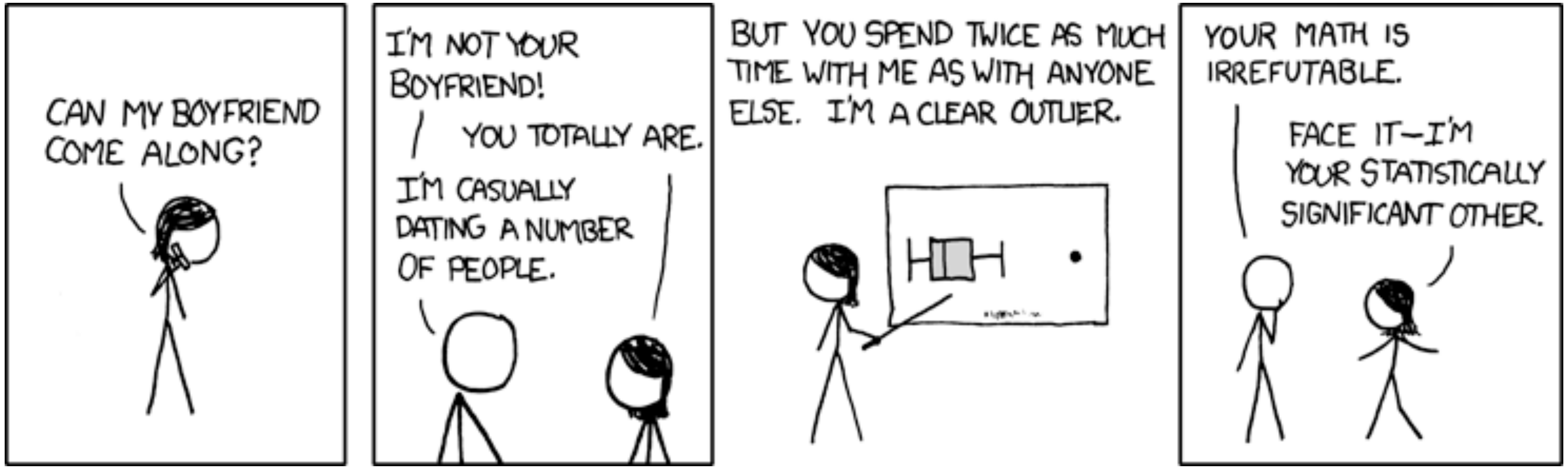
CS-5630 / CS-6630 Visualization for Data Science
Filtering & Aggregation

Alexander Lex
alex@sci.utah.edu



[xkcd]

Reducing Items and Attributes

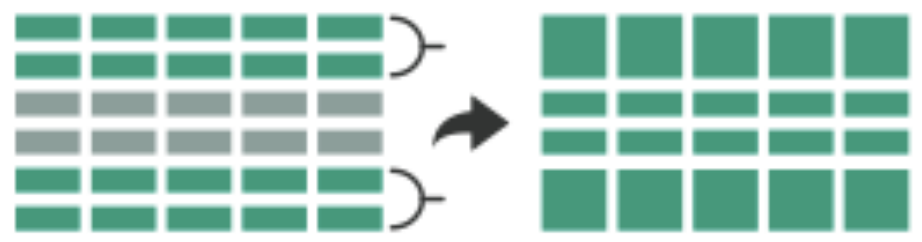
➔ Filter

→ Items

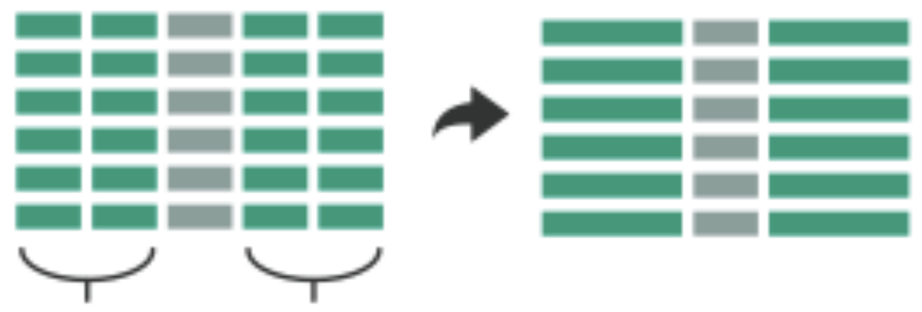
→ Attributes

➔ Aggregate

→ Items



→ Attributes



Filter

elements are eliminated

What drives filters?

Any possible function that partitions a dataset into two sets

- Bigger/smaller than x
- Fold-change
- Noisy/insignificant

Dynamic Queries / Filters

coupling between encoding and interaction so that user can immediately see the results of an action

Queries: start with 0, add in elements

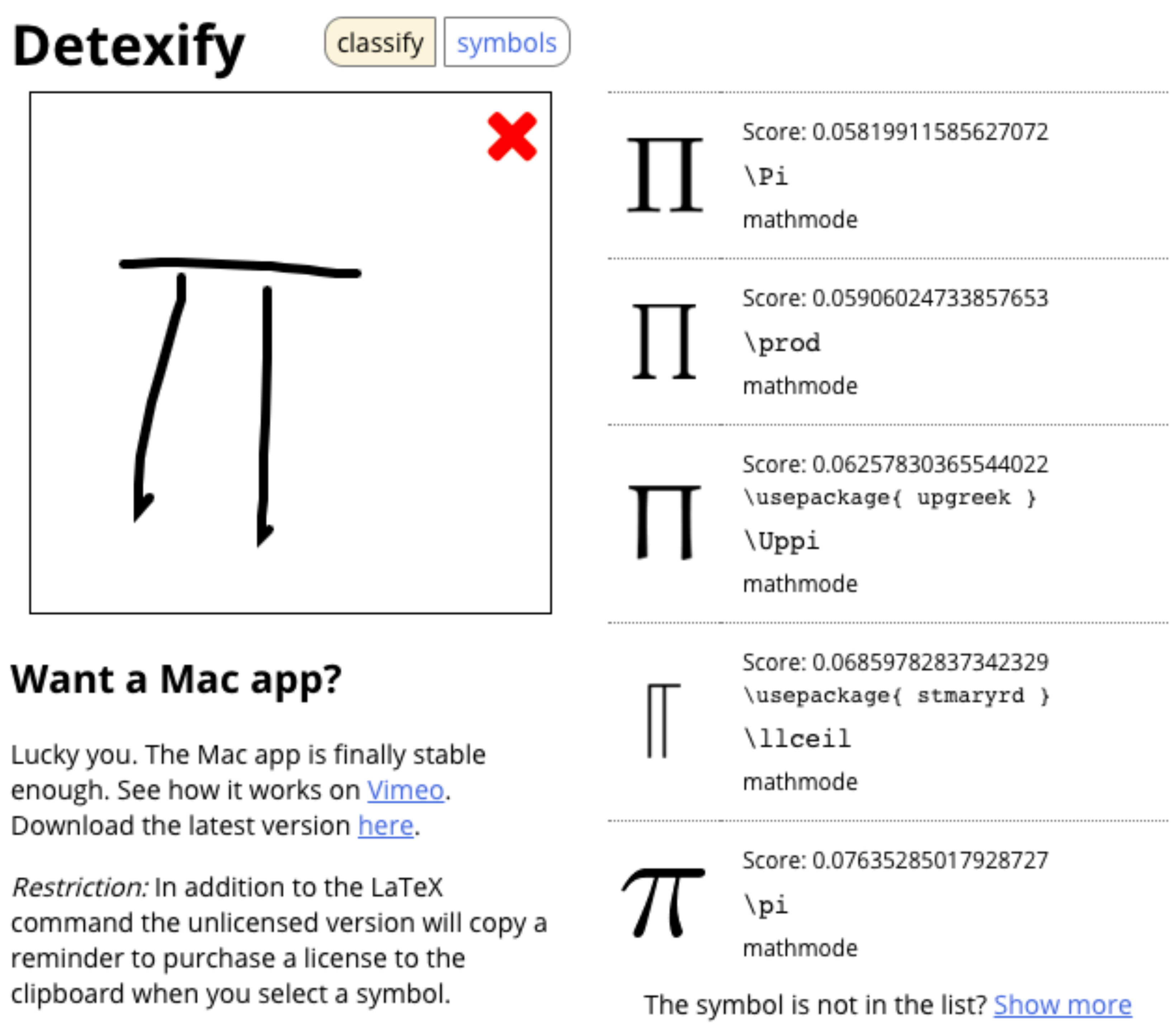
Filters: start with all, remove elements

Approach depends on dataset size

Sketch-based Queries

Idea: we have a mental model of a pattern.

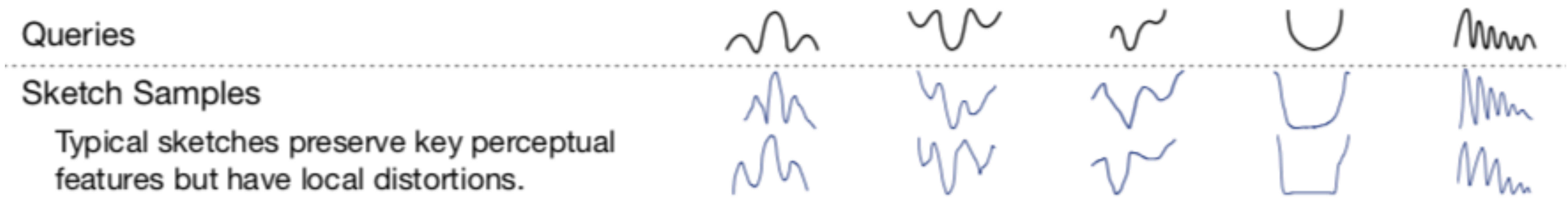
Let user sketch it!



http://detexify.kirelabs.org/classify.html

Sketch-based Queries

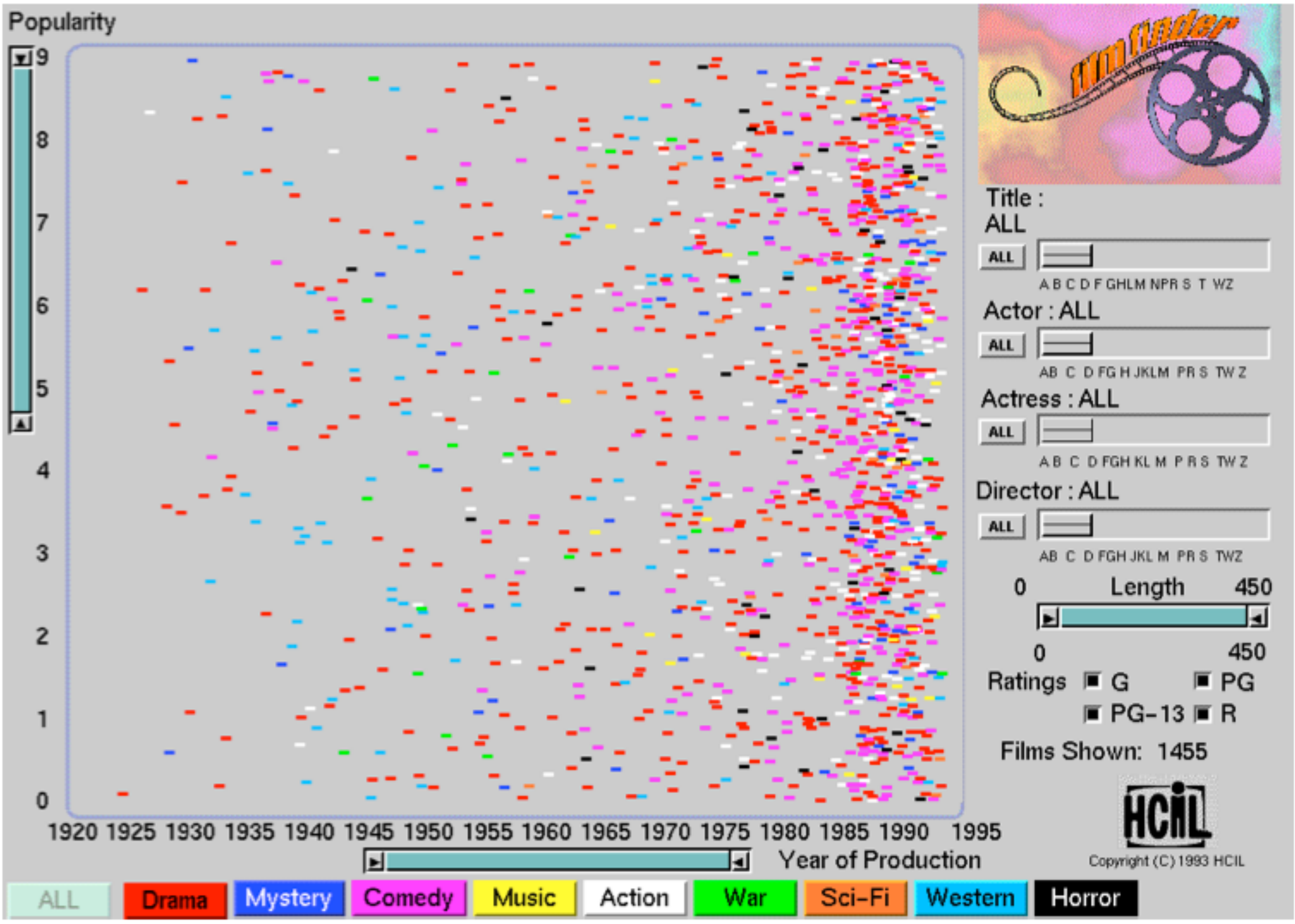
Time Series

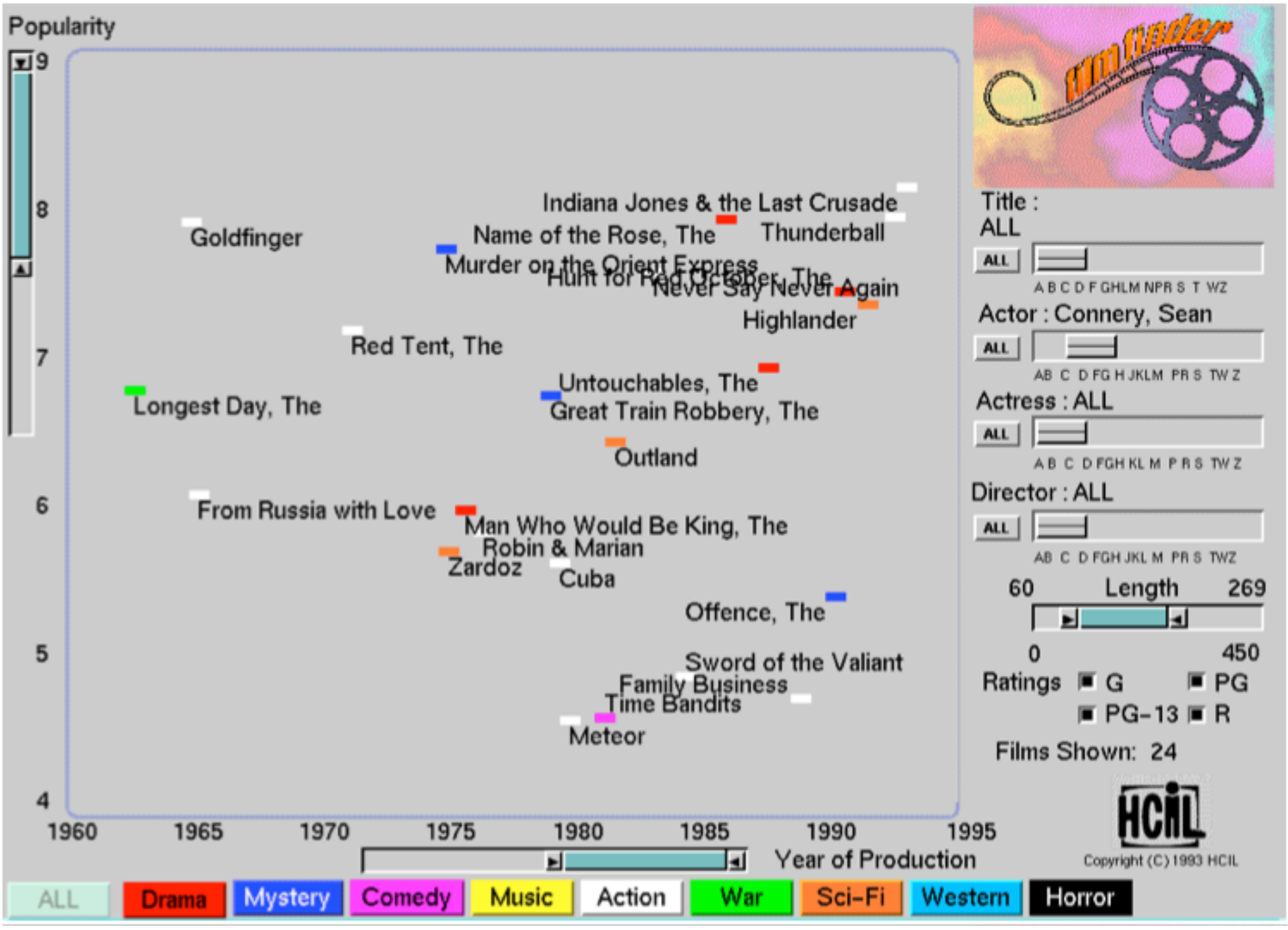


https://www.youtube.com/watch?v=4YQTuUuIFbI

[Mannino, Abouzied, 2018]

ITEM FILTERING



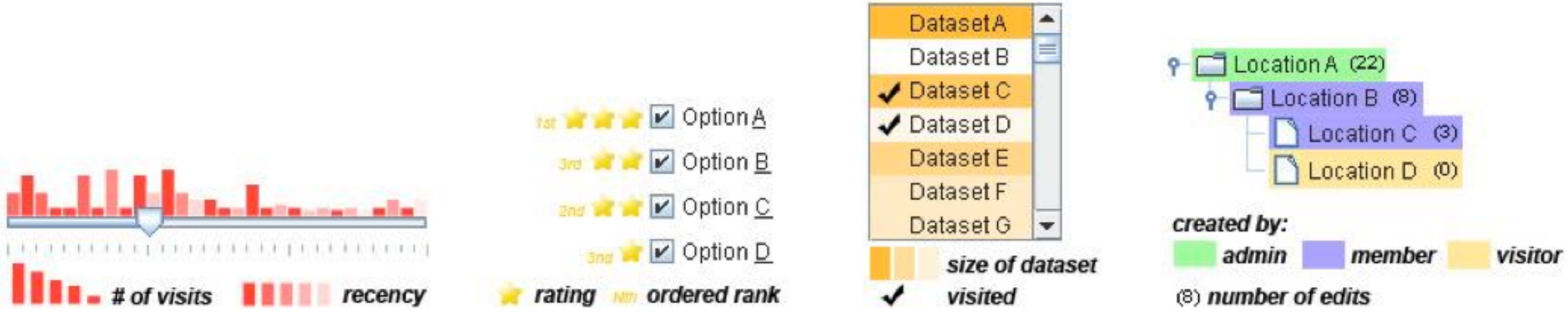


Ahlberg 1994

Scented Widgets

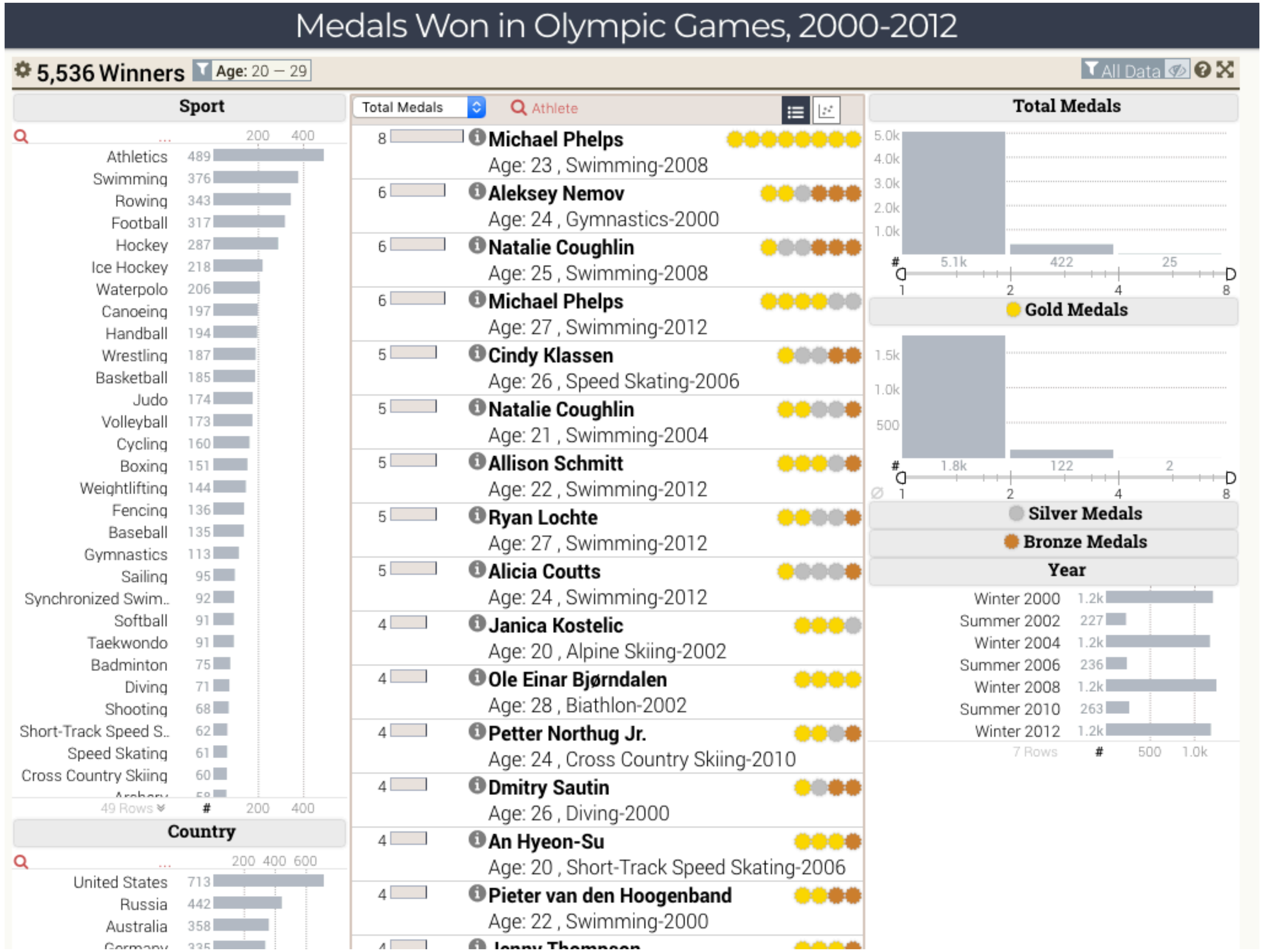
information scent: user's (imperfect) perception of data

GOAL: lower the cost of information foraging through better cues



Willett 2007

Item Filtering with Scented Widgets

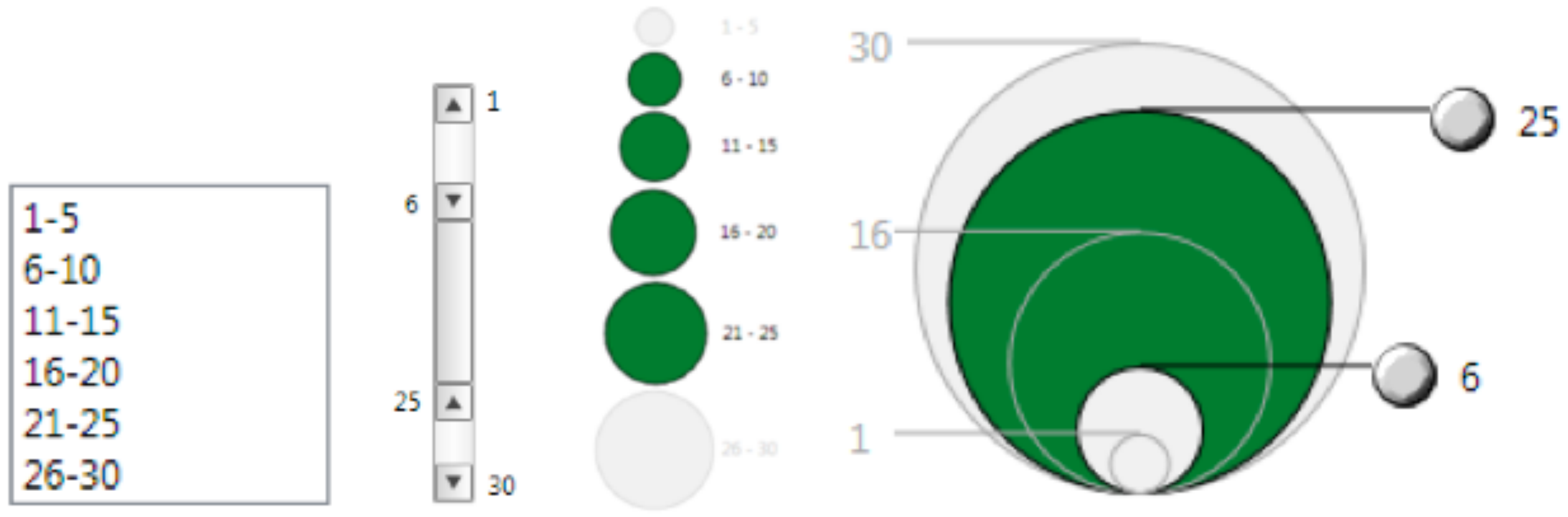


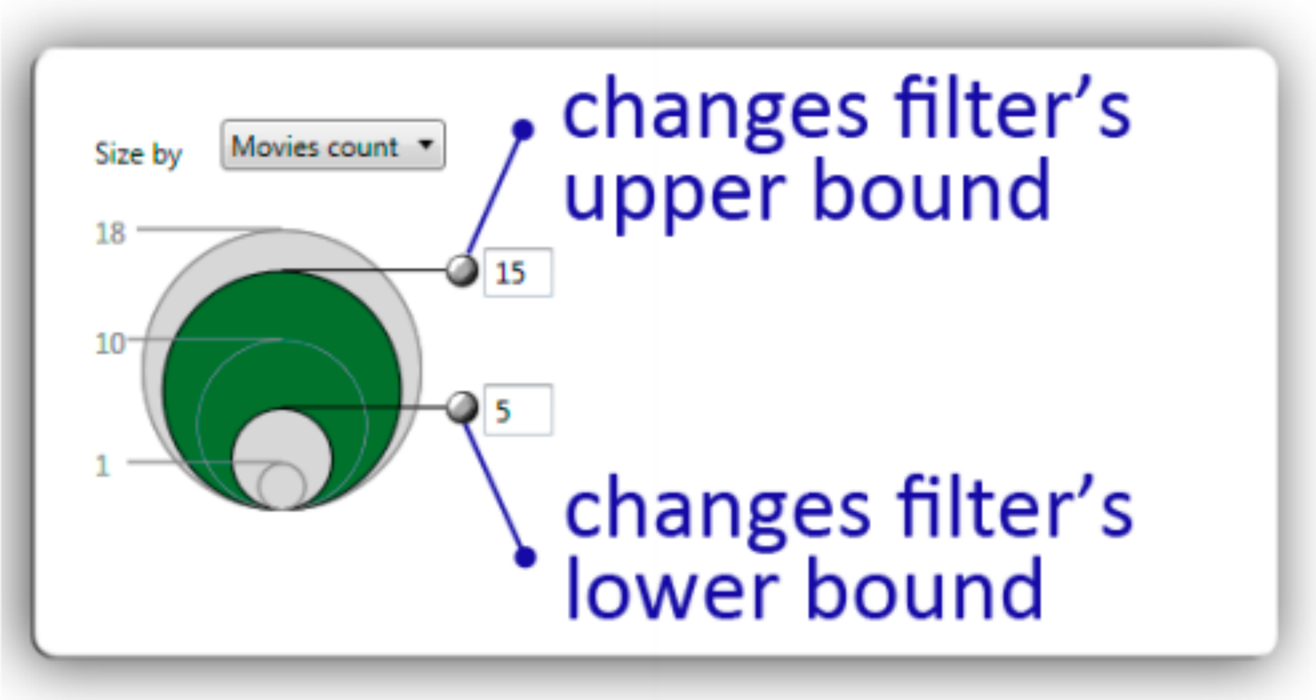
https://keshif.me/gallery/olympics

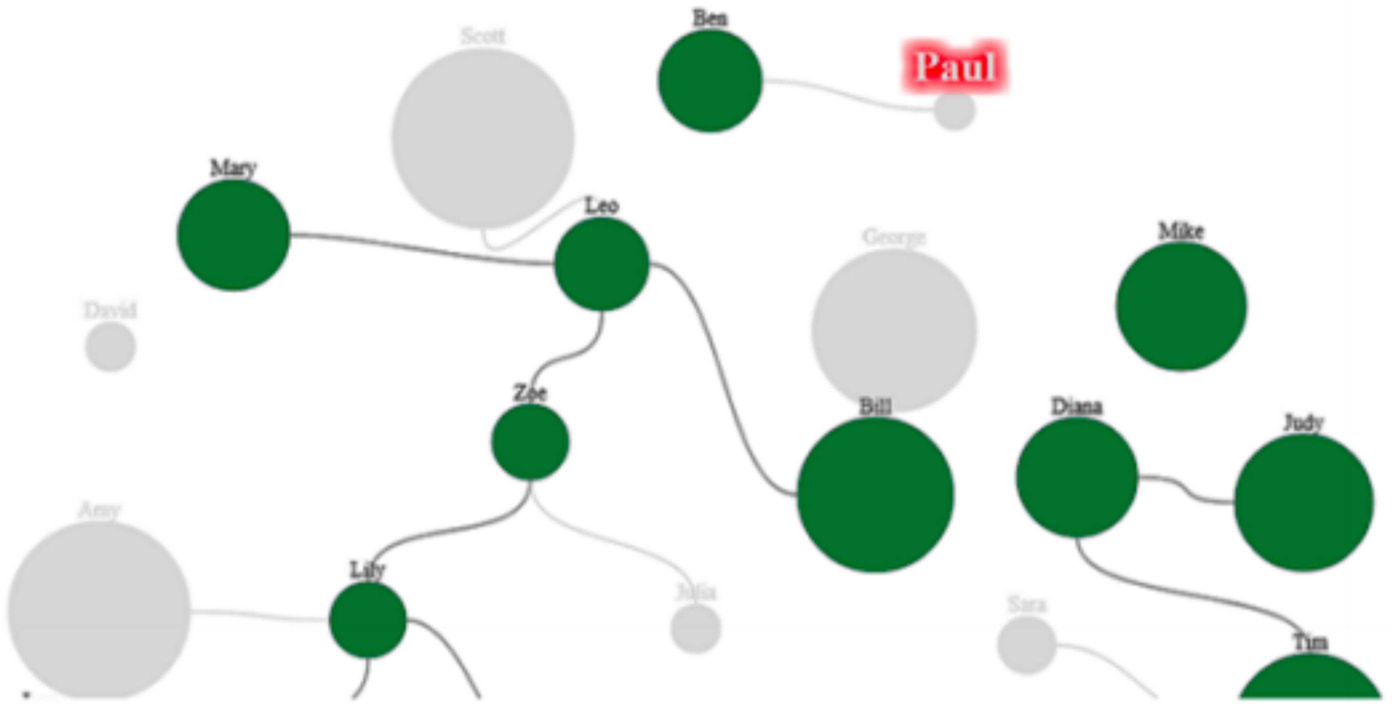
Interactive Legends

Controls combining the visual representation of static legends with interaction mechanisms of widgets

