



Tamara Munzner

Visualization

<http://www.ugrad.cs.ubc.ca/~cs314/Vjan2013>

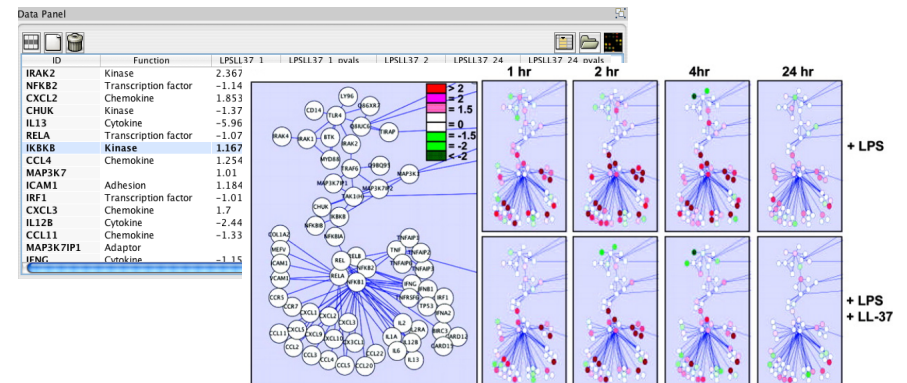
Nonspatial/Information Visualization

Reading

- FCG Chap 27
 - N/A 2nd edition, available online at
<http://www.cs.ubc.ca/labs/imager/tr/2009/VisChapter>

Why Do Visualization?

- pictures help us think
 - substitute perception for cognition
 - external memory: free up limited cognitive/memory resources for higher-level problems



+ LPS

+ LPS + LL-37

Information Visualization

- interactive visual representation of abstract data
 - help human perform some task more effectively
- bridging many fields
 - computer graphics: interact in realtime
 - cognitive psychology: find appropriate representation
 - HCI: use task to guide design and evaluation
- external representation
 - reduces load on working memory
 - offload cognition
 - familiar example: multiplication/division
 - infovis example: topic graphs

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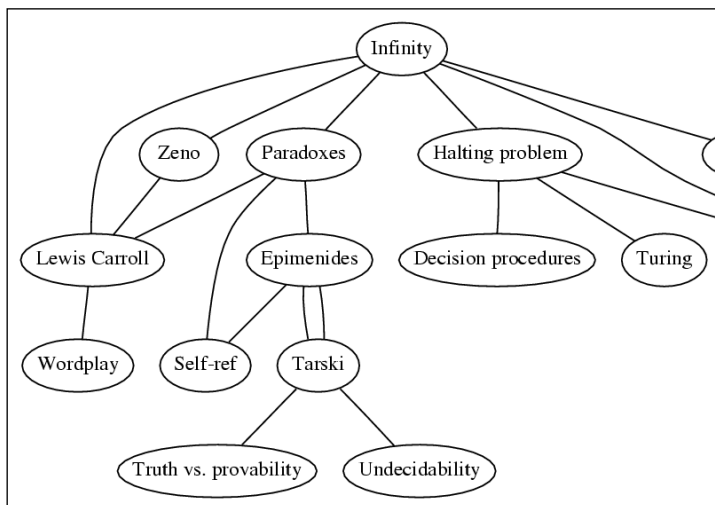
External Representation: Topic Graphs

- hard to find topics two hops away from target
 - [Godel, Escher, Bach: The Eternal Golden Braid. Hofstadter 1979]
- **Paradoxes** - Lewis Carroll
- Turing - Halting problem
- Halting problem - Infinity
- Paradoxes - Infinity
- Infinity - Lewis Carroll
- Infinity - Unpredictably long searches
- Infinity - Recursion
- Infinity - Zeno
- Infinity - Paradoxes
- Lewis Carroll - Zeno
- Lewis Carroll - Wordplay
- Halting problem - Decision procedures
- BlooP and FlooP - AI
- Halting problem - Unpredictably long searches
- BlooP and FlooP - Unpredictably long searches
- BlooP and FlooP - Recursion
- Tarski - Truth vs. provability
- Tarski - Epimenides
- Tarski - Undecidability
- Paradoxes - Self-ref
- [...]

