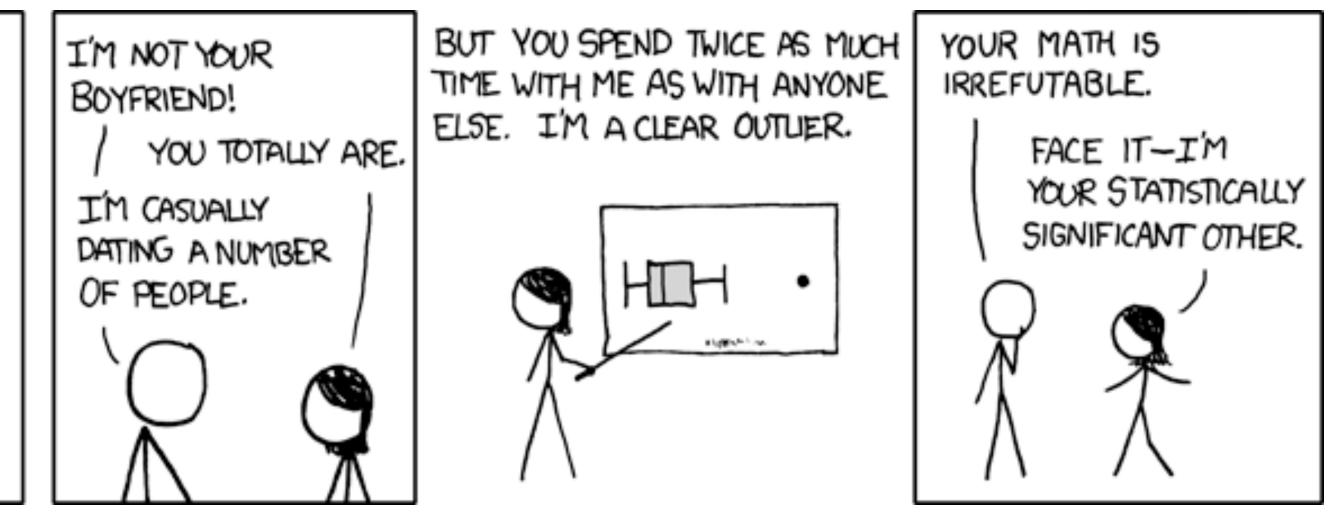
## CS-5630 / CS-6630 Uisualization Fitering & Aggregation



CAN MY BOYFRIEND COME ALONG?

### Alexander Lex alex@sci.utah.edu



### Administrativa

## This/Next Week

Tomorrow: Group announcement Saturday: Homework 5 Monday: Project Proposal Put proposal into github repo Submit only link via canvas Tuesday: Peer Feedback (mandatory, graded) Thursday: Class cancelled



## Filter & Flggregate

### **Reducing Items and Attributes**

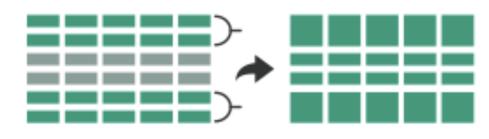
- → Filter
  - → Items



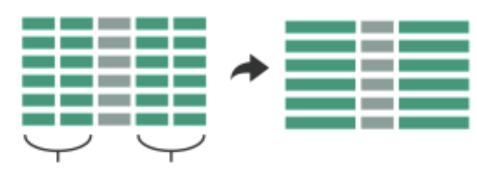
→ Attributes



- → Aggregate
  - → Items



→ Attributes





### Filter

elements are eliminated What drives filters?

Any possible function that partitions a dataset into two sets

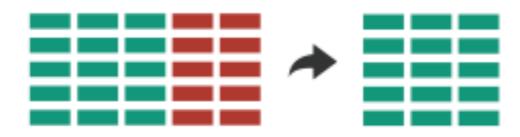
Bigger/smaller than x

Fold-change

Noisy/insignificant



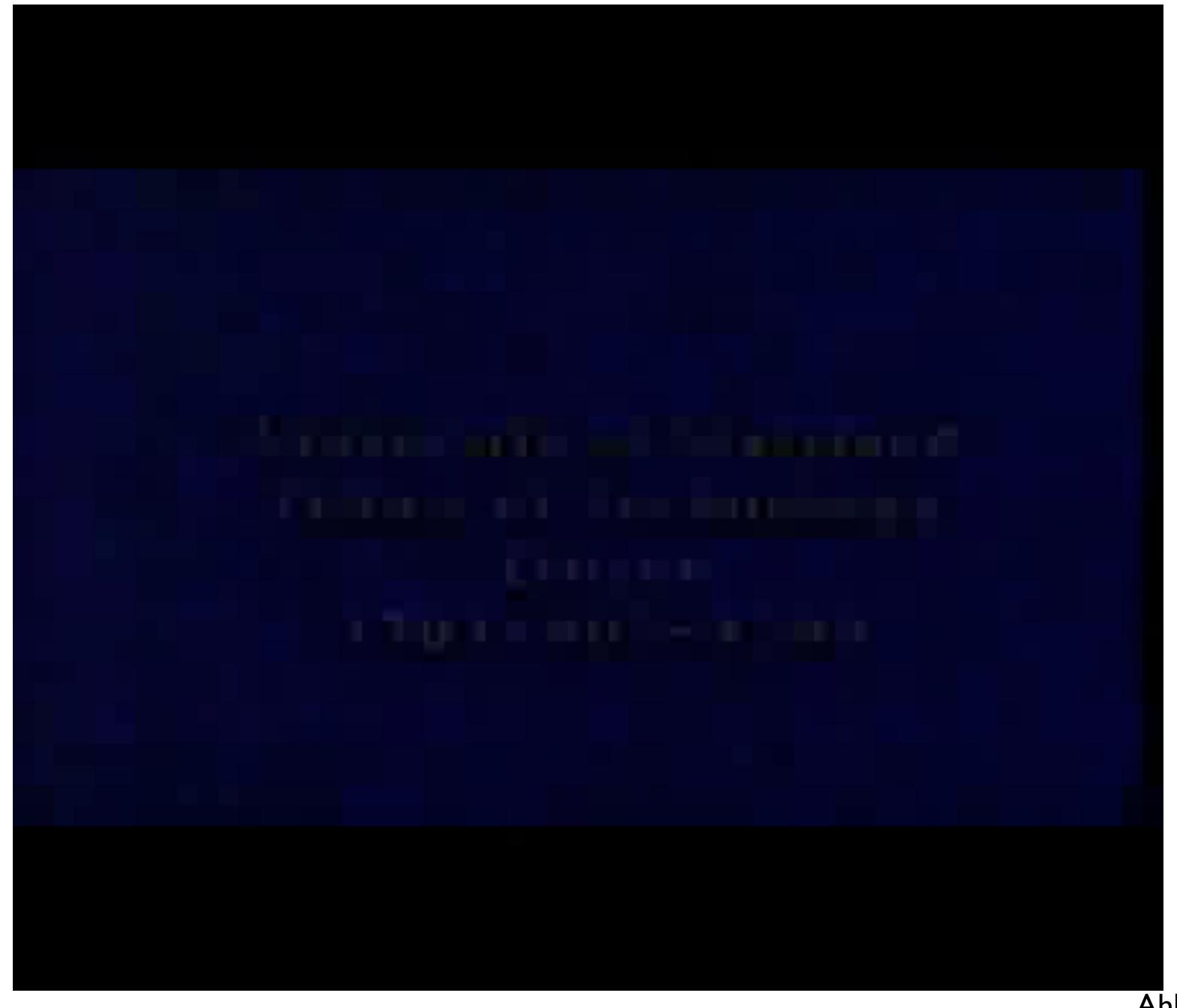
→ Attributes



## **Dynamic Queries / Filters**

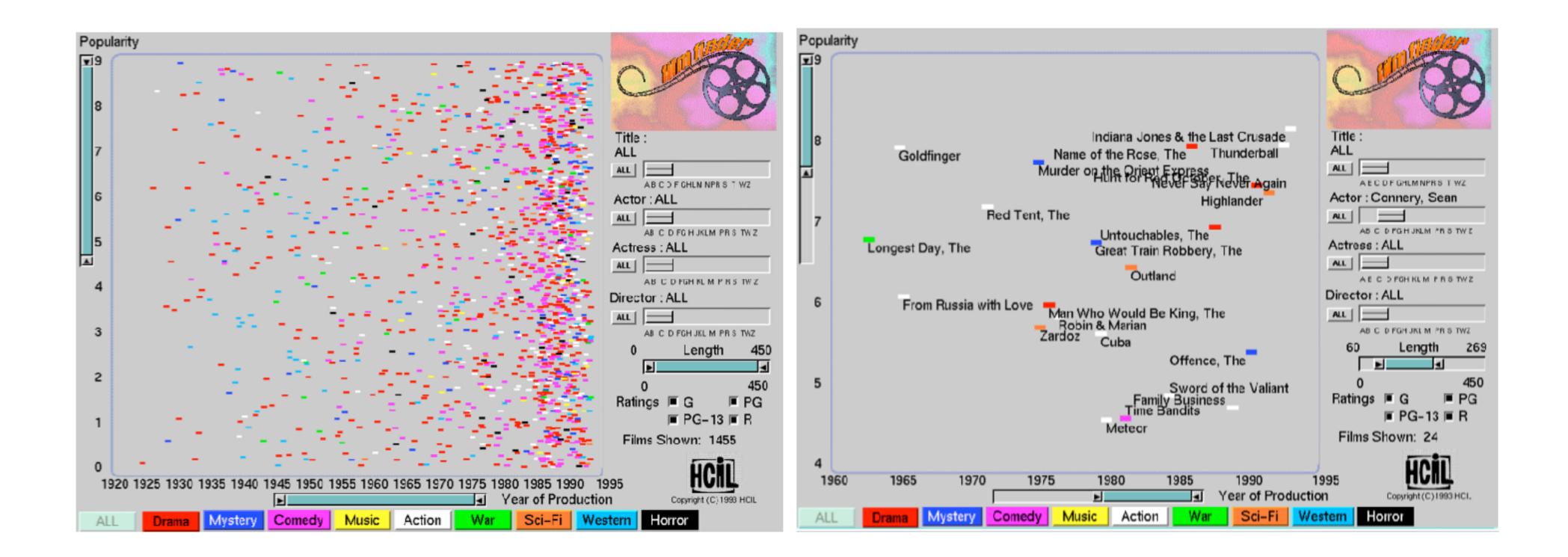
- coupling between encoding and interaction so that user can immediately see the results of an action

Queries: start with 0, add in elements Filters: start with all, remove elements Approach depends on dataset size



Ahlberg 1994

### ITEM FILTERING

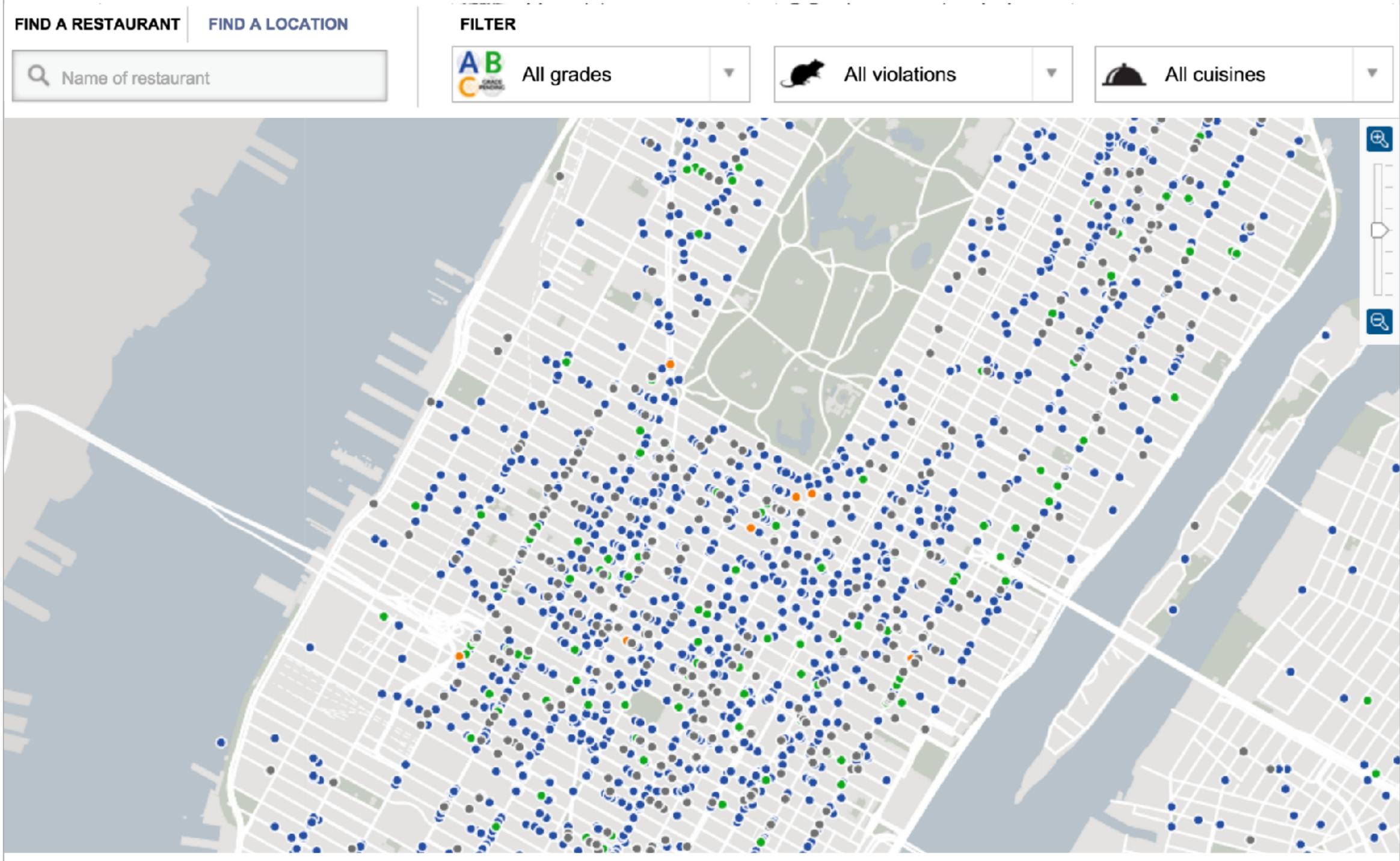




Ahlberg 1994

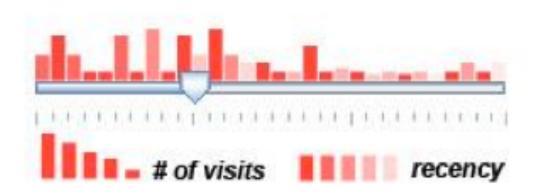




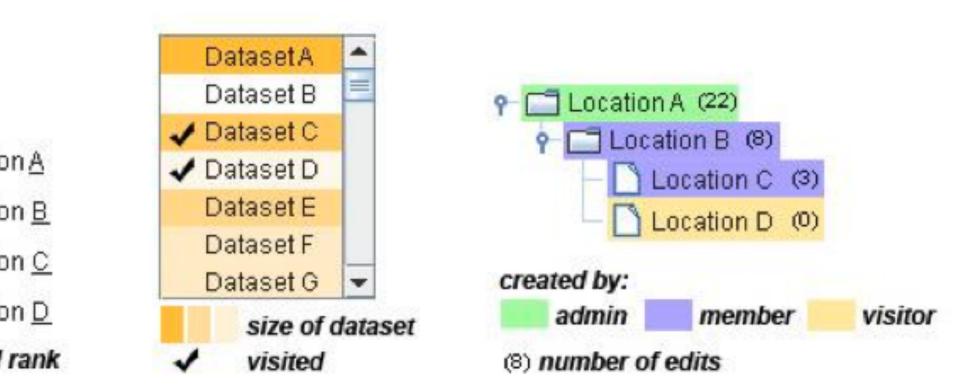


### Scented Widgets

# **information scent:** user's (imperfect) perception of data GOAL: lower the cost of information foraging through better cues

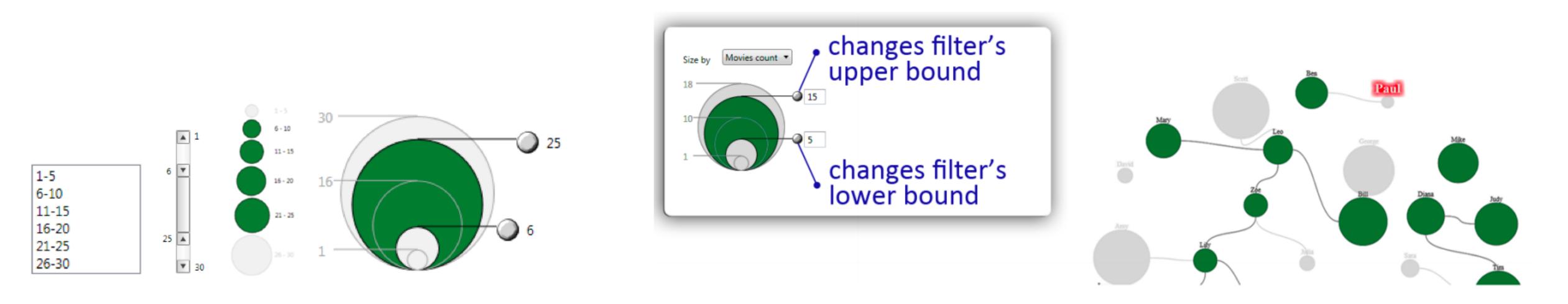






## Interactive Legends

# Controls combining the visual representation of static legends with interaction mechanisms of widgets Define and control visual display together

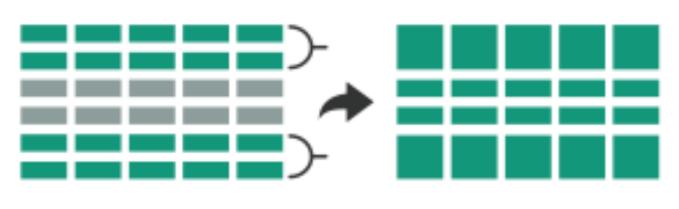


### flggregation

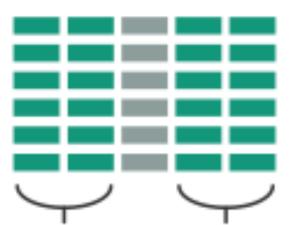
### Aggregate

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

→ Items

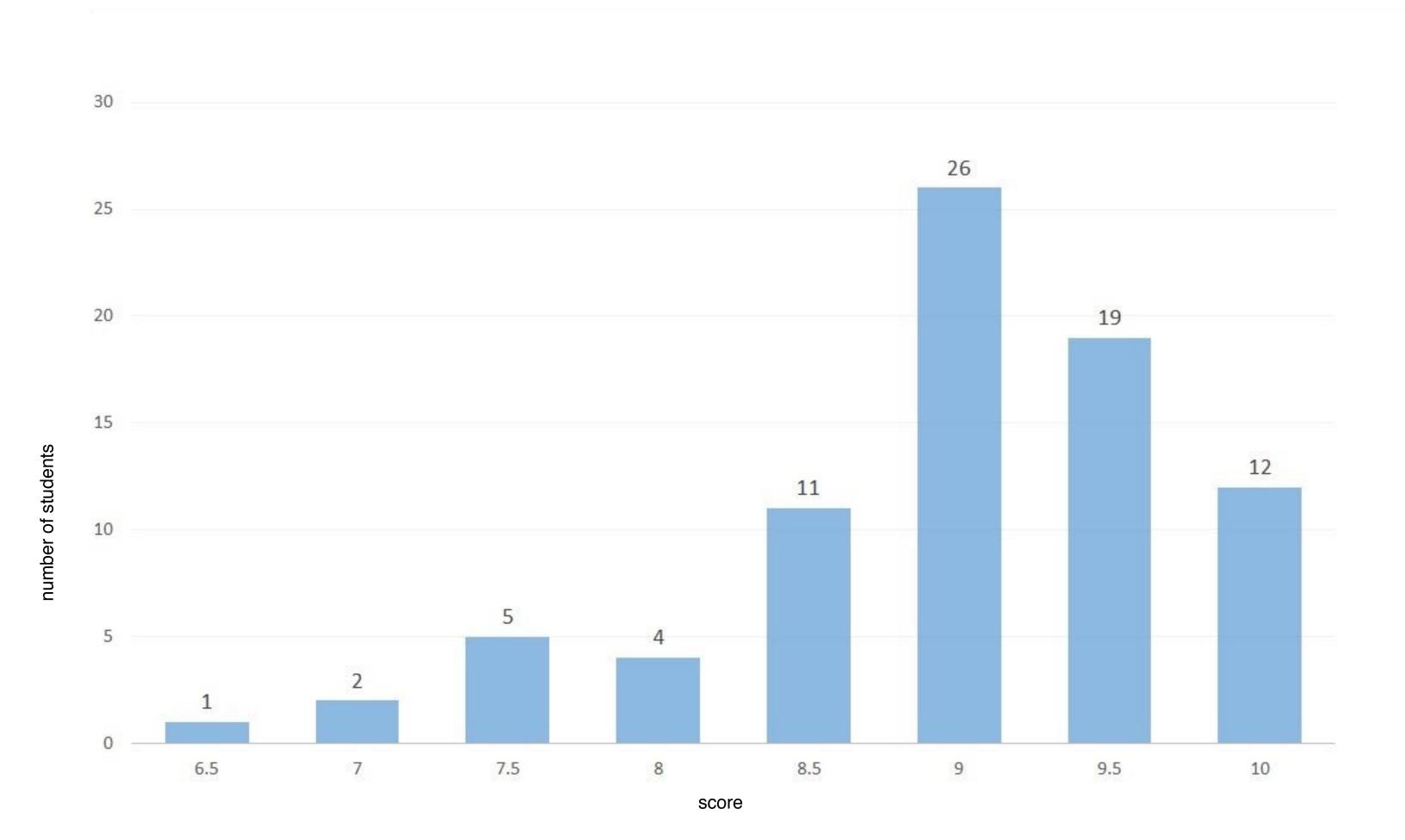


→ Attributes



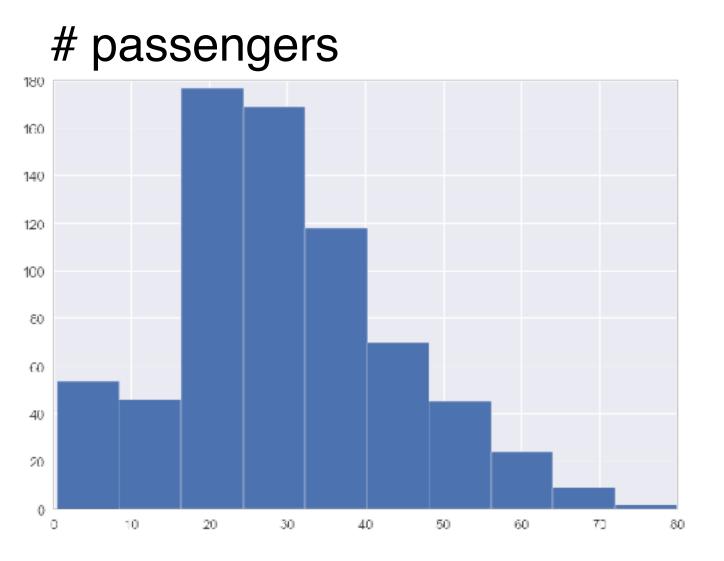
## Item Aggregation

### Histogram

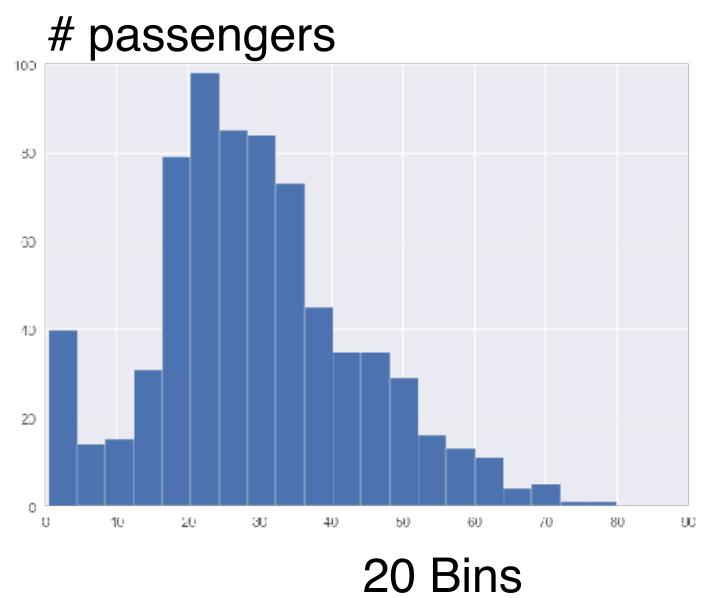


### Histogram

Good #bins hard to predict make interactive! rule of thumb: #bins = sqrt(n)



