Information Visualization
Reduce: Aggregation & Filtering
Project Peer Reviews

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University of British Columbia

Week 11, 17 Nov 2021

https://www.cs.ubc.ca/~tmm/courses/547-21

Today

- first: project peer reviews
  - join your matched teams
    - you've already read other team's written update
      - let me know by private Piazza post if your counterpart(s) weren't prepared
  - record discussion/thoughts in gdoc (freeform)
  - first A critiques B; then B critiques A
- break
- Q&A overflow from before
  - Ch 11, Interact, cont
  - Ch 12, Multiple Views
- Q&A / mini-lecture this time
  - Ch 13, Reduce

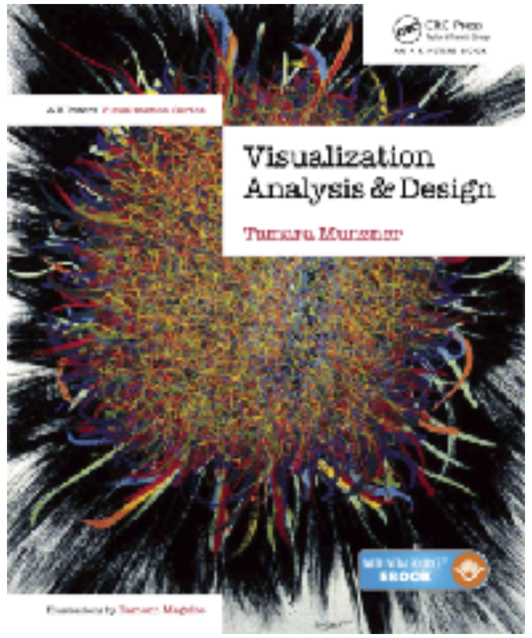
Peer reviews

- rough structure (adapt as you like, aim for ~45-60 min)
  - talk through initial thoughts when read updates
  - ask clarifying questions
  - get demo to see look/feel & any interaction
  - discuss tradeoffs, design choices, suggestions
  - when conversation winds down, critiquers record braindump (if not done as you go)
  - write DONE at top of your gdoc section & switch!
- tips on giving feedback
  - state what you think is good about the work, and why you think so
  - state what you think needs improvement, including why/rationale
  - offer specific suggestions on how to improve it, as followup
  - keep your feedback focused on the work, not the person who did it

Upcoming

- next week (W12)
  - async: last week of readings / discussion (light, 2 readings)
    - Ch 14: Embed - Focus+Context
    - paper: Visualizing Dataflow Graphs of Deep Learning Models in TensorFlow.
      Kanit Wongsuphasawat, Daniel Smilkov, James Wexler, Jimbo Wilson, Dandelion Mané, Doug Fritz, Dilip Krishnan, Fernanda B. Viégas, and Martin Wattenberg.
      IEEE TVCG (Proc. VAST 2017) 24(1):1-12, 2018.
      [**type: design study**]
  - in class: post-update meetings with Tamara
    - oral feedback on project progress, after I've read them
- last week of classes (W13)
  - async: **no** readings/discussion
  - in class: evals
  - in class: Q&A wrapup (W12)
  - in class: lecture on research process and final writeup expectations

Q&A / Backup Slides



Visualization Analysis & Design

Reduce: Aggregation & Filtering (Ch 13)

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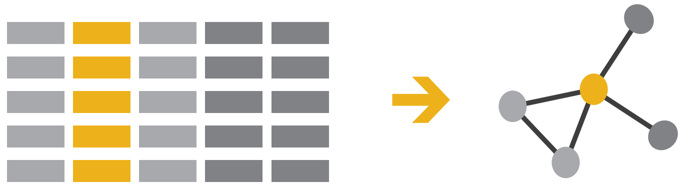
How to handle complexity: 3 previous strategies

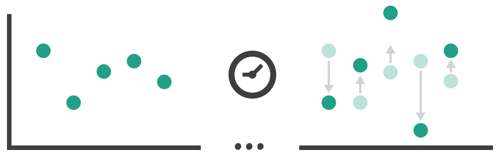
➔ *Derive*



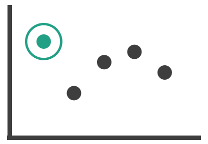
- derive new data to show within view
- change view over time
- facet across multiple views

Manipulate

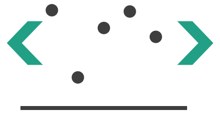
Change



Select

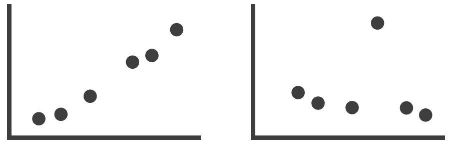


Navigate

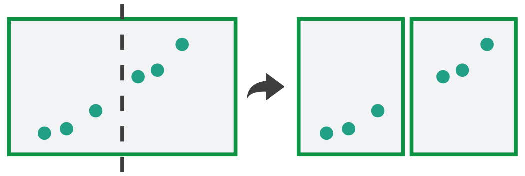


Facet

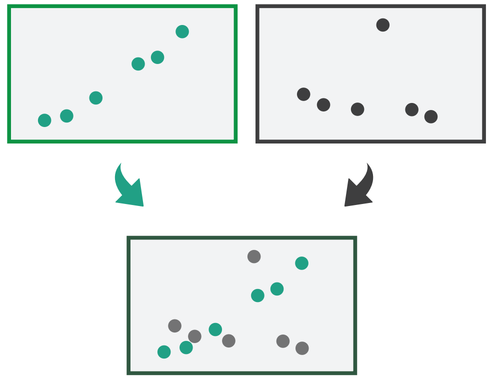
Juxtapose



Partition



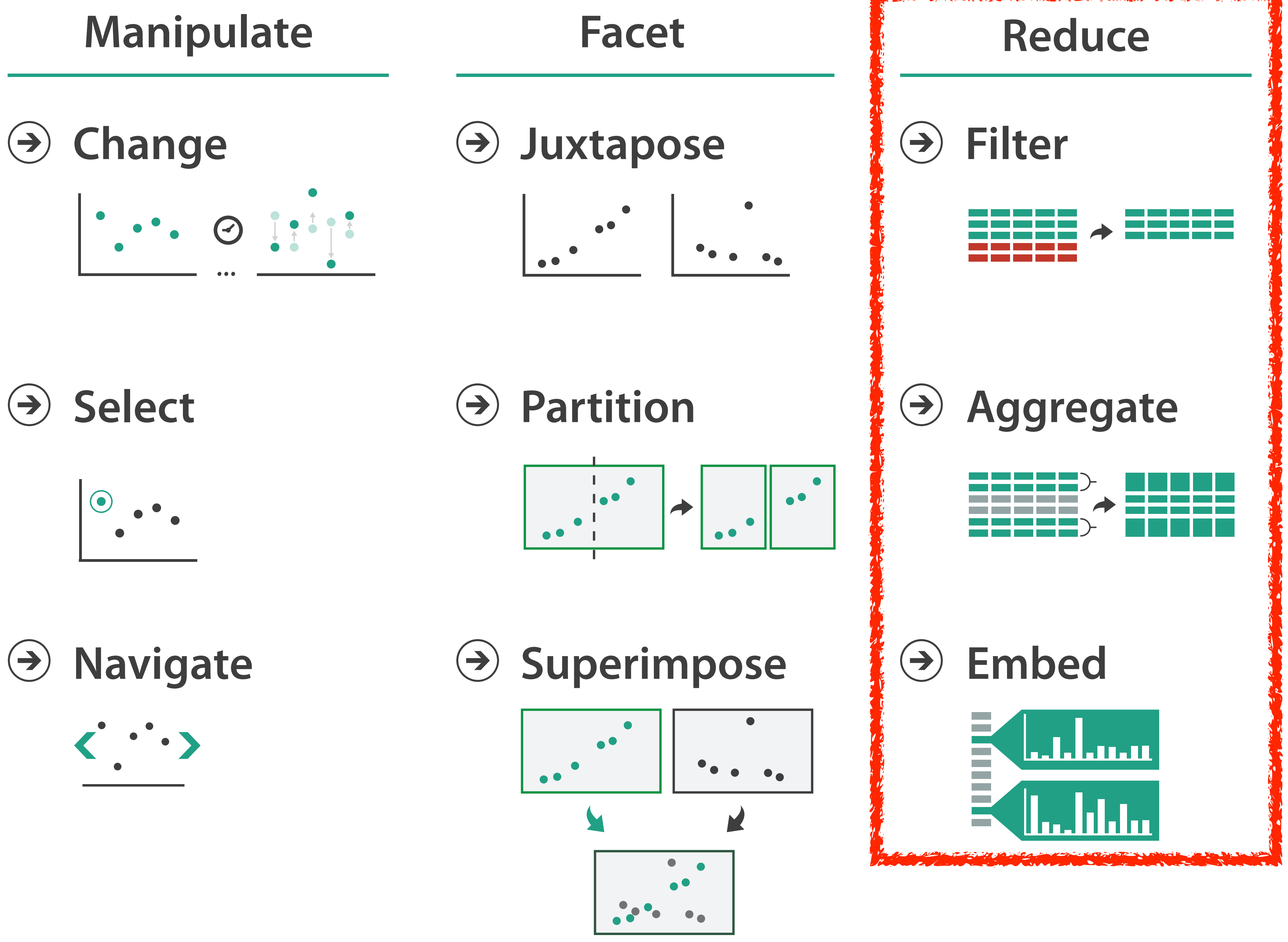
Superimpose



How to handle complexity: 3 previous strategies + 1 more

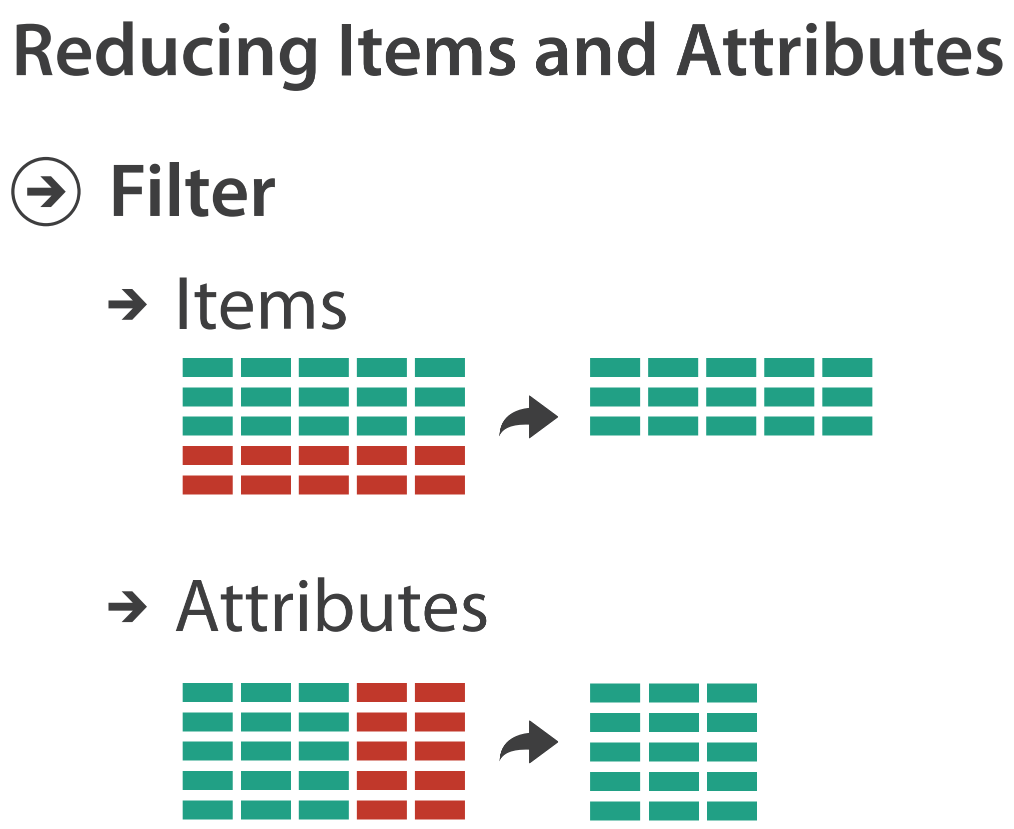
→ *Derive*

- derive new data to show within view
- change view over time
- facet across multiple views
- reduce items/attributes within single view



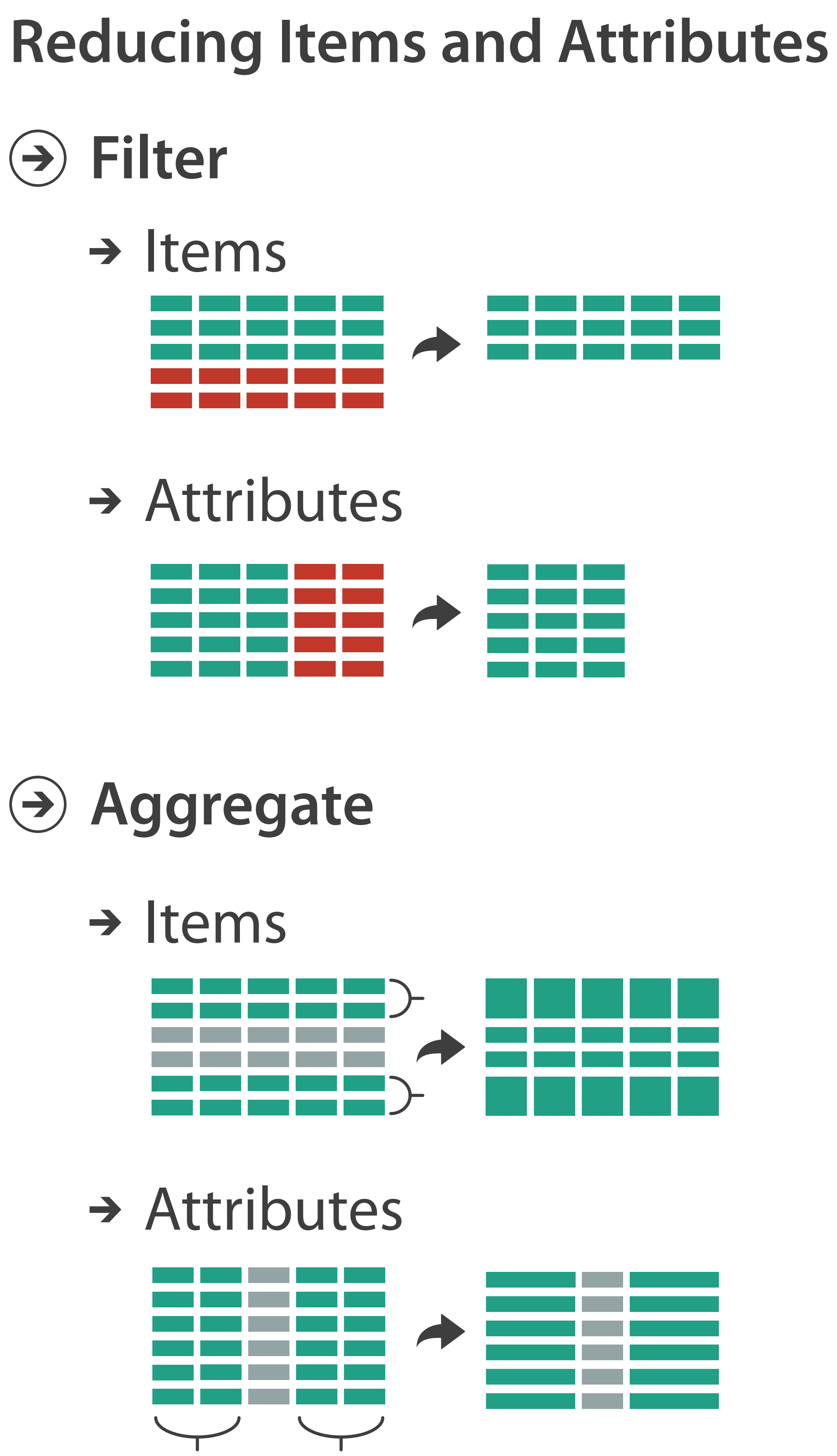
Reduce items and attributes

- reduce/increase: inverses
- filter
  - pro: straightforward and intuitive
    - to understand and compute
  - con: out of sight, out of mind



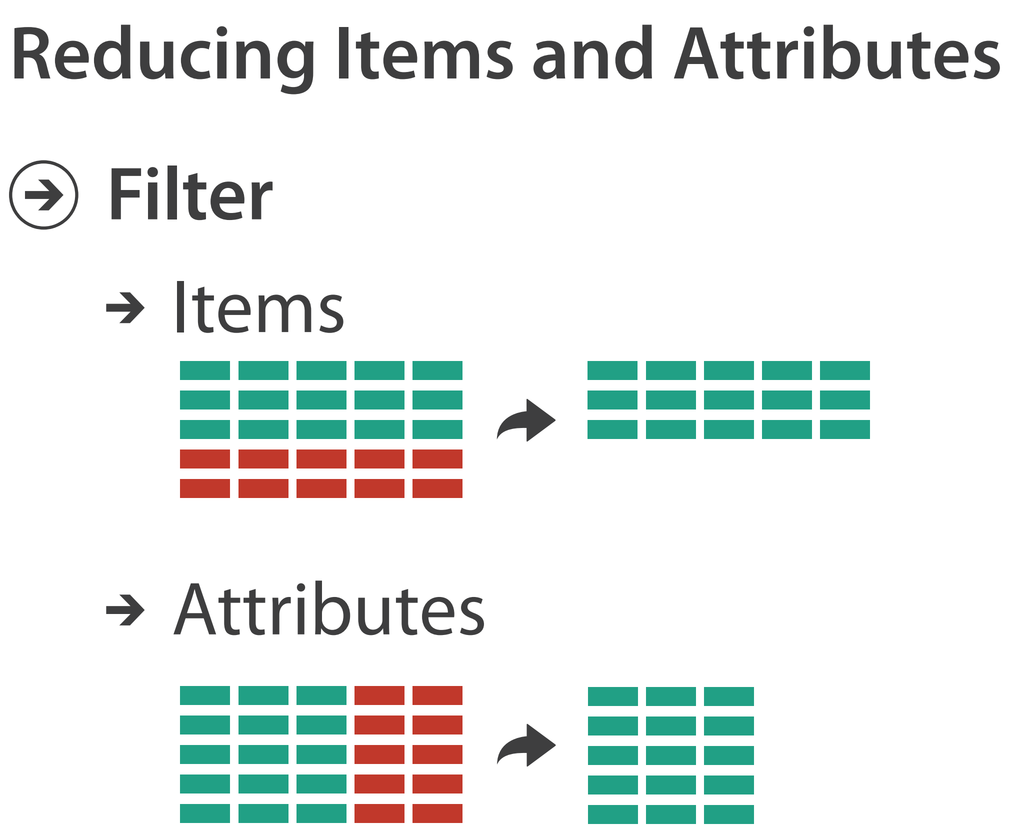
Reduce items and attributes

- reduce/increase: inverses
- filter
  - pro: straightforward and intuitive
    - to understand and compute
  - con: out of sight, out of mind
- aggregation
  - pro: inform about whole set
  - con: difficult to avoid losing signal
- not mutually exclusive
  - combine filter, aggregate
  - combine reduce, change, facet



