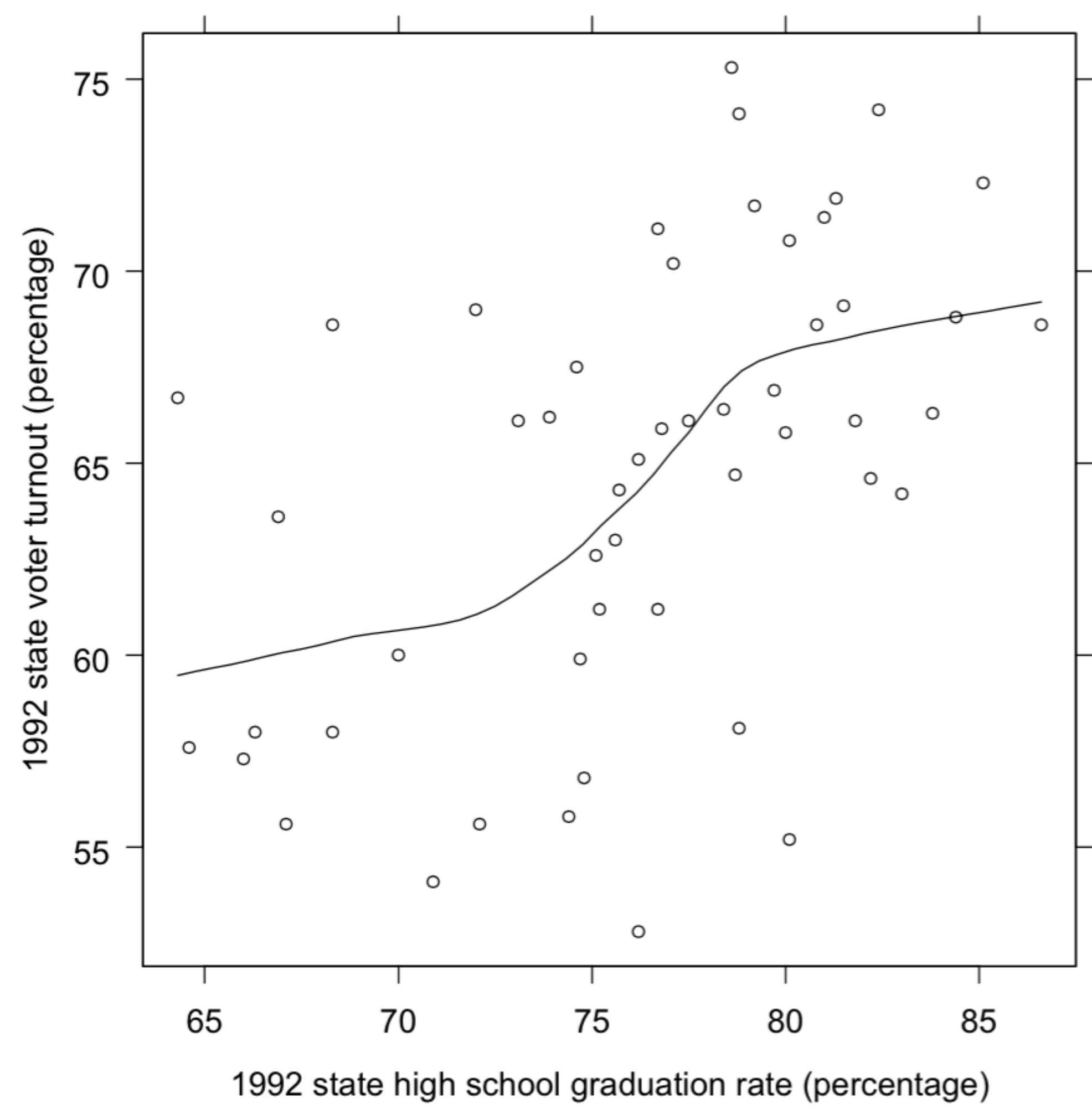
- To truly get at nonlinearity, it'd be nice to find simple ways to represent variable relationships besides lines
- Enter *scatterplot smoothing* - a very simple type of “nonparametric” regression
 - Specify no functional form, just average values across the axis
 - Generates a smooth curve that follows center of Y distribution across a range of X values