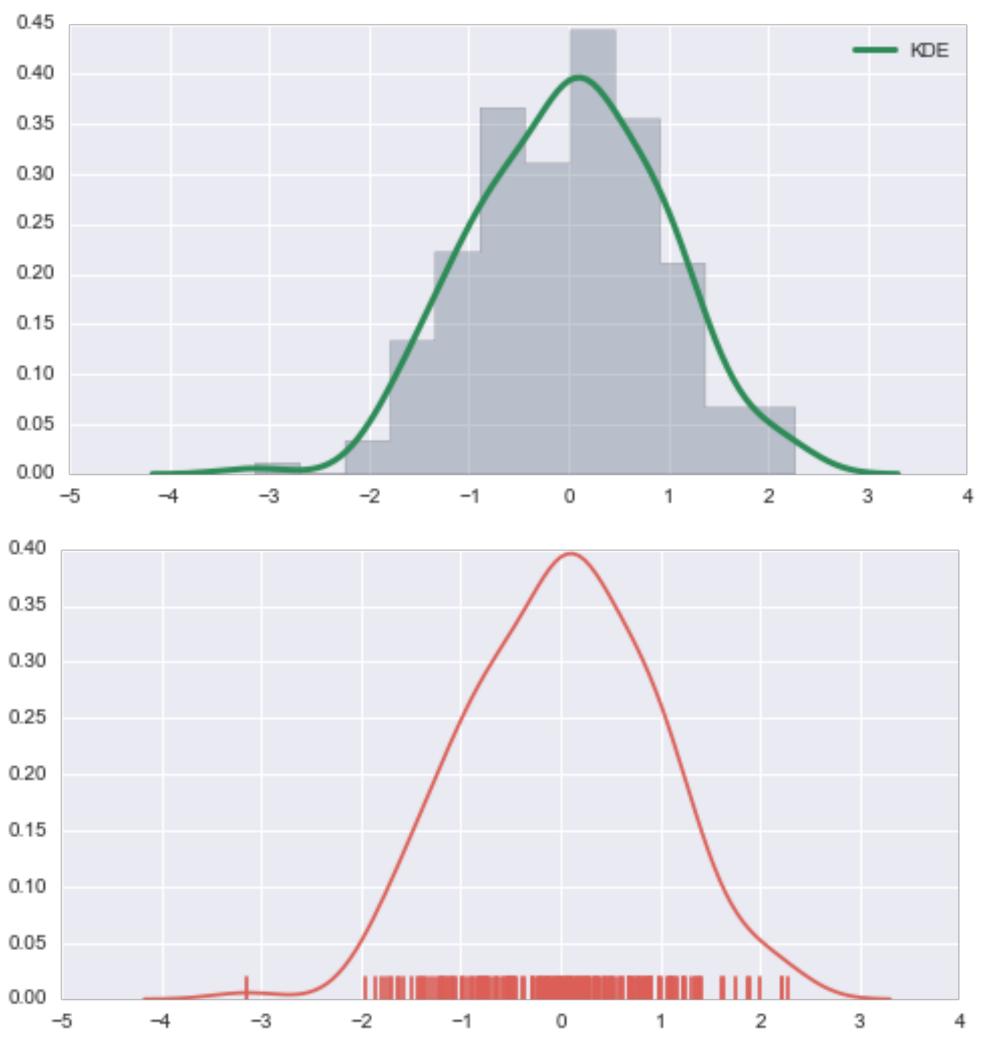




age



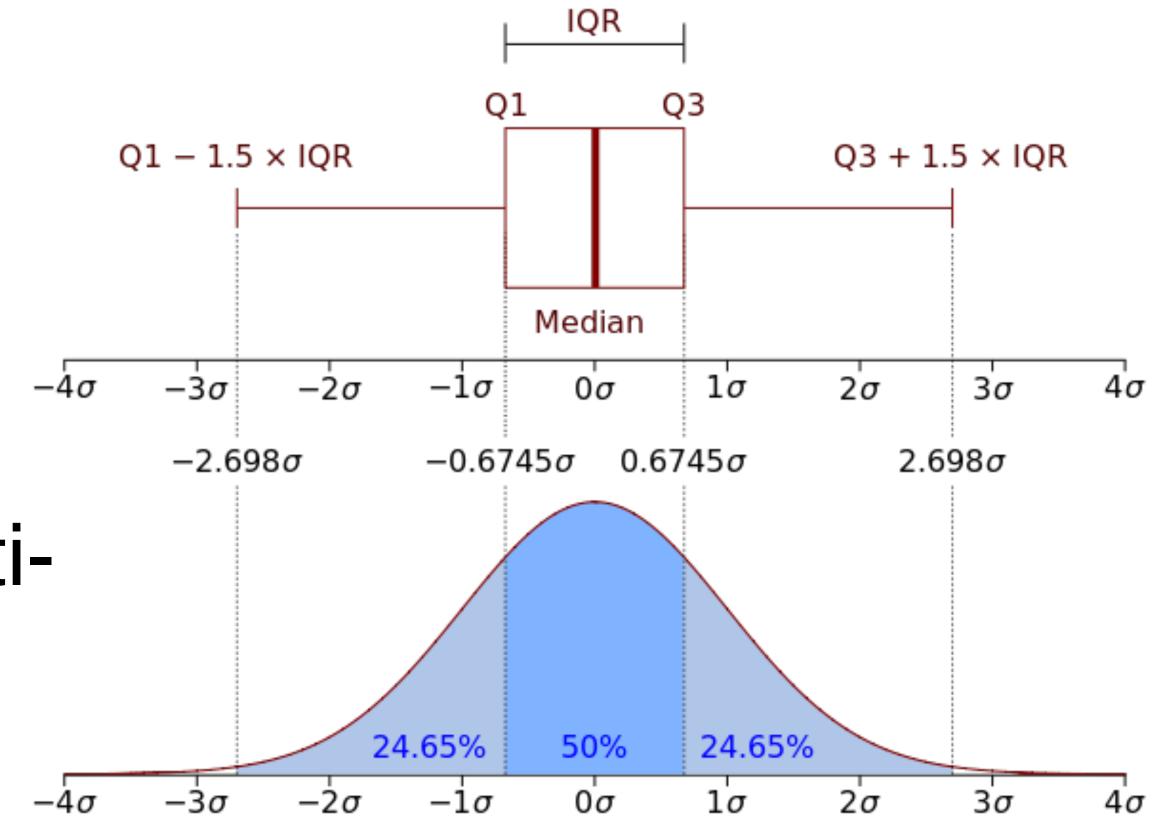
### **Density Plots**



http://web.stanford.edu/~mwaskom/software/seaborn/tutorial/plotting\_distributions.html

### **Box Plots**

- aka Box-and-Whisker Plot Show outliers as points!
- Not so great for non-normal distributed data
- Especially bad for bi- or multimodal distributions



Wikipedia

### **One Boxplot, Four Distributions**

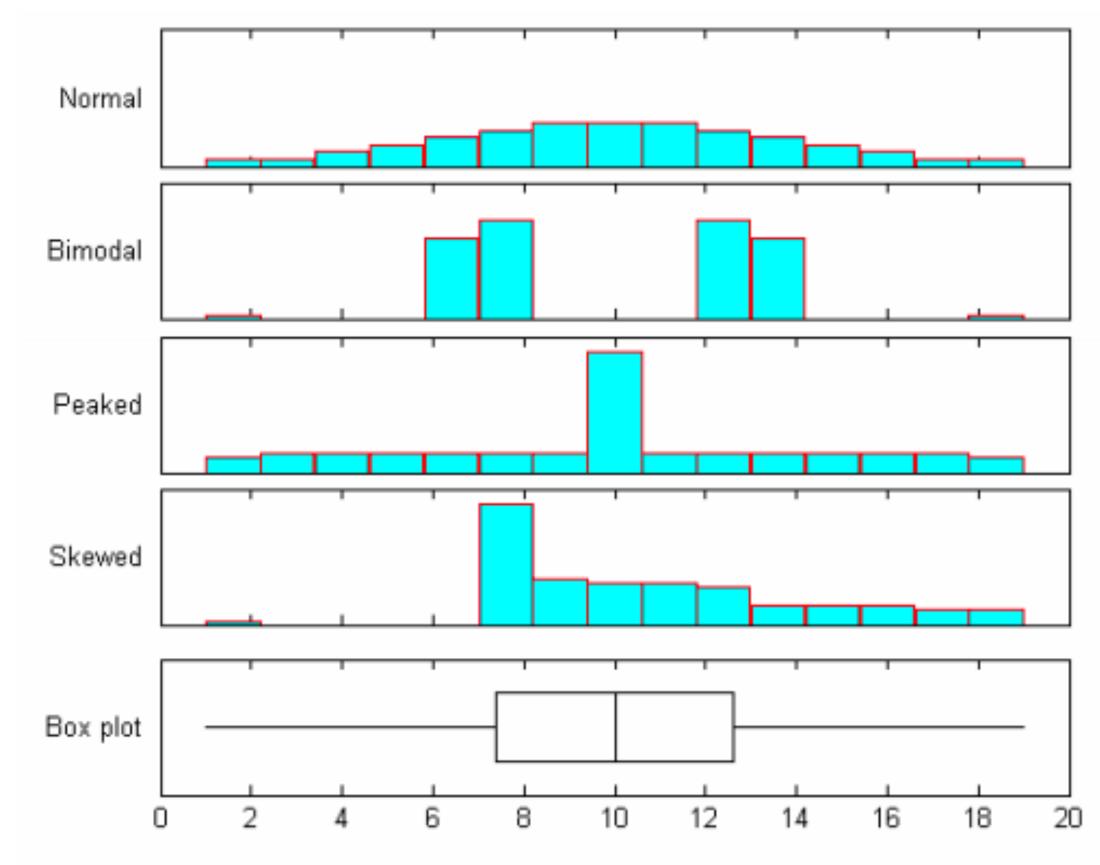


Figure 1: Histograms and box plot: four samples each of size 100

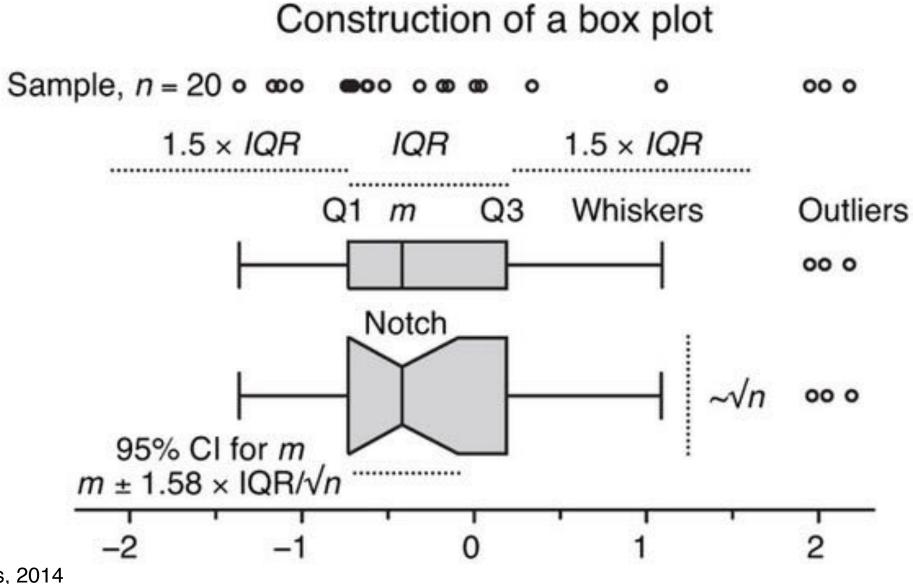
http://stat.mq.edu.au/wp-content/uploads/2014/05/Can\_the\_Box\_Plot\_be\_Improved.pdf

### **Notched Box Plots**

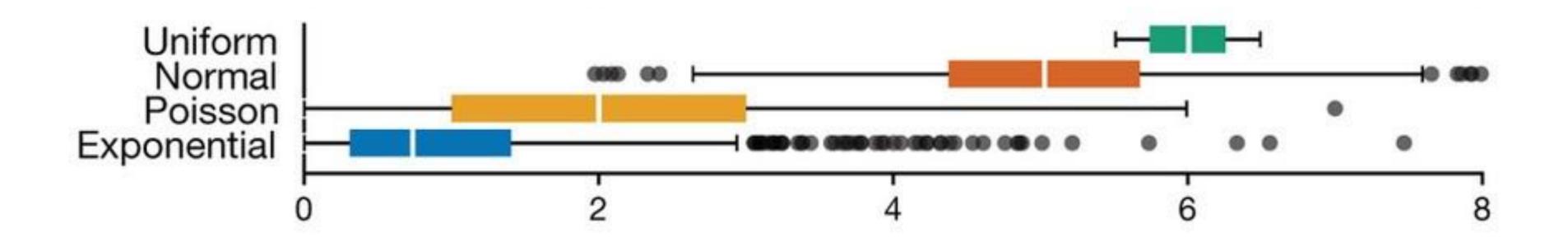
### Notch shows m +/- 1.5i x IQR/sqrt(n)

A guide to statistical significance.

Kryzwinski & Altman, PoS, Nature Methods, 2014

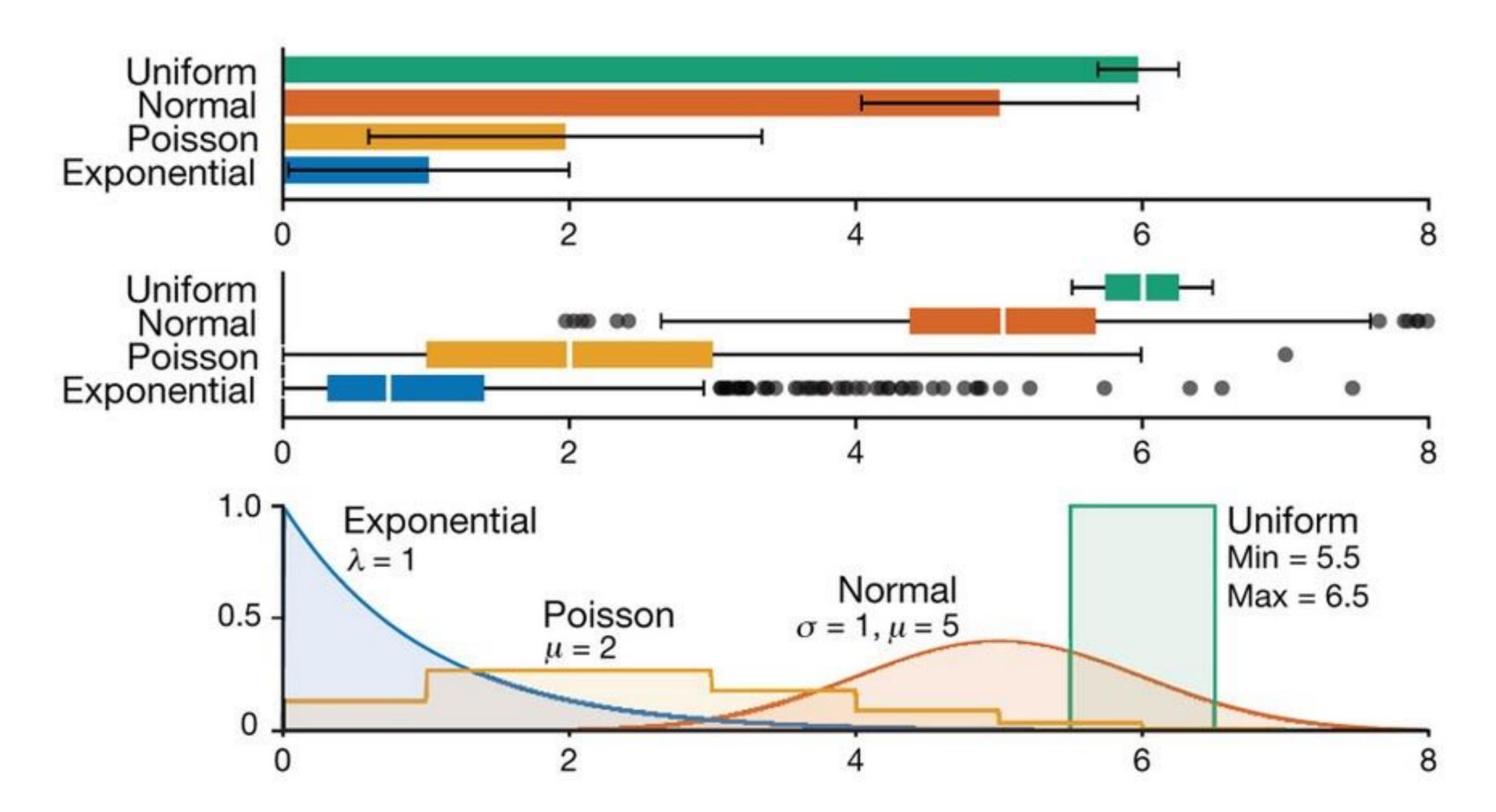


## **Box(and Whisker) Plots**



http://xkcd.com/539/

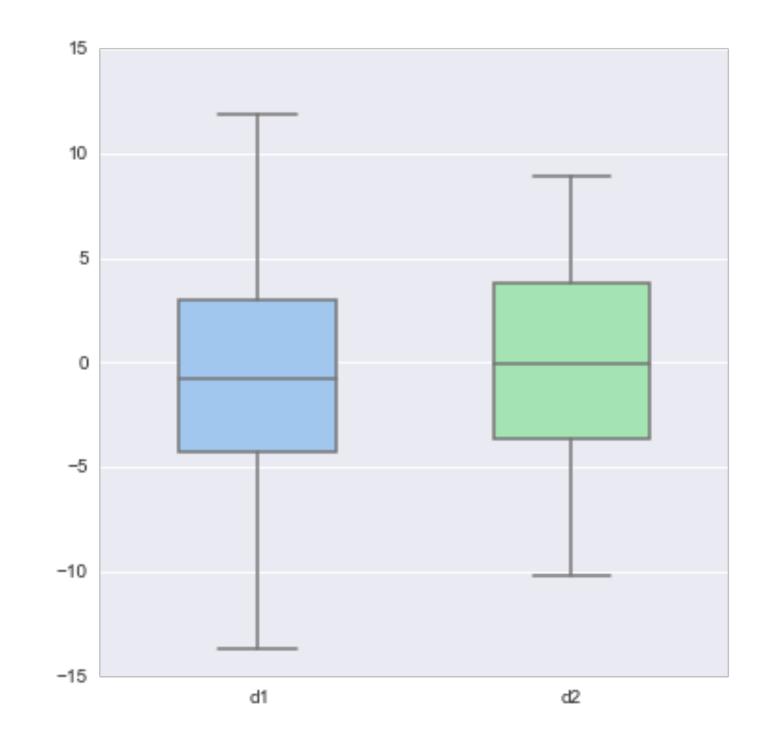
### Comparison



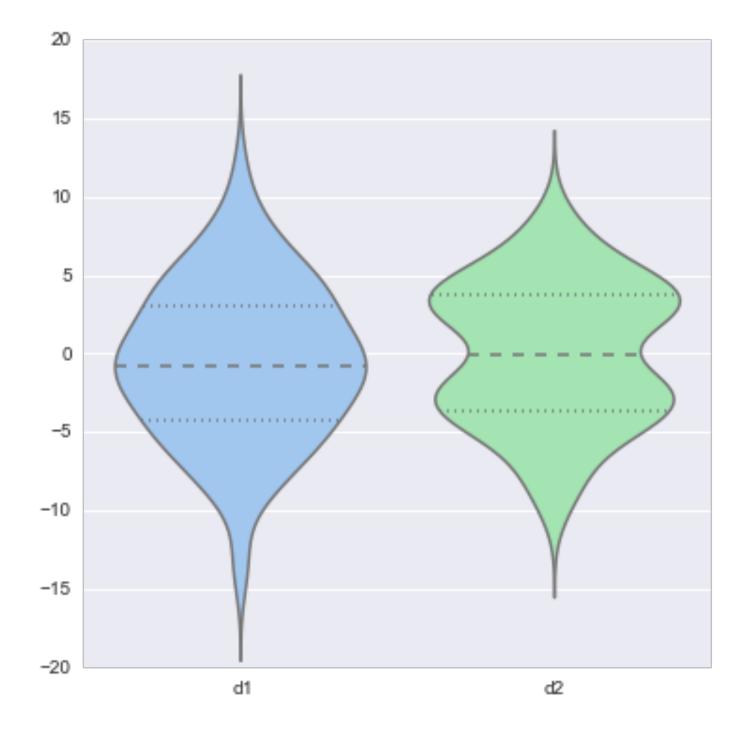
Streit & Gehlenborg, PoV, Nature Methods, 2014