Define and control visual display together





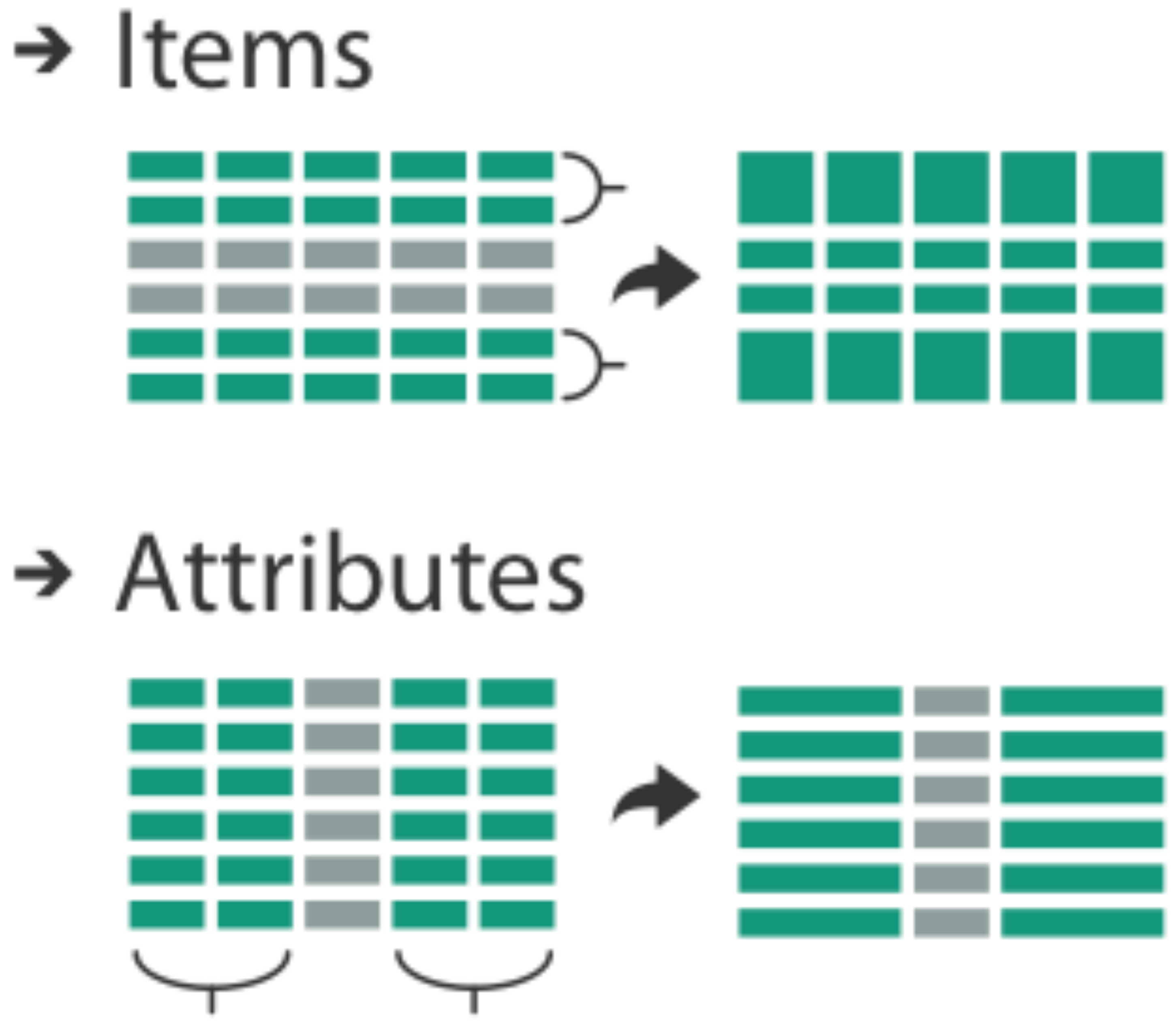


Riche 2010

Aggregation

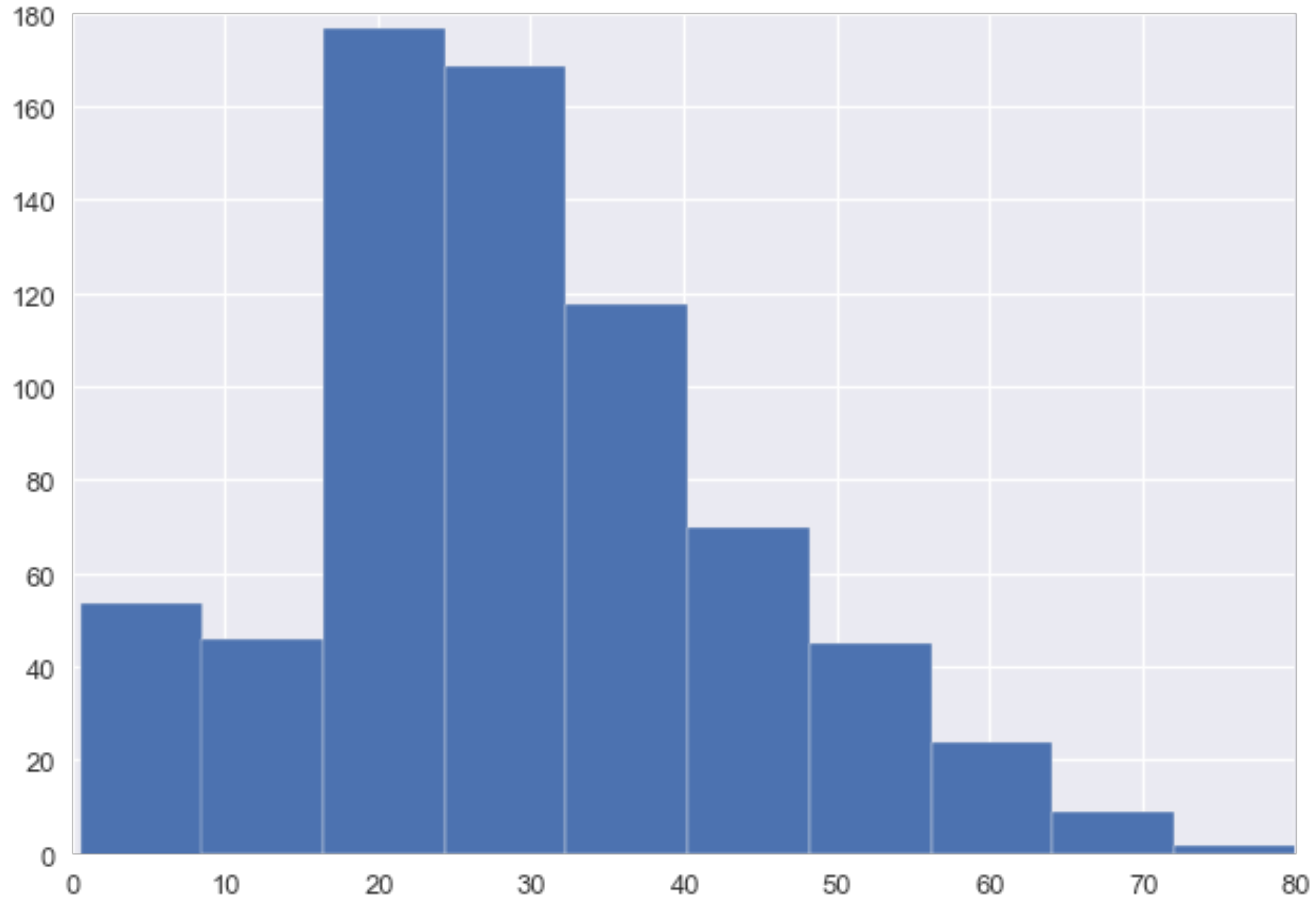
Aggregate

a group of elements is represented by a (typically smaller) number of derived elements

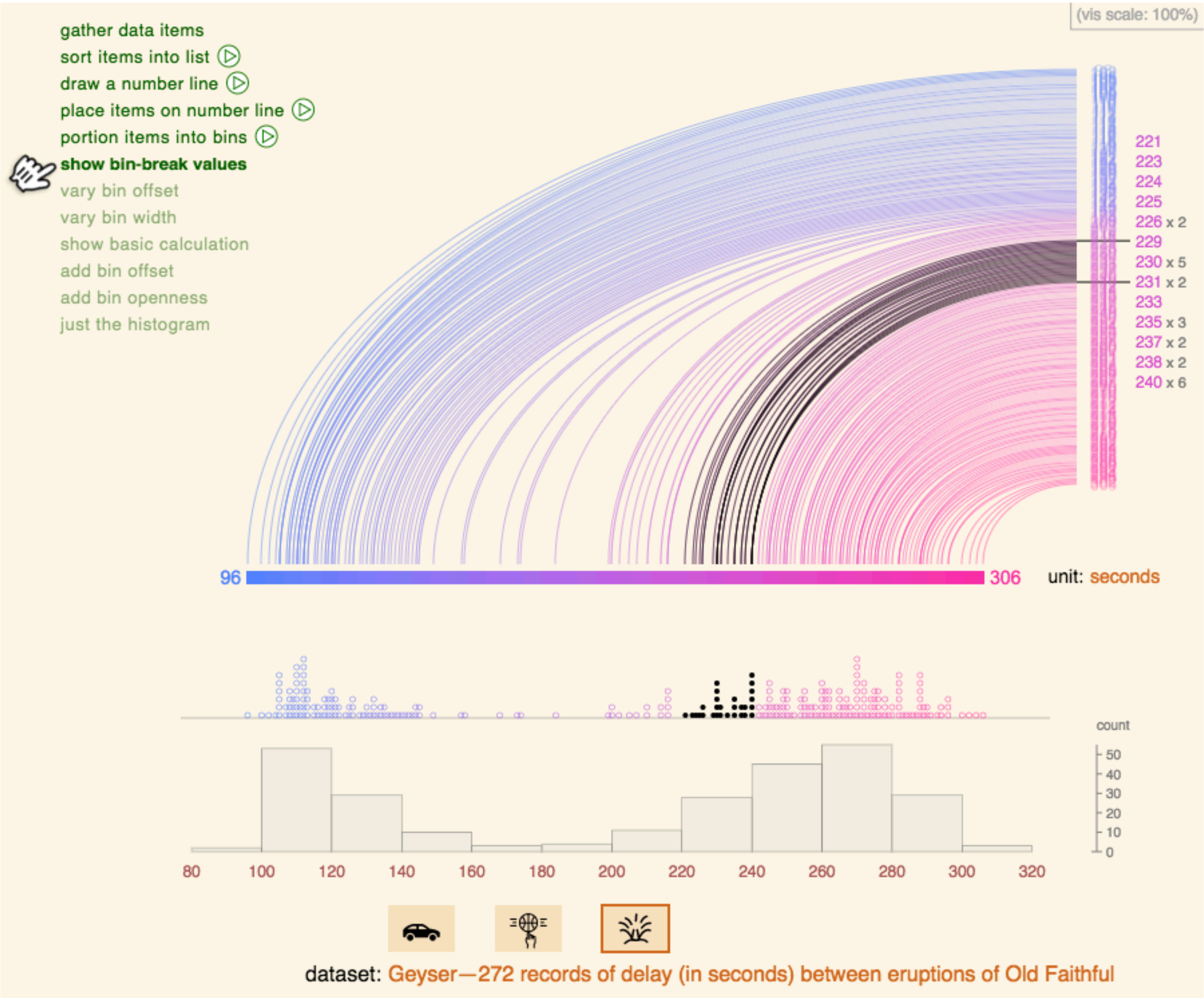


Why Aggregate?

What’s a histogram?



Histograms Explained



http://tinlizzie.org/histograms/

Histogram

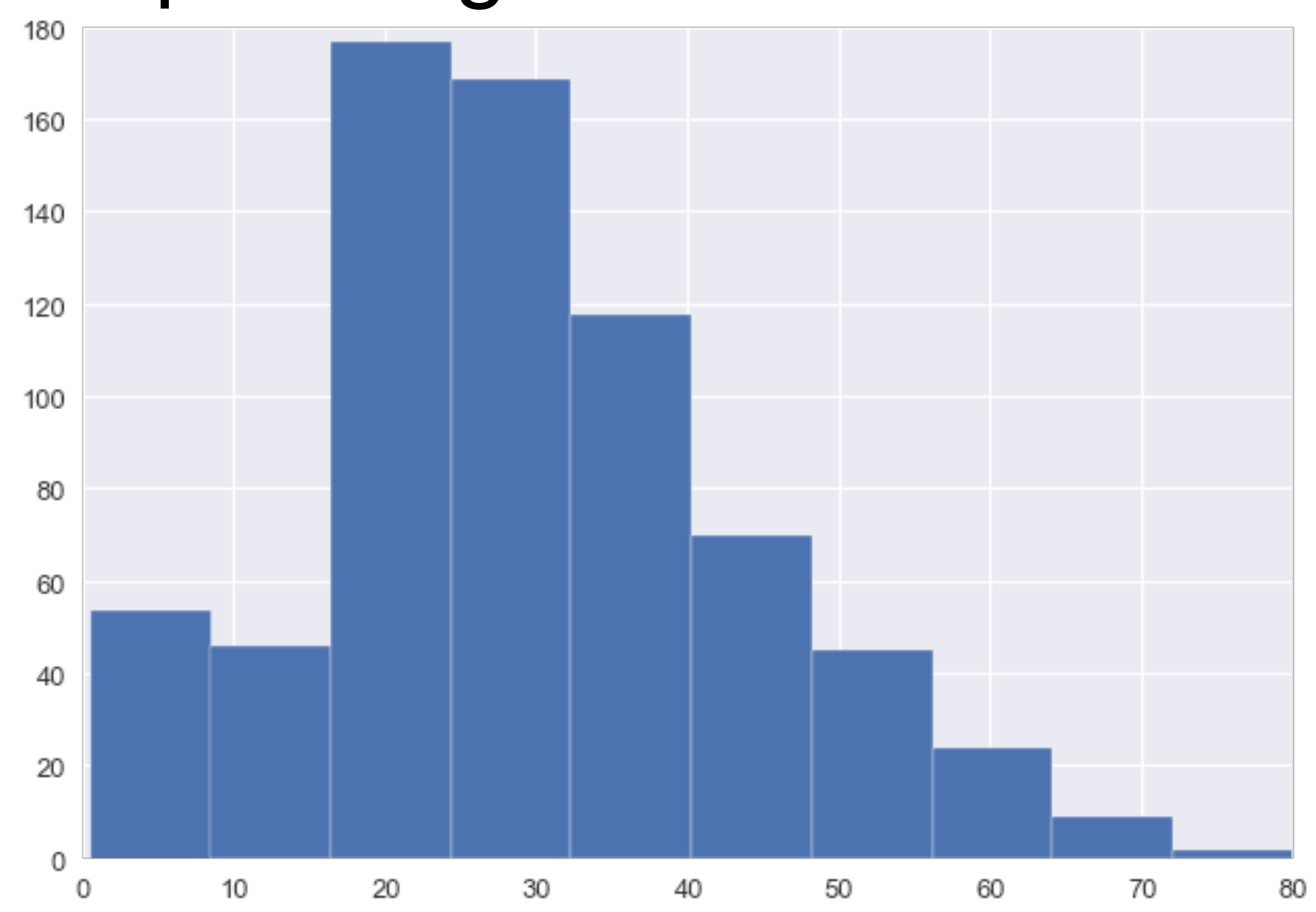
Good #bins hard to predict

make interactive!

rules of thumb:

- #bins = sqrt(n)
- #bins = log2(n) + 1

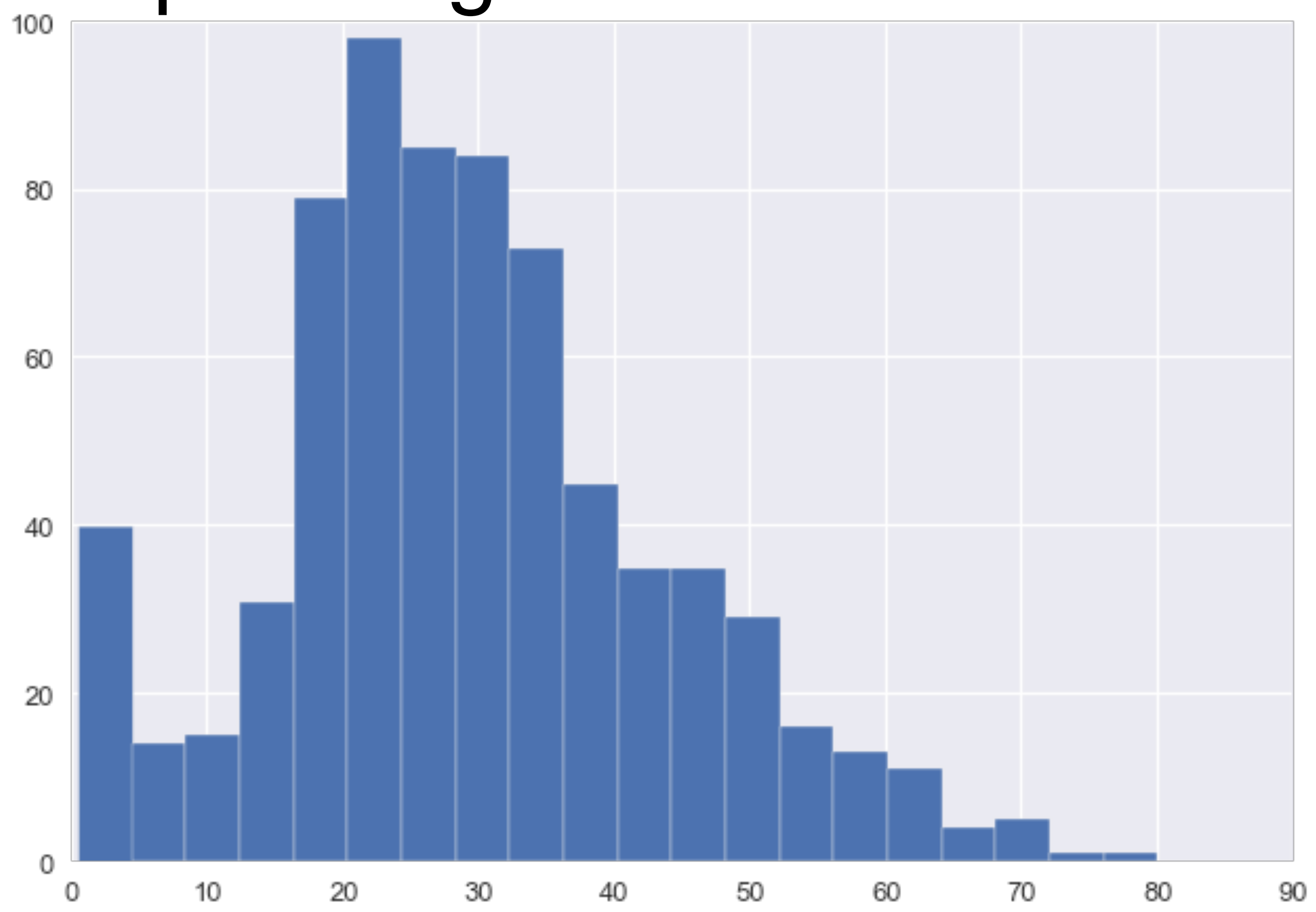
passengers



age

10 Bins

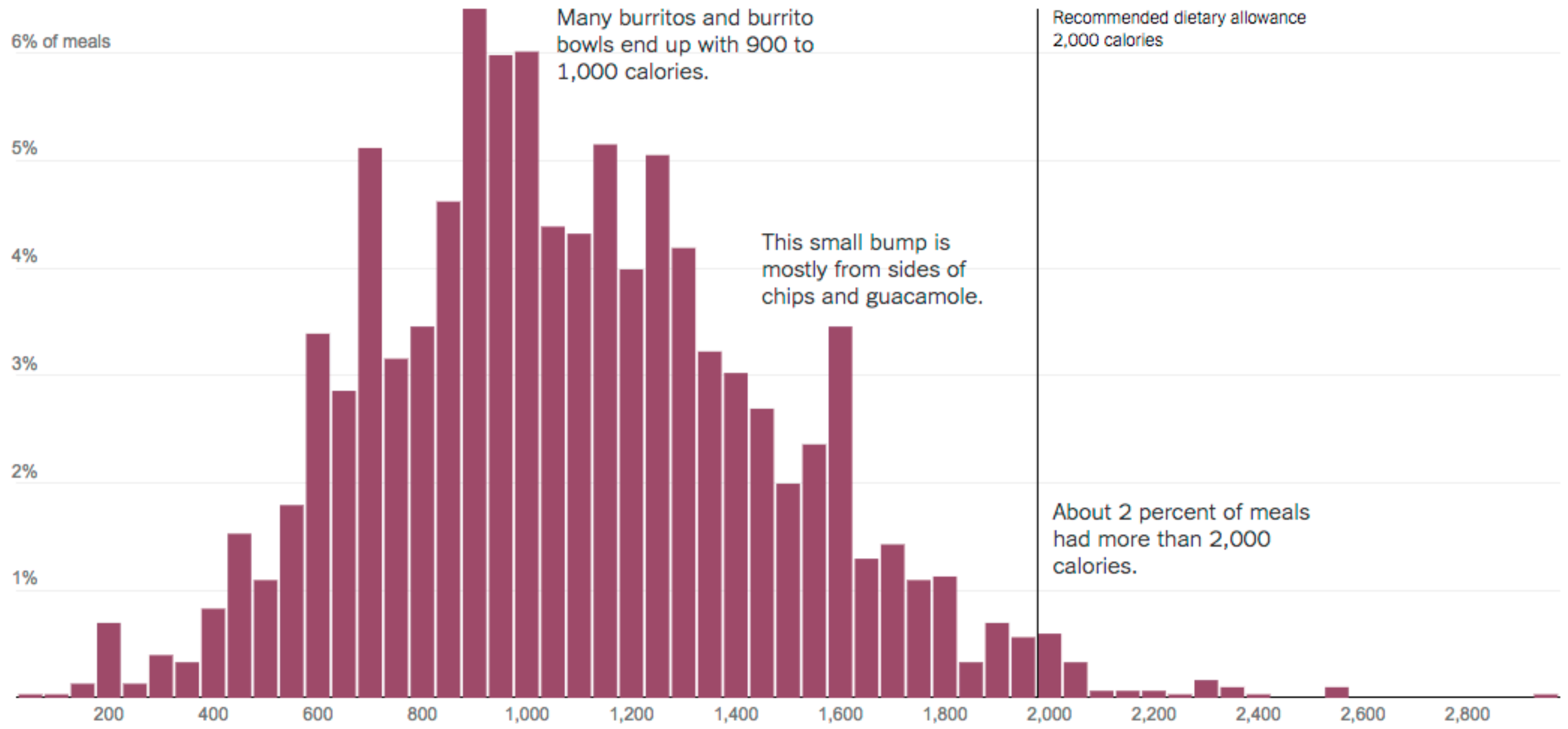
passengers

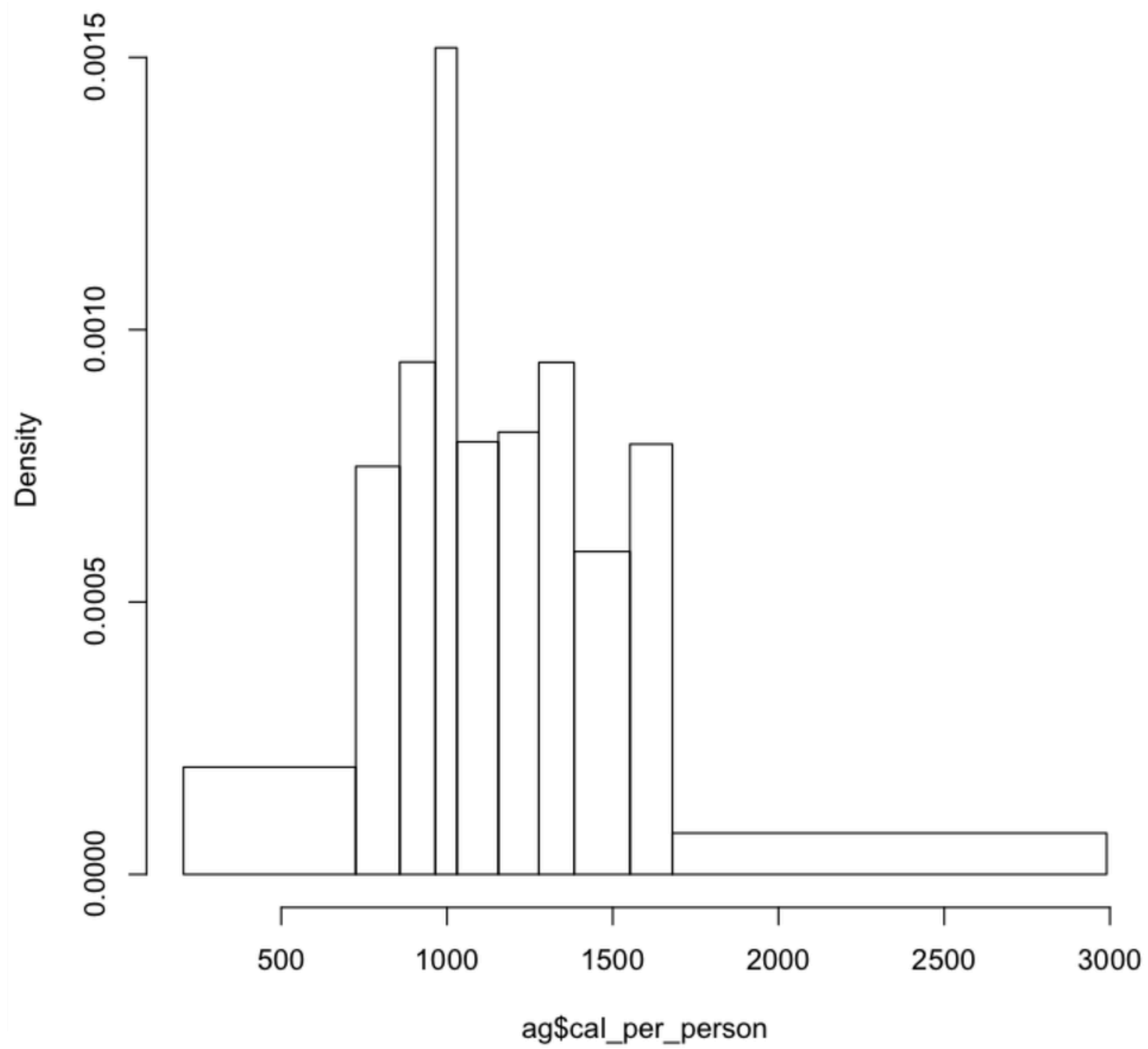


age

20 Bins

Unequal Bin Width



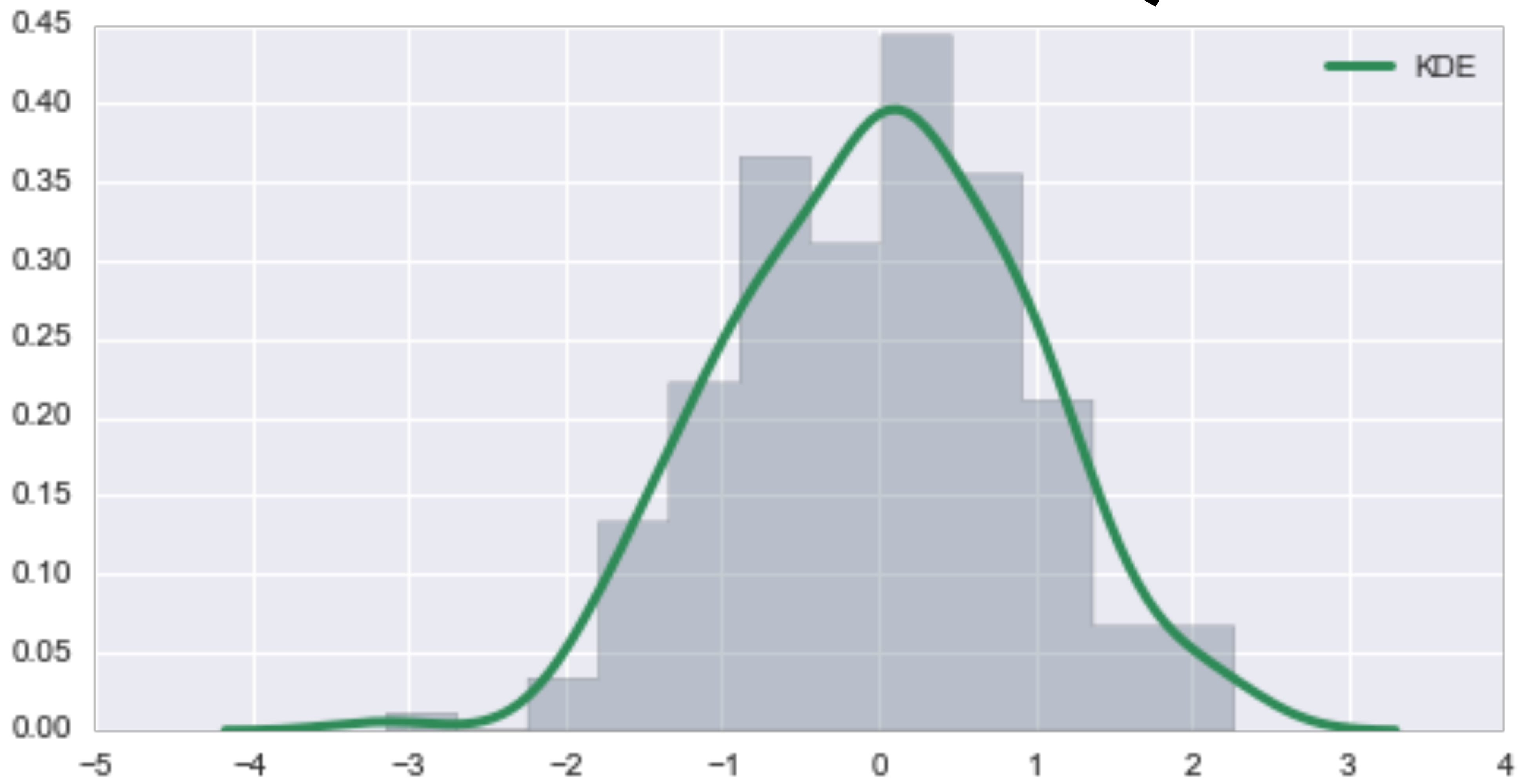


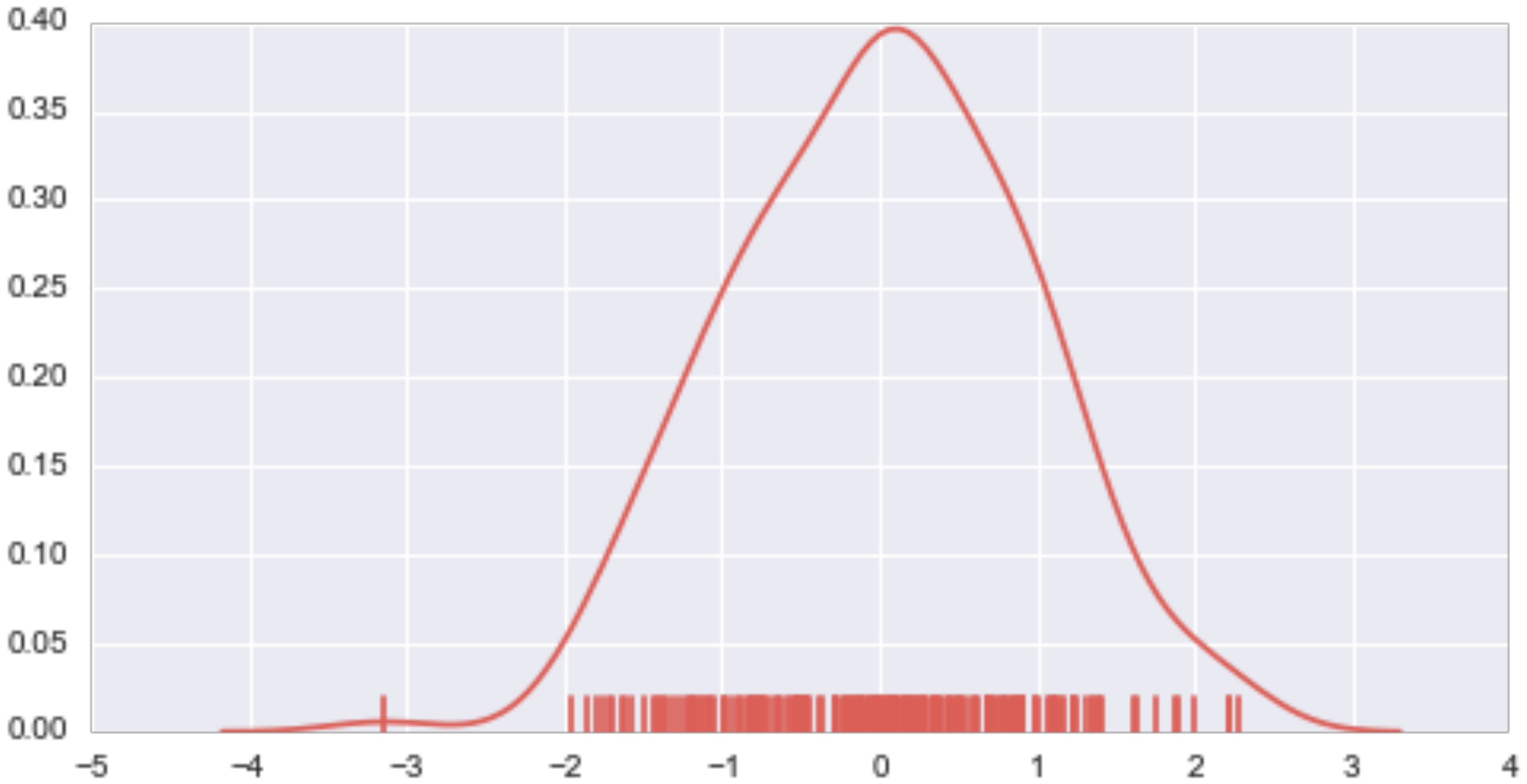
Can be useful if data is much sparser in some areas than others