Loess smoothing

Loess = *Local* Regression

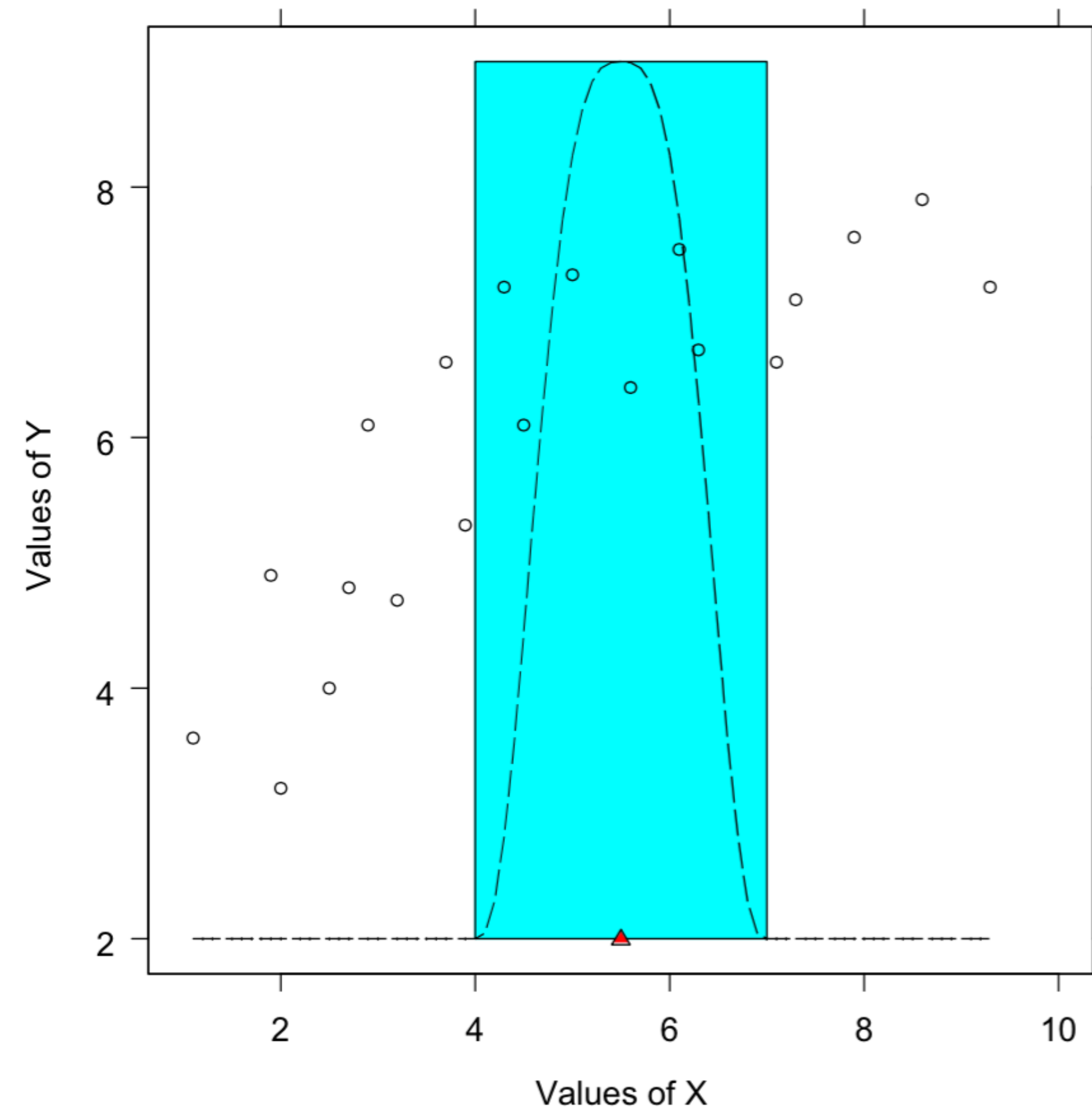
- Loess carries out a series of regressions within a “window” that “moves” across the range of X values
- Define equally space locations across X, perform a regression at each space, *weighting* according to proximity to the central point of the space
- Use regression estimates to predict value for current central Y point at X, and plot that
- As window moves across, plot all predicted value points and connect them with lines

So what does this look like?

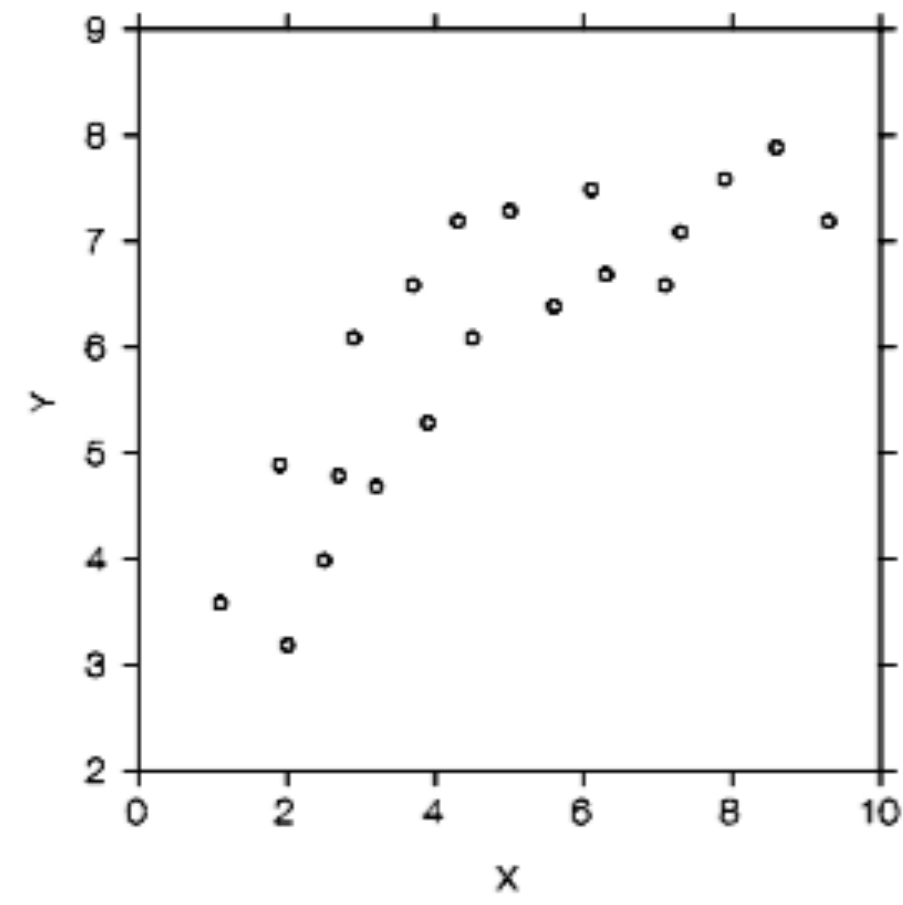


How does it work?