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External Representation: Topic Graphs

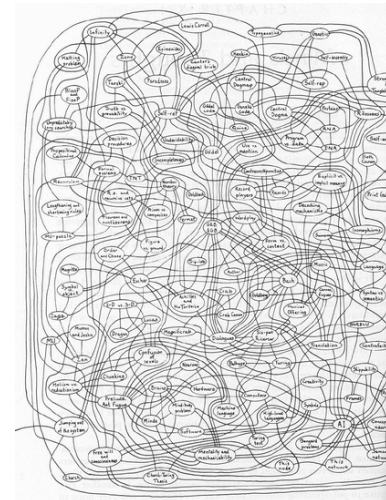
- offload cognition to visual system



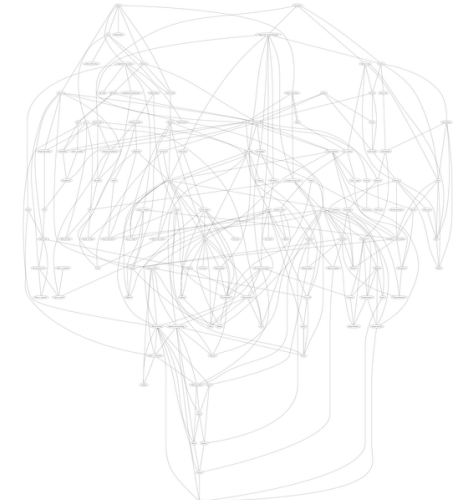
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Automatic Node-Link Graph Layout

- manual: hours, days
- automatic: seconds



[Godel, Escher, Bach. Hofstadter 1979]



[dot, Gansner et al, 1973.]

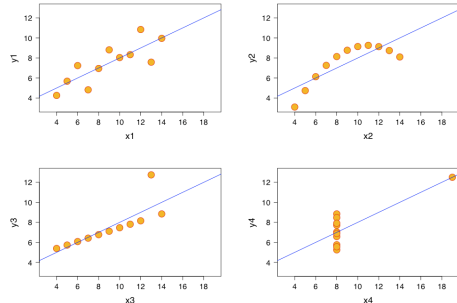
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When To Do Vis?

- need a human in the loop
 - augment, not replace, human cognition
 - for problems that cannot be (completely) automated
- simple summary not adequate
 - statistics may not adequately characterize complexity of dataset distribution

Anscombe's quartet:
same

- mean
- variance
- correlation coefficient
- linear regression line

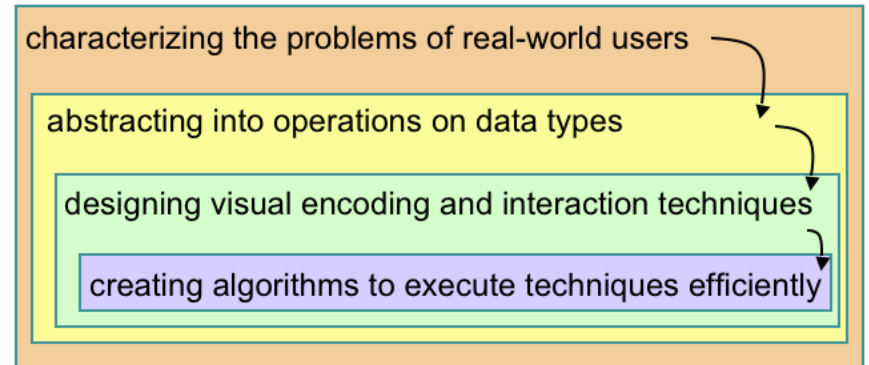


<http://upload.wikimedia.org/wikipedia/commons/b/b6/Anscombe.svg>

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Visualization Design Layers

- depends on both data and task



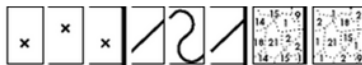
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Visual Encoding

marks: geometric primitives
points lines areas

attributes

position



size



grey level



texture



color



orientation



shape



- attributes

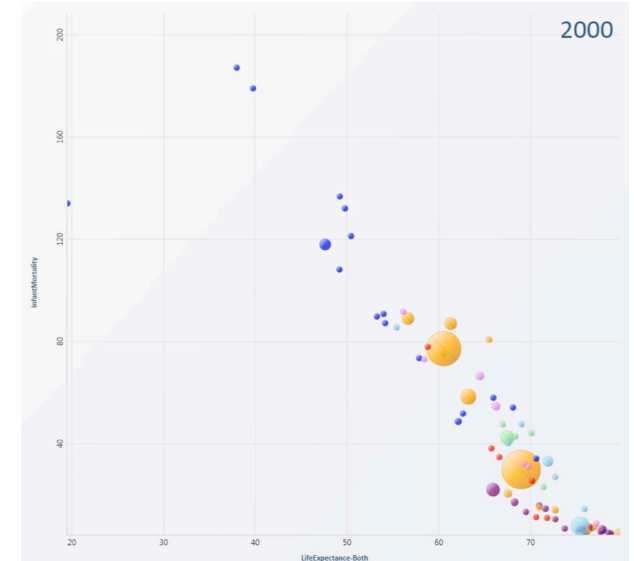
- parameters control mark appearance
- separable channels flowing from retina to brain

