Data Visualization (CSCI 627/490)

Aggregation & Focus+Context

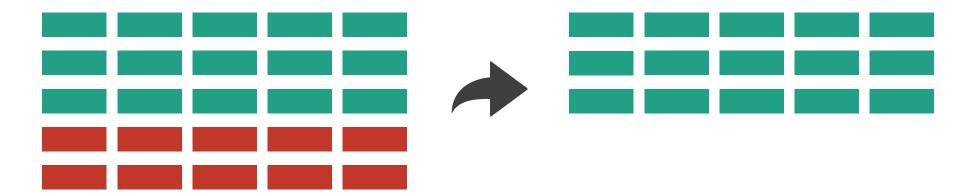
Dr. David Koop



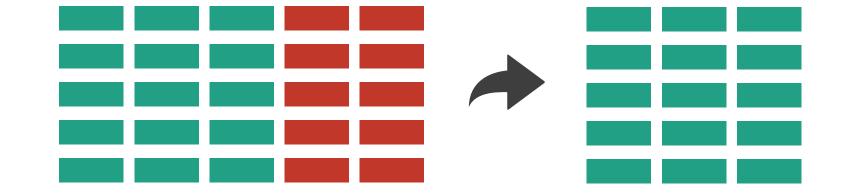
Overview: Reducing Items & Attributes

→ Filter



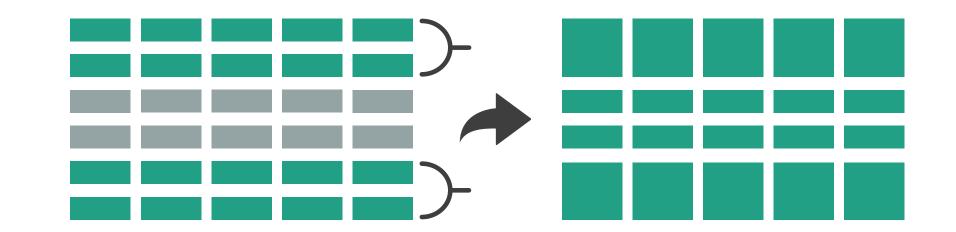


→ Attributes

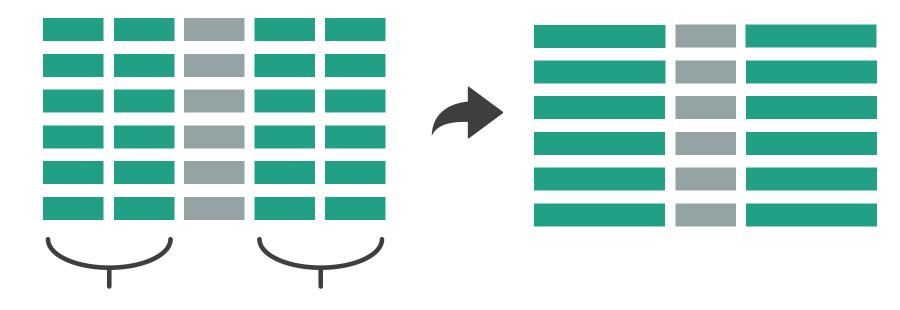


Aggregate

→ Items



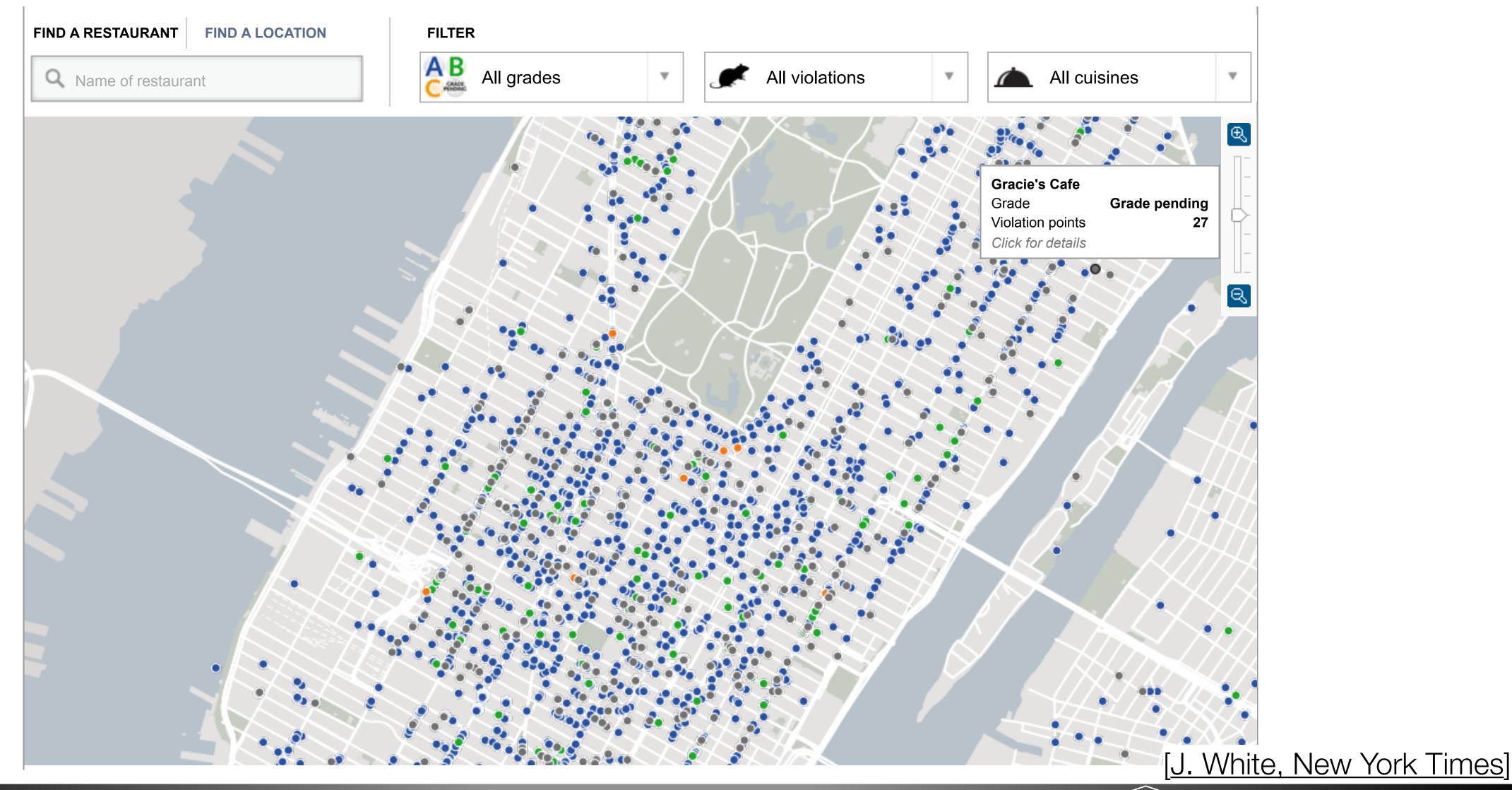
→ Attributes



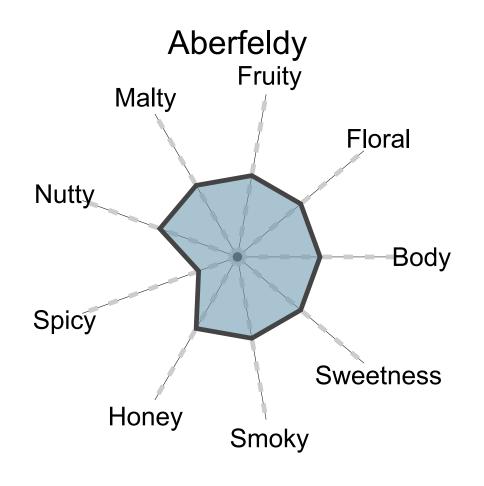
[Munzner (ill. Maguire), 2014]

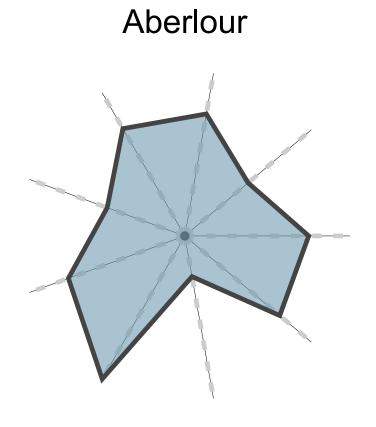


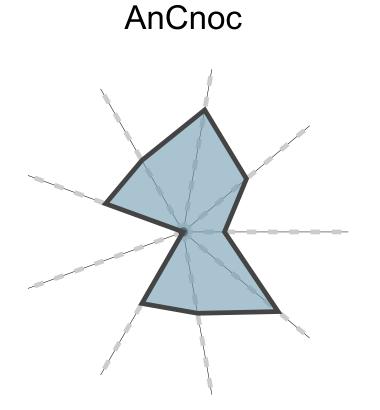
Item Filtering on Maps

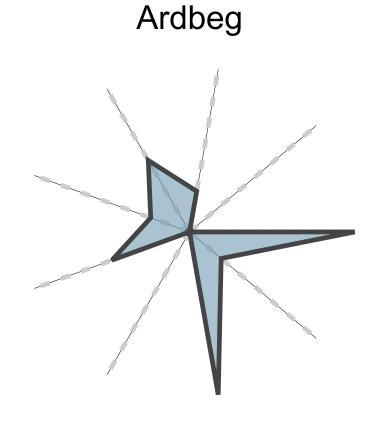


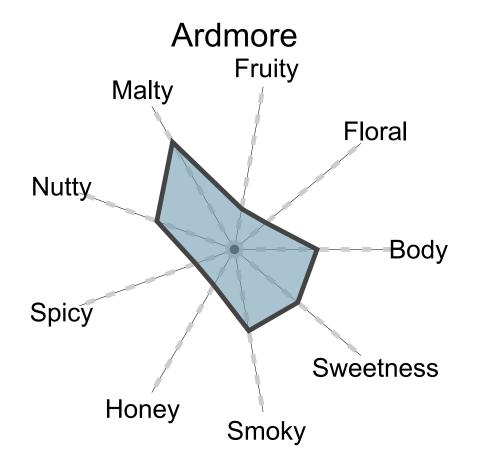
Star Plots (aka Radar Charts)

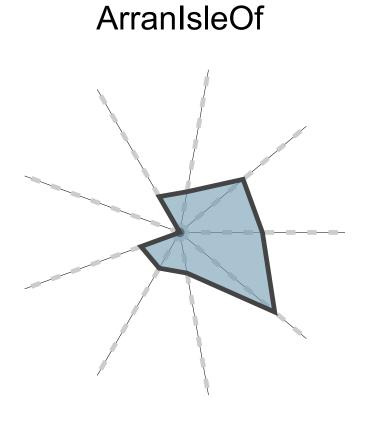


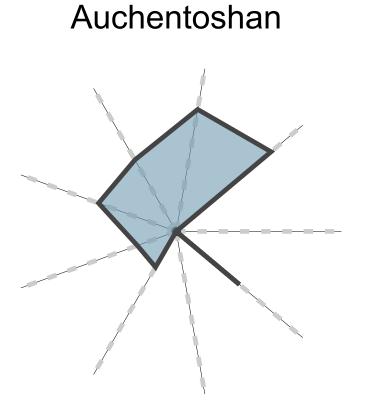


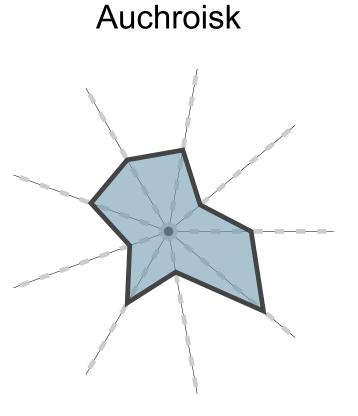






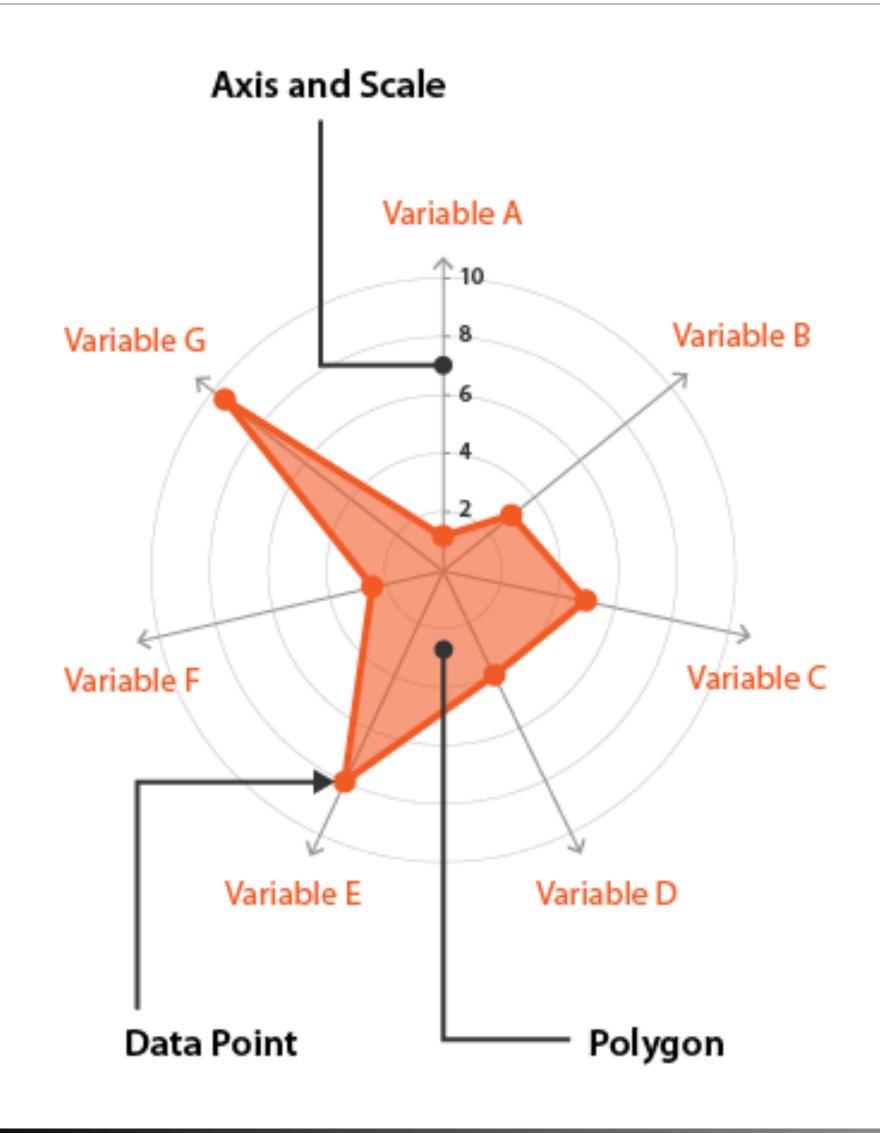






[K. Schaul]

