Information Visualization
Facet, Reduce, ScalableInsets
Ex: Complexity Families

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Week 5, 2 Oct 2025

https://www.cs.ubc.ca/~tmm/courses/547-25

Plan for today

- small group exercises
  - Complexity Families
- break
- mini-lecture / Q&A responses
  - Facet
  - Reduce
  - Scalable Insets

Upcoming

- tomorrow (Fri Oct 3): Groups finalized by noon, tell me via Piazza post
- next week (W6)
  - to read & discuss (async, before next class)
    - VAD book, Ch 14: Embed
    - paper: TensorFlowGraph [design study]
    - paper: TBD (see Piazza)
  - in class
    - pre-proposal meetings with each team
    - project work together when I'm not meeting with your team

In-Class Exercise

Break: 4-4:10

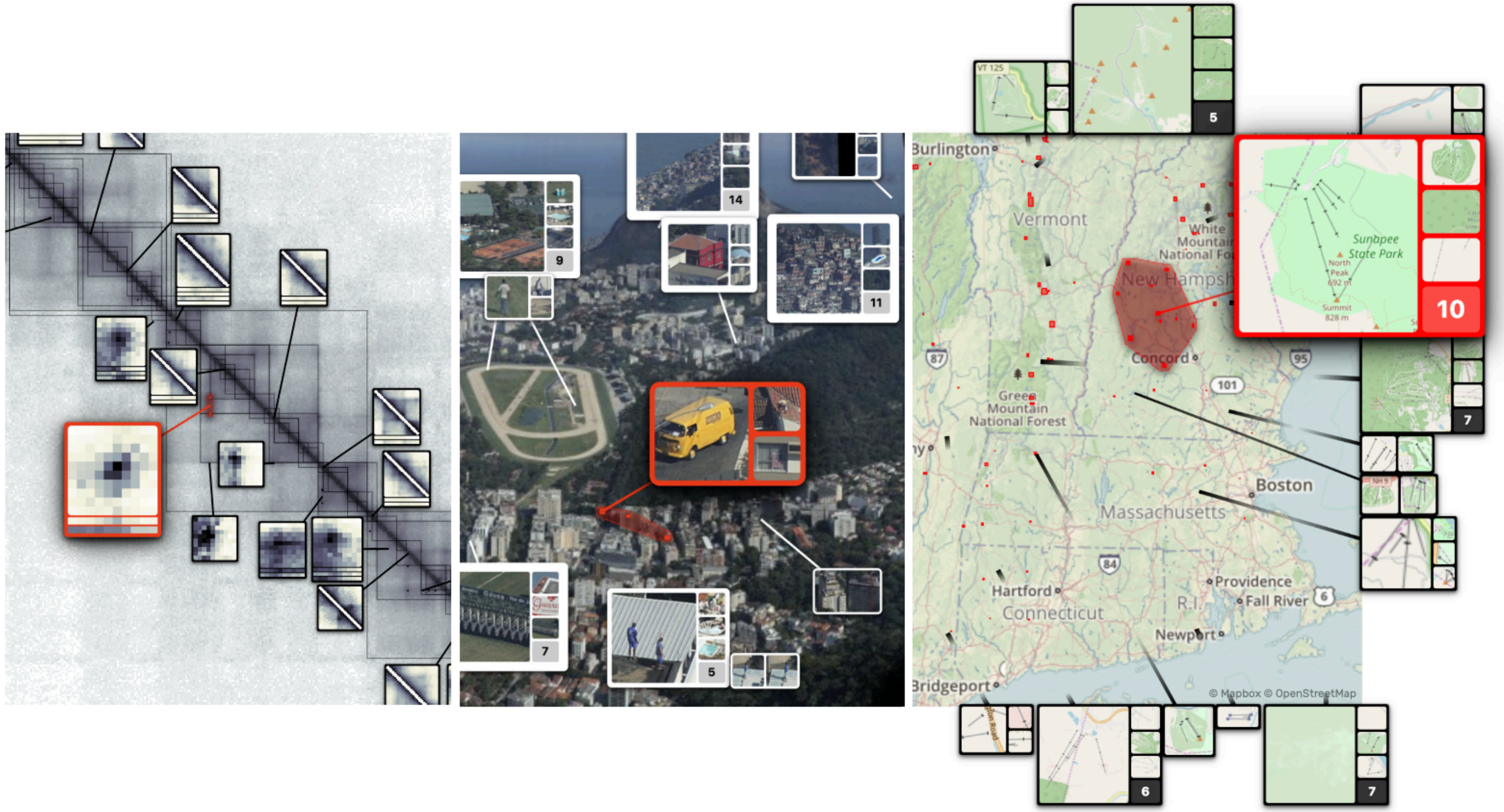
Mini-Lecture

Scalable Insets

Scalable Insets

- Pattern-Driven Navigation in 2D Multiscale Visualizations with Scalable Insets.
  Lekschas, Behrisch, Bach, Kerpedjiev, Gehlenborg, Pfister. IEEE TVCG (Proc. VIS 2019) 26(1):611 - 621, 2020

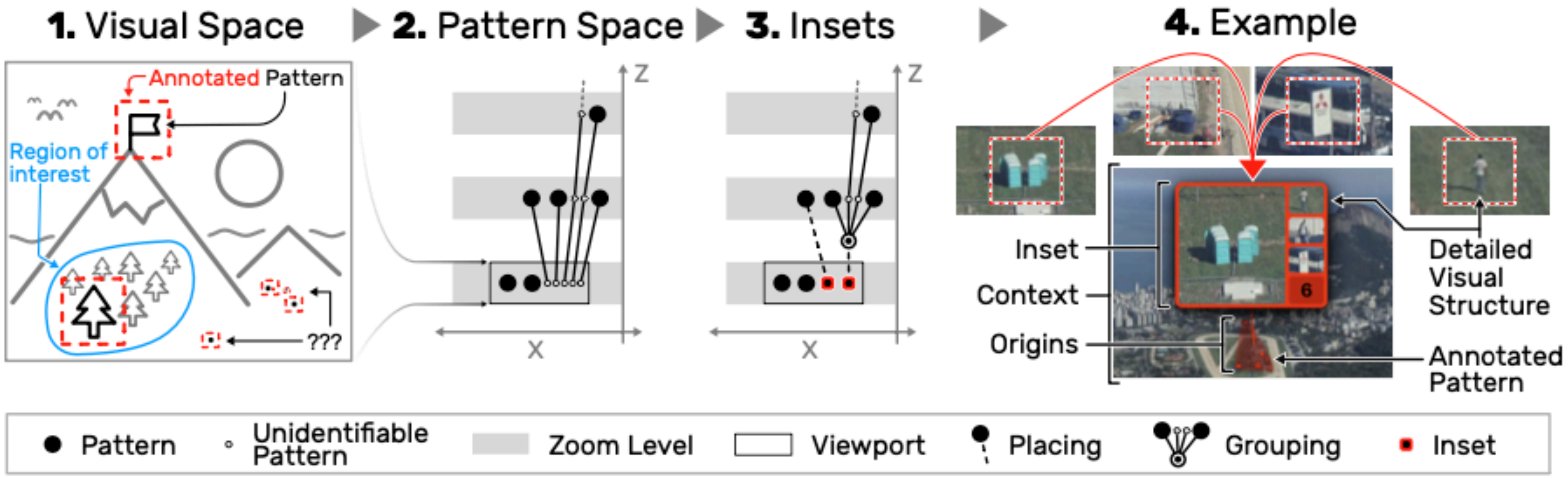
- good example for
  - multiple views
  - aggregation
- technique paper
  - idiom combines encoding & interaction



Pattern-Driven Navigation in 2D Multiscale Visualizations with Scalable Insets. Lekschas, Behrisch, Bach, Kerpedjiev, Gehlenborg, Pfister. IEEE TVCG (Proc. VIS 2019) 26(1):611 - 621, 2020. Fig 1

Key ideas

- multiscale problem: things of interest too small to see from overview
  - pan & zoom (navigation), overview & detail (multiple windows), detail-in-context
  - focus+context: more on this next week (Embed)
  - highlighting
  - aggregation & simplification



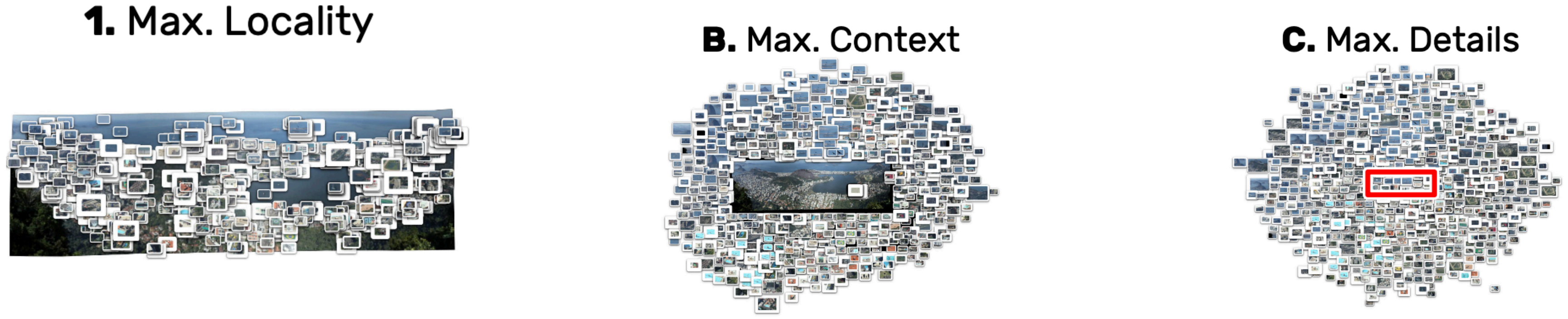
Pattern-Driven Navigation in 2D Multiscale Visualizations with Scalable Insets. Lekschas, Behrisch, Bach, Kerpedjiev, Gehlenborg, Pfister. *IEEE TVCG* (Proc. VIS 2019) 26(1):611 - 621, 2020. Fig 2

Use cases

- technique shown in three applications
  - **large-scale structural genomics matrices**
    - underlying motivation...
  - gigapixel images
  - geographic maps

Key ideas

- framing tradeoff: locality, context, details

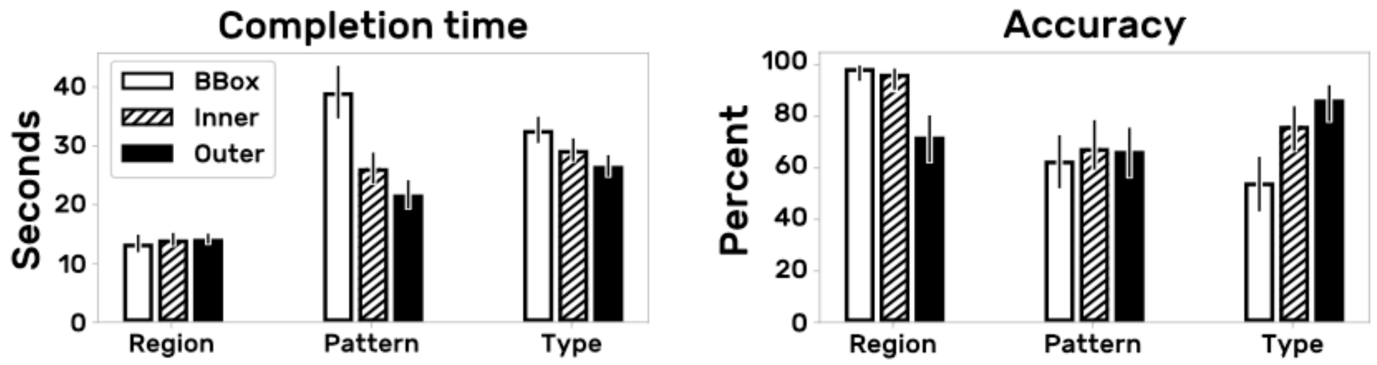


- algorithms
  - inset placement with simulated annealing
    - cost function as main contribution
  - aggregation
    - derived data: clustering (density-based dynamic) - as discussed in chapter
    - encoding: pile-based gallery

Pattern-Driven Navigation in 2D Multiscale Visualizations with Scalable Insets. Lekschas, Behrisch, Bach, Kerpedjiev, Gehlenborg, Pfister. IEEE TVCG (Proc. VIS 2019) 26(1):611 - 621, 2020. Fig 2 & 3

Evaluation

- quant confirmatory study (N=18)
  - 3 methods: compare baseline (bbox) to proposed (SI inside, SI outside)
  - 3 tasks: region, pattern type
  - 5 trials per condition
  - measured time & errors
  - mixed results, some tradeoffs



- qual exploratory study with genomics domain experts (N=6)
  - how did people use it

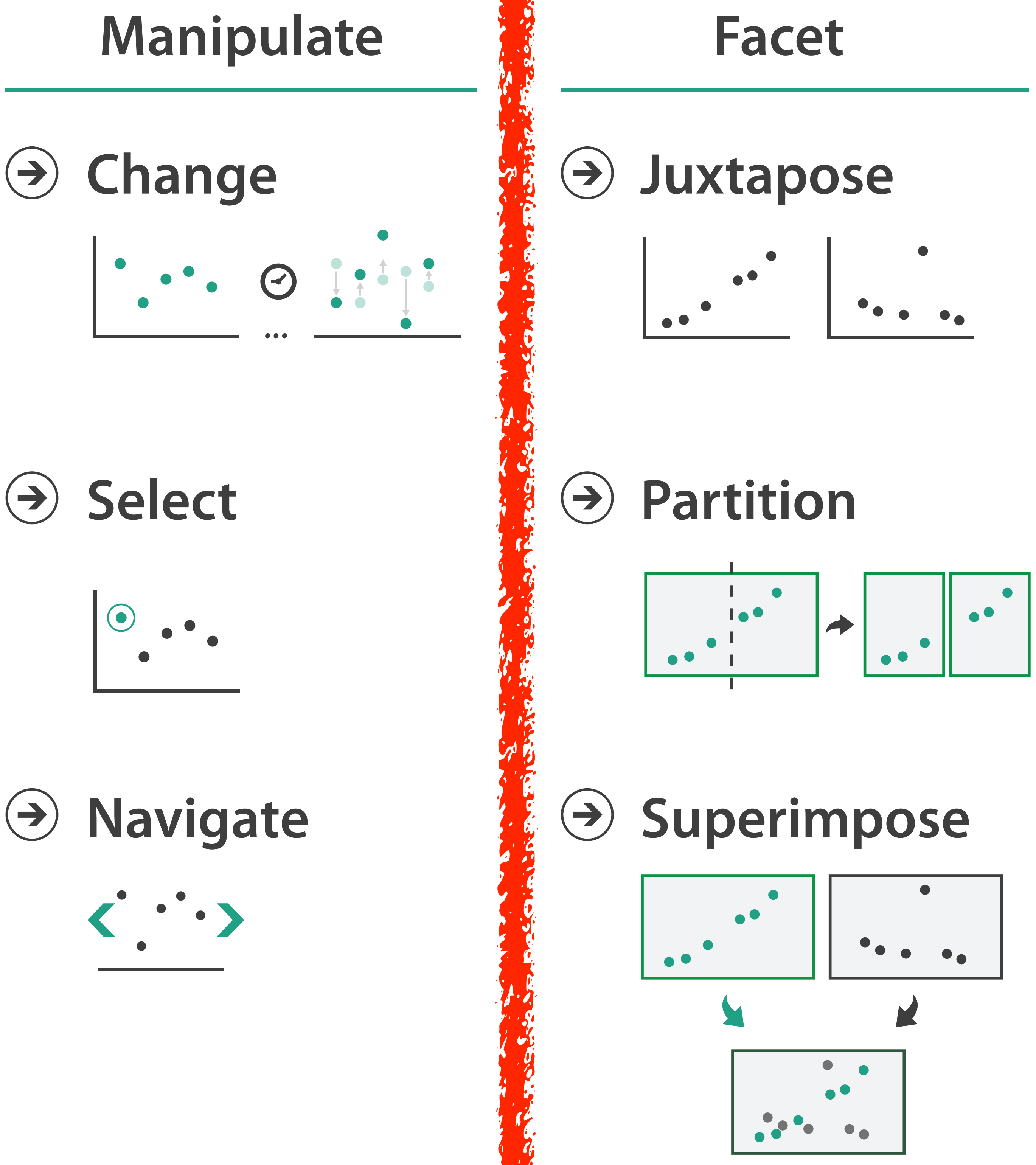
- computational benchmarks
  - frame rate as # insets increases

Multiple Views

How to handle complexity: 1 previous strategy + 2 more

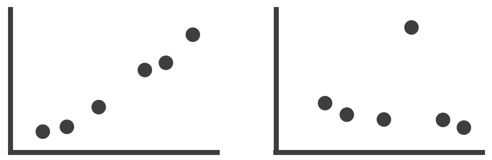
→ *Derive*

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

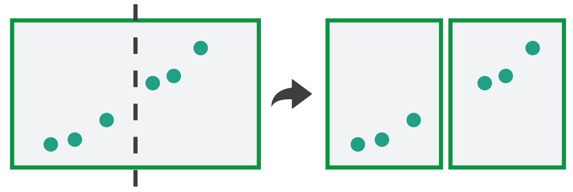


Facet

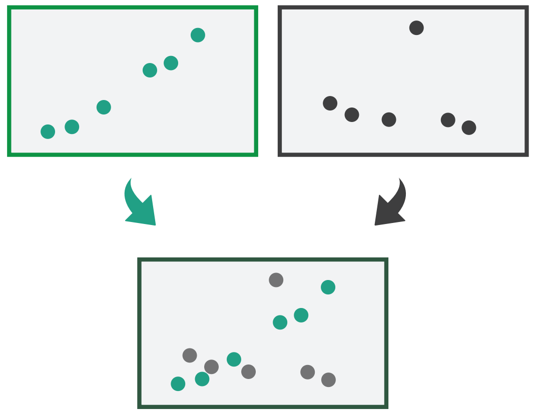
- Juxtapose



- Partition



- Superimpose

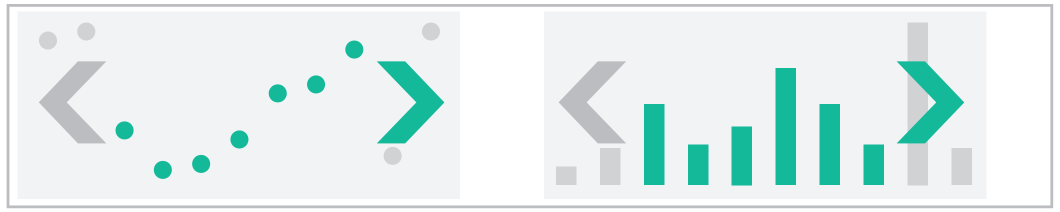


Juxtapose and coordinate views

- Share Encoding: Same/Different
  - *Linked Highlighting*

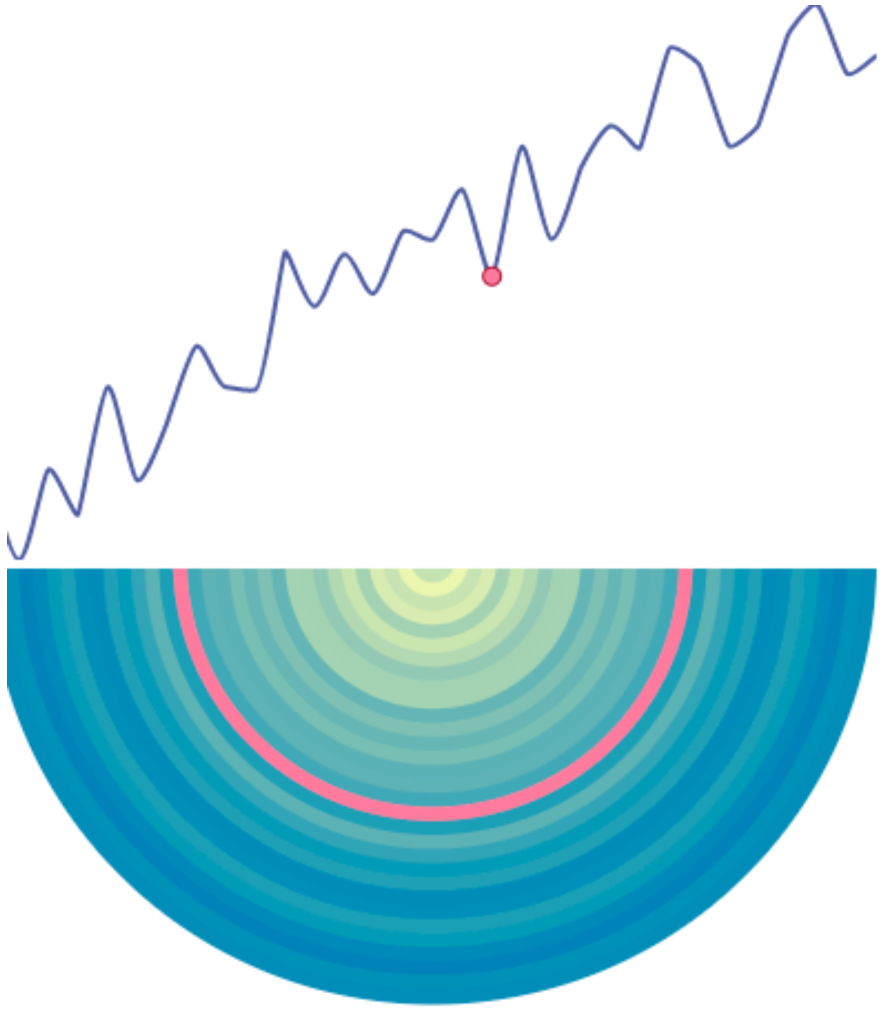
- Share Data: All/Subset/None

- Share Navigation



Linked views: Directionality

- unidirectional vs bidirectional linking
  - bidirectional almost always better!

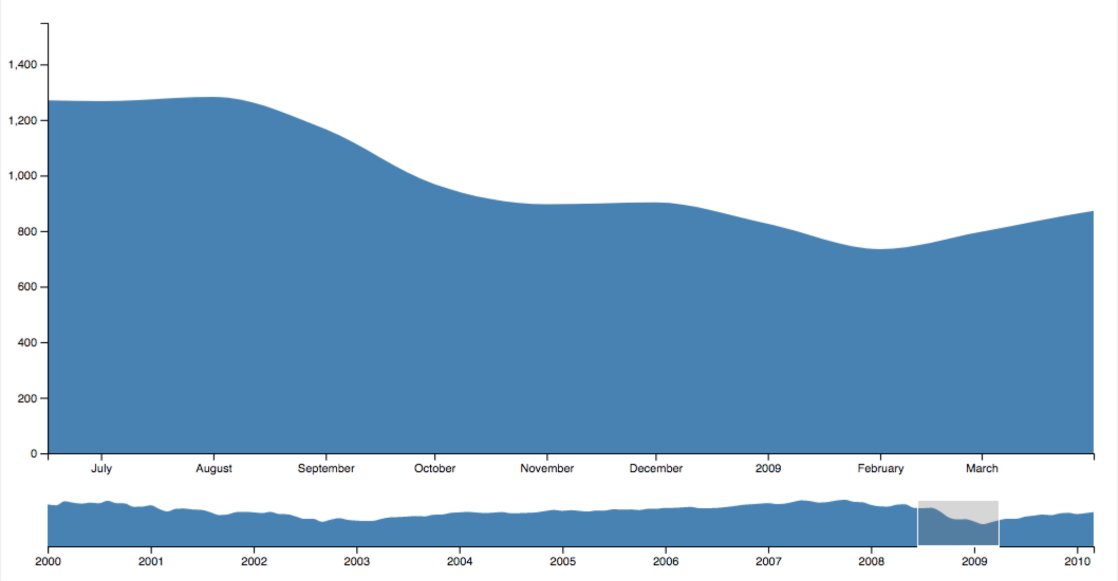


http://pbeshai.github.io/linked-highlighting-react-vega-redux/

https://medium.com/@pbesh/linked-highlighting-with-react-d3-js-and-reflux-16e9c0b2210b

Idiom: **Overview-detail navigation**

- encoding: same or different
- data: subset shared
- navigation: shared
  - unidirectional linking
  - select in small overview,
    change extent in large detail view