Semiology of Graphics. Jacques Bertin, Gauthier-Villars 1967, EHESS 1998

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Visual Encoding Example: Scatterplot

- x position
- y position
- hue
- size

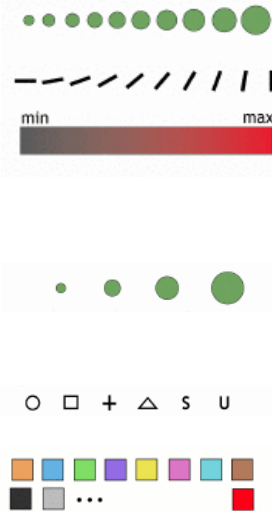


Robertson et al. Effectiveness of Animation in Trend Visualization. IEEE TVCG (Proc. InfoVis08) 14:6 (2008), 1325-1332.

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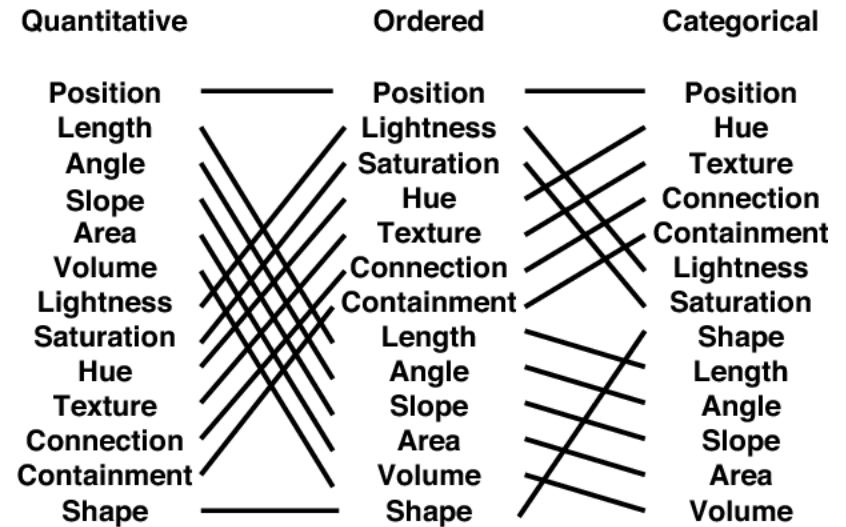
Data Types

- quantitative
 - lengths: 10 inches, 17 inches, 23 inches
- ordered
 - sizes: small, medium, large
 - days: Mon, Tue, Wed, ...
- categorical
 - fruit: apples, oranges, bananas



[Stolte and Hanrahan. Polaris: A System for Query, Analysis and Visualization of Multi-dimensional Relational Databases. Proc InfoVis 2000. graphics.stanford.edu/projects/polaris/] 13

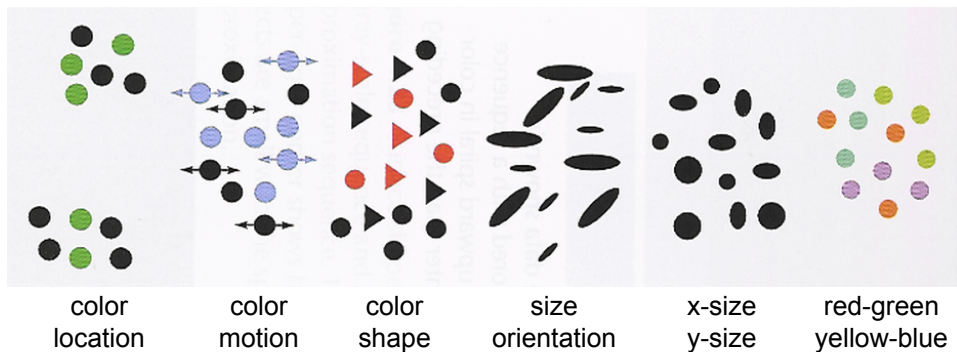
Channel Ranking Varies By Data Type



[Mackinlay, Automating the Design of Graphical Presentations of Relational Information, ACM TOG 5:2, 1986] 14

Integral vs. Separable Dimensions

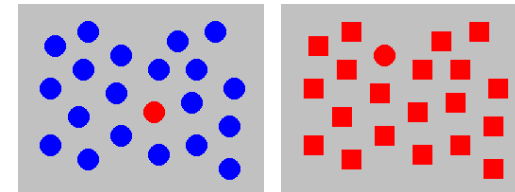
- not all dimensions separable



[Colin Ware, Information Visualization: Perception for Design. Morgan Kaufmann 1999.]