## Violin Plot

### = Box Plot + Probability Density Function



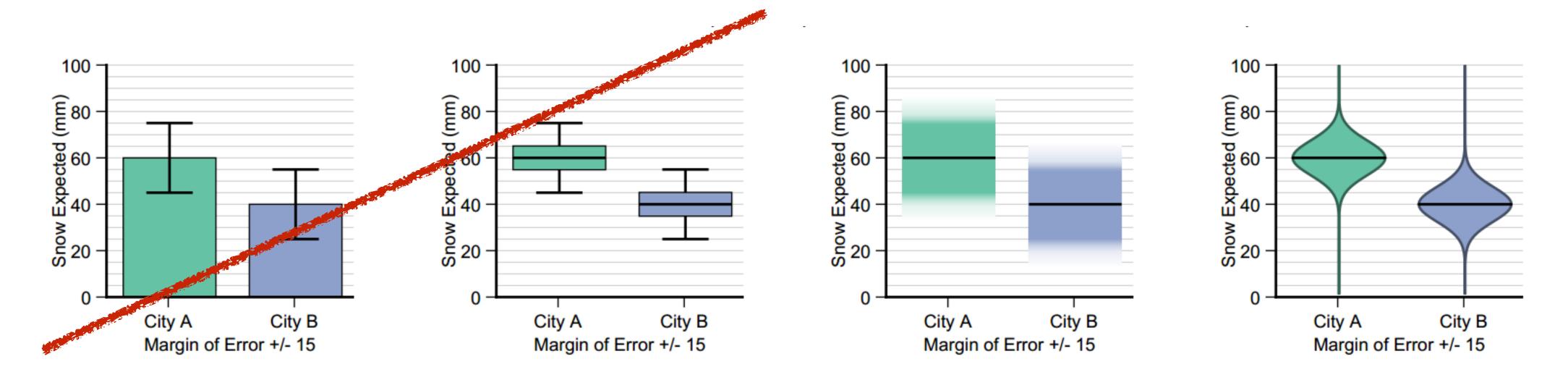




http://web.stanford.edu/~mwaskom/software/seaborn/tutorial/plotting\_distributions.html



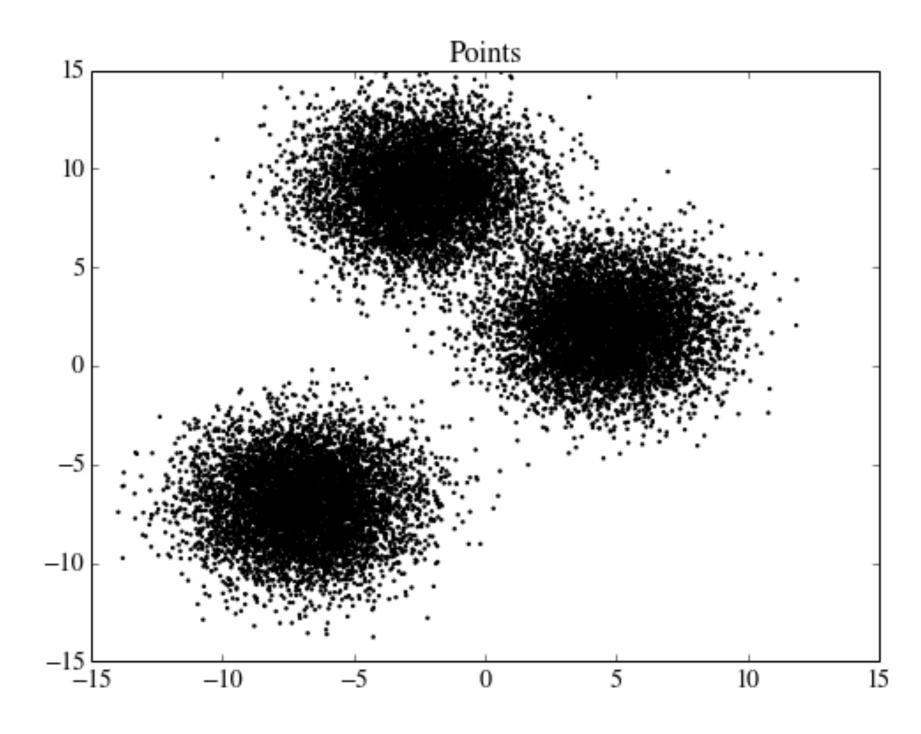
## Showing Expected Values & Uncertainty NOT a distribution!

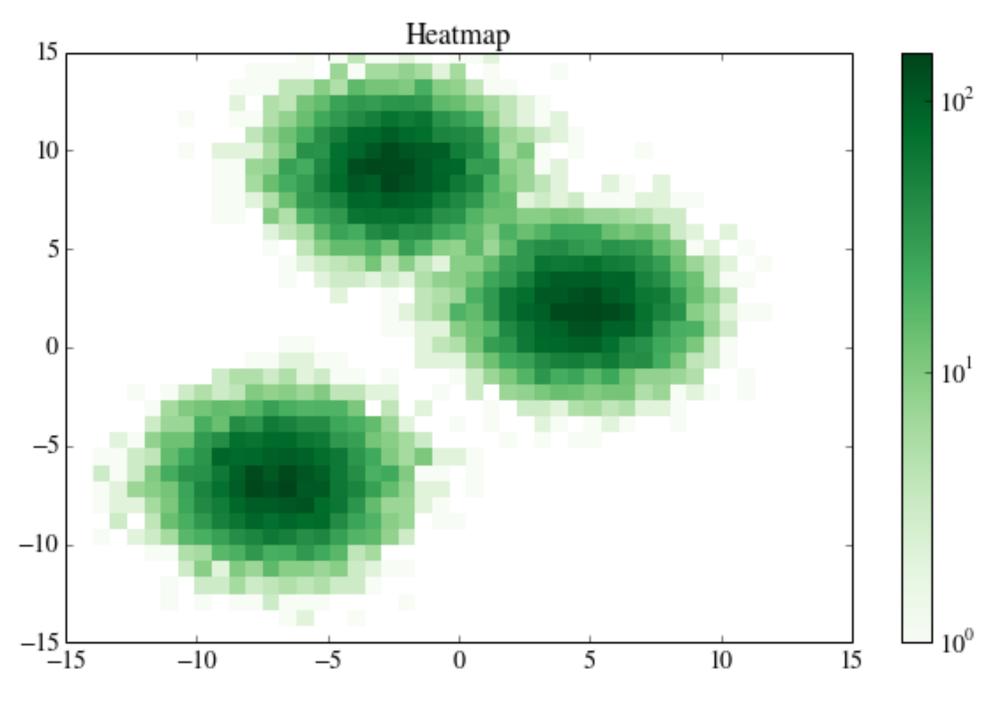


Error Bars Considered Harmful: Exploring Alternate Encodings for Mean and Error Michael Correll, and Michael Gleicher

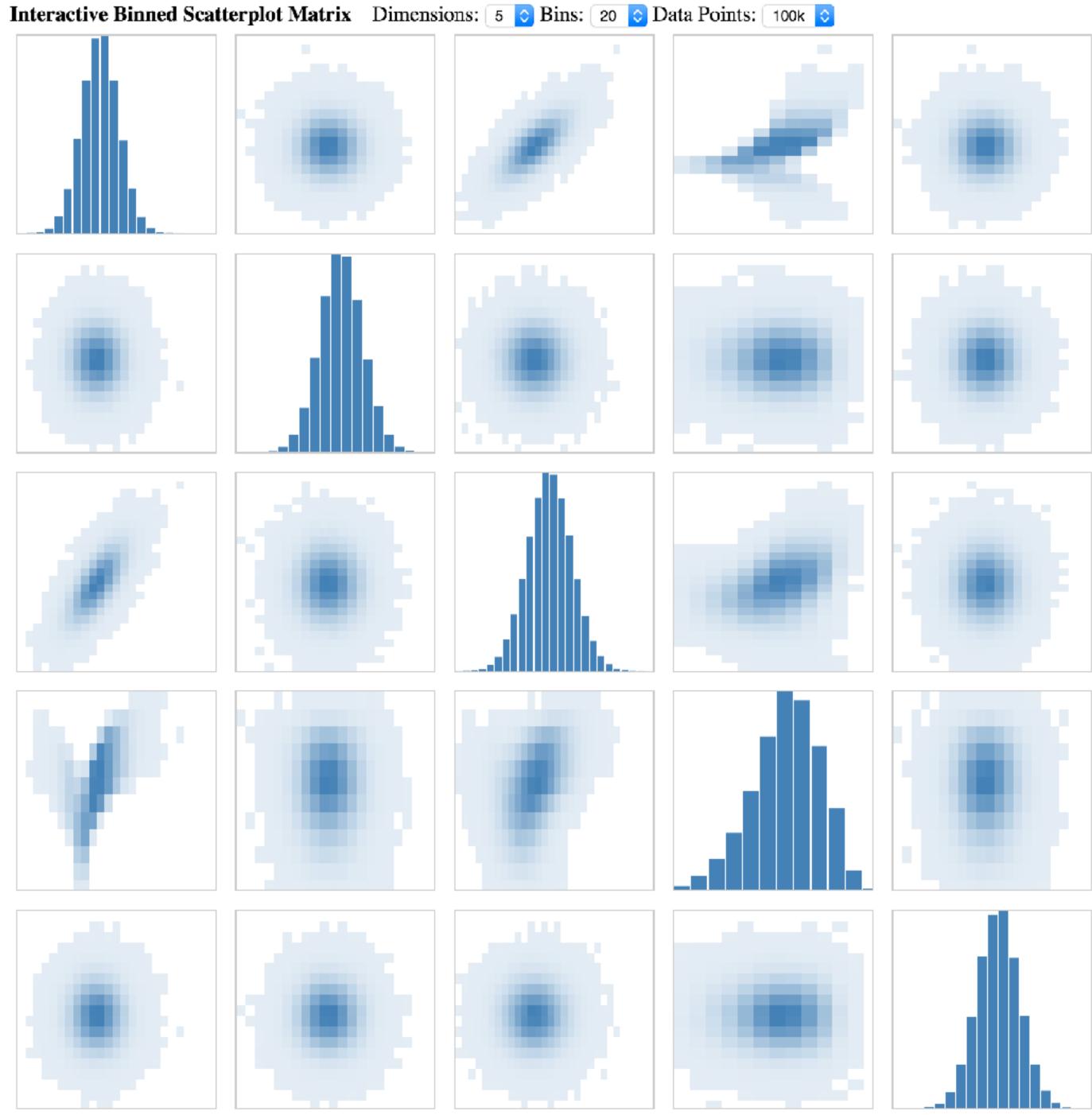
### Heat Maps

### binning of scatterplots instead of drawing every point, calculate grid and intensities



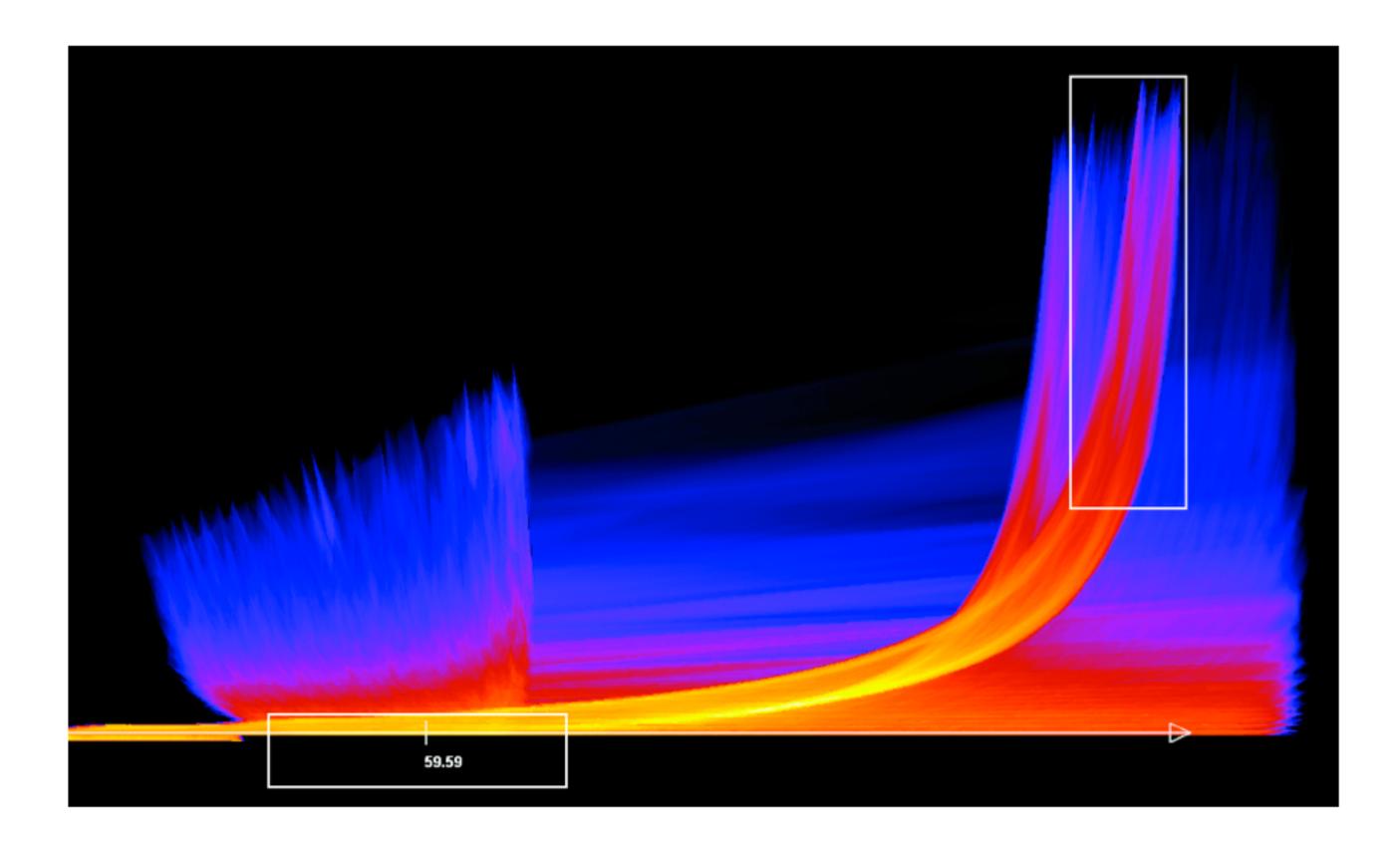


<sup>2</sup>D Density Plots



Powered by Datavore and D3.