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

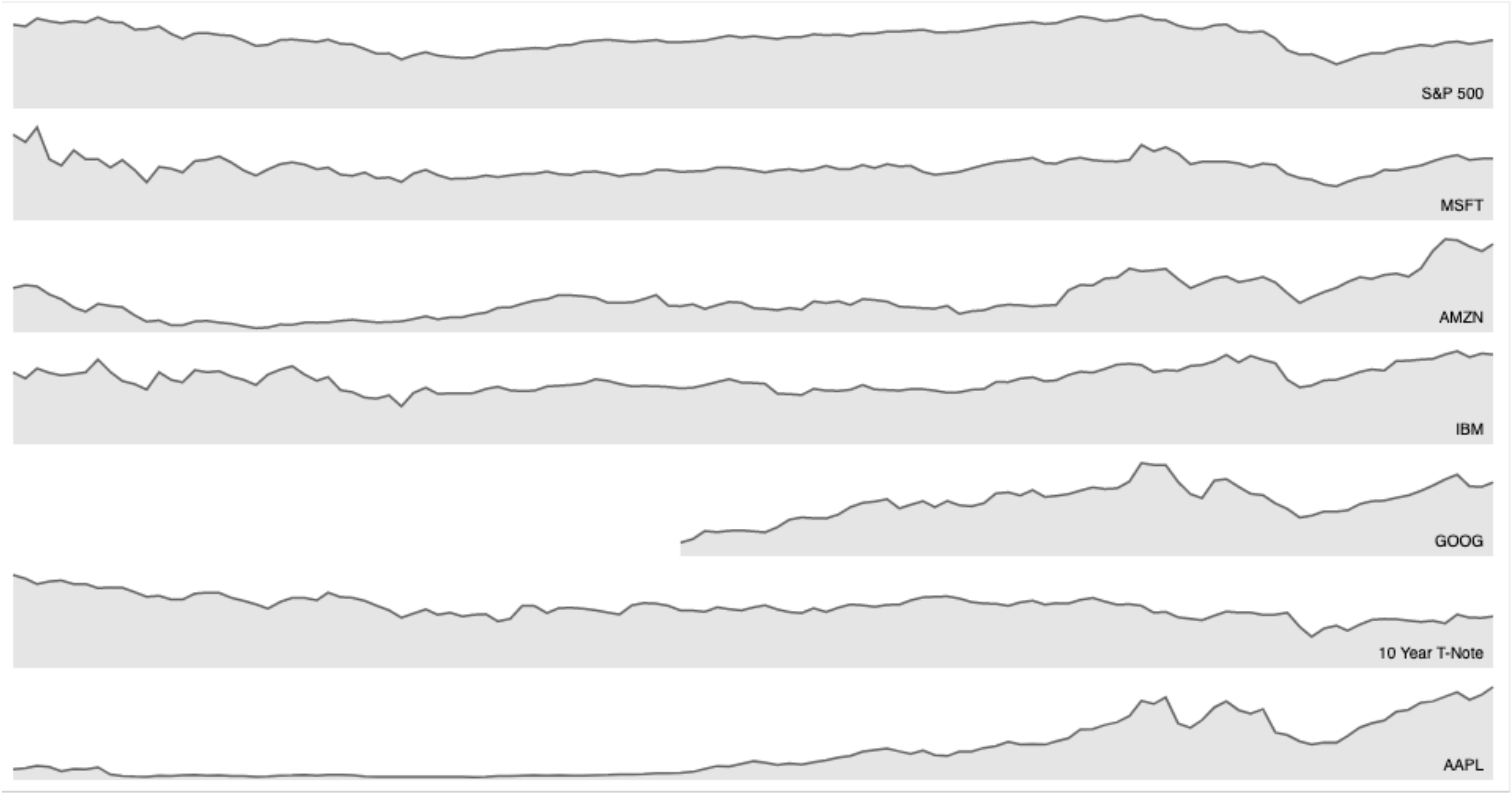
Idiom: **Tooltips**

- popup information for selection
  - hover or click
  - specific case of detail view:
    provide useful additional detail on demand
  - beware: does not support overview!
    - always consider if there's a way to visually encode directly to provide overview
    - "If you make a rollover or tooltip, assume nobody will see it. If it's important, make it explicit."
      - Gregor Aisch, NYTimes

[https://www.highcharts.com/demo/dynamic-master-detail]

Idiom: **Small multiples**

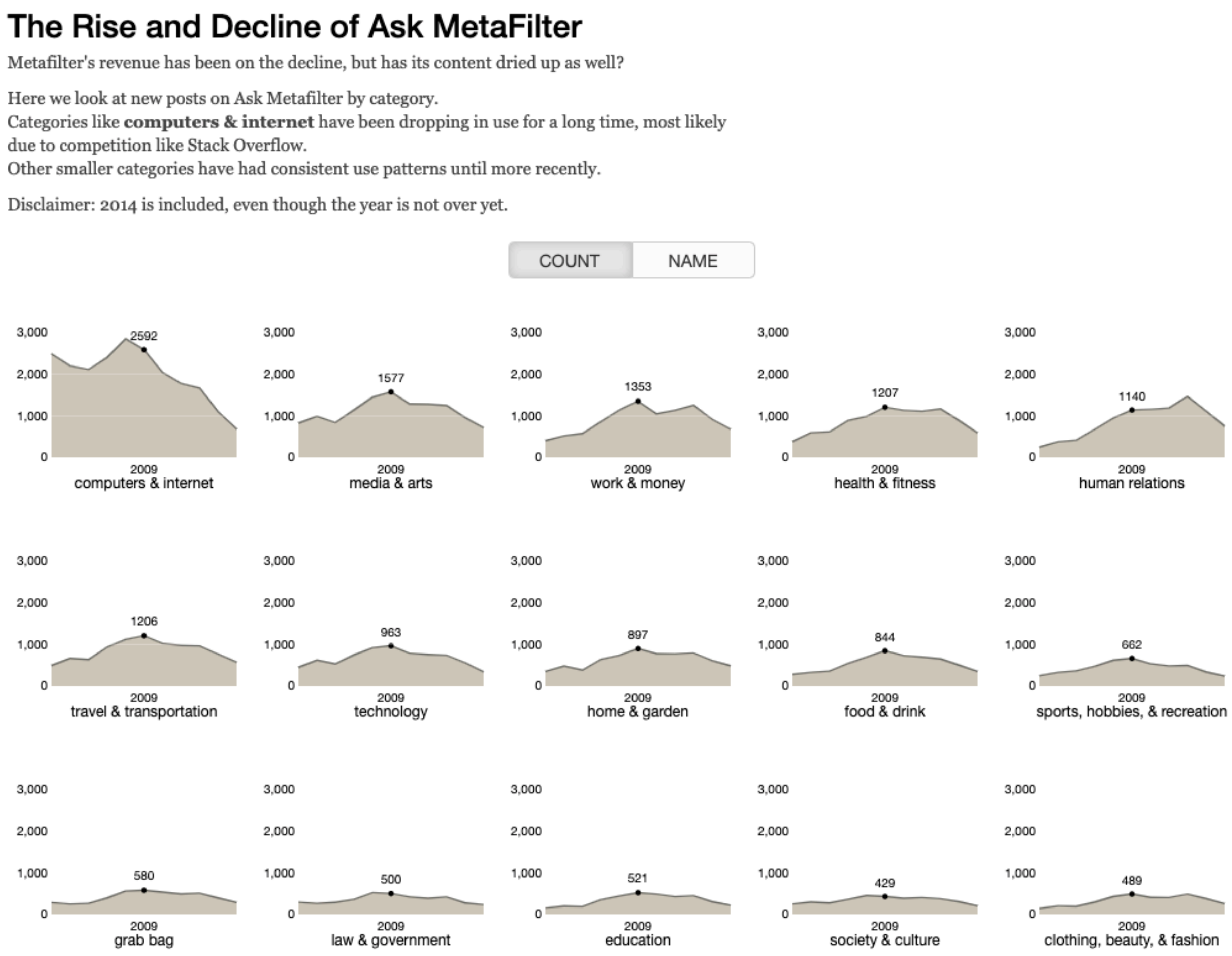
- encoding: same
  - ex: line charts
- data: none shared
  - different slices of dataset
    - items or attributes
    - ex: stock prices for different companies



[https://bl.ocks.org/mbostock/1157787]

Interactive small multiples

- linked highlighting: analogous item/attribute across views
  - same year highlighted across all charts if hover within any chart



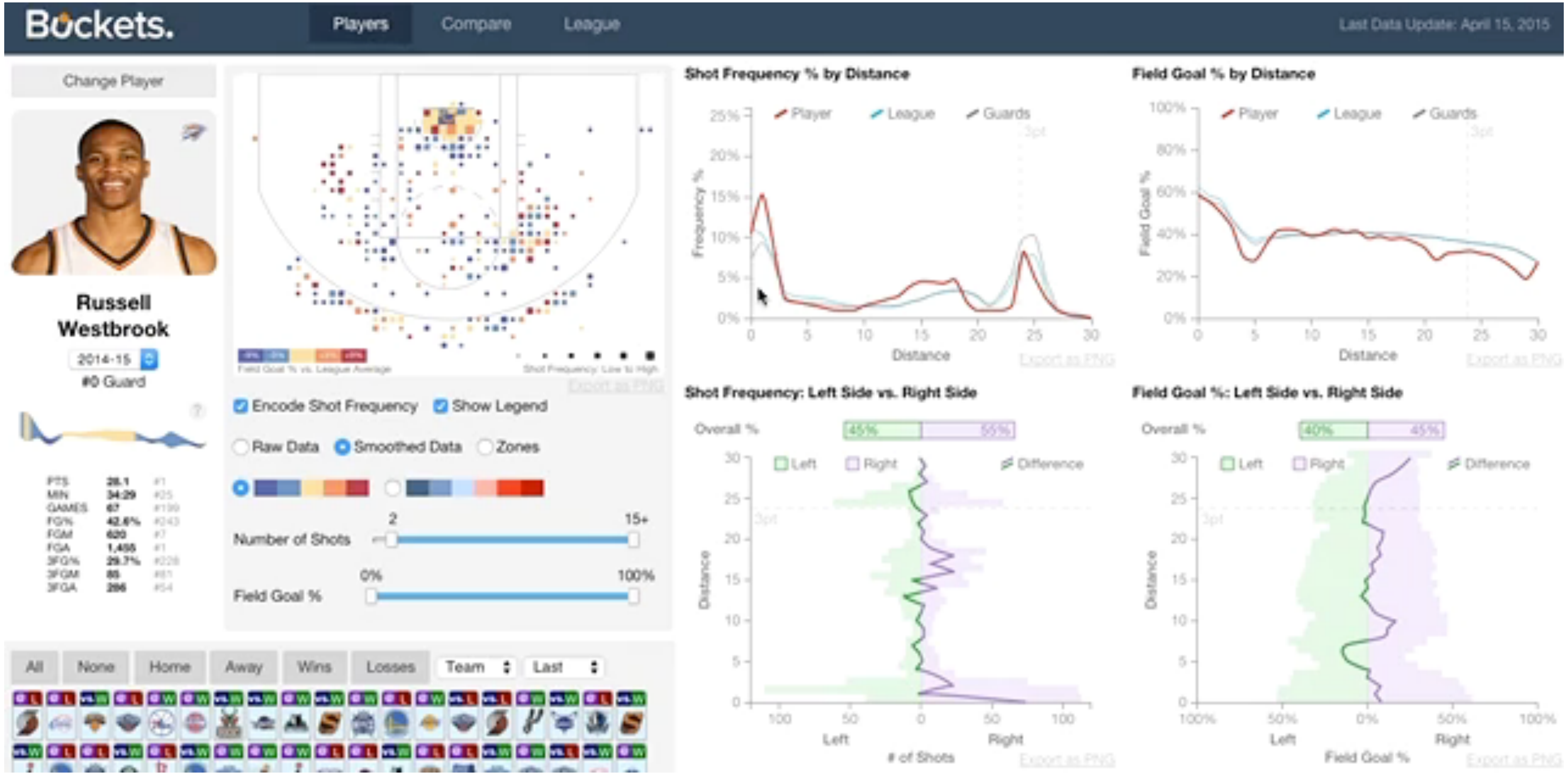
[https://bl.ocks.org/ColinEberhardt/3c780088c363d1515403f50a87a87121]

[https://blog.scottlogic.com/2017/04/05/interactive-responsive-small-multiples.html]

[http://projects.flowingdata.com/tut/linked_small_multiples_demo/]

Example: Combining many interaction idioms

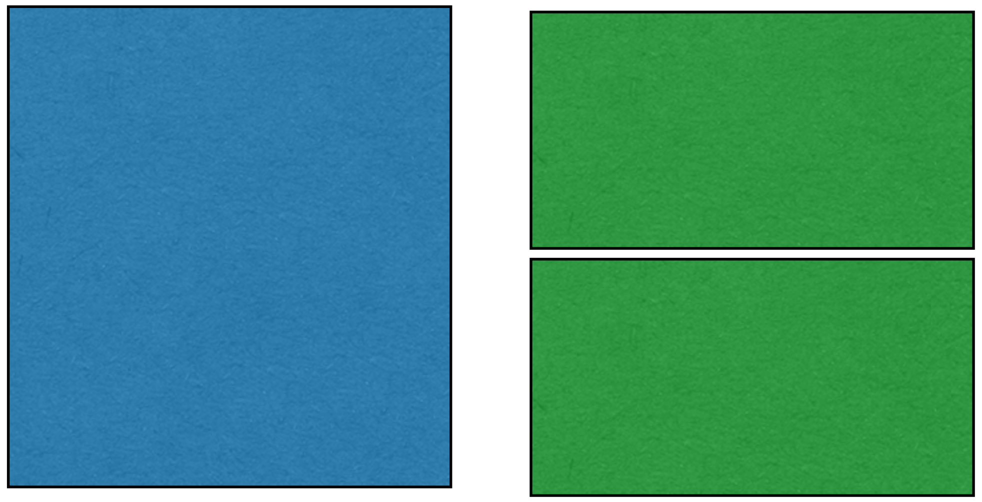
System: **Buckets**



- multiform
- multidirectional linked highlighting of small multiples
- tooltips

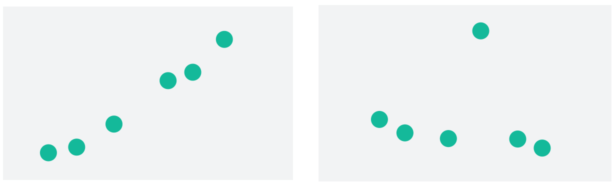
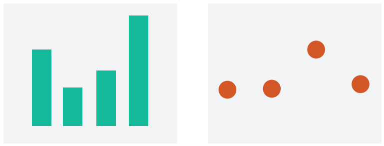
http://buckets.peterbeshai.com/

Juxtapose views: tradeoffs



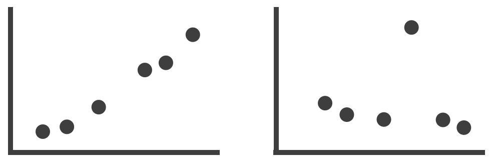
- juxtapose costs
  - display area
    - 2 views side by side: each has only half the area of one view
- juxtapose benefits
  - cognitive load: eyes vs memory
    - lower cognitive load: move eyes between 2 views
    - higher cognitive load: compare single changing view to memory of previous state

View coordination: Design choices

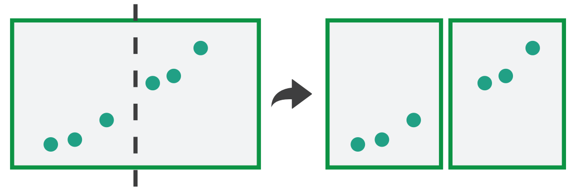
		Data		
		All	Subset	None
Encoding	Same	Redundant	 Overview/ Detail	 Small Multiples
	Different	 Multiform	 Multiform, Overview/ Detail	No Linkage

Facet

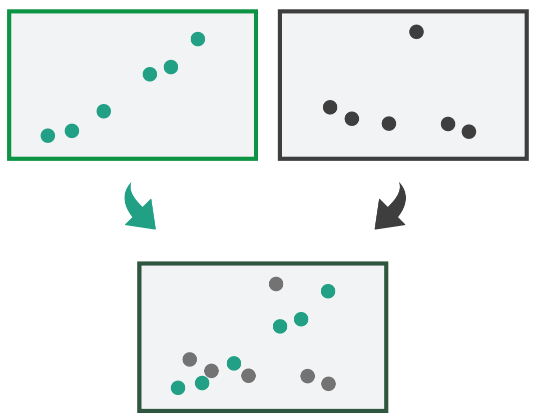
- Juxtapose



- Partition



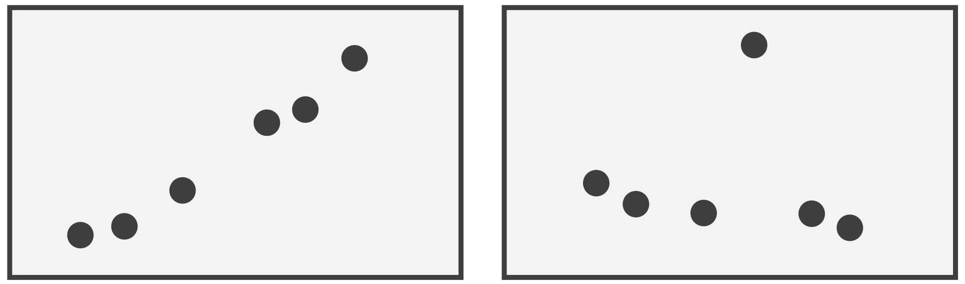
- Superimpose



Partition into views

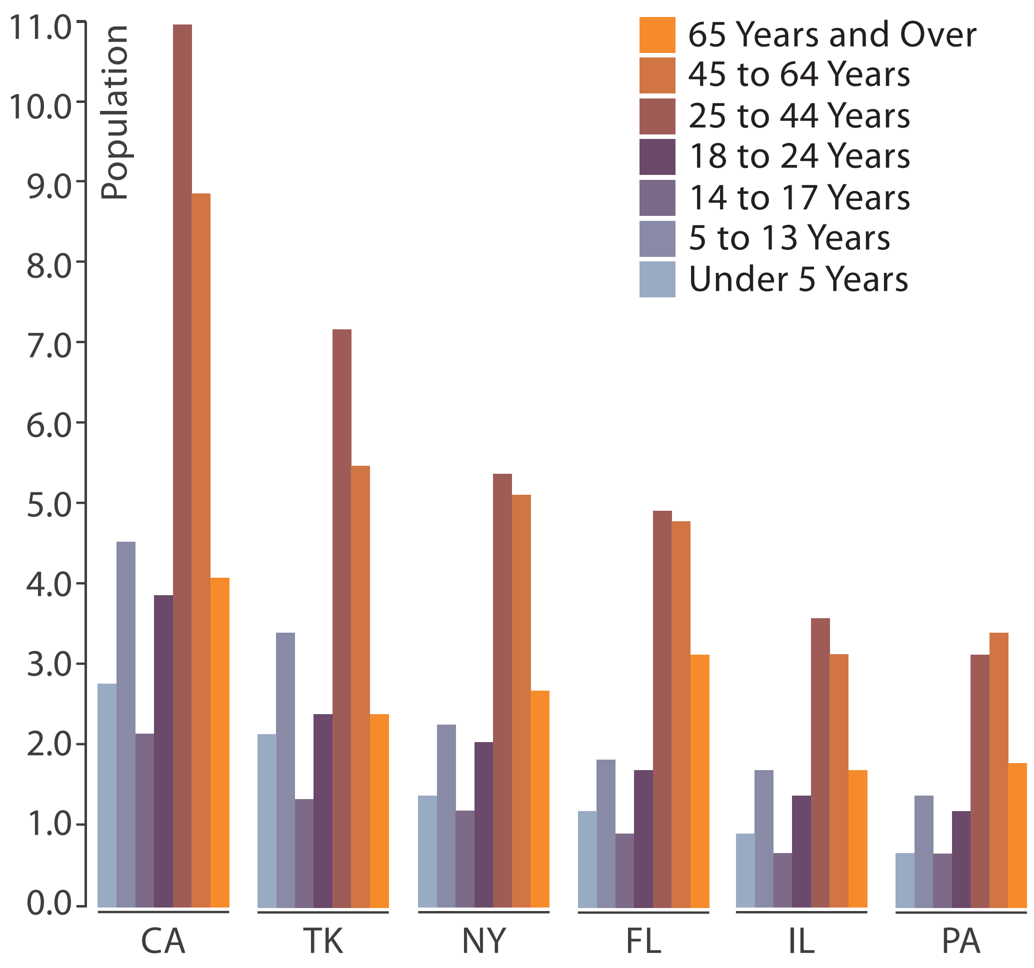
- how to divide data between views
  - split into regions by attributes
  - encodes association between items using spatial proximity
  - order of splits has major implications for what patterns are visible

Partition into Side-by-Side Views



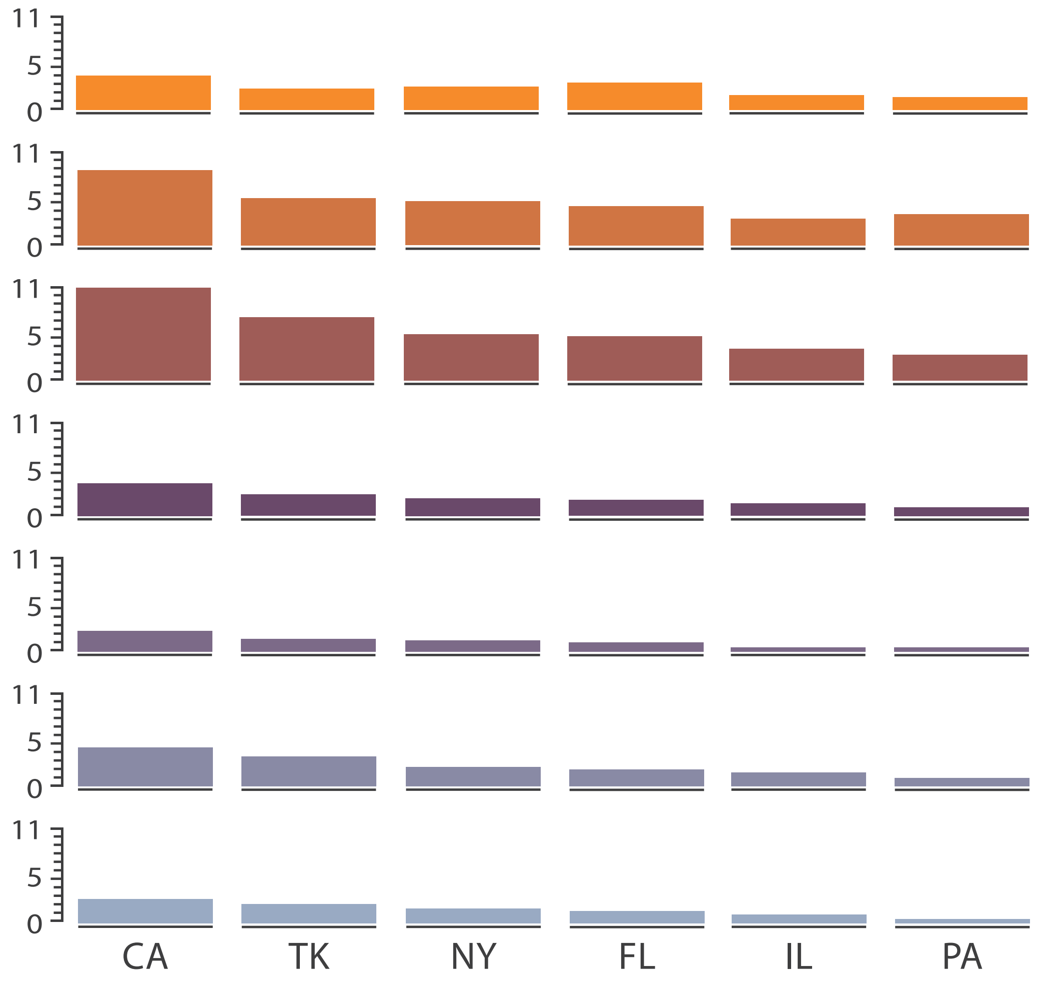
Partitioning: Grouped vs small-multiple bars

- single bar chart with grouped bars
  - split by state into regions
    - complex glyph within each region showing all ages
  - compare: easy within state, hard across ages



[https://observablehq.com/@d3/grouped-bar-chart]

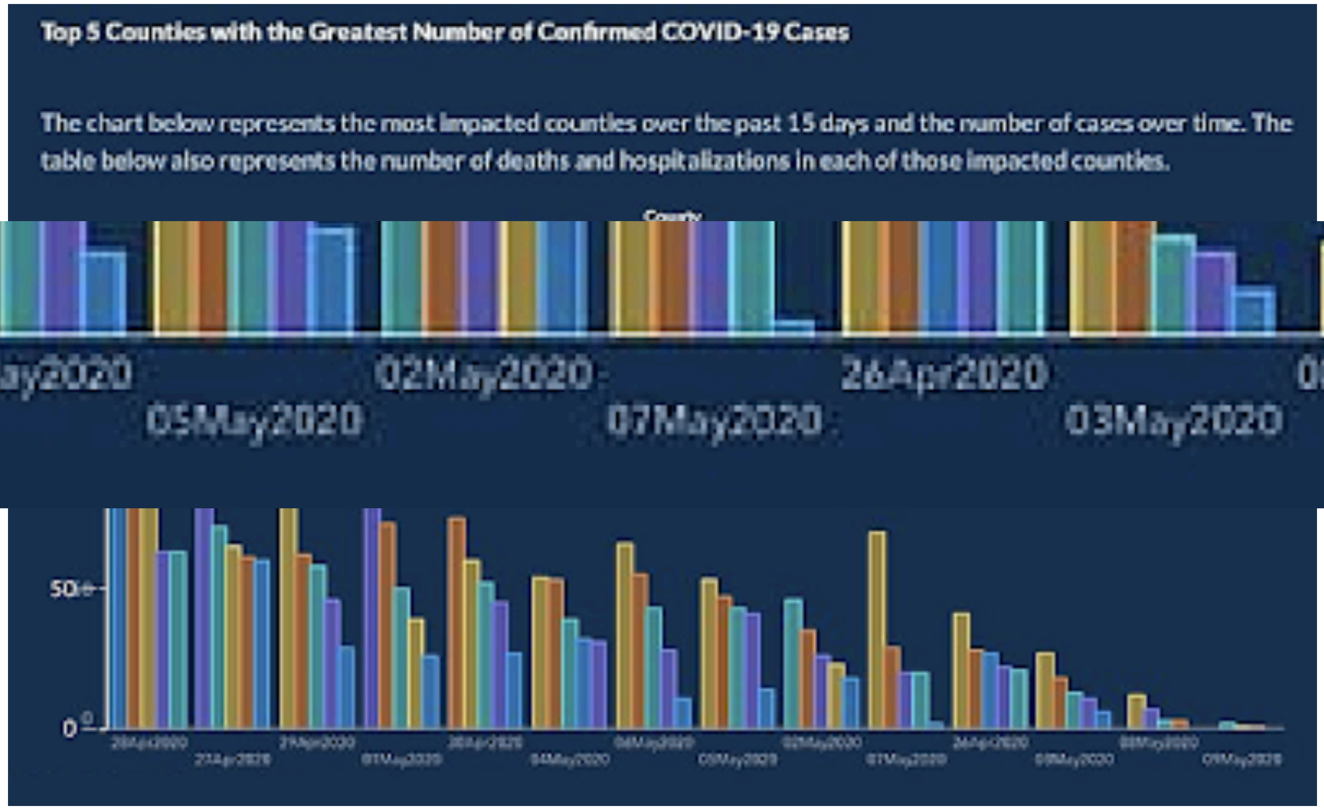
- small-multiple bar charts
  - split by age into regions
    - one chart per region
  - compare: easy within age, harder across states