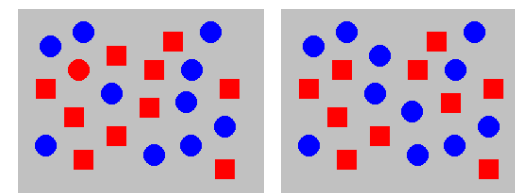
Preattentive Visual Channels

- color alone, shape alone: preattentive



- combined color and shape: requires attention

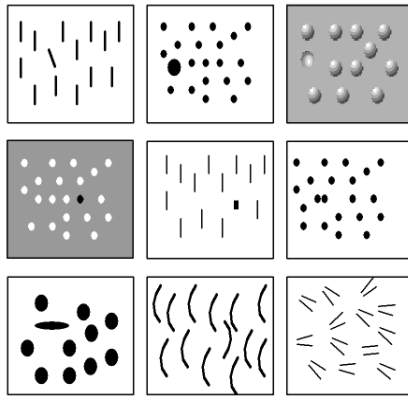
- search speed linear with distractor count



[Christopher Healey, [www.csc.ncsu.edu/faculty/healey/PP/PP.html]]

Preattentive Visual Channels

- preattentive channels include
 - hue
 - shape
 - texture
 - length
 - width
 - size
 - orientation
 - curvature
 - intersection
 - intensity
 - flicker
 - direction of motion
 - stereoscopic depth
 - lighting direction
 - many more...

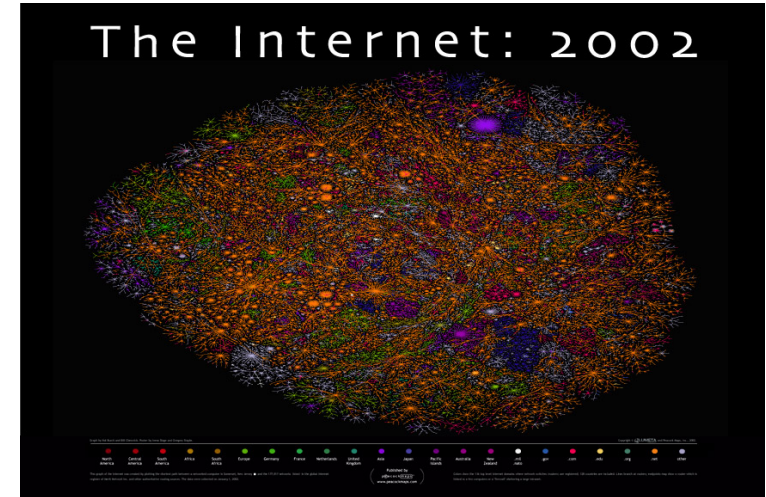


[Healey, [www.csc.ncsu.edu/faculty/healey/PP/PP.html]]

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Coloring Categorical Data

- 22 colors, but only ~8 distinguishable



[www.peacockmaps.com, research.lumeta.com/ches/map]

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Coloring Categorical Data

- discrete small patches separated in space
- limited distinguishability: around 8-14
 - channel dynamic range low
 - best to choose bins explicitly
- maximal saturation for small areas

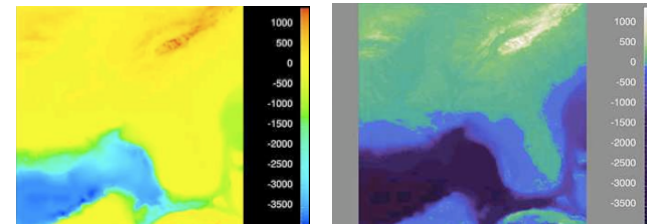


[Colin Ware, Information Visualization: Perception for Design. Morgan Kaufmann 1999.]

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Quantitative Colormaps

- dangers of rainbows
 - perceptually nonlinear
 - arbitrary not innate ordering
- other approaches
 - explicitly segmented colormaps
 - monotonically increasing/(decreasing) luminance, plus hue to semantically distinguish regions

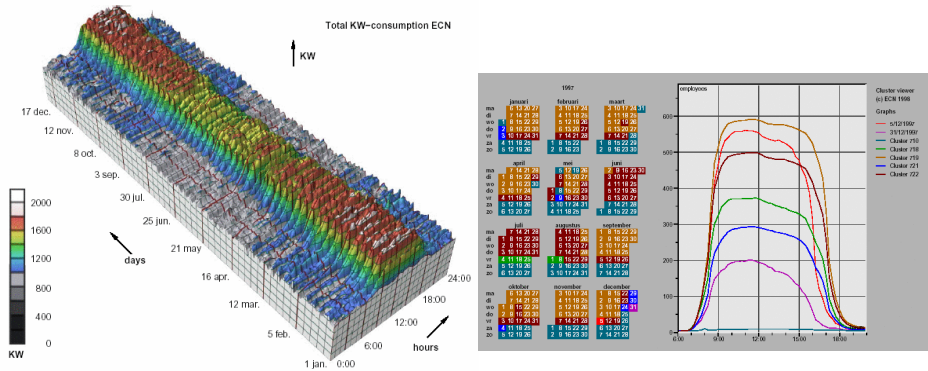


Rogowitz and Treinish. Data Visualization: The End of the Rainbow. IEEE Spectrum 35(12):52-59, Dec 1998.