Star Plot / Radar Chart

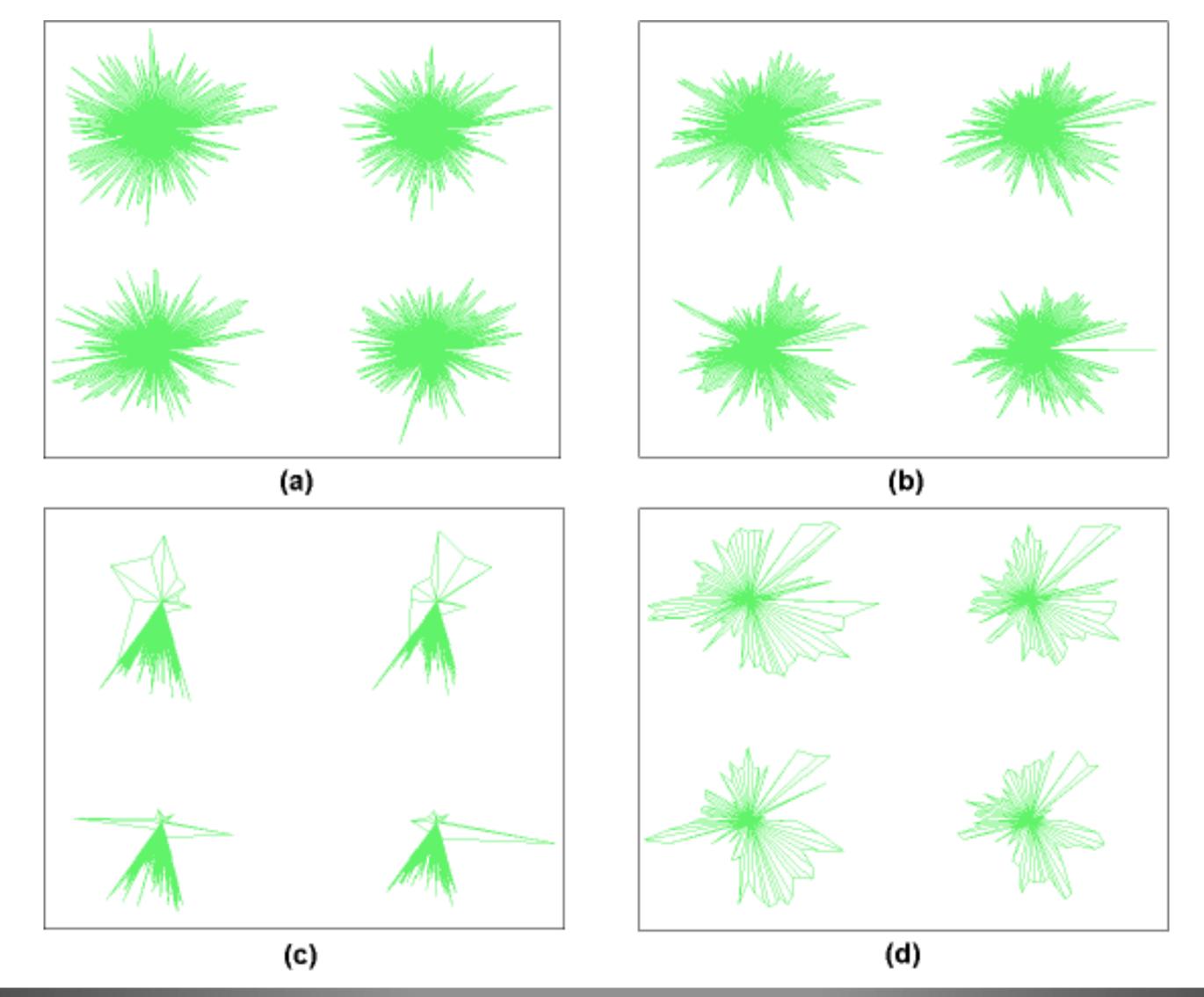


• Use:

- Compare variables
- Similarities/differences of items
- Locate outliers
- Considerations:
 - Order of axes
 - Too many axes cause problems

[S. Ribecca]

Attribute Filtering on Star Plots



[Yang et al., 2003]

Attribute Filtering

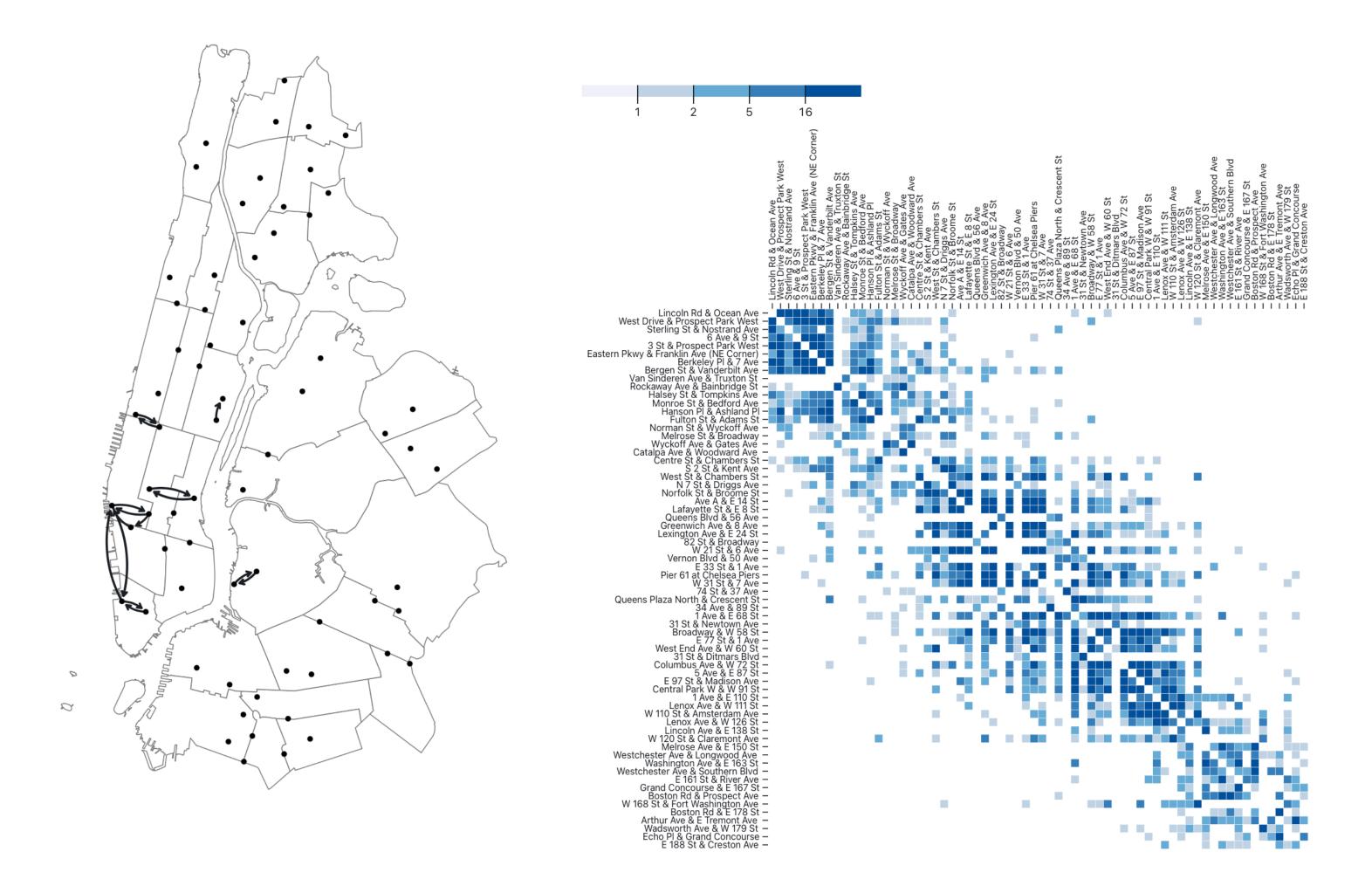
- How to choose which attributes should be filtered?
 - User selection?
 - Statistics: similarity measures, attributes with low variance are not as interesting when comparing items
- Can be combined with item filtering

Project Design

- Think about:
 - Data Manipulation?
 - Questions lead, not technique!
 - Be creative! (interaction too) https://xeno.graphics
- Work on turning your visualization ideas into designs
- Turn in:
 - Three Design Sketches (like sheets 2-4 from 5 Sheet Design)
 - One Bad Design Sketch (like sheets 2-4: here, justify why bad)
 - Progress on Implementation
- Due Friday

Assignment 5

- Create Multiple Views
- Filtering
- Linked Highlighting
- Aggregation



Aggregation

Aggregation

- Usually involves derived attributes
- Examples: mean, median, mode, min, max, count, sum
- Remember expressiveness principle: still want to avoid implying trends or similarities based on aggregation

				III		IV	
X	У	X	У	X	У	X	У
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

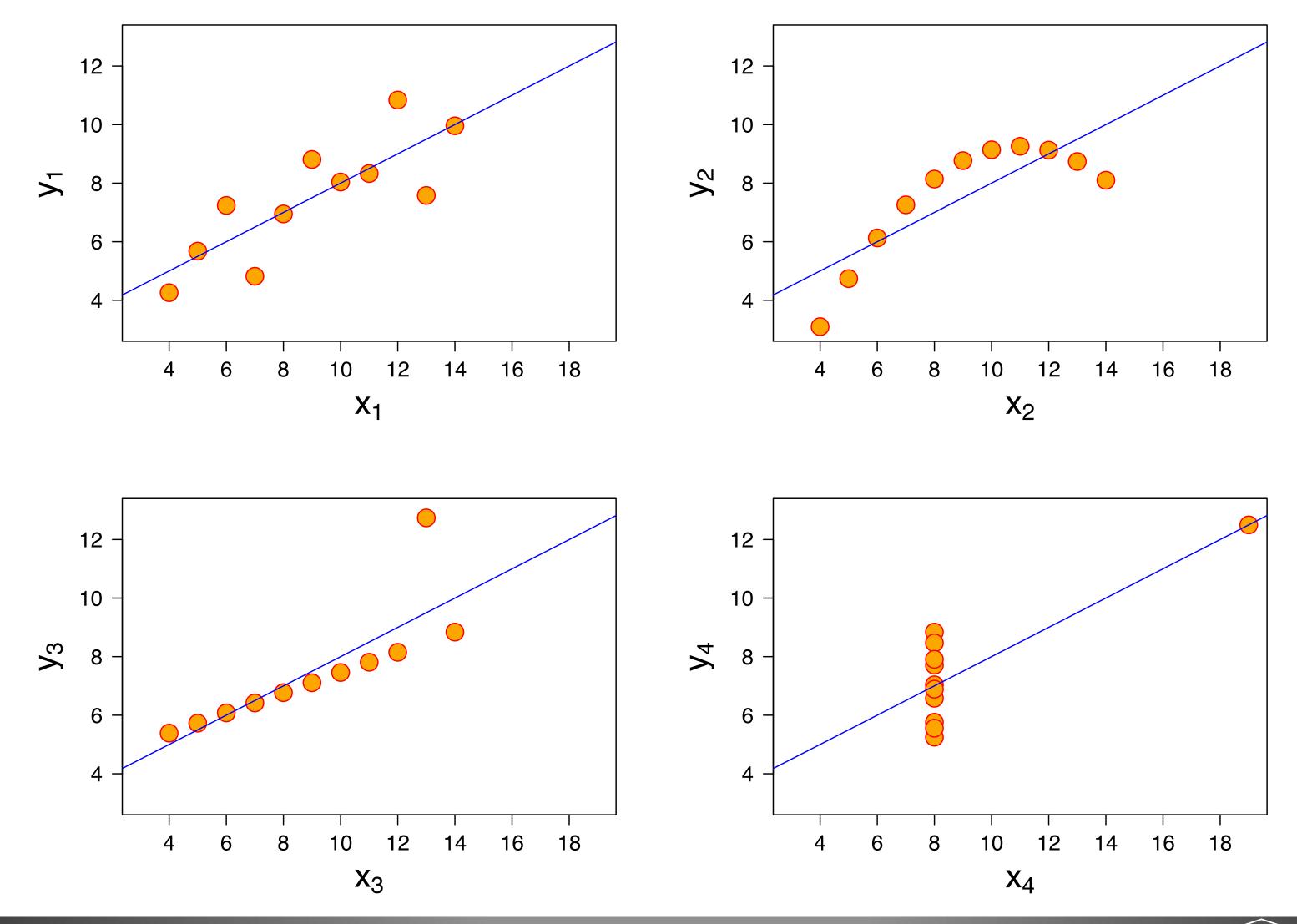
Aggregation

- Usually involves derived attributes
- Examples: mean, median, mode, min, max, count, sum
- Remember expressiveness principle: still want to avoid implying trends or similarities based on aggregation

Mean of x	9		
Variance of x	11		
Mean of y	7.50		
Variance of y	4.122		
Correlation	0.816		

				III		IV	
X	У	X	У	X	У	X	У
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
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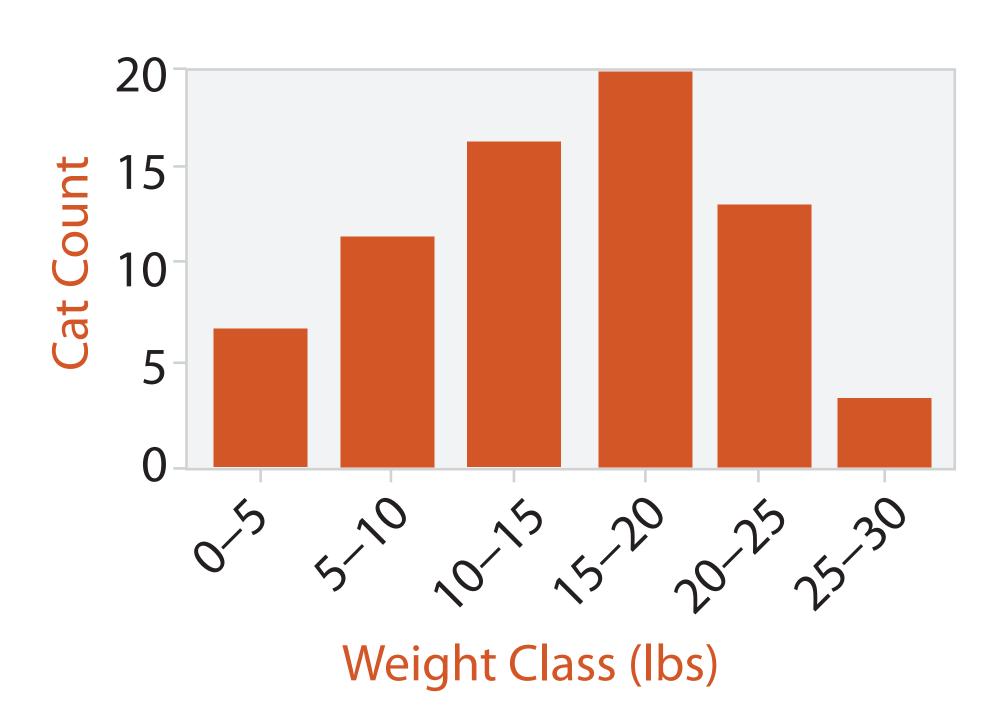
Anscombe's Quartet



[F. J. Anscombe]