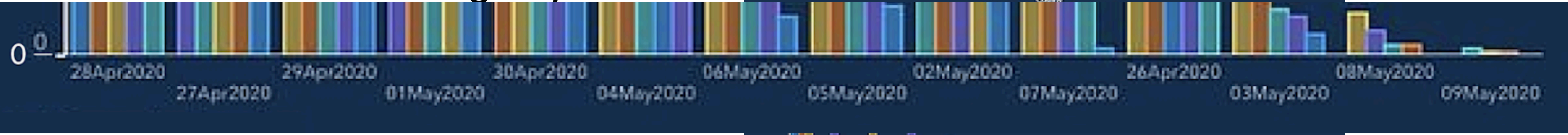


[https://bl.ocks.org/mbostock/4679202]

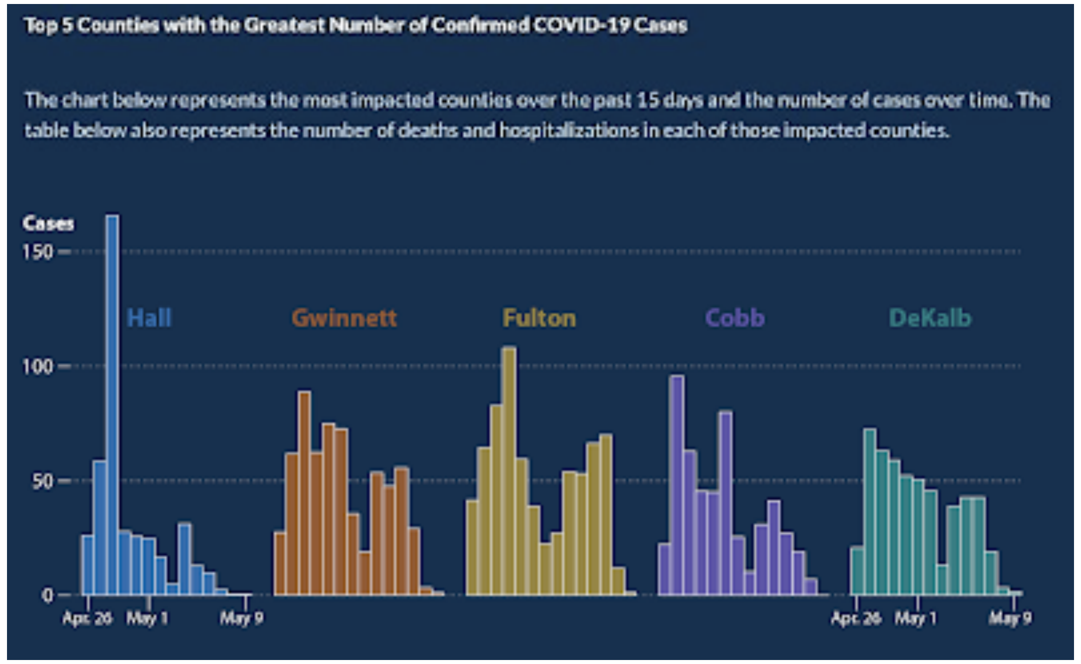
Partioning: Grouped vs small multiples

- misleading graph
  - sorted non-chronologically





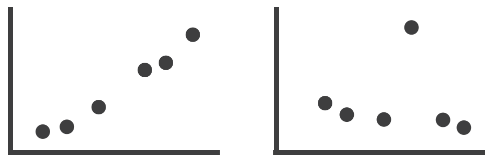
- Alberto Cairo redesign:
  - separate by county then sort chronologically



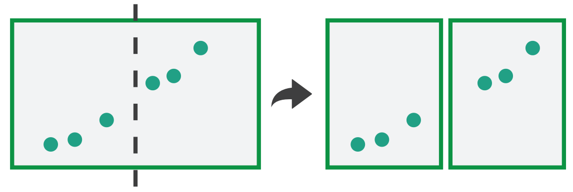
https://thefunctionalart.blogspot.com/2020/05/about-that-weird-georgia-chart.html

Facet

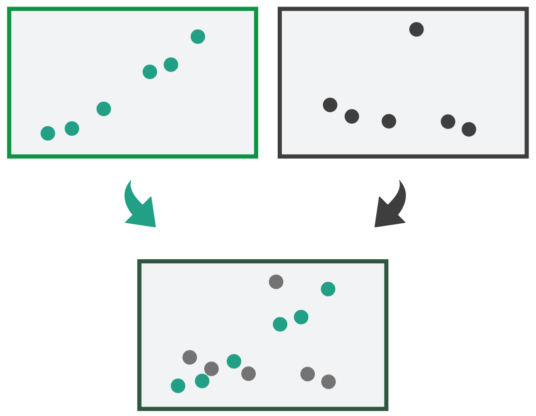
- Juxtapose



- Partition

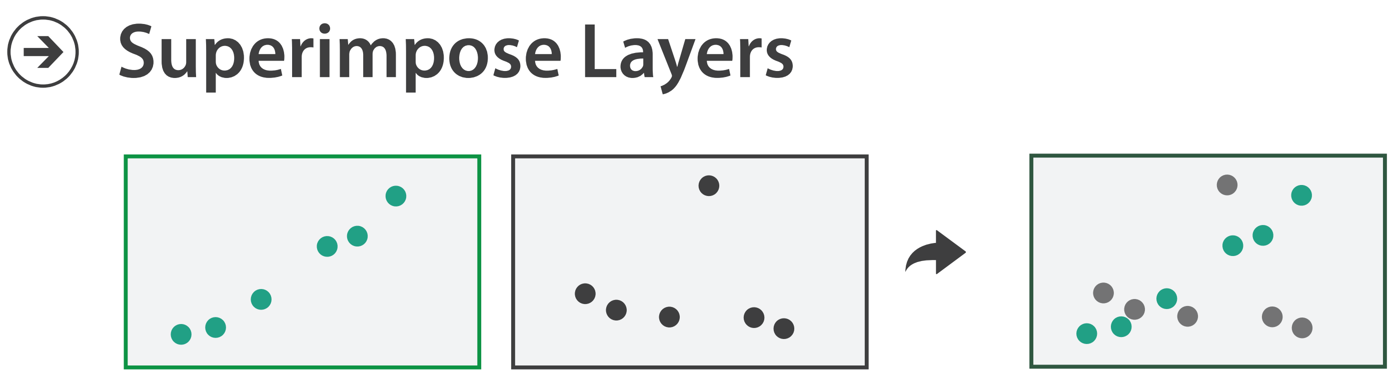


- Superimpose



Superimpose layers

- layer: set of objects spread out over region
  - each set is visually distinguishable group
  - extent: whole view
- design choices
  - how many layers, how to distinguish?
    - encode with different, nonoverlapping channels
    - two layers achievable, three with careful design
  - small static set, or dynamic from many possible?



Static visual layering

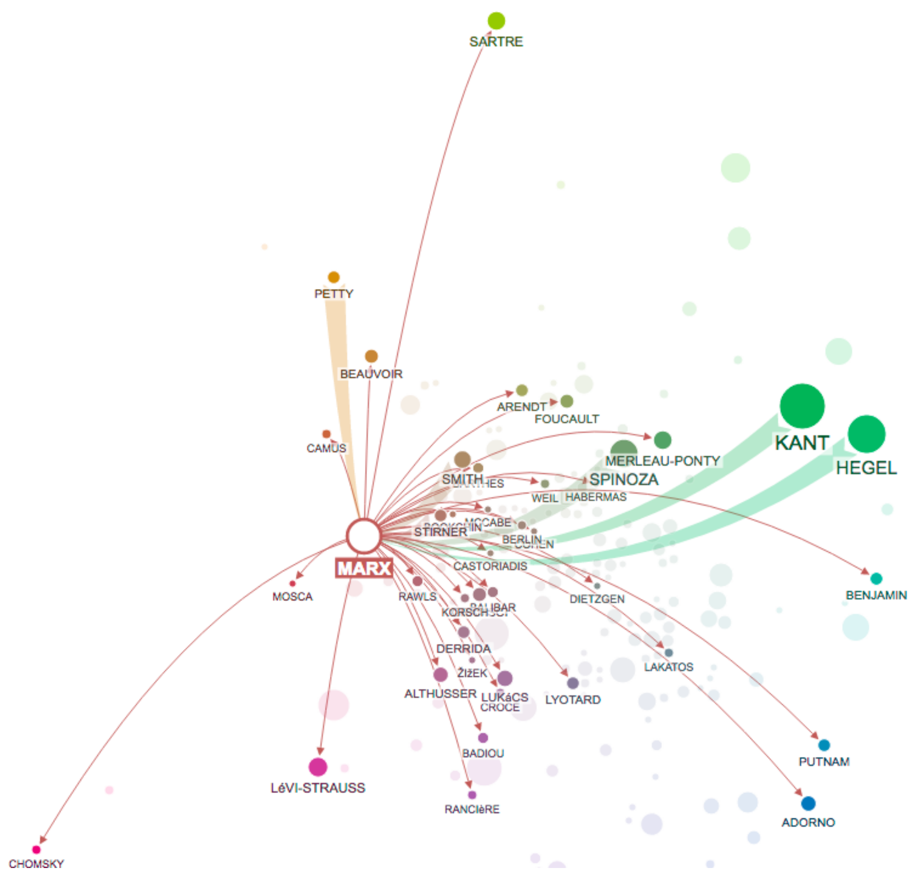
- foreground layer: roads
  - hue, size distinguishing main from minor
  - high luminance contrast from background
- background layer: regions
  - desaturated colors for water, parks, land areas
- user can selectively focus attention

[Get it right in black and white. Stone. 2010. http://www.stonesc.com/wordpress/2010/03/get-it-right-in-black-and-white]

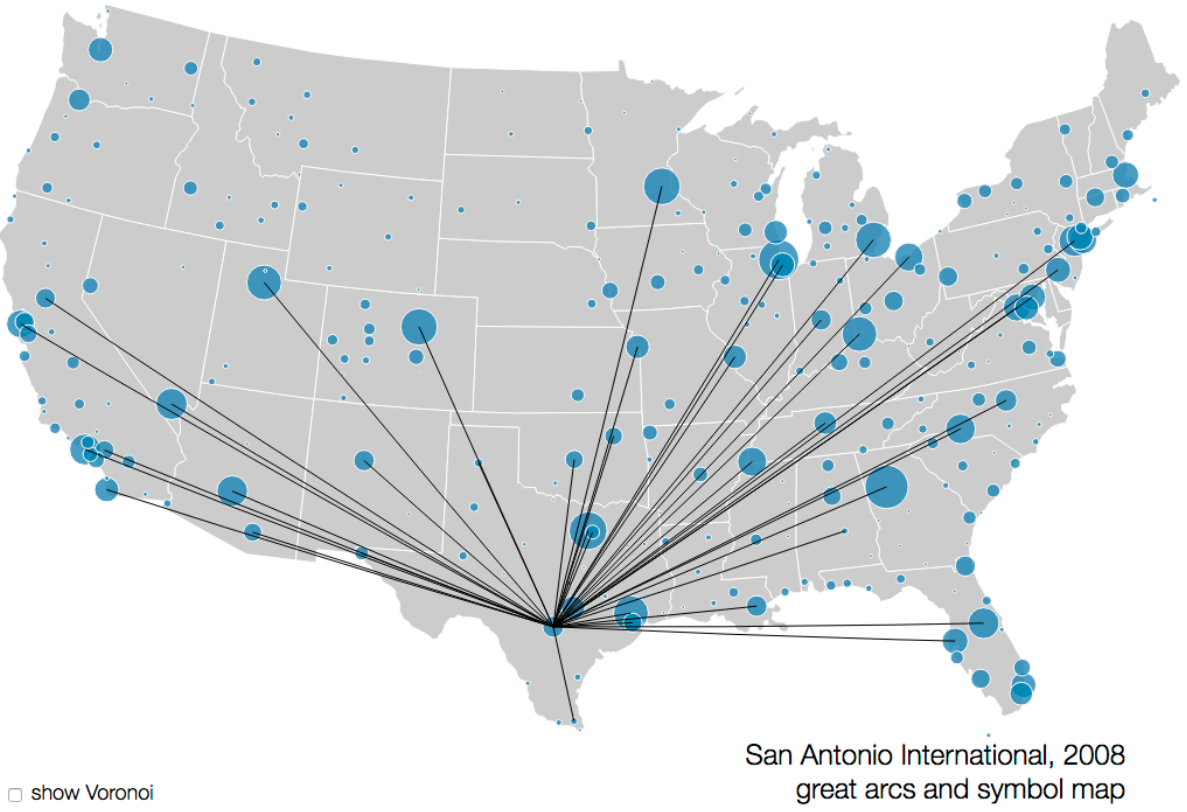
Dynamic visual layering

- interactive, based on selection
- one-hop neighbour highlighting

click (heavyweight)



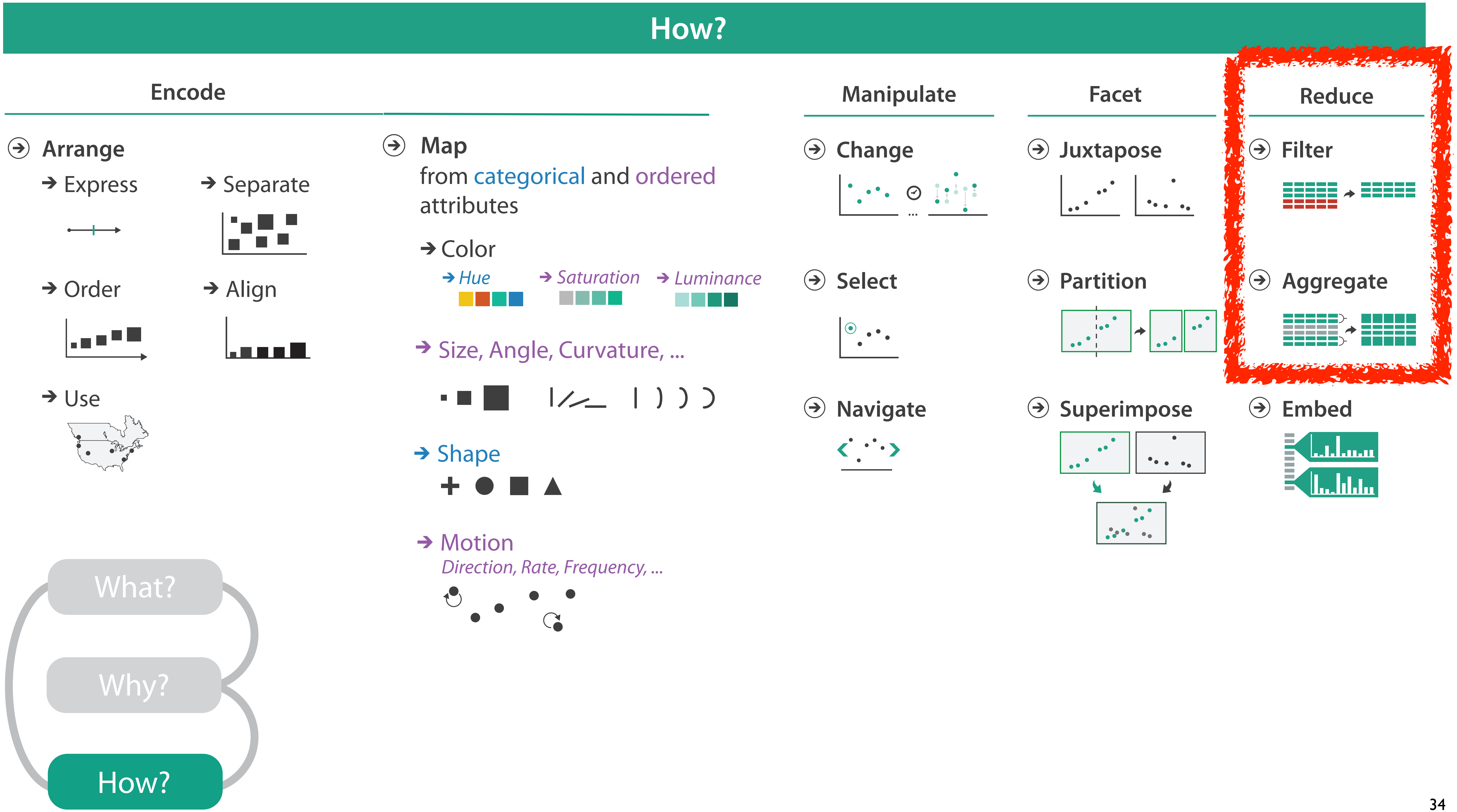
hover (fast)



https://mariandoerk.de/edgemaps/demo/

http://mbostock.github.io/d3/talk/20111116/airports.html

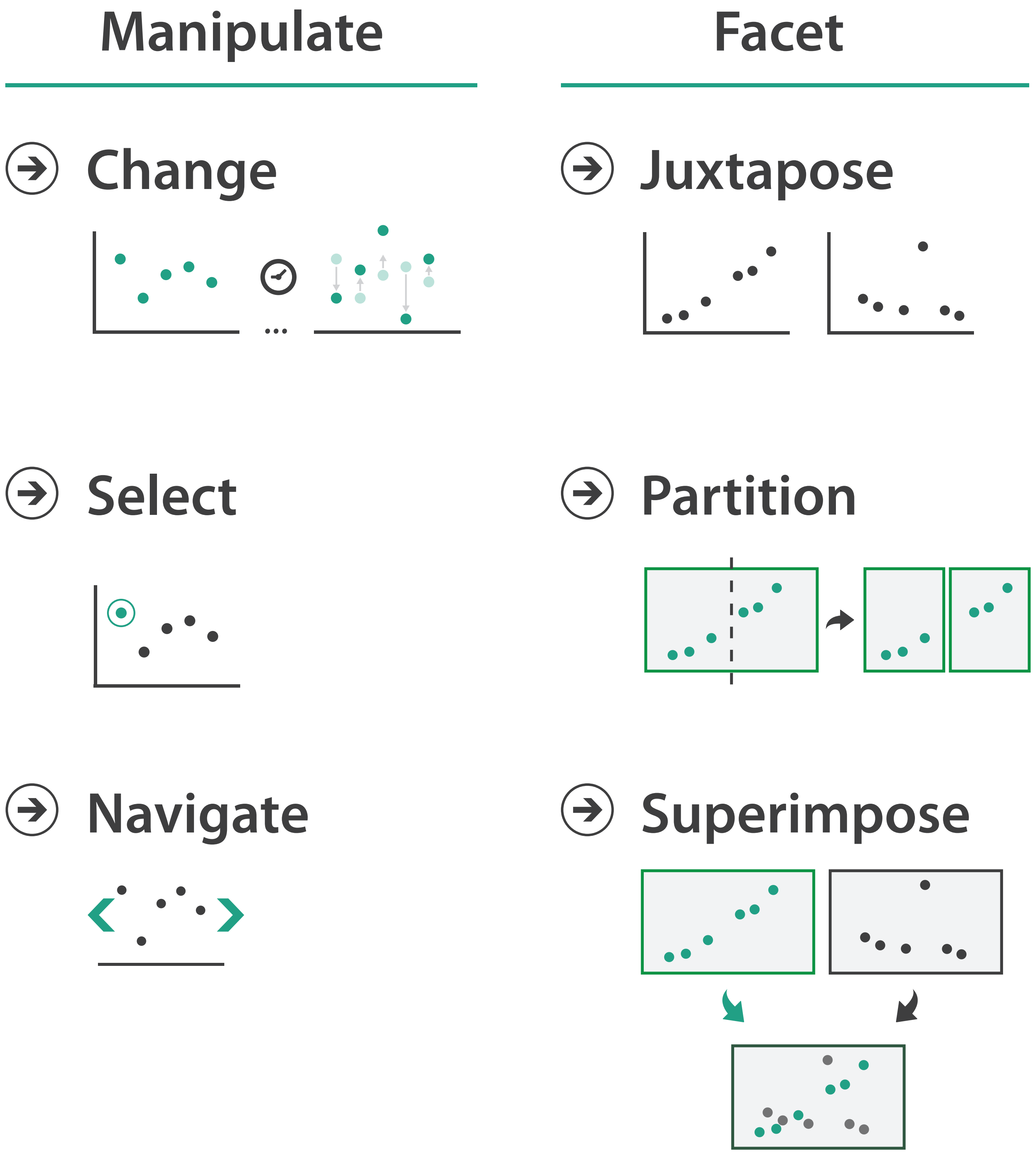
Reduce: Aggregation & Filtering


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?

How to handle complexity: 3 previous strategies

→ *Derive*

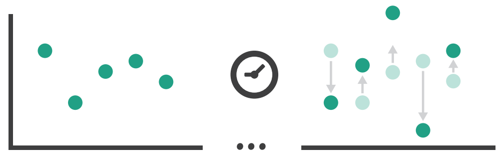
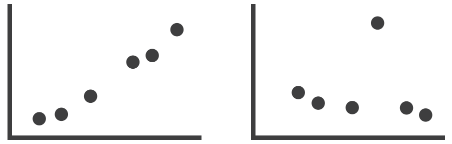
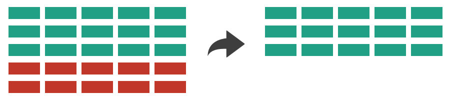
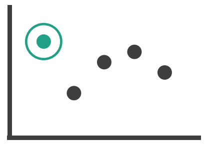
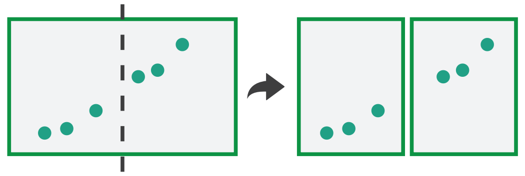
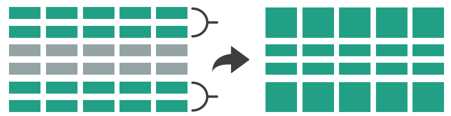
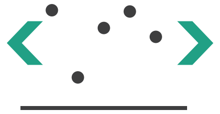
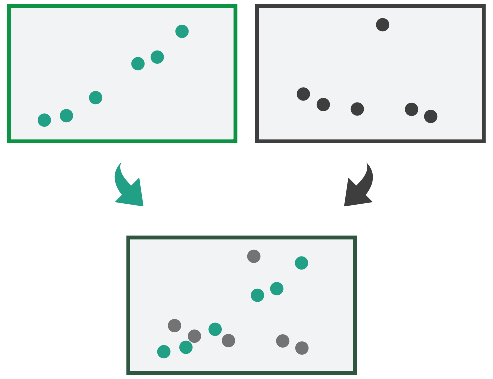
- derive new data to show within view
- change view over time
- facet across multiple views



How to handle complexity: 3 previous strategies + 1 more

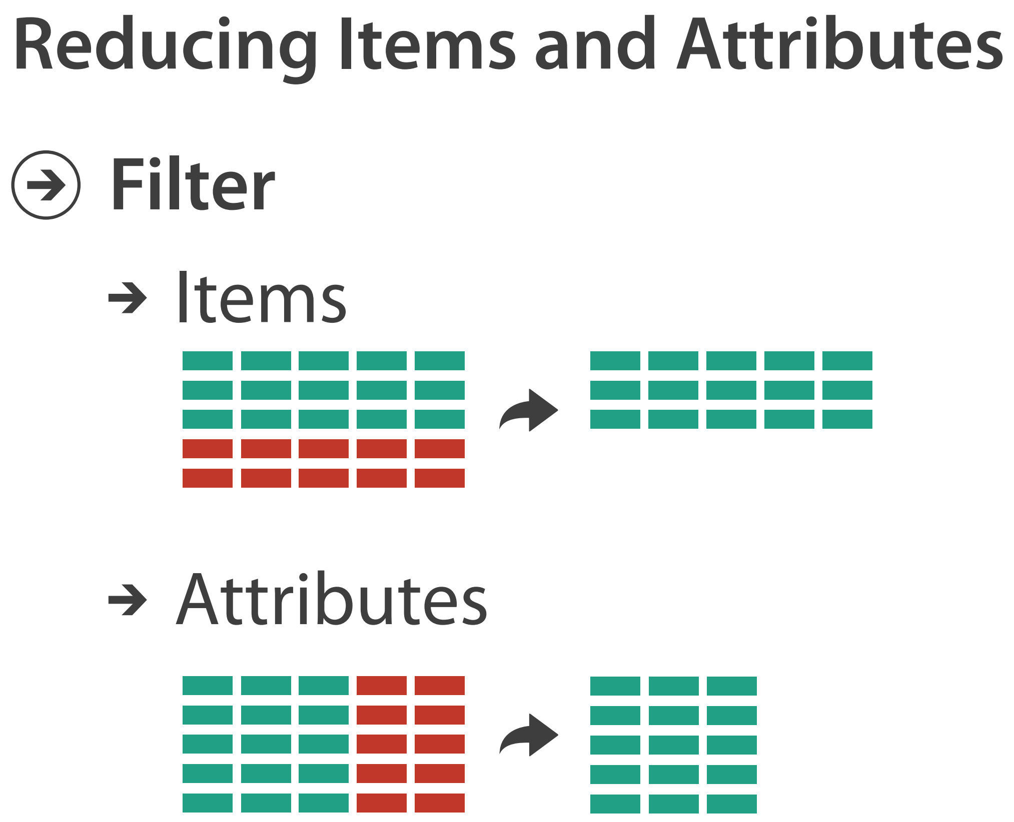
➔ *Derive*

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

Manipulate	Facet	Reduce
➔ Change 	➔ Juxtapose 	➔ Filter 
➔ Select 	➔ Partition 	➔ Aggregate 
➔ Navigate 	➔ Superimpose 	➔ Embed 