## **Continuous Scatterplot**

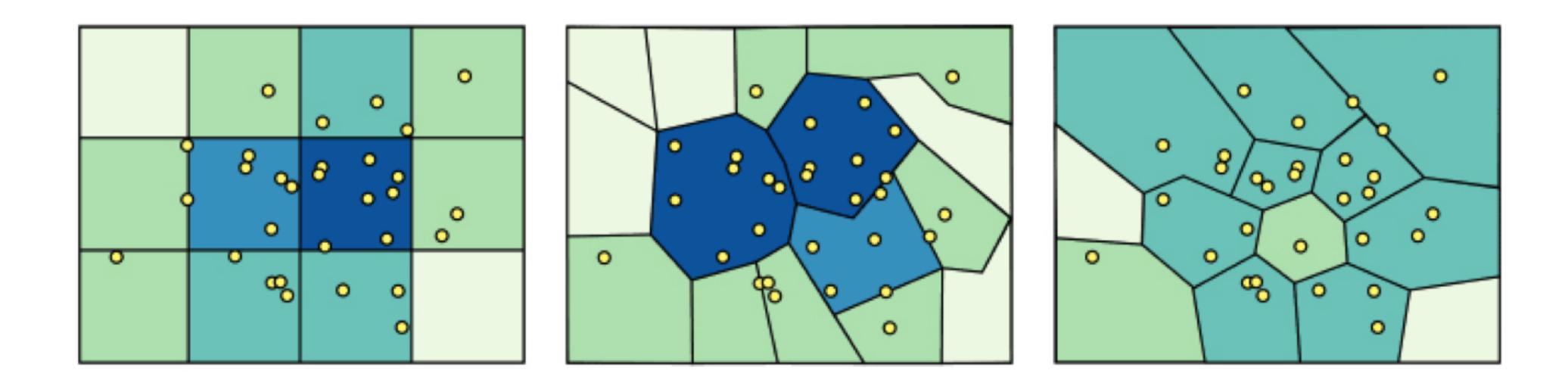


Bachthaler 2008

## Spatial Aggregation

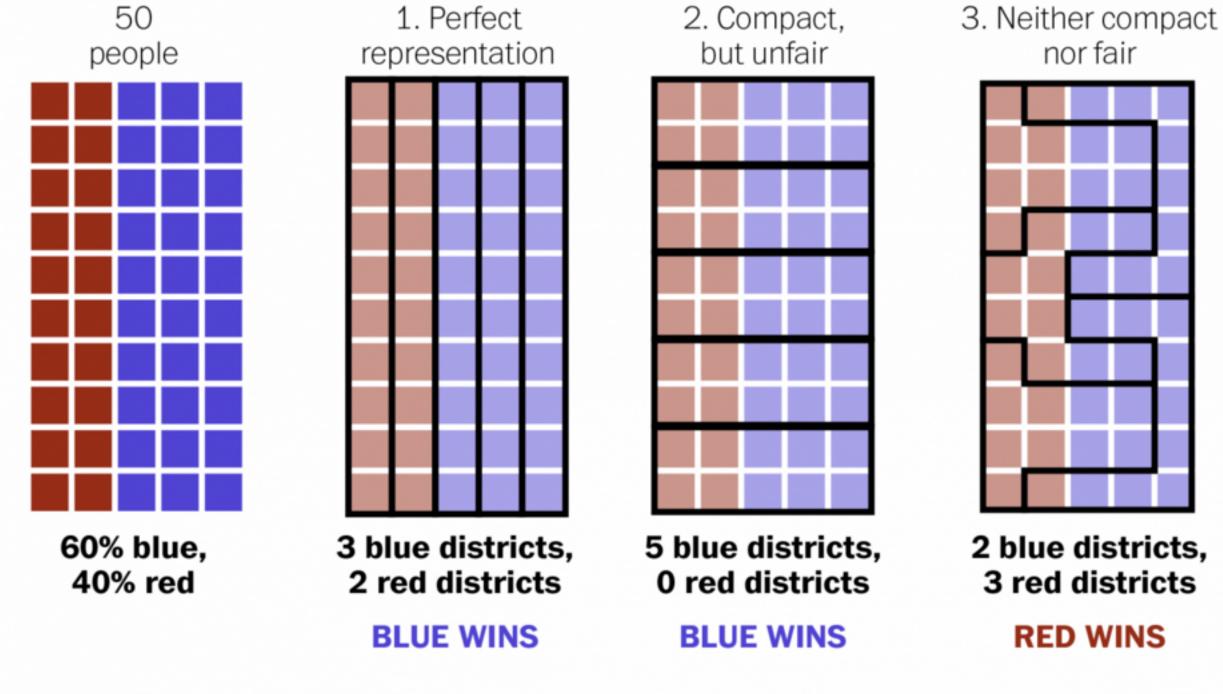
### modifiable areal unit problem

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



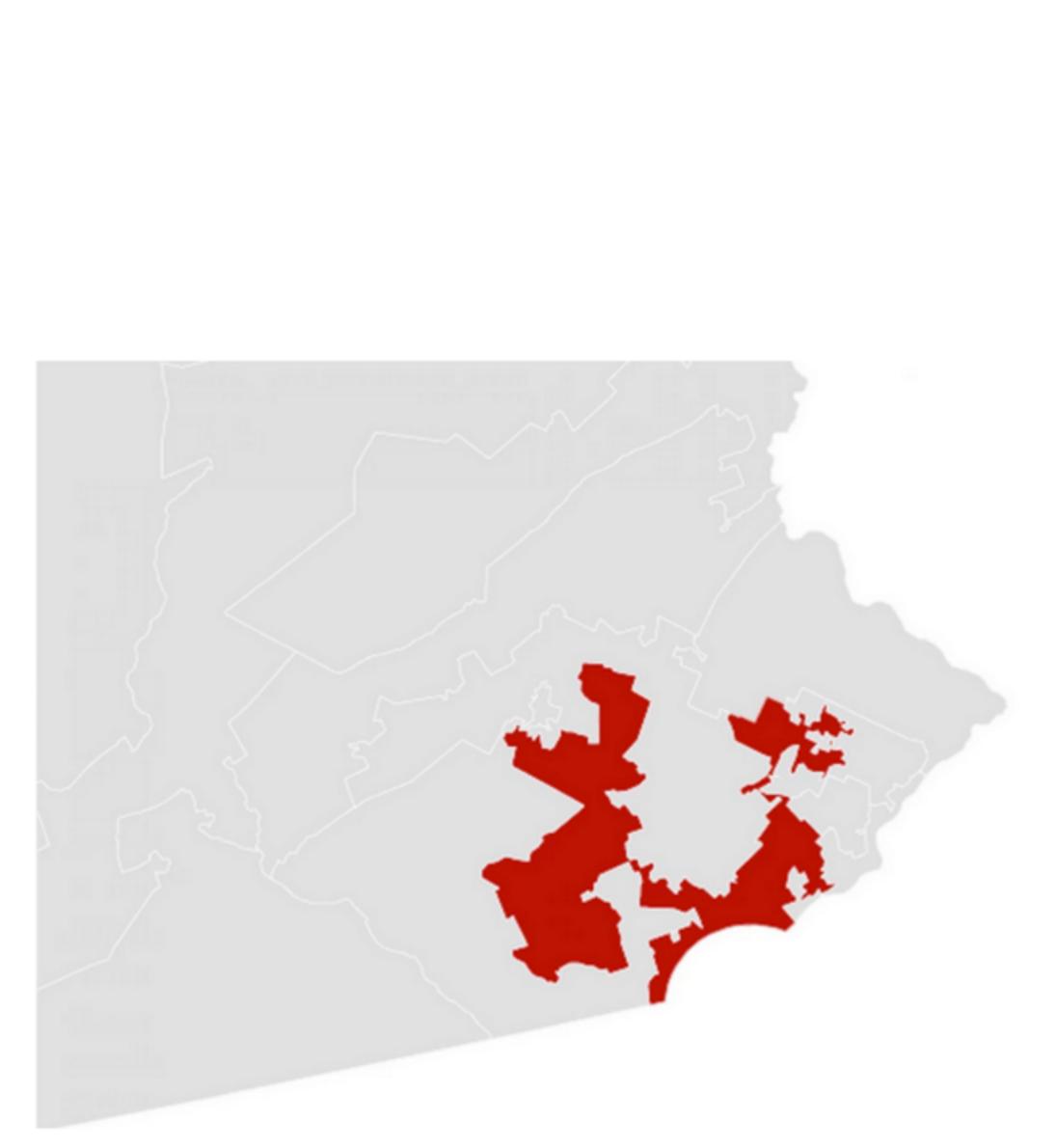
### Gerrymandering, explained

Three different ways to divide 50 people into five districts

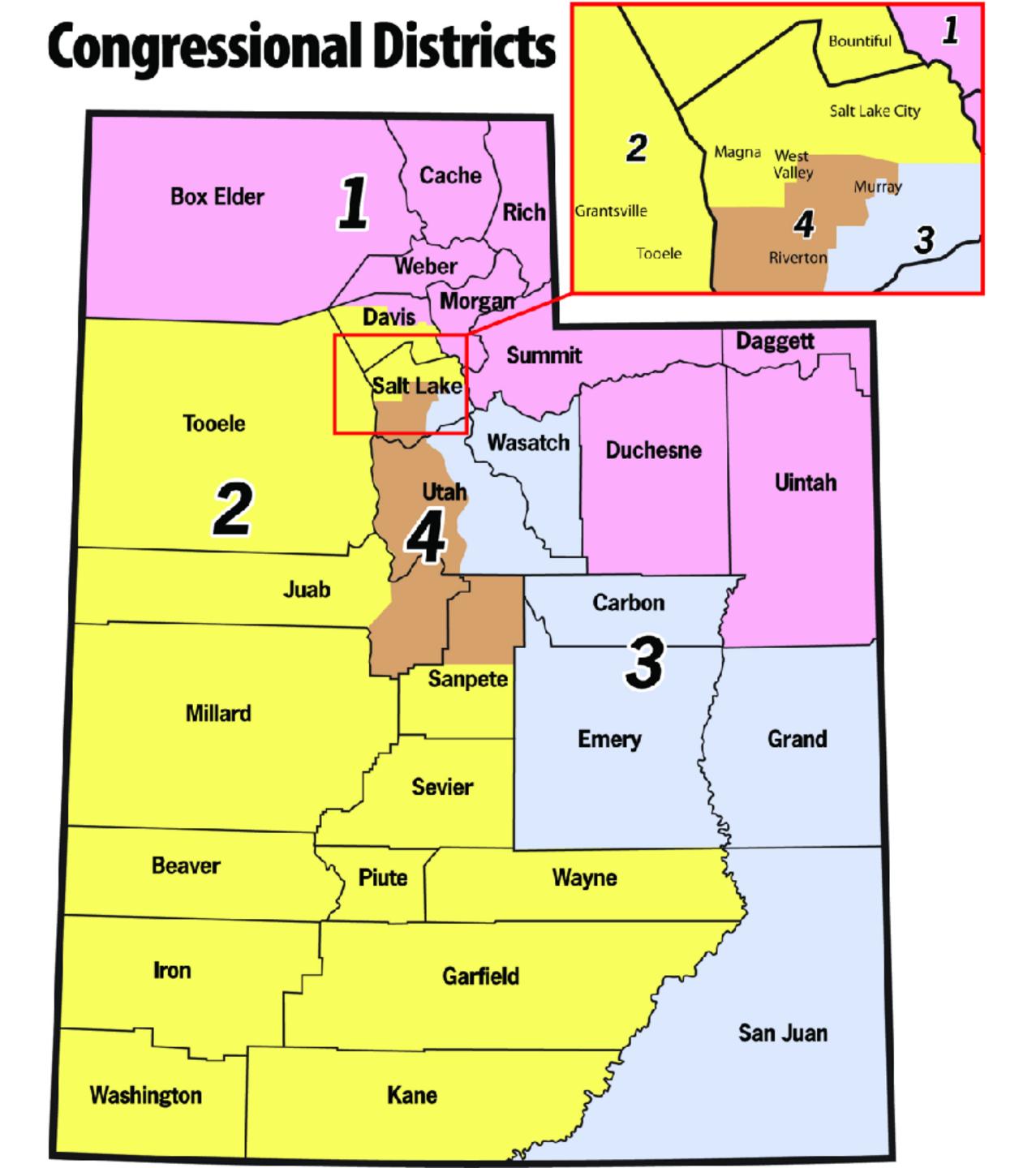


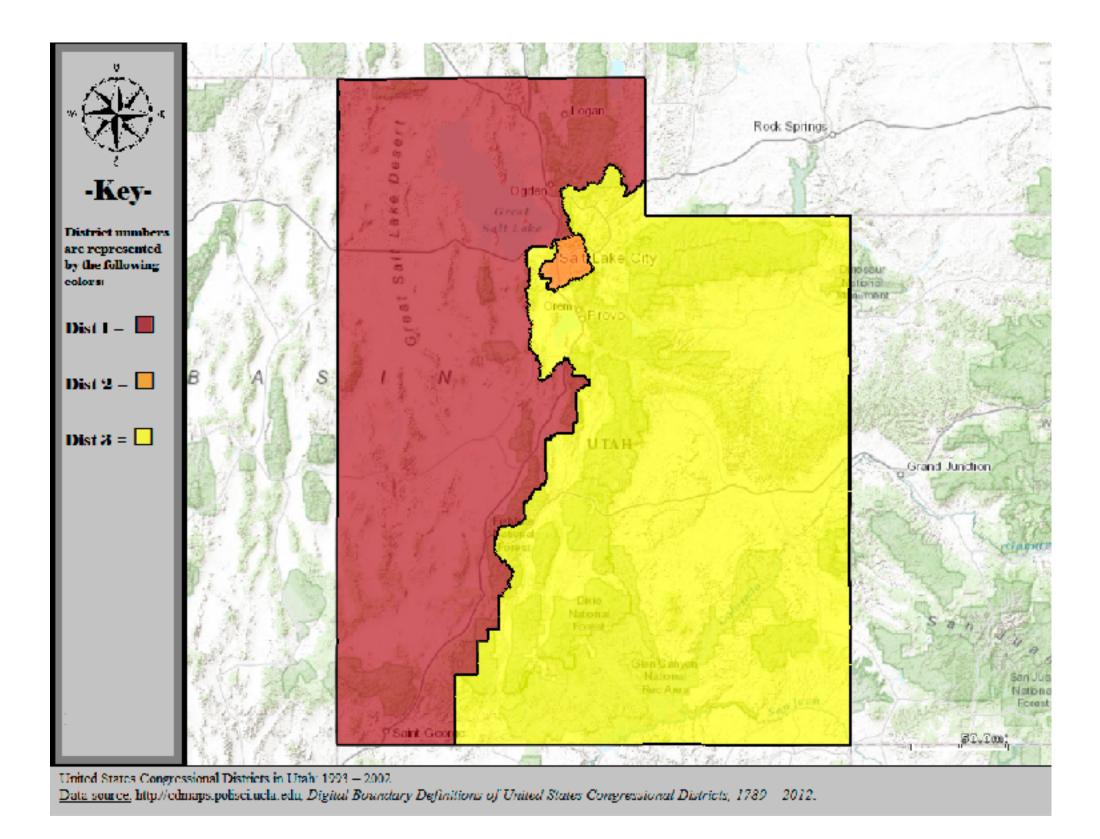
WASHINGTONPOST.COM/WONKBLOG

Adapted from Stephen Nass



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





### Valid till 2002

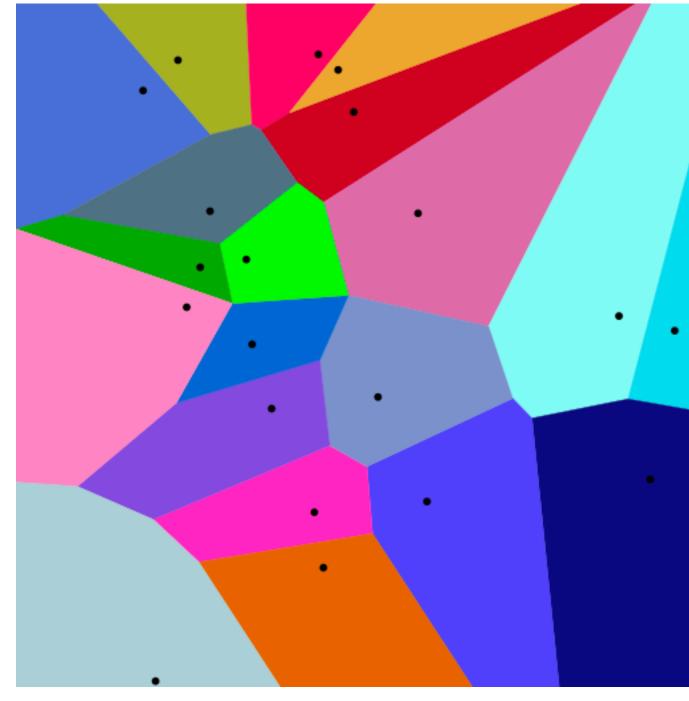
### http://www.sltrib.com/opinion/ 1794525-155/lake-salt-republicancounty-http-utah

## Voronoi Diagrams

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

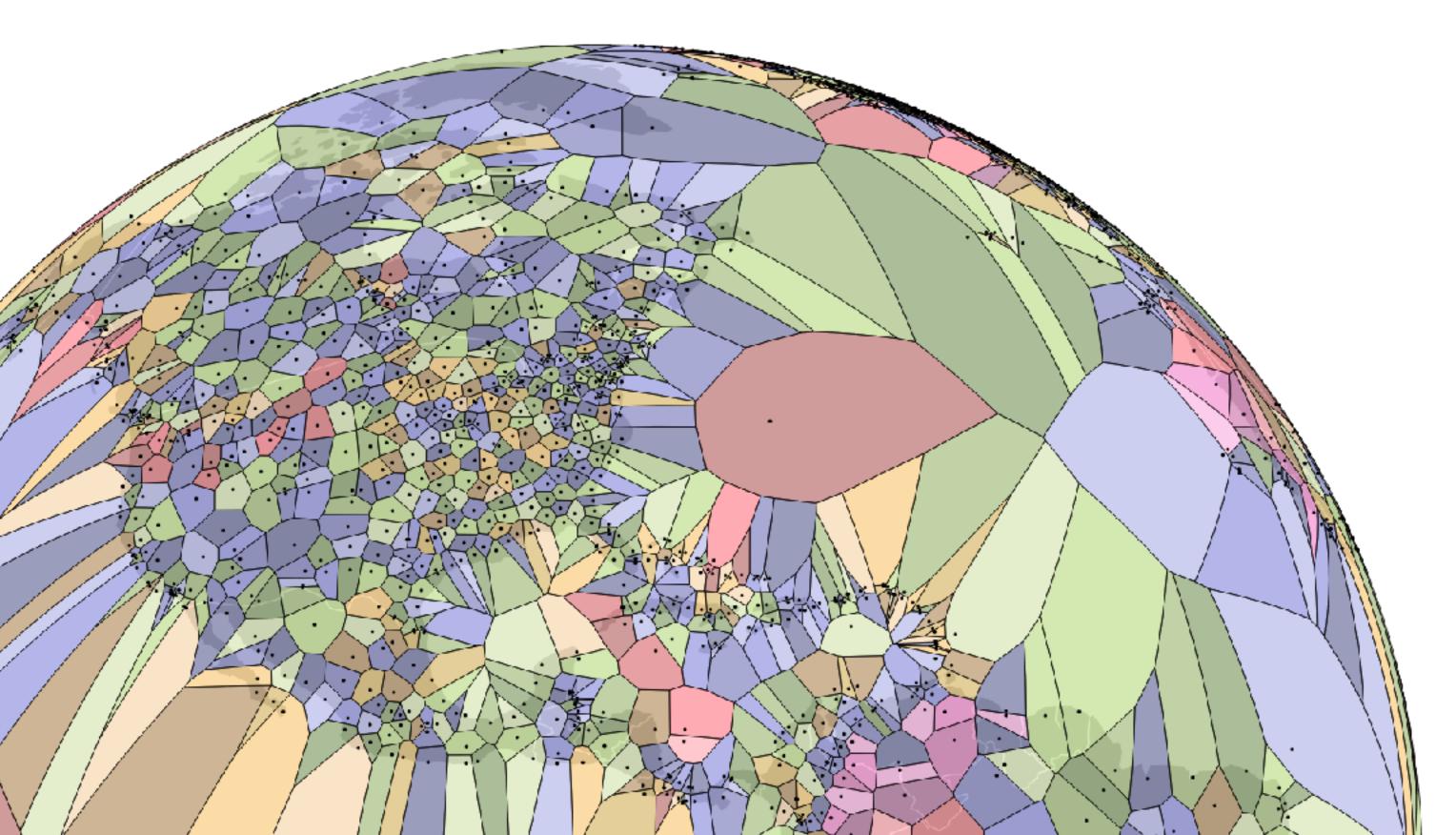
### D3 Voronoi Layout:

https://github.com/mbostock/d3/wiki/ Voronoi-Geom



### Voronoi Examples

### World Airports Voronoi



Sidenote: Voronoi for Interaction

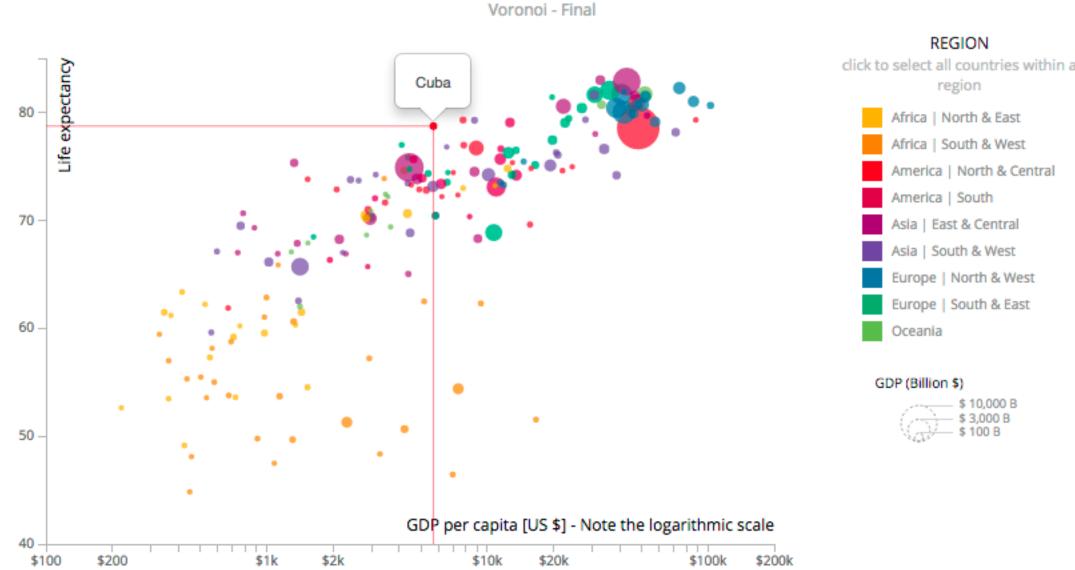


### Voronoi for Interaction

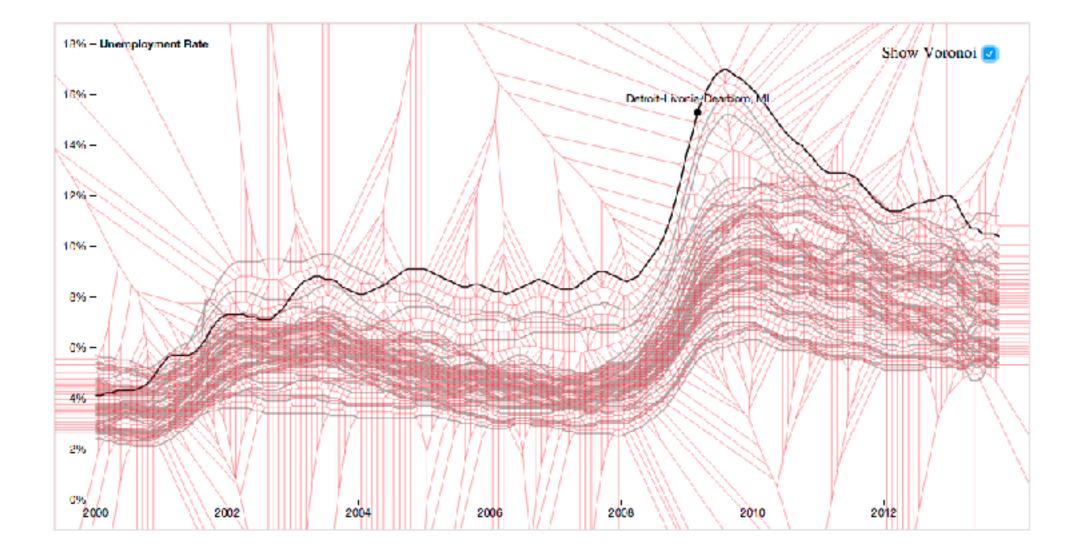
Useful for interaction: Increase size of target area to click/hover

Instead of clicking on point, hover in its region

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



### Life expectancy versus GDP per Capita



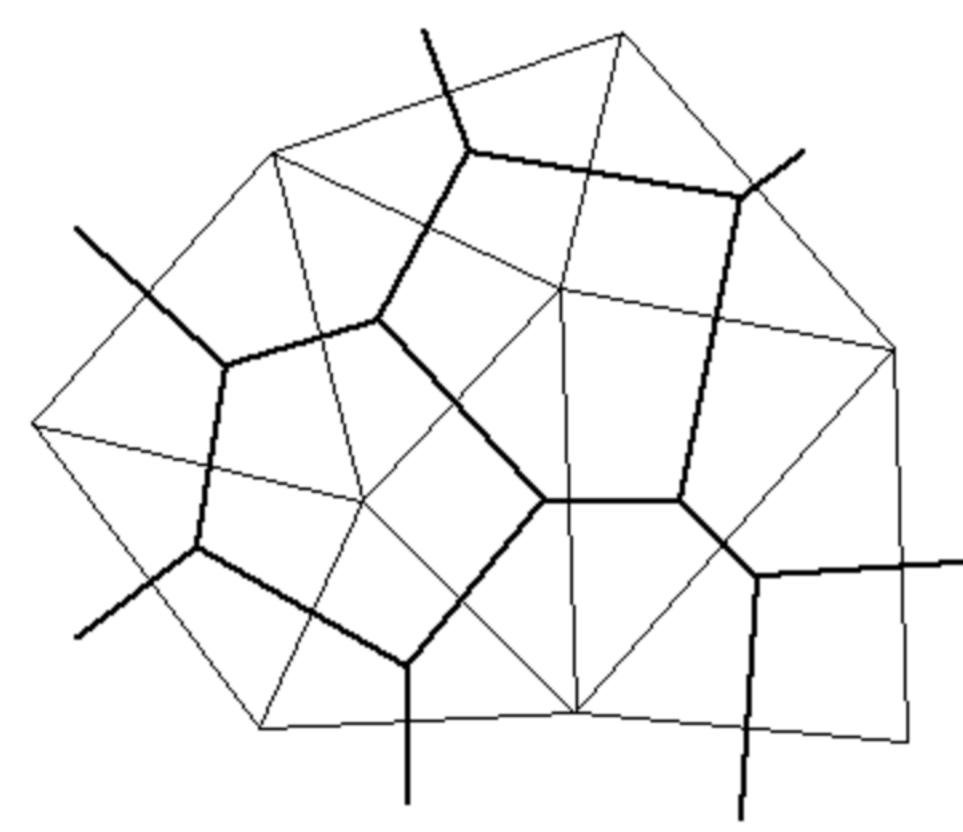
North & West

South & East

### **Constructing a Voronoi Diagram**

Calculate a Delauney triangulation

Voronoi edges are perpendicular to triangle edges.