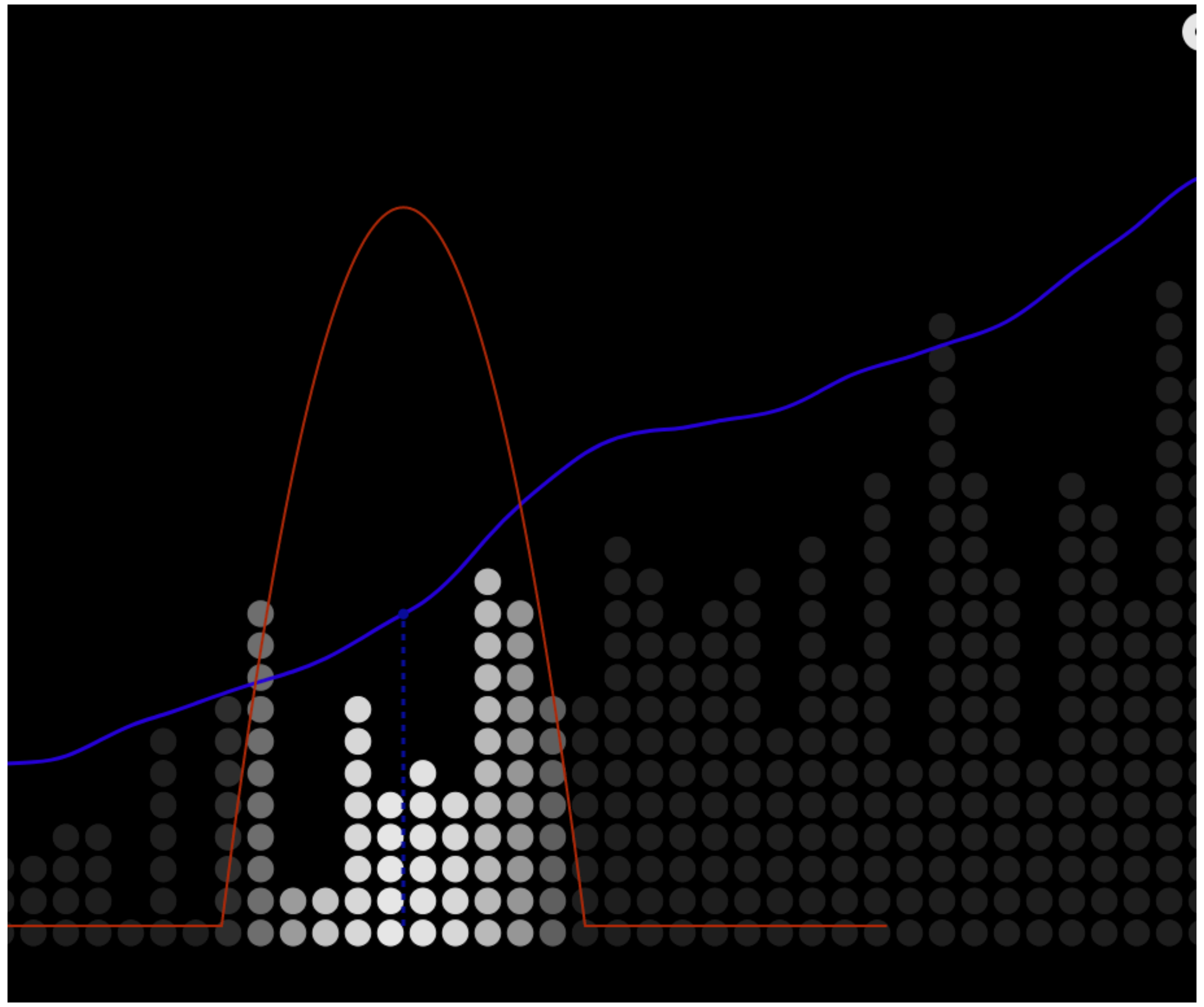
Show density as area, not hight.

https://www.nytimes.com/interactive/2015/02/17/upshot/what-do-people-actually-order-at-chipotle.html?_r=1

Density Plots (Kernel Density Estimation)







http://web.stanford.edu/~mwaskom/software/seaborn/tutorial/plotting_distributions.html

One of these things is not like the other...

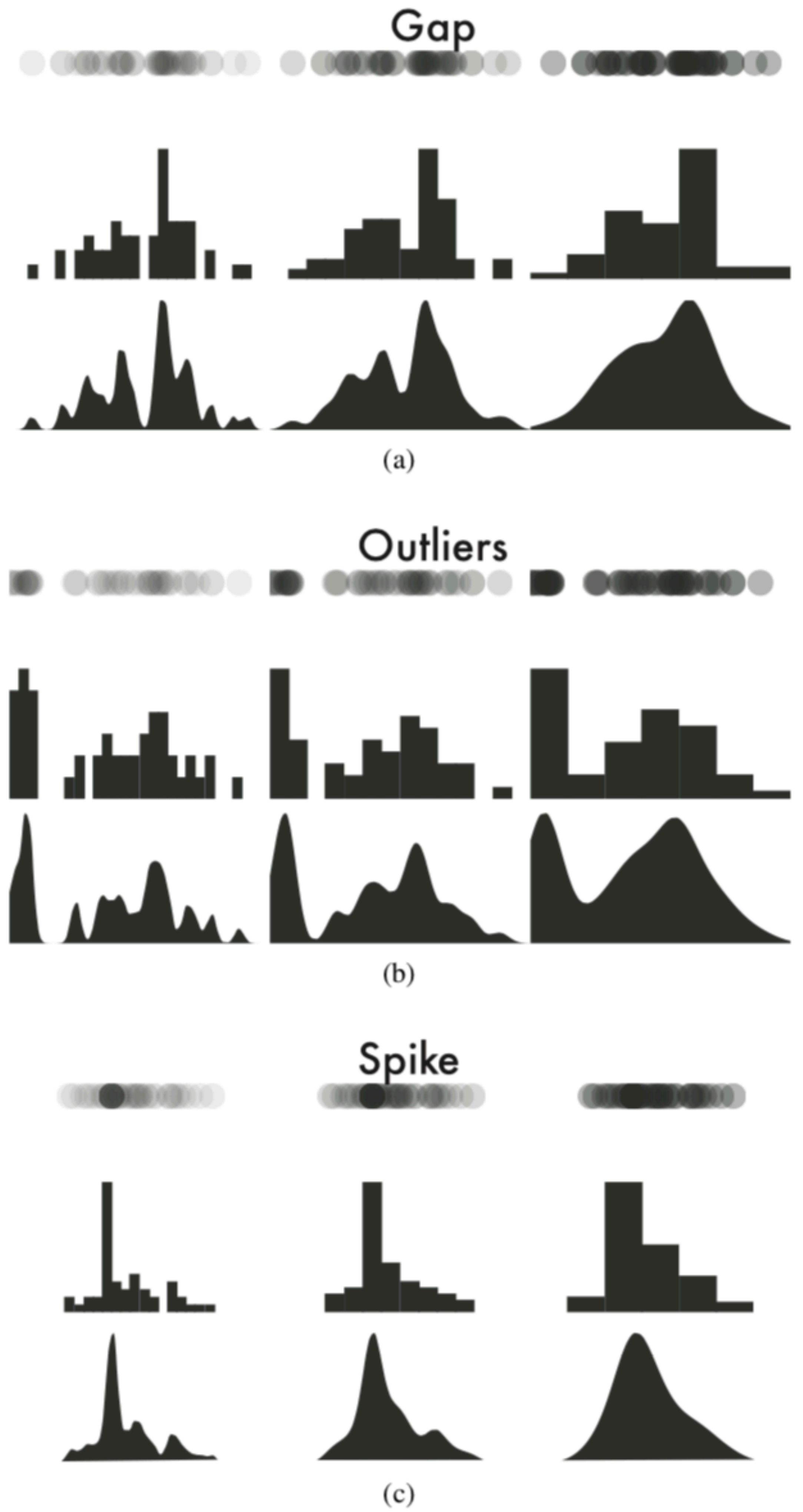
19 charts are random samples from a gaussian.
1 chart has 20% of samples with identical value

[Corell et al, InfoVis 2019]

Detecting Data Flaws

Tricky with aggregate visualization

Bin size / kernel type / bandwidth / visualization choice all affect different situations



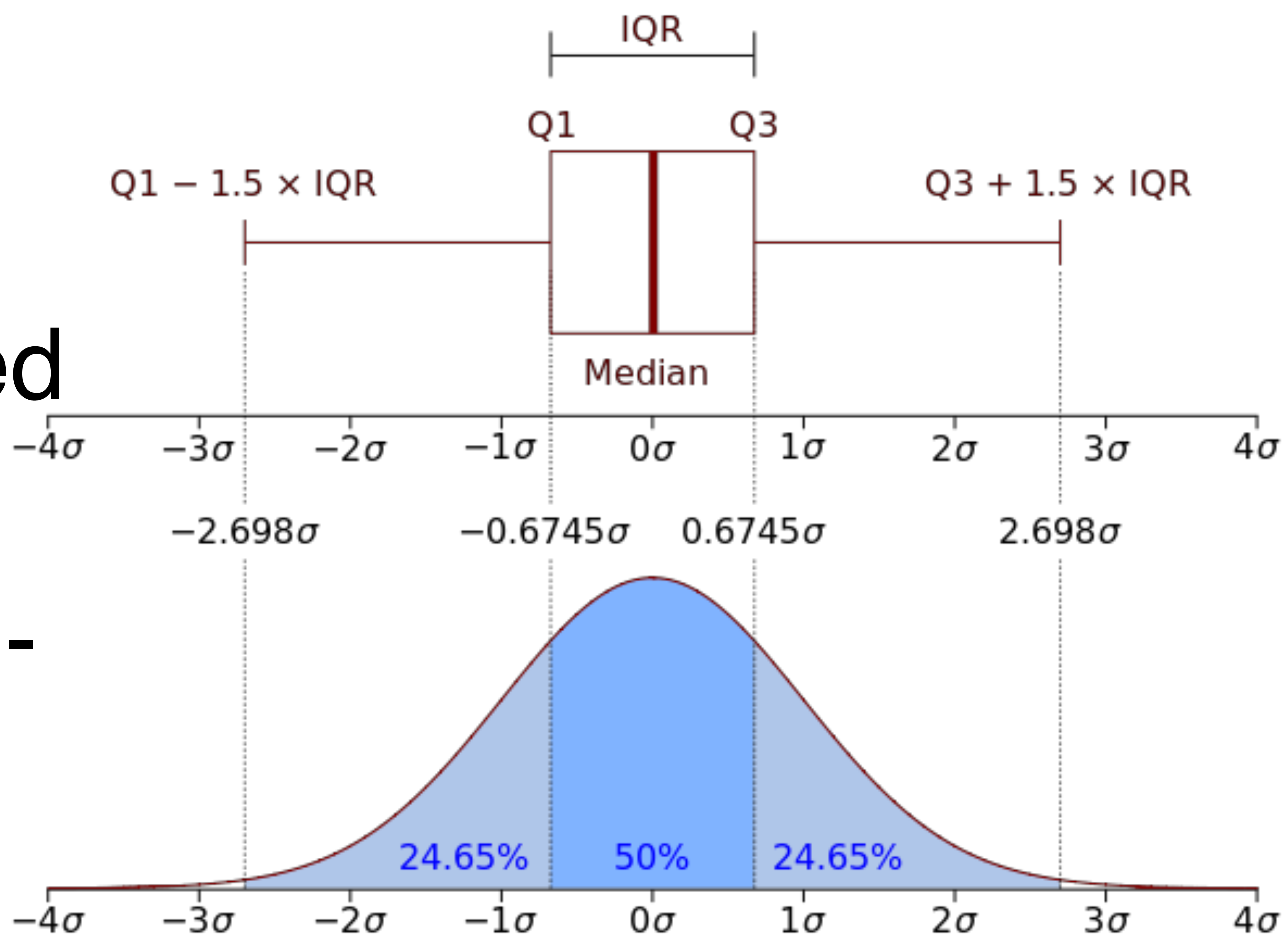
Box Plots

aka Box-and-Whisker Plot

Show outliers as points!

Bad for non-normal distributed data

Especially bad for bi- or multi-modal distributions



Wikipedia

One Boxplot, Four Distributions

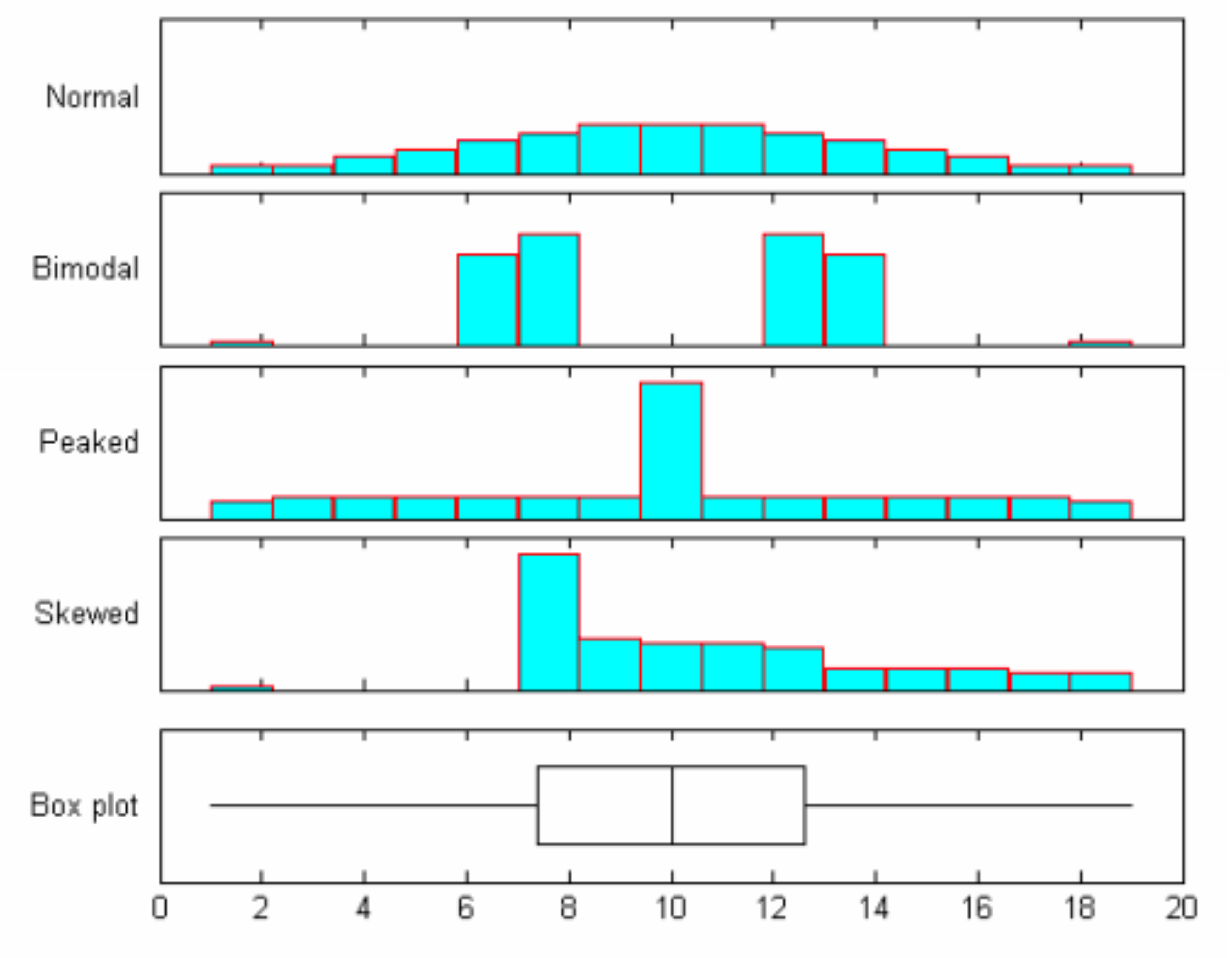


Figure 1: Histograms and box plot: four samples each of size 100

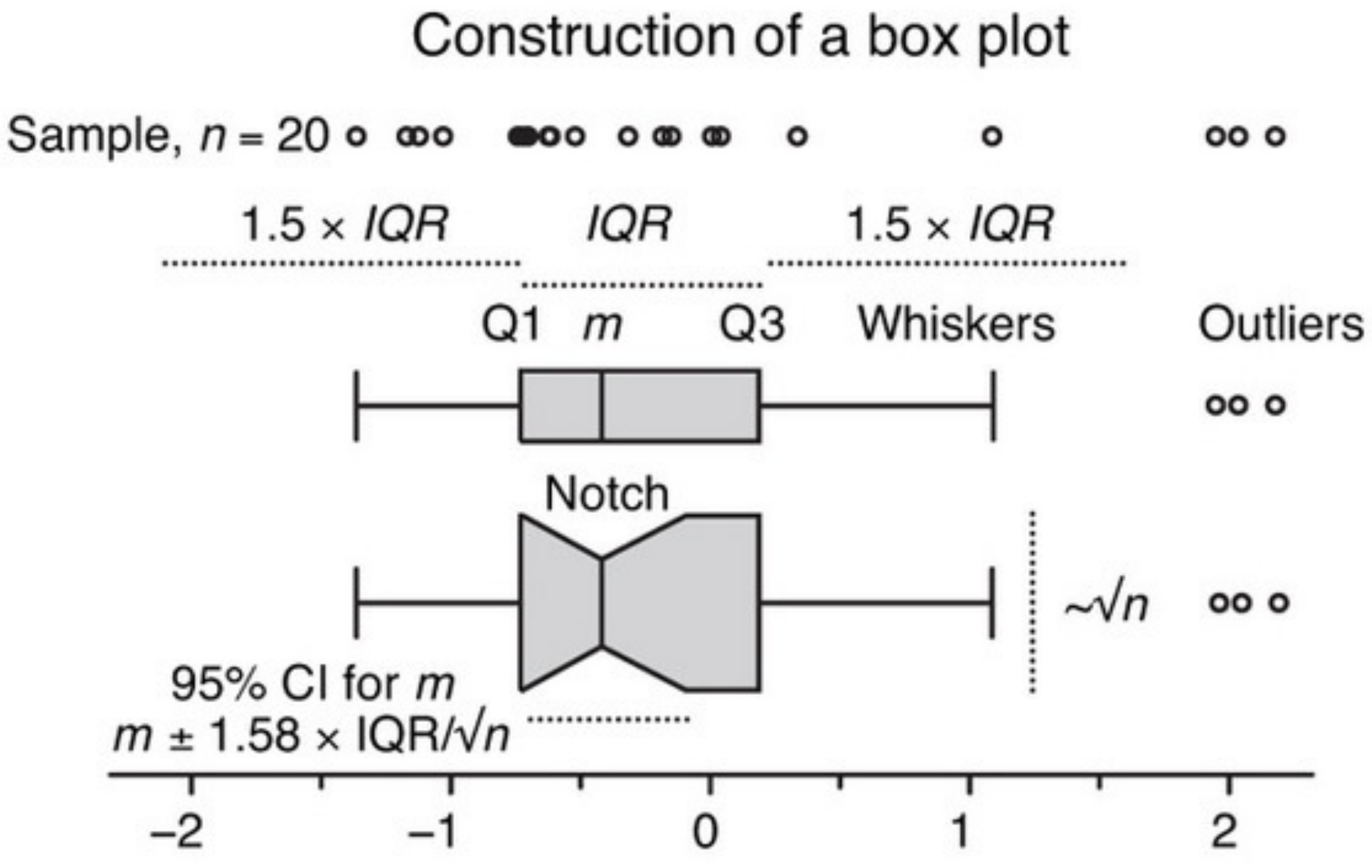
http://stat.mq.edu.au/wp-content/uploads/2014/05/Can_the_Box_Plot_be_Improved.pdf

Notched Box Plots

Notch shows
m +/- 1.5i x IQR/sqrt(n)

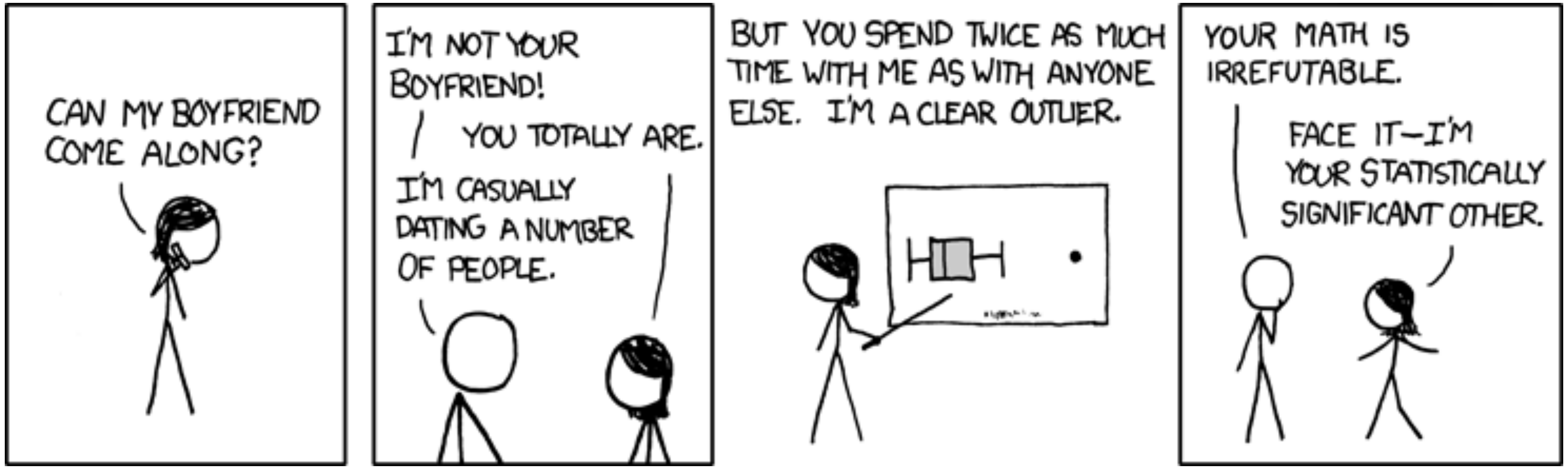
-> 95% Confidence Intervall

A guide to statistical significance.

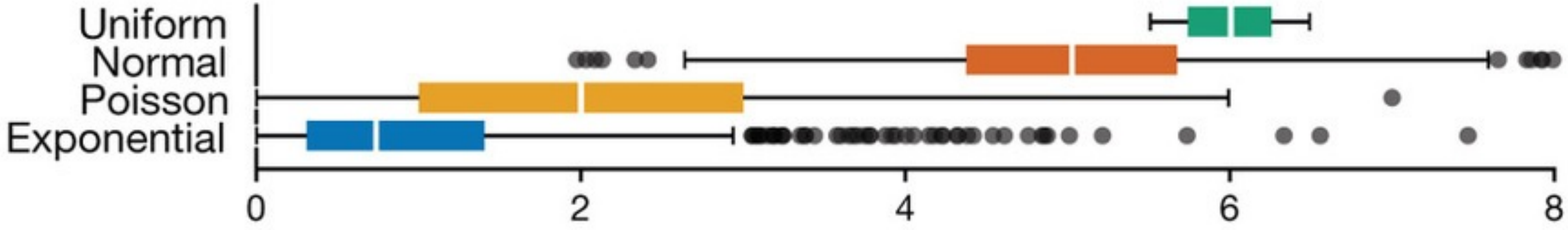


Kryzwinski & Altman, PoS, Nature Methods, 2014

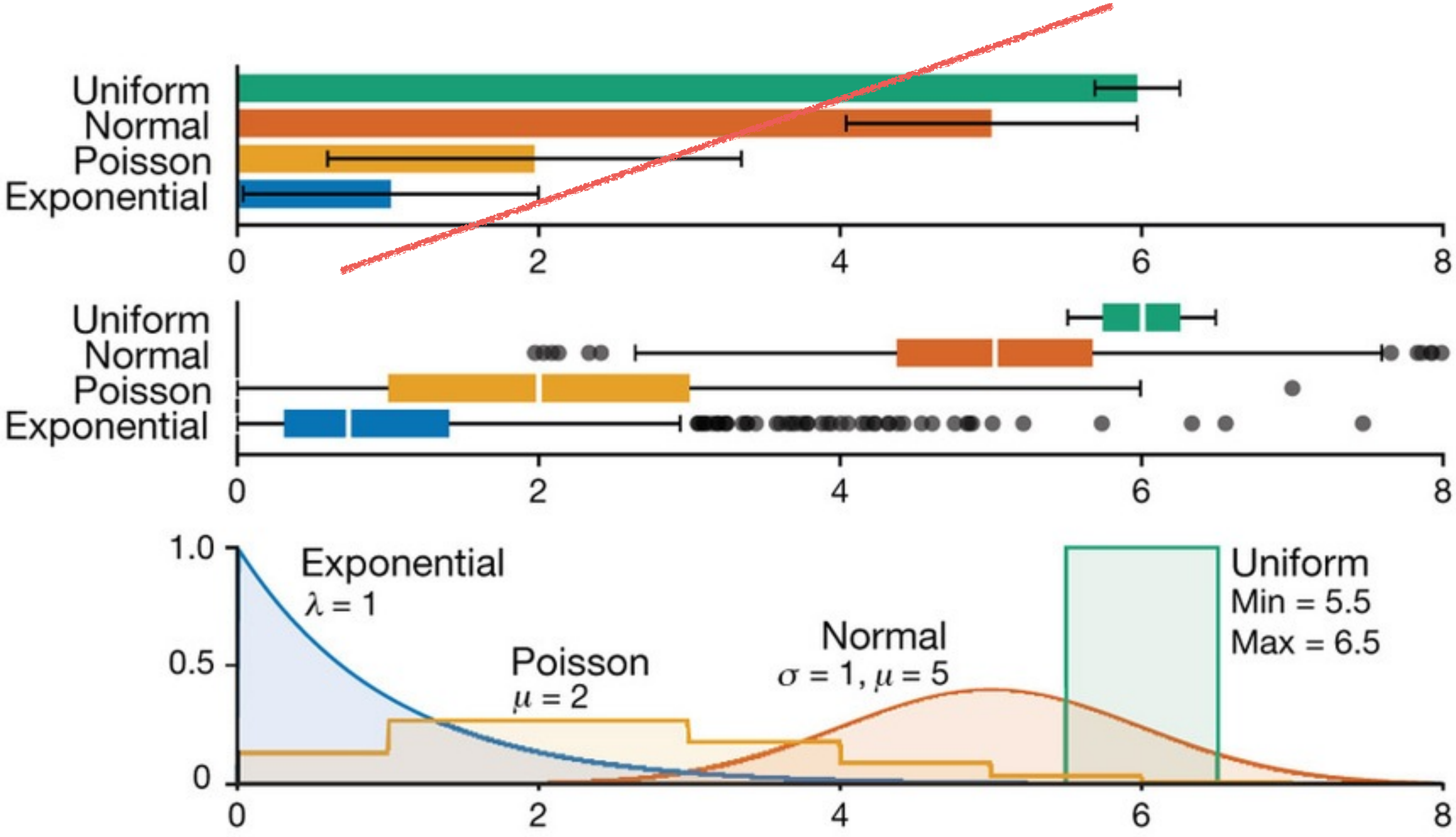
Box(and Whisker) Plots



http://xkcd.com/539/

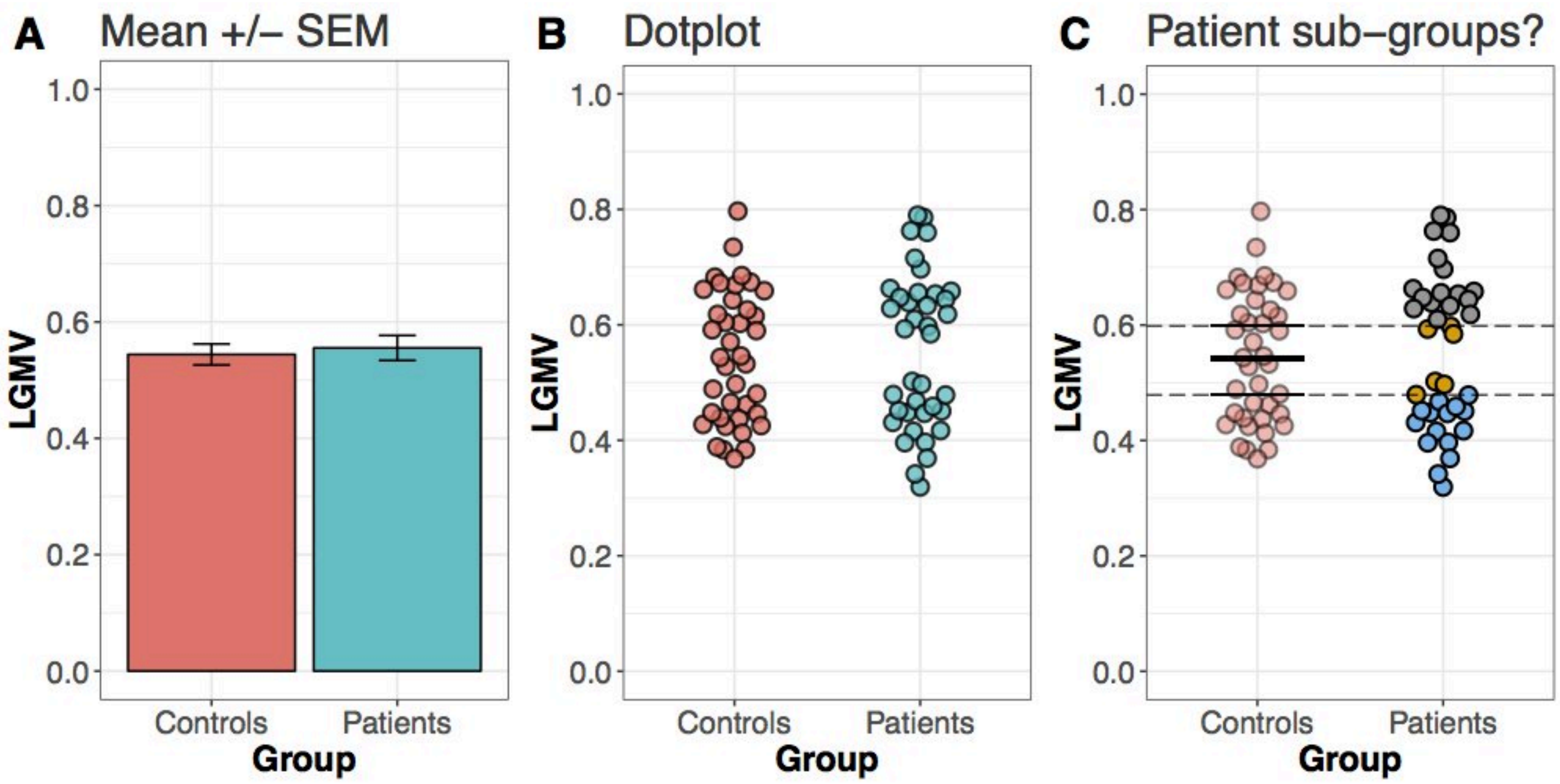


Comparison



Streit & Gehlenborg, PoV, Nature Methods, 2014

Bar Charts vs Dot Plots

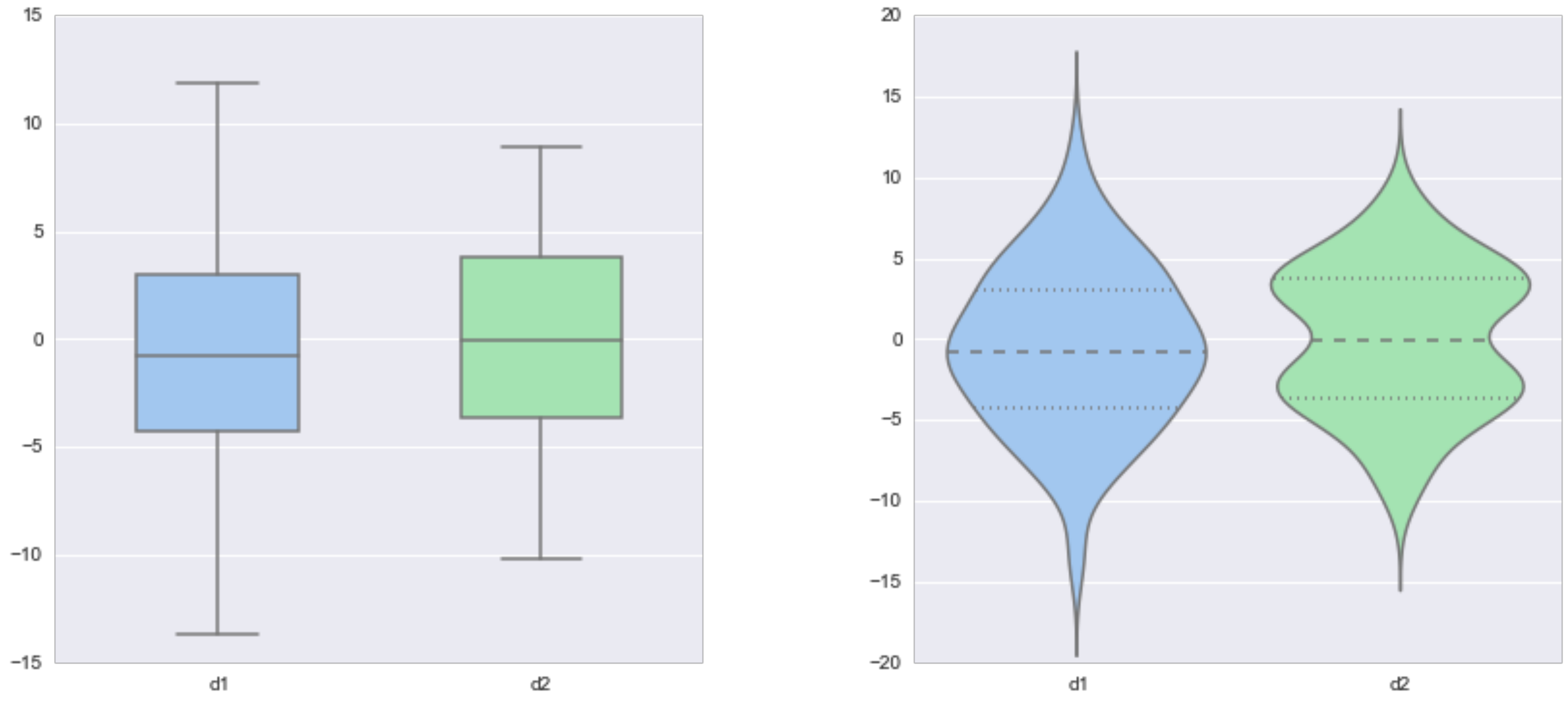


Data Source https://bmcneurosci.biomedcentral.com/articles/10.1186/1471-2202-10-67