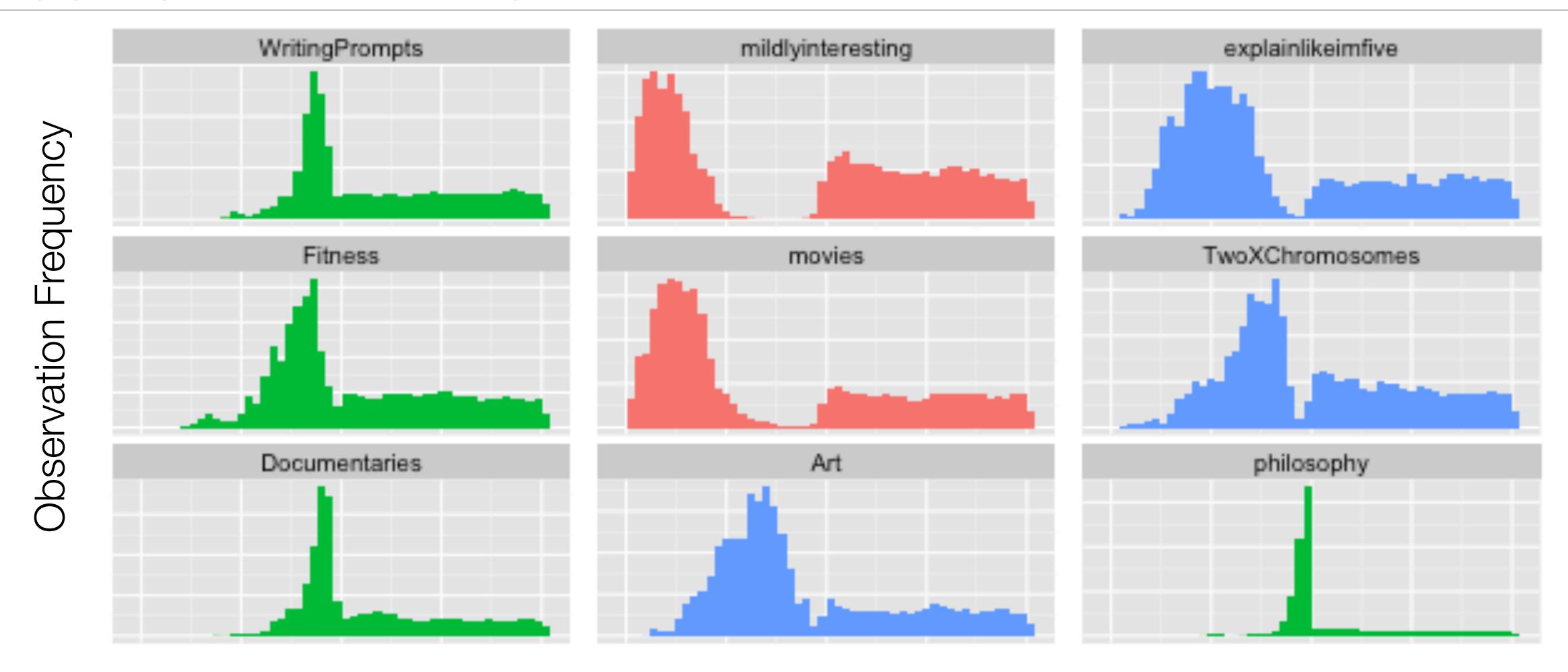
Aggregation: Histograms



- Very similar to bar charts
- Often shown without space between (continuity)
- Choice of number of bins
 - Important!
 - Viewers may infer different trends based on the layout

[Munzner (ill. Maguire), 2014]

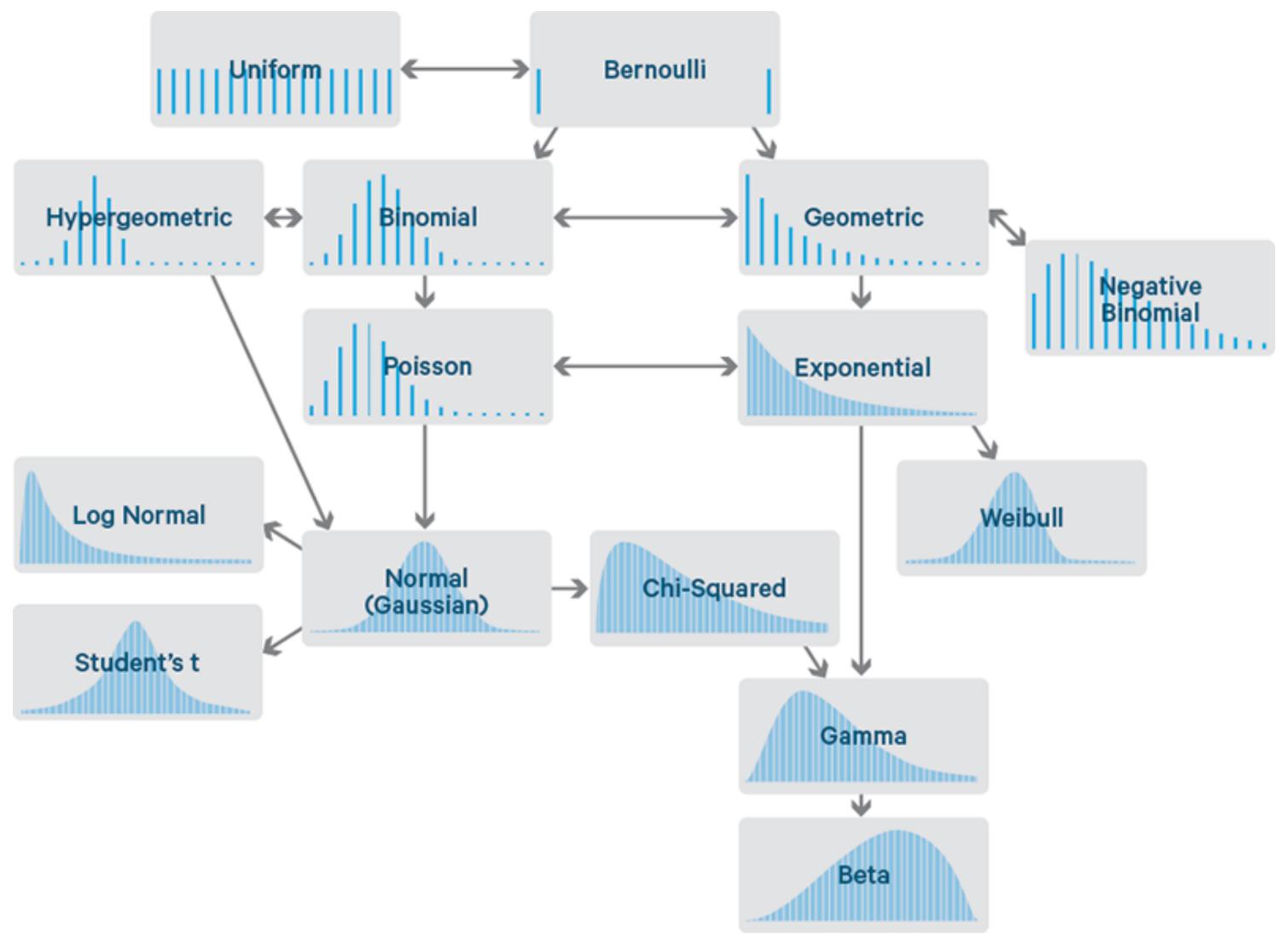
Aggregation: Histograms



Observed ranks of posts by subreddit

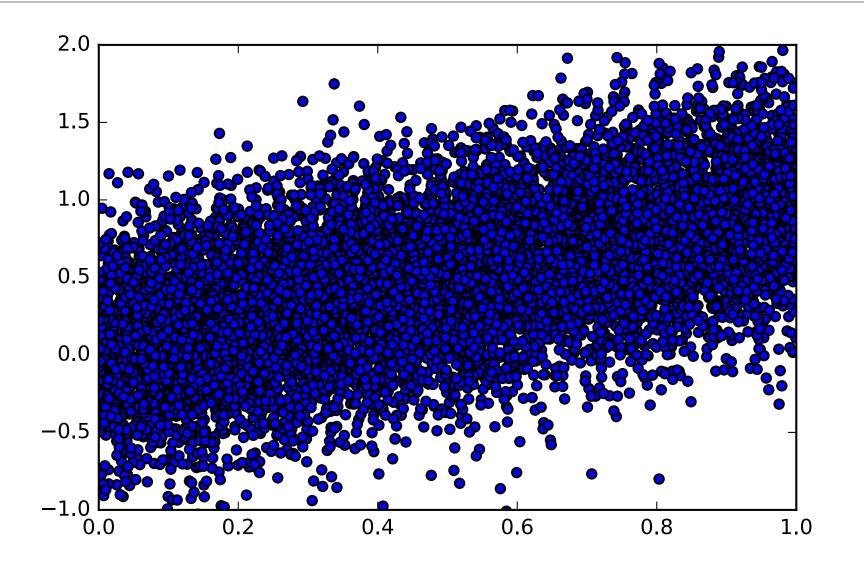
["The reddit Front Page is Not a Meritocracy", T. W. Schneider]

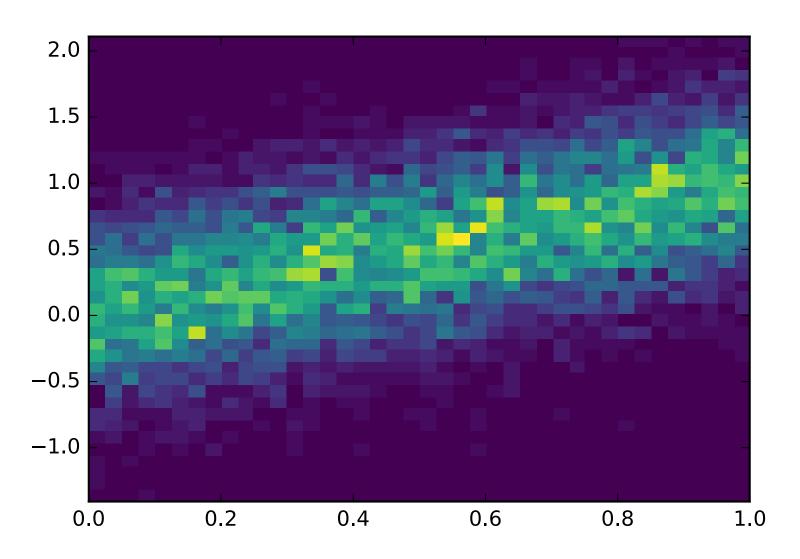
Common Distributions



Binning Scatterplots

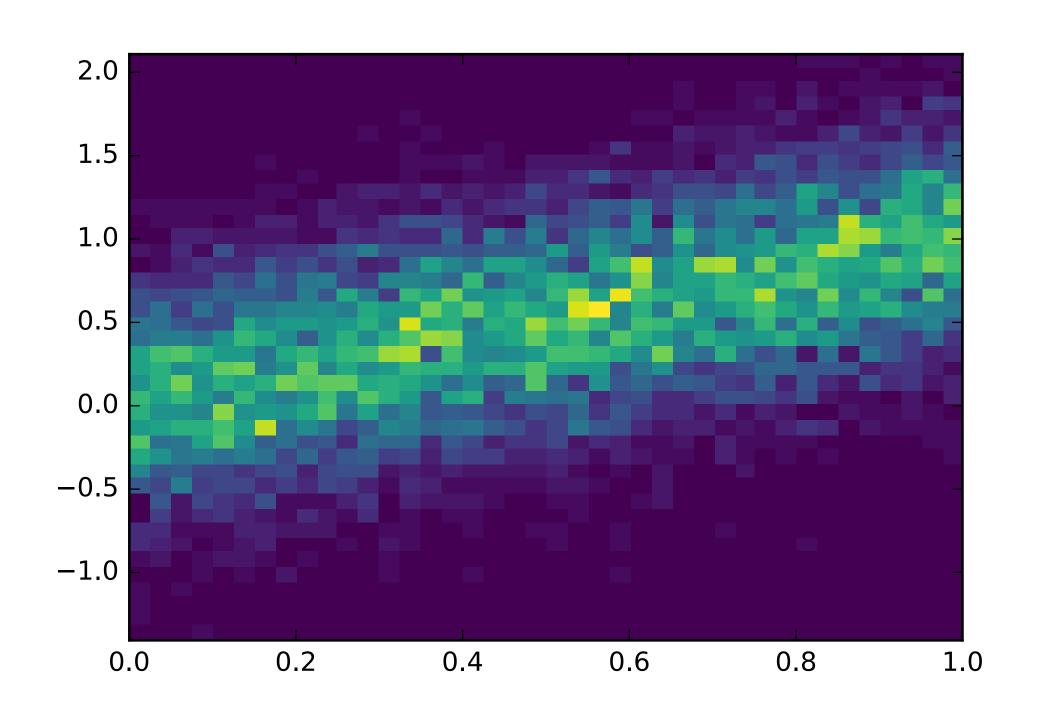
- At some point, cannot see density
- Blobs on top of blobs
- 2D Histogram is a histogram in 2D encoded using color instead of height
- Each region is aggregated

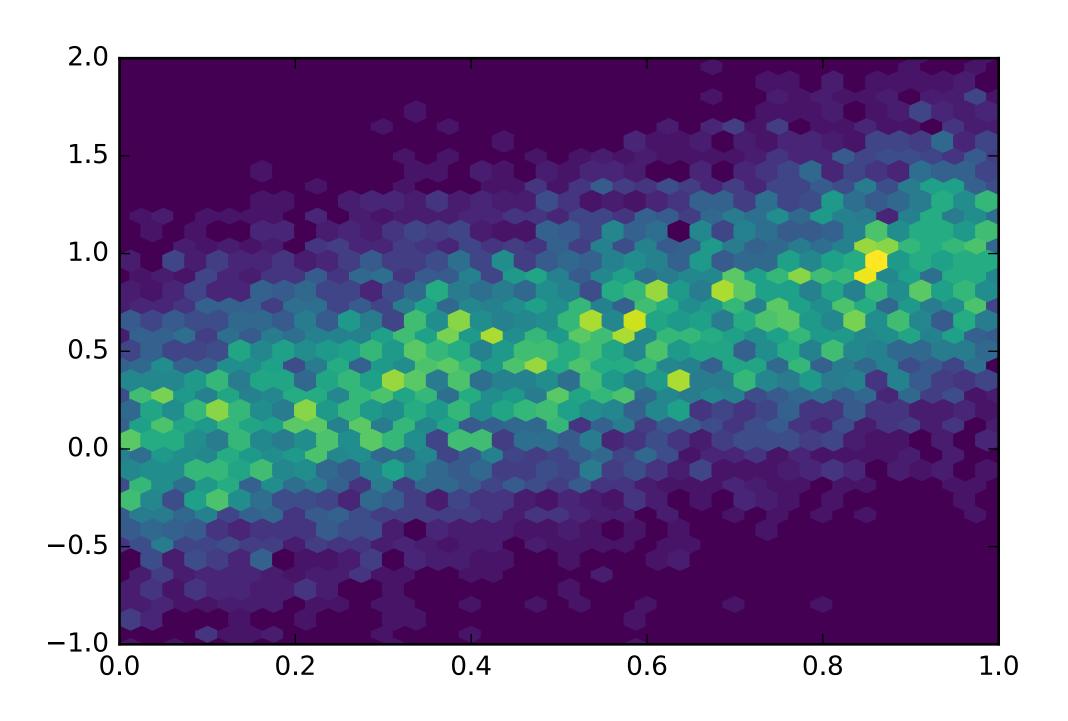




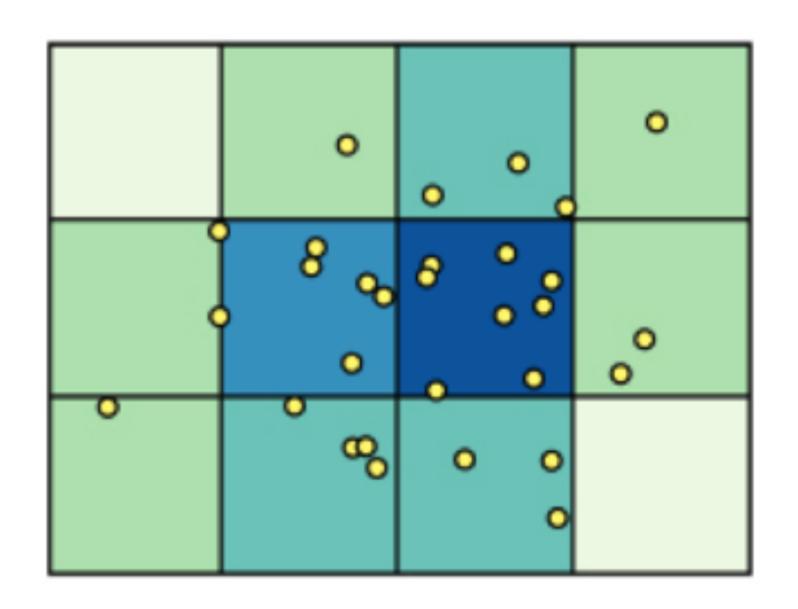
Binning

- Hexagonal bins are more circular
- Distance to the edge is not as variable
- More efficient aggregation around the center of the bin