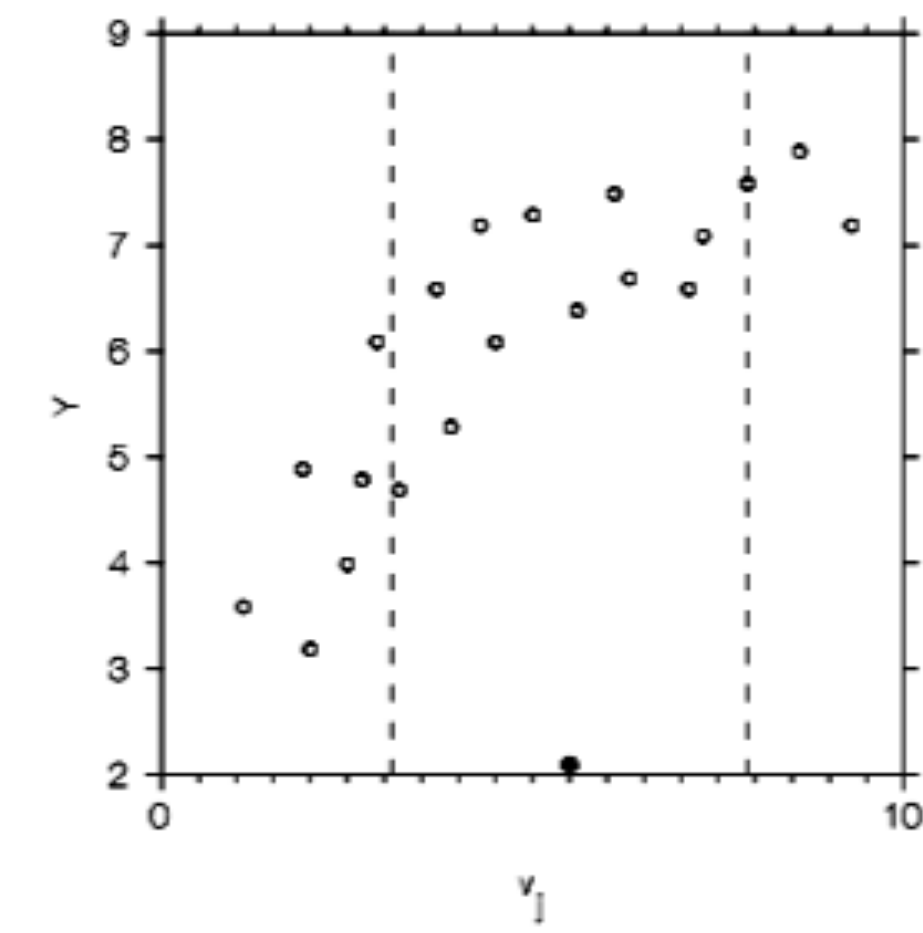
An illustration



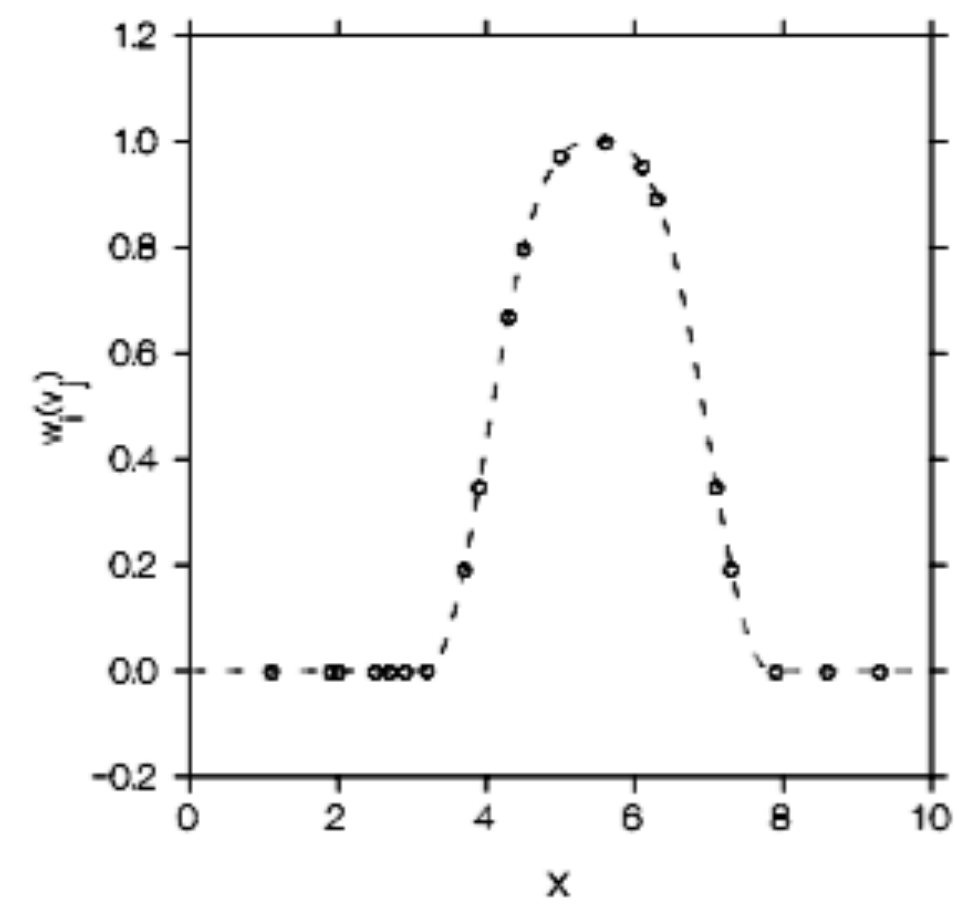
A. Hypothetical Data for Loess Fit.



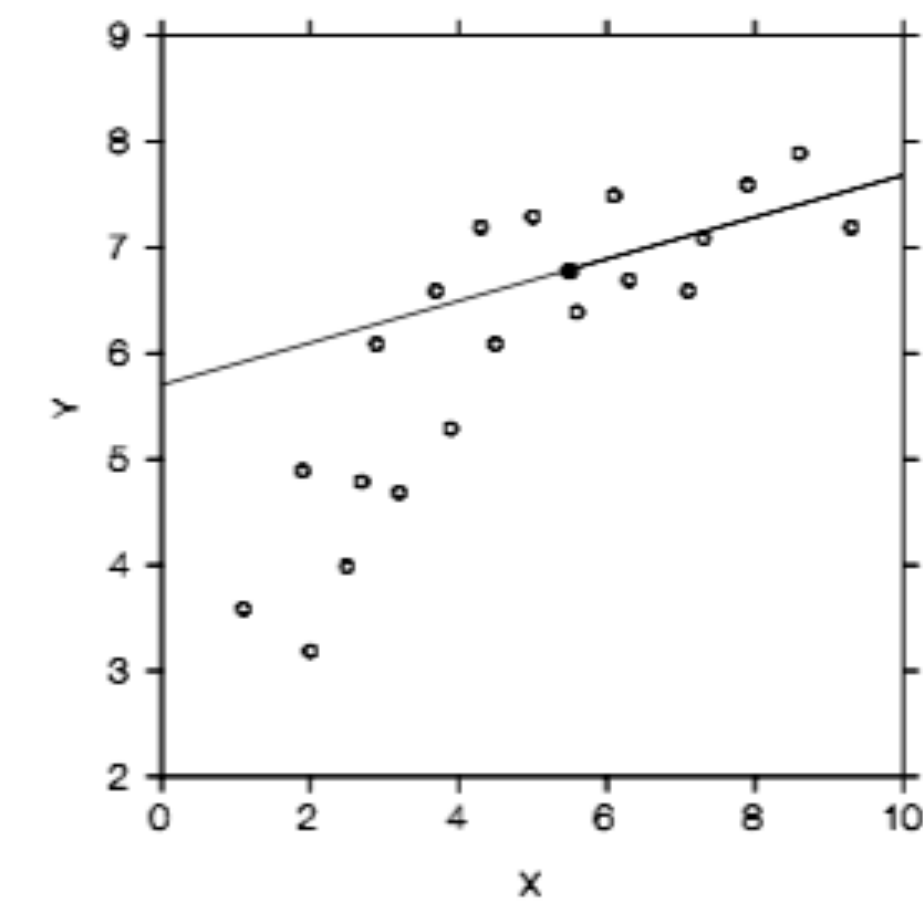
B. Window for $v_j=5.5$ and $\alpha=0.6$.



