Chap 13: Reduce Items and Attributes
Paper: Glimmer

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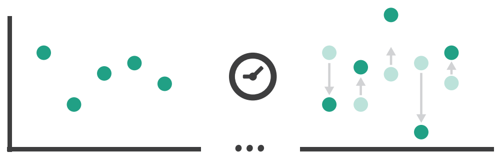
UBC CPSC 547: Information Visualization
Wed Oct 29 2014

http://www.cs.ubc.ca/~tmm/course/547-14/#chap13

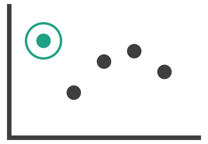
Idiom design choices: Part 2

Manipulate

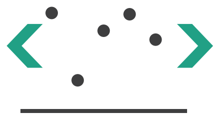
Change



Select

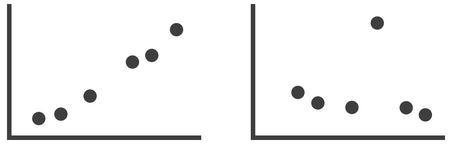


Navigate

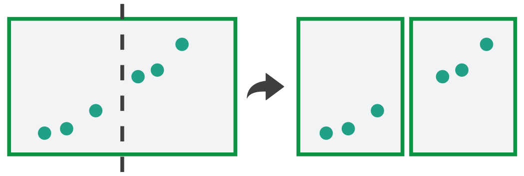


Facet

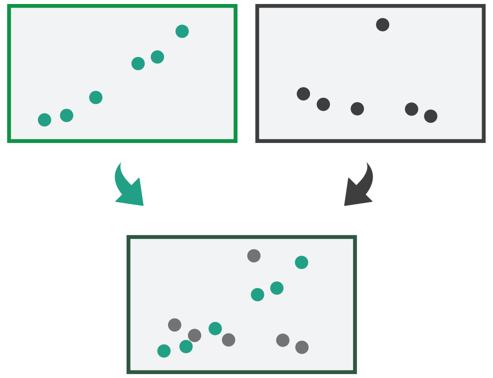
Juxtapose



Partition

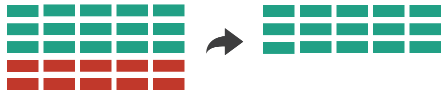


Superimpose

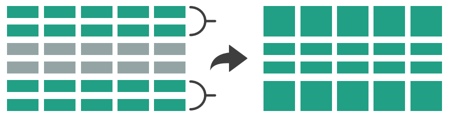


Reduce

Filter



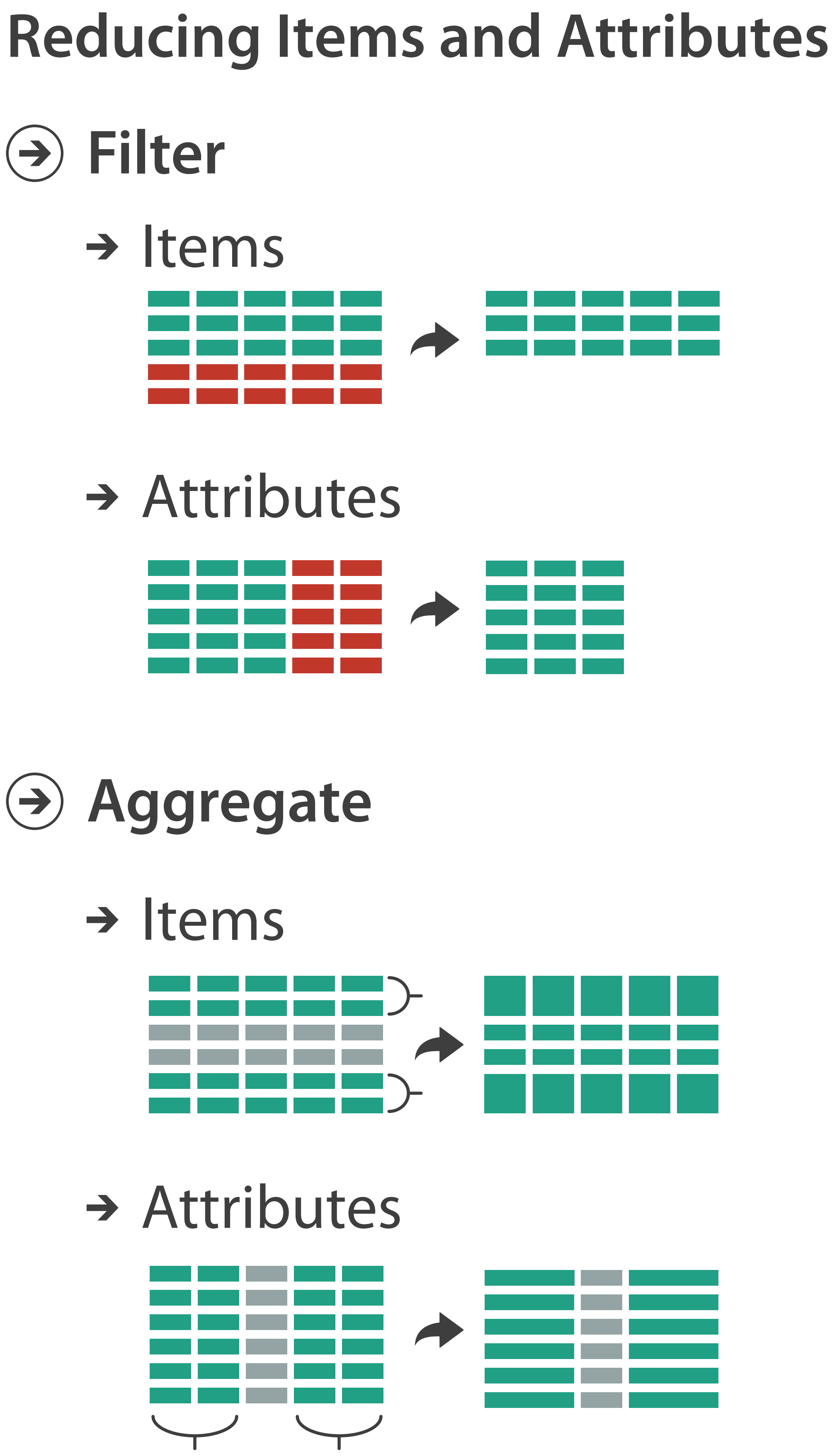
Aggregate

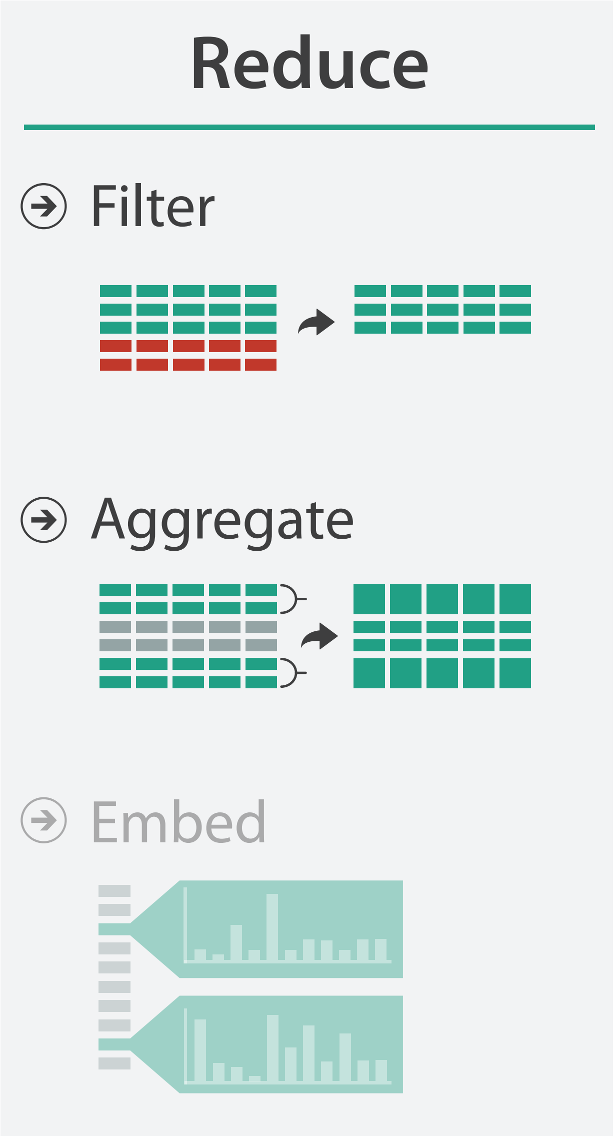


Embed

Reduce items and attributes

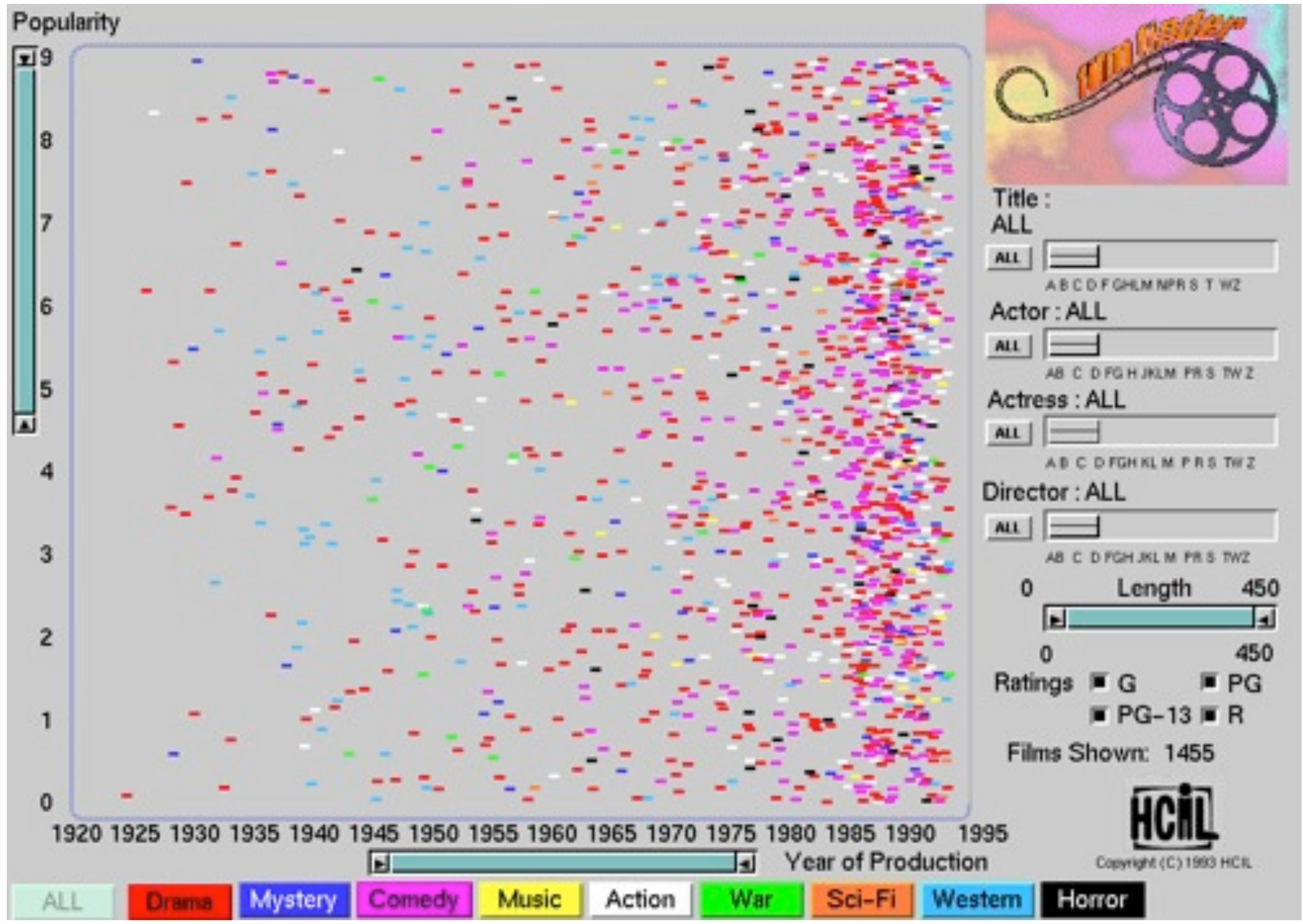