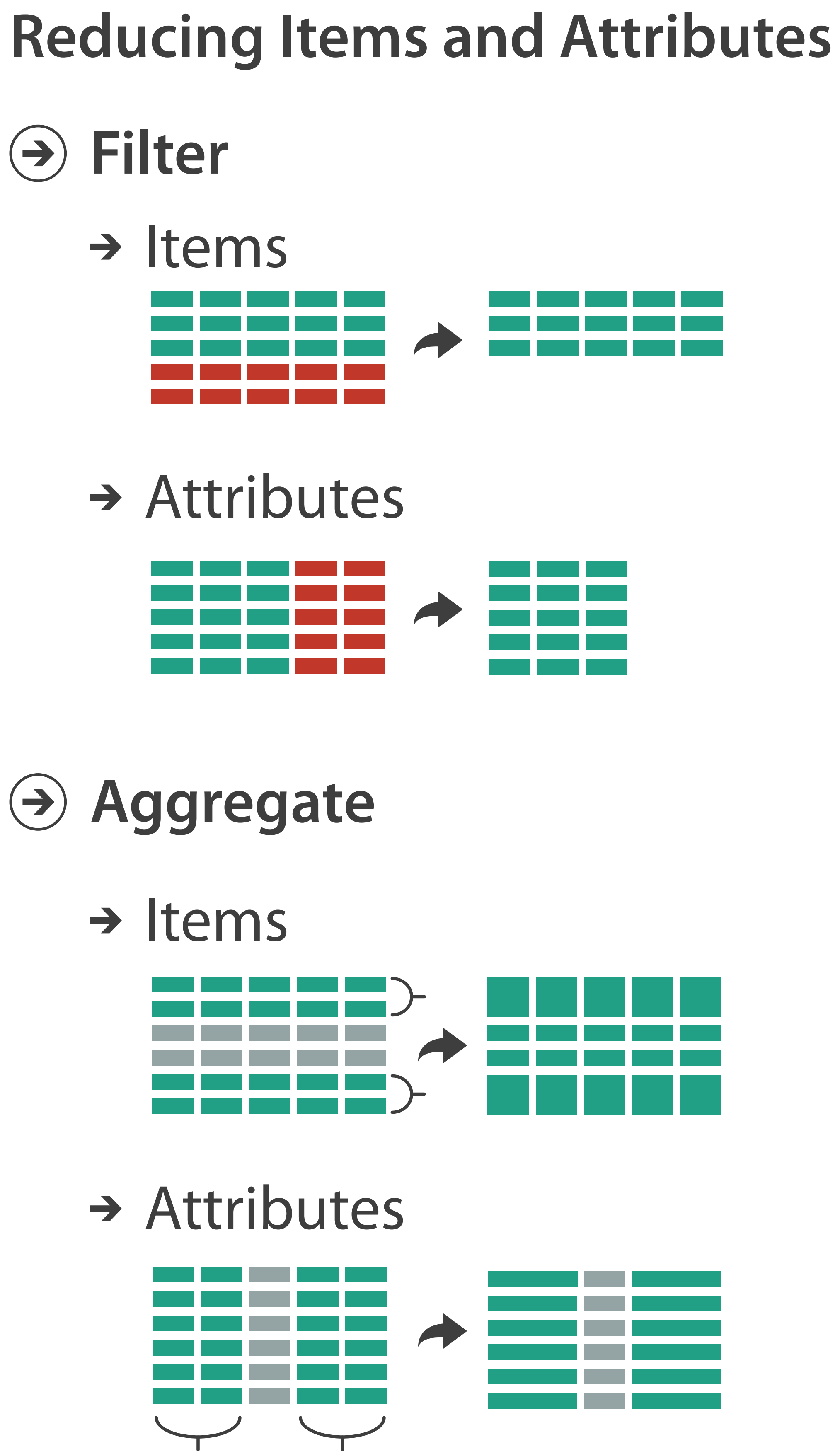
Reduce items and attributes

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



Reduce items and attributes

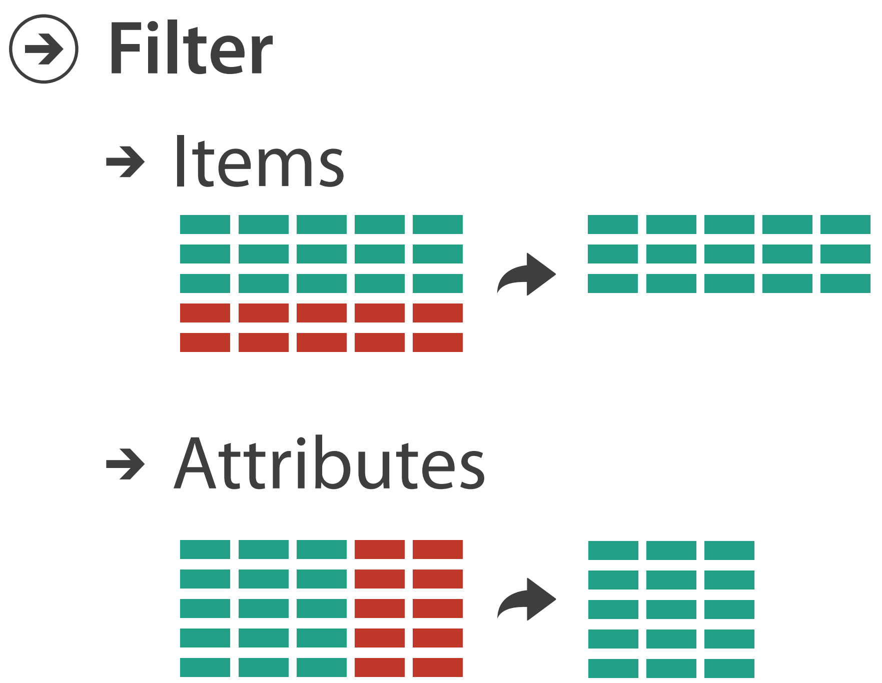
- reduce/increase: inverses
- filter
  - pro: straightforward and intuitive
    - to understand and compute
  - con: out of sight, out of mind
- aggregation
  - pro: inform about whole set
  - con: difficult to avoid losing signal
- not mutually exclusive
  - combine filter, aggregate
  - combine reduce,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



Filter

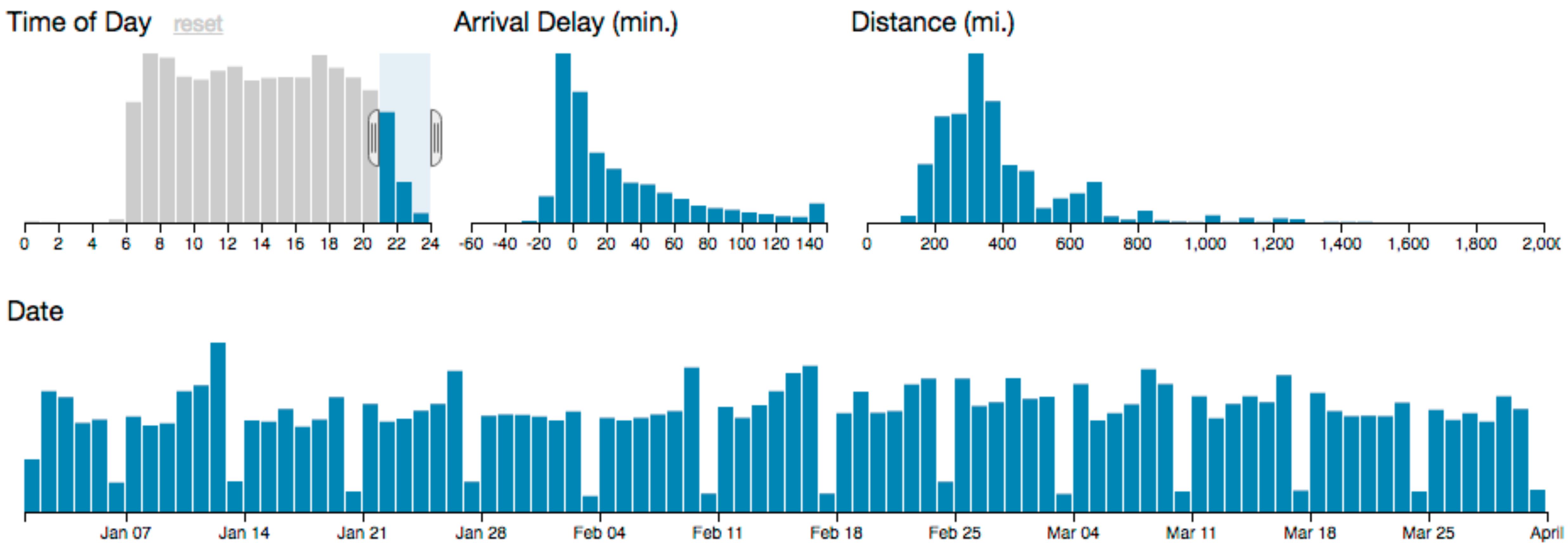
- eliminate some elements
  - either items or attributes
- according to what?
  - any possible function that partitions dataset into two sets
    - attribute values bigger/smaller than x
    - noise/signal
- filters vs queries
  - query: start with nothing, add in elements
  - filters: start with everything,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

Reducing Items and Attributes



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

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

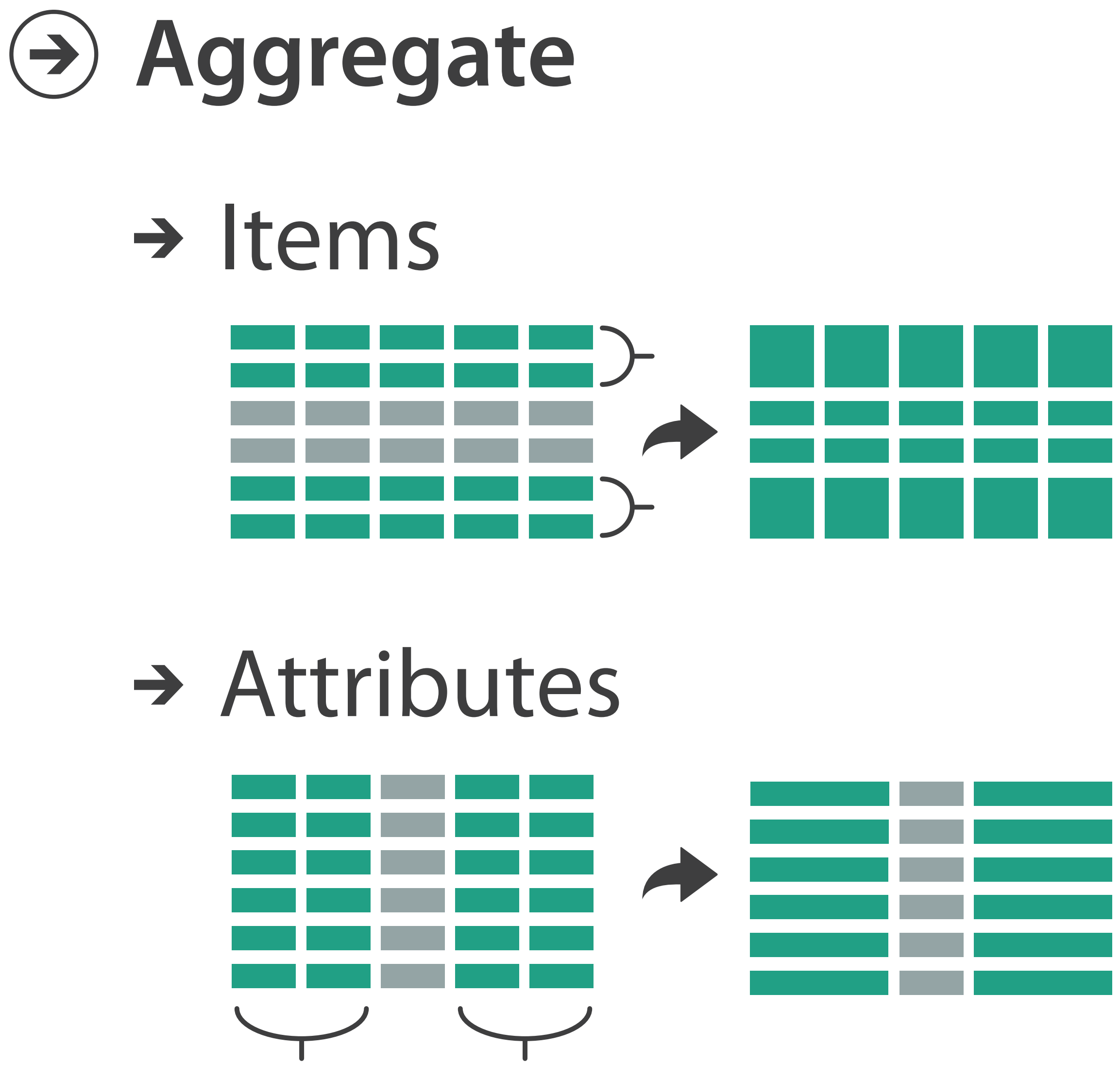


http://square.github.io/crossfilter/

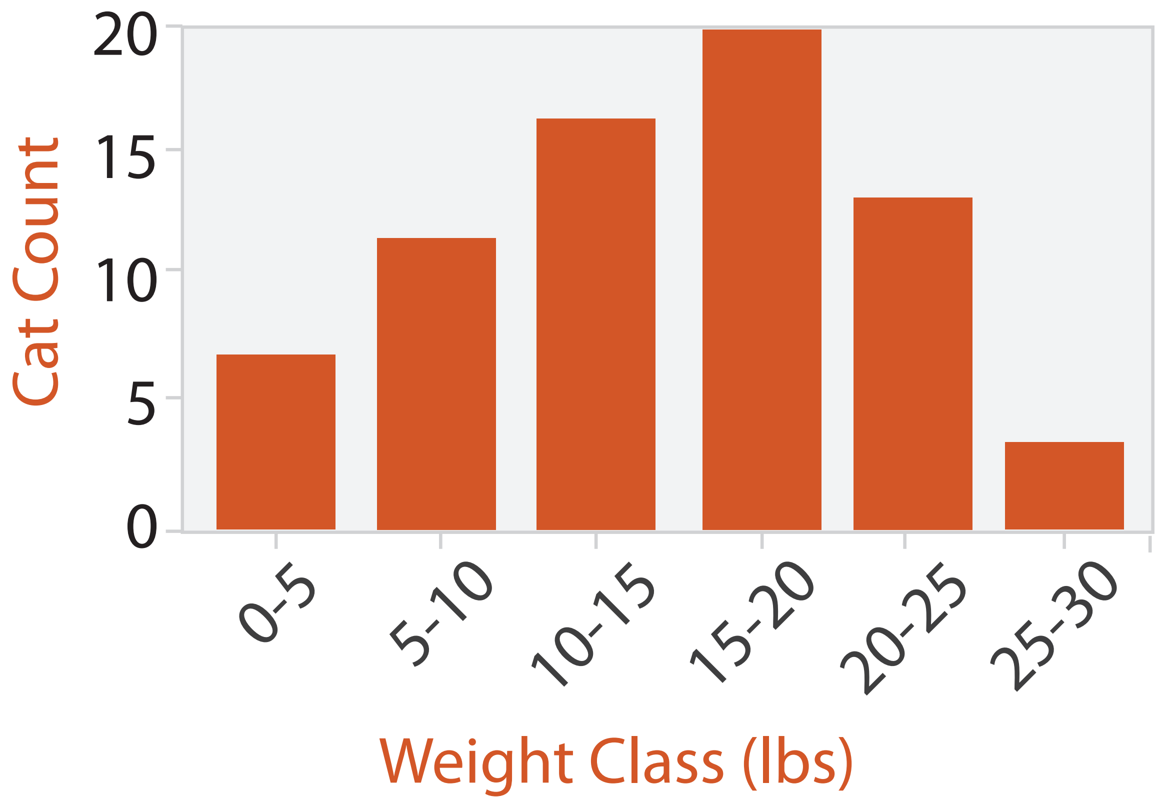
https://observablehq.com/@uwdata/interaction

Aggregate

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



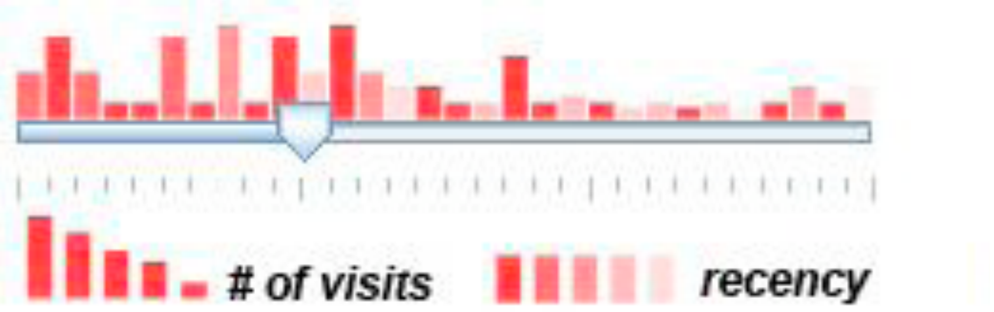
Idiom: **histogram**



- 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**

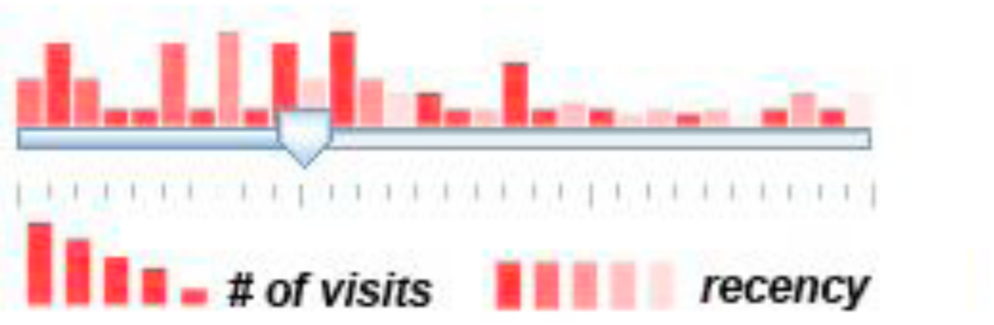
- augmented widgets show *information scent*
  - better cues for *information foraging*: show whether value in drilling down further vs looking elsewhere
- concise use of space: histogram on slider



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

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



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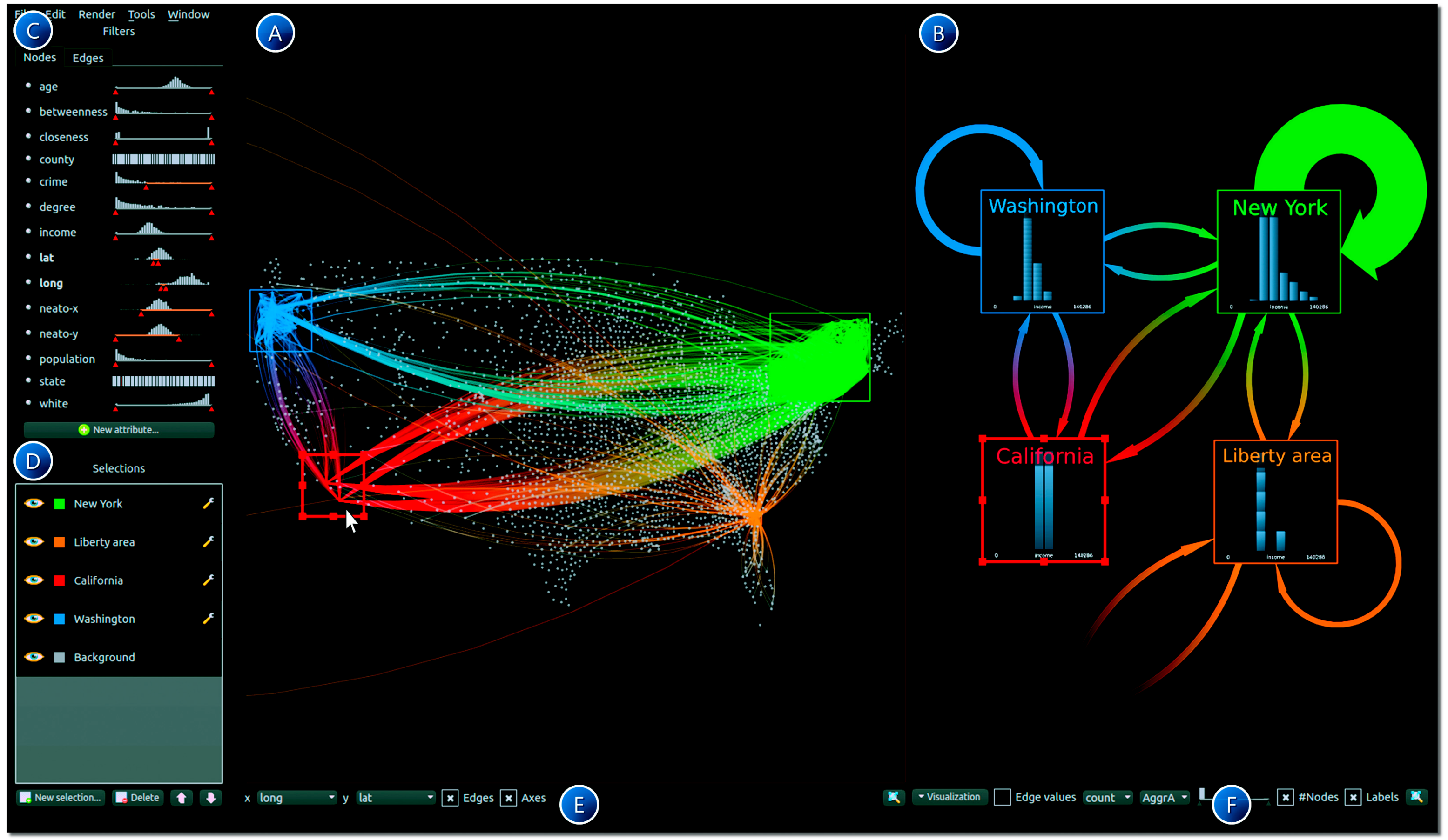

[Multivariate Network Exploration and Presentation: From Detail to Overview via Selections and Aggregations. van den Elzen, van Wijk, IEEE TVCG 20(12): 2014 (Proc. InfoVis 2014).]