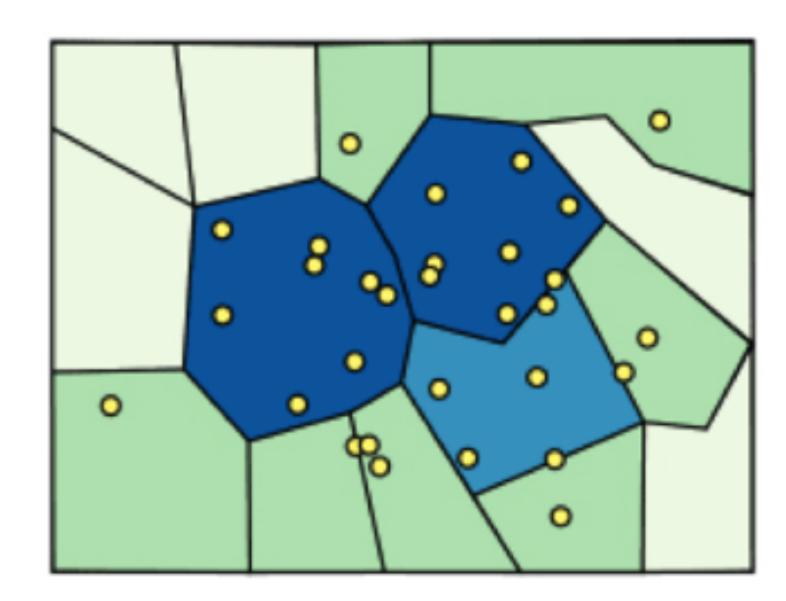




Spatial Aggregation

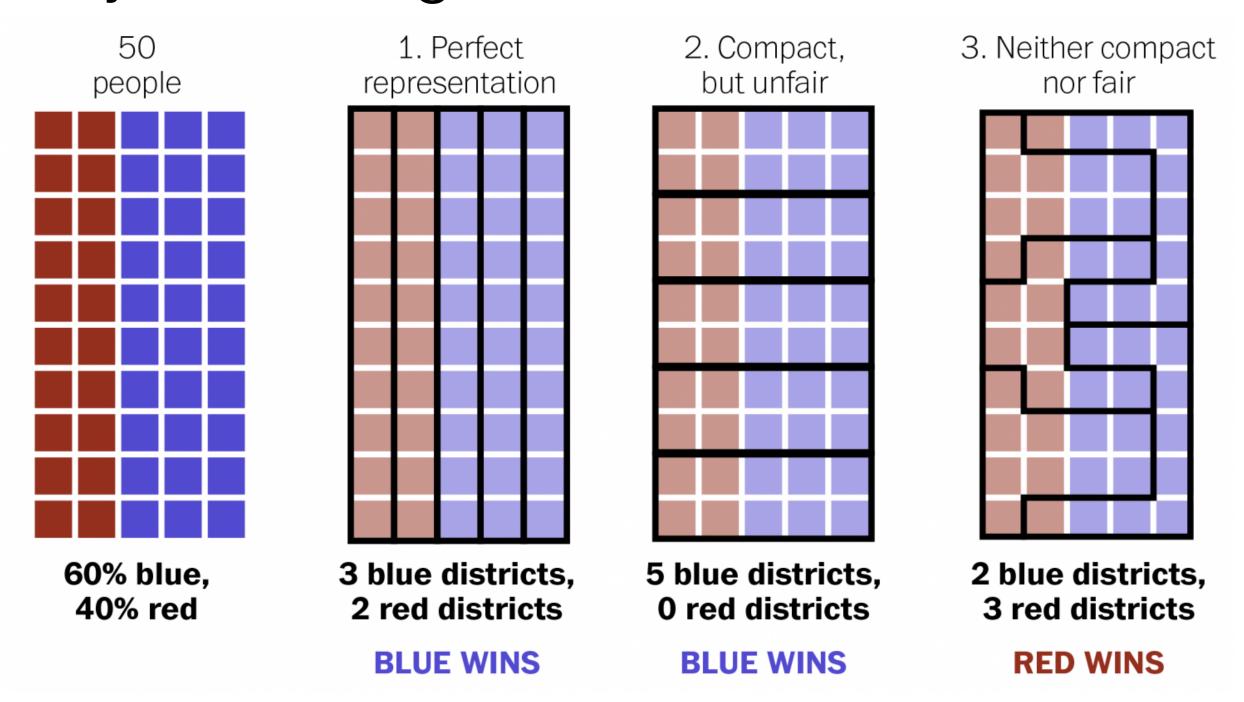


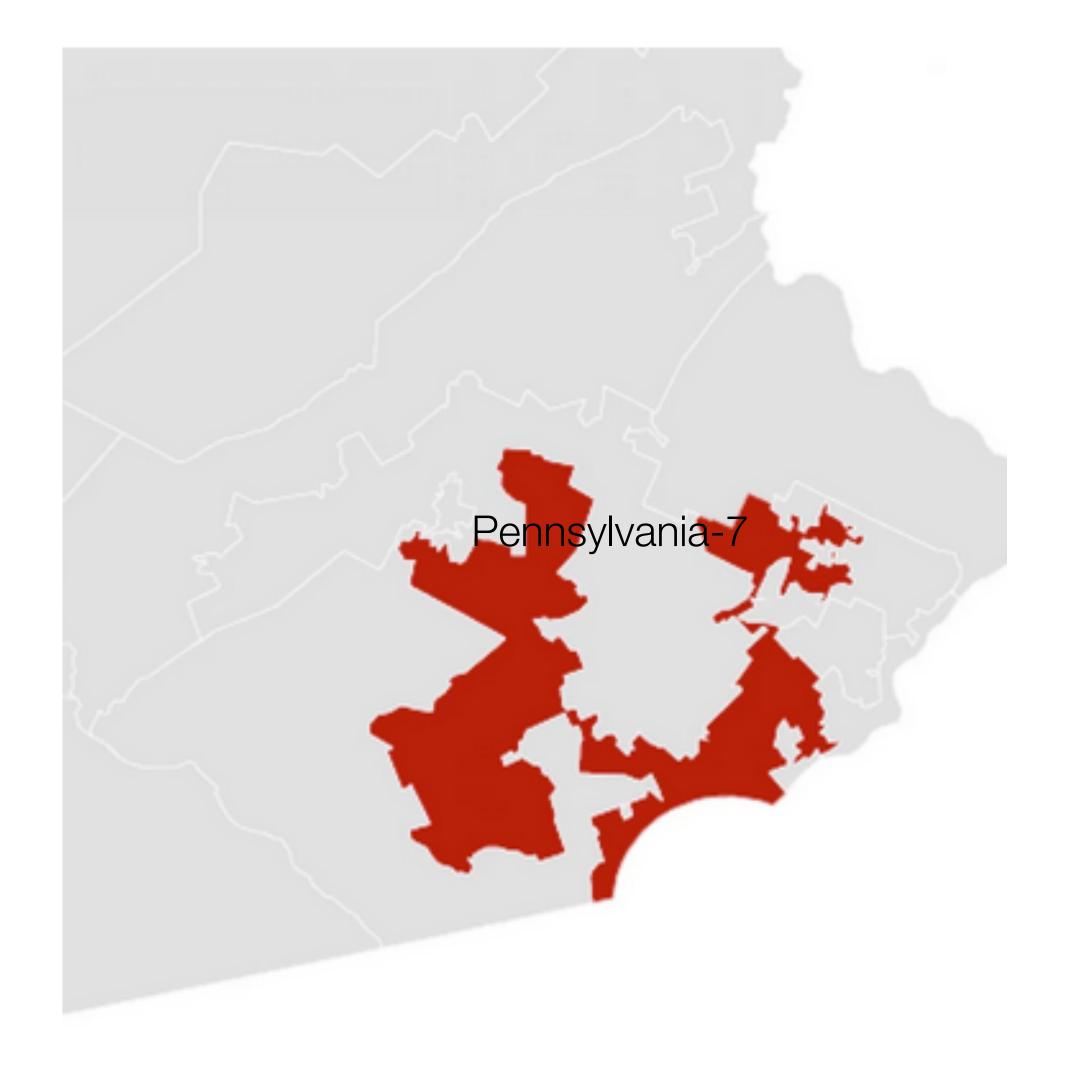




Modifiable Areal Unit Problem

- How you draw boundaries impacts the type of aggregation you get
- Similar to bins in histograms
- Gerrymandering

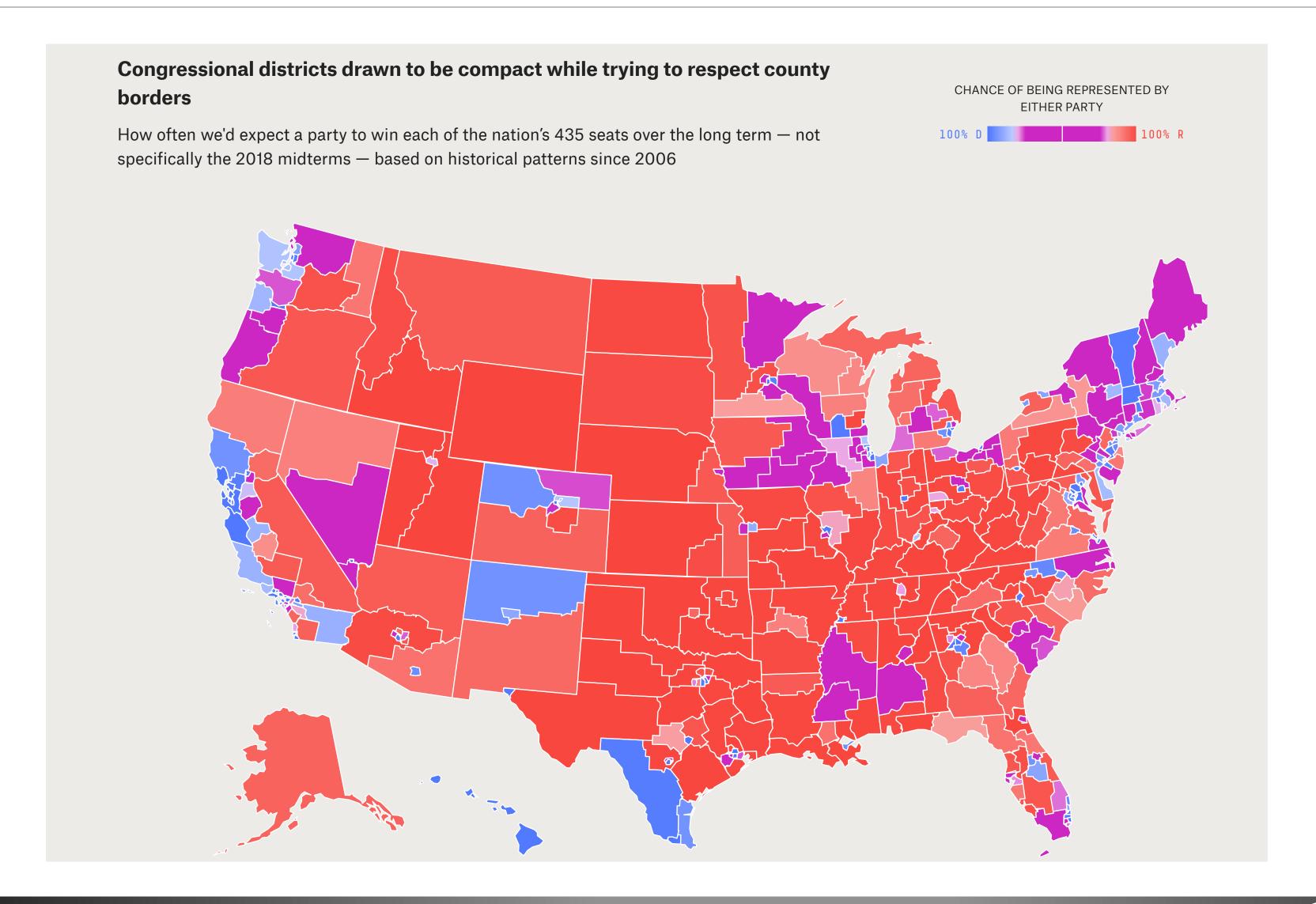




[Wonkblog, Washington Post, Adapted from S. Nass]

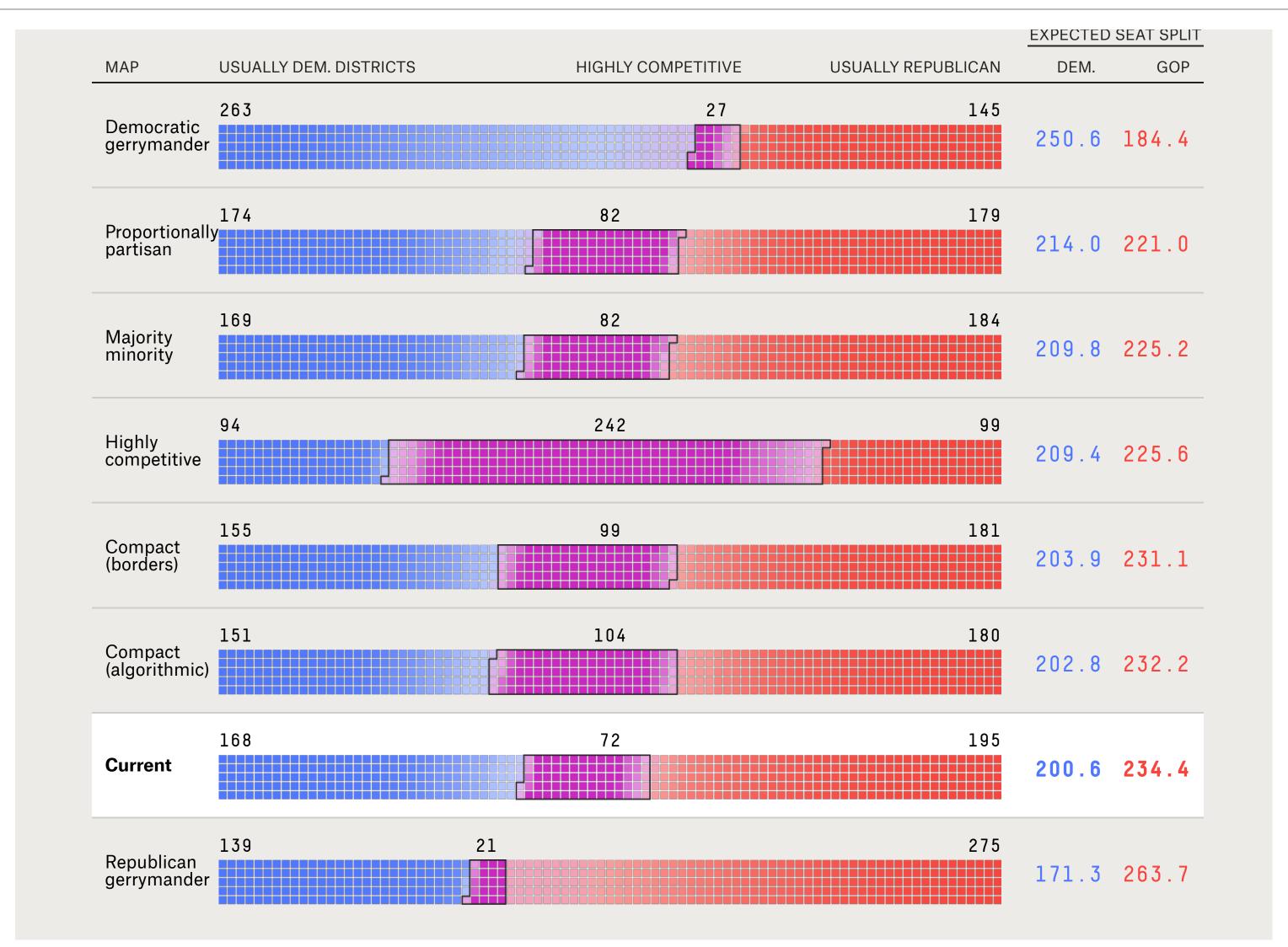


Drawing Different Maps: Compactness



[A. Bycoffe et al., <u>538</u>]