- reduce/increase: inverses
- filter
  - pro: straightforward and intuitive
    - to understand and compute
  - con: out of sight, out of mind
- aggregation
  - pro: inform about whole set
  - con: difficult to avoid losing signal
- not mutually exclusive
  - combine filter, aggregate
  - combine reduce,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

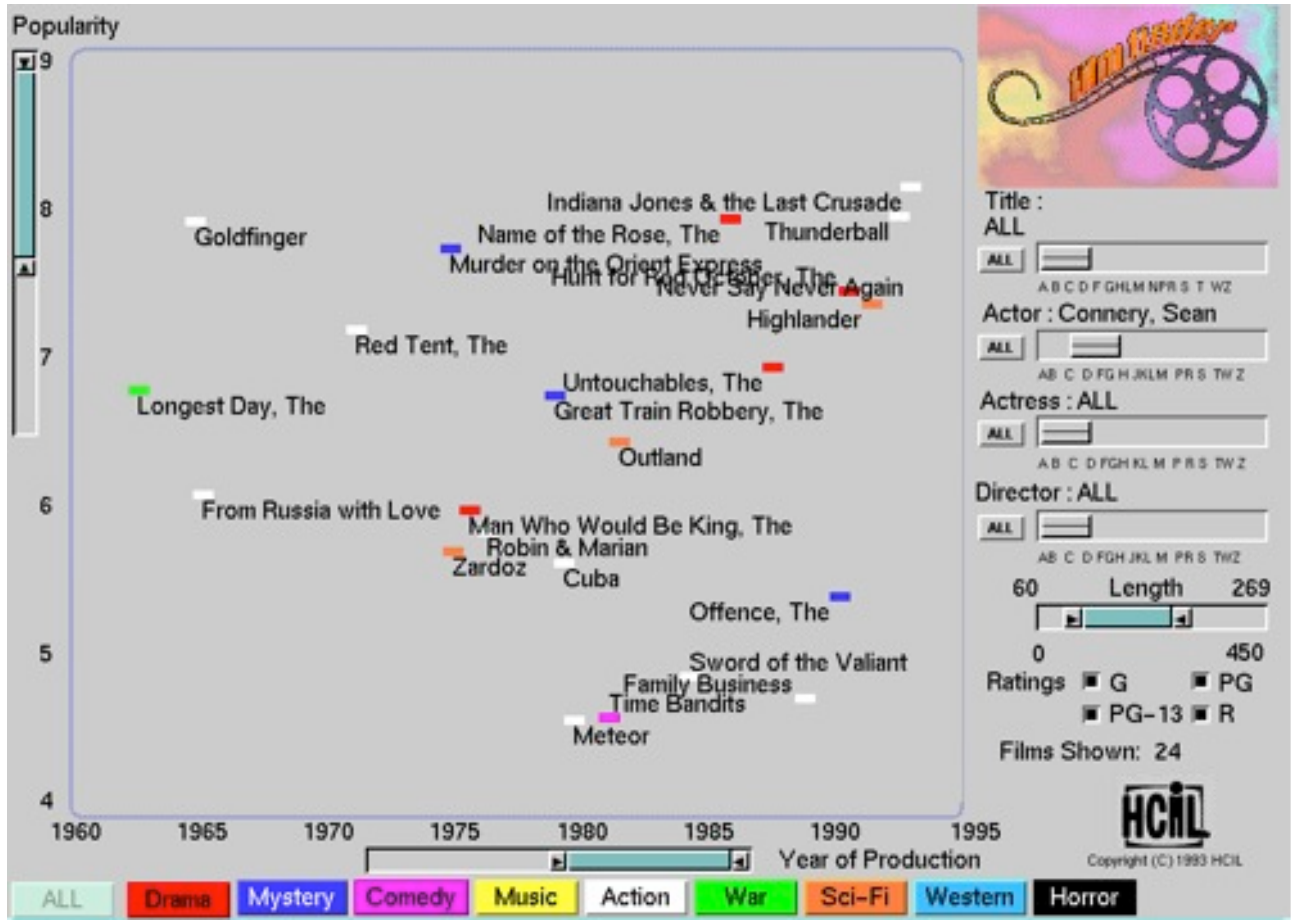




Idiom: **dynamic filtering** System: **FilmFinder**

- item filtering
- browse through tightly coupled interaction
  - alternative to queries that might return far too many or too few

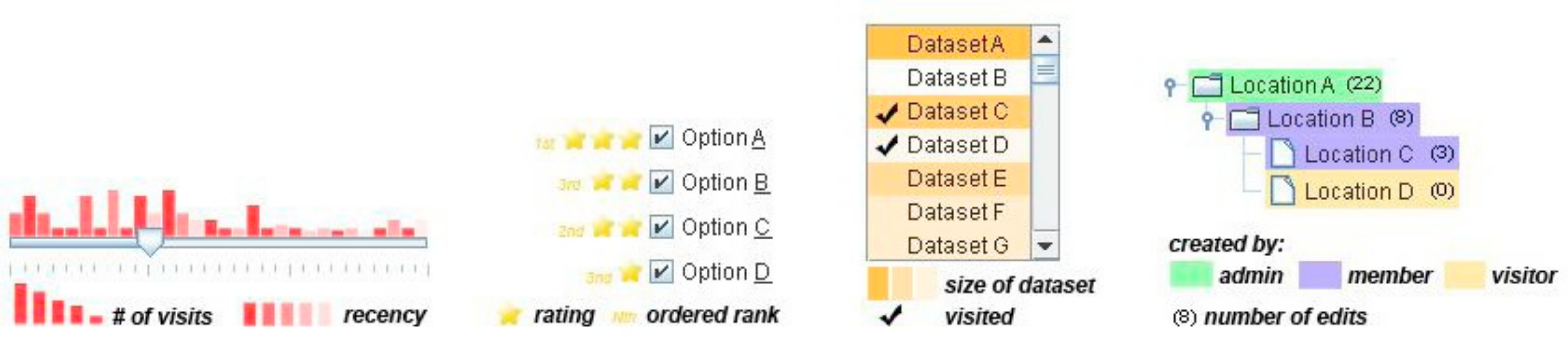




[Visual information seeking: Tight coupling of dynamic query filters with starfield displays. Ahlberg and Shneiderman. Proc. ACM Conf. on Human Factors in Computing Systems (CHI), pp. 313–317, 1994.]