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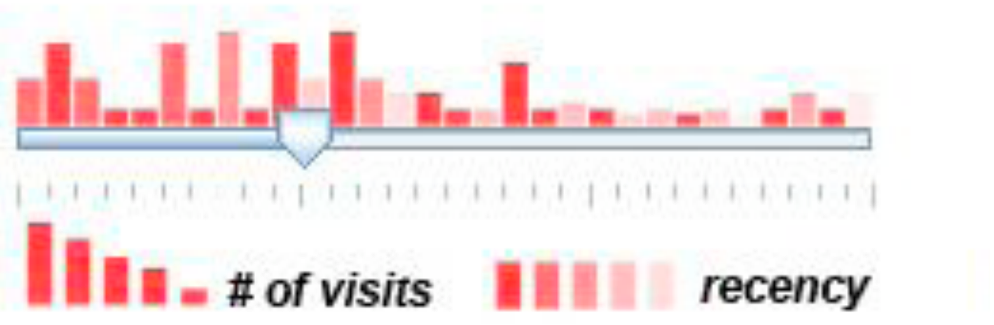

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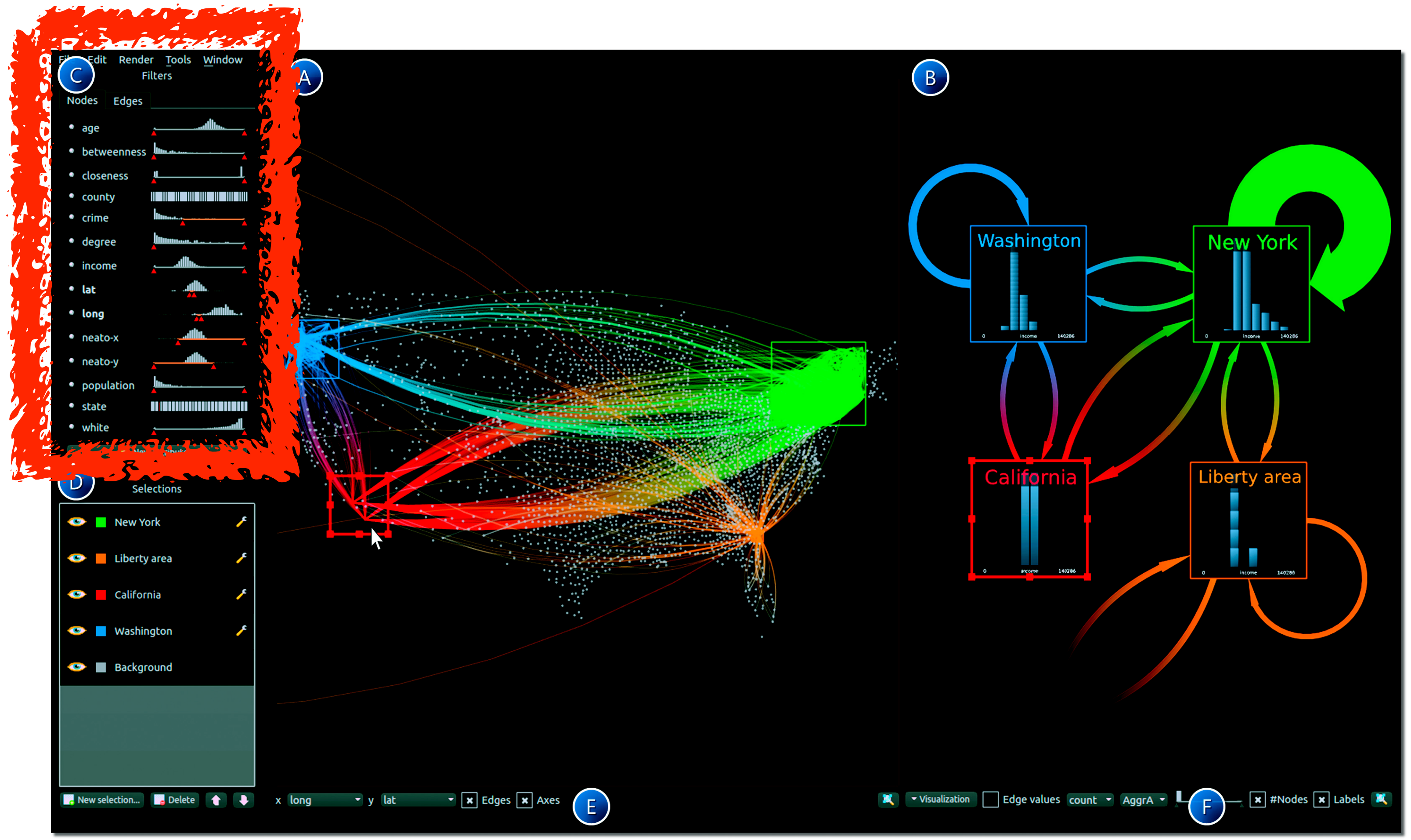

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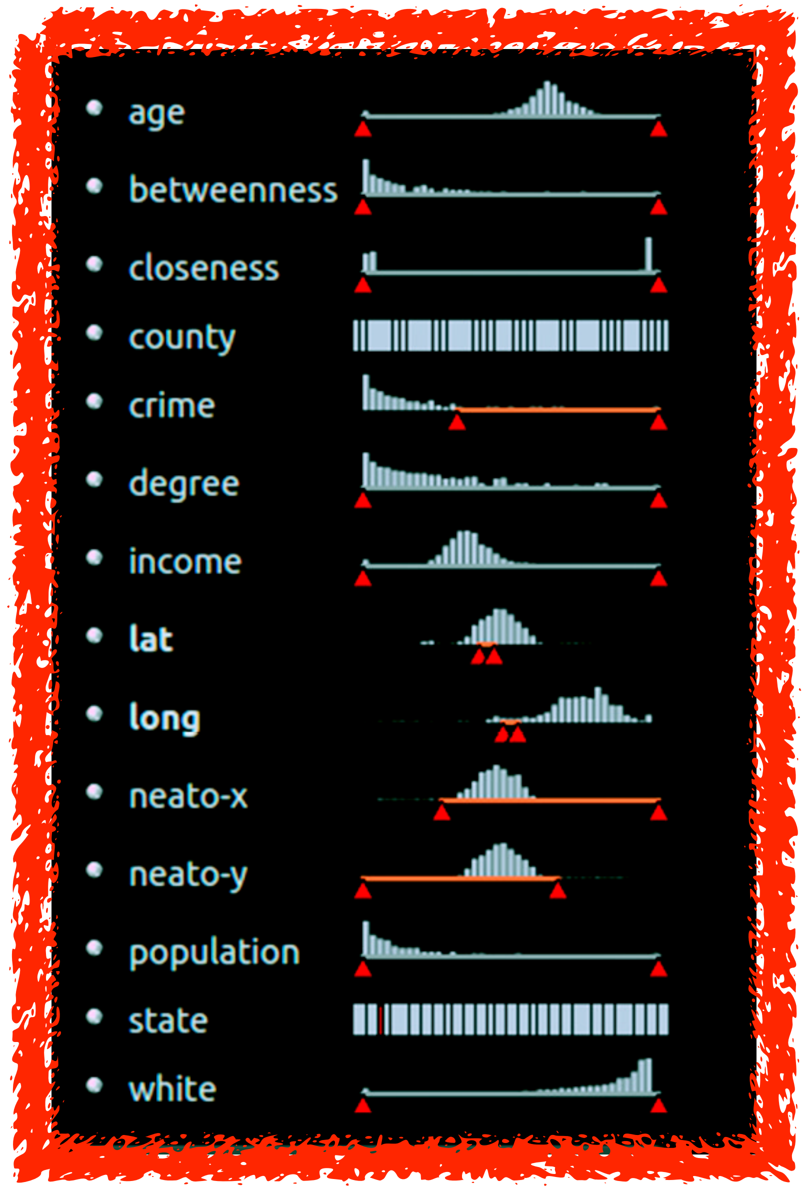
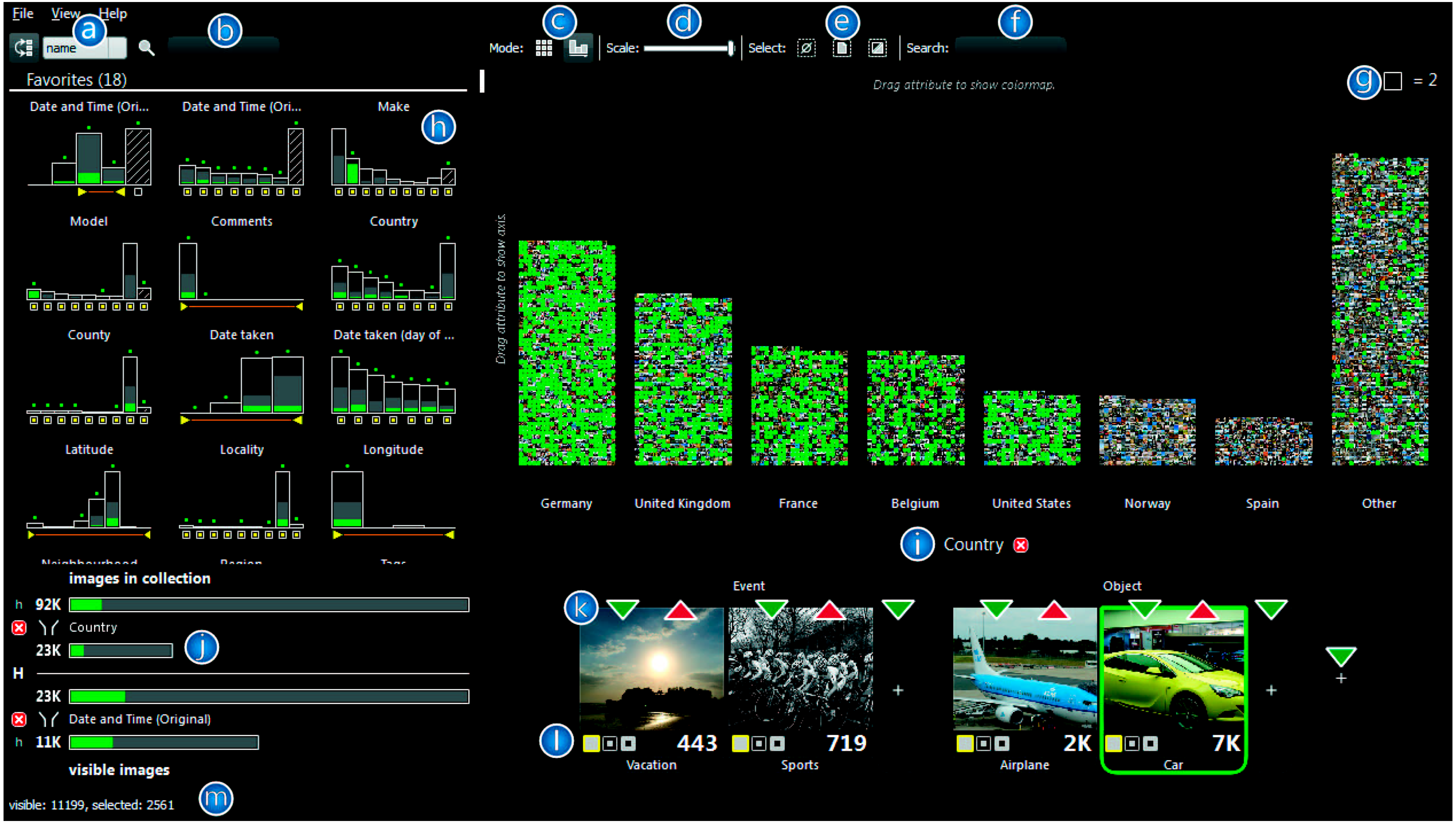


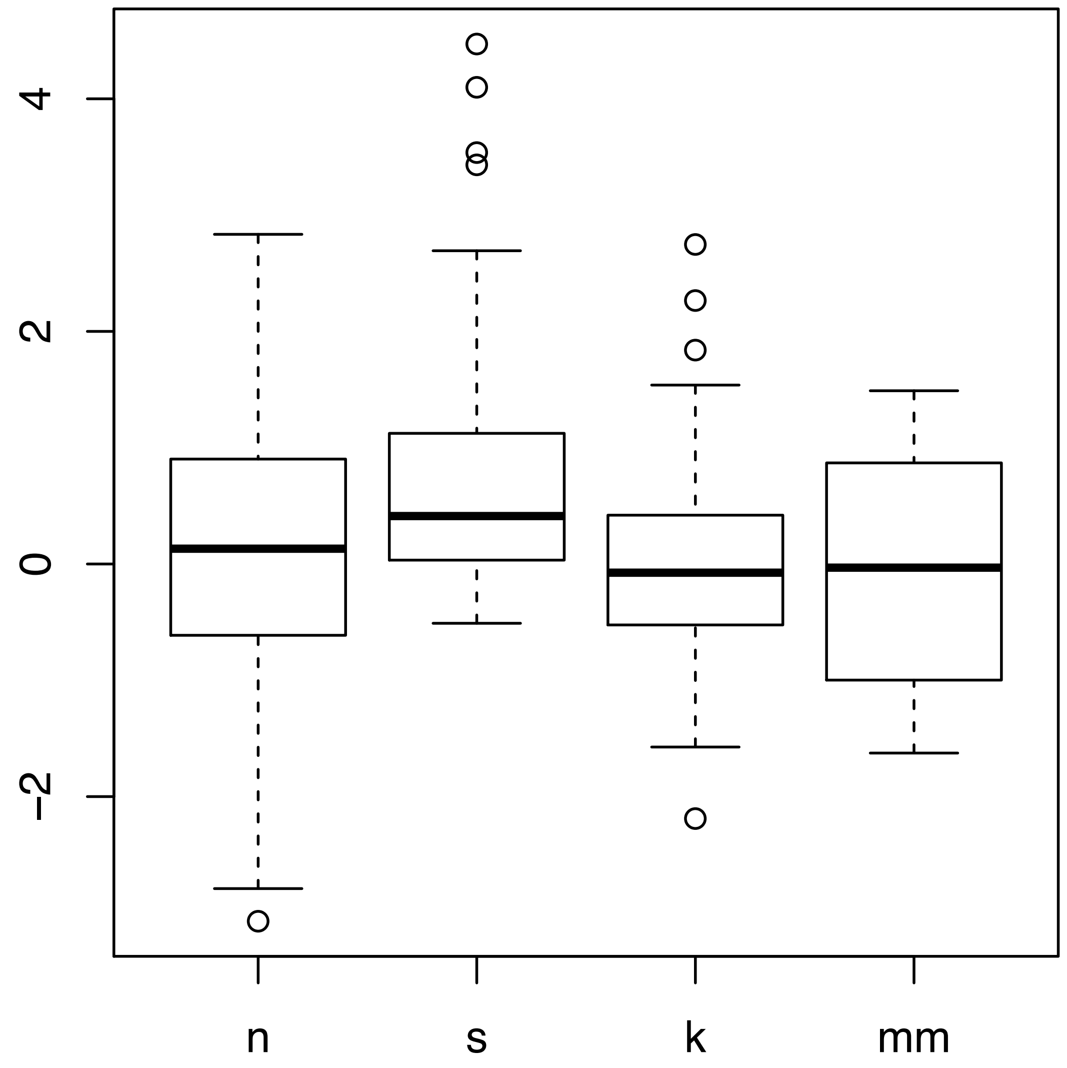
Scented histogram bisliders: detailed



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

Idiom: **boxplot**

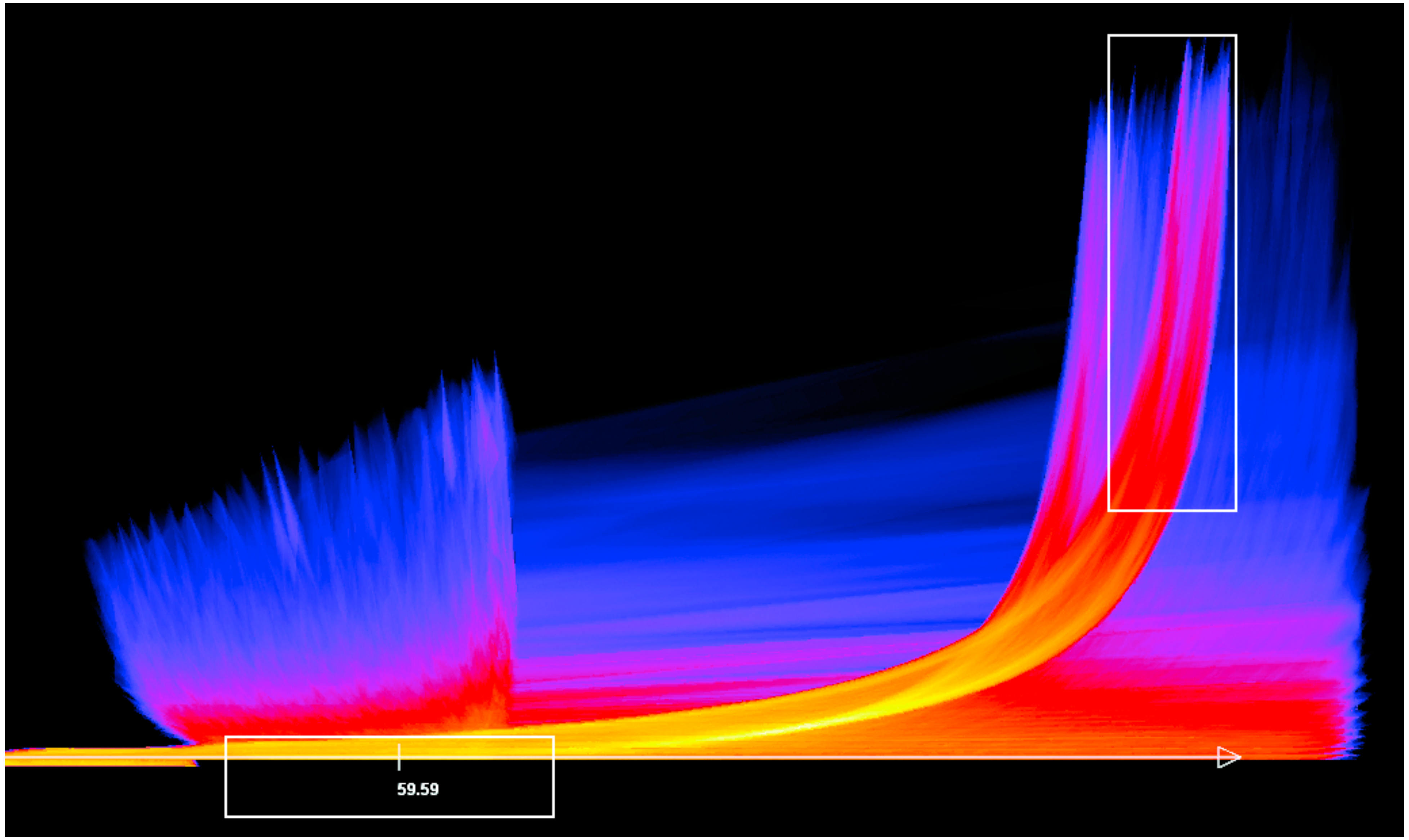
- static item aggregation
- task: find distribution
- data: table
- derived data
  - 5 quant attribs
    - median: central line
    - lower and upper quartile: boxes
    - lower upper fences: whiskers
      - values beyond which items are outliers
  - outliers beyond fence cutoffs explicitly shown
-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



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

Idiom: **Continuous scatterplot**

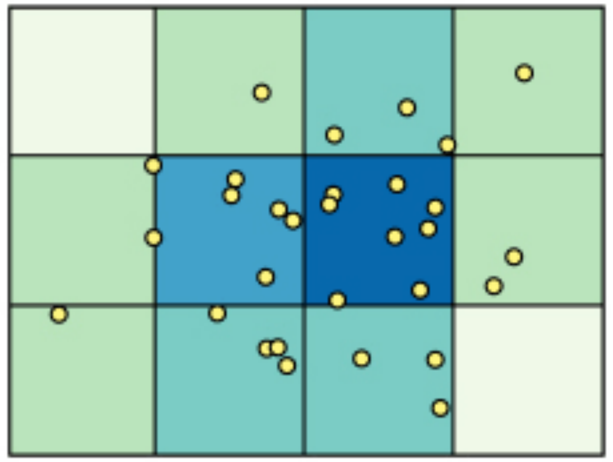
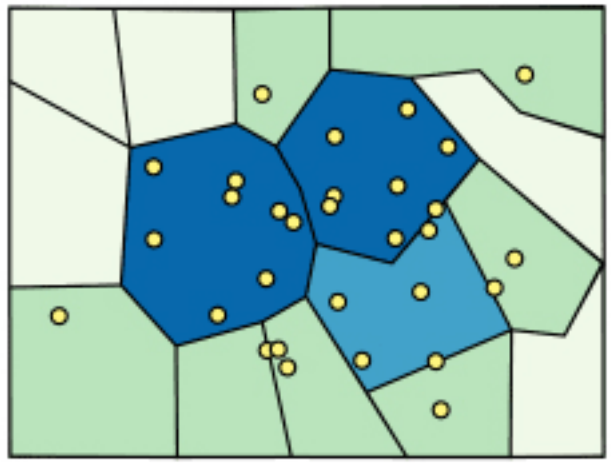
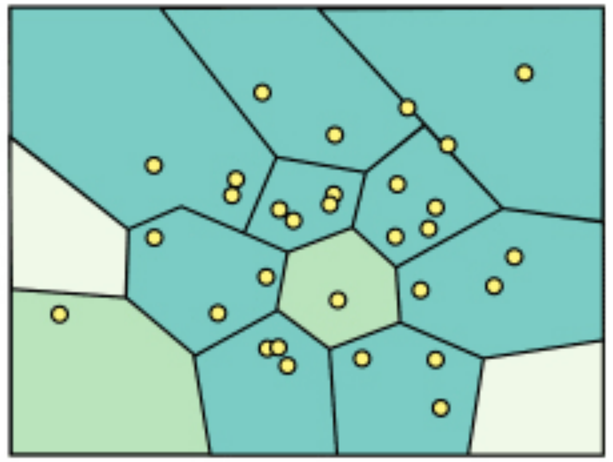
- static item aggregation
- data: table
- derived data: table
  - key attribs x,y for pixels
  - quant attrib: overplot density
- dense space-filling 2D matrix
- color:
  sequential categorical hue +
  ordered luminance colormap
- scalability
  - no limits on overplotting:
    millions of items



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

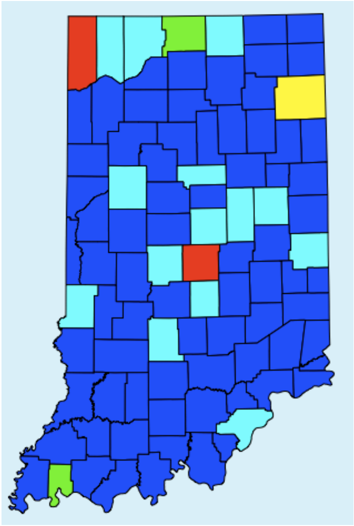
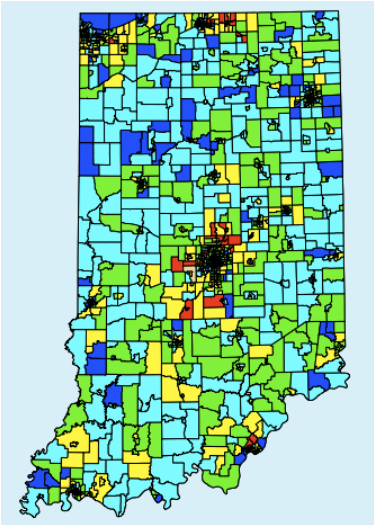
Spatial aggregation

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

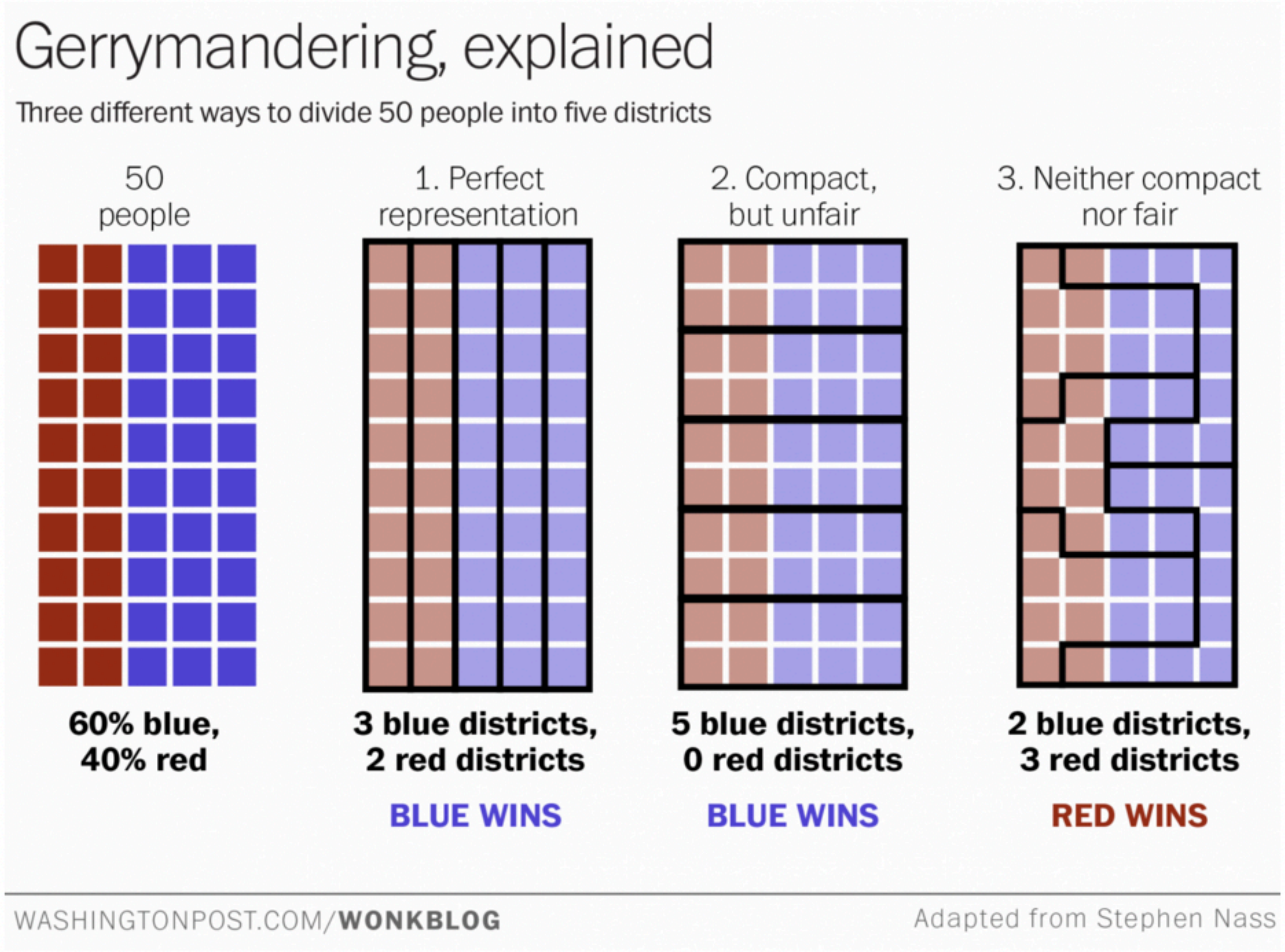
[http://www.e-education.psu/edu/geog486/l4_p7.html, Fig 4.cg.6]