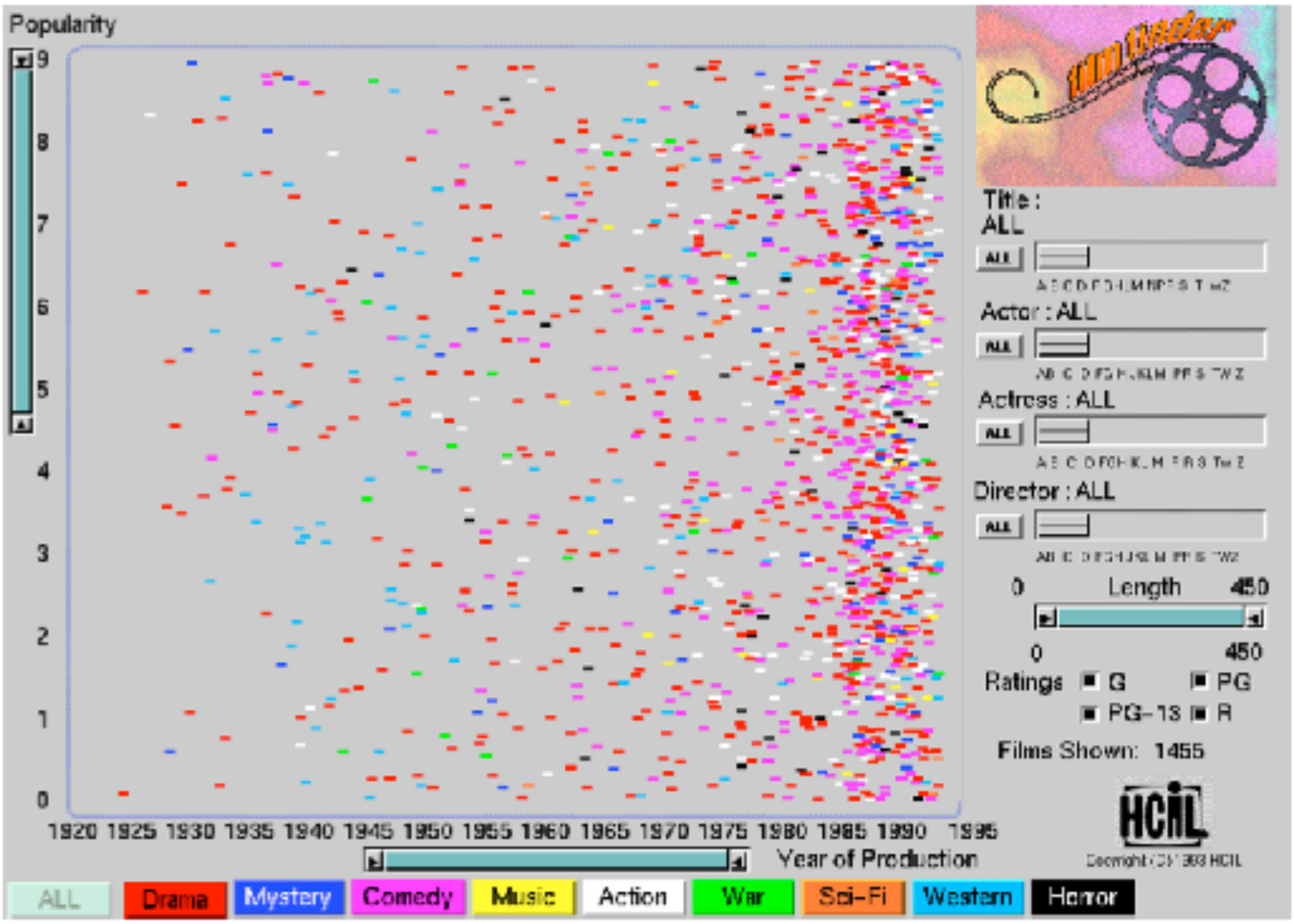
Filter

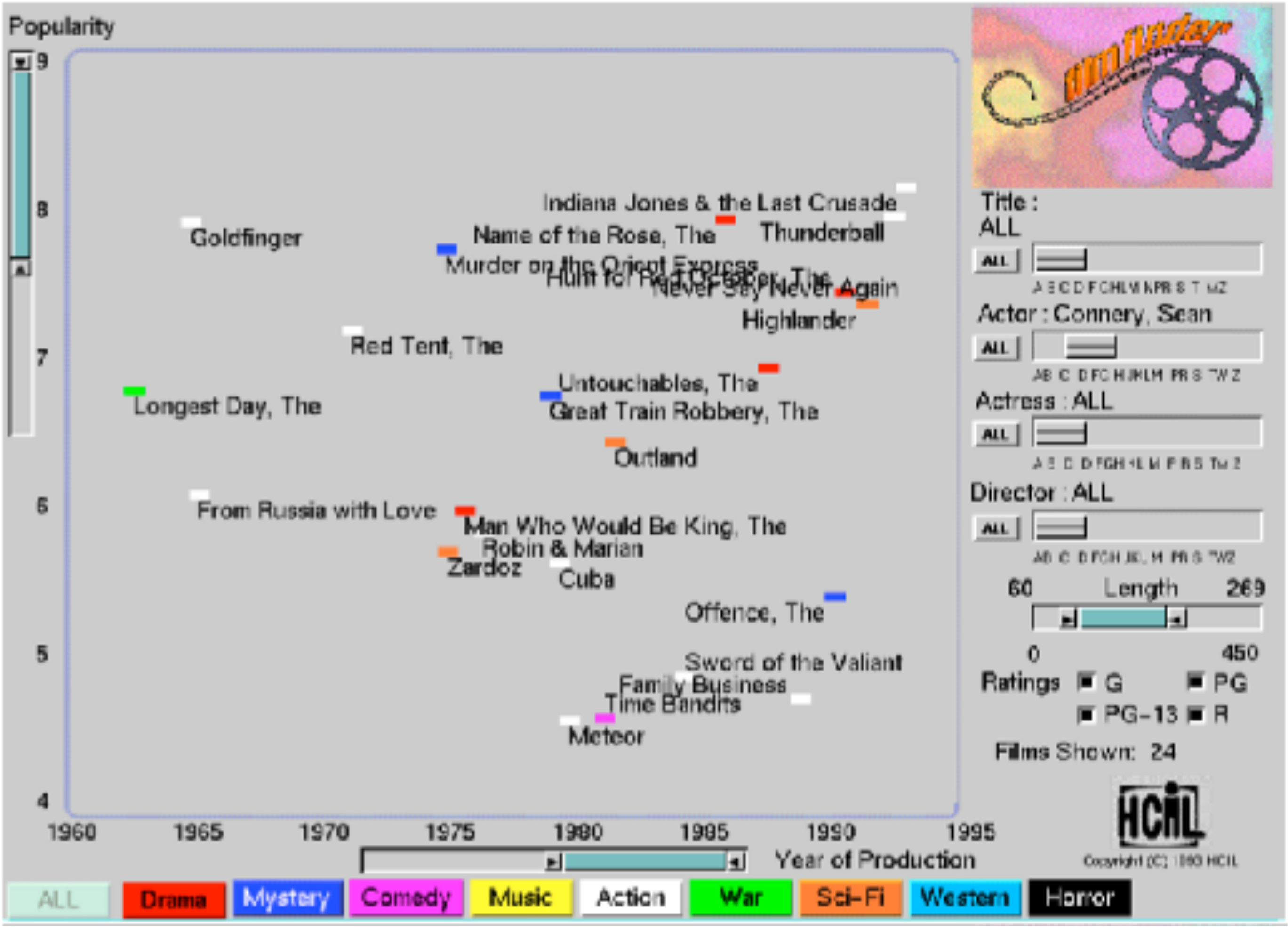
- eliminate some elements
  - either items or attributes
- according to what?
  - any possible function that partitions dataset into two sets
    - attribute values bigger/smaller than x
    - noise/signal
- filters vs queries
  - query: start with nothing, add in elements
  - filters: start with everything, remove elements
  - best approach depends on dataset size



Idiom: **FilmFinder**

- dynamic queries/filters for items
  - tightly coupled interaction and visual encoding idioms, so user can immediately see results of action

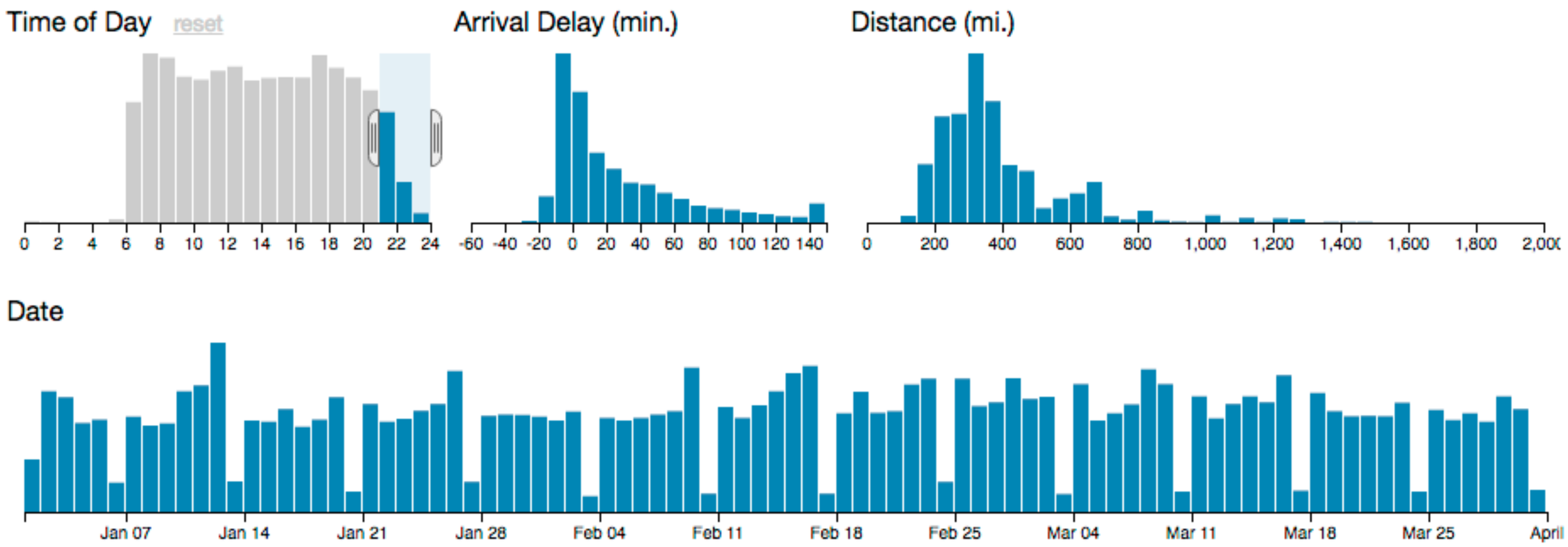




[Ahlberg & Shneiderman, Visual Information Seeking: Tight Coupling of Dynamic Query Filters with Starfield Displays. CHI 1994.]

Idiom: **cross filtering** System: **Crossfilter**

- item filtering
- coordinated views/controls combined
  - all scented histogram bisliders update when any ranges change

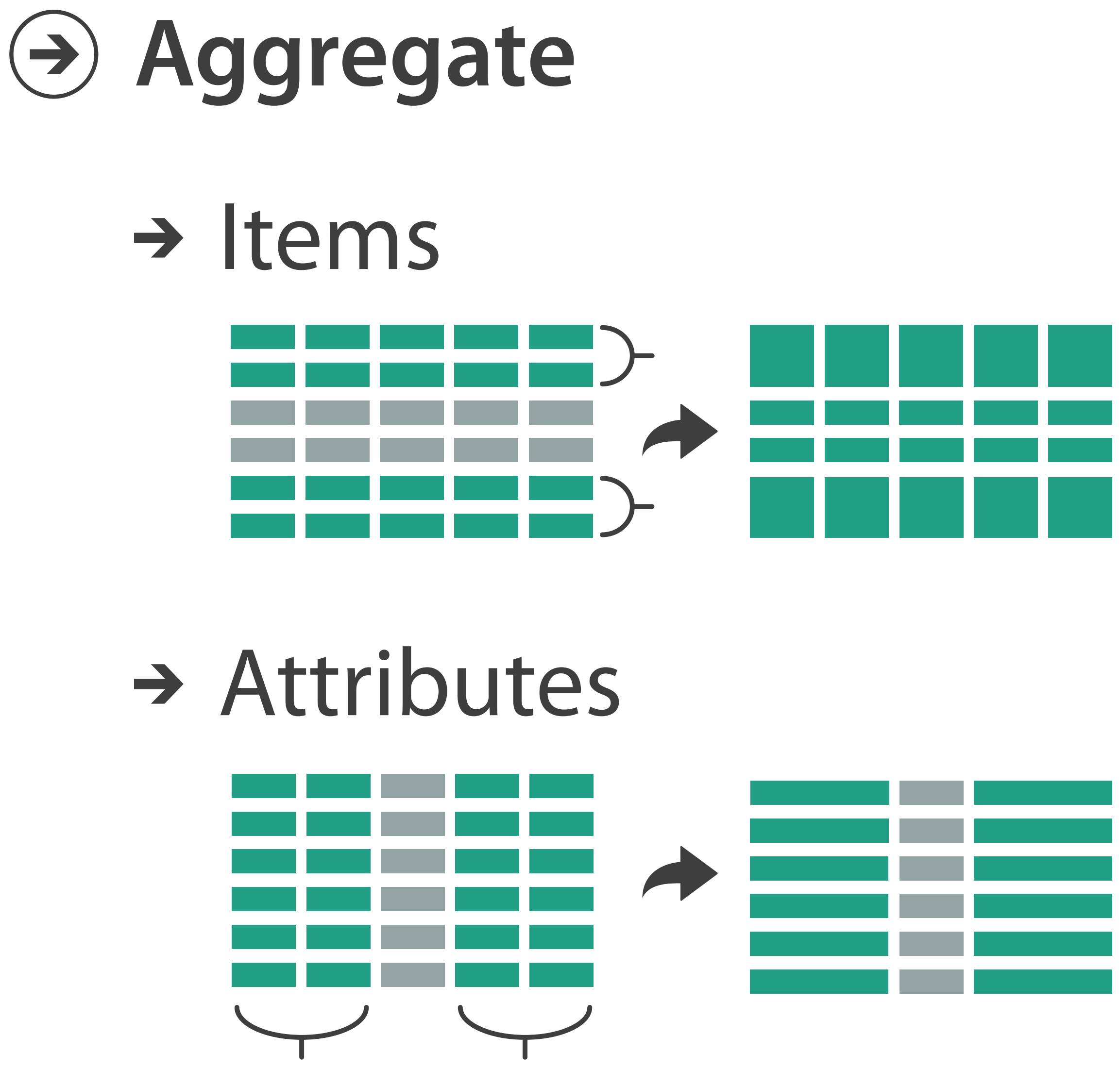


http://square.github.io/crossfilter/

https://observablehq.com/@uwdata/interaction

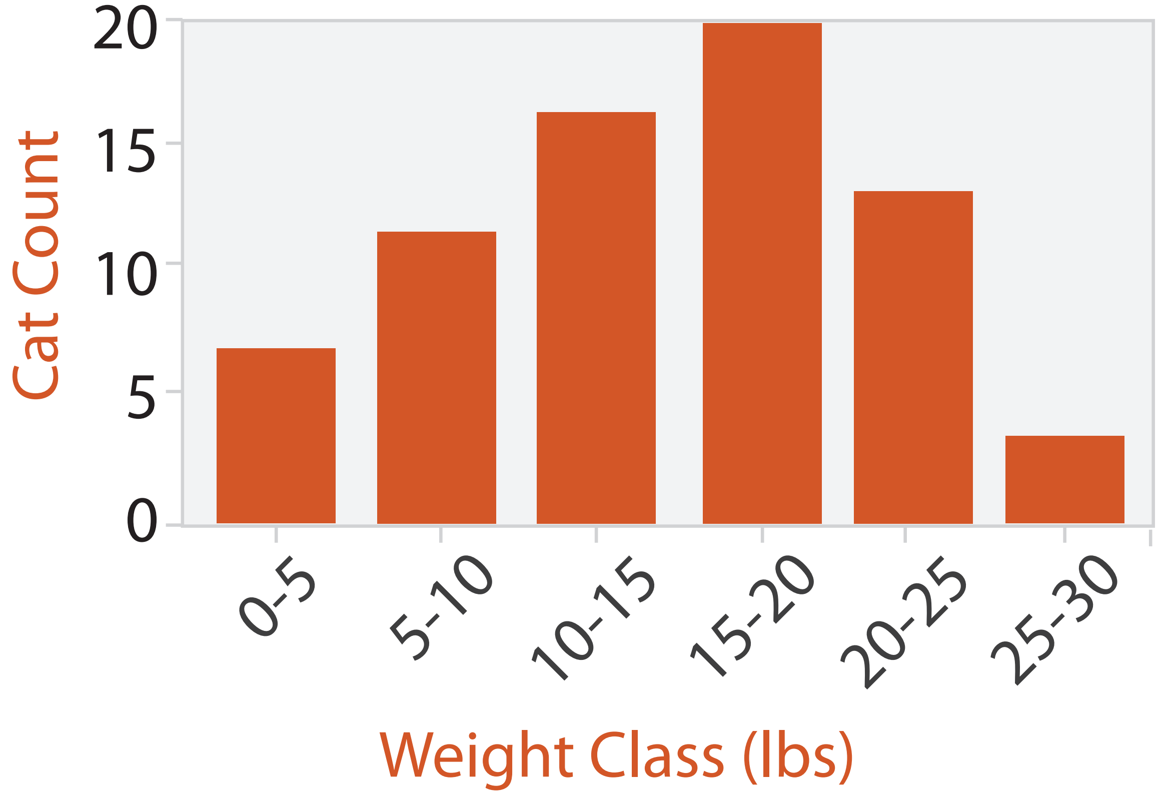
Aggregate

- a group of elements is represented by a smaller number of derived elements



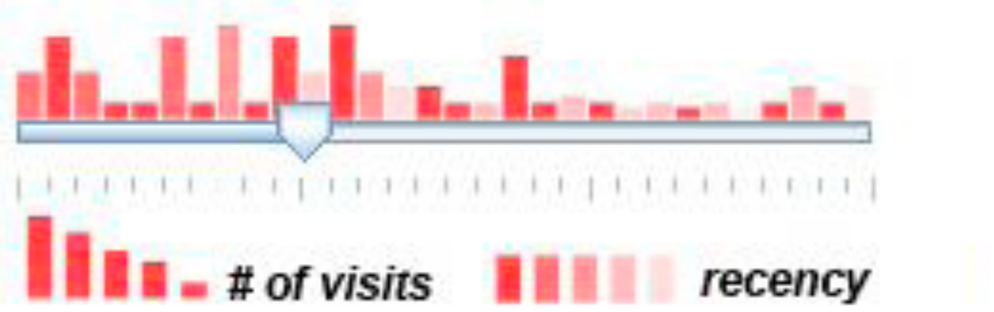
Idiom: **histogram**

- static item aggregation
- task: find distribution
- data: table
- derived data
  - new table: keys are bins, values are counts
- bin size crucial
  - pattern can change dramatically depending on discretization
  - opportunity for interaction: control bin size on the fly



Idiom: **scented widgets**

- augmented widgets show *information scent*
  - better cues for *information foraging*: show whether value in drilling down further vs looking elsewhere
- concise use of space: histogram on slider



[Scented Widgets: Improving Navigation Cues with Embedded Visualizations. Willett, Heer, and Agrawala. IEEE TVCG (Proc. InfoVis 2007) 13:6 (2007), 1129–1136.]