Idiom: **scented widgets**

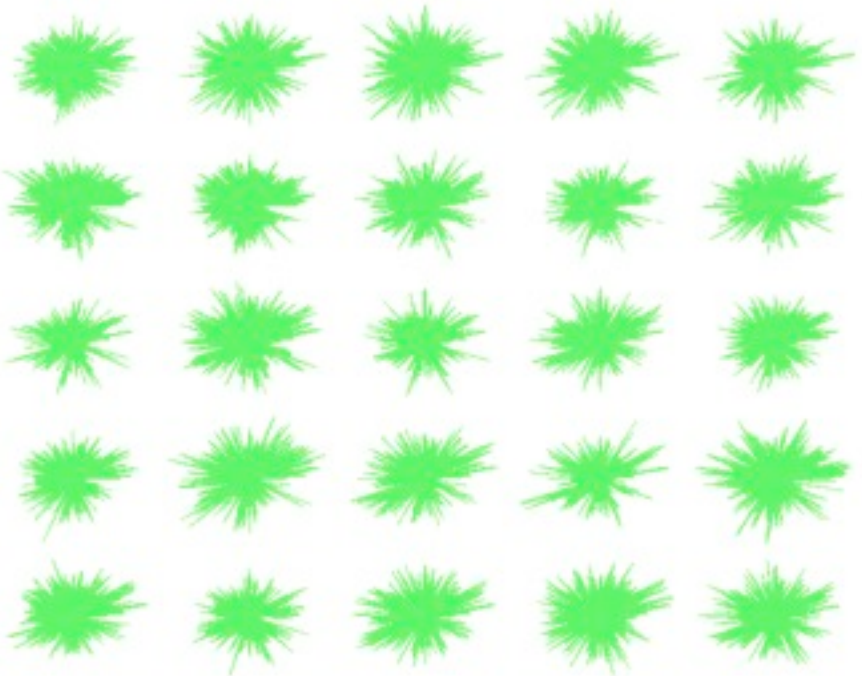
- augment widgets for filtering to show ***information scent***
  - cues to show whether value in drilling down further vs looking elsewhere
- concise, in part of screen normally considered control panel

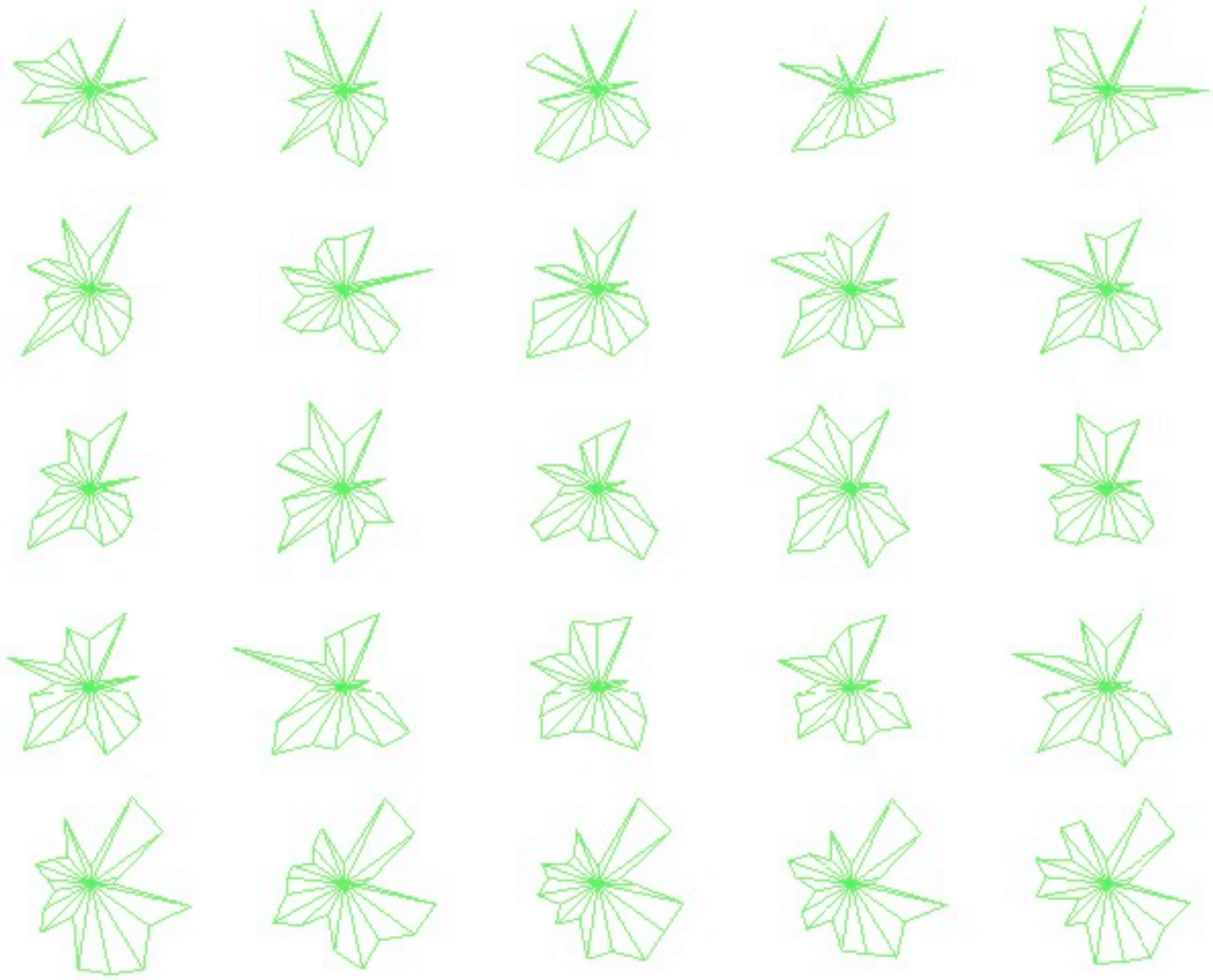


[Scented Widgets: Improving Navigation Cues with Embedded Visualizations. Willett, Heer, and Agrawala. IEEE Trans. Visualization and Computer Graphics (Proc. InfoVis 2007) 13:6 (2007), 1129–1136.]

Idiom: **DOSFA**

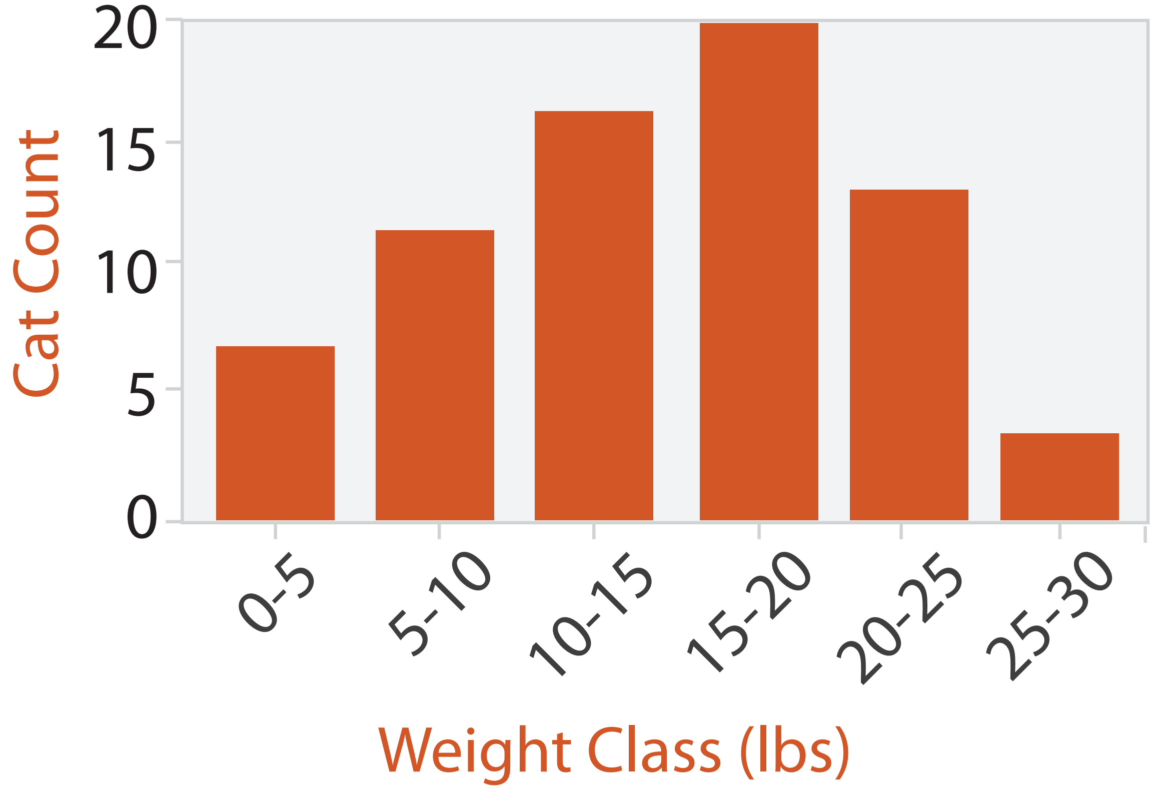
- attribute filtering
- encoding: star glyphs





[Interactive Hierarchical Dimension Ordering, Spacing and Filtering for Exploration Of High Dimensional Datasets. Yang, Peng, Ward, and. Rundensteiner. Proc. IEEE Symp. Information Visualization (InfoVis), pp. 105–112, 2003.]