Drawing Different Maps

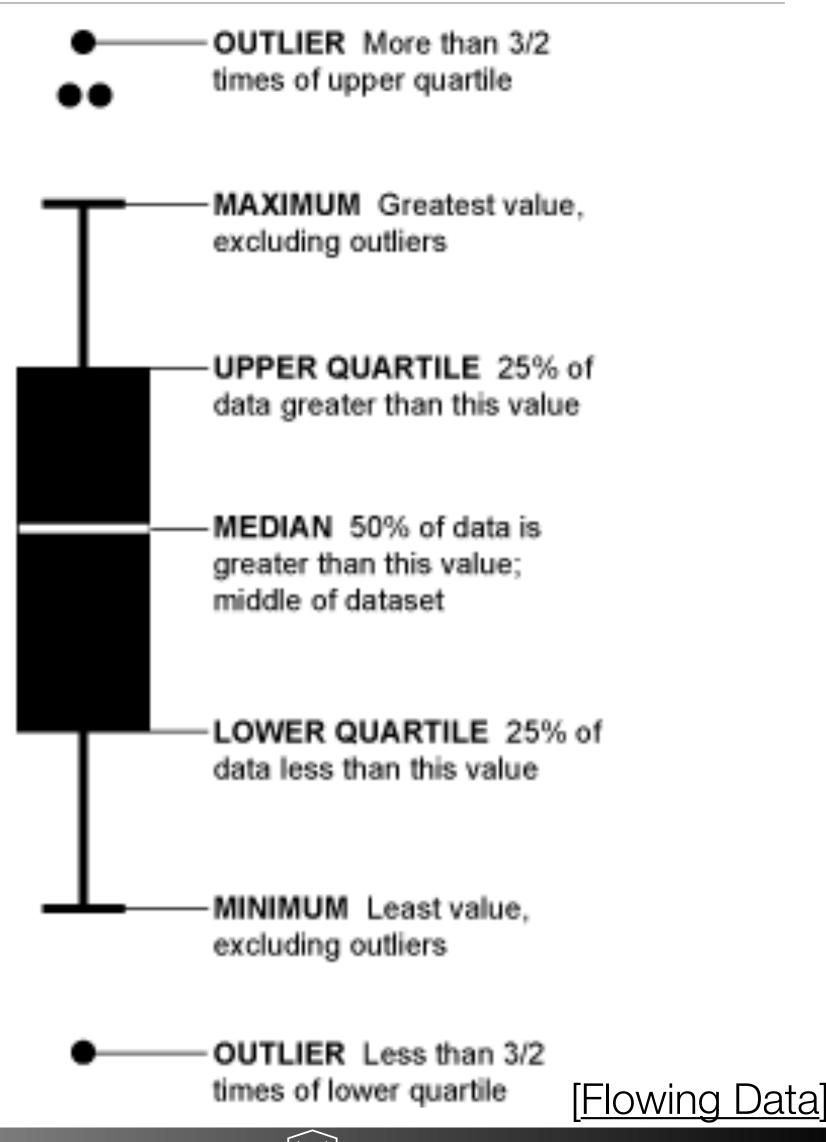


[A. Bycoffe et al., <u>538</u>]

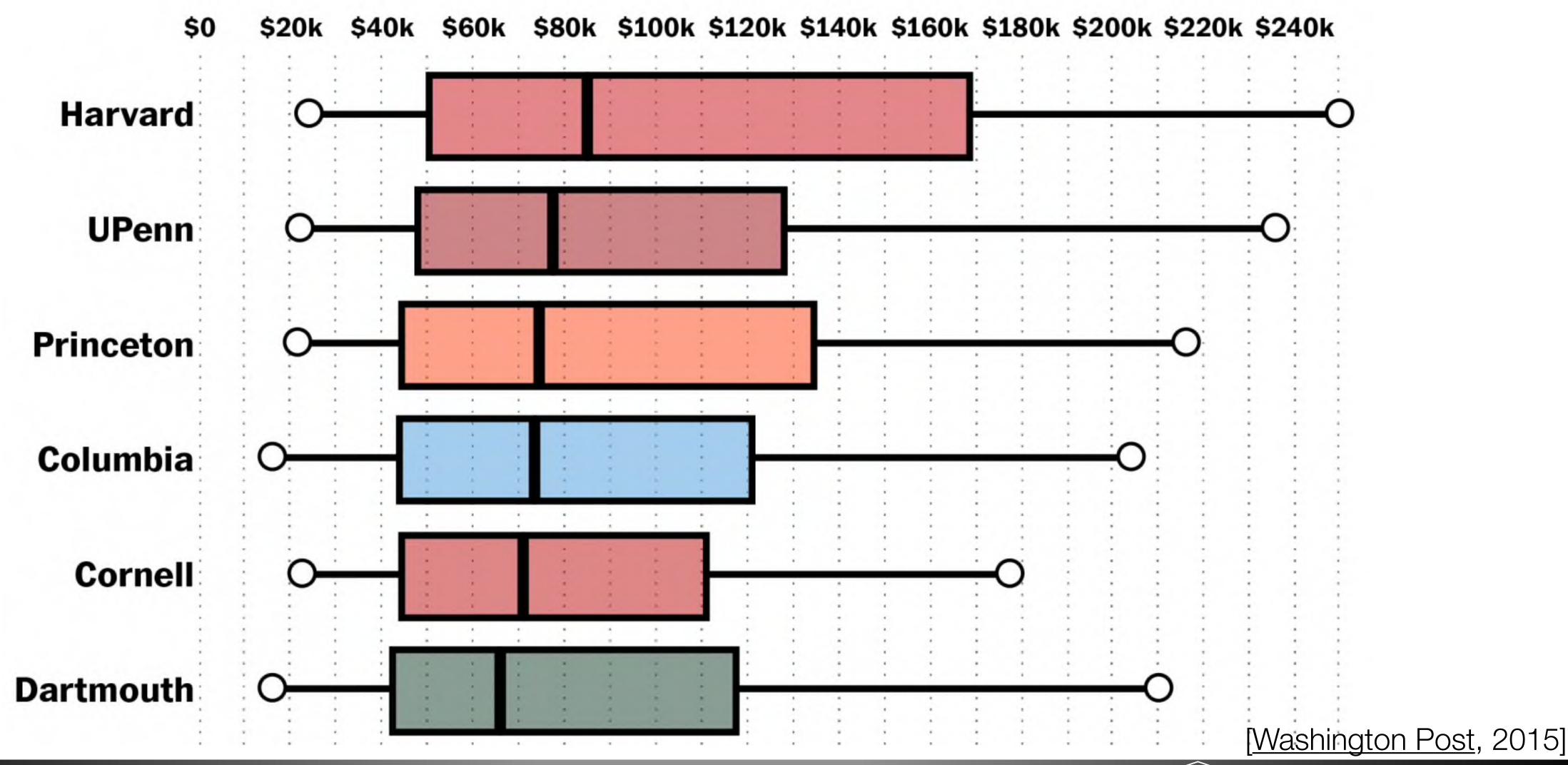


Boxplots

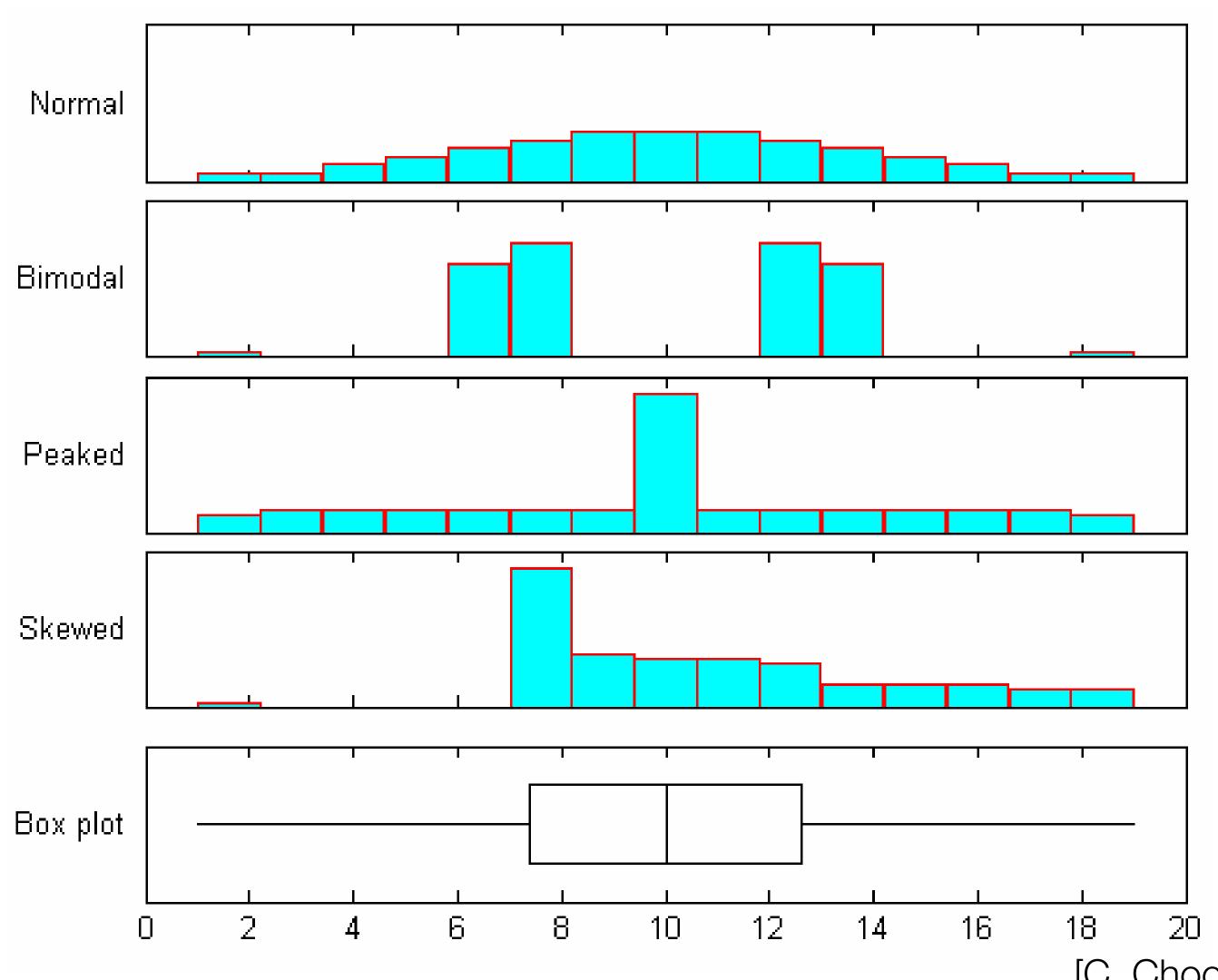
- Show distribution
- Single value (e.g. mean, max, min, quartiles)
 doesn't convey everything
- Created by John Tukey
- Show spread and skew of data
- Best for unimodal data
- Variations like vase plot for multimodal data
- Aggregation here involves many different marks



Aggregation: Boxplots

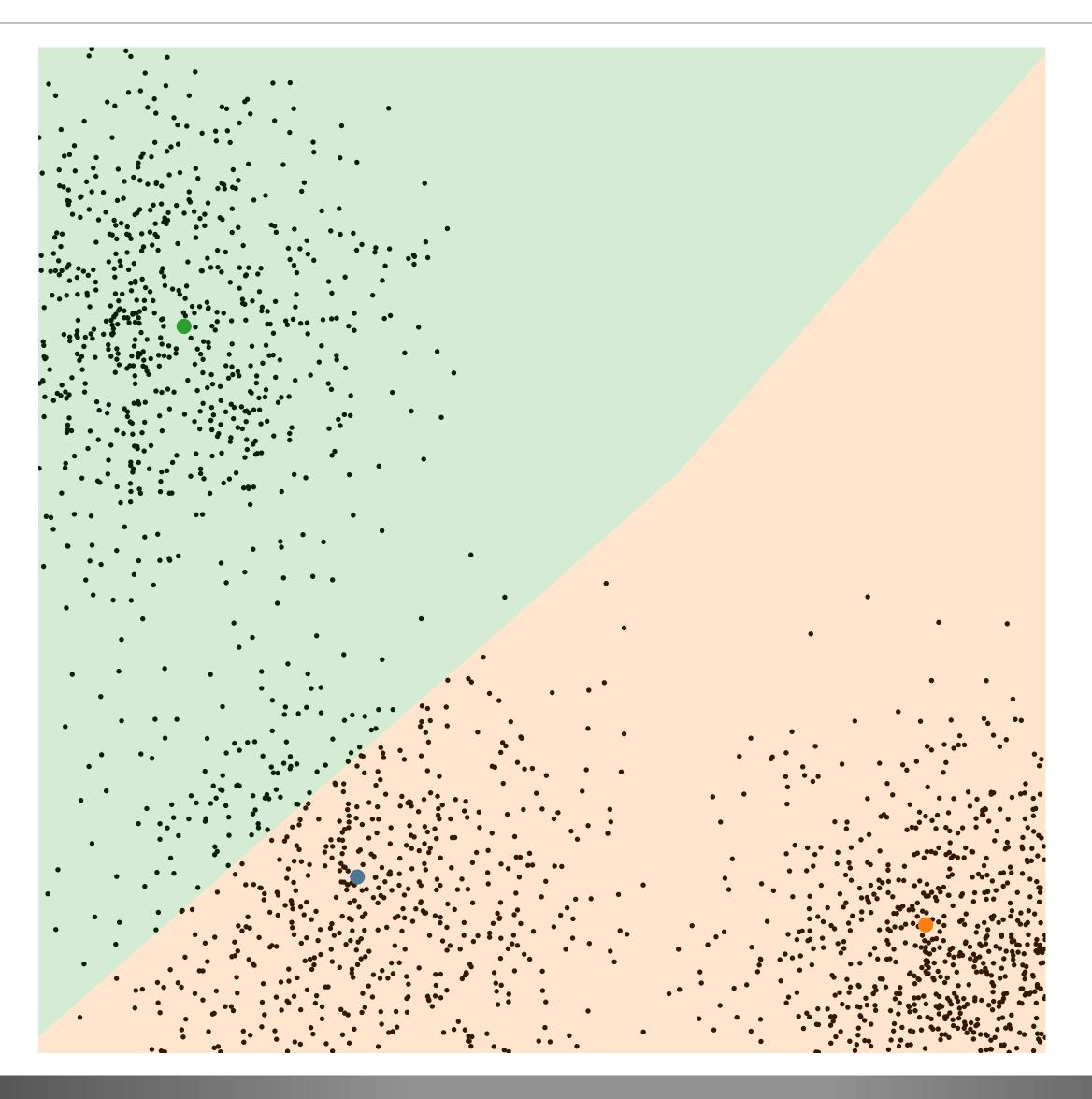


Four Distributions, Same Boxplot...