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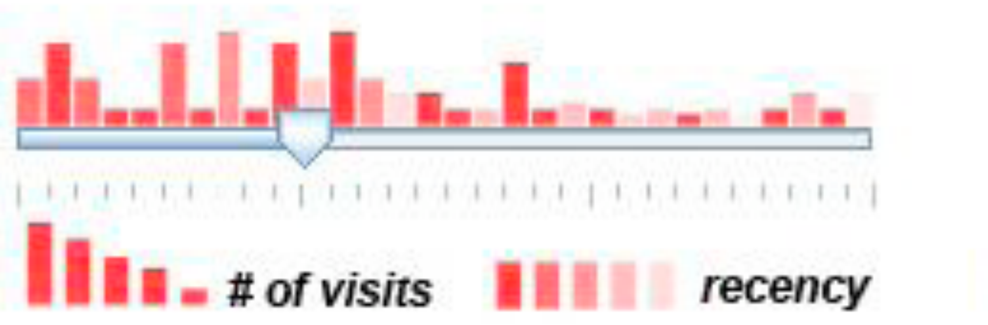

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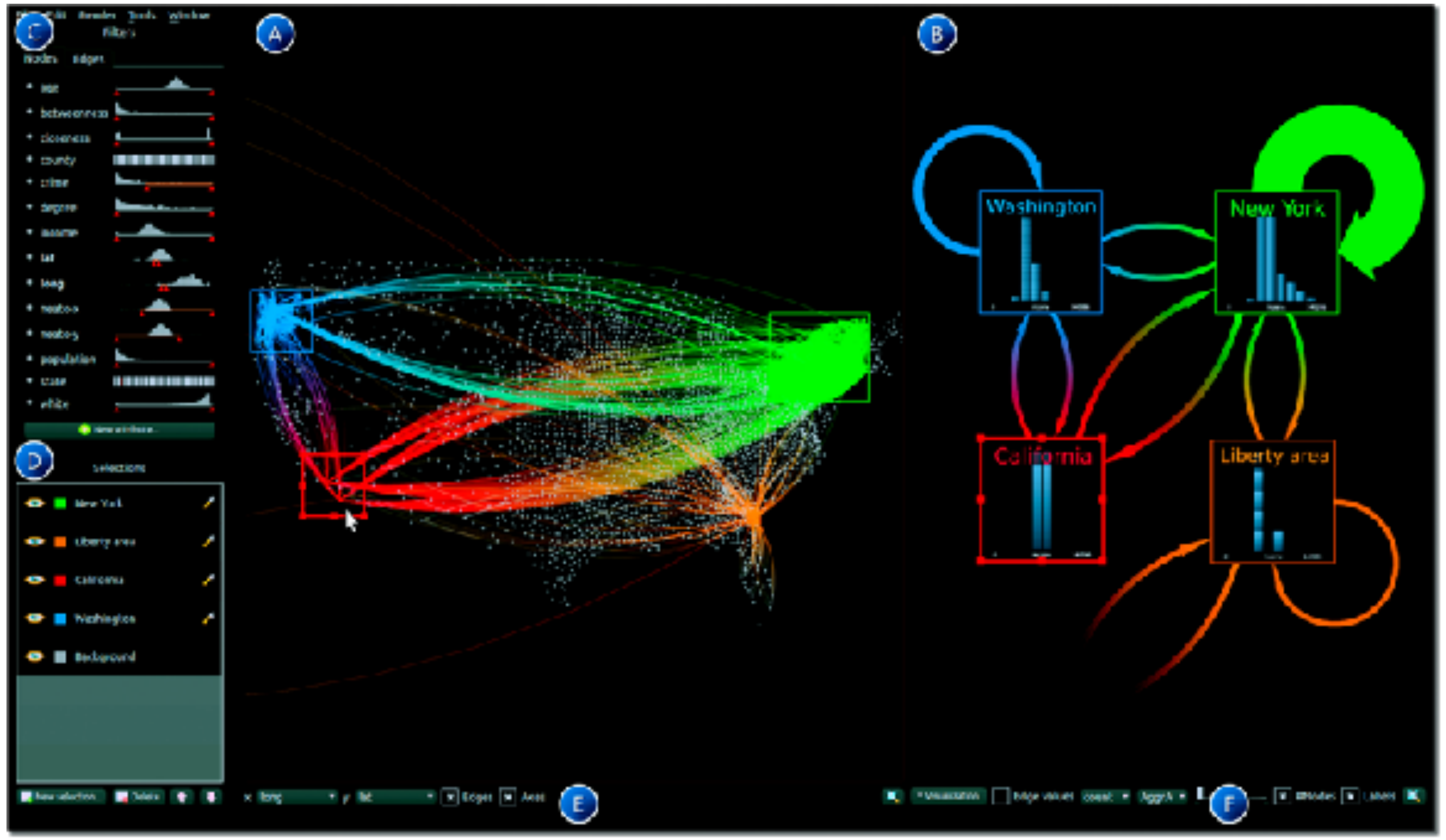

[Multivariate Network Exploration and Presentation: From Detail to Overview via Selections and Aggregations. van den Elzen, van Wijk, IEEE TVCG 20(12): 2014 (Proc. InfoVis 2014).]

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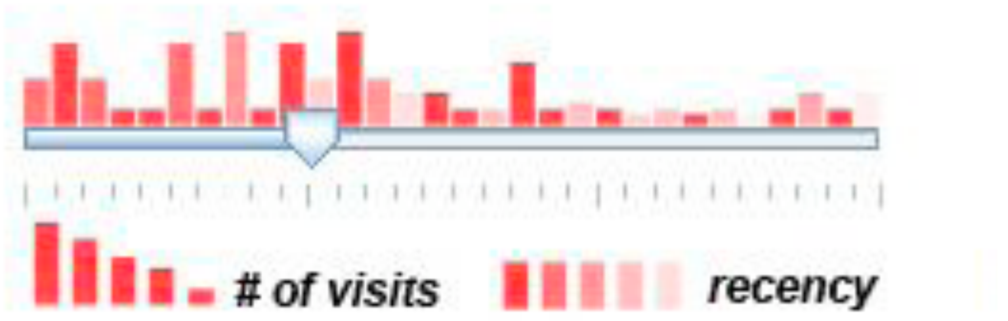

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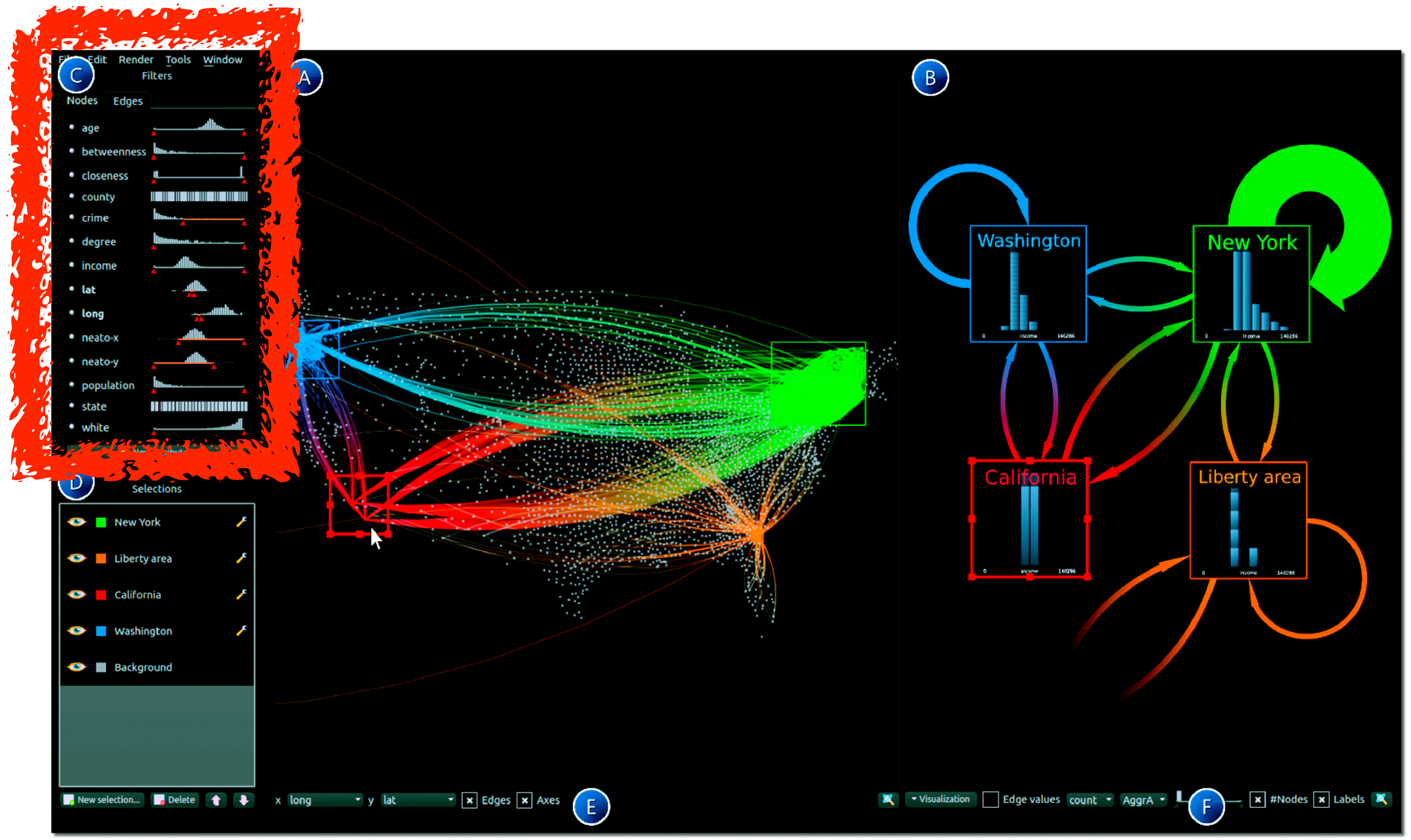

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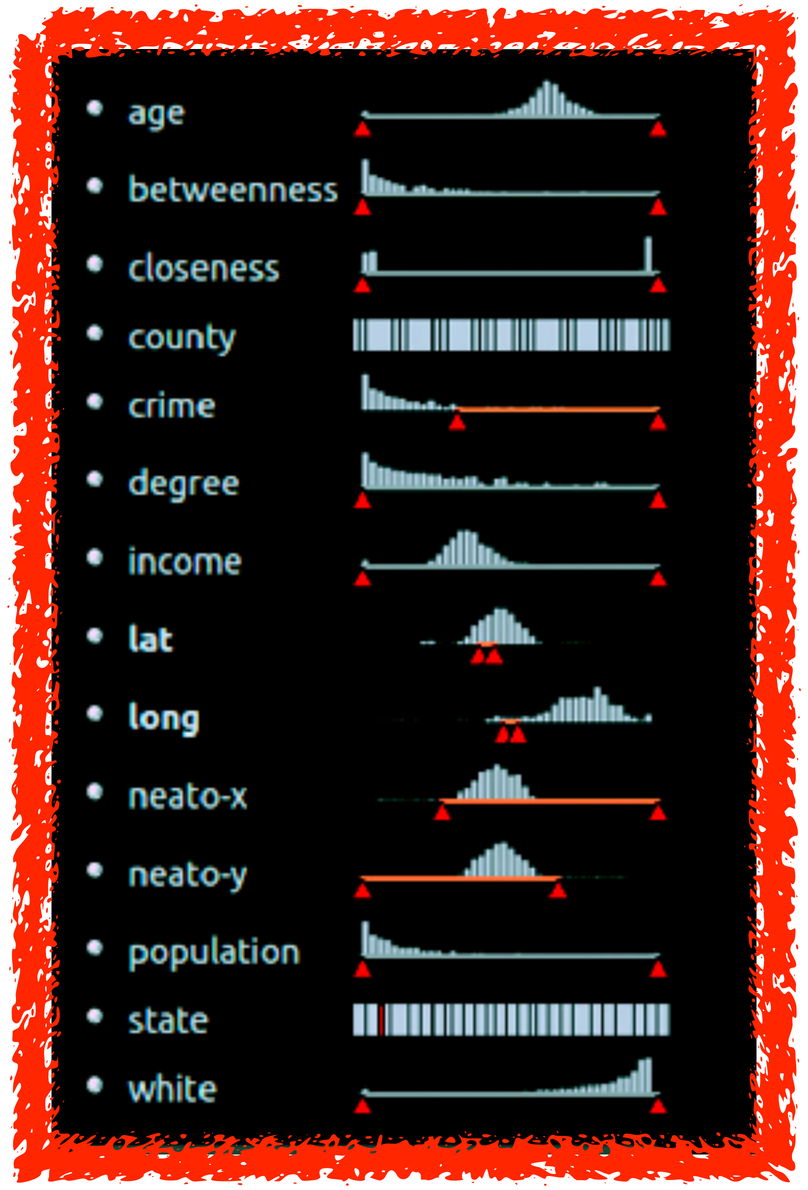
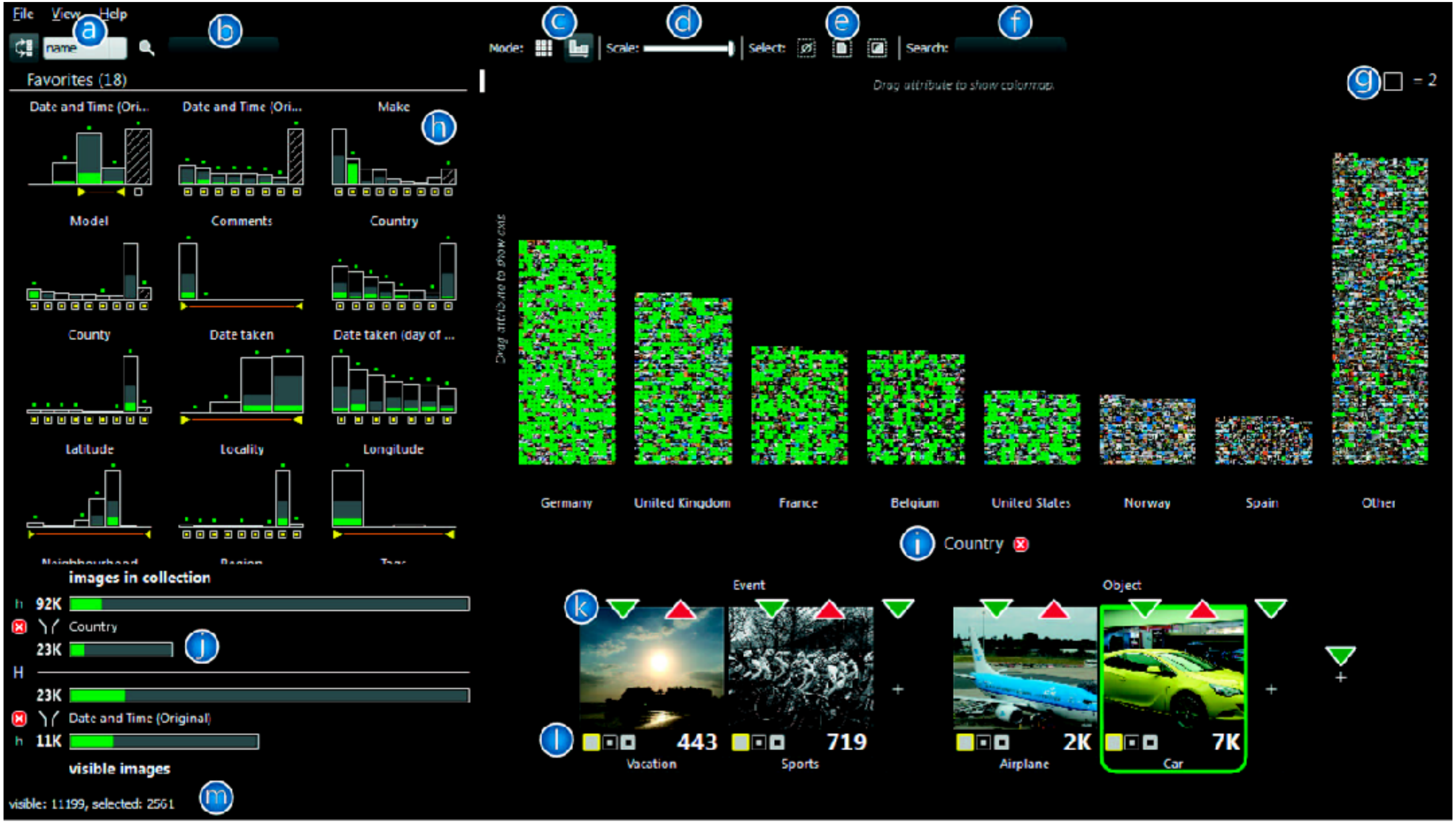