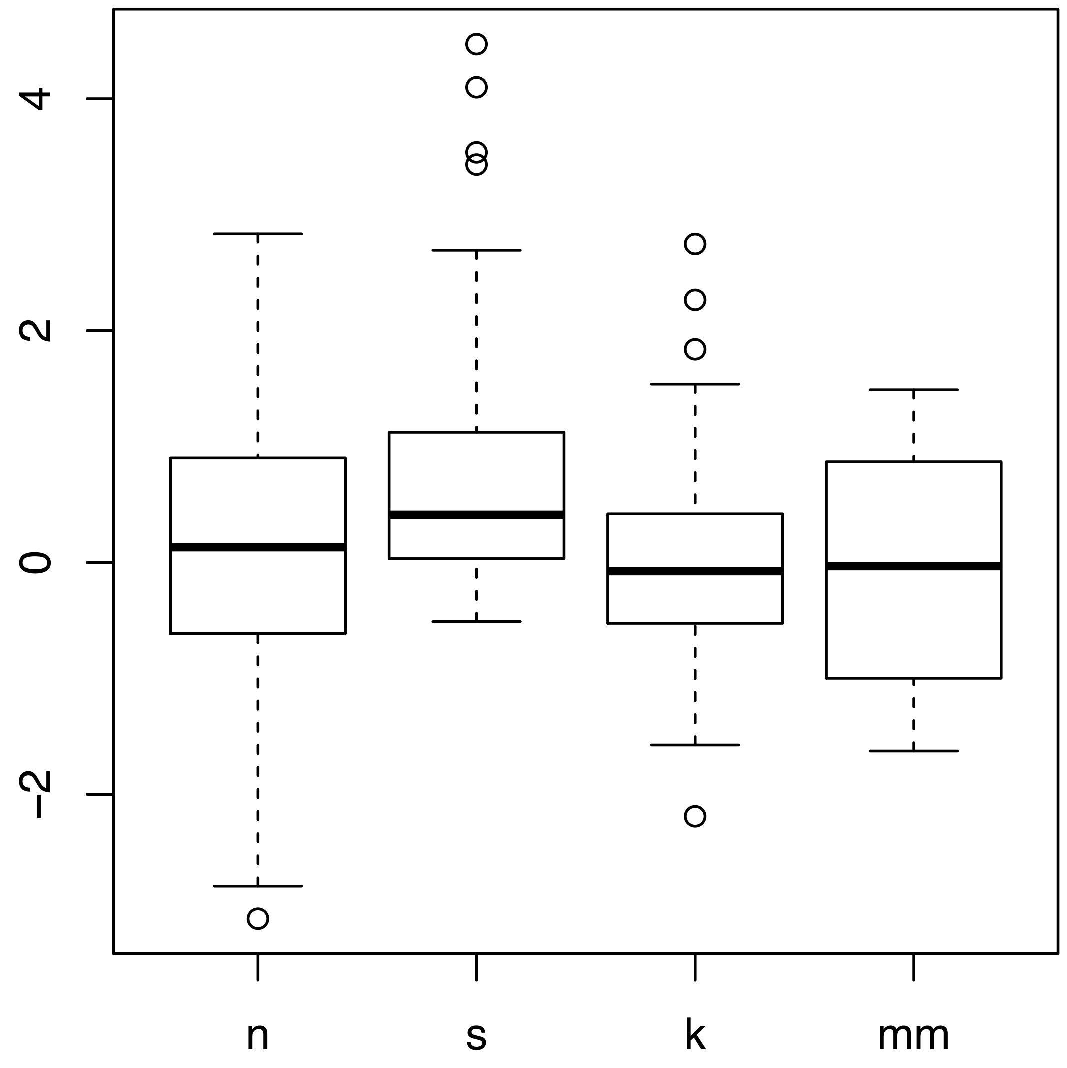
Idiom: **histogram**



- 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: **boxplot**

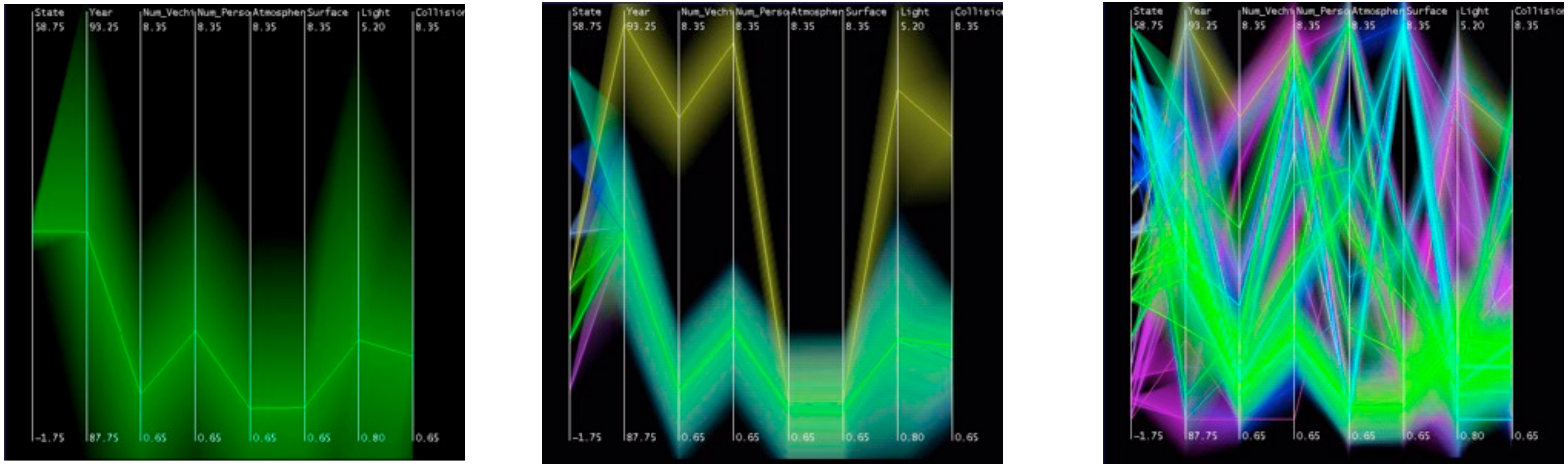
- static item aggregation
- task: find distribution
- data: table
- derived data
  - 5 quant attribs
    - median: central line
    - lower and upper quartile: boxes
    - lower upper fences: whiskers
      - values beyond which items are outliers
  - outliers beyond fence cutoffs explicitly shown



[40 years of boxplots. Wickham and Stryjewski. 2012. had.co.nz]

Idiom: **Hierarchical parallel coordinates**

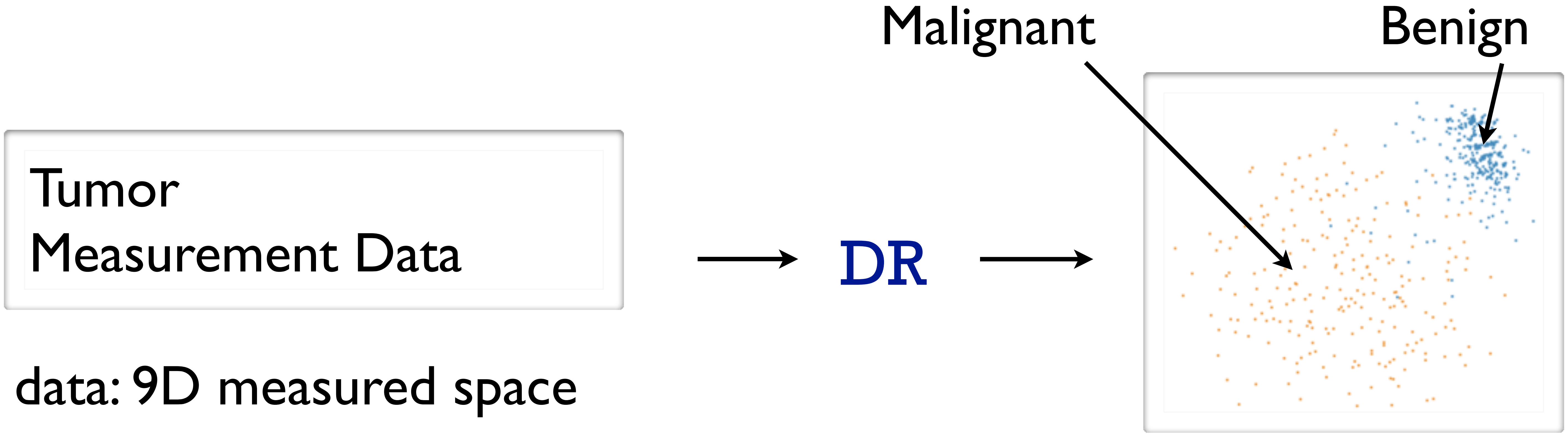
- dynamic item aggregation
- derived data: ***hierarchical clustering***
- encoding:
  - cluster band with variable transparency, line at mean, width by min/max values
  - color by proximity in hierarchy



[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
  - derive low-dimensional target space from high-dimensional measured space
  - 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



data: 9D measured space

derived data: 2D target space

Dimensionality reduction for documents

Task 1

In
HD data

Out
2D data

What?

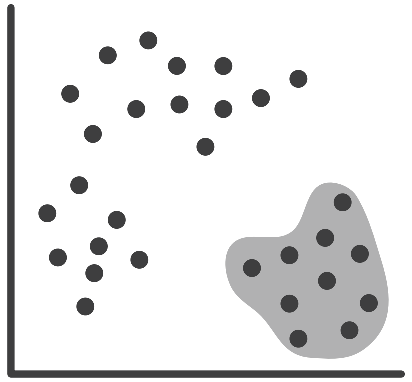
- **In High-dimensional data**
- **Out 2D data**

Why?

- **Produce**
- **Derive**

Task 2

In
2D data



Out
Scatterplot
Clusters & points

What?

- **In 2D data**
- **Out Scatterplot**
- **Out Clusters & points**

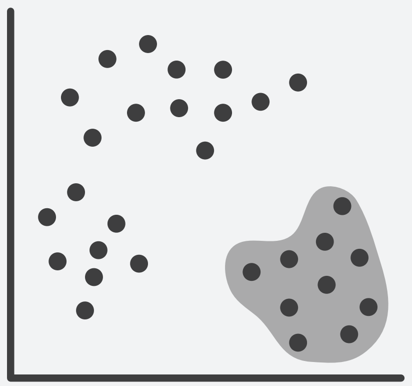
Why?

- **Discover**
- **Explore**
- **Identify**

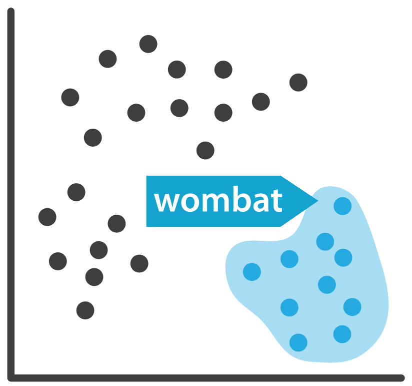
How?