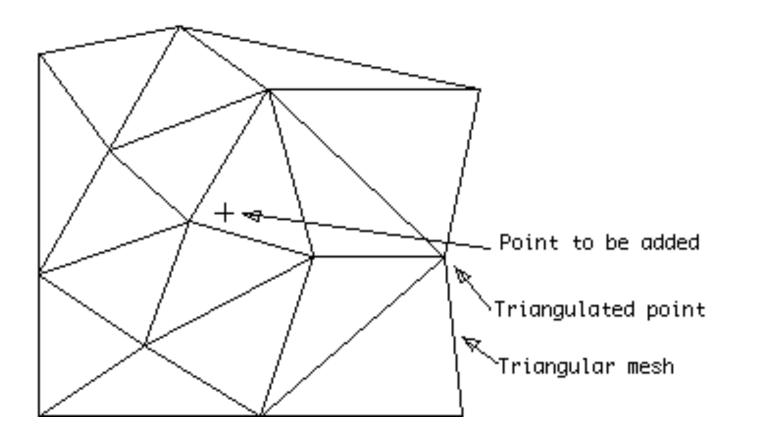
http://paulbourke.net/papers/triangulate/



## **Delauney Triangulation**

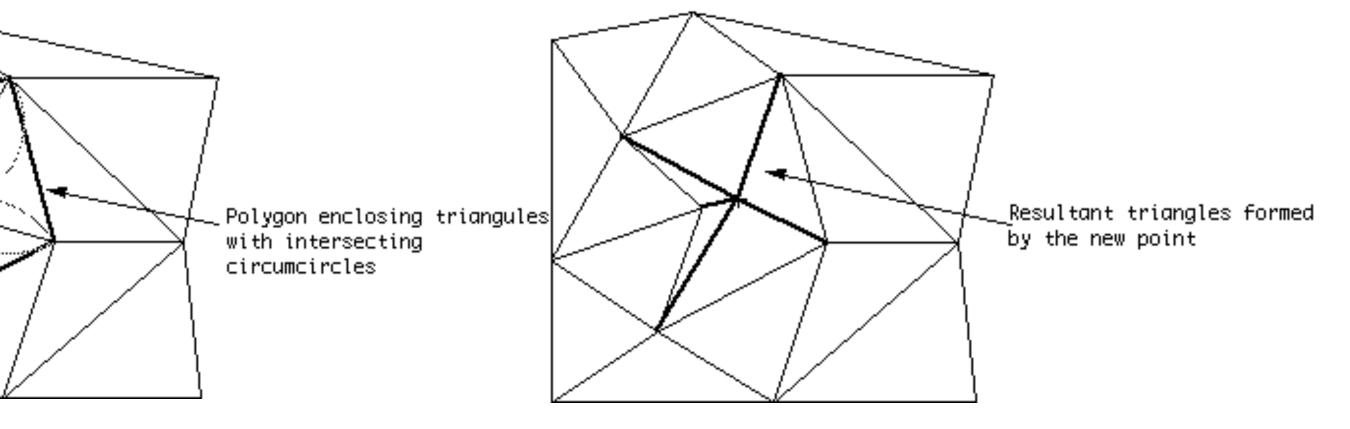
## Start with all-encompassing fake triangle

For existing triangles: check if circumcircle contains new point





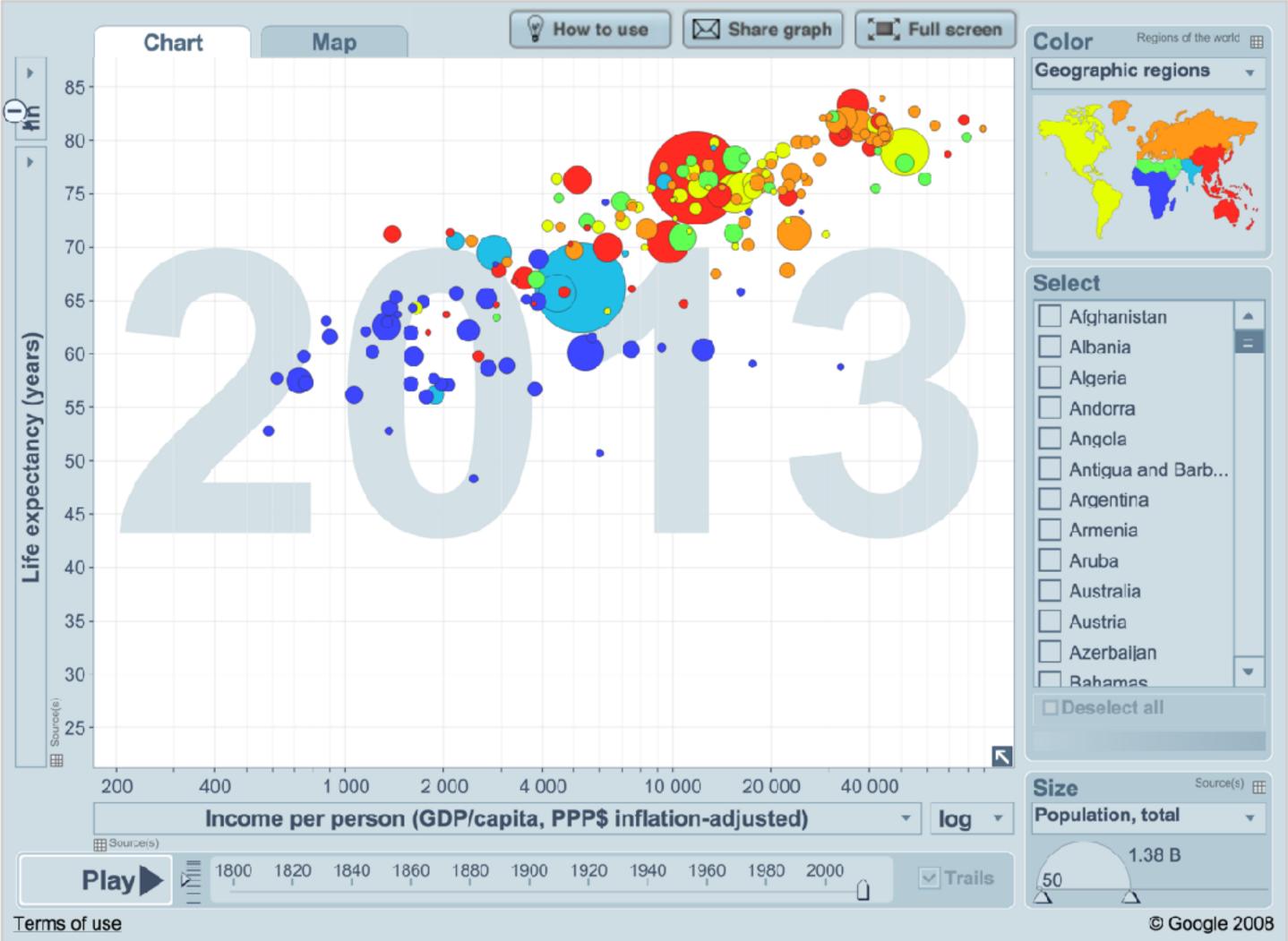
Outer edges of triangles form polygon, delete all inner edges Create triangle connecting all outer edges to new point.



### Design Critique

### GapMinder

#### https://goo.gl/Fcx28n Tool: http://goo.gl/jWNOUb



# Attribute aggregation

- 1) group attributes and compute a similarity score across the set
- 2) dimensionality reduction, to preserve meaningful structure

# Attribute aggregation

- 1) group attributes and compute a similarity score across the set
- 2) dimensionality reduction, to preserve meaningful structure

# 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., kmeans) or automatically determined (e.g., affinity propagation)

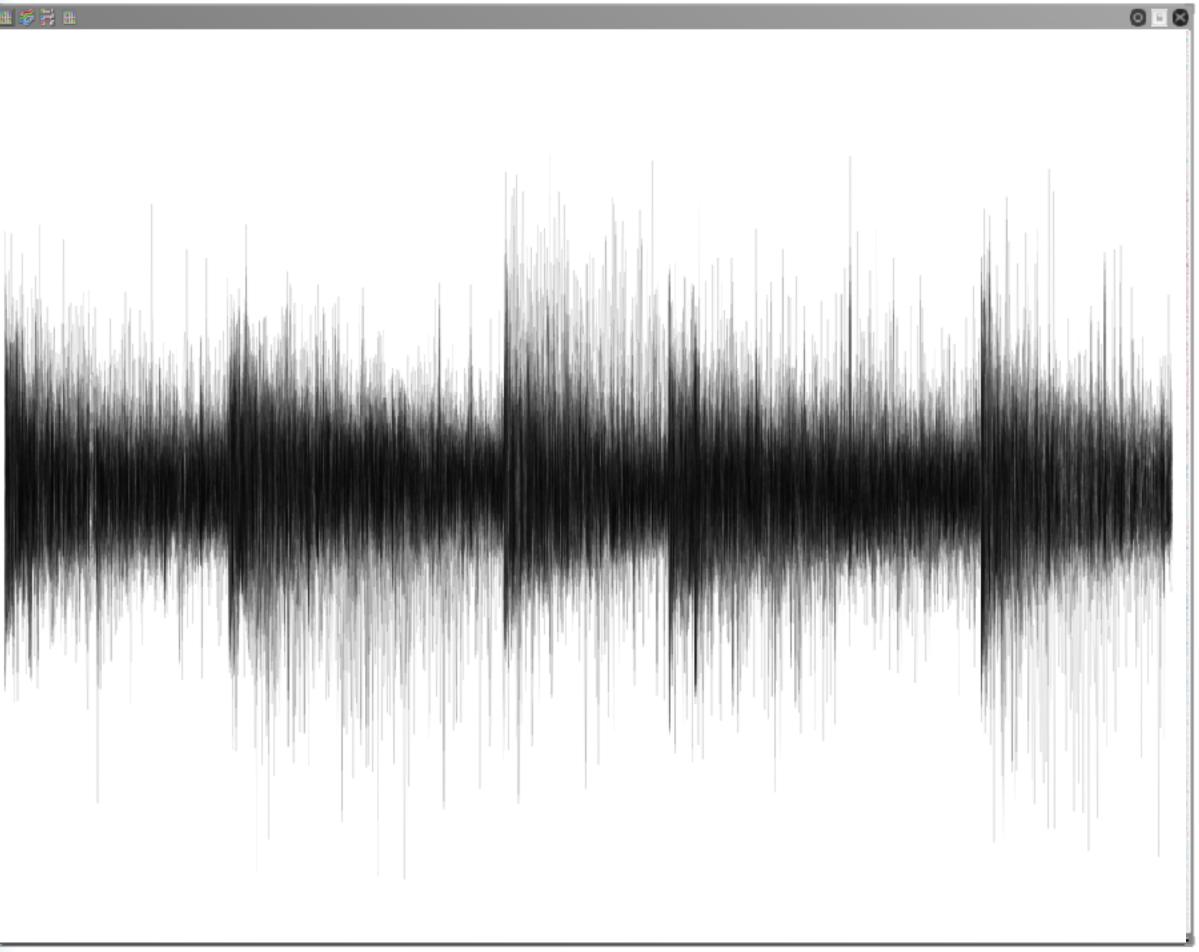
- Hierarchical Algorithms Produce "similarity tree" – dendrogram
- **Bi-Clustering**
- Clusters dimensions & records
- Fuzzy clustering
  - allows occurrence of elements in multiples clusters

# **Clustering Applications**

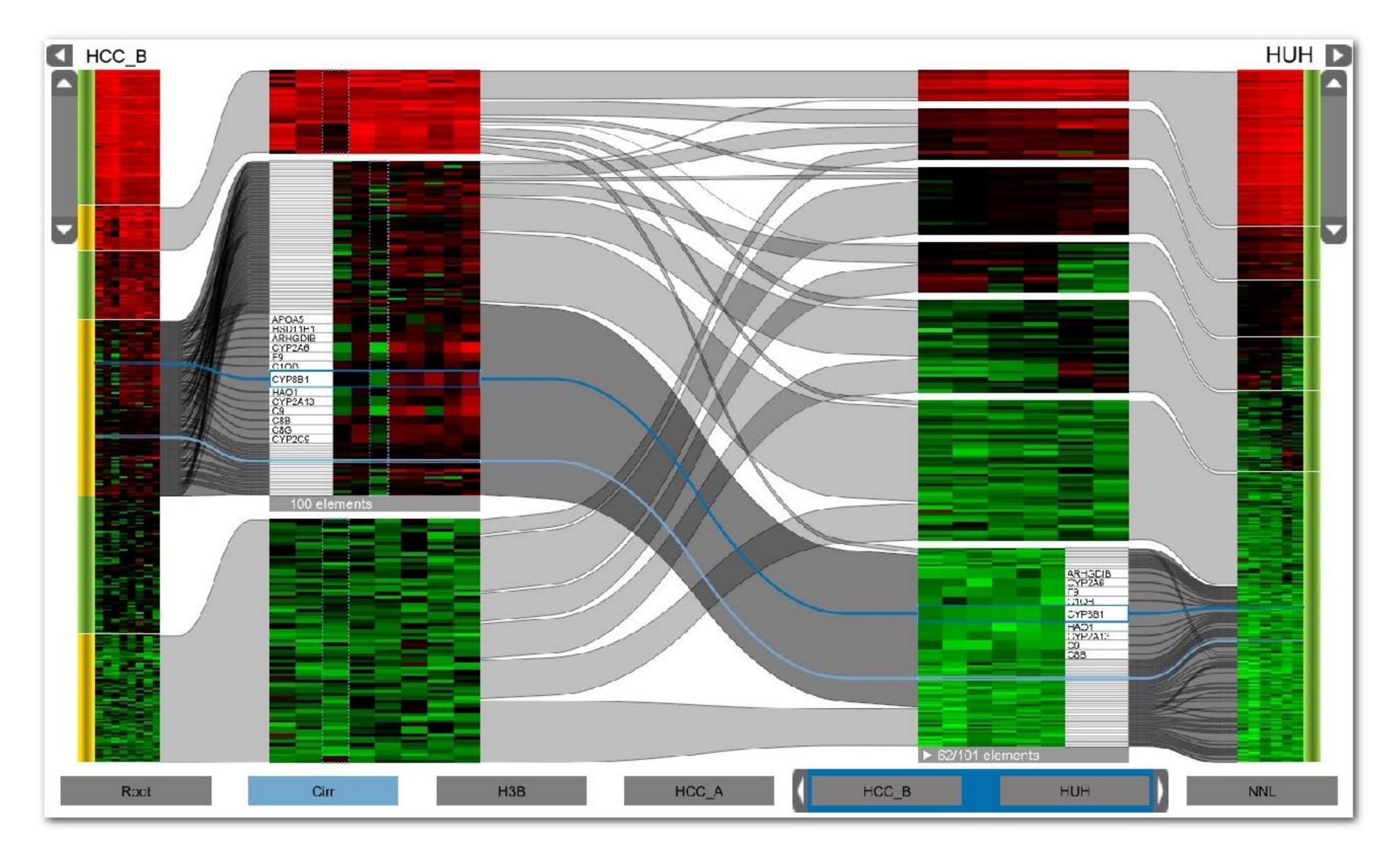
Clusters can be used to order (pixel based techniques) brush (geometric techniques) aggregate Aggregation cluster more homogeneous than whole dataset statistical measures, distributions, etc. more meaningful

#### **Clustered Heat Map**

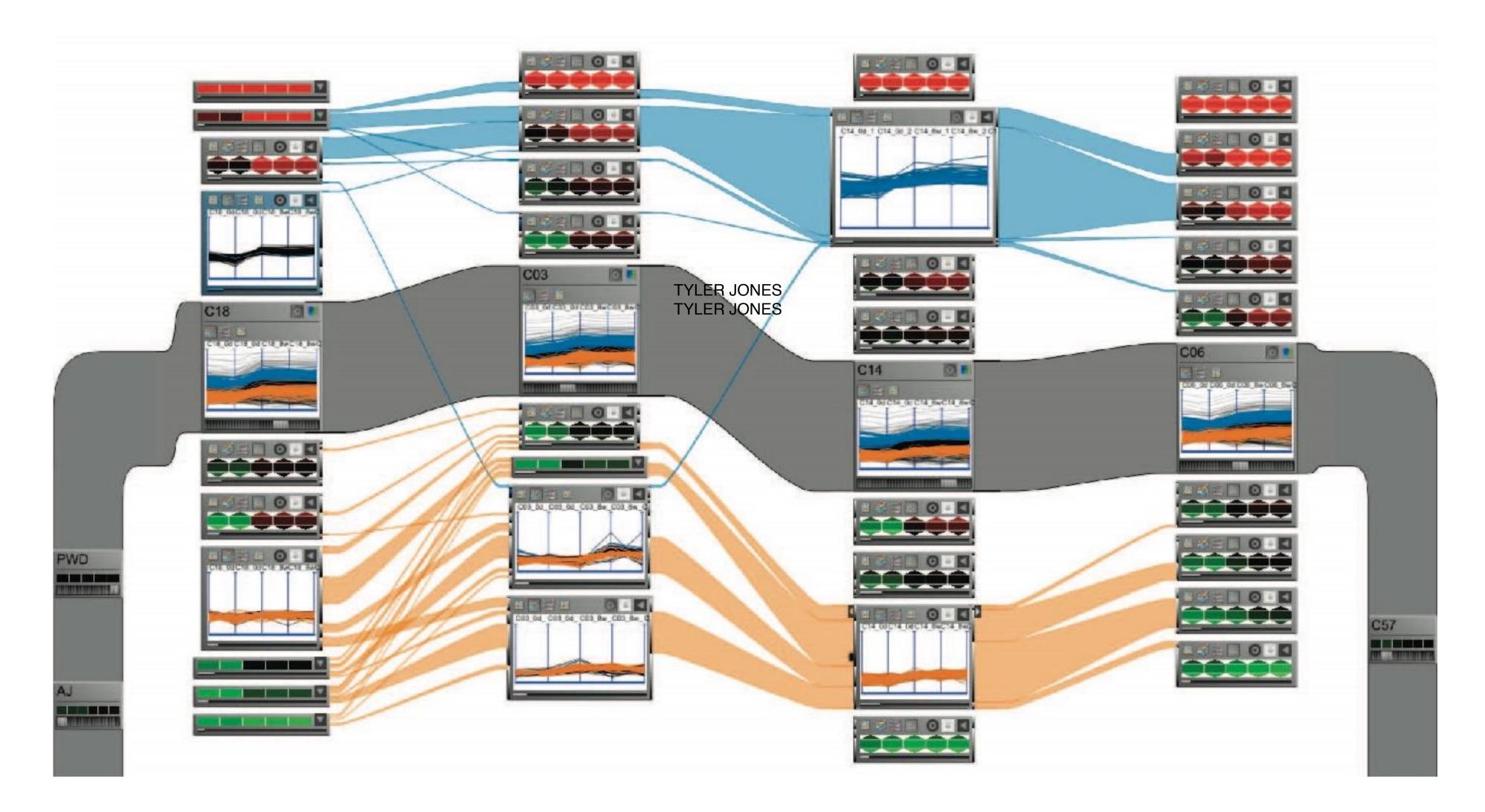
mRNA - Ground Truth/All g	
Neural	
Classical	
Mesenchymal	
Proneural	



# Cluster Comparison

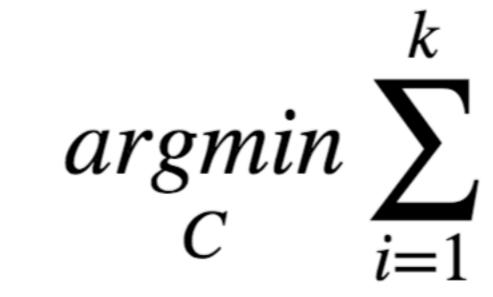


### Aggregation



### **Example: K-Means**

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



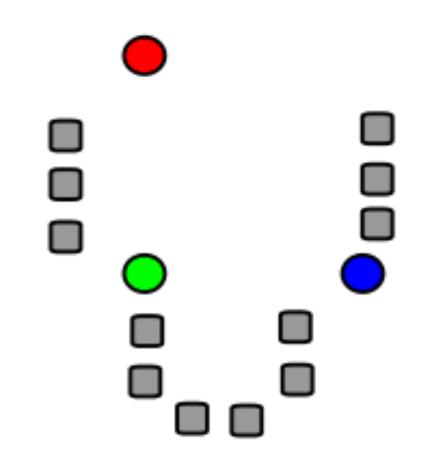
total squared distance from point to center of its cluster for euclidian distance: this is the variance measure of how internally coherent clusters are