Attribute Aggregation

K-Means

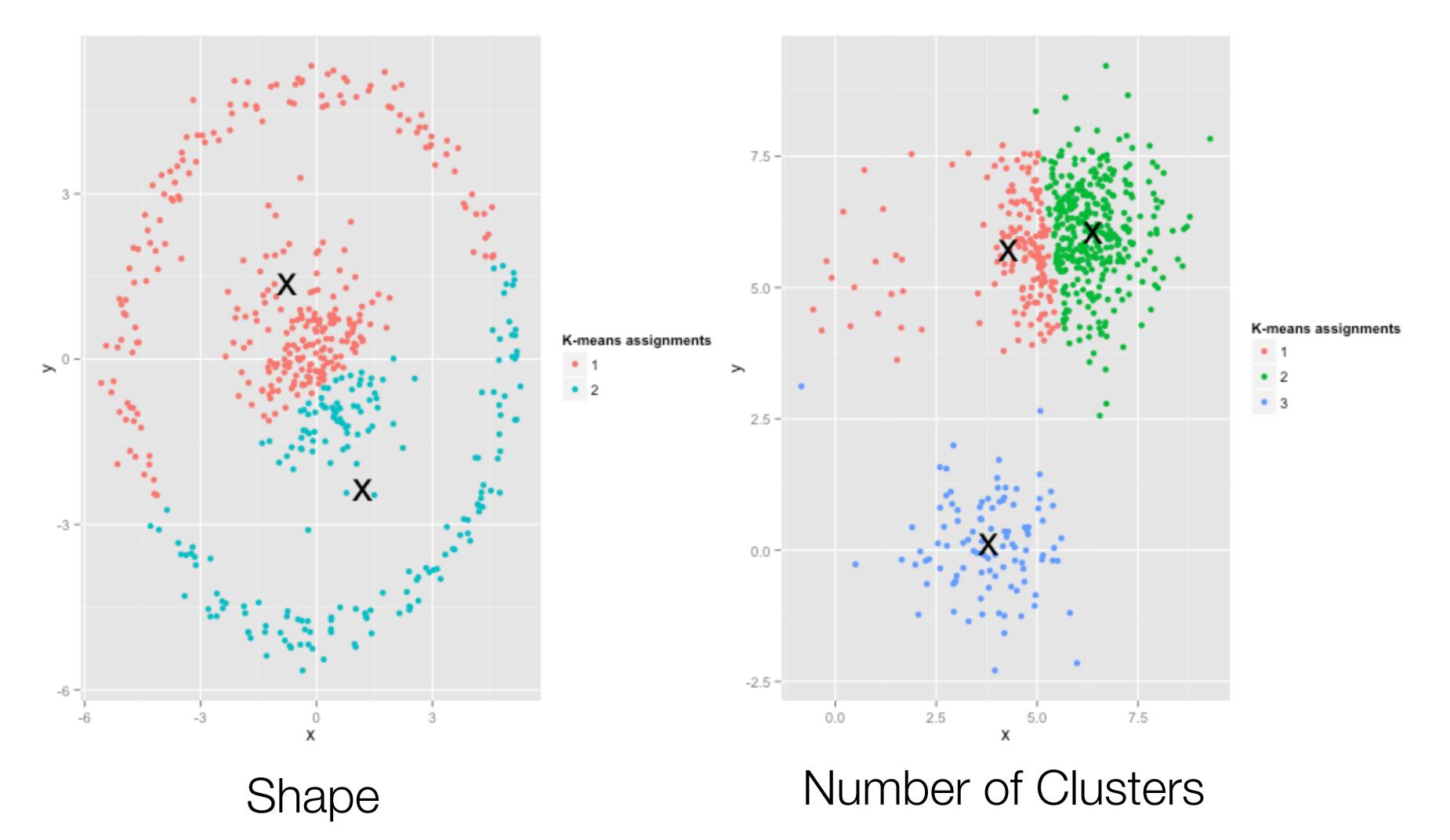


<u>Run</u>

[C. Polis, 2014]



K-Means Issues



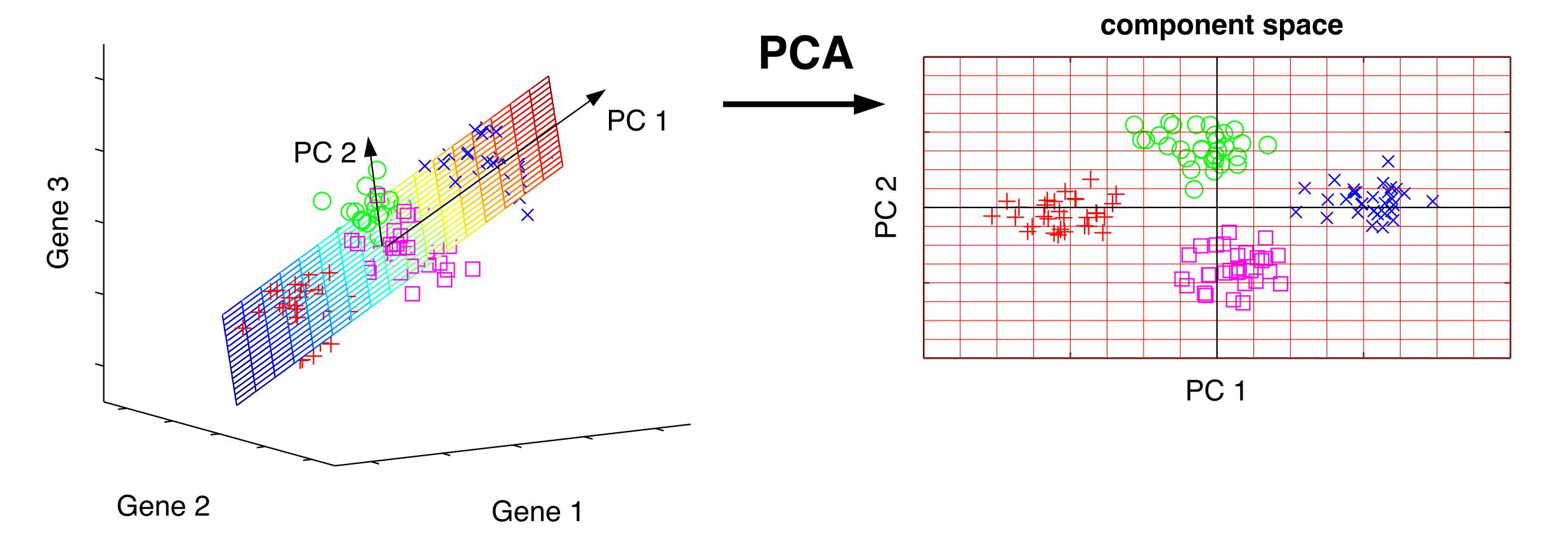
[D. Robinson, 2015]

Dimensionality Reduction

- Attribute Aggregation: Use fewer attributes (dimensions) to represent items
- Combine attributes in a way that is more instructive than examining each individual attribute
- Example: Understanding the language in a collection of books
 - Count the occurrence of each non-common word in each book
 - Huge set of features (attributes), want to represent each with an aggregate feature (e.g. high use of "cowboy", lower use of "city") that allows clustering (e.g. "western")
 - Don't want to have to manually determine such rules
- Techniques: Principle Component Analysis, Multidimensional Scaling family of techniques

Principle Component Analysis (PCA)

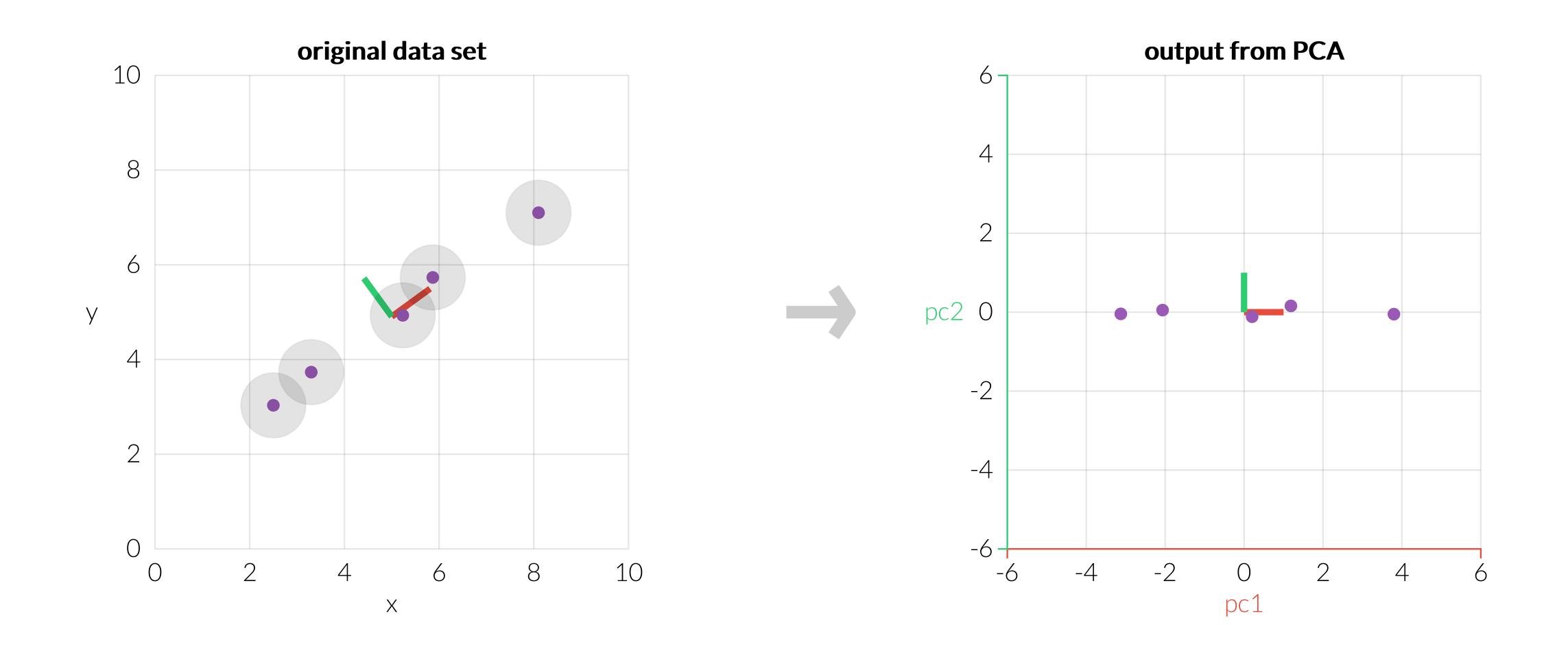
original data space



[M. Scholz, CC-BY-SA 2.0]



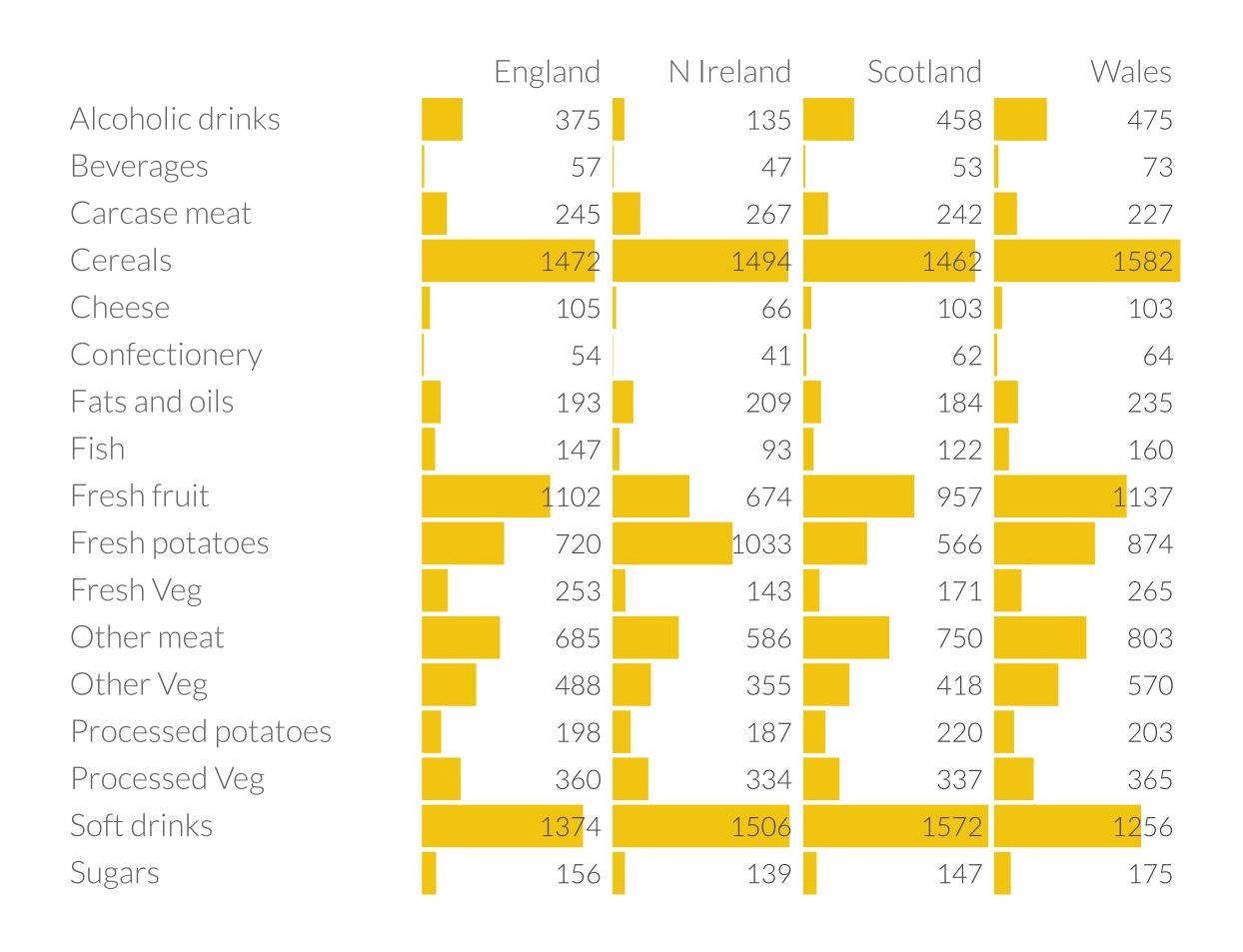
PCA

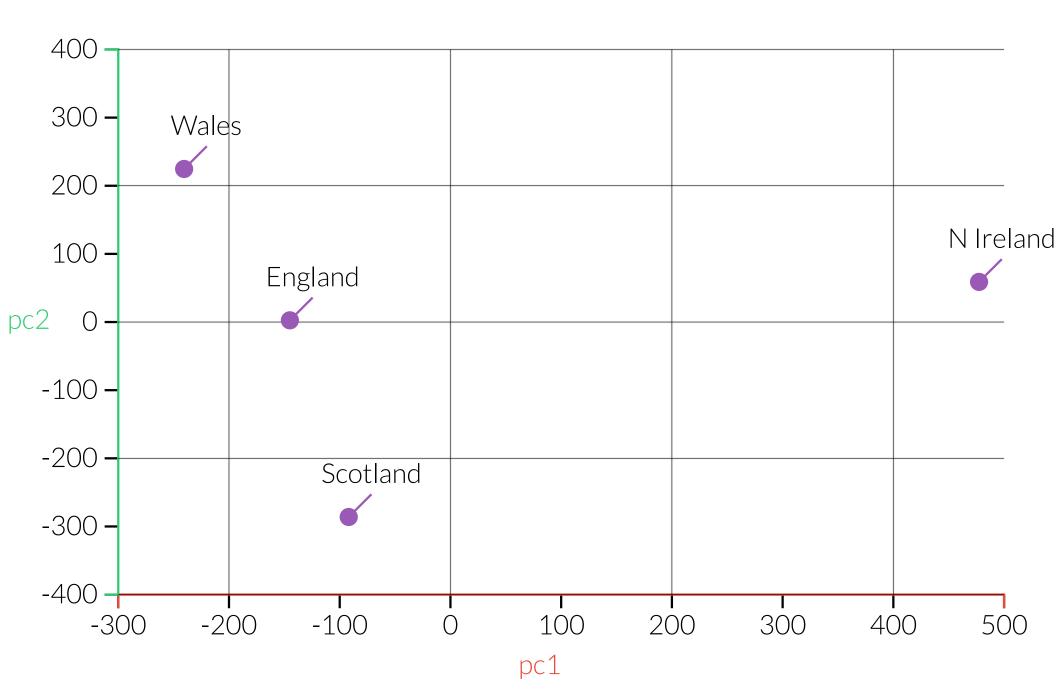


[Principle Component Analysis Explained, Explained Visually, V. Powell & L. Lehe, 2015]