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3D vs 2D Representations

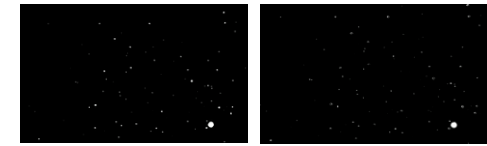
- curve comparison difficult: perspective distortion, occlusion
 - dataset is abstract, not inherently spatial
 - after data transformation to clusters, linked 2D views of representative curves show more



[van Wijk and van Selow, Cluster and Calendar based Visualization of Time Series Data, InfoVis99 21]

Space vs Time: Showing Change

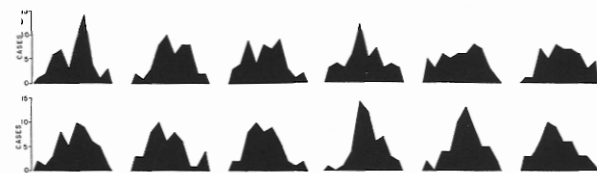
- animation: show time using temporal change
 - good: show process
 - good: flip between two things
 - bad: flip between between many things
 - interference between intermediate frames



[Outside In excerpt. www.geom.uiuc.edu/docs/outreach/oi/evert.mpg
www.astroshow.com/ccdpho/pluto.gif
 [Edward Tufte. The Visual Display of Quantitative Information, p 172]

Space vs Time: Showing Change

- small multiples: show time using space
 - overview: show each time step in array
 - compare: side by side easier than temporal
 - external cognition vs internal memory
 - general technique, not just for temporal changes



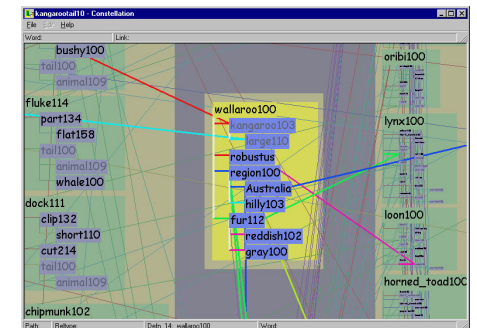
[Edward Tufte. The Visual Display of Quantitative Information, p 172]

Composite Views

- pixel-oriented views
 - overviews with high information density
- superimposing/layering
 - shared coordinate frame
 - redundant visual encoding



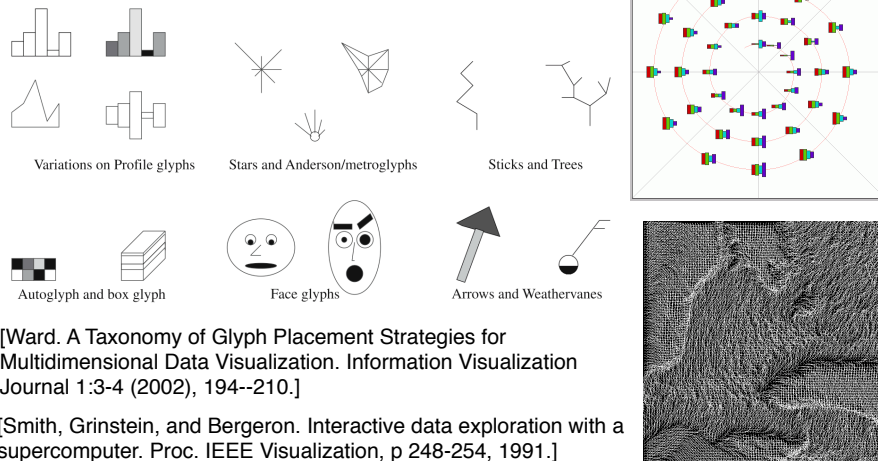
[Jones, Harrold, and Stasko. Visualization of Test Information to Assist Fault Localization. Proc. ICSE 2002, p 467-477.]