- **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**

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

Estimating true dimensionality

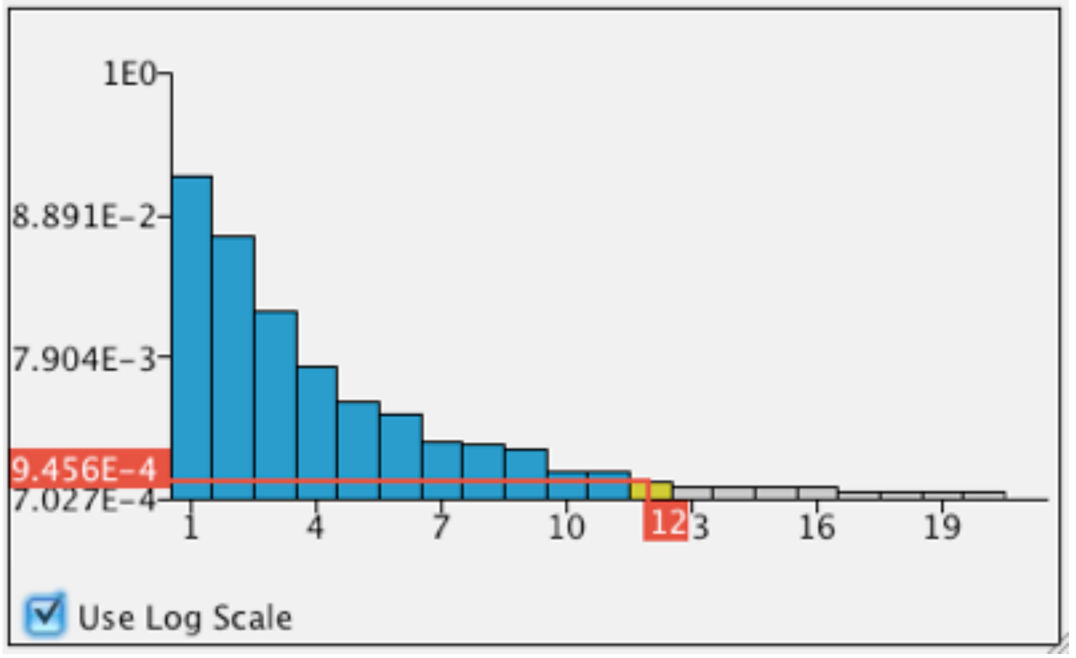
- how do you know when you would benefit from DR?
  - consider error for low-dim projection vs high-dim projection
- no single correct answer; many metrics proposed
  - cumulative variance that is not accounted for
  - strain: match variations in distance (vs actual distance values)
  - stress: difference between interpoint distances in high and low dims

$$stress(D, \Delta) = \sqrt{\frac{\sum_{ij}(d_{ij} - \delta_{ij})^2}{\sum_{ij} \delta_{ij}^2}}$$

- D: matrix of lowD distances
- Δ: matrix of hiD distances δ_{ij}

Estimating true dimensionality

- scree plots as simple way: error against # attribs



  - original dataset: 294 dims
  - estimate: almost all variance preserved with < 20 dims

[Fig 2. DimStiller: Workflows for dimensional analysis and reduction. Ingram et al. Proc. VAST 2010, p 3-10]

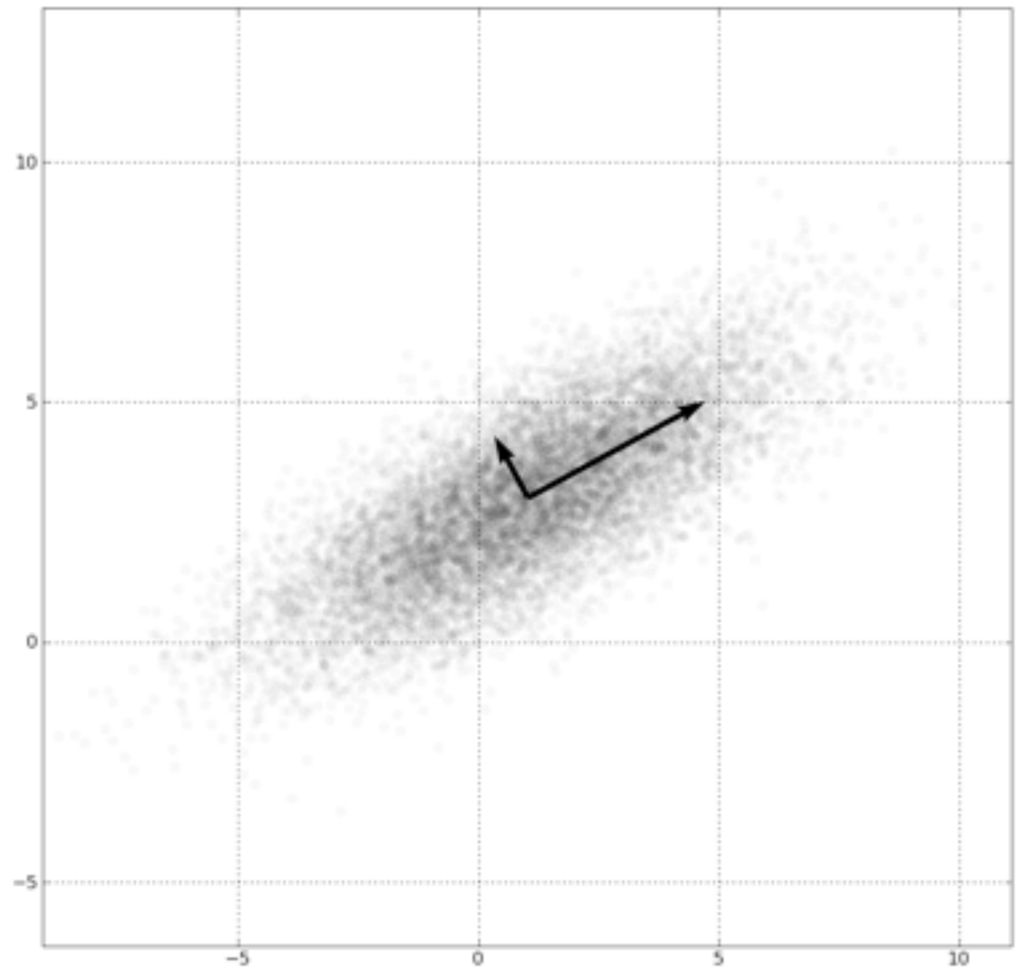
Dimensionality Reduction

- why do people do DR?
  - improve performance of downstream algorithm
    - avoid curse of dimensionality
  - data analysis
    - if look at the output: visual data analysis!
- DR tasks
  - dimension-oriented task sequences
    - name synthetic dimensions, map synthetic dims to original ones
  - cluster-oriented task sequences
    - verify clusters, name clusters, match clusters and classes

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

Linear dimensionality reduction

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



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

Nonlinear dimensionality reduction

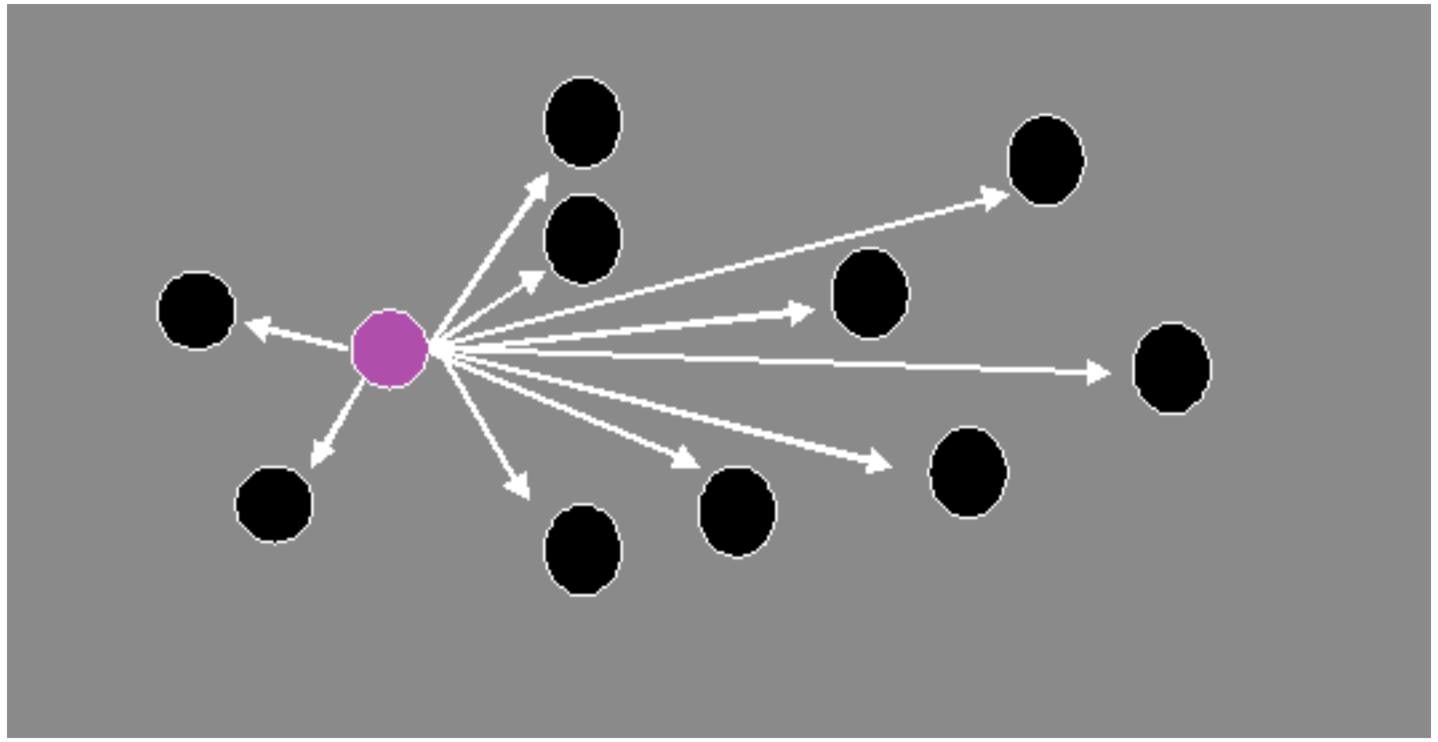
- many techniques proposed
  - MDS, charting, isomap, LLE, T-SNE
  - many literatures: visualization, machine learning, optimization, psychology, ...
- pro: can handle curved rather than linear structure
- cons: lose all ties to original dims/attribs
  - new dimensions cannot be easily related to originals