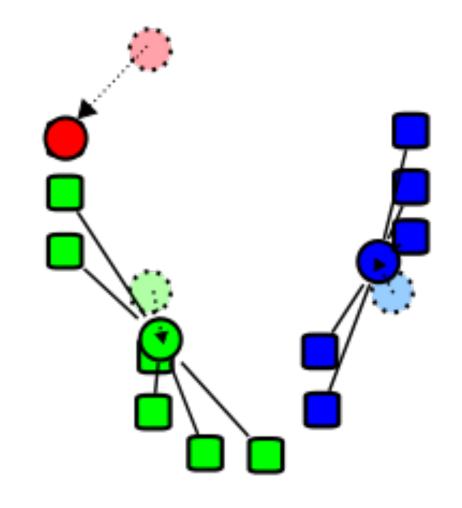
$$\sum_{x \in C_i} \|x - \mu_i\|^2$$

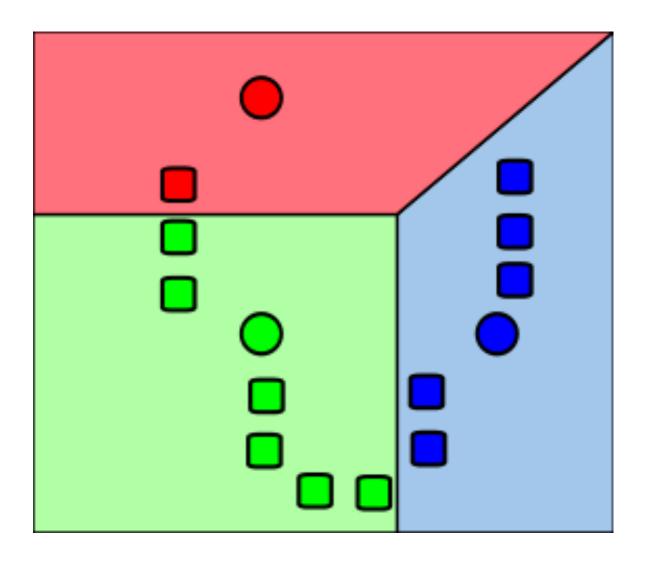
# Lloyd's Algorithm

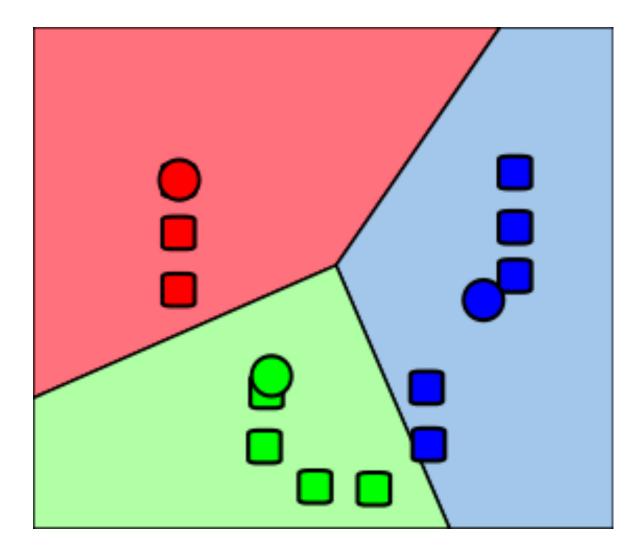
Input: set of records  $x_1 \dots x_n$ , and k (nr clusters) Pick k starting points as centroids  $c_1 \dots c_k$ While not converged:

- 1. for each point  $x_i$  find closest centroid  $c_i$ 
  - for every  $c_i$  calculate distance  $D(x_i, c_i)$
  - assign  $x_i$  to cluster *j* defined by smallest distance
- 2. for each cluster *j*, compute a new centroid  $c_i$ 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

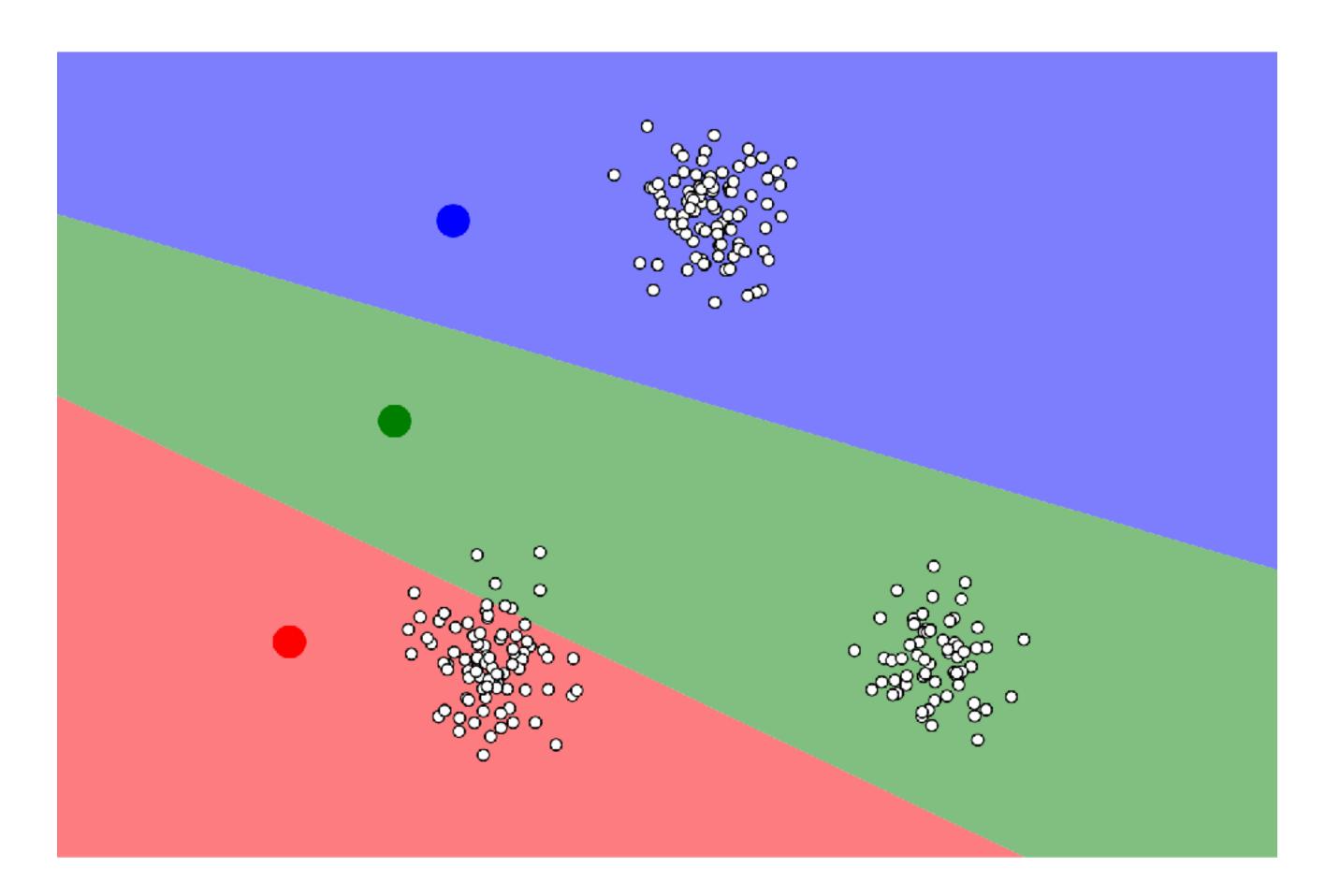






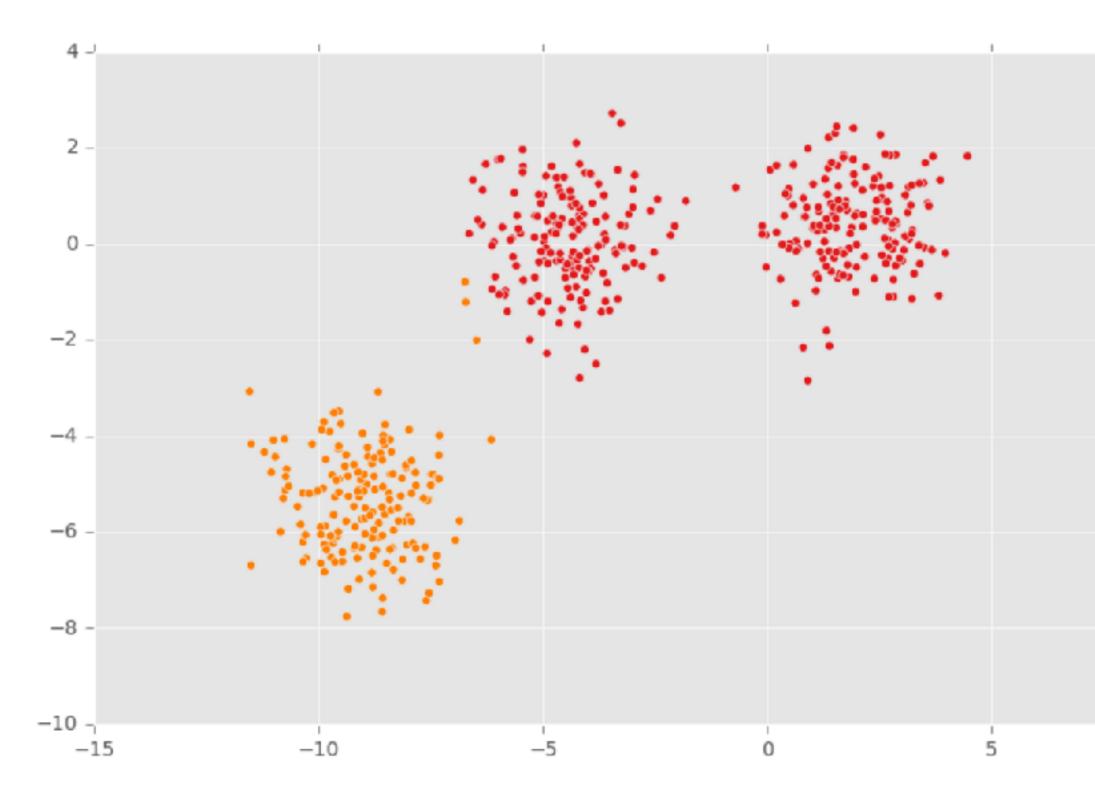


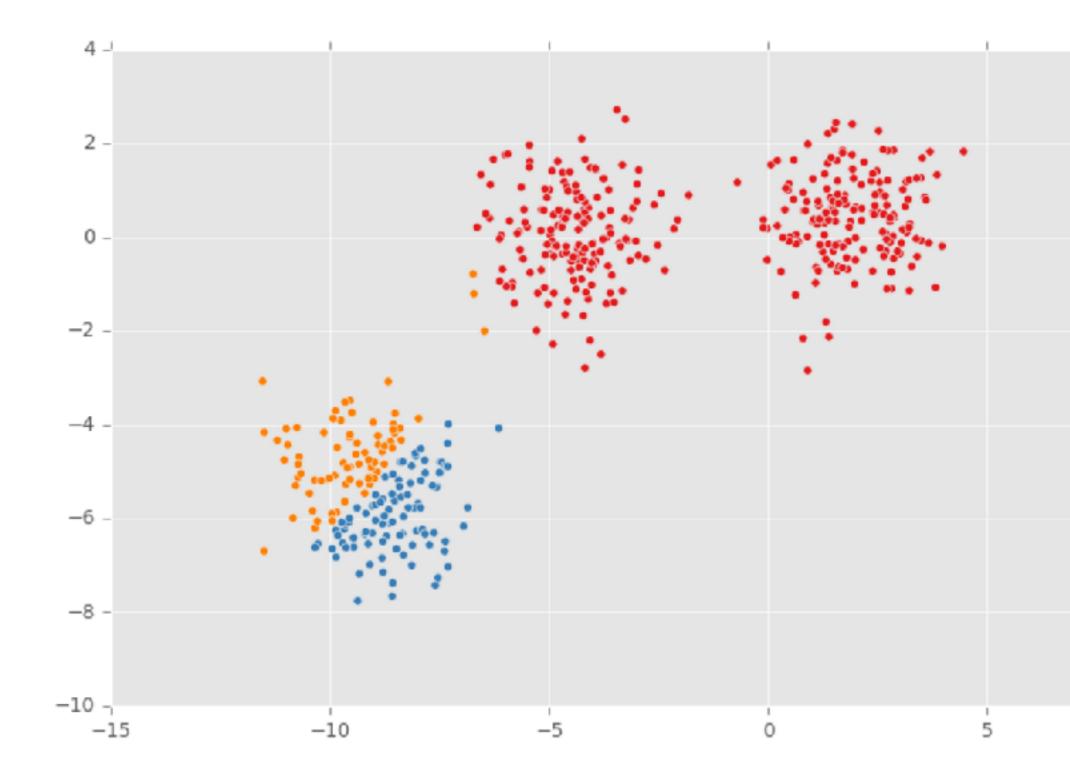
#### Illustrated



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

#### Choosing K





10

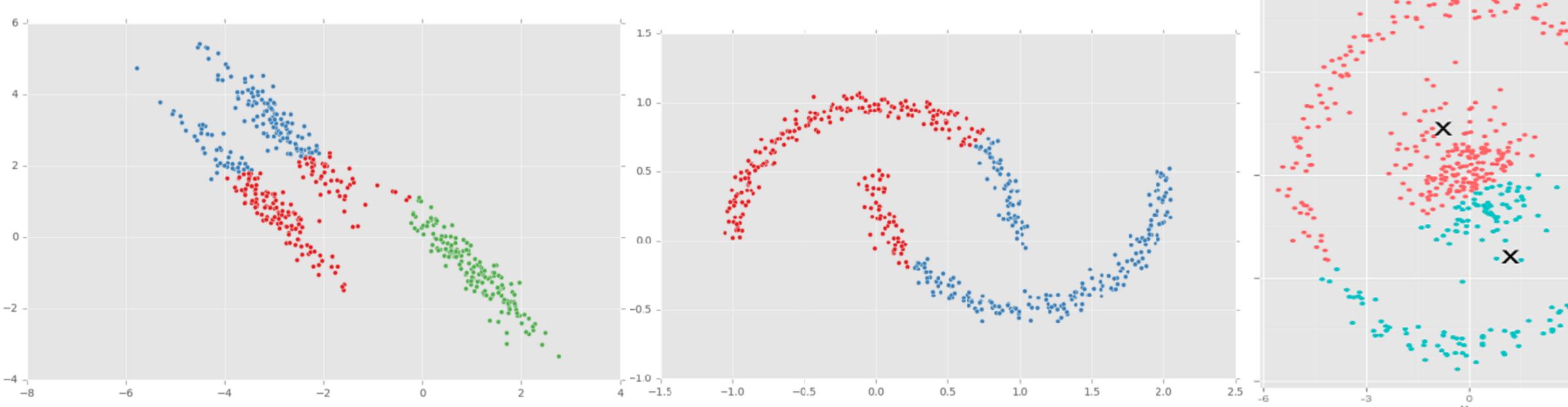


### Properties

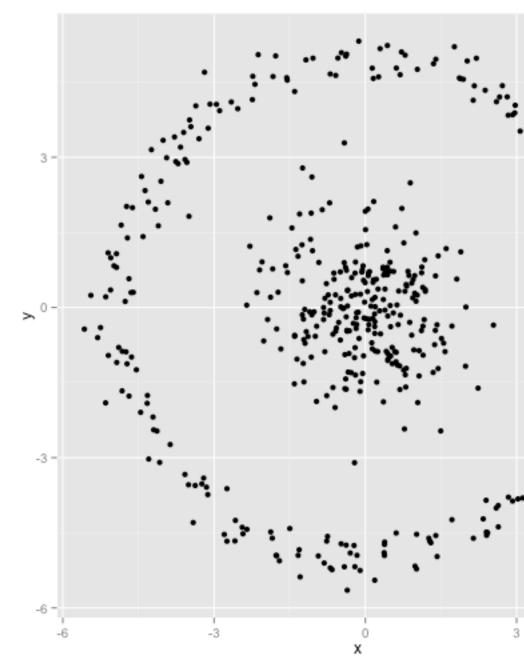
Lloyds algorithm doesn't find a global optimum Instead it finds a local optimum It is very fast: common to run multiple times and pick the solution with the minimum inertia

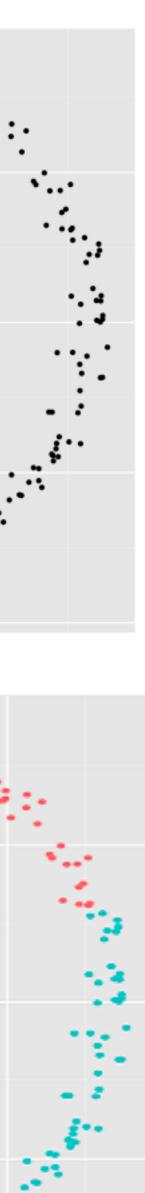
### **K-Means Properties**

#### Assumptions about data: roughly "circular" clusters of equal size

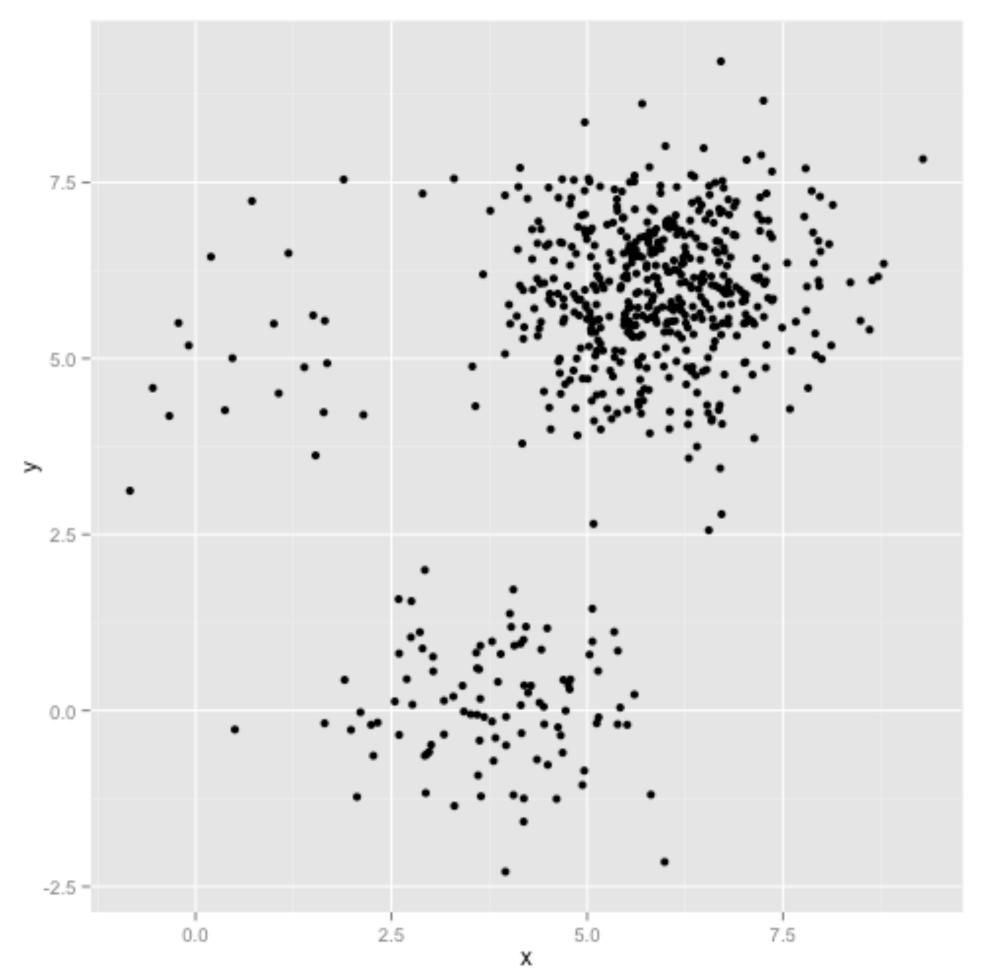




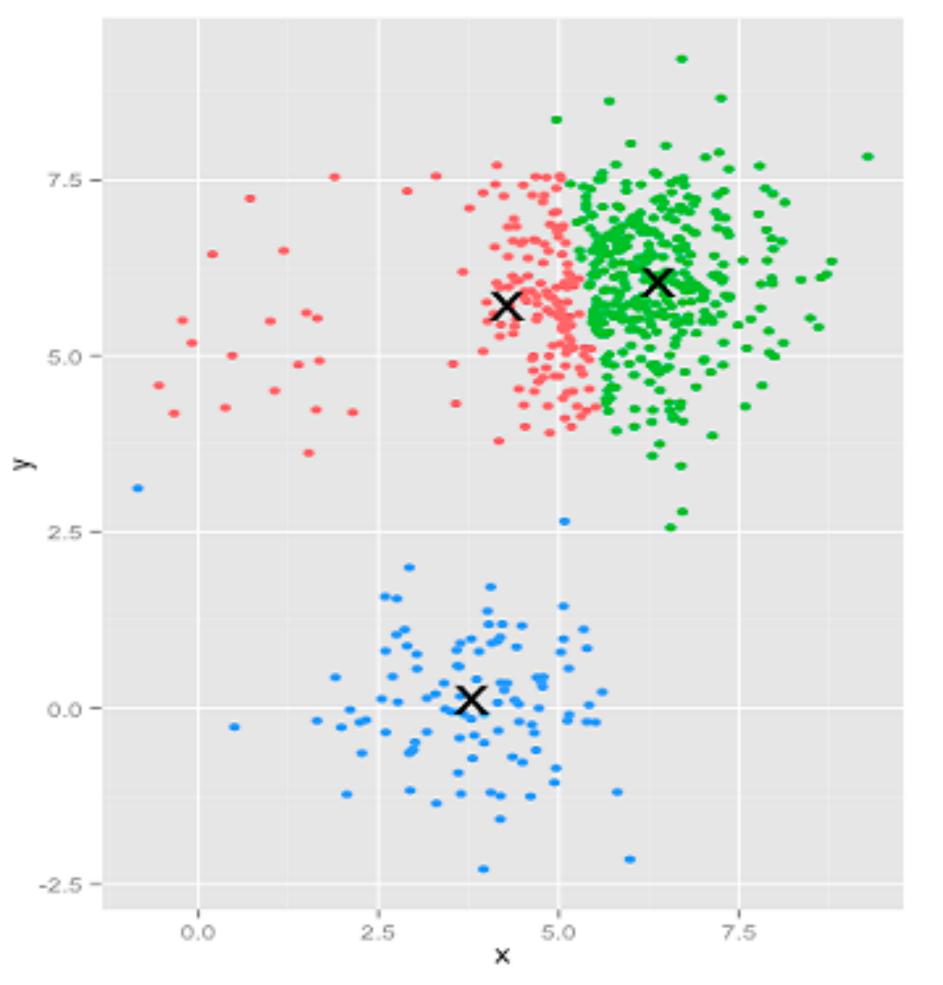




#### **K-Means Unequal Cluster Size**



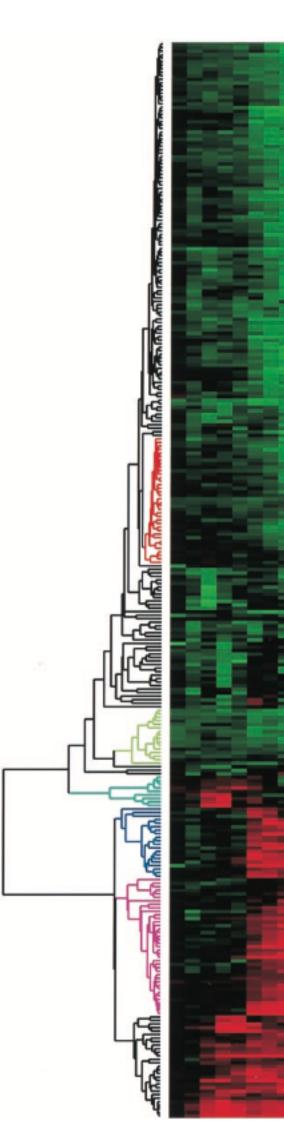
http://stats.stackexchange.com/questions/133656/how-to-understand-the-drawbacks-of-k-means