C. Tricube Neighborhood Weights.

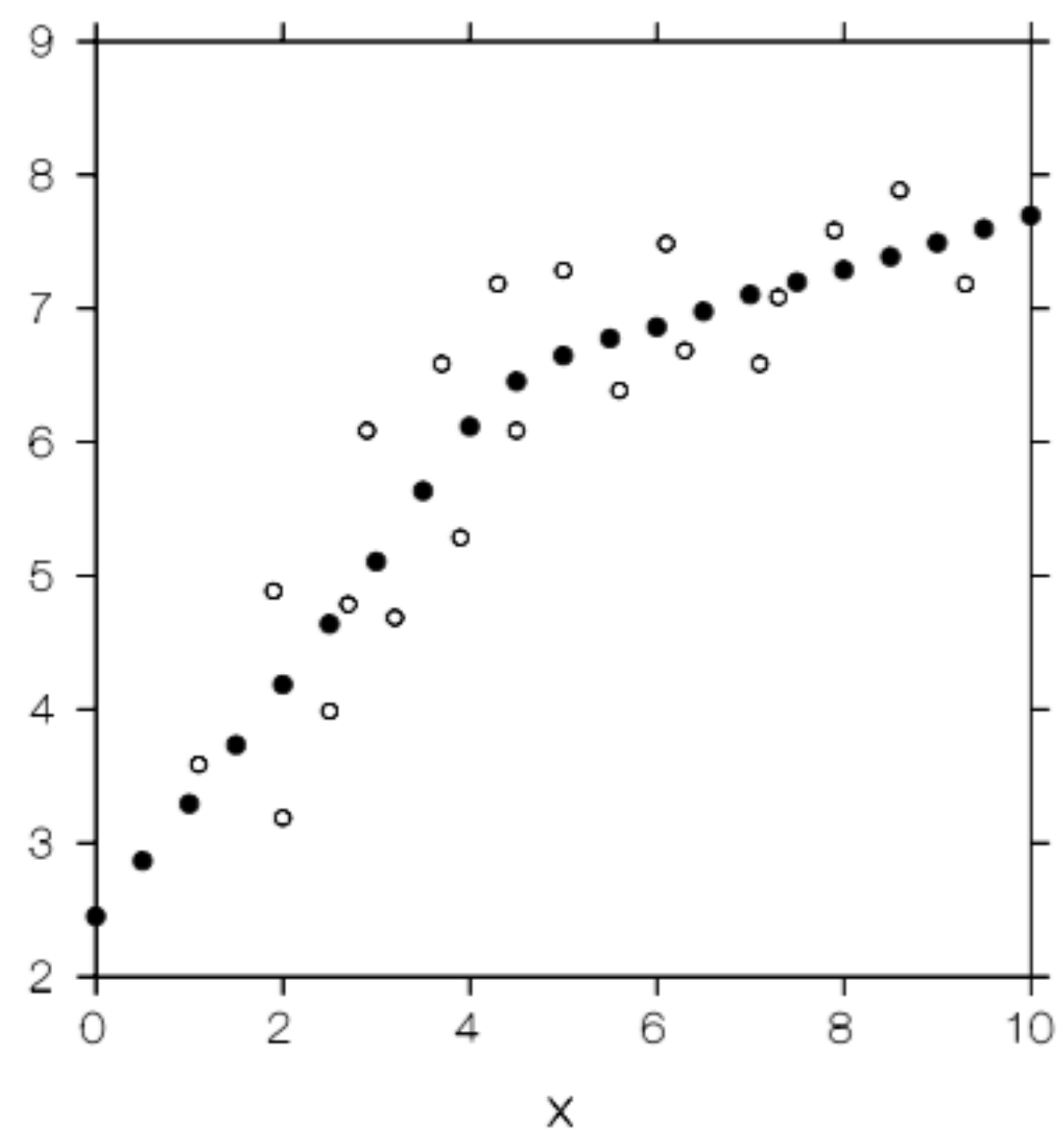


D. Initial Regression Line and Fitted Value.

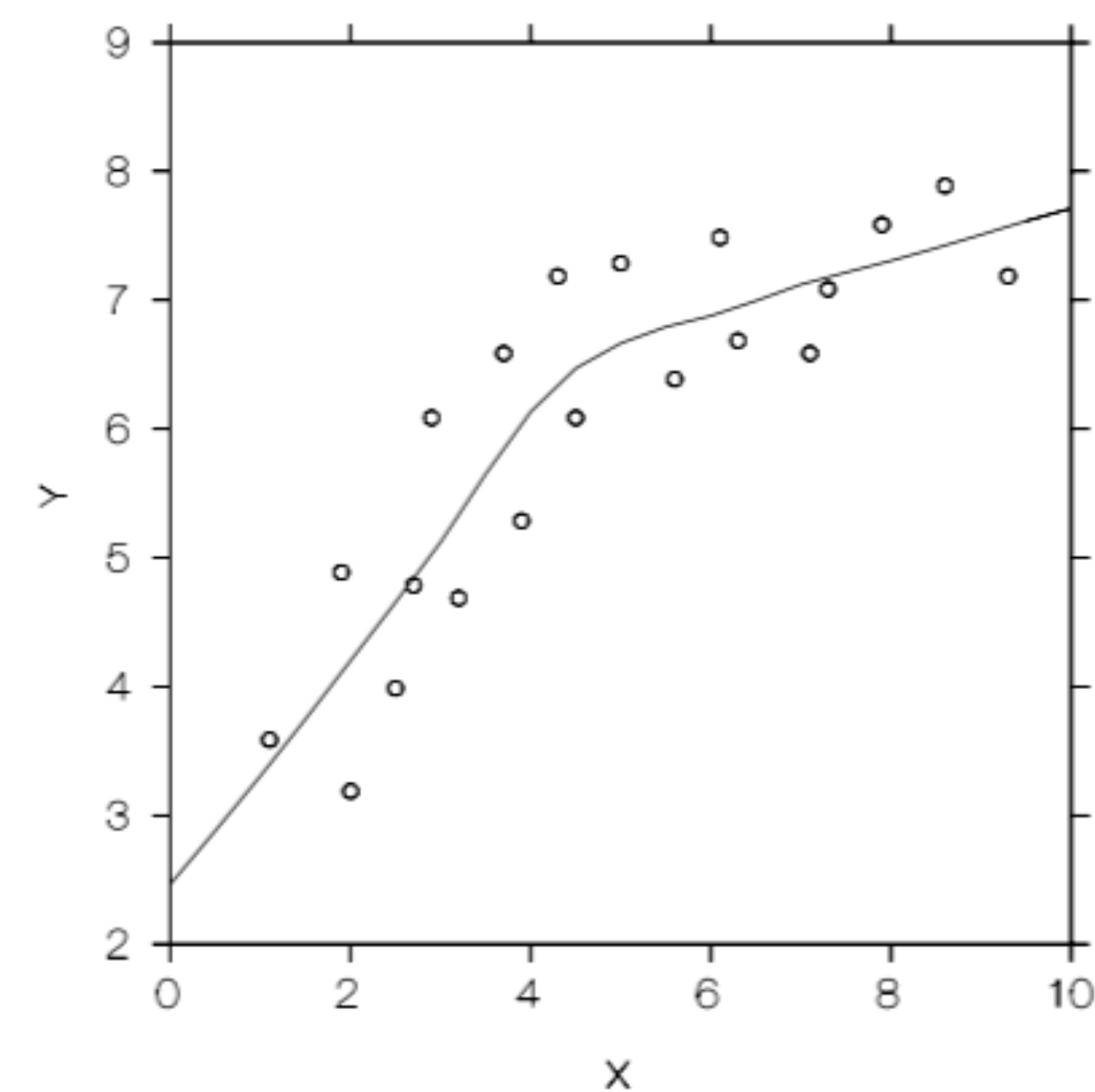


The final line

E. Complete Set of Fitted Values.



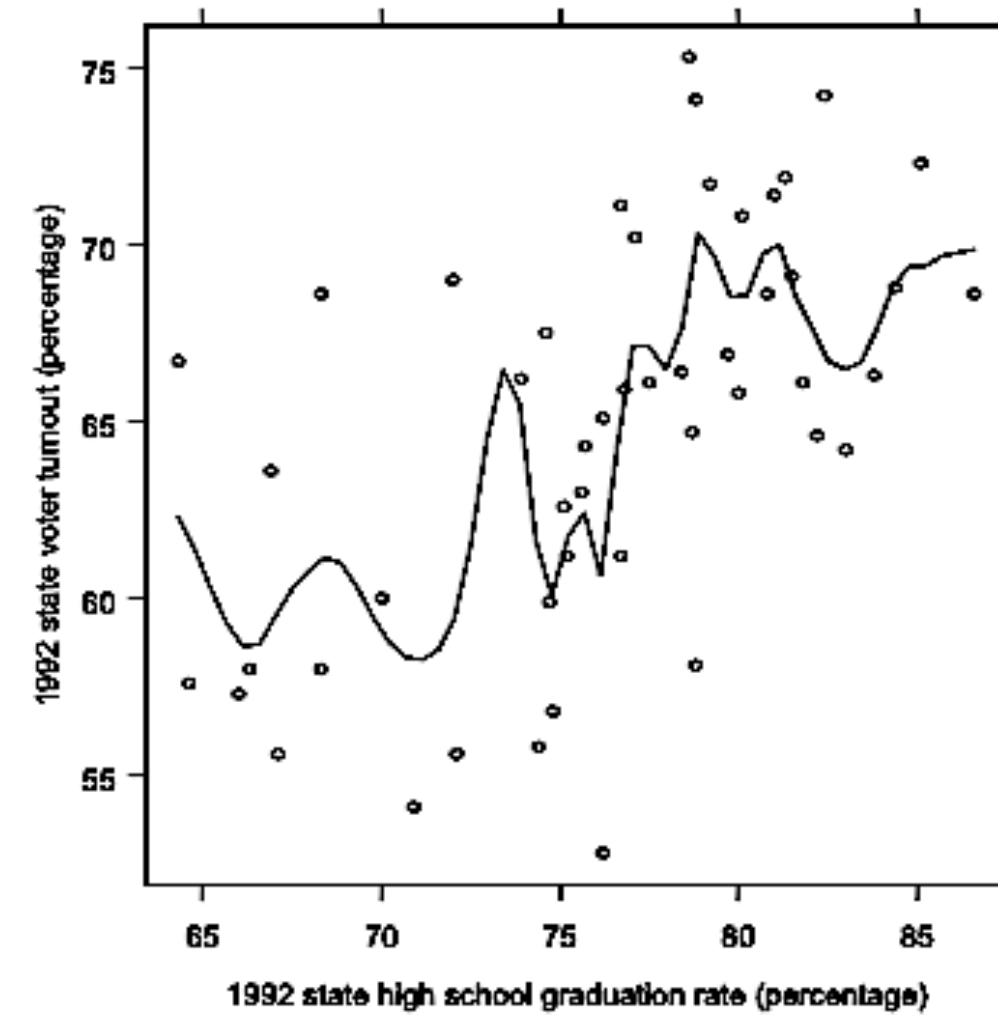