[Munzner. Interactive Visualization of Large Graphs and Networks. Stanford CS, 2000]

Composite Views: Glyphs

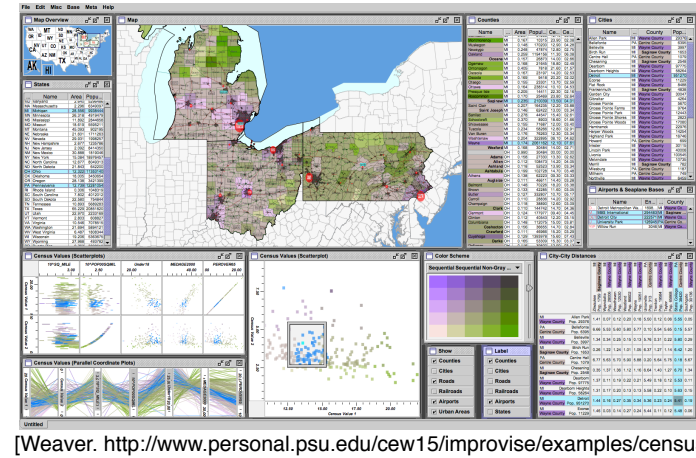
- internal structure where subregions have different visual channel encodings



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Adjacent: Multiple Views

- different visual encodings show different aspects of the data
- linked highlighting to show where contiguous in one view distributed within another



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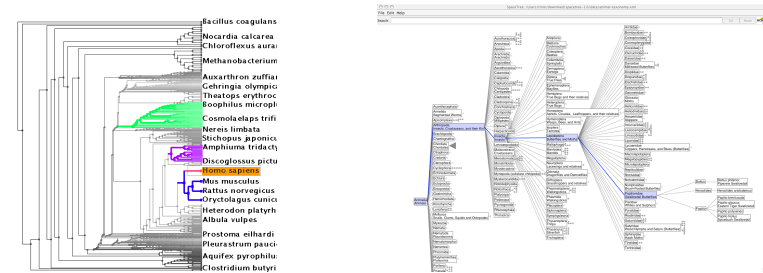
Adjacent Views

- overview and detail
 - same visual encoding, different resolutions
- small multiples
 - same visual encoding, different data

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Data Reduction

- overviews as aggregation
- focus+context
 - show details embedded within context
 - distortion: TreeJuxtaposer video
 - filtering: SpaceTree demo



[Munzner et al. TreeJuxtaposer: Scalable Tree Comparison using Focus+Context with Guaranteed Visibility. Proc SIGGRAPH 2003, p 453-462]

[Plaisant, Grosjean, and Bederson. SpaceTree: Supporting Exploration in Large Node Link Tree, Design Evolution and Empirical Evaluation. Proc. InfoVis 2002]

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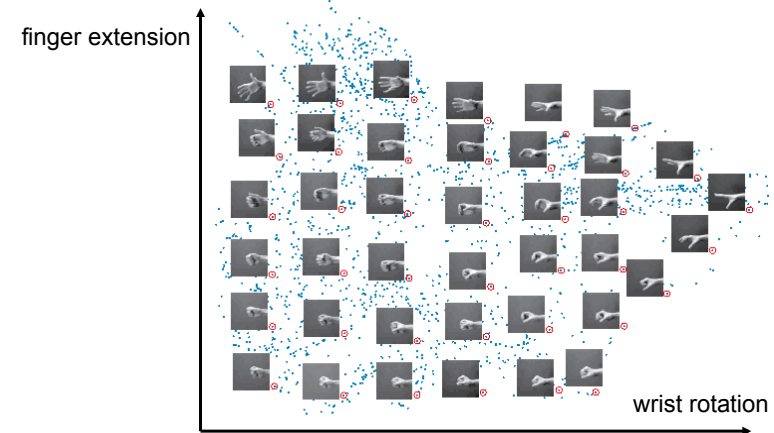
Dimensionality Reduction

- mapping from high-dimensional space into space of fewer dimensions
 - generate new synthetic dimensions
- why is lower-dimensional approximation useful?
 - assume **true/intrinsic** dimensionality of dataset is (much) lower than measured dimensionality!
 - only indirect measurement possible?
 - fisheries: want spawn rates. have water color, air temp, catch rates...
 - sparse data in verbose space?
 - documents: word occurrence vectors. 10K+ dimensions, want dozens of topic clusters

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DR Example: Image Database

- 4096 D (pixels) to 2D (hand gesture)
 - no semantics of new synthetic dimensions from alg.
 - assigned by humans after inspecting results



[A Global Geometric Framework for Nonlinear Dimensionality Reduction. Tenenbaum, de Silva and Langford. *Science* 290 (5500): 2319-2323, 30 2000, isomap.stanford.edu]

DR Technique: MDS

- multidimensional scaling
 - minimize differences between interpoint distances in high and low dimensions
- minimize objective function: stress

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

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



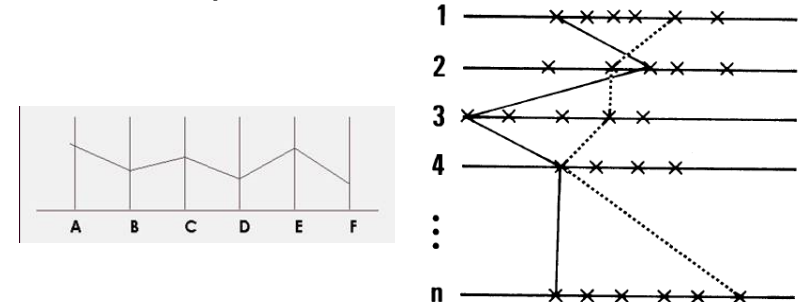
- Glimmer: MDS on the GPU

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

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Parallel Coordinates

- only two orthogonal axes in the plane
- instead, use parallel axes!