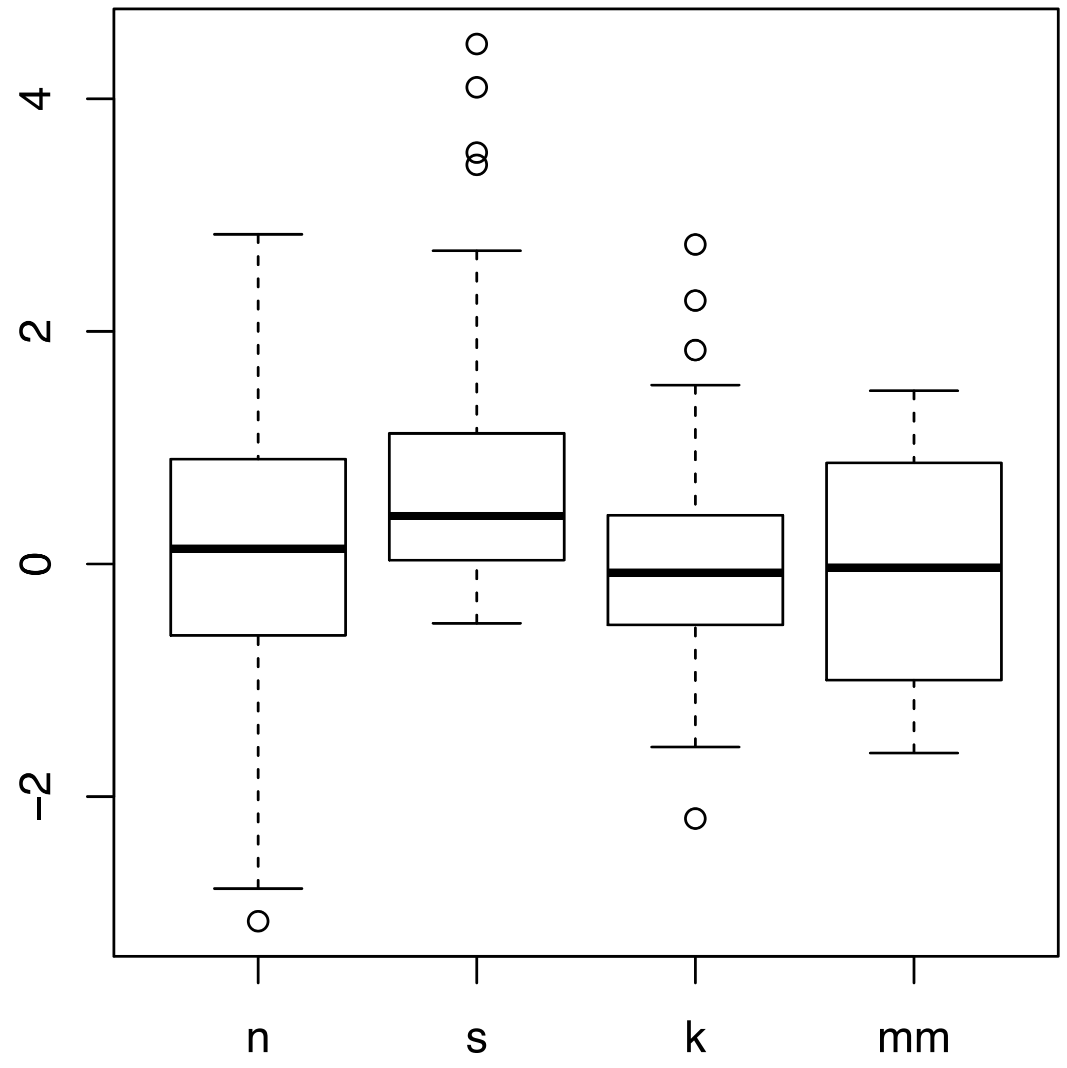
Scented histogram bisliders: detailed



[ICLIC: Interactive categorization of large image collections. van der Corput and van Wijk. Proc. PacificVis 2016.]

Idiom: **boxplot**

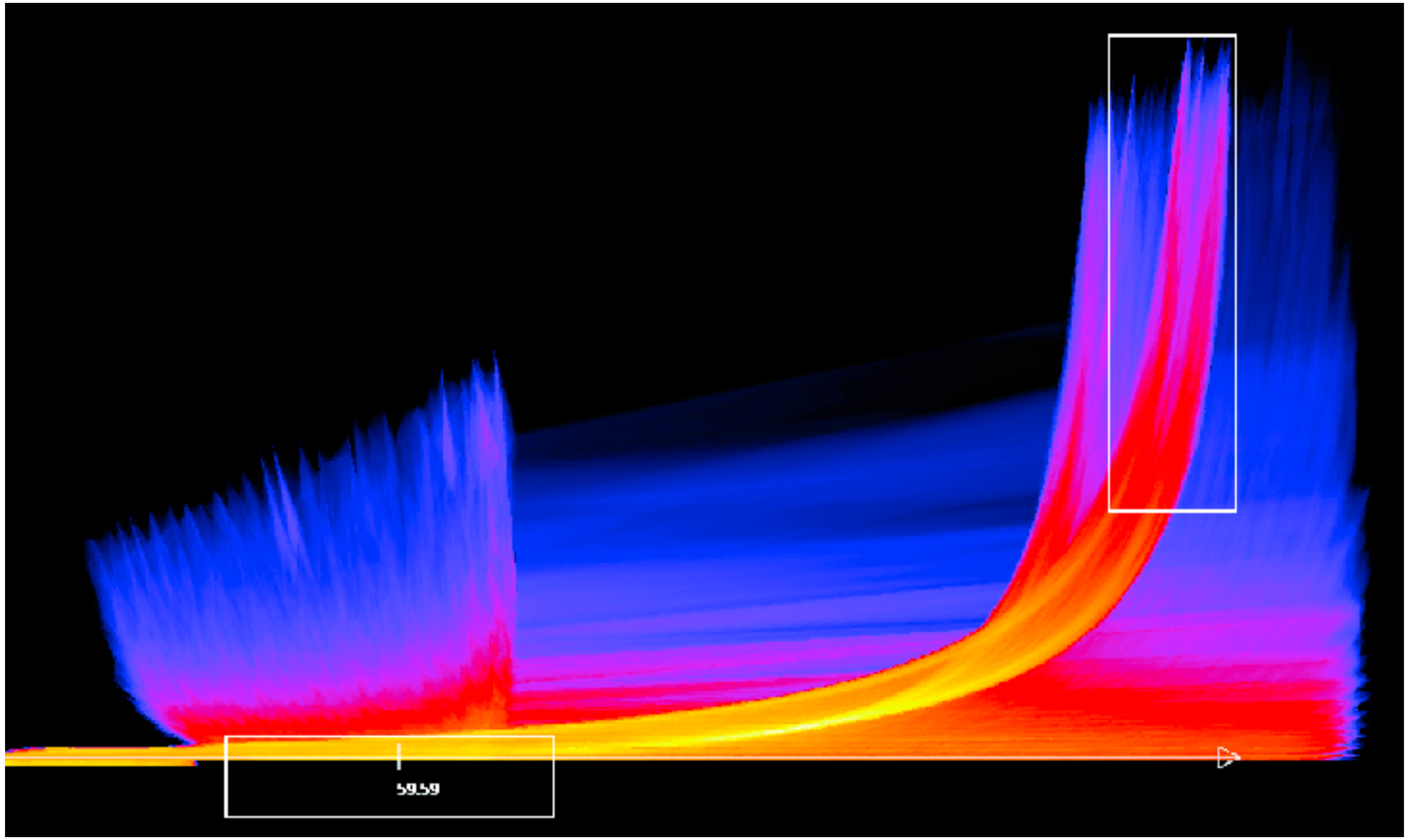
- static item aggregation
- task: find distribution
- data: table
- derived data
  - 5 quant attribs
    - median: central line
    - lower and upper quartile: boxes
    - lower upper fences: whiskers
      - values beyond which items are outliers
  - outliers beyond fence cutoffs explicitly shown
- scalability
  - unlimited number of items!



[40 years of boxplots. Wickham and Stryjewski. 2012]

Idiom: **Continuous scatterplot**

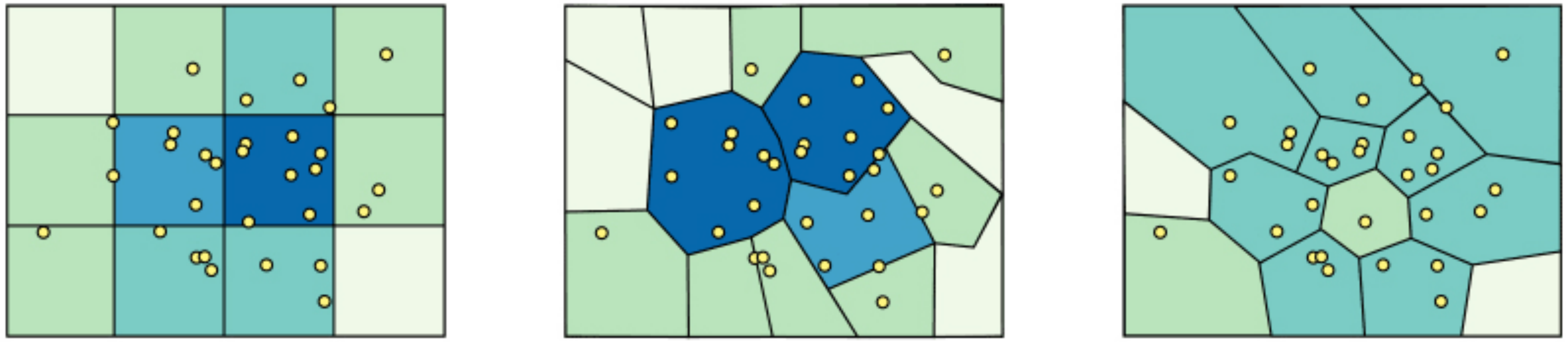
- static item aggregation
- data: table
- derived data: table
  - key attribs x,y for pixels
  - quant attrib: overplot density
- dense space-filling 2D matrix
- color:
  sequential categorical hue +
  ordered luminance colormap
- scalability
  - no limits on overplotting:
    millions of items



[Continuous Scatterplots. Bachthaler and Weiskopf.
IEEE TVCG (Proc. Vis 08) 14:6 (2008), 1428–1435. 2008.]

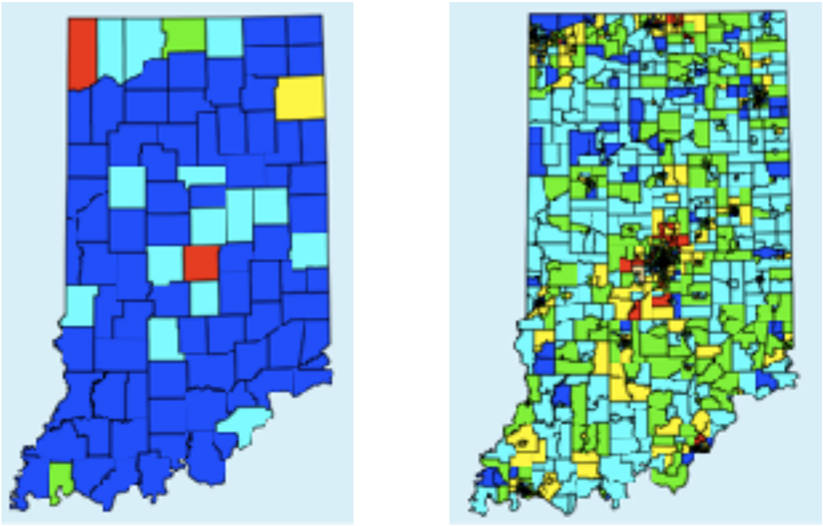
Spatial aggregation

- MAUP: Modifiable Areal Unit Problem
  - changing boundaries of cartographic regions can yield dramatically different results
  - zone effects



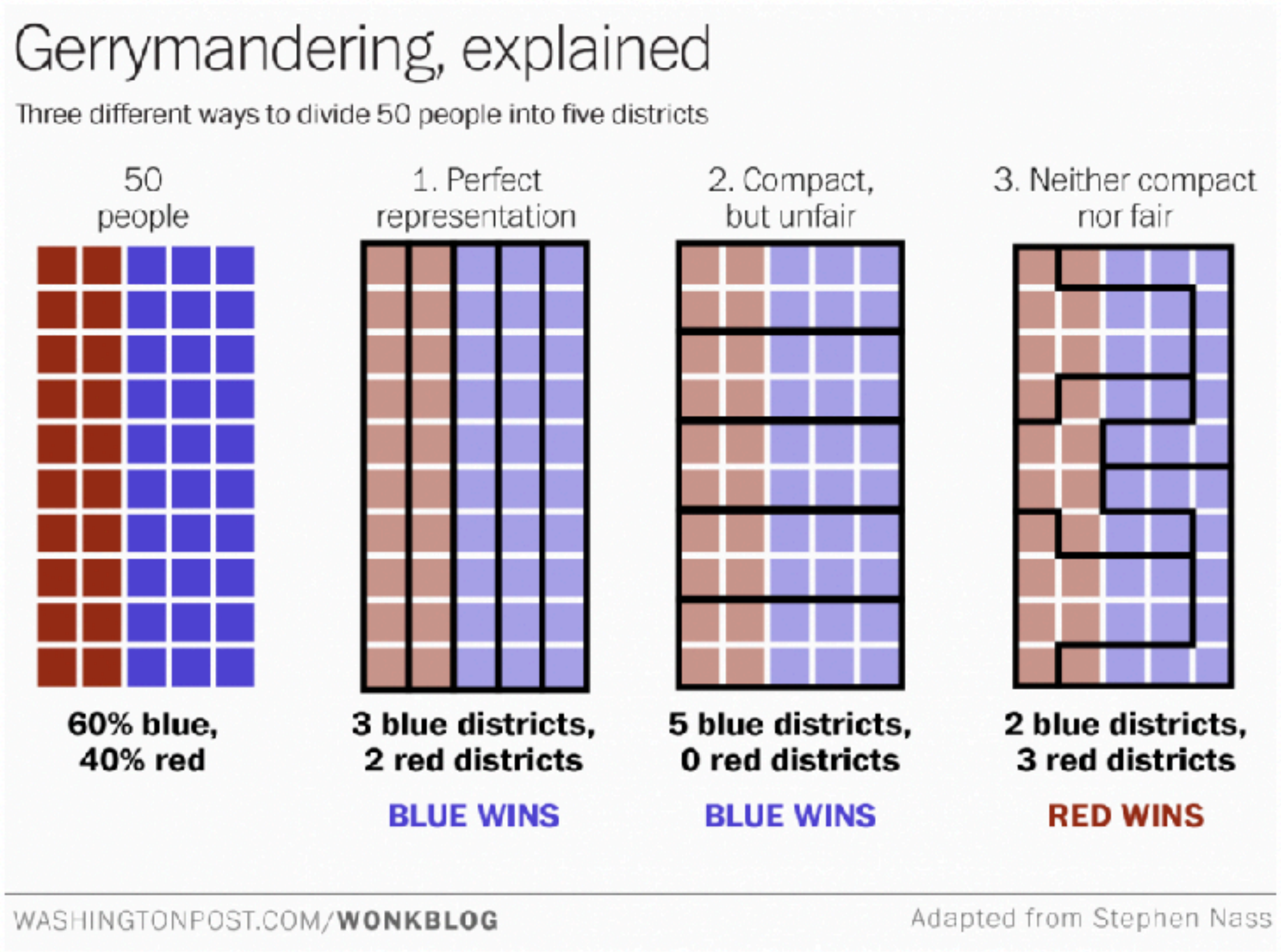
[http://www.e-education.psu/edu/geog486/l4_p7.html, Fig 4.cg.6]