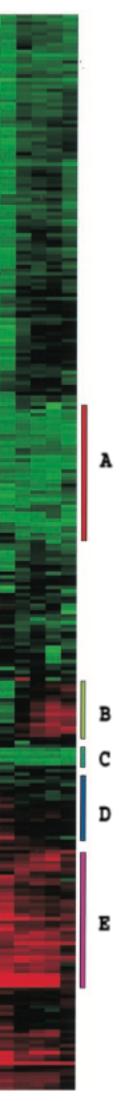


#### K-means assignments

# **Hierarchical Clustering**

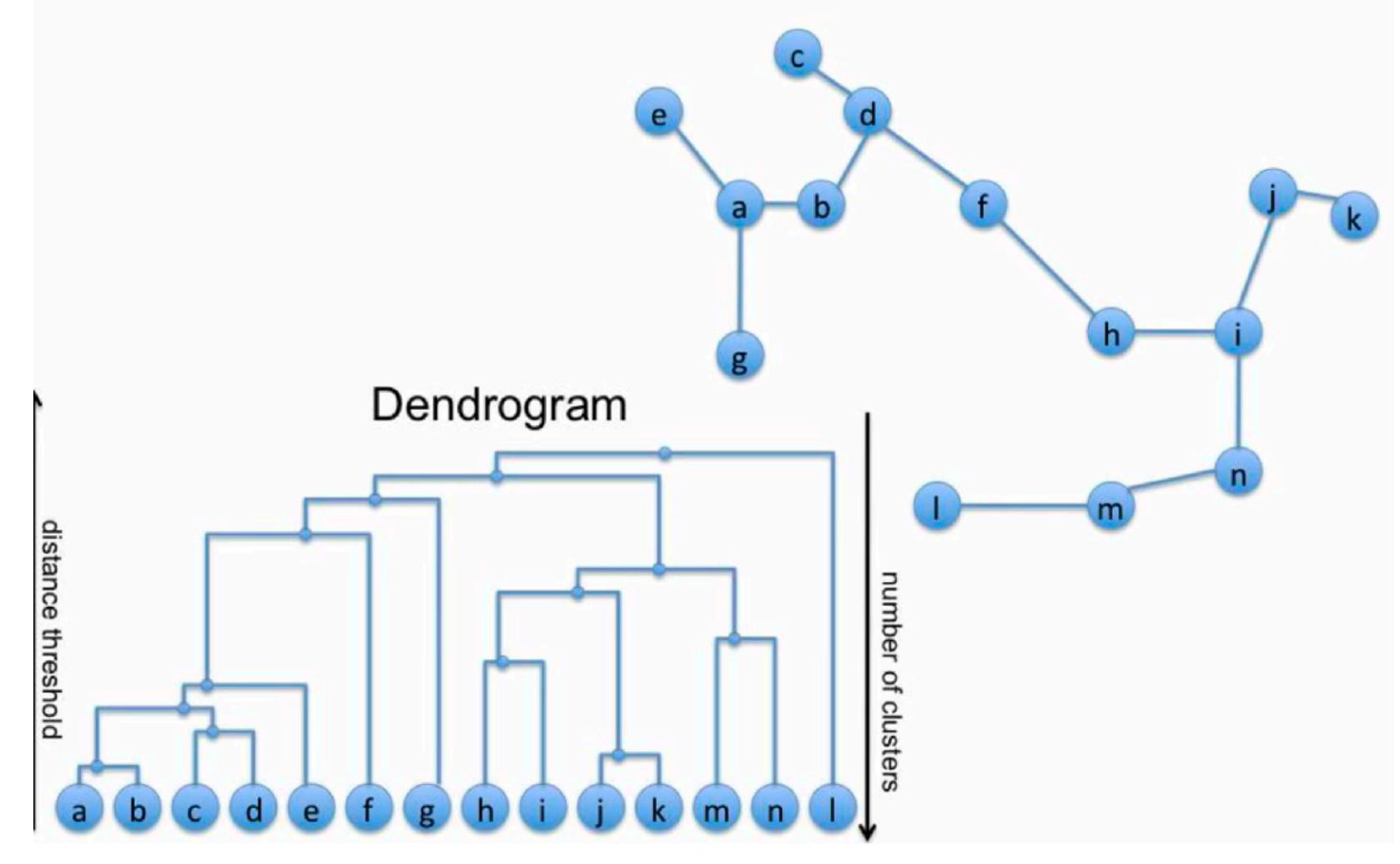
Two types: agglomerative clustering start with each node as a cluster and merge divisive clustering start with one cluster, and split





## **Agglomerative Clustering Idea**

## **Agglomerative Clustering Idea**



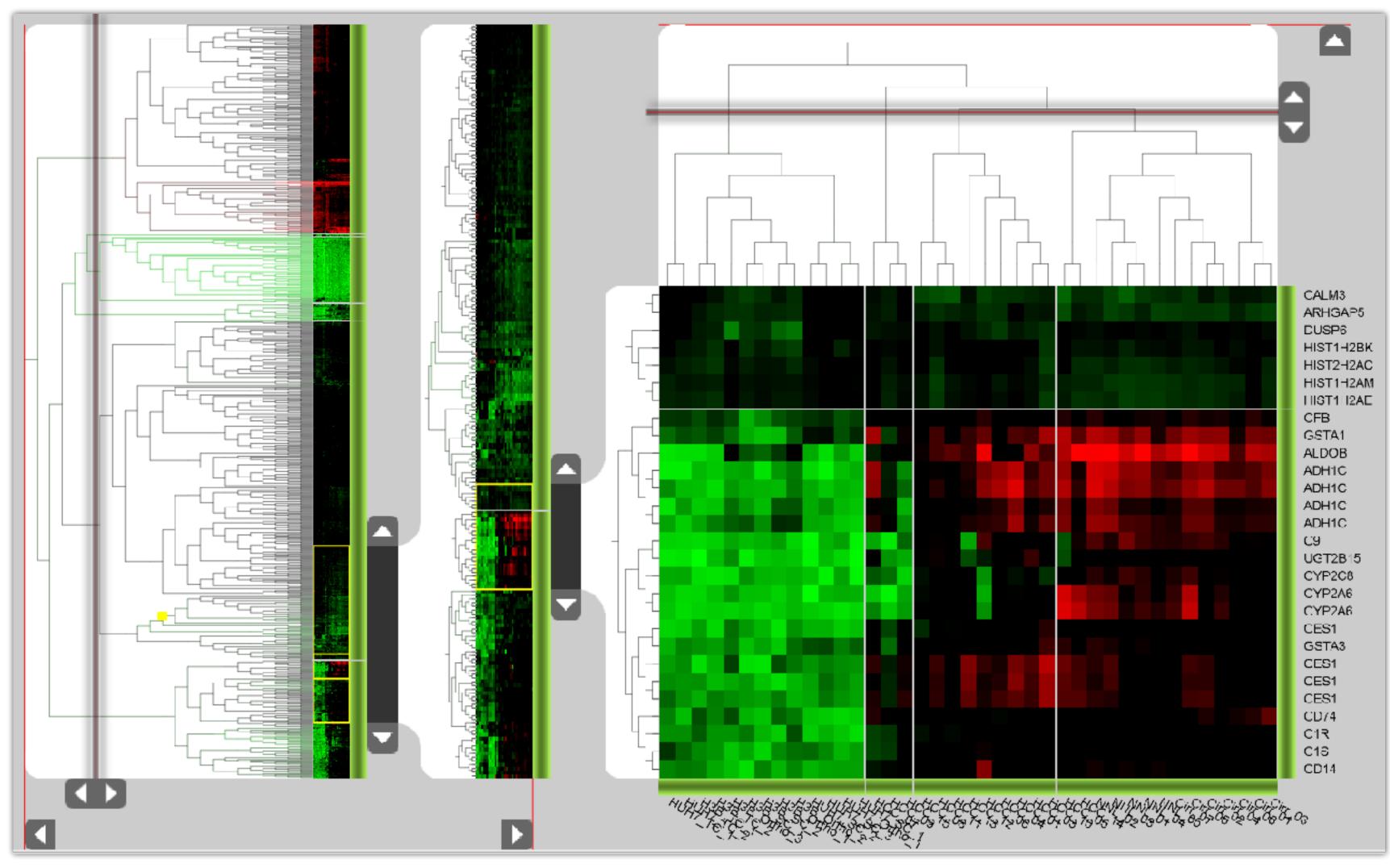
# Linkage Criteria

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

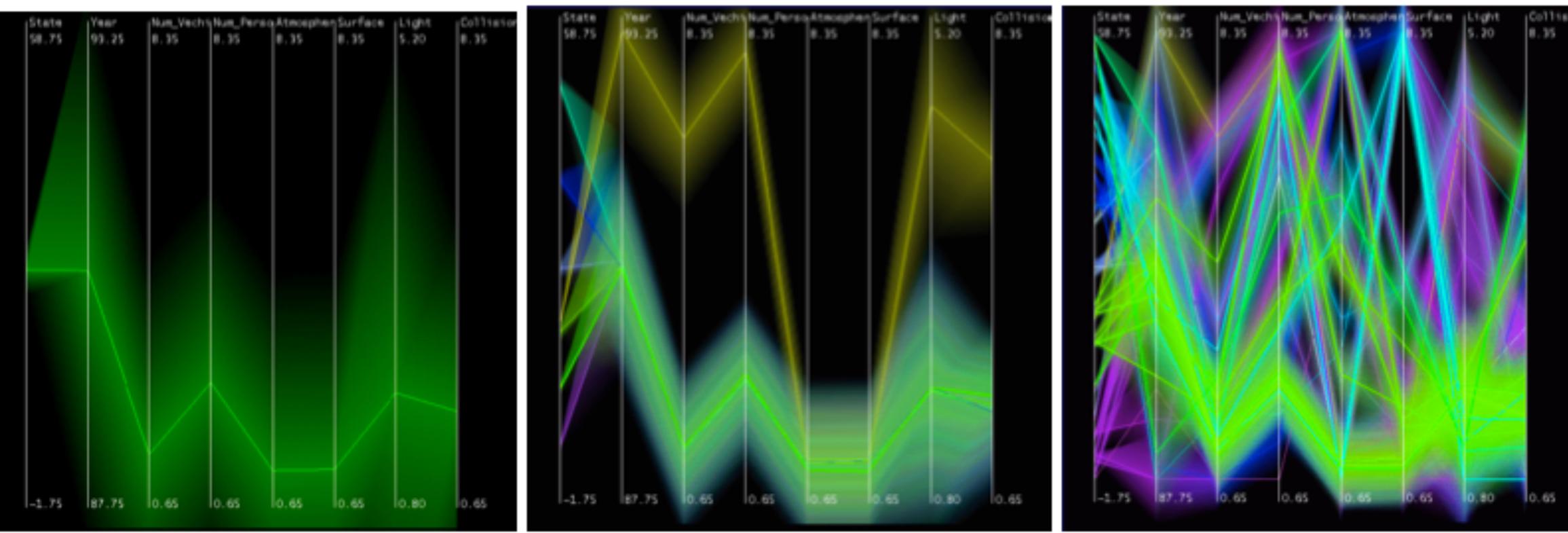
- use maximum linkage distance
- use minimum linkage distance
- use average linkage distance
- use centroid distance

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

### F+C Approach, with Dendrograms



#### **Hierarchical Parallel Coordinates**



Fua 1999

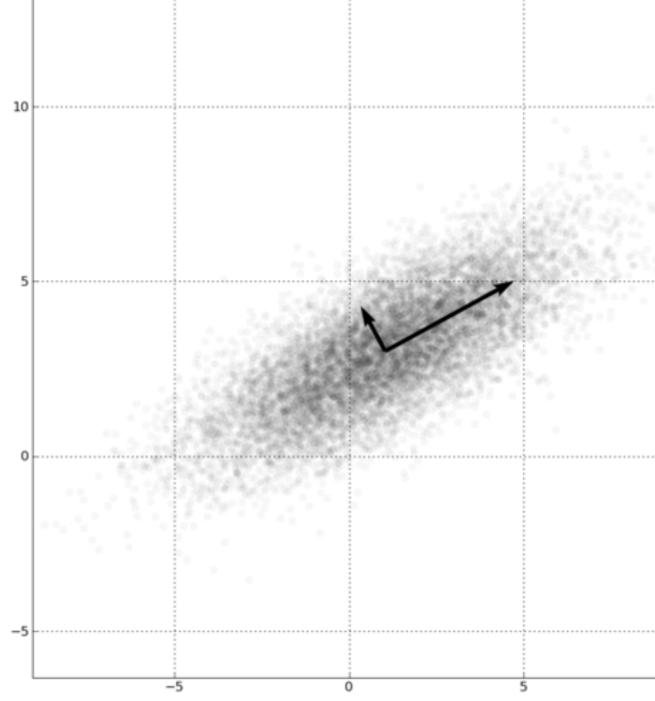


# Attribute aggregation

- 1) group attributes and compute a similarity score across the set
- 2) dimensionality reduction, to preserve meaningful structure