https://twitter.com/robustgar/status/859318971920769024

Violin Plot

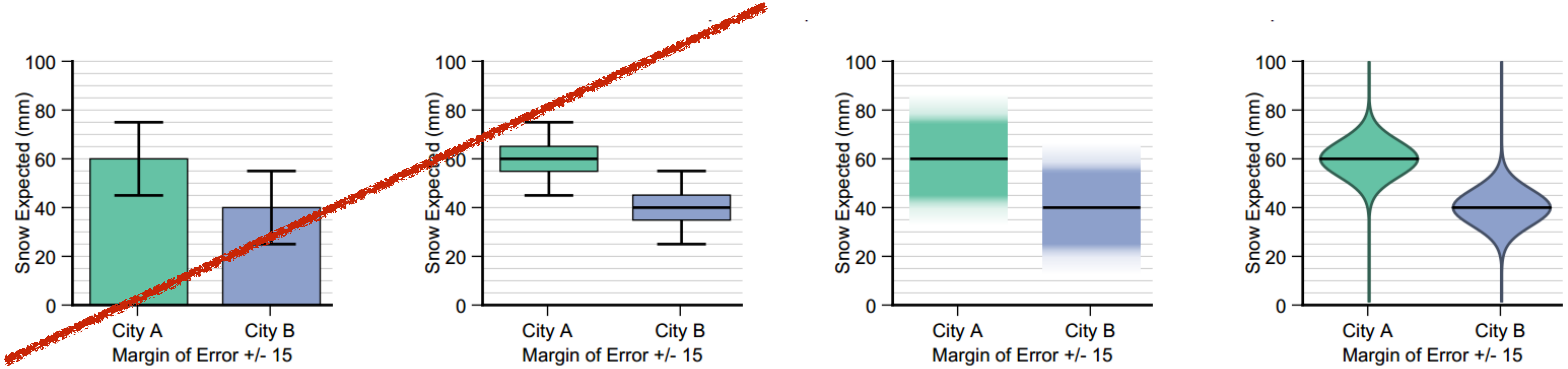
= Box Plot + Probability Density Function



http://web.stanford.edu/~mwaskom/software/seaborn/tutorial/plotting_distributions.html

Showing Expected Values & Uncertainty

NOT a distribution!

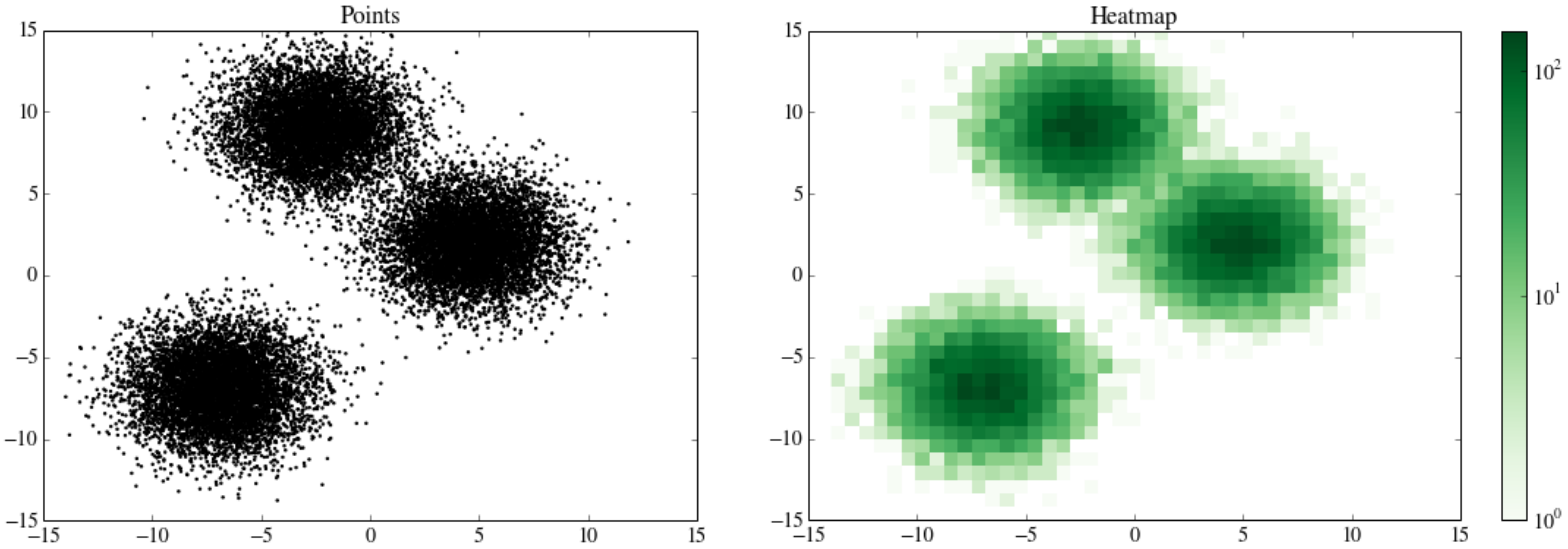


Error Bars Considered Harmful:
Exploring Alternate Encodings for Mean and Error
Michael Correll, and Michael Gleicher

Heat Maps

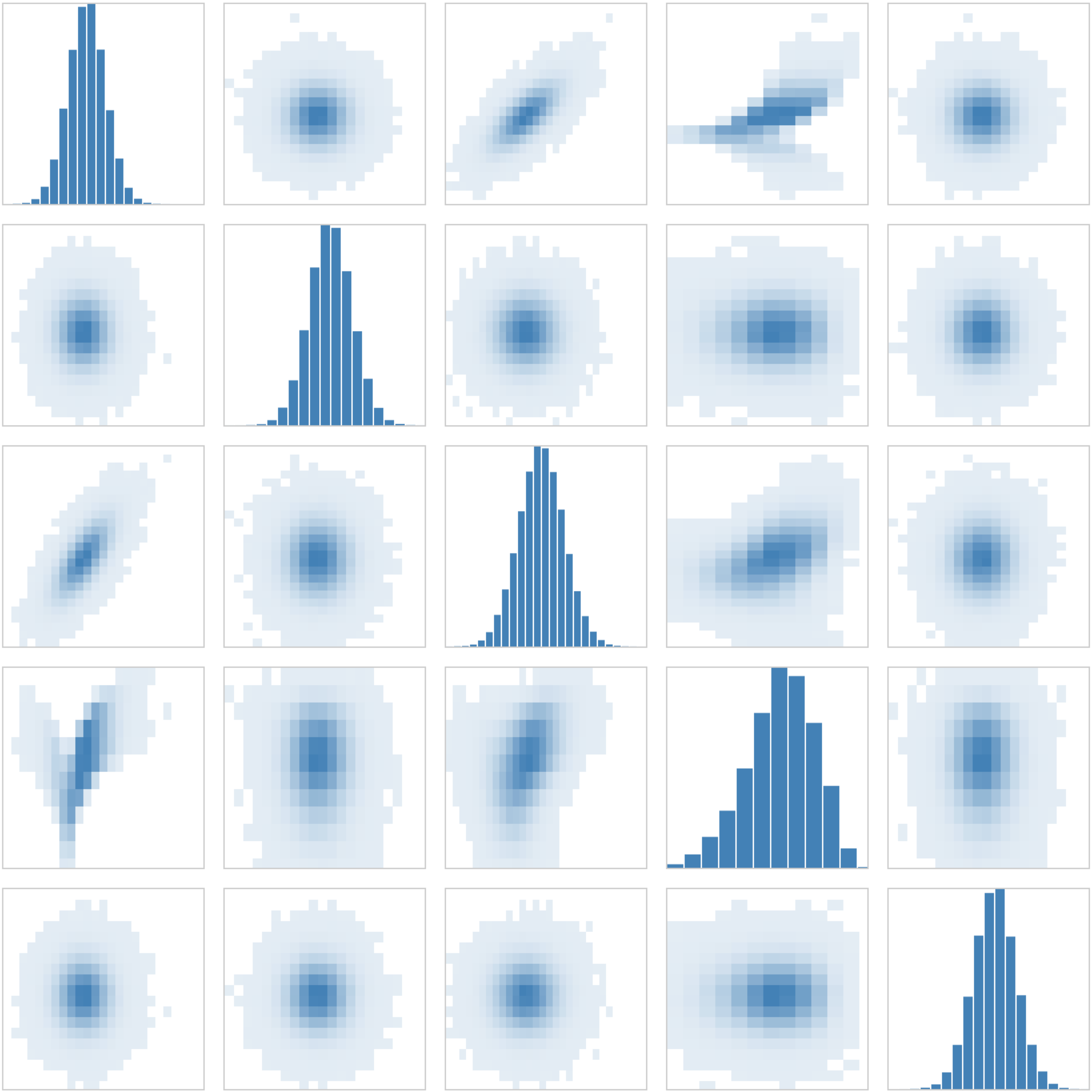
binning of scatterplots

instead of drawing every point, calculate grid and intensities



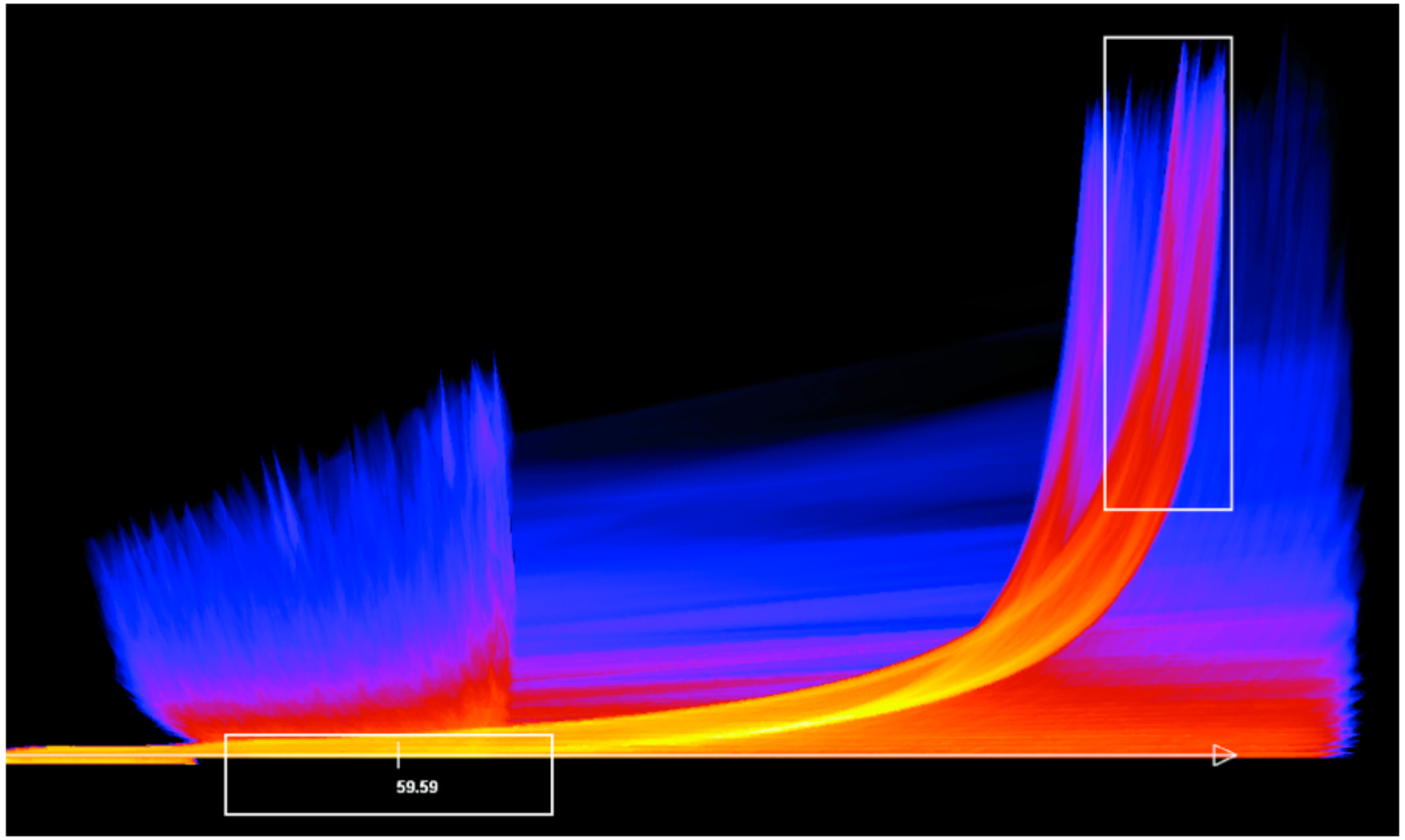
2D Density Plots

Interactive Binned Scatterplot Matrix Dimensions: 5 Bins: 20 Data Points: 100k



Powered by Datavore and D3.

Continuous Scatterplot



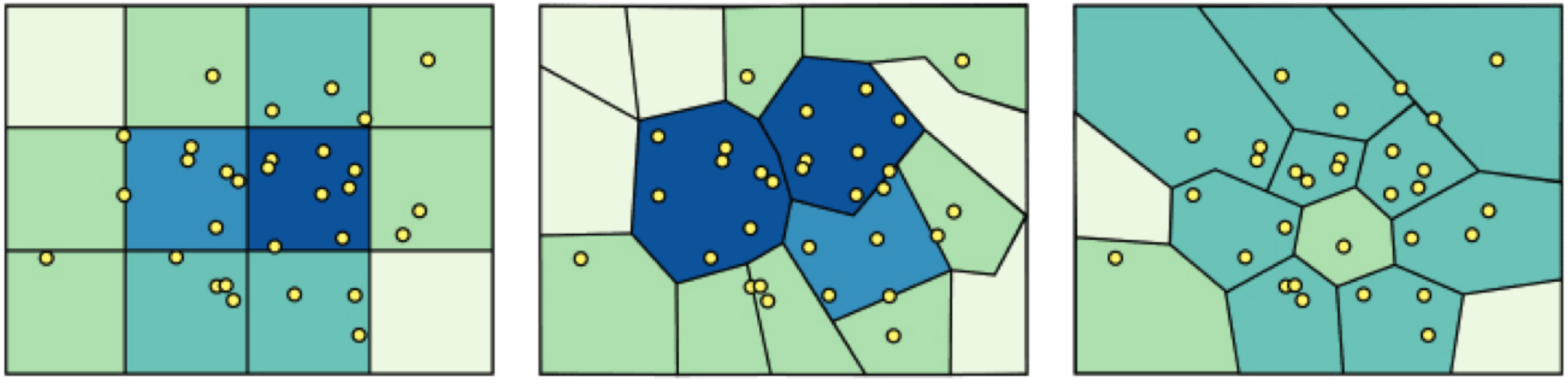
Bachthaler 2008

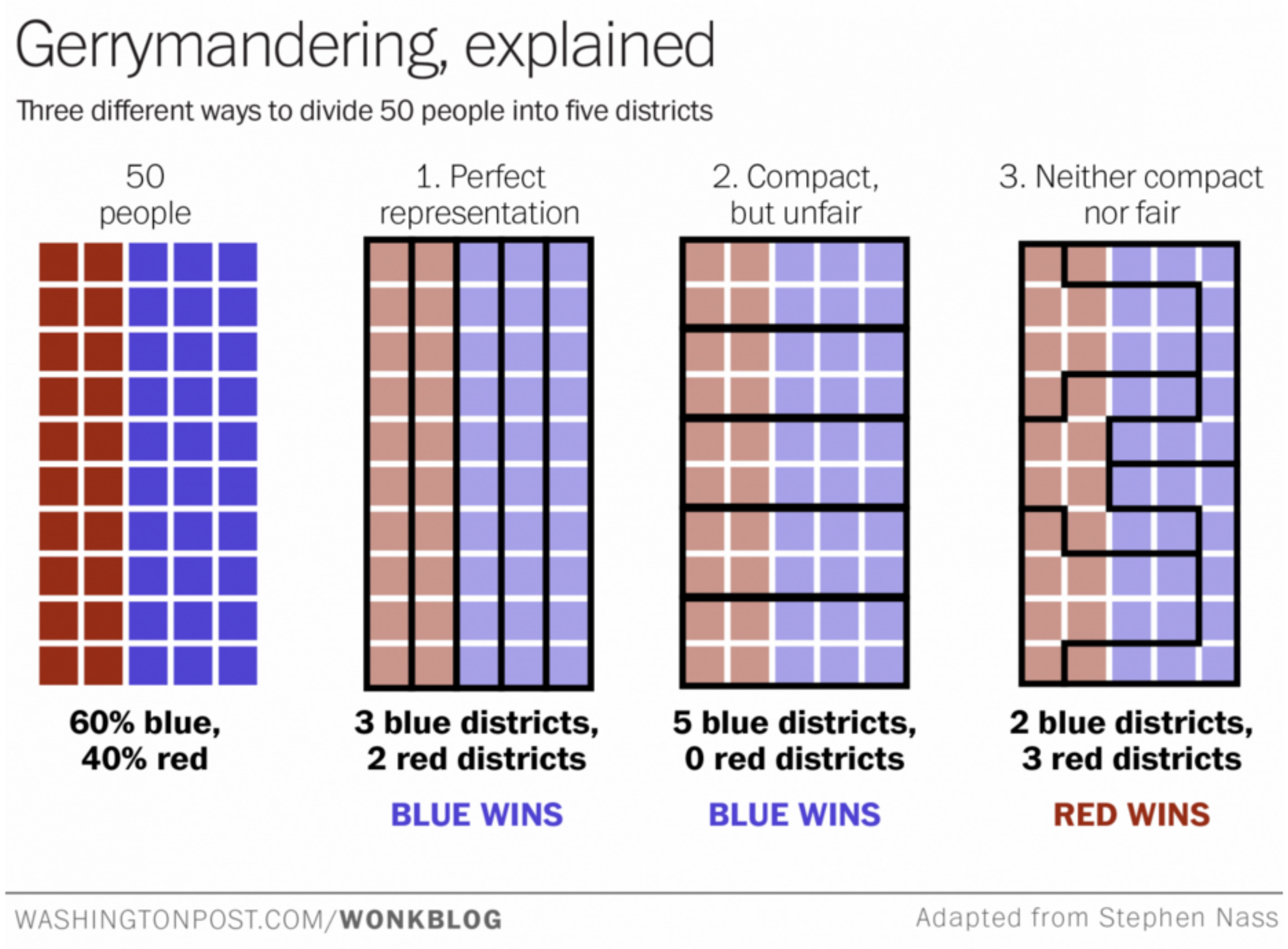
Spatial Aggregation

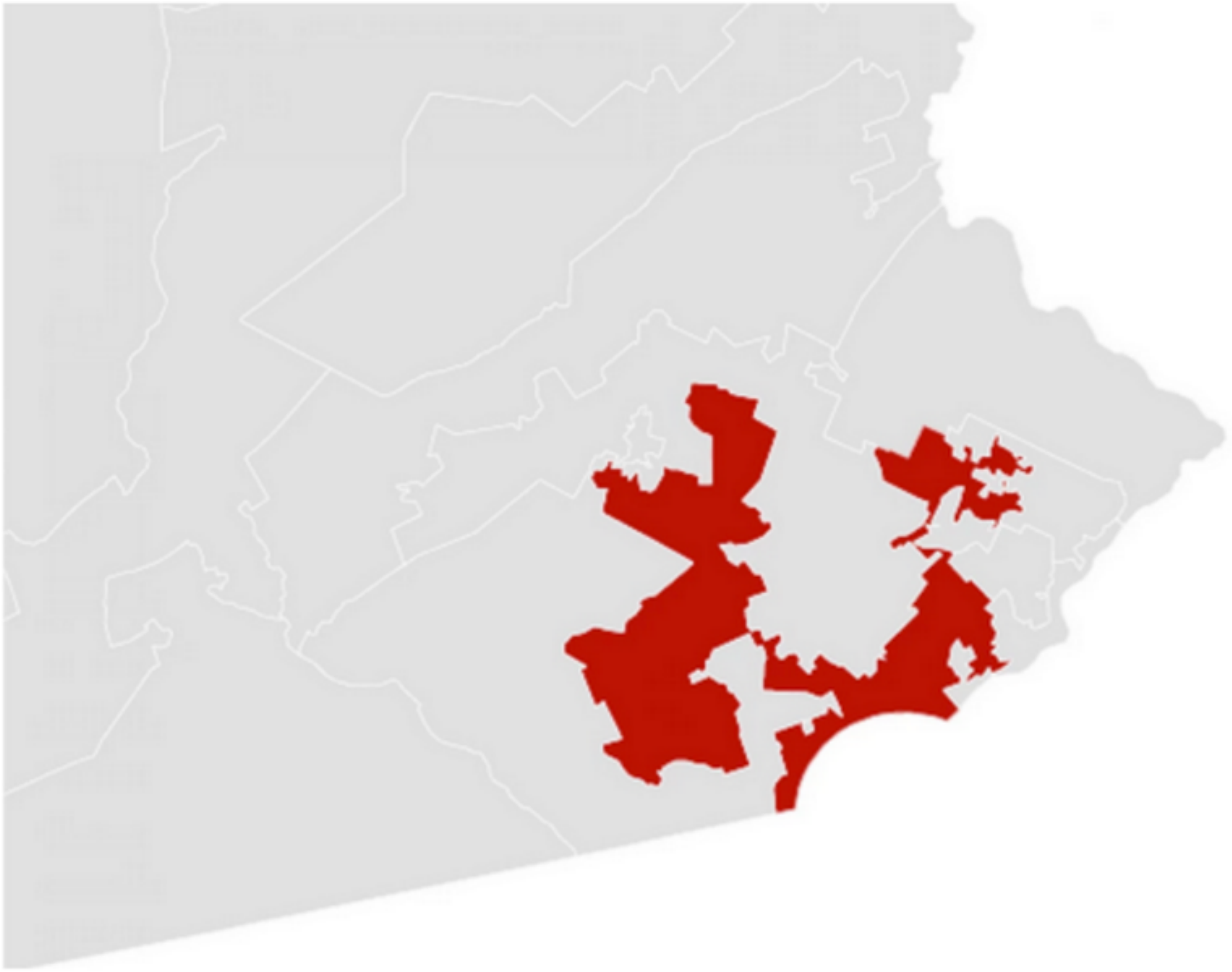
Spatial Aggregation

modifiable areal unit problem

in cartography, changing the boundaries of the regions used to analyze data can yield dramatically different results

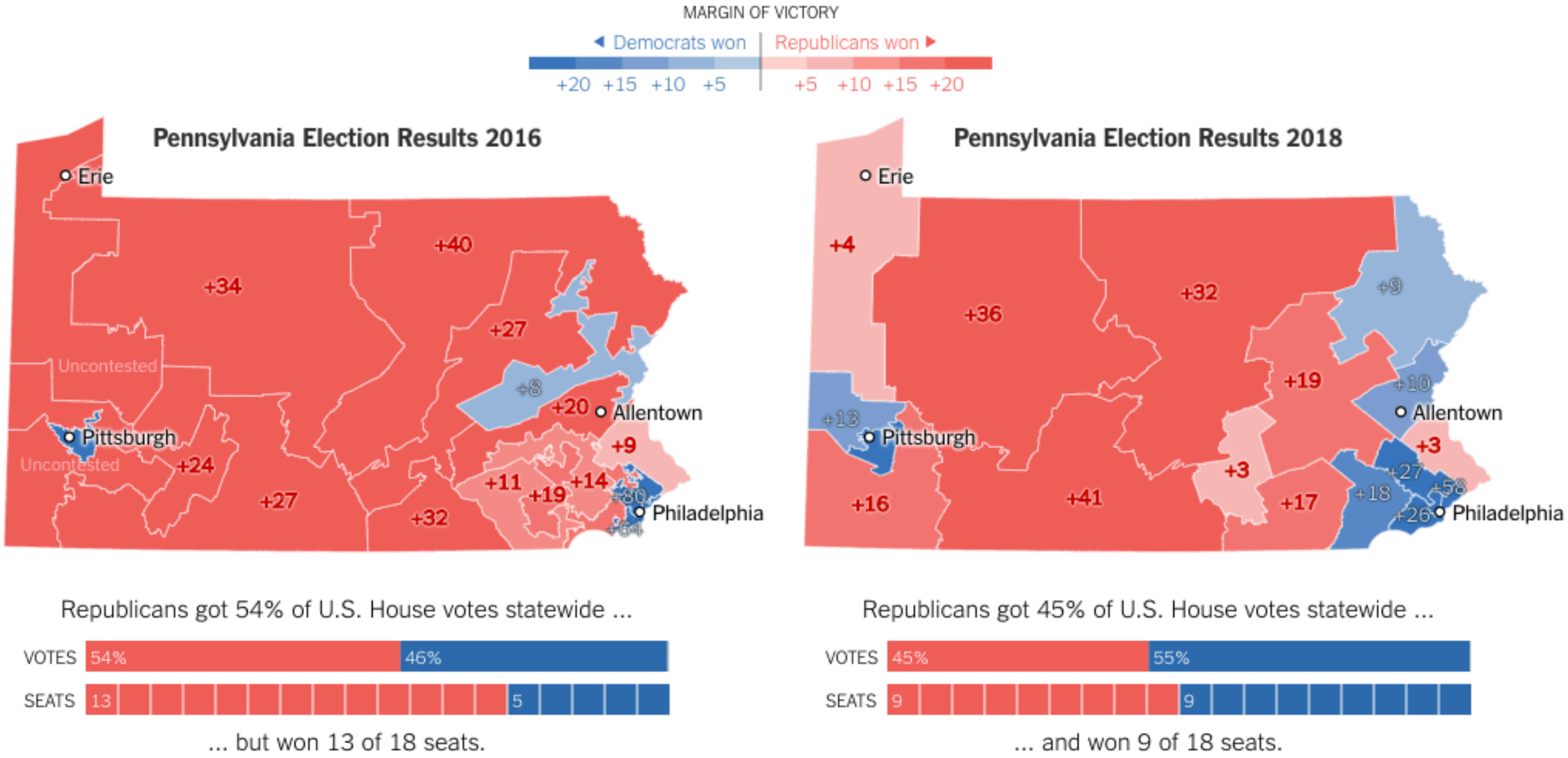






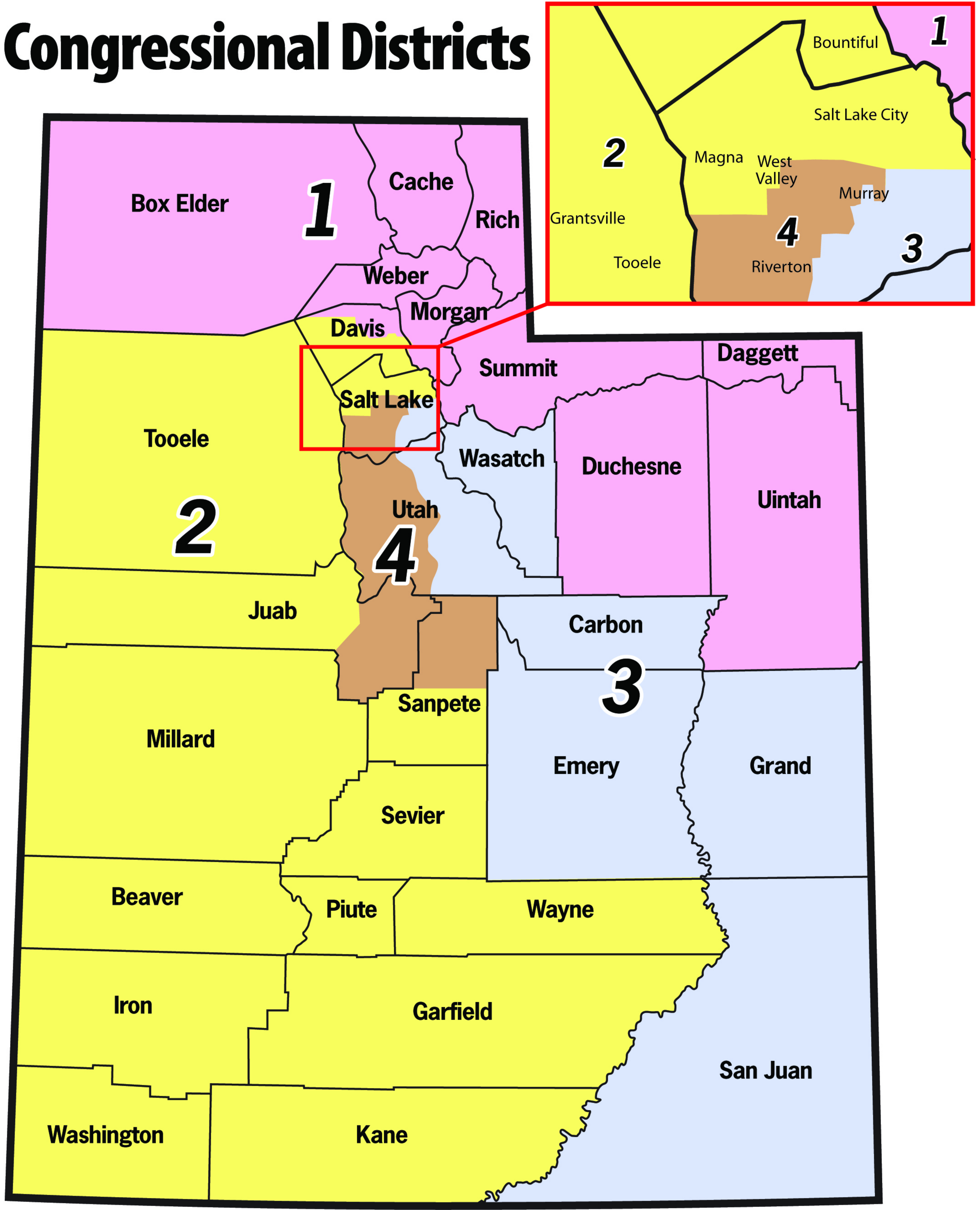
A real district in Pennsylvania
Democrats won 51% of the vote
but only 5 out of 18 house seats