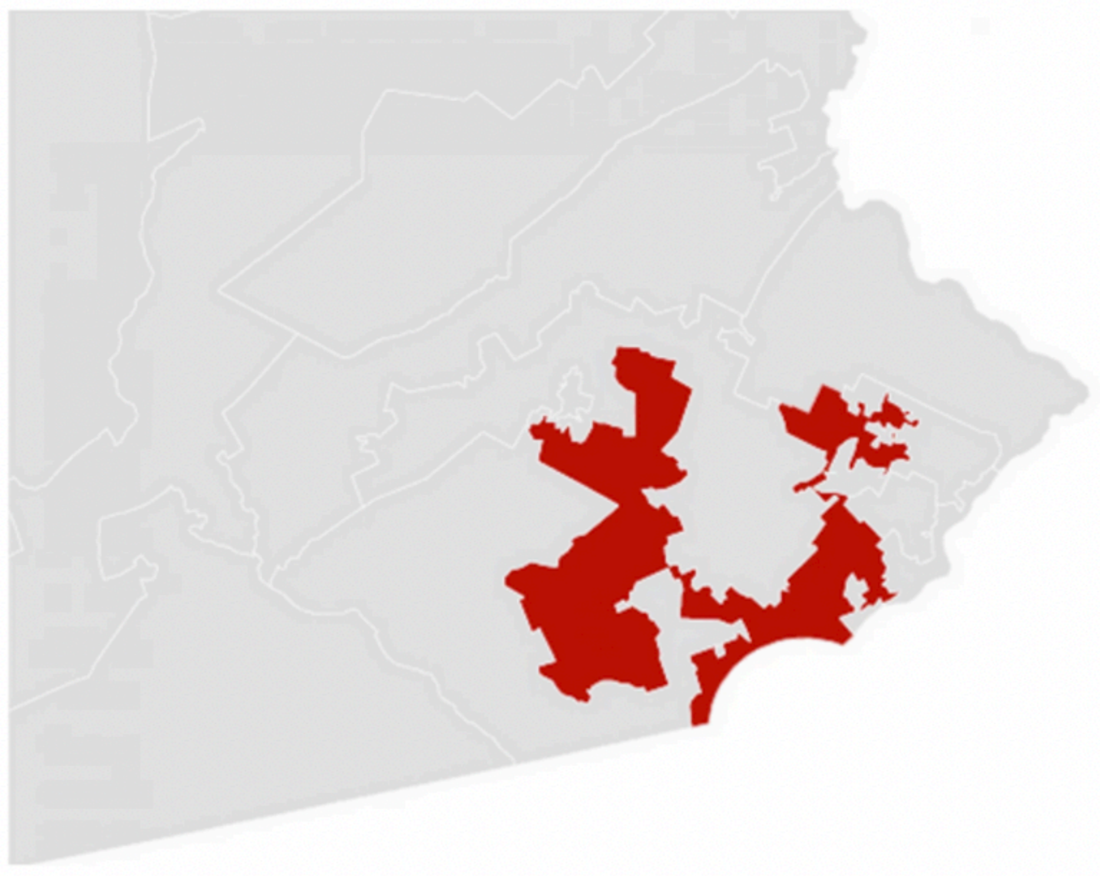
  - scale effects

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

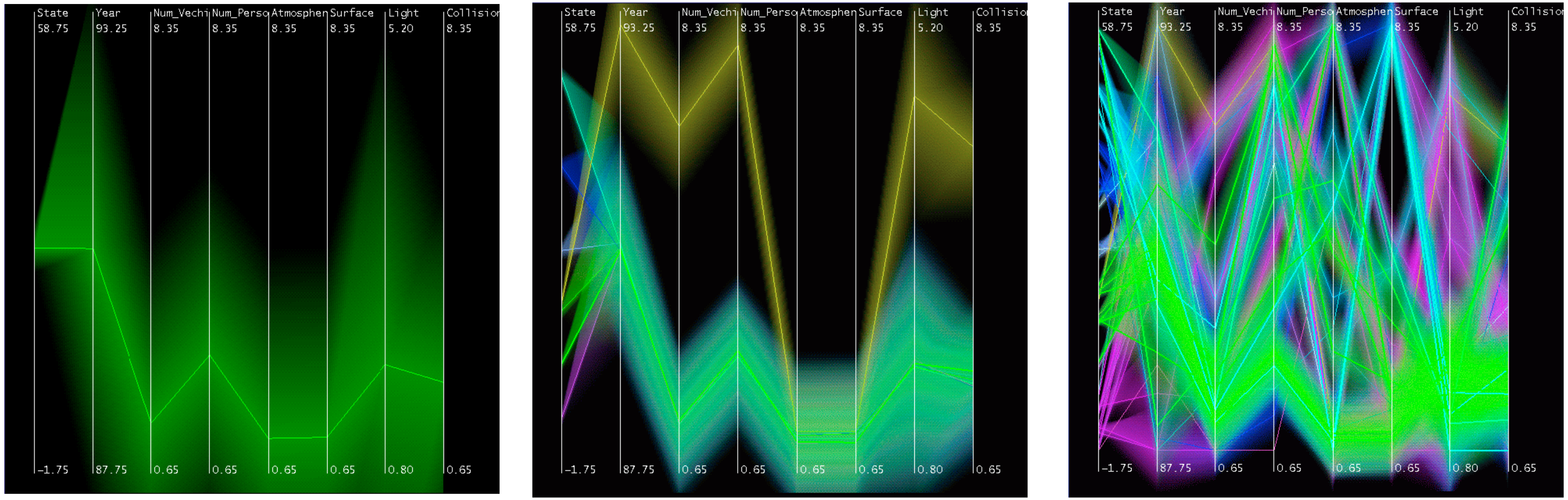
https://www.washingtonpost.com/news/wonk/wp/2015/03/01/this-is-the-best-explanation-of-gerrymandering-you-will-ever-see/

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



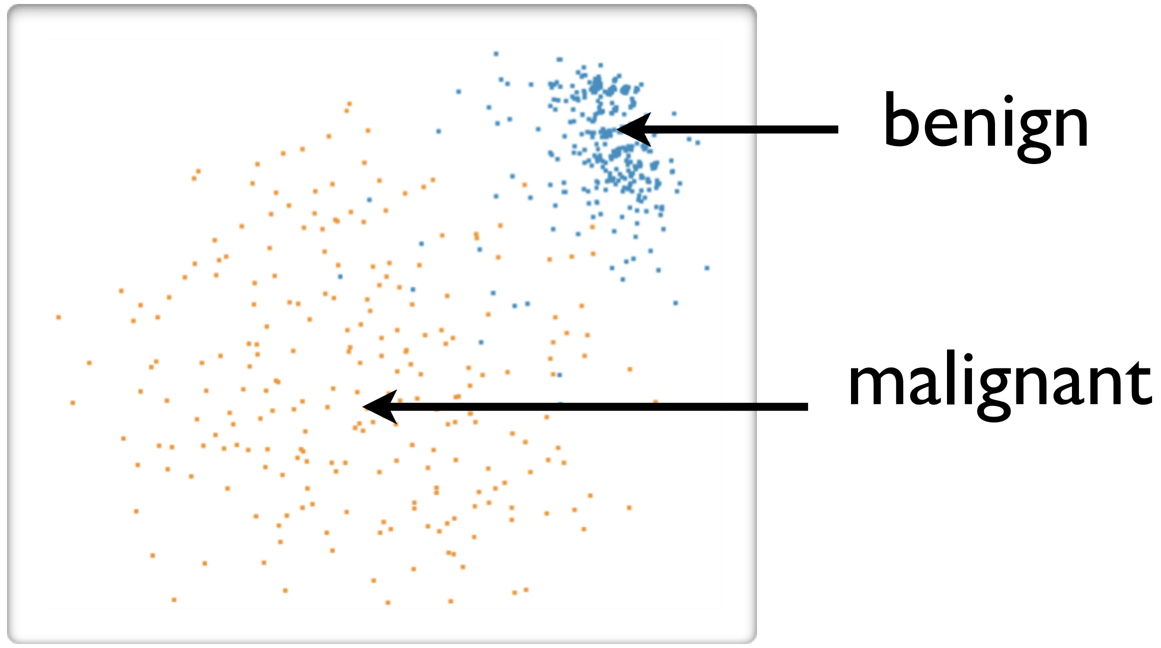
[Hierarchical Parallel Coordinates for Exploration of Large Datasets. Fua, Ward, and Rundensteiner. Proc. IEEE Visualization Conference (Vis '99), pp. 43– 50, 1999.]

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

tumor measurement data → **DR** →



data:
9D measured space

derived data:
2D target space

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

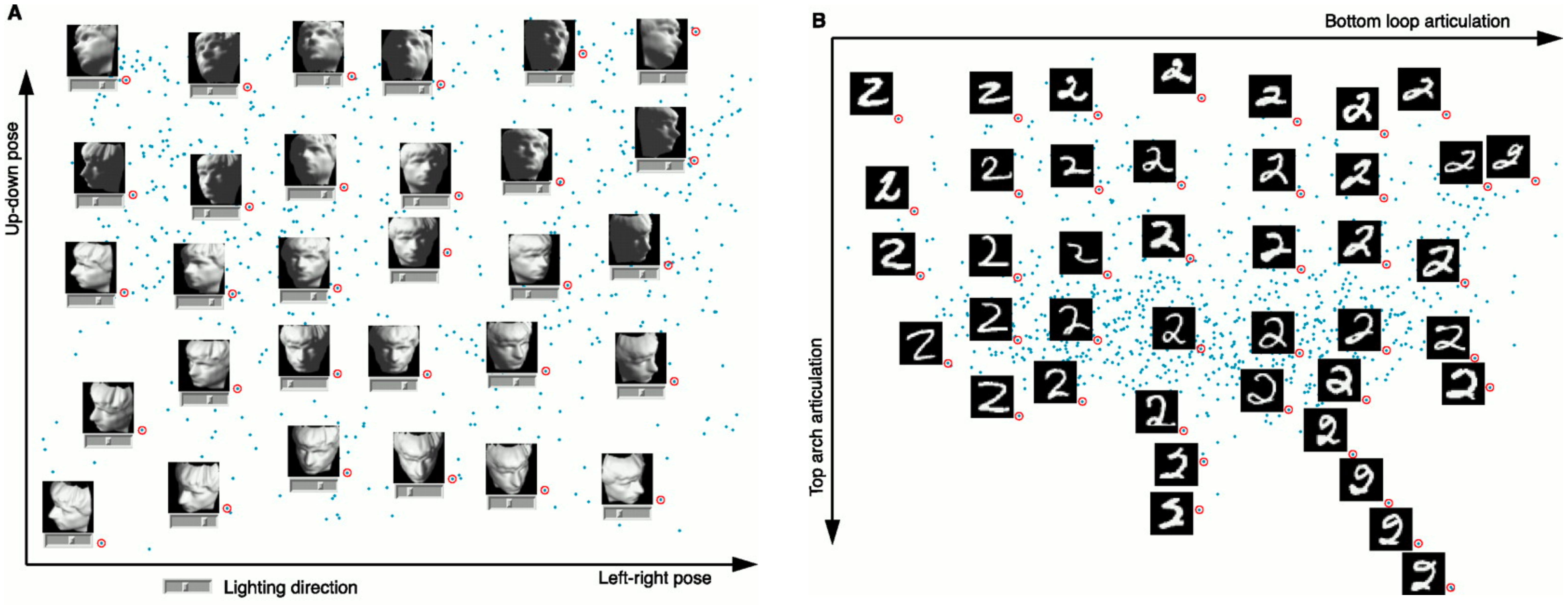
Dimensionality reduction & visualization

- 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

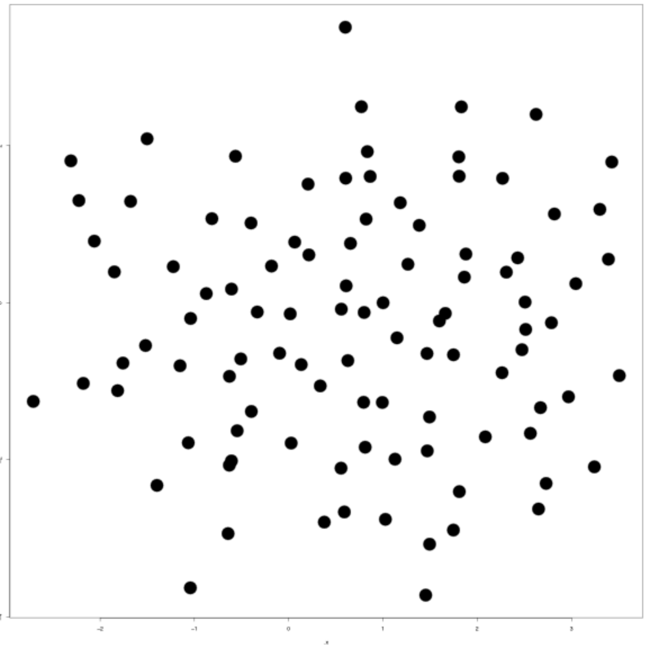


[A global geometric framework for nonlinear dimensionality reduction. Tenenbaum, de Silva, and Langford. Science, 290(5500):2319–2323, 2000.]

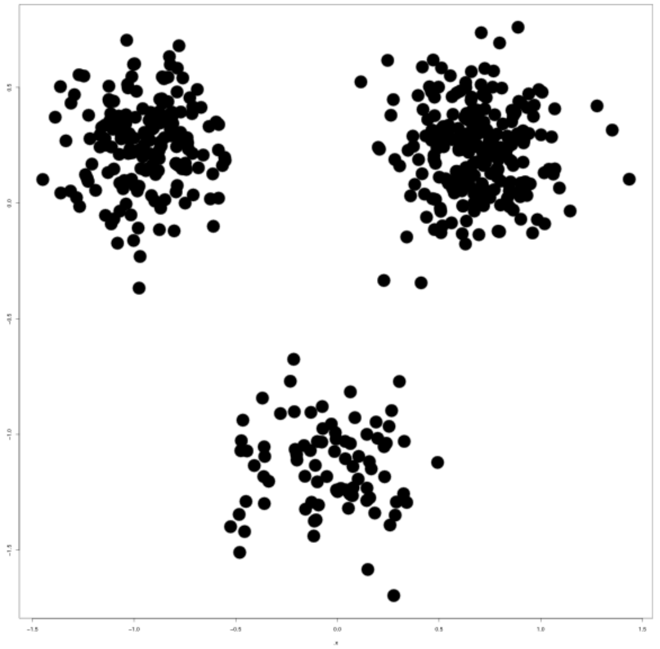
Cluster-oriented tasks

- verifying, naming, matching to classes

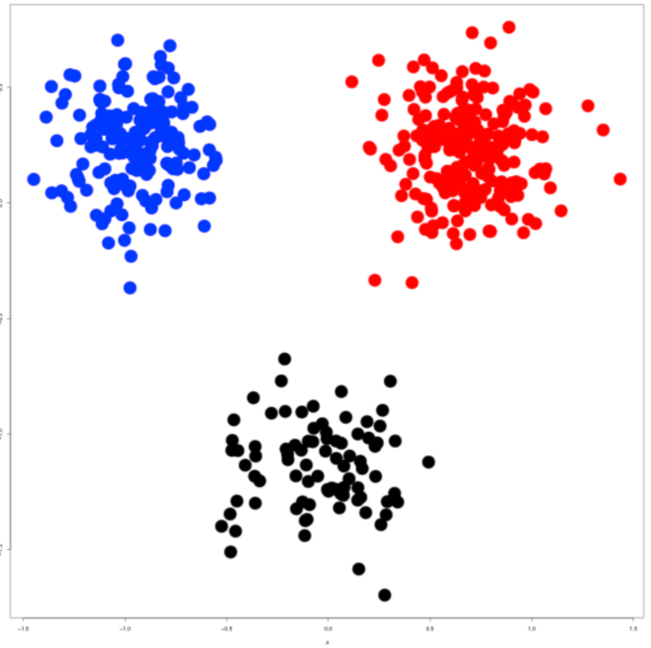
no discernable clusters



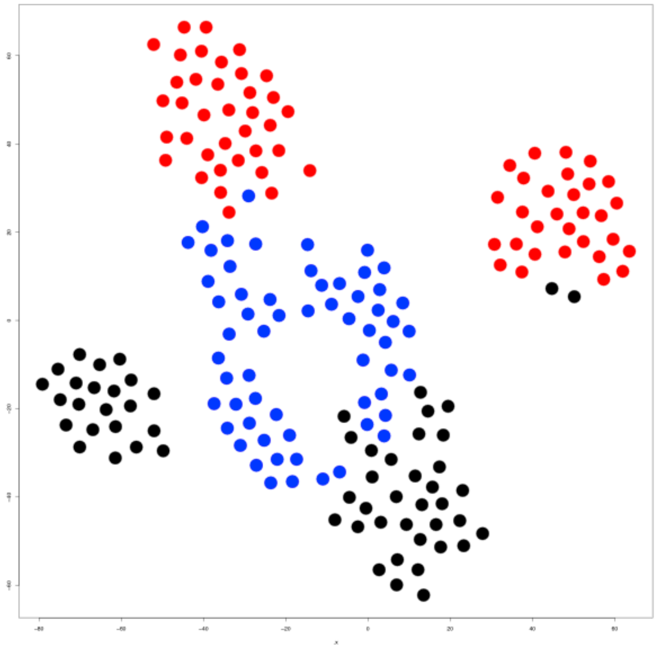
clearly discernable clusters



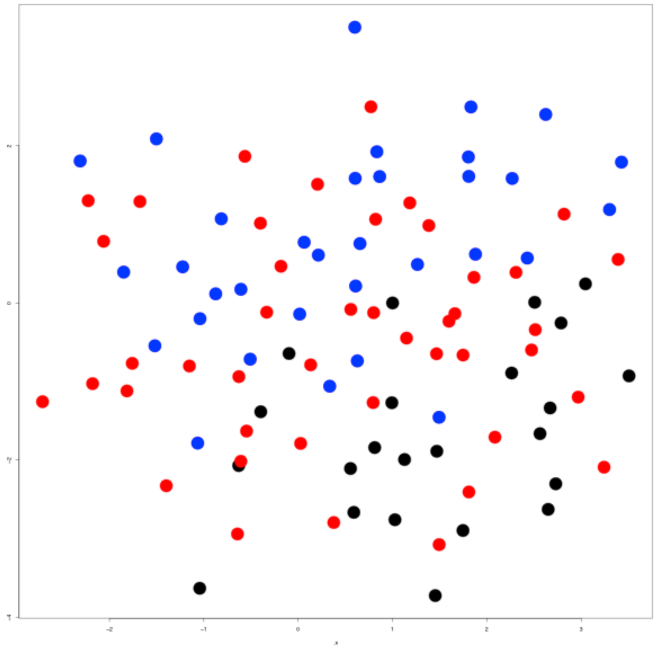
clear match cluster/class



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

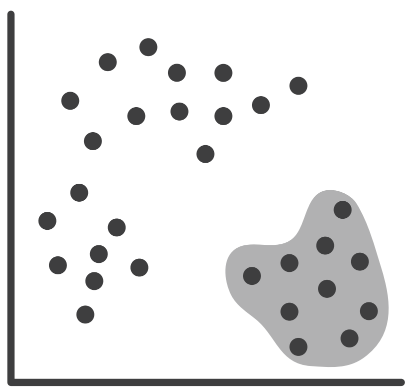
What?
- In High-dimensional data
- Out 2D data

Why?
- Produce
- Derive

→

Task 2

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



In
2D data → Out
Scatterplot
Clusters & points

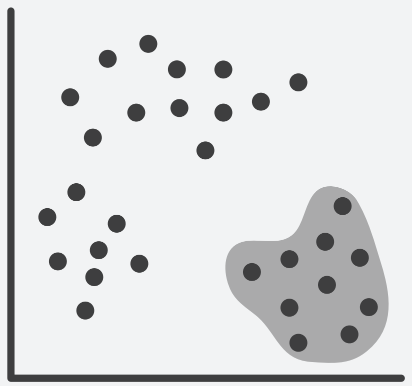
What?
- In 2D data
- Out Scatterplot
- Out Clusters & points

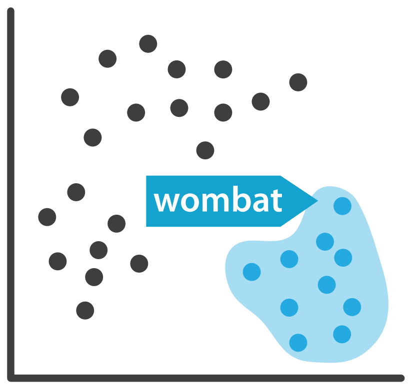
Why?
- Discover
- Explore
- Identify

How?
- Encode
- Navigate
- Select

→

Task 3





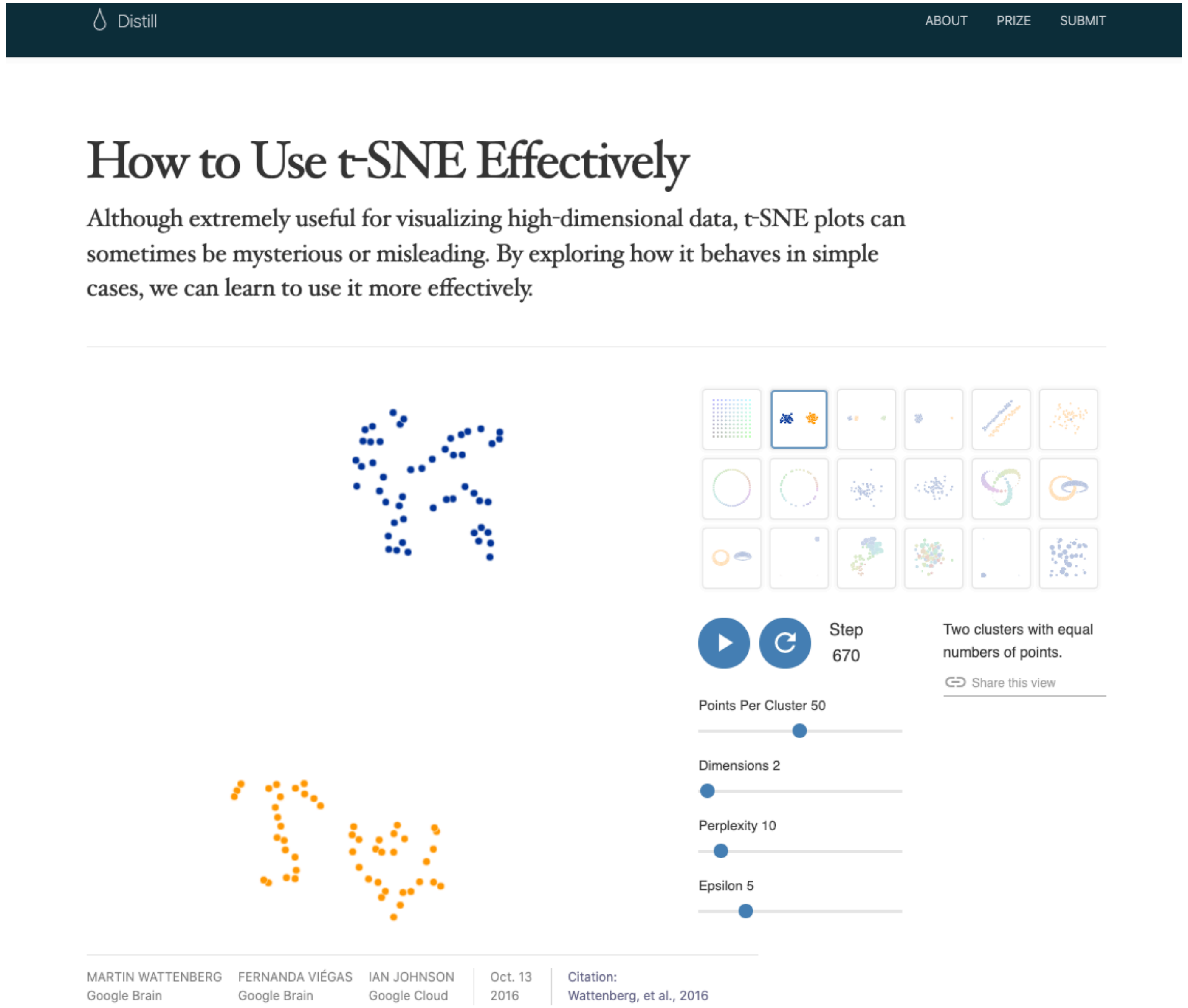
In
Scatterplot
Clusters & points → Out
Labels for clusters

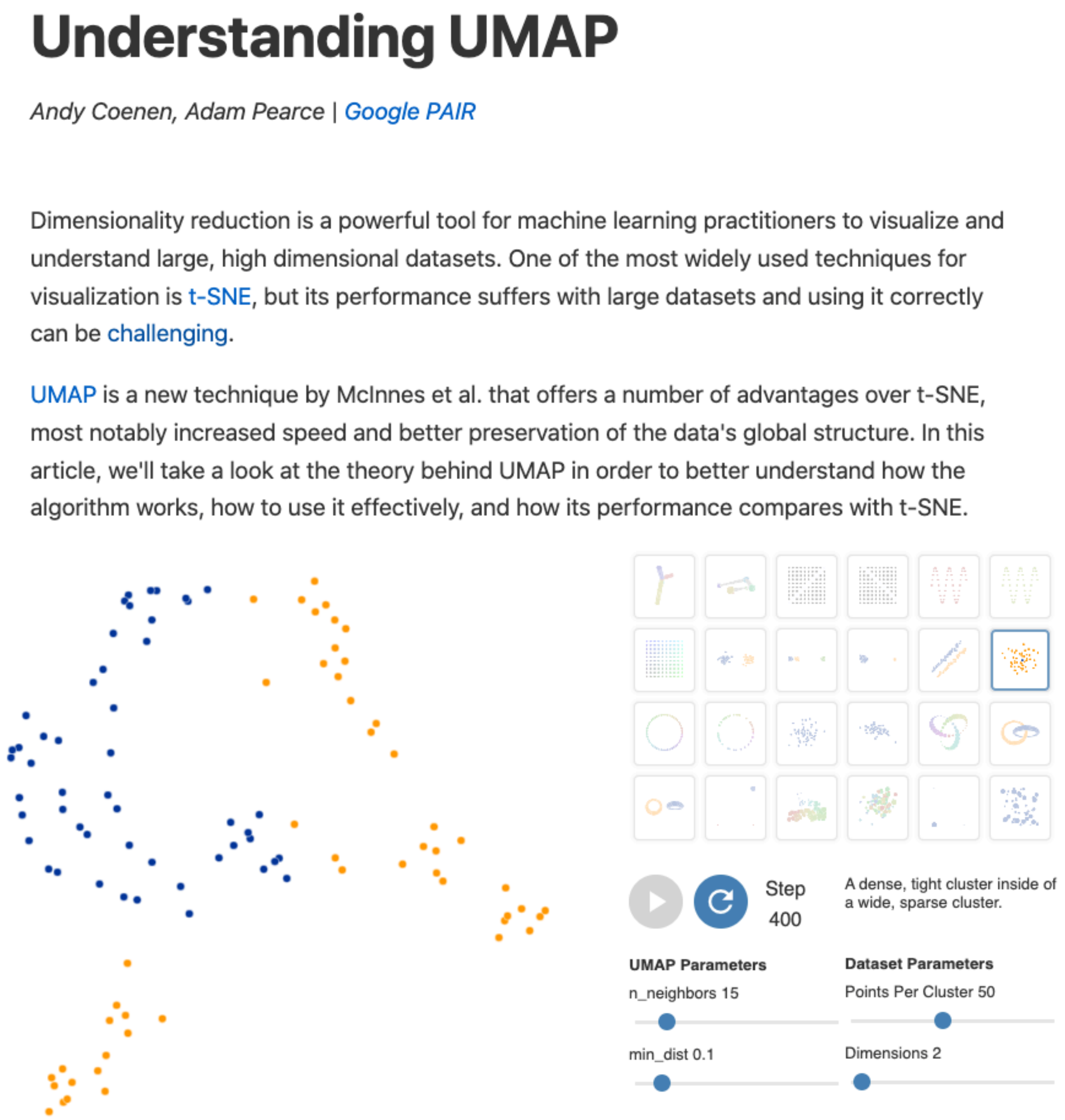
What?
- In Scatterplot
- In Clusters & points
- Out Labels for clusters