17 dimensions to 2

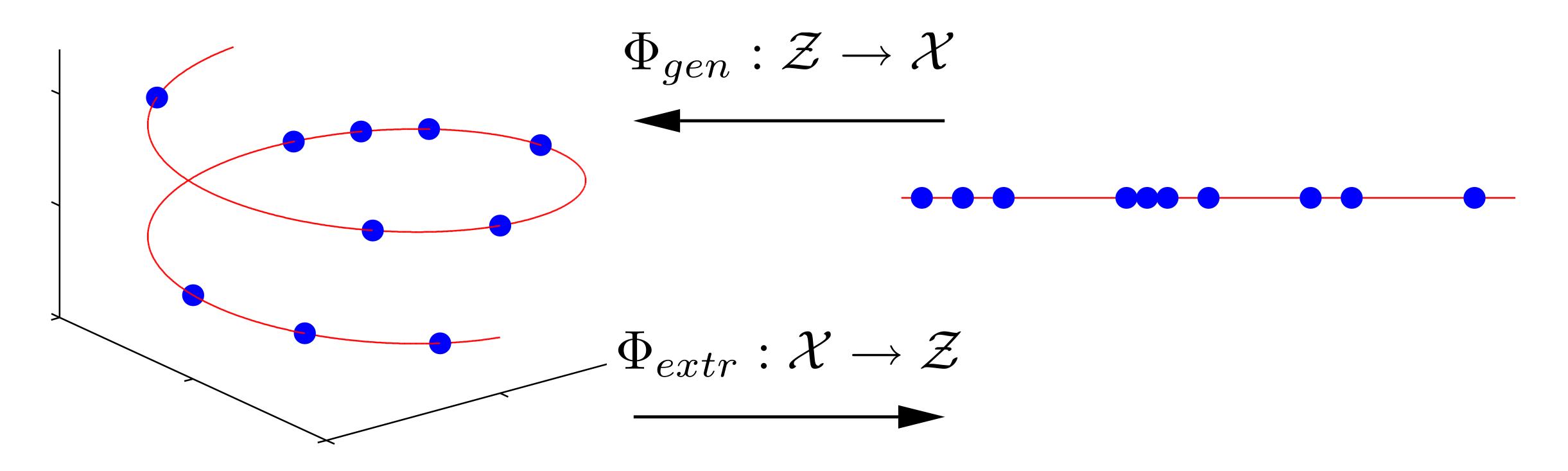




[Principle Component Analysis Explained, Explained Visually, V. Powell & L. Lehe, 2015]

Scotland

Non-linear Dimensionality Reduction

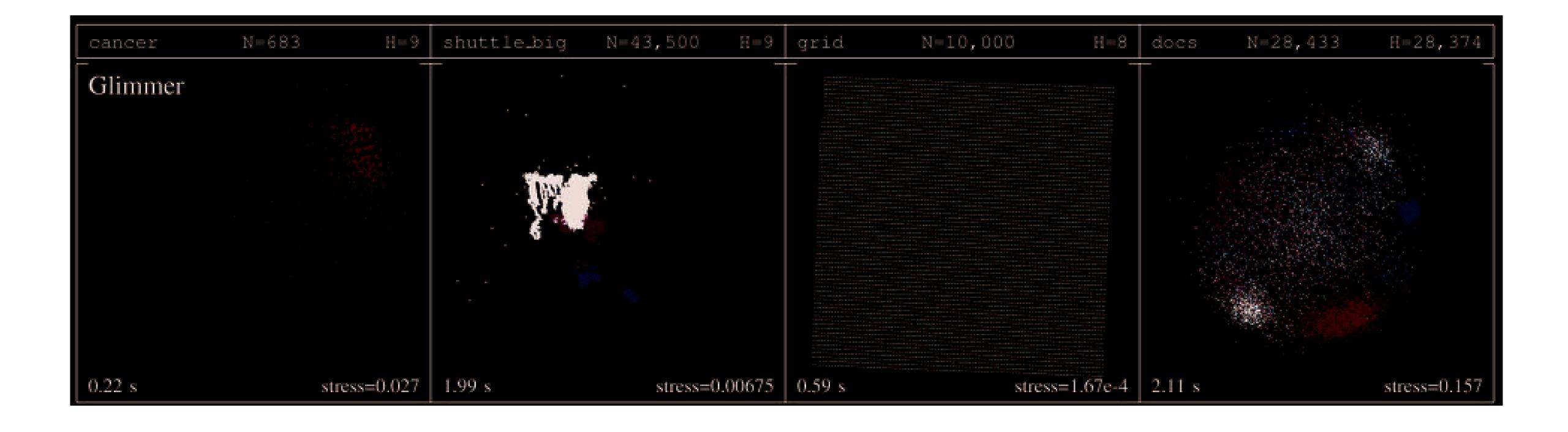


original data space \mathcal{X}

component space \mathcal{Z}

[M. Scholz, CC-BY-SA 2.0]

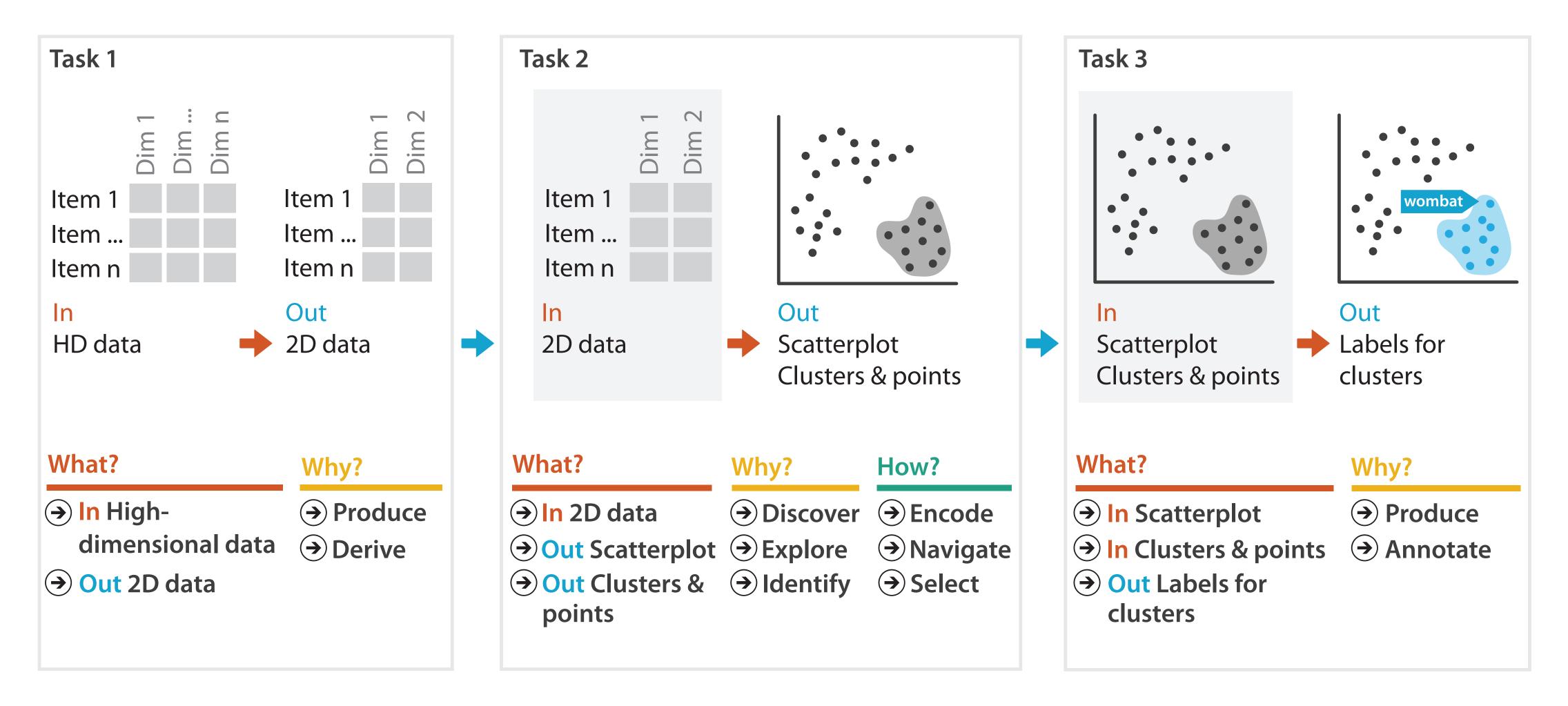
Dimensionality Reduction in Visualization



[Glimmer, Ingram et al., 2009]



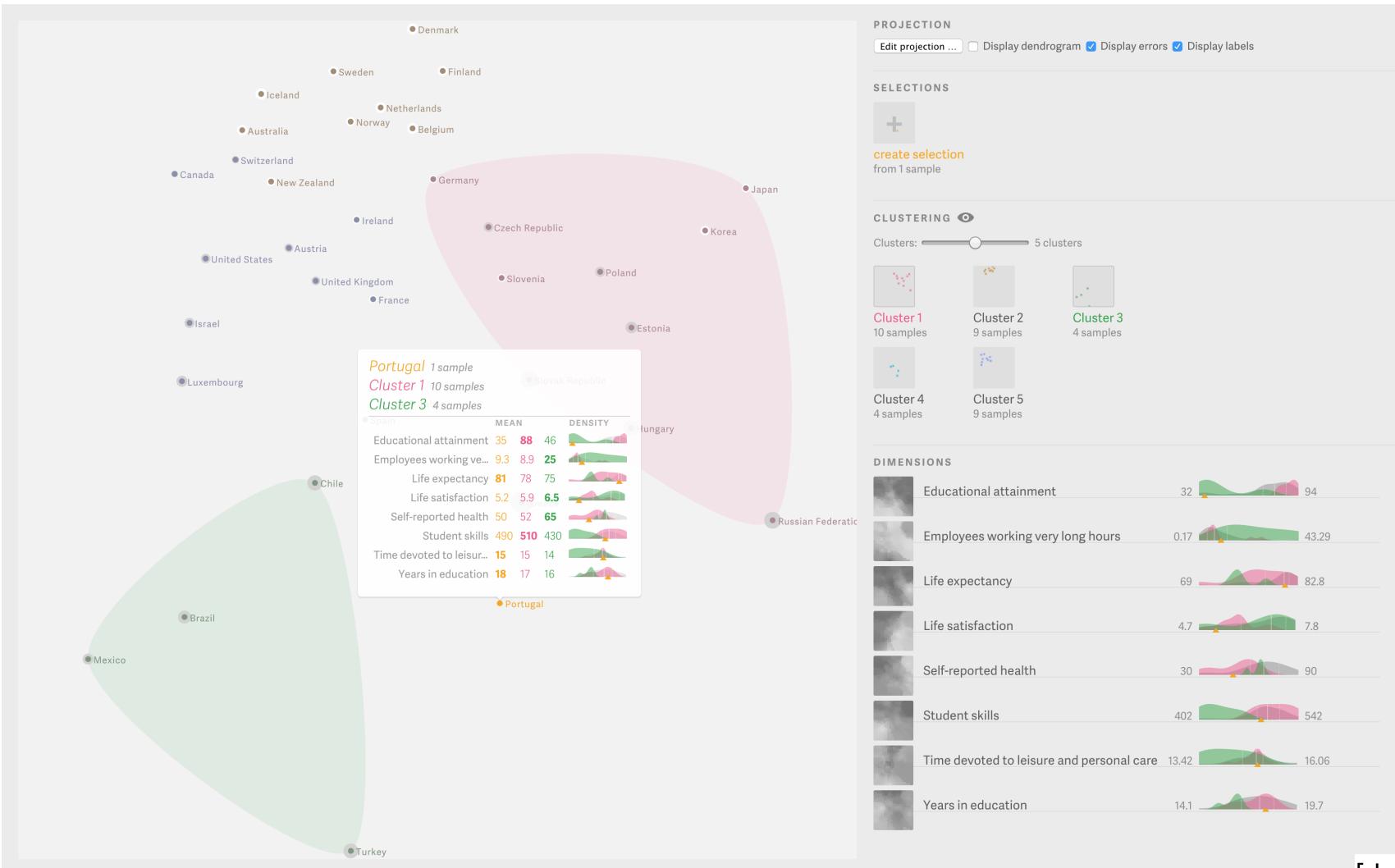
Tasks in Understanding High-Dim. Data



[Munzner (ill. Maguire), 2014]



Probing Projections



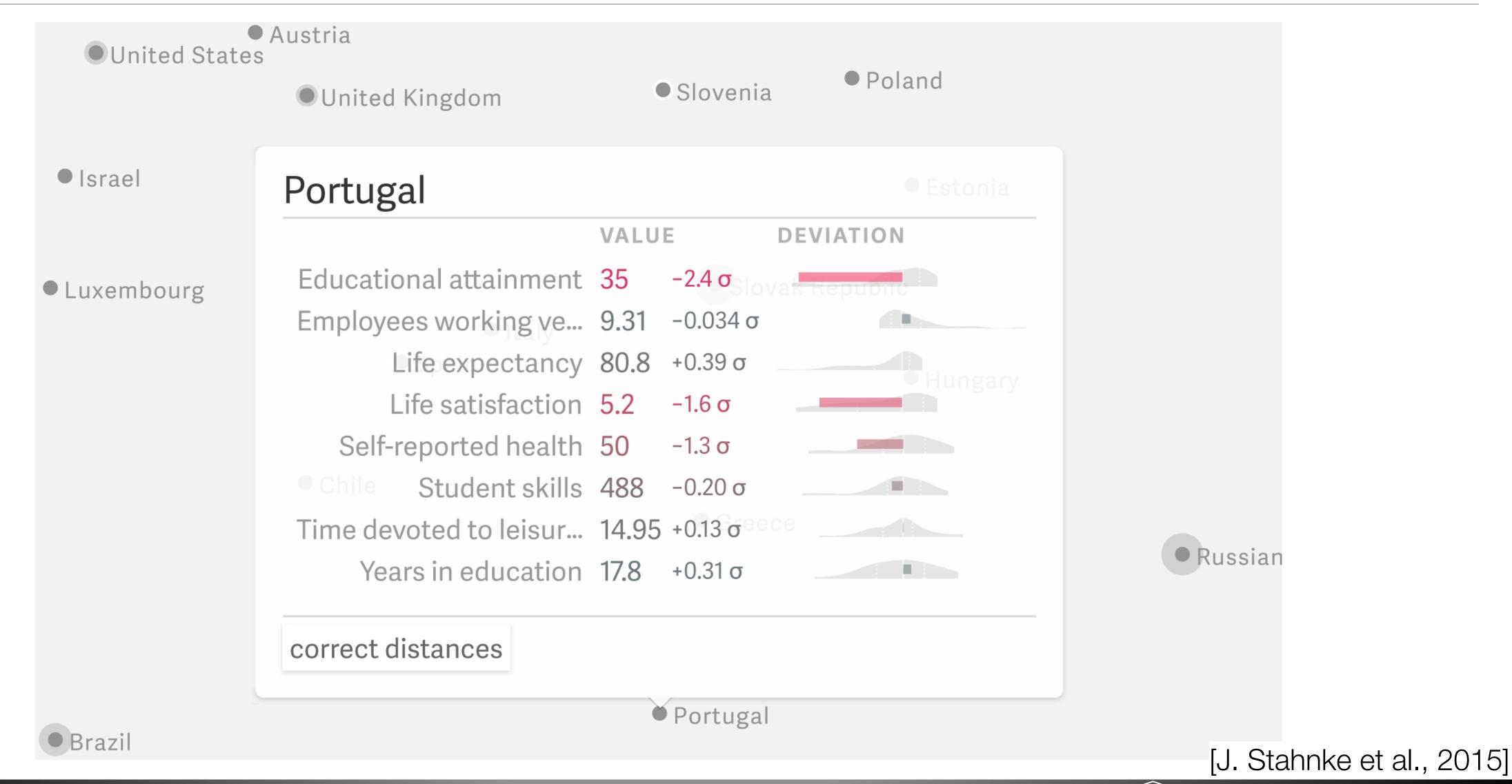
[J. Stahnke et al., 2015]