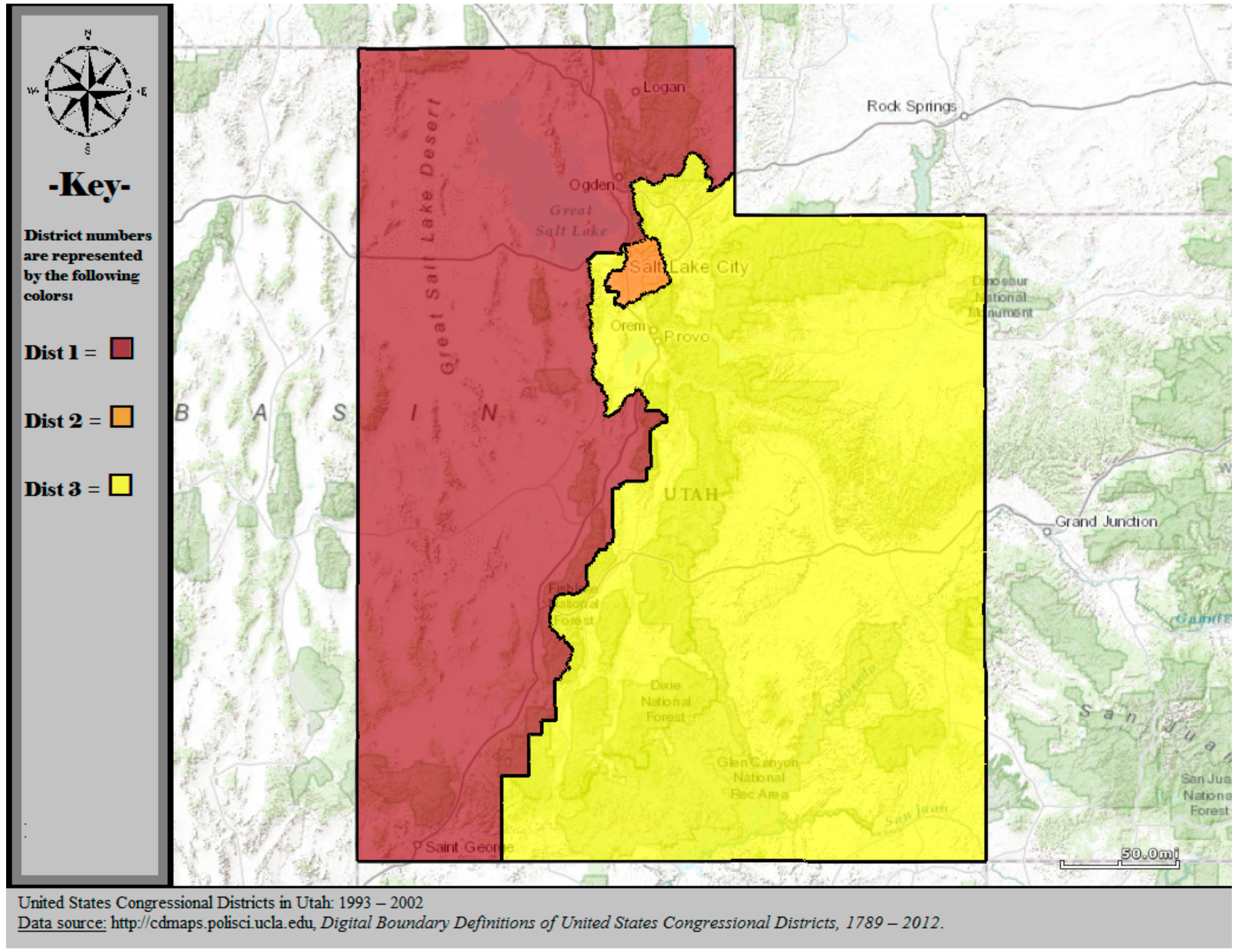
Updated Map after Court Decision



https://www.nytimes.com/interactive/2018/11/29/us/politics/north-carolina-gerrymandering.html?action=click&module=Top%20Stories&pgtype=Homepage

Congressional Districts

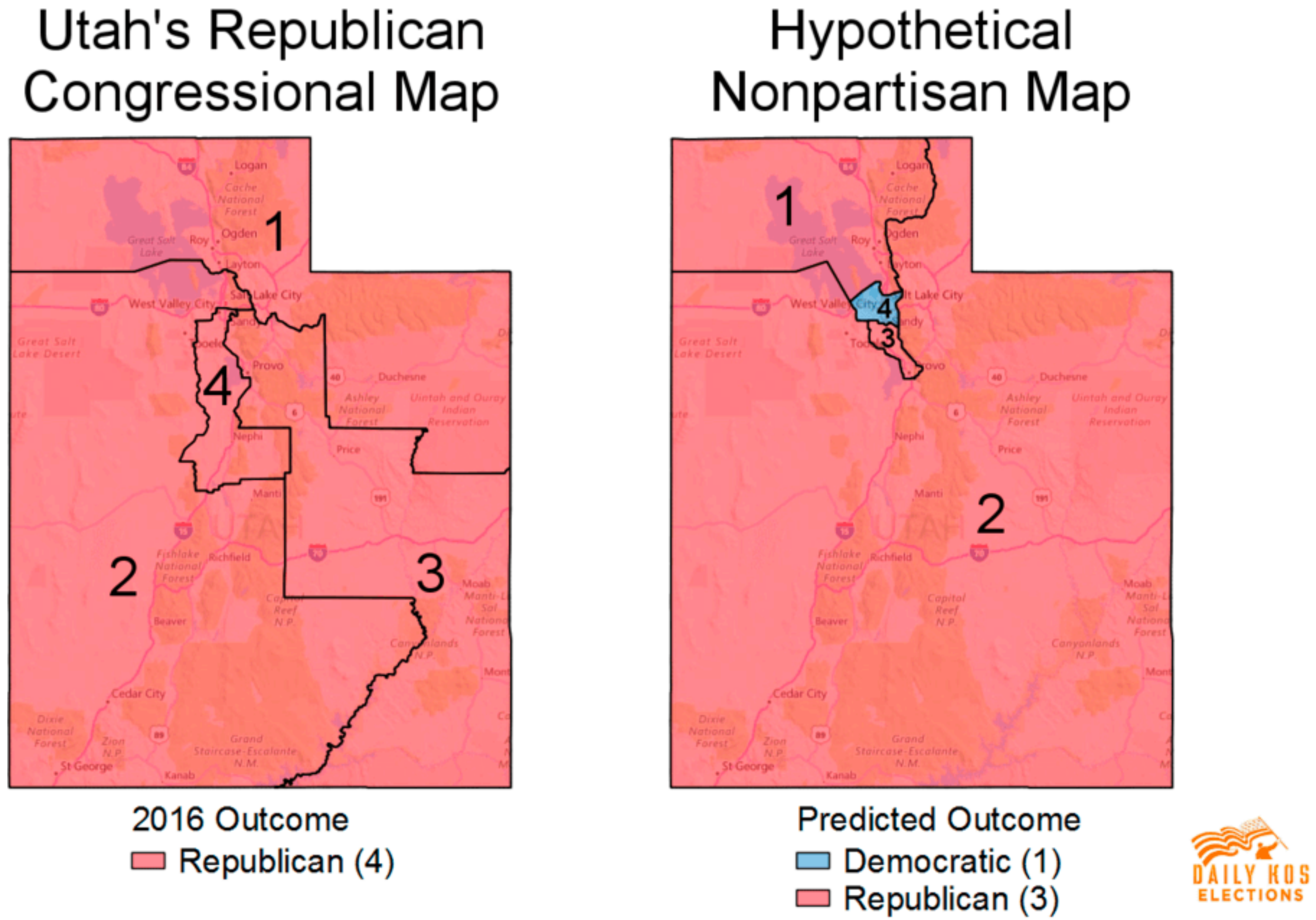




Valid till 2002

http://www.sltrib.com/opinion/1794525-155/lake-salt-republican-county-http-utah

2016 Congressional Elections



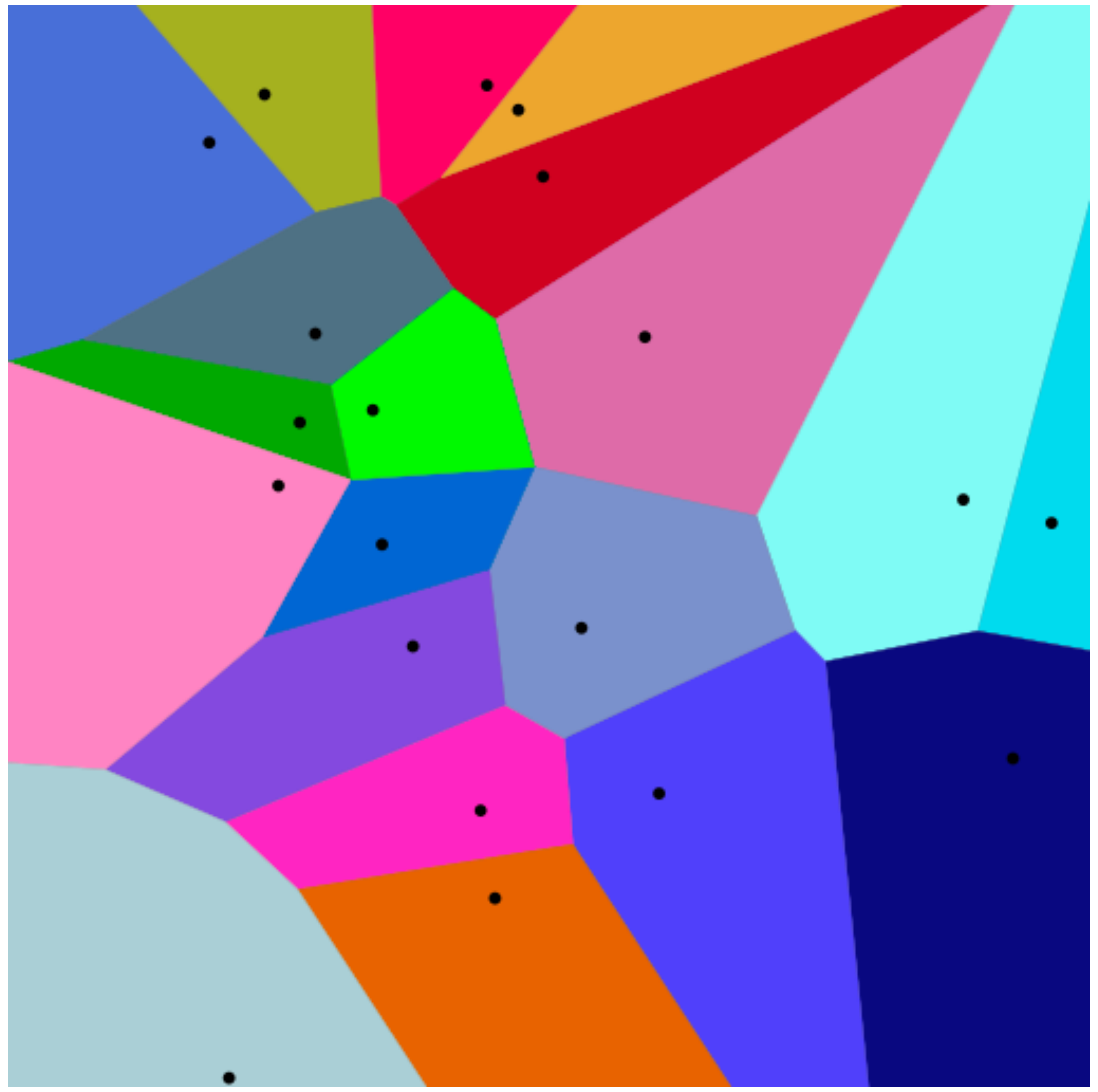
https://www.dailykos.com/stories/2016/12/29/1611906/-Here-s-what-Utah-might-have-looked-like-in-2016-without-congressional-gerrymandering

Voronoi Diagrams

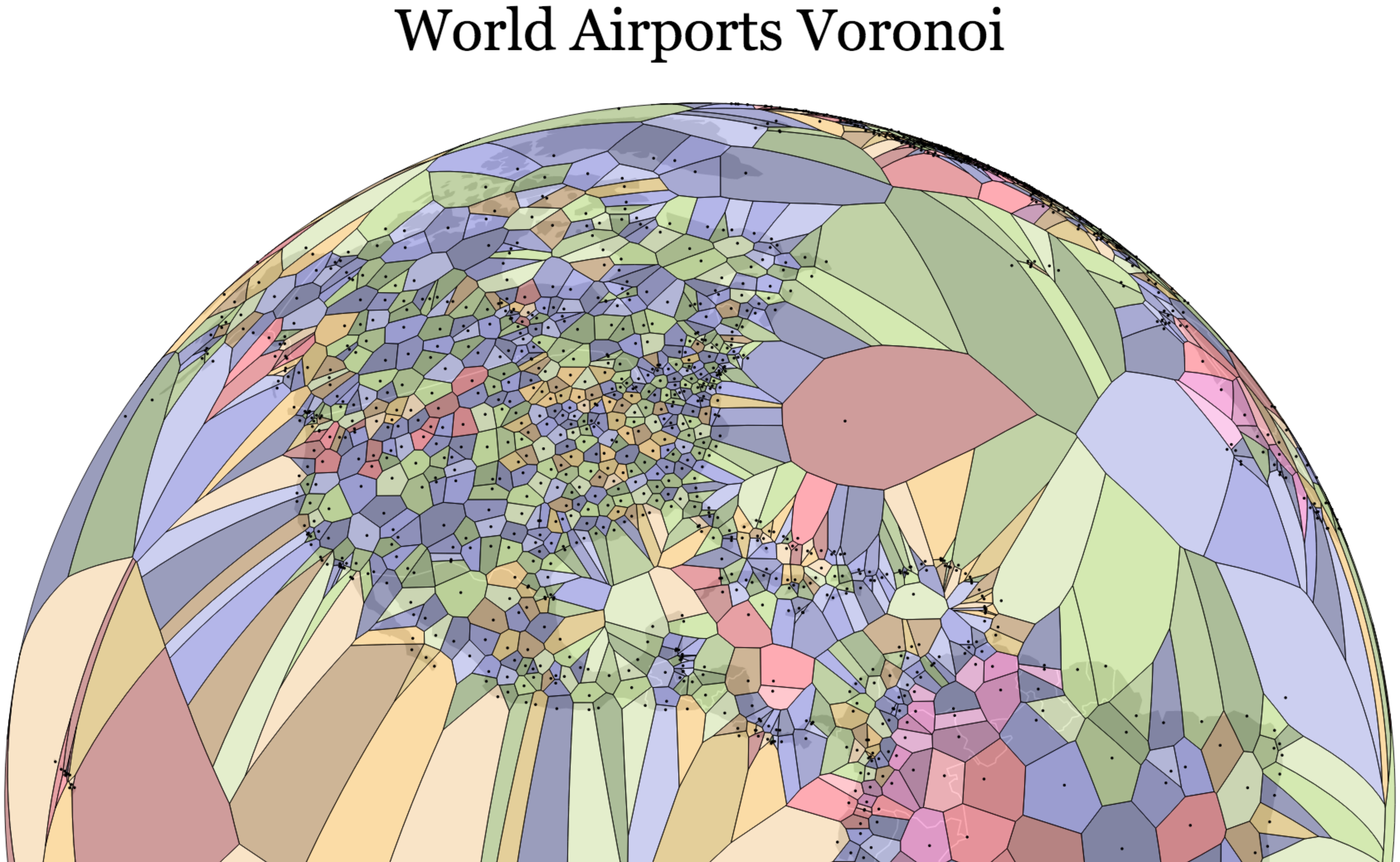
Given a set of locations, for which area is a location n closest?

D3 Voronoi Layout:

https://github.com/d3/d3-voronoi



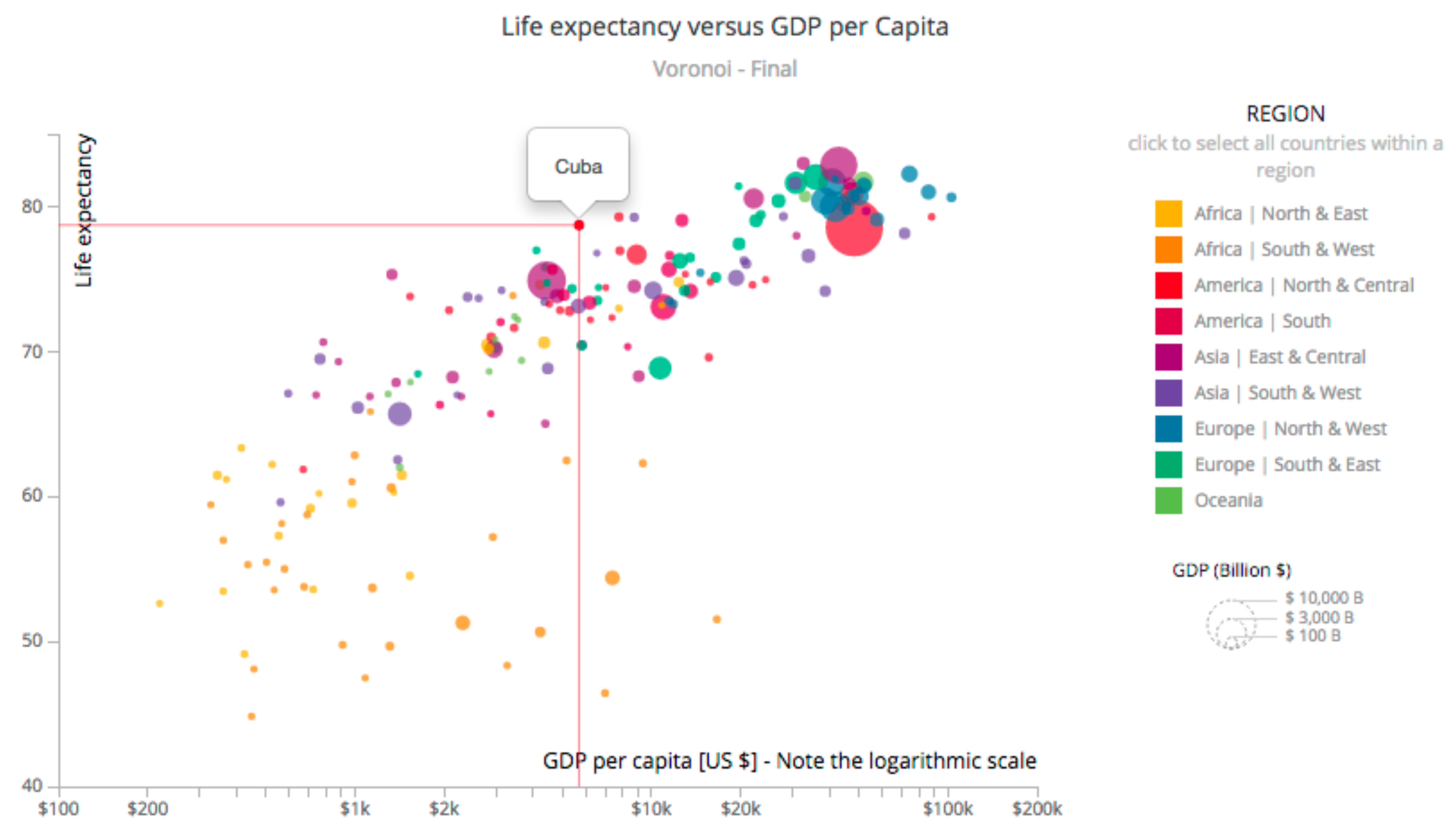
Voronoi Examples

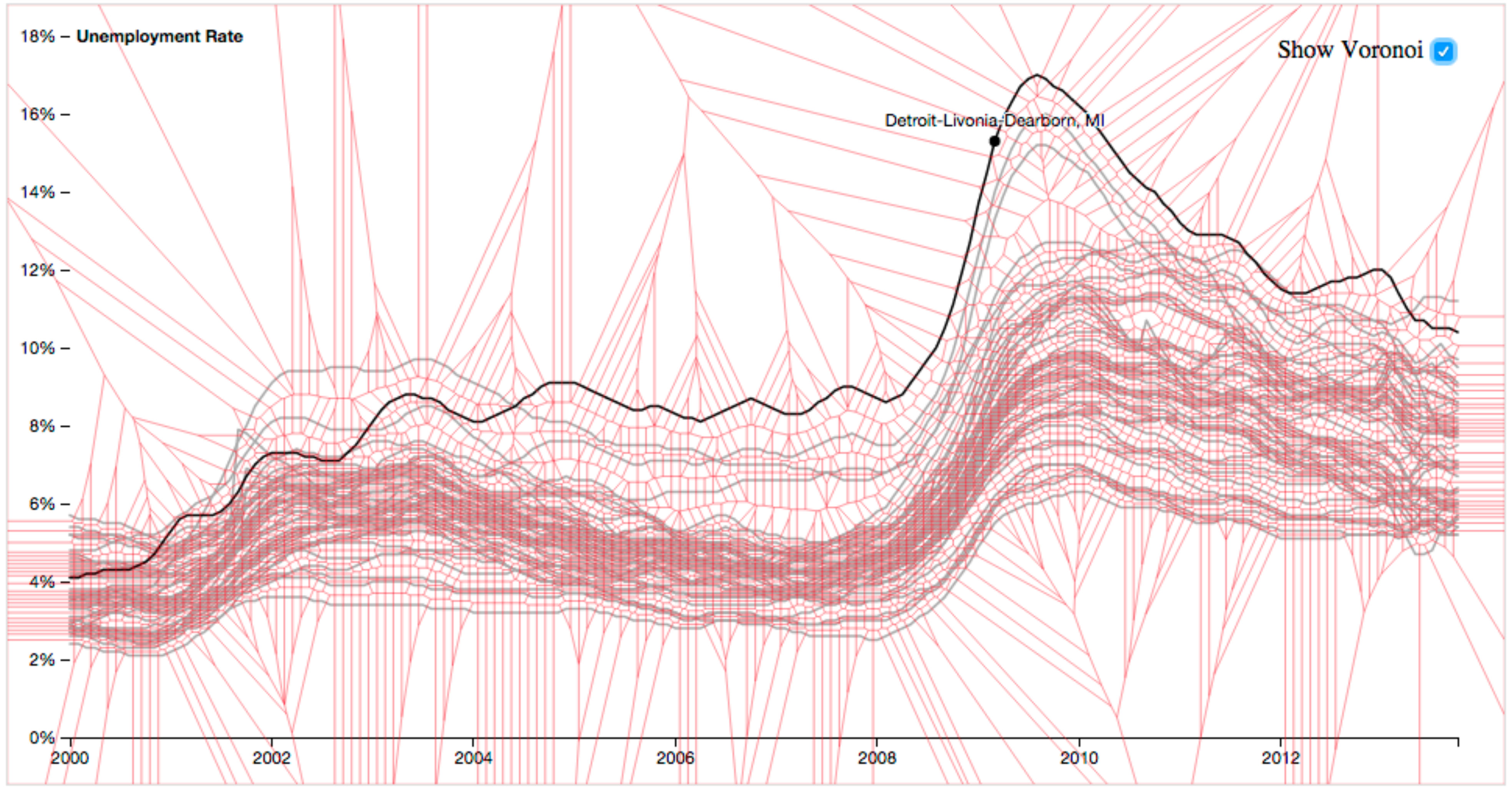


Voronoi for Interaction

Useful for interaction:
Increase size of target area to click/hover

Instead of clicking on point, hover in its region





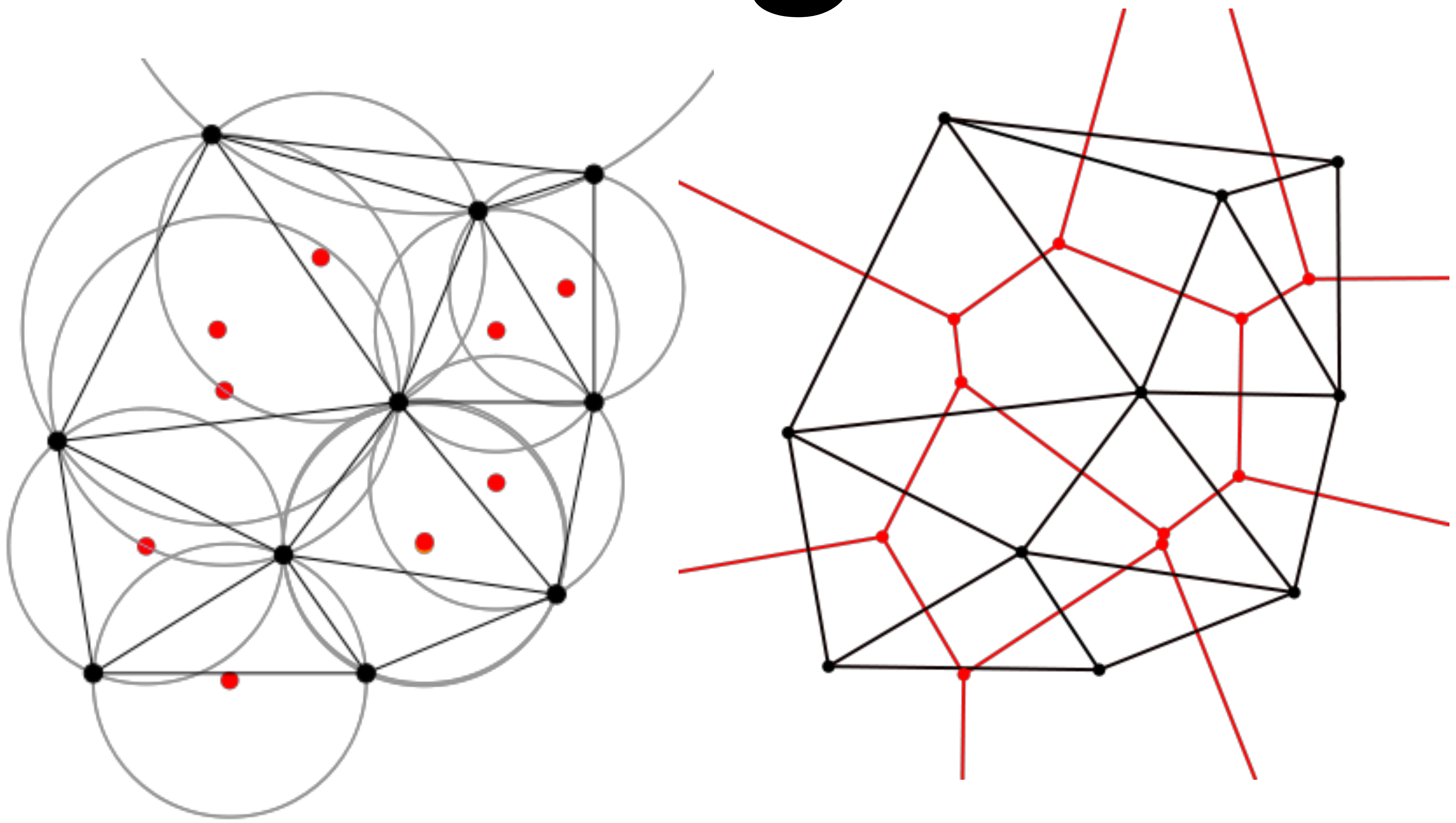
https://github.com/d3/d3-voronoi/

Constructing a Voronoi Diagram

Calculate a Delauney triangulation

- Triangulation where no vertices are in a circle described by the vertices of a triangle

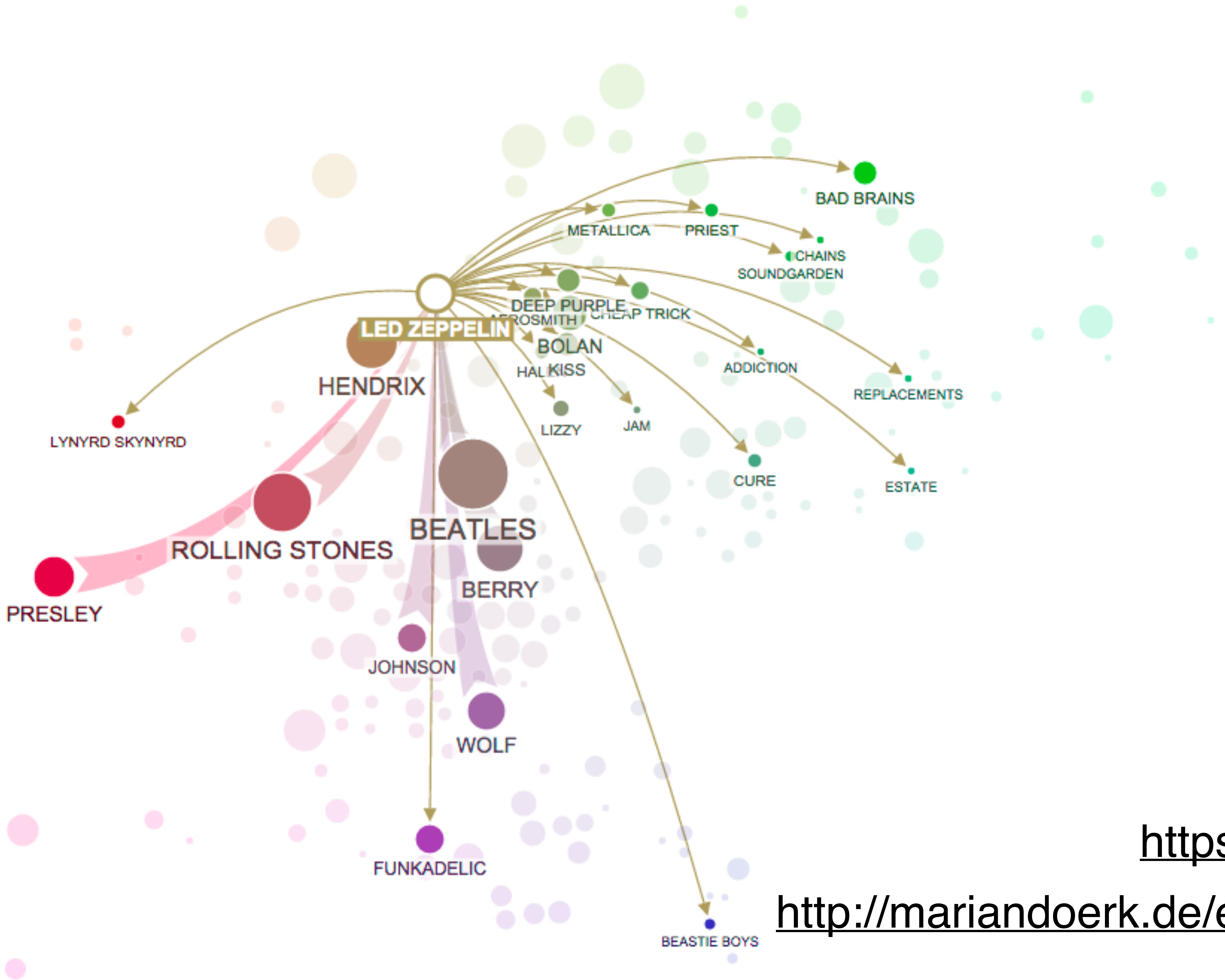
Voronoi edges are perpendicular to triangle edges.



https://en.wikipedia.org/wiki/Delaunay_triangulation

http://paulbourke.net/papers/triangulate/

Design Critique



https://goo.gl/IDRXDI

http://mariandoerk.de/edgemaps/demo/

Clustering

Clustering

Classification of items into “similar” bins

Based on similarity measures

- Euclidean distance, Pearson correlation, ...