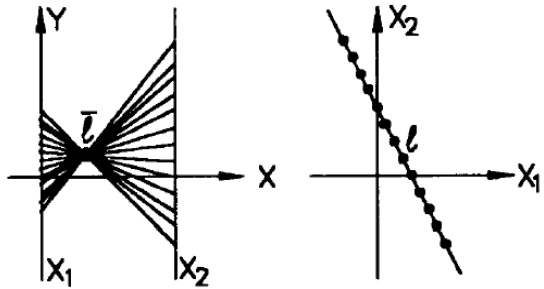


[Hyperdimensional Data Analysis Using Parallel Coordinates. Edward J. Wegman. *Journal of the American Statistical Association*, Vol. 85, No. 411. (Sep., 1990), pp. 664-675.]

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Parallel Coordinates

- point in Cartesian coords is line in par coords
- point in par coords is line in Cartesian n-space



[Inselberg and Dimdale. Parallel Coordinates: A Tool for Visualizing Multi-Dimensional Geometry. IEEE Visualization '90.]

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Par Coords: Correlation

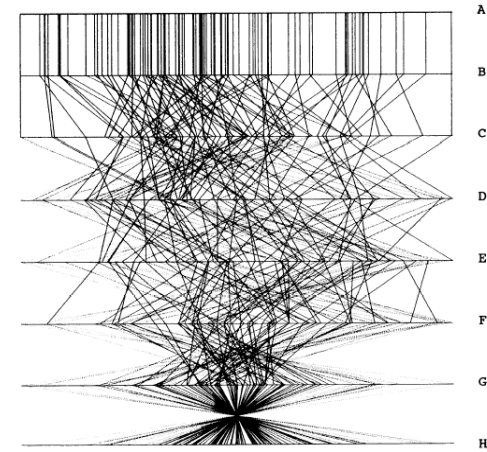
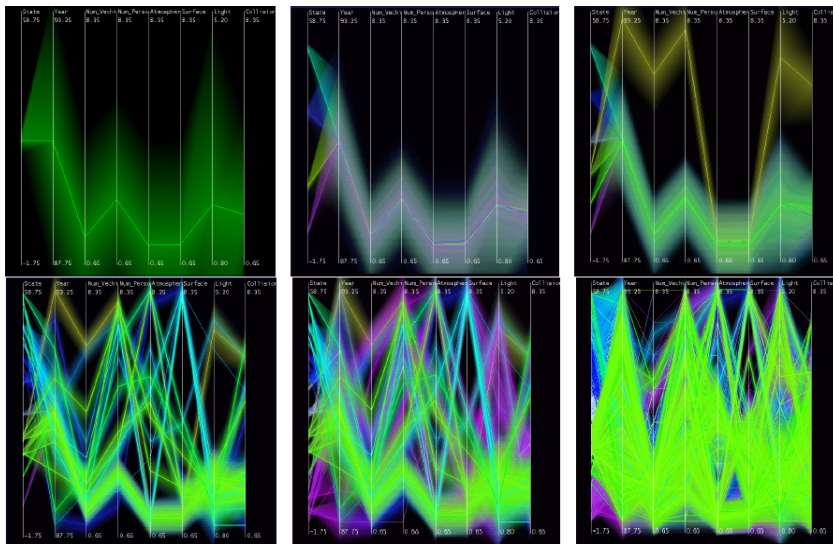


Figure 3. Parallel Coordinate Plot of Six-Dimensional Data Illustrating Correlations of $\rho = 1, .8, .2, 0, -.2, -.8, \text{ and } -1$.

[Hyperdimensional Data Analysis Using Parallel Coordinates. Wegman. Journal of the American Statistical Association, Vol. 85, No. 411. (Sep., 1990), pp. 664-675.]