F. Loess Curve



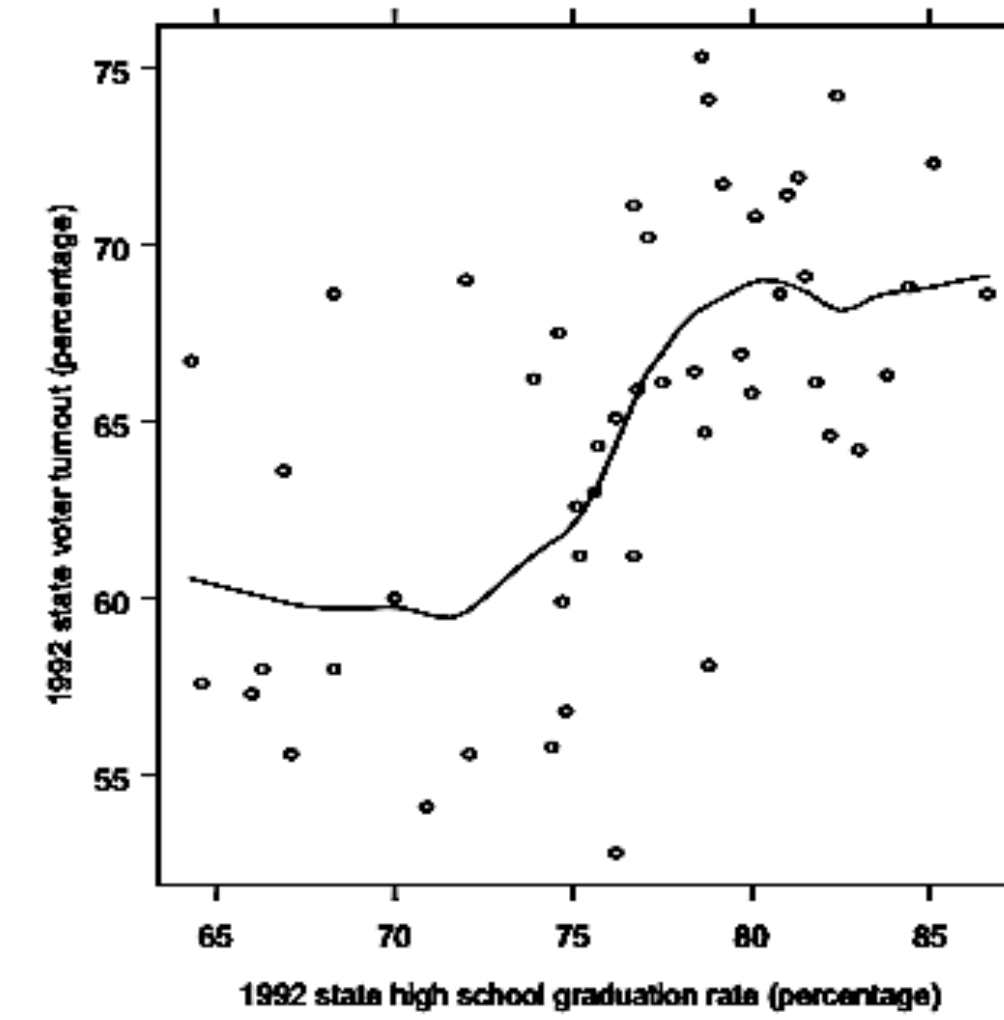
What are the limitations of loess?

- This is kind of similar to kernel density plots
- There's a similar parameter (α) identifying the “space” considered in each moving window
- And when that window changes . . .