Partitional Algorithms

- divide data into set of bins
- # bins either manually set (e.g., k-means) or automatically determined (e.g., affinity propagation)

Hierarchical Algorithms

- Produce “similarity tree” – dendrogram

Bi-Clustering

- Clusters dimensions & records

Fuzzy clustering

- allows occurrence of elements in multiples clusters

Clustering Applications

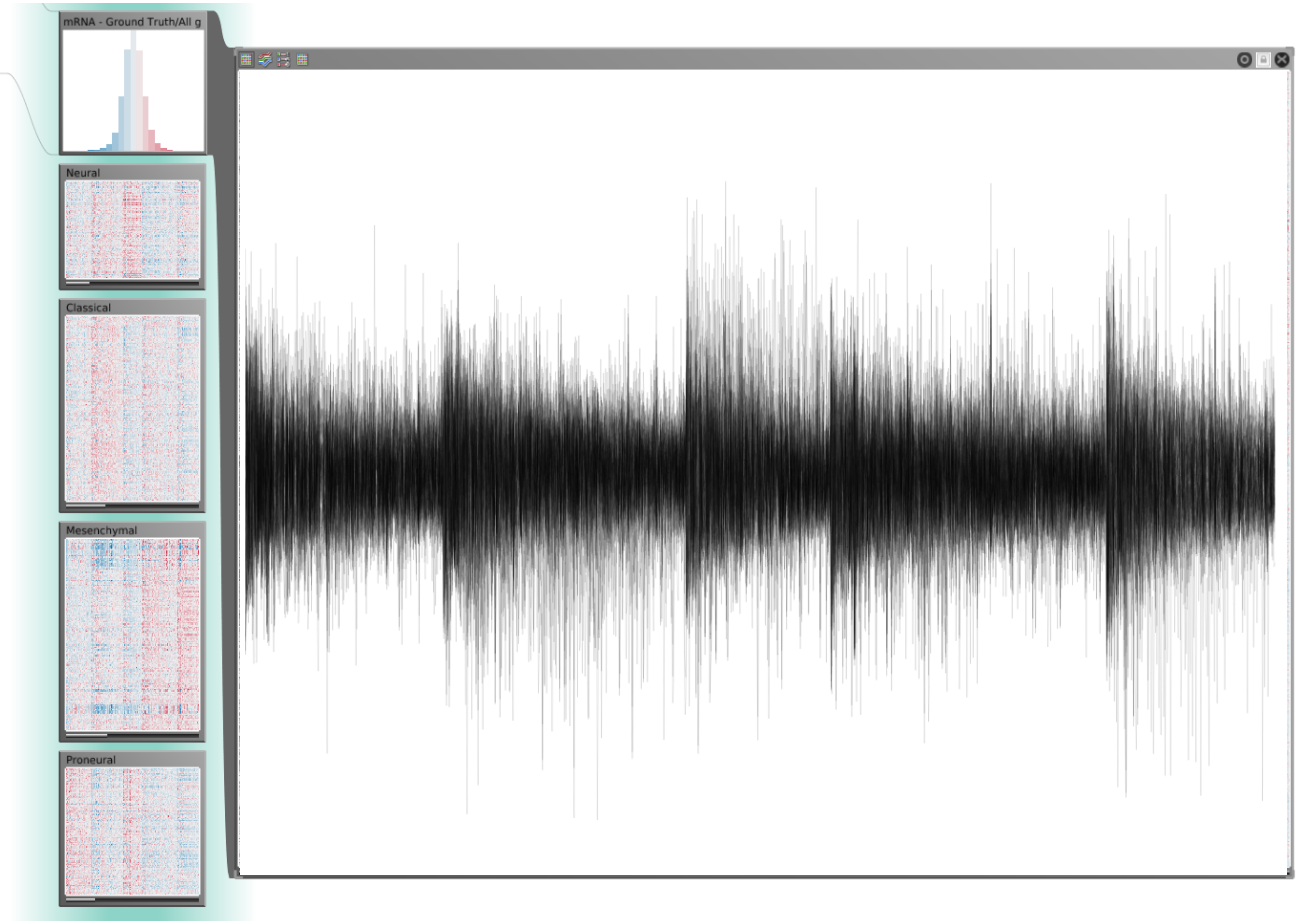
Clusters can be used to

- order (pixel based techniques)
- brush (geometric techniques)
- aggregate

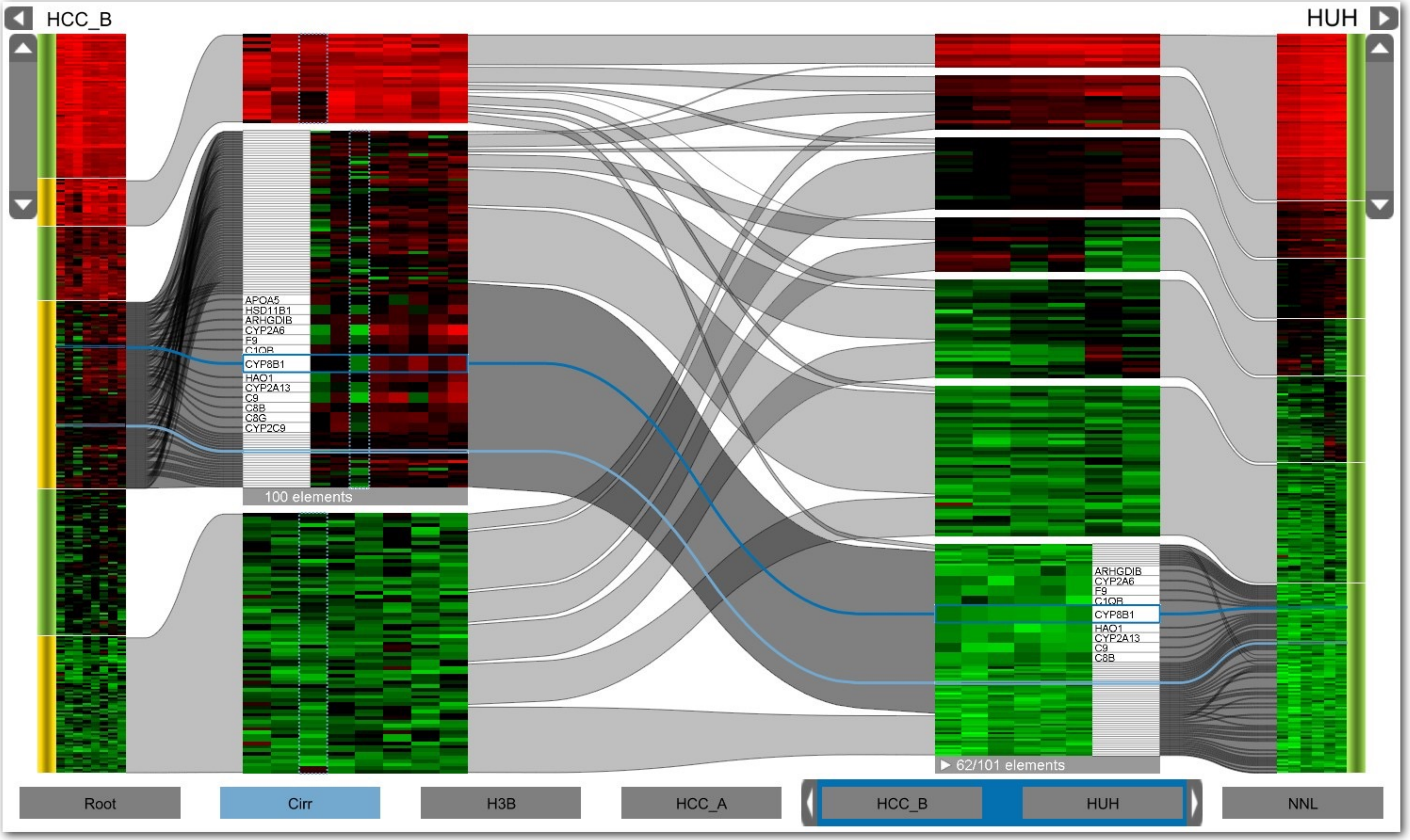
Aggregation

- cluster more homogeneous than whole dataset
- statistical measures, distributions, etc. more meaningful

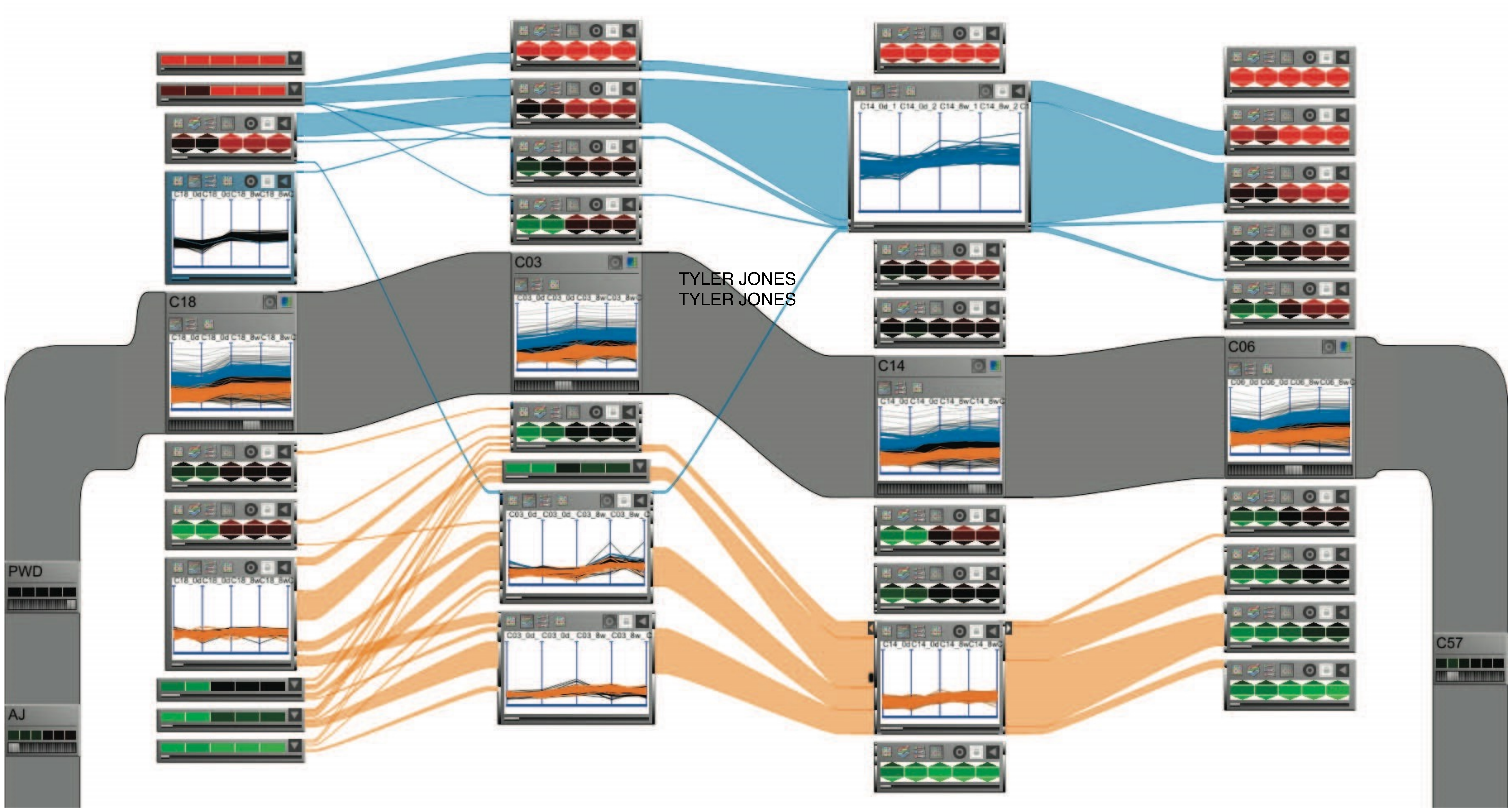
Clustered Heat Map



Cluster Comparison



Aggregation



Example: K-Means

Goal: Minimize aggregate intra-custer distance (*inertia*)

$$\underset{C}{argmin} \sum_{i=1}^{k} \sum_{x \in C_i} ||x - \mu_i||^2$$

total squared distance from point to center of its cluster

for euclidian distance: this is the variance

measure of how internally coherent clusters are

Lloyd’s Algorithm

Input: set of records $x_1 \ldots x_n$, and k (nr clusters)

Pick k starting points as centroids $c_1 \ldots c_k$

While not converged:

1. for each point x_i find closest centroid c_j
   - for every c_j calculate distance $D(x_i, c_j)$
   - assign x_i to cluster j defined by smallest distance
2. for each cluster j, compute a new centroid c_j
   by calculating the average of all x_i assigned to cluster j

Repeat until convergence, e.g.,

no point has changed cluster

distance between old and new centroid below threshold

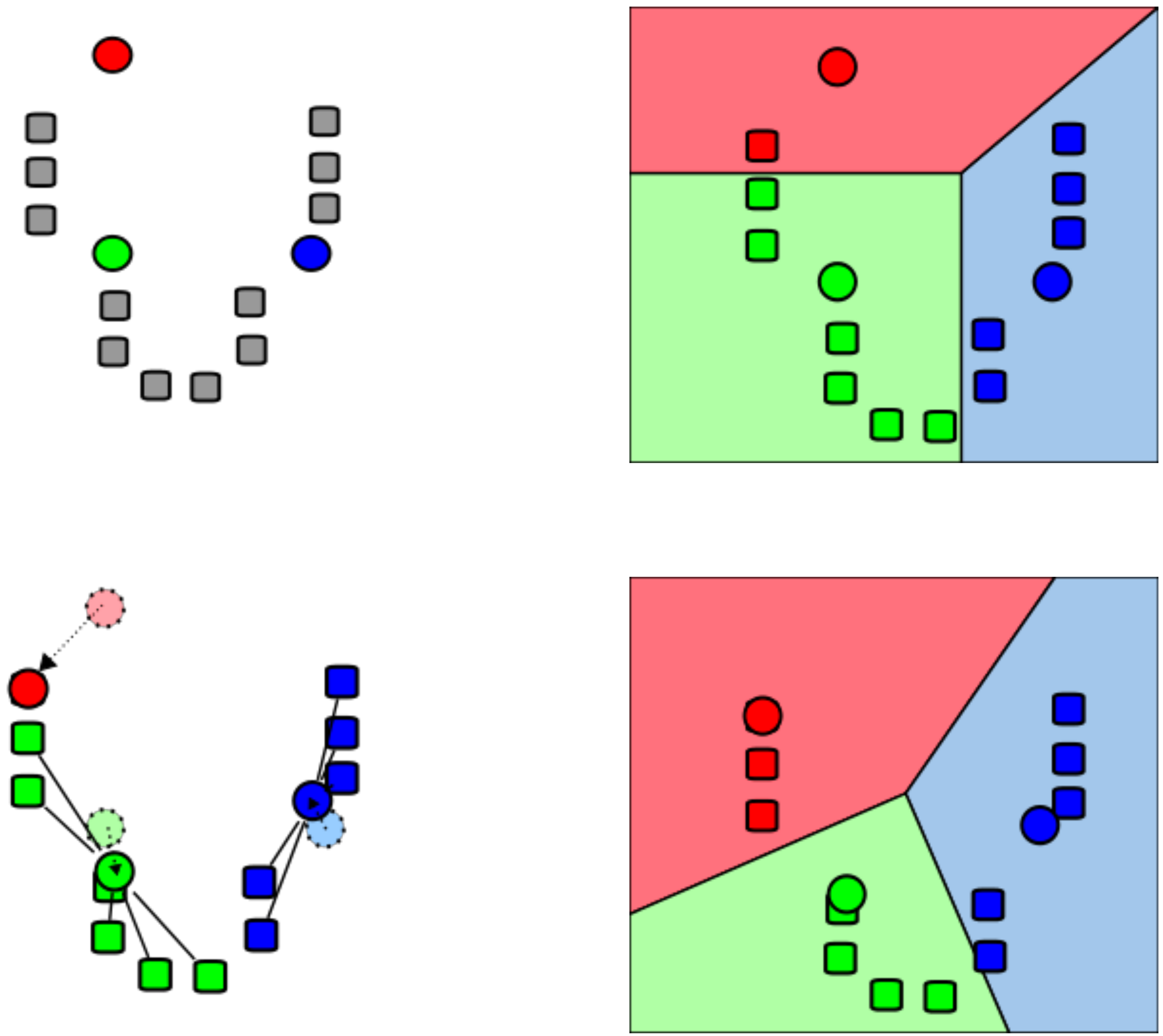
number of max iterations reached

1. Initialization

2. Assign Clusters

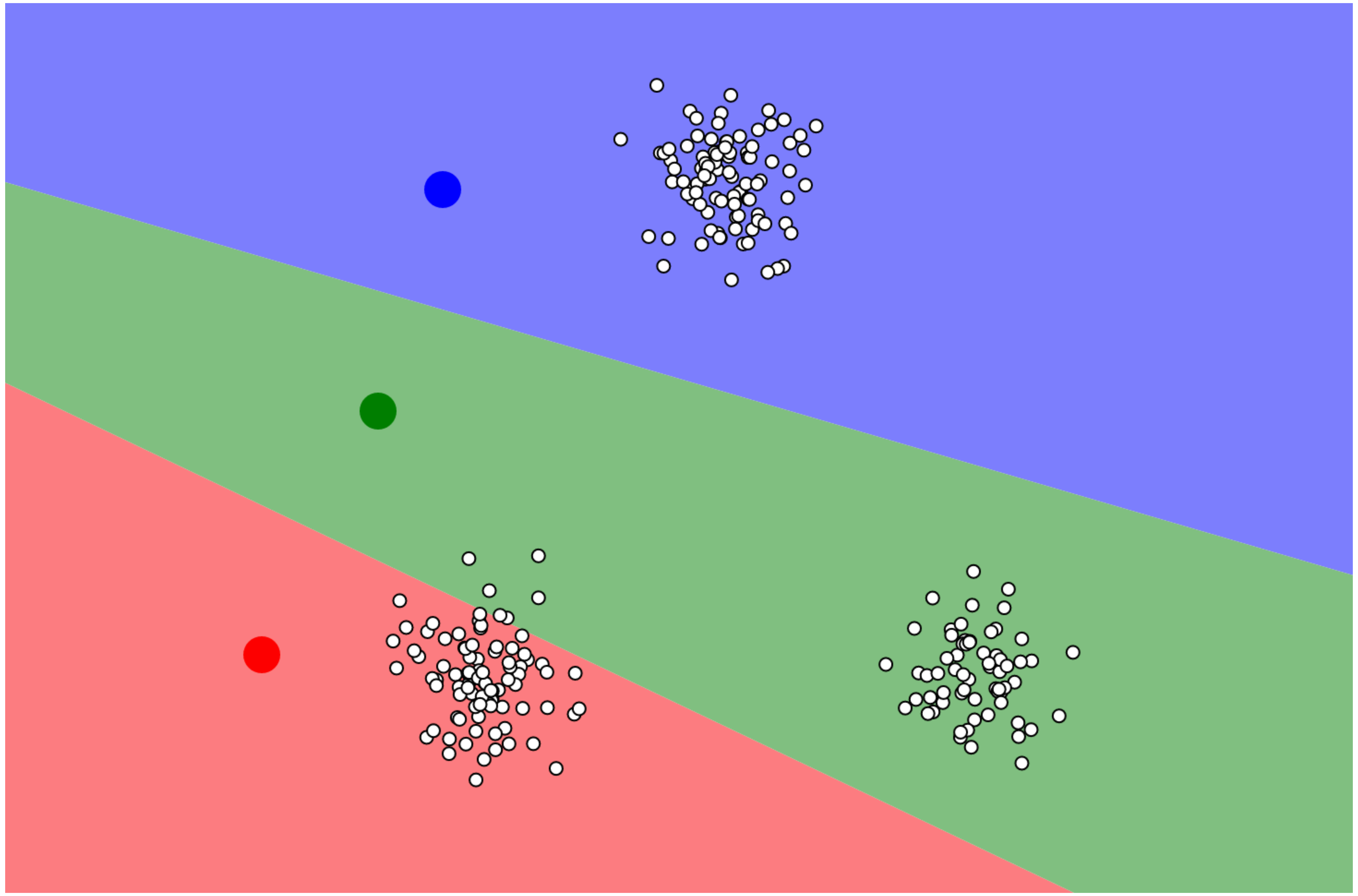
3. Update Centroids

4. Assign Clusters



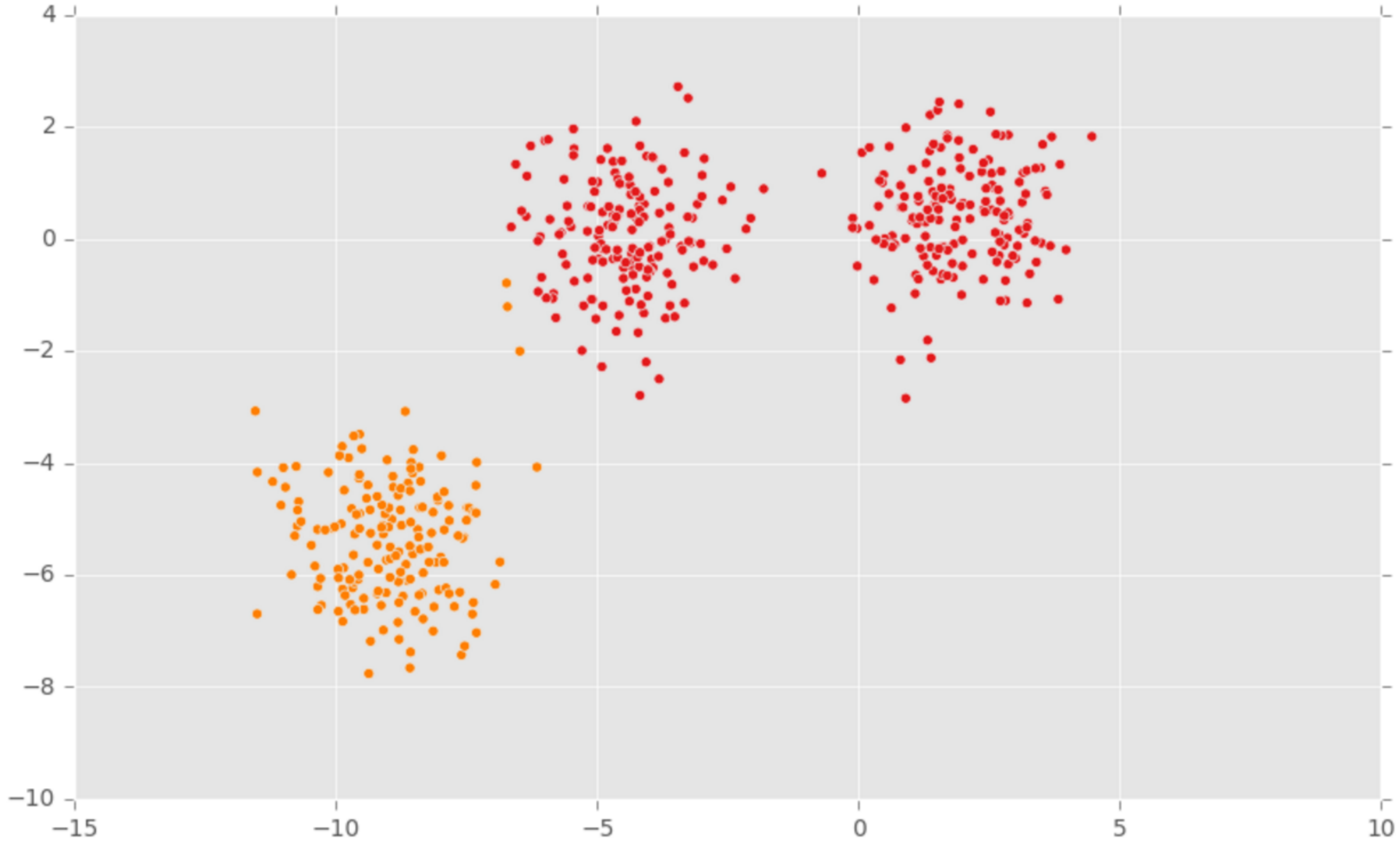
And repeat until converges

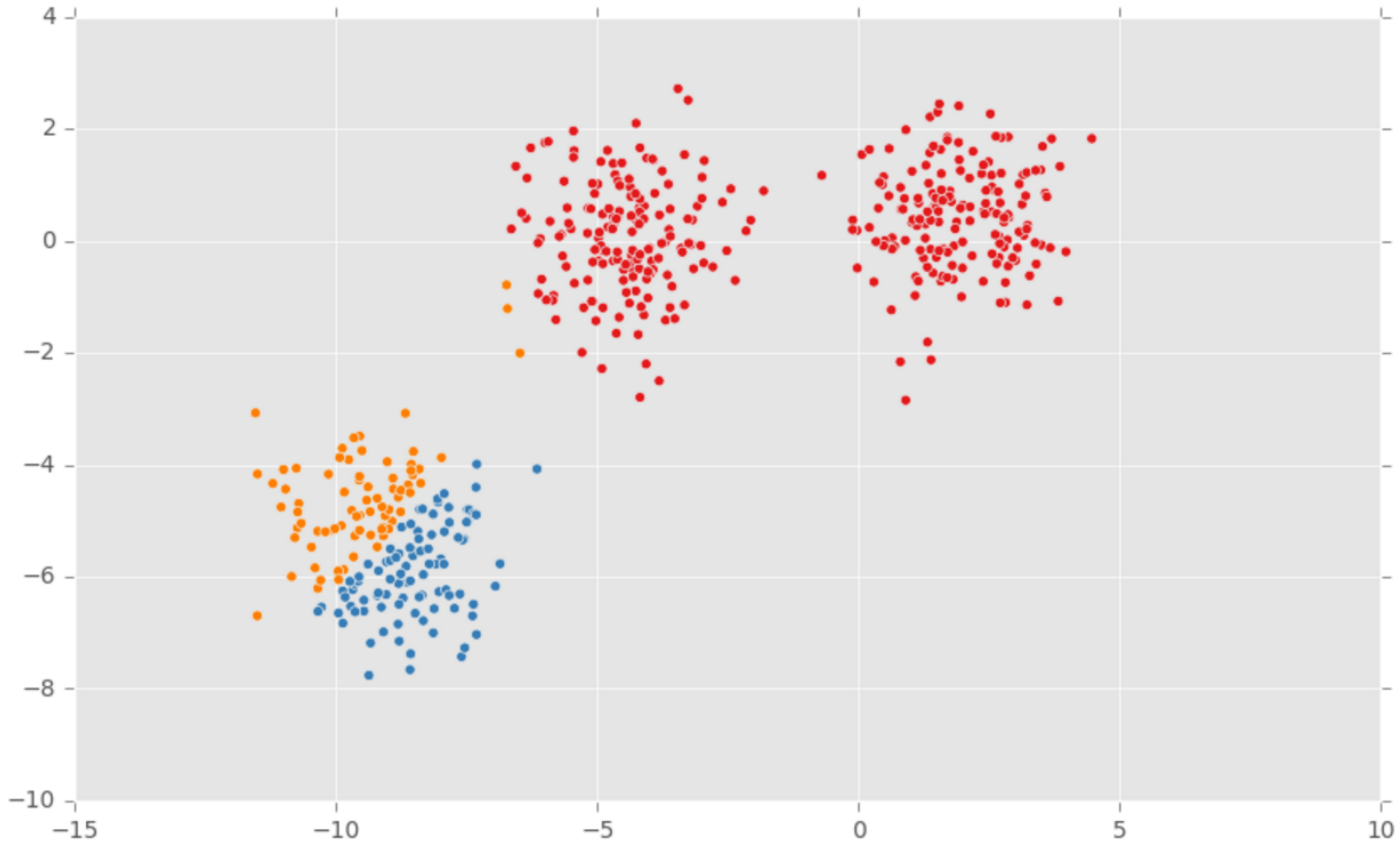
Illustrated



https://www.naftaliharris.com/blog/visualizing-k-means-clustering/

Choosing K





Properties

Lloyds algorithm doesn’t find a global optimum

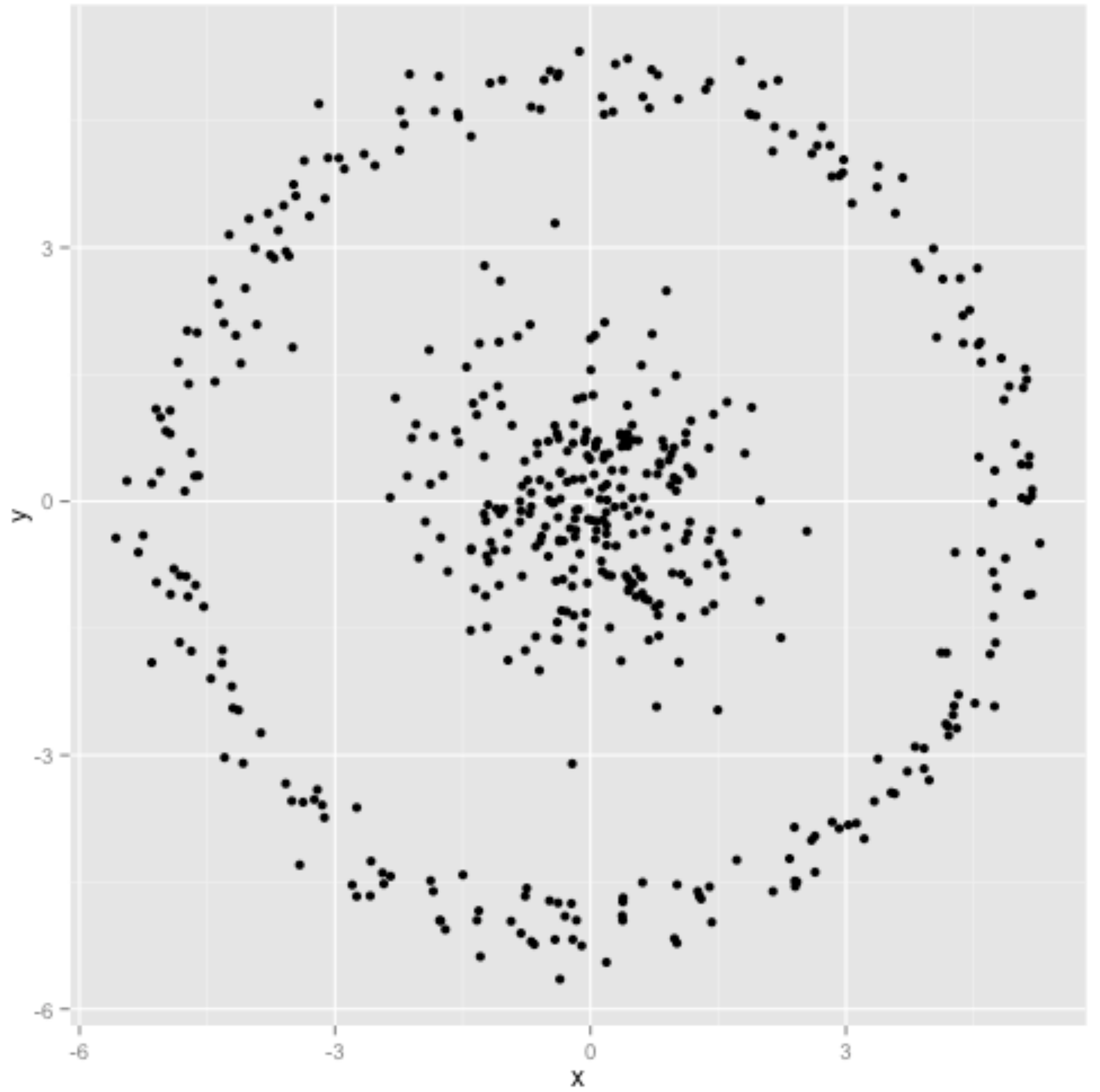
Instead it finds a local optimum

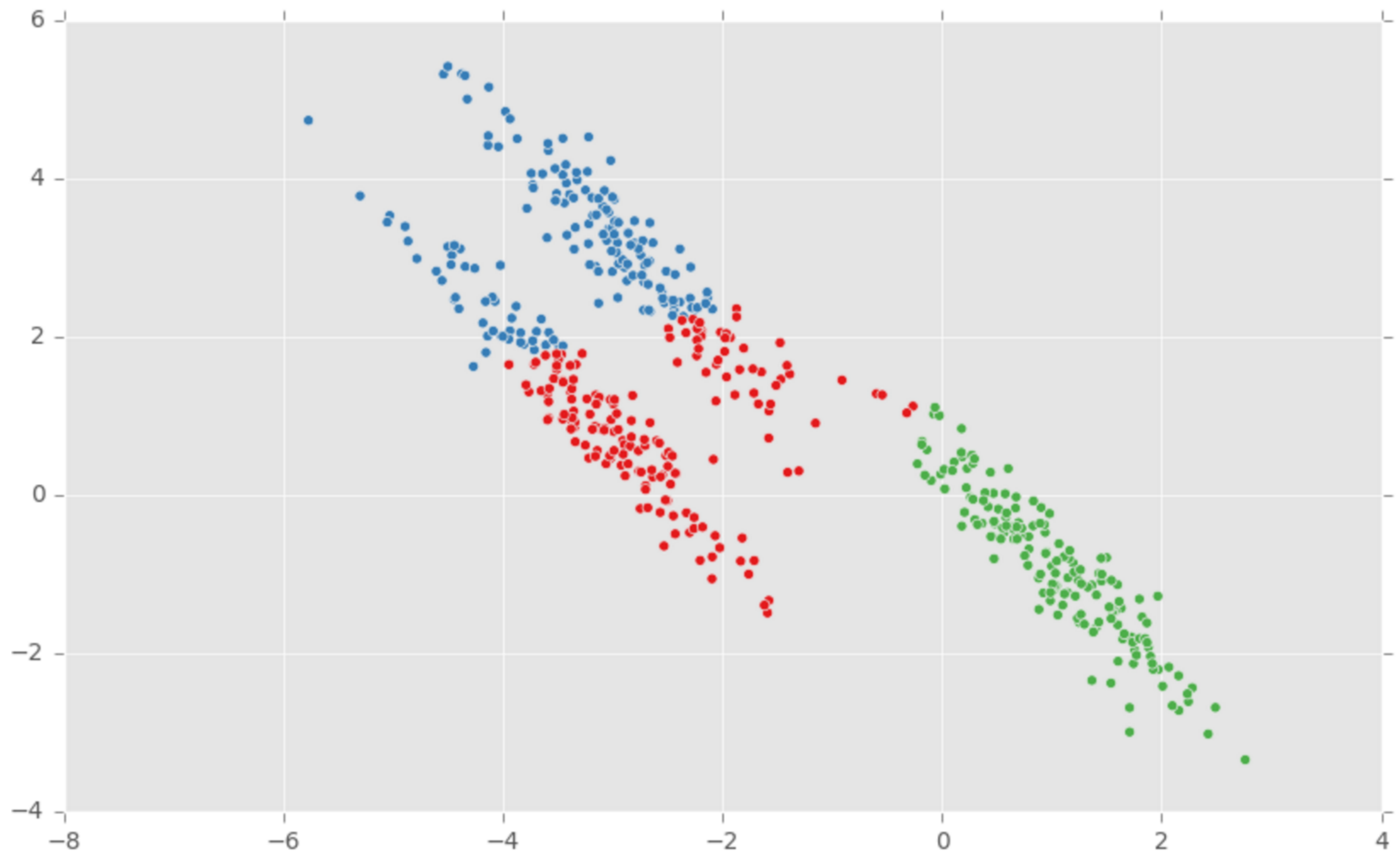
It is very fast:

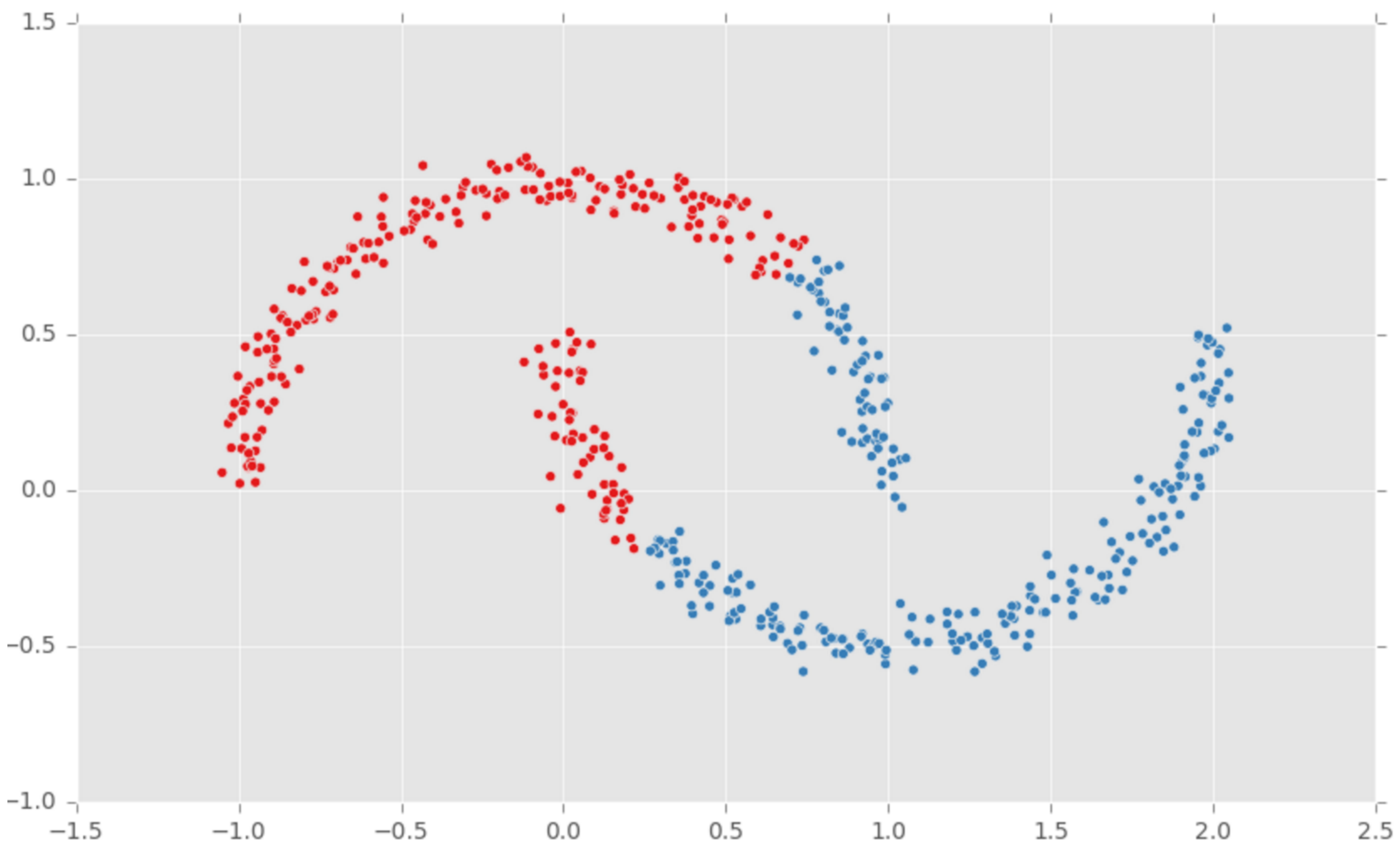
- common to run multiple times and pick the solution with the minimum inertia

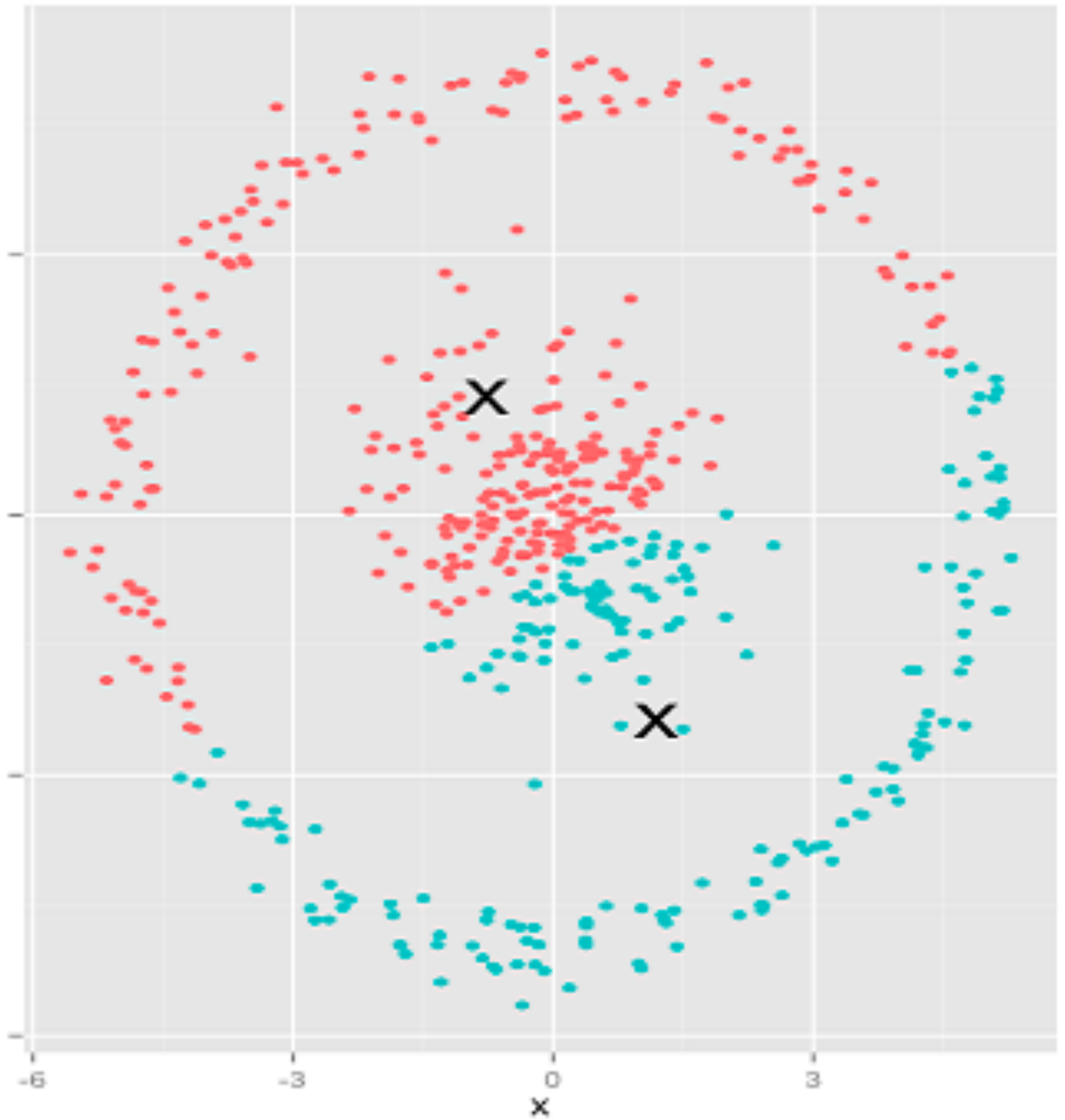
K-Means Properties

Assumptions about data:
roughly “circular” clusters of
equal size

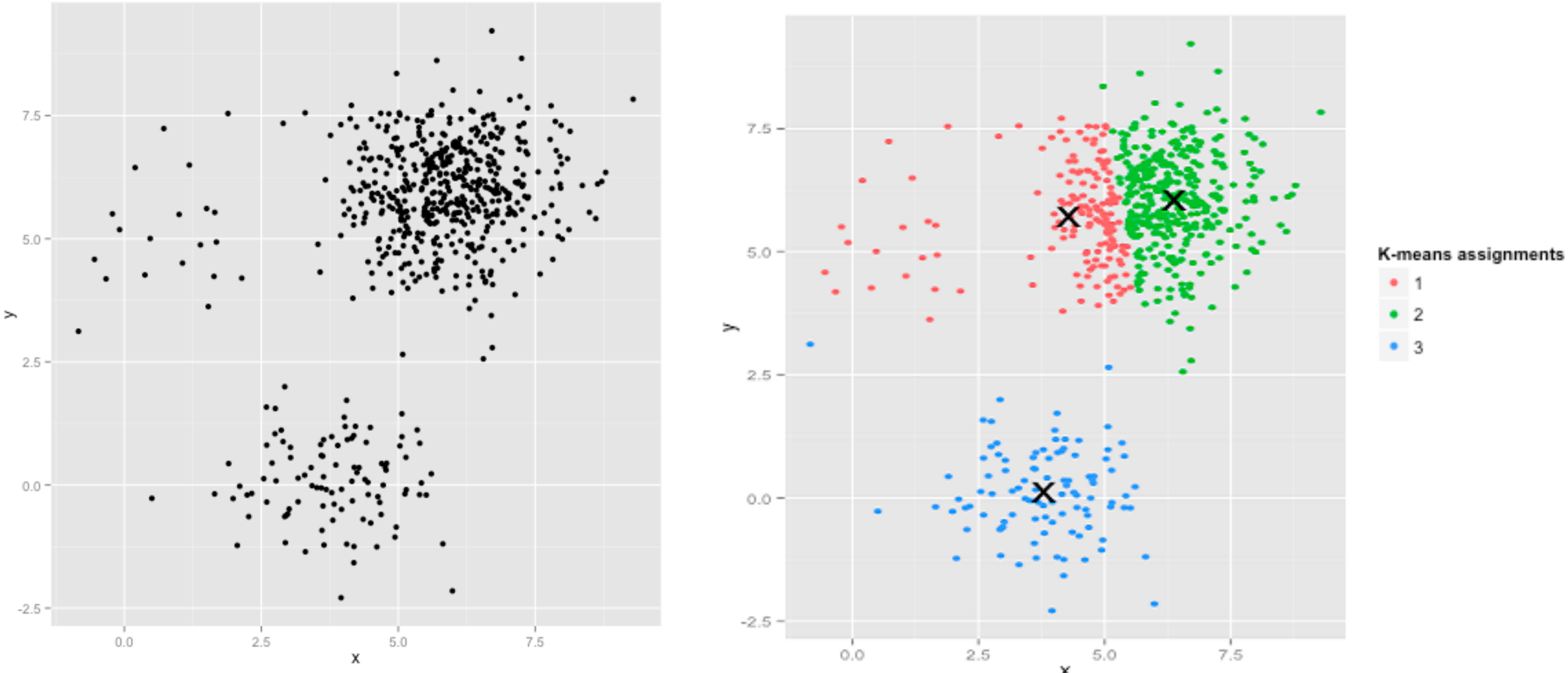








K-Means Unequal Cluster Size



http://stats.stackexchange.com/questions/133656/how-to-understand-the-drawbacks-of-k-means

DBScan

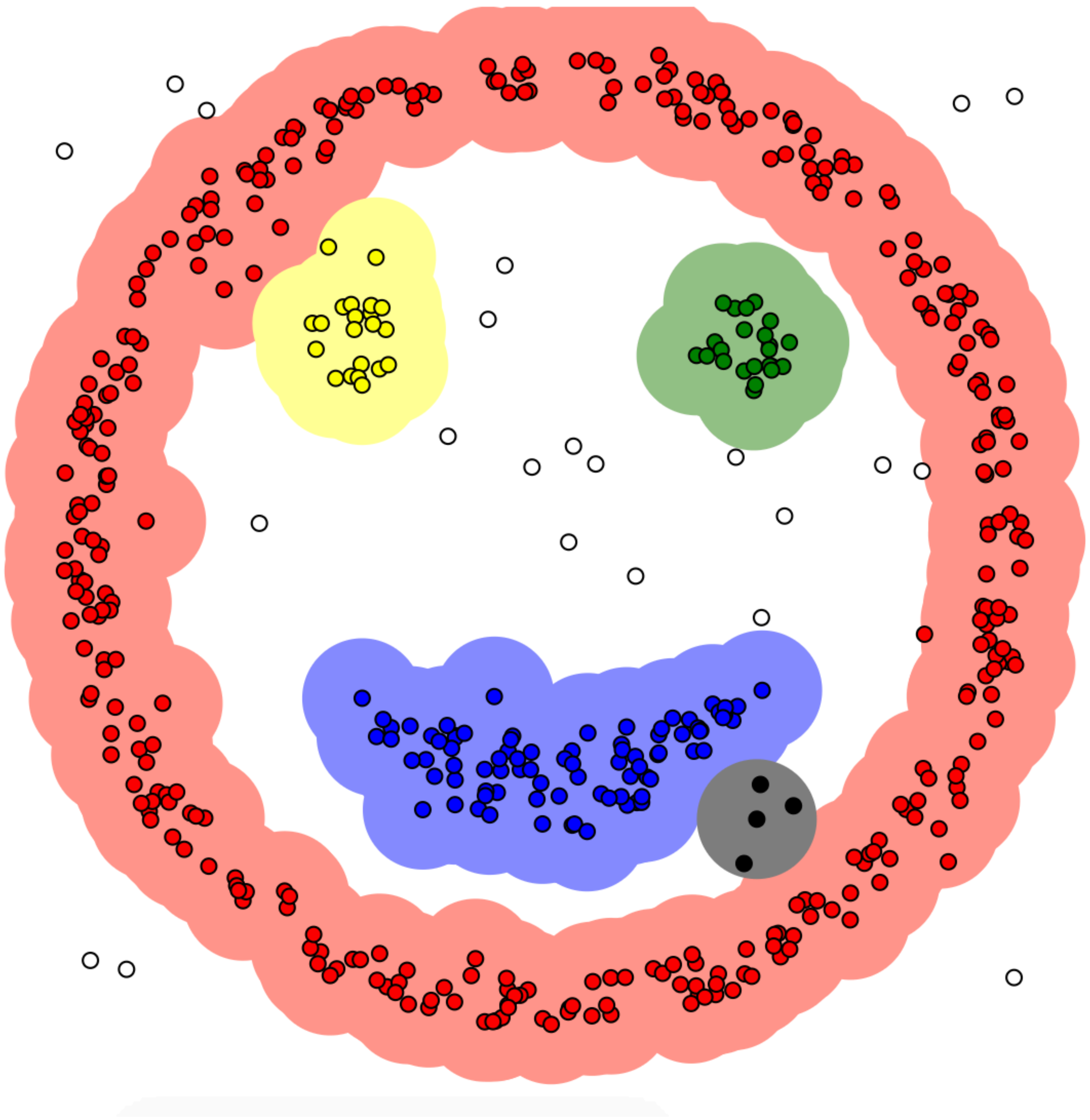
Density-based spatial clustering of applications with noise

Idea: Clusters are dense groups

if point belongs to a cluster, it should be near to lots of other points in that cluster.

Parameters:

- Epsilon: if new point distance to closest point in cluster is < epsilon, add to cluster
- Min points: what's the smallest cluster (outliers)



https://www.naftaliharris.com/blog/visualizing-dbscan-clustering/

Hierarchical Clustering

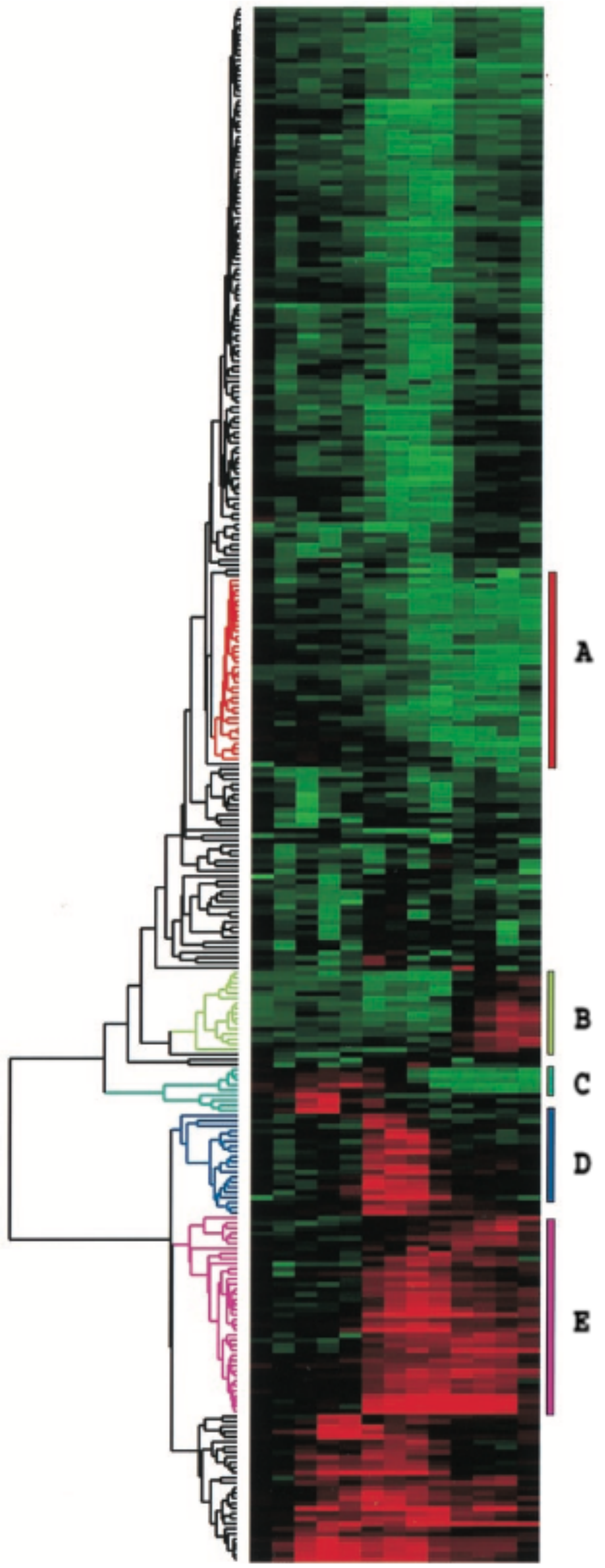
Two types:

agglomerative clustering

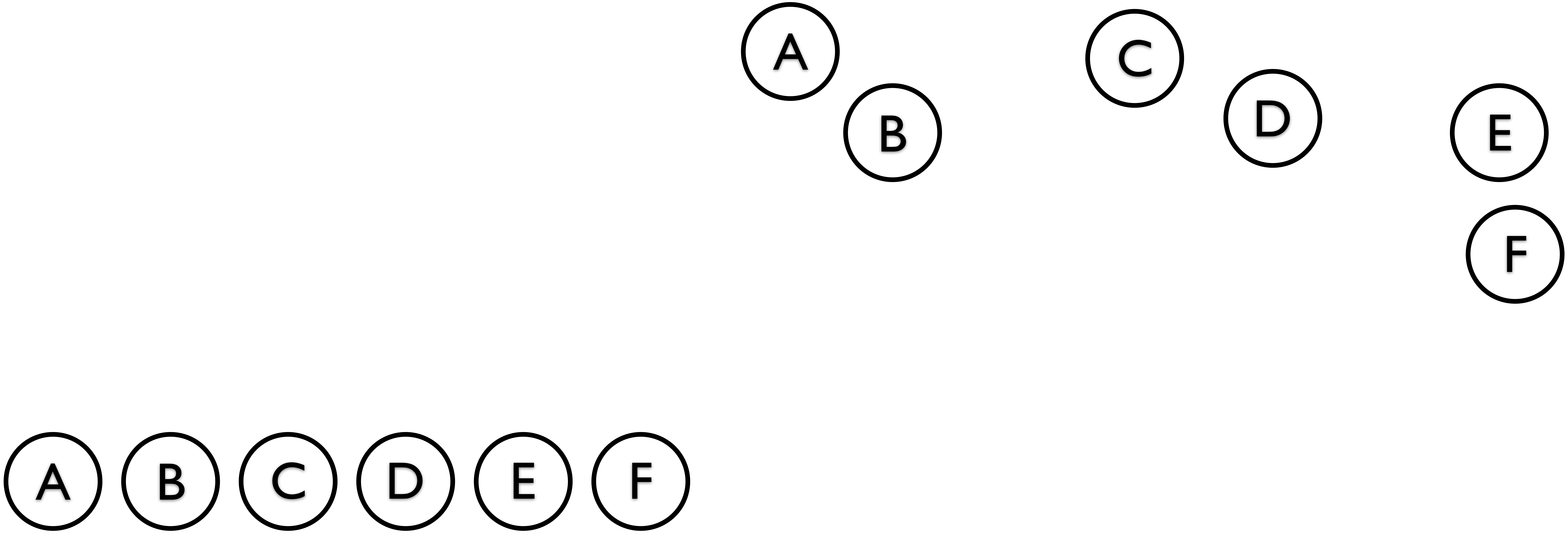
start with each node as a cluster and merge

divisive clustering

start with one cluster, and split



Agglomerative Clustering Idea



https://youtu.be/XJ3194AmH40?t=4m29s

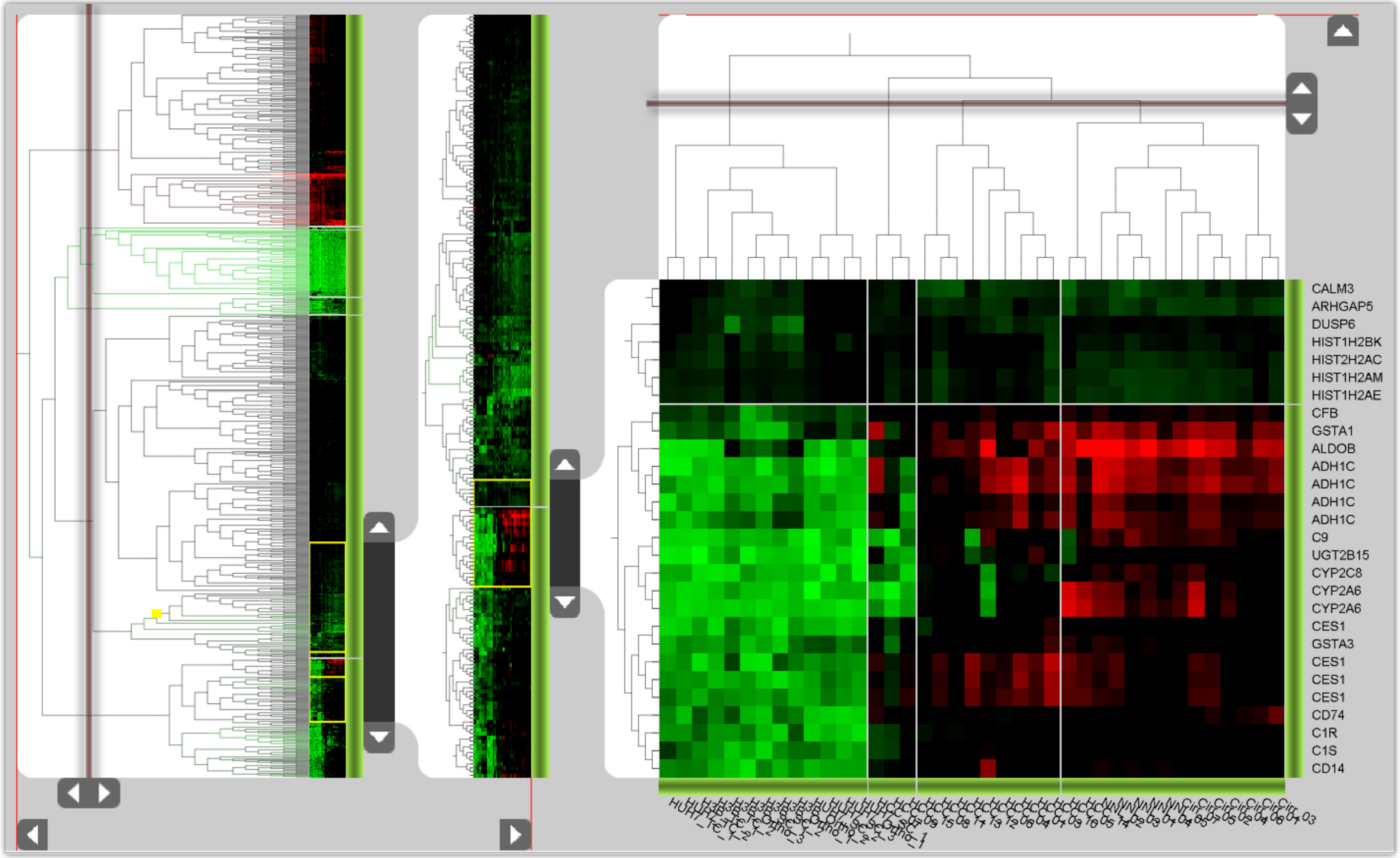
Linkage Criteria

How do you define similarity between two clusters to be merged (A and B)?

- maximum linkage distance: two elements that are apart the furthest
- use minimum linkage distance: the two closest elements
- use average linkage distance
- use centroid distance

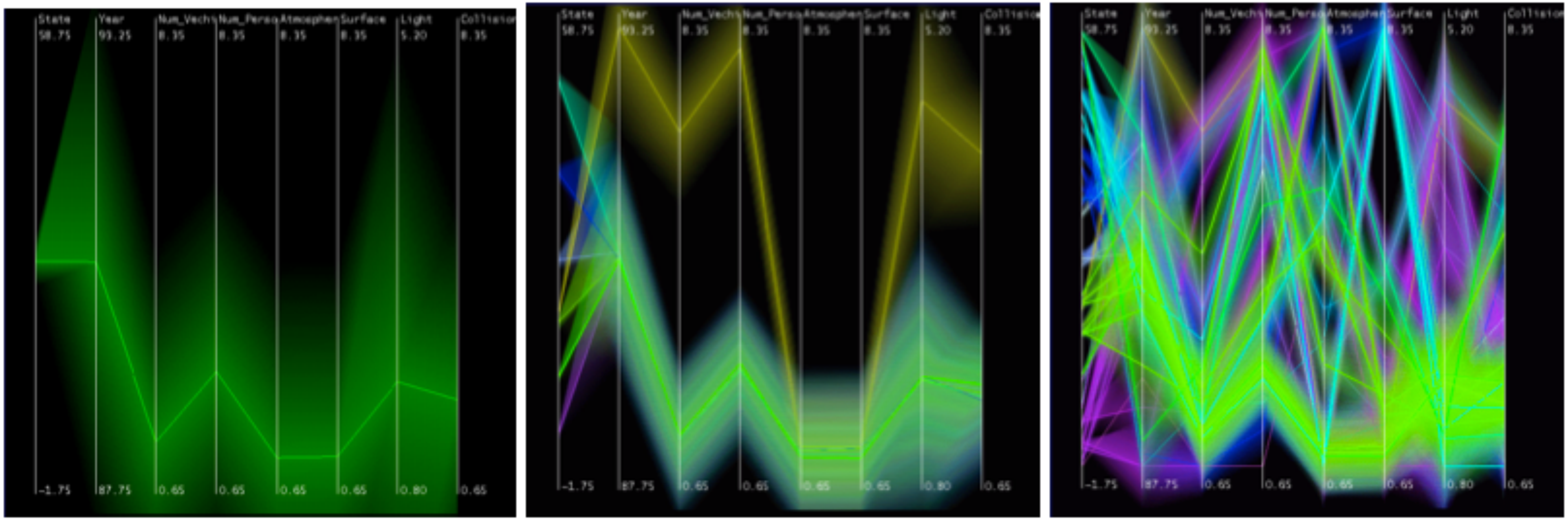
Names	Formula
Maximum or complete-linkage clustering	$\max\{\, d(a,b) : a \in A,\, b \in B \,\}.$
Minimum or single-linkage clustering	$\min\{\, d(a,b) : a \in A,\, b \in B \,\}.$
Mean or average linkage clustering, or UPGMA	$\frac{1}{\lvert A\rvert \lvert B\rvert} \sum_{a \in A} \sum_{b \in B} d(a,b).$
Centroid linkage clustering, or UPGMC	$\lVert c_s - c_t \rVert$ where c_s and c_t are the centroids of clusters s and t, respectively.