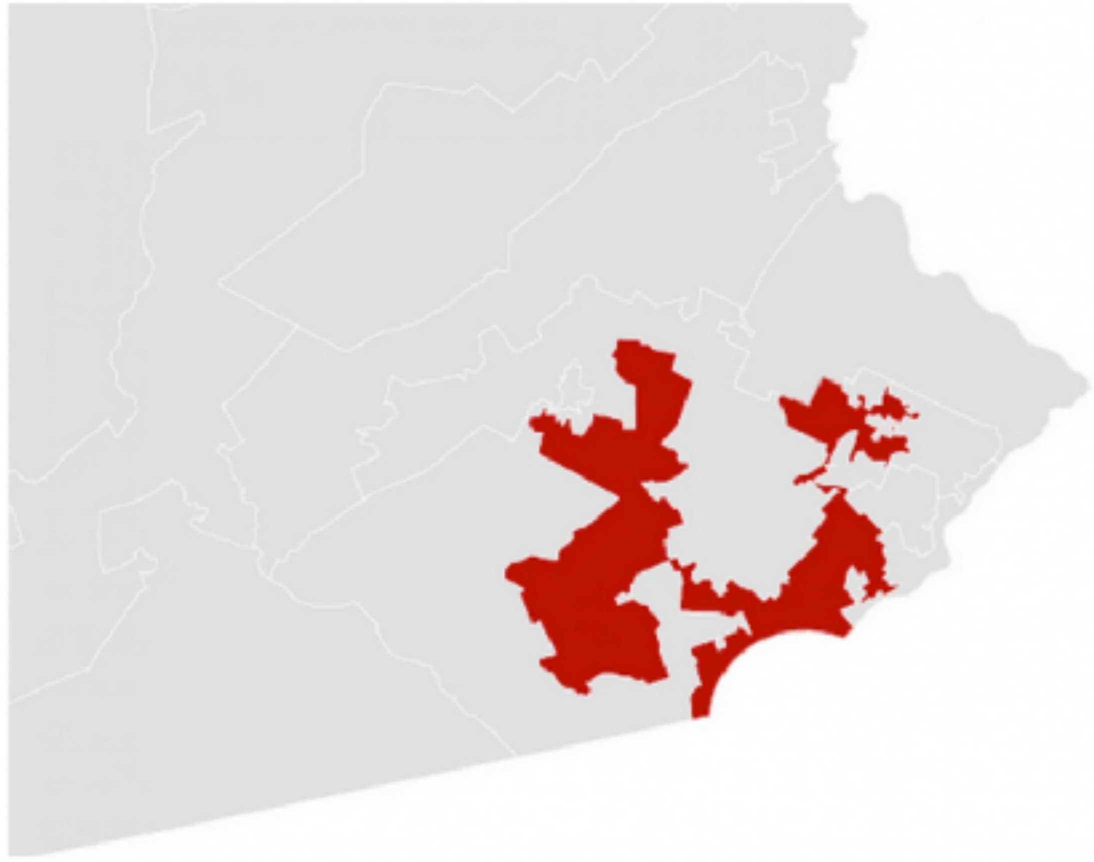
  - scale effects



https://blog.cartographica.com/blog/2011/5/19/the-modifiable-areal-unit-problem-in-gis.html

Gerrymandering: MAUP for political gain





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

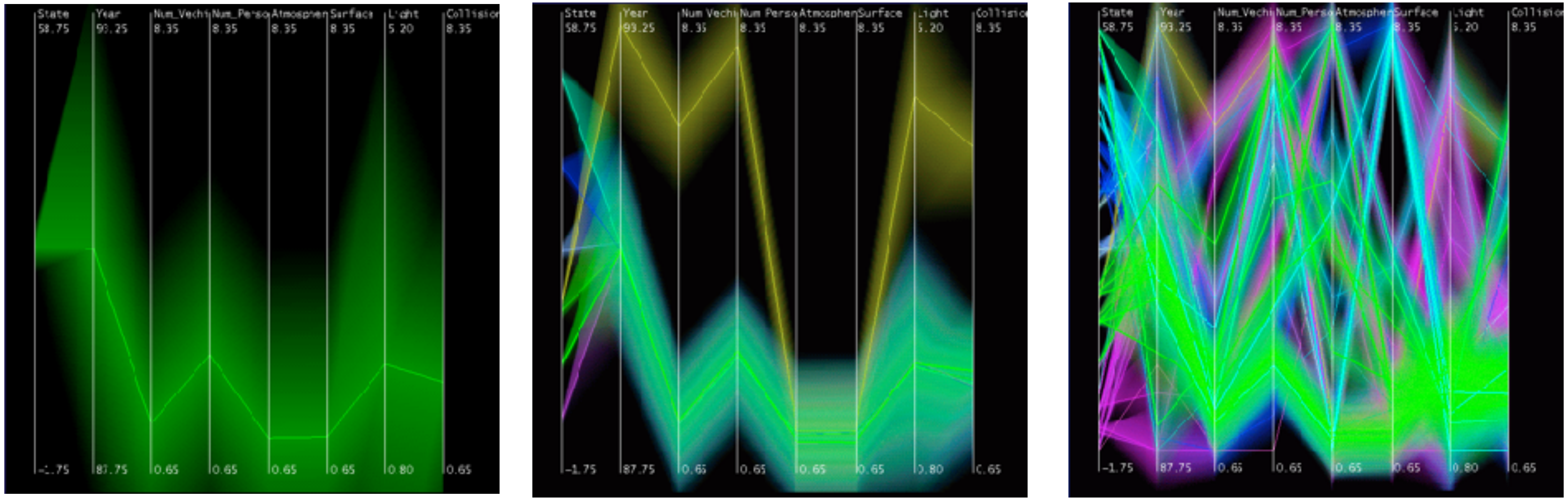
https://www.washingtonpost.com/news/wonk/wp/2015/03/01/this-is-the-best-explanation-of-gerrymandering-you-will-ever-see/

Dynamic aggregation: Clustering

- clustering: classification of items into similar bins
  - based on similiarity measure
  - hierarchical algorithms produce "similarity tree": cluster hierarchy
    - agglomerative clustering: start w/ each node as own cluster, then iteratively merge
- cluster hierarchy: derived data used w/ many dynamic aggregation idioms
  - cluster more homogeneous than whole dataset
    - statistical measures & distribution more meaningful

Idiom: **Hierarchical parallel coordinates**

- dynamic item aggregation
- derived data: **cluster hierarchy**
- encoding:
  - cluster band with variable transparency, line at mean, width by min/max values
  - color by proximity in hierarchy

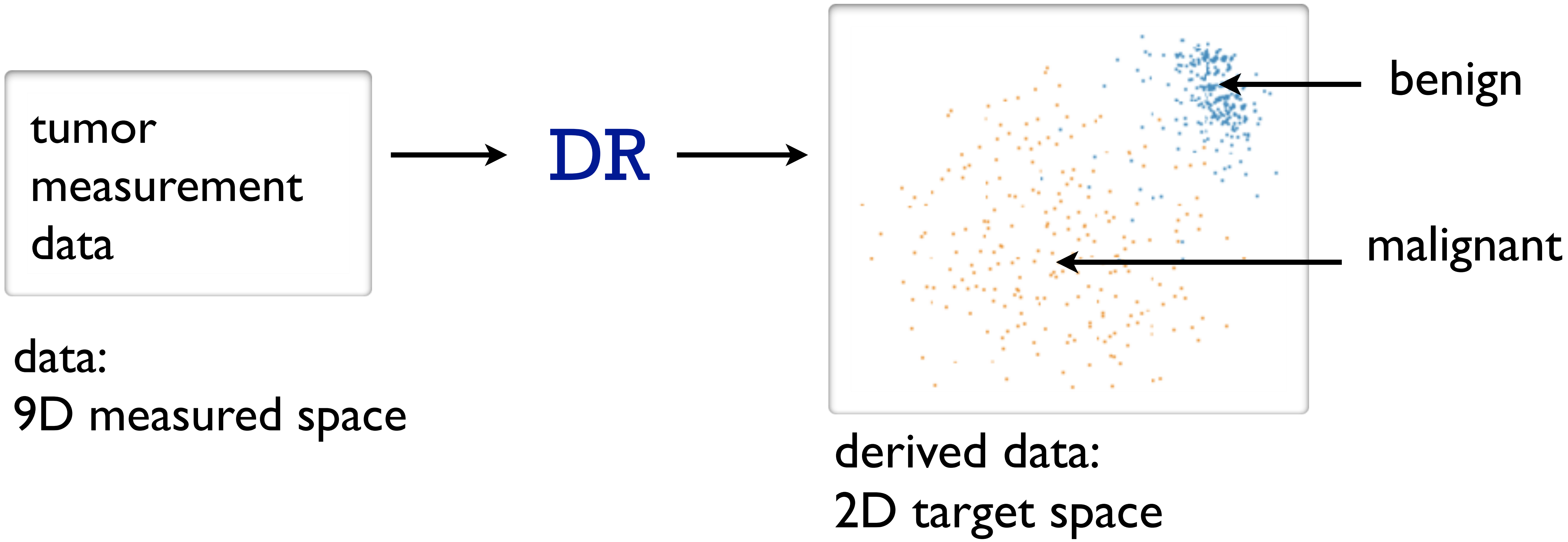


[Hierarchical Parallel Coordinates for Exploration of Large Datasets. Fua, Ward, and Rundensteiner. Proc. IEEE Visualization Conference (Vis '99), pp. 43– 50, 1999.]

Dimensionality Reduction

Attribute aggregation: Dimensionality reduction

- attribute aggregation
  - derive low-dimensional target space from high-dimensional measured space
    - capture most of variance with minimal error
  - use when you can’t directly measure what you care about
    - true dimensionality of dataset conjectured to be smaller than dimensionality of measurements
    - latent factors, hidden variables



Dimensionality vs attribute reduction

- vocab use in field not consistent
  - dimension/attribute
- attribute reduction: reduce set with filtering
  - includes orthographic projection
- dimensionality reduction: create smaller set of new dims/attribs
  - typically implies dimensional aggregation, not just filtering
  - vocab: projection/mapping

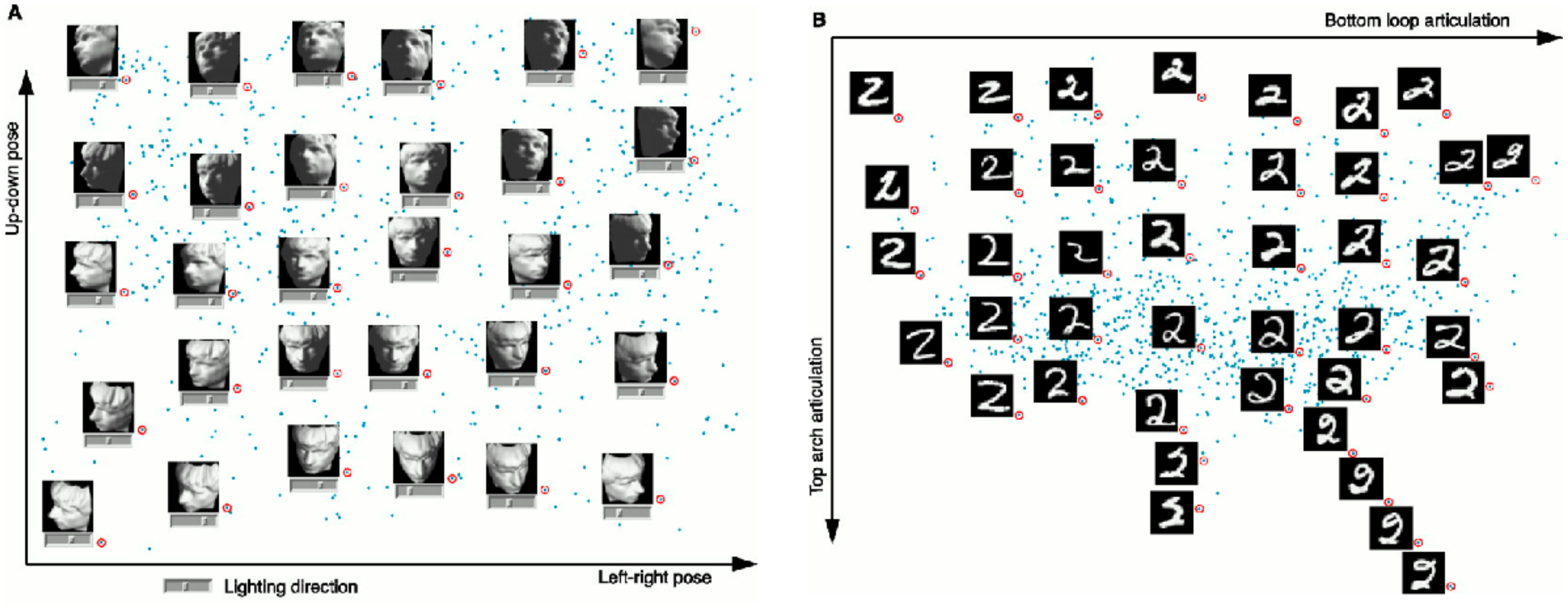
Dimensionality reduction & visualization

- why do people do DR?
  - improve performance of downstream algorithm
    - avoid curse of dimensionality
  - data analysis
    - if look at the output: visual data analysis
- abstract tasks when visualizing DR data
  - dimension-oriented tasks
    - naming synthesized dims, mapping synthesized dims to original dims
  - cluster-oriented tasks
    - verifying clusters, naming clusters, matching clusters and classes

[Visualizing Dimensionally-Reduced Data: Interviews with Analysts and a Characterization of Task Sequences. Brehmer, Sedlmair, Ingram, and Munzner. Proc. BELIV 2014.]

Dimension-oriented tasks

- naming synthesized dims: inspect data represented by lowD points



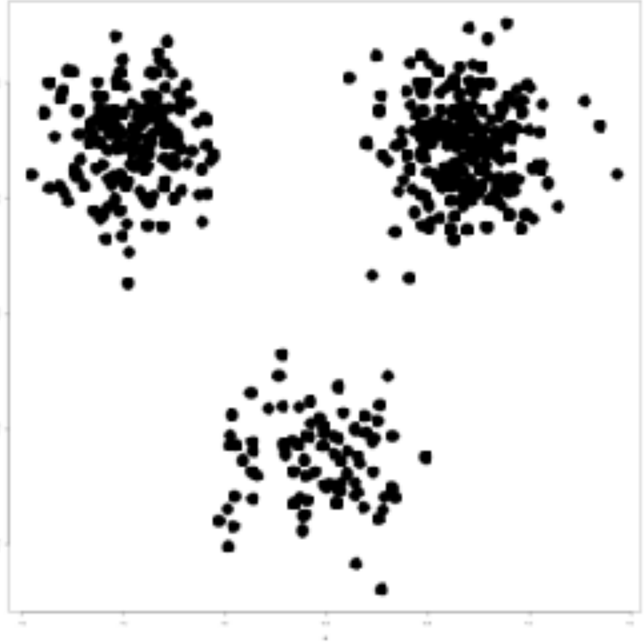
[A global geometric framework for nonlinear dimensionality reduction. Tenenbaum, de Silva, and Langford. Science, 290(5500):2319–2323, 2000.]

Cluster-oriented tasks

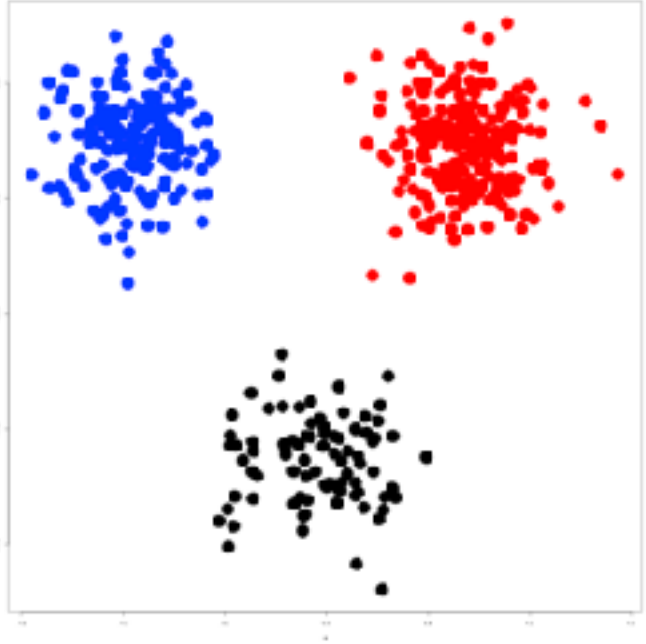
- verifying, naming, matching to classes

no discernable clusters

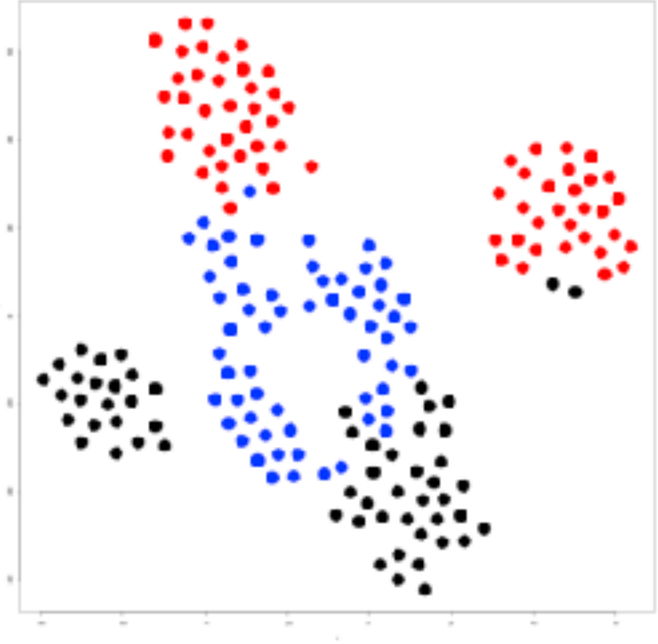
clearly discernable clusters



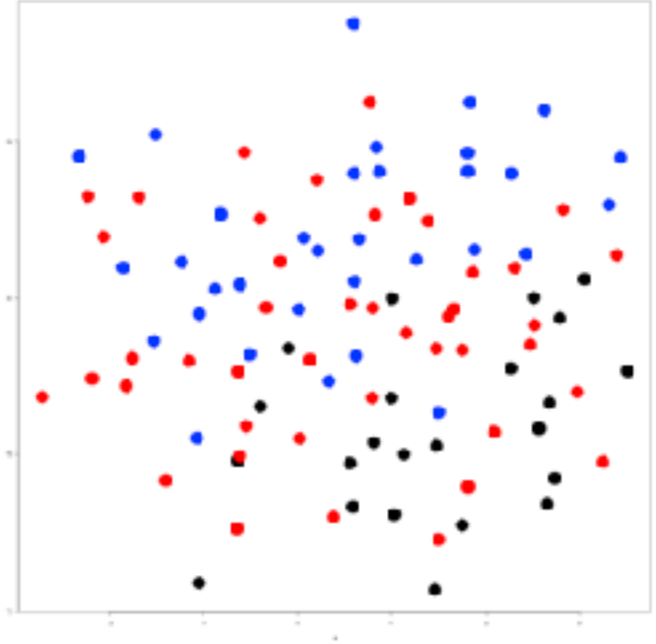
clear match cluster/class



partial match cluster/class



no match cluster/class



[Visualizing Dimensionally-Reduced Data: Interviews with Analysts and a Characterization of Task Sequences. Brehmer, Sedlmair, Ingram, and Munzner. Proc. BELIV 2014.]