Why?
- Produce
- Annotate

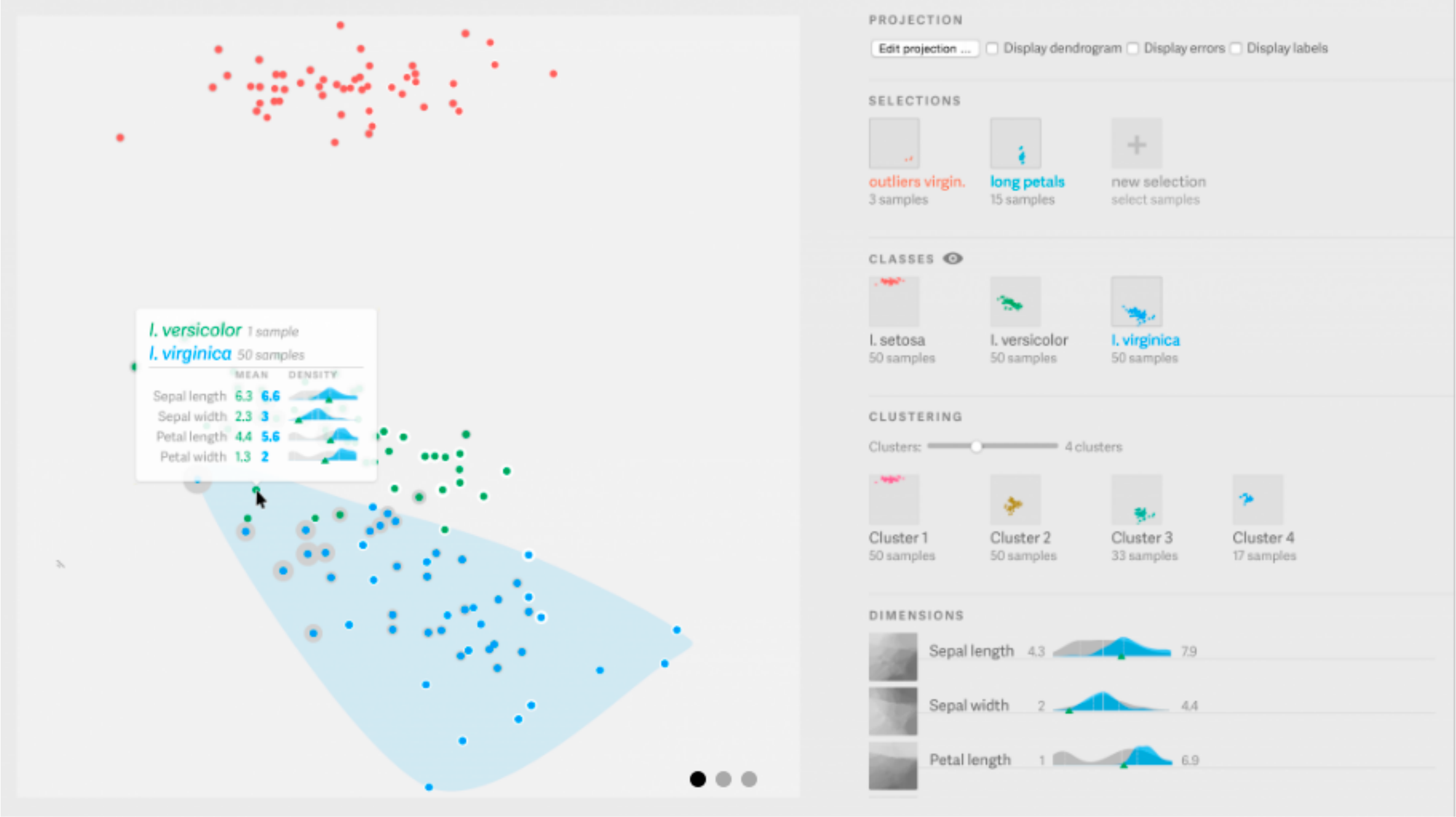
Latest algorithms: t-SNE, UMAP

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





Interacting with dimensionally reduced data

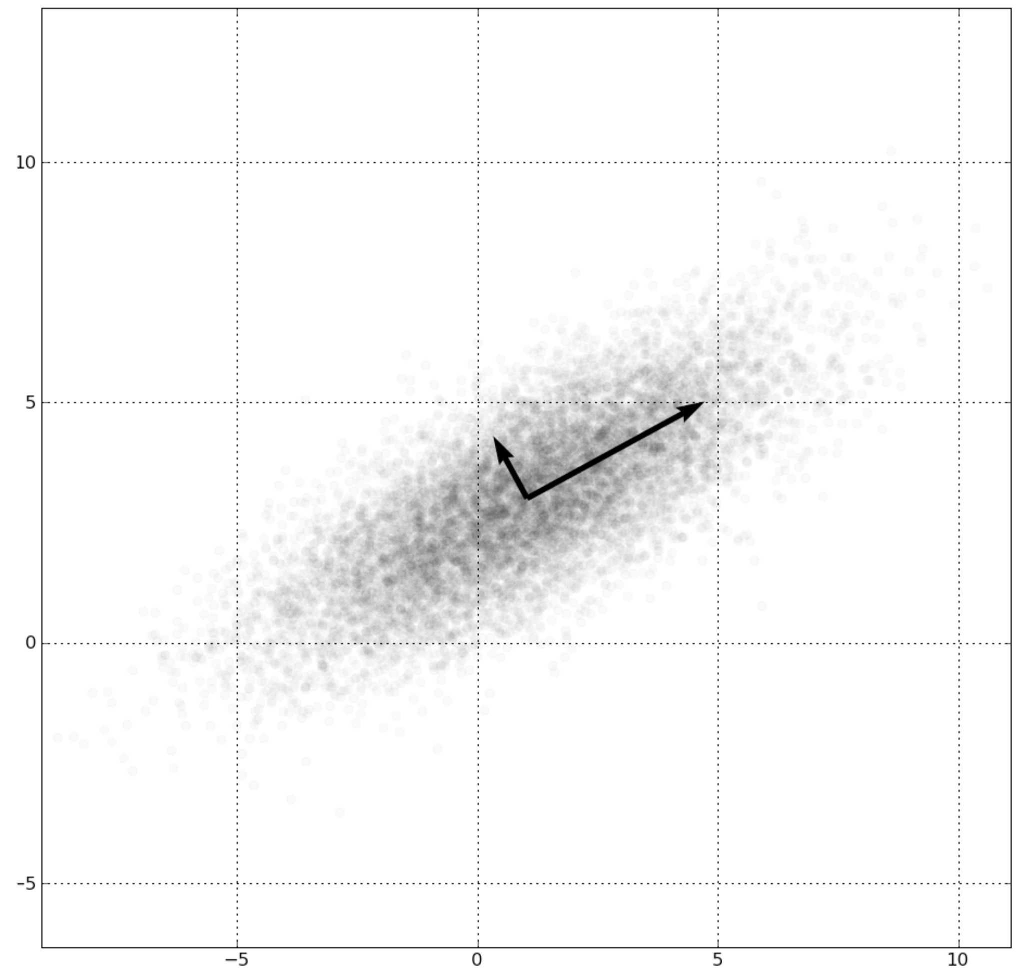


[https://uclab.fh-potsdam.de/projects/probing-projections/]

[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

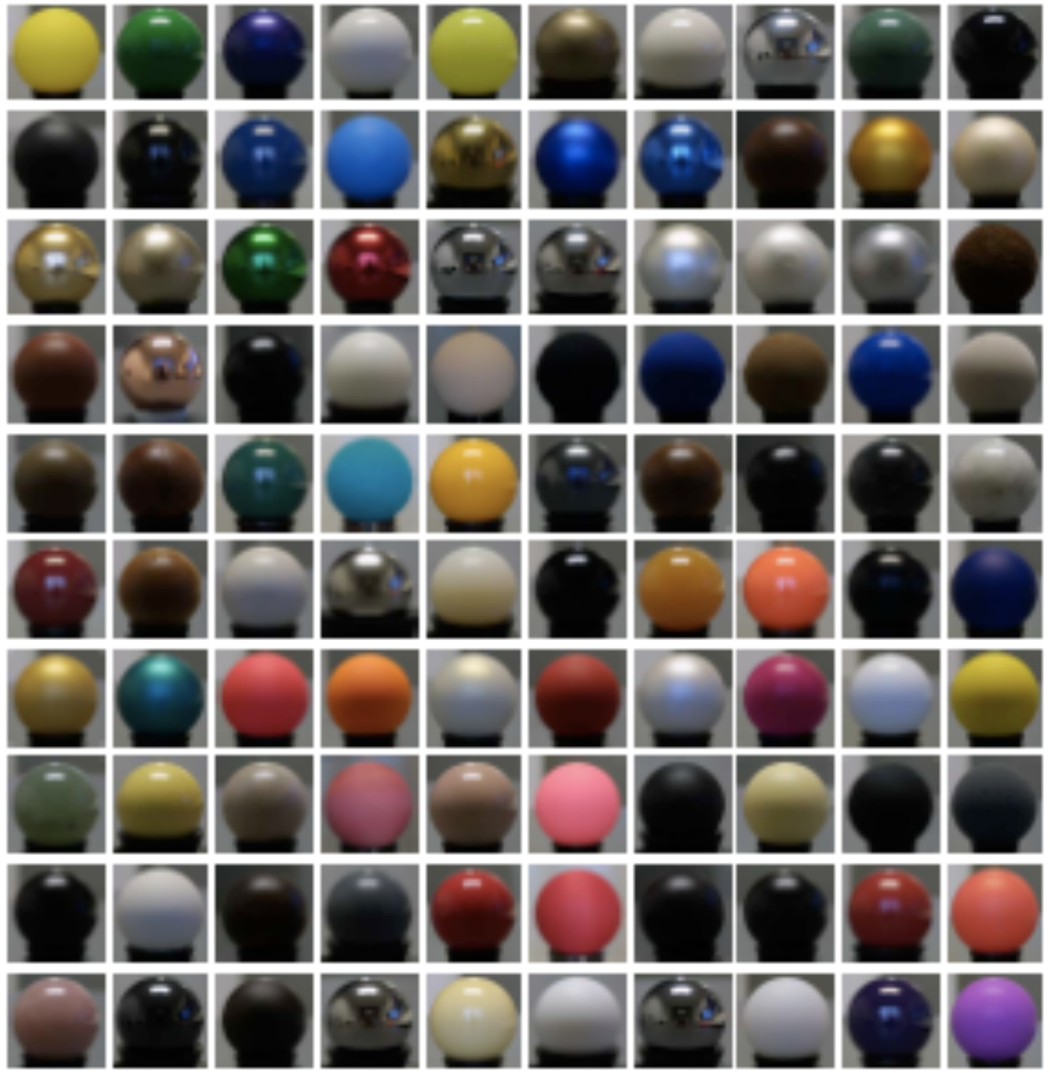
VDA with DR example: nonlinear vs linear

- 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

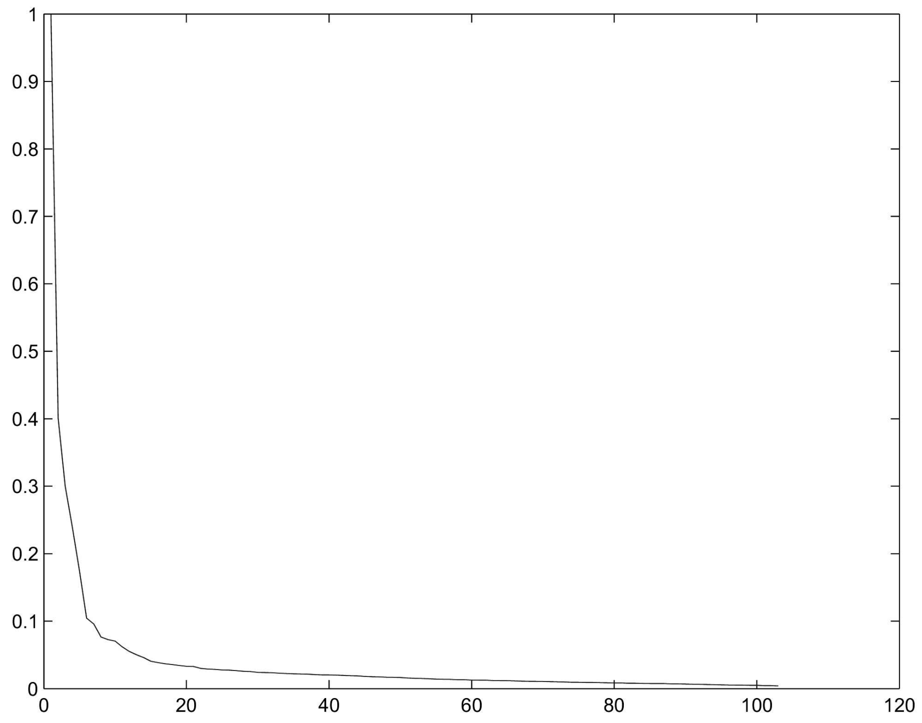
- reflectance measurement: interaction of light with real materials (spheres)
- result: 104 high-res images of material
  - each image 4M pixels
- goal: image synthesis
  - simulate completely new materials
- need for more concise model
  - 104 materials * 4M pixels = 400M dims
  - want concise model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

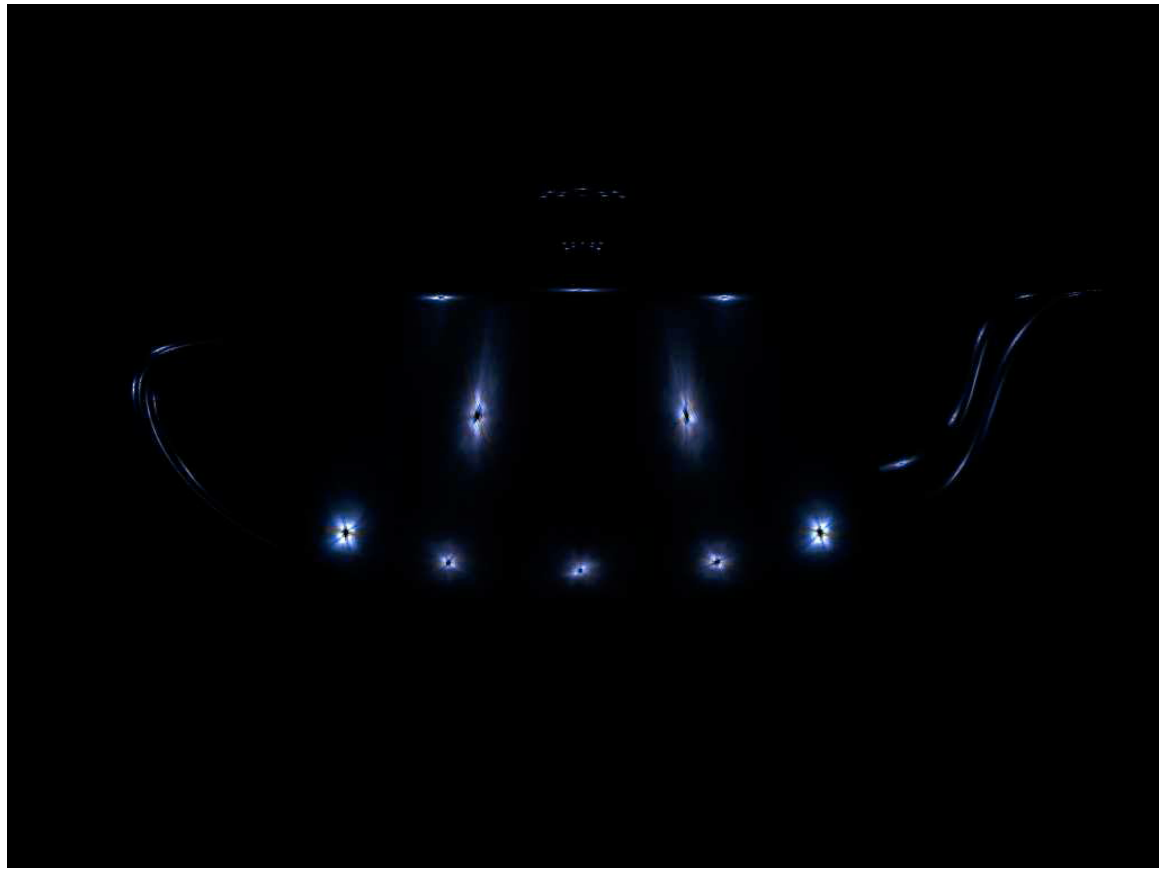


[Figs 5/6. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

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!

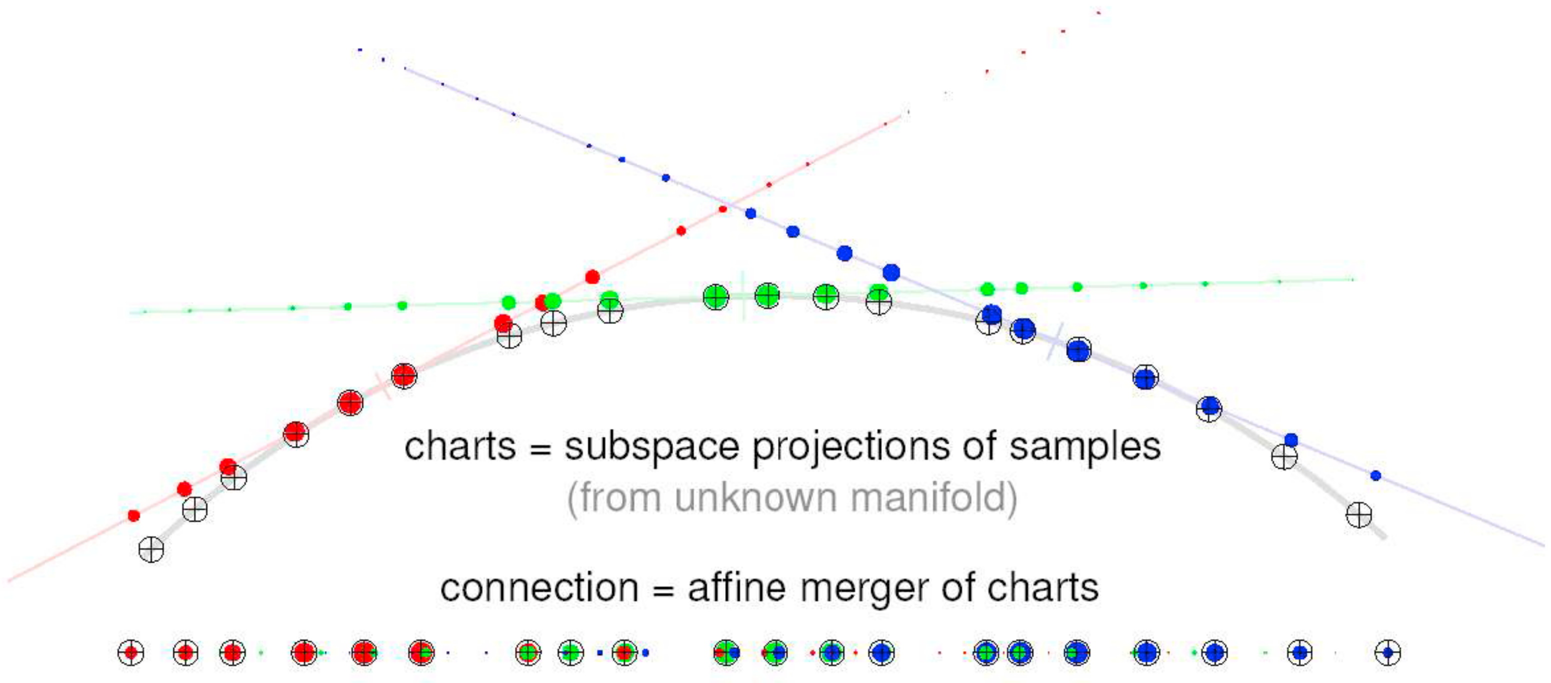


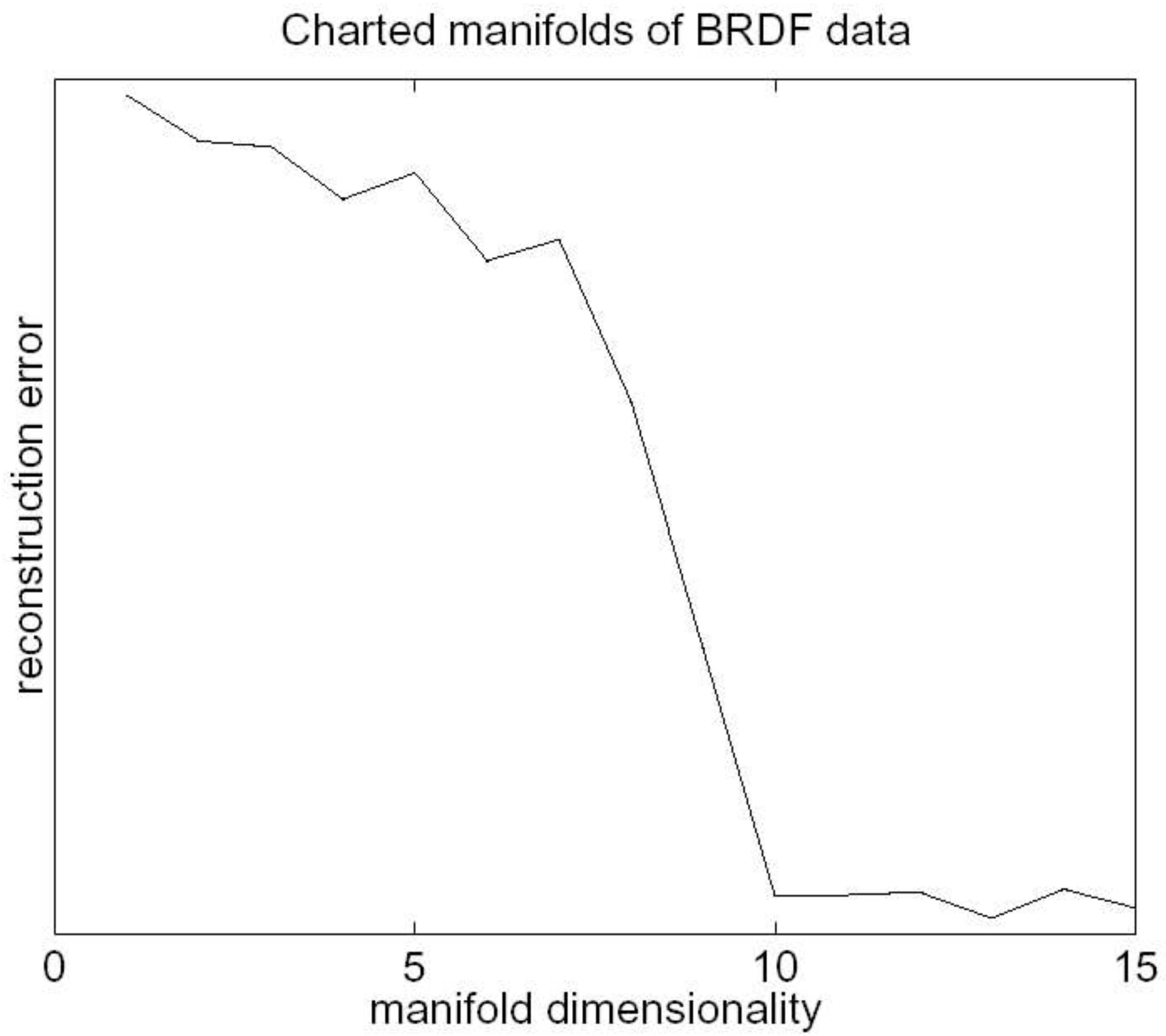


[Figs 6/7. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Nonlinear DR

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

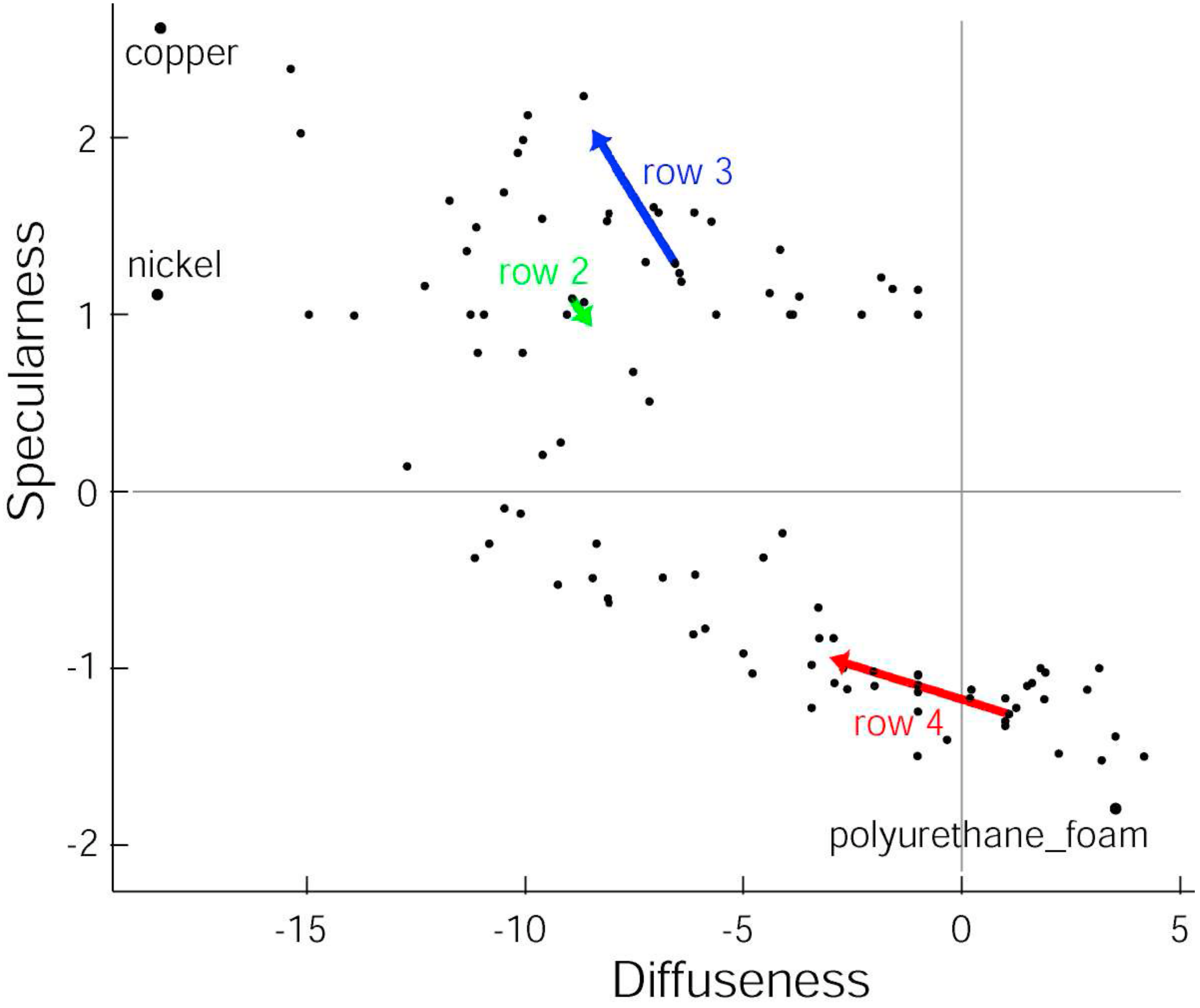




[Fig 10/11. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Finding semantics for synthetic dimensions