MDS: Multidimensional Scaling

- confusingly: entire family of methods, linear and nonlinear!
- classical scaling: minimize strain
  - early formulation equivalent to PCA (linear)
  - Nystrom/spectral methods approximate eigenvectors: O(N)
    - Landmark MDS [de Silva 2004], PivotMDS [Brandes & Pich 2006]
  - limitations: quality for very high dimensional sparse data
- distance scaling: minimize stress
  - nonlinear optimization: $O(N^2)$
    - SMACOF [de Leeuw 1977]
  - force-directed placement: $O(N^2)$
    - Stochastic Force [Chalmers 1996]
    - limitations: quality problems from local minima
- Glimmer goal: O(N) speed and high quality

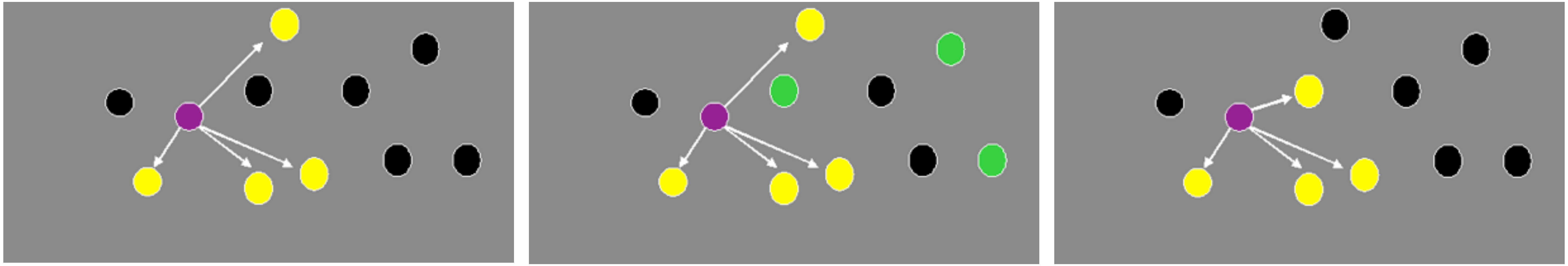
Spring-based MDS: naive

- repeat for all points
  - compute spring force to all other points
  - difference between high dim, low dim distance
  - move to better location using computed forces
- compute distances between all points
  - $O(N^2)$ iteration, $O(N^3)$ algorithm



Faster spring model: Stochastic

- compare distances only with a few points
  - maintain small local neighborhood set
  - each time pick some randoms, swap in if closer
- small constant: 6 locals, 3 randoms (typically)
  - $O(N)$ iteration, $O(N^2)$ algorithm



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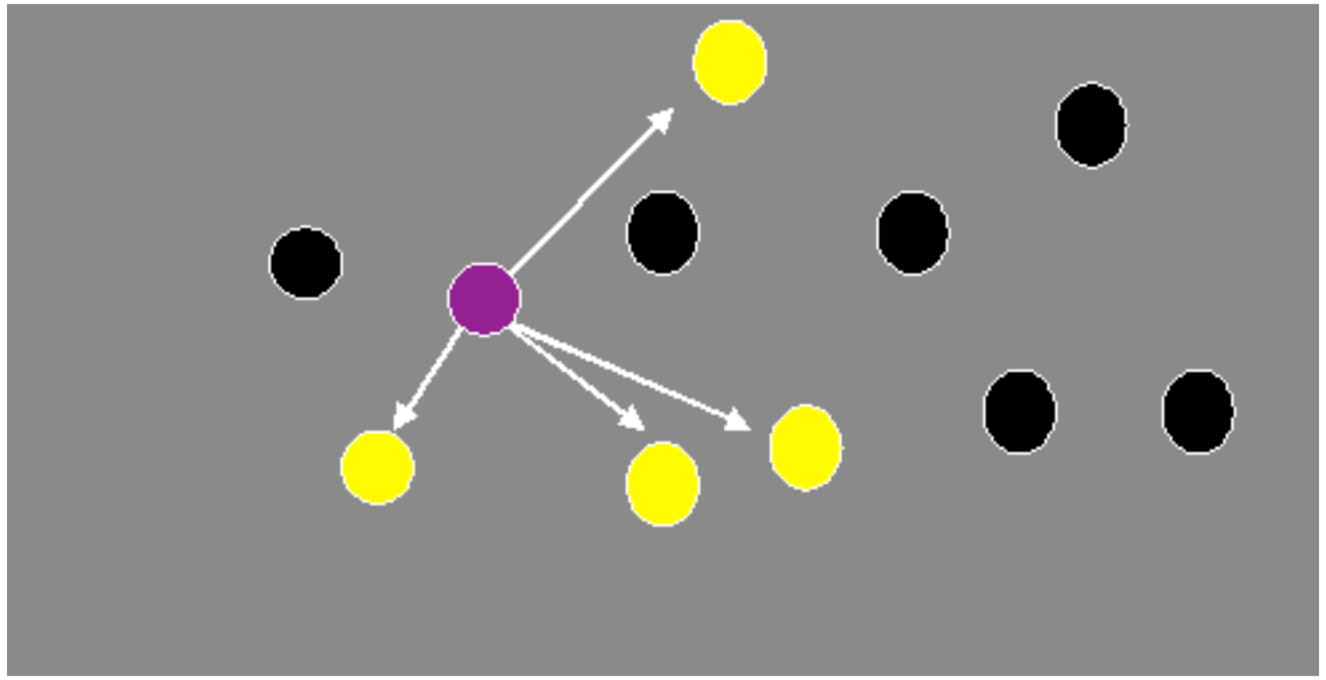
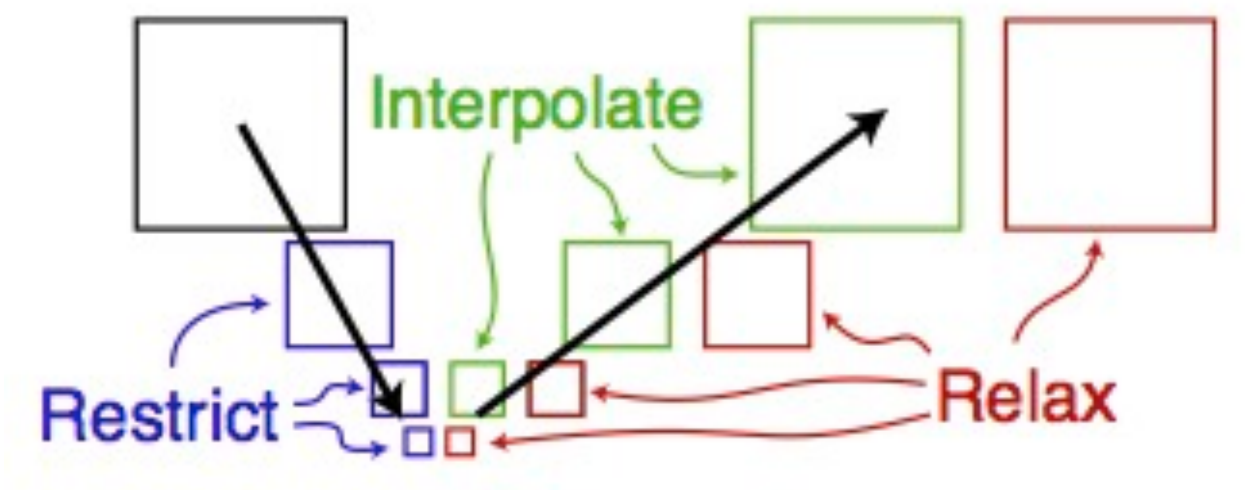
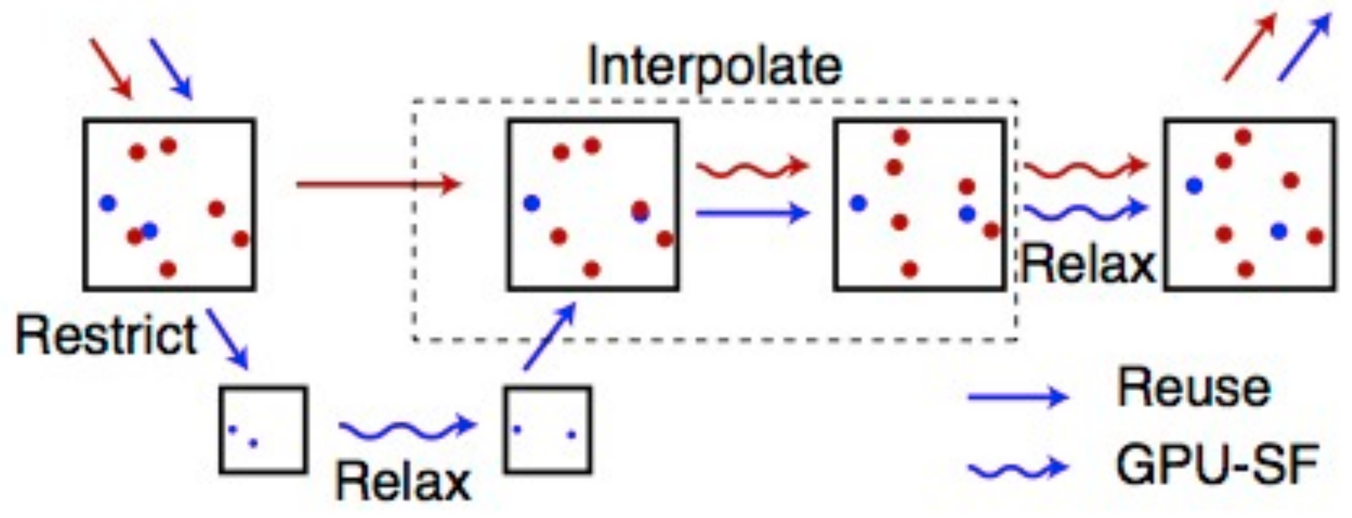