Idiom: **Dimensionality reduction for documents**

Task 1

	Dim 1	Dim ...	Dim n
Item 1			
Item ...			
Item n			

	Dim 1	Dim 2
Item 1		
Item ...		
Item n		

In
HD data → Out
2D data

What?
- In High-dimensional data
- Out 2D data

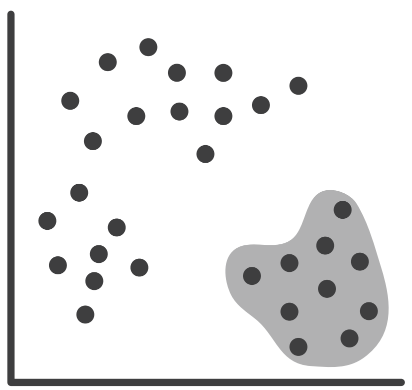
Why?
- Produce
- Derive

→

Task 2

	Dim 1	Dim 2
Item 1		
Item ...		
Item n		

In
2D data



→ Out
Scatterplot
Clusters & points

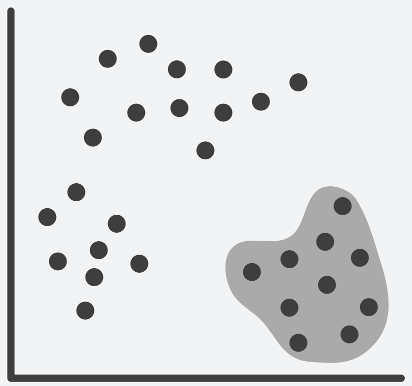
What?
- In 2D data
- Out Scatterplot
- Out Clusters & points

Why?
- Discover
- Explore
- Identify

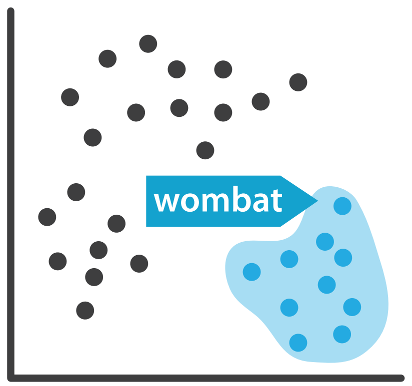
How?
- Encode
- Navigate
- Select

→

Task 3



In
Scatterplot
Clusters & points



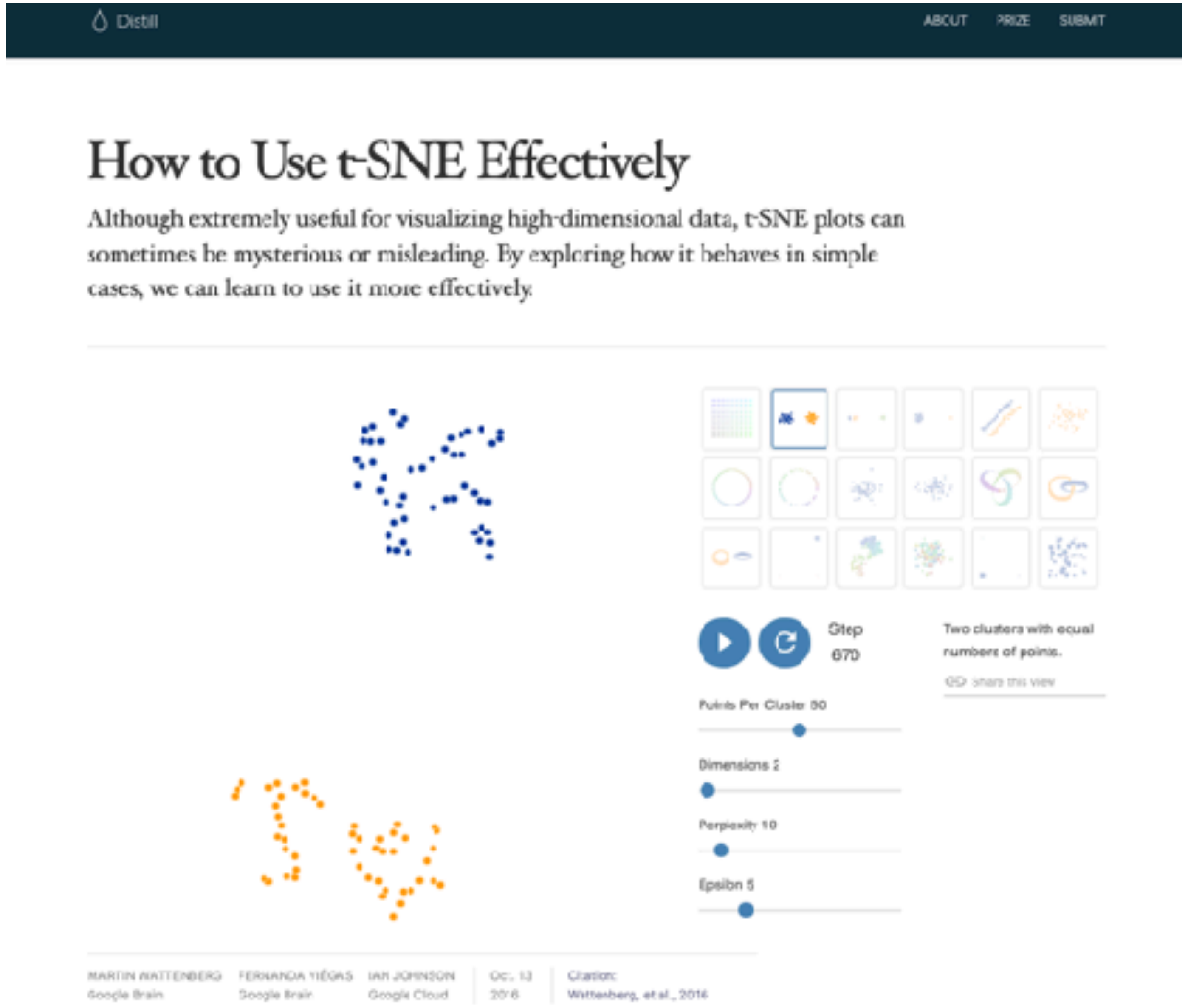
→ Out
Labels for clusters

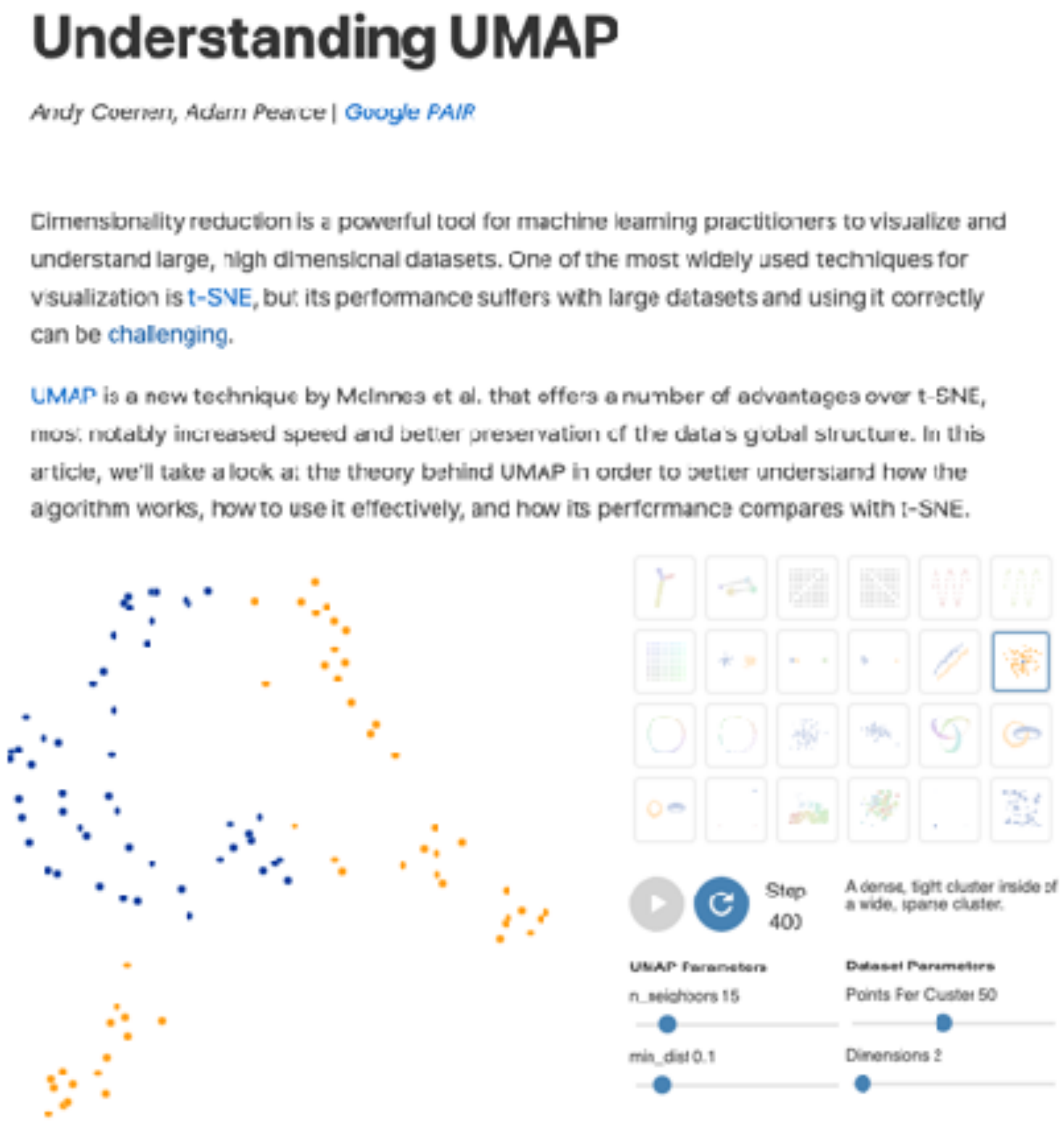
What?
- In Scatterplot
- In Clusters & points
- Out Labels for clusters

Why?
- Produce
- Annotate

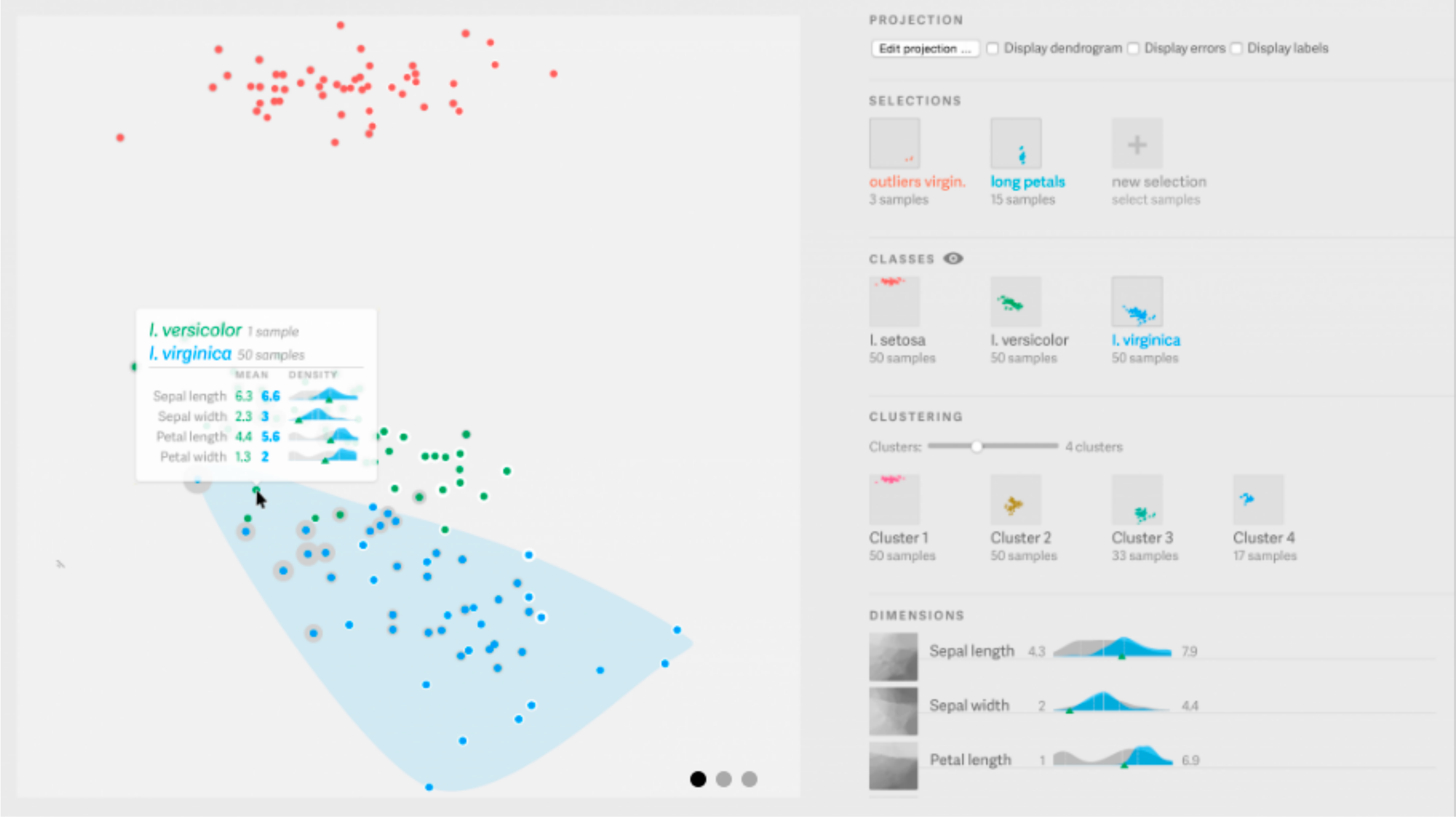
Latest algorithms: t-SNE, UMAP

- t-SNE https://distill.pub/2016/misread-tsne/
- UMAP https://pair-code.github.io/understanding-umap/





Interacting with dimensionally reduced data

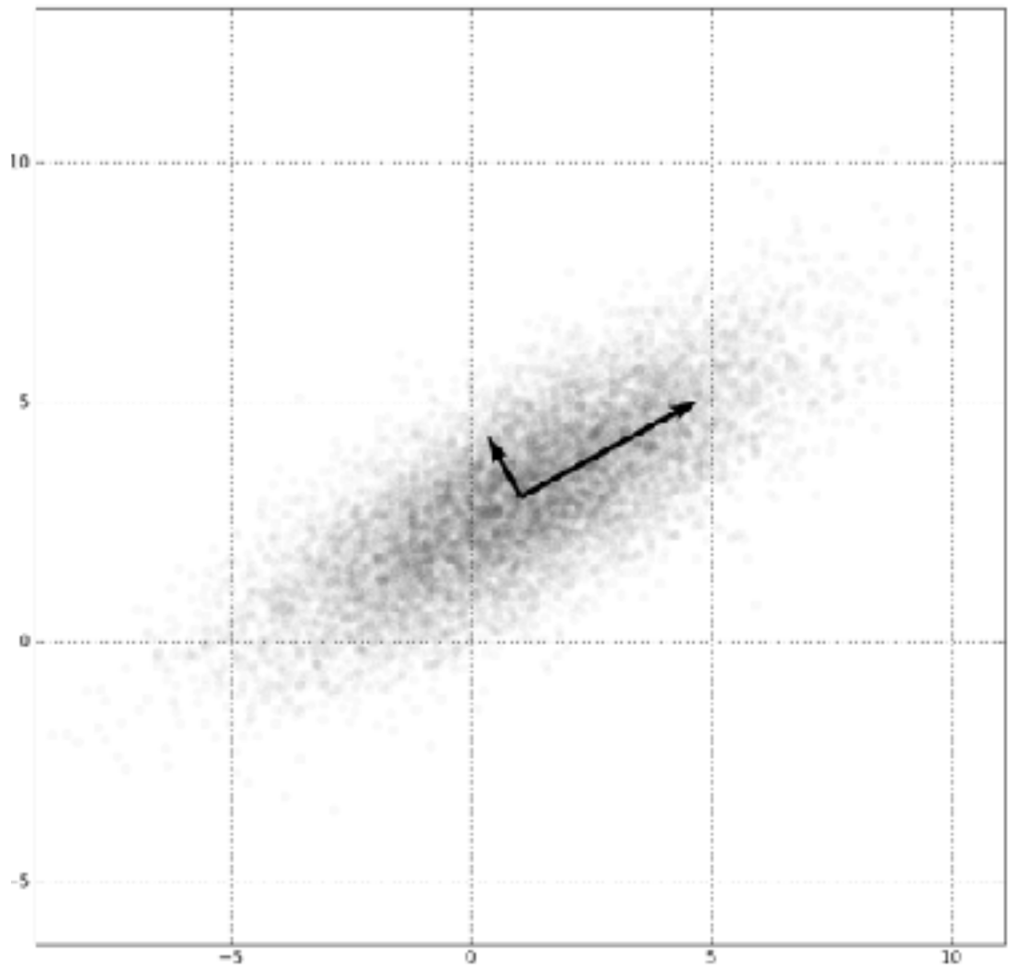


[https://uclab.fh-potsdam.de/projects/probing-projections/]

[Probing Projections: Interaction Techniques for Interpreting Arrangements and Errors of Dimensionality Reductions. Stahnke, Dörk, Müller, and Thom. IEEE TVCG (Proc. InfoVis 2015) 22(1):629-38 2016.]