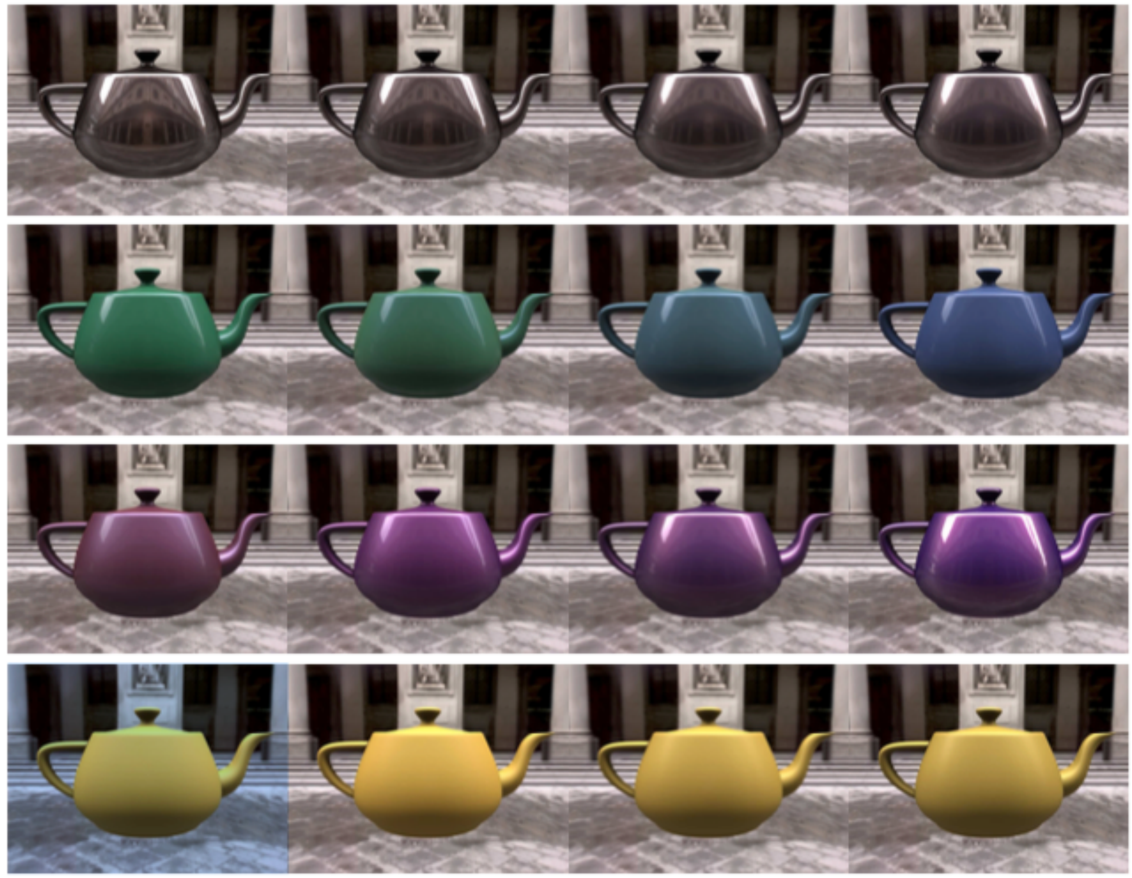
- look for meaning in scatterplots
  - synthetic dims created by algorithm but named by human analysts
  - points represent real-world images (spheres)
  - people inspect images corresponding to points to decide if axis could have meaningful name
- cross-check meaning
  - arrows show simulated images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



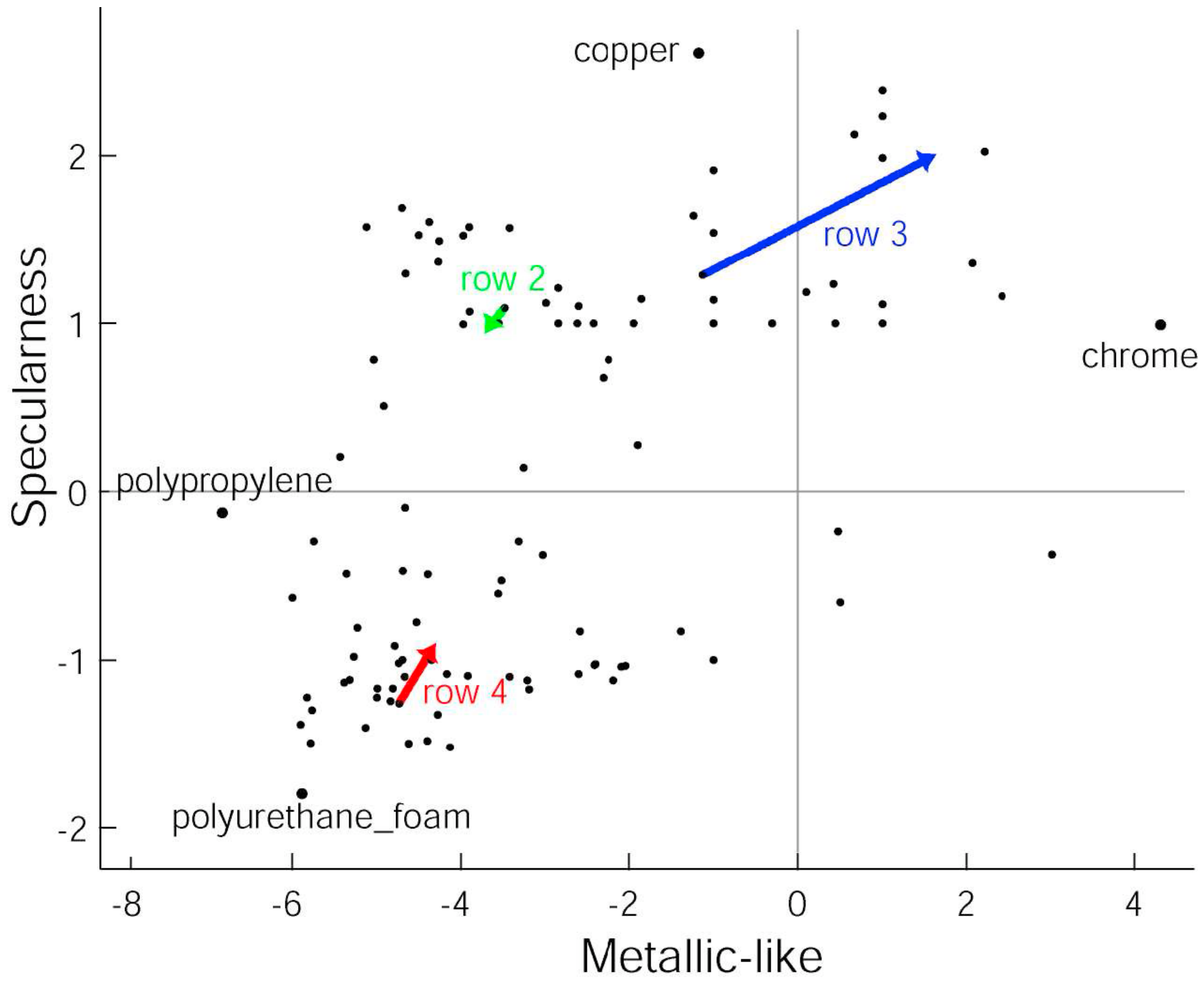
row 4

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

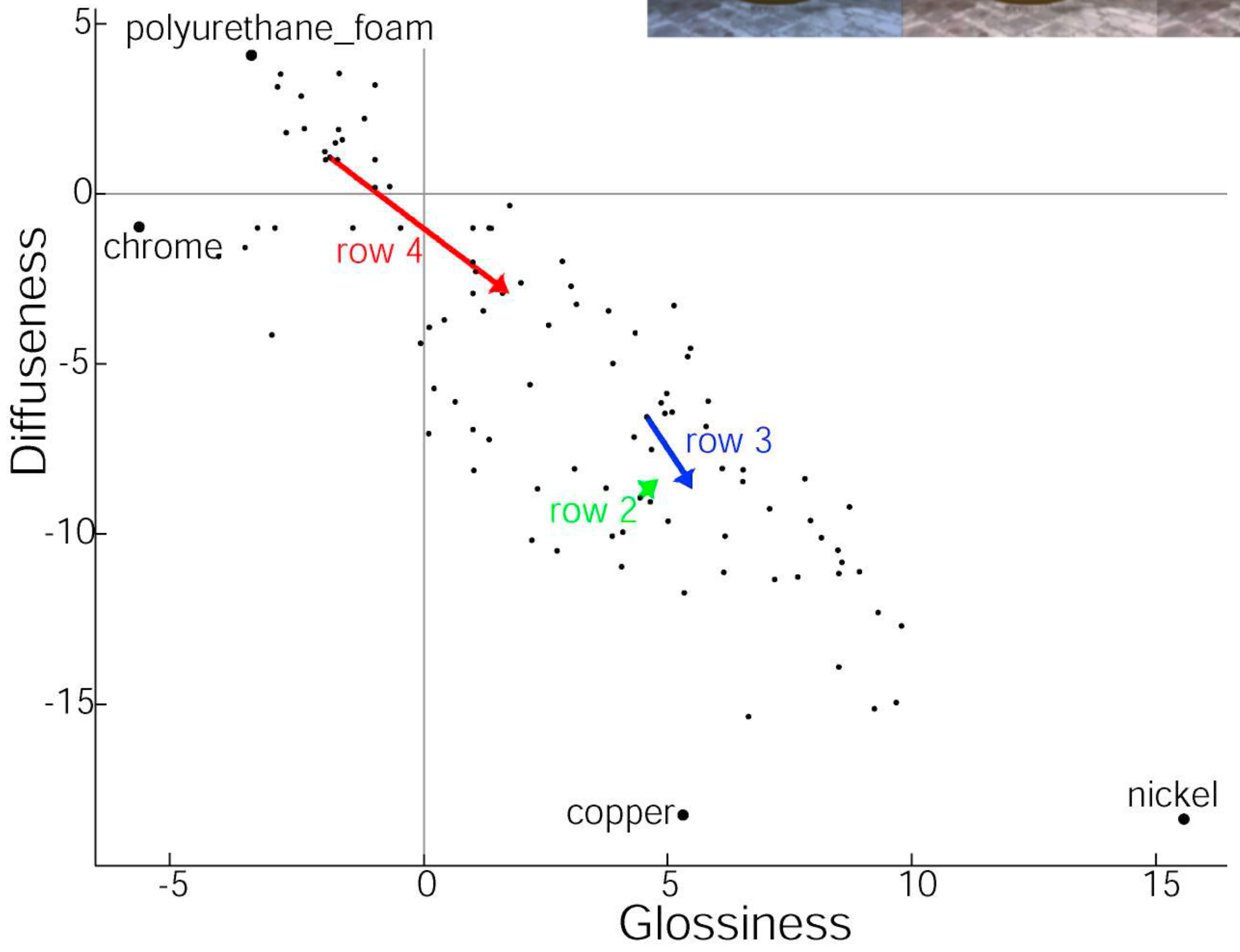
Understanding synthetic dimensions



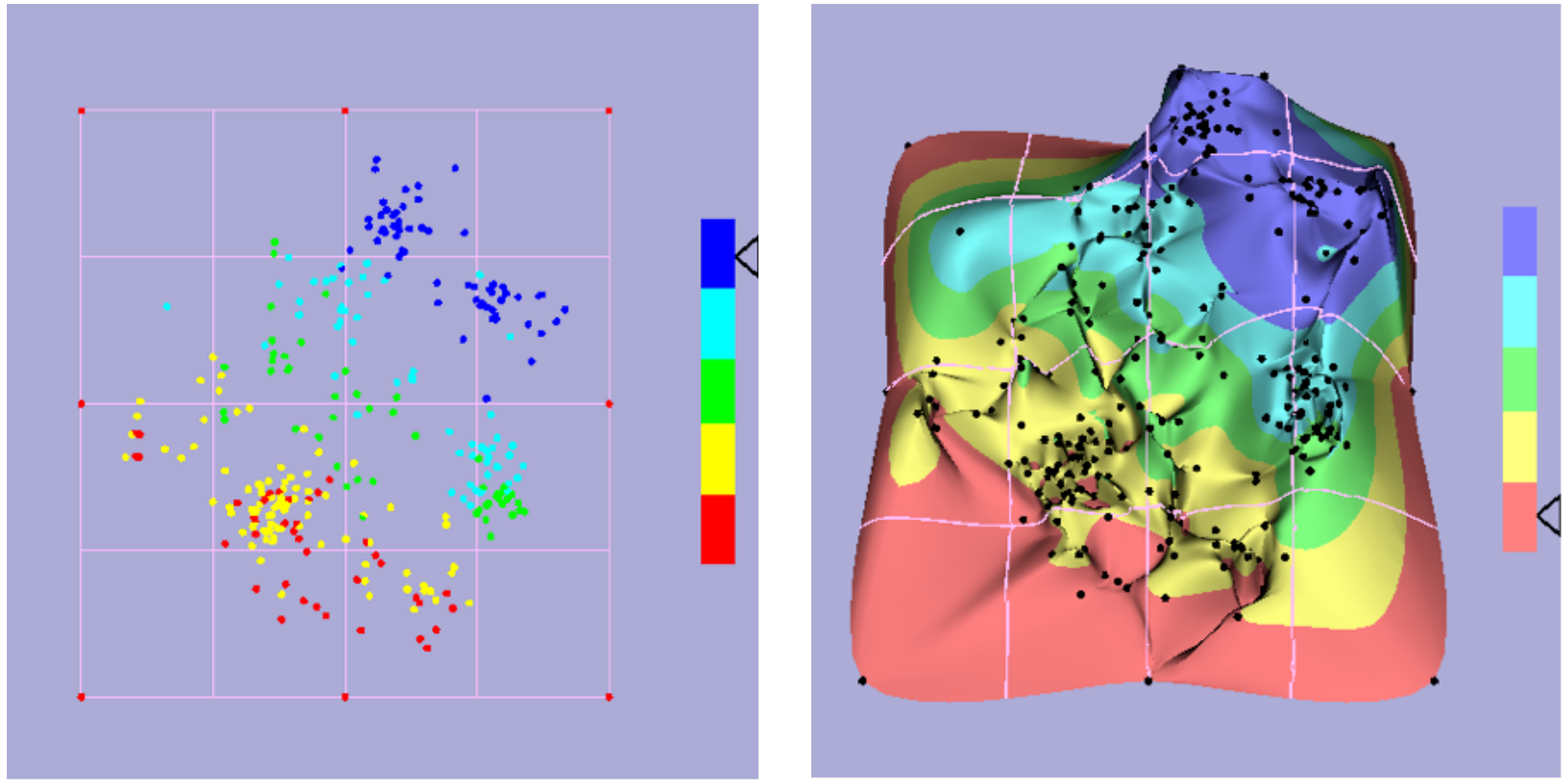
Specular-Metallic



Diffuseness-Glossiness



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



Spatialization Design

Comparing Points and Landscapes

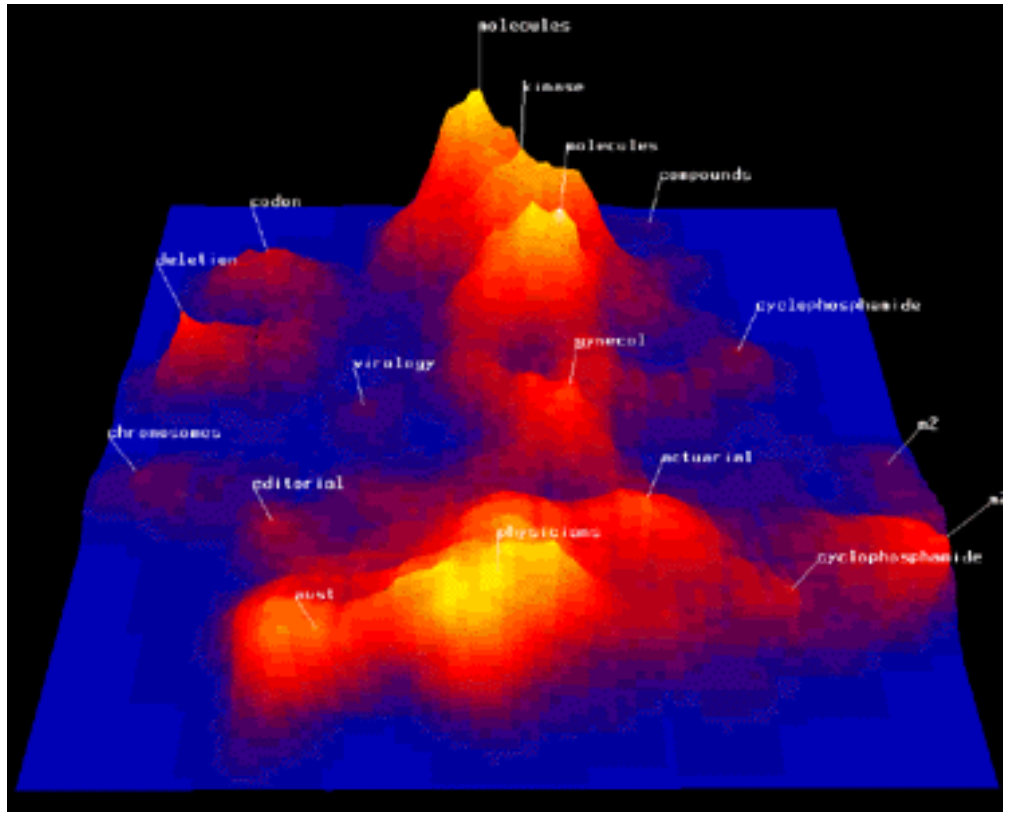
joint work with:
Melanie Tory, David W. Sprague, Fuqu Wu, Wing Yan So

http://webhome.cs.uvic.ca/~mtory/publications/infovis2007.pdf

Spatialization Design: Comparing Points and Landscapes.
Tory, Sprague, Wu, So, and Munzner.
IEEE TVCG 13(6):1262–1269, 2007 (Proc. InfoVis 07).

Information Landscapes

- 2D or 3D landscape from set of DR points
  - –height based on density
- oddly popular choice in DR
  - –despite known occlusion/distortion problems with 3D
  - –assertions: pattern recognition, spatial reasoning, familiar



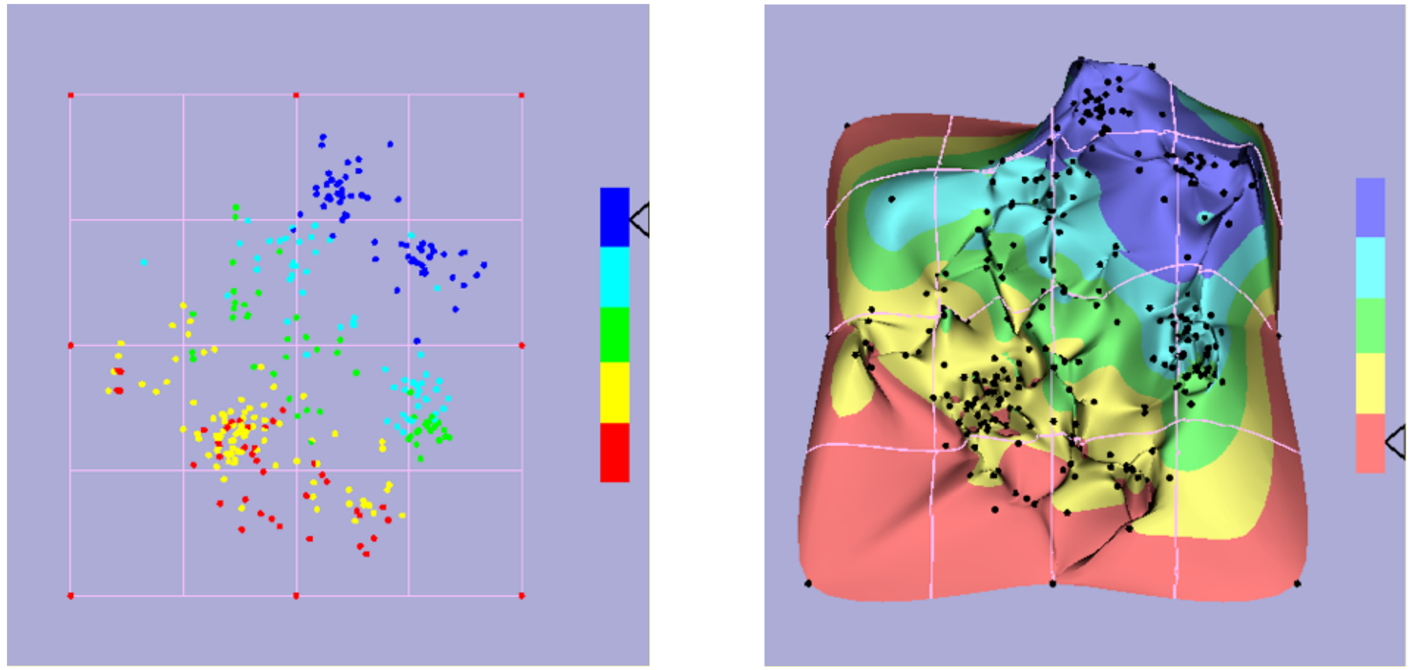
Themescape:
[http://www.k-n-o-r-z.de/publ/example/retriev1.htm]

[Guide to MicroPatent Aureka 9 ThemeScape]

Understanding User Task

- abstract: search involving spatial areas and estimation

  Estimate which grid cell has the most points of the target color



- domain-specific examples

  "Where in the display are people with high incomes?"
  "Does this area also have high education levels?"
  "Does this area correspond to a particular work sector?"

- non-trivial complexity yet fast response time
- frequent subtask in pilot test of real data analysis

Lab Study: Test Human Response Time and Error

- hypotheses
  - points are better than landscapes
    - result: yes!
    - much better: 2-4 × faster, 5-14 × more accurate
  - 2D landscapes (color only) better than 3D landscapes (color + height redundantly encoded)
    - result: yes
    - significantly faster, no significant difference in accuracy