F+C Approach, with Dendrograms



[Lex, PacificVis 2010]

Hierarchical Parallel Coordinates



Fua 1999

Dimensionality Reduction

Dimensionality Reduction

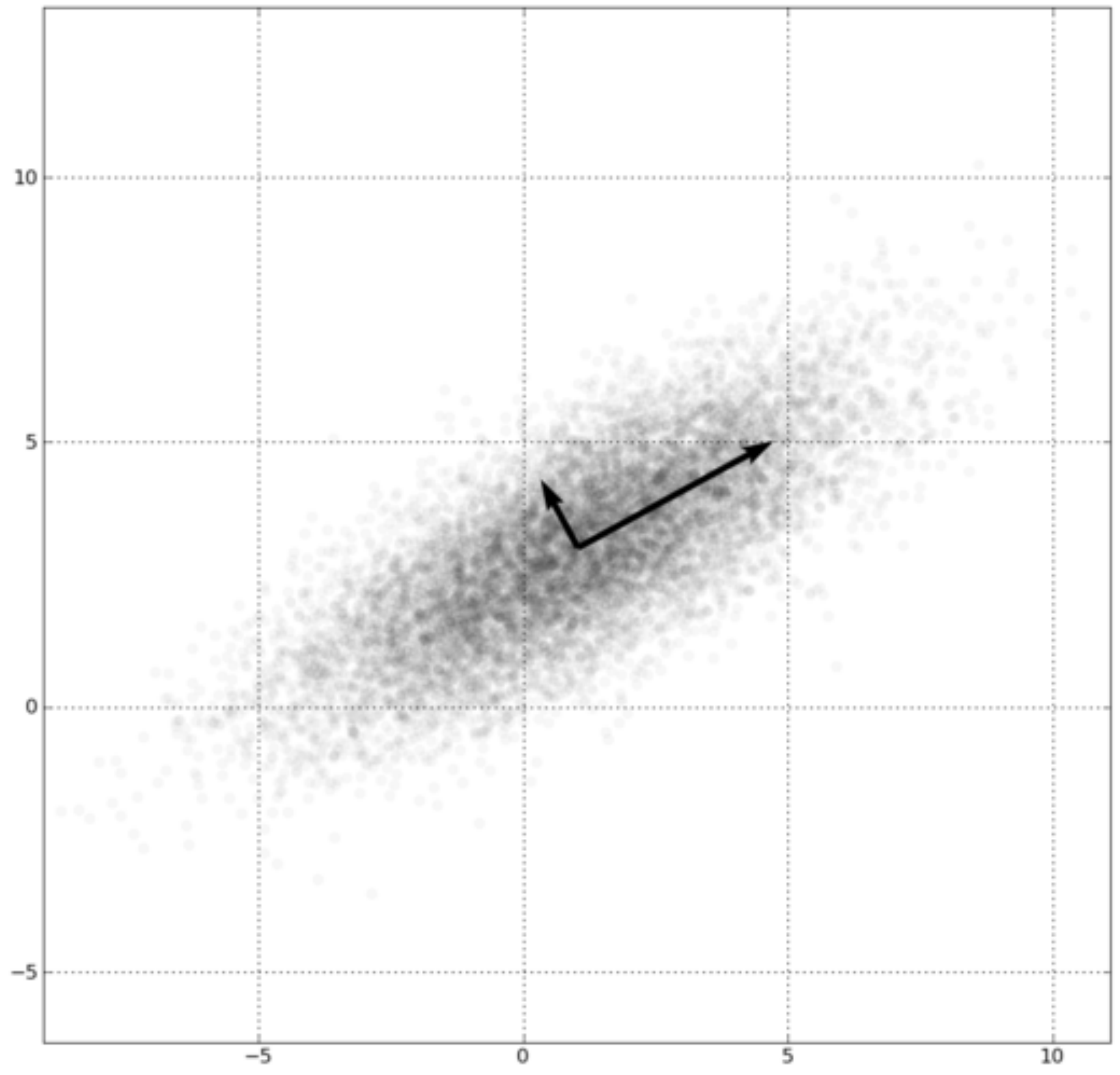
Reduce high dimensional to lower dimensional space

Preserve as much of variation as possible

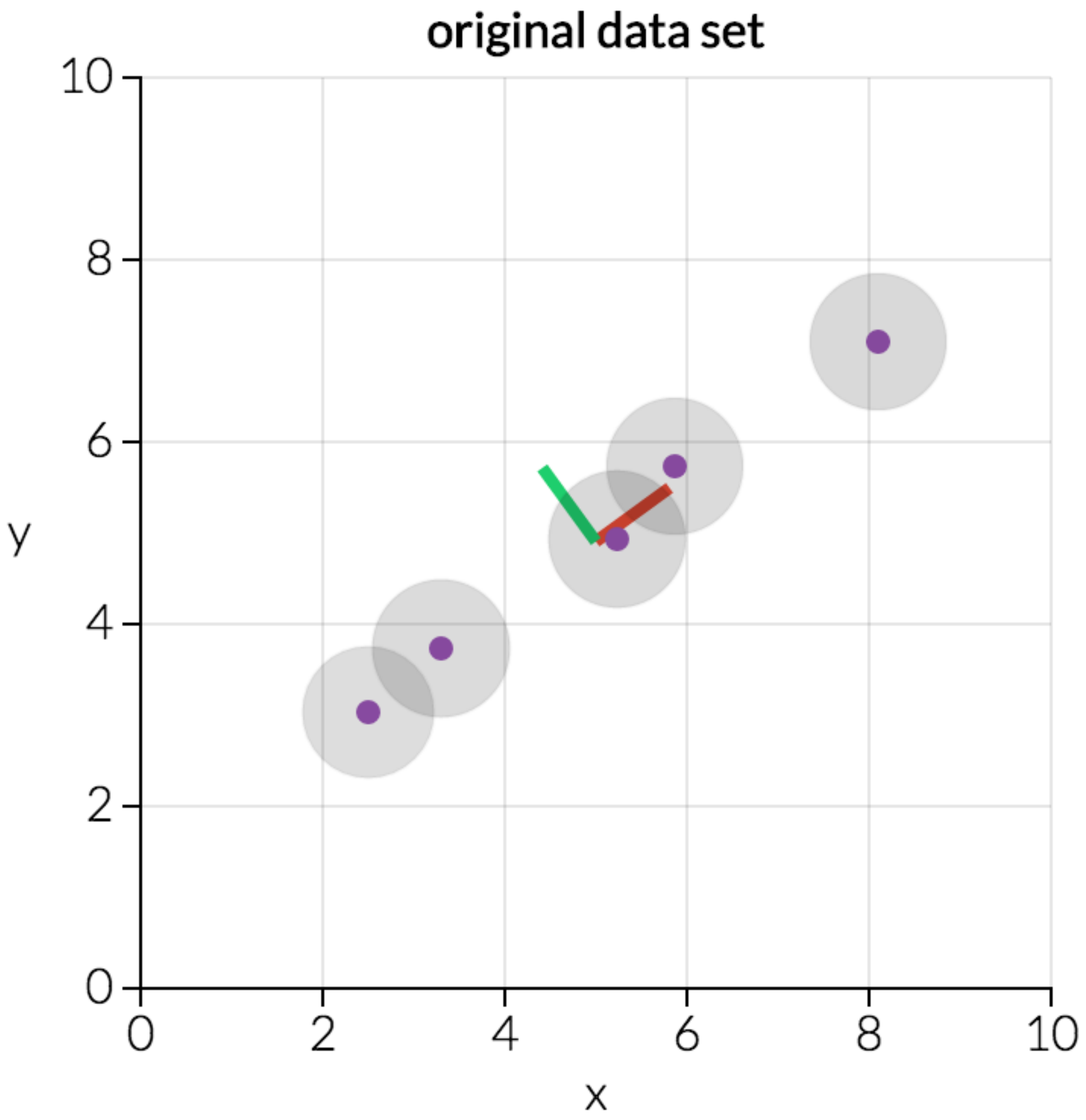
Plot lower dimensional space

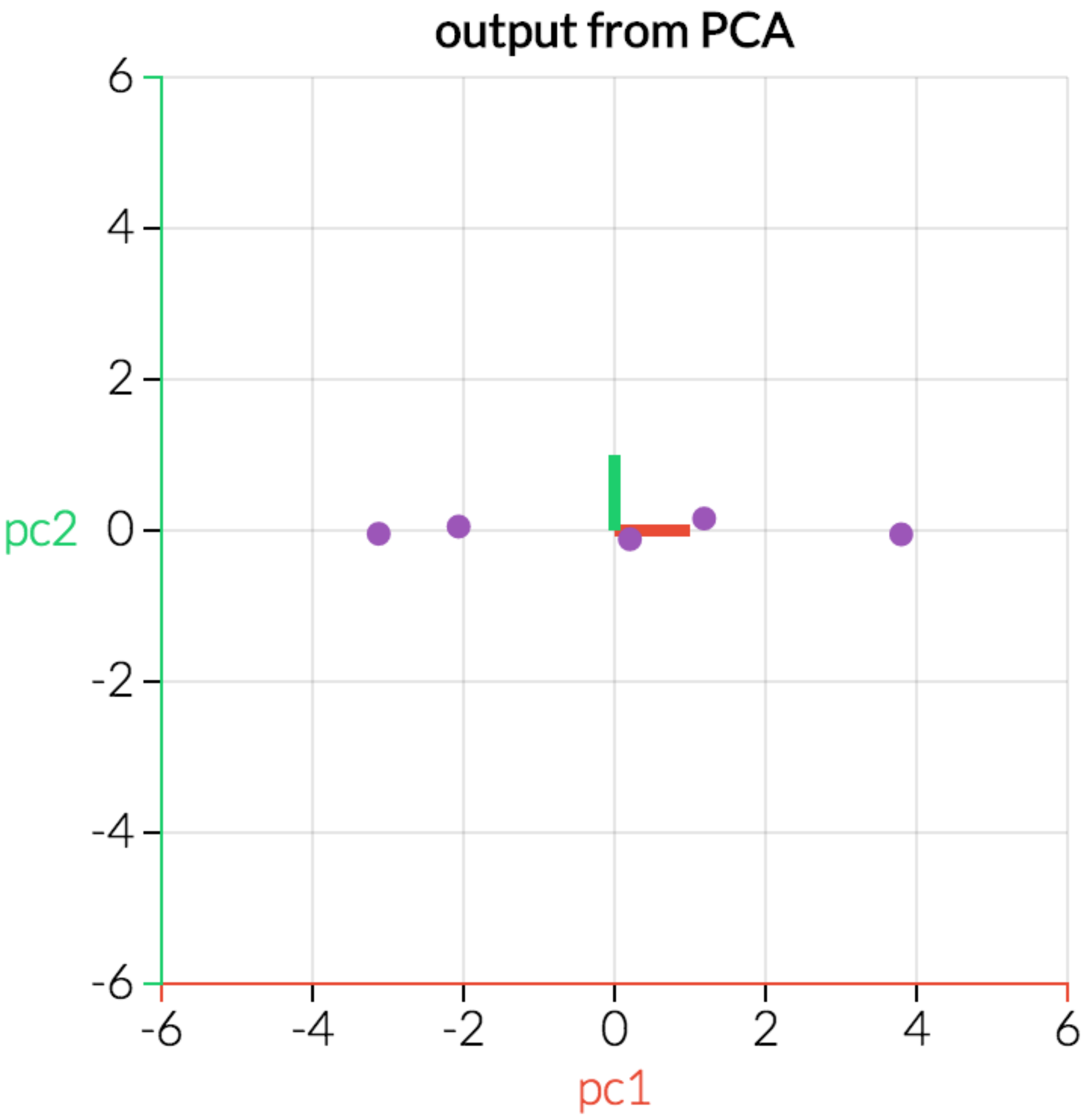
Principal Component Analysis (PCA)

linear mapping, by order of variance



PCA


original data set
10
8
6
4
2
0
y
0
2
4
6
8
10
x


output from PCA
6
4
2
0
-2
-4
-6
pc2
-6
-4
-2
0
2
4
6
pc1

Multidimensional Scaling

Multiple approaches

Works based on projecting a similarity matrix

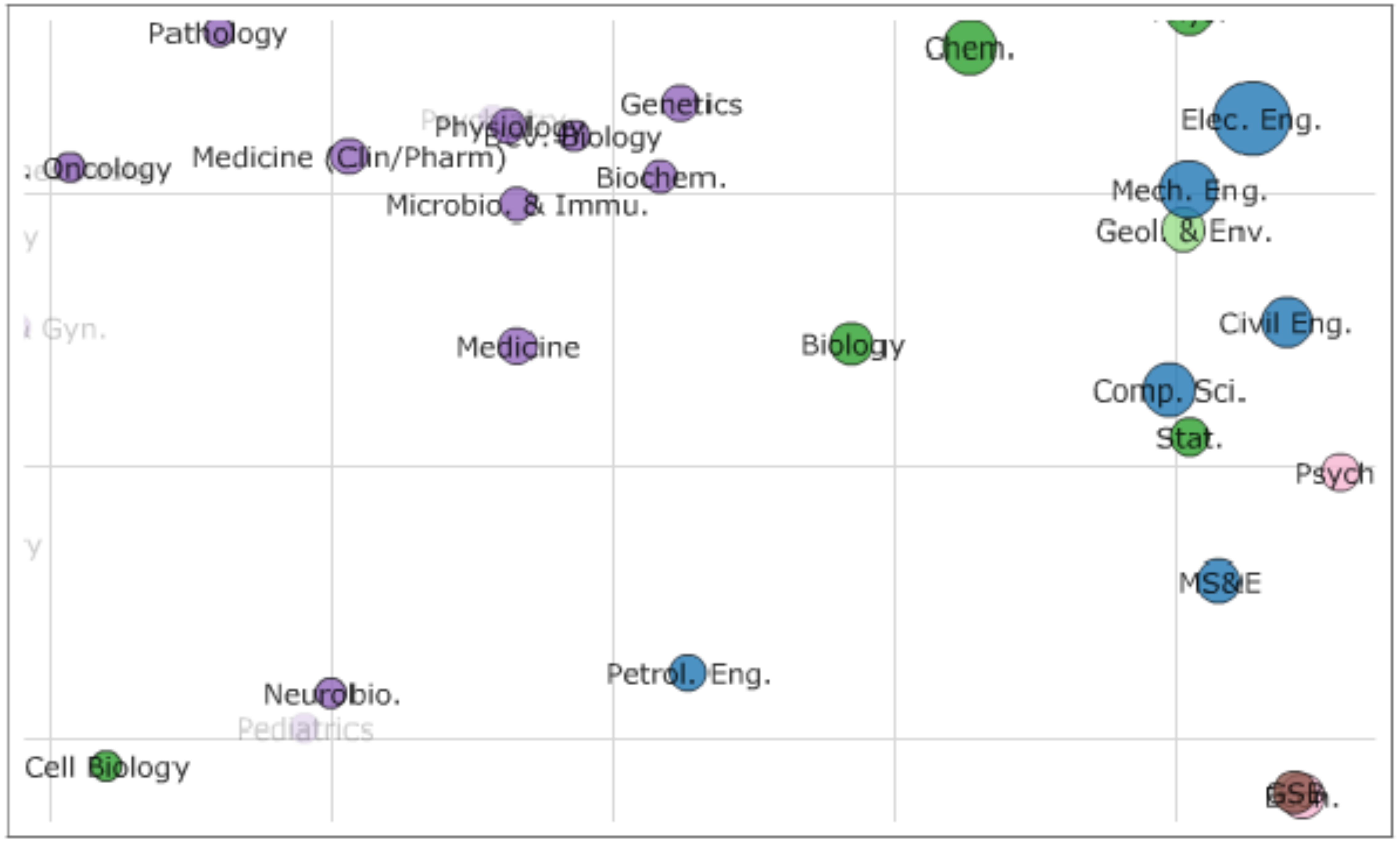
- How do you compute similarity?
- How do you project the points?

Popular for text analysis

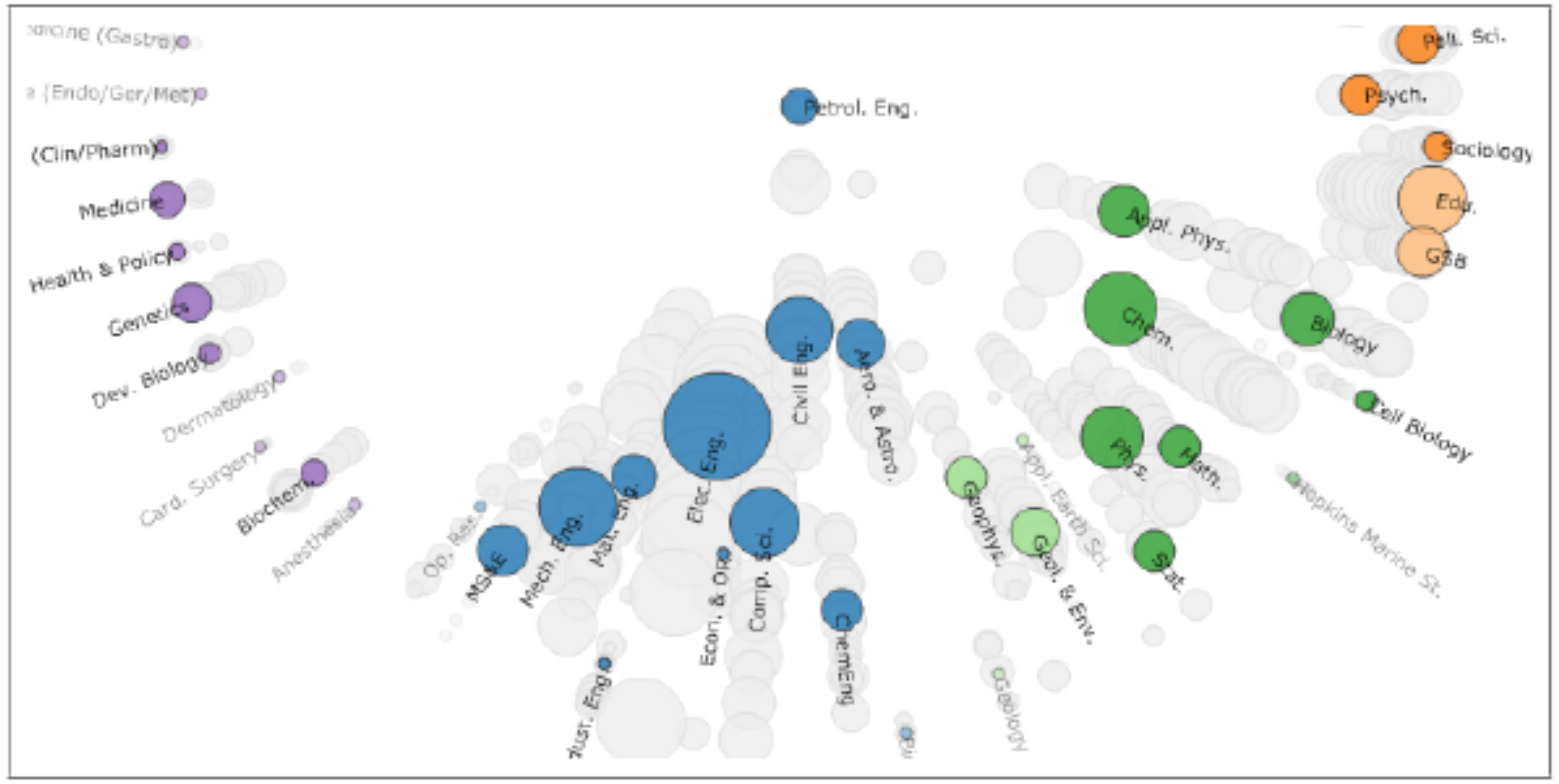
[Doerk 2011]

Can we Trust Dimensionality Reduction?

Topical distances between departments in a 2D projection



Topical distances between the selected Petroleum Engineering and the others.



[Chuang et al., 2012]

http://www-nlp.stanford.edu/projects/dissertations/browser.html

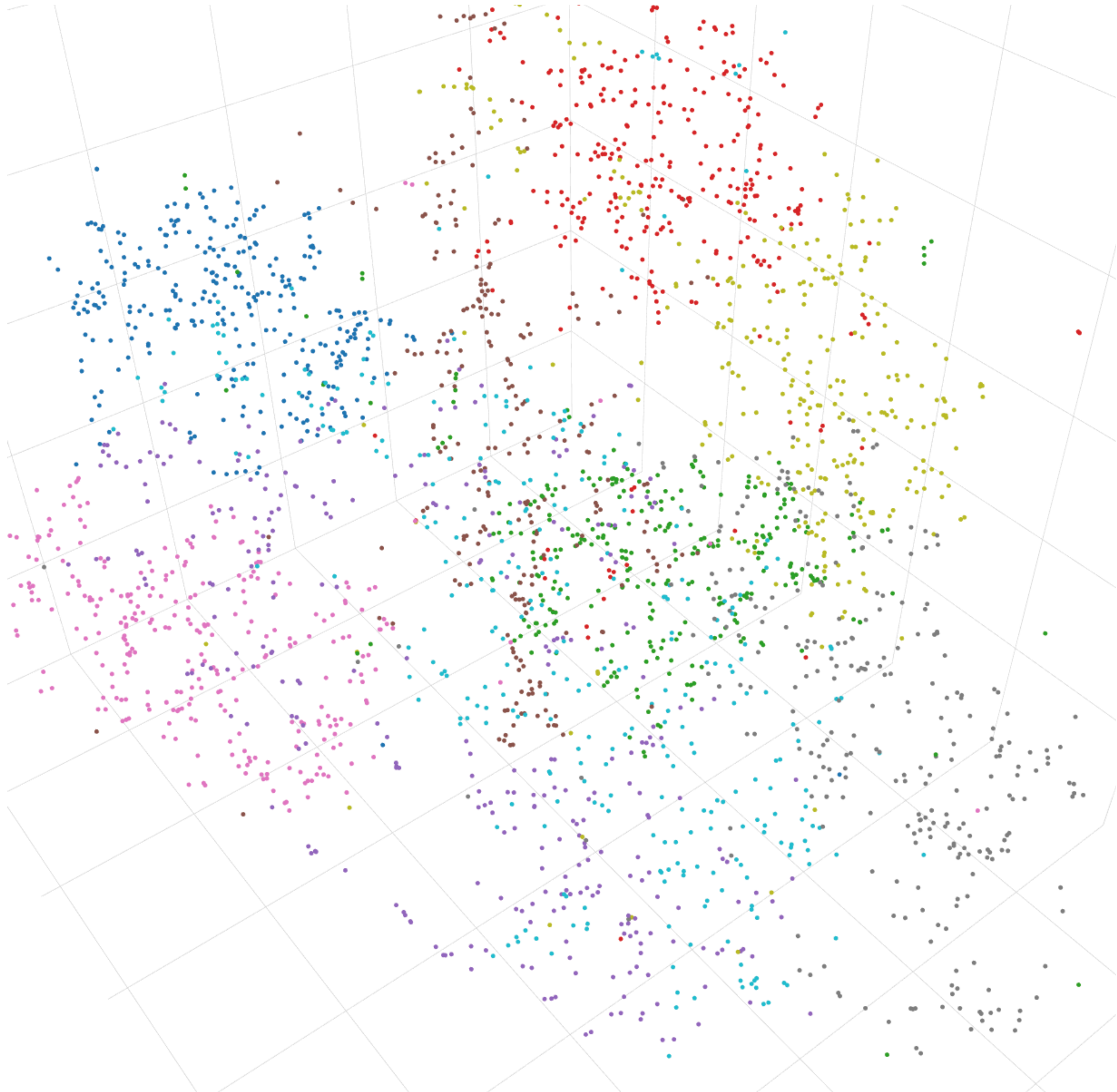
Probing Projections

http://julianstahnke.com/probing-projections/

t-SNE

t-distributed stochastic neighbor embedding

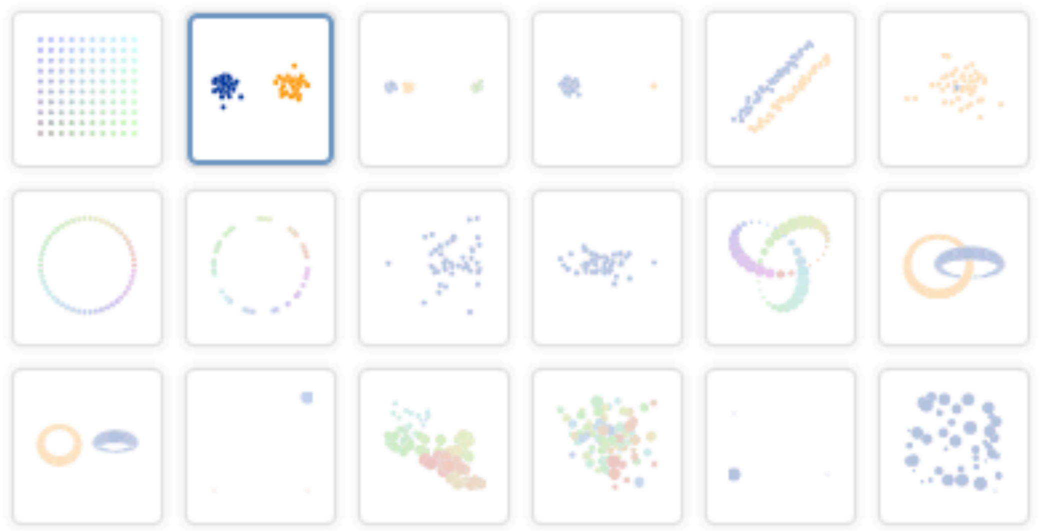
non-linear algorithm: different transformations for different regions



Visualizing data using t-SNE, Maaten and Hinton, 2008

How to Use t-SNE Effectively

Although extremely useful for visualizing high-dimensional data, t-SNE plots can sometimes be mysterious or misleading. By exploring how it behaves in simple cases, we can learn to use it more effectively.



Step
5,000

Two clusters with equal numbers of points.

Share this view

Points Per Cluster 50

Dimensions 2

Perplexity 10

Epsilon 5

MARTIN WATTENBERG
Google Brain

FERNANDA VIÉGAS
Google Brain

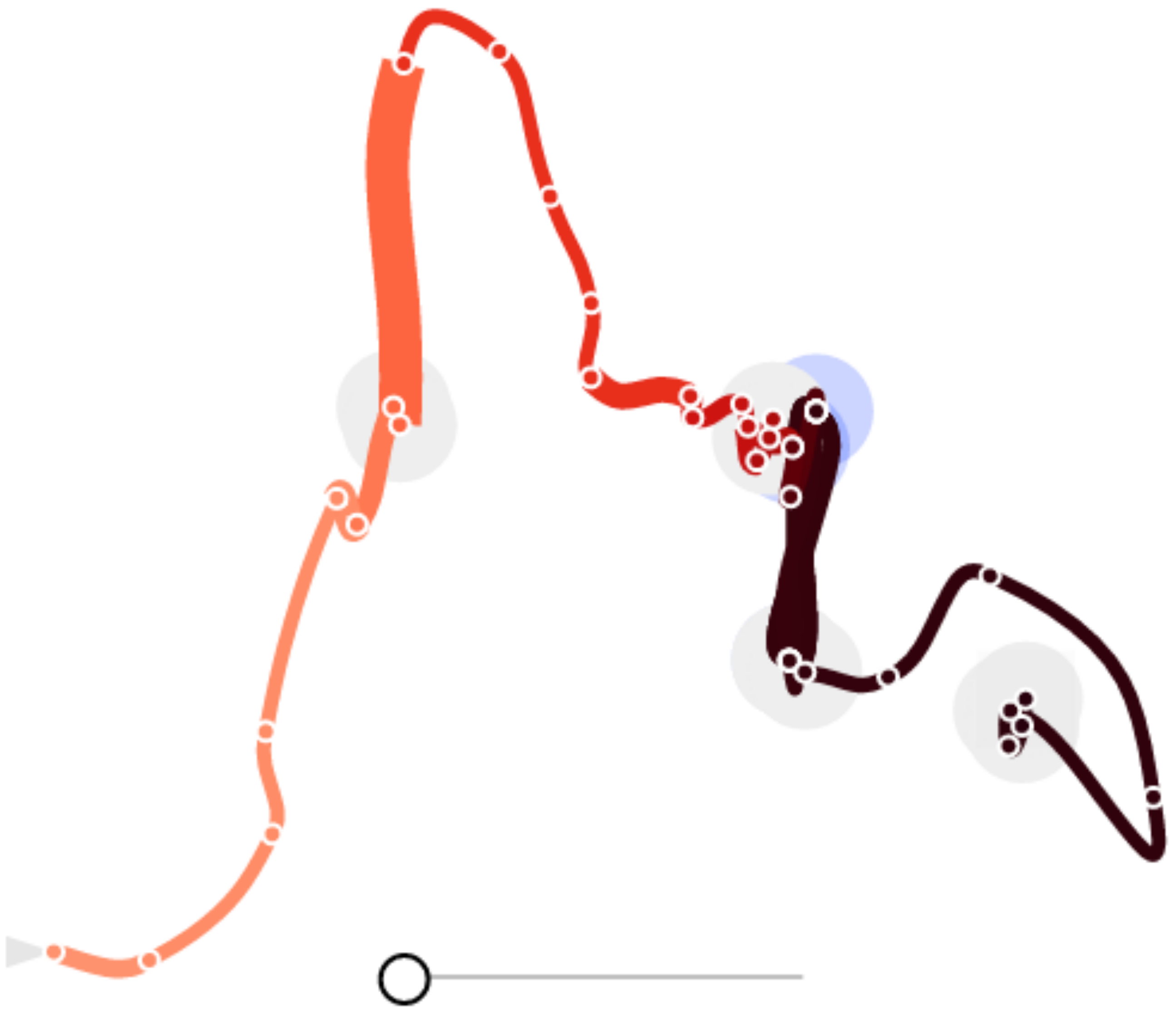
IAN JOHNSON
Google Cloud

Oct. 13
2016

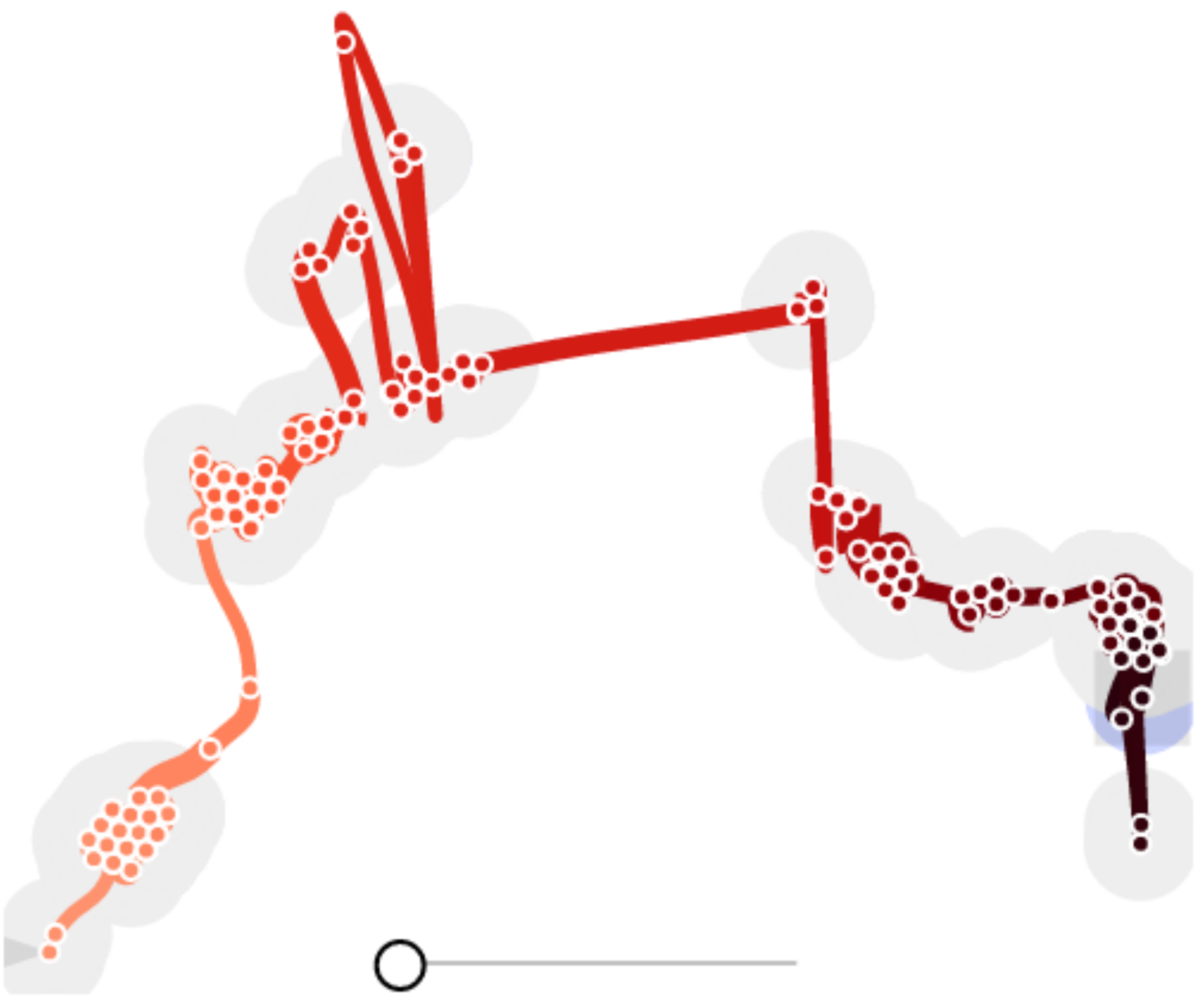
Citation:
Wattenberg, et al., 2016

MDS for Temporal Data: TimeCurves

Video: Global Cloud Circulation (146)



Wikipedia: Chocolate (46)



Wikipedia: Palestine 200 1 (200)

http://aviz.fr/~bbach/timecurves/