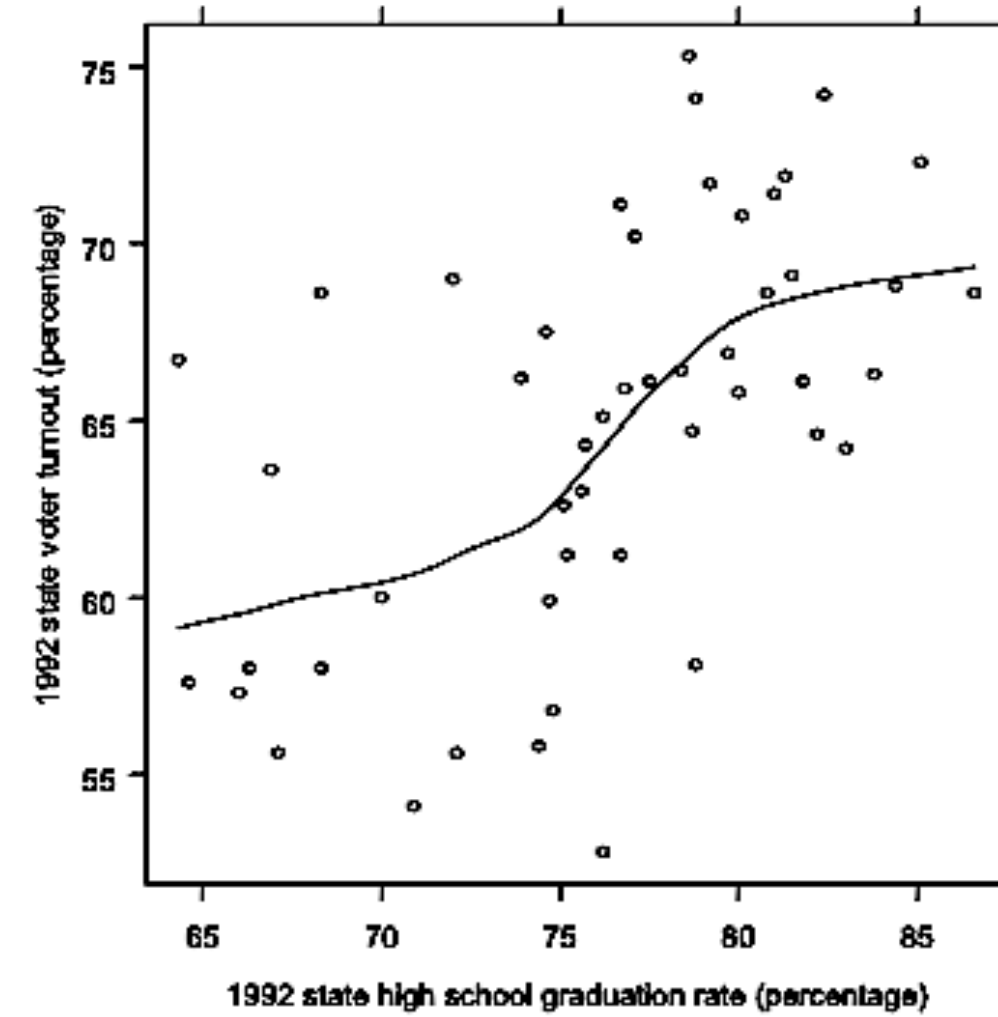
A. Loess Curve with $\alpha = 0.15$



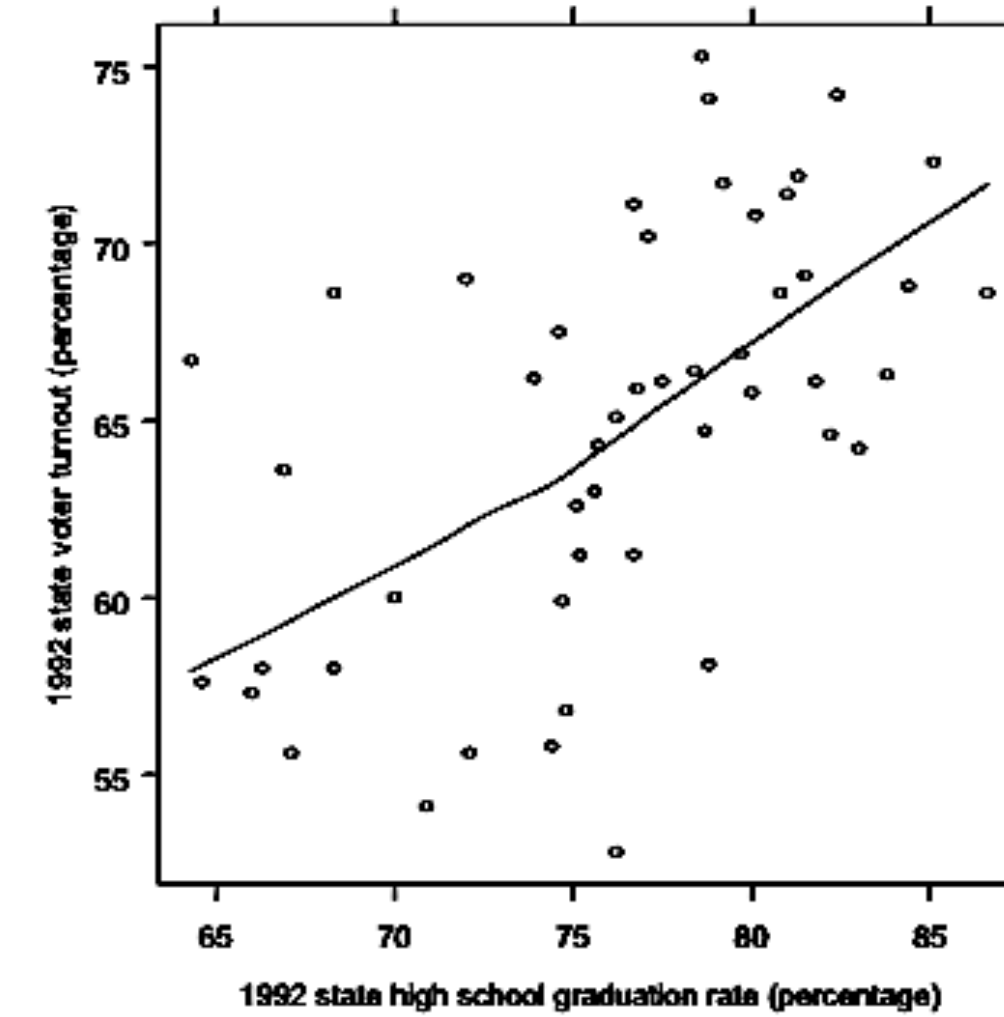
B. Loess Curve with $\alpha = 0.35$



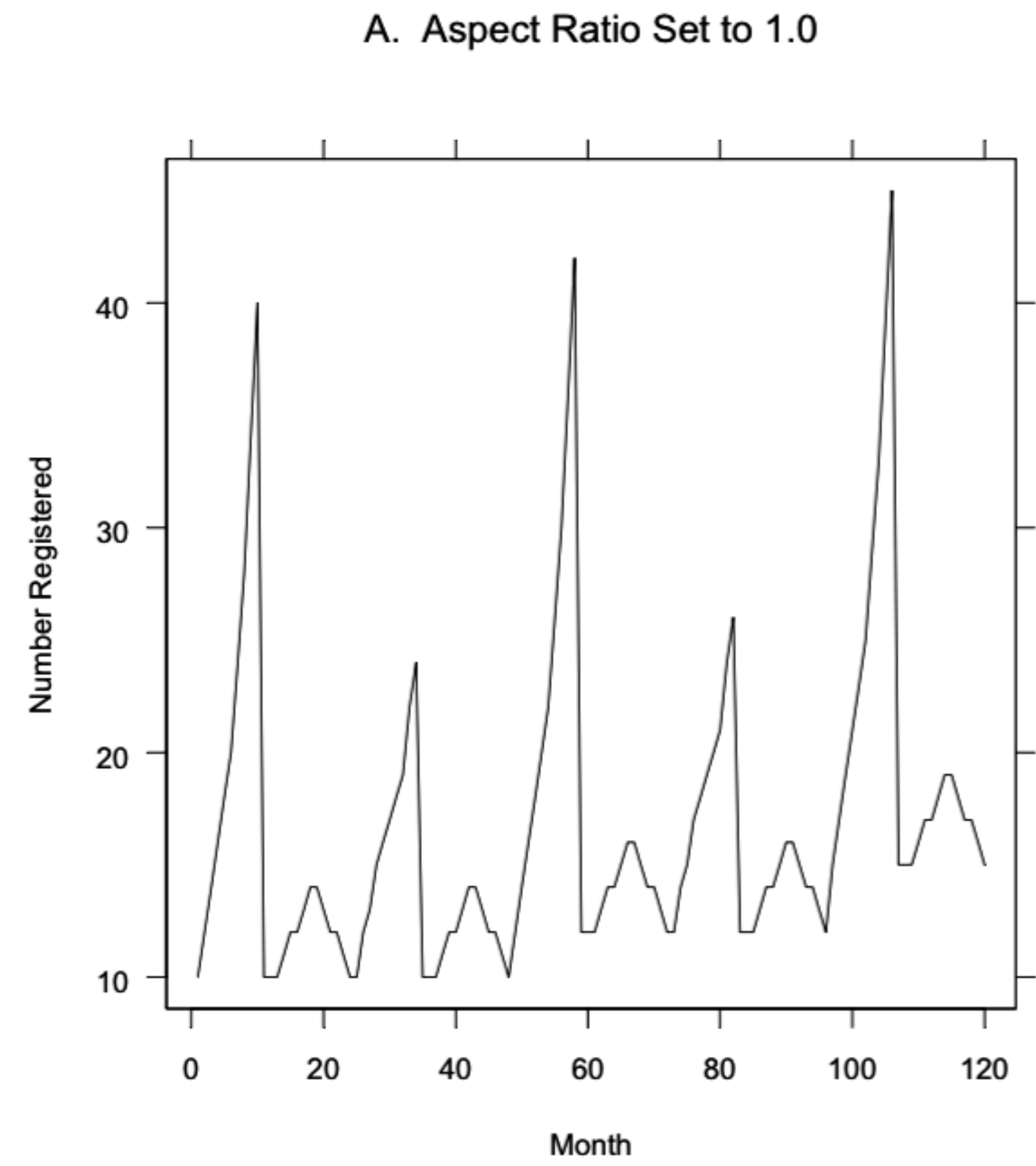
C. Loess Curve with $\alpha = 0.75$



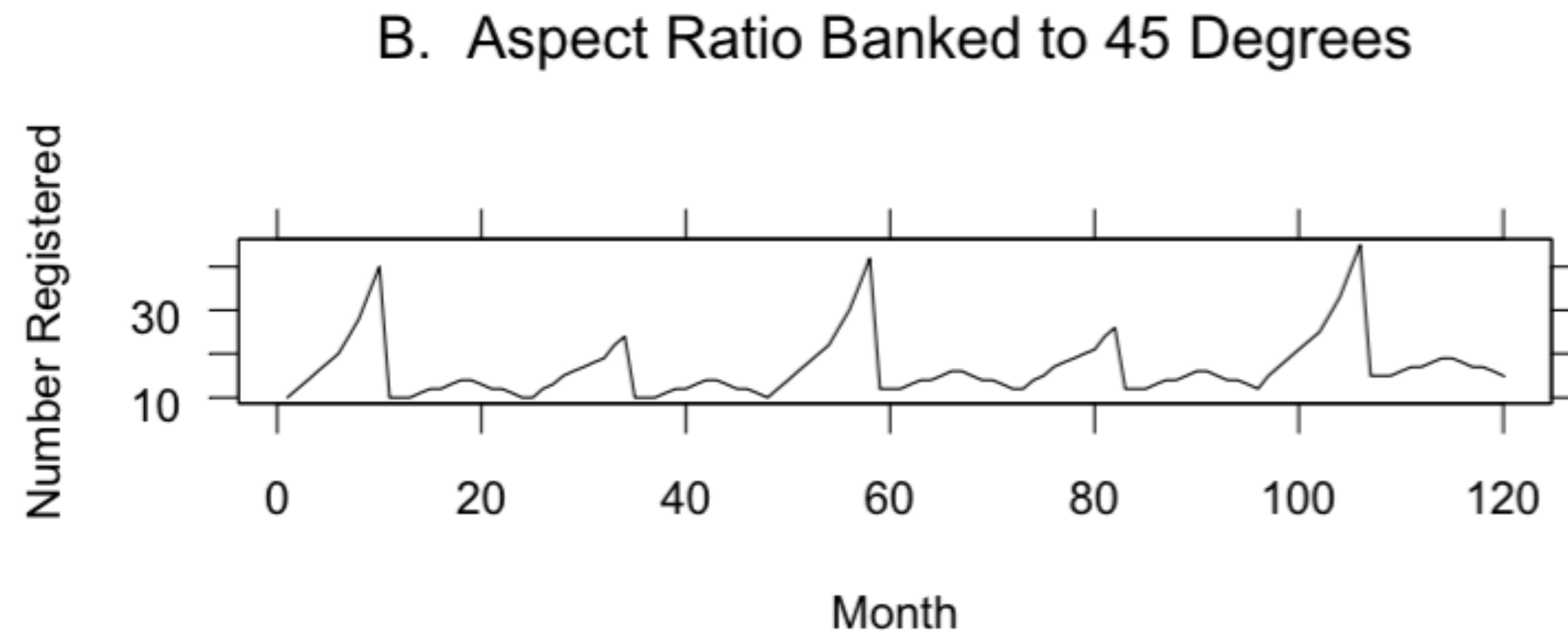
D. Loess Curve with $\alpha = 1.00$



Finally, consider your scales



Tells a different story here, eh?



Same data . . . allows for better interpretation of “functional dependence”

Summing up

- There are not as many bivariate displays as univariate displays - the scatterplot covers a lot
- Same principles apply
- Consider using a loess smoothed line to examine linearity

Where else can I find about graphics?

- *The source of much of these lectures:*
 - “Statistical Graphics for Univariate and Bivariate Data”, Sage #117.
 - “Statistical Graphics for Visualizing Multivariate Data”, Sage #120.
- *Class text:* Kieran Healy’s book, “Data Visualization: A Practical Introduction” <http://socviz.co> and print
 - Nice overview of all three components (perception, principle, and practice) as well as developing graphical “taste”
 - Lots of kinds of graphics: univariate, bivariate, GIS, time, etc
- *The Godfather:* Tufte, assorted books, but especially “The Visual Display of Quantitative Information”
- Contemporary and technical: Yau, *Visualize This: The Flowing Data Guide*