Glimmer algorithm

- multilevel to avoid local minima, designed to exploit GPU



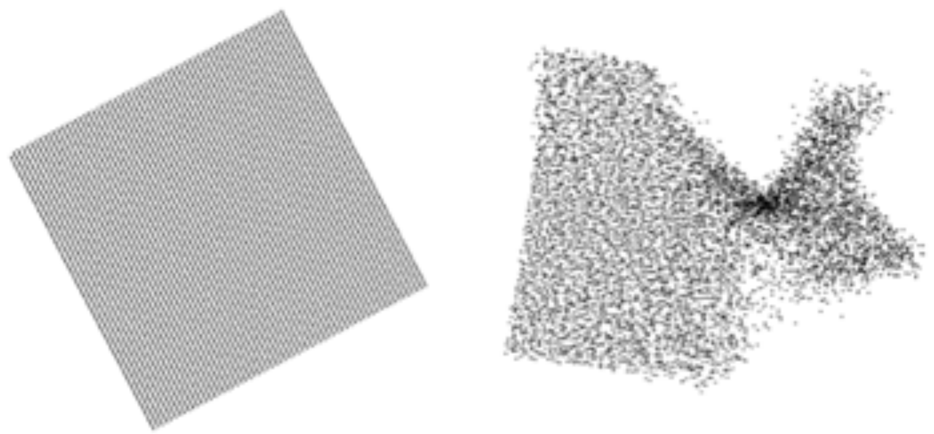
- restriction to decimate
- relaxation as core computation
- relaxation to interpolate up to next level



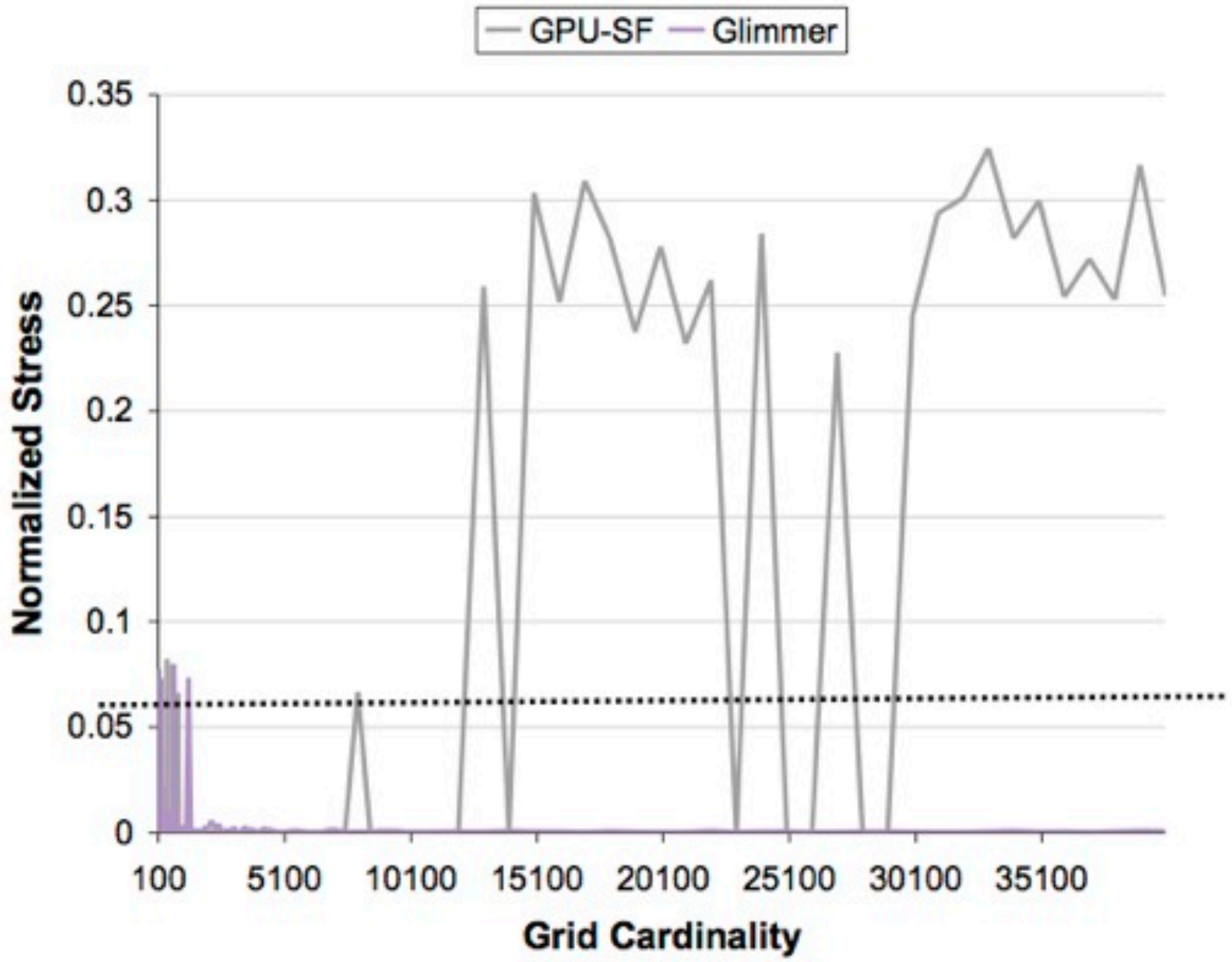
[Glimmer: Multilevel MDS on the GPU. Ingram, Munzner, Olano. IEEE TVCG 15(2):249-261, 2009.]

Glimmer Strategy

- stochastic force alg suitable for fast GPU port
  - but systematic testing shows it often terminates too soon



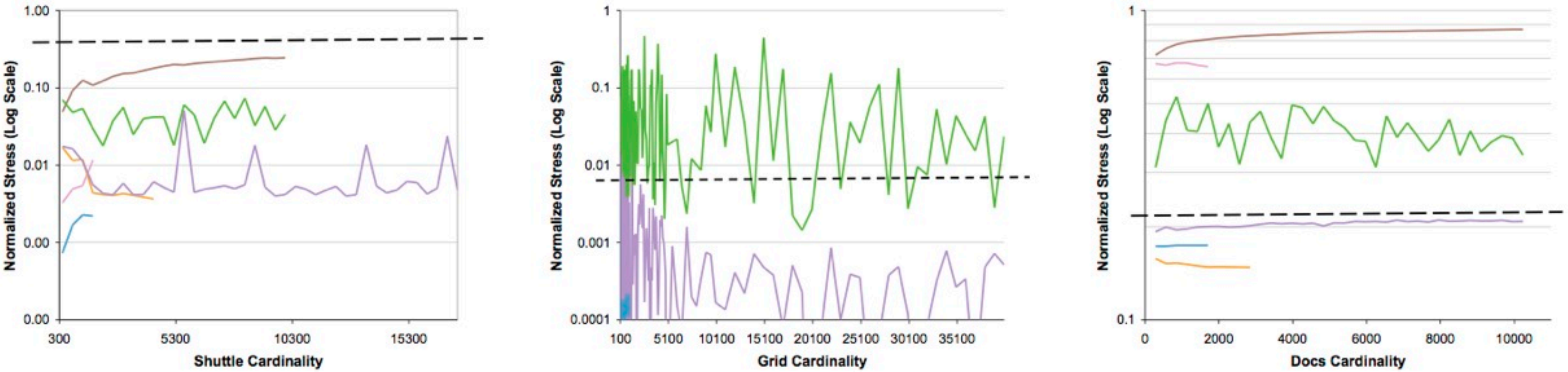
- use as subsystem within new multilevel GPU alg with much better convergence properties



[Fig 2,4. Glimmer: Multilevel MDS on the GPU. Ingram, Munzner, Olano. IEEE TVCG 15(2):249-261, 2009.]