Linear dimensionality reduction

- principal components analysis (PCA)
  - finding axes: first with most variance, second with next most, …
  - describe location of each point as linear combination of weights for each axis
    - mapping synthesized dims to original dims



[http://en.wikipedia.org/wiki/File:GaussianScatterPCA.png]

Nonlinear dimensionality reduction

- pro: can handle curved rather than linear structure
- cons: lose all ties to original dims/attribs
  - new dimensions often cannot be easily related to originals
    - mapping synthesized dims to original dims task is difficult
- many techniques proposed
  - many literatures: visualization, machine learning, optimization, psychology, ...
  - techniques: t-SNE, MDS (multidimensional scaling), charting, isomap, LLE,…
    - t-SNE: excellent for clusters
      - but some trickiness remains: http://distill.pub/2016/misread-tsne/
    - MDS: confusingly, entire family of techniques, both linear and nonlinear
      - minimize stress or strain metrics
      - early formulations equivalent to PCA

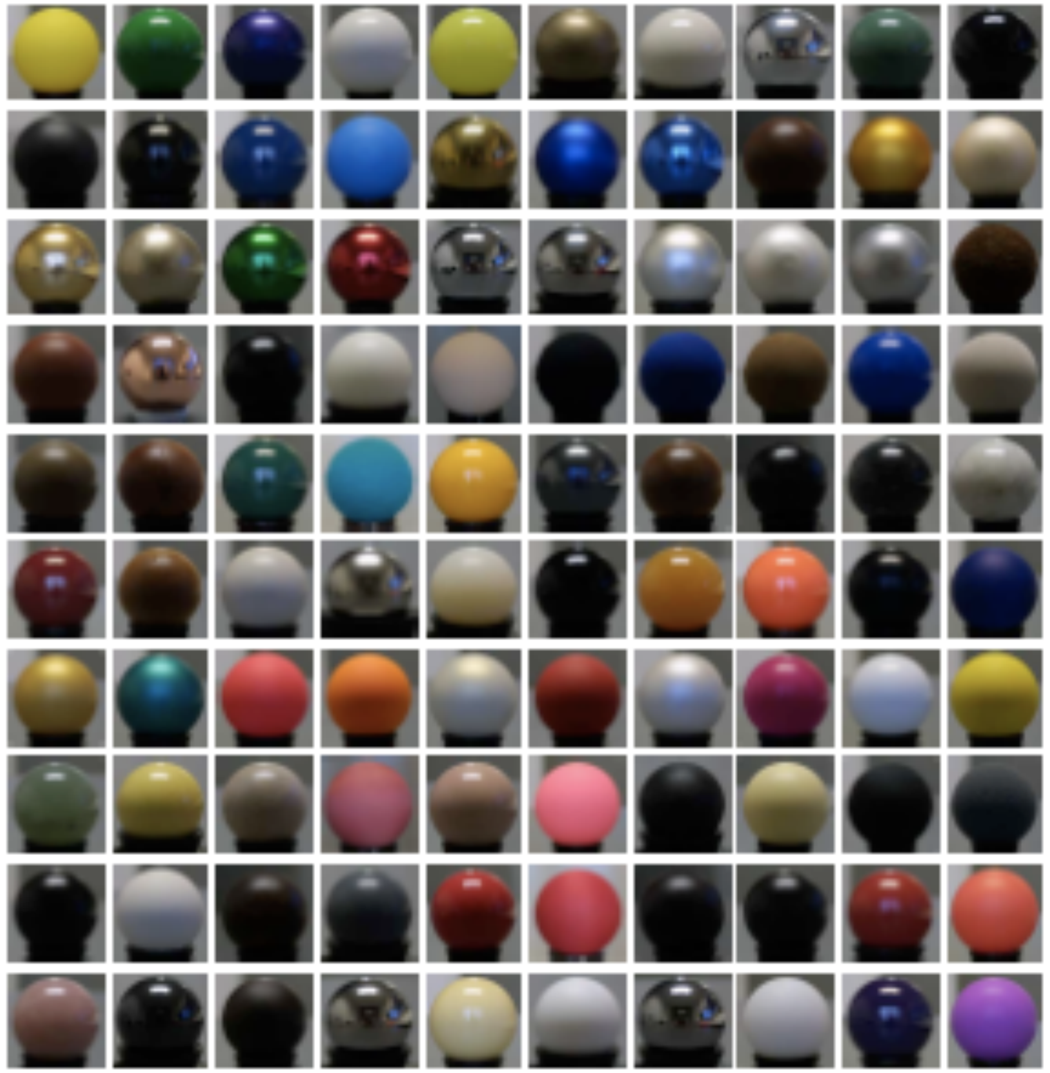
VDA with DR example: nonlinear vs linear

- DR for computer graphics reflectance model
  - goal: simulate how light bounces off materials to make realistic pictures
    - computer graphics: BRDF (reflectance)
  - idea: measure what light does with real materials

[Fig 2. Matusik, Pfister, Brand, and McMillan. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Capturing & using material reflectance

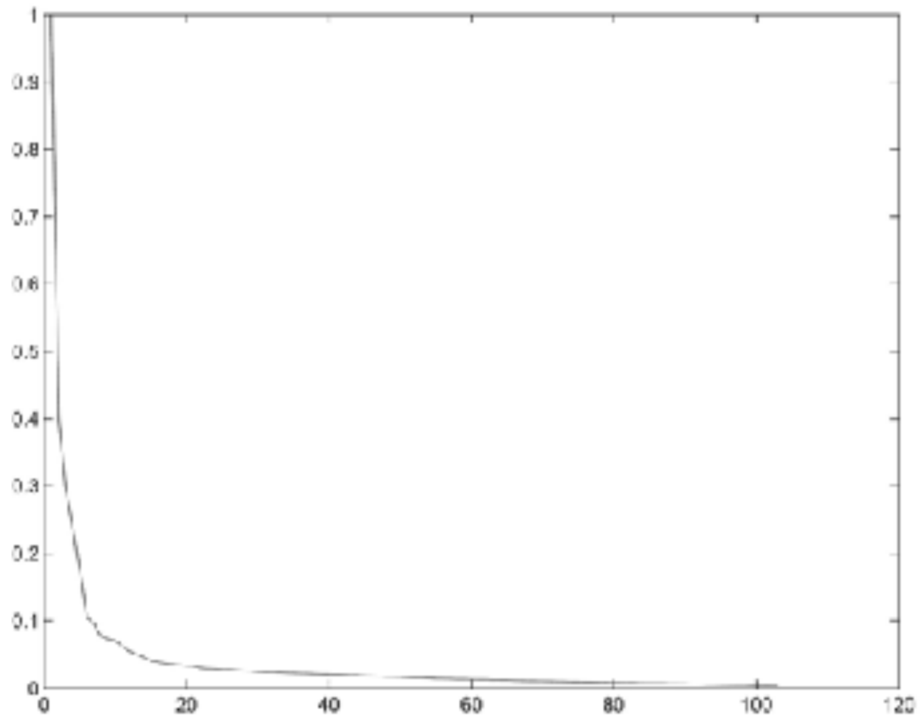
- reflectance measurement: interaction of light with real materials (spheres)
- result: 104 high-res images of material
  - each image 4M pixels
- goal: image synthesis
  - simulate completely new materials
- need for more concise model
  - 104 materials * 4M pixels = 400M dims
  - want concise model with meaningful knobs
    - how shiny/greasy/metallic
    - DR to the rescue!

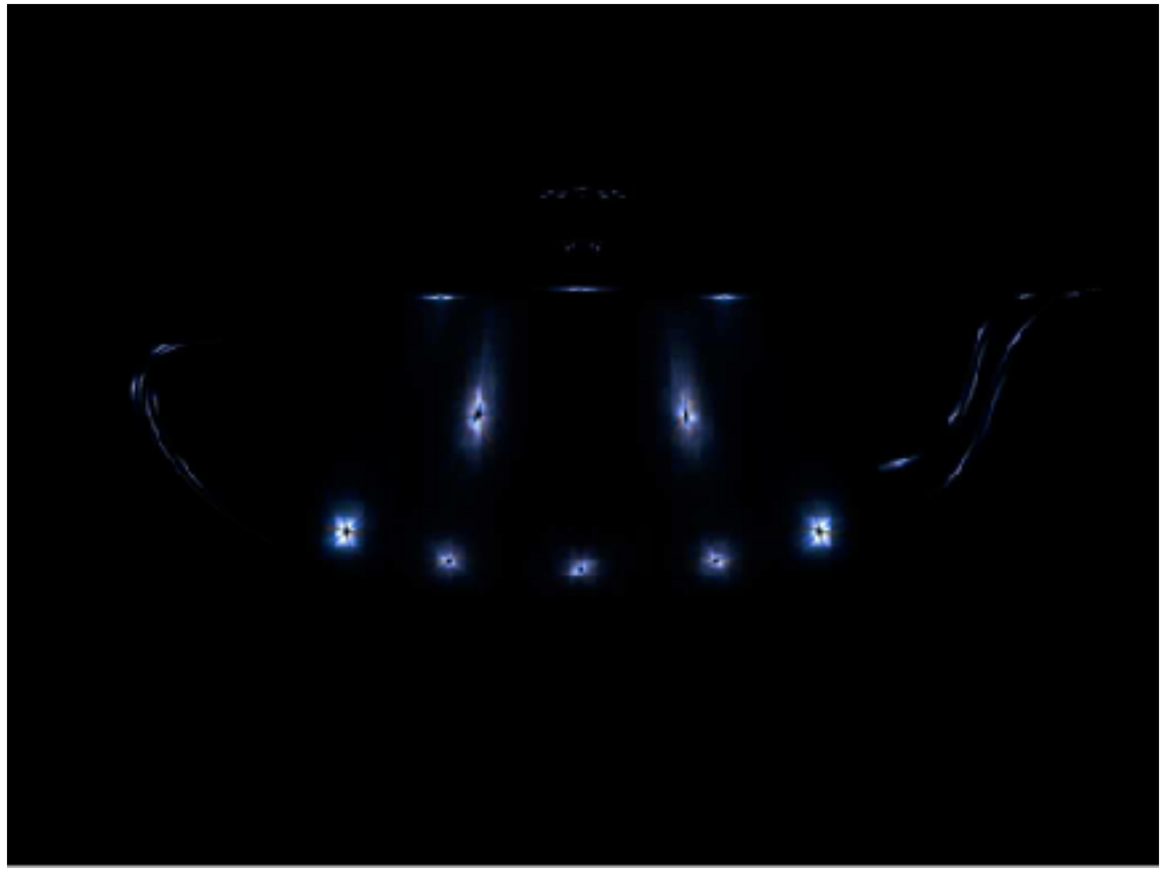


[Figs 5/6. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Linear DR

- first try: PCA (linear)
- result: error falls off sharply after ~45 dimensions
  - scree plots: error vs number of dimensions in lowD projection
- problem: physically impossible intermediate points when simulating new materials
  - specular highlights cannot have holes!

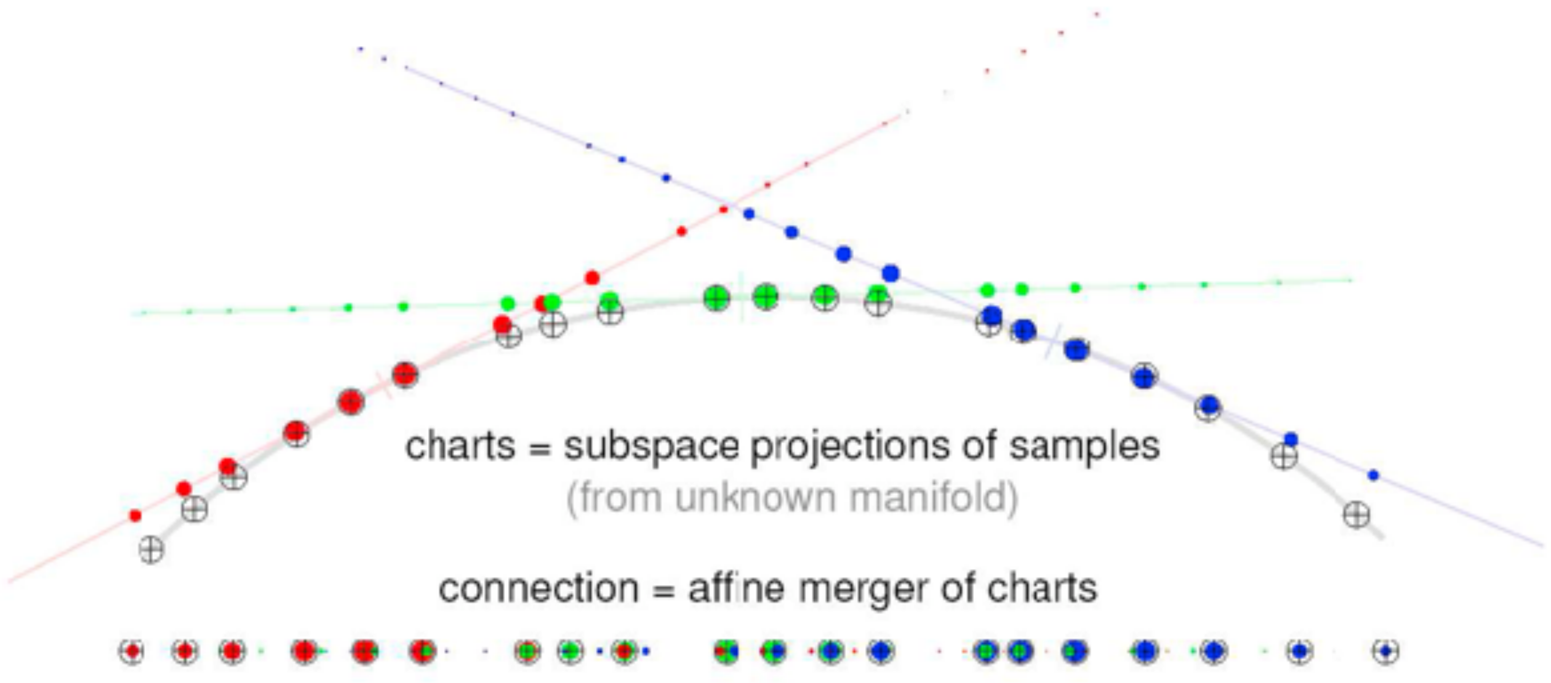


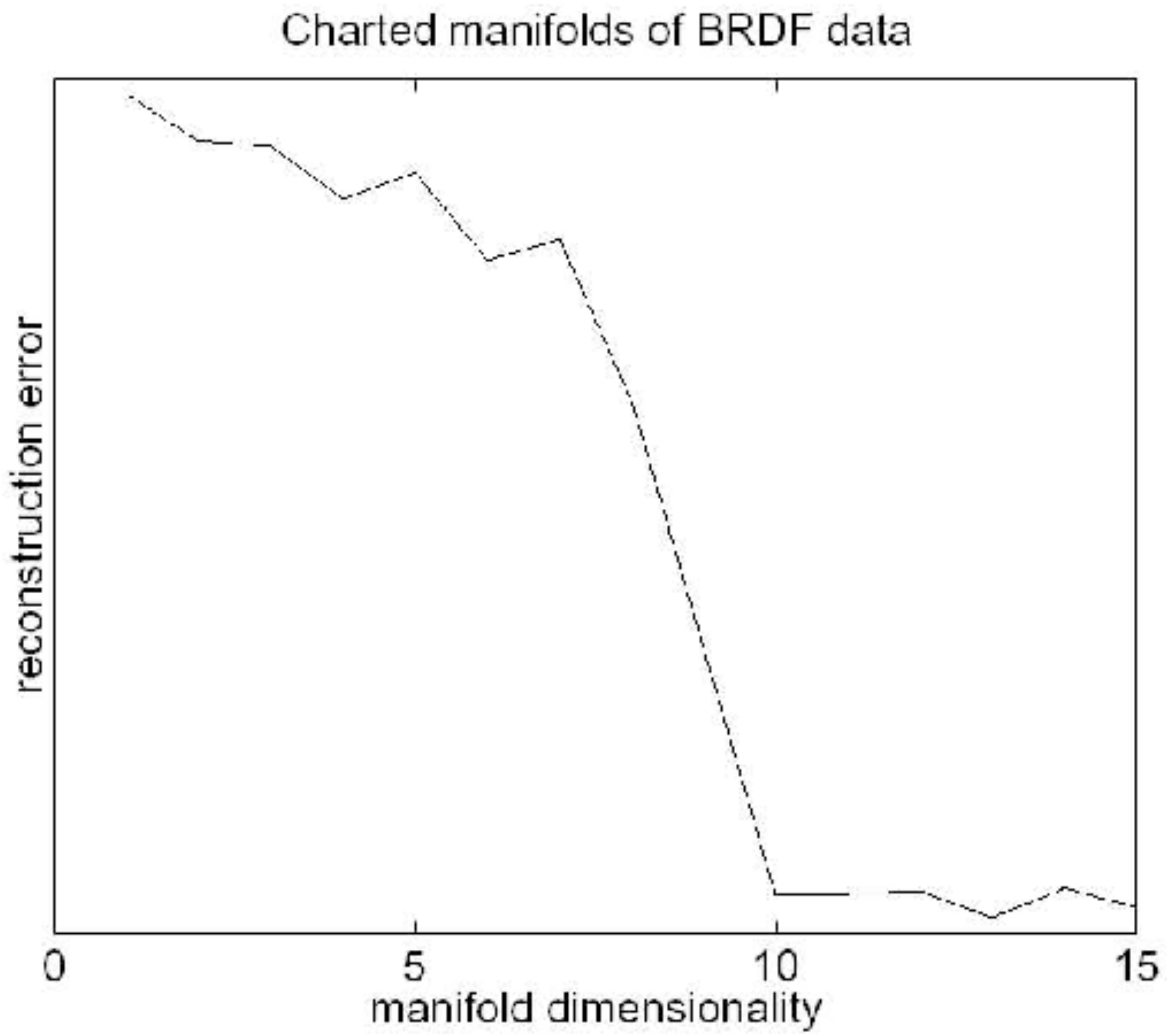


[Figs 6/7. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Nonlinear DR

- second try: charting (nonlinear DR technique)
  - scree plot suggests 10-15 dims
  - note: dim estimate depends on technique used!