Probing Projection Goals

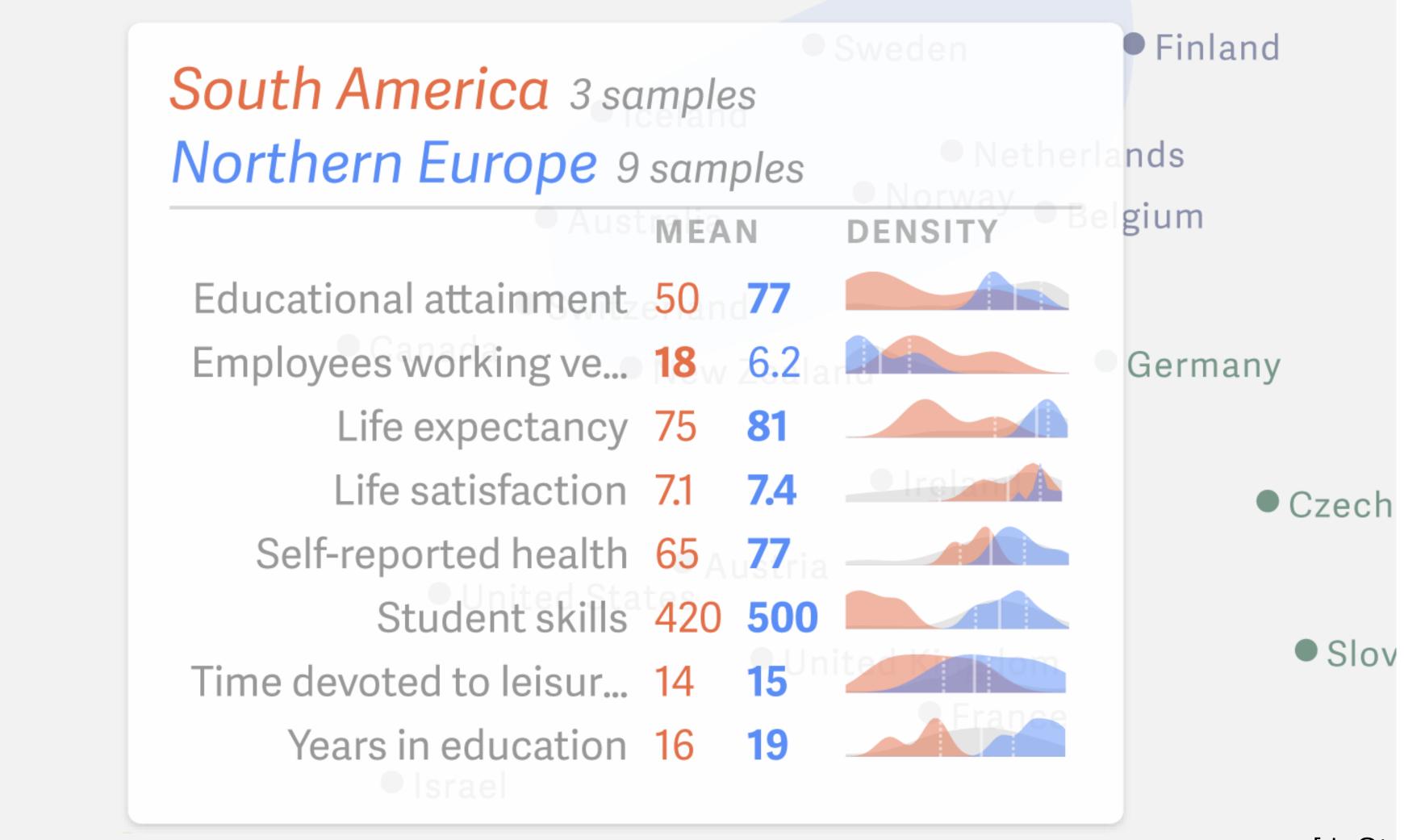
- Examining the Projection
- Exploring the Data
- Design Goals:
 - Show and correct approximation errors
 - Allow for multi-level comparisons
 - Spatial orientation
 - Consistent design
- Allow grouping of samples
 - Selections
 - Classes
 - Clusters

[J. Stahnke et al., 2015]

Tooltips with statistics



Comparing Two Groups

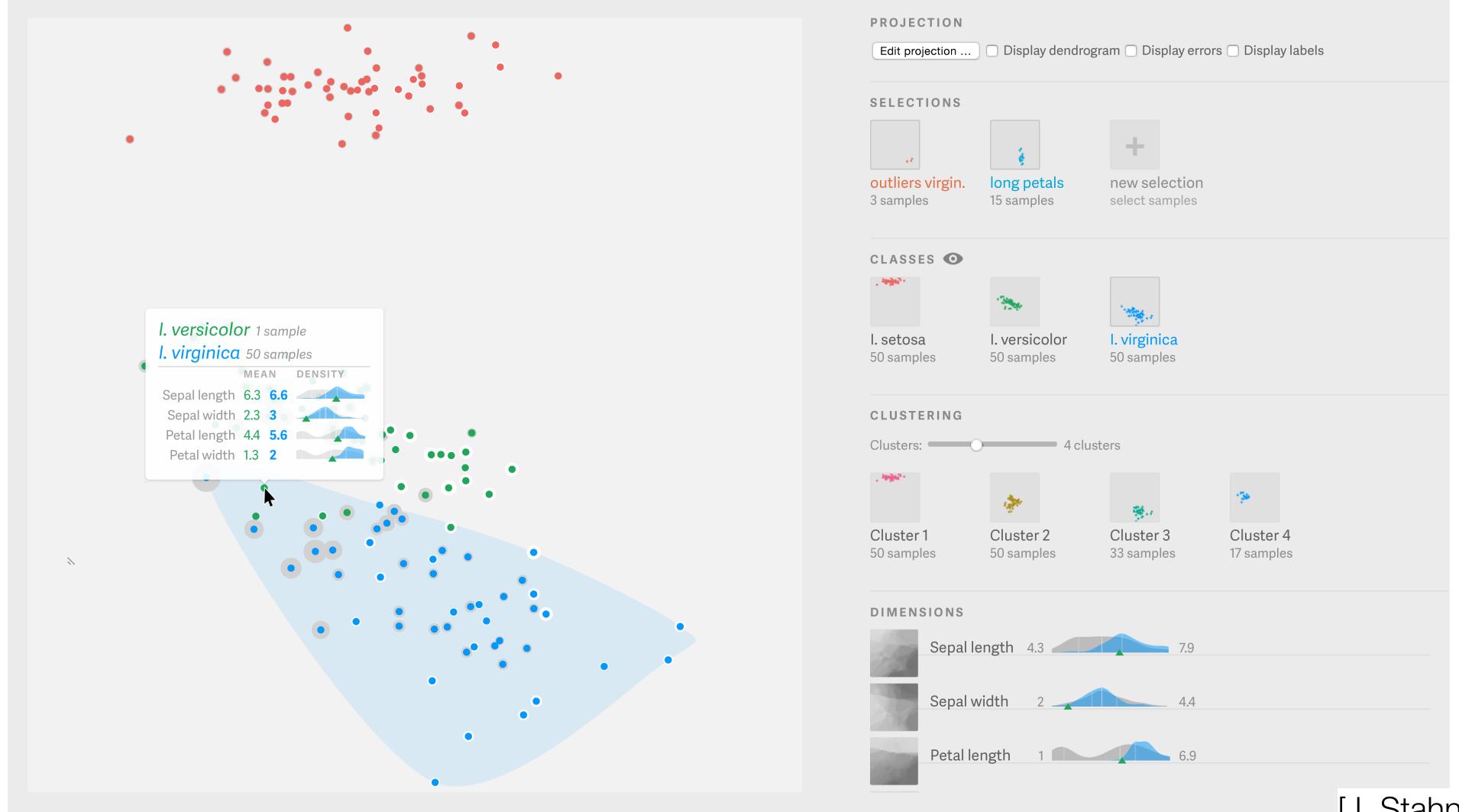


[J. Stahnke et al., 2015]

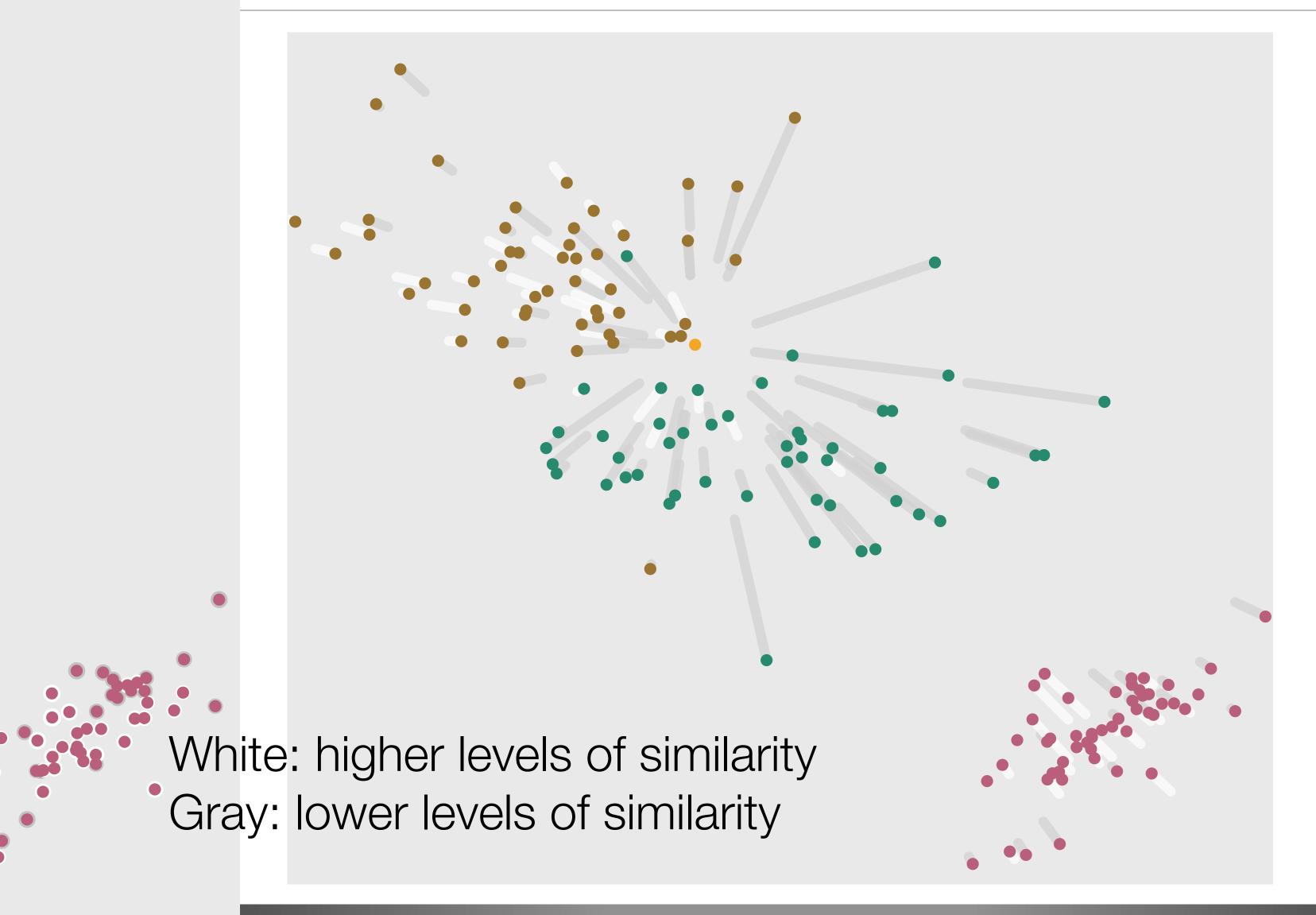
Heatmap from Dimension Hover



Showing Error via Sample-centric Halos



Showing Projection Errors



[J. Stahnke et al., 2015]



User Study & Results

- Types of Questions:
 - How would you try to characterize the type X?
 - In what way are X and Y different in their properties?
 - Are the projections of X and Y correct or do they deviate? How do you interpret this?
 - Can you discover which parts of the cluster combinations are A, B, and C?
- Discussion:
 - Learnability: need more effective mechanisms for grasping the concepts behind dimensionality reduction
 - Manipulation: What happens with results?
 - Large data: What about text corpora?

[J. Stahnke et al., 2015]



Focus+Context

Focus+Context

- Show everything at once but compress regions that are not the current focus
 - User shouldn't lose sight of the overall picture
 - May involve some aggregation in non-focused regions
 - "Nonliteral navigation" like semantic zooming
- Elision
- Superimposition: more directly tied than with layers
- Distortion

Focus+Context Overview

Embed

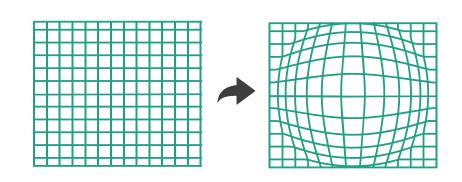
→ Elide Data

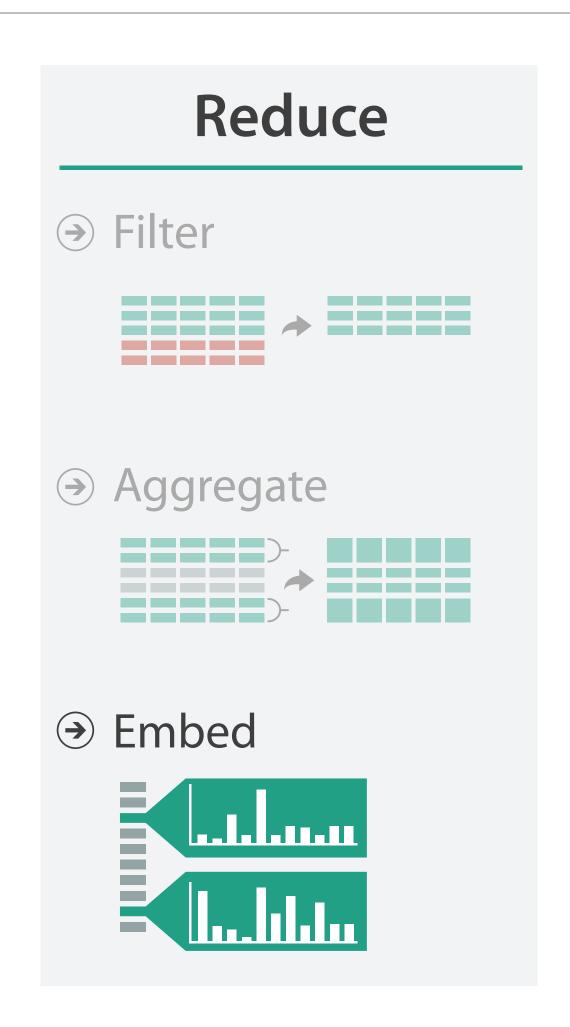


→ Superimpose Layer



→ Distort Geometry





[Munzner (ill. Maguire), 2014]