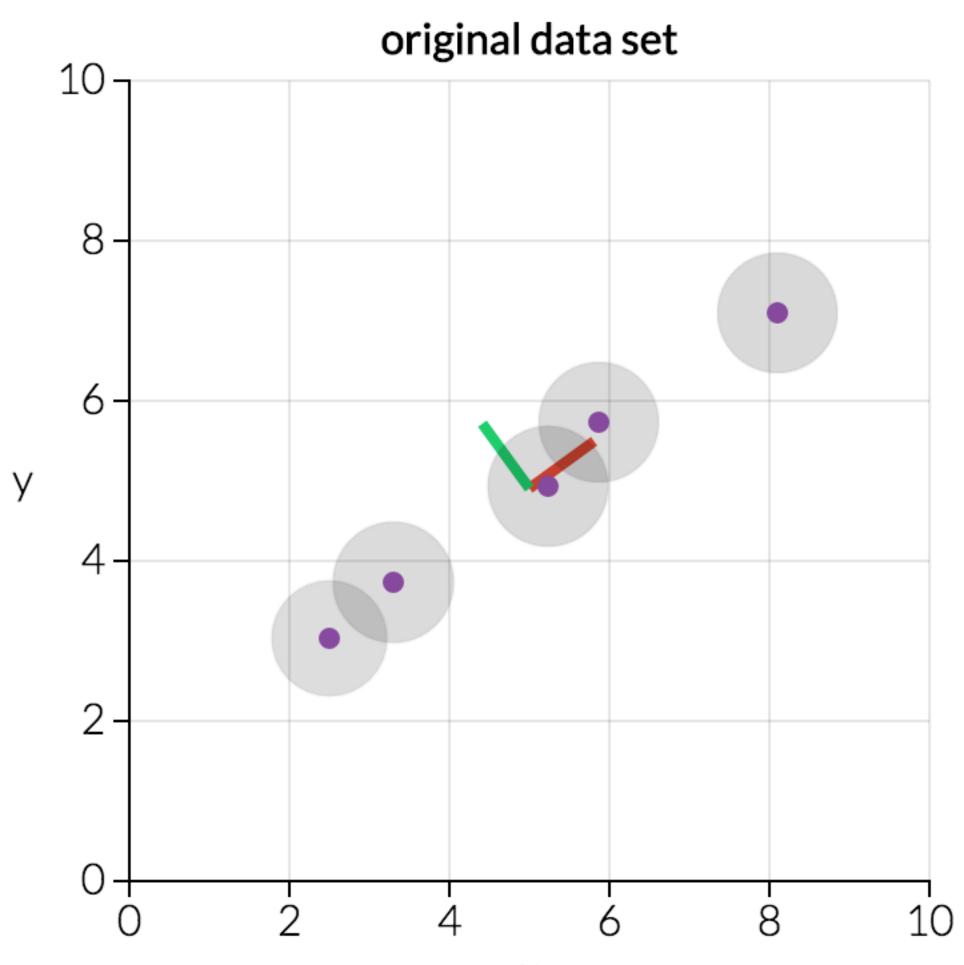
## **Dimensionality Reduction**

- 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

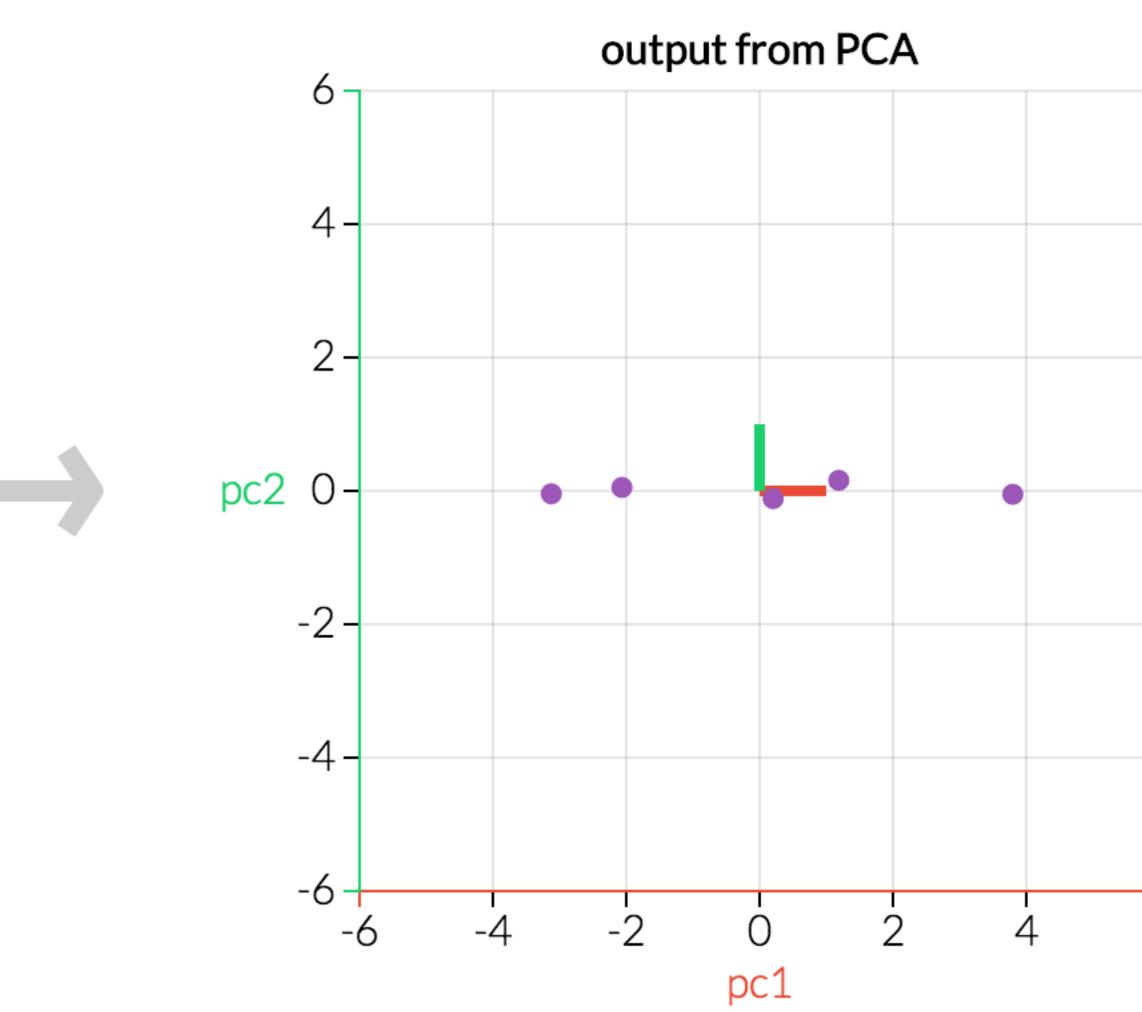






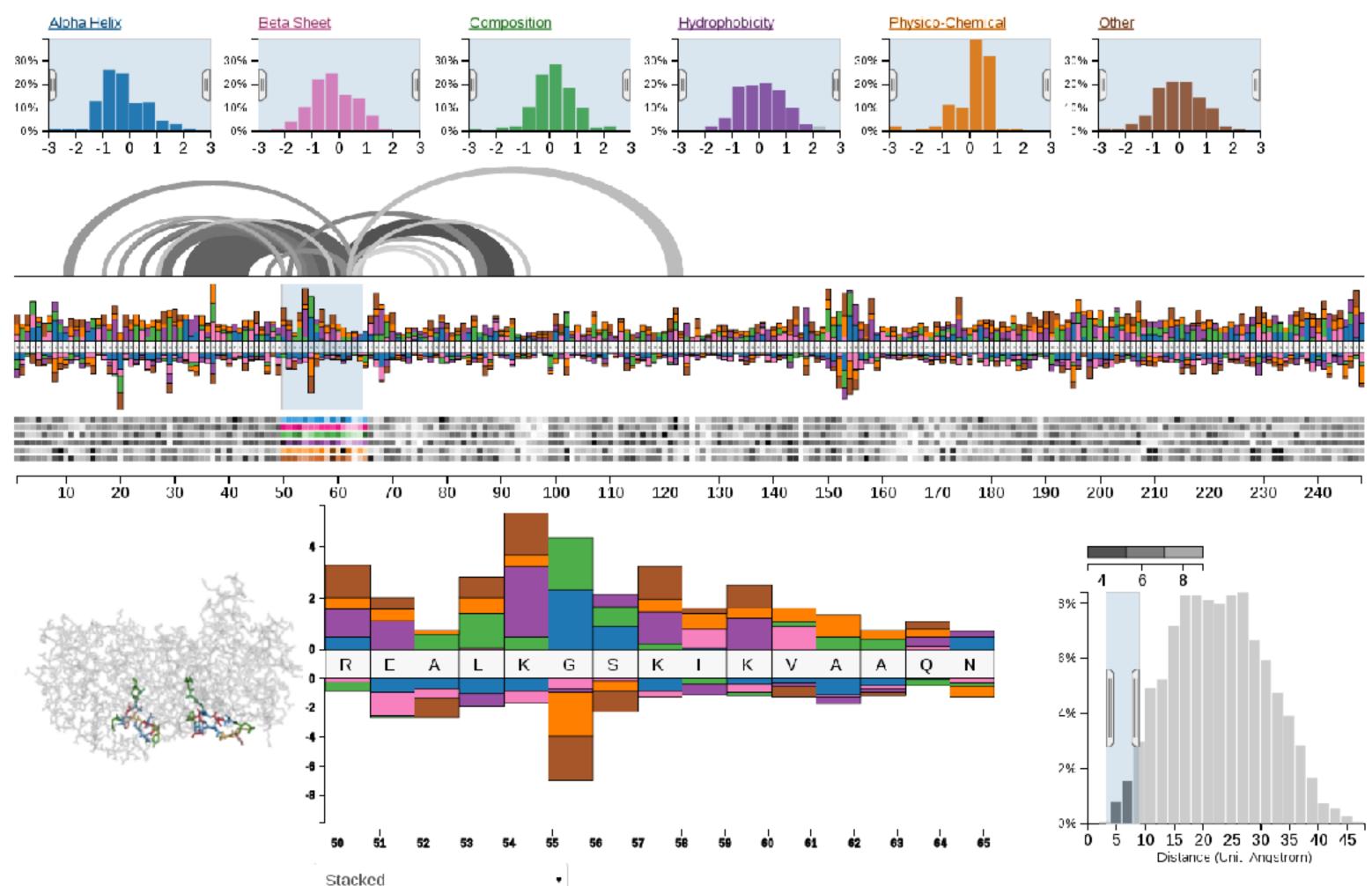


Х





#### PCA Example – Class Project 2013



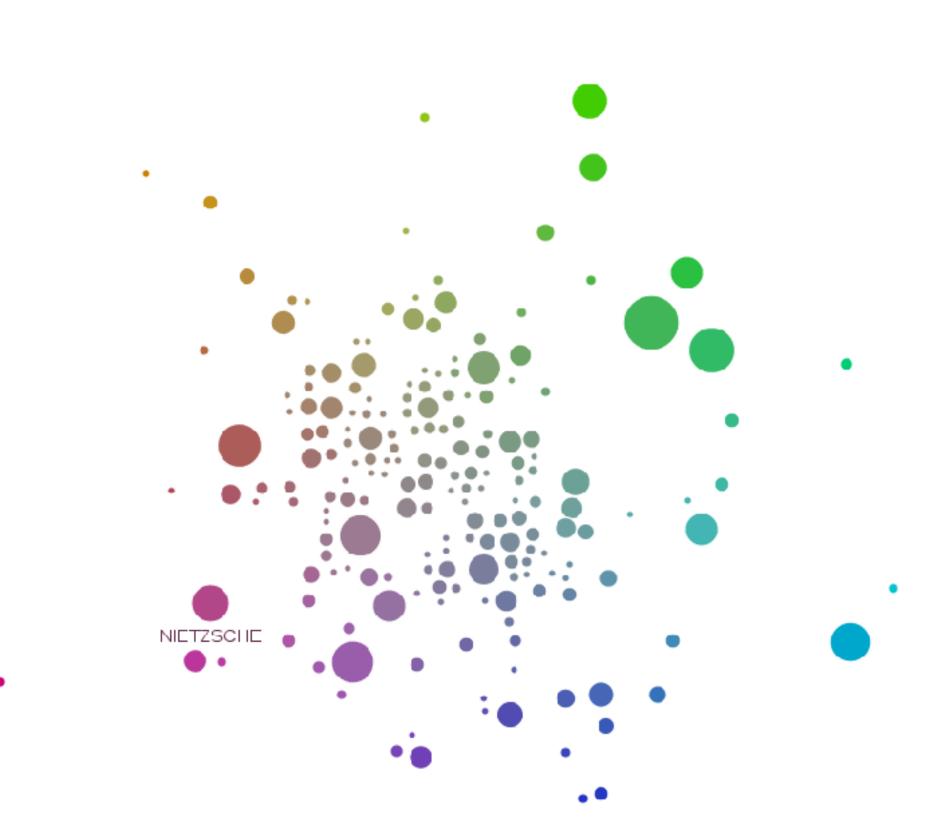
#### http://mu-8.com/

#### [Mercer & Pandian]

## **Multidimensional Scaling**

- Nonlinear, better suited for some DS
- Multiple approaches
- Works based on projecting a similarity matrix
  - How do you compute similarity?
  - How do you project the points?
- Popular for text analysis

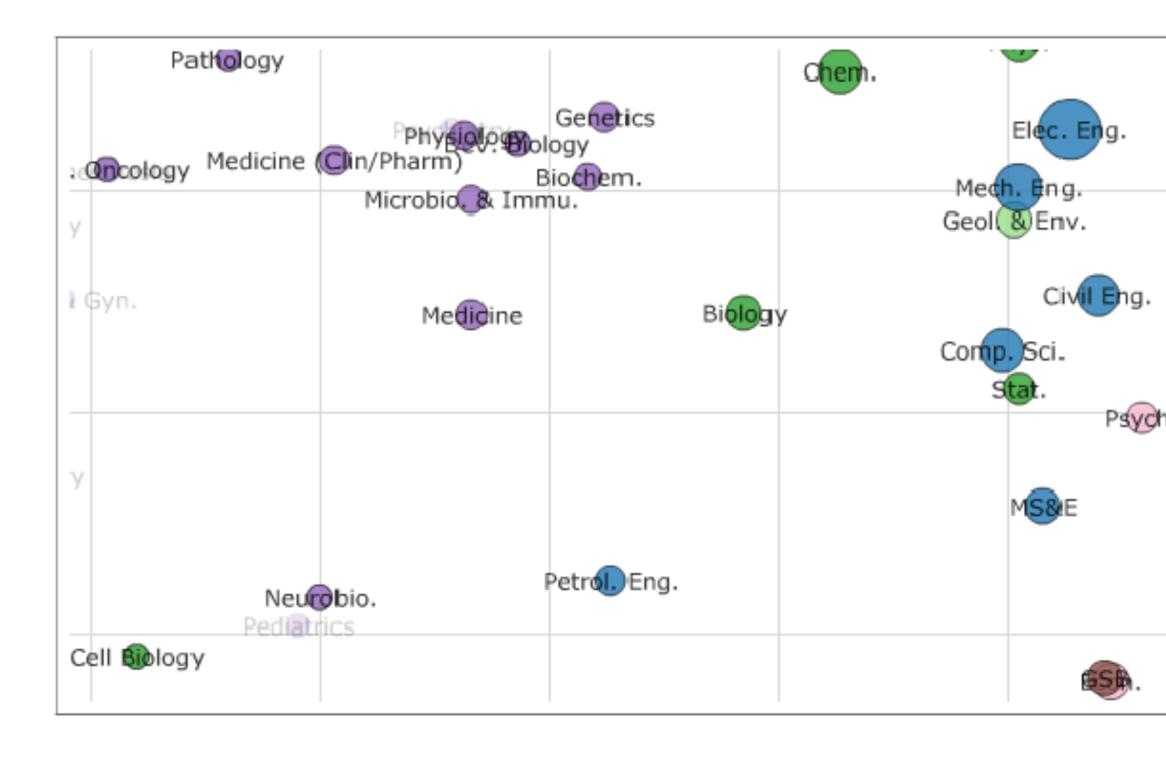




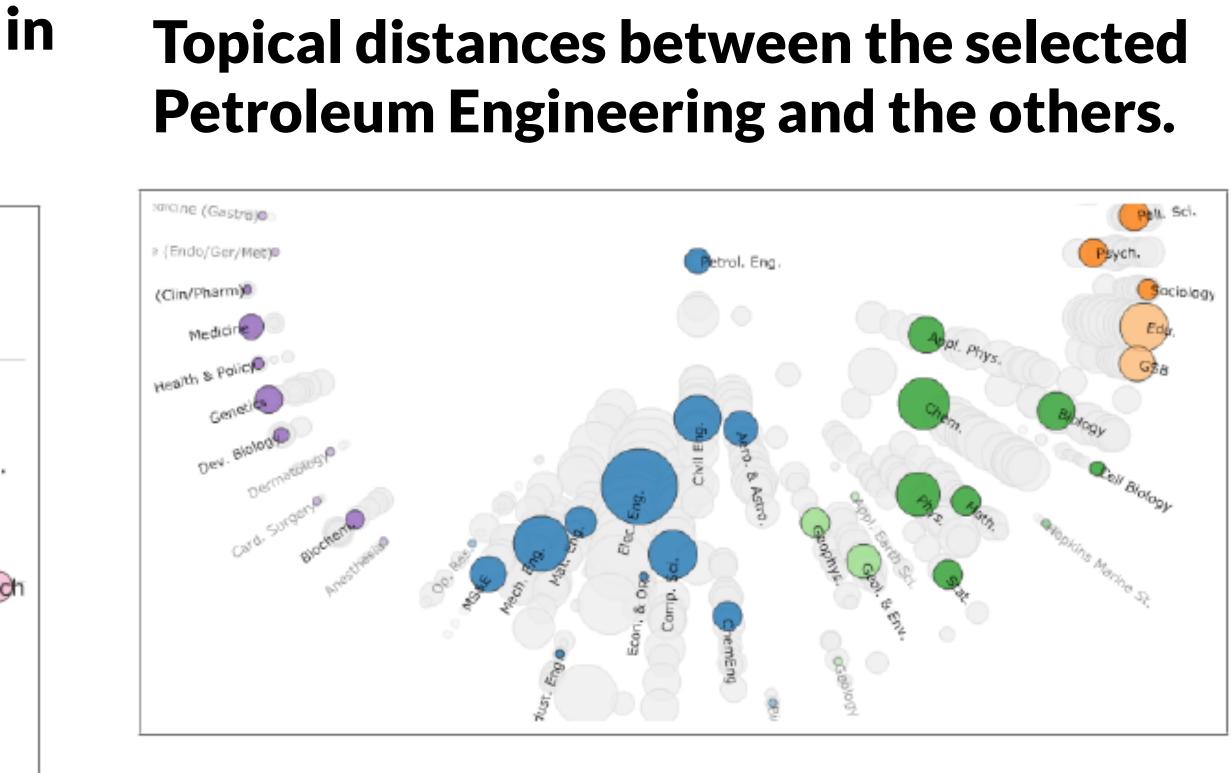
[Doerk 2011]

#### **Can we Trust Dimensionality Reduction?**

#### **Topical distances between departments in** a 2D projection



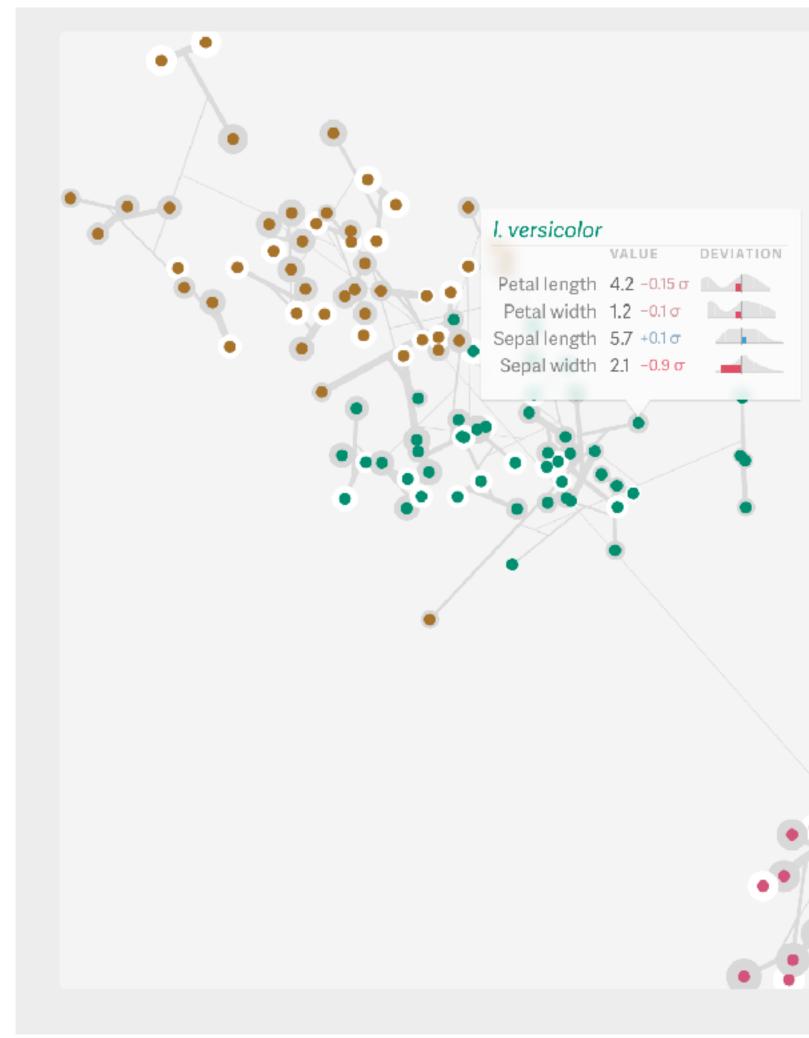
#### http://www-nlp.stanford.edu/projects/dissertations/browser.html



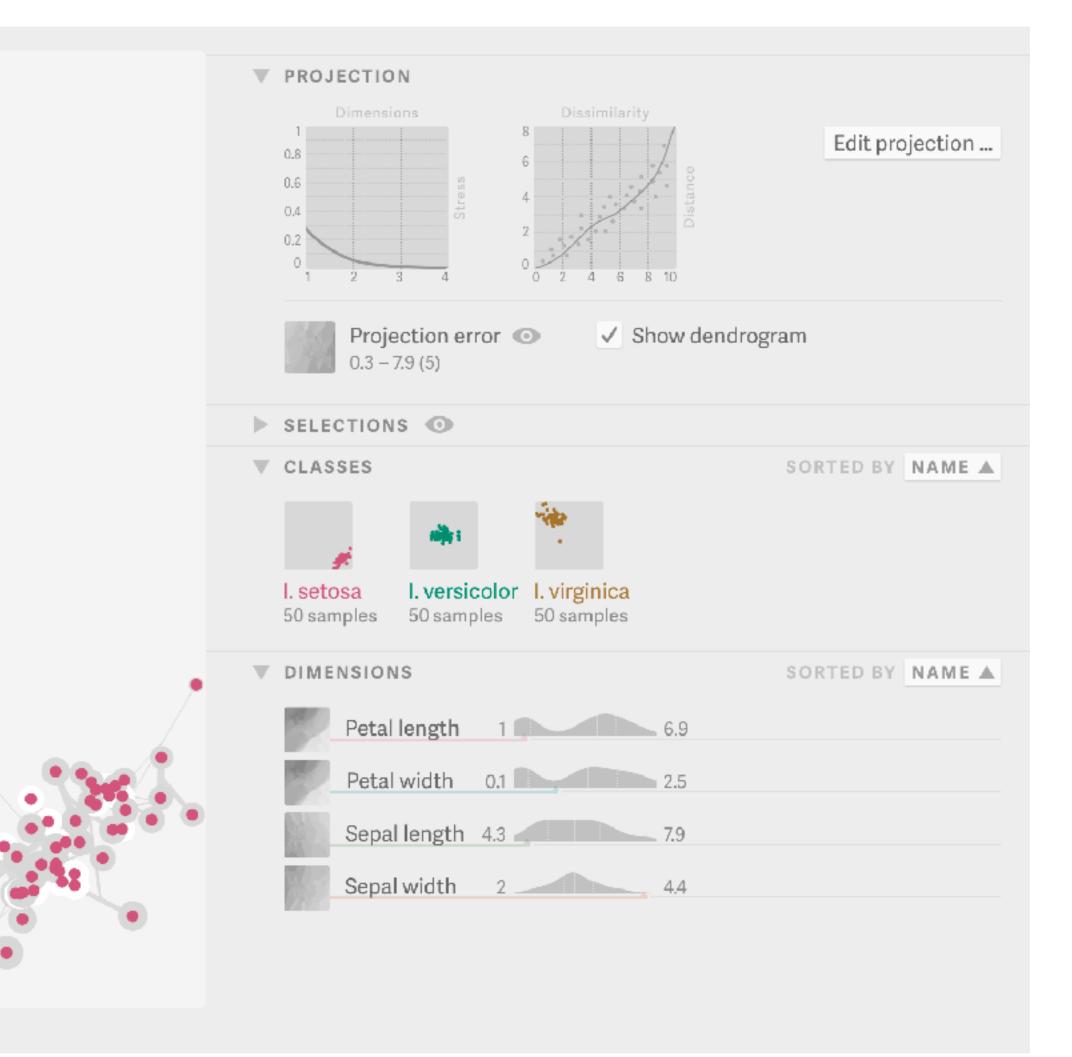
#### [Chuang et al., 2012]



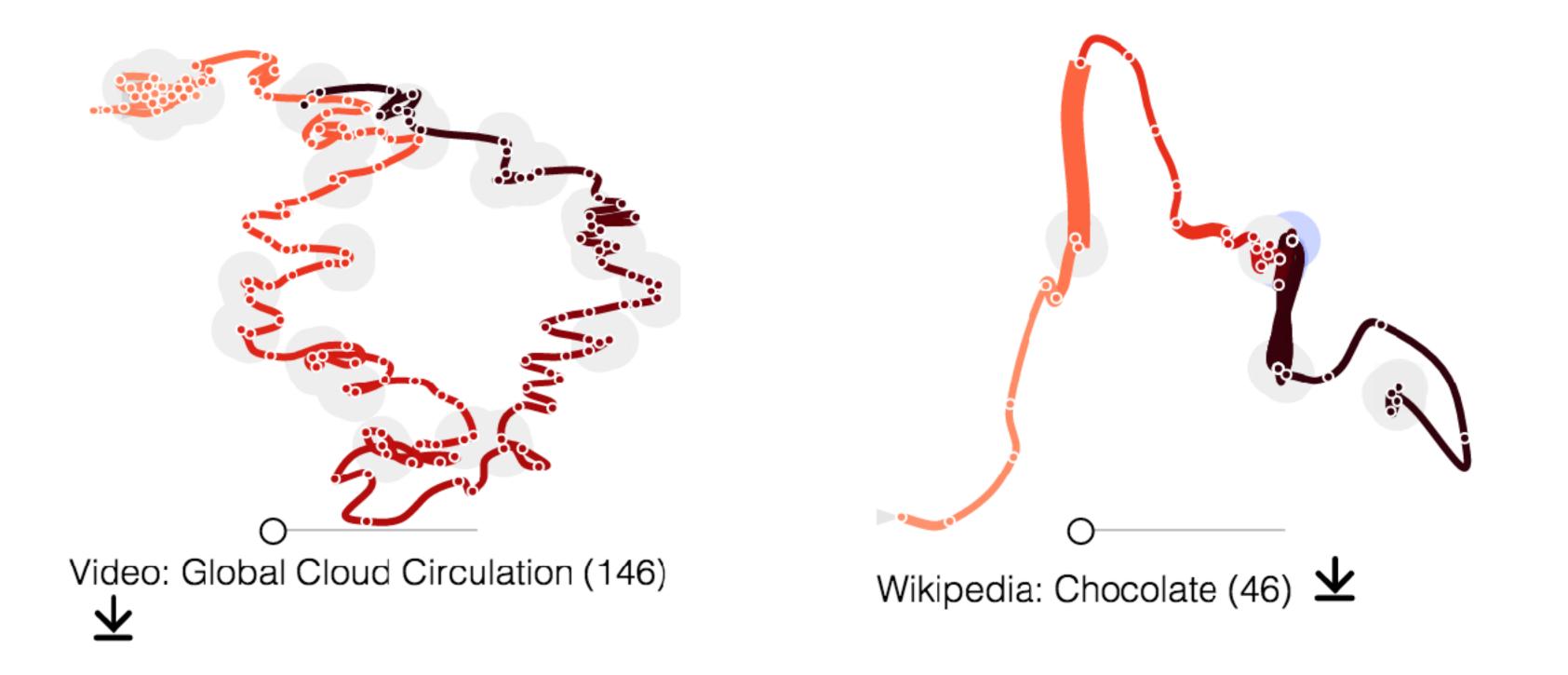
# **Probing Projections**



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



#### **MDS for Temporal Data:** TimeCurves



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