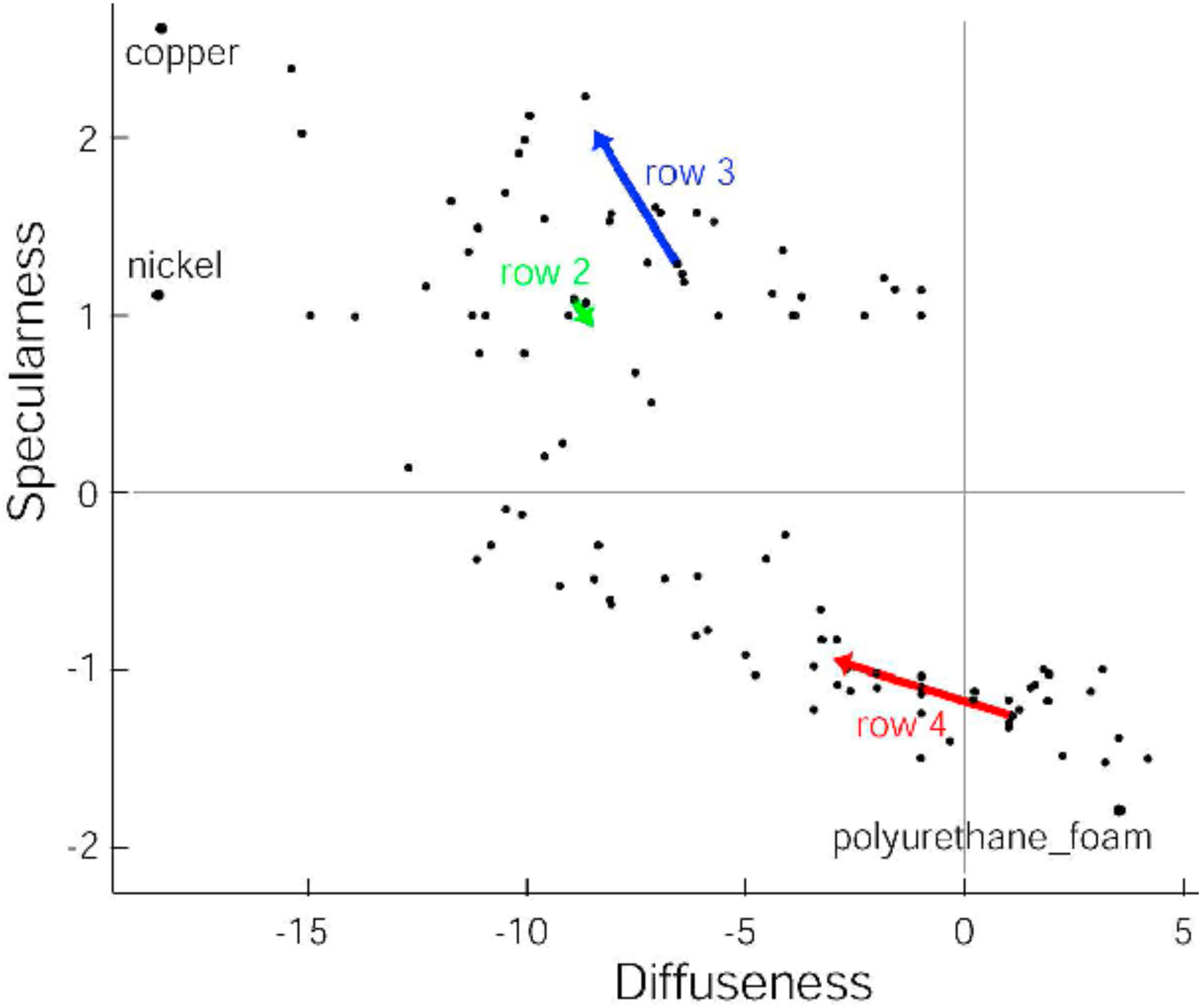




[Fig 10/11. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Finding semantics for synthetic dimensions

- look for meaning in scatterplots
  - synthetic dims created by algorithm but named by human analysts
  - points represent real-world images (spheres)
  - people inspect images corresponding to points to decide if axis could have meaningful name
- cross-check meaning
  - arrows show simulated images (teapots) made from model
  - check if those match dimension semantics

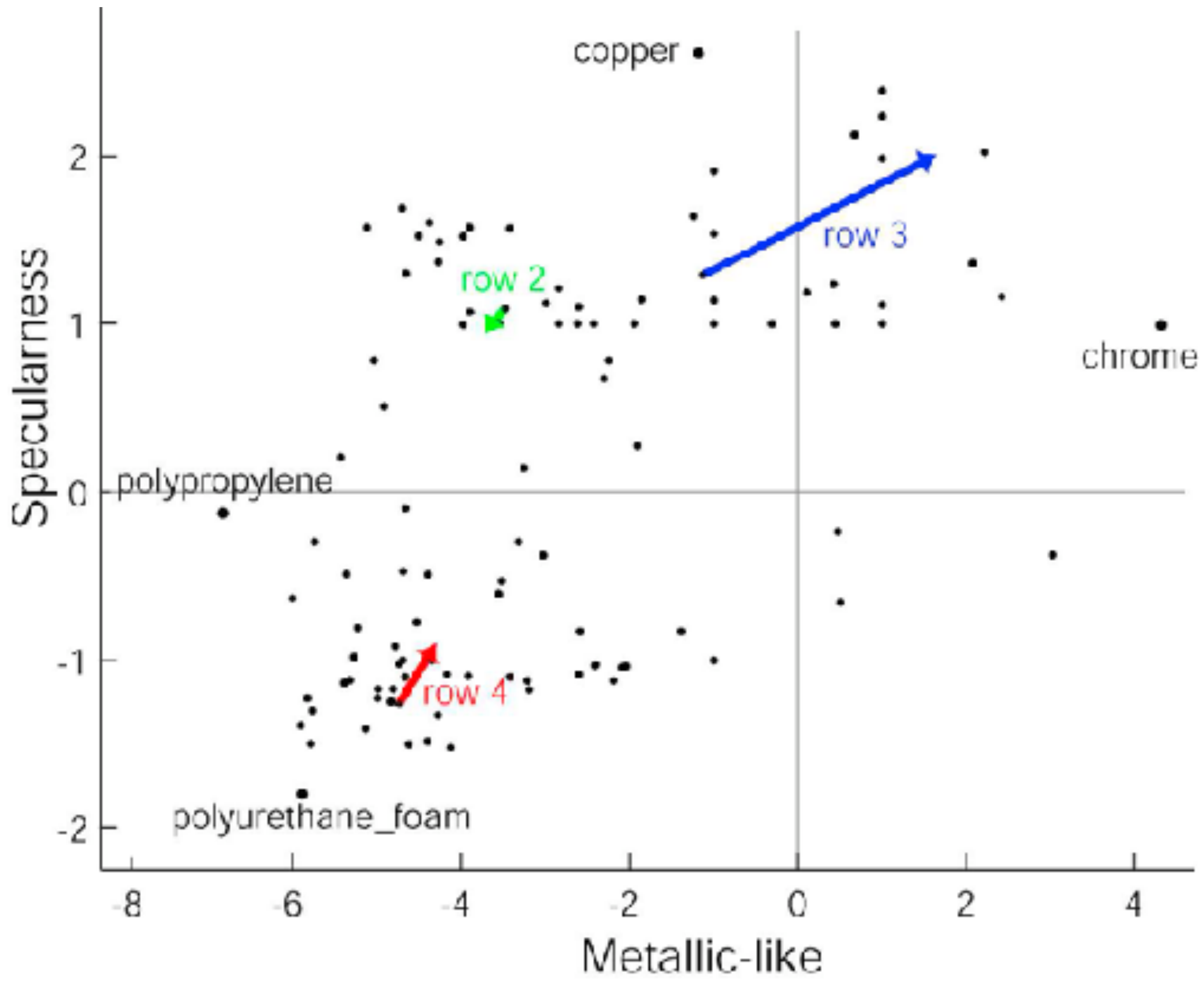


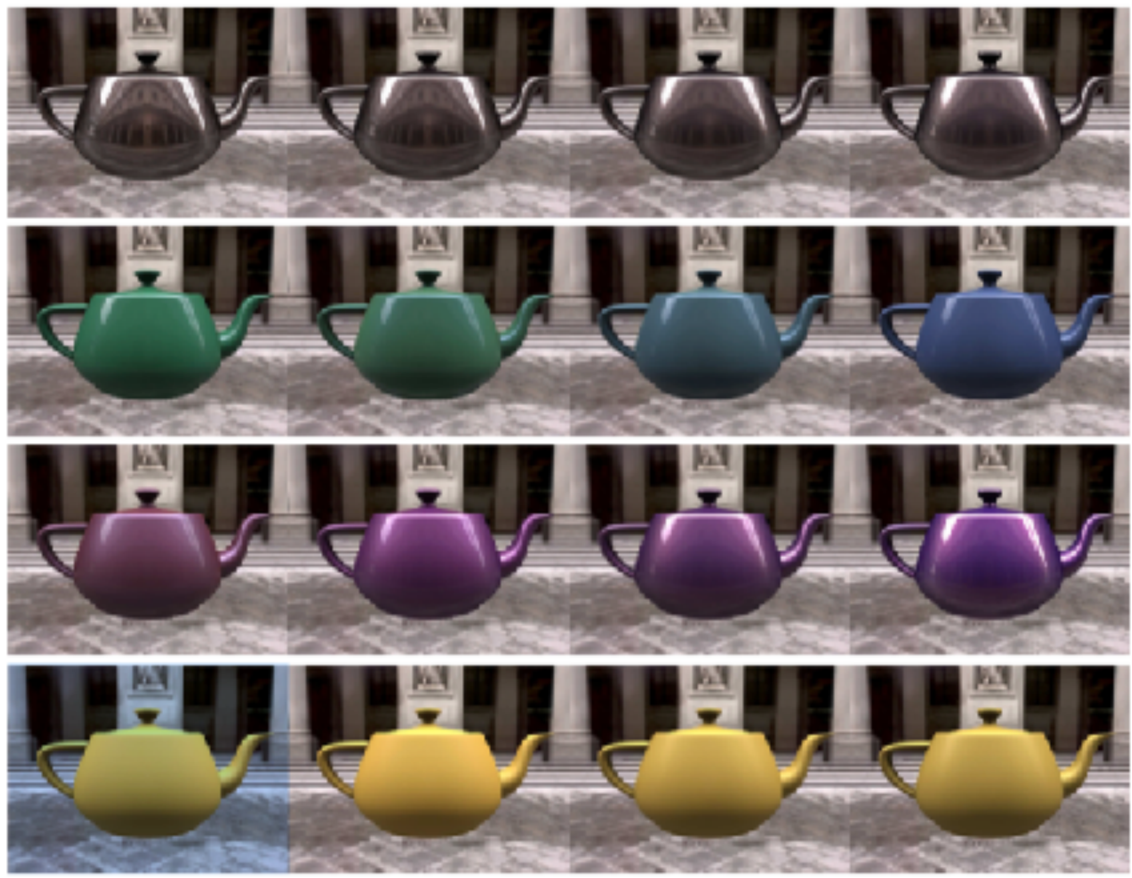
row 4

[Fig 12/16. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

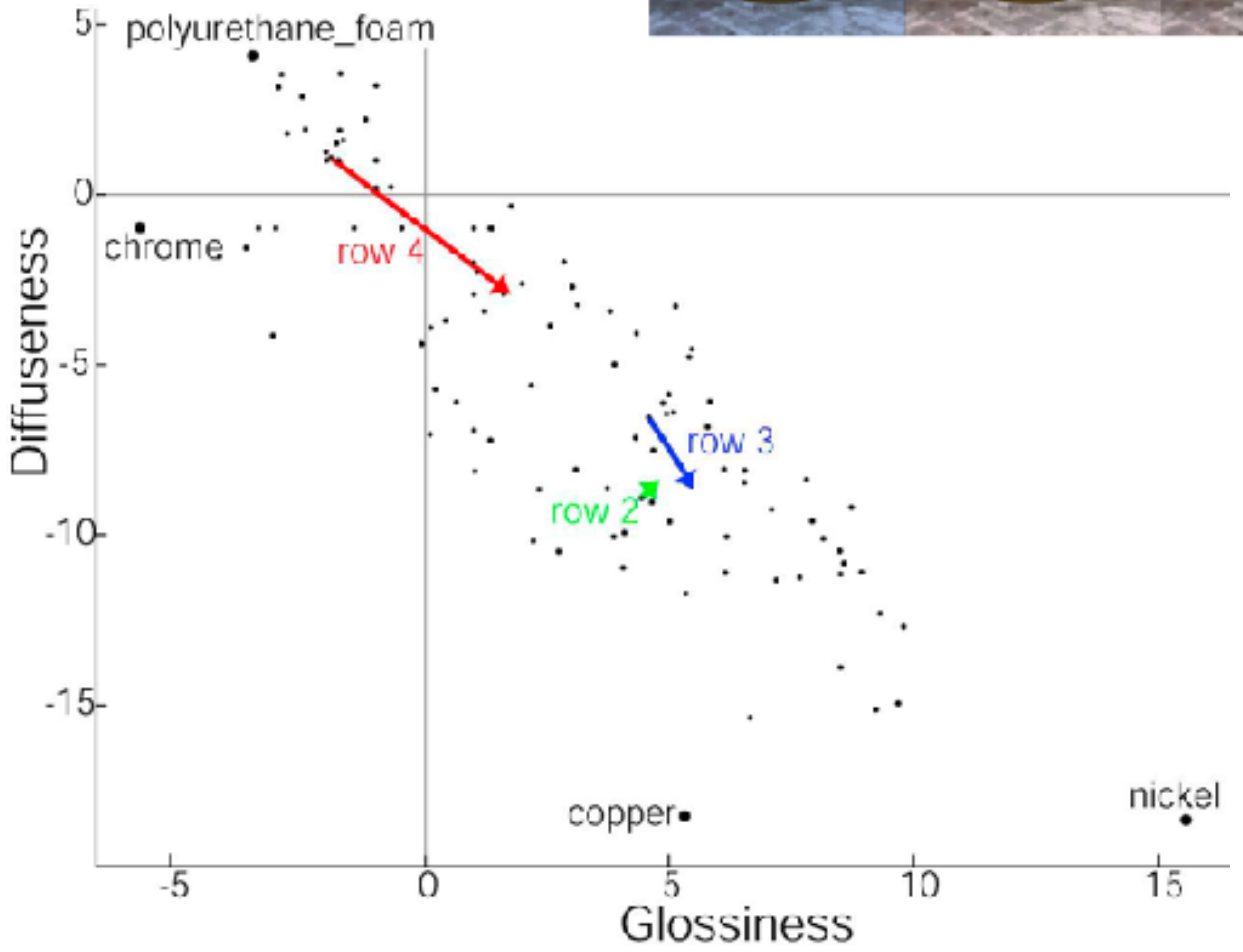
Understanding synthetic dimensions

Specular-Metallic

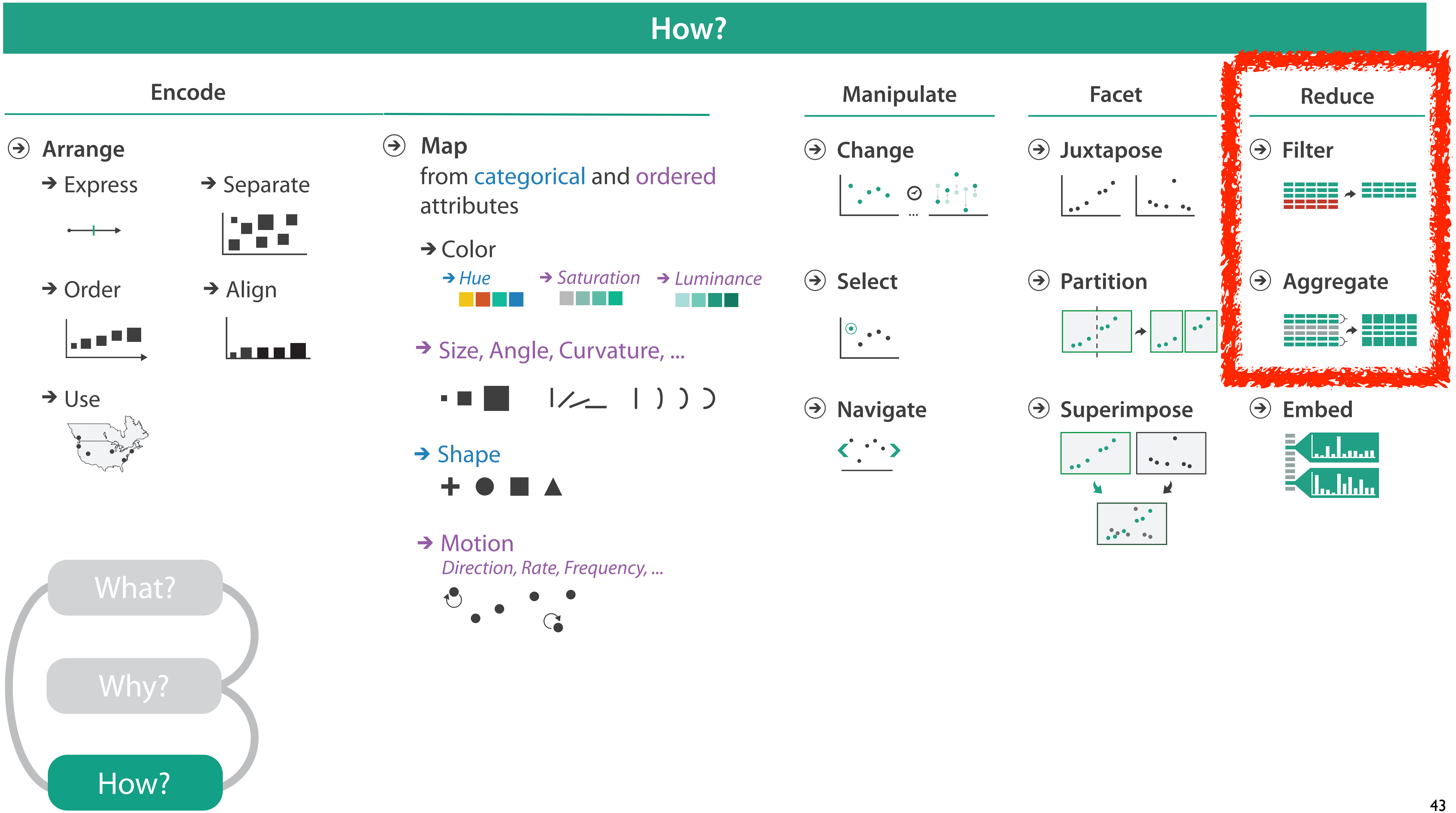




Diffuseness-Glossiness



[Fig 13/14/16. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]


How?
Encode
Arrange
Express
Separate
Order
Align
Use
Map
from categorical and ordered attributes
Color
Hue
Saturation
Luminance
Size, Angle, Curvature, ...
Shape
Motion
Direction, Rate, Frequency, ...
Manipulate
Change
Select
Navigate
Facet
Juxtapose
Partition
Superimpose
Reduce
Filter
Aggregate
Embed
What?
Why?
How?