Hierarchical Parallel Coords: LOD

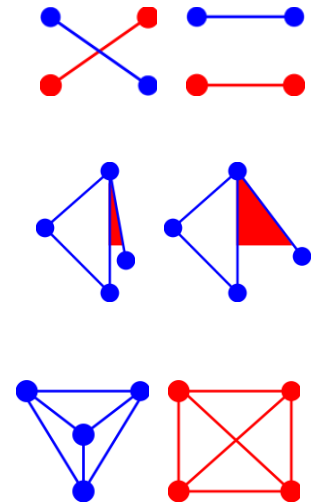


[Hierarchical Parallel Coordinates for Visualizing Large Multivariate Data Sets. Fua, Ward, and Rundensteiner. IEEE Visualization '99.]

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Node-Link Graph Layout

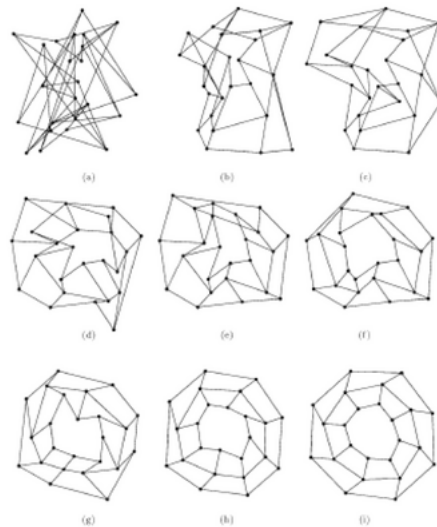
- minimize
 - crossings, area, bends/curves
- maximize
 - angular resolution, symmetry
- most criteria individually NP-hard
 - cannot just compute optimal answer
 - heuristics: try to find something reasonable
- criteria mutually incompatible



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Force-Directed Placement

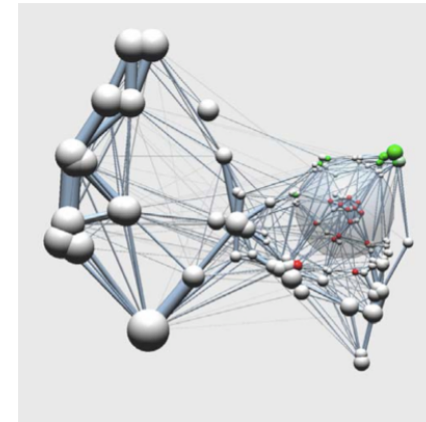
- nodes: repel like magnets
- edges: attract like springs
 - start from random positions, run to convergence
- very well studied area!
 - many people reinvent the wheel



[www.csse.monash.edu.au/~berndm/CSE460/Lectures/cse460-7.pdf] 37

Interactive Graph Exploration

- geometric and semantic fisheye

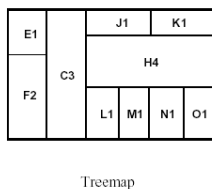
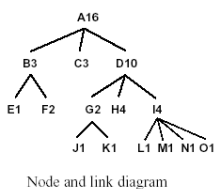


van Ham and van Wijk. Interactive Visualization of Small World Graphs. Proc. InfoVis 2005

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Treemaps

- containment rather than connection
 - emphasize node attributes, not topological structure



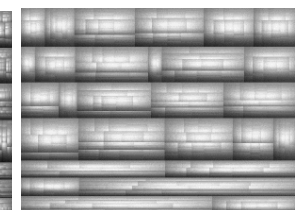
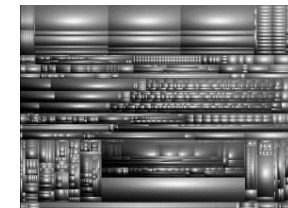
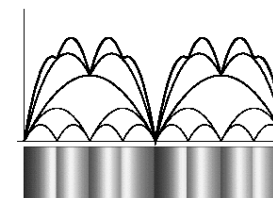
[van Wijk and van de Wetering. Cushion Treemaps. Proc InfoVis 1999]

[Fekete and Plaisant. Interactive Information Visualization of a Million Items. Proc InfoVis 2002.

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Cushion Treemaps

- show structure with shading
 - single parameter controls global vs local view



[van Wijk and van de Wetering. Cushion Treemaps. Proc InfoVis 1999]

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Now What?

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Beyond 314: Other Graphics Courses

- 424: Geometric Modelling
 - was offered this year
- 426: Computer Animation
 - will be offered next year

- 514: Image-Based Rendering - Heidrich
- 526: Algorithmic Animation - van de Panne
- 533A: Digital Geometry - Sheffer
- 533B: Animation Physics - Bridson
- 547: Information Visualization - Munzner

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Beyond UBC CS

- SIGGRAPH conference back in Vancouver August 2014!
 - 15K-20K people: incredible combination of research, entertainment, art
 - Electronic Theater, Exhibit, ETech, ...
 - pricey: but student rate, student volunteer program
- local SIGGRAPH chapter
 - talk series, SPARK FX festival, ...
 - <http://siggraph.ca>

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