Stochastic termination

- how do you know when it's done?
  - no absolute threshold, depends on the dataset
  - interactive click to stop does not work for subsystem



- sparse normalized stress approximation
  - minimal overhead to compute (vs full stress)
  - low pass filter

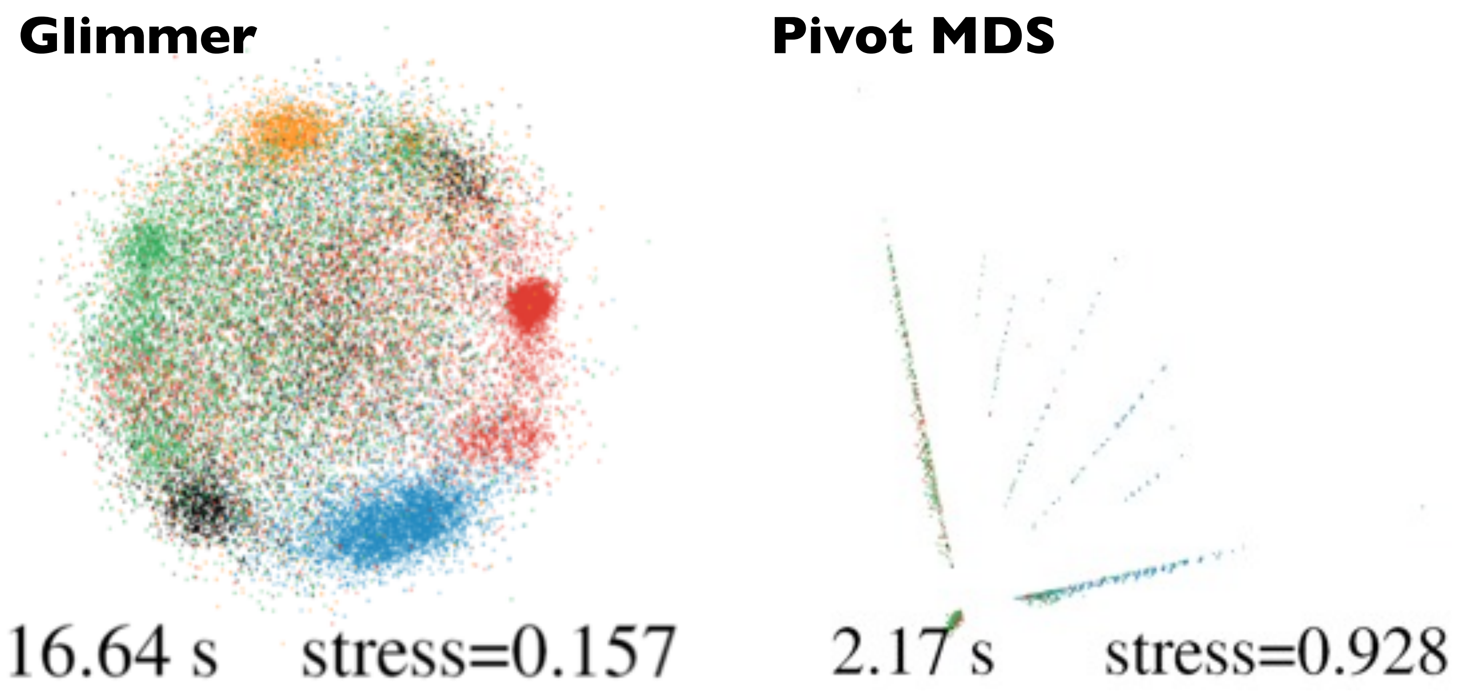
[Fig 9. Glimmer: Multilevel MDS on the GPU. Ingram, Munzner, Olano. IEEE TVCG 15(2):249-261, 2009.]

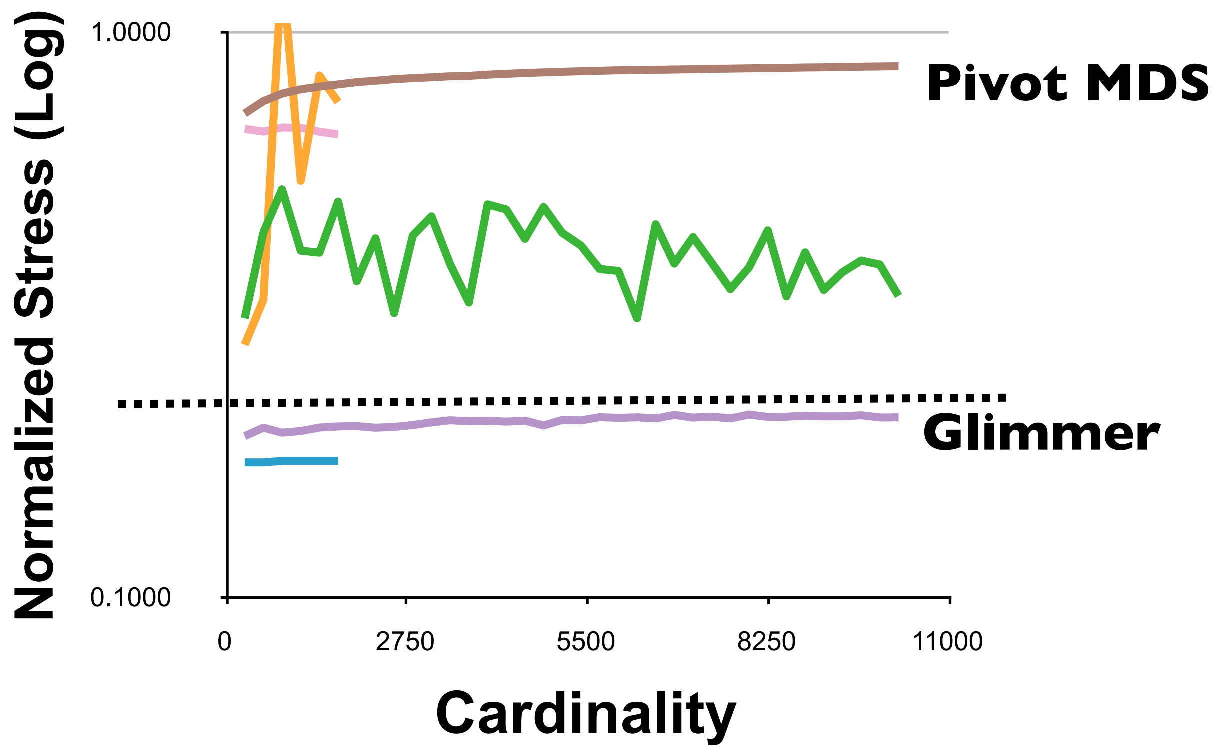
GPUs

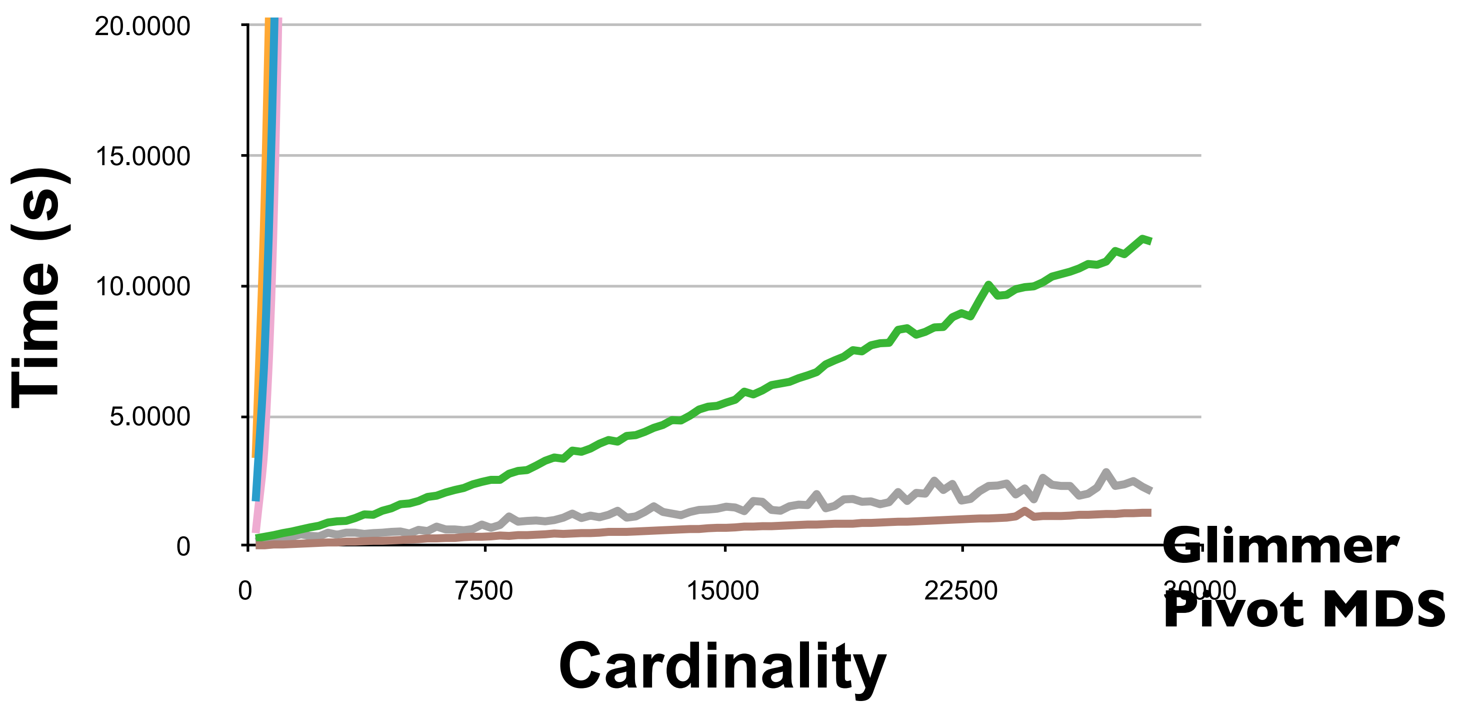
- characteristics
  - small set of localized texture accesses
  - output at predetermined locations
  - no variable length looping
  - avoid conditionals: all floating point units execute same instr at same time
- mapping problems to GPU
  - arrays become textures
  - inner loops become fragment shader code
  - program execution becomes rendering

Finding and verifying clusters

- sparse docs dataset
  - 28K dims, 28K points
    - speed equivalent to classical
    - quality major improvement







[Fig 8, 9. Glimmer: Multilevel MDS on the GPU. Ingram, Munzner, Olano. IEEE TVCG 15(2):249-261, 2009.]

Methods and outcomes

- methods
  - quantitative algorithm benchmarks: speed, quality
    - systematic comparison across 1K-10K instances vs a few spot checks
  - qualitative judgements of layout quality
- outcomes
  - characterized kinds of datasets where technique yields quality improvements
    - sparse documents
- followup work
  - Q-SNE: millions of documents

[Dimensionality Reduction for Documents with Nearest Neighbor Queries. Ingram, Munzner. Neurocomputing. Special Issue Visual Analytics using Multidimensional Projections, to appear 2014.]